SpaceX

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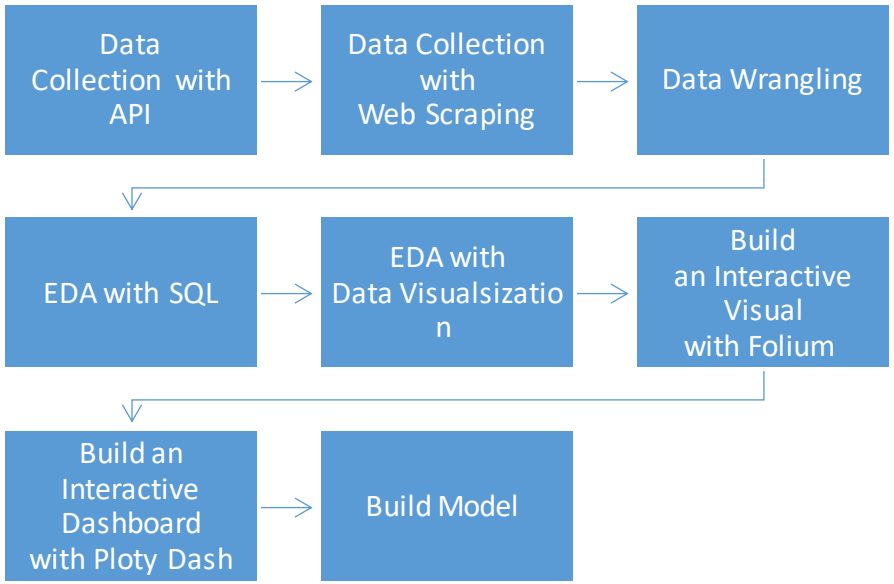
EXECUTIVE SUMMARY



INTRODUCTION

- **Background :**

The commercial space age is here, companies are making space travel affordable foreveryone. SpaceX advertises Falcon 9 rocket launches on its website with a cost of 62 million dollars; other providers cost upwards of 165 million dollars each, much of the savings is because SpaceX can reuse the first stage.

- **Problem to Solve:**
- Determine if the first stage will land, and determine the cost of a launch.
- Determine if SpaceX will reuse the first stage.

METHODOLOGIES

Data Collection (API)

- we were working with SpaceX launch data that is gathered from an API, specifically the SpaceX REST API. This API will give us data about launches, such as rocket used, payload delivered, launch specifications, landing specifications, and landing outcome.
- The link to the notebook :
- https://github.com/marAlsolami/Coursera-/blob/main/jupyter-labs-spacex-data-collection-api.ipynb

The data from these requests will be stored in lists and will be used to create a new dataframe.

```
#Global variables
BoosterVersion = []
PayloadMass = []
Orbit = []
LaunchSite = []
Outcome = []
Flights = []
GridFins = []
Reused = []
Legs = []
LandingPad = []
Block = []
ReusedCount = []
Serial = []
Longitude = []
Latitude = []
```

These functions will apply the outputs globally to the above variables. Let's take a looks at `BoosterVe` `getBoosterVersion` the list is empty:

```
BoosterVersion
```

```
[]
```

```
def getBoosterVersion(data):
    for x in data['rocket']:
       if x:
        response = requests.get("https://api.spacexdata.com/v4/rockets/"+str(x)).json()
        BoosterVersion.append(response['name'])
```

Now, let's apply `getBoosterVersion` function method to get the booster version

```
# Call getBoosterVersion
getBoosterVersion(data)
```

the list has now been update

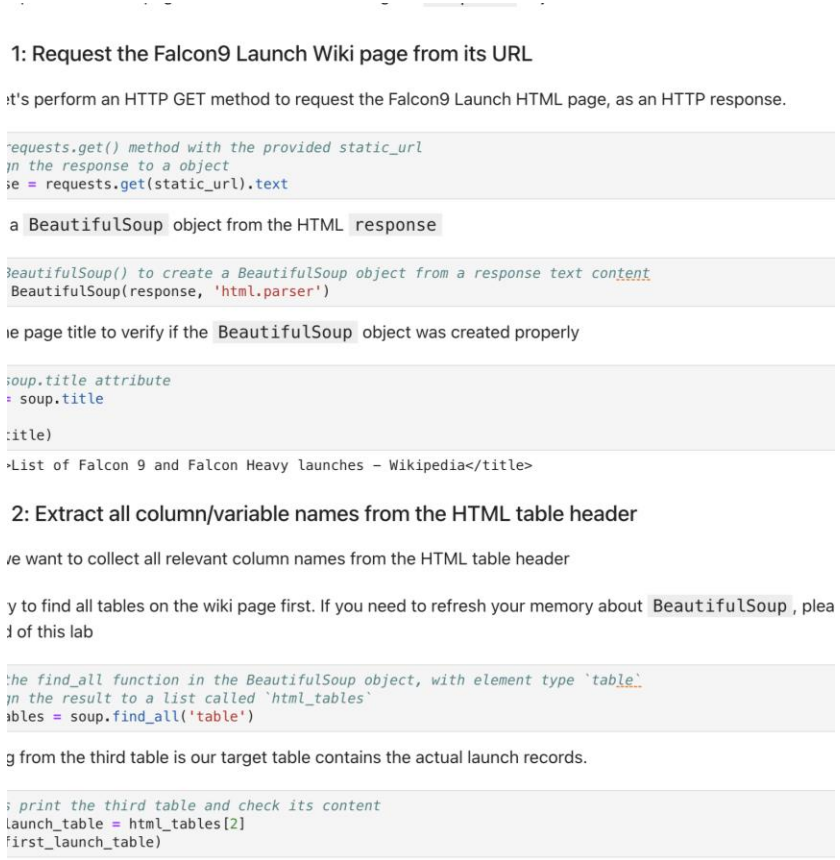
```
BoosterVersion[0:4]
```

```
['Falcon 1', 'Falcon 1', 'Falcon 1', 'Falcon 1']
```

Data Collection(Web Scraping)

- We Perform web scraping to collect Falcon 9 historical launch records from a Wikipedia page titled List of Falcon 9 and Falcon Heavy launches.
- We do Web scrap to extract Falcon 9 launch records with BeautifulSoup library.Extract a Falcon 9 launch records HTML table from Wikipedia.Parse the table and convert it into a Pandas data frame
- The link to the notebook :
- https://github.com/marAlsolami/Coursera-/blob/main/jupyter-labs-webscraping.ipynb

- Rrefrence
- https://en.wikipedia.org/wiki/List_of_Falcon_9_and_Falcon_Heavy_launches

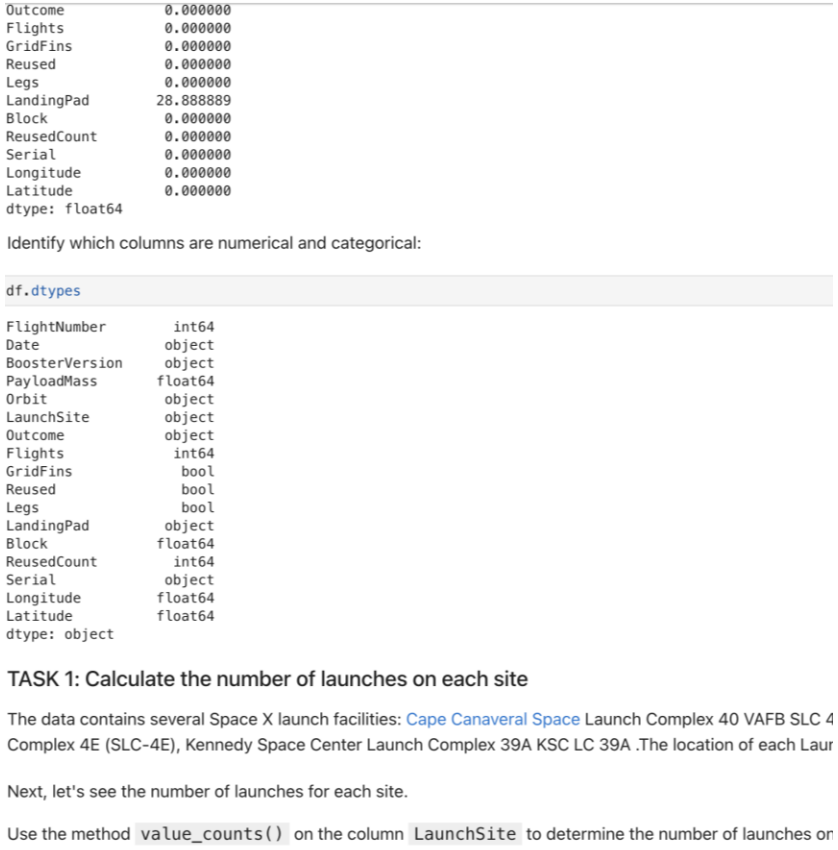


Data Wrangling

we were perform some Exploratory Data Analysis (EDA) to find some patterns in the data and determine what would be the label for training supervised models. Such as Calculate the number of launches on each site, Calculate the number and occurrence of each orbit, and Calculate the number and occurence of mission outcome of the orbits.

