INTRODUCTION

I am creating this solution/product to demonstrate how a basic Machine Learning program works. I am using the infamous Titanic datset for this purpose.

Objective: is for E-learning, understand how to create Machine Learning solutions

Target Audience: Students, Professionals who are willing to start learning Machine Learning

```
from IPython.display import Image
Image("../input/image1/Titanic.png")
```

TITANIC Exploratory Data Analysis and Prediction

1. Import Libraries

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

```
/kaggle/input/titanic-extended/train.csv
/kaggle/input/titanic-extended/full.csv
/kaggle/input/titanic-extended/test.csv
/kaggle/input/image1/Titanic.png
```

2. Get datasets and read them

```
df_train = pd.read_csv('../input/titanic-extended/train.csv')
df_test = pd.read_csv('../input/titanic-extended/test.csv')
```

```
df_train.shape
```

```
(891, 21)
```

```
df_test.shape
```

```
(418, 20)
```

```
df_train.head()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	...	Embarke
0	1	0.0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	...	S
1	2	1.0	1	Cumings, Mrs. John Bradley (Florence Briggs Thayer)	female	38.0	1	0	PC 17599	71.2833	...	C
2	3	1.0	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	...	S
3	4	1.0	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	...	S
4	5	0.0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	...	S

5 rows × 21 columns

```
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 21 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
```

```
 0   PassengerId  891 non-null    int64
 1   Survived     891 non-null    float64
 2   Pclass       891 non-null    int64
 3   Name         891 non-null    object
 4   Sex          891 non-null    object
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64
 7   Parch        891 non-null    int64
 8   Ticket       891 non-null    object
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object
 11  Embarked     889 non-null    object
 12  WikiId       889 non-null    float64
 13  Name_wiki    889 non-null    object
 14  Age_wiki     887 non-null    float64
 15  Hometown     889 non-null    object
 16  Boarded      889 non-null    object
 17  Destination  889 non-null    object
 18  Lifeboat     345 non-null    object
 19  Body         87 non-null     object
 20  Class        889 non-null    float64
dtypes: float64(6), int64(4), object(11)
memory usage: 146.3+ KB
```

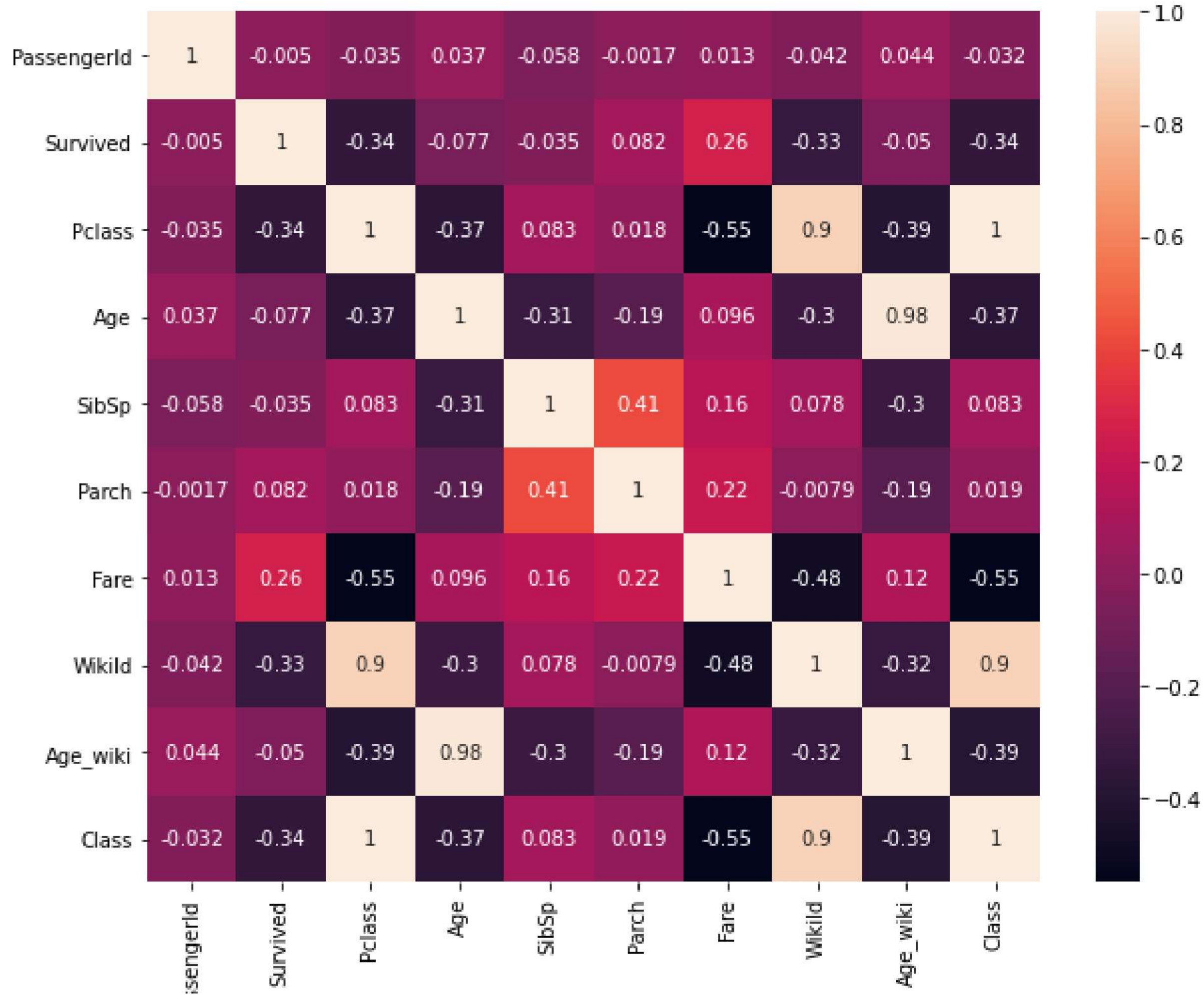
3. Exploratory Data Analysis

We will perform Correlation between variables in the dataset

