# renjini_forest_covertype_prediction

April 10, 2019

## 0.1 Project Title: Prediction of Forest Cover Type

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## 0.2 Introduction

Source of the data: The UCI machine learning repository (url: https://archive.ics.uci.edu/ml/datasets/Covertype)

Original sources: Original owners of database: Remote Sensing and GIS Program, Department of Forest Sciences, College of Natural Resources, Colorado State University, Fort Collins, CO 80523 (contact Jock A. Blackard, jblackard 'at' fs.fed.us or Dr. Denis J. Dean, denis.dean 'at' utdallas.edu)

The data for forest cover type determination was downloaded from the url (https://archive.ics.uci.edu/ml/machine-learning-databases/covtype/covtype.data.gz). The data was comprised of cartographic variables, derived from data originally obtained from US Geological Survey (USGS) and USFS data. The actual cover type for each observation was determined from US Forest Service (USFS) Region 2 Resource Information System (RIS) data.

There were 581012 rows and 55 columns. The columns represented the the following attributes: Elevation (meters), Aspect (azimuth), Slope (degrees), Horizontal_Distance_To_Hydrology (meters), Vertical_Distance_To_Hydrology (meters), Horizontal_Distance_To_Roadways (meters), Hillshade_9am (0 to 255 index), Hillshade_Noon (0 to 255 index), Hillshade_3pm (0 to 255 index), Horizontal_Distance_To_Fire_Points (meters), Wilderness_Area (4 binary columns), Soil_Type (40 binary columns), Cover_Type (7 types).

The final task is to build a predictive machine learning model that can reliably predict the forest cover type from the provided cartographic variables. For optimizing the classifier model, the attribute 'Cover_Type', represents the muticlass forest cover type classification. The summary of the observations, resulting from the statistical data analyses and the predicitve modeling, is provided at the bottom of the notebook.

```
In [1]: # Load necessary libraries
        import requests
        import gzip
        import pandas as pd
        import numpy as np
        import seaborn as sb
        import scipy.stats as ss
        from sklearn.linear_model import LogisticRegression
        from sklearn.ensemble import RandomForestClassifier
        from sklearn.tree import DecisionTreeClassifier
```

```
from sklearn.model_selection import train_test_split
from sklearn.metrics import *
import matplotlib.pyplot as plt
%matplotlib inline
```

```
In [2]: # Function to bin numerical columns
        def bins(x, n):
            BinWidth = (max(x) - min(x))/n
            bound1 = float('-inf')
            bound2 = min(x) + 1 * BinWidth
            bound3 = min(x) + 2 * BinWidth
            bound4 = float('inf')
            Binned = np.array([" "]*len(x))
            Binned[(bound1 < x) & (x <= bound2)] = 1 # Low
            Binned[(bound2 < x) & (x <= bound3)] = 2 # Med
            Binned[(bound3 < x) & (x  < bound4)] = 3 # High
            return Binned
```

```
In [3]: # Location of dataset
        url = "https://archive.ics.uci.edu/ml/machine-learning-databases/covtype/covtype.data.g
```

```
In [4]: # Gather the data
        response = requests.get(url, stream = True)
        decompressed_file = gzip.GzipFile(fileobj=response.raw)
```

```
In [5]: # Load the data into a dataframe (takes a minute to load)
        df1 = pd.read_csv(decompressed_file, sep=',', header = None)
```

```
In [6]: # Add column names
        df1.columns = ['elevation', 'aspect', 'slope', 'hdist_to_hydro', 'vdist_to_hydro', 'hd
```

```
In [7]: df = df1.copy()
```

## 0.3 Exploratory Data Analyses

```
In [8]: # View the first few rows
        df.head()
```

```
Out[8]:    elevation  aspect  slope  hdist_to_hydro  vdist_to_hydro  hdist_to_road  \
        0       2596      51      3             258               0            510
        1       2590      56      2             212              -6            390
        2       2804     139      9             268              65           3180
        3       2785     155     18             242             118           3090
        4       2595      45      2             153              -1            391

           hillshade_9am  hillshade_noon  hillshade_3pm  hdist_to_fire     ...      \
        0            221             232            148           6279     ...
        1            220             235            151           6225     ...
        2            234             238            135           6121     ...
```

```
3          238          238          122         6211   ...
4          220          234          150         6172   ...

   32  33  34  35  36  37  38  39  40  cover_type
0   0   0   0   0   0   0   0   0   0           5
1   0   0   0   0   0   0   0   0   0           5
2   0   0   0   0   0   0   0   0   0           2
3   0   0   0   0   0   0   0   0   0           2
4   0   0   0   0   0   0   0   0   0           5

[5 rows x 55 columns]
```

