

Linear and Quadratic Programming (with CGAL)

Bernd Gärtner, Algorithms Lab

November 21, 2011

Linear Programming (LP)

- ❖ **Problem:** Minimize a linear function in n variables subject to m linear (in)equality constraints!

Linear Programming

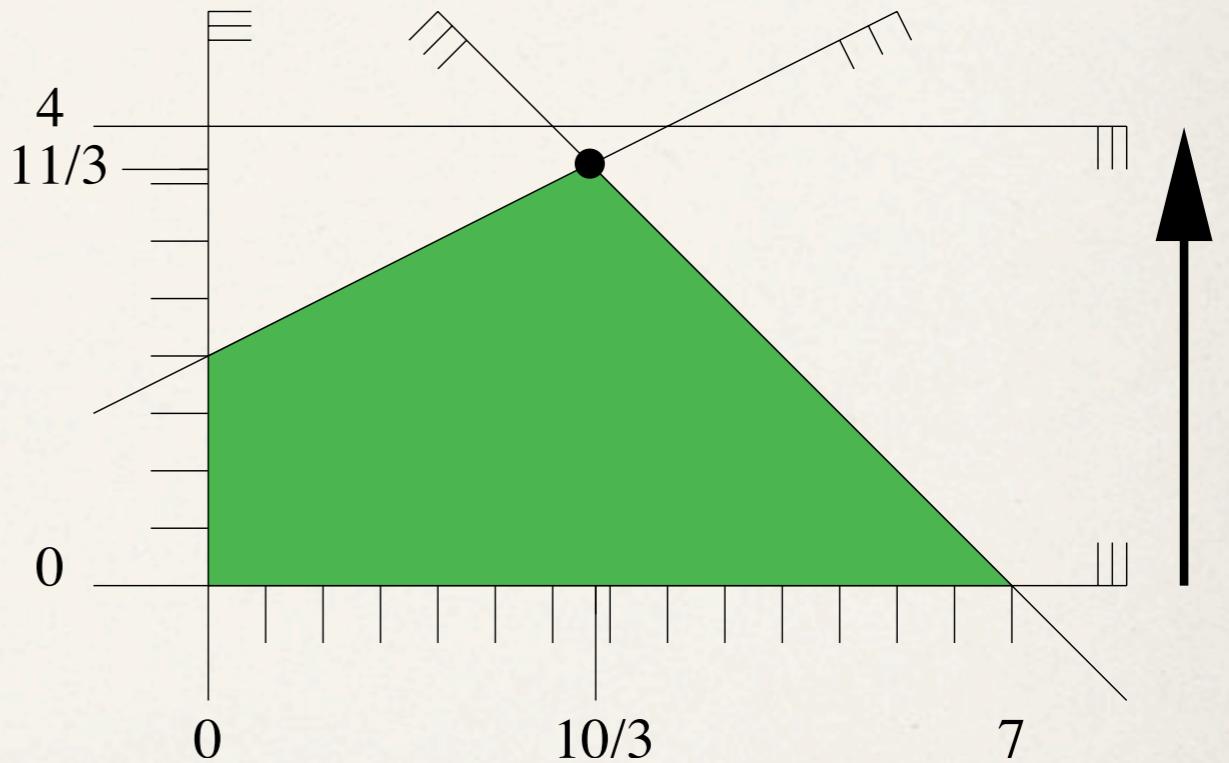
- **Problem:** Minimize a linear function in n variables subject to m linear (in)equality constraints!
- **Example** ($n=2, m=5$):

$$\begin{array}{lll} \text{minimize} & -32y + 64 \\ \text{subject to} & x + y & \leq 7 \\ & -x + 2y & \leq 4 \\ & x & \geq 0 \\ & y & \geq 0 \\ & y & \leq 4 \end{array}$$

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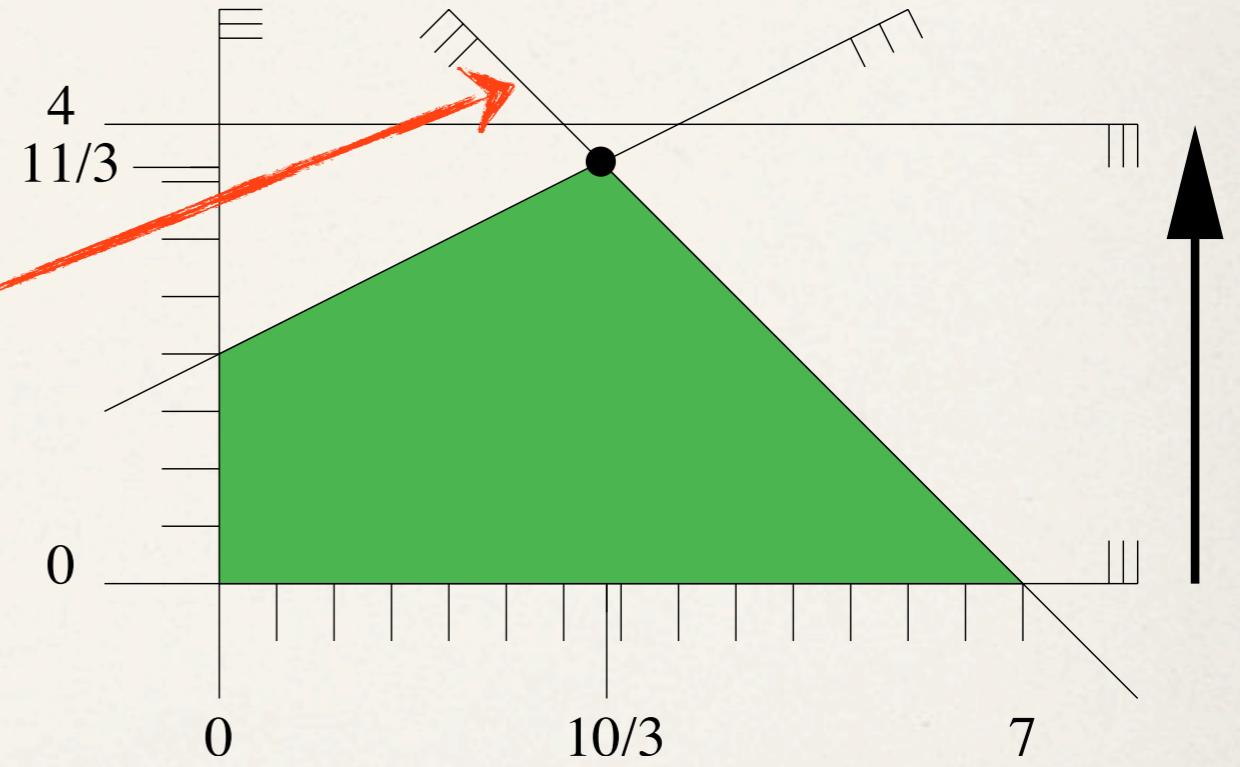


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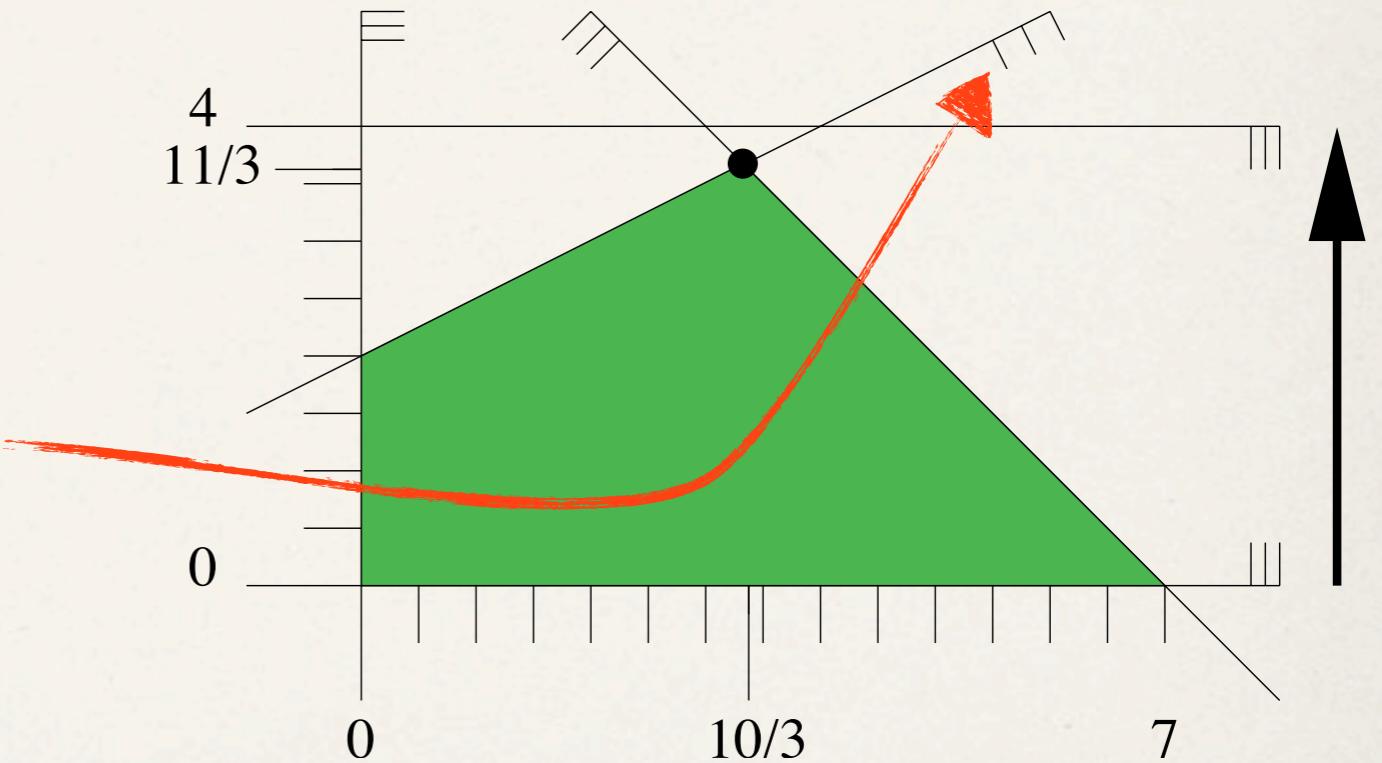


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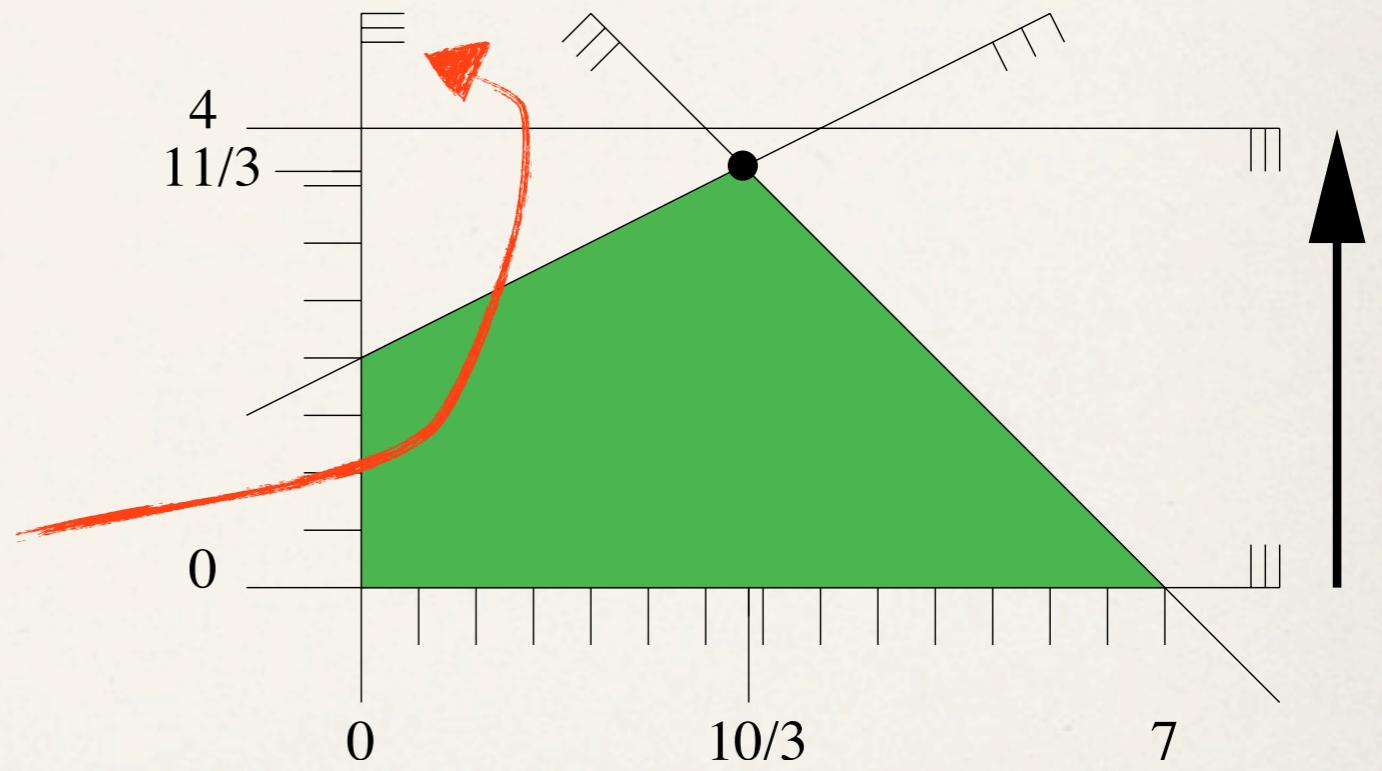


