Algorithmic Social Intervention

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Social and behavioral intervention

- Social problems: disease, poverty, homelessness…
- Intervention: services, outreach, education
- Limited resources

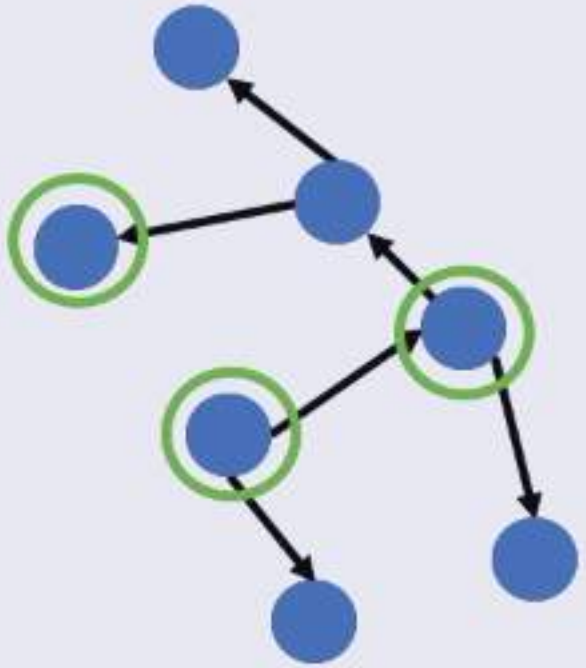
Motivating question

How can AI be used to improve socially impactful decisions?

Technical focus

- Improving interventions is often a *combinatorial optimization* problem

$$\max_{S \in X} f(S) \quad X \subseteq \{0,1\}^n$$



- Select from discrete sets of objects
  - Peer leaders from a social network
  - Assign housing to applicants
  - Patients for extra follow-up
  - …
- Resources are limited: intervention is subject to constraints

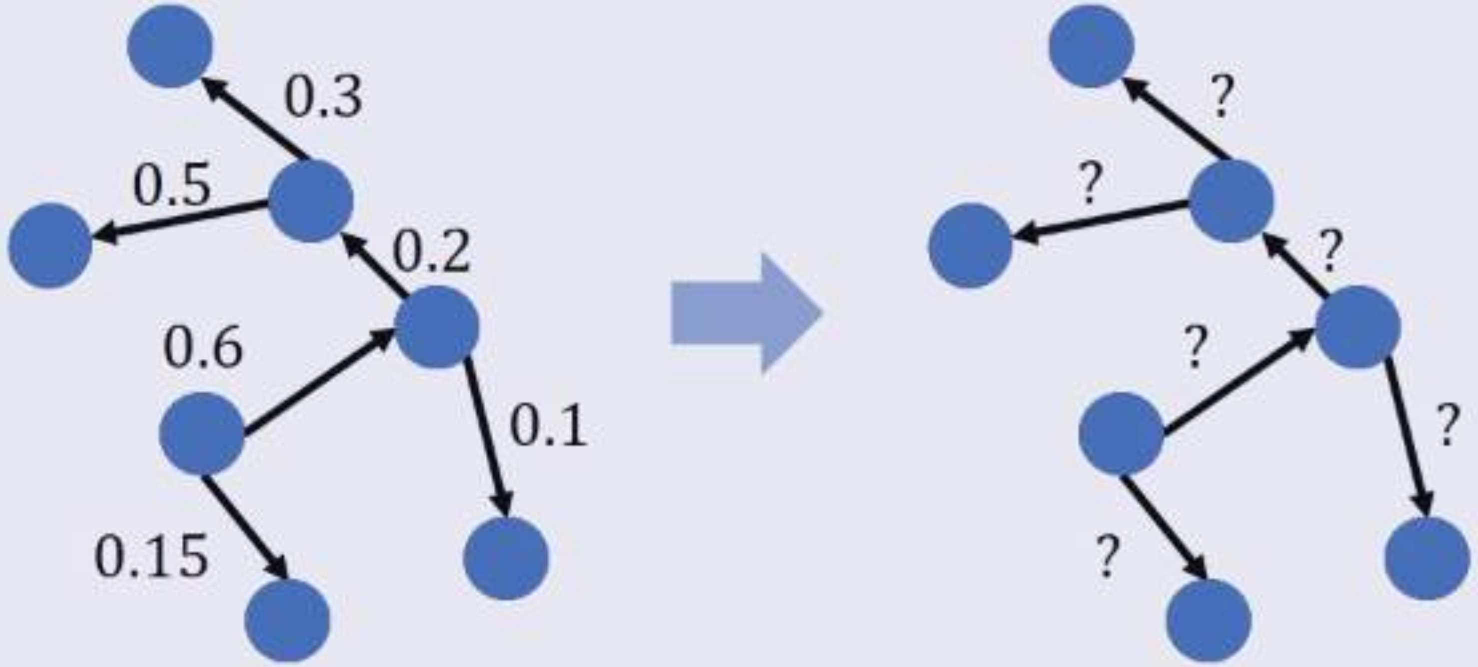
Challenge

- We understand *fully specified* combinatorial optimization problems

$$\max_{S \in X} f(S, \theta)$$

Decision Parameter

- But in most social good domains, we don't know θ!



Research question

How do we solve combinatorial optimization problems which depend on unknown parameters?

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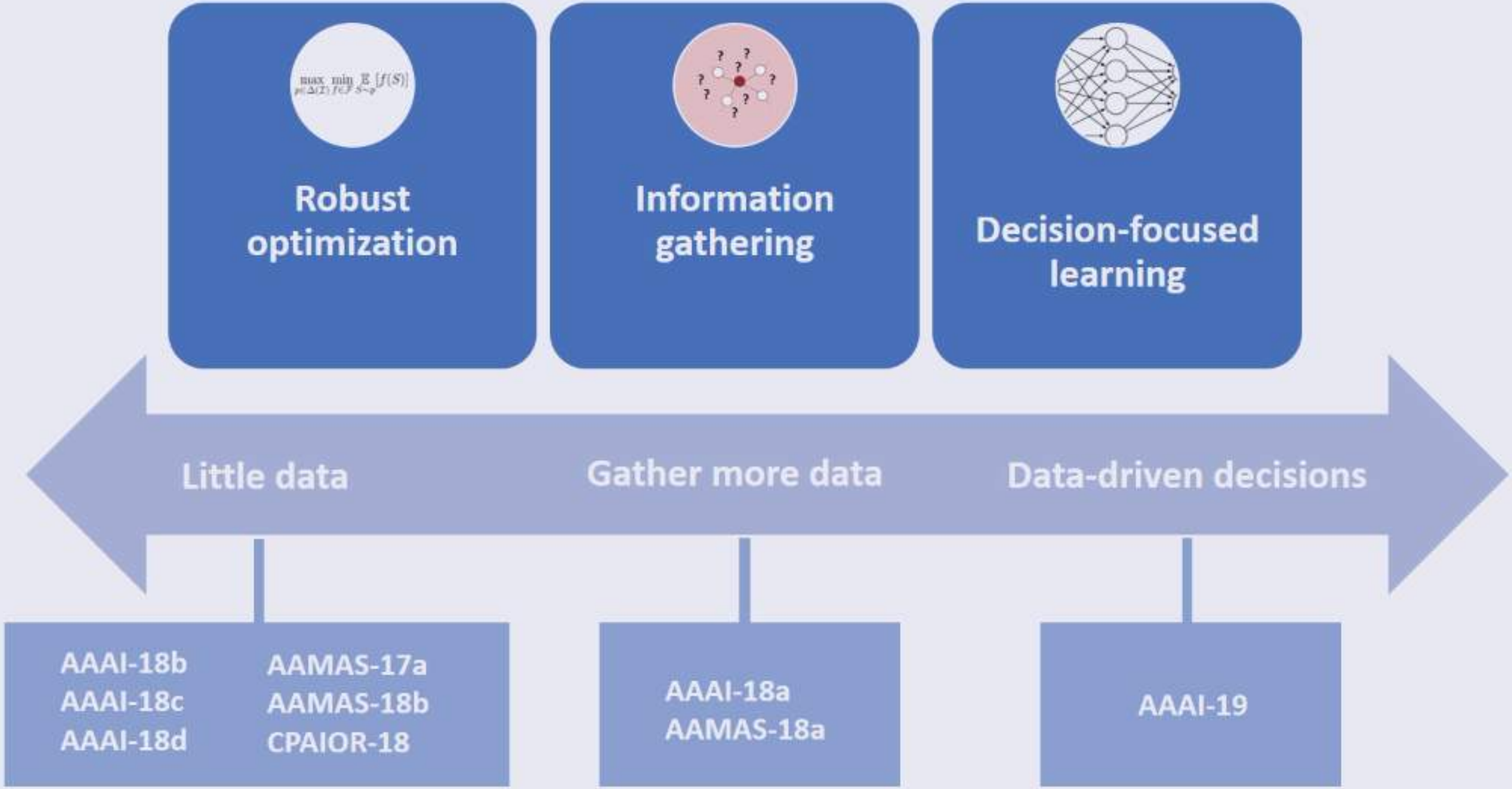
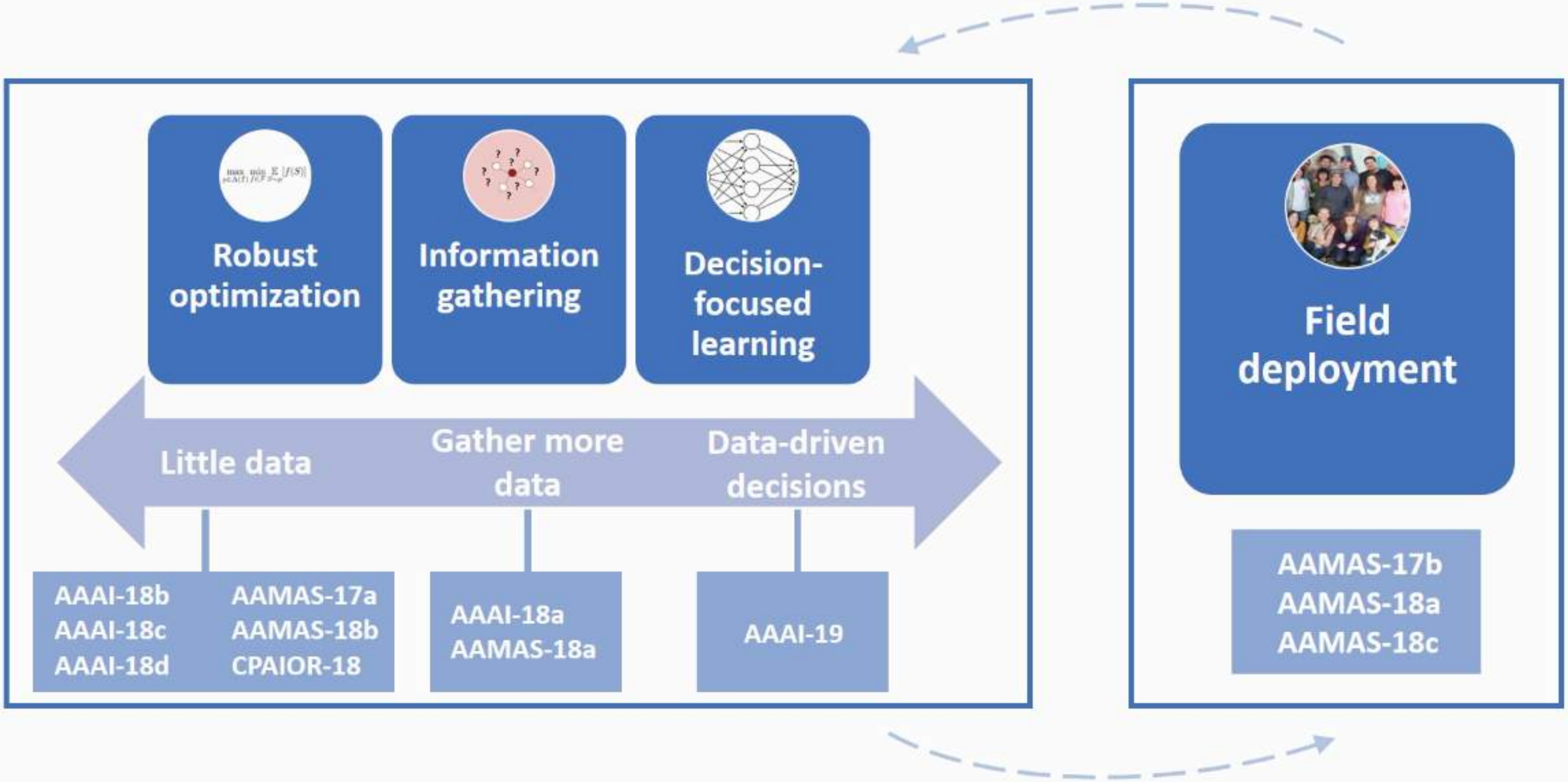
Unique Challenges:

- Unified approach to data/learning and decision making
- Closing the loop from the lab to field evaluation



Robust optimization
Information gathering
Decision-focused learning
Little data
Gather more data
Data-driven decisions
AAAI-18b
AAAI-18c
AAAI-18d
AAMAS-17a
AAMAS-18b
CPAIOR-18
AAAI-18a
AAMAS-18a
AAAI-19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Field deployment
AAMAS-17b
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Field immersion

- Start from real problem
- Work closely with domain experts
- Translate algorithms into practice

Administering survey at homeless youth drop-in center, Hollywood CA

Tuberculosis treatment and prevention, Sonapur India

Childhood obesity prevention training for home visitors, Antelope Valley CA

Outline

- Deployed application: HIV prevention
  - Have applied similar ideas to obesity prevention, public housing allocation, tuberculosis prevention, etc.
- Robust optimization: handling model uncertainty
- Information gathering: sampling to learn the network
- Field results: deployment with two LA-area drop in centers
- Recent work: decision-focused learning

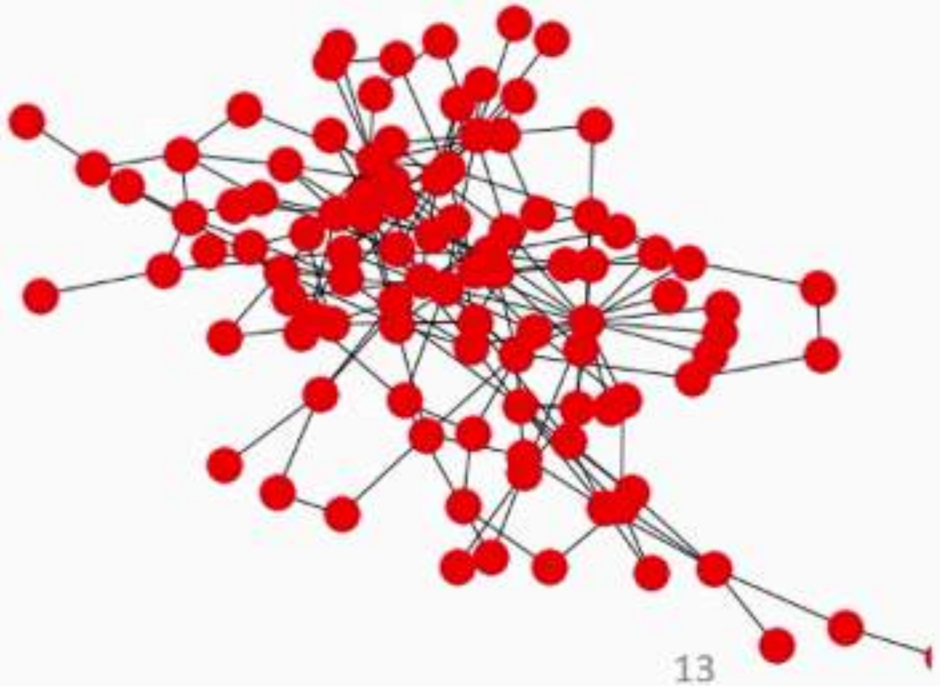
Example: HIV and homelessness

- 6,000 homeless youth
- 10x HIV prevalence vs general population

Mayor Eric Garcetti: "the moral and humanitarian crisis of our time"

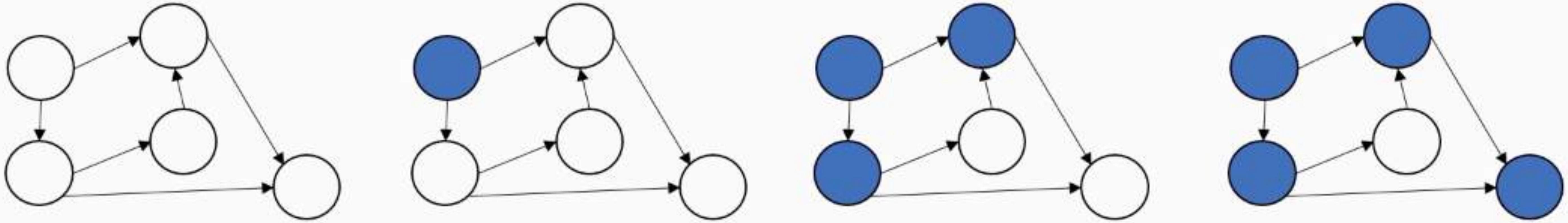
Example: HIV and homelessness

- Shelters conduct educational interventions
- Resource constraints: work with 4-6 youth at a time
- *Peer leaders*: spread message through social network



Example: HIV and homelessness

- Limited budget for total peer leaders trained
- Which nodes lead to greatest influence spread?
- Influence maximization problem



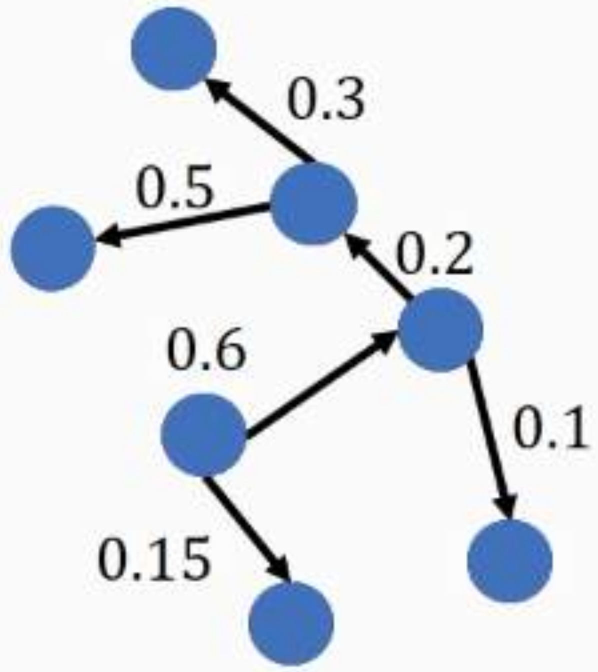
Computational problem

- Limited budget of seed nodes to recruit from a graph $G = (V, E)$
- For $S \subseteq V$, let $f(S, \theta)$ be the expected number of nodes reached when S is recruited as seeds ($\theta =$ model parameters)
- Problem:

$$\max_{|S| \leq k} f(S, \theta)$$

Independent cascade model

- Most common model in the literature
- Each edge (u, v) has a propagation probability $p_{u,v}$
- When u is influenced, v is influenced w.p. $p_{u,v}$
- $\theta = (p_{1,1}, p_{1,2}, \dots)$



Background: submodularity

Diminishing returns:

$$f(A \cup \{v\}) - f(A) \leq f(B \cup \{v\}) - f(B) \quad \forall v, \qquad B \subseteq A$$

Theorem *[Nemhauser, Wolsey, Fisher 1978]: The greedy algorithm obtains a* $\left(1 - \frac{1}{e}\right)$*-approximation for maximizing a monotone submodular function subject to cardinality constraint.*

Background: submodularity

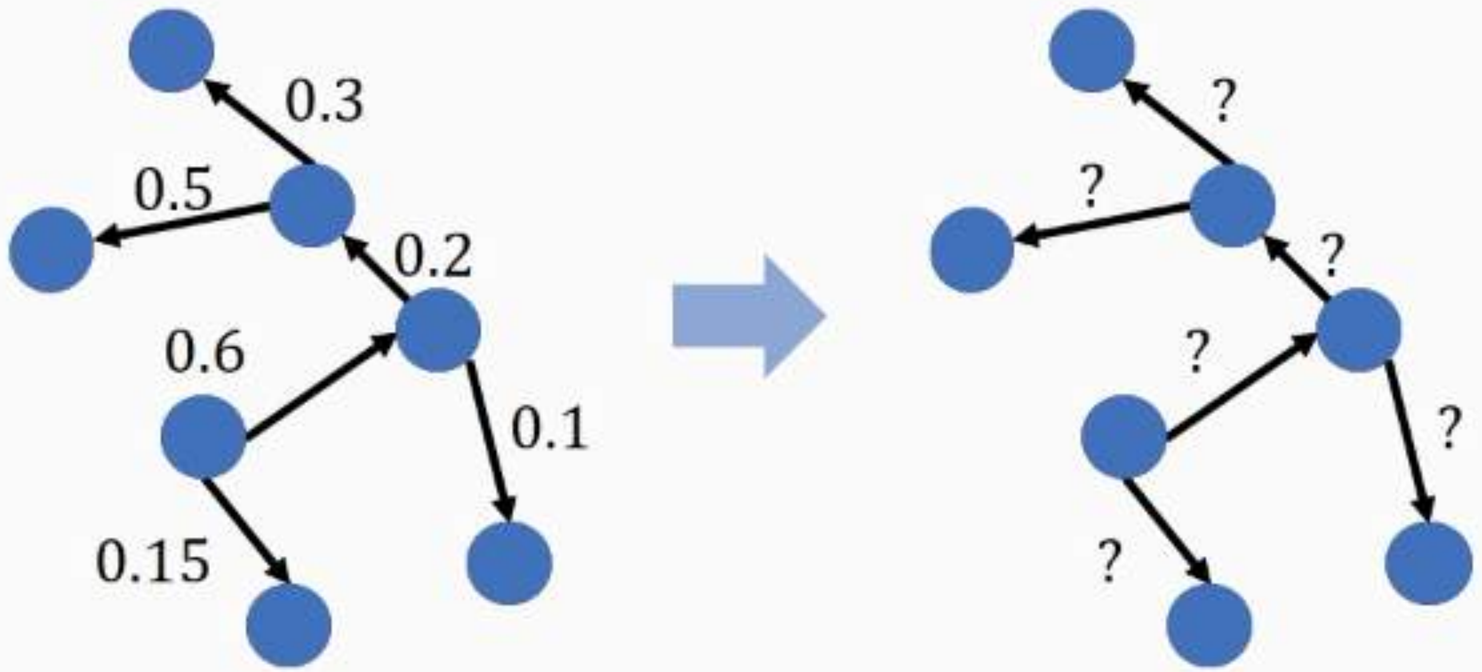
- Alternate approach: continuous relaxation F
- Fractional decision variable x
- x_i = probability include node i
- $F(x) = \mathrm{E}_{S\sim x}[f(S)]$
- Maximizing F in continuous space + rounding also gives $\left(1 - \frac{1}{e}\right)$-approximation

Influence maximization in the field

Previous work applies these techniques to influence maximization…

[Kempe et al 2003, Chen et al 2011, Tang et al 2014…]

But assumes model is known exactly!



Influence maximization in the field

- What happens when we don't know how influence propagates?
  - Little-to-no data available about homeless youth populations
- Or what the structure of the social network is?
  - Gathering network data requires in-person surveys, week+ of effort

Influence maximization in the field

- Together with social work partners, developed and deployed algorithms addressing these issues
- More than doubled the intervention's impact compared to status quo

my friend's place

S.P.Y
safe place for youth

LOS ANGELES LGBT CENTER

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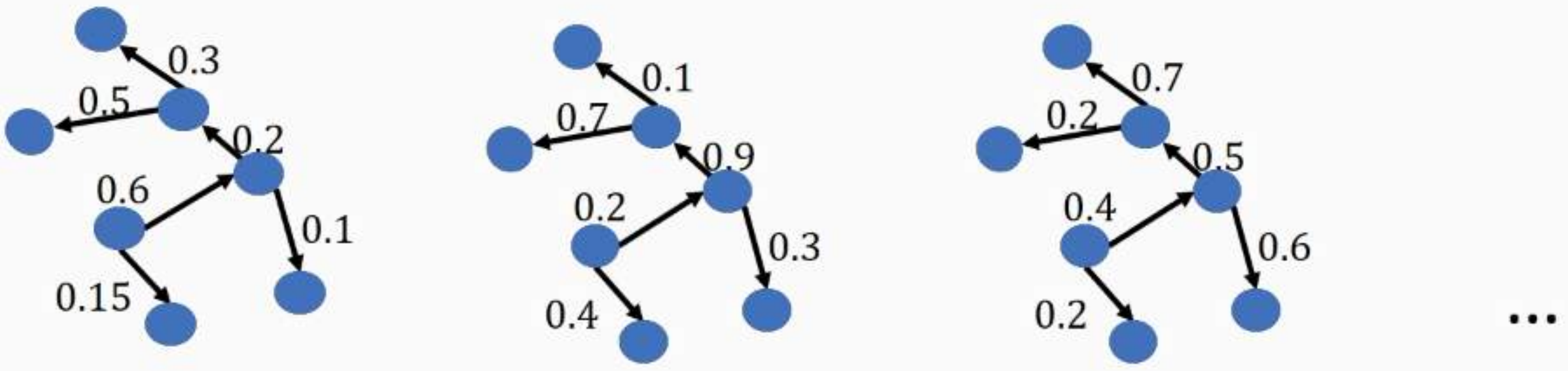
Robust optimization

- Given candidate objective functions $f_1 \ldots f_m$ induced by different models, solve

$$\max_{|S| \leq k} \min_{i=1 \ldots m} f_i(S)$$



f_1 f_2 f_3

Robust optimization

- Max-min is much more difficult than a single submodular function…
  - NP-hard to even approximate, must relax

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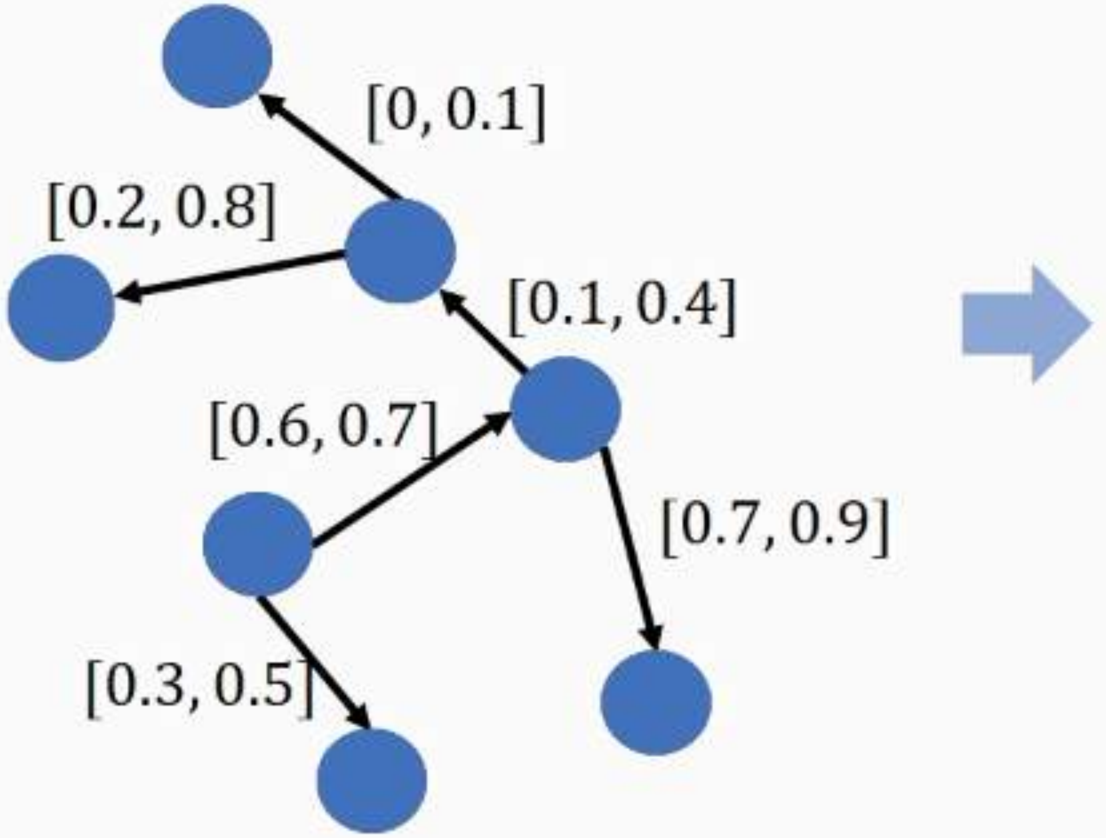
- And for influence maximization, m can be exponentially large!



$$m = 2^{|E|}$$

Robust optimization

- Max-min is much more difficult than a single submodular function…
  - NP-hard to even approximate, must relax
- And for influence maximization, m can be exponentially large!
- Existing approaches, building on greedy, are either heuristic or take exponential time *[Krause et al 2008, He and Kempe 2017]*

Robust optimization

- Main contribution: first polynomial-time approximation algorithm for robust submodular optimization with runtime **independent** of m
- Just requires "adversary oracle" (find worst case function)
- Empirically: 10-100x speedup over previous best heuristics

Approach

- Relax to zero-sum game:

$$\max_{p\text{: distribution over sets}} \min_{i=1\ldots m} \mathrm{E}_{S\sim p}[f_i(S)]$$

- Now, optimizing over *continuous* distribution

Approach

- Relax to zero-sum game:

$$\max_{p\text{: distribution over sets}} \min_{i=1\ldots m} \mathrm{E}_{S\sim p}[f_i(S)]$$

- Now, optimizing over *continuous* distribution
- Let $F_1 \ldots F_m$ be the continuous relaxation of each objective
- Strategy: maximize $G(x) = \min_{i=1\ldots m} \mathrm{F_i}(\mathrm{x})$

Approach

- Relax to zero-sum game:

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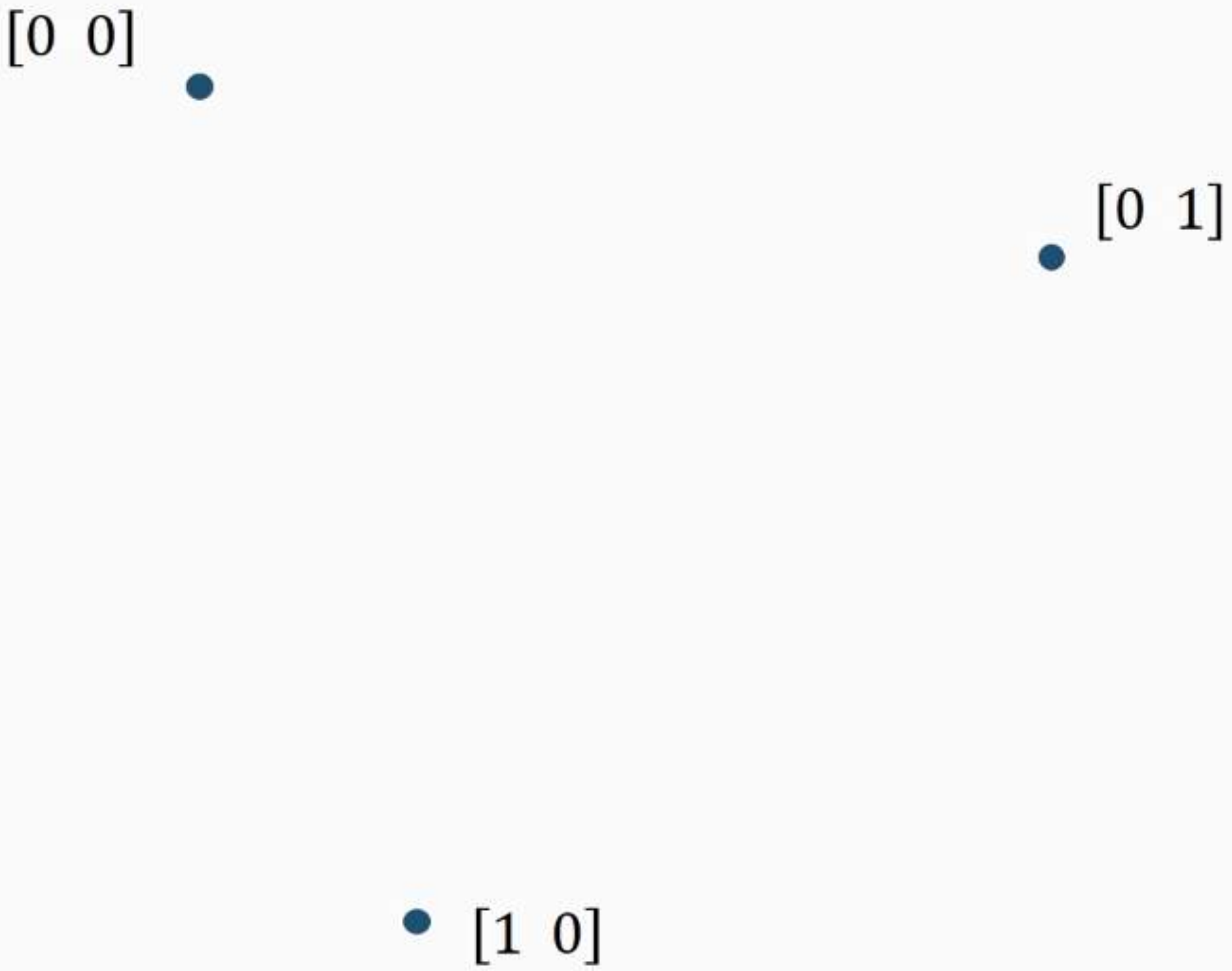
- Now, optimizing over *continuous* distribution
- Let $F_1 \ldots F_m$ be the continuous relaxation of each objective
- Strategy: maximize $G(x) = \min_{i=1\ldots m} \mathrm{F_i(x)}$
- Key technical contribution: extending continuous approaches to max-min allows exponential speedup for large m

EQUATOR Algorithm

- Apply gradient-based method to the function $G(x) = \min F_i(x)$
  - Frank-Wolfe algorithm
- Get a (super)gradient of G just by finding the minimizing F_i
  - Never need to evaluate all gradients explicitly!
- Technical issues (see paper for details):
  - Controlled random perturbations ensure smoothness of gradients
  - Use *correlation gap* to design rounding procedure

EQUATOR Algorithm



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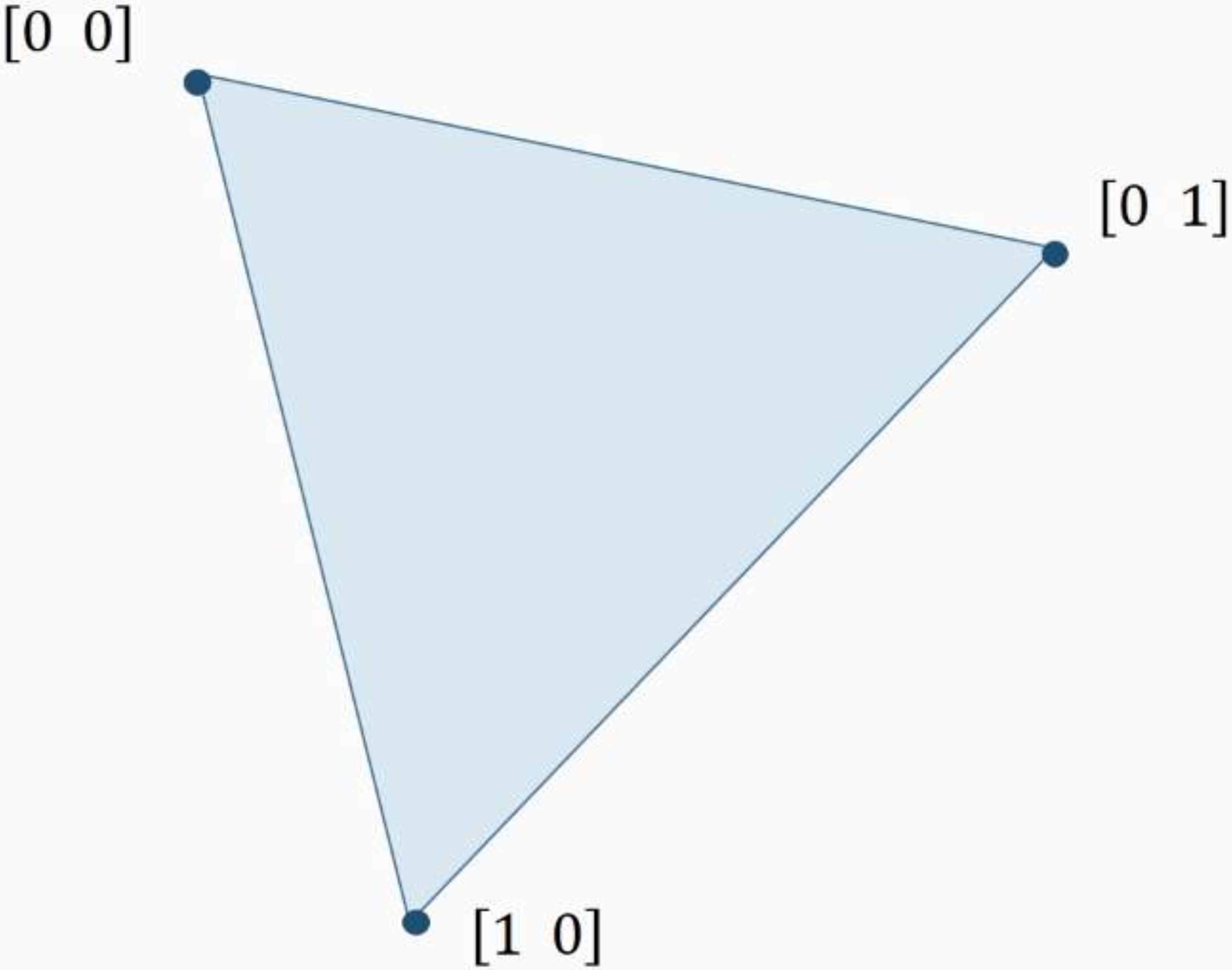

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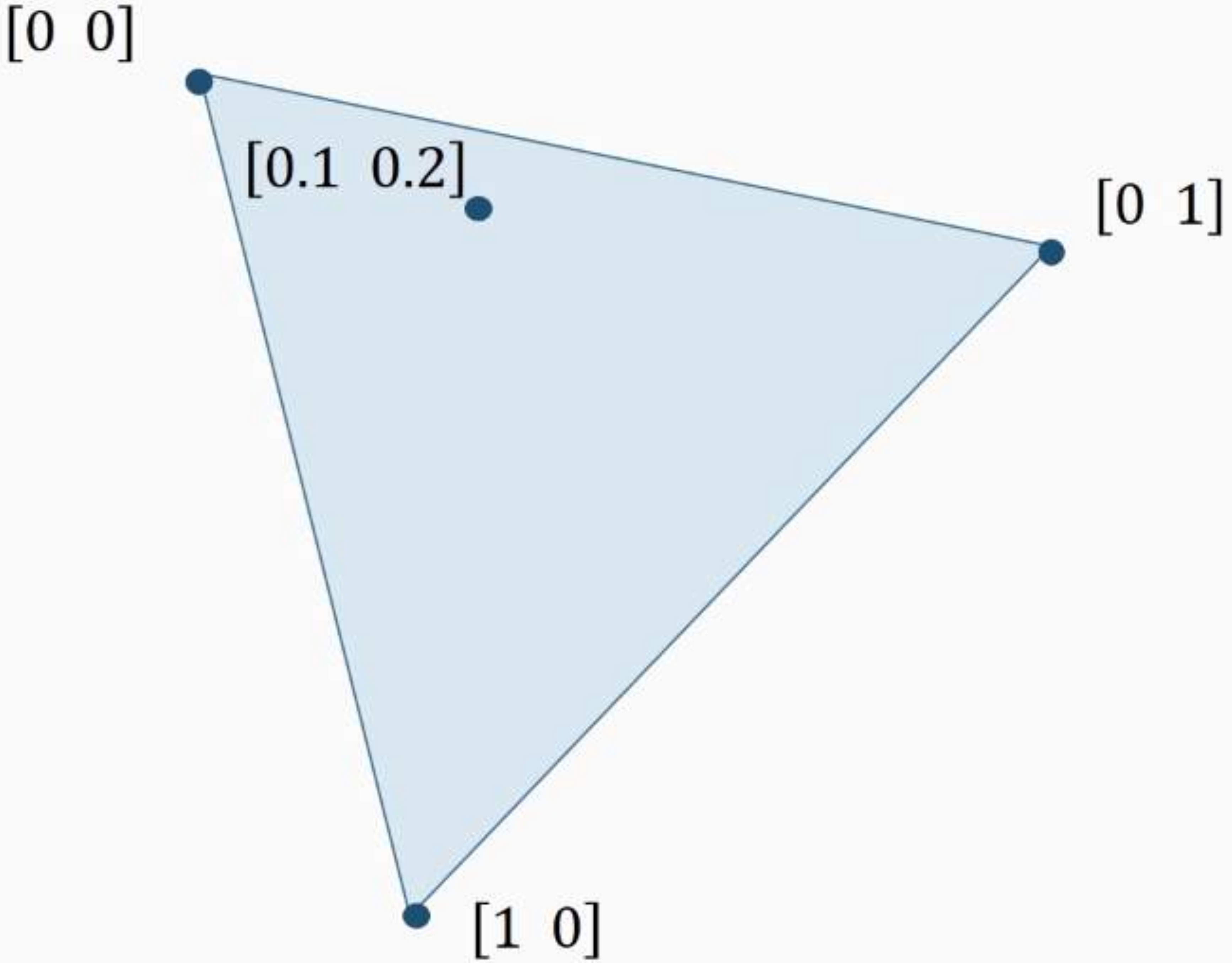

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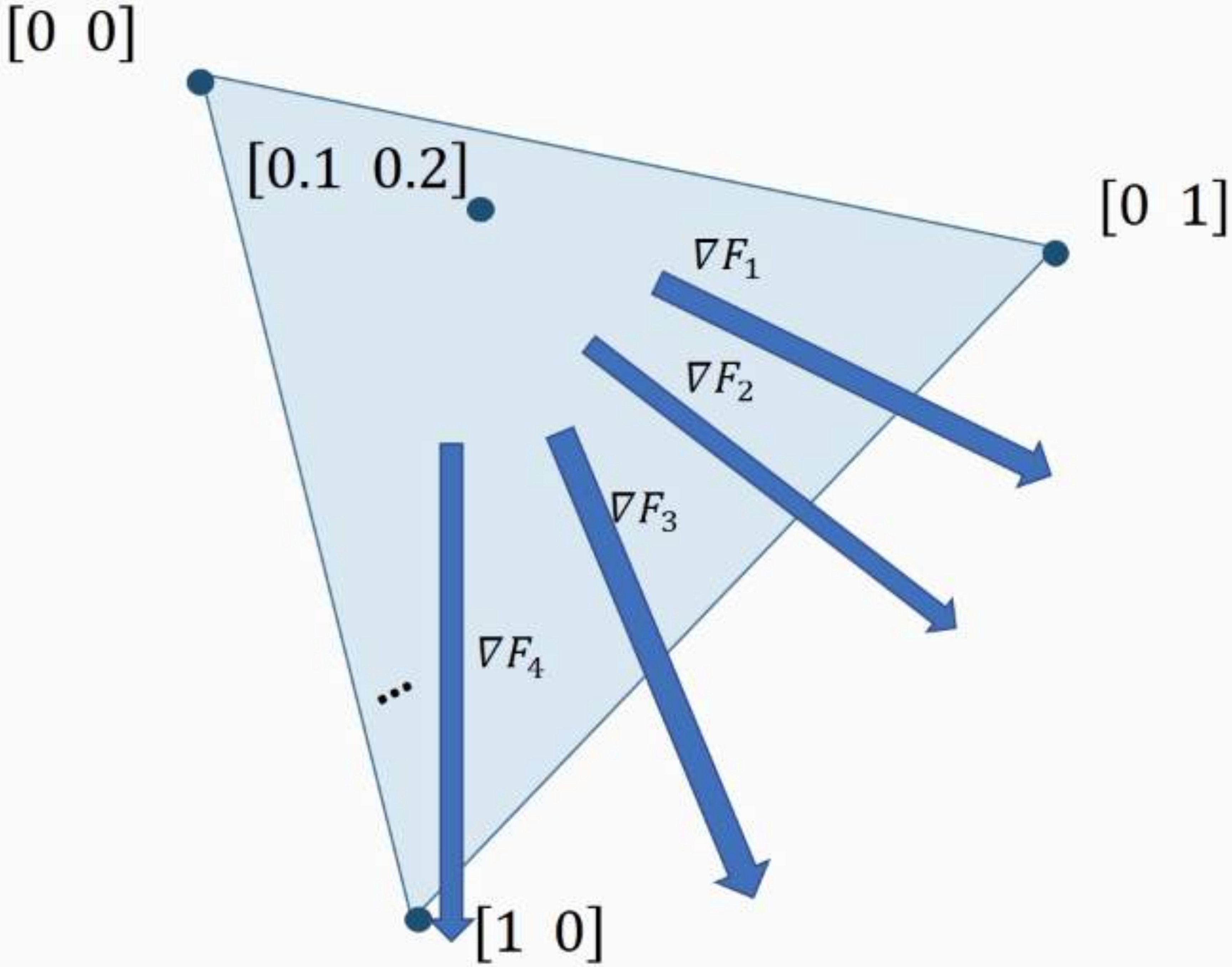

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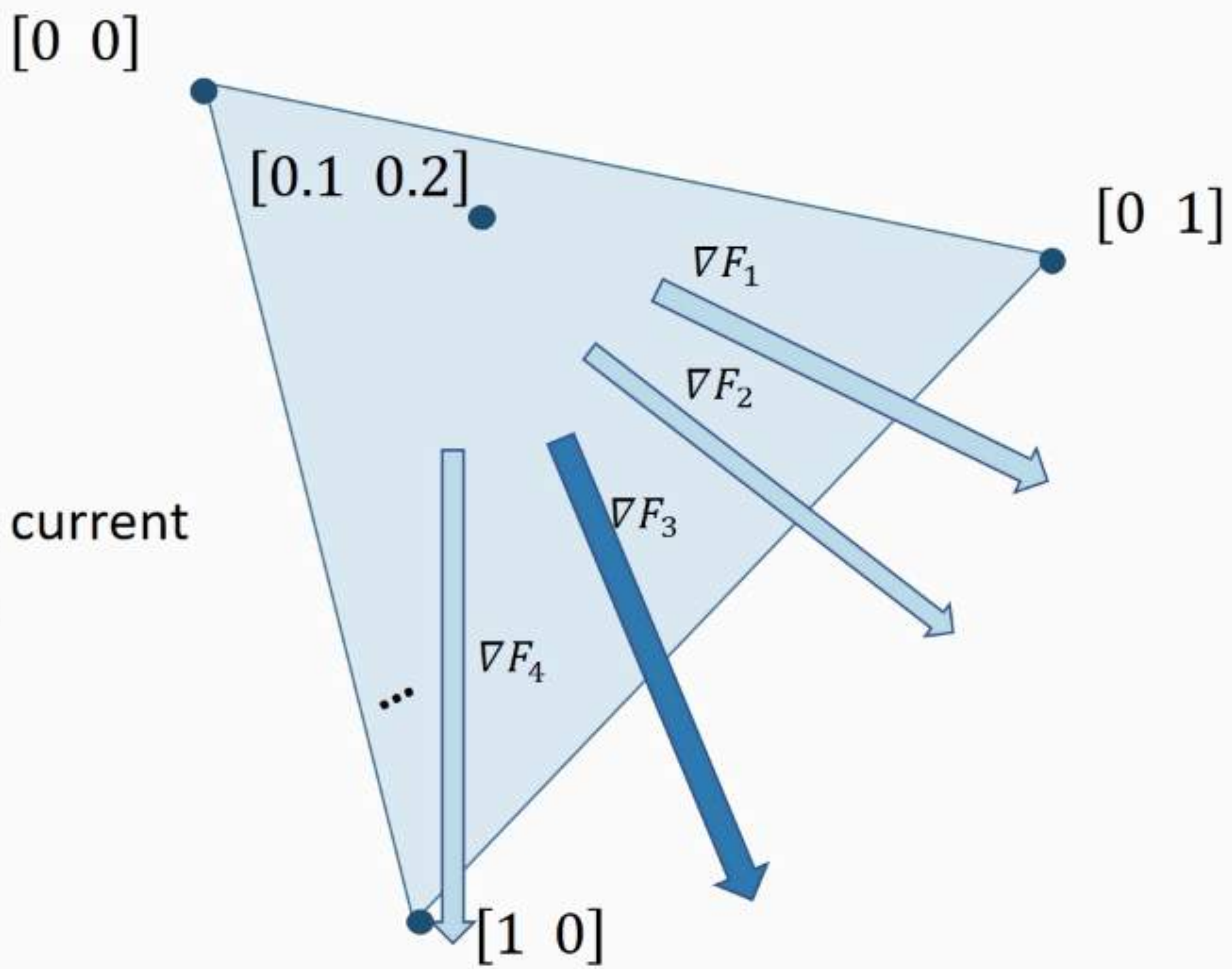
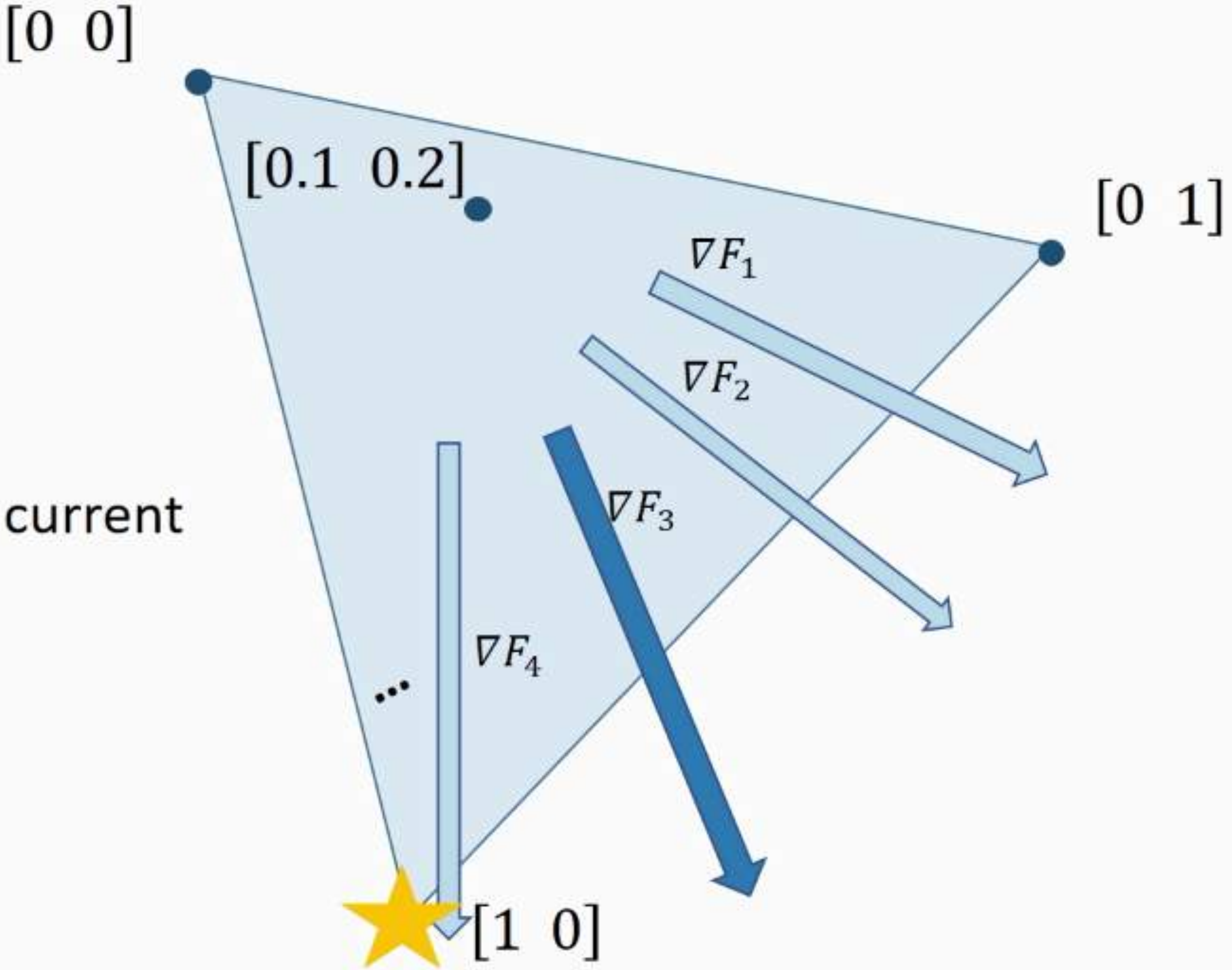


Adversary oracle: current lowest value is F_3

EQUATOR Algorithm



Adversary oracle: current lowest value is F_3

Approximation guarantee

Theorem: *EQUATOR gives a* $\left(1-\frac{1}{e}\right)$*-approximation to the optimal solution of the robust problem.*

Bryan Wilder. Equilibrium computation and robust optimization in zero sum games with submodular structure. AAAI 2018.

Robust optimization conclusion

- Nuanced models of influence spread are computationally involved
- Scalable algorithms via continuous relaxation
- For a given graph, enables planning under modeling uncertainty
- Next: how do we get that graph?

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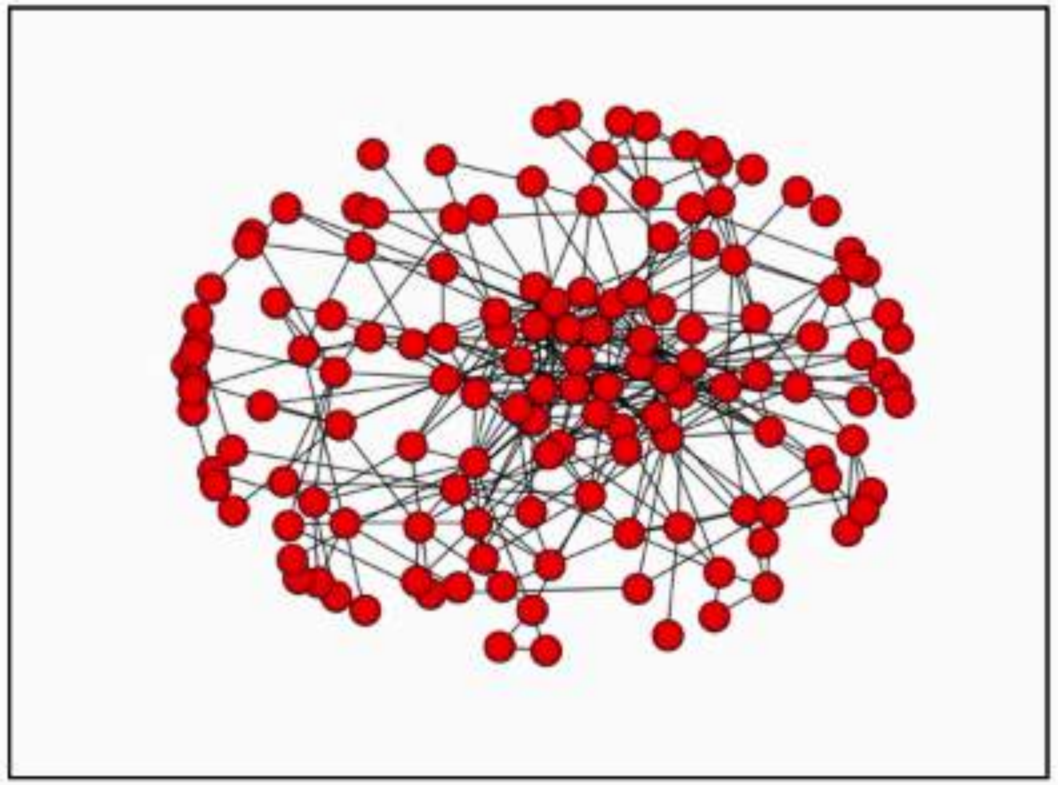
Where does the network come from?

Assumed starting point



Real starting point

?

Where does the network come from?

- Data collection is costly and time consuming
  - Digital sources are often inaccurate or missing
  - Week+ for social workers to interview 100 or more people

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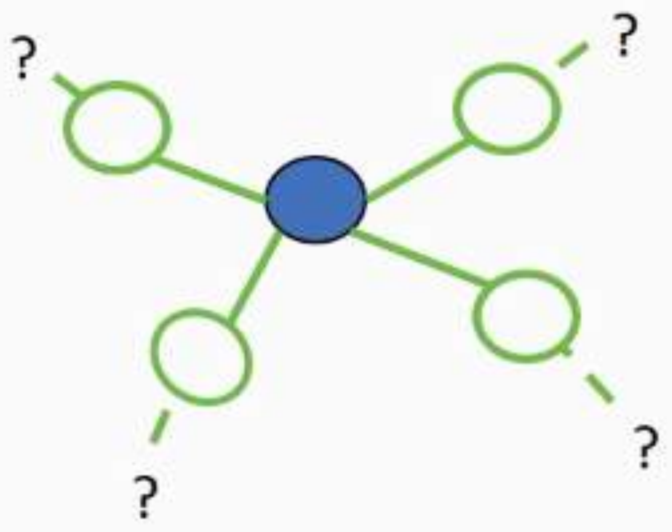
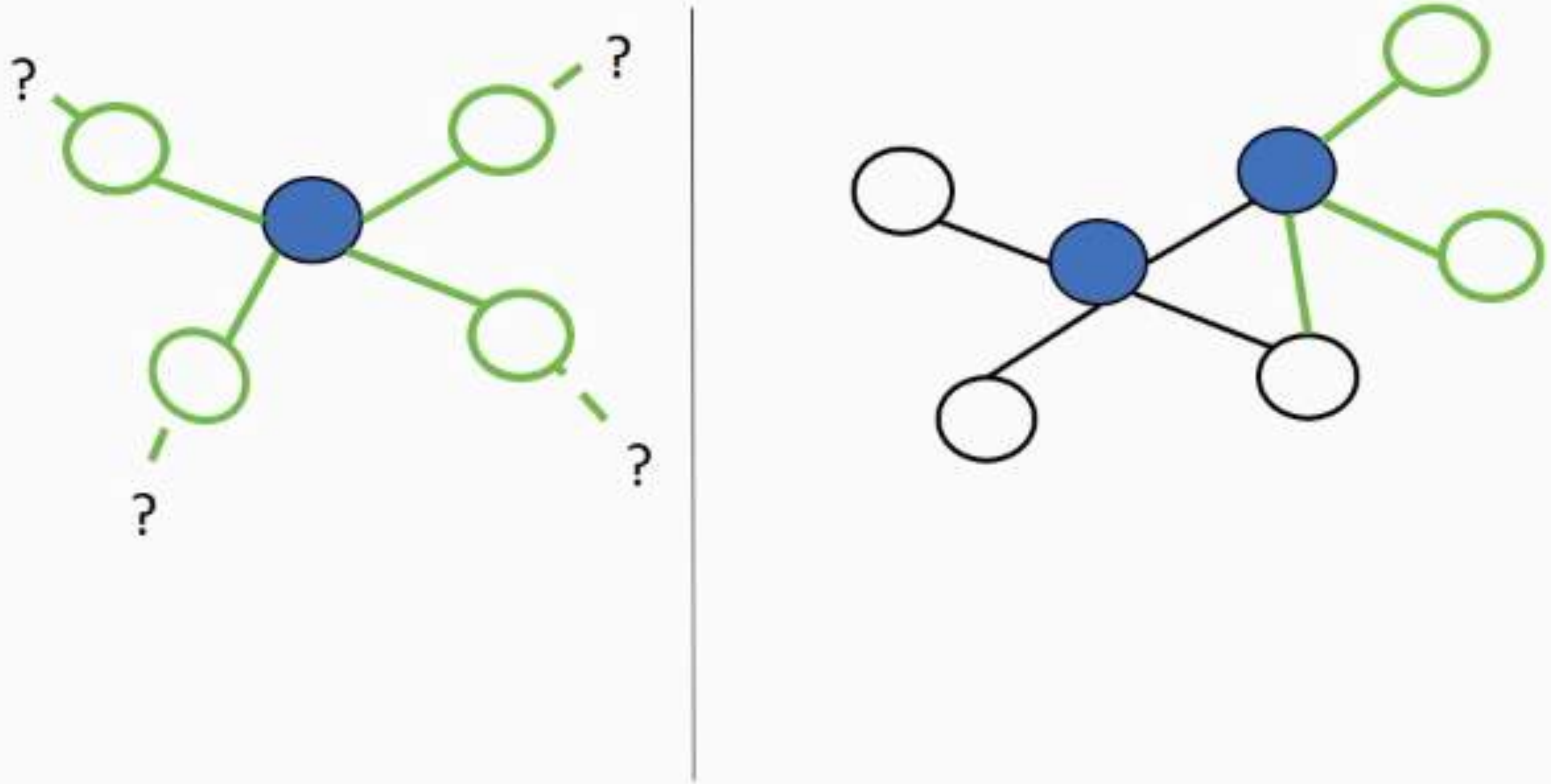
- Data collection is costly and time consuming
  - Digital sources are often inaccurate or missing
  - Week+ for social workers to interview 100 or more people
- Do we really need to gather the entire network?

Network sampling



Network sampling



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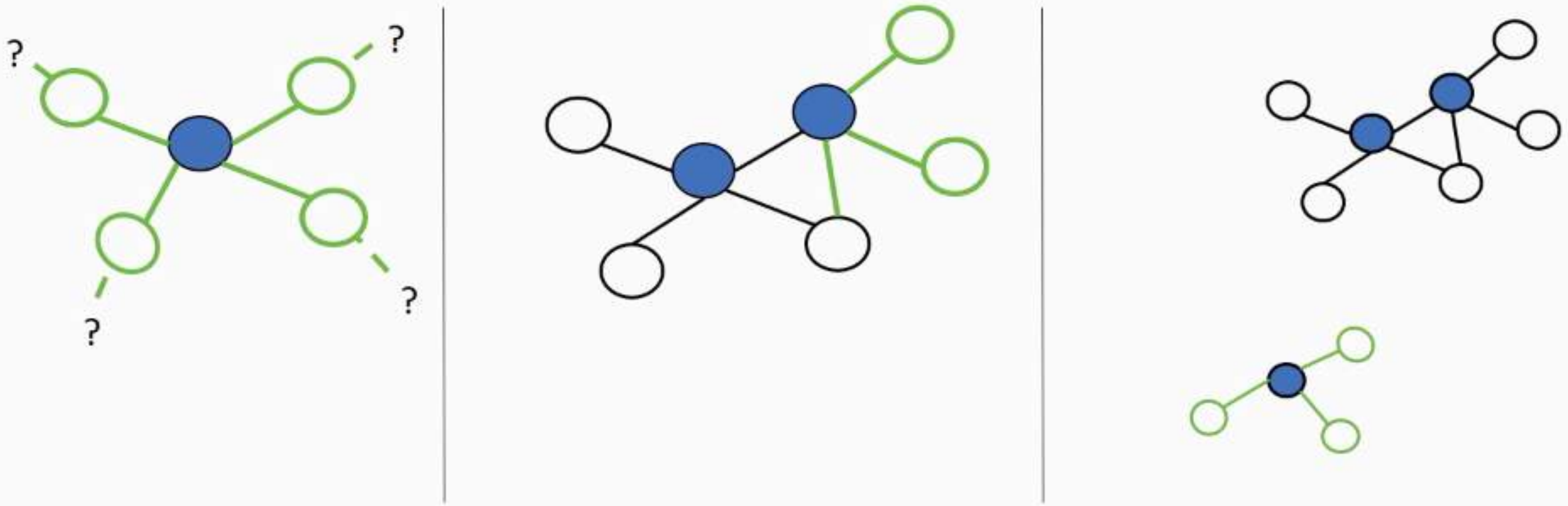

Objective

- Query cost: how many nodes were surveyed?
  - Should grow very slowly with n (# nodes)
- Influence spread: what is the expected number of nodes reached?
- Comparison to OPT, best influence spread by algorithm which sees entire network

$$\text{approx. ratio} = \frac{E[\text{algorithm's influence spread}]}{OPT}$$

Hardness

Theorem: *There is a family of graphs on which any algorithm with strictly sublinear query cost has approximation ratio tending to* 0 *as* $n \to \infty$

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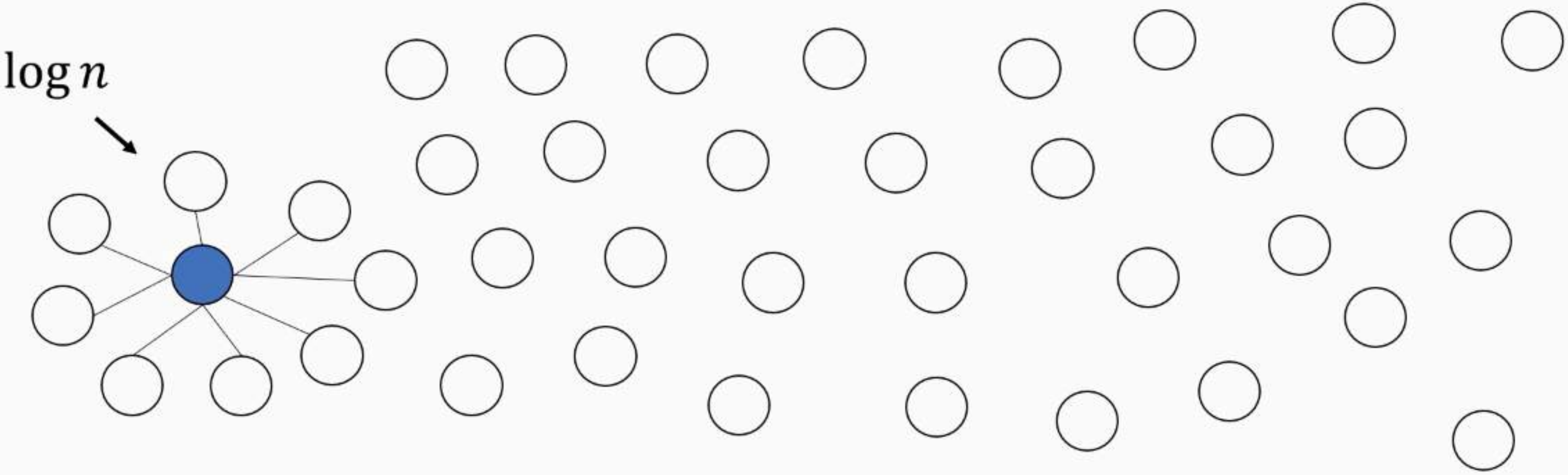
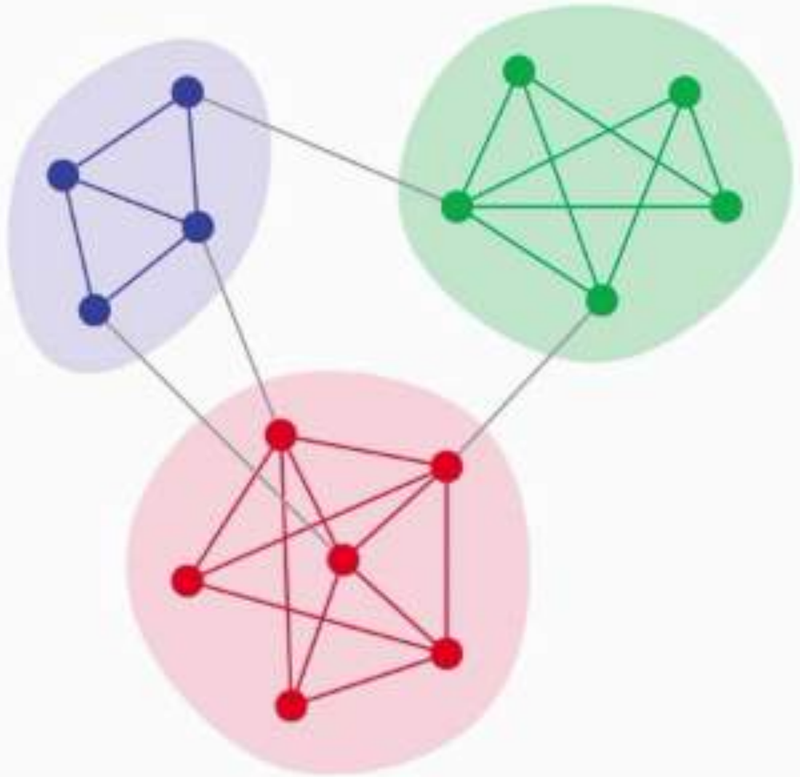


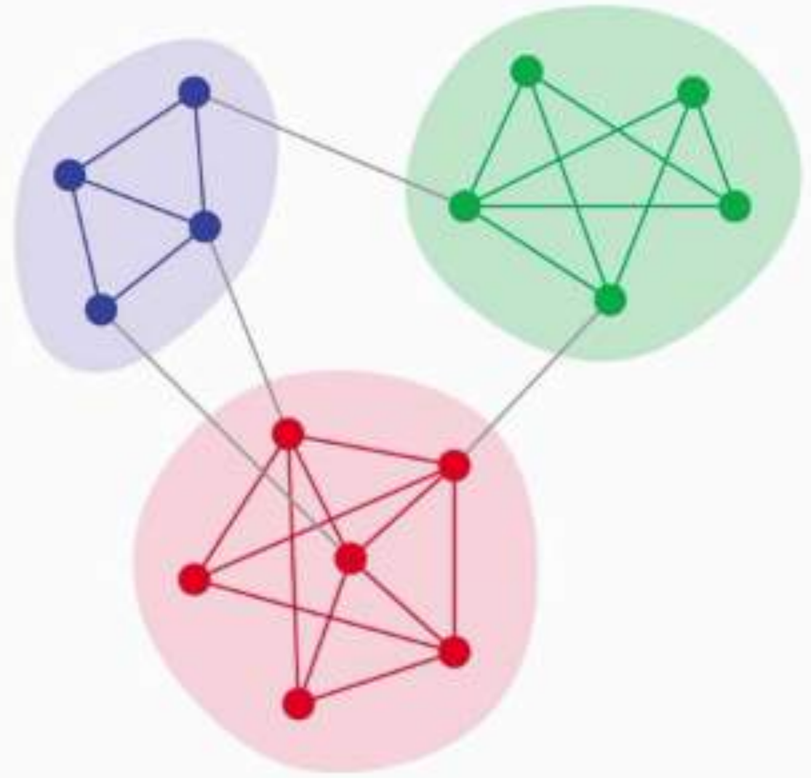
What now?

- Real networks have useful structure
- Here: two examples
  - Community structure
  - Friendship paradox



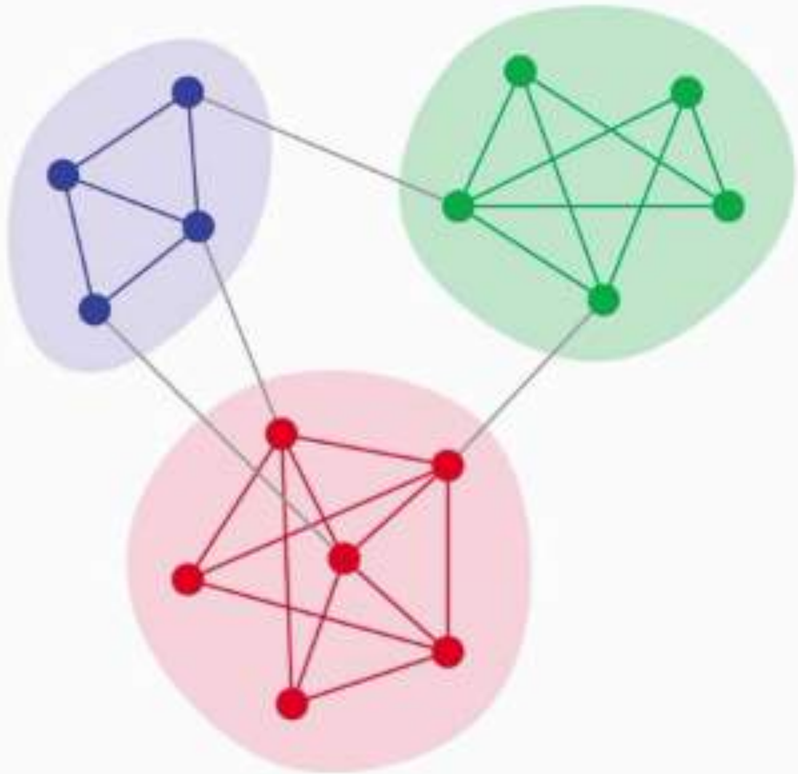
Community structure

- Intuition: influence mostly spreads locally, within communities
- We'd like to put one seed in each of the largest k communities



Community structure

- ARISEN algorithm repeatedly:
  - Randomly samples a node
  - Explores that node's neighborhood via a random walk
  - Estimates the size of that node's community
- And then seeds nodes that correspond to largest k communities



Community structure

Theorem: *For community-structured graphs, ARISEN obtains a constant-factor approximation to the optimal influence spread using polylog(n) queries.*

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Asymptotically: exponential improvement over exhaustive surveys!

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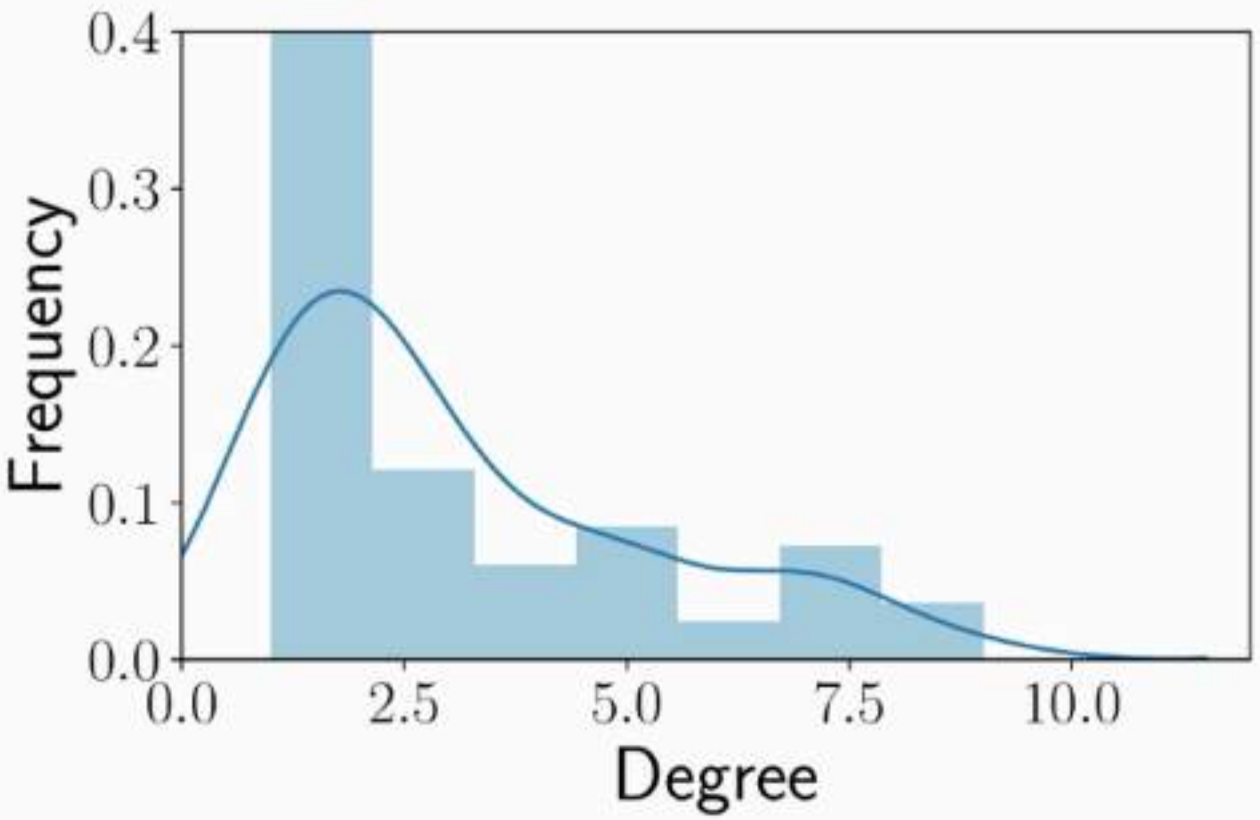
Community structure

- Downside: difficult to implement in some settings
- Homeless youth: can't find a series of 5-10 youth to simulate a random walk

