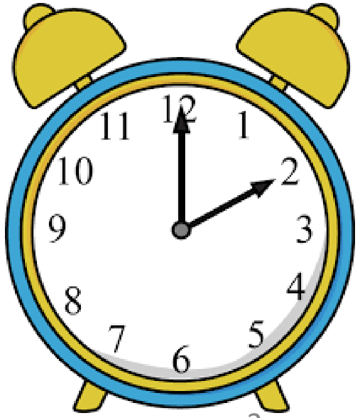
Next Location Prediction Challenge using

mobility traces of taxi cabs in San Francisco

Why the next location problem for taxi cabs is important

- Optimize efficiency of movement that can reduce traffic jams
- Reduce taxi idle times (time spent looking around for passengers)
- Reduce customer wait time



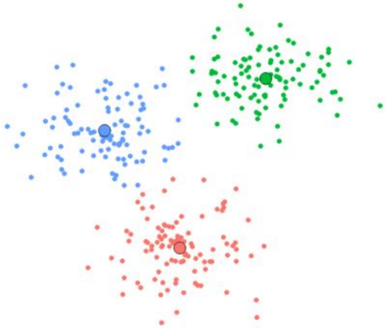
Outline of approach

Data cleaning

- Converting the data into a tidy format
- Each observation is a ride
- Based on consecutive pattern recognition

Exploratory Data Analysis

- Summary statistics
- Distribution of rides, cabs
- Feature associations
- Outlier identification

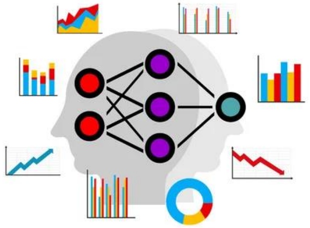


Region Detection

- Kmeans clustering
- Elbow method
- 11 clusters
- Weekdays, hour of the day, previous week's demand, week, minute of the day

Convert to ML problem

- Binary classification problem
- Predict pickup for each region individually
- Class up sampling for class imbalance problems
- One hot encoding of weekday variables



Model Training and Evaluation

- Random guess of Bernoulli trials (baseline model)
- Logistic regression
- XGBoost
- LSTM
- ROC, AUC model evaluation

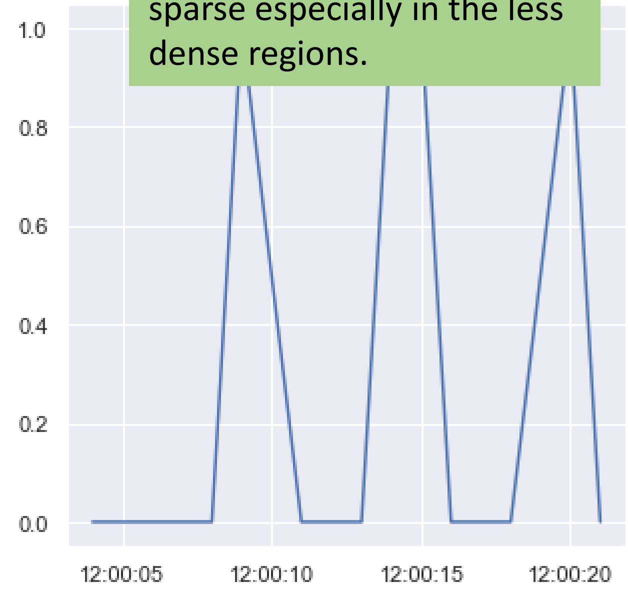
Feature engineering

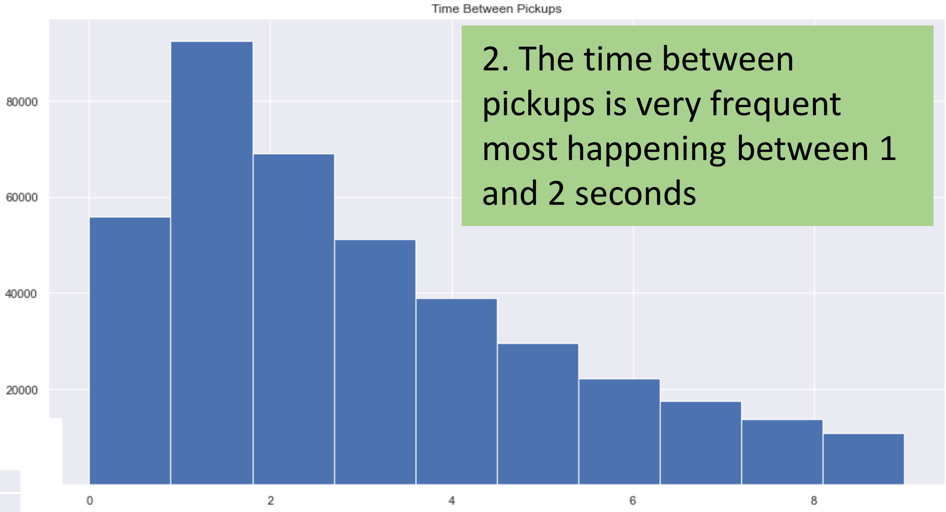
What do we know about the data?

pickup_time	0	1	2	3	4	5	6	7	8	9	10
2008-05-17 12:00:04	0	0	0	0	0	1	1	0	0	0	0
2008-05-17 12:00:05	0	0	0	0	0	0	0	0	0	0	1
2008-05-17 12:00:07	1	0	0	0	0	1	0	1	0	3	0
2008-05-17 12:00:08	0	0	0	0	0	1	0	0	0	1	0
2008-05-17 12:00:09	0	0	1	1	0	0	0	0	0	1	0

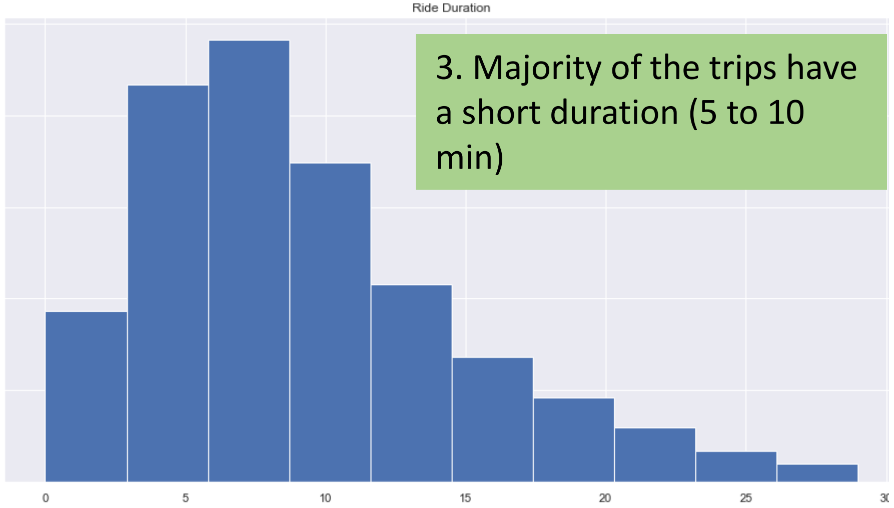
(column header: cluster)

