



IBM Developer  
SKILLS NETWORK

# Winning Space Race with Data Science

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# Outline

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- Methodology
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# Executive Summary

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- Summary of methodologies
  - Data Collection through API
  - Data Collection with Web Scraping
  - Data Wrangling
  - Exploratory Data Analysis with SQL
  - Exploratory Data Analysis with Data Visualization
  - Interactive Visual Analytics with Folium
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- Summary of all results
  - Exploratory Data Analysis result
  - Interactive analytics in screenshots
  - Predictive Analytics result

# Introduction

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- Project background and context
  - SpaceX advertises the cost of a Falcon 9 rocket launch on its website as **\$62 million**, significantly lower than other providers whose costs typically exceed **\$165 million** per launch. The substantial savings are primarily due to SpaceX's ability to reuse the rocket's first stage.
  - Determining whether the first stage of a rocket will successfully land is critical for assessing the overall cost-effectiveness of a launch. By predicting the success of the first stage landing, we can estimate the associated costs and provide competitive insights for other companies aiming to bid against SpaceX for rocket launches.
- Key Questions to Address
  1. **What factors influence the success of a rocket landing?**  
Understanding the variables and conditions that determine whether a rocket will land successfully is essential to optimizing the landing process.
  2. **How do various features interact to affect the likelihood of a successful landing?**  
Investigating the relationships and dependencies among different factors is critical to identifying the key drivers of success.
  3. **What operating conditions are required to ensure a reliable landing program?**  
Establishing the necessary environmental, technical, and operational criteria is vital to achieving consistent landing success.



Section 1

# Methodology

# Methodology

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## Executive Summary

- **Data Collection Methodology:**

Data was gathered using the **SpaceX API** and **web scraping** techniques from Wikipedia to ensure comprehensive coverage of relevant information.

- **Data Wrangling:**

Applied **one-hot encoding** to transform categorical variables into a format suitable for analysis and modeling.

- **Exploratory Data Analysis (EDA):**

Conducted in-depth EDA using **visualizations** and **SQL queries** to uncover insights, identify patterns, and prepare the data for advanced analytics.

- **Interactive Visual Analytics:**

Utilized tools such as **Folium** for geospatial visualizations and **Plotly Dash** for creating dynamic, interactive dashboards.

- **Predictive Analysis:**

Developed classification models to predict key outcomes. This included:

- **Model building:** Constructing robust predictive models.
- **Model tuning:** Optimizing hyperparameters for improved performance.
- **Model evaluation:** Assessing the effectiveness of models using appropriate metrics

## Data Collection

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This project involved a multi-faceted approach to data collection and preparation:

- SpaceX API:** We utilized GET requests to access the SpaceX API, retrieving data in JSON format. This data was then parsed using the `.json()` function and transformed into a structured Pandas DataFrame using `.json_normalize()`
- Data Cleaning and Preprocessing:** To ensure data quality, we performed thorough cleaning, including handling missing values and addressing any inconsistencies
- Wikipedia Web Scraping:** We employed BeautifulSoup to scrape Falcon 9 launch records from Wikipedia, extracting HTML tables and converting them into Pandas DataFrames for subsequent analysis

# Data Collection – SpaceX API

- We used the get request to the SpaceX API to collect data, clean the requested data and did some basic data wrangling and formatting.
- The link to the notebook is [https://github.com/Shahzad627/IBM-Data-science-Capstone-SpaceX/blob/main/jupyter-labs-spacex-data-collection-api%20\(2\).ipynb](https://github.com/Shahzad627/IBM-Data-science-Capstone-SpaceX/blob/main/jupyter-labs-spacex-data-collection-api%20(2).ipynb)

1. Get request for rocket launch data using API

```
In [6]: spacex_url="https://api.spacexdata.com/v4/launches/past"
```

```
In [7]: response = requests.get(spacex_url)
```

2. Use json\_normalize method to convert json result to dataframe

```
In [12]: # Use json_normalize method to convert the json result into a dataframe
          # decode response content as json
          static_json_df = res.json()
```

```
In [13]: # apply json_normalize
          data = pd.json_normalize(static_json_df)
```

3. We then performed data cleaning and filling in the missing values

```
In [30]: rows = data_falcon9['PayloadMass'].values.tolist()[0]

          df_rows = pd.DataFrame(rows)
          df_rows = df_rows.replace(np.nan, PayloadMass)

          data_falcon9['PayloadMass'][0] = df_rows.values
          data_falcon9
```



