Titanic Survivor Classification

Description

This is notebook to build classification for Titanic passengers to classify if those passengers survived or not. Our aim is to get model with the most accuracy possible.

source : https://www.kaggle.com/competitions/titanic/data

Data Overview

In [1]:

```
import pandas as pd
data = pd.read_csv('train.csv')
data.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
```

In [2]:

```
data.describe()
```

Out[2]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

In [3]:

```
data.head()
```

Out[3]:

	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

In [4]:

```
data.nunique()
```

Out[4]:

```
PassengerId    891
Survived         2
Pclass           3
Name           891
Sex              2
Age             88
SibSp            7
Parch            7
Ticket         681
Fare           248
Cabin          147
Embarked         3
dtype: int64
```

So, here is Describe for each column

- PassengerId : id for each passenger for this data
- Survived : if this passenger survived or not (0 = No, 1 = Yes)
- Pclass : Ticket class (1 = 1st, 2 = 2nd, 3 = 3rd)
- Name : name of passenger
- Sex : sex of passenger
- Age : age of passenger
- SibSp : number of siblings / spouses aboard the Titanic
- Parch : number of parents / children aboard the Titanic
- Ticket : Ticket number
- Fare : Passenger fare
- Cabin : Cabin number
- Embarked : Port of Embarkation (C = Cherbourg, Q = Queenstown, S = Southampton)

Clean Up

Remove column that we are not going to use and fill null data.

In [5]:
```
# remove cloumns PassengerId, Name, Ticket and Cabin Since it have high cardinality.
data = data[['Survived','Pclass','Sex','Age','SibSp','Parch','Fare','Embarked']]
```

In [6]:
```
# get mean age
mean_age = data['Age'].mean()

print('mean age = ', mean_age)

# show histogram for Embarked for impute with the most frequent value
mode_emb = data['Embarked'].mode()
print('mode Embarked = ', mode_emb[0])
```

```
mean age =  29.69911764705882
mode Embarked =  S
```

In [7]:
```
# impute missing data
values = {'Age' : mean_age, 'Embarked': 'S'}
data = data.fillna(value=values)
```

In [8]:
```
# convert Sex to int and Embarked to 3 int columns
data['Sex'] = data.Sex.apply(lambda x: int(x =='male'))
data['Emb_C'] = data.Embarked.apply(lambda x: int(x =='C'))
data['Emb_Q'] = data.Embarked.apply(lambda x: int(x =='Q'))
data['Emb_S'] = data.Embarked.apply(lambda x: int(x =='S'))

data = data[['Survived','Pclass','Sex','Age','SibSp','Parch','Fare','Emb_C', 'Emb_Q', 'Emk
data.head()
```

Out[8]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Emb_C	Emb_Q	Emb_S
0	0	3	1	22.0	1	0	7.2500	0	0	1
1	1	1	0	38.0	1	0	71.2833	1	0	0
2	1	3	0	26.0	0	0	7.9250	0	0	1
3	1	1	0	35.0	1	0	53.1000	0	0	1
4	0	3	1	35.0	0	0	8.0500	0	0	1

Visual Display

In [9]:
```
import seaborn as sns
import matplotlib.pyplot as plt

sns.pairplot(data, kind="hist")
plt.savefig('pair_plot1.png')
```

In [10]:

```
corr_data = data.corr()
print(corr_data)
```

```
          Survived    Pclass       Sex       Age     SibSp     Parch  \
Survived  1.000000 -0.338481 -0.543351 -0.069809 -0.035322  0.081629
Pclass   -0.338481  1.000000  0.131900 -0.331339  0.083081  0.018443
Sex      -0.543351  0.131900  1.000000  0.084153 -0.114631 -0.245489
Age      -0.069809 -0.331339  0.084153  1.000000 -0.232625 -0.179191
SibSp    -0.035322  0.083081 -0.114631 -0.232625  1.000000  0.414838
Parch     0.081629  0.018443 -0.245489 -0.179191  0.414838  1.000000
Fare      0.257307 -0.549500 -0.182333  0.091566  0.159651  0.216225
Emb_C     0.168240 -0.243292 -0.082853  0.032024 -0.059528 -0.011069
Emb_Q     0.003650  0.221009 -0.074115 -0.013855 -0.026354 -0.081228
Emb_S    -0.149683  0.074053  0.119224 -0.019336  0.068734  0.060814

              Fare     Emb_C     Emb_Q     Emb_S
Survived  0.257307  0.168240  0.003650 -0.149683
Pclass   -0.549500 -0.243292  0.221009  0.074053
Sex      -0.182333 -0.082853 -0.074115  0.119224
```