4. At the region level the time between rides is more sparse especially in the less dense regions.

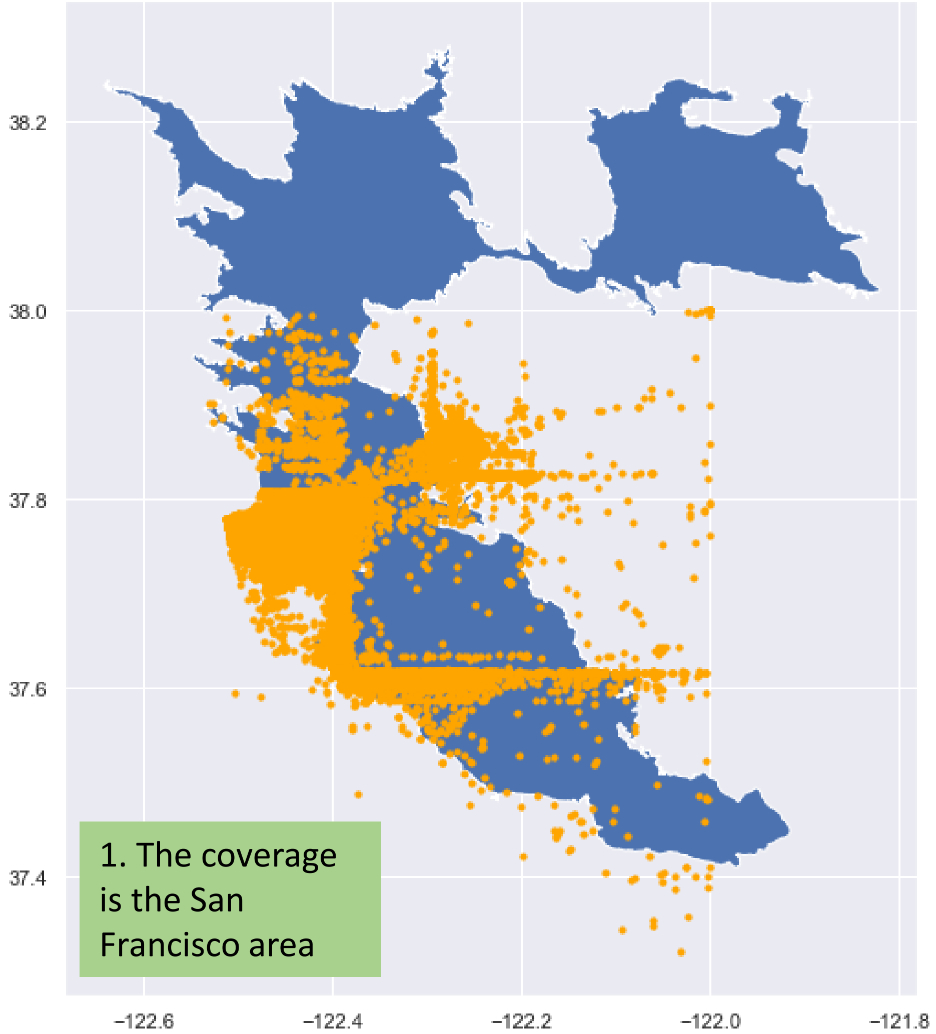




2. The time between pickups is very frequent most happening between 1 and 2 seconds

