Prediction of Accident Severity

Justin Sierchio

Applied Data Science Capstone

IBM Data Science Professional Certificate

August 27, 2020

Outline

- Introduction
- Data
- Methodology
- Results
- Discussion
- Conclusion

Introduction

- Almost 40,000 people are killed each year in the US due to traffic fatalities (https://en.wikipedia.org/wiki/Motor_vehicle_fatality_rate_in_U.S._by_year) .
- To better understand the reasons behind those accidents a data science study into the attributes leading to those accidents is warranted.
- Will be evaluating Seattle traffic accidents for past 15 years.
- This study will be of interest to:
  - drivers and pedestrians in the greater Seattle metropolitan area
  - pedestrians
  - city planners
  - emergency responders
  - road construction crews
  - insurance companies.

Data

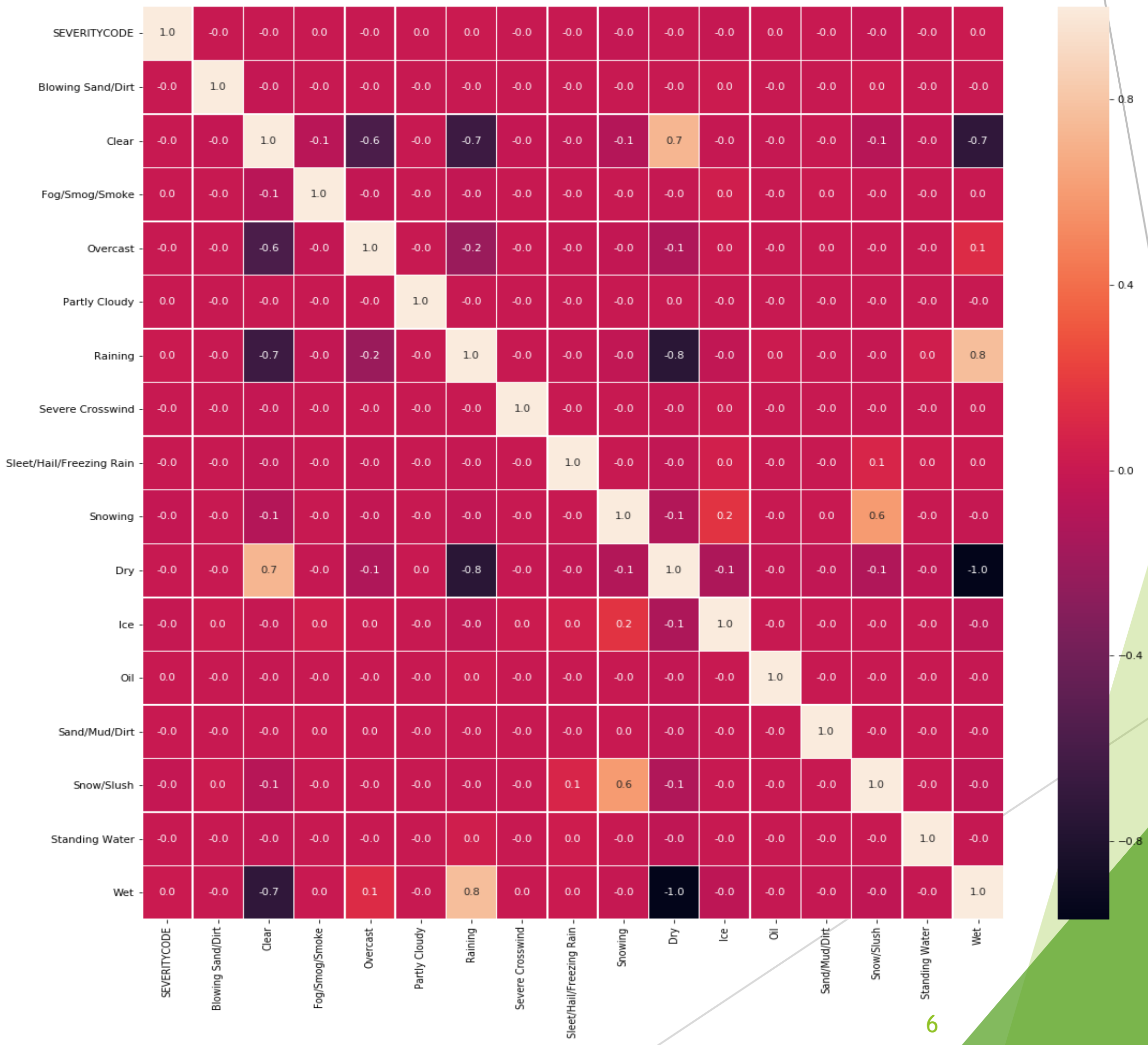
- Study data comes from Seattle Police Department:
  - https://s3.us.cloud-object-storage.appdomain.cloud/cf-courses-data/CognitiveClass/DP0701EN/version-2/Data-Collisions.csv,
  - Records from 2004 to present updated weekly.
  - Data stored in a .csv file
- Study data includes the following information:
  - the severity of the accident
  - type of collision
  - number of fatalities and/or injuries
  - weather conditions
  - road conditions
  - any pedestrians or non-automobiles involved
  - and other factors.
- Metadata explaining these attributes is located at:
  - https://s3.us.cloud-object-storage.appdomain.cloud/cf-courses-data/CognitiveClass/DP0701EN/version-2/Metadata.pdf.

