#### **Extended Formulations for Quadratic Mixed** Integer Programming

#### Juan Pablo Vielma Massachusetts Institute of Technology

SIAM Conference on Optimization, May 2014 – San Diego, California

### **Nonlinear MIP B&B Algorithms**

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NLP (QCP) Based B&B

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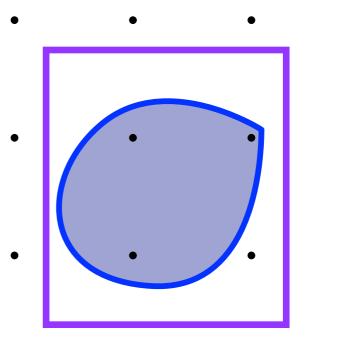
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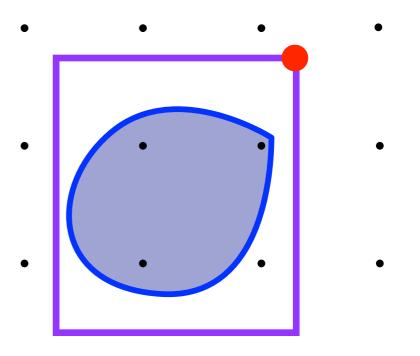
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NLP (QCP) Based B&B
(Dynamic) LP Based B&B
Few cuts = high speed.
Possible slow convergence.



