Cross City Deep Transfer Learning Model for Crime Prediction

Nazia Afreen (1605015)
Anisha Islam (1605038)

Supervised By:
Dr.Tanzima Hashem
Professor
Department of CSE, BUET

Motivation

- Efficient allocation of human resources in high-risk areas

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- Safety of people

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- Crime Prediction in regions where no crime data is available
  - Assumption of crime data availability in existing crime prediction models
  - Crime data not properly recorded in developing countries
  - Inability to predict crime in those regions by the current architectures

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We introduce Transfer Learning in crime domain

Existing Crime Prediction Models

- Use cross-domain data like geographical data, demographic data, points of interest data, check-in data [1,2,3]

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[2] Rayhan et al., 2020
[3] Rumi et al., EPJ Data Science., 2018

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- Use cross-domain data like geographical data, demographic data, points of interest data, check-in data [1,2,3]
- Capture temporal dependency between different crimes, inter-relation between different categories of crime, correlation between crime and ubiquitous data [1]

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- Use cross-domain data like geographical data, demographic data, points of interest data, check-in data [1,2,3]
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- Incorporate dynamic intra-region temporal dependency, inter-region spatial correlation [4,5]

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[1] Huang et al., CIKM., 2018
[2] Rayhan et al., 2020
[3] Rumi et al., EPJ Data Science., 2018
[4] Huang et al., The World Wide Web Conference, 2019
[5] Sun et al., ECML PKDD, 2020

Existing Crime Prediction Models

Limitation

Use of historical crime data [1]–[5]

Related Works

	Objective	Region Similarity	External Features Used	Cross-City	Target Domain Data Used
[6]	Predict crowd flow using bike flow data	Pearson Coefficient	Check-ins	Yes	Yes
[7]	Detect ride-sharing cars using taxi and bus data	-	-	-	Yes
[8]	Chain store site recommendation	Autoencoder	POI, Check-ins	Yes	-
[9]	Thermal comfort prediction	-	Indoor and outdoor environmental features, Age, Gender	Yes	Yes
[10]	Trajectory based routing preference learning	Jaccard Similarity	Road network	-	Yes
[11]	Transfer urban human mobility via POI embeddings	-	-	Yes	Yes
[12]	Taxi volume prediction, bike volume prediction, water quality prediction	-	-	Yes	Yes

Thesis Goal

- Develop Transfer Learning based deep learning model in the crime domain to predict crimes of various categories at a particular time instance in a target city region

Problem Formulation

- Input
  - Source City

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    - Region Graph
    - Point of Interest
    - Road Network
    - Taxi Trip (Inflow and Outflow)
    - Type wise Crime Event
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  - Target City
    - Region Graph
    - Point of Interest
      - Arts, Education, Shops, Professional, Travel etc
    - Road Network
    - Taxi Trip (Inflow and Outflow)

Problem Formulation

- Output
  - Prediction of the number of crime occurrences of different categories at a particular time in a specific region of a target city

Challenges

- Find out the attributes that affect the crime occurrences in a region

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- Find out the attributes that affect the crime occurrences in a region
- Identify the similar regions that have similar crime patterns based on external attributes

Solution Overview

- Address the issues, our proposed model consists of four units

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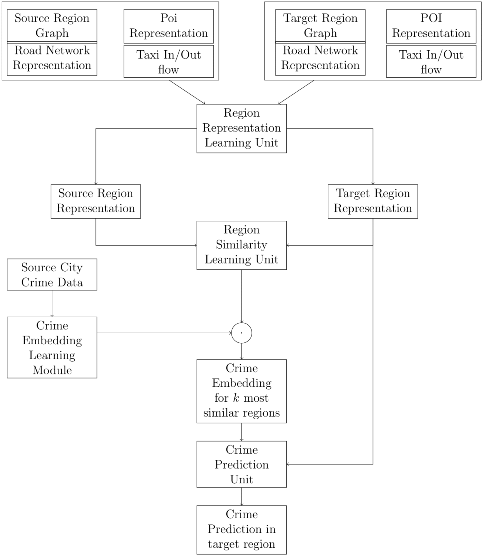
Solution Overview: Pipeline



