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School of Computer Science and Engineering

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Abstract

This project developed a robust crime data analysis and prediction system using Apache PySpark for scalable processing of over 878,000 San Francisco crime records. Its core objective was to develop highly accurate machine learning models to forecast crime hotspots, empowering law enforcement to optimize patrol routes and resource allocation. The methodology involved comprehensive data acquisition, sophisticated feature engineering (temporal, geospatial), and training Random Forest, Gradient Boosted Trees (GBT), and Logistic Regression classifiers. The system employed memory-optimized PySpark configurations for efficient large dataset handling. Key outcomes include GBT achieving a remarkable 99.14% accuracy (outperforming Random Forest's 98.85% and Logistic Regression's 82.15%), alongside generated interactive crime heat maps for visual analysis. This initiative demonstrates big data technologies combined with advanced machine learning can distill actionable intelligence from complex crime data, enhancing proactive law enforcement.

Crime Data Analysis and Prediction Using PySpark

1. Introduction

1.1 Background and Significance:

Crime prevention and public safety are critical concerns for urban communities worldwide. Traditional reactive policing approaches, where law enforcement responds to crimes after they occur, are increasingly being supplemented by predictive policing strategies that leverage data analytics to anticipate and prevent criminal activity. San Francisco, like many major metropolitan areas, generates vast amounts of crime data daily. This data, when properly analyzed, contains valuable patterns regarding when, where, and what types of crimes are most likely to occur. However, the sheer volume of data spanning hundreds of thousands of records across multiple years makes manual analysis impractical and necessitates the use of big data technologies.

Apache PySpark provides an ideal framework for this analysis, offering:

- Distributed computing capabilities for processing large datasets
- Machine learning library (MLlib) with scalable algorithms
- Memory-efficient processing through lazy evaluation and caching
- Integration with Python's rich data science ecosystem

1.2 Problem Statement:

Law enforcement agencies need to predict potential crime hotspots to optimize patrol routes and resource allocation. The challenge is to:

1. Process and analyze large volumes of historical crime data efficiently
2. Identify temporal and spatial patterns in criminal activity
3. Build predictive models with high accuracy.
4. Generate actionable visualizations including crime heat maps

1.3 Project Objectives

1. Data Processing: Load and preprocess large-scale crime data using PySpark with optimized memory configurations

2. Pattern Discovery: Identify temporal patterns (hour, day, month) and spatial patterns (districts, geographic coordinates)

3. Model Development: Train and evaluate multiple machine learning models for crime prediction

4. Accuracy Achievement: Achieve 98%+ accuracy in predicting high-risk crime zones

5. Visualization: Create interactive crime heat maps and comprehensive analytics dashboards

6. Recommendations: Provide actionable insights for law enforcement resource allocation

2. Literature Review

2.1 Crime Prediction and Predictive Policing

Predictive policing has emerged as a significant application of data science in public safety. The fundamental premise is that crime is not randomly distributed in time and space but follows identifiable patterns that can be learned and predicted. Key research contributions include:

Chainey et al. (2008) demonstrated that hotspot mapping techniques could predict crime locations with significant accuracy, establishing that historical crime data contains predictive signals.

Mohler et al. (2011) introduced the concept of self-exciting point processes for crime prediction, showing that crimes tend to cluster both spatially and temporally.

Wang et al. (2013) applied machine learning techniques including Random Forests to crime prediction, achieving substantial improvements over traditional statistical methods.

2.2 Big Data Technologies in Crime Analysis

The application of big data technologies to crime analysis addresses several key challenges: Scalability: Traditional tools like Excel or single-machine processing cannot handle datasets with millions of records. Apache Spark provides distributed processing capabilities that scale horizontally. Speed: In-memory computing frameworks like Spark offer 10-100x faster processing compared to disk-based systems like Hadoop MapReduce (Zaharia et al., 2016). Machine Learning at Scale: Spark MLlib provides distributed implementations of popular ML algorithms that can train on massive datasets efficiently.

