Data Science Capstone Project

SpaceX

First Stage Reuse

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Presentation Contents

Executive Summary

Summary of Methodologies

The research attempts to identify the factors for a successful rocket landing. To make this determination, the following methodologies where used:

- **Collect** data using SpaceX REST API and web scraping techniques
- **Wrangle** data to create success/fail outcome variable
- **Explore** data with data visualization techniques, considering the following factors: payload, launch site, flight number and yearly trend
- **Analyze** the data with SQL, calculating the following statistics: total payload, payload range for successful launches, and total # of successful and failed outcomes
- **Explore** launch site success rates and proximity to geographical markers
- **Visualize** the launch sites with the most success and successful payload ranges
- **Build Models** to predict landing outcomes using logistic regression, support vector machine (SVM), decision tree and K-nearest neighbor (KNN)

Results

Exploratory Data Analysis:
- Launch success has improved over time
- KSC LC-39A has the highest success rate among landing sites
- Orbits ES-L1, GEO, HEO, and SSO have a 100% success rate

Visualization/Analytics:
- Most launch sites are near the equator, and all are close to the coast

Predictive Analytics:
- All models performed similarly on the test set. The decision tree model slightly outperformed

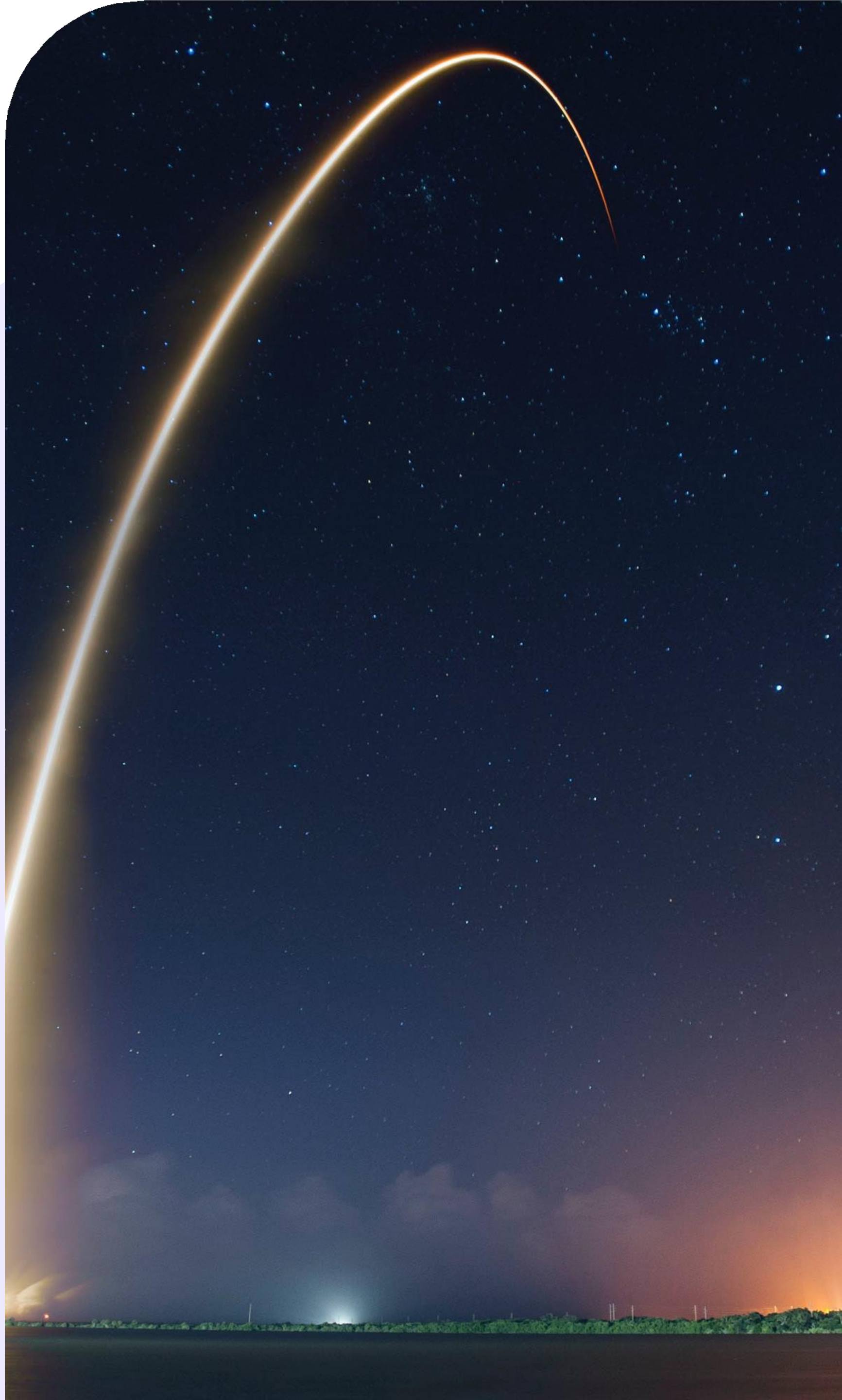
Introduction

Background

SpaceX, a leader in the space industry, strives to make space travel affordable for everyone. Its accomplishments include sending spacecraft to the international space station, launching a satellite constellation that provides internet access and sending manned missions to space. SpaceX can do this because the rocket launches are relatively inexpensive ($62 million per launch) due to its novel reuse of the first stage of its Falcon 9 rocket. Other providers, which are not able to reuse the first stage, cost upwards of $165 million each. By determining if the first stage will land, we can determine the price of the launch. To do this, we can use public data and machine learning models to predict whether SpaceX – or a competing company – can reuse the first stage.

Explore

- How payload mass, launch site, number of flights, and orbits affect first-stage landing success
- Rate of successful landings over time
- Best predictive model for successful landing (binary classification)

