

# Communicating with convexity

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“Nothing takes place in the world whose meaning is not that of some maximum or minimum.”

LEONHARD EULER (1707-1783)

## INTRODUCTION

Convexity is an important property in optimisation. This is because if a problem is convex then the task of finding a global minimum is reduced to that of finding a local minimum. The importance of finding these minima efficiently in science and engineering has driven the development of software packages, such as `cvxpy`.

Here we show that an interesting problem in communications has a convex formulation that can be easily implemented computationally using the `cvxpy` Python module. This demonstrates `cvxpy` as an invaluable tool for both students and researchers in many areas of science and engineering. First let us introduce what convexity means.

### Convex functions

If a set  $C$  is *convex*, then for any two points  $x, y \in C$ , any point  $z$  along the  $x, y$  line must also  $\in C$  [1, p.23]. More formally, for  $x, y \in C$  and  $\theta \in [0, 1]$ :

$$\theta x + (1 - \theta)y \in C. \quad (1)$$

A function  $f$ , where  $f : \mathbb{R}^n \rightarrow \mathbb{R}$ , is *convex* if  $\forall x, y \in \text{dom} f$  and  $0 \leq \theta \leq 1$  [1, p.67]:

$$f(\theta x + (1 - \theta)y) \leq \theta f(x) + (1 - \theta)f(y). \quad (2)$$

This means that the function is less than or equal to linear, as shown in Fig. 1. A concave function can be made convex by the operation  $f \rightarrow -f$ .

### Convex optimisation

A *convex optimisation problem* has three components:

- a convex *objective function*  $f_0(x)$ ,
- $m$  convex *inequality constraint functions*  $f_i(x)$ ,
- $k$  convex *equality constraint functions*  $g_j(x)$ ,

where  $f, g : \mathbb{R}^n \rightarrow \mathbb{R}$  [1, p.141]. We seek an optimum,  $x^* \in \mathbb{R}^n$ , where  $f_0(x^*)$  is a minimum. Formally the problem is defined as:

$$\begin{aligned} &\text{minimise} && f_0(x) \\ &\text{subject to} && f_i(x) \leq 0, && i \in \{1, \dots, m\} \\ &&& g_j(x) = 0, && j \in \{1, \dots, k\}. \end{aligned} \quad (3)$$

Any local optimum  $x^*$  for a convex optimisation problem is also a global optimum [1, pp.138-139], however an optimum may not be unique.

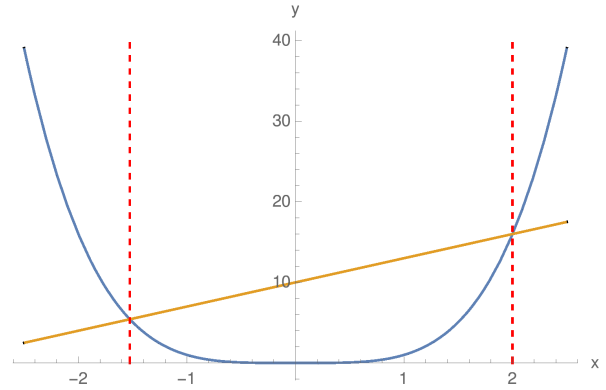


Figure 1. The function  $f(x) = x^4$  is plotted in blue. The convexity of this function can be seen by picking any two values of  $x$  and noting that  $f(x)$  will always lie below or on the chord connecting these two points.

### Disciplined convex programming

In order to solve convex optimisation problems, we used `cvxpy`, a symbolic programming module for *Python*[3]. It uses a set of rules, called *disciplined convex programming* (DCP), to determine whether a function is convex. This is implemented using predefined classes containing functions with their curvature and sign, and using general composition theorems from convex analysis [2]. If DCP rules can be applied then interior point methods guarantee an optimal solution. Interior point methods work by applying Newton's algorithm to sequences of equally constrained problems. The algorithm works by

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picking a step and direction to travel in the interior of the feasible convex set, such that the solution progresses towards optimality, for more details on barrier methods and primal-dual methods see [1, p.561].

