APPLICATION OF ARTIFICIAL INTELLIGENCE / MACHINE LEARNING IN ENTITY (PERSON OF INTEREST) SCORING (RISK PROFILING) FOR NATIONAL SECURITY

by

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DECLARATION

I, the undersigned, **SALA MUTHUKRISHNAN**, declare that this thesis, titled “APPLICATION OF ARTIFICIAL INTELLIGENCE / MACHINE LEARNING IN ENTITY (PERSON OF INTEREST) SCORING (RISK PROFILING) FOR NATIONAL SECURITY,” is my original work, which I have done after registering for the degree of **DOCTOR OF BUSINESS ADMINISTRATION** at **SWISS SCHOOL OF BUSINESS AND MANAGEMENT GENEVA**. I have not submitted this thesis or any part of it to any other institution for any degree, diploma, or qualification. I have acknowledged all the sources of information and data that I have used in this thesis. I have also obtained the necessary permissions for any copyrighted material I have included in this thesis.

M.

Signature: Date: **19-09-2023**

Name: **SALA MUTHUKRISHNAN**

DEDICATION

This thesis is dedicated to the National Security sector, National Security analysts, and a team of security analytics who are grappling intensely with the challenges and opportunities of the evolving global landscape. They are the ones responsible for safeguarding, strategizing, and preserving the most crucial asset of any nation: its security and safety. They are the individuals applying data-driven insights and evidence-based tactics to enhance national defense, citizen protection, and overall security. They are the torchbearers making a significant difference in society and on the international stage with their dedication. They merit acknowledgment, gratitude, and backing for their relentless endeavors and accomplishments. This thesis is a modest contribution to their domain of expertise, championing data-driven strategies and operations across various sectors.

ACKNOWLEDGEMENT

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ABSTRACT

APPLICATION OF ARTIFICIAL INTELLIGENCE / MACHINE LEARNING IN ENTITY (PERSON OF INTEREST) SCORING (RISK PROFILING) FOR NATIONAL SECURITY

SALA MUTHUKRISHNAN
2023

Dissertation Chair: **Luka Lesko**

In recent years, the imperative to maintain national security has led to the evolution of risk assessment methodologies, particularly the risk scoring of entities, encompassing both individuals and organizations. This paper delves into the intricacies of "Entity Risk Scoring" within the context of national security, examining its historical roots, modern methodologies, data sources, and associated ethical concerns. With the advent of machine learning and artificial intelligence, contemporary risk scoring has transcended traditional models, promising more holistic, data-driven insights. The utilization of diversified data sources, such as Open Source Intelligence (OSINT) and financial records, has further enhanced the accuracy and comprehensiveness of entity profiles. This paper discusses the enhancement of risk scoring for persons of interest through the application of AI. While the adoption of AI-driven techniques promises increased accuracy, it's essential to apply them with a clear emphasis on transparency, accountability, and the protection of basic human rights. The overarching objective is to fortify national security without impinging on the core values inherent to democratic societies.]

Keywords:

Data-Driven Decision making; Artificial Intelligence; Machine Learning; Risk Scoring; Anomaly Detection for Risk Scoring assessment; Early signal identification; National Security.

CHAPTER I

INTRODUCTION

1.1 INTRODUCTION

The research topic is Application of Artificial Intelligence/Machine Learning in entity (Person of Interest) scoring, specifically for national security purposes. The key objectives of this research are as follows:

- Utilizing AI models to achieve more accurate risk assessment for persons of interest in comparison to manual scoring methods.
- Automating the process of improving anomaly detection rules in POI risk assessment by incorporating AI/ML models.
- Establishing a framework for applying AI/ML in entity risk scoring.
- Utilizing AI/ML models to identify weak signals through listening and to improve entity risk scoring.

1.2 RESEARCH PROBLEM

With 29 years of experience in analytics and seven years in the government sector's analytics, in my opinion, the application of AI is yet to be evolved and applied in the government sector. Limited progress is made in classifying entities as "risk entities" more accurately, other than manually maintaining a watch list across borders. A preliminary literature review shows that past studies are primarily focused on understanding and modeling a particular type of profile, such as financial, and economical risk profiles. Limited progress has been made on classifying "unknown" signals, according to their characteristics in a comprehensive manner. For example, identification of risk and increasing the risk scoring for entities; internal and external knowledge-based systems were used to automate risk score generation; What can further be improved in risk profiling is, early identification of weak signals and its related entities in the network, from structured and unstructured information across the sources; which can further be improved by unearthing “unknown unknowns”, and making it as repeated input to further improve the accuracy of prediction.

1.3 PURPOSE OF RESEARCH

As previously stated, this research program aims to achieve the following objectives across four distinct areas of inquiry:

- Employing AI models to enhance the accuracy of risk assessment for individuals of interest, in contrast to conventional manual scoring methods.
- Automating the refinement of anomaly detection rules in risk assessments for persons of interest by incorporating AI/ML models into the process.
- Developing a framework for implementing AI/ML in entity risk scoring.
- Utilizing AI/ML models to identify weak signals via active listening and subsequently improving entity risk scoring accuracy.

As part of achieving this goal, a few key activities to be included are:

- Evaluate the effectiveness of AI/ML-based risk scoring models in real-world scenarios, through case studies, to demonstrate their practical utility in national security contexts.

- Develop advanced AI/ML approach that improves the accuracy of risk scoring for POIs by effectively analyzing various data sources and identifying relevant patterns, trends, and relationships.
- Investigate the role of feature selection and engineering in enhancing the performance of AI/ML models for risk scoring, ensuring that the most relevant and informative attributes are considered in the analysis.
- Explore methods to combine different AI/ML models and techniques (e.g., ensemble learning) to improve the accuracy and robustness of risk-scoring predictions.
- Analyze the impact of incorporating temporal information and historical trends in risk-scoring models, allowing for more dynamic and adaptable assessments of POIs.
- Assess the importance of context awareness in AI/ML-based risk scoring, considering factors such as geographical location, social networks, and cultural aspects that may influence a POI's risk profile.
- Develop strategies for mitigating potential false positives and negatives in risk scoring, refining the AI/ML models to minimize errors and improve overall reliability.
- Examine the ethical, legal, and privacy considerations associated with AI/ML-based risk scoring for POIs, proposing guidelines and recommendations for responsible use in national security contexts.

1.4 SIGNIFICANCE OF THE STUDY

The main impetus for exploring this research area can be summarized as:

Real-world impact: Research in this area has the potential to make a significant impact on national security and public safety. By developing innovative AI/ML-based risk profiling solutions, you can contribute to protecting nations from potential threats and enhancing security worldwide.

Industry Experience: Artificial Intelligence and Machine learning is the emerging technology across all domains, in terms of interacting, reasoning, and learning like humans. With 25 years of experience in analytics and seven years in the government sector's analytics, in my opinion, the application of AI is yet to be evolved and applied in the government sector. Limited progress is made in classifying entities as "risk entities" more accurately, other than manually maintaining a watch list across borders. A preliminary literature review shows that past studies are primarily focused on understanding and modeling a particular type of profile, such as financial, and economical risk profiles. Limited progress has been made on classifying "unknown" signals, according to their characteristics in a comprehensive manner. For example, identification of risk and increasing the risk scoring for entities; internal and external knowledge-based systems were used to automate risk score generation; What can further be improved in risk profiling is, early identification of weak signals and its related entities in the network, from structured and unstructured information across the sources; which can further be improved by unearthing “unknown unknowns”, and making it as repeated input to further improve the accuracy of prediction.

High demand for expertise: Finally, as AI/ML technologies become increasingly important in national security, there is a growing demand for professionals with specialized knowledge in this area. A doctoral degree can equip you with the skills needed to become an expert in the field, making you highly sought after by employers.

Research in the application of AI/ML for entity risk profiling in national security is essential for several reasons:

Advancing technology: The field of AI/ML is rapidly evolving, with new techniques and approaches emerging regularly. Research is necessary to stay at the cutting edge of technological advancements, ensuring that national security agencies can leverage the most effective and efficient tools available.

Developing best practices and Framework of application: Research in this area can help establish best practices for AI/ML-based risk profiling, such as creating guidelines for data usage, maintaining transparency, addressing potential biases, and managing false positives and negatives.

Ensuring ethical use: AI/ML applications in national security can raise ethical concerns, including privacy, discrimination, and fairness. Research in this area can help identify potential issues and develop solutions that strike the right balance between security and individual rights.

Interdisciplinary collaboration: Research in this field often requires collaboration between experts in AI/ML, national security, ethics, law, and social sciences. This cross-disciplinary approach can lead to innovative solutions that consider multiple perspectives and address complex challenges.

Evaluating effectiveness: Rigorous research is necessary to evaluate the effectiveness of AI/ML-based risk profiling tools in detecting threats and improving national security. This helps ensure that resources are allocated efficiently and that AI/ML systems are not causing unintended consequences.

Customization and adaptability: AI/ML algorithms must be tailored to the specific needs of national security agencies and the unique challenges they face. Research can help develop customized solutions that address these specific requirements and adapt to changing threats.

Fostering public trust: By conducting research and sharing findings openly, national security agencies can foster public trust in the use of AI/ML for risk profiling. This transparency is crucial for maintaining support and ensuring the responsible use of technology.

Preparing for future challenges: As AI/ML continues to advance and becomes more widely adopted, new risks and challenges may arise. Research in this area can help anticipate these challenges and develop proactive strategies to address them.

1.5 RESEARCH GOALS, QUESTIONS, & OUTCOMES

More specifically, the following research questions need to be addressed:

Research Question 1: Can AI/ML models outperform traditional risk profiling methods in predicting potential national security threats associated with persons of interest?

Hypothesis 1: AI/ML models will significantly outperform traditional risk profiling methods in predicting potential national security threats associated with persons of interest.

Research Question 2: How can AI/ML models be incorporated to automate the process of improving anomaly detection rules in POI (Person of Interest) risk assessment for national security?

Hypotheses 2:

H1: Incorporating AI/ML models into the process of anomaly detection will significantly improve the accuracy and efficiency of POI risk assessment.

H0: There will be no significant improvement in the accuracy and efficiency of POI risk assessment when incorporating AI/ML models into the process of anomaly detection.

Research Question 3: Can AI/ML models effectively identify early or weak signals of potential national security threats associated with persons of interest?

Hypothesis 3: AI/ML models will be able to effectively identify early or weak signals of potential national security threats associated with persons of interest.

CHAPTER II

REVIEW OF LITERATURE

2.1 THEORY OF REASONED ACTION

In recent years, Artificial Intelligence (AI) has emerged as a powerful tool for risk management in various domains, including finance, healthcare, and security. One area where AI is increasingly being applied is entity risk scoring, which involves assessing the risk associated with individuals, organizations, or nations. Entity risk scoring is particularly important for national security, where accurate and timely risk assessments can help to prevent potential threats to national security. However, there are challenges and disagreements associated with the use of AI for entity risk scoring, including interpretability, bias, data quality, scalability, human oversight, and regulatory compliance.

Research on the application of AI in entity scoring for national security is highly relevant, especially considering the potential to identify early signals of potential threats. One area of interest is early signal identification based on social media data. By analyzing social media data using AI algorithms, it is possible to identify patterns and behaviors that may indicate a potential threat.

The use of AI in entity scoring can provide many benefits, such as improving accuracy, efficiency, and timeliness of risk assessments. Moreover, the use of AI can help to identify subtle patterns and signals that might not be detectable through traditional methods, thereby enhancing the effectiveness of national security measures. However, it is important to address concerns regarding privacy, transparency, and ethics when it comes to the use of AI (Govinsider).

Additionally, the use of AI in entity scoring can help to automate processes that are currently performed manually, reducing the risk of human error and enabling more effective use of resources.

Therefore, research on the application of AI in entity scoring for national security, including the identification of early signals based on social media data, is highly relevant and can have a significant impact on the safety and security of individuals and societies.

2.1.1 CATEGORIES OF RISK AGAINST NATIONAL SECURITY

Entity risk scoring plays a vital role in national security by assessing the potential risks posed by various entities. This paper provides a detailed review of different categories of entity risk scoring applicable to national security, including financial risk, counterterrorism risk, and more.

In the context of national security, entity risk scoring aims to evaluate the level of risk associated with different entities. Various categories of risk scoring are relevant to national security, encompassing different aspects such as financial risk, counterterrorism risk, proliferation risk, and more. This section outlines different categories of entity risk scoring applicable to national security:

Financial Risk Scoring

Financial risk scoring is an essential component of maintaining financial stability and national security. It encompasses a variety of processes aimed at detecting, evaluating, and mitigating the risk factors associated with different types of financial transactions and behaviors. These risk factors can range from individual creditworthiness to institutional insolvency risks, all the way to national concerns around money laundering and illicit financing activities.

Individual and Institutional Financial Risk

At an individual level, financial risk scoring is used to assess a person's creditworthiness, a process usually undertaken by credit bureaus or financial institutions when an individual applies for credit, such as a loan or a credit card (Turner et al., 2009). This assessment involves examining the individual's credit history, repayment behavior, current financial obligations, and a variety of other factors. The resulting credit score provides a snapshot of the individual's risk level, allowing lenders to make informed decisions.

On an institutional level, financial risk scoring can assess the likelihood of a company or a bank becoming insolvent. This process includes analysis of factors like capital adequacy, asset quality, management quality, earnings, and liquidity. This kind of risk scoring informs decisions about investment, lending, and regulatory oversight (Altman & Saunders, 1998).

At a national level, financial risk scoring involves monitoring and evaluating the risks of money laundering and illicit financing activities, which can threaten a country's economic stability and national security. Anti-money laundering (AML) and counter-terrorist financing (CTF) regulations mandate that financial institutions conduct due diligence on their customers and report suspicious activities. This practice involves assigning risk scores to customers based on factors like their transaction patterns, location, occupation, and political exposure (Van Der Does De Willebois et al., 2011).

Machine learning and AI have begun to play a vital role in enhancing the capabilities of these systems, helping to detect anomalous behavior and identify potential threats more effectively (Bholat et al., 2019).

2.1.4 Counter terrorism Risk Scoring

Counterterrorism risk scoring aims to evaluate the level of risk posed by individuals or organizations involved in terrorist activities, radicalization, or support for terrorist networks. Techniques employed in this category include social network analysis, sentiment analysis, and anomaly detection.

2.1.5 Proliferation Risk Scoring

Proliferation risk scoring focuses on entities involved in the proliferation of weapons of mass destruction (WMD), including nuclear, chemical, and biological weapons. It encompasses the identification of entities associated with the production, acquisition, transportation, or financing of WMD-related materials.

2.1.6 Cybersecurity Risk Scoring

Cybersecurity risk scoring assesses the potential risks posed by entities involved in cyber threats, such as hacking, data breaches, or information warfare. This category involves analyzing entities' digital footprint, network activity, and vulnerabilities to identify potential risks to national security.

2.1.7 Insider Threat Risk Scoring

Insider threat risk scoring is an essential aspect of modern risk management, particularly within organizations that handle sensitive information or control critical infrastructure. Unlike external threats that typically aim to breach perimeter defenses, insider threats come from within an organization—individuals who have been granted authorized access to sensitive information or systems. These individuals could be employees, contractors, or any other stakeholders who have privileged access (Greitzer & Frincke, 2010).

Behavioral patterns are a crucial component of insider threat risk scoring. The primary purpose of studying these patterns is to identify any deviation from normal behavior that might indicate a potential threat. This could include changes in work habits, erratic behavior, or violations of company policies.

Abnormal behavior in the digital realm might include unusual access times, frequent access to sensitive data, or an increase in data transfers. In the physical world, this might involve employees regularly staying late at the office, showing signs of stress or discontent, or exhibiting other changes in behavior. These changes, especially when sudden or significant, can often indicate a potential insider threat (Bishop, Engle, Peisert, Whalen, & Gates, 2009).

Access logs provide a detailed record of user activities within an information system. By analyzing these logs, organizations can track who accessed what information, when, and from where. These logs can also show if any attempts were made to access restricted areas or whether any unauthorized activities took place.

Anomaly detection is a key technique used in the analysis of access logs. It identifies unusual or unexpected patterns that deviate significantly from the norm. Anomalies can be benign (such as a system malfunction), but they can also indicate a potential insider threat. Machine learning techniques have proved useful in anomaly detection, helping to identify complex patterns and subtle deviations that might otherwise go unnoticed (Chandola, Banerjee, & Kumar, 2009).

Risk scoring is just one component of a comprehensive approach to mitigating insider threats. Preventive measures can include robust access control policies, ongoing employee training, and promoting a positive work culture. Organizations also need to have incident response plans in place for when an insider threat is identified. These plans should focus not only on addressing the immediate threat but also on understanding the root cause to prevent similar occurrences in the future (Cappelli et al., 2012).

2.1.2 IMPORTANCE OF TIME AND HISTORY

Risk scoring for Persons of Interest (POIs) is an essential process in various fields, such as law enforcement, national security, and financial institutions. The role of time and history in this process is crucial, as it can provide insights into a person's behavior, tendencies, past interactions, and potential risks.

Historical data is significant because it helps establish patterns in an individual's behavior. For example, in finance, an individual with a history of financial malpractice is considered a high risk (Bierstaker, Brody, & Pacini, 2006). Similarly, in law enforcement, a person with a history of criminal activity is typically treated as a person of interest (Bennell, Jones, Taylor, & Snook, 2007).

The time factor is pivotal in risk scoring as it can help determine the recency of the behavior or activity of interest. This information is essential because the recency of specific behavior can imply the likelihood of its recurrence. For instance, a person with a recent criminal record may pose more of a risk than someone with a historical yet non-recent criminal record (Bonta, Law, & Hanson, 1998).

In addition to providing context and understanding recency, time also facilitates longitudinal studies. These studies enable risk assessors to monitor changes in an individual's behavior over time, thereby allowing for a more comprehensive understanding of their risk levels (Moffitt, Caspi, Harrington, & Milne, 2002).

A key area of focus in national security is the threat posed by terrorists. Historical data and temporal factors play critical roles in assessing the risks associated with individuals linked to terrorist activities. Terrorists with a history of violent activities or those involved in recent incidents are typically rated as high-risk (Sandler, Arce, & Enders, 2008).

History and time also matter in evaluating the risk posed by potential insiders. A person with a history of disloyal actions or suspicious behavior can be a significant risk. The recency of such actions or behaviors can further elevate this risk (Shaw, Ruby, & Post, 1998).

In border security, persons of interest with a history of illegal cross-border activities or those involved in recent incidents can be considered high-risk (Andreas, 2003).

In the context of human trafficking, individuals or groups with a history of involvement in such activities are seen as high-risk. If they have been active recently, their risk rating can increase significantly (Cho, Dreher, & Neumayer, 2014).

By assessing historical and temporal data, national security agencies can predict the potential risks that various individuals or groups pose, allowing for more proactive and effective measures to counter these threats. The implications of time and history in risk scoring are, therefore, substantial and highly relevant.

2.2 AI/ML MODEL IN RISK SCORING

2.2.1 Logistic Regression

Logistic regression is a statistical model used for binary classification, making it suitable for risk scoring tasks. It estimates the probability of an event occurring based on input features. Logistic regression assumes a linear relationship between the features and the log-odds of the target variable. It is interpretable, as the coefficients associated with each feature can provide insights into their impact on the risk score. However, logistic regression may struggle to capture complex relationships and interactions in the data.

Logistic regression is a robust statistical tool with numerous advantages. It is especially prized for its interpretability, allowing for the clear identification of pivotal risk factors (Hosmer Jr et al., 2013). Additionally, the method is versatile, capable of handling both categorical and numerical features with efficacy (Hosmer Jr et al., 2013). One of its most valuable characteristics in risk assessment scenarios is its ability to provide probabilistic risk scores, which can be instrumental in ranking and prioritizing risks (Hosmer Jr et al., 2013).

Problem Definition:

National Security Risk Scoring: The objective is to develop a risk scoring model that assigns a risk score to individuals based on their characteristics, activities, or behaviors, which can help identify potential threats or risks to national security.

Data Collection and Preparation:

- **Relevant Features:** Gather data on individuals, including demographic information, travel history, communication patterns, affiliations, financial transactions, and any other relevant indicators that may contribute to the risk assessment.
- **Labeling:** Assign a binary label to each individual, indicating whether they are a potential risk to national security based on known information or historical incidents.
- **Model Representation:** Logistic regression models the probability of an individual being a risk (positive class) based on a set of input features. It uses the logistic function (sigmoid) to map the output to a probability value between 0 and 1.
- **Feature Encoding:** Convert categorical features into numerical representations using techniques like one-hot encoding or ordinal encoding, making them suitable for logistic regression.

- **Model Training:** Split the labeled data into training and validation sets. Fit the logistic regression model to the training data, optimizing the parameters through the maximum likelihood estimation or gradient descent algorithms.
- **Model Evaluation:** Assess the performance of the logistic regression model on the validation set, using metrics such as accuracy, precision, recall, and F1 score to evaluate the model's ability to correctly identify potential risks.

Interpretation and Explainability:

- **Coefficient Analysis:** Analyze the coefficients of the logistic regression model to understand the impact of each feature on the risk score. Positive coefficients indicate features that increase the risk score, while negative coefficients indicate features that decrease the risk score.
- **Feature Importance:** Rank the features based on their coefficient magnitudes to identify the most influential factors contributing to the risk score.
- **Threshold Determination:** Set a threshold on the predicted risk probabilities to classify individuals into risk or non-risk categories, based on the desired balance between false positives and false negatives.
- **Alert Generation:** Define thresholds or rules that trigger alerts when the risk scores exceed certain thresholds or exhibit significant changes, enabling timely intervention or investigation.

Pros and Cons:

- Logistic regression is interpretable, allowing for the identification of key risk factors.
- It handles both categorical and numerical features effectively.
- Logistic regression can provide probabilistic risk scores, allowing for ranking and prioritization of risks.
- Logistic regression assumes a linear relationship between features and risk scores, limiting its ability to capture complex nonlinear relationships.
- It may struggle with high-dimensional data or a large number of features.
- The accuracy of logistic regression heavily relies on the quality and relevance of the selected features and the availability of labeled data for training.
- It is important to note that the success of a logistic regression model for risk scoring in national security depends on the quality and representativeness of the data, the relevance of the chosen features, and the expertise and domain knowledge of the analysts involved in feature selection and model interpretation.

2.2.2 DECISION TREES

Decision trees are a non-parametric method employed extensively for classification and regression tasks, encompassing risk scoring applications (Breiman et al., 1984). The core operation of these trees is to partition the feature space based on an ordered sequence of if-else conditions, leading to prediction outcomes. A salient strength of decision trees is their transparency and ease of interpretation, as the entire tree structure essentially mirrors a compendium of rules (Breiman et al., 1984). However, these trees are not devoid of challenges. A common pitfall with decision trees is their proclivity to overfit the training data, which can culminate in subpar generalization to new, unseen data (Breiman et al., 1984). To counteract this, several techniques, such as pruning and the instatement of depth limits, have been recommended (Breiman et al., 1984).

Problem Definition:

National Security Risk Scoring: The goal is to develop a risk scoring model that assigns a risk score to individuals based on their attributes, behaviors, or activities, aiding in the identification of potential threats to national security.

Data Collection and Preparation:

- **Relevant Features:** Collect data on individuals, including demographic information, travel history, communication patterns, affiliations, financial transactions, and any other relevant indicators that may contribute to the risk assessment.
- **Labeling:** Assign a binary label to each individual indicating whether they pose a potential risk to national security based on known information or historical incidents.

- **Model Representation:** A decision tree is a hierarchical structure that splits the data based on a series of decisions and feature conditions. Each internal node represents a decision point, and each leaf node represents a risk score or class label.
- **Feature Selection:** Identify the most relevant features for risk scoring based on domain knowledge and data analysis. Consider features that provide discriminatory power in distinguishing between high-risk and low-risk individuals.
- **Model Training:** Split the labeled data into training and validation sets. Fit the decision tree model to the training data, where the tree structure and decision rules are learned based on the chosen features and the labeled data.
- **Model Evaluation:** Assess the performance of the decision tree model on the validation set, using metrics such as accuracy, precision, recall, and F1 score to evaluate its ability to correctly identify potential risks.

Interpretation and Explainability:

- **Rule Extraction:** Decision trees provide a set of rules that can be extracted to understand how the risk scores are determined. Each path from the root to a leaf represents a set of conditions that lead to a specific risk score.
- **Feature Importance:** Analyze the structure of the decision tree to determine the most influential features for risk scoring. Features appearing high up in the tree or closer to the root have a greater impact on the final risk score.

- **Visualization:** Visualize the decision tree to gain a better understanding of the decision process and to communicate the risk scoring logic to stakeholders.
- **Alert Generation:** Define thresholds or rules based on the decision tree structure that trigger alerts when risk scores exceed certain thresholds or exhibit significant changes, facilitating timely intervention or investigation.

Pros and Cons:

- Decision trees are interpretable and provide transparent rules for risk scoring.
- They can handle both categorical and numerical features effectively.
- Decision trees can capture complex relationships and interactions between features.
- Decision trees may be prone to overfitting, resulting in poor generalization to unseen data.
- They can be sensitive to small variations in the training data, leading to different tree structures and risk scores.
- Decision trees may struggle with imbalanced datasets or rare events, where risks are heavily skewed towards one class.
- It's worth noting that decision trees can be improved and optimized through techniques like pruning, ensemble methods (e.g., random forests), and hyper-parameter tuning to enhance their accuracy and robustness in risk scoring for national security. The choice of decision tree algorithm and specific parameter settings should be carefully evaluated based on the nature

2.2.3 RANDOM FOREST

Random forest is an ensemble technique that synergistically amalgamates multiple decision trees to enhance predictive accuracy (Breiman, 2001). It spawns numerous trees by leveraging bootstrap sampling coupled with feature randomization (Breiman, 2001). A key advantage of the random forest is its adeptness at curbing overfitting, achieved by averaging the forecasts of the individual constituent trees (Breiman, 2001). It possesses the prowess to efficiently manage high-dimensional datasets and unravel intricate relationships and interactions embedded within the data (Breiman, 2001). Although random forest models sacrifice some interpretability compared to singular decision trees, they typically compensate with superior predictive precision (Breiman, 2001)

Problem Definition:

National Security Risk Scoring: The objective is to develop a risk scoring model that assigns a risk score to individuals based on their attributes, behaviors, or activities, aiding in the identification of potential threats to national security.

Data Collection and Preparation:

- **Relevant Features:** Gather data on individuals, including demographic information, travel history, communication patterns, affiliations, financial transactions, and any other relevant indicators that may contribute to the risk assessment.

- **Labeling:** Assign a binary label to each individual indicating whether they pose a potential risk to national security based on known information or historical incidents.
- **Model Representation:** Random Forest is an ensemble of decision trees. Each tree is trained on a randomly sampled subset of the data, and the final risk score is determined by aggregating the predictions of all trees.
- **Feature Selection:** Randomly select a subset of features at each split in the decision tree, ensuring diversity and reducing the risk of overfitting.
- **Model Training:** Split the labeled data into training and validation sets. Fit multiple decision trees to different subsets of the training data, where each tree is trained independently using different random samples.
- **Model Evaluation:** Assess the performance of the Random Forest model on the validation set, using metrics such as accuracy, precision, recall, and F1 score to evaluate its ability to correctly identify potential risks.

Interpretation and Explainability:

- **Feature Importance:** Random Forest provides a measure of feature importance based on the average reduction in impurity (e.g., Gini index) achieved by each feature across all trees. Features with higher importance contribute more to the risk scoring process.
- **Visualization:** Visualize the collective decision-making process of the Random Forest by examining the consensus and consistency of decisions

made by different trees. This can provide insights into the risk factors considered by the model.

- **Alert Generation:** Define thresholds or rules based on the aggregated risk scores from the Random Forest model that trigger alerts when risk scores exceed certain thresholds or exhibit significant changes, facilitating timely intervention or investigation.

Pros and Cons:

- Random Forest provides high accuracy and robustness by aggregating predictions from multiple decision trees.
- It handles both categorical and numerical features effectively and can capture complex relationships and interactions.
- Random Forest offers a measure of feature importance, aiding in the identification of key risk factors.
- Random Forest models are less interpretable compared to individual decision trees, as the overall decision-making process is a combination of multiple trees.
- The training process and prediction can be computationally intensive, especially with large datasets or a large number of trees.
- Random Forest may struggle with imbalanced datasets or rare events, where risks are heavily skewed towards one class, requiring additional techniques for handling class imbalance.

- When applying Random Forest for risk scoring in national security, it is crucial to carefully select the number of trees, tune hyperparameters, and handle imbalanced data appropriately to optimize the model's performance and achieve accurate risk scores.

