HW 16-17

Imports

In [1]:
```
import warnings

import numpy as np
import pandas as pd
from matplotlib import pyplot as plt

warnings.filterwarnings("ignore")
```

HW 16

In [2]:
```
# Setup: copied from HW 13
data: np.ndarray = pd.read_csv("uspopulation.txt", delimiter=" ").values.ast

years = data[:,0]
pops = data[:,1]
```

In [3]:
```
# A
tau = np.linspace(-1, 1, len(years)+1)
tau_pre = tau[:-1]
tau_20 = tau[-1]
```

In [4]:
```
# B

# a design matrix is created as follows:
def design_mat(k: int, vec) -> np.ndarray:
    """ copied from HW 13 """
    A = np.stack([np.polynomial.legendre.Legendre.basis(i)(vec) for i in rar
    return A

# for example, the design matrix given our data and a monomial basis up to k
des_mat = design_mat(11, tau_pre)
pd.DataFrame(des_mat)
```

Out[4]:

	0	1	2	3	4	5	6	7
0	1.0	-1.000000	1.000000	-1.000000	1.000000	-1.000000	1.000000	-1.00000
1	1.0	-0.833333	0.541667	-0.196759	-0.119309	0.336372	-0.414476	0.35313
2	1.0	-0.666667	0.166667	0.259259	-0.427469	0.305556	-0.017233	-0.24056
3	1.0	-0.500000	-0.125000	0.437500	-0.289062	-0.089844	0.323242	-0.22314
4	1.0	-0.333333	-0.333333	0.407407	0.012346	-0.333333	0.193416	0.16598
5	1.0	-0.166667	-0.458333	0.238426	0.274209	-0.273003	-0.145090	0.27891
6	1.0	0.000000	-0.500000	0.000000	0.375000	0.000000	-0.312500	0.00000
7	1.0	0.166667	-0.458333	-0.238426	0.274209	0.273003	-0.145090	-0.27891
8	1.0	0.333333	-0.333333	-0.407407	0.012346	0.333333	0.193416	-0.16598
9	1.0	0.500000	-0.125000	-0.437500	-0.289062	0.089844	0.323242	0.22314
10	1.0	0.666667	0.166667	-0.259259	-0.427469	-0.305556	-0.017233	0.24056
11	1.0	0.833333	0.541667	0.196759	-0.119309	-0.336372	-0.414476	-0.35313

In [5]:

```
# C: adapted from HW 13

df = pd.DataFrame(
     {
          "K": [i+1 for i in range(11)],
          "sum of squared error": [0 for i in range(11)],
          "predicted population in 2020": [0 for i in range(11)],
          "condition number": [0 for i in range(11)]
      }
)

# Let's loop to solve
for i, row in df.iterrows():
     k = row["K"]
     A = design_mat(k, tau_pre)
     theta_hat, sse, rank, s = np.linalg.lstsq(A, pops)
     df.loc[i, "sum of squared error"] = sse
     df.loc[i, "predicted population in 2020"] = design_mat(k, np.array([tau
     df.loc[i, "condition number"] = s[0]/s[-1]


# Here are our results
df

## What do you notice?
# I notice that the predicted population for 2020 still fluctuates as in hom
```

Out[5]:

	K	sum of squared error	predicted population in 2020	condition number
0	1	64833.089851	177.340667	1.000000
1	2	1211.729360	314.443621	1.756048
2	3	106.477333	342.047136	2.432760
3	4	105.948478	341.124798	3.311827
4	5	86.107178	332.065503	4.625532
5	6	65.260770	348.063864	6.922458
6	7	64.757088	352.746326	11.415503
7	8	27.127825	267.999303	21.459975
8	9	20.248611	181.742205	47.127184
9	10	7.605490	508.822167	124.648564
10	11	0.504120	-345.904083	419.481914

HW 17

In [6]:

```
# setup

data: np.ndarray = pd.read_csv("bias-variance-trade.txt", delimiter=" ", hea
x1 = data[:, 0]
y1 = data[:, 1]
x2 = data[:, 2]
y2 = data[:, 3]
```

In [7]:

```
# A

# let's use the function and methods from HW 13 and 16 (copied/adapted from
df = pd.DataFrame(
    {
        "K": [i+1 for i in range(11)],
        "sum of squared error": [0 for i in range(11)],
    }
)

theta_holder_1 = {}

# Let's loop to solve
for i, row in df.iterrows():
    k = row["K"]
    A = design_mat(k, x1)
    theta_hat, sse, rank, s = np.linalg.lstsq(A, y1)
    df.loc[i, "sum of squared error"] = sse
    theta_holder_1[k] = theta_hat

df
```

Out[7]:

	K	sum of squared error
0	1	3.041412
1	2	3.040519
2	3	3.040433
3	4	3.040249
4	5	2.952330
5	6	2.952087
6	7	2.778459
7	8	2.750194
8	9	0.994671
9	10	0.923089
10	11	0.142081

In [8]:
```
# B

# let's use the function and methods from HW 13 and 16 (copied/adapted from
df = pd.DataFrame(
    {
        "K": [i+1 for i in range(11)],
        "sum of squared error": [0 for i in range(11)],
    }
)

theta_holder_2 = {}

# Let's loop to solve
for i, row in df.iterrows():
    k = row["K"]
    A = design_mat(k, x2)
    theta_hat, sse, rank, s = np.linalg.lstsq(A, y2)
    df.loc[i, "sum of squared error"] = sse
    theta_holder_2[k] = theta_hat

df
```

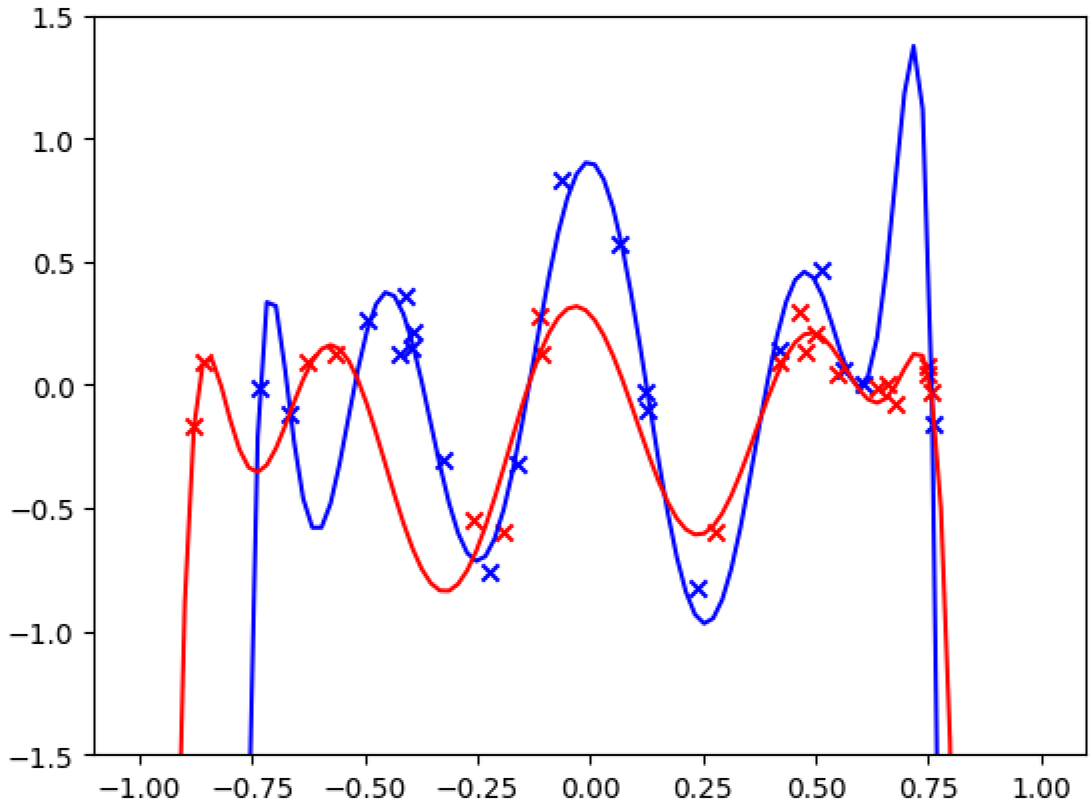
Out[8]:

	K	sum of squared error
0	1	1.331521
1	2	1.301472
2	3	1.239674
3	4	1.225391
4	5	1.110006
5	6	1.103873
6	7	1.025801
7	8	0.864047
8	9	0.479757
9	10	0.477410
10	11	0.165095

In [9]:

```
# C

plt.scatter(x1, y1, color = "b", marker="x")
k1_to_plot = 11
bfx1 = np.linspace(-1, 1, 100)
ttp1 = theta_holder_1[k1_to_plot]
atp1 = design_mat(k1_to_plot, bfx1)
bfy1 = atp1@ttp1
plt.plot(bfx1, bfy1, color="b")

plt.scatter(x2, y2, color = "r", marker="x")
k2_to_plot = 11
bfx2 = np.linspace(-1, 1, 100)
ttp2 = theta_holder_2[k2_to_plot]
atp2 = design_mat(k2_to_plot, bfx2)
bfy2 = atp2@ttp2
plt.plot(bfx2, bfy2, color="r")

plt.ylim(-1.5, 1.5)

# How well does one model fit the data used to train the other model?
# not well -- the models are specific to their datas
```

Out[9]: (-1.5, 1.5)



Acknowledgment

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