#### EXAMPLE: POWER MINIMISATION IN COMMUNICATIONS

To demonstrate the applicability of cvxpy to a real-world example, we consider a system of  $n$  transmitters each of power  $p_k$ , ( $k = 1, 2, \dots, n$ ) and  $m$  receivers, all in 2D Euclidean space[5]. In this problem we are constrained to having a minimum signal-to-interference-plus-noise ratio (SINR or  $\gamma$ ) at each receiver

$$\gamma = \frac{S}{I + \sigma} \quad (4)$$

where  $S$  is the power of the desired signal,  $I$  is the interference power and  $\sigma$  is the background noise at a receiver.

How can we minimise the total power consumption,  $P$ , of transmitters, yet achieve this minimum SINR,  $\gamma_0$ , for all  $i$  receivers ( $i = 1, 2, \dots, m$ )? This question is relevant to telecoms companies who want to offer a service at a minimum quality standard. We formulate the problem with a given square path gain matrix,  $G$ , background noise level vector  $\sigma$ , a maximum power constraint  $P_{\max}$  of each transmitter and the fact that all transmitters must have positive power:

$$\begin{aligned} & \underset{p}{\text{minimise}} && \sum_k p_k \\ & \text{subject to} && p_k \leq P_{\max} \\ & && p_k \geq 0 \\ & && \gamma_i \geq \gamma_0. \end{aligned}$$

Supposing that we want to receive a signal at receiver  $i$  from transmitter  $k$ , we define the recipient matrix,  $\delta$ , as

$$\delta_{ij} = \begin{cases} 1, & j = k \\ 0, & j \neq k \end{cases},$$

and our signal potential matrix  $\hat{S}$  as  $\hat{S} = G * \delta$ . This means that signal received at transmitter  $i$  is,  $S_i = \hat{S}_{ik}p_k = G_{ik}p_k$ . While the interference potential matrix is defined as  $\hat{I} = G - \hat{S}$ , giving the interference at  $i$  is  $I_i = (\hat{I} * p)_i = \sum_{j \neq k} G_{ij}p_j$ . We must note that DCP does not allow division of the optimisation variable  $p_i$ , as it cannot guarantee curvature, so

$$\gamma_i \geq \gamma_0 \iff \frac{S_i}{\sigma_i + I_i} = \frac{\hat{S}_{ik}p_k}{\sigma_i + (\hat{I} * p)_i} \geq \gamma_0, \quad \forall i$$

is rearranged to,

$$\hat{S}_{ik}p_k - \gamma_0(\sigma_i + (\hat{I} * p)_i) \geq 0, \quad \forall i,$$

which is affine, and hence a DCP function.

#### Path gain

In a physical context, the path gain from transmitter  $j$  to receiver  $i$ , as shown in Fig. 2, will depend on the distance,  $d_{ij}$  between them. Assuming isotropic propagation from each transmitter, the fraction of power from  $j$  that reaches  $i$  is:

$$G_{ij} = A_i/d_{ij}^\alpha \quad (5)$$

where  $\alpha$  is the pathloss coefficient and  $k$  is a proportionality constant specific to the receiver  $i$ . For free space  $\alpha = 2$ , while in urban environments  $\alpha \sim 3.5$  [4]. Further physical complexities, such as the stochastic effects from Rayleigh fading can be easily incorporated, whilst remaining within the DCP framework.

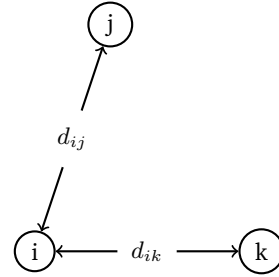


Figure 2. Path lengths between receiver  $i$  and transmitters  $j$  and  $k$ .

#### Implementation

For ease of terminology, we will make a few simplifying assumptions. First, we set the number of transmitters equal to the number of receivers, so  $n = m$ . We also pair receiver  $i$  to transmitter  $k$  such that  $i = k$ . This means that the recipient matrix  $\delta$  is the  $n \times n$  identity matrix.

All the parameters we will take as dimensionless to give simple numbers to work with. The maximum available power,  $P_{\max}$  is set to 1. We have chosen the background noise vector  $\sigma$  as constant for each receiver, with  $\sigma_i = 5$ . Similarly, the receiver coefficient  $A$  was set to 0.025 for each receiver.

