Slides: bit.ly/lcl-slides
Preprint: bit.ly/lcl-paper
Code: bit.ly/lcl-code
Data: bit.ly/lcl-data

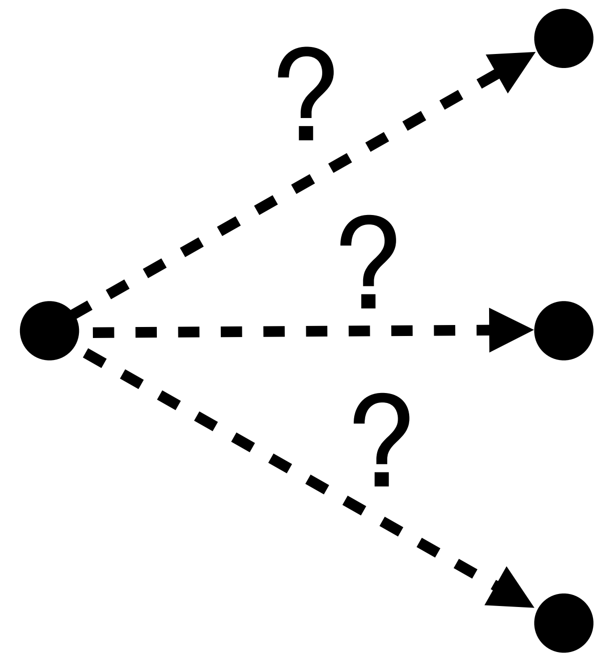
Learning Context Effects in Triadic Closure

Kiran Tomlinson

SINM 2020

research with Austin R. Benson

What factors drive edge formation?



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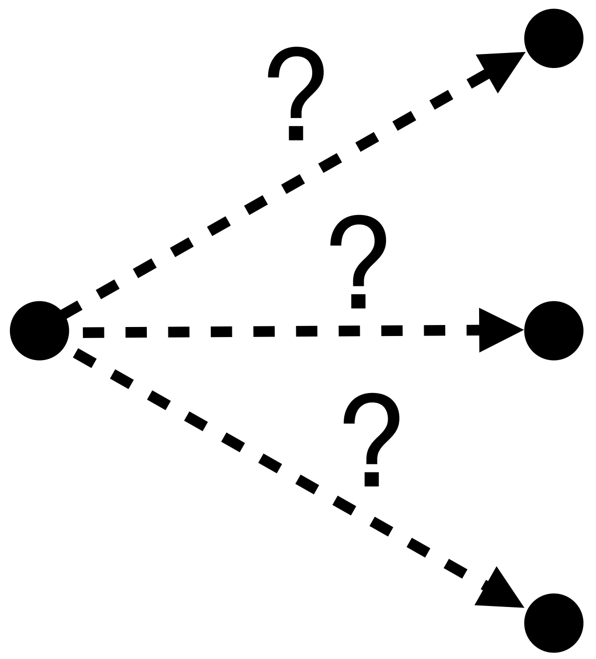
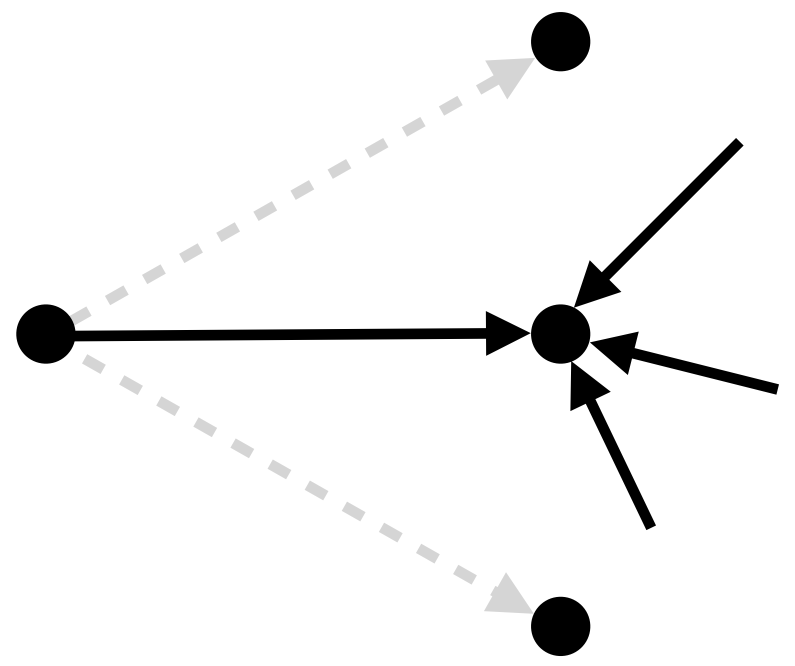


Preferential attachment
(Barabási & Albert, *Science* 1999)



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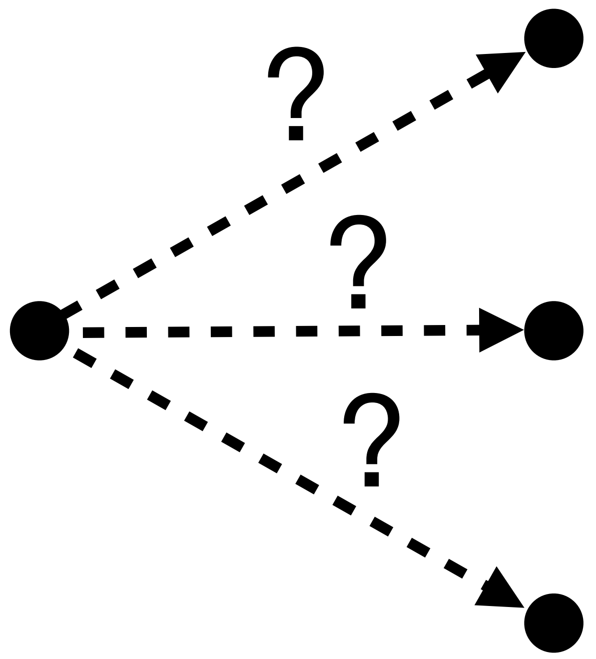

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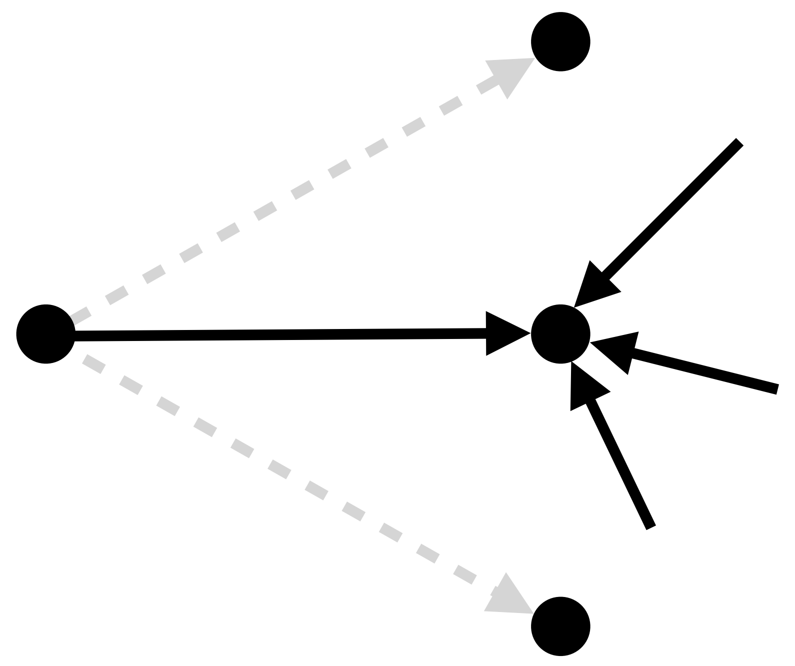

Homophily

(McPherson et al., *Annual Review of Sociology* 2001)
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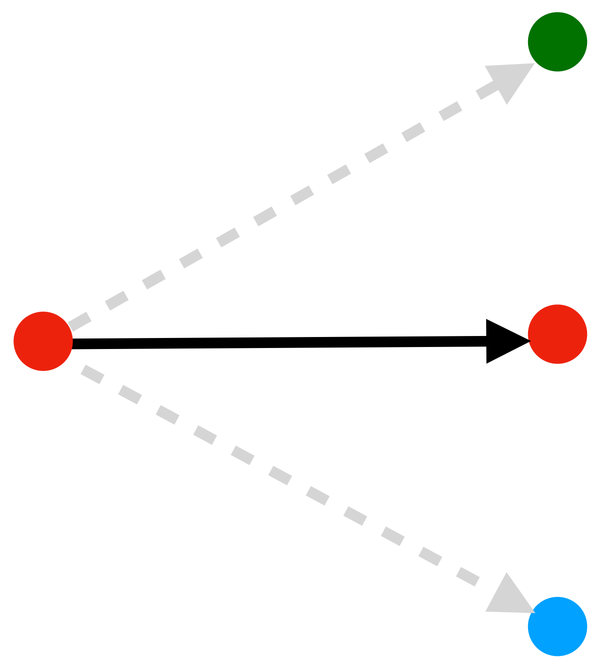

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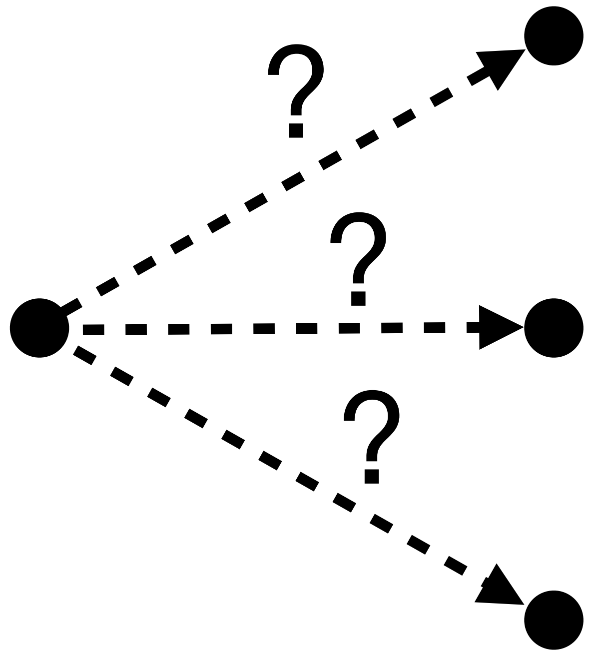

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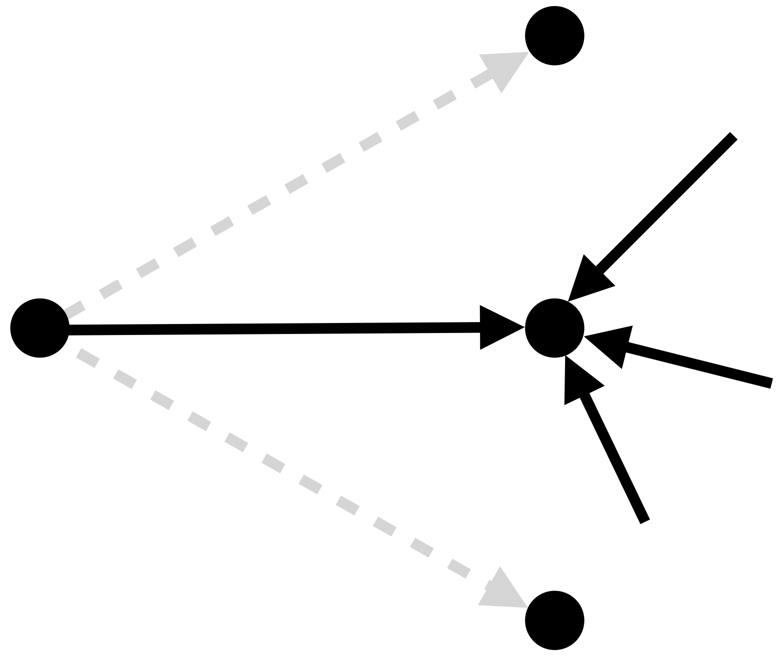

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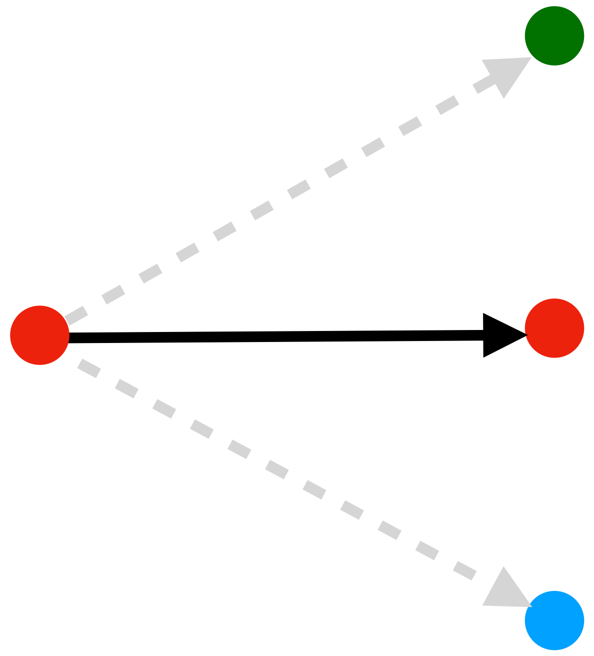
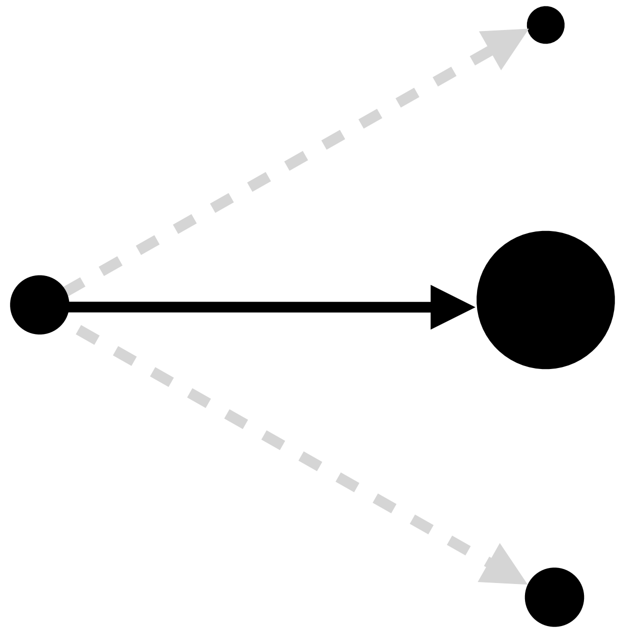


