



IBM Developer  
SKILLS NETWORK

# Winning Space Race with Data Science

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# Outline

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

# Executive Summary

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- **SUMMARY OF METHODOLOGIES**
  - Data Collection
  - Data Wrangling
  - Exploratory Analysis using SQL
  - Exploratory Analysis using Pandas and Matplotlib
  - Interactive Visual Analytics with Folium lab
  - Interactive Visual Analytics with Plotly Dash
  - Predictive Analysis (Classification)
- **SUMMARY OF ALL RESULTS**
  - Exploratory Analysis
  - Interactive Visual Analytics
  - Predictive Analytics

# Introduction

- Project background and context

SpaceX advertises Falcon 9 rocket launches cost 62 million dollars(pre-inflation); other providers cost upward of 165 million dollars each, much of the savings is because SpaceX can reuse the first stage.

- Problems you want to find answers

In this project will predict if the Falcon 9 first stage will land successfully defining the accuracy of the landing.

## CAPABILITIES & SERVICES

SpaceX offers competitive pricing for its Falcon 9 and Falcon Heavy launch services. Modest discounts are available, for contractually committed, multi-launch purchases. SpaceX can also offer crew transportation services to commercial customers seeking to transport astronauts to alternate LEO destinations.

PRICE *	FALCON 9	FALCON HEAVY
STANDARD PAYMENT PLAN (THROUGH 2022)	<b>\$67 M</b> UP TO 5.5 mT TO GTO	<b>\$97 M</b> UP TO 8 mT TO GTO
DESTINATION	PERFORMANCE †	PERFORMANCE †
LOW EARTH ORBIT (LEO)	22,800 kg 50,265 lbs	63,800 kg 140,660 lbs
GEOSYNCHRONOUS TRANSFER ORBIT (GTO)	8,300 kg 18,300 lbs	26,700 kg 58,860 lbs
PAYLOAD TO MARS	4,020 kg 8,860 lbs	16,800 kg 37,040 lbs

\*Pricing adjustments made in March 2022 to account for excessive levels of inflation. Missions purchased in 2022 but flown beyond 2023 may be subject to additional adjustments due to inflation.  
†Performance represents max capability on fully expendable vehicle.

Inclination: LEO = 28.5°, GTO = 27°

<https://www.spacex.com/vehicles/falcon-9/>



Section 1

# Methodology

# Methodology

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## Executive Summary

- Data collection methodology:
  - SpaceX Rest API ( " spacex\_url=<https://api.spacexdata.com/v4/launches/past> )
  - Web Scrapping
- Perform data wrangling
  - The information collected incorporates data from both successful and unsuccessful launches, at this point the data is labeled prior to applying the machine learning models.
- Perform exploratory data analysis (EDA) using visualization and SQL
- Perform interactive visual analytics using Folium and Plotly Dash
- Perform predictive analysis using classification models
  - Training and test data to find the best Hyperparameter for SVM, Classification Trees, and Logistic Regression.

# Data Collection

## Describe how data sets were collected.

1. SpaceX launch data is collected from the REST API (<https://api.spacexdata.com/v4/launches/past>)

2. The REST API include enough information referring

FlightNumber, Date, BoosterVersion, PayloadMass, Orbit, LaunchSite,  
Outcome, Flights, GridFins, Reused, Legs, LandingPad, Block,  
ReusedCount, Serial, Longitude, Latitude

## 1. API call

## 2. Pandas data frame

### 3. Filter the data to only include Falcon9

#### 4. Save to .csv

```
data falcon9.to_csv('dataset part 1.csv', index=False)
```

# Data Collection – SpaceX API

## 1. Data Collection

```
spacex_url="https://api.spacexdata.com/v4/launches/past"
response = requests.get(spacex_url)
print(response.content)
```

```
b'{"fairings":{"reused":false,"recovery_attempt":false,"recovered":false,"ships":[]},"links":{"patch":{"small":"https://images2.imgbox.com/94/f2/W6P45r_o.png","large":"https://images2.imgbox.com/5b/02/QcW4b5V_o.png"},"reddit":{"campaign":null,"launch":null,"media":null,"recovery":null},"flickr":{"small":{"original":"","presskit":null,"webcast":"https://www.youtube.com/watch?v=0a_00n1_Y88","youtube_id":"0a_00n1_Y88"},"article":"https://www.space.com/2196-spacex-inaugural-falcon-1-rocket-lost-launch.html"},"wikipedia":"https://en.wikipedia.org/wiki/DemoSat"},"static_fire_date_utc":"2006-03-17T00:00:00.000Z","static_fire_date_unix":1142553600,"net":false,"window":0,"rocket":"5e9d0d95eda69955f709d1eb","success":false,"failures":[{"time":33,"altitude":null,"reason":"merlin engine failure"}],"details":"Engine failure at 33 seconds and loss of vehicle","crew":[],"ships":[],"capsules":[{"payloads":["5eb0e4b5b6c3bb0006eeb1e1"],"launchpad":"5e9e4502f5090955de566f86","flight_number":1,"name":"FalconSat","date_utc":"2006-03-24T22:30:00.000Z","date_unix":1143339400,"date_local":"2006-03-25T10:30:00+12:00","date_precision":"hour","upcoming":false,"cores":[{"core":"5e9e289df3591803d3b2623","flight":1,"gridfins":false,"legs":false,"reused":false,"landing_attempt":false}]}]}
```

## 2. Convert the .json() result into a dataframe

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

## 3. First Data Processing

```
data = data[['rocket', 'payloads', 'launchpad', 'cores', 'flight_number', 'date_utc']]
```

```
# Lets take a subset of our dataframe keeping only the features we want and the flight number, and date_utc.
data = data[['rocket', 'payloads', 'launchpad', 'cores', 'flight_number', 'date_utc']]

# We will remove rows with multiple cores because those are falcon rockets with 2 extra rocket boosters and rows that have multiple launchpads.
data = data[data['cores'].map(len)==1]
data = data[data['payloads'].map(len)==1]

# Since payloads and cores are lists of size 1 we will also extract the single value in the list and replace the feature.
data['cores'] = data['cores'].map(lambda x : x[0])
data['payloads'] = data['payloads'].map(lambda x : x[0])

# We also want to convert the date_utc to a datetime datatype and then extracting the date leaving the time
data['date'] = pd.to_datetime(data['date_utc']).dt.date

# Using the date we will restrict the dates of the launches
data = data[data['date'] <= datetime.date(2020, 11, 13)]
```

## 4. Filter to only keep the features needed for Falcon 9 Launches

```
data_falcon9=df[df['BoosterVersion']!='Falcon 1']
```

	FlightNumber	Date	BoosterVersion
4	1	2010-06-04	Falcon 9
5	2	2012-05-22	Falcon 9
6	3	2013-03-01	Falcon 9
7	4	2013-09-29	Falcon 9
8	5	2013-12-03	Falcon 9
...	...	...	...
89	86	2020-09-03	Falcon 9
90	87	2020-10-06	Falcon 9
91	88	2020-10-18	Falcon 9
92	89	2020-10-24	Falcon 9
93	90	2020-11-05	Falcon 9


90 rows × 4 columns



# Data Collection - Scraping

1. Requests.get method

```
# use requests.get() method with the provided static_url
page = requests.get(static_url)
```



2. Create BeautifulSoup Object

```
# Use BeautifulSoup() to create a BeautifulSoup object from a response text content
soup = BeautifulSoup(page.text, 'html.parser')
```

3. Assign the result to a list (html\_tables)


```
# Use the find_all function in the BeautifulSoup object, with element type `table`
# Assign the result to a list called `html_tables`
html_tables = soup.find_all('table')
```

4. Get column names

```
# Apply find_all() function with `th` element on first_launch_table
# Iterate each th element and apply the provided extract_column_from_header() to get a column name
# Append the non-empty column names (if name is not None and len(name) > 0) into a list called column_names

column_names = []
table_headers = first_launch_table.find_all('th')
# print(table_headers)
for j, table_header in enumerate(table_headers):
    name = extract_column_from_header(table_header)
    if name is not None and len(name) > 0:
        column_names.append(name)
print(column_names)

['Flight No.', 'Date and time ( )', 'Launch site', 'Payload', 'Payload mass', 'Orbit', 'Customer', 'Launch outcome']
```




5. Create an empty dictionary and convert into a Pandas dataframe

```
launch_dict = dict.fromkeys(column_names)

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

# Let's initialize the launch_dict with each value to be an empty list
launch_dict['Flight No.'] = []
launch_dict['Launch site'] = []
launch_dict['Payload'] = []
launch_dict['Payload mass'] = []
launch_dict['Orbit'] = []
launch_dict['Customer'] = []
launch_dict['Launch outcome'] = []

# Added some new columns
launch_dict['Version Booster'] = []
launch_dict['Booster landing'] = []
launch_dict['Date'] = []
launch_dict['Time'] = []
```



6. Export to CSV

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

# Data Wrangling

1. Calculate the number of launches on each site

```
# Apply value_counts() on column LaunchSite
df.LaunchSite.value_counts()
```

2. Calculate the number and occurrence of each orbit

```
# Apply value_counts on Orbit column
df.Orbit.value_counts()
```

GTO	27
ISS	21
VLEO	14
PO	9
LEO	7
SSO	5
MEO	3
ES-L1	1
HEO	1
SO	1
GEO	1

3. Calculate the number and occurrence of each orbit

```
# landing_outcomes = values on Outcome column
landing_outcomes=df.Outcome.value_counts()
landing_outcomes
```

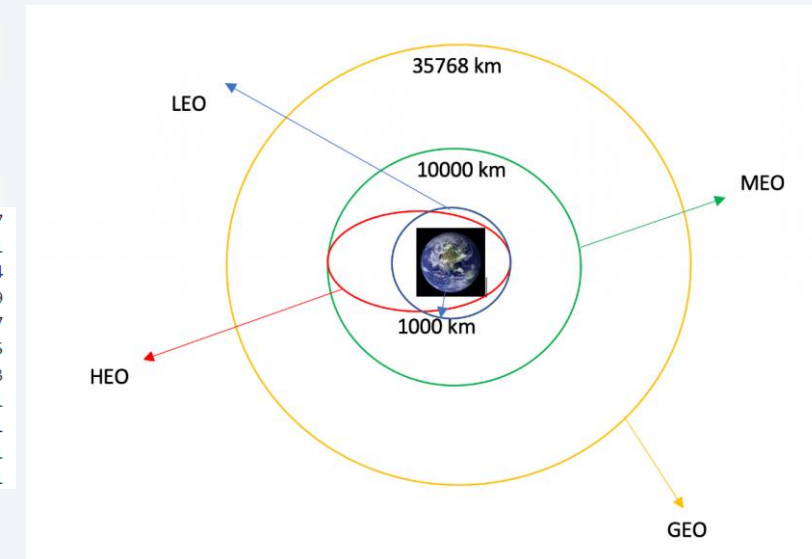
True	ASDS	41
None	None	19
True	RTLS	14
False	ASDS	6
True	Ocean	5
False	Ocean	2
None	ASDS	2
False	RTLS	1

