Interior-point Methods and the Maximum Flow Problem

Aleksander Mądry



What will this talk be about?

At a first glance: It is just a talk about recent progress on the maximum flow problem

But also: A "success story" of combining combinatorial alg., continuous optimization and linear-algebraic tools

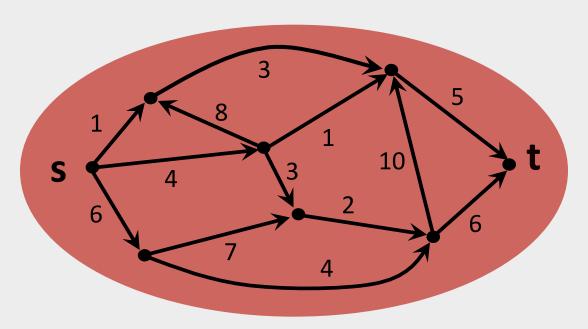


Additionally: An example where employing interior-point method (IPM) leads to very fast algorithms

Bonus: New(?) understanding of IPM's convergence

Maximum flow problem

Input: Directed graph G, integer capacities u_e, source s and sink t

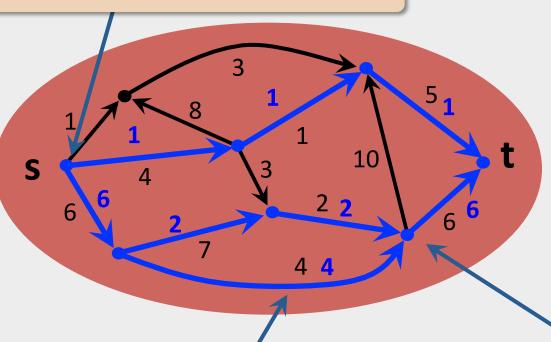


Task: Find a feasible s-t flow of max value

Maximum flow problem

value = net flow out of s

Input: Directed graph G, integer capacities u_e, source s and sink t



Max flow value F*=10

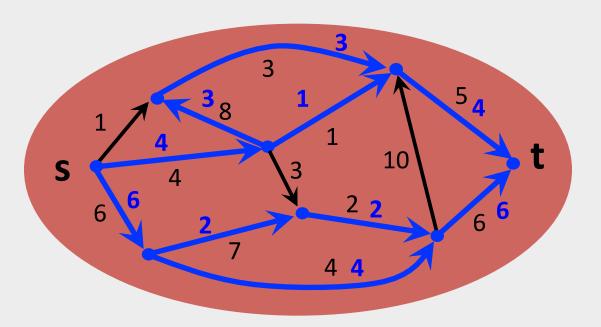
no overflow on arcs: $0 \le f(e) \le u(e)$

no leaks at all v≠s,t

Task: Find a feasible s-t flow of max value

Maximum flow problem

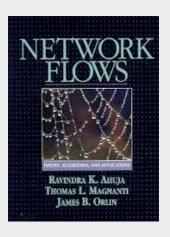
Input: Directed graph G, integer capacities u_e, source s and sink t



Max flow value F*=10

Task: Find a feasible s-t flow of max value

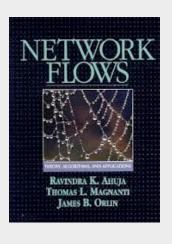
A **LOT** of previous work



A (very) rough history outline

[Dantzig '51]
[Ford Fulkerson '56]
[Dinitz '70]
[Dinitz '70] [Edmonds Karp '72]
[Dinitz '73] [Edmonds Karp '72]
[Dinitz '73] [Gabow '85]
[Goldberg Rao '98]
[Lee Sidford '14]

O(mn² U)
O(mn U)
O(mn²)
O(m²n)
O(m² log U)
O(mn log U)
Õ(m min(m^{1/2},n^{2/3}) log U)
Õ(mn^{1/2} log U)



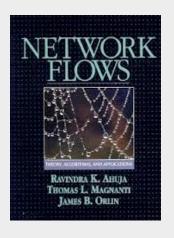
Our focus: Sparse graph (m=O(n)) and unit-capacity (U=1) regime

- → It is a good benchmark for combinatorial graph algorithms
- → Already captures interesting problems, e.g., bipartite matching

 $(n = # of vertices, m = # of arcs, U = max capacity, <math>\tilde{O}()$ hides polylogs)

