

WINNING SPACE RACE WITH DATA SCIENCE

**A Thesis Submitted
In Partial Fulfilment of the Requirements
for the Degree of**

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by

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Training Certificate



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TO WHOM IT MAY CONCERN

This is to certify that MR. SACHIN RATHI (University Roll No - 190029014029) S/o. Mr. DEVENDRA RATHI, Masters of Computer Application Student from KIET Ghaziabad has successfully completed the project at our organization from 15TH Feb'22 to 13th May'22. Under training period he has worked on the project entitled "Winning Space Race" using Data Science Technology under the guidance of our Technical Head Mr. Ritesh. During this project he was an active member of the team working on the project. The work carried by him was satisfactory and wish him all the best for his future assignments.



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Winning Space Race with Data Science

Sachin Rathi

ABSTRACT

This project will give you a taste of what data scientists go through in real life when working with real datasets. You will assume the role of a Data Scientist working for a start-up intending to compete with SpaceX, and in the process follow the Data Science methodology involving data collection, data wrangling, exploratory data analysis, data visualization, model development, model evaluation, and reporting your results to stakeholders.

In this project, we will predict if the Falcon 9 first stage will land successfully.

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. In this module, you will be provided with an overview of the problem and the tools you need to complete the course.



Figure 1 Winning Space Race with Data Science

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Chapter 1

INTRODUCTION

1.1 DESCRIPTION OF THE PROJECT

The commercial space age is here, companies are making space travel affordable for everyone. Virgin Galactic is providing suborbital spaceflights. Rocket Lab is a small satellite provider. Blue Origin manufactures sub-orbital and orbital reusable rockets. Perhaps the most successful is SpaceX. SpaceX's accomplishments include Sending spacecraft to the International Space Station. Starlink, a satellite internet constellation providing satellite Internet access. Sending manned missions to Space. One reason SpaceX can do this is the rocket launches are relatively inexpensive. 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.



Figure 2 Fail.gif



Figure 3 Success.gif

In this capstone, I take the role of a data scientist working for a new rocket company. Space Y that would like to compete with SpaceX founded by Billionaire industrialist Alon Musk. My job is to determine the price of each launch. I must do this by gathering information about Space X and creating dashboards for my team. I also determine if SpaceX will reuse the first stage. Instead of using rocket science to determine if the first stage will land successfully, I will train a machine learning model and use public information to predict if SpaceX will reuse the first stage.

CHAPTER 2

Literature Review

2.1. Abstract:

Since the evolution of internet, the amount of data produced each minute is increasing substantially. To manage this data, there has to be some mechanism. Thousands of terabytes produced each year need to be stored securely and should be accessible easily, this needs high amount of research and development. This new concern has given birth to field known as “data science” and people “data scientist”. Today data scientists are working hard to develop new solutions to process and store large amount of data using new techniques. Another major concern today is efficient use of available energy resources, data science helps immensely to predict the usage of resources and minimizing the wastage. This paper is about data science, current and future development in this field. The primary focus is on literature review of data science and various applications of data science.

2.2. Introduction:

The word “Science” is defined by Oxford as “it is a systematic enterprise that builds and organizes knowledge in the form of testable explanations and predictions about the universe” (Heilbron, 2003). Considering this definition data science can be defined as organizing data knowledge that can be used for experiments and prediction. The need for data science developed due to the immense increase in the amount of raw data such as images, text, video and others. As shown in the figure compared to 2012 the amount of data produced in 2015 is significantly high and in order to organize and use this data efficiently we need data science and data scientist. Source: (Dhar, 2013) Every field is contributing to this ever increasing data such as Engineering, mining, healthcare, hospitality, energy etc. Data scientists are developing various algorithms and techniques in order to process and analyze this data and make the best use out of it. Previously health industry used hard paper to store data regarding patients and other medical issues. But the new trend has helped doctors to store this data in electronic form (Raghupathi & Raghupathi, 2014). Space

exploration has produced a large amount of data considering the recent space missions, data scientists have also helped to store this data and use it for prediction to carry out further missions. Implementing business logics and strategies need data analysis and predictions which can be now easily done by the use of prediction algorithms. Energy companies are using data prediction algorithms to manage the energy production based on demands and supply. This prediction has aided to use the available energy efficiently. In coming years machines will have the ability to predict and generate the required resource as per the supply and demand. The current upcoming technology Artificial Intelligence is also being helped tremendously by the use of data mining and prediction algorithms.

2.3. Data Science:

History and Present As a method of prediction previously many years statistics was used. Until recent years these statistics have been transformed into data analysis. Ten to twenty years ago this data analysis was further urged to develop into a new stream known as data science. As maximum amount of data was stored electronically extracting and analysing it itself became a science. Around fifty years ago Jhon Tucky evolved statistics into the term data analysis (Donoho, 2015). Later around twenty years ago this data analysis was further evolved into new stream known as data science by John Chambers, Bill Cleveland and Leo Breiman (Donoho, 2015). Data Mining has been the oldest form of technique for data science. Various algorithms are being developed to aid this process. The evolution of these algorithms' dates back to 1957. In 2006 IEEE announced top 10 algorithms used for data mining (Wu et al., 2007):

- C4.5 and beyond
- The k-means algorithm
- Support vector machines
- The Apriori algorithm
- The EM algorithm
- PageRank

- AdaBoost
- kNN: k-nearest neighbor classification
- Naive Bayes
- CART: Classification and Regression Trees

All these algorithms have been widely used in all the fields. Although these algorithms do have some limitations and cannot be implemented in all the fields but still are helpful in many. Presently with the help of these algorithms various fields are using data mining and data science techniques to grow and aid their own field. One of the most efficient field using data science techniques is the medical field. The main concern for medical industry is analyzing supply and demand. In order to regulate this scenario researcher are using big data and data sciences. Prediction based cures for many illnesses are now available for many patients. Researchers at Tamil Nadu University have developed genetic algorithm to detect diabetes. This algorithm uses data mining algorithm for accuracy and prediction. Fuzzy logics and neural networks are used to learn more about the disease (S, Tamilarasi, & Pravin Kumar, 2012).

Climate control department also is using prediction methods to predict the climate changes and develop prevention measures. These algorithms have been successfully implemented in many countries and produced great results. One of the main algorithm used is the clustering and k-means algorithms. These algorithms have given most accurate results up till now. Also various new algorithms are developed recently. Researchers have developed specialized pattern-mining algorithms to overcome previous issues in climate anomaly detection (James H et al., 2014). In order to detect temperature changes for a specific area it is vital to represent data in gridded form in which each grid represents a location. “The NCEP/NCAR Re analysis from the National Centers for Environmental Protection and the National Center for Atmospheric Research, has a 10,000-gridpoint resolution. Each grid point has 12 monthly observations for each of the 30 years, and numerous variables such as wind and rainfall might impact temperatures in Brazil” (James H et al., 2014). As per James H et al these technology has helped immensely to predict the data for climate changes accurately.

2.4. Future scope:

Taking into account all this current research in each field data science technology has helped mankind in many ways. Still this field needs a lot of exploration and researchers are continuously doing it. One of the major points for successful data analysis is to obtain the P-values within the data set, today it is one of the major issue. Strategies such as manual extraction, web cleaning and data cleaning are used but these methodologies don't produce accurate results. Hence, we still have to wait until new methods are introduced to obtain appropriate values and develop good computational data sets. Donoho, D. and Matan Gavish have proposed various new methods to extract data which have given better results up till now. Donoho and Matan have proposed to use Verifiable Computational Result, cloud computing and cloud storage to record and store values and results, also retrieving those with help of URL's (Donoho, 2015).

Many researchers are also developing models for data science useful in business. One such example is BDS model developed by Russell Newman and others. This business model is developed and under experimentation for various business logics. Various big companies are now interested in data science to have the user databases and other business logics. The BDS model has following basic steps to get the dataset.

Algorithm: (Newman, Chang, Walters, & Wills, 2016).

- Collect data. Actual metrics to be derived from model.
- Run analysis to establish a quantified benchmark for the dot-com bubble period.
- Run the same analysis on a subsequent period.
- a Compare results for this period to the benchmark created in step 2. Any similarities/differences in the results may be indicative of the presence/absence of a bubble state.
- Return to step 3 for additional time periods (optional)

2.5. Conclusion:

These new developments in the field of data science will change the world and help humans to predict the data usage. The old methods of statistical analysis will not be

completely overpowered but still these new techniques will be more efficient than the old ways. Considering the progress speed there will be accurate and efficient techniques in next few years.

CHAPTER 3

Feasibility Study

The Feasibility Study determines the likelihood of a project's success. It delivers a single measure of this probability but comprises two independent evaluations. The first is the probability of Technical Success — $P(T)$. It focuses on the project prototype or a proof of concept. The second determines the probability of Commercial Success — $P(C)$. It evaluates the likelihood that the prototype can be scaled to production and adopted by the company or its customers. The product of these two measures is the Probability of Success: $P(S) = P(T)P(C)$. We treat each measure as an independent variable. When evaluating the probability of commercial success, we assume that the prototype has already been successfully developed.

Before unpacking the derivation for each score I should clarify that our approach is seldom static. Most data science and research projects do share characteristics and benefit from a consistent approach to risk assessment. However, it is often necessary to adapt the details of an assessment to the organizational peculiarities of a project, and to take into account the nuances of industry verticals. Please consider, as we must with every project, what fits your needs. Do so with the intent to remain objective and to avoid the temptation to adjust the parameters of an assessment so that your favorite projects return a better, but inflated, score.

3.1. Technical Success Evaluation:

Estimating the probability of technical success — designated as $P(T)$ from now on — is an exercise in identifying the salient risk factors, then scoring each individually on a consistent scale before plugging the values into a mathematical function. Easy. But what exactly is “technical success”?

The definition of $P(T)$ is as follows: a likelihood that, given existing data, available technologies, required research, and development, the prototype will be completed

and will perform the defined function in a curated laboratory or constrained production environment. $P(T)$ is given as a percentage.

The definition is important as it sets expectations for the deliverables. We limit the scope of $P(T)$ to the prototype designed to test the technologies and convince a moderate sceptic that the approach works. The tests should run in a limited but representative case and use a vetted data set. Why the limitations? They decrease the time needed to develop the prototype without compromising the evaluation. They reduce the chance of misalignment with final goals by facilitating minor, continual adjustments. They reduce the risk

of investment. At the same time, the process still validates the difficult components and algorithms required for the production solution.

We defined the specifics of the prototype in the prior engagement stage: Concept Development. This is the subject for a different article, and we will assume that our prototype has a clear purpose, associated user persona, definition of function, and unacceptable failure modes.

Now, we evaluate what it takes to build the prototype. I will compress the process into a series of questions which elicit investigation and result in a score from 1 to 10, where 1 is a categorical no and 10 is a categorical yes. We group the evaluation into four equally weighted categories: Data, Technology, Business, and Expertise.

Data:

1. We have all required data features
2. The data for each feature is complete
3. The data for each feature is clean and accurate
4. We have ability to synthetically simulate sample data
5. We can access data without bureaucratic roadblocks

Technology:

6. The Technology Readiness Level (TRL) for the majority of the required technology. (See NASA https://www.nasa.gov/directorates/heo/scan/engineering/technology/technology_readiness_level)
7. Lowest TRL of an individual required component
8. We have access to source-code or libraries for a related solution
9. We have access to comprehensive documentation for the low TRL components.
10. We have the computational capacity to achieve adequate results
11. We have a clear path to validate the correctness of the result

Business:

12. The project has a strong internal champion
13. The project has a strong internal ROI
14. The project team has a defined charter
15. The project has an adequate budget

Expertise:

16. Client has an internal subject matter expert
17. The team (Ordinal Science) has the exact alignment of expertise with the low TRL components
18. The team has successfully concluded research and prototype development in a conceptually similar space
19. The team has access to external resources available for consulting on low TRL components
20. The team is granted a degree of independence during the initial research phase

We assign a score to each of the 20 parameters, then plug the numbers into the formula we developed. We call the resulting number the “ORA Score” — Ordinal Risk Assessment Score.

$$P(T) = \prod_{i=0}^N \frac{\ln(\hat{s}_i + C)}{\ln(S_{max} + C)}, \text{ where}$$

$$\hat{s}_i = S_{max} - \lfloor (w_i * (S_{max} - s_i)) \rfloor$$

ORA Score

S is an array of individual parameter scores, where s is an integer between 1 and 10

N is a number of parameters, in our case $N = 20$

C is a compression coefficient, $C = aN$, where $a = 3$ (empirically chosen)

W is an array of parameter weights that determine the criticality of each parameter, where s is an integer between 1 and 6. $w = 6$ for a single parameter when $s = 1$ will have an effect of suppressing the $P(T)$ below 0.5.

w for all W is the safest, unless the reasons for particular weights are well understood. If you said “Huh?” to the above, no worries — give us a call and we will do the Feasibility assessment for you. That is our function. If you followed along then a word of caution on the weights. They matter very much and must make sense in the context of your business. They are not equal to 1 for all features all the time. How we derive our weight vectors is a bit of a trade secret, but with much experimentation you may arrive at a reasonable set for your context.

The primary purpose of defining the $P(T)$ is to decide whether to continue to the next phase. What is the right threshold for moving forward? I don’t know. We generally gate our projects at 70% likelihood of technical success, but the context matters as well as the risk tolerance of the client. The proper threshold should be determined by a business discussion with stakeholders.

Chapter 4

Data Collection and Wrangling

4.1. Collecting the Data via API:

SpaceX Falcon 9 first stage Landing Prediction:

Lab 1: Collecting the data

In this capstone, we will predict if the Falcon 9 first stage will land successfully. 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. In this lab, you will collect and make sure the data is in the correct format from an API. The following is an example of a successful and launch.

Several examples of an unsuccessful landing are shown here:

Most unsuccessful landings are planned. Space X performs a controlled landing in the oceans.

Objectives:

In this lab, you will make a get request to the SpaceX API. You will also do some basic data wrangling and formatting.

- Request to the SpaceX API
- Clean the requested data

Import Libraries and Define Auxiliary Functions:

We will import the following libraries into the lab

In [1]:

```
# Requests allows us to make HTTP requests which we will use to get data from an API
import requests
# Pandas is a software library written for the Python programming language for data manipulation and analysis.
import pandas as pd
# NumPy is a library for the Python programming language, adding support for large, multi-dimensional arrays and matrices, along with a large collection of high-level mathematical functions to operate on these arrays
import numpy as np
# Datetime is a library that allows us to represent dates
import datetime

# Setting this option will print all columns of a dataframe
pd.set_option('display.max_columns', None)
# Setting this option will print all of the data in a feature
pd.set_option('display.max_colwidth', None)
```

Below we will define a series of helper functions that will help us use the API to extract information using identification numbers in the launch data.

From the rocket column we would like to learn the booster's name.

In [2]:

```
# Takes the dataset and uses the rocket column to call the API and append the data to the list
def getBoosterVersion(data):
    for x in data['rocket']:
        response =
requests.get("https://api.spacexdata.com/v4/rockets/"+str(x)).json()
        BoosterVersion.append(response['name'])
```

From the launchpad we would like to know the name of the launch site being used, the longitude, and the latitude.

In [3]:

```
# Takes the dataset and uses the launchpad column to call the API  
and append the data to the list  
def getLaunchSite(data):  
    for x in data['launchpad']:  
        response =  
requests.get("https://api.spacexdata.com/v4/launchpads/"+str(x)).json()  
  
        Longitude.append(response['longitude'])  
        Latitude.append(response['latitude'])  
        LaunchSite.append(response['name'])
```

From the payload we would like to learn the mass of the payload and the orbit that it is going to.

In [4]:

```
# Takes the dataset and uses the payloads column to call the API and  
append the data to the lists  
def getPayloadData(data):  
    for load in data['payloads']:  
        response =  
requests.get("https://api.spacexdata.com/v4/payloads/"+load).json()  
  
        PayloadMass.append(response['mass_kg'])  
        Orbit.append(response['orbit'])
```

From cores we would like to learn the outcome of the landing, the type of the landing, number of flights with that core, whether grid fins were used, whether the core is reused, whether legs were used, the landing pad used, the block of the core which is a number used to separate version of cores, the number of times this specific core has been reused, and the serial of the core.

In [5]:

```
# Takes the dataset and uses the cores column to call the API and  
append the data to the lists  
def getCoreData(data):  
    for core in data['cores']:  
        if core['core'] != None:  
            response =  
requests.get("https://api.spacexdata.com/v4/cores/"+core['core']).json()  
  
on()
```



```

        Block.append(response['block'])
        ReusedCount.append(response['reuse_count'])
        Serial.append(response['serial'])
    else:
        Block.append(None)
        ReusedCount.append(None)
        Serial.append(None)
    Outcome.append(str(core['landing_success'])+'
'+str(core['landing_type']))
    Flights.append(core['flight'])
    GridFins.append(core['gridfins'])
    Reused.append(core['reused'])
    Legs.append(core['legs'])
    LandingPad.append(core['landpad'])

```

Now let's start requesting rocket launch data from SpaceX API with the following URL:

In [6]:

```
spacex_url="https://api.spacexdata.com/v4/launches/past"
```

In [7]:

```
response = requests.get(spacex_url)
```

Check the content of the response

In [8]:

```
print(response.content)
```

Task 1: Request and parse the SpaceX launch data using the GET request

To make the requested JSON results more consistent, we will use the following static response object for this project:

In [9]:

```
static_json_url='https://cf-courses-data.s3.us.cloud-object-
storage.appdomain.cloud/IBM-DS0321EN-
SkillsNetwork/datasets/API_call_spacex_api.json'
```

We should see that the request was successful with the 200-status response code

In [10]:

```
response.status_code
```

Out[10]:

```
200
```

Now we decode the response content as a Json using `.json()` and turn it into a Pandas data frame using `.json_normalize()`

In [14]:

```
# Use json_normalize meethod to convert the json result into a dataframe
json_data = requests.get(static_json_url).json()
data=pd.json_normalize(json_data)
```

Using the data frame data print the first 5 rows

In [15]:

```
# Get the head of the dataframe
data.head()
```

You will notice that a lot of the data are IDs. For example, the rocket column has no information about the rocket just an identification number.

We will now use the API again to get information about the launches using the IDs given for each launch. Specifically, we will be using columns rocket, payloads, launchpad, and cores.

In [16]:

```
# 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 payloads in a single rocket.
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)]

```

- From the rocket we would like to learn the booster name
- From the payload we would like to learn the mass of the payload and the orbit that it is going to
- From the launchpad we would like to know the name of the launch site being used, the longitude, and the latitude.
- From cores we would like to learn the outcome of the landing, the type of the landing, number of flights with that core, whether grid fins were used, whether the core is reused, whether legs were used, the landing pad used, the block of the core which is a number used to separate version of cores, the number of times this specific core has been reused, and the serial of the core.

