



IBM Developer
SKILLS NETWORK

WINNING THE SPACE RACE

WITH DATA SCIENCE

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OUTLINE

1. EXECUTIVE SUMMARY
2. INTRODUCTION
3. METHODOLOGY
4. RESULTS FROM EDA
5. LAUNCH SITE PROXIMITY ANALYSIS
6. BUILDING A DASHBOARD
7. PREDICTIVE ANALYSIS
8. CONCLUSION
9. APPENDIX



EXECUTIVE SUMMARY

- SpaceX Data Collection API
 - Normalized
 - Cleaned
 - Stored in Db2
- Queried with SQL
- Plotted and Visualized
 - Scatter Plots, Line Graphs, Pie Charts, etc.
 - Location map w/ Folium
 - Interactive dashboard
- Predictive Analysis
 - K-Nearest Neighbor
 - Decision Tree
 - Support Vector Machine
 - Logistic Regression

Ability Gained:

Having done all this, it will be possible to predict the outcome of a landing based on any given set of variables to a reasonably accurate degree.

Application:

With this knowledge, it should be possible to choose only missions with the highest chance of success, thereby only bidding on profitable missions.

ONCE AGAIN, HUMANITY HAS TURNED ITS SIGHTS TO THE STARS. IN RECENT YEARS, THE NEW SPACE RACE HAS BEEN DOMINATED BY PRIVATE COMPANIES: SPACEX, BLUE ORIGIN, VIRGIN GALACTIC – THE LIST GOES ON.

NOW, A NEWCOMER HAS ARRIVED!



BILLIONAIRE ELON MUSK HAS STARTED SPACEX WITH THE INTENTION OF OUTBIDDING HIS COUNTERPART AT BLUE ORIGIN ON FUTURE ROCKET LAUNCHES!

INTRODUCTION

THE RACE IS ON!

INTRODUCTION

BUT WHAT DOES HE NEED TO KNOW?

Which launch site has the largest successful launches?

Which site has the highest launch success rate?

Which payload range has the highest launch success rate?

Which payload range has the lowest launch success rate?

Which Falcon 9 booster version has the highest launch success rate?

METHODOLOGY

Section 1

Methodology:

- Data Collection:
 - Using SpaceX REST API to collect, filter, and store data in Python
 - Finding and replacing missing values using `mean()` + `replace()` methods
- Data Wrangling:
 - Exploring data types and variable distribution; what relationships exist between variables
 - Finding the target variable and creating a class; converting the data to fit the class
- Exploratory Data Analysis:
 - Querying with SQL
 - Visualization with scatter plots and other charts
- Building an Interactive Map with Folium:
 - Marking locations and their proximities
- Building a Plotly Dashboard:
 - Which charts were used and why
- Predictive Analysis:
 - Preparing and splitting the data
 - Building a predictive model

Data Collection

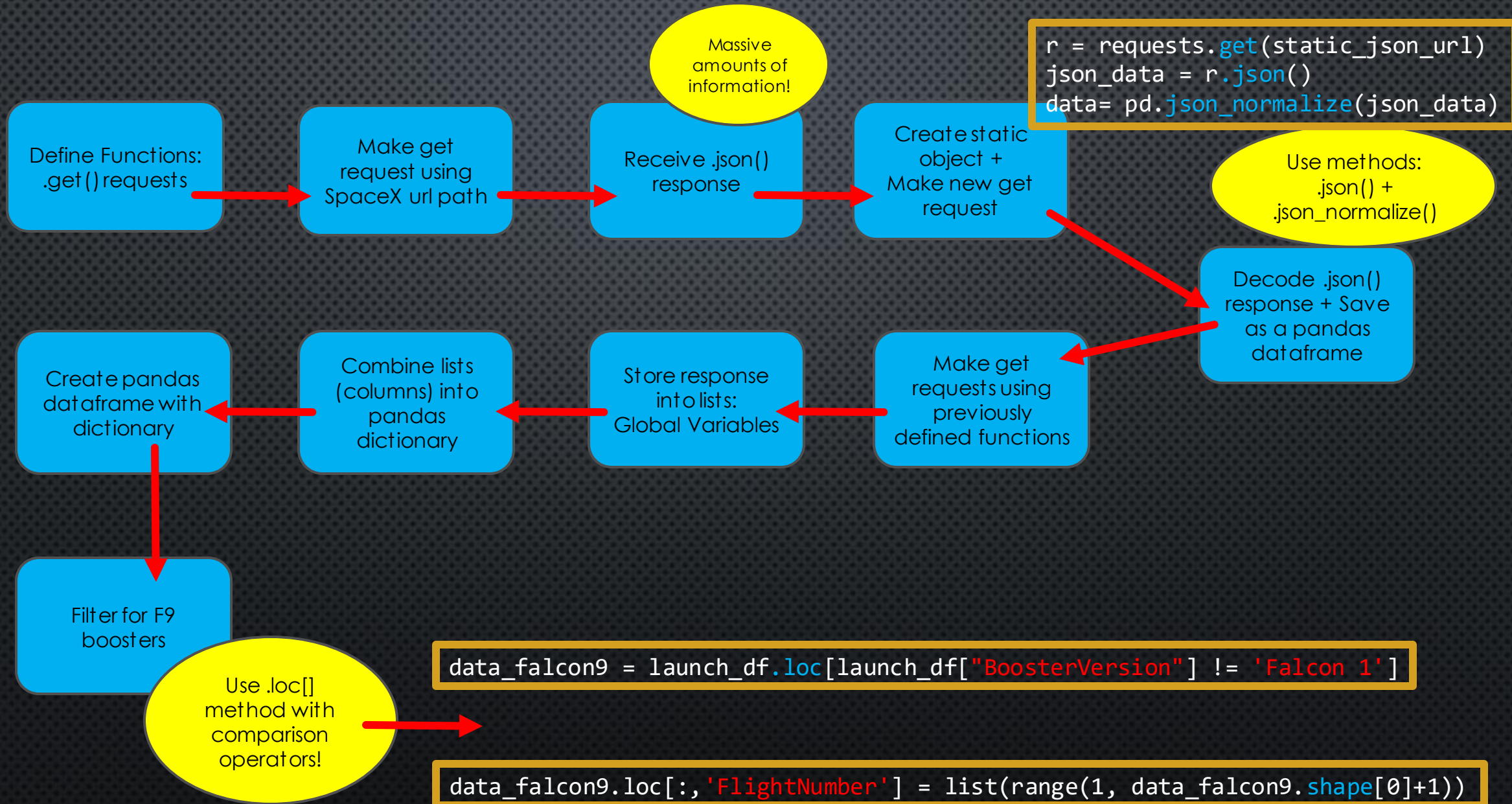
Link to GitHub repository:

<https://github.com/ZTD273/AppliedDataScience>

Link to view notebook directly using Jupyter Notebook Viewer:

<https://nbviewer.org/github/ZTD273/AppliedDataScience/blob/ff47e1e2f111fa1387f733914a545fa0e2b2106c/Data%20Collection%20API.ipynb>

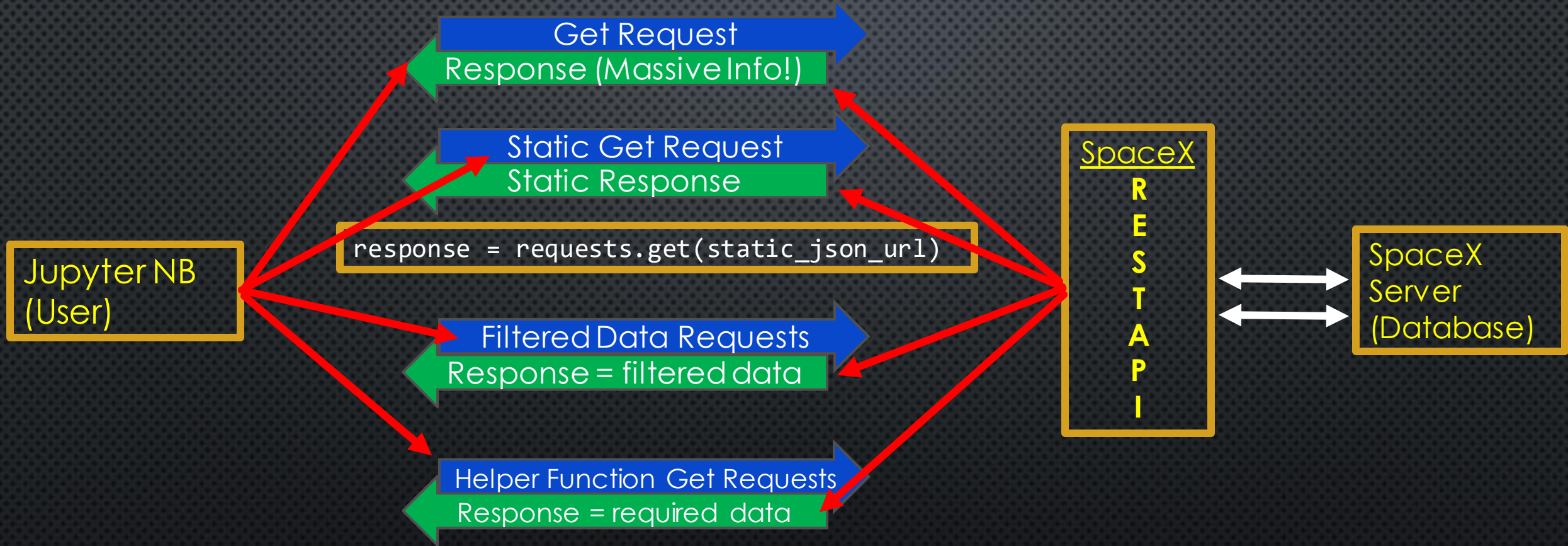
Data Collection:



