

Winning Space Race with Data Science

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Outline

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

Executive Summary

Summary of methodologies

- Data Collection with SpaceX REST API and Web Scraping
- Exploratory Data Analysis with SQL and Visualization
- Data Wrangling
- Interactive Visual Analytics with Folium and Plotly Dashboard
- Machine Learning Prediction

Summary of all results

• The SVM, KNN, and Logistic Regression models are the best in terms of prediction accuracy for this dataset.

Introduction

- Project background and context
 - SpaceX advertises Falcon 9 rocket launches on its website with a cost of 62 million dollars; other
 providers cost upward of 165 million dollars each, much of the savings is because SpaceX can
 reuse the first stage. Therefore if we can determine if the first stage will land, we can determine
 the cost of a launch. This information can be used if an alternate company wants to bid against
 SpaceX for a rocket launch.
- Problems you want to find answers
 - Can we predict if the Falcon 9 first stage will land successfully?



Methodology

Executive Summary

- Data collection methodology:
 - SpaceX RESR API
 - Webscraping with related wiki pages
- Perform data wrangling
 - Filling missing value with `mean`; Converting outcomes into Training Labels with `1` means the booster successfully landed `O` means it was unsuccessful
- Perform exploratory data analysis (EDA) using visualization and SQL
- Perform interactive visual analytics using Folium and Plotly Dash
- Perform predictive analysis using classification models
 - LR, KNN, SVM, DT models were built and evaluated for the best model

Data Collection

SpaceX API.



WebScraping



Data Collection – SpaceX API

 https://github.com/ringo-alin/IBE-DataScience-Assignments/blob/main/Course%2 010/jupyter-labs-spacex-datacollection-api.ipynb

```
spacex url="https://api.spacexdata.com/v4/launches/past"
response = requests.get(spacex url)
# Use json normalize meethod to convert the json result into a dat
data = pd.json_normalize(response.json())
# Lets take a subset of our dataframe keeping only the features we
data = data[['rocket', 'payloads', 'launchpad', 'cores', 'flight nu
 launch dict = {'FlightNumber': list(data['flight number']),
 'Date': list(data['date']),
 'BoosterVersion':BoosterVersion,
# Create a data from launch dict
                                                         8
data = pd.DataFrame(launch dict)
```

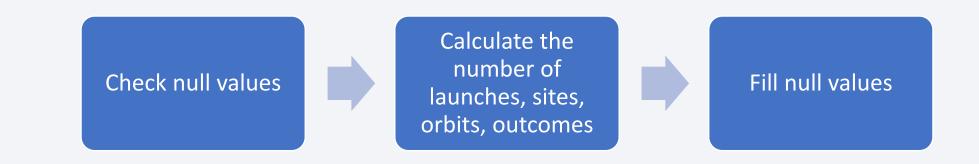
Data Collection - Scraping

 https://github.com/ringoalin/IBE-DataScience-Assignments/blob/main/Cour se%2010/jupyter-labswebscraping.ipynb

```
static_url = "https://en.wikipedia.org/w/index.php?title=List_of_Fa
response = requests.get(static url).text
soup = BeautifulSoup(response)
 html_tables = soup.find_all('table')
first_launch_table = html_tables[2]
launch dict= dict.fromkeys(column names)
# Remove an irrelvant column
del launch_dict['Date and time ( )']
# Let's initial the launch_dict with each value to be an empty list
 #Extract each table
 for table number, table in enumerate(soup.find all('table', "wikitable")
  # get table row
    for rows in table.find_all("tr"):
  #check to see if first table heading is as number correspon
 if rows.th:
  if rows.th.string:
```