4. Create a landing outcome label from outcome column

```
# landing_class = 0 if bad_outcome
landing_class = [0 if x in bad_outcomes else 1 for x in df['Outcome']]
df['Class']=landing_class
print(df[['Class']].head(8))
print(df["Class"].mean()) # probability of positive outcome 2/3
print(df.head(5))
```

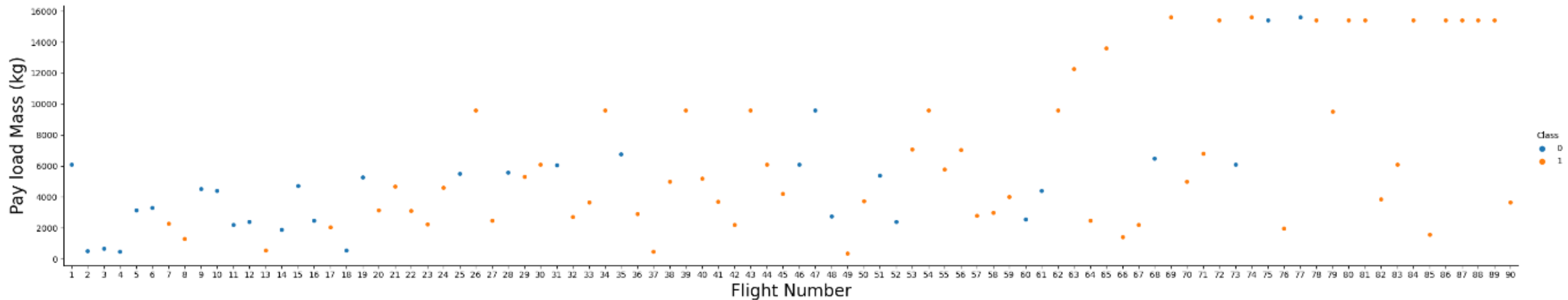
5. Export to CSV

```
# landing_class = 1 otherwise
```

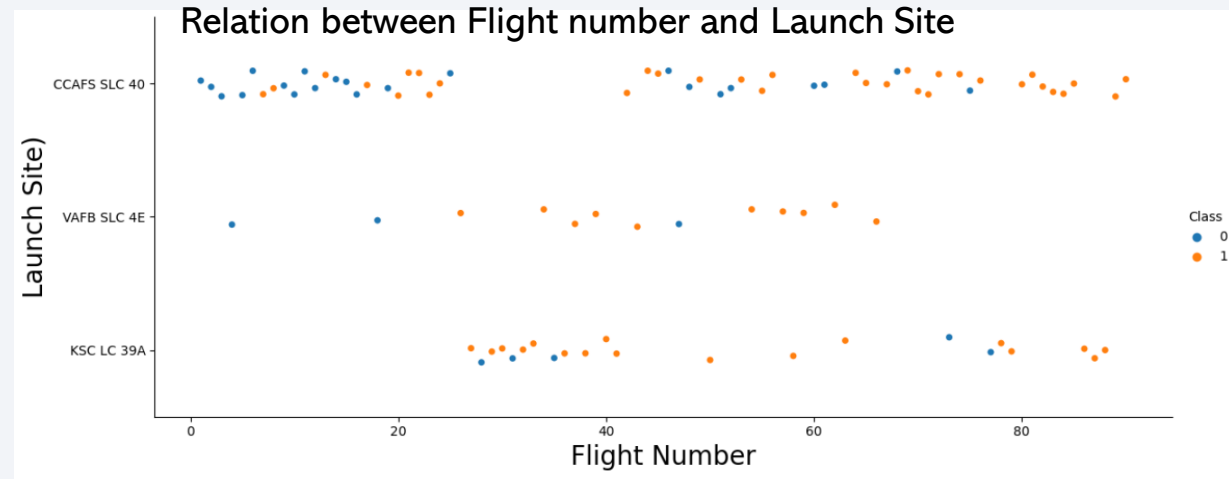


# EDA with Data Visualization

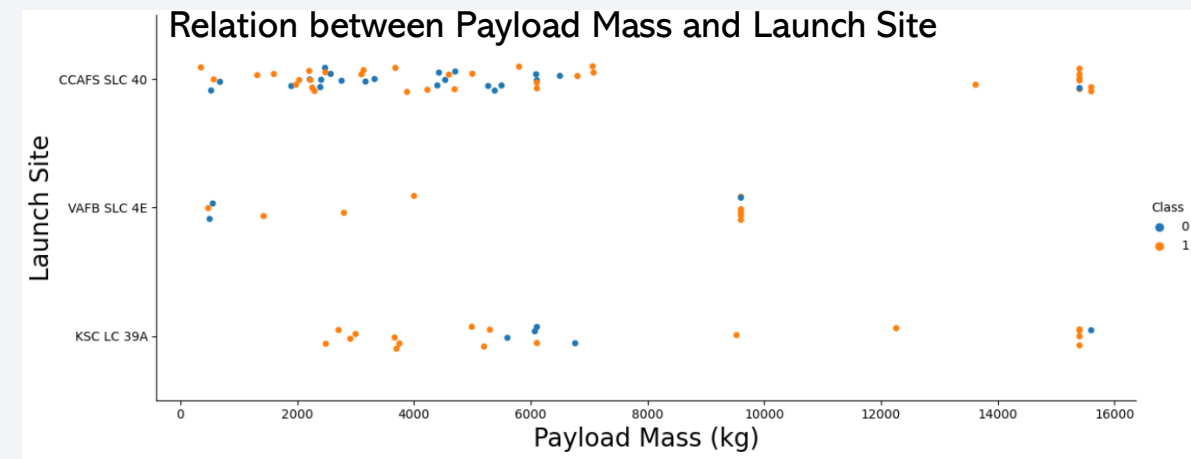
According to the Flight numbers are increasing the Payload Mass (kg)



Relation between Flight number and Launch Site

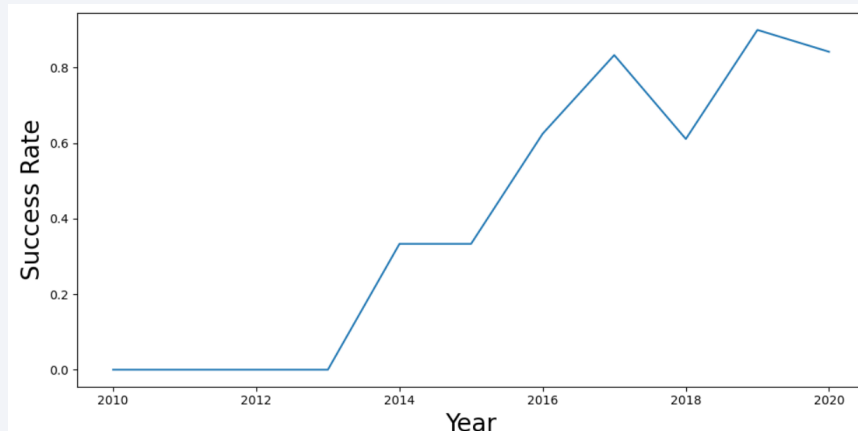
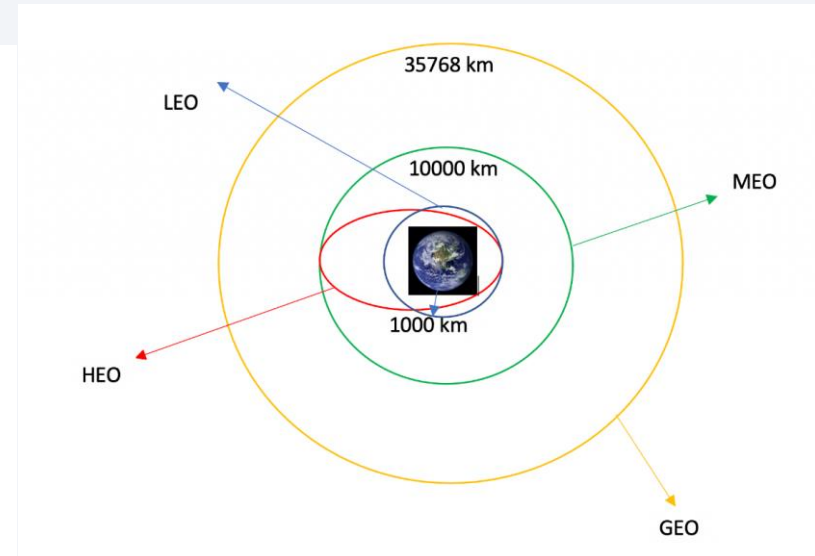
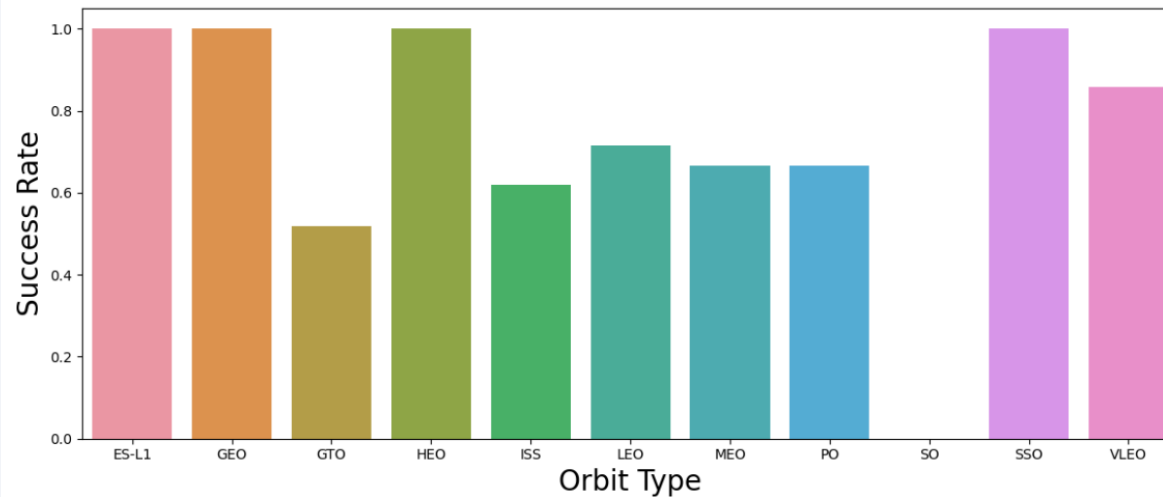


Relation between Payload Mass and Launch Site



# EDA with Data Visualization

Relation between Success Rate according to each orbit



Launch success yearly trend  
– increasing remarkably –



# EDA with SQL

---

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

```
conn = sqlite3.connect(':memory:') # in memory database
df.to_sql(name="spacexdata", con=conn, if_exists="replace")
```