Data Collection: SpaceX API

Use the REST API to make `.get()` requests for relevant data

- Helper functions = previously defined functions



Data Collection: Handle Missing Values

Check for missing values

```
data_falcon9.isnull().sum()
```

Calculate average value
of the column

```
avg_PayloadMass = data_falcon9["PayloadMass"].astype("float").mean(axis=0)
```

Replace missing values
with calculated mean


```
data_falcon9["PayloadMass"].replace(np.nan, avg_PayloadMass, inplace=True)
```

Double-check for success!

```
data_falcon9.isnull().sum()
```

```
FlightNumber    0
Date            0
BoosterVersion  0
PayloadMass     5
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
```

```
FlightNumber    0
Date            0
BoosterVersion  0
PayloadMass     0
Orbit           0
LaunchSite      0
Outcome         0
Flights         0  ( . . . )
```



Data Wrangling

Link to GitHub repository:

<https://github.com/ZTD273/AppliedDataScience>

Link to view notebook directly using Jupyter Notebook Viewer:

<https://nbviewer.org/github/ZTD273/AppliedDataScience/blob/ff47e1e2f111fa1387f733914a545fa0e2b2106c/Data%20Wrangling.ipynb>

Data Wrangling:

```
df=pd.read_csv("file path")
```

Load file with Launch dataframe created previously

```
df.isnull().sum()/df.count()*100
```

Identify and calculate the percentage of missing values in each attribute

```
df.dtypes
```

Identify which columns are Numerical and which are Categorical

Calculate number and occurrence of mission outcome per orbit type

```
df.value_counts("Outcome") + for Loop
```

Create a landing outcome label from the Outcome column

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

Calculate number + occurrence of each orbit type

```
df.value_counts("Orbit")
```

Create a set of outcomes where the second stage did not land successfully

```
Write an if/else statement + df['Class']=landing_class
```

Calculate number of launches at each site

```
df.value_counts("LaunchSite")
```

Determine success rate

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

Export to .csv file

```
df.to_csv()
```


Exploratory Data Analysis

Link to GitHub repository:

<https://github.com/ZTD273/AppliedDataScience>

Link to view notebook directly using Jupyter Notebook Viewer: with SQL:

<https://nbviewer.org/github/ZTD273/AppliedDataScience/blob/ff47e1e2f111fa1387f733914a545fa0e2b2106c/EDA%20with%20SQL.ipynb>

Link to view notebook directly using Jupyter Notebook Viewer: with Visualization:

<https://nbviewer.org/github/ZTD273/AppliedDataScience/blob/ff47e1e2f111fa1387f733914a545fa0e2b2106c/EDA%20with%20Visualization.ipynb>

EDA with SQL:

Find unique launch sites

DISTINCT
clause

When was the first successful
landing achieved?

min() +
WHERE =

Display 5 records starting with
string 'CCA'

LIKE
predicate

Find which boosters have
success in drone ship while
carrying a payload mass
between 4,000kg and
6,000kg

DISTINCT +
WHERE,
AND,
BETWEEN

Find which records showing
failure in drone ship during
year 2015. Include: month,
booster version, and launch
site

WHERE =
AND

Find total payload mass
carried by boosters launched
by NASA (CRS)

sum() +
WHERE
w/ LIKE

What is the total number of
successful missions? Total of
failed missions?

SELECT as,
count()

Find average payload mass
carried by Falcon9 booster
v1.1

avg() +
WHERE w/
LIKE

Which booster versions have
carried the maximum
payload?

WHERE =
(subquery)

Rank the count of successful
landing outcomes between
June 4, 2010 and March 20,
2017 in descending order

GROUP BY,
ORDER BY,
desc

EDA with Visualization:

Chart Type

Purpose of use

1. Scatter Plots:

- What is the relationship between Payload Mass and Flight Number?
- What is the relationship between Flight Number and Launch Site?
- What is the relationship between Payload Mass and Launch Site?
- What is the relationship between Flight Number and Orbit type?
- What is the relationship between Payload Mass and Orbit type?

2. Bar Graph:

- What is the success rate for each Orbit type?

3. Line graph:

- How has the success rate changed over the years?

Interactive Maps with Folium

Link to GitHub repository:

<https://github.com/ZTD273/AppliedDataScience>

Link to view notebook directly using Jupyter Notebook Viewer:

<https://nbviewer.org/github/ZTD273/AppliedDataScience/blob/5b5058beda39663548f6086e1264f14d4877e0fe/Launch%20Site%20Location%20Maps%20%28Folium%29.ipynb>

Building an Interactive Map using Folium:

Locations Mapped: *Marked with circles*

CCAFS SLC-40 (Cape Canaveral Space Launch Complex)

CCAFS LC-40 (Cape Canaveral Launch Complex)

KSC LC-39A (Kennedy Space Center Launch Complex)

VAFB SLC-4E (Vandenberg Air Force Base Space Launch Complex)

Other Objects Mapped:

Failed and Successful Launches at each location

Mouse position on the map

Distance lines from each location to the nearest:

- City
- Railroad
- Highway
- Coast

Methods Used:

Folium.circle()

Folium.marker()

Marker_cluster()

Mouse_position()

Folium.Polyline()

Site_map.add_child()

Why?

Marking these objects gives at least a preliminary idea as to what is necessary for deciding where to build a launch site, as well as giving consideration to how easily parts and labor can reach the site.

Plotly Dashboard

Link to GitHub repository:

<https://github.com/ZTD273/AppliedDataScience>

Direct Link to dashboard code file:

https://github.com/ZTD273/AppliedDataScience/blob/ab8ba2abc0548fe903fd1f848bec35c27f89444d/SpaceX_Dash_App.py

Plotly Dashboard: Includes:

- Pie Chart: Successful outcomes for all launch sites
- Drop-down menu to choose a specific launch site
- Pie Chart: Total successes and failures for a selected launch site
- Payload range slider: 0 kg -> 10,000 kg
- Scatter plot: All successful and failed missions compared to payload mass
 - Default is all launches, all sites
 - Drop-down menu will narrow data to selected launch site
- Compare total successes between sites
- Added to specify returned data
- Specific site data to find success rate
- Narrows data to find most successful payload mass
- Gives a detailed look at how the size of a payload may affect a mission's success

Predictive Analysis

Link to GitHub repository:

<https://github.com/ZTD273/AppliedDataScience>

Direct Link to dashboard code file:

<https://nbviewer.org/github/ZTD273/AppliedDataScience/blob/ff47e1e2f111fa1387f733914a545fa0e2b2106c/Machine%20Learning%20Predictions.ipynb>

Prepare the Data:

Import
required
libraries

Create
NumPy
Array

```
Y = data['Class'].to_numpy()
```

Define
necessary
functions

Standardize
(transform)
the data

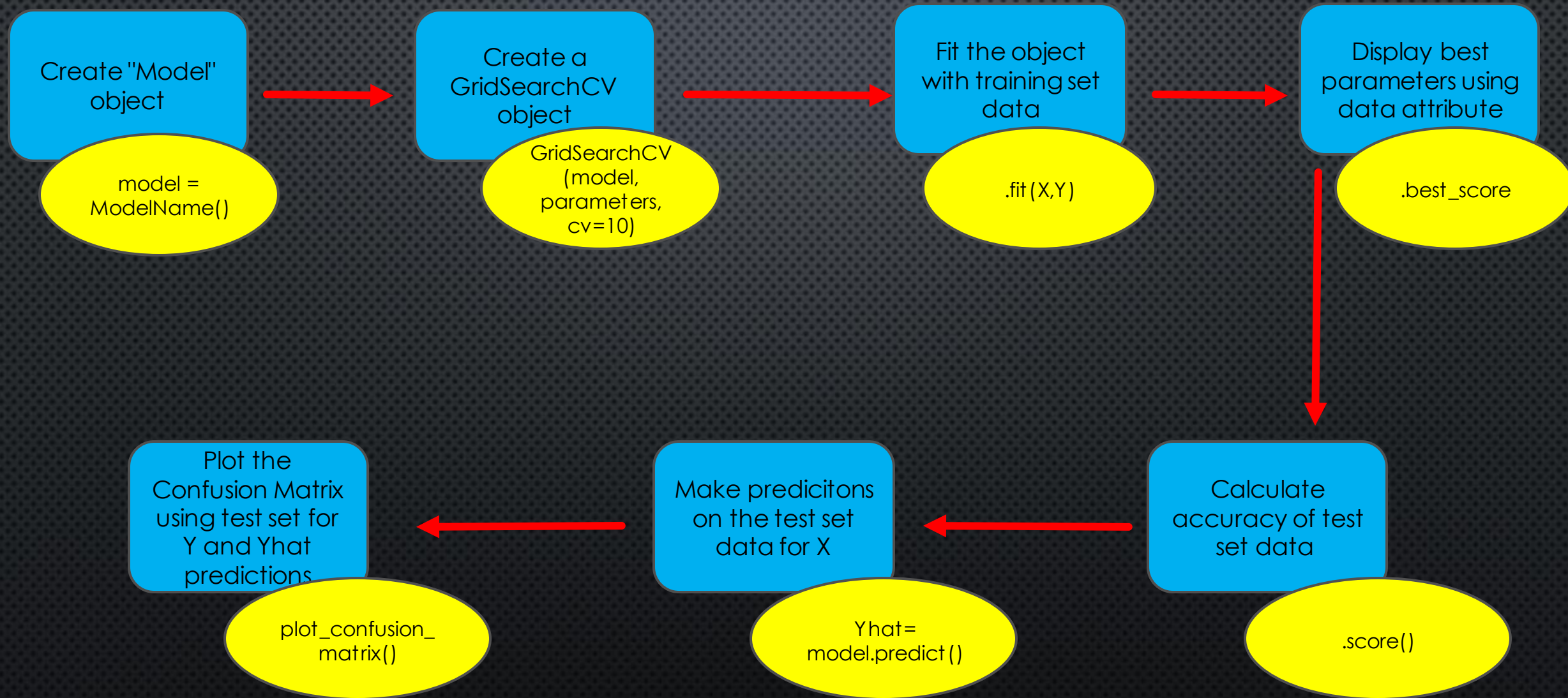
```
transform = preprocessing.StandardScaler()  
X = transform.fit_transform(X)
```

Load the
dataframe

Split data
into Training
+ Testing
sets

```
x_train, x_test, y_train, y_test =  
train_test_split(X, y, test_size=0.2, random_state=2)
```


Building a Predictive Model:



RESULTS FROM EDA

Section 2

ALL LAUNCH SITE NAMES

```
select distinct(LAUNCH_SITE)  
from SPACEXTBL
```

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

LAUNCH SITE NAMES BEGIN WITH 'CCA'

```
select * from SPACEXTBL  
where LAUNCH_SITE like "CCA%" limit 5
```

Date	Time (UTC)	Booster_Version	Launch_Site	Payload	PAYLOAD_MASS_KG_	Orbit	Customer	Mission_Outcome	Landing_Outcome
04-06-2010	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	Success	Failure (parachute)
08-12-2010	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)
22-05-2012	07:44:00	F9 v1.0 B0005	CCAFS LC-40	Dragon demo flight C2	625	LEO (ISS)	NASA (COTS)	Success	No attempt
08-10-2012	00:35:00	F9 v1.0 B0006	CCAFS LC-40	SpaceX CRS-1	500	LEO (ISS)	NASA (CRS)	Success	No attempt
01-03-2013	15:10:00	F9 v1.0 B0007	CCAFS LC-40	SpaceX CRS-2	677	LEO (ISS)	NASA (CRS)	Success	No attempt

TOTAL PAYLOAD MASS

```
select sum(PAYLOAD_MASS_KG_)
as "Total Payload Mass in KG launched by Nasa (CRS)"
from SPACEXTBL where "Customer" like "NASA%CRS%"
```

Total Payload Mass in KG launched by Nasa (CRS)
48213

AVERAGE PAYLOAD MASS BY F9 V1.1

```
select avg(PAYLOAD_MASS_KG_)  
as "Average Payload Mass carried by F9v1.1 Booster"  
from SPACEXTBL where "Booster_Version" like "F9%v1.1%"
```

Average Payload Mass carried by F9v1.1 Booster
--

2534.6666666666665

FIRST SUCCESSFUL GROUND LANDING DATE

```
select min("Date")  
as "First Successful Landing on Ground Pad"  
from SPACEXTBL  
where "LANDING _OUTCOME" = "Success (ground pad)"
```

First Successful Landing on Ground Pad
01-05-2017

SUCCESSFUL DRONE SHIP LANDING WITH PAYLOAD BETWEEN 4000 AND 6000

```
select distinct("Booster_Version")  
as "Successful Boosters of the Given Parameters"  
from SPACEXTBL  
where "LANDING _OUTCOME" = "Success (drone ship)"  
and PAYLOAD_MASS__KG_ between 4000 and 6000
```

Successful Boosters of the Given Parameters

F9 FT B1022

F9 FT B1026

F9 FT B1021.2

F9 FT B1031.2

TOTAL NUMBER OF SUCCESSFUL AND FAILURE MISSION OUTCOMES

```
select MISSION_OUTCOME as "Outcome", count(*)  
as "Total Missions" from SPACEXTBL  
group by MISSION_OUTCOME
```

Outcome	Total Missions
Failure (in flight)	1
Success	98
Success	1
Success (payload status unclear)	1

BOOSTERS CARRIED MAXIMUM PAYLOAD

```
select "Booster_Version"  
as "Boosters That Carried Max Payload" from SPACEXTBL  
where PAYLOAD_MASS_KG_ =  
(select max(PAYLOAD_MASS_KG_) from SPACEXTBL)
```

Sub-Query

Boosters That Carried 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 B1080.2
F9 B5 B1058.3
F9 B5 B1051.6
F9 B5 B1080.3
F9 B5 B1049.7

2015 LAUNCH RECORDS

```
select substr(Date, 4, 2) as "Month",  
"LANDING _OUTCOME" as "Landing Outcome",  
"Booster_Version" as "Booster",  
LAUNCH_SITE as "Launch Site"  
from SPACEXTBL  
where "LANDING _OUTCOME" = "Failure (drone ship)"  
and substr(Date, 7, 4) = '2015'
```

Note: SQLite
does not
support
monthnames

Month	Landing Outcome	Booster	Launch Site
01	Failure (drone ship)	F9 v1.1 B1012	CCAFS LC-40
04	Failure (drone ship)	F9 v1.1 B1015	CCAFS LC-40

