# CS6220 Project Report: Understanding Victim-Perpetrator Dynamics and Patterns of Exploitation in Human Trafficking

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## Abstract

When it comes to human trafficking, many people in developed countries may think it is far away from their daily lives. It commonly appears in many developing countries and areas. The victims vary in age and gender. Forced labor and sexual exploitation are two major kinds of human trafficking. Even though many governments have made significant efforts to combat this situation, such as developing targeted interventions, conducting corresponding policies, and strengthening survivor support mechanisms, there is still room for improvement.

With the utilization of a synthetic dataset from the Anti-Trafficking Data Collaboration (CTDC), this project aims to analyze the patterns of human trafficking, identify trends in forced labor and sexual exploitation, and explore the relationship between victim demographics and exploitation types so that we can provide actionable insights to help policymakers, researchers and some relevant society organizations to consider effective anti-trafficking strategies.

To achieve the goals, a combination of exploratory data analysis(EDA) and predictive modeling techniques are conducted in this project. Starting from data preparation, including handling missing values, standardizing binary fields, and expanding multi-value fields into binary flags, we find some key trends that are not surprising, for instance, the higher prevalence of forced labor in Asia as well as the prevalence of sexual exploitation in Africa. One finding worth mentioning is the important role played by family and intimate partners in sexual exploitation. For predictive modeling, binary classification is implemented to predict the exploitation types, and multi-class classification is conducted to predict the region of exploitation and the source of victims. Moreover, evaluation metrics (accuracy, precision, recall, and F1 score) were used to assess the effectiveness of the models.

Results show that the binary classification models achieved higher accuracy in forced labor prediction (XGBoost performed best, achieving an overall accuracy of 75.3%, and an F1 score of 78.6% for forced labor). However, the reliability of sexual exploitation prediction was lower, with an F1 score of 45.9% because of data imbalance. For multi-class classification, the prediction of exploitation regions was challenging (XGBoost achieved 54% accuracy). Furthermore, Europe was the most accurately predicted region due to its clearer patterns of demographic and exploitation features. Africa and Asia were more difficult to distinguish, which indicates feature overlap and a lack of contextual factors such as trafficking routes or socioeconomic indicators.

Based on the challenges faced in this project (e.g., data imbalance and model limitations), future work should focus on alternative modeling approaches including neural networks and

ensemble methods to better match for sparse and imbalanced data and improve predictions for complex tasks such as regions of exploitation.

In conclusion, this project suggests that data-driven approaches play a critical role in combating human trafficking and contribute to the foundation of more effective interventions by identifying patterns of forced labor and sexual exploitation and understanding regional and demographic impacts. Results for the project indicate the potential of predictive models for global anti-trafficking efforts and provide actionable insights for stakeholders seeking to address this pressing issue.

# 1. Introduction

Human trafficking remains one of the most severe global issues, affecting millions of men, women, and children every year across both developing and developed countries. Victims vary in age, race, gender, and nationality, but they are often from marginalized or vulnerable communities.

## 1.1 Problem Statement

The dynamics of exploitation vary significantly across regions, types of exploitation, and victim demographics. Analyzing these dynamics is helpful for understanding which factors contribute to different types of exploitation, identifying the most vulnerable victim profiles, and determining how relationships between victims and traffickers impact the methods of control used. This research aims to explore the following questions:

- How do trends in different types of exploitation (e.g., forced labor vs. sexual exploitation) evolve over time and across regions?
- What is the relationship between victim demographics (such as age, gender) and specific types of exploitation?

## 1.2. Why Is It Important to Solve These Problems?

As different areas have different exploitation patterns, it is necessary to identify the trends that change over regions to help policymakers to consider and implement corresponding interventions that are suitable for local situations. For instance, labor laws should be strengthened with respect to places that suffer mainly from forced labor while strong victim support systems should be built in areas with significant sexual exploitation.

Secondly, understanding the trends of change will contribute to resource allocation. For most areas of exploitation, governments and NGOs often have limited resources to combat trafficking, which requires the efficient allocation of resources to areas with the highest need.

Thirdly, the networks of exploitation usually respond to the local policy in a short time, understanding evolving trends helps authorities anticipate these shifts and stay one step ahead of traffickers.

Last but not least, it is more effective for law enforcement and social workers to use demographic patterns to identify potential trafficking victims. For example, young girls traveling alone in high-risk regions might indicate sexual exploitation and migrant men in industrial zones may be at risk of forced labor. There is no denying that better identification leads to quicker interventions and reduced victimization.

### 1.3. Background Information and literature survey

Human trafficking is a complicated issue with respect to a wide range of exploitation types and victim-perpetrator relationships. There are multiple factors that could affect the exploitation dynamics: economic conditions, migration compositions, and cultural background.
To better know about human trafficking, it is commonly agreed to pay attention to three aspects: the exploitation types, the trends that the exploitation varies from region, and the victim-perpetrator relationship.
Forced labor and sexual exploitation are two main types of exploitation. The former often relate to industries such as agriculture, construction, and manufacturing(Allain, J., Crane, A., LeBaron, G., Behbahani, L., 2013) and in the areas that are relatively in a poor economic condition so that the perpetrators could take advantage of such vulnerability. As for the latter, research found that it was seen to be strongly associated with cross-border movement(Plant, R., Kotiswaran, P., 2017).
For regional trends, research has shown that there were significantly instances of forced labour in European countries, especially in the northeastern part of Europe and in the Baltic Sea region(Jokinen, A., Ollus, N., Aromaa, K., 2011), and it is not surprising that Asia exhibits higher instances of forced labor due to economic development levels for most Asian countries and inadequate labor protections(Reid, A., 2021). With regard to sexual exploitation, it is commonly seen in armed conflict areas in Africa, Asia, and the Middle East, in which girls are forced to get married at a young age(McAlpine, A., Hossain, M., Zimmerman, C., 2016).
For victim-perpetrator relationships, most research focuses on how adults take advantage of a power imbalance to force or entice children into engaging in sexual activity. However, there is a notable gap in the literature regarding the specific dynamics between adult victims and their perpetrators. Studies on adult trafficking victims often lack detailed exploration of the relationships that enable exploitation. For instance: are adult victims more likely to be exploited by strangers, acquaintances, or family members? This could be explored in the project later.