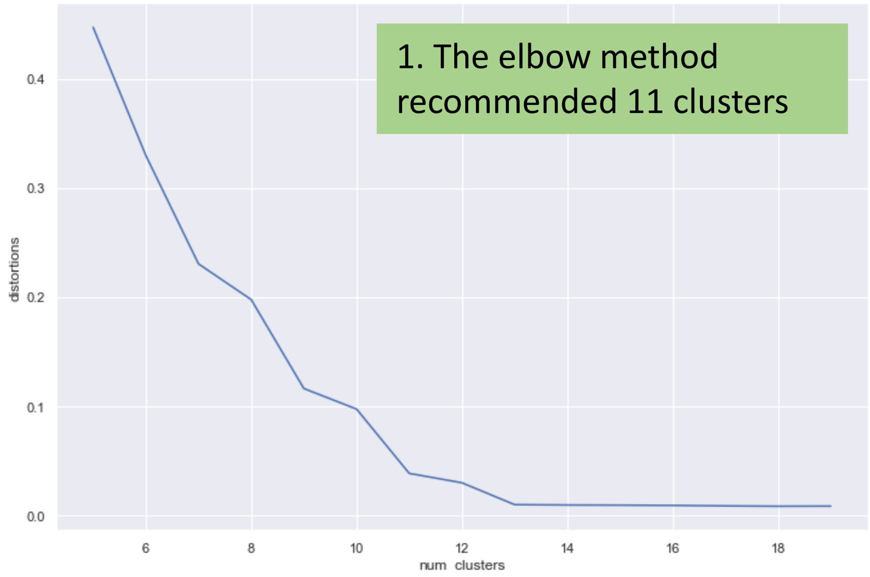


3. Majority of the trips have a short duration (5 to 10 min)

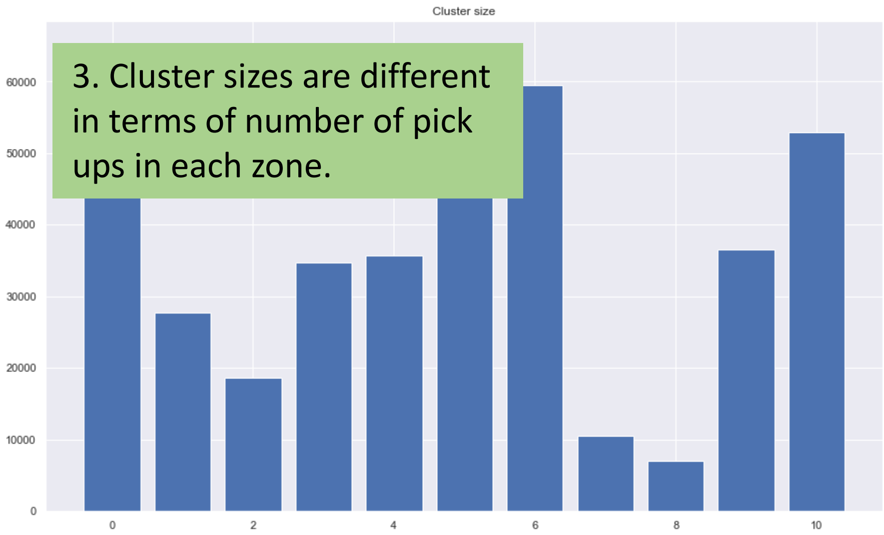


1. The coverage is the San Francisco area

