INNOV8 HACKATHON

PART-2

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A-Key Features and Their Contributions

1. **Family Tree of Soldier**
   - Contribution: Connections to known traitors or influential individuals can create loyalty conflicts. Soldiers may feel pressured to align with family members, potentially swaying their loyalty away from the kingdom.
2. **Any Person of Opponent Kingdom**
   - Contribution: Relationships with individuals from the enemy kingdom may lead to feelings of camaraderie or loyalty that can undermine allegiance to one's own clan, especially if these connections promise benefits.
3. **Promotional Aspirations**
   - Contribution: High ambitions can make soldiers more susceptible to temptations offered by the enemy. If the Phrygians promise rewards that align with their aspirations, soldiers may be more inclined to defect.
4. **Fluctuations in Attendance and Behaviour Spikes**

- Contribution: Unusual patterns in attendance or behaviour may indicate dissatisfaction or discontent. Soldiers displaying erratic behaviour may be more likely to consider betrayal as an option.

5. **Peer Group of Guilty More Likely**
   - Contribution: Soldiers who associate with known traitors may be influenced by their peers' actions and attitudes, creating an environment where betrayal becomes normalized or accepted.
6. **Monetary Issues**
   - Contribution: Financial instability can create desperation. Soldiers facing monetary problems may be more tempted by promises of wealth from the enemy, making them more vulnerable to betrayal.
7. **Cognitive Bases of Individuals (Greed Level)**
   - Contribution: A soldier's inherent greed can drive decisions. Those with higher levels of greed may prioritize personal gain over loyalty, making them more likely to defect for promised rewards.
8. **History of Trauma**
   - Contribution: Soldiers with traumatic pasts may have altered perceptions of loyalty and trust. Trauma can affect decision-making, potentially leading to betrayal as a coping mechanism or due to feelings of alienation.
9. **Behaviour Analysis**
   - Contribution: Consistent monitoring of behaviour can reveal signs of disloyalty or disengagement. Soldiers showing signs of dissent or dissatisfaction may be more prone to betrayal.

10. **"Ladki Ka Chakkar" (Romantic Interests)**

   - Contribution: Romantic relationships with individuals from the opposing side can create strong emotional ties that challenge loyalty to the kingdom. A soldier may prioritize their partner over their duty.

B-Priority Order of Key Features for Betrayal Prediction (according to our analysis)

To enhance the model's efficiency, it's beneficial to initialize feature values close to actual conditions, even though the model will learn the parameters by itself. This approach can help the model converge more effectively and improve its predictive accuracy from the outset.

1. **Connections to Opponent Kingdom**: Immediate influence on a soldier's loyalty; critical to identify known links.
2. **Peer Group Influence**: Social dynamics are powerful; close relationships with disloyal peers should be flagged first.
3. **behaviour Analysis via Peer Reports**: Direct insights into a soldier's behaviour and potential changes in loyalty.
4. **Fluctuations in Attendance and Behavioural Spikes**: Patterns in attendance and sudden behavioural changes are strong indicators of discontent.
5. **Monetary Issues**: Financial vulnerability can lead to higher susceptibility to betrayal; prioritize data collection on soldiers' financial status.
6. **Promotional Aspirations**: Understanding a soldier's ambition can reveal motivations for potential defection.

7. **Cognitive Biases and Greed**: Psychological evaluations can provide insights into loyalty and susceptibility to offers from the enemy.
8. **Family Tree of Soldier**: While important, family connections may be less immediate than social influences.
9. **History of Trauma**: Understanding past experiences can highlight vulnerabilities but may require deeper psychological assessment.

10.“Ladki Ka Chakkar” (Romantic Interests): While relevant, this factor can be more contextual; prioritize later in the analysis.

C-Quantifying Data for Predicting Soldier Defection Risk

We will use a scoring system ranging from -1 to 1, where 1 indicates the highest likelihood of defection. Here’s how we’ll initialize the values based on priority:

1. **Connections to Opponent Kingdom:** Start at 0.8 (high risk).
2. **Peer Group Influence:** Assign 0.7 for close friends and family, decreasing to -0.3 for very supportive peer groups.
3. **Behaviour Analysis (Peer Reports)**: Initialize at 0.6; if positive reports indicate strong loyalty, assign a value of -0.6.
4. **Fluctuations in Attendance and Behavioural Spikes:** Set at 0.5; consistent attendance could result in -0.5.
5. **Monetary Issues**: Begin with a value of 0.4; if a soldier has financial security, consider -0.4.
6. **Promotional Aspirations**: Assign 0.3; strong job satisfaction might lead to -0.3.

