

Prediction of Car Accident Severity

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Applied Data Science Capstone

IBM Data Science Professional Certificate

Outline

- ▶ Introduction
- ▶ Data
- ▶ Methodology
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- ▶ 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

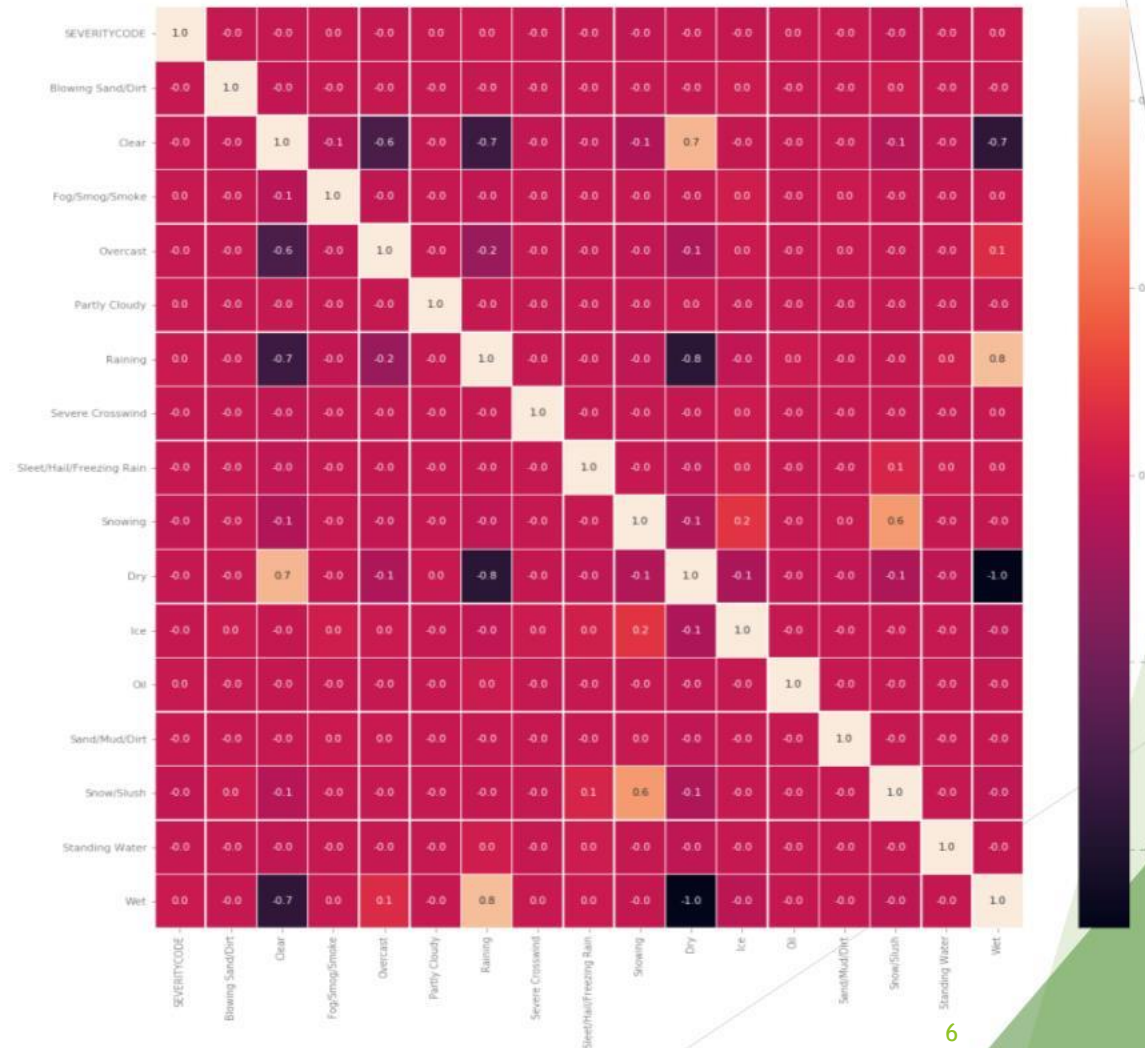
Cleaning

- ▶ 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

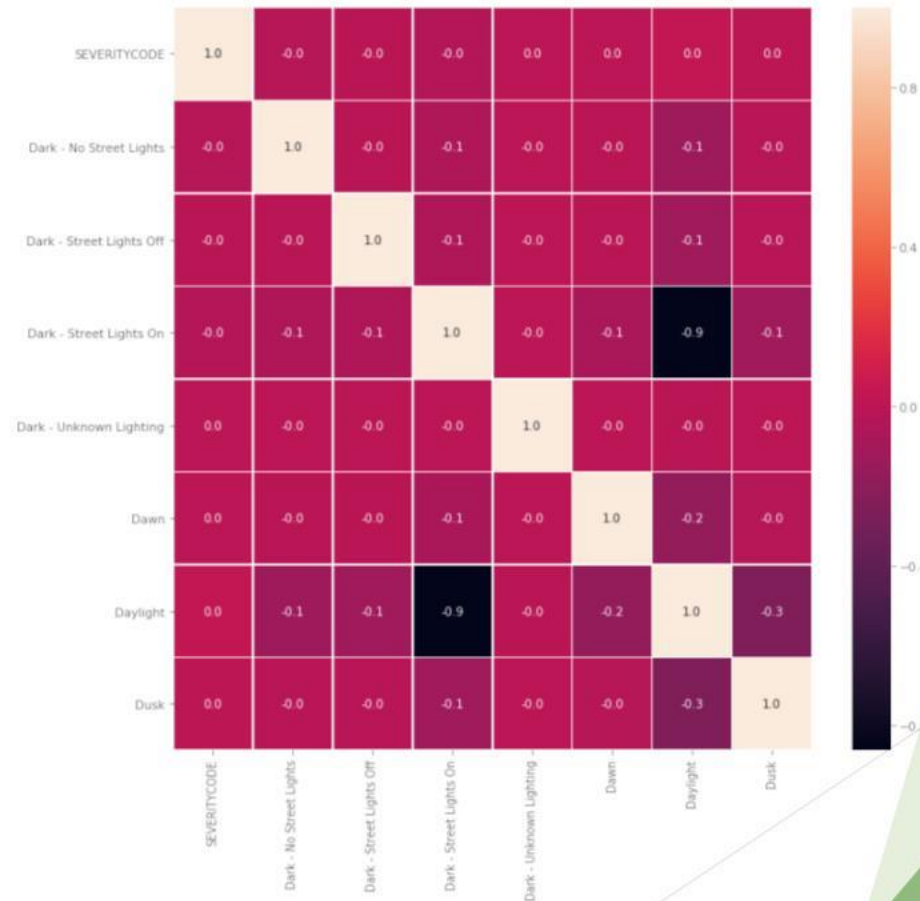
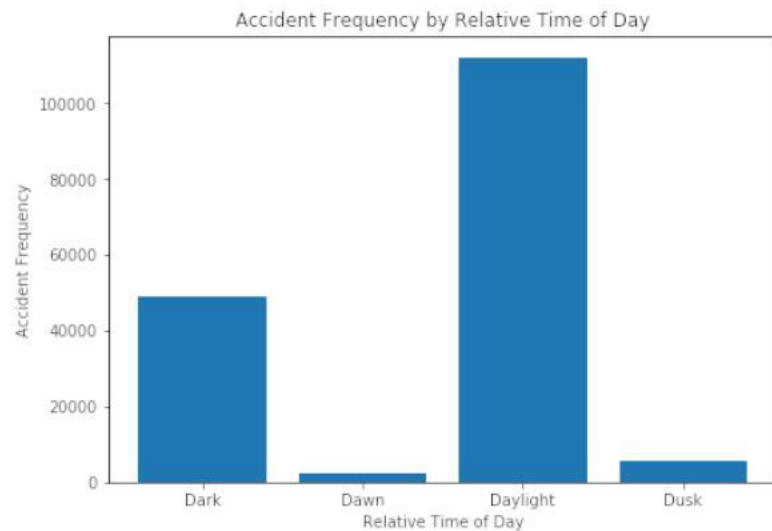
- No correlation between weather or road conditions and accident severity.