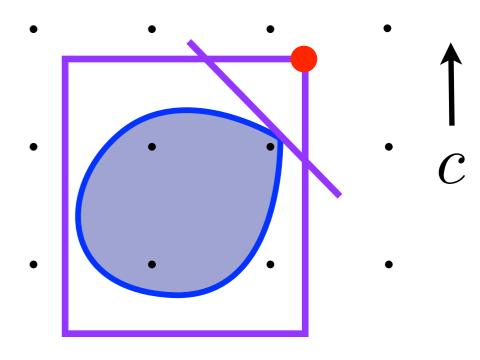
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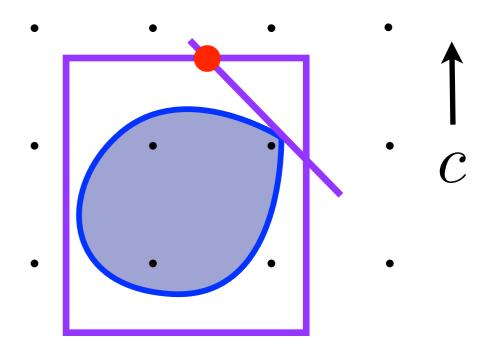
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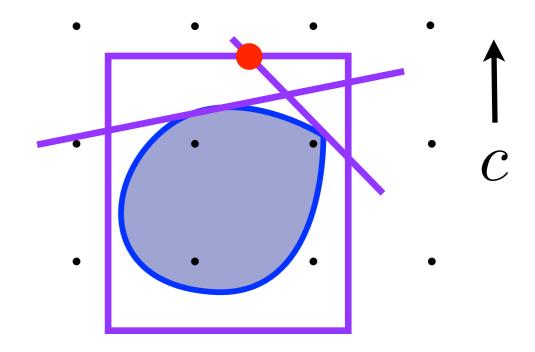
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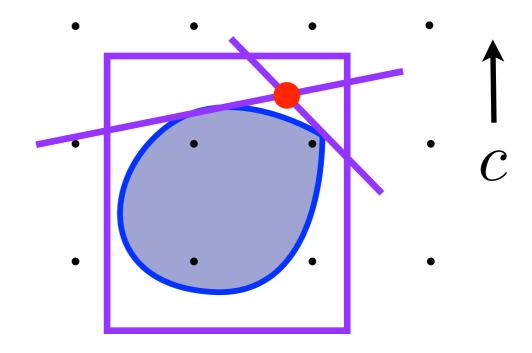
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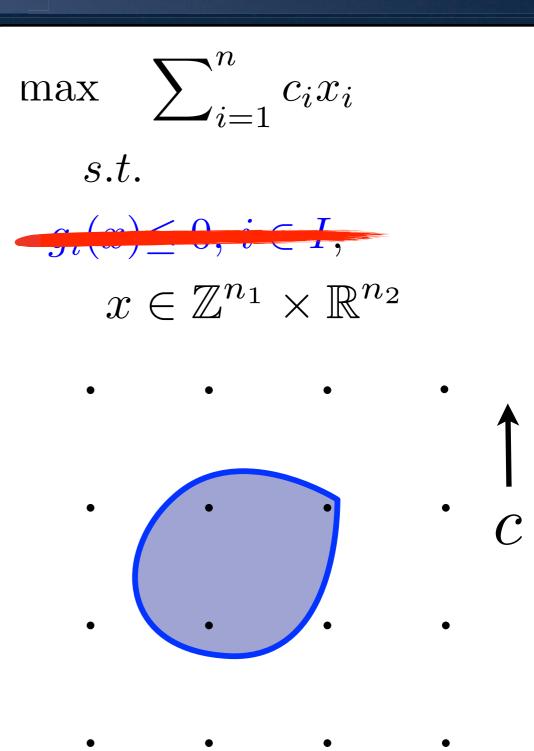
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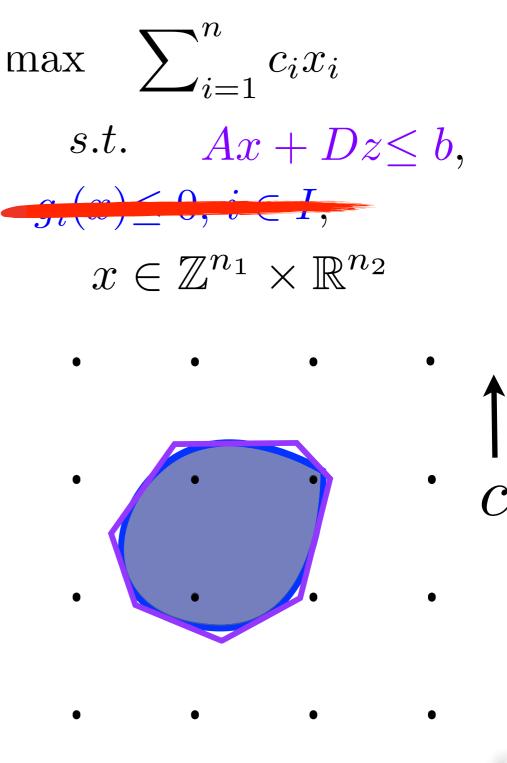
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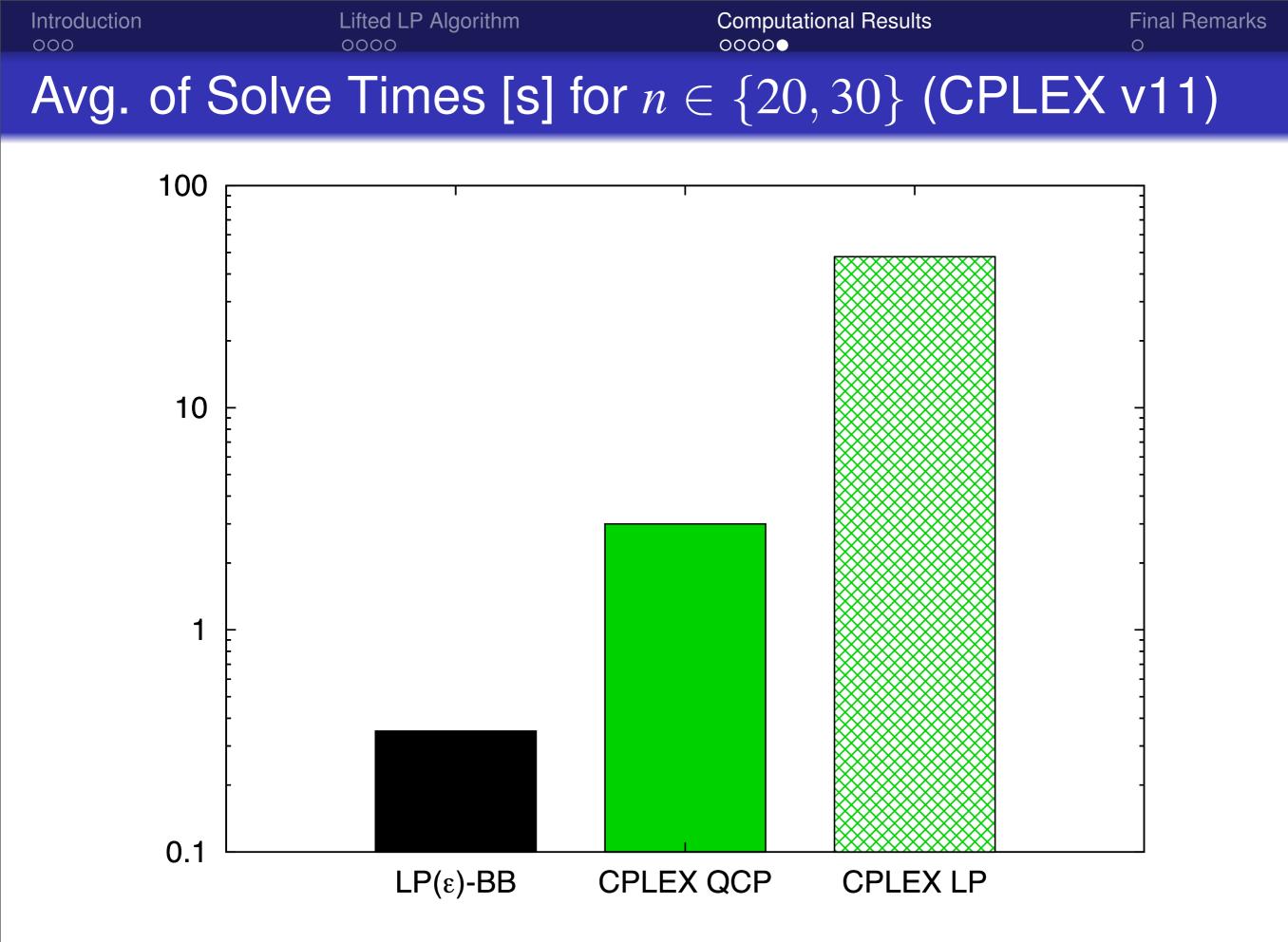


Computational Results

#### Problem 1: Classical

- āy max x, y*s.t*.  $||Q^{1/2}y||_2 \le \sigma$  $\sum_{j=1}^{n} y_j = 1$ i=1 $y_j \leq x_j \qquad \forall j \in \{1,\ldots,n\}$  $\sum x_j \leq 10$ i=1 $x \in \{0, 1\}^n$  $y \in \mathbb{R}^n_+$
- y fraction of the portfolio invested in each of n assets.
- ā expected returns of assets.
- $Q^{1/2}$  positive semidefinite square root of the covariance matrix Q of returns.
- Hold at most 10 assets.

