Data Science Capstone project

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Outline

Executive Summary

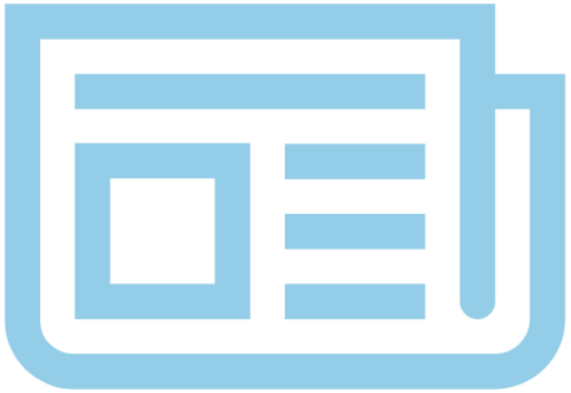
We performed exploratory data analysis (EDA) and built a predictive model to understand and predict SpaceX Falcon 9 booster landing outcomes. Data was collected from SpaceX REST API and by webscraping the SpaceX Wikipedia page. EDA showed landing successes improved with number of flights and by year. The payload mass and launch orbit also appeared to play a role in landing outcomes. All variables were converted to onehot encoding format to build predictive models. Data was converted to numpy array and transformed by the standard scaler method in SciKitLearn. GridSearchCV method was used to search the best model parameters to predict Falcon 9 booster landings. Decision tree was the most accurate model for our prediction. The decision model incorporated landing pad, landing legs, booster version, flight number, and launch orbit as the most important variables for prediction.

Introduction

- In this capstone, we create a model to predict if the SpaceX Falcon 9 first stage will land successfully. SpaceX advertises Falcon 9 rocket launches on its website with a cost of 62 million dollars; other providers cost upward of 165 million dollars each, much of the savings is because SpaceX can reuse the first stage. Therefore, if we can determine if the first stage will land, we can determine the cost of a launch. This information can be used if an alternate company wants to bid against SpaceX for a rocket launch.

- We explore a variety of predictive models to determine the best way to predict Falcon 9 booster landing.

Methodology

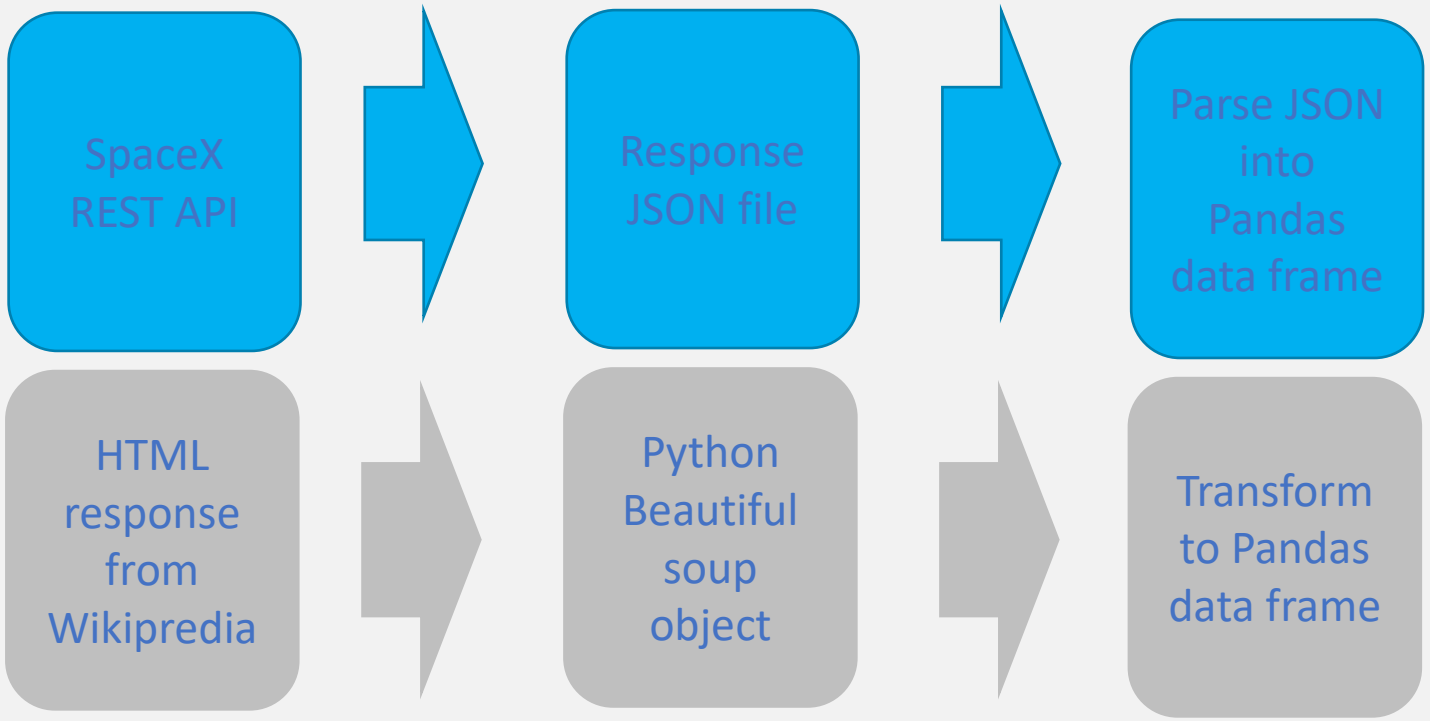


- Data collection methodology:
  - Web scraping (source: Wikipedia) and REST API (source: SpaceX)
- Perform data wrangling
  - Data frame (using pandas to produce clean data of relevant features).
  - One hot encoding and normalization for predictive models
- Perform exploratory data analysis (EDA) using visualization and SQL
- Perform interactive visual analytics using Folium and Plotly Dash
- Perform predictive analysis using classification models
  - Build a numpy database which can be read by the SciKitLearn package
  - Search for best parameters for logistic regression, decision tree, support vector machine and K-nearest neighbor models and identify the best performing model for prediction

Methodology

Data collection

- Data sets were collected SpaceX REST API and Wikipedia SpaceX html page. The datasets were transformed into a pandas data frame for further processing.



Data collection – SpaceX API

1. Get response from API

```
spacex_url="https://api.spacexdata.com/v4/launches/past"
```

```
response = requests.get(spacex_url)
```

2. Convert response to .json file

```
data = pd.json_normalize(response.json())
```

3. Apply custom functions to pull out data from .json

4. Assign values to dataframe

```
launch_dict = {'FlightNumber': list(data['flight_number']),
'Date': list(data['date']),
'BoosterVersion':BoosterVersion,
'PayloadMass':PayloadMass,
'Orbit':Orbit,
'LaunchSite':LaunchSite,
'Outcome':Outcome,
'Flights':Flights,
'GridFins':GridFins,
'Reused':Reused,
'Legs':Legs,
'LandingPad':LandingPad,
'Block':Block,
'ReusedCount':ReusedCount,
'Serial':Serial,
'Longitude': Longitude,
'Latitude': Latitude}
```

Then, we need to create a Pandas data frame from the dictionary launch_dict.

```
# Create a data from launch_dict
df=pd.DataFrame(launch_dict)
```

Review the JUPYTR notebook linked here

Data collection – Web scraping

1. Get response from HTML

```
static_url = "https://en.wikipedia.org/w/index.php?title=List_of_Falcon_9_and_Falcon_Heavy_launches&oldid=1027686922"
```

```
response = requests.get(static_url).text
```

2. Convert HTML to a BeautifulSoup Object

```
soup = BeautifulSoup(response, 'html5lib')
```

3. Find table contents

```
html_tables = soup.find_all('table')
```

4. Iterate through tables pull out relevant column data

```
launch_dict= dict.fromkeys(column_names)

# Remove an irrelvant column
del launch_dict['Date and time ( )']

# Let's initial the launch_dict with each value to be an empty list
launch_dict['Flight No.'] = []
launch_dict['Launch site'] = []
launch_dict['Payload'] = []
launch_dict['Payload mass'] = []
launch_dict['Orbit'] = []
launch_dict['Customer'] = []
launch_dict['Launch outcome'] = []
# Added some new columns
```