# Data Collection - Scraping

- We applied web scrapping to webscrap Falcon 9 launch records with BeautifulSoup
- We parsed the table and converted it into a pandas dataframe.
- The link to the notebook is <https://github.com/Shahzad627/IBM-Data-science-Capstone-SpaceX/blob/main/jupyter-labs-webscraping.ipynb>

```
1. Apply HTTP Get method to request the Falcon 9 rocket launch page

In [4]: static_url = "https://en.wikipedia.org/w/index.php?title=List_of_Falcon_9_and_Falcon_Heavy_launches&oldid=1027686922"

In [5]: # use requests.get() method with the provided static_url
        # assign the response to a object
        html_data = requests.get(static_url)
        html_data.status_code

Out[5]: 200

2. Create a BeautifulSoup object from the HTML response

In [6]: # Use BeautifulSoup() to create a BeautifulSoup object from a response text content
        soup = BeautifulSoup(html_data.text, 'html.parser')

        Print the page title to verify if the BeautifulSoup object was created properly

In [7]: # Use soup.title attribute
        soup.title

Out[7]: <title>List of Falcon 9 and Falcon Heavy launches - Wikipedia</title>

3. Extract all column names from the HTML table header

In [10]: 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 name ('if name is not None and len(name) > 0') into a list called column_names

        element = soup.find_all('th')
        for row in range(len(element)):
            try:
                name = extract_column_from_header(element[row])
                if (name is not None and len(name) > 0):
                    column_names.append(name)
            except:
                pass

4. Create a dataframe by parsing the launch HTML tables
5. Export data to csv
```

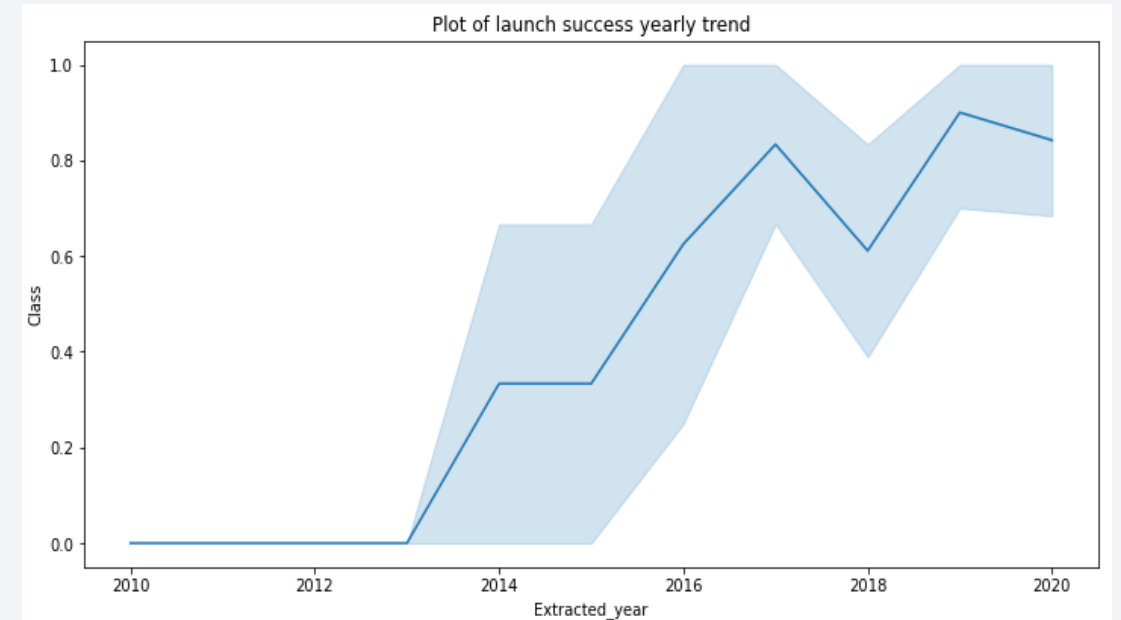
# Data Wrangling



- We performed exploratory data analysis and determined the training labels.
- We calculated the number of launches at each site, and the number and occurrence of each orbits
- We created landing outcome label from outcome column and exported the results to csv.
- The link to the notebook is [https://github.com/Shahzad627/IBM-Data-science-Capstone-SpaceX/blob/main/labs-jupyter-spacex-Data%20wrangling%20\(1\).ipynb](https://github.com/Shahzad627/IBM-Data-science-Capstone-SpaceX/blob/main/labs-jupyter-spacex-Data%20wrangling%20(1).ipynb)

# EDA with Data Visualization

- We explored the data by visualizing the relationship between flight number and launch Site, payload and launch site, success rate of each orbit type, flight number and orbit type, the launch success yearly trend.



