

# Disciplined Convex Optimization with CVXR

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useR! Conference 2016

Convex Optimization

CVXR

Examples

Future Work

# Outline

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## Convex Optimization

$$\begin{array}{ll}\text{minimize} & f_0(x) \\ \text{subject to} & f_i(x) \leq 0, \quad i = 1, \dots, M \\ & Ax = b\end{array}$$

with variable  $x \in \mathbf{R}^n$

- ▶ Objective and inequality constraints  $f_0, \dots, f_M$  are convex
- ▶ Equality constraints are linear

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Why?

- ▶ We can solve convex optimization problems
- ▶ There are many applications in many fields, including machine learning and statistics

## Convex Problems in Statistics

- ▶ Least squares, nonnegative least squares
- ▶ Ridge and lasso regression
- ▶ Isotonic regression
- ▶ Huber (robust) regression
- ▶ Logistic regression
- ▶ Support vector machine
- ▶ Sparse inverse covariance
- ▶ Maximum entropy and related problems
- ▶ ... and new methods being invented every year!

## Domain Specific Languages for Convex Optimization

- ▶ Special languages/packages for general convex optimization
- ▶ CVX, CVXPY, YALMIP, Convex.jl
- ▶ Slower than custom code, but extremely flexible and enables fast prototyping

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```
from cvxpy import *  
beta = Variable(n)  
cost = norm(X * beta - y)  
prob = Problem(Minimize(cost))  
prob.solve()  
beta.value
```



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# CVXR

A modeling language in R for convex optimization

- ▶ Connects to many open source solvers
- ▶ Uses disciplined convex programming to verify convexity
- ▶ Mixes easily with general R code and other libraries

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## Ordinary Least Squares (OLS)

- ▶ minimize  $\|X\beta - y\|_2^2$
- ▶  $\beta \in \mathbf{R}^n$  is variable,  $X \in \mathbf{R}^{m \times n}$  and  $y \in \mathbf{R}^m$  are constants

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```
library(CVXR)
beta <- Variable(n)
obj <- sum_squares(y - X %*% beta)
prob <- Problem(Minimize(obj))
result <- solve(prob)
result$value
result$getValue(beta)
```

- ▶  $X$  and  $y$  are constants;  $\beta$ ,  $\text{obj}$ , and  $\text{prob}$  are S4 objects
- ▶ `solve` method returns a list that includes optimal  $\beta$  and objective value

## Non-Negative Least Squares (NNLS)

- ▶ minimize  $\|X\beta - y\|_2^2$  subject to  $\beta \geq 0$

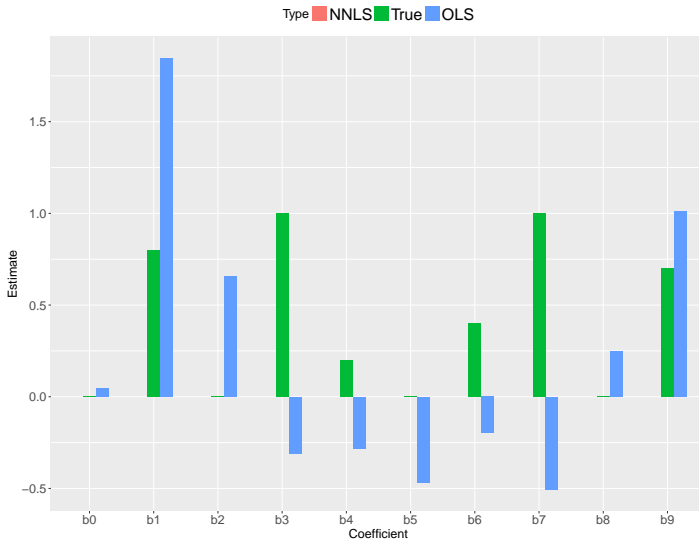
## Non-Negative Least Squares (NNLS)

- ▶ minimize  $\|X\beta - y\|_2^2$  subject to  $\beta \geq 0$

```
constr <- list(beta >= 0)
prob2 <- Problem(Minimize(obj), constr)
result2 <- solve(prob2)
result2$value
result2$getValue(beta)
```