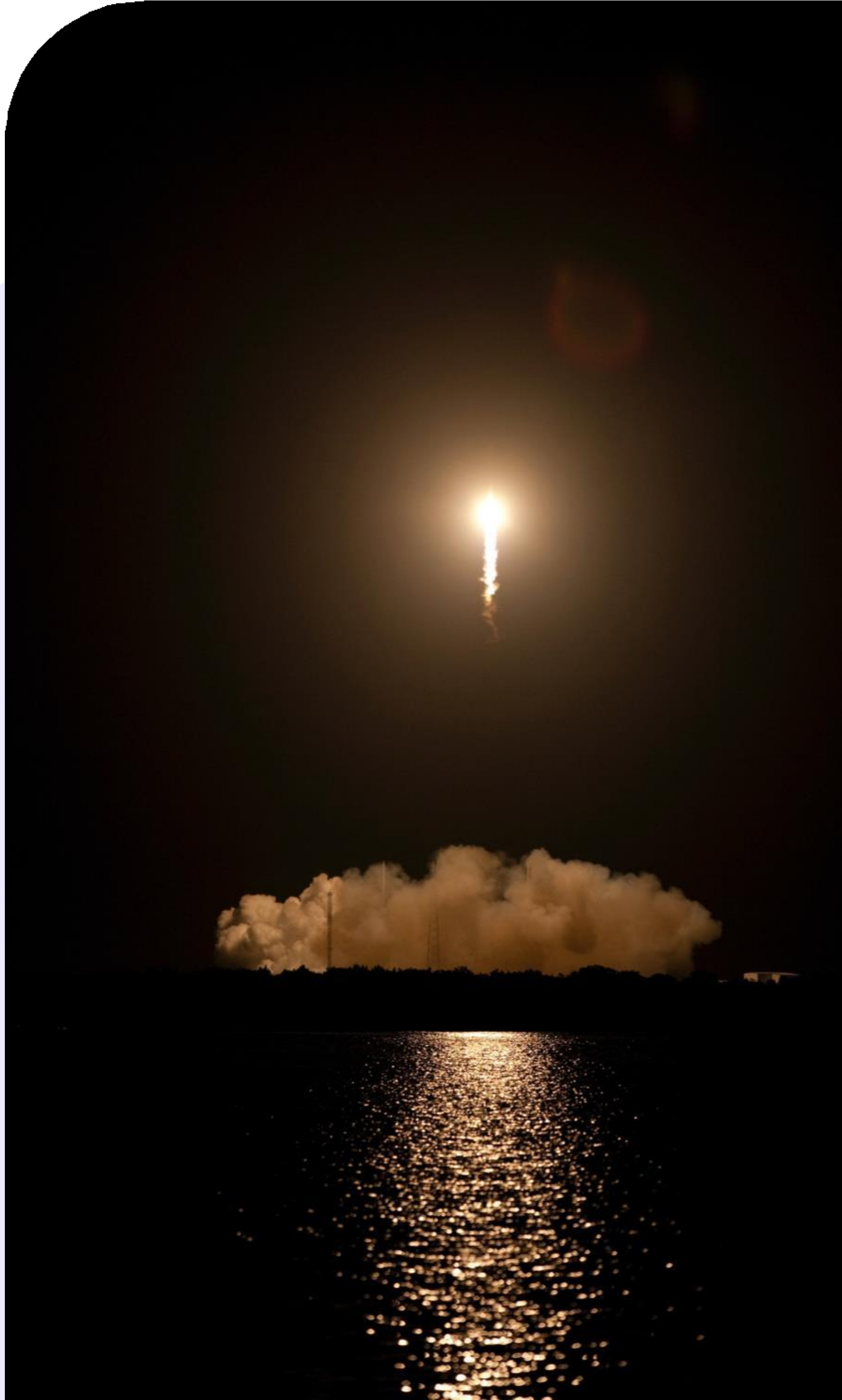


Methodology

Methodology

Steps

- **Collect** data using SpaceX REST API and web scraping techniques
- **Wrangle** data – by filtering the data, handling missing values and applying one hot encoding – to prepare the data for analysis and modeling
- **Explore** data via EDA with SQL and data visualization techniques
- **Visualize** the data using Folium and Plotly Dash
- **Build Models** to predict landing outcomes using classification models. Tune and evaluate models to find best model and parameters



Data Collection –API

Steps

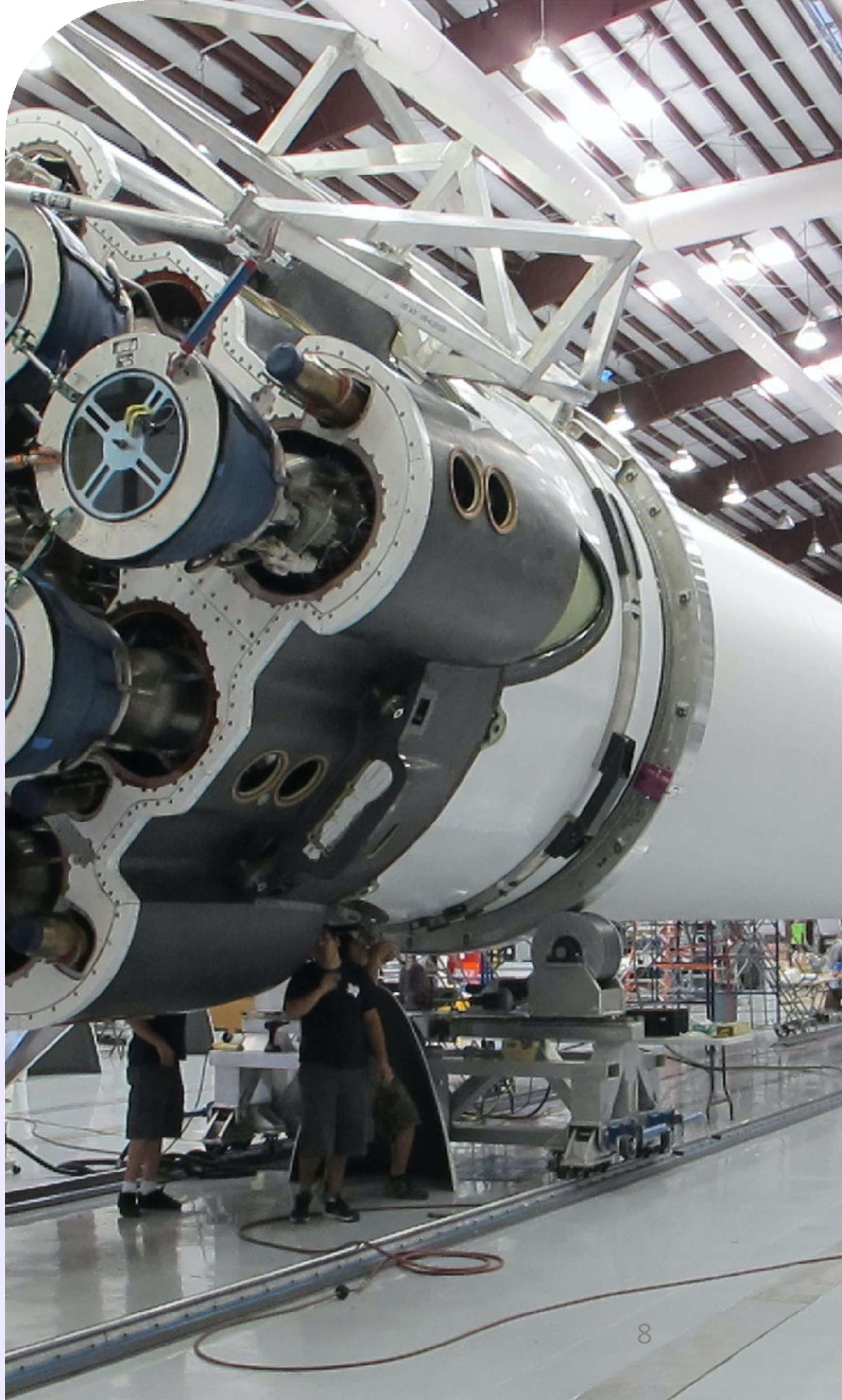
- **Request data** from SpaceX API (rocket launch data)
- **Decode response** using .json() and convert to a dataframe using .json_normalize()
- **Request information** about the launches from SpaceX API using custom functions
- **Create dictionary** from the data
- **Create dataframe** from the dictionary
- **Filter dataframe** to contain only Falcon 9 launches
- **Replace missing values** of Payload Mass with calculated .mean()
- **Export data** to csv file

[GitHub URL: Data Collection API]

Data Collection –Web Scraping

Steps

- **Request data** (Falcon 9 launch data) from Wikipedia
- **Create BeautifulSoup object** from HTML response
- **Extract column names** from HTML table header
- **Collect data** from parsing HTML tables
- **Create dictionary** from the data
- **Create dataframe** from the dictionary
- **Export data** to csv file



GitHub URL: Data Collection with Web Scraping

Data Wrangling

Steps

- **Perform EDA** and determine data labels
- **Calculate:**
    - # of launches for each site
    - # and occurrence of orbit
    - # and occurrence of mission outcome per orbit type]
- **Create binary** landing outcome column (dependent variable)
- **Export data** to csv file

Landing Outcome

- Landing was not always successful
- **True Ocean:** mission outcome had a successful landing to a specific region of the ocean

Landing Outcome Cont.

- **False Ocean:** represented an unsuccessful landing to a specific region of ocean
- **True RTLS:** meant the mission had a successful landing on a ground pad
- **False RTLS:** represented an unsuccessful landing on a ground pad
- **True ASDS:** meant the mission outcome had a successful landing on a drone ship
- **False ASDS:** represented an unsuccessful landing on drone ship
- **Outcomes converted** into 1 for a successful landing and 0 for an unsuccessful landing

[GitHub URL: Data Wrangling]

EDA with Visualization

Charts

- Flight Number vs. Payload
- Flight Number vs. Launch Site
- Payload Mass (kg) vs. Launch Site
- Payload Mass (kg) vs. Orbit type

Analysis

- **View relationship** by using **scatter plots**. The variables could be useful for machine learning if a relationship exists
- **Show comparisons** among discrete categories with **bar charts**. Bar charts show the relationships among the categories and a measured value.

[GitHub URL: EDA with Data Visualization]

EDA with SQL

Queries

Display:

- Names of unique launch sites
- 5 records where launch site begins with ‘CCA’
- Total payload mass carried by boosters launched by NASA (CRS)
- Average payload mass carried by booster version F9 v1.1.