A (very) rough history outline

[Dantzig '51]	O(n ³)
[Ford Fulkerson '56]	O(n ²)
[Dinitz '70]	$O(n^3)$
[Dinitz '70] [Edmonds Karp '72]	O(n³)
[Dinitz '73] [Edmonds Karp '72]	Õ(n²)
[Dinitz '73] [Gabow '85]	Õ(n²)
[Goldberg Rao '98]	$\tilde{O}(n^{3/2})$
[Lee Sidford '14]	Õ(n ^{3/2})



Our focus: Sparse graph (m=O(n)) and unit-capacity (U=1) regime

- → It is a good benchmark for combinatorial graph algorithms
- → Already captures interesting problems, e.g., bipartite matching

 $(n = # of vertices, m = # of arcs, U = max capacity, <math>\tilde{O}()$ hides polylogs)

Emerging barrier: $O(n^{3/2})$

[Even Tarjan '75, Karzanov '73]: Achieved this bound for U=1 long time ago

Last 40 years: Matching this bound in increasingly more general settings, but **no improvement**

This indicates a fundamental limitation of our techniques

Our goal: Show a new approach finally breaking this barrier

 $(n = # of vertices, m = # of arcs, U = max capacity, <math>\tilde{O}()$ hides polylogs)

Breaking the O(n^{3/2}) barrier

Undirected graphs and approx. answers (O(n^{3/2}) barrier still holds here)

[CKMST '11]: (1- ϵ)-approx. to max flow in $\tilde{O}(n^{4/3}\epsilon^{-3})$ time



[LSR '13, S '13, KLOS '14, P '14]: (1- ε)-approx. in $\tilde{O}(n\varepsilon^{-2})$ time

[M '13]: Exact
$$\tilde{O}(n^{10/7})=\tilde{O}(n^{1.43})$$
-time alg. for directed graphs

 $(n = # of vertices, \tilde{O}() hides polylog factors)$

Previous approach

Augmenting paths framework

[Ford Fulkerson '56]

Basic idea:

Repeatedly find s-t paths in the residual graph

Advantage: Simple, purely combinatorial and greedy (flow is built path-by-path)

Problem: Very difficult to analyze

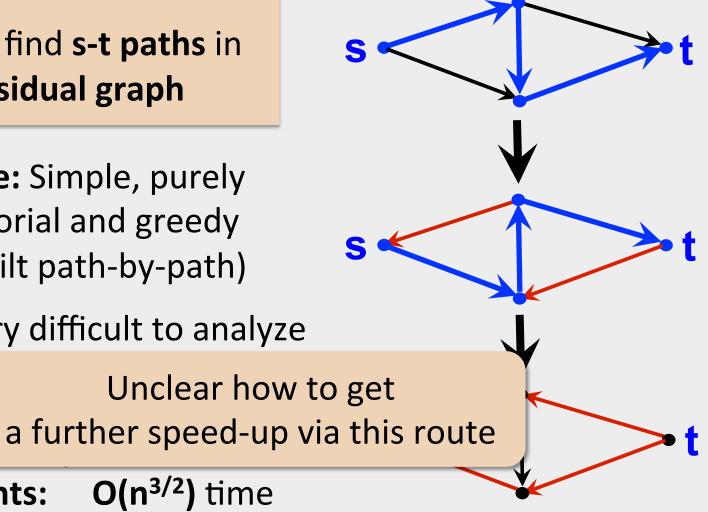
Naïve impl

Unclear how to get

Sophisticat

and arguments: $O(n^{3/2})$ time

[Karzanov '73] [Even Tarjan '75]



Beyond augmenting paths

New approach:

Bring linear-algebraic techniques into play

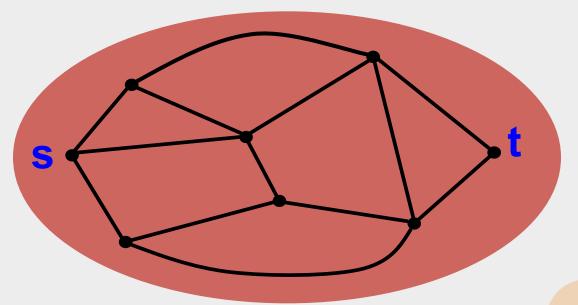
Idea: Probe the **global flow structure** of the graph by **solving linear systems**

How to relate **flow structure** to **linear algebra**? (And why should it even help?)