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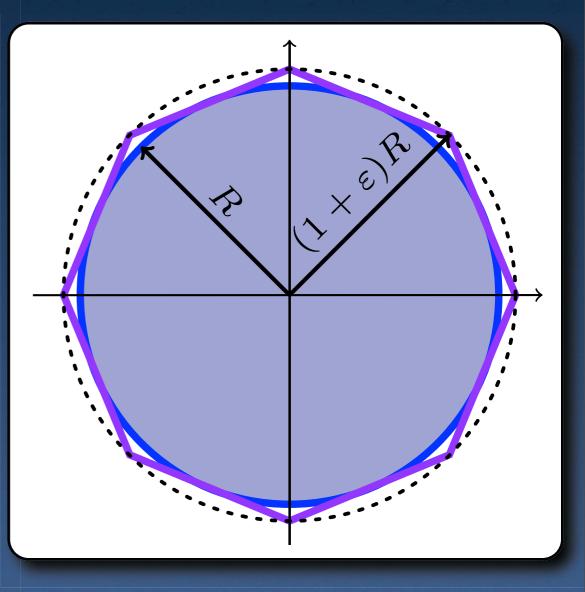


### **Extended Formulation for Lifted LP**

 Approximation of Second Order Cone by Ben-Tal and Nemirovski (Glineur).

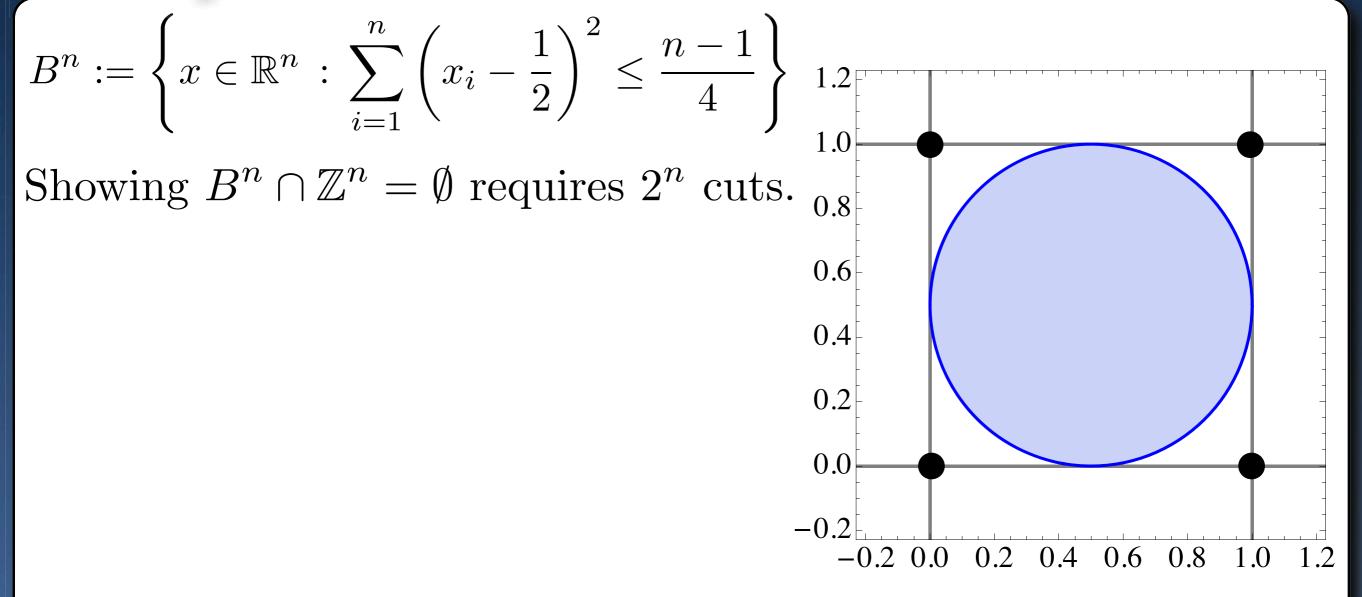
# • $O(d \log(1/\varepsilon))$ variables and constraints for quality $\varepsilon$ .

 Problem:
 Fixed a-priori quality: no dynamic improvement.
 e.g. ε = 0.01 for portfolio had to be calibrated.

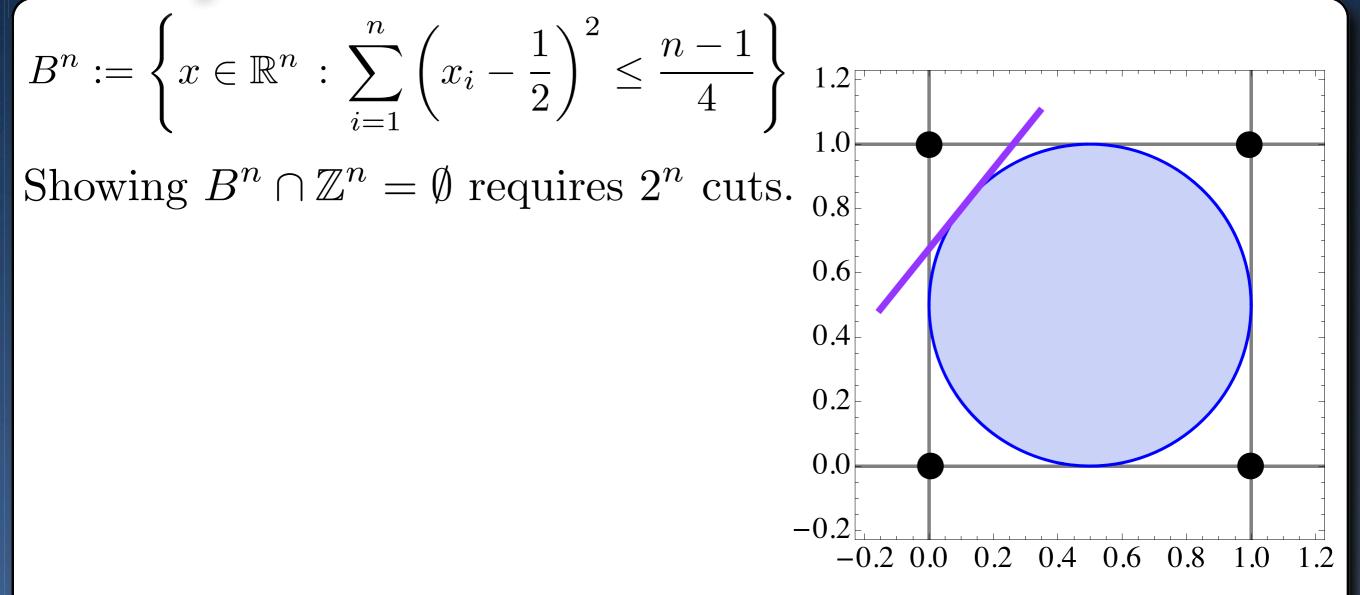


# **Dynamic Lifted Approximations**

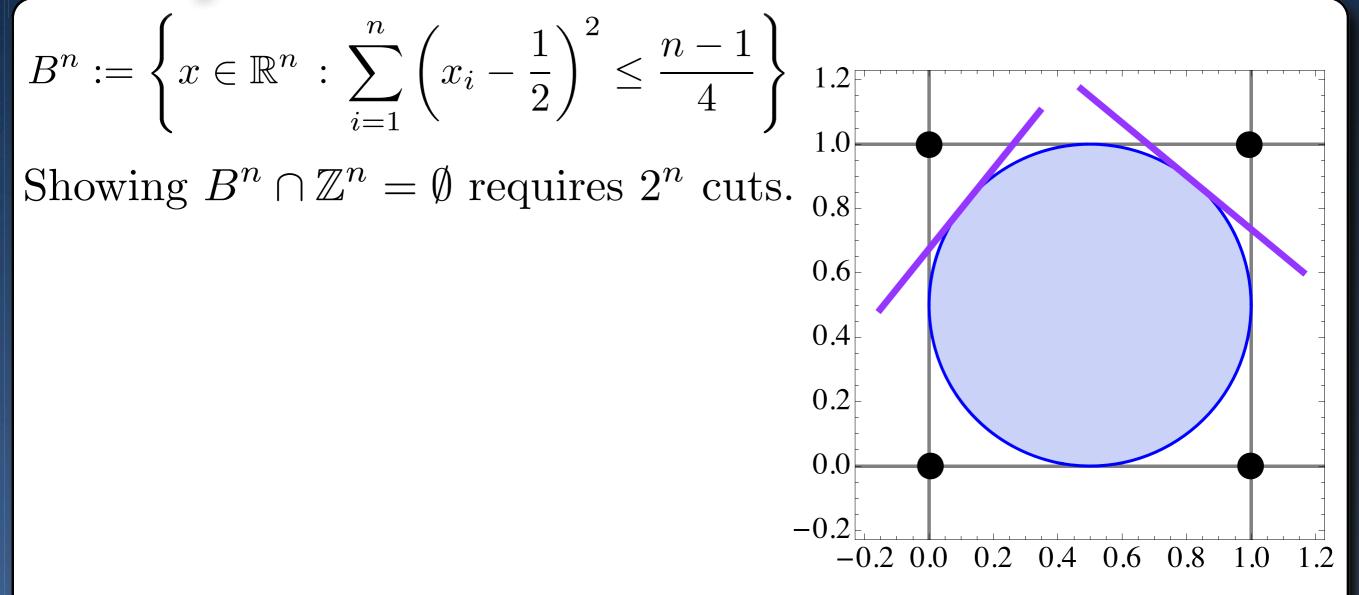
### **Towards a Dynamic Lifted LP**



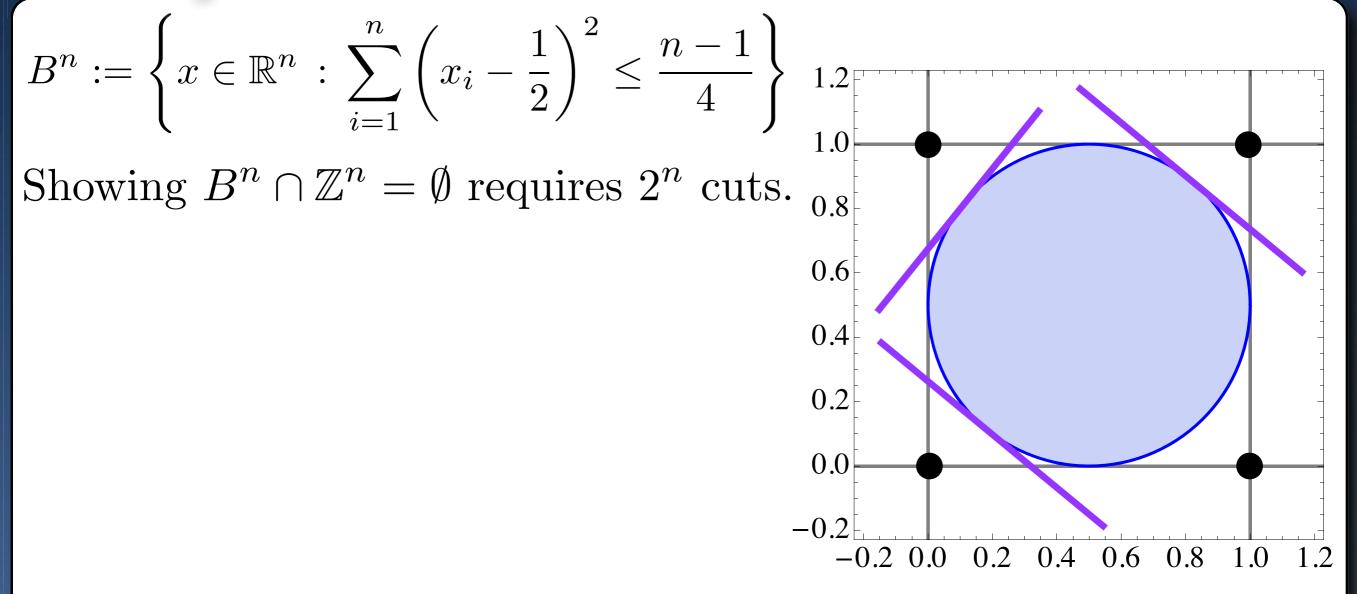
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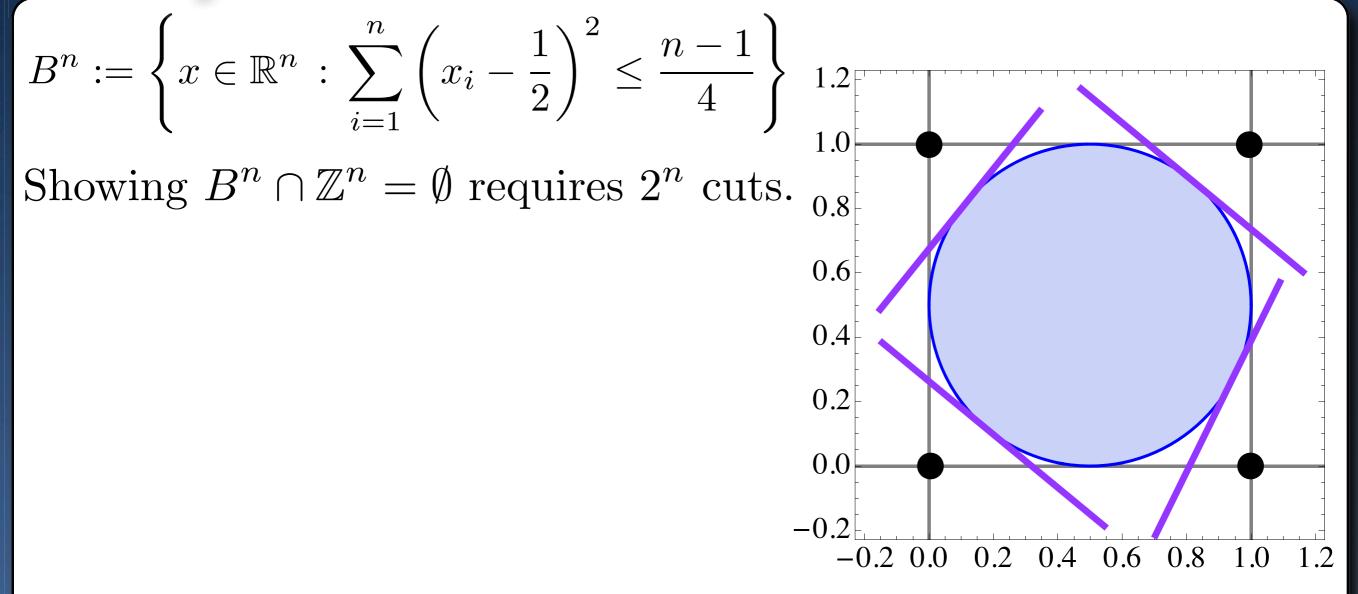
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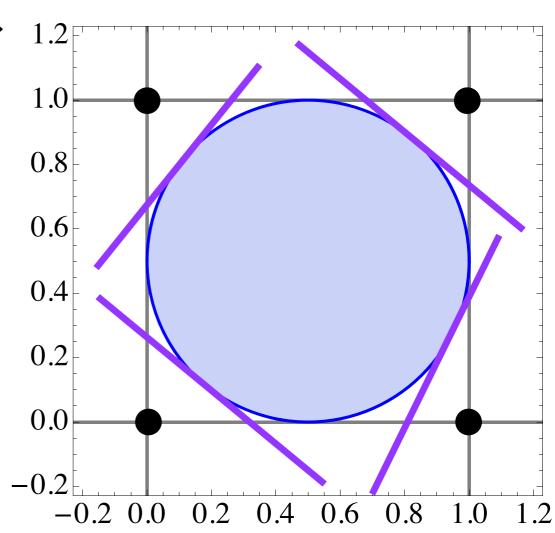
### Towards a Dynamic Lifted LP

 Separable approach by Tawarmalani and Sahinidis '05 and Hijazi et al. '14

$$B^{n} := \left\{ x \in \mathbb{R}^{n} : \sum_{i=1}^{n} \left( x_{i} - \frac{1}{2} \right)^{2} \le \frac{n-1}{4} \right\}$$

Extended formulation of  $B^n$ :

$$\left(x_i - \frac{1}{2}\right)^2 \le z_i \qquad \forall i \in [n]$$
$$\sum_{i=1}^n z_i \le \frac{n-1}{4}$$



### **Towards a Dynamic Lifted LP**

$$B^{n} := \left\{ x \in \mathbb{R}^{n} : \sum_{i=1}^{n} \left( x_{i} - \frac{1}{2} \right)^{2} \leq \frac{n-1}{4} \right\}_{0.4}^{Z_{i}}$$
  
Extended formulation of  $B^{n}$ :  
$$\left( x_{i} - \frac{1}{2} \right)^{2} \leq z_{i} \qquad \forall i \in [n]$$
  
$$\sum_{i=1}^{n} z_{i} \leq \frac{n-1}{4}$$
  
$$B^{n} \cap \mathbb{Z}^{n} = \emptyset \text{ with only } 2n \text{ cuts}$$
  
on extended formulation.