Fitness

(Bianconi & Barabási, *Europhysics Letters* 2001)
(Caldarelli et al., *Physical Review Letters* 2002)



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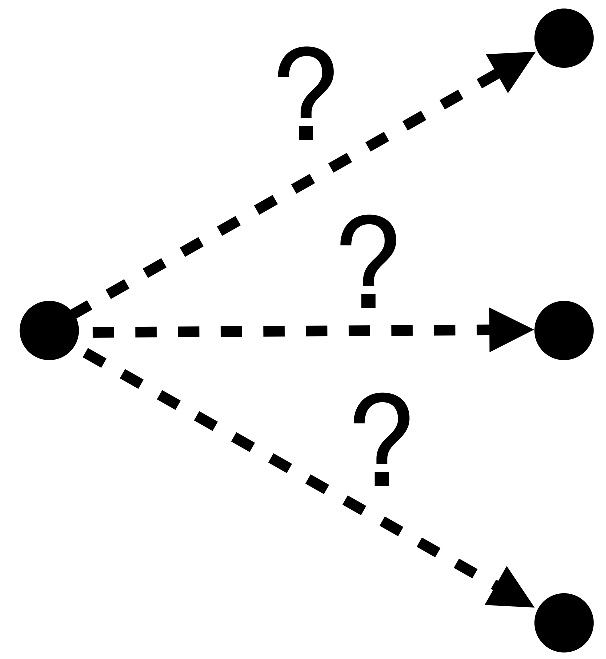

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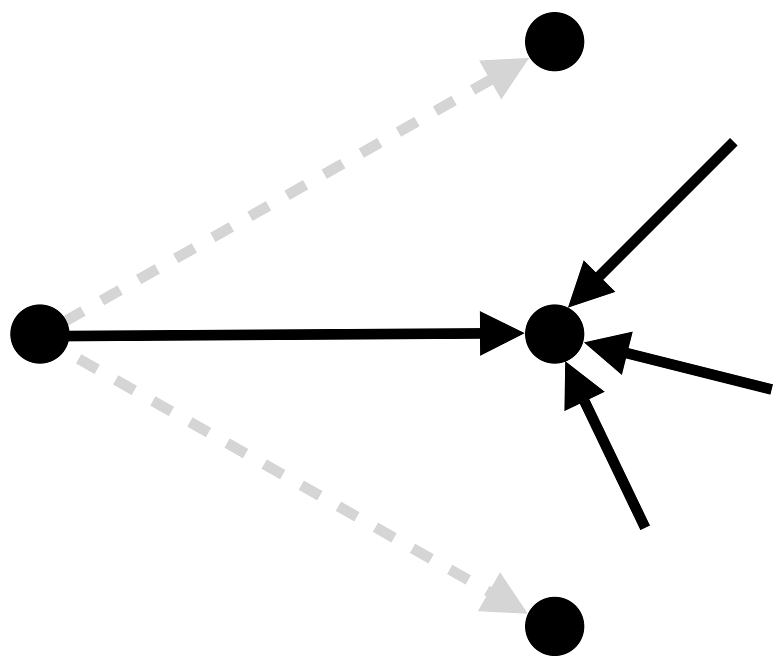

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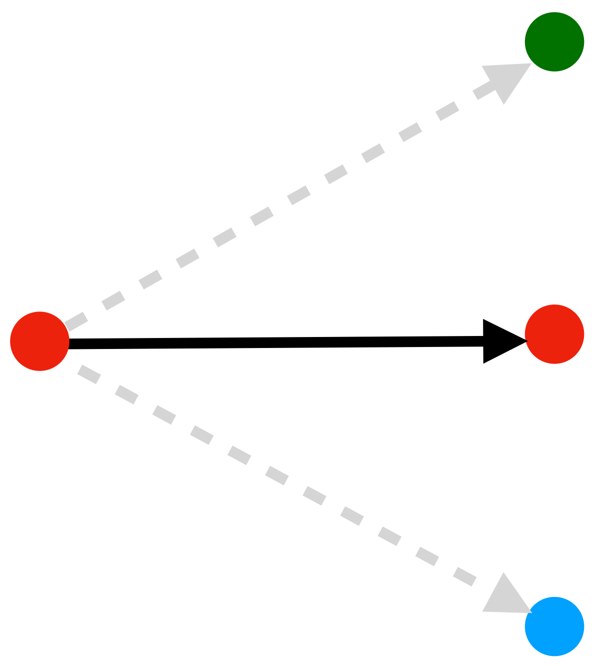

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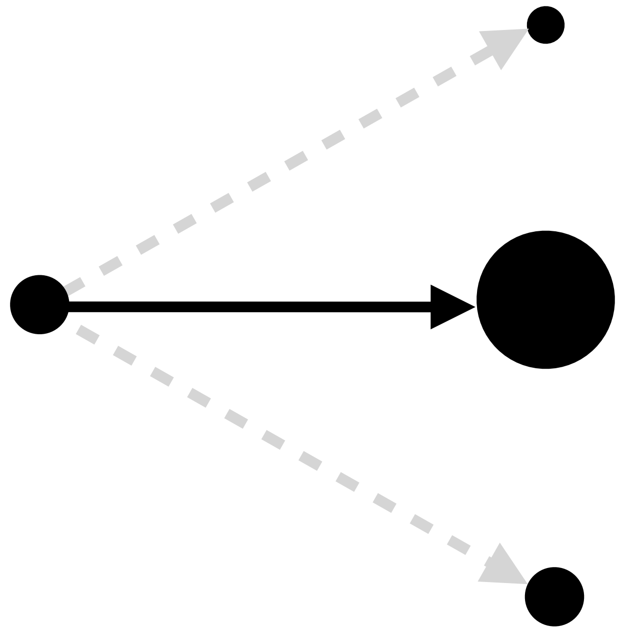
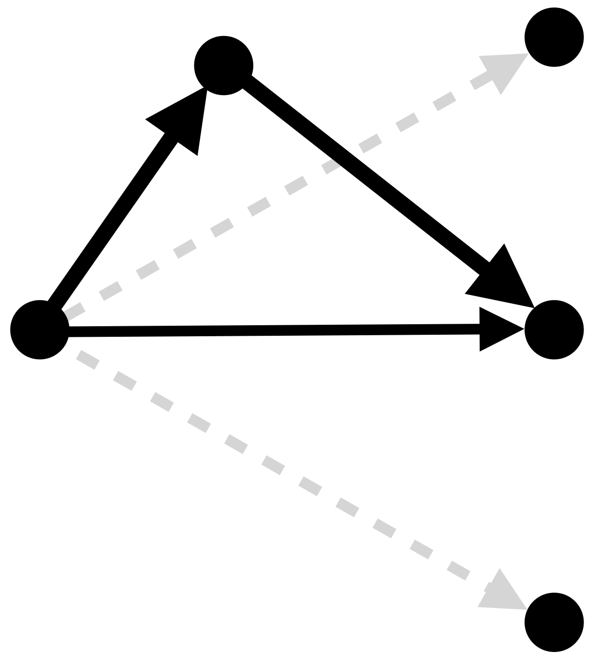


Triadic closure

(Rapoport, *Bulletin of Mathematical Biophysics* 1953)
(Jin et al., *Physical Review E* 2001)



“Choosing to grow a graph”

(Overgoor et al., *SINM* ’19 & *WWW* ’19)
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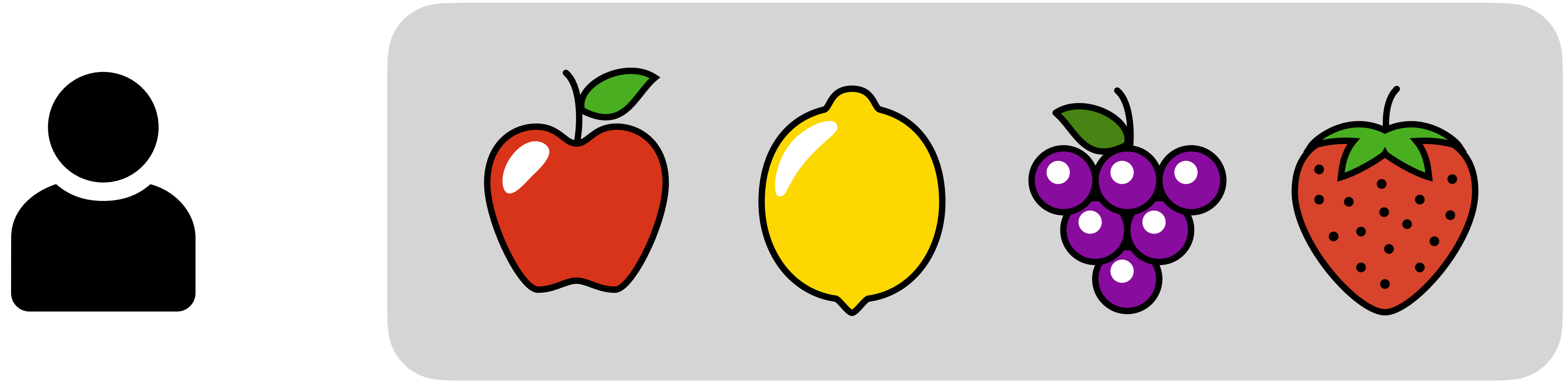

chooser *choice set*

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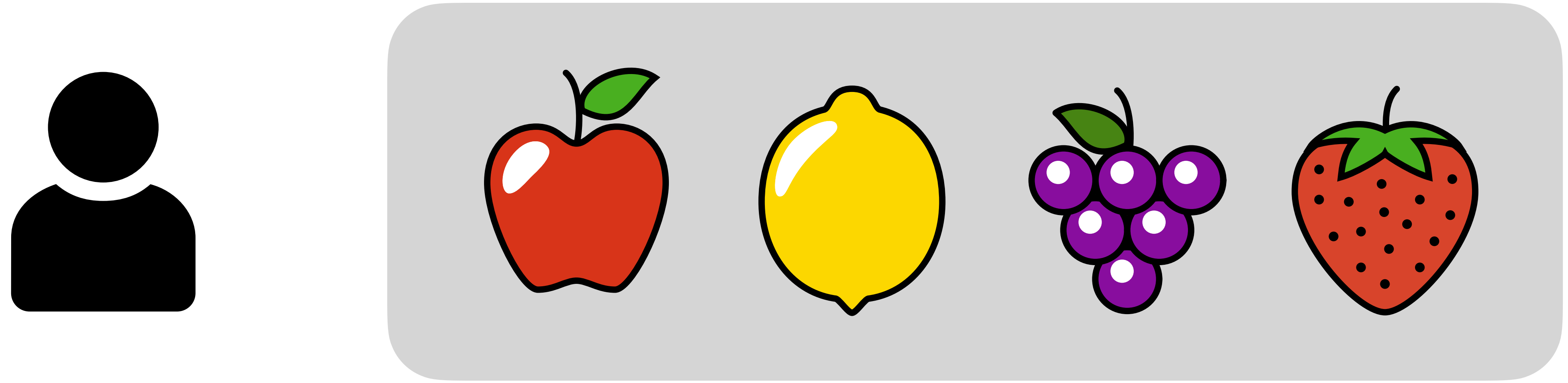

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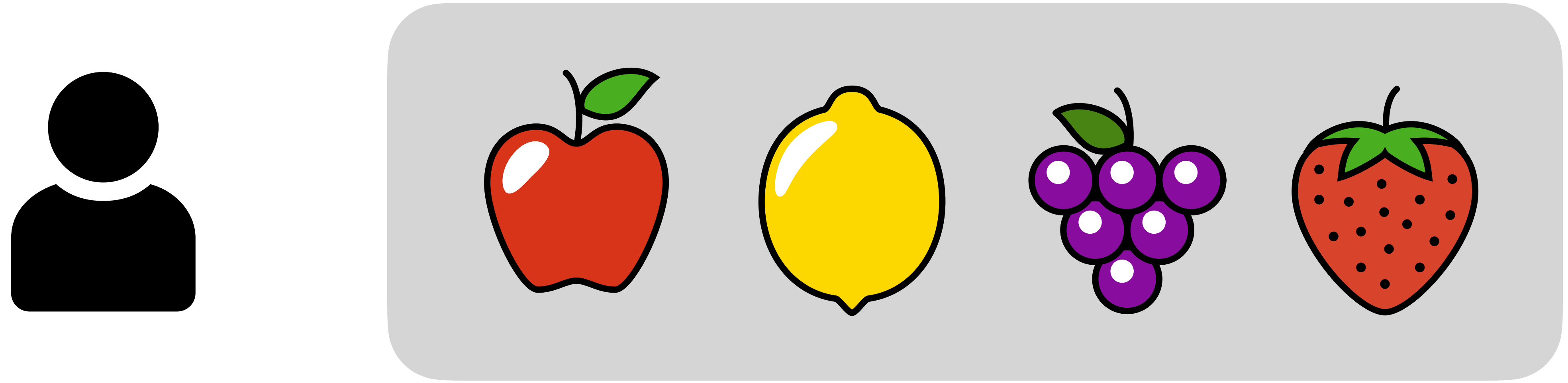

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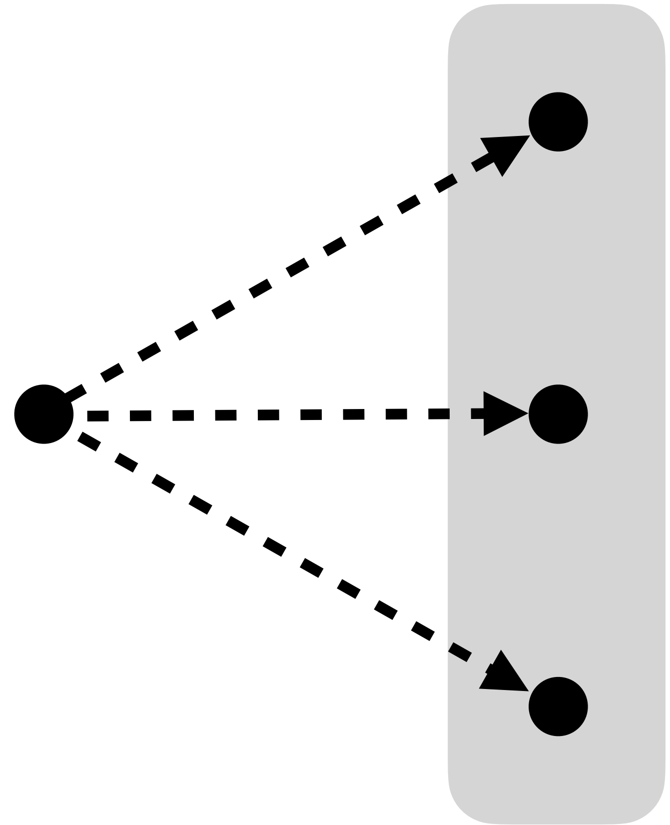
chooser