List:

- Date of first successful landing on ground pad
- Names of boosters which had success landing on drone ship and have payload mass greater than 4,000 but less than 6,000
- Total number of successful and failed missions
- Names of booster versions which have carried the max payload
- Failed landing outcomes on drone ship, their booster version and launch site for the months in the year 2015
- Count of landing outcomes between 2010-06-04 and 2017-03-20 (desc)

[GitHub URL: EDA with SQL]

Map with Folium

Markers Indicating Launch Sites

- Added **blue circle** at **NASA Johnson Space Center's coordinate** with a **popup label** showing its name using its latitude and longitude coordinates
- Added **red circles** at **all launch sites coordinates** with a **popup label** showing its name using its name using its latitude and longitude coordinates

Colored Markers of Launch Outcomes

- Added **colored markers** of **successful** (**green**) and **unsuccessful** (**red**) **launches** at each launch site to show which launch sites have high success rates

Distances Between a Launch Site to Proximities

- Added **colored lines** to **show distance between** launch site **CCAFS SLC-40 and** its proximity to the **nearest coastline, railway, highway, and city**

[GitHub URL: Interactive Visual Analytics with Folium]

Dashboard with Plotly Dash

Dropdown List with Launch Sites

- Allow user to select all launch sites or a certain launch site

Pie Chart Showing Successful Launches

- Allow user to see successful and unsuccessful launches as a percent of the total

Slider of Payload Mass Range

- Allow user to select payload mass range

Scatter Chart Showing Payload Mass vs. Success Rate by Booster Version

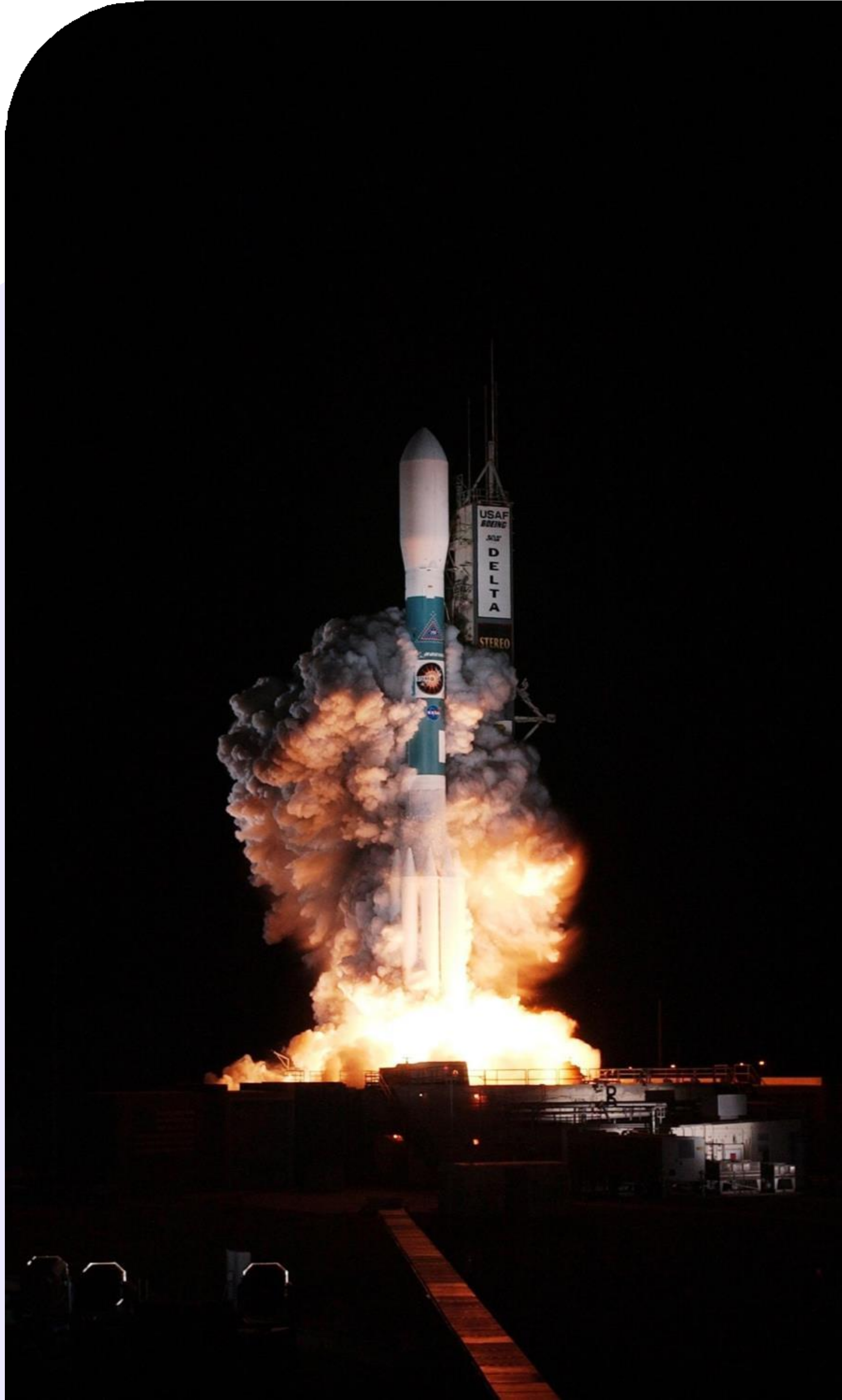
- Allow user to see the correlation between Payload and Launch Success

GitHub URL: SpaceX Dash App

Predictive Analytics

Charts

- **Create** NumPy array from the Class column
- **Standardize** the data with StandardScaler. Fit and transform the data.
- **Split** the data using train_test_split
- **Create** a GridSearchCV object with cv=10 for parameter optimization
- **Apply** GridSearchCV on different algorithms: logistic regression (LogisticRegression()), support vector machine (SVC()), decision tree (DecisionTreeClassifier()), K-Nearest Neighbor (KNeighborsClassifier())
- **Calculate** accuracy on the test data using .score() for all models
- **Assess** the confusion matrix for all models
- **Identify** the best model using Jaccard_Score, F1_Score and Accuracy



[GitHub URL: Machine Learning Prediction]

Results

Results Summary

Exploratory Data Analysis

- Launch success has improved over time
- KSC LC-39A has the highest success rate among landing sites
- Orbits ES-L1, GEO, HEO and SSO have a 100% success rate

Visual Analytics

- Most launch sites are near the equator, and all are close to the coast
- Launch sites are far enough away from anything a failed launch can damage (city, highway, railway), while still close enough to bring people and material to support launch activities