7. **Cognitive Biases and Greed**: Set at 0.2; if a soldier shows selflessness, assign -0.2.
8. **Family Tree of Soldier:** Start at 0.1; strong family loyalty could lead to -0.1.
9. **History of Trauma:** Assign a value of 0.1; if trauma has led to resilience, consider -0.1.
10. **Ladki Ka Chakkar**: We will use beautiful girl analysis, where we divide the girls of the neighbouring kingdom into age groups from 18 to 40—the most vulnerable age range of the armies. We will utilize pretrained beauty models, such as the one by Christoph Hess, to determine the most beautiful age groups. In the range of ±2 years, we will assign higher chances of deflection to soldiers.

This structured approach allows for a nuanced evaluation of each soldier's risk of betrayal while considering various personal and social factors.

D-Data Generation Methods for Predicting Soldier Defection Risk

1. **Peer Reports for Behaviour Analysis**:

- Surveys/Interviews: Conduct structured surveys or interviews among peers to gather insights into each soldier’s behaviour, loyalty, and social connections. Peers can anonymously rate others on trustworthiness, mood swings, and interactions with questionable individuals.

- AI-based behaviour Analysis: Use AI models trained to analyse text-based peer reports or soldiers’ written responses. Natural

Language Processing (NLP) can identify patterns of discontent or behavioural anomalies in soldiers over time. The AI would flag unusual behavioural trends based on this data.

- Self-Reports: Soldiers could also fill out self-assessment surveys, with AI models scanning these for red flags like dissatisfaction or low morale.

2. **Family Tree and Peer Group Data:**

- Genealogy Surveys: Gather detailed family and social background information. Soldiers indicate family connections within the kingdom and any ties to individuals from the opposing faction.

- Social Proximity Assessment: Closer relationships (e.g., family members, best friends) get higher risk values. This proximity could be mapped through surveys and analysed to assess defection risk.

3. **Financial Status and Monetary Issues**:

- Financial Surveys: Simple surveys would ask soldiers about debts, financial strain, or changes in their economic status. Those facing significant financial stress could be marked at higher risk.

- Simple Financial Risk Score: Survey responses can be translated into a financial risk score indicating the soldier's level of vulnerability based on monetary concerns.

4. **Cognitive & Psychological Factors (Greed, Temptation):**

- Psychometric Surveys: Use psychometric questionnaires to assess traits such as greed and ambition. AI models can analyse the survey responses to flag soldiers more prone to bribery or betrayal based on cognitive biases.

- AI-based Personality Profiling: Employ AI models that evaluate psychometric data and flag soldiers with high-risk personality traits, such as an elevated appetite for reward or susceptibility to external influence.

5. **History of Trauma:**

- Medical and Service Records: Use available records to identify soldiers with a history of trauma, such as injuries or emotional stress, which may make them more vulnerable to manipulation.

- Personal Questionnaires: Incorporate questions about past trauma to gauge how much emotional stress each soldier has experienced.

6. **"Ladki Ka Chakkar" (Beautiful Girl Analysis)**:

- Social Network Information: Collect details about soldiers' romantic involvements through voluntary self-reporting. Soldiers could indicate relationships with individuals from the neighbouring kingdom.

- Beautiful Girl Analysis (Christoph Hess): Apply a beauty ranking method based on Christoph Hess' pre-trained beauty models. Divide women from the neighbouring kingdom into age groups (18-40) and assign higher defection risks to soldiers romantically involved with women deemed most attractive. The risk is elevated for relationships with women within ±2 years of the soldier’s age.

7. **Attendance and Performance Records**:

- Manual Logs: Track soldiers' attendance at drills and training through manual or digital logs. Soldiers with irregular attendance or declining performance can be flagged as high-risk.

- Simple Alert System: Implement a system that triggers alerts for soldiers showing significant drops in attendance or performance. These alerts feed into the overall risk score.

E-Model Design: Ensemble Approach for Predicting Soldier Betrayal

To predict the likelihood of betrayal within the army, an ensemble model can be an effective strategy. Here's a breakdown of the model approach, incorporating a summation-based model and other techniques:

Core Concept: Summation-Based Model with Weighted Parameters

The summation-based model will act as the primary decision-making model. Each soldier is evaluated on multiple features (behavior, financial status, peer group, etc.), and each of these features contributes a weighted score between -1 and 1. The total score represents the soldier's risk of defection.