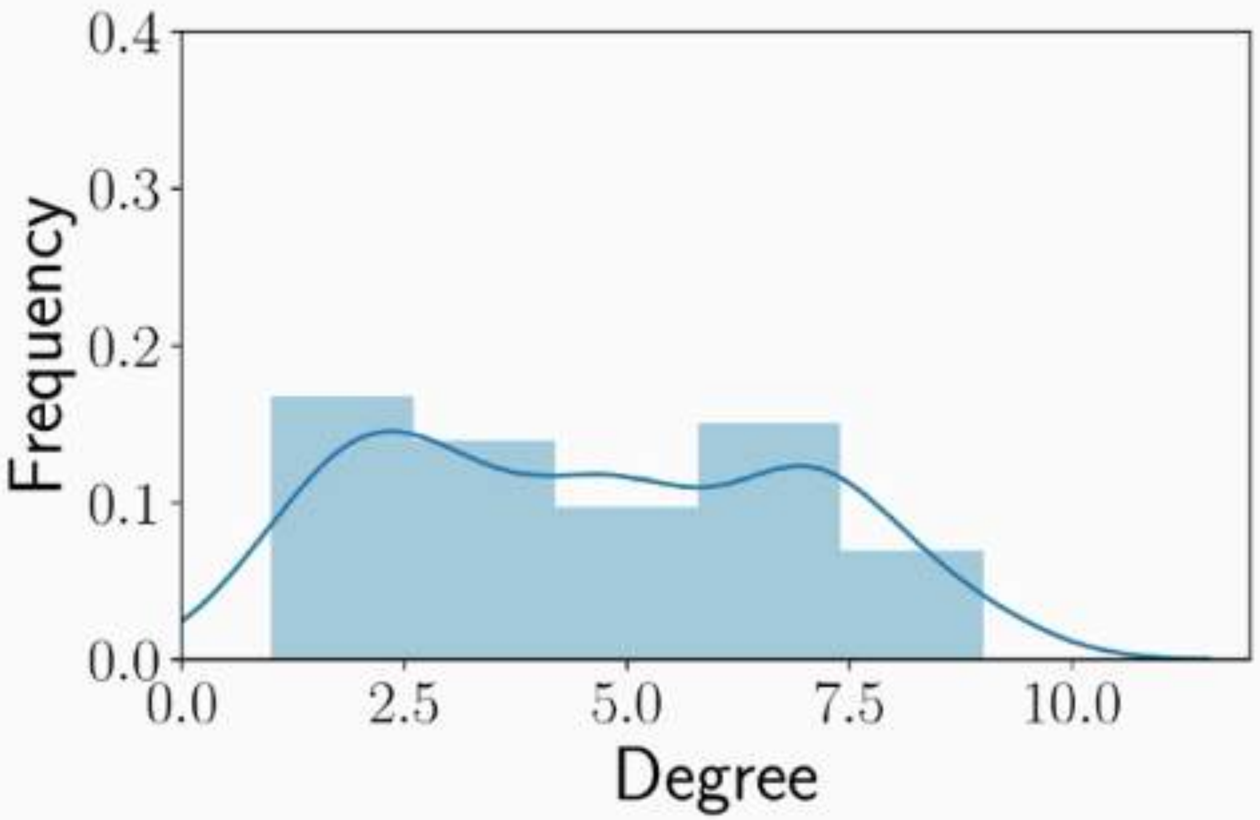
Friendship paradox

- On average, your friends are more popular than you

Degree distribution of a random **node**



Degree distribution of a random **neighbor**

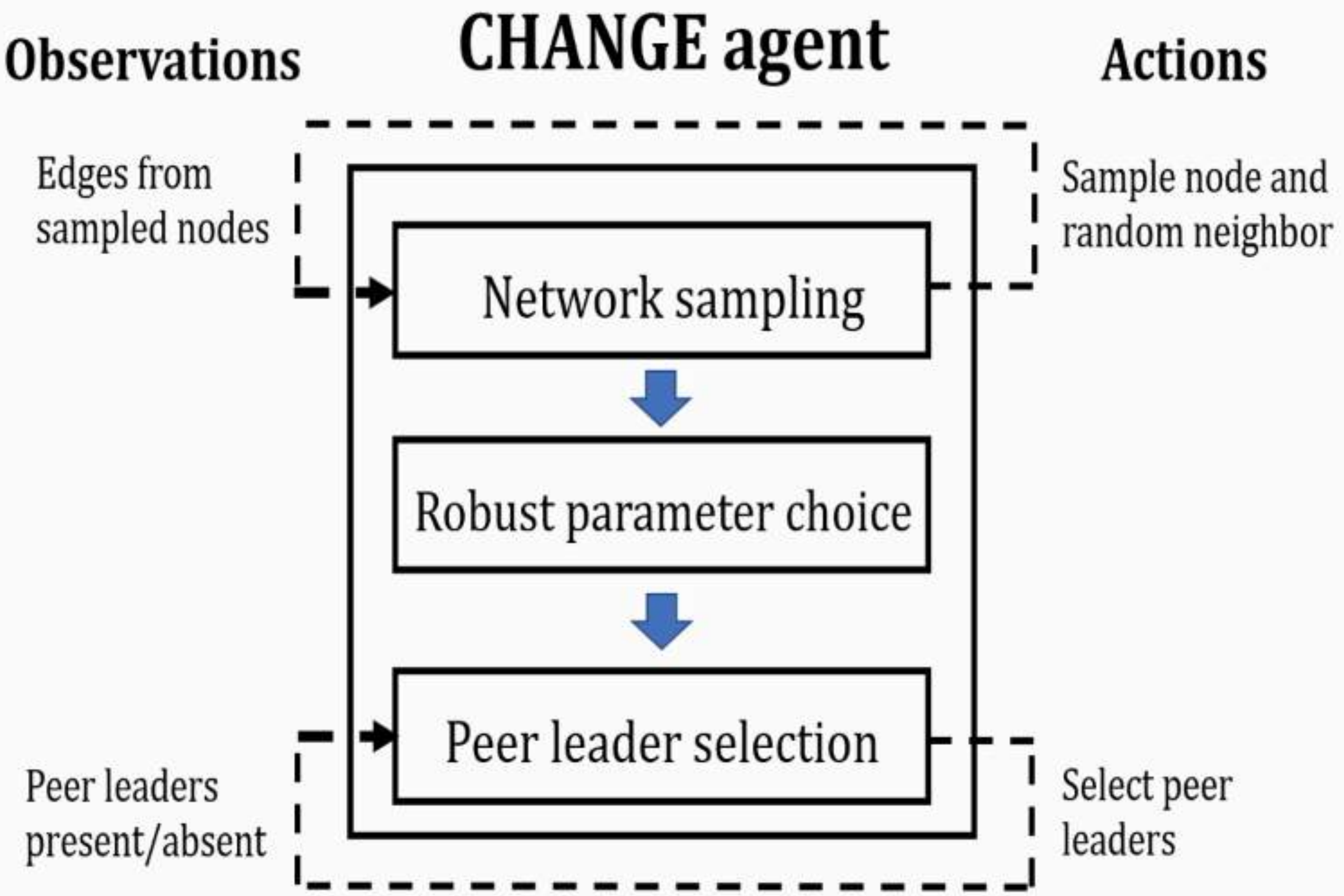


Friendship paradox

- Repeatedly
  - Survey a random node
  - Survey one of its neighbors
- First step encourages diversity, second biases towards high-degree/central nodes

Putting it all together

- Combine these ideas into a single system which works in the field
- Needs to minimize need for data, expertise, resources
- Needs to handle domain-specific challenges
    - Homeless youth: peer leaders often don’t attend intervention



Bryan Wilder, Laura Onasch-Vera, Juliana Hudson, Jose Luna, Nicole Wilson, Robin Petering, Darlene Woo, Milind Tambe, Eric Rice. End-to-End Influence Maximization in the Field. AAMAS 2018.

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Field study

Deployment in collaboration with social work and community partners

my friend's place

S.P.Y
safe place for youth

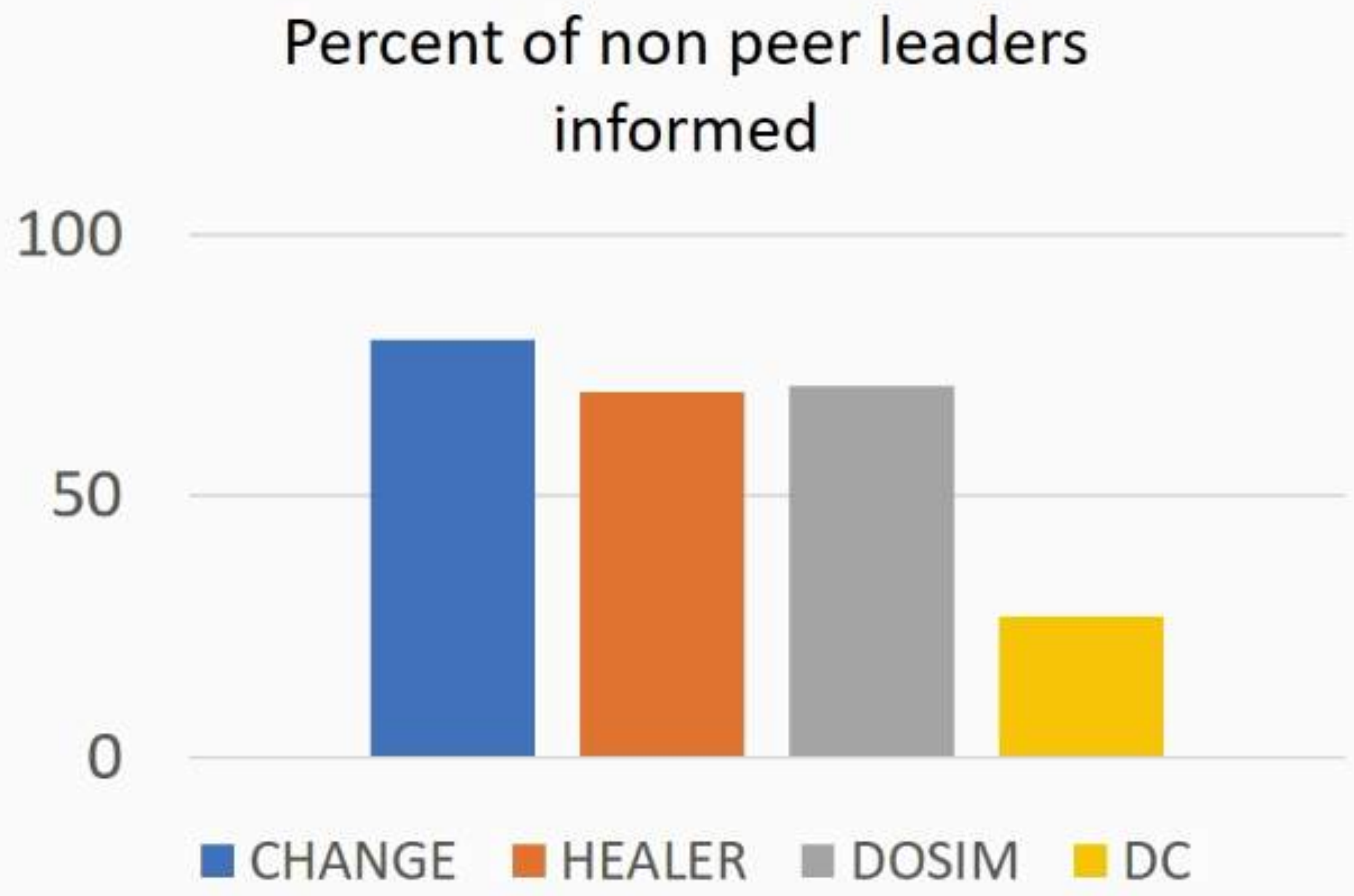
LOS ANGELES LGBT CENTER

- Recruit ~60 youth
- Survey social network
- Train 10-12 peer leaders over 3 interventions
- 1 month follow-up survey

Comparison

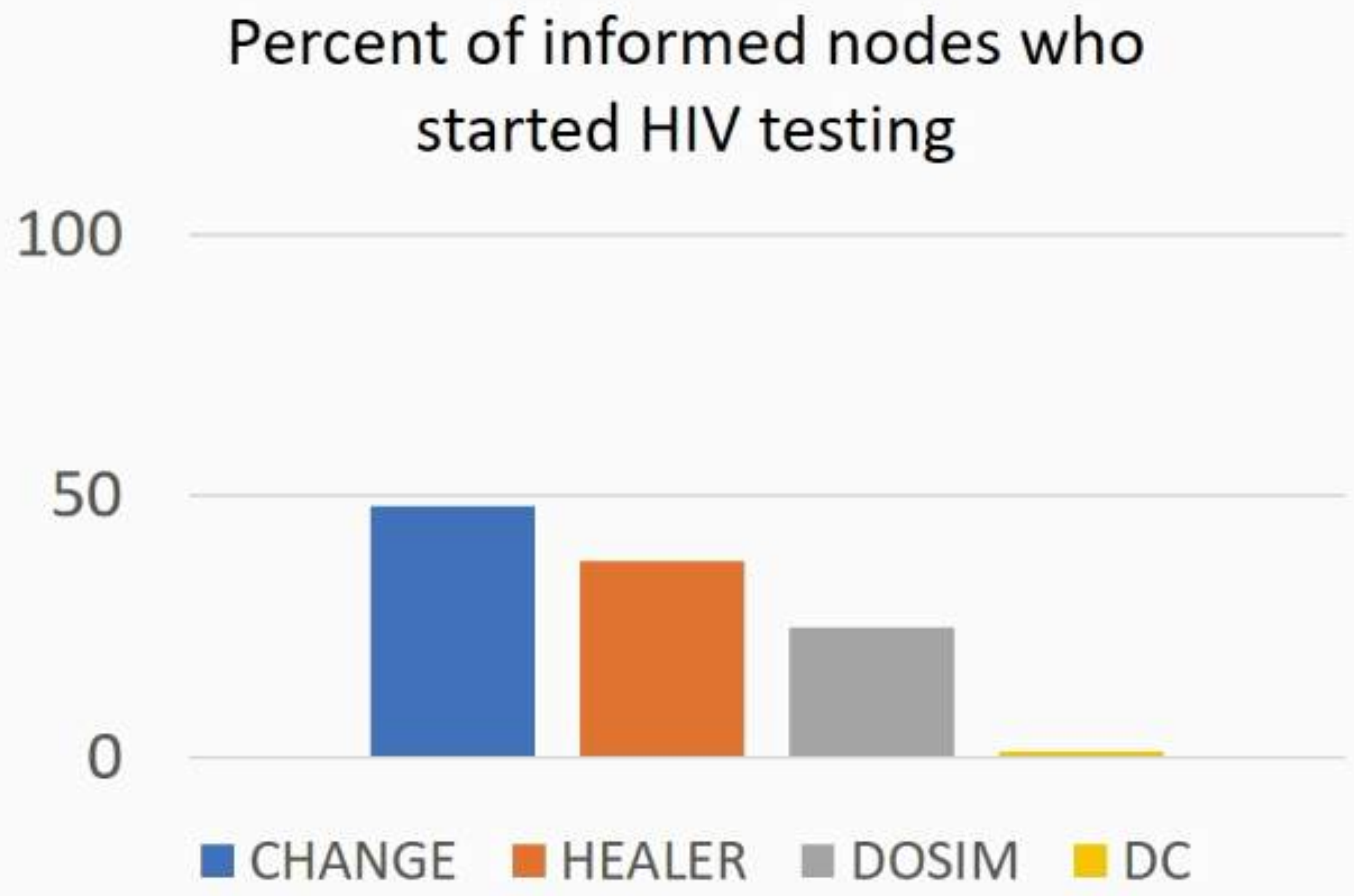
- Conducted (so far) 4 studies, each with different algorithm
- Status quo: degree centrality (DC)
- AI-based algorithms: CHANGE, HEALER, DOSIM
  - CHANGE only surveys ~20% of nodes
  - HEALER and DOSIM survey 100%

Results: information spread



- AI-based algorithms dramatically outperform status quo **(27% → 70+%)**
- CHANGE performs comparable to HEALER/DOSIM, but surveyed only **18%** of youth!

