

Delivery driver location optimization with Causal Inference

ML Project

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Conclusion and Future plan

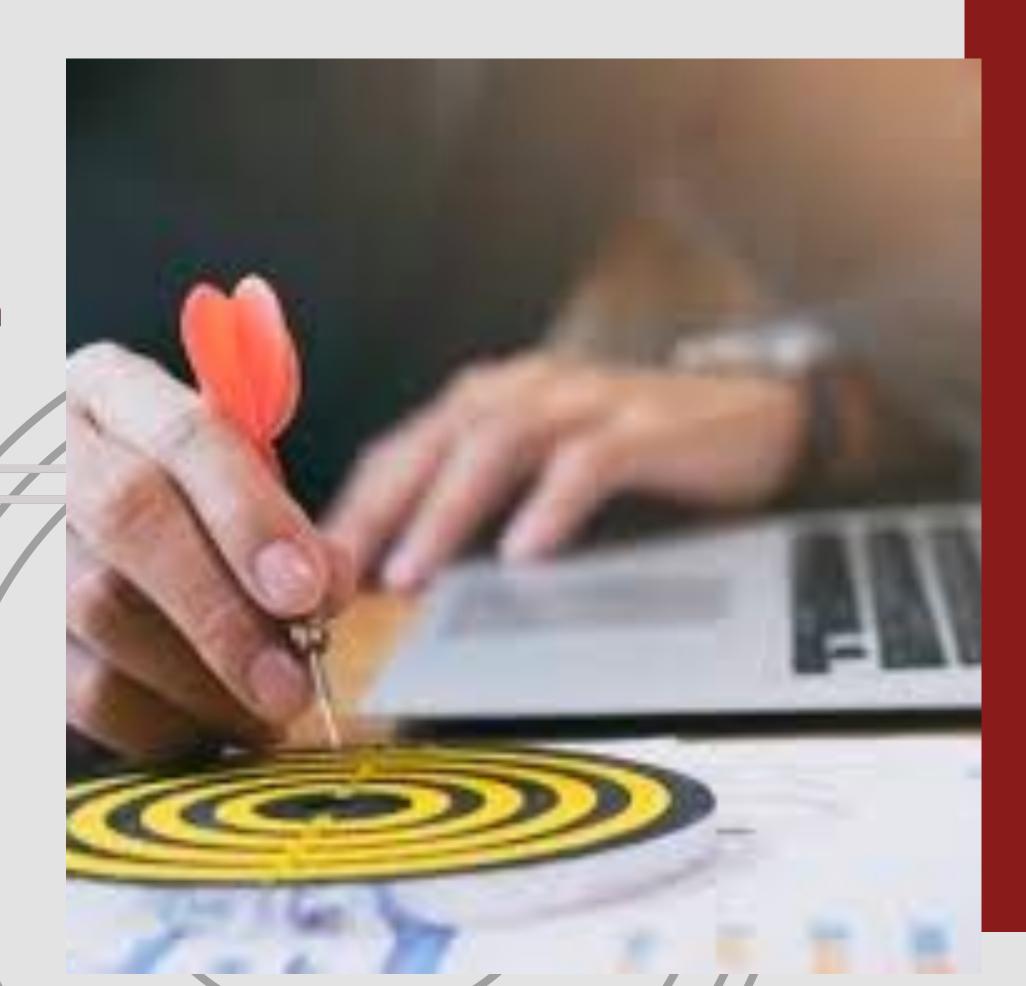
