

DELAY ESTIMATION AND SHORTEST FLIGHT PATH ANALYSIS

CME 4416 INTRODUCTION TO DATA MINING

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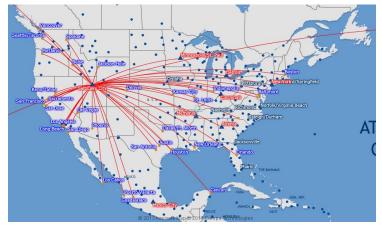


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INTRODUCTION

- Flight information between US cities in October 2014 is used.
- The estimation of delays that may occur in flights was made using many features.
- The shortest flight between the two cities was tried to be found.



LIBRARIES

Networkx

Pandas

NetworkX Network Analysis in Python



- Numpy
- Scikit-Learn





Matplotlib



DATASET

Dataset Name: International Air Transportation Performance

Dataset Source: Kaggle



RangeIndex: 49101 entries, 0 to 49100

Data #	columns (total 50 col Column	umns): Non-Null Count	Dtype
	COLUMN	Non-Null Count	DLype
0	Year	49101 non-null	int64
1		49101 non-null	int64
2	Quarter		int64
3	Month DayofMonth	49101 non-null 49101 non-null	int64
4		49101 non-null	int64
5	DayOfWeek	49101 non-null	
6	FlightDate	49101 non-null	object
	UniqueCarrier		object
7	TailNum	49042 non-null	object
- T	FlightNum	49101 non-null	int64
9	Origin	49101 non-null	object
11	OriginCityName	49101 non-null	object
12	OriginState OriginStateFips	49101 non-null 49101 non-null	object int64
13	OriginStatePips OriginStateName	49101 non-null	object
14	Dest	49101 non-null	object
15	DestCityName	49101 non-null	object
16	DestState DestStateFips	49101 non-null	object int64
18	DestStateFips DestStateName	49101 non-null	
19	CRSDepTime	49101 non-null	object
		49101 non-null	int64
20	DepTime	48599 non-null	float64
22	DepDelay	48599 non-null	float64
	DepDelayMinutes	48599 non-null	float64
23	DepDel15	48599 non-null	float64
	DepartureDelayGroups	48599 non-null	float64
25 26	DepTimeBlk TaxiOut	49101 non-null 48583 non-null	object
27	WheelsOff	48583 non-null 48583 non-null	float64 float64
28	WheelsOn		float64
29	TaxiIn		float64
30	CRSArrTime	48567 non-null 49101 non-null	int64
31	ArrTime	49101 non-null	float64
32	ArrDelay		
			float64
33 34	ArrDelayMinutes	48495 non-null	float64
	ArrDel15	48495 non-null	float64
35 36	ArrivalDelayGroups ArrTimeBlk	48495 non-null	float64
37	Cancelled	49101 non-null 49101 non-null	object
38	CancellationCode		int64
39		522 non-null	object
	Diverted	49101 non-null	int64
40	CRSElapsedTime	49101 non-null	int64
41	Distan	48495 non-null	float64
42	AirTime	48495 non-null	float64
43	Distance	49101 non-null	int64
44	DistanceGroup	49101 non-null	int64
45	CarrierDelay	9124 non-null	float64
46	WeatherDelay	9124 non-null	float64
47	NASDelay	9124 non-null	float64
48	SecurityDelay	9124 non-null	float64
49	LateAircraftDelay	9124 non-null	float64

PREPROCESSING

- Dropped Columns
- Delay Classification
- Flight Range Calculations
- KNN Imputer for NaN values

- Converted Data Types
- Generated New Columns
- Outlier Detection

CONVERTED DATA TYPES

• The dataset had data types of object, float, and integer. All of them have been converted to numerical form in order to be included in the model. All our features have been converted to integer type.

Thus, memory usage is also saved.

DROPPED COLUMNS

• The dataset had 50 features

• Some were dropped because they increased the correlation, didn't work at all, and some were dropped because they were combined to create new meaningful columns.

