energy-data-PCA-SVR

September 28, 2020

1 PCA and SVR Analysis

1.1 Using the data on electricity production in Denmark

Figure out the largest contributing factors to CO2 emissions using PCA

[1]:
```
import pandas as pd
from pandas import DataFrame
```

[2]:
```
h_start = 0     # start of header names, inclusive
h_end = 20      # end of header names, exclusive
d_start = 22    # start of data values,
dates = [0,]    # Column zero is a date and Pandas must interpret it as a date
```

[3]:
```
with open("20161208_onlinedata.csv", encoding="latin1") as f:
    data_fields = f.readlines()[h_start:h_end]
    f.seek(0,0)
    data_values = pd.read_csv(f, skiprows=d_start-1, sep=';',␣
 ↪infer_datetime_format=True, parse_dates=dates)
```

[4]:
```
# Clean leading and trailing spaces, tabs, newlines
# split on first space only, and then only take the text field -> ['first␣
 ↪header name', 'second header name']
headers = [d.strip() for d in data_fields]
headers = [h.split(" ", maxsplit=1)[1] for h in headers]
```

[5]:
```
# Insert the name of the time column
headers.insert(0, "Dato og tid")
```

[6]:
```
# Drop the last empty column
data_values = data_values.drop('Unnamed: 21', axis=1)  # We drop column with␣
 ↪name 21, on the 1st axis (columns)
```

[7]:
```
# Make a new final object
df = data_values.copy(deep=True)

# Set the header names
```

```
df.columns = headers

# Set the Date to be the index
df = df.set_index(df.columns[0])
```

1.2 We now have a final dataset

Now, begin to make it ready for PCA

[8]:
```
# Create a df to do PCA on
df2 = df.copy(deep=True)
```

[9]:
```
# Pop out the CO2 column and save it
CO2 = df2.pop('CO2 udledning')
```

[10]:
```
# Pop off and discard the two unusable columns
df2.pop('Vindhastighed i Malling');
df2.pop('Temperatur i Malling');
```

1.2.1 Import PCA model

[11]:
```
import numpy as np
from sklearn.decomposition import PCA
```

[12]:
```
pca_model = PCA(n_components=1)
```

Attempt to make a model with just one component, i.e. make 1 new variable by combining the 20 old variables into 1 new variable

[13]:
```
pca_model.fit(df2)
```

[13]:
```
PCA(n_components=1)
```

Show how many percent of total variance in the data can be explained with just the 1 component

[14]:
```
print(pca_model.explained_variance_ratio_)
```

```
[0.79257213]
```

[15]:
```
z = zip(pca_model.components_.T[:,0], df2.columns.T)
list(z)
```

[15]:
```
[(0.12597996986359525, 'Centrale kraftværker DK1'),
 (0.012639045915224245, 'Centrale kraftværker DK2'),
 (0.059873862966092824, 'Decentrale kraftværker DK1'),
 (0.0148157729728281l, 'Decentrale kraftværker DK2'),
```

```
(-0.44167102846258777, 'Vindmøller DK1'),
(-0.07026999074319044, 'Vindmøller DK2'),
(0.6743662578385146, 'Udveksling Jylland-Norge'),
(-0.06515162528706121, 'Udveksling Jylland-Sverige'),
(-0.15354756286331547, 'Udveksling Jylland-Tyskland'),
(0.3009366106917083, 'Udveksling Sjælland-Sverige'),
(-0.07732449721545338, 'Udveksling Sjælland-Tyskland'),
(0.001093797833095818, 'Udveksling Bornholm-Sverige'),
(0.009799592537681373, 'Udveksling Fyn-Sjaelland'),
(-0.06904898350365901, 'Havmøller DK'),
(-0.4428941383377205, 'Landmøller DK'),
(-0.00042083450054026346, 'Solceller DK1'),
(-3.396703926453231e-05, 'Solceller DK2')]
```

Perform the transformation, i.e. make the new variable by applying weights to each column and taking sum

[16]:
```python
x = pca_model.fit(df2).transform(df2)
```

Make a small new dataset with the CO2 data and the new PCA variable

[17]:
```python
cmp = CO2.to_frame()   # Make the Series object into a DataFrame
cmp["PCA"] = x[:,0]    # Make a new column with the PCA variable
```

[18]:
```python
cmp
```

[18]:
```
                      CO2 udledning          PCA
Dato og tid
2016-12-08 00:00:00             190 -1771.556285
2016-12-08 00:05:00             184 -1815.747534
2016-12-08 00:10:00             180 -1823.303024
2016-12-08 00:15:00             175 -1813.974267
2016-12-08 00:20:00             170 -1833.460103
…                                 …            …
2016-12-08 23:35:00             292    33.259697
2016-12-08 23:40:00             294    46.548923
2016-12-08 23:45:00             297    66.868377
2016-12-08 23:50:00             299    66.033229
2016-12-08 23:55:00             299    73.095850

[288 rows x 2 columns]
```