- The link to the notebook :

https://github.com/marAlsolami/Coursera-/blob/main/labs-jupyter-spacex-Data%20wrangling.ipynb



```
Outcome          0.000000
Flights          0.000000
GridFins         0.000000
Reused           0.000000
Legs             0.000000
LandingPad      28.888889
Block            0.000000
ReusedCount      0.000000
Serial           0.000000
Longitude        0.000000
Latitude         0.000000
dtype: float64
```

Identify which columns are numerical and categorical:

```
df.dtypes
```

```
FlightNumber        int64
Date               object
BoosterVersion     object
PayloadMass       float64
Orbit              object
LaunchSite         object
Outcome            object
Flights             int64
GridFins             bool
Reused               bool
Legs                 bool
LandingPad         object
Block             float64
ReusedCount         int64
Serial             object
Longitude         float64
Latitude          float64
dtype: object
```

TASK 1: Calculate the number of launches on each site

The data contains several Space X launch facilities: Cape Canaveral Space Launch Complex 40 VAFB SLC 4
Complex 4E (SLC-4E), Kennedy Space Center Launch Complex 39A KSC LC 39A .The location of each Laur

Next, let's see the number of launches for each site.

Use the method `value_counts()` on the column `LaunchSite` to determine the number of launches or

EDA with SQL

We perform Exploratory Data Analysis and Feature Engineering using SQL queries .

- The link to the notebook :

https://github.com/marAlsolami/Coursera-/blob/main/jupyter-labs-eda-sql-coursera_sqllite.ipynb

Tasks

Now write and execute SQL queries to solve the assignment tasks.

Note: If the column names are in mixed case enclose it in double quotes For Example "Landing

Task 1 ¶

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

```
%sql select  DISTINCT Launch_Site from SPACEXTABLE;
```

```
 * sqlite:///my_data1.db
Done.
```

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

Task 2

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

```
%%sql select * from SPACEXTABLE WHERE Launch_Site LIKE '%CCA%'
limit 5
```

```
 * sqlite:///my_data1.db
Done.
```

Date	Time (UTC)	Booster_Version	Launch_Site	Payload	PAYLOAD_MASS__K
2010-06-04	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit	
2010-12-08	15:43:00	F9 v1.0 B0004	CCAFS LC-40	Dragon demo flight C1, two CubeSats, barrel of Brouere cheese	
2012-05-22	7:44:00	F9 v1.0 B0005	CCAFS LC-40	Dragon demo flight C2	5

EDA with Data Visualsization

- We Perform exploratory Data Analysis and Feature Engineering using 'Pandas' and 'Matplotlib' libraries.
- The link to the notebook :

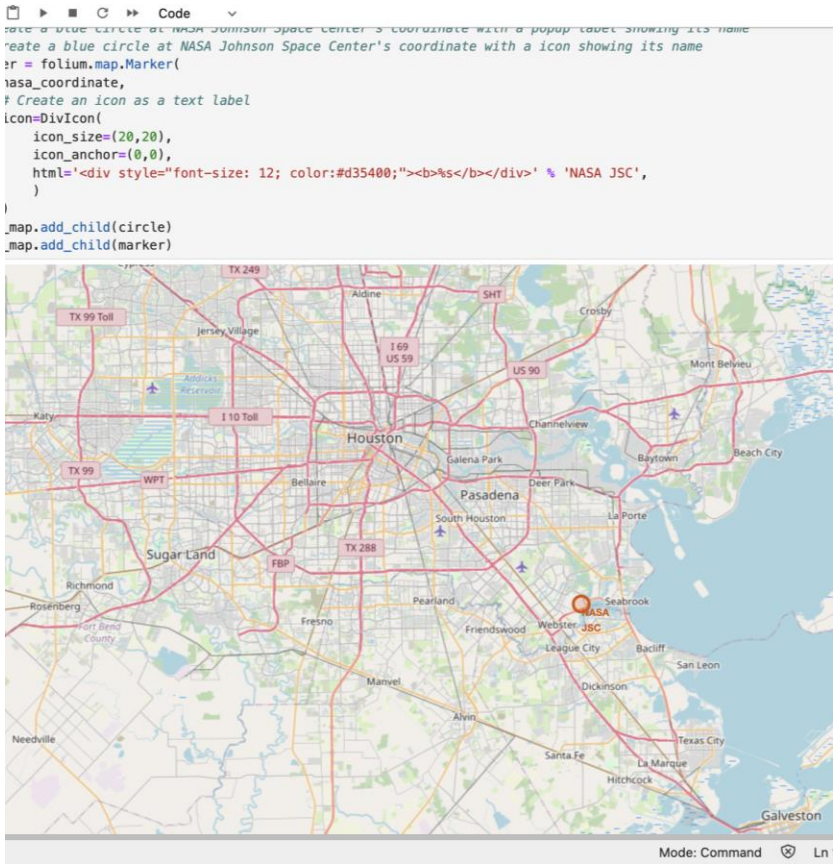
https://github.com/marAlsolami/Coursera-/blob/main/jupyter-labs-eda-dataviz.ipynb.jupyterlite.ipynb

Build an Interactive Visual with Folium

We analyze launch site geo and proximities with Folium. We will first mark the launch site locations and their close proximities on an interactive map. Then, we can explore the map with those markers and try to discover any patterns from them. Finally, we should be able to explain how to choose an optimal launch site.

- The link to the notebook :

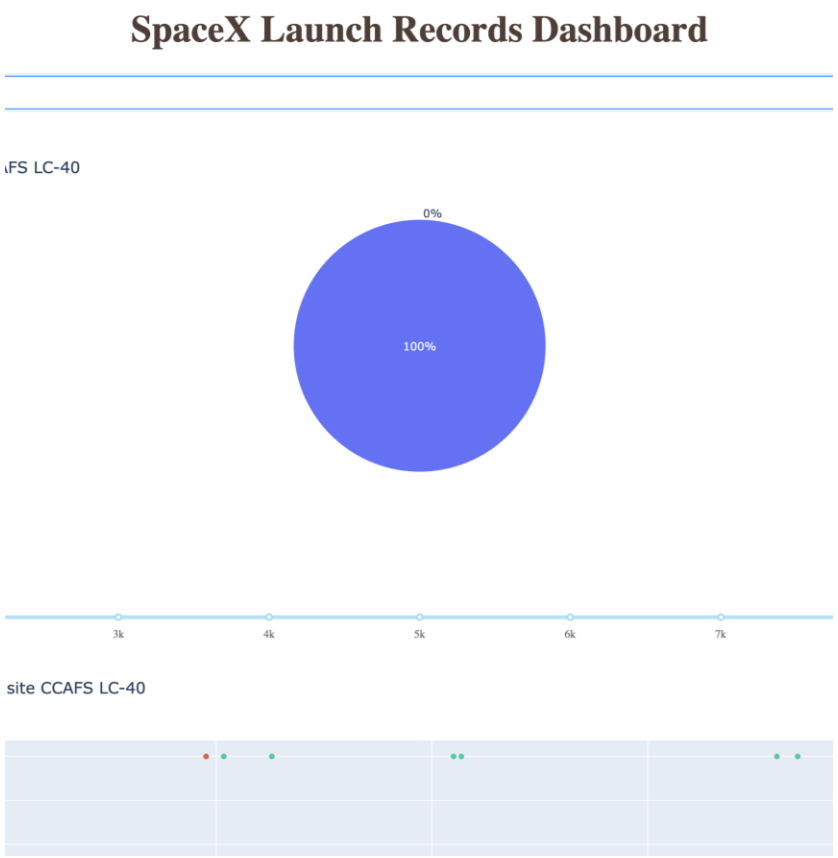
https://github.com/marAlsolami/Coursera-/blob/main/lab_jupyter_launch_site_location.jupyterlite.ipynb



Build an Interactive Dashboard with Ploty Dash

- We build a dashboard application with the Python Plotly Dash package. This dashboard application contains input components such as a dropdown list and a range. slider to interact with a pie chart and a scatter point chart. After the dashboard is built, we can use it to find more insights from the SpaceX dataset more easily
- The link to the notebook :

https://github.com/marAlsolami/Coursera-/blob/main/Hands-on%20Lab%3A%20Build%20an%20Interactive%20Dashboard%20with%20Ploty%20Dash

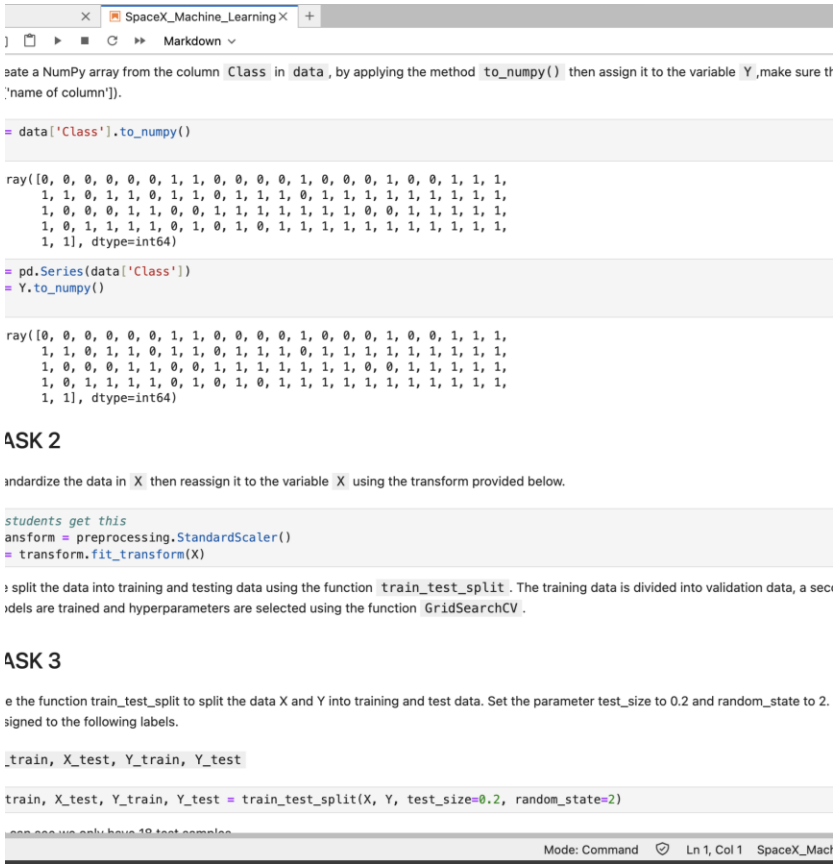


Build Model

we will build a machine learning pipeline to predict if the first stage of the Falcon 9 lands successfully. We test Logistic Regression, Support Vector machines, Decision Tree Classifier, and K-nearest neighbors.