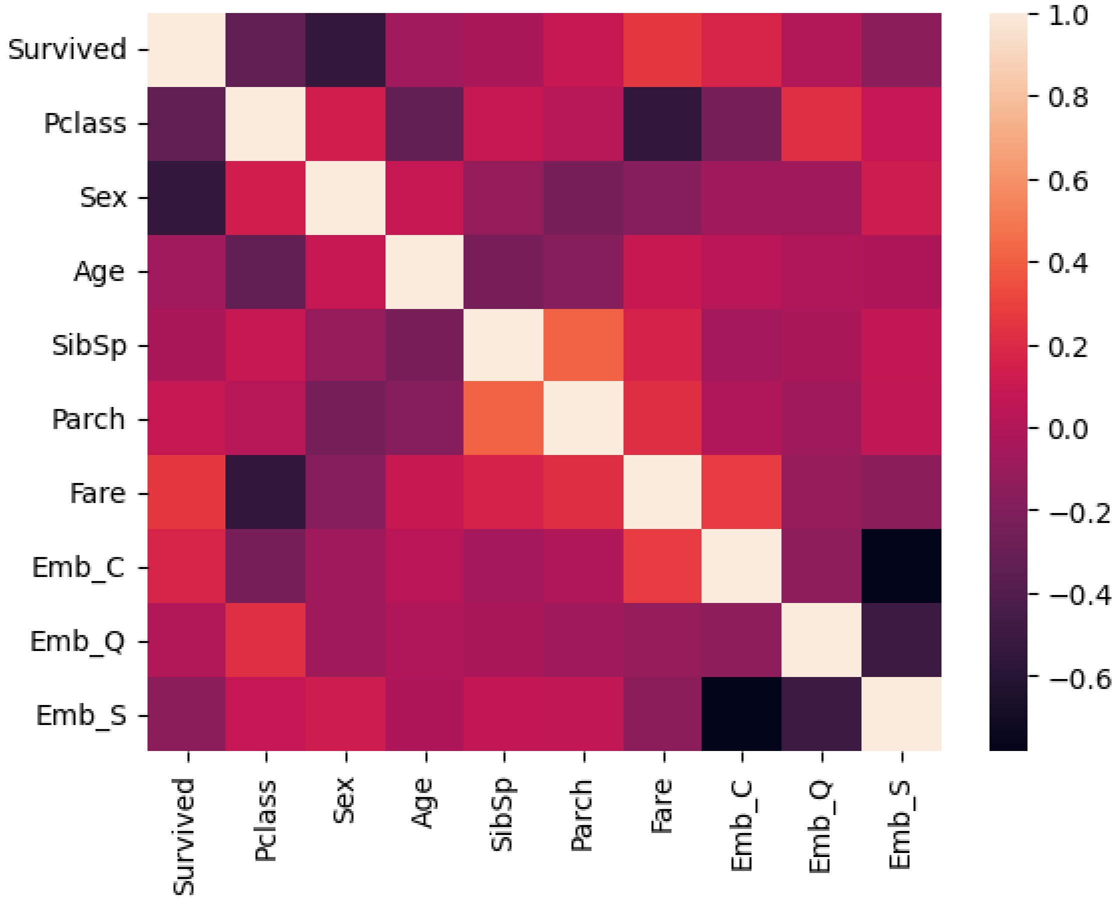
```
Age       0.091566  0.032024 -0.013855 -0.019336
SibSp     0.159651 -0.059528 -0.026354  0.068734
Parch     0.216225 -0.011069 -0.081228  0.060814
Fare      1.000000  0.269335 -0.117216 -0.162184
Emb_C     0.269335  1.000000 -0.148258 -0.782742
Emb_Q    -0.117216 -0.148258  1.000000 -0.499421
Emb_S    -0.162184 -0.782742 -0.499421  1.000000
```