Business objective

 customers wish to utilize Gokada to ship their parcels

The inefficient positioning of drivers

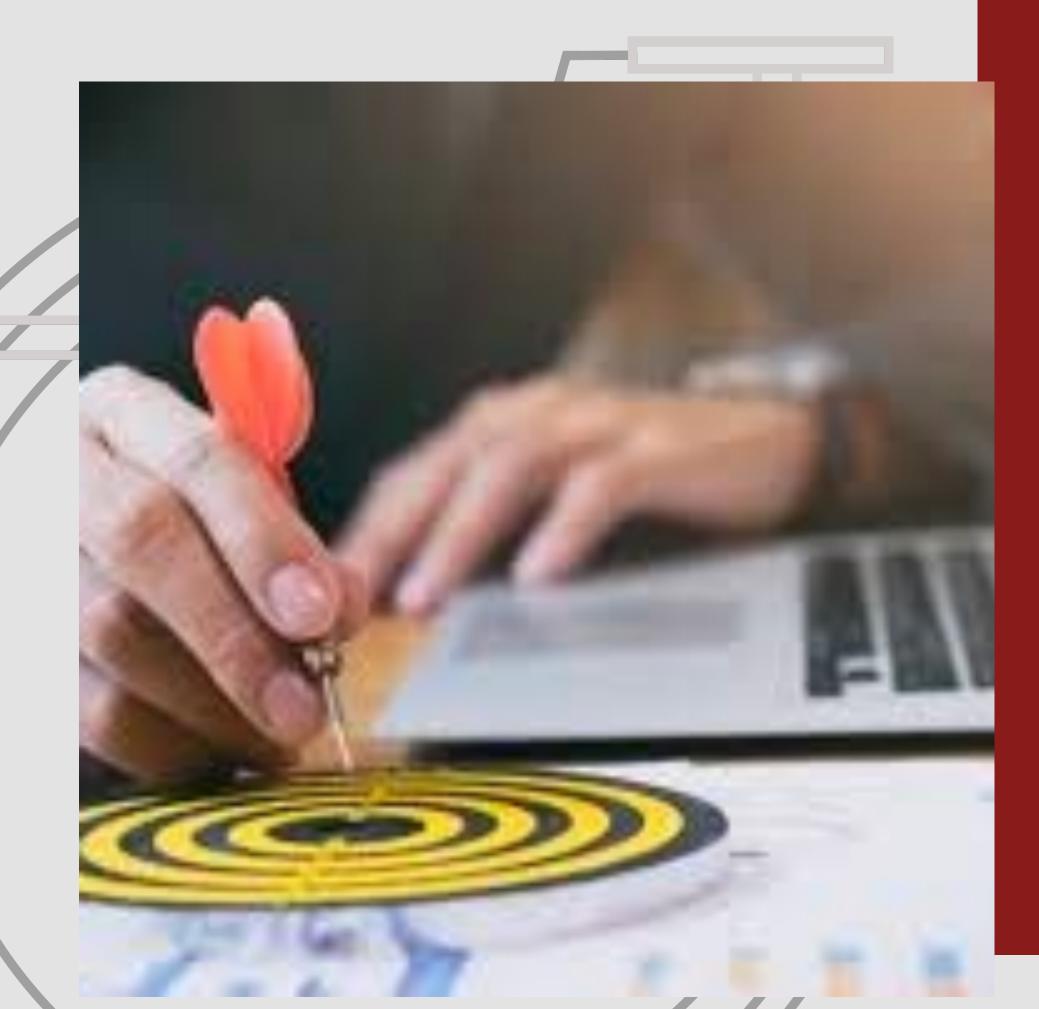
 This has caused many delivery orders to be unmet.



