# **Code Generation for Embedded Convex Optimization**

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# Convex optimization

- Problems solvable reliably and efficiently
- Widely used in scheduling, finance, engineering design
- Solve every few minutes or seconds

Code generation for embedded convex optimization

Replace 'minutes' with 'milliseconds' and eliminate failure

# Agenda

- I. Introduction to embedded convex optimization and CVXGEN
- II. Demonstration of CVXGEN
- III. Techniques for constructing fast, robust solvers
- IV. Verification of technical choices
- V. Final notes and conclusions

### Part I: Introduction

- 1. Embedded convex optimization
- 2. Embedded solvers
- 3. CVXGEN

# Embedded convex optimization: Requirements

Embedded solvers must have:

- Time limit, sometimes strict, in milliseconds or microseconds
- Simple footprint for portability and verification
- No failures, even with somewhat poor data

# Embedded convex optimization: Exploitable features

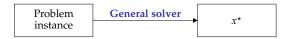
Embedded solvers can exploit:

- Modest accuracy requirements
- Fixed dimensions, sparsity, structure
- Repeated use
- Custom design in pre-solve phase

# Embedded convex optimization: Applications

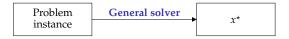
- Signal processing, model predictive control
- Fast simulations, Monte Carlo
- Low power devices
- Sequential QP, branch-and-bound

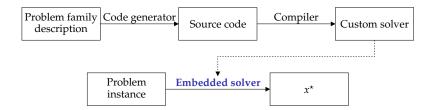
## Embedded convex optimization: Pre-solve phase



#### Part I: Introduction

### Embedded convex optimization: Pre-solve phase





#### Part I: Introduction

### **CVXGEN**

- Code generator for embedded convex optimization
- Mattingley, Boyd
- Disciplined convex programming input
- Targets small QPs in flat, library-free C

### Part II: Demonstration

- 1. Manipulating optimization problems with CVXGEN
- 2. Generating and using solvers
- 3. Important hidden details

## **CVXGEN:** Problem specification

• • • • cvxgen: initial example				
vxgen: initial e	xample · saved a moment ago · no errors · no codegen	jem@cvxgen.cor		
PROBLEM	1 # Welcome to cvxgen.			
edit	2 # Here's a sample problem to get you started. 3			
view	4 dimensions 5 n = 10			
std form	6 end			
	8 parameters 9 A (8,n)			
CODEGEN	10 b (8)			
generate C	11 c (n) 12 end			
matlab	13 14 variables			
	15 x (n) 16 end			
CODE INFO	17 18 minimize			
statistics	19 c'*x + norm1(x)			
kkt sparsity	20 subject to 21 A*x == b			
	22 x >= −1 23 end			
OTHER OUTPUT				
latex spec				
latex math				
cvx				
cvxmod				
OTHER TOOLS				
user's guide				
report a bug				

# CVXGEN: Automatic checking

00	Cvxgen: initial example				
vxgen: initial e	xample + saved a minute ago + 1 error + no codegen		jem@cvxgen.con		
PROBLEM	1 # Welcome to cvxgen. 2 # Here's a sample problem to get you started.	19 objective must be convex.			
view std form	dimensions n = 10 end parameters				
CODEGEN	9 A $(8,n)$ 10 b $(8)$ 11 C $(n)$				
generate C matlab	12 end 13   14 variables				
CODE INFO statistics kkt sparsity	<pre>15 x (n) 16 end 17 18 minimize 19 c'*x + norm1(x) - (1/10)*norminf(x) 20 subject to 21 A*x == 0 22 x &gt;= -1</pre>				
OTHER OUTPUT	23 end				
latex spec latex math					
cvx					
OTHER TOOLS user's guide					
report a bug					