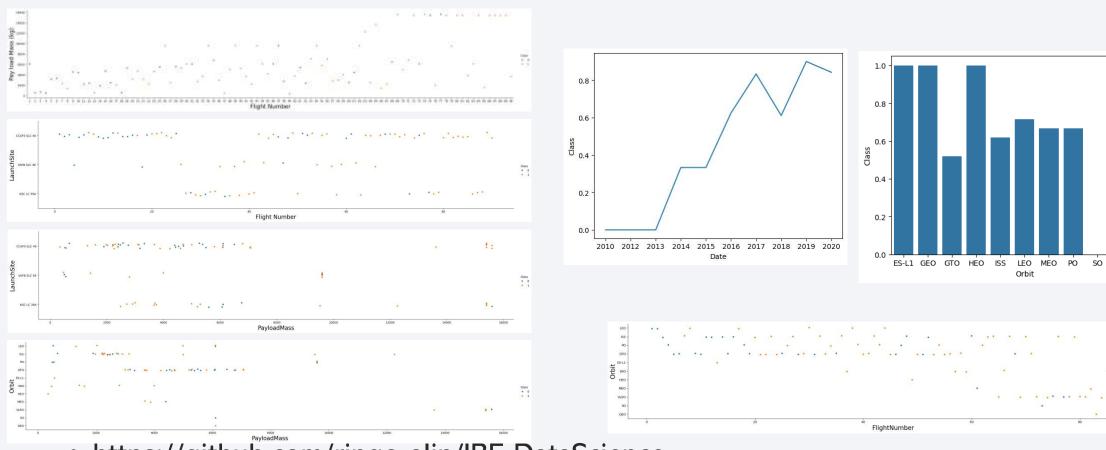
Data Wrangling

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• https://github.com/ringo-alin/IBE-DataScience-Assignments/blob/main/Course%2010/labs-jupyter-spacex-Data%20wrangling.ipynb

EDA with Data Visualization



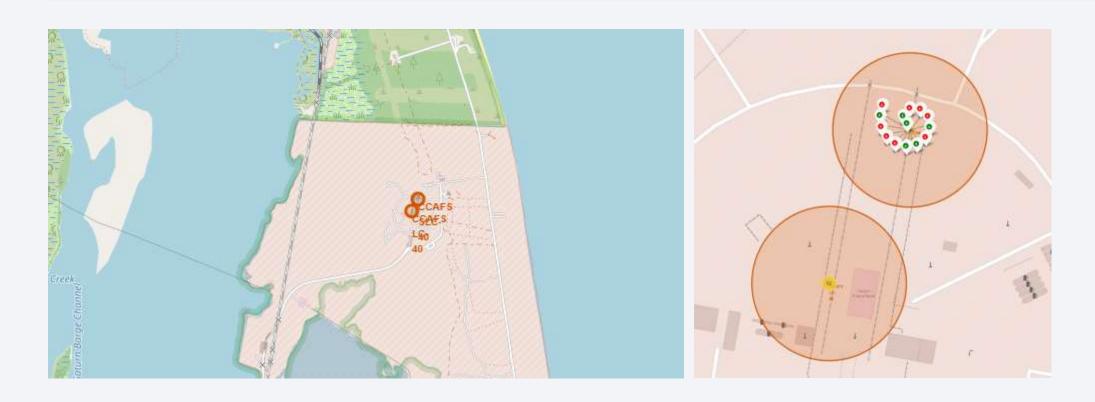
 https://github.com/ringo-alin/IBE-DataScience-Assignments/blob/main/Course%2010/jupyter-labs-edadataviz.ipynb.jupyterlite.ipynb

EDA with SQL

• SQL queries

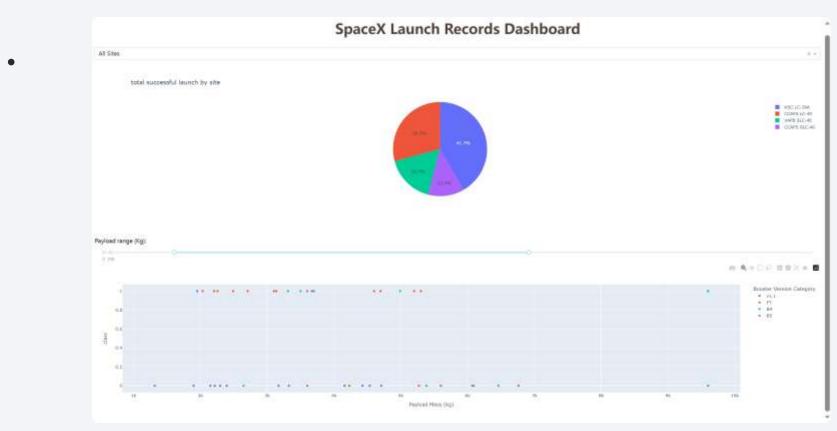
- select distinct(Launch_Site) from SPACEXTABLE
- select Launch_Site from SPACEXTABLE limit 5
- select distinct(Landing_Outcome) from SPACEXTABLE
- select sum(PAYLOAD_MASS__KG_) from SPACEXTABLE where Customer == "NASA (CRS)"
- select avg(PAYLOAD_MASS__KG_) from SPACEXTABLE where Booster_Version == "F9 v1.1"
- select min(Date) from SPACEXTABLE where Landing_Outcome=='Success (ground pad)'
- select Booster_Version from SPACEXTABLE where (PAYLOAD_MASS__KG_ > 4000) and (PAYLOAD_MASS__KG_ < 6000) and (Mission_Outcome == "Success")
- select Mission_Outcome, count(*) from SPACEXTABLE group by Mission_Outcome
- https://github.com/ringo-alin/IBE-DataScience-Assignments/blob/main/Course%2010/jupyter-labs-eda-sql-coursera_sqllite.ipynb

