

forest_cover-type

May 11, 2019

```
In [1]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
In [4]: train = pd.read_csv("/Users/DoryChen/Downloads/forest-cover-type-prediction/train.csv")
Test=pd.read_csv("/Users/DoryChen/Downloads/forest-cover-type-prediction/test.csv")
test=Test
```

```
In [5]: train.head(10)
```

```
Out[5]:
```

	Id	Elevation	Aspect	Slope	Horizontal_Distance_To_Hydrology	\
0	1	2596	51	3		258
1	2	2590	56	2		212
2	3	2804	139	9		268
3	4	2785	155	18		242
4	5	2595	45	2		153
5	6	2579	132	6		300
6	7	2606	45	7		270
7	8	2605	49	4		234
8	9	2617	45	9		240
9	10	2612	59	10		247

	Vertical_Distance_To_Hydrology	Horizontal_Distance_To_Roadways	\
0	0		510
1	-6		390
2	65		3180
3	118		3090
4	-1		391
5	-15		67
6	5		633
7	7		573
8	56		666
9	11		636

	Hillshade_9am	Hillshade_Noon	Hillshade_3pm	\
0	221	232	148	
1	220	235	151	

2	234	238	135
3	238	238	122
4	220	234	150
5	230	237	140
6	222	225	138
7	222	230	144
8	223	221	133
9	228	219	124

	Horizontal_Distance_To_Fire_Points	Wilderness_Area1	Wilderness_Area2	\
0	6279	1	0	
1	6225	1	0	
2	6121	1	0	
3	6211	1	0	
4	6172	1	0	
5	6031	1	0	
6	6256	1	0	
7	6228	1	0	
8	6244	1	0	
9	6230	1	0	

	Wilderness_Area3	Wilderness_Area4	Soil_Type1	Soil_Type2	Soil_Type3	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	
5	0	0	0	0	0	
6	0	0	0	0	0	
7	0	0	0	0	0	
8	0	0	0	0	0	
9	0	0	0	0	0	

	Soil_Type4	Soil_Type5	Soil_Type6	Soil_Type7	Soil_Type8	Soil_Type9	\
0	0	0	0	0	0	0	
1	0	0	0	0	0	0	
2	0	0	0	0	0	0	
3	0	0	0	0	0	0	
4	0	0	0	0	0	0	
5	0	0	0	0	0	0	
6	0	0	0	0	0	0	
7	0	0	0	0	0	0	
8	0	0	0	0	0	0	
9	0	0	0	0	0	0	

	Soil_Type10	Soil_Type11	Soil_Type12	Soil_Type13	Soil_Type14	\
0	0	0	0	0	0	
1	0	0	0	0	0	

2	0	0	1	0	0
3	0	0	0	0	0
4	0	0	0	0	0
5	0	0	0	0	0
6	0	0	0	0	0
7	0	0	0	0	0
8	0	0	0	0	0
9	0	0	0	0	0

	Soil_Type15	Soil_Type16	Soil_Type17	Soil_Type18	Soil_Type19	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	
5	0	0	0	0	0	
6	0	0	0	0	0	
7	0	0	0	0	0	
8	0	0	0	0	0	
9	0	0	0	0	0	

	Soil_Type20	Soil_Type21	Soil_Type22	Soil_Type23	Soil_Type24	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	
5	0	0	0	0	0	
6	0	0	0	0	0	
7	0	0	0	0	0	
8	0	0	0	0	0	
9	0	0	0	0	0	

	Soil_Type25	Soil_Type26	Soil_Type27	Soil_Type28	Soil_Type29	\
0	0	0	0	0	1	
1	0	0	0	0	1	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	1	
5	0	0	0	0	1	
6	0	0	0	0	1	
7	0	0	0	0	1	
8	0	0	0	0	1	
9	0	0	0	0	1	

	Soil_Type30	Soil_Type31	Soil_Type32	Soil_Type33	Soil_Type34	\
0	0	0	0	0	0	
1	0	0	0	0	0	

2	0	0	0	0	0
3	1	0	0	0	0
4	0	0	0	0	0
5	0	0	0	0	0
6	0	0	0	0	0
7	0	0	0	0	0
8	0	0	0	0	0
9	0	0	0	0	0