Methodology

Analysis - Lighting vs. Accident Severity

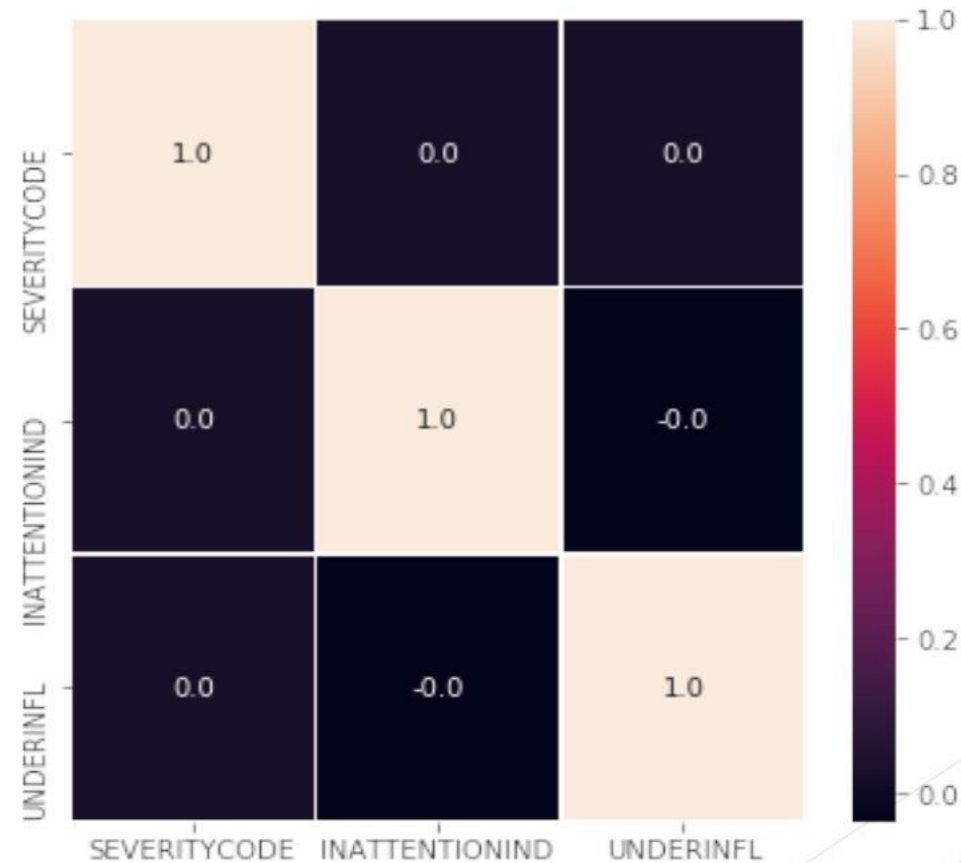
- ▶ No correlation between lighting conditions and accident severity.
- ▶ Most accidents occur during daytime.



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

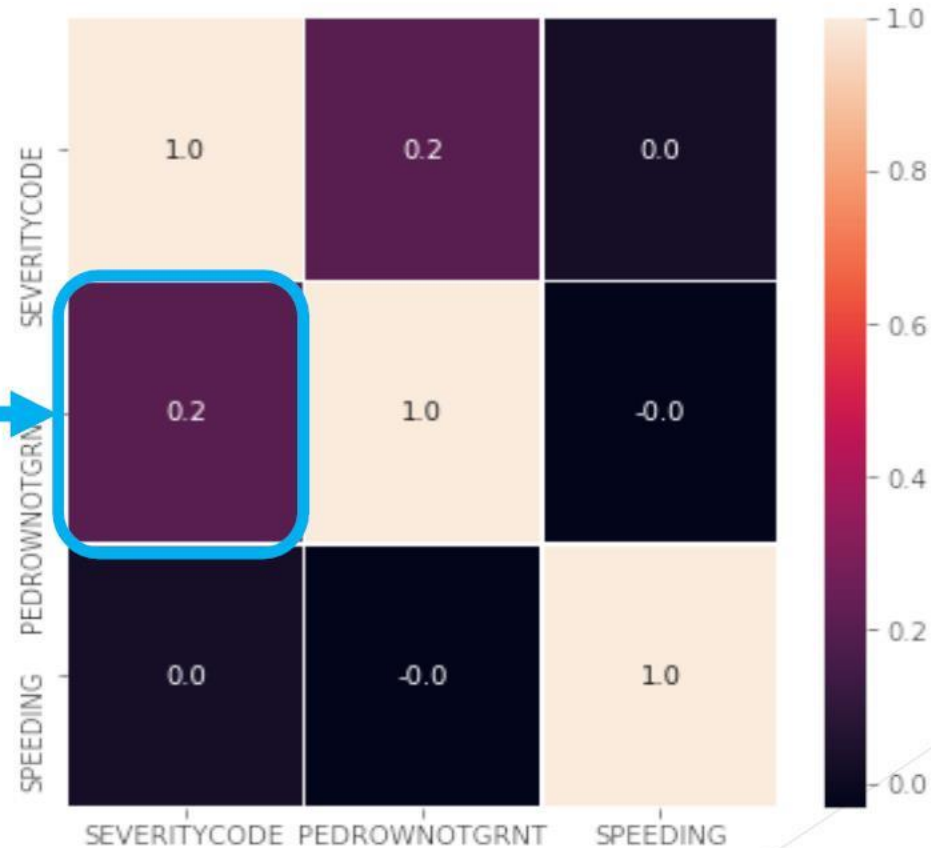
- Correlation between the number of pedestrians and/or bicyclists and accident severity.