- The link to the notebook :

https://github.com/marAlsolami/Coursera-/blob/main/SpaceX_Machine_Learning_Prediction_Part_5.jupyterlite.ipynb



Results

Results

- EDA with visualization results
- EDA with SQL Results
- Interactive map with Folium results
- Plotly Dash dashboard results
- Predictive analysis (classification) results

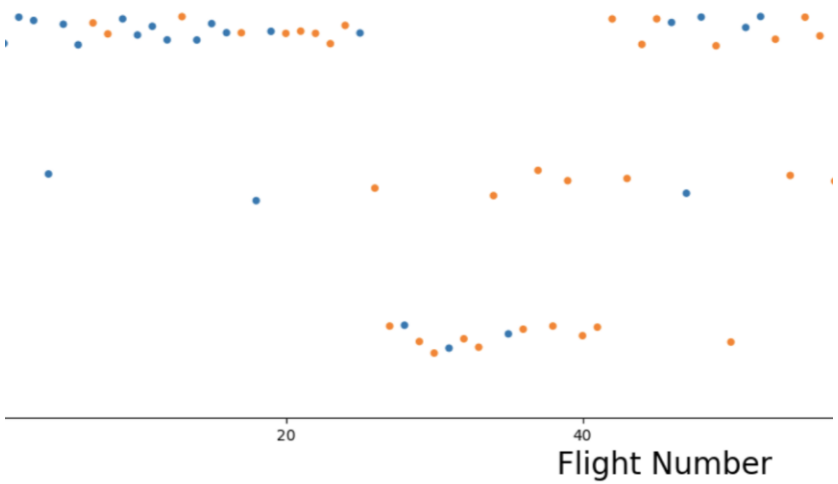
EDA with Visualization Results

Visualize the relationship between Flight Number and Launch Site

he relationship between Flight Number and Launch Site

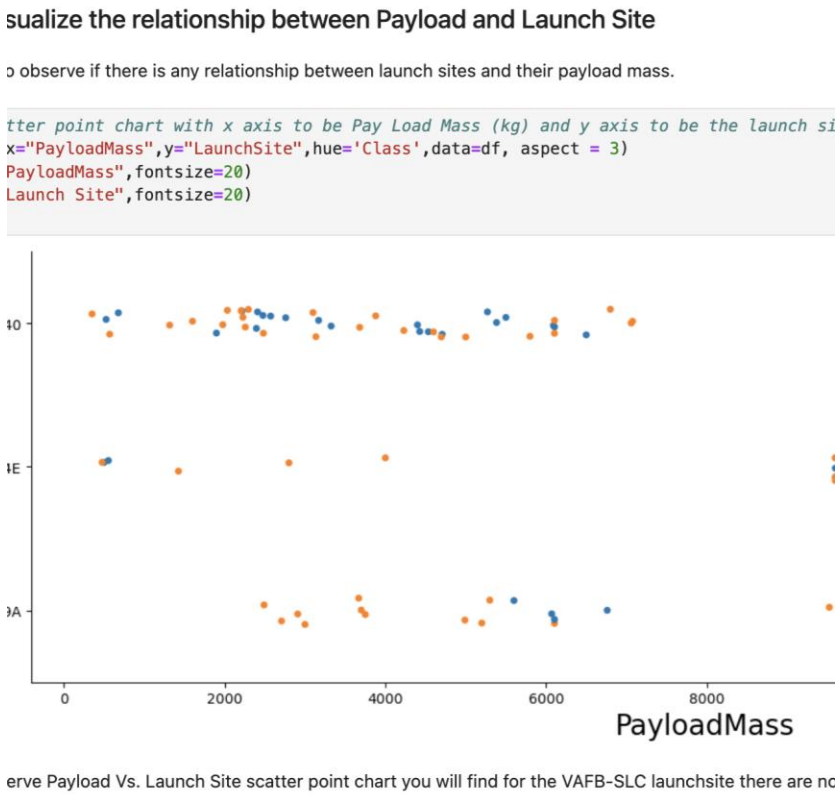
t to plot FlightNumber vs LaunchSite, set the parameter x parameter to FlightNum

```
t chart with x axis to be Flight Number and y axis to be the launch site, and
Site", x="FlightNumber",hue='Class',data=df, aspect = 3)
mber",fontsize=20)
te",fontsize=20)
```



EDA with Visualization Results

Visualize the relationship between Payload and Launch Site



EDA with Visualization Results

- Visualize the relationship between success rate of each orbit type

SK 3: Visualize the relationship between success rate of each orbit type

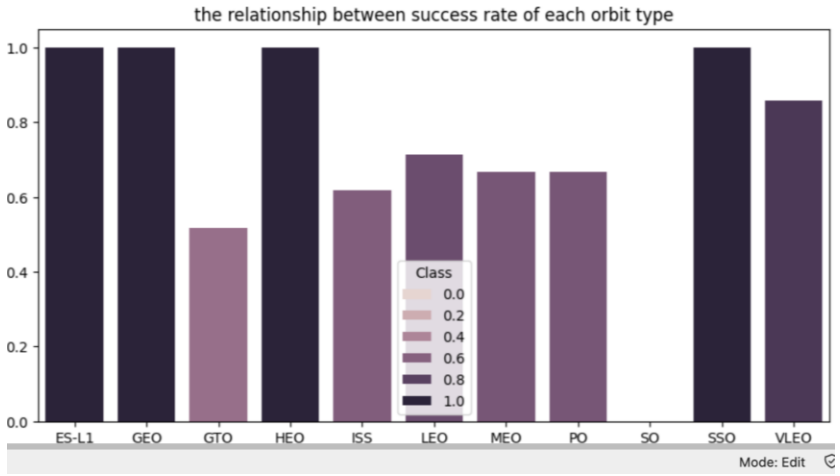
t, we want to visually check if there are any relationship between success rate and orbit type.

s create a `bar chart` for the sucess rate of each orbit

```
INT use groupby method on Orbit column and get the mean of Class column
it_x = df.groupby('Orbit').mean()
```

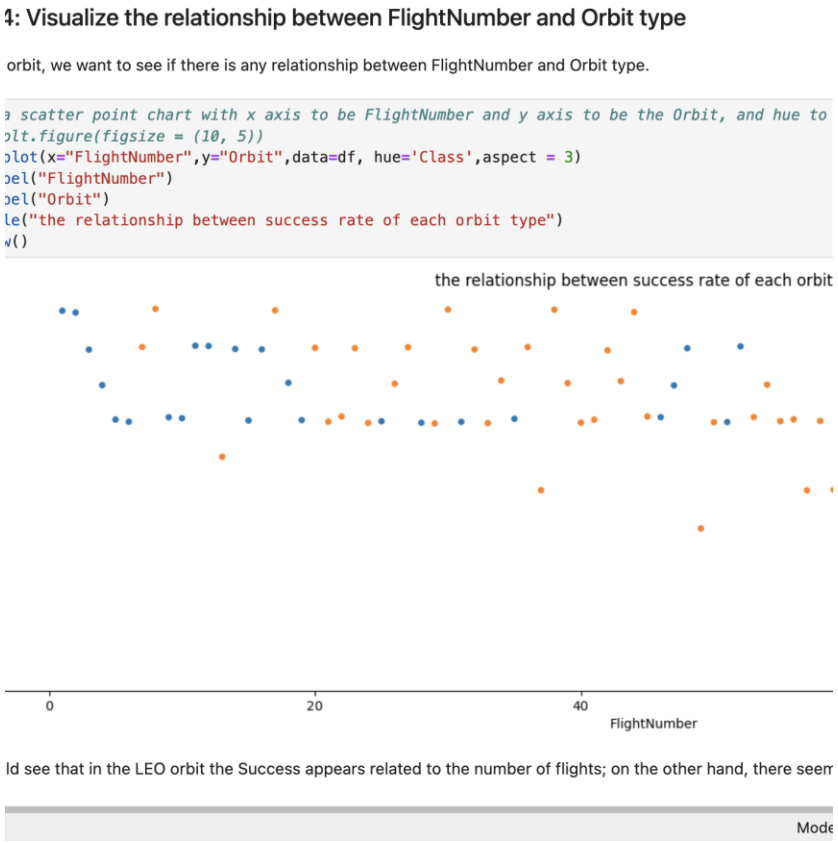
```
ython-input-53-26b8e13e41ae>:2: FutureWarning: The default value of numeric_only in DataFrameGroupBy.mea
l default to False. Either specify numeric_only or select only columns which should be valid for the fu
rbit_x = df.groupby('Orbit').mean()
```

```
 = plt.figure(figsize = (10, 5))
.barplot(x="Orbit",y="Class",data=orbit_x, hue='Class')
.xlabel("Orbit")
.ylabel("Class")
.title("the relationship between success rate of each orbit type")
.show()
```