	Soil_Type35	Soil_Type36	Soil_Type37	Soil_Type38	Soil_Type39	\
0	0	0	0	0	0	0
1	0	0	0	0	0	0
2	0	0	0	0	0	0
3	0	0	0	0	0	0
4	0	0	0	0	0	0
5	0	0	0	0	0	0
6	0	0	0	0	0	0
7	0	0	0	0	0	0
8	0	0	0	0	0	0
9	0	0	0	0	0	0

	Soil_Type40	Cover_Type
0	0	5
1	0	5
2	0	2
3	0	2
4	0	5
5	0	2
6	0	5
7	0	5
8	0	5
9	0	5

```
In [7]: #pd.set_option('display.max_columns', None)
train.describe()
```

```
Out[7]:
```

	Id	Elevation	Aspect	Slope	\
count	15120.00000	15120.000000	15120.000000	15120.000000	
mean	7560.50000	2749.322553	156.676653	16.501587	
std	4364.91237	417.678187	110.085801	8.453927	
min	1.00000	1863.000000	0.000000	0.000000	
25%	3780.75000	2376.000000	65.000000	10.000000	
50%	7560.50000	2752.000000	126.000000	15.000000	
75%	11340.25000	3104.000000	261.000000	22.000000	
max	15120.00000	3849.000000	360.000000	52.000000	

	Horizontal_Distance_To_Hydrology	Vertical_Distance_To_Hydrology	\
count	15120.000000	15120.000000	

mean	227.195701	51.076521
std	210.075296	61.239406
min	0.000000	-146.000000
25%	67.000000	5.000000
50%	180.000000	32.000000
75%	330.000000	79.000000
max	1343.000000	554.000000

	Horizontal_Distance_To_Roadways	Hillshade_9am	Hillshade_Noon	\
count	15120.000000	15120.000000	15120.000000	
mean	1714.023214	212.704299	218.965608	
std	1325.066358	30.561287	22.801966	
min	0.000000	0.000000	99.000000	
25%	764.000000	196.000000	207.000000	
50%	1316.000000	220.000000	223.000000	
75%	2270.000000	235.000000	235.000000	
max	6890.000000	254.000000	254.000000	

	Hillshade_3pm	Horizontal_Distance_To_Fire_Points	Wilderness_Area1	\
count	15120.000000	15120.000000	15120.000000	
mean	135.091997	1511.147288	0.237897	
std	45.895189	1099.936493	0.425810	
min	0.000000	0.000000	0.000000	
25%	106.000000	730.000000	0.000000	
50%	138.000000	1256.000000	0.000000	
75%	167.000000	1988.250000	0.000000	
max	248.000000	6993.000000	1.000000	

	Wilderness_Area2	Wilderness_Area3	Wilderness_Area4	Soil_Type1	\
count	15120.000000	15120.000000	15120.000000	15120.000000	
mean	0.033003	0.419907	0.309193	0.023479	
std	0.178649	0.493560	0.462176	0.151424	
min	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	
50%	0.000000	0.000000	0.000000	0.000000	
75%	0.000000	1.000000	1.000000	0.000000	
max	1.000000	1.000000	1.000000	1.000000	

	Soil_Type2	Soil_Type3	Soil_Type4	Soil_Type5	Soil_Type6	\
count	15120.000000	15120.000000	15120.000000	15120.000000	15120.000000	
mean	0.041204	0.063624	0.055754	0.010913	0.042989	
std	0.198768	0.244091	0.229454	0.103896	0.202840	
min	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	0.000000	
50%	0.000000	0.000000	0.000000	0.000000	0.000000	
75%	0.000000	0.000000	0.000000	0.000000	0.000000	
max	1.000000	1.000000	1.000000	1.000000	1.000000	

	Soil_Type7	Soil_Type8	Soil_Type9	Soil_Type10	Soil_Type11	\
count	15120.0	15120.000000	15120.000000	15120.000000	15120.000000	
mean	0.0	0.000066	0.000661	0.141667	0.026852	
std	0.0	0.008133	0.025710	0.348719	0.161656	
min	0.0	0.000000	0.000000	0.000000	0.000000	
25%	0.0	0.000000	0.000000	0.000000	0.000000	
50%	0.0	0.000000	0.000000	0.000000	0.000000	
75%	0.0	0.000000	0.000000	0.000000	0.000000	
max	0.0	1.000000	1.000000	1.000000	1.000000	