Build an Interactive Map with Folium



• https://github.com/ringo-alin/IBE-DataScience-Assignments/blob/main/Course%2010/lab_jupyter_launch_site_location.jupyterlite.ipynb

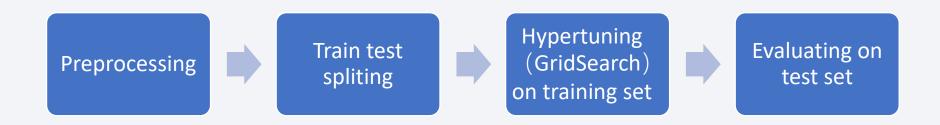
Build a Dashboard with Plotly Dash



 https://github.com/ringo-alin/IBE-DataScience-Assignments/blob/main/Course%2010/spacex_dash_app.py

Predictive Analysis (Classification)

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 https://github.com/ringo-alin/IBE-DataScience-Assignments/blob/main/Course%2010/SpaceX_Machine_Learning_Prediction _Part_5.jupyterlite.ipynb

Results

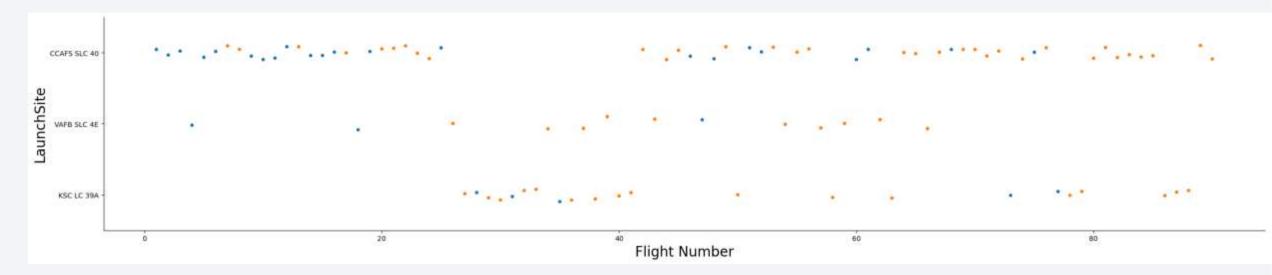
Accuracy on test set

Model	Accuracy
Logistic regression	0.83
SVM	0.83
Decision Tree	0.78
KNN	0.83



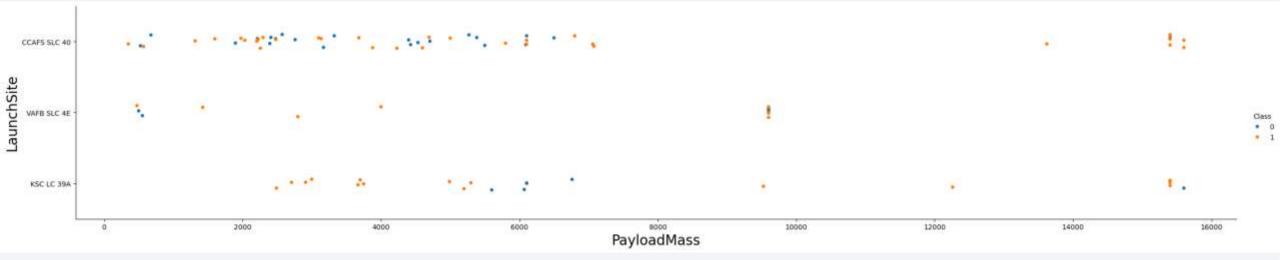
Flight Number vs. Launch Site

• As the flight number increases, the first stage is more likely to land successfully



