Titanic Survival Prediction

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Follow to kaggle project : https://www.kaggle.com/c/titanic

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My upwork profile : https://www.upwork.com/freelancers/~01ab6f69eacc2cd33a

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Data Science Pathway (According to Data Science Foundation: Fundamentals course in LinkedIn Learning)

Planning

1. Define Goals : Predicts survival passengers in Titanic
2. Organize Resource
3. Coordinate people
4. Schedule Project

Wrangling/Preparation

1. Get data : from kaggle (https://www.kaggle.com/competitions/titanic)
2. Clean data : Making data easy for use
3. Explore data : Data visualization
4. Refine data : Clean and shape it

Modeling

1. Create model
2. Validate model
3. Evaluate model
4. Refine model

Applying

1. Present model
2. Deploy model
3. Revisit model
4. Archive assets

Contents

Import Library

In [259…

```
import numpy as np # for linear algebra and operation
import pandas as pd # for dataframe
import matplotlib.pyplot as plt # for data visualization
import seaborn as sns # for data visualization
%matplotlib inline
```

This project has 3 files

train, test, gender_submission

Import files

In [260…

```
train = pd.read_csv('train.csv')
test = pd.read_csv('test.csv')
```

In [261…

```
train.head(10)
```

Out[261…

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S
5	6	0	3	Moran, Mr. James	male	NaN	0	0	330877	8.4583	NaN	Q
6	7	0	1	McCarthy, Mr. Timothy J	male	54.0	0	0	17463	51.8625	E46	S
7	8	0	3	Palsson, Master. Gosta Leonard	male	2.0	3	1	349909	21.0750	NaN	S
8	9	1	3	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	female	27.0	0	2	347742	11.1333	NaN	S
9	10	1	2	Nasser, Mrs. Nicholas (Adele Achem)	female	14.0	1	0	237736	30.0708	NaN	C

In [262…

```
test.head(10)
```

Out[262…

	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	892	3	Kelly, Mr. James	male	34.5	0	0	330911	7.8292	NaN	Q
1	893	3	Wilkes, Mrs. James (Ellen Needs)	female	47.0	1	0	363272	7.0000	NaN	S
2	894	2	Myles, Mr. Thomas Francis	male	62.0	0	0	240276	9.6875	NaN	Q
3	895	3	Wirz, Mr. Albert	male	27.0	0	0	315154	8.6625	NaN	S
4	896	3	Hirvonen, Mrs. Alexander (Helga E Lindqvist)	female	22.0	1	1	3101298	12.2875	NaN	S
5	897	3	Svensson, Mr. Johan Cervin	male	14.0	0	0	7538	9.2250	NaN	S
6	898	3	Connolly, Miss. Kate	female	30.0	0	0	330972	7.6292	NaN	Q
7	899	2	Caldwell, Mr. Albert Francis	male	26.0	1	1	248738	29.0000	NaN	S
8	900	3	Abrahim, Mrs. Joseph (Sophie Halaut Easu)	female	18.0	0	0	2657	7.2292	NaN	C
9	901	3	Davies, Mr. John Samuel	male	21.0	2	0	A/4 48871	24.1500	NaN	S

For survival : 0 = No, 1 = Yes

pclass = Ticket class : 1 = 1st, 2 = 2nd, 3 = 3rd

sibsp = of siblings / spouses aboard the Titanic

parch = of parents / children aboard the Titanic

embarked = Port of Embarkation : C = Cherbourg, Q = Queenstown, S = Southampton

Data analysis

In [263…

```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  891 non-null    int64
 1   Survived     891 non-null    int64
 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
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

Numerical : Age, Sibsp, Parch, Fare

Characterist : Survives, Pclass, Sex, Embarked

Alphabet-Numerical : Ticket, Cabin

In [264…

```
pd.isnull(train).sum()
```

Out[264…

```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

Data Visualization

Before visualization, try to assumpt what are factors that affect to survival chance.

Sex : According to survival passengers, males let females escape away from a ship before them

Class : Sound fascinating!

Age : Are children escape before adult?

