```
from sklearn.datasets import load_diabetes
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn import metrics
from sklearn.linear_model import ElasticNet, Lasso, Ridge
from sklearn.model_selection import KFold, cross_val_score


diabetes = load_diabetes()


print(diabetes['DESCR'])
```

```
.. _diabetes_dataset:

Diabetes dataset
----------------

Ten baseline variables, age, sex, body mass index, average blood
pressure, and six blood serum measurements were obtained for each of n =
442 diabetes patients, as well as the response of interest, a
quantitative measure of disease progression one year after baseline.

**Data Set Characteristics:**

  :Number of Instances: 442

  :Number of Attributes: First 10 columns are numeric predictive values

  :Target: Column 11 is a quantitative measure of disease progression one year after bas

  :Attribute Information:
      - age     age in years
      - sex
      - bmi     body mass index
      - bp      average blood pressure
      - s1      tc, total serum cholesterol
      - s2      ldl, low-density lipoproteins
      - s3      hdl, high-density lipoproteins
      - s4      tch, total cholesterol / HDL
      - s5      ltg, possibly log of serum triglycerides level
      - s6      glu, blood sugar level

Note: Each of these 10 feature variables have been mean centered and scaled by the stanc

Source URL:
https://www4.stat.ncsu.edu/~boos/var.select/diabetes.html

For more information see:
Bradley Efron, Trevor Hastie, Iain Johnstone and Robert Tibshirani (2004) "Least Angle R
(https://web.stanford.edu/~hastie/Papers/LARS/LeastAngle_2002.pdf)
```

```
diabetes.data.shape
```

```
(442, 10)
```

```
diabetes.target.shape
```

```
(442,)
```

```
diabetes.feature_names
```

```
['age', 'sex', 'bmi', 'bp', 's1', 's2', 's3', 's4', 's5', 's6']
```

```
import pandas as pd
```

```
pd.set_option('precision', 4)
```

```
pd.set_option('max_columns', 11)
```

```
pd.set_option('display.width', None)
```

```
diabetes_df = pd.DataFrame(diabetes.data, columns=diabetes.feature_names)
diabetes_df['DiseaseProg'] = pd.Series(diabetes.target)
```

```
diabetes_df
```

	age	sex	bmi	bp	s1	s2	s3	s4	s5	s6	D
0	0.0381	0.0507	0.0617	0.0219	-0.0442	-0.0348	-0.0434	-0.0026	0.0199	-0.0176	
1	-0.0019	-0.0446	-0.0515	-0.0263	-0.0084	-0.0192	0.0744	-0.0395	-0.0683	-0.0922	
2	0.0853	0.0507	0.0445	-0.0057	-0.0456	-0.0342	-0.0324	-0.0026	0.0029	-0.0259	
3	-0.0891	-0.0446	-0.0116	-0.0367	0.0122	0.0250	-0.0360	0.0343	0.0227	-0.0094	
4	0.0054	-0.0446	-0.0364	0.0219	0.0039	0.0156	0.0081	-0.0026	-0.0320	-0.0466	
...	...	...	...	...	...	...	...	...	...	...	
437	0.0417	0.0507	0.0197	0.0597	-0.0057	-0.0026	-0.0287	-0.0026	0.0312	0.0072	
438	-0.0055	0.0507	-0.0159	-0.0676	0.0493	0.0792	-0.0287	0.0343	-0.0181	0.0445	
439	0.0417	0.0507	-0.0159	0.0173	-0.0373	-0.0138	-0.0250	-0.0111	-0.0469	0.0155	
440	-0.0455	-0.0446	0.0391	0.0012	0.0163	0.0153	-0.0287	0.0266	0.0445	-0.0259	
441	-0.0455	-0.0446	-0.0730	-0.0814	0.0837	0.0278	0.1738	-0.0395	-0.0042	0.0031	

