



IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

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Outline

- Executive Summary
- Introduction
- Methodology
- Results
- Conclusion
- Appendix

Executive Summary

- Methodology (see methodology section for more details)
 - Data collection methodology:
 - Perform data wrangling
 - Perform exploratory data analysis (EDA) using visualization and SQL
 - Perform interactive visual analytics using Folium and Plotly Dash
 - Perform predictive analysis using classification models
- Key results (see results section for more details):
 - The average success rate for a SpaceX launch is 66%, but it increased significantly over the years (from 33% in 2014/2015 to 90% in 2019)
 - Our best model (Decision Tree classifier) can correctly predict the outcome in 17 out of 18 launches contained in the test set, yielding an accuracy of 94.4%.

Introduction

- Project background and context
 - In order to compete against Space X, we have to understand better their cost of each launch.
 - The key determinant of the launch price is whether the first stage does land (and can be reused) or not.
 - Instead of using rocket science, we want to approach this question the "data science way", by using publicly available information to train a machine learning model to predict the launch success.
- Problems you want to find answers
 - For a given launch (with given parameters), will the first stage land or not?

Section 1

Methodology

Methodology

Executive Summary

- Data collection methodology:
 - Webscraping
 - SpaceX's public API
- Perform data wrangling
 - Calculate number of launches from each site, occurrence of each orbit and mission outcomes
 - Create landing outcome label, save it to dataframe and calculate average success rate
- Perform exploratory data analysis (EDA) using visualization and SQL
- Perform interactive visual analytics using Folium and Plotly Dash
- Perform predictive analysis using classification models
 - Evaluate 4 different models (Logistic Regression, SVM, Decision Tree and KNN)
 - Optimize parameters for each of these models with the help of GridSearchCV

Data Collection

Data was collected in 2 ways:

1. Accessing SpaceX's public API [<https://api.spacexdata.com/v4/launches/past>, <https://api.spacexdata.com/v4/rockets/>, <https://api.spacexdata.com/v4/launchpads/>, <https://api.spacexdata.com/v4/payloads/>, <https://api.spacexdata.com/v4/cores/>]

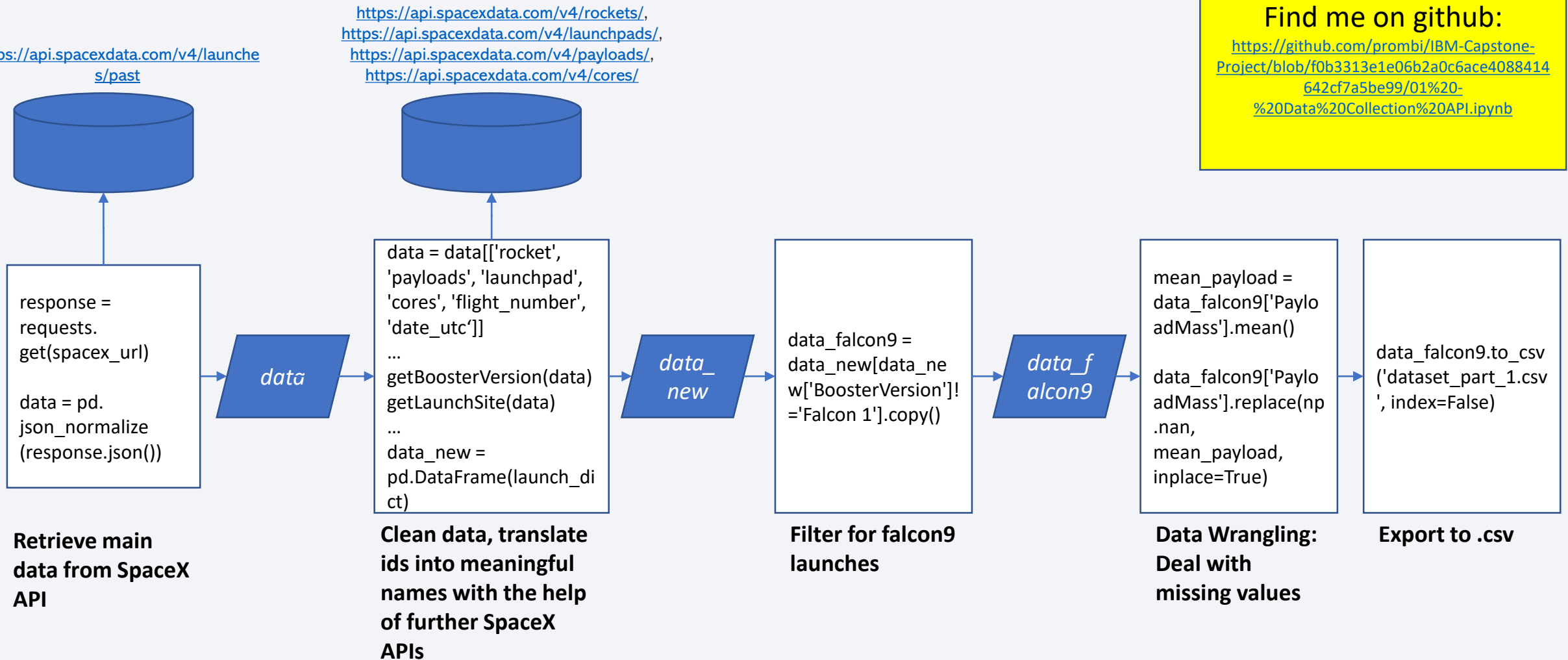
2. Web Scraping from Wikipedia Article on List of Falcon 9 and Falcon Heavy launches [https://en.wikipedia.org/wiki/List_of_Falcon_9_and_Falcon_Heavy_launches]

Data Collection – SpaceX API



Find me on github:

<https://github.com/prombi/IBM-Capstone-Project/blob/f0b3313e1e06b2a0c6ace4088414642cf7a5be99/01%20-%20Data%20Collection%20API.ipynb>



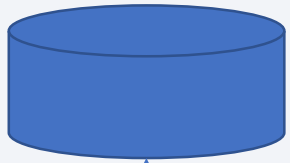
Data Collection - Scraping



Find me on github:

<https://github.com/prombi/IBM-Capstone-Project/blob/f0b3313e1e06b2a0c6ace4088414642cf7a5be99/02%20-%20Data%20Collection%20webscraping.ipynb>

[https://en.wikipedia.org/w/index.php?title=List of Falcon 9 and Falcon Heavy launches&oldid=1027686922](https://en.wikipedia.org/w/index.php?title=List_of_Falcon_9_and_Falcon_Heavy_launches&oldid=1027686922)



```
response =  
requests.get(static_  
url)  
  
soup =  
BeautifulSoup(respo  
nse.content)
```

Retrieve soup
object from
Wikipedia Site

soup

```
html_tables =  
soup.find_all('table')  
first_launch_table =  
html_tables[2]  
...
```

Get html table,
extract column
names

*data_
new*

```
launch_dict=  
dict.fromkeys(colu  
mn_names)  
...
```

Parse html table
to create launch-
dict

*launch_
dict*

```
df=pd.DataFrame(l  
aunch_dict)
```

Create
dataframe from
launch_dict

```
df.to_csv('spacex_w  
eb_scraped.csv',  
index=False)
```

Export to .csv

Data Wrangling



Find me on github:

<https://github.com/prombi/IBM-Capstone-Project/blob/f0b3313e1e06b2a0c6ace4088414642cf7a5be99/03%20-%20Data%20Wrangling.ipynb>

```
CCAFS SLC 40    55
KSC  LC 39A    22
VAFB SLC 4E    13
Name: LaunchSite, dtype: int64
```

```
GTO    27
ISS    21
VLEO   14
PO      9
LEO     7
SSO     5
MEO     3
ES-L1   1
HEO     1
SO      1
GEO     1
Name: Orbit, dtype: int64
```

```
df= pd.read_csv("
(...)dataset_part_1
.csv")
```

df

```
df['LaunchSite'].
value_counts()

```

```
df['Orbit'].
value_counts()

```

```
landing_outcomes =
df['Outcome'].
value_counts()