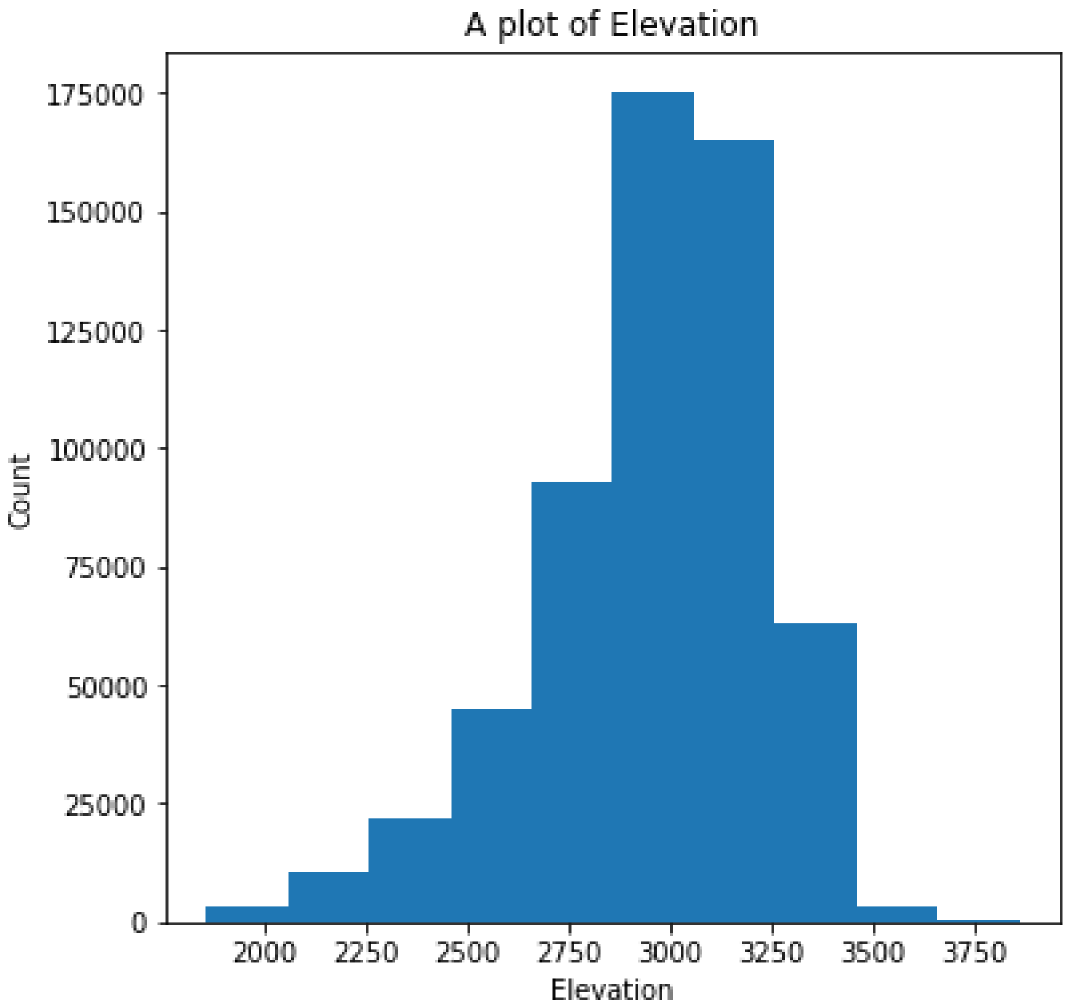
In [9]:
```
df.describe()
```

Out[9]:
```
           elevation         aspect          slope  hdist_to_hydro  \
count  581012.000000  581012.000000  581012.000000   581012.000000
mean     2959.365301     155.656807      14.103704      269.428217
std       279.984734     111.913721       7.488242      212.549356
min      1859.000000       0.000000       0.000000        0.000000
25%      2809.000000      58.000000       9.000000      108.000000
50%      2996.000000     127.000000      13.000000      218.000000
75%      3163.000000     260.000000      18.000000      384.000000
max      3858.000000     360.000000      66.000000     1397.000000

       vdist_to_hydro  hdist_to_road  hillshade_9am  hillshade_noon  \
count   581012.000000  581012.000000  581012.000000   581012.000000
mean        46.418855    2350.146611     212.146049      223.318716
std         58.295232    1559.254870      26.769889       19.768697
min       -173.000000       0.000000       0.000000        0.000000
25%          7.000000    1106.000000     198.000000      213.000000
50%         30.000000    1997.000000     218.000000      226.000000
75%         69.000000    3328.000000     231.000000      237.000000
max        601.000000    7117.000000     254.000000      254.000000

       hillshade_3pm  hdist_to_fire      ...                   32  \
count  581012.000000  581012.000000      ...        581012.000000
mean      142.528263    1980.291226      ...             0.090392
std        38.274529    1324.195210      ...             0.286743
min         0.000000       0.000000      ...             0.000000
25%       119.000000    1024.000000      ...             0.000000
50%       143.000000    1710.000000      ...             0.000000
75%       168.000000    2550.000000      ...             0.000000
max       254.000000    7173.000000      ...             1.000000

                  33             34             35             36  \
count  581012.000000  581012.000000  581012.000000  581012.000000
mean        0.077716       0.002773       0.003255       0.000205
std         0.267725       0.052584       0.056957       0.014310
```

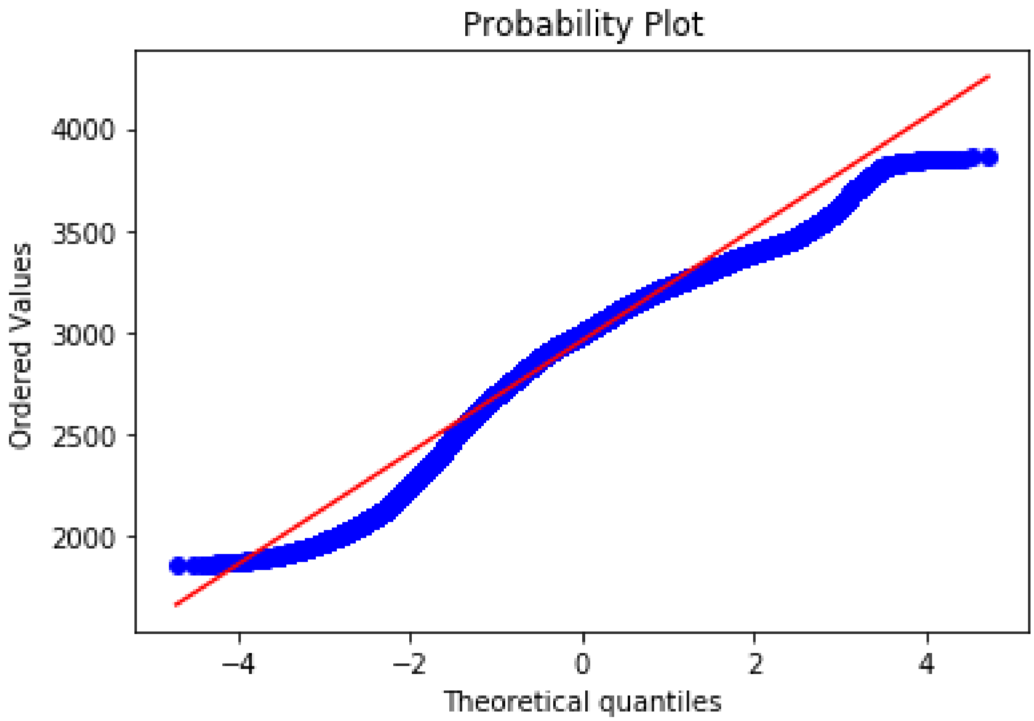
```
min        0.000000       0.000000       0.000000       0.000000
25%        0.000000       0.000000       0.000000       0.000000
50%        0.000000       0.000000       0.000000       0.000000
75%        0.000000       0.000000       0.000000       0.000000
max        1.000000       1.000000       1.000000       1.000000

                 37             38             39             40  \
count  581012.000000  581012.000000  581012.000000  581012.000000
mean        0.000513       0.026803       0.023762       0.015060
std         0.022641       0.161508       0.152307       0.121791
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       0.000000       0.000000       0.000000
max         1.000000       1.000000       1.000000       1.000000

           cover_type
count  581012.000000
mean        2.051471
std         1.396504
min         1.000000
25%         1.000000
50%         2.000000
75%         2.000000
max         7.000000

[8 rows x 55 columns]
```