To generate the gain matrix  $G$ , we randomly sample distances from a given distribution. For paired transmitters and receivers ( $k = i$ ), we sample  $d$  from a scaled  $\beta(2, 2)$  distribution, such that  $d_{ii} \sim 0.2 \times \text{Beta}(2, 2)$ . For unpaired transmitters and receivers ( $k \neq i$ ), we sample  $d$  from a uniform distribution, such that  $d_{ik} \sim \text{Uniform}(0, 1)$ . This is illustrated in Figure 3.

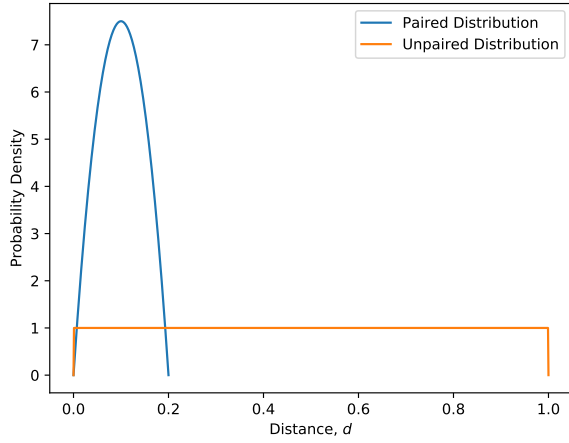


Figure 3. The distance between unpaired transmitters and receivers has a higher variance than paired ones, but on average the unpaired distances are expected to be greater.

### Example code

To indicate the brevity of code implementation in cvxpy we show a minimal working example below. For the random seed of 100 given, the optimal total power consumption is  $P = 0.381$ , with  $p_1, p_2, p_3 = (0.139, 0.072, 0.169)$ . Around 70% of the simulations with these parameters have a feasible solution, with an average optimal power consumption of  $P \sim 0.4$ .

```
import cvxpy as cvx
import numpy as np

np.random.seed(100)

# Define variables
n = 3 # number of transmitters = receivers
A = 0.025 # uniform receiver coefficient
δ = np.identity(n) # identity matrix
# unwanted transmitters d ∈ U[0,1] from receivers
d_unpair = np.random.rand(n,n)
# desired transmitters d ∈ 0.2B[2,2] from receivers
d_pair = np.random.beta(2,2,size=n)*0.20
# make the matrix symmetric
d = np.tril(d_unpair) + np.tril(d_unpair, -1).T - np.diag(d_unpair)*δ + d_pair*δ

G = np.zeros((n,n)) # gain matrix G
G = A / d ** 3.5
S_hat = G * δ # signal potential matrix
I_hat = G - S_hat # interference potential matrix

σ = 5.0 * np.ones(n)
γ = 1.0 # minimum acceptable SINR
Pmax = 1.0 # total power for each transmitter

# Define optimisation variable as the transmitter powers
p = cvx.Variable(n)

# Define objective function as the total power
obj = cvx.Minimize(cvx.sum_entries(p))

# Define constraints
constraints = [p >= 0,
```

```
S_hat * p - γ * (I_hat * p + σ) >= 0,
p <= Pmax]

# Solve problem and print solution
prob = cvx.Problem(obj, constraints)
prob.solve()
powers = np.asarray(p.value)

print('Solution status = {0}'.format(prob.status))
print('Optimal solution = {0:.3f}'.format(prob.value))
if prob.status == 'optimal':
    for j in range(n):
        print('Power {0} = {1:.3f}'.format(j, powers[j][0]))
```

### OUTLOOK

The authors hope that this article shows the utility of cvxpy for simple ‘toy’ problems of real-world relevance. cvxpy can handle problems with up to  $\sim 10^3$  transmitters, however this takes  $\sim 10^4 - 10^5$  ms to run, hence for large real-world problems a faster implementation would likely be required (e.g. C++ based library). However there is obviously a trade off in terms of ease of understanding with these packages.

We believe that cvxpy is an invaluable resource for researchers wanting to test the applicability of convex optimisation in new fields. The module could also be easily incorporated into a course on optimisation, providing students with an accessible environment to practise techniques for convex optimisation. Full code for other communication examples can be found at <https://github.com/cvxgrp/cvxpy/tree/master/examples/communications>.

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### Author Biography

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