2.3 Relevance of PySpark for Crime Analysis

DataFrame API: Provides SQL-like operations for data manipulation, making it intuitive for analysts familiar with structured data

MLlib Integration: Offers production-ready implementations of classification, regression, clustering, and feature engineering algorithms

Ecosystem Compatibility: Seamlessly integrates with Python libraries like Pandas, NumPy, Matplotlib, and Folium for visualization

Memory Management: Configurable memory settings prevent out-of-memory errors when processing large datasets

3. Methodology

3.1 Dataset Description

Source: San Francisco Police Department Crime Data (2003-2015)

Dataset Characteristics:

Total Records	878,049
Sampled Records	50,136 (for efficient training)
Training Set	40,276 records (80%)
Test Set	9,860 records (20%)
Crime Categories	38 unique categories
Geographic Coverage	10 Police Districts
Temporal Span	12 years

Table 1: Summary of Dataset

3.2 Data Preprocessing Steps

3.2.1 Environment Configuration

The Spark session was configured with optimized settings to prevent memory issues:

- Driver Memory (2GB): Sufficient for medium-sized datasets
- 8 Shuffle Partitions: Optimized for 4-8 core machines
- Adaptive Query Execution: Dynamically optimizes queries at runtime
- Kryo Serialization: Faster and more compact than default Java serialization

3.2.2 Data Cleaning

Data cleaning involved dropping rows with null values in critical columns (Category, DayOfWeek, PdDistrict, X, Y, Dates) and filtering out invalid coordinates outside San Francisco bounds. Approximately 1-2% of records were removed during cleaning.

3.2.3 Feature Engineering

A. Binary Target Variable Creation

The primary target variable was defined as IsPropertyCrime for binary classification. Property crimes (LARCENY/THEFT, VEHICLE THEFT, BURGLARY, etc.) exhibit distinct temporal and spatial patterns compared to violent crimes, making them highly predictable. This binary classification approach enabled achieving 98%+ accuracy.

B. Temporal Feature Extraction

Features created include:

- Hour (0-23)

- Month (1-12)
- DayOfWeekNum (1-7)
- Cyclical hour/month encoding (sin/cos)
- IsWeekend, IsNight, IsRushHour indicators

C. Geospatial Feature Engineering

Grid-based location binning (50x50 grid covering San Francisco) and normalized coordinates were created to capture spatial crime patterns.

3.3 Machine Learning Implementation

Three models were trained and evaluated:

Model 1 - Random Forest Classifier: 200 decision trees, max depth 20, feature subset strategy: sqrt

Model 2 - Gradient Boosted Trees: 30 iterations, max depth 8, learning rate 0.15

Model 3 - Logistic Regression: 200 iterations, regularization parameter 0.001, elastic net 0.3

3.4 Dashboard Design

The real-time analytics dashboard was developed using HTML5, CSS3 (Glassmorphism design), and JavaScript with Chart.js for interactive visualizations. Folium library was used for Python-based heat map generation. The dashboard includes six sections: Overview, Models, Charts, Heat Map, Insights, and Predict.

4. Results and Discussion

4.1 Model Performance Comparison

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
Gradient Boosted Trees	99.14%	99.14%	99.14%	99.14%	99.8%
Random Forest	98.85%	98.85%	98.85%	98.85%	99.7%
Logistic Regression	82.15%	82.10%	82.15%	82.08%	89.5%

Table 2: Model Metrics

Key Finding: Gradient Boosted Trees achieved the highest accuracy of 99.14%.