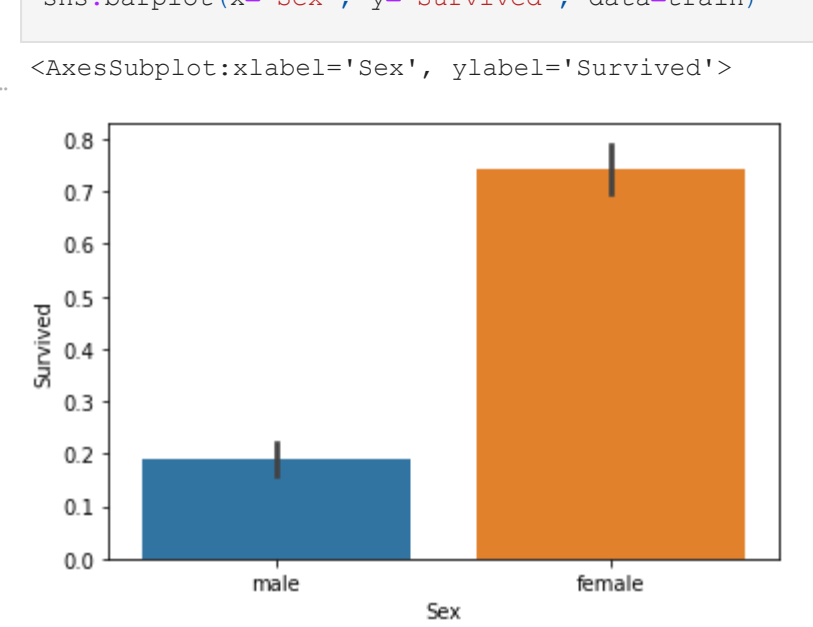
Survival by sex

In [265…

```
sns.barplot(x='Sex', y='Survived', data=train)
```

Out[265…

```
<AxesSubplot:xlabel='Sex', ylabel='Survived'>
```



In [266…

```
train['Survived'][train['Sex'] == 'female'].value_counts(normalize = True)
```

Out[266…

```
1    0.742038
0    0.257962
Name: Survived, dtype: float64
```

Survival Female = 0.742038

Unservival Female = 0.257962

In [267…

```
train['Survived'][train['Sex'] == 'male'].value_counts(normalize = True)
```

Out[267…

```
0    0.811092
1    0.188908
Name: Survived, dtype: float64
```

Survival Male = 0.188908

Unservival Male = 0.811092

Conclution, Females are more likely survive than males

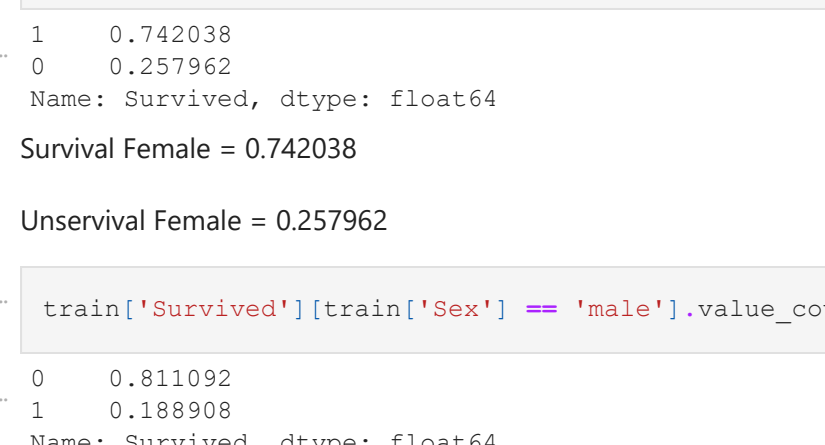
Survival by Pclass

In [268…

```
sns.barplot(x='Pclass', y='Survived', data=train)
```

Out[268…

```
<AxesSubplot:xlabel='Pclass', ylabel='Survived'>
```



In [269…

```
train['Survived'][train['Pclass'] == 1].value_counts(normalize = True)
```

Out[269…

```
1    0.62963
0    0.37037
Name: Survived, dtype: float64
```

For 1st class passenger

Survived = 0.62963

Unservived = 0.37037

In [270…

```
train['Survived'][train['Pclass'] == 2].value_counts(normalize = True)
```