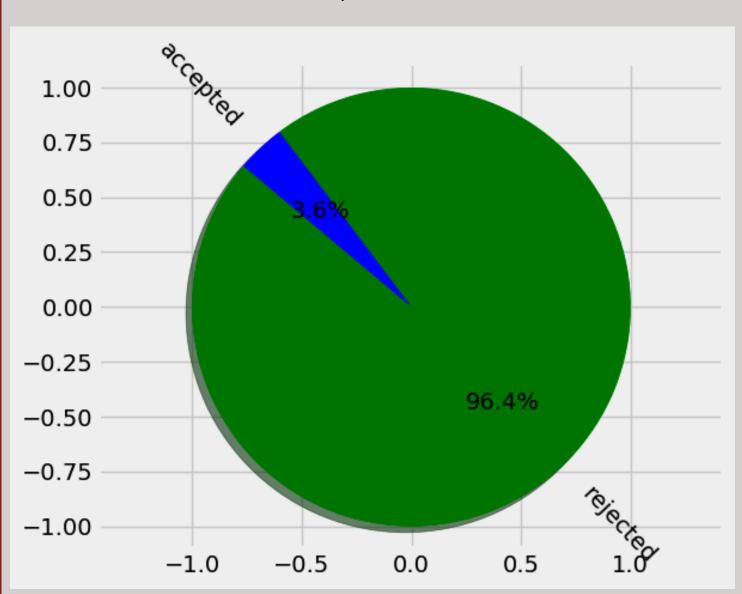


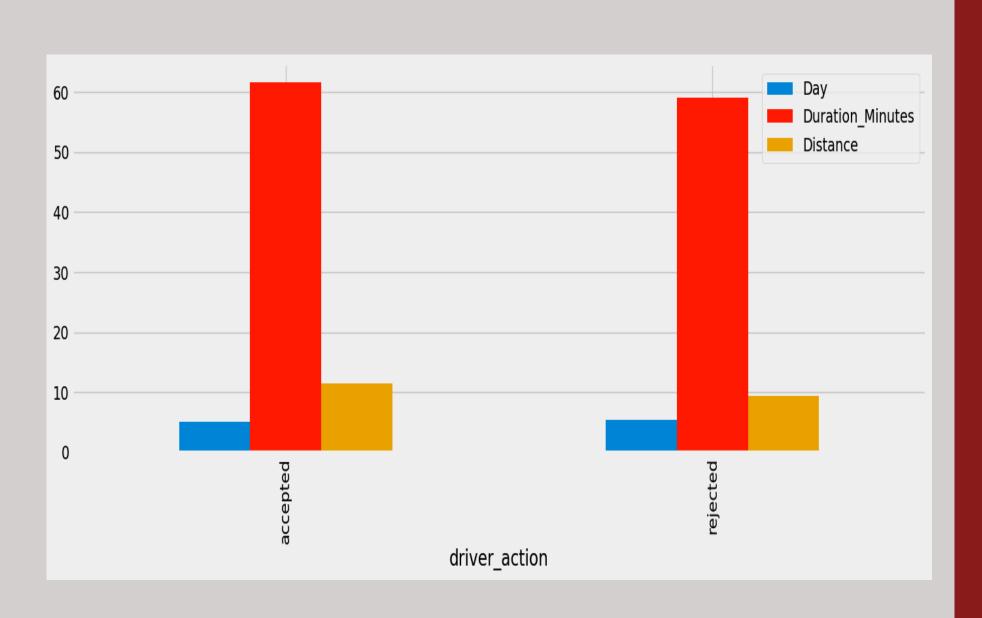
Business objective

- Understand the primary causes of unfulfilled requests
- come up with solutions
- recommend drivers locations that increase the fraction of complete orders