## **CVXGEN:** Formatted problem statement

0 🔿 🔿 cvxgen: initial example				
vxgen: initial o	example · saved a moment ago · no errors · no codegen	jem@cvxgen.con		
PROBLEM	Problem statement			
edit	minimize $c^T x +   x  _1$			
view	subject to $Ax = b$			
std form	$x \ge -1$			
	Parameters			
CODEGEN	$A\in \mathbf{R}^{8 imes 10}$ , $b\in \mathbf{R}^{8}$ , $c\in \mathbf{R}^{10}$			
generate C				
matlab	Optimization variables			
	$x \in \mathbf{R}^{10}$			
CODE INFO				
statistics				
kkt sparsity				
OTHER OUTPUT				
latex spec				
latex math				
cvx				
cyxmod				
CVXIIIOU				
OTHER TOOLS				
user's guide				
report a bug				

# **CVXGEN: Single-button code generation**

cvxgen: initial example     vxgen: initial example     · saved a moment ago - no errors - no codegen     jem@cvxgen.com				
edit	Your problem has 306 non-zero KKT matrix entries, which is relatively few. Code gener fast.	ation should be relatively		
view	(cvxgen is best for optimization problems with up to around 2000 entries.)			
std form				
	Code generation status			
CODEGEN	You have not generated code for this problem.			
generate C	Generate code			
matlab				
CODE INFO				
statistics				
kkt sparsity				
OTHER OUTPUT				
latex spec				
latex math				
cvx				
cvxmod				
OTHER TOOLS				
user's guide				
report a bug				

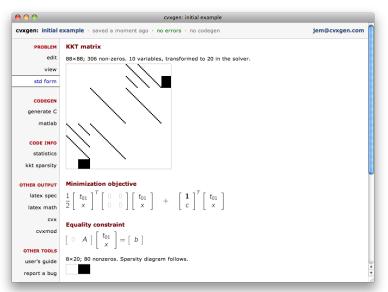
## **CVXGEN:** Completed code generation

vxgen: initial e	xample · saved a minute		nitial example up-to-date codegen		jem@cvxgen.con
PROBLEM	Problem size				
edit view std form	fast.		ntries, which is relatively f h up to around 2000 entrie		ation should be relatively
	Code generation statu	IS			
CODEGEN	You generated code a mo	ment ago. The code	matches the problem state	ement.	
generate C					
matlab	Generate code again				
matiab	Generated files				
CODE INFO	cvxgen.zip	complete	download zip	26 k	
statistics	cvxgen.tar.gz	complete	download tar	23 k	
	Makefile	complete	preview · download	1 k	
kkt sparsity	csolve.c	complete	preview · download	6 k	
	csolve.m	complete	preview · download	1 k	
OTHER OUTPUT	cvxsolve.m	complete	preview · download	1 k	
latex spec	ldl.c	complete	preview · download	89 k	
latex math	make_csolve.m	complete	preview · download	1 k	
cvx	matrix_support.c	complete	preview · download	8 k	
	solver.c	complete	preview · download	8 k	
cvxmod	solver.h	complete	preview · download	4 k	
OTHER TOOLS	testsolver.c	complete	preview · download	5 k	
	util.c	complete	preview · download	3 k	
user's guide					
report a bug					

# CVXGEN: Fast, problem-specific code

preview of solver.c			close 🖨 be relatively
<pre>// Produced by cvxgen, 2010-08 // cvxgen is Copyright (C) 2000</pre>			
<pre>// Filename: solver.c. // Description: Main solver fi</pre>	le.		
#include "solver.h"			
<pre>void set_defaults(void) {    settings.resid_tol = 1e-6;    settings.eps = 1e-4;</pre>			
<pre>settings.max_iters = 25; settings.refine_steps = 1;</pre>			
cvxgen.tar.gz			
settings.z_init = 1;			
settings.debug = 0;			
<pre>settings.verbose = 1; settings.verbose refinement =</pre>	e.complete		
JT cvxsolve.m	complete		
<pre>settings.kkt_reg = 1e-7; }</pre>			
th make_csolve.m			
<pre>double eval_gap(void) {     int i;</pre>			
double gap;			
qap = 0;			-
for (i = 0; i < 30; i++)			Ŧ

