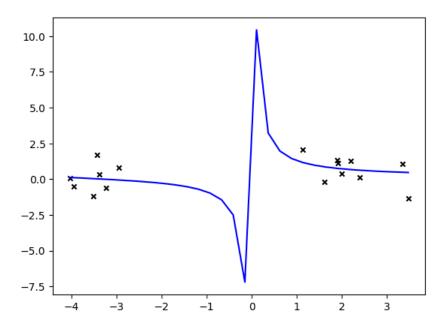
## RYL 6

```
In [1]: # dependencies
        import numpy as np
        import pandas as pd
        from matplotlib import pyplot as plt
        \textbf{from} \ \texttt{scipy.optimize} \ \textbf{import} \ \texttt{minimize}
In [2]: # look at our data
        data = pd.read_csv("ryl6-points.txt", delimiter=r'\s+', header=None).values
        u = data[:, 0]
        y = data[:, 1]
        plt.scatter(u, y)
Out[2]: <matplotlib.collections.PathCollection at 0x116e781a0>
         2.0
         1.5
         1.0
         0.5
         0.0
        -0.5
        -1.0
        -1.5
                                                                ż
                               -2
                                       -1
                                                0
               -4
                       -3
                                                         1
In [3]: # define the model
        def f(theta, u):
             th1, th2, th3, th4 = theta
             numer = th1*u+th2
             denom = th3*u*(u+th4)
             return numer/denom
In [4]: # (a) Fit this model to the data provided.
        # cost
        def c(theta, u, y):
             y_hat = f(theta, u)
             diff = y_hat-y
             return 0.5*np.linalg.norm(diff, ord=2)**2
        # fit. NOTE: 5,5,5,5 was the best I found after trial—and—error with a few combinations
        fit = minimize(c, np.array([5, 5, 5, 5]), (u, y))
        print(f'The best-fit parameters based on a starting point of 5, 5, 5, 5 are: {fit.x}')
        # visualize
        plotting_u = np.linspace(min(u), max(u), 30)
        plotting_y = f(fit.x, plotting_u)
        plt.scatter(u, y, marker="x", color="black", s=20)
        plt.plot(plotting_u, plotting_y, color="blue")
       The best-fit parameters based on a starting point of 5, 5, 5, 5 are: [ 3.10967646 10.24952639 1.09197515
       8.44448953]
```

Out[4]: [<matplotlib.lines.Line2D at 0x11701ad50>]



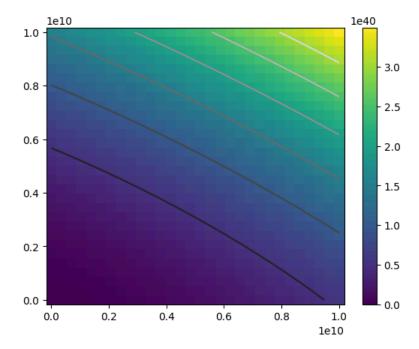
In [5]: # (b) Identify the regimes in parameter space in which one parameter is practically unidentifiable.
# For each regime, find the effective model and fit it to the data. Qualitatively describe the
# feature in the data that the unidentifiable parameter controlled for.

# Let's discuss this by inspection first:
# We can see that th1\*u+th2 / th3\*u\*(u+th4) expands to
# th1\*u + th2 / th3\*u\*\*2 + th3\*th4\*u
# because of this, th3 will overwhelm all other parameters as it goes to infinity by
# effecting u\*\*2--this makes the rest of the parameters practically unidentifiable.
# Oppositely, th2 is only a constant, so it is practically unidentifiable for large u.
# Setting these constant, th1\*u/(th3\*th4\*u) evaluates to 1 when th1==th3\*th4. th3/th4 is
# unidentifiable because in the model th4 is always multiplied by th3.
# setting th2 and th3 constant, th1 and th4 have an equal effect on the function.

```
In [7]: # th1 vs. th2
    plt.contour(*my_meshgrid, cost_surface[:, :, 0, 0], cmap="grey")
    p = plt.pcolormesh(*my_meshgrid, cost_surface[:, :, 0, 0])
    plt.colorbar(p)

# Here we see a positive relationship between th1 and th2. For
# constant th3 & th4 the function effectively becomes th1*u + th2 / u**2.
```