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

In [17]:

```

#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 look at BoosterVersion variable. Before we apply getBoosterVersion the list is empty:

Task 2: Filter the data frame to only include Falcon 9 launches

Finally, we will remove the Falcon 1 launches keeping only the Falcon 9 launches. Filter the data frame using the Booster Version column to only keep the Falcon 9 launches. Save the filtered data to a new data frame called data_falcon9.

In [27]:

```

# Hint data['BoosterVersion']!='Falcon 1'
data_falcon9 = launch_df[launch_df['BoosterVersion'] != 'Falcon 9']
data_falcon9

```

Now that we have removed some values, we should reset the FlightNumber column

In [28]:

```

data_falcon9.loc[:, 'FlightNumber'] = list(range(1,
data_falcon9.shape[0]+1))
data_falcon9

```

Data Wrangling:

We can see below that some of the rows are missing values in our dataset.

In [29]:

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

Out[29]:

```

FlightNumber      0
Date              0
BoosterVersion    0
PayloadMass       0
Orbit             0
LaunchSite        0
Outcome           0

```

```

Flights      0
GridFins     0
Reused       0
Legs         0
LandingPad   0
Block        0
ReusedCount  0
Serial       0
Longitude    0
Latitude     0
dtype: int64

```

Before we can continue, we must deal with these missing values. The Landing Pad column will retain No values to represent when landing pads were not used.

Task 3: Dealing with Missing Values

Calculate below the mean for the Payload Mass using the `mean()`. Then use the mean and the `replace()` function to replace `np.nan` values in the data with the mean you calculated.

In [30]:

```

# Calculate the mean value of PayloadMass column
PayloadMass =
pd.DataFrame(data_falcon9['PayloadMass'].values.tolist()).mean(1)

# Replace the np.nan values with its mean value
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.head()
# Replace the np.nan values with its mean value

```

You should see the number of missing values of the PayloadMass change to zero.

In [31]:

```
data_falcon9.to_csv('dataset_part\1.csv', index=False)
```

Now we should have no missing values in our dataset except for in Landing Pad.

We can now export it to a **CSV** for the next section, but to make the answers consistent, in the next lab we will provide data in a pre-selected date range.

4.2. Collecting the Data via Web Scraping:

Space X Falcon 9 First Stage Landing Prediction:

Web scraping Falcon 9 and Falcon Heavy Launches Records from Wikipedia

In this lab, you will be performing web scraping to collect Falcon 9 historical launch records from a Wikipedia page titled List of Falcon 9 and Falcon Heavy launches

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

Falcon 9 first stage will land successfully

Several examples of an unsuccessful landing are shown here:

More specifically, the launch records are stored in a HTML table shown below:

Objectives:

Web scrap Falcon 9 launch records with Beautiful Soup:

- Extract a Falcon 9 launch records HTML table from Wikipedia
- Parse the table and convert it into a Pandas data frame

First let's import required packages for this lab

In [1]:

```
!pip3 install beautifulsoup4
!pip3 install requests
Requirement already satisfied: beautifulsoup4 in /home/jupyterlab/conda/envs/python/lib/python3.7/site-packages (4.11.1)
Requirement already satisfied: soupsieve>1.2 in /home/jupyterlab/conda/envs/python/lib/python3.7/site-packages (from beautifulsoup4) (2.3.2.post1)
```

Requirement already satisfied: charset-normalizer~=2.0.0 in /home/jupyterlab/conda/envs/python/lib/python3.7/site-packages (from requests) (2.0.12)

In [7]:

```
import sys
```

```
import requests
```

```
from bs4 import BeautifulSoup
```

```
import re
```

```
import unicodedata
```

```
import pandas as pd
```

and we will provide some helper functions for you to process web scraped HTML table

In [8]:

```
def date_time(table_cells):
```

```
    """
```

```
    This function returns the data and time from the HTML table
    cell
```

```
    Input: the element of a table data cell extracts extra row
```

```
    """
```

```
    return [data_time.strip() for data_time in
    list(table_cells.strings)][0:2]
```

```
def booster_version(table_cells):
```

```
    """
```

```
    This function returns the booster version from the HTML table
    cell
```

```
    Input: the element of a table data cell extracts extra row
```

```
    """
```

```
    out=''.join([booster_version for i,booster_version in enumerate(
    table_cells.strings) if i%2==0][0:-1])
```

```
    return out
```

```
def landing_status(table_cells):
```

```
    """
```

```
    This function returns the landing status from the HTML table
    cell
```

```
    Input: the element of a table data cell extracts extra row
```

```
    """
```

```
    out=[i for i in table_cells.strings][0]
```

```

    return out

def get_mass(table_cells):
    mass=unicodedata.normalize("NFKD", table_cells.text).strip()
    if mass:
        mass.find("kg")
        new_mass=mass[0:mass.find("kg")+2]
    else:
        new_mass=0
    return new_mass

def extract_column_from_header(row):
    """
    This function returns the landing status from the HTML table
    cell
    Input: the element of a table data cell extracts extra row
    """
    if (row.br):
        row.br.extract()
    if row.a:
        row.a.extract()
    if row.sup:
        row.sup.extract()

    column_name = ' '.join(row.contents)

    # Filter the digit and empty names
    if not(column_name.strip().isdigit()):
        column_name = column_name.strip()
    return column_name

```

To keep the lab tasks consistent, you will be asked to scrape the data from a snapshot of the List of Falcon 9 and Falcon Heavy launches Wiki page updated on 9th June 2021

In [9]:

```

static_url =
"https://en.wikipedia.org/w/index.php?title=List_of_Falcon_9_and_Fal
con_Heavy_launches&oldid=1027686922"

```


Next, request the HTML page from the above URL and get a response object

TASK 1: Request the Falcon9 Launch Wiki page from its URL

First, let's perform an HTTP GET method to request the Falcon9 Launch HTML page, as an HTTP response.

In [14]:

```
# 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[14]:

```
200
```

Create a BeautifulSoup object from the HTML response

In [15]:

```
# 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 [16]:

```
# Use soup.title attribute
soup.title
```

Out[16]:

```
<title>List of Falcon 9 and Falcon Heavy launches - Wikipedia</title>
>
```

TASK 2: Extract all column/variable names from the HTML table header

Next, we want to collect all relevant column names from the HTML table header

Let's try to find all tables on the wiki page first. If you need to refresh your memory about BeautifulSoup, please check the external reference link towards the end of this lab

In [17]:

```
# 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')
```

Starting from the third table is our target table contains the actual launch records.

In [18]:

```
# Let's print the third table and check its content
first_launch_table = html_tables[2]
print(first_launch_table)
```

Next, we just need to iterate through the <th> elements and apply the provided `extract_column_from_header()` to extract column name one by one

```
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
for row in first_launch_table.find_all('th'):
    names = extract_column_from_header(row)
    column_names.append(names)
```

Check the extracted column names

In [22]:

```
print(column_names)
['Flight No.', 'Date and time ( )', '', 'Launch site', 'Payload', 'P
ayload mass', 'Orbit', 'Customer', 'Launch outcome', '', None, None,
None, None, None, None, None]
```

4.3. Data Wrangling:

Space X Falcon 9 First Stage Landing Prediction:

Lab 2: Data wrangling

Estimated time needed: **60** minutes

In this lab, we will perform some Exploratory Data Analysis (EDA) to find some patterns in the data and determine what would be the label for training supervised models.

In the data set, there are several different cases where the booster did not land successfully. Sometimes a landing was attempted but failed due to an accident; for example, True Ocean means the mission outcome was successfully landed to a specific region of the ocean while False Ocean means the mission outcome was unsuccessfully landed to a specific region of the ocean. True RTLS means the mission outcome was successfully landed to a ground pad False RTLS means the mission outcome was unsuccessfully landed to a ground pad. True ASDS means the mission outcome was successfully landed on a drone ship False ASDS means the mission outcome was unsuccessfully landed on a drone ship.

In this lab we will mainly convert those outcomes into Training Labels with 1 means the booster successfully landed 0 means it was unsuccessful.

Falcon 9 first stage will land successfully

Several examples of an unsuccessful landing are shown here:

Objectives:

Perform exploratory Data Analysis and determine Training Labels

- Exploratory Data Analysis
- Determine Training Labels

Import Libraries and Define Auxiliary Functions:

We will import the following libraries.

In [1]:

```
# Pandas is a software library written for the Python programming  
language for data manipulation and analysis.  
import pandas as pd  
#NumPy is a library for the Python programming language, adding  
support for large, multi-dimensional arrays and matrices, along with  
a large collection of high-level mathematical functions to operate  
on these arrays  
import numpy as np
```

Data Analysis:

Load Space X dataset, from last section.

In [2]:

```
df=pd.read_csv("https://cf-courses-data.s3.us.cloud-object-  
storage.appdomain.cloud/IBM-DS0321EN-  
SkillsNetwork/datasets/dataset_part_1.csv")  
df.head(10)
```

Identify and calculate the percentage of the missing values in each attribute

In [3]:

```
df.isnull().sum()/df.count()*100  
FlightNumber      0.000  
Date              0.000  
BoosterVersion    0.000  
PayloadMass       0.000  
Orbit             0.000  
LaunchSite        0.000  
Outcome           0.000  
Flights           0.000  
GridFins          0.000  
Reused            0.000  
Legs              0.000  
LandingPad        40.625  
Block             0.000
```

```

ReusedCount      0.000
Serial            0.000
Longitude         0.000
Latitude          0.000
dtype: float64

```

Identify which columns are numerical and categorical:

In [4]:

```
df.dtypes
```

Out[4]:

```

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 4E](#) , Vandenberg Air Force Base Space Launch Complex 4E (**SLC-4E**), Kennedy Space Centre Launch Complex 39A **KSC LC 39A** .The location of each Launch Is placed in the column Launch Site

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 on each site:

In [5]:

```
# Apply value_counts() on column LaunchSite
df['LaunchSite'].value_counts()
```

Out[5]:

```
CCAFS SLC 40      55
KSC LC 39A       22
VAFB SLC 4E      13
Name: LaunchSite, dtype: int64
```

Each launch aims to a dedicated orbit, and here are some common orbit types:

- **LEO:** Low Earth orbit (LEO) is an Earth-centred orbit with an altitude of 2,000 km (1,200 mi) or less (approximately one-third of the radius of Earth),^[1] or with at least 11.25 periods per day (an orbital period of 128 minutes or less) and an eccentricity less than 0.25.^[2] Most of the manmade objects in outer space are in LEO [\[1\]](#).
- **VLEO:** Very Low Earth Orbits (VLEO) can be defined as the orbits with a mean altitude below 450 km. Operating in these orbits can provide a number of benefits to Earth observation spacecraft as the spacecraft operates closer to the observation [\[2\]](#).
- **GTO** A geosynchronous orbit is a high Earth orbit that allows satellites to match Earth's rotation. Located at 22,236 miles (35,786 kilometres) above Earth's equator, this position is a valuable spot for monitoring weather, communications and surveillance. Because the satellite orbits at the same speed that the Earth is turning, the satellite seems to stay in place over a single longitude, though it may drift north to south," NASA wrote on its Earth Observatory website [\[3\]](#).
- **SSO (or SO):** It is a Sun-synchronous orbit also called a Heli synchronous orbit is a nearly polar orbit around a planet, in which the satellite passes over any given point of the planet's surface at the same local mean solar time [\[4\]](#).

- **ES-L1** :At the Lagrange points the gravitational forces of the two large bodies cancel out in such a way that a small object placed in orbit there is in equilibrium relative to the centre of mass of the large bodies. L1 is one such point between the sun and the earth [\\[5\]](#) .
- **HEO** A highly elliptical orbit, is an elliptic orbit with high eccentricity, usually referring to one around Earth [\\[6\]](#).
- **ISS** A modular space station (habitable artificial satellite) in low Earth orbit. It is a multinational collaborative project between five participating space agencies: NASA (United States), Ros cosmos (Russia), JAXA (Japan), ESA (Europe), and CSA (Canada) [\\[7\]](#)
- **MEO** Geocentric orbits ranging in altitude from 2,000 km (1,200 mi) to just below geosynchronous orbit at 35,786 kilometres (22,236 mi). Also known as an intermediate circular orbit. These are "most commonly at 20,200 kilometres (12,600 mi), or 20,650 kilometres (12,830 mi), with an orbital period of 12 hours [\\[8\]](#)
- **HEO** Geocentric orbits above the altitude of geosynchronous orbit (35,786 km or 22,236 mi) [\\[9\]](#)
- **GEO** It is a circular geosynchronous orbit 35,786 kilometres (22,236 miles) above Earth's equator and following the direction of Earth's rotation [\\[10\]](#)
- **PO** It is one type of satellites in which a satellite passes above or nearly above both poles of the body being orbited (usually a planet such as the Earth [\\[11\]](#)

some are shown in the following plot:

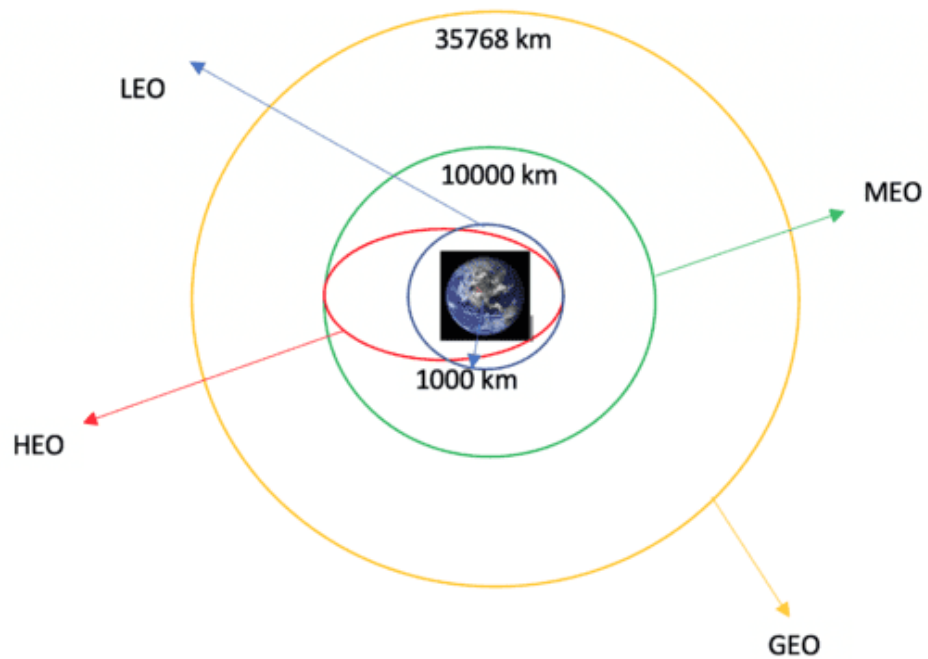


Figure 4: Orbit Information

TASK 2: Calculate the number and occurrence of each orbit

Use the method `.value_counts()` to determine the number and occurrence of each orbit in the column **Orbit**

In [6]:

```
# Apply value_counts on Orbit column
df['Orbit'].value_counts()
```

Out[6]:

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


```
GEO          1
Name: Orbit, dtype: int64
```

TASK 3: Calculate the number and occurrence of mission outcome per orbit type

Use the method `.value_counts()` on the column **Outcome** to determine the number of **landing_outcomes**. Then assign it to a variable `landing_outcomes`.

In [8]:

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

Out[8]:

```
True ASDS      41
None None       19
True RTLS       14
False ASDS       6
True Ocean       5
False Ocean       2
None ASDS        2
False RTLS        1
Name: Outcome, dtype: int64
```

True Ocean means the mission outcome was successfully landed to a specific region of the ocean while False Ocean means the mission outcome was unsuccessfully landed to a specific region of the ocean. True RTLS means the mission outcome was successfully landed to a ground pad False RTLS means the mission outcome was unsuccessfully landed to a ground pad. True ASDS means the mission outcome was successfully landed to a drone ship False ASDS means the mission outcome was unsuccessfully landed to a drone ship. None ASDS and None these represent a failure to land.

In [9]:

```
for i,outcome in enumerate(landing_outcomes.keys()):
    print(i,outcome)
0 True ASDS
1 None None
2 True RTLS
3 False ASDS
```

```
4 True Ocean
5 False Ocean
6 None ASDS
7 False RTLS
```

We create a set of outcomes where the second stage did not land successfully:

In [10]:

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

Out[10]:

```
{'False ASDS', 'False Ocean', 'False RTLS', 'None ASDS', 'None None'
}
```

TASK 4: Create a landing outcome label from Outcome column

Using the Outcome, create a list where the element is zero if the corresponding row in Outcome is in the set bad_outcome; otherwise, it's one. Then assign it to the variable landing_class:

In [11]:

```
# landing_class = 0 if bad_outcome
# landing_class = 1 otherwise
landing_class = []

for row in df['Outcome']:
    if row in bad_outcomes:
        landing_class.append(0)
    else:
        landing_class.append(1)
```

This variable will represent the classification variable that represents the outcome of each launch. If the value is zero, the first stage did not land successfully; one means the first stage landed Successfully

In [12]:

```
df['Class']=landing_class
df[['Class']].head(8)
```

Out[12]:

	Class
0	0
1	0
2	0
3	0
4	0
5	0
6	1
7	1

In [13]:

```
df.head(5)
df["Class"].mean()
```

Out[14]:

```
0.6666666666666666
```

We can now export it to a CSV for the next section, but to make the answers consistent, in the next lab we will provide data in a pre-selected date range.

In [15]:

```
df.to_csv("dataset_part\2.csv", index=False)
df.to_csv("dataset_part\2.csv", index=False)
```

CHAPTER 5

Exploratory Data Analysis (EDA)

5.1. Exploratory Analysis Using SQL:

Assignment: SQL Notebook for Peer Assignment:

Estimated time needed: 60 minutes.

Introduction:

Using this Python notebook, you will:

1. Understand the SpaceX DataSet
2. Load the dataset into the corresponding table in a Db2 database
3. Execute SQL queries to answer assignment questions

Overview of the Dataset:

SpaceX has gained worldwide attention for a series of historic milestones.

It is the only private company ever to return a spacecraft from low-earth orbit, which it first accomplished in December 2010. SpaceX advertises Falcon 9 rocket launches on its website with a cost of 62 million dollars whereas other providers cost upward of 165 million dollars each, much of the savings is because Space X 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.

This dataset includes a record for each payload carried during a SpaceX mission into outer space.

Download the datasets

This assignment requires you to load the spacex dataset.

In many cases the dataset to be analyzed is available as a .CSV (comma separated values) file, perhaps on the internet. Click on the link below to download and save the dataset (.CSV file):

[SpaceX Dataset](#)

Store the dataset in database table
it is highly recommended to manually load the table using the database console LOAD tool in DB2.