1. **Feature Weights and Summation**:
   - **Weighted Scores**: Each factor will be assigned a numerical value between -1 and 1. Positive values indicate a higher likelihood of defection, while negative values represent strong loyalty. For example:
     - Closer relationships with defected soldiers will have high positive values.

  - Strong financial stability may get a negative score, reducing defection probability.
- The final defection risk score is the weighted sum of these individual feature scores. A simple formula for the summation model could be: Risk Score=$\sum(w_i \cdot f_i)$
- Where:
- w_i is the weight (importance) of each factor, and
- f_i is the feature score for the soldier.
- This equation sums the weighted contributions of each feature to calculate the overall defection risk score.
- A higher score indicates a greater risk of defection.

Additional Models for Ensemble:

1. **Decision Trees/Random Forests**:
   - **Use Case**: Decision trees can be used to identify patterns based on non-linear relationships between features. For example, soldiers with high temptation levels, combined with financial issues, may be more prone to defect.
   - **Ensemble Role**: Random forests (an ensemble of decision trees) can learn these intricate patterns and improve the prediction accuracy by averaging multiple decision trees' outcomes.
2. **Logistic Regression**:
   - **Use Case**: Logistic regression is useful for binary classification tasks like defection or loyalty. It can help identify the probability of defection based on the factors you define (e.g., greed, trauma).

  - **Ensemble Role**: Logistic regression can offer a simple, interpretable model for calculating defection probabilities. It will complement more complex models like random forests by adding a probabilistic angle to the ensemble.

3. **Neural Networks** (Optional for more complex data):
   - **Use Case**: Neural networks, especially multi-layer large networks, can be trained to identify hidden patterns in more complex datasets (e.g., cognitive traits, behaviour trends).
   - **Ensemble Role**: While not necessary for simpler features, neural networks can be introduced as the dataset grows in complexity. Their ability to learn from large, nonlinear data structures makes them valuable for future expansion.

Combining Models in an Ensemble:

- **Averaging Predictions**: The final ensemble prediction will combine predictions from the summation-based model, decision trees, and logistic regression. Averaging the outputs from these models allows for balanced predictions:
- Final Risk Score=$\sum(\text{Model}_i(\text{features}))/n$
- This represents the final risk score as the average of predictions from multiple models.

Each model contributes equally to the final score, ensuring that both linear and non-linear relationships are considered.

- **Stacking Approach**: Another approach would be stacking, where the output from one model (e.g., decision trees or logistic regression) is fed into another (e.g., neural network), improving accuracy by building layers of predictions.

F-Future Data and Evolution of the Model:

1. **Data Growth**:
   - **Increased Complexity**: As more data becomes available (e.g., more behavioural reports, financial data), the model can evolve to account for more intricate relationships. For example, a neural network may be trained on this expanded dataset to capture hidden patterns and predict defection more accurately.
   - **Continuous Learning**: New data can be continuously fed into the model for retraining. Techniques like online learning can help the model adapt in real-time, updating weights and feature importance as the situation evolves.
2. **Improving Feature Weights**:
   - **Data-Driven Adjustments**: As more data comes in, the weights assigned to each feature in the summation model can be fine-tuned based on empirical results. For instance, if "peer group" turns out to be more predictive than "financial stability," its weight will automatically increase during model training.
   - **New Features**: Additional factors can be introduced (e.g., sudden spikes in defection due to external political changes), making the model more robust. New data points such as social media monitoring or personal histories can be integrated to improve accuracy.
3. **Adaptive Decision-Making**:
   - **Model Evolution**: The model can evolve as it gathers more data over time, adapting to trends and anomalies. For example, a soldier's loyalty score may improve if their

financial condition stabilizes, or it may degrade if they begin associating with known defectors.

- **Scalability**: The system can scale with larger armies or more complex datasets. By continuously feeding it new data points, the model becomes more adaptive, making the decision-making process more refined and less prone to outliers.

Final Remarks on the Model's Evolution:

The ensemble approach provides flexibility to analyse different dimensions of betrayal risk while ensuring robustness through multiple models. As the dataset grows, especially with new features like behavioural patterns or financial status, the model will evolve, becoming more adept at predicting defection risk.