The summary statistics indicated that some attributes followed a more or less normal distribution like the 'elevation' and 'hillshade at 3pm', while some others followed skewed distributions like 'horizontal distance to hydrology' and 'horizontal distance to roadways'. These were confirmed by plotting histograms and q-q plots.

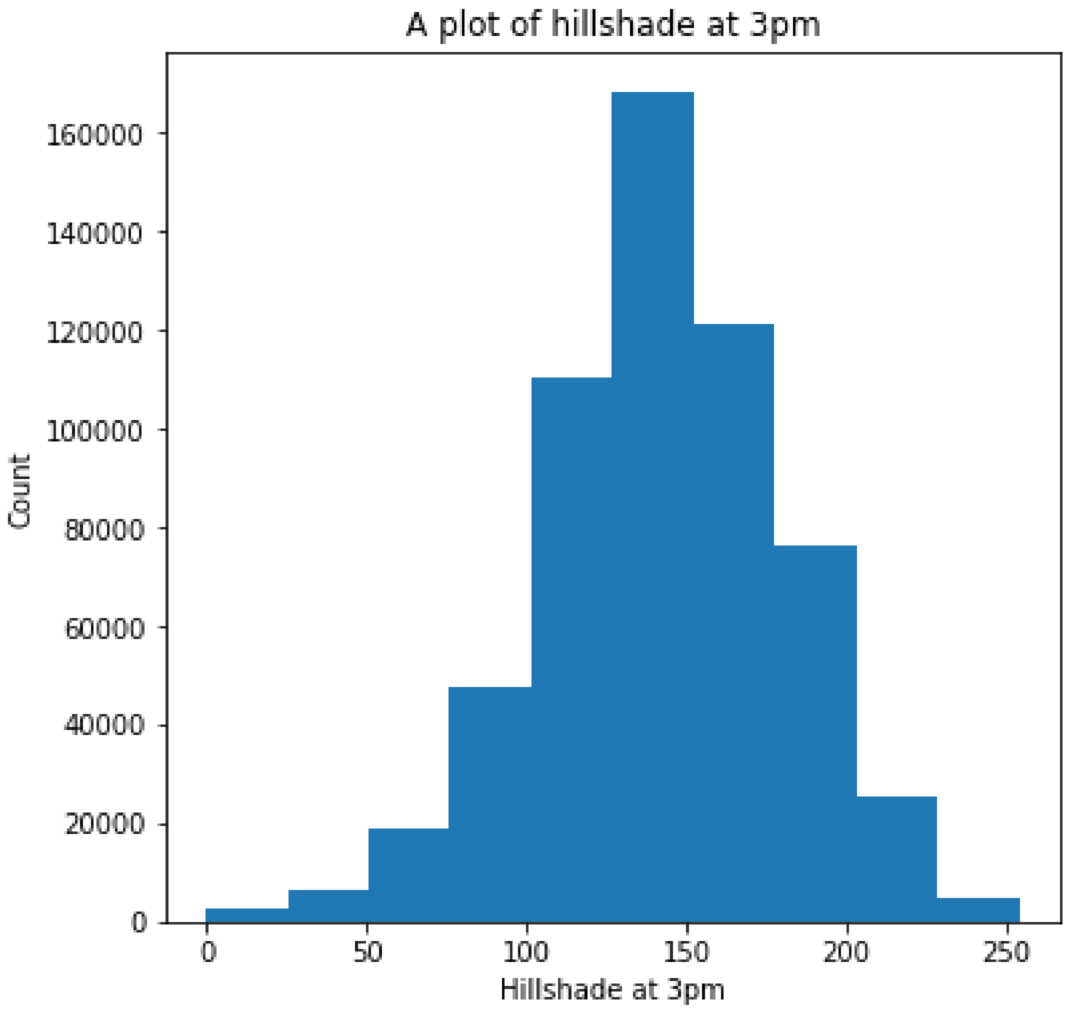
```
In [10]: # Plot a histogram of the elevation
         ax = plt.figure(figsize = (6, 6)).gca()
         plt.hist(data = df, x = 'elevation')
         ax.set_title('A plot of Elevation') # Give the plot a main title
         ax.set_ylabel('Count')# Set text for y axis
         ax.set_xlabel('Elevation');
```