2.2.4 SUPPORT VECTOR MACHINE

SVM, or Support Vector Machine, stands as a potent supervised learning algorithm employed predominantly for classification and regression challenges, inclusive of risk scoring tasks (Vapnik, 1995). Its principal mechanism is to discern an optimal hyperplane that adeptly segregates classes by maximizing the separating margin (Vapnik, 1995). A hallmark of SVM is its versatility; it exhibits efficacy in addressing both linear and non-linear conundrums, a prowess attributed to the incorporation of kernel functions (Vapnik, 1995). Furthermore, SVM is proficient in handling high-dimensional data, demonstrating a robust resistance to overfitting (Vapnik, 1995). However, it's pertinent to note that while SVM excels in delineating the most efficient decision boundary, it does not inherently shed light on the importance or significance of individual features, thereby limiting its interpretability (Vapnik, 1995).

Problem Definition:

National Security Risk Scoring: The goal is to develop a risk scoring model that assigns a risk score to individuals based on their attributes, behaviors, or activities, aiding in the identification of potential threats to national security.

Data Collection and Preparation:

- **Relevant Features:** Gather data on individuals, including demographic information, travel history, communication patterns, affiliations, financial transactions, and any other relevant indicators that may contribute to the risk assessment.
- **Labeling:** Assign a binary label to each individual indicating whether they pose a potential risk to national security based on known information or historical incidents.
- **Model Representation:** SVM aims to find an optimal hyperplane that separates the data points of different classes with the maximum margin. The hyperplane is determined by a subset of support vectors, which are the data points closest to the decision boundary.
- **Feature Scaling:** Normalize or standardize the features to ensure they are on a similar scale, as SVM is sensitive to the scale of the input features.
- **Model Training:** Split the labeled data into training and validation sets. Train the SVM model by finding the hyperplane that maximizes the margin between the classes while minimizing classification errors.

- **Kernel Functions:** SVM can utilize kernel functions to transform the data into a higher-dimensional space, enabling the creation of nonlinear decision boundaries. Common kernel functions include linear, polynomial, radial basis function (RBF), and sigmoid kernels.
- **Model Evaluation:** Assess the performance of the SVM model on the validation set, using metrics such as accuracy, precision, recall, and F1 score to evaluate its ability to correctly identify potential risks.

Interpretation and Explainability:

- **Support Vectors:** Identify the support vectors, which are the data points closest to the decision boundary. These support vectors play a crucial role in defining the risk scores and can provide insights into the most influential individuals.
- **Margin Analysis:** Analyze the margin around the decision boundary to understand the level of confidence in the risk scores assigned by the SVM model. A larger margin indicates a more confident prediction.
- **Alert Generation:** Define thresholds based on the distance from the decision boundary or confidence measures to trigger alerts when risk scores exceed certain thresholds or exhibit significant changes, facilitating timely intervention or investigation.

Pros and Cons:

- SVM can effectively handle high-dimensional data and is suitable for scenarios with a large number of features.
- It can capture complex decision boundaries and is capable of modeling nonlinear relationships through the use of kernel functions.
- SVM is less affected by local optima and can generalize well to unseen data when properly trained.
- SVM can be computationally expensive, especially with large datasets or complex kernel functions.
- Interpretability of the SVM model can be challenging, particularly when using nonlinear kernels, making it difficult to explain the risk scores in terms of specific features.
- SVM may struggle with imbalanced datasets, requiring additional techniques such as class weighting or resampling to address class imbalance effectively.

2.2.5 Neural Network

Neural networks, especially those tailored for deep learning, have emerged as compelling candidates for tasks like risk scoring, largely credited to their prowess in encapsulating intricate data relationships (Goodfellow et al., 2016). At their core, neural networks are constituted by a cascade of interconnected layers of nodes, colloquially termed as neurons, which are adept at learning layered representations of data, often manifesting as hierarchies (Goodfellow et al., 2016). Their inherent flexibility enables them to effectively handle a gamut of data types, be it numerical or categorical, and one of their crowning features is their ability to autonomously discern and learn salient features from input data (Goodfellow et al., 2016). However, they demand voluminous datasets and substantial computational firepower for their training regimen. A persistent challenge in the realm of neural networks is their interpretability, as they frequently earn the epithet of 'black box' models owing to the opacity in understanding their decision-making rationale (Goodfellow et al., 2016)

Problem Definition:

National Security Risk Scoring: The objective is to develop a risk scoring model that assigns a risk score to individuals based on their attributes, behaviors, or activities, aiding in the identification of potential threats to national security.

Data Collection and Preparation:

- **Relevant Features:** Gather data on individuals, including demographic information, travel history, communication patterns, affiliations, financial transactions, and any other relevant indicators that may contribute to the risk assessment.
- **Labeling:** Assign a binary label to each individual indicating whether they pose a potential risk to national security based on known information or historical incidents.
- **Model Architecture:** Design a neural network model that consists of multiple layers of interconnected artificial neurons. Deep learning models, such as feedforward neural networks or recurrent neural networks (RNNs), are commonly used for risk scoring.

- **Input Representation:** Encode the input features appropriately, considering one-hot encoding, normalization, or other techniques to ensure compatibility with the neural network model.
- **Hidden Layers and Activation Functions:** Determine the number of hidden layers and the number of neurons in each layer. Choose suitable activation functions, such as ReLU (Rectified Linear Unit), sigmoid, or tanh, to introduce non-linearity and capture complex relationships in the data.
- **Training:** Split the labeled data into training and validation sets. Train the neural network model using an optimization algorithm, such as stochastic gradient descent (SGD), backpropagation, or more advanced methods like Adam or RMSprop, to minimize the prediction error.
- **Model Evaluation:** Evaluate the performance of the neural network model on the validation set, using metrics such as accuracy, precision, recall, F1 score, or area under the receiver operating characteristic (ROC) curve to assess its ability to correctly identify potential risks.

Interpretation and Explainability:

- **Feature Importance:** Analyze the learned weights or feature importance measures to understand which features have the most significant influence on risk scoring. Techniques like gradient-based feature attribution or saliency maps can provide insights into the relevance of individual features.

- **Visualization:** Visualize the learned representations within the neural network, such as intermediate layer activations or attention weights in RNNs, to gain a better understanding of the decision-making process and to provide explanations for risk scores.
- **Alert Generation:** Define thresholds or rules based on risk scores or prediction probabilities generated by the neural network model to trigger alerts when risks exceed certain thresholds or exhibit significant changes, facilitating timely intervention or investigation.

Pros and Cons:

- Neural networks can capture complex patterns and relationships in data, making them effective for risk scoring in national security.
- They can handle both structured and unstructured data, allowing for the incorporation of various types of information, such as text or image data.
- Neural networks have the potential for high accuracy and can generalize well to unseen data when properly trained.
- Neural networks can be computationally expensive and require significant computational resources, especially for deep learning models with many

2.2.6 Gradient Boosting Methods

Gradient boosting methods are ensemble learning techniques that sequentially train weak models. They iteratively build models to correct the mistakes of previous models. Gradient boosting methods, like XGBoost and LightGBM, are highly effective for risk scoring tasks. They handle complex relationships and feature interactions well. Similar to random forests, gradient boosting models can be less interpretable but provide high predictive performance. Remember, the choice of algorithm for risk scoring depends on various factors such as the nature of the data, interpretability requirements, computational resources, and the desired trade-off between accuracy and explainability. It's important to evaluate and compare these algorithms on relevant metrics and consider their strengths and limitations in the specific context of risk profiling.

Problem Definition:

National Security Risk Scoring: The objective is to develop a risk scoring model that assigns a risk score to individuals based on their attributes, behaviors, or activities, aiding in the identification of potential threats to national security.

Data Collection and Preparation:

- **Relevant Features:** Gather data on individuals, including demographic information, travel history, communication patterns, affiliations, financial transactions, and any other relevant indicators that may contribute to the risk assessment.

- **Labeling:** Assign a binary label to each individual indicating whether they pose a potential risk to national security based on known information or historical incidents.
- **Model Architecture:** Gradient Boosting methods create an ensemble of weak prediction models, typically decision trees, to create a strong predictive model.
- **Base Learners:** In each iteration, a weak prediction model (e.g., decision tree) is added to the ensemble, which tries to correct the mistakes made by the previous models.
- **Gradient Descent:** The models are trained using gradient descent optimization, where subsequent models are fitted to the residuals (errors) of the previous models.
- **Weighted Voting:** The final prediction is obtained by aggregating the predictions from all the models in the ensemble, with each model's prediction weighted based on its performance and contribution.

Model Training and Optimization:

- **Hyper-parameter Tuning:** Tune the hyper-parameters specific to the gradient boosting algorithm, such as the learning rate, the number of base learners (trees), maximum tree depth, minimum samples per leaf, and subsampling rate, to optimize the model's performance.

- **Regularization:** Apply regularization techniques, such as shrinkage (learning rate) and tree complexity constraints, to prevent overfitting and improve the generalization ability of the model.
- **Early Stopping:** Utilize early stopping criteria, based on a validation set, to halt the training process when the model's performance no longer improves, avoiding overfitting and saving computation time.

Interpretation and Explainability:

- **Feature Importance:** Analyze the feature importance derived from the gradient boosting model to understand which features contribute most to risk scoring. Importance measures like gain, coverage, or permutation importance can provide insights into the relevance of individual features.
- **Partial Dependence Plots:** Generate partial dependence plots to visualize the relationship between individual features and the risk scores, holding other features constant. This can help explain how specific attributes impact risk assessment.
- **Alert Generation:** Define thresholds based on risk scores or prediction probabilities generated by the gradient boosting model to trigger alerts when risks exceed certain thresholds or exhibit significant changes. This facilitates timely intervention or investigation.

Pros and Cons:

- Gradient Boosting methods have high predictive accuracy and can capture complex interactions between features, making them effective for risk scoring in national security.
- They handle a mixture of feature types (categorical and numerical) and can automatically handle missing data.
- Gradient Boosting methods can be computationally expensive and require substantial computational resources, especially when dealing with large datasets and complex models.
- They may be more prone to overfitting compared to other algorithms, necessitating careful regularization and hyperparameter tuning.
- The interpretability of the ensemble model can be challenging, as the final prediction is a combination of multiple weak models.

Handling Imbalanced Data:

Class Imbalance: If the risk scoring dataset is imbalanced, consider using techniques such as class weights, oversampling the minority class, or undersampling the majority class to address the imbalance and prevent the model from being biased towards the majority class.

Model Evaluation and Validation:

- Cross-Validation: Utilize techniques like k-fold cross-validation to assess the generalization performance of the gradient boosting model and ensure its reliability on unseen data.

- Performance Metrics: Evaluate the risk scoring accuracy using metrics such as accuracy, precision, recall, F1 score, or area under the receiver operating characteristic (ROC) curve. Select the metrics based on the specific risk scoring objectives and considerations.

2.2.7 Naive Bayes

Naive Bayes emerges as a probabilistic classifier, predicated on the assumption of independence among features (Mitchell, 1997). At its heart, it employs Bayes' theorem to compute the probability of a given class based on feature values (Mitchell, 1997). It stands out for its computational efficiency, demonstrating aptitude in managing high-dimensional datasets. Beyond its acclaimed application in text classification, Naive Bayes can be harnessed for risk scoring as well (Mitchell, 1997). Nevertheless, a caveat with Naive Bayes is its foundational assumption about feature independence, which, in many real-world scenarios, might be overly optimistic or might not hold true (Mitchell, 1997).

Problem Definition:

National Security Risk Scoring: The objective is to develop a risk scoring model that assigns a risk score to individuals based on their attributes, behaviors, or activities, aiding in the identification of potential threats to national security.

Data Collection and Preparation:

- **Relevant Features:** Gather data on individuals, including demographic information, travel history, communication patterns, affiliations, financial transactions, and any other relevant indicators that may contribute to the risk assessment.
- **Labeling:** Assign a binary label to each individual indicating whether they pose a potential risk to national security based on known information or historical incidents.
- **Probability and Bayes' Theorem:** Naive Bayes calculates the probability of an individual belonging to a particular risk category based on the features observed. It uses Bayes' theorem to update the prior probability with new evidence.
- **Independence Assumption:** Naive Bayes assumes independence among features, meaning that each feature contributes to the risk score independently of others, given the class variable.
- **Likelihood Estimation:** Naive Bayes estimates the likelihood of observing specific feature values given each risk category based on the training data.
- **Prior Probability:** Naive Bayes calculates the prior probability of each risk category based on the training data.
- **Posterior Probability:** Using Bayes' theorem, Naive Bayes computes the posterior probability of each risk category given the observed features.

Model Training and Optimization:

- **Feature Encoding:** Encode categorical features using techniques such as one-hot encoding or label encoding to represent them in a numerical format suitable for Naive Bayes.
- **Laplace Smoothing:** To handle unseen feature values in the test set, apply Laplace smoothing (additive smoothing) to avoid zero probabilities and ensure robustness in the estimation process.
- **Model Selection:** Choose the appropriate variant of Naive Bayes, such as Gaussian Naive Bayes for continuous features or Multinomial Naive Bayes for discrete features, depending on the nature of the data.

Interpretation and Explainability:

- **Feature Importance:** Although Naive Bayes does not directly provide feature importance measures, it can still offer insights into which features contribute most to risk scoring. Higher conditional probabilities for specific feature values suggest stronger predictive power for those features.
- **Alert Generation:** Define thresholds based on risk scores or probabilities generated by Naive Bayes to trigger alerts when risks exceed certain thresholds or exhibit significant changes. This facilitates timely intervention or investigation.

Pros and Cons:

- Naive Bayes is computationally efficient and can handle large-scale datasets, making it suitable for risk scoring in national security.

- It performs well with high-dimensional data and is robust to irrelevant or redundant features.
- Naive Bayes is easy to implement, requires minimal tuning of hyperparameters, and can provide quick initial results.
- The independence assumption of Naive Bay

2.2.8 K-Nearest Neighbors

KNN, or the K-Nearest Neighbors algorithm, is a non-parametric approach that assigns classifications to data points contingent on their vicinity to previously labeled instances (Duda et al., 2000). In essence, it designates a new data point to the class which prevails as the most common among its 'k' closest neighbors (Duda et al., 2000). A virtue of KNN is its straightforward implementation, paired with its capability to manage multi-class classification scenarios (Duda et al., 2000). For risk scoring endeavors, KNN is particularly adept when the decision boundary is nonlinear or in scenarios where deciphering local patterns holds paramount importance (Duda et al., 2000). However, a potential bottleneck with KNN is its computational intensity during the inference stage, a challenge that exacerbates with the growth in dataset sizes (Duda et al., 2000).

Problem Definition:

National Security Risk Scoring: The objective is to develop a risk scoring model that assigns a risk score to individuals based on their attributes, behaviors, or activities, aiding in the identification of potential threats to national security.

Data Collection and Preparation:

- **Relevant Features:** Gather data on individuals, including demographic information, travel history, communication patterns, affiliations, financial transactions, and any other relevant indicators that may contribute to the risk assessment.
- **Labeling:** Assign a binary label to each individual indicating whether they pose a potential risk to national security based on known information or historical incidents.
- **Data Representation:** Represent the individuals and their features as data points in a multi-dimensional feature space.
- **Nearest Neighbor Search:** KNN finds the k nearest neighbors to a given individual based on a distance metric, such as Euclidean distance or cosine similarity.
- **Majority Voting:** The risk score for the individual is determined by the majority label of its k nearest neighbors.
- **Weighted Voting:** Optionally, assign weights to the neighbors based on their proximity to the individual, giving more influence to closer neighbors in the voting process.

Model Training and Optimization:

- **Feature Scaling:** Normalize or standardize the features to ensure that they are on a similar scale and contribute equally to the distance calculations.
- **Choosing the Value of K:** Determine the appropriate value of k, the number of nearest neighbors, through techniques like cross-validation or grid search to optimize the model's performance.
- **Distance Metric Selection:** Select an appropriate distance metric based on the nature of the features and the problem domain. Euclidean distance is commonly used for numerical features, while other metrics like cosine similarity can handle text or categorical features.

Interpretation and Explainability:

- **Nearest Neighbor Analysis:** Examine the risk profiles and attributes of the k nearest neighbors to gain insights into how specific features or behaviors influence risk scoring.
- **Local Explanations:** KNN allows for local interpretability, as the risk score is based on the neighboring data points. It can provide explanations by identifying which features or attributes of the neighbors contribute to the risk score.
- **Alert Generation:** Define thresholds based on risk scores or the number of neighbors belonging to a particular risk category to trigger alerts when risks

exceed certain thresholds or exhibit significant changes. This facilitates timely intervention or investigation.

Pros and Cons:

- KNN is easy to implement, as it does not require model training and can quickly make predictions based on stored data.
- It can capture complex decision boundaries and non-linear relationships between features, making it suitable for risk scoring in national security.
- KNN is robust to outliers and can handle both numerical and categorical features.
- KNN can be computationally expensive, especially when dealing with large datasets or high-dimensional feature spaces, as it requires calculating distances between data points.
- The performance of KNN can be sensitive to the choice of the distance metric and the value.

2.2.9 Significance of LLM models with OSINT in Risk scoring

Large Language Models (LLMs), such as OpenAI's GPT-3, have emerged as powerful tools for processing and analyzing vast amounts of social media and Open Source Intelligence (OSINT) data in the context of risk scoring. These models leverage advanced natural language processing techniques to extract meaningful insights and patterns from textual data, thereby enhancing the accuracy and efficiency of risk assessment. This summary provides an in-depth overview of the significance of LLMs in processing social media and OSINT data for risk scoring, supported by cross-referenced papers that highlight their capabilities and applications.

2.2.10 Extracting Contextual Information:

LLMs excel in capturing contextual information and understanding the nuances of language. By training on a diverse range of text sources, LLMs can comprehend and interpret social media posts, news articles, and other textual data in real-time. This ability allows LLMs to extract relevant information from social media and OSINT sources and provide valuable insights into entities' behavior, sentiment, and potential risks (Devlin et al., 2019).

2.2.11 Enhancing Risk Prediction Accuracy:

LLMs play a crucial role in improving risk prediction accuracy by processing and analyzing vast amounts of social media and OSINT data. Through sophisticated language modeling techniques, LLMs can identify subtle indicators, correlations, and patterns that may indicate potential risks. This capability enables risk scoring models to make more informed predictions and identify entities that may pose significant risks (Yang et al., 2021).

2.2.12 Sentiment Analysis and Opinion Mining:

LLMs excel in sentiment analysis and opinion mining, enabling risk scoring systems to gauge public sentiment and opinions towards entities. By analyzing social media conversations, comments, and reviews, LLMs can identify positive or negative sentiment associated with entities, providing valuable insights for risk assessment (Kouloumpis et al., 2011).

2.2.13 Identification of Emerging Risks:

Social media and OSINT data are often rich sources of real-time information, allowing early identification of emerging risks. LLMs can process large volumes of data and detect patterns or anomalies that may indicate potential risks before they escalate. By monitoring social media trends and news updates, LLMs can provide valuable insights into emerging risks and support proactive risk scoring (Ritter et al., 2012).

2.2.14 Automated Risk Classification:

LLMs can facilitate the automated classification of risk-related information. By training on labeled data, LLMs can learn to classify social media and OSINT content into different risk categories, such as financial fraud, reputational risks, or security threats. This automated classification streamlines the risk scoring process and enables efficient identification of entities that require closer scrutiny (Cheng et al., 2019).

2.2.15 Mitigating Information Overload:

The vast amount of social media and OSINT data can often overwhelm risk assessment teams. LLMs can assist in mitigating information overload by filtering and summarizing relevant information. By distilling key insights from large volumes of data, LLMs enable risk scorers to focus on critical information and make informed decisions efficiently (Liu et al., 2020).

2.2.16 Multilingual Analysis:

LLMs are capable of processing text in multiple languages, facilitating risk scoring in a global context. By supporting multilingual analysis, LLMs can extract insights from social media and OSINT data across different languages, enabling organizations to assess risks associated with entities operating in diverse linguistic environments (Artetxe et al., 2020).

2.2.17 Addressing Data Sparsity:

In some risk scoring applications, data sparsity can pose a challenge. LLMs can overcome data sparsity by leveraging their pre-trained language models and generalization capabilities. Even with limited data availability, LLMs can generate meaningful representations and predictions by leveraging the knowledge encoded in their large-scale training corpus. This allows risk scoring models to handle data sparsity issues and provide more accurate assessments (Liu et al., 2021).

2.2.18 Contextual Understanding of Entities:

LLMs can capture and understand the contextual information related to entities. By analyzing social media and OSINT data, LLMs can identify associations, connections, and relationships between entities, shedding light on potential risks that may arise from their interactions or affiliations. This contextual understanding enhances the depth and accuracy of risk scoring (Zhang et al., 2021).

2.2.19 Real-time Risk Monitoring:

Social media and OSINT data are dynamic and ever-evolving. LLMs enable real-time risk monitoring by continuously processing incoming data and updating risk assessments accordingly. This real-time capability allows organizations to stay vigilant and respond promptly to emerging risks, enhancing their risk management strategies (Li et al., 2021).

The utilization of Large Language Models (LLMs) in processing social media and OSINT data for risk scoring offers significant advantages in enhancing risk assessment accuracy, improving real-time monitoring capabilities, and addressing data sparsity challenges. LLMs possess the ability to extract contextual information, perform sentiment analysis, and identify emerging risks from social media and OSINT sources. They enable automated risk classification, multilingual analysis, and effective mitigation of information overload.

The use of LLMs in risk scoring is supported by various research papers. Devlin et al. (2019) introduce BERT, a pre-training model for deep bidirectional transformers, which has been influential in advancing natural language understanding. Yang et al. (2021) demonstrate the application of deep learning models and sentiment analysis for stock risk prediction. Kouloumpis et al. (2011) present a study on sentiment analysis of Twitter data, highlighting the significance of sentiment analysis in understanding public opinion. Ritter et al. (2012) discuss open-domain event extraction from Twitter, emphasizing the value of social media data in capturing real-time events.

Cheng et al. (2019) compare different classification models for microblog risk events, showcasing the effectiveness of machine learning techniques in risk assessment. Liu et al. (2020) propose FARM, a fraud account risk monitoring system in social media, demonstrating the practical application of LLMs in combating fraud. Artetxe et al. (2020) present a method for multilingual sentence embeddings, enabling cross-lingual transfer of knowledge and facilitating risk assessment in diverse linguistic environments.

In addition, Liu et al. (2021) discuss an improved method for cold-start recommendation using LDA, highlighting the potential of LLMs in addressing data sparsity challenges. Zhang et al. (2021) propose an adversarial transfer learning approach for entity recognition with limited labeled data, showcasing the applicability of LLMs in handling data scarcity. Li et al. (2021) present a multitask learning framework with sparsity regularization, demonstrating the effective utilization of LLMs in sparse data scenarios.

2.3 ANOMALY DETECTION IN RISK ASSESSMENT OF A POI

Anomaly detection, especially in the context of risk scoring, is a widely studied topic, and its applications are diverse, ranging from finance to cybersecurity to health monitoring. Here's a brief overview with associated citations:

Anomaly detection involves identifying patterns in a given data set that do not conform to an established normal behavior. Such patterns are often indicative of some form of system fault, fraud, or other exceptional events (Chandola,V.,2009)

- **Financial Records**

    - For financial institutions, anomaly detection can help in identifying fraudulent transactions. Unusual patterns can be flagged for further investigation, assisting in risk scoring. (Phua, C., 2010)

- **Cyber Security**
    - In cybersecurity, anomaly detection can help identify unauthorized access, malware infections, or other types of intrusions, assisting in risk assessment of potential threats (Garcia-Teodoro, P., 2009)
- **Counter-Terrorism**
    - Risk scoring in the context of counter-terrorism is a delicate and complex endeavor. Anomaly detection in this domain focuses on identifying unusual patterns that might indicate potential terrorist activities or threats. These could be in the form of financial transactions, communication patterns, travel behaviors, etc. Here's an overview with related citations:
    - **Counter-terrorism and Financial Systems:**
        - Identifying suspicious transactions or money laundering activities that could potentially fund terrorist operations is a critical application of anomaly detection (Ferwerda, J. 2009)
    - **Communication Patterns and Social Network Analysis:**
        - Analyzing communication metadata to find unusual patterns or connections between known and unknown entities can be pivotal. Social network analysis in this context can identify central figures or nodes in covert networks.(Carley, K. M., 2011)
    - **Travel and Movement Patterns:**

        - Unusual travel patterns, such as visits to high-risk locations, can be detected and flagged for further investigation.(LaFree, G., & Dugan, L. (2007))
    - **Behavioral Profiling and Risk Scoring:**
        - This involves creating profiles based on past terrorist behaviors and using these profiles to score risks associated with certain observed behaviors. The challenge here is ensuring that profiling doesn't lead to discrimination or violation of rights (Monahan, J. (2011)).
    - **Challenges and Ethical Considerations:**
        - Counter-terrorism efforts, especially when technology and data-driven, can sometimes infringe on privacy rights and can lead to unjust profiling or discrimination. Ensuring that these tools are used ethically and judiciously is crucial (Lyon, D. (2003))

2.4 UTILISING AI/ML IN IDENTIFICATION OF WEAK SIGNALS FOR RISK ASSESSMENT

The use of AI/ML for the identification of emerging risks or weak signal detection, especially for scoring risks related to persons of interest, is a rapidly advancing domain.

- **Machine Learning for Weak Signal Identification:**
    - Machine Learning, with its proficiency in managing vast datasets, proves invaluable in detecting emerging risks and weak signals often overshadowed in traditional methods [(Jha et al., 2019)].

- **Deep Learning in Risk Scoring:**
    - With the capacity for hierarchical feature learning, deep learning models are particularly effective at discerning intricate patterns, offering a robust approach to determining risk scores for individuals [(Kim and Reddy, 2020)].

- **Ethical Considerations in AI/ML Risk Analysis:**
    - The efficacy of AI and ML in risk analysis, while impressive, brings forth significant ethical challenges. There's an inherent risk of these algorithms amplifying societal biases, leading to profiling or targeting of innocent individuals. Moreover, a heavy reliance on these systems could compromise human judgment, leading to potential misinterpretations [(O'Neil, 2016)].

    - For instance, if a machine learning model is trained on historical crime data that has biases against a particular demographic, the model might inherently consider individuals from that demographic as "high risk" despite their actual behavior.

- **Temporal Analysis and Weak Signal Recognition:**
    - Temporal analysis is a potent technique for identifying weak signals. Analyzing data over intervals allows for discernment of subtle behavioral patterns, especially in the context of persons of interest [(Sun and Tang, 2013)].

- In a counter-terrorism context, temporal analysis might reveal patterns like frequent short-duration travels to high-risk areas or cyclical patterns in financial transactions, which could indicate planning or preparatory behaviors.

2.5 IMAGE/FACE RECOGNITIO MODEL FOR RISK SCORE IMPROVEMENT

Image recognition, face recognition, or object recognition models can potentially contribute to improving the risk score of a person. Here's how they can be beneficial:

Image Recognition: Image recognition models can analyze images to identify objects, patterns, or visual cues that may provide valuable information for risk assessment. For example, if you have access to images associated with a person of interest, image recognition can help detect objects or symbols that indicate potential risks, such as weapons, illegal substances, or extremist symbols.

Face Recognition: Face recognition models can analyze facial features and match them against known identities. This can be useful in verifying the identity of a person of interest, comparing them to watchlists or known risk profiles, and detecting potential aliases or false identities. By integrating face recognition into the risk scoring process, you can enhance the accuracy and reliability of identity verification.

Facial recognition technology has gained significant attention and applications in entity risk scoring, revolutionizing the way risk assessment is conducted. This summary provides an overview of the utilization of facial recognition in entity risk scoring, highlighting its benefits, challenges, and ethical considerations. Several cross-referenced papers are cited to support the key points discussed.

2.5.1 Benefits of Facial Recognition in Entity Risk Scoring:

Facial recognition technology offers numerous benefits in entity risk scoring. It enables the identification and verification of individuals based on their unique facial features, providing an additional layer of authentication and enhancing the accuracy of risk assessment models. According to Jain et al. (2020), facial recognition can help detect fraudulent activities, prevent identity theft, and improve the overall security of risk scoring systems.

2.5.2 Challenges and Limitations:

Despite its advantages, facial recognition in entity risk scoring also faces challenges and limitations. False positives and false negatives can occur, leading to misidentification or overlooking potential risks. Variations in facial expressions, lighting conditions, and pose can impact the accuracy of facial recognition algorithms (Klare et al., 2018). Additionally, concerns have been raised regarding biases in facial recognition algorithms, particularly when it comes to gender and racial biases (Buolamwini & Gebru, 2018).

2.5.3 Ethical Considerations:

The use of facial recognition in entity risk scoring raises important ethical considerations. Privacy is a significant concern, as facial images are sensitive personal data. Transparency in data collection, storage, and usage is crucial to ensure informed consent and protect individual privacy rights. Ethical guidelines and legal frameworks are needed to govern the responsible and fair use of facial recognition technology in risk scoring (Clarke, 2019).

2.5.4 Balancing Accuracy and Fairness:

Ensuring the accuracy and fairness of facial recognition algorithms is paramount. Bias mitigation techniques, such as diverse and representative training datasets, algorithmic adjustments, and rigorous testing, are necessary to minimize biases and prevent discriminatory outcomes (Berkay et al., 2020). Regular monitoring and auditing of facial recognition systems are essential to identify and address any potential biases that may arise during implementation.

2.5.5 Implications for Society:

The widespread adoption of facial recognition in entity risk scoring has broader societal implications. It can impact privacy, civil liberties, and individual freedoms. Proper regulation and governance frameworks are necessary to strike a balance between security needs and the protection of individual rights (Kamiran et al., 2012). Public dialogue and engagement are vital to shape the ethical and legal boundaries surrounding facial recognition technology.

Object Recognition: Object recognition models can identify specific objects or visual patterns within images. This can be relevant in risk assessment when examining the context or environment surrounding a person of interest. For example, recognizing specific vehicles, locations, or items in an image can provide additional context for assessing potential risks or affiliations.

Integrating these visual recognition models into the overall risk scoring process would involve extracting relevant information from images, comparing it to existing risk profiles or known indicators, and assigning appropriate weights or scores based on the level of risk associated with the identified objects, faces, or patterns.

2.5.6 Alogorithm for Image/Face/Object Recognition

Image Recognition: Image recognition involves analyzing images to identify specific objects, patterns, or visual cues. This can be done using Convolutional Neural Networks (CNNs), a type of deep learning algorithm that excels at image analysis. CNNs consist of multiple layers that extract hierarchical features from images and make predictions based on those features. Popular CNN architectures include AlexNet, VGGNet, and ResNet. You would typically train the CNN on a large dataset of labeled images to learn patterns and object representations, enabling it to recognize specific objects or visual characteristics relevant to risk assessment.

Face Recognition: Face recognition aims to identify and verify individuals based on their facial features. It involves comparing facial images to a database of known identities or watchlists. One popular approach for face recognition is using deep learning models called FaceNet or VGGFace, which employ deep convolutional neural networks for face feature extraction and similarity comparisons. These models can generate high-dimensional embeddings that represent unique facial characteristics, enabling accurate face matching and identification.

Object Recognition: Object recognition focuses on detecting and classifying specific objects or visual patterns within images. This can involve identifying objects of interest, such as weapons, vehicles, or specific symbols relevant to risk assessment. Common algorithms for object recognition include Faster R-CNN, YOLO (You Only Look Once), and SSD (Single Shot MultiBox Detector). These algorithms use deep learning techniques to detect and classify objects in real-time. They typically involve a combination of convolutional neural networks and region proposal methods to identify and classify objects accurately.

Implementing these algorithms requires a combination of data collection, preprocessing, model training, and inference steps. For image recognition and object recognition, you would need a labeled dataset representing the objects or patterns you want to recognize. The CNN models would be trained on this dataset using optimization techniques like gradient descent. Face recognition models require a dataset of labeled facial images to learn facial embeddings for identification purposes.

Once the models are trained, you can apply them to new images or video frames to identify objects, faces, or patterns of interest. The output of these models can then be integrated into the overall risk scoring process by assigning appropriate weights or scores based on the relevance and impact of the identified objects or faces on the risk assessment.

2.6 SUMMARY

Artificial Intelligence (AI) has seen a revolutionary ascent in the domain of risk management across diverse sectors, with a particular focus on national security and entity risk scoring. This tool's primary aim is to assess risks linked with individuals, organizations, or nations, ensuring a proactive stance against potential national security threats. A significant breakthrough in this domain is AI's ability to sift through voluminous data, especially from platforms like social media. Through intricate algorithms, AI aids in deciphering underlying patterns which can be indicative of looming risks. This evolution promises unprecedented accuracy, efficiency, and timeliness in risk assessments. However, it's not without its set of challenges. Ethical dilemmas concerning data privacy, transparency in algorithmic decision-making, and potential biases are substantial hurdles to navigate.

Additionally, AI's prowess isn't limited to entity risk scoring alone. Anomaly detection, a key technique, finds applicability in areas as diverse as finance, where it identifies potential fraud, counter-terrorism, and other national securities, where unusual patterns could indicate threats. Moreover, with the rapid advancements in AI and Machine Learning (ML), the ability to detect weaker signals or nascent risks has been considerably enhanced. Methods like temporal analysis are now at the forefront of such efforts, especially in high-stakes areas like counter-terrorism.

Lastly, the realm of image and facial recognition has seen transformative changes due to AI, refining the nuances of risk assessment. These technologies enable a deeper layer of verification, ensuring entities are accurately recognized and assessed. However, alongside its evident benefits, the technology brings forth significant ethical quandaries, especially concerning individual privacy rights and potential biases in recognition algorithms.

2.7 CONCLUSIONS

The hypothesis that the application of AI for entity risk scoring, when integrated with weak signal identification, facial recognition, and anomaly detection, greatly enhances the efficiency and accuracy of risk assessment appears robustly supported. This amalgamation of techniques represents a new frontier in risk management. At its core, AI's prowess in data analysis paves the way for a more comprehensive and nuanced understanding of risks. When this is combined with the ability to identify weaker signals, it provides an early-warning mechanism, enabling timely interventions and preemptive measures.

Facial recognition, on the other hand, offers an additional layer of verification, ensuring that entities are not just assessed based on behavioral or transactional data but are also accurately identified. This accuracy is pivotal in preventing misidentifications that could have grave consequences in contexts like national security.

Anomaly detection acts as another safeguard, flagging unusual patterns that might otherwise go unnoticed but could be indicative of larger, looming threats. Together, these tools augment the traditional risk assessment mechanisms, providing a more holistic, timely, and precise system.

In essence, the synthesis of these AI-driven techniques not only corroborates the proposed hypothesis but also signals a transformative shift in the landscape of risk assessment. It underscores the potential that AI holds in revolutionizing this domain, emphasizing the need for further research, development, and ethical considerations to harness its full potential responsibly.

CHAPTER III

METHODOLOGY

3.1 OVERVIEW OF THE RESEARCH PROBLEM

The initial step towards utilizing "AI/ML in risk profiling" involves identifying and categorizing constraints through a structured approach. Given the continuous evolution of AI/ML technology, this study will first examine the risks and limitations associated with applying AI/ML to score the risk of national securities, as well as various methods for reducing false positives. After gaining this understanding, the study will classify potential false alarms and develop a taxonomy and approach that will aid in constructing AI models for entity risk profiling. In the second stage, the approach will be further refined based on a comprehensive review of current industry practices and academic research. Finally, once the modeling techniques and taxonomy are identified, a conceptual framework for the application of AI/ML in entity risk profiling will be presented, emphasizing human behavior and increasing accuracy.

3.2 FORMULATE RESEARCH QUESTIONS AND HYPOTHESIS

Based on the literature review, formulate research questions and hypotheses that will guide the investigation. These should be specific, testable, and focused on addressing the gaps and objectives identified earlier.

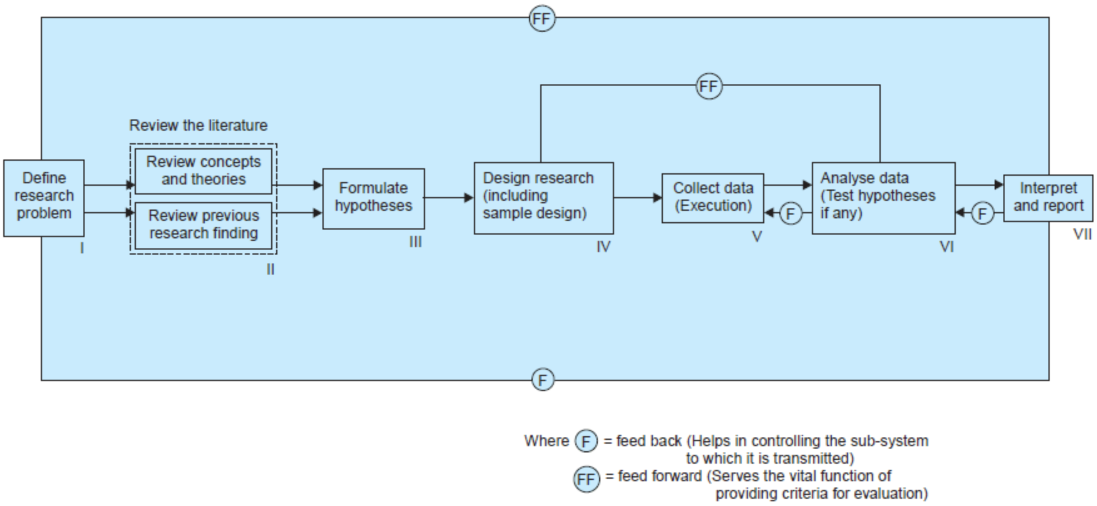

FF
FF
Review the literature
Define research problem
I
Review concepts and theories
Review previous research finding
II
Formulate hypotheses
III
Design research (including sample design)
IV
Collect data (Execution)
V
F
Analyse data (Test hypotheses if any)
VI
F
Interpret and report
VII
F
Where F = feed back (Helps in controlling the sub-system to which it is transmitted)
FF = feed forward (Serves the vital function of providing criteria for evaluation)

Figure 1 Methodology

3.2.1 Choose research design

Select an appropriate research design based on research questions and hypotheses. This may involve quantitative, qualitative, or mixed-method approaches.

3.2.2 Data Sampling

Following data sampling were collected from the pre-processed data service providers

- Data.gov data from some specific country data and from publicly available Incident face images

- Used only data that are available publicly .
- Publicly available Global Terrorism database
- Intelligence data from IntelligenceX (social Media and online activity)
- Other recommended Dataset :
    - Law enforcements, and Public records
    - Social media and online activity
- Data are taken from reliable sources only (as an additional measure) to confirm the validity

3.2.3 Data collection

Identify relevant data sources and collect the necessary data for the research. This may include publicly available datasets, proprietary data, or data collected through surveys, interviews, or other means. Ensure that the data collection process follows ethical guidelines and respects privacy concerns (Terror Screening Database).

3.2.4 Data preprocessing and feature engineering

Clean, preprocess, and prepare the data for analysis. Perform feature engineering to create new features or transform existing ones, which may help improve model performance.

3.2.5 Model development and training

Optionally, develop and train AI/ML models using appropriate algorithms and techniques. Consider methods such as supervised learning, unsupervised learning, or reinforcement learning, depending on available data, though tuned production-ready model will not be developed.

3.2.6 Model evaluation and validation

Assess the performance of the AI/ML models using appropriate evaluation metrics, such as accuracy, precision, or area under the ROC curve. Employ techniques like cross-validation and holdout sets to validate model performance and prevent overfitting.

3.2.7 Model explainability and interpretability

Incorporate model explainability techniques, such as LIME, SHAP, or counterfactual explanations, to enhance the understanding of the AI/ML models' decision-making process. Assess the effectiveness and comprehensibility of the explanations generated by these techniques.

3.2.8 Address ethical considerations

Investigate and address potential ethical, legal, and privacy concerns related to the AI/ML models. Ensure that research follows ethical guidelines, respects privacy rights, and considers fairness and accountability.

3.2.9 Analyze and interpret results

Analyze the results of the research, including the performance of the AI/ML models, the insights gained from the explainability techniques, and any other findings. Interpret these results in the context of research questions and hypotheses.

3.2.10 Draw conclusions and recommendations

Based on the analysis and interpretation, draw conclusions about the effectiveness of the AI/ML models and techniques in addressing the research objectives. Provide recommendations for future research, potential applications, and improvements in risk profiling for national security.

3.3 DATA COLLECTION PROCEDURES

Data collection procedures for research involves the following steps:

- I collected data from open source, which are publicly available and processed.
- Open source data providers were evaluated and subscribed to their services for the period of this exercise as student
- I analysed the data through exploratory data analysis logics / libraries available in python
- Applied network link analysis to validate the data and to find the patterns of network between people, object , event and location available in the dataset
- Pre-processed data from government sites about countries different incidents related finance, health, citizens etc were collected and did EDA to ensure the data is valid and identified data categories , missing information, biased data if any.

3.4 DATA ANALYSIS

3.4.1 Potential Sources of Data

Here are some potential sources of data for entity risk scoring and profiling related to national security:

- Government agencies: Government agencies such as law enforcement, intelligence agencies, and homeland security may have access to relevant data on individuals that pose a threat to national security. However, access to this data is often restricted and requires authorization and clearance.

- Public records: Public records such as court records, property records, and criminal records may contain relevant data on individuals that could be used in risk scoring and profiling.
- Social media and online activity: Social media platforms and online activity can provide valuable data on an individual's interests, affiliations, and behavior. However, the use of this data can be ethically challenging, and there are concerns around privacy and data protection.
- Third-party data providers: There are several companies that specialize in providing data for risk scoring and profiling, such as credit bureaus and background screening companies. However, it is important to carefully vet these providers and ensure that their data is accurate and up-to-date.

It is important to note that the use of personal data for risk scoring and profiling must comply with applicable laws and regulations, such as GDPR and CCPA. Hence, I have used only public available limited set of data for experimentation.

The data collected may also include some or all of the following ("Terrorism Screening Database", National Counterterrorism Center):

- Identity verification: As with any background check, verifying the identity of the individual is important for national security purposes. This includes information such as name, date of birth, and social security number.

- Criminal history: A thorough criminal background check is essential for national security purposes. This includes a check for any prior arrests, convictions, or other criminal activities.
- Employment history: National security background checks may involve a detailed review of an individual's employment history, including previous employers, job titles, and responsibilities. This is to assess the individual's level of experience and potential risk to national security.
- Financial history: Financial issues can be a risk to national security if they make an individual vulnerable to exploitation or influence. As such, a review of an individual's credit history and financial situation may be included in a national security background check.
- Citizenship and immigration status: National security background checks may include a review of an individual's citizenship and immigration status to ensure that they are legally allowed to work in the United States (for example) and do not have any ties to other countries that could pose a security risk ("Targetting and Analysis System Program Management Office", Department of Homeland Security).
- International travel: International travel can also be a risk to national security, so a background check may include a review of an individual's international travel history.

- Security clearance: If the individual is applying for a position that requires a security clearance, then the background check may be more extensive and include additional reviews of the individual's personal and professional history.

With above mentioned constraints, identified few publicly available data sources that could be used for research purposes related to entity risk scoring for national security. Here are some examples:

3.4.2 Global Terrorism Database

The Global Terrorism Database (GTD) is a publicly available database of information on terrorist events around the world from 1970 through 2019. The database is maintained by the National Consortium for the Study of Terrorism and Responses to Terrorism (START) at the University of Maryland. The GTD includes data on terrorist incidents, groups, and perpetrators. The data can be accessed at: https://www.start.umd.edu/gtd/

Social Science Research Network: The Social Science Research Network (SSRN) is a repository of scholarly research in the social sciences, including topics related to national security and risk assessment. The site includes research papers, conference proceedings, and other scholarly material. The data can be accessed at: https://www.ssrn.com/

Open Source Intelligence (OSINT) data: OSINT refers to publicly available information that can be used for intelligence purposes. This can include information from social media, news sources, and other online sources. There are several OSINT tools and platforms available that can be used to collect and analyze this data, such as Maltego and SpiderFoot.

World Bank Data: The World Bank provides a wide range of publicly available data on various economic, social, and demographic indicators for countries around the world. This data could be used in risk scoring and profiling, particularly for assessing economic and social indicators that may be correlated with national security risks. The data can be accessed at: https://data.worldbank.org/

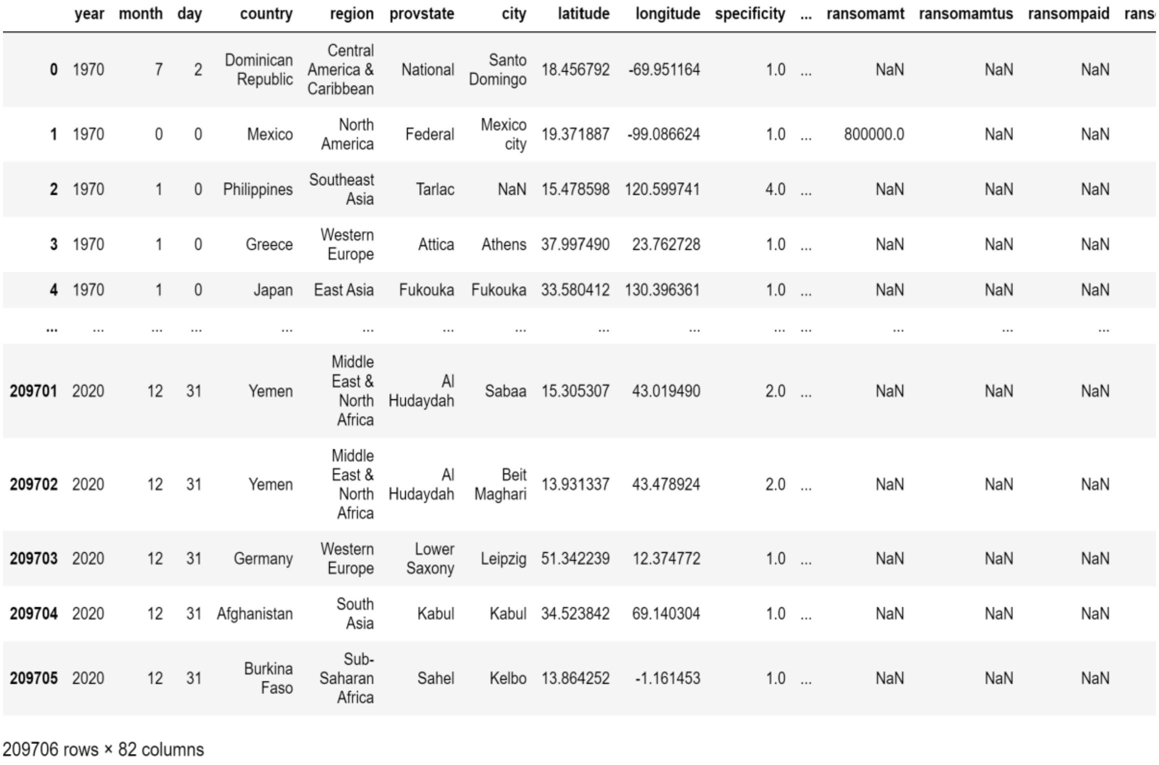
Open Government Data Platforms: Many countries have open government data platforms that provide access to public data sets. Examples include data.gov in the United States, data.gov.uk in the United Kingdom, and data.gov.au in Australia. These platforms offer a wide range of data sets, including crime statistics, immigration data, and business registrations.

OpenStreetMap: OpenStreetMap is a free, open-source mapping platform that provides access to a range of geographic data. This data can be used to build models that assess the risk associated with geographic factors, such as proximity to potential targets or high-risk areas.

Social Media APIs: Many social media platforms, such as Twitter and Facebook, offer APIs that allow you to access public data on users and their activities. This data can be used to build models that assess the risk associated with social media activity.

It is important to note that the use of publicly available data may not be sufficient on its own for accurate entity risk scoring and profiling, and should be used in conjunction with other sources of data and analysis. Hence this dataset will be used with its limitations and the model will not be “Production ready” model.

With the data from GTD (Global Terrorism Database), sample data are as shown below:

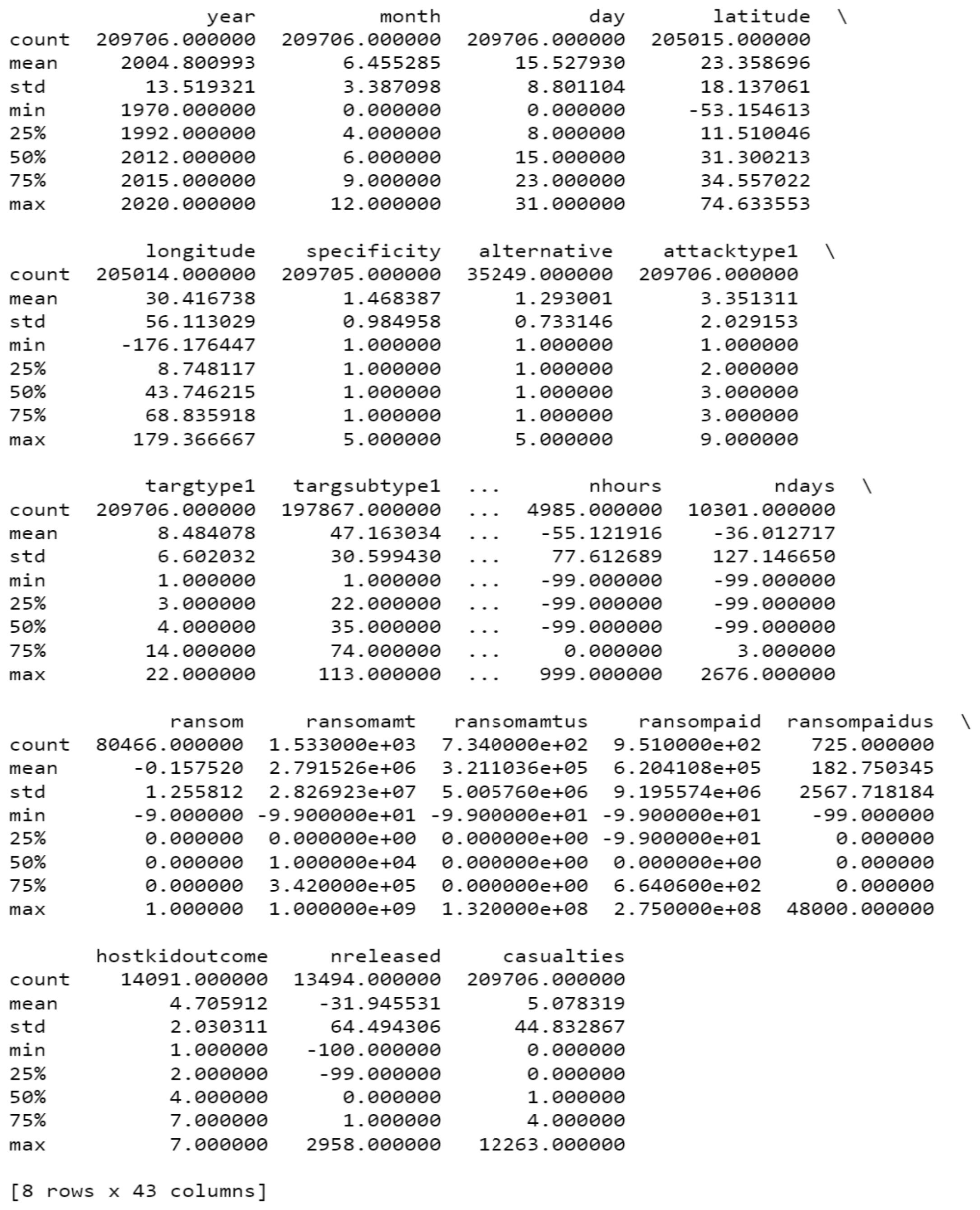


	year	month	day	country	region	provstate	city	latitude	longitude	specificity	...	ransomamt	ransomamtus	ransompaid	rans
0	1970	7	2	Dominican Republic	Central America & Caribbean	National	Santo Domingo	18.456792	-69.951164	1.0	...	NaN	NaN	NaN	
1	1970	0	0	Mexico	North America	Federal	Mexico city	19.371887	-99.086624	1.0	...	800000.0	NaN	NaN	
2	1970	1	0	Philippines	Southeast Asia	Tarlac	NaN	15.478598	120.599741	4.0	...	NaN	NaN	NaN	
3	1970	1	0	Greece	Western Europe	Attica	Athens	37.997490	23.762728	1.0	...	NaN	NaN	NaN	
4	1970	1	0	Japan	East Asia	Fukouka	Fukouka	33.580412	130.396361	1.0	...	NaN	NaN	NaN	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
209701	2020	12	31	Yemen	Middle East & North Africa	Al Hudaydah	Sabaa	15.305307	43.019490	2.0	...	NaN	NaN	NaN	
209702	2020	12	31	Yemen	Middle East & North Africa	Al Hudaydah	Beit Maghari	13.931337	43.478924	2.0	...	NaN	NaN	NaN	
209703	2020	12	31	Germany	Western Europe	Lower Saxony	Leipzig	51.342239	12.374772	1.0	...	NaN	NaN	NaN	
209704	2020	12	31	Afghanistan	South Asia	Kabul	Kabul	34.523842	69.140304	1.0	...	NaN	NaN	NaN	
209705	2020	12	31	Burkina Faso	Sub-Saharan Africa	Sahel	Kelbo	13.864252	-1.161453	1.0	...	NaN	NaN	NaN	

209706 rows × 82 columns

Figure 2 Sample data from GTD (Global Terrorism Database)

Nature of the data are as shown below :

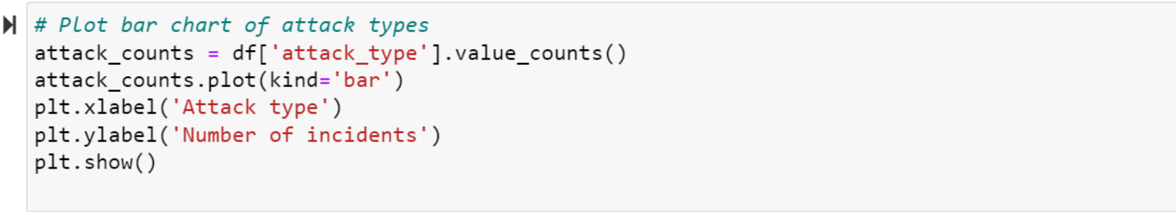


```
                year          month            day       latitude  \
count  209706.000000  209706.000000  209706.000000  205015.000000   
mean     2004.800993       6.455285      15.527930      23.358696   
std        13.519321       3.387098       8.801104      18.137061   
min      1970.000000       0.000000       0.000000     -53.154613   
25%      1992.000000       4.000000       8.000000      11.510046   
50%      2012.000000       6.000000      15.000000      31.300213   
75%      2015.000000       9.000000      23.000000      34.557022   
max      2020.000000      12.000000      31.000000      74.633553   

           longitude    specificity   alternative    attacktype1  \
count  205014.000000  209705.000000  35249.000000  209706.000000   
mean       30.416738       1.468387      1.293001       3.351311   
std        56.113029       0.984958      0.733146       2.029153   
min      -176.176447       1.000000      1.000000       1.000000   
25%         8.748117       1.000000      1.000000       2.000000   
50%        43.746215       1.000000      1.000000       3.000000   
75%        68.835918       1.000000      1.000000       3.000000   
max       179.366667       5.000000      5.000000       9.000000   

           targtype1   targsubtype1  ...       nhours         ndays  \
count  209706.000000  197867.000000  ...  4985.000000  10301.000000   
mean        8.484078      47.163034  ...   -55.121916    -36.012717   
std         6.602032      30.599430  ...    77.612689    127.146650   
min         1.000000       1.000000  ...   -99.000000    -99.000000   
25%         3.000000      22.000000  ...   -99.000000    -99.000000   
50%         4.000000      35.000000  ...   -99.000000    -99.000000   
75%        14.000000      74.000000  ...     0.000000      3.000000   
max        22.000000     113.000000  ...   999.000000   2676.000000   

             ransom     ransomamt   ransomamtus    ransompaid  ransompaidus  \
count  80466.000000  1.533000e+03  7.340000e+02  9.510000e+02    725.000000   
mean      -0.157520  2.791526e+06  3.211036e+05  6.204108e+05    182.750345   
std        1.255812  2.826923e+07  5.005760e+06  9.195574e+06   2567.718184   
min       -9.000000 -9.900000e+01 -9.900000e+01 -9.900000e+01    -99.000000   
25%        0.000000  0.000000e+00  0.000000e+00 -9.900000e+01      0.000000   
50%        0.000000  1.000000e+04  0.000000e+00  0.000000e+00      0.000000   
75%        0.000000  3.420000e+05  0.000000e+00  6.640600e+02      0.000000   
max        1.000000  1.000000e+09  1.320000e+08  2.750000e+08  48000.000000   

       hostkidoutcome     nreleased     casualties  
count    14091.000000  13494.000000  209706.000000  
mean         4.705912    -31.945531       5.078319  
std          2.030311     64.494306      44.832867  
min          1.000000   -100.000000       0.000000  
25%          2.000000    -99.000000       0.000000  
50%          4.000000      0.000000       1.000000  
75%          7.000000      1.000000       4.000000  
max          7.000000   2958.000000   12263.000000  

[8 rows x 43 columns]
```