In [11]:

```
sns.heatmap(corr_data)
```

Out[11]:

```
<AxesSubplot:>
```

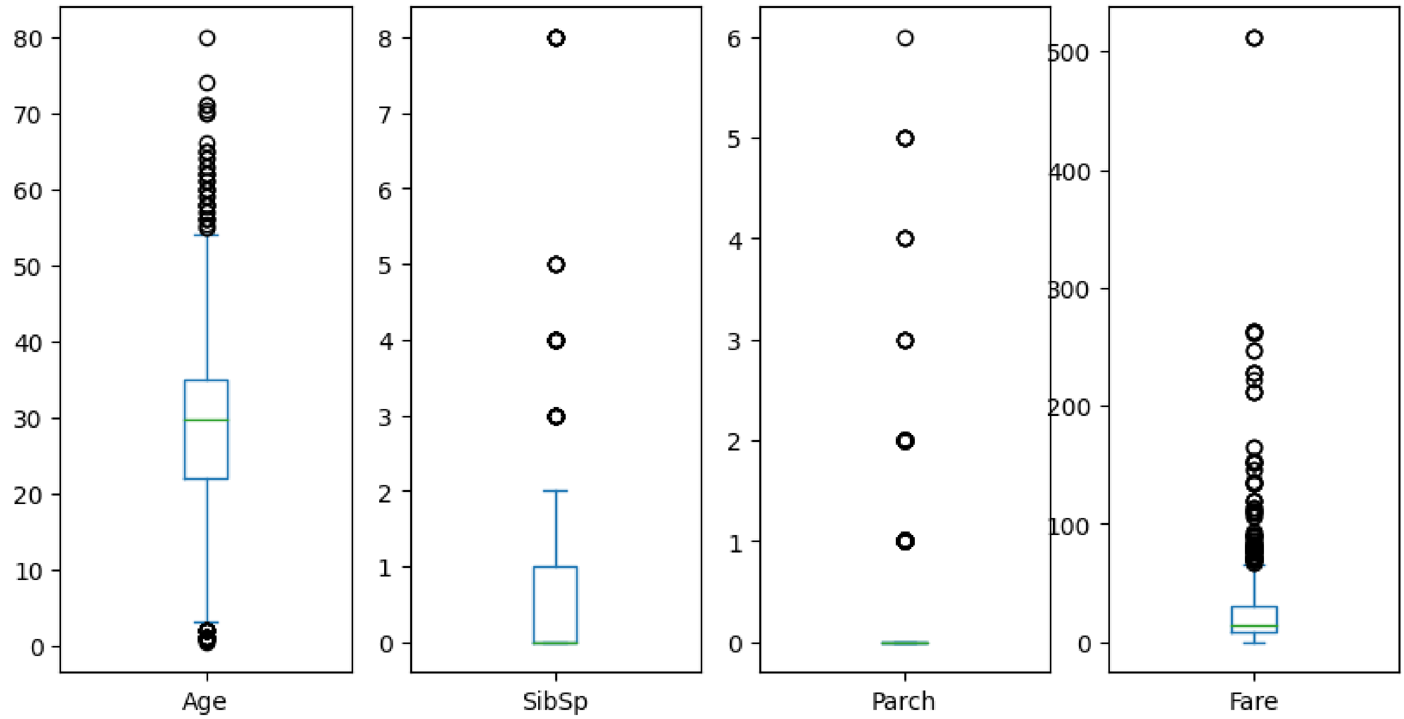


In [12]:

```
plot_data = data[['Age','SibSp','Parch','Fare']]
plot_data.plot(kind="box", subplots=True, figsize =(10, 5))
```