```

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

landing_class = [0 if
(outcome in
bad_outcomes) else 1
for outcome in
df['Outcome']]

df['Class']=landing_class

```

0.6666666666666666

```
df["Class"].mean()

```

```
df.to_csv("dataset_
part_2.csv",
index=False)

```

Import launch
data from saved
csv

Task 1: Calculate
number of
launches from
each site

Task 2:
Calculate the
number and
occurrence of
each orbit

Task 3:
Calculate
number of
mission
outcomes

Task 4: Create
landing
outcome label
and save it to
df

Calculate
average success
rate

Export to .csv

EDA with Data Visualization



Find me on github:

<https://github.com/prombi/IBM-Capstone-Project/blob/f0b3313e1e06b2a0c6ace4088414642cf7a5be99/05%20-%20EDA%20with%20Visualization.ipynb>

Plotted Charts:

1. Relationship between Flight Number and Launch Site (Catplot FlightNumber vs LaunchSite):
Check whether the usage of different launch sites over time has an impact on the success rate of these sites
2. Relationship between Payload and Launch Site (Catplot Payload vs. LaunchSite): Check whether certain payload mass ranges are (not) launched from certain sites.
3. Relationship between Orbit type and success rate (Bar plot Payload vs. LaunchSite): See how the orbit type impacts success rate.
4. Relationship between Flight Number and Orbit Type (Catplot FlightNumber vs LaunchSite):
Check whether the for different orbits the success depends on flight number. This is the case for LEO orbit, whereas for GTO orbit there is no such relationship.
5. Relationship between Payload and Orbit Type (Catplot Payload vs. Orbit Type): Check dependence of success rate on payload & orbit.
6. Launch Success yearly trend (Line Plot Years vs. Success Rate): See how success rate develops over time. Clear upward trend from 2010 to 2020!

EDA with SQL



Find me on github:

<https://github.com/prombi/IBM-Capstone-Project/blob/f0b3313e1e06b2a0c6ace4088414642cf7a5be99/04%20-%20EDA%20with%20SQL.ipynb>

SQL queries performed:

1. Display the names of the unique launch sites in the space mission:
`%sql SELECT DISTINCT launch_site FROM SPACEXDATASET`
2. Display 5 records where launch sites begin with the string 'CCA':
`%sql SELECT * FROM SPACEXDATASET WHERE launch_site LIKE 'CCA%' LIMIT 5`
3. Display the total payload mass carried by boosters launched by NASA (CRS):
`%sql SELECT COUNT(Date), SUM(payload_mass__kg_) FROM SPACEXDATASET WHERE customer = 'NASA (CRS)'`
4. Display average payload mass carried by booster version F9 v1.1:
`%sql SELECT COUNT(Date) AS Count, AVG(payload_mass__kg_) AS Avg_Payload_Mass FROM SPACEXDATASET WHERE booster_version = 'F9 v1.1'`
5. List the date when the first successful landing outcome in ground pad was achieved:
`%sql SELECT MIN(Date) FROM SPACEXDATASET WHERE landing__outcome = 'Success (ground pad)'`
6. List the names of the boosters which have success in drone ship and have payload mass greater than 4000 but less than 6000:
`%sql SELECT DISTINCT(booster_version) FROM SPACEXDATASET WHERE landing__outcome = 'Success (drone ship)' AND payload_mass__kg_ BETWEEN 4000 AND 6000`
7. List the total number of successful and failure mission outcomes:
`%sql SELECT mission_outcome, COUNT(Date) AS COUNT FROM SPACEXDATASET GROUP BY mission_outcome`
8. List the names of the booster_versions which have carried the maximum payload mass:
`%sql SELECT DISTINCT(booster_version), payload_mass__kg_ FROM SPACEXDATASET WHERE payload_mass__kg_ = (SELECT MAX(payload_mass__kg_) FROM SPACEXDATASET)`
9. List the failed landing_outcomes in drone ship, their booster versions, and launch site names for in year 2015:
`%sql SELECT Date, landing__outcome, booster_version, launch_site FROM SPACEXDATASET WHERE landing__outcome = 'Failure (drone ship)' AND YEAR(Date) = '2015'`
10. Rank the count of landing outcomes (such as Failure (drone ship) or Success (ground pad)) between the date 2010-06-04 and 2017-03-20, in descending order:
`%sql SELECT landing__outcome, COUNT(landing__outcome) AS Count FROM SPACEXDATASET WHERE Date BETWEEN '2010-06-04' AND '2017-03-20' GROUP BY landing__outcome ORDER BY Count DESC`

Build an Interactive Map with Folium

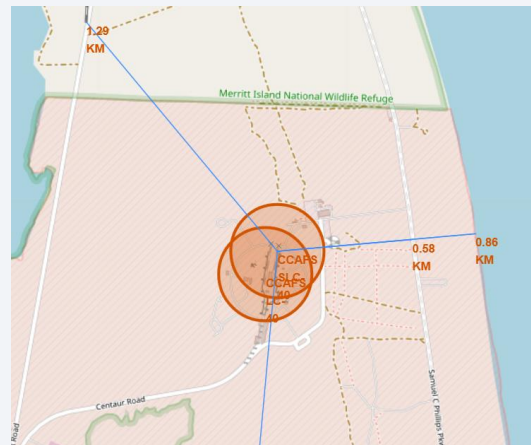


Find me on github:

https://github.com/prombi/IBM-Capstone-Project/blob/f0b3313e1e06b2a0c6ace4088414642cf7a5be99/06%20-%20lab_jupyter_launch_site_location.ipynb

Map objects created:

- Per each launch site (4 total)
 - Circle around launch site → to find the sites on the map:
`circle = folium.Circle(coordinate, radius=200, color='#d35400', fill=True).add_child(folium.Popup(name))`
 - Marker with launch site name → to identify the site names:
`marker = folium.map.Marker(coordinate, icon=DivIcon(icon_size=(20,20), icon_anchor=(0,0), html='<div style="font-size: 12; color:#d35400;">%s</div>' % name,))`
 - Marker cluster with success/failed launches → to see the number of and success of all launches from this site:
`marker = folium.Marker(location = [record['Lat'], record['Long']], icon = folium.Icon(color='white', icon_color=record['marker_color']))`
- For CCAFS SLC 40:
 - Marker and line to closest coast
 - Marker and line to closest city
 - Marker and line to closest highway
 - Marker and line to closest railroad



Build a Dashboard with Plotly Dash



Find me on github:

https://github.com/prombi/IBM-Capstone-Project/blob/f0b3313e1e06b2a0c6ace4088414642cf7a5be99/07%20-%20spacex_dash_app.py

Plots/graphs and interactions added to the dashboard:

1. Dropdown site selection
→ to enable the user to drill down the following analyses into specific sites
2. Pie chart showing successful launches (if 'all sites' selected), respectively success vs. fail counts for the selected site
→ giving an overview of success rates
3. Slider to select payload range
→ allow user to drill down analysis by payload ranges
4. Scatter chart to show correlation btw. Payload and launch success
→ overview of success for different payloads

Predictive Analysis (Classification)



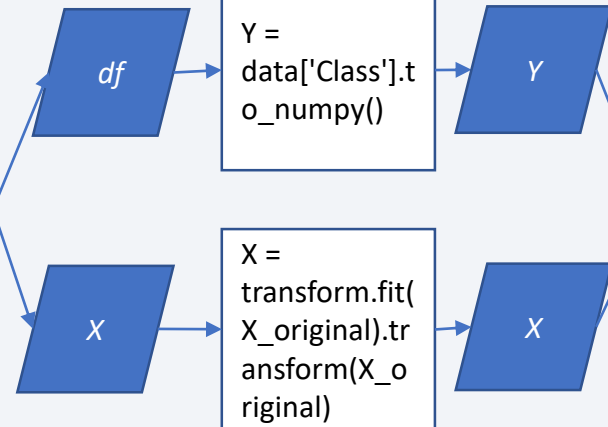
Find me on github:

https://github.com/prombi/IBM-Capstone-Project/blob/f0b3313e1e06b2a0c6ace4088414642cf7a5be99/08%20-%20SpaceX_Machine%20Learning%20Prediction_Part_5.ipynb

Task 1: Create NumPy Array from column Class

```
data = pd.read_csv(, .../dataset_part_2.csv")  
  