	Soil_Type12	Soil_Type13	Soil_Type14	Soil_Type15	Soil_Type16	\
count	15120.000000	15120.000000	15120.000000	15120.0	15120.000000	
mean	0.015013	0.031481	0.011177	0.0	0.007540	
std	0.121609	0.174621	0.105133	0.0	0.086506	
min	0.000000	0.000000	0.000000	0.0	0.000000	
25%	0.000000	0.000000	0.000000	0.0	0.000000	
50%	0.000000	0.000000	0.000000	0.0	0.000000	
75%	0.000000	0.000000	0.000000	0.0	0.000000	
max	1.000000	1.000000	1.000000	0.0	1.000000	

	Soil_Type17	Soil_Type18	Soil_Type19	Soil_Type20	Soil_Type21	\
count	15120.000000	15120.000000	15120.000000	15120.000000	15120.000000	
mean	0.040476	0.003968	0.003042	0.009193	0.001058	
std	0.197080	0.062871	0.055075	0.095442	0.032514	
min	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	0.000000	
50%	0.000000	0.000000	0.000000	0.000000	0.000000	
75%	0.000000	0.000000	0.000000	0.000000	0.000000	
max	1.000000	1.000000	1.000000	1.000000	1.000000	

	Soil_Type22	Soil_Type23	Soil_Type24	Soil_Type25	Soil_Type26	\
count	15120.000000	15120.000000	15120.000000	15120.000000	15120.000000	
mean	0.022817	0.050066	0.016997	0.000066	0.003571	
std	0.149326	0.218089	0.129265	0.008133	0.059657	
min	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	0.000000	
50%	0.000000	0.000000	0.000000	0.000000	0.000000	
75%	0.000000	0.000000	0.000000	0.000000	0.000000	
max	1.000000	1.000000	1.000000	1.000000	1.000000	

	Soil_Type27	Soil_Type28	Soil_Type29	Soil_Type30	Soil_Type31	\
count	15120.000000	15120.000000	15120.000000	15120.000000	15120.000000	
mean	0.000992	0.000595	0.085384	0.047950	0.021958	
std	0.031482	0.024391	0.279461	0.213667	0.146550	
min	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	0.000000	
50%	0.000000	0.000000	0.000000	0.000000	0.000000	
75%	0.000000	0.000000	0.000000	0.000000	0.000000	

