```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from statsmodels.tsa.stattools import adfuller
from sklearn.preprocessing import OrdinalEncoder
from sklearn.model_selection import train_test_split
from statsmodels.tsa.seasonal import seasonal_decompose

from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import ParameterGrid
from sklearn.ensemble import GradientBoostingRegressor
```

```python
df = pd.read_csv('train.csv', index_col = 'datetime', parse_dates = True)
df
```

datetime	ID	temperature	var1	pressure	windspeed	var2	electricity_consumption
2013-07-01 00:00:00	0	-11.4	-17.1	1003.0	571.910	A	216.0
2013-07-01 01:00:00	1	-12.1	-19.3	996.0	575.040	A	210.0
2013-07-01 02:00:00	2	-12.9	-20.0	1000.0	578.435	A	225.0
2013-07-01 03:00:00	3	-11.4	-17.1	995.0	582.580	A	216.0
2013-07-01 04:00:00	4	-11.4	-19.3	1005.0	586.600	A	222.0
...	...	...	...	...	...	...	...
2017-06-23 19:00:00	34891	-0.7	-15.0	1009.0	51.685	A	225.0
2017-06-23 20:00:00	34892	-2.9	-11.4	1005.0	56.105	A	213.0
2017-06-23 21:00:00	34893	-1.4	-12.9	995.0	61.275	A	213.0
2017-06-23 22:00:00	34894	-2.9	-11.4	996.0	67.210	A	210.0
2017-06-23 23:00:00	34895	-2.1	-11.4	1009.0	71.880	A	210.0

26496 rows × 7 columns

Changing var2 from letters to numbers

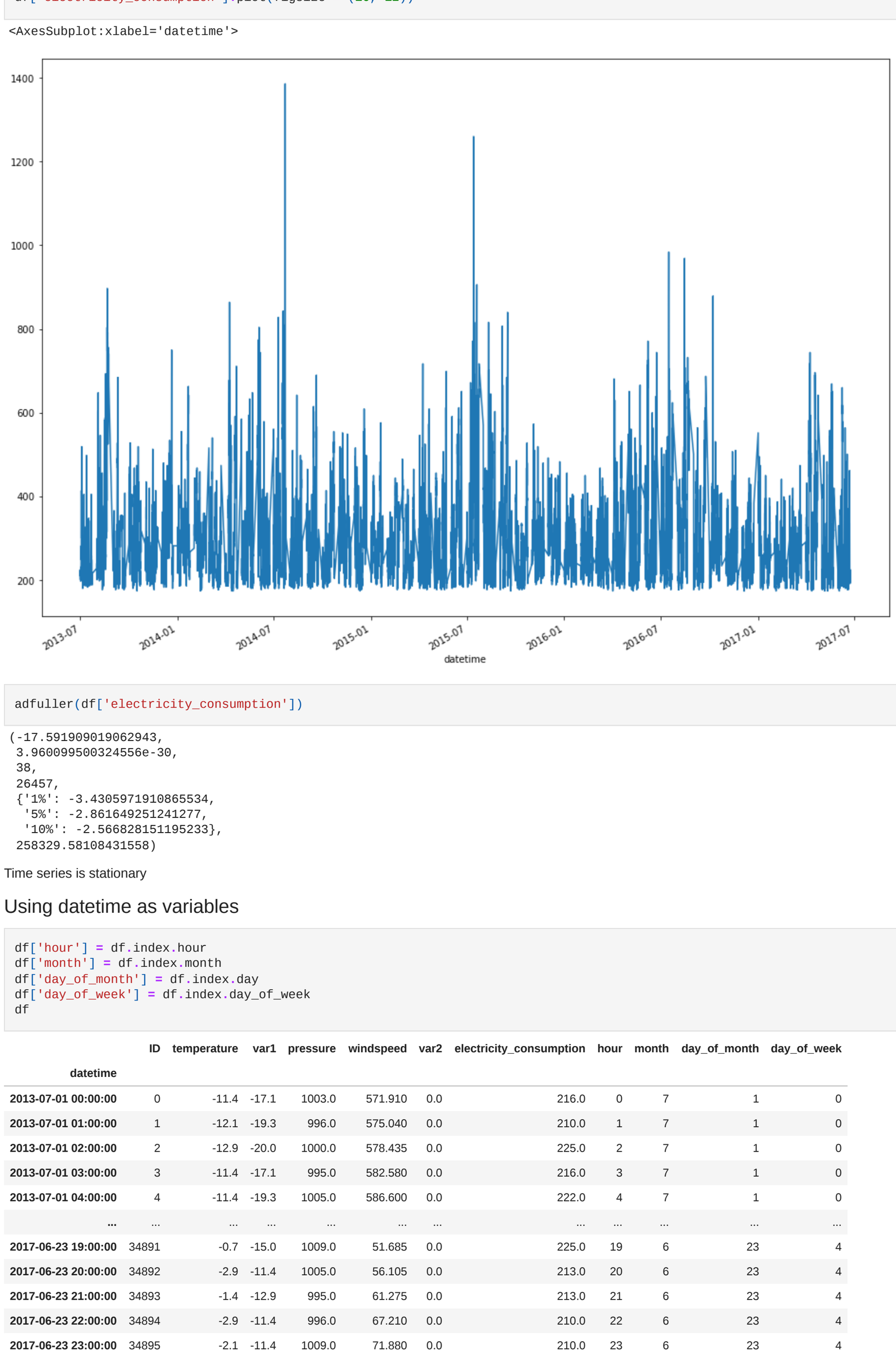
```python
enc = OrdinalEncoder()
enc.fit(df[['var2']])
df['var2'] = enc.transform(df[['var2']])
df
```

