HI3_handl_and_expl

November 8, 2017

1 Hand-in 3, Part 1: Data handling and exploration

In this first notebook you will show us how you handle data being separated over several files, as well as exploring the quality and properties of your data.

Section 1: bash scripting You have downloaded a zip file containing 5 CSV files, each containing part of the data you need. First, use your bash tools to look at the headers and size of the file. What do the different files contain?

Write a bash script that concatenates the 4 data files (except the flow_criticality_data.csv file). Exlain in the markdown cell below, what each part of your script does.

Q#1 *Explain your script here (by double clicking on this text).*

- Define that we are using bash

```
#! /bin/bash
```

- Quick explanation of what the bashscript does

```
# Joining the files
#
# Usage "./collect_data.sh
```

- Make temp1.csv containing half the data -t, means the file is comma seperated, -a1 and -a2 means that it will also print any unpairable line -oauto means that it will automatically format the data

```
join -t, -a1 -a2 -oauto energy_demand_data.csv exchange_data.csv > temp1.csv
```

- Make temp2.csv containing the other half of data

```
join -t, -a1 -a2 -oauto renewable_production_data.csv generator_production_data.csv > temp
```

- Combine the temp files, to one whole file

```
join -t, -a1 -a2 -oauto temp1.csv temp2.csv > joined_data.csv
```

- Clean up by removing the temp files

```
rm temp1.csv
rm temp2.csv
```

1.1 Section 2: Visualizing the data

Here you will plot the resulting data file from the previous section, and plot it in order to identify missing data and see if you can already draw some conclusions on the data.

- *Hint: remember the hint given in Exc.13.3, on how to find out if your data contains NaN values*

```
In [1]: # Importing the packages we need
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns
        %matplotlib inline
        import numpy as np
        import scipy
```

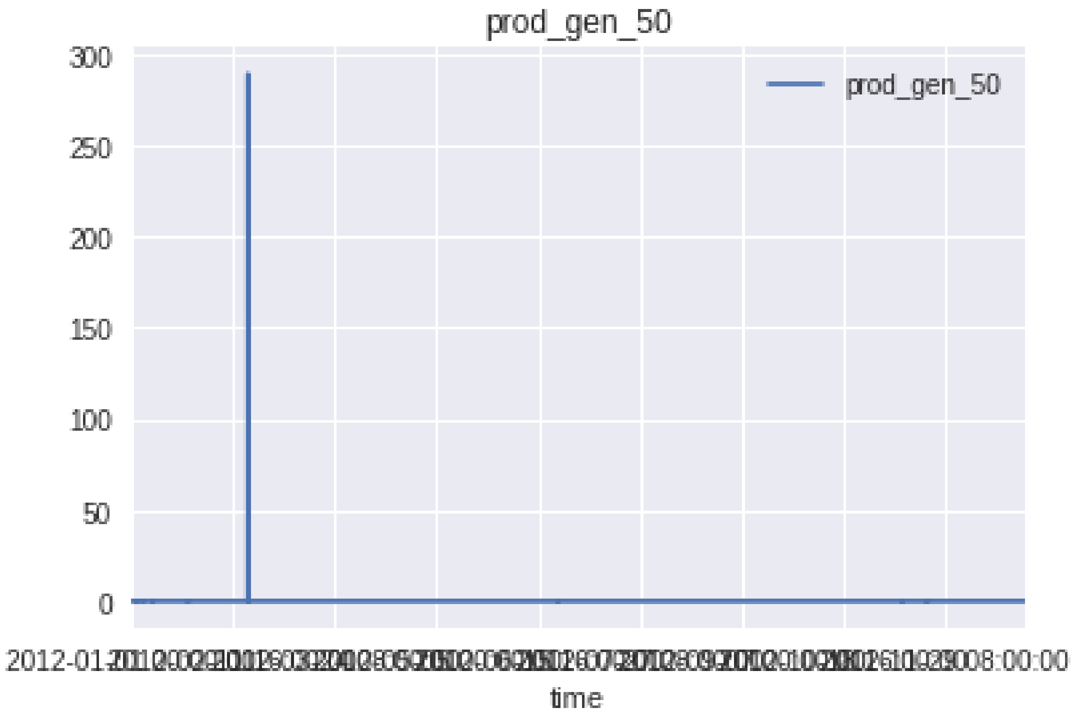
```
/home/student/.local/lib/python3.5/site-packages/matplotlib/__init__.py:800: MatplotlibDeprecat
  mplDeprecation)
```

```
In [2]: # Import of the data created with the bash script
        data  = pd.read_csv('joined_data.csv')
```

