Applications of nonlinear network flow models to market equilibria

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Bellairs Workshop on Algorithmic Game Theory April 8 2012

Friday, April 13, 2012

Linear Fisher markets

- * B: buyers, G: goods.
- * Buyer *i* has budget m_i , 1 divisible unit of each good *j*.
- * Utility U_{ij} for buyer *i* on 1 unit of good *j*.
- * Market clearing: prices p_j and allocations x_{ij} if:
 - * everything is sold
 - * all money is spent
 - * only best bang-per-buck purchases: max. U_{ij}/p_{j} .



Linear Fisher markets

- * Formulated by Fisher in 1891.
- * Special case of the Arrow-Debreu model.
 - * An equilibrium exists under very general conditions (Arrow, Debreu, 1954).
 - * Nonconstructive proof based on Kakutani's fixed point theorem.
- * The linear Fisher model can be captured by the convex program by Eisenberg and Gale '59.

Eisenberg-Gale convex program, 1959

$$\begin{aligned} \max \sum_{i \in B} m_i \log U_i \\ U_i &\leq \sum_{j \in G} U_{ij} x_{ij} \quad \forall i \in B \\ \sum_{i \in B} x_{ij} &\leq 1 \quad \forall j \in G \\ x_{ij} &\geq 0 \quad \forall i \in B, j \in G \end{aligned}$$

* Optimal solution corresponds to equilibrium prices.

* There exists a rational optimal solution.

Combinatorial algorithms for linear Fisher markets

- * Devanur, Papadimitriou, Saberi, Vazirani '02: polynomial time combinatorial algorithm.
- * Several extensions and generalizations studied during the last decade.
- * Fisher's market with separable piecewise linear concave utilities: PPAD-complete (Vazirani&Yannakakis '11).

Market equilibria with rational convex programs and combinatorial algorithms

Linear Fisher	DPSV '02/'08 Orlin '10: strongly poly.	
Perfect price discrimination	Goel&Vazirani '10	
Spending constraint utilities	Devanur&Vazirani '04/ '10	
Arrow-Debreu Nash bargaining	Vazirani '11	
Nonsymmetric ADNB		

Convex extensions of classical flow models:

- * Concave generalized flows (CGF):
 - * Truemper '78, Shigeno '06
 - * We give the first combinatorial polytime algorithm.
- * Minimum cost flows with separable convex objectives (MCCF):
 - * Combinatorial polytime algorithms: Minoux '86, Hochbaum&Shantikumar '92, Karzanov&McCormick '97
 - * We give a strongly poly algorithm for certain classes of objectives.

Market equilibria with (rationa) convex programs and combinatorial algorithms

Linear Fisher	DPSV '02/'08 Orlin '10: strongly poly.	CGF	MCCF: strongly poly
Perfect price discrimination	Goel&Vazirani '10	CGF	
Spending constraint utilities	Devanur&Vazirani '04/ '10		MCCF: strongly poly
Arrow-Debreu Nash bargaining	Vazirani '11	CGF	
Nonsymmetric ADNB	?	CGF	

CGF: concave generalized flows V. '12b MCCF: min. cost separable convex flows V. '12a