The Clusters



1. The elbow method recommended 11 clusters



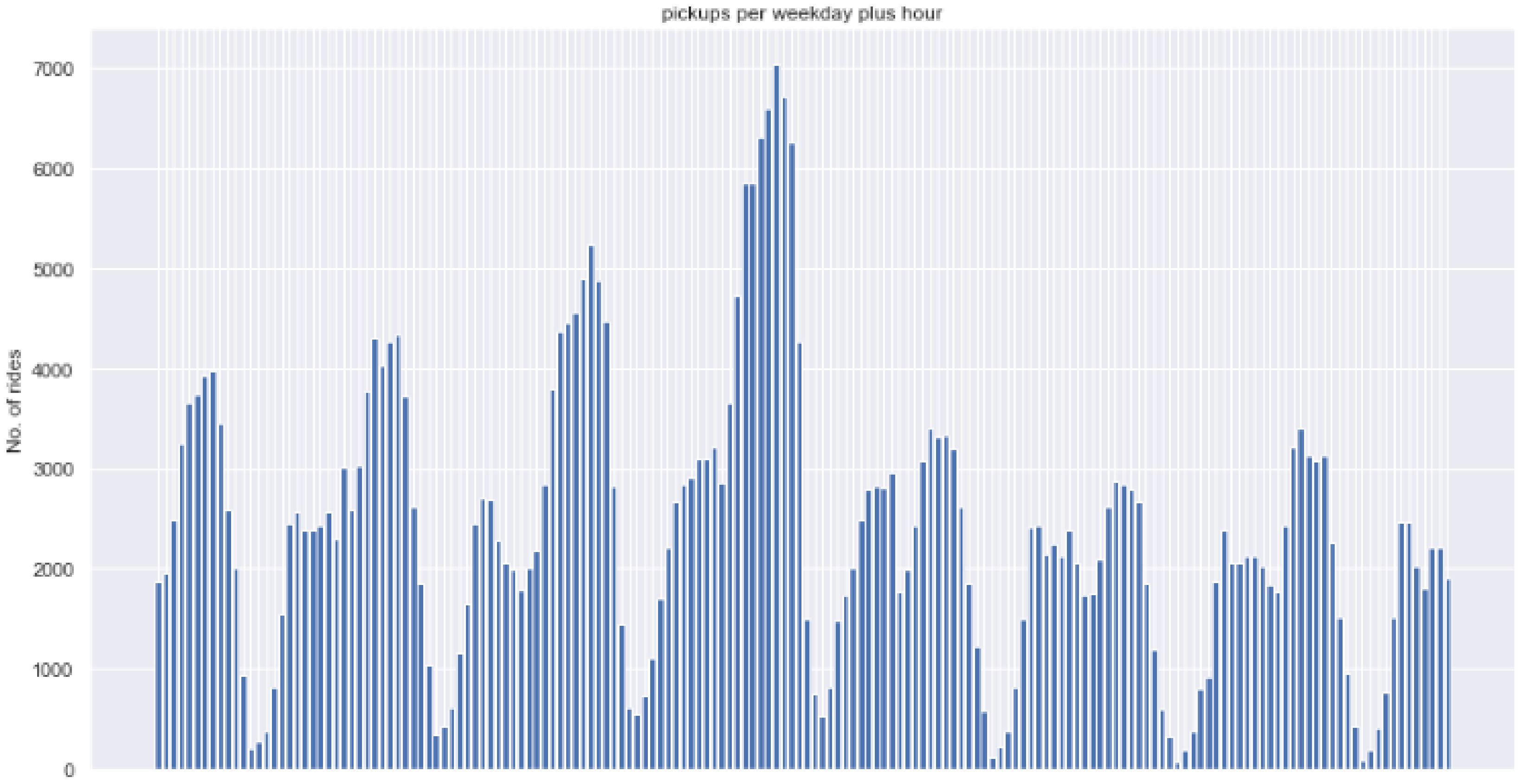
3. Cluster sizes are different in terms of number of pick ups in each zone.