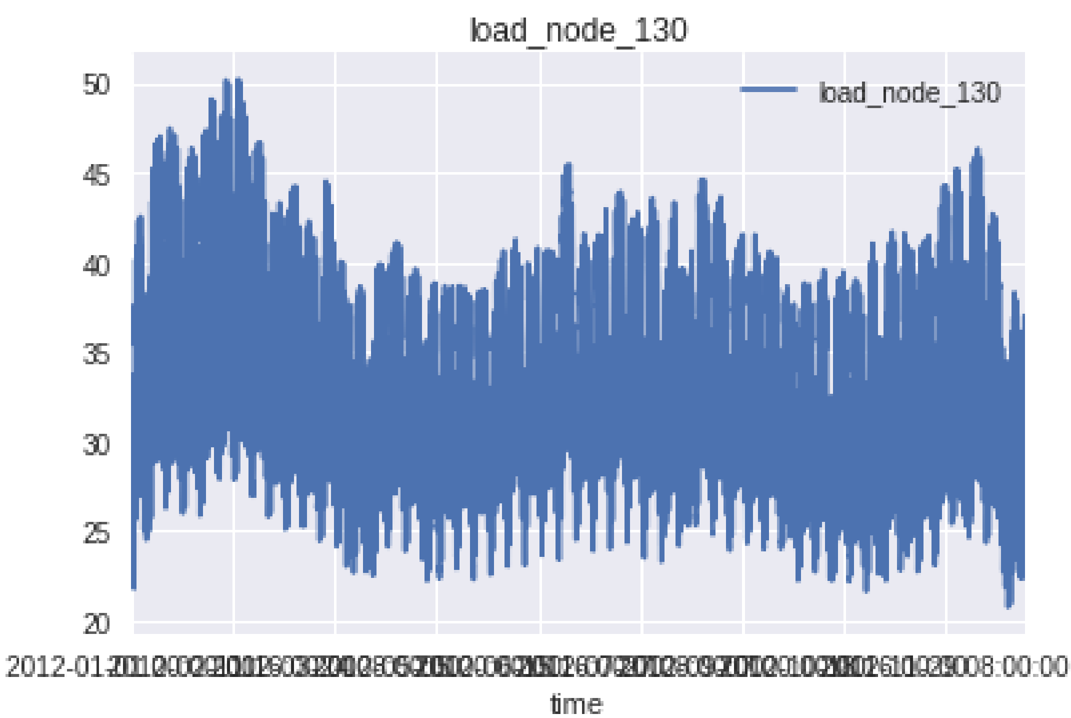
```
In [3]: # Simple plots showing a small pick of our data

        data.plot(x='time',y='prod_gen_50',title='prod_gen_50')
        data.plot(x='time',y='load_node_130',title='load_node_130')
        data.plot(x='time',y='renew_node_24',title='renew_node_24')
```

```
/home/student/.local/lib/python3.5/site-packages/matplotlib/__init__.py:830: MatplotlibDeprecat
  mplDeprecation)
```