Generalized Flows

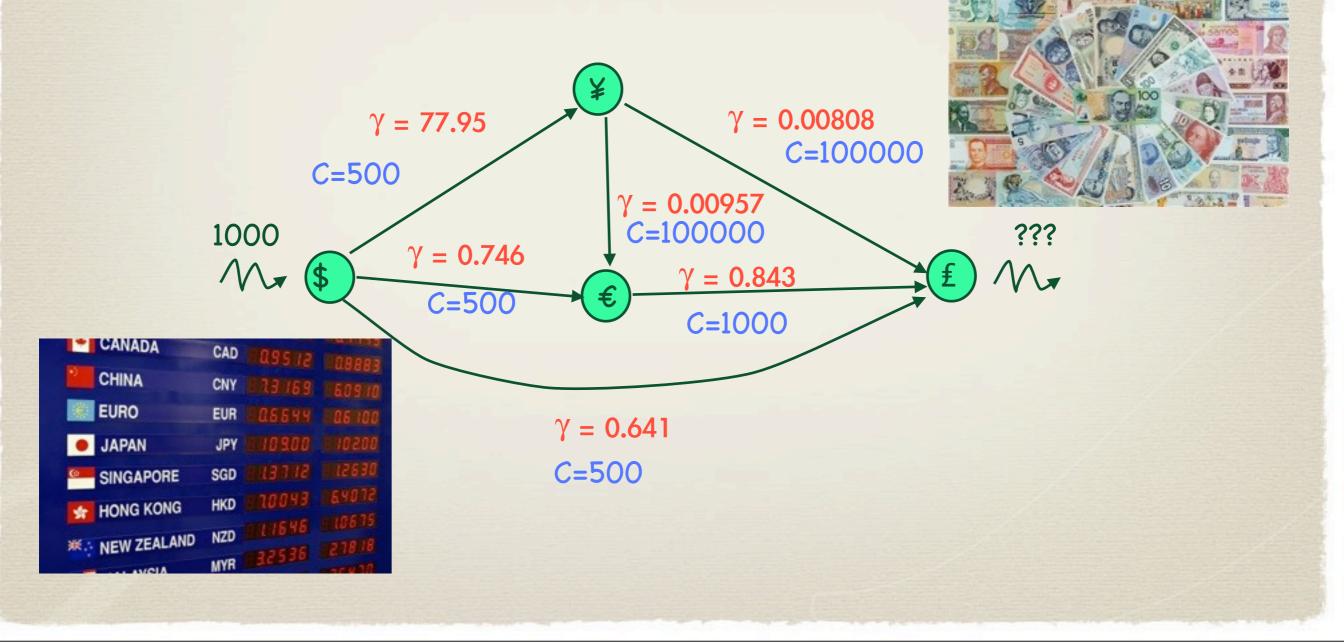
* Network flow model, with gain factors on the arcs.

* Maximize the flow amount reaching the sink t.

- * Introduced by Kantorovich '39, Dantzig '62.
- * Several applications: financial analysis, transportation, management, etc.

Generalized Flows

★ Currency conversion with bounds: obtain the most £ from 1000\$.



Generalized Flows

- * Linear program.
- * Early combinatorial algorithms: Onaga '66, Truemper '77.
- * First polynomial time combinatorial algorithm: Goldberg, Plotkin, Tardos '91.
- * Followed by Cohen&Megiddo '94, Goldfarb&Jin '96, Goldfarb, Jin&Orlin '97, Tardos&Wayne '98, Wayne '02, Radzik '04, Restrepo&Williamson '09, etc.

Concave Generalized Flows

* Instead of gain factors, concave increasing gain functions.

 $\begin{array}{c} \alpha & \Gamma(.) \\ \mathcal{N}_{\star} \bigcirc & & & & \\ \end{array}$ Γ(α)) //_

Convex Program

$$\max \sum_{j:jt\in E} \Gamma_{jt}(f_{jt}) - \sum_{j:tj\in E} f_{tj}$$
$$\sum_{j:ji\in E} \Gamma_{ji}(f_{ji}) - \sum_{j:ij\in E} f_{ij} \ge b_i \quad \forall i \in V - t$$
$$\ell_{ij} \le f_{ij} \le u_{ij} \quad \forall ij \in E$$

Concave Generalized Flows

- * First defined by Truemper '78.
- * Solvable via general purpose convex solver.
- * Shigeno 'o6 gave a combinatorial algorithm that is polynomial for some special classes of gain functions, including piecewise linear.
- * We give a polynomial combinatorial algorithm for finding an ε-approximate solution in running time

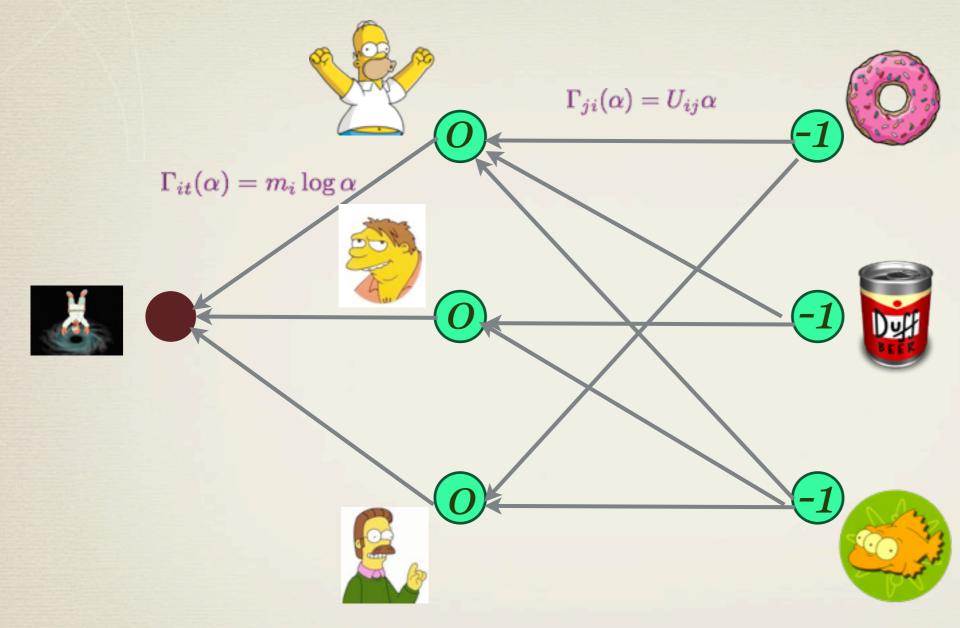
 $O(m(m + \log n) \log(MUm/\varepsilon))$