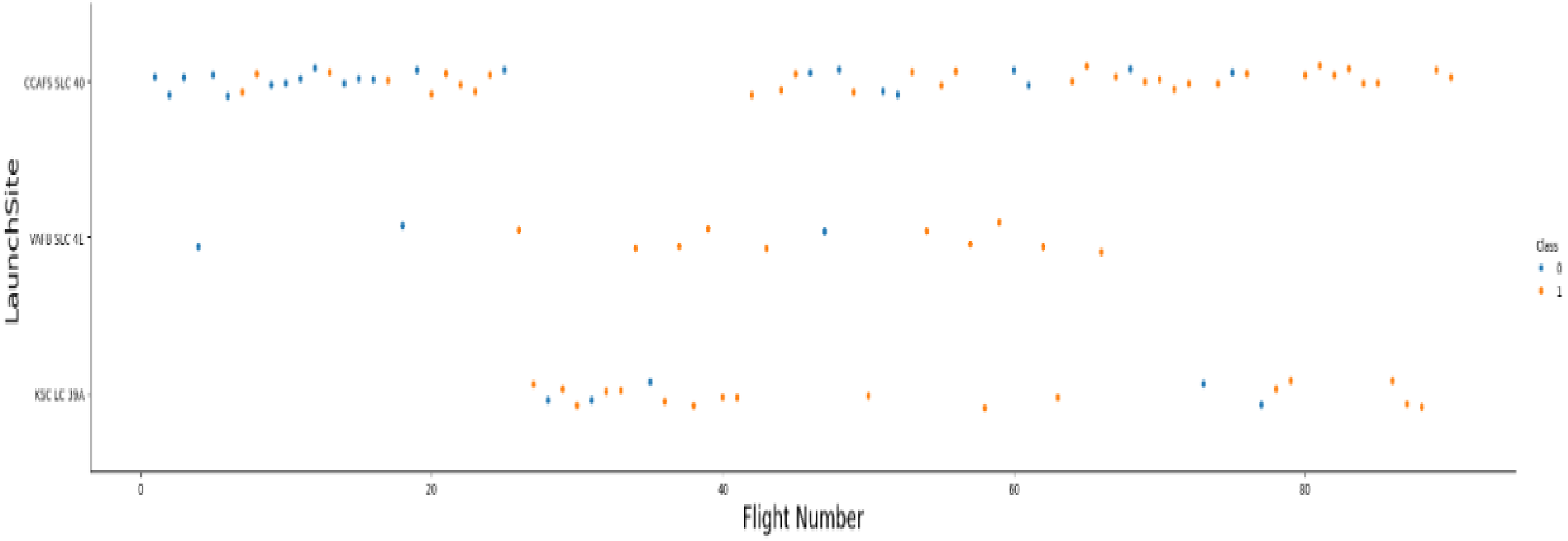
Predictive Analytics

- Decision Tree model is the best predictive model for the dataset

Flight Number vs. Launch Site

Exploratory Data Analysis

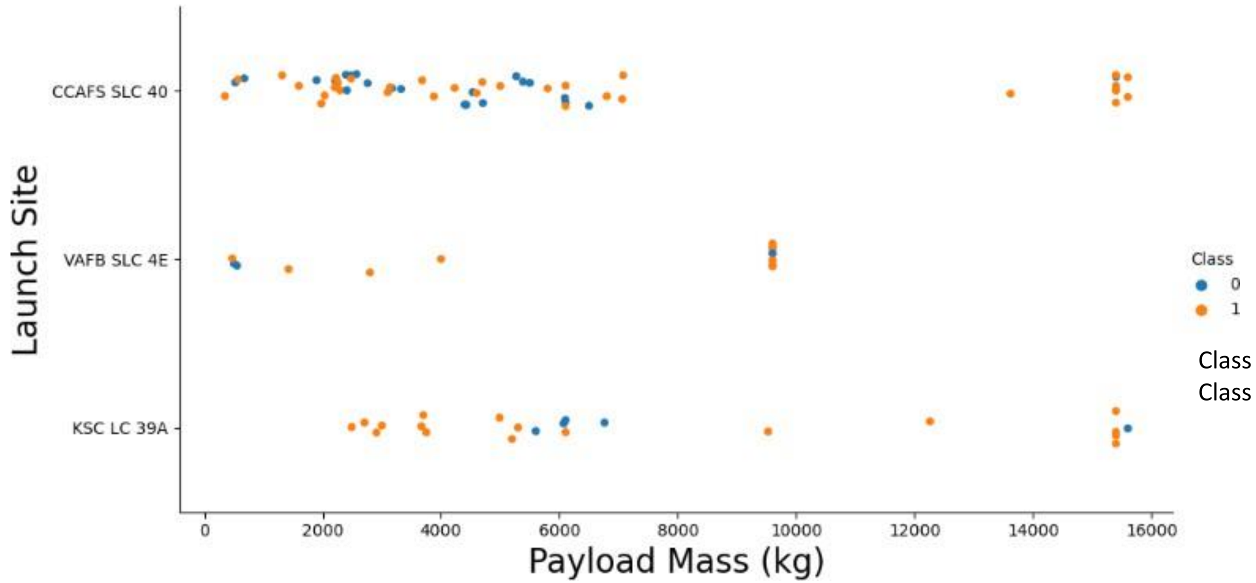
- **Earlier flights** had a **lower success rate** (**blue = fail**)
- **Later flights** had a **higher success rate** (**orange = success**)
- Around half of launches were from CCAFS SLC 40 launch site
- VAFB SLC 4E and KSC LC 39A have higher success rates
- We can infer that new launches have a higher success rate



Payload vs. Launch Site

Exploratory Data Analysis

- Typically, the **higher** the **payload mass** (kg), the **higher** the **success rate**
- Most launces with a payload greater than 7,000 kg were successful
- KSC LC 39A has a 100% success rate for launches less than 5,500 kg
- VAFB SKC 4E has not launched anything greater than ~10,000 kg

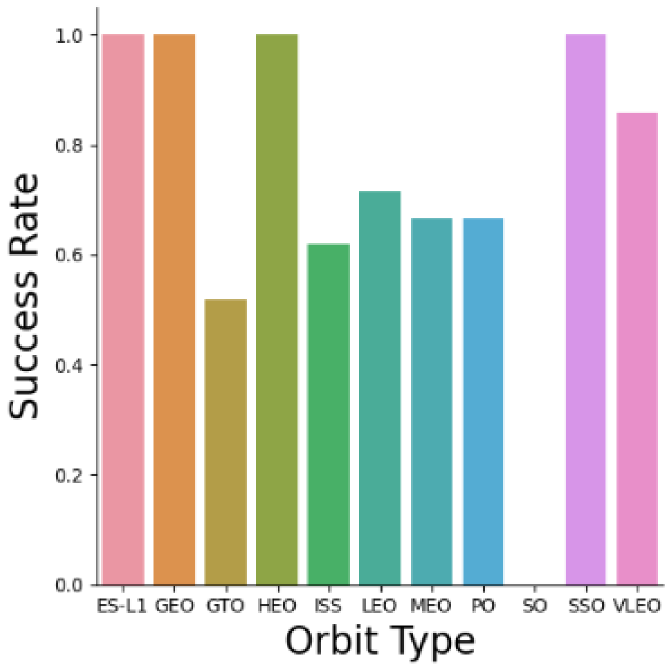


Class 0 = Fail
Class 1 = Success

Success Rate by Orbit

Exploratory Data Analysis

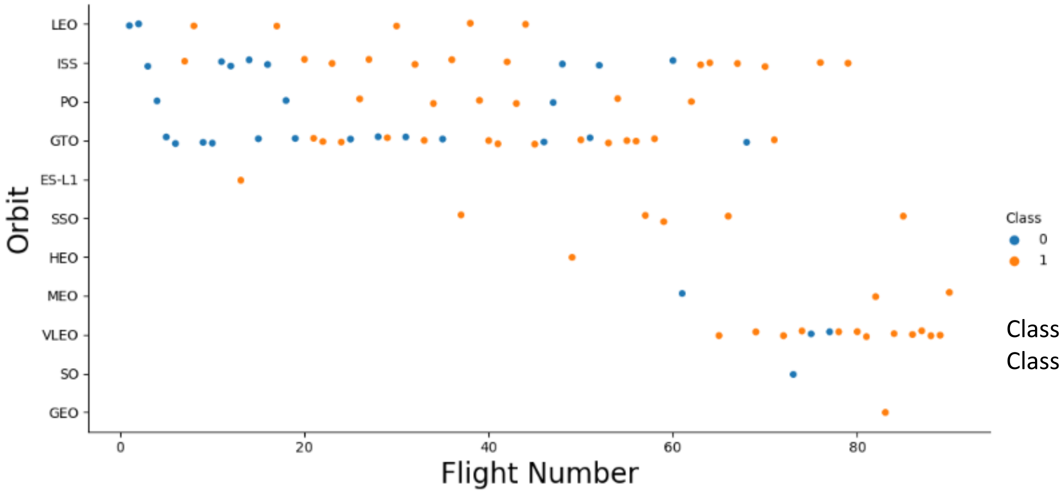
- **100% Success Rate**: ES-L1, GEO, HEO and SSO
- **50%-80% Success Rate**: GTO, ISS, LEO, MEO, PO
- **0% Success Rate**: SO



Flight Number vs. Orbit

Exploratory Data Analysis

- The success rate typically increases with the number of flights for each orbit
- This relationship is highly apparent for the LEO orbit
- The GTO orbit, however, does not follow this trend

