Assignment 3: Group 11

FlightDelays dataset

Goal: Accurately predict whether or not a new flight will be delayed (outcome 1 = delayed and 0 = on time).
Data: 2001 record with 5 predictors. All flights from the Washington, DC area into the New Your City area during January 2004.

Variables in the dataset:

CRS_DEP_TIME: Computer Reservation Systems departure Time
CARRIER: Airlines
DEP_TIME: Actual Departure time
DEST: Destination Airport
DISTANCE: Distance travelled by flight
FL_DATE: Flight date
FL_NUM: Flight Number
ORIGIN: Origin Airport
Weather: Weather conditions
DAY_WEEK: Weekdays starting from 1 to 7, 1 = Monday, 2 = Tuesday, 3 = Wednesday..., 7 = Sunday
DAY_OF_MONTH: Day of a month
TAIL_NUM: Tail number
Flight Status: Status of the flight that is ontime or delayed.

In [50]:

```
#Importing Libraries

import numpy as np
import math
import pandas as pd
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import accuracy_score , roc_curve , auc
import matplotlib.pylab as plt
from dmba import regressionSummary , classificationSummary
from dmba import liftChart , gainsChart
from sklearn.naive_bayes import MultinomialNB
from sklearn.tree import export_graphviz
import graphviz
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.linear_model import LogisticRegression
```

In [2]:
```
# Reading the dataset
flight_df = pd.read_csv("FlightDelays.csv")
flight_df.sample(10)
```

Out[2]:

	CRS_DEP_TIME	CARRIER	DEP_TIME	DEST	DISTANCE	FL_DATE	FL_NUM	ORIGI
1985	1455	OH	1455	JFK	184	1/29/2004	5935	BV
1333	630	DH	627	EWR	213	1/19/2004	7305	IA
2005	1230	DL	1230	LGA	214	1/29/2004	1752	DC
1043	1400	MQ	1400	LGA	214	1/15/2004	4966	DC
1040	800	MQ	800	LGA	214	1/15/2004	4954	DC
1049	630	US	627	LGA	214	1/15/2004	1479	DC
19	1830	MQ	1822	JFK	213	01/01/2004	4784	DC
1126	1000	US	958	LGA	214	1/16/2004	2166	DC
1563	800	US	754	LGA	214	1/22/2004	2162	DC
1566	1100	US	1055	LGA	214	1/22/2004	2168	DC

In [3]:
```
#Displaying all columns
flight_df.columns
```

Out[3]:
```
Index(['CRS_DEP_TIME', 'CARRIER', 'DEP_TIME', 'DEST', 'DISTANCE', 'FL_DAT
E',
       'FL_NUM', 'ORIGIN', 'Weather', 'DAY_WEEK', 'DAY_OF_MONTH', 'TAIL_N
UM',
       'Flight Status'],
      dtype='object')
```

In [4]:
```
flight_df.dtypes
```

Out[4]:
```
CRS_DEP_TIME      int64
CARRIER          object
DEP_TIME          int64
DEST             object
DISTANCE          int64
FL_DATE          object
FL_NUM            int64
ORIGIN           object
Weather           int64
DAY_WEEK          int64
DAY_OF_MONTH      int64
TAIL_NUM         object
Flight Status    object
dtype: object
```

Target Variable - Flight Status: ontime or delayed

In [5]:
```
flight_df['Flight Status'].unique()
```

Out[5]:
```
array(['ontime', 'delayed'], dtype=object)
```

A. Which variables are quantitative/numerical? Which are ordinal? Which are nominal?

From the variables listed above:

Quantitative/Numerical Variables:

CRS_DEP_TIME (Integer)
DEP_TIME (Integer)
DISTANCE (Integer)
FL_NUM (Integer)
Weather (Integer)
DAY_WEEK (Integer)
DAY_OF_MONTH (Integer)

Categorical Variables:

Nominal Variables:

CARRIER (String)
DEST (String)
FL_DATE (String)
ORIGIN (String)
TAIL_NUM (String)
Flight Status (Boolean)

In [6]:

```
flight_df.describe()
```

Out[6]:

	CRS_DEP_TIME	DEP_TIME	DISTANCE	FL_NUM	Weather	DAY_WEEK
count	2201.000000	2201.000000	2201.000000	2201.000000	2201.000000	2201.000000
mean	1371.938664	1369.298955	211.871422	3815.086324	0.014539	3.905498
std	432.697149	442.462754	13.316815	2409.750224	0.119725	1.903149
min	600.000000	10.000000	169.000000	746.000000	0.000000	1.000000
25%	1000.000000	1004.000000	213.000000	2156.000000	0.000000	2.000000
50%	1455.000000	1450.000000	214.000000	2385.000000	0.000000	4.000000
75%	1710.000000	1709.000000	214.000000	6155.000000	0.000000	5.000000
max	2130.000000	2330.000000	229.000000	7924.000000	1.000000	7.000000

In [7]:

```
#Creating a subset dataframe with only numerical variables for statistical
subset_flight_df = flight_df[["CRS_DEP_TIME", "DEP_TIME", "DISTANCE", "FL_
subset_flight_df.head()
```

Out[7]:

	CRS_DEP_TIME	DEP_TIME	DISTANCE	FL_NUM	Weather	DAY_WEEK	DAY_OF_MONTH
0	1455	1455	184	5935	0	4	1
1	1640	1640	213	6155	0	4	1
2	1245	1245	229	7208	0	4	1
3	1715	1709	229	7215	0	4	1
4	1039	1035	229	7792	0	4	1

A. Data Preprocessing

Do some statistics on the variables

In [8]:

```
#Compute mean, standard deviation, min, max, median, length, and missing v

pd.DataFrame({'mean': subset_flight_df.mean(),
                'Sd': subset_flight_df.std(),
                'min': subset_flight_df.min(),
                'max': subset_flight_df.max(),
                'median': subset_flight_df.median(),
                'length': len(subset_flight_df),
                'miss.val': subset_flight_df.isnull().sum(),
                })
```

