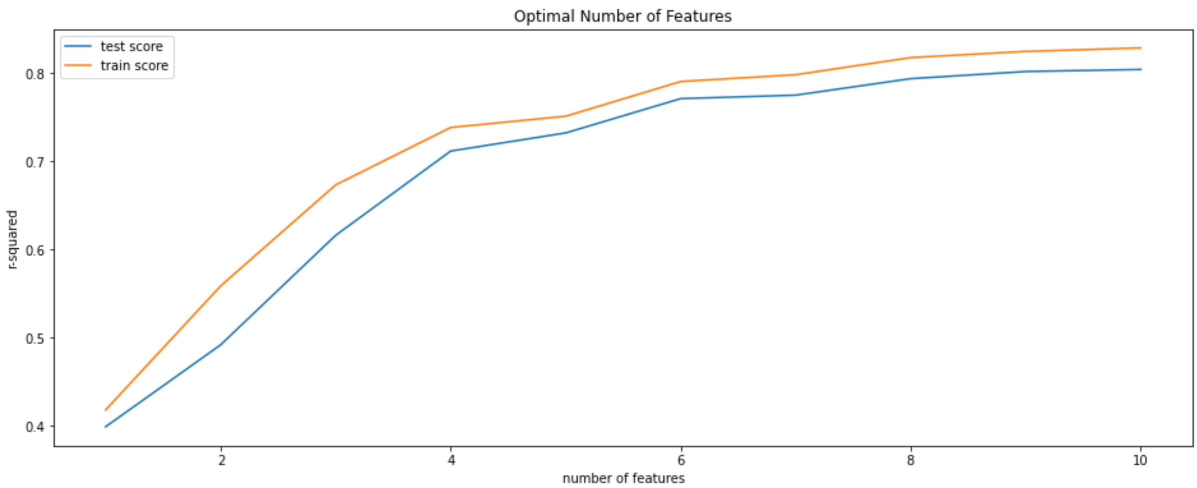
Due to the corona pandemic, many businesses worldwide were shut down, and many are still facing a considerable drop in revenues. One such example is BoomBikes, a US-based bike provider for renting. The bike company is finding it difficult to sustain itself in the present market. Therefore, they want to change the strategy of their business plan to accelerate the revenue collections. Specifically, they tried to know the factors most affecting the demand for bike usage in the US market.
So the findings will be
i) significant variables for the business
ii) How well the model describes the business.
With the previous year's record of bike-sharing, the company made a dataset on the daily bike demands based on some features of bike rent.
The dataset was downloaded from the Boombike dataset from Kaggle [1]. The data features were taken from the data dictionary.

Methods:

The model was built by taking the 'cnt' as a target variable. The variables 'weathersit' and 'season' have numeric data 1, 2, 3, 4 …, with specific levels described in the data dictionary. So, converted these feature values into categorical data. The recursive feature elimination (RFE) process was used to select the features. Then, the cross-validation (CV) with linear regression will fit the model for a good score for the business model.
The linear regression model was chosen to determine the 'variables' strength of connections. The regression analysis tells how much the variables are explained in the model by measuring the R-square value. It also helps to know the most statistically significant variables for the model. 70% of training and 30 % of test data were split from the primary dataset.

To select training and test sets, we can follow a) simply split into train and test: but the result is dependent on the train-test split. b) Split into train, validation and test sets: it will reduce the number of training data. And finally, c) Cross-validation: Split into train and test, and train multiple sets by sampling the train data. The CV is used as a limited sample for better model performance. GridSearchCV is finding the optimal factors with fitting five folds for each of 10 candidates.

Results:



In the above graph the train and test score are very low with 1 to 4 features. As the number of features are increased the R-square score also goes high. So, with the 10 number of factor the R-square value is quite high. Therefore for the linear regression model n_features_optimal = 10 taken. And fit the model with train data. Finally, the trained model is used to predict and calculate the R-square score for the test dataset. That gives 0.83, which is a very good score for the train and test datasets.

Conclusion:

The R-square value is satisfactory and the most significant feature to describe the model are 'yr', 'holiday', 'atem p', 'hum', 'windspeed', 'season_2', 'season_4','mnth_8', 'mnth_9' and 'weathersit_3'.

Bibliography/References

[1] Fanaee-T, Hadi, and Gama, Joao, "Event labeling combining ensemble detectors and background knowledge", Progress in Artificial Intelligence (2013): pp. 1-15, Springer Berlin Heidelberg, doi:10.1007/s13748-013-0040-3.

@article{
year={2013},
issn={2192-6352},
journal={Progress in Artificial Intelligence},
doi={10.1007/s13748-013-0040-3},
title={Event labeling combining ensemble detectors and background knowledge},
url={http://dx.doi.org/10.1007/s13748-013-0040-3},
publisher={Springer Berlin Heidelberg},
keywords={Event labeling; Event detection; Ensemble learning; Background knowledge},
author={Fanaee-T, Hadi and Gama, Joao},
pages={1-15}
}

The data-dictionary is given below.

===
Dataset characteristics
===

day.csv have the following fields:

- instant: record index
- dteday : date
- season : season (1:spring, 2:summer, 3:fall, 4:winter)
- yr : year (0: 2018, 1:2019)
- mnth : month (1 to 12)
- holiday : weather day is a holiday or not (extracted from http://dchr.dc.gov/page/holiday-schedule)
- weekday : day of the week
- workingday : if day is neither weekend nor holiday is 1, otherwise is 0.
+ weathersit :
    - 1: Clear, Few clouds, Partly cloudy, Partly cloudy
    - 2: Mist + Cloudy, Mist + Broken clouds, Mist + Few clouds, Mist
    - 3: Light Snow, Light Rain + Thunderstorm + Scattered clouds, Light Rain + Scattered clouds
    - 4: Heavy Rain + Ice Pallets + Thunderstorm + Mist, Snow + Fog
- temp : temperature in Celsius
- atemp: feeling temperature in Celsius
- hum: humidity
- windspeed: wind speed
- casual: count of casual users
- registered: count of registered users
- cnt: count of total rental bikes including both casual and registered

===
License
===

Use of this dataset in publications must be cited to the following publication:

[1] Fanaee-T, Hadi, and Gama, Joao, "Event labeling combining ensemble detectors and background knowledge", Progress in Artificial Intelligence (2013): pp. 1-15, Springer Berlin Heidelberg, doi:10.1007/s13748-013-0040-3.

```
@article{
	year={2013},
	issn={2192-6352},
	journal={Progress in Artificial Intelligence},
	doi={10.1007/s13748-013-0040-3},
	title={Event labeling combining ensemble detectors and background knowledge},
	url={http://dx.doi.org/10.1007/s13748-013-0040-3},
	publisher={Springer Berlin Heidelberg},
	keywords={Event labeling; Event detection; Ensemble learning; Background knowledge},
```

```
	author={Fanaee-T, Hadi and Gama, Joao},
	pages={1-15}
}
```

===
Contact
===

For further information about this dataset please contact Hadi Fanaee-T (hadi.fanaee@fe.up.pt)

BONUS_TASK

July 1, 2022

[1]:
```python
# import all libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import re

import sklearn
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import PolynomialFeatures
from sklearn.preprocessing import scale
from sklearn.feature_selection import RFE
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold
from sklearn.model_selection import GridSearchCV
from sklearn.pipeline import make_pipeline

import warnings # supress warnings
warnings.filterwarnings('ignore')
```

[2]:
```python
# Read the given CSV file, and view some sample records

bike = pd.read_csv("day.csv")
bike.head()
```

[2]:
```
   instant      dteday  season  yr  mnth  holiday  weekday  workingday  \
0        1  01-01-2018       1   0     1        0        6           0
1        2  02-01-2018       1   0     1        0        0           0
2        3  03-01-2018       1   0     1        0        1           1
3        4  04-01-2018       1   0     1        0        2           1
4        5  05-01-2018       1   0     1        0        3           1

   weathersit       temp     atemp      hum  windspeed  casual  registered  \
0           2  14.110847  18.18125  80.5833  10.749882     331         654
1           2  14.902598  17.68695  69.6087  16.652113     131         670
```

```
2           1   8.050924   9.47025  43.7273  16.636703     120         1229
3           1   8.200000  10.60610  59.0435  10.739832     108         1454
4           1   9.305237  11.46350  43.6957  12.522300      82         1518

    cnt
0   985
1   801
2  1349
3  1562
4  1600
```

[3]:
```python
bike = bike.drop(['instant'], axis=1)
bike.head()
```

[3]:
```
      dteday  season  yr  mnth  holiday  weekday  workingday  weathersit  \
0  01-01-2018       1   0     1        0        6           0           2
1  02-01-2018       1   0     1        0        0           0           2
2  03-01-2018       1   0     1        0        1           1           1
3  04-01-2018       1   0     1        0        2           1           1
4  05-01-2018       1   0     1        0        3           1           1

        temp     atemp      hum  windspeed  casual  registered   cnt
0  14.110847  18.18125  80.5833  10.749882     331         654   985
1  14.902598  17.68695  69.6087  16.652113     131         670   801
2   8.050924   9.47025  43.7273  16.636703     120        1229  1349
3   8.200000  10.60610  59.0435  10.739832     108        1454  1562
4   9.305237  11.46350  43.6957  12.522300      82        1518  1600
```

[4]:
```python
bike.describe()
```

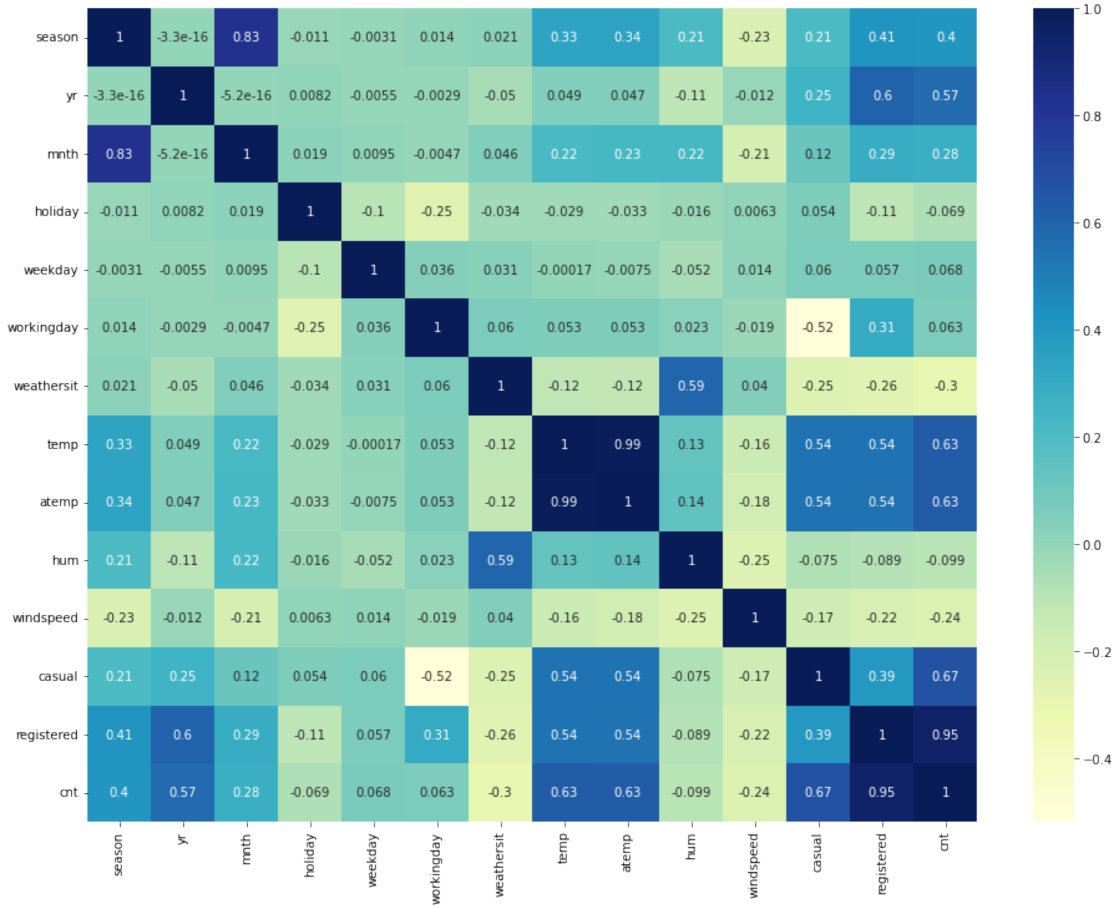
[4]:
```
           season          yr        mnth     holiday     weekday  workingday  \
count  730.000000  730.000000  730.000000  730.000000  730.000000  730.000000
mean     2.498630    0.500000    6.526027    0.028767    2.997260    0.683562
std      1.110184    0.500343    3.450215    0.167266    2.006161    0.465405
min      1.000000    0.000000    1.000000    0.000000    0.000000    0.000000
25%      2.000000    0.000000    4.000000    0.000000    1.000000    0.000000
50%      3.000000    0.500000    7.000000    0.000000    3.000000    1.000000
75%      3.000000    1.000000   10.000000    0.000000    5.000000    1.000000
max      4.000000    1.000000   12.000000    1.000000    6.000000    1.000000

       weathersit        temp       atemp         hum   windspeed  \
count  730.000000  730.000000  730.000000  730.000000  730.000000
mean     1.394521   20.319259   23.726322   62.765175   12.763620
std      0.544807    7.506729    8.150308   14.237589    5.195841
min      1.000000    2.424346    3.953480    0.000000    1.500244
25%      1.000000   13.811885   16.889713   52.000000    9.041650
50%      1.000000   20.465826   24.368225   62.625000   12.125325
```

```
75%      2.000000   26.880615   30.445775   72.989575   15.625589
max      3.000000   35.328347   42.044800   97.250000   34.000021

            casual   registered          cnt
count   730.000000   730.000000   730.000000
mean    849.249315  3658.757534  4508.006849
std     686.479875  1559.758728  1936.011647
min       2.000000    20.000000    22.000000
25%     316.250000  2502.250000  3169.750000
50%     717.000000  3664.500000  4548.500000
75%    1096.500000  4783.250000  5966.000000
max    3410.000000  6946.000000  8714.000000
```

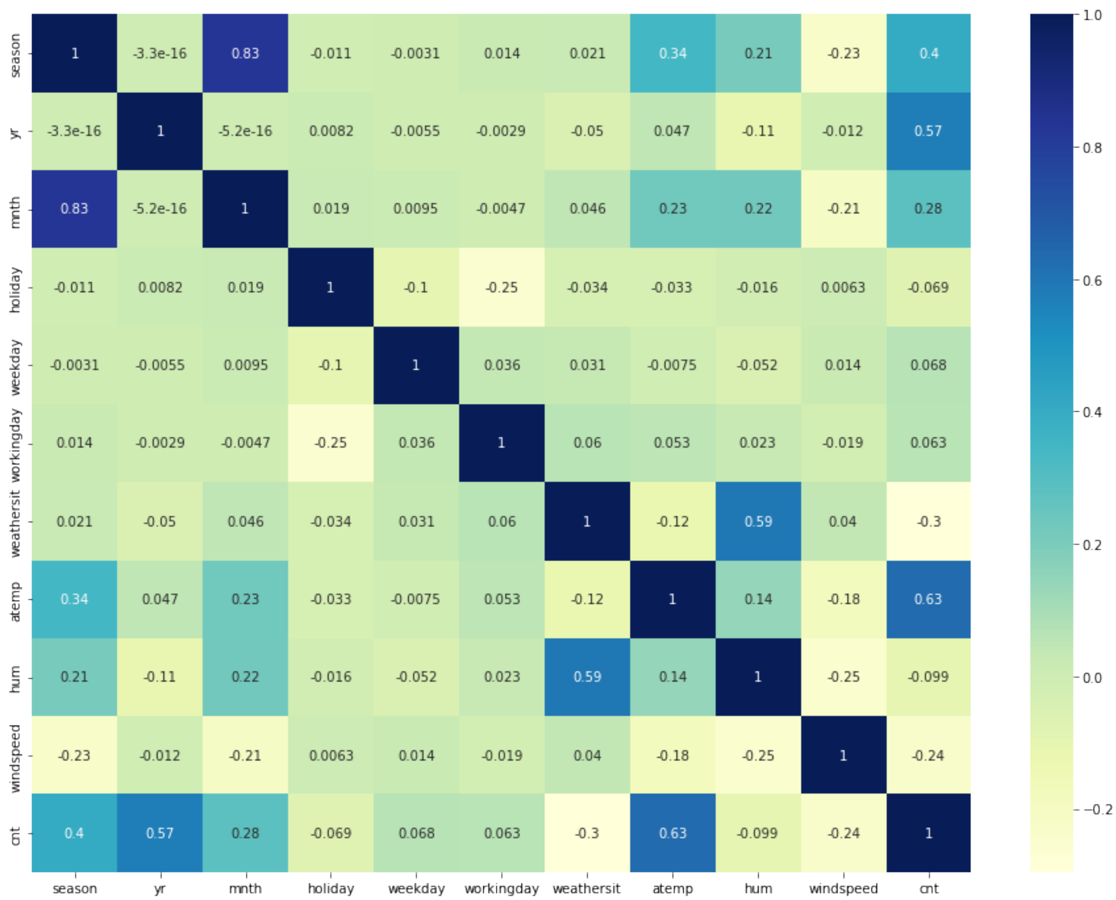
[5]:
```
bike.isnull().sum()    # Missing value check
```

[5]:
```
dteday        0
season        0
yr            0
mnth          0
holiday       0
weekday       0
workingday    0
weathersit    0
temp          0
atemp         0
hum           0
windspeed     0
casual        0
registered    0
cnt           0
dtype: int64
```

[6]:
```
plt.figure(figsize=(16,12))
sns.heatmap(bike.corr(), cmap="YlGnBu", annot = True)
plt.show()
```



[7]:
```python
bike = bike.drop(['temp','casual','registered'], axis=1)  # dropping
↪'temp','casual','registered', because all are highly correlated
plt.figure(figsize=(16,12))
sns.heatmap(bike.corr(), cmap="YlGnBu", annot = True)
plt.show()
```



[8]:
```
bike.head()
```

[8]:
```
      dteday  season  yr  mnth  holiday  weekday  workingday  weathersit  \
0  01-01-2018       1   0     1        0        6           0           2
1  02-01-2018       1   0     1        0        0           0           2
2  03-01-2018       1   0     1        0        1           1           1
3  04-01-2018       1   0     1        0        2           1           1
4  05-01-2018       1   0     1        0        3           1           1

      atemp      hum  windspeed   cnt
0  18.18125  80.5833  10.749882   985
1  17.68695  69.6087  16.652113   801
2   9.47025  43.7273  16.636703  1349
3  10.60610  59.0435  10.739832  1562
4  11.46350  43.6957  12.522300  1600
```

[9]:
```
bike = bike.drop(['dteday'], axis=1)  # It seems that the analysis can be␣
↪possible by dropping 'dteday'.
```

[10]:
```
bike.shape
```

[10]:
```
(730, 11)
```

[11]:
```
bike1=bike
bike1.columns
```

[11]:
```
Index(['season', 'yr', 'mnth', 'holiday', 'weekday', 'workingday',
       'weathersit', 'atemp', 'hum', 'windspeed', 'cnt'],
      dtype='object')
```

[12]:
```
# Get the dummy variables for the feature 'season','mnth','weekday' &␣
↪'weathersit'.
bike1['season']=bike1['season'].astype('category')
bike1['mnth']=bike1['mnth'].astype('category')
bike1['weekday']=bike1['weekday'].astype('category')
bike1['weathersit']=bike1['weathersit'].astype('category')

#status = pd.get_dummies(bike['season'])#,'mnth','weekday','weathersit'])
```

[13]:
```
bike1 = pd.get_dummies(bike1,drop_first = True)
```

[14]:
```
bike1.head()
```

[14]:
```
   yr  holiday  workingday     atemp      hum  windspeed   cnt  season_2  \
0   0        0           0  18.18125  80.5833  10.749882   985         0
1   0        0           0  17.68695  69.6087  16.652113   801         0
2   0        0           1   9.47025  43.7273  16.636703  1349         0
3   0        0           1  10.60610  59.0435  10.739832  1562         0
4   0        0           1  11.46350  43.6957  12.522300  1600         0

   season_3  season_4  …  mnth_11  mnth_12  weekday_1  weekday_2  weekday_3  \
0         0         0  …        0        0          0          0          0
1         0         0  …        0        0          0          0          0
2         0         0  …        0        0          1          0          0
3         0         0  …        0        0          0          1          0
4         0         0  …        0        0          0          0          1

   weekday_4  weekday_5  weekday_6  weathersit_2  weathersit_3
0          0          0          1             1             0
1          0          0          0             1             0
2          0          0          0             0             0
3          0          0          0             0             0
4          0          0          0             0             0

[5 rows x 29 columns]
```

[20]:
```
# filter only atemp=temperature and cnt=price
df = bike1.loc[:, ['atemp', 'cnt']]
df.head()
```

[20]:

	atemp	cnt
0	18.18125	985
1	17.68695	801
2	9.47025	1349
3	10.60610	1562
4	11.46350	1600

[21]:
```
# making normalised value for the two variables
df_columns = df.columns
scaler = MinMaxScaler()
df = scaler.fit_transform(df)
```

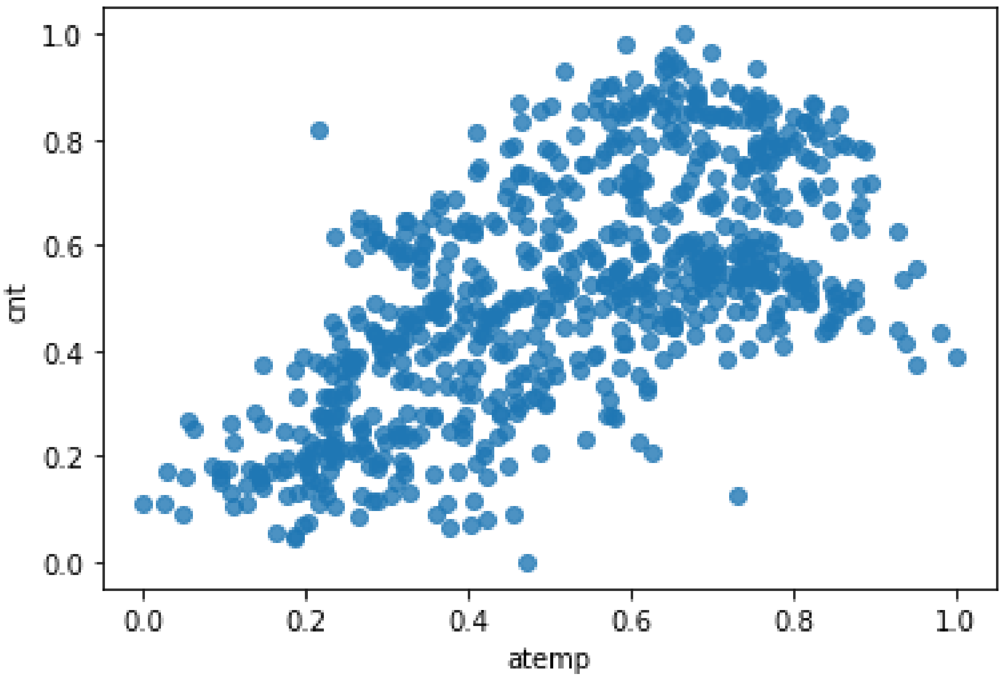
[22]:
```
# rename columns (since now its an np array)
df = pd.DataFrame(df)
df.columns = df_columns

df.head()
```

[22]:

	atemp	cnt
0	0.373517	0.110792
1	0.360541	0.089623
2	0.144830	0.152669
3	0.174649	0.177174
4	0.197158	0.181546

[23]:
```
# visualise temperature-price relationship
sns.regplot(x="atemp", y="cnt", data=df, fit_reg=False)
```

[23]:
```
<AxesSubplot:xlabel='atemp', ylabel='cnt'>
```



[24]:
```
# split into train and test
df_train, df_test = train_test_split(df,
                                     train_size = 0.7,
                                     test_size = 0.3,
                                     random_state = 10)
print(len(df_train))
print(len(df_test))
```

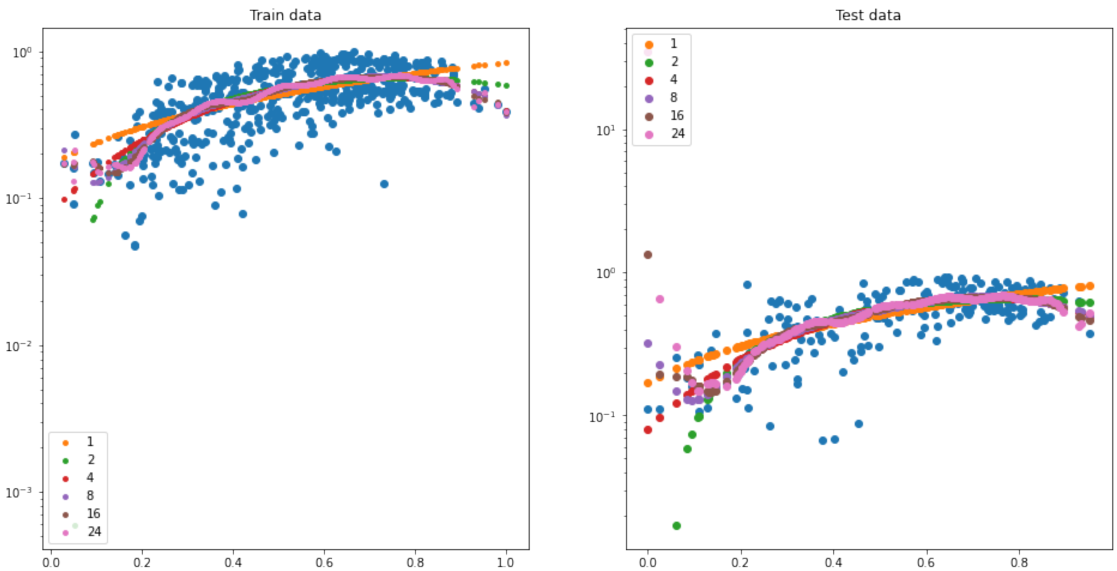
```
510
219
```

[25]:
```
# split into X and y for both train and test sets
# reshaping is required since sklearn requires the data to be in shape
X_train = df_train['atemp']
X_train = X_train.values.reshape(-1, 1)
y_train = df_train['cnt']

X_test = df_test['atemp']
X_test = X_test.values.reshape(-1, 1)
y_test = df_test['cnt']
```

0.0.1 Polynomial Regression

[26]:
```
# fit multiple polynomial features
degrees = [1, 2, 4, 8, 16, 24]

# initialise y_train_pred and y_test_pred matrices to store the train and test␣
↪predictions
# each row is a data point, each column a prediction using a polynomial of some␣
↪degree
y_train_pred = np.zeros((len(X_train), len(degrees)))
y_test_pred = np.zeros((len(X_test), len(degrees)))

for i, degree in enumerate(degrees):

    # make pipeline: create features, then feed them to linear_reg model
    model = make_pipeline(PolynomialFeatures(degree), LinearRegression())
    model.fit(X_train, y_train)

    # predict on test and train data
    # store the predictions of each degree in the corresponding column
    y_train_pred[:, i] = model.predict(X_train)
    y_test_pred[:, i] = model.predict(X_test)
```

[27]:
```
# visualise train and test predictions
# note that the y axis is on a log scale

plt.figure(figsize=(16, 8))

# train data
plt.subplot(121)
plt.scatter(X_train, y_train)
plt.yscale('log')
plt.title("Train data")
for i, degree in enumerate(degrees):
    plt.scatter(X_train, y_train_pred[:, i], s=15, label=str(degree))
    plt.legend(loc='lower left')

# test data
plt.subplot(122)
plt.scatter(X_test, y_test)
plt.yscale('log')
plt.title("Test data")
for i, degree in enumerate(degrees):
    plt.scatter(X_test, y_test_pred[:, i], label=str(degree))
    plt.legend(loc='upper left')
```




```
[28]: print("R-squared values: \n")

      for i, degree in enumerate(degrees):
          train_r2 = round(sklearn.metrics.r2_score(y_train, y_train_pred[:, i]), 2)
          test_r2 = round(sklearn.metrics.r2_score(y_test, y_test_pred[:, i]), 2)
          print("Polynomial degree {0}: train score={1}, test score={2}".
       ↪format(degree,
                                                                                    ␣
       ↪train_r2,
                                                                                    ␣
       ↪test_r2))
```

```
R-squared values:

Polynomial degree 1: train score=0.39, test score=0.43
Polynomial degree 2: train score=0.45, test score=0.46
Polynomial degree 4: train score=0.46, test score=0.49
Polynomial degree 8: train score=0.46, test score=0.48
Polynomial degree 16: train score=0.46, test score=0.35
Polynomial degree 24: train score=0.47, test score=-117.9
```

0.0.2 Model Without Cross-Validation

Let's now build a multiple regression model. First, let's build a vanilla MLR model without any cross-validation etc.

```
[29]: bike1.head()
```

[29]:

```
   yr  holiday  workingday     atemp      hum  windspeed   cnt  season_2  \
0   0        0           0  18.18125  80.5833  10.749882   985         0
1   0        0           0  17.68695  69.6087  16.652113   801         0
2   0        0           1   9.47025  43.7273  16.636703  1349         0
3   0        0           1  10.60610  59.0435  10.739832  1562         0
4   0        0           1  11.46350  43.6957  12.522300  1600         0

   season_3  season_4  …  mnth_11  mnth_12  weekday_1  weekday_2  weekday_3  \
0         0         0  …        0        0          0          0          0
1         0         0  …        0        0          0          0          0
2         0         0  …        0        0          1          0          0
3         0         0  …        0        0          0          1          0
4         0         0  …        0        0          0          0          1

   weekday_4  weekday_5  weekday_6  weathersit_2  weathersit_3
0          0          0          1             1             0
1          0          0          0             1             0
2          0          0          0             0             0
3          0          0          0             0             0
4          0          0          0             0             0

[5 rows x 29 columns]
```

[24]:

```
bike1.holiday.value_counts()
```

[24]:

```
0    709
1     21
Name: holiday, dtype: int64
```

[30]:

```
# train-test 70-30 split
df_train, df_test = train_test_split(bike1,
                                     train_size = 0.7,
                                     test_size = 0.3,
                                     random_state = 100)

# normalize the features
scaler = MinMaxScaler()

# apply scaler() to all the numeric columns
numeric_vars = ['atemp', 'hum', 'windspeed', 'cnt']
df_train[numeric_vars] = scaler.fit_transform(df_train[numeric_vars])
df_train.head()
```

[30]:

```
     yr  holiday  workingday     atemp       hum  windspeed       cnt  \
653   1        0           1  0.501133  0.575354   0.300794  0.864243
576   1        0           1  0.766351  0.725633   0.264686  0.827658
426   1        0           0  0.438975  0.640189   0.255342  0.465255
```

```
728   1         0           0  0.200348  0.498067   0.663106  0.204096
482   1         0           0  0.391735  0.504508   0.188475  0.482973

     season_2  season_3  season_4  …  mnth_11  mnth_12  weekday_1  \
653         0         0         1  …        0        0          0
576         0         1         0  …        0        0          0
426         0         0         0  …        0        0          0
728         0         0         0  …        0        1          0
482         1         0         0  …        0        0          0

     weekday_2  weekday_3  weekday_4  weekday_5  weekday_6  weathersit_2  \
653          1          0          0          0          0             0
576          1          0          0          0          0             0
426          0          0          0          0          1             1
728          0          0          0          0          0             0
482          0          0          0          0          1             1

     weathersit_3
653             0
576             0
426             0
728             0
482             0

[5 rows x 29 columns]
```

[31]:
```
# apply rescaling to the test set also
df_test[numeric_vars] = scaler.fit_transform(df_test[numeric_vars])
df_test.head()
```

[31]:
```
     yr  holiday  workingday     atemp       hum  windspeed       cnt  \
184   0        1           0  0.778767  0.534223   0.149393  0.704300
535   1        0           1  0.855132  0.470417   0.231142  0.725421
299   0        0           1  0.492359  0.777843   0.443398  0.278853
221   0        0           1  0.805661  0.236659   0.449707  0.545512
152   0        0           1  0.749249  0.070765   0.682387  0.569148

     season_2  season_3  season_4  …  mnth_11  mnth_12  weekday_1  \
184         0         1         0  …        0        0          1
535         1         0         0  …        0        0          0
299         0         0         1  …        0        0          0
221         0         1         0  …        0        0          0
152         1         0         0  …        0        0          0

     weekday_2  weekday_3  weekday_4  weekday_5  weekday_6  weathersit_2  \
184          0          0          0          0          0             1
535          0          1          0          0          0             0
```

```
299            0            0            1            0            0              1
221            0            1            0            0            0              0
152            0            0            1            0            0              0

     weathersit_3
184              0
535              0
299              0
221              0
152              0

[5 rows x 29 columns]
```

[32]:
```
# divide into X_train, y_train, X_test, y_test
y_train = df_train.pop('cnt')
X_train = df_train

y_test = df_test.pop('cnt')
X_test = df_test
```

Using RFE

[33]:
```
# num of max features
len(X_train.columns)
```

[33]: 28

[34]:
```
# first model with an arbitrary choice of n_features, running RFE with number␣
 ↪of features=10

lm = LinearRegression()
lm.fit(X_train, y_train)

rfe = RFE(lm, n_features_to_select=10)
rfe = rfe.fit(X_train, y_train)
```

[35]:
```
# tuples of (feature name, whether selected, ranking)
list(zip(X_train.columns,rfe.support_,rfe.ranking_))
```

[35]:
```
[('yr', True, 1),
 ('holiday', True, 1),
 ('workingday', False, 6),
 ('atemp', True, 1),
 ('hum', True, 1),
 ('windspeed', True, 1),
 ('season_2', True, 1),
 ('season_3', False, 3),
```

```
('season_4', True, 1),
('mnth_2', False, 12),
('mnth_3', False, 8),
('mnth_4', False, 10),
('mnth_5', False, 7),
('mnth_6', False, 9),
('mnth_7', False, 11),
('mnth_8', True, 1),
('mnth_9', True, 1),
('mnth_10', False, 4),
('mnth_11', False, 16),
('mnth_12', False, 19),
('weekday_1', False, 13),
('weekday_2', False, 14),
('weekday_3', False, 17),
('weekday_4', False, 18),
('weekday_5', False, 15),
('weekday_6', False, 5),
('weathersit_2', False, 2),
('weathersit_3', True, 1)]
```

[36]:
```
# predict prices of X_test
y_pred = rfe.predict(X_test)

# evaluate the model on test set
r2 = sklearn.metrics.r2_score(y_test, y_pred)
print(r2)
```

```
0.7959862955703852
```

[39]:
```
# when RFE with 5 features
lm = LinearRegression()
lm.fit(X_train, y_train)

rfe = RFE(lm, n_features_to_select=5)
rfe = rfe.fit(X_train, y_train)

# predict prices of X_test
y_pred = rfe.predict(X_test)
r2 = sklearn.metrics.r2_score(y_test, y_pred)
print(r2)
```

```
0.710265394985923
```

0.0.3 Cross-Validation in sklearn

Let's now experiment with k-fold CV.

