IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

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Outline

- Executive Summary
- Introduction
- Methodology
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- Conclusion
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Executive Summary

The research attempts to identify the factors for a successful landing of Falcon 9. 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)

Introduction

- SpaceX, a leading player in the space industry, has prioritized affordability and accessibility in space travel. Its achievements include sending spacecraft to the International Space Station, deploying a satellite constellation for global internet access, and conducting crewed missions to space. SpaceX's cost-efficiency stems from its innovative reuse of the first stage of its Falcon 9 rocket, reducing launch costs to $62 million per launch compared to competitors' costs of $165 million without reusability.
- Predicting the success of first stage landings using machine learning models can determine launch prices for SpaceX and competitors, providing crucial insights for decision-making in the competitive space launch market.

Section 1

Methodology

Methodology

- Data collection methodology:
  - ✓ Request to the SpaceX API
  - ✓ Clean the requested data
- Perform data wrangling
  - ✓ Exploratory Data Analysis
  - ✓ Determine Training Labels
- Perform exploratory data analysis (EDA) using visualization and SQL
- Perform interactive visual analytics using Folium and Plotly Dash
- Perform predictive analysis using classification models
  - ✓ How to build, tune, evaluate classification models

Data Collection

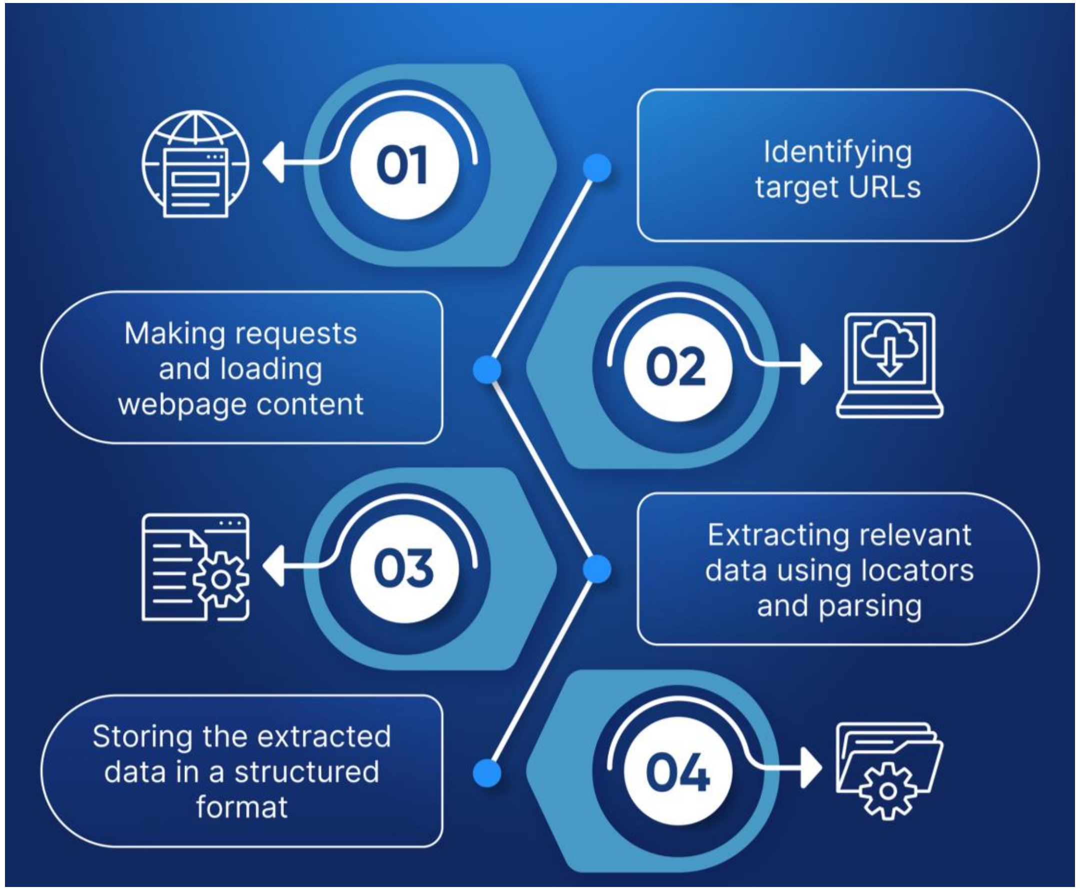
- **Request data** from SpaceX API (rocket launch data)
- **Decode response** using .json() and convert to a dataframe using .json_normalize()
- **Request information** about the launches from SpaceX API using custom functions
- **Create dictionary** from the data
- **Create dataframe** from the dictionary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

Data Collection – SpaceX API

1. **Authentication:** Authenticate with SpaceX REST API using API key.
2. **Endpoint for Launch Data:** Call SpaceX API endpoint to retrieve launch data.
   Use phrases like "GET /v4/launches" to fetch information about past launches.
3. **Filtering Data:** Apply filters to retrieve specific data, such as successful landings.
   Use phrases like "filter=success:true" to get successful landing data.
4. **Pagination:** Handle pagination to retrieve large datasets.
   Use phrases like "limit=100" and "offset=100" for pagination.
5. **Data Parsing:** Parse the received JSON data to extract relevant information.
   Use phrases like "json.loads(response)" to parse JSON data.
6. **Error Handling:** Implement error handling for failed API requests.
   Use phrases like "try-except" to handle exceptions.

Data Collection - Scraping

- **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



Data Wrangling

Process

- **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** & Costs

- **True Ocean:** mission outcome had a successful landing to a specific region of the ocean
- **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

EDA with Data Visualization

Charts used

- 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.