Out[12]:

```
Age         AxesSubplot(0.125,0.11;0.168478x0.77)
SibSp    AxesSubplot(0.327174,0.11;0.168478x0.77)
Parch    AxesSubplot(0.529348,0.11;0.168478x0.77)
Fare     AxesSubplot(0.731522,0.11;0.168478x0.77)
dtype: object
```



Analysis

From information above, seems there is no strong correlation between features as you and see from correlation heatmap or raw data (>0.7). You may see Emb_C and Emb_S have high value but those columns was extracted from Embarked feature. There are lot of outiler data as you can see. But, I think those are all valid. Age are in reasonable range (more than 0 and less than 90). SibSp and Parch also resonable because most of people board alone. Fare also reasonbale for me.

Classification

I want to use Random Forest Tree to solve this problem. Because we have only fews features.

First, split data in to train and test (test for 20%).

In [23]:

```
from sklearn.model_selection import train_test_split

X = data[['Pclass','Sex','Age','SibSp','Parch','Fare','Emb_C', 'Emb_Q', 'Emb_S']]
Y = data['Survived']
x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_state=1992

print(len(x_train), len(x_test))
```

```
712 179
```

Then, Build first model to be our base line.

In [24]:

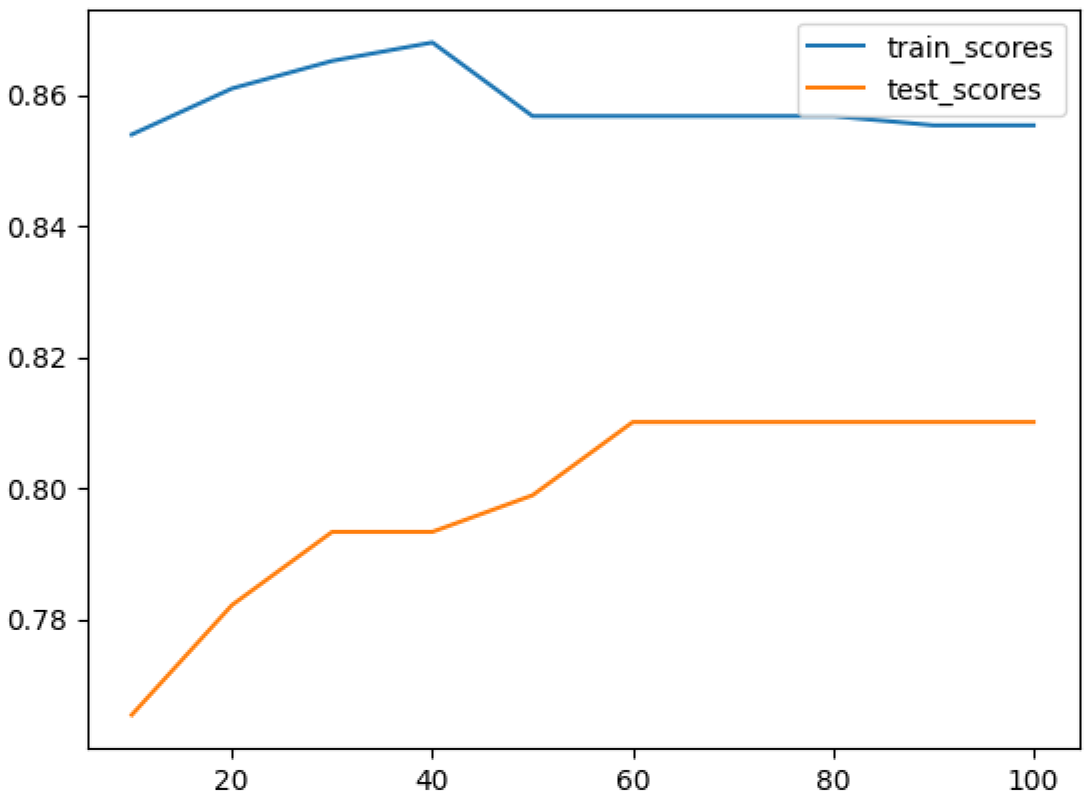
```
from sklearn.ensemble import RandomForestClassifier

bl_model = RandomForestClassifier(n_estimators=10, max_depth=5, random_state=1992).fit(x_t
print('score with training data = ',bl_model.score(x_train,y_train))
print('score with test data = ',bl_model.score(x_test,y_test))
```

```
score with training data =  0.8539325842696629
score with test data =  0.7653631284916201
```