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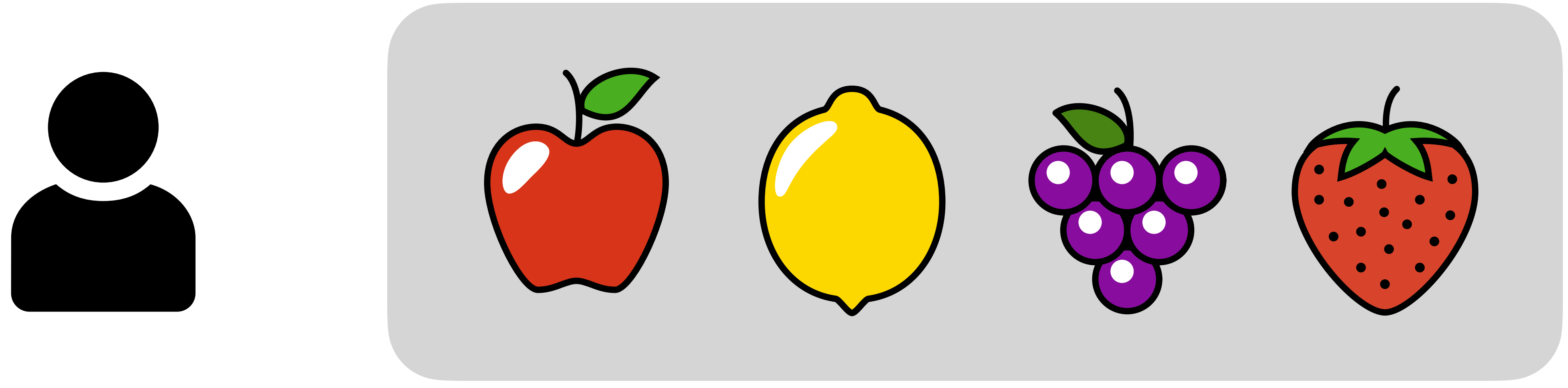

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→ in network growth

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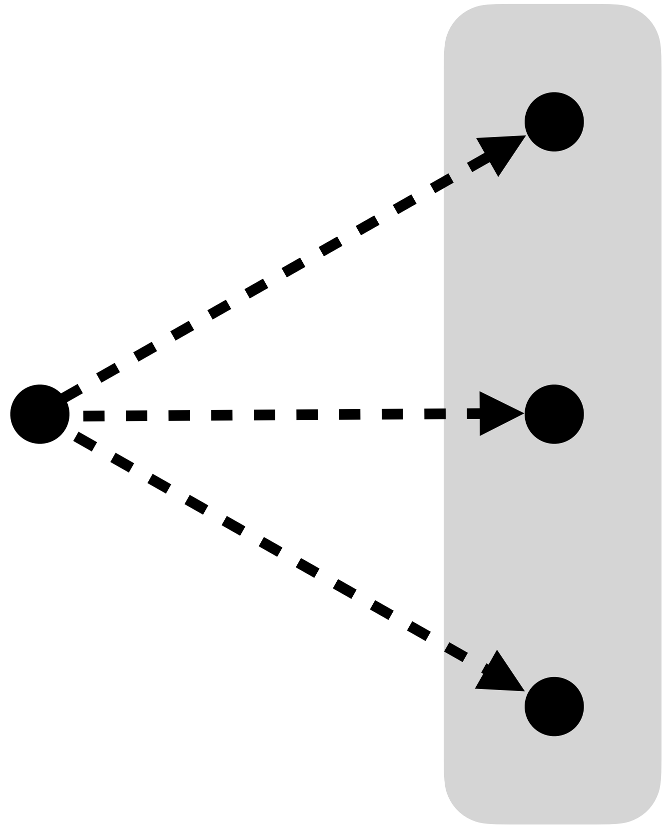

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Key usage

Timestamped edges
→ meaningful choice sets

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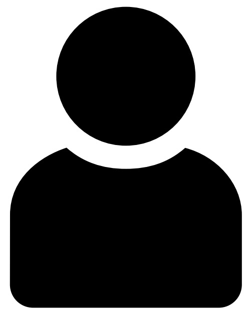

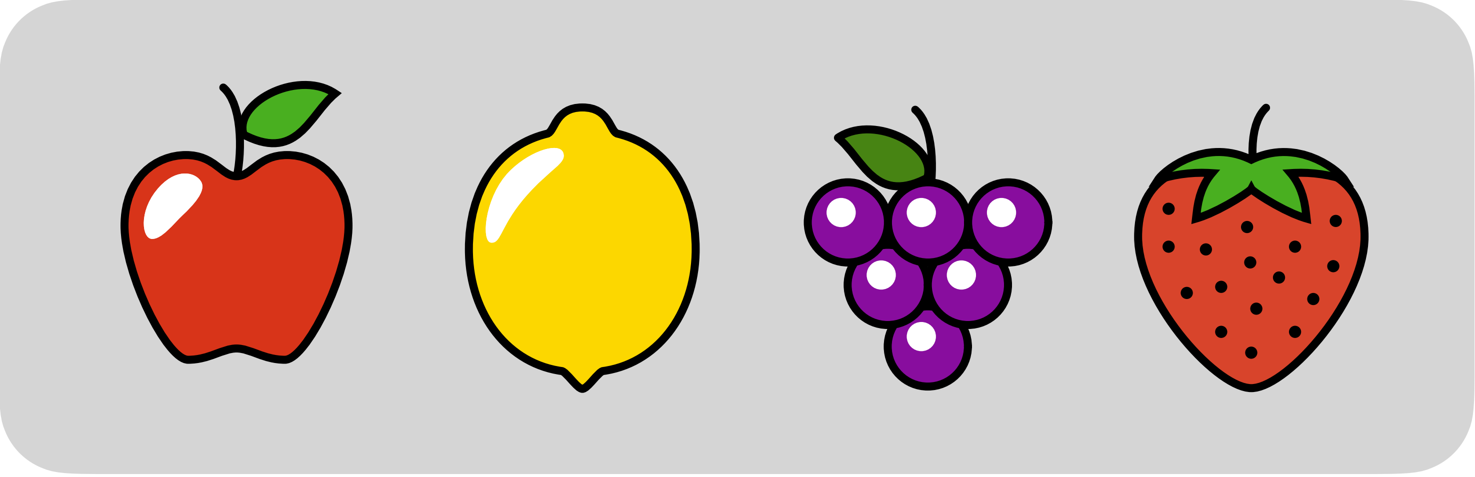

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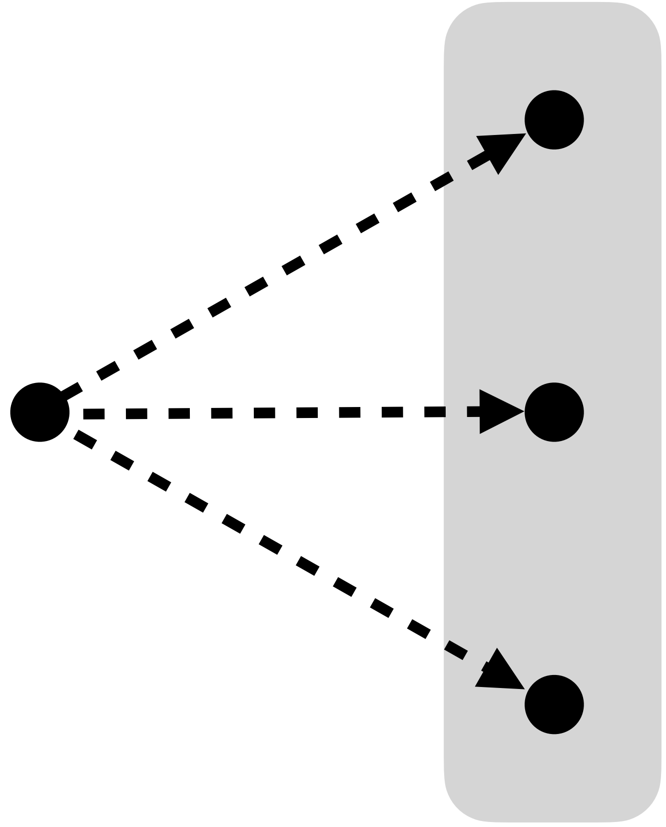

choice set

Key usage

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Infer relative importance of edge formation mechanisms from data

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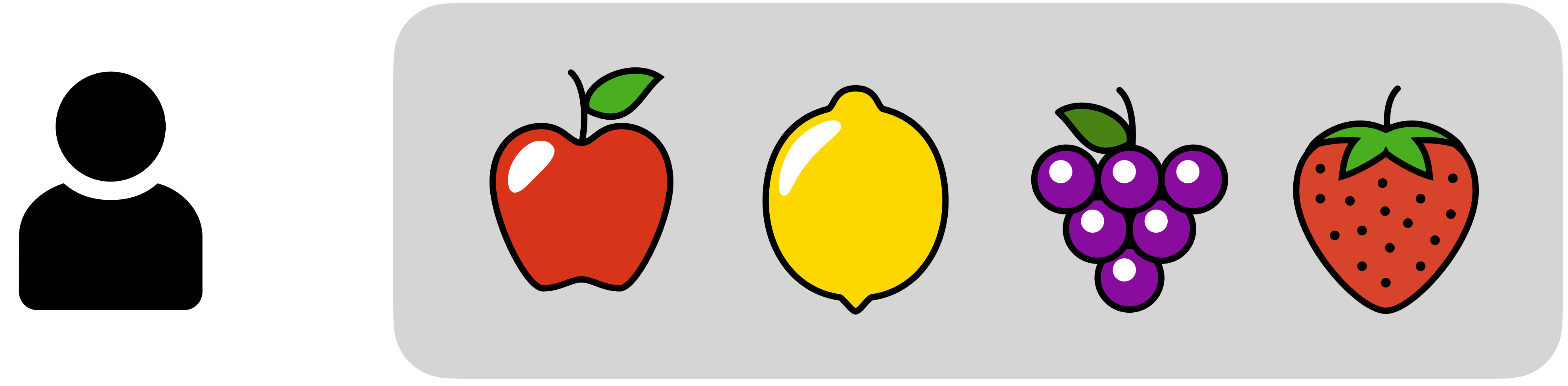

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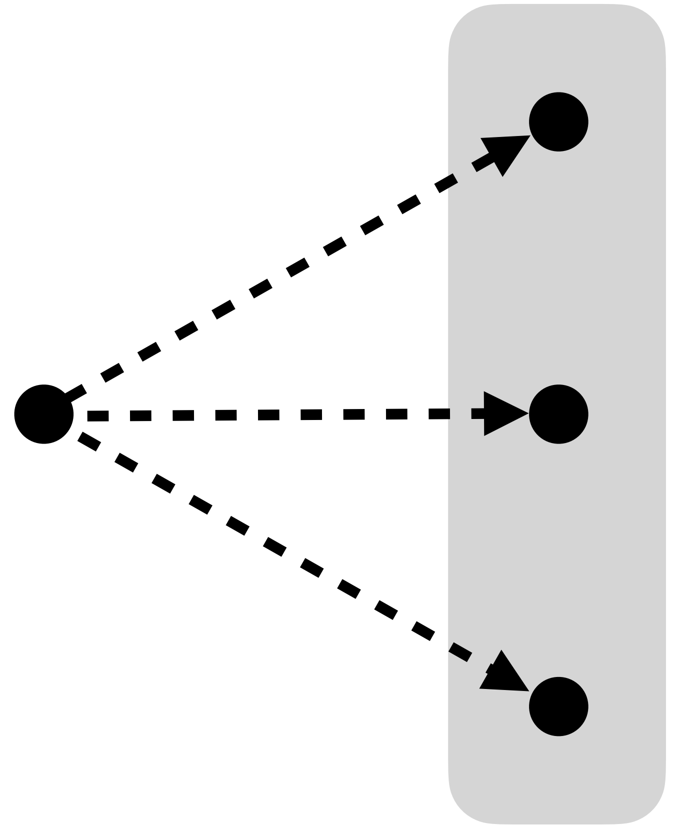

choice set

Key usage

Timestamped edges
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Infer relative importance of edge formation mechanisms from data

$$\Pr(i, C) = \frac{\exp(\theta^T x_i)}{\sum_{j \in C} \exp(\theta^T x_j)}$$

Multinomial logit (MNL) (McFadden, 1973)

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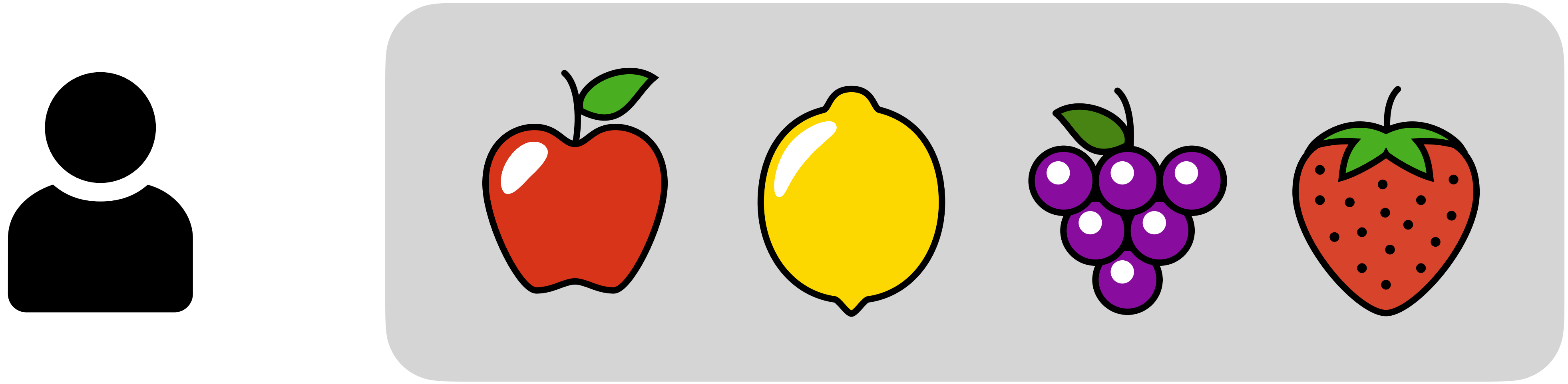

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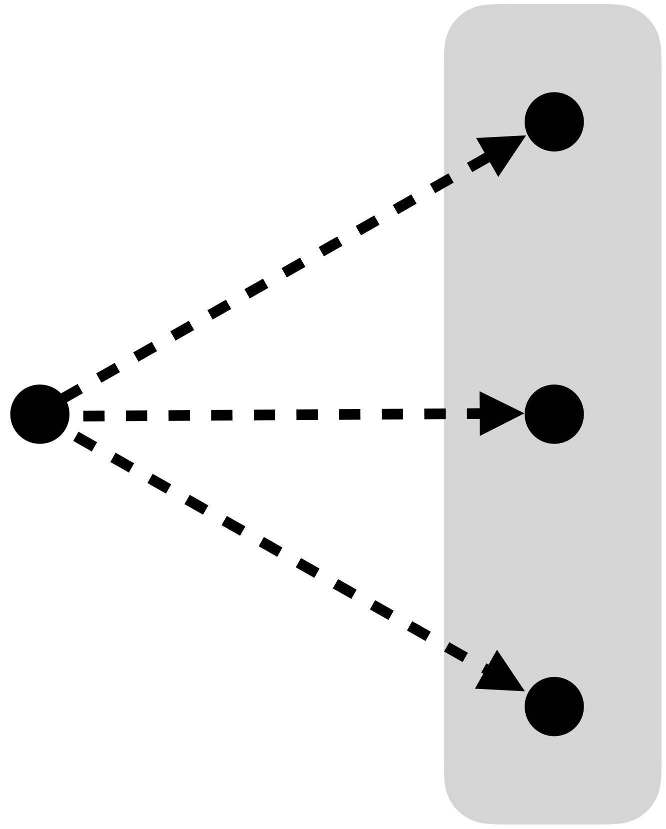

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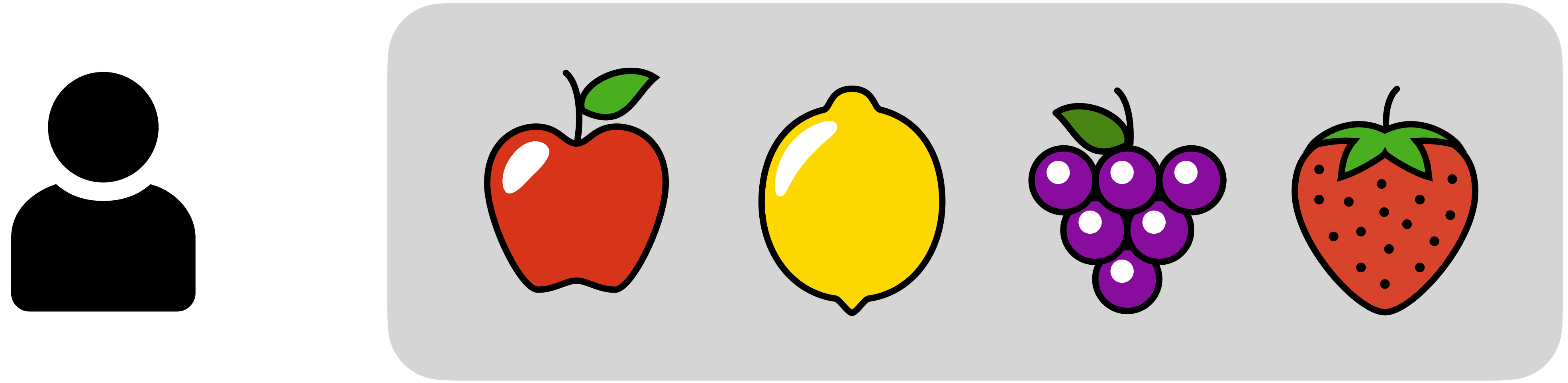

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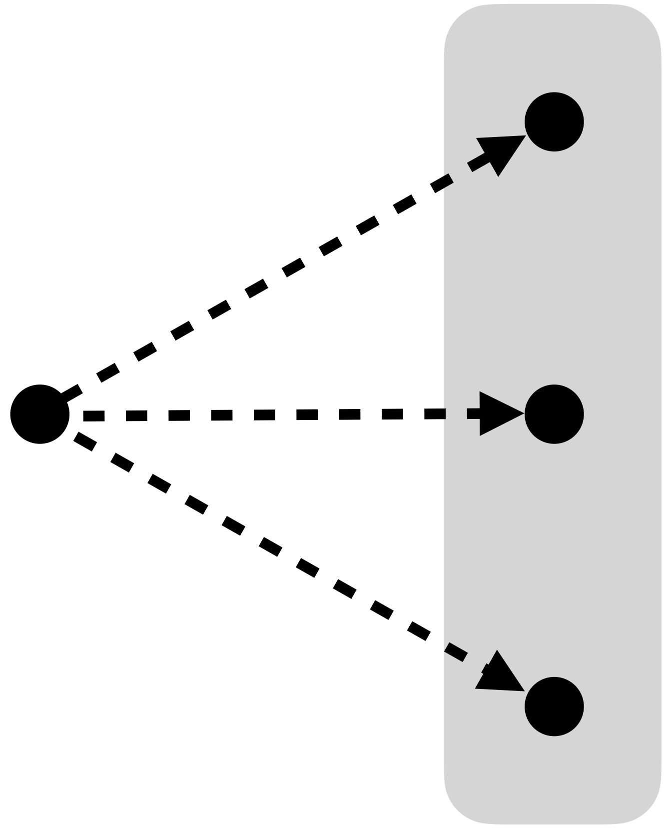

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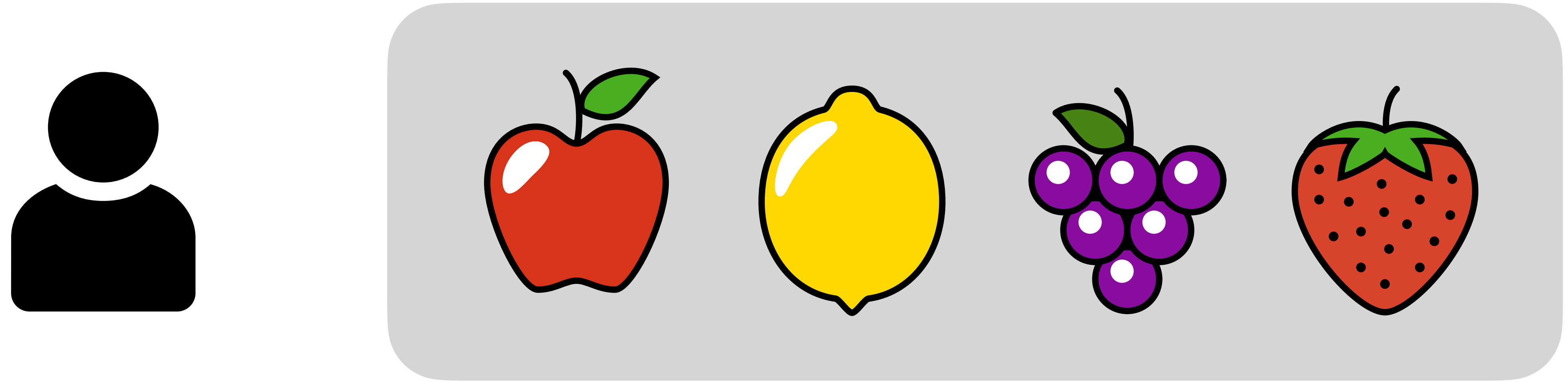

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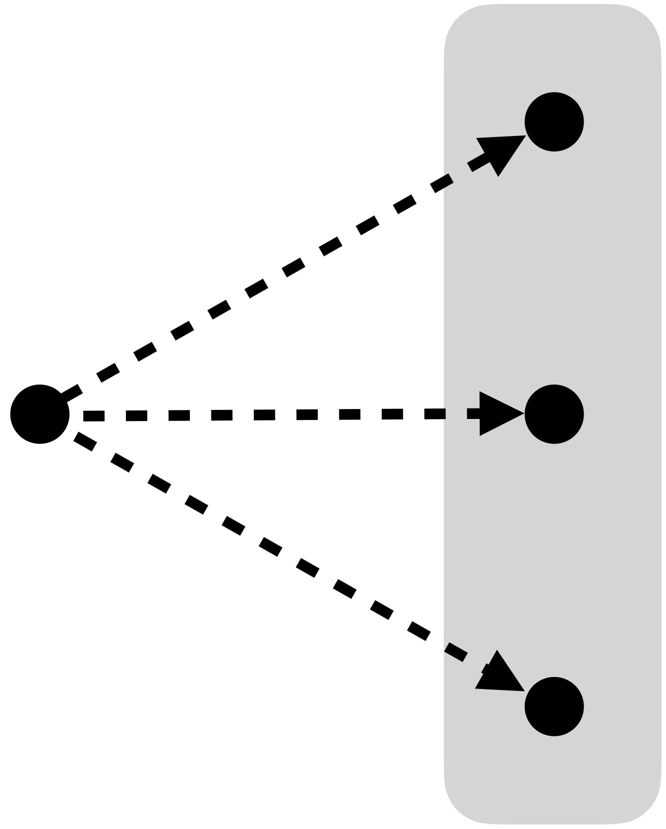

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Key usage

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Infer relative importance of edge formation mechanisms from data

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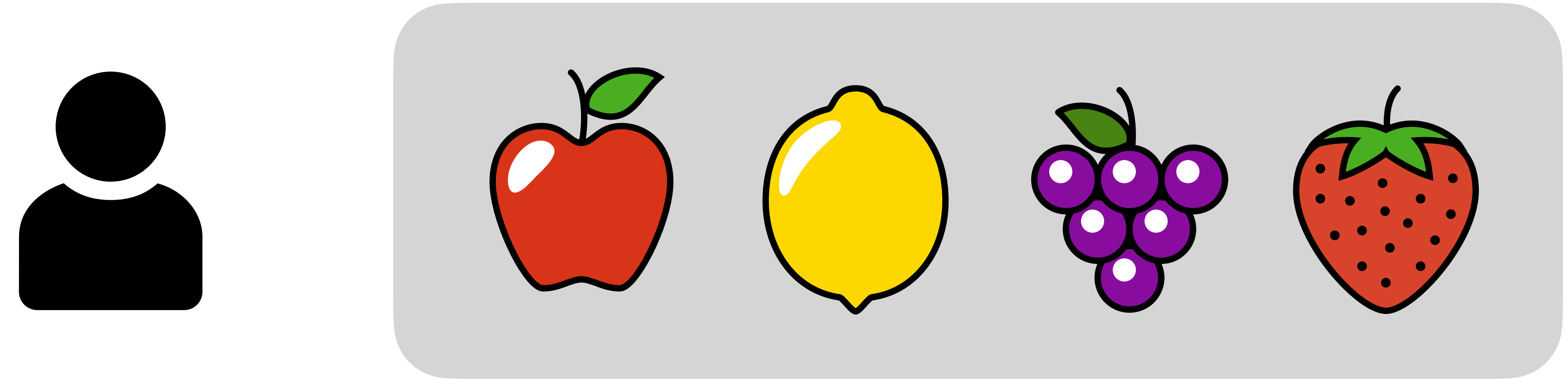

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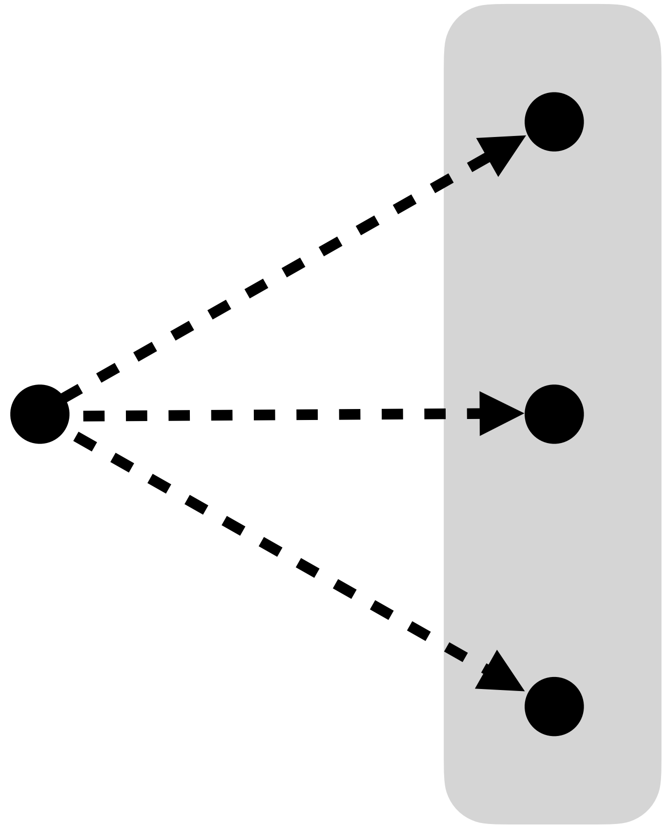

choice set

Key usage

Timestamped edges
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Infer relative importance of edge formation mechanisms from data

preferences node features

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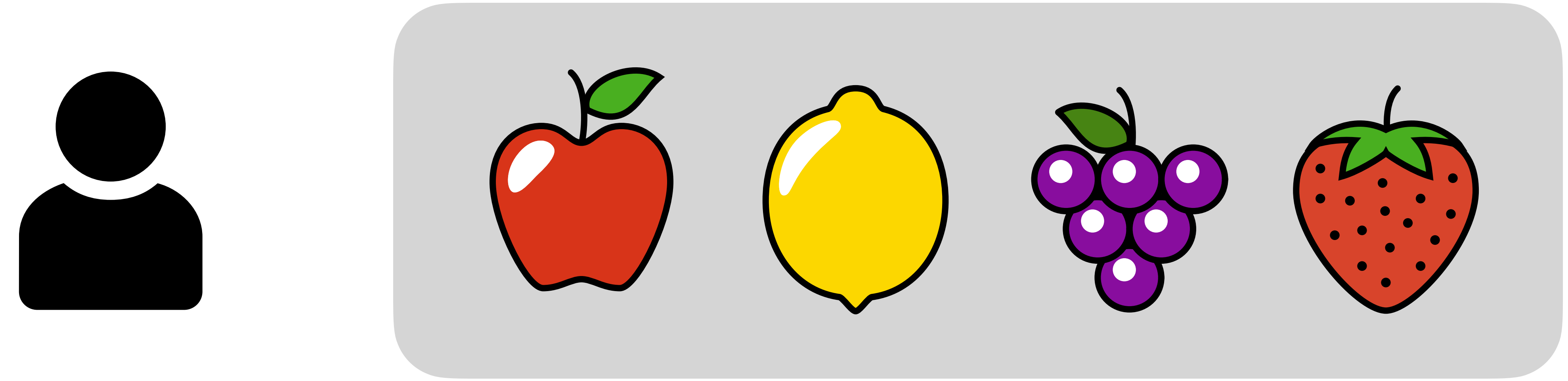