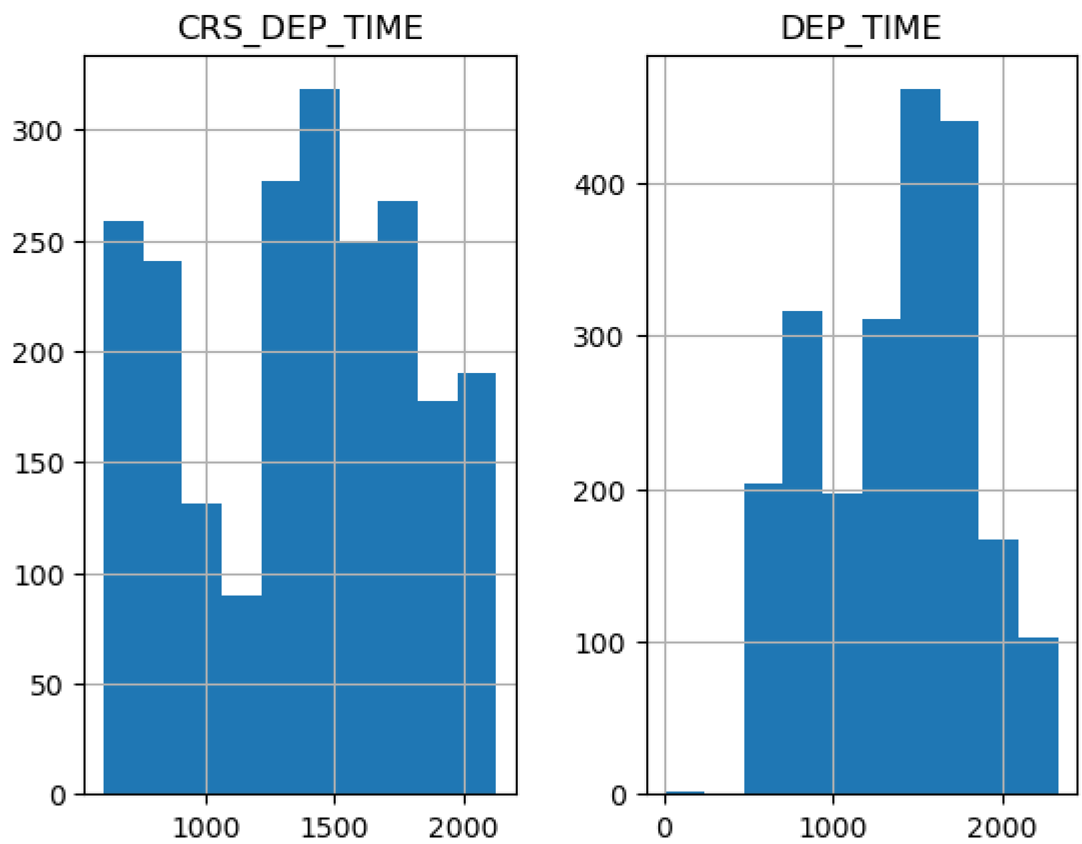
Out[8]:

	mean	Sd	min	max	median	length	miss.val
CRS_DEP_TIME	1371.938664	432.697149	600	2130	1455.0	2201	0
DEP_TIME	1369.298955	442.462754	10	2330	1450.0	2201	0
DISTANCE	211.871422	13.316815	169	229	214.0	2201	0
FL_NUM	3815.086324	2409.750224	746	7924	2385.0	2201	0
Weather	0.014539	0.119725	0	1	0.0	2201	0
DAY_WEEK	3.905498	1.903149	1	7	4.0	2201	0
DAY_OF_MONTH	16.024989	8.677390	1	31	16.0	2201	0

C. Using histogram and summary statistics

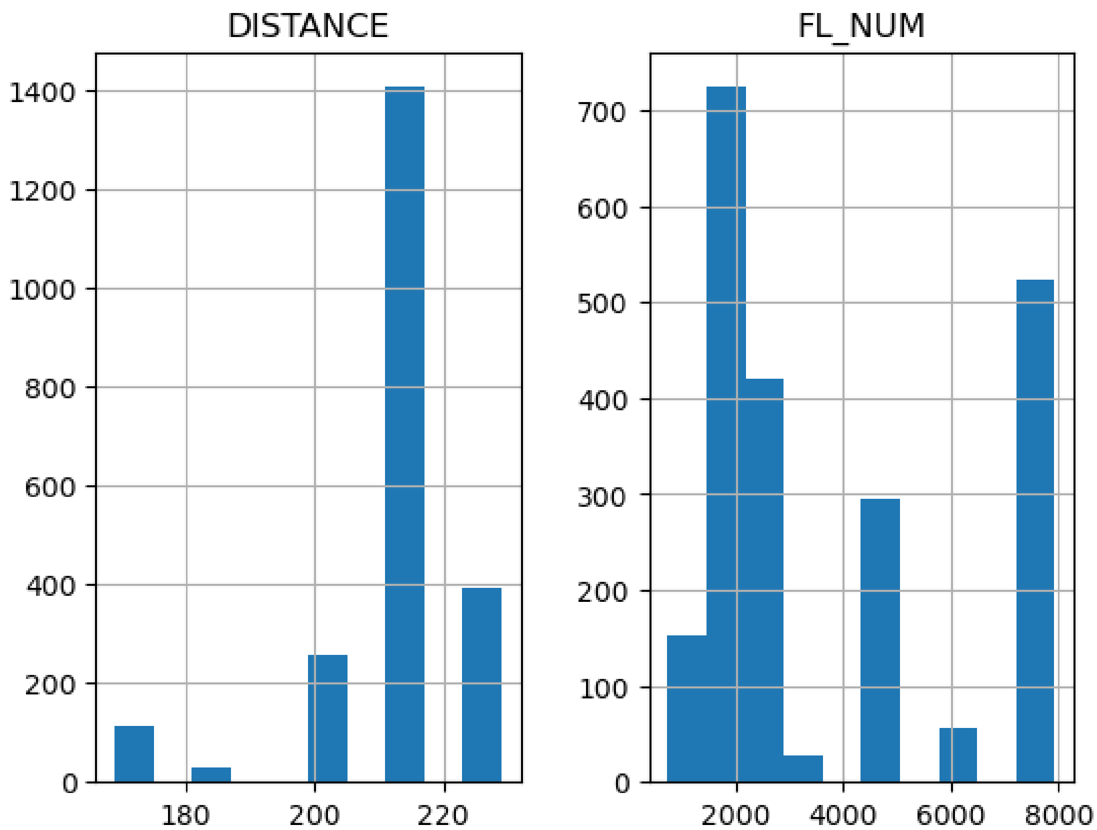
In [9]:

```
fig, axes = plt.subplots(1, 2)

subset_flight_df.hist('CRS_DEP_TIME', ax=axes[0])
subset_flight_df.hist('DEP_TIME', ax=axes[1])

plt.show()
```



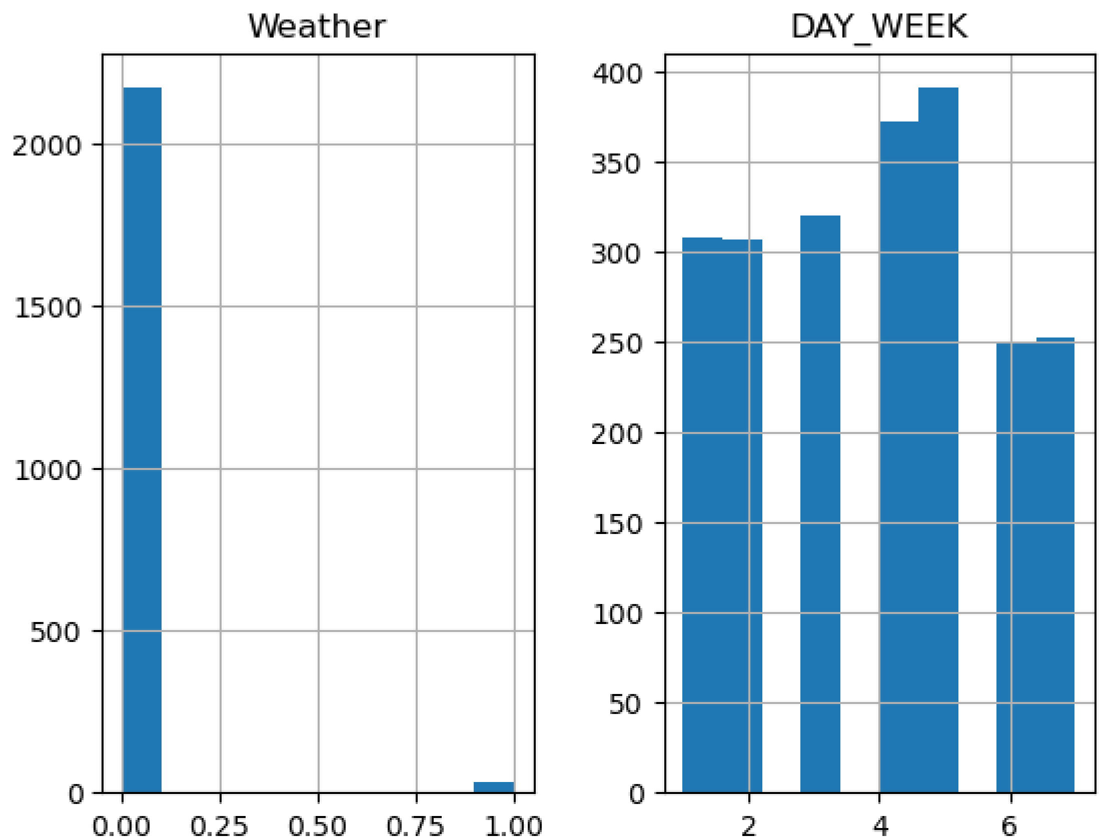
In [10]:

```
fig, axes = plt.subplots(1, 2)

subset_flight_df.hist('DISTANCE', ax=axes[0])
subset_flight_df.hist('FL_NUM', ax=axes[1])
plt.show()
```

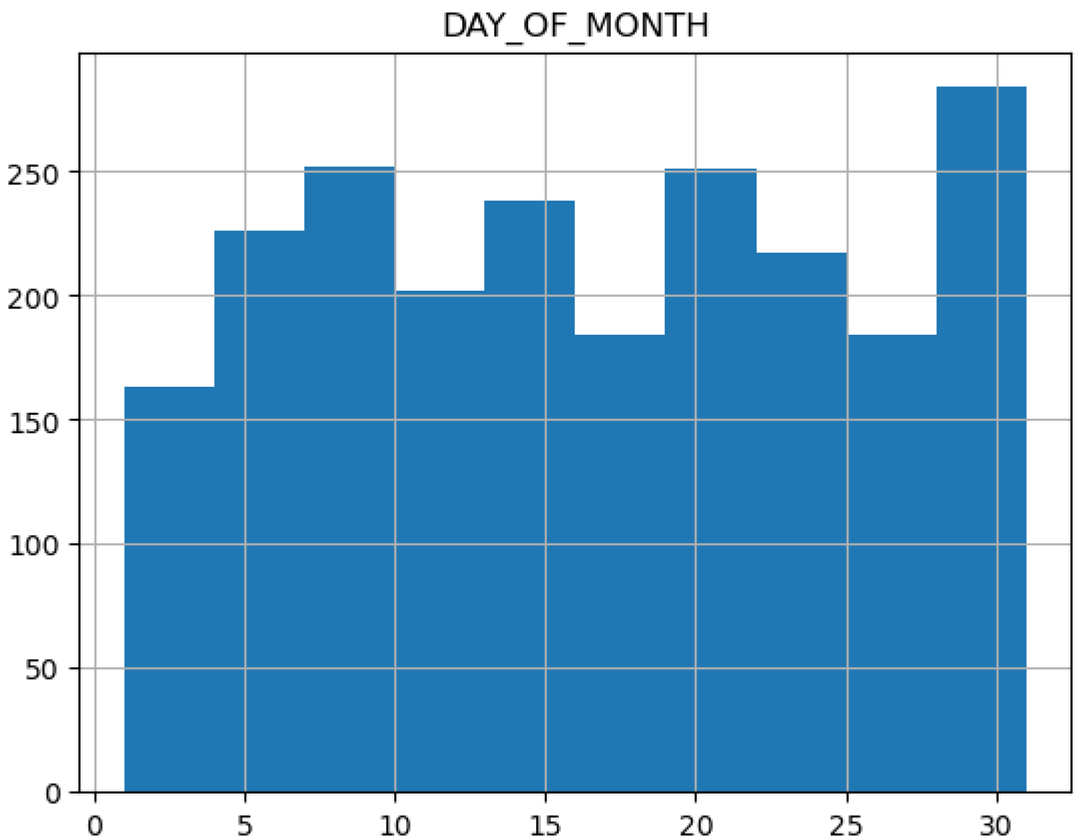


In [11]:

```
fig, axes = plt.subplots(1, 2)

subset_flight_df.hist('Weather', ax=axes[0])
subset_flight_df.hist('DAY_WEEK', ax=axes[1])
plt.show()
```



In [12]:
```
subset_flight_df.hist('DAY_OF_MONTH')
plt.show()
```

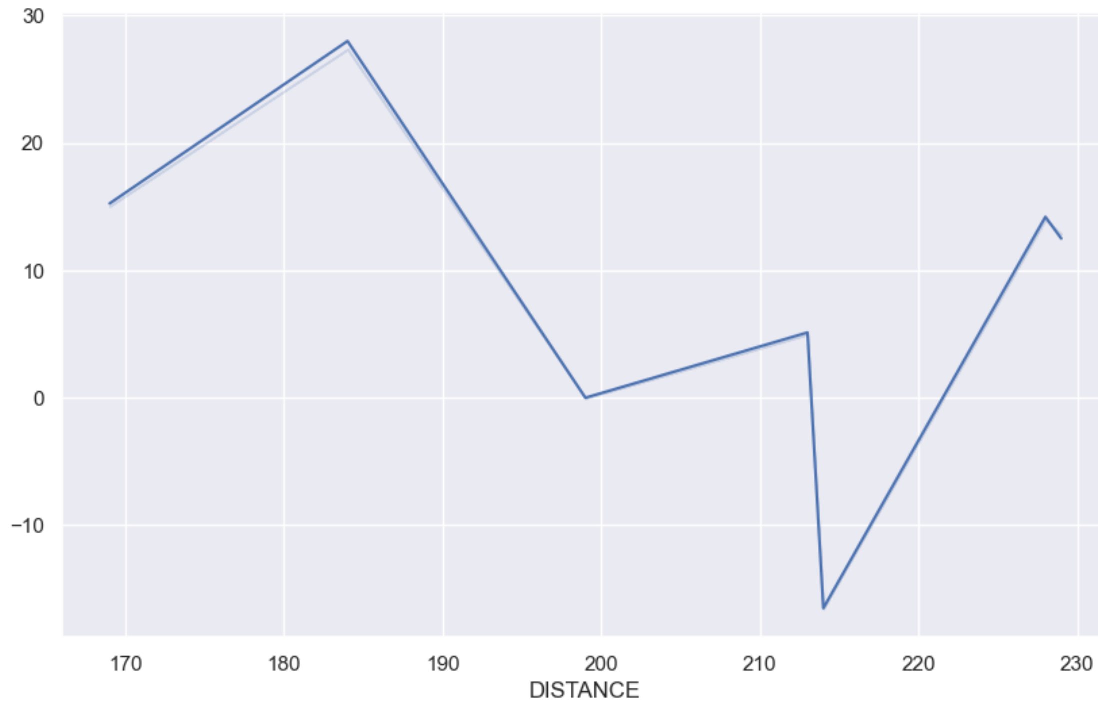


Using different plots to compare between variables.