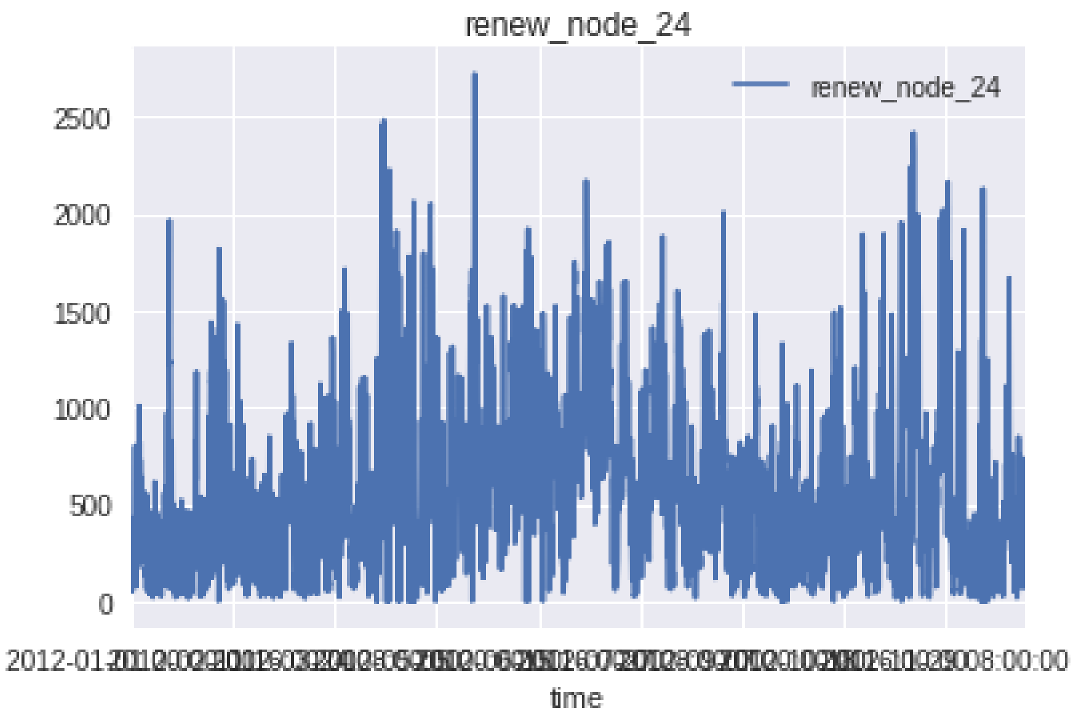
```
Out[3]: <matplotlib.axes._subplots.AxesSubplot at 0x7f1e07d6fcf8>
```



prod_gen_50
prod_gen_50
300
250
200
150
100
50
0
time



load_node_130
load_node_130
50
45
40
35
30
25
20
time



Would it be practical to plot all possible scatter plots (scatter matrix)?
Not really, unless you use a cluster to compute the data, as there are way too many datapoints and columns

Q#2 For this data, what is the reasonable approach to dealing with the NaN values? Why?
As there appears to be only small sample times missing, we use interpolation to remove the NaN's

```
In [4]: # Removal of NaN's


        print("Total number of NaN's before removal: " +str(data.isnull().sum().sum()))
        # Interpolate any row containing any NaN's
        data_nona = data.interpolate('linear')
        print("Total number of NaN's after removal: " +str(data_nona.isnull().sum().sum()))
```

```
Total number of NaN's before removal: 1711
Total number of NaN's after removal: 0
```

1.1.1 Feature reduction

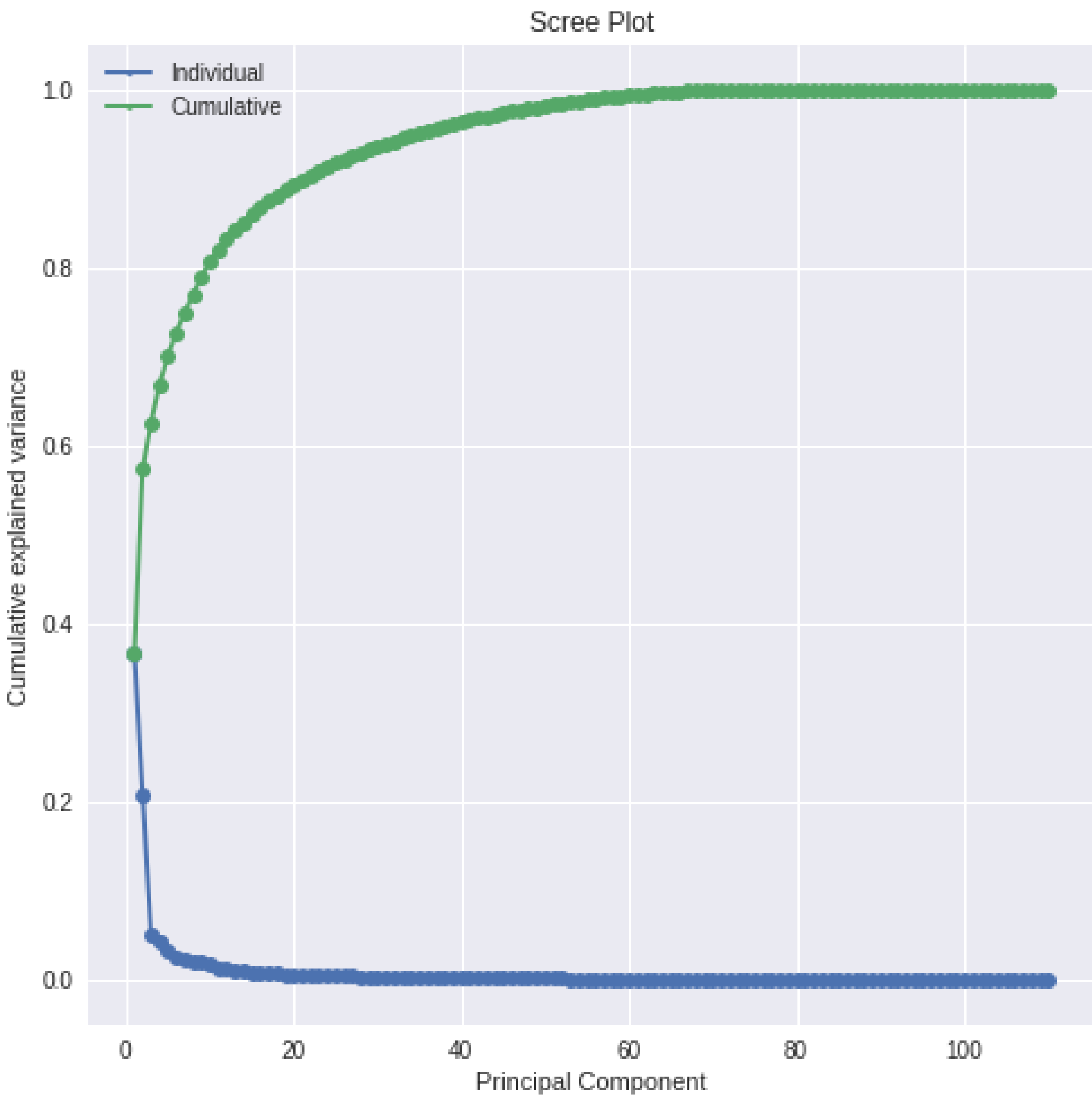
Since you must reduce the amount of sensors, you need to find out which ones you can get rid of.

Q#3 Why would PCA be useful for this?
It shows you which components are principal for your data. Thereby showing which sensors are impacting the overall data the most

With that in mind, you can narrow down the amount of sensors used to generate data. Obviously you will lose some data, but choosing the correct amount of components, you can get pretty close to the original

```
In [5]: from sklearn.decomposition import PCA

        # Removal of the time column, as this is not usable in math
        datanotime = data_nona.drop('time',1)


        # Removing any column where more than 90% of the data is zero
        data_notime2 = datanotime.loc[:, (datanotime != 0).sum()>len(datanotime)*.1]

        # First we standardize the data
        data_stand = (data_notime2 - data_notime2.mean()) / data_notime2.std()

        # The standardization created a lot of NaN's
        # These came from dividing by zero, as a lot of the prod_gen sensors had only zero's
        data_stand = data_stand.dropna(axis='columns',how='all')



        print("NaN's in data set: " + str(data_stand.isnull().sum().sum()))

        # Then instantiate the data, and make the fit
        comp=data_stand.shape[1]
        pca = PCA(n_components=comp)
        pca_data=pca.fit(data_stand)

        # Plotting the explained variance
        fig = plt.figure(figsize=(8,8))
        sing_vals = np.arange(comp) + 1
        plt.plot(sing_vals, pca.explained_variance_ratio_, 'o-', linewidth=2)
        plt.title('Scree Plot')
        plt.xlabel('Principal Component')
        plt.ylabel('Cumulative explained variance')
        plt.plot(sing_vals, pca.explained_variance_ratio_.cumsum(), 'o-', linewidth=2)

        plt.legend(['Individual','Cumulative'], loc='best', borderpad=0.3,
                   shadow=False,
                   markerscale=0.4)

        # Saving the pca components
        data_components = pca.components_

        #with pd.option_context('display.max_rows', None, 'display.max_columns', 3):
        #    print((datanotime != 0).sum())
```

```
NaN's in data set: 0
```




```
In [6]: # Find the number of components needed to explain 90% of the variance
        for i in range(0,comp):
            if pca.explained_variance_ratio_.cumsum()[i] >= 0.9:
                print("with " +str(i+1) +" components you explain " + str(pca.explained_varian
                new_comp=(i+1)
                break;
```

```
with 22 components you explain 90.3623534875%
```

1.1.2 Scree plot

Q#4 How many principal components do you need to explain 90 % of the variance

22 pricipal components would be needed to explain more than 90% of the variance
22 components will explain 90.36% of the variance

1.1.3 Clustering

You want to reduce the amount of field sensors to 20. You should now have from the previous question, an array with all your loading vectors (pca.components_), one vector per principal component, with 137 elements (one per each sensor). Use clustering to group sensors that behave the same.