RANK LANDING OUTCOMES BETWEEN 2010-06-04 AND 2017-03-20

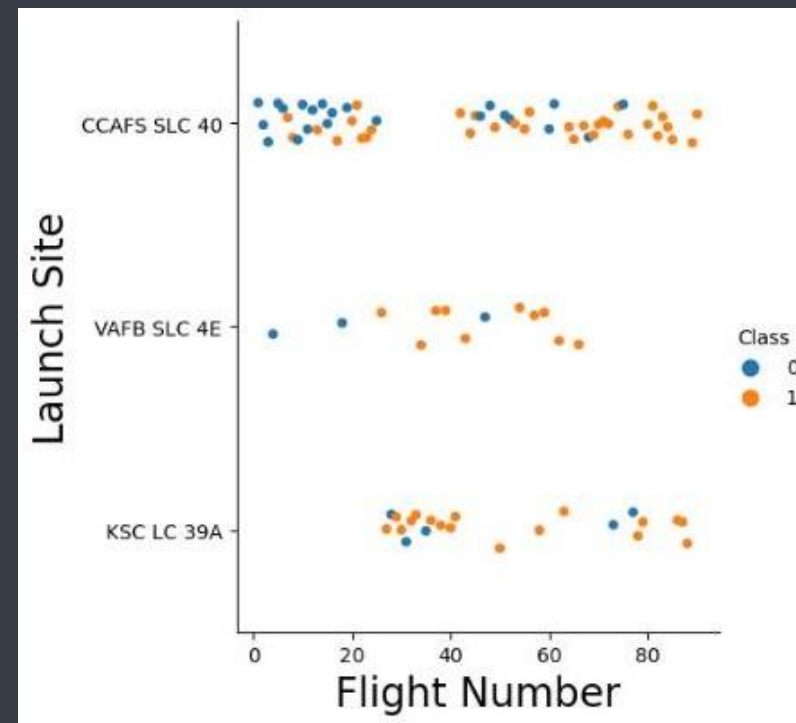
```
select "Date", "LANDING _OUTCOME" as "Outcome",  
count("LANDING _OUTCOME") as "Number of Successes"  
from SPACEXTBL  
where substr(Date,7,4)||substr(Date,4,2)||substr(Date,1,2)  
between '20100604' and '20170320'  
group by "LANDING _OUTCOME"  
order by count("LANDING _OUTCOME") desc
```

Note: SQLite
does not
support
monthnames

Date	Outcome	Number of Successes
07-08-2018	Success	20
08-10-2012	No attempt	10
08-04-2016	Success (drone ship)	8
18-07-2016	Success (ground pad)	6
10-01-2015	Failure (drone ship)	4
05-12-2018	Failure	3
18-04-2014	Controlled (ocean)	3
04-06-2010	Failure (parachute)	2
06-08-2019	No attempt	1

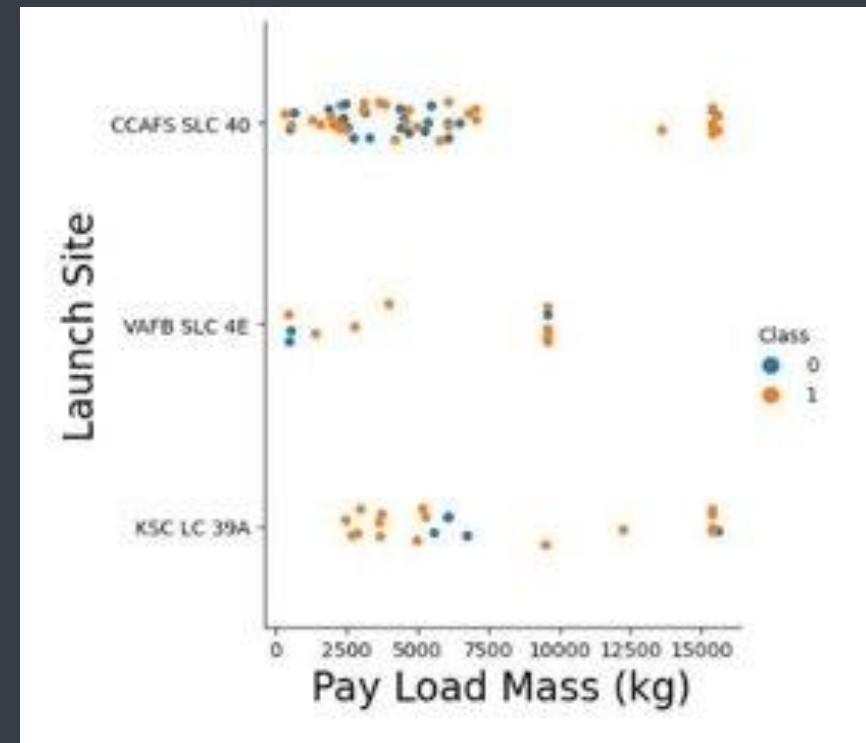
FLIGHT NUMBER VS. LAUNCH SITE

Scatterplot shows the distribution and frequency of launches between sites, as well as how many launches were successes or failures.



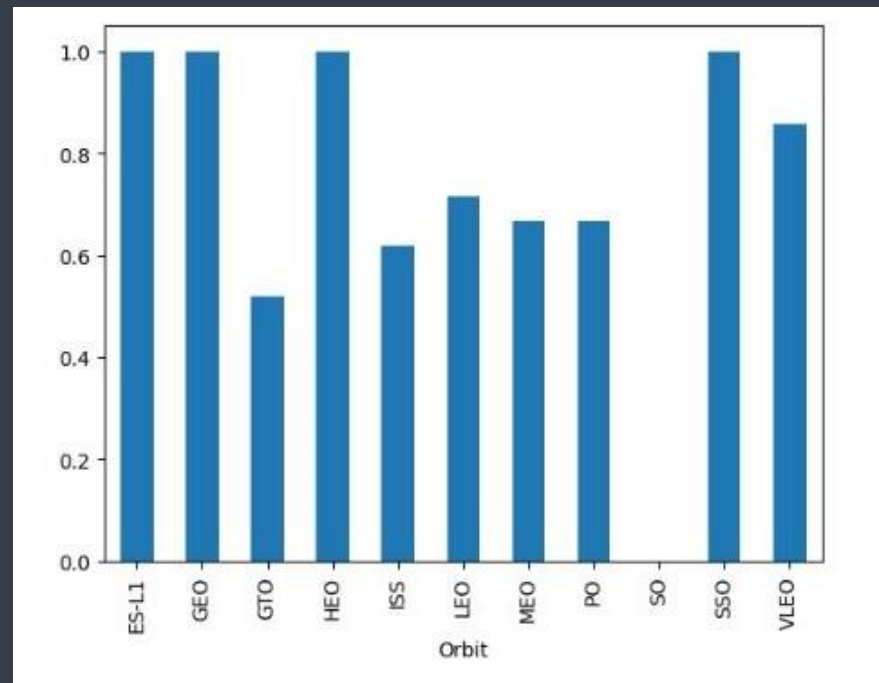
PAYLOAD MASS VS. LAUNCH SITE

Scatterplot shows which sites launch the heaviest payloads, which payload sizes are launched most frequently, and whether they are successful or not.

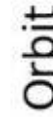


SUCCESS RATE VS. ORBIT TYPE

Bar chart shows which orbits are the most successful.

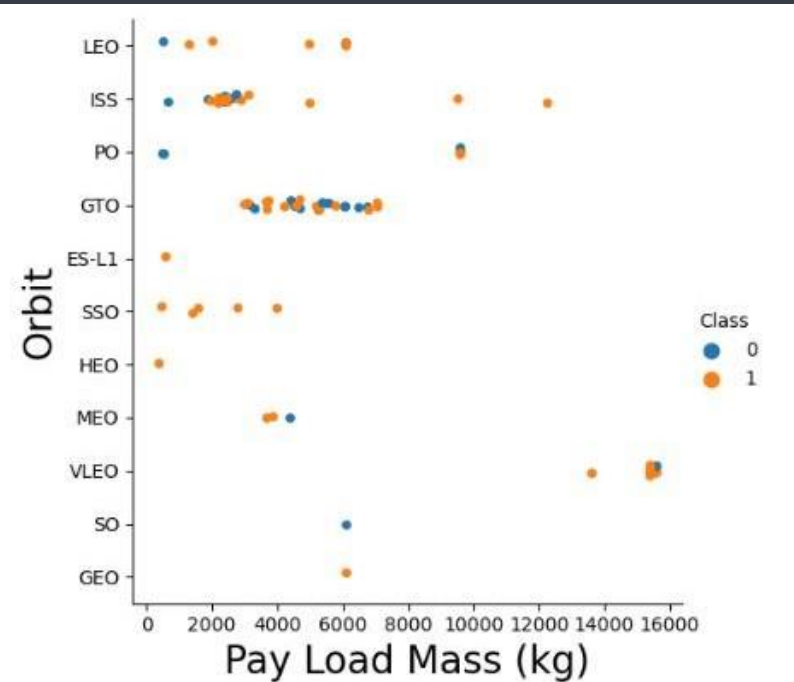


Scatterplot shows how often different orbit types are launched and if they are successful or not.