## 2. Data Sources

This study utilizes the Victim-Perpetrator Synthetic Dataset from the [Counter-Trafficking Data Collaborative (CTDC)](). The dataset includes detailed information on over 17,000 victims and survivors of human trafficking from 123 countries/territories and records on approximately 37,000 perpetrators. This dataset represents one of the most comprehensive compilations of trafficking data available for analysis.

The data is synthetically generated using [differential privacy algorithms]() developed at Microsoft Research. This process ensures the privacy of individuals by maintaining statistical properties of the data while anonymizing specific details. This enables researchers to analyze patterns and relationships in trafficking without exposing sensitive information.

The dataset includes:

- Victim demographic information such as gender, age, and region of origin.
- Perpetrator details including roles, relationships with victims, and control mechanisms.
- Types of exploitation experienced by victims, such as forced labor or sexual exploitation.
- Geographic and temporal patterns of trafficking activities.

For this project, we focus specifically on three key regions of exploitation: Europe, Asia, and Africa. This allows for comparative analyses across these diverse regions while maintaining a manageable scope for analysis and prediction tasks.

## 3. Methodology

### 3.1 Data Cleaning and Preparation

The raw dataset contained missing values and inconsistencies that required preprocessing before analysis:

1. Handling Missing Data:
    - Categorical fields with missing values were filled with the category "**Unknown**".
    - Binary columns (e.g., **isForcedLabour**, **IP_ControlAbuseKidnap**) were standardized by replacing **NaN** with **0**, ensuring a binary representation (**1** for presence, **0** for absence).
2. Multi-Value Fields:
    - Fields like **IP_Relation** (e.g., "**FamilyIntimatePartner**;**StrangerUnknownOther**") and **IP_ageBroad** were expanded into binary flags for each category to facilitate analysis.
3. Data Type Adjustments:
    - Ensured categorical and numerical fields matched the expected formats, reducing memory usage and improving processing efficiency.

### 3.2 Exploratory Data Analysis (EDA)

Purpose:

1. Identify demographic trends.
2. Explore regional differences in exploitation patterns.
3. Examine victim-perpetrator relationships to uncover dynamics influencing exploitation types.

Techniques:

1. Visualizations (e.g., bar charts, heatmaps) to highlight key patterns.
2. Summary statistics to provide a quantitative overview of exploitation trends.

### 3.3 Predictive Modeling

Purpose:

1. Predict exploitation type: forced labor vs. sexual exploitation
2. Predict regional characteristics: region of exploitation and region of origin

Techniques:

1. Binary Classification: predict forced labor vs. sexual exploitation
2. Multiclass Classification: predict regions of exploitation (Africa, Asia, Europe) and regions of origin (Africa, Asia, Europe)

Models:

Logistic Regression, Random Forest, XGBoost

Evaluation Metrics:

1. Accuracy, precision, recall, and F1-score to assess performance.
2. Confusion matrices to identify areas of misclassification.

## 4. Brief Explanation of Code

### 4.1 Data preparation

1. List of binary columns identified from the codebook and dictionary and replace NaN values with 0 in these binary columns:

```
binary_columns = [

    'isForcedLabour', 'isSexualExploit', 'IP_RecruiterBroker',

    'IP_TransactionProcess', 'IP_ControlAbuseKidnap', 'IP_Exploiter',

    'IP_PayMoney']

data[binary_columns] = data[binary_columns].fillna(0)
```

2. Split multi-value categories into separate binary columns:

```
split_columns = ['IP_ageBroad', 'IP_citizen_UNRegion', 'IP_Relation']

for col in split_columns:

    expanded = data[col].str.get_dummies(sep=';')
```

```
data = pd.concat([data, expanded], axis=1)
```

3. Data types corrections:

```
for col, dtype in dtype_corrections.items():
    if dtype == 'category':
        data[col] = data[col].astype('category')
    elif dtype == 'int64':
        data[col] = data[col].fillna(0).astype('int64')  # Handle NaN for binary columns
    else:
        data[col] = data[col].astype(dtype)
```

**4.2 Exploratory Data Analysis**

1. Count and visualize gender distribution:

```
gender_counts = data['gender'].value_counts()

gender_counts.plot(kind='bar', title='Victim Gender Distribution', ylabel='Count',
xlabel='Gender')
```

2. Explore regional exploitation and time trends:

```
region_counts = data['UN_COE_Region'].value_counts()

year_counts = data['yearRegister'].value_counts().sort_index()

year_counts = year_counts[year_counts.index != 'Unknown']
```

3. Explore relations between IP_Relation and exploitation types

```
relation_forced_labour = pd.crosstab(data['IP_Relation'], data['isForcedLabour'])

relation_sexual_exploit = pd.crosstab(data['IP_Relation'], data['isSexualExploit'])
```

4. Explore the victims-perpetrator relationships by region

```
actions_region = data.groupby('UN_COE_Region')[['IP_ControlAbuseKidnap',
'IP_RecruiterBroker']].sum()

relation_region = pd.crosstab(data['UN_COE_Region'], data['IP_Relation'])
```

5. Explore the exploitation types for minors by regions and genders:

minors_exploitation_by_gender = minors_data.groupby(['UN_COE_Region', 'gender'])[['isForcedLabour', 'isSexualExploit']].sum()

**4.3 Predict modeling**

1. Design function for binary classification task to predict exploitation types:

```
def evaluate_model_as_table(base_model, model_name):
    model = MultiOutputClassifier(base_model)
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    results = []
    for i, column in enumerate(y.columns):
        report = classification_report(y_test.iloc[:, i], y_pred[:, i], target_names=['No', 'Yes'], output_dict=True, zero_division=0)
        results.append({
            'Model': model_name,
            'Target': column,
            'Accuracy': report['accuracy'],
            'Precision (No)': report['No']['precision'],
            'Recall (No)': report['No']['recall'],
            'F1-Score (No)': report['No']['f1-score'],
            'Precision (Yes)': report['Yes']['precision'],
            'Recall (Yes)': report['Yes']['recall'],
            'F1-Score (Yes)': report['Yes']['f1-score']
        })
    return results
```

