

MACHINE LEARNING PROJECT

Forest Cover Type Prediction

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Source : <https://www.kaggle.com/c/forest-cover-type-prediction/data> (<https://www.kaggle.com/c/forest-cover-type-prediction/data>)

Motivation :

The data is cartographic variables (as opposed to remotely sensed data). The actual forest cover type for a given 30 x 30 meter cell was determined from US Forest Service (USFS) Region 2 Resource Information System data. Independent variables were then derived from data obtained from the US Geological Survey and USFS. The data is in raw form (not scaled) and contains binary columns of data for qualitative independent variables such as wilderness areas and soil type. The areas of forest under study represent forests with minimal human-caused disturbances, so that existing forest cover types are more a result of ecological processes rather than forest management practices.

Data Overview :

The study area includes four wilderness areas located in the Roosevelt National Forest of northern Colorado which are as follows:

- 1 - Rawah Wilderness Area
- 2 - Neota Wilderness Area
- 3 - Comanche Peak Wilderness Area
- 4 - Cache la Poudre Wilderness Area

Our goal is to predict the forest cover type. The seven types of forest cover are :

- 1 - Spruce/Fir
- 2 - Lodgepole Pine
- 3 - Ponderosa Pine
- 4 - Cottonwood/Willow
- 5 - Aspen
- 6 - Douglas-fir
- 7 - Krummholz

- This is a classification problem where the target could belong to any of the seven classes.

Data Fields:

Elevation - Elevation in meters

Aspect - Aspect in degrees azimuth

Slope - Slope in degrees

Horizontal_Distance_To_Hydrology - Horz Dist to nearest surface water features

Vertical_Distance_To_Hydrology - Vert Dist to nearest surface water features

Horizontal_Distance_To_Roadways - Horz Dist to nearest roadway

Hillshade_9am (0 to 255 index) - Hillshade index at 9am, summer solstice

Hillshade_Noon (0 to 255 index) - Hillshade index at noon, summer solstice

Hillshade_3pm (0 to 255 index) - Hillshade index at 3pm, summer solstice

Horizontal_Distance_To_Fire_Points - Horz Dist to nearest wildfire ignition points

Wilderness_Area (4 binary columns, 0 = absence or 1 = presence) - Wilderness area designation

Soil_Type (40 binary columns, 0 = absence or 1 = presence) - Soil Type designation

Cover_Type (7 types, integers 1 to 7) - Forest Cover Type designation

Question: Given the other attributes, what will be the 'Cover_Type'?

The training set (15120 observations) contains both features and the Cover_Type. The test set (565892 observations) contains only the features.

Assumptions:

1. Ecology of the areas across which the data is collected is similar.
2. Seasonal changes are constant across all the observations.
3. The dataset is recently collected.

Limitations:

1. Environmental factors affecting the growth of any cover type is not taken into consideration.
2. Human error while collecting data is not accounted for.
3. Management practices that might have affected the growth is not accounted for.

About the data :

```
In [49]: %matplotlib inline
import warnings
import seaborn as sns
warnings.filterwarnings("ignore")
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
dataset = pd.read_csv("train.csv")
```

```
In [50]: dataset = dataset.iloc[:,1:]
print(dataset.shape)

(15120, 55)
```

```
In [51]: print(dataset.dtypes)
```

Elevation	int64
Aspect	int64
Slope	int64
Horizontal_Distance_To_Hydrology	int64
Vertical_Distance_To_Hydrology	int64
Horizontal_Distance_To_Roadways	int64
Hillshade_9am	int64
Hillshade_Noon	int64
Hillshade_3pm	int64
Horizontal_Distance_To_Fire_Points	int64
Wilderness_Area1	int64
Wilderness_Area2	int64
Wilderness_Area3	int64
Wilderness_Area4	int64
Soil_Type1	int64
Soil_Type2	int64
Soil_Type3	int64
Soil_Type4	int64
Soil_Type5	int64
Soil_Type6	int64
Soil_Type7	int64
Soil_Type8	int64
Soil_Type9	int64
Soil_Type10	int64
Soil_Type11	int64
Soil_Type12	int64
Soil_Type13	int64
Soil_Type14	int64
Soil_Type15	int64
Soil_Type16	int64
Soil_Type17	int64
Soil_Type18	int64
Soil_Type19	int64
Soil_Type20	int64
Soil_Type21	int64
Soil_Type22	int64
Soil_Type23	int64
Soil_Type24	int64
Soil_Type25	int64
Soil_Type26	int64
Soil_Type27	int64
Soil_Type28	int64
Soil_Type29	int64
Soil_Type30	int64
Soil_Type31	int64
Soil_Type32	int64
Soil_Type33	int64
Soil_Type34	int64
Soil_Type35	int64
Soil_Type36	int64
Soil_Type37	int64
Soil_Type38	int64
Soil_Type39	int64
Soil_Type40	int64
Cover_Type	int64

dtype: object

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Data Pre-processing

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```
In [52]: pd.set_option('display.max_columns', None)
         print(dataset.describe())
```

	Elevation	Aspect	Slope \
count	15120.000000	15120.000000	15120.000000
mean	2749.322553	156.676653	16.501587
std	417.678187	110.085801	8.453927
min	1863.000000	0.000000	0.000000
25%	2376.000000	65.000000	10.000000
50%	2752.000000	126.000000	15.000000
75%	3104.000000	261.000000	22.000000
max	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

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000			
25%	106.000000	730.000000	0.000
000			
50%	138.000000	1256.000000	0.000
000			
75%	167.000000	1988.250000	0.000
000			
max	248.000000	6993.000000	1.000
000			

	Wilderness_Area2	Wilderness_Area3	Wilderness_Area4	Soil_Typ
e1 \				
count	15120.000000	15120.000000	15120.000000	15120.0000
00				
mean	0.033003	0.419907	0.309193	0.0234
79				
std	0.178649	0.493560	0.462176	0.1514
24				
min	0.000000	0.000000	0.000000	0.0000
00				
25%	0.000000	0.000000	0.000000	0.0000
00				
50%	0.000000	0.000000	0.000000	0.0000
00				
75%	0.000000	1.000000	1.000000	0.0000
00				
max	1.000000	1.000000	1.000000	1.0000
00				

	Soil_Type2	Soil_Type3	Soil_Type4	Soil_Type5	Soil_T
ype6 \					
count	15120.000000	15120.000000	15120.000000	15120.000000	15120.00
0000					
mean	0.041204	0.063624	0.055754	0.010913	0.04
2989					
std	0.198768	0.244091	0.229454	0.103896	0.20
2840					
min	0.000000	0.000000	0.000000	0.000000	0.00
0000					
25%	0.000000	0.000000	0.000000	0.000000	0.00
0000					
50%	0.000000	0.000000	0.000000	0.000000	0.00
0000					
75%	0.000000	0.000000	0.000000	0.000000	0.00
0000					
max	1.000000	1.000000	1.000000	1.000000	1.00
0000					

	Soil_Type7	Soil_Type8	Soil_Type9	Soil_Type10	Soil_Type
11 \					
count	15120.0	15120.000000	15120.000000	15120.000000	15120.0000
00					
mean	0.0	0.000066	0.000661	0.141667	0.0268
52					
std	0.0	0.008133	0.025710	0.348719	0.1616
56					
min	0.0	0.000000	0.000000	0.000000	0.0000

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00					
25%	0.0	0.000000	0.000000	0.000000	0.0000
00					
50%	0.0	0.000000	0.000000	0.000000	0.0000
00					
75%	0.0	0.000000	0.000000	0.000000	0.0000
00					
max	0.0	1.000000	1.000000	1.000000	1.0000
00					

	Soil_Type12	Soil_Type13	Soil_Type14	Soil_Type15	Soil_Typ
e16 \					
count	15120.000000	15120.000000	15120.000000	15120.0	15120.000
000					
mean	0.015013	0.031481	0.011177	0.0	0.007
540					
std	0.121609	0.174621	0.105133	0.0	0.086
506					
min	0.000000	0.000000	0.000000	0.0	0.000
000					
25%	0.000000	0.000000	0.000000	0.0	0.000
000					
50%	0.000000	0.000000	0.000000	0.0	0.000
000					
75%	0.000000	0.000000	0.000000	0.0	0.000
000					
max	1.000000	1.000000	1.000000	0.0	1.000
000					

	Soil_Type17	Soil_Type18	Soil_Type19	Soil_Type20	Soil_Ty
pe21 \					
count	15120.000000	15120.000000	15120.000000	15120.000000	15120.00
0000					
mean	0.040476	0.003968	0.003042	0.009193	0.00
1058					
std	0.197080	0.062871	0.055075	0.095442	0.03
2514					
min	0.000000	0.000000	0.000000	0.000000	0.00
0000					
25%	0.000000	0.000000	0.000000	0.000000	0.00
0000					
50%	0.000000	0.000000	0.000000	0.000000	0.00
0000					
75%	0.000000	0.000000	0.000000	0.000000	0.00
0000					
max	1.000000	1.000000	1.000000	1.000000	1.00
0000					

	Soil_Type22	Soil_Type23	Soil_Type24	Soil_Type25	Soil_Ty
pe26 \					
count	15120.000000	15120.000000	15120.000000	15120.000000	15120.00
0000					
mean	0.022817	0.050066	0.016997	0.000066	0.00
3571					
std	0.149326	0.218089	0.129265	0.008133	0.05
9657					
min	0.000000	0.000000	0.000000	0.000000	0.00

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0000					
25%	0.000000	0.000000	0.000000	0.000000	0.00
0000					
50%	0.000000	0.000000	0.000000	0.000000	0.00
0000					
75%	0.000000	0.000000	0.000000	0.000000	0.00
0000					
max	1.000000	1.000000	1.000000	1.000000	1.00
0000					

	Soil_Type27	Soil_Type28	Soil_Type29	Soil_Type30	Soil_Ty
pe31 \					
count	15120.000000	15120.000000	15120.000000	15120.000000	15120.00
0000					
mean	0.000992	0.000595	0.085384	0.047950	0.02
1958					
std	0.031482	0.024391	0.279461	0.213667	0.14
6550					
min	0.000000	0.000000	0.000000	0.000000	0.00
0000					
25%	0.000000	0.000000	0.000000	0.000000	0.00
0000					
50%	0.000000	0.000000	0.000000	0.000000	0.00
0000					
75%	0.000000	0.000000	0.000000	0.000000	0.00
0000					
max	1.000000	1.000000	1.000000	1.000000	1.00
0000					

	Soil_Type32	Soil_Type33	Soil_Type34	Soil_Type35	Soil_Ty
pe36 \					
count	15120.000000	15120.000000	15120.000000	15120.000000	15120.00
0000					
mean	0.045635	0.040741	0.001455	0.006746	0.00
0661					
std	0.208699	0.197696	0.038118	0.081859	0.02
5710					
min	0.000000	0.000000	0.000000	0.000000	0.00
0000					
25%	0.000000	0.000000	0.000000	0.000000	0.00
0000					
50%	0.000000	0.000000	0.000000	0.000000	0.00
0000					
75%	0.000000	0.000000	0.000000	0.000000	0.00
0000					
max	1.000000	1.000000	1.000000	1.000000	1.00
0000					

	Soil_Type37	Soil_Type38	Soil_Type39	Soil_Type40	Cover_
Type					
count	15120.000000	15120.000000	15120.000000	15120.000000	15120.00
0000					
mean	0.002249	0.048148	0.043452	0.030357	4.00
0000					
std	0.047368	0.214086	0.203880	0.171574	2.00
0066					
min	0.000000	0.000000	0.000000	0.000000	1.00

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0000					
25%	0.000000	0.000000	0.000000	0.000000	2.00
0000					
50%	0.000000	0.000000	0.000000	0.000000	4.00
0000					
75%	0.000000	0.000000	0.000000	0.000000	6.00
0000					
max	1.000000	1.000000	1.000000	1.000000	7.00
0000					

- No attribute is missing as count is 15120 for all attributes. So, no deletion is required.
- Attributes Soil_Type7 and Soil_Type15 can be removed as they are constant.
- Wilderness_Area and Soil_Type are one hot encoded. Hence, they could be converted back for some analysis.
- Scales are not the same for all. Hence, rescaling and standardization may be necessary for some algorithms.
- Negative values are present in Vertical_Distance_To_Hydrology. Hence, some tests such as chi-sq cant be used.

Descriptive Statistics

```
In [53]: print(dataset.skew())
```

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
Wilderness_Area1	1.231244
Wilderness_Area2	5.228781
Wilderness_Area3	0.324594
Wilderness_Area4	0.825798
Soil_Type1	6.294716
Soil_Type2	4.617019
Soil_Type3	3.575995
Soil_Type4	3.872721
Soil_Type5	9.416209
Soil_Type6	4.506716
Soil_Type7	0.000000
Soil_Type8	122.963409
Soil_Type9	38.849712
Soil_Type10	2.055410
Soil_Type11	5.854551
Soil_Type12	7.977205
Soil_Type13	5.366836
Soil_Type14	9.300318
Soil_Type15	0.000000
Soil_Type16	11.387050
Soil_Type17	4.663945
Soil_Type18	15.781426
Soil_Type19	18.048915
Soil_Type20	10.286265
Soil_Type21	30.695081
Soil_Type22	6.391991
Soil_Type23	4.126701
Soil_Type24	7.474026
Soil_Type25	122.963409
Soil_Type26	16.645076
Soil_Type27	31.704896
Soil_Type28	40.955261
Soil_Type29	2.967651
Soil_Type30	4.231913
Soil_Type31	6.524804
Soil_Type32	4.354839
Soil_Type33	4.646742
Soil_Type34	26.161230
Soil_Type35	12.052838
Soil_Type36	38.849712
Soil_Type37	21.018939
Soil_Type38	4.221771
Soil_Type39	4.479186
Soil_Type40	5.475256
Cover_Type	0.000000

dtype: float64

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- Values close to 0 show less skew
- Several attributes in Soil_Type show a large skew. Hence, some algos may benefit if skew is corrected

```
In [54]: rem = []

#Add constant columns as they don't help in prediction process
for c in dataset.columns:
    if dataset[c].std() == 0: #standard deviation is zero
        rem.append(c)

#drop the columns
dataset.drop(rem,axis=1,inplace=True)

print(rem)

['Soil_Type7', 'Soil_Type15']
```

```
In [55]: dataset.groupby('Cover_Type').size()
# We see that all classes have an equal presence. No class re-balancing
is required.
```

```
Out[55]: Cover_Type
1      2160
2      2160
3      2160
4      2160
5      2160
6      2160
7      2160
dtype: int64
```

```
In [56]: dataset.corr()
```

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Out[56]:

	Elevation	Aspect	Slope	Horizontal_Distance
Elevation	1.000000	-0.011096	-0.312640	0.412712
Aspect	-0.011096	1.000000	0.028148	0.040732
Slope	-0.312640	0.028148	1.000000	-0.055976
Horizontal_Distance_To_Hydrology	0.412712	0.040732	-0.055976	1.000000
Vertical_Distance_To_Hydrology	0.122092	0.056412	0.265314	0.652142
Horizontal_Distance_To_Roadways	0.578659	0.066184	-0.277049	0.203397
Hillshade_9am	0.097900	-0.593997	-0.200072	-0.033803
Hillshade_Noon	0.215782	0.324912	-0.612613	0.080047
Hillshade_3pm	0.089518	0.635022	-0.326887	0.080833
Horizontal_Distance_To_Fire_Points	0.443563	-0.052169	-0.239527	0.158817
Wilderness_Area1	0.330417	-0.131262	-0.152820	-0.009402
Wilderness_Area2	0.261729	0.028238	-0.065923	0.087484
Wilderness_Area3	0.354025	0.032578	-0.113033	0.200532
Wilderness_Area4	-0.783651	0.075228	0.286985	-0.239303
Soil_Type1	-0.218818	-0.024538	0.099355	-0.084766
Soil_Type2	-0.147947	-0.020970	-0.081498	0.024234
Soil_Type3	-0.307523	-0.069120	0.265541	-0.089578
Soil_Type4	-0.125342	0.018019	0.087841	-0.059398
Soil_Type5	-0.141478	0.000343	0.074720	-0.025247
Soil_Type6	-0.187354	-0.006066	-0.047868	0.021203
Soil_Type8	0.002934	0.001723	-0.012989	0.002819
Soil_Type9	-0.010571	-0.019391	-0.022220	-0.005523
Soil_Type10	-0.357816	0.111959	0.255804	-0.112852
Soil_Type11	-0.037906	-0.034549	-0.109798	0.026150
Soil_Type12	0.017432	-0.044142	-0.115088	0.034306
Soil_Type13	0.039304	0.024312	0.119863	0.026595
Soil_Type14	-0.140619	0.001181	-0.054085	-0.111878
Soil_Type16	-0.066252	0.027121	-0.064321	-0.084804
Soil_Type17	-0.200663	0.029870	-0.124375	-0.159717
Soil_Type18	-0.035173	-0.042140	-0.069326	-0.018282
Soil_Type19	0.029808	0.007570	-0.047742	-0.033946
Soil_Type20	0.008548	-0.023330	-0.068508	-0.062873

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	Elevation	Aspect	Slope	Horizontal_Distance
Soil_Type21	0.032509	0.018815	-0.033935	-0.025207
Soil_Type22	0.146236	0.022301	-0.076393	-0.007840
Soil_Type23	0.159872	0.041880	-0.184528	-0.087963
Soil_Type24	0.097647	0.005480	0.017982	0.046915
Soil_Type25	0.010586	-0.002340	0.011062	-0.004615
Soil_Type26	0.020669	-0.009775	-0.030700	0.027879
Soil_Type27	0.040019	0.018986	0.012295	0.064616
Soil_Type28	-0.001077	0.026330	0.036082	0.019663
Soil_Type29	0.165304	-0.063428	-0.083108	0.033854
Soil_Type30	0.048204	-0.086897	0.118725	-0.032540
Soil_Type31	0.093191	0.008160	-0.076851	0.060886
Soil_Type32	0.172349	0.003700	-0.147258	0.138275
Soil_Type33	0.123821	0.018719	0.072027	0.062121
Soil_Type34	0.021876	0.012927	-0.030590	0.072485
Soil_Type35	0.120157	-0.004235	-0.048855	-0.015446
Soil_Type36	0.040571	0.003160	-0.004570	0.077251
Soil_Type37	0.073825	-0.046309	0.003129	-0.009549
Soil_Type38	0.323440	0.043860	-0.148342	0.131444
Soil_Type39	0.296405	-0.031342	0.051900	0.066284
Soil_Type40	0.306755	0.007208	-0.043513	0.242304
Cover_Type	0.016090	0.008015	0.087722	-0.010515