EDA with Visualization Results

Visualize the relationship between FlightNumber and Orbit type



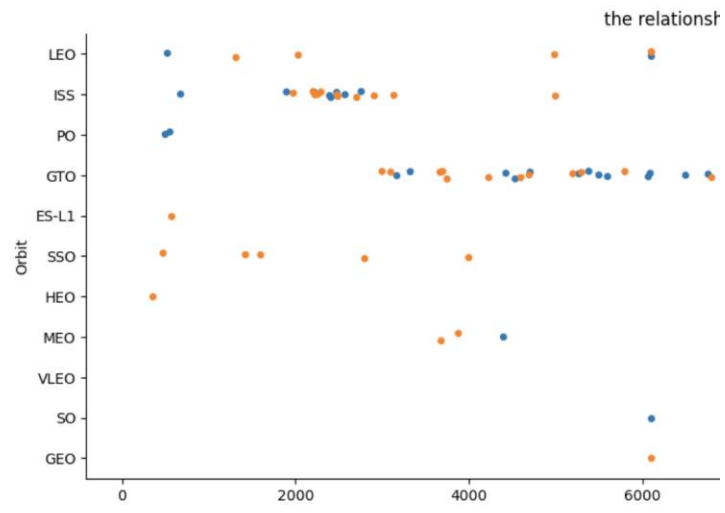
EDA with Visualization Results

Visualize the relationship between Payload and Orbit type

TASK 5: Visualize the relationship between Payload and Orbit

Similarly, we can plot the Payload vs. Orbit scatter point charts to reveal the relations

[62]:
```
# Plot a scatter point chart with x axis to be Payload and y axis to b
sns.catplot(x="PayloadMass",y="Orbit",data=df, hue='Class',aspect = 3)
plt.xlabel("PayloadMass")
plt.ylabel("Orbit")
plt.title("the relationship between Payload and Orbit type")
plt.show()
```

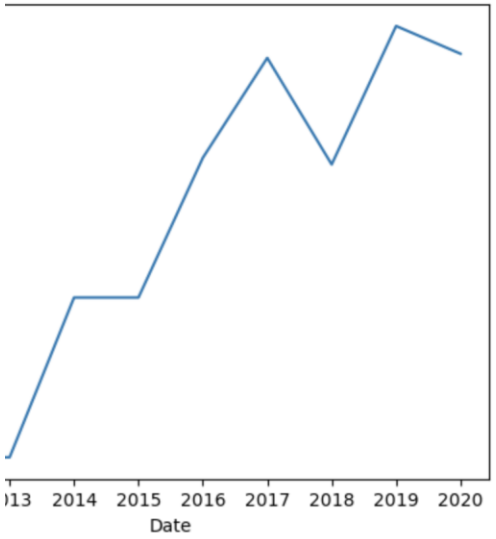


EDA with Visualization Results

Visualize the launch success yearly trend

```
th x axis to be the extracted year and y axis to be the success rate
roupby(by="Date").mean()
index(inplace=True)
ar['Date'], average_by_year['Class'])
```

```
9073ace0>:2: FutureWarning: The default value of numeric_only in DataFrameGroupBy.
 Either specify numeric_only or select only columns which should be valid for the
.groupby(by="Date").mean()
```



Mode: Edit

EDA with Visualization Results

- Create dummy variables to categorical columns

7: Create dummy variables to categorical columns

function `get_dummies` and `features` dataframe to apply OneHotEncoder to the column
`features_one_hot`, display the results using the method head. Your result dataframe must

```
# Use get_dummies() function on the categorical columns
s_one_hot = pd.get_dummies(features, columns=['Orbit','LaunchSite', 'LandingP
s_one_hot
```

htNumber	PayloadMass	Flights	GridFins	Reused	Legs	Block	ReusedCount	Orbit_
1	6104.959412	1	False	False	False	1.0	0	
2	525.000000	1	False	False	False	1.0	0	
3	677.000000	1	False	False	False	1.0	0	
4	500.000000	1	False	False	False	1.0	0	
5	3170.000000	1	False	False	False	1.0	0	
...	...	...	...	...	...	...	...	
86	15400.000000	2	True	True	True	5.0	2	
87	15400.000000	3	True	True	True	5.0	2	
88	15400.000000	6	True	True	True	5.0	5	
89	15400.000000	3	True	True	True	5.0	2	
90	3681.000000	1	True	False	True	5.0	0	

: 80 columns

EDA with Visualization Results

Cast all numeric columns to float64

TASK 8: Cast all numeric columns to `float64`

Now that our `features_one_hot` dataframe only contains numbers cas

[84]:
```
# HINT: use astype function
features_one_hot = features_one_hot.astype('float64')
features_one_hot
```

[84]:

	FlightNumber	PayloadMass	Flights	GridFins	Reused	Legs	Bl
0	1.0	6104.959412	1.0	0.0	0.0	0.0	
1	2.0	525.000000	1.0	0.0	0.0	0.0	
2	3.0	677.000000	1.0	0.0	0.0	0.0	
3	4.0	500.000000	1.0	0.0	0.0	0.0	
4	5.0	3170.000000	1.0	0.0	0.0	0.0	
...	...	...	...	...	...	...	
85	86.0	15400.000000	2.0	1.0	1.0	1.0	
86	87.0	15400.000000	3.0	1.0	1.0	1.0	
87	88.0	15400.000000	6.0	1.0	1.0	1.0	
88	89.0	15400.000000	3.0	1.0	1.0	1.0	
89	90.0	3681.000000	1.0	1.0	0.0	1.0	

90 rows × 80 columns

EDA with SQL Results

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

Task 1

Display the names of the unique launch site

```
l0]: %sql select  DISTINCT Launch_Site fr
 * sqlite:///my_data1.db
Done.
```

l0]:

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

EDA with SQL Results

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

h sites begin with the string 'CCA'

```
XTABLE WHERE Launch_Site LIKE '%CCA%'
```

_Version	Launch_Site	Payload	PAYLOAD_MAS
0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit	
0 B0004	CCAFS LC-40	Dragon demo flight C1, two CubeSats, barrel of Brouere cheese	
0 B0005	CCAFS LC-40	Dragon demo flight C2	
0 B0006	CCAFS LC-40	SpaceX CRS-1	
0 B0007	CCAFS LC-40	SpaceX CRS-2	

EDA with SQL Results

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

Task 3

Display the total payload mass carried by boosters launche

```
[26]: %sql select SUM(PAYLOAD_MASS__KG_) from SPACEXTABL
 * sqlite:///my_data1.db
Done.
```

[26]:

SUM(PAYLOAD_MASS__KG_)
45596

Task 4

Display average payload mass carried by booster version F

```
[27]: %sql select AVG(PAYLOAD_MASS__KG_) from SPACEXTABL
 * sqlite:///my_data1.db
Done.
```

[27]:

AVG(PAYLOAD_MASS__KG_)
2928.4

EDA with SQL Results

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

Task 3

Display the total payload mass carried by boosters launche

```
[26]: %sql select SUM(PAYLOAD_MASS__KG_) from SPACEXTABL
 * sqlite:///my_data1.db
Done.
```

[26]:	SUM(PAYLOAD_MASS__KG_)
	45596

Task 4

Display average payload mass carried by booster version F

```
[27]: %sql select AVG(PAYLOAD_MASS__KG_) from SPACEXTABL
 * sqlite:///my_data1.db
Done.
```

[27]:	AVG(PAYLOAD_MASS__KG_)
	2928.4

EDA with SQL Results

List the date when the first succesful landing outcome in ground pad was acheived.