Methodology
Cleaning

- The raw dataset has 194673 rows and 38 columns.
- Duplicate columns were dropped.
- Unclear values were set to → NaN and later dropped.
- Categorical variables were converted to Numerical variables.
- Several variable sets (i.e. WEATHER, ROADCOND, LIGHTCOND) were split into dummy variables using their underlying characteristics.
- Final cleaned dataset has 194673 rows and 35 features.

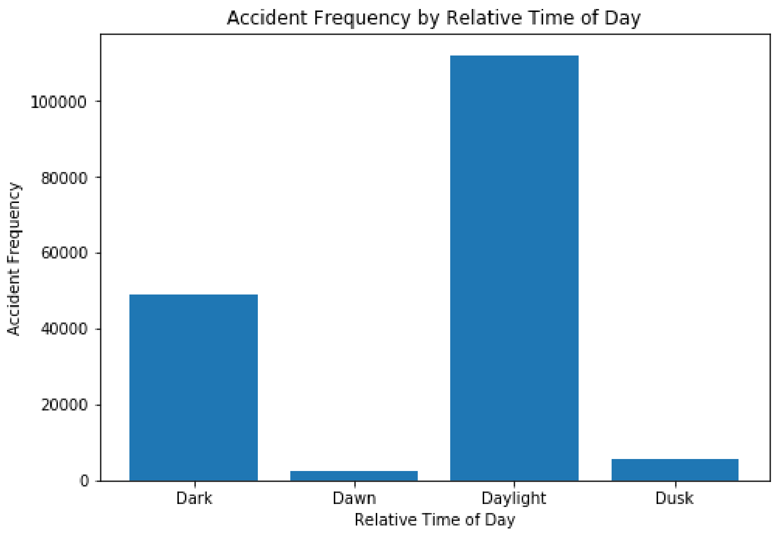
Methodology
Analysis – Weather vs. Accident Severity

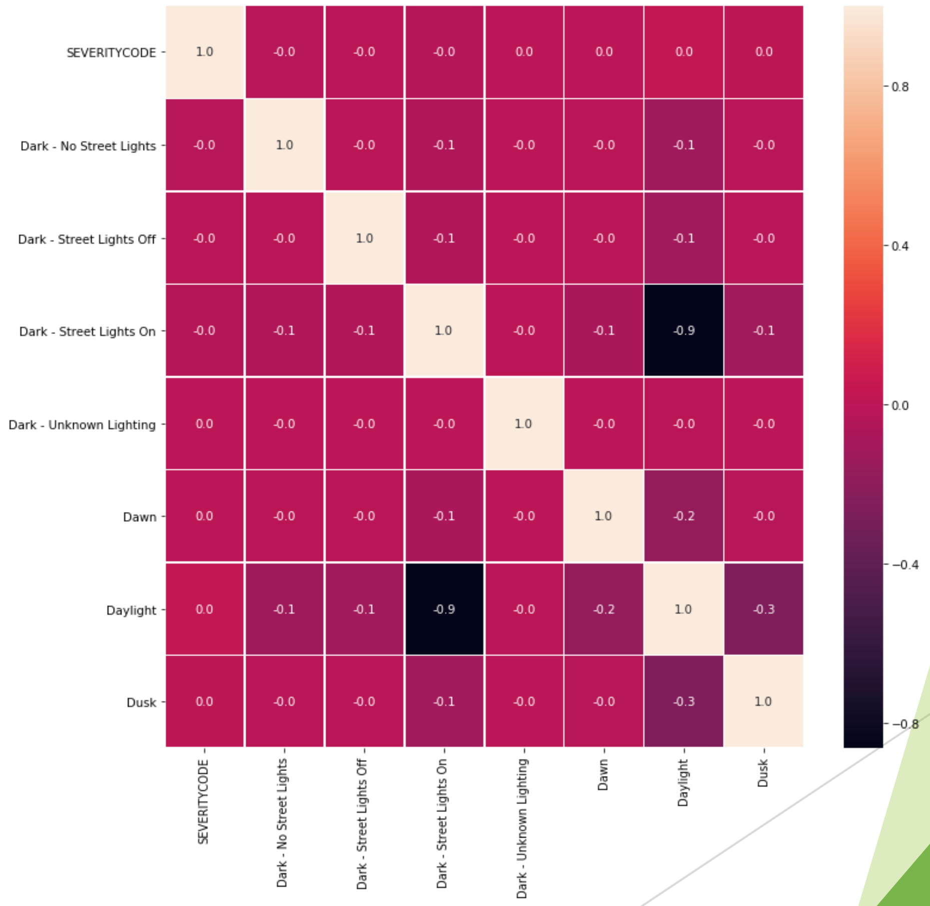
- No correlation between weather or road conditions and accident severity.



Methodology
Analysis – Lighting vs. Accident Severity

- No correlation between lighting conditions and accident severity.
- Most accidents occur during daytime.

