In [ ]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

1. Dataset

Load the prostate dataset.

In [ ]:

```
train_frame = pd.read_csv('./data/prostate_train.csv')
test_frame = pd.read_csv('./data/prostate_test.csv')
```

We will use the target $y =$lpsa throughout this exercise, and all other features as predictors X, so split the train and test sets by X, y.

In [ ]:

```
Xtrain = train_frame.drop('lpsa', axis=1)
ytrain = train_frame['lpsa'].copy()
Xtest = test_frame.drop('lpsa', axis=1)
ytest = test_frame['lpsa'].copy()
```

2. Ridge Regression

Perform Ridge regression with target lpsa and all other features as predictors. Do so for different regularization parameters λ. Plot the resulting coefficients depending on λ, as in ISLR, p.238, Fig. 6.4.

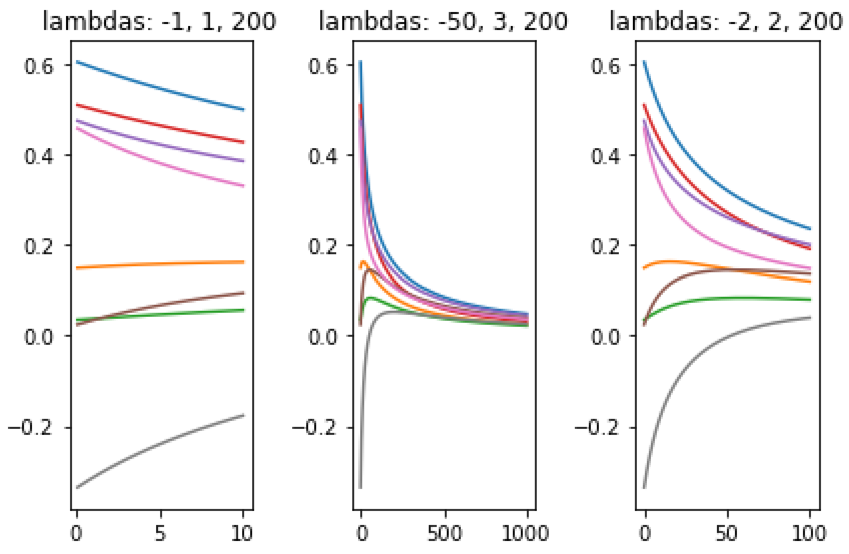
In [ ]:

```
from sklearn.linear_model import Ridge

# This is an example of possible values for the lambda that you can consider.
lambdas = [np.logspace(-1, 1, 200),
            np.logspace(-1, 3, 200),
            np.logspace(-1, 2, 200)]
lambda_labels = ["lambdas: -1, 1, 200", "lambdas: -1, 3, 200", "lambdas: -1, 2, 200"]
def graph(lambdas):
            for l in lambdas:
                ridge = Ridge(alpha=l, fit_intercept=False)
                ridge.fit(Xtrain, ytrain)
                coefs.append(ridge.coef_)

fig, axs = plt.subplots(1,3)
for i in range(3):
    coefs = []
    graph(lambdas[i])
    axs[i].plot(lambdas[i], coefs)
    axs[i].set_title(f"{lambda_labels[i]}")

fig.tight_layout()
plt.show()
```



3. Cross Validation & Ridge

Perform 10-fold cross-validation on the training set to determine the optimal value for λ for the ridge regression model.

In [ ]:
```
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score as cvs

# K-fold cross validation
kf = KFold(n_splits = 10)
ridge = Ridge(alpha=1)
ridge.fit(Xtrain, ytrain)
scores_train = cvs(ridge, Xtrain, ytrain, cv=kf, n_jobs=-1)
scores_test = cvs(ridge, Xtest, ytest, cv=kf, n_jobs=-1)
print(ridge.coef_)
print(scores_train)
print(np.mean(scores_train))
print(scores_test)
print(np.mean(scores_test)) # -0.6516392629457897
```

```
[ 0.65403029  0.30533086 -0.02195116  0.07941491  0.43089049 -0.21907192
  0.01088324  0.10616645]
[-1.27445955e-01 -1.09978052e-01 -1.94520448e+00 -1.90110417e+01
 -3.33274083e+01 -1.05572344e+02 -5.26934966e-01  9.34640581e-02
  5.56247282e-01  5.66930778e-01]
-15.940371493677569
[ 0.96582613  0.08566869  0.25743074 -0.54099494  0.17755024 -1.61104649
  0.59010176 -1.64765749  0.54249855  0.62960077]
-0.05510220240554851
```

Report train and test error measured in MSE for this λ.

In [ ]:

4. Lasso Regression

Perform Lasso regression with target lpsa and all other features as predictors. Do so for different parameters λ.