2. The 11 distinct clusters are the regions/zones

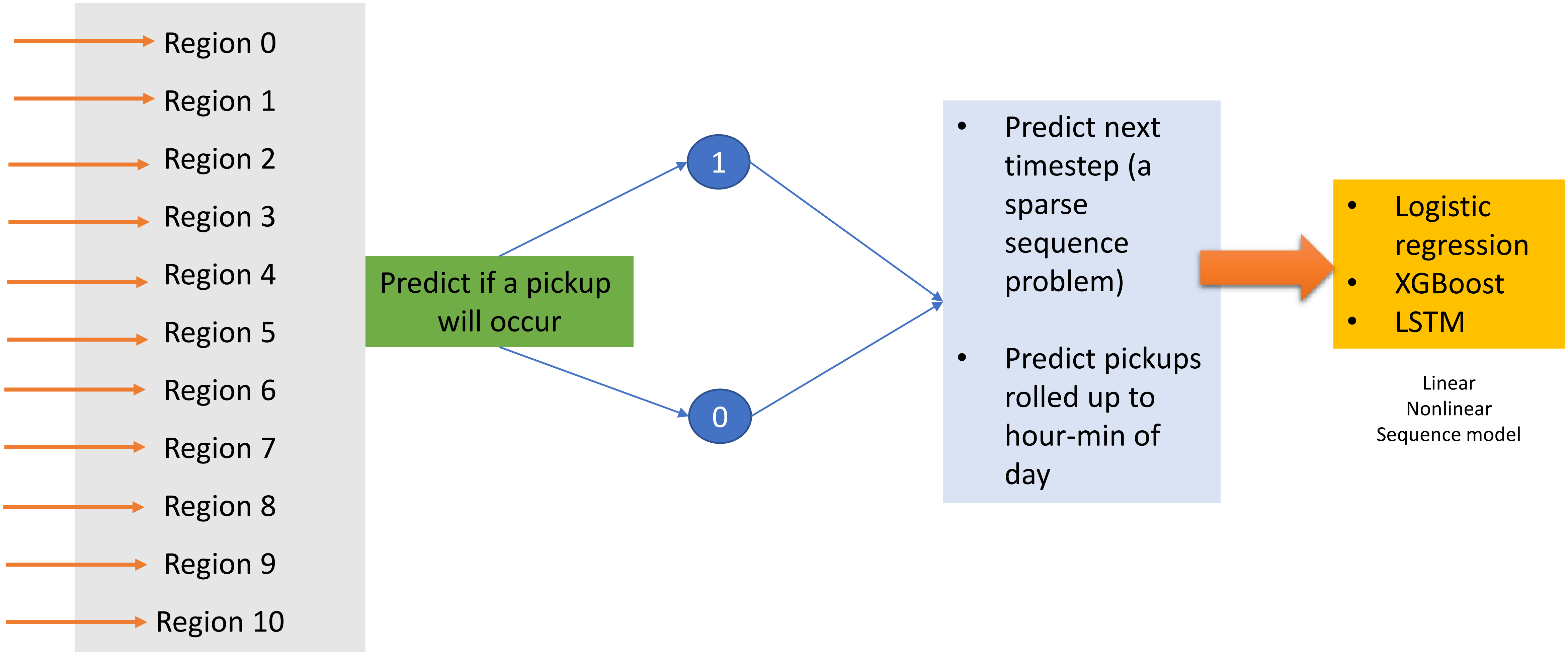
Feature Selection

The EDA revealed that there is much variability in:

- Count of rides each hour (e.g. Not many rides at midnight)
- Count of daily pickups day of the week (e.g. Saturday was most busy)
- Variability within zones
- Weekly dependencies
- No. of pickups in the previous timestep (for the LSTM model)