```

In [57]: dataset_corr = dataset.corr()

# Set the threshold to select only only highly correlated attributes
threshold = 0.5

# List of pairs along with correlation above threshold
corr_list = []
cols=dataset.columns
#len(dataset)
size = len(dataset_corr)
#Search for the highly correlated pairs
for i in range(0,size): #for 'size' features
    for j in range(i+1,size): #avoid repetition
        if (dataset_corr.iloc[i,j] >= threshold and dataset_corr.iloc[i,
j] < 1) or (dataset_corr.iloc[i,j] < 0 and dataset_corr.iloc[i,j] <= -th
reshold):
            corr_list.append([dataset_corr.iloc[i,j],i,j]) #store correl
ation and columns index

#Sort to show higher ones first
s_corr_list = sorted(corr_list,key=lambda x: -abs(x[0]))

#Print correlations and column names
for v,i,j in s_corr_list:
    print ("%s and %s = %.2f" % (cols[i],cols[j],v))

```

```

Elevation and Wilderness_Area4 = -0.78
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
Wilderness_Area3 and Wilderness_Area4 = -0.57
Wilderness_Area1 and Soil_Type29 = 0.55

```

```

In [58]: con = ['Elevation' , 'Aspect' , 'Slope' , 'Horizontal_Distance_To_Hydrology' , 'Vertical_Distance_To_Hydrology' , 'Horizontal_Distance_To_Roadways' , 'Hillshade_9am' , 'Hillshade_Noon' , 'Hillshade_3pm' , 'Horizontal_Distance_To_Fire_Points']
con_variables = dataset[con]

#Cor = con_variables.iloc[:,0:10]
Cor_matrix = con_variables.corr(method='pearson', min_periods=1)
#print(Cor_matrix)

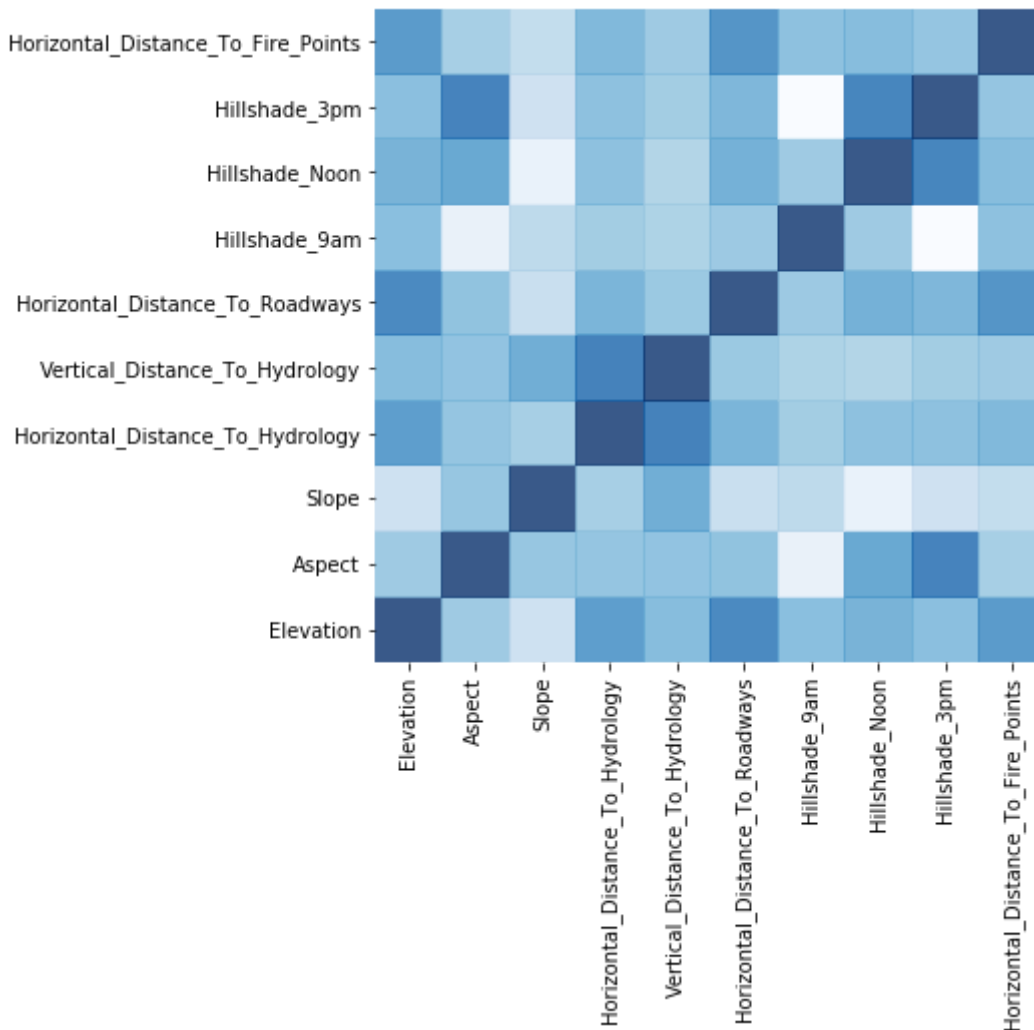
fig, ax = plt.subplots()
heatmap = ax.pcolor(Cor_matrix, cmap=plt.cm.Blues, alpha=0.8)
fig = plt.gcf()
fig.set_size_inches(6, 6)
ax.set_frame_on(False)
ax.set_yticks(np.arange(10) + 0.5, minor=False)
ax.set_xticks(np.arange(10) + 0.5, minor=False)
ax.set_xticklabels(con[0:10], minor=False)
ax.set_yticklabels(con[0:10], minor=False)
plt.xticks(rotation=90)

```

```

Out[58]: (array([ 0.5,  1.5,  2.5,  3.5,  4.5,  5.5,  6.5,  7.5,  8.5,  9.5]),
<a list of 10 Text xticklabel objects>)

```



```

In [59]: # define the data/predictors as the pre-set feature names
df = pd.DataFrame(dataset, columns=["Elevation"])

# Put the target in another DataFrame
target = pd.DataFrame(dataset, columns=["Cover_Type"])

import statsmodels.api as sm

X = df["Elevation"]
y = target["Cover_Type"]

# Note the difference in argument order
model = sm.OLS(y, X).fit()
# make the predictions by the model
predictions = model.predict(X)

# Print out the statistics
model.summary()

```

Out[59]: OLS Regression Results

Dep. Variable:	Cover_Type	R-squared:	0.784
Model:	OLS	Adj. R-squared:	0.784
Method:	Least Squares	F-statistic:	5.483e+04
Date:	Wed, 18 Apr 2018	Prob (F-statistic):	0.00
Time:	06:14:19	Log-Likelihood:	-32521.
No. Observations:	15120	AIC:	6.504e+04
Df Residuals:	15119	BIC:	6.505e+04
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
Elevation	0.0014	6.08e-06	234.165	0.000	0.001	0.001

Omnibus:	5998.494	Durbin-Watson:	1.144
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1320.370
Skew:	-0.482	Prob(JB):	1.93e-287
Kurtosis:	1.920	Cond. No.	1.00

- We can see here that this model has a much higher R-squared value of 0.784, meaning that this model explains 78.4% of the variance in our dependent variable.

```

In [60]: # define the data/predictors as the pre-set feature names
df = pd.DataFrame(dataset, columns=["Slope"])

# Put the target in another DataFrame
target = pd.DataFrame(dataset, columns=["Cover_Type"])

import statsmodels.api as sm

X = df["Slope"]
y = target["Cover_Type"]

# Note the difference in argument order
model = sm.OLS(y, X).fit()
# make the predictions by the model
predictions = model.predict(X)

# Print out the statistics
model.summary()

```

Out[60]: OLS Regression Results

Dep. Variable:	Cover_Type	R-squared:	0.662
Model:	OLS	Adj. R-squared:	0.662
Method:	Least Squares	F-statistic:	2.968e+04
Date:	Wed, 18 Apr 2018	Prob (F-statistic):	0.00
Time:	06:14:22	Log-Likelihood:	-35891.
No. Observations:	15120	AIC:	7.178e+04
Df Residuals:	15119	BIC:	7.179e+04
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
Slope	0.1963	0.001	172.269	0.000	0.194	0.199

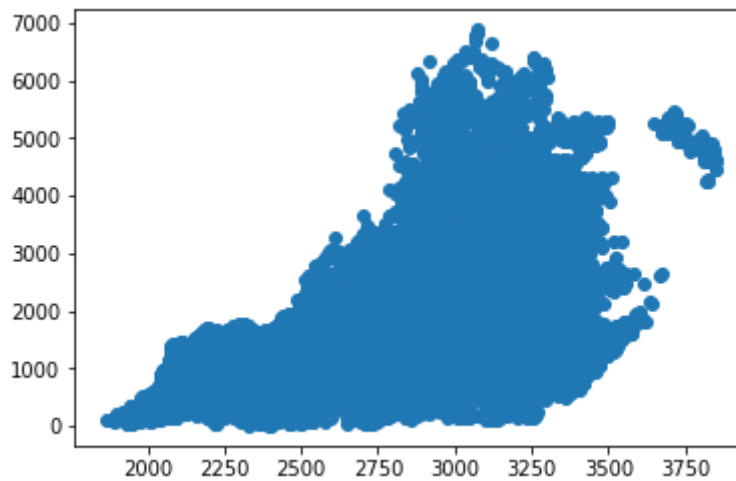
Omnibus:	517.060	Durbin-Watson:	1.205
Prob(Omnibus):	0.000	Jarque-Bera (JB):	255.416
Skew:	0.107	Prob(JB):	3.44e-56
Kurtosis:	2.400	Cond. No.	1.00

- We can see here that this model has a much higher R-squared value of 0.662.

Data Visualization

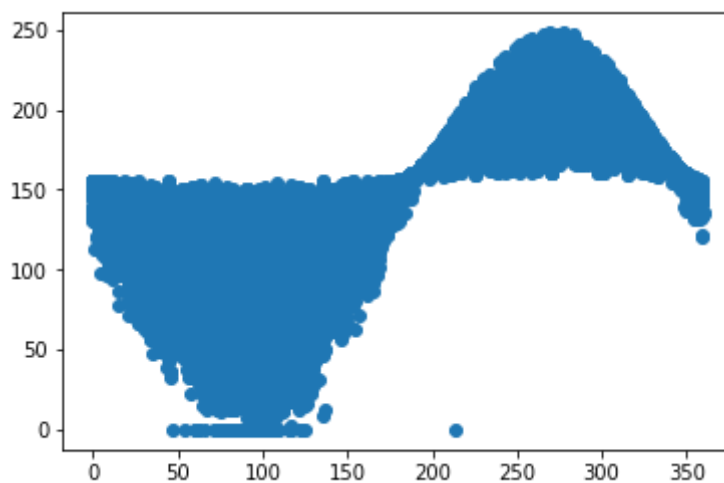
```
In [61]: #Scatter Plot for Elevation and Horizontal_Distance_To_Roadways
x = dataset['Elevation']
y = dataset['Horizontal_Distance_To_Roadways']

plt.scatter(x,y)
plt.show()
```



```
In [62]: #Scatter Plot for Aspect vs Hillshade_3pm
x = dataset['Aspect']
y = dataset['Hillshade_3pm']

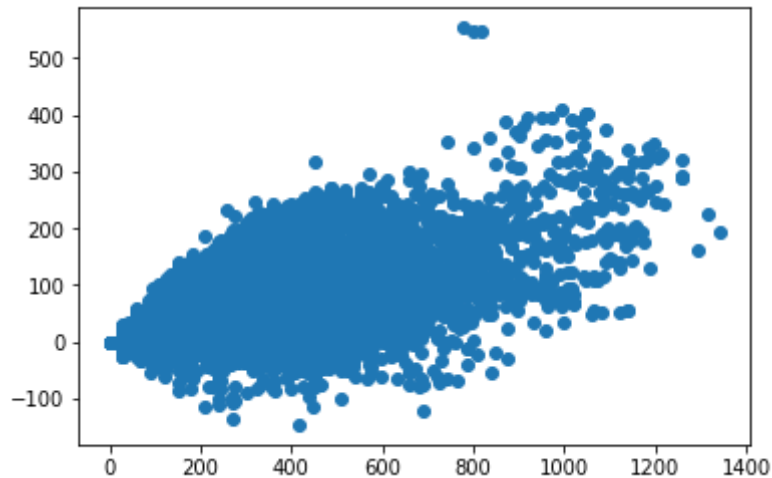
plt.scatter(x,y)
plt.show()
```



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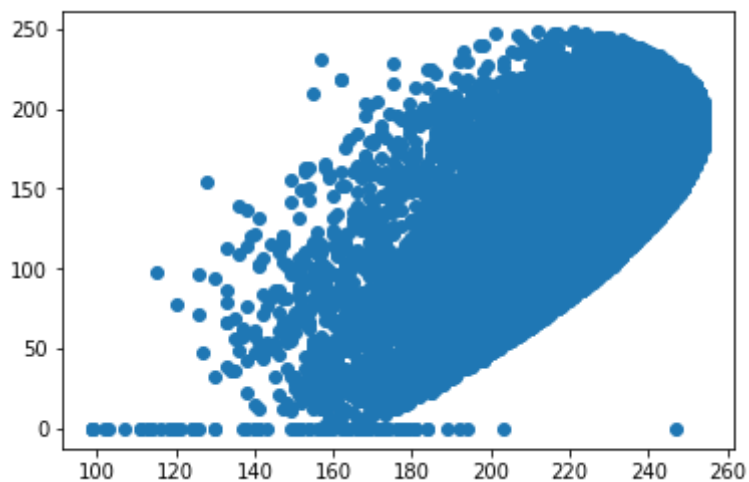
```
In [63]: #Scatter Plot for Horizontal_Distance_To_Hydrology vs the Vertical Distance
x = dataset['Horizontal_Distance_To_Hydrology']
y = dataset['Vertical_Distance_To_Hydrology']

plt.scatter(x,y)
plt.show()
```



```
In [64]: #ScatterPlot for Hillshade_Noon vs Hillshade_3pm
x = dataset['Hillshade_Noon']
y = dataset['Hillshade_3pm']