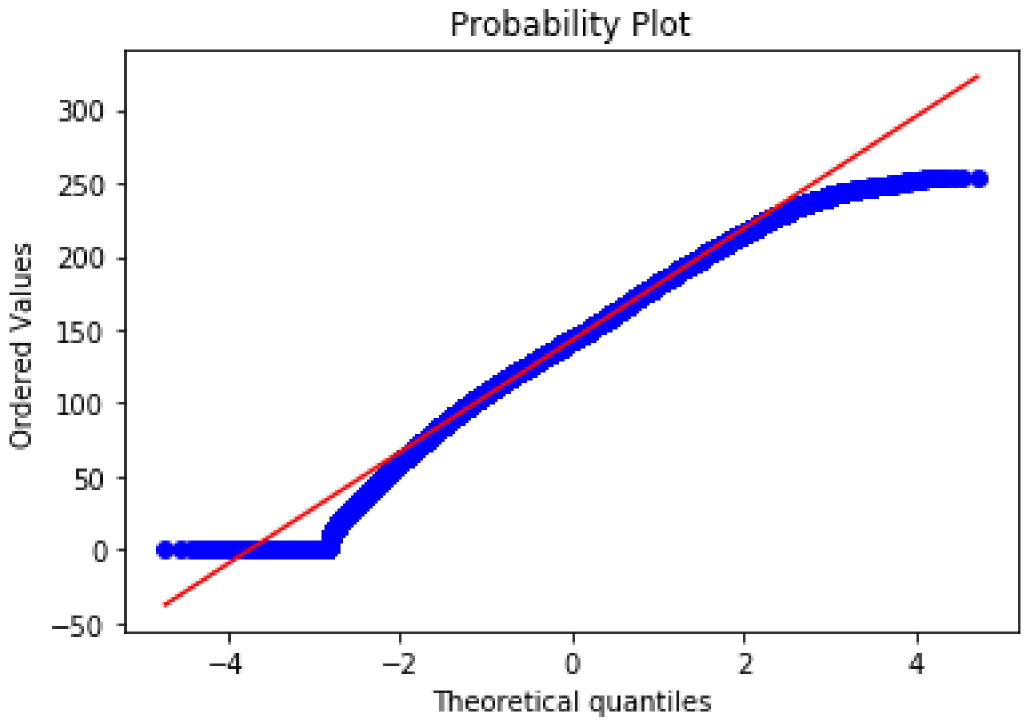

In [11]:
```
# Check whether elevation follows a normal distribution by q-q plot
ss.probplot(df['elevation'], plot = plt);
```



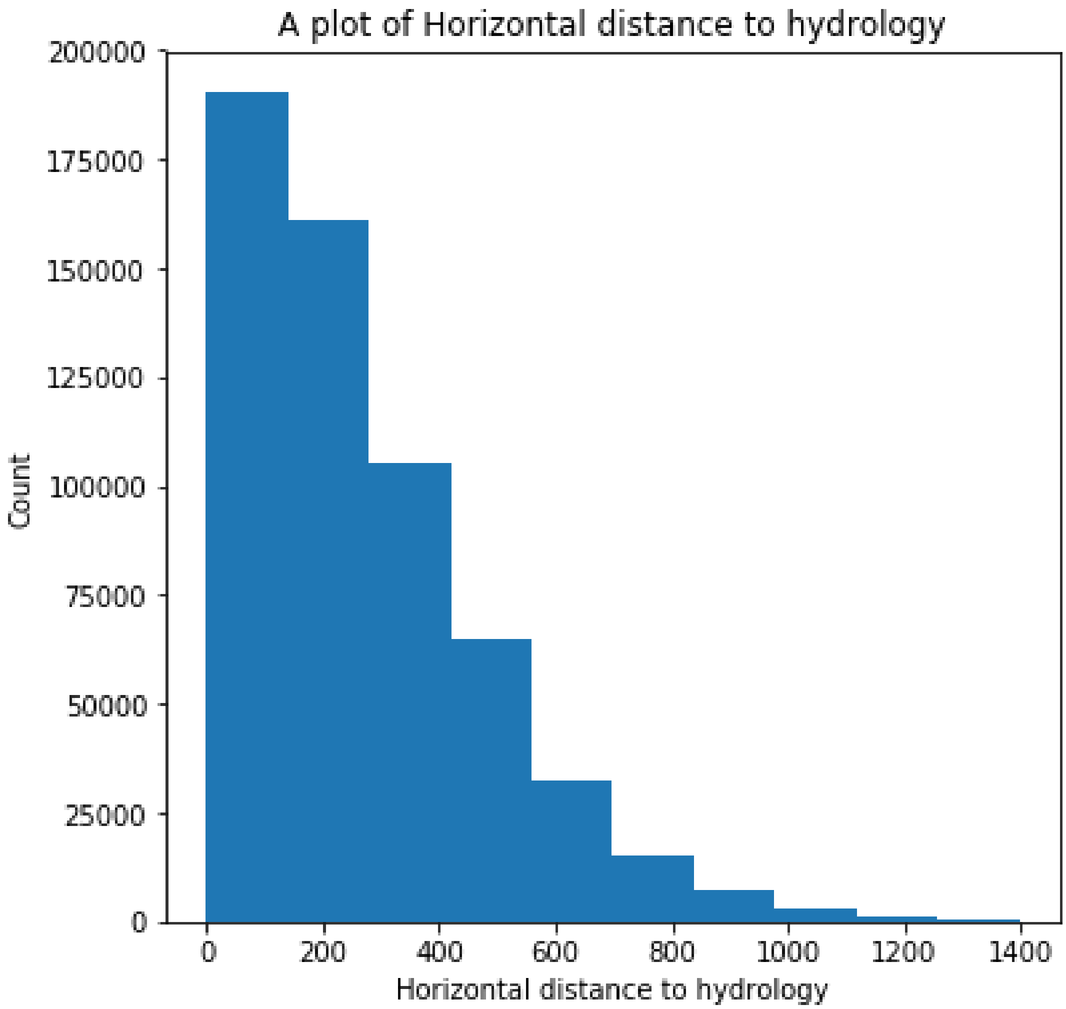

```
In [12]: # Plot a histogram of hillshade at 3pm
         ax = plt.figure(figsize = (6, 6)).gca()
         plt.hist(data = df, x = 'hillshade_3pm')
         ax.set_title('A plot of hillshade at 3pm') # Give the plot a main title
         ax.set_ylabel('Count')# Set text for y axis
         ax.set_xlabel('Hillshade at 3pm');
```