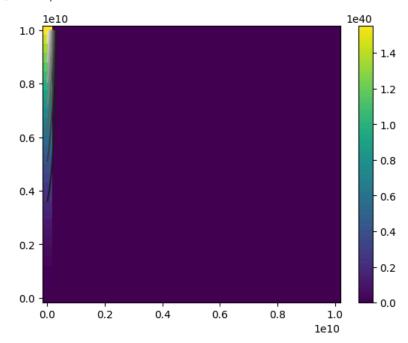
Out[7]: <matplotlib.colorbar.Colorbar at 0x116e79be0>



```
In [8]: # th1 vs. th3
plt.contour(*my_meshgrid, cost_surface[:, 0, :, 0], cmap="grey")
p = plt.pcolormesh(*my_meshgrid, cost_surface[:, 0, :, 0])
plt.colorbar(p)

# Here we see th3 overwhelming th1, making th1 practically unidentifiable as
# previously discussed.
```

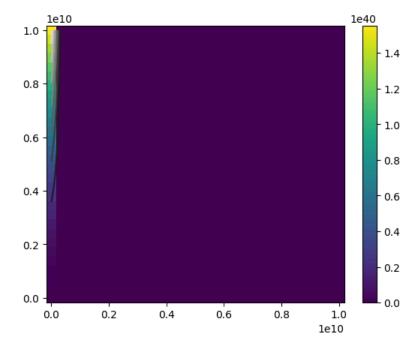
Out[8]: <matplotlib.colorbar.Colorbar at 0x117383110>



```
In [9]: # th1 vs. th4
plt.contour(*my_meshgrid, cost_surface[:, 0, 0, :], cmap="grey")
p = plt.pcolormesh(*my_meshgrid, cost_surface[:, 0, 0, :])
plt.colorbar(p)

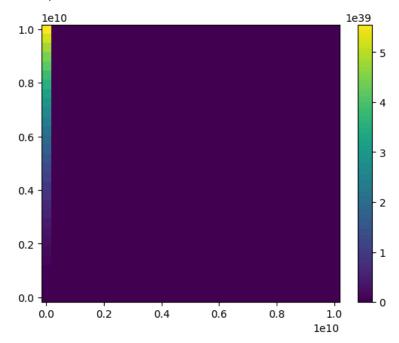
# as th4 goes to infinity, it makes th1 practically unidentifiable.
# this is because th4 is not actually unidentifiable, but is tied to th3,
# which has polynomial effect on the function.
```

Out[9]: <matplotlib.colorbar.Colorbar at 0x1174707d0>



```
In [10]: # th2 vs. th3
# plt.contour(*my_meshgrid, cost_surface[0, :, :, 0], cmap="grey")
p = plt.pcolormesh(*my_meshgrid, cost_surface[0, :, :, 0])
plt.colorbar(p)
# th3 makes th2 practically unidentifiable as discussed above.
```

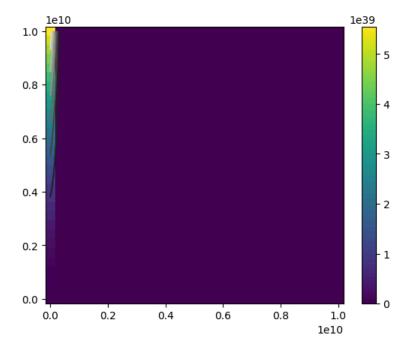
Out[10]: <matplotlib.colorbar.Colorbar at 0x117529a90>



```
In [11]: # th2 vs. th4
plt.contour(*my_meshgrid, cost_surface[0, :, 0, :], cmap="grey")
p = plt.pcolormesh(*my_meshgrid, cost_surface[0, :, 0, :])
plt.colorbar(p)

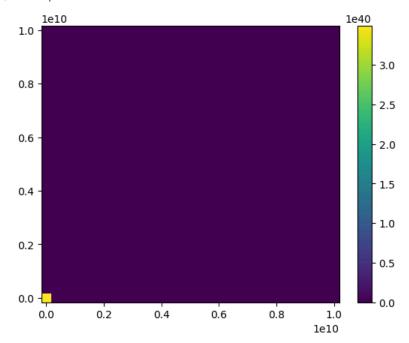
# th4 makes th2 practically unidentifiable as discussed with th1 vs. th4:
# this is because th4 is not actually unidentifiable, but is tied to th3,
# which has polynomial effect on the function.
```

Out[11]: <matplotlib.colorbar.Colorbar at 0x1175e9d10>



```
In [12]: # th3 vs. th4
# plt.contour(*my_meshgrid, cost_surface[15, 0, :, :], cmap="grey")
p = plt.pcolormesh(*my_meshgrid, cost_surface[29, 29, :, :])
plt.colorbar(p)
# th3/th4 is unidentifiable, corresponding to this uninteresting,
# virtually constant 0 loss surface
```

Out[12]: <matplotlib.colorbar.Colorbar at 0x1176a9e50>



## Note

I did not use the one page of notes allowed for RYL's