* For problems with a rational optimal solution, we can find it in polynomial time with a final rounding.

Eisenberg-Gale convex program, 1959

$$\max \sum_{i \in B} m_i \log U_i$$
$$U_i \le \sum_{j \in G} U_{ij} x_{ij} \quad \forall i \in B$$
$$\sum_{i \in B} x_{ij} \le 1 \quad \forall j \in G$$
$$x_{ij} \ge 0 \quad \forall i \in B, j \in G$$

Reduction for linear Fisher market



Extensions of linear Fisher markets
* Goel, Vazirani '10: perfect price discrimination
* (Piecewise linear) concave increasing utilities.

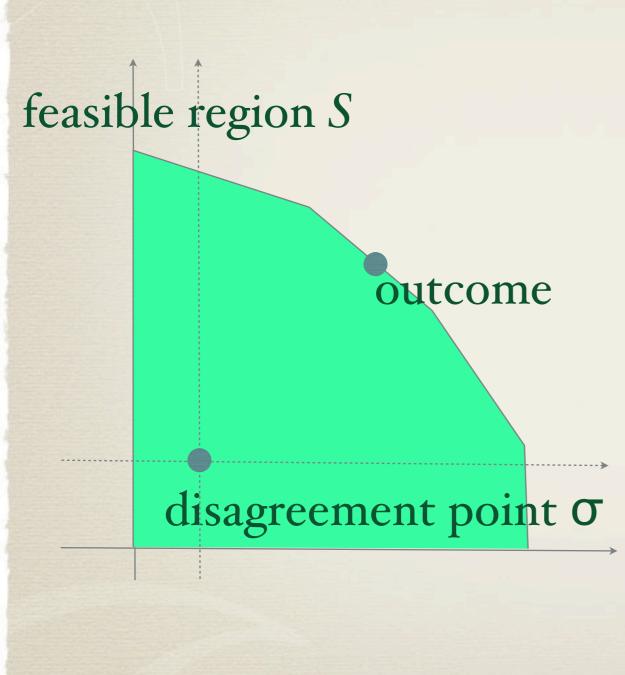
- * Middleman between buyers and firms. He charges different costumers at different rates they are capable of paying.
- * Replace $\Gamma_{ji}(\alpha) = U_{ij}\alpha$ by a piecewise linear concave function.
- * Using our model, it can be replaced by arbitrary concave!

Nash bargaining, 1950

* n players, set of possible outcomes S ⊆ ℝⁿ₊
* In outcome s = (s₁,...,s_n) ∈ S, player i gets utility s_i.
* Disagreement point (status quo): σ ∈ S
* The players have to agree together in an outcome. If

they cannot agree, the status quo remains.

Nash bargaining, 1950



* Which is the best outcome?

- * Four criteria:
 - * Pareto optimality
 - * Invariance under affine transformations
 - * Symmetry
 - * Indifference of independent alternatives

Nash bargaining, 1950

feasible region S

outcome

disagreement point σ

Theorem (Nash, 1950)

For a convex feasible region, there exists a unique optimal solution, the one maximizing

 $\sum_{i\in[n]}\log(s_i-\sigma_i)$

Arrow-Debreu Nash bargaining: Vazirani '12

- * Nash bargaining between agents, each of them having an initial endowment of goods, giving utility c_i to player i.
- * Possible outcomes: distributions of goods.

