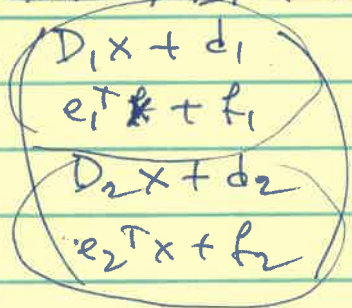


$$A \times B = \{(a, b) : a \in A, b \in B\}$$

$$\begin{aligned} (D_1 x + d_1, e_1^T x + f_1) &\in Q_1 \\ (D_2 x + d_2, e_2^T x + f_2) &\in Q_2 \end{aligned}$$

$$\Leftrightarrow (\cancel{D_1 x + d_1}, \cancel{e_1^T x + f_1}) \in Q_1 \times Q_2$$



$$\in Q_1 \times Q_2$$

$$\begin{bmatrix} tI & x \\ x^T & t \end{bmatrix} \succeq 0 \Leftrightarrow tI - \frac{xx^T}{t} \succeq 0$$

$$\Leftrightarrow t^2 I - xx^T \succeq 0.$$

$$\Leftrightarrow \|x\|_2^2 \leq t^2$$

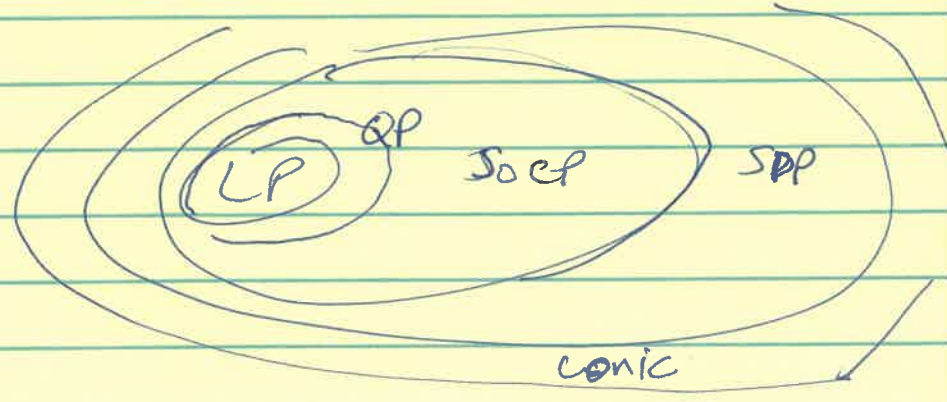
or $\|x\|_2 \leq t$

Schar complement.

$$a^T (t^2 I - xx^T) a \geq 0$$

all a

$$t^2 \|x\|_2^2 - \|x\|_2^4 \geq 0.$$

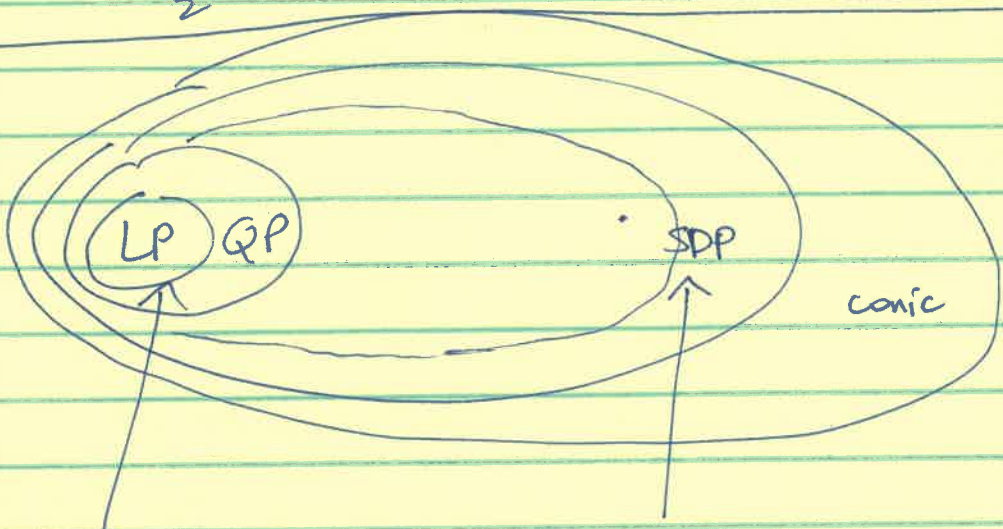


symmetric square root $Q^{1/2}Q^{1/2} = Q$.