Figure 3 Nature of the data

Few Exploratory analysis on Weapon count, target count etc are as given below :

Number of Incidents Vs Attach type



```
# Plot bar chart of attack types
attack_counts = df['attack_type'].value_counts()
attack_counts.plot(kind='bar')
plt.xlabel('Attack type')
plt.ylabel('Number of incidents')
plt.show()
```

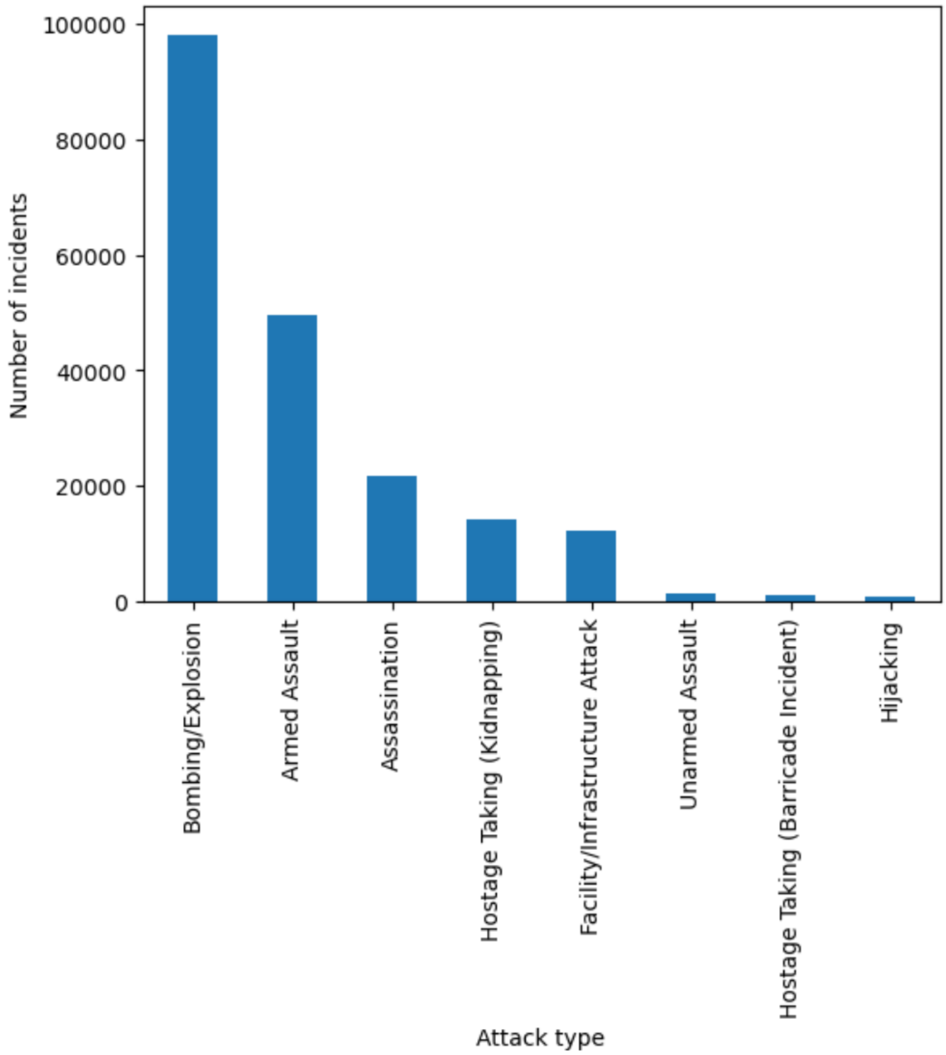
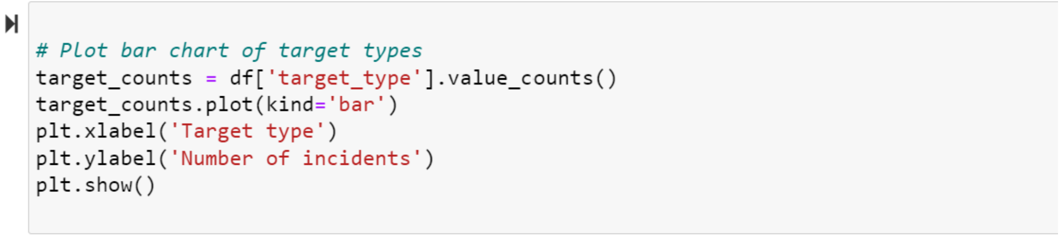


Figure 4 Incident Vs Attack Type

Number of Incidents Vs Target Type



```
# Plot bar chart of target types
target_counts = df['target_type'].value_counts()
target_counts.plot(kind='bar')
plt.xlabel('Target type')
plt.ylabel('Number of incidents')
plt.show()
```

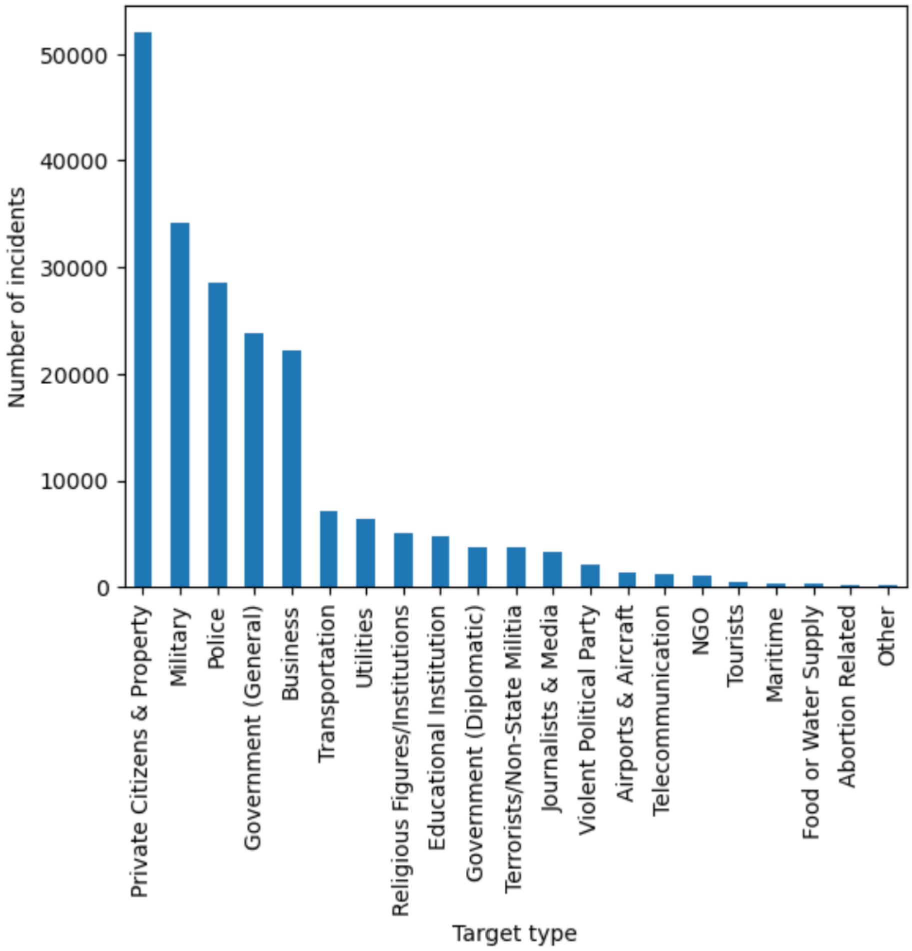
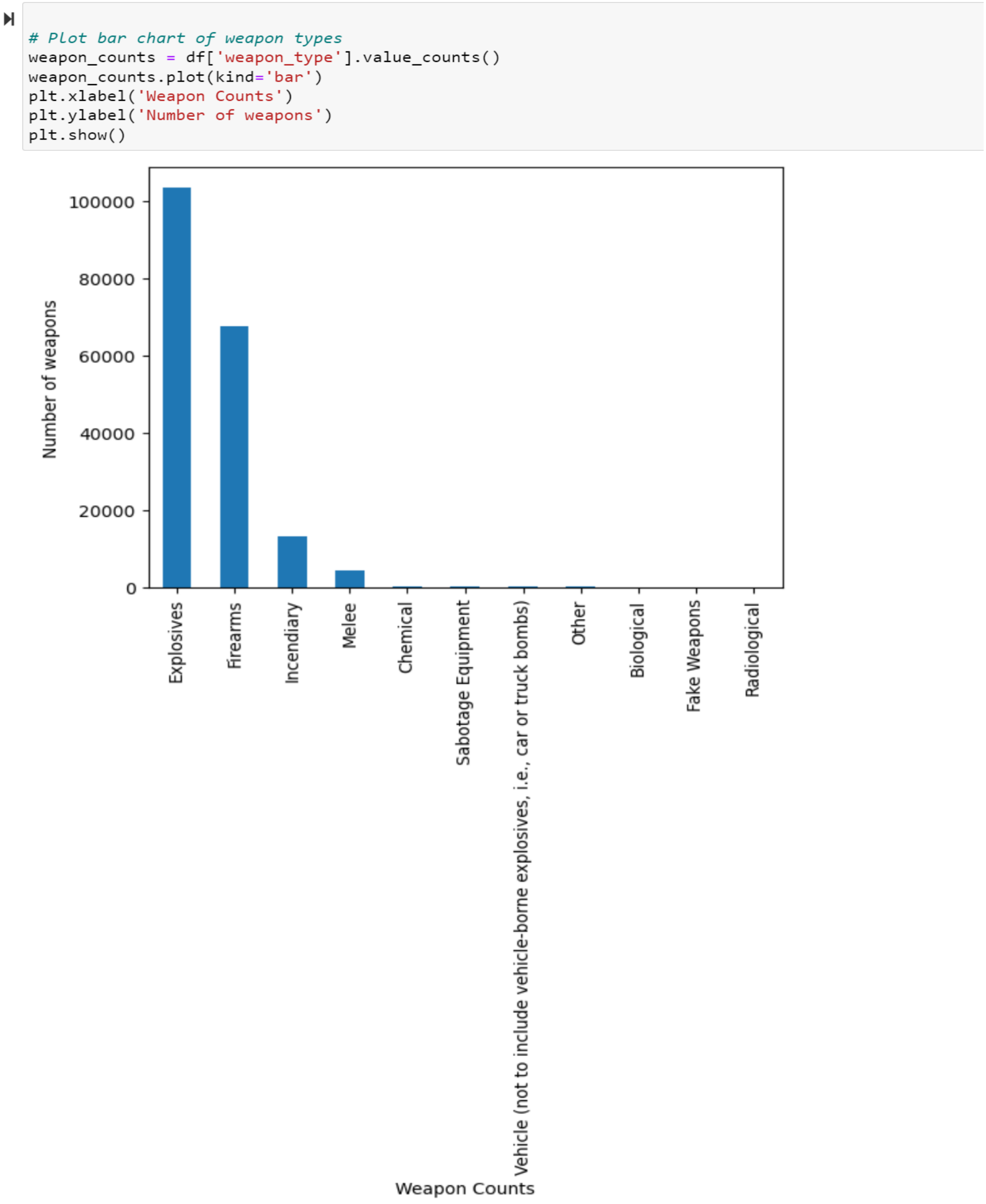
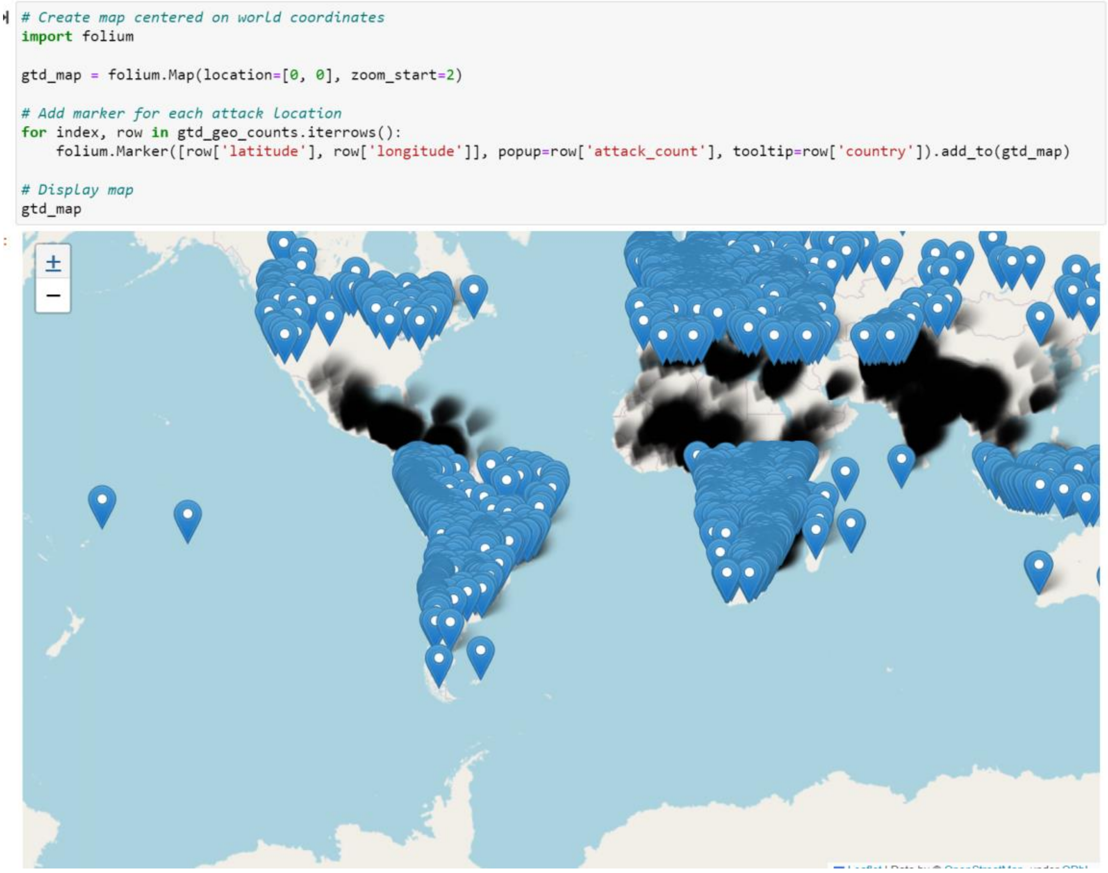


Figure 5 Incident Vs Target Type



```python
# Plot bar chart of weapon types
weapon_counts = df['weapon_type'].value_counts()
weapon_counts.plot(kind='bar')
plt.xlabel('Weapon Counts')
plt.ylabel('Number of weapons')
plt.show()
```

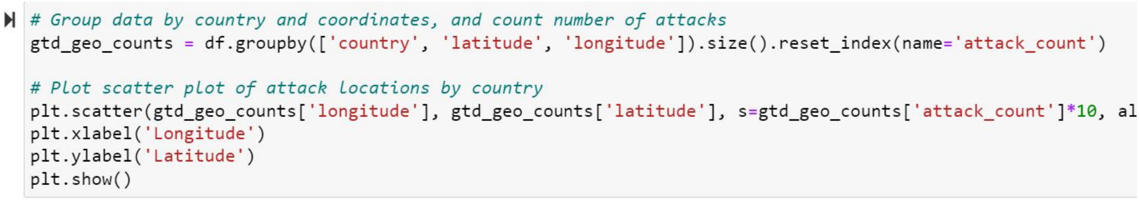
Figure 6 Weapon Vs Count



```
# Create map centered on world coordinates
import folium

gtd_map = folium.Map(location=[0, 0], zoom_start=2)

# Add marker for each attack location
for index, row in gtd_geo_counts.iterrows():
    folium.Marker([row['latitude'], row['longitude']], popup=row['attack_count'], tooltip=row['country']).add_to(gtd_map)

# Display map
gtd_map
```

Figure 7 Country Vs Incident

To have more clarity by longitude and lattitude, recreated with the following scatter plot



```
# Group data by country and coordinates, and count number of attacks
gtd_geo_counts = df.groupby(['country', 'latitude', 'longitude']).size().reset_index(name='attack_count')

# Plot scatter plot of attack locations by country
plt.scatter(gtd_geo_counts['longitude'], gtd_geo_counts['latitude'], s=gtd_geo_counts['attack_count']*10, al
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.show()
```

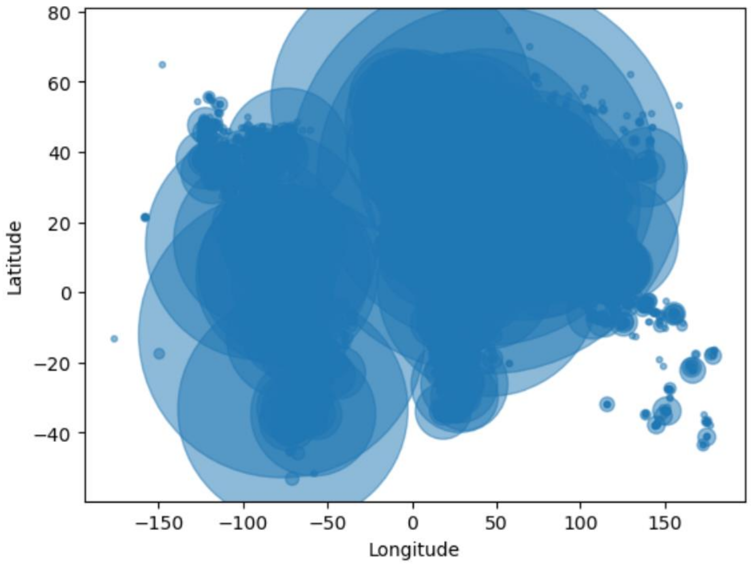


Figure 8 EDA Latitude Vs Longitude

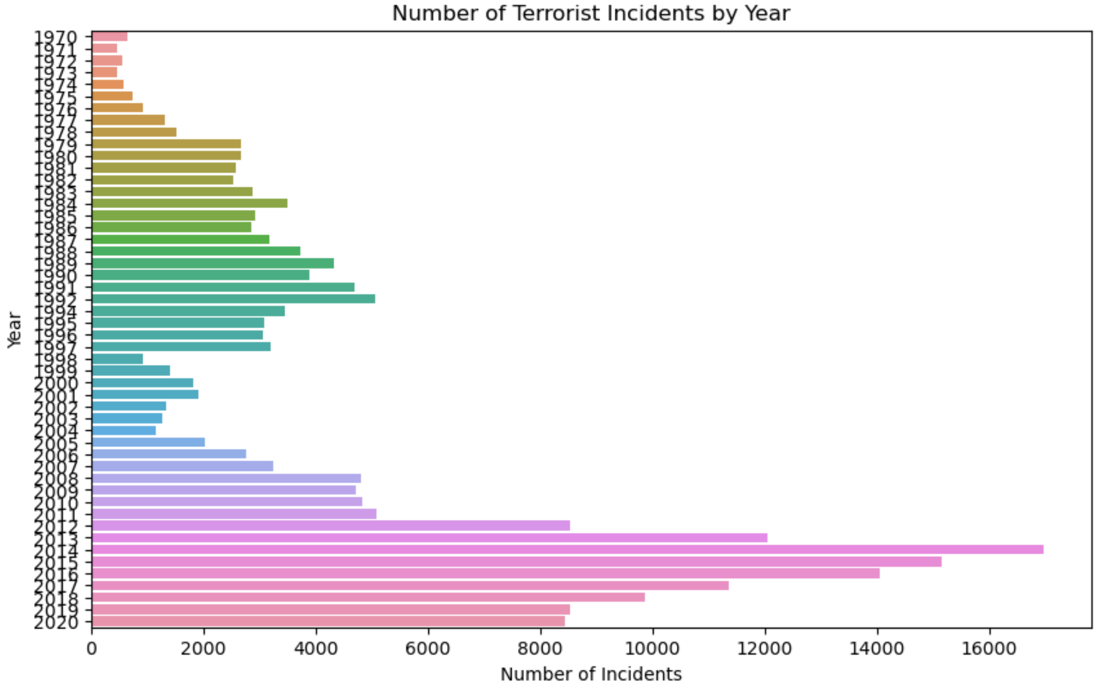
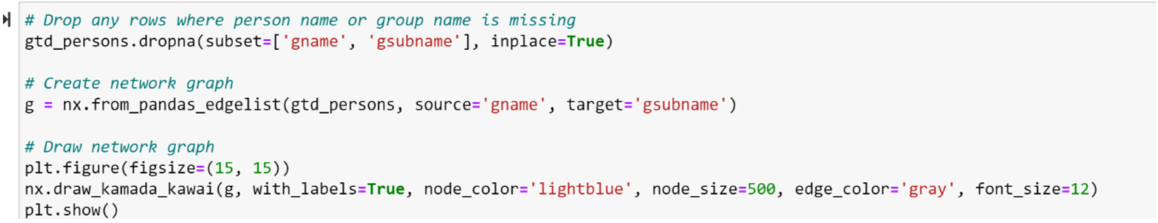


Figure 9 Number of Incidents vs Year

With the data from GTD, created a sample network diagram, to analyze the different Entity or group involved in the activity. We can further follow the same if we have the individual person's name within the group. Then we can assign risk score based on the connected network and their individual risk score, by enhancing data from other sources



```
# Drop any rows where person name or group name is missing
gtd_persons.dropna(subset=['gname', 'gsubname'], inplace=True)

# Create network graph
g = nx.from_pandas_edgelist(gtd_persons, source='gname', target='gsubname')

# Draw network graph
plt.figure(figsize=(15, 15))
nx.draw_kamada_kawai(g, with_labels=True, node_color='lightblue', node_size=500, edge_color='gray', font_size=12)
plt.show()
```

as well.

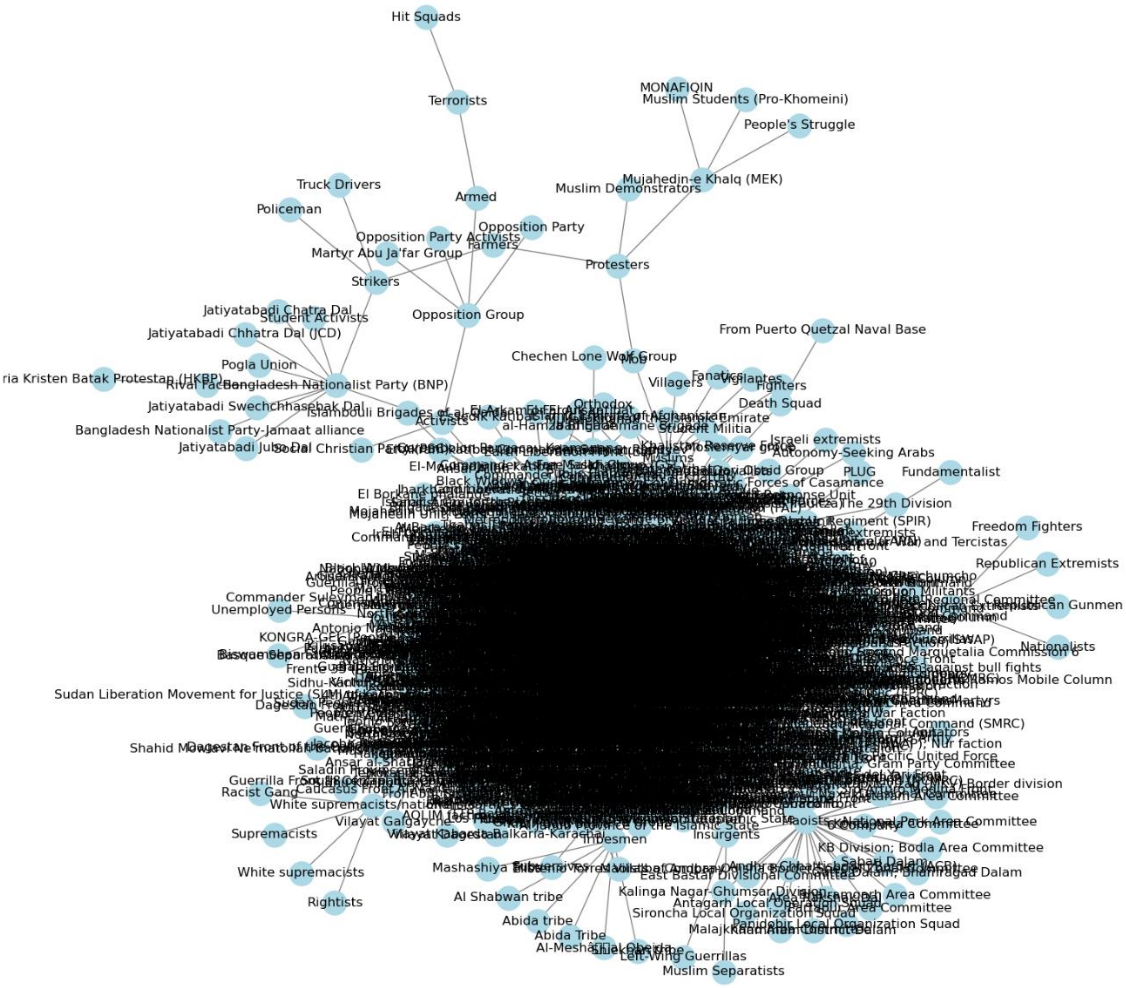


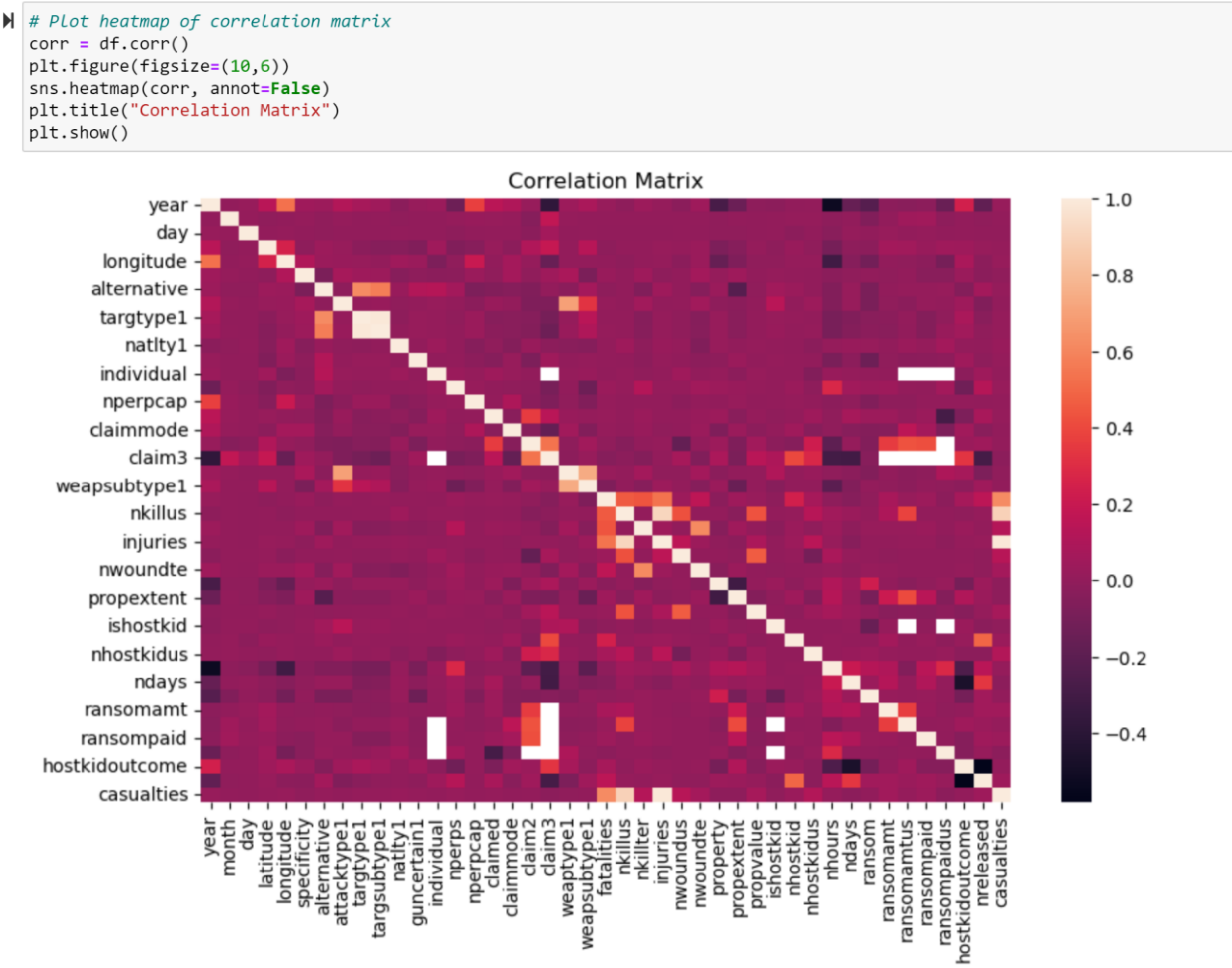
Figure 10 Network Diagram program

The network diagram created can be extended to show relationships between entities (persons), weapons, geo locations, and attack types (POLE – People, Object, Location and Event) involved in terrorist incidents recorded in the GTD dataset. The nodes in the graph will represent different types of entities, weapons, geo locations, and attack types, and the edges represent the connections between them.