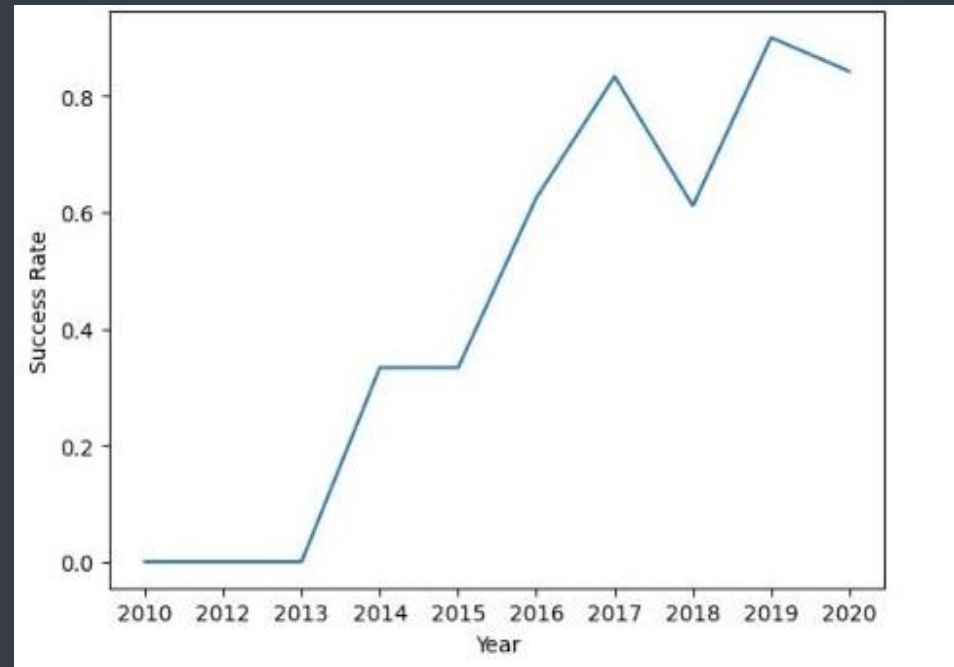
PAYLOAD MASS VS. ORBIT TYPE

Scatterplot shows how often different payload sizes are launched into what orbit and if they are successful or not.



YEARLY TREND OF LAUNCH SUCCESSES

Line graph shows the success rate over time.

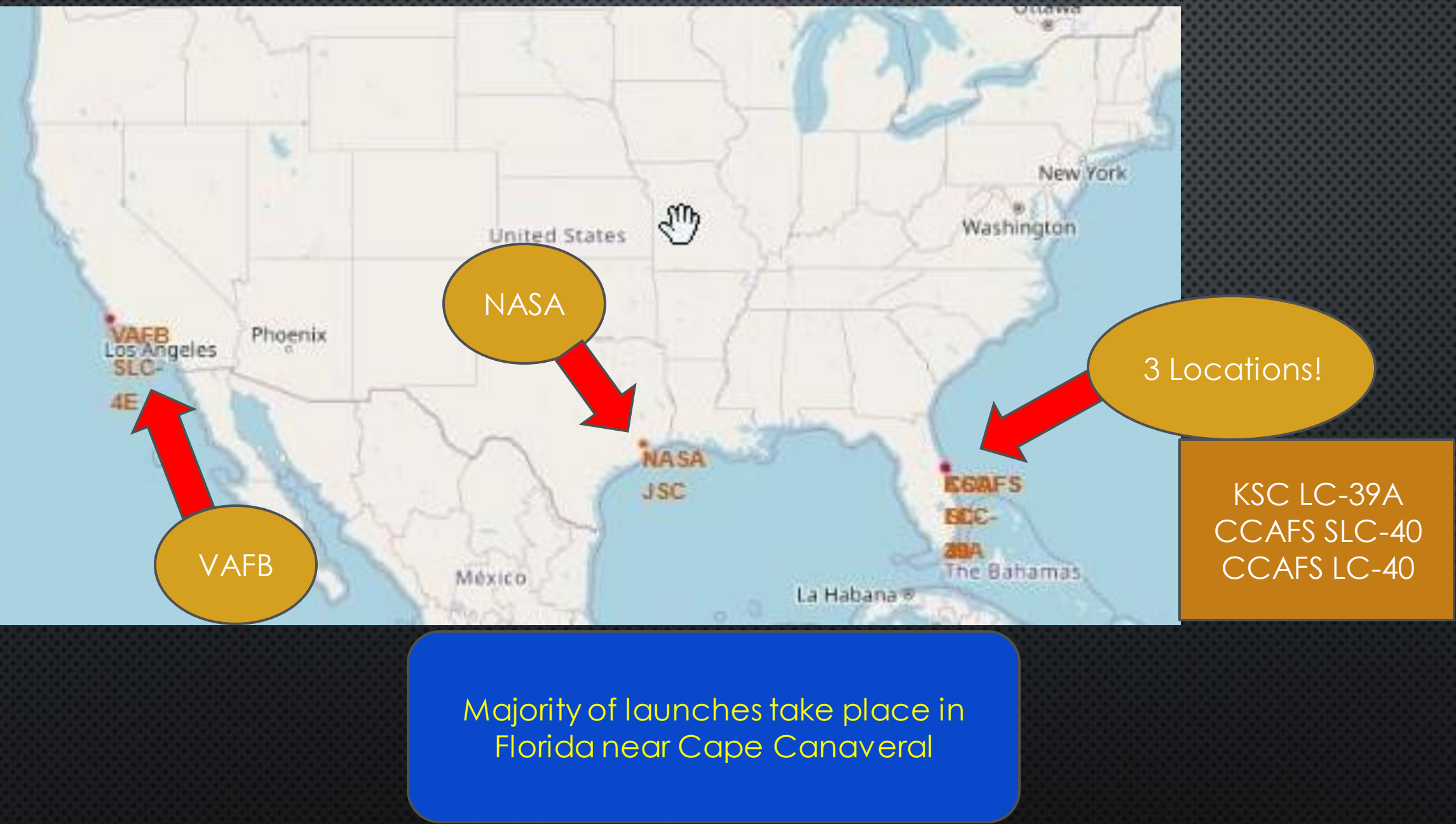


The background features a dark, textured globe with a network of white lines and dots, suggesting a global or technological theme. The lines are thin and connect various points, some of which are highlighted with small circles.

LAUNCH SITE PROXIMITY ANALYSIS

Section 3

Launch Site Locations



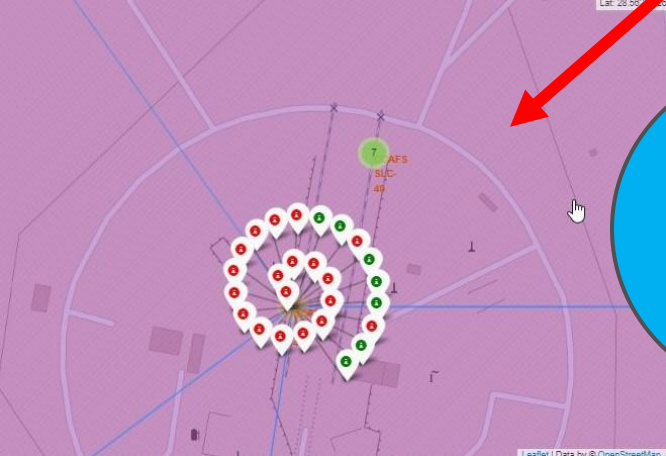
Launch outcomes at each launch site

VAFB SLC-4E



4 Successes
10 Attempts
40% Success

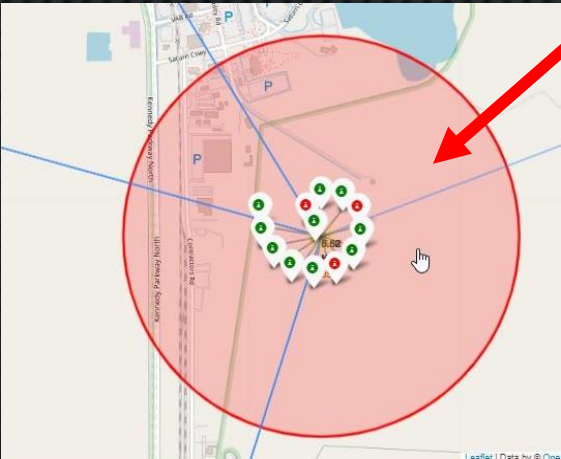
CCAFS LC-40



7 Successes
26 Attempts
26.9% Success

Most launches!

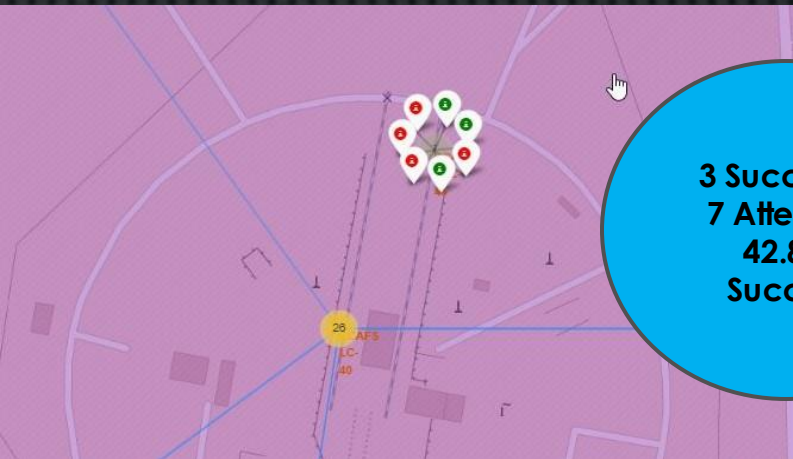
KSC LC-39A



10 Successes
13 Attempts
76.9% Success

Highest rate of success!

CCAFS SLC-40



3 Successes
7 Attempts
42.8% Success

Green = Successful
Red = Failure

Launch site proximities

VAFB SLC-4E



Closest railway = 9.4 km
Closest coast = 6.78 km
Closest highway = 5.89 km
Closest city = 26.29 km

Closest railway = 1.3 km
Closest coast = 1.34 km
Closest highway/city = 14.02 km

Launch sites need to be close to a coast, a railway, and a highway while being far away from population centers.

Closest railway = 1.33 km
Closest coast = 0.93 km
Closest highway = 6.89 km
Closest city = 18.05 km



KSC LC-39A

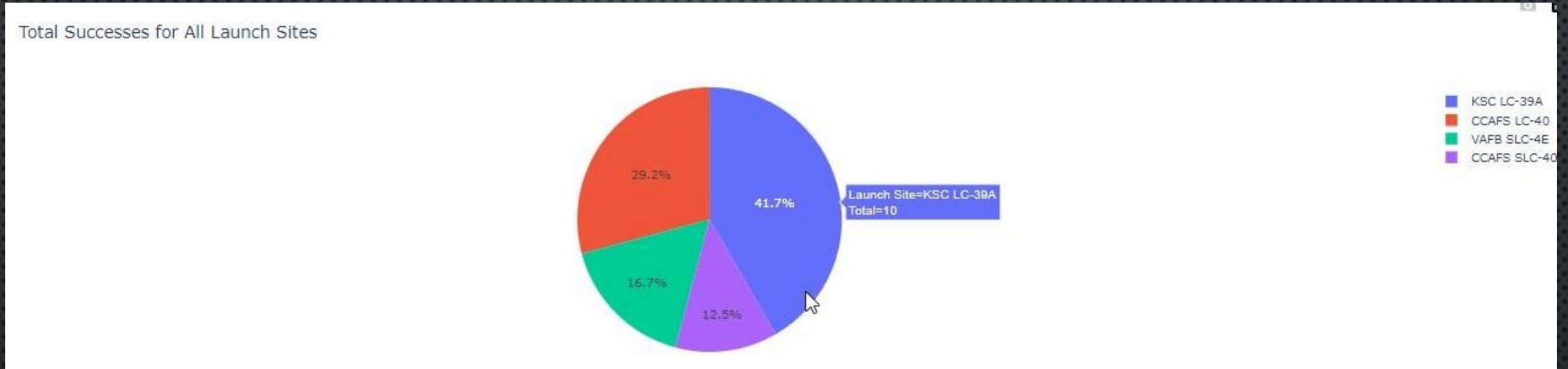
CCAFS LC-40
CCAFS SLC-40



BUILD A DASHBOARD WITH PLOTLY DASH

Section 4

Number of successful launches: All Launch Sites



Success totals in descending order:

KSC LC-39A = 10 successes

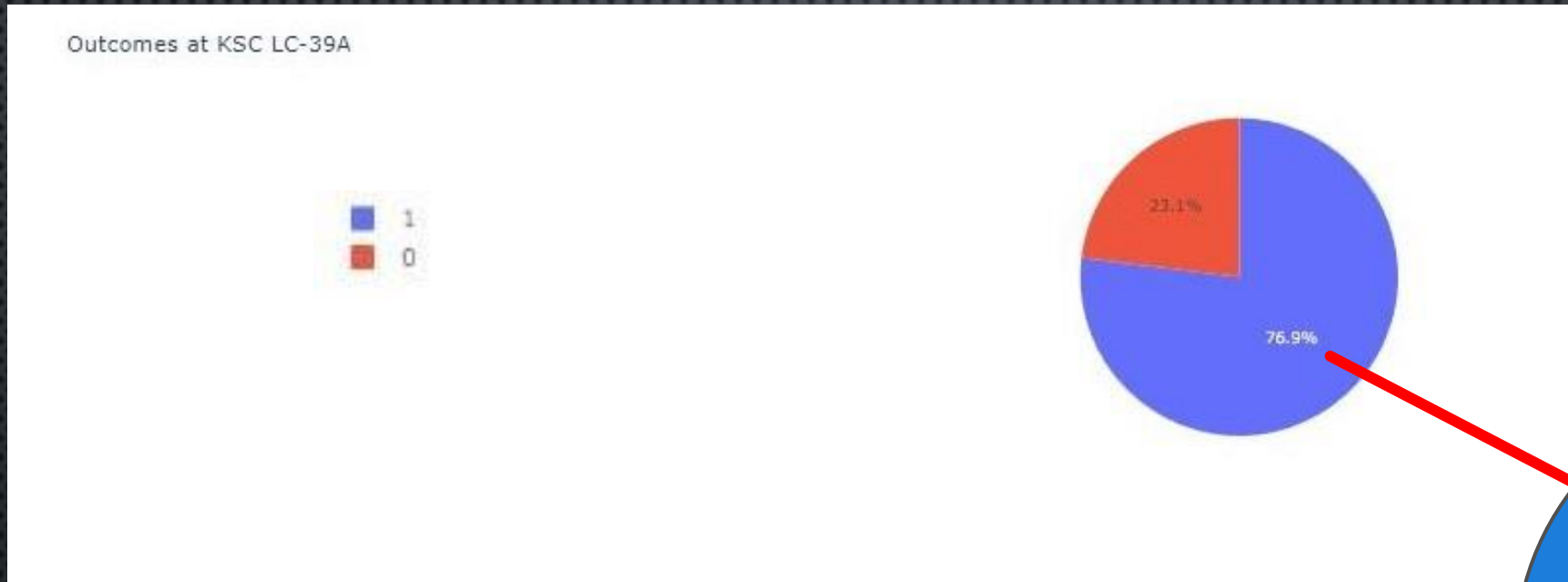
CCAFS LC-40 = 7 successes

VAFB SLC-4E = 4 successes

CCAFS SLC-40 = 3 successes

Which Launch Site has the highest success ratio?

KSC LC-39A : Kennedy Space Center Launch Complex 39-A



Success Ratio = (Successes) / (Attempts)

Success Ratio = 10 / 13

Success Ratio = 0.7692307692

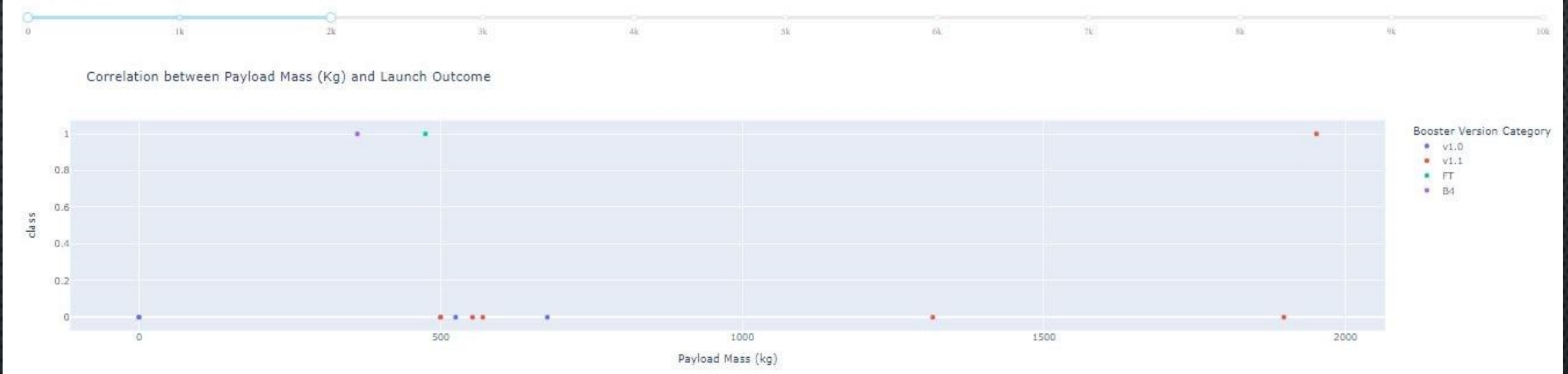
Success =
76.9%

Payload Range vs. Launch Outcome: All Launch Sites

0 kg

2,000
kg

Payload range (kg):