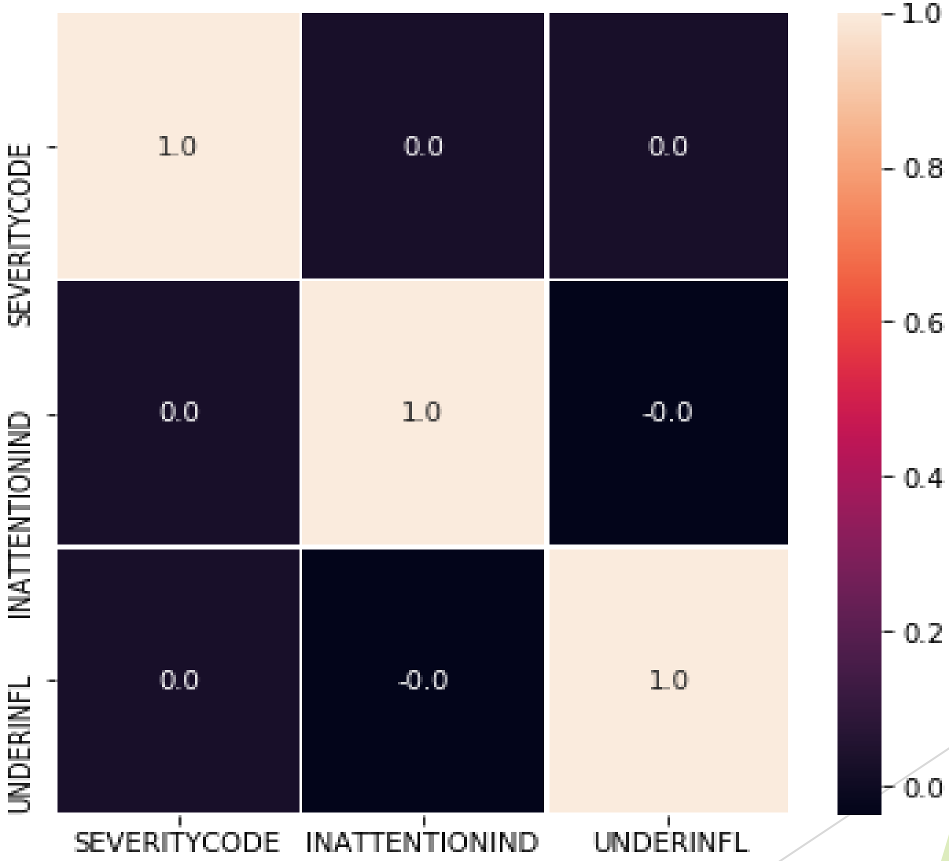




Methodology

Analysis –Impairment/Attention vs. Accident Severity

- No correlation between driver impairment or attention and accident severity.



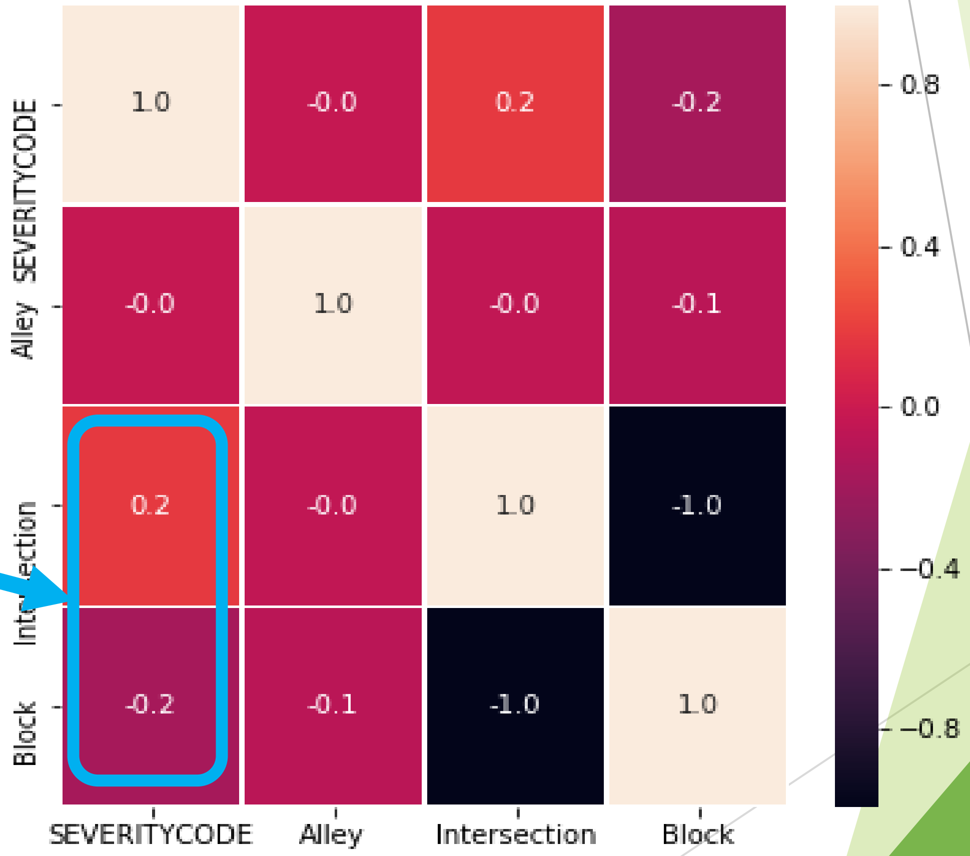
Methodology

Analysis – Location vs. Accident Severity

Out[23]:

	Accident Location	Severity = 1	Severity = 2	% Difference btwn Sev=1, Sev=2
0	Alley	516	77	0.850775
1	Intersection	34463	26808	0.222122
2	Block	78726	28657	0.635991