datetime	ID	temperature	var1	pressure	windspeed	var2	electricity_consumption
2013-07-01 00:00:00	0	-11.4	-17.1	1003.0	571.910	0.0	216.0
2013-07-01 01:00:00	1	-12.1	-19.3	996.0	575.040	0.0	210.0
2013-07-01 02:00:00	2	-12.9	-20.0	1000.0	578.435	0.0	225.0
2013-07-01 03:00:00	3	-11.4	-17.1	995.0	582.580	0.0	216.0
2013-07-01 04:00:00	4	-11.4	-19.3	1005.0	586.600	0.0	222.0
...	...	...	...	...	...	...	...
2017-06-23 19:00:00	34891	-0.7	-15.0	1009.0	51.685	0.0	225.0
2017-06-23 20:00:00	34892	-2.9	-11.4	1005.0	56.105	0.0	213.0
2017-06-23 21:00:00	34893	-1.4	-12.9	995.0	61.275	0.0	213.0
2017-06-23 22:00:00	34894	-2.9	-11.4	996.0	67.210	0.0	210.0
2017-06-23 23:00:00	34895	-2.1	-11.4	1009.0	71.880	0.0	210.0

26496 rows × 7 columns

```python
df['electricity_consumption'].plot(figsize = (16, 12))
```

<AxesSubplot:xlabel='datetime'>



```python
adfuller(df['electricity_consumption'])
```

```
(-17.591909019062943,
 3.960099500324556e-30,
 38,
 26457,
 {'1%': -3.4305971910865534,
  '5%': -2.861649251241277,
  '10%': -2.566828151195233},
 258329.58108431558)
```

Time series is stationary

Using datetime as variables

```python
df['hour'] = df.index.hour
df['month'] = df.index.month
df['day_of_month'] = df.index.day
df['day_of_week'] = df.index.day_of_week
df
```

datetime	ID	temperature	var1	pressure	windspeed	var2	electricity_consumption	hour	month	day_of_month	day_of_week
2013-07-01 00:00:00	0	-11.4	-17.1	1003.0	571.910	0.0	216.0	0	7	1	0
2013-07-01 01:00:00	1	-12.1	-19.3	996.0	575.040	0.0	210.0	1	7	1	0
2013-07-01 02:00:00	2	-12.9	-20.0	1000.0	578.435	0.0	225.0	2	7	1	0
2013-07-01 03:00:00	3	-11.4	-17.1	995.0	582.580	0.0	216.0	3	7	1	0
2013-07-01 04:00:00	4	-11.4	-19.3	1005.0	586.600	0.0	222.0	4	7	1	0
...	...	...	...	...	...	...	...	...	...	...	...
2017-06-23 19:00:00	34891	-0.7	-15.0	1009.0	51.685	0.0	225.0	19	6	23	4
2017-06-23 20:00:00	34892	-2.9	-11.4	1005.0	56.105	0.0	213.0	20	6	23	4
2017-06-23 21:00:00	34893	-1.4	-12.9	995.0	61.275	0.0	213.0	21	6	23	4
2017-06-23 22:00:00	34894	-2.9	-11.4	996.0	67.210	0.0	210.0	22	6	23	4
2017-06-23 23:00:00	34895	-2.1	-11.4	1009.0	71.880	0.0	210.0	23	6	23	4

26496 rows × 11 columns

Splitting dataset into predictor values and what we're looking for

```python
X = df.iloc[:, [1, 2, 3, 4, 5, 7, 8, 9, 10]].values
X
```

```
array([[-1.140e+01, -1.710e+01,  1.003e+03, ...,  7.000e+00,  1.000e+00,
         0.000e+00],
       [-1.210e+01, -1.930e+01,  9.960e+02, ...,  7.000e+00,  1.000e+00,
         0.000e+00],
       [-1.290e+01, -2.000e+01,  1.000e+03, ...,  7.000e+00,  1.000e+00,
         0.000e+00],
       ...,
       [-1.400e+00, -1.290e+01,  9.950e+02, ...,  6.000e+00,  2.300e+01,
         4.000e+00],
       [-2.900e+00, -1.140e+01,  9.960e+02, ...,  6.000e+00,  2.300e+01,
         4.000e+00],
       [-2.100e+00, -1.140e+01,  1.009e+03, ...,  6.000e+00,  2.300e+01,
         4.000e+00]])
```

```python
Y = df.iloc[:, 6].values
Y
```

```
array([216., 210., 225., ..., 213., 210., 210.])
```

```python
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.2, random_state = 42)
```

P1: Random Forest Regressor

Grid search

```python
grid = {'n_estimators' : [200], 'max_depth' : [2, 3, 4, 5, 6, 7, 8, 9, 10], 'max_features': [2, 3, 4, 5, 6, 7, 8, 9], 'random_state': [17, 18, 19]}
rfr = RandomForestRegressor()
test_scores = []
for g in ParameterGrid(grid):
    rfr.set_params(**g) #unpacking parameters from dictionary
    rfr.fit(X_train, Y_train) #fitting data
    test_scores.append(rfr.score(X_test, Y_test)) #getting score
```

```python
best_idx = np.argmax(test_scores)
print(test_scores[best_idx], ParameterGrid(grid)[best_idx])
```

```
0.5796844001345003 {'random_state': 19, 'n_estimators': 200, 'max_features': 8, 'max_depth': 10}
```

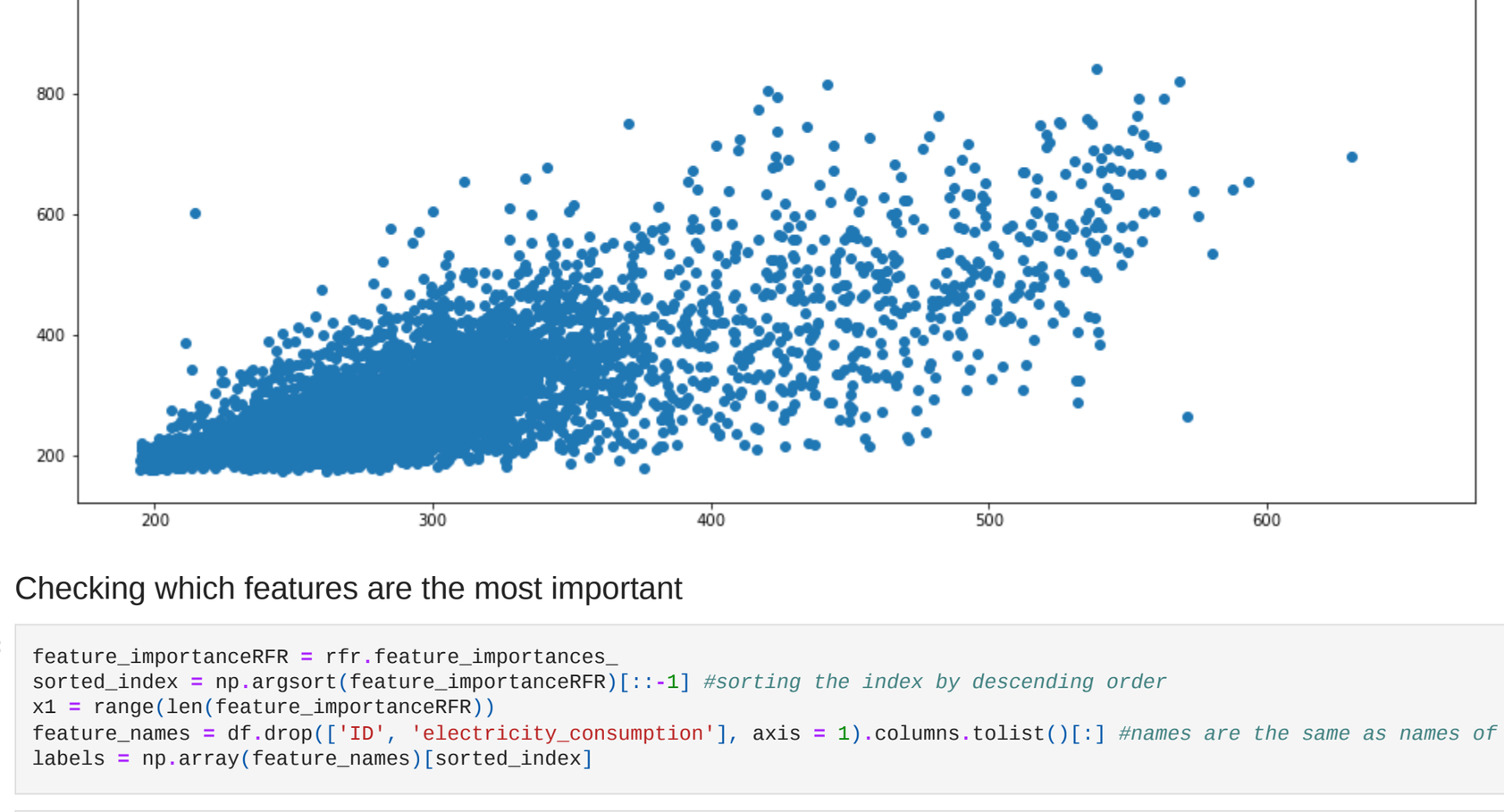
```python
rfr = RandomForestRegressor(random_state = 19, n_estimators = 200, max_features = 8, max_depth = 10)
rfr.fit(X_train, Y_train)
print(rfr.score(X_train, Y_train))
print(rfr.score(X_test, Y_test))
```

```
0.6801601415872389
0.5796844001345003
```