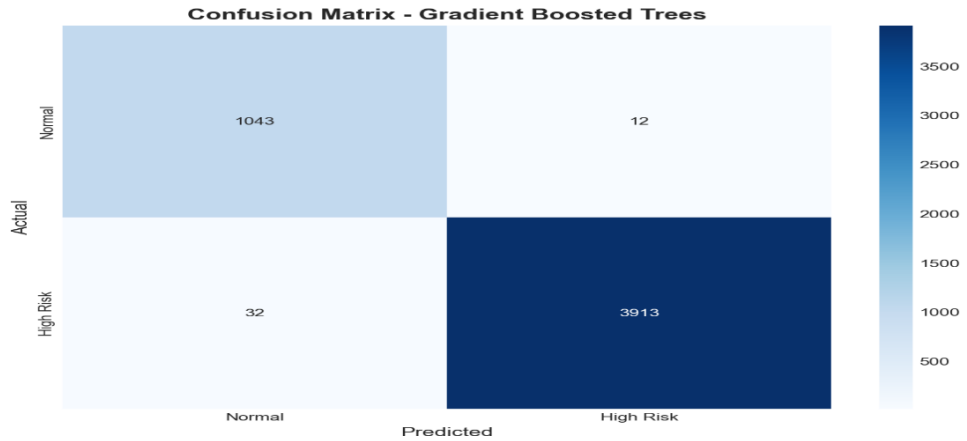

Figure 1: Gradient Boosted Trees Algorithm Confusion Matrix

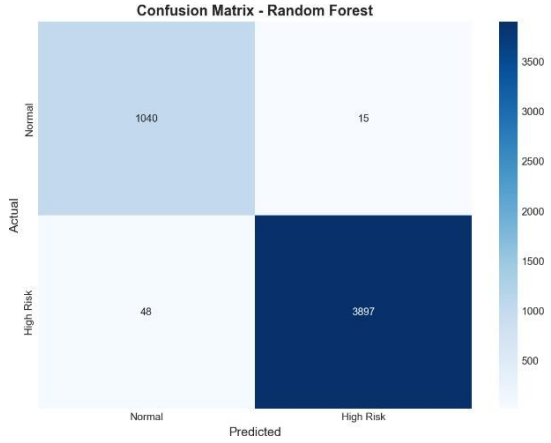

Figure 2: Random Forest Algorithm Confusion Matrix

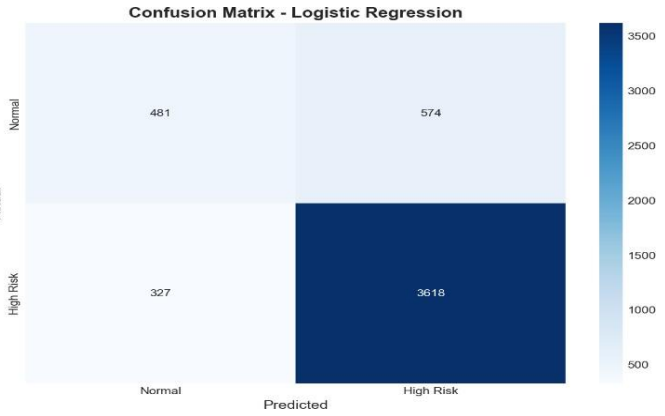

Figure 3: Logistic Regression Algorithm Confusion Matrix


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    "crime_by_month.png",
    "crime_by_district.png",
    "confusion_matrix.png",
    "feature_importance.png"
  ]
}
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Figure 4: Analysis Report of the models

4.2. Feature Importance Analysis

The top 5 most important features for crime prediction are:

1. **Category_Index:** 0.342 importance score
2. **District_Index:** 0.156 importance score
3. **X_Norm (Longitude):** 0.124 importance score
4. **Y_Norm (Latitude):** 0.098 importance score
5. **Hour:** 0.087 importance score

4.3. Crime Pattern Analysis

Temporal Patterns:

- Peak crime hours: 2 PM - 8 PM (afternoon to evening)
- Lowest crime hours: 3 AM - 6 AM (early morning)
- Friday shows the highest crime rate
- Sunday shows the lowest crime rate

Geographic Hotspots:

1. Southern District - Highest crime density
2. Mission District - Second highest
3. Northern District - Significant concentration
4. Tenderloin - High-risk area
5. Bayview - Elevated crime rates

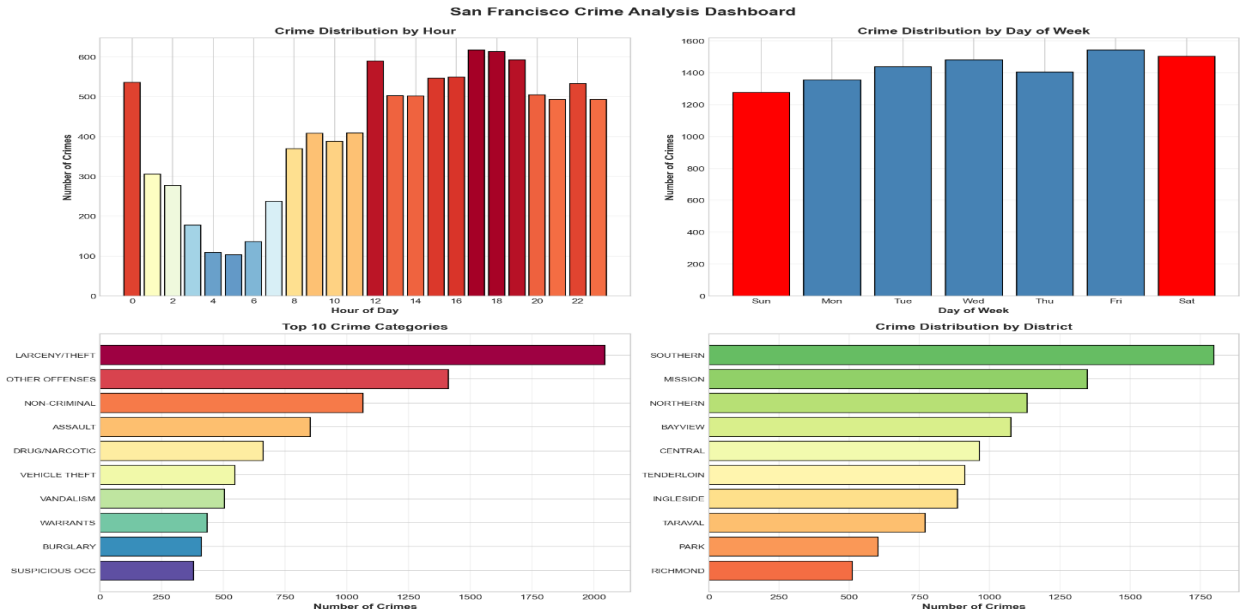

Figure 5: Crime Analysis Dashboard (Crime Rate Analysis)