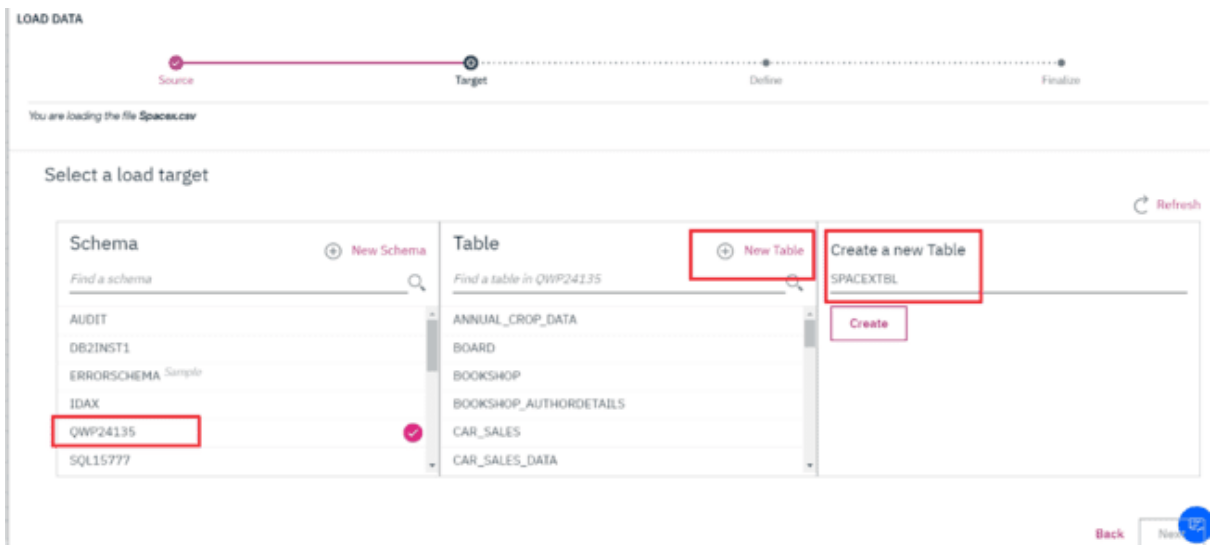


Figure 5: Load Data in New Table

Now open the Db2 console, open the LOAD tool, Select / Drag the .CSV file for the dataset, Next create a New Table, and then follow the steps on-screen instructions to load the data. Name the new table as follows:

SPACEX DATASET:

Follow these steps while using old DB2 UI which is having Open Console Screen

Note:While loading SpaceX dataset, ensure that detect datatypes is disabled. Later click on the pencil icon(edit option).

1. Change the Date Format by manually typing DD-MM-YYYY and timestamp format as DD-MM-YYYY HH\ :MM:SS.

Here you should place the cursor at Date field and manually type as DD-MM-YYYY.

2. Change the PAYLOADMASS_KG_ datatype to INTEGER.

LOAD DATA

Source Target Define Finalize

You are loading the file `SpaceX.csv` into `QWP24035.SPACEX7BL`

Code page (character encoding): **1208 (UTF-8)** Separator: `,` Header in first row: ☒ Time & date format: **DD-MM-YYYY HH:MM:SS** Detect data types: ☐

Date format: **DD-MM-YYYY** Time format: **HH:MM:SS** Timestamp format: **DD-MM-YYYY HH:MM:SS**

LAUNCH_SITE	PAYLOAD	PAYLOAD_MASS_KG	ORBIT	CUSTOMER
VARCHAR(32)	VARCHAR(32)	INTEGER	VARCHAR(32)	VARCHAR(32)
CCAFS LC-40	Dragon Spacecraft Qualification Unit	0	LEO (ISS)	SpaceX
CCAFS LC-40	Dragon demo flight C1, two CubeSats, barrel of Brouere cheese	0	LEO (ISS)	NASA (COTS) NRO
CCAFS LC-40	Dragon demo flight C2	525	LEO (ISS)	NASA (COTS)
CCAFS LC-40	SpaceX CRS-1	500	LEO (ISS)	NASA (CRS)
CCAFS LC-40	SpaceX CRS-2	677	LEO (ISS)	NASA (CRS)
WAFB SLC-4E	CASSIOPE	500	Polar LEO	MDA
CCAFS LC-40	SES-8	3170	GTO	SES
CCAFS LC-40	Thaicom 6	3325	GTO	Thaicom
CCAFS LC-40	SpaceX CRS-3	2296	LEO (ISS)	NASA (CRS)
CCAFS LC-40	OG2 Mission 1.6 Orbcomm-OG2 satellites	1316	LEO	Orbcomm

Back New

Figure 6: SpaceX.csv

Changes to be considered when having DB2 instance with the new UI having Go to UI screen

- Refer to this instruction in this [link](#) for viewing the new Go to UI screen.
- Later click on **Data link(below SQL)** in the Go to UI screen and click on **Load Data** tab.
- Later browse for the downloaded spacex file.

IBM Db2 on Cloud

Load Data Load History Tables Views Indexes Aliases MQTs Sequences Application objects

Source Target Define Finalize

You are loading the file

My Computer
A single delimited text file (CSV) without header row.

Amazon S3

Cloud Object Storage

File selection

Drag a file here or [browse files](#)

Figure 7: File Selection and Load the file

- Once done select the schema and load the file.

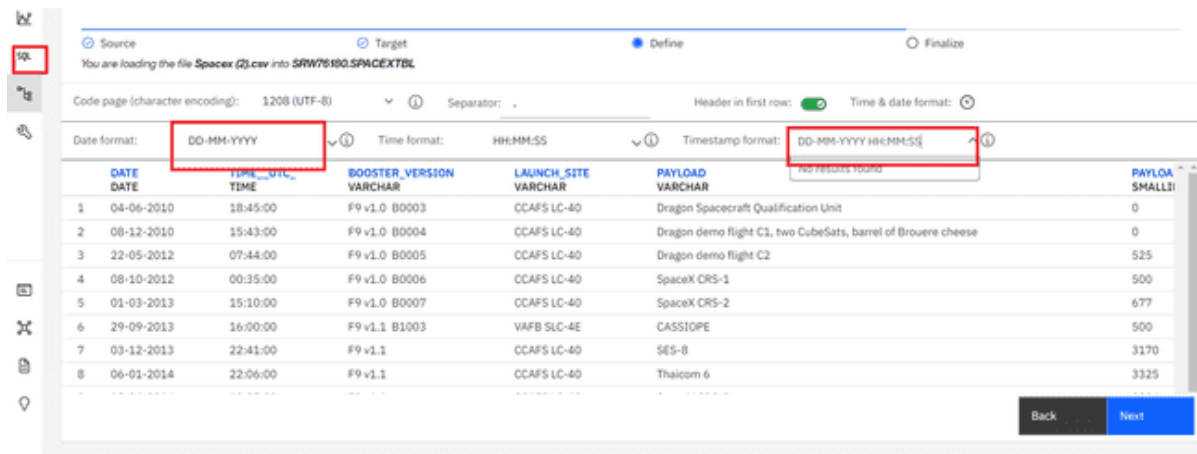


Figure 8: SpaceX(2).csv

In [1]:

```
!pip install sqlalchemy==1.3.9
!pip install ibm_db_sa
!pip install ipython-sql
Collecting sqlalchemy==1.3.9
  Downloading SQLAlchemy-1.3.9.tar.gz (6.0 MB)
-----
6.0/6.0 MB 53.7 MB/s eta 0:00:00:00:0100:01
Preparing metadata (setup.py) ... done
Building wheels for collected packages: sqlalchemy
  Building wheel for sqlalchemy (setup.py) ... done
Requirement already satisfied: matplotlib-inline in /home/jupyterlab/conda/envs/python/lib/python3.7/site-packages (from ipython>=1.0->ipython-sql) (0.1.3)
Requirement already satisfied: zipp>=0.5 in /home/jupyterlab/conda/envs/python/lib/python3.7/site-packages (from importlib-metadata->prettytable->ipython-sql) (3.8.0)
```

Connect to the database

Let us first load the SQL extension and establish a connection with the database

In [2]:

```
%load_ext sql
```

DB2 magic in case of old UI service credentials.

In the next cell enter your db2 connection string. Recall you created Service Credentials for your Db2 instance before. From the **uri** field of your Db2 service credentials copy

everything after db2:// (except the double quote at the end) and paste it in the cell below after ibm_db_sa://

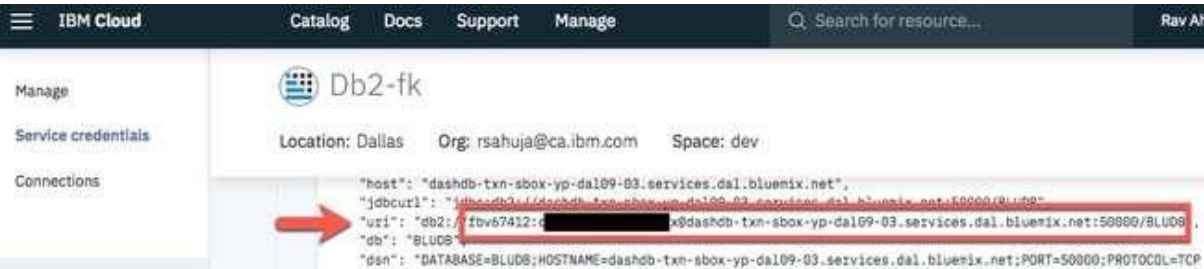


Figure 9: Db2-fk

in the following format

%sql ibm_db_sa://my-username:my-password\@my-hostname:my-port/my-db-name

DB2 magic in case of new UI service credentials.



Figure 10: %sql ibm_db_sa://my-username:my-password\@my-hostname:my-port/my-db-name

- Use the following format.
- Add security=SSL at the end

%sql ibm_db_sa://my-username:my-password\@my-hostname:my-port/my-db-name?security=SSL

In [6]:

```
%sql ibm_db_sa://glq09342:qwptGfJNs4DgeVNk@1bbf73c5-d84a-4bb0-85b9-ab1a4348f4a4.c3n41cmd0nqnrk39u98g.databases.appdomain.cloud:32286/BLUDB?security=SSL
```

Out[6]:

```
'Connected: glq09342@BLUDB'
```

In [8]:

```
%sql select * from spacex
* ibm_db_sa://glq09342:***@1bbf73c5-d84a-4bb0-85b9-ab1a4348f4a4.c3n41cmd0nqnrk39u98g.databases.appdomain.cloud:32286/BLUDB
Done.
```

Out[8]:

Table 1: Dataset

DATE	time	boost	launch	payload	payload	orb	customer	mission	landing
	__ut	r_vers	ch_s	oad	mass__k	bit	er	_outco	__outco
E	c_	ion	ite		g_			me	me
2010-06-04	18:45:00	F9 v1.0 B0003	CC AFS LC-40	Dragon	0	LEO	SpaceX	Success	Failure (parachute)
				Spacecraft					
				Qualification					
				on Unit					
2011-02-08	15:43:00	F9 v1.0 B0004	CC AFS LC-40	Dragon	0	LEO	NASA (COTS) NRO	Success	Failure (parachute)
				demo flight					
				C1, two Cube Sats,					
				barrel of Brouere					

D A T E	time __ut c_	booste r_vers ion	laun ch_s ite	payl oad	payload_ mass__k g_	o r b it	custom er	mission _outco me	landing __outco me
				chees e					
20 1 2- 0 5- 2 2	07:4 4:00	F9 v1.0 B0005	CC AFS LC- 40	Drag on demo flight C2	525	L E O (I S S)	NASA (COTS)	Success	No attempt
20 1 2- 1 0- 0 8	00:3 5:00	F9 v1.0 B0006	CC AFS LC- 40	Spac eX CRS- 1	500	L E O (I S S)	NASA (CRS)	Success	No attempt
20 1 3- 0 3- 0 1	15:1 0:00	F9 v1.0 B0007	CC AFS LC- 40	Spac eX CRS- 2	677	L E O (I S S)	NASA (CRS)	Success	No attempt
20 1 3- 0 9- 2 9	16:0 0:00	F9 v1.1 B1003	VAF B SLC -4E	CAS SIOP E	500	P o l a r L E O	MDA	Success	Uncontr olled (ocean)

D A T E	time __ut c_	booste r_vers ion	laun ch_s ite	payl oad	payload_ mass__k g_	o r b it	custom er	mission _outco me	landing __outco me
20 1 3- 1 2- 0 3	22:4 1:00	F9 v1.1	CC AFS LC- 40	SES- 8	3170	G T O	SES	Success	No attempt
20 1 4- 0 1- 0 6	22:0 6:00	F9 v1.1	CC AFS LC- 40	Thaic om 6	3325	G T O	Thaico m	Success	No attempt
20 1 4- 0 4- 1 8	19:2 5:00	F9 v1.1	CC AFS LC- 40	Spac eX CRS- 3	2296	L E O (I S S)	NASA (CRS)	Success	Controll ed (ocean)
20 1 4- 0 7- 1 4	15:1 5:00	F9 v1.1	CC AFS LC- 40	OG2 Missi on 1 6 Orbc omm - OG2 satell ites	1316	L E O	Orbco mm	Success	Controll ed (ocean)

D A T E	time __ut c_	booste r_vers ion	laun ch_s ite	payl oad	payload_ mass__k g_	o r b it	custom er	mission _outco me	landing __outco me
20 1 4- 0 8- 0 5	08:0 0:00	F9 v1.1	CC AFS LC- 40	Asia Sat 8	4535	G T O	AsiaSa t	Success	No attempt
20 1 4- 0 9- 0 7	05:0 0:00	F9 v1.1 B1011	CC AFS LC- 40	Asia Sat 6	4428	G T O	AsiaSa t	Success	No attempt
20 1 4- 0 9- 2 1	05:5 2:00	F9 v1.1 B1010	CC AFS LC- 40	Spac eX CRS- 4	2216	L E O (I S S)	NASA (CRS)	Success	Uncontr olled (ocean)
20 1 5- 0 1- 1 0	09:4 7:00	F9 v1.1 B1012	CC AFS LC- 40	Spac eX CRS- 5	2395	L E O (I S S)	NASA (CRS)	Success	Failure (drone ship)
20 1 5- 0 2-	23:0 3:00	F9 v1.1 B1013	CC AFS LC- 40	DSC OVR	570	H E O	U.S. Air Force NASA NOAA	Success	Controll ed (ocean)

D A T E	time __ut c_	booste r_vers ion	laun ch_s ite	payl oad	payload_ mass__k g_	o r b it	custom er	mission _outco me	landing __outco me
1 1									
20 1 5- 0 3- 0 2	03:5 0:00	F9 v1.1 B1014	CC AFS LC- 40	ABS- 3A Eutel sat 115 West B	4159	G T O	ABS Eutelsa t	Success	No attempt
20 1 5- 0 4- 1 4	20:1 0:00	F9 v1.1 B1015	CC AFS LC- 40	Spac eX CRS- 6	1898	L E O (I S S)	NASA (CRS)	Success	Failure (drone ship)
20 1 5- 0 4- 2 7	23:0 3:00	F9 v1.1 B1016	CC AFS LC- 40	Turk men 52 / Mon acoS AT	4707	G T O	Turkm enistan Nation al Space Agenc y	Success	No attempt
20 1 5- 0 6- 2 8	14:2 1:00	F9 v1.1 B1018	CC AFS LC- 40	Spac eX CRS- 7	1952	L E O (I S S)	NASA (CRS)	Failure (in flight)	Preclude d (drone ship)

D A T E	time __ut c_	booste r_vers ion	laun ch_s ite	payl oad	payload_ mass__k g_	o r b it	custom er	mission _outco me	landing __outco me
20 1 5- 1 2- 2 2	01:2 9:00	F9 FT B1019	CC AFS LC- 40	OG2 Missi on 2 11 Orbc omm - OG2 satell ites	2034	L E O	Orbco mm	Success	Success (ground pad)
20 1 6- 0 1- 1 7	18:4 2:00	F9 v1.1 B1017	VAF B SLC -4E	Jason -3	553	L E O	NASA (LSP) NOAA CNES	Success	Failure (drone ship)
20 1 6- 0 3- 0 4	23:3 5:00	F9 FT B1020	CC AFS LC- 40	SES- 9	5271	G T O	SES	Success	Failure (drone ship)
20 1 6- 0 4- 0 8	20:4 3:00	F9 FT B1021. 1	CC AFS LC- 40	Spac eX CRS- 8	3136	L E O (I S S)	NASA (CRS)	Success	Success (drone ship)

D A T E	time __ut c_	booste r_vers ion	laun ch_s ite	payl oad	payload_ mass__k g_	o r b it	custom er	mission _outco me	landing __outco me
20 1 6- 0 5- 0 6	05:2 1:00	F9 FT B1022	CC AFS LC- 40	JCS AT- 14	4696	G T O	SKY Perfect JSAT Group	Success	Success (drone ship)
20 1 6- 0 5- 2 7	21:3 9:00	F9 FT B1023. 1	CC AFS LC- 40	Thaic om 8	3100	G T O	Thaico m	Success	Success (drone ship)
20 1 6- 0 6- 1 5	14:2 9:00	F9 FT B1024	CC AFS LC- 40	ABS- 2A Eutel sat 117 West B	3600	G T O	ABS Eutelsa t	Success	Failure (drone ship)
20 1 6- 0 7- 1 8	04:4 5:00	F9 FT B1025. 1	CC AFS LC- 40	Spac eX CRS- 9	2257	L E O (I S S)	NASA (CRS)	Success	Success (ground pad)
20 1 6- 0 8-	05:2 6:00	F9 FT B1026	CC AFS LC- 40	JCS AT- 16	4600	G T O	SKY Perfect JSAT Group	Success	Success (drone ship)

D A T E	time __ut c_	booste r_vers ion	laun ch_s ite	payl oad	payload_ mass__k g_	o r b it	custom er	mission _outco me	landing __outco me
1 4									
20 1 7- 0 1- 1 4	17:5 4:00	F9 FT B1029. 1	VAF B SLC -4E	Iridiu m NEX T 1	9600	P o l a r L E O	Iridium Comm unicati ons	Success	Success (drone ship)
20 1 7- 0 2- 1 9	14:3 9:00	F9 FT B1031. 1	KSC LC- 39A	Spac eX CRS- 10	2490	L E O (I S S)	NASA (CRS)	Success	Success (ground pad)
20 1 7- 0 3- 1 6	06:0 0:00	F9 FT B1030	KSC LC- 39A	Echo Star 23	5600	G T O	EchoSt ar	Success	No attempt
20 1 7- 0 3- 3 0	22:2 7:00	F9 FT B1021. 2	KSC LC- 39A	SES- 10	5300	G T O	SES	Success	Success (drone ship)

D A T E	time __ut c_	booste r_vers ion	laun ch_s ite	payl oad	payload_ mass__k g_	o r b it	custom er	mission _outco me	landing __outco me
20 1 7- 0 5- 0 1	11:1 5:00	F9 FT B1032. 1	KSC LC- 39A	NRO L-76	5300	L E O	NRO	Success	Success (ground pad)
20 1 7- 0 5- 1 5	23:2 1:00	F9 FT B1034	KSC LC- 39A	Inma rsat- 5 F4	6070	G T O	Inmars at	Success	No attempt
20 1 7- 0 6- 0 3	21:0 7:00	F9 FT B1035. 1	KSC LC- 39A	Spac eX CRS- 11	2708	L E O (I S S)	NASA (CRS)	Success	Success (ground pad)
20 1 7- 0 6- 2 3	19:1 0:00	F9 FT B1029. 2	KSC LC- 39A	Bulg ariaS at-1	3669	G T O	Bulsatc om	Success	Success (drone ship)

Tasks

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

Task 1

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

In [9]:

```
%sql select distinct launch_site from spacex
* ibm_db_sa://glq09342:***@1bbf73c5-d84a-4bb0-85b9-ab1a4348f4a4.c3n
41cmd0nqnrk39u98g.databases.appdomain.cloud:32286/BLUDB
Done.
```

Out[9]:

Table 2: Launch_site

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

Task 2

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

In [18]:

```
%sql select * from Spacex where launch_site like 'CCA%' limit 5
* ibm_db_sa://glq09342:***@1bbf73c5-d84a-4bb0-85b9-ab1a4348f4a4.c3n
41cmd0nqnrk39u98g.databases.appdomain.cloud:32286/BLUDB
Done.
```

Out[18]:

Table 3: Display 5 records where launch sites begin with the string 'CCA'

D A T E	time _ut c_	booster _versio _n	laun ch_s ite	paylo ad	payload_ mass__k g_	o r b it	cust om er	mission _outco me	landing_ _outcom e
2010-06-04	18:45:00	F9 v1.0 B0003	CCA FS LC-40	Dragon Space craft Quali ficati on Unit	0	L E O	Spa ceX	Success	Failure (parachu te)
2010-12-08	15:43:00	F9 v1.0 B0004	CCA FS LC-40	Dragon demo flight C1, two Cube Sats, barrel of Brou ere chees e	0	L E O (I S S)	NA SA (C OT S) NR O	Success	Failure (parachu te)
2012-05-22	07:44:00	F9 v1.0 B0005	CCA FS LC-40	Dragon on demo flight C2	525	L E O (I S S)	NA SA (C OT S)	Success	No attempt
2012-10	00:35:00	F9 v1.0 B0006	CCA FS	Space X	500	L E O (I	NA SA	Success	No attempt

D A T E	time __ut c_	booster _versio _n	laun ch_s ite	paylo ad	payload_ mass__k g_	o r b it	cust om er	mission _outco me	landing_ _outcom e
- 08			LC- 40	CRS- 1		S S)	(C RS)		
20 13 - 03 - 01	15:1 0:00	F9 v1.0 B0007	CCA FS LC- 40	Space X CRS- 2	677	L E O (I S S)	NA SA (C RS)	Success	No attempt

Task 3

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

```
In [19]:

%sql select sum(payload_mass__kg_) from spacex where customer like
'NASA%'

* ibm_db_sa://glq09342:***@1bbf73c5-d84a-4bb0-85b9-ab1a4348f4a4.c3n
41cmd0nqnrk39u98g.databases.appdomain.cloud:32286/BLUDB
Done.
```

Out[19]:

Table 4: Display the total payload mass carried by boosters launched by NASA (CRS)

1
99980

Task 4

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

In [20]:

```
%sql select AVG(payload_mass__kg_) from spacex where booster_version
like 'F9 v1.1%'
* ibm_db_sa://glq09342:***@1bbf73c5-d84a-4bb0-85b9-ab1a4348f4a4.c3n
41cmd0nqnrk39u98g.databases.appdomain.cloud:32286/BLUDB
Done.
```

Out[20]:

Table 5: Display average payload mass carried by booster version F9 v1.1

1
2534

Task 5

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

Hint: Use min function

In [21]:

```
%sql select MIN(DATE) from spacex where landing__outcome like
'%ground pad%'
* ibm_db_sa://glq09342:***@1bbf73c5-d84a-4bb0-85b9-ab1a4348f4a4.c3n
41cmd0nqnrk39u98g.databases.appdomain.cloud:32286/BLUDB
Done.
```

Out[21]:

Table 6: List the date when the first successful landing outcome in ground pad was achieved.