Key object: Electrical flows

Electrical flows (Take I)

Input: Undirected graph G,
resistances r_e,
source s and sink t



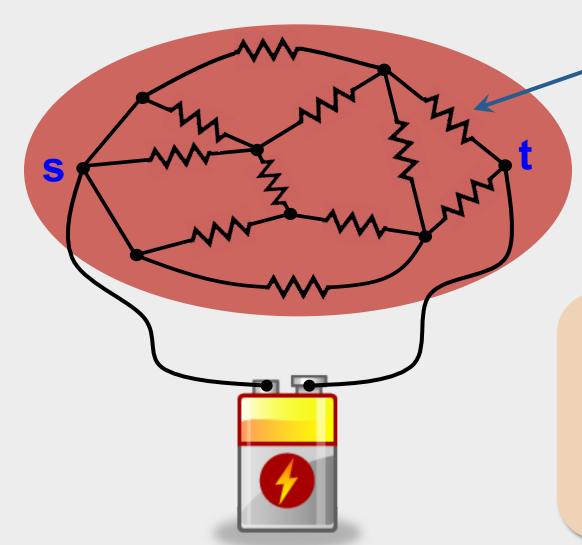
Recipe for elec. flow:

1) Treat edges as resistors

Electrical flows (Take I)

Input: Undirected graph G,
resistances r_e,
source s and sink t

resistance r_e



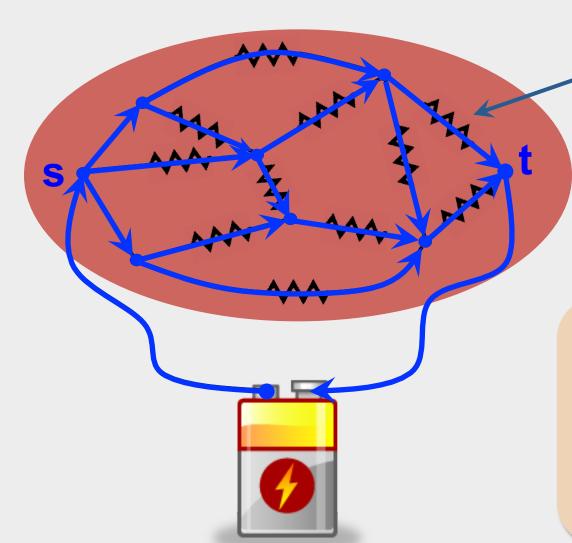
Recipe for elec. flow:

- 1) Treat edges as resistors
- 2) Connect a battery to s and t

Electrical flows (Take I)

Input: Undirected graph G, resistances r_e, source s and sink t

resistance r_e



Recipe for elec. flow:

- 1) Treat edges as resistors
- 2) Connect a battery to s and t

Electrical flows (Take II)

Input: Undirected graph G, resistances r_e, source s and sink t

Principle of least energy

Electrical flow of value F:

The unique minimizer of the energy

$$E(f) = \Sigma_e r_e f(e)^2$$

among all s-t flows f of value F

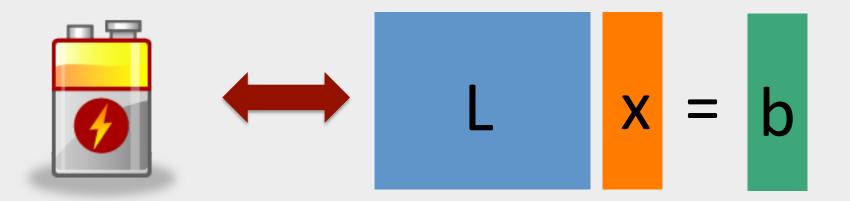
Electrical flows = ℓ_2 -minimization

How to compute an electrical flow?

Solve a linear system!

How to compute an electrical flow?

Solve a Laplacian system!



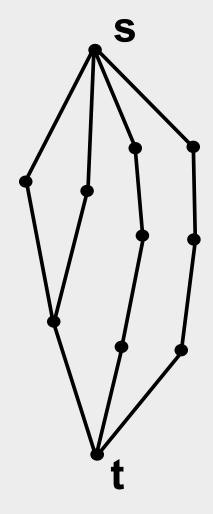
Result: Electrical flow is a nearly-linear time primitive [ST '04, KMP '10, KMP '11, KOSZ '13, LS '13, CKPPR '14]

How to employ it?