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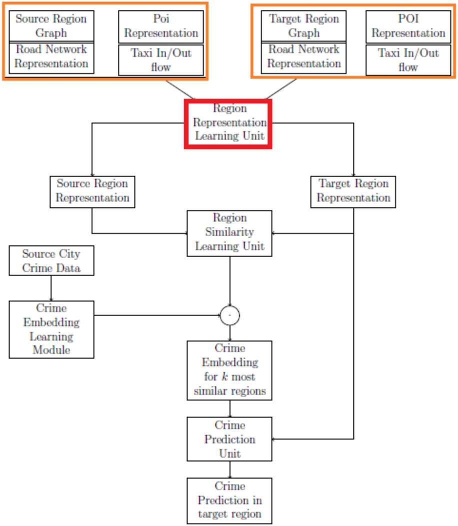


Region Representation Learning Unit

- Crime occurrences demonstrate
  - Spatial dependency
  - Temporal dependency
  - External feature correlation
    - Point of Interest
    - Taxi Inflow and Outflow
    - Road Junction
- Dynamically incorporates all three interrelations to learn region embedding

Spatial Dependency

- Crime occurrences exhibit spatial dependency

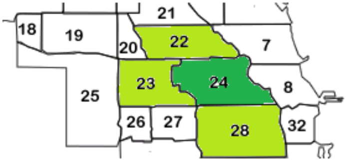


Figure: Chicago Community Areas

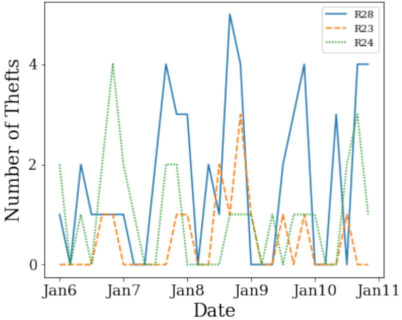


Figure: Spatial Dependency

Temporal Dependency

- Crime occurrences show temporal correlation

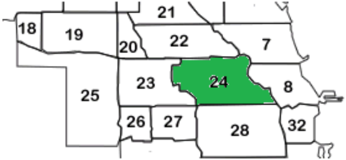


Figure: Chicago Community Area 24

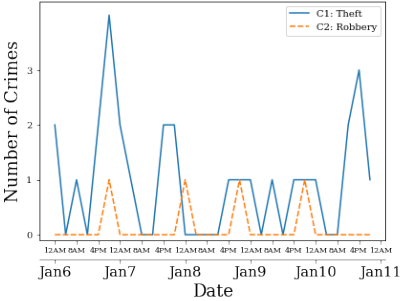


Figure: Temporal Dependency

External Feature Correlation

- Crime occurrences exhibit correlation with taxi outflow data

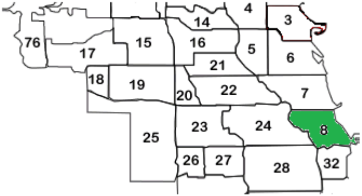


Figure: Chicago Community Area 8

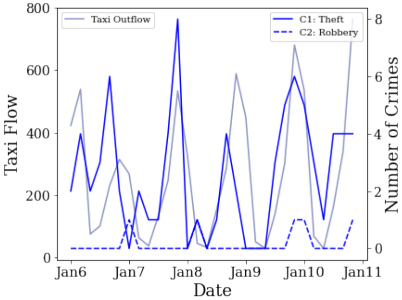
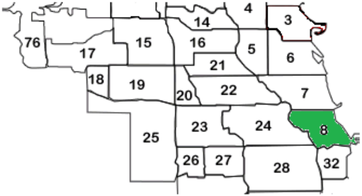


Figure: Influence of Taxi Outflow data

External Feature Correlation

- Crime occurrences exhibit correlation with taxi inflow data



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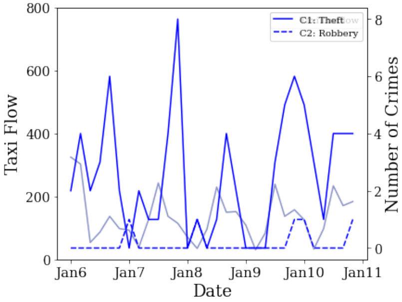