1
2015-12-22

Task 6

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

In [22]:

```
%sql select distinct booster_version from spacex where
(payload_mass__kg_ < 6000 AND payload_mass__kg_ > 4000) AND
(landing__outcome like '%drone%ship%')
* ibm_db_sa://glq09342:***@1bbf73c5-d84a-4bb0-85b9-ab1a4348f4a4.c3n
41cmd0nqnrk39u98g.databases.appdomain.cloud:32286/BLUDB
Done.
```

Out[22]:

Table 7: List the names of the boosters which have success in drone ship and have payload mass greater than 4000 but less than 6000

booster_version
F9 FT B1021.2
F9 FT B1031.2
F9 FT B1020
F9 FT B1022
F9 FT B1026

Task 7

List the total number of successful and failure mission outcomes

In [23]:

```
%sql SELECT mission_outcome, count(*) AS total FROM spacex GROUP BY
mission_outcome
```

```
* ibm_db_sa://glq09342:***@1bbf73c5-d84a-4bb0-85b9-ab1a4348f4a4.c3n
41cmd0nqnrk39u98g.databases.appdomain.cloud:32286/BLUDB
Done.
```

Out[23]:

Table 8: List the total number of successful and failure mission outcomes

mission_outcome	total
Failure (in flight)	1
Success	99
Success (payload status unclear)	1

Task 8

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

In [24]:

```
%sql SELECT DISTINCT (booster_version) from spacex where
payload_mass__kg_ = (SELECT MAX(payload_mass__kg_) from spacex)
* ibm_db_sa://glq09342:***@1bbf73c5-d84a-4bb0-85b9-ab1a4348f4a4.c3n
41cmd0
nqnrk39u98g.databases.appdomain.cloud:32286/BLUDB
Done.
```

Out[24]:

Table 9: List the names of the booster versions which have carried the maximum payload mass. Use a subquery

booster_version
F9 B5 B1048.4
F9 B5 B1048.5
F9 B5 B1049.4

booster_version

F9 B5 B1049.5

F9 B5 B1049.7

F9 B5 B1051.3

F9 B5 B1051.4

F9 B5 B1051.6

F9 B5 B1056.4

F9 B5 B1058.3

F9 B5 B1060.2

F9 B5 B1060.3

Out[25]:

5.2. Exploratory Analysis Using Pandas and Matplotlib:

SpaceX Falcon 9 First Stage Landing Prediction:

Assignment: Exploring and Preparing Data

Estimated time needed: **70** minutes

In this assignment, we will predict if the Falcon 9 first stage will land successfully. 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.

In this lab, you will perform Exploratory Data Analysis and Feature Engineering.

Falcon 9 first stage will land successfully

Several examples of an unsuccessful landing are shown here:

Most unsuccessful landings are planned. Space X performs a controlled landing in the oceans.

Objectives:

Perform exploratory Data Analysis and Feature Engineering using **Pandas** and **Matplotlib**

- Exploratory Data Analysis
- Preparing Data Feature Engineering

Import Libraries and Define Auxiliary Functions:

We will import the following libraries the lab

In [6]:

```
# andas is a software library written for the Python programming  
language for data manipulation and analysis.
```

```
import pandas as pd
```

```
#NumPy is a library for the Python programming language, adding  
support for large, multi-dimensional arrays and matrices, along with
```

a large collection of high-level mathematical functions to operate on these arrays

```
import numpy as np

# Matplotlib is a plotting library for python and pyplot gives us a
# MatLab like plotting framework. We will use this in our plotter
# function to plot data.

import matplotlib.pyplot as plt

#Seaborn is a Python data visualization library based on matplotlib.
# It provides a high-level interface for drawing attractive and
# informative statistical graphics

import seaborn as sns
```

Exploratory Data Analysis:

First, let's read the SpaceX dataset into a Pandas dataframe and print its summary

In [7]:

```
df=pd.read_csv("https://cf-courses-data.s3.us.cloud-object-
storage.appdomain.cloud/IBM-DS0321EN-
SkillsNetwork/datasets/dataset_part_2.csv")

# If you were unable to complete the previous lab correctly you can
# uncomment and load this csv

# df = pd.read_csv('https://cf-courses-data.s3.us.cloud-object-
# storage.appdomain.cloud/IBMDeveloperSkillsNetwork-DS0701EN-
# SkillsNetwork/api/dataset_part_2.csv')

df.head(5)
```

Out[7]:

Table 10: SpaceX dataset into a Pandas dataframe and its summary

Flight Number		Booster Version	Payload Mass	Orbit	Launch Site	Outcome	Flight Hours	Grid Fins	Reusable	Legs	Landed	Block	Reuse Count	Serial	Longitude	Latitude	Class
0	1	2010-01-06-04	Falcon 9	61499412	LEO	Commercial	1	115e	115e	115e	NaN	10	0	B00366	-80.5733	28.5617	0
		2011-02-05-02	Falcon 9	5000000	LEO	Commercial	1	115e	115e	115e	NaN	10	0	B00366	-80.5733	28.5617	0
		2012-05-02-02	Falcon 9	5000000	LEO	Commercial	1	115e	115e	115e	NaN	10	0	B00366	-80.5733	28.5617	0
		2013-03-01-03	Falcon 9	7700000	ISS	Commercial	1	115e	115e	115e	NaN	10	0	B00366	-80.5733	28.5617	0
		2013-03-01-03	Falcon 9	7700000	ISS	Commercial	1	115e	115e	115e	NaN	10	0	B00366	-80.5733	28.5617	0
1	2	2012-01-20-05	Falcon 9	5000000	LEO	Commercial	1	115e	115e	115e	NaN	10	0	B00366	-80.5733	28.5617	0
		2012-02-08-02	Falcon 9	5000000	LEO	Commercial	1	115e	115e	115e	NaN	10	0	B00366	-80.5733	28.5617	0
		2012-03-01-02	Falcon 9	5000000	LEO	Commercial	1	115e	115e	115e	NaN	10	0	B00366	-80.5733	28.5617	0
		2012-04-01-02	Falcon 9	5000000	LEO	Commercial	1	115e	115e	115e	NaN	10	0	B00366	-80.5733	28.5617	0
		2012-05-02-02	Falcon 9	5000000	LEO	Commercial	1	115e	115e	115e	NaN	10	0	B00366	-80.5733	28.5617	0
2	3	2010-01-06-04	Falcon 9	61499412	LEO	Commercial	1	115e	115e	115e	NaN	10	0	B00366	-80.5733	28.5617	0
		2011-02-05-02	Falcon 9	5000000	LEO	Commercial	1	115e	115e	115e	NaN	10	0	B00366	-80.5733	28.5617	0
		2012-05-02-02	Falcon 9	5000000	LEO	Commercial	1	115e	115e	115e	NaN	10	0	B00366	-80.5733	28.5617	0
		2013-03-01-03	Falcon 9	7700000	ISS	Commercial	1	115e	115e	115e	NaN	10	0	B00366	-80.5733	28.5617	0
		2013-03-01-03	Falcon 9	7700000	ISS	Commercial	1	115e	115e	115e	NaN	10	0	B00366	-80.5733	28.5617	0

Flight Number	Booster Version	Payload Mass	Orbit	Launch Site	Orbit Name	Flight Hours	Grid	Reused	Legs	Land	Block	Reusable Count	Sever	Longitude	Latitude	Classes
3	4	03-01			Solar		ssss						07	17	18	
					Launch									36	77	
					04									66		
					00											
		2013-09-02			50000000											
					00000000											
					00000000											
					00000000											
					00000000											
					00000000											
4	5	03-01			Launch											
					04											
					00											
					00000000											
					00000000											
					00000000											
					00000000											
					00000000											
					00000000											
					00000000											
4	5	03-01			Launch											
					04											
					00											
					00000000											
					00000000											
					00000000											
					00000000											
					00000000											
					00000000											
					00000000											

First, let's try to see how the **FlightNumber** (indicating the continuous launch attempts.) and **Payload** variables would affect the launch outcome.

We can plot out the **FlightNumber** vs. **PayloadMass** and overlay the outcome of the launch. We see that as the flight number increases, the first stage is more likely to land successfully. The payload mass is also important; it seems the more massive the payload, the less likely the first stage will return.

In [8]:

```
sns.catplot(y="PayloadMass", x="FlightNumber", hue="Class", data=df,
            aspect = 5)
plt.xlabel("Flight Number",fontsize=20)
plt.ylabel("Pay load Mass (kg)",fontsize=20)
plt.show()
```

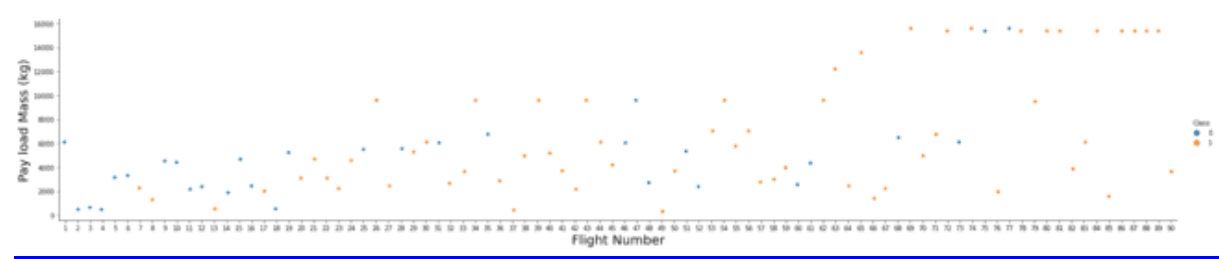


Figure 11: FlightNumber vs. PayloadMass

We see that different launch sites have different success rates. **CCAFS LC-40**, has a success rate of 60 %, while **KSC LC-39A** and **VAFB SLC 4E** has a success rate of 77%.

Next, let's drill down to each site visualize its detailed launch records.

TASK 1: Visualize the relationship between Flight Number and Launch Site

Use the function **catplot** to plot **FlightNumber** vs **LaunchSite**, set the parameter **x** parameter to **FlightNumber**, set the **y** to **Launch Site** and set the parameter **hue** to 'class'

Now try to explain the patterns you found in the Flight Number vs. Launch Site scatter point plots.

In [10]:

```
# Plot a scatter point chart with x axis to be Flight Number and y
axis to be the launch site, and hue to be the class value
sns.catplot(x="FlightNumber", y="LaunchSite", data=df, hue="Class",
            aspect = 5)
plt.xlabel("Flight Number")
```

```
plt.ylabel("LaunchSite")
plt.show()
```

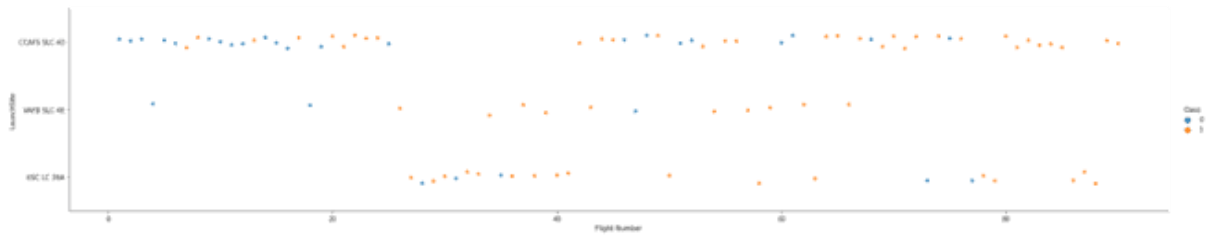


Figure 12: Visualize the relationship between Flight Number and Launch Site

TASK 2: Visualize the relationship between Payload and Launch Site

We also want to observe if there is any relationship between launch sites and their payload mass.

In [11]:

```
# Plot a scatter point chart with x axis to be Pay Load Mass (kg)
# and y axis to be the launch site, and hue to be the class value
sns.catplot(x="PayloadMass", y="LaunchSite", hue="Class", data=df,
            aspect = 5)
plt.xlabel("Flight Number")
plt.ylabel("LaunchSite")
plt.show()
```

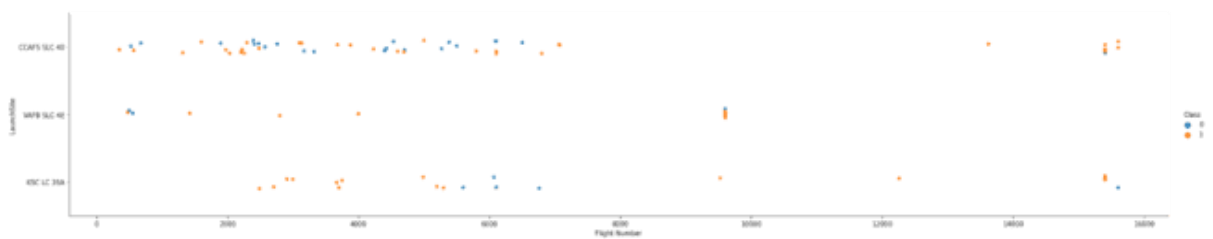


Figure 13: Visualize the relationship between Payload and Launch Site

Now if you observe Payload Vs. Launch Site scatter point chart you will find for the VAFB-SLC launchsite there are no rockets launched for heavypayload mass(greater than 10000).

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

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

Let's create a bar chart for the success rate of each orbit

In [13]:

```
# HINT use groupby method on Orbit column and get the mean of Class column
Orbitttype=df.groupby(by="Orbit", axis=0).mean()["Class"]

Orbitttype=pd.DataFrame(Orbitttype)
Orbitttype['orbit'] = Orbitttype.index

sns.catplot(x="orbit", y="Class", data=Orbitttype, kind="bar",
            aspect=5)
```

Out[13]:

<seaborn.axisgrid.FacetGrid at 0x7f2b5972d490>

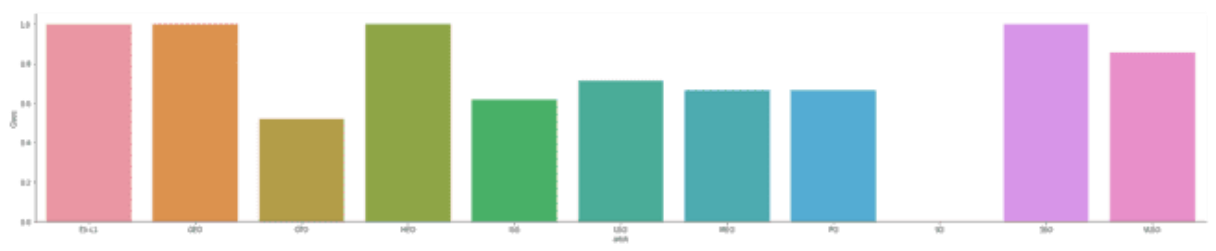


Figure 14: Visualize the relationship between success rate of each orbit type

Analyze the plotted bar chart try to find which orbits have high success rate.

Explain the patterns - which orbits have high success rate.

ES-L1, GEO, HEO, SO has highest Success rates. SO has poorest.

TASK 4: Visualize the relationship between FlightNumber and Orbit type

For each orbit, we want to see if there is any relationship between FlightNumber and Orbit type.

In [14]:

```
# Plot a scatter point chart with x axis to be FlightNumber and y
axis to be the Orbit, and hue to be the class value
sns.catplot(x="FlightNumber", y="Orbit", hue="Class", data=df,
aspect = 5)
plt.xlabel("Flight Number")
plt.ylabel("Orbit")
plt.show()
```

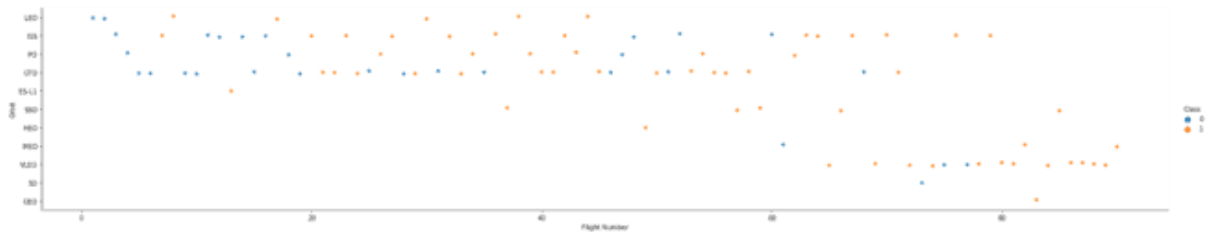


Figure 15: Visualize the relationship between success rate of each orbit type

You should see that 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.

