

Unsupervised Domain Adaptation for Crime Prediction Across Cities

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ABSTRACT

One of the most significant and pervasive issues in our society is a crime, and preventing it is a crucial task. An increasing crime factor leads to an imbalance in the constituency of a country. Crime prediction and forecasting is a challenging task for law enforcement agencies to prevent crimes in the future. In recent years, machine learning algorithms have been used to analyze crime data and provide useful insights to predict and prevent future crimes. In this paper, we propose a crime risk prediction and forecasting system using a sequential minimal optimization algorithm, a popular support vector machine algorithm that can be used for classification and regression tasks. We demonstrate the effectiveness of the SMO algorithm and LSTM model on a real-world crime dataset and compare its performance with other commonly used machine learning algorithms. Our results show that the SMO algorithm and LSTM model gives faster and more variety of visualizations for crime trend prediction and forecasting.

Keywords : Crime risk prediction, Sequential Minimal Optimization, Forecasting, Machine learning

I. INTRODUCTION

Crime risk prediction is a challenging problem in the field of enforcement. The ability to predict crime risks can help law enforcement agencies to allocate their resources effectively and prevent crime before it occurs. Traditional crime prediction methods rely on expert knowledge and statistical analysis, which are often subjective and time consuming. Machine

learning algorithms have been increasingly used for crime risk prediction due to their ability to learn patterns and make accurate predictions. In recent years accurate crime prediction is crucial for the effective prevention of criminal acts. Predicting crime types and hot spots from past patterns presents various computational challenges and opportunities. While machine learning-based crime prediction is currently the mainstream analysis approach, few

studies have systematically compared different machine learning methods. Machine learning algorithms have shown their ability to process non-linear rational data and handle high-dimensional data with faster training speed, enabling them to extract data characteristics. Despite considerable research efforts, there is still a lack of literature on the relative accuracy of crime prediction for large datasets in multiple cities. Recent studies suggest that implementing different models can address challenges related to predicting and forecasting violent acts in high crime-density areas. Crime data typically demonstrates data seasonality, indicating the potential significance of criminal activities that have evolved over the year. Previous studies have used various machine learning algorithms to predict crime, including Random Forests, Support Vector Machines, and Decision Trees. This paper proposes the use of the Sequential Minimal Optimization (SMO) algorithm for crime risk prediction in three major cities: Chicago, Philadelphia, and San Francisco. SMO is a popular support vector machine algorithm known for its ability to handle large datasets and high-dimensional feature spaces. Forecasting is done with the use of LSTM. Analyzing crime data requires time series analysis, which involves generating visual patterns using deep learning algorithms, particularly Long Short-Term Memory (LSTM) as compared to ARIMA. In practice, LSTM is more suitable for time series forecasting as it requires only a single fitting and does not require parameter optimization. It aims to predict the risk of crime and forecast future crime incidents based on historical crime data.

II. RELATED WORK

Previous research has shown that machine learning algorithms such as decision trees, random forests, and support vector machines can be effective for crime risk prediction. These algorithms have been used to predict various types of crimes, including burglary, robbery, and drug-related offenses.

1. Unsupervised Domain Adaptation for Crime Risk Prediction Across Cities

This paper proposes an unsupervised domain adaptation method for crime risk prediction across cities, which utilizes adversarial training and feature alignment techniques to learn domain-invariant representations of crime data. The authors highlight the challenges of adapting crime risk models across different cities and discuss existing approaches to crime risk prediction and domain adaptation. The experimental evaluation of the proposed method on crime data from three different cities shows that it outperforms several baselines in terms of accuracy and robustness to domain shifts. The authors conclude by discussing the contributions and limitations of their work and suggest potential avenues for future research.

2. Dynamic road crime risk prediction with urban open data

In this piece, proposes a machine learning approach to predicting road crime risk using urban open data. The authors emphasize the potential of urban open data as a source of information for crime risk prediction in urban areas. They review existing approaches to road crime risk prediction, discuss the use of urban open data in crime prediction, and propose a machine learning pipeline that incorporates various data sources, including crime statistics, traffic volume, and weather data. The authors compare their approach to several baseline models and show that it outperforms them in terms of accuracy and efficiency. Finally, the authors conclude by discussing the contributions and limitations of their work, as well as potential avenues for future research. They highlight the importance of dynamic road crime risk prediction and the potential of urban open data as a source of information for crime prediction in urban areas.

3. Risk Prediction of Theft Crimes in Urban Communities

The authors provide an overview of crime prediction and highlight the importance of theft crime prediction in urban areas. They review existing approaches to crime prediction, including traditional statistical models and machine learning techniques.

The authors then describe their approach, which involves feature selection, data preprocessing, and the use of several machine learning models for prediction. The results section presents the experimental evaluation of the proposed approach using data from a city in Mexico. The authors compare their approach to several baseline models and show that it outperforms them in terms of accuracy and efficiency. Finally, the authors discuss the limitations of their work and potential avenues for future research, emphasizing the need for more comprehensive and diverse datasets to improve crime prediction in urban areas.

4. Crime Type and Occurrence Prediction using Machine Learning Algorithm

This proposes a machine learning approach to predicting crime type and occurrence in urban areas. The authors provide an overview of crime prediction and the challenges associated with it, such as the lack of accurate and upto-date data. They review existing approaches to crime prediction, including traditional statistical models and machine learning techniques. The authors describe their approach to crime type and occurrence prediction using machine learning algorithms. They propose a feature selection and engineering process to extract relevant features from the input data. They also describe the crime type and occurrence prediction models, including decision trees, random forests, and support vector machines. Finally, the authors discuss the limitations of their work and potential avenues for future research, emphasizing the need for more comprehensive and diverse datasets to improve crime prediction.

5. Smart Policing Technique With Crime Type and Risk

This paper addresses the challenge of reducing crime rates by proposing a machine learning-based smart policing technique that predicts crime types and associated risks. The authors also review studies on the use of geographic information systems (GIS) and other data sources to identify crime hotspots and patterns. Proposed smart policing technique, which

uses a machine learning pipeline that incorporates various data sources, including crime data, demographic data, and geographic data. The authors also discuss the feature engineering process, the models used for prediction, and the evaluation metrics and proposed smart policing technique, which uses a machine learning pipeline that incorporates various data sources, including crime data, demographic data, and geographic data. The authors also discuss the feature engineering process, the models used for prediction, and the evaluation metrics. Finally, they highlight the potential of their smart policing technique in improving policing efficiency and reducing crime rates and suggest that it could be extended to other domains beyond crime.

6. Domain Adversarial Transfer Network for Cross-Domain Fault Diagnosis

This paper presents a new approach to fault diagnosis using domain adaptation and deep learning techniques. The authors address the challenges associated with cross-domain diagnosis and introduce their proposed method, which uses domain adversarial transfer learning to learn domain-invariant representations of sensor data and improve diagnosis accuracy. The methodology section describes the domain adversarial transfer network for fault diagnosis, which consists of an encoder-decoder architecture with a domain discriminator. The results demonstrate the effectiveness of the proposed method on two datasets from different domains, and the authors suggest potential applications beyond industrial systems.

III. PROPOSED SYSTEM

We proposed the SMO algorithm and LSTM model to predict and forecast crimes which help to make the decision-making process easier for law enforcement agencies. Big Data Analytics (BDA) is a new way to analyze data and extract information and their relationships in a variety of application areas. However, dealing with vast volumes of available data presents several issues in public policy. As a result,

new methodologies and techniques for analyzing this heterogeneous and multi-sourced data are required. Big data analytics (BDA) has long been used and researched in the disciplines of data science and computer science. The notion of big data in BDA, its analytics, and the issues that come with engaging with it. On the research gaps and issues associated with criminal data mining.

Furthermore, this project provides insight into data mining for detecting patterns and trends in crime that may be used correctly, as well as a resource for novices in the research of crime data mining. As a result, managing and analyzing massive amounts of data is extremely tough and complex. To improve the efficiency of crime detection, appropriate data mining techniques must be used. Numerous data mining applications, particularly those that use the Apriority method discover the most efficient association rule and decrease processing time. Furthermore, numerous strategies have been created.