Figure: Influence of Taxi Inflow data

External Feature Correlation

- Crime occurrences has dependency with POI

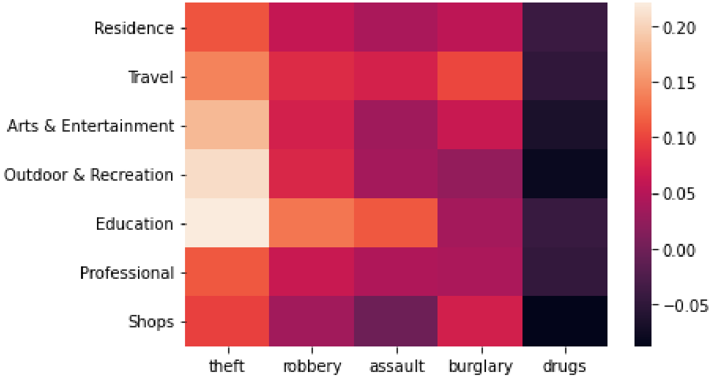
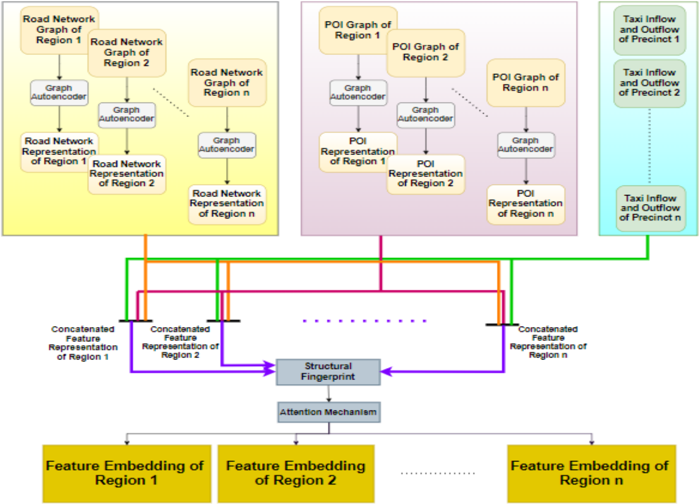


Figure: Correlation between density of POI and crime occurrences of Chicago City

Region Representation Learning Unit



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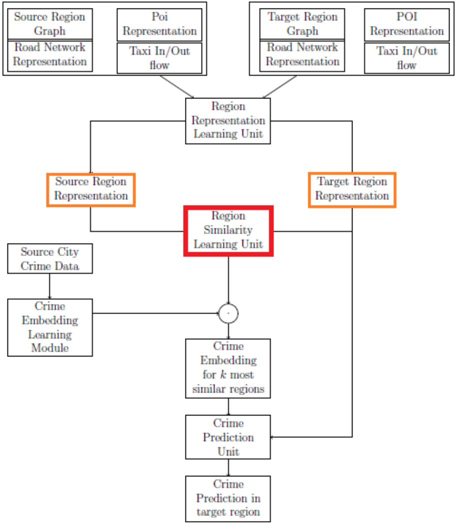

Region Similarity Learning Unit

- Region matching as the basis for transfer learning
  - Similar regions have similar crime patterns
- For a specific target region, topmost k similar source regions are learned