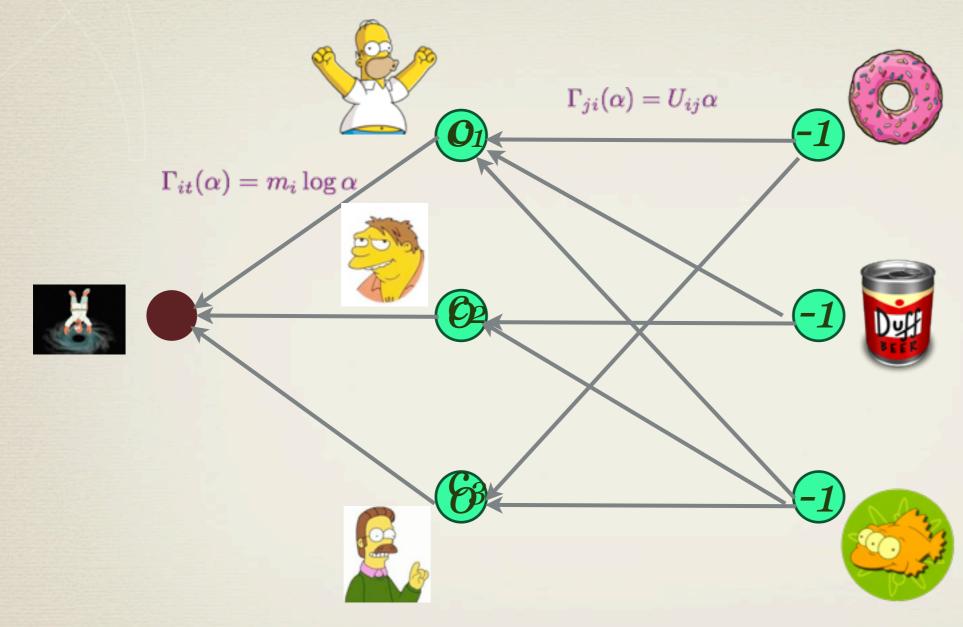
$$\max \sum_{i \in B} \log(U_i - c_i)$$
$$U_i \le \sum_{j \in G} U_{ij} x_{ij} \quad \forall i \in B$$
$$\sum_{i \in B} x_{ij} \le 1 \quad \forall j \in G$$
$$x_{ij} \ge 0 \quad \forall i \in B, j \in G$$

Arrow-Debreu Nash bargaining: Vazirani '12

* Vazirani '12: sophisticated two phase algorithm, first deciding feasibility, then optimality.

$$\max \sum_{i \in B} \log(U_i - c_i)$$
$$U_i \le \sum_{j \in G} U_{ij} x_{ij} \quad \forall i \in B$$
$$\sum_{i \in B} x_{ij} \le 1 \quad \forall j \in G$$
$$x_{ij} \ge 0 \quad \forall i \in B, j \in G$$

Reduction to Concave Generalized Flows



Arrow-Debreu Nash bargaining: Vazirani, '12

 $\max \sum_{i \in B} m_i \log(U_i - c_i)$ $U_i \le \sum_{j \in G} U_{ij} x_{ij} \quad \forall i \in B$ $\sum_{i \in B} x_{ij} \le 1 \quad \forall j \in G$ $x_{ij} \ge 0 \quad \forall i \in B, j \in G$

* Nonsymmetric Nash bargaining: Kalai '77

* Different weights m_i for player i.

* Finding a combinatorial algorithm was left open. Our model also captures this, solving in

 $O(m^2(\log C_{\max} + n\log(nU_{\max}M_{\max})))$

* Vazirani '12 for symmetric: $O(n^8 \log U_{\max} + n^4 \log C_{\max})$

Further applications of concave generalized flows

- * Jain, Vazirani '10: single source multiple sink flow markets.
- * Jain '11: online matching with concave utilities (offline optimum)

Linear and convex flow problems I.

flows

generalized flows

Linear

Minimum cost circulations Edmonds&Karp '72 Generalized flows Goldberg, Plotkin, Tardos'91

Convex

Minimum cost circulations w. separable convex cost Minoux '86

Concave generalized flows V. '12b Linear minimum cost flow problem

- * G=(V,E) directed graph
- * On each arc ij, lower and upper capacities l_{ij} , u_{ij} .
- * On each node i, node demand b_i : incoming flow minus outgoing flow should be b_i .
- * Minimum cost flow problem: for a cost function *c* on the arcs, find a minimum cost feasible flow
- * First weakly polynomial algorithm: Edmonds, Karp '72
- * Strongly polynomial algorithms: Tardos '85, Goldberg, Tarjan '88, Orlin '93, ...