```
import seaborn as sns # We will use for Data visualization purposes
import matplotlib.pyplot as plt

correlation = df_train.corr()
plt.figure(figsize=(10,8))
sns.heatmap(correlation,annot = True)
```

```
<AxesSubplot:>
```



We will use an auto EDA package using Pandas Profiling to understand the data

```
import pandas_profiling as pp
```

```
pp.ProfileReport(df_train)
```

```
Summarize dataset:   0%|          | 0/34 [00:00<?, ?it/s]
Generate report structure:   0%|          | 0/1 [00:00<?, ?it/s]
Render HTML:   0%|          | 0/1 [00:00<?, ?it/s]
```

`Cabin` has 687 (77.1%) missing values	**Missing**
`Lifeboat` has 546 (61.3%) missing values	**Missing**
`Body` has 804 (90.2%) missing values	**Missing**
`PassengerId` is uniformly distributed	**Uniform**
`Name` is uniformly distributed	**Uniform**
`Ticket` is uniformly distributed	**Uniform**
`Cabin` is uniformly distributed	**Uniform**
`Name_wiki` is uniformly distributed	**Uniform**
`Body` is uniformly distributed	**Uniform**
`PassengerId` has unique values	**Unique**
`Name` has unique values	**Unique**
`SibSp` has 608 (68.2%) zeros	**Zeros**
`Parch` has 678 (76.1%) zeros	**Zeros**
`Fare` has 15 (1.7%) zeros	**Zeros**

Reproduction

Analysis started	2021-06-12 09:29:45.734795
Analysis finished	2021-06-12 09:30:00.624562
Duration	14.89 seconds
Software version	pandas-profiling v2.11.0 (https://github.com/pandas-profiling/pandas-profiling)

Download configuration	config.yaml (data:text/plain;charset=utf-8,title%3A%20Pandas%20Profiling%20Report%0Adataset% %20%5B%27true%27%2C%20%27false%27%5D%0A%20%20%20%20file%3A%0A%20%20%20%

```
# Let's drop columns - which have more NULL values

df_train = df_train.drop(['Cabin'], axis=1)
df_test = df_test.drop(['Cabin'], axis=1)

df_train = df_train.drop(['Body'], axis=1)
df_test = df_test.drop(['Body'], axis=1)

df_train = df_train.drop(['Lifeboat'], axis=1)
df_test = df_test.drop(['Lifeboat'], axis=1)

# Let's drop WikiId column - may not be useful for our analysis
#PassengerId we will keep, since that is our key

df_train = df_train.drop(['WikiId'], axis=1)
df_test = df_test.drop(['WikiId'], axis=1)

# Let's drop name columns - these may not be useful for our analysis as well

df_train = df_train.drop(['Name'], axis=1)
df_test = df_test.drop(['Name'], axis=1)

df_train = df_train.drop(['Name_wiki'], axis=1)
df_test = df_test.drop(['Name_wiki'], axis=1)


df_train.head(3)
```

	PassengerId	Survived	Pclass	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked	Age_wiki	Ho

```
df_train.isnull().sum()
```

```
PassengerId      0
Survived         0
Pclass           0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Embarked         2
Age_wiki         4
Hometown         2
Boarded          2
Destination      2
Class            2
dtype: int64
```

```
# We will use an automated library to prepare our dataset to handle categorical and numerical values both exist
import fastai
from fastai import *
from fastai.tabular.all import *

# cont_names = Continuous variables in the dataset
# cat_names = Categorical variables in the dataset
procs = [Categorify, FillMissing, Normalize]
splits = RandomSplitter(valid_pct = 0.20)(range_of(df_train))
cont_names, cat_names = cont_cat_split(df_train, 1, 'Survived')

to = TabularPandas(df_train,procs,cat_names,cont_names,y_names='Survived',splits=splits)
to.show(5)
```

	Sex	Ticket	Embarked	Hometown	Boarded	Destination	Age_na	Age_wiki_na	Class_na	Passe
286	male	345774	S	Aspelare, East Flanders, Belgium	Southampton	Detroit, Michigan, US	False	False	False	
433	male	STON/O 2. 3101274	S	Kauhajoki, Finland	Southampton	Sudbury, Ontario, Canada	False	False	False	
675	male	349912	S	Tofta, Uppland, Sweden	Southampton	Joliet, Illinois, US	False	False	False	

4. Model Development

```
x_train, y_train = to.train.xs, to.train.y
x_test, y_test = to.valid.xs, to.valid.y
```

```
# We are just using Random Forest from sklearn
from sklearn.ensemble import RandomForestClassifier

rf_classifier = RandomForestClassifier(n_estimators=100, n_jobs=-1)
rf_classifier.fit(x_train, y_train)
```

```
RandomForestClassifier(n_jobs=-1)
```

```
# We are just using Logistic Regression from sklearn
from sklearn.linear_model import LogisticRegression

lr_classifier = LogisticRegression(solver='lbfgs', max_iter=5000)
lr_classifier.fit(x_train, y_train)
```

```
LogisticRegression(max_iter=5000)
```

5. Model Evaluation

```
from sklearn.metrics import accuracy_score

y_pred = rf_classifier.predict(x_test)
accuracy_score(y_test, y_pred)
```

```
0.8314606741573034
```

```
y_pred = lr_classifier.predict(x_test)
accuracy_score(y_test, y_pred)
```

```
0.8202247191011236
```

6. Final Output Interpretation and Result

```
to_test = TabularPandas(df_test, procs, cat_names, cont_names)

outcome = rf_classifier.predict(to_test.xs.drop('Fare_na', axis=1))
output= pd.DataFrame({'PassengerId':df_test.PassengerId, 'Survived': outcome.astype(int)})
output.to_csv('./submission_titanic.csv', index=False)
```