X = pd.read_csv(, .../dataset_part_3.csv')
```

Import launch data from saved csv



Task 2: Standardize X

Task 3: Split data into training and test data

```
parameters = {...}  
lr = LogisticRegression()  
logreg_cv = GridSearchCV(lr, parameters, cv=10)  
logreg_cv.fit(X_train, Y_train)
```

```
lr_score = logreg_cv.score(X_test, Y_test)
```

```
parameters = {...}  
svm = SVC()  
svm_cv = GridSearchCV(svm, parameters, cv=10)  
svm_cv.fit(X_train, Y_train)
```

```
svm_score = svm_cv.score(X_test, Y_test)
```

```
parameters = {...}  
tree = DecisionTreeClassifier()  
tree_cv = GridSearchCV(tree, parameters, cv=10)  
tree_cv.fit(X_train, Y_train)
```

```
tree_score = tree_cv.score(X_test, Y_test)
```

```
parameters = {...}  
knn = KNeighborsClassifier()  
knn_cv = GridSearchCV(knn, parameters, cv=10)  
knn_cv.fit(X_train, Y_train)
```

```
knn_score = knn_cv.score(X_test, Y_test)
```

Task 4 / 6 / 8 / 10: Create Logistic Regression / SVM / Tree / KNN object and find best parameters using GridSearchCV object

Task 5 / 7 / 9 / 11: Calculate accuracy on the test data