From electrical flows to undirected max flow

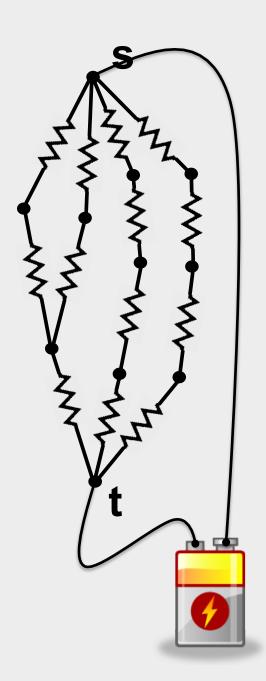
Assume: F* known (via binary search)

→ Treat edges as resistors of resistance 1



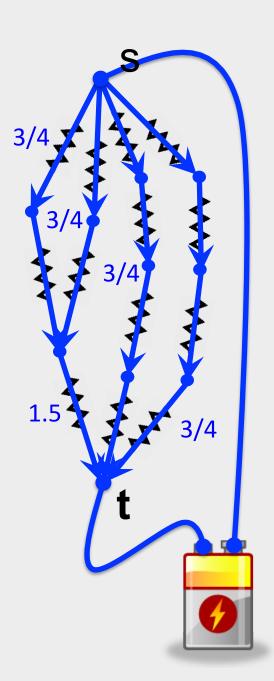
Assume: F* known (via binary search)

- → Treat edges as resistors of resistance 1
- → Compute electrical flow of value **F***



Assume: F* known (via binary search)

- → Treat edges as resistors of resistance 1
- → Compute electrical flow of value F* (This flow has no leaks, but can overflow some edges)



Assume: F* known (via binary search)

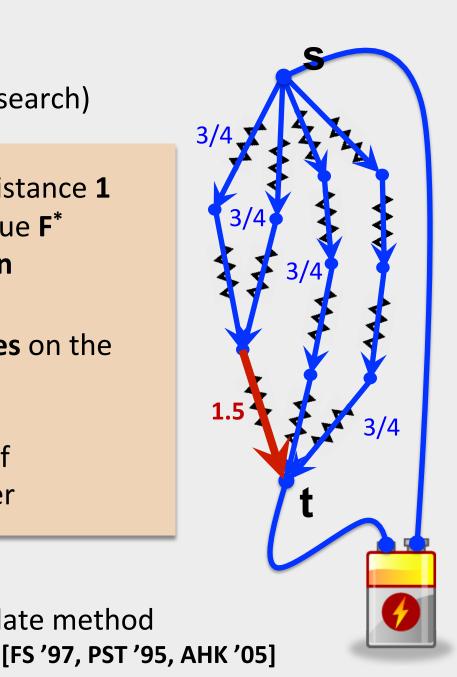
- → Treat edges as resistors of resistance 1
- → Compute electrical flow of value F* (This flow has no leaks, but can overflow some edges)
- → To fix that: Increase resistances on the overflowing edges

Repeat

→ At the end: Take an average of all the flows as the final answer

Evolution of resistances:

Based on Multiplicative Weight Update method



Bounding the running time

- \rightarrow Each iteration runs in $\tilde{O}(n)$ time
- → How many iterations do we need?

Can show: # of iterations ≈ worst-case overflow **p**

Think: ρ measures the electrical vs. max flow difference Key question: If f_E = elect. flow of value F^* wrt all r_e =1 What is $\rho = \max_e f_E(e)$?

Claim: $\rho \le m^{1/2} = O(n^{1/2})$

Proof: Suffices to show that $E(f_E) \le m$

Bounding the running time

- \rightarrow Each iteration runs in $\tilde{O}(n)$ time
- → How many iterations do we need?

Can show: # of iterations ≈ worst-case overflow ρ

Think: ρ measures the electrical vs. max flow difference Key question: If f_E = elect. flow of value F^* wrt all r_e =1 What is $\rho = \max_e f_E(e)$?