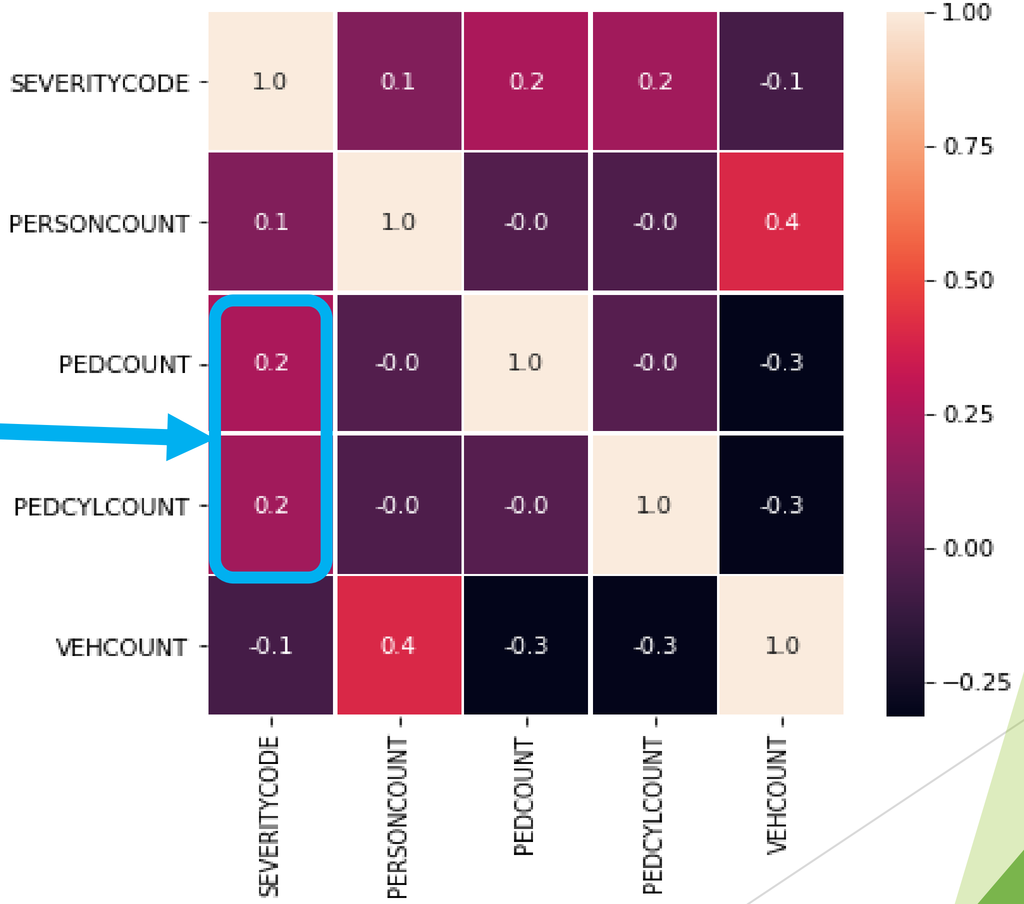
- Correlation between intersection accidents and accident severity.