EDA with SQL

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)

Build an Interactive 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**

Build a 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

Predictive Analysis (Classification)

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

Results

Exploratory Data Analysis

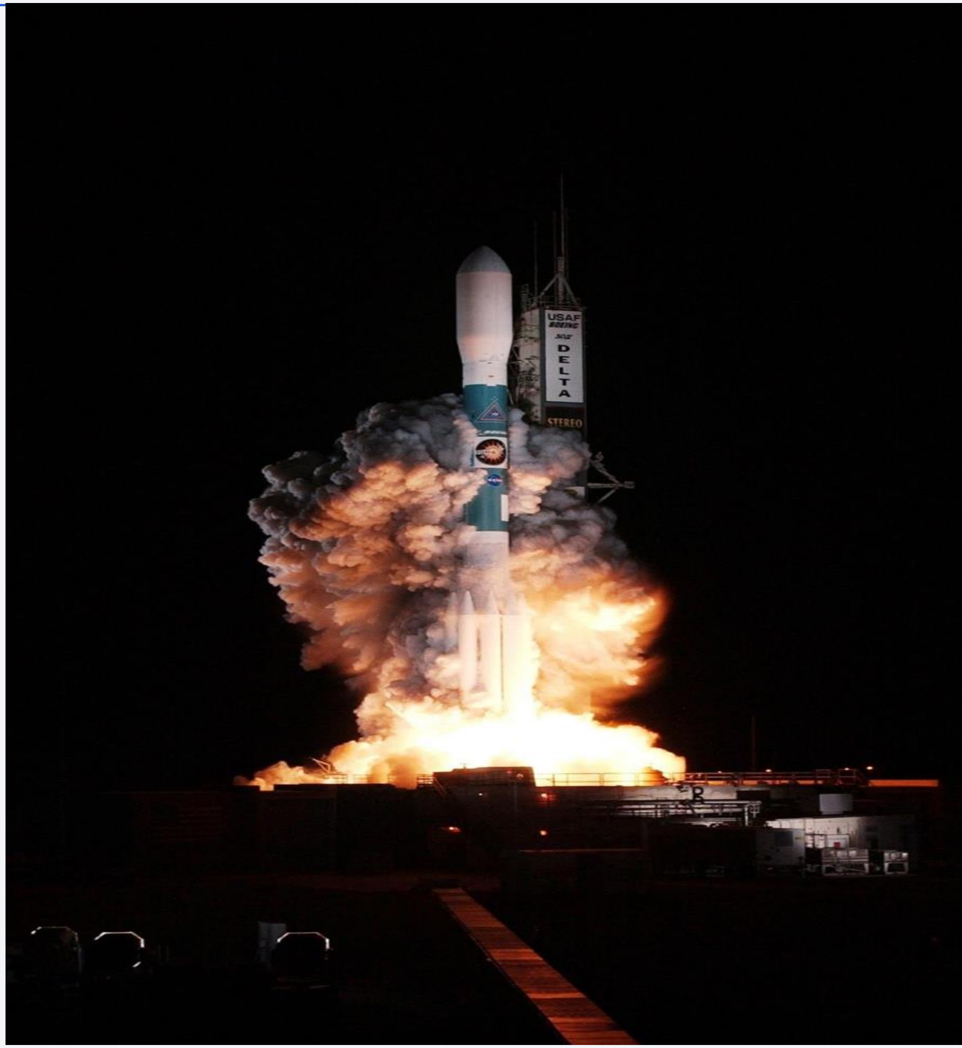
- Launch success has improved over time
- KSC LC-39A has the highest success rate among landing sites
- Orbits ES-L1, GEO, HEO and SSO have a 100% success rate