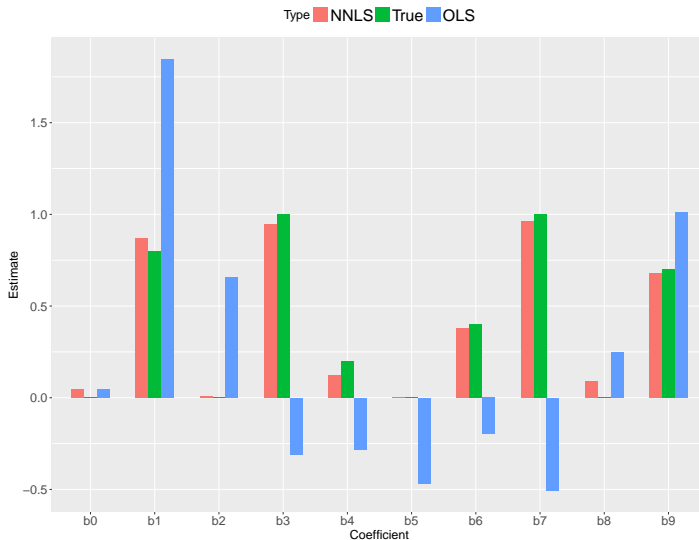
- ▶ Construct new problem with list `constr` of constraints formed from constants and variables
- ▶ Variables, parameters, expressions, and constraints exist outside of any problem

## True vs. Estimated Coefficients





## True vs. Estimated Coefficients



## Direct Standardization

- ▶ Samples  $(X, y)$  drawn **non-uniformly** from a distribution
- ▶ Expectations of columns of  $X$  have known values  $b \in \mathbf{R}^n$

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- ▶ Samples  $(X, y)$  drawn **non-uniformly** from a distribution
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- ▶ Empirical distribution  $y = y_i$  w.p.  $1/m$  is **not** a good estimate of distribution of  $y$
- ▶ Let's use weighted empirical distribution  $y = y_i$  w.p.  $w_i$
- ▶ Choose  $w = (w_1, \dots, w_m)$  to match known expectations, maximize entropy

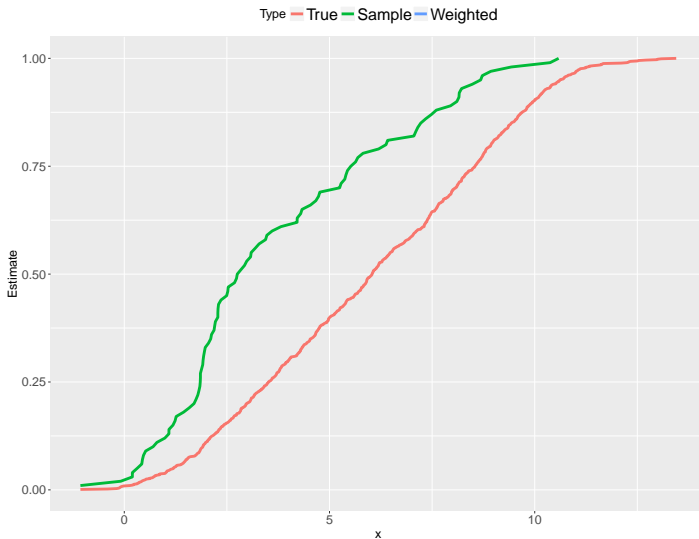
$$\begin{array}{ll} \text{maximize} & \sum_i^m -w_i \log w_i \\ \text{subject to} & w \geq 0 \quad \mathbf{1}^T w = 1 \quad X^T w = b \end{array}$$

## Direct Standardization

```
w <- Variable(m)
obj <- sum(entr(w))
constr <- list(w >= 0, sum(w) == 1, t(X) %*% w == b)
prob <- Problem(Maximize(obj), constr)
result <- solve(prob)
result$getValue(w)
```

- ▶ `entr` is the elementwise entropy function
- ▶ `result$getValue(w)` returns an R vector of weights

# True vs. Estimated Cumulative Distribution



# True vs. Estimated Cumulative Distribution



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## Future Work

- ▶ Connect to more solvers: MOSEK, GUROBI, ...
- ▶ Flesh out convex functions in library
- ▶ Develop more applications and examples
- ▶ Add warm start support

Github repo: <https://github.com/anqif/cvxr>