### Towards a Dynamic Lifted LP

#### Separable approach by Tawarmalani and Sahinidis '05 and Hijazi et al. '14

Separable approach works for any set of the form:

$$C = \left\{ x \in \mathbb{R} : \sum_{i=1}^{n} f_i(x_i) \le 1 \right\}$$

$$C = \left\{ (x, t) \in \mathbb{R} \times \mathbb{R} : \sum_{i=1}^{n} f_i(x_i) \le t \right\}$$

for convex  $f_i : \mathbb{R} \to \mathbb{R}$ 

Computational Results

#### Problem 1: Classical

- āy max x, y*s.t*.  $||Q^{1/2}y||_2 \le \sigma$  $\sum_{j=1}^{n} y_j = 1$ i=1 $y_j \leq x_j \qquad \forall j \in \{1,\ldots,n\}$  $\sum x_j \leq K$ i=1 $x \in \{0, 1\}^n$  $y \in \mathbb{R}^n_+$
- y fraction of the portfolio invested in each of n assets.
- ā expected returns of assets.
- $Q^{1/2}$  positive semidefinite square root of the covariance matrix Q of returns.
- *K* maximum number of assets to hold.

Computational Results

#### Problem 2 : Shortfall

- āy max x, y*s.t*.  $||Q^{1/2}y||_2 \le \sigma$  $\sum_{j=1}^{n} y_j = 1$ i=1 $y_j \leq x_j \qquad \forall j \in \{1,\ldots,n\}$  $\sum x_j \leq K$ i=1 $x \in \{0, 1\}^n$  $y \in \mathbb{R}^n_+$
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Computational Results

#### Problem 2 : Shortfall

āy

j=1

$$\max_{x,y}$$

*s.t*.

$$|Q^{1/2}y||_2 \le \frac{\bar{a}y - W_i^{low}}{\Phi^{-1}(\eta_i)}$$
  $i \in \{1, 2\}$ 

 $x \in \{0, 1\}^n$ 

 $\mathbf{y} \in \mathbb{R}^n_+$ 

$$\sum_{j=1}^{n} y_j = 1$$
  

$$y_j \le x_j \qquad \forall j \in \{1, \dots, n\}$$
  

$$\sum_{j=1}^{n} x_j \le K$$

- y fraction of the portfolio invested in each of n assets.
- $\bar{a}$  expected returns of assets.
- Q<sup>1/2</sup> positive semidefinite square root of the covariance matrix Q of returns.
- *K* maximum number of assets to hold.
- Approximation of  $Prob(\bar{a}y \ge W_i^{low}) \ge \eta_i$

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i=1

### **Extended Formulation for SOCP**

$$L^{n} = \left\{ (x, t) \in \mathbb{R} \times \mathbb{R} : ||x|| \le t \right\}$$

Extended formulation of  $L^n =$ homogenization of  $B^n$  formulation:

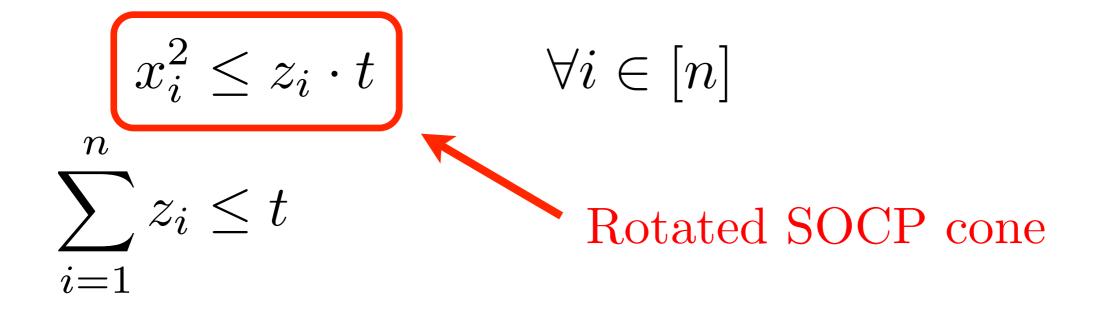
$$x_i^2 \le z_i \cdot t \qquad \forall i \in [n]$$