5. Form a dataframe

```
In [112]: extracted_row = 0
#Extract each table
for table_number,table in enumerate(soup.find_all('table',"wikitable plainrowheaders collapsible")):
   # get table row
    for rows in table.find_all("tr"):
        #check to see if first table heading is as number corresponding to launch a number
        if rows.th:
            if rows.th.string:
                flight_number=rows.th.string.strip()
                flag=flight_number.isdigit()
        else:
            flag=False
        #get table element
        row=rows.find_all('td')
        #if it is number save cells in a dictonary
        if flag:
            extracted_row += 1
            ## Flight Number value
            ## TODO: Append the flight_number into launch_dict with key `Flight No.`
            ## print(flight_number)
            datatimelist=date_time(row[0])
            launch_dict['Flight No.'].append(extracted_row)
            print("flight number:",extracted_row)

            ## Date value
            ## TODO: Append the date into launch_dict with key `Date`
            date = datatimelist[0].strip(',')
```

Review the JUPYTR notebook linked here

Data wrangling

- Key the landing outcomes as positive or not for each row in the dataset

```
for i,outcome in enumerate(landing_outcomes.keys()):
    print(i,outcome)
```

```
0 True ASDS
1 None None
2 True RTLS
3 False ASDS
4 True Ocean
5 False Ocean
6 None ASDS
7 False RTLS
```

We create a set of outcomes where the second stage did not land successfully:

```
bad_outcomes=set(landing_outcomes.keys()[[1,3,5,6,7]])
bad_outcomes
```

```
{'False ASDS', 'False Ocean', 'False RTLS', 'None ASDS', 'None None'}
```

- Handle null values

```
In [39]: # Calculate the mean value of PayloadMass column
         x = data_falcon9['PayloadMass'].mean()
         data_falcon9['PayloadMass'] = data_falcon9['PayloadMass'].replace(np.nan, x)

         # Replace the np.nan values with its mean value

In [40]: data_falcon9.isnull().sum()

Out[40]: FlightNumber      0
         Date              0
         BoosterVersion    0
         PayloadMass       0
         Orbit             0
         LaunchSite        0
         Outcome           0
         Flights           0
         GridFins          0
         Reused            0
         Legs              0
         LandingPad       26
         Block             0
         ReusedCount       0
         Serial            0
         Longitude         0
         Latitude          0
         dtype: int64
```

Review the JUPYTR notebook linked **here**

EDA with data visualization

Launches with successful and failed landings were plotted to investigate relationships between various variables

- Flight Number VS. Payload Mass
- Flight Number VS. Launch Site
- Payload VS. Launch Site
- Orbit VS. Flight Number
- Payload VS. Orbit Type
- Orbit VS. Payload Mass

Review the JUPYTR notebook linked **here**

EDA with SQL

SQL queries were performed to investigate relationship of payload mass, lauch site, launch date, booster versions, and landing success.

- Total payload mass
- Average payload mass
- First successful ground landing date
- Successful drone ship landing with payload between 4000 and 6000 kg
- Total number of successful and failed missions
- Boosters that carried the maximum payloads
- List the launch site and booster of 2015 failed landings
- Rank the failed landing outcome descriptions between 2010-06-04 and 2017-030-20

Review the JUPYTR notebook linked **here**

Build an interactive map with Folium

- The location of the launch site were visualized in an interactive map to gain location specific insights about the launch sites used.
- Lat/Long coordinates were used to place markers of the launch sites in Folium.
- The successful and failed booster landings from the launch site was visualized using color coded circles.
- The launch site proximity to geographic feature and transport infrastructure was noted using distance lines.

Review the JUPYTR notebook linked **here**

Build a Dashboard with Plotly Dash

- An interactive dashboard was created to quickly visualize relation ship between landing success and launch sites.
- A module was added to further show the relationship between payload and landing outcome at launch sites.

Reviewthe JUPYTR notebook linked **here**

Predictive analysis (Classification)

GridSearchCV tool in the SciKitLearn library was sued to determine the best predictive model for Falcon 9 landing outcome.

1. All features were converted to one hot encoding

```
features_one_hot = pd.get_dummies(features[['Orbit','LaunchSite','LandingPad','Serial']])
features_one_hot.head()
```

3]:

	Orbit_ES-L1	Orbit_GEO	Orbit_GTO	Orbit_HEO	Orbit_ISS	Orbit_LEO	Orbit_MEO	Orbit_PO	Orbit_SO	Orbit
0	0	0	0	0	0	1	0	0	0	
1	0	0	0	0	0	1	0	0	0	
2	0	0	0	0	1	0	0	0	0	
3	0	0	0	0	0	0	0	1	0	
4	0	0	1	0	0	0	0	0	0	

5 rows × 72 columns

2. Features were standardized to each other by the standard scaler method

```
In [6]: # students get this
transform = preprocessing.StandardScaler().fit(X).transform(X.astype(float))
transform[0:5]

Out[6]: array([[-1.71291154e+00, -1.94814463e-16, -6.53912840e-01,
                -1.57589457e+00, -9.73440458e-01, -1.05999788e-01,
                -1.05999788e-01, -6.54653671e-01, -1.05999788e-01,
                -5.51677284e-01,  3.44342023e+00, -1.85695338e-01
```

3. The data set was split to train and test sample sets to build and test the models

```
X_train, X_test, Y_train, Y_test = train_test_split( transform, Y, test_size=0.
2, random_state=3)
```

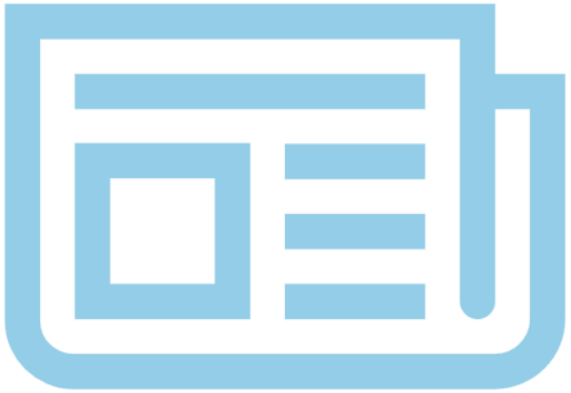
4. The logistic regression, decision tree, k-nearest neighbors, and support vector machine were the models tested and scored

```
In [10]: parameters ={"C":[0.01,0.1,1],'penalty':['l2'], 'solver':['lbfgs']}# l1 lasso l2 ridge
lr=LogisticRegression()

In [11]: logreg_cv=GridSearchCV(lr, parameters)
logreg_cv.fit(X_train, Y_train)
```