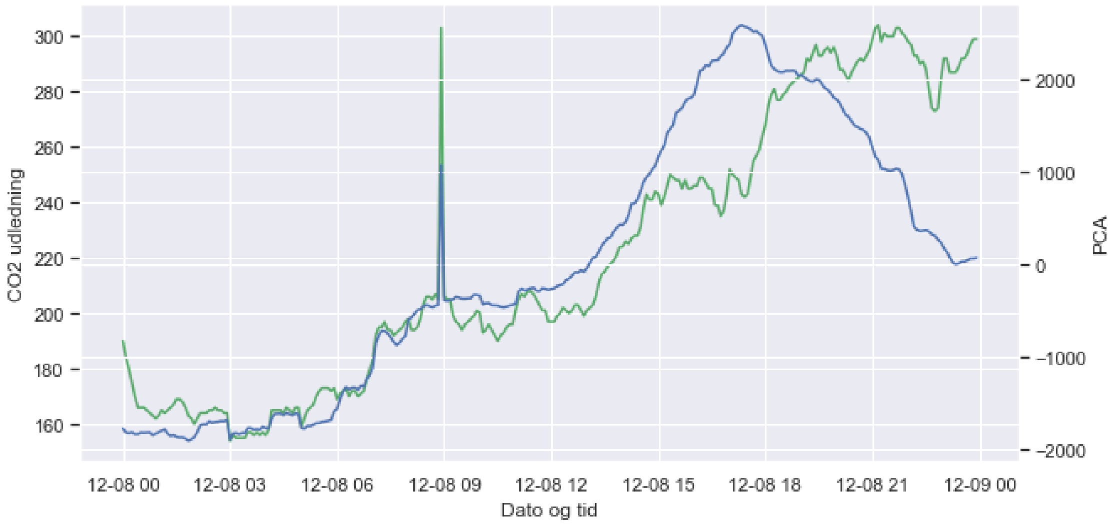
1.2.2 Look at the results

Compare the CO2 value to the 1 new variable. We plot on different axes, as the two series are not equally scaled

Use seaborn to make it look nicer

[19]:
```python
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_theme()
```

[20]:
```python
plt.figure(figsize=(10,5))
sns.lineplot(data=cmp['CO2 udledning'], color="g");
ax2 = plt.twinx()
sns.lineplot(data=cmp['PCA'], color="b", ax=ax2);
```



This shows how the new single variable explains most of the variation in CO2 emissions.

2 SVR Regression model

[72]:
```python
from sklearn.svm import SVR
```

[56]:
```python
SVR?
```

[73]:
```python
svr_rbf = SVR(kernel='rbf')
svr_lin = SVR(kernel='linear')
svr_poly = SVR(kernel='poly')
```

2.0.1 Set up independent variable matrix

[74]:
```
X = df.drop(
    columns=['Vindmøller DK1',
             'Vindmøller DK2',
             'Temperatur i Malling',
             'Vindhastighed i Malling',
             'Havmøller DK',
             'Landmøller DK',
             'Solceller DK1',
             'Solceller DK2']
)
```

2.0.2 Set up dependent variable

[75]:
```
y = X.pop('CO2 udledning')
```

2.0.3 Fit the models on the energy production data

[76]:
```
svr_rbf.fit(X,y)
svr_lin.fit(X,y)
svr_poly.fit(X,y)
```

[76]:
```
SVR(kernel='poly')
```

2.0.4 Set up DataFrame to store comparisons

[77]:
```
y_data = y.to_frame()
```

2.0.5 In-sample prediction

[78]:
```
yhat_rbf = svr_rbf.predict(X)
yhat_lin = svr_lin.predict(X)
yhat_poly = svr_poly.predict(X)
```

Save the predicted values in the pandas array

[79]:
```
y_data["y rbf fit"] = yhat_rbf    # Make a new column with the SVR variable
y_data["y lin fit"] = yhat_lin
y_data["y poly fit"] = yhat_poly
```

[80]:
```
y_data
```

[80]:

```
                     CO2 udledning   y rbf fit   y lin fit  y poly fit
Dato og tid
2016-12-08 00:00:00            190  171.481458  194.922431  171.326255
2016-12-08 00:05:00            184  173.604700  190.030728  175.392295
2016-12-08 00:10:00            180  174.732142  183.697624  177.409074
2016-12-08 00:15:00            175  174.900000  178.719788  178.879199
2016-12-08 00:20:00            170  174.725156  172.615635  179.008417
…                              …         …           …          …
2016-12-08 23:35:00            292  188.507406  293.616533  193.710268
2016-12-08 23:40:00            294  188.516874  294.100272  193.730870
2016-12-08 23:45:00            297  188.063583  288.452679  193.108591
2016-12-08 23:50:00            299  188.415553  293.055310  193.323640
2016-12-08 23:55:00            299  190.923278  302.098764  195.447846

[288 rows x 4 columns]
```

[81]:

```
plt.figure(figsize=(10,5))
sns.lineplot(data=y_data);
```

The plot shows that a linear model fits the data best. Possibly, the one large outlier affects the RBF and Poly models more than the linear model.

2.0.6 Find out something more about the linear model

Regression coefficients

[88]:

```
svr_lin.coef_
```

[88]:
```
array([[ 1.56649847e-01,  1.08930240e-01,  1.28524788e-01,
        -1.67562331e-02,  3.40426721e-02,  5.98768504e-02,
         2.09232413e-04, -9.67824319e-02, -9.70612859e-02,
         7.22001177e-01,  1.17920562e-01]])
```

[89]:
```
svr_lin.score?
```

The score is the R^2: 96% of the variance in the data is explained by the model.

[90]:
```
svr_lin.score(X,y)
```

[90]:
```
0.9602532734483797
```