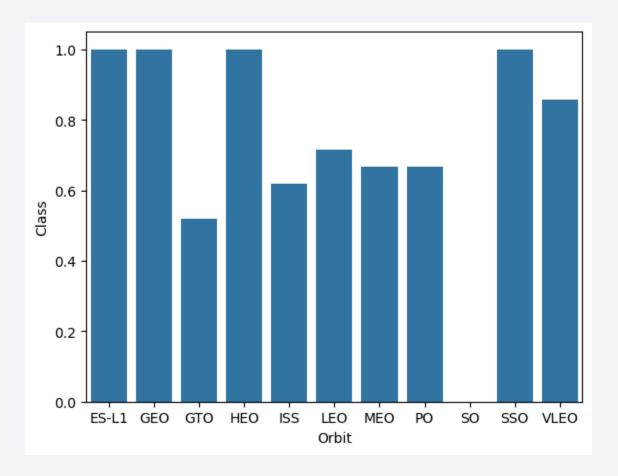
Payload vs. Launch Site

• the VAFB-SLC launchsite there are no rockets launched for heavypayload mass(greater than 10000).



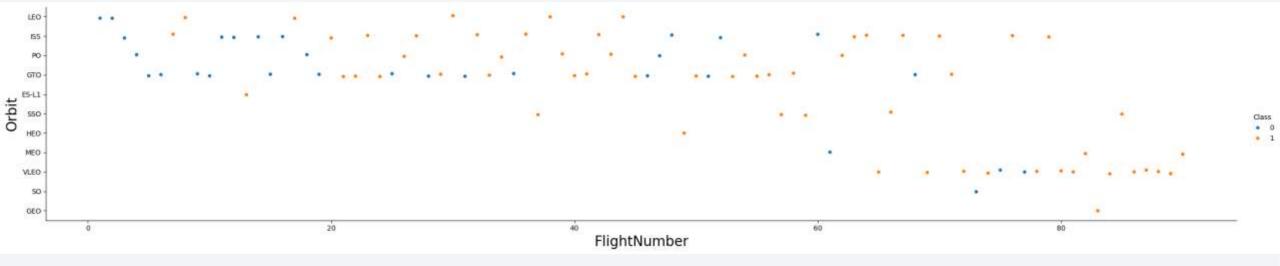
Success Rate vs. Orbit Type

• ES-L1, GEO, HEO, SSO have high success rate



Flight Number vs. Orbit Type

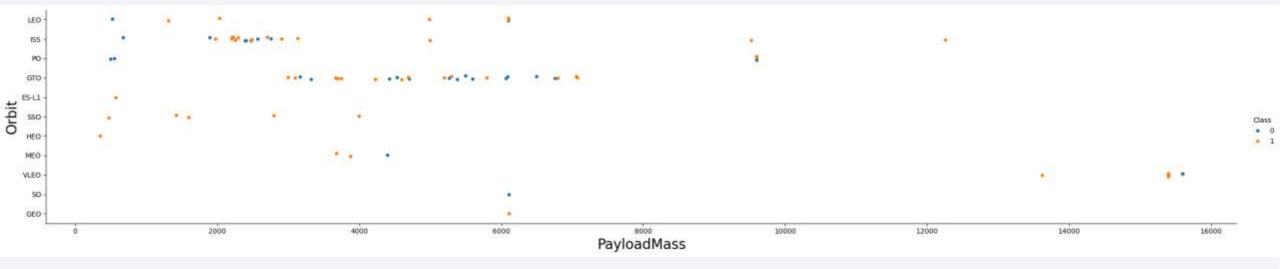
• in the LEO orbit the Success appears related to the number of flights; on the other hand, there seems to be no relationship between flight number when in GTO orbit.



Payload vs. Orbit Type

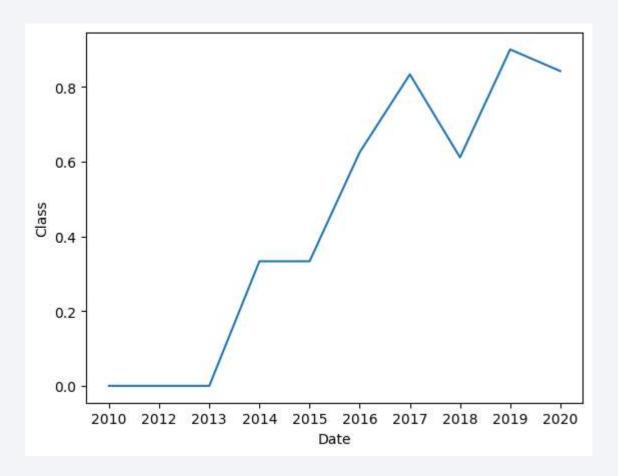
• With heavy payloads the successful landing or positive landing rate are more for Polar, LEO and ISS.