- The link to the notebook is <https://github.com/Shahzad627/IBM-Data-science-Capstone-SpaceX/blob/main/EDA%20with%20Visualization.ipynb>

# EDA with SQL

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- We loaded the SpaceX dataset into a MySQL database without leaving the jupyter notebook.
- We applied EDA with SQL to get insight from the data. We wrote queries to find out for instance:
  - The names of unique launch sites in the space mission.
  - The total payload mass carried by boosters launched by NASA (CRS)
  - The average payload mass carried by booster version F9 v1.1
  - The total number of successful and failure mission outcomes
  - The failed landing outcomes in drone ship, their booster version and launch site names.
- The link to the notebook is [https://github.com/Shahzad627/IBM-Data-science-Capstone-SpaceX/blob/main/jupyter-labs-eda-sql-coursera\\_sqllite.ipynb](https://github.com/Shahzad627/IBM-Data-science-Capstone-SpaceX/blob/main/jupyter-labs-eda-sql-coursera_sqllite.ipynb)

# Build an Interactive Map with Folium

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- We marked all launch sites, and added map objects such as markers, circles, lines to mark the success or failure of launches for each site on the folium map.
- We assigned the feature launch outcomes (failure or success) to class 0 and 1.i.e., 0 for failure, and 1 for success.
- Using the color-labeled marker clusters, we identified which launch sites have relatively high success rate.
- We calculated the distances between a launch site to its proximities. We answered some question for instance:
  - Are launch sites near railways, highways and coastlines.
  - Do launch sites keep certain distance away from cities.



# Build a Dashboard with Plotly Dash

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- We built an interactive dashboard with Plotly dash
- We plotted pie charts showing the total launches by a certain sites
- We plotted scatter graph showing the relationship with Outcome and Payload Mass (Kg) for the different booster version.
- The link to the notebook is [https://github.com/Shahzad627/IBM-Data-science-Capstone-SpaceX/blob/main/spacex\\_dash\\_app%20\(1\).py](https://github.com/Shahzad627/IBM-Data-science-Capstone-SpaceX/blob/main/spacex_dash_app%20(1).py)

# Predictive Analysis (Classification)

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- We loaded the data using numpy and pandas, transformed the data, split our data into training and testing.
- We built different machine learning models and tune different hyperparameters using GridSearchCV.
- We used accuracy as the metric for our model, improved the model using feature engineering and algorithm tuning.
- We found the best performing classification model.
- The link to the notebook is [https://github.com/Shahzad627/IBM-Data-science-Capstone-SpaceX/blob/main/SpaceX\\_Machine%20Learning%20Prediction\\_Part\\_5%20\(1\).ipynb](https://github.com/Shahzad627/IBM-Data-science-Capstone-SpaceX/blob/main/SpaceX_Machine%20Learning%20Prediction_Part_5%20(1).ipynb)

# Results

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



The background of the slide is a complex, abstract composition. It features a dark blue base color on the left, which transitions into a vibrant, multi-colored area on the right. This transition area is filled with numerous thin, diagonal streaks in shades of red, orange, and yellow, creating a sense of motion and energy. Overlaid on these streaks is a faint, grid-like pattern of small, light-colored squares, reminiscent of a digital or data visualization theme.

Section 2

# Insights drawn from EDA



# Flight Number vs. Launch Site

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- From the plot, we found that the larger the flight amount at a launch site, the greater the success rate at a launch site.





## Payload vs. Launch Site



The greater the payload mass for launch site CCAFS SLC 40 the higher the success rate for the rocket.



# Success Rate vs. Orbit Type

- From the plot, we can see that ES-L1, GEO, HEO, SSO, VLEO had the most success rate.



# Flight Number vs. Orbit Type

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- The plot below shows the Flight Number vs. Orbit type. We observe that in the LEO orbit, success is related to the number of flights whereas in the GTO orbit, there is no relationship between flight number and the orbit.



# Payload vs. Orbit Type

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- We can observe that with heavy payloads, the successful landing are more for PO, LEO and ISS orbits.



# Launch Success Yearly Trend

- From the plot, we can observe that success rate since 2013 kept on increasing till 2020.





