

# **ORF307 – Optimization**

## **17. Interior-point methods**

**Bartolomeo Stellato – Spring 2022**

# Ed Forum

- We learned about networks this lecture and in another class, I learned about neural networks. I get that the two things are similar, in the sense that there exists weights to the edges. In neural networks, there also the bias on a node. However in our examples in lecture, the  $b$  is referenced as a supply vector. I was wondering if the two were the same.
- In our example, we only looked at the case where the external supply came into certain nodes while the external demand came into others, but we never looked at nodes that had both supply and demand coming in. Can this ever happen and if so how would this affect  $b$  since it appears the values of  $b$  are usually broken up into positive for supply and negative for demand?

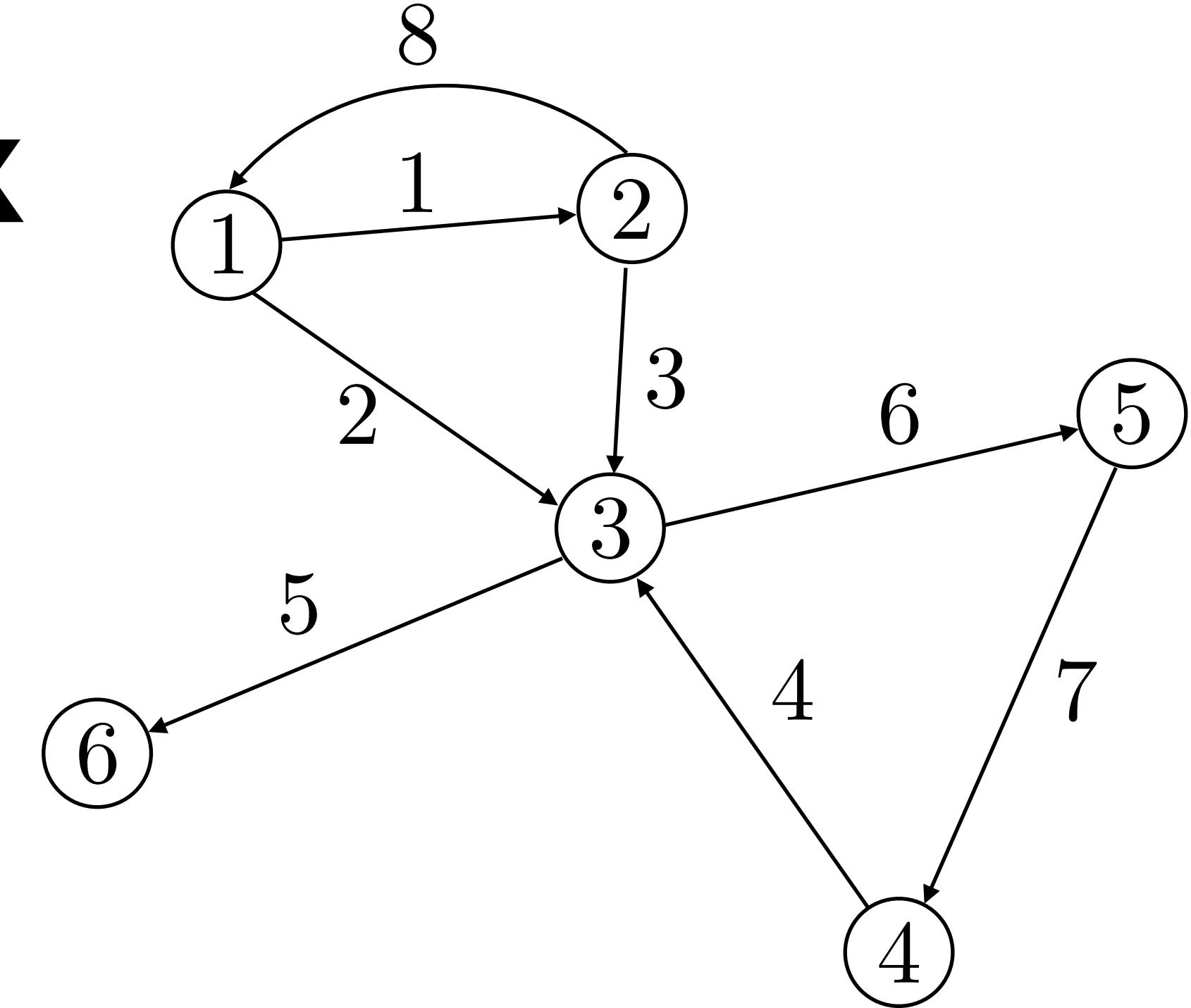
# Recap

# Arc-node incidence matrix

$m \times n$  matrix  $A$  with entries

$$A_{ij} = \begin{cases} 1 & \text{if arc } j \text{ starts at node } i \\ -1 & \text{if arc } j \text{ ends at node } i \\ 0 & \text{otherwise} \end{cases}$$

**Note** Each column has  
one  $-1$  and one  $1$

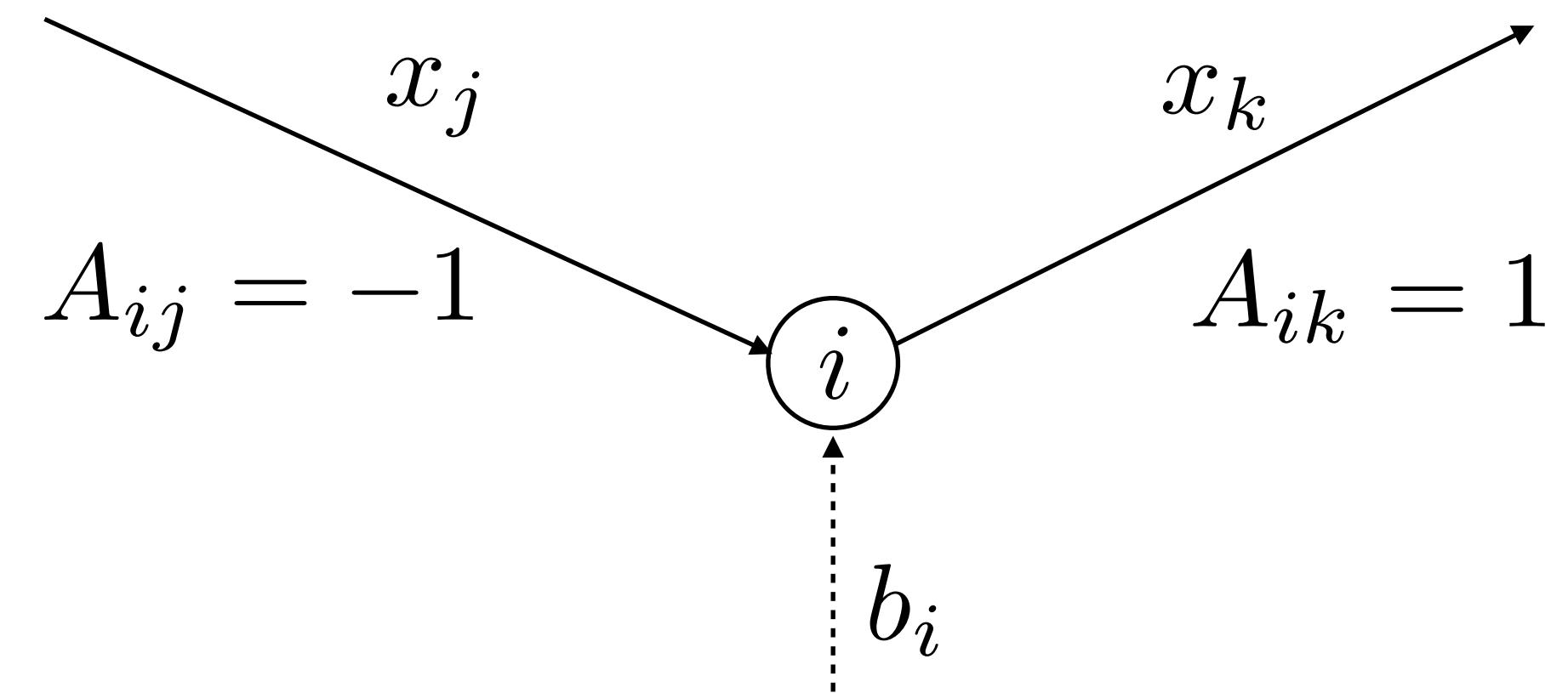


$$A = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 & 0 & -1 \\ -1 & 0 & 1 & 0 & 0 & 0 & 0 & 1 \\ 0 & -1 & -1 & -1 & 1 & 1 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & -1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & -1 & 1 \\ 0 & 0 & 0 & 0 & -1 & 0 & 0 & 0 \end{bmatrix}$$