### **CVXGEN:** Automatic problem transformations



# **CVXGEN:** Automatically generated Matlab interface

0 0	cvxgen: initial example	
cvxgen: initial	example · saved a minute ago · no errors · up-to-date codegen jem@cvx	gen.com
PROBLEM	Follow these instructions to download and build a Matlab mex solver.	
edit	Step 1: Download the build script	
view		
std form	You only need this step once, to put cvxgen.m in your current directory or Matlab path.	
	Copy to clipboard and paste into Matlab.	
CODEGEN	<pre>urlwrite('http://cvxgen.stanford.edu/download/cvxgen.m', 'cvxgen.m');</pre>	
generate C		
matlab	Step 2: Download custom code for this problem	
CODE INFO	Use this code for one-step download and build of a custom mex solver in Matlab.	
statistics	Copy to clipboard and paste into Matlab.	
	cvxgen(368256)	
kkt sparsity		
OTHER OUTPUT		
latex spec		
latex math		
cvx		
cvxmod		
OTHER TOOLS		
user's guide		
report a bug		

## Important hidden details

Important details not seen in demonstration:

- Extremely high speeds
- Bounded computation time
- Algorithm robustness

# Part III: Techniques

- 1. Transformation to canonical form
- 2. Interior-point algorithm
- 3. Solving the KKT system
  - Permutation
  - Regularization
  - Factorization
  - Iterative refinement
  - Eliminating failure
- 4. Code generation

### Transformation to canonical form

- Problem description uses high-level langauge
- Solve problems in canonical form: with variable  $x \in \mathbf{R}^n$ ,

minimize  $(1/2)x^TQx + q^Tx$ subject to  $Gx \leq h$ , Ax = b

- Transform high-level description to canonical form automatically:
  - 1. Expand convex functions via epigraphs.
  - 2. Collect optimization variables into single vector variable.
  - 3. Shape parameters into coefficient matrices and constants.
  - 4. Replace certain products with more efficient pre-computations.
- Generate code for forwards, backwards transformations

### Transformation to canonical form: Example

• Example problem in original form with variables *x*, *y*:

minimize  $x^TQx + c^Tx + \alpha ||y||_1$ subject to  $A(x-b) \leq 2y$ 

• After epigraphical expansion, with new variable *t*:

minimize  $x^TQx + c^Tx + \alpha \mathbf{1}^T t$ subject to  $A(x-b) \leq 2y, \quad -t \leq y \leq t$ 

After reshaping variables and parameters into standard form:

$$\begin{array}{ll} \text{minimize} & \begin{bmatrix} x \\ y \\ t \end{bmatrix}^T \begin{bmatrix} Q & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x \\ y \\ t \end{bmatrix} + \begin{bmatrix} c \\ \alpha \mathbf{1} \\ 0 \end{bmatrix}^T \begin{bmatrix} x \\ y \\ t \end{bmatrix}$$
$$\begin{array}{l} \text{subject to} & \begin{bmatrix} A & -2I & 0 \\ 0 & -I & -I \\ 0 & I & I \end{bmatrix} \begin{bmatrix} x \\ y \\ t \end{bmatrix} \leqslant \begin{bmatrix} Ab \\ 0 \\ 0 \end{bmatrix}$$

# Solving the standard-form QP

- Standard primal-dual interior-point method with Mehrotra correction
- ▶ Reliably solve to high accuracy in 5–25 iterations
- Mehrotra '89, Wright '97, Vandenberghe '09

### Algorithm

Initialize via least-squares. Then, repeat:

- 1. Stop if the residuals and duality gap are sufficiently small.
- 2. Compute affine scaling direction by solving

$$\begin{bmatrix} Q & 0 & G^T & A^T \\ 0 & Z & S & 0 \\ G & I & 0 & 0 \\ A & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \Delta x^{\text{aff}} \\ \Delta s^{\text{aff}} \\ \Delta y^{\text{aff}} \end{bmatrix} = \begin{bmatrix} -(A^Ty + G^Tz + Px + q) \\ -Sz \\ -(Gx + s - h) \\ -(Ax - b) \end{bmatrix}.$$