• However for GTO we cannot distinguish this well as both positive landing rate and negative landing(unsuccessful mission) are both there here.



Launch Success Yearly Trend

 the sucess rate since 2013 kept increasing till 2020



All Launch Site Names

• Find the names of the unique launch sites



Launch Site Names Begin with 'CCA'

Find 5 records where launch sites begin with `CCA`

```
%sql select Launch_Site from SPACEXTABLE limit 5
* sqlite://my data1.db
Done.
 Launch_Site
CCAFS LC-40
CCAFS LC-40
CCAFS LC-40
CCAFS LC-40
CCAFS LC-40
```

Total Payload Mass

Calculate the total payload carried by boosters from NASA

```
%sql select sum(PAYLOAD_MASS__KG_) from SPACEXTABLE where Customer == "NASA (CRS)"

* sqlite://my_data1.db
Done.

sum(PAYLOAD_MASS__KG_)

45596
```

Average Payload Mass by F9 v1.1

Calculate the average payload mass carried by booster version F9 v1.1

```
%sql·select avg(PAYLOAD_MASS__KG_) from SPACEXTABLE where Booster_Version == "F9 v1.1"

* sqlite://my_data1.db
Done.

avg(PAYLOAD_MASS__KG_)

2928.4
```

First Successful Ground Landing Date

• Find the dates of the first successful landing outcome on ground pad

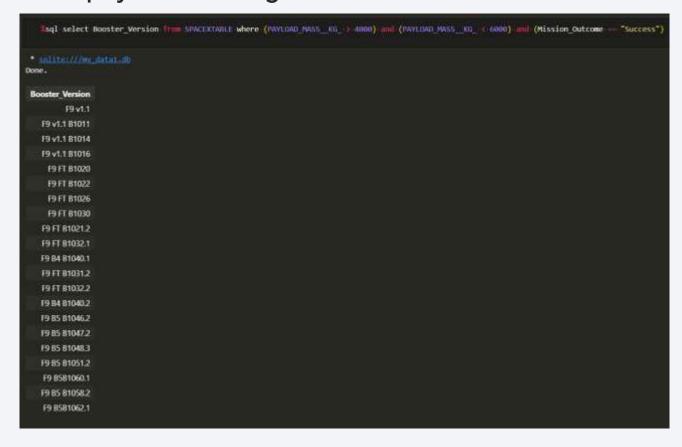
```
%sql select min(Date) from SPACEXTABLE where Landing_Outcome== 'Success (ground pad)'

* sqlite://my_data1.db
Done.

min(Date)
2015-12-22
```

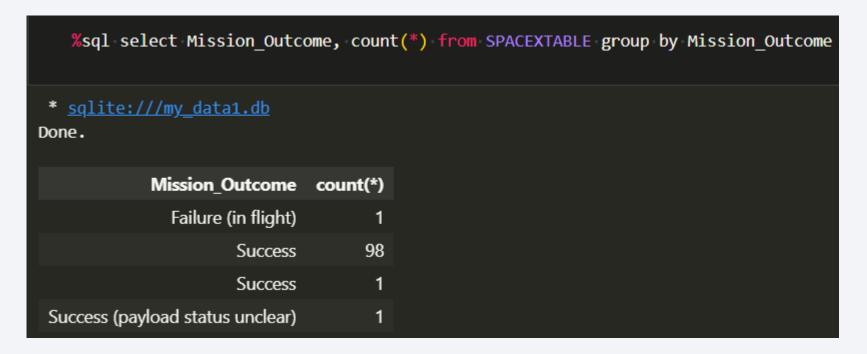
Successful Drone Ship Landing with Payload between 4000 and 6000

 List the names of boosters which have successfully landed on drone ship and had payload mass greater than 4000 but less than 6000