3/11
Succeed

Success=
27.27 %

Payload Range vs. Launch Outcome: All Launch Sites

2,000
kg

4,000
kg

Best performing
Booster = FT

Payload range (kg):



12/20
Succeed

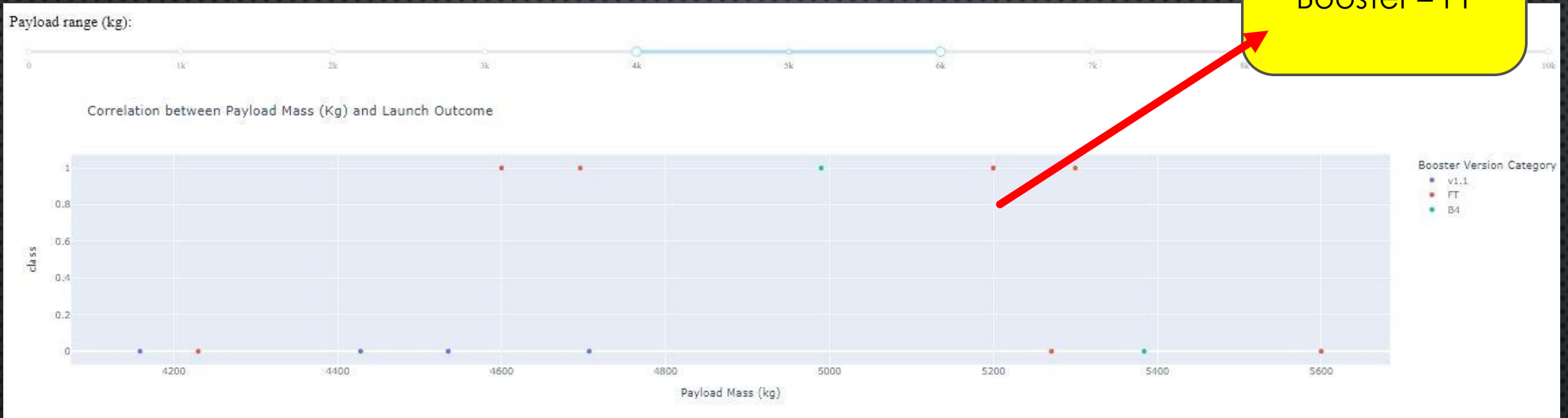
Success=
60 %

Payload Range vs. Launch Outcome: All Launch Sites

4,000
kg

6,000
kg

Best performing
Booster = FT



5/13
Succeed

Success=
38.46 %

Payload Range vs. Launch Outcome: All Launch Sites

No Successes

6,000
kg

8,000
kg

Payload range (kg):



0/4
Succeed

Success=
0.0 %

Payload Range vs. Launch Outcome: All Launch Sites

Only Success:
Booster B4

8,000
kg

10,000
kg



1/2
Succeed

Success=
50 %

PREDICTIVE ANALYSIS: CLASSIFICATION

Section 5

LOGISTIC REGRESSION

```
LR = LogisticRegression()
```

```
logreg_cv = GridSearchCV(LR, parameters, cv=10)
```

```
logreg_cv.fit(X_train, Y_train)
```

```
print("tuned hyperparameters:(best parameters)", logreg_cv.best_params_)
```

```
print("accuracy:", logreg_cv.best_score_)
```

```
logreg_cv.score(x_test, y_test)
```

```
0.8333333333333334
```

```
parameters = {'C':[0.01,0.1,1],  
              'penalty':['l2'],  
              'solver':['lbfgs']}
```

```
tuned hyperparameters: (best parameters)  
{'C': 0.01, 'penalty': 'l2', 'solver': 'lbfgs'}  
accuracy : 0.8472222222222222
```

```
log_hat=logreg_cv.predict(x_test)  
plot_confusion_matrix(y_test, log_hat)
```


SUPPORT VECTOR MACHINES

```
svm = SVC()
```

```
svm_cv = GridSearchCV(svm, parameters, cv=10)
```

```
svm_cv.fit(X_train, Y_train)
```

```
print("tuned hyperparameters:(best parameters)", svm_cv.best_params_)
```

```
print("accuracy:", svm_cv.best_score_)
```

```
svm_cv.score(x_test, y_test)
```

```
0.8333333333333334
```

```
parameters = {'kernel':  
              ('linear','rbf','poly','rbf','sigmoid'),  
              'C': np.logspace(-3, 3, 5),  
              'gamma':np.logspace(-3, 3, 5)}
```

```
tuned hyperparameters:(best parameters)  
{'C': 1.0, 'gamma': 0.03162277660168379, 'kernel': 'sigmoid'}  
accuracy : 0.8472222222222222
```

```
svm_hat=svm_cv.predict(x_test)  
plot_confusion_matrix(y_test,svm_hat)
```


DECISION TREE CLASSIFIER

```
tree = DecisionTreeClassifier()
```

```
tree_cv = GridSearchCV(tree, parameters, cv=10)
```

```
tree_cv.fit(X_train, Y_train)
```

```
print("tuned hyperparameters:(best parameters)", tree_cv.best_params_)
```

```
print("accuracy:", tree_cv.best_score_)
```

```
tree_cv.score(x_test, y_test)
```

```
0.8333333333333334
```

```
parameters = {'criterion': ['gini', 'entropy'],  
              'splitter': ['best', 'random'],  
              'max_depth': [2*n for n in range(1,10)],  
              'max_features': ['auto', 'sqrt'],  
              'min_samples_leaf': [1, 2, 4],  
              'min_samples_split': [2, 5, 10]}
```

```
tuned hyperparameters:(best parameters)  
{'criterion': 'entropy', 'max_depth': 4, 'max_features': 'sqrt',  
  'min_samples_leaf': 2, 'min_samples_split': 2, 'splitter': 'best'}  
accuracy : 0.875
```

```
tree_hat = tree_cv.predict(x_test)  
plot_confusion_matrix(y_test, tree_hat)
```


K-NEAREST NEIGHBOR

```
KNN= KNearestNeighbor()
```

```
knn_cv = GridSearchCV(KNN, parameters, cv=10)
```

```
knn_cv.fit(X_train,Y_train)
```

```
print("tuned hyperparameters:(best parameters)", knn_cv.best_params_)
```

```
print("accuracy:", knn_cv.best_score_)
```

```
tuned hyperparameters:(best parameters)
{'algorithm': 'auto', 'n_neighbors': 9, 'p': 1}
accuracy : 0.8472222222222222
```