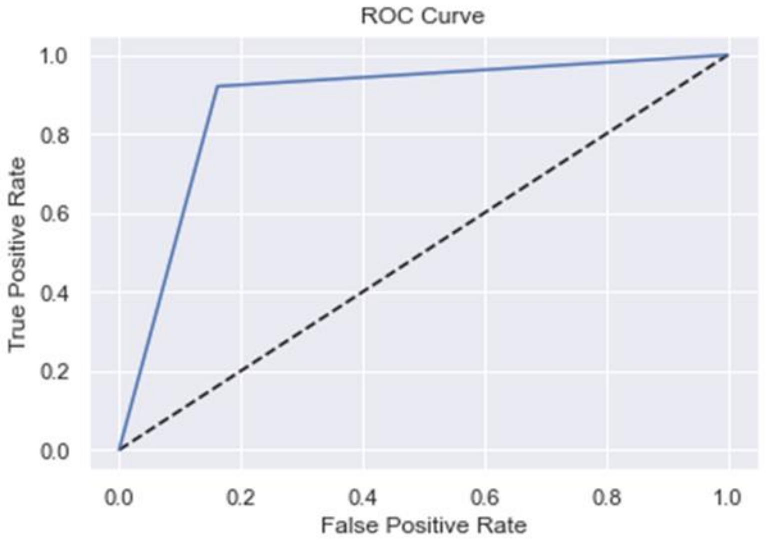


Machine Learning Model Formulation

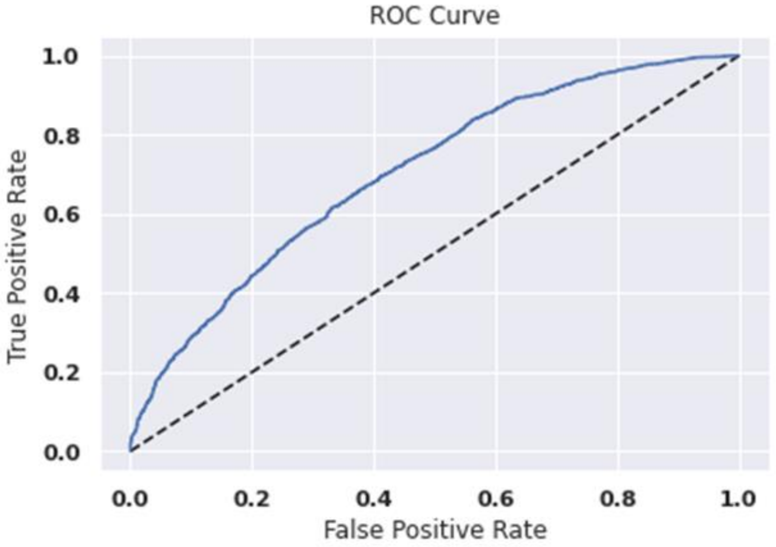


Model Evaluation Metric

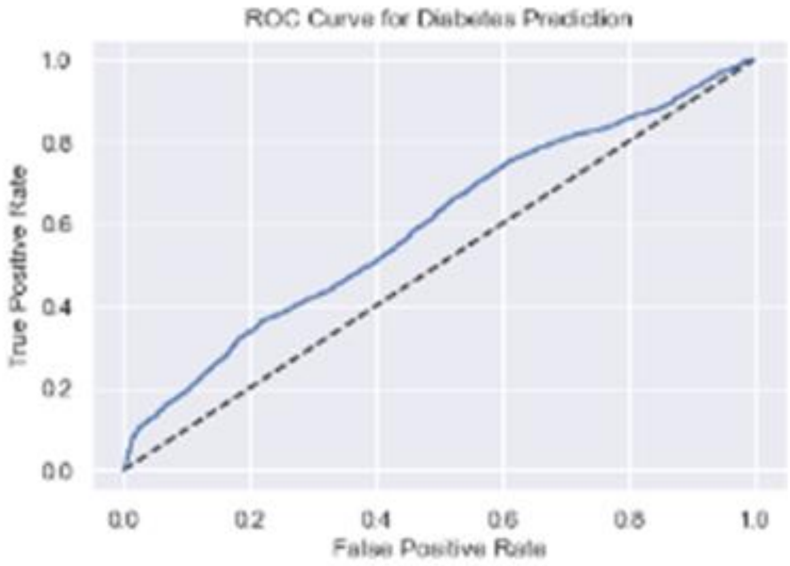
- AUC (Area under the curve) was used to evaluate model performance.
- This measures how well a model can distinguish between classes.
- We also used accuracy for the xgboost model, this measures how many classifications the model predicted correctly.