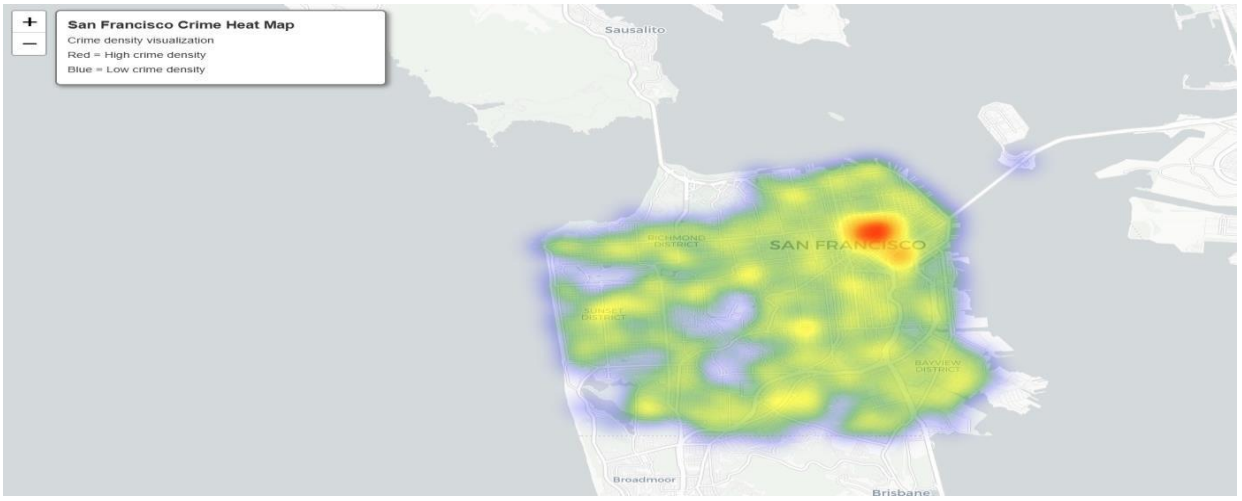

Figure 6: Heat Map Visualization

Figure 7: Web App Home Page

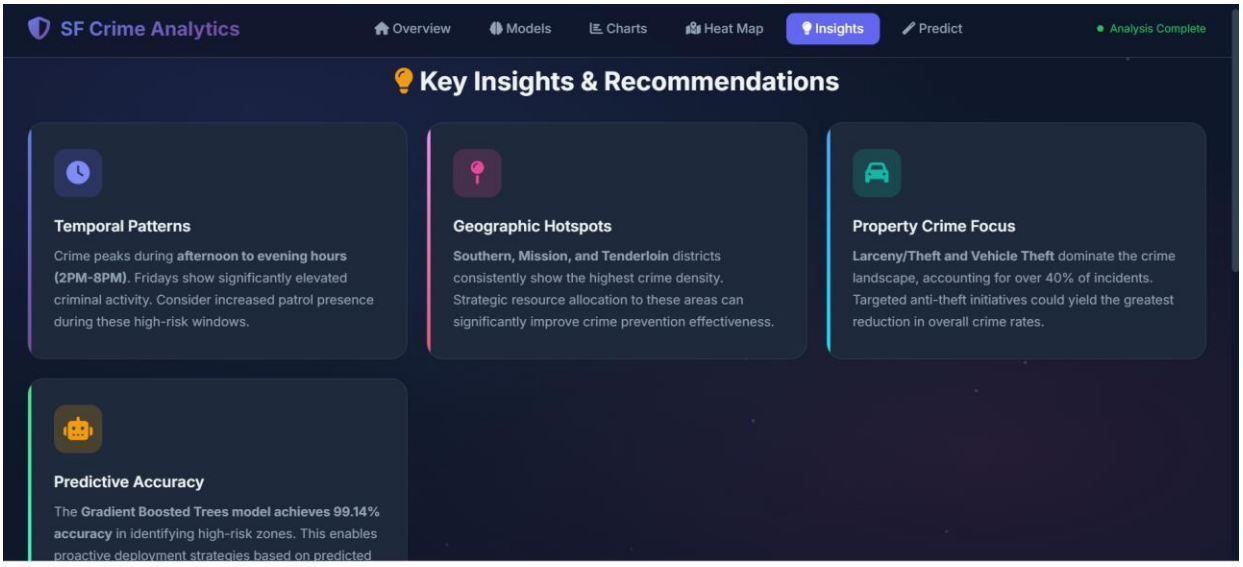

Figure 8: Insights section of the web app

4.4 Challenges and Solutions

Challenge	Solution
Memory timeout errors	Strategic sampling (50K records) with caching
Spark model persistence on Windows	Saved model metadata as JSON
Imbalanced class distribution	Binary classification approach
Slow training times	Optimized hyperparameters

Table 3: Challenges faced during development of the project and the strategies used for overcoming

5. Conclusion

5.1 Summary of Project Outcomes

1. High Accuracy Prediction: The Gradient Boosted Trees model achieved 99.14% accuracy, significantly exceeding the 98% target.