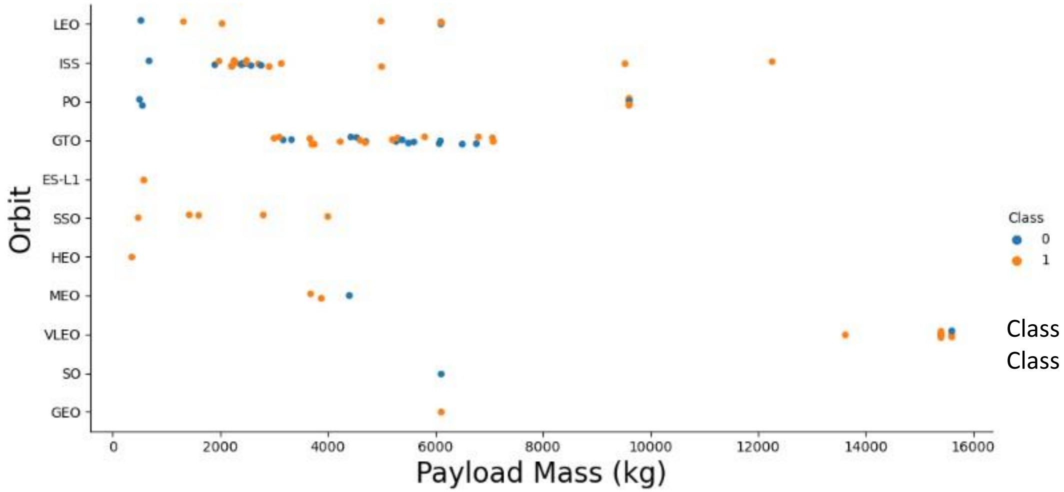


Class 0 = Fail
Class 1 = Success

Payload vs. Orbit

Exploratory Data Analysis

- Heavy payloads are better with LEO, ISS and PO orbits
- The GTO orbit has mixed success with heavier payloads

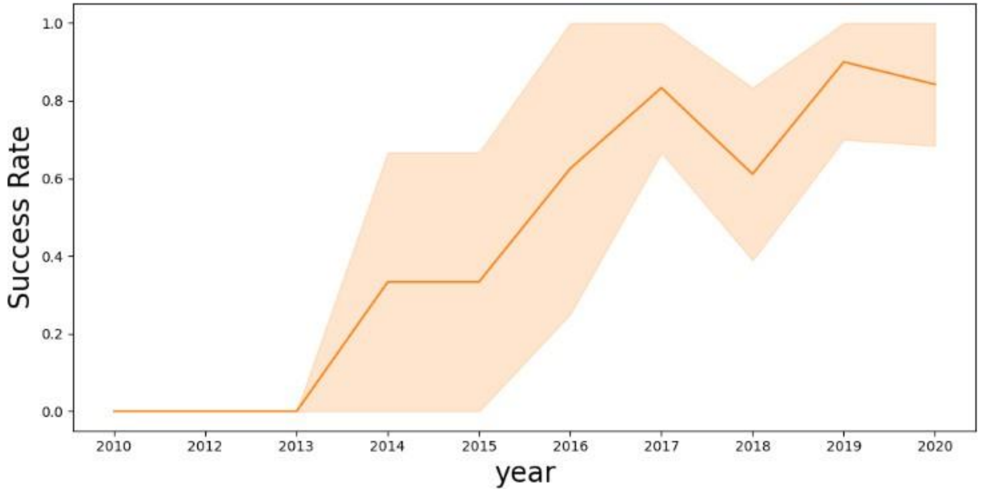


Class 0 = Fail
Class 1 = Success

Launch Success over Time

Exploratory Data Analysis

- The success rate improved from 2013-2017 and 2018-2019
- The success rate decreased from 2017-2018 and from 2019-2020
- Overall, the success rate has improved since 2013



Launch Site Information

Launch Site Names

- CCAFS LC-40
- CCAFS SLC-40
- KSC LC-39A
- VAFB SLC-4E

Landing Outcome Cont.

```
[30]: %sql ibm_db_sa://yyy33800:dwNKg8J3L0IBd6CP@1bbf73c5
      %sql SELECT Unique(LAUNCH_SITE) FROM SPACEXTBL;

       * ibm_db_sa://yyy33800:***@1bbf73c5-d84a-4bb0-85b9
         sqlite:///my_data1.db
      Done.
```

[30]:

launch_site
CCAFS LC-40
CCAFS SLC-40
KSC LC-39A
VAFB SLC-4E

Records with Launch Site Starting with CCA

- Displaying 5 records below

```
%sql SELECT * \
    FROM SPACEXTBL \
    WHERE LAUNCH_SITE LIKE'CCA%' LIMIT 5;

 * ibm_db_sa://yyy33800:***@1bbf73c5-d84a-4bb0-85b9-ab1a4348f4a4.c3n41cmd0nqnrk39u98g.databases.appdomain.cloud:32286/BLUDB
   sqlite:///my_data1.db
Done.
```

DATE	time_utc_	booster_version	launch_site	payload	payload_mass_kg_	orbit	customer	mission_outcome	landing_outcome
2010-06-04	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	Success	Failure (parachute)
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)	NASA (COTS) NRO	Success	Failure (parachute)
2012-05-22	07:44:00	F9 v1.0 B0005	CCAFS LC-40	Dragon demo flight C2	525	LEO (ISS)	NASA (COTS)	Success	No attempt
2012-10-08	00:35:00	F9 v1.0 B0006	CCAFS LC-40	SpaceX CRS-1	500	LEO (ISS)	NASA (CRS)	Success	No attempt
2013-03-01	15:10:00	F9 v1.0 B0007	CCAFS LC-40	SpaceX CRS-2	677	LEO (ISS)	NASA (CRS)	Success	No attempt

Payload Mass

Total Payload Mass

- **111268 kg** (total) carried by boosters launched by NASA (CRS)

```
sql SELECT SUM(PAYLOAD_MASS__KG_) AS TOTAL_PAYLOAD F

 * sqlite:///my_data1.db
Done.
TOTAL_PAYLOAD
111268
```

Average Payload Mass

- **2,928 kg** (average) carried by booster version F9 v1.1

```
%sql SELECT AVG(PAYLOAD_MASS__KG_) \
    FROM SPACEXTBL \
    WHERE BOOSTER_VERSION = 'F9 v1.1';

 * ibm_db_sa://yyy33800:***@1bbf73c5-d84a-4
   sqlite:///my_data1.db
Done.
   1
2928
```

Landing & Mission Info

1st Successful Landing in Ground Pad

- 22/12/2015

```
%sql SELECT MIN(DATE) \
FROM SPACEXTBL \
WHERE LANDING__OUTCOME = 'Success (ground pad)'
```

```
 * ibm_db_sa://yyy33800:***@1bbf73c5-d84a-4bb0-85b
   sqlite:///my_data1.db
Done.
```

1
2015-12-22

Booster Drone Ship Landing

- Booster mass greater than 4,000 but less than 6,000
- F9 FT B1022, F9 FT B1026, F9 FT B1021.2, F9 FT B1031.2

```
[ ]  sql SELECT DISTINCT BOOSTER_VERSION FROM SPACEXTBL
```

```
 * sqlite:///my_data1.db
Done.
```

Booster_Version
F9 FT B1022
F9 FT B1026
F9 FT B1021.2
F9 FT B1031.2

Total Number of Successful and Failed Mission Outcomes

- 1 Failure in Flight
- 99 Success
- 1 Success (payload status unclear)

```
%sql SELECT MISSION_OUTCOME, COUNT(*) as total_number \
FROM SPACEXTBL \
GROUP BY MISSION_OUTCOME;
```

```
 * sqlite:///my_data1.db
Done.
```

Mission_Outcome	total_number
Failure (in flight)	1
Success	98
Success	1
Success (payload status unclear)	1

Boosters

Carrying Max Payload

- F9 B5 B1048.4
- F9 B5 B1049.4
- F9 B5 B1051.3
- F9 B5 B1056.4
- F9 B5 B1048.5
- F9 B5 B1051.4
- F9 B5 B1049.5
- F9 B5 B1060.2
- F9 B5 B1058.3
- F9 B5 B1051.6
- F9 B5 B1060.3
- F9 B5 B1049.7

```
%sql SELECT BOOSTER_VERSION \
FROM SPACEXTBL \
WHERE PAYLOAD_MASS__KG_ = (SELECT MAX(PAYLOAD_MASS__KG_) FROM SPACEXTBL);
```

```
 * sqlite:///my_data1.db
Done.
```

Booster_Version
F9 B5 B1048.4
F9 B5 B1049.4
F9 B5 B1051.3
F9 B5 B1056.4
F9 B5 B1048.5
F9 B5 B1051.4
F9 B5 B1049.5
F9 B5 B1060.2
F9 B5 B1058.3
F9 B5 B1051.6
F9 B5 B1060.3
F9 B5 B1049.7