Task 5

List the date when the first succesful landing outcome in grou

Hint:Use min function

```
%sql select MIN (Date) from SPACEXTABLE where Landin
```

```
 * sqlite:///my_data1.db
Done.
```

MIN (Date)
2015-12-22

```
####################
```

```
%sql select * from SPACEXTABLE WHERE Launch_Site LIK
```

```
 * sqlite:///my_data1.db
Done.
```

Time

d (additional servers needed) Python | Idle Mem: 419.33 / 6144.0

EDA with SQL Results

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

Task 6

List the names of the boosters which have success in drone ship and have payload mass greate

[65]:
```
%%sql select Booster_Version,PAYLOAD_MASS__KG_,Landing_Outcome
from SPACEXTABLE
where Landing_Outcome == 'Success (drone ship)' AND PAYLOAD_MASS__KG_ between '4
```

```
 * sqlite:///my_data1.db
Done.
```

[65]:

Booster_Version	PAYLOAD_MASS__KG_	Landing_Outcome
F9 FT B1022	4696	Success (drone ship)
F9 FT B1026	4600	Success (drone ship)
F9 FT B1021.2	5300	Success (drone ship)
F9 FT B1031.2	5200	Success (drone ship)

Task 7

List the total number of successful and failure mission outcomes

[93]:
```
%%sql select count(Mission_Outcome) as success
from SPACEXTABLE where  Mission_Outcome like 'Success%'
```

```
 * sqlite:///my_data1.db
Done.
```

[93]:

success
100

[95]:
```
%%sql select count(Mission_Outcome) as fail
from SPACEXTABLE where  Mission_Outcome like 'Failure%'
```

```
 * sqlite:///my_data1.db
Done.
```

[95]:

fail
1

EDA with SQL Results

List the total number of successful and failure mission outcomes

Task 6

List the names of the boosters which have success in drone ship and have payload mass greate

[65]:
```
%%sql select Booster_Version,PAYLOAD_MASS__KG_,Landing_Outcome
from SPACEXTABLE
where Landing_Outcome == 'Success (drone ship)' AND PAYLOAD_MASS__KG_ between '4
```

```
 * sqlite:///my_data1.db
Done.
```

[65]:

Booster_Version	PAYLOAD_MASS__KG_	Landing_Outcome
F9 FT B1022	4696	Success (drone ship)
F9 FT B1026	4600	Success (drone ship)
F9 FT B1021.2	5300	Success (drone ship)
F9 FT B1031.2	5200	Success (drone ship)

Task 7

List the total number of successful and failure mission outcomes

[93]:
```
%%sql select count(Mission_Outcome) as success
from SPACEXTABLE where  Mission_Outcome like 'Success%'
```

```
 * sqlite:///my_data1.db
Done.
```

[93]:

success
100

[95]:
```
%%sql select count(Mission_Outcome) as fail
from SPACEXTABLE where  Mission_Outcome like 'Failure%'
```

```
 * sqlite:///my_data1.db
Done.
```

[95]:

fail
1

EDA with SQL Results

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

Task 8

List the names of the booster_versions which have carried the maximum payload ma

```
%%sql select Booster_Version
from SPACEXTABLE
where  PAYLOAD_MASS__KG_ = (select Max(PAYLOAD_MASS__KG_ from SPACEXTAB
```

```
 * sqlite:///my_data1.db
(sqlite3.OperationalError) near "from": syntax error
[SQL: select Booster_Version
from SPACEXTABLE
where  PAYLOAD_MASS__KG_ = (select Max(PAYLOAD_MASS__KG_ from SPACEXTAB
(Background on this error at: http://sqlalche.me/e/e3q8)
```

```
%sql select * from SPACEXTABLE limit 5;
```

```
 * sqlite:///my_data1.db
Done.
```

Date	Time (UTC)	Booster_Version	Launch_Site	Paylo
2010-06-04	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualificati U
2010-12-08	15:43:00	F9 v1.0 B0004	CCAFS LC-40	Dragon demo flight C1, t CubeSats, barrel of Broue chee
2012-05-22	7:44:00	F9 v1.0 B0005	CCAFS LC-40	Dragon demo flight
2012-10-08	0:35:00	F9 v1.0 B0006	CCAFS LC-40	SpaceX CRS
2013-03-01	15:10:00	F9 v1.0 B0007	CCAFS LC-40	SpaceX CRS

EDA with SQL Results

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.

ask 9

st the records which will display the month names, failure landing_outcomes in drone ship ,booster versions, launch_site for the

ote: SQLLite does not support monthnames. So you need to use substr(Date, 6,2) as month to get the months
ear.

```
sql select substr(Date, 6,2) as month,substr(Date,0,5)='2015' as year
om SPACEXTABLE ;
```

sqlite:///my_data1.db
ne.

onth	year
06	0
12	0
05	0
10	0
03	0
09	0
12	0
01	0
04	0
07	0
08	0
09	0
09	0
01	1
02	1
03	1
04	1
04	1
06	1
12	1
01	0

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EDA with SQL Results

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.

Task 10

Rank the count of landing outcomes (such as Failure (drone ship) or Success (ground

```
3]: %%sql select * from SPACEXTABLE
    where Date between '2010-06-04'and '2017-03-20'
    group by Landing_Outcome;
```

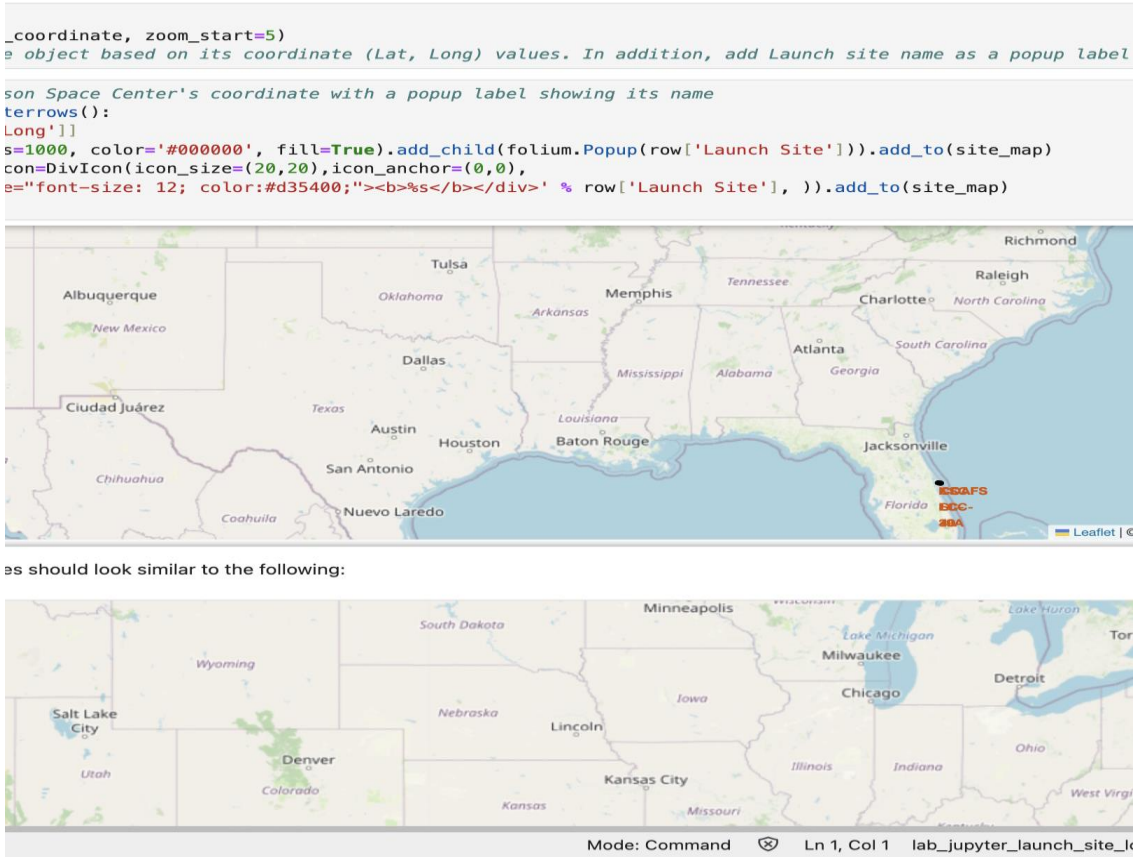
```
 * sqlite:///my_data1.db
Done.
```

3]:

Date	Time (UTC)	Booster_Version	Launch_Site	Payload
2014-04-18	19:25:00	F9 v1.1	CCAFS LC-40	SpaceX CRS-3
2015-01-10	9:47:00	F9 v1.1 B1012	CCAFS LC-40	SpaceX CRS-5
2010-06-04	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit
2012-05-22	7:44:00	F9 v1.0 B0005	CCAFS LC-40	Dragon demo flight C2
2015-06-28	14:21:00	F9 v1.1 B1018	CCAFS LC-40	SpaceX CRS-7
2016-04-08	20:43:00	F9 FT B1021.1	CCAFS LC-40	SpaceX CRS-8
2015-12-22	1:29:00	F9 FT B1019	CCAFS LC-40	OG2 Mission 2 11 Orbcomm-OG2 satellites
2013-09-29	16:00:00	F9 v1.1 B1003	VAFB SLC-4E	CASSIOPE