2. Evaluate Logistic Regression,  Random Forest, XGBoost for multiclass classification:

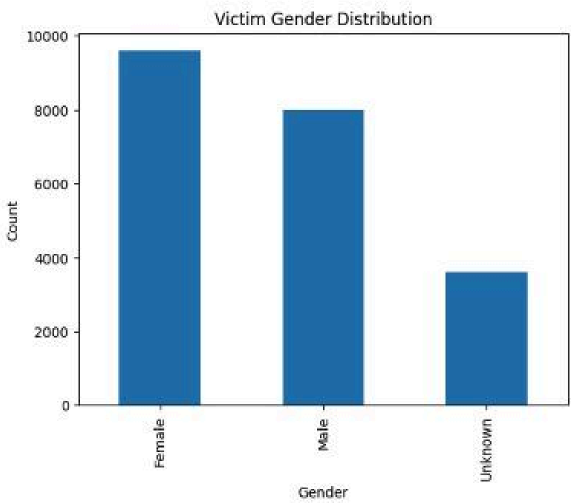
```
lr_model = LogisticRegression(max_iter=500, multi_class='multinomial',
random_state=42)

rf_model = RandomForestClassifier(n_estimators=100, class_weight='balanced',
random_state=42)

xgb_model = XGBClassifier(objective='multi:softmax', num_class=3,
random_state=42)
```

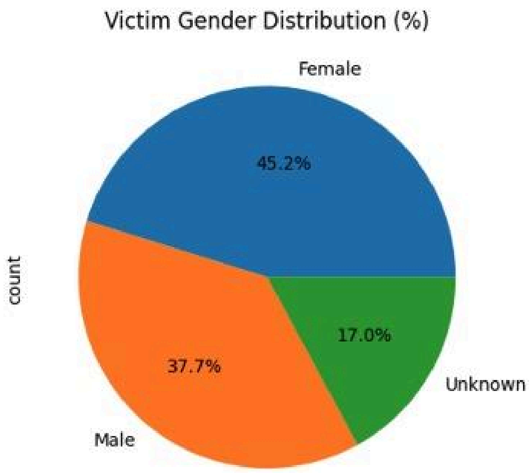
## 5. Results

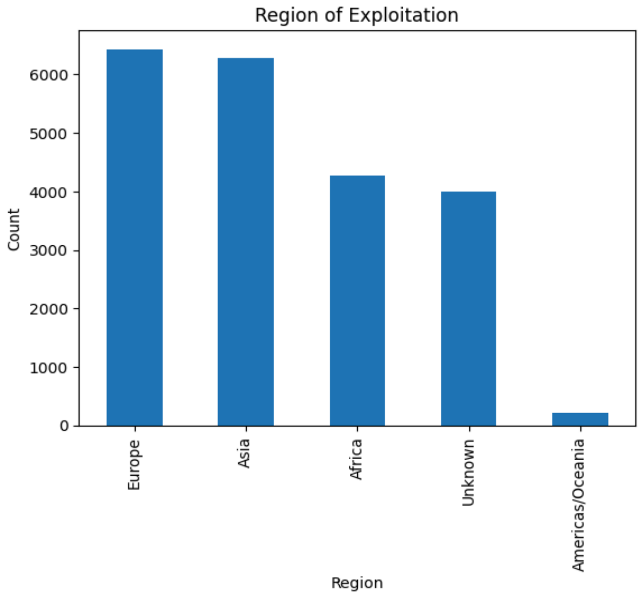
### 5.1 Exploratory Data Analysis

Initial analyses focused on understanding victim and perpetrator dynamics:

1. Demographics: Gender distribution: Females accounted for the majority of victims in sexual exploitation, while males were more prevalent in forced labor.Age distribution: Minors were overrepresented in certain regions compared to adults.