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

```
q = pd.read_sql("select * from spacexdata where Launch_Site like 'CCA%' limit 5", conn)
```

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

```
q = pd.read_sql("select sum(PAYLOAD_MASS_KG_) from spacexdata where Customer='NASA (CRS)'", conn)
```

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

```
q = pd.read_sql("select avg(PAYLOAD_MASS_KG_) from spacexdata where Booster_Version='F9 v1.1'", conn)
```

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

```
q = pd.read_sql("select min(Date) from spacexdata where Landing__Outcome='Success (ground pad)'", conn)
```

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

```
q = pd.read_sql("select distinct Booster_Version from spacexdata where Landing__Outcome='Success (drone ship)'
```

List the total number of successful and failure mission outcomes

```
q = pd.read_sql("select substr(Mission_Outcome,1,7) as Mission_Outcome, count(*) from spacexdata group by 1", conn)
```

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

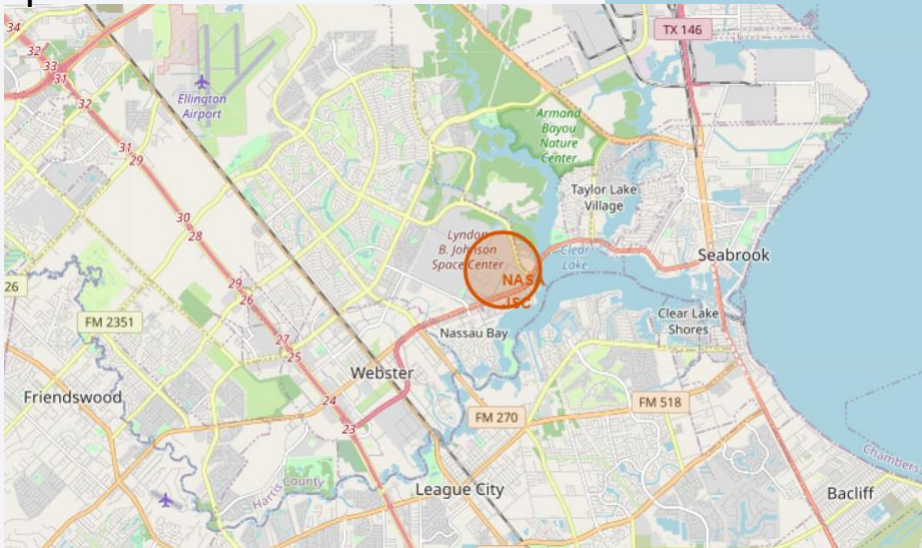
```
q = pd.read_sql("select distinct Booster_Version from spacexdata where PAYLOAD_MASS_KG_ = (select max(PAYLOAD_MASS_KG_) from spacexdata)", conn)
```

List the records which will display the month names, failure landing outcomes in drone ship ,booster versions, launch site for the months in year 2015.

Rank the count of successful landing outcomes between the date 04-06-2010 and 20-03-2017 in descending order.

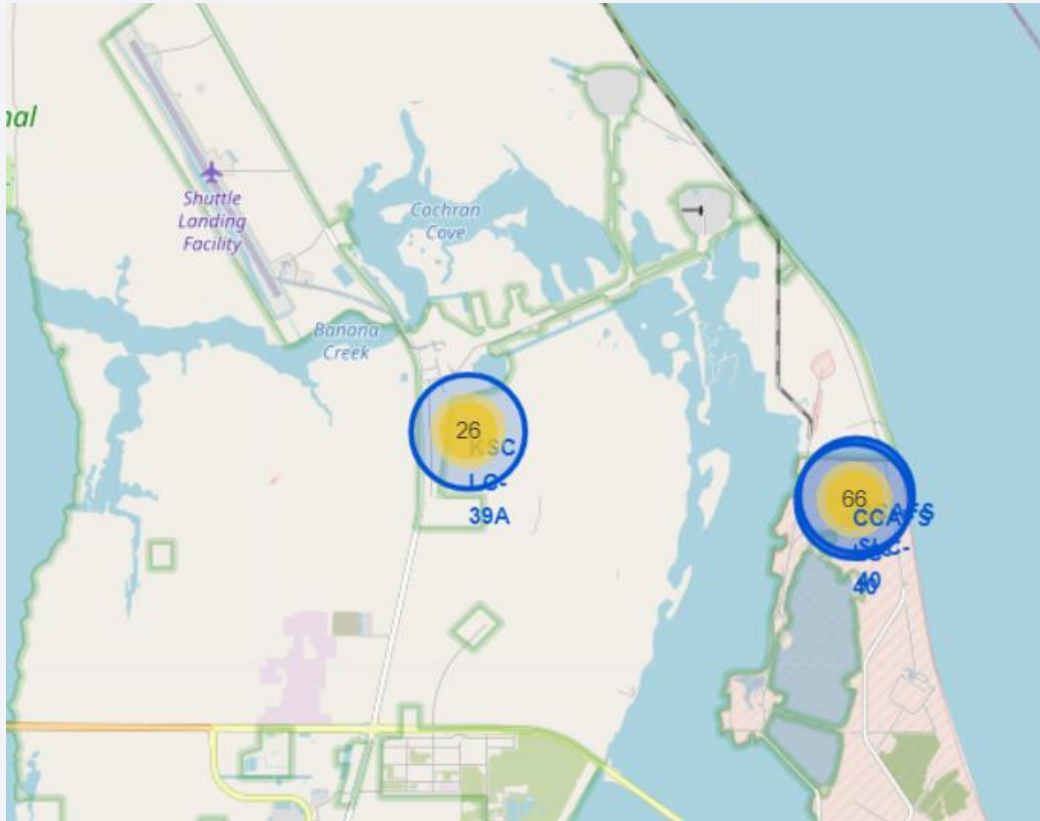
# Build an Interactive Map with Folium

Blue circle at NASA Johnson Space Center's coordinate



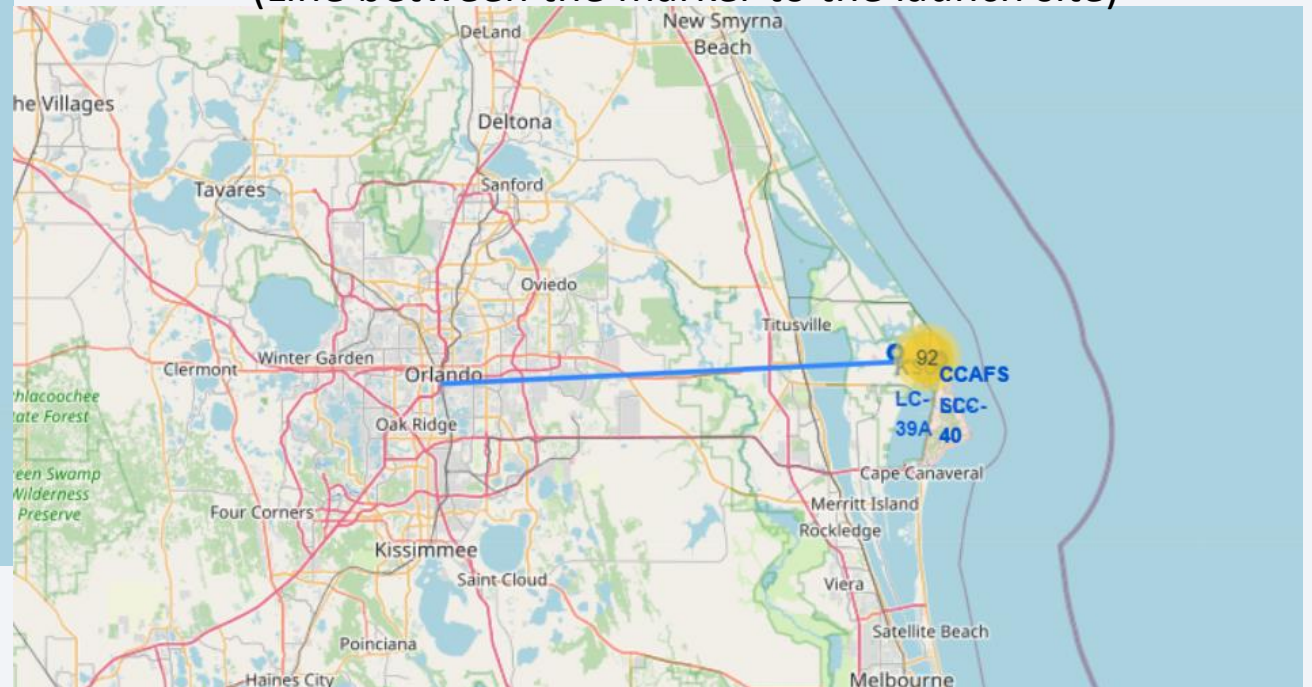
Coordinate (Lat, Long) for a mouse over on the map

# Build an Interactive Map with Folium



`folium.PolyLine` object using the coastline coordinates and launch site coordinate

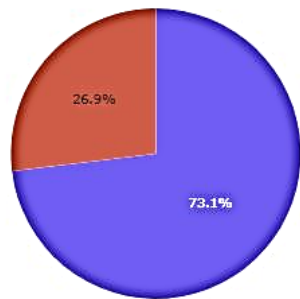
Marker with distance to a closest city.  
(Line between the marker to the launch site)



# Build a Dashboard with Plotly Dash

## SpaceX Launch Records Dashboard

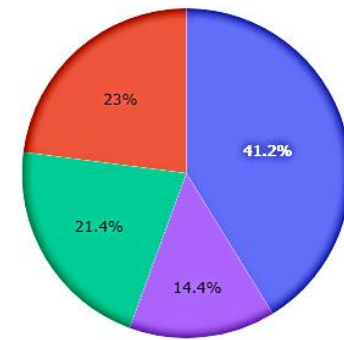
### Cape Canaveral Launch Complex 40 (CAFS LC-40)