Out[270…

```
0    0.527174
1    0.472826
Name: Survived, dtype: float64
```

For 2nd class passenger

Survived = 0.472826

Unservived = 0.527174

In [271…

```
train['Survived'][train['Pclass'] == 3].value_counts(normalize = True)
```

Out[271…

```
0    0.757637
1    0.242363
Name: Survived, dtype: float64
```

For 3nd class passenger

Survived = 0.242363

Unservived = 0.757637

Conclusion, the passengers who have high potential ticket are more likely survive than lower them

Survival by age

Firstly, we need to fill NaN to 'Age' column because they have 177 null data

So we need to fill both train and test data

In [272…

```
train['Age'] = train['Age'].fillna(-0.5)
test['Age']= test['Age'].fillna(-0.5)
```

I fill -0.5 for 'Age' null data because we don't know how old are them, when we plot a graph we can label as 'Unknown'

Next, label age groups

In fact, we have many age categories because every year we have new research about age categories

Thus, I would like to classified 4 group.

Child (0-12 years), Adolescence (13-18 years), Adult (19-59 years) and Senior Adult (60 years and above)

In [273…

```
secs = [-1, 0, 13, 19, 60, np.inf]
label = ['Unknown', 'Child', 'Adolescence', 'Adult', 'Senior Adult']
```

Create new column 'Age group'

In [274…

```
train['Age group'] = pd.cut(train['Age'], secs, labels = label)
test['Age group'] = pd.cut(test['Age'], secs, labels = label)
```

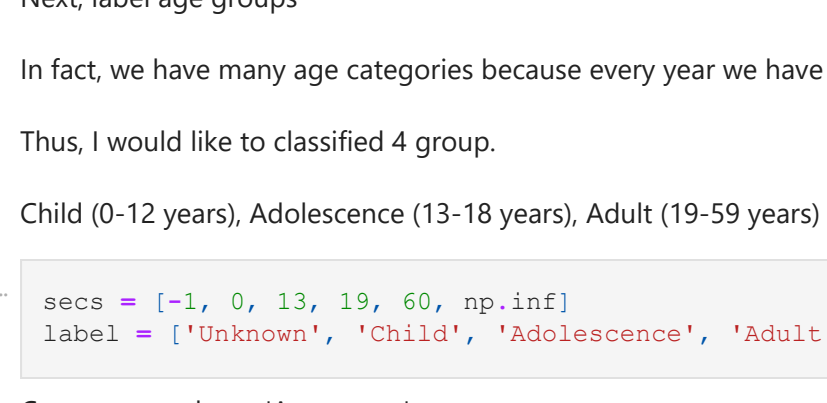
Try visualizing

In [275…

```
sns.barplot(x="Age group", y="Survived", data=train)
```

Out[275…

```
<AxesSubplot:xlabel='Age group', ylabel='Survived'>
```



I don't focus on unknown

In [276…

```
train['Survived'][train['Age group'] == 'Child'].value_counts(normalize = True)
```

Out[276…

```
1    0.591549
0    0.408451
Name: Survived, dtype: float64
```

For Children

Survived = 0.591549

Unservived = 0.408451

In [277…

```
train['Survived'][train['Age group'] == 'Adolescence'].value_counts(normalize = True)
```

Out[277…

```
0    0.602151
1    0.397849
Name: Survived, dtype: float64
```

For Adolescence

Survived = 0.397849

Unservived = 0.602151

In [278…

```
train['Survived'][train['Age group'] == 'Adult'].value_counts(normalize = True)
```

Out[278…

```
0    0.609848
1    0.390152
Name: Survived, dtype: float64
```

For Adult

Survived = 0.390152

Unservived = 0.609848

In [279…

```
train['Survived'][train['Age group'] == 'Senior Adult'].value_counts(normalize = True)
```