TASK 5: Visualize the relationship between Payload and Orbit type

Similarly, we can plot the Payload vs. Orbit scatter point charts to reveal the relationship between Payload and Orbit type

In [15]:

```
# Plot a scatter point chart with x axis to be Payload and y axis to
be the Orbit, and hue to be the class value
sns.catplot(x="PayloadMass", y="Orbit", data=df, hue="Class", aspect
= 5)
plt.xlabel("PayloadMass")
plt.ylabel("Orbit")
plt.show()
```

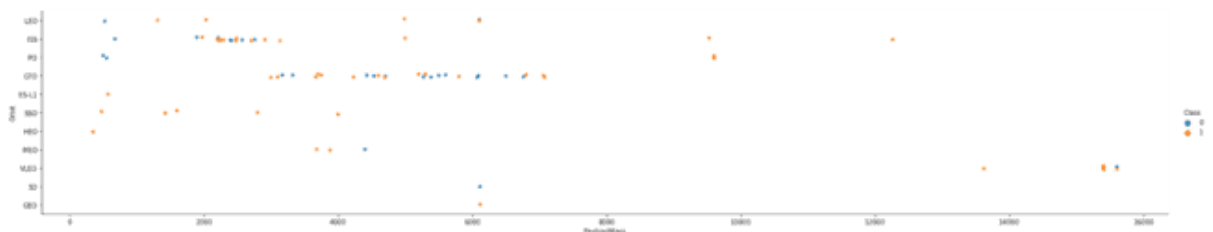


Figure 16: Visualize the relationship between Payload and Orbit type

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(unsuccesful mission) are both there here.

TASK 6: Visualize the launch success yearly trend

You can plot a line chart with x axis to be Year and y axis to be average success rate, to get the average launch success trend.

The function will help you get the year from the date:

In [19]:

```
# A function to Extract years from the date
year=[]
def Extract_year(date):
    for i in df["Date"]:
        year.append(i.split("-")[0])
    return year

df['year']=Extract_year(df)
by_year=df.groupby(by="year", axis=0).mean()["Class"]
by_year = pd.DataFrame(by_year)
by_year.reset_index(level=0, inplace=True)
by_year
```

Out[19]:

Table 11: Data Years from the date

	year	Class
0	2010	0.000000
1	2012	0.000000
2	2013	0.000000
3	2014	0.333333

	year	Class
4	2015	0.333333
5	2016	0.625000
6	2017	0.833333
7	2018	0.611111
8	2019	0.900000
9	2020	0.842105

In [20]:

```
# Plot a line chart with x axis to be the extracted year and y axis
to be the success rate
sns.lineplot( x="year", y="Class", data=by_year)
plt.xlabel("year")
plt.ylabel("class")
plt.show()
```

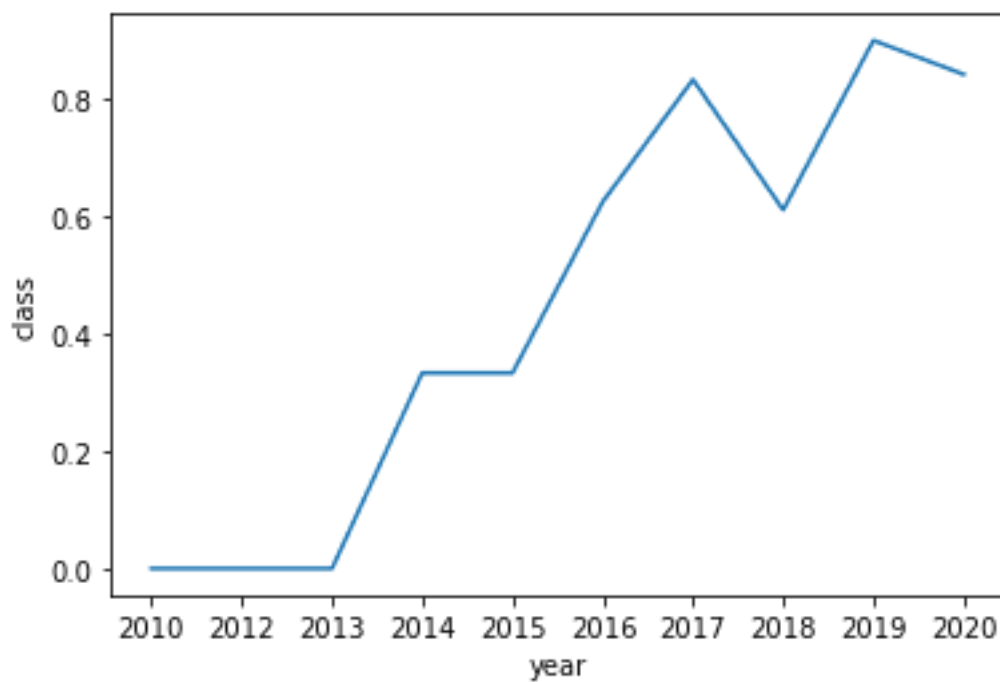


Figure 17: Visualize the launch success yearly trend

you can observe that the success rate since 2013 kept increasing till 2020

Features Engineering:

By now, you should obtain some preliminary insights about how each important variable would affect the success rate, we will select the features that will be used in success prediction in the future module.

In [27]:

```
features = df[['FlightNumber', 'PayloadMass', 'Orbit', 'LaunchSite',
'Flights', 'GridFins', 'Reused', 'Legs', 'LandingPad', 'Block',
'ReusedCount', 'Serial']]
features.head()
```

Out[27]:

Table 12:

	Flight Num ber	PayloadMass	Orbit	LaunchSite	Flights	GridFins	Reused	Legs	LandingPad	Block	ReusedCount	Serial
0	1	6104.959412	L	CC AFS SLC 40	1	False	False	False	NaN	1.0	0	B0003
1	2	525.00000	L	CC AFS SLC 40	1	False	False	False	NaN	1.0	0	B0005
2	3	677.00000	I	CC AFS SLC 40	1	False	False	False	NaN	1.0	0	B0007

	Flight Num ber	Payload Mass	Orbit	Launch Site	Flights	Grid Files	Reused	Lengths	Landing Pads	Block	Reusable Count	Serial
3	4	500.00000	P O	VAF B SLC 4E	1	False	False	Falses	NaN	1.0	0	B 1 0 0 3
4	5	3170.00000	G T O	CC AFS SLC 40	1	False	False	Falses	NaN	1.0	0	B 1 0 0 4

CHAPTER 6

INTERACTIVE VISUAL ANALYTICS AND DASHBOARD

6.1:Interactive Visual Analytics with Folium

Launch Sites Locations Analysis with Folium:

Estimated time needed: **40** minutes

The launch success rate may depend on many factors such as payload mass, orbit type, and so on. It may also depend on the location and proximities of a launch site, i.e., the initial position of rocket trajectories. Finding an optimal location for building a launch site certainly involves many factors and hopefully we could discover some of the factors by analyzing the existing launch site locations.

In the previous exploratory data analysis labs, you have visualized the SpaceX launch dataset using matplotlib and seaborn and discovered some preliminary correlations between the launch site and success rates. In this lab, you will be performing more interactive visual analytics using Folium.

Objectives:

This lab contains the following tasks:

- **TASK 1:** Mark all launch sites on a map
- **TASK 2:** Mark the success/failed launches for each site on the map
- **TASK 3:** Calculate the distances between a launch site to its proximities

After completed the above tasks, you should be able to find some geographical patterns about launch sites.

Let's first import required Python packages for this lab:

In [1]:

```
!pip3 install folium
!pip3 install wget
Requirement already satisfied: certifi>=2017.4.17 in /Users/debdatta
sarkar/opt/anaconda3/lib/python3.8/site-packages (from requests->fol
ium) (2020.12.5)
Requirement already satisfied: wget in /Users/debdattasarkar/opt/ana
conda3/lib/python3.8/site-packages (3.2)
```

In [2]:

```
import folium
import wget
import pandas as pd
```

In [3]:

```
# Import folium MarkerCluster plugin
from folium.plugins import MarkerCluster
# Import folium MousePosition plugin
from folium.plugins import MousePosition
# Import folium DivIcon plugin
from folium.features import DivIcon
```

Task 1: Mark all launch sites on a map

First, let's try to add each site's location on a map using site's latitude and longitude coordinates

The following dataset with the name `spacex_launch_geo.csv` is an augmented dataset with latitude and longitude added for each site.

In [4]:

```
# Download and read the `spacex_launch_geo.csv`
spacex_csv_file = wget.download('https://cf-courses-
data.s3.us.cloud-object-storage.appdomain.cloud/IBM-DS0321EN-
SkillsNetwork/datasets/spacex_launch_geo.csv')
spacex_df=pd.read_csv(spacex_csv_file)
```

Now, you can take a look at what are the coordinates for each site.

In [5]:

```
# Select relevant sub-columns: `Launch Site`, `Lat(Latitude)`,
`Long(Longitude)`, `class`
spacex_df = spacex_df[['Launch Site', 'Lat', 'Long', 'class']]
```

```
launch_sites_df = spacex_df.groupby(['Launch Site'],
as_index=False).first()
launch_sites_df = launch_sites_df[['Launch Site', 'Lat', 'Long']]
launch_sites_df
```

Out[5]:

Table 13: Mark all launch sites on a map

	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	-120.610746

Above coordinates are just plain numbers that cannot give you any intuitive insights about where those are launch sites. If you are very good at geography, you can interpret those numbers directly in your mind. If not, that's fine too. Let's visualize those locations by pinning them on a map.

We first need to create a folium Map object, with an initial centre location to be NASA Johnson Space Centre at Houston, Texas.

In [6]:

```
# Start location is NASA Johnson Space Center
nasa_coordinate = [29.559684888503615, -95.0830971930759]
site_map = folium.Map(location=nasa_coordinate, zoom_start=10)
We could use folium.Circle to add a highlighted circle area with a text label on a specific
coordinate. For example,
```

In [7]:

```
# Create a blue circle at NASA Johnson Space Center's coordinate
with a popup label showing its name

# Circle should be blue so changing color code from #d35400 to
#2572e6
```

```

circle = folium.Circle(nasa_coordinate, radius=1000,
color='#2572e6', fill=True).add_child(folium.Popup('NASA Johnson
Space Center'))
# Create a blue circle at NASA Johnson Space Center's coordinate
with a icon showing its name
marker = folium.map.Marker(
    nasa_coordinate,
    # Create an icon as a text label
    icon=DivIcon(
        icon_size=(20,20),
        icon_anchor=(0,0),
        html='<div style="font-size: 12;
color:#d35400;"><b>s</b></div>' % 'NASA JSC',
    )
)
site_map.add_child(circle)
site_map.add_child(marker)

```

Out[7]:

Make this Notebook Trusted to load map: File -> Trust Notebook
and you should find a small yellow circle near the city of Houston, and you can zoom-in to
see a larger circle.

Now, let's add a circle for each launch site in data frame **launch_sites**

TODO: Create and add **folium.Circle** and **folium.Marker** for each launch site on the site map

Converting the dataframe to dictionary:

In [8]:

```

launch_sites_dict = launch_sites_df.set_index('Launch
Site').T.to_dict('list')

```

```

launch_sites_dict

```

Out[8]:

```

{'CCAFS LC-40': [28.56230196799018, -80.57735647504778],
 'CCAFS SLC-40': [28.563197177407144, -80.57682003124195],
 'KSC LC-39A': [28.57325457037815, -80.64689528960382],
 'VAFB SLC-4E': [34.632834161782775, -120.61074553068327]}

```

My Own Custom Functions for Markers:

In [9]:


```

def add_marker_on_map(name, coordinate, circle_color='#d35400'):
    circle = folium.Circle(coordinate, radius=1000,
color=circle_color, fill=True).add_child(folium.Popup(name))
    marker = folium.map.Marker(
        coordinate,
        icon=DivIcon(
            icon_size=(20,20),
            icon_anchor=(0,0),
            html="<div style='font-size: 12;
color:{}; '><b>{}</b></div>". format(circle_color,name)
        )
    )
    site_map.add_child(circle)
    site_map.add_child(marker)

def add_text_distance_marker_on_map(name, coordinate, distance,
ccolor='#4d0f1d'):
    txt="{}", {:.2f} km".format(name, distance)
    folium.Marker(
        location=coordinate,
        icon=DivIcon(
            icon_size=(150,30),
            icon_anchor=(0,0),
            html='<div style="font-size: 9pt; font-weight:bold;
color: {}">{}</div>'.format(ccolor, txt))
    ).add_to(site_map)

def add_type_marker_on_map(name, coordinate, ccolor='red',
icon_type='train'):
    marker = folium.map.Marker(
        location=coordinate,
        popup=name,
        tooltip='click',
        icon=folium.Icon(color=ccolor, icon=icon_type, prefix='fa')
    )
    site_map.add_child(marker)

```

In [10]:

```

# Initial the map
# site_map = folium.Map(location=nasa_coordinate, zoom_start=5)

```

```
# Zooming on a launch site 'VAFB SLC-4E' rather than NASA for better
visibiliy of work mentioned in below tasks.
VAFB_SLC_4E = [34.632834, -120.610746]
site_map = folium.Map(location=VAFB_SLC_4E, zoom_start=3)
# CCAFS_SLC_40 = [28.563197177407144, -80.57682003124195]
# site_map = folium.Map(location=CCAFS_SLC_40, zoom_start=5)
# For each launch site, add a Circle object based on its coordinate
(Lat, Long) values. In addition, add Launch site name as a popup
label
for name,coordinate in launch_sites_dict.items():
    add_marker_on_map(name, coordinate)
site_map
```

Out[10]:

Make this Notebook Trusted to load map: File -> Trust Notebook

The generated map with marked launch sites should look like the following:

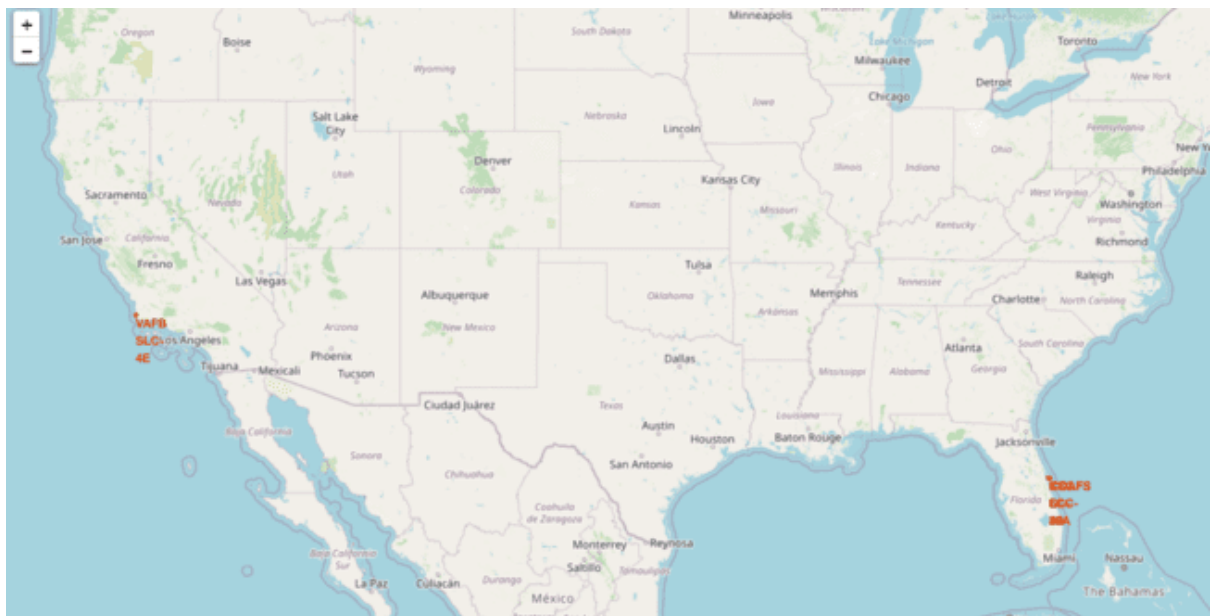


Figure 18: Mark all launch sites on a map

Now, you can explore the map by zoom-in/out the marked areas, and try to answer the following questions:

- Are all launch sites in proximity to the Equator line?
- Are all launch sites in very close proximity to the coast?

Also please try to explain your findings.

Task 2: Mark the success/failed launches for each site on the map

Next, let's try to enhance the map by adding the launch outcomes for each site, and see which sites have high success rates. Recall that data frame `spacex_df` has detailed launch records, and the `class` column indicates if this launch was successful or not

In [11]:

```
spacex_df.tail(10)
```

Out[11]:

Table 14: Mark the success/failed launches for each site on the map

	Launch Site	Lat	Long	class
46	KSC LC-39A	28.573255	-80.646895	1
47	KSC LC-39A	28.573255	-80.646895	1
48	KSC LC-39A	28.573255	-80.646895	1
49	CCAFS SLC-40	28.563197	-80.576820	1
50	CCAFS SLC-40	28.563197	-80.576820	1
51	CCAFS SLC-40	28.563197	-80.576820	0
52	CCAFS SLC-40	28.563197	-80.576820	0
53	CCAFS SLC-40	28.563197	-80.576820	0
54	CCAFS SLC-40	28.563197	-80.576820	1
55	CCAFS SLC-40	28.563197	-80.576820	0

Next, let's create markers for all launch records. If a launch was successful (class=1), then we use a green marker and if a launch was failed, we use a red marker (class=0)

Note that a launch only happens in one of the four launch sites, which means many launch records will have the exact same coordinate. Marker clusters can be a good way to simplify a map containing many markers having the same coordinate.

