

## Homework 6: Least Squares

Due date: Sunday March 29, 2020

See the course website for instructions and submission details.

1. **Hovercraft rendezvous.** Alice and Bob are cruising on Lake Mendota in their hovercrafts. Each hovercraft has the following dynamics:

$$\begin{aligned} \text{Dynamics of each hovercraft:} \quad x_{t+1} &= x_t + \frac{1}{3600}v_t \\ v_{t+1} &= v_t + u_t \end{aligned}$$

At time  $t$  (in seconds),  $x_t \in \mathbb{R}^2$  is the position (in miles),  $v_t \in \mathbb{R}^2$  is the velocity (in miles per hour), and  $u_t \in \mathbb{R}^2$  is the thrust in normalized units. At  $t = 1$ , Alice has a speed of 20 mph going North, and Bob is located **half a mile East of Alice**, moving due East at 30 mph. Alice and Bob would like to rendezvous at exactly  $t = 60$  seconds. **The location where they meet is up to you.**

- a) **Find** the sequence of thruster inputs for Alice ( $u^A$ ) and Bob ( $u^B$ ) that achieves a rendezvous at  $t = 60$  while minimizing the total energy used by both hovercraft:

$$\text{total energy} = \sum_{t=1}^{60} \|u_t^A\|^2 + \sum_{t=1}^{60} \|u_t^B\|^2$$

**Plot** the trajectories of each hovercraft to **verify that they do indeed rendezvous.**

- b) In addition to arriving at the same place at the same time, Alice and Bob should also make sure their **velocity vectors match** when they rendezvous (otherwise, they might crash!) Solve the rendezvous problem again with the additional velocity matching constraint and plot the resulting trajectories. **Is the optimal rendezvous location different from the one found in the first part?**

2. **Quadratic form positivity.** You're presented with the constraint:

$$2x^2 + 2y^2 + 9z^2 + 8xy - 6xz - 6yz \leq 1 \tag{1}$$

- a) Write the constraint (1) in the standard form  $v^T Q v \leq 1$ . Where  $Q$  is a symmetric matrix. What is  $Q$  and what is  $v$ ?
- b) It turns out the above constraint is *not* convex. In other words, the set of  $(x, y, z)$  satisfying the constraint (1) is not an ellipsoid. Explain why this is the case.

**Note:** you can perform an orthogonal decomposition of a symmetric matrix  $Q$  in Julia like this:

```
(L,U) = eigen(Q)    # L is the vector of eigenvalues and U is orthogonal
U * diagm(L) * U'    # this is equal to Q (as long as Q was symmetric to begin with)
```

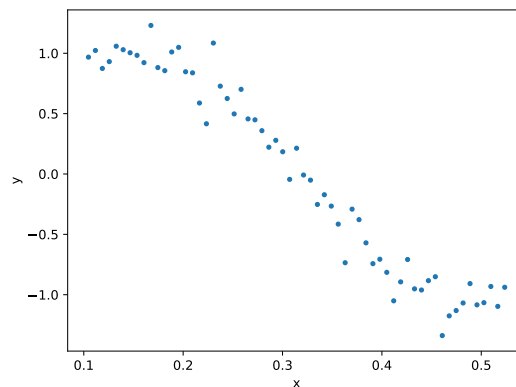
- c) We can also write the constraint (1) using norms by putting it in the form:

$$\|Av\|^2 - \|Bv\|^2 \leq 1$$

What is  $v$  and what are the matrices  $A$  and  $B$  that make the constraint above equivalent to (1)?

- d) Explain how to find a direction for vector  $(x, y, z)$  such that  $\|(x, y, z)\|_2$  (norm) is unbounded (can be made arbitrarily large) while satisfying the constraint (1).

**3. Lasso regression.** Consider the data  $(x, y)$  plotted below, available in `lasso_data.csv`.



In this problem, we will investigate different approaches for performing polynomial regression.

- a) Perform ordinary polynomial regression. Make plots that show the data as well as the best fit to the data for polynomials of degree  $d = 5$  and  $d = 15$ . Also comment on the magnitudes of the coefficients in the resulting polynomial fits. Are they small or large?
- b) In order to get smaller coefficients, we will use ridge regression ( $L_2$  regularization). Re-solve the  $d = 15$  version of the problem using a regularization parameter  $\lambda = 10^{-6}$  and plot the new fit. How does the fit change compared to the non-regularized case of part a? How do the magnitudes of the coefficients in the resulting polynomial fit change?
- c) Our model is still complicated because it has so many parameters. One way to simplify our model is to look for a sparse model (where many of the parameters are zero). Solve the  $d = 15$  problem once more, but this time use the Lasso ( $L_1$  regularization). Start with a large  $\lambda$  and progressively make  $\lambda$  smaller until you obtain a model with a small number of parameters that fits the data reasonably well. Note: due to numerical inaccuracy in the solver, you may need to round very small coefficients (say less than  $10^{-5}$ ) down to zero. Plot the resulting fit.