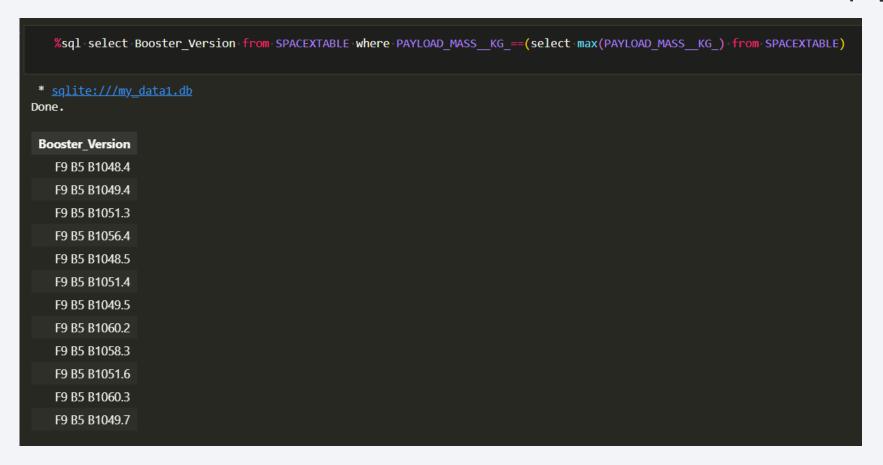
Total Number of Successful and Failure Mission Outcomes

Calculate the total number of successful and failure mission outcomes



Boosters Carried Maximum Payload

• List the names of the booster which have carried the maximum payload mass



2015 Launch Records

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

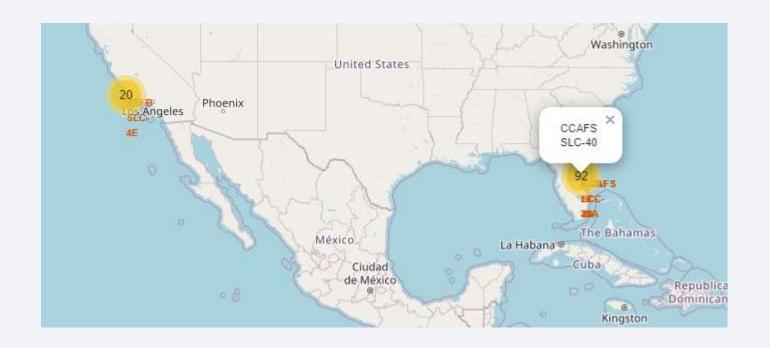
```
%sql select Landing_Outcome, count(Landing_Outcome) from SPACEXTABLE where (Date between '2010-06-04' and '2017-03-20') group by Landing_Outcome
```

* sqlite:///my_data1.db
Done.