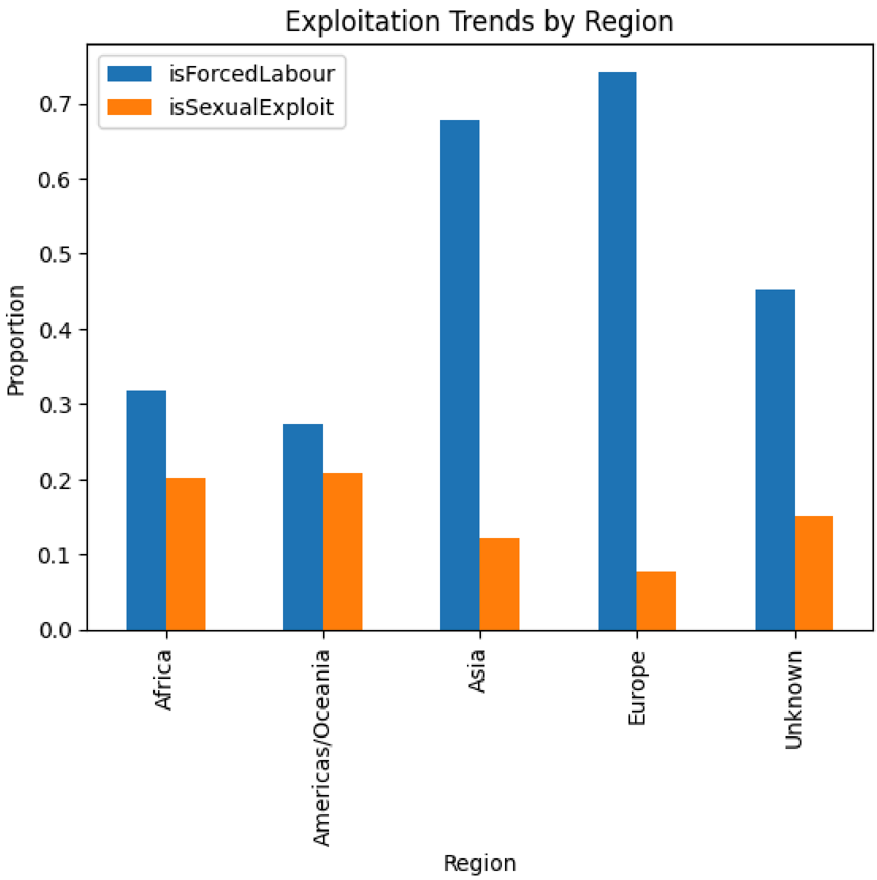





2. Exploitation Types:

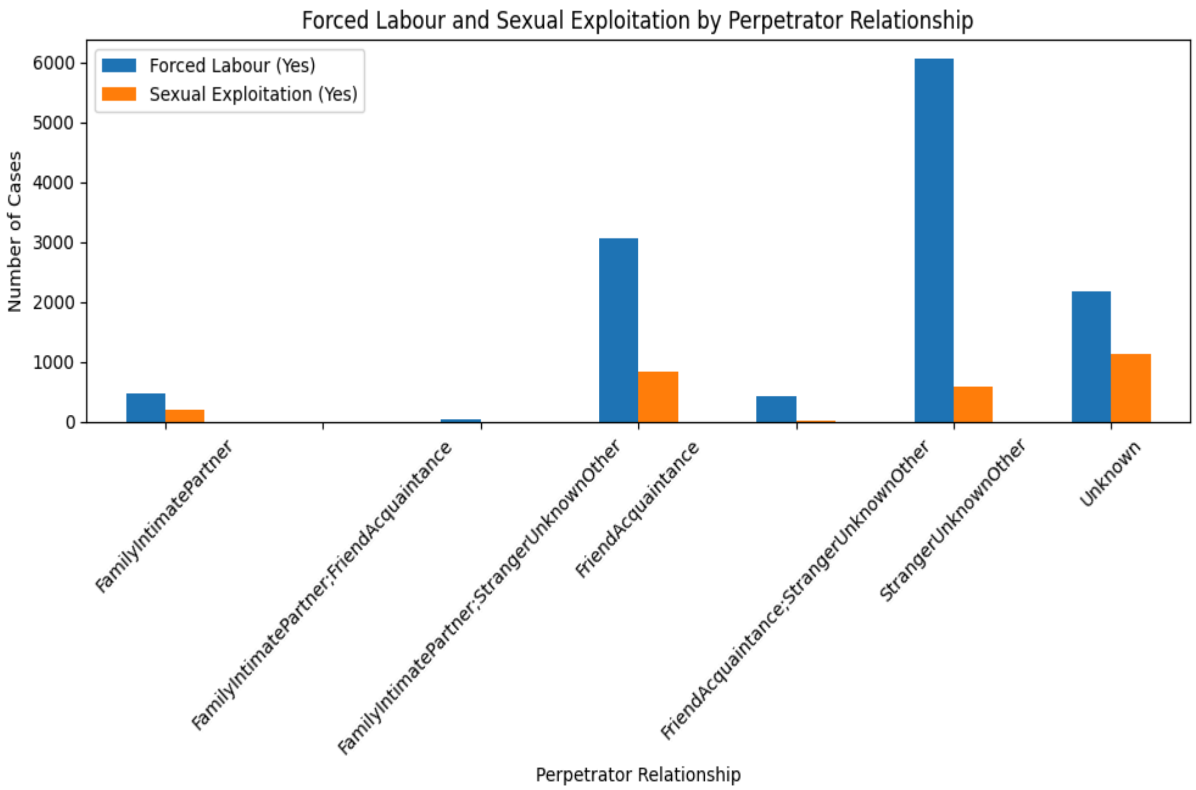
   Forced labor was proportionally more dominant in Asia and Europe, and there was a higher proportion of sexual exploitation in Africa and the Americas. However, across the board, we can see that forced labor is more prevalent in all regions.



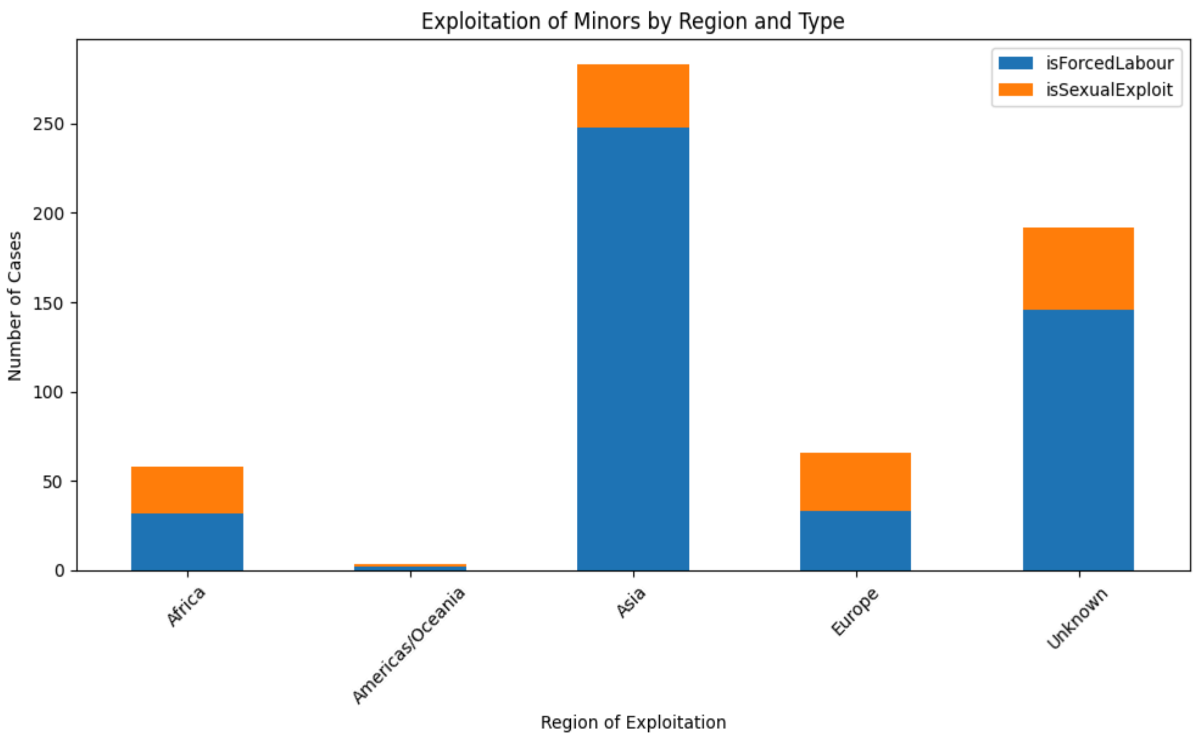
3. Victim-Perpetrator Relationships: Family members and intimate partners were more commonly associated with sexual exploitation, whereas strangers played a significant role in forced labor.