442 rows × 11 columns

```
diabetes_df.describe()
```

	age	sex	bmi	bp	s1	s2	s3
count	4.4200e+02	4.4200e+02	4.4200e+02	4.4200e+02	4.4200e+02	4.4200e+02	4.4200e+02
mean	-3.6396e-16	1.3099e-16	-8.0140e-16	1.2898e-16	-9.0425e-17	1.3011e-16	-4.5640e-16
std	4.7619e-02	4.7619e-02	4.7619e-02	4.7619e-02	4.7619e-02	4.7619e-02	4.7619e-02
min	-1.0723e-01	-4.4642e-02	-9.0275e-02	-1.1240e-01	-1.2678e-01	-1.1561e-01	-1.0231e-01
25%	-3.7299e-02	-4.4642e-02	-3.4229e-02	-3.6656e-02	-3.4248e-02	-3.0358e-02	-3.5117e-02
50%	5.3831e-03	-4.4642e-02	-7.2838e-03	-5.6706e-03	-4.3209e-03	-3.8191e-03	-6.5845e-03

```
sample_df = diabetes_df.sample(frac=0.1, random_state=17)
```

```
sample_df.head()
```

	age	sex	bmi	bp	s1	s2	s3	s4	s5	s6	D
80	0.0708	-0.0446	0.0121	0.0425	0.0714	0.0535	0.0523	-0.0026	0.0254	-0.0052	
325	-0.0019	-0.0446	0.0542	-0.0665	0.0727	0.0566	-0.0434	0.0849	0.0845	0.0486	
227	0.0671	0.0507	-0.0299	0.0574	-0.0002	-0.0157	0.0744	-0.0506	-0.0385	0.0072	
298	0.0235	0.0507	-0.0375	-0.0470	-0.0910	-0.0755	-0.0324	-0.0395	-0.0308	-0.0135	
58	0.0417	-0.0446	-0.0644	0.0356	0.0122	-0.0580	0.1812	-0.0764	-0.0006	-0.0508	

```
import matplotlib.pyplot as plt

import seaborn as sns

sns.set(font_scale=2)

sns.set_style('whitegrid')


#Remove the commenting from these lines to see the corollary graphs of features to target.
#I commented it out because it made it annoying to scroll through the document.
#for feature in diabetes.feature_names:
  #plt.figure(figsize=(16, 9))
  #sns.scatterplot(data=sample_df, x=feature, y='DiseaseProg', hue='DiseaseProg', palette='co


X_train, X_test, y_train, y_test = train_test_split(diabetes.data, diabetes.target, random_st
```

```
#X_train
#X_test
#y_train
y_test
```

```
array([219.,  70., 202., 230., 111.,  84., 242., 272.,  94.,  96.,  94.,
       252.,  99., 297., 135.,  67., 295., 264., 170., 275., 310.,  64.,
       128., 232., 129., 118., 263.,  77.,  48., 107., 140., 113.,  90.,
       164., 180., 233.,  42.,  84., 172.,  63.,  48., 108., 156., 168.,
        90.,  52., 200.,  87.,  90., 258., 136., 158.,  69.,  72., 171.,
        95.,  72., 151., 168.,  60., 122.,  52., 187., 102., 214., 248.,
       181., 110., 140., 202., 101., 222., 281.,  61.,  89.,  91., 186.,
       220., 237., 233.,  68., 190.,  96.,  72., 153.,  98.,  37.,  63.,
       184., 144., 150., 280., 125.,  59.,  65., 281., 277., 167.,  90.,
        72., 178.,  88., 270., 101., 197.,  97.,  53.,  71., 262.,  52.,
       102.])
```

```
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

```
((331, 10), (111, 10), (331,), (111,))
```

```
lin_reg = LinearRegression()
```

```
lin_reg.fit(X=X_train, y=y_train)
```

```
LinearRegression()
```

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

```
LinearRegression(normalize=False)
```

```
for i, name in enumerate(diabetes.feature_names): print(f'{name:>10}: {lin_reg.coef_[i]}')
#positive result = direct relationship
#negative result = indirect relationship
```

```
       age: 47.74657117353083
       sex: -241.99180361087875
       bmi: 531.9685689647108
        bp: 381.5652992182253
        s1: -918.4902055208906
        s2: 508.2514738468459
        s3: 116.9404049801572
        s4: 269.4850857088445
        s5: 695.8062205026963
        s6: 26.323431441266933
```

```
predicted = lin_reg.predict(X_test)
expected = y_test
```

```
predicted[:5]
```

```
array([137.94979889, 182.53621462, 129.85554049, 292.55738727,
       124.86559124])
```

```
expected[:5]
```

```
array([219.,  70., 202., 230., 111.])
```

```
df = pd.DataFrame()
df['Expected'] = pd.Series(expected)
df['Predicted'] = pd.Series(predicted)
```

```
figure = plt.figure(figsize=(11, 11))
axes = sns.scatterplot(data=df, x='Expected', y='Predicted', hue='Predicted', palette='cool',
```


```
start = min(expected.min(), predicted.min())
end = max(expected.max(), predicted.max())
```

```
axes.set_xlim(start, end)
```

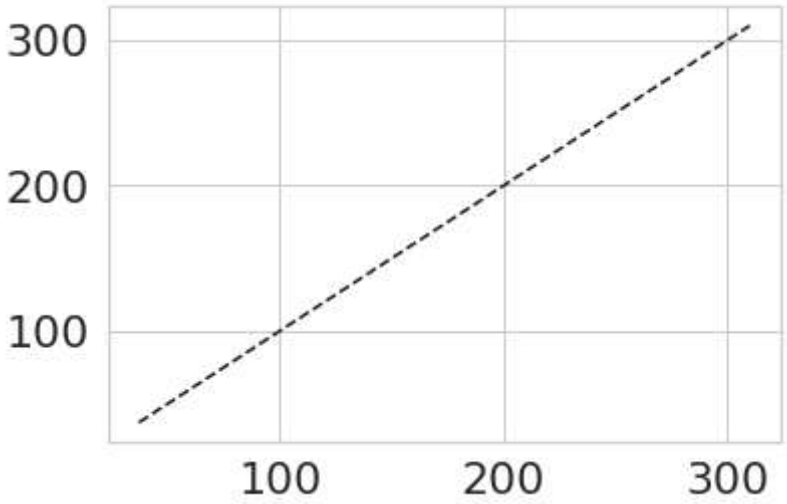
```
(37.0, 310.0)
```