1. What is the relation of Delay and Distance of a flight of our Dataset?

In [13]:
```
sns.set(rc={"figure.figsize":(10, 6)})
sns.lineplot(x=subset_flight_df['DISTANCE'], y=(subset_flight_df['DEP_TIME
```

Out[13]: <AxesSubplot:xlabel='DISTANCE'>



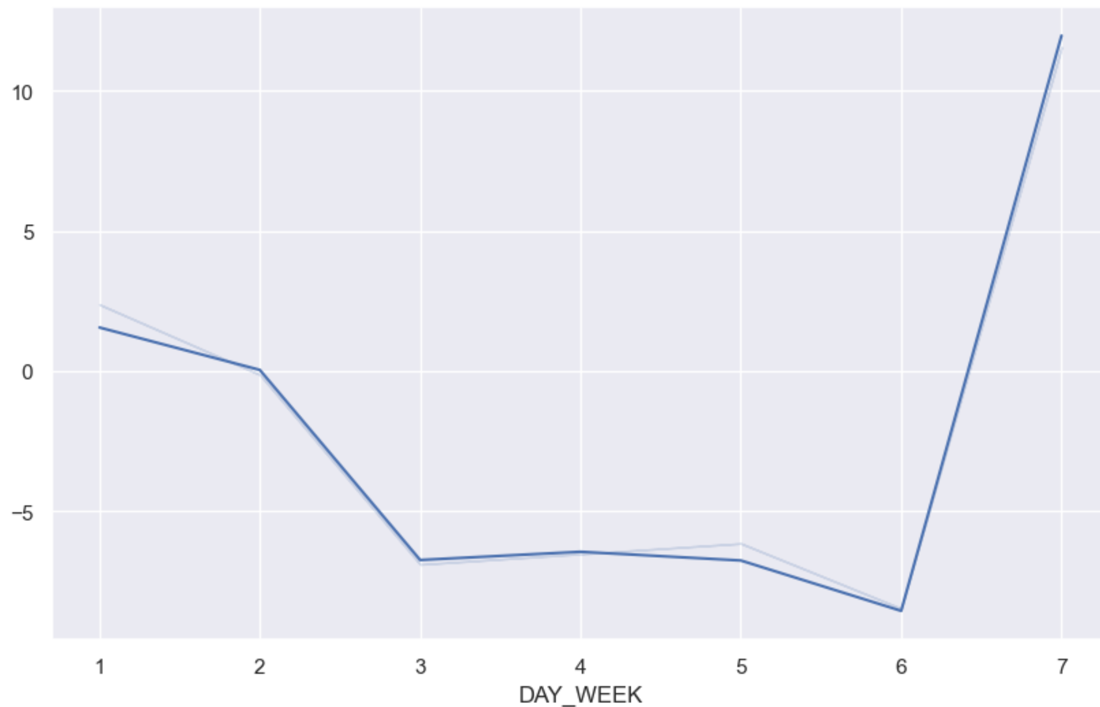
The figure above shows the delay is higher for the flights at smaller disctance rather than the flights at longer distance.

This makes sense as generally short distance flights are generally the cheaper flights, which run a jam packed schedule which creates a threat of delay even as there is a very cool down period between each journey.

2. Which day of the week witnesses the highest delay.

In [14]:
```
sns.lineplot(x=subset_flight_df['DAY_WEEK'],y=(subset_flight_df['DEP_TIME'
```

Out[14]: <AxesSubplot:xlabel='DAY_WEEK'>



We can see according to our data most of the delay happens on 7th day of the week, i.e. Sunmday

Correlation between Quantitative variables

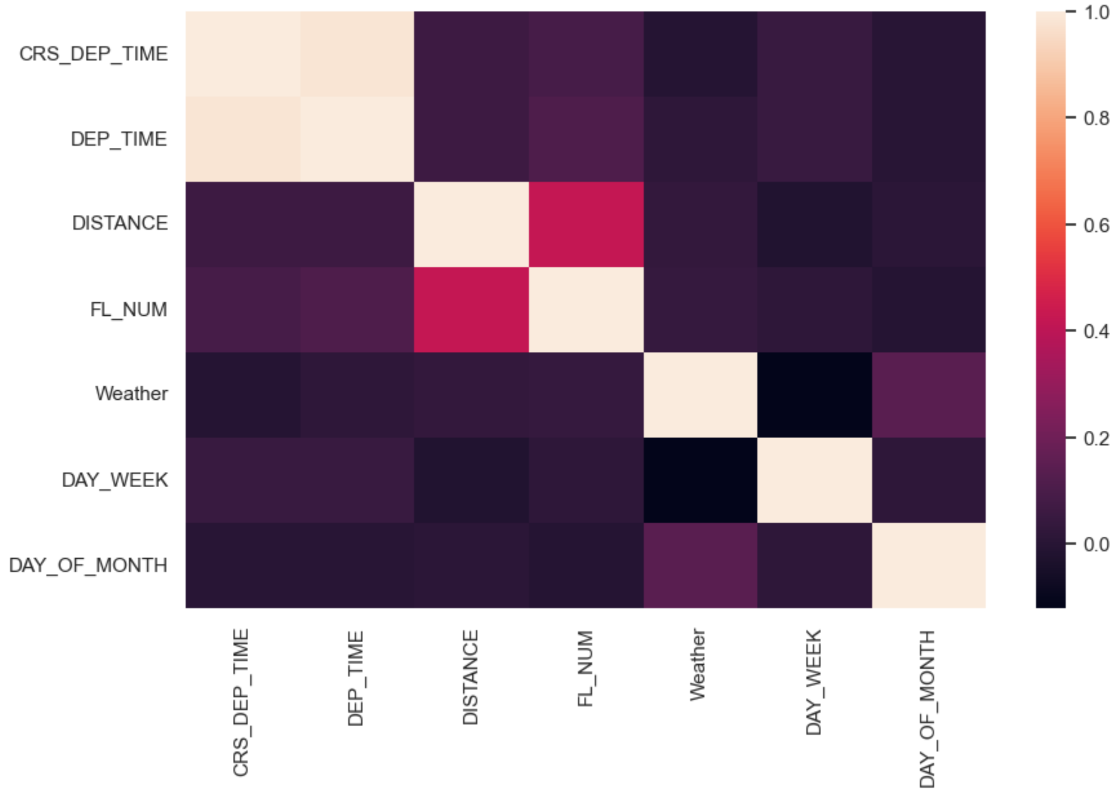
In [15]:
```
# Checking correlation between variables using corr() function

subset_flight_df.corr().round(2)
```