Failed Landings on Drone Ship

In 2015

- Showing month, date, booster version, launch site for failure landing outcome in drone ship

```
%sql SELECT substr(Date,4,2) as month, DATE,BOOSTER_VERSION, LAUNCH_SITE, [Landing _Outcome] \
FROM SPACEXTBL \
where [Landing _Outcome] = 'Failure (drone ship)' and substr(Date,7,4)='2015';
```

```
 * sqlite:///my_data1.db
Done.
```

month	Date	Booster_Version	Launch_Site	Landing _Outcome
01	10-01-2015	F9 v1.1 B1012	CCAFS LC-40	Failure (drone ship)
04	14-04-2015	F9 v1.1 B1015	CCAFS LC-40	Failure (drone ship)

Count of Successful Landings

Ranked Descending

- Count of landing outcomes between 2010-06-04 and 2017-03-20 in descending order

```
%%sql sqlite:///my_data1.db
SELECT Landing_Outcome, COUNT(*) AS QTY
FROM SPACEXTBL
WHERE Date BETWEEN '2010-06-04' AND '2017-03-20'
GROUP BY Landing_Outcome
ORDER BY QTY DESC;
```

Done.

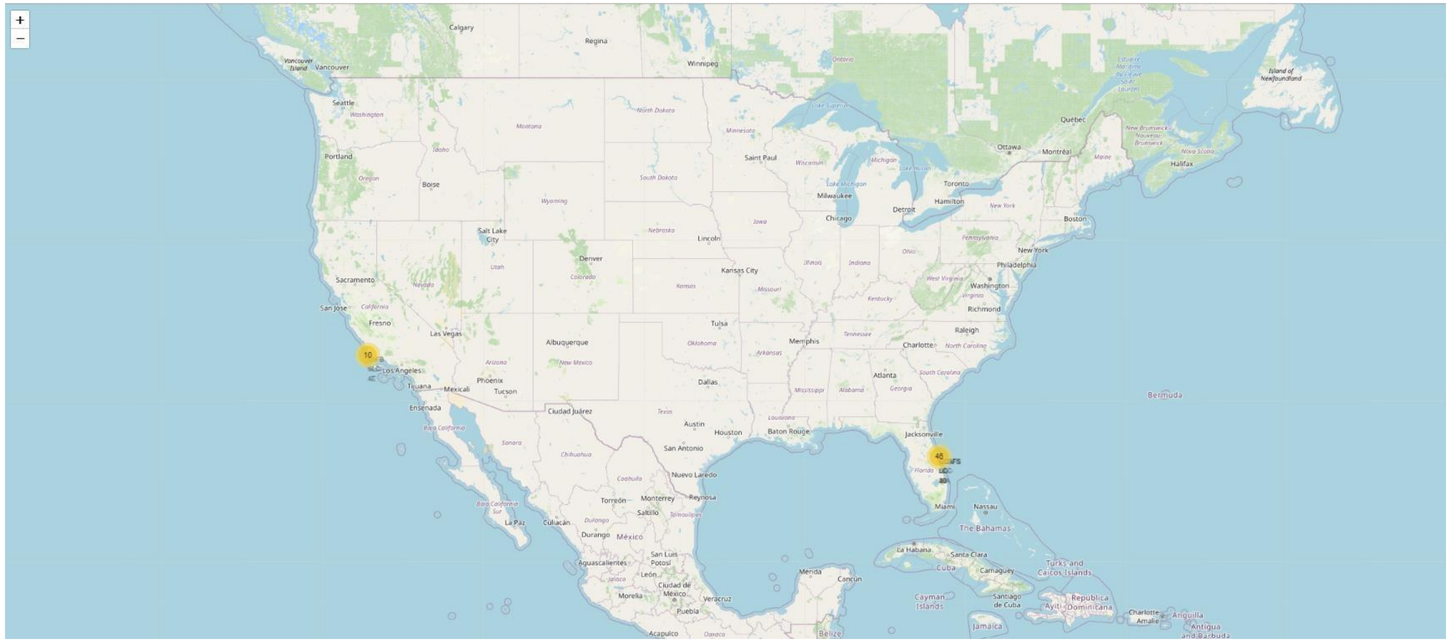
Landing_Outcome	QTY
No attempt	10
Success (drone ship)	5
Failure (drone ship)	5
Success (ground pad)	3
Controlled (ocean)	3
Uncontrolled (ocean)	2
Failure (parachute)	2
Precluded (drone ship)	1

Launch Site Analysis

Launch Sites

With Markers

- **Near Equator**: the closer the launch site to the equator, the **easier** it is **to launch** to equatorial orbit, and the more help you get from Earth's rotation for a prograde orbit. Rockets launched from sites near the equator get an **additional natural boost** - due to the rotational speed of earth - that **helps save the cost** of putting in extra fuel and boosters.



Launch Outcomes

At Each Launch Site

- **Outcomes**:
- **Green** markers for successful launches
- **Red** markers for unsuccessful launches
- Launch site **CCAFS SLC-40** has a **3/7 success rate** (**42.9%**)

Distance to Proximities

CCAFS SLC-40

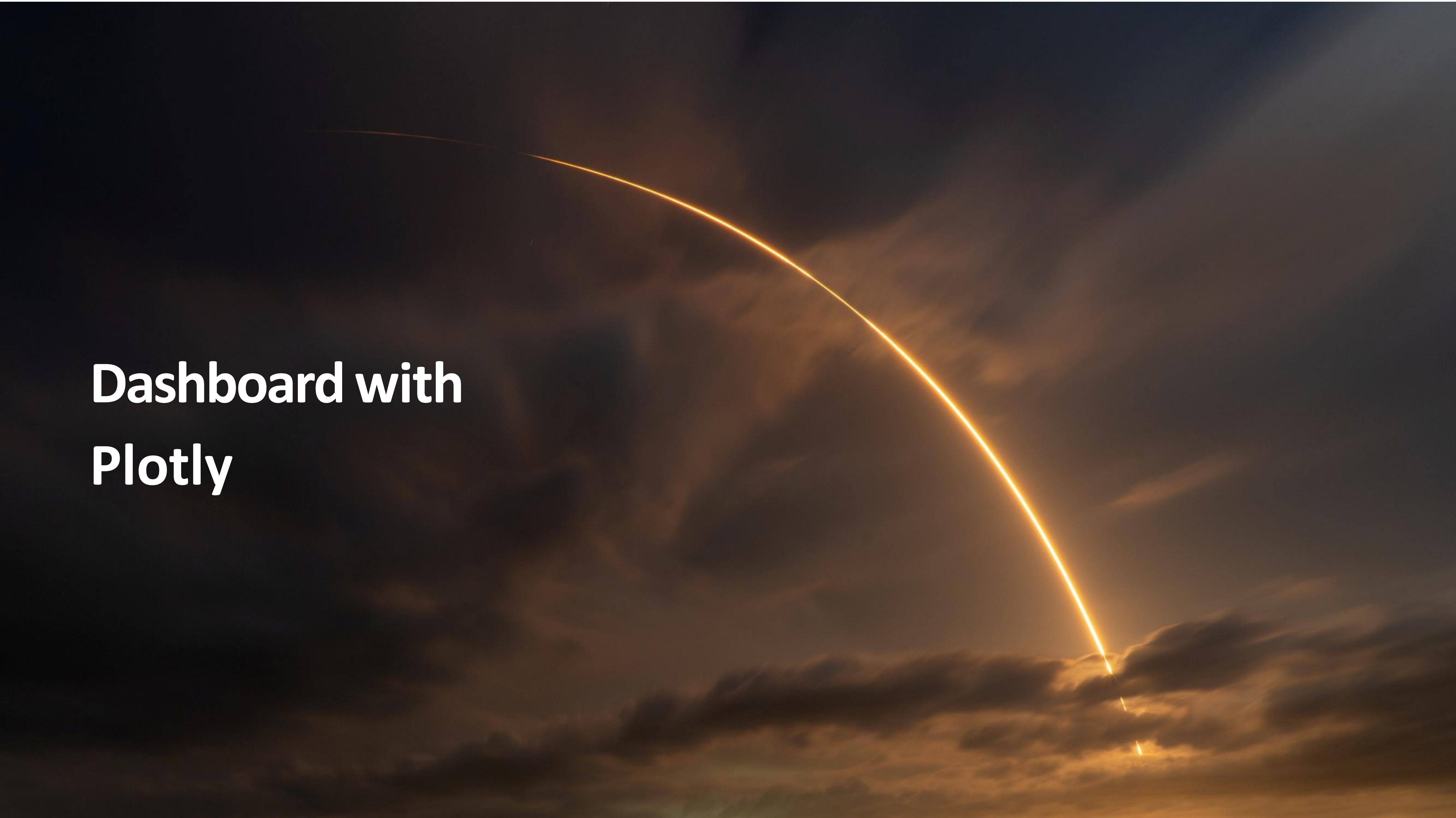
- **.86 km** from nearest coastline
- **21.96 km** from nearest railway
- **23.23 km** from nearest city
- **26.88 km** from nearest highway