# All Launch Site Names

- We used the key word **DISTINCT** to show only unique launch sites from the SpaceX data.

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

```
In [10]: task_1 = '''
          SELECT DISTINCT LaunchSite
          FROM SpaceX
          ...
          create_pandas_df(task_1, database=conn)
```

```
Out[10]:
```

	launchsite
0	KSC LC-39A
1	CCAFS LC-40
2	CCAFS SLC-40
3	VAFB SLC-4E

# Launch Site Names Begin with 'CCA'

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

In [11]:

```
task_2 = '''
SELECT *
FROM SpaceX
WHERE LaunchSite LIKE 'CCA%'
LIMIT 5
'''

create_pandas_df(task_2, database=conn)
```

Out[11]:

	date	time	boosterversion	launchsite	payload	payloadmasskg	orbit	customer	missionoutcome	landingoutcome
0	2010-04-06	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	Success	Failure (parachute)
1	2010-08-12	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	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
3	2012-08-10	00:35:00	F9 v1.0 B0006	CCAFS LC-40	SpaceX CRS-1	500	LEO (ISS)	NASA (CRS)	Success	No attempt
4	2013-01-03	15:10:00	F9 v1.0 B0007	CCAFS LC-40	SpaceX CRS-2	677	LEO (ISS)	NASA (CRS)	Success	No attempt

- We used the query above to display 5 records where launch sites begin with 'CCA'

# Total Payload Mass

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- We calculated the total payload carried by boosters from NASA as 45596 using the query below

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

```
In [12]: task_3 = '''
          SELECT SUM(PayloadMassKG) AS Total_PayloadMass
          FROM SpaceX
          WHERE Customer LIKE 'NASA (CRS)'
          '''
          create_pandas_df(task_3, database=conn)
```

Out[12]:

	total_payloadmass
0	45596

# Average Payload Mass by F9 v1.1

- We calculated the average payload mass carried by booster version F9 v1.1 as 2928.4

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

```
In [13]: task_4 = '''
          SELECT AVG(PayloadMassKG) AS Avg_PayloadMass
          FROM SpaceX
          WHERE BoosterVersion = 'F9 v1.1'
          '''
          create_pandas_df(task_4, database=conn)
```

```
Out[13]:
```

	avg_payloadmass
0	2928.4

# First Successful Ground Landing Date

- We observed that the dates of the first successful landing outcome on ground pad was 22<sup>nd</sup> December 2015

In [14]:

```
task_5 = '''
    SELECT MIN(Date) AS FirstSuccessfull_landing_date
    FROM SpaceX
    WHERE LandingOutcome LIKE 'Success (ground pad)'
    '''

create_pandas_df(task_5, database=conn)
```

Out[14]:

	firstsuccessfull_landing_date
--	-------------------------------

0	2015-12-22
---	------------



# Successful Drone Ship Landing with Payload between 4000 and 6000

```
In [15]: task_6 = '''
          SELECT BoosterVersion
          FROM SpaceX
          WHERE LandingOutcome = 'Success (drone ship)'
             AND PayloadMassKG > 4000
             AND PayloadMassKG < 6000
          ...
          create_pandas_df(task_6, database=conn)
```

```
Out[15]:
```

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

- We used the **WHERE** clause to filter for boosters which have successfully landed on drone ship and applied the **AND** condition to determine successful landing with payload mass greater than 4000 but less than 6000

# Total Number of Successful and Failure Mission Outcomes

List the total number of successful and failure mission outcomes

```
In [16]: task_7a = '''
          SELECT COUNT(MissionOutcome) AS SuccessOutcome
          FROM SpaceX
          WHERE MissionOutcome LIKE 'Success%'
          '''

          task_7b = '''
          SELECT COUNT(MissionOutcome) AS FailureOutcome
          FROM SpaceX
          WHERE MissionOutcome LIKE 'Failure%'
          '''

          print('The total number of successful mission outcome is:')
          display(create_pandas_df(task_7a, database=conn))
          print()
          print('The total number of failed mission outcome is:')
          create_pandas_df(task_7b, database=conn)
```

The total number of successful mission outcome is:

	successoutcome
0	100

The total number of failed mission outcome is:

```
Out[16]: failureoutcome
0         1
```

- We used wildcard like '%' to filter for **WHERE** MissionOutcome was a success or a failure.