GENERATED NEW COLUMNS

- The class attribute was obtained by summing the ArrDel15 and DepDel15 columns. The newly created column was named Del15.
- "OriginCityName", "DestCityName", "OriginStateName" and "DestStateName" have been converted to numeric. However, when converted to numeric, the numbers in the two columns did not represent the same city or state. This was done in alphabetical order.
- After sorting, new features with numerical values were created. Also, while there were 293 origin cities, there were 292 destination cities.
- This prevented the creation of meaningful rankings.

KNN IMPUTER FOR NAN VALUES

• The number of null values in the data set was quite low (3% or 4%).

• We decided that KNN is the best approach to fill in nulls. We did not want to delete this data directly and filled the blanks with KNN.

• In the KNN approach, we determined the number of neighbors as 4.

DELAY CLASSIFICATION

• Delays may occur in the departure and arrival times of a plane. We classified delays by 15 minutes so that customers are less affected by these delays.

FLIGHT RANGE CALCULATIONS

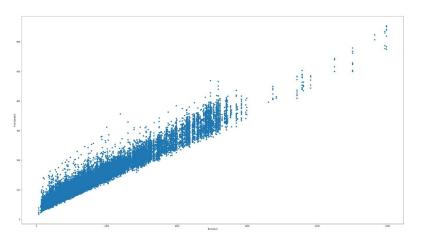
Air Time: Arrival time of the plane from one point to another point Taxi In & Taxi Out: The time passengers spend on and off the plane

Air Time + Taxi In + Taxi Out= Flight Length

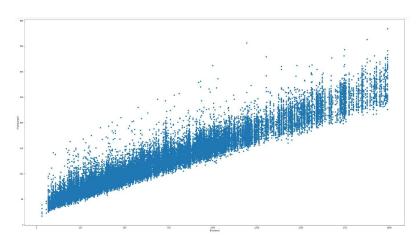
We combined flight information, which is an important detail for a customer, in a single column, resulting in a more understandable result.

DETECTED OUTLIERS



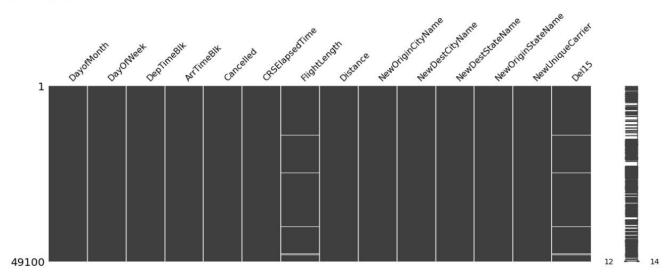


AFTER

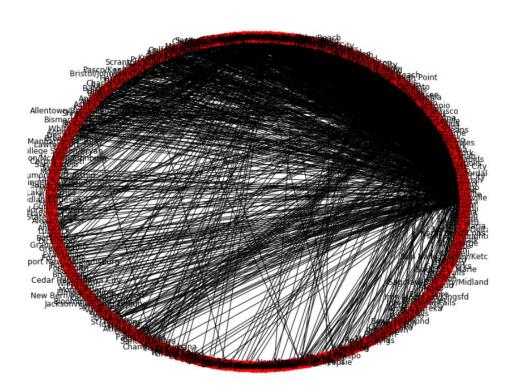


NaN Values for Mining Dataset

<AxesSubplot:>



Roads between cities with no distance



Datasets after Preprocessing

• Dataset of the Data Mining Side

Data	columns (total 14 c	olumns):	
#	Column	Non-Null Count	Dtype
0	DayofMonth	46130 non-null	int32
1	DayOfWeek	46130 non-null	int32
2	DepTimeBlk	46130 non-null	int32
3	ArrTimeBlk	46130 non-null	int32
4	Cancelled	46130 non-null	int32
5	CRSElapsedTime	46130 non-null	int32
6	FlightLength	46130 non-null	int32
7	Distance	46130 non-null	int32
8	NewOriginCityName	46130 non-null	int32
9	NewDestCityName	46130 non-null	int32
10	NewDestStateName	46130 non-null	int32
11	NewOriginStateName	46130 non-null	int32
12	NewUniqueCarrier	46130 non-null	int32
13	Del15	46130 non-null	int32
dtype	es: int32(14)		
memoi	ry usage: 2.8 MB		