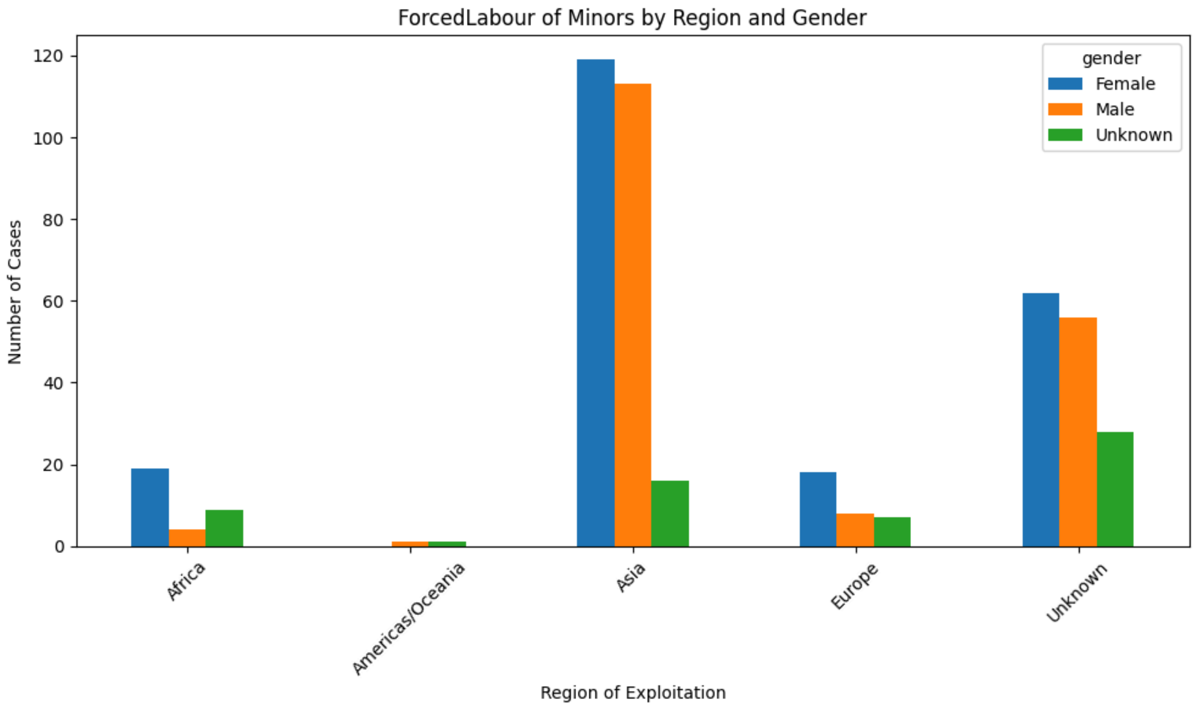
| **Forced Labor: Victim-Perpetrator Relationships** | | |
|---|---|---|
| Relation to Perpetrator | No | Yes |
| FamilyIntimatePartner | 506 | 461 |
| FamilyIntimatePartner;FriendAcquaintance | 6 | 0 |
| FamilyIntimatePartner;StrangerUnknownOther | 35 | 38 |
| FriendAcquaintance | 1548 | 3069 |
| FriendAcquaintance;StrangerUnknownOther | 153 | 435 |
| StrangerUnknownOther | 2255 | 6066 |
| Unknown | 4444 | 2179 |

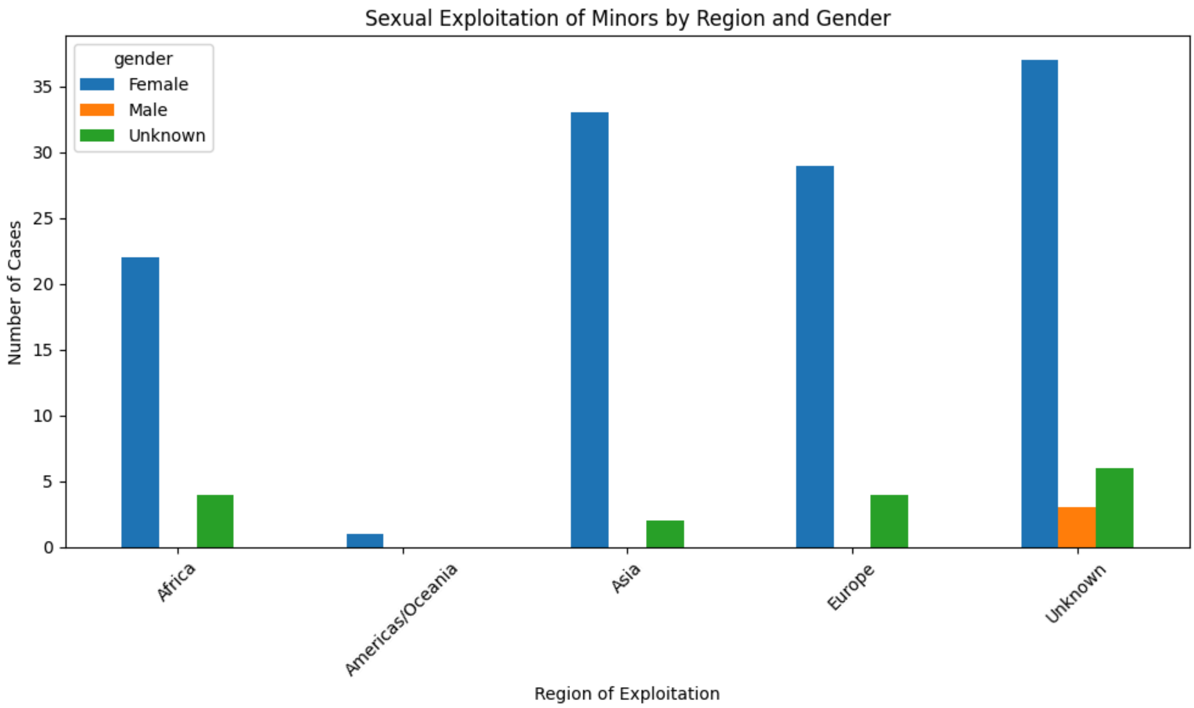
| Sexual Exploitation: Victim-Perpetrator Relationships | | |
|---|---|---|
| Relation to Perpetrator | No | Yes |
| FamilyIntimatePartner | 767 | 200 |
| FamilyIntimatePartner;FriendAcquaintance | 6 | 0 |
| FamilyIntimatePartner;StrangerUnknownOther | 73 | 0 |
| FriendAcquaintance | 3790 | 827 |
| FriendAcquaintance;StrangerUnknownOther | 570 | 18 |
| StrangerUnknownOther | 7728 | 593 |
| Unknown | 5486 | 1137 |