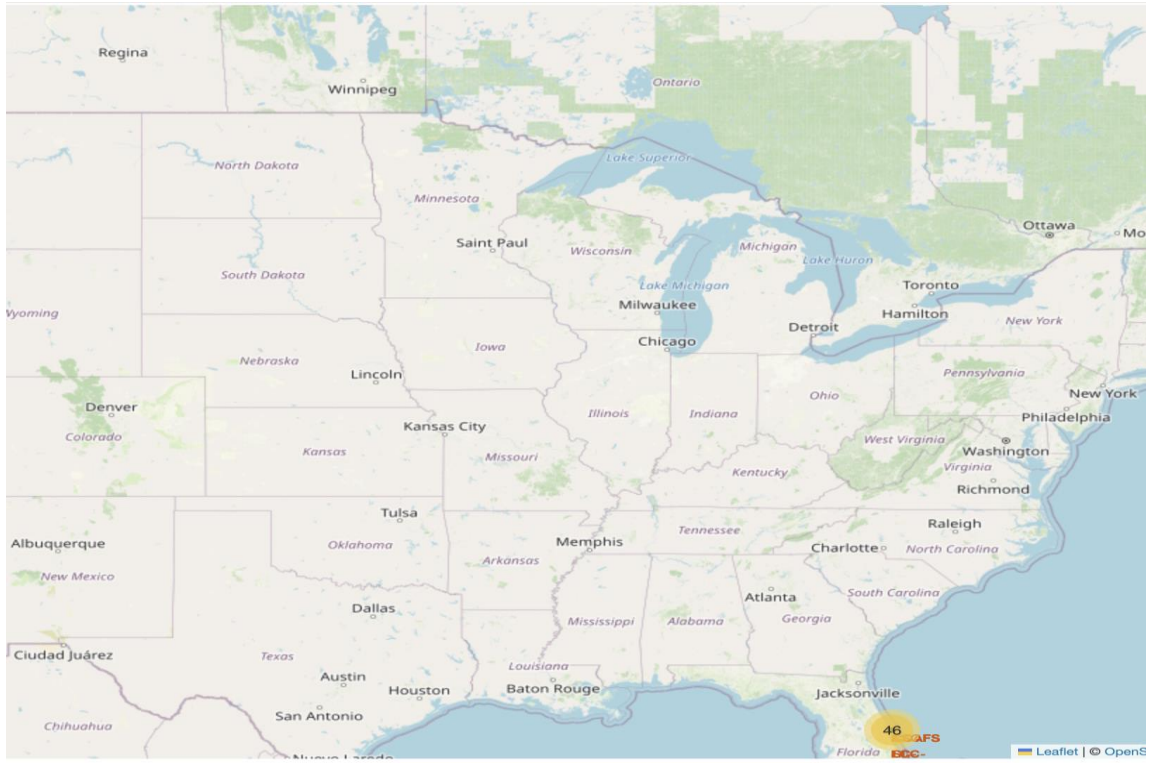
Interactive Map with Folium Results

Mark all launch sites on a map



Interactive Map with Folium Results

Mark the success/failed launches for each site on the map



reenshots:

Interactive Map with Folium Results

Calculate the distances between a launch site to its proximities

[19]:

```
# Create and add a folium.Marker on your selected closest coastline point on the map
# Display the distance between coastline point and launch site using the icon property
# for example
# distance_marker = folium.Marker(
#    coordinate,
#    icon=DivIcon(
#        icon_size=(20,20),
#        icon_anchor=(0,0),
#        html='<div style="font-size: 12; color:#d35400;"><b>%s</b></div>' % "{:10.2f} KM".
#        )
#    )
# Given coordinates
launch_site_lat = 28.56341
launch_site_lon = -80.57678

# Closest coastline point
coastline_lat = 28.56342
coastline_lon = -80.56744

# Calculating distance
distance_coastline = calculate_distance(launch_site_lat, launch_site_lon, coastline_lat, co

# Create a map centered on the launch site
m = folium.Map(location=[launch_site_lat, launch_site_lon], zoom_start=15)

# Create a marker for the launch site
folium.Marker(
    location=[launch_site_lat, launch_site_lon],
    icon=folium.Icon(color='red', icon='rocket', prefix='fa')
).add_to(m)

# Create a marker for the coastline point and add the distance
distance_marker = folium.Marker(
    location=[coastline_lat, coastline_lon],
    icon=DivIcon(
        icon_size=(20, 20),
        icon_anchor=(0, 0),
        html='<div style="font-size: 20; color:#d35400;"><b>%s</b></div>' % "{:10.2f} KM".f
    )
)

distance_marker.add_to(m)
```

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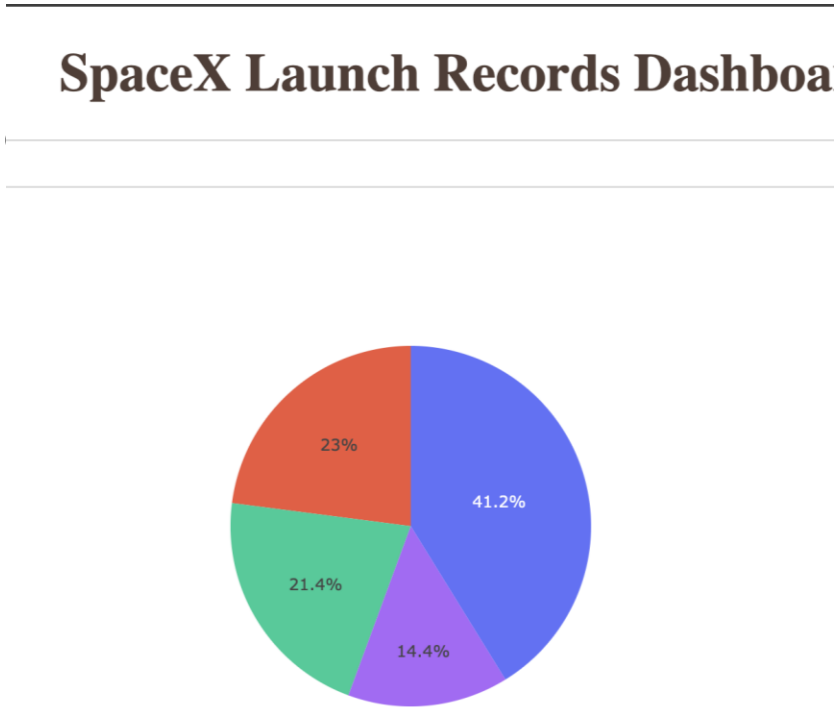
Plotly Dash dashboard Results

From Plotly dashboard we find that is the most su
lunches sites.

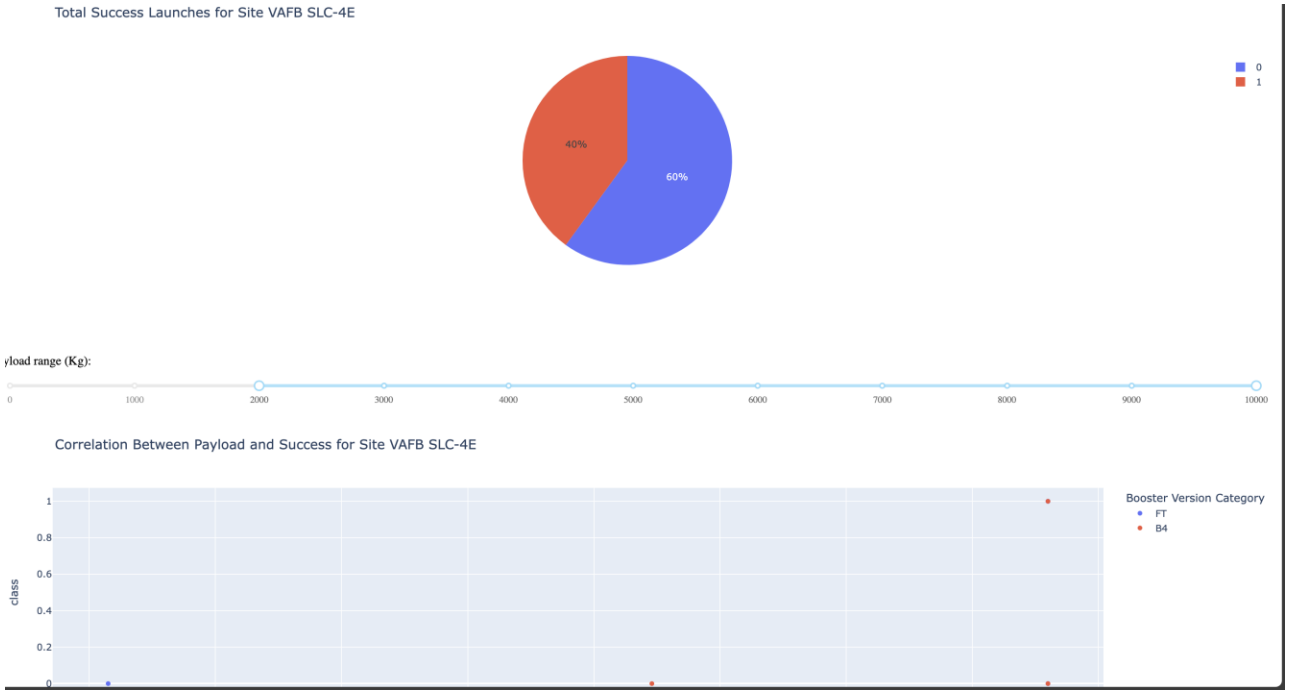


Plotly Dash dashboard Results

- At 1000 kg Payloads we find all Booster verisions have successfful lunches.
- For CCAFS LC-40 we find when we increase Payload only the booster FT has successful lunches.

Plotly Dash dashboard Results

For VAFB SLC-4E we
find when we increase Payload no one has successful lunches



Predictive Analysis (classification) Results

We use Grid Search which is a hyperparameter tuning technique used in machine learning to find the best combination of hyperparameters for a given model. Hyperparameters are variables that are not learned by the model, but rather set by the user before training.

