

# Convex optimisation in communications with cvxpy

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

LEONARD 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 not only has a convex formulation (as shown in [1]), but can be easily implemented computationally using the *cvxpy* Python module. The ease of implementation makes *cvxpy* an invaluable tool for both students and researchers in many areas of science and engineering.

### Convex Sets and 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  $\theta \in [0, 1]$ :

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

In terms of a function  $f$ , where  $f : \mathbb{R}^n \rightarrow \mathbb{R}$ . For  $f$  to be *convex* then the domain of  $f$ ,  $\text{dom} f$ , must be a convex set and  $\forall x, y \in \text{dom} f$  [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. This can be seen graphically 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  $g_j(x)$ ,

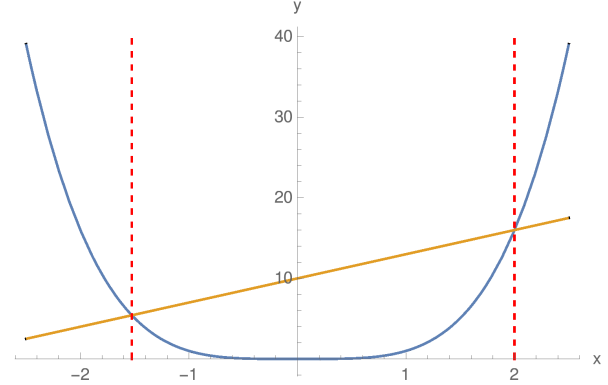


Figure 1. A chord showing convexity of the function  $x^4$ .

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]. An optimum of a convex optimisation problem may not be unique: consider the convex function  $f(x) = \text{const}$ , which has line of optima  $x^*$ .

### Disciplined convex programming

*cvxpy* is a symbolic programming language for *Python* developed by Diamond and Boyd at Stanford[3]. It uses a set of rules, called *disciplined convex programming* (DCP), to determine whether a function is convex. If *cvxpy* finds that the function is convex, then interior point methods can be safely applied, which are guaranteed to find the optimal solution.

To implement DCP, the *cvxpy* package has a set of predefined functions in classes containing their curvature and sign. By only allowing certain operations with these known functions, general composition theorems from convex analysis can be applied to determine the convexity of the more complex expression. See Fig. 2.

The set of available DCP functions do not define the complete set of convex functions. However, as we will show later, a large class of interesting convex problems can be written in DCP format.

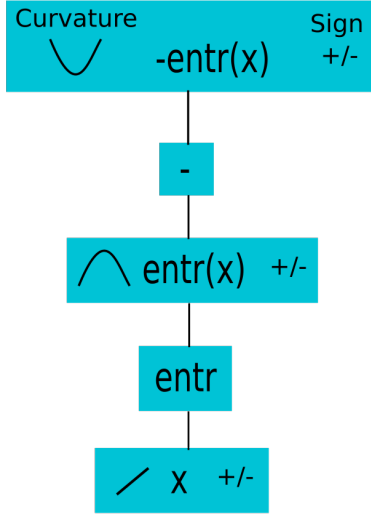


Figure 2. Application of DCP rules to a set of `cvxpy` functions, where  $\text{entr}(x) = -x \log(x)$ . Figure adapted from the Stanford DCP Analyzer [2].

We will show how `cvxpy` can be used simply to test a variety of optimisation problems, as a powerful easy-to-use tool for gaining insight into real-world problems.

#### MINIMUM POWER FOR A GIVEN SINR

How can we minimise the total power consumption  $P$  of  $n$  transmitters each with power  $p_i$ , yet achieve a minimum SINR  $\gamma_0$  for all  $m$  receivers? This question is relevant to a telecoms company 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  $\sigma$  and maximum power value that any transmitter can reach  $P_{\max}$ :

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

(where symbols  $\succ, \succeq$  denote elementwise inequalities between vectors or matrices.)