Out[279…

```
0    0.772727
1    0.227273
Name: Survived, dtype: float64
```

For Senior Adult

Survived = 0.227273

Unservived = 0.772727

Conclustion, the passengers who have lower age are more likely survive

Cleaning Data

My goal is refine to int. data all of them

Check our test data

In [280…

```
test.describe(include = 'all')
```

Out[280…

	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked	Age group
count	418.000000	418.000000	418	418	418.000000	418.000000	418.000000	418	417.000000	91	418	418
unique	NaN	NaN	418	2	NaN	NaN	NaN	363	NaN	76	3	5
top	NaN	NaN	Kelly, Mr. James	male	NaN	NaN	NaN	PC 17608	NaN	B57 B59 B63 B66	S	Adult
freq	NaN	NaN	1	266	NaN	NaN	NaN	5	NaN	3	270	260
mean	1100.500000	2.265550	NaN	NaN	23.941388	0.447368	0.392344	NaN	35.627188	NaN	NaN	NaN
std	120.810458	0.841838	NaN	NaN	17.741080	0.896760	0.981429	NaN	55.907576	NaN	NaN	NaN
min	892.000000	1.000000	NaN	NaN	-0.500000	0.000000	0.000000	NaN	0.000000	NaN	NaN	NaN
25%	996.250000	1.000000	NaN	NaN	9.000000	0.000000	0.000000	NaN	7.895800	NaN	NaN	NaN
50%	1100.500000	3.000000	NaN	NaN	24.000000	0.000000	0.000000	NaN	14.454200	NaN	NaN	NaN
75%	1204.750000	3.000000	NaN	NaN	35.750000	1.000000	0.000000	NaN	31.500000	NaN	NaN	NaN
max	1309.000000	3.000000	NaN	NaN	76.000000	8.000000	9.000000	NaN	512.329200	NaN	NaN	NaN

- Number of passengers are 418
- count on 'Fare' is 417 (It means 'Fare' has a missing data)
- 'Cabin' only has 91

Drop datas which I think it is not necessary

In [281…

```
test = test.drop(['Cabin'], axis = 1)
train = train.drop(['Cabin'], axis = 1)

test = test.drop(['Ticket'], axis = 1)
train = train.drop(['Ticket'], axis = 1)
```

Combine train + test

In [282…

```
combine = [train, test]
```

Extract the title of names

In [283…

```
for dataset in combine:
    dataset['Title'] = dataset.Name.str.extract(' ([A-Za-z]+)\.', expand = False)

pd.crosstab(train['Title'],train['Sex'])
```

Out[283…

Sex	female	male
Title		
Capt	0	1
Col	0	2
Countess	1	0
Don	0	1
Dr	1	6
Jonkheer	0	1
Lady	1	0
Major	0	2
Master	0	40
Miss	182	0
Mlle	2	0
Mme	1	0
Mr	0	517
Mrs	125	0
Ms	1	0
Rev	0	6
Sir	0	1

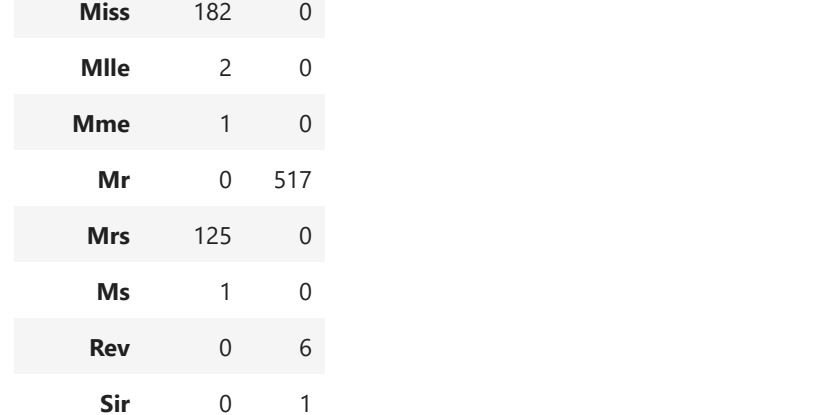
Try visualizing

In [284…

```
sns.barplot(x="Title", y="Survived", data=train)
```

Out[284…

```
<AxesSubplot:xlabel='Title', ylabel='Survived'>
```



Too many title, so we need to replace datas

'Rare' replace from 'Capt', 'Col','Don', 'Dr', 'Major', 'Rev', 'Jonkheer', 'Dona'