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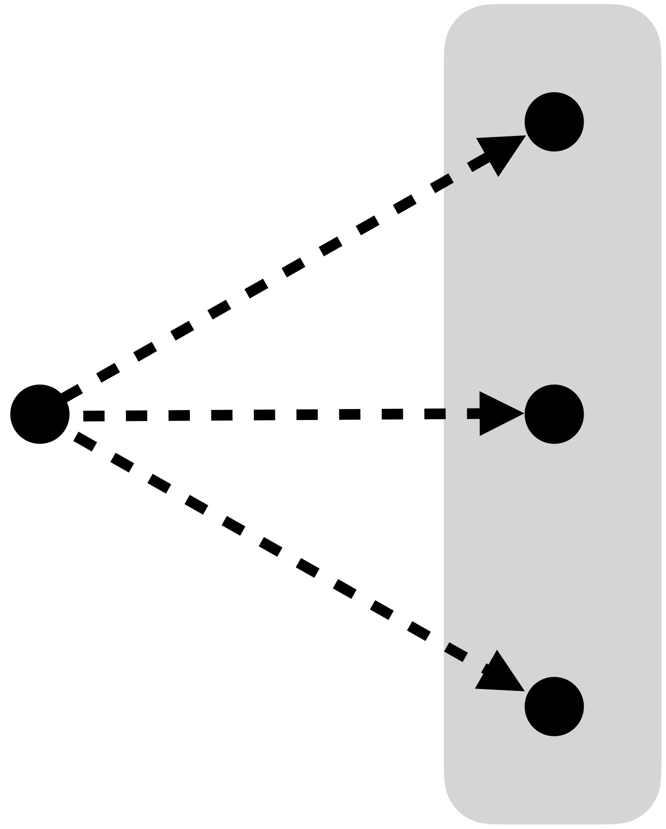

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preferences — node features (similarity, in-degree, fitness…)

node — choice set

Multinomial logit (MNL) (McFadden, 1973)

The choice set affects preferences

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Context effects

(Huber et al., *Journal of Consumer Research* 1982)
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e.g., *compromise effect*:

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In networks
e.g., how do preferences change
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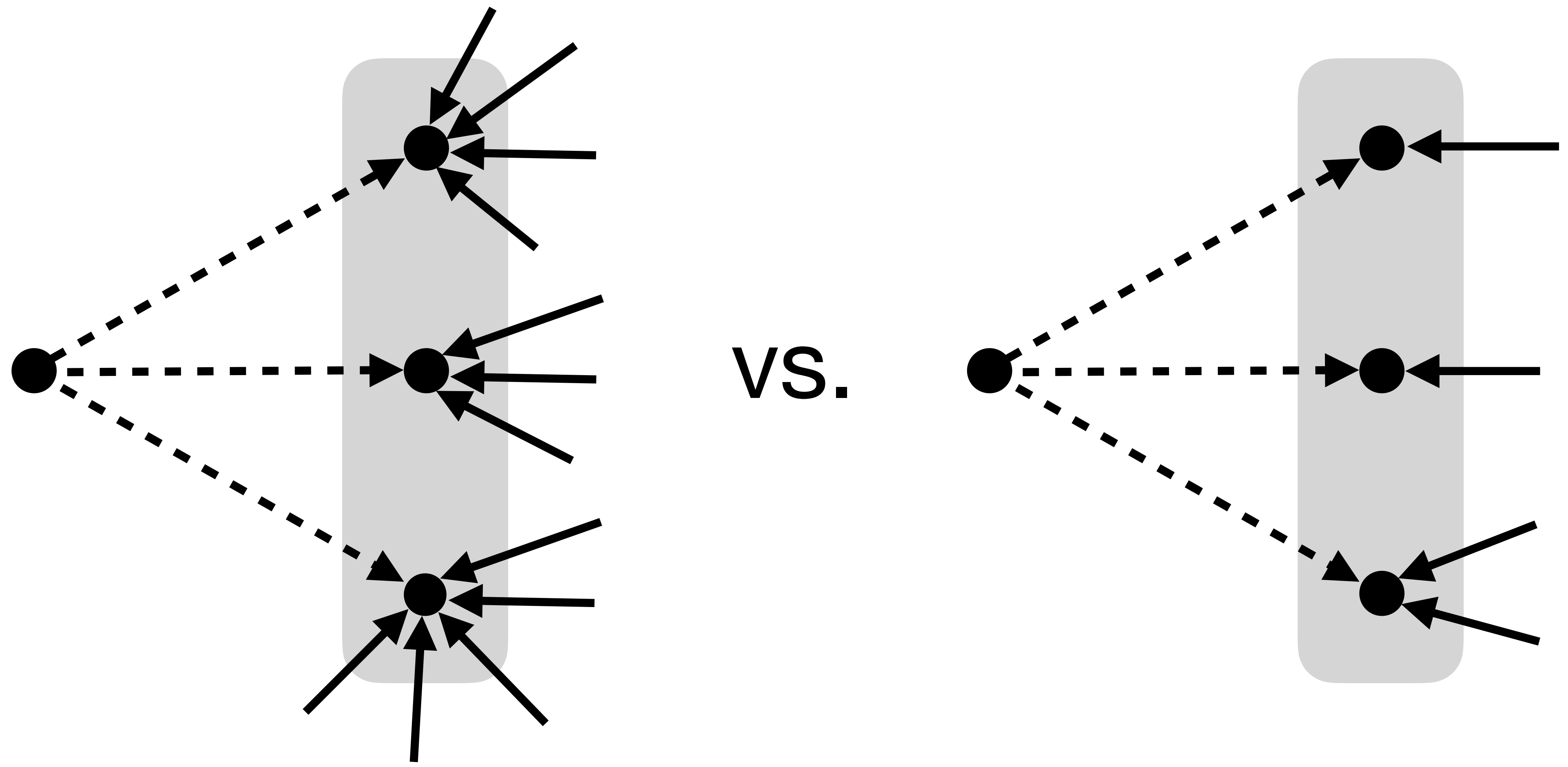

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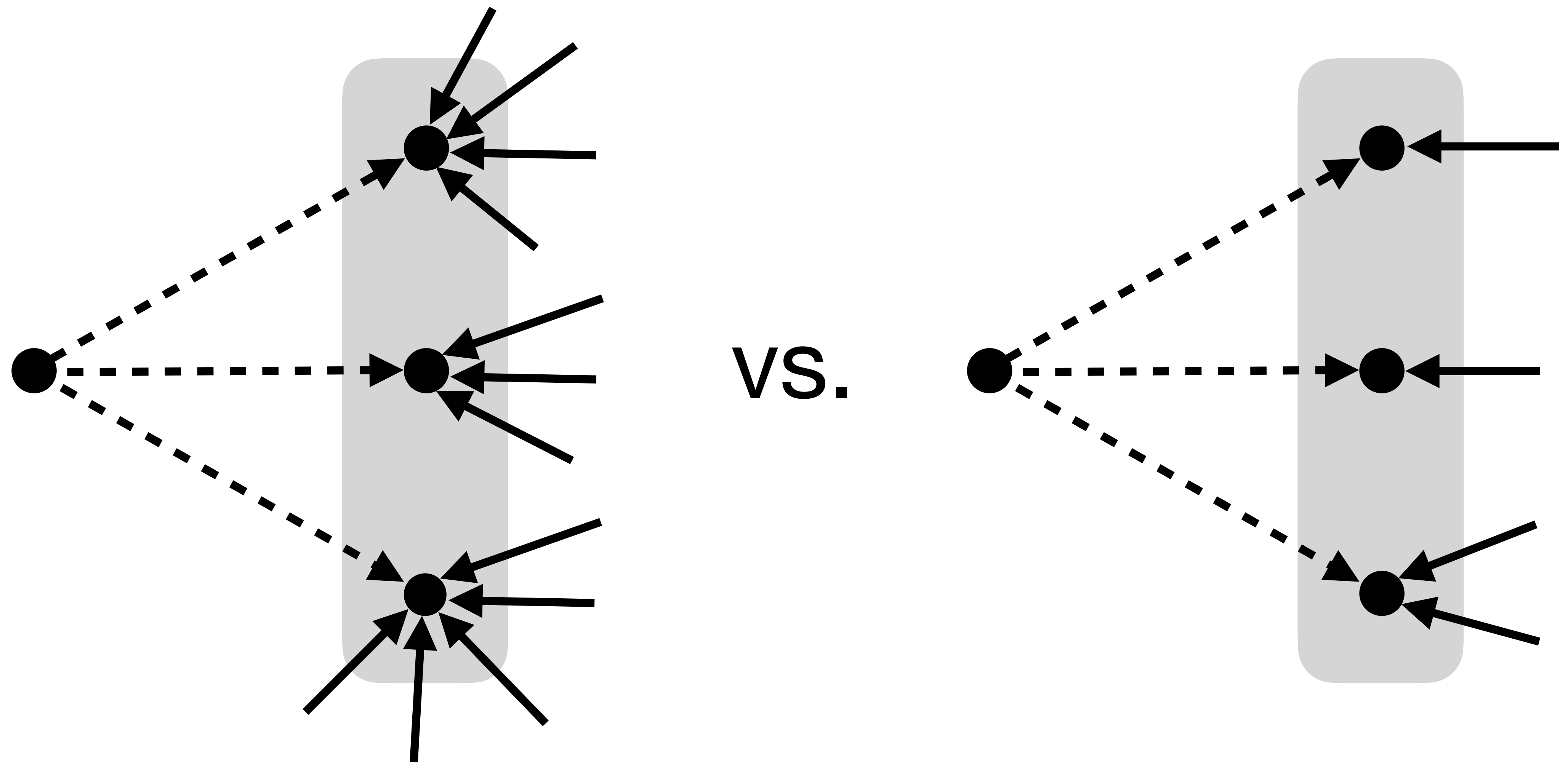

Our model:

Linear context logit (LCL)

$$\Pr(i, C) = \frac{\exp\left(\left[\theta + A x_C\right]^T x_i\right)}{\sum_{j \in C} \exp\left(\left[\theta + A x_C\right]^T x_j\right)}$$

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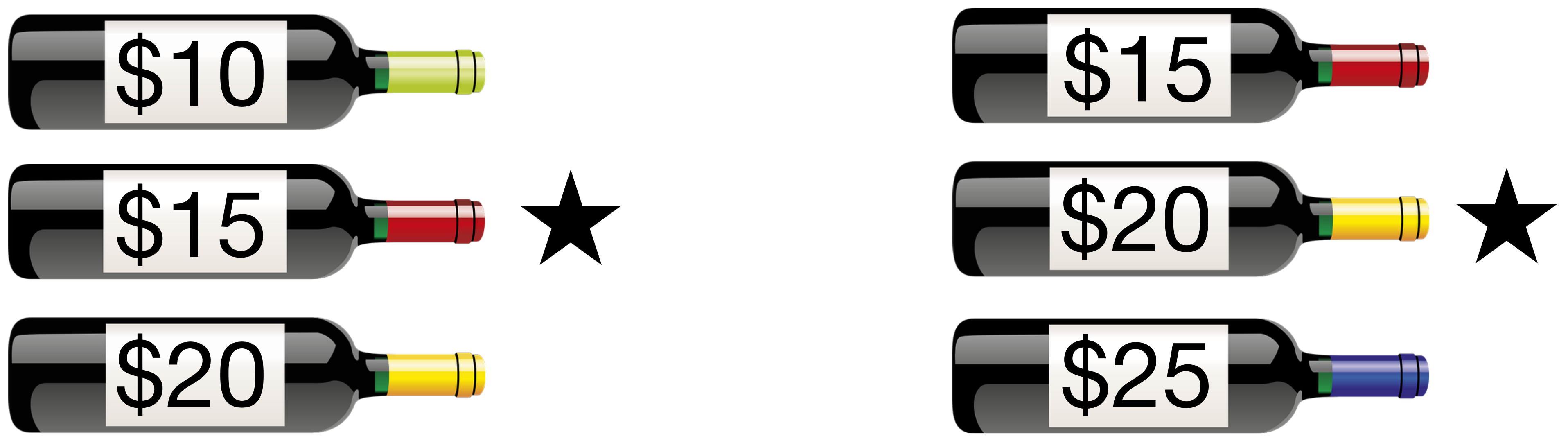

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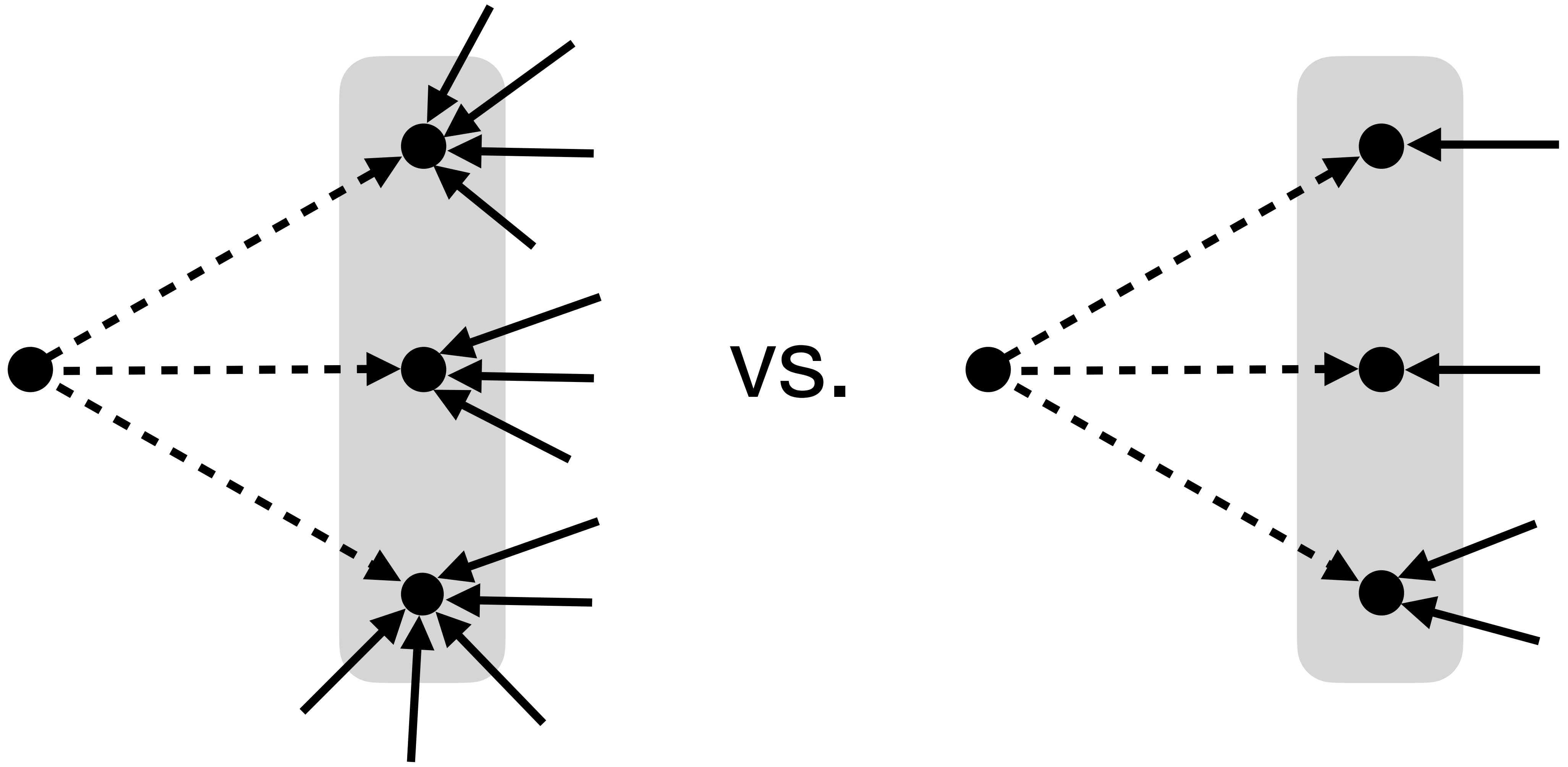