Strongly polynomial algorithms

- * Problem given by N integers in the input, each at most C.
- * (Weakly) polynomial algorithm: the running time is poly(N, log C).
- * Strongly polynomial algorithm: the algorithm consists of *poly(N)* elementary arithmetic operations, independent from *C*.
 - * The numbers in the operations are at most poly(C).
 - * Alternatively, we may allow computation with real numbers, assuming we can perform basic arithmetic operations in *O(1)* time.

Minimum cost flows with separable convex objectives

- * G=(V,E) directed graph
- * On each arc ij, lower and upper capacities l_{ij} , u_{ij} .
- * On each node i, node demand b_i : incoming flow minus outgoing flow should be b_i .
- * We want to minimize $\Sigma C_{ij}(f_{ij})$ over feasible flows, where on each arc ij, C_{ij} is a convex function.
- * Convex program with several applications: traffic management, matrix balancing, stick percolation...

Minimum cost flows with separable convex objectives

1

x

* Selfish routing in urban traffic networks: transition time on a road is an increasing function of the traffic amount.

0

X

1

Minimum cost flows with separable convex objectives

1

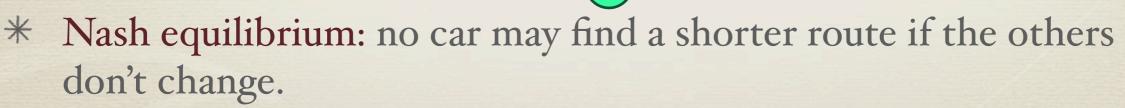
X

* Selfish routing in urban traffic networks: transition time on a road is an increasing function of the traffic amount.

0

X

1



* Computing a Nash-equilibrium is a separable convex cost flow problem.

Linear Fisher market: convex formulations

i

* Eisenberg&Gale, '59

* Shmyrev; Devanur '09

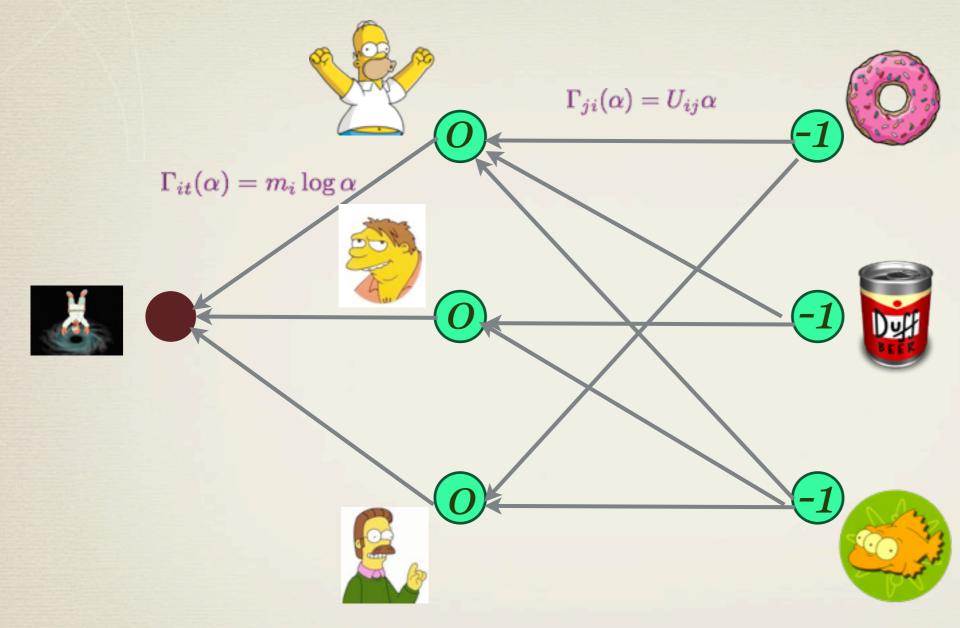
$$\begin{aligned} x_{ij} &: \text{amount of good } j \text{ purchased by} \\ \max \sum_{i \in B} m_i \log U_i \\ U_i &\leq \sum_{j \in G} U_{ij} x_{ij} \quad \forall i \in B \\ \sum_{i \in B} x_{ij} &\leq 1 \quad \forall j \in G \\ x &\geq 0 \end{aligned}$$