Review the JUPYTR notebook linked **here**

Results

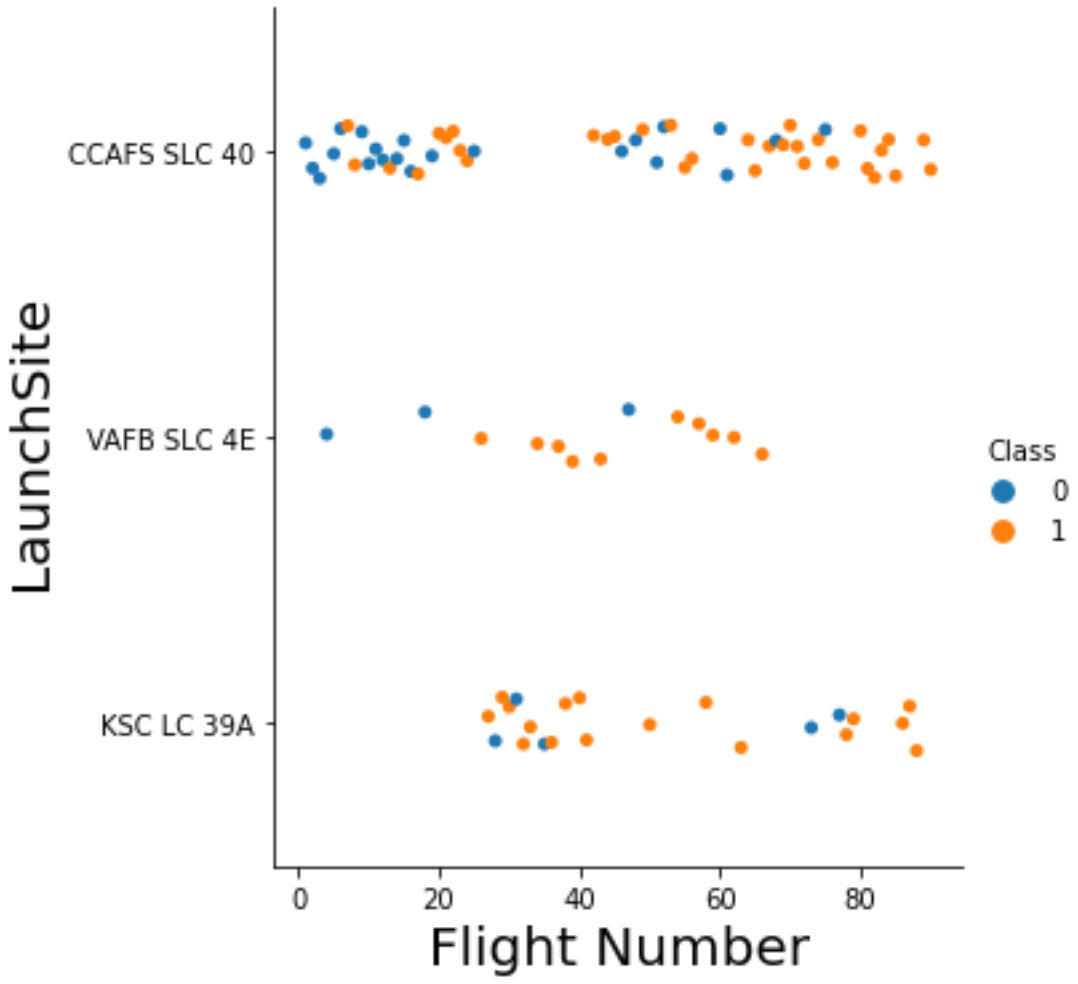


- Exploratory data analysis (EDA) results
- Interactive analytics demo in screenshots
- Predictive analysis results

EDA with Visualization

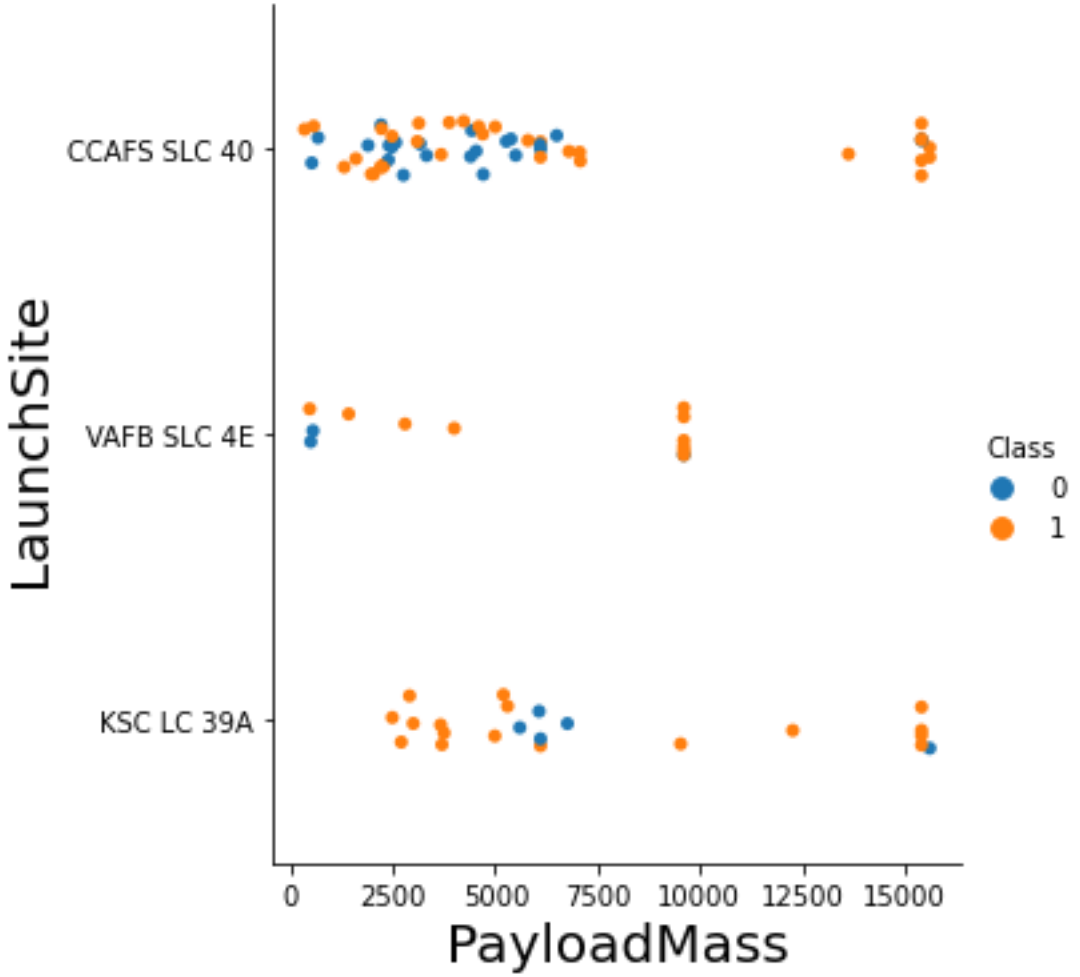
Flight Number vs. Launch Site

- Earlier flights occurred at CCAFS SLC 40 launch sites.
- Earlier flight numbers were more likely to have a negative landing outcome shown in blue (class = 0)
- In later flight numbers, launches occur from all site with majority of flights ending with successful landings shown in orange (class = 1)



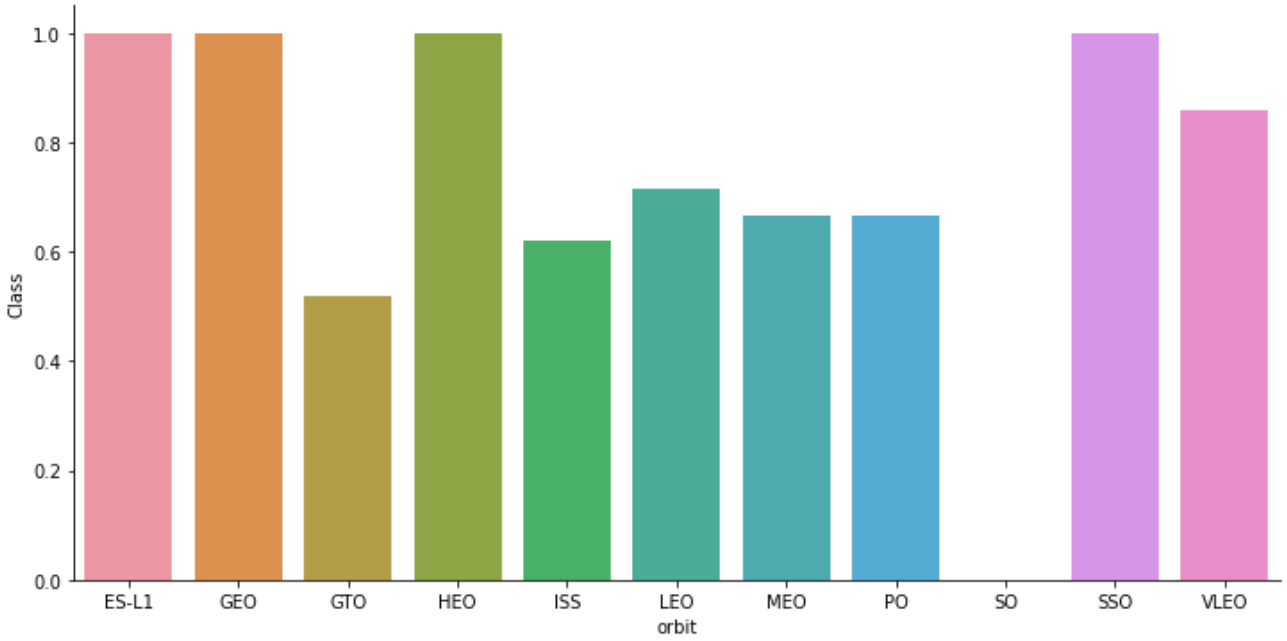
Payload vs. Launch Site

- Many of the lower payload mass launches occurred at CCAFS SLC 40.
- Higher payload mass launches appear to have higher landing success rate.