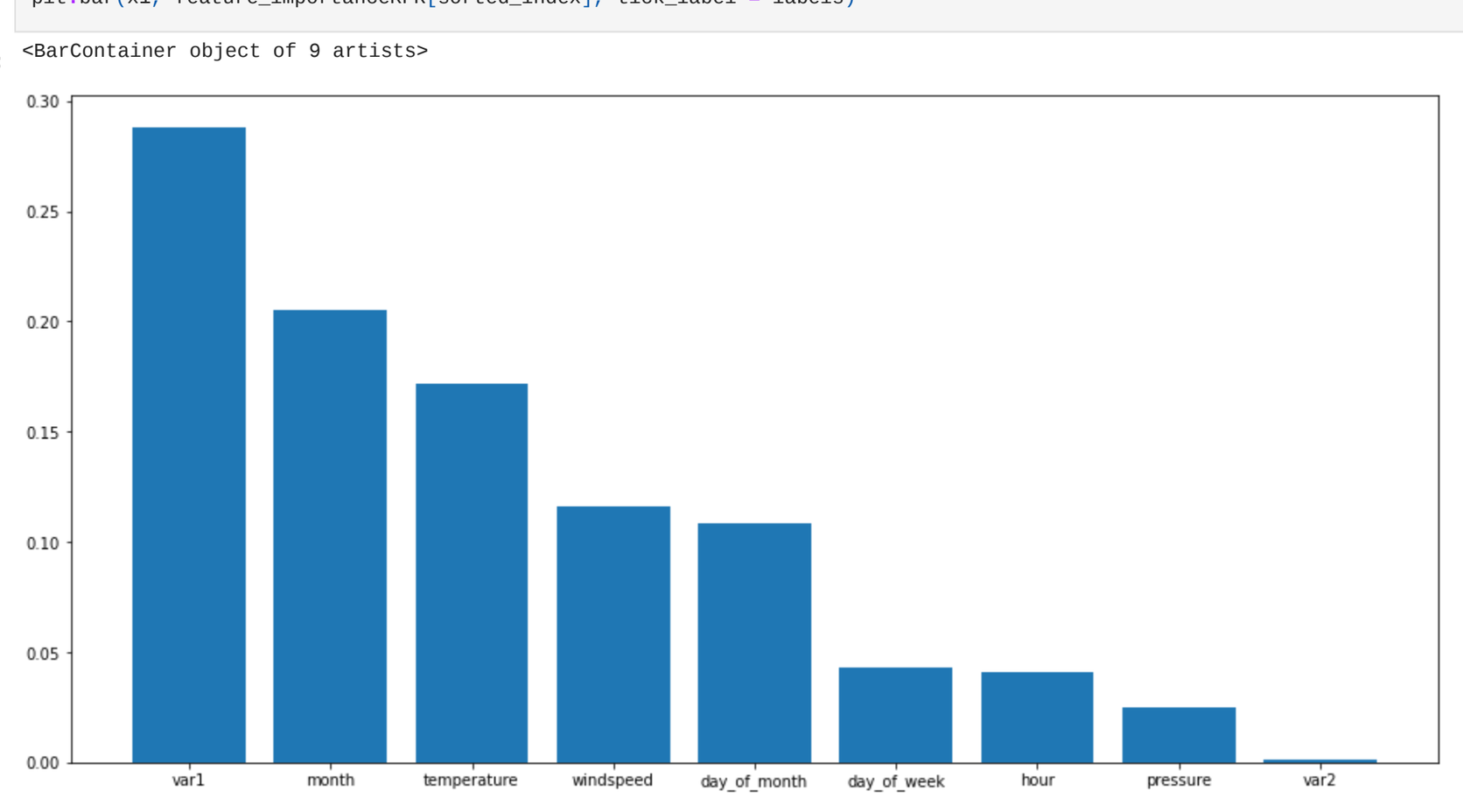
Making predictions

```python
train_prediction = rfr.predict(X_train)
test_prediction = rfr.predict(X_test)
```

```python
plt.rc("figure", figsize = (16, 8))
plt.scatter(train_prediction, Y_train);
```



```python
plt.scatter(test_prediction, Y_test);
```



Checking which features are the most important

```python
feature_importanceRFR = rfr.feature_importances_
sorted_index = np.argsort(feature_importanceRFR)[::-1] #sorting the index by descending order
x1 = range(len(feature_importanceRFR))
feature_names = df.drop(['ID', 'electricity_consumption'], axis = 1).columns.tolist()[:] #names are the same as names of collumns
labels = np.array(feature_names)[sorted_index]
```

```python
plt.bar(x1, feature_importanceRFR[sorted_index], tick_label = labels)
```

<BarContainer object of 9 artists>

Final forecast

```python
df1 = pd.read_csv('test.csv', index_col = 'datetime', parse_dates = True)

#turning var2 into numbers
enc1 = OrdinalEncoder()
enc1.fit(df1[['var2']])
df1['var2'] = enc1.transform(df1[['var2']])

#datetime as variables
df1['hour'] = df1.index.hour
df1['month'] = df1.index.month
df1['day_of_month'] = df1.index.day
df1['day_of_week'] = df1.index.day_of_week

#X values for predictiom
X_pred = df1.iloc[:, 1:].values

#model
rfr = RandomForestRegressor(random_state = 19, n_estimators = 200, max_features = 8, max_depth = 10)
rfr.fit(X, Y)
prediction = rfr.predict(X_pred)
```

```python
df1['electricity_consumption'] = prediction
df1['electricity_consumption'].plot()
```