4. Exploitation of Minors






We can observe that there are virtually few cases of sexual exploitation of male minors. With regard to forced labor, we can see that Asia has a relatively balanced distribution of male and female victims, while the remaining regions appear to have significantly more female victims.

### 5.2 Predictive Modeling

The goal of this project is to experiment with various predictive modeling methodologies that are suitable for this dataset. Noting that it contained sparse data, and often had a lot of missing information, we embraced this as an opportunity to explore appropriate predictive modeling approaches that could still yield meaningful insights for stakeholders like policy makers, civil society organizations, or academics. Specifically, we performed the following tasks:

- **Binary Classification** to determine whether a victim is likely to be subjected to forced labor or sexual exploitation based on demographics, perpetrator roles, and geographical context.
- **Multiclass Classification** to predict the region of origin (**UN_COO_Region**) of a victim, leveraging victim demographics, perpetrator roles, and exploitation types as features. Similarly, we also wanted to see if we can predict *where* someone was being exploited (**UN_COE_Region**) based on similar features.

These models provide insight into the key risk factors and relationships in trafficking, which can guide interventions and support strategies.

For each of the problems, we compared the efficacy of using **Linear Regression, Random Forest, and Gradient Boosting methods.**

### 5.2.1 Binary Classification: Forced Labor vs. Sexual Exploitation

The principal challenge with predicting Forced Labor vs Sexual Exploitation was that the overall number of instances of sexual exploitation were significantly lower, making it an imbalanced dataset. The majority class (No) dominates the **isSexualExploit** dataset with 5519 samples. The minority class (Yes) has only 840 samples. Models like Logistic Regression struggle with such imbalance and default to predicting the majority class (No) to optimize overall accuracy. Therefore we experimented with using class weights to adjust for the imbalance.

Below are the final results comparing each of the three methods:

| **Model** | **Target** | **Accuracy** | **Precision (No)** | **Recall (No)** | **F1-Score (No)** | **Precision (Yes)** | **Recall (Yes)** | **F1-Score (Yes)** |
|---|---|---|---|---|---|---|---|---|
| Logistic Regression | isForcedLabour | 0.7457 | 0.7025 | 0.6976 | 0.7001 | 0.7773 | 0.7813 | 0.7793 |
| Logistic Regression | isSexualExploit | 0.6732 | 0.9694 | 0.6438 | 0.7737 | 0.2702 | 0.8667 | 0.412 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Random Forest | isForcedLabour | 0.7485 | 0.6949 | 0.729 | 0.7115 | 0.7918 | 0.763 | 0.7771 |
| Random Forest | isSexualExploit | 0.7368 | 0.9643 | 0.7235 | 0.8267 | 0.312 | 0.8238 | 0.4526 |
| XGBClassifier | isForcedLabour | 0.7531 | 0.7123 | 0.7039 | 0.7081 | 0.7827 | 0.7895 | 0.7861 |
| XGBClassifier | isSexualExploit | 0.7618 | 0.9556 | 0.7608 | 0.8472 | 0.3282 | 0.7679 | 0.4599 |

Unsurprisingly, given the sparse nature of the dataset described above, the predictive modeling results indicate that the models performed better for predicting forced labor compared to sexual exploitation.

For **isForcedLabour**, all three models—Logistic Regression, Random Forest, and XGBClassifier—achieved similar overall accuracies of around **0.75**. Notably, **Random Forest** and **XGBClassifier** balanced their predictions well, achieving relatively consistent F1-scores for both 'No' and 'Yes'. For instance, the **XGBClassifier** had an F1-score of **0.7081** for 'No' and **0.7861** for 'Yes', indicating balanced performance across both outcomes.

In **isSexualExploit** classification, the models showed high precision for 'No', suggesting they were effective at identifying non-sexual exploitation cases, but at the expense of lower precision for 'Yes' (ranging from **0.2702** to **0.3282**). This discrepancy indicates that while the models excelled at correctly predicting non-exploitation instances, they tended to overpredict positive cases of sexual exploitation, resulting in lower precision. However, the **XGBClassifier** showed a moderate improvement with a **F1-score of 0.4599** for 'Yes', which was the highest among the models for this target.

Overall, while the models were generally effective for **forced labor** predictions with balanced performance for both 'No' and 'Yes' classes, there was a tendency to overpredict cases of **sexual exploitation**, which was reflected in lower precision and inconsistent F1-scores for 'Yes'. The **XGBClassifier** performed slightly better in balancing these predictions compared to the other models.

One of the other key takeaways here is that class weights notably improve \`Yes\` predictions, but at the cost of reduced performance for \`No\`.

### 5.2.2 Multiclass Classification: Region of Exploitation

The next task was to predict the **region of exploitation** (Africa, Asia, or Europe) using features related to victim demographics, types of exploitation, and perpetrator roles. Since Americas/Oceania only had 212 entries, we omitted that region, and similarly ignored "Unknown" in order to remove noise from the dataset and focus on three regions where we do have information.