Claim: $\rho \le m^{1/2} = O(n^{1/2})$

Proof: Suffices to show that $E(f_E) = \Sigma_e r_e f_E(e)^2 = \Sigma_e f_E(e)^2 \le m$

Note: if f^* is the max flow (of value F^*) then $E(f^*) = \Sigma_e r_e f^*(e)^2 = \Sigma_e f^*(e)^2$

Bounding the running time

- \rightarrow Each iteration runs in $\tilde{O}(n)$ time
- → How many iterations do we need?

Can show: # of iterations ≈ worst-case overflow **p**

Think: ρ measures the electrical vs. max flow difference Key question: If f_E = elect. flow of value F^* wrt all r_e =1 What is $\rho = \max_e f_E(e)$?

Claim: $\rho \le m^{1/2} = O(n^{1/2})$

Proof: Suffices to show that $E(f_E) = \Sigma_e r_e f_E(e)^2 = \Sigma_e f_E(e)^2 \le m$

Note if f* is the may flow (of value F*) then

This gives an $\tilde{O}(n\rho\epsilon^{-3}) = \tilde{O}(n^{3/2}\epsilon^{-3})$ time (1- ϵ)-approx algorithm

B

Claim: $\rho \le m^{1/2} = O(n^{1/2})$

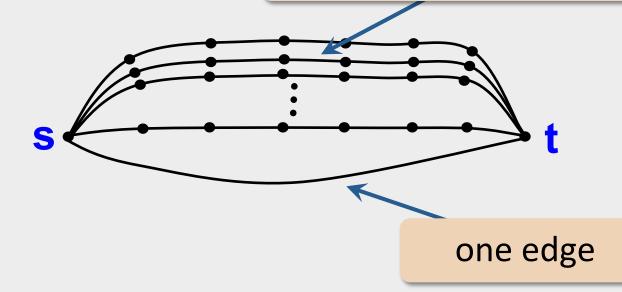
Is this bound tight?

Will be so **only** if there exists an edge that (single-handily) contributes **most of the energy** of f_E

(Recall: We showed $\rho^2 = \max_e f_E(e)^2 \le \Sigma_e f_E(e)^2 = E(f_E) \le m$)

Can this even happen?

≈n^{1/2} paths with ≈n^{1/2} vertices each



Claim: $\rho \le m^{1/2} = O(n^{1/2})$

Is this bound tight?

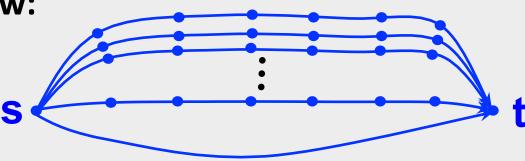
Will be so **only** if there exists an edge that (single-handily) contributes **most of the energy** of f_E

(Recall: We showed $\rho^2 = \max_e f_E(e)^2 \le \Sigma_e f_E(e)^2 = E(f_E) \le m$)

Can this even happen?

Unfortunately, yes

Max flow:

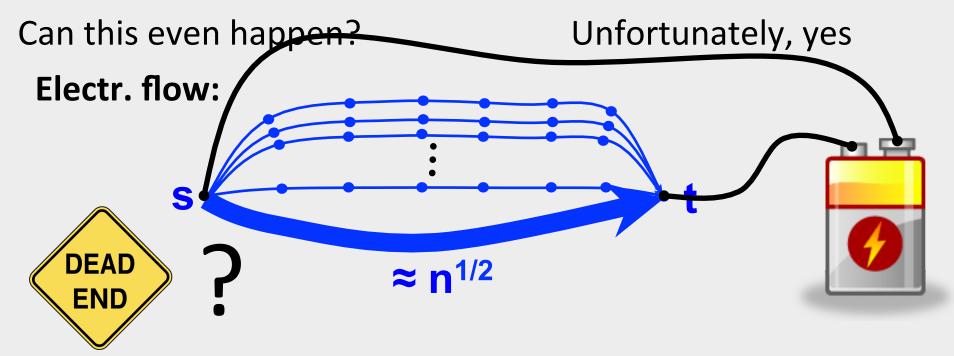


F*≈n½

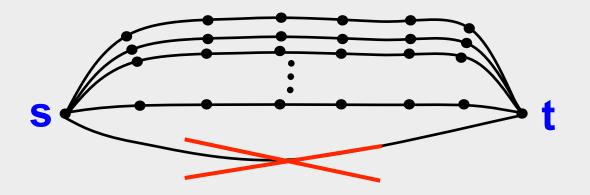
Claim: $\rho \le m^{1/2} = O(n^{1/2})$

Is this bound tight?