Launch Success Rate for CCAFS LC-40

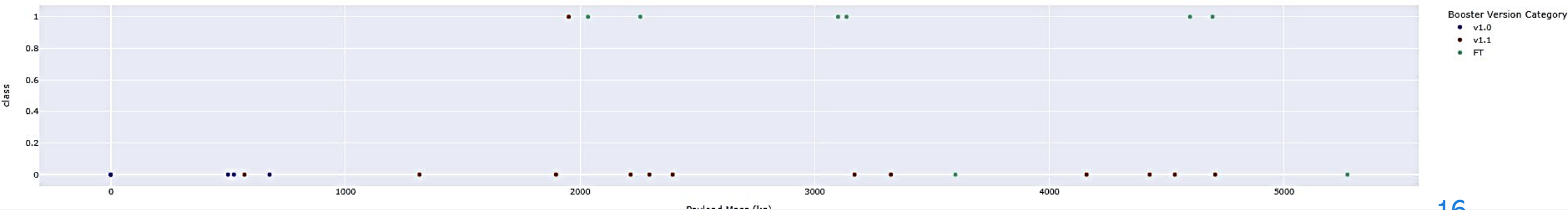
■ Failure  
■ Success

### Launch Success Rate For All Sites



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

Launch Success Rate For CCAFS LC-40



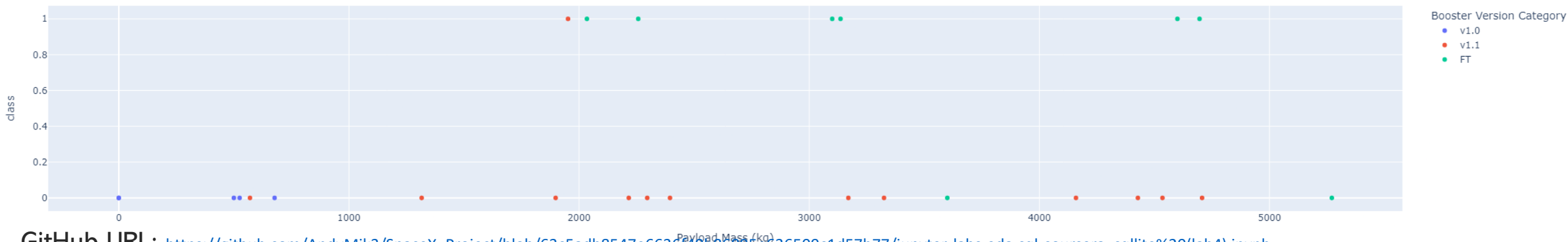


# Build a Dashboard with Plotly Dash

Launch Success Rate For CCAFS LC-40



Launch Success Rate For CCAFS LC-40



GitHub URL: [https://github.com/AndyMik3/SpaceX\\_Project/blob/63c5adb8547e6636f40b86895e636509c1d57b77/jupyter-labs-eda-sql-coursera\\_sqlite%20\(lab4\).ipynb](https://github.com/AndyMik3/SpaceX_Project/blob/63c5adb8547e6636f40b86895e636509c1d57b77/jupyter-labs-eda-sql-coursera_sqlite%20(lab4).ipynb)

# Predictive Analysis (Classification)

---

1. Create a column for the Class



2. Standardize the data



3. Split into training data and test data



4. Find best Hyperparameter for SVM, Classification Trees and Logistic Regression



5. Find the method that performs best using test data

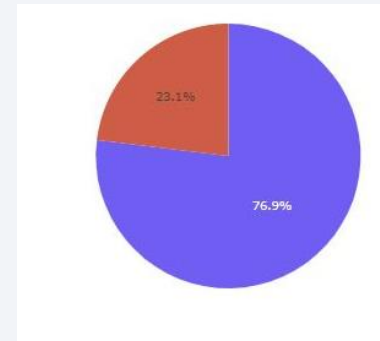
	method	accuracy
0	Logistic regression	0.833333
1	Support vector machine	0.833333
2	Decision tree classifier	0.777778
3	K nearest neighbors	0.833333

# Results

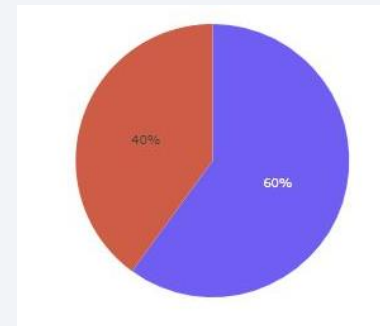
The Support vector machine, logistic regression and K-nearest neighbors share the same value of accuracy

	method	accuracy
0	Logistic regression	0.833333
1	Support vector machine	0.833333
2	Decision tree classifier	0.777778
3	K nearest neighbors	0.833333

The success rate for KSC LC-39A was 76.9%



The success rate for VAFB SLC-4E was 60%







Section 2

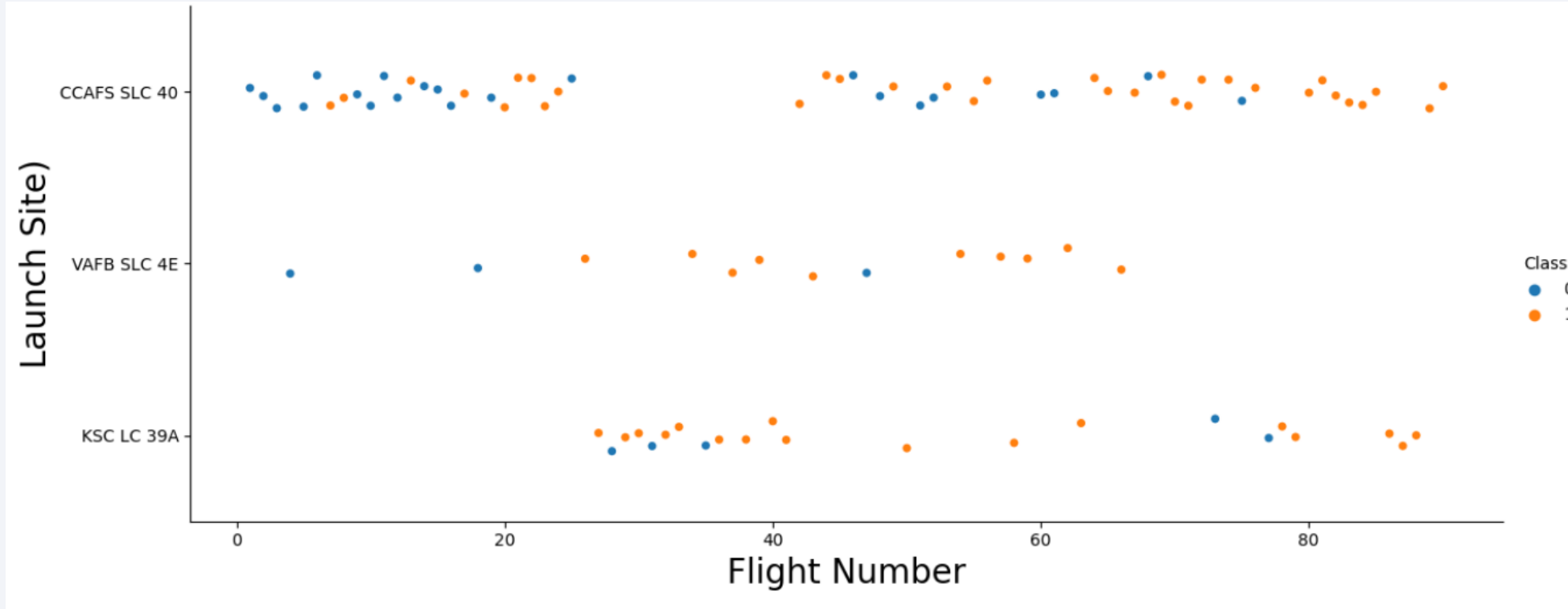
# Insights drawn from EDA



# Flight Number vs. Launch Site

---

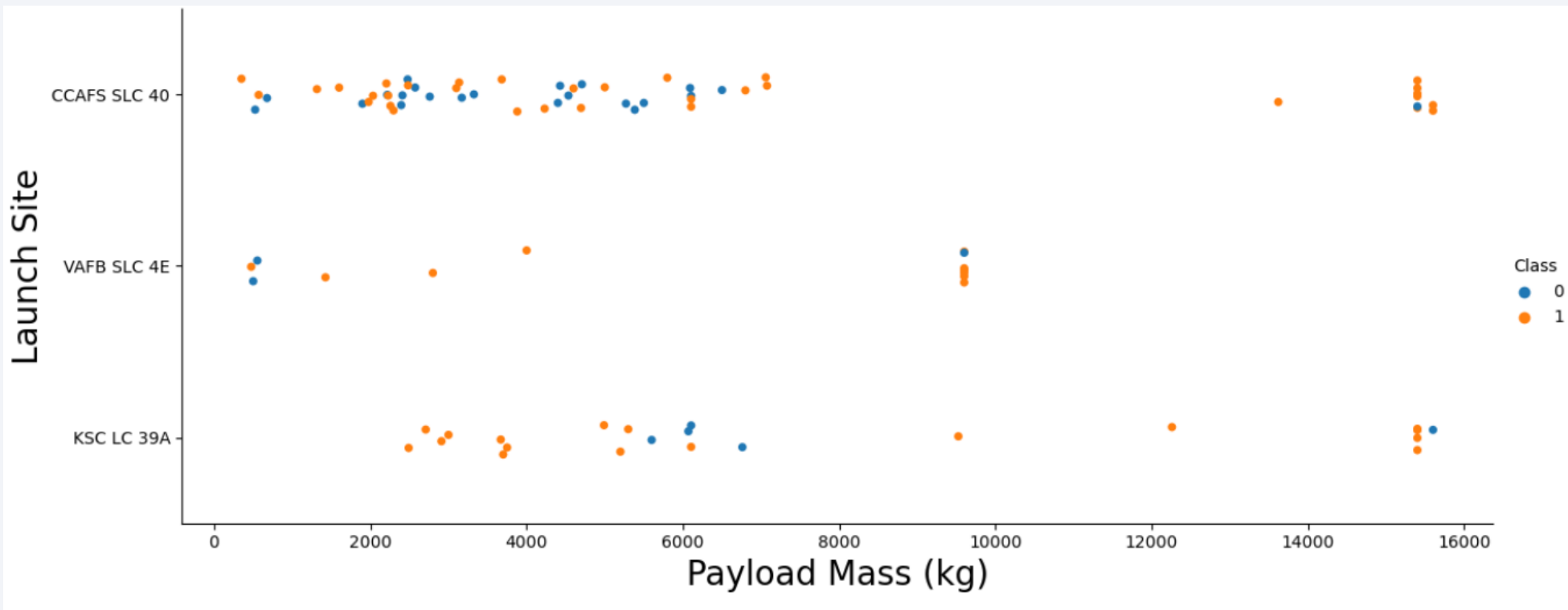
According to the flight number the CCAFS SLC 40 is notably the launch site most used



# Payload vs. Launch Site

---

The payload mass is sent with a mass between 1000kg to 8000kg with few very specific launches close to 15000kg



# Success Rate vs. Orbit Type

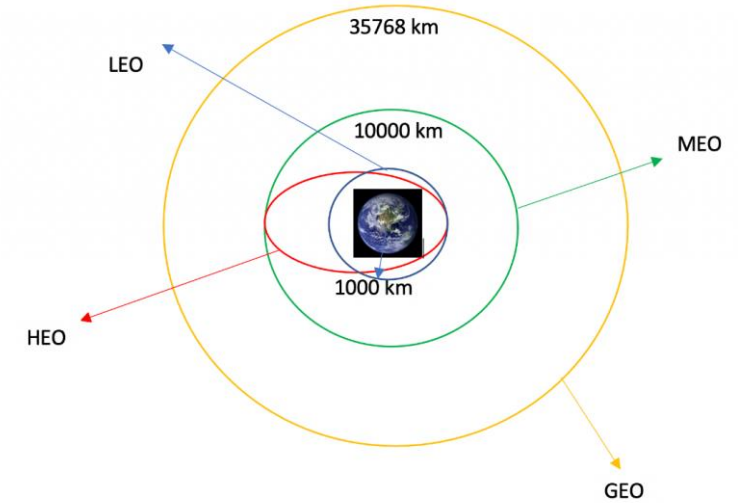
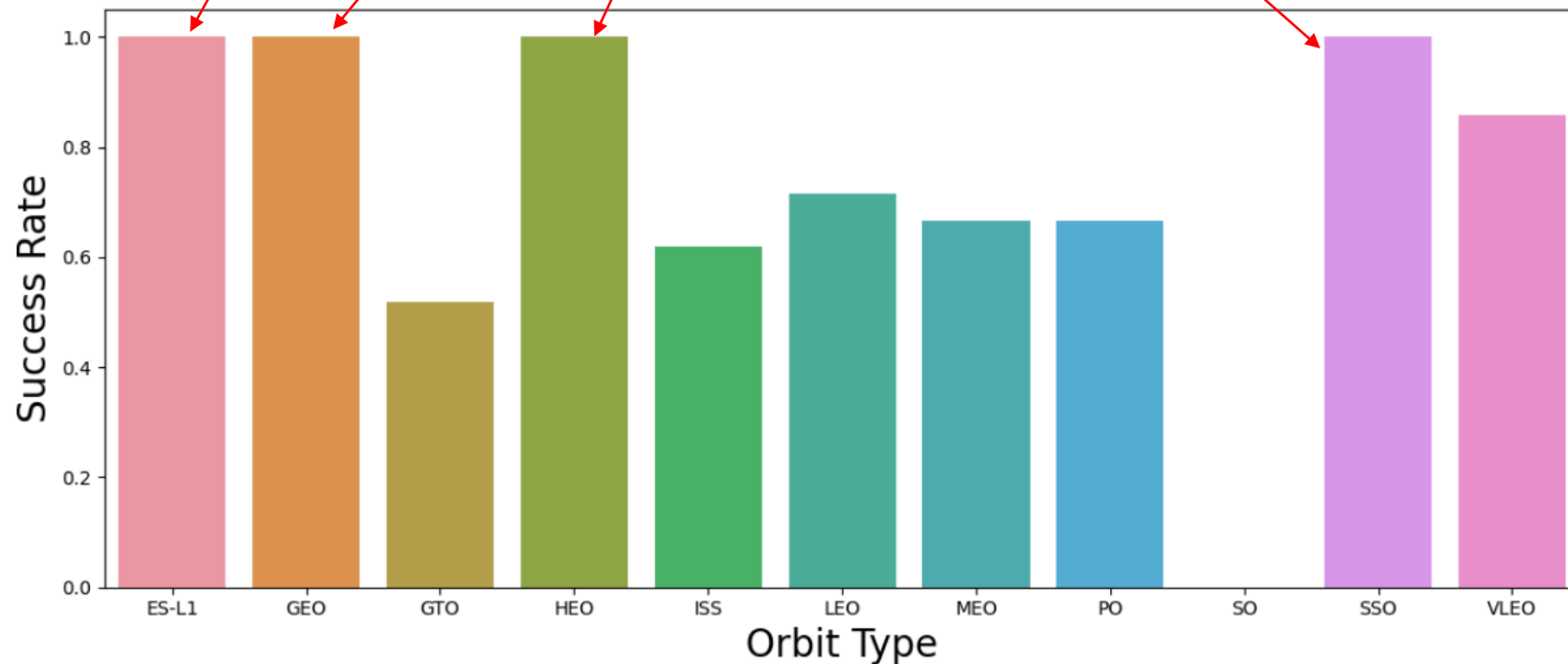
High Success Rate for these launches

ES-L1

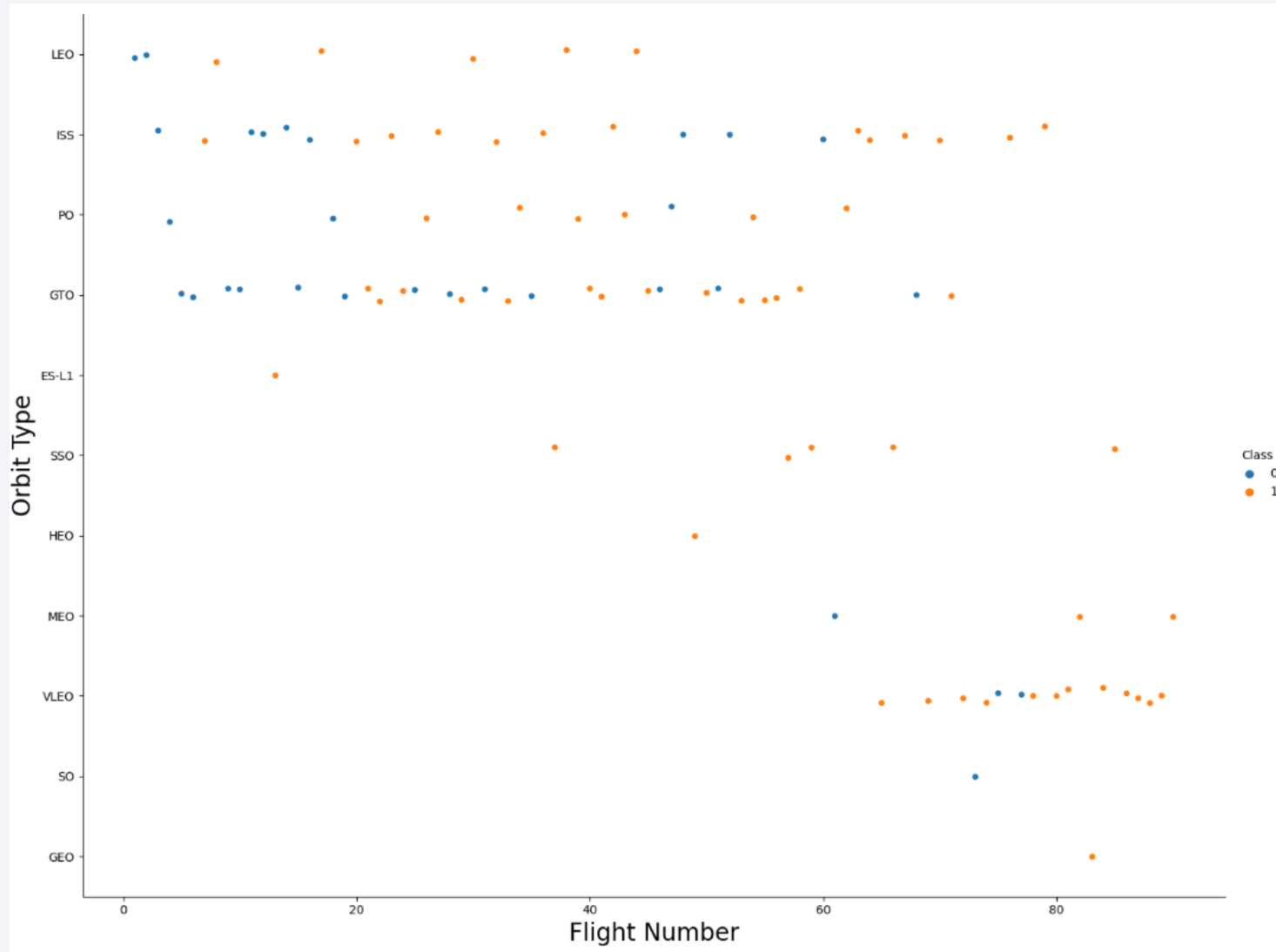
GEO

HEO

SSO



# Flight Number vs. Orbit Type



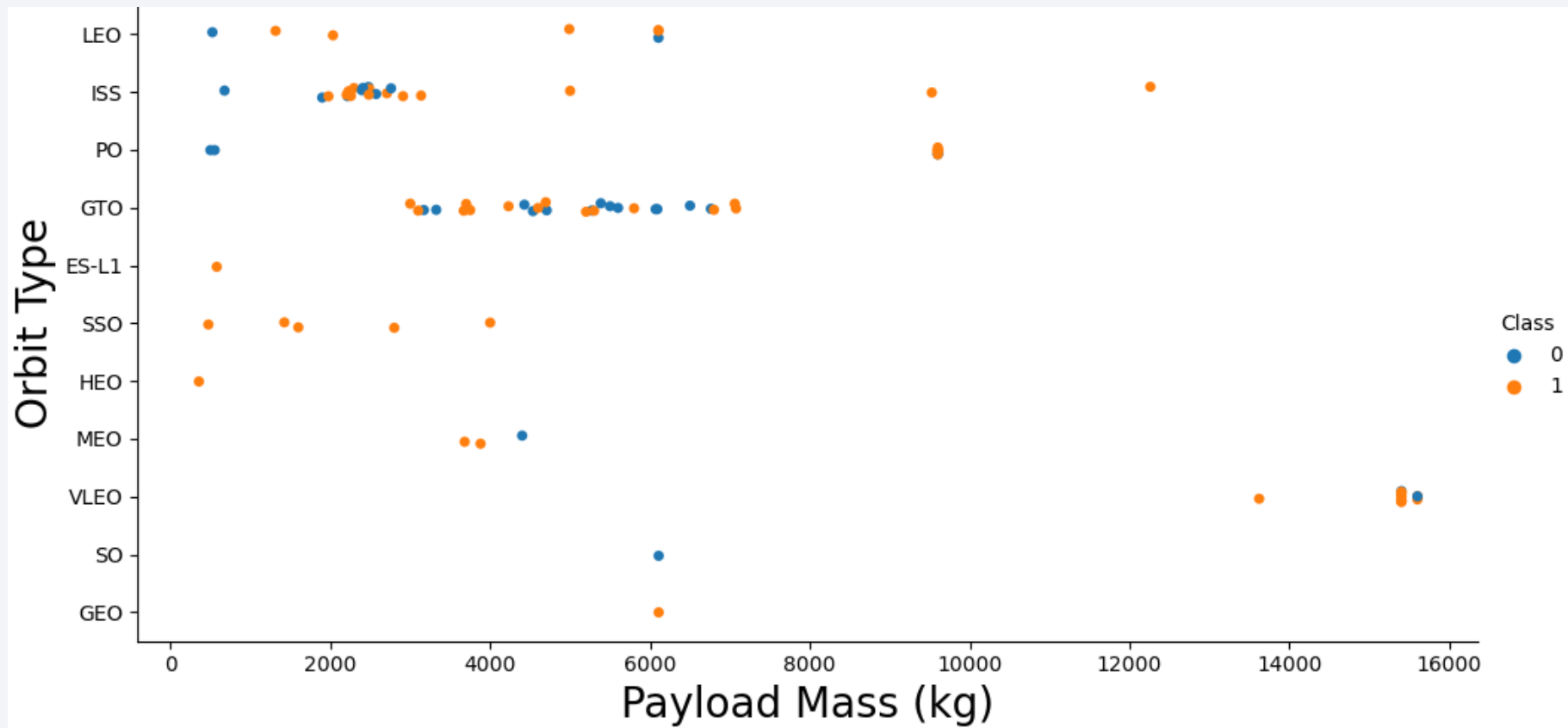
The launches made initially were indistinct for LEO, ISS, PO, GTO orbits, as the number of flights increased, the range of the launch orbits also increased.