$$\sum_{i=1}^{n} z_i < t$$

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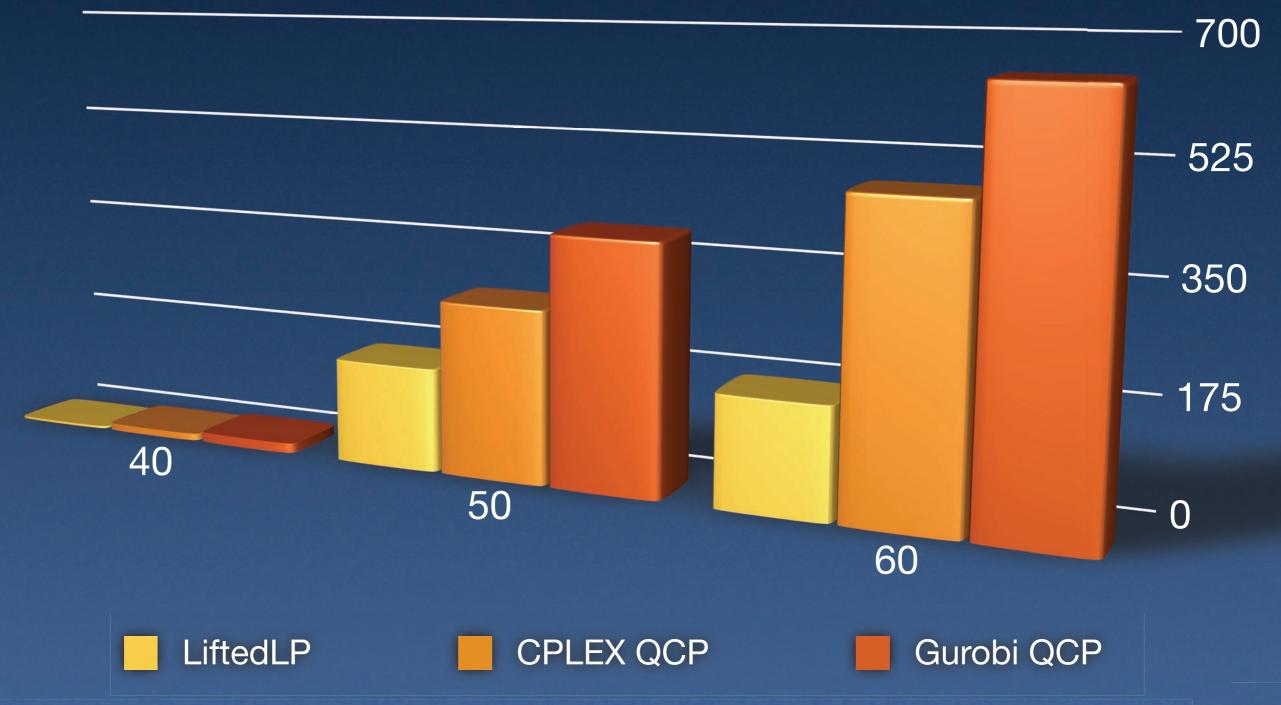
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- Averages over 20 instances:
  - Classical and Shortfall. 40, 50 and 60 stocks.

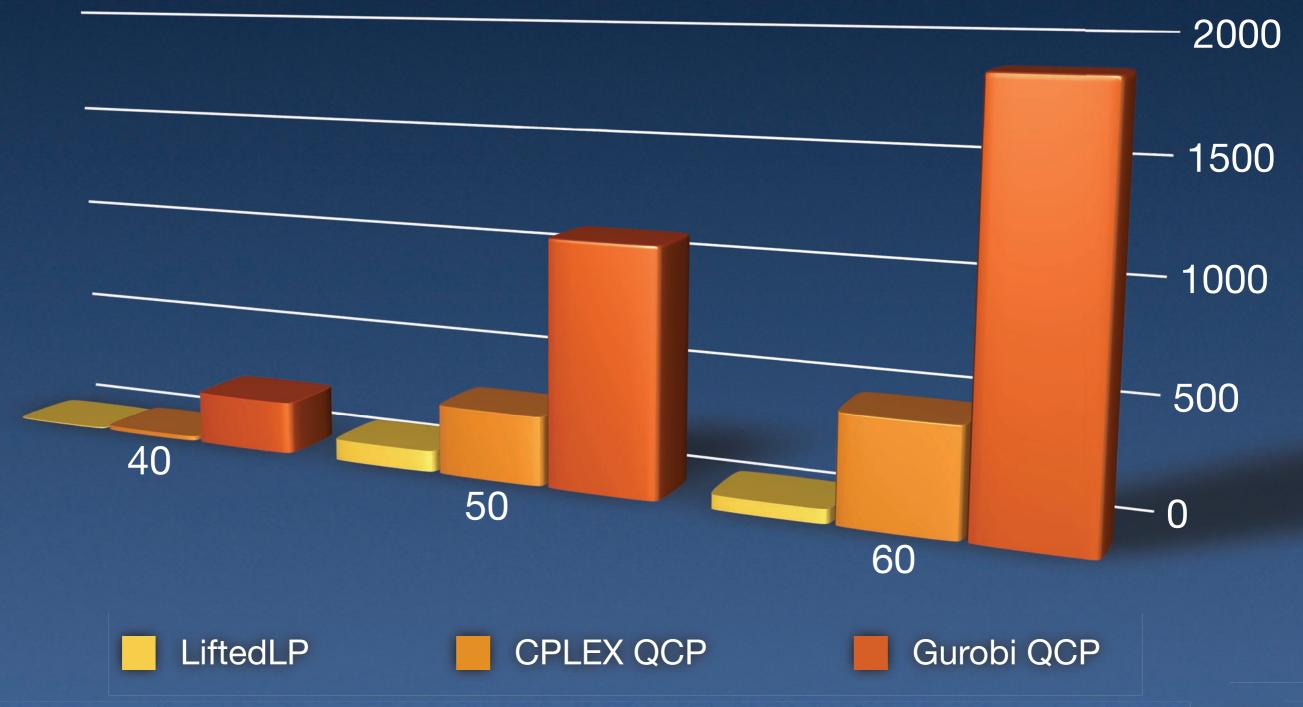
#### Solvers:

- CPLEX/Gurobi QCP-BB on original formulation .
- Lifted LP: Implemented in JuMP using CPLEX's branch, incumbent and heuristic callback.
- CPLEX/Gurobi LP-BB on extended "separable" reformulation.