Plot the resulting coefficients depending on λ, as in ISLR, p.242, Fig. 6.6.

In [ ]:

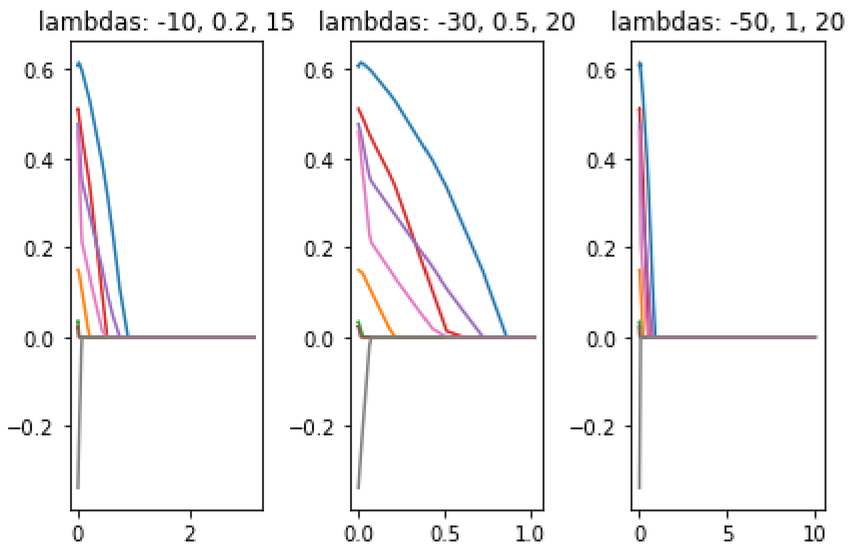
```
from sklearn.linear_model import Lasso

# This is an example of possible values for the lambda that you can consider.
lambdas = [np.logspace(-15, 0.5, 200), # I don't know how to find lambdas that give nic
            np.logspace(-15, 0.01, 200),
            np.logspace(-15, 1, 200)]
lambda_labels = ["lambdas: -15, 0.5, 200", "lambdas: -15, 0.01, 200", "lambdas: -15, 1,

def graph(lambdas):
            for l in lambdas:
                ridge = Lasso(alpha=l, fit_intercept=False)
                ridge.fit(Xtrain, ytrain)
                coefs.append(ridge.coef_)

fig, axs = plt.subplots(1,3)
for i in range(3):
    coefs = []
    graph(lambdas[i])
    axs[i].plot(lambdas[i], coefs)
    axs[i].set_title(f"{lambda_labels[i]}")

fig.tight_layout()
plt.show()
```



5. Cross Validation & Lasso

Perform 10-fold cross-validation on the training set to determine the optimal value for λ in the Lasso. Report train and test error measured in MSE for this λ.

In [ ]:

```
kf = KFold(n_splits = 10)
lasso = Lasso()
lasso.fit(Xtrain, ytrain)
scores_train = cvs(lasso, Xtrain, ytrain, cv=kf, n_jobs=-1)
scores_test = cvs(lasso, Xtest, ytest, cv=kf, n_jobs=-1)
print(lasso.coef_)
print(scores_train)
print(np.mean(scores_train))
print(scores_test)
print(np.mean(scores_test))
```

```
[0. 0. 0. 0. 0. 0. 0. 0.]
[-1.52277598e+00 -6.37610841e-01 -7.26522137e+00 -9.45034810e+00
 -3.76589734e-02 -3.31891211e+01 -1.42816551e+01 -1.55119808e-01
 -1.22333304e+00 -3.02102964e-02]
-6.779305465492792
[-0.00995492 -0.75939607 -0.12880435 -5.29032473  0.01168275 -6.6089785
 -0.54800478 -0.60570702 -0.1283322   0.0862591 ]
-1.398156072270996
```

How many and which features are used? Compare this to the coefficients determined for ridge regression in part 3 of this exercise.

6.

Compare the performance, in terms of MSE, of the best models in parts 3. and 5. Which model would you choose and why? What alternative model could have been used?

Confession:

I feel as though I'm falling further and further behind in this course. I understand the intuition behind most of the concepts in lecture, and for the most part I can brute-force my way through the theoretical questions on the assignments. But when it comes to the programming exercises, there's such a gap between what we've gone over together, and what is being asked in the questions. Assignment 1 and 2 I got most of the programming part correct, but it's just a sea of package documentation, and I'm often not sure what the questions are asking for me to do. It's such a step up from the way we've worked through the concepts, it feels like there's not scaffolding or support to get me from A to B. I would hate to drop the course now, after putting in so much work, but I barely feel like I understand what's happening in these assignments.