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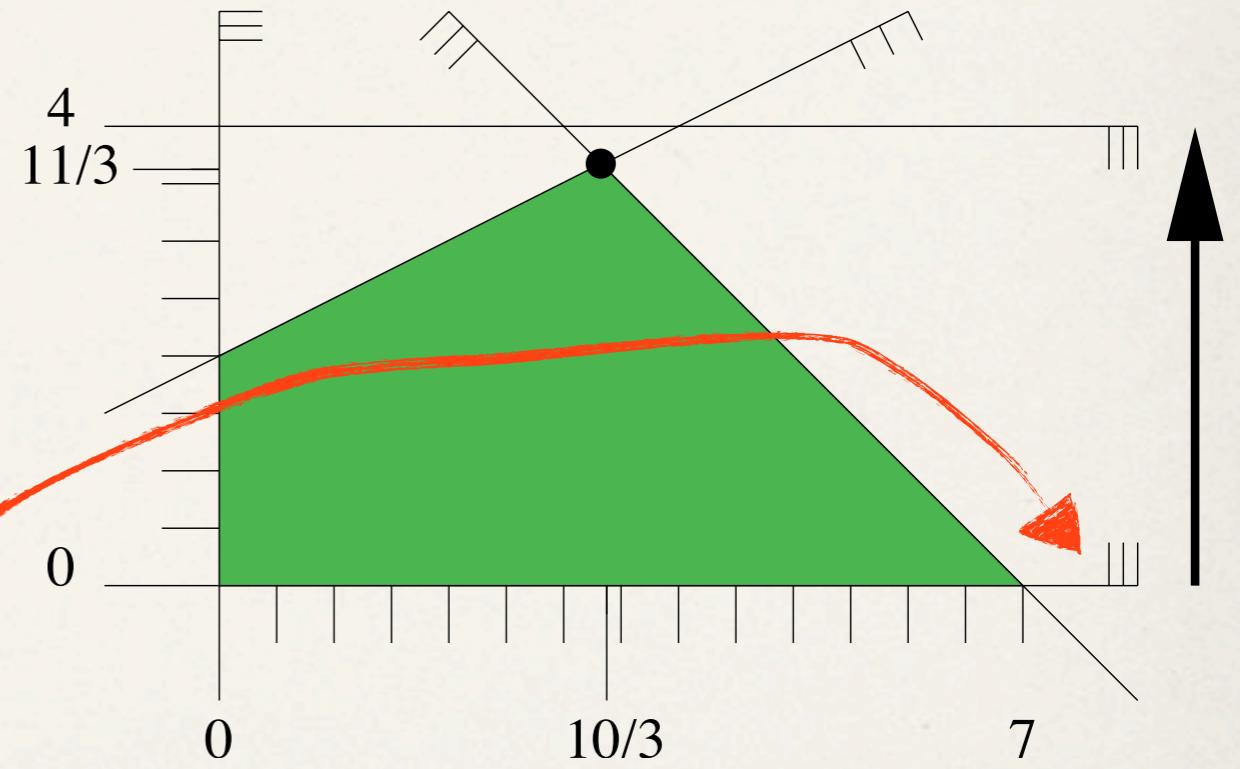


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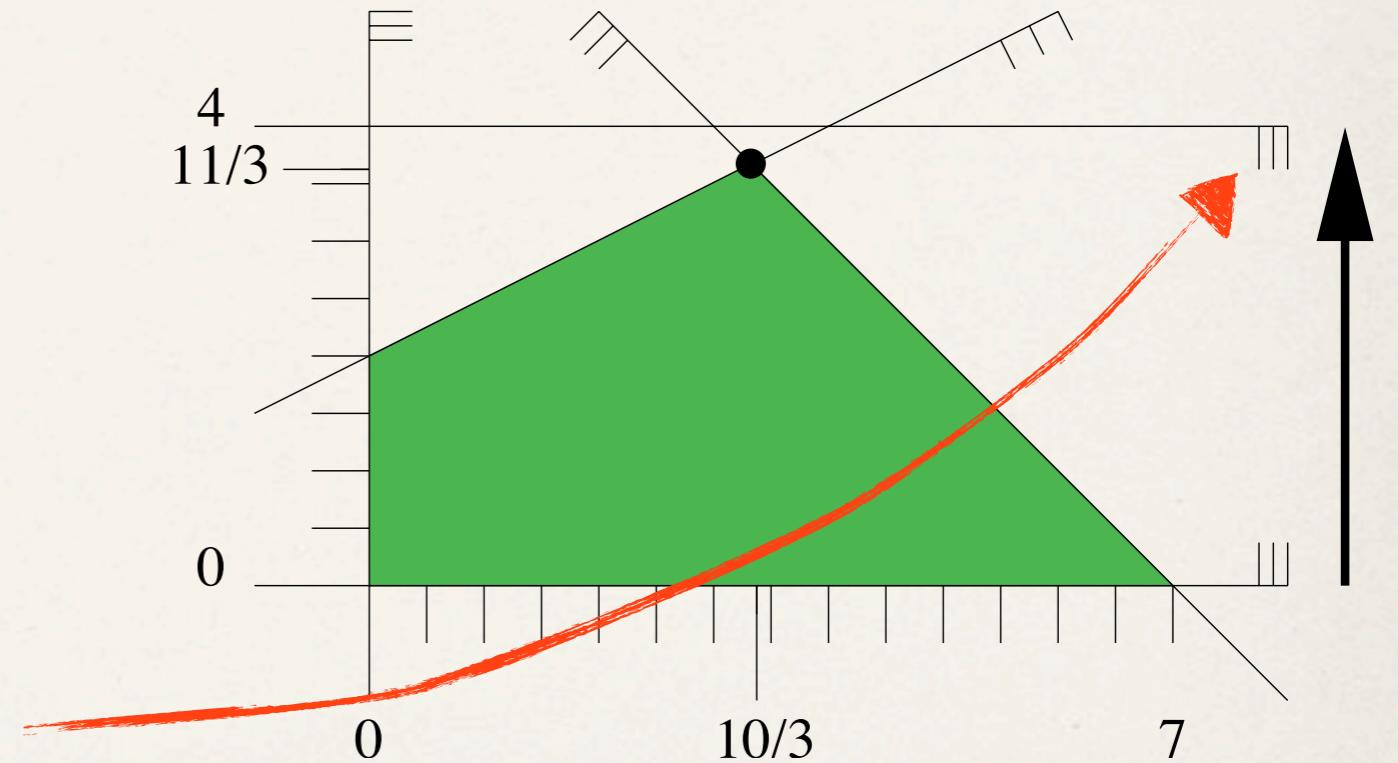
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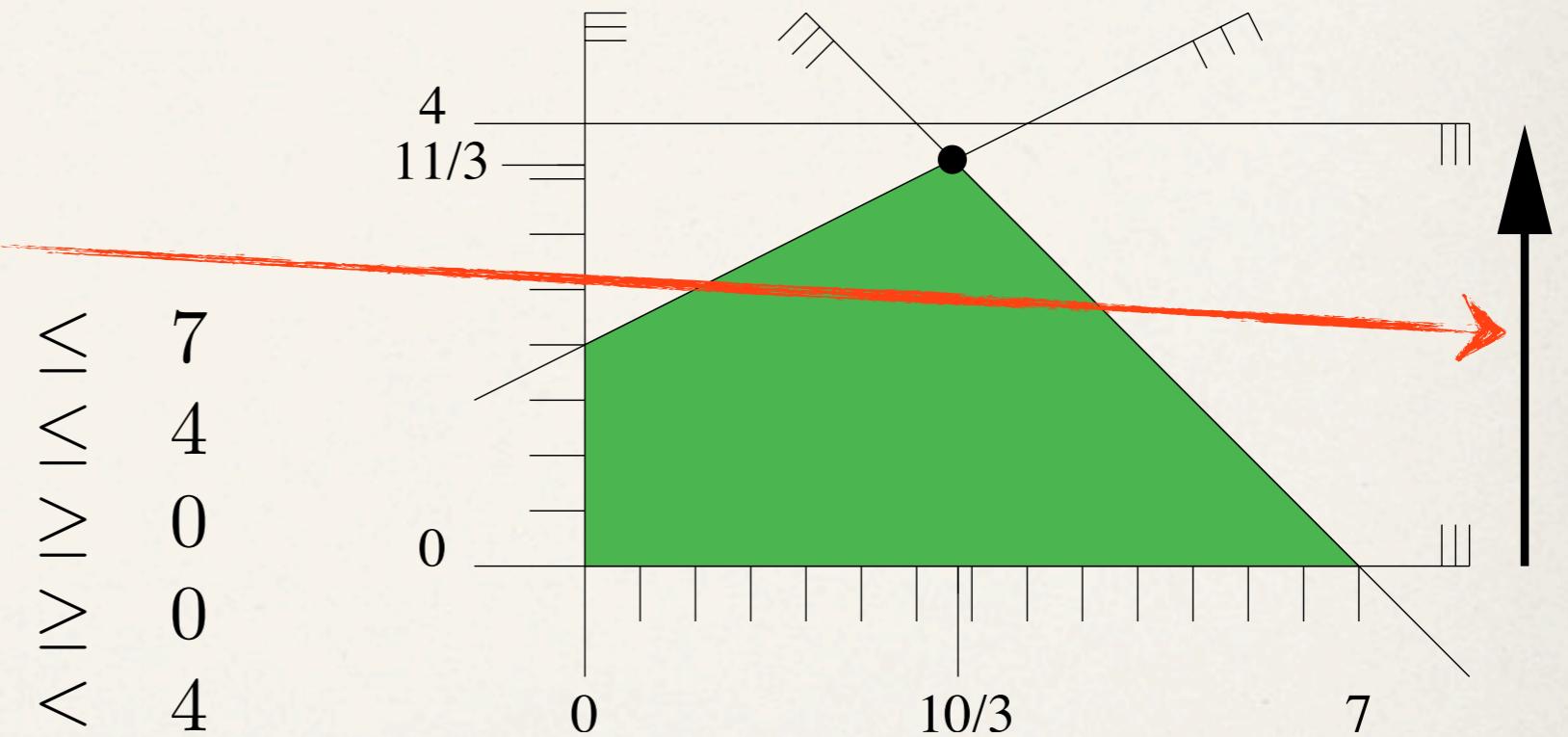
minimize $-32y + 64$
subject to $x + y \leq 7$
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 $x \geq 0$
 $y \geq 0$
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Linear Programming

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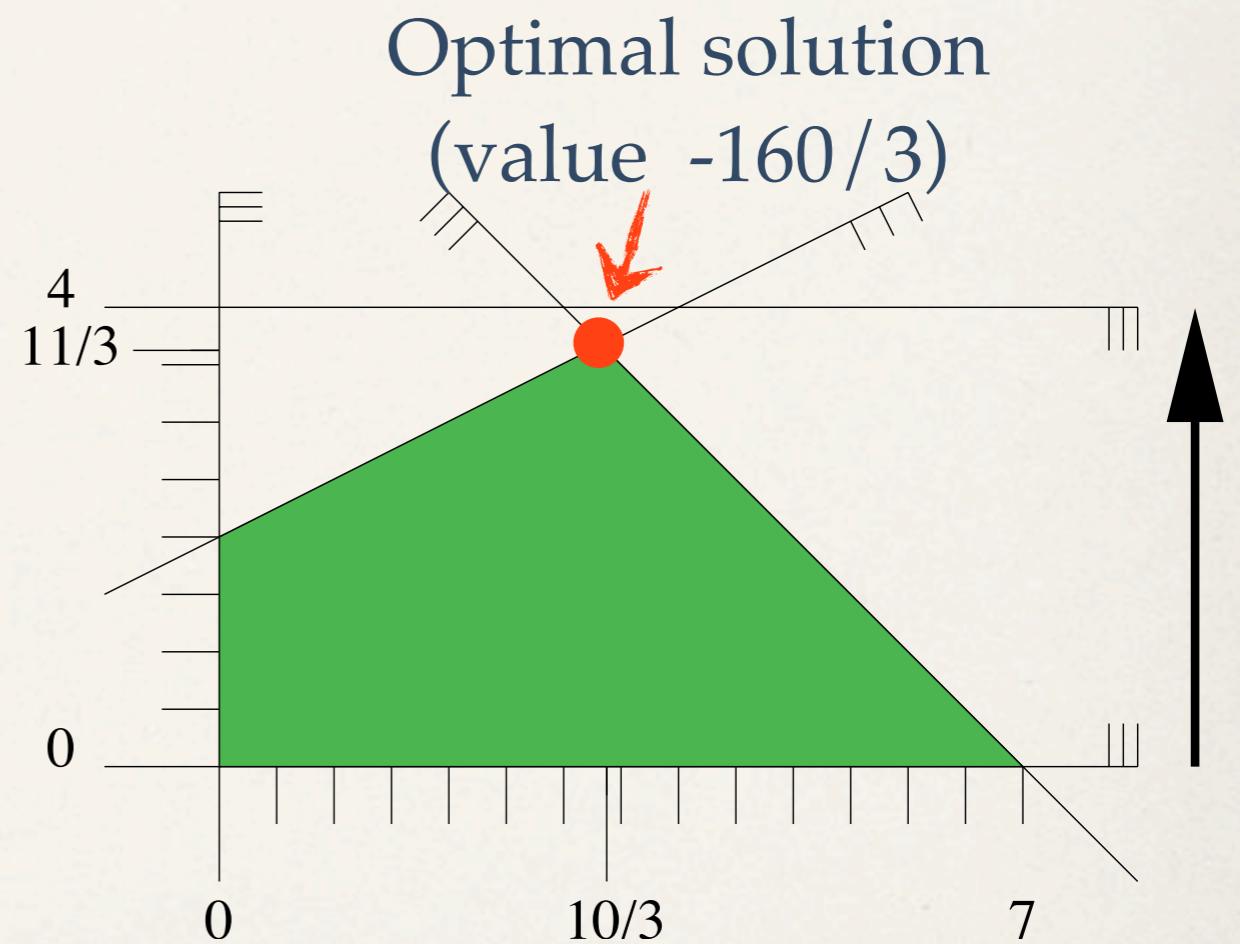
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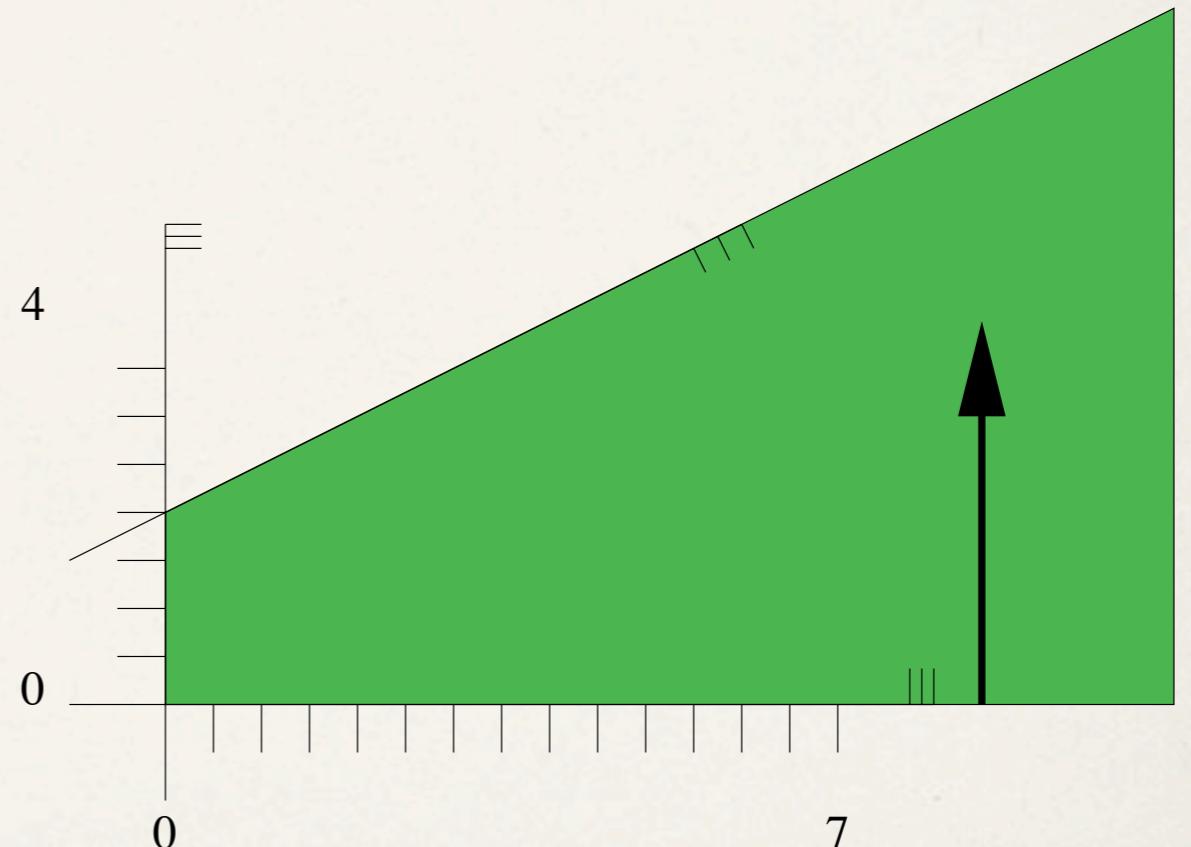


Linear Programming

- ❖ **Problem:** Minimize a linear function in n variables subject to m linear (in)equality constraints!
- ❖ **Unbounded linear programs:**

minimize
subject to

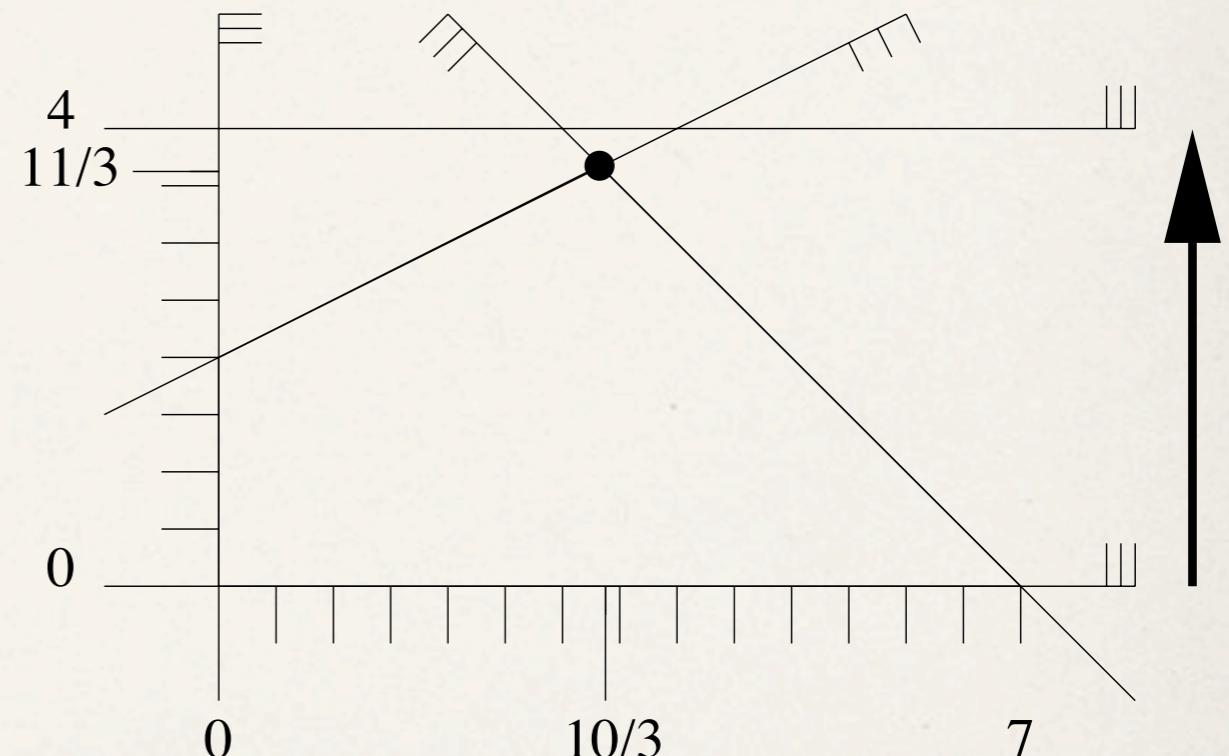
$$\begin{array}{ll} -32y + 64 \\ \begin{aligned} x + y &\leq 7 \\ -x + 2y &\leq 4 \\ x &\geq 0 \\ y &\geq 0 \\ y &\leq 4 \end{aligned} \end{array}$$



Linear Programming

- ❖ **Problem:** Minimize a linear function in n variables subject to m linear (in)equality constraints!
- ❖ **Infeasible linear programs:**

$$\begin{array}{ll} \text{minimize} & -32y + 64 \\ \text{subject to} & x + y \leq 7 \\ & -x + 2y \leq 4 \\ & x \geq 0 \\ & y \geq 0 \\ & y \leq 4 \end{array}$$



Linear Programming ... in CGAL

- * **General form of LP in CGAL:**

$$\begin{aligned} \text{minimize} \quad & c^T x + c_0 \\ \text{subject to} \quad & Ax \geq b \\ & l \leq x \leq u \end{aligned}$$

$$(x, c, l, u \in \mathbb{R}^n, \quad A \in \mathbb{R}^{m \times n}, \quad b \in \mathbb{R}^m, \quad c_0 \in \mathbb{R})$$

Linear Programming ... in CGAL

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$$\begin{array}{ll} \text{minimize} & c^T x + c_0 \\ \text{subject to} & Ax \leq b \\ & l \leq x \leq u \end{array}$$

$\leq, =, \text{ or } \geq$ (individually
for each constraint)

variables

objective function

lower and upper bounds

constraint matrix

right-hand side

shift

($x, c, l, u \in \mathbb{R}^n, A \in \mathbb{R}^{m \times n}, b \in \mathbb{R}^m, c_0 \in \mathbb{R}$)

Linear Programming ... in CGAL

$$\begin{array}{ll} \text{minimize} & -32y + 64 \\ \text{subject to} & x + y \leq 7 \\ & -x + 2y \leq 4 \\ & x \geq 0 \\ & y \geq 0 \\ & y \leq 4 \end{array}$$

- * Preamble: Choice of input type and exact internal number type

Gnu
Multi-
precision
Library
(GMP)

CGAL

```
#include <iostream>
#include <cassert>
#include <CGAL/basic.h>
#include <CGAL/QP_models.h>
#include <CGAL/QP_functions.h>

// choose exact integral type
#ifdef CGAL_USE_GMP
#include <CGAL/Gmpz.h>
typedef CGAL::Gmpz ET;
#else
#include <CGAL/MP_Float.h>
typedef CGAL::MP_Float ET;
#endif

// program and solution types
typedef CGAL::Quadratic_program<int> Program;
typedef CGAL::Quadratic_program_solution<ET> Solution;
```

input type

exact internal type

for linear *and* quadratic programs

GMP used internally

Linear Programming ... in CGAL

$$\begin{array}{ll} \text{minimize} & -32y + 64 \\ \text{subject to} & x + y \leq 7 \\ & -x + 2y \leq 4 \\ & x \geq 0 \\ & y \geq 0 \\ & y \leq 4 \end{array}$$

* Setup: Enter the program data

```
int main() {
    // by default, we have a nonnegative LP with Ax <= b
    Program lp (CGAL::SMALLER, true, 0, false, 0);

    // now set the non-default entries
    const int X = 0;
    const int Y = 1;
    lp.set_a(X, 0, 1); lp.set_a(Y, 0, 1); lp.set_b(0, 7);    // x + y <= 7
    lp.set_a(X, 1, -1); lp.set_a(Y, 1, 2); lp.set_b(1, 4);    // -x + 2y <= 4
    lp.set_u(Y, true, 4);
    lp.set_c(Y, -32);
    lp.set_c0(64);
```

$l =$

$(0, 0, \dots, 0)$

$u = (\infty, \infty, \dots, \infty)$

last argument: value

variable index (0,1,...)

constraint index (0,1,...)

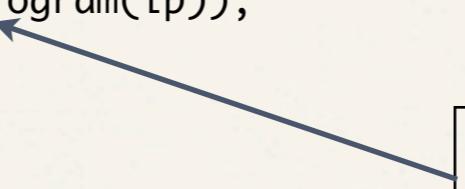
Linear Programming ... in CGAL

- * **Solve:** Call the linear programming solver and output solution

```
// solve the program, using ET as the exact type
Solution s = CGAL::solve_linear_program(lp, ET());
assert (s.solves_linear_program(lp));

// output solution
std::cout << s;
return 0;
}
```

independent verification



Linear Programming ... in CGAL

- * **Solve:** Call the linear programming solver and output solution

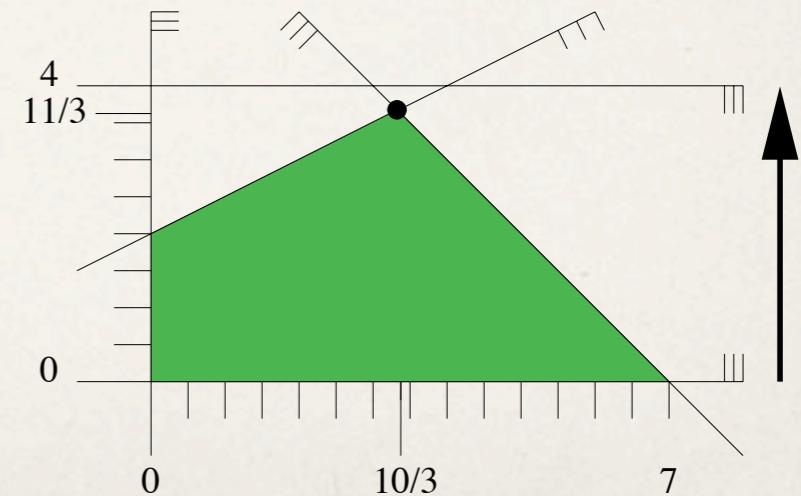
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independent verification

- * **Output:**

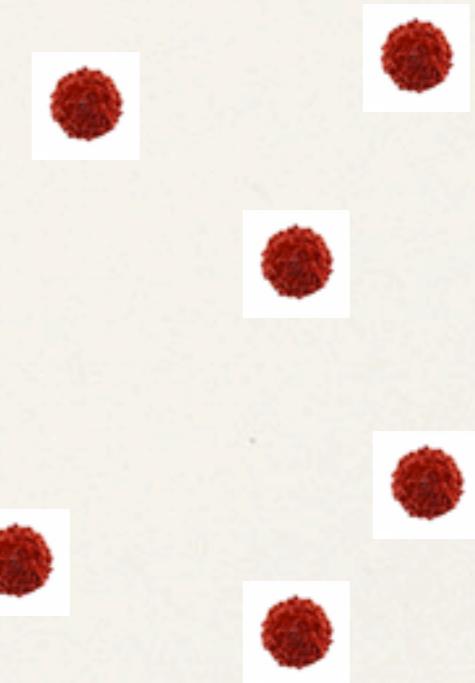
```
status: OPTIMAL
objective value: -160/3
variable values:
 0: 10/3
 1: 11/3
```



Linear Programming

Application I: Cancer Therapy

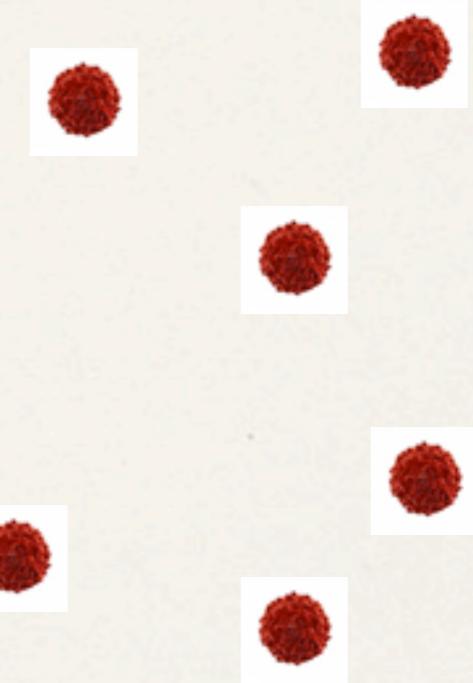
- * **Given:** locations of cancer cells (red)



Linear Programming

Application I: Cancer Therapy

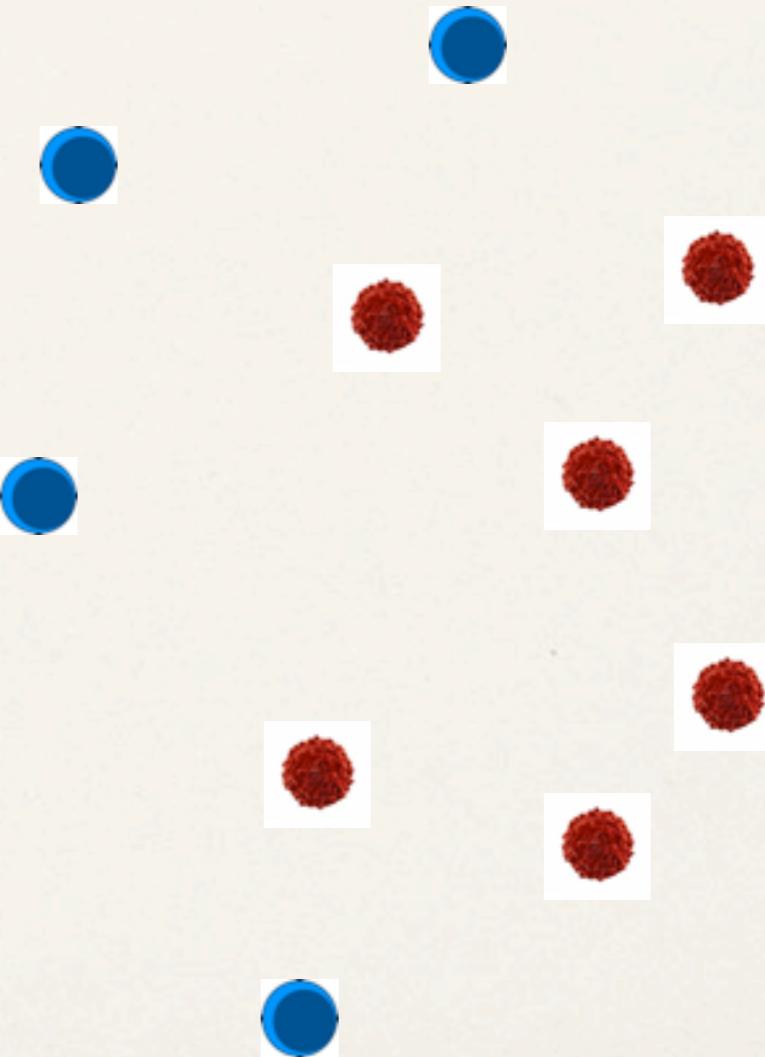
- * **Given:** locations of cancer cells (red) and healthy cells (blue)



Linear Programming

Application I: Cancer Therapy

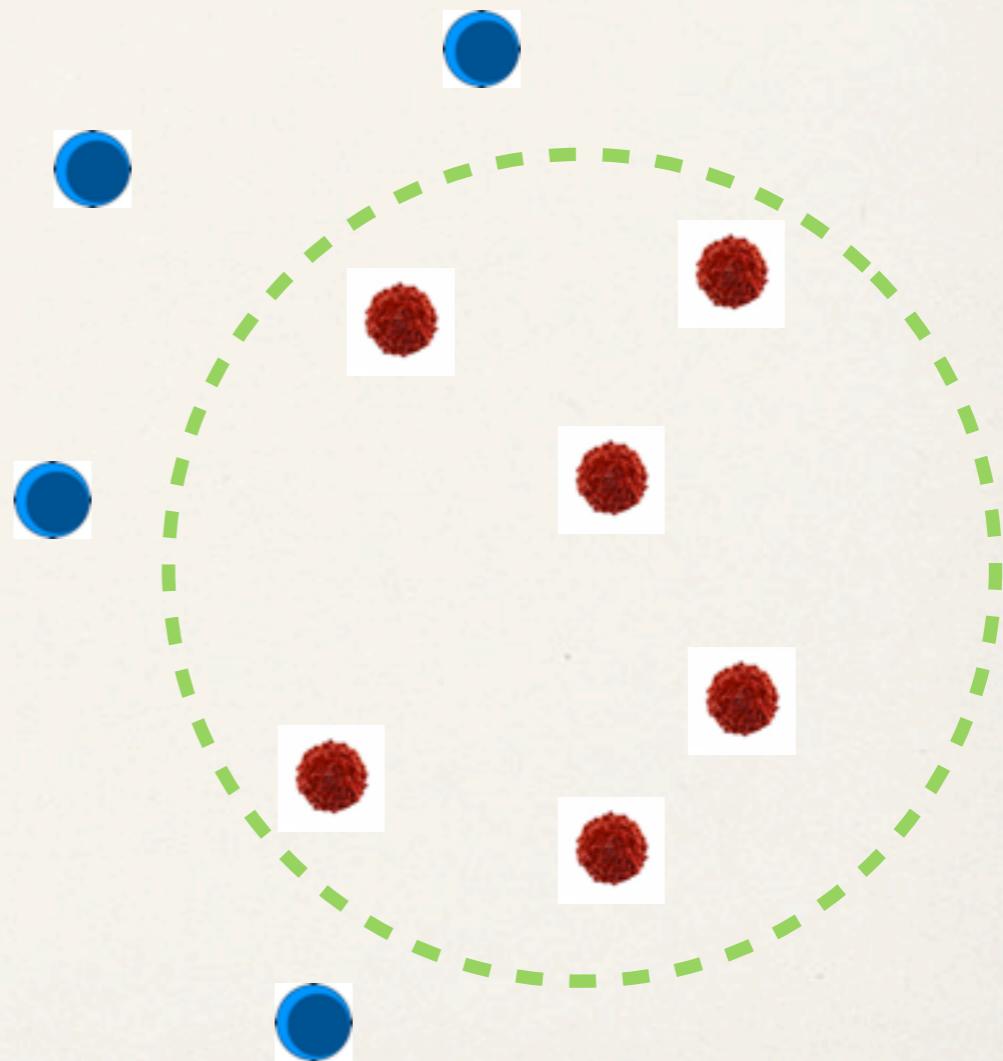
- Given: locations of cancer cells (red) and healthy cells (blue)
- Wanted: center and radius of exposure so that all cancer cells are killed and all healthy cells are unaffected.



Linear Programming

Application I: Cancer Therapy

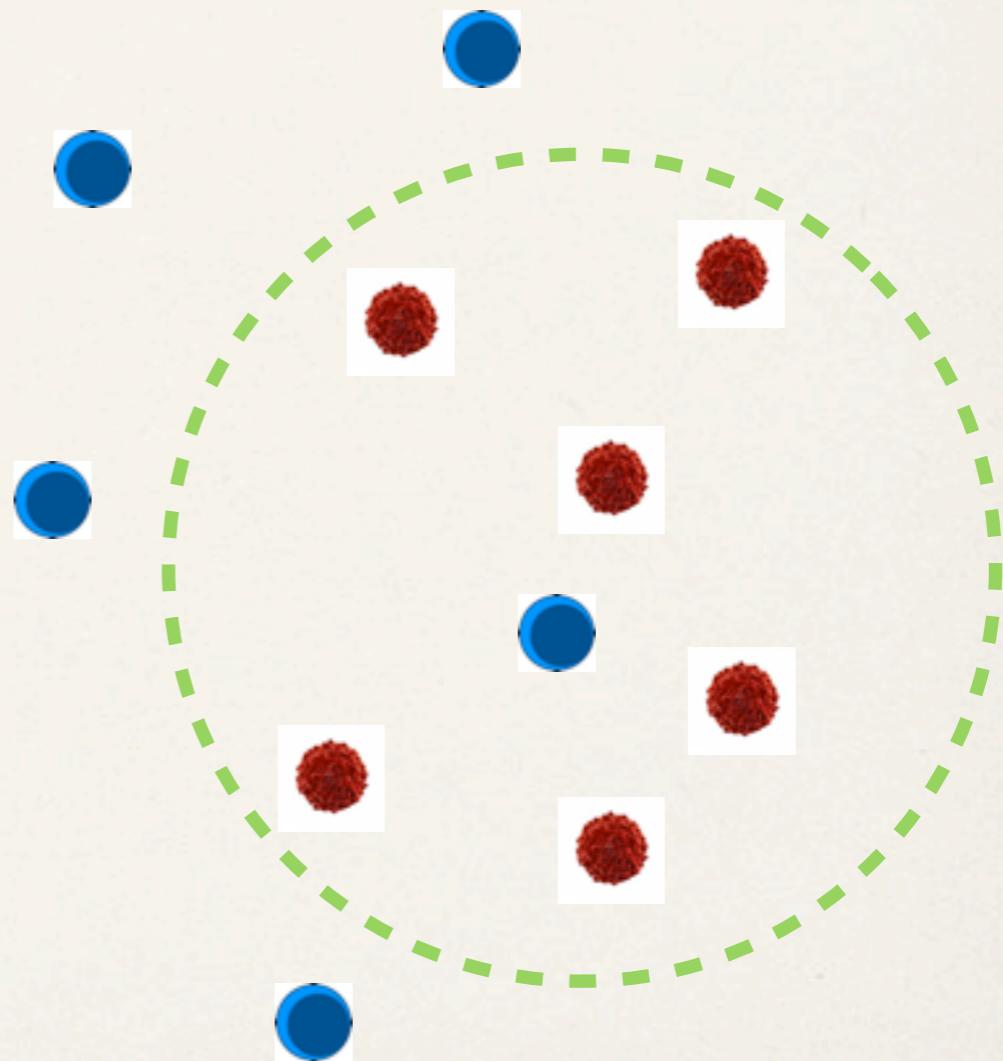
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- This may be possible...



Linear Programming

Application I: Cancer Therapy

- Given: locations of cancer cells (red) and healthy cells (blue)
- Wanted: center and radius of exposure so that all cancer cells are killed and all healthy cells are unaffected.
- This may be possible... or not.



Linear Programming

Application I: Cancer Therapy

- * **The geometric problem:** Given two finite sets R and B in the plane, does there exist a disk that contains R and is disjoint from B ?

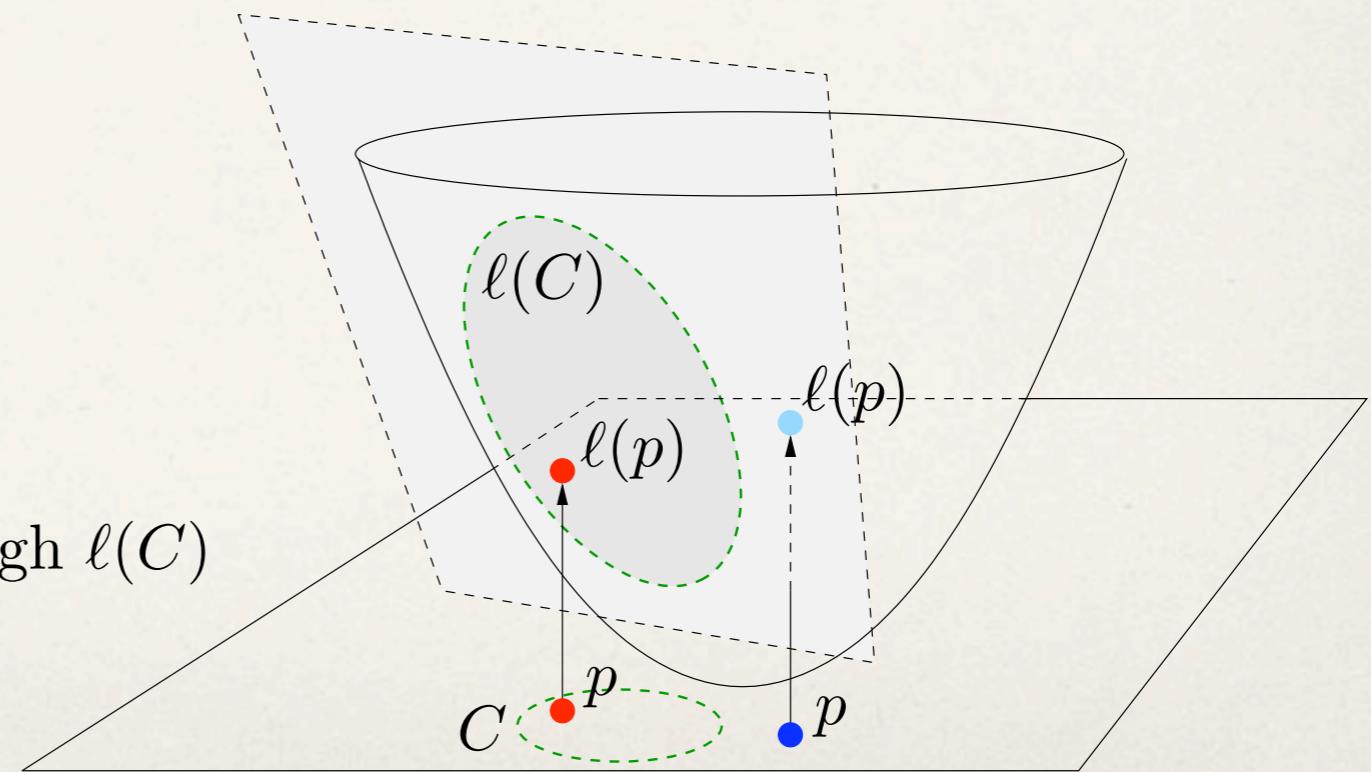
Linear Programming Application I: Cancer Therapy

- **The geometric problem:** Given two finite sets R and B in the plane, does there exist a disk that contains R and is disjoint from B ?
- Apply *lifting map* $\ell : (x, y) \mapsto (x, y, x^2 + y^2)$

$$p \left\{ \begin{array}{l} \text{inside} \\ \text{on} \\ \text{outside} \end{array} \right\} C$$

\Updownarrow

$$\ell(p) \left\{ \begin{array}{l} \text{below} \\ \text{on} \\ \text{above} \end{array} \right\} \text{the plane through } \ell(C)$$



Linear Programming

Application I: Cancer Therapy

- * **The geometric problem (lifted space):** Given the lifted sets R' and B' in space, is there a plane that has R' below/on it and B' above?

Linear Programming

Application I: Cancer Therapy

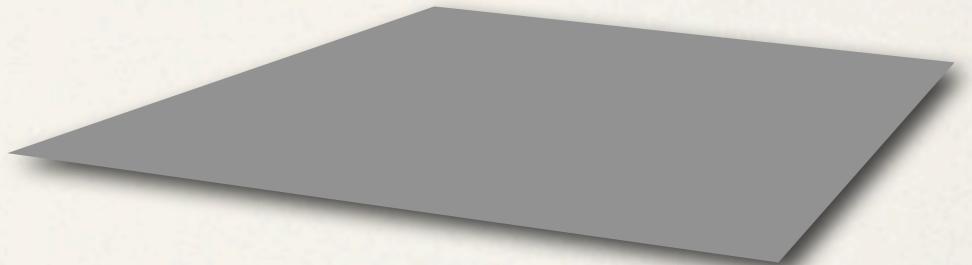
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- This is linear programming!

Linear Programming

Application I: Cancer Therapy

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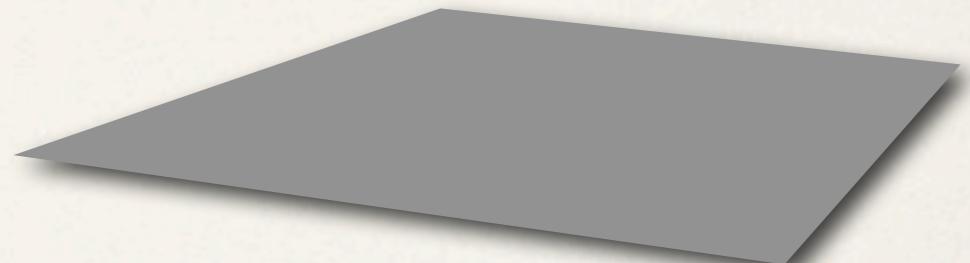
$$\text{plane: } z = \alpha x + \beta y + \gamma$$



Linear Programming

Application I: Cancer Therapy

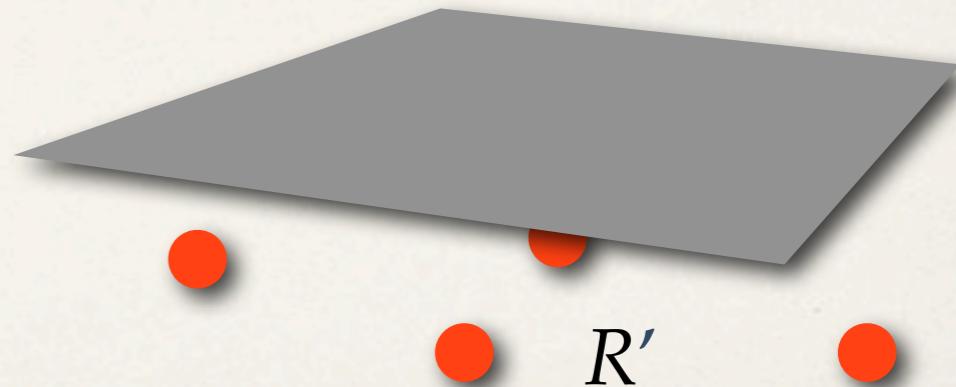
- **The geometric problem (lifted space):** Given the lifted sets R' and B' in space, is there a plane that has R' below/on it and B' above?
- This is linear programming!
- Find $\alpha, \beta, \gamma, \delta > 0$ such that...
plane: $z = \alpha x + \beta y + \gamma$



Linear Programming

Application I: Cancer Therapy

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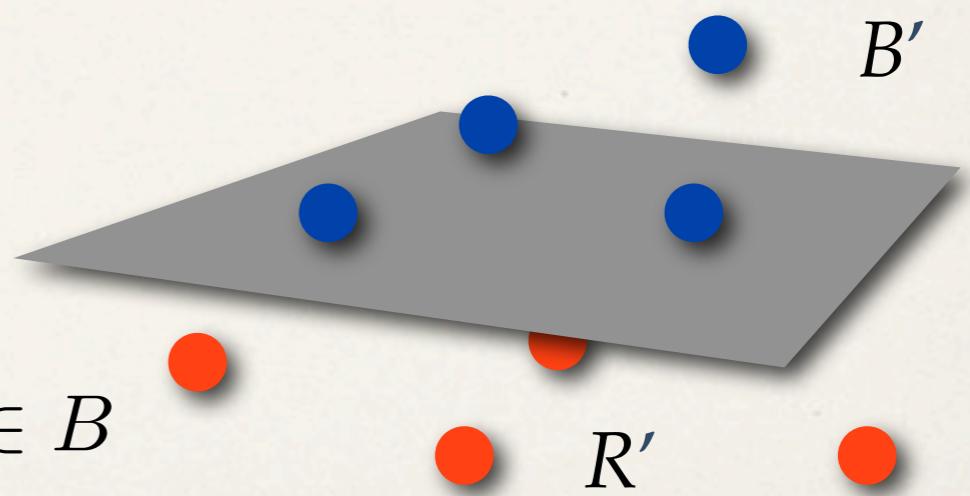
$$x^2 + y^2 \leq \alpha x + \beta y + \gamma, \quad (x, y) \in R$$

Linear Programming

Application I: Cancer Therapy

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$$\text{plane: } z = \alpha x + \beta y + \gamma$$



$$x^2 + y^2 \geq \alpha x + \beta y + \gamma + \delta, \quad (x, y) \in B'$$

$$x^2 + y^2 \leq \alpha x + \beta y + \gamma, \quad (x, y) \in R'$$

Linear Programming

Application I: Cancer Therapy

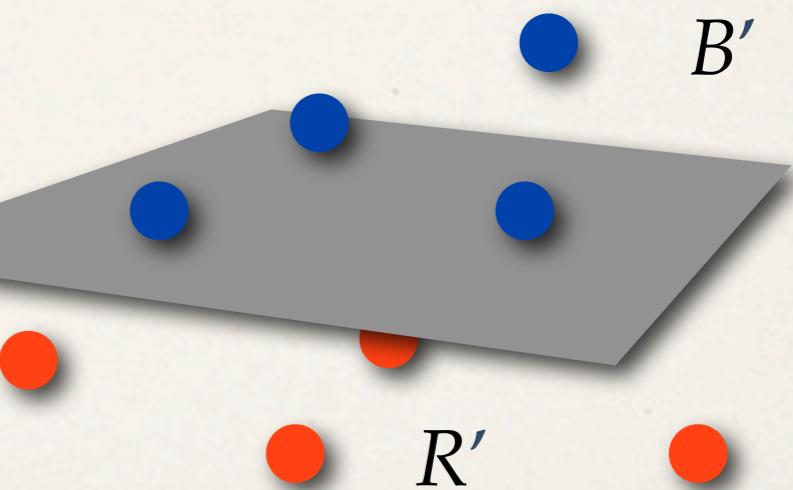
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- Find $\alpha, \beta, \gamma, \delta > 0$ such that...

maximize δ
subject to

$$x^2 + y^2 \geq \alpha x + \beta y + \gamma + \delta, \quad (x, y) \in B'$$
$$x^2 + y^2 \leq \alpha x + \beta y + \gamma, \quad (x, y) \in R'$$

4 variables
 $|B'| + |R'|$ constraints

plane: $z = \alpha x + \beta y + \gamma$



Linear Programming

Application I: Cancer Therapy

- * **Fact:** Exposure is possible if and only if the following linear program has positive value.

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Linear Programming

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- * **Reconstructing the exposure from an optimal solution $(\alpha, \beta, \gamma, \delta)$:**



$$= \{(x, y) : x^2 + y^2 = \alpha x + \beta y + \gamma\}$$

Linear Programming

Application I: Cancer Therapy

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Linear Programming

Application I: Cancer Therapy

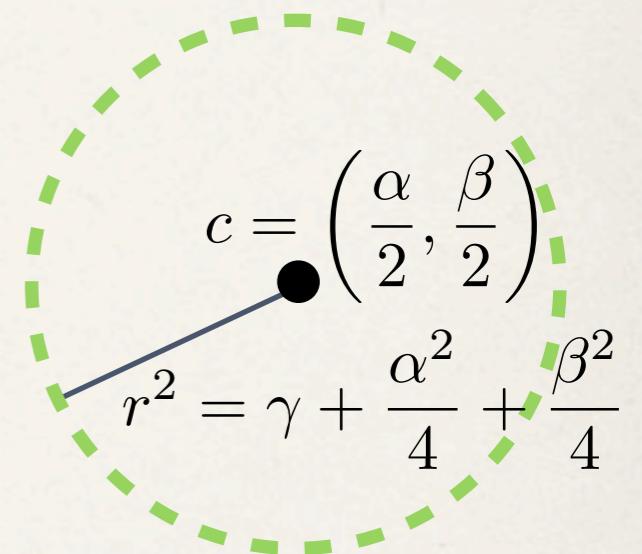
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Linear Programming

Application I: Cancer Therapy

- * **Implementation in CGAL:**

$$\begin{array}{lll} \text{minimize} & -\delta \\ \text{subject to} & x^2 + y^2 \geq \alpha x + \beta y + \gamma + \delta, & (x, y) \in B \\ & x^2 + y^2 \leq \alpha x + \beta y + \gamma, & (x, y) \in R \\ & \delta \leq 1 \end{array}$$

Avoids unbounded program

maximize $c^T x \rightarrow$ minimize $-c^T x$ and negate resulting value

Linear Programming

Application I: Cancer Therapy

- Implementation in CGAL: Setup and Solve (Preamble as before)

```
int main() {
    // by default, we have an LP with Ax <= b and no bounds for
    // the four variables alpha, beta, gamma, delta
    Program lp (CGAL::SMALLER, false, 0, false, 0);
    const int alpha = 0;
    const int beta = 1;
    const int gamma = 2;
    const int delta = 3;

    // number of red and blue points
    int m; std::cin >> m;
    int n; std::cin >> n;

    // read the red points (cancer cells)
    for (int i=0; i<m; ++i) {
        int x; std::cin >> x;
        int y; std::cin >> y;
        // set up <= constraint for point inside/on circle:
        // -alpha x - beta y - gamma <= -x^2 - y^2
        lp.set_a (alpha, i, -x);
        lp.set_a (beta, i, -y);
        lp.set_a (gamma, i, -1);
        lp.set_b (i, -x*x - y*y);
    }
}
```

```
// read the blue points (healthy cells)
for (int j=0; j<n; ++j) {
    int x; std::cin >> x;
    int y; std::cin >> y;
    // set up <= constraint for point outside circle:
    // alpha x + beta y + gamma + delta <= x^2 + y^2
    lp.set_a (alpha, m+j, x);
    lp.set_a (beta, m+j, y);
    lp.set_a (gamma, m+j, 1);
    lp.set_a (delta, m+j, 1);
    lp.set_b (m+j, x*x + y*y);
}

// objective function: -delta (the solver minimizes)
lp.set_c(delta, -1);

// enforce a bounded problem:
lp.set_u (delta, true, 1);

// solve the program, using ET as the exact type
Solution s = CGAL::solve_linear_program(lp, ET());
assert (s.solves_linear_program(lp));
```

Linear Programming

Application I: Cancer Therapy

* Implementation in CGAL: Output

negate resulting value!

```
// output exposure center and radius, if they exist
if (s.is_optimal() && (s.objective_value() < 0)) {
    // *opt := alpha, *(opt+1) := beta, *(opt+2) := gamma
    CGAL::Quadratic_program_solution<ET>::Variable_value_iterator
        opt = s.variable_values_begin();
    CGAL::Quotient<ET> alpha = *opt;
    CGAL::Quotient<ET> beta = *(opt+1);
    CGAL::Quotient<ET> gamma = *(opt+2);
    std::cout << "There is a valid exposure:\n";
    std::cout << " Center = ("           // (alpha/2, beta/2)
        << alpha/2 << ", " << beta/2
        << ")\n";
    std::cout << " Squared Radius = " // gamma + alpha^2/4 + beta^2/4
        << gamma + alpha*alpha/4 + beta*beta/4 << "\n";
} else
    std::cout << "There is no valid exposure.";
std::cout << "\n";
return 0;
}
```

Linear Programming

Application I: Cancer Therapy

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    // *opt := alpha, *(opt+1) := beta, *(opt+2) := gamma
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        << gamma + alpha*alpha/4 + beta*beta/4 << "\n";
} else
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```

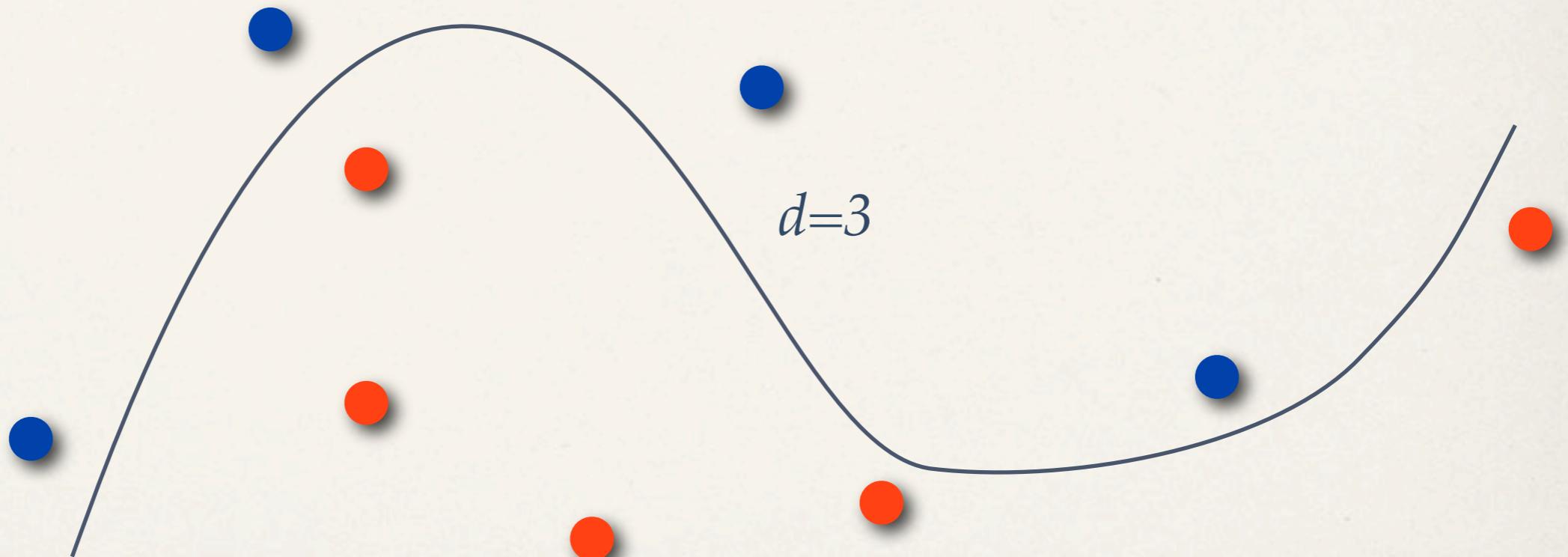
negate resulting value!

"Pointer" to first variable of optimal solution

The quotient
*** (opt+i)** is the value of the variable x_i in the optimal solution

Linear Programming Beyond Cancer Therapy

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- This is linear separability in 8-dimensional space, under the generalized lifting map $(x, y) \rightarrow (x^3, x^2y, xy^2, y^3, x^2, xy, y^2, x, y)$

Linear Programming Further Applications

- * Linear-fractional programming LFP:

$$\begin{array}{ll} \text{minimize} & \frac{c^T x + d}{e^T x + f} \\ \text{subject to} & \begin{array}{lll} Ax & \geq & b \\ e^T x + f & \geq & 0 \end{array} \end{array}$$

Linear Programming Further Applications

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- * Reduce to LP through “homogeneous coordinates”:

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Linear Programming Further Applications

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x feasible with value t

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Linear Programming Further Applications

$x = \frac{y}{z}$ feasible with value t

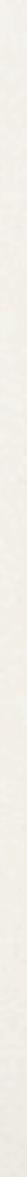
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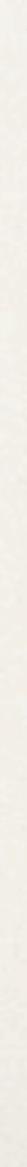
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$z = 0$: can be handled if LFP is feasible

y, z feasible with value t

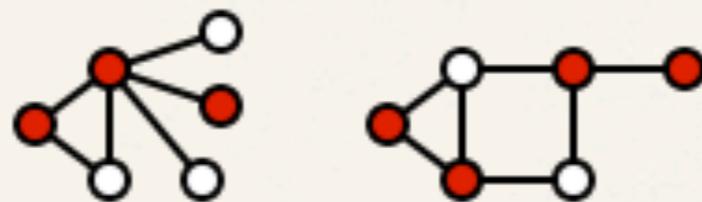


Linear Programming Further Applications

- * Linear programming relaxations for hard combinatorial problems

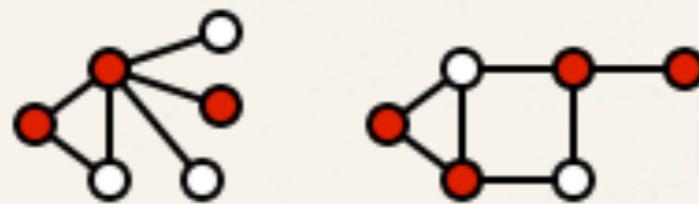
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- * **Vertex Cover:** Given a graph $G=(V,E)$, find a smallest subset of vertices (a vertex cover) such that every edge is incident to one vertex of the cover.



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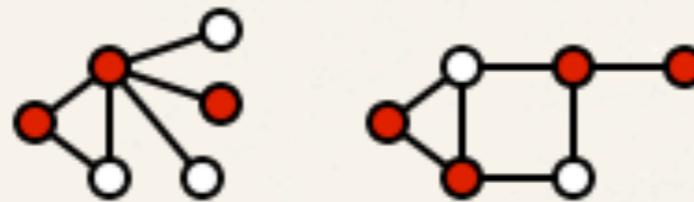


- * Formulation as “LP”: x_i indicates whether vertex i is in the cover (0: not in the cover, 1: in the cover):

$$\begin{array}{ll} \text{minimize} & \sum_{i=1}^n x_i \\ \text{subject to} & x_i + x_j \geq 1 \quad \forall \{i,j\} \in E \\ & 0 \leq x_i \leq 1 \quad \forall i \in V \end{array}$$

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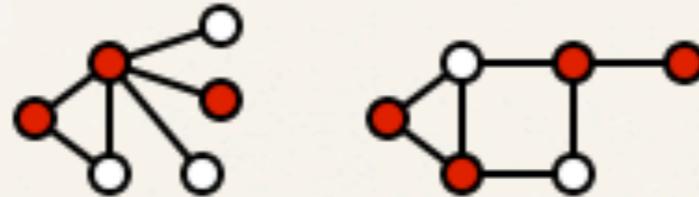


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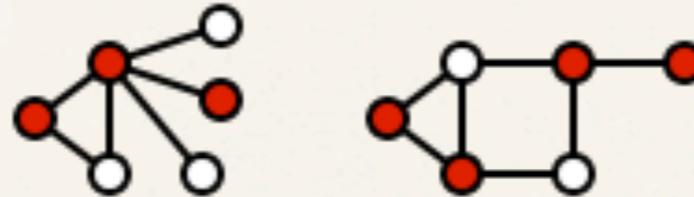


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- **Theorem:** $C = \{i : x_i^* \geq 1/2\}$ is a vertex cover of size at most 2 opt.

Linear vs. Integer Programming

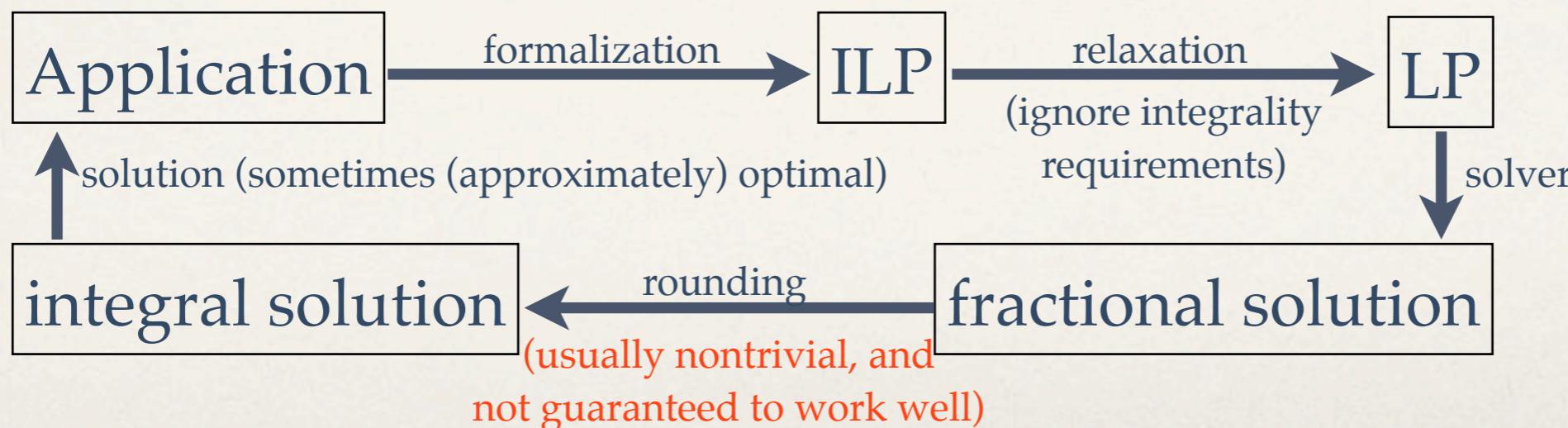
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- Typical approach (e.g. vertex cover):



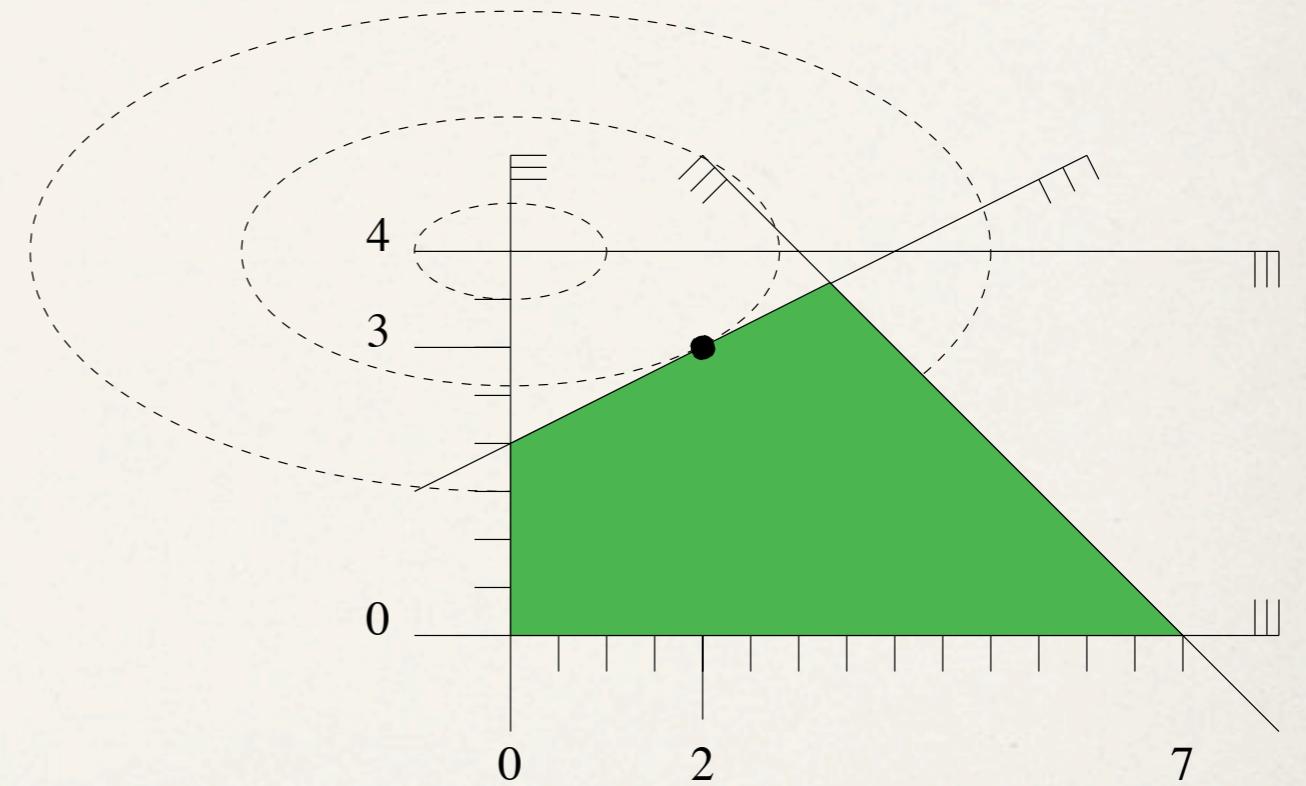
Quadratic Programming (QP)

- * **Problem:** Minimize a convex quadratic function in n variables subject to m linear (in)equality constraints!

Quadratic Programming

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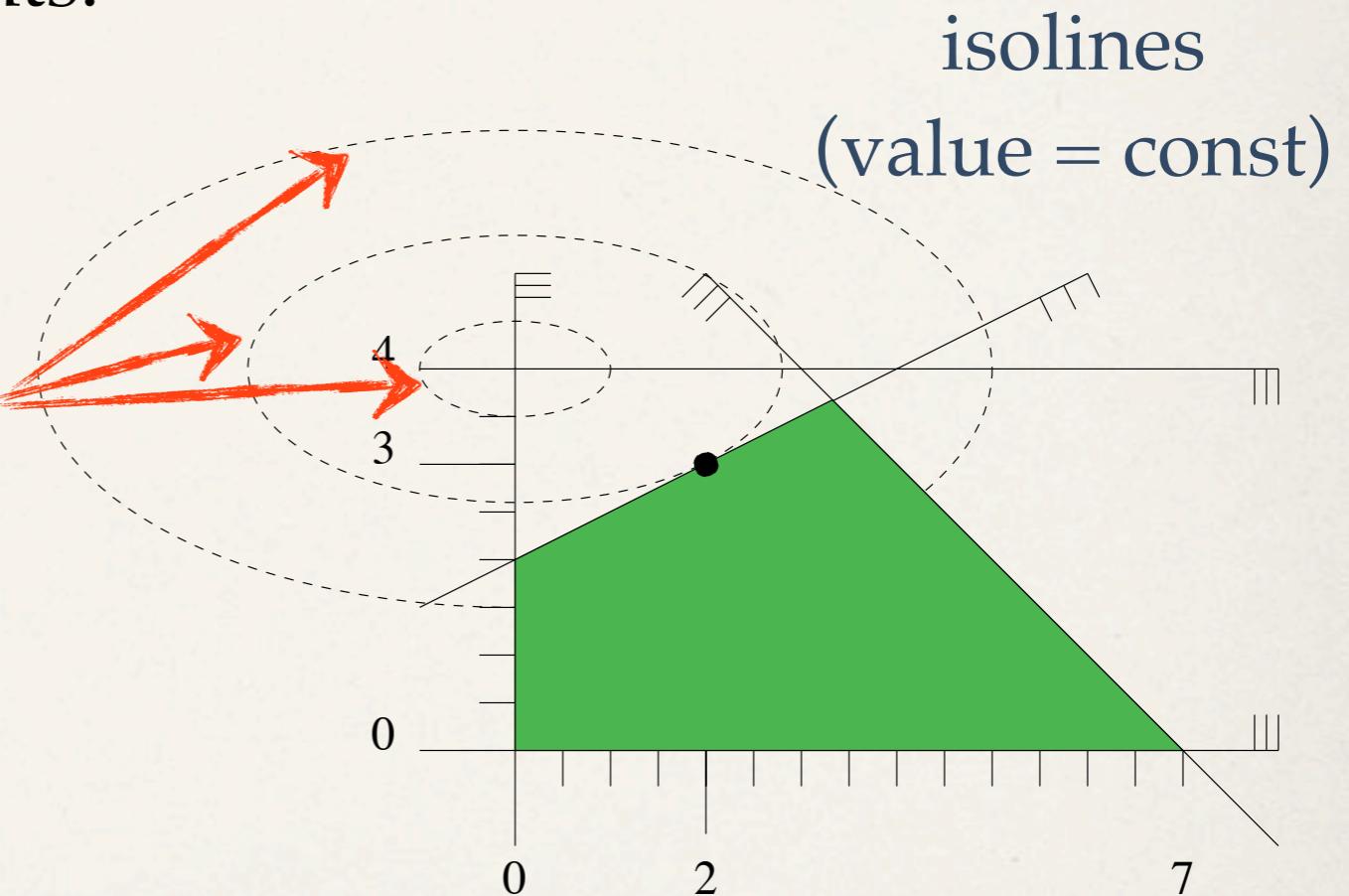
$$\begin{array}{ll}\text{minimize} & x^2 + 4y^2 - 32y + 64 \\ \text{subject to} & x + y \leq 7 \\ & -x + 2y \leq 4 \\ & x \geq 0 \\ & y \geq 0 \\ & y \leq 4\end{array}$$



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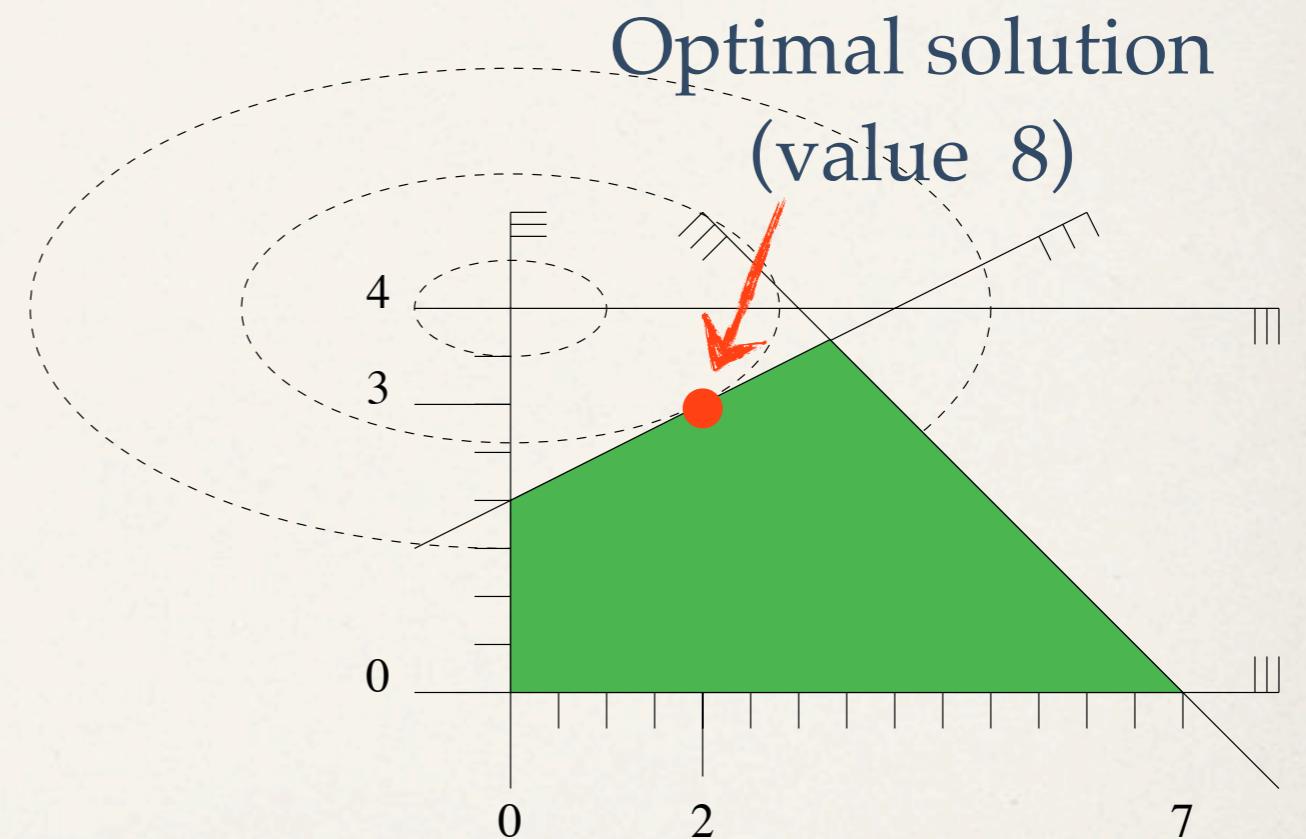


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$$\begin{array}{ll}\text{minimize} & x^T D x + c^T x + c_0 \\ \text{subject to} & Ax \gtrless b \\ & l \leq x \leq u\end{array}$$

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- * **Relax:** In the applications, we know from theory that D is “good”

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- * **Code:** at the very end of this presentation...

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Quadratic Programming: Support Vector Machines

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- * Training phase: the system gets to see letters 'A' and 'B' plus the information whether it's an 'A' or a 'B'
- * After the training phase, the system is supposed to decide on its own which letter it sees.

Quadratic Programming: Support Vector Machines

- * Solution: map training letters to points in some high-dimensional space, with label 'A' (blue) or 'B' (red), based e.g. on a pixel-based representation



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- Classify an unknown letter according to this hyperplane (● = 'B')

Quadratic Programming: Support Vector Machines

- Other separating shapes (e.g. spheres as in the cancer therapy application, or zero sets of polynomials) can make sense
- Through lifting, we can often reduce the problem for a given separating shape to the problem of finding the maximum-margin separating hyperplane in some higher (sometimes even infinite-dimensional space). In the end, we just need to solve a quadratic program!

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- In the world of support vector machines, the problem of selecting the appropriate separating shape is called *kernel design*.

Quadratic Programming Application: Low-Risk Investment

- * **Problem:** How to invest money such that the expected return is maximized but the risk is minimized?

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- ❖ **Risk-tolerant strategy:** Minimize the risk under a given lower bound for the expected return!

Quadratic Programming Application: Low-Risk Investment

- ✿ Possible investments:
 - * $1, 2, \dots, n$ (e.g. 1 = Swatch shares, 2 = Credit Suisse shares,...)
- ✿ Investment Characteristics (not at all easy to know/estimate):
 - * R_i : return rate of investment i (assumed to be a random variable)
 - * r_i : expected return rate of investment i, $E [R_i]$
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Credit Suisse shares	51% (0.51)

v_{ij}	Swatch shares	Credit Suisse shares
Swatch shares	0.09	-0.05
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Negative correlation: if CS does worse than expected, Swatch will probably do better, and vice versa

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Read as: standard deviation of return rate is $\sqrt{0.25} = 0.5$
(actual return rate could easily be off by 0.5)

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- * **Investment strategy:**

$$(x_1, x_2, \dots, x_n), \quad \sum_{i=1}^n x_i = 1, \quad x_i \geq 0 \forall i$$

Meaning: An x_i fraction of your money goes into investment i

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- * **Example:** half the money in Swatch shares, half in Credit Suisse shares; expected return rate is

$$\frac{1}{2} \cdot 0.1 + \frac{1}{2} \cdot 0.51 = 0.305 = 30.5\%$$

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Straightforward calculations

$D = (v_{ij})_{1 \leq i, j \leq n}$ is the *covariance matrix*

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less than each individual risk!

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- * **The risk-tolerant case:** Find the investment strategy with lowest risk that guarantees expected return rate at least ρ !

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Fact: the covariance matrix is positive semidefinite, so this is indeed a convex QP.

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- * **The risk-tolerant case:** Find the investment strategy with lowest risk that guarantees expected return rate at least ρ !

$$\begin{aligned} & \text{minimize} && \sum_{i=1}^n \sum_{j=1}^n v_{ij} x_i x_j \leftarrow \boxed{\text{risk}} \\ & \text{subject to} && \sum_{i=1}^n r_i x_i \geq \rho \\ & && \sum_{i=1}^n x_i = 1 \quad \boxed{\text{expected return rate}} \\ & && x_i \geq 0, \quad i = 1, \dots, n \\ & \boxed{\text{strategy}} && \end{aligned}$$

Fact: the covariance matrix is positive semidefinite, so this is indeed a convex QP.

- * **Example:** $\rho = 0.4$: 26.8% Swatch, 73.2% Credit Suisse; risk = 0.121

Low-Risk Investment Example ... in CGAL

- * **Preamble:** This time, it's floating-point input...

Gnu
Multi-
precision
Library
(GMP)

CGAL

```
#include <iostream>
#include <cassert>
#include <CGAL/basic.h>
#include <CGAL/QP_models.h>
#include <CGAL/QP_functions.h>

// choose exact floating-point type
#ifdef CGAL_USE_GMP
#include <CGAL/Gmpzf.h>
typedef CGAL::Gmpzf ET;
#else
#include <CGAL/MP_Float.h>
typedef CGAL::MP_Float ET;
#endif

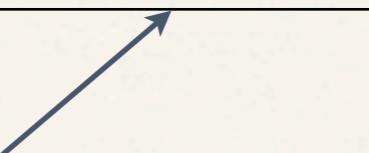
// program and solution types
typedef CGAL::Quadratic_program<double> Program;
typedef CGAL::Quadratic_program_solution<ET> Solution;
```

Low-Risk Investment Example ... in CGAL

- * **Input:** Desired expected return

```
int main() {  
    // read minimum expected return rate  
    std::cout << "What is your desired expected return rate? ";  
    double rho; std::cin >> rho;
```

for example, $0.4 = 40\%$



Low-Risk Investment Example ... in CGAL

- * **Setup:** Make sure to enter matrix 2D (customary in QP solvers)! 

```
// by default, we have a nonnegative QP with Ax >= b
Program qp (CGAL::LARGER, true, 0, false, 0);

// now set the non-default entries:
const int sw = 0;
const int cs = 1;

// constraint on expected return: 0.1 sw + 0.51 cs >= rho
qp.set_a(sw, 0, 0.1);
qp.set_a(cs, 0, 0.51);
qp.set_b( 0, rho);

// strategy constraint: sw + cs = 1
qp.set_a(sw, 1, 1);
qp.set_a(cs, 1, 1);
qp.set_b( 1, 1);
qp.set_r( 1, CGAL::EQUAL); // override default >=

// objective function: 0.09 sw^2 - 0.1 sw cs - 0.1 cs sw + 0.25 cs^2
// we need to specify the entries of the symmetric matrix 2D, on and below the diagonal
qp.set_d(sw, sw, 0.18); // 0.09 sw^2
qp.set_d(cs, sw, -0.10); // -0.05 cs sw
qp.set_d(cs, cs, 0.5); // 0.25 cs^2
```

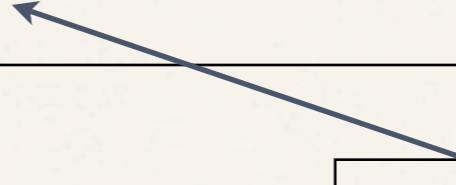
 **j ≤ i in `set_d (i, j)`**

Low-Risk Investment Example ... in CGAL

- * **Solve:** ...as nonnegative quadratic program (a little faster)

```
// solve the program, using ET as the exact type
Solution s = CGAL::solve_nonnegative_quadratic_program(qp, ET());
assert (s.solves_quadratic_program(qp));
```

independent verification



Low-Risk Investment Example ... in CGAL

- * **Output:** query programming status; if feasible, output strategy / risk

```
// output
if (s.status() == CGAL::QP_INFEASIBLE) {
    std::cout << "Expected return rate " << rho << " cannot be achieved.\n";
} else {
    assert (s.status() == CGAL::QP_OPTIMAL);
    Solution::Variable_value_iterator opt =
        s.variable_values_begin();
    CGAL::Quotient<ET> sw_fraction = *opt;
    CGAL::Quotient<ET> cs_fraction = *(opt+1);
    std::cout << "Minimum risk investment strategy:\n";
    std::cout << 100.0*CGAL::to_double(sw_fraction)
        << "%" << " into Swatch\n";
    std::cout << 100.0*CGAL::to_double(cs_fraction)
        << "%" << " into Credit Suisse\n";
    std::cout << "Risk = " << CGAL::to_double(s.objective_value()) << "\n";
}
return 0;
}
```

Sources and Further Reading

- ❖ **LP/QP Solver:** Online manual at www.cgal.org: Online Manual → Combinatorial Algorithms → Linear and Quadratic Programming Solver
- ❖ **Cancer Therapy:** J. O'Rourke, S. Kosaraju, and N. Megiddo: Computing Circular Separability, *Discrete & Computational Geometry* 1:105-113 (1986)
- ❖ **Support Vector Machines:** B. Schölkopf, A. J. Smola: *Learning with Kernels*, MIT Press, 2002
- ❖ **Low-Risk Investment:** H. Markowitz: Portfolio Selection, *Journal of Finance* 7(1): 77-91 (1952)