# External supply

**supply vector**  $b \in \mathbf{R}^m$

- $b_i$  is the external supply at node  $i$  (if  $b_i < 0$ , it represents demand)
- We must have  $\mathbf{1}^T b = 0$  (total supply = total demand)



## Balance equations

$$\sum_{j=1}^n A_{ij}x_j = (Ax)_i = b_i, \quad \text{for all } i$$

Total leaving flow      Supply

—————>  $Ax = b$

# Minimum cost network flow problem

$$\begin{aligned} & \text{minimize} && c^T x \\ & \text{subject to} && Ax = b \\ & && 0 \leq x \leq u \end{aligned}$$

- $c_i$  is unit cost of flow through arc  $i$
- Flow  $x_i$  must be nonnegative
- $u_i$  is the maximum flow capacity of arc  $i$
- Many network optimization problems are just special cases

# Today's lecture

## Interior point methods

- History
- Newton's method
- Central path
- Primal-dual path-following algorithm
- Logarithmic barrier functions

# History

# A brief history of linear optimization

1940s :

- Foundations and applications in economics and logistics (Kantorovich, Koopmans)
- **1947** : Development of the **simplex method** by Dantzig

1950s – 70s:

- Applications expand to engineering, OR, computer science...
- **1975** : Nobel prize in economics for Kantorovich and Koopmans

1980s:

- Development of polynomial time algorithms for LPs
- **1984** : Development of the **interior point method** by Karmarkar

— Today:

- Continued algorithm development. Expansion to very large problems.

# Ellipsoid method

## Khachian (1979)

**Answer to major question**  
Is worst-case LP complexity polynomial? Yes!

### Drawbacks

Very inefficient. Much slower than simplex!

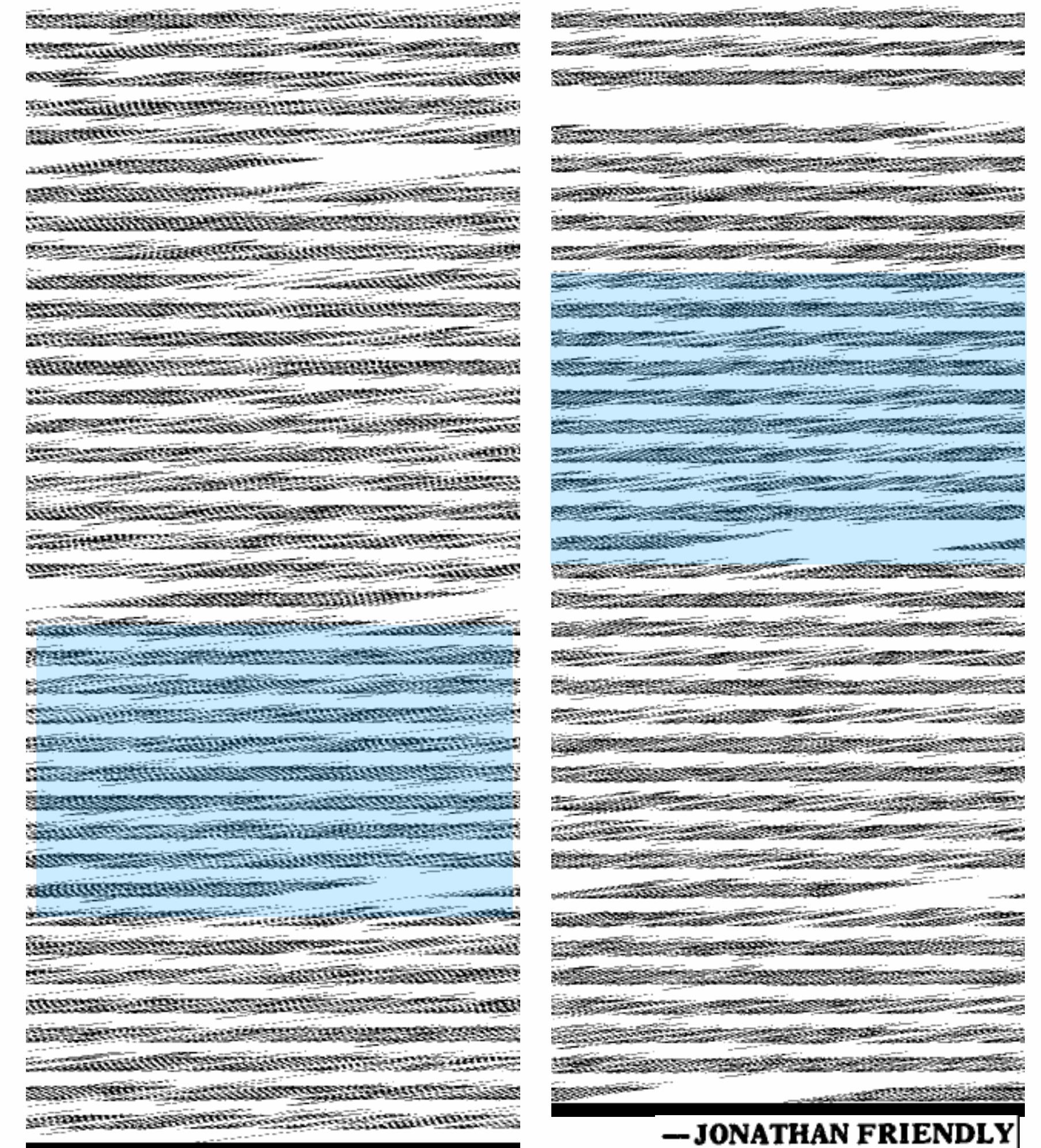
### Benefits

Motivated new research directions

## Shazam! A Shortcut for Computers

A garment manufacturer has three kinds of dresses — A, B and C. On kind he has 17 bolts of one cloth and hand another, as well as 200 buttons. 25 of another. He has three cutters, 10 and 75 bakers and one finisher. Dress A, on which he makes a profit of \$1.25 a unit, requires one combination of unit, material, accessories and work; the material with a \$1.50 profit, takes a B dress, combination, and the \$2.25 different cost. A third set of requirements. Dress C has yet to be scheduled his requirements. How should he schedule his production to make the most money? That is an easy example of a kind of problem that is eminently practical, but difficult becomes computationally variable because of the number of factors and constraints that must be handled to get a best solution. As the number of variables and constraints grows — as, for instance, in model of the national economy or in scheduling of production at any refinery — the difficulty must increase. Even the most powerful computers might have to run for hours to tell a plant manager how to handle a small change in, say, the amount of crude oil being delivered to his tanks. And adding one new restriction can substantially increase the number of possible answers and thus the time required to check them for an optimum solution.

Last week, intrigued mathematicians were trying to sort out the meaning of what looked like a stun-



— JONATHAN FRIENDLY

The New York Times

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# Interior-point methods

## 1980s-1990s: interior point methods

- Karmarkar's algorithm (1984)
- Competitive with simplex, often faster for larger problems
- Began huge effort in algorithm development for convex optimization

**AMERICANS IN POLL VIEW GOVERNMENT MORE CONFIDENTLY**

**Postelection Inquiry Also Finds Most Think Reagan Will Ask Rise in Taxes**

**By ADAM CLYMER**

The American public, far from being jubilant in government, is becoming increasingly apprehensive about its political leaders, according to a new report President Reagan is to avoid in his annual budget speech next week. The report, which makes a case for a balanced budget, is to make a strong argument for an arms control treaty, a New York Times reporter has learned.

At the same time, the public appears less likely to support the president's proposal to increase taxes, while Congress is to vote on increases in taxes. Fifty-seven percent of those surveyed said they would support a rise in taxes if their own voters expect him to ask for higher taxes.

The poll detailed the depth and nature of the nation's swing toward the Republicans, whose new plan easily divided between supporters and opponents who identify with the Democrats.

**'Major Reversal'**

That was the finding of a leading Republican pollster, Robert M. Stein, who, in a telephone survey, found that personal income taxes, similar to those proposed over the weekend, were the most popular among both parties. One in three Americans supports the idea, up from 20 percent in the previous survey.

But at the same time, the public appears less likely to support the president's proposal to increase taxes, while Congress is to vote on increases in taxes. Fifty-seven percent of those surveyed said they would support a rise in taxes if their own voters expect him to ask for higher taxes.

The poll detailed the depth and nature of the nation's swing toward the Republicans, whose new plan easily divided between supporters and opponents who identify with the Democrats.

**Cocaine Traffickers Kill 17 in Peru Raid On Antidrug Team**

**By ALAN COWELL**

Eighteen Americans were killed yesterday in a jagged exchange and gun battle with anti-drug agents and their Peruvian counterparts, who had been employed by a United States-based anti-drug team to capture a major drug smuggling organization, the police said today.