Distance to Proximities

CCAFS SLC-40

- **Coasts**: help ensure that spent stages dropped along the launch path or failed launches don't fall on people or property.
- **Safety / Security:** needs to be an exclusion zone around the launch site to keep unauthorized people away and keep people safe.
- **Transportation/Infrastructure and Cities**: need to be away from anything a failed launch can damage, but still close enough to roads/rails/docks to be able to bring people and material to or from it in support of launch activities.

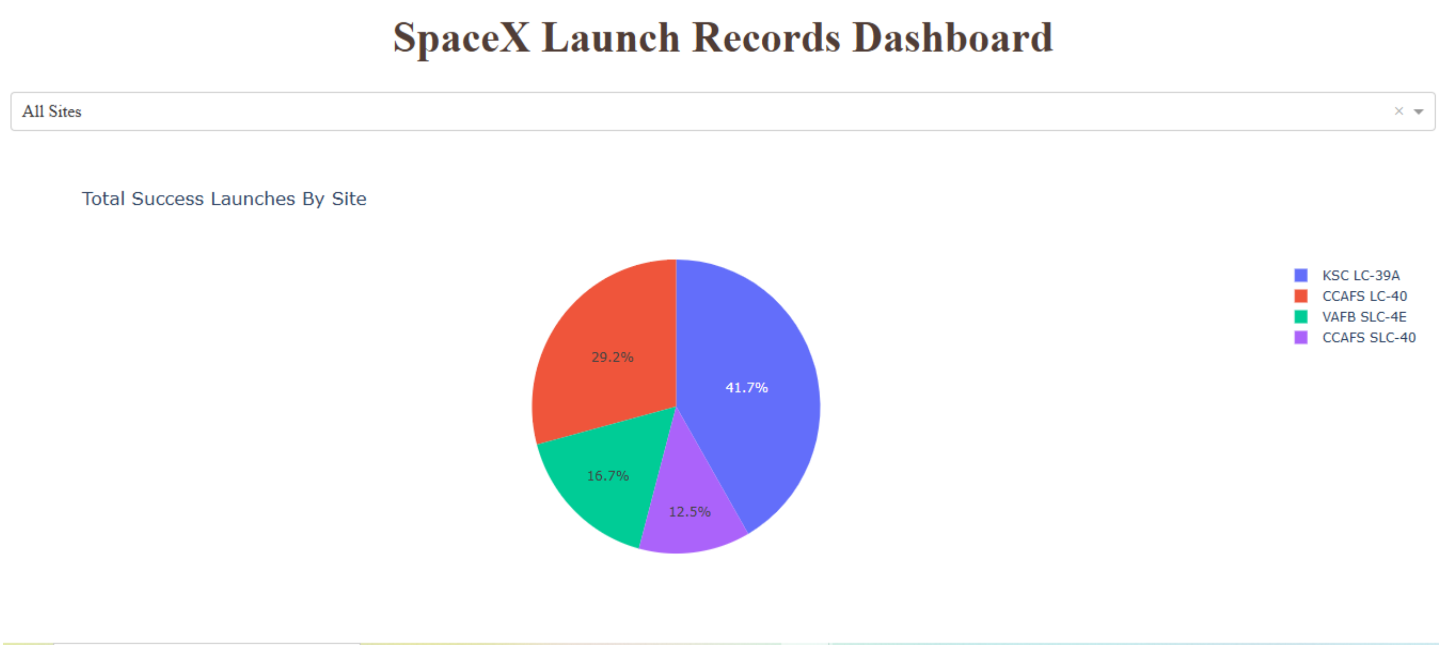
Dashboard with Plotly



Launch Success by Site

Success as Percent of Total

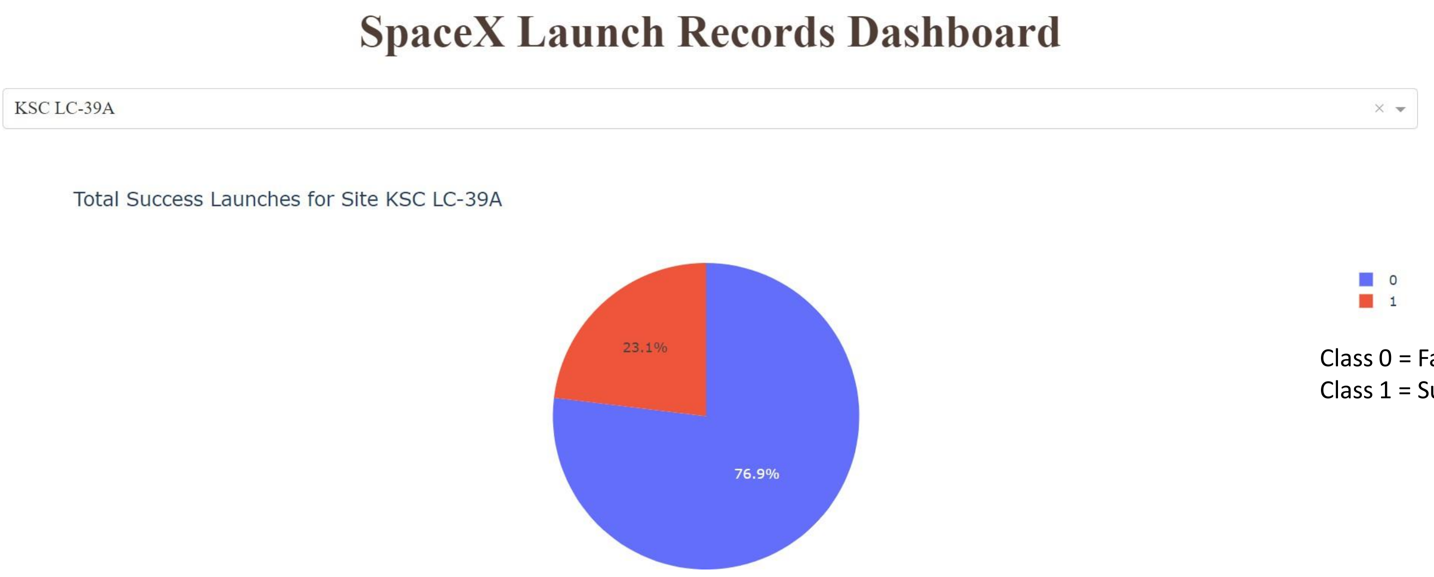
- **KSC LC-39A** has the **most successful launches** amongst launch sites (**41.7%**)