The last flights have been up to the VLEO orbit.



# Payload vs. Orbit Type

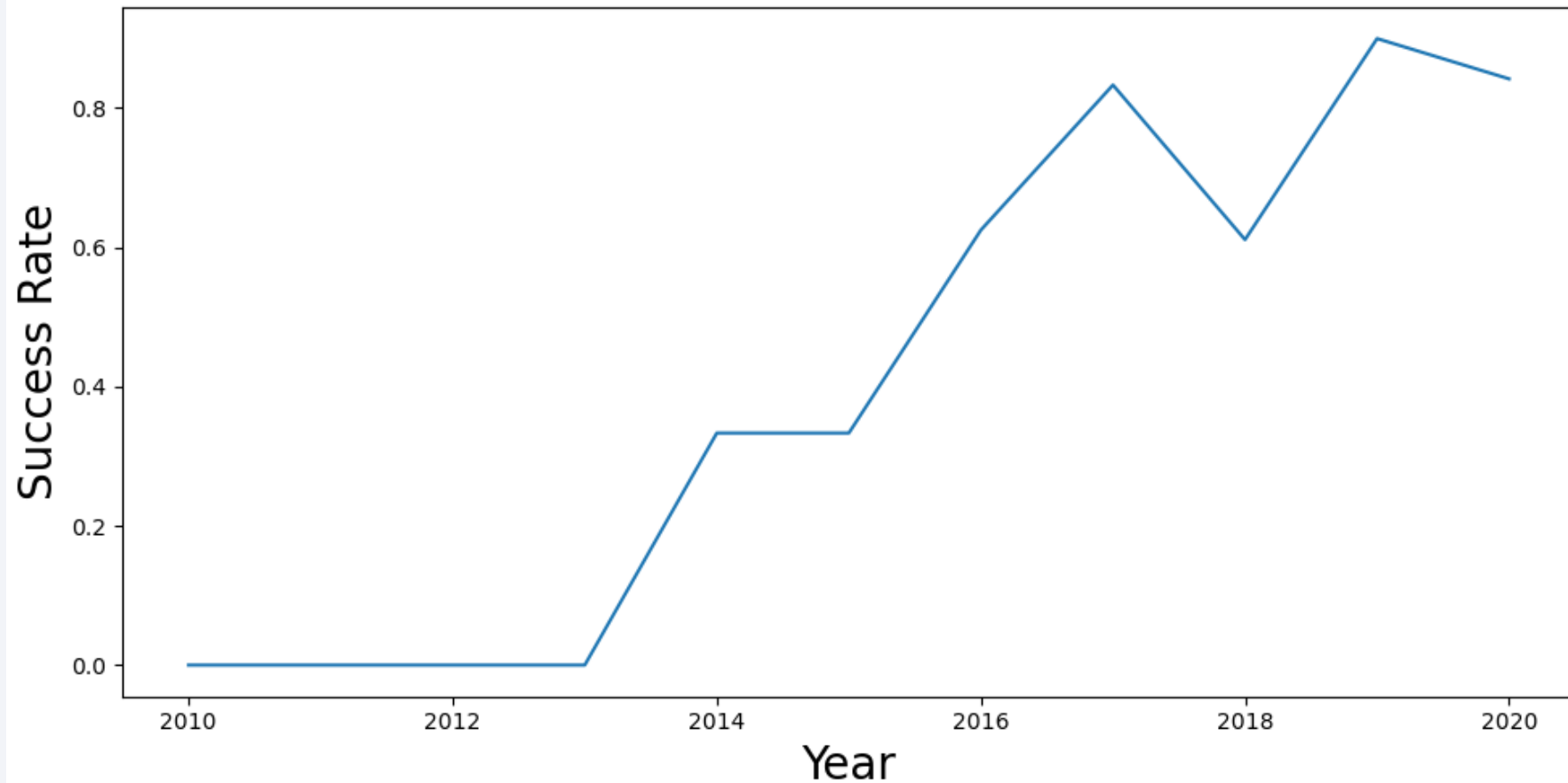
The relationship between the payload mass and the launch orbit is clear.  
When the payload mass is approximately 2000kg to 3000kg, the launch is to the ISS orbit.  
When the payload mass is in a range between 3000kg to 7000kg the orbit is the GTO.



# Launch Success Yearly Trend

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The success rate has increased remarkably over the years.



# All Launch Site Names

---

Launch sites are presented with their latitude and longitude:

	Launch Site	Lat	Long
0	CCAFS LC-40	28.562302	-80.577356
1	CCAFS SLC-40	28.563197	-80.576820
2	KSC LC-39A	28.573255	-80.646895
3	VAFB SLC-4E	34.632834	-120.610745

# Launch Site Names Begin with 'CCA'

---

```
q = pd.read_sql("select * from spacexdata where Launch_Site like 'CCA%' limit 5", conn)
q
```

index		Date	Time_(UTC)	Booster_Version	Launch_Site	Payload	PAYLOAD_MASS_KG_	Orbit	Customer	Mission_Outcome	Landing_Outcome
0	0	2010-06-04 00:00:00	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	Success	Failure (parachute)
1	1	2010-12-08 00:00:00	15:43:00	F9 v1.0 B0004	CCAFS LC-40	Dragon demo flight C1, two CubeSats, barrel of...	0	LEO (ISS)	NASA (COTS) NRO	Success	Failure (parachute)
2	2	2012-05-22 00:00:00	07:44:00	F9 v1.0 B0005	CCAFS LC-40	Dragon demo flight C2	525	LEO (ISS)	NASA (COTS)	Success	No attempt
3	3	2012-10-08 00:00:00	00:35:00	F9 v1.0 B0006	CCAFS LC-40	SpaceX CRS-1	500	LEO (ISS)	NASA (CRS)	Success	No attempt
4	4	2013-03-01 00:00:00	15:10:00	F9 v1.0 B0007	CCAFS LC-40	SpaceX CRS-2	677	LEO (ISS)	NASA (CRS)	Success	No attempt

# Total Payload Mass

---

```
q = pd.read_sql("select sum(PAYLOAD_MASS_KG_) from spacexdata where Customer='NASA (CRS)'", conn)
q
```

sum(PAYLOAD_MASS_KG_)	
0	45596



# Average Payload Mass by F9 v1.1

---

```
q = pd.read_sql("select avg(PAYLOAD_MASS_KG_) from spacexdata where Booster_Version='F9 v1.1'", conn)
q
```

avg(PAYLOAD_MASS_KG_)	
0	2928.4

# First Successful Ground Landing Date

---

```
q = pd.read_sql("select min(Date) from spacexdata where Landing__Outcome='Success (ground pad)'", conn)
q
```

	min(Date)
0	2015-12-22 00:00:00

# Successful Drone Ship Landing with Payload between 4000 and 6000

---

```
q = pd.read_sql("select distinct Booster_Version from spacexdata where Landing__Outcome='Success (drone ship)' and PAYLOAD_MASS__KG_ between 4000 and 6000", q)
```

Booster_Version	
0	F9 FT B1022
1	F9 FT B1026
2	F9 FT B1021.2
3	F9 FT B1031.2

Boosters which have successfully landed on drone ship and had payload mass greater than 4000 but less than 6000

# Total Number of Successful and Failure Mission Outcomes

---

```
q = pd.read_sql("select substr(Mission_Outcome,1,7) as Mission_Outcome, count(*) from spacexdata group by 1", conn)
q
```

	Mission_Outcome	count(*)
0	Failure	1
1	Success	100

# Boosters Carried Maximum Payload

---

```
q = pd.read_sql("select distinct Booster_Version from spacexdata where PAYLOAD_MASS__KG_ = (select max(PAYLOAD_MASS__KG_) from spacexdata)", conn)
q
```

	Booster_Version
0	F9 B5 B1048.4
1	F9 B5 B1049.4
2	F9 B5 B1051.3
3	F9 B5 B1056.4
4	F9 B5 B1048.5
5	F9 B5 B1051.4
6	F9 B5 B1049.5
7	F9 B5 B1060.2
8	F9 B5 B1058.3
9	F9 B5 B1051.6
10	F9 B5 B1060.3
11	F9 B5 B1049.7



# 2015 Launch Records

---

```
q = pd.read_sql("select distinct Landing__Outcome, Booster_Version, Launch_Site from spacexdata where Landing__Outcome='Failure (drone ship)'", conn)
q
```

	Landing__Outcome	Booster_Version	Launch_Site
0	Failure (drone ship)	F9 v1.1 B1012	CCAFS LC-40
1	Failure (drone ship)	F9 v1.1 B1015	CCAFS LC-40
2	Failure (drone ship)	F9 v1.1 B1017	VAFB SLC-4E
3	Failure (drone ship)	F9 FT B1020	CCAFS LC-40
4	Failure (drone ship)	F9 FT B1024	CCAFS LC-40

List of the failed landing\_outcomes in drone ship, booster versions, and launch site names in year 2015

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

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	Landing__Outcome	count(*)
0	No attempt	10
1	Success (drone ship)	5
2	Failure (drone ship)	5
3	Success (ground pad)	3
4	Controlled (ocean)	3
5	Uncontrolled (ocean)	2
6	Precluded (drone ship)	1

Rank of landing outcomes between 2010-06-04 and 2017-03-20 for:

- Failure (drone ship)
- Success (ground pad)