* concave generalized flow

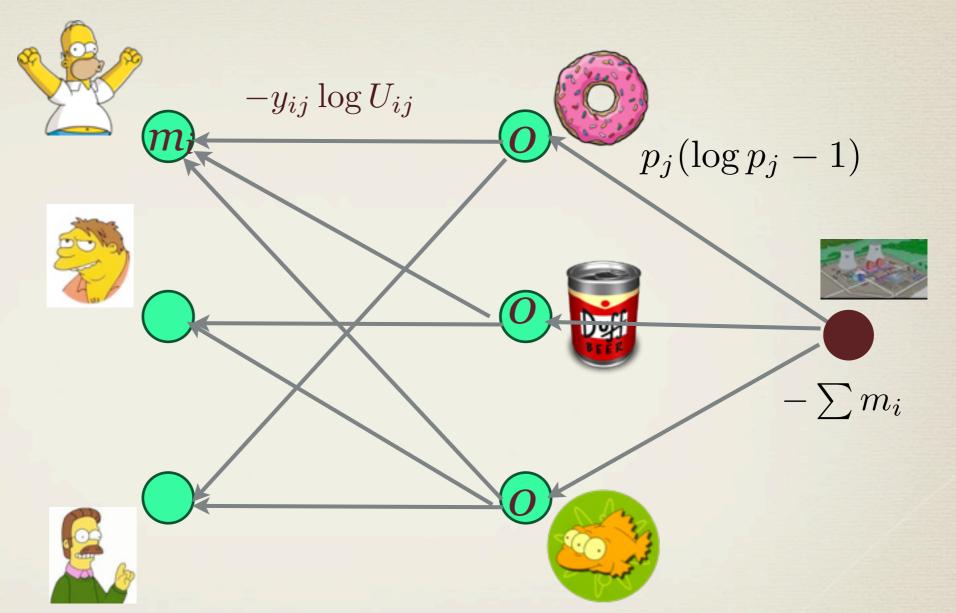
 $y_{ij}: \text{ amount of money payed by } i \text{ for } j$ $\min \sum_{i \in G} p_j (\log p_j - 1) - \sum_{ij \in E} y_{ij} \log U_{ij}$ $\sum_{j \in G} y_{ij} = m_i \quad \forall i \in B$ $\sum_{i \in B} y_{ij} = p_j \quad \forall j \in G$ $y \ge 0$

* flow with separable convex objective

Reduction for linear Fisher market



Reduction for linear Fisher market



Extensions of linear Fisher markets

* Devanur&Vazirani '04: spending constraint utilities

* The utility of the buyers is a piecewise linear concave function of the *amount of money spent on*. *the good*.

- * Vazirani '10: combinatorial algorithm (extension of DPSV'02)
- * Devanur et al. '11: discovered the convex programming relaxation.
- * V. '12a: strongly polynomial algorithm

When is there a strongly polynomial algorithm for MCCF?

G = (V, E) directed graph $C_{ij} : [\ell_{ij}, u_{ij}] \to \mathbb{R} \text{ convex, (differentiable)}$ $\min \sum_{ij \in E} C_{ij}(f_{ij})$ $\sum_{j:ji \in E} f_{ji} - \sum_{j:ij \in E} f_{ij} = b_i \quad \forall i \in V$ $\ell_{ij} \leq f_{ij} \leq u_{ij} \quad \forall ij \in E$

Previously known cases

- * Linear costs $(C_{ij}(x)=c_{ij}x)$
- * Quadratic costs ($C_{ij}(x)=c_{ij}x^2+d_{ij}x, c_{ij}\geq 0$)
 - * Series parallel graphs: Tamir '93.
 - * Transportation problem with fixed number of sources: Cosares&Hochbaum '94.
- * Other nonlinear
 - * Fisher's market with linear utilities: Orlin '10.

Negative results for strongly polynomiality

- * Optimal solution can be irrational (even non-algebraic!)
- * Q: is it possible to find an ε -approximate solution in time polynomial in the input size and log 1/ ε ?
 - * Even this is impossible if the C_{ij} 's are polynomials of degree ≥3 (Hochbaum '94)
 - * Reason: impossible to ε-approximate roots of polynomials in strongly polynomial time (Renegar '87)
- * This does not apply for quadratic objectives!