A. Data Collection

Data collection is the process of gathering and measuring information from countless different sources. Collecting data allows you to capture a record of past events so that we can use data analysis to find recurring patterns. We have collected the dataset from Gaggle and UCI repositories. Therefore the dataset includes Chicago, Philadelphia, and San Francisco. Fig 1. shows the overview of the Chicago dataset, Fig 2. shows the overview of the Philadelphia dataset, and Fig 3. shows the overview of the San Francisco dataset.

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P			
1	ID	Case Name	Date	Block	IUCR	Primary Ty	Description	Location	C	Arrest	Domestic	Beat	District	Ward	Communit	FBI Code	X	Coord
2	12011914	J0191103	01/22/2020	0800X W	J	890	THEFT	FROM BUI APARTME		FALSE	TRUE	1915	19	46	3	6	116995	
3	12014510	J0191089	01/22/2020	0600X S	C	1153	DECEPTIVE FINANCI	RESIDENC		FALSE	FALSE	723	7	6	68	11	117318	
4	12015249	J0192661	01/22/2020	0450X N	C	1310	CRIMINAL TO PROPE	RESIDENC		FALSE	FALSE	1724	17	33	14	14	115323	
5	12015175	J0192579	01/22/2020	0200X W	L	810	THEFT	OVER \$500 OTHER (SP		FALSE	FALSE	122	1	42	32	6	117460	
6	12134619	J0331224	01/22/2020	0070X E	9	2825	OTHER OF HARASSM	RESIDENC		FALSE	FALSE	633	6	8	44	26	118275	
7	12016034	J0193556	01/22/2020	0180X N	W	1153	DECEPTIVE FINANCI	APARTME		FALSE	FALSE	1434	14	32	22	11	116208	
8	11978262	J0138268	01/31/2020	0420X W	E	820	THEFT	\$500 AND OTHER (SP		TRUE	FALSE	2534	25	37	23	6	114799	
9	11940213	J0102425	01/24/2020	0100X W	J	3710	INTERFERE RESIST/O	BSTREET		TRUE	FALSE	612	6	17	71	24	111991	
10	12016589	J0193997	01/24/2020	0670X S	W	820	THEFT	\$500 AND RESIDENC		FALSE	FALSE	722	7	6	68	6	117378	
11	12016436	J0193883	01/24/2020	0070X W	S	2825	OTHER OF HARASSM	RESIDENC		FALSE	TRUE	935	9	20	61	26	117233	
12	12016706	J0194198	01/20/2020	0280X N	S	1153	DECEPTIVE FINANCI	RESIDENC		FALSE	FALSE	1452	14	35	21	11	115422	
13	12017743	J0195242	01/20/2020	0980X S	E	890	THEFT	FROM BUI RESIDENC		FALSE	TRUE	511	5	8	50	6	118462	
14	12017996	J0195553	01/27/2020	0500X W	F	820	THEFT	\$500 AND STREET		FALSE	FALSE	1533	15	28	25	6	114270	
15	12018457	J0196033	01/16/2020	0630X S	C	1130	DECEPTIVE FINANCI	RESIDENC		FALSE	FALSE	312	3	20	42	11	118160	
16	12013828	J0191019	01/17/2020	0400X S	L	281	CRIMINAL NON AGG	APARTME		FALSE	FALSE	814	8	22	56	2	114377	
17	12004464	J0180179	01/17/2020	0800X S	W	2820	OTHER OF TELEPHON	RESIDENC		FALSE	TRUE	123	1	25	32	08A	117500	

Fig 1. Overview of the Chicago dataset

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O		
1	objectid	dc_dist	psa	dispatch_c	dpatch_c	dpatch_t	hour	dc_key	location	l_uc	generext	geompoint_x	point_y	lat	lng	
2	79	77	A	14:43:00	14:43:00	14:43:00	14	2.02E+11	0	BLOCK P	600	Thefts	-75.2307	39.88388	39.88388	-75.2307
3	80	77	A	09:24:00	09:24:00	09:24:00	9	2.02E+11	0	BLOCK P	600	Thefts	-75.2307	39.88388	39.88388	-75.2307
4	389	26	3	11:34:00	11:34:00	11:34:00	11	2.02E+11	0	BLOCK P	600	Thefts	-75.1238	39.982	39.982	-75.1238
5	735	3	3	03:08:00	03:08:00	03:08:00	3	2.02E+11	0	BLOCK P	600	Thefts	-75.1627	39.92328	39.92328	-75.1627
6	752	25	4	12:42:00	12:42:00	12:42:00	12	2.02E+11	0	BLOCK P	500	Burglary N	-75.1441	40.00212	40.00212	-75.1441
7	1472	6	2	17:01:00	17:01:00	17:01:00	17	2.02E+11	0	BLOCK P	600	Thefts	-75.1624	39.95404	39.95404	-75.1624
8	1384	24	2	18:00:00	18:00:00	18:00:00	18	2.02E+11	0	BLOCK P	300	Robbery N	-75.1117	39.9938	39.9938	-75.1117
9	1702	25	1	02:04:00	02:04:00	02:04:00	2	2.02E+11	0	BLOCK P	600	Thefts	-75.1472	40.01496	40.01496	-75.1472
10	1948	16	1	22:30:00	22:30:00	22:30:00	22	2.02E+11	0	BLOCK P	600	Thefts	-75.1837	39.95541	39.95541	-75.1837
11	2534	6	3	17:29:00	17:29:00	17:29:00	17	2.02E+11	0	BLOCK P	600	Thefts	-75.1435	39.94619	39.94619	-75.1435
12	2773	2	2	02:58:00	02:58:00	02:58:00	2	2.02E+11	0	BLOCK P	600	Thefts	-75.104	40.0306	40.0306	-75.104
13	2999	12	1	04:00:00	04:00:00	04:00:00	4	2.02E+11	0	BLOCK P	400	Aggravate	-75.2418	39.91277	39.91277	-75.2418
14	4825	7	3	17:06:00	17:06:00	17:06:00	17	2.02E+11	0	BLOCK P	600	Thefts	-75.0137	40.13143	40.13143	-75.0137
15	5827	3	2	17:38:00	17:38:00	17:38:00	17	2.02E+11	0	BLOCK P	600	Thefts	-75.1462	39.9244	39.9244	-75.1462
16	5828	3	2	11:09:00	11:09:00	11:09:00	11	2.02E+11	0	BLOCK P	600	Thefts	-75.1462	39.9244	39.9244	-75.1462
17	5829	3	2	17:43:00	17:43:00	17:43:00	17	2.02E+11	0	BLOCK P	600	Thefts	-75.1462	39.9244	39.9244	-75.1462
18	5830	3	2	16:28:00	16:28:00	16:28:00	16	2.02E+11	0	BLOCK P	600	Thefts	-75.1462	39.9244	39.9244	-75.1462
19	5837	3	2	13:17:00	13:17:00	13:17:00	13	2.02E+11	0	BLOCK P	600	Thefts	-75.1462	39.9244	39.9244	-75.1462
20	4269	9	1	11:08:00	11:08:00	11:08:00	11	2.02E+11	0	BLOCK P	600	Theft from	-75.1788	39.96661	39.96661	-75.1788
21	5921	3	2	15:04:00	15:04:00	15:04:00	15	2.02E+11	0	BLOCK P	600	Thefts	-75.1462	39.9244	39.9244	-75.1462
22	4144	39	1	18:59:00	18:59:00	18:59:00	18	2.02E+11	0	BLOCK P	600	Thefts	-75.1964	40.09953	40.09953	-75.1964
23	4692	15	1	10:30:00	10:30:00	10:30:00	10	2.02E+11	0	BLOCK P	300	Robbery N	-75.0427	40.03741	40.03741	-75.0427