### LiftedLP v/s QCP: Classical

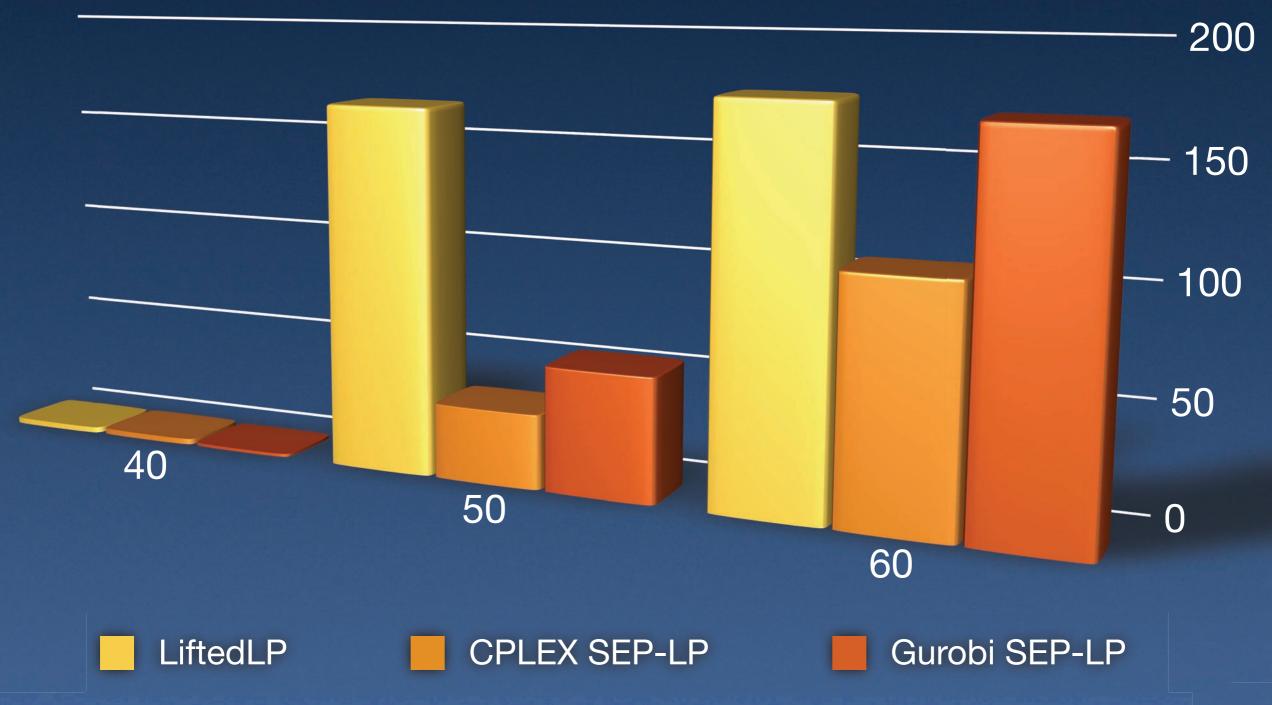


### LiftedLP v/s QCP: Shortfall

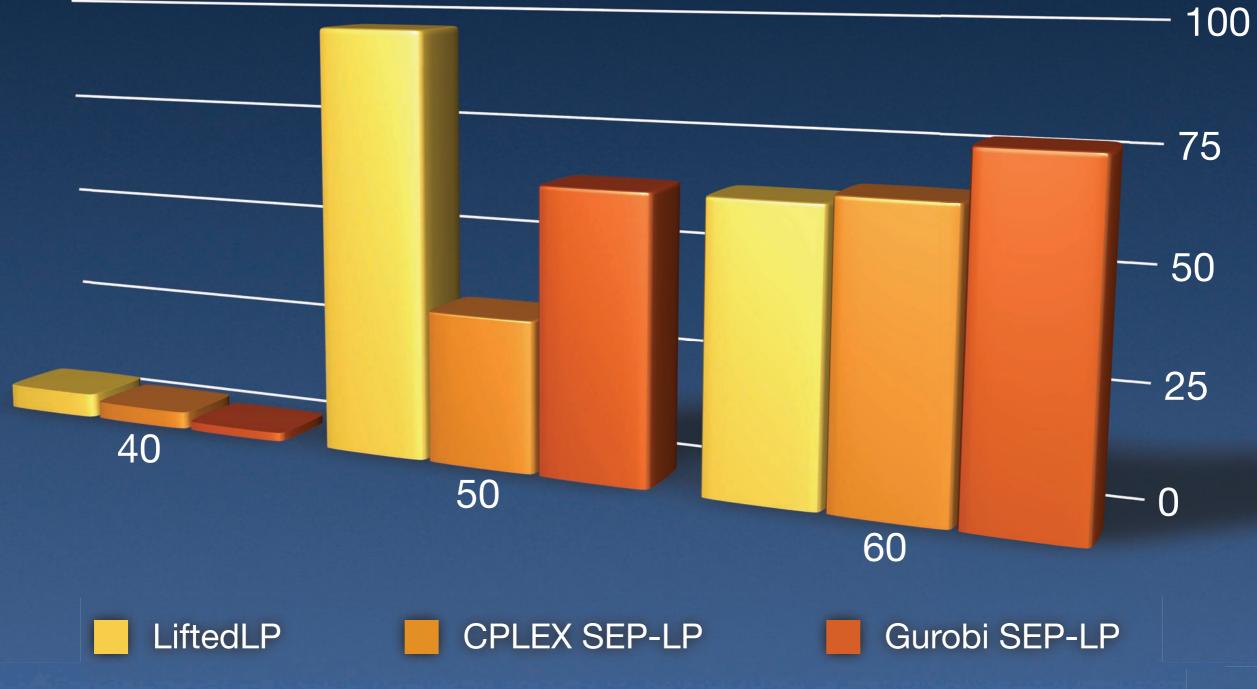


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### LiftedLP v/s Dynamic : Classical



### LiftedLP v/s Dynamic : Shortfall



### Summary

Lifted LP: 200 lines of JuMP code in a weekend.

- Developed by ORC students lain Dunning, Joey Huchette and Miles Lubin
- https://github.com/JuliaOpt/JuMP.jl
  Poster at MIP 2014. OSU, July 21st
- Talk at INFORMS. San Francisco, November
- Dynamic Lifted LP:
  - Comparable performance with simple reformulation.