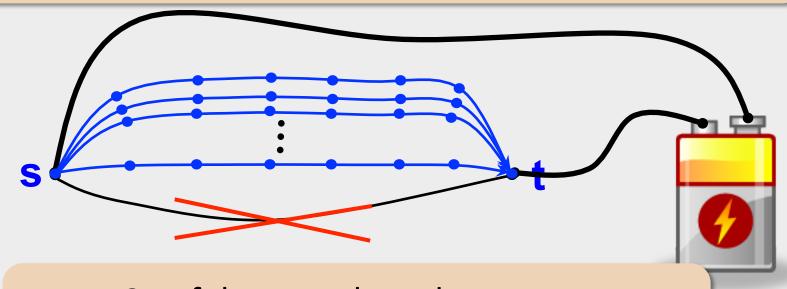
Will be so **only** if there exists an edge that (single-handily) contributes **most of the energy** of f_E (**Recall:** We showed $\rho^2 = \max_e f_E(e)^2 \le \Sigma_e f_E(e)^2 = E(f_E) \le m$)



Key idea: Perturb the graph by removing such high-energy edges whenever they emerge



Key idea: Perturb the graph by removing such high-energy edges whenever they emerge



Careful energy-based argument gives the desired $\tilde{O}(n^{4/3}\,\epsilon^{-3})$ time algorithm

Later on: [LSR '13, S '13, KLOS '14, P'14]: (1- ϵ)-approx. in $\tilde{O}(n\epsilon^{-2})$ time via a version of an ℓ_{∞} -based gradient descent

Directed Maximum Flow

Why the progress on **approx. undirected** max flow does not apply to the **directed** case?

Key problem: To solve **directed** max flow (even approx.), one needs to solve **exact undirected** max flow

First-order methods are inherently unable to deliver good enough accuracy here

We need a bigger hammer



(Path-following) Interior-point method (IPM)

[Dikin '67, Karmarkar '84, Renegar '88,...]

A powerful framework for solving general LPs (and more)

LP: $min c^Tx$

s.t. Ax = b

x ≥ 0

Idea: Take care of "hard" constraints by adding a "barrier" to the objective

"easy" constraints
 (use projection)

"hard" constraints

(Path-following) Interior-point method (IPM)

[Dikin '67, Karmarkar '84, Renegar '88,...]

A powerful framework for solving general LPs (and more)

LP(
$$\mu$$
): min c^Tx - $\mu \Sigma_i \log x_i$
s.t. Ax = b

Idea: Take care of "hard" constraints by adding a "barrier" to the objective

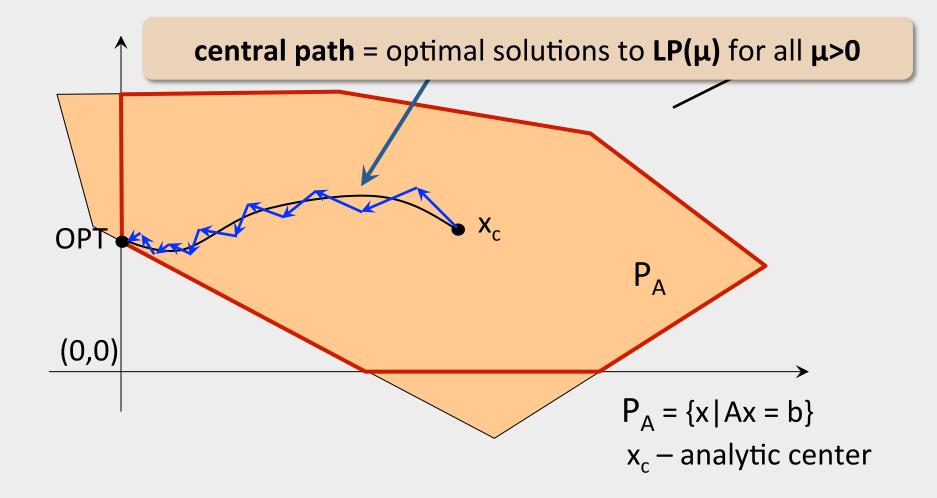
Observe: The barrier term enforces $x \ge 0$ implicitly