Predictive Analysis (classification) Results

First machine learning model is logistic regression. We Create a logistic regression object then create a GridSearchCV object logreg_cv with cv = 10. Fit the object to find the best parameters from the dictionary parameters.after that We output the GridSearchCV object for logistic regression. We display the best parameters using the data attribute best_params_ and the accuracy on the validation data using the data attribute best_score_. Then we calcaulate thhe accuracy of logistic Regression model by score function.

[19]: (18,)

TASK 4

Create a logistic regression object then create a GridSearchCV object `logreg_cv` with cv = 10. Fit the object to find the best parameters from the dictionary `parameters`.

[20]:
```
parameters ={'C':[0.01,0.1,1],
             'penalty':['l2'],
             'solver':['lbfgs']}
```

[21]:
```
parameters ={"C":[0.01,0.1,1],'penalty':['l2'], 'solver':['lbfgs']}# l1 lasso l2 ridge
lr=LogisticRegression()
```

[24]:
```
logreg_cv = GridSearchCV(lr,parameters, cv=10)
logreg_cv.fit(X_train, Y_train)
```

[24]:
GridSearchCV
estimator: LogisticRegression
LogisticRegression

We output the `GridSearchCV` object for logistic regression. We display the best parameters using the data attribute `best_params_` and the accuracy on the validation data using the data attribute `best_score_`.

[25]:
```
print("tuned hpyerparameters :(best parameters) ",logreg_cv.best_params_)
print("accuracy :",logreg_cv.best_score_)
```

```
tuned hpyerparameters :(best parameters)  {'C': 0.01, 'penalty': 'l2', 'solver': 'lbfgs'}
accuracy : 0.8464285714285713
```

Predictive analysis (classification) Results

- Second machine learning model is support vector machine. We Create a support vector machine object then create a GridSearchCV object svm_cv with cv - 10. Fit the object to find the best parameters from the dictionary parameters.after that We output the GridSearchCV object for logistic regression. We display the best parameters
using the data attribute best_params_ and the accuracy on the validation data using the
data attribute best_score_. Then we calcaulate thhe accuracy of support vector machinemodel by score function.

TASK 6 ¶

Create a support vector machine object then create a `GridSearchCV` object `svm_cv`

[34]:
```
parameters = {'kernel':('linear', 'rbf','poly','rbf', 'sigmoid'),
              'C': np.logspace(-3, 3, 5),
              'gamma':np.logspace(-3, 3, 5)}
svm = SVC()
```

[37]:
```
svm_cv = GridSearchCV(svm,parameters,cv=10)
svm_cv.fit(X_train, Y_train)
```

[37]:
GridSearchCV
estimator: SVC
SVC

[38]:
```
print("tuned hpyerparameters :(best parameters) ",svm_cv.best_params_)
print("accuracy :",svm_cv.best_score_)
```

```
tuned hpyerparameters :(best parameters)  {'C': 1.0, 'gamma': 0.0316227
accuracy : 0.8482142857142856
```

TASK 7

Calculate the accuracy on the test data using the method `score`:

[60]:
```
score_svm_cv = svm_cv.score(X_train, Y_train)
score_svm_cv
```

[60]:
```
0.8888888888888888
```

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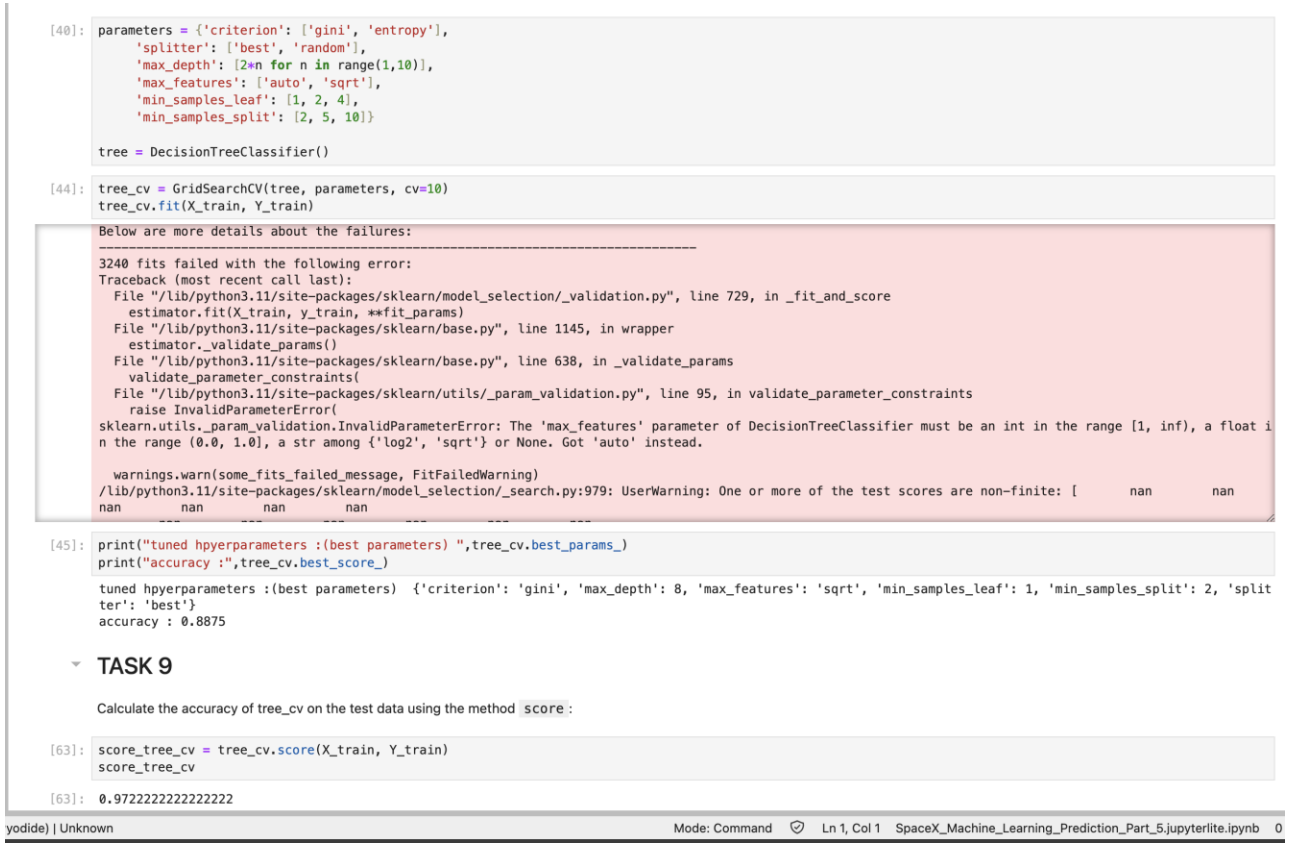
Predictive analysis (classification) Results

Third machine learning model is decision tree machine. We Create a decision tree classifier object then create a GridSearchCV object tree_cv with cv = 10. First find the best parameters from the dictionary parameters.after that We output the GridSearch CV object for decision tree. We display the best parameters using the data attribute best_params_ and the accuracy on the validation data using the data attribute best_score_. Then we calcaulate the accuracy of decision tree model by score function.



[40]:
```
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]}

tree = DecisionTreeClassifier()
```

[44]:
```
tree_cv = GridSearchCV(tree, parameters, cv=10)
tree_cv.fit(X_train, Y_train)
```

```
Below are more details about the failures:
--------------------------------------------------------------------------------
3240 fits failed with the following error:
Traceback (most recent call last):
  File "/lib/python3.11/site-packages/sklearn/model_selection/_validation.py", line 729, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/lib/python3.11/site-packages/sklearn/base.py", line 1145, in wrapper
    estimator._validate_params()
  File "/lib/python3.11/site-packages/sklearn/base.py", line 638, in _validate_params
    validate_parameter_constraints(
  File "/lib/python3.11/site-packages/sklearn/utils/_param_validation.py", line 95, in validate_parameter_constraints
    raise InvalidParameterError(
sklearn.utils._param_validation.InvalidParameterError: The 'max_features' parameter of DecisionTreeClassifier must be an int in the range [1, inf), a float i
n the range (0.0, 1.0], a str among {'log2', 'sqrt'} or None. Got 'auto' instead.

  warnings.warn(some_fits_failed_message, FitFailedWarning)
/lib/python3.11/site-packages/sklearn/model_selection/_search.py:979: UserWarning: One or more of the test scores are non-finite: [       nan        nan
nan        nan        nan        nan
```

[45]:
```
print("tuned hpyerparameters :(best parameters) ",tree_cv.best_params_)
print("accuracy :",tree_cv.best_score_)
```

```
tuned hpyerparameters :(best parameters)  {'criterion': 'gini', 'max_depth': 8, 'max_features': 'sqrt', 'min_samples_leaf': 1, 'min_samples_split': 2, 'split
ter': 'best'}
accuracy : 0.8875
```

TASK 9

Calculate the accuracy of tree_cv on the test data using the method `score`:

[63]:
```
score_tree_cv = tree_cv.score(X_train, Y_train)
score_tree_cv
```

[63]:
```
0.9722222222222222
```

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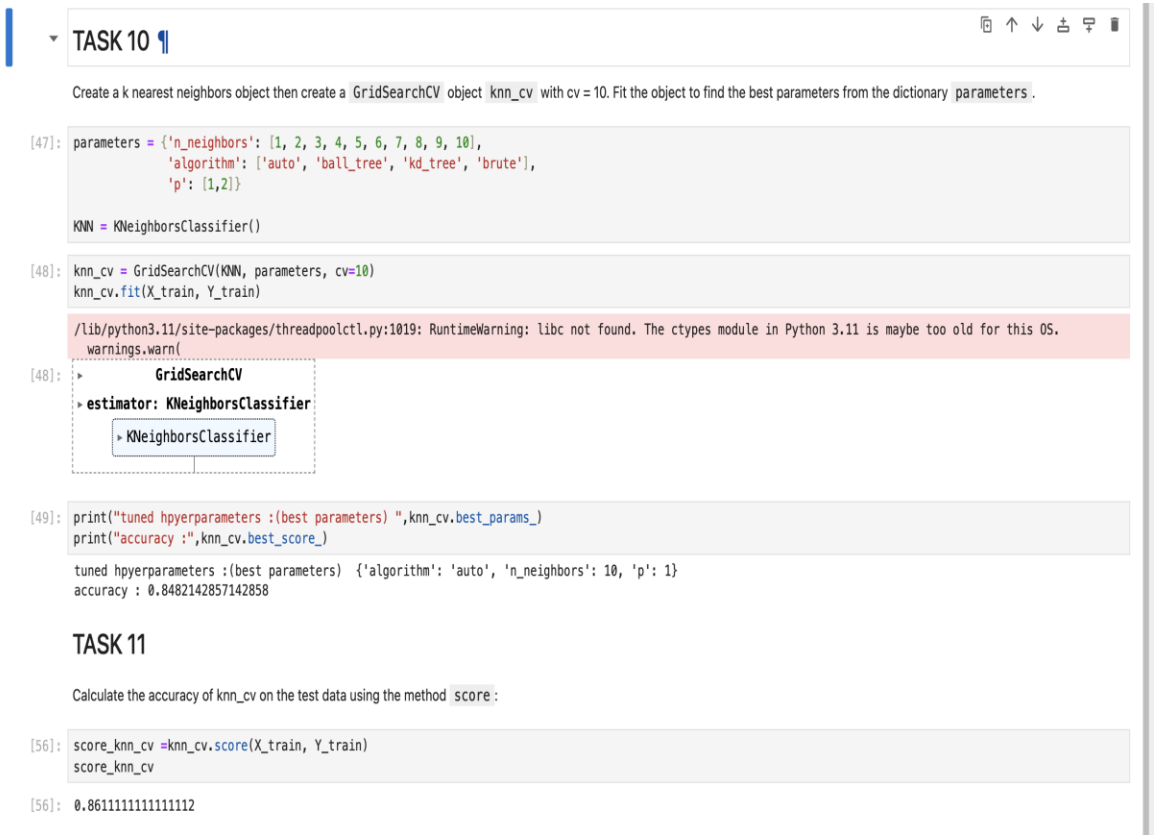
Predictive analysis (classification) Results

- Last machine learning model is k nearest neighbors machine. Create a k nearest neighbors object then create a GridSearchCV object knn_cv with cv = 10. Fit the object to find the best parameters from the dictionary parameters.after that We output the Grid SearchCV object for k nearest neighbors . We display the best parameters using the data attribute best_params_ and the accuracy on the validation data using the data attribute best_score_. Then we calcaulate the accuracy of decision tree model by score function.



TASK 10 ¶

Create a k nearest neighbors object then create a `GridSearchCV` object `knn_cv` with cv = 10. Fit the object to find the best parameters from the dictionary `parameters`.

[47]:
```
parameters = {'n_neighbors': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10],
              'algorithm': ['auto', 'ball_tree', 'kd_tree', 'brute'],
              'p': [1,2]}

KNN = KNeighborsClassifier()
```

[48]:
```
knn_cv = GridSearchCV(KNN, parameters, cv=10)
knn_cv.fit(X_train, Y_train)
```

```
/lib/python3.11/site-packages/threadpoolctl.py:1019: RuntimeWarning: libc not found. The ctypes module in Python 3.11 is maybe too old for this OS.
  warnings.warn(
```

[48]:
```
GridSearchCV
estimator: KNeighborsClassifier
KNeighborsClassifier
```

[49]:
```
print("tuned hpyerparameters :(best parameters) ",knn_cv.best_params_)
print("accuracy :",knn_cv.best_score_)
```

```
tuned hpyerparameters :(best parameters)  {'algorithm': 'auto', 'n_neighbors': 10, 'p': 1}
accuracy : 0.8482142857142858
```

TASK 11

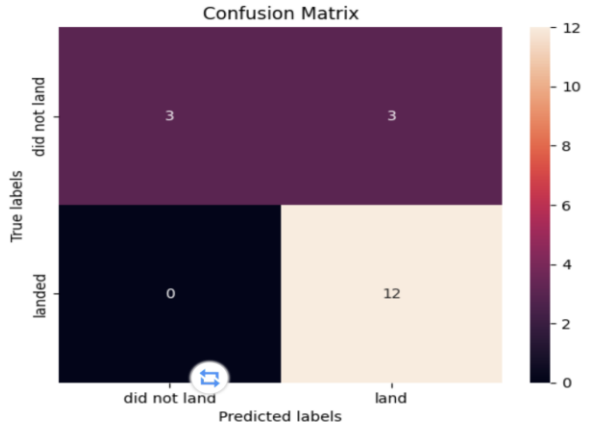
Calculate the accuracy of knn_cv on the test data using the method `score`:

[56]:
```
score_knn_cv =knn_cv.score(X_train, Y_train)
score_knn_cv
```

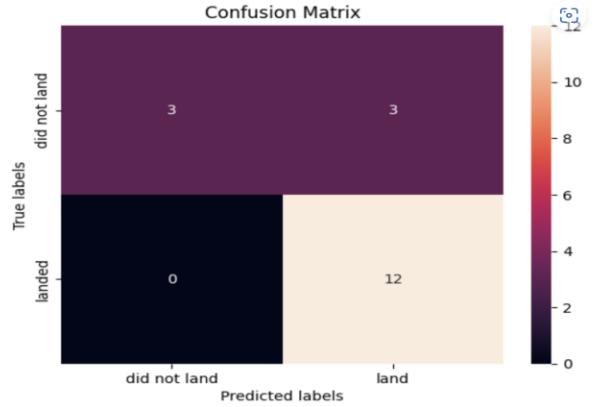
[56]:
```
0.8611111111111112
```

Predictive analysis (classification) Results

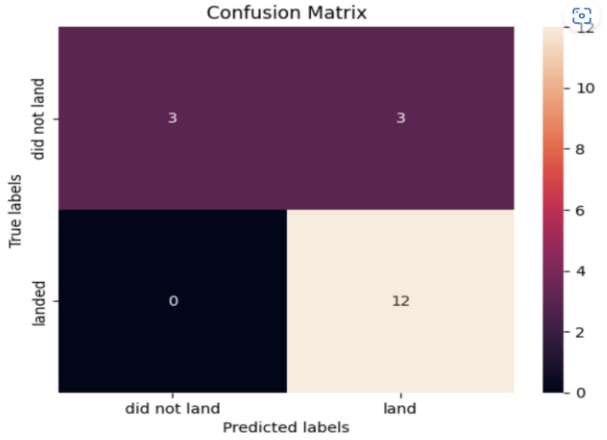
Here is the confision matrix for all machine learning models



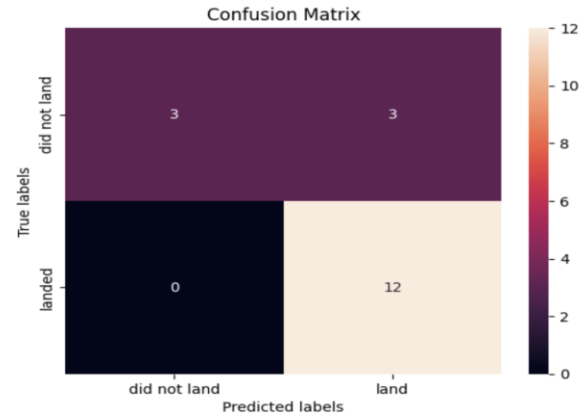
Support Vector Machine Confusion Matrix



Logistic Regression Confusion Matrix



Confusion Matrix k-Nearest Neighbors



Decison Tree Confusion Matrixx

Conclusion

Conclusion

- Lunches sites:
- CCAFS LC-40 has 26.9% successful lunches
- VAFB SLC-4E has 40% successful lunches
- KSC LC-39A has 23.1% successful lunches
- CCAFS SLC-40 has 42.9% successful lunches
- Booster Version:
- At CCAFS LC-40 only FT Booster Version has successful lunch
- At VAFB SLC-4E only B4 Booster Version has successful lunch
- At KSC LC-39A only FT Booster Version has successful lunch
- At CCAFS LC-40 only FT Booster Version has successful lunch

Conclusion

- PayloadMass:
- When we increase Payload, FT booster Version has successful luunch.
- Model Performance:
- When we calculate the accuracy of models by score function we find that the decision tree has the most accurate model which is equal to 0.97


Thank You