3. Compute centering-plus-corrector direction by solving

$$\begin{bmatrix} Q & 0 & G^T & A^T \\ 0 & Z & S & 0 \\ G & I & 0 & 0 \\ A & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \Delta x^{cc} \\ \Delta s^{cc} \\ \Delta z^{cc} \\ \Delta y^{cc} \end{bmatrix} = \begin{bmatrix} 0 \\ \sigma \mu \mathbf{1} - \mathbf{diag}(\Delta s^{aff}) \Delta z^{aff} \\ 0 \end{bmatrix},$$

with

$$\begin{split} \mu &= s^{T} z / p \qquad \sigma = \left( (s + \alpha \Delta s^{\text{aff}})^{T} (z + \alpha \Delta z^{\text{aff}}) / (s^{T} z) \right)^{3} \\ \alpha &= \sup\{\alpha \in [0, 1] \mid s + \alpha \Delta s^{\text{aff}} \geqslant 0, \ z + \alpha \Delta z^{\text{aff}} \geqslant 0 \} \end{split}$$

.

# Algorithm (continued)

4. Combine the updates with

$$\begin{split} \Delta x &= \Delta x^{\rm aff} + \Delta x^{\rm cc} \qquad \Delta s &= \Delta s^{\rm aff} + \Delta s^{\rm cc} \\ \Delta y &= \Delta y^{\rm aff} + \Delta y^{\rm cc} \qquad \Delta z &= \Delta z^{\rm aff} + \Delta z^{\rm cc} \end{split} .$$

### 5. Find

$$\alpha = \min\{1, \ 0.99 \sup\{\alpha \ge 0 \mid s + \alpha \Delta s \ge 0, \ z + \alpha \Delta z \ge 0\}\},\$$

and update

$$x := x + \alpha \Delta x$$
  $s := s + \alpha \Delta s$   
 $y := y + \alpha \Delta y$   $z := z + \alpha \Delta z$ 

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## Solving KKT system

- Most computation effort, typically 80%, is solution of KKT system
- Each iteration requires two solves with (symmetrized) KKT matrix

$$K = \begin{bmatrix} Q & 0 & G^T & A^T \\ 0 & S^{-1}Z & I & 0 \\ \hline G & I & 0 & 0 \\ A & 0 & 0 & 0 \end{bmatrix}$$

- Quasisemidefinite: block diagonals PSD, NSD
- ▶ Use permuted *LDL<sup>T</sup>* factorization with diagonal *D*, unit lower-triangular *L*

# Solving KKT system: Permutation issues

- Factorize  $PKP^T = LDL^T$ , with permutation matrix P
- L, D unique, if they exist
- ▶ *P* determines nonzero count of *L*, thus computation time
- Standard method: choose P at solve time
  - Uses numerical values of K
  - Maintains stability
  - Slow (complex data structures, branching)
- CVXGEN: choose P at development time
  - Factorization does not even exist, for some P
  - Even if factorization exists, stability highly dependent on P
  - How do we fix this?

# Solving KKT system: Regularization

- Use regularized KKT system  $\tilde{K}$  instead
- Choose regularization constant  $\epsilon > 0$ , then instead factor:

$$P\left(\begin{bmatrix} Q & 0 & | G^T & A^T \\ 0 & S^{-1}Z & I & 0 \\ \hline G & I & 0 & 0 \\ A & 0 & | 0 & 0 \end{bmatrix} + \begin{bmatrix} \epsilon I & 0 \\ \hline 0 & -\epsilon I \end{bmatrix}\right)P^T = P\widetilde{K}P^T = LDL^T$$

- $\widetilde{K}$  now quasidefinite: block diagonals PD, ND
- Factorization always exists (Gill et al, '96)

# Solving KKT system: Selecting the permutation

- Select P at development time to minimize nonzero count of L
- Simple greedy algorithm:

Create an undirected graph from  $\tilde{K}$ .