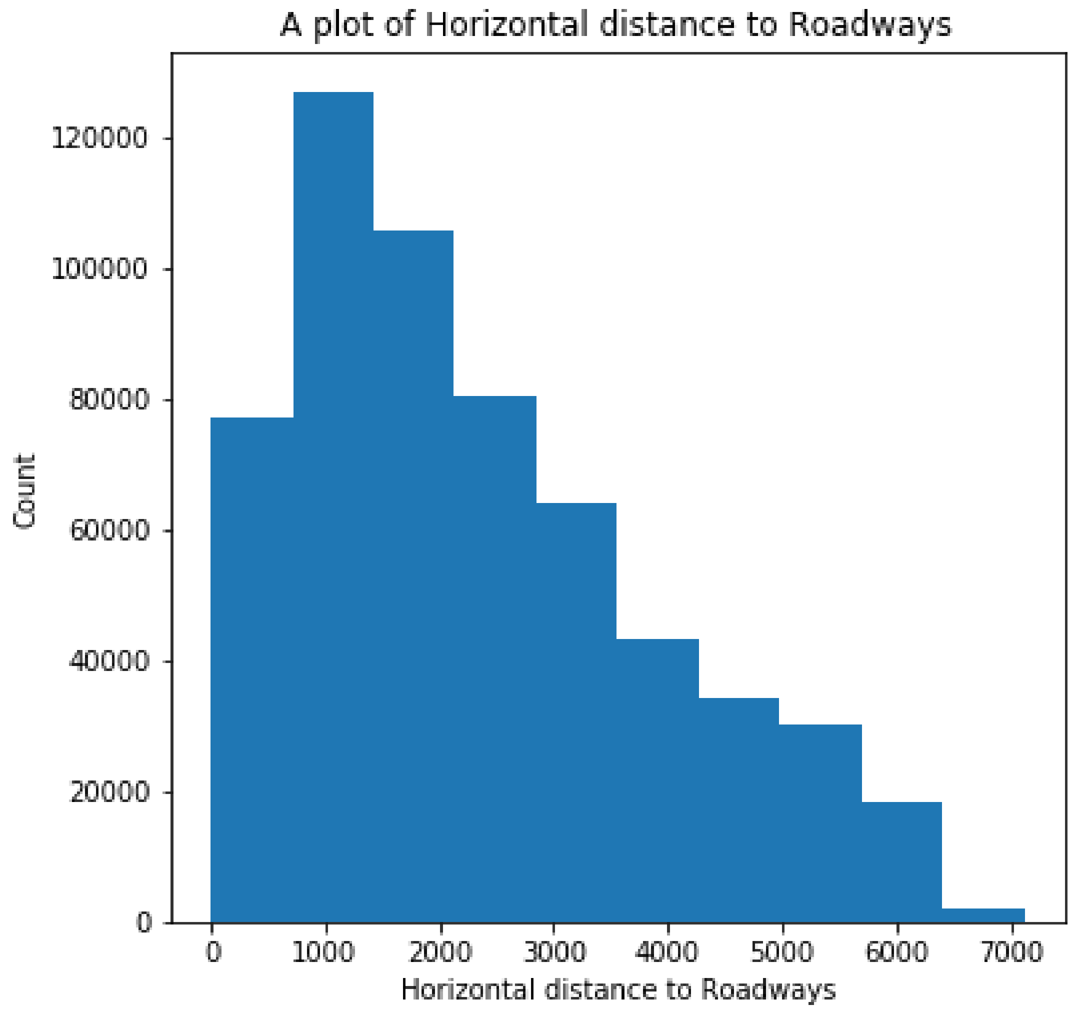

In [13]:
```
# Check whether hillshade at 3pm follows a normal distribution by q-q plot
ss.probplot(df['hillshade_3pm'], plot = plt);
```



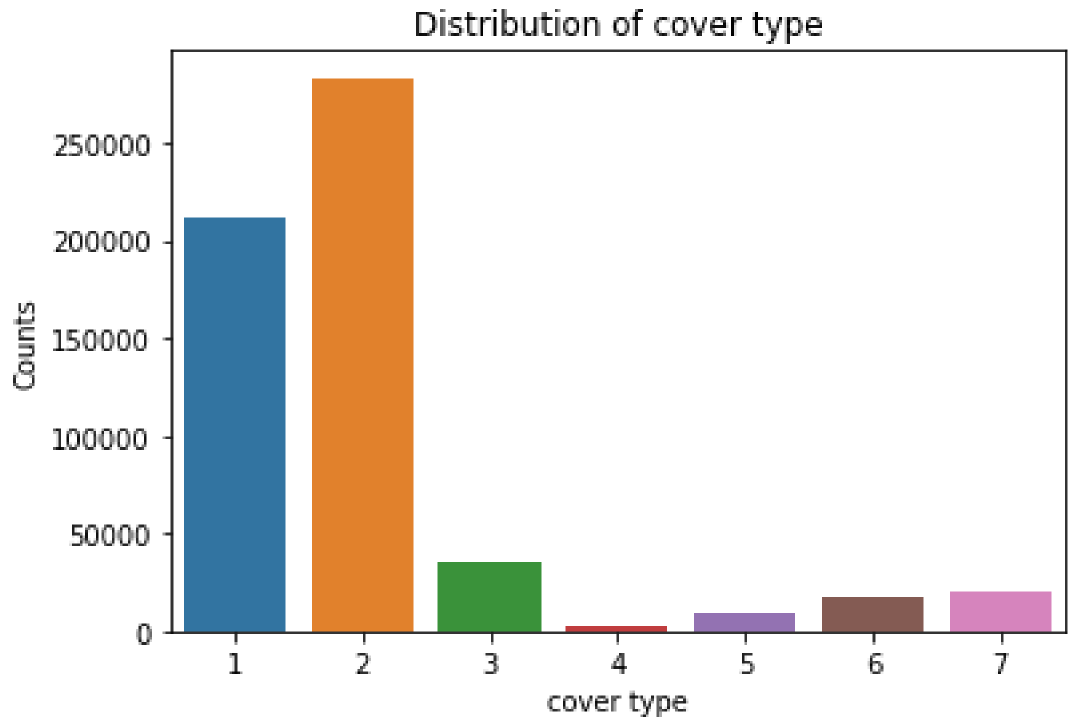

```
In [14]: # Plot a histogram of hdist_to_hydro
         ax = plt.figure(figsize = (6, 6)).gca()
         plt.hist(data = df, x = 'hdist_to_hydro')
         ax.set_title('A plot of Horizontal distance to hydrology') # Give the plot a main tit
         ax.set_ylabel('Count')# Set text for y axis
         ax.set_xlabel('Horizontal distance to hydrology');
```



