

# Disciplined Geometric Programming

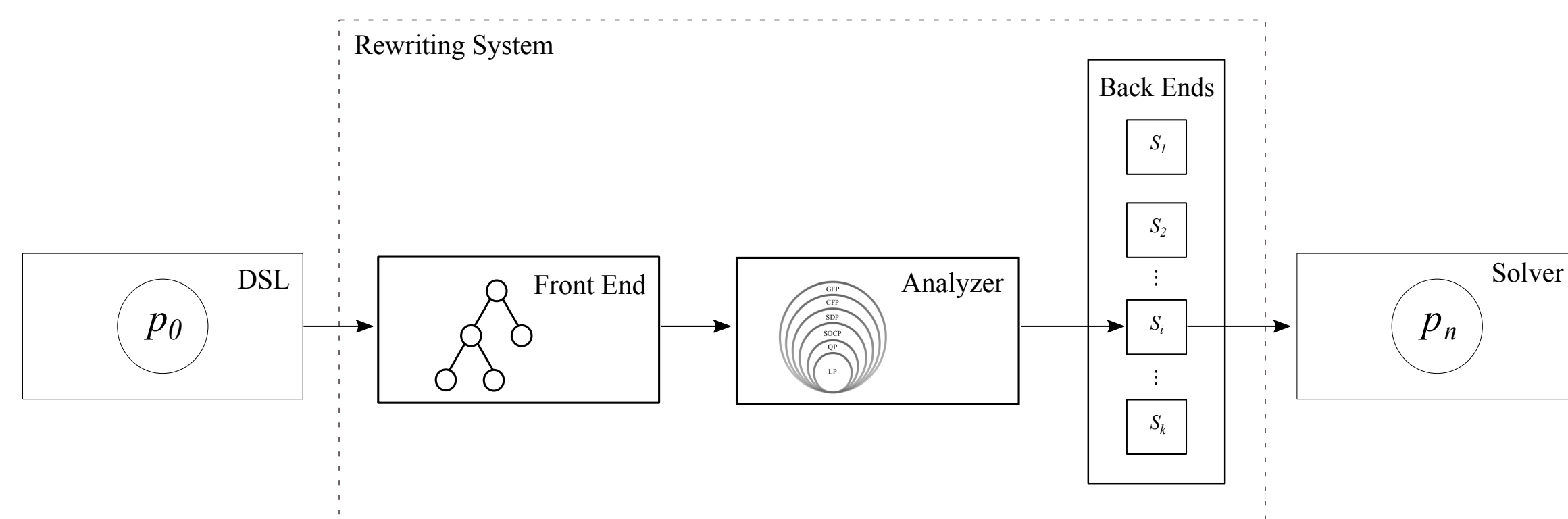
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## Domain-specific languages (DSLs) for convex optimization

- DSLs for convex optimization make it easy to specify and solve convex problems
- Modern DSLs (CVXPY, CVXR, Convex.jl, CVX) based on disciplined convex programming (DCP) [6]
- DCP is a library of functions (atoms) with known curvature and monotonicity, and a composition rule for combining them.



## Geometric programming

A geometric program (GP) [5] is an optimization problem

$$\begin{aligned} & \text{minimize} && f_0(x) \\ & \text{subject to} && f_i(x) \leq 1, \quad i = 1, \dots, m \\ & && g_i(x) = 1, \quad i = 1, \dots, p, \end{aligned}$$

- $g_i : \mathbf{R}_{++}^n \rightarrow \mathbf{R}$  are monomials:  $(x_1, \dots, x_n) \mapsto cx_1^{a_1} \cdots x_n^{a_n}$ ,  $c > 0$ .
- $f_i : \mathbf{R}_{++}^n \rightarrow \mathbf{R}$  are posynomials: sums of monomials

Solving a GP reduces to solving a convex optimization problem, so GPs can be solved reliably and efficiently. Applications include [3]:

- chemical engineering
- circuit design
- transformer design
- aircraft design
- mechanical engineering
- communications

## Log-log convex programs

We introduce log-log convex programs (LLCPs), which generalize GPs

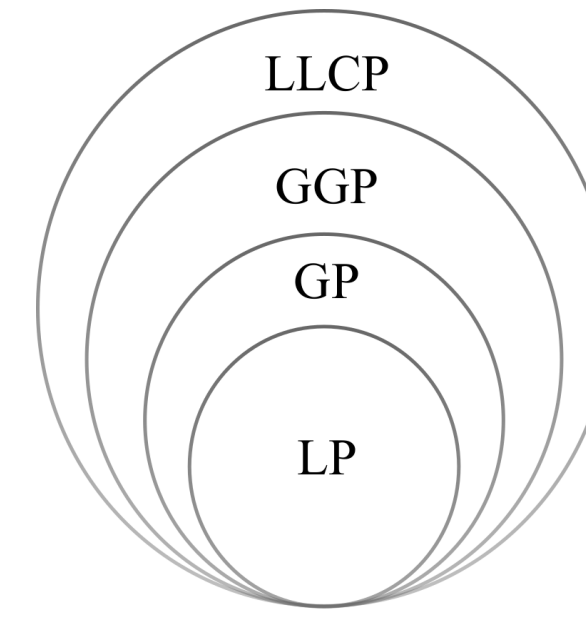
- For  $f : D \rightarrow \mathbf{R}_{++}$ ,  $D \subseteq \mathbf{R}_{++}^n$ ,  $F(u) = \log f(e^u)$  is its log-log transformation
- $f$  is log-log convex, log-log concave, or log-log affine if  $F$  is convex, concave, or affine (resp.)
- A log-log convex program is like a GP but with  $f_i$  log-log convex,  $g_i$  log-log affine

Direct analogue of the composition rule for convex functions holds for log-log convex functions

- For example, if  $f : \mathbf{R}_{++}^k \rightarrow \mathbf{R}_{++}$  is log-log convex and increasing in each argument, and if  $f_1, \dots, f_n$  are log-log convex, then  $f(f_1(x), \dots, f_n(x))$  is log-log convex

## Hierarchy of optimization problems.

LLCPs generalize GPs and so-called generalized geometric programs (GGPs)



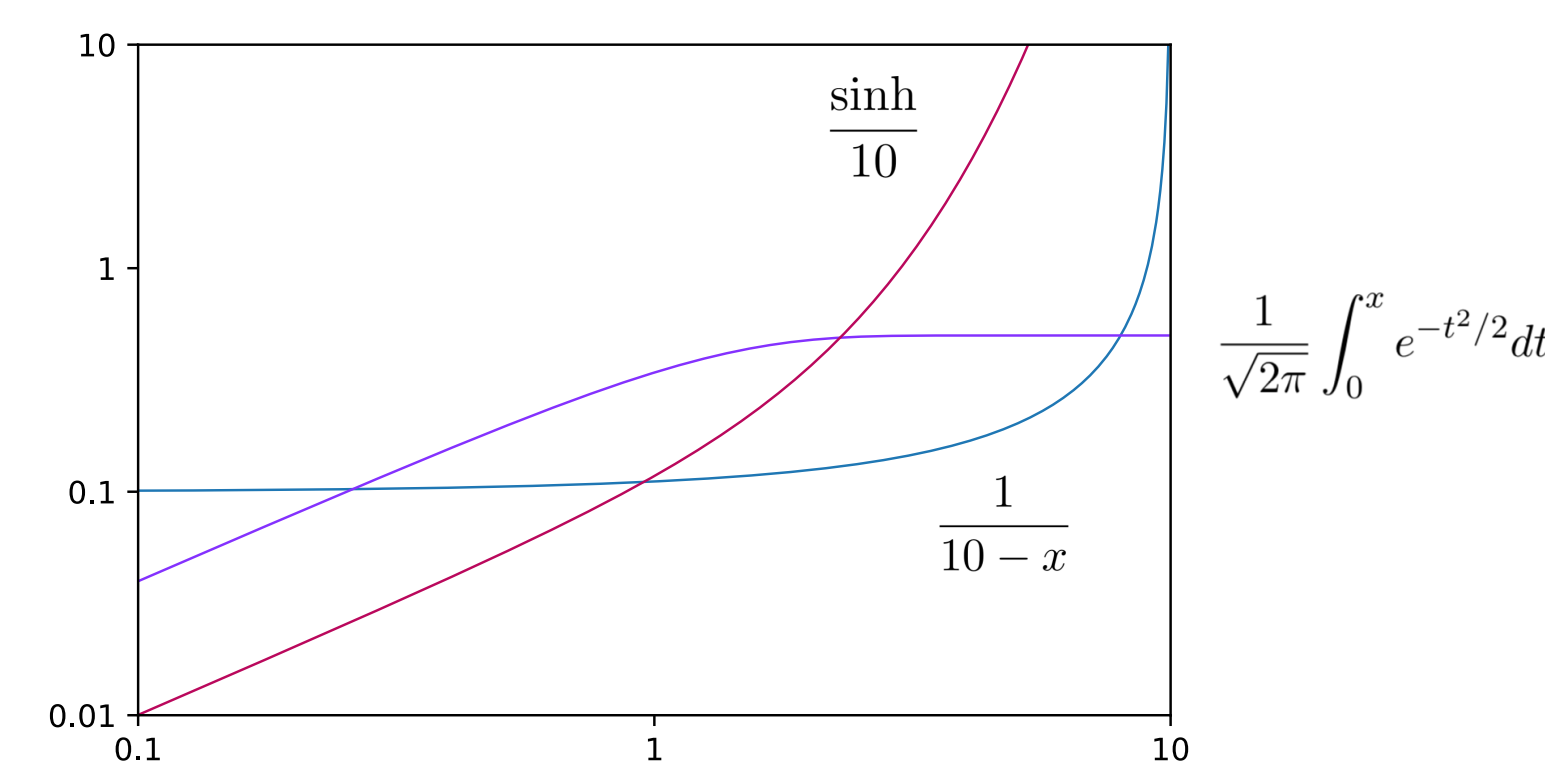
## Properties

**Convexity with respect to the geometric mean.**  $f$  is log-log convex if (and only if) it is convex with respect to the geometric mean, i.e.

$$f(x^\theta \circ y^{1-\theta}) \leq f(x)^\theta f(y)^{1-\theta},$$

for  $\theta \in [0, 1]$  and  $x, y \in \text{dom } f$  ( $\circ$  is the elementwise product, and the powers are meant elementwise)

**Scalar functions.** Scalar log-log convex functions are convex on a log-log plot



## Examples

### Log-log affine functions

- products
- ratios
- powers

### Log-log convex functions

- $x_1 + x_2$ ,  $\max(x_1, x_2)$
- posynomials
- $\ell_p$  norms
- $(I - X)^{-1}$ , (spectral radius of  $X$  less than 1)

### Log-log concave functions

- $x_1 - x_2$ , with  $x_1 > x_2 > 0$
- $-x \log x$ ,  $x \in (0, 1)$
- complementary CDF of a log-concave density, e.g.  $\frac{1}{\sqrt{2\pi}} \int_x^\infty e^{-t^2/2} dt$

## Disciplined geometric programming

Analogue of DCP, but for LLCPPs

- Library of atoms with known log-log curvature (sum, product, ratio, exp, ...)
- Atoms may be combined using the composition rule
- Can express LLCPPs of the form

$$\begin{aligned} & \text{minimize} && f_0(x) \\ & \text{subject to} && f_i(x) \leq \tilde{f}_i(x), \quad i = 1, \dots, m \\ & && g_i(x) = \tilde{g}_i(x), \quad i = 1, \dots, p, \end{aligned} \quad (1)$$

with  $f_i$  log-log convex,  $\tilde{f}_i$  log-log concave,  $g_i$  and  $\tilde{g}_i$  log-log affine (must be verifiable by the composition rule)

## Implementation

DGP implemented as a reduction in CVXPY 1.0:

<https://www.cvxpy.org/tutorial/dgp/index.html>

- User types in a DGP-compliant LLCPP and calls a single method to solve it
- CVXPY reduces the LLCPP to a (disciplined) convex program, solves it, and returns a solution to the original problem

```
import cvxpy as cp
x = cp.Variable(pos=True)
y = cp.Variable(pos=True)
z = cp.Variable(pos=True)
objective_fn = x*y*z
constraints = [4*x*y*z + 2*x*z <= 10, x <= 2*y, y <= 2*x, z >= 1]
problem = cp.Problem(cp.Maximize(objective_fn), constraints)
problem.solve(gp=True)
print(problem.value)
print(x.value, y.value, z.value)
```

## References

- Akshay Agrawal, Steven Diamond, and Stephen Boyd. Disciplined geometric programming. *Optimization Letters*, 2019.
- Akshay Agrawal, Robin Verschueren, Steven Diamond, and Stephen Boyd. A rewriting system for convex optimization problems. *Journal of Control and Decision*, 5(1):42–60, 2018.
- Stephen Boyd, Seung-Jean Kim, Lieven Vandenbergh, and Arash Hassibi. A tutorial on geometric programming. *Optimization and engineering*, 8(1):67, 2007.
- Edward Burnell and Warren Hoburg. GPKIT software for geometric programming. <https://github.com/convexengineering/gpkit>, 2018. Version 0.7.0.
- Richard Duffin, Elmor Peterson, and Clarence Zener. Geometric programming — theory and application, 1967.
- Michael Grant, Stephen Boyd, and Yinyu Ye. Disciplined convex programming. In *Global optimization*, pages 155–210. Springer, 2006.
- Constantin Niculescu. Convexity according to the geometric mean. *Mathematical Inequalities and Applications*, 3(2):155–167, 04 2000.