While nodes remain, repeat:

- 1. For each uneliminated node, calculate the fill-in if it were eliminated next.
- 2. Eliminate the node with lowest induced fill-in.
- ▶ Can prove that *P* determines signs of *D<sub>ii</sub>* (will come back to this)

# Solving KKT system: Solution

• Algorithm requires two solutions  $\ell$  with different residuals r, of

$$K\ell = r$$

Instead, solve

$$\ell = \widetilde{K}^{-1}r = P^{T}L^{-T}D^{-1}L^{-1}Pr$$

- Use cached factorization, forward- and backward-substitution
- But: solution to wrong system
- Use iterative refinement

# Solving KKT system: Iterative refinement

- Want solution to  $K\ell = r$ , only have operator  $\widetilde{K}^{-1} \approx K^{-1}$
- Use iterative refinement:

Solve  $\widetilde{K}\ell^{(0)} = r$ .

Want correction  $\delta \ell$  such that  $K(\ell^{(0)} + \delta \ell) = r$ . Instead:

- 1. Compute approximate correction by solving  $\tilde{K}\delta\ell^{(0)} = r K\ell^{(0)}$ .
- 2. Update iterate  $\ell^{(1)} = \ell^{(0)} + \delta \ell^{(0)}$ .
- 3. Repeat until  $\ell^{(k)}$  is sufficiently accurate.
- Iterative refinement with  $\tilde{K}$  provably converges
- CVXGEN uses only one refinement step

# Solving KKT system: Eliminating failure

- Regularized factorization cannot fail with exact arithmetic
- Numerical errors can still cause divide-by-zero exceptions
- Only divisions in algorithm are by D<sub>ii</sub>
- ▶ Factorization computes  $\hat{D}_{ii} \neq D_{ii}$ , due to numerical errors
- Therefore, given sign  $\xi_i$  of  $D_{ii}$ , use

$$D_{ii} = \xi_i((\xi_i \widehat{D}_{ii})_+ + \epsilon)$$

- Makes division 'safe'
- Iterative refinement still provably converges

# Code generation

- Code generation converts symbolic representation to compilable code
- Use templates [color key: C code, control code, C substitutions]

```
void kkt_multiply(double *result, double *source) {
    - kkt.rows.times do |i|
    result[#{i}] = 0;
    - kkt.neighbors(i).each do |j|
        - if kkt.nonzero? i, j
        result += #{kkt[i,j]}*source[#{j}];
}
```

Generate extremely explicit code

## Code generation: Extremely explicit code

Embedded constants, exposed for compiler optimizations:

```
// r3 = -Gx - s + h.
multbymG(r3, x);
for (i = 0; i < 36; i++)
r3[i] += -s[i] + h[i];</pre>
```

Computing single entry in factorization:

### Parameter stuffing:

```
b[4] = params.A[4]*params.x_0[0] + params.A[9]*params.x_0[1]
+ params.A[14]*params.x_0[2] + params.A[19]*params.x_0[3]
+ params.A[24]*params.x_0[4];
```

### Part IV: Verification

- 1. Computation speed
- 2. Reliability

# Computation speeds

- Maximum execution time more relevant than average
- Test millions of problem instances to verify performance

## Computation speeds: Examples

	Scheduling	Battery	Suspension
Variables	279	153	104
Constraints	465	357	165
CVX, Intel i7	4.2 s	1.3 s	2.6 s

## Computation speeds: Examples

	Scheduling	Battery	Suspension
Variables	279	153	104
Constraints	465	357	165
CVX, Intel i7	4.2 s	1.3 s	2.6 s
CVXGEN, Intel i7	$850 \ \mu s$	360 µs	110 µs

## Computation speeds: Examples

	Scheduling	Battery	Suspension
Variables	279	153	104
Constraints	465	357	165
CVX, Intel i7	4.2 s	1.3 s	2.6 s
CVXGEN, Intel i7	850 μs	360 μs	110 μs
CVXGEN, Atom	7.7 ms	4.0 ms	1.0 ms