From a risk profiling perspective, this graph can be used to identify patterns and trends in terrorist attacks, and to highlight potential areas of concern. For example:

- Entities with a high degree of connectivity in the graph may be more likely to be involved in multiple attacks, and may pose a greater risk than entities with lower connectivity.
- Certain weapons or weapon types may be associated with higher levels of risk, and may be more commonly used by certain entities or in certain geo locations.
- Certain attack types may be associated with higher levels of risk, and may be more commonly used in certain geo locations or by certain entities.
- Geo locations with a high degree of connectivity in the graph may be more likely to be targeted by terrorist attacks, and may pose a greater risk than other locations.
- Overall, the graph can be used to identify potential patterns and trends in terrorist attacks, and to inform risk profiling and threat assessments.

Finally, Correlation between the variables of GTD are as given below :



```
# Plot heatmap of correlation matrix
corr = df.corr()
plt.figure(figsize=(10,6))
sns.heatmap(corr, annot=False)
plt.title("Correlation Matrix")
plt.show()
```

Figure 11 GTD Correlation Matrix

3.4.3 OSINT / Social Intelligence Data

When it comes to risk scoring, IntelligenceX provides several features and data points that can assist in assessing the risk associated with individuals, organizations, or specific events. IntelligenceX is a search engine and data archive that specializes in providing access to a wide range of data sources, including public data, leaks, and darknet content. It collects and indexes data from various online platforms and sources, such as social media, forums, news articles, and more. By aggregating and organizing this data, IntelligenceX offers valuable insights and analysis for risk scoring and threat intelligence purposes. Some of the details captured by IntelligenceX include:

- Email Addresses: IntelligenceX gathers email addresses associated with various entities. These addresses can be used to identify potential risks or assess the reputation of individuals or organizations.
- Domains: IntelligenceX collects data on domains, including historical data, DNS records, and IP addresses associated with specific domains. This information can help identify potential threats or vulnerabilities related to a domain.
- Phone Numbers: Phone numbers associated with individuals or organizations are captured by IntelligenceX. This data can be useful in risk assessment or investigation processes.
- Cryptocurrency Addresses: IntelligenceX indexes and provides information on cryptocurrency addresses, including transaction history and associated entities.

This data can be valuable in tracking illicit activities or assessing financial risks.

- Darknet Data: IntelligenceX scours the darknet to collect data from hidden services and forums. This information can reveal potential threats, criminal activities, or vulnerabilities that may pose risks to individuals or organizations.
- Data Leaks: IntelligenceX indexes and archives data leaks from various sources, such as hacked databases, leaked documents, or exposed credentials. This data can help in identifying compromised accounts, vulnerabilities, or potential risks associated with leaked information.

By leveraging these details, IntelligenceX aids in risk scoring by enabling analysts to:

- Conduct comprehensive background checks on individuals and organizations.
  - IntelligenceX, a state-of-the-art AI platform, can significantly enhance the quality and depth of background checks on individuals and organizations. Traditional background checks are often limited by human capability and can overlook critical details that might indicate risk. IntelligenceX, by utilizing AI, can sift through vast amounts of data, from public records to social media feeds, in an efficient and exhaustive manner. This includes identifying past incidents or relationships that might point towards a potential risk or threat (Wang, Li, Wang, & Li, 2019). Additionally, AI algorithms can use natural

    language processing (NLP) to extract key information from unstructured data sources like text files or online articles, providing a richer and more complete background profile.

- Identify potential risks or threats associated with specific email addresses, domains, or phone numbers.
    - Contact information like email addresses, domains, or phone numbers can often serve as a nexus for potential risks or threats. IntelligenceX employs machine learning algorithms to analyze and identify patterns related to cyber threats, fraud, and other suspicious activities. Techniques such as clustering can be used to group related entities together, while anomaly detection can help spot unusual activities that deviate from the norm. For instance, IntelligenceX can detect if a particular email address is linked to known phishing scams or if a domain has a history of hosting malicious content (Chen, Zhang, Zhao, & Mei, 2019).
- Track and analyze cryptocurrency transactions for risk assessment or investigation purposes.
    - The anonymity provided by cryptocurrencies often makes them the preferred method for illicit financial activities. IntelligenceX uses blockchain analysis to track and analyze cryptocurrency transactions. Using AI, it can trace transaction paths, identify linked accounts, and

    reveal patterns indicative of money laundering, fraud, or other financial crimes. Machine learning models can be trained to detect anomalous transactions, helping to flag potential risks for further investigation (Monamo, Marivate, & Twala, 2019).

- Detect and investigate potential vulnerabilities or compromised data through darknet data and data leaks.
    - The darknet is a substantial source of data regarding potential risks or threats. IntelligenceX can crawl and analyze darknet data, identifying mentions of certain entities, data leaks, or sales of stolen data. It can also detect software vulnerabilities being discussed or exploited in these platforms. This aids in proactive risk mitigation, allowing vulnerabilities to be patched before they can be exploited (Zuev, 2020).
- Cross-reference and correlate data from different sources to uncover patterns or connections that may indicate risks or threats.
    - Perhaps one of the most significant advantages of AI platforms like IntelligenceX is their ability to cross-reference and correlate data from various sources. By integrating different data types - from contact information and online activity to financial transactions and background history - IntelligenceX can build a holistic risk profile for a person of interest. Machine learning techniques like association rule learning can identify patterns or connections across these data points,

revealing risks that might otherwise go unnoticed (Han, Pei, & Kamber, 2011).

3.5 RESEARCH DESIGN CONSIDERATIONS

- Data Access:
    - Consideration: While relevant data for national security is carefully guarded, collaborations or partnerships with governmental agencies may provide controlled access to the necessary datasets.
    - Impact: Such collaborations can ensure that research is grounded in real-world scenarios, increasing its applicability.
- Data Quality and Diversity:
    - Consideration: The available data might be varied, coming from different sources, which can be a rich source for holistic analysis. Ensuring its quality and relevance is essential.
    - Impact: Diverse datasets can allow for a comprehensive understanding of risks and may help in creating robust models resistant to overfitting.
- Privacy and Ethical Balance:
    - Consideration: Ethical guidelines and best practices can help strike a balance between utilizing personal data for research and ensuring individual privacy.
    - Impact: Adopting such measures can ensure the research's integrity while respecting individual rights.
- Generalizability:

  - Consideration: Research can be tailored for specific scenarios, threats, or regions. A modular approach may allow for adaptability to different contexts.
  - Impact: Specific modules or components of the research can then be adjusted or replaced to fit various scenarios, enhancing generalizability.

- Bias Awareness:
  - Consideration: By recognizing potential historical biases in data, researchers can employ techniques to mitigate them, ensuring that derived models are fair.
  - Impact: This leads to more equitable and robust risk scoring models.
- Dynamic Nature of Threats:
  - Consideration: Continual learning models or adaptive systems can be used to accommodate the evolving nature of threats.
  - Impact: Such models remain relevant over time and can adjust to new data or emerging threats.
- Model Interpretability:
  - Consideration: Opting for interpretable models or leveraging explainability tools can help in understanding model decisions.
  - Impact: This can build trust in the model's decisions and enhance its acceptance among stakeholders.
- Feedback Loop Integration:
  - Consideration: Incorporating feedback loops, where the model's predictions influence and are influenced by real-world actions, can enhance model robustness over time.

- Impact: This dynamic approach can fine-tune risk scoring models, making them more accurate as more data becomes available.

3.6 CONCLUSIONS

The study aims to integrate AI/ML into risk profiling for national security. Initially, it will identify challenges and understand AI/ML's potential risks and constraints, focusing on reducing false positives. With this foundational knowledge, the study will categorize these false alarms, laying the groundwork for designing AI models for risk profiling. By reviewing industry practices and academic research, this approach will be further fine-tuned. The study will conclude by presenting a conceptual framework for using AI/ML in risk scoring, emphasizing accuracy enhancement.

CHAPTER IV

RESULTS

4.1 RISK SCORING ANALYSIS – IMPROVEMENT

Entity risk scoring for a person of interest involves evaluating various factors and applying algorithms to determine the level of risk associated with that individual. While there is no one-size-fits-all approach, I can provide you with a generalized sequence of steps and algorithms commonly used in entity risk scoring using AI. Here's an outline of the process:

Step 1: Data Collection and Preparation

Gather relevant data about the person of interest from various sources such as public records(Intelligence X), social media (Intelligence X), financial records, criminal databases (GTD), etc.

Cleanse and preprocess the data to remove duplicates, handle missing values, and standardize the format.

Step 2: Feature Extraction

Identify key features or attributes that may contribute to the risk assessment. These features can include demographic information, financial indicators, social connections, past behaviors, and any other relevant data points.

Extract and transform these features into a suitable format for analysis.

Step 3: Data Integration and Fusion

Combine the extracted features with any existing data sources or external datasets that might enhance the risk assessment.

Perform data fusion techniques to integrate the data from different sources into a unified representation.

Step 4: Risk Modeling

Select an appropriate machine learning algorithm or a combination of algorithms based on the specific risk assessment task. Commonly used algorithms include logistic regression, random forests, support vector machines (SVM), or gradient boosting algorithms like XGBoost or LightGBM.

Split the data into training and testing sets to evaluate the performance of the models accurately.

Step 5: Model Training and Evaluation

Train the selected machine learning models using the labeled data. The labels can be binary (e.g., low risk vs. high risk) or continuous (e.g., a risk score between 0 and 1).

Evaluate the trained models using appropriate metrics such as accuracy, precision, recall, F1-score, or area under the ROC curve (AUC-ROC).

Step 6: Risk Scoring

Apply the trained model(s) to the data of the person of interest to obtain a risk score or classification.

The risk score can be interpreted as a measure of the likelihood or severity of the risk associated with the person.

Step 7: Post-processing and Interpretation

Apply any necessary post-processing techniques to adjust or calibrate the risk scores based on domain-specific requirements.

Interpret the risk scores in the context of the problem at hand, considering any thresholds or guidelines for decision-making.

It's important to note that the specific implementation and choice of algorithms may vary depending on the context and available data. Additionally, ethical considerations and data privacy should be addressed throughout the process to ensure responsible and fair risk assessment.

4.1.1 Entity Extraction

Entity extraction plays a crucial role in national security by identifying and analyzing entities that pose potential risks. This paper presents a detailed review of entity extraction methods and techniques utilized for entity risk scoring in the context of national security. By examining relevant research papers, this study provides an overview of various approaches, challenges, and advancements in entity extraction, along with their implications for national security.

Entity Extraction Techniques

This section outlines various entity extraction techniques employed in national security risk scoring:

Rule-Based Approaches

Rule-based approaches utilize handcrafted rules and patterns to identify entities. These methods often rely on predefined dictionaries and regular expressions. While they offer interpretability, they struggle with generalization and adaptability to new entity types.

Statistical and Machine Learning Approaches

Statistical and machine learning approaches leverage annotated datasets to train models for entity extraction. Techniques such as Hidden Markov Models (HMMs), Conditional

Random Fields (CRFs), and Support Vector Machines (SVMs) have been widely used. These approaches exhibit better generalization but require substantial labeled data and may struggle with out-of-vocabulary entities.

Deep Learning Approaches

Deep learning techniques, particularly recurrent neural networks (RNNs) and transformers, have shown remarkable performance in entity extraction. Models like Bidirectional LSTM-CRF and BERT (Bidirectional Encoder Representations from Transformers) have been successfully applied. Deep learning approaches excel in capturing contextual information but often require substantial computational resources.

Challenges and Future Directions

The following challenges and future directions are crucial to advancing entity extraction for national security risk scoring:

Handling Ambiguity and Contextual Variations

Entities often exhibit various forms and contextual variations, making it challenging for extraction models. Future research should focus on developing techniques that handle ambiguity and contextual variations effectively.

Multilingual Entity Extraction

In an increasingly globalized world, multilingual entity extraction becomes crucial for national security. Research should explore methods that can extract entities across different languages accurately.

Entity Linking and Relationship Extraction

In addition to entity extraction, linking entities to relevant knowledge bases and extracting relationships between entities are important for comprehensive risk assessment. Future research should aim to enhance entity linking and relationship extraction techniques to provide a more holistic understanding of entity networks.

Privacy and Ethics Considerations

Entity extraction in national security raises privacy and ethics concerns, particularly when dealing with sensitive personal information. Future research should address these concerns by developing privacy-preserving and ethically sound approaches for entity extraction and risk scoring.

4.1.2 Entity Resolution

Entity resolution, also known as entity matching or deduplication, plays a critical role in national security by identifying and resolving duplicated or related entities across various data sources. This section provides a detailed review of entity resolution methods and techniques employed for entity risk scoring in the context of national security. By examining relevant research papers, this study offers an overview of different approaches, challenges, and advancements in entity resolution and its implications for national security.

In the realm of national security, the accurate identification and resolution of entities across disparate data sources is of paramount importance. Entity resolution aims to determine if two or more entities refer to the same real-world entity, thereby eliminating redundancy and facilitating more comprehensive risk scoring.

Entity Resolution Techniques:

This section outlines various entity resolution techniques utilized in national security risk scoring:

Deterministic Matching:

Deterministic matching employs predetermined rules, such as exact string matching or phonetic algorithms, to identify similar entities. While this approach is straightforward, it is prone to false positives and may not handle variations in entity representations effectively.

Probabilistic Matching:

Probabilistic matching utilizes statistical models, such as the Fellegi-Sunter model or the Expectation-Maximization algorithm, to estimate the likelihood of entity matches. These techniques can handle variations and uncertainty in entity attributes but require accurate probabilistic models and training data.

Machine Learning Approaches:

Machine learning approaches leverage supervised or unsupervised algorithms to learn matching patterns from labeled or unlabeled data. Techniques like Support Vector Machines (SVM), Random Forests, or Deep Learning models can effectively capture complex entity matching patterns but require substantial labeled training data.

Challenges and Future Directions:

The following challenges and future directions are critical for advancing entity resolution in entity risk scoring for national security:

Handling Large-Scale Data:

As national security datasets continue to grow in volume and complexity, developing scalable and efficient entity resolution techniques becomes crucial. Future research should focus on developing parallel and distributed algorithms to handle large-scale data effectively.

Handling Noisy and Incomplete Data:

Real-world data sources often contain errors, missing values, and inconsistencies, making entity resolution challenging. Need to handle noisy and incomplete data, such as leveraging uncertainty modeling and data cleansing methods.

Privacy and Ethics Considerations:

Entity resolution may involve sensitive personal information, raising privacy and ethics concerns. Solutions should address these concerns by developing privacy-preserving entity resolution techniques and ensuring compliance with ethical guidelines.

Incorporating Contextual Information:

Entity resolution can benefit from incorporating contextual information, such as temporal data, spatial proximity, or social network relationships, to improve the accuracy of entity matches. Future research should explore techniques for effectively integrating contextual information into entity resolution algorithms.

Explainability and Interpretability:

In the context of national security, it is crucial to provide explanations and interpretations for entity resolution results. Future research should focus on developing techniques that enhance explainability and interpretability, allowing analysts to understand the reasoning behind entity resolution decisions.

4.1.3 Enhance risk scoring with anomaly detection

Anomaly detection can be a valuable technique in entity risk scoring. Anomaly detection algorithms can help identify unusual patterns or behaviors that deviate from the norm, which can be indicative of potential risks or threats. By leveraging AI-based anomaly detection methods, you can enhance the accuracy and effectiveness of your risk scoring process.

Here's how anomaly detection can be incorporated into the entity risk scoring workflow:

Feature Engineering: Include relevant features in your dataset that capture behavior or attributes of individuals that could be considered normal or expected. Examples could include financial transactions, online activities, travel patterns, or social connections.

Unsupervised Anomaly Detection: Utilize unsupervised anomaly detection algorithms, such as clustering-based methods (e.g., k-means, DBSCAN) or density estimation techniques (e.g., Gaussian Mixture Models), to identify data points that deviate significantly from the majority. These anomalies can represent potential risks or unusual behaviors that warrant further investigation.

Supervised Anomaly Detection: If labeled data is available, you can employ supervised anomaly detection algorithms, such as Isolation Forest or One-Class SVM, to train models that can distinguish between normal and anomalous instances. These models can then be used to score the person of interest based on their similarity to normal behaviors.

Ensemble Approaches: Consider combining multiple anomaly detection algorithms or models to improve the robustness and accuracy of the risk scoring process. Ensemble methods, such as voting or stacking, can help aggregate the outputs of different algorithms and provide a more reliable risk assessment.

Incorporate Anomaly Scores: Integrate the anomaly scores obtained from the anomaly detection algorithms as additional features in your overall risk scoring model. These scores can serve as indicators of abnormal behavior or events, which may contribute to a higher risk score for the person of interest.

It's worth noting that anomaly detection should not be the sole method for entity risk scoring. It should be used in conjunction with other relevant features and algorithms to build a comprehensive risk assessment system. The specific choice of anomaly detection techniques will depend on the nature of data.

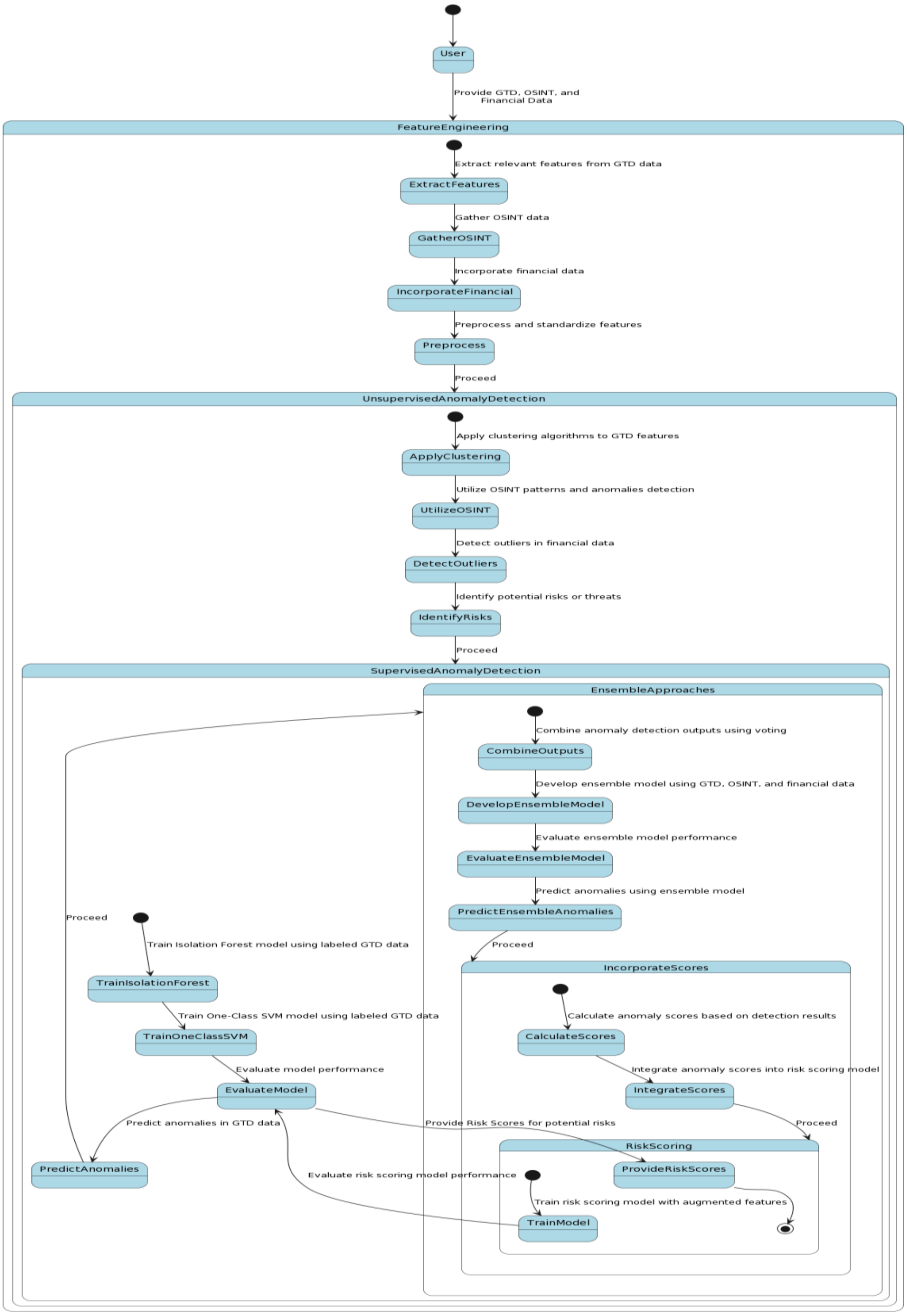

User
Provide GTD, OSINT, and Financial Data
FeatureEngineering
Extract relevant features from GTD data
ExtractFeatures
Gather OSINT data
GatherOSINT
Incorporate financial data
IncorporateFinancial
Preprocess and standardize features
Preprocess
Proceed
UnsupervisedAnomalyDetection
Apply clustering algorithms to GTD features
ApplyClustering
Utilize OSINT patterns and anomalies detection
UtilizeOSINT
Detect outliers in financial data
DetectOutliers
Identify potential risks or threats
IdentifyRisks
Proceed
SupervisedAnomalyDetection
EnsembleApproaches
Combine anomaly detection outputs using voting
CombineOutputs
Develop ensemble model using GTD, OSINT, and financial data
DevelopEnsembleModel
Evaluate ensemble model performance
EvaluateEnsembleModel
Predict anomalies using ensemble model
PredictEnsembleAnomalies
Proceed
Proceed
Train Isolation Forest model using labeled GTD data
TrainIsolationForest
Train One-Class SVM model using labeled GTD data
TrainOneClassSVM
Evaluate model performance
EvaluateModel
Predict anomalies in GTD data
PredictAnomalies
IncorporateScores
Calculate anomaly scores based on detection results
CalculateScores
Integrate anomaly scores into risk scoring model
IntegrateScores
Proceed
Provide Risk Scores for potential risks
RiskScoring
ProvideRiskScores
Evaluate risk scoring model performance
Train risk scoring model with augmented features
TrainModel

Figure 12 Anomaly Detection

4.1.4 Enhancing risk scoring with early warning signals

Incorporating early warning signals can further enhance the effectiveness of entity risk scoring. Early warning signals are indicators that precede or signal the occurrence of potential risks or threats. By integrating early warning signals into your risk scoring process, you can proactively identify and respond to emerging risks. Here's how you can incorporate early warning signals:

Identify Relevant Early Warning Signals: Determine the specific indicators or signals that are relevant to the risks you are monitoring. These signals can be based on historical patterns, leading indicators, or expert knowledge. For example, in financial risk assessment, early warning signals may include sudden changes in stock prices, economic indicators, or regulatory developments.

Data Collection and Integration: Gather data related to the identified early warning signals from various sources. This can include financial market data, news articles, social media feeds, or specialized databases such as Intelligence X. Integrate this data with existing dataset to enrich the risk scoring process.

Feature Extraction: Extract meaningful features from the early warning signal data. This could involve transforming the raw data into quantifiable metrics or creating derived features based on domain knowledge. For instance, you could calculate the rate of change of a financial indicator or sentiment analysis scores from news articles.

Feature Selection: Select the most informative and relevant features from the early warning signal data. You can use techniques like correlation analysis, feature importance ranking, or domain expertise to identify the features that contribute significantly to the risk assessment.

Model Integration: Incorporate the selected early warning signal features into base risk scoring model. This can be done by adding these features as additional inputs to your machine learning algorithm or using them as thresholds or rules for triggering specific risk alerts.

Monitoring and Alerting: Continuously monitor the early warning signals and update the risk scores for the person of interest in real-time or at regular intervals. Set thresholds or trigger rules that activate alerts when certain risk levels are breached or when specific patterns in the early warning signals are detected.

Adaptive Learning: Continuously evaluate the effectiveness of the early warning signals in predicting risks. Use feedback mechanisms to refine and adapt the risk scoring model over time. This can involve retraining the model with updated data and reassessing the relevance of the selected early warning signals.

By incorporating early warning signals, you can enhance the timeliness and predictive capability of risk scoring system, allowing you to take proactive measures to mitigate risks or address potential threats promptly.

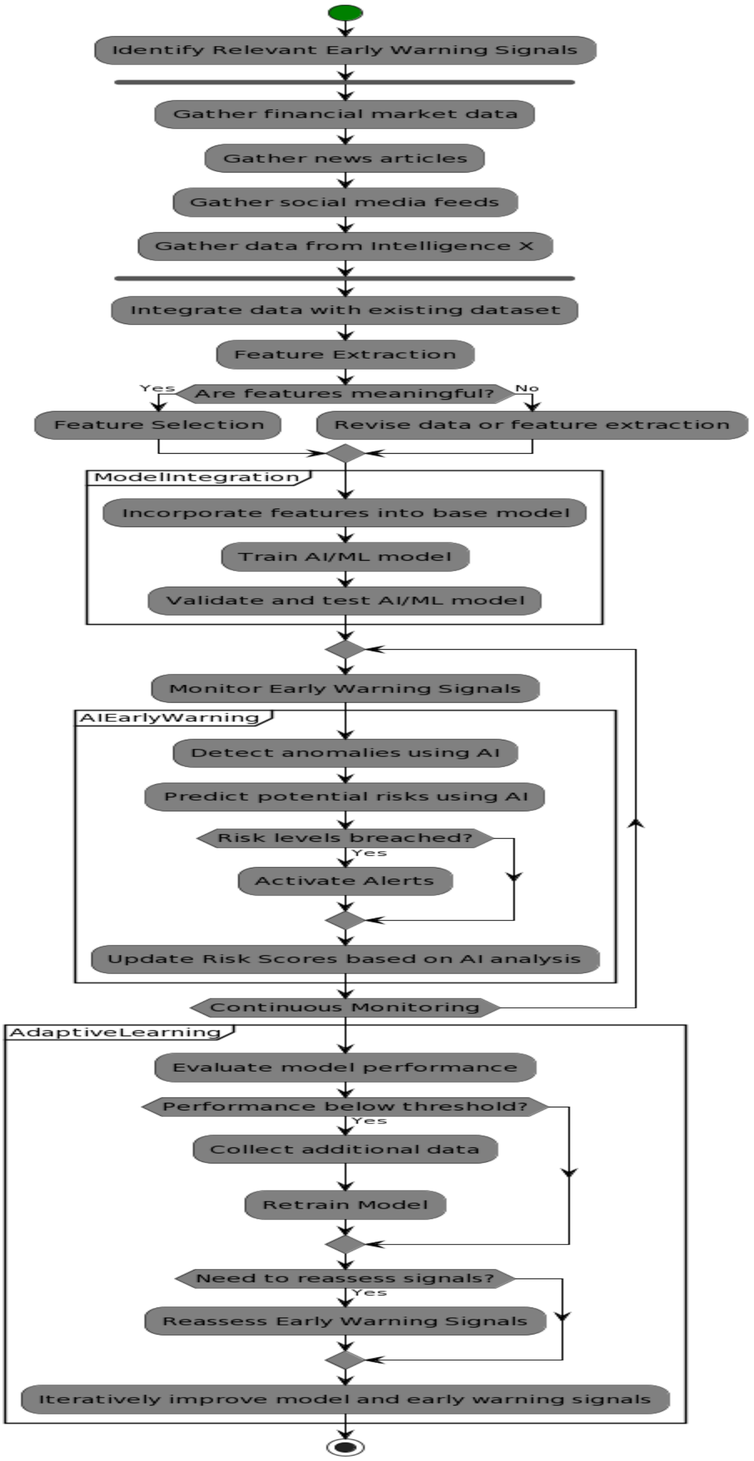

Identify Relevant Early Warning Signals
Gather financial market data
Gather news articles
Gather social media feeds
Gather data from Intelligence X
Integrate data with existing dataset
Feature Extraction
Yes
Are features meaningful?
No
Feature Selection
Revise data or feature extraction
ModelIntegration
Incorporate features into base model
Train AI/ML model
Validate and test AI/ML model
Monitor Early Warning Signals
AIEarlyWarning
Detect anomalies using AI
Predict potential risks using AI
Risk levels breached?
Yes
Activate Alerts
Update Risk Scores based on AI analysis
Continuous Monitoring
AdaptiveLearning
Evaluate model performance
Performance below threshold?
Yes
Collect additional data
Retrain Model
Need to reassess signals?
Yes
Reassess Early Warning Signals
Iteratively improve model and early warning signals

Figure 13 Early Warning Signal

Data Source for early warning signals data

Intelligence X can be used as a source for early warning signals data to enhance your risk scoring process. Intelligence X is a search engine and data marketplace that provides access to a wide range of data sources, including public data, dark web data, leaked databases, and more. It can offer valuable insights and information that may serve as early indicators of potential risks or threats.