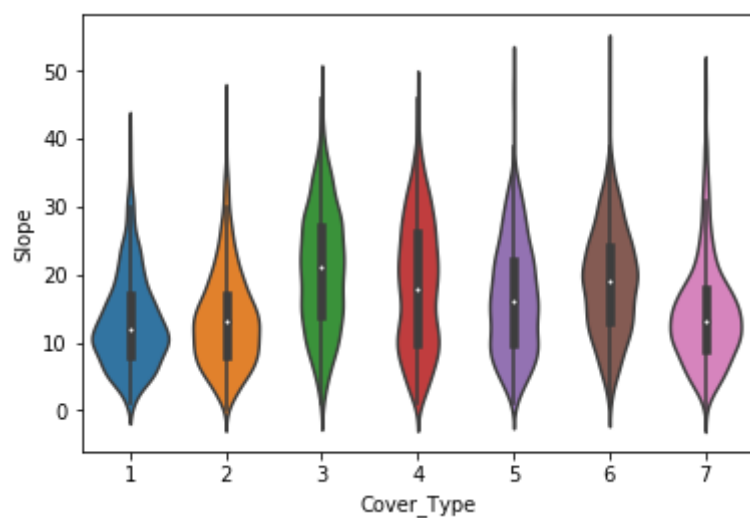
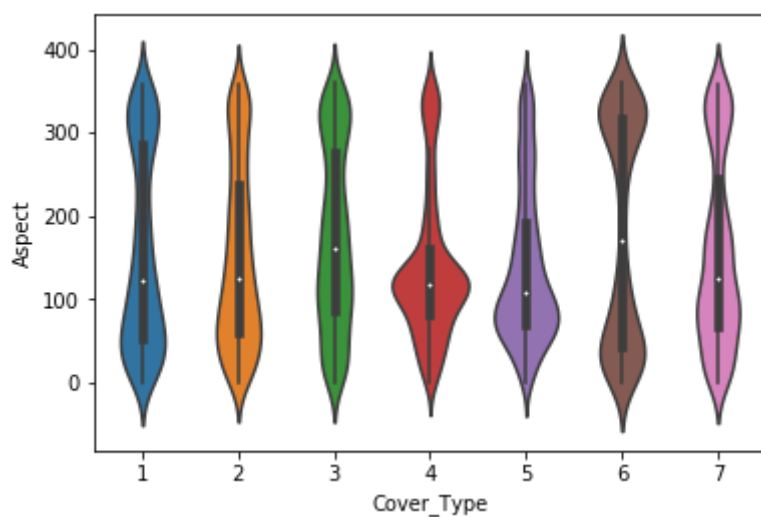
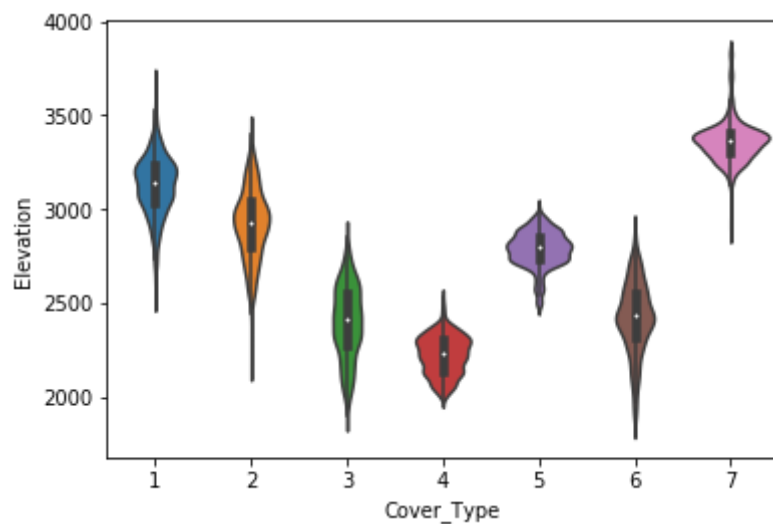
plt.scatter(x,y)
plt.show()
```



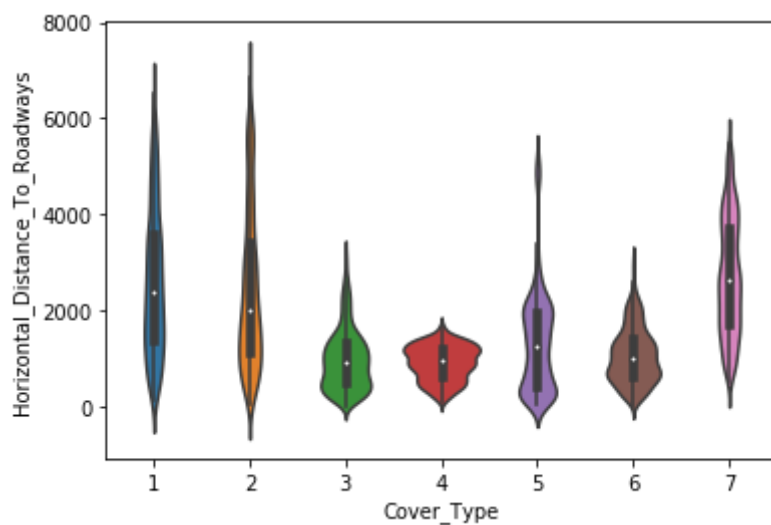
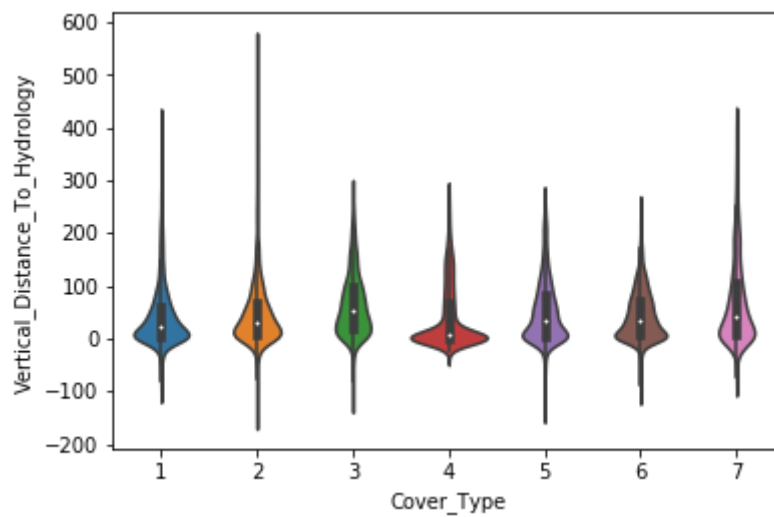
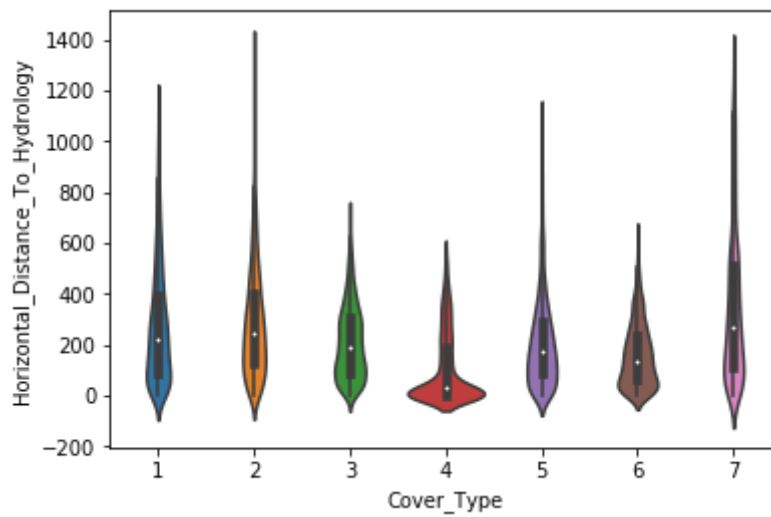
```
In [65]: cols = dataset.columns
size = len(cols)-1
x = cols[size]
y = cols[0:size]
```



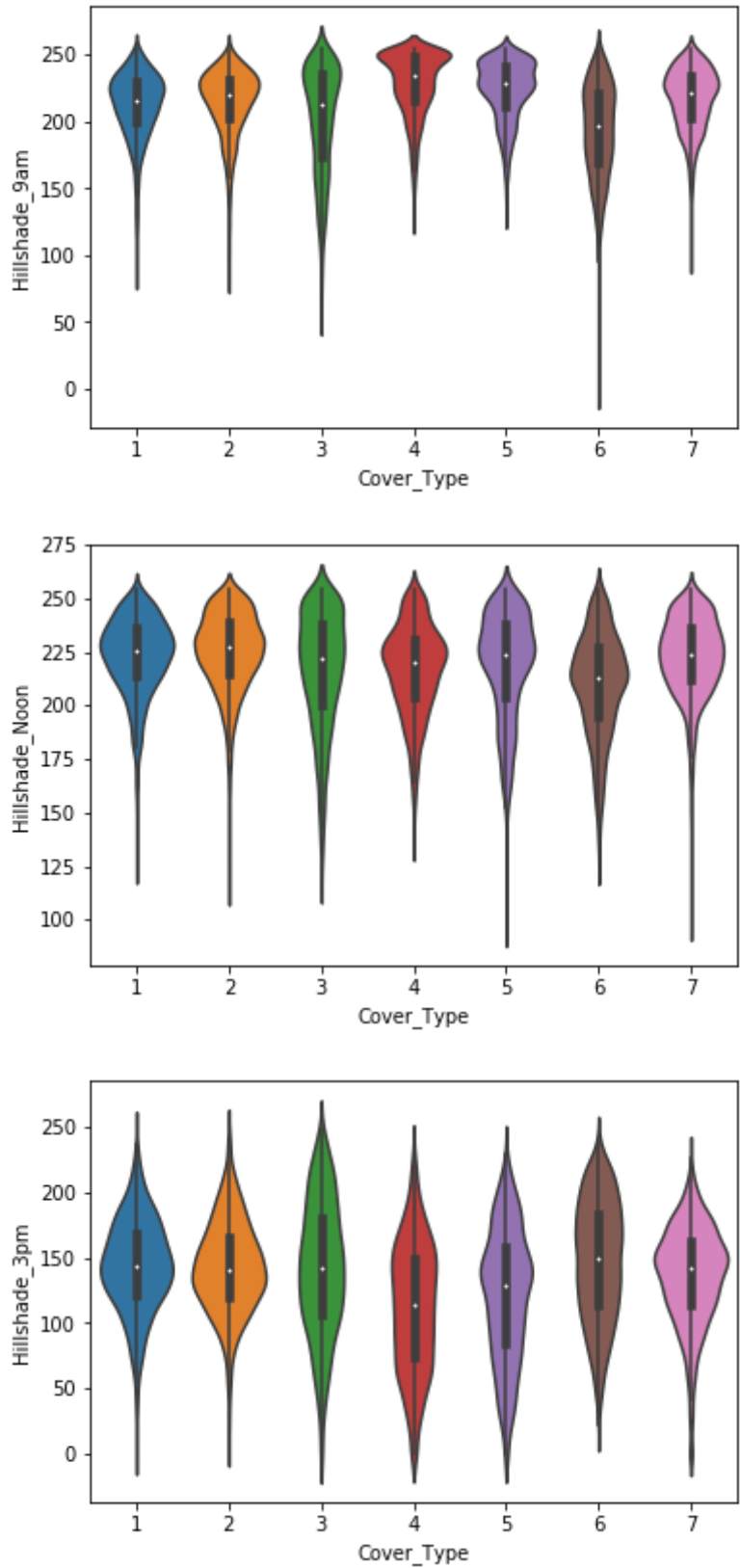
```
In [66]: for i in range(0,size):  
         sns.violinplot(data=dataset,x=x,y=y[i])  
         plt.show()
```



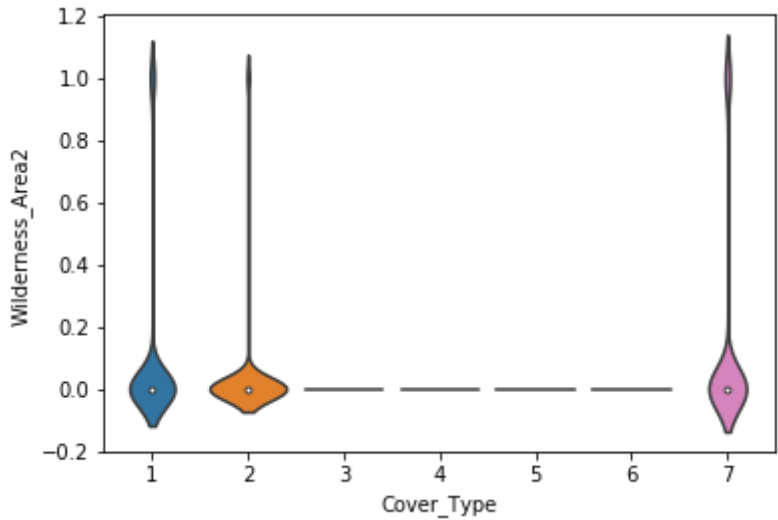
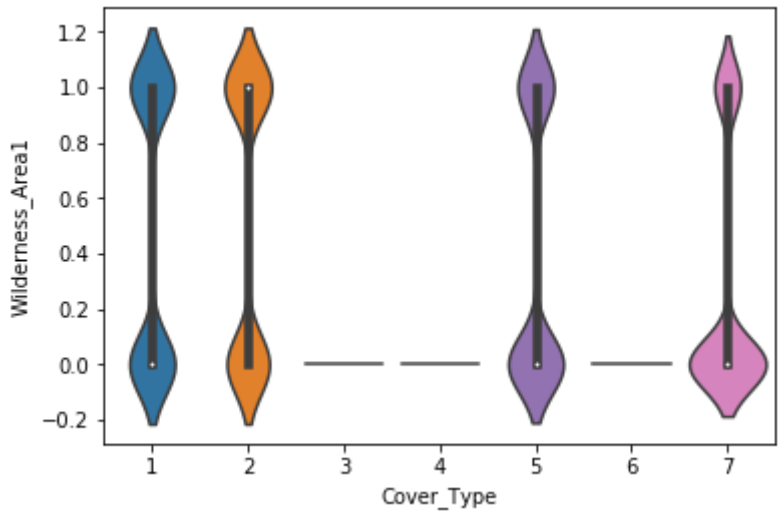
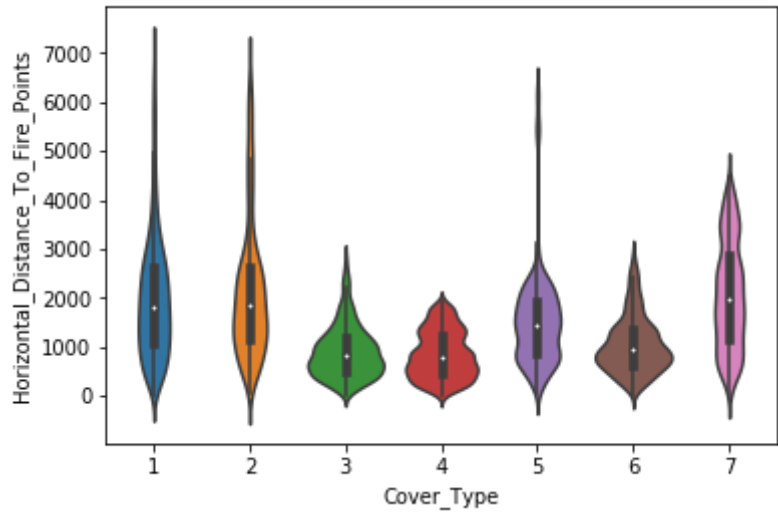
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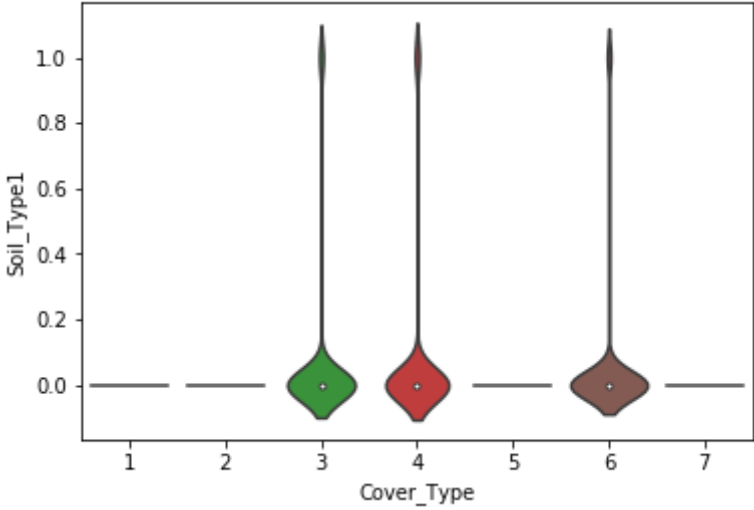
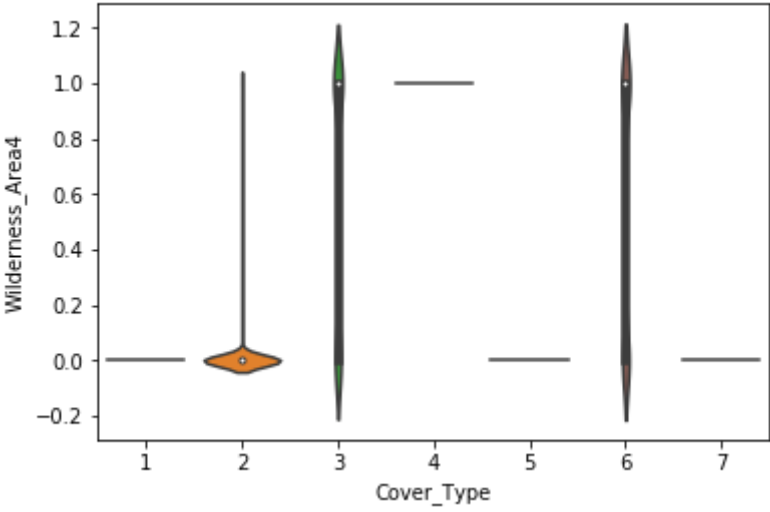
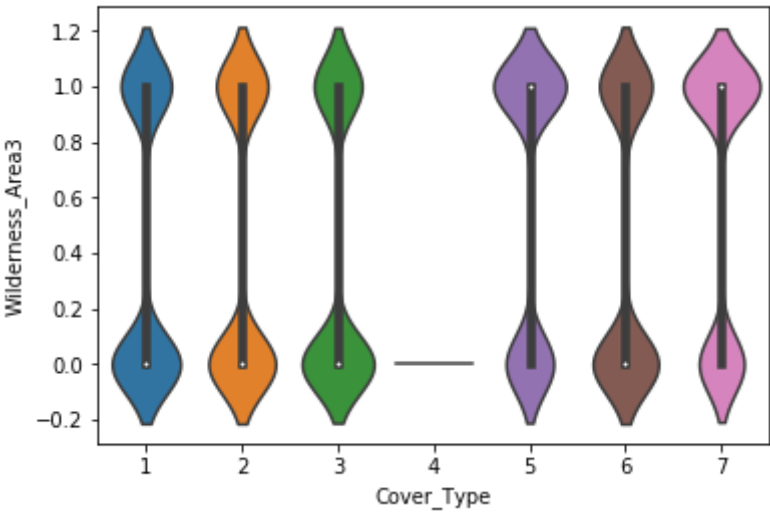


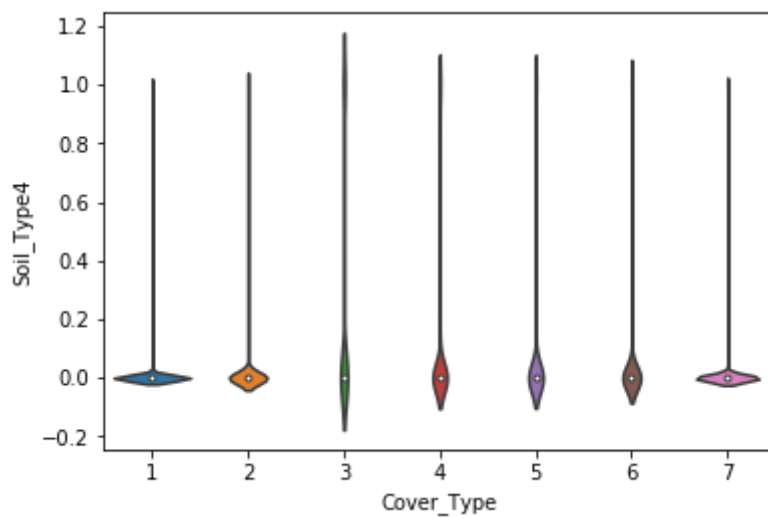
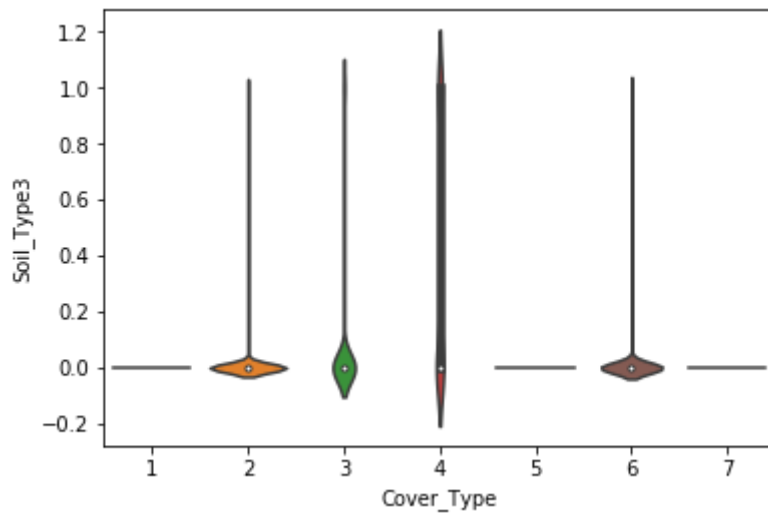
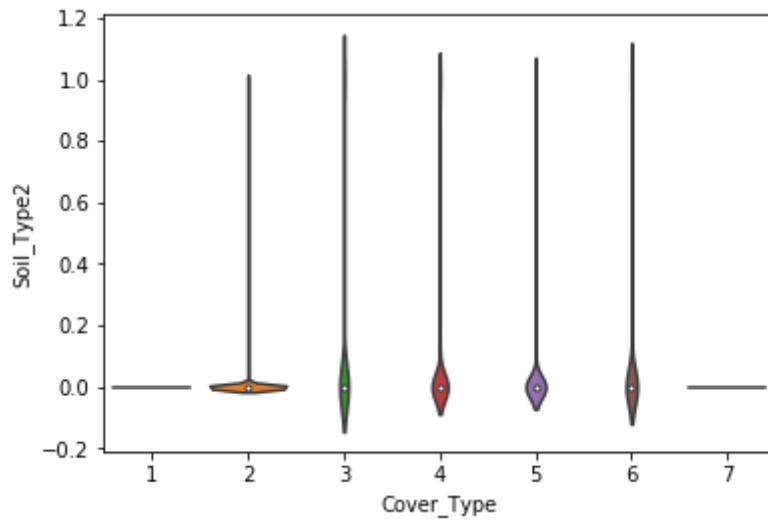
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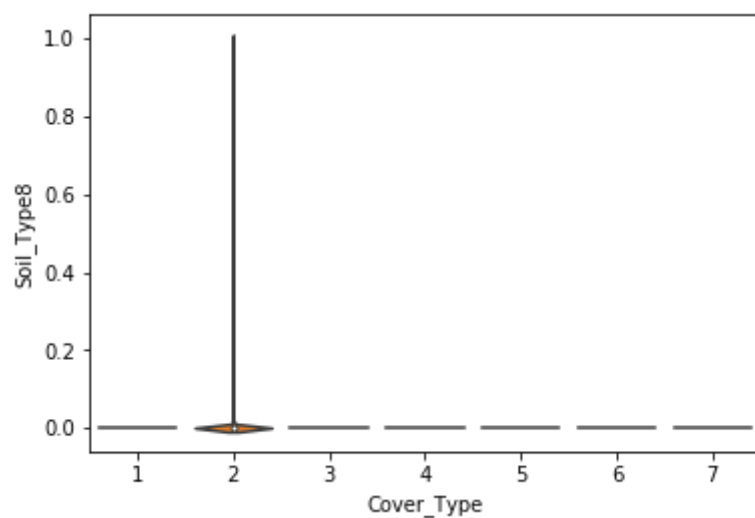