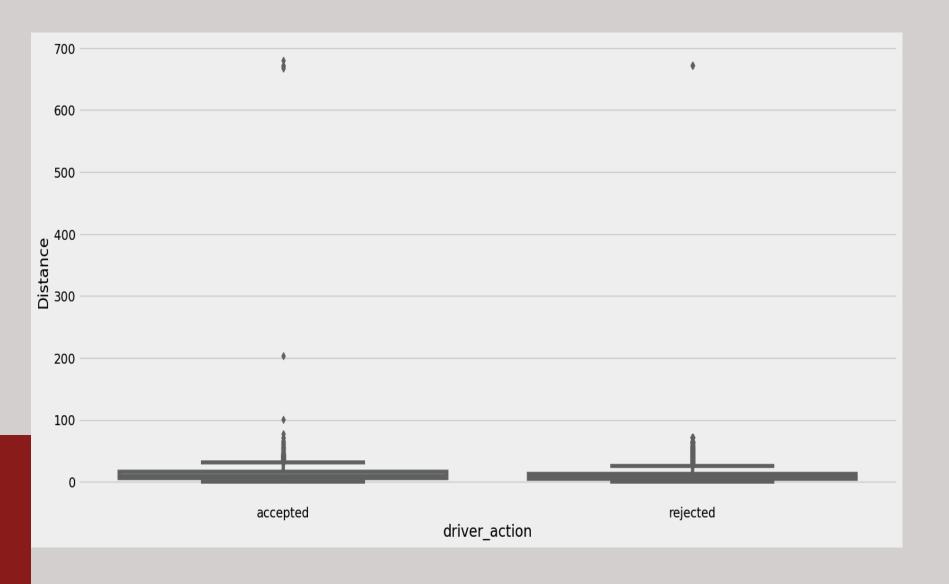


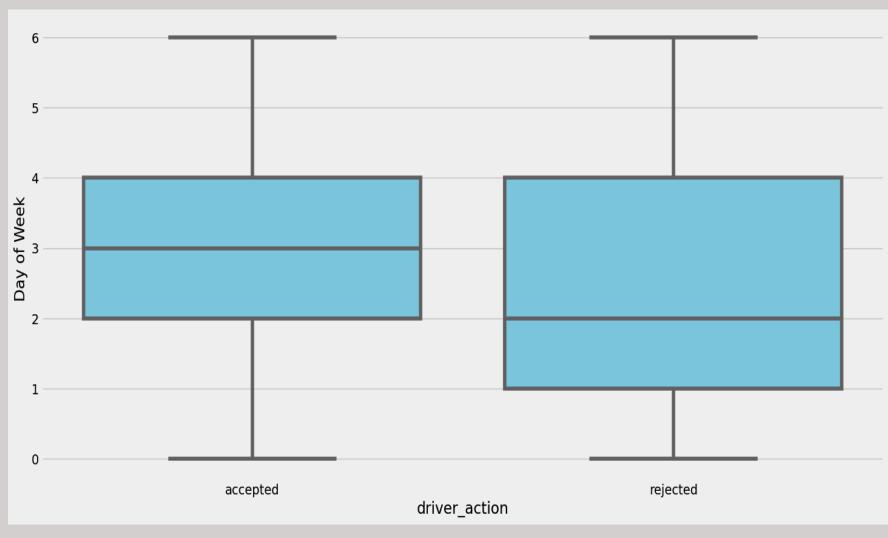






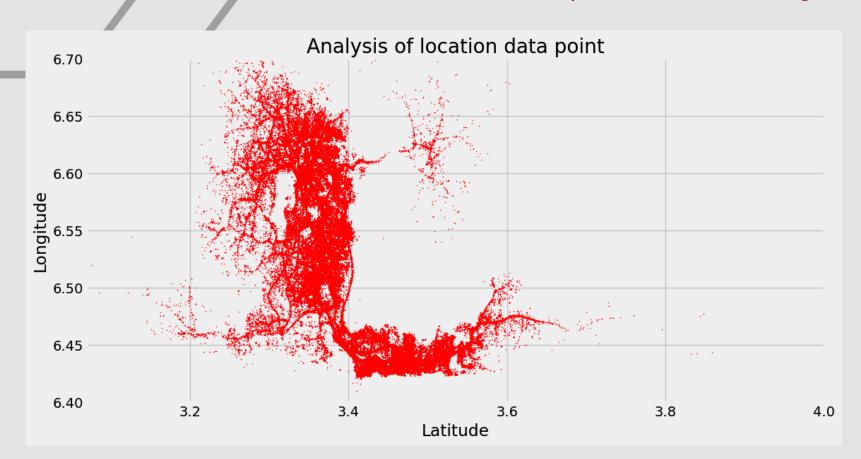
Action of the drivers given the distance average plot shows that distance doesn't really have a big difference between the rejection and acceptance.

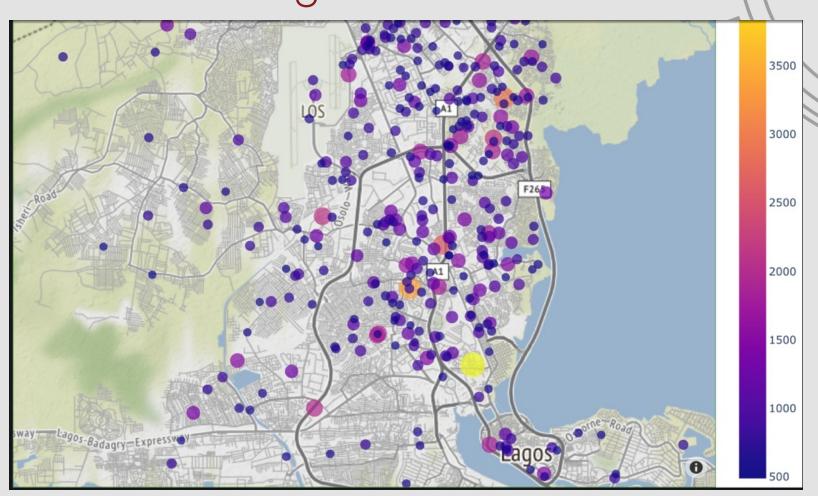




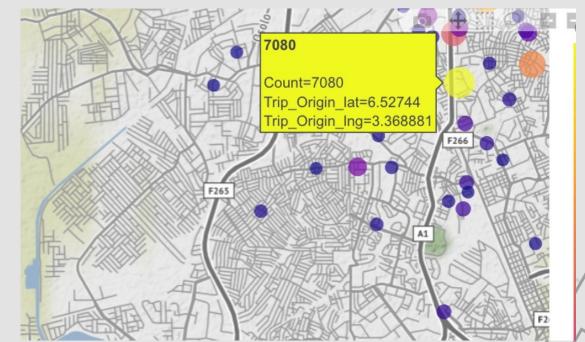
Outliers detection.