All those killed in the attack, which took place in a jungle area, were members of the anti-drug team, led by a former member of the Senate Select Committee on Narcotics Abuse and Control, Robert D. Torricelli, who had been assigned to the mission.

Those officials numbered 7 or 8; the remaining 10 Americans were anti-drug agents. They had been sent to the area to help capture the leaders of the Shining Path, a Marxist guerrilla group that has been the principal source of cocaine in South America.

"Maybe it will pick up," one of them said. "The other day, we had some success, but I'm not sure if it will continue."

Substantive traps offered

That prediction about half of the world's coca, cocaine and heroin production was not included, but the police said the total cost of the mission was \$10 million.

Workers in the program say that the United States has been instrumental in helping the United States raid about 60 percent of the cocaine and heroin seized in South America since 1982, and began shooting

**Breakthrough in Problem Solving**

**By JAMES GLEICK**

A 23-year-old mathematician at AT&T Bell Laboratories has made a startling theoretical breakthrough in the solving of systems of equations that often grow too vast and complex for the most powerful computers.

The discovery, which is to be formally published next month, is already circulating rapidly through the mathematical world. It has also set off a deluge of inquiries from brokerage houses, oil companies and airlines, industries with millions of dollars at stake in problems known as linear programming.

These problems are fiendishly complicated systems, often with thousands of variables. They arise in a variety of commercial and government applications, ranging from allocating time on a communications satellite to routing millions of telephone calls over long distances. Linear programming is particularly useful whenever a limited, expensive resource must be spread most efficiently among competing users. And investment companies use the approach in creating portfolios with the best mix of stocks and bonds.

**Faster Solutions Seen**

The Bell Labs mathematician, Dr. Narendra Karmarkar, has devised a radically new procedure that may speed the routine handling of such problems by businesses and Government agencies and also make it possible to tackle problems that are now far out of reach.

"This is a path-breaking result," said Dr. Ronald L. Graham, director of mathematical sciences for Bell Labs in Murray Hill, N.J. "Science has its mo-

**Vote Comes to a 'Homeland,' But African Problems Linger**

**By JOHN BARNARD**

Rep. John W. Larson, a leading Republican pollster, Robert M. Stein, told reporters yesterday that the personal income taxes similar to those proposed over the weekend were the most popular among both parties. One in three Americans supports the idea, up from 20 percent in the previous survey.

At the same time, however, Republicans appear less likely to support the president's proposal to increase taxes, while Congress is to vote on increases in taxes. Fifty-seven percent of those surveyed said they would support a rise in taxes if their own voters expect him to ask for higher taxes.

**Continued on Page A17, Column 5**

**Breakthrough in Problem Solving**

**By JAMES GLEICK**

After years of stagnation, the search for a breakthrough in linear programming has taken a turn. The solving of systems of equations that often grow too vast and complex for the most powerful computers.

Dr. Narendra Karmarkar, 23, of Bell Labs, has devised a radically new procedure that may speed the routine handling of such problems by businesses and Government agencies and also make it possible to tackle problems that are now far out of reach.

"This is a path-breaking result," said Dr. Ronald L. Graham, director of mathematical sciences for Bell Labs in Murray Hill, N.J. "Science has its mo-

**Homeless Spend Nights in City Welfare Office**

**By SARA HESLER**

The city's welfare office, which has been housed in a former church on West End Avenue, has been overwhelmed by a surge of emergency applicants, mostly mothers with children under age 18. The city has opened an emergency shelter for the homeless at the former church, which has been converted into a temporary shelter for about 100 people.

City officials acknowledged the problem yesterday, and said they were working to find a permanent solution to the increasing need for emergency assistance.

This weekend the city spent more than \$100,000 to convert the former church into a temporary shelter for about 100 people.

It is the third time this fall that the city has had to turn away emergency applicants, said Michael J. DeGrazia, director of the city's emergency services unit. "It's been a real challenge," he said.

"It's a real challenge," he said.