try to play with n_estimators and max_depth

In [25]:
```
es = list(range(10,110,10))
train_scores = []
test_scores = []
for e in es:
    model = RandomForestClassifier(n_estimators=e, max_depth=5, random_state=1992).fit(x_t
    train_scores.append(model.score(x_train,y_train))
    test_scores.append(model.score(x_test,y_test))

print('train_scores = ', train_scores)
print('test_scores = ', test_scores)

plt.plot(es, train_scores)
plt.plot(es, test_scores)

plt.legend(['train_scores', 'test_scores'])
plt.show()
```

```
train_scores =  [0.8539325842696629, 0.8609550561797753, 0.8651685393258427, 0.86797752808
98876, 0.8567415730337079, 0.8567415730337079, 0.8567415730337079, 0.8567415730337079, 0.8
553370786516854, 0.8553370786516854]
test_scores =  [0.7653631284916201, 0.7821229050279329, 0.7932960893854749, 0.793296089385
4749, 0.7988826815642458, 0.8100558659217877, 0.8100558659217877, 0.8100558659217877, 0.81
00558659217877, 0.8100558659217877]
```

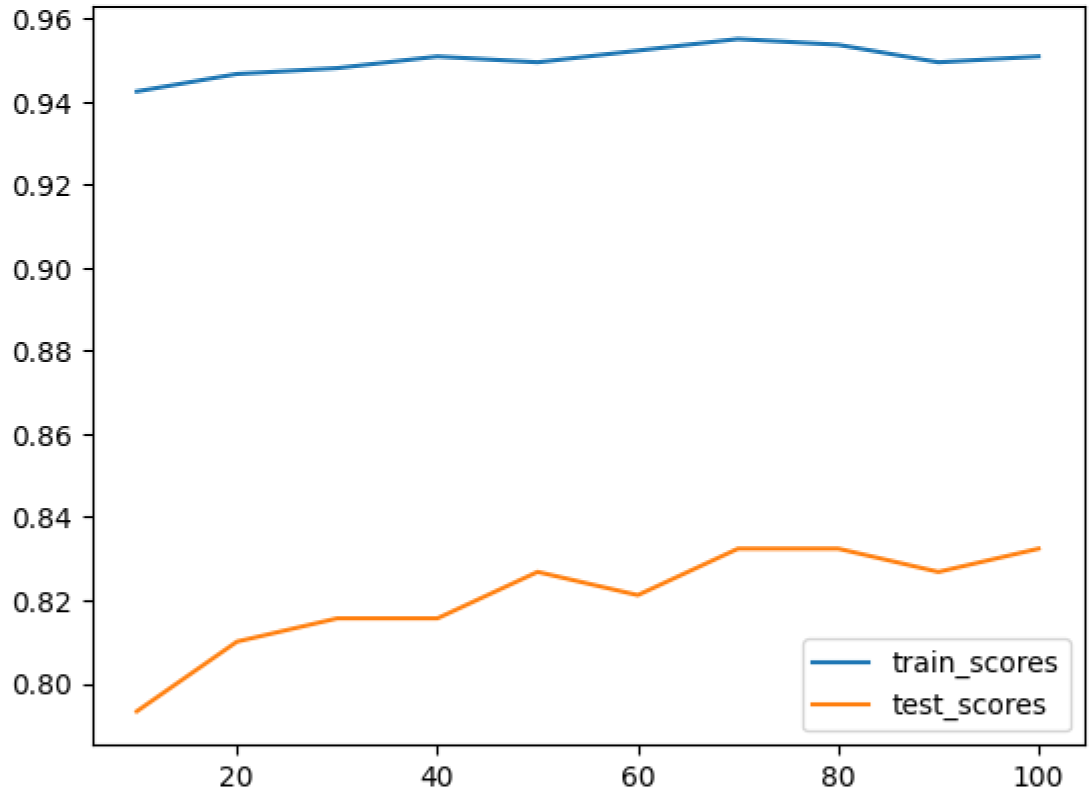


Try with max_depth=10

In [28]:
```