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



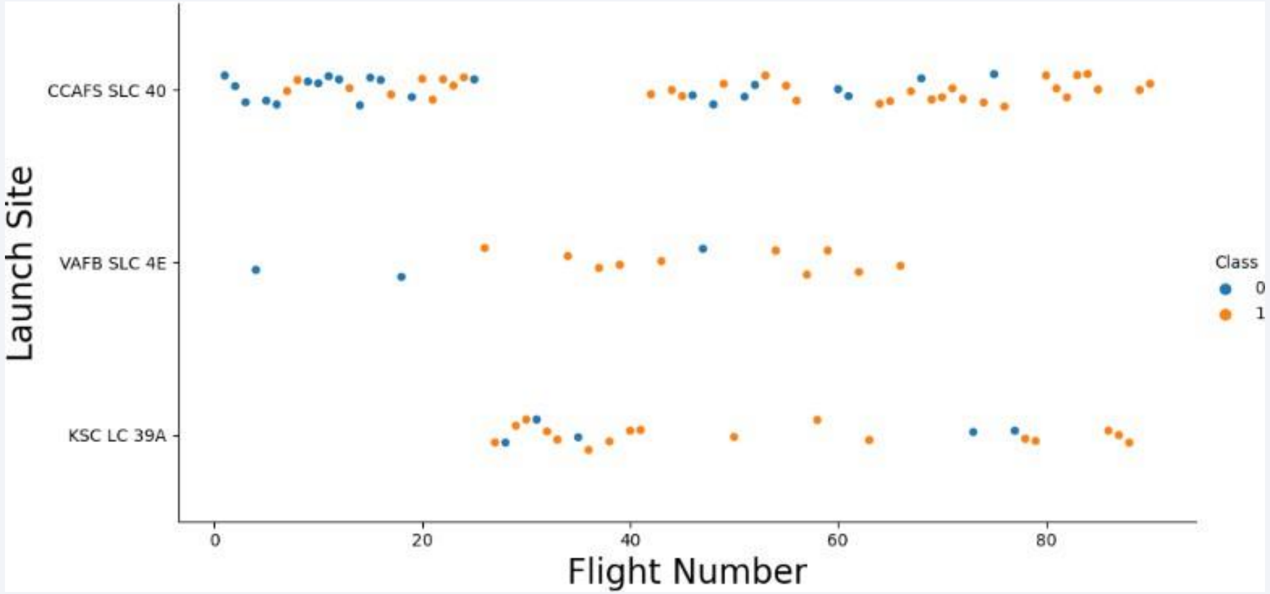
Section 2

Insights drawn from EDA

Flight Number vs. Launch Site

Exploratory Data Analysis

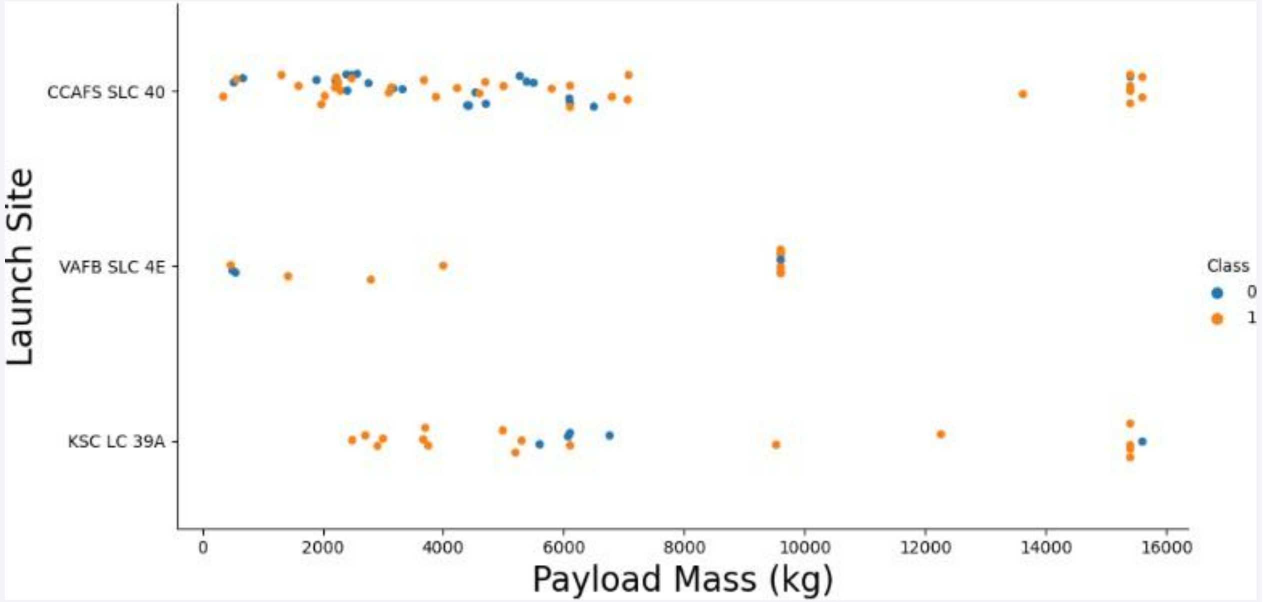
- **Earlier flights** had a **lower success rate** (blue = fail)
- **Later flights** had a **higher success rate** (orange = success)
- Around half of launches were from CCAFS SLC 40 launch site
- VAFB SLC 4E and KSC LC 39A have higher success rates
- We can infer that new launches have a higher success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



Payload vs. Launch Site

Exploratory Data Analysis

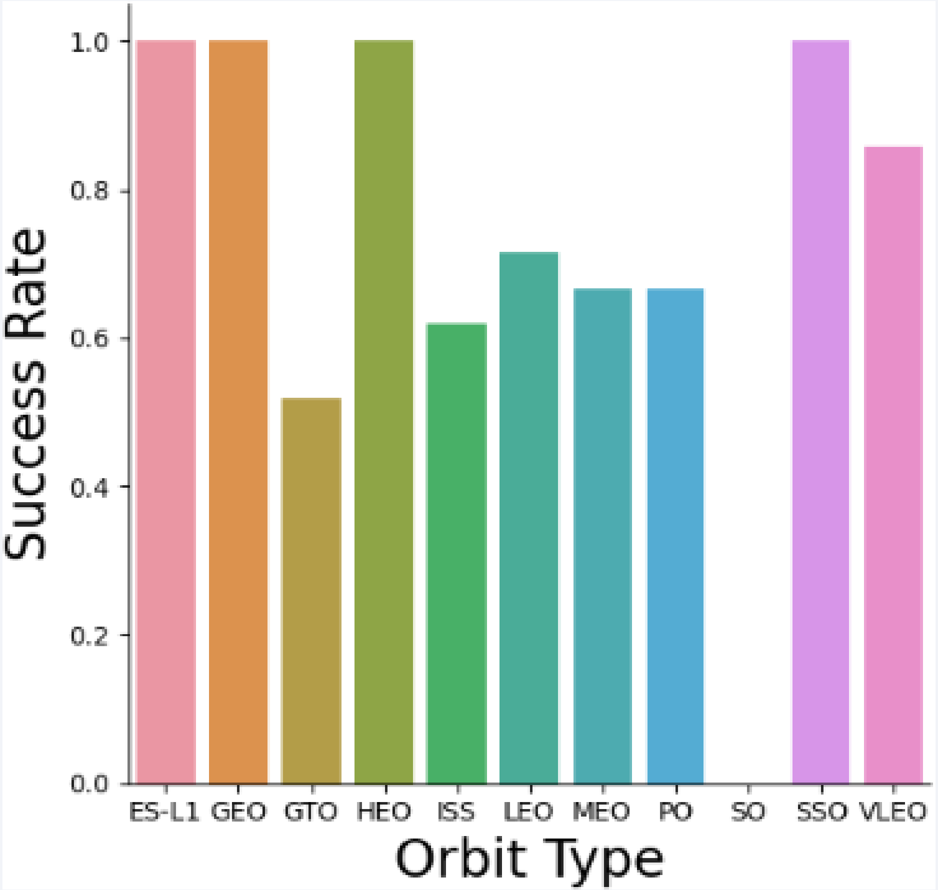
- Typically, the **higher** the **payload mass** (kg), the **higher** the **success rate**
- Most launces with a payload greater than 7,000 kg were successful
- KSC LC 39A has a 100% success rate for launches less than 5,500 kg
- VAFB SKC 4E has not launched anything greater than ~10,000 kg