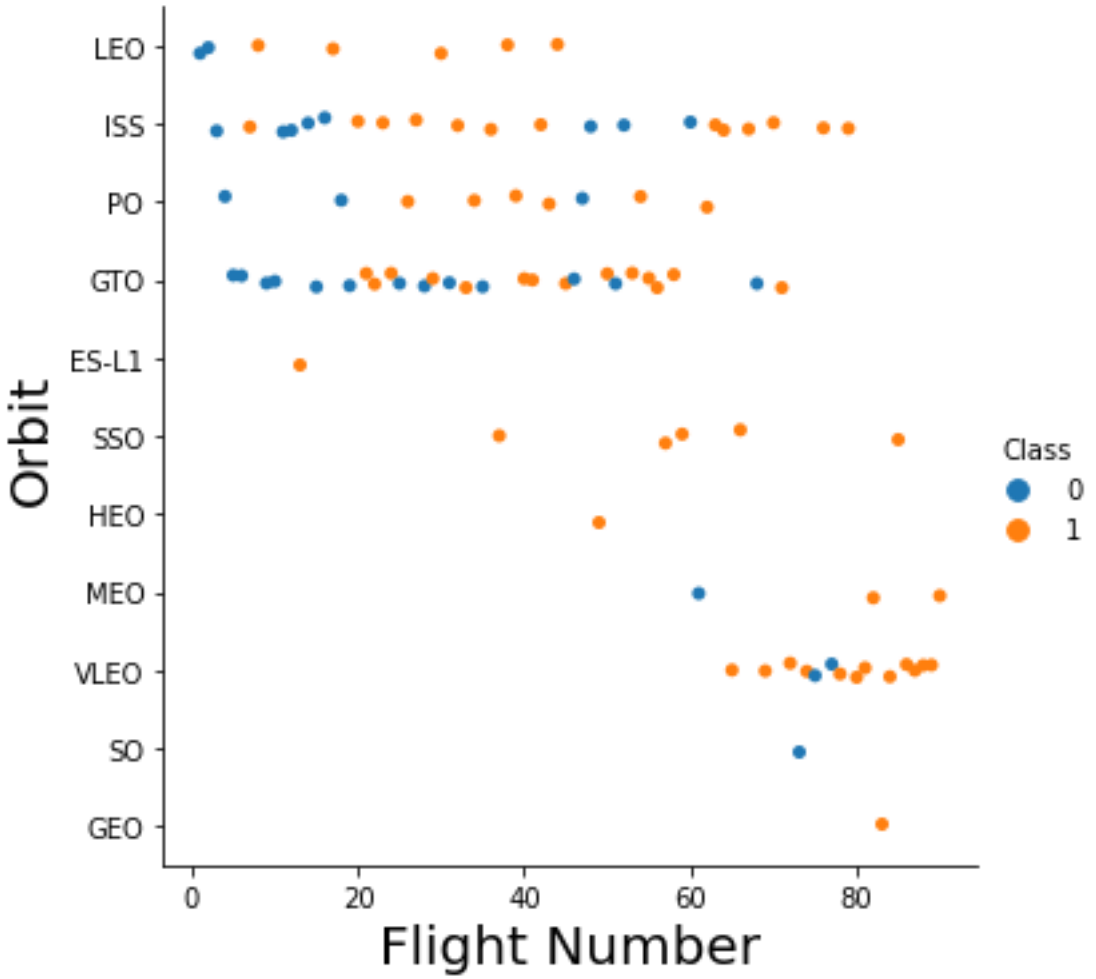
Success rate vs. Orbit type

Landing success rate differs by the orbit type. Some of the more difficult to reach orbit may require tight margins on fuel and weight. Its possible some orbits and weight combination make booster landings impossible or impractical.



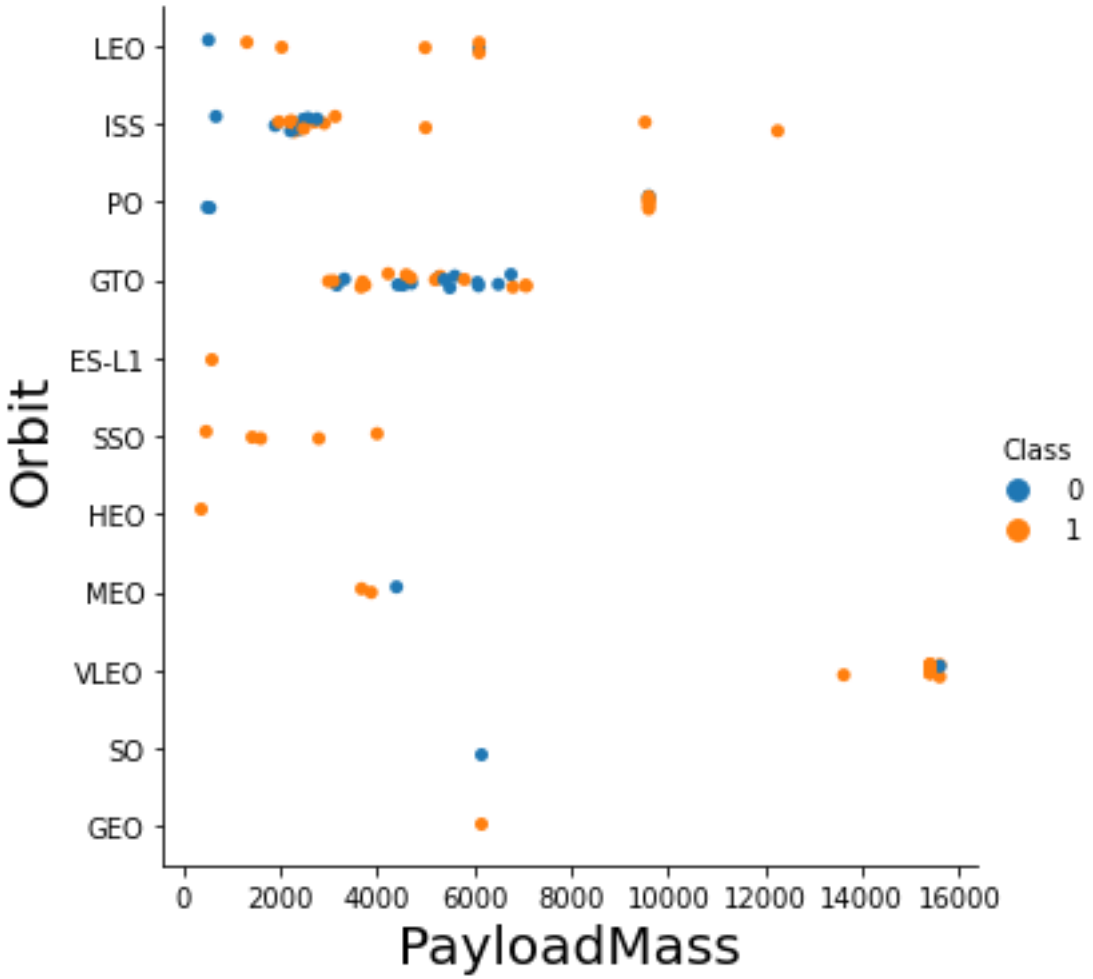
Flight Number vs. Orbit type

- Some orbits were not attempted in early flights
- Early flights had failed landing attempts
- LEO launches had successful landings early on. This trajectory might allow for more leeway for booster landings to occur because of the lower amount of energy required to reach this orbit.