es = list(range(10,110,10))
train_scores = []
test_scores = []
for e in es:
    model = RandomForestClassifier(n_estimators=e, max_depth=10, random_state=1992).fit(x_
    train_scores.append(model.score(x_train,y_train))
    test_scores.append(model.score(x_test,y_test))

print('train_scores = ', train_scores)
print('test_scores = ', test_scores)

plt.plot(es, train_scores)
plt.plot(es, test_scores)
```

```
plt.legend(['train_scores', 'test_scores'])
plt.show()
```

```
train_scores =  [0.9424157303370787, 0.9466292134831461, 0.9480337078651685, 0.95084269662
92135, 0.949438202247191, 0.952247191011236, 0.9550561797752809, 0.9536516853932584, 0.949
438202247191, 0.9508426966292135]
test_scores =  [0.7932960893854749, 0.8100558659217877, 0.8156424581005587, 0.815642458100
5587, 0.8268156424581006, 0.8212290502793296, 0.8324022346368715, 0.8324022346368715, 0.82
68156424581006, 0.8324022346368715]
```



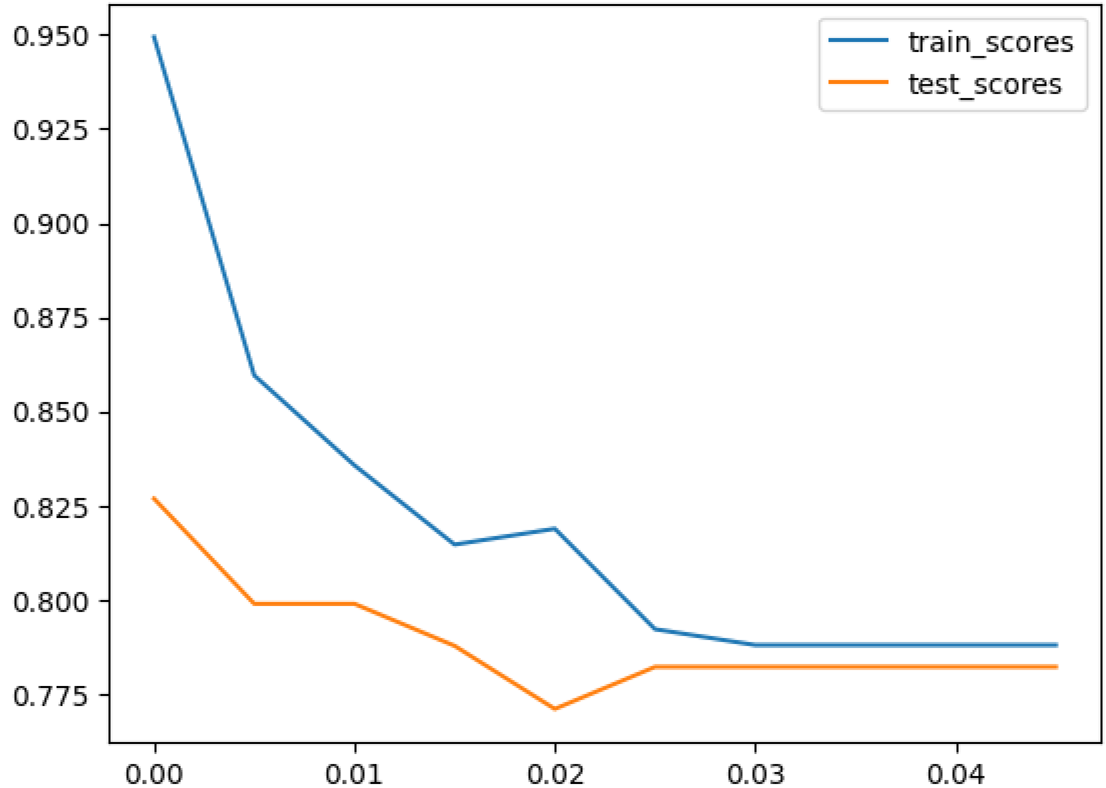
From graphs we can see that using max_depth=10 is better. And the reasonal n_estimators is 50.