Methodology

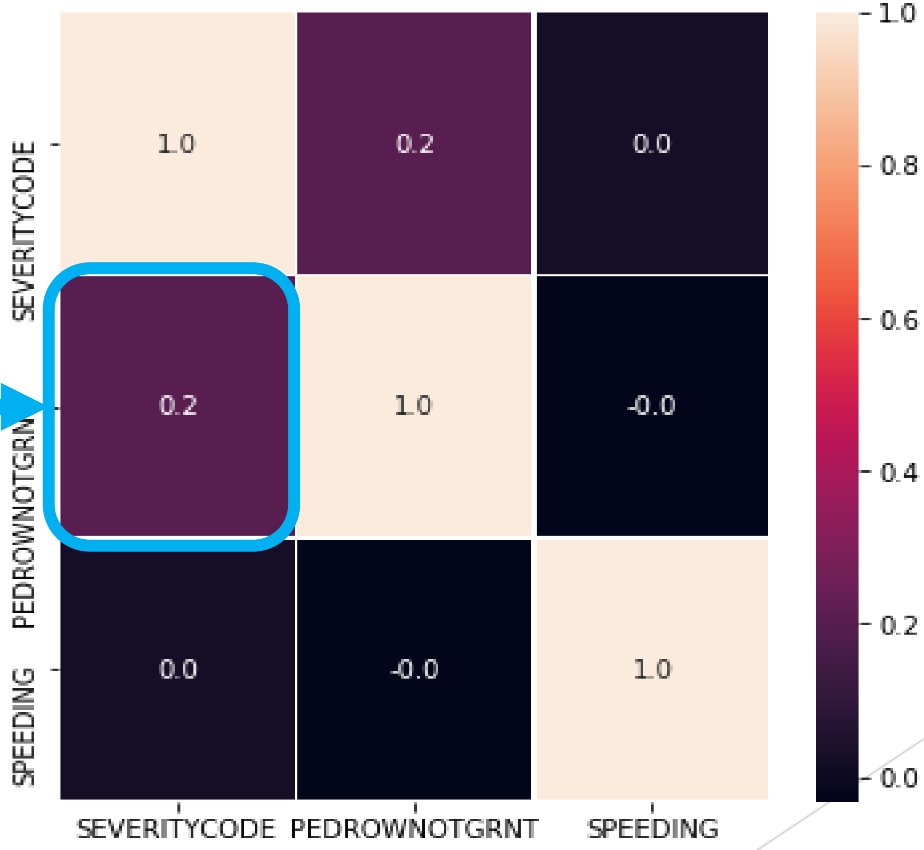
Analysis – Pedestrians vs. Accident Severity

- Correlation between the number of pedestrians and/or bicyclists and accident severity.



Methodology
Analysis – Speeding / Pedestrian ROW

- Correlation between pedestrian failed to be yielded right of way and accident severity.



Machine Learning Models
Decision Trees

- Decision Trees – depth – 8 gives best accuracy values.

In [31]:
```
# Create Jaccard and F1 Score Objects
depthRange = range(1, 9)
jaccardSimilarityScore = []
f1Score = []

# For Varying Depths, calculate jaccard similarity and f1 scores
for n in depthRange:
    dTree = DecisionTreeClassifier(criterion = 'gini', max_depth = n)
    dTree.fit(X_train, y_train)
    dTree_yhat = dTree.predict(X_test)
    jaccardSimilarityScore.append(jaccard_similarity_score(y_test, dTree_yhat))
    f1Score.append(f1_score(y_test, dTree_yhat, average = 'weighted'))
```

In [32]:
```
# Present the resulting data in a DataFrame
dTree_result = pd.DataFrame([jaccardSimilarityScore, f1Score],
                             index = ['Jaccard Sim', 'F1'], columns = ['d = 1','d = 2','d = 3','d = 4','d = 5','d = 6','d = 7', 'd = 8'])
dTree_result.columns.name = 'Depths'
dTree_result
```

Out[32]:

Depths	d = 1	d = 2	d = 3	d = 4	d = 5	d = 6	d = 7	d = 8
Jaccard Sim	0.706470	0.729897	0.729897	0.729867	0.731640	0.732555	0.7340[illegible]2	0.735923
F1	0.616746	0.664202	0.664202	0.664151	0.675052	0.688503	0.6840[illegible]0	0.690943

Machine Learning Models
Logistic Regression

- Logistic Regression – Lib-Linear Solver, Regularization Value = 0.01 give best accuracy values.