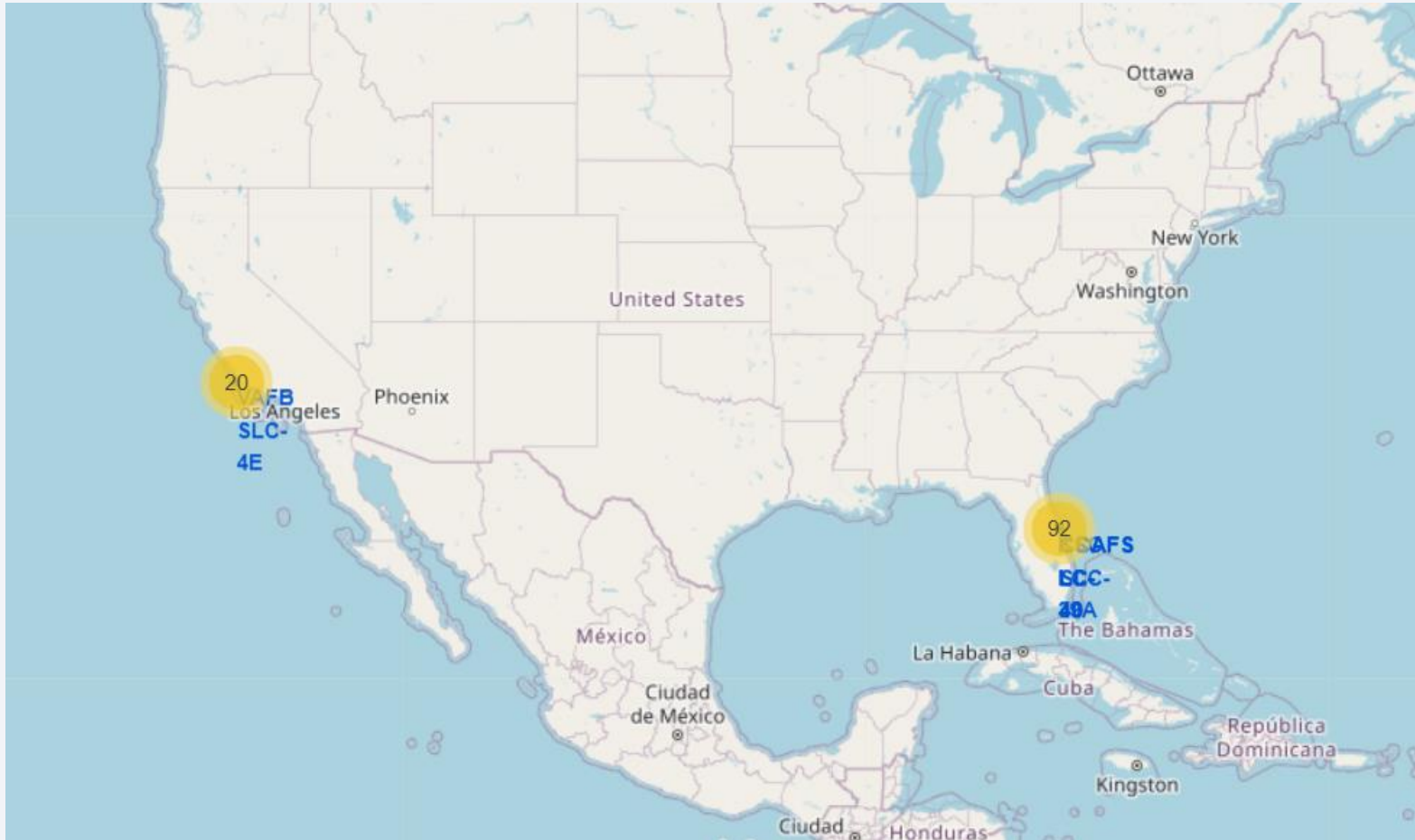
A satellite view of Earth from space, showing the curvature of the planet and city lights at night. The background is a deep blue gradient.

Section 3

# Launch Sites Proximities Analysis

# SpaceX Launch Sites Locations (Folium map)

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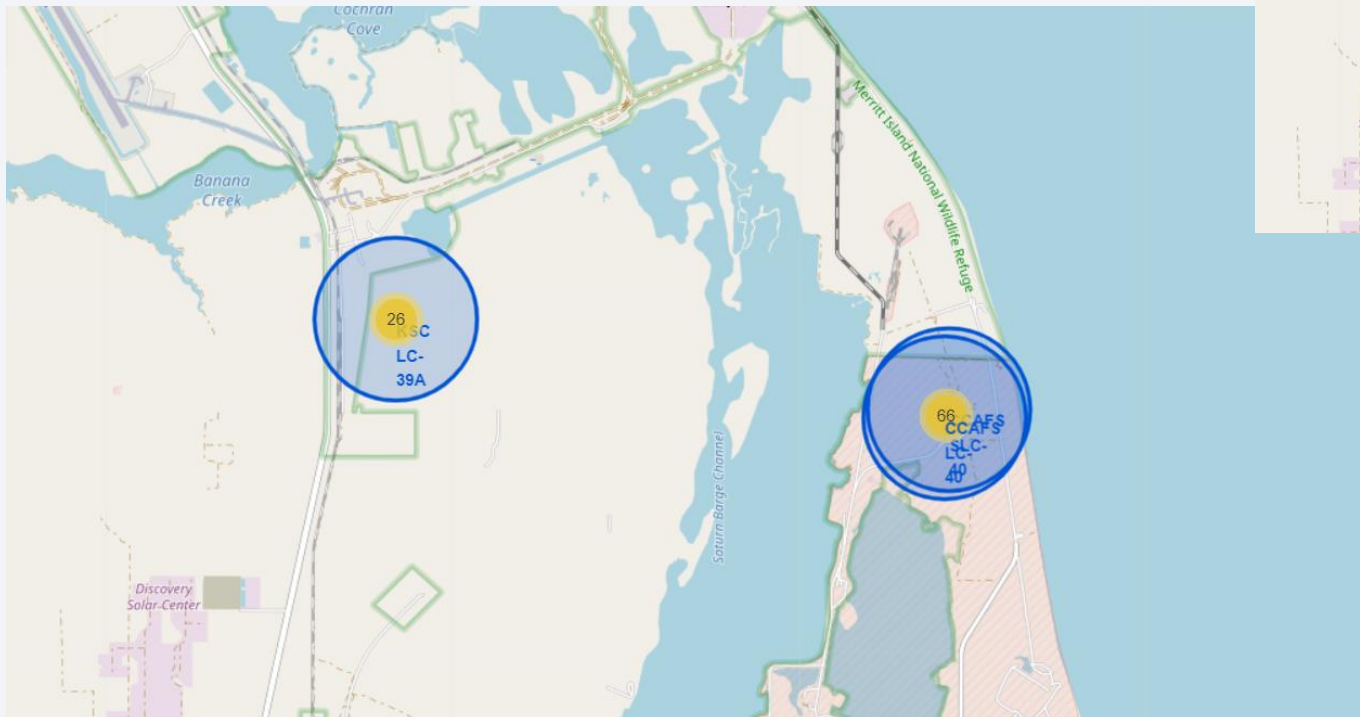
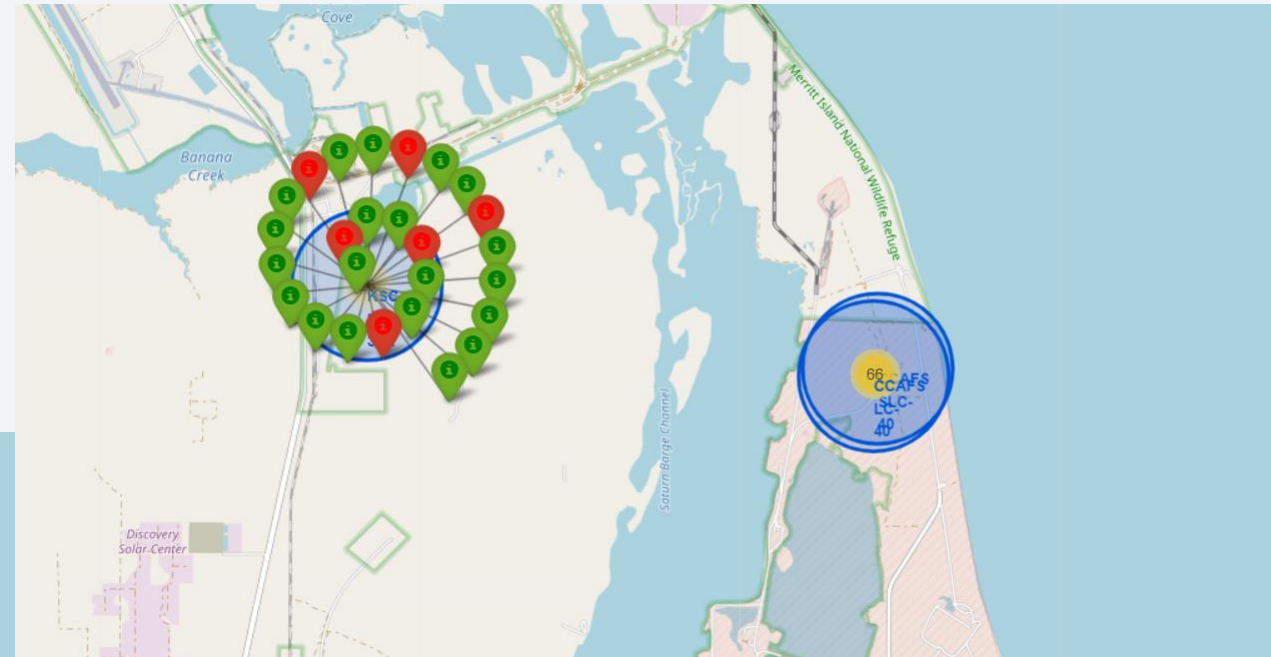
All the launch sites are near to the coast

# Success and Failed launches

Successful launches are shown in green and failed launches in red.

In the visual map it is possible to zoom in on the study area to learn more about the launches made.