# Boosters Carried Maximum Payload

- We determined the booster that have carried the maximum payload using a subquery in the **WHERE** clause and the **MAX()** function.

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

In [17]:

```
task_8 = '''
SELECT BoosterVersion, PayloadMassKG
FROM SpaceX
WHERE PayloadMassKG = (
    SELECT MAX(PayloadMassKG)
    FROM SpaceX
)
ORDER BY BoosterVersion
'''
create_pandas_df(task_8, database=conn)
```

Out[17]:

	boosterversion	payloadmasskg
0	F9 B5 B1048.4	15600
1	F9 B5 B1048.5	15600
2	F9 B5 B1049.4	15600
3	F9 B5 B1049.5	15600
4	F9 B5 B1049.7	15600
5	F9 B5 B1051.3	15600
6	F9 B5 B1051.4	15600
7	F9 B5 B1051.6	15600
8	F9 B5 B1056.4	15600
9	F9 B5 B1058.3	15600
10	F9 B5 B1060.2	15600
11	F9 B5 B1060.3	15600

# 2015 Launch Records

---

- We used a combinations of the **WHERE** clause, **LIKE**, **AND**, and **BETWEEN** conditions to filter for failed landing outcomes in drone ship, their booster versions, and launch site names for year 2015

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

```
In [18]: task_9 = '''
          SELECT BoosterVersion, LaunchSite, LandingOutcome
          FROM SpaceX
          WHERE LandingOutcome LIKE 'Failure (drone ship)'
             AND Date BETWEEN '2015-01-01' AND '2015-12-31'
          ...
          create_pandas_df(task_9, database=conn)
```

Out[18]:

	boosterversion	launchsite	landingoutcome
0	F9 v1.1 B1012	CCAFS LC-40	Failure (drone ship)
1	F9 v1.1 B1015	CCAFS LC-40	Failure (drone ship)

# 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))

```
In [19]: task_10 = '''
          SELECT LandingOutcome, COUNT(LandingOutcome)
          FROM SpaceX
          WHERE DATE BETWEEN '2010-06-04' AND '2017-03-20'
          GROUP BY LandingOutcome
          ORDER BY COUNT(LandingOutcome) DESC
          '''
          create_pandas_df(task_10, database=conn)
```

```
Out[19]:
```

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

- We selected Landing outcomes and the **COUNT** of landing outcomes from the data and used the **WHERE** clause to filter for landing outcomes **BETWEEN** 2010-06-04 to 2010-03-20.
- We applied the **GROUP BY** clause to group the landing outcomes and the **ORDER BY** clause to order the grouped landing outcome in descending order.

Section 4

# Launch Sites Proximities Analysis





# All launch sites global map markers





# Markers showing launch sites with color labels



# Launch Site distance to landmarks



- Are launch sites in close proximity to railways? No
- Are launch sites in close proximity to highways? No
- Are launch sites in close proximity to coastline? Yes
- Do launch sites keep certain distance away from cities? Yes





Section 5

# Build a Dashboard with Plotly Dash

## Pie chart showing the success percentage achieved by each launch site

Total Success Launches By all sites



***We can see that KSC LC-39A had the most successful launches from all the sites***

Pie chart showing the Launch site with the highest launch success ratio



***KSC LC-39A achieved a 76.9% success rate while getting a 23.1% failure rate***

## Scatter plot of Payload vs Launch Outcome for all sites, with different payload selected in the range slider



*We can see the success rates for low weighted payloads is higher than the heavy weighted payloads*





Section 6

# Predictive Analysis (Classification)



# Classification Accuracy

- The decision tree classifier is the model with the highest classification accuracy

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

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

Best model is DecisionTree with a score of 0.8732142857142856

Best params is : {'criterion': 'gini', 'max\_depth': 6, 'max\_features': 'auto', 'min\_samples\_leaf': 2, 'min\_samples\_split': 5, 'splitter': 'random'}

# Confusion Matrix

- The confusion matrix for the decision tree classifier shows that the classifier can distinguish between the different classes. The major problem is the false positives .i.e., unsuccessful landing marked as successful landing by the classifier.



# Conclusions

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We can conclude that:

- The larger the flight amount at a launch site, the greater the success rate at a launch site.
- Launch success rate started to increase in 2013 till 2020.
- Orbits ES-L1, GEO, HEO, SSO, VLEO had the most success rate.
- KSC LC-39A had the most successful launches of any sites.
- The Decision tree classifier is the best machine learning algorithm for this task.

Thank you!