K-Fold CV

[51]:
```
# k-fold = 5, CV
lm = LinearRegression()
scores = cross_val_score(lm, X_train, y_train, scoring='r2', cv=5)
scores
```

[51]:
```
array([0.81768614, 0.83230968, 0.82617838, 0.81066002, 0.84610108])
```

[53]:
```
# mean score
scores.mean()
```

[53]:
```
0.826587059227623
```

[54]:
```
# Score for  MSE
scores = cross_val_score(lm, X_train, y_train,␣
↪scoring='neg_mean_squared_error', cv=5)
scores
```

[54]:
```
array([-0.00766272, -0.00874205, -0.00910812, -0.00822085, -0.0092011 ])
```

[55]:
```
# number of features in X_train
len(X_train.columns)
```

[55]:
```
28
```

[56]:
```
# step-1: create a cross-validation scheme
folds = KFold(n_splits = 5, shuffle = True, random_state = 100)

# step-2: specify range of hyperparameters to tune
hyper_params = [{'n_features_to_select': list(range(1, 11))}]


# step-3: perform grid search
# 3.1 specify model
lm = LinearRegression()
lm.fit(X_train, y_train)
rfe = RFE(lm)

# 3.2 call GridSearchCV()
model_cv = GridSearchCV(estimator = rfe,
                        param_grid = hyper_params,
                        scoring= 'r2',
                        cv = folds,
                        verbose = 1,
                        return_train_score=True)

# fit the model
```

```
model_cv.fit(X_train, y_train)
```

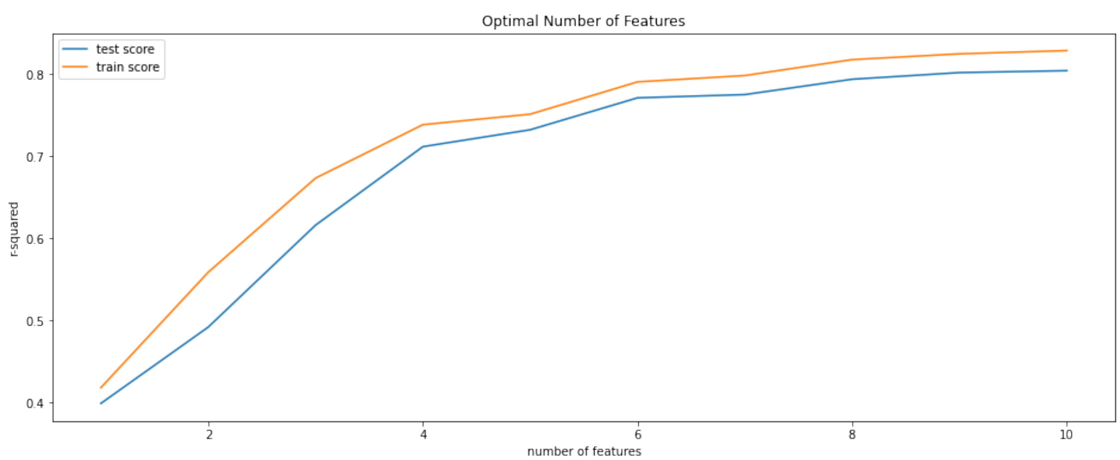
```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
```

[56]:
```
GridSearchCV(cv=KFold(n_splits=5, random_state=100, shuffle=True),
             estimator=RFE(estimator=LinearRegression()),
             param_grid=[{'n_features_to_select': [1, 2, 3, 4, 5, 6, 7, 8, 9,
                                                   10]}],
             return_train_score=True, scoring='r2', verbose=1)
```

[57]:
```
# cv results
cv_results = pd.DataFrame(model_cv.cv_results_)
```

[58]:
```
# plotting cv results
plt.figure(figsize=(16,6))

plt.plot(cv_results["param_n_features_to_select"],␣
 ↪cv_results["mean_test_score"])
plt.plot(cv_results["param_n_features_to_select"],␣
 ↪cv_results["mean_train_score"])
plt.xlabel('number of features')
plt.ylabel('r-squared')
plt.title("Optimal Number of Features")
plt.legend(['test score', 'train score'], loc='upper left')
```

[58]:
```
<matplotlib.legend.Legend at 0x7fac91b4f910>
```



[59]:
```
# final model
n_features_optimal = 10

lm = LinearRegression()
```

```python
lm.fit(X_train, y_train)

rfe = RFE(lm, n_features_to_select=n_features_optimal)
rfe = rfe.fit(X_train, y_train)

# predict prices of X_test
y_pred = lm.predict(X_test)
r2 = sklearn.metrics.r2_score(y_test, y_pred)
print(r2)
```

```
0.8307648240178435
```

the test score is very close to the 'mean test score' on the k-folds (about 83%).

[60]:
```python
#Most important features
col = X_train.columns[rfe.support_]
col
```

[60]:
```
Index(['yr', 'holiday', 'atemp', 'hum', 'windspeed', 'season_2', 'season_4',
       'mnth_8', 'mnth_9', 'weathersit_3'],
      dtype='object')
```

[61]:
```python
#least important features
col = X_train.columns[~rfe.support_]
col
```

[61]:
```
Index(['workingday', 'season_3', 'mnth_2', 'mnth_3', 'mnth_4', 'mnth_5',
       'mnth_6', 'mnth_7', 'mnth_10', 'mnth_11', 'mnth_12', 'weekday_1',
       'weekday_2', 'weekday_3', 'weekday_4', 'weekday_5', 'weekday_6',
       'weathersit_2'],
      dtype='object')
```