```
pd.DataFrame({'Model': ['Logistic Regression', 'Support Vector Machine', 'Decision Tree', 'K Nearest Neighbors'], 'Score': [lr_score, svm_score, tree_score, knn_score]})
```

Task 12: Find model that performs best

Results

- Exploratory data analysis results
- Interactive analytics demo in screenshots
- Predictive analysis results

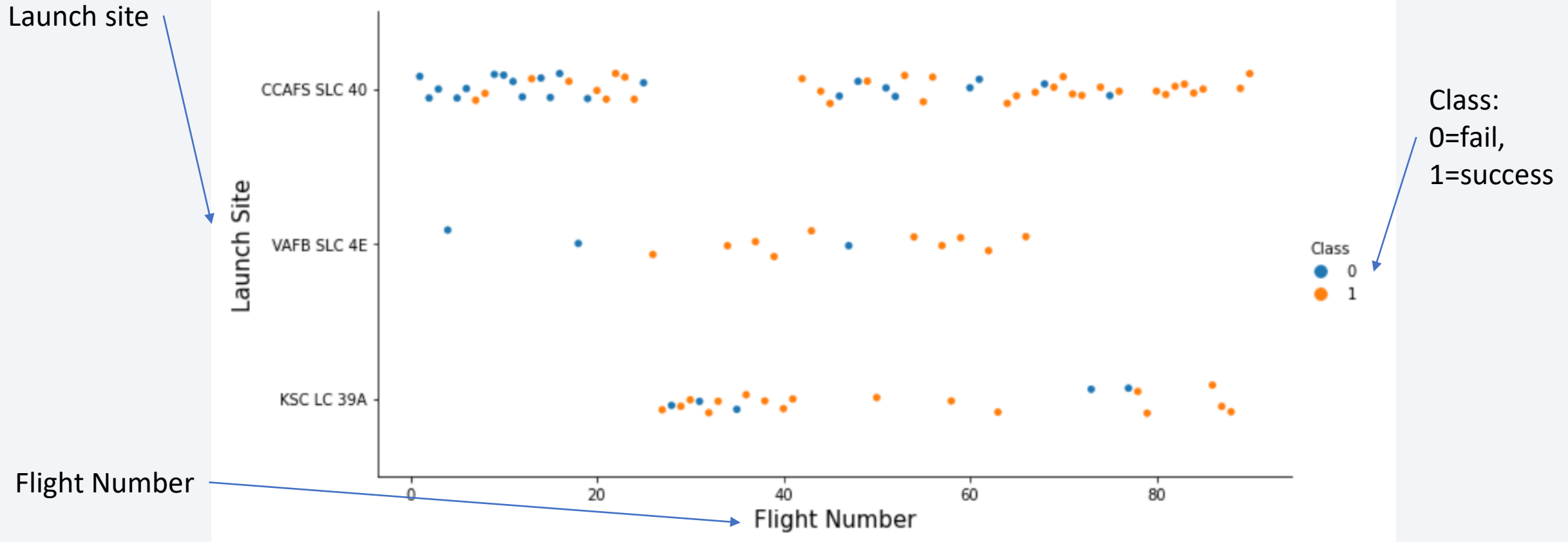
→ See next slides

The background of the slide is an abstract composition. It features a dark blue base color. Overlaid on this are numerous diagonal streaks in shades of red and cyan. A faint, light blue grid pattern is also visible, particularly in the lower half of the image. The overall effect is dynamic and technological.

Section 2

Insights drawn from EDA

Flight Number vs. Launch Site

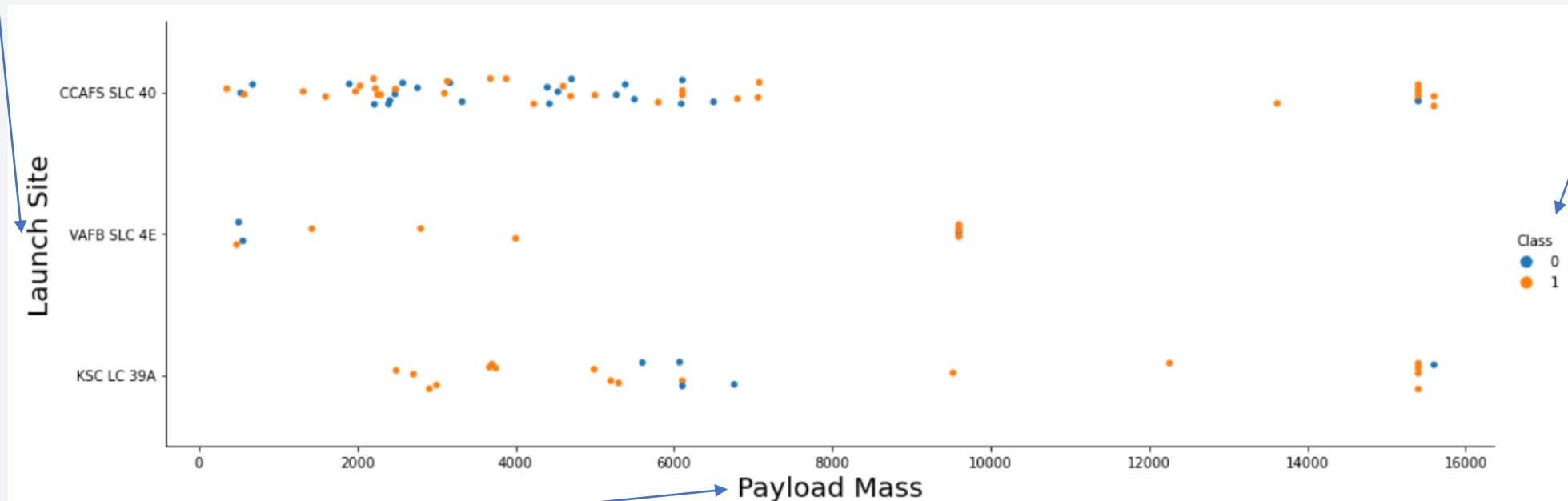


Findings:

1. CCAFS SLC40 is the Launch site with the most starts (55) as compared to KSC (22) and VAFB (13)
2. Particularly in the beginning (first 25 starts) when the success rate was still quite low, CCAFS was used almost exclusively (only 2 starts from VAFB, 23 starts from CCAFS). Counting only starts from 26 onwards, success rate for CCAFS is also at 75%

Payload vs. Launch Site

Launch site



Class:
0=fail,
1=success

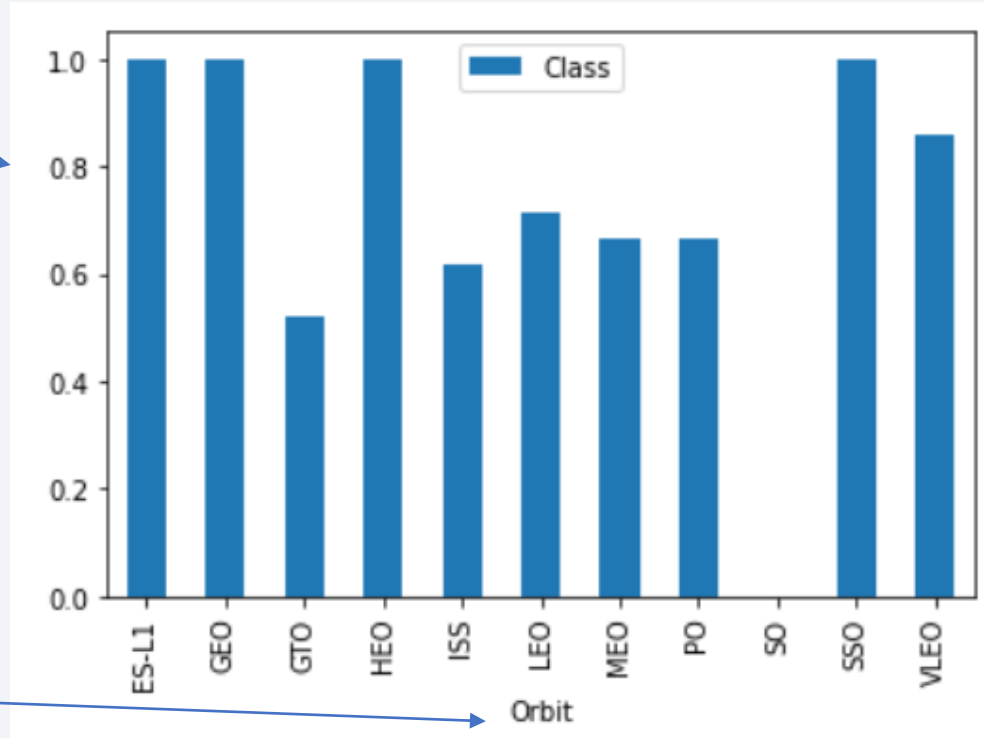
Payload mass

Findings:

1. Lighter payloads (<8000kg) are predominantly performed from CCAFS SLC 40
2. Heavy payloads (>10000kg) are only done from KSC and CCAFS, not VAFB

Success Rate vs. Orbit Type

Success rate



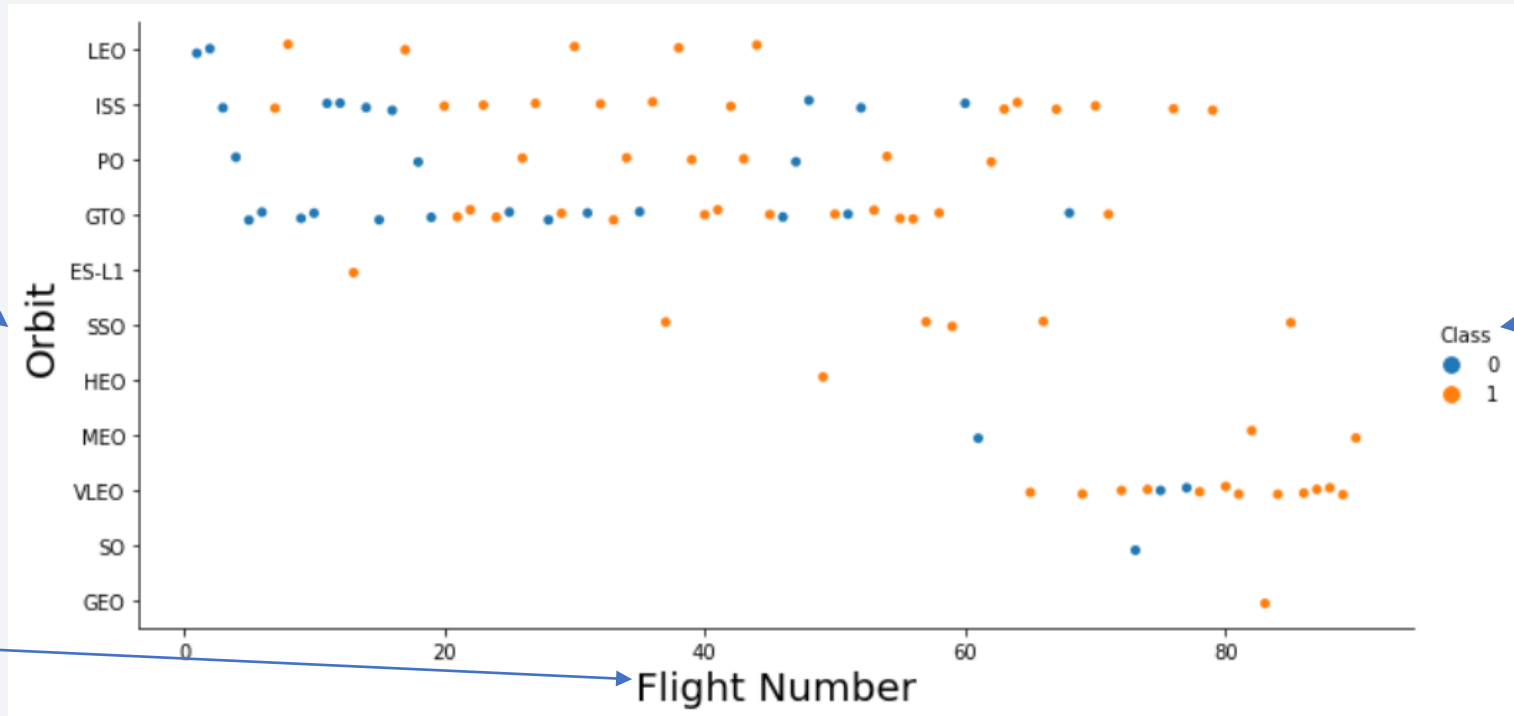
Orbit

Finding: Orbits with highest success rate (counting only orbits with 5 or more launches):

1. SSO: 100% @ 5 launches
2. VLEO: 86% @ 14 launches
3. LEO: 71% @ 7 launches
4. PO: 67% @ 9 launches
5. ISS: 62% @ 21 launches
6. GTO: 52% @ 27 launches

Flight Number vs. Orbit Type

Orbit



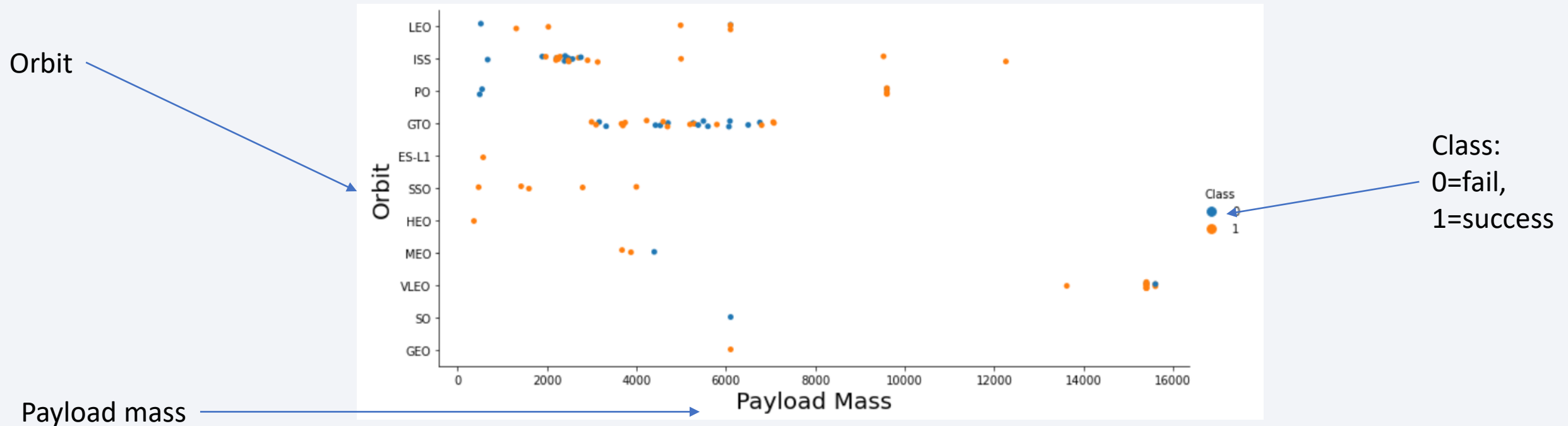
Class:
0=fail,
1=success

Flight no.

Findings:

1. For LEO orbit, the success increases with number of flights;
2. No such relationship for GTO orbit.

Payload vs. Orbit Type

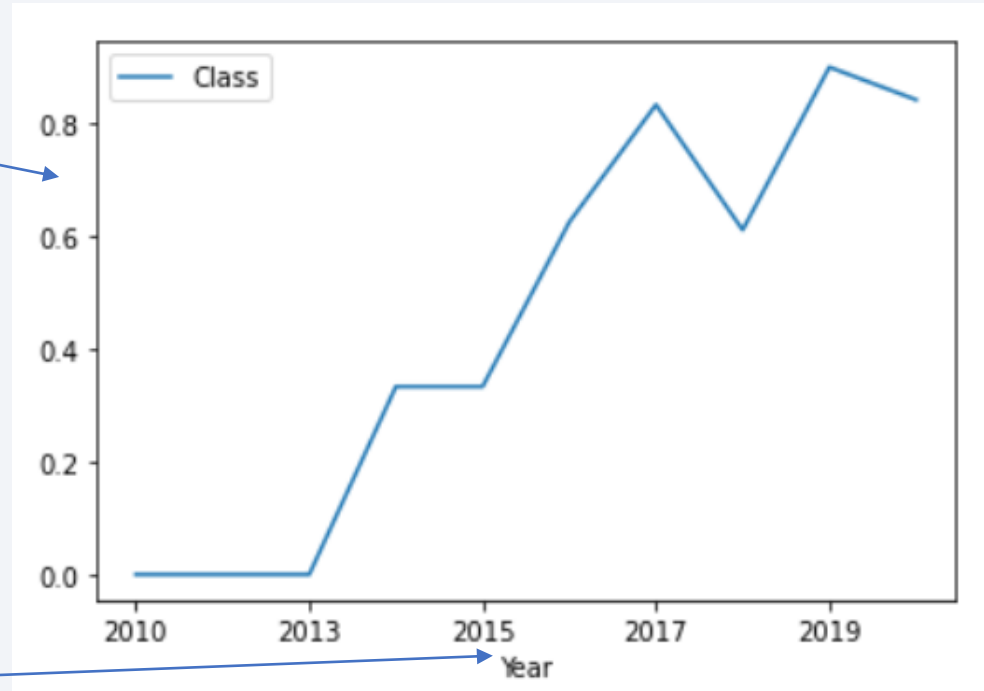


Findings:

1. Heavy payloads ($\geq 10000\text{kg}$) are only launched to ISS, PO and VLEO, with a very high success rate (only 1 fail in VLEO)
2. For GTO, the payload is btw. ~ 3500 and ~ 7000 kg, with successful and failed landing outcomes evenly distributed

Launch Success Yearly Trend

Success rate



Year

Findings:

1. There is a very clear upward trend (learning curve) btw. 2013 and 2017
2. After 2017, the learning curve seems to flatten, with drops in 2018 and 2020 (but still 2020 is on the level of 2017)
3. The highest success rate (90%) was achieved in 2019

All Launch Site Names

Display the names of the unique launch sites in the space mission

```
In [10]: 1 %sql SELECT DISTINCT launch_site FROM SPACEXDATASET
          * ibm_db_sa://hdw01742:***@ea286ace-86c7-4d5b-8580-3fbfa46
          Done.
```

```
Out[10]: launch_site
          CCAFS LC-40
          CCAFS SLC-40
          KSC LC-39A
          VAFB SLC-4E
```

There are 4 distinct launch sites

Launch Site Names Begin with 'CCA'

Display 5 records where launch sites begin with the string 'CCA'

```
1 %sql SELECT * FROM SPACEXDATASET WHERE launch_site LIKE 'CCA%' LIMIT 5
```

```
* ibm_db_sa://hdw01742:***@ea286ace-86c7-4d5b-8580-3fbfa46b1c66.bs2io90l08kqb1od8lcg.databases.appdomain.cloud:31505/bludb
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

... 5 examples of records where launch site name begins with „CCA“

Total Payload Mass

Display the total payload mass carried by boosters launched by NASA (CRS)

```
: 1 %sql SELECT COUNT(DATE), SUM(payload_mass__kg_) FROM SPACEXDATASET WHERE customer = 'NASA (CRS)'  
* ibm_db_sa://hdw01742:***@ea286ace-86c7-4d5b-8580-3fbfa46b1c66.bs2io90l08kqb1od8l1cg.databases.appdo  
Done.  
: 1 2  
20 45596
```

There are in total 20 launches by NASA (CRS), with a total payload mass of 45596 kg

Average Payload Mass by F9 v1.1

Display average payload mass carried by booster version F9 v1.1

```
1 %sql SELECT COUNT(DATE) AS Count, AVG(payload_mass__kg_) AS Avg_Payload_Mass FROM SPACEXDATASET
2 WHERE booster_version = 'F9 v1.1'
```

```
* ibm_db_sa://hdw01742:***@ea286ace-86c7-4d5b-8580-3fbfa46b1c66.bs2io90108kqb1od8lcg.databases.appdon
Done.
```

COUNT	avg_payload_mass
5	2928

There are in total 5 carried by booster version F9 v1.1, with an average payload mass of 2928 kg

First Successful Ground Landing Date

List the date when the first successful landing outcome in ground pad was achieved.

Hint: Use min function

```
1 %sql SELECT MIN(Date) FROM SPACEXDATASET WHERE landing__outcome = 'Success (ground pad)'
```

```
* ibm_db_sa://hdw01742:***@ea286ace-86c7-4d5b-8580-3fbfa46b1c66.bs2io90l08kqb1od8lcg.databases  
Done.
```

```
1
```

```
2015-12-22
```

The first successful landing outcome in ground pad was on 12/22, 2015

Successful Drone Ship Landing with Payload between 4000 and 6000

List the names of the boosters which have success in drone ship and have payload mass greater than 4000 but less than 6000

```
1 %sql SELECT DISTINCT(booster_version) FROM SPACEXDATASET
2 WHERE landing__outcome = 'Success (drone ship)'
3 AND payload_mass__kg_ BETWEEN 4000 AND 6000
```

```
* ibm_db_sa://hdw01742:***@ea286ace-86c7-4d5b-8580-3fbfa46b1c66.bs2io90l08kqb1od8l1cg.databases.appdomain.clou
Done.
```

booster_version

F9 FT B1021.2

F9 FT B1031.2

F9 FT B1022

F9 FT B1026

There were 4 boosters which had success in drone ship and payload btw. 4000 and 6000 kg

Total Number of Successful and Failure Mission Outcomes

List the total number of successful and failure mission outcomes

```
1 %sql SELECT mission_outcome, COUNT(Date) AS COUNT FROM SPACEXDATASET GROUP BY mission_outcome
```

```
* ibm_db_sa://hdw01742:***@ea286ace-86c7-4d5b-8580-3fbfa46b1c66.bs2io90l08kqb1od8l1cg.databases.app  
Done.
```

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

Of 101 flights, 99 had successful missions (which does not mean that the landing was also successful)

Boosters Carried Maximum Payload

List the names of the booster_versions which have carried the maximum payload mass. Use a subquery

```
1 %%sql SELECT DISTINCT(booster_version), payload_mass__kg_ FROM SPACEXDATASET WHERE
2 payload_mass__kg_ =
3 (SELECT MAX(payload_mass__kg_) FROM SPACEXDATASET)
```

booster_version	payload_mass__kg_
F9 B5 B1048.4	15600
F9 B5 B1048.5	15600
F9 B5 B1049.4	15600
F9 B5 B1049.5	15600
F9 B5 B1049.7	15600
F9 B5 B1051.3	15600
F9 B5 B1051.4	15600
F9 B5 B1051.6	15600
F9 B5 B1056.4	15600
F9 B5 B1058.3	15600
F9 B5 B1060.2	15600
F9 B5 B1060.3	15600