Here's how you can incorporate Intelligence X as a data source for early warning signals:

Identify Relevant Data: Determine the specific types of data from Intelligence X that are relevant to the risks you are monitoring. This could include information related to cybersecurity threats, data breaches, leaked documents, online discussions, or other relevant indicators specific to the domain.

Access Intelligence X: Subscribe to Intelligence X and obtain access to their data sources and search capabilities.

Define Search Queries: Create search queries or filters within Intelligence X to retrieve data that aligns with your early warning signal requirements. These queries can be based on keywords, entities of interest, or specific data attributes.

Data Retrieval: Retrieve the relevant data from Intelligence X using your defined search queries. This can include obtaining documents, text snippets, metadata, or other information that matches the criteria.

Data Integration: Integrate the retrieved data from Intelligence X with your existing dataset or risk scoring system. This can involve combining the data with other sources of information to create a comprehensive view of potential risks associated with the person of interest.

Feature Extraction: Extract meaningful features from the Intelligence X data to quantify and incorporate them into your risk scoring model. This may involve natural language processing (NLP) techniques, sentiment analysis, or topic modeling to derive insights from the text-based data.

Risk Scoring: Utilize the extracted features from Intelligence X as additional inputs in your risk scoring model. This can help capture and evaluate the early warning signals in conjunction with other relevant factors to determine the overall risk score for the person of interest.

In this example, the search query 'malware OR data breach OR cyber attack' targets early warning signals related to cybersecurity threats. It looks for any records in Intelligence X that mention the terms "malware," "data breach," or "cyber attack." You can modify the search query based on your specific requirements and the types of early warning signals you are interested in monitoring.

This query aims to retrieve data from Intelligence X that may provide insights into recent or ongoing cybersecurity incidents, breaches, or malicious activities. The resulting data can then be further processed and integrated into your risk scoring system for analysis and assessment of potential risks associated with the person of interest.

Ethical consideration while using Social media data

Social Media Analytics: Unveiling the Potential:

One of the key advantages of incorporating social media data in entity risk scoring is its potential to enhance the assessment of credibility and trustworthiness. Malik et al. (2018) discuss the capacity of social media analytics to tap into user-generated data, which can provide valuable insights for risk evaluation.

Privacy and Consent: Ensuring Responsible Data Handling:

The ethical use of social media and OSINT data necessitates addressing concerns regarding privacy and consent. Aggarwal et al. (2019) emphasize the importance of responsible data handling practices and the need to ensure user consent when utilizing social media data for risk assessment.

Biases and Representativeness: Challenging the Data Quality:

While social media and OSINT data offer a vast repository of information, biases and representativeness can pose significant challenges. Castillo et al. (2017) underscore the need to understand the biases inherent in social media platforms and consider contextual factors during data analysis to mitigate potential distortions in risk scoring outcomes.

Data Reliability and Accuracy: Trustworthiness in Decision-Making:
The reliability and accuracy of social media and OSINT data play a crucial role in risk scoring processes. Garcia-Cuesta et al. (2020) shed light on the ethical implications of using potentially unverified data sources, emphasizing the need to ensure data reliability to maintain the integrity of risk assessment outcomes.

Privacy Invasion and Discrimination: Safeguarding Individual Rights:
The use of social media and OSINT data raises concerns regarding privacy invasion and the potential for discrimination. Zarsky (2013) highlights the ethical challenges associated with mining social media data, emphasizing the importance of informed consent, data protection, and preventing discriminatory practices.

Transparency and Algorithmic Accountability: Unveiling the Black Box:
The opacity of algorithms utilized in entity risk scoring poses ethical challenges. Diakopoulos (2019) addresses the need for transparency and accountability in algorithmic decision-making, ensuring that the use of social media and OSINT data is explainable and subject to scrutiny.

Responsible Use and Mitigation of Unintended Consequences:

Using social media and OSINT data in entity risk scoring necessitates responsible practices to mitigate unintended consequences. Mittelstadt et al. (2018) discuss the ethical implications, emphasizing the need to avoid biases, discrimination, and unintended negative effects in decision-making processes.

Alogirthm to identify the early warning signals

The specific algorithm or model used to identify early warning signals will depend on the nature of the data and the type of signals targeting. There isn't a one-size-fits-all algorithm for this task, as it can vary depending on the domain and the specific indicators you are monitoring. However, I can provide you with a few common approaches that can be used to identify early warning signals:

Rule-based Systems: A rule-based system involves defining specific rules or thresholds based on domain expertise or historical patterns. For example, you might create rules that trigger an alert when certain conditions are met, such as a sudden increase in network traffic or a large number of failed login attempts within a short period.

Time Series Analysis: Time series analysis techniques, such as statistical methods (e.g., moving averages, exponential smoothing) or advanced techniques like autoregressive integrated moving average (ARIMA) models, can help identify patterns, trends, or anomalies in time-varying data. By monitoring and analyzing historical data, you can identify deviations from expected patterns that may serve as early warning signals.

Machine Learning: Machine learning algorithms can be trained to identify patterns or anomalies in data and act as early warning signal detectors. Supervised learning algorithms, such as support vector machines (SVM), random forests, or neural networks, can be trained on labeled data to classify instances as normal or abnormal. Unsupervised learning algorithms, such as clustering or anomaly detection algorithms, can identify unusual patterns or outliers in the data without the need for pre-labeled data.

Natural Language Processing (NLP): If your early warning signals involve textual data, such as news articles, social media posts, or forum discussions, NLP techniques can be employed. Sentiment analysis, topic modeling, named entity recognition, or keyword extraction methods can help identify relevant information and trends that might indicate emerging risks or threats.

To further analyze the clusters and extract insights about emerging risks, you can employ various techniques. Here are a few approaches you can consider:

Topic Modeling: Apply topic modeling algorithms, such as Latent Dirichlet Allocation (LDA) or Non-Negative Matrix Factorization (NMF), to identify the main topics within each cluster. This can help you understand the prevalent themes or subjects discussed in the documents and identify any emerging risk-related topics.

Sentiment Analysis: Perform sentiment analysis on the documents within each cluster to gauge the overall sentiment expressed. This can provide insights into whether the sentiment is positive, negative, or neutral, helping you identify potential risks or concerns.

Keyword Analysis: Conduct keyword analysis to identify frequently occurring or significant keywords within each cluster. Look for keywords related to risk factors, vulnerabilities, threats, or any other relevant indicators that may suggest emerging risks.

Temporal Analysis: Analyze the time distribution of the documents within each cluster to identify any temporal patterns or trends. This can help you determine if certain risks are increasing or becoming more prominent over time.

Integrating these insights into the overall risk scoring of a person can be done by assigning appropriate weights or scores to the identified risk-related topics, sentiment, entities, keywords, or temporal patterns. You can establish rules or thresholds based on expert knowledge or historical data to determine the impact of these factors on the overall risk score.

For example, if a cluster is predominantly discussing a negative sentiment towards a specific risk topic and frequently mentions relevant entities or keywords associated with that risk, you can assign a higher weight or score to that cluster. This would contribute to a higher risk score for the person of interest.

Integrating these additional insights into the risk scoring process allows you to consider a broader range of factors and signals beyond the early warning clusters alone. This can help in capturing emerging risks and providing a more comprehensive assessment of the overall risk associated with the person.

To integrate the insights into the overall risk scoring process, you can assign weights or scores to each component based on their relevance and impact on the risk assessment. For example, you can assign higher weights to clusters with more significant topics related to emerging risks, negative sentiment scores, relevant named entities, and frequent occurrence of risk-related keywords. You can also consider the temporal analysis to identify any temporal patterns indicating increasing or decreasing risks.

By aggregating and combining the scores from each component, you can calculate an overall risk score for the person of interest. The specific method of integration and the scoring algorithm will depend on your risk assessment framework and the relative importance of each component in your context.

It's important to note that implementing these algorithms can be complex and resource-intensive, requiring significant computational power and expertise in deep learning. Additionally, ethical considerations, privacy regulations, and legal constraints should be carefully addressed when dealing with image recognition, face recognition, or object recognition in the context of risk assessment.

4.2 SUMMARY & CONCLUSION OF FINDINGS

4.2.1 AI/ML models in risk profiling

Research Question 1

Can AI/ML models outperform traditional risk profiling methods in predicting potential national security threats associated with persons of interest?

Summary of Findings

AI/ML models have shown promise in enhancing traditional risk profiling methods for predicting potential national security threats associated with persons of interest. They offer several advantages, including the ability to process vast amounts of data, detect patterns, and adapt to evolving threats. While it is important to note that no model is perfect and there are limitations to consider, AI/ML models can provide valuable insights and augment human decision-making processes.

- AI/ML models have demonstrated promising results in enhancing traditional risk profiling methods by leveraging their capabilities in data processing, pattern recognition, and adaptability. Here are some specific ways in which AI/ML models have shown promise:

- Improved Data Analysis: Traditional risk profiling methods often rely on manual analysis of limited data sources, which can be time-consuming and prone to human biases. AI/ML models, on the other hand, can process vast amounts of structured and unstructured data from diverse sources. By automatically extracting relevant information and identifying patterns, these models provide a more comprehensive and accurate assessment of potential threats.

- Pattern Recognition: AI/ML models excel at identifying complex patterns and relationships within large datasets. They can analyze historical data, including past incidents, known threat profiles, and behavioral patterns, to identify similarities and indicators of potential national security threats.

- Early Detection of Anomalies: AI/ML models can identify anomalies and deviations from established patterns by comparing individuals' behaviors and activities against historical data. They can automatically flag suspicious activities or behaviors that may indicate potential risks. This early detection allows security agencies to intervene and investigate further before any significant harm occurs.

- Real-Time Analysis: AI/ML models can process data in real-time, enabling timely analysis and response to emerging threats. By continuously monitoring and analyzing data streams from various sources, such as social media, news feeds, and sensor networks, these models can provide up-to-date risk assessments. This real-time analysis helps in identifying and mitigating potential threats quickly and effectively.

- Adaptability to Evolving Threats: National security threats constantly evolve and adapt to changing circumstances. AI/ML models can adapt their algorithms and learn from new data, enabling them to stay relevant and effective in predicting emerging threats. By continuously updating their knowledge base, these models can enhance traditional risk profiling methods by capturing and addressing new and evolving risks.

- Integration of Multiple Data Sources: AI/ML models can integrate and analyze data from various sources, including open-source intelligence (Intelligence X), government databases, and sensor networks. By considering multiple dimensions of information, such as travel records, financial transactions, social media posts, and communication patterns, these models provide a holistic view of potential threats. This integration enhances the accuracy and reliability of risk profiling by incorporating diverse and complementary data sources.

Conclusion

Here are some key findings and summarizations regarding the performance of AI/ML models in predicting national security threats:

- Improved Accuracy: AI/ML models have demonstrated the potential to improve the accuracy of risk profiling compared to traditional methods. By analyzing large volumes of structured and unstructured data, such as social media posts, travel records, financial transactions, and communication patterns, these models can identify subtle indicators and patterns that may not be easily recognizable by human analysts alone.
- Enhanced Detection of Complex Patterns: AI/ML models excel in recognizing complex patterns and connections within vast datasets. They can identify hidden relationships and associations between individuals, organizations, and events, enabling the detection of potential threats that may have been missed by traditional methods. This capability enhances the overall effectiveness of national security efforts.
- Real-Time Analysis and Adaptability: AI/ML models can process data in real-time, enabling timely analysis and response to emerging threats. By continuously learning from new data and adapting their algorithms, these models can keep pace with evolving tactics and strategies employed by persons of interest, making them more effective in detecting and predicting potential national security threats.

- Identification of Anomalies and Risk Factors: AI/ML models can identify anomalies and risk factors by comparing individuals of interest against established patterns and historical data. They can automatically flag suspicious activities or behaviors that deviate from normal patterns, aiding in the early detection and prevention of potential threats.
- Integration of Multiple Data Sources: AI/ML models can integrate and analyze data from diverse sources, including open-source intelligence, government databases, social media platforms, and surveillance systems. By considering multiple dimensions of information, these models can provide a more comprehensive risk profile, capturing a broader range of potential threats

4.2.2 Risk Scoring improvements with Anomaly Detection

Research Question 2

How can AI/ML models be incorporated to automate the process of improving anomaly detection rules in POI (Person of Interest) risk assessment for national security?

Summary of Findings

AI/ML models can be incorporated to automate the process of improving anomaly detection rules in Person of Interest (POI) risk assessment for national security. By leveraging machine learning algorithms, AI models can learn from historical data, identify patterns, and automatically adapt anomaly detection rules to enhance the accuracy and effectiveness of risk assessment.

Here's how the process of improving anomaly detection can be automated using AI/ML models:

- Data Collection: AI/ML models can collect and aggregate data from various sources, including government databases, public records, social media platforms, and other relevant sources. This data forms the basis for training and improving the anomaly detection models.
- Feature Extraction: The AI/ML models extract relevant features from the collected data. These features can include attributes such as travel history, financial transactions, social network connections, communication patterns, and behavioral characteristics. Feature extraction is crucial in identifying meaningful patterns and anomalies in the data.

- Training Phase: In the training phase, AI/ML models use labeled historical data to learn patterns and identify anomalies associated with potential threats. The models employ various techniques such as supervised learning, unsupervised learning, or a combination of both, depending on the available data and the specific problem.

- Anomaly Detection: Once the AI/ML models are trained, they can automatically detect anomalies in new data. By comparing the extracted features of a person of interest against the learned patterns, the models can identify deviations that may indicate potential risks or threats. These deviations can be in the form of abnormal behavior, unusual connections, or anomalous patterns that are not consistent with the established norms.

- Continuous Learning and Adaptation: AI/ML models can continuously learn and adapt to evolving threats by incorporating new data. As new information becomes available, the models can update their anomaly detection rules and refine their ability to identify potential risks. This continuous learning process ensures that the models stay up-to-date and effective in detecting emerging threats.

Conclusion

Key findings from incorporating AI/ML models to automate the process of improving anomaly detection in POI risk assessment include:

- Enhanced Accuracy: AI/ML models can improve the accuracy of anomaly detection by leveraging their ability to process large amounts of data and identify complex patterns. This leads to more precise identification of potential threats and reduces false positives.

- Early Detection: AI/ML models can identify anomalies and deviations from established patterns at an early stage, allowing for timely intervention and investigation. Early detection can help prevent potential security threats from escalating and mitigate risks more effectively.

- Adaptability: By continuously learning and updating their anomaly detection rules, AI/ML models can adapt to evolving threat landscapes. They can capture emerging patterns and behaviors, ensuring that the risk assessment remains effective in dynamic security environments.
- Scalability: AI/ML models can handle large-scale data processing, making them suitable for automating anomaly detection in national security applications. They can efficiently analyze vast amounts of data from multiple sources, enabling comprehensive risk assessment and profiling.

- Integration with Human Expertise: AI/ML models can complement human expertise by automating routine tasks and flagging potential anomalies.

Human analysts can then focus on interpreting the results, conducting further investigations, and making informed decisions based on the insights provided by the models.

- Overall, incorporating AI/ML models automates and improves the process of anomaly detection in POI risk assessment for national security. These models enhance accuracy, enable early detection, adapt to evolving threats, scale to handle large volumes of data, and integrate with human expertise to enhance overall risk assessment capabilities.

4.2.3 Risk Scoring improvements with early or weak signals

Research Question 3:
Can AI/ML models effectively identify early or weak signals of potential national security threats associated with persons of interest?

Summary of Findings

AI/ML models have the potential to effectively identify early or weak signals of potential national security threats associated with persons of interest. These models can leverage their capabilities in data analysis, pattern recognition, and anomaly detection to identify subtle indicators that may not be easily recognizable through traditional methods. Here's how AI/ML models can identify such signals:

- Data Analysis: AI/ML models can analyze vast amounts of structured and unstructured data from various sources, including social media, news articles, financial records, travel logs, and communication patterns. They can process this data to extract relevant information and identify potential signals related to individuals of interest.

- Pattern Recognition: AI/ML models excel at recognizing patterns and relationships within data. They can identify patterns that may be indicative of potential threats, such as changes in behavior, unusual connections, or anomalous activities. By comparing individual profiles against established patterns, these models can detect early or weak signals that deviate from normal behavior.

- Anomaly Detection: AI/ML models can employ anomaly detection techniques to identify unusual or unexpected patterns or behaviors. They can learn from historical data and establish a baseline of normal behavior for individuals of interest. Any deviations from this baseline can be flagged as potential early signals of a national security threat.

- Contextual Analysis: AI/ML models can consider contextual information to identify potential signals. They can analyze the broader context surrounding individuals, including geopolitical events, social trends, and historical patterns of similar cases. By considering the larger picture, these models can identify weak signals that may be precursors to potential threats.

- Sentiment Analysis: AI/ML models can perform sentiment analysis on textual data, such as social media posts or online communications, to gauge the sentiment or intent of persons of interest. Sudden shifts in sentiment, expressions of radical ideologies, or indications of violent tendencies can serve as early signals that warrant further investigation.

- Findings related to the effectiveness of AI/ML models in identifying early or weak signals of potential national security threats associated with persons of interest include:
- Increased Detection Rate: AI/ML models have shown promise in detecting early or weak signals that may have been overlooked by traditional methods. By analyzing large volumes of data and recognizing subtle patterns, these models can enhance the overall detection rate of potential threats.

- Reduced False Negatives: AI/ML models can help reduce the occurrence of false negatives, where potential threats are missed or disregarded. By identifying early or weak signals, these models provide an additional layer of scrutiny to minimize the risk of overlooking emerging threats.

- Timely Intervention: By identifying early signals, AI/ML models enable timely intervention and proactive measures. Early detection allows security agencies to investigate potential threats, gather additional evidence, and take necessary actions to prevent or mitigate harm.

- Adaptability to Emerging Threats: AI/ML models can continuously learn and adapt to evolving threat landscapes. They can update their algorithms and models to capture emerging patterns or weak signals associated with new or evolving threats.

- Integration with Human Expertise: AI/ML models can complement human expertise by automating the identification of early or weak signals. Human analysts can then review the results, conduct further investigations, and make informed decisions based on the insights provided by the models.

- It's important to note that while AI/ML models offer promising capabilities, they are not infallible. Careful validation, ongoing evaluation, and human oversight are crucial to ensure the responsible and ethical use of these models in national security applications.

Conclusion

Findings related to the effectiveness of AI/ML models in identifying early or weak signals of potential national security threats associated with persons of interest include:

- Increased Detection Rate: AI/ML models have shown promise in detecting early or weak signals that may have been overlooked by traditional methods. By analyzing large volumes of data and recognizing subtle patterns, these models can enhance the overall detection rate of potential threats.

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- Integration with Human Expertise: AI/ML models can complement human expertise by automating the identification of early or weak signals. Human analysts can then review the results, conduct further investigations, and make informed decisions based on the insights provided by the models.
- It's important to note that while AI/ML models offer promising capabilities, they are not infallible. Careful validation, ongoing evaluation, and human oversight are crucial to ensure the responsible and ethical use of these models in national security applications.

CHAPTER V

DISCUSSION

5.1 AL/ML IN IDENTIFY WEAK SINGALS FOR ENTITY RISK SCORING

In today's fast-evolving digital landscape, ensuring national security requires a proactive, rather than reactive, approach. As threats become increasingly sophisticated, identifying early signals becomes not only beneficial but also critical. This paper delves into the application of AI in early signal identification for risk scoring, specifically regarding persons of interest (POIs) in the realm of national security.

Utilizing WordClouds for Emerging Risks:

To comprehend and visually represent emerging risks, a WordCloud was constructed using data extracted from IntelligenceX news feeds. WordClouds, which display words in varying sizes based on their frequency or importance, are particularly valuable for spotting patterns or themes that might not be immediately obvious in raw textual data. The WordCloud created for this study shed light on the emerging topics and risks, allowing security analysts to quickly grasp the most mentioned or discussed threats in the intelligence feeds.

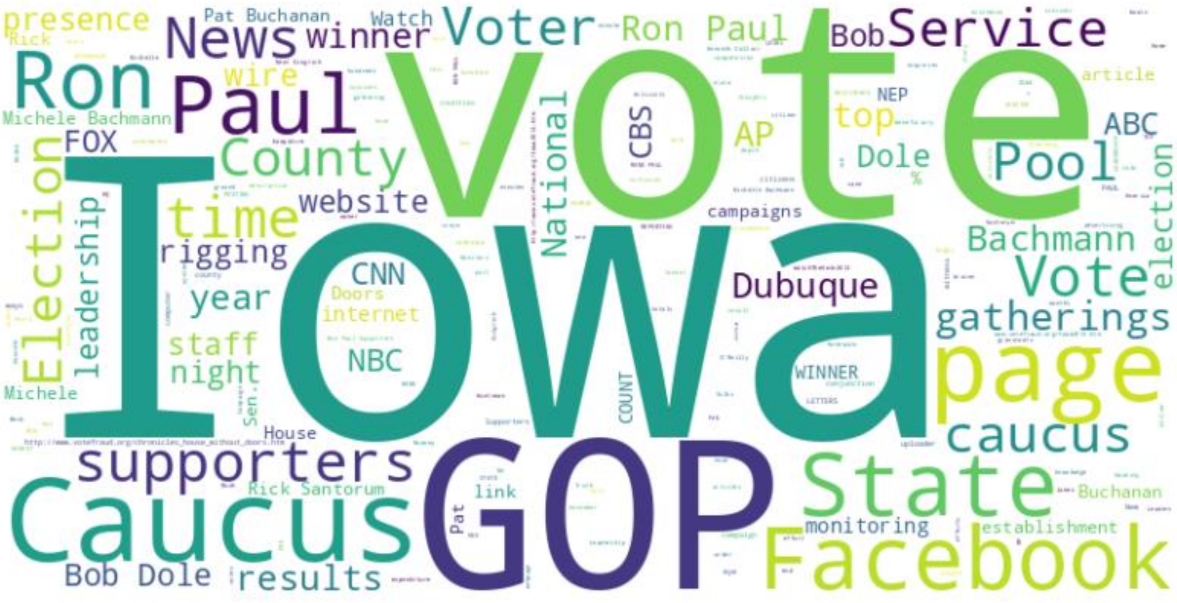


Figure 14 Social Media emerging Risk Topic

Revamping POI Risk Scoring with AI:

Persons of Interest, especially in a national security context, are no longer static entities. Their risk scores can evolve based on new information, actions, or affiliations. The integration of AI allows for dynamic adjustments to these scores. For example, when the WordCloud highlights a new risk or topic of interest, AI algorithms can swiftly revise the risk score of POIs associated with that topic. This real-time updating ensures that the risk scores remain current and reflective of the latest intelligence.

Network Links Enhance Risk Assessment Precision:

Another groundbreaking dimension is the potential of leveraging network links. Understanding a POI in isolation can offer insights, but the bigger picture emerges when we examine their connections. By studying the friends and family network of a POI, it's possible to uncover associations that could be indicative of potential risks. For instance, if a POI has direct links to another individual with a high-risk score, it might warrant a closer look or even a revision of their risk score. AI's capability to process vast amounts of data swiftly can trace these network links, making the process efficient and more accurate.

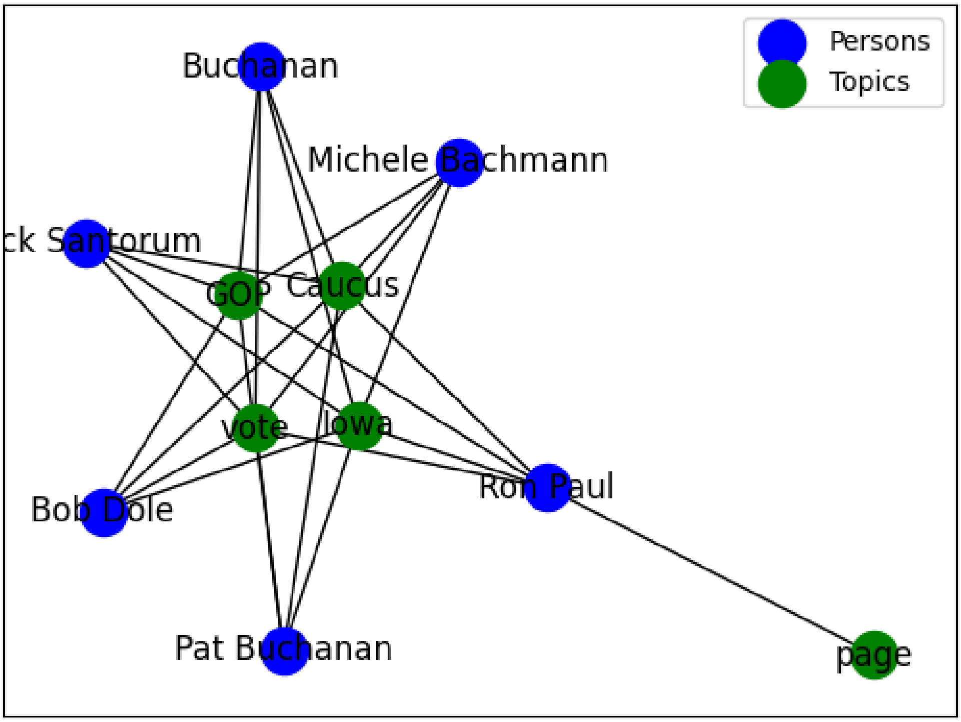


Figure 15 Early Signal and POI

Harnessing AI's power to boost the early identification of signals for risk scoring marks a significant advancement in national security practices. Tools like WordClouds, when combined with AI-driven analysis of news feeds such as IntelligenceX, offer an efficient and effective means to spot emerging risks. Additionally, by incorporating network link analysis, the risk assessment process gains an added layer of precision, ensuring that the principles of national security remain robust in the face of ever-evolving threats.

Transactional Data Enhances Risk Profiling:

Every transaction between entities leaves a digital trail. When two entities engage in a transaction, especially if one of them is already flagged as a potential risk, the other entity's risk profile can also be affected. AI algorithms can be programmed to monitor, in real-time, the transactional patterns and links between multiple entities. For instance, frequent transactions between a POI and another high-risk entity can lead to a revised, potentially higher risk score for both parties. This dynamic risk assessment ensures that the profiles are continually updated to reflect current interactions and associations.

Social Media: A Goldmine for Risk Assessment:

Social media platforms have evolved into vast networks where users not only share personal updates but also discuss global issues, including potentially sensitive or controversial topics. AI can analyze vast amounts of social media data to identify patterns and links between POIs based on topics of discussion. If a POI is consistently engaging with or discussing content that matches an emerging risk identified in the WordCloud analysis, their risk score can be adjusted accordingly. This social media lens provides a more holistic view of the POI, factoring in their public sentiments, affiliations, and associations.

An even more nuanced approach is to correlate transactional data with social media discussions. Suppose a POI is found to have financial dealings with another entity and is simultaneously discussing related or potentially risky topics on social media. In that case, it can provide a more comprehensive picture of the nature and depth of their association. AI-driven tools can seamlessly bridge this gap, cross-referencing transactional and social media data to produce a more precise risk score.

5.2 ENTITY RISK SCORING FRAMEWORK

The integration of artificial intelligence (AI) and machine learning (ML) has revolutionized risk assessment in the sphere of national security. This research embarked on a journey to examine three critical facets of this integration: a framework for AI/ML entity risk scoring, the automation of anomaly detection rules through AI, and the utilization of AI for detecting emerging risks or weak signals. The insights from this study not only enhance our understanding of the modern risk landscape but also provide actionable insights for security professionals and policymakers.