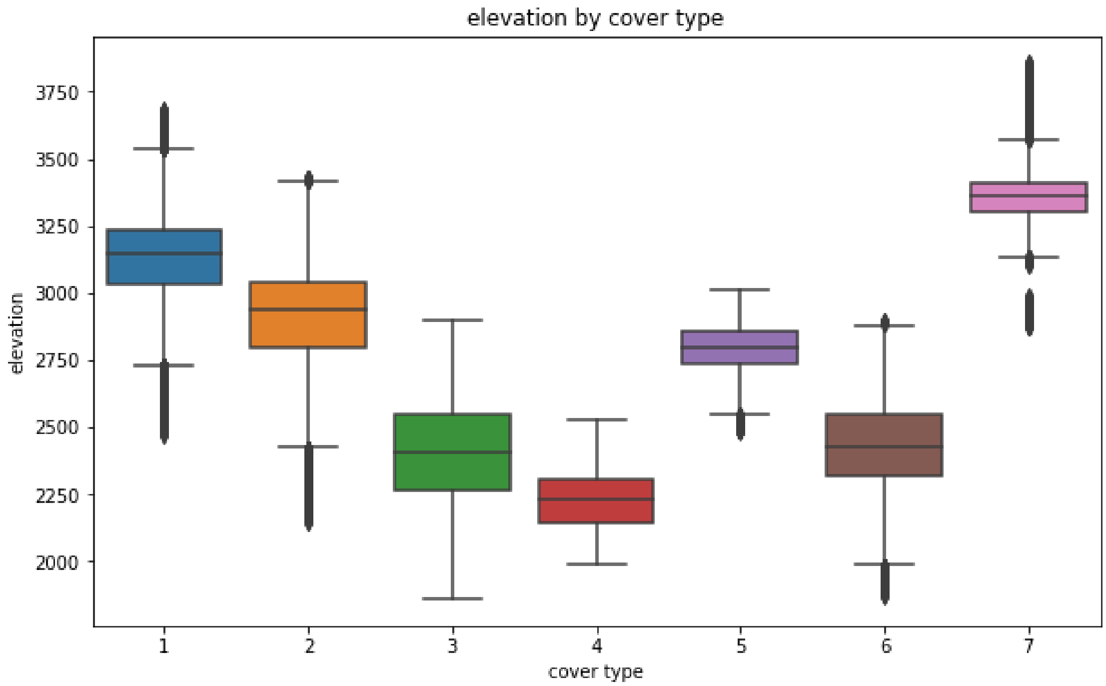

```
In [15]: # Plot a histogram of hdist_to_road
         ax = plt.figure(figsize = (6, 6)).gca()
         plt.hist(data = df, x = 'hdist_to_road')
         ax.set_title('A plot of Horizontal distance to Roadways') # Give the plot a main titl
         ax.set_ylabel('Count')# Set text for y axis
         ax.set_xlabel('Horizontal distance to Roadways');
```




In [16]:
```
# Distribution of cover types
ax = sb.countplot(data = df, x = 'cover_type')
ax.set_title('Distribution of cover type') # Give the plot a main title
ax.set_ylabel('Counts')# Set text for y axis
ax.set_xlabel('cover type');
```




```
In [17]: # Plot the elevation by cover type
         ax = plt.figure(figsize = (10, 6)).gca()
         sb.boxplot(data = df, x = 'cover_type', y = 'elevation', ax = ax)
         ax.set_title('elevation by cover type') # Give the plot a main title
         ax.set_ylabel('elevation')# Set text for y axis
         ax.set_xlabel('cover type');
```




The cover types 1 and 2 seem most common, having 200,000 - 300,000 entries, while the rest (3-7) classes were constituted by less than 5000 instances each. Elevation seems to be a good variable at aiding classification of the cover types into groups, with some amount of overlaps between the classes.

In [18]:
```
# Bin some of the numerical columns, hillshade_9am, vdist_to_hydro and hdist_to_road;
# hillshade_9am - Equal-width Binning using numpy
x = np.array(df['hillshade_9am'])
df['Binned_hillshade_9am'] = bins(x, 10)
df.drop('hillshade_9am', axis = 1, inplace = True)

# vdist_to_hydro - Equal-width Binning using numpy
x = np.array(df['vdist_to_hydro'])
df['Binned_vdist_to_hydro'] = bins(x, 6)
df.drop('vdist_to_hydro', axis = 1, inplace = True)

# hdist_to_road - Equal-width Binning using numpy
x = np.array(df['hdist_to_road'])
df['Binned_hdist_to_road'] = bins(x, 6)
df.drop('hdist_to_road', axis = 1, inplace = True)
```

In [19]:
```
# Change the datatype of binned columns to int
df['Binned_hillshade_9am'] = df['Binned_hillshade_9am'].astype('int', inplace = True)
df['Binned_vdist_to_hydro'] = df['Binned_vdist_to_hydro'].astype('int', inplace = Tru
df['Binned_hdist_to_road'] = df['Binned_hdist_to_road'].astype('int', inplace = True)
```