Success Rate vs. Orbit Type

Exploratory Data Analysis

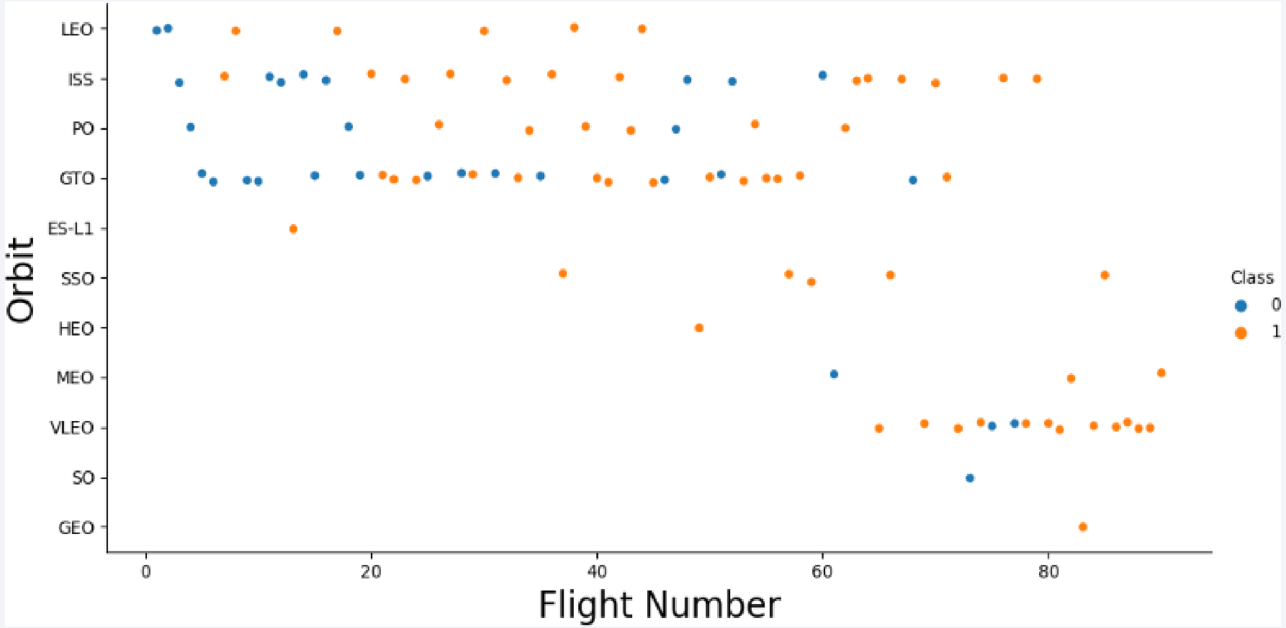
- 100% Success Rate: ES-L1, GEO, HEO and SSO
- 50%-80% Success Rate: GTO, ISS, LEO, MEO, PO
- 0% Success Rate: SO



Flight Number vs. Orbit Type

Exploratory Data Analysis

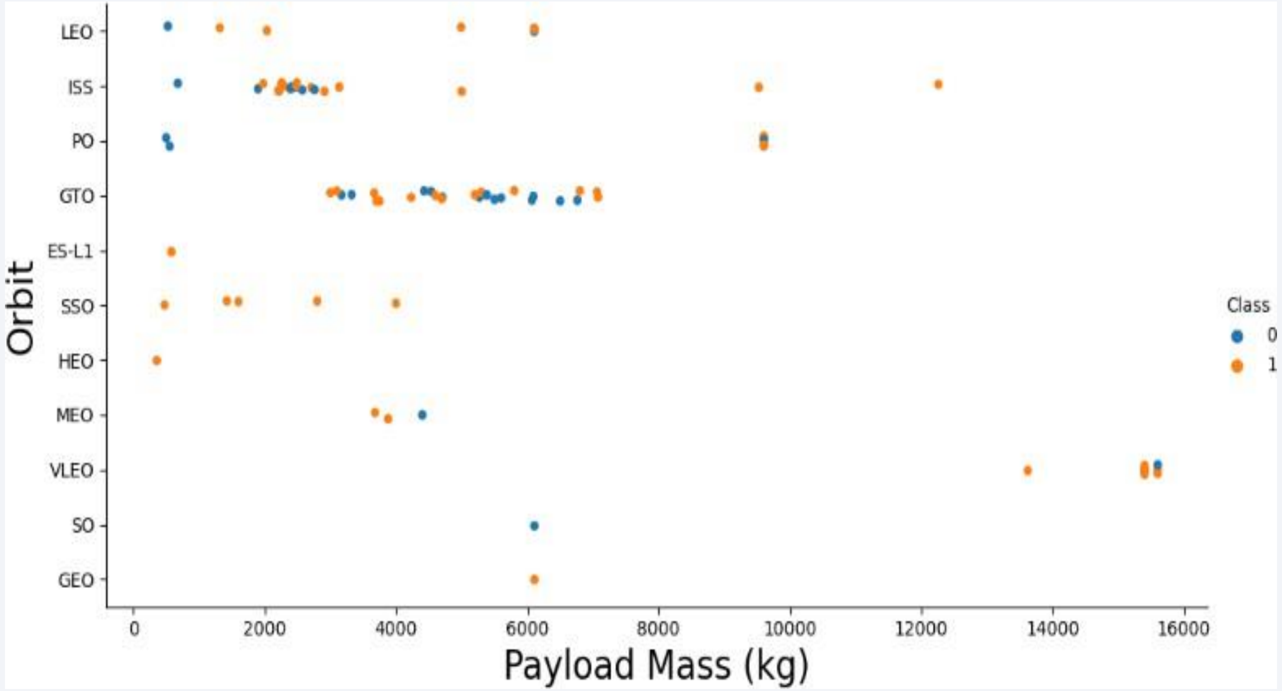
- The success rate typically increases with the number of flights for each orbit
- This relationship is highly apparent for the LEO orbit
- The GTO orbit, however, does not follow this trend