- Support Vector Machine
- Logistic Regression
- k Nearest Neighbours

(SUPPORT VECTOR MACHINE)

```
cv = KFold(n_splits=10, random_state=1, shuffle=True)

# create model

model = svm.SVC(kernel='poly', C=100.0)

# evaluate model

scores = cross_val_score(model, X, y, scoring='accuracy', cv=cv, n_jobs=-1)

# report performance

print('Accuracy: %.3f (%.3f)' % (np.mean(scores), np.std(scores)))

w
```

		precision	recall	f1-score	support
	0	0.89	1.00	0.94	3639
	1	1.00	0.54	0.70	974
accur	racy			0.90	4613
macro	avg	0.95	0.77	0.82	4613
eighted	avg	0.91	0.90	0.89	4613

Accuracy: 0.899 (0.004)

(LOGISTIC REGRESSION)

```
cv = KFold(n_splits=10, random_state=1, shuffle=True)
# create model
model = LogisticRegression()
# evaluate model
scores = cross_val_score(model, X, y, scoring='accuracy', cv=cv, n_jobs=-1)
# report performance
print('Accuracy: %.3f (%.3f)' % (np.mean(scores), np.std(scores)))
```

Accuracy: 0.865 (0.014)

	precision	recall	f1-score	support
0	0.87	0.94	0.90	3639
1	0.69	0.46	0.55	974
accuracy			0.84	4613
macro avg	0.78	0.70	0.73	4613
weighted avg	0.83	0.84	0.83	4613

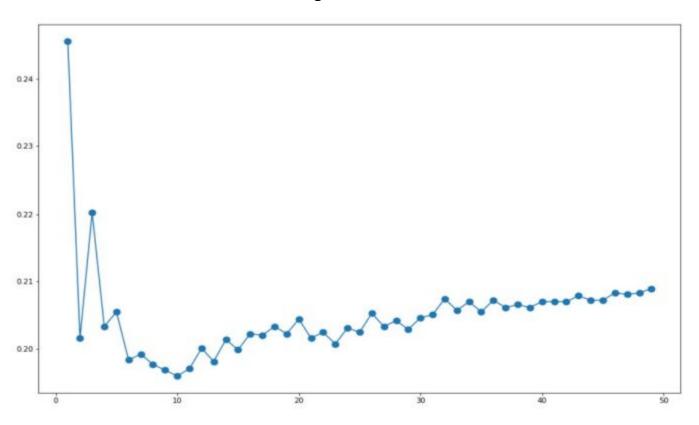
(K - NEAREST NEIGHBOURS)

```
cv = KFold(n_splits=10, random_state=1, shuffle=True)
# create model
model = KNeighborsClassifier(n_neighbors = 10)
# evaluate model
scores = cross_val_score(model, X, y, scoring='accuracy', cv=cv, n_jobs=-1)
# report performance
print('Accuracy: %.3f (%.3f)' % (np.mean(scores), np.std(scores)))
```

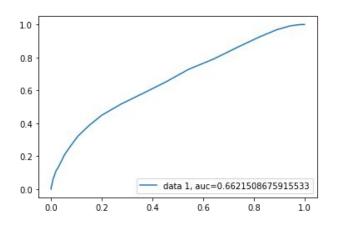
	precision	recall	f1-score	support
0	0.82	0.95	0.88	3639
1	0.54	0.24	0.33	974
accuracy			0.80	4613
macro avg	0.68	0.59	0.60	4613
weighted avg	0.76	0.80	0.76	4613

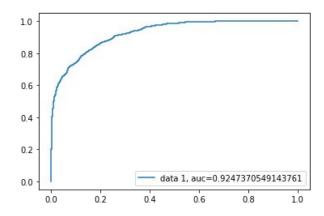
Accuracy: 0.798 (0.006)

Finding Best Fit K Value



ROC CURVES





KNeighbors

LogReg

THANKS FOR LISTENING!