Our model:

Linear context logit (LCL)

base preferences

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The choice set affects preferences

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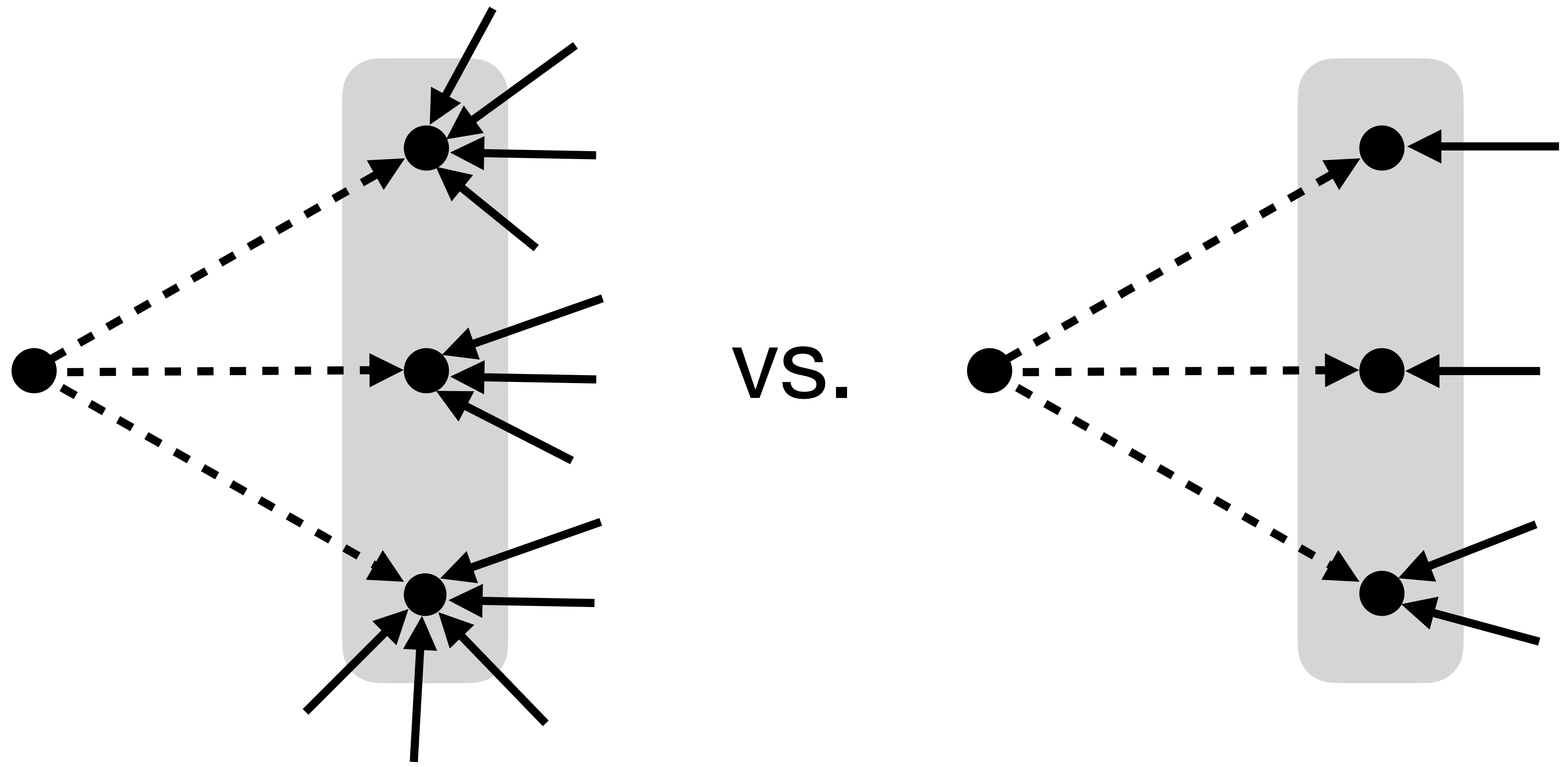

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context effect matrix

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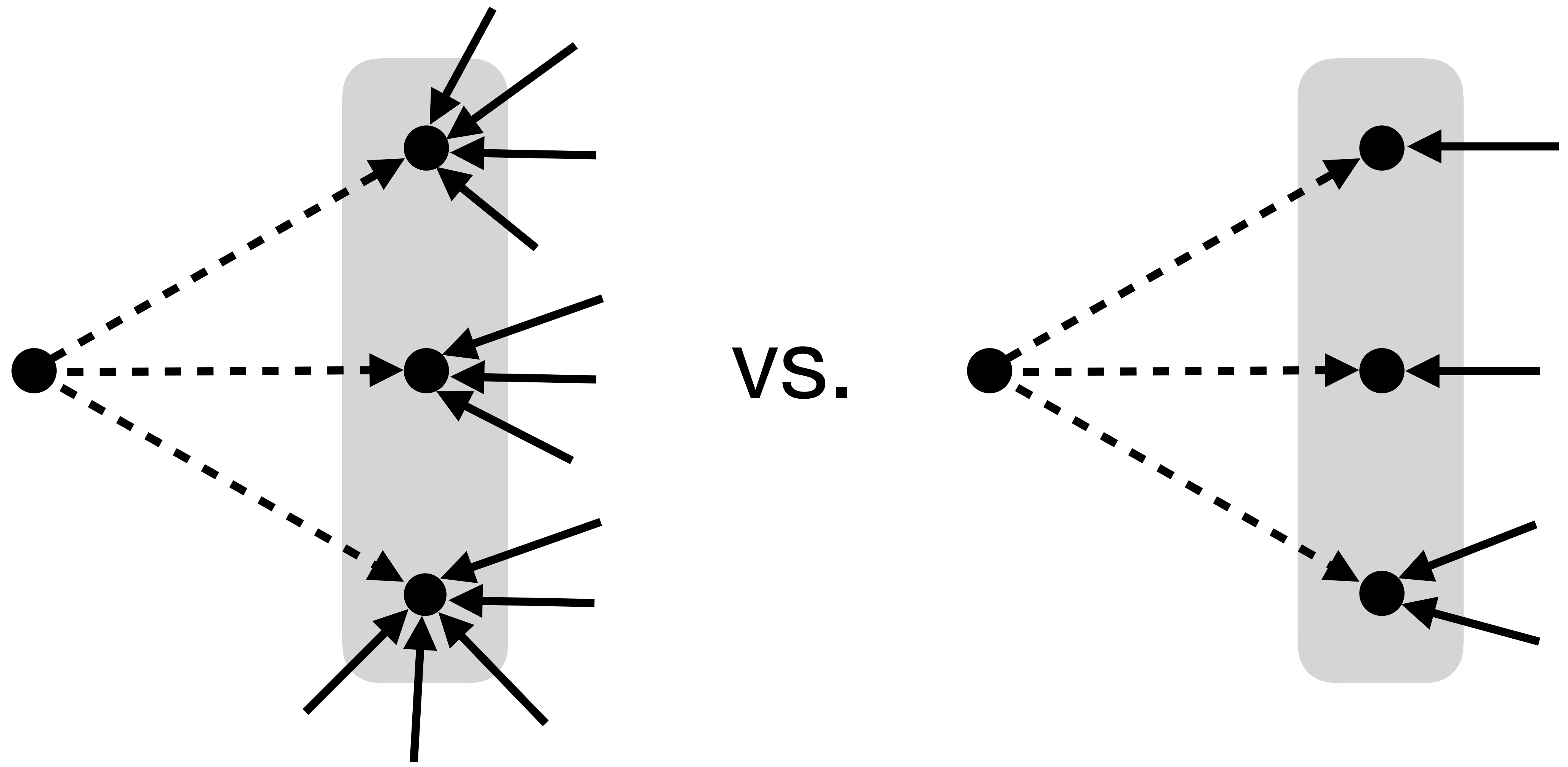

Our model:

Linear context logit (LCL)

base preferences

context effect matrix

mean features over choice set

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Choosing to close triangles

Triadic closure offers small choice sets
→ tractable inference
→ varied choice sets

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Our data
Timestamped edges
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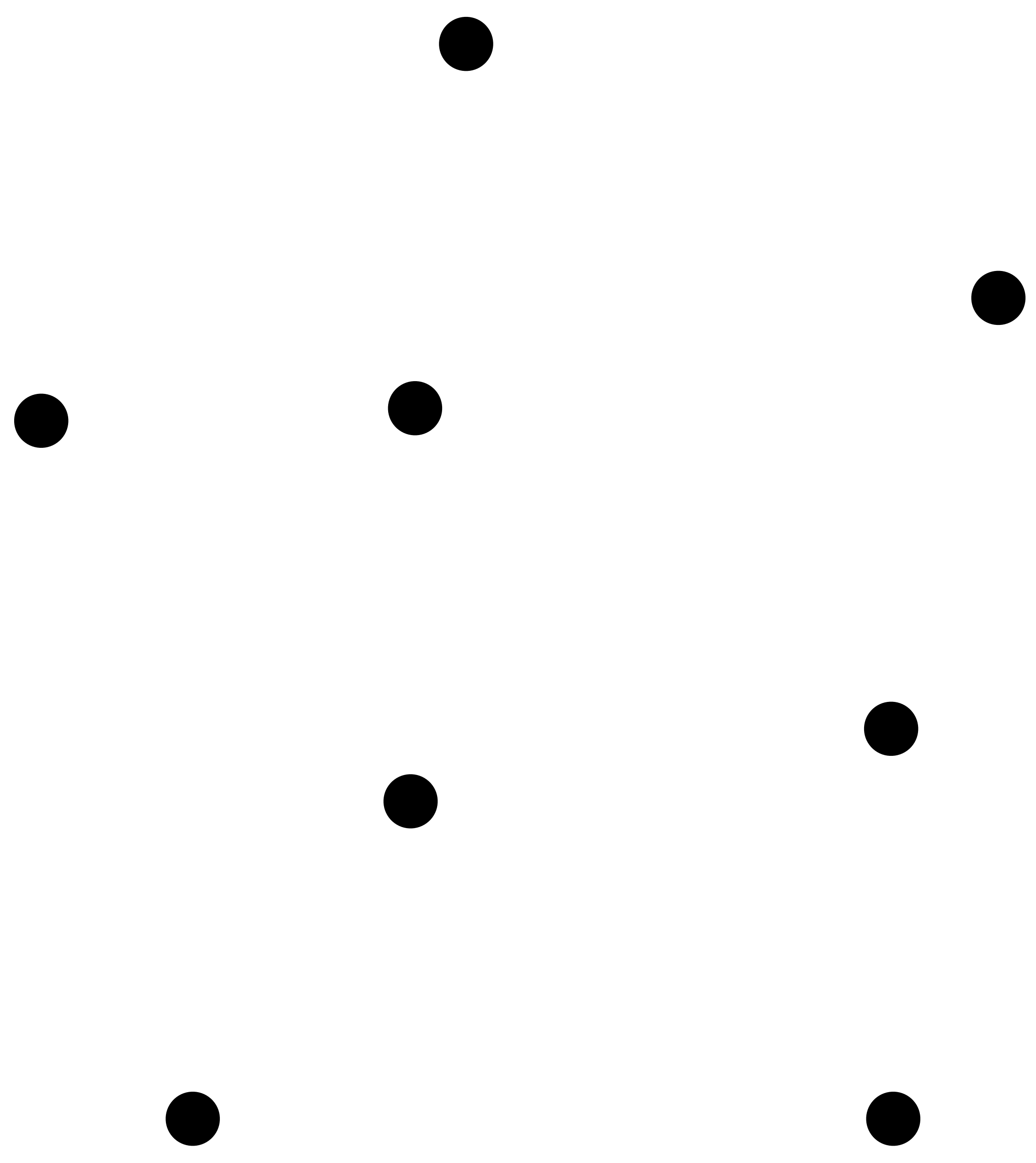