Methodology

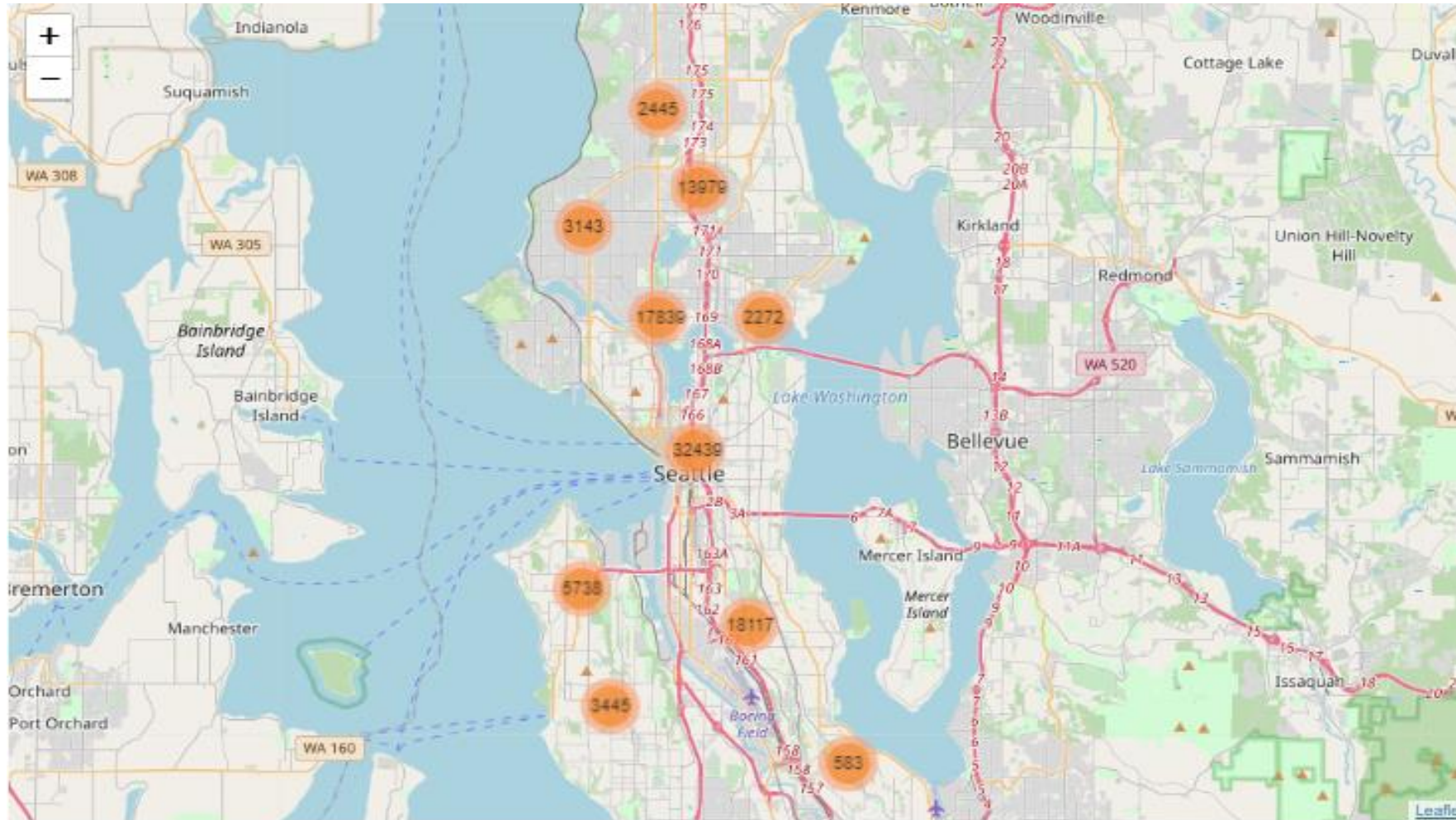
Analysis - Speeding / Pedestrian ROW

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



Methodology

Map Showing Location of Accidents



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'))