# Reliability testing

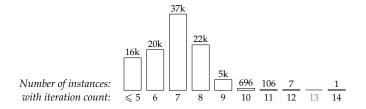
- Analyzed millions of instances from many problem families
- Goal: tune algorithm for total reliability, high speed
- Investigated:
  - > Algorithms: primal-barrier, primal-dual, primal-dual with Mehrotra
  - Initialization methods including two-phase, infeasible-start, least-squares
  - Regularization and iterative refinement
  - > Algebra: dense, library-based, sparse, flat; all with different solution methods
  - Code generation, using profiling to compare strategies
  - Compiler integration, using profiling and disassembly

## Reliability testing: Example

- Computation time proportional to iteration count
- Thus, simulate many instances and record iteration count
- Example:  $l_1$ -norm minimization with box constraints

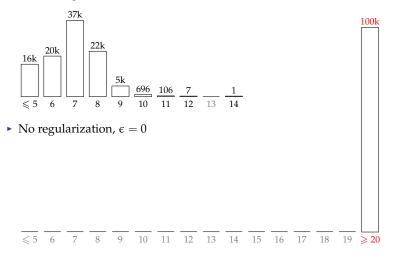
#### Reliability testing: Example

- Computation time proportional to iteration count
- Thus, simulate many instances and record iteration count
- Example:  $l_1$ -norm minimization with box constraints
- Iteration count with default settings:



Reliability testing: No KKT regularization

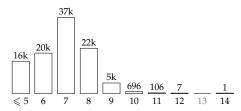
• Default regularization,  $\epsilon = 10^{-7}$ 



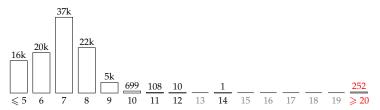
Part IV: Verification

### Reliability testing: Decreased KKT regularization

• Default regularization,  $\epsilon = 10^{-7}$ 

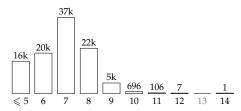


• Decreased regularization,  $\epsilon = 10^{-11}$ 

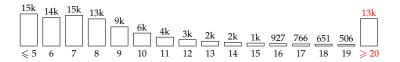


#### Reliability testing: Increased KKT regularization

• Default regularization,  $\epsilon = 10^{-7}$ 



• Increased regularization,  $\epsilon = 10^{-2}$ 

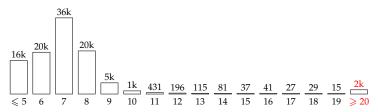


Part IV: Verification

#### Reliability testing: Iterative refinement

• Default of 1 iterative refinement step, with  $\varepsilon = 10^{-2}$ 

• Increased to 10 iterative refinement steps, with  $\epsilon = 10^{-2}$ 



## Reliability testing: Summary

- Regularization and iterative refinement allow reliable solvers
- Iteration count relatively insensitive to parameters

### Part V: Final notes

- 1. Conclusions
- 2. Contributions
- 3. Extensions
- 4. Publications
- 5. Acknowledgements

### Conclusions

Contributions

- Framework for embedded convex optimization
- Design and demonstration of reliable algorithms
- First application of code generation to convex optimization

#### CVXGEN

- Fastest solvers ever written
- Already in use

#### Extensions

- Blocking, for larger problems
- More general convex families
- Different hardware

#### Publications

- CVXGEN: A Code Generator for Embedded Convex Optimization, J. Mattingley and S. Boyd, manuscript
- Code Generation for Receding Horizon Control, J. Mattingley, Y. Wang and S. Boyd, in review, IEEE Control Systems Magazine
- Code Generation for Receding Horizon Control, J. Mattingley, Y. Wang and S. Boyd, *Proceedings IEEE Multi-Conference on Systems and Control*, pp. 985–992, Yokohama, Japan, September 2010
- Real-Time Convex Optimization in Signal Processing, J. Mattingley and S. Boyd, *IEEE Signal Processing Magazine*, 27(3):50–61, May 2010
- Automatic Code Generation for Real-Time Convex Optimization,
   J. Mattingley and S. Boyd, chapter in *Convex Optimization in Signal Processing and Communications*, Y. Eldar and D. Palomar, Eds., Cambridge University Press, 2009