**Continued on Page B16, Column 1**

# Newton's method

# Newton's root finding method

**Goal:** solve

$$h(x) = 0$$

**Method**

1. Make a guess  $x^k$  and a linear approximation

$$h(x) \approx h(x^k) + \frac{\partial h}{\partial x^k}(x^k)(x - x^k)$$

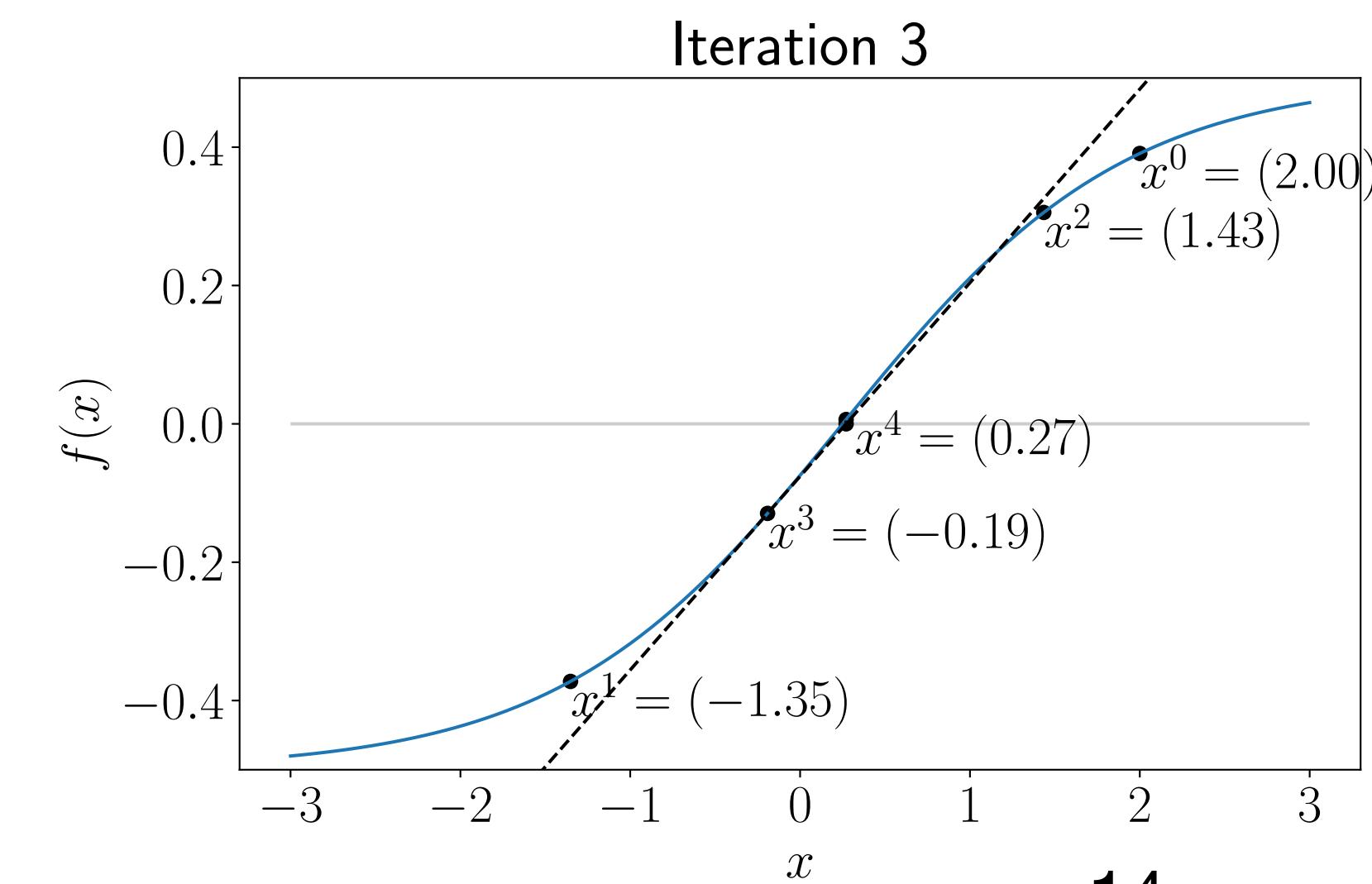
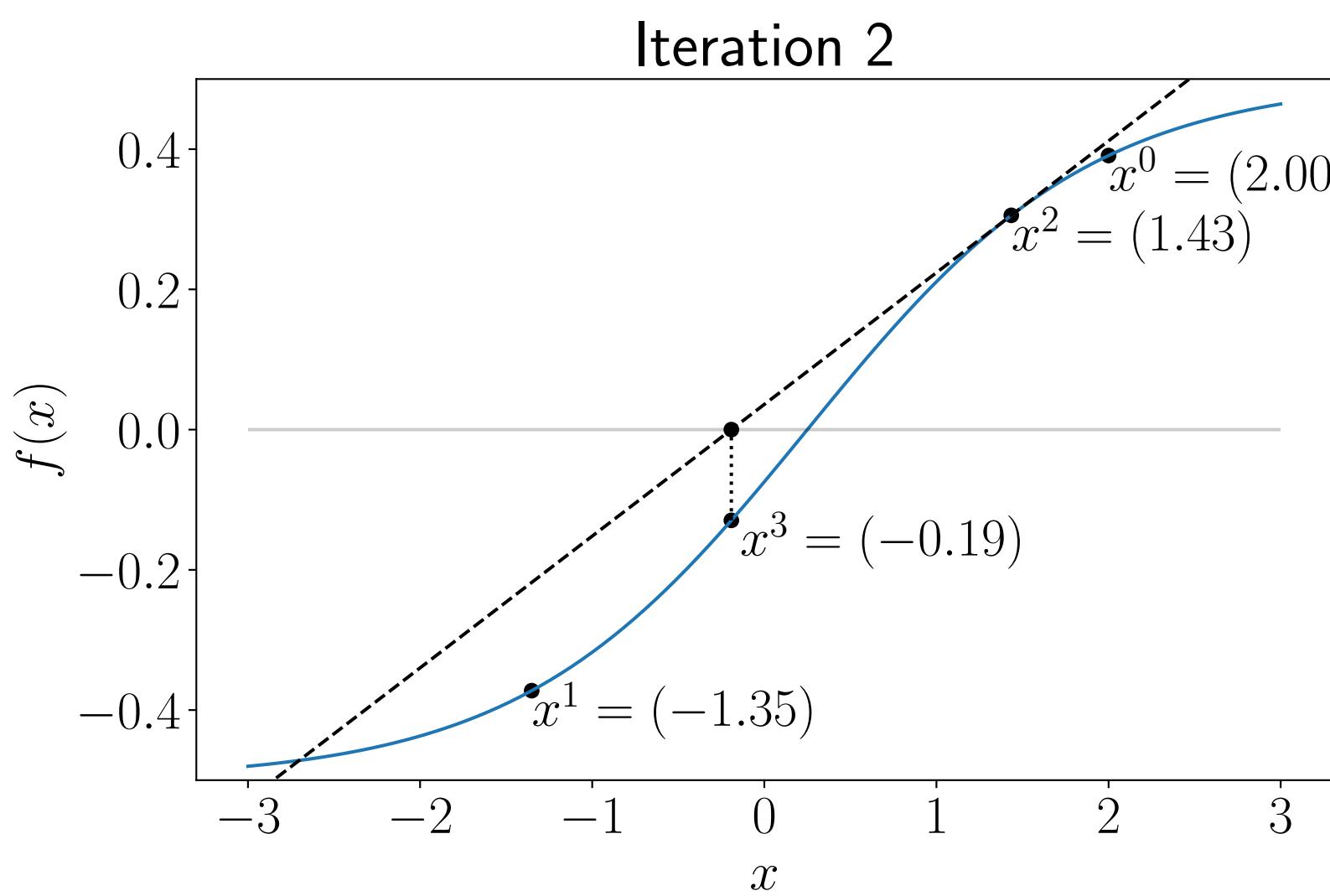
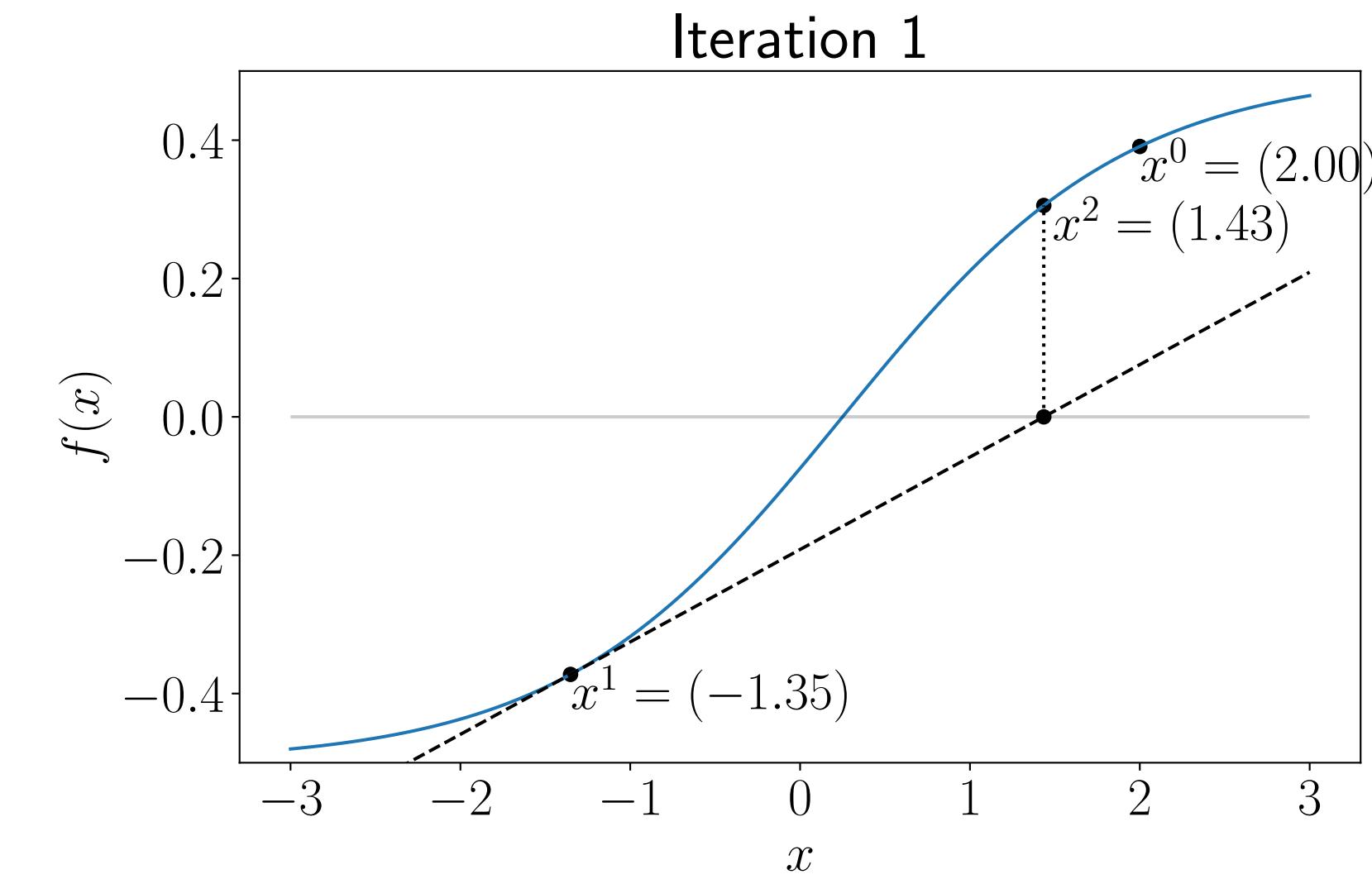
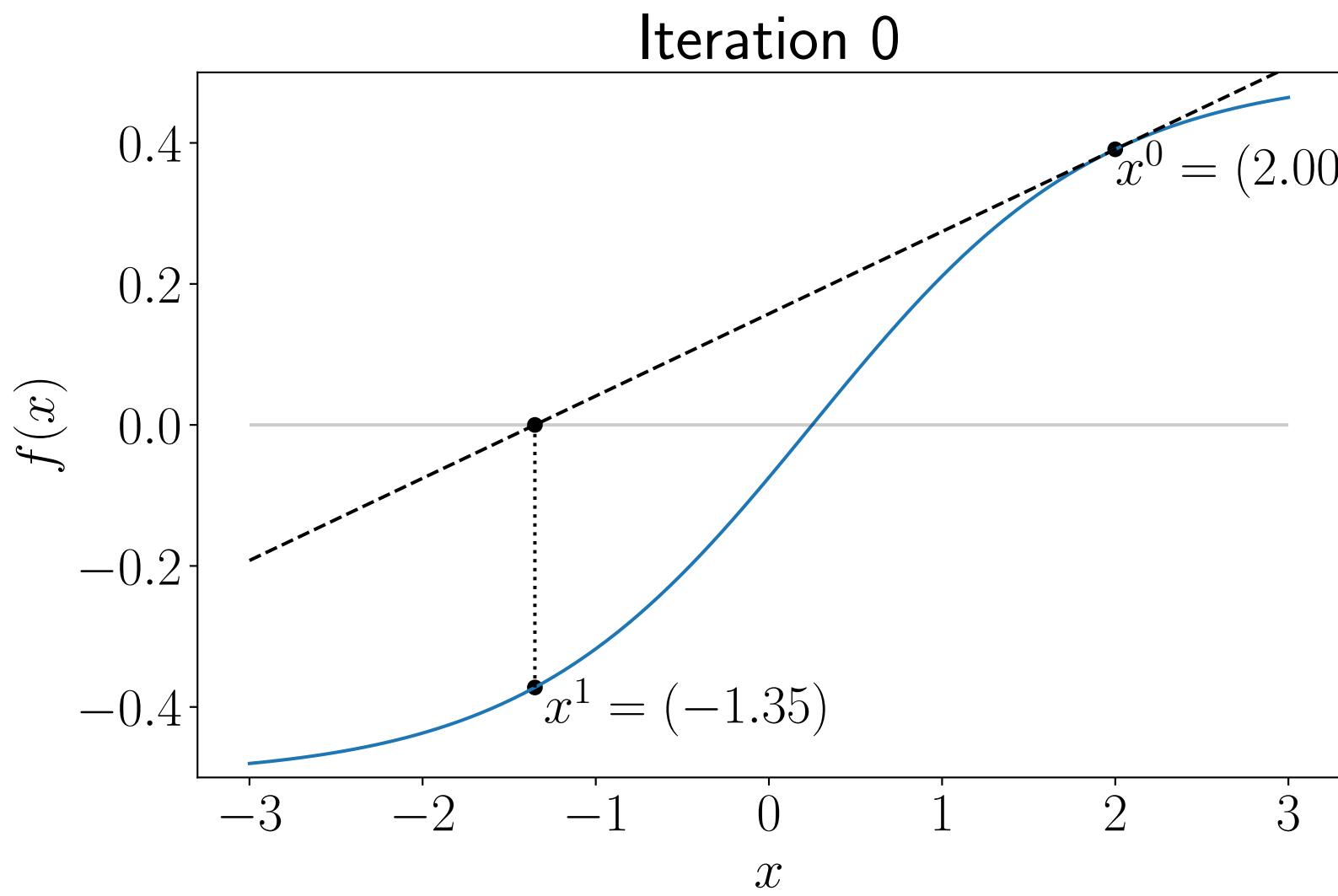
2. Iteratively set  $h(x^k)$  to 0

$$h(x^k) + \frac{\partial h}{\partial x^k}(x^k)(x^{k+1} - x^k) = 0$$

# Newton's method example

$$f(x) = \frac{1}{1 + e^{-1.2x+0.3}} - 0.5$$

$$\begin{aligned} f(x) &= 0 \\ \downarrow & \\ x^* &= 0.3 \end{aligned}$$



# Newton's root finding method (multivariable)

**Goal:** solve

$$h(x) = 0$$

## Method

1. Make a guess  $x^k$  and a linear approximation

$$h(x) \approx h(x^k) + Dh(x^k)(x - x^k)$$

2. Iteratively set  $h(x^k)$  to 0

$$h(x^k) + Dh(x^k)(x^{k+1} - x^k) = 0$$

## Derivative

$$Dh = \begin{bmatrix} \frac{\partial h_1}{\partial x_1} & \dots & \frac{\partial h_1}{\partial x_n} \\ \vdots & \vdots & \vdots \\ \frac{\partial h_m}{\partial x_1} & \dots & \frac{\partial h_m}{\partial x_n} \end{bmatrix}$$

# Newton method iterations

$$h(x^k) + D h(x^k) \frac{(x^{k+1} - x^k)}{\Delta x} = 0$$

## Iterations

- Solve  $D h(x^k) \Delta x = -h(x^k)$
- $x^{k+1} \leftarrow x^k + \Delta x$

## Remarks

- Iterations can be **expensive** (linear system solution)
- **Fast convergence** close to the solution  $x^*$

# Linear optimization as a root finding problem

## Optimality conditions

	<b>Primal</b>	
minimize $c^T x$	→	minimize $c^T x$
subject to $Ax \leq b$		subject to $Ax + s = b$
		$s \geq 0$
		<b>Dual</b>
		maximize $-b^T y$
		subject to $A^T y + c = 0$
		$y \geq 0$

### KKT conditions

$$Ax + s - b = 0$$

$$A^T y + c = 0$$

$$s_i y_i = 0, \quad i = 1, \dots, m$$

$$s, y \geq 0$$

# Linear optimization as a root finding problem

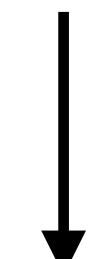
$$Ax + s - b = 0$$

$$A^T y + c = 0$$

$$s_i y_i = 0, \quad i = 1, \dots, m$$

$$s, y \geq 0$$

**Diagonalize complementary slackness**

$$S = \text{diag}(s) = \begin{bmatrix} s_1 & & & \\ & s_2 & & \\ & & \ddots & \\ & & & s_m \end{bmatrix}$$
$$Y = \text{diag}(y) = \begin{bmatrix} y_1 & & & \\ & y_2 & & \\ & & \ddots & \\ & & & y_m \end{bmatrix}$$
$$SY\mathbf{1} = \text{diag}(s)\text{diag}(y)\mathbf{1} = \begin{bmatrix} s_1 y_1 & & & \\ & s_2 y_2 & & \\ & & \ddots & \\ & & & s_m y_m \end{bmatrix} \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix} = \begin{bmatrix} s_1 y_1 \\ s_2 y_2 \\ \vdots \\ s_m y_m \end{bmatrix}$$
$$s_i y_i = 0, \quad i = 1, \dots, m \quad \iff \quad SY\mathbf{1} = 0$$


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# Main idea

## Optimality conditions

$$h(y, x, s) = \begin{bmatrix} Ax + s - b \\ A^T y + c \\ SY\mathbf{1} \end{bmatrix} = \begin{bmatrix} r_p \\ r_d \\ SY\mathbf{1} \end{bmatrix} = 0 \quad \begin{aligned} S &= \mathbf{diag}(s) \\ Y &= \mathbf{diag}(y) \end{aligned}$$
$$s, y \geq 0$$

- Apply variants of Newton's method to solve  $h(x, s, y) = 0$
- Enforce  $s, y > 0$  (strictly) at every iteration
- **Motivation** avoid getting stuck in “corners”

# Newton's method for optimality conditions

## Optimality conditions

$$h(y, x, s) = \begin{bmatrix} Ax + s - b \\ A^T y + c \\ SY1 \end{bmatrix} = \begin{bmatrix} r_p \\ r_d \\ SY1 \end{bmatrix} = 0$$
$$s, y \geq 0$$

## Derivative

$$Dh(y, x, s) = \begin{bmatrix} 0 & A & I \\ A^T & 0 & 0 \\ S & 0 & Y \end{bmatrix}$$

## Iterations

- Solve  $Dh(y^k, x^k, s^k)\Delta(y^k, x^k, s^k) = -h(y^k, x^k, s^k)$

$$\begin{bmatrix} y^{k+1} \\ x^{k+1} \\ s^{k+1} \end{bmatrix} \leftarrow \begin{bmatrix} y^k \\ x^k \\ s^k \end{bmatrix} + \Delta(y^k, x^k, s^k)$$

**Caution!**

It might make  $(s, y)$  negative!

# Central path

# Line search to stay feasible

Root-finding equation

$$h(y, x, s) = \begin{bmatrix} Ax + s - b \\ A^T y + c \\ SY\mathbf{1} \end{bmatrix} = \begin{bmatrix} r_p \\ r_d \\ SY\mathbf{1} \end{bmatrix} = 0$$

Linear system

$$Dh \quad \begin{bmatrix} 0 & A & I \\ A^T & 0 & 0 \\ S & 0 & Y \end{bmatrix} \begin{bmatrix} \Delta y \\ \Delta x \\ \Delta s \end{bmatrix} = \begin{bmatrix} -h \\ -r_p \\ -r_d \\ -SY\mathbf{1} \end{bmatrix}$$

Residuals

$$r_p = Ax + s - b$$

$$r_d = A^T y + c$$

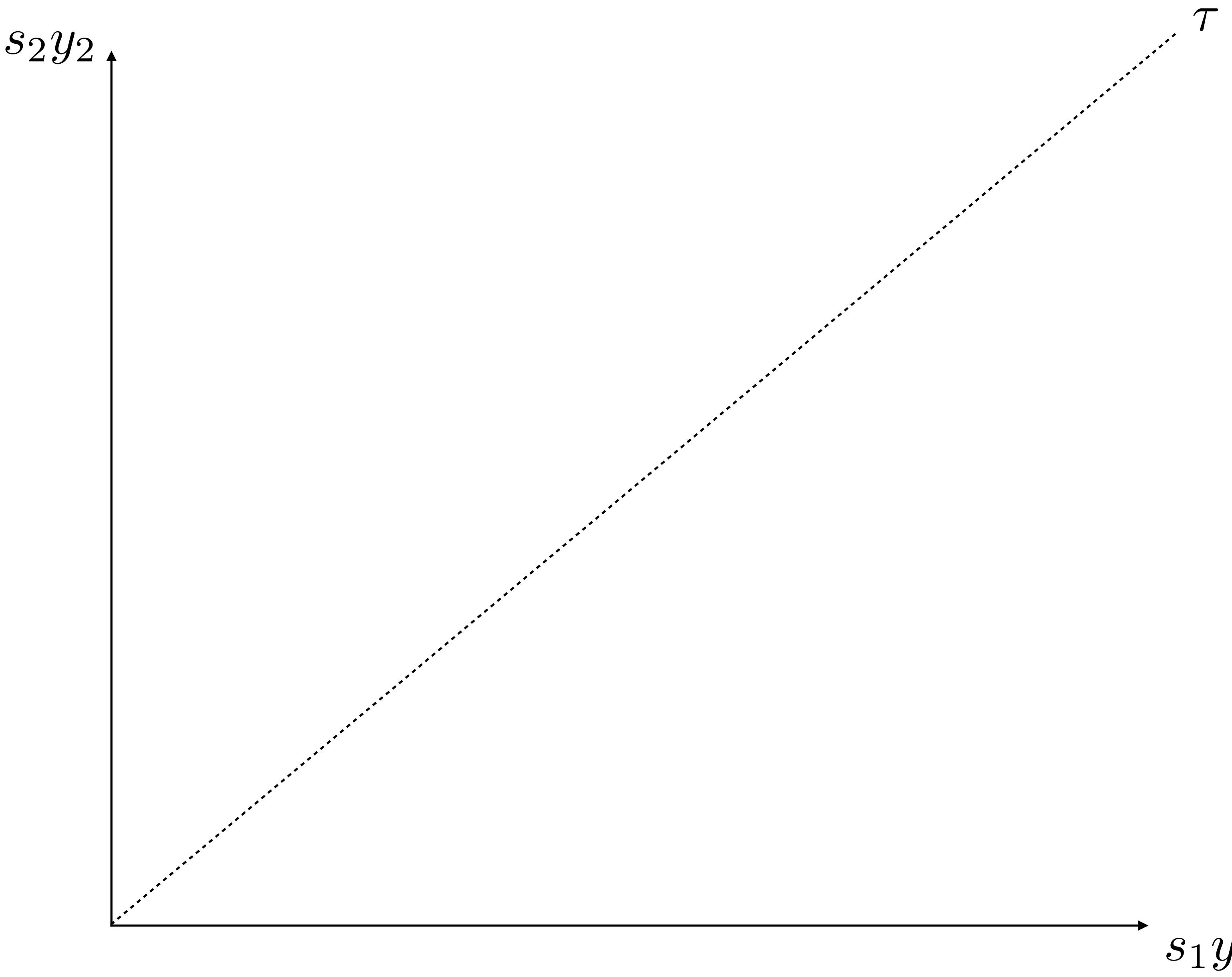
Issue

Pure **Newton's step** does not allow significant progress towards  $h(y, x, s) = 0$  and  $s, y \geq 0$ .

Line search to enforce  $s, y > 0$

$$(y, x, s) \leftarrow (y, x, s) + \alpha(\Delta y, \Delta x, \Delta s)$$

# The central path



# Smoothed optimality conditions

## Optimality conditions

$$Ax + s - b = 0$$

$$A^T y + c = 0$$

$$s_i y_i = \tau \quad \longleftarrow \quad \text{Same } \tau \text{ for every pair}$$

$$s, y \geq 0$$

Same optimality conditions for a “smoothed” version of our problem

## Duality gap

$$s^T y = (b - Ax)^T y = b^T x - x^T A^T y = b^T y + c^T x$$

# Newton's method for smoothed optimality conditions

## Smoothed optimality conditions

$$h_\tau(y, x, s) = \begin{bmatrix} Ax + s - b \\ A^T y + c \\ SY\mathbf{1} - \tau\mathbf{1} \end{bmatrix} = 0$$
$$s, y \geq 0$$

## Linear system

$$\begin{bmatrix} 0 & A & I \\ A^T & 0 & 0 \\ S & 0 & Y \end{bmatrix} \begin{bmatrix} \Delta y \\ \Delta x \\ \Delta s \end{bmatrix} = \begin{bmatrix} -r_p \\ -r_d \\ -SY + \tau\mathbf{1} \end{bmatrix}$$

**Line search** to enforce  $s, y > 0$

$$(y, x, s) \leftarrow (y, x, s) + \alpha(\Delta y, \Delta x, \Delta s)$$

# The path parameter

## Duality measure

$\mu = \frac{s^T y}{m}$  (average value of the pairs  $s_i y_i$ )

## Linear system

$$\begin{bmatrix} 0 & A & I \\ A^T & 0 & 0 \\ S & 0 & Y \end{bmatrix} \begin{bmatrix} \Delta y \\ \Delta x \\ \Delta s \end{bmatrix} = \begin{bmatrix} -r_p \\ -r_d \\ -SY\mathbf{1} + \sigma\mu\mathbf{1} \end{bmatrix}$$

## Centering parameter

$$\sigma \in [0, 1]$$

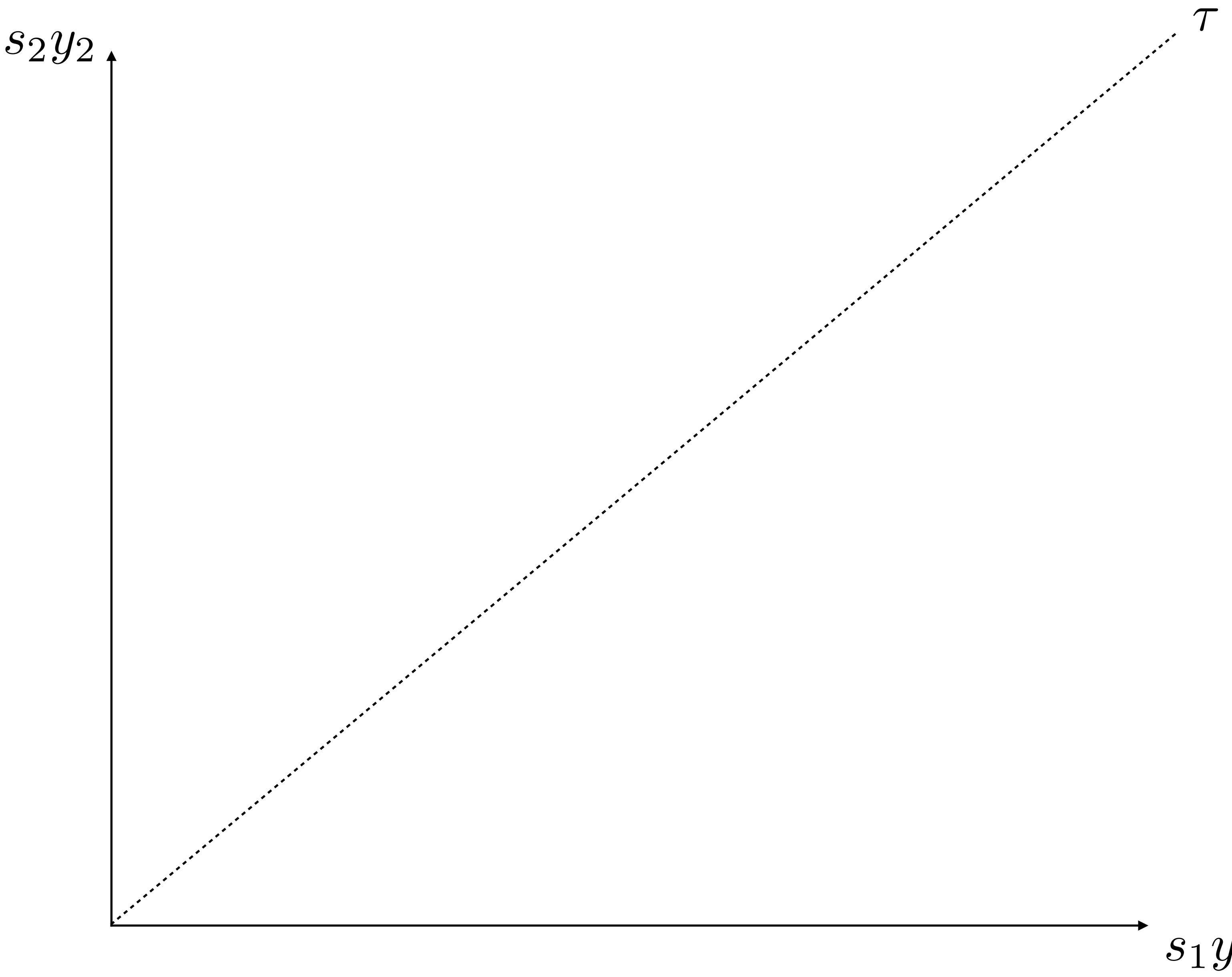
$\sigma = 0 \Rightarrow$  Newton step

$\sigma = 1 \Rightarrow$  Centering step towards  $(y^*(\mu), x^*(\mu), s^*(\mu))$