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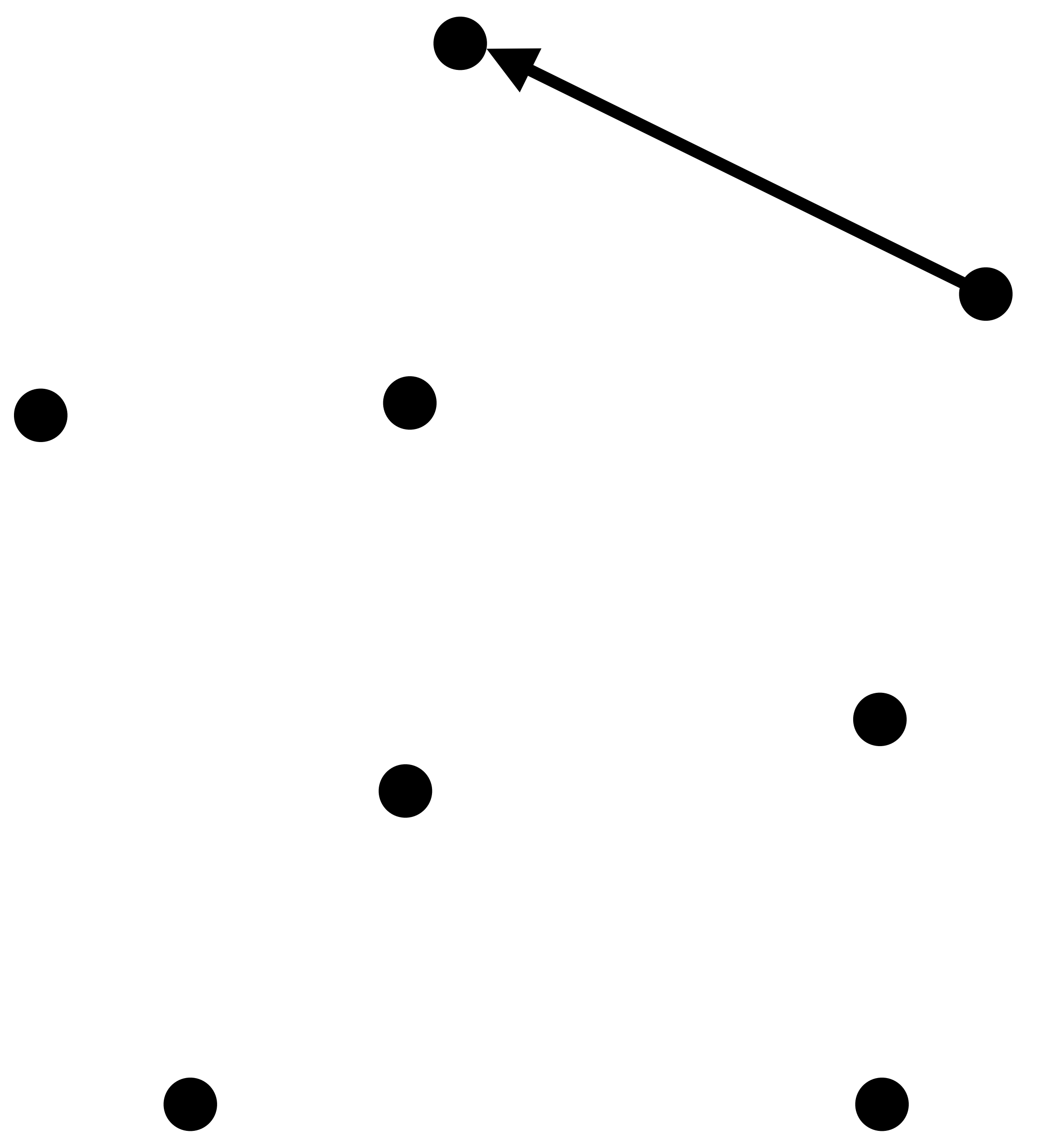

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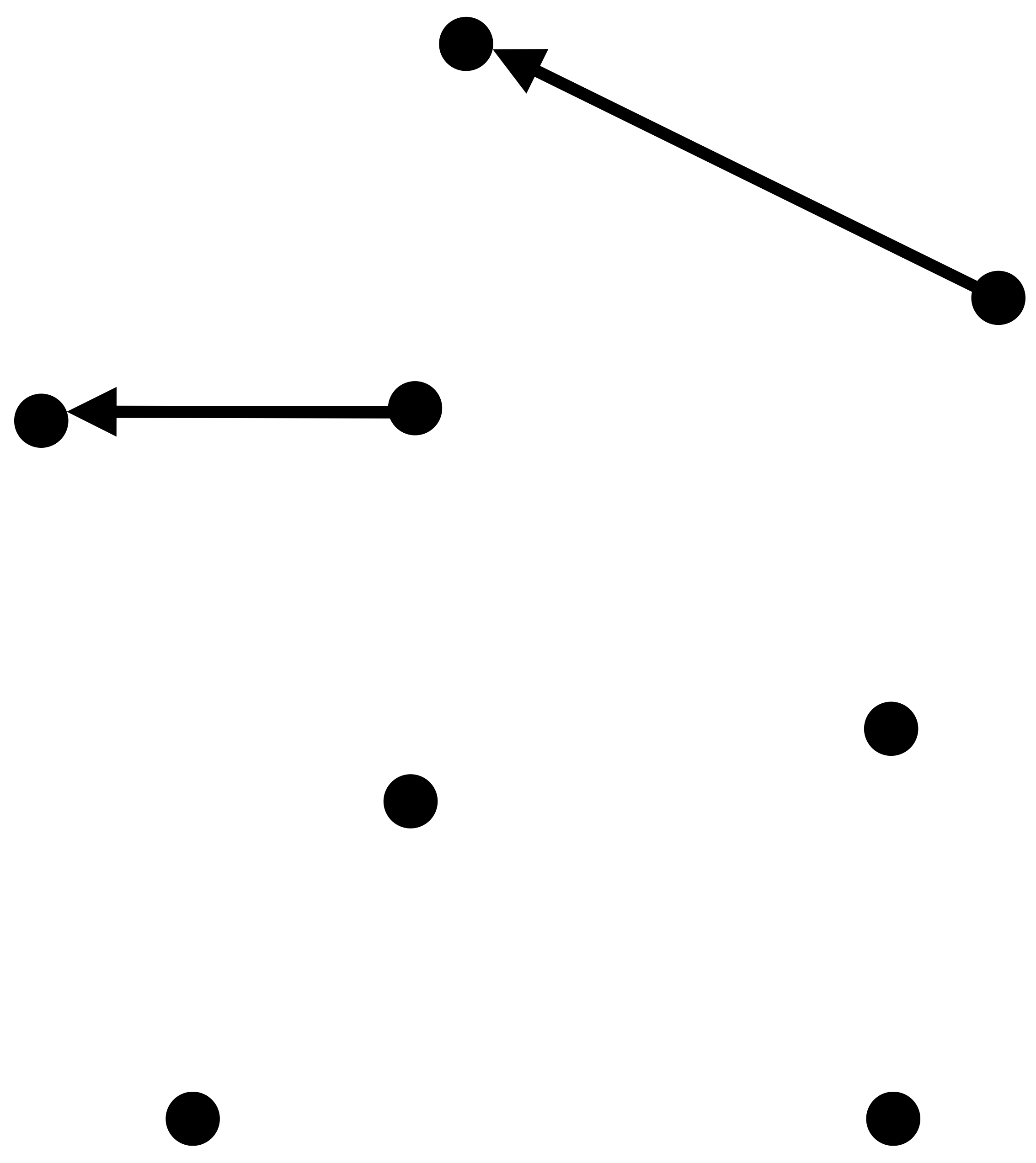
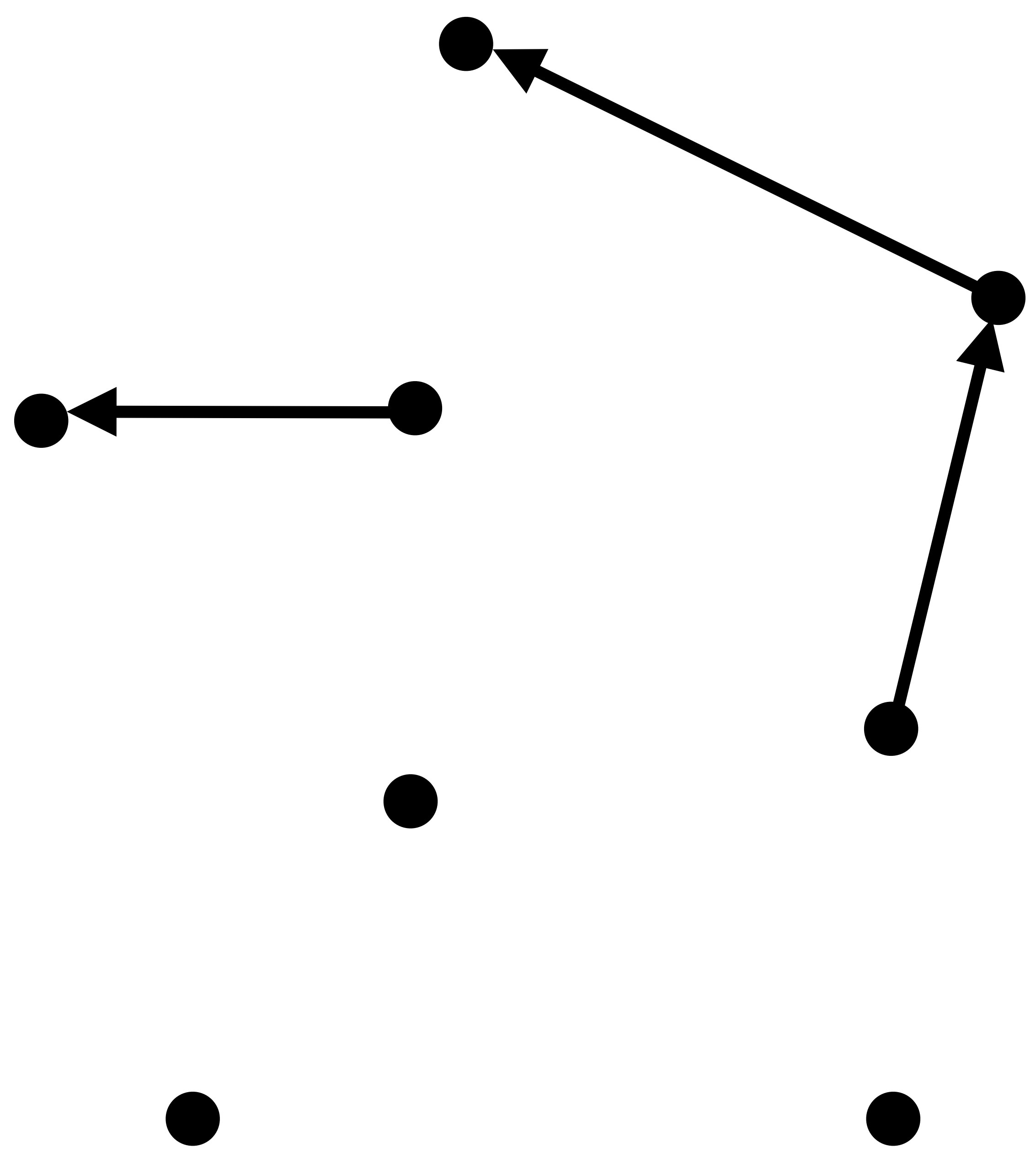


Our data
Timestamped edges
(including repeats)

Choosing to close triangles

Triadic closure offers small choice sets
→ tractable inference
→ varied choice sets



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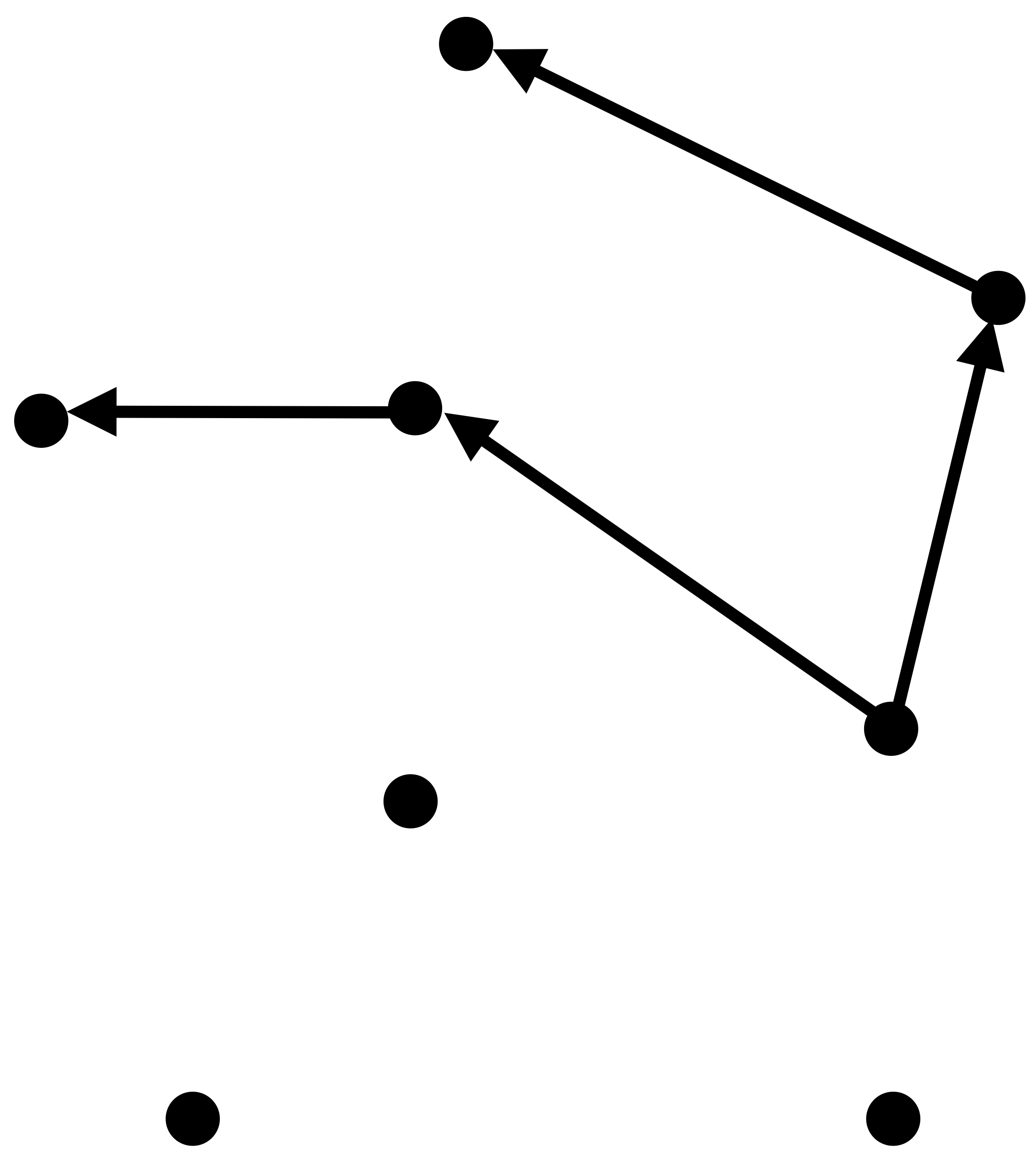

