Predicting Trip Destinations with BIXI Data

Concordia University SOEN 499

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Introduction

Presentation of the problem

- BIXI trip history dataset (2014 to 2019)
- Predict the destination of a trip based on:
 - o Starting location
 - Time
 - Extra: weather data
- Classification vs. Regression

- > Dataset
- > Technologies
- Data Preprocessing
- > Algorithms

Two types of CSVs per year:

- Monthly trip histories
 - start_date
 - start_station_code
 - o end_date
 - end_station_code
 - duration_sec
 - o is_member
- Bike Stations
 - o code
 - name
 - latitude
 - longitude

- > Dataset
- > Technologies
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Apache Spark

- Using the Python library pyspark
- Data preprocessing
- Machine learning with MLlib

Folium

- Python data visualization library for creating Leaflet.js maps
- Helpful for viewing bike stations when evaluating predictions.

- > Dataset
- > Technologies
- > Data Preprocessing
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- Replace start/end station codes with the coordinates of their corresponding station.
- Skip samples with missing features.
- Break down start_date into hour, day of the week, and month.
- Encode the hour to account for its cyclical nature.

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Dealing with Imbalanced Data

Classifying into clusters:

 Use random undersampling to balance the number of trips ending in each cluster.

Unsampled data

End Cluster	Count
1	947,379
2	25,010,384
3	131,229
4	15,998
5	3,178,611
6	5,532,257
7	12,283,466
8	8,444,028
9	13,358
10	1,173,774

Resampled with 1:2 Ratio

End Cluster	Count
1	26,556
2	26,630
3	26,467
4	15,998
5	26,878
6	26,739
7	26,711
8	26,626
9	13,358
10	26,882

- > Dataset
- > Technologies
- > Data Preprocessing
- > Algorithms

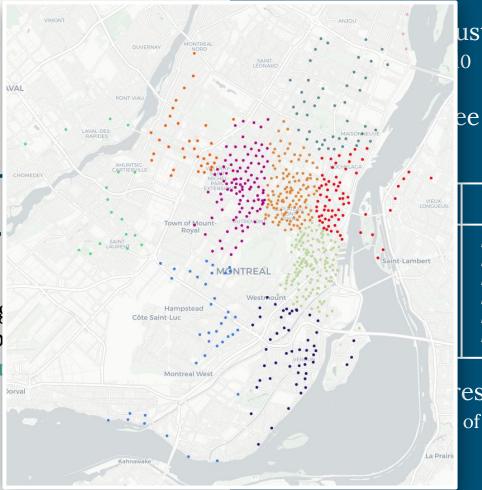
- K-Means Clustering
 - \circ With K = 10
- Decision Tree
 - Features:

Classification	Regression
□ start_name/ start_cluster □ month □ day_of_week □ hour_sin □ hour_cos	□ start_longitude □ start_latitude □ month □ day_of_week □ hour_sin □ hour_cos

- Random Forest
 - Ensemble of 20 trees

Materia Meth

- Dataset
- Technolog
- Data Prep
- Algorithn



ustering

Regression

- start_longitude start_latitude
- month
- day_of_week
- hour_sin
- hour_cos

est of 20 trees

Results

- > Classification
- > Regression

Ran 4 versions of the classifiers to compare performance:

- . Using individual start station to predict end station
- 2. Using start cluster to predict an end cluster
- 3. Using start cluster and temperature to predict end cluster
- 4. Using resampled clusters to predict end cluster

Classification Metrics

Version 1	Decision Tree	Random Forest
Accuracy	1.88%	2.19%
Precision	0.82%	1.43%
Recall	1.89%	2.20%
F1-Score	0.53%	0.83%

Version 3	Decision Tree	Random Forest
Accuracy	52.87%	49.83%
Precision	52.64%	45.05%
Recall	52.92%	49.88%
F1-Score	52.50%	45.66%

Version 2	Decision Tree	Random Forest
Accuracy	52.90%	51.25%
Precision	52.65%	50.52%
Recall	52.87%	51.20%
F1-Score	52.48%	48.22%

Version 4	Decision Tree	Random Forest
Accuracy	52.77%	51.54%
Precision	61.72%	61.86%
Recall	52.66%	51.08%
F1-Score	55.30%	53.09%

Results

- > Classification
- > Regression

Ran 2 versions of the regressors to compare performance:

- Using provided features from data to predict latitude and longitude
- 2. Using temperature to predict latitude and longitude

Regression Metrics

Version 1	Decision Tree	Random Forest
Lat. RMSE	0.01496307668	0.01597791819
Long. RMSE	0.01744732295	0.01804911382

Version 2	Decision Tree	Random Forest
Lat. RMSE	0.0149691975	0.01576569645
Long. RMSE	0.01743998037	0.01791527498

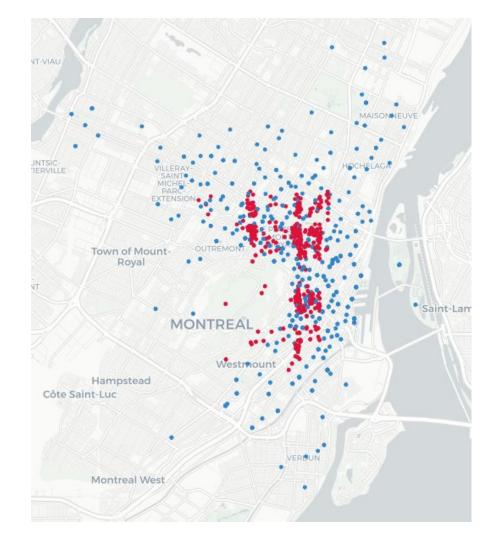
Regression Metrics

Decision Tree V2 Visual Result

- actual location
- predicted location



- actual location
- predicted location



Conclusions

- Predicting end stations is a hard problem
- Used clustering to improve classification
- Used separate regressors for lat/long
- Accuracy/RMSE is better with Decision Tree

Thank You!