Below are the summarized results comparing Logistic Regression, Random Forest, and XGBoost for this classification task.

| Model | Region | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|---|
| Logistic Regression | Africa | 0.53 | 0.53 | 0.50 | 0.52 |
| Logistic Regression | Asia | 0.53 | 0.48 | 0.57 | 0.52 |
| Logistic Regression | Europe | 0.53 | 0.61 | 0.51 | 0.55 |
| Random Forest | Africa | 0.53 | 0.47 | 0.67 | 0.55 |
| Random Forest | Asia | 0.53 | 0.50 | 0.48 | 0.49 |
| Random Forest | Europe | 0.53 | 0.64 | 0.48 | 0.55 |
| XGBoost | Africa | 0.54 | 0.55 | 0.47 | 0.51 |
| XGBoost | Asia | 0.54 | 0.48 | 0.59 | 0.53 |
| XGBoost | Europe | 0.54 | 0.61 | 0.53 | 0.57 |

Immediately, we can appreciate that the results are quite moderate. A random guess would be accurate 33% of the time, and our models improve this to about 55% with **XGBoost**, but this would not be considered reliable.

To clarify the above table a bit further, the identical accuracy scores across the three models are a result of their similar overall correctness in predicting the region of exploitation, irrespective of class-specific nuances. However, the variance in precision, recall, and F1-scores highlights differences in the models' ability to distinguish between specific regions, reflecting challenges such as overlapping feature characteristics and varying class difficulty. The reader can review the .ipynb file and execute it to see the varying confusion matrices for a more granular look.

**Observations**:

Across all models, **Europe** showed the highest **precision** and **F1-scores**, with **XGBoost** performing particularly well with an **F1-score of 0.5669**. This suggests that the features used are most effective at predicting cases in Europe.

**Africa** had higher recall compared to precision, particularly with the **Random Forest** model, which achieved a **recall of 0.6705**. This means that the model effectively identified instances of exploitation in Africa, but at the cost of increased false positives.

**Asia** proved to be the most challenging to predict accurately, with **precision and recall** values generally lower across models. The **XGBoost** model slightly outperformed others with a **recall of 0.5921** and an **F1-score of 0.5306**, indicating some balance between correct predictions and false negatives.

**Conclusion**: The models showed moderate success in predicting regions of exploitation, with **XGBoost** performing slightly better overall. However, the relatively low precision and recall values for **Asia** and **Africa** suggest further work is needed to improve feature selection and potentially incorporate additional data to differentiate these regions more effectively.

While the results here are lackluster, they provide an interesting counterpoint to the next section.

### 5.2.3 Multiclass Classification: Region of Origin

In this section, we aimed to predict the **Country of Origin (COO)** for each victim using the same features related to demographics, exploitation types, and perpetrator roles (as in the previous section). Again, we focused on the same three distinct regions: **Africa, Asia, and Europe**.

Below are the summarized results:

| **Model** | **Region** | **Accuracy** | **Precision** | **Recall** | **F1-Score** |
|---|---|---|---|---|---|
| Logistic Regression | Africa | 0.78 | 0.83 | 0.76 | 0.80 |
| Logistic Regression | Asia | 0.78 | 0.74 | 0.72 | 0.73 |
| Logistic Regression | Europe | 0.78 | 0.78 | 0.87 | 0.82 |
| Random Forest | Africa | 0.79 | 0.78 | 0.86 | 0.82 |
| Random Forest | Asia | 0.79 | 0.79 | 0.68 | 0.73 |
| Random Forest | Europe | 0.79 | 0.80 | 0.85 | 0.83 |

| | | | | | |
|---|---|---|---|---|---|
| XGBoost | Africa | 0.80 | 0.81 | 0.84 | 0.82 |
| XGBoost | Asia | 0.80 | 0.76 | 0.71 | 0.74 |
| XGBoost | Europe | 0.80 | 0.82 | 0.84 | 0.83 |

**Observations**:

The **XGBoost** model consistently showed the best performance with an overall accuracy of **0.80** across the regions, with particularly high **precision** and **recall** for **Africa** and **Europe**.

**Random Forest** and **Logistic Regression** had similar overall accuracies around **0.78-0.79**, with the highest **recall** observed for **Europe** in the Logistic Regression model (**0.87**).

**Asia** showed lower precision and recall compared to the other regions across all models, suggesting that the feature set was less effective in differentiating instances from Asia. **XGBoost** had a slight edge over the other models for this region, with an **F1-score of 0.74**.

**Conclusion**: The models demonstrated consistent accuracy when predicting the country of origin, with **XGBoost** performing slightly better overall. However, differences in **precision, recall, and F1-scores** highlight challenges in predicting certain regions, particularly **Asia**, which may be due to overlapping feature characteristics with other regions. These results emphasize the need for additional or more distinctive features to improve differentiation among regions.

***Reflection: Why are the models so much better at predicting Region of Origin vs Region of Exploitation?***
We think that the **Region of Origin** task outperformed the **Region of Exploitation** task primarily due to clearer feature-target relationships and more distinct class boundaries. Features such as demographics are directly linked to the origin of a victim, making the associations stronger and easier for the model to learn. In contrast, we suspect that Region of Exploitation is influenced by additional external factors not captured in the dataset, such as trafficking routes, border enforcement policies, regional demand, etc.. The absence of these critical factors means the model has to rely on incomplete information, making it difficult to distinguish between different regions effectively and thereby complicating the classification task.

## 6. Discussion

The results of EDA indicate that forced labor was more prevalent in Asia and Europe while Africa takes up a large portion of sexual exploitation. When aligning these findings with global trafficking patterns, the labor exploitation in Asian and European countries may be attributed to the economic development levels and the lack of labor protections. For sexual exploitation in Africa, this may be caused by the instability of the society, the low social status of African women and the huge gaps between each social class. It makes sense that women and children are more easily subjected to sexual exploitation than men and vice versa for forced labor. That is because the women and children are the vulnerable parties for the perpetrator to control. And it is common for men to work cross-border to make a living, making them the victims of forced labor. For victim-perpetrator relationships, we found that family members and intimate partners were often associated with sexual exploitation, which underscores the necessity for community based intervention and awareness campaigns.