```
axes.set_ylim(start, end)
```

```
(37.0, 310.0)
```

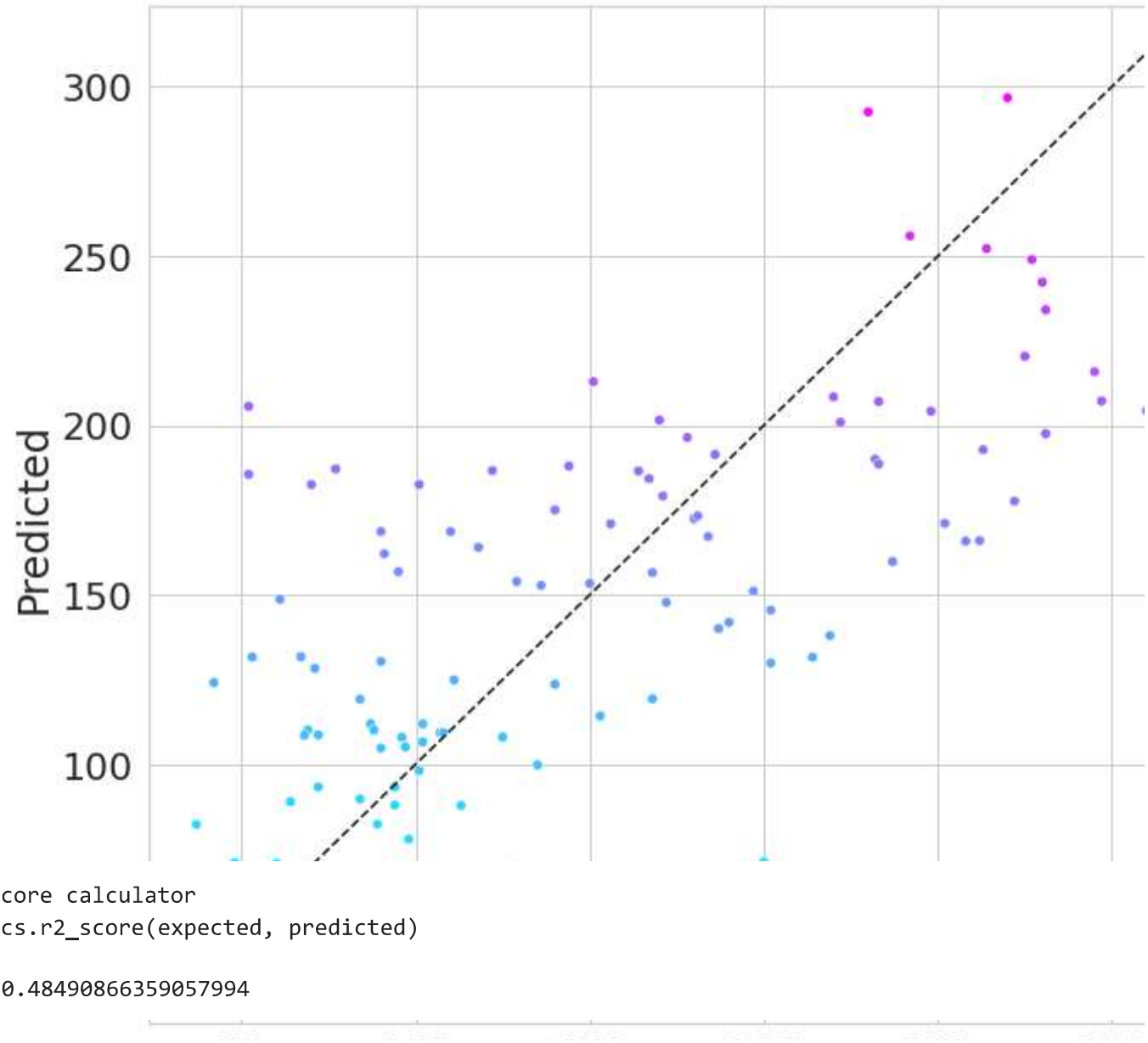
```
#perfect prediction line
plt.plot([start, end], [start, end], 'k--')
```

```
[<matplotlib.lines.Line2D at 0x7f2f4ae5a150>]
```




```
#scatterplot with overlay of the perfect prediction line
figure = plt.figure(figsize=(11, 11))
axes = sns.scatterplot(data=df, x='Expected', y='Predicted', hue='Predicted', palette='cool',
plt.plot([start, end], [start, end], 'k--')
```

```
[<matplotlib.lines.Line2D at 0x7f2f4ae9ba50>]
```




```
#R2 score calculator
metrics.r2_score(expected, predicted)
```

```
0.48490866359057994
```

```
#Mean Squared Error Calculation
metrics.mean_squared_error(expected, predicted)
```

```
2848.2953079329445
```

```
estimators = {'LinearRegression': lin_reg, 'ElasticNet': ElasticNet(), 'Lasso': Lasso(), 'Rid
```

```
#This loop tests several models and returns the R2 score for each
#Since being closer to 1 is best, it looks like the Linear Regression and Rigde scored highes
for estimator_name, estimator_object in estimators.items():
    kfold = KFold(n_splits=10, random_state=11, shuffle=True)
    scores = cross_val_score(estimator=estimator_object, X=diabetes.data, y=diabetes.target,
    print(f'{estimator_name:>16}: ' + f'mean of r2 scores={scores.mean():.3f}')
```

```
LinearRegression: mean of r2 scores=0.475
```

```
ElasticNet: mean of r2 scores=-0.002
     Lasso: mean of r2 scores=0.339
     Ridge: mean of r2 scores=0.421
```