'Royal' replace from 'Countess', 'Lady', 'Sir'

'Mlle' replace to 'Miss'

Ms replace to 'Miss'

Mme replace tp 'Mrs'

In [285…

```
for dataset in combine:
    dataset['Title'] = dataset['Title'].replace(['Capt', 'Col','Don', 'Dr', 'Major', 'Rev', 'Jonkheer', 'Dona']
    dataset['Title'] = dataset['Title'].replace(['Countess', 'Lady', 'Sir'], 'Royal')
    dataset['Title'] = dataset['Title'].replace('Mlle', 'Miss')
    dataset['Title'] = dataset['Title'].replace('Ms', 'Miss')
    dataset['Title'] = dataset['Title'].replace('Mme', 'Mrs')

train[['Title', 'Survived']]
```

Out[285…

	Title	Survived
0	Mr	0
1	Mrs	1
2	Miss	1
3	Mrs	1
4	Mr	0
...	...	...
886	Rare	0
887	Miss	1
888	Miss	0
889	Mr	1
890	Mr	0

891 rows × 2 columns

Check Title more

In [286…

```
train[['Title', 'Survived']].groupby(['Title']).mean()
```

Out[286…

	Survived
Title	
Master	0.575000
Miss	0.702703
Mr	0.156673
Mrs	0.793651
Rare	0.250000
Royal	1.000000

In [287…

```
sns.barplot(x="Title", y="Survived", data=train)
```

Out[287…

```
<AxesSubplot:xlabel='Title', ylabel='Survived'>
```

Change 'Title' into numberical value, Follow to survived value

In [288…

```
title_map = {
    'Mr' : 1,
    'Rare' : 2,
    'Master' : 3,
    'Miss' : 4,
    'Mrs' : 5,
    'Royal' : 6
}

for dataset in combine:
    dataset['Title'] = dataset['Title'].map(title_map)
    dataset['Title'] = dataset['Title'].fillna(0)

train.head(10)
```

Out[288…

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Fare	Embarked	Age group	Title
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	7.2500	S	Adult	1
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	71.2833	C	Adult	5
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	7.9250	S	Adult	4
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	53.1000	S	Adult	5
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	8.0500	S	Adult	1
5	6	0	3	Moran, Mr. James	male	-0.5	0	0	8.4583	Q	Unknown	1
6	7	0	1	McCarthy, Mr. Timothy J	male	54.0	0	0	51.8625	S	Adult	1
7	8	0	3	Palsson, Master. Gosta Leonard	male	2.0	3	1	21.0750	S	Child	3
8	9	1	3	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	female	27.0	0	2	11.1333	S	Adult	5
9	10	1	2	Nasser, Mrs. Nicholas (Adele Achem)	female	14.0	1	0	30.0708	C	Adolescence	5

Change 'Age group' into numberical values

In [289…

```
age_group = {
    'Unknown' : 0,
    'Child' : 1,
    'Adolescence' : 2,
    'Adult' : 3,
    'Senior Adult' : 4
}

for dataset in combine:
    dataset['Age group'] = dataset['Age group'].map(age_group)
    dataset['Age group'] = dataset['Age group'].fillna(0)

train.head(10)
```

Out[289…

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Fare	Embarked	Age group	Title
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	7.2500	S	3	1
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	71.2833	C	3	5
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	7.9250	S	3	4
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	53.1000	S	3	5
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	8.0500	S	3	1
5	6	0	3	Moran, Mr. James	male	-0.5	0	0	8.4583	Q	0	1
6	7	0	1	McCarthy, Mr. Timothy J	male	54.0	0	0	51.8625	S	3	1
7	8	0	3	Palsson, Master. Gosta Leonard	male	2.0	3	1	21.0750	S	1	3
8	9	1	3	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	female	27.0	0	2	11.1333	S	3	5
9	10	1	2	Nasser, Mrs. Nicholas (Adele Achem)	female	14.0	1	0	30.0708	C	2	5

We would like to drop 'Age' because we already have 'Age group'

In [290…

```
train = train.drop(['Age'], axis = 1)
test = test.drop(['Age'], axis = 1)
```

We would like to drop 'Name'

In [291…

```
train = train.drop(['Name'], axis = 1)
test = test.drop(['Name'], axis = 1)
```

Change 'Sex' into numberical value

In [292…

```
sex_group = {
    'male' : 0,
    'female' : 1
}

train['Sex'] = train['Sex'].map(sex_group)
test['Sex'] = test['Sex'].map(sex_group)

train.head(10)
```

Out[292…

	PassengerId	Survived	Pclass	Sex	SibSp	Parch	Fare	Embarked	Age group	Title
0	1	0	3	0	1	0	7.2500	S	3	1
1	2	1	1	1	1	0	71.2833	C	3	5
2	3	1	3	1	0	0	7.9250	S	3	4
3	4	1	1	1	1	0	53.1000	S	3	5
4	5	0	3	0	0	0	8.0500	S	3	1
5	6	0	3	0	0	0	8.4583	Q	0	1
6	7	0	1	0	0	0	51.8625	S	3	1
7	8	0	3	0	3	1	21.0750	S	1	3
8	9	1	3	1	0	2	11.1333	S	3	5
9	10	1	2	1	1	0	30.0708	C	2	5

Change 'Embarked' into numberical value

In [293…

```
embarked_map = {
    'S' : 1,
    'C' : 2,
    'Q' : 3
}

train['Embarked'] = train['Embarked'].map(embarked_map)
test['Embarked'] = test['Embarked'].map(embarked_map)


train.head(10)
```

Out[293…

	PassengerId	Survived	Pclass	Sex	SibSp	Parch	Fare	Embarked	Age group	Title
0	1	0	3	0	1	0	7.2500	1.0	3	1
1	2	1	1	1	1	0	71.2833	2.0	3	5
2	3	1	3	1	0	0	7.9250	1.0	3	4
3	4	1	1	1	1	0	53.1000	1.0	3	5
4	5	0	3	0	0	0	8.0500	1.0	3	1
5	6	0	3	0	0	0	8.4583	3.0	0	1
6	7	0	1	0	0	0	51.8625	1.0	3	1
7	8	0	3	0	3	1	21.0750	1.0	1	3
8	9	1	3	1	0	2	11.1333	1.0	3	5
9	10	1	2	1	1	0	30.0708	2.0	2	5

I would like to drop 'Fare' because we have 'Pclass'

In [294…

```
train = train.drop(['Fare'], axis = 1)
test = test.drop(['Fare'], axis = 1)

train.head(10)
```

Out[294…

	PassengerId	Survived	Pclass	Sex	SibSp	Parch	Embarked	Age group	Title
0	1	0	3	0	1	0	1.0	3	1
1	2	1	1	1	1	0	2.0	3	5
2	3	1	3	1	0	0	1.0	3	4
3	4	1	1	1	1	0	1.0	3	5
4	5	0	3	0	0	0	1.0	3	1
5	6	0	3	0	0	0	3.0	0	1
6	7	0	1	0	0	0	1.0	3	1
7	8	0	3	0	3	1	1.0	1	3
8	9	1	3	1	0	2	1.0	3	5
9	10	1	2	1	1	0	2.0	2	5

In [295…

```
test.head(10)
```

Out[295…

	PassengerId	Pclass	Sex	SibSp	Parch	Embarked	Age group	Title
0	892	3	0	0	0	3	3	1
1	893	3	1	1	0	1	3	5
2	894	2	0	0	0	3	4	1
3	895	3	0	0	0	1	3	1
4	896	3	1	1	1	1	3	5
5	897	3	0	0	0	1	2	1
6	898	3	1	0	0	3	3	4
7	899	2	0	1	1	1	3	1
8	900	3	1	0	0	2	2	5
9	901	3	0	2	0	1	3	1

Checking Before Modeling

In [296…

```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 9 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  891 non-null    int64
 1   Survived     891 non-null    int64
 2   Pclass       891 non-null    int64
 3   Sex          891 non-null    int64
 4   SibSp        891 non-null    int64
 5   Parch        891 non-null    int64
 6   Embarked     889 non-null    float64
 7   Age group    891 non-null    category
 8   Title        891 non-null    int64
dtypes: category(1), float64(1), int64(7)
memory usage: 56.9 KB
```