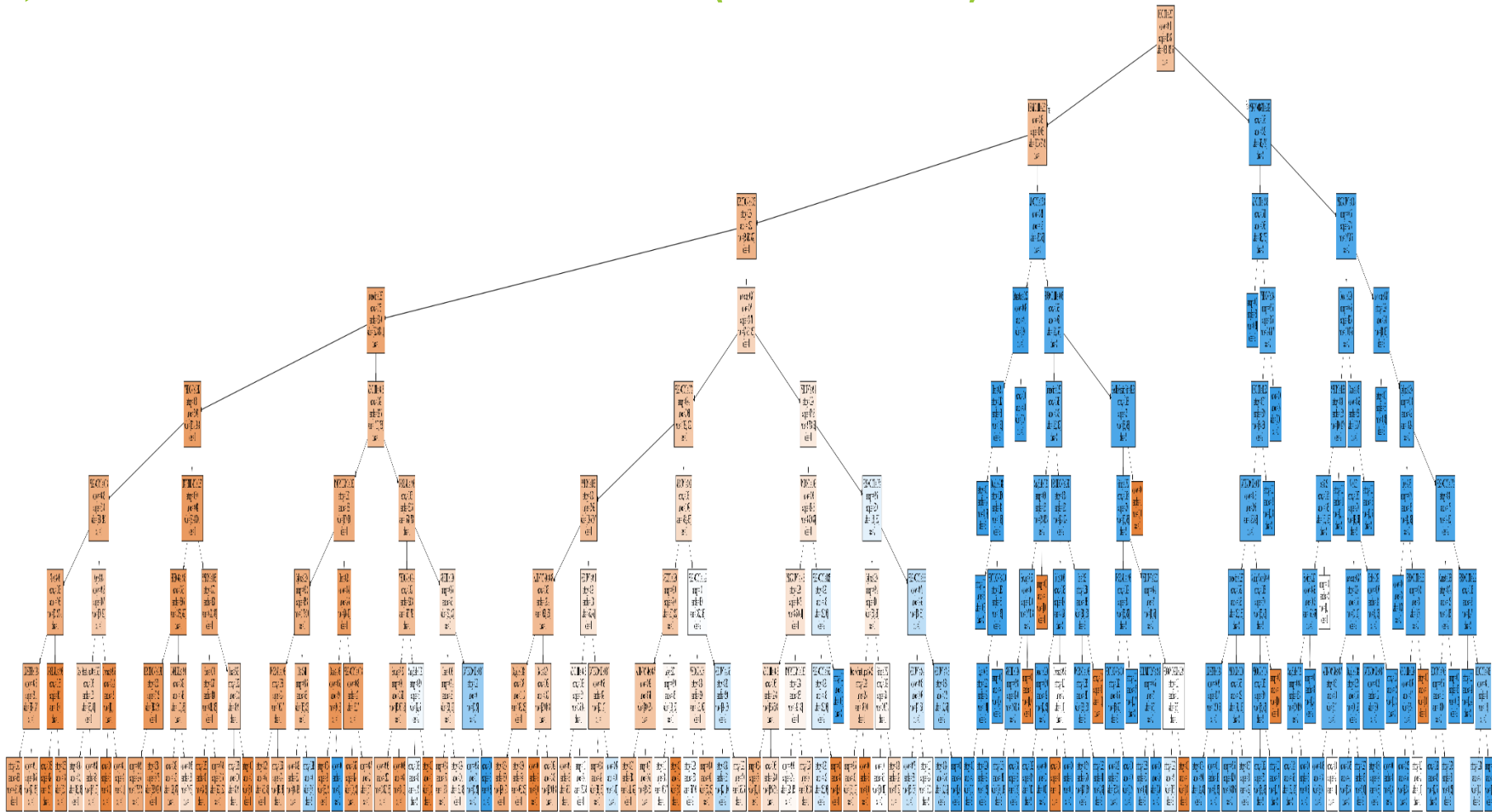
In [32]: # Present the resulting data in a DataFrame
dTree_result = pd.DataFrame([jaccardSimilarityScore, f1Score],
                             index = ['Jaccard Sim', 'F1'], columns = ['d = 1', 'd = 2', 'd = 3', 'd = 4', 'd = 5', 'd = 6', 'd = 7', 'd = 8'])
dTree_result.columns.name = 'Depths'
dTree_result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

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	0.734012	0.735923
F1	0.616746	0.664202	0.664202	0.664151	0.675052	0.688503	0.684010	0.690943

Machine Learning Models

► Let's see the decision tree(click here)



Machine Learning Models

Logistic Regression

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

```
In [35]: # 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 : 0.5561091101536626
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 : 0.5561093544008128
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.

The background features abstract, overlapping green geometric shapes, primarily triangles and polygons, in various shades of green, creating a modern and dynamic visual effect.

Thank you!