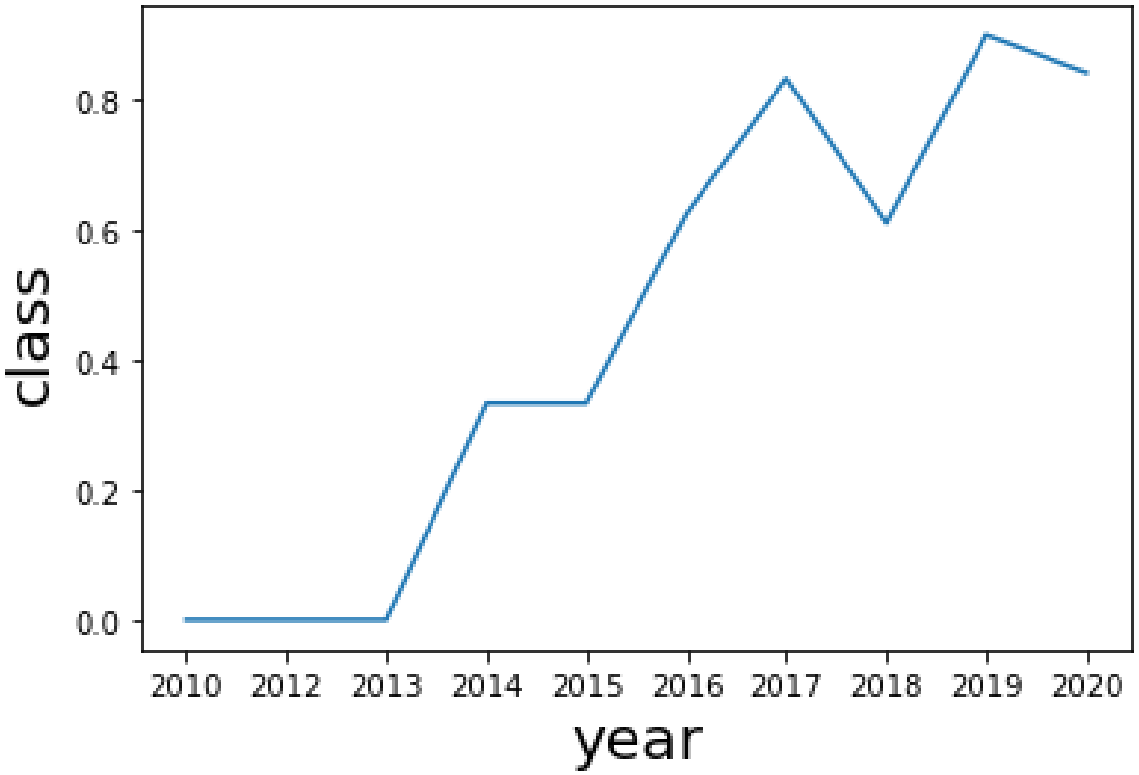
Payload vs. Orbit type

- Geostationary transfer (GTO) and International space station (ISS) orbits had the most failed landing outcomes.
- GTO and ISS orbits are higher energy and might require ocean landings. The payload mass were lower for these orbits also.
- Ocean landings might come with more risk.



Launch success yearly trend

- Yearly trend shows constant improvement in landing outcomes.
- One of the best predictors of landing outcomes may turn out to be flight number and year, because learnings from past landing attempts are incorporated in new flights.



EDA with SQL

Showing SQL database connection

```
%sql select * from spacex
```

DATE	time__utc_	booster_version	launch_site	payload	payload_mass__kg_	orbit
2010-06-04	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit	0	LEO
2010-12-08	15:43:00	F9 v1.0 B0004	CCAFS LC-40	Dragon demo flight C1, two CubeSats, barrel of Brouere cheese	0	LEO (ISS)
2012-05-22	07:44:00	F9 v1.0 B0005	CCAFS LC-40	Dragon demo flight C2	525	LEO (ISS)
2012-10-08	00:35:00	F9 v1.0 B0006	CCAFS LC-40	SpaceX CRS-1	500	LEO (ISS)
2013-03-01	15:10:00	F9 v1.0 B0007	CCAFS LC-40	SpaceX CRS-2	677	LEO (ISS)

Total payload mass

```
%sql select sum(payload_mass__kg_) from spacex where customer like 'NASA%'
```

```
 * ibm_db_sa://phq62734:***@fbd88901-ebdb-4a4f-a32e-9822b9fb237b.c1ogj3sd0tgtu0
lqde00.databases.appdomain.cloud:32731/bludb
Done.
```

1
99980

- SpaceX has launched almost 100,000 kg (100 tons) of mass into space.

Average payload mass by F9 v1.1

```
%sql select AVG(payload_mass__kg_) from spacex where booster_version like 'F9 v
1.1%'
```

```
 * ibm_db_sa://phq62734:***@fbd88901-ebdb-4a4f-a32e-9822b9fb237b.c1ogj3sd0tgtu0
lqde00.databases.appdomain.cloud:32731/bludb
Done.
```

1
2534

- The average payload mass for booster version F9 v1.1 is 2534 kg. About the weight of a small car.

First successful ground landing date

```
%sql select MIN(DATE) from spacex where landing__outcome like '%ground pad%'
```

```
 * ibm_db_sa://phq62734:***@fbd88901-ebdb-4a4f-a32e-9822b9fb237b.c1ogj3sd0tgtu0
lqde00.databases.appdomain.cloud:32731/bludb
Done.
```

1
2015-12-22

- First successful landing pad booster landing was 2015-12-22

Successful drone ship landing with payload between 4000 and 6000

```
%sql select distinct booster_version from spacex where (landing__outcome like '%
drone ship%') AND (payload_mass__kg_ < 6000 AND payload_mass__kg_ > 4000)
```

booster_version
F9 FT B1021.2
F9 FT B1031.2
F9 FT B1020
F9 FT B1022
F9 FT B1026

- Booster version is not the only predictor for successful ocean drone ship landings. Many booster versions have succeeded with drone ship landings.

Total number of successful and failure mission outcomes

```
%sql SELECT mission_outcome, count(*) AS total FROM spacex GROUP BY mission_outc
ome
```

mission_outcome	total
Failure (in flight)	1
Success	99
Success (payload status unclear)	1

- The launch success does not correlate to booster landing success. The mission can succeed while booster landing fails or booster is sacrificed on purpose.

Boosters carried maximum payload

```
%sql SELECT DISTINCT (booster_version) from spacex where payload_mass__kg_ = (SE
LECT MAX(payload_mass__kg_) from spacex)
```

booster_version
F9 B5 B1048.4
F9 B5 B1048.5
F9 B5 B1049.4
F9 B5 B1049.5
F9 B5 B1049.7
F9 B5 B1051.3
F9 B5 B1051.4
F9 B5 B1051.6

- The F9 B5 booster versions carry the heaviest weight payloads. One of the upgrades for the Falcon 9 block 5 boosters were higher power engines to allow for heavier payloads.

2015 launch records

```
%sql select booster_version, launch_site from spacex where landing__outcome = 'F
ailure (drone ship)' AND DATE like '2015%'
```

```
 * ibm_db_sa://phq62734:***@fbd88901-ebdb-4a4f-a32e-9822b9fb237b.c1ogj3sd0tgtu0
lqde00.databases.appdomain.cloud:32731/bludb
Done.
```

booster_version	launch_site
F9 v1.1 B1012	CCAFS LC-40
F9 v1.1 B1015	CCAFS LC-40

- In 2015, the failed drone ship landing outcomes originated from launches from CCAFS LC-40 with F9 1.1 boosters

Rank success count between 2010-06-04 and 2017-03-20

```
%sql SELECT * from (SELECT landing__outcome, count(*)
AS total FROM spacex WHERE DATE between '2010-06-04' and '2017-03-20'
GROUP BY landing__outcome) ORDER BY total DESC
```

landing__outcome	total
No attempt	10
Failure (drone ship)	5
Success (drone ship)	5
Controlled (ocean)	3
Success (ground pad)	3
Failure (parachute)	2
Uncontrolled (ocean)	2
Precluded (drone ship)	1

