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'),
 (0.01481577297282811, '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]:
```
x = pca_model.fit(df2).transform(df2)
```

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

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

[18]:
```
cmp
```

[18]:

Dato og tid	CO2 udledning	PCA
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]

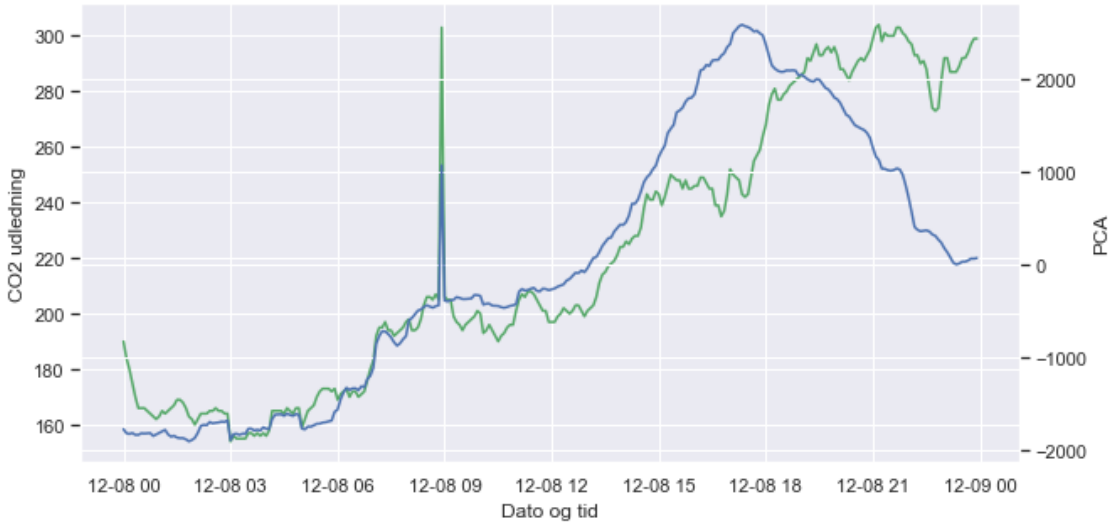
1.2.2 Look at the results

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

[20]:
```
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]:
```
from sklearn.svm import SVR
```

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

[73]:
```
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]:

Dato og tid	CO2 udledning	y rbf fit	y lin fit	y poly fit
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);
```

[ ]: