# gpcvx <br> A Matlab Solver for Geometric Programs in Convex Form 

Kwangmoo Koh<br>deneb1@stanford.edu<br>Almir Mutapcic<br>almirm@stanford.edu

Seungjean Kim<br>sjkim@stanford.edu<br>Stephen Boyd<br>boyd@stanford.edu

May 22, 2006
gpcvx solves a geometric program (GP) using a phase I/phase II method. The phase I and the phase II solutions are found using gppd2, a primal-dual interior point method described in the book Convex Optimization [BV04].

## 1 The problem

The log-sum-exp function on $\mathbf{R}^{k}$ is defined as

$$
\begin{equation*}
\operatorname{lse}(x)=\log \left(e^{x_{1}}+\cdots+e^{x_{k}}\right) \tag{1}
\end{equation*}
$$

where $x=\left(x_{1}, \ldots, x_{k}\right)$. The entropy function on $\mathbf{R}_{+}^{k}$ is defined as

$$
\begin{equation*}
\operatorname{entr}(y)=-\sum_{i=1}^{k} y_{i} \log y_{i} \tag{2}
\end{equation*}
$$

where $y=\left(y_{1}, \ldots, y_{k}\right)$. For both functions, the number of terms $k$ is determined from context.
gpcvx solves an optimization problem of the form

$$
\begin{array}{ll}
\operatorname{minimize} & \operatorname{lse}\left(A^{(0)} x+b^{(0)}\right) \\
\text { subject to } & \operatorname{lse}\left(A^{(i)} x+b^{(i)}\right) \leq 0, \quad i=1, \ldots, m, \\
& G x+h=0,  \tag{3}\\
& l \preceq x \preceq u,
\end{array}
$$

with variable $x \in \mathbf{R}^{n}$ and parameters $A^{(i)} \in \mathbf{R}^{K_{i} \times n}, b^{(i)} \in \mathbf{R}^{K_{i}}$ for $i=0, \ldots, m, G \in \mathbf{R}^{p \times n}$, $h \in \mathbf{R}^{p}$, and $l, u \in \mathbf{R}^{n}$. Here $\preceq$ means componentwise inequality between vectors. We refer
to the problem (3) as a geometric program in convex form. For more information about geometric programming, see [BV04, BKVH].

To make it easier to derive the dual problem, we form a problem equivalent to (3). We introduce new variables $y^{(i)} \in \mathbf{R}^{K_{i}}$, as well as new equality constraints $y^{(i)}=A^{(i)} x+b^{(i)}$ for $i=0, \ldots, m$. Then we can write the problem (3) as

$$
\begin{array}{ll}
\operatorname{minimize} & \operatorname{lse}\left(y^{(0)}\right) \\
\text { subject to } & \operatorname{lse}\left(y^{(i)}\right) \leq 0, \quad i=1, \ldots, m \\
& A^{(i)} x+b^{(i)}=y^{(i)}, \quad i=0, \ldots, m  \tag{4}\\
& G x+h=0 \\
& l \preceq x \preceq u,
\end{array}
$$

The dual problem of (4) is

$$
\begin{array}{ll}
\operatorname{maximize} & \sum_{i=0}^{m} b^{(i)^{T}} \nu^{(i)}+h^{T} \mu+\lambda_{l}^{T} l-\lambda_{u}^{T} u+\operatorname{entr}\left(\nu^{(0)}\right)+\sum_{i=1}^{m} \lambda^{(i)} \operatorname{entr}\left(\nu^{(i)} / \lambda^{(i)}\right) \\
\text { subject to } & \lambda^{(i)} \geq 0, \quad i=1, \ldots, m, \\
& \nu^{(i)} \succeq 0, \quad i=0, \ldots, m, \\
& \mathbf{1}^{T} \nu^{(0)}=1,  \tag{5}\\
& \mathbf{1}^{T} \nu^{(i)}=\lambda^{(i)}, \quad i=1, \ldots, m, \\
& \sum_{i=0}^{m} A^{(i)^{T}} \nu^{(i)}+G^{T} \mu+\lambda_{u}-\lambda_{l}=0 .
\end{array}
$$

with variables $\mu \in \mathbf{R}^{p}, \lambda_{l}, \lambda_{u} \in \mathbf{R}_{+}^{n}, \lambda^{(i)} \in \mathbf{R}_{+}$for $i=1, \ldots, m$, and $\nu^{(i)} \in \mathbf{R}_{+}^{K_{i}}$ for $i=$ $0, \ldots, m$.

## 2 Calling sequences

The complete calling sequence of gpcvx is
>> [x,status,lambda,nu,mu] = gpcvx(A,b,szs,G,h,l,u,quiet);

Input arguments represent the problem data of (4). Output arguments are the optimal point (if feasible), the solution status, and the dual variables.

### 2.1 Input arguments

- A: matrix with $n$ columns and $\sum_{i=0}^{m} K_{i}$ rows that stacks $A^{(0)}, \ldots, A^{(m)}$ in (4), i.e.,

$$
A=\left[\begin{array}{c}
A^{(0)} \\
\vdots \\
A^{(m)}
\end{array}\right]
$$

A can be in sparse format.

- b: vector of length $\sum_{i=0}^{m} K_{i}$ that stacks $b^{(0)}, \ldots, b^{(m)}$ in (4), i.e.,

$$
b=\left[\begin{array}{c}
b^{(0)} \\
\vdots \\
b^{(m)}
\end{array}\right]
$$

- szs: vector of length $m+1$ that specifies the number of exponential terms in each objective and inequality constraints, i.e., $\left(K_{0}, \ldots, K_{m}\right)$.
- G: matrix with $n$ columns and $p$ rows that specifies $G$ in (4). G can be in sparse format.
- h: $p$-vector that specifies $h$ in (4).
- l: $n$-vector that specifies lower bounds on $x$. If not given, it will be set to the default lower bounds $(-250, \ldots,-250)$.
- u: $n$-vector that specifies upper bounds on $x$. If not given, it will be set to the default upper bounds ( $250, \ldots, 250$ ).
- quiet: boolean. Suppresses print messages during execution if true. The default value is false.


### 2.2 Output arguments

- $\mathrm{x}: n$-vector. x is the optimal point of the problem if the problem is feasible, and x is the last primal iterate of phase I if the problem is infeasible.
- status: string; possible values are 'Solved', 'Infeasible' and 'Failed'.
- lambda: vector of length $m+2 n$; the dual variables associated with inequality constraints if the problem is feasible. The first $m$ elements, lambda ( $1: m$ ), are the dual variables of the $m$ inequality constraints, the next $n$ elements, lambda ( $\mathrm{m}+1: \mathrm{m}+\mathrm{n}$ ), are those of the lower bound constraints ( $l \preceq x)$, and the last $n$ elements, lambda ( $\mathrm{m}+\mathrm{n}: \mathrm{m}+2 * \mathrm{n}$ ), are those of the upper bound constraints $(x \preceq u)$. If the problem is infeasible, lambda is a dual variable vector of phase I, which is a certificate of infeasibility (see [BKVH, §5.8.1,§11.4.3]).
- nu: vector of length $\sum_{i=0}^{m} K_{i}$; the dual variables associated with equality constraints $\left(A^{(i)} x+b^{(i)}=y^{(i)}\right)$ if the problem is feasible. If infeasible, nu is a dual variable vector of phase I, which is a certificate of infeasibility (see [BKVH, §5.8.1,§11.4.3]).
- mu: vector of length $p$; the dual variables associated with equality constraints ( $G x+h=$ 0 ) if the problem is feasible. If the problem is infeasible, mu is a dual variable vector of phase I, which is a certificate of infeasibility (see [BKVH, §5.8.1,§11.4.3]). mu is an empty matrix when there is no equality constraint.


### 2.3 Other calling sequences

Other calling sequences supported by gpcvx are:

```
>> [x,status,lambda,nu,mu] = gpcvx(A,b,szs);
>> [x,status,lambda,nu,mu] = gpcvx(A,b,szs,G,h);
>> [x,status,lambda,nu,mu] = gpcvx(A,b,szs,G,h,l,u);
>> [x,status,lambda,nu,mu] = gpcvx(A,b,szs,[],[],l,u);
>> [x,status,lambda,nu,mu] = gpcvx(A,b,szs,G,h,[],[],quiet);
>> [x,status,lambda,nu,mu] = gpcvx(A,b,szs,[],[],l,u,quiet);
>> [x,status,lambda,nu,mu] = gpcvx(A,b,szs,[],[],[],[],quiet);
```


### 2.4 Caveats

- The equality constraint matrix, G, must be full rank.
- If your problem is large and sparse, be sure that A and G are in sparse format.
- Equality constraints should be explicitly specified as $G x+h=0$. You cannot represent an equality constraint as a pair of opposing inequality constraints.


## 3 Example

Consider the problem

$$
\begin{array}{ll}
\operatorname{minimize} & z_{1}^{-1} z_{2}^{-1 / 2} z_{3}^{-1}+2.3 z_{1} z_{3}+4 z_{1} z_{2} z_{3} \\
\text { subject to } & (1 / 3) z_{1}^{-2} z_{2}^{-2}+(4 / 3) z_{2}^{1 / 2} z_{3}^{-1} \leq 1,  \tag{6}\\
& 0.1 z_{1}+0.2 z_{2}+0.3 z_{3} \leq 1, \\
& (1 / 2) z_{1} z_{2}=1,
\end{array}
$$

with variables $z_{1}, z_{2}$ and $z_{3}$. This is a GP in posynomial form. (If you want to solve a GP in posynomial form directly, use gpposy.) This problem can be converted into the convex form (3) by a change of variables $\left(x_{i}=\log z_{i}\right)$ and a transformation of the objective and constraint functions [BV04, BKVH]. Then, the problem (6) can be converted into

$$
\begin{array}{ll}
\operatorname{minimize} & \operatorname{lse}\left(A^{(0)} x+b^{(0)}\right) \\
\text { subject to } & \operatorname{lse}\left(A^{(1)} x+b^{(1)}\right) \leq 0, \\
& \operatorname{lse}\left(A^{(2)} x+b^{(2)}\right) \leq 0,  \tag{7}\\
& G x+h=0, \\
& l \preceq x \preceq u,
\end{array}
$$

with varible $x=\left(x_{1}, x_{2}, x_{3}\right)$. The problem data are

$$
A^{(0)}=\left[\begin{array}{ccc}
-1 & -0.5 & -1 \\
1 & 0 & 1 \\
1 & 1 & 1
\end{array}\right], \quad A^{(1)}=\left[\begin{array}{ccc}
-2 & -2 & 0 \\
0 & 0.5 & -1
\end{array}\right], \quad A^{(2)}=\left[\begin{array}{lll}
1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1
\end{array}\right]
$$

$$
\begin{gathered}
b^{(0)}=\left[\begin{array}{c}
\log (1) \\
\log (2.3) \\
\log (4)
\end{array}\right], \quad b^{(1)}=\left[\begin{array}{c}
\log (1 / 3) \\
\log (4 / 3)
\end{array}\right], \quad b^{(2)}=\left[\begin{array}{c}
\log (0.1) \\
\log (0.2) \\
\log (0.3)
\end{array}\right], \\
G=\left[\begin{array}{lll}
1 & 1 & 0
\end{array}\right], \quad h=\log (0.5) .
\end{gathered}
$$

The Matlab code for solving this problem is as follows:

```
% Matlab script that solves the above problem
>> AO = [ -1 -0.5 -1 ;...
        1 llll
>> A1 = [\begin{array}{llll}{-2 -2 0 ;...}\end{array}]
>> A2 [ [\begin{array}{lll}{0}&{0.5}&{-1}\end{array}];
>> A2 = [ llllll
            0 0 1];
> A = [ A0; A1; A2 ];
>> b0 = log([ 1; 2.3; 4 ]);
>> b1 = log([ 1/3; 4/3 ]);
>> b2 = log([ 0.1; 0.2; 0.3 ]);
>> b = [ b0; b1; b2 ];
>> G = [ [ 1 1 1 0 ];
>> h = log(0.5);
>> szs = [ size(A0,1); size(A1,1); size(A2,1) ]; %i.e., [ 3; 2; 3 ]
>> [x,status,lambda,nu,mu] = gpcvx(A,b,szs,G,h);
```

After executing the code, you can see the result by typing x in Matlab.

```
>> x
ans =
    1.2465
    -0.5534
        0.0980
```


## 4 Performance

gpcvx is not optimized for performance, but shows reasonable speed. The following table shows the execution times of gpcvx on some typical problems. These times given are for a
2.8GHz Pentium 4, 512Mb RAM, Linux operating system.

| Problem | $n$ | $m$ | $w$ | $p$ | nnz | Execution time |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| test1 | 100 | 100 | 5 | 50 | 5000 | 2 sec |
| test2 | 1000 | 1000 | 5 | 0 | 50000 | 36 sec |
| test3 | 1000 | 10000 | 5 | 0 | 500000 | 171 sec |
| test4 | 100 | 1000 | 50 | 50 | 500000 | 53 sec |
| test5 | 1000 | 1000 | 50 | 0 | 500000 | 138 sec |

Here, $n$ is the number of variables, $m$ is the number of inequality constraints, $w$ is the number of terms (summands) per inequality constraint, and $p$ is the number of equality constraints. The matrices A and G are sparse; nnz is the number of nonzero elements in the A matrix. The code that runs these experiments, as well as the test problems, can be found in the examples_gpsolver directory.

## References

[BKVH] S. Boyd, S.-J. Kim, L. Vandenberghe, and A. Hassibi. A tutorial on geometric programming. To appear in Optimization and Engineering, 2005. Available at www.stanford.edu/~boyd/gp_tutorial.html.
[BV04] S. Boyd and L. Vandenberghe. Convex Optimization. Cambridge University Press, 2004. Available at www.stanford.edu/~boyd/cvxbook.html.