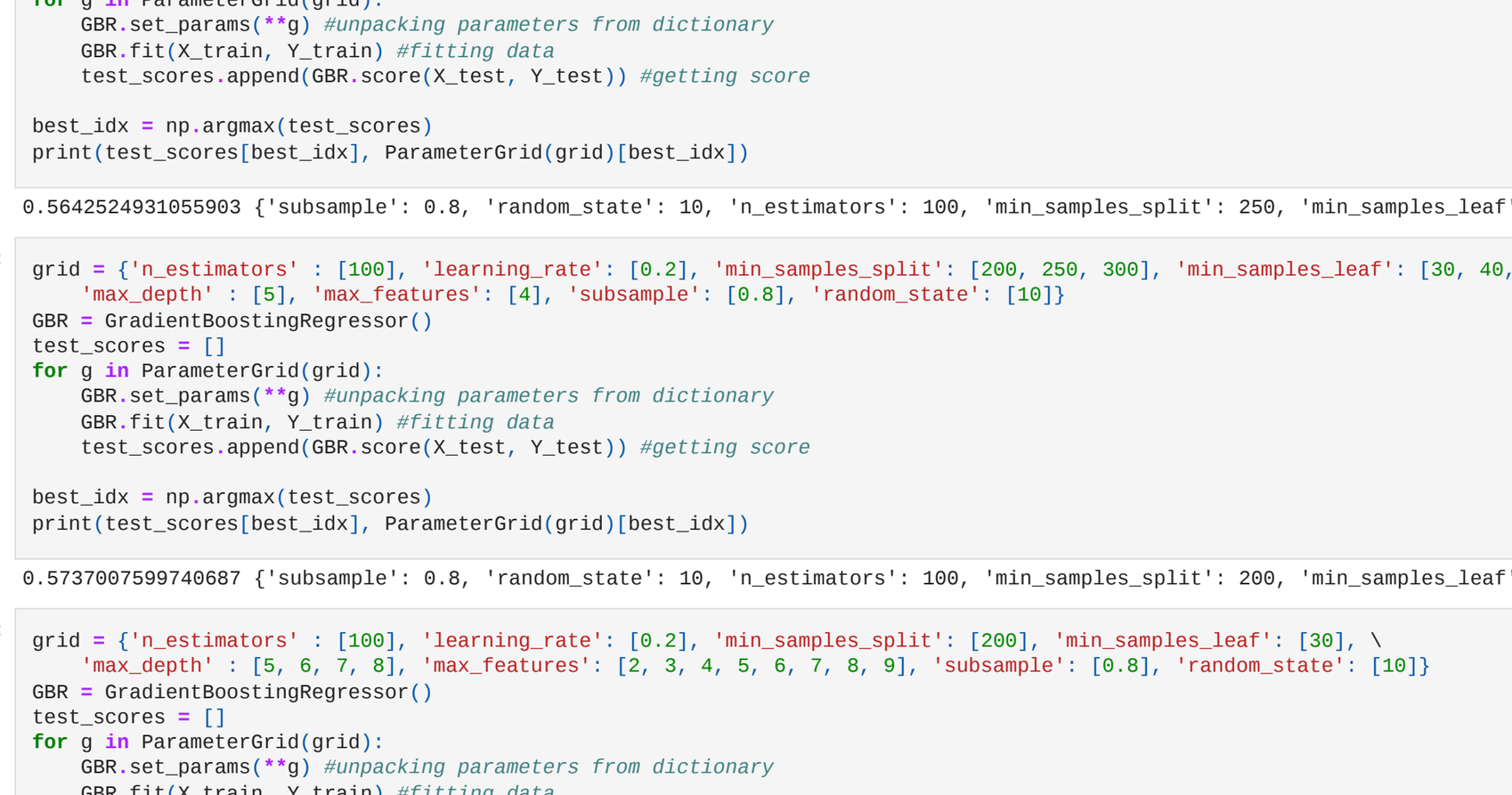
<AxesSubplot:xlabel='datetime'>

Saving predictions to file

```python
df2 = pd.read_csv('sample_submission.csv')
df2['electricity_consumption'] = prediction
df2.set_index('ID', inplace = True)
df2.to_csv('sample_prediction.csv')
```

Score: lower is better

```python
import matplotlib.image as mpimg
img = mpimg.imread('RandomForestResult.png')
imgplot = plt.imshow(img)
plt.show()
```



P2: Gradient Boosted Regressor

Grid search to tune parameters

```python
grid = {'n_estimators' : [50, 75, 100], 'learning_rate': [0.1, 0.15, 0.2], 'min_samples_split': [250], 'min_samples_leaf': [50], \
    'max_depth' : [5], 'max_features': [4], 'subsample': [0.8], 'random_state': [10]}
GBR = GradientBoostingRegressor()
test_scores = []
for g in ParameterGrid(grid):
    GBR.set_params(**g) #unpacking parameters from dictionary
    GBR.fit(X_train, Y_train) #fitting data
    test_scores.append(GBR.score(X_test, Y_test)) #getting score

best_idx = np.argmax(test_scores)
print(test_scores[best_idx], ParameterGrid(grid)[best_idx])
```

```
0.5642524931055903 {'subsample': 0.8, 'random_state': 10, 'n_estimators': 100, 'min_samples_split': 250, 'min_samples_leaf': 50, 'max_features': 4, 'max_depth': 5, 'learning_rate': 0.2}
```

```python
grid = {'n_estimators' : [100], 'learning_rate': [0.2], 'min_samples_split': [200, 250, 300], 'min_samples_leaf': [30, 40, 50, 60], \
    'max_depth' : [5], 'max_features': [4], 'subsample': [0.8], 'random_state': [10]}
GBR = GradientBoostingRegressor()
test_scores = []
for g in ParameterGrid(grid):
    GBR.set_params(**g) #unpacking parameters from dictionary
    GBR.fit(X_train, Y_train) #fitting data
    test_scores.append(GBR.score(X_test, Y_test)) #getting score

best_idx = np.argmax(test_scores)
print(test_scores[best_idx], ParameterGrid(grid)[best_idx])
```

```
0.5737007599740687 {'subsample': 0.8, 'random_state': 10, 'n_estimators': 100, 'min_samples_split': 200, 'min_samples_leaf': 30, 'max_features': 4, 'max_depth': 5, 'learning_rate': 0.2}
```

```python
grid = {'n_estimators' : [100], 'learning_rate': [0.2], 'min_samples_split': [200], 'min_samples_leaf': [30], \
    'max_depth' : [5, 6, 7, 8], 'max_features': [2, 3, 4, 5, 6, 7, 8, 9], 'subsample': [0.8], 'random_state': [10]}
GBR = GradientBoostingRegressor()
test_scores = []
for g in ParameterGrid(grid):
    GBR.set_params(**g) #unpacking parameters from dictionary
    GBR.fit(X_train, Y_train) #fitting data
    test_scores.append(GBR.score(X_test, Y_test)) #getting score

best_idx = np.argmax(test_scores)
print(test_scores[best_idx], ParameterGrid(grid)[best_idx])
```

```
0.6453190407020191 {'subsample': 0.8, 'random_state': 10, 'n_estimators': 100, 'min_samples_split': 200, 'min_samples_leaf': 30, 'max_features': 7, 'max_depth': 8, 'learning_rate': 0.2}
```

```python
grid = {'n_estimators' : [100], 'learning_rate': [0.2], 'min_samples_split': [200], 'min_samples_leaf': [30], \
    'max_depth' : [8], 'max_features': [7], 'subsample': [0.6, 0.7, 0.8, 0.9], 'random_state': [10]}
GBR = GradientBoostingRegressor()
test_scores = []
for g in ParameterGrid(grid):
    GBR.set_params(**g) #unpacking parameters from dictionary
    GBR.fit(X_train, Y_train) #fitting data
    test_scores.append(GBR.score(X_test, Y_test)) #getting score

best_idx = np.argmax(test_scores)
print(test_scores[best_idx], ParameterGrid(grid)[best_idx])
```

```
0.6453190407020191 {'subsample': 0.8, 'random_state': 10, 'n_estimators': 100, 'min_samples_split': 200, 'min_samples_leaf': 30, 'max_features': 7, 'max_depth': 8, 'learning_rate': 0.2}
```