Out[15]:

	CRS_DEP_TIME	DEP_TIME	DISTANCE	FL_NUM	Weather	DAY_WEEK	D
CRS_DEP_TIME	1.00	0.98	0.06	0.09	-0.01	0.05	
DEP_TIME	0.98	1.00	0.06	0.11	0.02	0.05	
DISTANCE	0.06	0.06	1.00	0.42	0.03	-0.02	
FL_NUM	0.09	0.11	0.42	1.00	0.04	0.02	
Weather	-0.01	0.02	0.03	0.04	1.00	-0.12	
DAY_WEEK	0.05	0.05	-0.02	0.02	-0.12	1.00	
DAY_OF_MONTH	0.00	0.00	0.01	-0.01	0.14	0.02	

In [16]:
```
# Using seaborn
# Simple heatmap of correlations (without values)

import seaborn as sns
corr = subset_flight_df.corr().round(2)
sns.heatmap(corr)
```

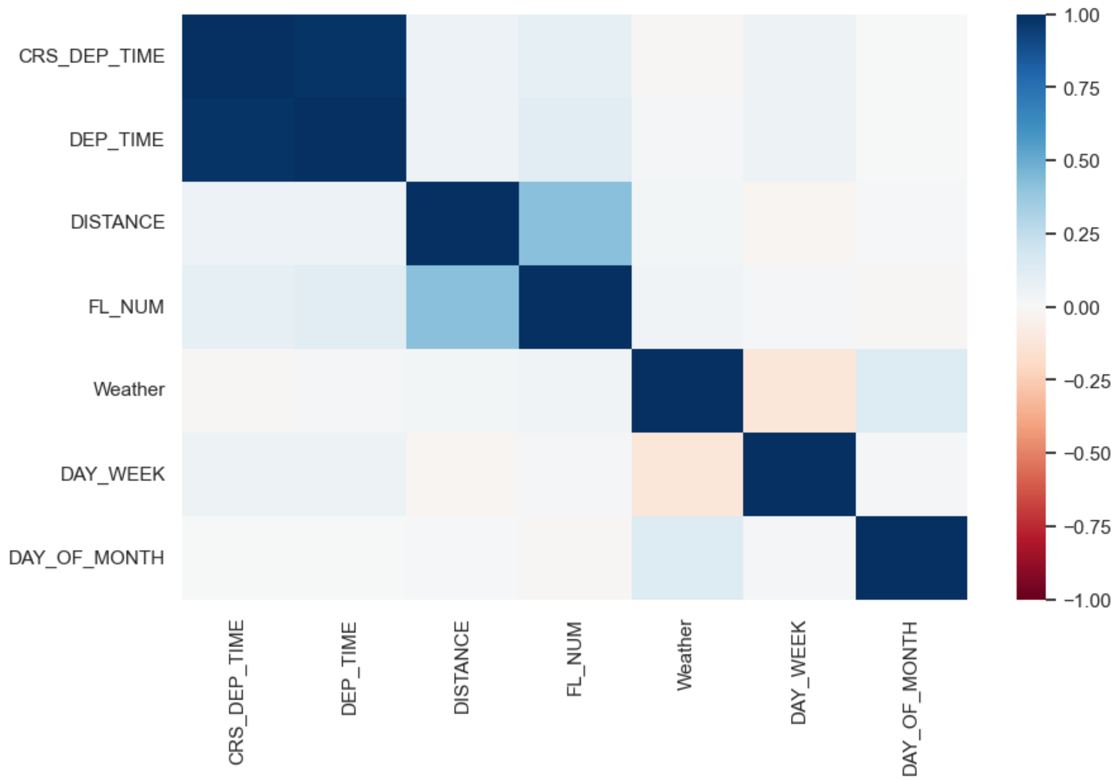
Out[16]: <AxesSubplot:>



In [17]:

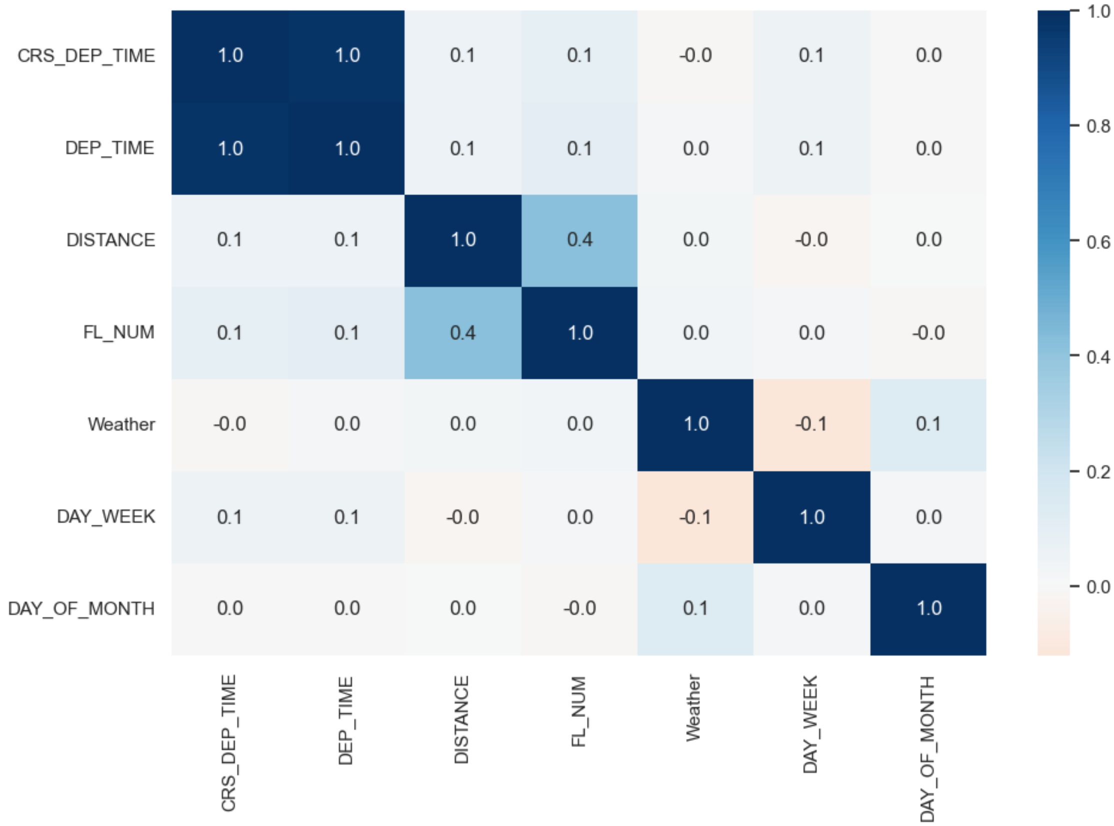
```
# Change to divergent scale and fix the range

sns.heatmap(corr, xticklabels=corr.columns, yticklabels=corr.columns, vmin
            vmax=1, cmap="RdBu")
```