Payload vs. Orbit Type

Exploratory Data Analysis

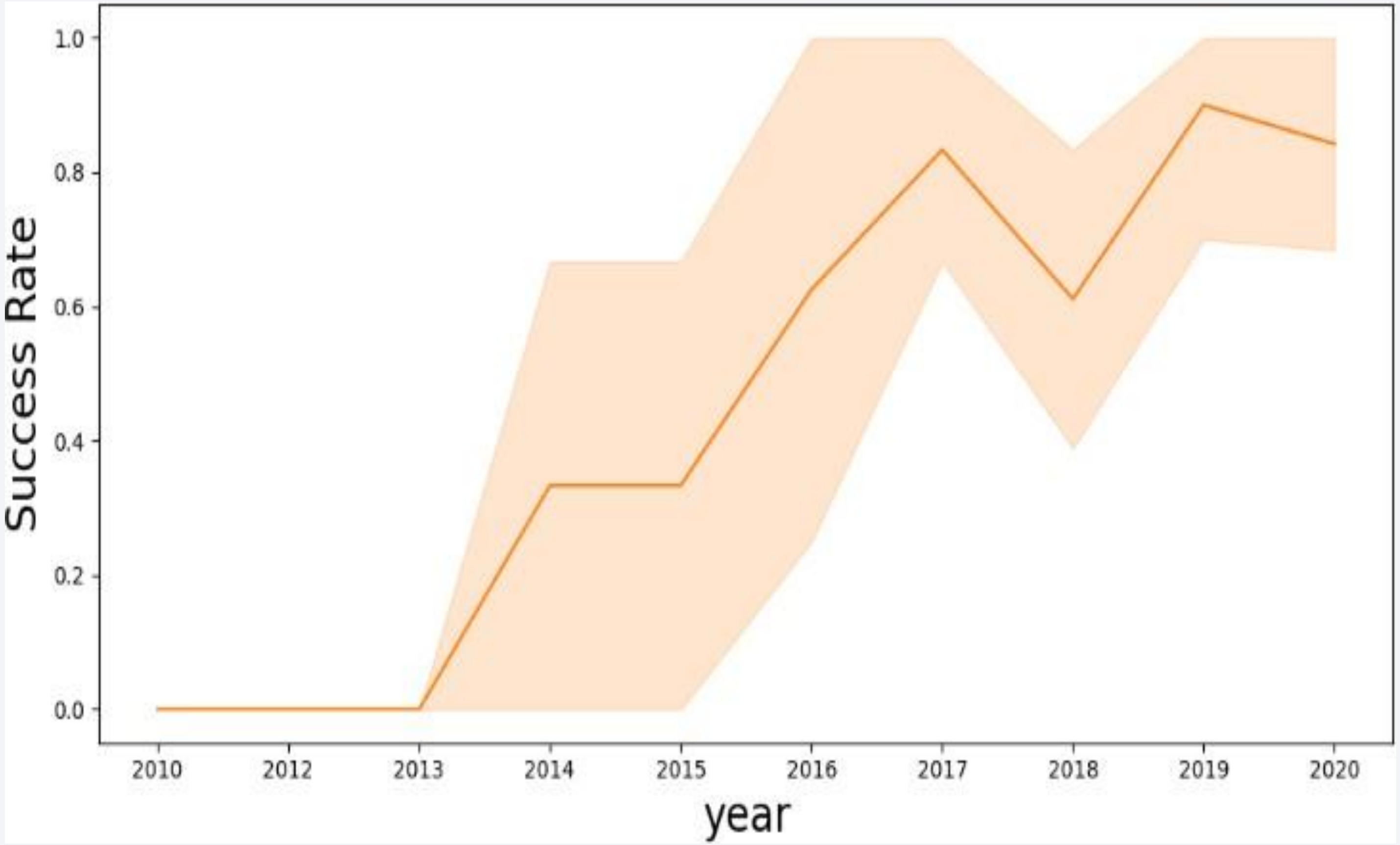
- **Heavy payloads** are better with LEO, ISS and PO orbits
- The **GTO orbit** has mixed success with heavier payloads



Launch Success Yearly Trend

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

Launch Site Names Begin with 'CCA'

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

Total Payload Mass

Total Payload Mass

45,596 kg (total) carried by boosters launched by NASA (CRS)

```
%sql SELECT SUM(PAYLOAD_MASS__KG_) \
    FROM SPACEXTBL \
    WHERE CUSTOMER = 'NASA (CRS)';
```

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

1
45596

Average Payload Mass by F9 v1.1

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

First Successful Ground Landing Date

1st Successful Landing in Ground Pad

12/22/2015

```
%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

Successful Drone Ship Landing with Payload between 4000 and 6000

Booster Drone Ship Landing

- Booster mass greater than 4,000 but less than 6,000
- JSCAT-14, JSCAT-16, SES-10, SES-11 / EchoStar 105