12 distinct booster versions carried maximum payload

2015 Launch Records

List the failed landing_outcomes in drone ship, their booster versions, and launch site names for in year 2015

```
1 %%sql SELECT Date, landing__outcome, booster_version, launch_site FROM SPACEXDATASET
2 WHERE landing__outcome = 'Failure (drone ship)' AND YEAR(Date) = '2015'
```

```
* ibm_db_sa://hdw01742:***@ea286ace-86c7-4d5b-8580-3fbfa46b1c66.bs2io90l08kqb1od8lcg.databases.
Done.
```

DATE	landing__outcome	booster_version	launch_site
2015-01-10	Failure (drone ship)	F9 v1.1 B1012	CCAFS LC-40
2015-04-14	Failure (drone ship)	F9 v1.1 B1015	CCAFS LC-40

2 failed landings in 2015

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

Rank the count of landing outcomes (such as Failure (drone ship) or Success (ground pad)) between the date 2010-06-04 and 2017-03-20, in descending order

```
1 %%sql SELECT landing__outcome, COUNT(landing__outcome) AS Count FROM SPACEXDATASET
2 WHERE Date BETWEEN '2010-06-04' AND '2017-03-20'
3 GROUP BY landing__outcome ORDER BY Count DESC
```

* ibm_db_sa://hdw01742:***@ea286ace-86c7-4d5b-8580-3fbfa46b1c66.bs2io90l08kqb1od8lcg.databases.appdomain.cloud:31505/bluc
Done.

landing__outcome	COUNT
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

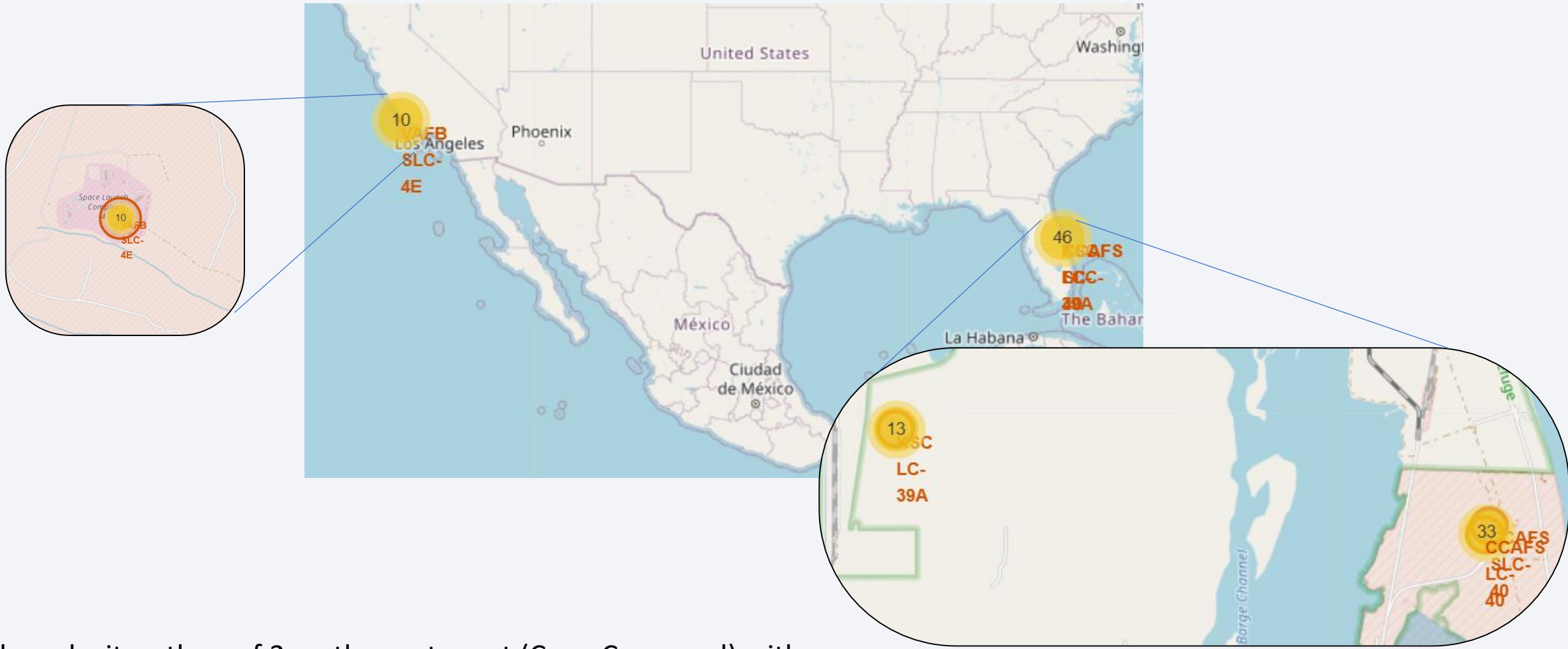
Most frequent landing outcomes in given timeframe were ,No attempt' (10x), ,Failure (drone ship)' (5x) and ,Success (drone ship)' (5x)

A satellite view of Earth from space, showing the curvature of the planet and city lights at night. The image is a composite of a dark blue sky with stars and a view of the Earth's surface from space. The Earth's surface is mostly dark, with a dense network of yellow and orange lights representing city lights at night. The lights are concentrated in the lower right portion of the image, following the curve of the Earth. The upper portion of the image shows the dark blue sky with a few stars.