Decreasing learning rate

```python
GBR = GradientBoostingRegressor(n_estimators = 400, learning_rate = 0.1, min_samples_split = 200, min_samples_leaf = 30, max_depth = 8, max_features = 7, subsample = 0.8, random_state = 10)
GBR.fit(X_train, Y_train) #fitting data
print(GBR.score(X_test, Y_test))
```

```
0.6590818505147575
```

```python
GBR = GradientBoostingRegressor(n_estimators = 800, learning_rate = 0.05, min_samples_split = 200, min_samples_leaf = 30, max_depth = 8, max_features = 7, subsample = 0.8, random_state = 10)
GBR.fit(X_train, Y_train) #fitting data
print(GBR.score(X_test, Y_test))
```

```
0.6676843399694897
```

Final parameters for best model:

n_estimators = 800,

learning_rate = 0.05,

min_samples_split = 200,

min_samples_leaf = 30,

max_depth = 8,

max_features = 7,

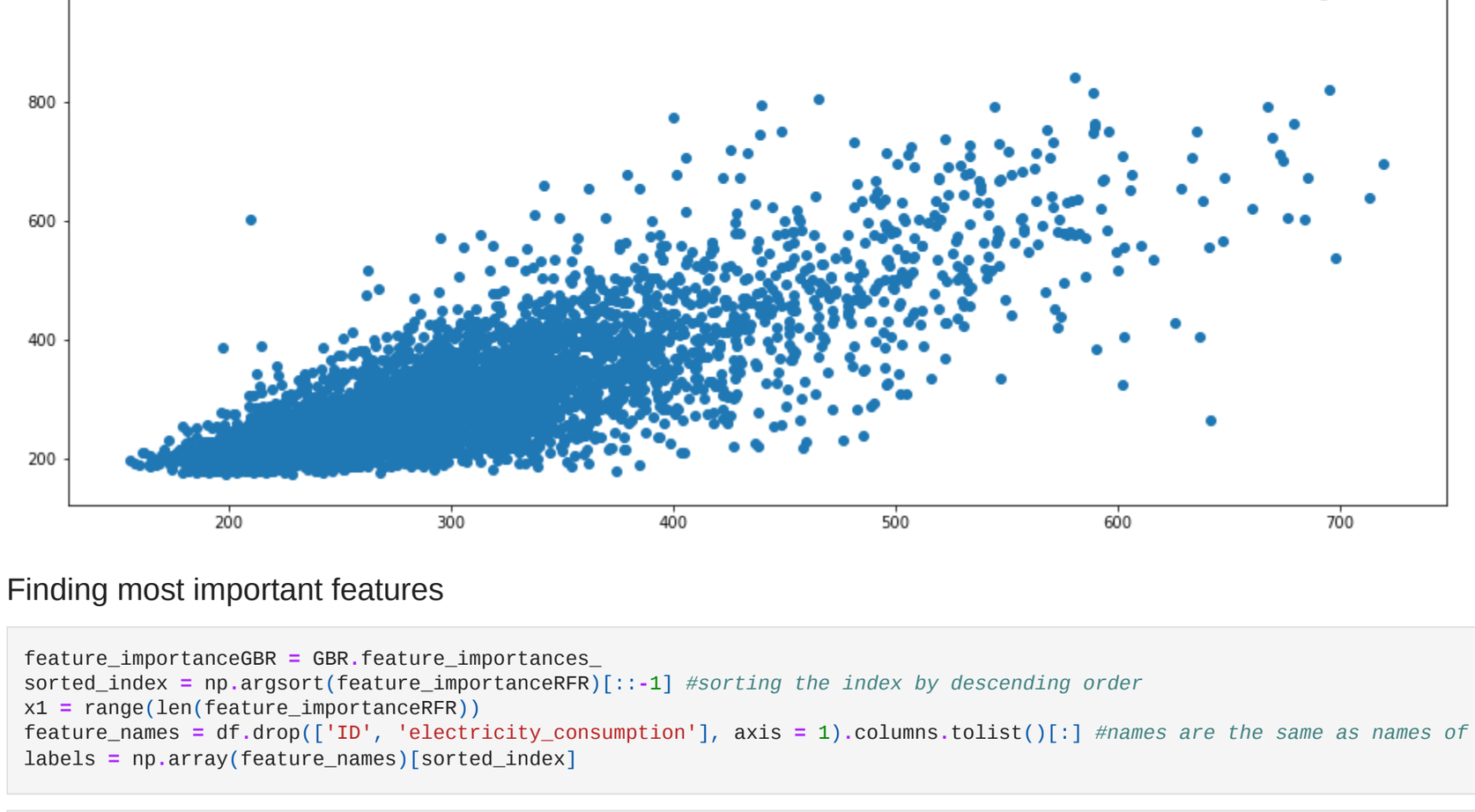
subsample = 0.8,

random_state = 10.

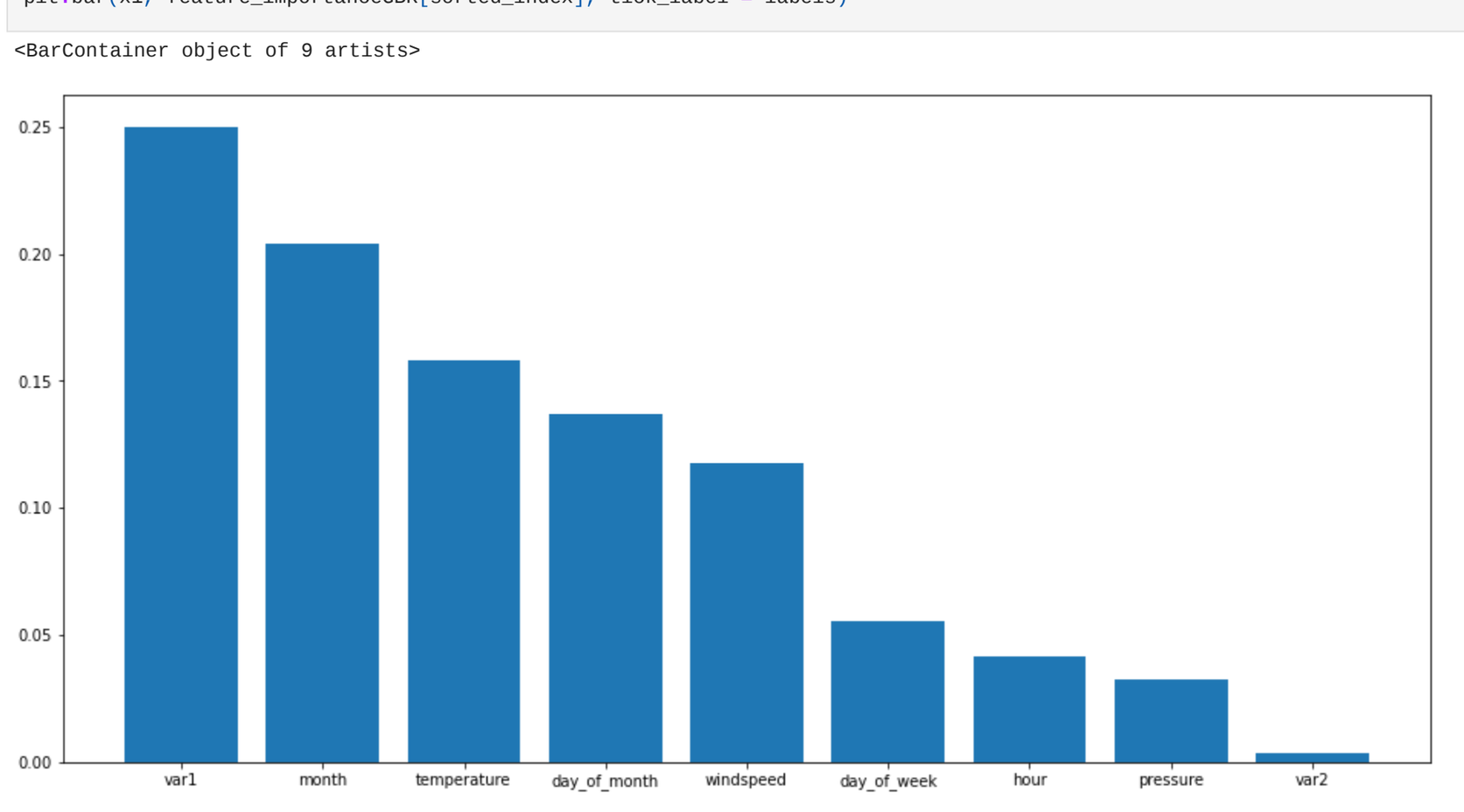
Making predictions

```python
train_prediction = GBR.predict(X_train)
test_prediction = GBR.predict(X_test)
```

```python
plt.rc("figure", figsize = (16, 8))
plt.scatter(train_prediction, Y_train);
```



```python
plt.scatter(test_prediction, Y_test);
```



Finding most important features

```python
feature_importanceGBR = GBR.feature_importances_
sorted_index = np.argsort(feature_importanceRFR)[::-1] #sorting the index by descending order
x1 = range(len(feature_importanceRFR))
feature_names = df.drop(['ID', 'electricity_consumption'], axis = 1).columns.tolist()[:] #names are the same as names of collumns
labels = np.array(feature_names)[sorted_index]
```

```python
plt.bar(x1, feature_importanceGBR[sorted_index], tick_label = labels)
```