```
%sql SELECT PAYLOAD \
FROM SPACEXTBL \
WHERE LANDING__OUTCOME = 'Success (drone ship)' \
AND PAYLOAD_MASS__KG_ BETWEEN 4000 AND 6000;
```

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

payload
JCSAT-14
JCSAT-16
SES-10
SES-11 / EchoStar 105

Total Number of Successful and Failure 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 Carried Maximum Payload

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

2015 Launch Records

Failed Landings on Drone Ship

Showing month, date, booster version, launch site and landing outcome

```
%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)

Rank Landing Outcomes Between 2010-06-04 and 2017-03-20

Ranked in descending order

```
%sql SELECT [Landing _Outcome], count(*) as count_outcomes \
FROM SPACEXTBL \
WHERE DATE between '04-06-2010' and '20-03-2017' group by [Landing _Outcome] order by count_outcomes DESC;
```

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

Landing _Outcome	count_outcomes
Success	20
No attempt	10
Success (drone ship)	8
Success (ground pad)	6
Failure (drone ship)	4
Failure	3
Controlled (ocean)	3
Failure (parachute)	2
No attempt	1

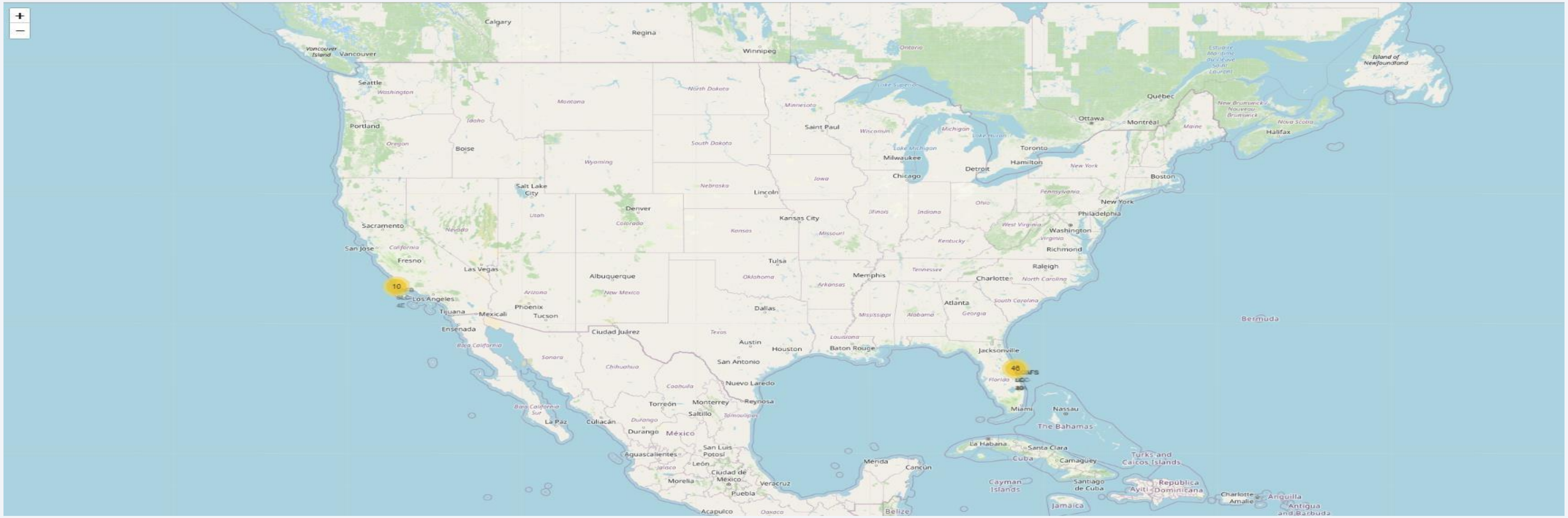
Section 3

Launch Sites Proximities 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

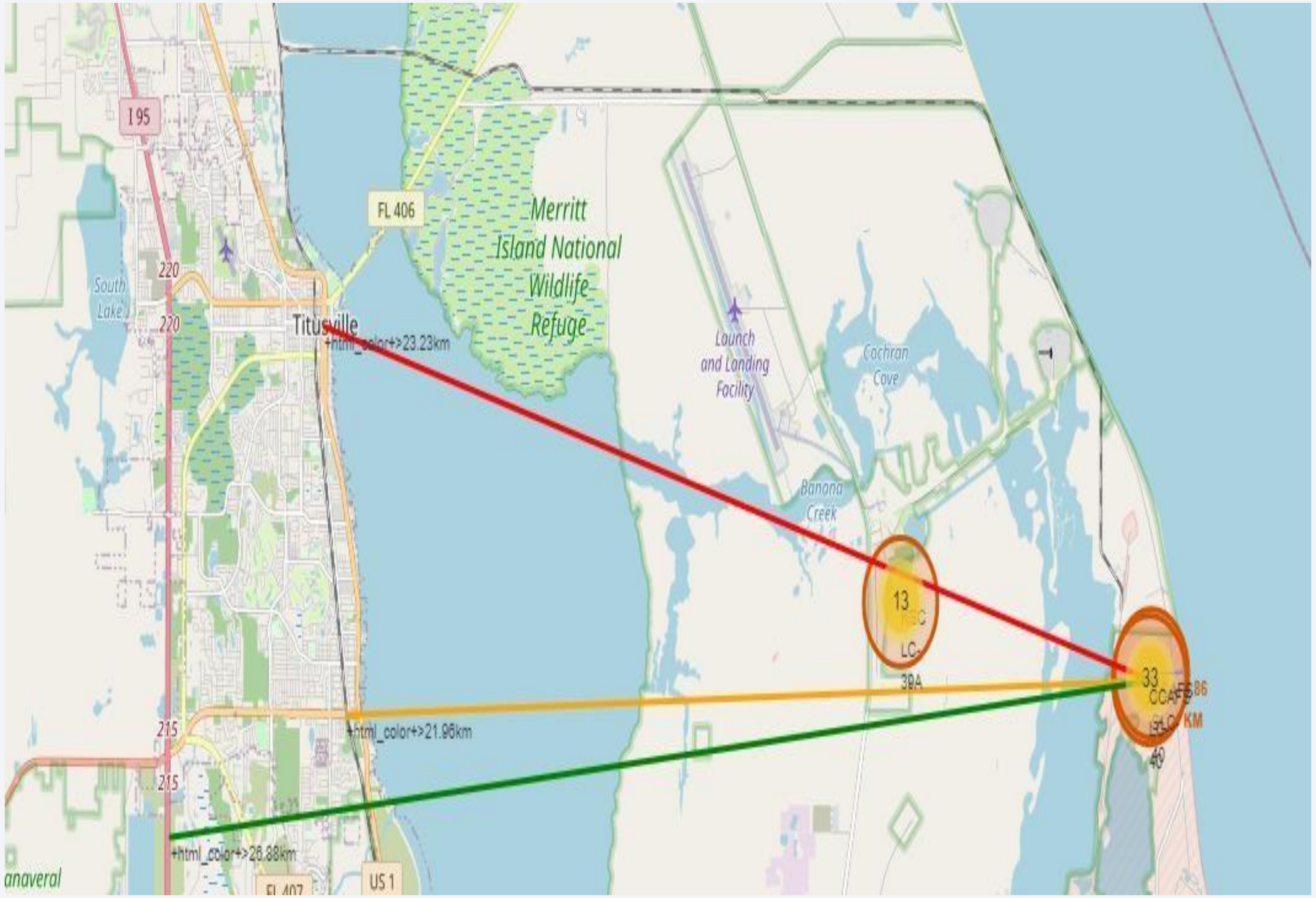
- **Outcomes**:
- Green markers for successful launches
- Red markers for unsuccessful launches
- Launch site **CCAFS SLC-40** has a **3/7 success rate (42.9%)**

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

- **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.