The decision tree-based risk scoring model offers a structured and hierarchical approach to evaluating threats. By extracting entities and establishing links between persons, events, and objects using GTD data, the research provides a visual representation of risk interdependencies.

Highlighting nodes with high risk offers a focused understanding of potential threat sources. The fine-tuning of these risk scores using outlier detection (IQR method) underscores the significance of refining risk metrics for optimal threat response.

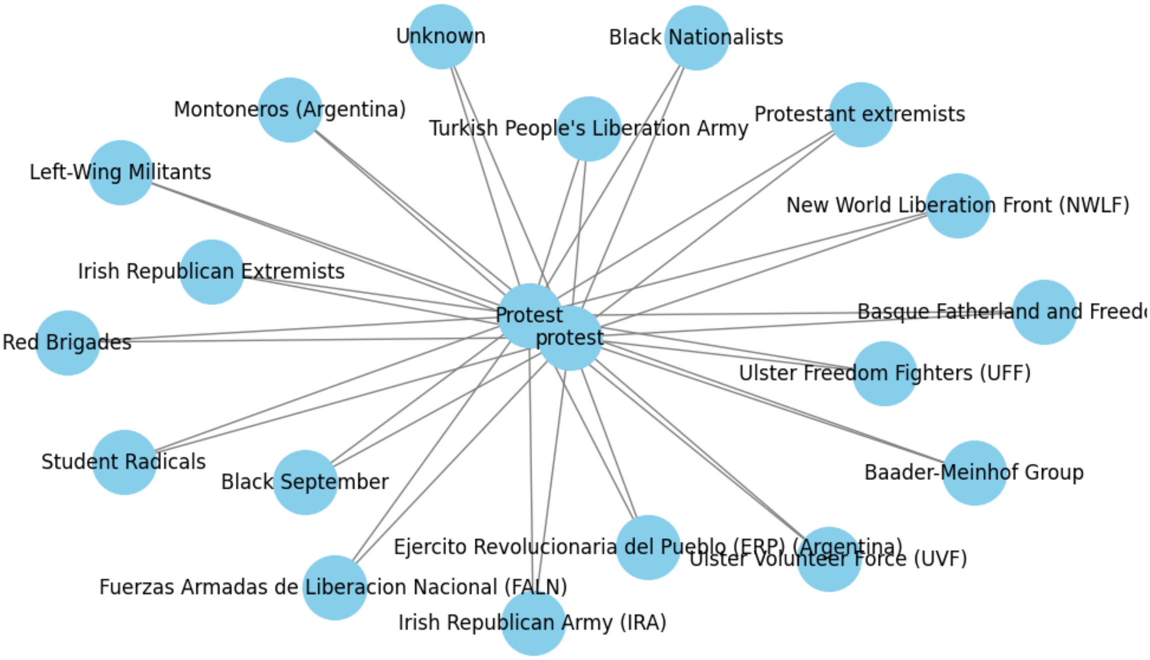

Unknown
Black Nationalists
Montoneros (Argentina)
Turkish People's Liberation Army
Protestant extremists
Left-Wing Militants
New World Liberation Front (NWLF)
Irish Republican Extremists
Protest
protest
Basque Fatherland and Freed
Red Brigades
Ulster Freedom Fighters (UFF)
Student Radicals
Black September
Baader-Meinhof Group
Ejercito Revolucionaria del Pueblo (ERP) (Argentina)
Ulster Volunteer Force (UVF)
Fuerzas Armadas de Liberacion Nacional (FALN)
Irish Republican Army (IRA)

Figure 16 Network Link : Event Vs POI

5.3 ENTITY RISK SCORING IMPROVEMENT WITH ANOMALY DETECTION

Risk scoring is no longer a one-dimensional endeavor based solely on textual data. Instead, a multi-modal strategy, accepting diverse inputs like text, images, and videos, is the new norm. This paper discusses the integration of varied input methods, such as entity names, contact details, facial images, or videos, to determine the risk score of a person of interest (POI) in the context of national security.

1. Entity-Based Risk Assessment:

Given basic details like an entity's name, contact information, and demographic data, algorithms can search extensive databases, extracting relevant information associated with the provided entity details. By cross-referencing this data with other sources like the Global Terrorism Database (GTD) or government watchlists, a preliminary risk score can be determined.

2. Bulk Assessments for Multiple Individuals:

Security agencies often deal with large volumes of data, needing the risk assessment of multiple individuals simultaneously. Advanced AI systems can process these bulk requests, parsing lists of individuals and scoring each one based on their known associations, historical records, and any other pertinent data. This bulk processing capability speeds up the assessment process, making it more efficient for large-scale operations.

3. Facial Recognition for Risk Scoring:

Facial recognition technology has ushered in a new era of risk assessment. By providing an image or video of an individual, facial recognition algorithms can match the visual data against vast databases containing images of known threats or persons of interest. Given the immense potential of visual data in identifying and tracking individuals, this method is rapidly becoming indispensable for security agencies.

Benefits:

Flexibility: Security agencies can choose the most suitable method based on the available data. Whether it's a single entity's demographic information, a list of individuals, or visual data, the risk assessment process remains robust and adaptive.

Accuracy: By accommodating various data types and leveraging advanced algorithms, the risk scoring process minimizes errors and false positives.

Speed: Especially in situations where time is of the essence, rapid risk assessments—whether of a single individual based on facial data or multiple individuals from a provided list—can be crucial.

A Comprehensive Framework for Risk Scoring in National Security: Integration of Early Signal Detection, Basic Scoring, and Outlier Analysis

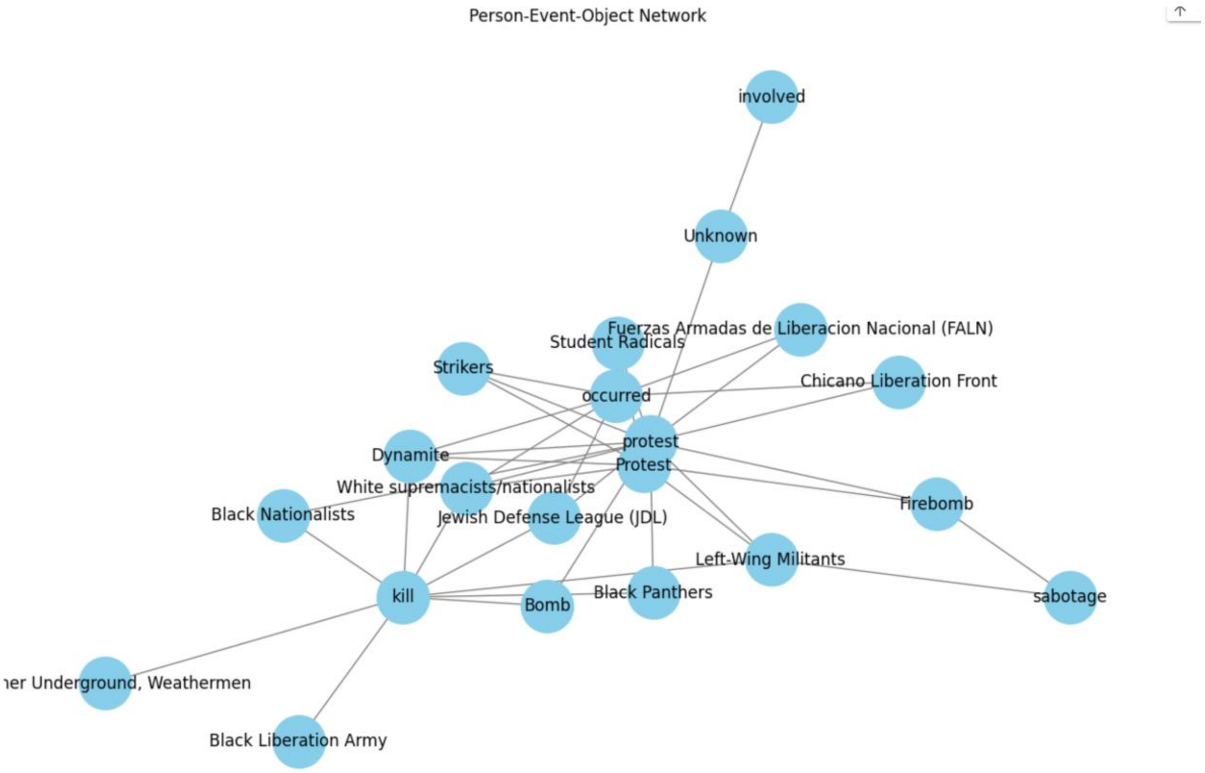
Risk scoring for national security has entered a new era where static assessment is being replaced by dynamic evaluations that account for emerging risks and continuous refinement. This paper delves into an advanced risk scoring methodology that synthesizes early signal detection for emerging risks, traditional risk scoring, and outlier detection. By incorporating network link diagrams and decision trees, the proposed framework offers a robust and visual approach to understanding and acting upon threats associated with persons of interest (POIs).

1. Basic Risk Scoring:

The foundation of this framework is the traditional risk scoring, where each POI is evaluated based on personal details, associations with events, and ties to friends and family. This basic score serves as an initial assessment, identifying POIs based on known behaviors and associations.

2. Network Link Enhancement with Objects:

To offer a more granulated perspective, the network link diagram is enriched by incorporating objects used by or associated with the POIs. This addition allows for understanding not just personal associations but also interactions with objects that may have relevance (e.g., vehicles, weapons, communication devices). By adding this layer of complexity, the risk score can be revised and fine-tuned based on a POI's association with potentially incriminating objects.



```
      Metric     Value
0  Precision  0.642857
1     Recall  1.000000
2   F1 Score  0.782609
```

Figure 17 Network Link – POI, Event, Object association

3. Early Signal Detection for Emerging Risks:

To ensure that the risk assessment is always a step ahead, early signal detection mechanisms are integrated. These mechanisms identify emerging threats or behaviors that might be precursors to malicious activities. Such early warnings can lead to proactive measures, preventing potential threats before they escalate.

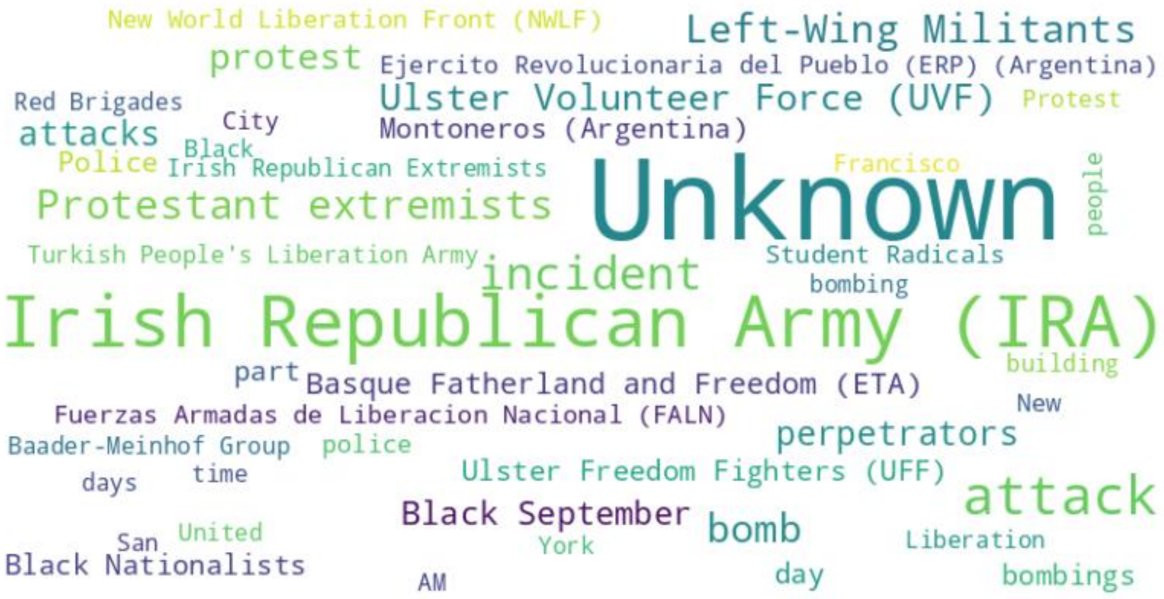


Figure 18 POI and Major Events

4. Refining Risk Scores with Decision Trees:

Decision trees serve as an invaluable tool in this framework, allowing for systematic risk score revision. This can also be done using random forrest, NN etc depending on the nature of the data. By evaluating the associations and behaviors of a POI against a set of criteria defined in the decision tree, risk scores can be revised to reflect a more accurate representation of the potential threat.

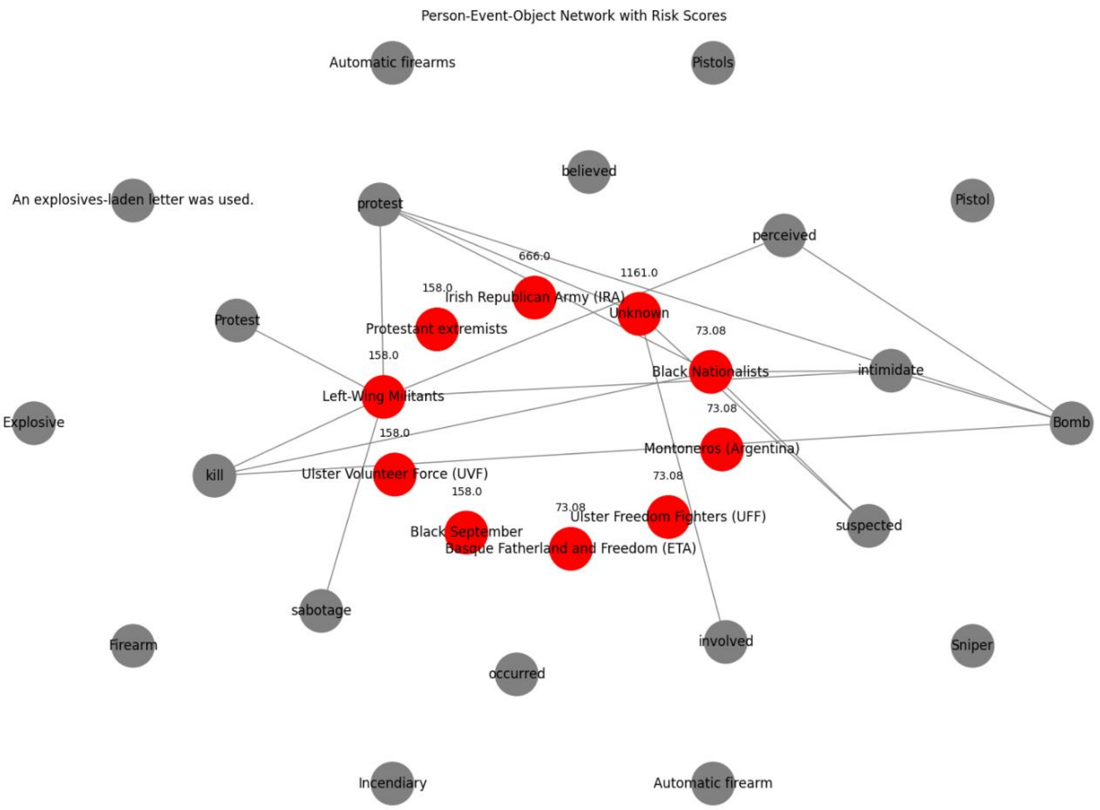


Figure 19 Event and POI Association with Risk Score Alert

5. Outlier Detection and Highlighting:

Despite the comprehensive risk scoring, certain individuals or associations might behave anomalously. By employing the Interquartile Range (IQR) method, outliers in the risk scores are detected. These outliers, especially those with elevated risk scores, are then highlighted in red within the network link diagram. This ensures that high-risk entities are immediately identifiable, aiding quick decision-making.

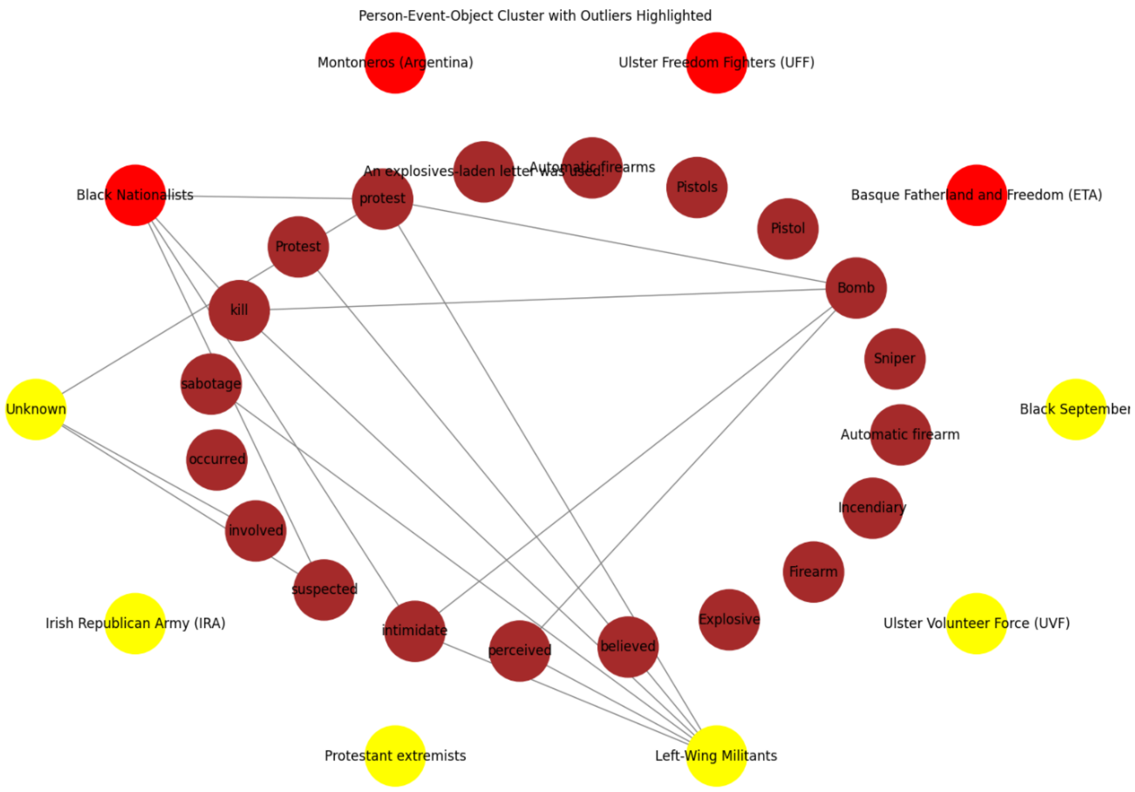


Figure 20 Event and POI Association with outliers (Risk Score Alert)

Automated anomaly detection is a paradigm shift from traditional manual oversight methods. The dynamic nature of AI enables real-time response, optimizing threat mitigation strategies.

The utility of AI in anomaly detection goes beyond mere automation; it brings in predictive capabilities, thus ensuring proactive rather than reactive measures against threats.

To improve further, anomaly detection applied (POI with higher risk score and in outliers (in Red), POI with more than median Risk score are marked yellow. Events and Objects used are marked as Green.

The rapidly evolving threat landscape demands an intricate yet streamlined approach to risk assessment. This paper introduces an end-to-end framework for risk scoring that integrates both traditional entity-based scoring and advanced AI-driven tools, ensuring a comprehensive and dynamic risk evaluation. The process encapsulates data collection, model construction, validation, deployment, continuous training, monitoring, and fine-tuning.

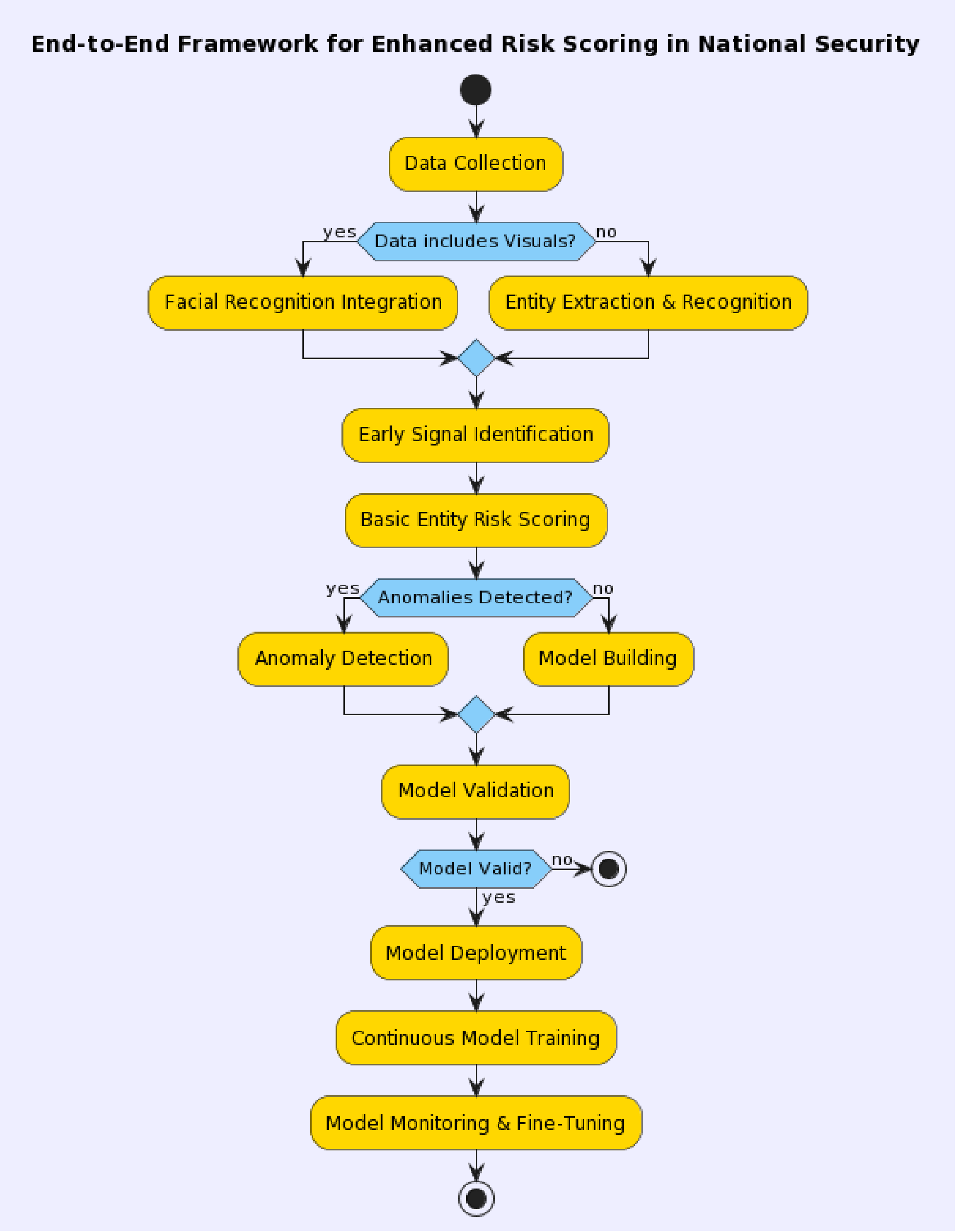

End-to-End Framework for Enhanced Risk Scoring in National Security
Data Collection
Data includes Visuals?
yes
no
Facial Recognition Integration
Entity Extraction & Recognition
Early Signal Identification
Basic Entity Risk Scoring
Anomalies Detected?
yes
no
Anomaly Detection
Model Building
Model Validation
Model Valid?
no
yes
Model Deployment
Continuous Model Training
Model Monitoring & Fine-Tuning

Figure 21 Framework of Risk Scoring for POI

CHAPTER VI

SUMMARY, IMPLICATIONS, AND RECOMMENDATIONS

6.1 SUMMARY OF ENHANCED RISK SCORING

Risk scoring of a person involves the evaluation and quantification of potential risks associated with that individual. The process typically begins with a base risk scoring model that utilizes available datasets, such as personal information, financial records, and historical behavior, to assess the inherent risk level. This model assigns an initial score based on predetermined criteria and factors.

To enhance the accuracy of the risk scoring, additional components can be integrated:

Anomaly Detection: Anomaly detection techniques are employed to identify abnormal patterns or behaviors that deviate significantly from expected norms. Statistical models, machine learning algorithms (such as clustering or autoencoders), or rule-based systems can be utilized to detect anomalies within the available dataset. Unusual activities, transactions, or deviations from established patterns can contribute to a higher risk score.

Early Warning Signals: Early warning signals are indicators that precede potential risks or adverse events. By monitoring specific metrics or patterns, such as changes in financial activities, social media behavior, or external environmental factors, it is possible to detect emerging risks. Various algorithms and methodologies, such as time series analysis, predictive modeling, or data mining techniques, can be employed to identify these signals. Integration of early warning signals can help adjust the risk score in a timely manner.

Image Recognition, Face Recognition, and Object Recognition: Visual recognition technologies, such as image recognition, face recognition, and object recognition, offer the ability to analyze images and extract valuable information. Image recognition models employ convolutional neural networks (CNNs) to identify objects or visual cues relevant to risk assessment, while face recognition models use deep learning techniques to match facial features against known identities. Object recognition algorithms can detect and classify specific objects within images. Integrating these techniques allows for the identification of potential risks or affiliations associated with visual elements present in the data.

By incorporating these components into the risk-scoring process, the overall risk assessment becomes more comprehensive and accurate. Anomalies and early warning signals help detect unusual or potentially risky activities, while image recognition, face recognition, and object recognition provide insights from visual data sources. Each component contributes to the refinement and adjustment of the risk score, enabling a more holistic evaluation of the person's risk profile.

It is crucial to note that the effectiveness of these components relies on the quality of data, appropriate algorithm selection, and continuous model training and evaluation. Ethical considerations, privacy regulations, and legal compliance must also be upheld when implementing these technologies to ensure responsible and fair risk assessment practices.

Integration of these components into the risk scoring process enables a multi-faceted and dynamic assessment of a person's risk. By leveraging a base risk scoring model, anomaly detection, early warning signals, and visual recognition technologies, organizations can gain deeper insights into potential risks associated with individuals.

The base risk scoring model forms the foundation by considering traditional factors such as personal information, financial records, and historical behavior. This model provides an initial risk score based on predetermined criteria and data analysis techniques.

Anomaly detection techniques add an extra layer of analysis by identifying abnormal patterns or behaviors that deviate significantly from the expected norms. By leveraging statistical models, machine learning algorithms, or rule-based systems, organizations can identify unusual activities or transactions that might indicate potential risks. Anomalies can contribute to a higher risk score, highlighting the need for closer scrutiny and investigation.

Early warning signals play a crucial role in risk assessment by providing indicators that precede potential risks or adverse events. By monitoring various metrics and patterns, organizations can detect emerging risks and take proactive measures to mitigate them. Advanced algorithms, such as time series analysis, predictive modeling, or data mining techniques, help identify these signals and integrate them into the risk scoring process. Timely response to early warning signals can significantly enhance risk mitigation strategies.

Visual recognition technologies, including image recognition, face recognition, and object recognition, offer valuable insights from visual data sources. Image recognition models employ deep learning algorithms, such as convolutional neural networks (CNNs), to identify specific objects or visual cues relevant to risk assessment. Face recognition models use deep learning techniques to match facial features against known identities or watchlists, aiding in identity verification and detecting potential aliases. Object recognition algorithms detect and classify specific objects within images, enabling the identification of risk-related items or environmental factors. Integrating these technologies into the risk scoring process enhances the understanding of potential risks and affiliations associated with visual elements.

To ensure the effectiveness of the risk scoring process, continuous model training, evaluation, and customization are essential. Models need to be trained on high-quality data, regularly updated to adapt to evolving risks, and validated against ground truth or expert judgment. Ethical considerations, privacy regulations, and legal compliance must be carefully addressed to ensure responsible and fair use of these technologies.

In conclusion, the integration of a base risk scoring model with anomaly detection, early warning signals, and visual recognition technologies enhances the accuracy and comprehensiveness of risk assessment. By leveraging data-driven techniques, organizations can gain deeper insights into potential risks associated with individuals, enabling them to make informed decisions, implement effective risk mitigation strategies, and protect against emerging threats.

Once the risk scoring process incorporates the base risk scoring model, anomaly detection, early warning signals, and visual recognition technologies, the next step is to integrate and interpret the insights derived from each component. This integration allows for a holistic view of the person's risk profile and provides actionable intelligence to make informed decisions.

The integration process involves assigning appropriate weights or scores to each component based on their relative importance and impact on the risk assessment. This step requires careful consideration and domain expertise to determine the significance of anomalies, early warning signals, and visual insights in relation to the overall risk score. Organizations can establish rules or algorithms that combine the scores from each component to calculate an aggregated risk score.