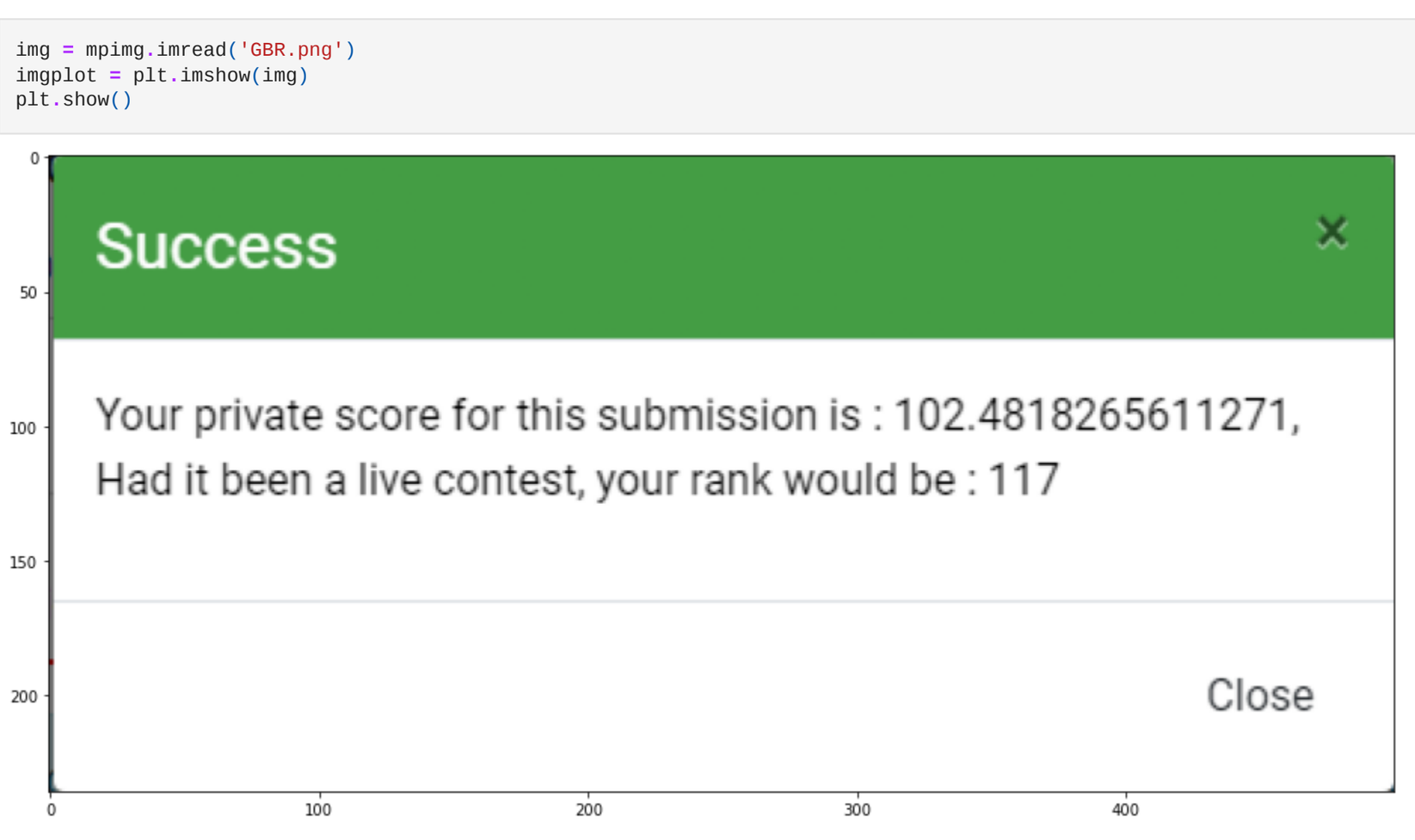
<BarContainer object of 9 artists>

Final forecast

```python
df3 = pd.read_csv('test.csv', index_col = 'datetime', parse_dates = True)

#turning var2 into numbers
enc3 = OrdinalEncoder()
enc3.fit(df3[['var2']])
df3['var2'] = enc3.transform(df3[['var2']])

#datetime as variables
df3['hour'] = df3.index.hour
df3['month'] = df3.index.month
df3['day_of_month'] = df3.index.day
df3['day_of_week'] = df3.index.day_of_week

#X values for predictiom
X_pred = df3.iloc[:, 1:].values

#model
GBR = GradientBoostingRegressor(n_estimators = 800, learning_rate = 0.05, min_samples_split = 200, min_samples_leaf = 30, max_depth = 8, max_features = 7, subsample = 0.8, random_state = 10)
GBR.fit(X, Y)
prediction = GBR.predict(X_pred)
```

```python
df3['electricity_consumption'] = prediction
df3['electricity_consumption'].plot()
```

<AxesSubplot:xlabel='datetime'>



Saving prediction to file

```python
df4 = pd.read_csv('sample_submission.csv')
df4['electricity_consumption'] = prediction
df4.set_index('ID', inplace = True)
df4.to_csv('sample_prediction_GBR.csv')
```

Score: lower is better

```python
img = mpimg.imread('GBR.png')
imgplot = plt.imshow(img)
plt.show()
```