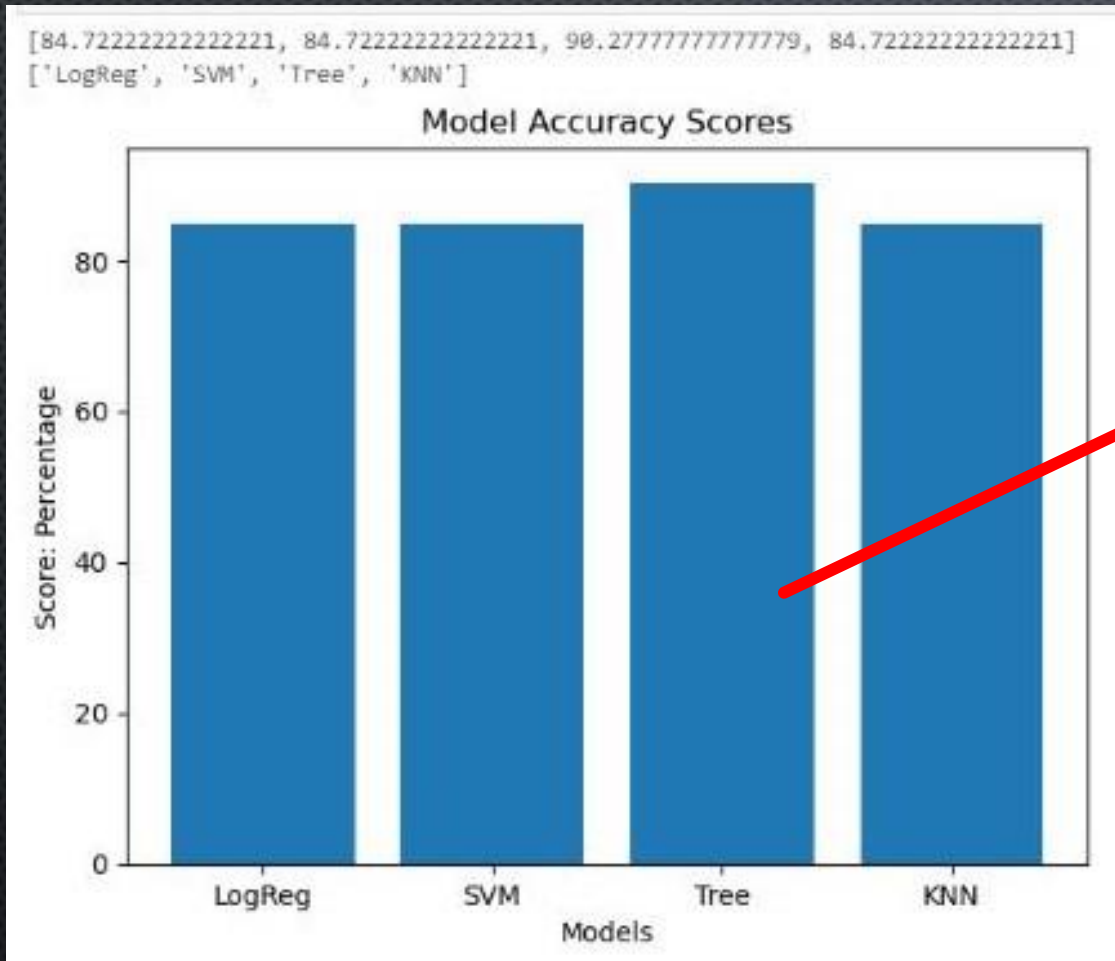
```
knn_cv.score(x_test, y_test)
```

```
0.8333333333333334
```

```
knn_hat=knn_cv.predict(x_test)
plot_confusion_matrix(y_test,knn_hat)
```

```
parameters = {
    'n_neighbors': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10],
    'algorithm': ['auto', 'ball_tree', 'kd_tree', 'brute'],
    'p': [1,2]}
```

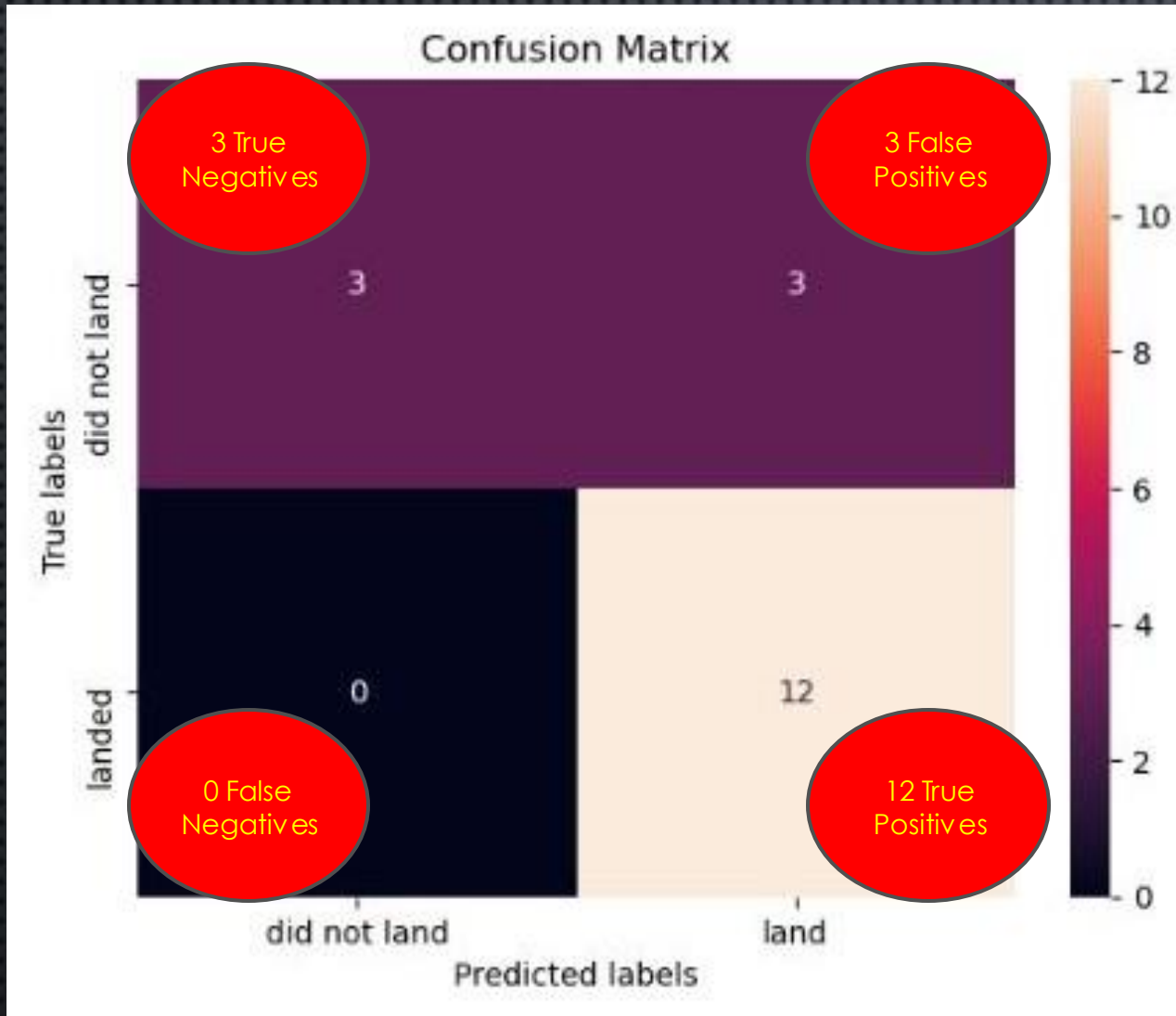

CLASSIFICATION ACCURACY



Most accurate model =
Decision Tree Classifier

90.27 %
Accuracy!

CONFUSION MATRIX



This is the confusion matrix for the best performing model: Decision Tree

This is also the same exact Confusion Matrix for all 3 of our other models.

$$\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Predictions}}$$

83.3 %
Accuracy

CONCLUSION

Section 6

Launch Site with the largest
successful launch?

VAFB SLC-4E: Vandenberg Air Force Base
9,600 Kg

9,600 Kg

Launch Site with the highest
success rate?

KSC SLC-39A: Kennedy Space Center

76.9 %
Success

Payload Range with the highest
success rates? The lowest?

Highest Success Rate = 2,000 – 4,000 Kg
Lowest Success Rate = 6,000 – 8,000 Kg

60 %
Success

0 %
Success

Falcon 9 Booster Version with
the highest success rate?

"FT" Booster Version:
14 Successes of 20 Attempts

70 %
Success

So, what does that all mean?

YES!

The outcome of a successful landing after launch CAN be reasonably predicted.

Therefore, it **IS** possible for SpaceY to correctly make these predictions to successfully outbid SpaceX.

Most
Profitable
Parameters?

Launch Site:
KSC LC-39A

Payload Mass:
2,000–4,000 Kg

Booster:
Version FT

APPENDIX

Section 7

**FINAL
THOUGHTS**

Enter
↵

This is a zoomed in shot from the Folium Map.

As you can see, there is a total overlap between **both** CCAFS launch sites.

SLC-40 previously **was** LC-40.
This is one launch site, not two.

Does not affect Conclusions.
However, this **does** affect their success rates!

LC-40 was reported at a 26.9 % success rate
SLC-40 was reported at a 42.9 % success rate

As one CCAFS launch site, the success rate is actually
30.30 %
(10 Successes out of 33 Attempts)

33

CCAFS

CCAFS

LC-40

40

0.92
KM

Conclusions were drawn
from the data in the
Plotly Dashboard

SQL Query gives a
different conclusion for
largest successful launch

Largest Successful Launches had a
payload mass of 15,600 Kg.
These launches took place at both
KSC LC-39A and CCAFS SLC-40

See Scatter Plot:
Payload Mass vs. Launch Site