In [297…

```
test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 8 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  418 non-null    int64
 1   Pclass       418 non-null    int64
 2   Sex          418 non-null    int64
 3   SibSp        418 non-null    int64
 4   Parch        418 non-null    int64
 5   Embarked     418 non-null    int64
 6   Age group    418 non-null    category
 7   Title        418 non-null    int64
dtypes: category(1), int64(7)
memory usage: 23.6 KB
```

In train, 'Embarked' still has null data

In [298…

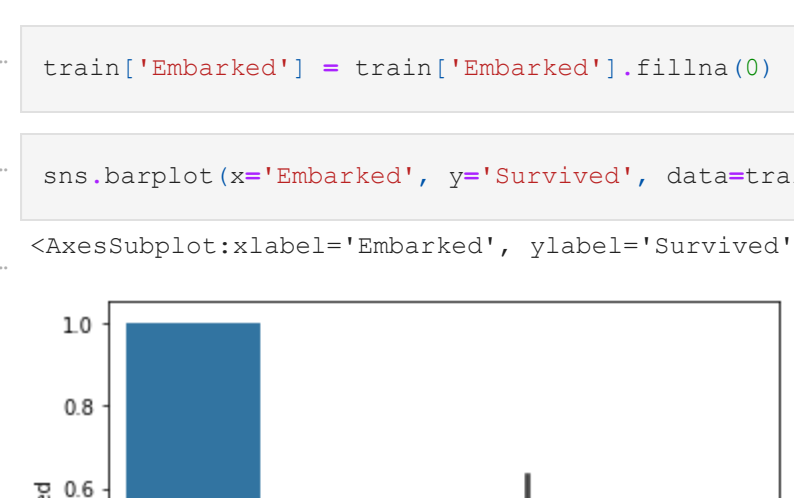
```
train['Embarked'] = train['Embarked'].fillna(0)
```

In [300…

```
sns.barplot(x='Embarked', y='Survived', data=train)
```

Out[300…

```
<AxesSubplot:xlabel='Embarked', ylabel='Survived'>
```



Modeling

Choosing the best model

Splitting the training data

I would like to use 30% of the training data to test the accurency of differential models

In [301…

```
from sklearn.model_selection import train_test_split
```

Don't forget to drop columns that is not important to choose

(Read what is train_test_split : https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.train_test_split.html)

In [302…

```
predictors = train.drop(['Survived', 'PassengerId'], axis = 1)
target = train['Survived']

x_train, x_val, y_train, y_val = train_test_split(predictors, target, test_size = 0.30)
```

Testing different models

I think this project relate to supervised learning (training data already labeled) for classifications

I need to try testing different models and checking which is best (Following to : https://www.simplilearn.com/regression-vs-classification-in-machine-learning-article?source=frs_left_nav_clicked)

- Decision Tree Classification
- K-Nearest Neighbors
- Logistic Regression
- Naïve Bayes
- Random Forest Classification
- Support Vector Machines

Import accuracy score for choosing the best of models

In [348…

```
from sklearn.metrics import accuracy_score
```

Decision Tree Classification

In [360…

```
from sklearn.tree import DecisionTreeClassifier

decision_tree = DecisionTreeClassifier()
decision_tree.fit(x_train, y_train)
prediction = decision_tree.predict(x_val)
accuracy_decision_tree = round(accuracy_score(prediction, y_val),3)

accuracy_decision_tree
```

Out[360…

```
0.847
```

K-Nearest Neighbors

In [350…

```
from sklearn.neighbors import KNeighborsClassifier

kNN = KNeighborsClassifier()
kNN.fit(x_train, y_train)
prediction = kNN.predict(x_val)
accuracy_kNN = round(accuracy_score(prediction, y_val),3)

accuracy_kNN
```