In [35]:
```python
# Create Solver and Accuracy Score Object
solverList = ['lbfgs', 'saga', 'liblinear', 'newton-cg', 'sag']
regularizationValueSet = [0.1, 0.01, 0.001]
index = []
lrAccuracy = []
iterations = 0

for p, q in enumerate(regularizationValueSet):
    for r, s in enumerate(solverList):
        index.append(p + r *5)
        iterations +=1
        lrModel = LogisticRegression(C = q, solver = s)
        lrModel.fit(X_train, y_train)
        lr_yhat = lrModel.predict(X_test)
        y_prob = lrModel.predict_proba(X_test)
        print('Test {}: With C = {} for solver = {}, LR Accuracy is : {}'.format(iterations, q, s, log_loss(y_test, y_prob) ))
        lrAccuracy.append(log_loss(y_test, y_prob))

    print('\n')
```

```
Test 1: With C = 0.1 for solver = lbfgs, LR Accuracy is : 0.5557660528012474
Test 2: With C = 0.1 for solver = saga, LR Accuracy is : 0.5557657197099635
Test 3: With C = 0.1 for solver = liblinear, LR Accuracy is : 0.5557664324634823
Test 4: With C = 0.1 for solver = newton-cg, LR Accuracy is : 0.5557659873630711
Test 5: With C = 0.1 for solver = sag, LR Accuracy is : 0.5557665902061812


Test 6: With C = 0.01 for solver = lbfgs, LR Accuracy is : 0.5557784963316049
Test 7: With C = 0.01 for solver = saga, LR Accuracy is : 0.5557786432657238
Test 8: With C = 0.01 for solver = liblinear, LR Accuracy is : 0.5557831061701002
Test 9: With C = 0.01 for solver = newton-cg, LR Accuracy is : 0.5557784099363405
Test 10: With C = 0.01 for solver = sag, LR Accuracy is : 0.5557783761980235


Test 11: With C = 0.001 for solver = lbfgs, LR Accuracy is : 0.556109110153662 6
Test 12: With C = 0.001 for solver = saga, LR Accuracy is : 0.5561102050102353
Test 13: With C = 0.001 for solver = liblinear, LR Accuracy is : 0.5562142720546198
Test 14: With C = 0.001 for solver = newton-cg, LR Accuracy is : 0.5561095344008128
Test 15: With C = 0.001 for solver = sag, LR Accuracy is : 0.5561097202183379
```

Machine Learning Models
Summary Statistics – Best model?

- According to the Jaccard Similarity Score, Decision Trees performed slightly better, though either technique could probably be used.

In [39]:
```
# Decision Tree Model Scores
f1_dTree = f1_score(y_test, dTree_yhat, average='weighted')
jss_dTree = jaccard_similarity_score(y_test, dTree_yhat)
ps_dTree = precision_score(y_test, dTree_yhat)
rs_dTree = recall_score(y_test, dTree_yhat)

#Logistic Regression Model Scores
f1_lr = f1_score(y_test, lr_yhat, average='weighted')
jss_lr = jaccard_similarity_score(y_test, lr_yhat)
ps_lr = precision_score(y_test, lr_yhat)
rs_lr = recall_score(y_test, lr_yhat)

# Present Results
ModelResults = {'Classification Model': ['Decision Trees', 'Logistic Regression'], 'f1 Score': [f1_dTree, f1_lr],
              'Jaccard': [jss_dTree, jss_lr], 'Precision Score': [ps_dTree, ps_lr], 'Recall Score': [rs_dTree, rs_lr]};
df_ModelResults = pd.DataFrame(ModelResults);
df_ModelResults
```

Out[39]:

	Classification Model	f1 Score	Jaccard	Precision Score	Recall Score
0	Decision Trees	0.69094	0.735923	0.731966	0.959823
1	Logistic Regression	0.67879	0.732201	0.724842	0.971696

Results and Discussion

- Decision Tree: 73.6% match between training and test set.
- Logistic Regression: 73.2% match between training and test set.

- Weather conditions, road conditions, lighting conditions, driver impairment and speeding have little correlation with the severity of accident.
- Accident severity is increased in situations involving traffic intersections and the presence of pedestrians and/or bicyclists.

- Two main lessons from this project:
  - Be very mindful of driving in intersections, as the likelihood of a severe accident is increased.
  - When encountering pedestrians or bicyclists, extra caution should be taken.

Conclusions and Future Work

- To better understand the potential impacts (and possibly mitigate them), it is important to understand the attributes that contribute to severe accidents.
- There is no doubt that the information gathered here will be useful to drivers, pedestrians, city planners, emergency responders and insurance companies going forward.

- For future work, I would try the following:
  - Evaluating the accuracy with other classification tools (i.e. K-Nearest Neighbor, Support Vector Machine) would be invaluable.
  - Perhaps evaluating the make and model of the vehicles involved would also provide insight into traffic safety.

Thank you!