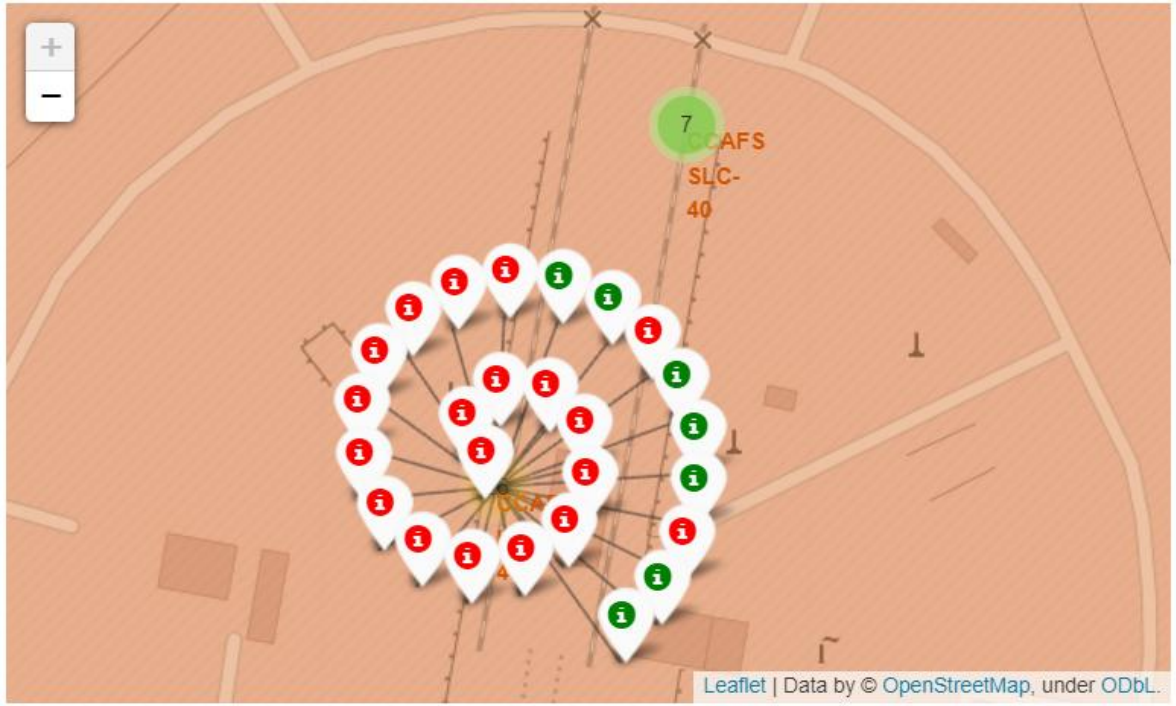
- The failed landing outcomes occur for a variety of reasons. Sometimes there is no attempt for a landing which could occur for old boosters, or if landings are not possible.

Interactive map with Folium

Launchsite mapping with Folium

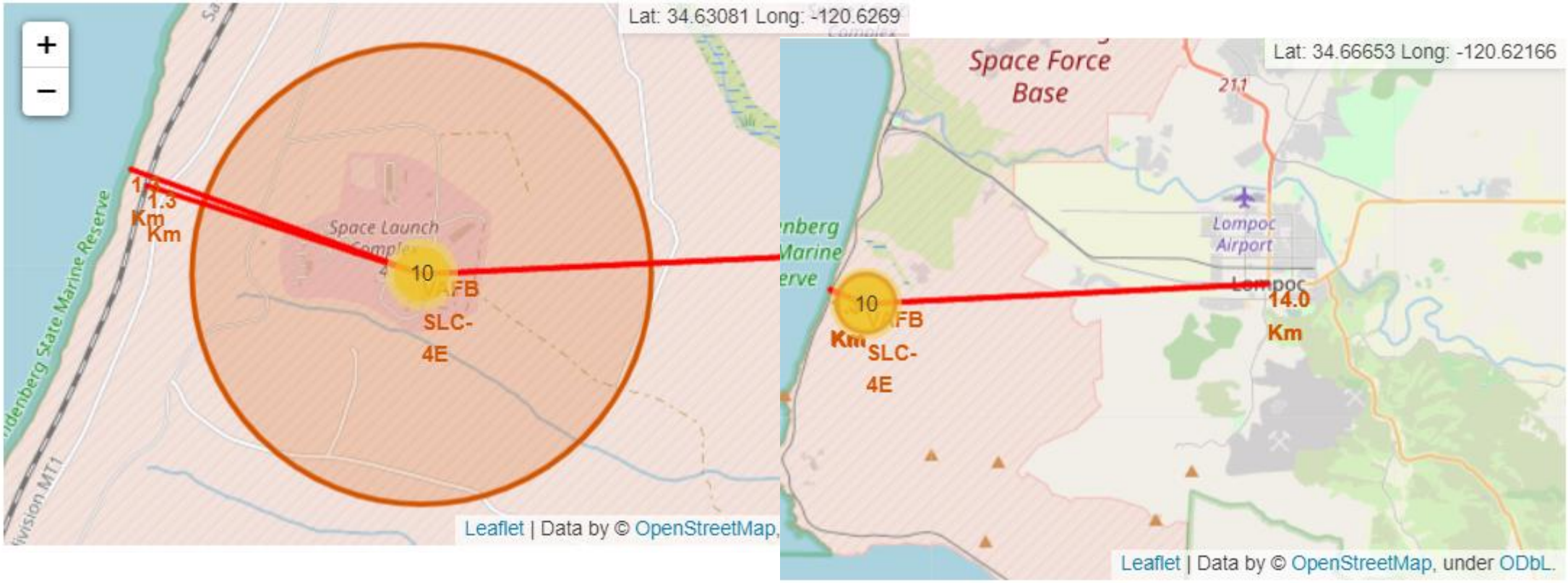
- The launch sites are located on coasts

Color-labeled launch records mapping



- The markers closer to the center occurred earlier. Many early launches did not end in a successful booster landing. Later launches are more likely to end in a landing.

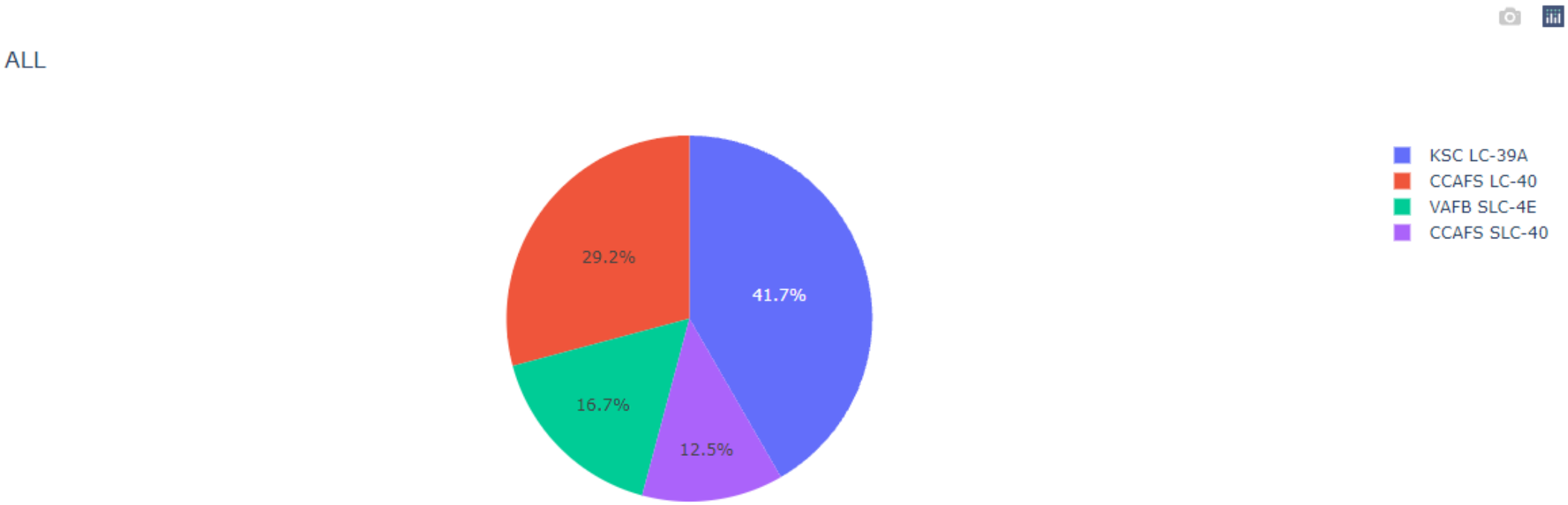
Launch site proximity to infrastructure



- The launch site are located close to the ocean and close to rail and highway infrastructure.