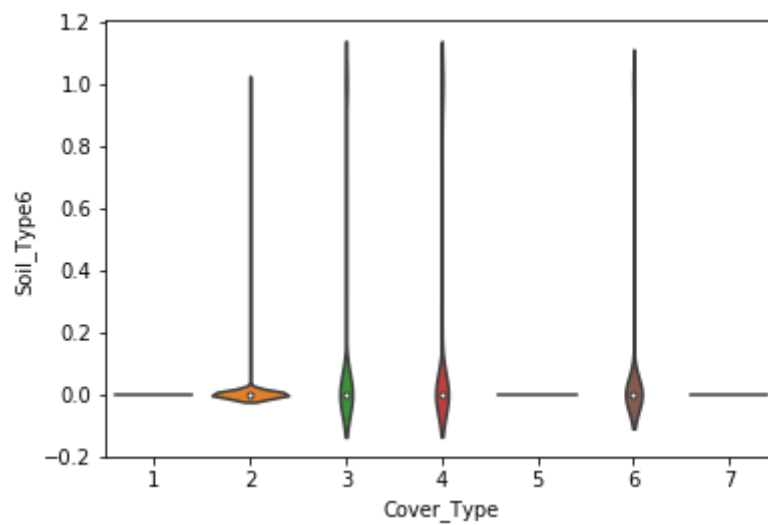
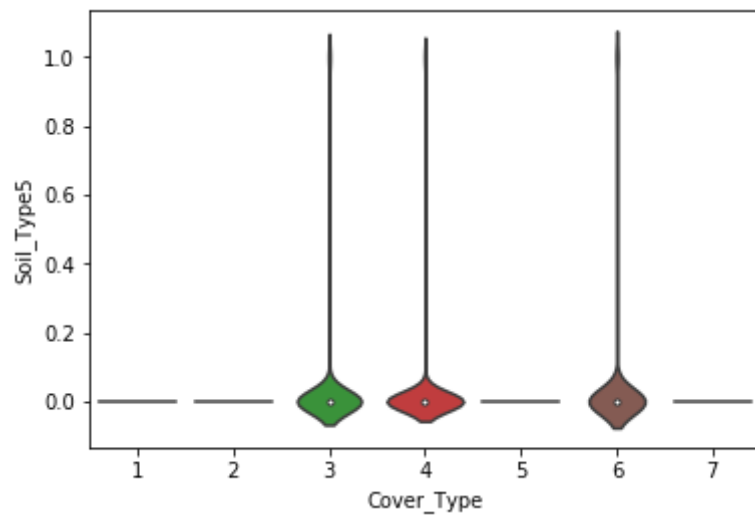
File failed to load: file:///Users/sakshikalani/Desktop/ML%20and%20Stats/Project_Group6_files/extensions/MathZoom.js



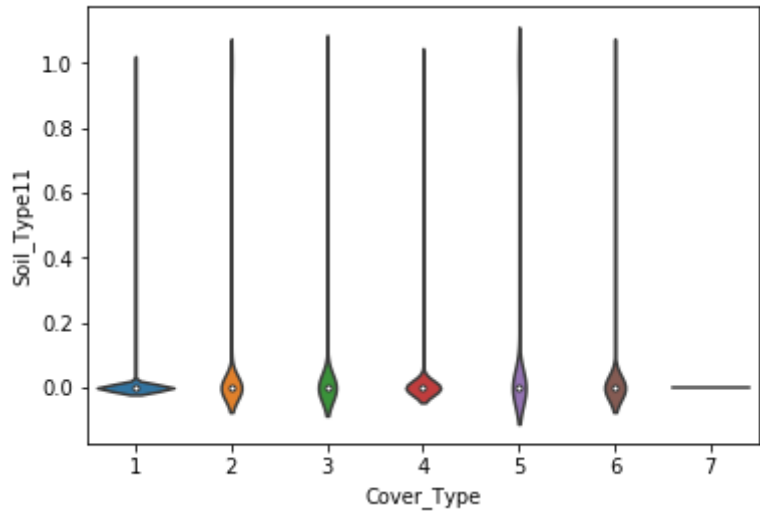
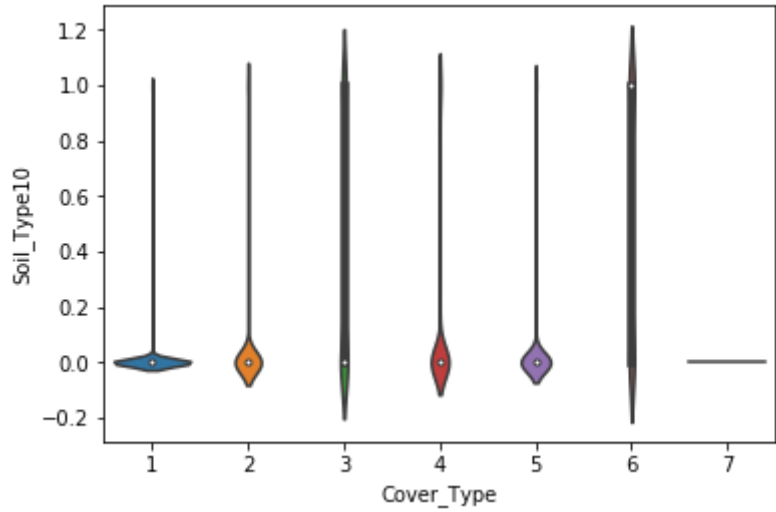
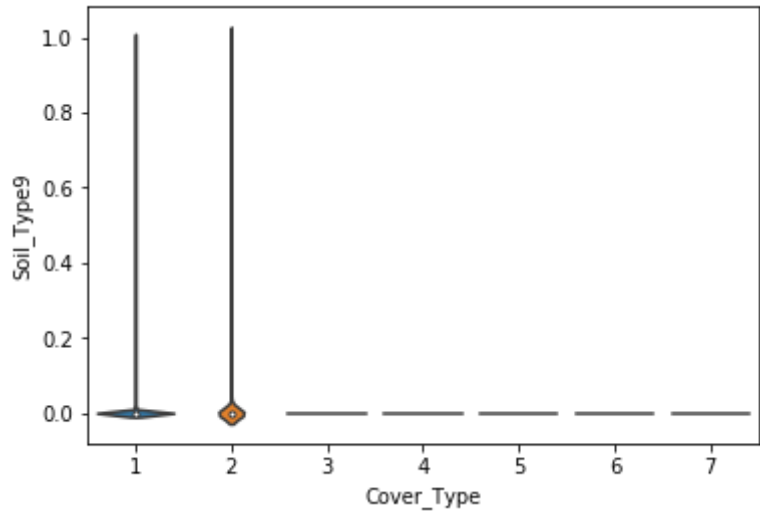




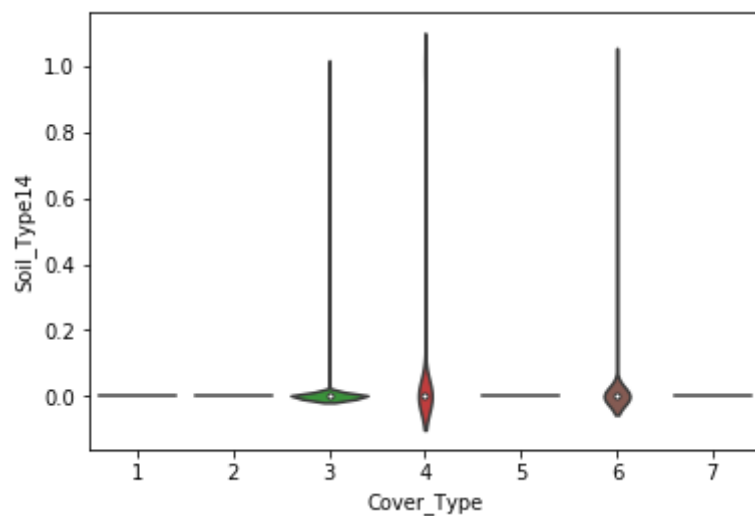
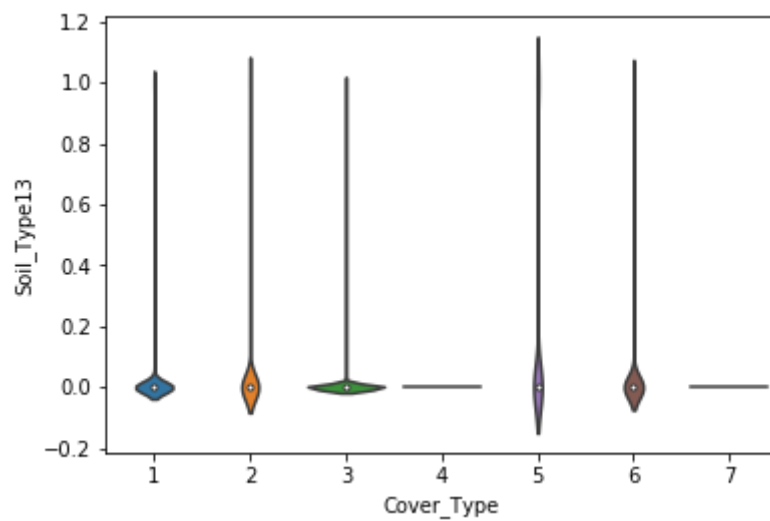
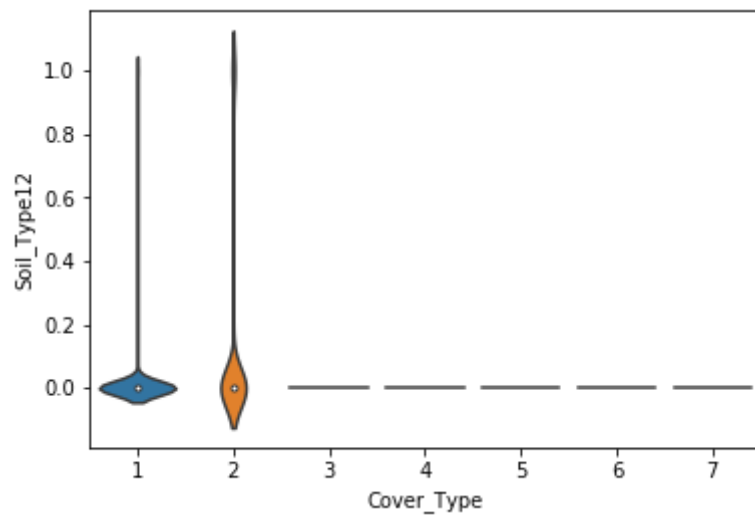
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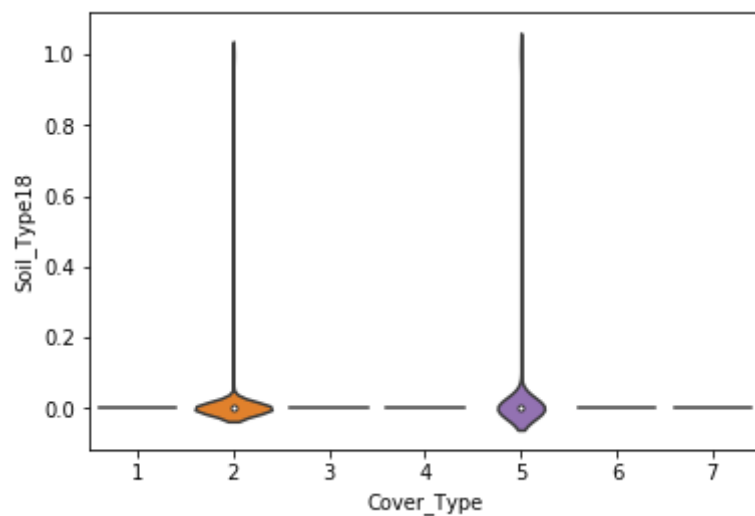
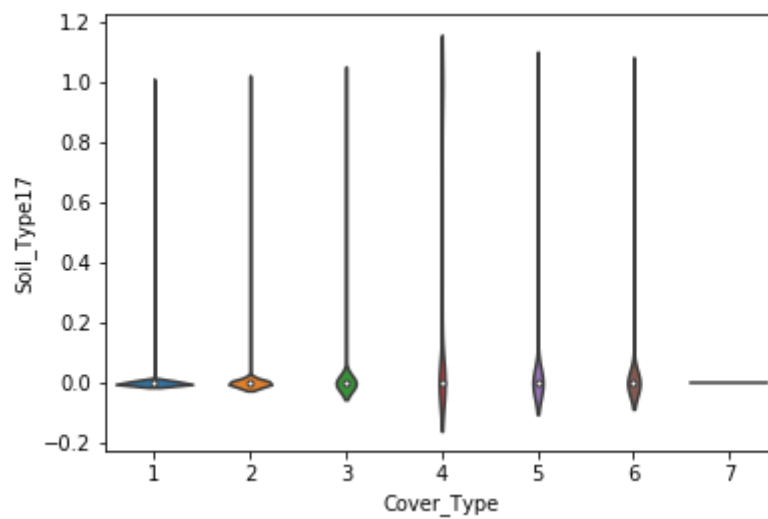
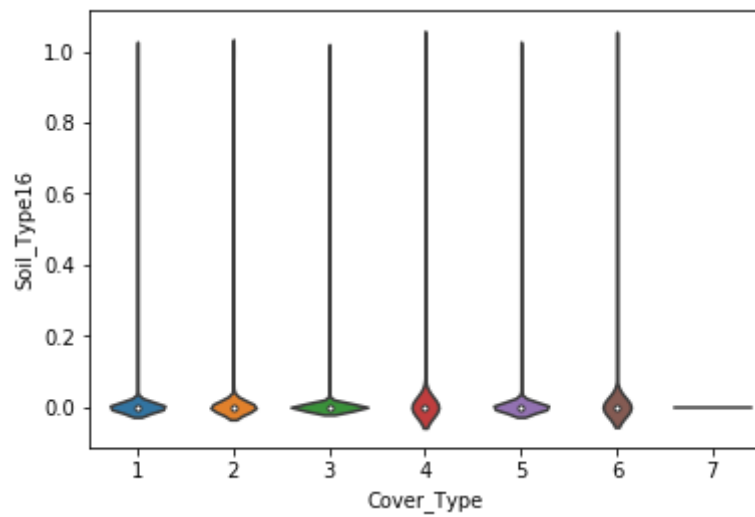
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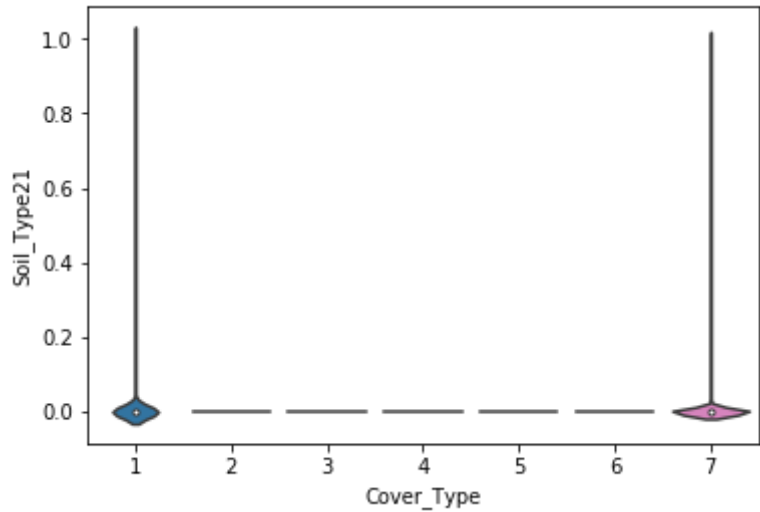
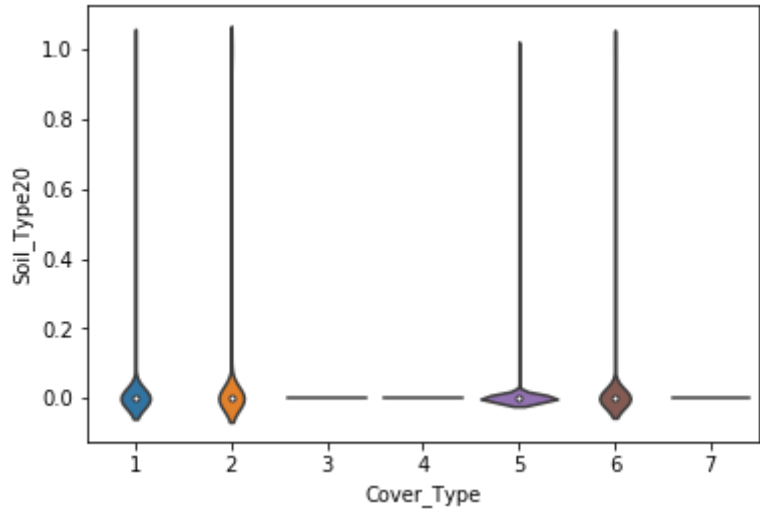
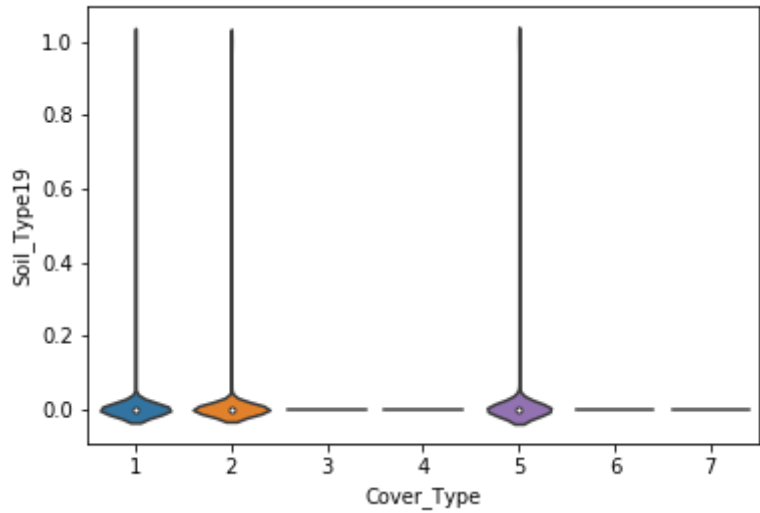
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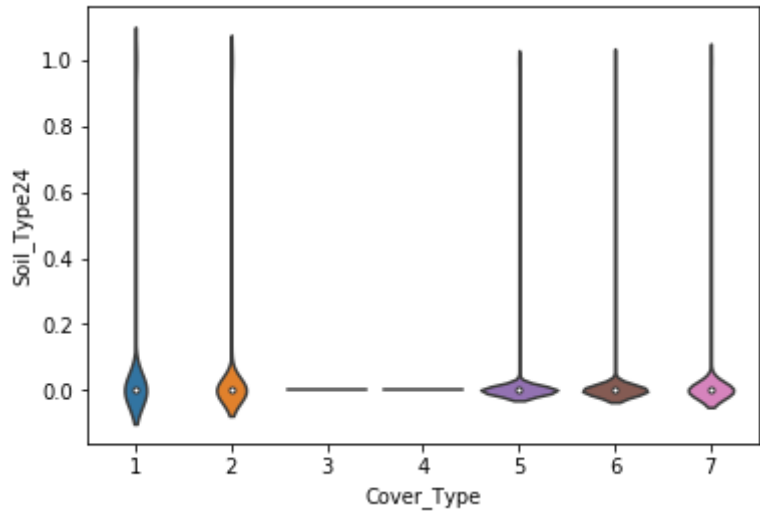
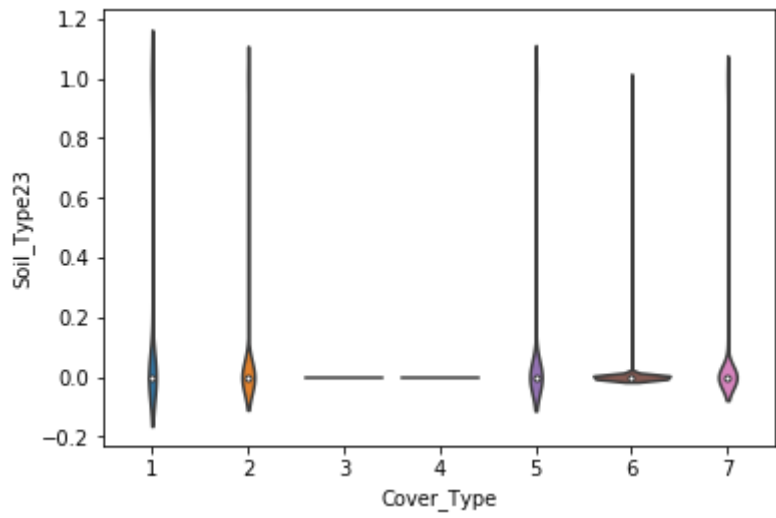
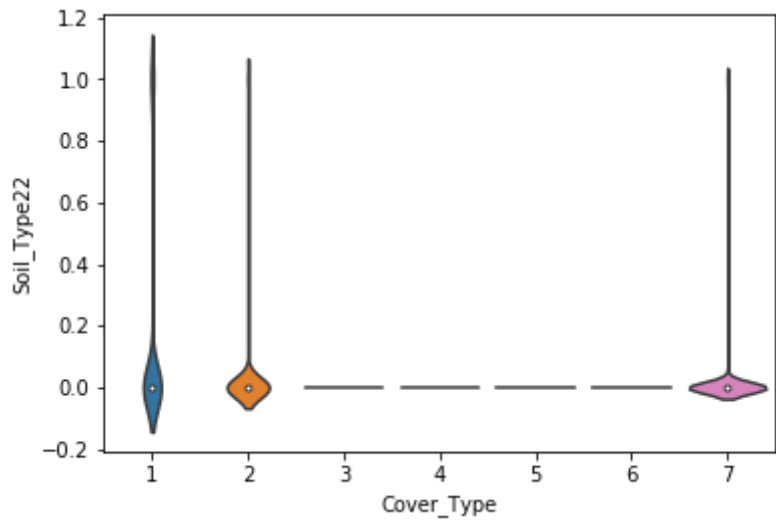