$$\| \left(\frac{1}{\sqrt{2}} Q^{1/2} x, \frac{1}{2} (1-t) \right) \|_2^2 \leq \frac{1}{2} (1+t)^2$$

$$\frac{1}{2} x^T Q x + \frac{1}{4} (1-2t+t^2) \leq \frac{1}{4} (1+2t+t^2)$$

$$\frac{1}{2} x^T Q x \leq t. \quad \checkmark$$

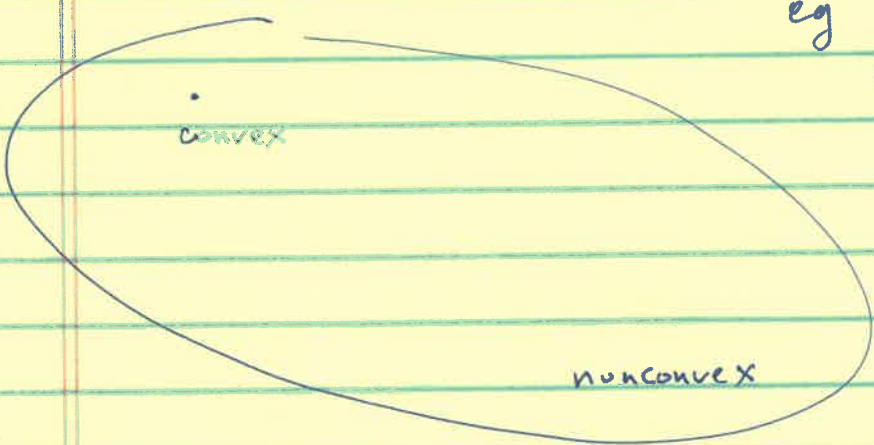


"easy"
algorithmically

"hard"

only very special
SDPs are easy to
solve!

eg graphical lasso.
trace norm imputation



$$f(y) \approx f(x) + \nabla f(x)^T (y-x)$$

$$= f(x) + t \nabla f(x)^T \Delta x$$

$$y = x + t \Delta x$$

assuming L Lipschitz $\iff \nabla^2 f(x) \preceq LI$ all x
twice differentiable

$$f(y) \leq f(x) + \nabla f(y)^T (y-x) + \frac{L}{2} \|y-x\|_2^2$$

$O(1/k)$ or to get ϵ -suboptimal solution

$$f(x^{(k)}) - f^* \leq \epsilon$$

$$\frac{c}{k} = \epsilon$$

$$k = \frac{c}{\epsilon}$$

$$O(1/\epsilon)$$

$$O(1/k^2)$$

equiv.

$$\frac{c}{k^2} = \epsilon$$

$$k = \sqrt{\frac{c}{\epsilon}}$$

$$O(1/\sqrt{\epsilon})$$

$$O(c^k)$$

$$c^k = \epsilon$$

$$k = \frac{\log(1/\epsilon)}{\log(c)} \cdot \text{const.}$$

$$f(\beta) = \frac{1}{2} \|y - X\beta\|_2^2$$

$$X^T(X\beta - y)$$

$$\nabla^2 f(\beta) = X^T X$$

" $\nabla f(\beta)$ "

$$f(y) \leq f(x) + \nabla f(x)^T (y-x) + \frac{L}{2} \|y-x\|_2^2 \quad \text{all } y$$

plug in $y = x - t \nabla f(x) := x^+$

$$\begin{aligned} f(x^+) &\leq f(x) - t \|\nabla f(x)\|_2^2 + \frac{Lt^2}{2} \|\nabla f(x)\|_2^2 \\ &= f(x) - \underbrace{t \left(1 - \frac{Lt}{2}\right)}_{\neq 0} \|\nabla f(x)\|_2^2. \end{aligned}$$

take $t \leq \frac{2}{L}$
 $w > 0$.

$$\|\nabla f(x)\|_2^2 \leq \frac{1}{w} (f(x) - f(x^+))$$

add up this bound over $i=0, \dots, k$

$$\begin{aligned} \sum \|\nabla f(x^{(i)})\|_2^2 &\leq \frac{1}{w} (f(x^{(0)}) - f(x^{(k+1)})) \\ &\leq \frac{1}{w} (f(x^{(0)}) - f^*) \end{aligned}$$

$(k+1) \min \|\nabla f(x^{(i)})\|_2^2 \leq$

$$\min \|\nabla f(x^{(i)})\|_2^2 \leq \frac{1}{w(k+1)} (f(x^{(0)}) - f^*)$$