Out[17]: <AxesSubplot:>



In [18]:
```
# Include information about values (example demonstrates how to control th
fig, ax = plt.subplots()
fig.set_size_inches(11, 7)
sns.heatmap(corr, annot=True, fmt=".1f", cmap="RdBu", center=0, ax=ax)
```

Out[18]: <AxesSubplot:>



Correlation between variables:

1. 'CRS_DEP_TIME' and 'DEP_TIME' are strongly correlated with a positive correlation of 1.0 (100% correlation)

PCA (Principle Component Analysis)

In [19]:
```
#Applying PCA

from sklearn.decomposition import PCA
pcs = PCA(n_components=2)
pcs.fit(subset_flight_df)
```

Out[19]: PCA(n_components=2)

In [20]:
```
# To explain the PCA use:
pcs.explained_variance_ratio_
```

Out[20]:
```
array([0.9387127 , 0.06074699])
```

Removing the Correlated Variables

In [21]:
```
flight_df = flight_df.drop(columns=['CRS_DEP_TIME'])
flight_df.columns
```

Out[21]:
```
Index(['CARRIER', 'DEP_TIME', 'DEST', 'DISTANCE', 'FL_DATE', 'FL_NUM',
       'ORIGIN', 'Weather', 'DAY_WEEK', 'DAY_OF_MONTH', 'TAIL_NUM',
       'Flight Status'],
      dtype='object')
```

In [22]:
```
flight_df.shape
```

Out[22]:
```
(2201, 12)
```

In [23]:
```
flight_df.sample(10)
```

Out[23]:

	CARRIER	DEP_TIME	DEST	DISTANCE	FL_DATE	FL_NUM	ORIGIN	Weather	DAY
1301	MQ	1559	LGA	214	1/19/2004	4970	DCA	0	
1127	US	1059	LGA	214	1/16/2004	2168	DCA	0	
1449	DL	931	LGA	214	1/21/2004	1746	DCA	0	
329	DL	1629	LGA	214	01/06/2004	1760	DCA	0	
2013	DL	2031	LGA	214	1/29/2004	1768	DCA	0	
1659	RU	1032	EWR	169	1/23/2004	2303	BWI	0	
1313	US	1353	LGA	214	1/19/2004	2174	DCA	0	
287	CO	1846	EWR	199	01/05/2004	814	DCA	0	
2065	RU	857	EWR	199	1/29/2004	2582	DCA	0	
426	MQ	1352	LGA	214	01/07/2004	4966	DCA	0	

In [24]:
```
#Split the data into training (60%) and testing (40%)

predictors = ['CARRIER', 'DEP_TIME', 'DEST', 'DISTANCE', 'FL_DATE', 'FL_NU
              'DAY_OF_MONTH', 'TAIL_NUM']
outcome = 'Flight Status'

X = pd.get_dummies(flight_df[predictors],drop_first=True)
y = flight_df[outcome]
classes = ['ontime', 'delayed']


# split into training and validation
X_train, X_valid, y_train, y_valid = train_test_split(X, y, test_size=0.4,
```

In [25]:
```
X_train.head(10)
```

Out[25]:

	DEP_TIME	DISTANCE	FL_NUM	Weather	DAY_WEEK	DAY_OF_MONTH	CARRIER_DI
1215	2110	229	7684	0	7	18	
1476	659	214	2160	0	3	21	
1897	858	214	2164	0	2	27	
83	1258	214	2172	0	5	2	
1172	1509	213	746	0	6	17	
1720	1252	199	808	0	6	24	
1816	929	214	1746	0	1	26	
1544	1831	214	1764	0	4	22	
2065	857	199	2582	0	4	29	
427	1457	214	4968	0	3	7	

10 rows × 595 columns

In [26]:
```
X_train.columns
```

Out[26]:
```
Index(['DEP_TIME', 'DISTANCE', 'FL_NUM', 'Weather', 'DAY_WEEK', 'DAY_OF_M
ONTH',
       'CARRIER_DH', 'CARRIER_DL', 'CARRIER_MQ', 'CARRIER_OH',
       ...
       'TAIL_NUM_N970DL', 'TAIL_NUM_N973CA', 'TAIL_NUM_N974DL',
       'TAIL_NUM_N975CA', 'TAIL_NUM_N983CA', 'TAIL_NUM_N986DL',
       'TAIL_NUM_N987DL', 'TAIL_NUM_N994DL', 'TAIL_NUM_N995CA',
       'TAIL_NUM_N997DL'],
      dtype='object', length=595)
```

In [27]:
```
X_train.shape
```

Out[27]:
```
(1320, 595)
```

B. K-Nearest Neighbors and Naive Bayes Classifier comparison

Naive Bayes Algorithm

In [28]:

```
# run naive Bayes
flight_nb = MultinomialNB(alpha=0.01)
flight_nb.fit(X_train, y_train)

# predict probabilities (Shows the belonging probabilities of each record
predProb_train = flight_nb.predict_proba(X_train)
predProb_valid = flight_nb.predict_proba(X_valid)

# predict class membership (shows the class instead of probability by sele
y_valid_pred = flight_nb.predict(X_valid)
y_train_pred = flight_nb.predict(X_train)
```

In [29]:

```
# Use the model to predict a new data

df = pd.concat([pd.DataFrame({'actual': y_valid, 'predicted': y_valid_pred
df.head(10)
```

Out[29]:

	actual	predicted
1276	ontime	delayed
1446	ontime	ontime
335	ontime	delayed
1458	ontime	ontime
2038	ontime	ontime
1314	ontime	ontime
389	ontime	delayed
1639	ontime	delayed
2004	ontime	ontime
403	ontime	ontime

In [30]:

```
from sklearn.metrics import accuracy_score, precision_score, recall_score,
# Calculate accuracy, precision, recall, and F1-score on the test data
accuracy = accuracy_score(y_valid, y_valid_pred)

precision = precision_score(y_valid, y_valid_pred, average='weighted')
recall = recall_score(y_valid, y_valid_pred, average='weighted')
f1 = f1_score(y_valid, y_valid_pred, average='weighted')
```

In [31]:
```
print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
print("F1-score:", f1)
```

```
Accuracy: 0.5845629965947786
Precision: 0.7189401801847995
Recall: 0.5845629965947786
F1-score: 0.6282279026455564
```

K-Nearest Neigbhor (KNN) Algorithm

In [32]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix
```

In [33]:
```
knn = KNeighborsClassifier(n_neighbors=3)
```

In [34]:
```
knn.fit(X_train, y_train)
```

Out[34]:
```
KNeighborsClassifier(n_neighbors=3)
```

In [35]:
```
y_pred_knn = knn.predict(X_valid)
```