Our result (STOC 2012)

* Strongly polynomial algorithm under certain oracle assumptions on the objective.

- * Key assumption: we can compute an optimal solution, provided its support.
- * Special cases include:
 - * Convex quadratic objectives.
 - * Fisher's market with linear and with spending constraint utilities.

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flows

generalized flows

Linear

Minimum cost circulations Edmonds&Karp '72 Generalized flows Goldberg, Plotkin, Tardos'91

Convex

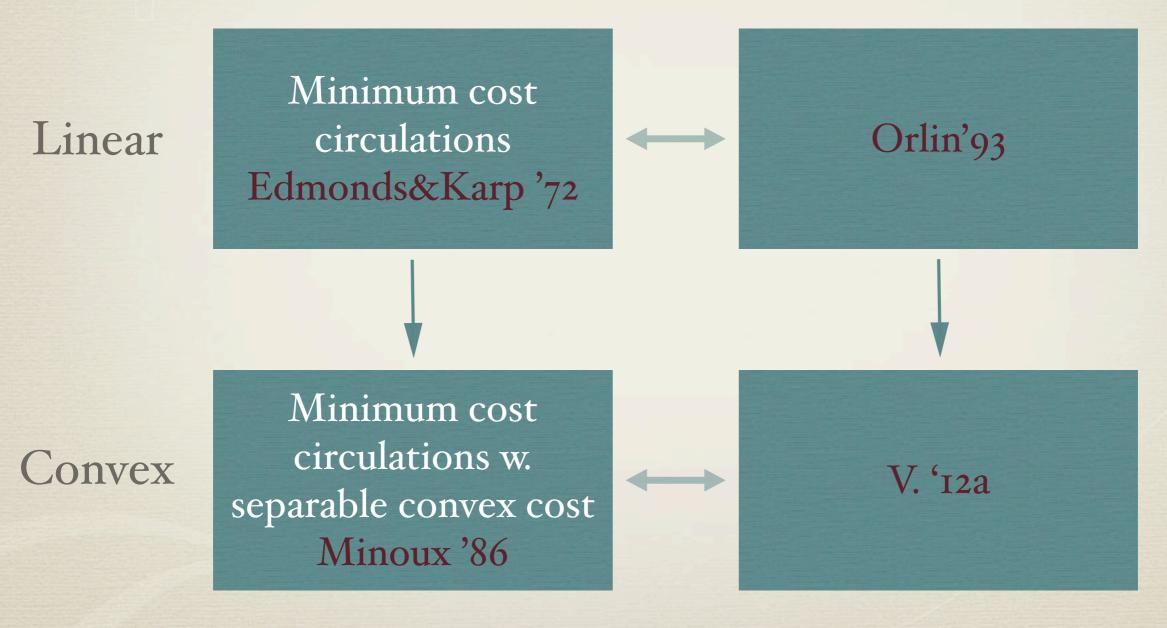
Minimum cost circulations w. separable convex cost Minoux '86

Concave generalized flows V. '12b

Linear and convex flow problems I.

weakly polynomial

strongly polynomial



Main algorithmic ideas

- * Edmonds, Karp '72: capacity scaling algorithm:
 - * Successive shortest paths method, first transporting the huge parts of the excesses.
- * Minoux '86: naturally extends to convex costs, with linearizing the cost in Δ chunks in the Δ -phase.

$$\frac{C_{ij}(f_{ij} + \Delta) - C_{ij}(f_{ij})}{\Delta}$$

Main algorithmic ideas

- * V'12a: apply Minoux's algorithm, and maintain a subset F of arcs guaranteed to be in the support of (the) optimal solution. F shall be extended in every O(log n) iterations.
- * In certain phases, we make a guess: *maybe*. *F* is already optimal? We compute an optimal solution based on the assumption that it's support is *F*.
 - * if yes: great!
 - * if not: either it still gives a better solution than the current one: Δ decreases radically;
 - * or it gives a guarantee that F must soon be extended.

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CGF: concave generalized flows V. '12b MCCF: min. cost separable convex flows V. '12a

Further questions

- * Concave generalized flows: the algorithm is not strongly polynomial
- * No strongly polynomial algorithm exists for linear generalized flows!
- * Solving that could help develop strongly poly. alg. for certain concave gain functions.
- * Linear Arrow-Debreu markets: no combinatorial algorithm known. Convex programming formulation: Nenakov&Primak '83, Jain '06.

Thank you for your attention!