Results: behavior change



- Information spread translates into real behavior change!
- CHANGE: comparable/slightly higher conversion rate

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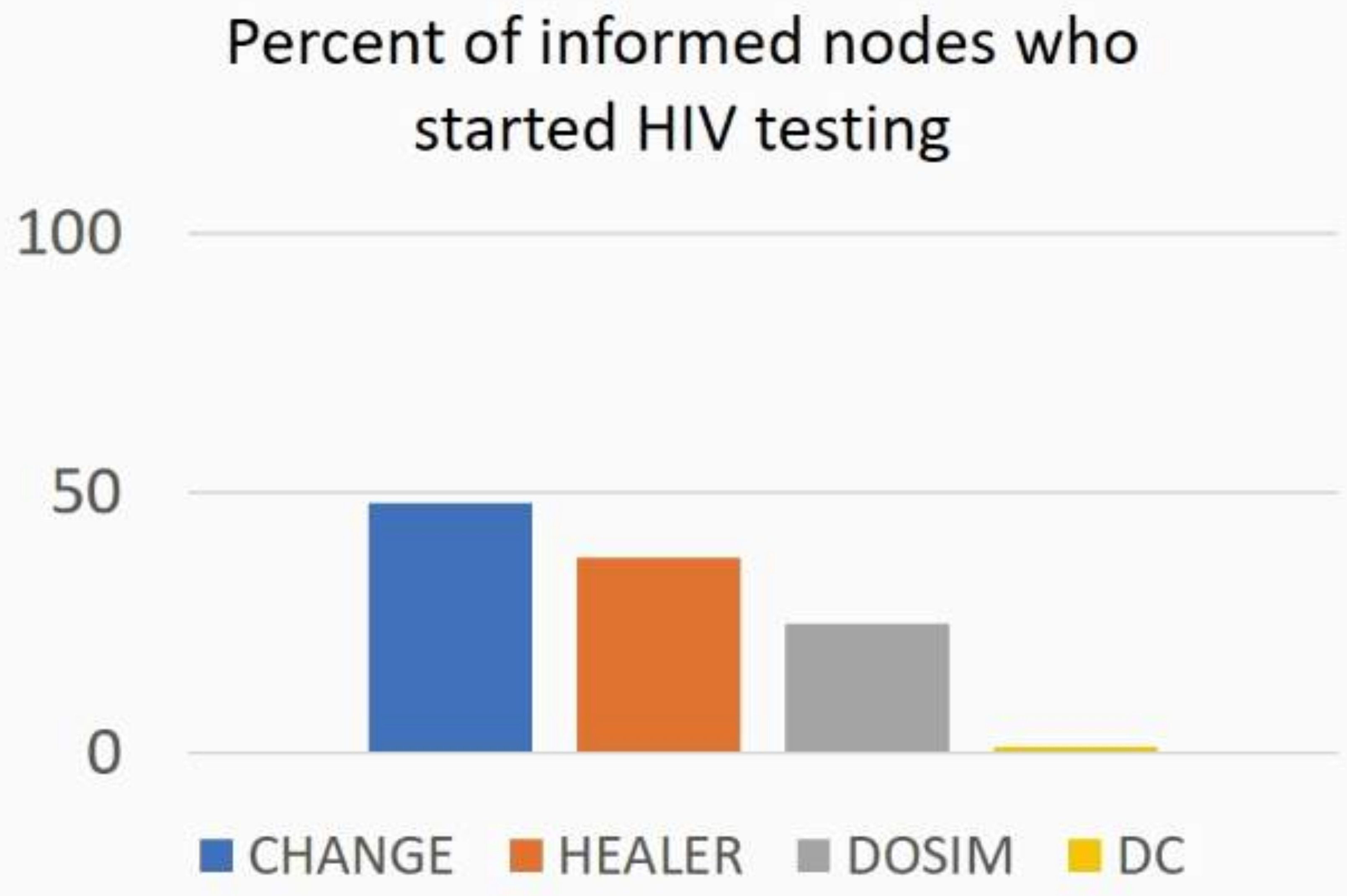

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Decision-focused learning

- Previously: coping with limited data
- Now, switch to settings where data is available
- How can machine learning support decision making?
- Example: could we use administrative data to infer the social network?
  - Program co-attendance, check-in times, etc.

Learning + optimization problem

Observe data

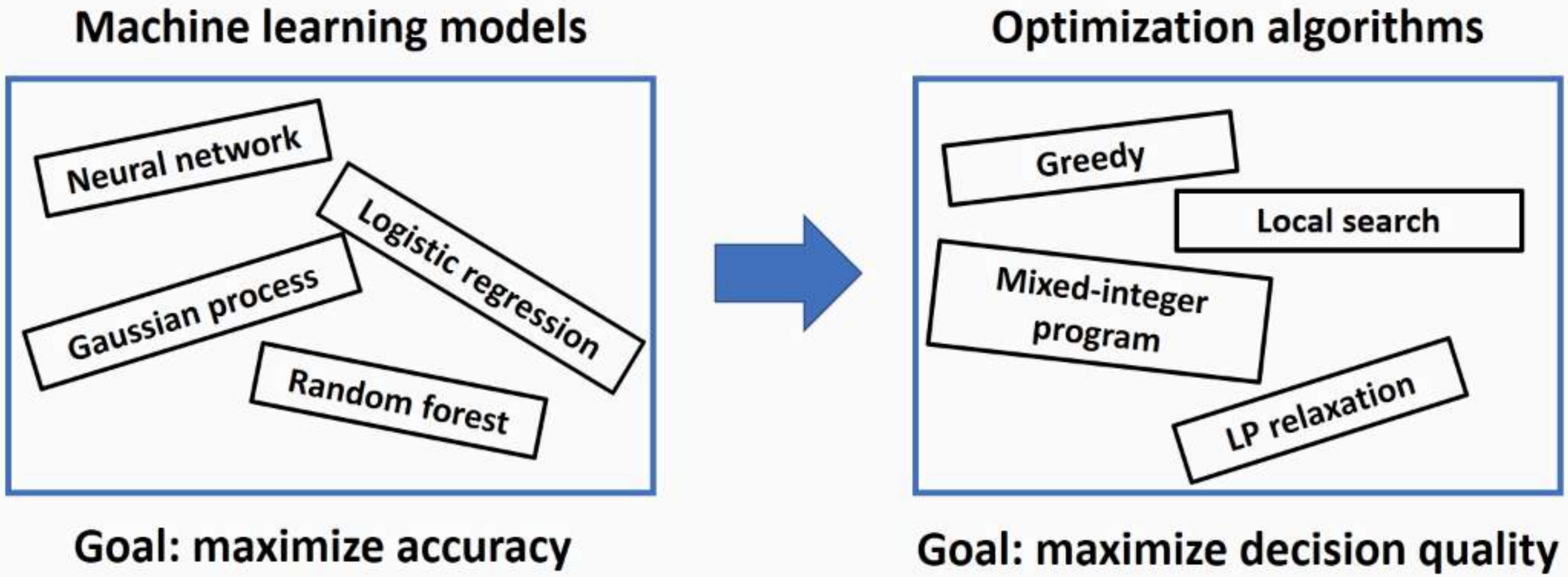
Predictive model

Infer parameter θ

Optimization algorithm

$$\max_{|S| \leq k} f(S, \theta)$$

Typical two-stage approach



Challenge

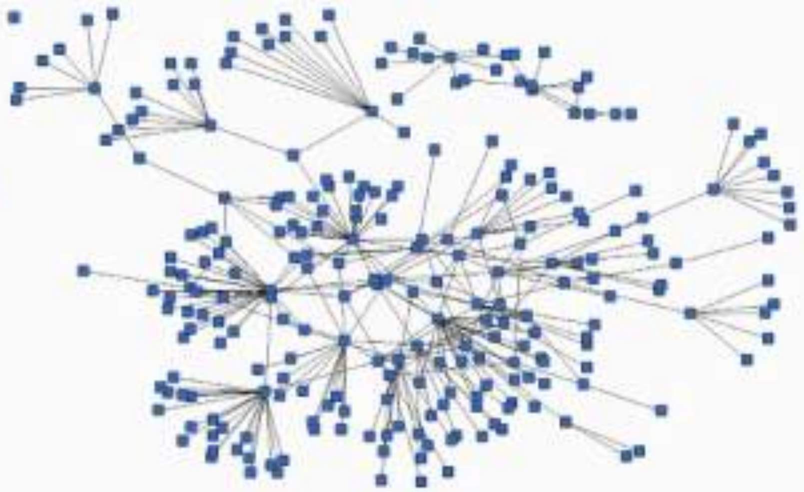
- Maximizing accuracy $\neq$ maximizing decision quality
- “All models are wrong, some are useful”
- Two-stage training doesn’t align with end goal

Two-stage training

1	0	0	0	0
0	1	0	0	0
0	0	0	0	1
0	0	0	1	0
1	0	0	0	0
0	1	0	0	0
0	1	0	0	0
0	1	0	0	0
0	0	0	0	1
1	0	0	0	0

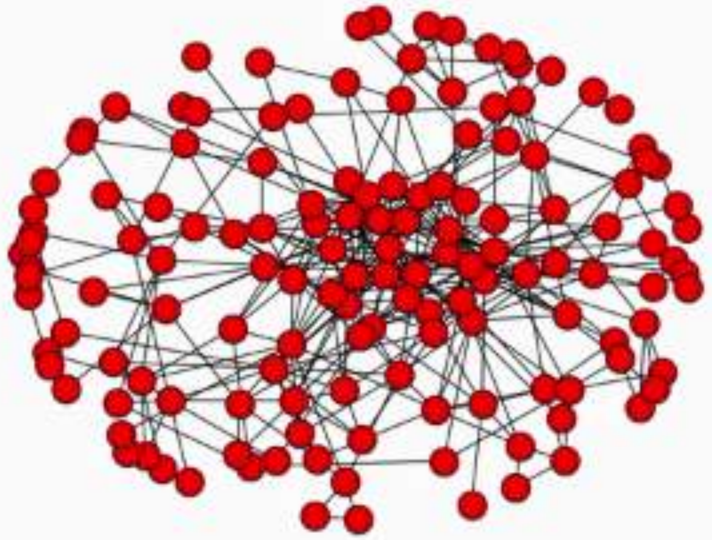
Node features

Predictive model



Predicted graph

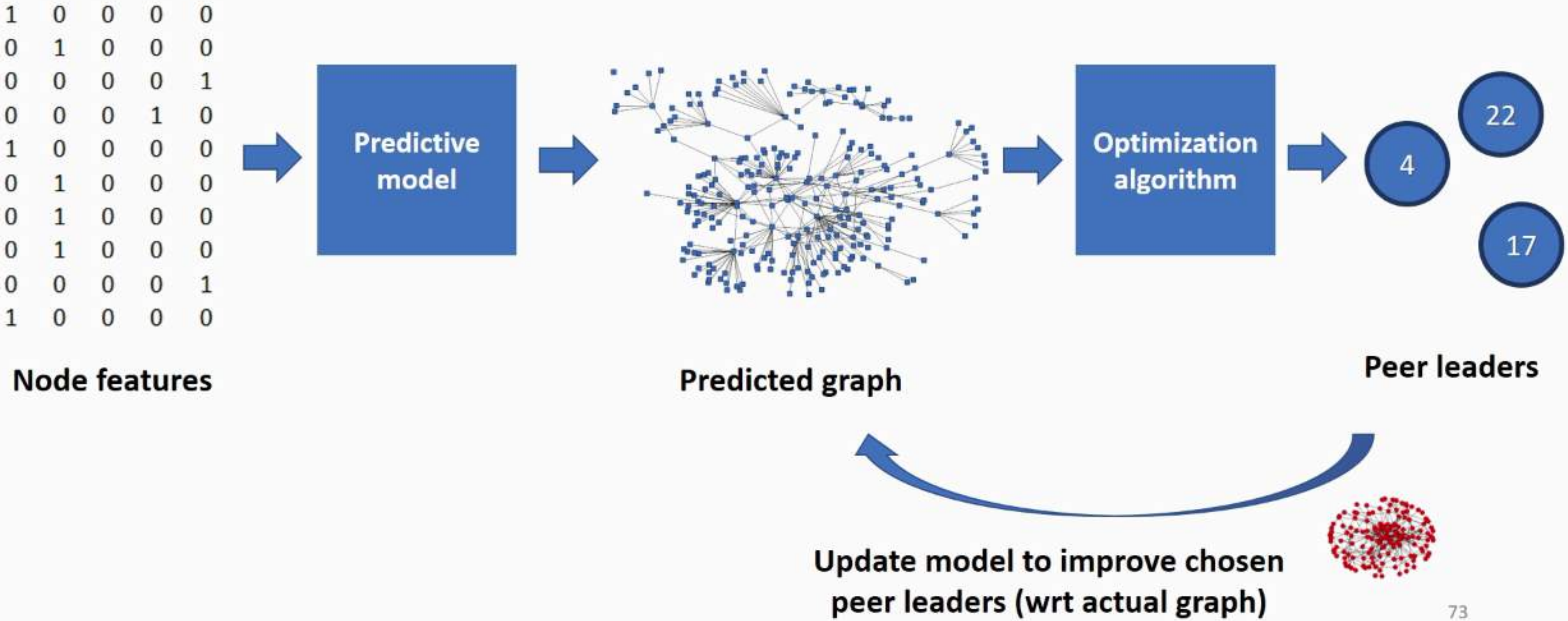
vs



Real graph

Update model to make predicted graph closer to real

Decision-focused learning



Approach

- Idea: differentiate optimal solution with respect to θ, train model via gradient descent
  - *Similar approach recently used for convex optimization [Donti et al '17]*
- Challenge: the optimization problem is discrete!