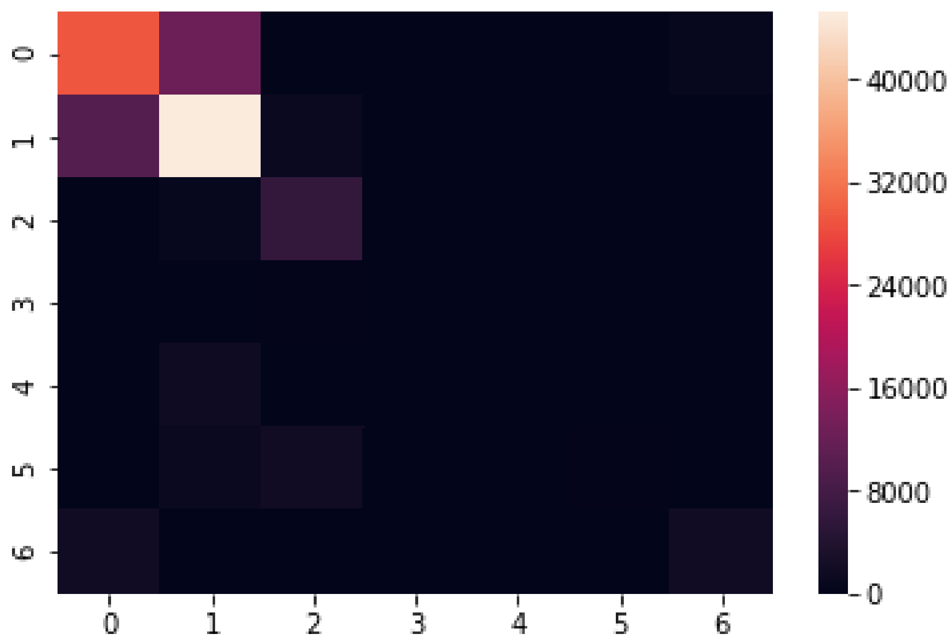
In [20]:
```
# Specify the independent and dependent variables
X = df[['elevation', 'aspect', 'slope', 'hdist_to_hydro', 'Binned_vdist_to_hydro', 'B
Y = df['cover_type']
```

In [21]:
```
# Specifying model training on 80% of the data, by using a test-size of 20%
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.20)
```

In [32]:
```
# Classification by Logistic Regression (warning - takes a few minutes)
clf = LogisticRegression(solver = 'liblinear')
clf.fit(X_train, Y_train)
Y_predslr = clf.predict(X_test)
# Confusion matrix
confusion_matrix(Y_test, Y_predslr)
```

Out[32]:
```
array([[29249, 12489,    34,     0,     2,     0,   742],
       [ 9924, 45175,  1327,     1,     4,    71,    60],
       [    0,   766,  6099,    46,     0,   145,     0],
       [    0,     0,   347,   125,     0,    50,     0],
       [   28,  1707,   174,     0,     1,     3,     0],
       [    2,  1291,  1977,     5,     0,   191,     0],
       [ 2045,    35,    12,     0,     0,     0,  2076]])
```

In [31]:
```
sb.heatmap(confusion_matrix(Y_test, Y_predslr));
```



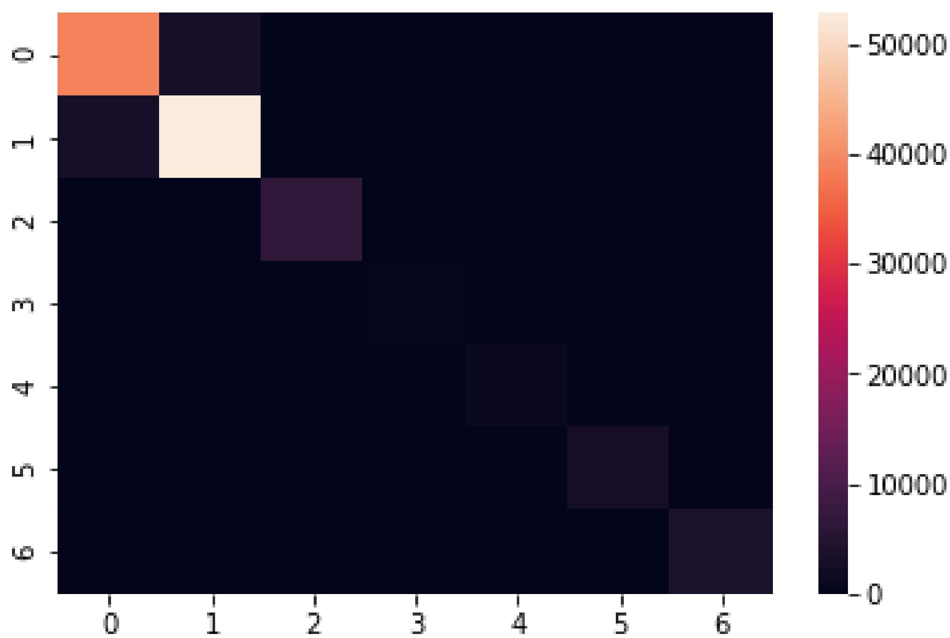

In [25]:
```
# Classification by DecisionTreeClassifier (warning - takes a few minutes)
clf = DecisionTreeClassifier()
```

```
clf.fit(X_train, Y_train)
Y_predsdt = clf.predict(X_test)
# Confusion matrix
confusion_matrix(Y_test, Y_predsdt)
```

Out[25]:
```
array([[38973,  3252,     1,     0,    58,     9,   223],
       [ 3150, 52711,   201,     1,   302,   149,    48],
       [    2,   197,  6444,    60,    12,   341,     0],
       [    0,     2,    70,   438,     0,    12,     0],
       [   40,   308,    16,     0,  1542,     7,     0],
       [   10,   151,   340,    15,     8,  2942,     0],
       [  259,    34,     0,     0,     0,     0,  3875]])
```