For the insights of predictive modeling, one of the limitations of the data imbalance of sexual exploitation, which causes the less reliable predictions for these exploitation types and suggest that future work should utilize alternative modeling approaches to deal with sparse data, or to explore and combine more dataset to fill the blank. When it comes to the exploitation regions, clearer patterns and more consistent data collection practices in the industrialized regions of Europe, and overlapping characteristics in Asia and Africa may contribute to the fact that multiclass classification task for the region of exploitation achieved moderate accuracy (~54%), with better precision for Europe compared to Asia and Africa, indicating the need for richer contextual data, such as trafficking routes and socio-economic factors.

In contrast, the models performed much better for the region of origin, achieving an accuracy of 80%, which indicates stronger feature-target relationships. This is because demographic factors such as age, gender, and regional attributes tied to origins are likely more distinct than those influencing exploitation locations, leading to improved predictions for origin classification.

## 7. Future Work

Moving forward, there are several areas where we can enhance the predictive power and insights gained from this dataset:

1. **Hyperparameter Tuning:** Conduct more exhaustive hyperparameter tuning for each model to further optimize their performance. Adjusting parameters like learning rates, maximum tree depths (for XGBoost and Random Forest), and regularization terms may yield better results, particularly for the multiclass tasks. The provided .ipynb file shows we attempted to experiment with this area, but yielded quite negligible results.
2. **Exploring Alternative Modeling Approaches:** Consider exploring other machine learning algorithms that may be better suited to this kind of sparse, imbalanced data. Techniques like Support Vector Machines (SVMs), Ensemble Methods, or even Neural Networks could be experimented with to assess their applicability to this context. We considered experimenting with neural networks, however felt that the data was too sparse and small for this, however it could be worth trying a simple neural network implementation with this dataset, or the larger global victim dataset.
3. **Feature Engineering and Data Enrichment:** Introduce new features that might help differentiate regions more clearly, such as combining different forms of victim-perpetrator relationships into interaction terms, or finding proxies for missing contextual data (e.g., economic indicators). In addition, more thorough feature selection processes may help reduce noise and improve classification performance. One idea we considered was looking at country-specific (or even regional/international) legislation related to trafficking, and seeing how the passage of

such laws may have affected trafficking over time. This is still a viable avenue to pursue, however would require much more data generation and mining than we had time for in this period.

4. **Combining Datasets:** To overcome the data sparsity and gain a richer context, future work could involve combining the victim-perpetrator dataset with the larger global synthetic dataset. This could help provide more context to each case and uncover additional insights that were not available in this project due to time constraints.
5. **Evaluating External Factors:** As mentioned in number 3 above, where possible, incorporating additional external data sources that could improve model accuracy for predicting Region of Exploitation, such as trafficking routes, socio-economic indicators, or regional law enforcement practices would have been helpful. While this data was not available in the current dataset, obtaining such information could provide the context necessary for more reliable exploitation region predictions.
6. **Principal Component Analysis (PCA):** Consider using Principal Component Analysis (PCA) for dimensionality reduction to address the high-dimensionality of the feature space, particularly with categorical variables expanded through one-hot encoding. PCA could help reduce noise by identifying and focusing on the most informative components, potentially leading to improved model performance and more efficient training times, especially for tasks with large numbers of features. This would have added an interesting layer to perhaps help understand which features may be most helpful in making predictions. Some preliminary implementation found that of the total 36 features we mostly examined, about 15 could account for 75% of the variance.
7. **Time-Series Analysis:** If sufficient data becomes available, consider performing a time-series analysis to understand how patterns in exploitation evolve over time. Such analyses could help identify seasonal trends or the impact of new anti-trafficking policies, thereby adding valuable predictive insights to the modeling efforts. The time-series data in the CTDC are too wide/vague, however we hope that future iterations of the dataset may improve this dimension.

Our goal was to explore data mining methods learned throughout the class and see what we might uncover on an interesting dataset that may provide social and academic value to a serious global issue that is under-examined and not well understood. By experimenting with various predictive modeling techniques, we aimed to extract meaningful insights that could aid policymakers, researchers, and civil society organizations in understanding the dynamics of human trafficking.

Despite the challenges of sparse and incomplete data, we demonstrated that meaningful predictions about forced labor, sexual exploitation, and regional trends are possible, and highlighted areas where more focused research and improved datasets could further enhance our understanding. This project not only applied our learning to a real-world problem but also underscored the importance of data quality, feature engineering, and context-specific understanding in tackling complex social issues.

While there is much room for improvement, the findings in this report provide a valuable starting point for continued exploration. With further tuning, enrichment of data, and more advanced modeling techniques, we hope that this work contributes a small but crucial step toward better understanding and combating human trafficking globally.

## 8. Conclusion

In this project, we explored predictive modeling for understanding victim-perpetrator dynamics in human trafficking using a synthetic dataset. Despite the challenges posed by sparse data and missing values, we experimented with multiple approaches, namely binary and multiclass classification tasks, to provide meaningful insights that can be used by stakeholders such as policymakers, civil society organizations, and researchers.

For the **Binary Classification of Forced Labor vs. Sexual Exploitation**, the models showed stronger performance for predicting forced labor, but struggled with the imbalanced nature of the dataset for sexual exploitation, despite employing class weights to mitigate this issue. The XGBoost model performed best overall, achieving a balance between precision and recall, although challenges in distinguishing the minority class (sexual exploitation) remained.

For the Multiclass Classification tasks, the **Region of Exploitation** proved difficult to predict reliably, with all models achieving moderate performance. This is likely due to overlapping feature characteristics and missing contextual information, such as trafficking routes and regional policies, which were not captured in the dataset. On the other hand, the **Region of Origin** task yielded significantly better results, likely due to clearer feature-target relationships, which allowed models to differentiate between regions more effectively.

Overall, our findings highlight the potential for predictive modeling in human trafficking research but also underscore the limitations of the available data. By identifying patterns in forced labor and predicting victim origins, we offer insights that could support intervention strategies, though further refinement and additional data are needed for reliable exploitation region predictions.

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