Furthermore, organizations may consider incorporating temporal analysis to identify temporal patterns and trends in the risk assessment. By analyzing the historical progression of risk scores and identifying patterns of increasing or decreasing risks, organizations can better anticipate and respond to potential risks.

It's important to note that the specific algorithms or methodologies used for integration will depend on the organization's risk assessment framework and the nature of the data. Machine learning techniques, statistical analysis, or rule-based systems can be employed to combine the scores and generate an overall risk score.

In addition to the integration step, organizations should also establish feedback loops to continuously evaluate and refine the risk scoring process. This involves monitoring the performance of the risk scoring model, assessing the effectiveness of anomaly detection and early warning systems, and conducting periodic reviews to ensure the accuracy and relevance of the visual recognition models. Regular updates and adaptations based on feedback and emerging risks are essential to maintaining the effectiveness of the risk-scoring process.

Lastly, it is crucial to have a clear and well-defined framework for interpreting and acting upon the risk scores. The risk scores should serve as a guide for decision-making, enabling organizations to allocate appropriate resources, implement targeted risk mitigation measures, and conduct further investigations if necessary.

In conclusion, the risk scoring of a person can be significantly enhanced by integrating a base risk scoring model with anomaly detection, early warning signals, and visual recognition technologies. The integration of these components provides a comprehensive and dynamic assessment of the person's risk profile, allowing organizations to make informed decisions and take proactive measures to mitigate risks effectively.

Once the overall risk score is determined by integrating the various components, it's important to further analyze the results to gain insights about emerging risks and potential mitigations. This analysis involves examining the factors contributing to the risk score and identifying patterns or trends that can inform risk management strategies.

Analyzing Clusters: One approach is to analyze the clusters identified during the text data analysis phase. By examining the topics and sentiments associated with each cluster, you can gain a deeper understanding of the emerging risks and their potential impact. Look for clusters that contain high-risk keywords, negative sentiment, or topics related to illicit activities, security threats, or financial irregularities. By analyzing the content within each cluster, you can identify specific areas of concern that contribute to the overall risk score.

Temporal Analysis: Consider conducting temporal analysis to identify trends and changes in the risk profile over time. By tracking the risk scores of individuals or groups over different time periods, you can identify patterns indicating increasing or decreasing risks. Temporal analysis can help you detect emerging risks, track the effectiveness of risk mitigation strategies, and make informed decisions based on the evolving risk landscape.

Integration into Overall Risk Scoring: To integrate the insights gained from the cluster analysis and temporal analysis into the overall risk scoring process, you can assign additional weights or scores based on their significance. High-risk clusters or emerging risk topics can be given higher weights, indicating their importance in the risk assessment. Similarly, temporal patterns indicating increasing risks can lead to an adjustment of the risk score to reflect the changing risk profile over time.

Mitigation Strategies: The insights gained from the analysis can also inform the development of targeted risk mitigation strategies. For example, if the analysis reveals emerging risks related to cybersecurity, organizations can implement measures to strengthen their security infrastructure and raise awareness among employees. If the analysis indicates potential financial irregularities, enhanced monitoring and auditing procedures can be put in place. By tailoring mitigation strategies to address the specific risks identified, organizations can effectively manage and mitigate potential threats.

It's important to note that the specific algorithms or methodologies for analyzing clusters and conducting temporal analysis will depend on the nature of the data and the desired outcomes. Natural language processing techniques, topic modeling algorithms, sentiment analysis methods, and time series analysis approaches can be employed to extract insights from the data and inform risk management decisions.

In conclusion, analyzing clusters, conducting temporal analysis, and integrating the findings into the overall risk-scoring process provide valuable insights into emerging risks and potential mitigations. This deeper level of analysis enhances the risk assessment process, enabling organizations to make informed decisions, implement targeted risk mitigation strategies, and monitor changes in the risk profile over time.

In addition to the steps mentioned earlier, the integration of image recognition, face recognition, and object recognition models can further enhance the risk scoring of a person. These technologies enable the analysis of visual data to extract valuable information and insights that can contribute to the overall risk assessment.

Image Recognition: Image recognition models, typically based on convolutional neural networks (CNNs), can be utilized to analyze images associated with a person of interest. These models can identify specific objects, patterns, or visual cues that are relevant to risk assessment. By training the model on a dataset of labeled images, it can learn to recognize and classify objects of interest. For example, it can detect weapons, illicit substances, or other items associated with high-risk behaviors. The output of the image recognition model can provide additional data points to adjust the person's risk score accordingly.

Face Recognition: Face recognition technology enables the identification and verification of individuals based on their facial features. Deep learning models, such as FaceNet or VGGFace, are commonly used for face recognition tasks. These models extract facial embeddings, which are high-dimensional representations of unique facial characteristics. By comparing facial embeddings with known identities or watchlists, it becomes possible to verify the identity of a person or identify potential aliases. Face recognition can provide valuable insights into the person's affiliations, connections, or past activities, contributing to a more accurate risk assessment.

Object Recognition: Object recognition models can identify and classify specific objects within images. This capability can be useful for detecting risk-related objects or environmental factors associated with a person of interest. For example, the model can identify vehicles, logos, or symbols that are relevant to the risk assessment process. By training the model on a labeled dataset of relevant objects, it can accurately detect and classify these items within images, providing additional information for risk scoring.

Integrating the outputs of image recognition, face recognition, and object recognition models into the overall risk scoring process requires careful consideration of their relevance and impact. The outputs can be assigned weights or scores based on the significance of the identified objects, faces, or visual patterns in relation to the risk assessment. These weights can then be combined with the scores from other components, such as the base risk scoring model, anomaly detection, and early warning signals, to generate a comprehensive risk score for the person.

In conclusion, integrating image recognition, face recognition, and object recognition models into the risk scoring process enhances the accuracy and depth of the risk assessment for a person of interest. These technologies enable the analysis of visual data, providing insights into objects, faces, and patterns that are relevant to risk assessment. By incorporating the outputs of these models into the overall risk scoring framework, organizations can make more informed decisions, identify potential risks or affiliations, and improve the effectiveness of their risk management strategies.

As a conclusion, Flow to get the Score for a given Individual :

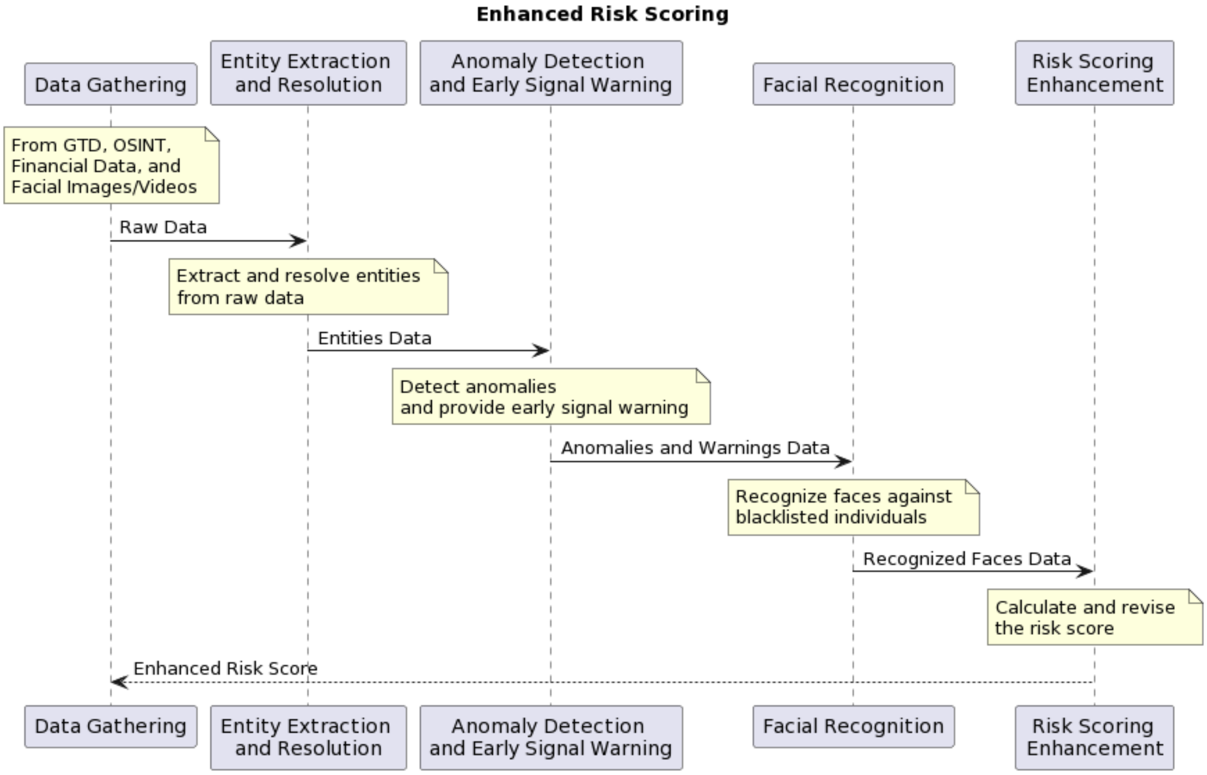

Enhanced Risk Scoring
Data Gathering
Entity Extraction and Resolution
Anomaly Detection and Early Signal Warning
Facial Recognition
Risk Scoring Enhancement
From GTD, OSINT, Financial Data, and Facial Images/Videos
Raw Data
Extract and resolve entities from raw data
Entities Data
Detect anomalies and provide early signal warning
Anomalies and Warnings Data
Recognize faces against blacklisted individuals
Recognized Faces Data
Calculate and revise the risk score
Enhanced Risk Score
Data Gathering
Entity Extraction and Resolution
Anomaly Detection and Early Signal Warning
Facial Recognition
Risk Scoring Enhancement

Figure 22 Flow to get the score for a given Individual.

Flow to get the Score for a give person’s image :

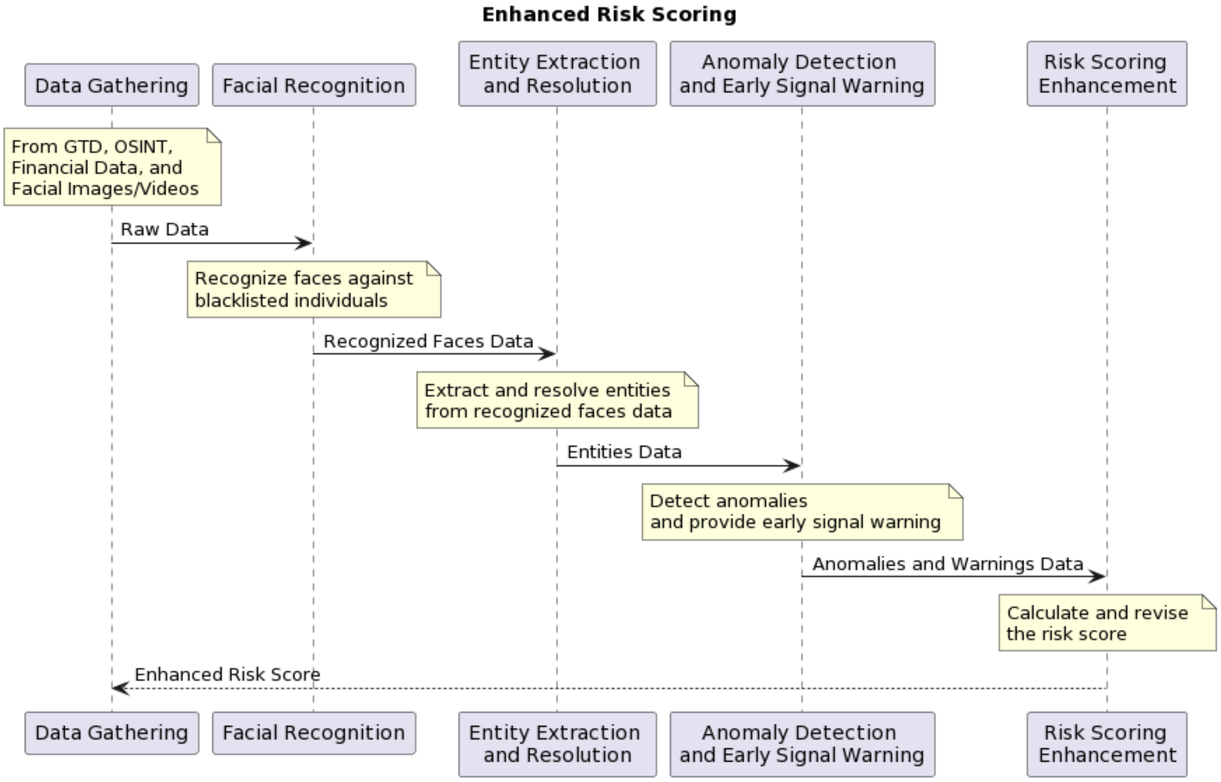

Enhanced Risk Scoring
Data Gathering
Facial Recognition
Entity Extraction and Resolution
Anomaly Detection and Early Signal Warning
Risk Scoring Enhancement
From GTD, OSINT, Financial Data, and Facial Images/Videos
Raw Data
Recognize faces against blacklisted individuals
Recognized Faces Data
Extract and resolve entities from recognized faces data
Entities Data
Detect anomalies and provide early signal warning
Anomalies and Warnings Data
Calculate and revise the risk score
Enhanced Risk Score
Data Gathering
Facial Recognition
Entity Extraction and Resolution
Anomaly Detection and Early Signal Warning
Risk Scoring Enhancement

Figure 23 Risk scoring by initiating with photo

Flow to get score for the given list of Individuals :

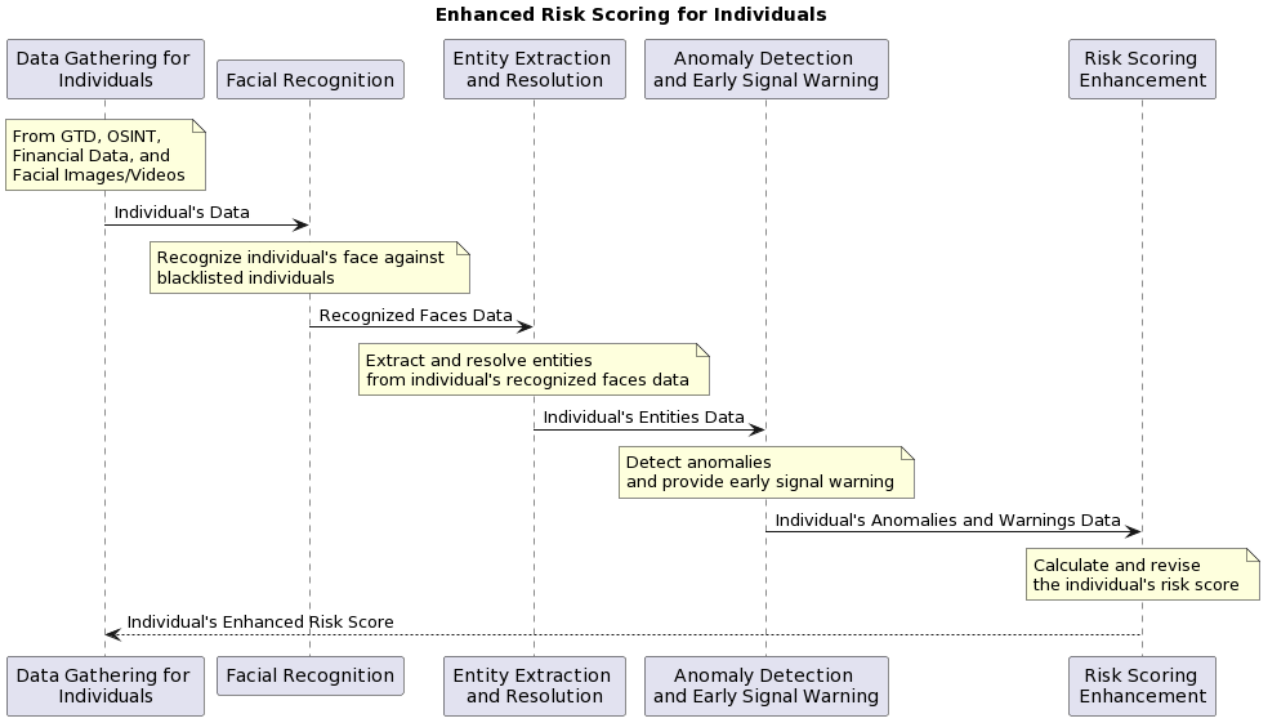

Enhanced Risk Scoring for Individuals
Data Gathering for Individuals
Facial Recognition
Entity Extraction and Resolution
Anomaly Detection and Early Signal Warning
Risk Scoring Enhancement
From GTD, OSINT, Financial Data, and Facial Images/Videos
Individual's Data
Recognize individual's face against blacklisted individuals
Recognized Faces Data
Extract and resolve entities from individual's recognized faces data
Individual's Entities Data
Detect anomalies and provide early signal warning
Individual's Anomalies and Warnings Data
Calculate and revise the individual's risk score
Individual's Enhanced Risk Score

Figure 24 Flow to get score for a given list of Individuals

Flow to get score for the individuals along with MLOps process

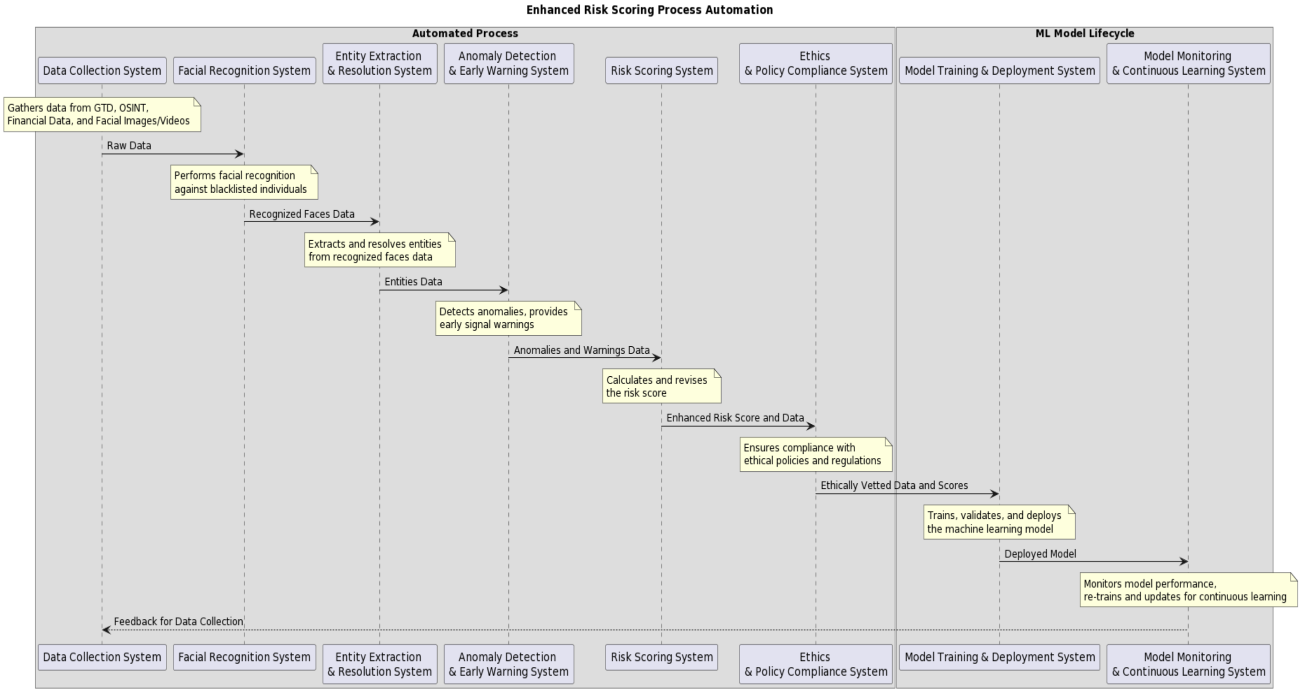

Enhanced Risk Scoring Process Automation
Automated Process
ML Model Lifecycle
Data Collection System
Facial Recognition System
Entity Extraction & Resolution System
Anomaly Detection & Early Warning System
Risk Scoring System
Ethics & Policy Compliance System
Model Training & Deployment System
Model Monitoring & Continuous Learning System
Gathers data from GTD, OSINT, Financial Data, and Facial Images/Videos
Raw Data
Performs facial recognition against blacklisted individuals
Recognized Faces Data
Extracts and resolves entities from recognized faces data
Entities Data
Detects anomalies, provides early signal warnings
Anomalies and Warnings Data
Calculates and revises the risk score
Enhanced Risk Score and Data
Ensures compliance with ethical policies and regulations
Ethically Vetted Data and Scores
Trains, validates, and deploys the machine learning model
Deployed Model
Monitors model performance, re-trains and updates for continuous learning
Feedback for Data Collection
Data Collection System
Facial Recognition System
Entity Extraction & Resolution System
Anomaly Detection & Early Warning System
Risk Scoring System
Ethics & Policy Compliance System
Model Training & Deployment System
Model Monitoring & Continuous Learning System

Figure 25 Flow to get POI risk score and MLOps Process

6.2 RECOMMENDATION

6.2.1 Privacy-Preserving Techniques

In an era where data privacy and security are paramount, developing privacy-preserving techniques for entity risk scoring is a critical research focus. Federated learning, for example, allows AI models to be trained across multiple decentralized devices or servers holding local data samples, without exchanging the data itself. This approach preserves the privacy of individual data points while allowing for global model updates (Konečnỳ et al., 2016).

Secure multi-party computation (SMC) is another privacy-preserving method worth investigating. SMC allows for computation on encrypted data, which means risk scoring can be conducted without revealing the actual data to the computing parties (Goldreich, 2004).

Differential privacy provides a mathematical guarantee that the privacy of individual data points will not be compromised, even when aggregate data is shared. Research into how to best apply differential privacy to risk scoring could provide new ways to balance data utility and privacy (Dwork, 2008).

6.2.2 Explainability and Interpretability

As AI models become increasingly complex, their decisions often become less interpretable, leading to the so-called "black-box" problem. Research into enhancing the explainability and interpretability of AI models is a critical frontier in entity risk scoring. Techniques such as LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive exPlanations) can provide insights into how the models make decisions, thereby increasing trust and acceptance among users (Ribeiro, Singh, & Guestrin, 2016; Lundberg & Lee, 2017).

6.2.3 Ethical Considerations and Bias Mitigation

Addressing ethical considerations and mitigating biases in entity risk scoring models is a crucial research area. Potential issues include disparate impact, where a seemingly neutral system might negatively affect certain groups, and confirmation bias, where the models amplify existing prejudices in the data. Techniques for bias mitigation can include bias correction algorithms, fairness-aware machine learning, and rigorous validation methods (Barocas, Hardt, & Narayanan, 2018).

6.2.4 Incorporating Temporal Dynamics

Risk is not static - it evolves over time. As such, understanding the temporal dynamics of risk and incorporating time-dependent factors into entity risk scoring models can lead to more effective risk assessments. Research in this area can explore techniques like recurrent neural networks (RNNs) or Hidden Markov Models (HMMs), which are capable of handling temporal data (Lipton, Berkowitz, & Elkan, 2015).

6.2.5 Potential LLM Impacts

The future of risk scoring for Persons of Interest (POI) with respect to national security appears poised to experience several key changes and improvements, influenced largely by advancements in artificial intelligence, machine learning, and particularly, Large Language Models (LLMs) like OpenAI's GPT series. The following are some prospective trends and potential research directions:

- Incorporation of Unstructured Data: With the massive volume of unstructured data available, risk scoring models will likely be designed to analyze text data, video and audio content, and social media posts. LLMs are particularly good at processing and understanding natural language, so their use could lead to more comprehensive risk profiles (Chen, H., Chiang, R.H., Storey, V.C., 2012. Business Intelligence and Analytics: From Big Data to Big Impact. MIS Quarterly, 36(4), pp.1165-1188).

- Real-time Risk Scoring: As data processing capabilities continue to improve, real-time risk scoring could become a reality. This would allow national security agencies to respond to potential threats more swiftly (Russom, P., 2011. Big data analytics. TDWI Best Practices Report, Fourth Quarter, pp.1-34).

- Increased Transparency and Accountability: As we move, there will likely be more emphasis on the transparency and accountability of these risk scoring systems. It will become increasingly important to understand how an AI system reached a particular decision or risk score, which could influence the development of "explainable AI" (Doshi-Velez, F., Kim, B., 2017. Towards A Rigorous Science of Interpretable Machine Learning. arXiv preprint arXiv:1702.08608).

- Ethical and Privacy Considerations: With the increased use of AI and ML in national security, ethical and privacy considerations will gain prominence. Research might focus on building systems that respect individual privacy rights while ensuring national security (Zwitter, A., Hadfield-Menell, D., 2020. Leveraging machine learning in the global fight against money laundering and terrorism financing: An affordances perspective. Journal of Money Laundering Control).

- Domain Adaptation and Transfer Learning: Using pre-trained models on new and specific tasks, known as transfer learning, will likely be increasingly important. LLMs such as GPT-4 could be fine-tuned to understand specific security-related terminologies or contexts, improving the accuracy of risk scoring (Pan, S.J., Yang, Q., 2010. A survey on transfer learning. IEEE Transactions on knowledge and data engineering, 22(10), pp.1345-1359).

- Multimodal Risk Assessment: Future research could also focus on multimodal risk assessment, combining textual, visual, and auditory data to generate more comprehensive risk scores. This could include social media posts, surveillance footage, phone calls, and more (Baltrušaitis, T., Ahuja, C., Morency, L.P., 2019. Multimodal machine learning: A survey and taxonomy. IEEE transactions on pattern analysis and machine intelligence, 41(2), pp.423-443).

6.3 CONCLUSION

The application of AI/ML in Person of Interest (POI) risk scoring for national security has significant implications in improving the accuracy, efficiency, and effectiveness of risk assessment processes. By leveraging the power of AI and machine learning algorithms, these models can analyze large volumes of data, detect patterns, and identify potential threats associated with individuals of interest. This overall summary will provide an in-depth overview of the application of AI/ML in POI risk scoring in the context of national security.

AI/ML models have the capability to process diverse data sources, including structured and unstructured data such as social media posts, financial records, travel logs, communication patterns, and more. By analyzing this data, these models can extract relevant features and identify patterns and anomalies that may indicate potential national security threats. The ability to consider multiple data sources provides a comprehensive view of the POI's activities, connections, and behaviors, enabling a more accurate risk assessment.

One of the key advantages of AI/ML models in POI risk scoring is their ability to identify early or weak signals of potential threats. By recognizing subtle indicators that may not be easily recognizable by human analysts alone, these models can provide an additional layer of scrutiny, enabling proactive intervention and prevention of potential risks. They can detect anomalies, deviations from normal behavior, and shifts in sentiment, which may serve as precursors to more significant threats. This early detection capability is crucial for national security agencies to stay ahead of evolving threats.

Moreover, AI/ML models continuously learn and adapt to changing circumstances. By analyzing historical data and integrating real-time information, these models can update their algorithms and anomaly detection rules to capture emerging threats. The adaptability of these models ensures that the risk assessment process remains effective in dynamic security environments. Additionally, AI/ML models can handle large-scale data processing, making them suitable for automating anomaly detection in national security applications. This scalability allows for efficient analysis of vast amounts of data, facilitating comprehensive risk assessment and profiling.

Another important aspect of AI/ML in POI risk scoring is the potential for improved accuracy and reduced false negatives. By leveraging advanced data analysis techniques and pattern recognition capabilities, these models can enhance the accuracy of risk assessments. They can identify hidden relationships, unusual behavior patterns, or connections that may indicate potential risks. This capability helps in reducing the occurrence of false negatives, where potential threats are missed or disregarded, thus enhancing the overall effectiveness of national security efforts.

To ensure responsible and ethical use, it is essential to address challenges related to biases, privacy concerns, explainability, and human oversight. Research efforts are ongoing to develop techniques that mitigate biases, enhance interpretability, and incorporate privacy-preserving mechanisms in AI/ML models. Ensuring fairness, transparency, and accountability in the risk scoring process is crucial to maintain public trust and confidence.

In conclusion, the application of AI/ML in POI risk scoring for national security offers significant advantages in terms of accuracy, early detection of threats, adaptability, scalability, and reduced false negatives. These models have the potential to enhance the efficiency and effectiveness of risk assessment processes by analyzing diverse data sources, identifying patterns, and recognizing subtle indicators of potential threats. However, responsible implementation, ongoing evaluation, and human expertise are essential to ensure the ethical and effective use of these technologies in national security applications.

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