I will try to tune ccp_alpha to reduce data overfitted.

In [29]:
```
alphas = []
for i in range(10):
    alphas.append(i*0.005)

train_scores = []
test_scores = []
for a in alphas:
    model = RandomForestClassifier(n_estimators=50, max_depth=10, ccp_alpha=a, random_stat
    train_scores.append(model.score(x_train,y_train))
    test_scores.append(model.score(x_test,y_test))

print('train_scores = ', train_scores)
print('test_scores = ', test_scores)

plt.plot(alphas, train_scores)
plt.plot(alphas, test_scores)

plt.legend(['train_scores', 'test_scores'])
plt.show()
```

```
train_scores =  [0.949438202247191, 0.8595505617977528, 0.8356741573033708, 0.814606741573
0337, 0.8188202247191011, 0.7921348314606742, 0.7879213483146067, 0.7879213483146067, 0.78
79213483146067, 0.7879213483146067]
test_scores =  [0.8268156424581006, 0.7988826815642458, 0.7988826815642458, 0.787709497206
```

```
7039, 0.770949720670391, 0.7821229050279329, 0.7821229050279329, 0.7821229050279329, 0.782
1229050279329, 0.7821229050279329]
```



Incrase ccp_alpha helps reduce over fitted problem. But, I don't want to sacrifice score fro this.

So, the best model for me is n_estimators=50, max_depth=10 and ccp_alpha=0

In [36]:

```
best_model = RandomForestClassifier(n_estimators=50, max_depth=10, ccp_alpha=0, random_sta
print('score with training data = ',bl_model.score(x_train,y_train))
print('score with test data = ',bl_model.score(x_test,y_test))
```

```
score with training data =  0.8539325842696629
score with test data =  0.7653631284916201
```

Use this setting and train with all data we have to predict test data from Kaggle.

In [31]:

```
best_model = RandomForestClassifier(n_estimators=50, max_depth=10, ccp_alpha=0, random_sta
print('score with training data = ',bl_model.score(X,Y))
```

```
score with training data =  0.8361391694725028
```

In [32]:

```
org_test_data = pd.read_csv('test.csv')
test_data = org_test_data[['Pclass','Sex','Age','SibSp','Parch','Fare','Embarked']]

mean_fare = data['Fare'].mean()

values = {'Age' : mean_age, 'Fare': mean_fare, 'Embarked': 'S'}
test_data = test_data.fillna(value=values)
```

In [33]:

```
test_data['Sex'] = test_data.Sex.apply(lambda x: int(x =='male'))
test_data['Emb_C'] = test_data.Embarked.apply(lambda x: int(x =='C'))
test_data['Emb_Q'] = test_data.Embarked.apply(lambda x: int(x =='Q'))
test_data['Emb_S'] = test_data.Embarked.apply(lambda x: int(x =='S'))

test_data = test_data[['Pclass','Sex','Age','SibSp','Parch','Fare','Emb_C', 'Emb_Q', 'Emb_
```

In [34]:
```
predictions = best_model.predict(test_data)
output = pd.DataFrame({'PassengerId': org_test_data.PassengerId, 'Survived': predictions})
output.to_csv('submission.csv', index=False)
print("Your submission was successfully saved!")
```

```
Your submission was successfully saved!
```

Score for submit this prediction to Kaggle = 0.77751

Conclusion

For this problem first we look at overview of data we have. Then, we clean it up (select only useful feature fill null data). After that we do analysis about corrlation and outlier. And, we build classification model with random forest tree and tune it to get the best model. Last, we use our best model to do prediction and submit it to Kaggle.

Actually, I also try Adaboost but it worst than this. But I still think that there are better approch to this problem which I havn't try it.

github : https://github.com/Satjarporn/Titanic

In [ ]:
```

```