```
C:\Users\sidha\anaconda3\lib\site-packages\sklearn\neighbors\_classificat
ion.py:228: FutureWarning: Unlike other reduction functions (e.g. `skew`,
`kurtosis`), the default behavior of `mode` typically preserves the axis
it acts along. In SciPy 1.11.0, this behavior will change: the default va
lue of `keepdims` will become False, the `axis` over which the statistic
is taken will be eliminated, and the value None will no longer be accepte
d. Set `keepdims` to True or False to avoid this warning.
  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
```

In [36]:
```
y_pred_knn
```

Out[36]:
```
array(['ontime', 'ontime', 'ontime', 'ontime', 'ontime', 'ontime',
       'ontime', 'ontime', 'ontime', 'delayed', 'ontime', 'ontime',
       'ontime', 'ontime', 'delayed', 'ontime', 'delayed', 'ontime',
       'ontime', 'ontime', 'ontime', 'ontime', 'ontime', 'ontime',
       'ontime', 'ontime', 'ontime', 'ontime', 'ontime', 'ontime',
       'ontime', 'ontime', 'ontime', 'ontime', 'delayed', 'ontime',
       'ontime', 'ontime', 'ontime', 'ontime', 'ontime', 'ontime',
       'ontime', 'delayed', 'ontime', 'ontime', 'delayed', 'ontime',
       'ontime', 'delayed', 'delayed', 'ontime', 'ontime', 'ontime',
       'ontime', 'ontime', 'ontime', 'ontime', 'ontime', 'delayed',
       'ontime', 'ontime', 'ontime', 'ontime', 'ontime', 'ontime',
       'ontime', 'ontime', 'ontime', 'ontime', 'ontime', 'ontime',
       'ontime', 'ontime', 'ontime', 'ontime', 'ontime', 'ontime',
       'ontime', 'ontime', 'ontime', 'ontime', 'ontime', 'ontime',
       'ontime', 'ontime', 'ontime', 'ontime', 'ontime', 'ontime',
       'ontime', 'ontime', 'ontime', 'ontime', 'ontime', 'ontime',
       'delayed', 'ontime', 'ontime', 'ontime', 'ontime', 'ontime',
       'delayed', 'ontime', 'ontime', 'ontime', 'ontime', 'ontime',
       'delayed', 'ontime', 'ontime', 'ontime', 'ontime', 'ontime',
```

Accuracy Measures

Accuracy: The proportion of correctly classified samples out of the total number of samples. It is calculated as accuracy = (TP + TN) / (TP + TN + FP + FN), where TP is the number of true positives, TN is the number of true negatives, FP is the number of false positives, and FN is the number of false negatives.

Precision: The proportion of true positives out of the total number of positive predictions. It is calculated as precision = TP / (TP + FP).

Recall (Sensitivity): The proportion of true positives out of the total number of actual positive samples. It is calculated as recall = TP / (TP + FN).

F1-score: The harmonic mean of precision and recall. It is calculated as F1 = 2 * (precision * recall) / (precision + recall).

KNN: Confusion Matrix

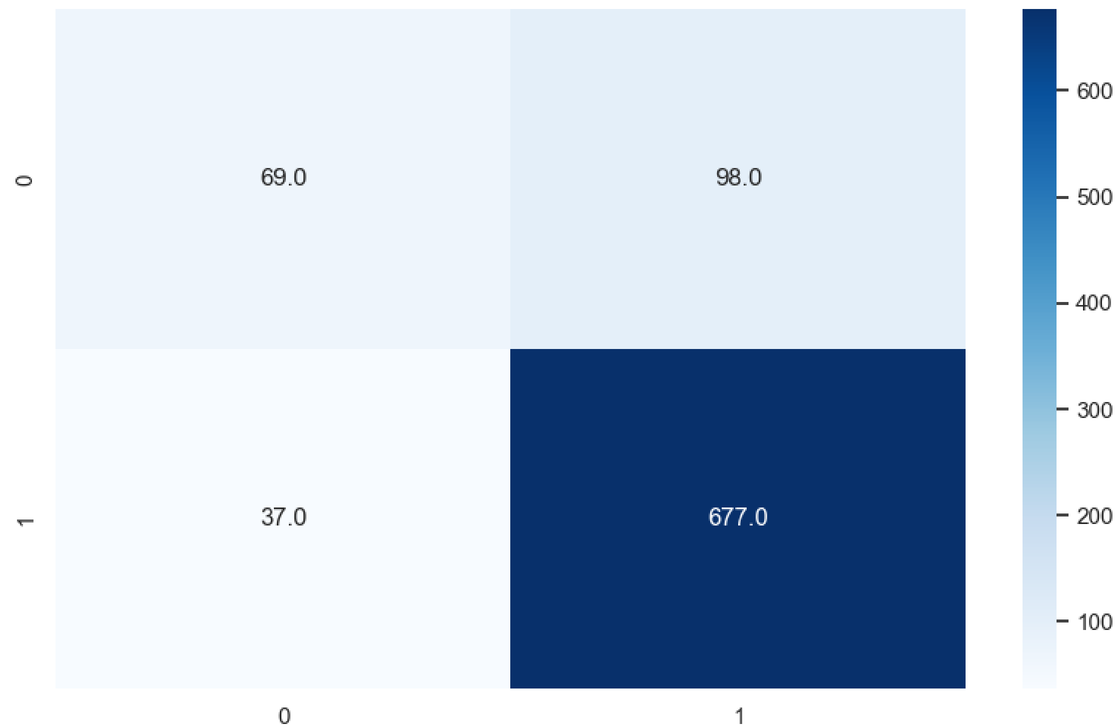
In [37]:
```
cm_knn = confusion_matrix(y_valid, y_pred_knn)
```

In [38]:
```
print(cm_knn)
```