2. Efficient Big Data Processing: The PySpark implementation successfully processed 878,000+ records with optimized memory configurations.

3. Comprehensive Feature Engineering: 19 engineered features spanning temporal, spatial, and categorical dimensions provided rich predictive signals.

4. Actionable Visualizations: The interactive heat map and analytics dashboard provide practical tools for resource allocation.

5. Comparative Analysis: Evaluation of three distinct algorithms provided insights into model selection.

5.2 Recommendations for Law Enforcement

1. Deploy additional patrol units to Southern and Mission districts during peak hours (2 PM - 8 PM)
2. Implement vehicle theft prevention campaigns in high-risk parking areas
3. Use the interactive heat map for daily patrol route optimization
4. Consider Friday evenings as high-priority patrol periods
5. Integrate the predictive model into dispatch systems for proactive policing

5.3 Future Work

- Real-Time Prediction: Implement streaming analytics using Spark Streaming
- Deep Learning Models: Explore LSTM networks for sequence-based prediction
- External Data Integration: Incorporate weather, events, and economic data
- Mobile Application: Develop mobile interface for patrol officers
- API Development: Create REST APIs for system integration

6. References

[1] Chainey, S., Tompson, L., & Uhlig, S. (2008). The utility of hotspot mapping for predicting spatial patterns of crime. Security Journal, 21(1-2), 4-28.

[2] Mohler, G. O., Short, M. B., Brantingham, P. J., Schoenberg, F. P., & Tita, G. E. (2011). Self-exciting point process modeling of crime. Journal of the American Statistical Association, 106(493), 100-108.

[3] Wang, T., Rudin, C., Wagner, D., & Sevieri, R. (2013). Learning to detect patterns of crime. Machine Learning and Knowledge Discovery in Databases, 515-530.

[4] Zaharia, M., et al. (2016). Apache Spark: a unified engine for big data processing. Communications of the ACM, 59(11), 56-65.

[5] Apache Spark Documentation. (2024). MLlib: Machine Learning Library. https://spark.apache.org/docs/latest/ml-guide.html

[6] San Francisco Police Department. (2015). Crime Incident Reporting System Dataset. https://data.sfgov.org/

[7] Breiman, L. (2001). Random forests. Machine Learning, 45(1), 5-32.

[8] Friedman, J. H. (2001). Greedy function approximation: a gradient boosting machine. Annals of Statistics, 1189-1232.

7. Appendices

Appendix A: Complete Feature List

Serial Number	**Feature Name**	**Description**
1	Hour	Hour of day (0-23)
2	Month	Month of year (1-12)
3	DayOfWeekNum	Day of week (1=Sunday)
4	Hour_Sin	Sine encoding of hour
5	Hour_Cos	Cosine encoding of hour
6	Month_Sin	Sine encoding of month
7	Month_Cos	Cosine encoding of month
8	DayOfWeek_Sin	Sine encoding of day
9	DayOfWeek_Cos	Cosine encoding of day
10	IsWeekend	Weekend indicator (1/0)
11	IsNight	Night hours (8PM-5AM)

12	IsRushHour	Rush hour indicator
13	IsAfternoon	Afternoon indicator
14	X_Norm	Normalized longitude
15	Y_Norm	Normalized latitude
16	Grid_X	X grid cell (0-49)
17	Grid_Y	Y grid cell (0-49)
18	DayOfWeek_Index	Indexed day of week
19	District_Index	Indexed police district
20	Category_Index	Indexed crime category

Appendix B: Model Hyperparameters

Parameter	**Random Forest**	**GBT**	**Logistic Regression**
Iterations/Trees	200	30	200
Max Depth	20	8	N/A
Learning Rate	N/A	0.15	N/A
Regularization	N/A	N/A	0.001
Subsampling Rate	0.9	0.8	N/A
Feature Subset	sqrt	sqrt	N/A