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- Challenge: the optimization problem is discrete!
- Solution: relax to continuous problem, differentiate, round

Discrete

$$\max_{|S| \leq k} f(S, \theta)$$

S = chosen set

Continuous

$$\max_{x : \sum_i x_i \leq k} F(x, \theta)$$

x_i = probability item i is chosen

Technical challenge

- How to compute $\frac{dx^*}{d\theta}$?
  - Differentiate the output of the optimization algorithm wrt predictions

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- How to compute $\frac{dx^*}{d\theta}$?
  - Differentiate the output of the optimization algorithm wrt predictions
- Idea: (locally) optimal solution must satisfy KKT conditions
- Differentiate those equations at optimum
- Provide appropriate relaxations/prove this works for:
  - Linear programming (bipartite matching, max flow, shortest path…)
  - Submodular maximization (influence maximization, facility location…)

Experiments

- On several domains, using real and synthetic data
- Compare decision-focused learning vs two-stage method
  - *Solution quality* and *accuracy*

Experiments

- On several domains, using real and synthetic data
- Compare decision-focused learning vs two-stage method
  - *Solution quality* and *accuracy*
- Decision-focused learning improves optimization by **15-70%,** but makes much less "accurate" predictions

	Budget allocation			Matching	Diverse recommendation		
$k =$	5	10	20	–	5	10	20
NN1-Decision	**49.18 ± 0.24**	**72.62 ± 0.33**	**98.95 ± 0.46**	0.20 ± 0.25	**15.81 ± 0.50**	**29.81 ± 0.85**	**52.43 ± 1.23**
NN2-Decision	44.35 ± 0.56	67.64 ± 0.62	93.59 ± 0.77	**6.15 ± 0.38**	13.34 ± 0.77	26.32 ± 1.38	47.79 ± 1.96
NN1-2Stage	32.13 ± 2.47	45.63 ± 3.76	61.88 ± 4.10	0.15 ± 0.20	4.08 ± 0.16	8.42 ± 0.29	19.16 ± 0.57
NN2-2Stage	9.69 ± 0.05	18.93 ± 0.10	36.16 ± 0.18	3.49 ± 0.32	11.63 ± 0.43	22.79 ± 0.66	42.37 ± 1.02
RF-2Stage	**48.81 ± 0.32**	**72.40 ± 0.43**	**98.82 ± 0.63**	3.66 ± 0.26	7.71 ± 0.18	15.73 ± 0.34	31.25 ± 0.64
Random	9.69 ± 0.04	18.92 ± 0.09	36.13 ± 0.14	0.13 ± 0.19	8.19 ± 0.19	16.15 ± 0.35	31.68 ± 0.71

Example

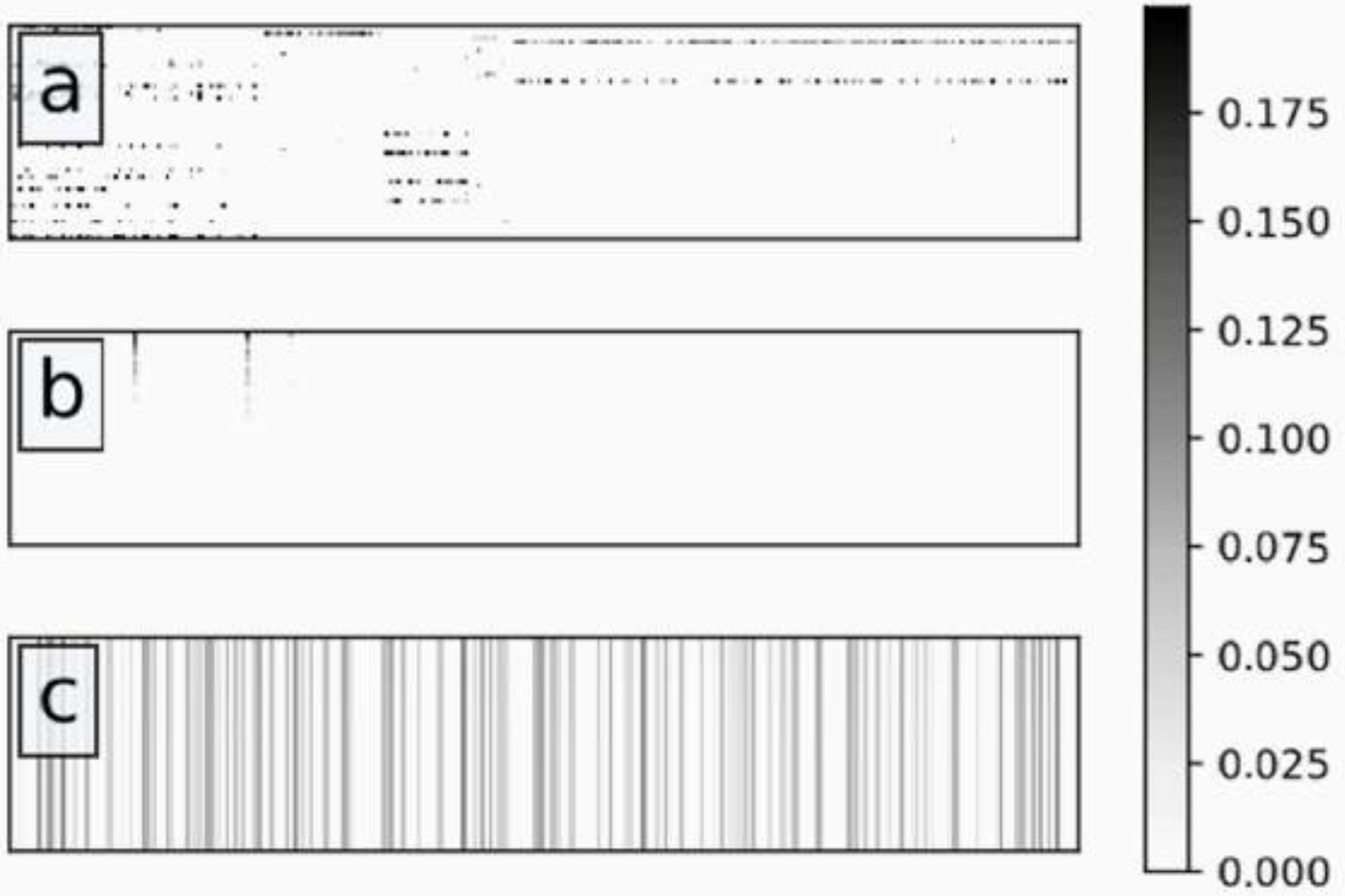
- Simulated network intervention task
- Variable to predict: probability each of a set of outreach channels will reach each network node

Example

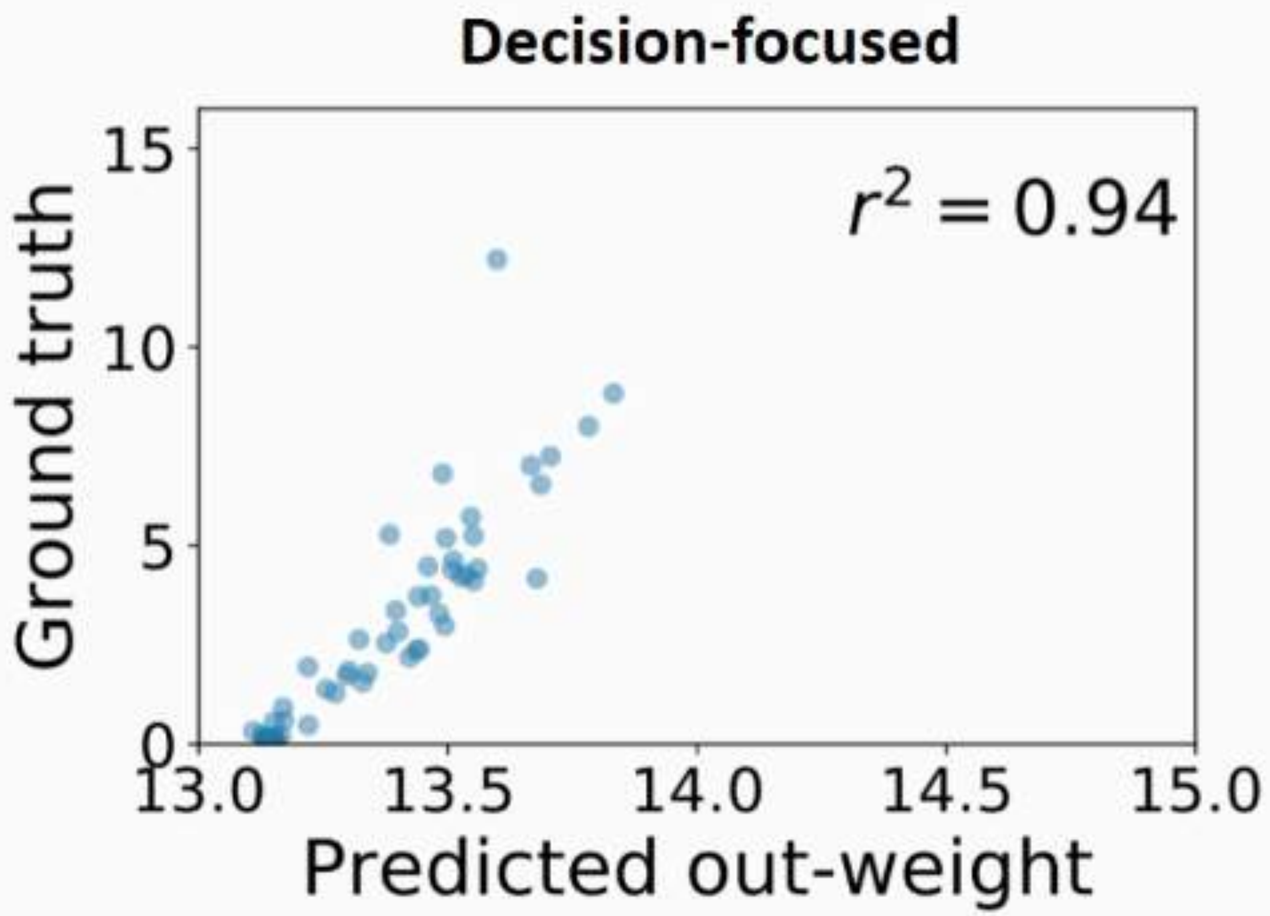
Ground truth

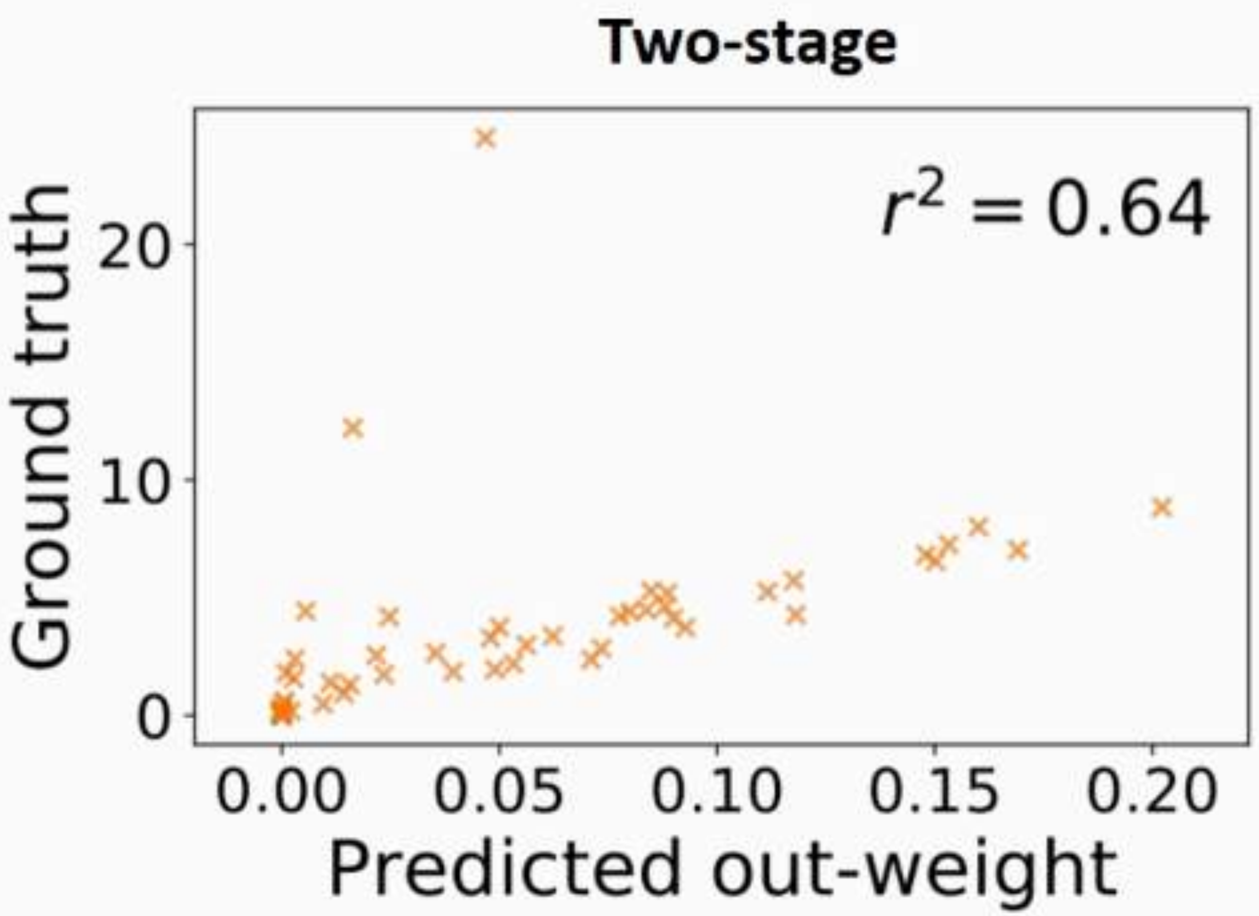
Two-stage prediction

Decision-focused prediction

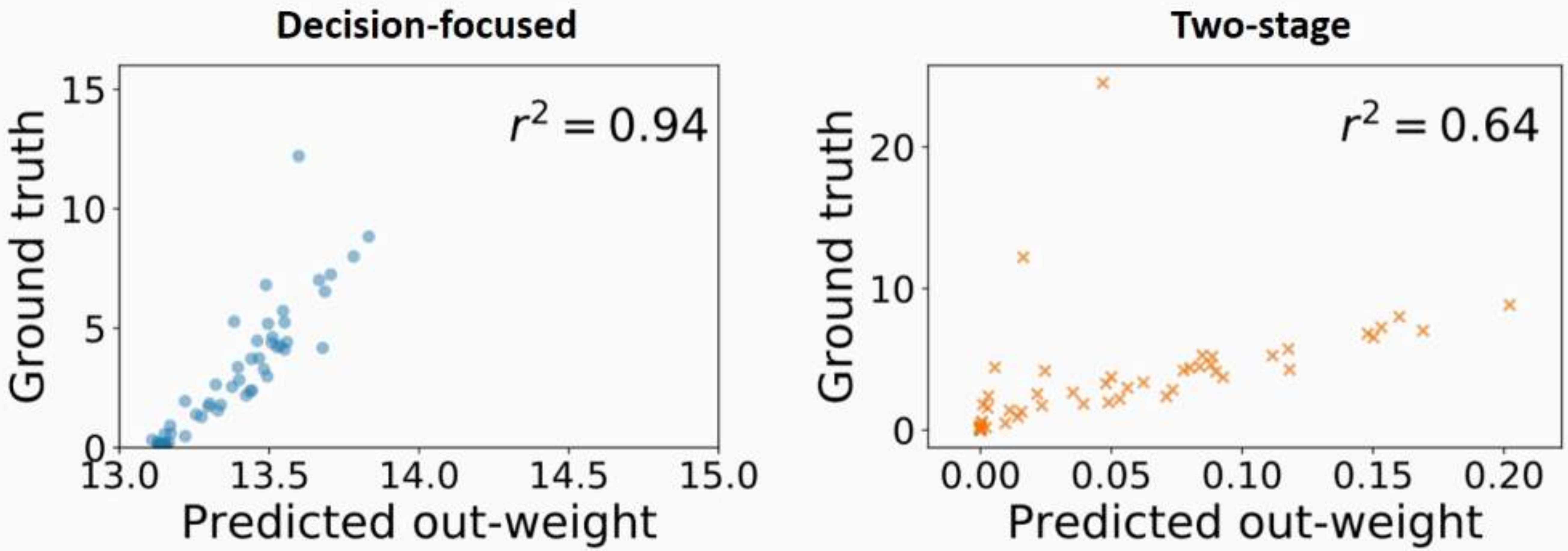


Explanation





Explanation



➡ Our method learns to focus on qualities needed for making good decisions!

Conclusion

- Critical social issues present optimization and learning problems
- Interventions for disease prevention, homelessness, and more can be transformed via computational techniques

Conclusion

- Deployable algorithms present new research challenges
- Must handle data and decisions in unified way
- With all the pieces put together, AI offers powerful means to improve our fellow humans' lives