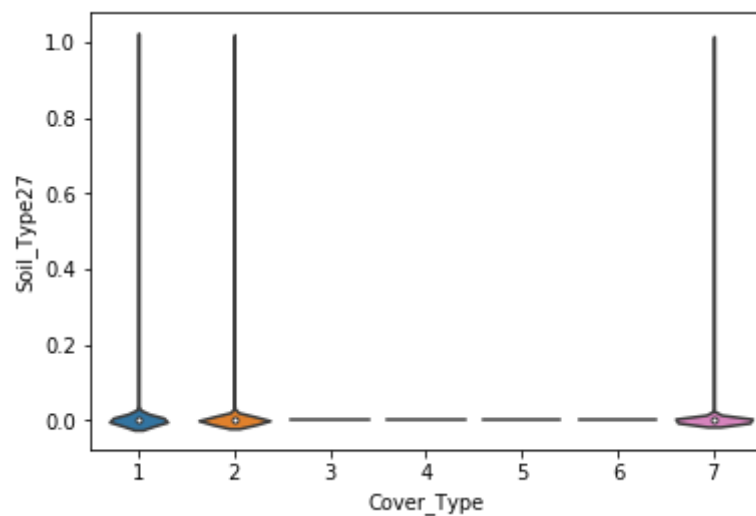
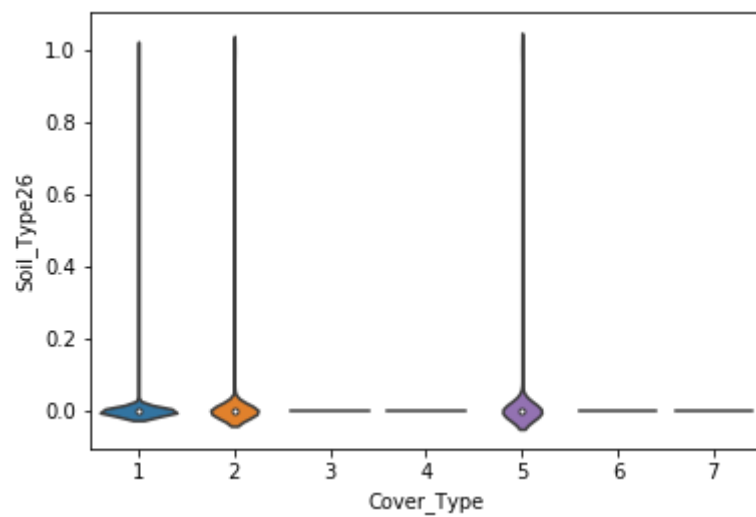
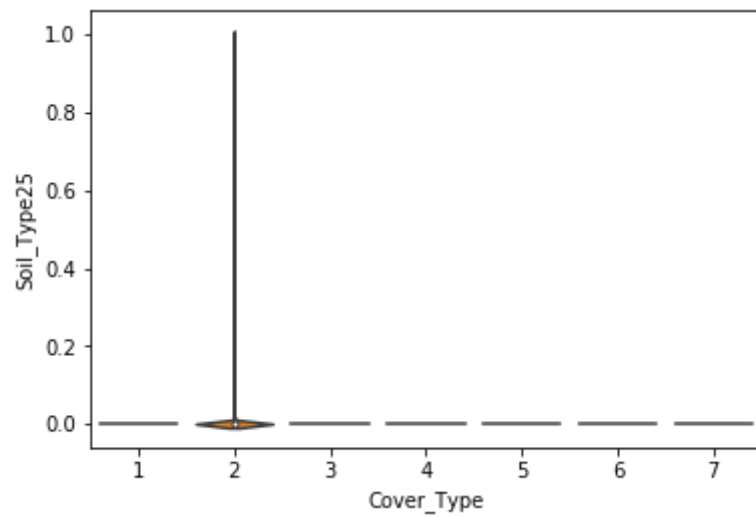
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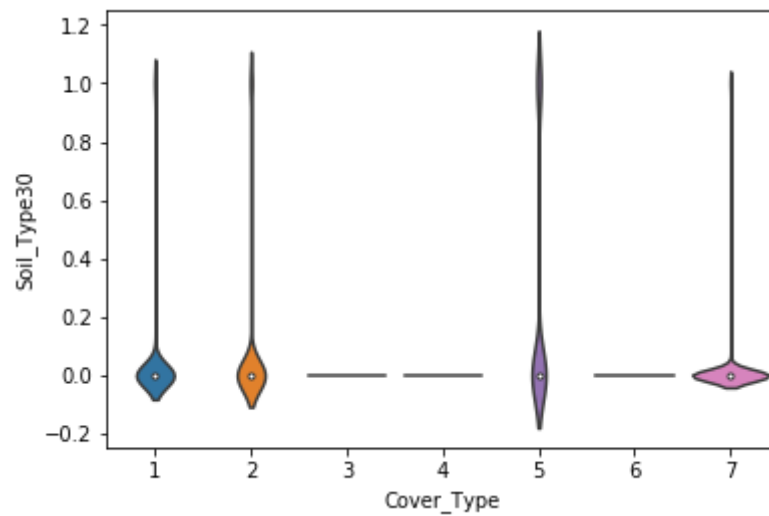
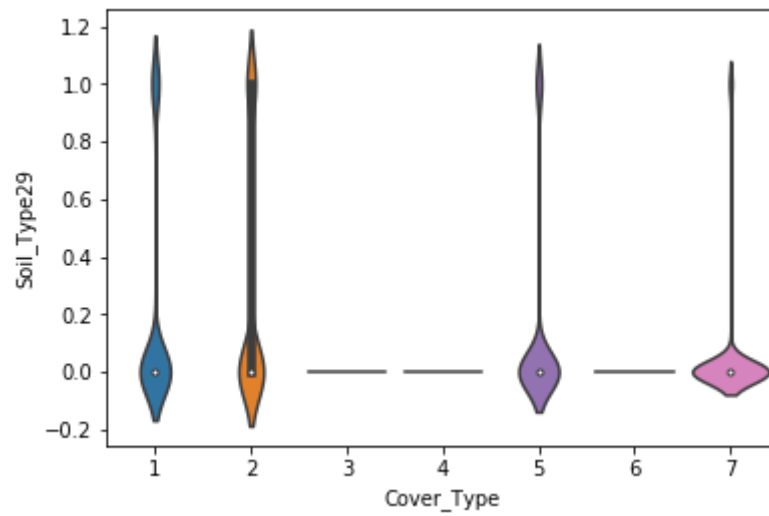
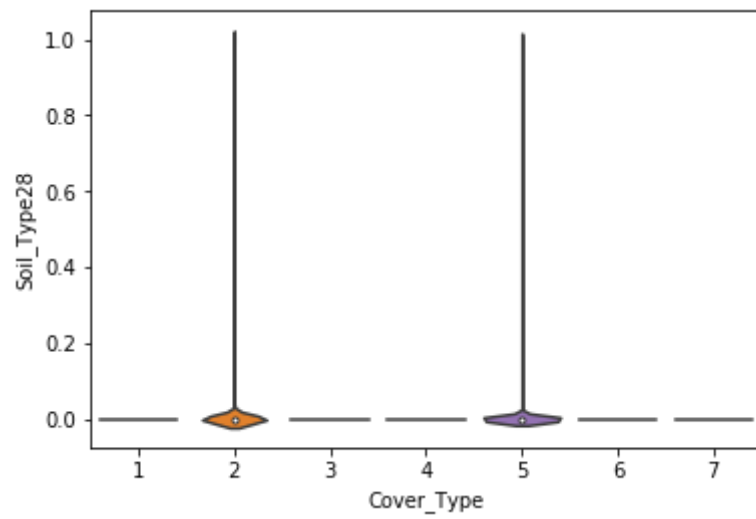
File failed to load: file:///Users/sakshikalani/Desktop/ML%20and%20Stats/Project_Group6_files/extensions/MathZoom.js

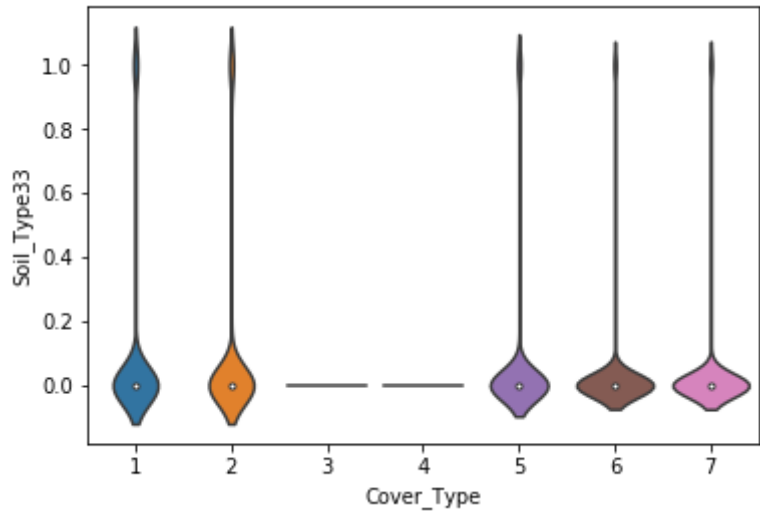
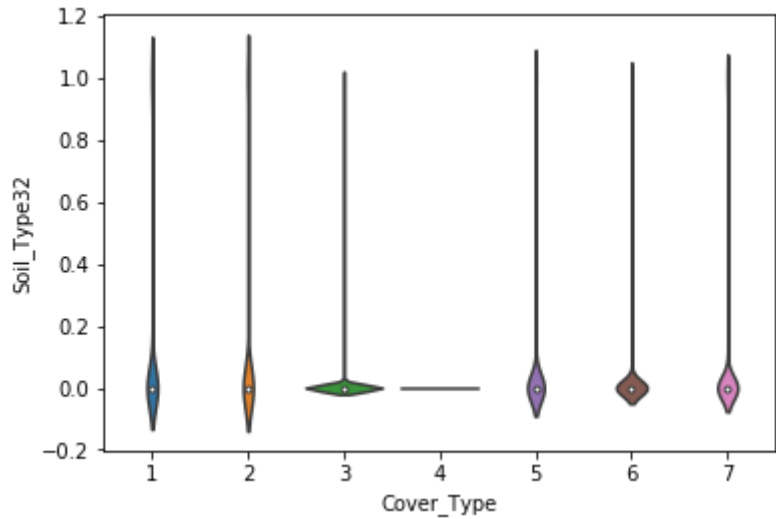
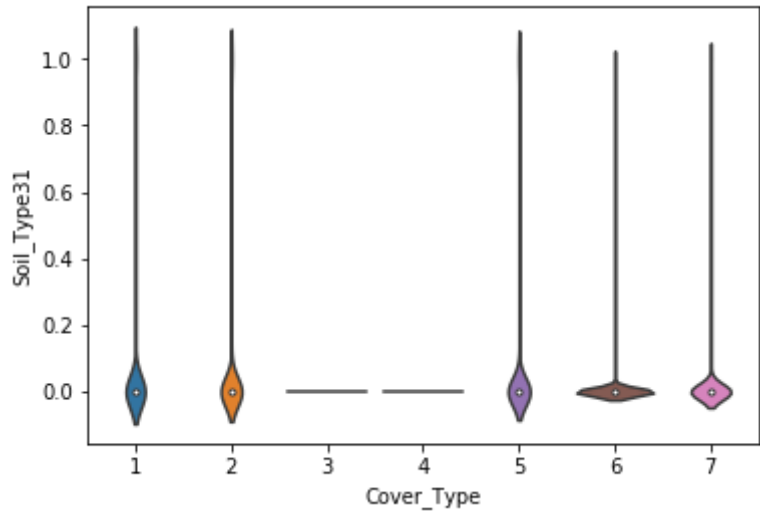


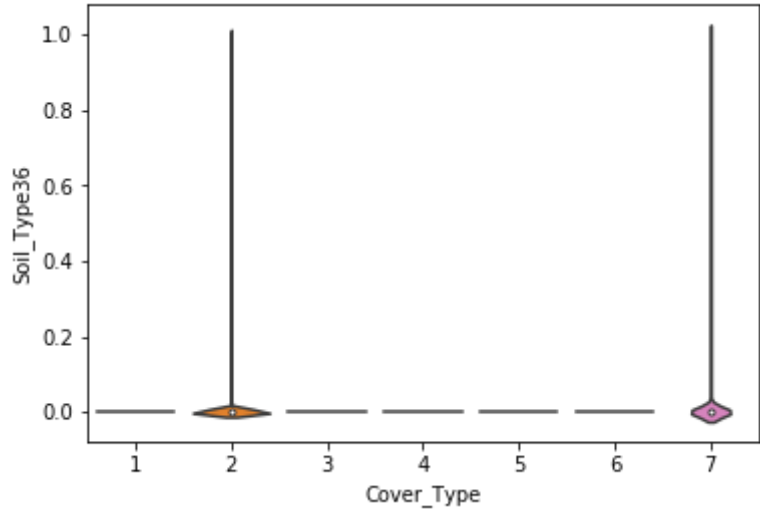
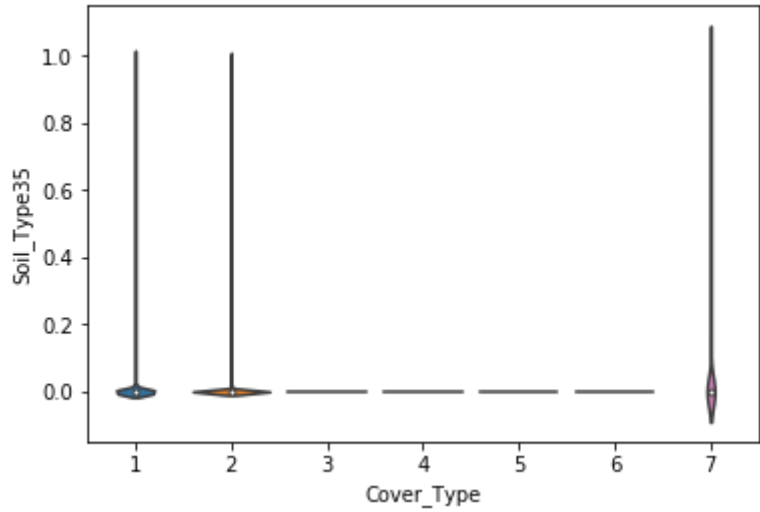
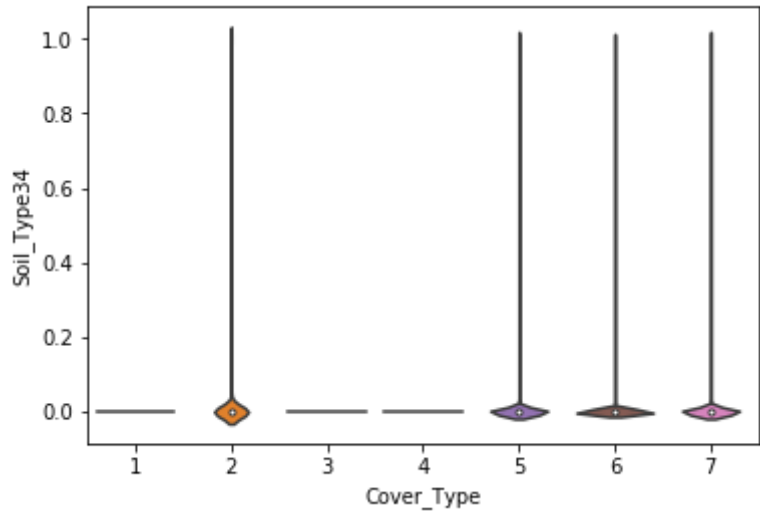




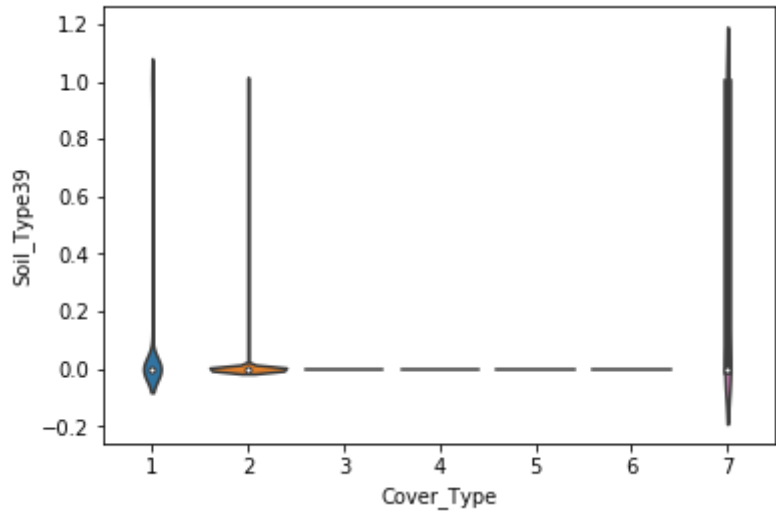
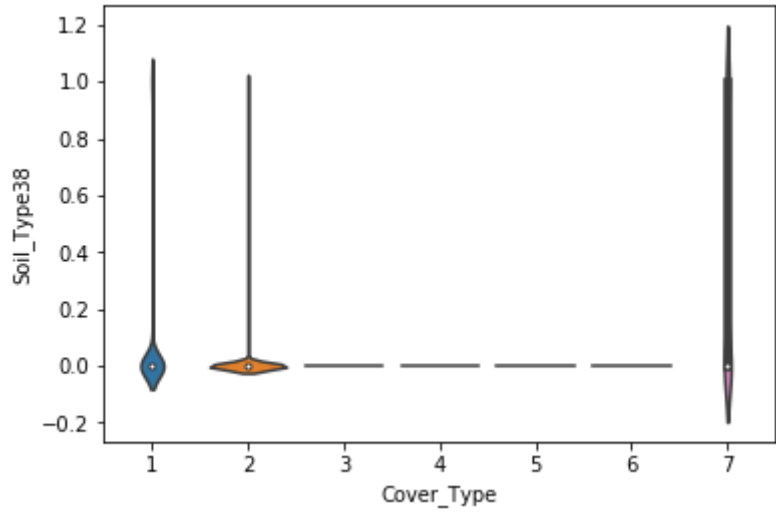
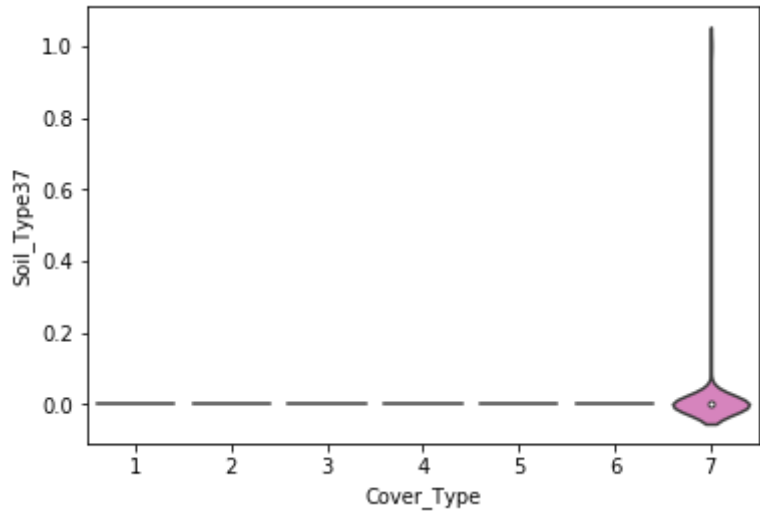
File failed to load: file:///Users/sakshikalani/Desktop/ML%20and%20Stats/Project_Group6_files/extensions/MathZoom.js

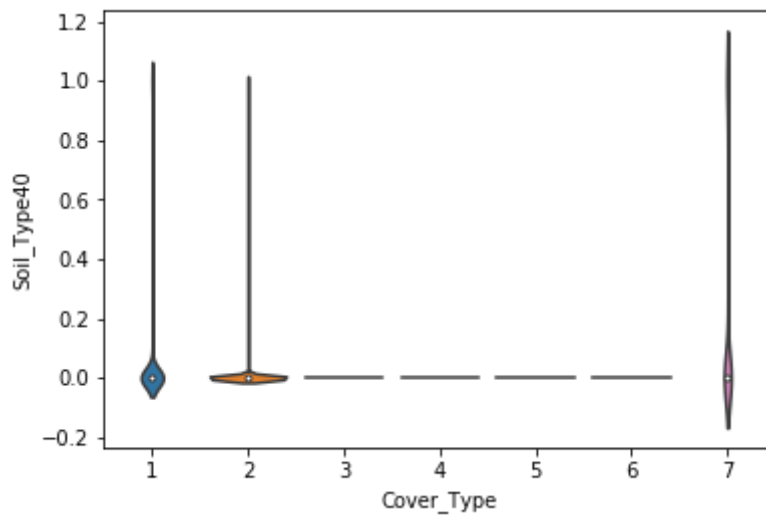






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Data Visualization