**Line search to enforce  $s, y > 0$**

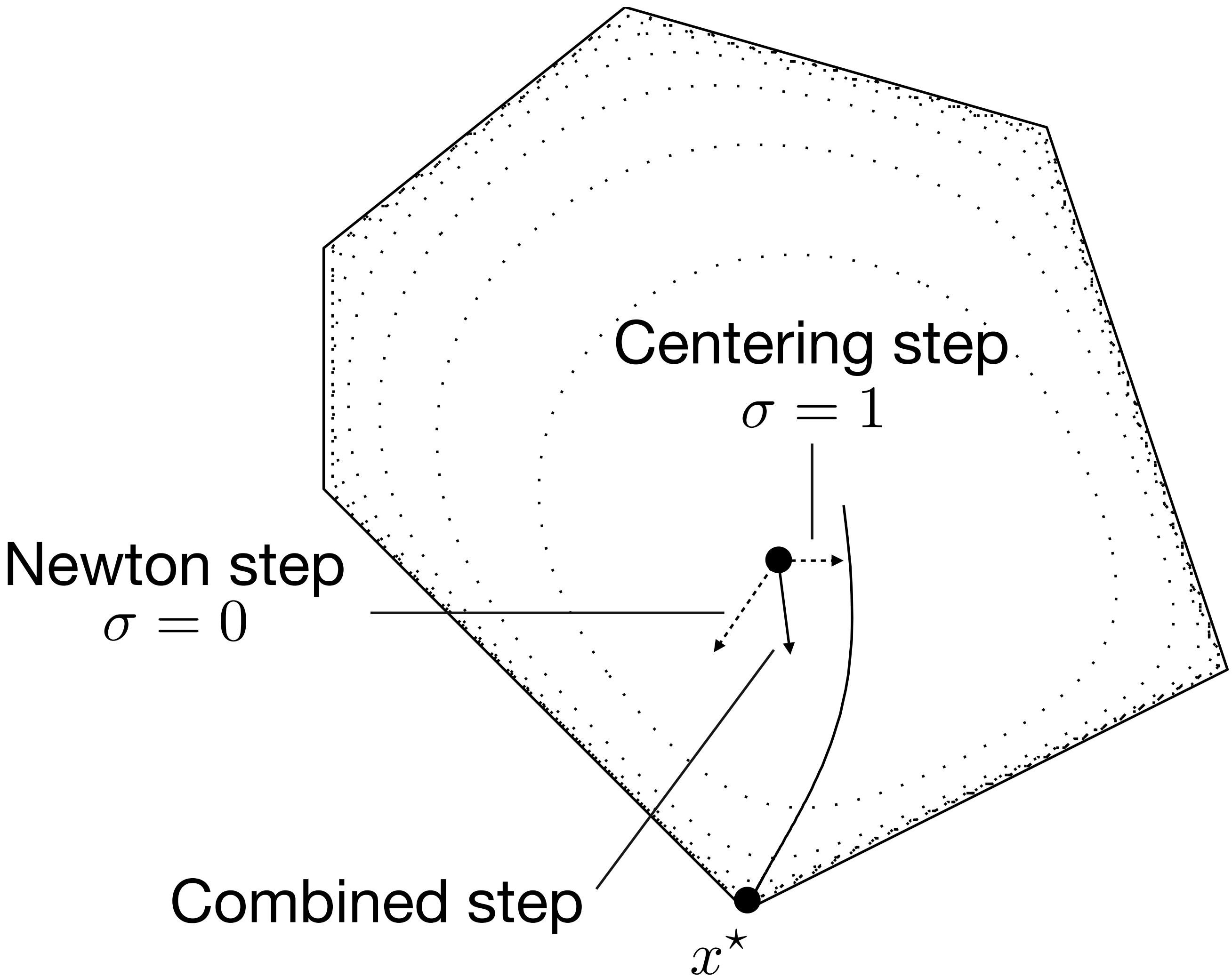
$$(y, x, s) \leftarrow (y, x, s) + \alpha(\Delta y, \Delta x, \Delta s)$$

# The central path



# Primal-dual path-following method

# Path-following algorithm idea



## Centering step

It brings towards the **central path** and is usually biased towards  $s, y > 0$ .

**No progress** on duality measure  $\mu$

## Newton step

It brings towards the **zero duality measure**  $\mu$ . Quickly violates  $s, y > 0$ .

## Combined step

Best of both worlds with longer steps

# Primal-dual path-following algorithm

## Initialization

1. Given  $(x_0, s_0, y_0)$  such that  $s_0, y_0 > 0$

## Iterations

1. Choose  $\sigma \in [0, 1]$

2. Solve 
$$\begin{bmatrix} 0 & A & I \\ A^T & 0 & 0 \\ S & 0 & Y \end{bmatrix} \begin{bmatrix} \Delta y \\ \Delta x \\ \Delta s \end{bmatrix} = \begin{bmatrix} -r_p \\ -r_d \\ -SY\mathbf{1} + \sigma\mu\mathbf{1} \end{bmatrix}$$
 where  $\mu = s^T y / m$

3. Find maximum  $\alpha$  such that  $y + \alpha\Delta y > 0$  and  $s + \alpha\Delta s > 0$
4. Update  $(y, x, s) \leftarrow (y, x, s) + \alpha(\Delta y, \Delta x, \Delta s)$

# Working towards optimality conditions

Optimality conditions satisfied **only at convergence**

## Primal residual

$$r_p = Ax + s - b \rightarrow 0$$

## Stopping criteria

$$\|r_p\| \leq \epsilon_{\text{pri}}$$

## Dual residual

$$r_d = A^T y + c \rightarrow 0$$

$$\|r_d\| \leq \epsilon_{\text{dua}}$$

## Complementary slackness

$$s^T y \rightarrow 0$$

$$s^T y \leq \epsilon_{\text{gap}}$$

# **Logarithmic barrier functions**

# Smoothed optimality conditions

## Optimality conditions

$$Ax + s - b = 0$$

$$A^T y + c = 0$$

$s_i y_i = \tau$  ← Same  $\tau$  for every pair

$$s, y \geq 0$$

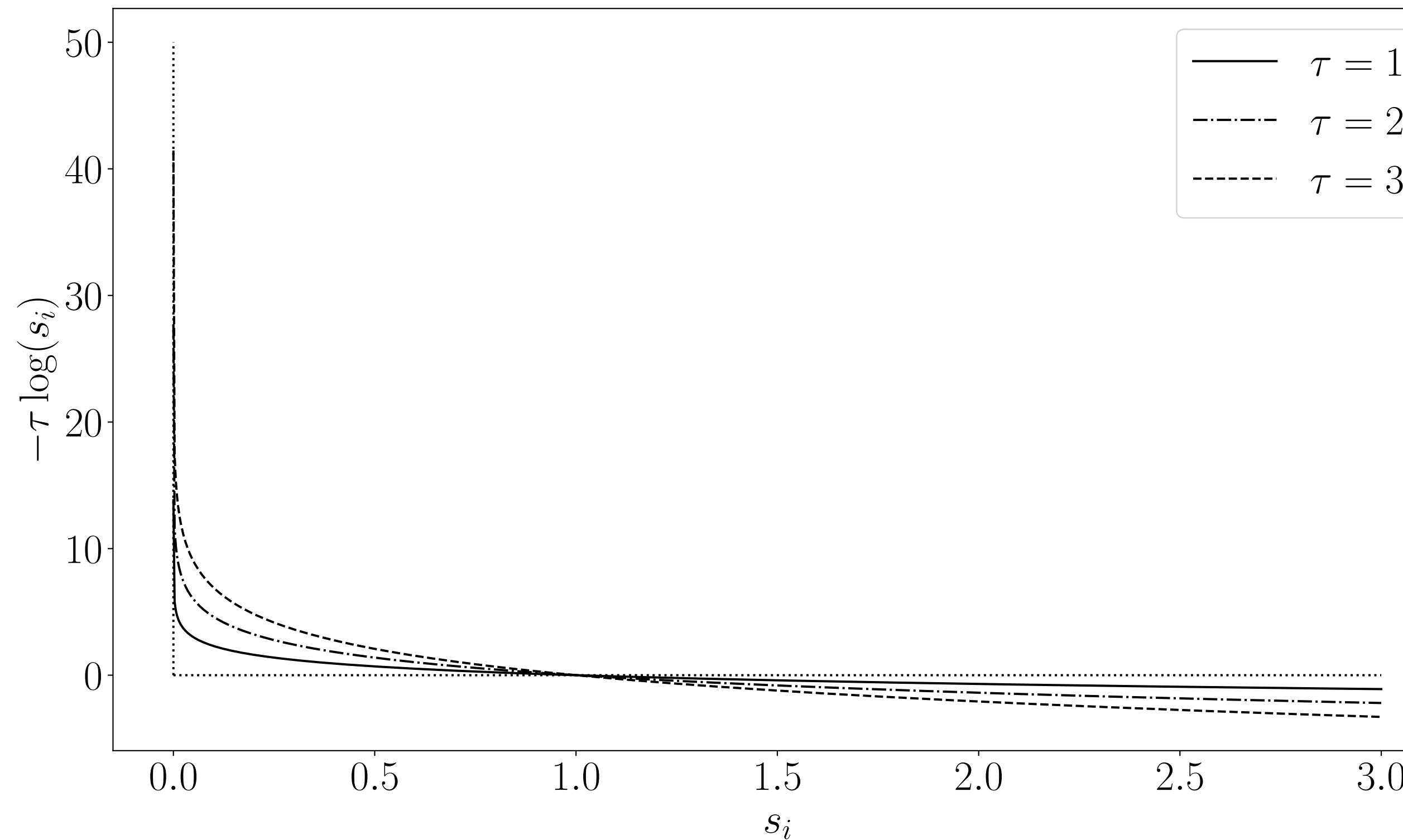
Same optimality conditions for a “smoothed” version of our problem