Let's first create a MarkerCluster object

In [12]:

```
marker_cluster = MarkerCluster()

TODO: Create a new column in launch_sites dataframe called marker_color to store the
marker colors based on the class value
```

In [13]:

```
# Apply a function to check the value of `class` column
# If class=1, marker_color value will be green
# If class=0, marker_color value will be red
```

In [14]:

```
# Function to assign color to launch outcome
def assign_marker_color(launch_outcome):
    if launch_outcome == 1:
        return 'green'
    else:
        return 'red'

spacex_df['marker_color'] =
spacex_df['class'].apply(assign_marker_color)
spacex_df.tail(10)
```

Out[14]:

Table 15: Mark the success/failed launches for each site on the map

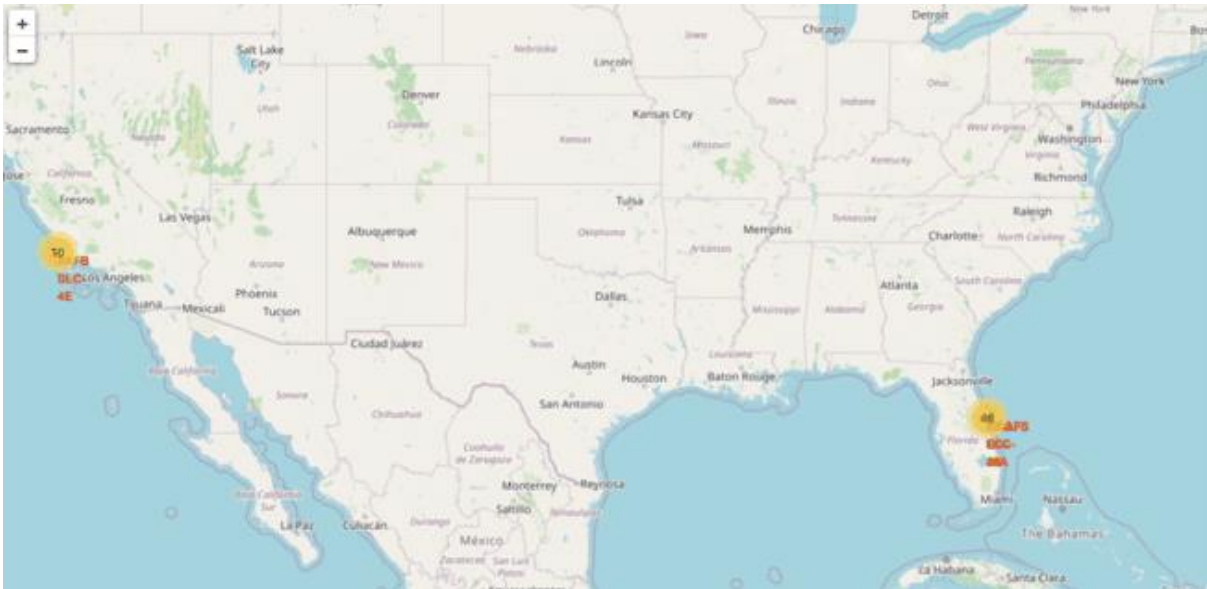
	Launch Site	Lat	Long	class	marker_color
46	KSC LC-39A	28.573255	-80.646895	1	green
47	KSC LC-39A	28.573255	-80.646895	1	green
48	KSC LC-39A	28.573255	-80.646895	1	green

	Launch Site	Lat	Long	class	marker_color
49	CCAFS SLC-40	28.563197	-80.576820	1	green
50	CCAFS SLC-40	28.563197	-80.576820	1	green
51	CCAFS SLC-40	28.563197	-80.576820	0	red
52	CCAFS SLC-40	28.563197	-80.576820	0	red
53	CCAFS SLC-40	28.563197	-80.576820	0	red
54	CCAFS SLC-40	28.563197	-80.576820	1	green
55	CCAFS SLC-40	28.563197	-80.576820	0	red

TODO: For each launch result in `spacex_df` data frame, add a `folium.Marker` to `marker_cluster`

Make this Notebook Trusted to load map: File -> Trust Notebook

Your updated map may look like the following screenshots:



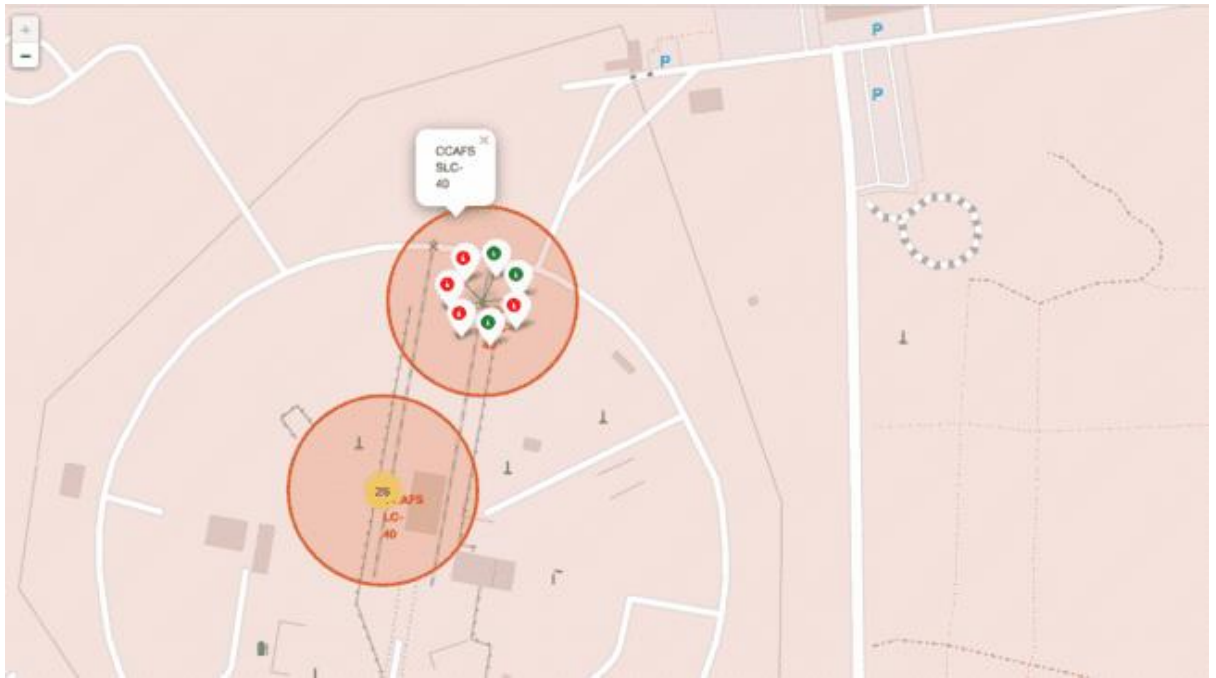


Figure 19: Mark the success/failed launches for each site on the map

From the color-labeled markers in marker clusters, you should be able to easily identify which launch sites have relatively high success rates.

TASK 3: Calculate the distances between a launch site to its proximities

Next, we need to explore and analyze the proximities of launch sites.

Let's first add a **MousePosition** on the map to get coordinate for a mouse over a point on the map. As such, while you are exploring the map, you can easily find the coordinates of any points of interests (such as railway)

In [16]:

```
# Add Mouse Position to get the coordinate (Lat, Long) for a mouse
over on the map
formatter = "function(num) {return L.Util.formatNum(num, 5);};"
mouse_position = MousePosition(
    position='topright',
    separator=' Long: ',
    empty_string='NaN',
    lng_first=False,
    num_digits=20,
    prefix='Lat:',
    lat_formatter=formatter,
    lng_formatter=formatter,
```

```
)
```

```
site_map.add_child(mouse_position)
site_map
```

Out[16]:

Make this Notebook Trusted to load map: File -> Trust Notebook

Now zoom in to a launch site and explore its proximity to see if you can easily find any railway, highway, coastline, etc. Move your mouse to these points and mark down their coordinates (shown on the top-left) in order to the distance to the launch site.

You can calculate the distance between two points on the map based on their Lat and Long values using the following method:

In [17]:

```
from math import sin, cos, sqrt, atan2, radians

def calculate_distance(lat1, lon1, lat2, lon2):
    # approximate radius of earth in km
    R = 6373.0

    lat1 = radians(lat1)
    lon1 = radians(lon1)
    lat2 = radians(lat2)
    lon2 = radians(lon2)

    dlon = lon2 - lon1
    dlat = lat2 - lat1

    a = sin(dlat / 2)**2 + cos(lat1) * cos(lat2) * sin(dlon / 2)**2
    c = 2 * atan2(sqrt(a), sqrt(1 - a))

    distance = R * c

    return distance
```

TODO: Mark down a point on the closest railway using MousePosition and calculate the distance between the railway point to the launch site.

In [18]:

```
spacex_df[spacex_df['Launch Site'] == 'VAFB SLC-4E']
```

Out[18]:

Table 16: Calculate the distances between a launch site to its proximities

	Launch Site	Lat	Long	class	marker_color
26	VAFB SLC-4E	34.632834	-120.610746	0	red
27	VAFB SLC-4E	34.632834	-120.610746	0	red
28	VAFB SLC-4E	34.632834	-120.610746	1	green
29	VAFB SLC-4E	34.632834	-120.610746	1	green
30	VAFB SLC-4E	34.632834	-120.610746	1	green
31	VAFB SLC-4E	34.632834	-120.610746	1	green
32	VAFB SLC-4E	34.632834	-120.610746	0	red
33	VAFB SLC-4E	34.632834	-120.610746	0	red
34	VAFB SLC-4E	34.632834	-120.610746	0	red
35	VAFB SLC-4E	34.632834	-120.610746	0	red

```
# points.append(VAFB_SLC_4E)
# points.append(guadalupe_amtrak)
# linetext = "{} , {:.2f} km".format(railway_name, distance_railway)
# folium.PolyLine(points, color='blue', weight=2.5,
# popup=linetext).add_to(site_map)
# add_text_distance_marker_on_map(railway_name, guadalupe_amtrak,
# distance_railway, ccolor='#4d0f1d')
# site_map
draw_equater_line()

launchsite_VAFB = {'name':'VAFB SLC-4E', 'coordinates':[34.632834, -
120.610746], 'placetype':'rocket'}
```



```

equator1 = {'name':'Equator Distance from VAFB SLC-4E',
'coordinates':[0, -120.61], 'placetype':'map'}
draw_distance_lines(launchsite_VAFB, equator1,'green', 'green',
'#325931')

launchsite_KSC = {'name':'KSC LC-39A', 'coordinates':[28.573255, -
80.646895], 'placetype':'rocket'}
equator2 = {'name':'Equator Distance from KSC LC-39A',
'coordinates':[0, -80.64651], 'placetype':'map'}
draw_distance_lines(launchsite_KSC, equator2, 'green', 'green',
'#325931')

site_map

```

Out[21]:

Make this Notebook Trusted to load map: File -> Trust Notebook

Your updated map with distance line should look like the following screenshot:

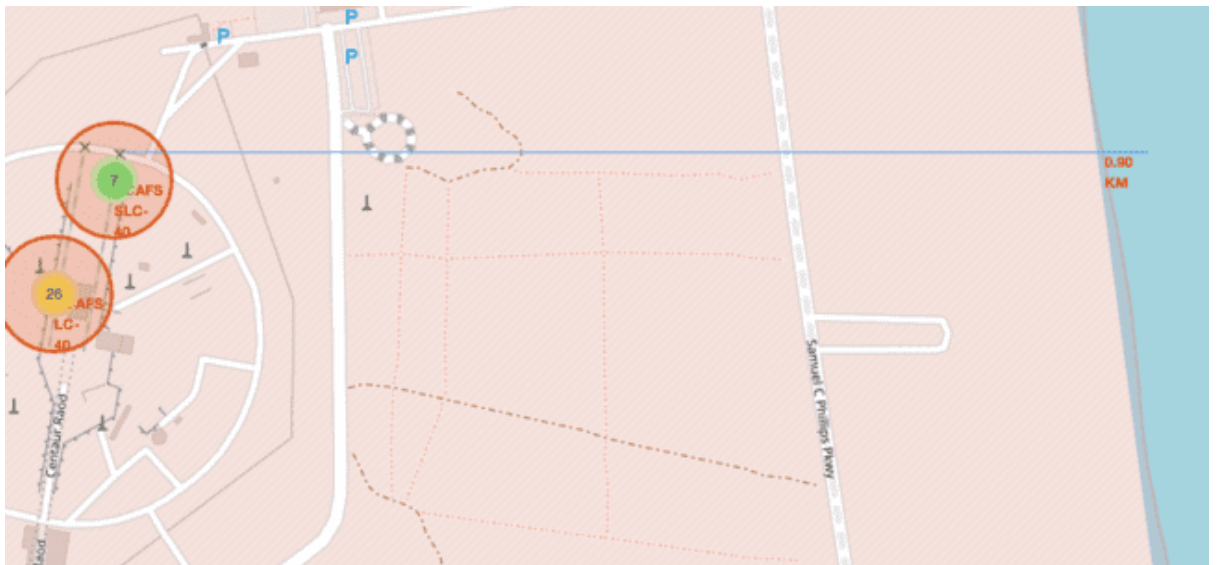


Figure 20: Calculate the distances between a launch site to its proximities

TODO: Similarly, you can draw a line between a launch site to its closest city, coastline, highway, etc.

In [22]:

Make this Notebook Trusted to load map: File -> Trust Notebook

After you plot distance lines to the proximities, you can answer the following questions easily:

- Are launch sites in close proximity to railways?

- Are launch sites in close proximity to highways?
- Are launch sites in close proximity to coastline?
- Do launch sites keep certain distance away from cities?

Also please try to explain your findings.

6.2. Plotly:

```
'''
Build a Dashboard Application with Plotly Dash
-----

In this lab, you will be building a Plotly Dash
application for users to perform interactive visual analytics
on SpaceX launch data in real-time.
'''

import dash
import dash_html_components as html
import dash_core_components as dcc
from dash.dependencies import Input, Output
import pandas as pd
import plotly.express as px

external_stylesheets = ['https://codepen.io/chriddyp/pen/bWLwgP.css']
app = dash.Dash(__name__, external_stylesheets=external_stylesheets)

spacex_df = pd.read_csv("spacex_launch_dash.csv")
max_payload = spacex_df['Payload Mass (kg)'].max()
min_payload = spacex_df['Payload Mass (kg)'].min()

unique_launch_sites = spacex_df['Launch Site'].unique().tolist()
launch_sites = []
launch_sites.append({'label': 'All Sites', 'value': 'All Sites'})
for launch_site in unique_launch_sites:
    launch_sites.append({'label': launch_site, 'value': launch_site})

app.layout = html.Div(children=[
    html.Div([
        html.H1('SpaceX Launch Records Dashboard',
            style={'textAlign': 'center', 'color': '#503D36', 'font-
size': 40}),
    ]),

    html.Div([
        # TASK 1: Add a Launch Site Drop-down Input Component
        dcc.Dropdown(
            id = 'site-dropdown',
            options = launch_sites,
            placeholder = 'Select a Launch Site here',
            searchable = True ,
```

```

        clearable = False,
        value = 'All Sites'
    ),
    # TASK 2: Add a callback function to render success-pie-chart
    based on selected site dropdown
    html.Div(dcc.Graph(id='success-pie-chart')),
    ], style={'padding': '0 30px'}),

    html.Div([
        # TASK 3: Add a Range Slider to Select Payload
        html.Div("Payload range (Kg):",
            style={'color': '#503D36', 'font-size': 20, 'padding': '0
30px', 'margin-left': '11px'}
        ),
        html.Div([
            dcc.RangeSlider(
                id = 'payload_slider',
                min = 0,
                max = 10000,
                step = 1000,
                marks = {
                    0: {'label': '0 Kg', 'style': {'color':
'#77b0b1'}},
                    1000: {'label': '1000 Kg'},
                    2000: {'label': '2000 Kg'},
                    3000: {'label': '3000 Kg'},
                    4000: {'label': '4000 Kg'},
                    5000: {'label': '5000 Kg'},
                    6000: {'label': '6000 Kg'},
                    7000: {'label': '7000 Kg'},
                    8000: {'label': '8000 Kg'},
                    9000: {'label': '9000 Kg'},
                    10000: {'label': '10000 Kg', 'style': {'color':
'#f50'}},
                },
                value = [min_payload,max_payload]
            ),
        ], style={'padding': '40px 30px'}),

        # TASK 4: Add a callback function to render the success-payload-
        scatter-chart scatter plot
        html.Div(dcc.Graph(id = 'success-payload-scatter-chart')),
    ]),

```

```

],style={'padding': '0 20px'})

# TASK 2: success-pie-chart callback based on selected site dropdown
@app.callback(
    Output(component_id = 'success-pie-chart', component_property =
'figure'),
    [Input(component_id = 'site-dropdown', component_property =
'value')]
)
def update_piegraph(site_dropdown):
    if (site_dropdown == 'All Sites' or site_dropdown == 'None'):
        all_sites = spacex_df[spacex_df['class'] == 1] # All Success
only for all sites.
        fig = px.pie(
            all_sites,
            names = 'Launch Site',
            title = 'Total Success Launches by All Sites',
            hole = .2,
            color_discrete_sequence = px.colors.sequential.RdBu
        )
    else:
        site_specific = spacex_df.loc[spacex_df['Launch Site'] ==
site_dropdown]
        fig = px.pie(
            site_specific,
            names = 'class',
            title = 'Total Success Launches for Site &#8608;
'+site_dropdown,
            hole = .2
        )
    return fig

# TASK 3, 4: Range Slider or Scatter Chart Callback
@app.callback(
    Output(component_id = 'success-payload-scatter-chart',
component_property = 'figure'),
    [Input(component_id = 'site-dropdown', component_property =
'value'),
    Input(component_id = "payload_slider", component_property =
"value")]
)
def update_scattergraph(site_dropdown,payload_slider):
    if (site_dropdown == 'All Sites' or site_dropdown == 'None'):

```

```

        low, high = payload_slider
        all_sites = spacex_df
        inrange = (all_sites['Payload Mass (kg)'] > low) &
(all_sites['Payload Mass (kg)'] < high)
        fig = px.scatter(
            all_sites[inrange],
            x = "Payload Mass (kg)",
            y = "class",
            title = 'Correlation Between Payload and Success for All
Sites',
            color="Booster Version Category",
            size='Payload Mass (kg)',
            hover_data=['Payload Mass (kg)']
        )
    else:
        low, high = payload_slider
        site_specific = spacex_df.loc[spacex_df['Launch Site'] ==
site_dropdown]
        inrange = (site_specific['Payload Mass (kg)'] > low) &
(site_specific['Payload Mass (kg)'] < high)
        fig = px.scatter(
            site_specific[inrange],
            x = "Payload Mass (kg)",
            y = "class",
            title = 'Correlation Between Payload and Success for
Site &#8608; '+site_dropdown,
            color="Booster Version Category",
            size='Payload Mass (kg)',
            hover_data=['Payload Mass (kg)']
        )
    return fig

if __name__ == '__main__':
    app.run_server(debug=True)

```

CHAPTER 7

PREDICTIVE ANALYSIS (CLASSIFICATION)

7.1: Machine Learning Prediction

Space X Falcon 9 First Stage Landing Prediction:

Assignment: Machine Learning Prediction

Estimated time needed: **60** minutes

Space X 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 Space X 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 space X for a rocket launch. In this lab, you will create a machine learning pipeline to predict if the first stage will land given the data from the preceding labs.

Several examples of an unsuccessful landing are shown here:

Most unsuccessful landings are planned. Space X; performs a controlled landing in the oceans.

Objectives:

Perform exploratory Data Analysis and determine Training Labels

- create a column for the class
- Standardize the data
- Split into training data and test data

-Find best Hyperparameter for SVM, Classification Trees and Logistic Regression

- Find the method performs best using test data

Import Libraries and Define Auxiliary Functions:

We will import the following libraries for the lab

In [1]:

```
# Pandas is a software library written for the Python programming language for data manipulation and analysis.
import pandas as pd
# NumPy is a library for the Python programming language, adding support for large, multi-dimensional arrays and matrices, along with a large collection of high-level mathematical functions to operate on these arrays
import numpy as np
# Matplotlib is a plotting library for python and pyplot gives us a MatLab like plotting framework. We will use this in our plotter function to plot data.
import matplotlib.pyplot as plt
#Seaborn is a Python data visualization library based on matplotlib. It provides a high-level interface for drawing attractive and informative statistical graphics
import seaborn as sns
# Preprocessing allows us to standarsize our data
from sklearn import preprocessing
# Allows us to split our data into training and testing data
from sklearn.model_selection import train_test_split
# Allows us to test parameters of classification algorithms and find the best one
from sklearn.model_selection import GridSearchCV
# Logistic Regression classification algorithm
from sklearn.linear_model import LogisticRegression
# Support Vector Machine classification algorithm
from sklearn.svm import SVC
# Decision Tree classification algorithm
from sklearn.tree import DecisionTreeClassifier
# K Nearest Neighbors classification algorithm
from sklearn.neighbors import KNeighborsClassifier
```

This function is to plot the confusion matrix.