```
In [211]: # Group one-hot encoded variables of a category into one single variable

#names of all the columns
cols = dataset.columns
#number of rows=r , number of columns=c
r,c = dataset.shape
#Create a new dataframe with r rows, one column for each encoded category,
#and target in the end
dataS = pd.DataFrame(index=np.arange(0, r),columns=['Wilderness_Area','Soil_Type','Cover_Type'])
```

```

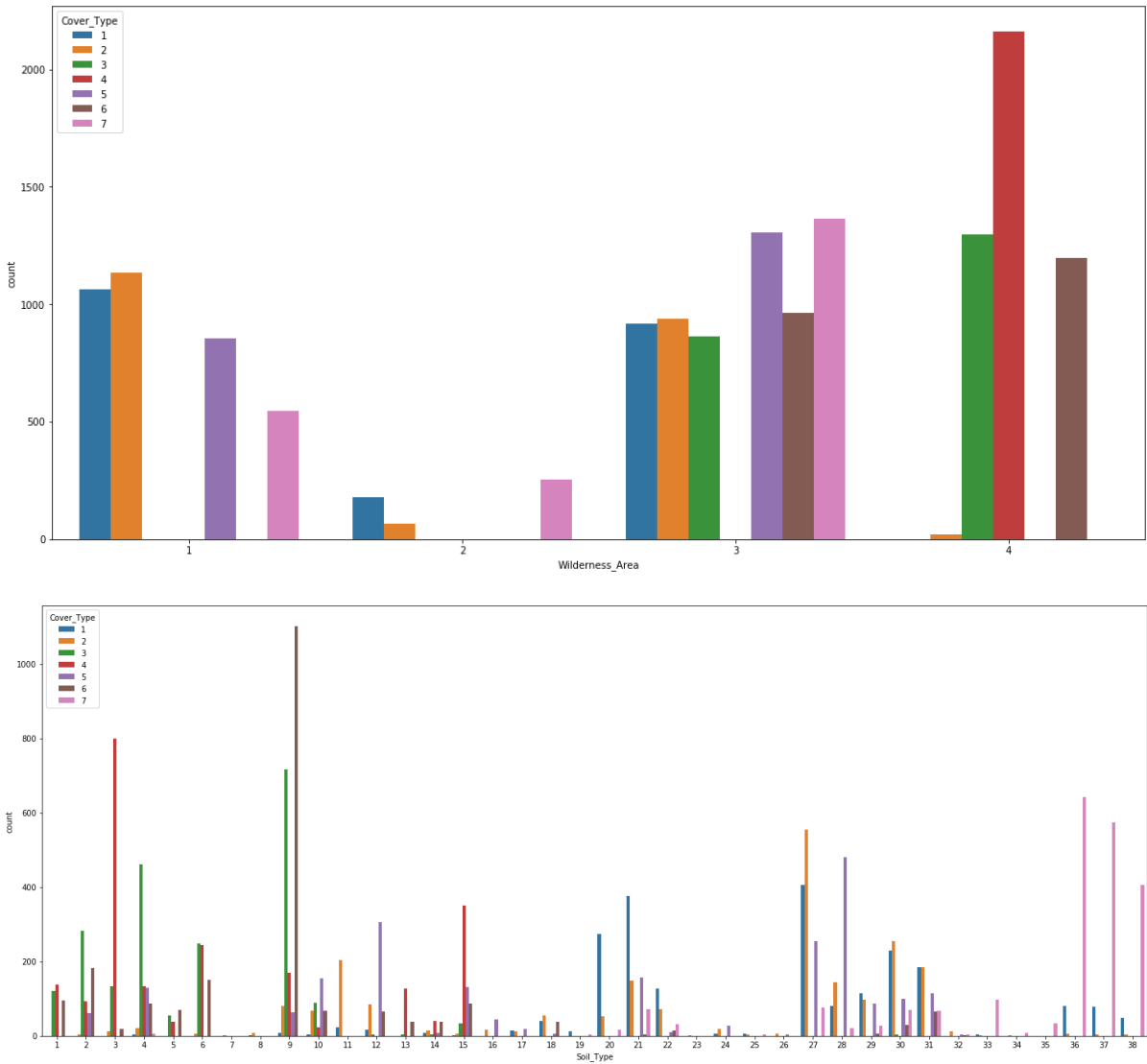
In [212]: #Make an entry in 'data' for each r as category_id, target value
for i in range(0,r):
    w=0;
    s=0;
    # Category1 range
    for j in range(10,14):
        if (dataset.iloc[i,j] == 1):
            w=j-9
            break
    # Category2 range
    for k in range(14,54):
        if (dataset.iloc[i,k] == 1):
            s=k-13
            break
    #Make an entry in 'data' for each r as category_id, target value

    dataS.iloc[i]=[w,s,dataset.iloc[i,c-1]]

#Plot for Category1
sns.countplot(x="Wilderness_Area", hue="Cover_Type", data=dataS)
plt.show()
#Plot for Category2
plt.rc("figure", figsize=(25, 10))
sns.countplot(x="Soil_Type", hue="Cover_Type", data=dataS)
plt.show()