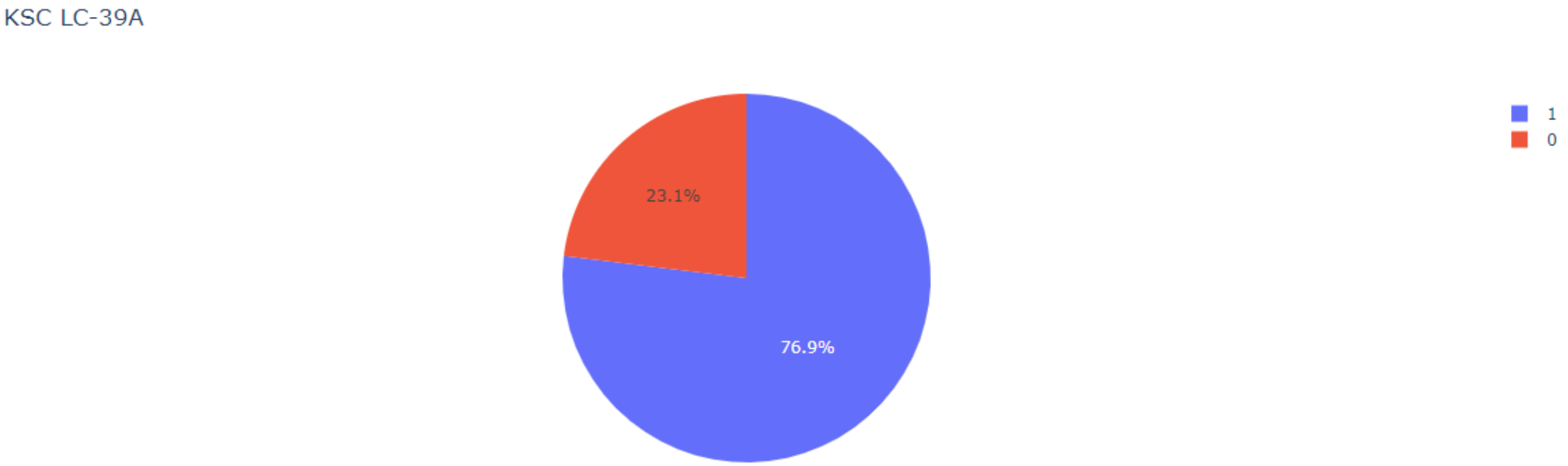
Build a Dashboard with Plotly Dash

Landing successes from launch sites



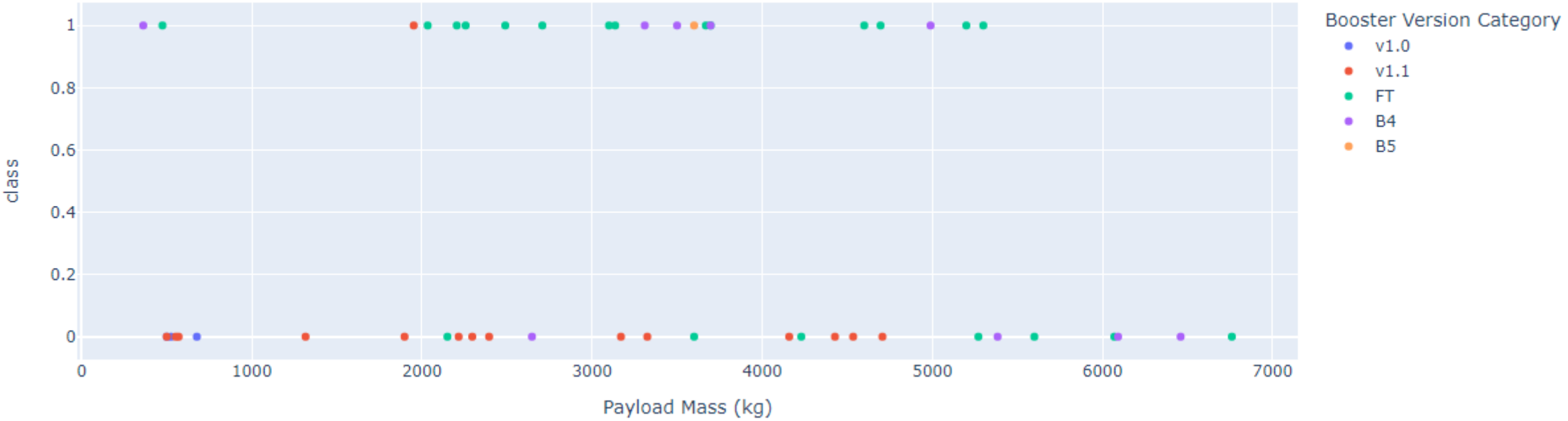
- Highest number of successful launch with booster landings occurred from KSC LC39A

Launch site with highest landing success ratio



- From KSC LC-39A 76.9% of launches have ended in successful landings

Payload vs. Launch Outcome



- When the payload mass is between 2000 to 4000 kg the success rate is higher than launches with payload size above 4000 kg. Payload size has some indication on landing outcome.

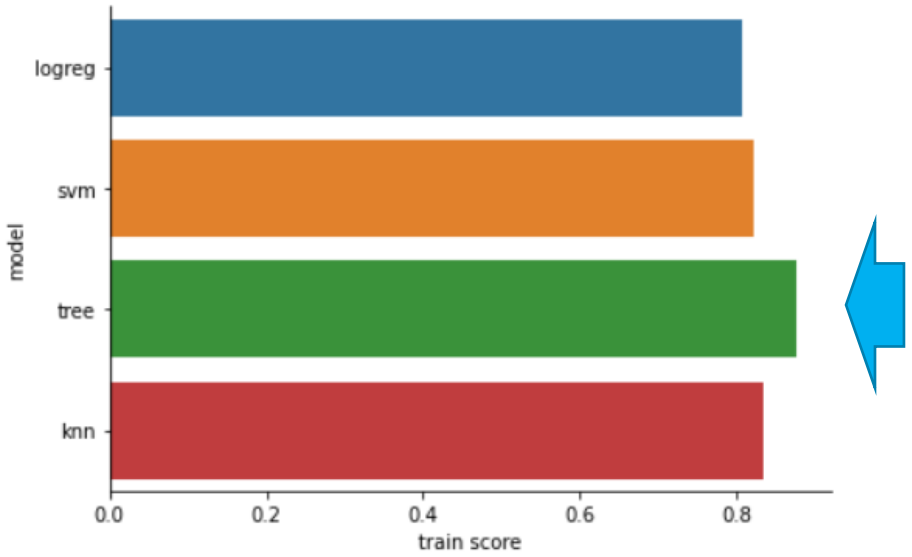
Predictive analysis (Classification)

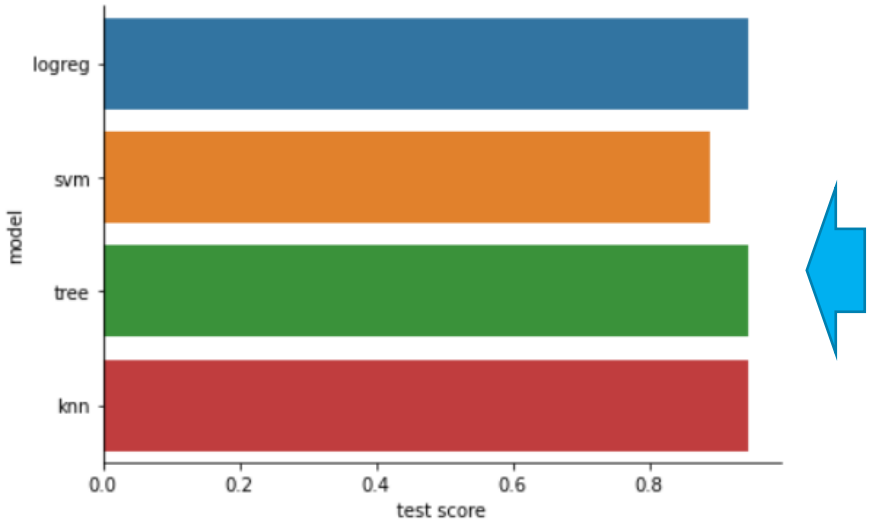
Classification Accuracy

The GridSearchCV tool was used to determine the best parameters for training 4 algorithms: Logistic regression (logreg), Support Vector Machine (SVM), Decision Tree (tree), and K-nearest neighbors (KNN)

The model accuracy for the training set and test set was determined by scoring tool.