In [30]:
```
sb.heatmap(confusion_matrix(Y_test, Y_predsdt))
```

Out[30]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f16627ee828>
```

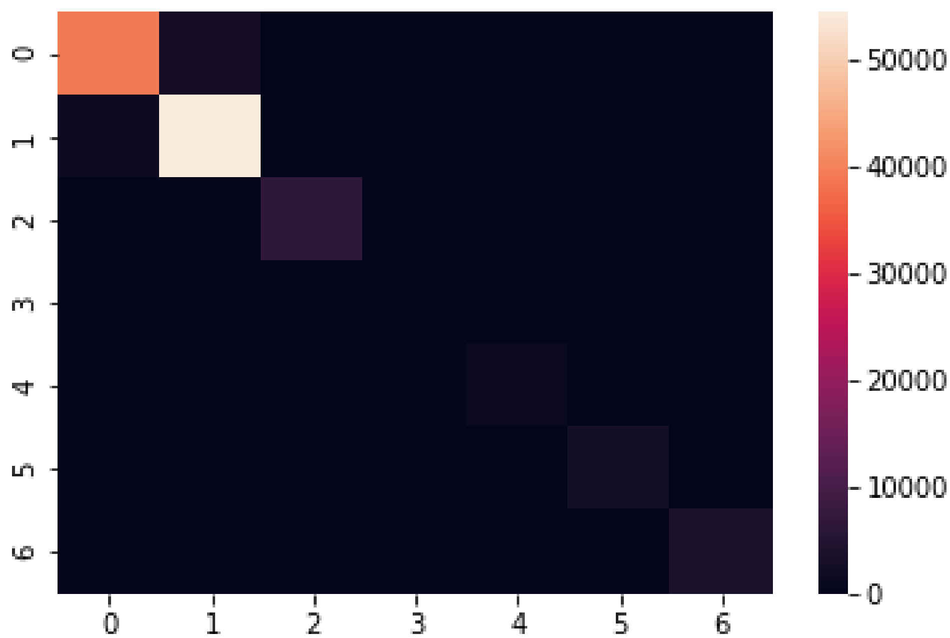



In [27]:
```
# Classification by Random forest (warning - takes a few minutes)
clf = RandomForestClassifier(n_estimators = 100, min_samples_split = 2)
clf.fit(X_train, Y_train)
Y_predsrf = clf.predict(X_test)
# Confusion matrix
confusion_matrix(Y_test, Y_predsrf)
```

Out[27]:
```
array([[39244,  3140,     1,     0,    20,     5,   106],
       [ 1886, 54347,   116,     1,    95,   103,    14],
```

```
 [    1,   136,  6685,    33,     3,   198,     0],
 [    0,     0,    64,   444,     0,    14,     0],
 [   27,   429,    20,     0,  1426,    11,     0],
 [    2,   135,   348,    12,     3,  2966,     0],
 [  255,    21,     0,     0,     0,     0,  3892]])
```

In [28]:
```python
sb.heatmap(confusion_matrix(Y_test, Y_predsrf));
```




In [29]:
```python
# Metrics analysis - Accuracy
ARlr = accuracy_score(Y_test, Y_predslr)
ARdt = accuracy_score(Y_test, Y_predsdt)
ARrf = accuracy_score(Y_test, Y_predsrf)
print("Accuracy score with Logistic regression: {:.4f}".format(ARlr))
print("Accuracy score with Decision Tree: {:.4f}".format(ARdt))
print("Accuracy score with Random forest: {:.4f}".format(ARrf))
```

```
Accuracy score with Logistic regression: 0.7135
Accuracy score with Decision Tree: 0.9202
Accuracy score with Random forest: 0.9380
```

## 0.4 Summary

**Source of the data:** The UCI machine learning repository (url: https://archive.ics.uci.edu/ml/datasets/Covertype). Original sources: Original owners of database: Remote Sensing and GIS Program, Department of Forest Sciences, College of Natural Resources, Colorado State University, Fort Collins, CO 80523 (contact Jock A. Blackard, jblackard 'at' fs.fed.us or Dr. Denis J. Dean, denis.dean 'at' utdallas.edu) #### Introduction: The data for forest cover type determination was downloaded from the url (https://archive.ics.uci.edu/ml/machine-learning-databases/covtype/covtype.data.gz). The data was comprised of cartographic variables, derived from data originally obtained from US Geological Survey (USGS) and USFS data. The actual cover type for each observation was determined from US Forest Service (USFS) Region 2 Resource Information System (RIS) data.

Initially, there were 581012 rows and 55 columns. The columns represented the the following attributes: Elevation (meters), Aspect (azimuth), Slope (degrees), Horizontal_Distance_To_Hydrology (meters), Vertical_Distance_To_Hydrology (meters), Horizontal_Distance_To_Roadways (meters), Hillshade_9am (0 to 255 index), Hillshade_Noon (0 to 255 index), Hillshade_3pm (0 to 255 index), Horizontal_Distance_To_Fire_Points (meters), Wilderness_Area (4 binary columns), Soil_Type (40 binary columns), Cover_Type (7 types).

The task is to build a predictive machine learning model that can reliably predict the forest cover type from the provided cartographic variables. For optimizing the classifier model, the attribute 'Cover_Type', represents the muticlass forest cover type classification.

**Data wrangling and analyses** After checking the loaded dataframe, it was seen that there were 55 attributes. Of the 55, 4 were binary columns for the type of wilderness area. 40 columns denoted the binary variables for the soil type attribute.

The summary statistics indicated that some attributes followed a more or less normal distribution like the 'elevation' and 'hillshade at 3pm', while some others followed skewed distributions like 'horizontal distance to hydrology' and 'horizontal distance to roadways'. These were confirmed by plotting histograms and q-q plots.

The cover types 1 and 2 seem most common, having 200,000 - 300,000 entries, while the rest (3-7) classes were constituted by less than 5000 instances each. Elevation seems to be a good variable at aiding classification of the cover types into groups, with some amount of overlaps between the classes.

The numerical attributes, hillshade_9am, 'vdist_to_hydro' and 'hdist_to_road' were binned by equal width binning, and the obsolete non-binned columns deleted. All 54 attributes were used for modeling.

**Classification by supervised learning** The instances were split into training and test (20%) sets and subjected to supervised learning. I used LogisticRegression, DecisionTreeClassifier and RandomForestClassifier from the scikit-learn package to model and predict the multiclasses. Upon analysis of the confusion matrix and metrics, it was seen that the accuracies of the classifiers were 71%, 92% and 94% for the logistic regression, decision tree and random forest classifications. Higher accuracy rates may be attained by more optimization of the hyper-parameters for each of the models (e.g. non-linear solver for logistic regression).