**Do solutions actually exist?**

**What do they represent?**

# Logarithmic barrier

$$\phi(s) = -\tau \sum_{i=1}^m \log(s_i) \quad \text{on domain} \quad s_i > 0$$



As  $\tau \rightarrow 0$  it approximates

$$\mathcal{I}_{s_i \geq 0} = \begin{cases} 0 & \text{if } s_i \geq 0 \\ \infty & \text{otherwise} \end{cases}$$

# Smoothed problem

$$\begin{array}{ll} \text{minimize} & c^T x \\ \text{subject to} & Ax + s = b \\ & s \geq 0 \end{array} \longrightarrow \begin{array}{ll} \text{minimize} & c^T x + \phi(s) = c^T x - \tau \sum_{i=1}^m \log(s_i) \\ \text{subject to} & Ax + s = b \end{array}$$

## Lagrangian function

$$L(x, s, y) = c^T x - \tau \sum_{i=1}^m \log(s_i) + y^T (Ax + s - b)$$

$$\frac{\partial L}{\partial x} = A^T y + c = 0$$

$$\frac{\partial L}{\partial s_i} = -\tau \frac{1}{s_i} + y_i = 0 \implies s_i y_i = \tau$$

# Central path

$$\begin{array}{ll}\text{minimize} & c^T x - \tau \sum_{i=1}^m \log(s_i) \\ \text{subject to} & Ax + s = b\end{array}$$

Set of points  $(x^*(\tau), s^*(\tau), y^*(\tau))$   
with  $\tau > 0$  such that

$$Ax + s - b = 0$$

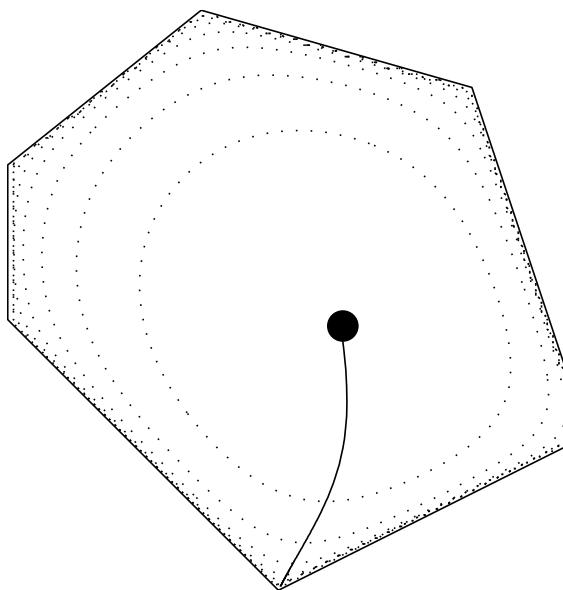
$$A^T y + c = 0$$

$$s_i y_i = \tau$$

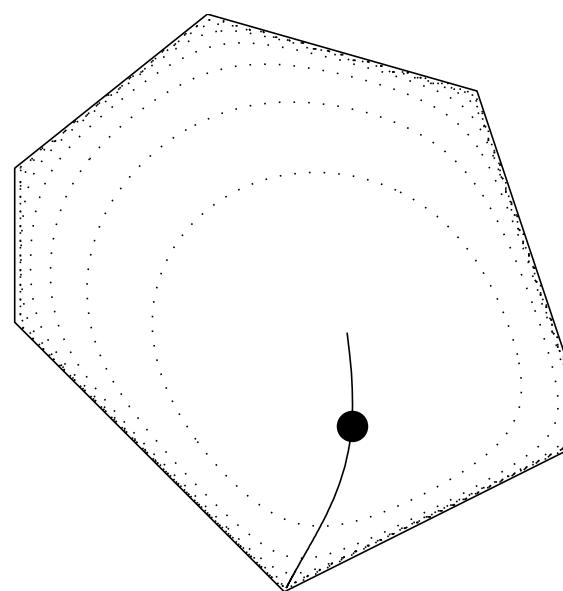
$$s, y \geq 0$$

Analytic  
Center

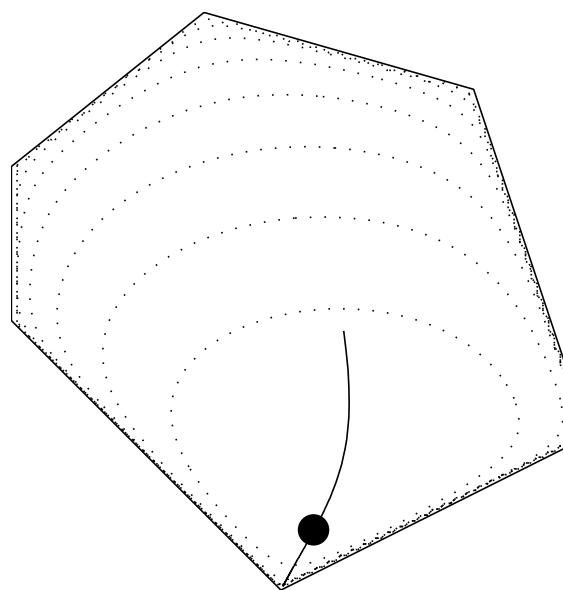
$$\tau \rightarrow \infty$$



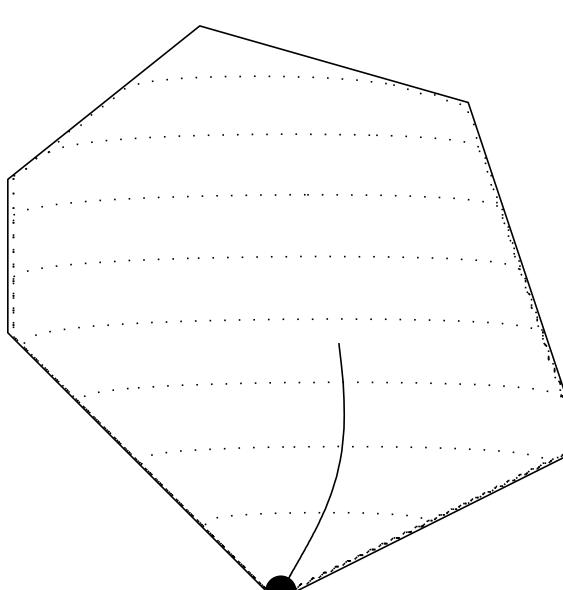
1000



1



1/5



1/100

$\tau$

Main idea

Follow central path as  $\tau \rightarrow 0$

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# Interior-point methods for linear optimization

Today, we learned to:

- **Apply** Newton's method to solve optimality conditions
- **Follow** the central path and the smoothed optimality conditions
- **Use logarithmic barrier functions** to interpret central path steps

# References

- D. Bertsimas and J. Tsitsiklis: Introduction to Linear Optimization
  - Chapter 9.4 – 9.6: Interior point methods
- R. Vanderbei: Linear Programming
  - Chapter 17: The Central Path
  - Chapter 15: A Path-Following Method

# Next lecture

- Practical interior-point method (Mehrotra predictor-corrector algorithm)
- Implementation details
- Interior-point vs simplices