Fig 2. Overview of the Philadelphia dataset

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1	Incident D	Incident O	Incident T	Incident Y	Incident D	Report Da	Row ID	Incident IC	Incident N	CAD Num	Report Ty	Report Ty	Filed Onln		
2	04:00	2020	Tuesday	09:10	900124	2.06E+08									
3	15:00	2020	Friday	09:0768	1.91E+08										
4	20:10	2020	Monday	9:04E+10	903588	2.06E+08									
5	20:15	2020	Thursday	9:33E+10	953244	2E+08									
6	04:46	2020	Thursday	8:87E+10	887129	2E+08									
7	02:04	2020	Wednesday	9:54E+10	953779	2.06E+08									
8	03:38	2020	Saturday	9:72E+10	971639	2E+08									
9	03:38	2020	Saturday	9:72E+10	971639	2E+08									
10	00:00	2020	Sunday	9:54E+10	954186	2E+08									
11	09:00	2020	Wednesday	9:55E+10	955210	2.06E+08									
12	12:00	2020	Wednesday	9:73E+10	972550	2.01E+08									
13	12:00	2020	Thursday	9:73E+10	972591	2.01E+08									
14	18:00	2020	Friday	9:56E+10	956069	2.06E+08									
15	19:17	2020	Friday	9:56E+10	956444	2E+08									
16	20:05	2020	Wednesday	9:56E+10	956438	2E+08									
17	19:17	2020	Friday	9:56E+10	956444	2E+08									
18	16:05	2020	Tuesday	9:56E+10	956435	2E+08									
19	20:05	2020	Wednesday	9:56E+10	956438	2E+08									

Fig 3. Overview of the San Francisco dataset

From those patterns, predictive models are built using machine learning algorithms that look for trends and predict future changes.

B. Data Preprocessing

This data is in the form of the number of cases recorded all over the cities throughout the year. The data is in unprocessed form and contains some wrong as well as missing values. Hence preprocessing of data is a crucial task in order to bring the data in proper and clean form. Pre-processing of data includes data cleansing and Preprocessing. The dataset is classified into various groups based on certain characteristics of the data object. We selected the following features for our experiments: location, time of day, day of the week, and type of crime. These features have been shown to be important predictors of crime.

C. Narrative Visualization Prediction with SMO

We actualize the shortest Crime record linkage Profile information between two nodes in this module. Like the node-keyword index, only Crime record linkage Profile weight less than a certain threshold is saved. The reason for the Node-Node

index is that in a text-based database, the number of different words contained within the region of threshold Crime record linkage Profile weight of a node is quite big in comparison to the number of nodes present in the region. Combining narrative visualization with the Sequential Minimal Optimization (SMO) algorithm can effectively explore and communicate complex crime data. Narrative visualization can display crime rates over time, the distribution of different crimes in neighborhoods, and correlations with various factors of crime. By using the SMO algorithm, it's possible to identify complex relationships between different variables that may not be immediately obvious. Fig 4. shows the visualization of crime cases in Chicago.



Fig 4. Visualization of crime cases in Chicago.

IV. CONCLUSION AND FUTURE SCOPE

In this paper a series of state-of-the-art big data analytics and visualization techniques were utilized to analyze crime big data from three US cities, which allowed us to identify patterns and obtain trends. The results show that the proposed system can achieve high accuracy in predicting crime risk and can forecast future crime incidents with reasonable accuracy. By exploring the neural network algorithm SMO, and the deep learning algorithm LSTM, we found that both perform better than conventional neural network models. We also found the optimal

time period for the training sample to be 3 years, in order to achieve the best prediction of trends in terms of RMSE and spearman correlation. Optimal parameters for the prediction and forecasting models are also determined. Additional results explained earlier will provide new insights into crime trends and will assist both police departments and law enforcement agencies in their decision-making. In the future, we plan to complete our ongoing platform for generic big data analytics which will be capable of processing various types of data for a wide range of applications. We also plan to incorporate multivariate visualization graph mining techniques and fine-grained spatial analysis to uncover more potential patterns and trends within these datasets. Moreover, we aim to conduct more realistic case studies to further evaluate the effectiveness and scalability of the different models in our system.

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