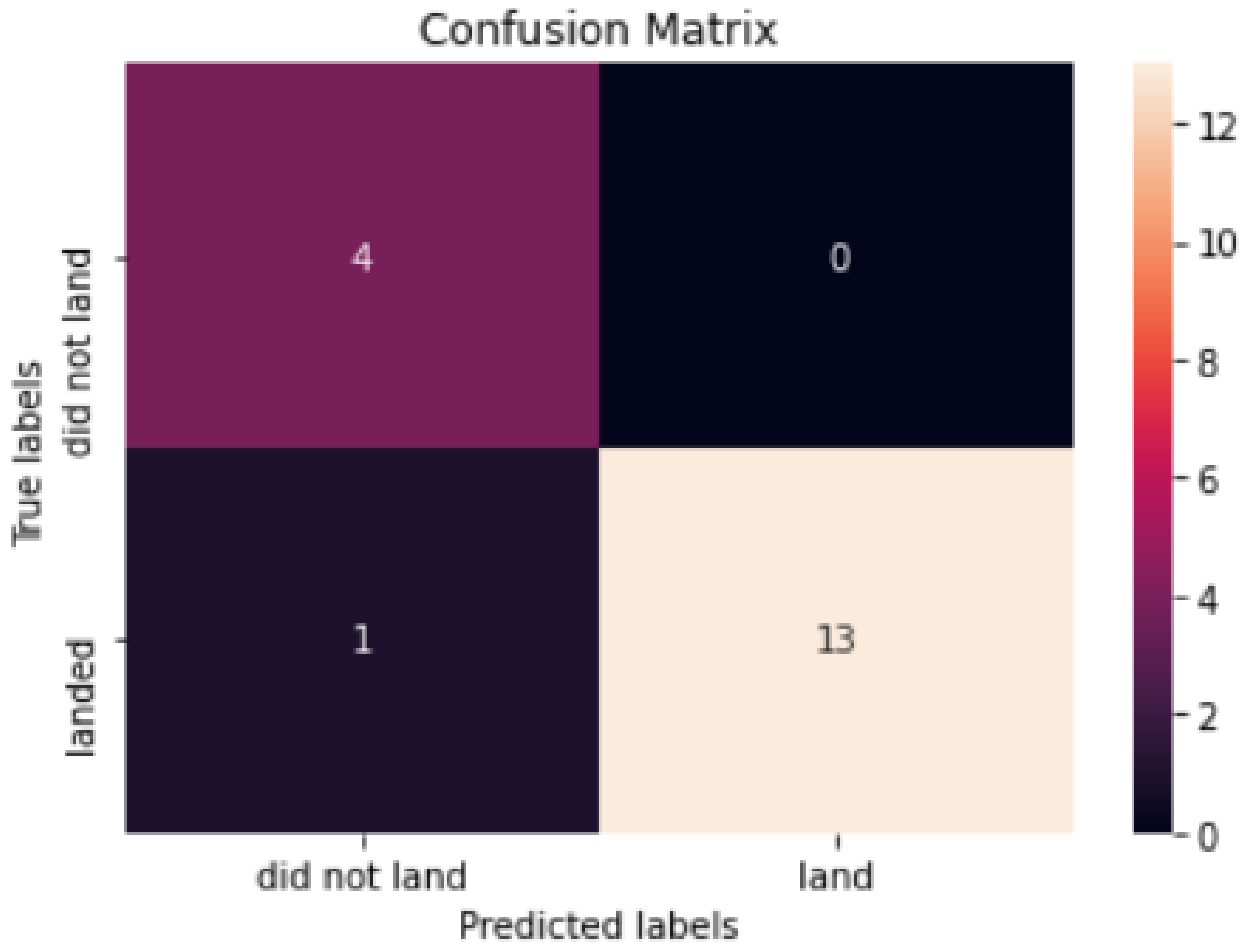
Decision tree fit the training dataset and the test data set best. Although all algorithms performed similarly.





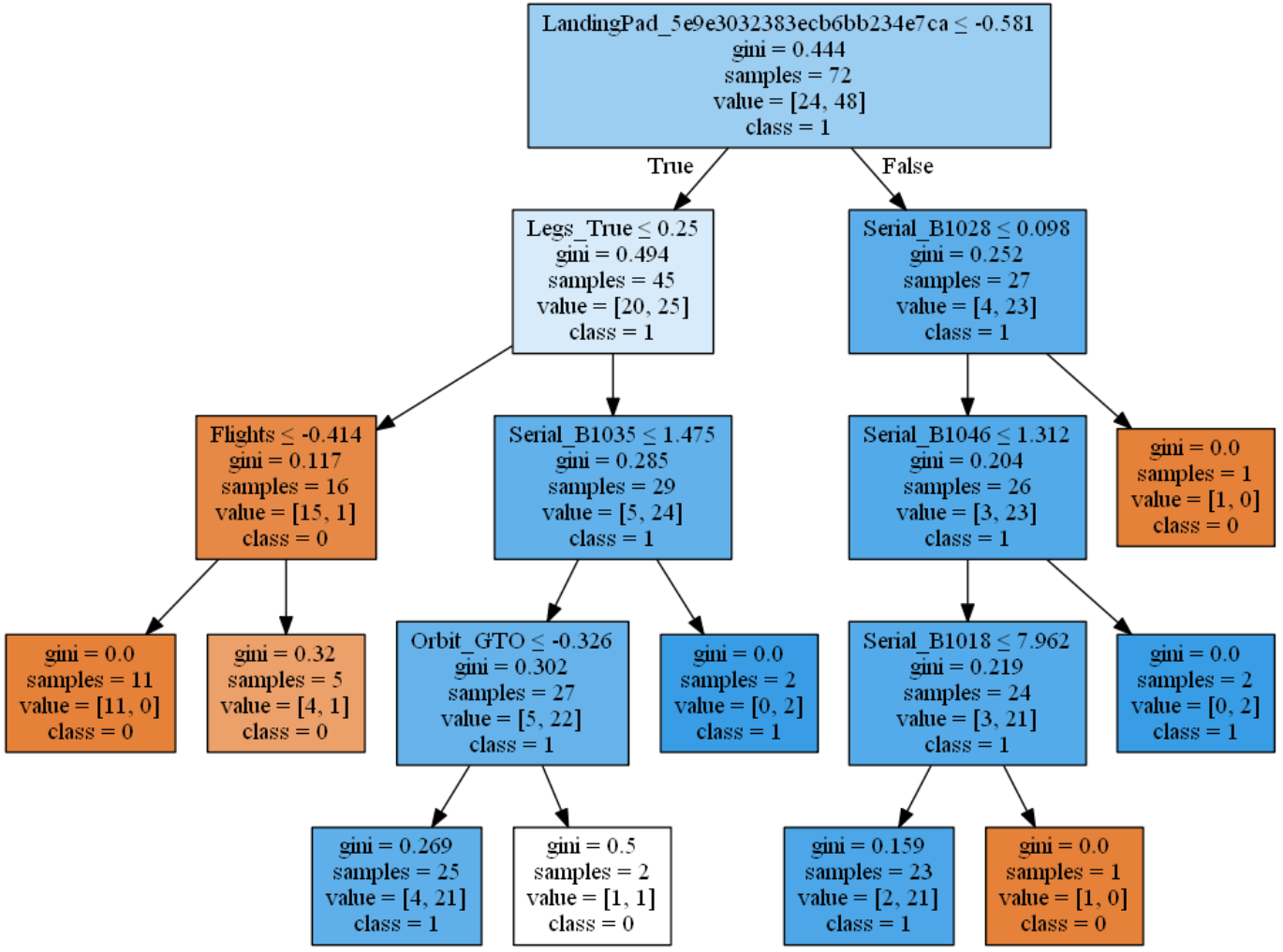
Confusion Matrix

Decision tree confusion matrix shows the model correctly predicted 13 landings and 4 failed landing outcomes. The model incorrectly labeled one landing as a failed landing outcome.



Decision Tree

Decision tree visualization shows that in this training iteration launch pad, presence of landing legs, booster serial number, flight number, and orbit as the most important determinant for predicting landing outcome.



CONCLUSION

- Decision tree was determined to be the best predictive model for Falcon 9 booster landing on any given launch.
- EDA showed the number of flights, orbit type, launch site, and payload weight had an influence on landing outcome.
- Parameters in decision tree model incorporated some of the EDA findings, such as booster version which correlate with the flight number.
- Some of the weaknesses in the decision tree model is that it does not take into account many of the physical parameters might determine landing success such as payload mass or some of the orbit types.

APPENDIX

Depiction of orbit types. Some orbits require less flight distance than others