Furthermore: for large μ , LP(μ) is easy to solve and

 $LP(\mu) \rightarrow \text{ original } LP, \text{ as } \mu \rightarrow 0^+$

Path-following routine:

- \rightarrow Start with (near-)optimal solution $x(\mu)$ to $LP(\mu)$ for large $\mu>0$
- \rightarrow Take an **improvement step** that gradually reduces μ while maintaining the (near-)optimality of $x(\mu)$ (wrt current μ)



Path-following routine:

- \rightarrow Start with (near-)optimal solution $x(\mu)$ to $LP(\mu)$ for large $\mu>0$
- \rightarrow Take an **improvement step** that gradually reduces μ while maintaining the (near-)optimality of $x(\mu)$ (wrt current μ)

Can we use IPM to get a faster max flow alg.?

Conventional wisdom: This will be too slow!

⇒ Each Newton's step = solving a linear system $O(n^{\omega})=O(n^{2.373})$ time (prohibitive!)

But: When solving flow problems – only Õ(m) time [DS '08]

Fundamental question: What is the number of iterations?

[Renegar '88]: $O(m^{1/2} \log \epsilon^{-1})$

Unfortunately: This gives only an $\tilde{O}(m^{3/2})$ -time algorithm

Improve the O(m^{1/2}) bound?

Although believed to be **very** suboptimal, its improvement is a major challenge





[M '13]: An improved O(m^{3/7}) iterations bound for unit-capacity max flow interior-point method

Observation: IPM is solving max flow using electrical flows too!

Result: Better grasp of step size choice (ℓ_2 vs. ℓ_4 interplay)

- A simple energy-based argument recovers the O(m^{1/2}) bound
- Lack of high-energy edges \rightarrow better than $O(m^{1/2})$ convergence

Problem: Removal of such high-energy edges is too drastic

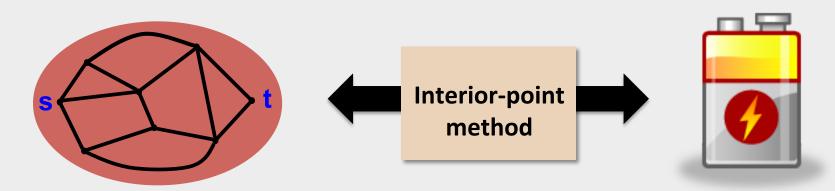
Instead: Apply a careful perturbation + preconditioning of the LP (This not only changes the current solution but also the central path) Use a new type of potential-based (non-local) convergence argument

Most of these elements seems broadly applicable (and new)

Will this lead to breaking the $\Omega(m^{1/2})$ convergence barrier for all LPs?

Conclusions and the Bigger Picture

Maximum Flows and Electrical Flows



Elect. flows + IPMs → A powerful new approach to max flow

Can this lead to a **nearly-linear time** algorithm for the **exact directed** max flow?

We seem to have the "critical mass" of ideas



Elect. flows = next generation of "spectral" tools?

- Better "spectral" graph partitioning,
- Algorithmic grasp of random walks,
- •

Max Flow and Interior-Point Methods

Contributing back: Max flow and electrical flows as a lens for analyzing general IPMs?

Our techniques can be lifted to the general LP setting

We can solve **any** LP within $\tilde{O}(m^{3/7}L)$ iterations **But:** this involves **perturbing** of this LP

Some (seemingly) new elements of our approach:

- Better grasp of ℓ_2 vs. ℓ_4 interplay wrt the step size δ
- Perturbing the central path when needed
- Usage of non-local convergence arguments

Can this lead to breaking the $\Omega(m^{1/2})$ barrier for all LPs?

[Lee Sidford '14]: $\tilde{O}(n^{1/2})$ iteration bound

Bridging the Combinatorial and the Continuous

paths, trees, partitions, routings, matchings, data structures...



matrices, eigenvalues, linear systems, gradients, convex sets...

Powerful approach: Exploiting the interplay of the two worlds

Some other early "success stories" of this approach:

- Spectral graph theory aka the "eigenvalue connection"
- Fast SDD/Laplacian system solvers
- Graph sparsification, random spanning tree generation
- Graph partitioning

...and this is just the beginning!

Thank you

Questions?