max	1.000000	1.000000	1.000000	1.000000	1.000000
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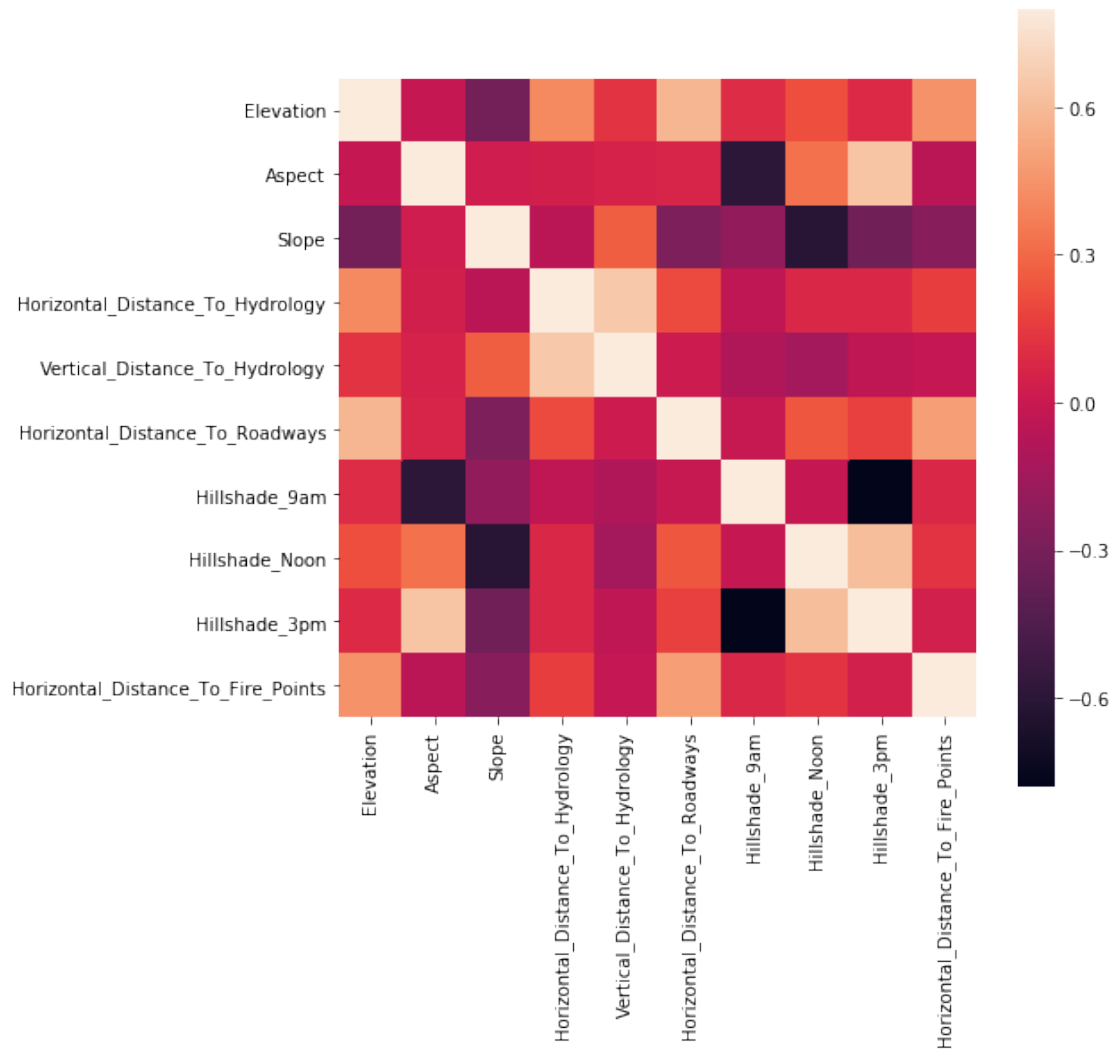
	Soil_Type32	Soil_Type33	Soil_Type34	Soil_Type35	Soil_Type36 \
count	15120.000000	15120.000000	15120.000000	15120.000000	15120.000000
mean	0.045635	0.040741	0.001455	0.006746	0.000661
std	0.208699	0.197696	0.038118	0.081859	0.025710
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000	1.000000	1.000000