#WildernessArea_4 has a lot of presence for cover_type 4. Good class distinction
#WildernessArea_3 has not much class distinction
#SoilType 1-6,10-14,17, 22-23, 29-33,35,38-40 offer lot of class distinction as counts for some are very high

```



Data Standardization

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```

In [192]: #get the number of rows and columns
r, c = dataset.shape

#get the list of columns
cols = dataset.columns
#create an array which has indexes of columns
i_cols = []
for i in range(0,c-1):
    i_cols.append(i)
#array of importance rank of all features
ranks = []

#Extract only the values
array = dataset.values

#Y is the target column, X has the rest
X_orig = array[:,0:(c-1)]
Y = array[:,(c-1):c]

#Validation chunk size
val_size = 0.1

#Use a common seed in all experiments so that same chunk is used for validation
seed = 0

#Split the data into chunks
from sklearn import cross_validation
X_train, X_val, Y_train, Y_val = cross_validation.train_test_split(X_orig, Y, test_size=val_size, random_state=seed)

#Import libraries for data transformations
from sklearn.preprocessing import Imputer
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import Normalizer

#All features
X_all = []
#Additionally we will make a list of subsets
X_all_add = []

#columns to be dropped
rem_cols = []
#indexes of columns to be dropped
i_rem = []

#Add this version of X to the list
X_all.append(['Orig', 'All', X_train, X_val, 1.0, cols[:c-1], rem_cols, ranks, i_cols, i_rem])

#point where categorical data begins
size=10

import numpy

```

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```

#Standardized
#Apply transform only for non-categorical data
X_temp = StandardScaler().fit_transform(X_train[:,0:size])
X_val_temp = StandardScaler().fit_transform(X_val[:,0:size])
#Concatenate non-categorical data and categorical
X_con = numpy.concatenate((X_temp,X_train[:,size:]),axis=1)
X_val_con = numpy.concatenate((X_val_temp,X_val[:,size:]),axis=1)
#Add this version of X to the list
X_all.append(['StdSca', 'All', X_con,X_val_con,1.0,cols,rem_cols,ranks,i_cols,i_rem])

#MinMax
#Apply transform only for non-categorical data
X_temp = MinMaxScaler().fit_transform(X_train[:,0:size])
X_val_temp = MinMaxScaler().fit_transform(X_val[:,0:size])
#Concatenate non-categorical data and categorical
X_con = numpy.concatenate((X_temp,X_train[:,size:]),axis=1)
X_val_con = numpy.concatenate((X_val_temp,X_val[:,size:]),axis=1)
#Add this version of X to the list
X_all.append(['MinMax', 'All', X_con,X_val_con,1.0,cols,rem_cols,ranks,i_cols,i_rem])

#Normalize
#Apply transform only for non-categorical data
X_temp = Normalizer().fit_transform(X_train[:,0:size])
X_val_temp = Normalizer().fit_transform(X_val[:,0:size])
#Concatenate non-categorical data and categorical
X_con = numpy.concatenate((X_temp,X_train[:,size:]),axis=1)
X_val_con = numpy.concatenate((X_val_temp,X_val[:,size:]),axis=1)
#Add this version of X to the list
X_all.append(['Norm', 'All', X_con,X_val_con,1.0,cols,rem_cols,ranks,i_cols,i_rem])

#Impute
#Imputer is not used as no data is missing

#List of transformations
trans_list = []

for trans,name,X,X_val,v,cols_list,rem_list,rank_list,i_cols_list,i_rem_list in X_all:
    trans_list.append(trans)

```

Feature Selection

```

In [215]: #Select top 75%,50%,25%
ratio_list = [0.75,0.50,0.25]

```

Feature Selection =- SelectPercentile

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```

In [216]: #List of feature selection models
          feat = []

          #List of names of feature selection models
          feat_list =[]

          #Libraries for SelectPercentile
          from sklearn.feature_selection import SelectPercentile
          from sklearn.feature_selection import f_classif

          n = 'SelK'
          feat_list.append(n)
          for val in ratio_list:
              comb.append("%s+%s" % (n,val))
              feat.append([n,val,SelectPercentile(score_func=f_classif,percentile=
              val*100)])

          #For all transformations of X
          for trans,s, X, X_val, d, cols, rem, ra, i_cols, i_rem in X_all:
              #For all feature selection models
              for name,v, model in feat:
                  #Train the model against Y
                  model.fit(X,Y_train)
                  #Combine importance and index of the column in the array joined
                  joined = []
                  for i, pred in enumerate(list(model.scores_)):
                      joined.append([i,cols[i],pred])
                  #Sort in descending order
                  joined_sorted = sorted(joined, key=lambda x: -x[2])
                  #Starting point of the columns to be dropped
                  rem_start = int((v*(c-1)))
                  #List of names of columns selected
                  cols_list = []
                  #Indexes of columns selected
                  i_cols_list = []
                  #Ranking of all the columns
                  rank_list =[]
                  #List of columns not selected
                  rem_list = []
                  #Indexes of columns not selected
                  i_rem_list = []
                  #Split the array. Store selected columns in cols_list and remove
                  d in rem_list
                  for j, (i, col, x) in enumerate(list(joined_sorted)):
                      #Store the rank
                      rank_list.append([i,j])
                      #Store selected columns in cols_list and indexes in i_cols_l
                      ist
                      if(j < rem_start):
                          cols_list.append(col)
                          i_cols_list.append(i)
                      #Store not selected columns in rem_list and indexes in i_rem
                      _list

                  else:

```

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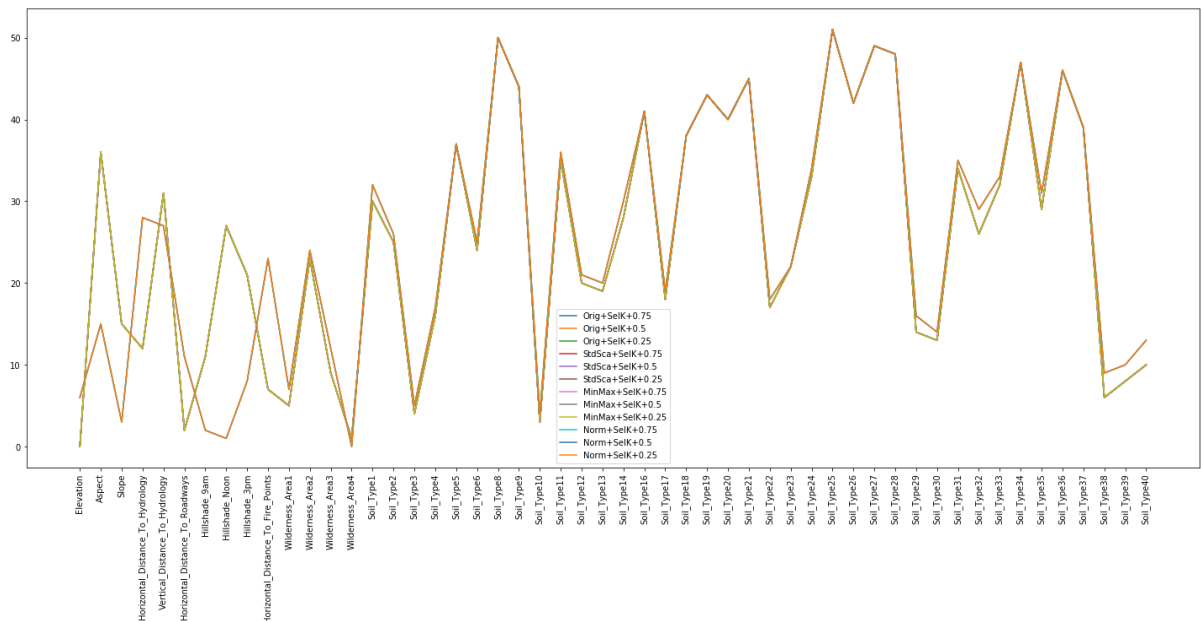

```

        i_rem_list.append(i)
        #Sort the rank_list and store only the ranks. Drop the index
        #Append model name, array, columns selected and columns to be re
moved to the additional list
        X_all_add.append([trans,name,X,X_val,v,cols_list,rem_list,[x[1]
for x in sorted(rank_list,key=lambda x:x[0])],i_cols_list,i_rem_list])

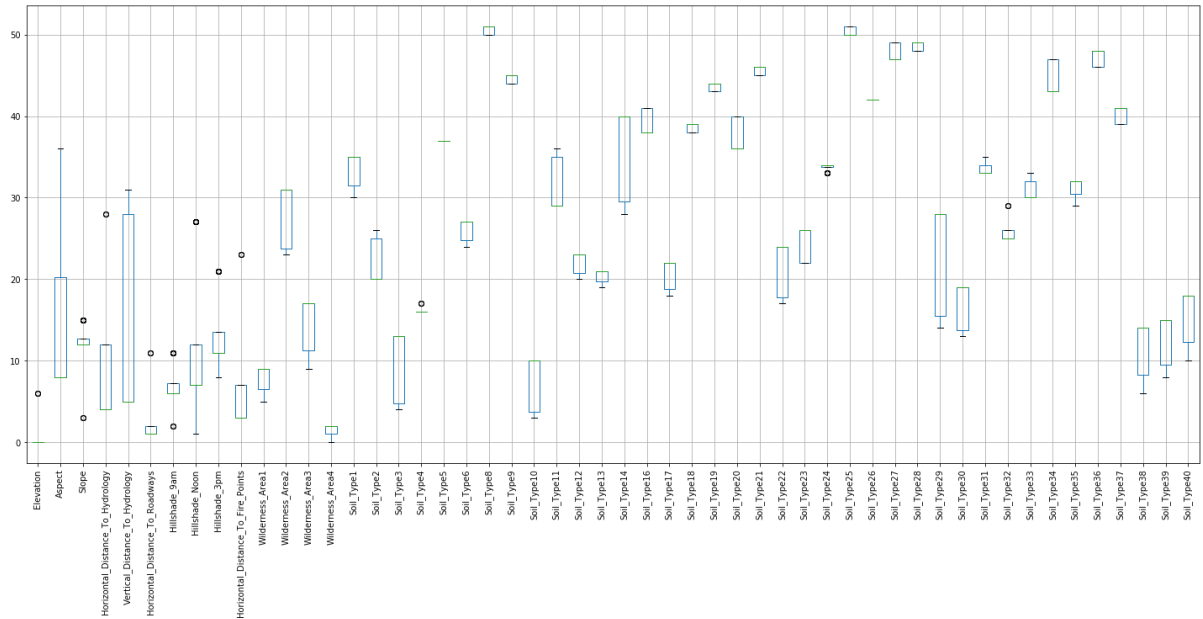
#Set figure size
plt.rc("figure", figsize=(25, 10))

#Plot a graph for different feature selectors
for f_name in feat_list:
    #Array to store the list of combinations
    leg=[]
    fig, ax = plt.subplots()
    #Plot each combination
    for trans,name,X,X_val,v,cols_list,rem_list,rank_list,i_cols_list,i_
rem_list in X_all_add:
        if(name==f_name):
            plt.plot(rank_list)
            leg.append(trans+" "+name+"%s"% v)
    #Set the tick names to names of columns
    ax.set_xticks(range(c-1))
    ax.set_xticklabels(cols[:c-1],rotation='vertical')
    #Display the plot
    plt.legend(leg,loc='best')
    #Plot the rankings of all the features for all combinations
    plt.show()

```



```
In [217]: rank_df = pd.DataFrame(data=[x[7] for x in X_all_add],columns=cols[:c-1]
      )
      _ = rank_df.boxplot(rot=90)
      #Below plot summarizes the rankings according to the standard feature se
      lection techniques
      #Top ranked attributes are ... first 10 attributes, Wilderness_Area1,4
      ...Soil_Type 3,4,10,38-40
```



Rank Features based on Median

```
In [218]: rank_df = pd.DataFrame(data=[x[7] for x in X_all_add],columns=cols[:c-1])
          med = rank_df.median()
          print(med)
```

Elevation	0.0
Aspect	8.0
Slope	12.0
Horizontal_Distance_To_Hydrology	4.0
Vertical_Distance_To_Hydrology	5.0
Horizontal_Distance_To_Roadways	1.0
Hillshade_9am	6.0
Hillshade_Noon	7.0
Hillshade_3pm	11.0
Horizontal_Distance_To_Fire_Points	3.0
Wilderness_Area1	9.0
Wilderness_Area2	31.0
Wilderness_Area3	17.0
Wilderness_Area4	2.0
Soil_Type1	35.0
Soil_Type2	20.0
Soil_Type3	13.0
Soil_Type4	16.0
Soil_Type5	37.0
Soil_Type6	27.0
Soil_Type8	51.0
Soil_Type9	45.0
Soil_Type10	10.0
Soil_Type11	29.0
Soil_Type12	23.0
Soil_Type13	21.0
Soil_Type14	40.0
Soil_Type16	38.0
Soil_Type17	22.0
Soil_Type18	39.0
Soil_Type19	44.0
Soil_Type20	36.0
Soil_Type21	46.0
Soil_Type22	24.0
Soil_Type23	26.0
Soil_Type24	34.0
Soil_Type25	50.0
Soil_Type26	42.0
Soil_Type27	47.0
Soil_Type28	49.0
Soil_Type29	28.0
Soil_Type30	19.0
Soil_Type31	33.0
Soil_Type32	25.0
Soil_Type33	30.0
Soil_Type34	43.0
Soil_Type35	32.0
Soil_Type36	48.0
Soil_Type37	41.0
Soil_Type38	14.0
Soil_Type39	15.0
Soil_Type40	18.0

dtype: float64

```

In [219]: #Select top 75%,50%,25%
ratio_list = [0.75,0.50,0.25]

#Median of rankings for each column
unsorted_rank = [0,8,11,4,5,2,5,7.5,9.5,3,8,28.5,14.5,2,35,19.5,12,14,37,25.5,50,44,9,28,20.5,19.5,40,38,20,38,43,35,44,22,24,33,49,42,46,47,27.5,19,31.5,23,28,42,30.5,46,40,12,13,18]

#List of feature selection models
feat = []

#Add Median to the list
n = 'Median'
for val in ratio_list:
    feat.append([n,val])

for trans,s, X, X_val, d, cols, rem_cols, ra, i_cols, i_rem in X_all:
    #Create subsets of feature list based on ranking and ratio_list
    for name, v in feat:
        #Combine importance and index of the column in the array joined
        joined = []
        for i, pred in enumerate(unsorted_rank):
            joined.append([i,cols[i],pred])
        #Sort in descending order
        joined_sorted = sorted(joined, key=lambda x: x[2])
        #Starting point of the columns to be dropped
        rem_start = int((v*(c-1)))
        #List of names of columns selected
        cols_list = []
        #Indexes of columns selected
        i_cols_list = []
        #Ranking of all the columns
        rank_list =[]
        #List of columns not selected
        rem_list = []
        #Indexes of columns not selected
        i_rem_list = []
        #Split the array. Store selected columns in cols_list and remove
        d in rem_list
        for j, (i, col, x) in enumerate(list(joined_sorted)):
            #Store the rank
            rank_list.append([i,j])
            #Store selected columns in cols_list and indexes in i_cols_list
            if(j < rem_start):
                cols_list.append(col)
                i_cols_list.append(i)
            #Store not selected columns in rem_list and indexes in i_rem_list
            else:
                rem_list.append(col)
                i_rem_list.append(i)
        #Sort the rank_list and store only the ranks. Drop the index
        #Append model name, array, columns selected and columns to be removed to the additional list

```

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```
X_all_add.append([trans,name,X,X_val,v,cols_list,rem_list,[x[1]  
for x in sorted(rank_list,key=lambda x:x[0])],i_cols_list,i_rem_list])
```

```
In [220]: #Import plotting library  
import matplotlib.pyplot as plt  
  
#Dictionary to store the accuracies for all combinations  
acc = {}  
  
#List of combinations  
comb = []  
  
#Append name of transformation to trans_list  
for trans in trans_list:  
    acc[trans]=[]
```

Machine Learning Algorithms

K Nearest Neighbours

```

In [224]: #Evaluation of various combinations of KNN Classifier using all the view
s

#Import the library
from sklearn.neighbors import KNeighborsClassifier

n_list = [1]

for n_neighbors in n_list:
    #Set the base model
    model = KNeighborsClassifier(n_jobs=-1,n_neighbors=n_neighbors)

    algo = "KNN"

    ##Set figure size
    #plt.rc("figure", figsize=(25, 10))

    #Accuracy of the model using all features
    for trans,name,X,X_val,v,cols_list,rem_list,rank_list,i_cols_list,i_
rem_list in X_all:
        model.fit(X[:,i_cols_list],Y_train)
        result = model.score(X_val[:,i_cols_list], Y_val)
        acc[trans].append(result)
        print(trans+" "+name+"+%d" % (v*(c-1)))
        print(result)
        comb.append("%s with n=%s+%s of %s" % (algo,n_neighbors,"All",1.0))

    #Accuracy of the model using a subset of features
    for trans,name,X,X_val,v,cols_list,rem_list,rank_list,i_cols_list,i_
rem_list in X_all_add:
        model.fit(X[:,i_cols_list],Y_train)
        result = model.score(X_val[:,i_cols_list], Y_val)
        acc[trans].append(result)
        print(trans+" "+name+"+%d" % (v*(c-1)))
        print(result)
    for v in ratio_list:
        comb.append("%s with n=%s+%s of %s" % (algo,n_neighbors,"Subset"
,v))

#print(acc)

##Plot the accuracies of all combinations
fig, ax = plt.subplots()
##Plot each transformation
for trans in trans_list:
    plt.plot(acc[trans])
##Set the tick names to names of combinations
ax.set_xticks(range(len(comb)))
ax.set_xticklabels(comb,rotation='vertical')
##Display the plot
plt.legend(trans_list,loc='best')
##Plot the accuracy for all combinations
plt.show()