Performed Spatial Analysis on Demand given the coordinate

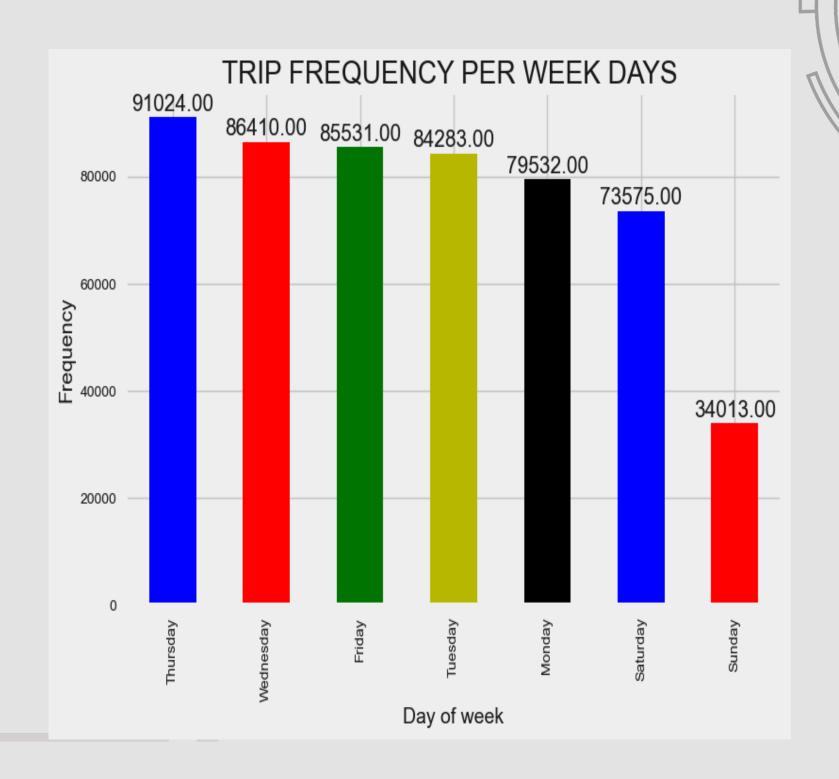




Analysis of location data point most orders are between 3.2 to 3.6 latitude and 6.43 to 6.70 of longitude