Out[350…

```
0.806
```

Logistic Regression

In [351…

```
from sklearn.linear_model import LogisticRegression

logistic_regress = LogisticRegression()
logistic_regress.fit(x_train, y_train)
prediction = logistic_regress.predict(x_val)
accuracy_logistic_regress = round(accuracy_score(prediction, y_val),3)

accuracy_logistic_regress
```

Out[351…

```
0.825
```

Naïve Bayes

In [366…

```
from sklearn.naive_bayes import GaussianNB

naive_bayes = GaussianNB()
naive_bayes.fit(x_train, y_train)
prediction = naive_bayes.predict(x_val)
accuracy_naive_bayes = round(accuracy_score(prediction, y_val),3)

accuracy_naive_bayes
```

Out[366…

```
0.821
```

Random Forest Classification

In [367…

```
from sklearn.ensemble import RandomForestClassifier

RFC = RandomForestClassifier()
RFC.fit(x_train, y_train)
prediction = RFC.predict(x_val)
accuracy_RFC = round(accuracy_score(prediction, y_val),3)

accuracy_RFC
```

Out[367…

```
0.832
```

Support Vector Machines

Note!

Support Vector Machines have both classification and regression. Then, I need to focus only classification

In [381…

```
from sklearn.svm import SVC

support_vector_machines = SVC()
support_vector_machines.fit(x_train, y_train)
prediction = support_vector_machines.predict(x_val)
accuracy_support_vector_machines = round(accuracy_score(prediction, y_val),3)

accuracy_support_vector_machines
```

Out[381…

```
0.854
```

Overview

In [377…

```
ML_models = pd.DataFrame({
    'Model' : ['Decision Tree Classification',
               'K-Nearest Neighbors',
               'Logistic Regression',
               'Naive Bayes',
               'Random Forest Classification',
               'Support Vector Machines'],
    'Score' : [accuracy_decision_tree,
               accuracy_kNN,
               accuracy_logistic_regress,
               accuracy_naive_bayes,
               accuracy_RFC,
               accuracy_support_vector_machines]
})

ML_models.sort_values(by = 'Score', ascending = False)
```

Out[377…

	Model	Score
5	Support Vector Machines	0.854
0	Decision Tree Classification	0.847
4	Random Forest Classification	0.832
2	Logistic Regression	0.825
3	Naive Bayes	0.821
1	K-Nearest Neighbors	0.806

Thus, I would like to use SVM for testing data

Present a model

I would like to create a table that shows 'PassengerId' and 'Survived'

In [387…

```
Pid = test['PassengerId']
predictions = support_vector_machines.predict(test.drop(['PassengerId'], axis = 1))
#'PassengerId' is not important for prediction processing

output = pd.DataFrame({
    'PassengerID' : Pid,
    'Survived' : predictions
})

output
```

Out[387…

	PassengerID	Survived
0	892	0
1	893	1
2	894	0
3	895	0
4	896	1
...	...	...
413	1305	0
414	1306	0
415	1307	0
416	1308	0
417	1309	1

418 rows × 2 columns

Create a output file

In [388…

```
output.to_csv('submission.csv', index = False)
```

Compare to gender_submission file

In [389…

```
gender_sub = pd.read_csv('gender_submission.csv')

from re import A
from sklearn.metrics import confusion_matrix,classification_report

print(confusion_matrix(gender_sub['Survived'],output['Survived']))
print(classification_report(gender_sub['Survived'],output['Survived']))
```

```
[[250  16]
 [  7 145]]
              precision    recall  f1-score   support

           0       0.97      0.94      0.96       266
           1       0.90      0.95      0.93       152

    accuracy                           0.94       418
   macro avg       0.94      0.95      0.94       418
weighted avg       0.95      0.94      0.95       418
```

Thank you :)

Source

- https://www.kaggle.com/code/nadintamer/titanic-survival-predictions-beginner
- https://scikit-learn.org/
- https://www.simplilearn.com
- https://ieeexplore.ieee.org/document/6416855 (For age classification)
- https://www.udemy.com/course/python-for-data-science-and-machine-learning-bootcamp/?fbclid=IwAR1HwADd1dTZ9uNej6-aW99mhzIjAUjgOoUWSPeL1tpe7w5duRKre8SaVE4