#Best estimated performance is close to 85% when n neighbors=1 and norma

```

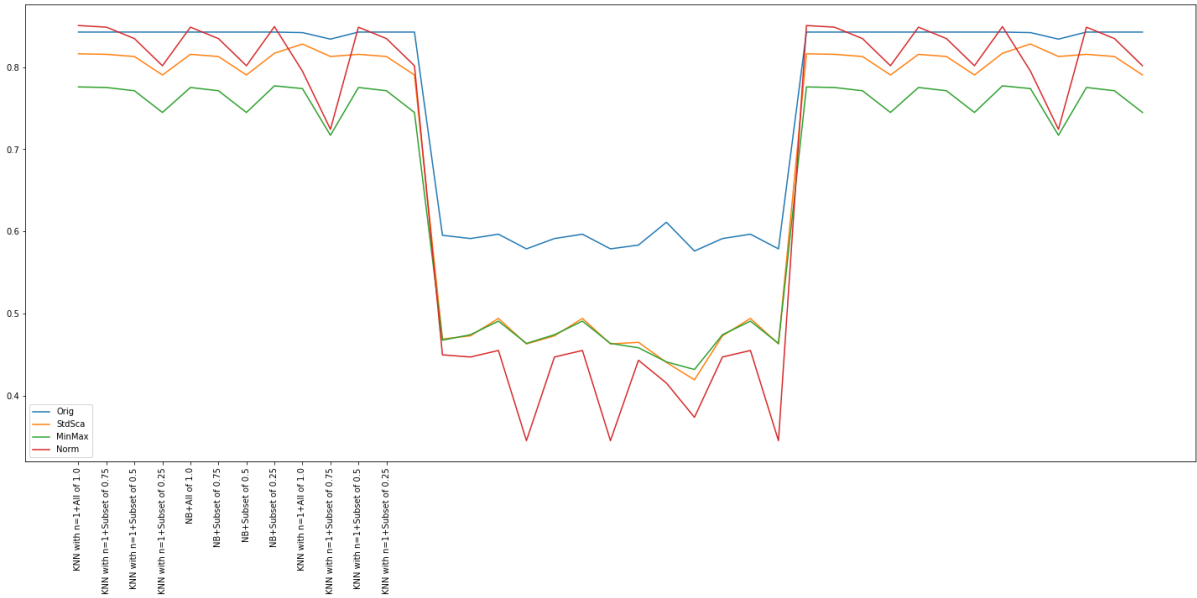
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File failed to load: file:///Users/sakshikalani/Desktop/ML%20and%20Stats/Project_Group6_files/extensions/MathZoom.js

Orig+All+52
0.842592592593
StdSca+All+52
0.816137566138
MinMax+All+52
0.775793650794
Norm+All+52
0.850529100529
Orig+Median+39
0.842592592593
Orig+Median+26
0.842592592593
Orig+Median+13
0.842592592593
StdSca+Median+39
0.815476190476
StdSca+Median+26
0.812830687831
StdSca+Median+13
0.790343915344
MinMax+Median+39
0.775132275132
MinMax+Median+26
0.771164021164
MinMax+Median+13
0.744708994709
Norm+Median+39
0.848544973545
Norm+Median+26
0.834656084656
Norm+Median+13
0.801587301587
Orig+Median+39
0.842592592593
Orig+Median+26
0.842592592593
Orig+Median+13
0.842592592593
StdSca+Median+39
0.815476190476
StdSca+Median+26
0.812830687831
StdSca+Median+13
0.790343915344
MinMax+Median+39
0.775132275132
MinMax+Median+26
0.771164021164
MinMax+Median+13
0.744708994709
Norm+Median+39
0.848544973545
Norm+Median+26
0.834656084656
Norm+Median+13
0.801587301587
Orig+SelK+39

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0.842592592593
Orig+SelK+26
0.841931216931
Orig+SelK+13
0.833994708995
StdSca+SelK+39
0.816798941799
StdSca+SelK+26
0.828042328042
StdSca+SelK+13
0.812830687831
MinMax+SelK+39
0.777116402116
MinMax+SelK+26
0.77380952381
MinMax+SelK+13
0.716931216931
Norm+SelK+39
0.849206349206
Norm+SelK+26
0.794973544974
Norm+SelK+13
0.724206349206
Orig+Median+39
0.842592592593
Orig+Median+26
0.842592592593
Orig+Median+13
0.842592592593
StdSca+Median+39
0.815476190476
StdSca+Median+26
0.812830687831
StdSca+Median+13
0.790343915344
MinMax+Median+39
0.775132275132
MinMax+Median+26
0.771164021164
MinMax+Median+13
0.744708994709
Norm+Median+39
0.848544973545
Norm+Median+26
0.834656084656
Norm+Median+13
0.801587301587



Naive Bayes

```

In [225]: #Evaluation of various combinations of Naive Bayes using all the views

#Import the library
from sklearn.naive_bayes import GaussianNB

#Set the base model
model = GaussianNB()
algo = "NB"

##Set figure size
plt.rcParams["figure", figsize=(25, 10))

#Accuracy of the model using all features
for trans,name,X,X_val,v,cols_list,rem_list,rank_list,i_cols_list,i_rem_
list in X_all:
    model.fit(X[:,i_cols_list],Y_train)
    result = model.score(X_val[:,i_cols_list], Y_val)
    acc[trans].append(result)
    print(trans+" "+name+"+%d" % (v*(c-1)))
    print(result)
comb.append("%s+%s of %s" % (algo,"All",1.0))

#Accuracy of the model using a subset of features
for trans,name,X,X_val,v,cols_list,rem_list,rank_list,i_cols_list,i_rem_
list in X_all_add:
    model.fit(X[:,i_cols_list],Y_train)
    result = model.score(X_val[:,i_cols_list], Y_val)
    acc[trans].append(result)
    print(trans+" "+name+"+%d" % (v*(c-1)))
    print(result)
for v in ratio_list:
    comb.append("%s+%s of %s" % (algo,"Subset",v))

##Plot the accuracies of all combinations
fig, ax = plt.subplots()
##Plot each transformation
for trans in trans_list:
    plt.plot(acc[trans])
##Set the tick names to names of combinations
ax.set_xticks(range(len(comb)))
ax.set_xticklabels(comb,rotation='vertical')
##Display the plot
plt.legend(trans_list,loc='best')
##Plot the accuracy for all combinations
plt.show()

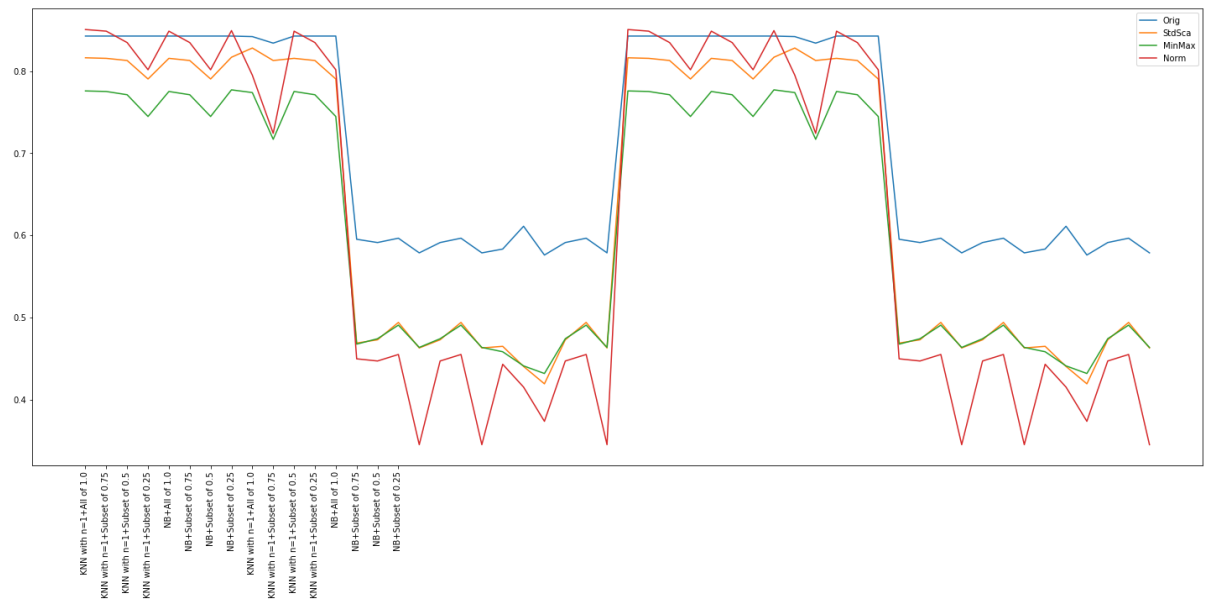
#Best estimated performance is close to 61%. Original with 50% subset ou
tperforms all transformations of NB

```

Orig+All+52
0.595238095238
StdSca+All+52
0.468915343915
MinMax+All+52
0.467592592593
Norm+All+52
0.449735449735
Orig+Median+39
0.59126984127
Orig+Median+26
0.596560846561
Orig+Median+13
0.578703703704
StdSca+Median+39
0.472883597884
StdSca+Median+26
0.494047619048
StdSca+Median+13
0.462962962963
MinMax+Median+39
0.474206349206
MinMax+Median+26
0.490740740741
MinMax+Median+13
0.463624338624
Norm+Median+39
0.44708994709
Norm+Median+26
0.455026455026
Norm+Median+13
0.345238095238
Orig+Median+39
0.59126984127
Orig+Median+26
0.596560846561
Orig+Median+13
0.578703703704
StdSca+Median+39
0.472883597884
StdSca+Median+26
0.494047619048
StdSca+Median+13
0.462962962963
MinMax+Median+39
0.474206349206
MinMax+Median+26
0.490740740741
MinMax+Median+13
0.463624338624
Norm+Median+39
0.44708994709
Norm+Median+26
0.455026455026
Norm+Median+13
0.345238095238
Orig+SelK+39

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0.5833333333333333
Orig+SelK+26
0.6111111111111111
Orig+SelK+13
0.576058201058
StdSca+SelK+39
0.464947089947
StdSca+SelK+26
0.440476190476
StdSca+SelK+13
0.419312169312
MinMax+SelK+39
0.4583333333333333
MinMax+SelK+26
0.441137566138
MinMax+SelK+13
0.431878306878
Norm+SelK+39
0.443121693122
Norm+SelK+26
0.415343915344
Norm+SelK+13
0.373677248677
Orig+Median+39
0.59126984127
Orig+Median+26
0.596560846561
Orig+Median+13
0.578703703704
StdSca+Median+39
0.472883597884
StdSca+Median+26
0.494047619048
StdSca+Median+13
0.462962962963
MinMax+Median+39
0.474206349206
MinMax+Median+26
0.490740740741
MinMax+Median+13
0.463624338624
Norm+Median+39
0.44708994709
Norm+Median+26
0.455026455026
Norm+Median+13
0.345238095238



Random Forest

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```

In [226]: #Evaluation of various combinations of Random Forest using all the views

#Import the library
from sklearn.ensemble import RandomForestClassifier

n_list = [100]

for n_estimators in n_list:
    #Set the base model
    model = RandomForestClassifier(n_jobs=-1,n_estimators=n_estimators,
    random_state=seed)

    algo = "RF"

    #Set figure size
    plt.rc("figure", figsize=(20, 10))

    #Accuracy of the model using all features
    for trans,name,X,X_val,v,cols_list,rem_list,rank_list,i_cols_list,i_
rem_list in X_all:
        model.fit(X[:,i_cols_list],Y_train)
        result = model.score(X_val[:,i_cols_list], Y_val)
        acc[trans].append(result)
        print(trans+" "+name+"+%d" % (v*(c-1)))
        print(result)
        comb.append("%s with n=%s+%s of %s" % (algo,n_estimators,"All",1.0))

    #Accuracy of the model using a subset of features
    for trans,name,X,X_val,v,cols_list,rem_list,rank_list,i_cols_list,i_
rem_list in X_all_add:
        model.fit(X[:,i_cols_list],Y_train)
        result = model.score(X_val[:,i_cols_list], Y_val)
        acc[trans].append(result)
        print(trans+" "+name+"+%d" % (v*(c-1)))
        print(result)
    for v in ratio_list:
        comb.append("%s with n=%s+%s of %s" % (algo,n_estimators,"Subse
t",v))

```

```

##Plot the accuracies of all combinations
fig, ax = plt.subplots()
##Plot each transformation
for trans in trans_list:
    plt.plot(acc[trans])
##Set the tick names to names of combinations
ax.set_xticks(range(len(comb)))
ax.set_xticklabels(comb,rotation='vertical')
##Display the plot
plt.legend(trans_list,loc='best')
##Plot the accuracy for all combinations
plt.show()

```

```

#Best estimated performance is close to 86% when n_estimators is 100

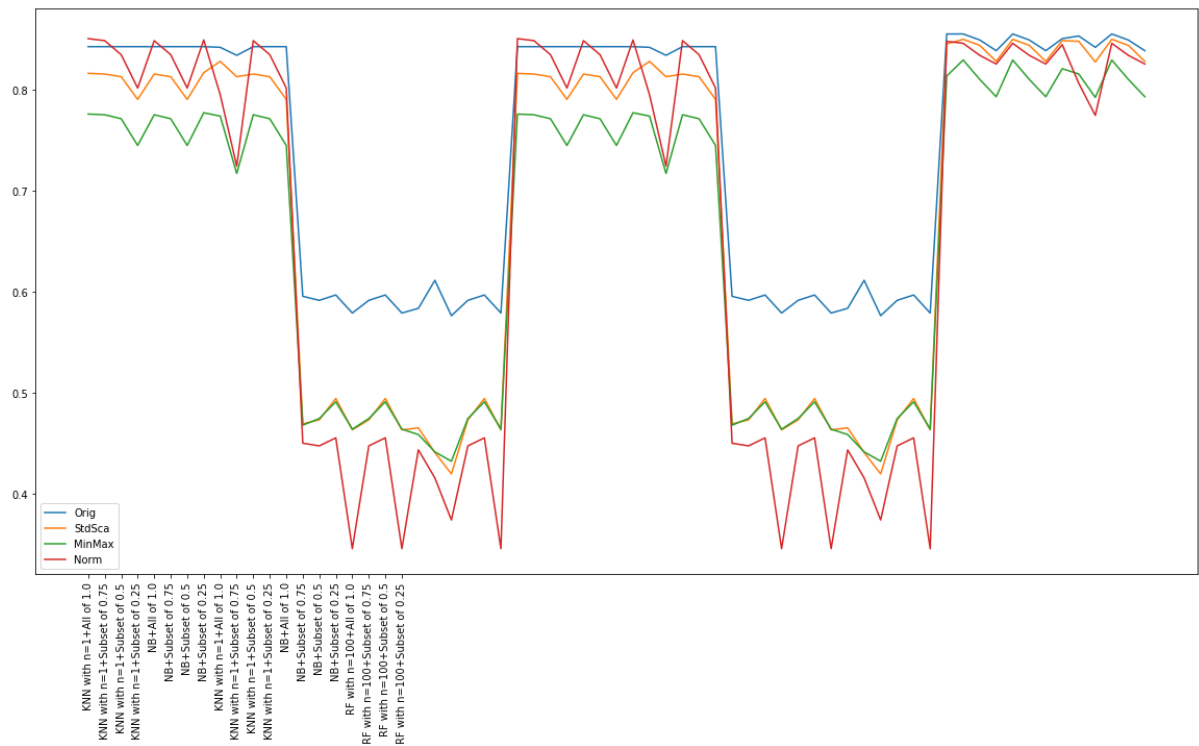
```


Orig+All+52
0.855158730159
StdSca+All+52
0.845238095238
MinMax+All+52
0.813492063492
Norm+All+52
0.847883597884
Orig+Median+39
0.855158730159
Orig+Median+26
0.849206349206
Orig+Median+13
0.838624338624
StdSca+Median+39
0.849867724868
StdSca+Median+26
0.843915343915
StdSca+Median+13
0.828042328042
MinMax+Median+39
0.829365079365
MinMax+Median+26
0.810185185185
MinMax+Median+13
0.792989417989
Norm+Median+39
0.845899470899
Norm+Median+26
0.833994708995
Norm+Median+13
0.825396825397
Orig+Median+39
0.855158730159
Orig+Median+26
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Norm+Median+26
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Norm+Median+13
0.825396825397
Orig+Median+39

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Orig+Median+39

0.850529100529
Orig+SelK+26
0.853174603175
Orig+SelK+13
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StdSca+SelK+39
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Norm+Median+13
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Make Predictions

In [231]: *# Make predictions using Random Forest Classifier + 0.5 subset as it gave the best estimated performance*

```
n_estimators = 100
```

```
#Obtain the list of indexes for the required model
```

```
indexes = []
```

```
for trans,name,X,X_val,v,cols_list,rem_list,rank_list,i_cols_list,i_rem_list in X_all_add:
```

```
    if v == 0.5:
```

```
        if trans == 'Orig':
```

```
            indexes = i_cols_list
```

```
        break
```

```
In [232]: #Best model definition
best_model = RandomForestClassifier(n_jobs=-1,n_estimators=n_estimators)
best_model.fit(X_orig[:,indexes],Y)

#Read test dataset
dataset_test = pd.read_csv("test.csv")
#Drop unnecessary columns
ID = dataset_test['Id']
dataset_test.drop('Id',axis=1,inplace=True)
dataset_test.drop('rem',axis=1,inplace=True)
X_test = dataset_test.values

#Make predictions using the best model
predictions = best_model.predict(X_test[:,indexes])
# Write submissions to output file in the correct format
with open("submission.csv", "w") as subfile:
    subfile.write("Id,Cover_Type\n")
    for i, pred in enumerate(list(predictions)):
        subfile.write("%s,%s\n"%(ID[i],pred))
```

Algorithms we have used :

- KNN
- Naive Bayes
- Random Forest Classifier

Conclusion :

- We have made use of feature scaling and feature importance to identify the best features.
- To understand how well the model performs, we checked accuracy on the complete training data and with a subset of training data.
- The best model was obtained from using Random Forest Classifier with an accuracy of 86%.
- Other models like Naive Bayes and KNN render an accuracy of 64% and 85% respectively.
- We have predicted the values of testing data using Random Forest Classifier.