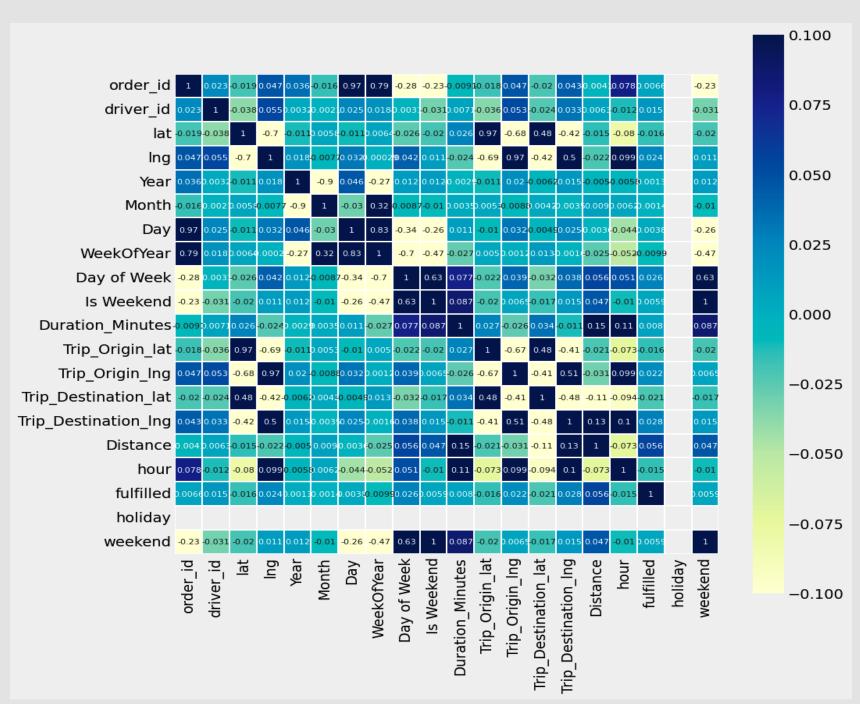


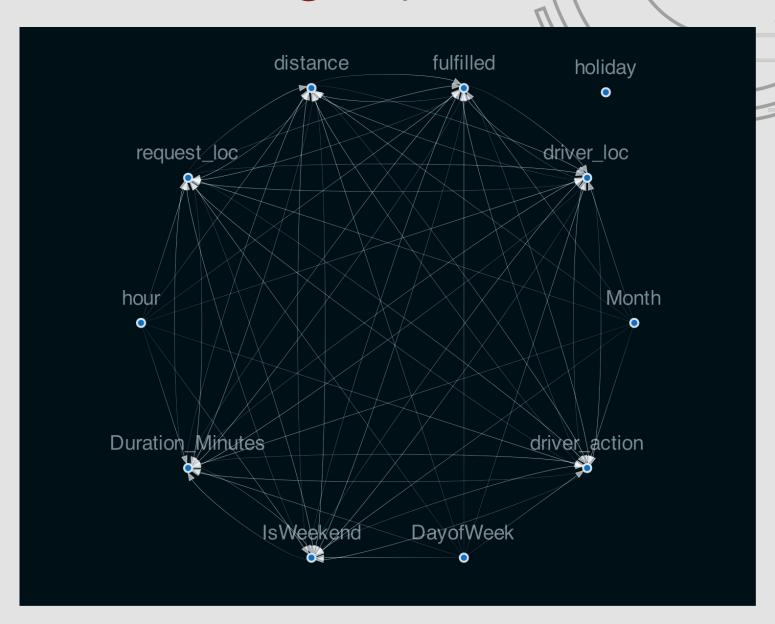


Methodology

correlation matrix

Causal inference graph

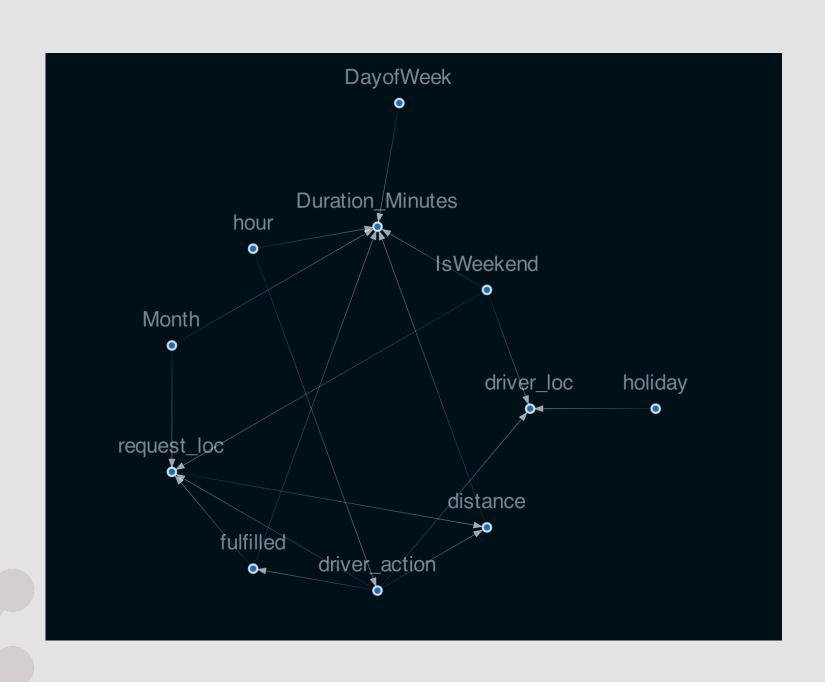




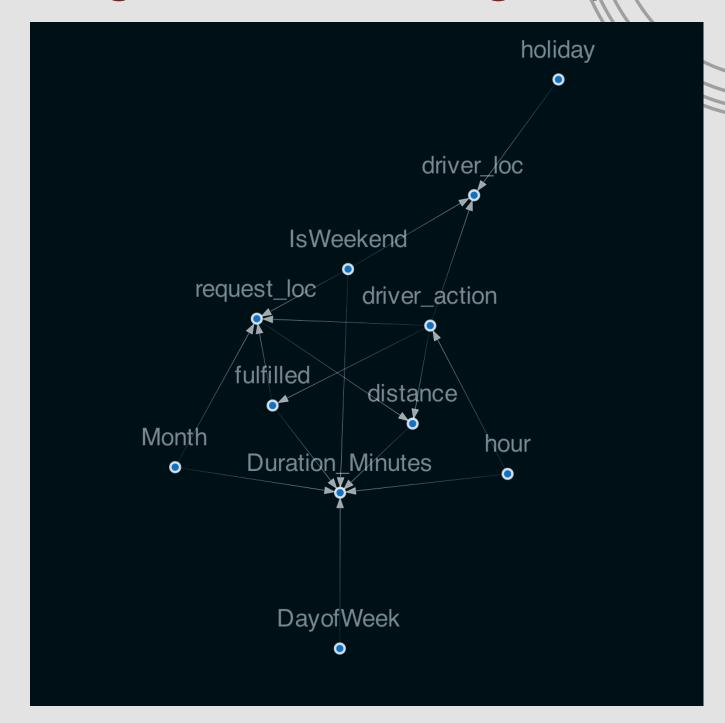
Causal inference aims at estimating the causal effect of a specific variable (treatment) over a certain outcome of interest.

Step 1: Preparing the Causal Graph

Causal inference graph



Largest stable graph



Causal inference aims at estimating the causal effect of a specific variable (treatment) over a certain outcome of interest.

The Causalnex package allows you to manually map the causal relationships between different features.

Preparing the Causal Graph

- Step 2: Fitting The Conditional
 Distribution of the Bayesian
 Network and preparing the Data
- Then can split the data after this as a train/test.
- Step 3: Modeling Probability
- Step 4: Predict the State from the input Data

```
# what will happen if all drivers were in 5km of the request
   print("marginal fulfilled", ie.query()["fulfilled"])
   ie.do_intervention("distance",
                      {'near': 1.0,
                       'far': 0.0})
   print("updated marginal fulfilled", ie.query()["fulfilled"])
   ie.reset do("distance")
marginal fulfilled {'no': 0.9722303727303858, 'yes': 0.027769627269613968}
updated marginal fulfilled {'no': 0.9722303727303858, 'yes': 0.027769627269613968}
   # what will happen if all drivers were in 5km of the request
   print("marginal action", ie.query()["driver action"])