Q#5 How would you choose which sensors in each cluster you should keep?

We pick the sensor closest to the cluster center from each of the 20 clusters we make in the 22-dimensions. This should give us a good approximation of the clusters data and a good variety of sensors

In [7]:
```
from sklearn.cluster import KMeans

# Slice the components we need. We take 22 as that gives us about 90% explained varian
slice=data_components[0:new_comp]

# Instanciate and fit the clusters
kmeans = KMeans(n_clusters=20, n_init=200, max_iter=300, tol=0.0001, verbose=0, random_
kmeans.fit(slice.T)
cluster_pred = kmeans.predict(slice.T)

# Prints the predicted clusters
print(cluster_pred)
```

```
[ 0  0  0  0 18  0 18  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
  0  0  0  0  0  0  0  0  0  0  0  2 10 13 10  4  0  2 14  2  7 10  3  5 10
  3  7 10  1  2  6 14 17 16 12 15 14 12 17 15 17 10 14 15  1 15 14  0 11 11
 11  8  5  8  5  7  5 10  7 16  9  6 19  2  2  3  6  9  3  6  4  9  9  9  3
  4  9  3 19  9  6  6  6  3  2]
```

In [8]:
```
import scipy

# Make a pandas dataframe of our sensors, and the clusters they belong to
clust = pd.DataFrame(data_stand.columns, columns=['sensors'])
clust['cluster'] = cluster_pred

# calculate the distance from a sensor to the cluster center
temp = []
for i in range(slice.T.shape[0]):
    A=slice.T[i]
    B=kmeans.cluster_centers_[clust.cluster[i]]
    temp.append(scipy.spatial.distance.euclidean(A, B))
clust['dist_to_center'] = temp

# Find the sensor in a cluster that is closest to the cluster centers
x=0
```

```
    data_reduced = []
    sensor_cluster = []
    while x <= max(clust.cluster):
        temp_min = 100000
        temp_ind = 0
        for i in range(slice.shape[1]):
            if clust.cluster[i] == x:
                if clust.dist_to_center[i] < temp_min:
                    temp_min = clust.dist_to_center[i]
                    temp_ind = i
        data_reduced.append(clust.sensors[temp_ind])
        x+=1

    # Make a new pandas dataframe witht the reduced sensor list
    data_reduced = pd.DataFrame(data_reduced, columns=['sensors'])

    # Sort the list of clusters by their distance to the center, for manual check up
    sorted_clust = clust.sort_values(by=['dist_to_center'])

    # For manual check
    #print(data_reduced.to_string(index=False))
    #with pd.option_context('display.max_rows', None, 'display.max_columns', 3):
    #    print(sorted_clust)
```

```
In [9]: x=0
        index = []
        for i in range(data_nona.shape[1]):
               for x in range(data_reduced.sensors.shape[0]):
                    if data_reduced.sensors.iloc[x] == data_nona.columns[i]:
                        index.append(i)
                        x+=1

        data_reduced = data_nona[index]
        print(data_reduced.columns)
```

```
Index(['load_node_16', 'load_node_98', 'export_node_68', 'export_node_170',
       'export_node_108', 'export_node_111', 'renew_node_143', 'renew_node_17',
       'renew_node_154', 'renew_node_155', 'renew_node_41', 'renew_node_202',
       'renew_node_86', 'renew_node_99', 'prod_gen_4', 'prod_gen_5',
       'prod_gen_9', 'prod_gen_31', 'prod_gen_34', 'prod_gen_41'],
      dtype='object')
```

1.1.4 Save your chosen sensors

Now that you have chosen 20 sensors which are representative of your data, create a DataFrame that contains these sensors. You can save them to csv file using the code in the following cell.

```
In [10]: # Assuming of course that your reduced data set is called data_reduced

         data_reduced['time']=data_nona['time']
         data_reduced.to_csv('reduced_field_data.csv')
```

```
/home/student/.local/lib/python3.5/site-packages/ipykernel_launcher.py:3: SettingWithCopyWarnin
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
  This is separate from the ipykernel package so we can avoid doing imports until
```