Attention Based Region Similarity

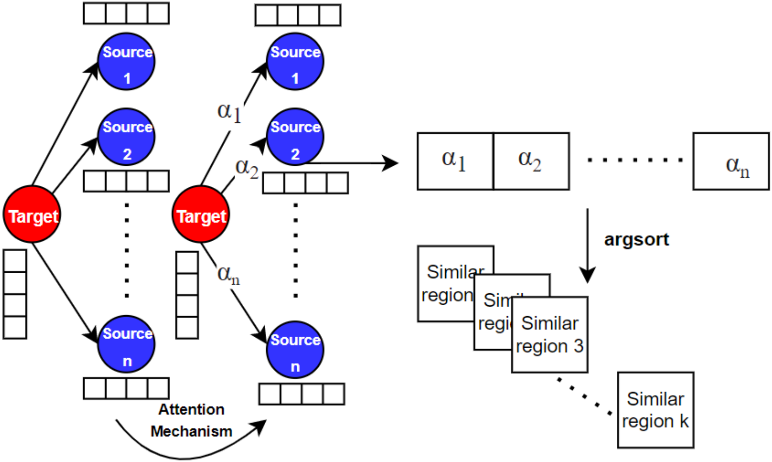

Figure: Attention based similarity

Pearson Correlation Based Region Similarity

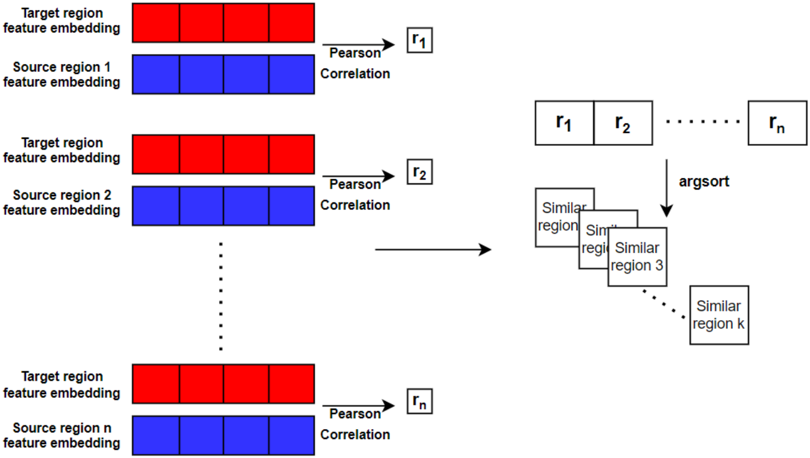

Figure: Pearson correlation based similarity

Regions with Similar Taxi Outflow

- For crime categories Theft and Robbery, for a target precinct 19, the source communities with similar taxi outflow

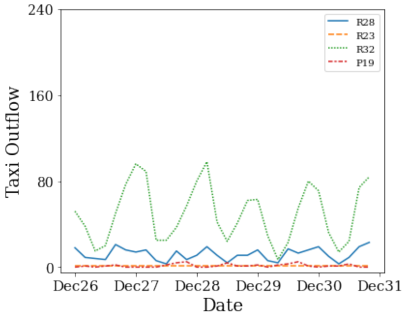

Figure: Similar Taxi Outflow for Theft for Precinct 19

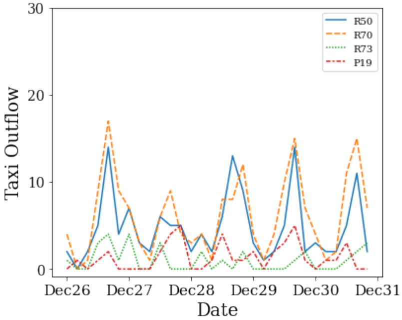

Figure: Similar Taxi Outflow for Robbery for Precinct 19

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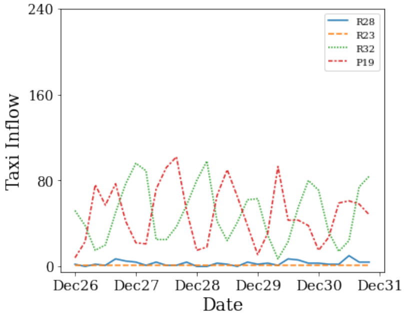

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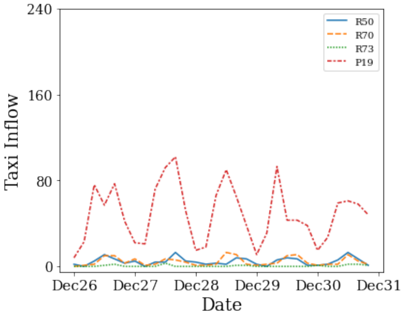

Figure: Similar Taxi Inflow for Robbery for Precinct 19

Regions with Similar POI

- For crime categories Theft and Robbery, for a target precinct 19, the source communities with similar POI category

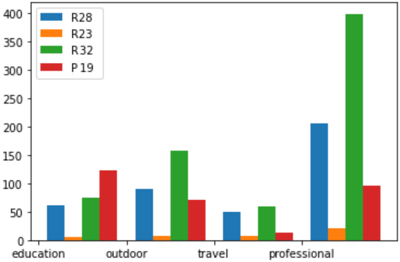

Figure: Similar POI for Theft for Precinct 19

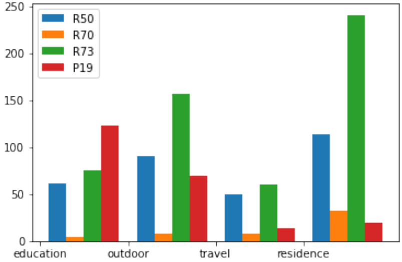

Figure: Similar POI for Robbery for Precinct 19

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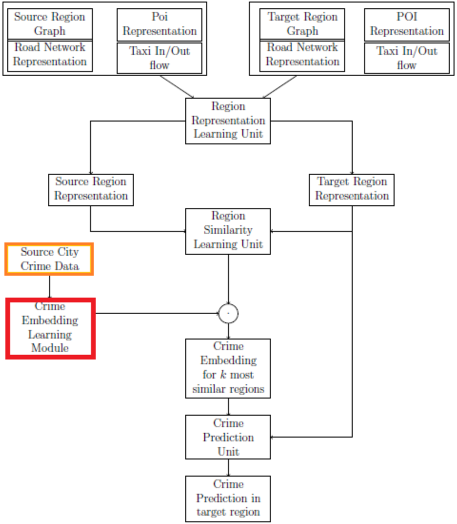


Crime Embedding Learning Unit

- Crime embedding of each source region is learned in this module

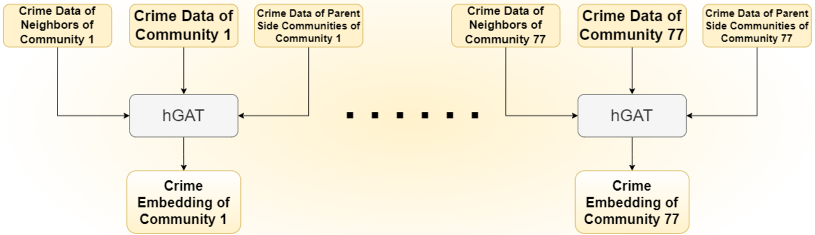
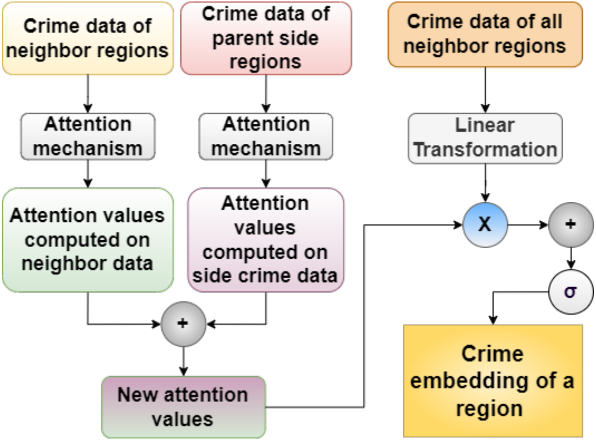


Figure: Crime embedding of source region

hGAT

- The architecture used to learn crime embedding



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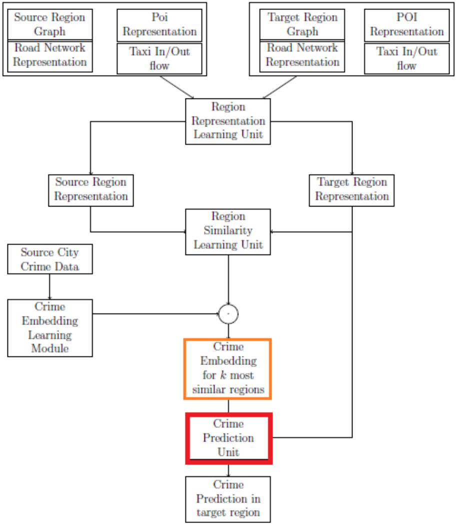

Crime Prediction Unit

- Predicts crime of different categories in a particular time step in a target region

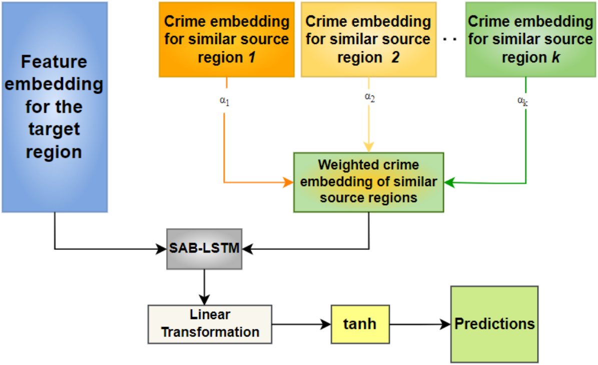

Figure: Crime prediction unit

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Datasets

Source Region		
Chicago Source City	Chicago Crime Data(2019)	167,638 crime records of five categories
	Chicago Taxi Trip Data(2019)	29,110,097 Taxi trip data of Green Taxi and Yellow Taxi
	Chicago POI Data(2019)	18,943 POIs of 7 categories
	Chicago Road Network Data	-

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	Chicago POI Data(2019)	18,943 POIs of 7 categories
	Chicago Road Network Data	-
Target Region		
New York Target City	NYC Taxi Trip Data(2019)	34,738,922 Taxi trip data of Green Taxi and Yellow Taxi
	NYC POI Data(2019)	20,500 POIs of 7 categories
	NYC Road Network Data	-

Models

With Transfer Learning			
Model Version	**Train(X,Y)**	**Test**	**Similarity Mechanism**
M1	(NYC feature embedding + Chicago crime embedding, Chicago crime data)	NYC crime data	Attention Based Similarity
M2	(NYC feature embedding + Chicago crime embedding, Chicago crime data)	NYC crime data	Pearson Correlation Based Similarity

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Without Transfer Learning			
Model Version	**Train(X,Y)**	**Test**	**Similarity Mechanism**
M3	(NYC feature embedding, NYC crime data)	NYC crime data	-
M4	(NYC feature embedding + NYC crime embedding, NYC crime data)	NYC crime data	-