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



Global location view



Zoom in



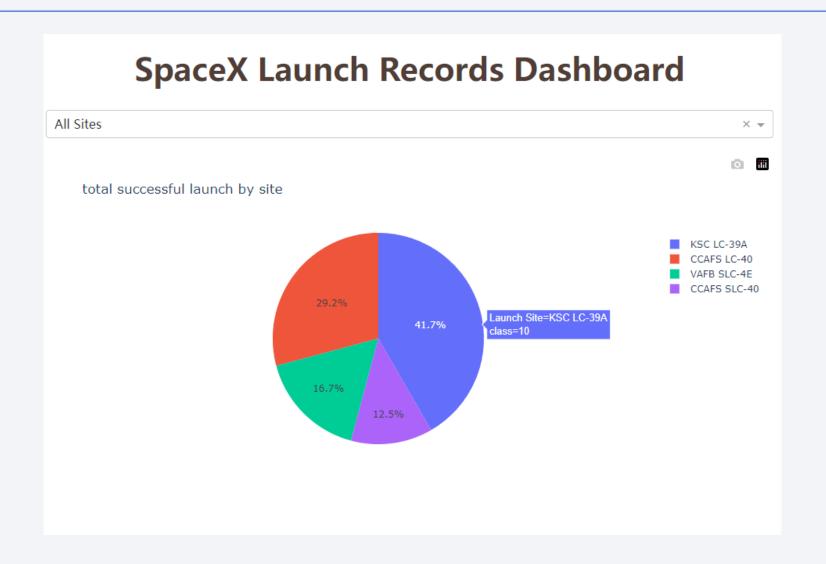


Distance

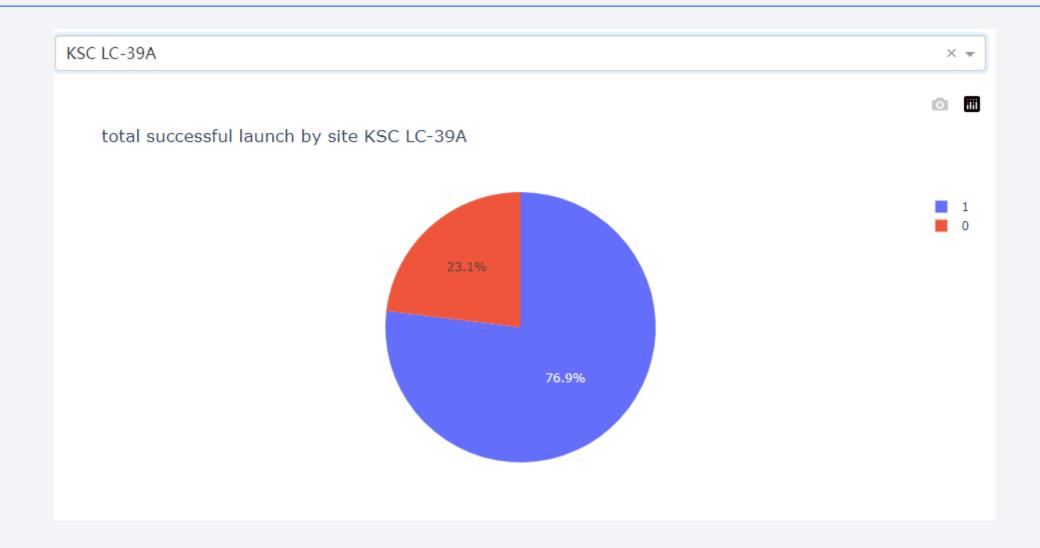




Launch success count for all sites



Success rate by site

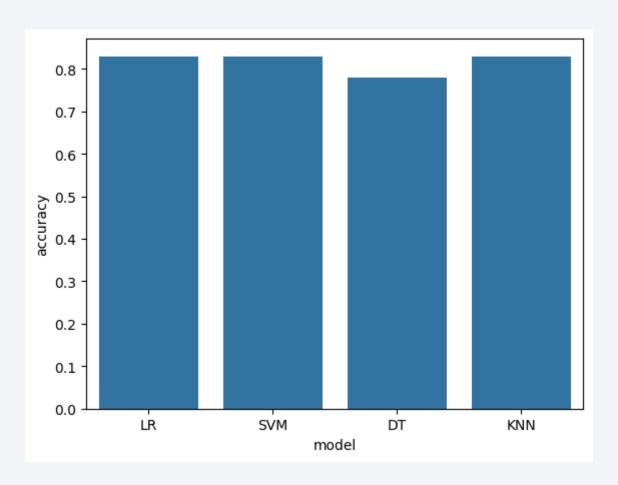


Payload vs launch outcome



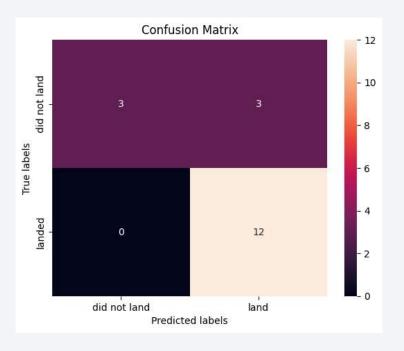


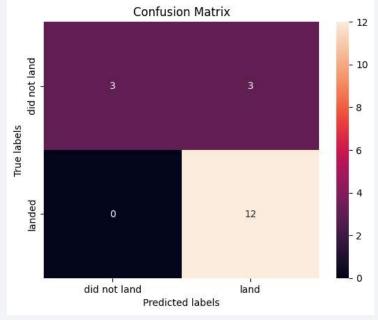
Classification Accuracy

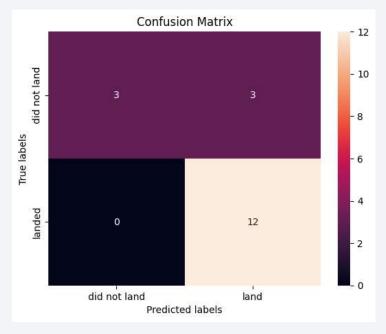


Confusion Matrix

• the confusion matrix of the best performing model







Conclusions

• The SVM, KNN, and Logistic Regression models are the best in terms of prediction accuracy for this dataset.