```
[[ 69  98]
 [ 37 677]]
```

In [39]:
```
sns.heatmap(cm_knn,annot=True,cmap = 'Blues', fmt = '0.1f')
```

Out[39]:
```
<AxesSubplot:>
```



Naive Bayes: Confusion Matrix

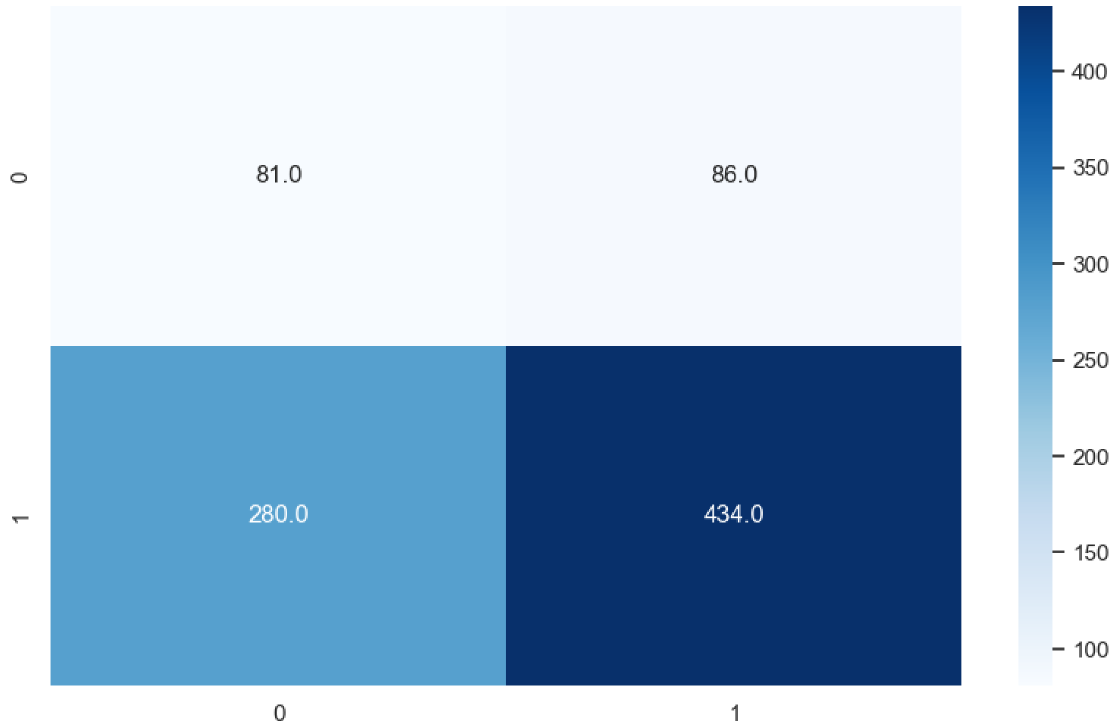
In [40]:
```
cm_nb= confusion_matrix(y_valid,y_valid_pred)
```

In [41]:
```
cm_nb
```

Out[41]:
```
array([[ 81,  86],
       [280, 434]], dtype=int64)
```

In [42]:
```
sns.heatmap(cm_nb,annot=True,cmap = 'Blues', fmt = '0.1f')
```

Out[42]: <AxesSubplot:>



In [43]:
```
Accuracy_Knn = (69+677)/(69+98+37+677)
Precision_knn = 69/(69+37)
Recall_knn = 69/(69+98)
F1_Score_knn = 2*Precision_knn*Recall_knn/(Precision_knn+Recall_knn)
```

In [44]:
```
Accuracy_nb = (81+434)/(81+86+280+434)
Precision_nb = 81/(81+280)
Recall_nb = 81/(81+86)
F1_Score_nb = 2*Precision_nb*Recall_nb/(Precision_nb+Recall_nb)
```

In [45]:
```
acc_score = {"Parameter": ['Accuracy','Precision','Recall','F1-Score'], "N
             "KNN": [Accuracy_Knn,Precision_knn,Recall_knn,F1_Score_knn]}
```

In [46]:
```
acc_score = pd.DataFrame(acc_score)
```

In [47]:
```
acc_score
```

Out[47]:

	Parameter	Naive Bayes	KNN
0	Accuracy	0.584563	0.846765
1	Precision	0.224377	0.650943
2	Recall	0.485030	0.413174
3	F1-Score	0.306818	0.505495

Conclusion:

We ran Naive Bayes and K-Nearest Neigbhor (KNN) algorithm on Delayed Flights dataset and predicted values for a test dataset for both. After analyzing and comparing the above accuracy measure results, we can say that KNN algorithm gives far better result than Naive Bayes model on our dataset.

1. KNN model gives 84.68 % accurate prediction.
2. Naive Bayes model gives 58.46 % accurate prediction.

C. Proposing extra algorithm(s)

1. CART Algorithm

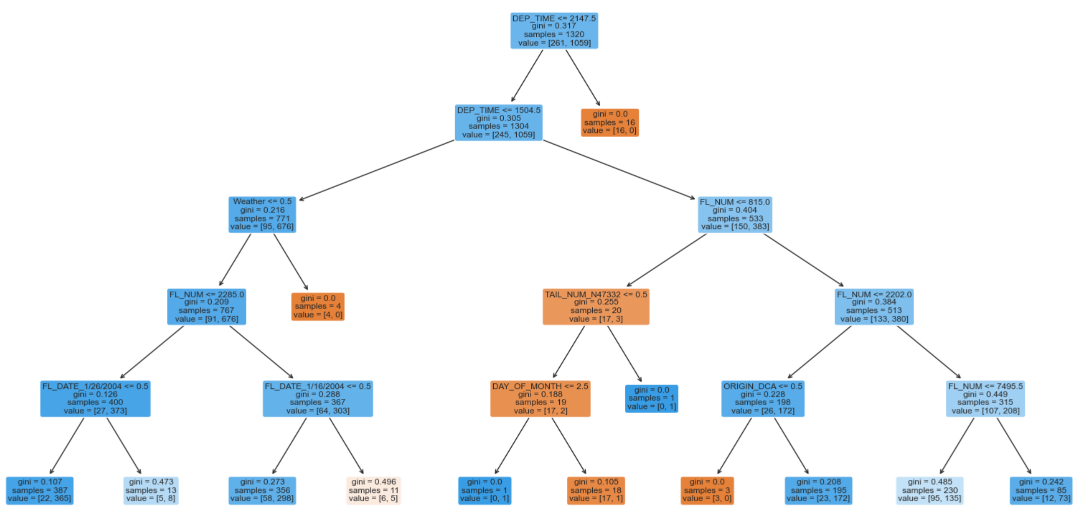
In [55]:

```
# Create the decision tree classifier and fit the data
flight_dt = DecisionTreeClassifier(max_depth=5)
flight_dt.fit(X_train, y_train)

# Predict the test data using the decision tree and calculate the accuracy
y_pred_dt = dt.predict(X_valid)
accuracy_dt = accuracy_score(y_valid, y_pred_dt)
print("Decision Tree Accuracy: ", accuracy_dt)
```

```
Decision Tree Accuracy:  0.8229284903518729
```

In [56]:

```python
# Fit a decision tree model
clf = DecisionTreeClassifier(max_depth=5)
clf.fit(X_train, y_train)

# Plot the decision tree
plt.figure(figsize=(20,10))
plot_tree(clf, filled=True, rounded=True, feature_names=X_train.columns)
plt.show()


# Generate Graphviz format file
dot_data = export_graphviz(clf, out_file=None,
                           feature_names=X_train.columns,
                           class_names=['ontime', 'delayed'],
                           filled=True, rounded=True,
                           special_characters=True)
# Convert Graphviz format to image format
graph = graphviz.Source(dot_data)
graph.format = 'png'

# Save the image to a file
graph.render('decision_tree')
```



Out[56]: 'decision_tree.png'

2. Logistic Regression

In [57]:

```
# Create the logistic regression classifier and fit the data
flight_lr = LogisticRegression()
flight_lr.fit(X_train, y_train)

# Predict the test data using logistic regression and calculate the accura
y_pred_lr = lr.predict(X_valid)
accuracy_lr = accuracy_score(y_valid, y_pred_lr)
print("Logistic Regression Accuracy: ", accuracy_lr)
```

```
Logistic Regression Accuracy:  0.8195232690124858

C:\Users\sidha\anaconda3\lib\site-packages\sklearn\linear_model\_logisti
c.py:814: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown i
n:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://s
cikit-learn.org/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-re
gression (https://scikit-learn.org/stable/modules/linear_model.html#logis
tic-regression)
  n_iter_i = _check_optimize_result(
```

Result:

After comparing the all above algorithms on the FlightDelay dataset, we can conclude that KNN is best fit model with highest accuracy.

1. KNN model gives 84.68 % accurate prediction.
2. Naive Bayes model gives 58.46 % accurate prediction.
3. CART model gives 82.29 % accurate prediction.
4. Logistic Regresion model gives 81.95 % accurate prediction.