Performance Comparison

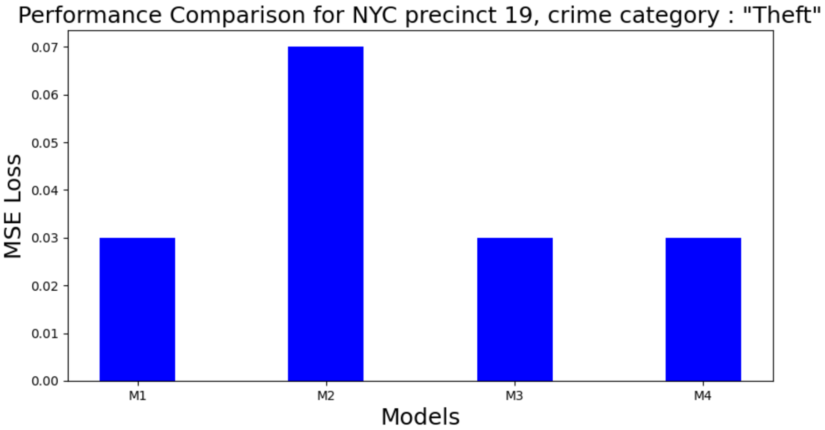

Figure: NYC Precinct 19, Crime Category: Theft

Performance Comparison

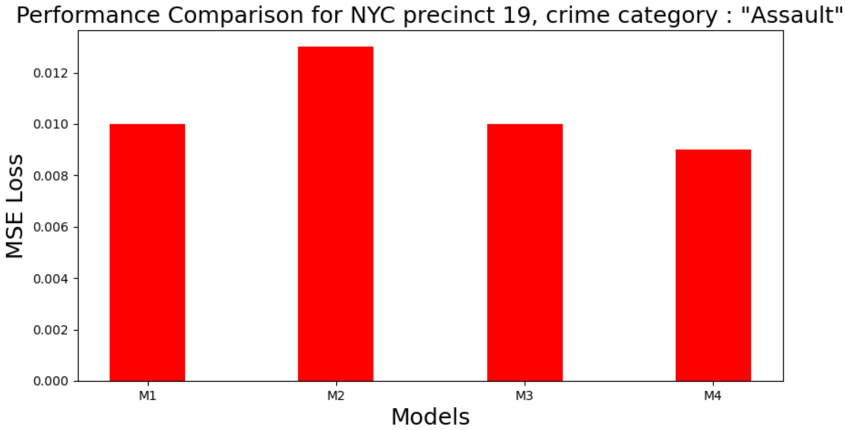

Figure: NYC Precinct 19, Crime Category: Assault

Performance Comparison

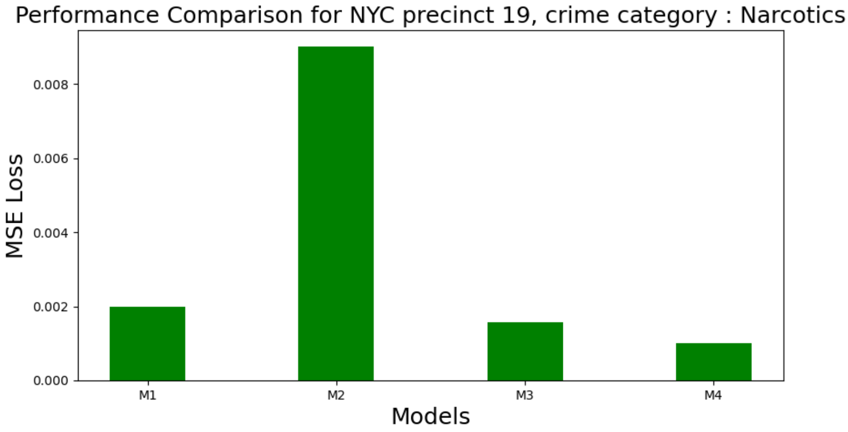

Figure: NYC Precinct 19, Crime Category: Narcotics

Comparison Between Similarity Measurement Techniques

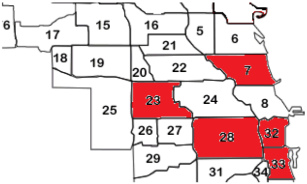

Figure: Similar Chicago regions for NYC Precinct: 19, and crime category : Theft based on Attention values

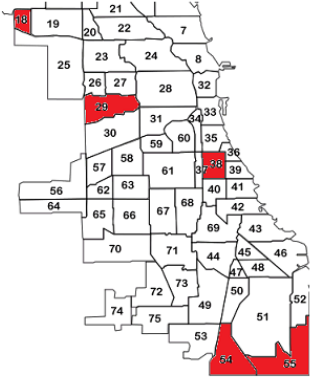

Figure: Similar Chicago regions for NYC Precinct: 19, and crime category : Theft based on Pearson Correlation values

Comparison Between Number Of Similar Regions

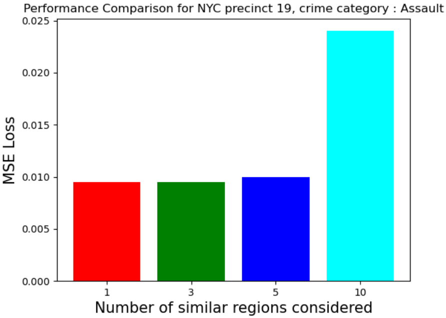

Figure: Optimal number of similar regions for Precinct 19

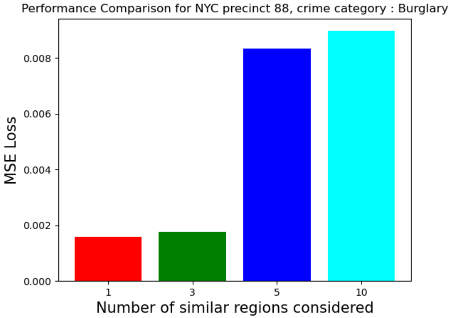

Figure: Optimal number of similar regions for Precinct 88

Our Contribution

- A novel transfer learning based deep learning model for crime prediction
- A novel dynamic region similarity approach as a basis of transfer learning
- Evaluate framework on real world dataset

Future Work

- Crime prediction using multiple source cities
- Adaptation of the model for cross-categorical crime prediction

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THANK YOU

Any Questions?