In [2]:


```
def plot_confusion_matrix(y, y_predict):
    "this function plots the confusion matrix"
    from sklearn.metrics import confusion_matrix

    cm = confusion_matrix(y, y_predict)
    ax= plt.subplot()
    sns.heatmap(cm, annot=True, ax = ax); #annot=True to annotate
cells
    ax.set_xlabel('Predicted labels')
    ax.set_ylabel('True labels')
    ax.set_title('Confusion Matrix');
    ax.xaxis.set_ticklabels(['did not land', 'land']);
    ax.yaxis.set_ticklabels(['did not land', 'landed'])
```

Load the dataframe:

Load the data

In [3]:

```
data = pd.read_csv("https://cf-courses-data.s3.us.cloud-object-
storage.appdomain.cloud/IBM-DS0321EN-
SkillsNetwork/datasets/dataset_part_2.csv")

# If you were unable to complete the previous lab correctly you can
uncomment and load this csv

# data = pd.read_csv('https://cf-courses-data.s3.us.cloud-object-
storage.appdomain.cloud/IBMDeveloperSkillsNetwork-DS0701EN-
SkillsNetwork/api/dataset_part_2.csv')

data.head()
```

Out[3]:

Flight Number	Booster Version	Payload Mass	Orbit	Launch Site	Outcome	Flight Hours	Grid Finish	Reusable Legs	Land Landing Pad	Reusable Count	Severities	Longitudes	Latitudes	Classes
0	1	2010-06-04	61499412	LC	Failure	1	1	1	1	1	0	0	0	0
		2010-06-04	61499412	LC	Failure	1	1	1	1	1	0	0	0	0
		2010-06-04	61499412	LC	Failure	1	1	1	1	1	0	0	0	0
		2010-06-04	61499412	LC	Failure	1	1	1	1	1	0	0	0	0
		2010-06-04	61499412	LC	Failure	1	1	1	1	1	0	0	0	0
1	2	2012-05-02	52000000	LC	Failure	1	1	1	1	1	0	0	0	0
		2012-05-02	52000000	LC	Failure	1	1	1	1	1	0	0	0	0
		2012-05-02	52000000	LC	Failure	1	1	1	1	1	0	0	0	0
		2012-05-02	52000000	LC	Failure	1	1	1	1	1	0	0	0	0
		2012-05-02	52000000	LC	Failure	1	1	1	1	1	0	0	0	0
2	3	2013-01-03	67700000	IS	Failure	1	1	1	1	1	0	0	0	0
		2013-01-03	67700000	IS	Failure	1	1	1	1	1	0	0	0	0
		2013-01-03	67700000	IS	Failure	1	1	1	1	1	0	0	0	0
		2013-01-03	67700000	IS	Failure	1	1	1	1	1	0	0	0	0
		2013-01-03	67700000	IS	Failure	1	1	1	1	1	0	0	0	0

Flight Number	Booster Version	Payload Mass	Orbit	Launch Site	Orbit Name	Flight Hours	Grid Coordinates	Reusable Legs	Land Design Pad	Reusable Count	Longitude	Latitude	Classes
3	4	3		0	L	n					7	8	
		-		0	C	e					3	5	
		0		0	4						6	7	
		1		0	0						6		
		2		5	V	F					-		
		0		0	A	a					1	3	
		1	Fa	0	F	l		F	F	F	2	4	
		3	lc	.	B	s		a	a	a	B	0	.
		-	o	0	P	e	1	l	l	l	1	.	6
		0	n	0	O	O		s	s	s	0	6	3
4	5	9	9	0	L	c		e	e	e	0	1	2
		-		0	C	e					3	0	0
		2		0	4	a					8	9	
		9		0	E	n					2	3	
											9		
		2		3	C						-		
		0		1	C	N					8	8	
		1	Fa	7	A	o		F	F	F	0	.	
		3	lc	0	F	n		a	a	a	B	.	5
		-	o	0	S	e	1	l	l	l	1	5	6
4	5	1		0	S	N		s	s	s	0	7	1
		2	n	0	L	o		e	e	e	0	7	8
		-	9	0	C	n					4	3	5
		0		0	4	e					6	7	
		3		0	0						6		
		2		3	C						-		2
		0		1	C	N					8	8	
		1	Fa	7	A	o		F	F	F	0	.	
		3	lc	0	F	n		a	a	a	B	.	5

```
X = pd.read_csv('https://cf-courses-data.s3.us.cloud-object-
storage.appdomain.cloud/IBM-DS0321EN-
SkillsNetwork/datasets/dataset_part_3.csv')

# If you were unable to complete the previous lab correctly you can
uncomment and load this csv

# X = pd.read_csv('https://cf-courses-data.s3.us.cloud-object-
storage.appdomain.cloud/IBMDeveloperSkillsNetwork-DS0701EN-
SkillsNetwork/api/dataset_part_3.csv')

X.head(100)
```

90 rows × 83 columns

TASK 1

Create a NumPy array from the column Class in data, by applying the method to_numpy() then assign it to the variable Y,make sure the output is a Pandas series (only one bracket df['name of column']).

In [5]:

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

TASK 2

Standardize the data in X then reassign it to the variable X using the transform provided below.

In [6]:

```
# students get this
transform = preprocessing.StandardScaler()
```

In [7]:

```
X = transform.fit(X).transform(X)
```

We split the data into training and testing data using the function train_test_split. The training data is divided into validation data, a second set used for training data; then the models are trained and hyperparameters are selected using the function GridSearchCV.

TASK 3

Use the function `train_test_split` to split the data `X` and `Y` into training and test data. Set the parameter `test_size` to 0.2 and `random_state` to 2. The training data and test data should be assigned to the following labels.

`X_train, X_test, Y_train, Y_test`

In [8]:

```
X_train, X_test, Y_train, Y_test = train_test_split(X, y,
test_size=0.2, random_state=2)
```

we can see we only have 18 test samples.

In [9]:

```
Y_test.shape
```

Out[9]:

```
(18,)
```

TASK 4

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

In [10]:

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

In [11]:

```
parameters = {"C": [0.01, 0.1, 1], 'penalty': ['l2'], 'solver': ['lbfgs']}#
11 lasso l2 ridge
lr=LogisticRegression()
gs_cv = GridSearchCV(lr, parameters, scoring='accuracy', cv=10)
logreg_cv = gs_cv.fit(X_train, Y_train)
```

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_`.

In [12]:

```
print("Tuned hyperparameters : (best parameters) ",
logreg_cv.best_params_)
print("Accuracy for logistic regression:", logreg_cv.best_score_)
```

```
Tuned hpyerparameters :(best parameters) {'C': 0.01, 'penalty': 'l2', 'solver': 'lbfgs'}
Accuracy for logistic regression: 0.8464285714285713
```

TASK 5

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

In [13]:

```
print('Accuracy for logistic regression using the method score:',
      logreg_cv.score(X_test, Y_test))
Accuracy for logistic regression using the method score: 0.8333333333333334
```

Lets look at the confusion matrix:

In [14]:

```
yhat=logreg_cv.predict(X_test)
plot_confusion_matrix(Y_test, yhat)
```

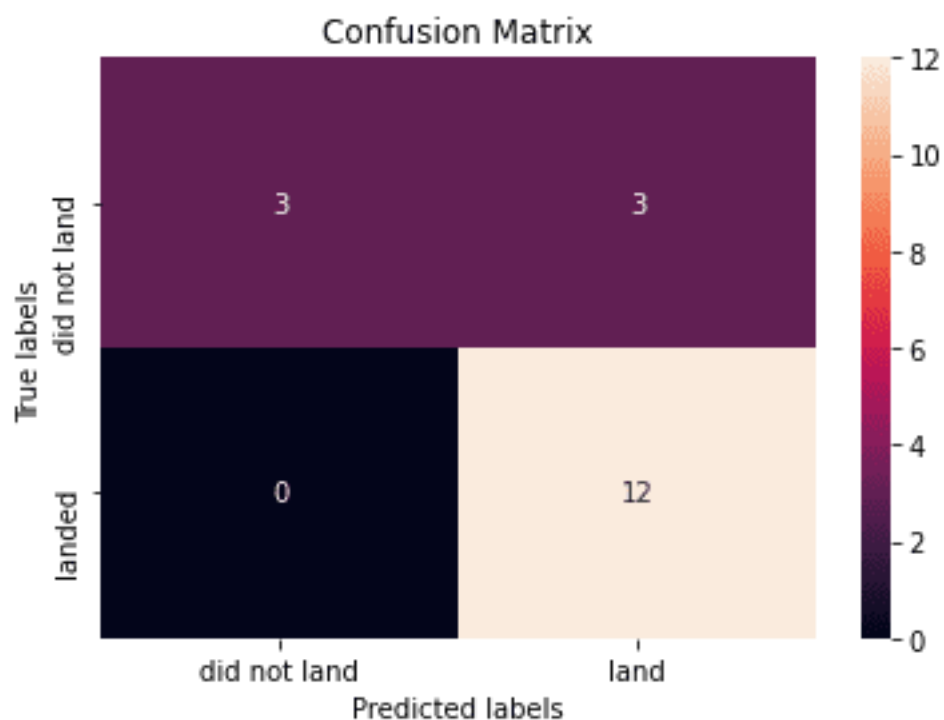


Figure 21: Calculate the accuracy on the test data using the method score:

Examining the confusion matrix, we see that logistic regression can distinguish between the different classes. We see that the major problem is false positives.

TASK 6

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.

In [15]:

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

svm = SVC()
```

In [16]:

```
gs_cv = GridSearchCV(svm,parameters, scoring='accuracy', cv=10)
svm_cv = gs_cv.fit(X_train, Y_train)
```

In [17]:

```
print("Tuned hyperparameters :(best parameters) ",
      svm_cv.best_params_)
print("Accuracy for support vector machine:", svm_cv.best_score_)
Tuned hyperparameters :(best parameters) {'C': 1.0, 'gamma': 0.0316
2277660168379, 'kernel': 'sigmoid'}
Accuracy for support vector machine: 0.8482142857142856
```

TASK 7

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

In [18]:

```
print("Accuracy for support vector machine on the test data using
the method score:", svm_cv.score(X_test, Y_test))
Accuracy for support vector machine on the test data using the metho
d score: 0.8333333333333334
```

We can plot the confusion matrix

In [19]:

```
yhat=svm_cv.predict(X_test)
plot_confusion_matrix(Y_test,yhat)
```

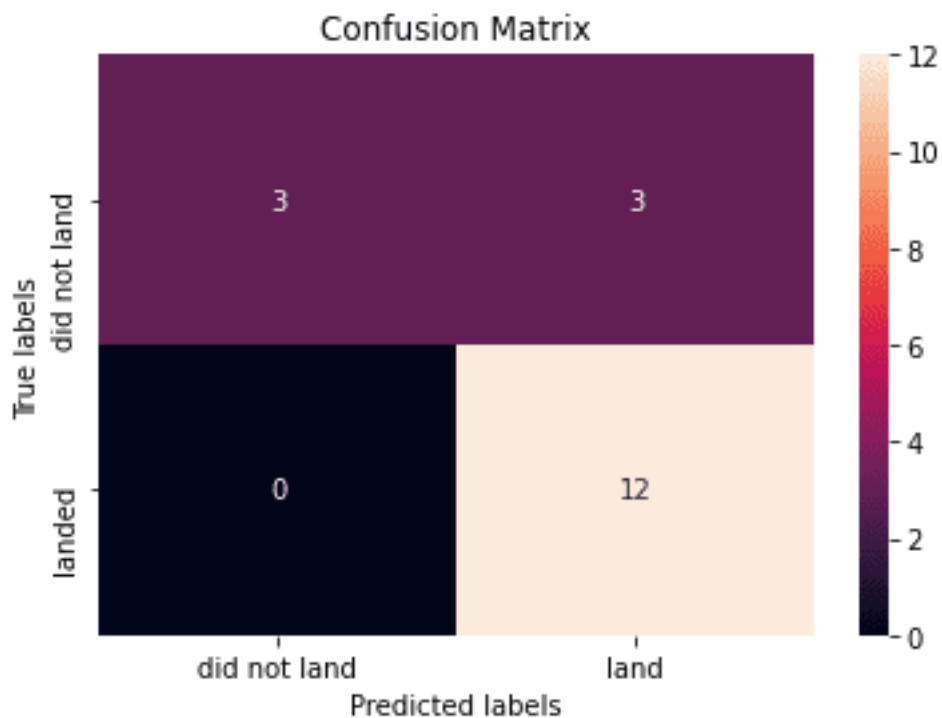


Figure 22: Calculate the accuracy on the test data using the method score:

TASK 8

Create a decision tree classifier object then create a GridSearchCV object tree_cv with cv = 10. Fit the object to find the best parameters from the dictionary parameters.

In [20]:

```
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()
```

In [21]:

```
gs_cv = GridSearchCV(tree,parameters, scoring='accuracy', cv=10)
tree_cv = gs_cv.fit(X_train, Y_train)
```

In [22]:

```
print("Tuned hpyerparameters :(best parameters) ",
      tree_cv.best_params_)
print("Accuracy for decision tree classifier:", tree_cv.best_score_)
```



```
Tuned hpyerparameters :(best parameters) {'criterion': 'gini', 'max
_depth': 10, 'max_features': 'sqrt', 'min_samples_leaf': 1, 'min_sam
ples_split': 2, 'splitter': 'best'}
Accuracy for decision tree classifier: 0.9017857142857144
```

TASK 9

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

In [23]:

```
print("Accuracy for decision tree classifier on the test data using
the method score:", tree_cv.score(X_test, Y_test))
Accuracy for decision tree classifier on the test data using the met
hod score: 0.8333333333333334
```

We can plot the confusion matrix

In [24]:

```
yhat = svm_cv.predict(X_test)
plot_confusion_matrix(Y_test, yhat)
```

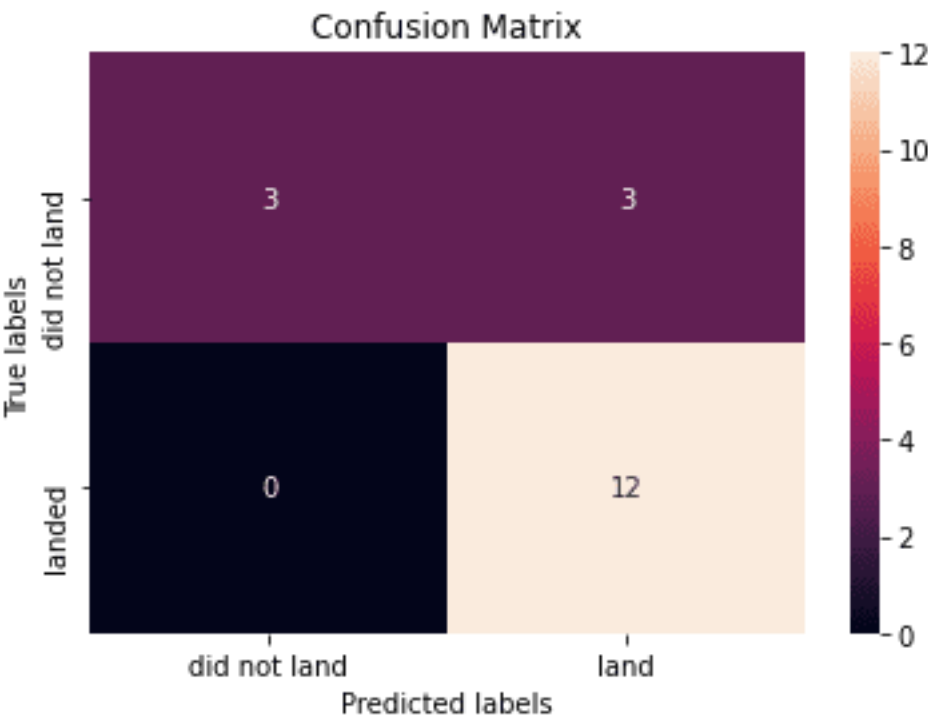


Figure 23: Calculate the accuracy of tree_cv on the test data using the method score:

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.

In [25]:

```
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()
```

In [26]:

```
gs_cv = GridSearchCV(KNN, parameters, scoring='accuracy', cv=10)
knn_cv = gs_cv.fit(X_train, Y_train)
```

In [27]:

```
print("Tuned hpyerparameters :(best parameters)
",knn_cv.best_params_)
print("Accuracy for k nearest neighbors:",knn_cv.best_score_)
Tuned hpyerparameters :(best parameters) {'algorithm': 'auto', 'n_n
eighbors': 10, 'p': 1}
Accuracy for k nearest neighbors: 0.8482142857142858
```

TASK 11

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

In [28]:

```
print("Accuracy for k nearest neighbors on the test data using the
method score: ",knn_cv.score(X_test, Y_test))
Accuracy for k nearest neighbors on the test data using the method s
core: 0.8333333333333334
```

We can plot the confusion matrix

In [29]:

```
yhat = knn_cv.predict(X_test)
plot_confusion_matrix(Y_test,yhat)
```

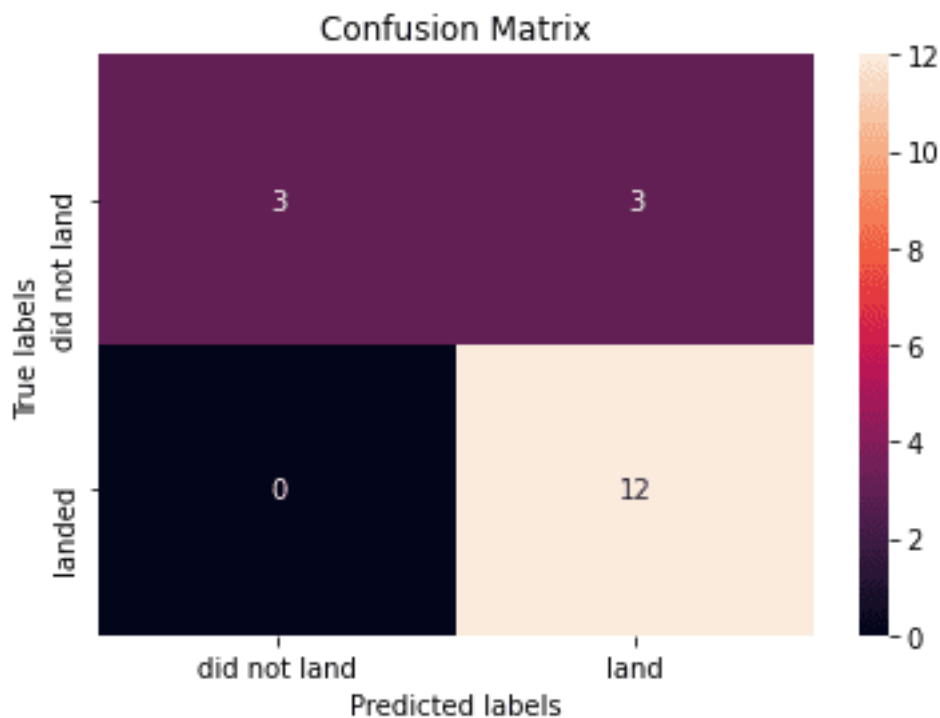


Figure 24: Calculate the accuracy of `tree_cv` on the test data using the method score:

TASK 12

Find the method performs best:

In [30]:

```
algorithms = {'KNN':knn_cv.best_score_, 'Decision
Tree':tree_cv.best_score_, 'Logistic
Regression':logreg_cv.best_score_, 'SVM':svm_cv.best_score_}
best_algorithm = max(algorithms, key= lambda x: algorithms[x])

print('The method which performs best is "',best_algorithm,'" with
a score of',algorithms[best_algorithm])
The method which performs best is " Decision Tree " with a score of
0.9017857142857144
```

In [31]:

```
algo_df = pd.DataFrame.from_dict(algorithms, orient='index',
columns=['Accuracy'])
```

In [32]:

```
algo_df.head()
```

Out[32]:

Table 17: Find the method performs best:

Accuracy		
	KNN	0.848214
	Decision Tree	0.901786
	Logistic Regression	0.846429
	SVM	0.848214

In [33]:

```
algo_df.sort_values(['Accuracy'], inplace=True)
```

In [34]:

```
algo_df.head()
```

Out[34]:

Accuracy		
	Logistic Regression	0.846429
	SVM	0.848214
	KNN	0.848214
	Decision Tree	0.901786

In [35]:

```
algo_df = algo_df.reset_index()
algo_df.head()
```

Out[35]:

	index	Accuracy
0	Logistic Regression	0.846429

	index	Accuracy
1	SVM	0.848214
2	KNN	0.848214
3	Decision Tree	0.901786

In [36]:

```
algo_df.rename(columns = {'index': 'Algorithm'}, inplace = True)
algo_df.head()
```

Out[36]:

	Algorithm	Accuracy
0	Logistic Regression	0.846429
1	SVM	0.848214
2	KNN	0.848214
3	Decision Tree	0.901786

In [37]:

```
import plotly.express as px
import plotly.graph_objects as go
```

In [38]:

```
fig = px.bar(algo_df, x='Algorithm', y='Accuracy',
             hover_data=['Algorithm', 'Accuracy'], color='Accuracy',
             color_continuous_scale='rdylbu')
fig.update_layout(title='Algorithm vs. Accuracy',
                  xaxis_title='Algorithm', yaxis_title='Accuracy' )
fig.show()
```

CHAPTER 8

PRESENT YOUR DATA-DRIVEN INSIGHTS

8.1. Present Your Data-Driven Insights with Presentation



SpaceX Industrial
Project.docx

Insights with Presentation 1



SpaceX_Industrial_Pr
oject_PPT_Slides.pdf

Insights with Presentation 2

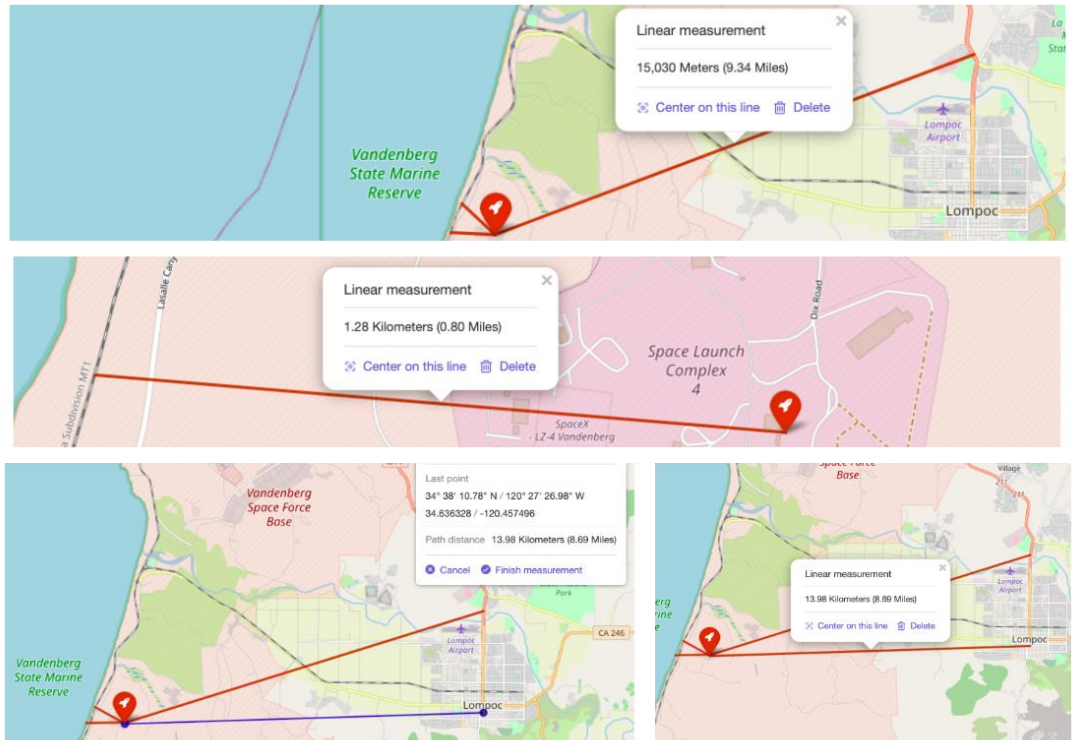


SpaceX Industrial
Project PPT.pptx

Insights with Presentation 3

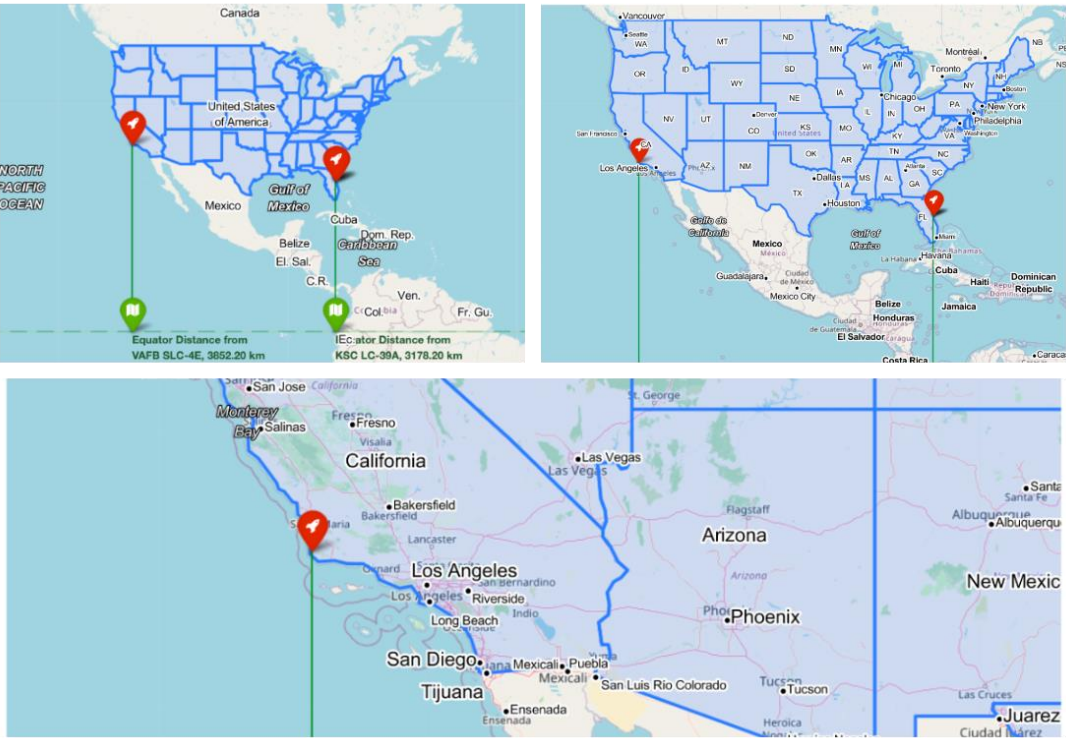
8.2. 🧠 Out of the Box Thinking:

- Advanced Folium Function [Measurement Control Plugin with Folium](#)



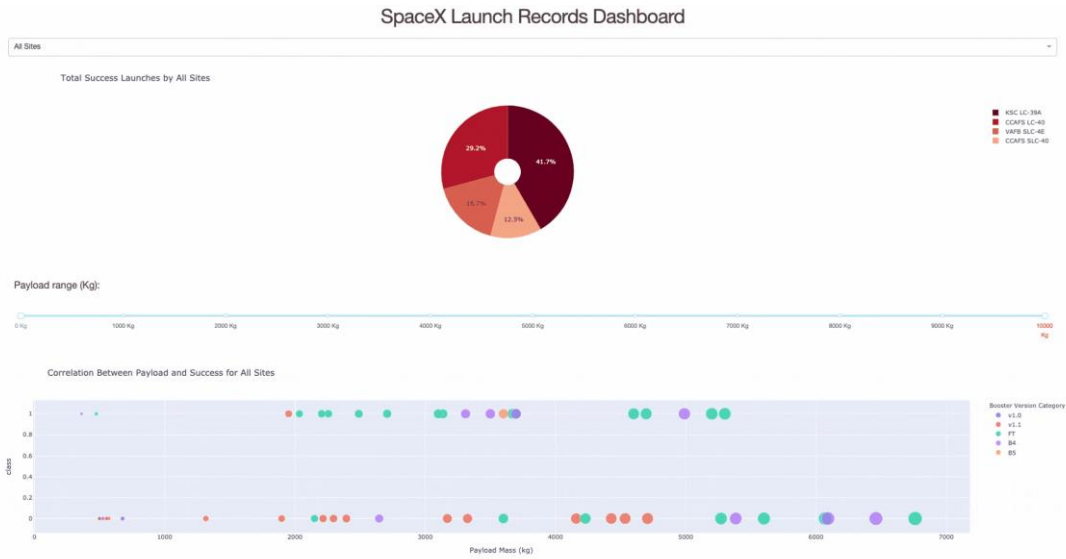
Insights with Presentation 4: measurementcontrol.png

- Advanced Folium Function Folium Custom Pane with Labels



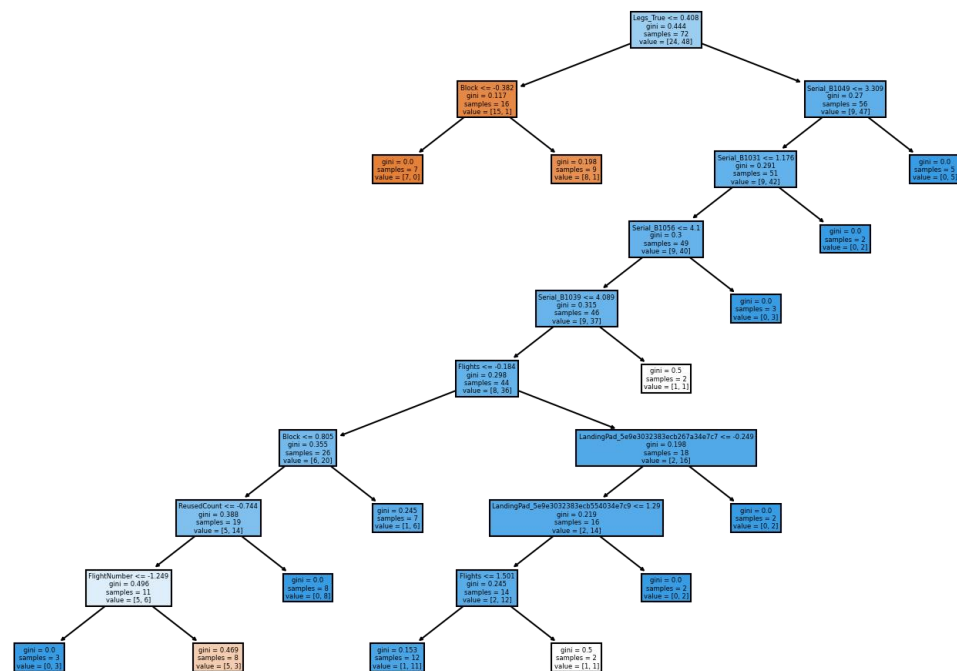
Insights with Presentation 5: custompanes.png

- Hosting the Plotly on "Python Anywhere" Server with Flask



Insights with Presentation 6: interactive-plotly.gif

- Machine Learning - Decision Tree**
Construction



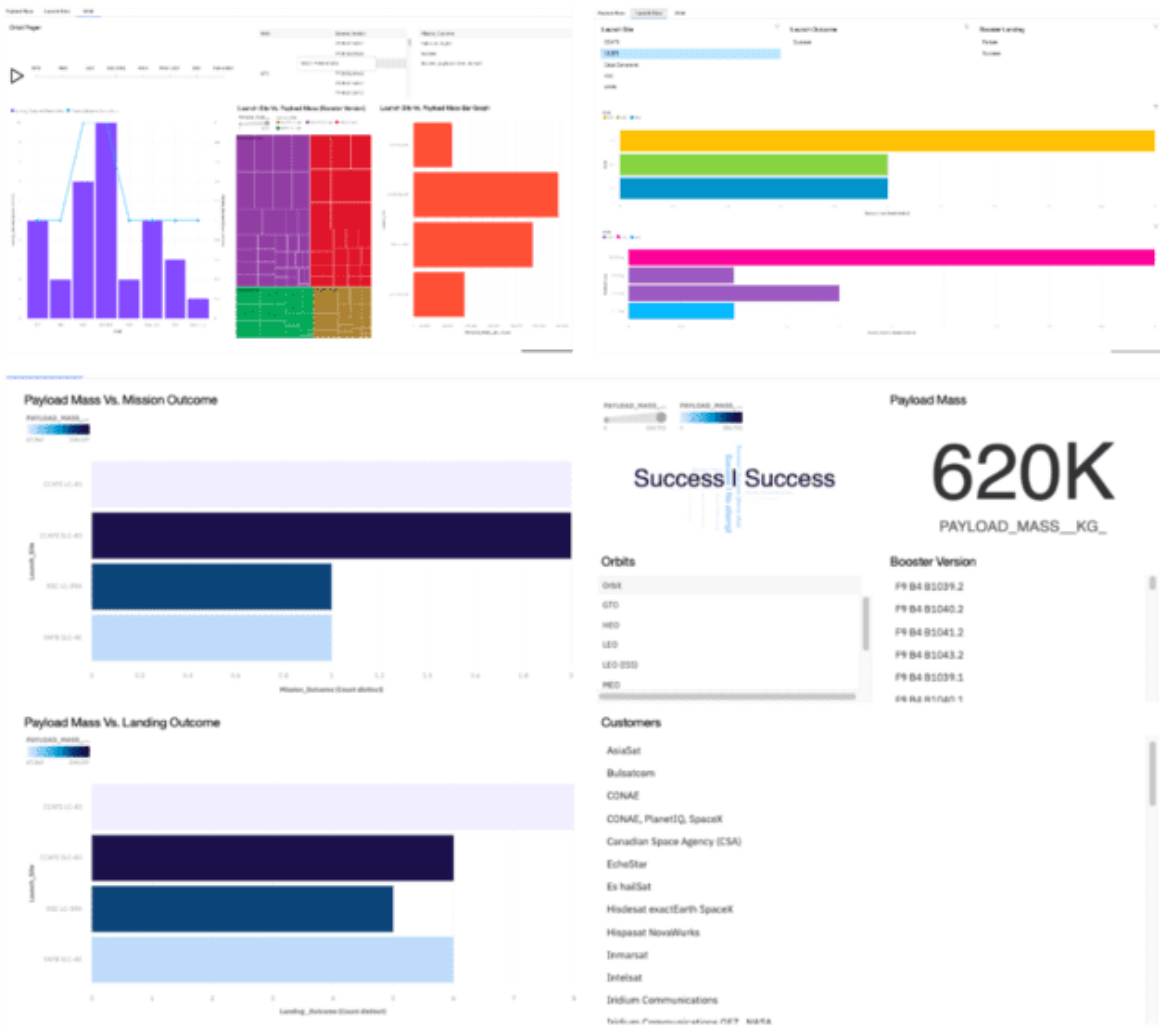
Insights with Presentation 7: decision-tree.png

- EDA Visualization with Interactive Plotly (Instead of Seaborn)**



Insights with Presentation 8: plotly.png

- [IBM Cognos Visualization with Player](#)



Insights with Presentation 9: IBM-Cognos.png

8.3 Built With:

- [Python](#) - Programming Language
- [IBM Watson Studio](#) - IBM's software platform for data science
- [IBM Db2](#) - Db2 is a family of data management products, including database servers, developed by IBM
- [Jupyter Notebooks](#) - Open-source web application that allows data scientists to create and share documents that integrate live code, equations, computational output, visualizations, and other multimedia resources.
- [Anaconda](#) - Local environment for practice
- [pythonanywhere.com](#) - Host your Python App via Flask
- [plotly.com](#) - Plotly stewards Python's leading data viz and UI libraries. With Dash Open Source, Dash apps run on your local laptop or server
- [IBM Cognos Dashboard](#) - IBM Cognos Analytics provides dashboards and stories to communicate your insights and analysis. You can assemble a view that contains visualizations such as a graph, chart, plot, table, map, or any other visual representation of data.
- [GitHub](#) - Repository for storing all files

8.4. 📄 Extra Study Materials:

Don't jump into labs without study. Take time to study previous labs step by step and practice on your own laptop locally by installing Anaconda. This will also limit the usage of IBM Cloud Trial version.

- [Plotly](#)
- [Folium](#)
- [Folium Examples](#)
- [Confusion Matrix](#)

REFERENCES

1. Joseph Santarcangelo has a PhD in Electrical Engineering, his research focused on using machine learning, signal processing, and computer vision to determine how videos impact human cognition. Joseph has been working for IBM since he completed his PhD.
2. Yan Luo
3. Nayef Abou Tayoun
4. Joseph Santarcangelo has a PhD in Electrical Engineering, his research focused on using machine learning, signal processing, and computer vision to determine how videos impact human cognition. Joseph has been working for IBM since he completed his PhD.
5. Nayef Abou Tayoun is a Data Scientist at IBM and pursuing a Master of Management in Artificial intelligence degree at Queen's University.
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<http://dx.doi.org/10.1016/j.ijinfomgt.2016.04.004>
14. Hands-on Lab: String Patterns, Sorting and Grouping
15. Hands-on Lab: Built-in functions
16. Hands-on Lab: Sub-queries and Nested SELECT Statements
17. Hands-on Tutorial: Accessing Databases with SQL magic
18. Hands-on Lab: Analysing a real-World Data Set



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BRIEF OVERVIEW / CAREER OBJECTIVE / SUMMARY

I want to become a data Scientist.

KEY EXPERTISE / SKILLS

Problem Solving Algorithms HTML CSS SQL Python NumPy Pandas C

EDUCATION

KIET Group of Institutions MCA - Computer Application Percentage: 67.00 / 100.00	2019 - 2022
IIMT Engineering College, Meerut BCA - Computer Applications Percentage : 56.00 / 100.00	2014 - 2017
Gyan Deep Public School, Muzaffarnagar 12 th CBSE Percentage: 49.00 / 100.00	2014
Gyan Deep Public School, Muzaffarnagar 10 th CBSE CGPA: 7.20 / 10.00	2012

PROJECTS

Privlok Mentor: Dr. Vipin Kumar Team Size: 4 Key Skills: SQLite Android Studio Java It is a password keeper app which stores data internally without the use of Cloud.	April 15, 2021 - June 15, 2021
Indoor Game Team Size: 2 Key Skills: HTML CSS Javascript Indoor game website(static).	Nov. 1, 2019 - Dec. 15, 2019

ACHIEVEMENTS

- 3rd level on 1st sem. (Department level competition)

PERSONAL INTERESTS / HOBBIES

- Badminton
- Singing
- Travelling
- Photography

IMs

- WhatsApp - 8755600635

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