Xgboost

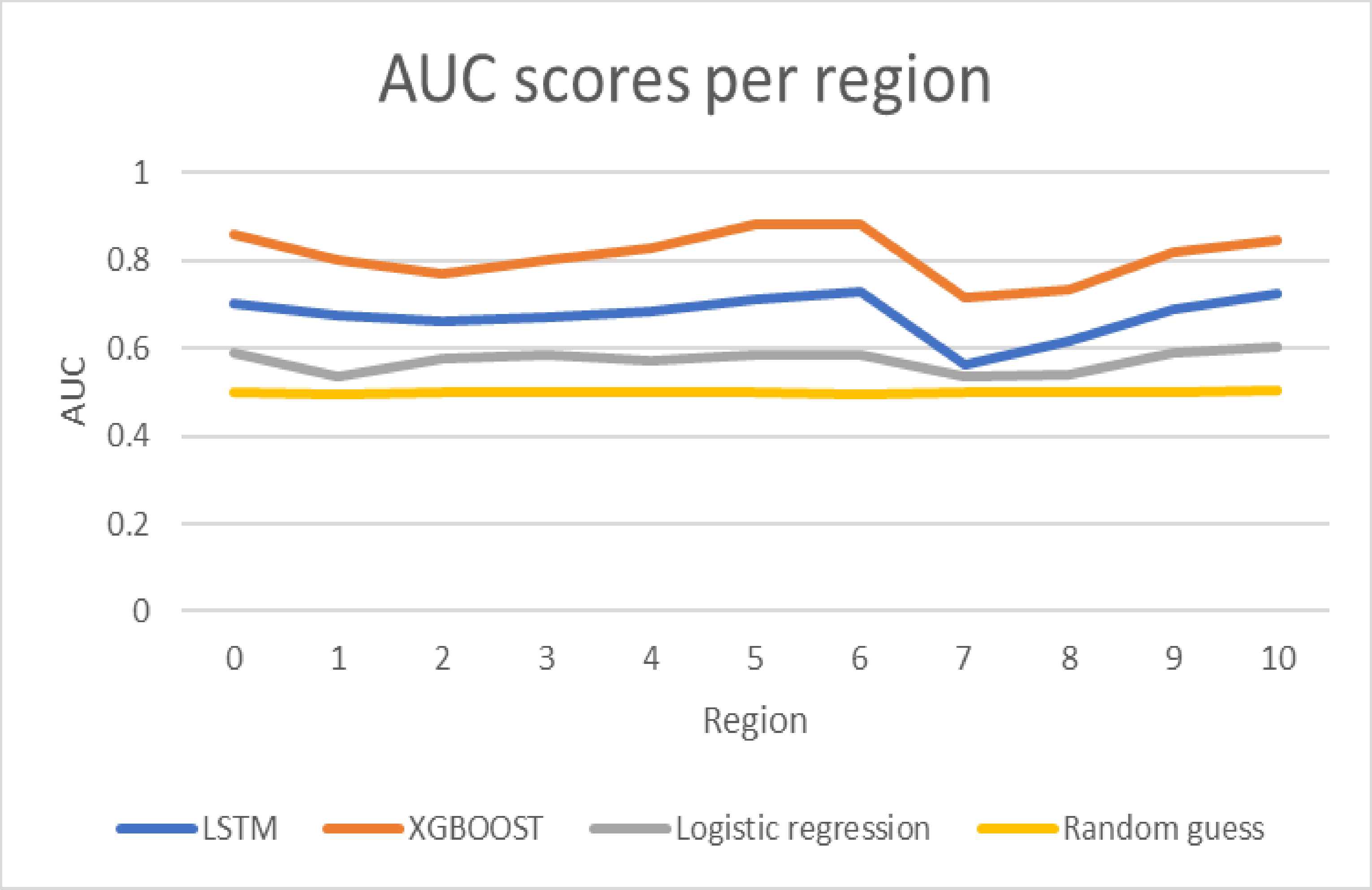


LSTM



Logistic regression

Model Evaluation



AUC	Category
0.9 – 1	excellent
0.8 – 0.9	good
0.7 – 0.8	fair
0.6– 0.7	poor
0.5-0.6	failed

- All models performed better than a random guess
- Xgboost model had the best performance
- LSTM was least sensitive to class imbalance and did not require any intervention. This is because the model relies on sequence and class imbalance techniques throw off the sequence.
- The timestep prediction problem with no aggregations (not shown here), the LSTM performed significantly better as it can handle sparse data much better than other models.
- Logistic regression is an over simplification of the problem as the data was not normally distributed.

Model Selection and Conclusion

- XGBoost provided better results.
- However LSTM was not optimized. It did not require data pre-processing and was more powerful for lower level predictions.
- The model selection will depend on what results the business finds more useful.
- Ex… is it better to know which location to be at during a specific hour of the day?
- What location to go to based on information of where the last pick up happened

		AUC		Accuracy		AUC
Cluster	**%class imbalance**	**LSTM**	**XGBOOST**	**XGBOOST**	**Logistic regression**	**Random guess**
0	0.444583333	0.703071	0.860167	85.52%	0.590991	0.497117695
1	0.326329365	0.673788	0.801313	76.57%	0.53574	0.495104344
2	0.261884921	0.659683	0.768891	69.56%	0.577181	0.500756709
3	0.375992063	0.667801	0.800175	77.10%	0.584551	0.500672586
4	0.377083333	0.682989	0.827769	80.83%	0.571713	0.499889758
5	0.481686508	0.711069	0.879048	87.76%	0.584597	0.501157056
6	0.459861111	0.726677	0.879488	87.62%	0.584597	0.495433947
7	0.170972222	0.561313	0.716254	59.44%	0.532811	0.498483858
8	0.122757937	0.614024	0.733306	59.31%	0.541368	0.500282174
9	0.382539683	0.689411	0.818973	79.64%	0.590174	0.500778661
10	0.434305556	0.724347	0.845249	83.45%	0.603384	0.50307699

Part two: how much CO_2 can we improve?

- Filtered the data to only get the trips with zero occupancy.
- Used the python h3 API to estimate the distance travelled while waiting for a customer.
- Calculated the total number of trips for the year (next month = current month*1.15).
- Estimated the total distance travelled calculating the sum of n samples (total number of empty trips for that month) sampled from an exponential distribution with lambda equal to the mean of the existing data set.
- The total CO_2 emissions was calculated as (total distance travelled in miles * 404 grams (grams of CO_2 emitted per mile).
- This gave us a value of **7646** grams.