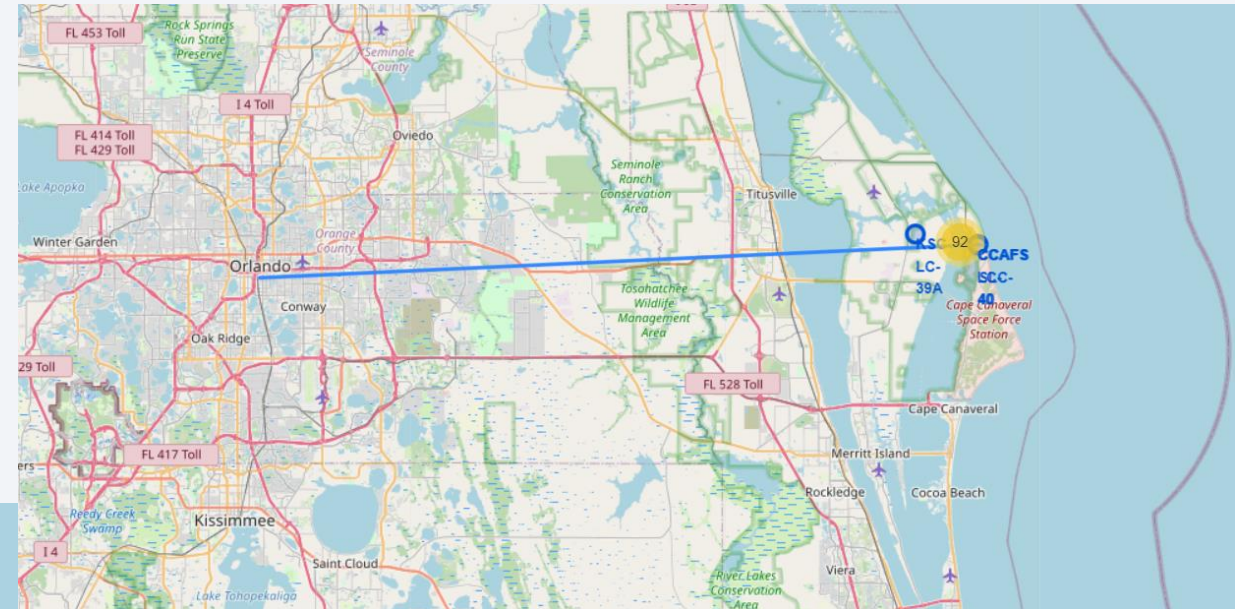
On the East coast there are bases with 26 and 66 pitches





# Distance to proximities

The closest distances to different points of interest are presented with a line.  
In the images the distance to the coastline is represented





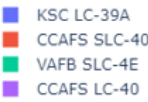
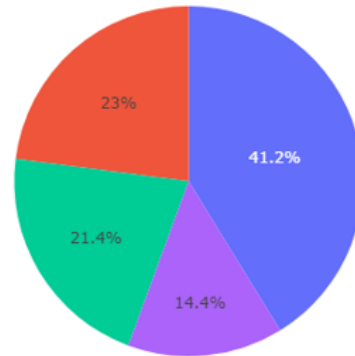
Section 4

# Build a Dashboard with Plotly Dash

# Launch Success Rate For All Sites

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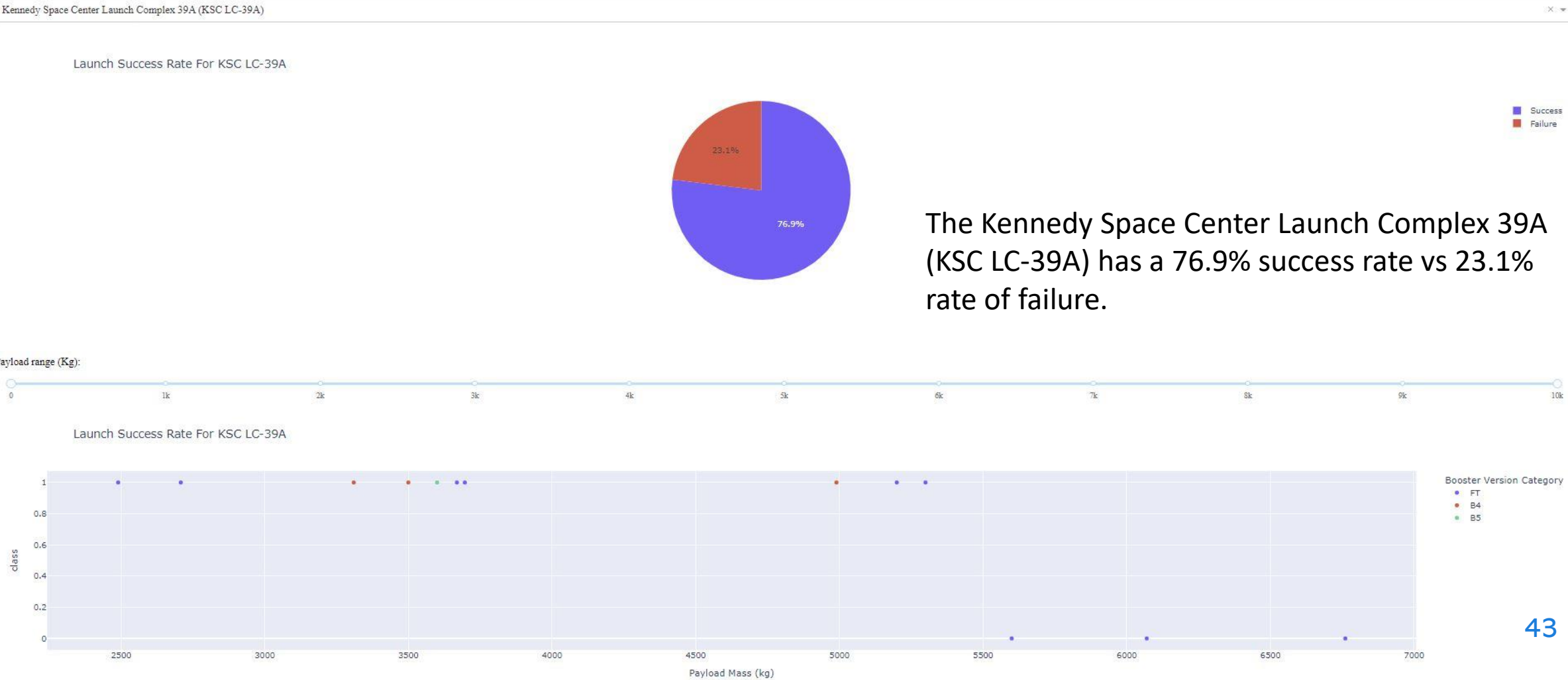
Launch Success Rate For All Sites





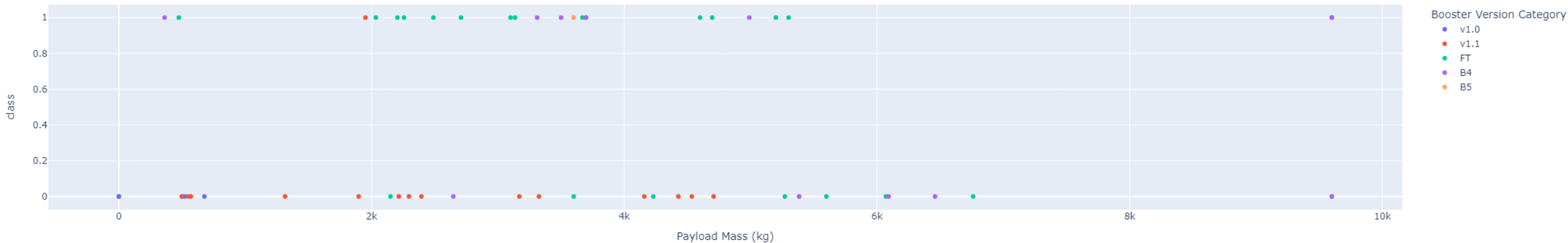
# Success rate for the highest launch site

## SpaceX Launch Records Dashboard



# Payload Mass

Launch Success Rate For All Sites



Payload mass (kg) for launch success rate in all sites  
There are a high number of launches when the payload mass is between 2k to 4k kg.





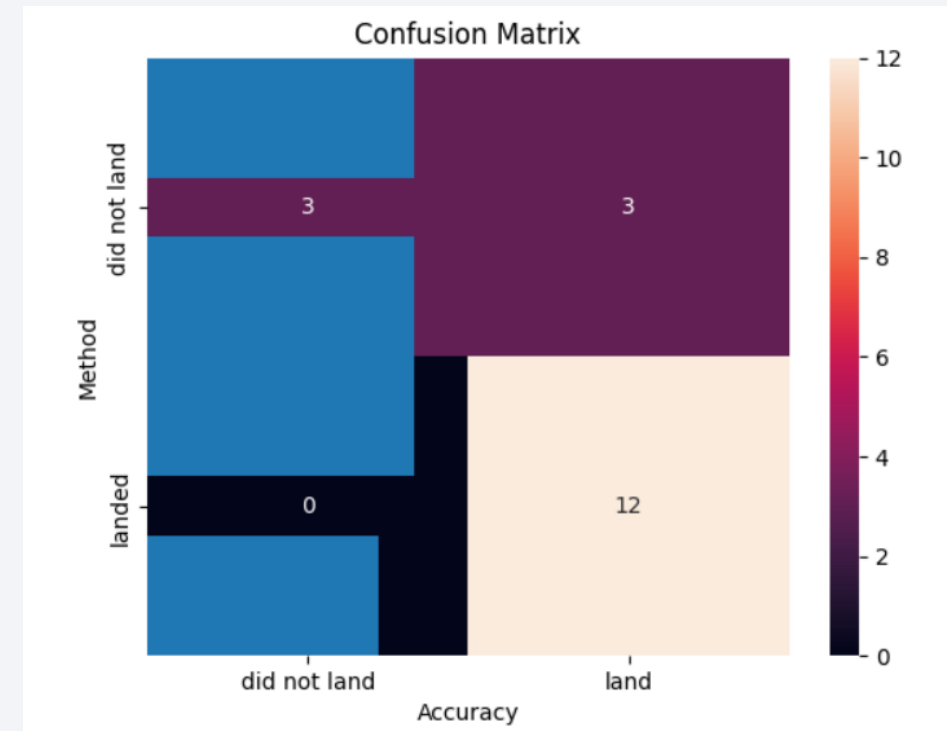
Section 5

# Predictive Analysis (Classification)

# Classification Accuracy

- The logistic regression, Support vector machine and K-nearest neighbors share a high percentage of accuracy with 0.83

	method	accuracy
0	Logistic regression	0.833333
1	Support vector machine	0.833333
2	Decision tree classifier	0.777778
3	K nearest neighbors	0.833333



# Conclusions

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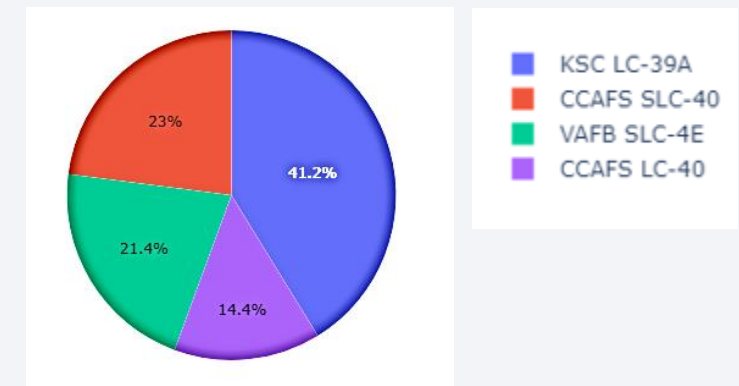
All the launch sites are near to the coastline for transport purposes and security

The Kennedy Space Center Launch Complex 39A (KSC LC-39A) has a 76.9% success rate vs 23.1% rate of failure.

The KSC LC-39A has the most success rate of all the launch sites.

The last flights have been up to the VLEO orbit.

The Support Vector Machine, Logistic Regression and K-nearest neighbors share the same value of accuracy equal to 0.84



# Appendix

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[https://github.com/AndyMik3/SpaceX\\_Project.git](https://github.com/AndyMik3/SpaceX_Project.git)

Thank you!