Section 3

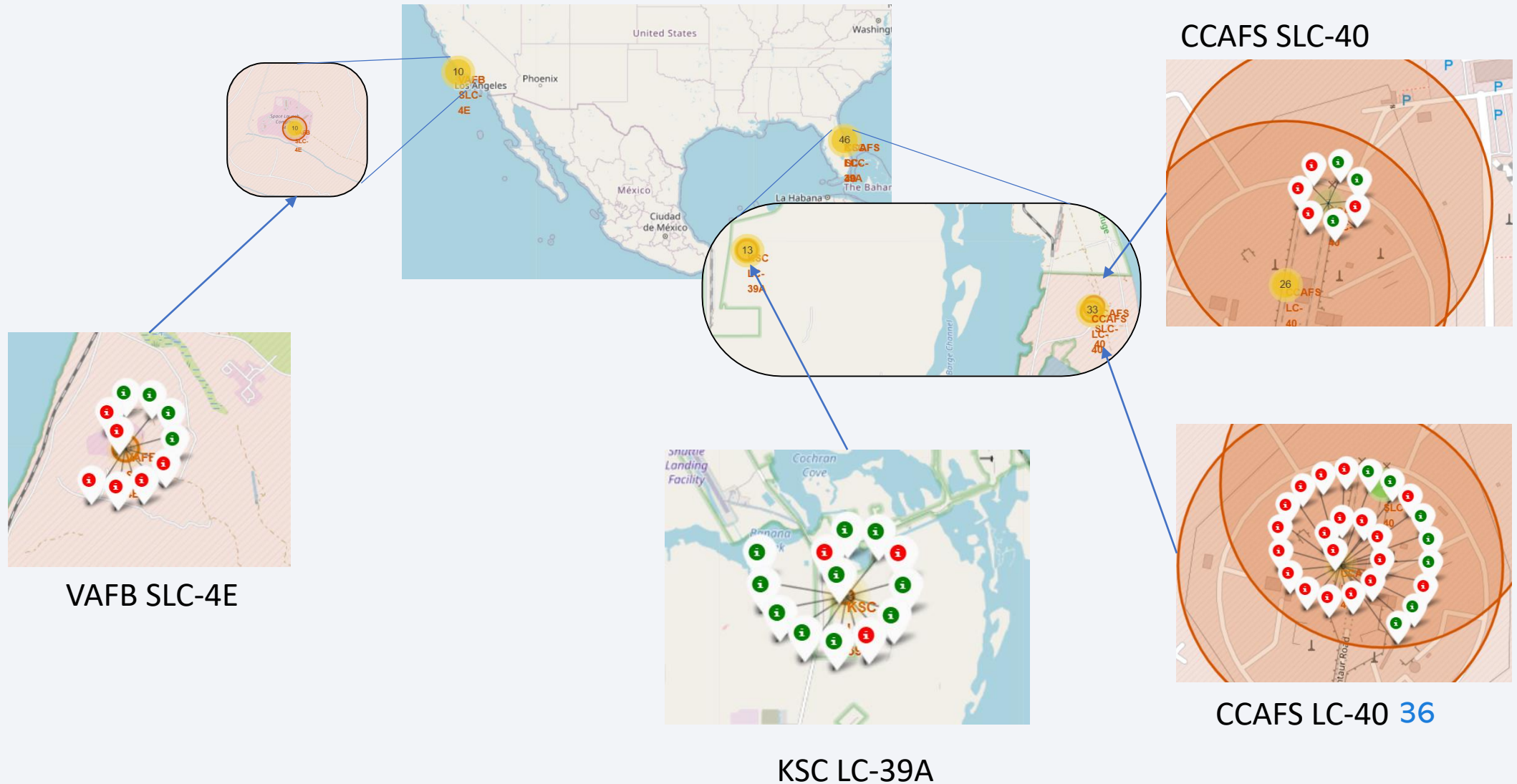
Launch Sites Proximities Analysis

Global map of all launch sites



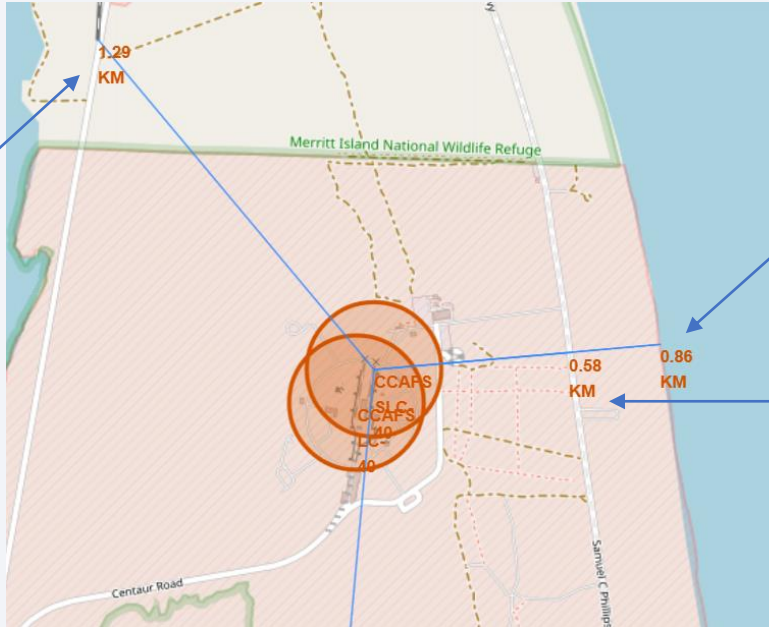
4 launch sites, thereof 3 on the east coast (Cape Canaveral) with a total of 46 launches, and one site on the west coast with 10 launches

Launch sites deep-dive: Launch outcomes



Deep dive: CCAFS SLC-40 proximities

Next railway: ~1.3km



Next coast: ~0.9km

Next highway: ~0.6km



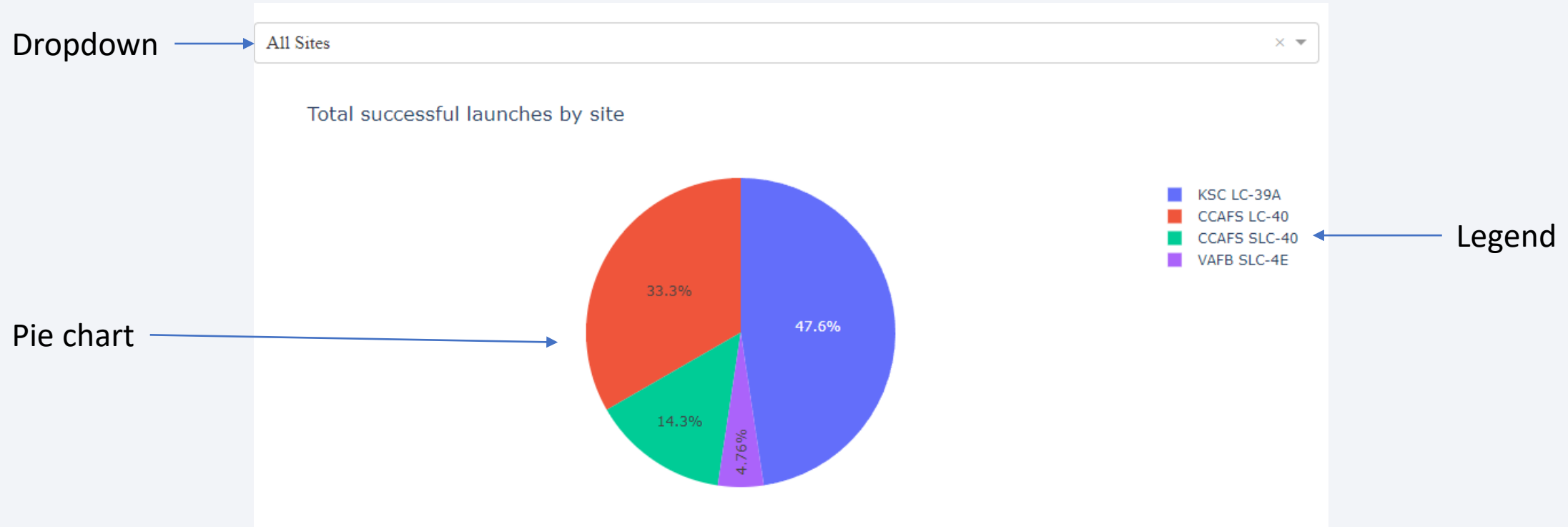
Next city: ~17km



Section 4

Build a Dashboard with Plotly Dash

Successful launches across all sites



Finding: Most successful launches from KSC LC-39A

Launch success for site with highest success ratio

Dropdown

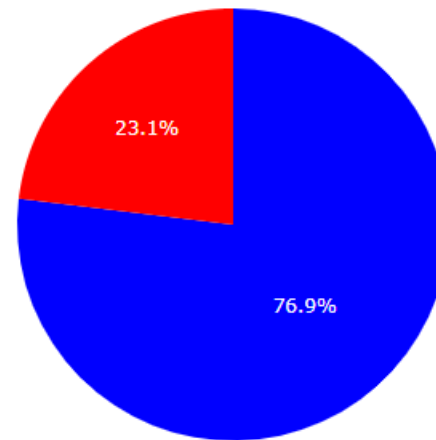


KSC LC-39A



Launch success rate for site KSC LC-39A

Pie chart



1
0

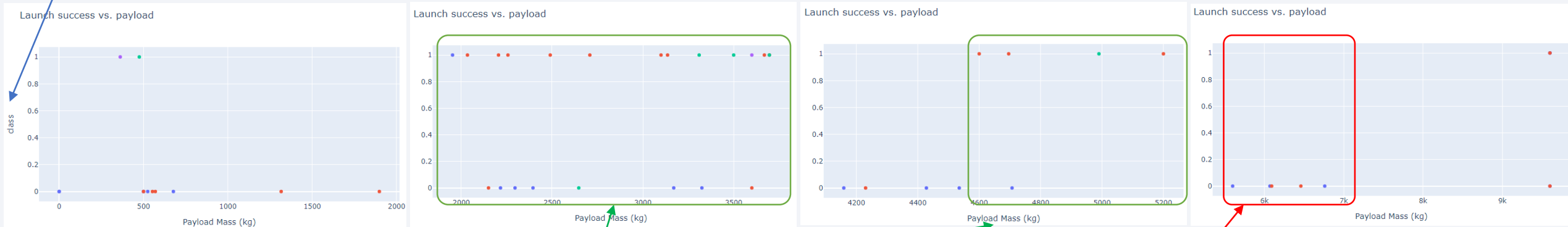
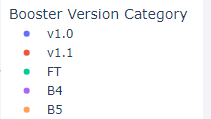
Legend
(0=fail, 1=success)

Finding: Success rate at KSC LC-39A is 76.9%

Payload vs. Launch Outcome for all sites

Launch outcome (1=successful, 0 = fail)