The desired signal to receiver  $i$  is denoted by  $S_i = G_{ik}p_k$ , while the interference to  $i$  is  $I_i = \sum_{j \neq k} G_{ij}p_j$ . However DCP does not allow division of the optimisation variable  $p_i$  so

$$\gamma_i \geq \gamma_0 \iff \frac{S_i}{\sigma_i + I_i} \geq \gamma_0, \quad \forall i$$

was rearranged to:

$$S_i - \gamma_0(\sigma_i + I_i) \geq 0, \quad \forall i$$

which is DCP.

#### Path gain

The path gain  $G_{ij}$  represents the proportion of power that reaches receiver  $i$  from transmitter  $j$ . Supposing that the desired signal to receiver  $i$  is from transmitter  $k$ , the power received is,

$$p_{ik}^{\text{rec}} = G_{ik}p_k. \quad (4)$$

The signal-to-interference-plus-noise ratio (SINR) is the strength of the desired signal  $S_i$  relative to the interference power  $I_i$  plus the background noise  $\sigma_i$  at  $i$ . Denoting the SINR at  $i$  by  $\gamma_i$ , we have

$$\gamma_i = \frac{G_{ik}p_k}{\sigma_i + \sum_{j \neq k} G_{ij}p_j} = \frac{S_i}{\sigma_i + I_i}. \quad (5)$$

In a physical context, the path gain from transmitter  $j$  to receiver  $i$  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 given by,

$$G_{ij} = k_i / d_{ij}^\alpha \quad (6)$$

where  $\alpha$  is the pathloss coefficient,  $k$  is a proportionality constant specific to the receiver  $i$ . For free space  $\alpha = 2$ , while for an urban environment  $\alpha \sim 3.5$ . Further physical complexities, such as the stochastic effects from Rayleigh fading can be easily implemented.

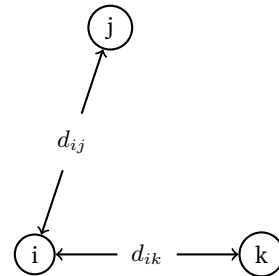


Figure 3. Path lengths between receiver  $i$  and transmitters  $j$  and  $k$ .

#### Example code

To indicate the brevity of code implementation in `cvxpy` we show an abridged version below:

```

# Declare variables
I = np.zeros((n,m)) # interference power matrix
S = np.zeros((n,m)) # signal power matrix
delta = np.identity(n)
S = G * delta # using gains matrix G
I = G - S

# Declare optimisation variable
p = cvx.Variable(n)

# Define objective function
obj = cvx.Minimize(
    cvx.sum_entries(p))

# Declare constraints
constraints = [p >= 0,
               S*p-alpha*(I*p+sigma)>=0,
               p <= Pmax]

# Solve problem
prob = cvx.Problem(obj, constraints)
prob.solve()

```

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- [1] Steven Boyd and L Vandenberghe. *Convex Optimization*. Cambridge University Press, 2004.
  - [2] S. Diamond. Stanford dcp analyzer. <http://dcp.stanford.edu/analyzer>, 2013.
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  - [4] Claude E. Shannon and Warren Weaver. *The mathematical theory of communication*. University of Illinois Press, 1949.

## CONCLUSIONS

This article has shown that a well-known convex problem in communications can be written in a DCP format, meaning that they can be easily implemented in cvxpy.

Our example code demonstrates a key strength of cvxpy, which is that the translation from the mathematical description to python code is straightforward and clear. Conversely, one can also infer the mathematical problem from reading the code.

While all problems that can be written in DCP are convex, not all convex problems of interest can be written in DCP. Over time, the library of available DCP functions in cvxpy has grown, increasing the scope of convex optimisation problems that cvxpy can solve. This expansion of scope of cvxpy is ongoing, with version 1.0 under development and expected in the near future.

## Acknowledgements

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## APPENDIX

Full code can be found at  
<https://github.com/cvxgrp/cvxpy/tree/master/examples/communications>.