	Soil_Type37	Soil_Type38	Soil_Type39	Soil_Type40	Cover_Type
count	15120.000000	15120.000000	15120.000000	15120.000000	15120.000000
mean	0.002249	0.048148	0.043452	0.030357	4.000000
std	0.047368	0.214086	0.203880	0.171574	2.000066
min	0.000000	0.000000	0.000000	0.000000	1.000000
25%	0.000000	0.000000	0.000000	0.000000	2.000000
50%	0.000000	0.000000	0.000000	0.000000	4.000000
75%	0.000000	0.000000	0.000000	0.000000	6.000000
max	1.000000	1.000000	1.000000	1.000000	7.000000

```
In [8]: #train = train.drop(['Soil_Type7', 'Soil_Type15'], axis = 1)
        #test = test.drop(['Soil_Type7', 'Soil_Type15'], axis = 1)

        #Drop 'id'  iloc[row,col]
        train=train.iloc[:,1:]
        test=test.iloc[:,1:]
```

```
In [11]: corrmatrix = train.iloc[:,1:10].corr()
        ax = plt.subplots(figsize = (8,8))
        sns.heatmap(corrmatrix,vmax=0.8,square=True);
```



```
In [14]: size=10
data=train.iloc[:,size]
cols = data.columns
data_corr=data.corr()
threshold=0.5
corr_list=[]
for i in range(0, 10):
    for j in range(i+1, 10):
        if data_corr.iloc[i,j]>= threshold and data_corr.iloc[i,j]<1\
or data_corr.iloc[i,j] <0 and data_corr.iloc[i,j]<=-threshold:
            corr_list.append([data_corr.iloc[i,j],i,j])

corr_list

Out[14]: [[0.5786589907340067, 0, 5],
          [-0.5939974281313112, 1, 6],
```



```
[0.635022364019874, 1, 8],
[-0.6126128724172692, 2, 7],
[0.6521424712357364, 3, 4],
[-0.779964742447544, 6, 8],
[0.6145263872475779, 7, 8]]
```

```
In [10]: s_corr_list = sorted(corr_list, key= lambda x: -abs(x[0]))
```

```
# print the higher values
for v,i,j in s_corr_list:
    print("%s and %s = %.2f" % (cols[i], cols[j], v))
```

```
Hillshade_9am and Hillshade_3pm = -0.78
Horizontal_Distance_To_Hydrology and Vertical_Distance_To_Hydrology = 0.65
Aspect and Hillshade_3pm = 0.64
Hillshade_Noon and Hillshade_3pm = 0.61
Slope and Hillshade_Noon = -0.61
Aspect and Hillshade_9am = -0.59
Elevation and Horizontal_Distance_To_Roadways = 0.58
```

```
In [11]: train.Wilderness_Area2.value_counts()
```

```
Out[11]: 0    14621
         1     499
         Name: Wilderness_Area2, dtype: int64
```

```
In [15]: # Group one-hot encoded variables of a category into one single variable
cols = train.columns
r,c = train.shape
```

```
# Create a new dataframe with r rows, one column for each encoded category, and target
new_data = pd.DataFrame(index= np.arange(0,r), columns=['Wilderness_Area', 'Soil_Type
```

```
# Make an entry in data for each r for category_id, target_value
```

```
for i in range(0,r):
    p = 0;
    q = 0;
    # Category1_range
    for j in range(10,14):
        if (train.iloc[i,j] == 1):
            p = j-9 # category_class
            break
    # Category2_range
    for k in range(14,54):
        if (train.iloc[i,k] == 1):
            q = k-13 # category_class
            break
    # Make an entry in data for each r
```

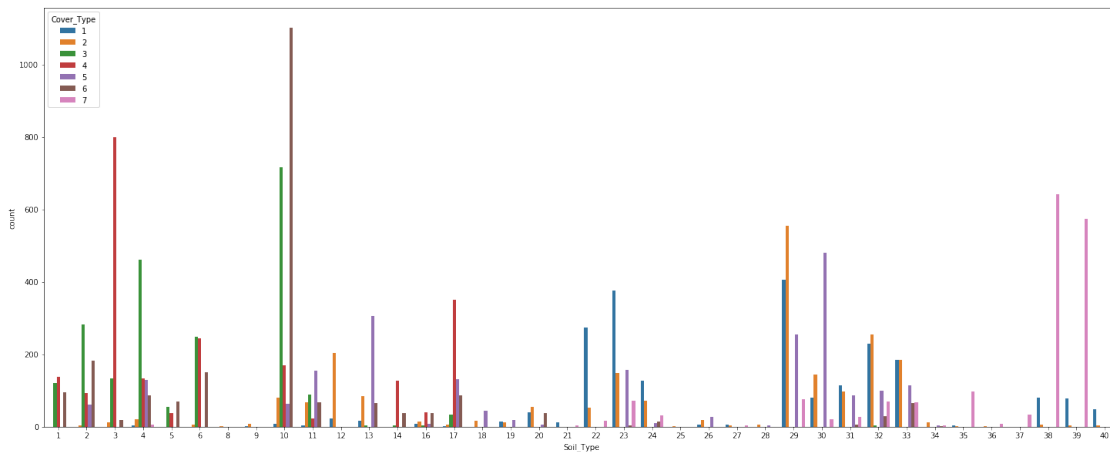
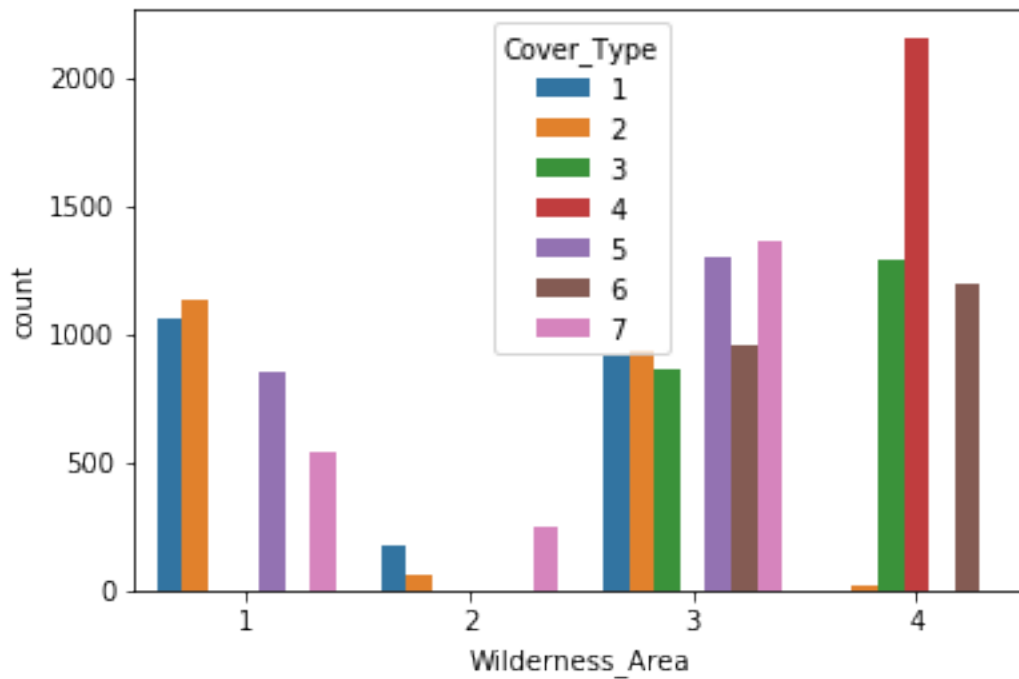
```

new_data.iloc[i] = [p,q,train.iloc[i, c-1]]

# plot for category1
sns.countplot(x = 'Wilderness_Area', hue = 'Cover_Type', data = new_data)
plt.show()

# Plot for category2
plt.rc("figure", figsize = (25,10))
sns.countplot(x='Soil_Type', hue = 'Cover_Type', data= new_data)
plt.show()

```



```

In [13]: #check normality of non-binary variables
         train.iloc[:,10].skew()

Out[13]: Elevation          0.075640
         Aspect            0.450935
         Slope             0.523658
         Horizontal_Distance_To_Hydrology  1.488052
         Vertical_Distance_To_Hydrology    1.537776
         Horizontal_Distance_To_Roadways    1.247811
         Hillshade_9am        -1.093681
         Hillshade_Noon       -0.953232
         Hillshade_3pm        -0.340827
         Horizontal_Distance_To_Fire_Points  1.617099
         dtype: float64

In [14]: from sklearn.ensemble import RandomForestClassifier
         from sklearn.model_selection import train_test_split

         r,c = train.shape
         X_train = train.iloc[:,c-1]
         y_train = train["Cover_Type"]

         # Setting parameters
         x_data, x_test_data, y_data, y_test_data = train_test_split(train, y_train, test_size=0.3)
         rf_para = [{'n_estimators':[50, 100], 'max_depth':[5,10,15], 'max_features':[0.1, 0.3, 0.5],
                        'min_samples_leaf':[1,3], 'bootstrap':[True, False]}]

In [15]: from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
         rfc = GridSearchCV(RandomForestClassifier(), param_grid=rf_para, cv = 10, n_jobs=-1)
         rfc.fit(x_data, y_data)
         rfc.best_params_

Out[15]: {'bootstrap': True,
         'max_depth': 15,
         'max_features': 0.3,
         'min_samples_leaf': 1,
         'n_estimators': 50}

In [16]: RFC = RandomForestClassifier(n_estimators=100, max_depth=15, max_features=0.3, bootstrap=False,
                                     n_jobs=-1)
         RFC.fit(X_train, y_train)
         rfc_pred=RFC.predict(test)

In [39]: solution = pd.DataFrame({'Id':Test.Id, 'Cover_Type':rfc_pred}, columns = ['Id','Cover_Type'])
         solution.to_csv('rfc_sol.csv', index=False)

In [ ]:

```