

Homework 4: Convex Functions

Instructions

Please submit a .qmd file along with a rendered pdf to the Brightspace page for this assignment. You may use whatever language you like within your qmd file, I recommend python, julia, or R.

Problem 1: (Exercise 3.2 in CVX Book)

- (a) The figure below shows three levels sets for a function f . The value of the function on the level set is indicated by the number next to each curve. For example, the curve labeled 1 corresponds to the points $\mathbf{x} \in \mathbb{R}^2$ satisfying $f(\mathbf{x}) = 1$. Determine whether it is possible for the function f to be convex, concave, quasiconvex, or quasiconcave. Give a brief justification for your answer. Note: it may be that several options are possible, that one is possible, or that none at all are.

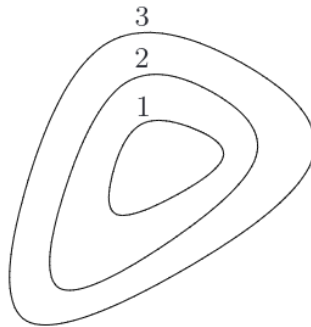


Figure 1: Level Curves of f

- (b) The figure below shows level sets for a different function g . Again determine whether it is possible for the function g to be convex, concave, quasiconvex, or quasiconcave. Note: it may be that several options are possible, that one is possible, or that none at all are.



Figure 2: Level Curves of g

Problem 2: (CVX Book Extended Exercises 3.1)

Determine the curvature of the functions below. Your responses can be affine, convex, concave, or none (meaning not convex or concave). Provide a brief justification

- (a) $f(x) = \min(2, x, \sqrt{x})$ with $\text{dom} f = \{x \mid x \geq 0\}$ (i.e. \mathbb{R}_+)
- (b) $f(x) = x^3$, with $\text{dom} f = \mathbb{R}$
- (c) $f(x) = x^3$, with $\text{dom} f = \{x \mid x \geq 1\}$
- (d) $f(x, y) = \sqrt{x \min(y, 2)}$, with $\text{dom} f = \{(x, y) \mid x \geq 0, y \geq 0\}$ (i.e. \mathbb{R}_+^2)
- (e) $f(x, y) = (\sqrt{x} + \sqrt{y})^2$ with $\text{dom} f = \{(x, y) \mid x \geq 0, y \geq 0\}$ (i.e. \mathbb{R}_+^2)

Problem 3: (Selected from CVX Book Extended Exercises 3.51-3.52)

For each of the following problems implement the following functions using Disciplined Convex Programming and CVX, and use CVX to verify that they are convex

- (a) $f(x, y) = \frac{1}{xy}$, with $\text{dom} f = \mathbb{R}_{++}^2$. Hint: Use the Atoms listed below part (b) as well as addition, subtraction, and scalar multiplication. There are multiple ways to solve this problem.
- (b) $f(x, y) = \sqrt{1 + \frac{x^2}{y}}$, with $\text{dom} f = \mathbb{R} \times \mathbb{R}_{++}$ (this means x is any real number and y is strictly greater than 0).

Hint: The following atoms may be helpful, there are multiple ways to solve this problem.

- `inv_pos(u)`, which is $1/u$, with domain \mathbb{R}_{++}
- `square(u)`, which is u^2 , with domain \mathbb{R}
- `sqrt(u)`, which is \sqrt{u} , with domain \mathbb{R}_+
- `geo_mean(u, v)`, which is \sqrt{uv} , with domain \mathbb{R}_+^2

- `quad_over_lin(u,v)`, which is u^2/v , with domain $\mathbb{R} \times \mathbb{R}_{++}$
- `norm2(u,v)`, which is $\sqrt{u^2 + v^2}$, with domain \mathbb{R}^2 .

Problem 4: Periodic Poisson Regression to predict Car Crashes

For this problem, we will be working with the dataset [nyc_crashes.csv](#), which contains a time series of the number of car crashes occurring in Manhattan every hour for a period of time. Here we will develop a Poisson regression model to predict rate of crashes during each time of day.

- (a) Consider the following statistical model for the number of crashes N_i during hour i of a given day.

$$N_i \sim \exp(-\lambda_i) \frac{\lambda_i^{N_i}}{N_i!}$$

where i ranges from 0 to 23 and corresponds to the hour of the day. Suppose that we have a dataset of counts for crashes where C_{ni} is the number of crashes that occur in the i th hour of the n th day. Then the log likelihood function for the parameters λ is:

$$-\log(p(C|\lambda)) = \sum_{n=1}^N \sum_{i=0}^{23} (\lambda_i - C_{ni} \log(\lambda_i) + \log(C_{ni}!))$$

However, we can drop terms that don't depend on λ because they will have no impact on the maximum likelihood solution. This lets us form a simpler objective function:

$$L(C|\lambda) = \sum_{n=1}^N \sum_{i=0}^{23} (\lambda_i - C_{ni} \log(\lambda_i))$$

or if we use matrix-vector notation:

$$L(C|\lambda) = N\mathbf{1}^T \lambda - \mathbf{1}^T C \log(\lambda)$$

where $\log(\lambda)$ is interpreted as a vector whose i th entry is $\log(\lambda_i)$ and the vector $\mathbf{1}^T$ has all entries equal to 1 and has the right dimension in each case to make the resulting expressions scalars (24 and N , for our dataset N will be 43).

Show that $L(C|\lambda)$ is a convex function of the coefficients λ on the domain $\lambda \in \mathbb{R}_{++}^{24}$.

- (b) The log-likelihood function L can be minimized to find the maximum likelihood estimate for the λ coefficients. Formulate this constrained optimization problem in CVX and solve it for the NYC crashes dataset, that is solve:

$$\min_{\lambda} L(C|\lambda) \lambda \in \mathbb{R}_+^{24}$$

Make a plot of the λ coefficients

- (c) It would be reasonable to expect that the rate of crashes in two adjacent hours should be similar, i.e. the observation that there has been a crash at 3:01PM should influence the estimate of the rate of crashes between 2:00PM and 3:00PM in addition to between 3:00PM and 4:00PM. One way to implement this is through the following regularization term, which applies a penalty proportional to the square of the difference between λ_i and λ_{i+1} :

$$L_{pen}(C|\lambda, \rho) = L(C|\lambda) + \rho \left(\sum_{i=1}^{23} (\lambda_i - \lambda_{i+1})^2 + (\lambda_0 - \lambda_{23})^2 \right)$$

Assuming that $\rho > 0$, show that $L_{pen}(C|\lambda)$ is a convex function on \mathbb{R}_{++}^{24}

- (d) Formulate the regularized maximum likelihood problem:

$$\min_{\lambda} L_{pen}(C|\lambda, \rho) \lambda \in \mathbb{R}_+^{24}$$

and solve it using **CVX**. Solve it for a range of positive values ρ such that for your smallest values the solution appears like your solution to (b) and for your largest values the λ show much less variation over time.

Hint: There are many ways to implement this penalty term in **cvx**. A way that you might find useful is to define a matrix S where $S_{ii} = 1$, $S_{i,i-1} = -1$ for $i > 1$ and $S_{1,24} = -1$, with $S = 0$ for all other entries:

Then $S\lambda = [(\lambda_1 - \lambda_{24}) \quad (\lambda_2 - \lambda_1) \quad \cdots \quad (\lambda_{24} - \lambda_{23})]^T$, and you can use **cvx.square** and **cvx.sum** to construct the objective.