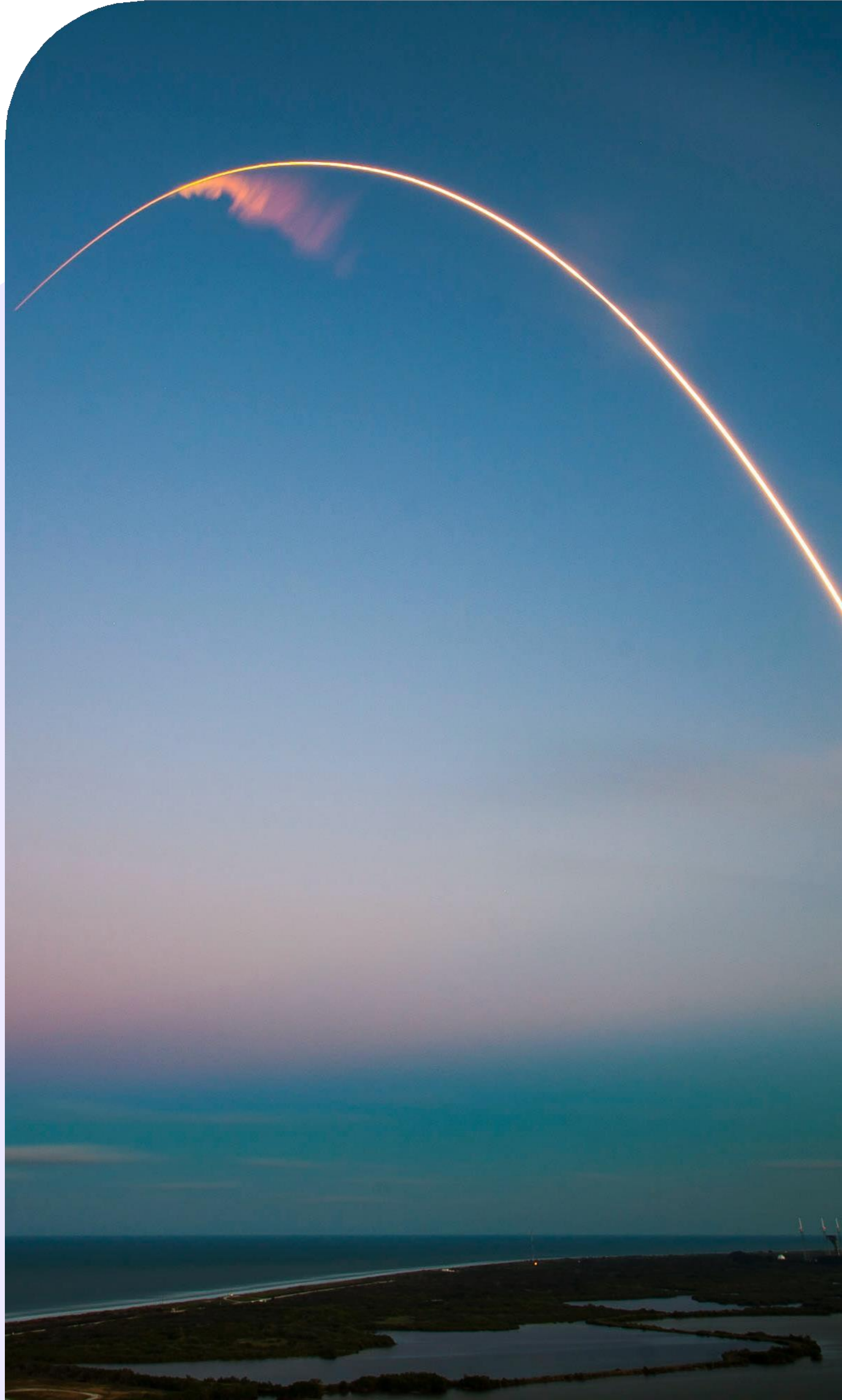
Launch Success (KSC LC-29A)

Success as Percent of Total

- **KSC LC-39A** has the **highest success rate** amongst launch sites (**76.9%**)
- 10 successful launches and 3 failed launches



Class 0 = Fail
Class 1 = Success



Payload Mass and Success

By Booster Version

- **Payloads between 2,000 kg** and **5,000 kg** have the **highest success rate**
- 1 indicating successful outcome and 0 indicating an unsuccessful outcome

Predictive Analytics

Classification

Accuracy

- **All** the **models** performed at about the same level and had the **same scores** and **accuracy**. This is likely due to the **small dataset**. The **Decision Tree model slightly outperformed** the rest when looking at .best_score_
- .best_score_ is the average of all cv folds for a single combination of the parameters

```
Model           Accuracy        TestAccuracy
LogReg          0.84643         0.83333
SVM             0.84821         0.83333
Tree            0.87321         0.72222
KNN             0.84821         0.83333
```

	LogReg	SVM	Tree	KNN
Jaccard_Score	0.833333	0.845070	0.882353	0.819444
F1_Score	0.909091	0.916031	0.937500	0.900763
Accuracy	0.866667	0.877778	0.911111	0.855556

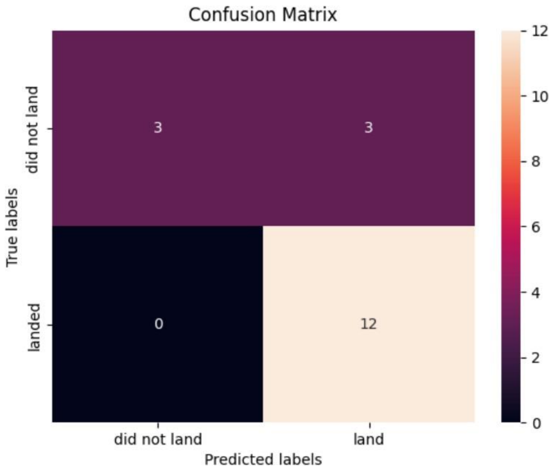
```python
print("Model\t\tAccuracy\tTestAccuracy")
print("LogReg\t\t{}\t\t{}".format(round(logreg_cv.best_score_, 5), round(logreg_cv.score(X_test, Y_test), 5)))
print("SVM\t\t{}\t\t{}".format(round(svm_cv.best_score_, 5), round(svm_cv.score(X_test, Y_test), 5)))
print("Tree\t\t{}\t\t{}".format(round(tree_cv.best_score_, 5), round(tree_cv.score(X_test, Y_test), 5)))
print("KNN\t\t{}\t\t{}".format(round(knn_cv.best_score_, 5), round(knn_cv.score(X_test, Y_test), 5)))

comparison = {}
comparison['LogReg'] = {'Accuracy': round(logreg_cv.best_score_, 5), 'TestAccuracy': round(logreg_cv.score(X_test, Y_test), 5)}
comparison['SVM'] = {'Accuracy': round(svm_cv.best_score_, 5), 'TestAccuracy': round(svm_cv.score(X_test, Y_test), 5)}
comparison['Tree'] = {'Accuracy': round(tree_cv.best_score_, 5), 'TestAccuracy': round(tree_cv.score(X_test, Y_test), 5)}
comparison['KNN'] = {'Accuracy': round(knn_cv.best_score_, 5), 'TestAccuracy': round(knn_cv.score(X_test, Y_test), 5)}
```

Confusion Matrices

Performance Summary

- A confusion matrix summarizes the performance of a classification algorithm
- All the confusion matrices were identical
- The fact that there are false positives (Type 1 error) is not good
- Confusion Matrix Outputs:
  - 12 True positive
  - 3 True negative
  - **3 False positive**
  - 0 False Negative



- **Precision** = TP / (TP + FP)
  - 12 / 15 = .80
- **Recall** = TP / (TP + FN)
  - 12 / 12 = 1
- **F1 Score** = 2 * (Precision * Recall) / (Precision + Recall)
  - 2 * (.8 * 1) / (.8 + 1) = .89
- **Accuracy** = (TP + TN) / (TP + TN + FP + FN) = .833

Conclusion

Research

- **Model Performance**: The models performed similarly on the test set with the decision tree model slightly outperforming
- **Equator**: Most of the launch sites are near the equator for an additional natural boost - due to the rotational speed of earth - which helps save the cost of putting in extra fuel and boosters
- **Coast**: All the launch sites are close to the coast
- **Launch Success**: Increases over time
- **KSC LC-39A**: Has the highest success rate among launch sites. Has a 100% success rate for launches less than 5,500 kg
- **Orbits**: ES-L1, GEO, HEO, and SSO have a 100% success rate
- **Payload Mass**: Across all launch sites, the higher the payload mass (kg), the higher the success rate

Conclusion

Things to Consider

- **Dataset**: A larger dataset will help build on the predictive analytics results to help understand if the findings can be generalizable to a larger data set
- **Feature Analysis / PCA**: Additional feature analysis or principal component analysis should be conducted to see if it can help improve accuracy
- **XGBoost**: Is a powerful model which was not utilized in this study. It would be interesting to see if it outperforms the other classification models

Appendix

Special Thanks to:

[Instructors]

[Coursera]

[IBM]