Booster version



Payload ranges with highest success rate: 1950-3700 kg, 4600-5300kg

Payload range with lowest success rate: 5600-6800 kg

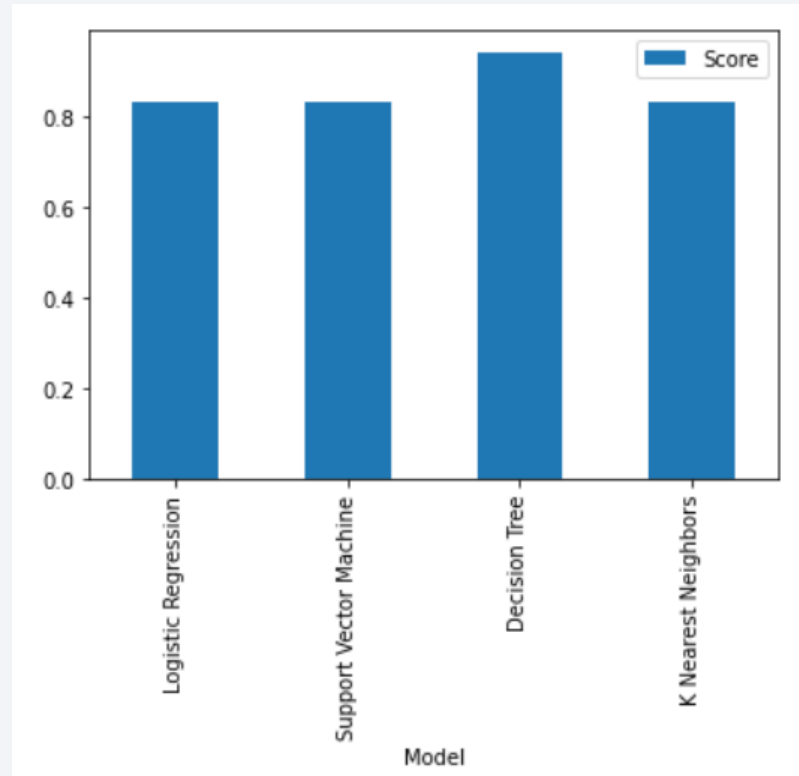
Booster versions with highest success rate:

- B5 (1/1 = 100%)
- FT (16/24 = 66%)

Section 5

Predictive Analysis (Classification)

Classification Accuracy

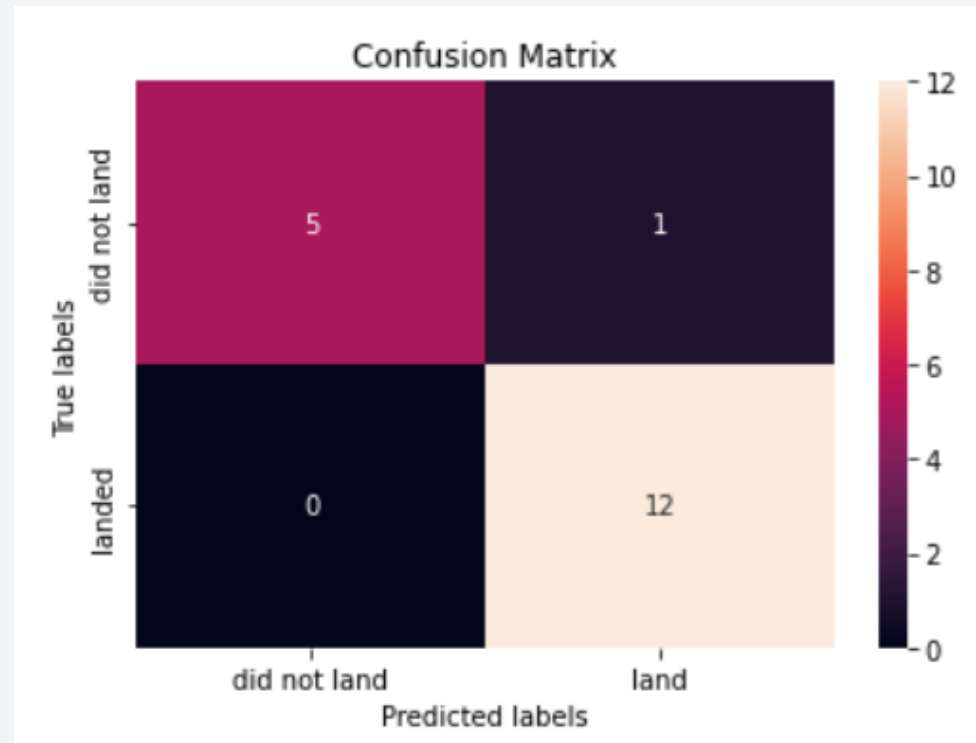


Decision tree has the highest classification accuracy on the test set (94.4%)*!

**Note: From run to run, the best parameters for the decision tree model can change and its performance can also vary btw. ~66% and 94%. We chose one of the best performing configurations here*

(parameters = {'criterion': 'gini', 'max_depth': 14, 'max_features': 'auto', 'min_samples_leaf': 1, 'min_samples_split': 10, 'splitter': 'best'})

Confusion Matrix for best model (decision tree)*



**Note: From run to run, the best parameters for the decision tree model can change and its performance can also vary btw. ~66% and 94%. We chose one of the best performing configurations here*

(parameters = {'criterion': 'gini', 'max_depth': 14, 'max_features': 'auto', 'min_samples_leaf': 1, 'min_samples_split': 10, 'splitter': 'best'})

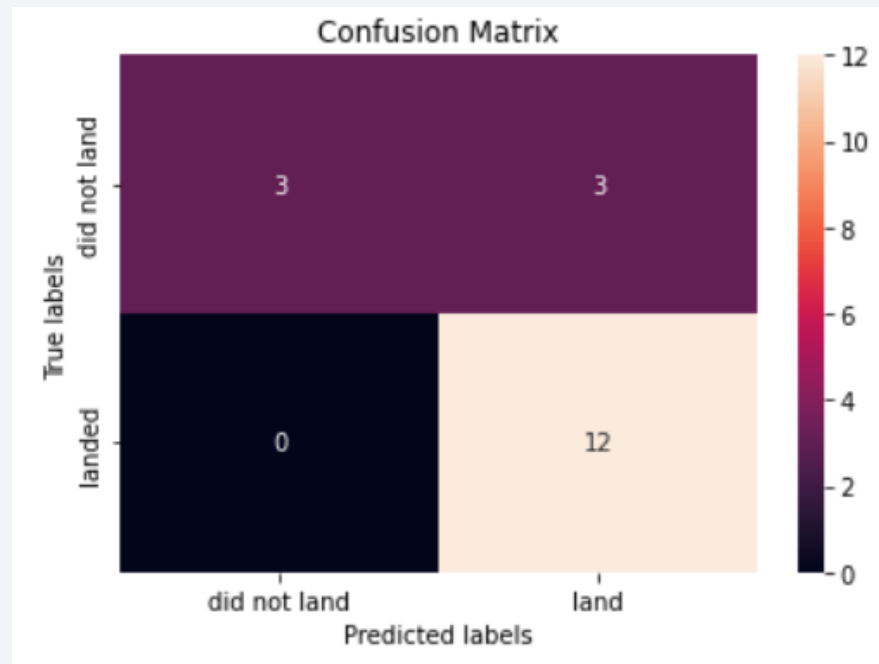
Conclusions

- LogReg, SVM and KNN yield the same outcomes:
Accuracy = 83.3%, Confusion Matrix see Appendix
- For Decision Tree model, the best parameters change from run to run:
 - In the best case, we find 94.4% accuracy and a confusion matrix as shown in the previous slides. This is the best model that we can find, with only one false positive and no false negatives.
 - In the worst case, we find 66.6% accuracy
 - There seems to be some randomness involved in the GridSearchCV optimization algorithm. Further analysis of this algorithm is in place (but goes beyond the scope of this assignment)

Appendix

Confusion Matrix for typical model

All models apart from decision tree, i.e. LogReg, SVM, KNN, have the same performance (83.3%), and the same confusion matrix shown here:



Thank you!