   ie.do intervention("distance",
                       {'near': 1.0,
                        'far': 0.0})
   print("updated marginal actions", ie.query()["driver action"])
   ie.reset_do("distance")
marginal action {'accepted': 0.030219775348635153, 'rejected': 0.9697802246513652}
updated marginal actions {'accepted': 0.030219775348635146, 'rejected': 0.969780224651365}
```

- If we decide to bring all the drivers in less that 5km of the requests, from the sampled dataset,
- we could have seen a slight decrease in accepted requests. however, fulfilled action will not be affected.

Preparing the Causal Graph

Classification Report:

- The BN shows good
 performance at classifying the
 minority class (unfulfilled
 requests) with good precision,
- but the recall and f1-score are zero for fulfilled.

```
aluation import classification report
  classification report(bn, test, "fulfilled")
{'fulfilled_no': {'precision': 1.0,
 'recall': 1.0,
 'f1-score': 1.0,
  'support': 50},
'fulfilled_yes': {'precision': 0.0,
 'recall': 0.0,
 'f1-score': 0.0,
 'support': 0},
 'micro avg': {'precision': 1.0,
 'recall': 1.0,
 'f1-score': 1.0,
 'support': 50},
 'macro avg': { 'precision': 0.5,
 'recall': 0.5,
 'f1-score': 0.5,
 'support': 50},
 'weighted avg': {'precision': 1.0,
 'recall': 1.0,
  'f1-score': 1.0,
  'support': 50}}
```

Future plan

- Solve the issue of the imbalanced dataset
- SQL database integration
- Finish ML
- Implement the integer | mixed integer programing

