Falcon9 landing Prediction

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EXECUTIVE SUMMARY

- **Objective of this Project**: Predicting successful landing of Falcon 9 first stage.

  - Stages involved:
  - Data Collection
  - Preprocessing
  - Analyzing using visualization tools .
  - Applying various ML algorithms to predict
  - Finding the best model which gives the best accuracy.

INTRODUCTION

- The **first stage landing** of space shuttles (or more accurately, **rockets** like those from SpaceX) plays a **critical role** in reducing the **cost, waste, and risk** of launching payloads into space
- **Cost Savings**:
  - The **first stage** is the **most expensive part** of a rocket (~60–80% of total cost).
  - Traditionally, it's discarded into the ocean after launch

Data Collection and Data Wrangling

	FlightNumber	Date	BoosterVersion	PayloadMass	Orbit	LaunchSite	Outcome	Flights	GridFins	Reused	Legs	
4	1	2010-06-04	Falcon 9	NaN	LEO	CCSFS SLC 40	None None	1	False	False	False	
5	2	2012-05-22	Falcon 9	525.0	LEO	CCSFS SLC 40	None None	1	False	False	False	
6	3	2013-03-01	Falcon 9	677.0	ISS	CCSFS SLC 40	None None	1	False	False	False	
7	4	2013-09-29	Falcon 9	500.0	PO	VAFB SLC 4E	False Ocean	1	False	False	False	
8	5	2013-12-03	Falcon 9	3170.0	GTO	CCSFS SLC 40	None None	1	False	False	False	
...	...	...	...	...	...	...	...	...	...	...	...	
89	86	2020-09-03	Falcon 9	15600.0	VLEO	KSC LC 39A	True ASDS	2	True	True	True	5e9e30323
90	87	2020-10-06	Falcon 9	15600.0	VLEO	KSC LC 39A	True ASDS	3	True	True	True	5e9e30323
91	88	2020-10-18	Falcon 9	15600.0	VLEO	KSC LC 39A	True ASDS	6	True	True	True	5e9e30323
92	89	2020-10-24	Falcon 9	15600.0	VLEO	CCSFS SLC 40	True ASDS	3	True	True	True	5e9e30333
93	90	2020-11-05	Falcon 9	3681.0	MEO	CCSFS SLC 40	True ASDS	1	True	False	True	5e9e30323

90 rows × 17 columns

- Data for this project is used from SpaceX API.
- Converting the JSON formatted data to Data Frame.
- Filtering out only Falcon9 air crafts as we are working on that.
- Dealing with missing values as the column PayLoadMass has 5 missing values.
- So now replacing the null values with mean of the data of the column PayLoadMass.

EDA and Interactive visual analytics

- Used Folium library to build interactive dashboards and visualisations.
- Marked all the launch sites on map
- Marked the success/failed launches for each site on the map for better understanding of the effect of sites on the launch.
- Caluclated the distances between a launch sites to its proximities.
- With above all steps we get clear understanding of effects of each factor on success rate of launches.

EDA results with SQL

```
%sql SELECT DISTINCT LAUNCH_SITE FROM SPACEXTBL;
```

* ibm_db_sa://cdm26718:***@98538591-7217-4024-b027-8baa776ffad1.c3n41cmd0nqnrk39u98g.databases.appdomain.cloud:30875/bludb
Done.
Out[71]:

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 [69]:

```
%sql SELECT LAUNCH_SITE from SPACEXTBL where (LAUNCH_SITE) LIKE 'CCA%' LIMIT 5;
```

* ibm_db_sa://cdm26718:***@98538591-7217-4024-b027-8baa776ffad1.c3n41cmd0nqnrk39u98g.databases.appdomain.cloud:30875/bludb
Done.
Out[69]:

launch_site
CCAFS LC-40
CCAFS LC-40
CCAFS LC-40
CCAFS LC-40
CCAFS LC-40

Task 3

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

In [72]:

```
%sql SELECT SUM(PAYLOAD_MASS__KG_) FROM SPACEXTBL WHERE Customer = 'NASA (CRS)';
```

* ibm_db_sa://cdm26718:***@98538591-7217-4024-b027-8baa776ffad1.c3n41cmd0nqnrk39u98g.databases.appdomain.cloud:30875/bludb
Done.
Out[72]:

1
45596

Task 4

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

In [74]:

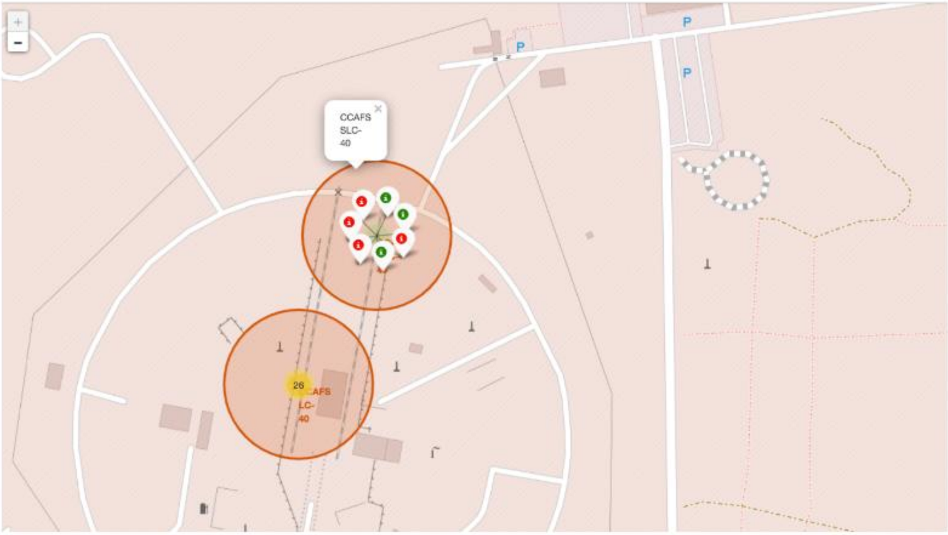
METHODOLOGY

```
%sql SELECT AVG(PAYLOAD_MASS__KG_) FROM SPACEXTBL WHERE Booster_Version LIKE 'F9 v1.0%';
```

* ibm_db_sa://cdm26718:***@98538591-7217-4024-b027-8baa776ffad1.c3n41cmd0nqnrk39u98g.databases.appdomain.cloud:30875/bludb
Done.
Out[74]:

1
340

EDA interactive results with Folium



Predictive analysis Slides

TASK 4

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

In [10]:

```
parameters ={"C":[0.01,0.1,1],'penalty':['l2'], 'solver':['lbfgs']}# l1 lasso l2 ridge
lr=LogisticRegression()
logreg_cv = GridSearchCV(lr,parameters,cv=10)
logreg_cv.fit(X_train, Y_train)
```

Out[10]:

```
GridSearchCV(cv=10, estimator=LogisticRegression(),
             param_grid={'C': [0.01, 0.1, 1], 'penalty': ['l2'],
                         'solver': ['lbfgs']})
```

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 [11]:

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

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

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 [14]:

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

In [15]:

```
svm_cv = GridSearchCV(svm,parameters,cv=10)
svm_cv.fit(X_train, Y_train)
```

Out[15]:

```
GridSearchCV(cv=10, estimator=SVC(),
             param_grid={'C': array([1.00000000e-03, 3.16227766e-02, 1.00000000e+00, 3.16227
766e+01,
       1.00000000e+03]),                                  EDA and Interactive visual analytics
                         'gamma': array([1.00000000e-03, 3.16227766e-02, 1.00000000e+00, 3.1
6227766e+01,
       1.00000000e+03]),
                         'kernel': ('linear', 'rbf', 'poly', 'rbf', 'sigmoid')})
```

In [16]:

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

```
tuned hpyerparameters :(best parameters)  {'C': 1.0, 'gamma': 0.03162277660168379, 'kernel':
'sigmoid'}
accuracy : 0.8482142857142856
```

In [19]:

```
parameters = {'criterion': ['gini', 'entropy'],
     'splitter': ['best', 'random'],
     'max_depth': [2*n for n in range(1,10) EDA and Interactive visual analytics
     'max_features': ['auto', 'sqrt'],
     'min_samples_leaf': [1, 2, 4],
     'min_samples_split': [2, 5, 10]}

tree = DecisionTreeClassifier()
```

In [20]:

```
tree_cv = GridSearchCV(tree,parameters,cv=10)
tree_cv.fit(X_train, Y_train)
```

Out[20]:

```
GridSearchCV(cv=10, estimator=DecisionTreeClassifier(),
             param_grid={'criterion': ['gini', 'entropy'],
                         'max_depth': [2, 4, 6, 8, 10, 12, 14, 16, 18],
                         'max_features': ['auto', 'sqrt'],
                         'min_samples_leaf': [1, 2, 4],
                         'min_samples_split': [2, 5, 10],
                         'splitter': ['best', 'random']})
```

In [21]:

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

```
tuned hpyerparameters :(best parameters)  {'criterion': 'gini', 'max_depth': 8, 'max_feature
s': 'sqrt', 'min_samples_leaf': 1, 'min_samples_split': 2, 'splitter': 'random'}
accuracy : 0.8875
```

Conclusions

- Used various techniques in data collection and data wrangling for cleaning data
- Used tools like Folium and Plotly for displaying various trends and insights for the given dataset.
- Used various ML algorithms :
- Logistic Regression:0.846
- Decision tree:0.8875
- KNN:0.84821
- SVM:0.8332