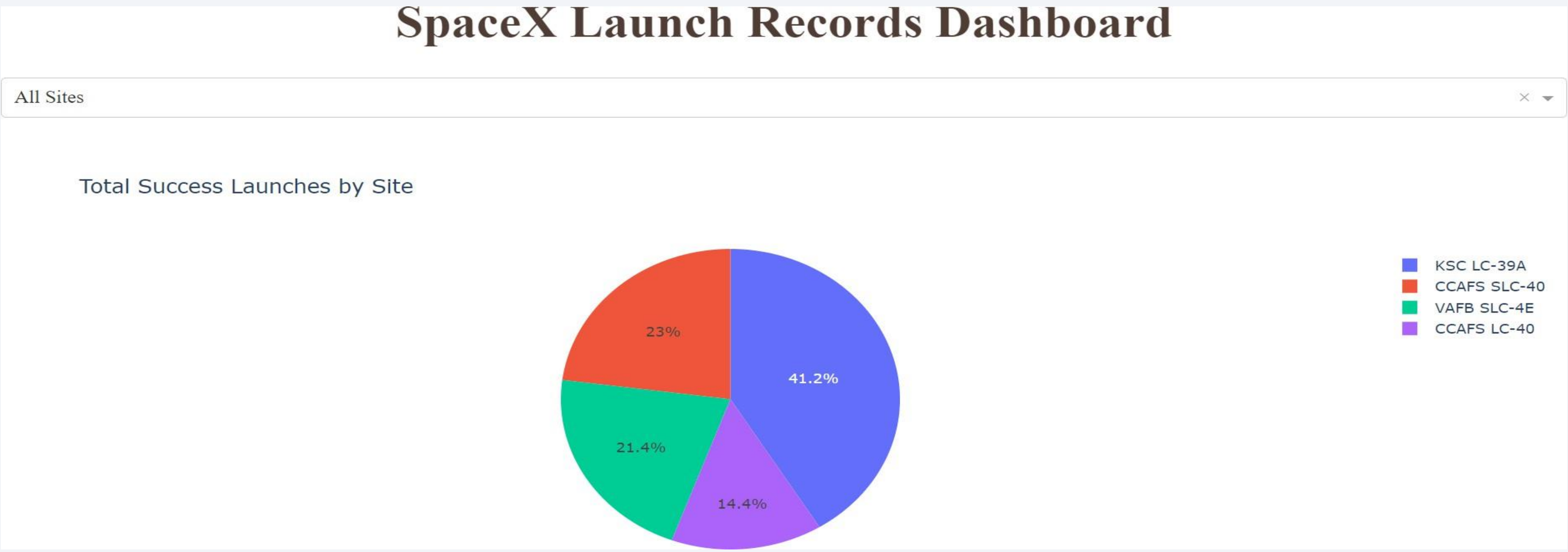
Section 4

Build a Dashboard with Plotly Dash

Launch Success by Site

Success as Percent of Total

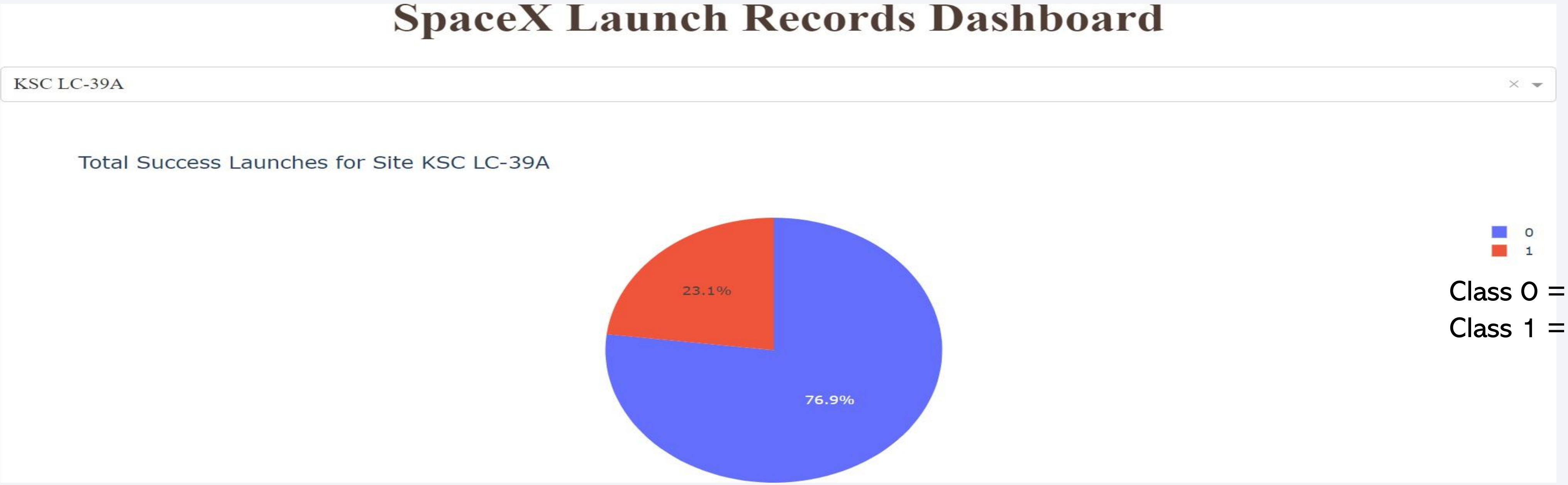
- **KSC LC-39A** has the **most successful launches** amongst launch sites (**41.2%**)



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

Section 5

Predictive Analysis (Classification)

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

	LogReg	SVM	Tree	KNN
Jaccard_Score	0.800000	0.800000	0.800000	0.800000
F1_Score	0.888889	0.888889	0.888889	0.888889
Accuracy	0.833333	0.833333	0.833333	0.833333

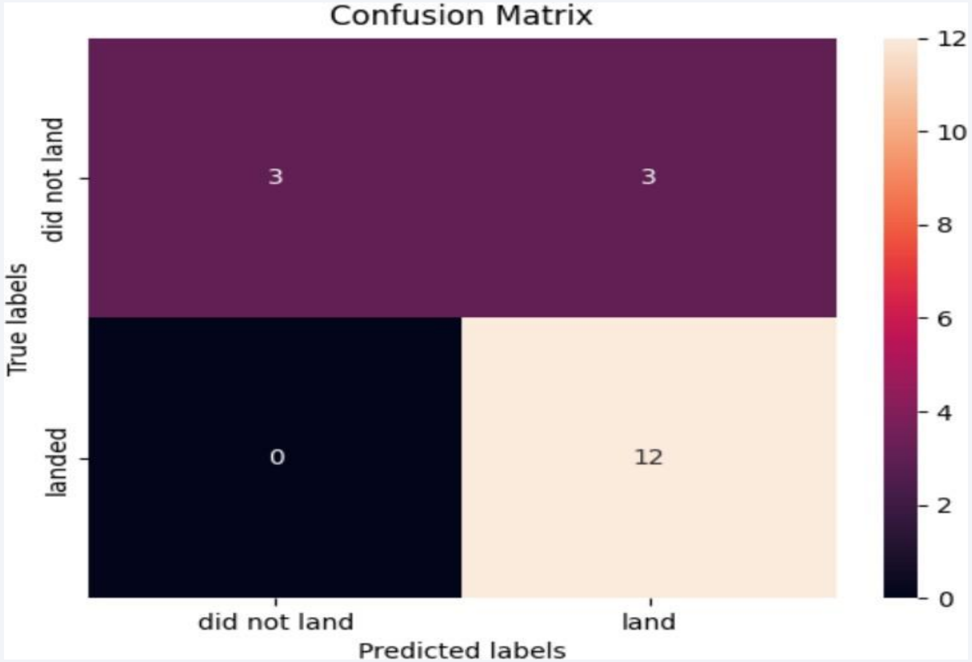
```
models = {'KNeighbors':knn_cv.best_score_,
              'DecisionTree':tree_cv.best_score_,
              'LogisticRegression':logreg_cv.best_score_,
              'SupportVector': svm_cv.best_score_}

bestalgorithm = max(models, key=models.get)
print('Best model is', bestalgorithm,'with a score of', models[bestalgorithm])
if bestalgorithm == 'DecisionTree':
    print('Best params is :', tree_cv.best_params_)
if bestalgorithm == 'KNeighbors':
    print('Best params is :', knn_cv.best_params_)
if bestalgorithm == 'LogisticRegression':
    print('Best params is :', logreg_cv.best_params_)
if bestalgorithm == 'SupportVector':
    print('Best params is :', svm_cv.best_params_)
```

```
Best model is DecisionTree with a score of 0.9017857142857142
Best params is : {'criterion': 'gini', 'max_depth': 16, 'max_features': 'auto', 'min_samples_leaf': 4, 'min_samples_split': 10, 'splitter': 'random'}
```

Confusion Matrix

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

Conclusions

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

Conclusions

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

Thank you!