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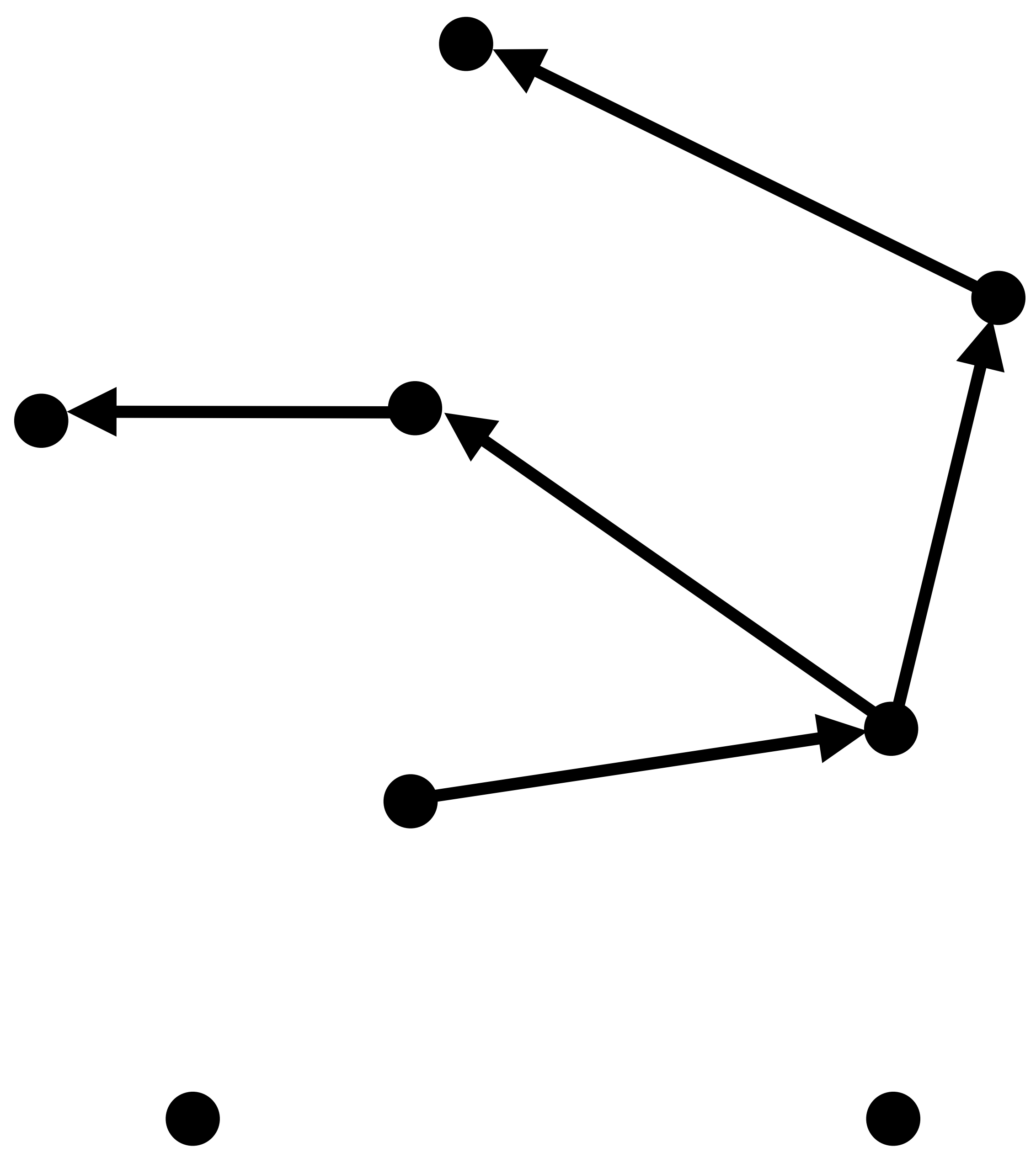

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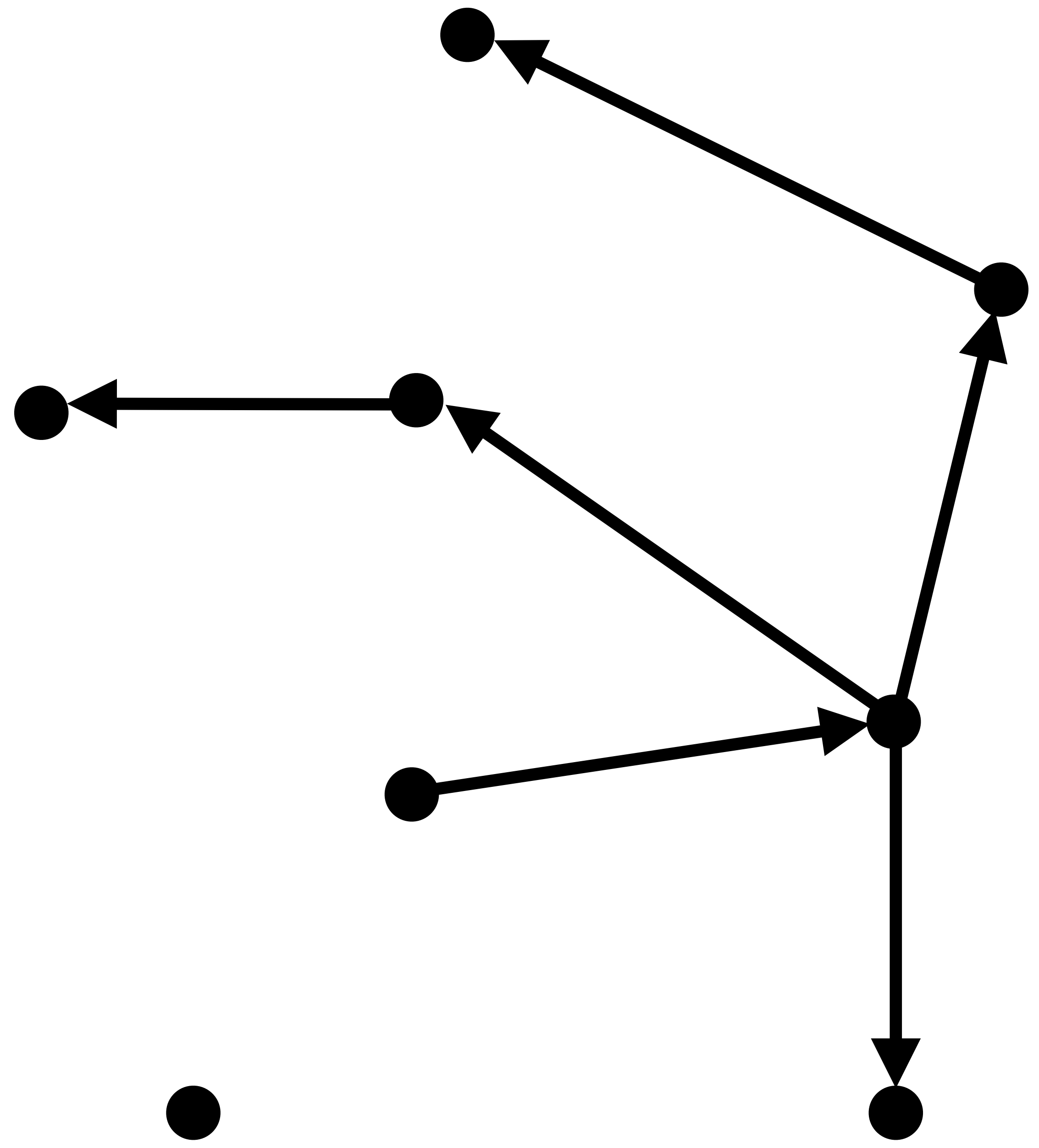

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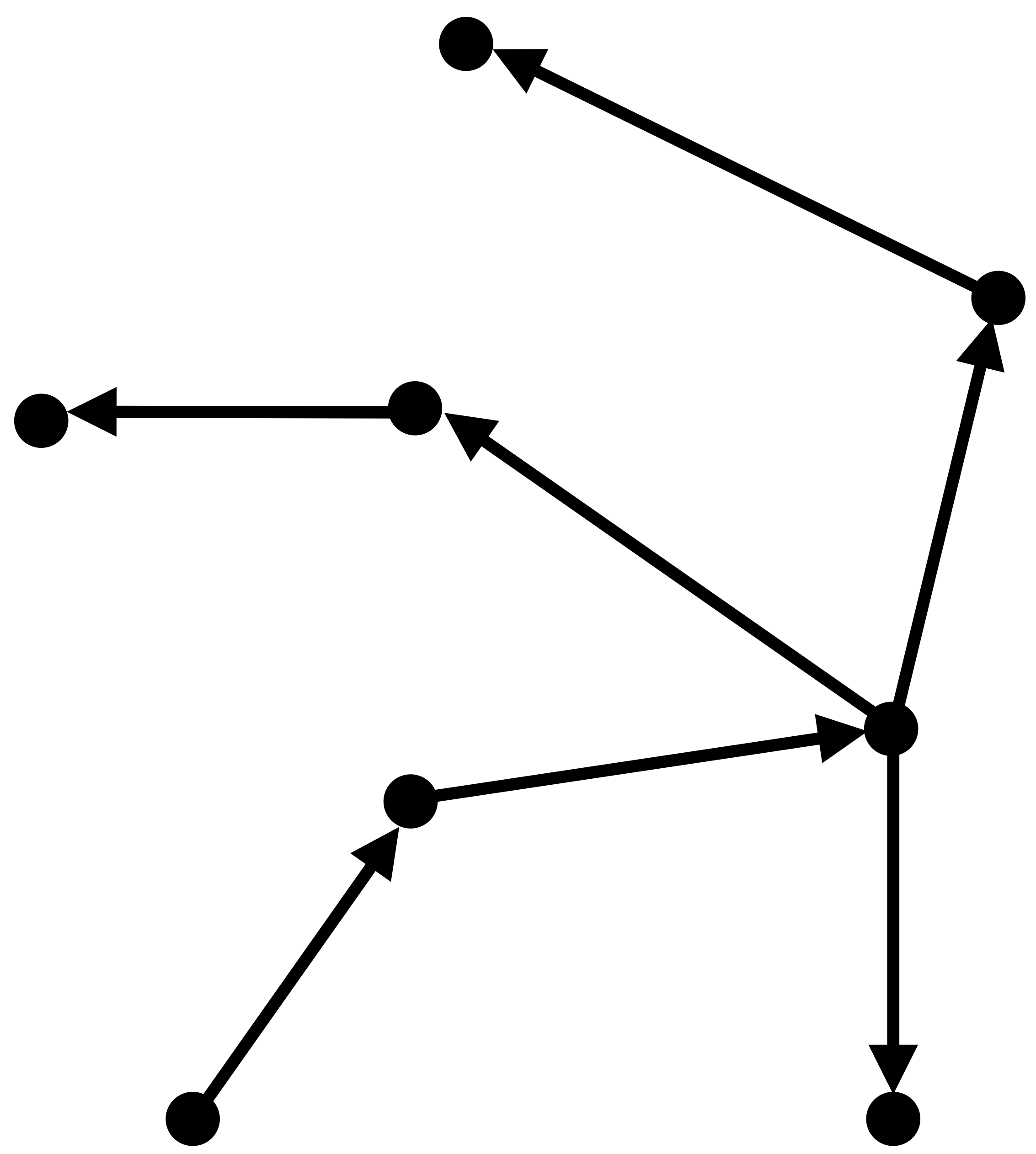

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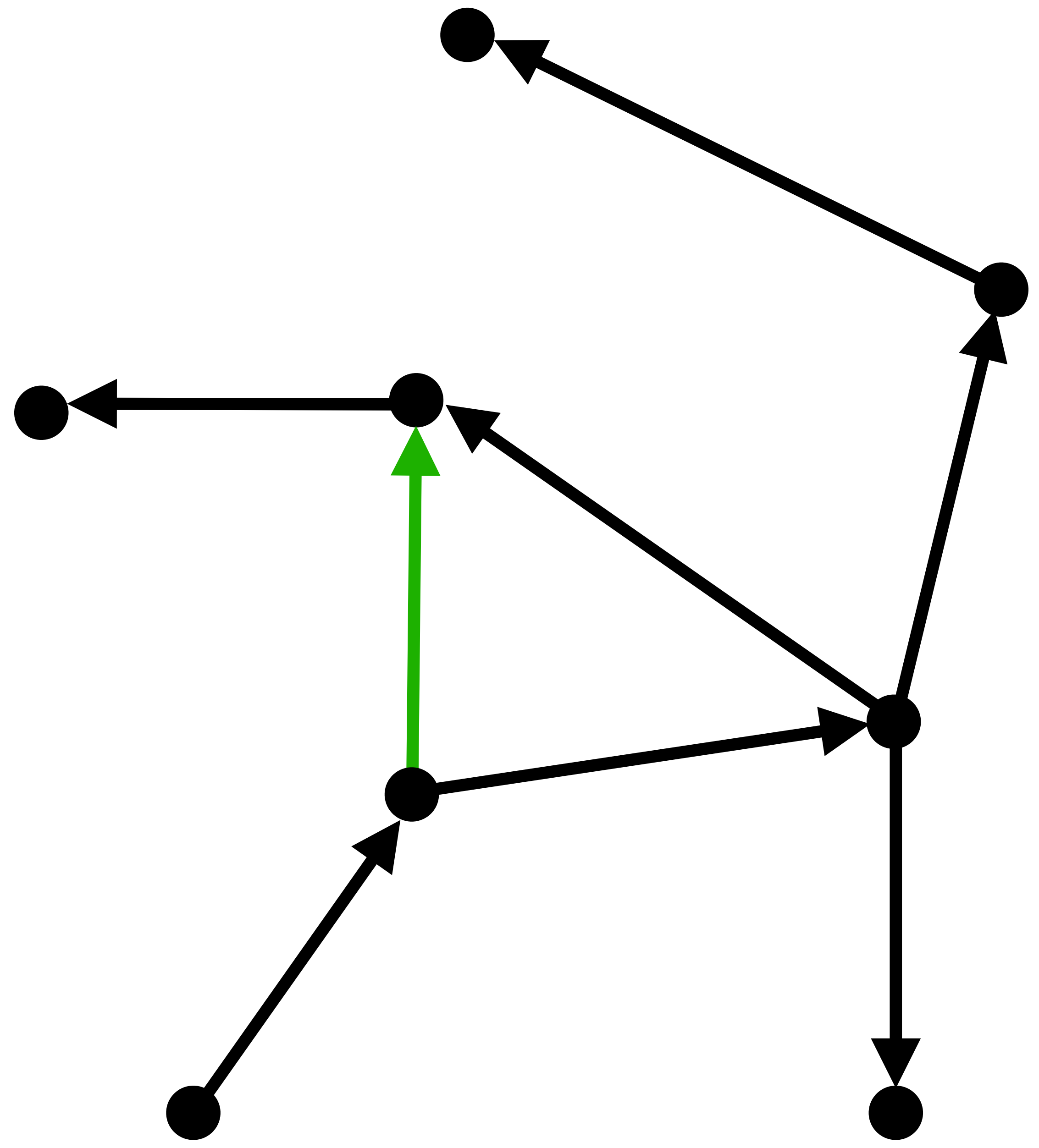

Our data
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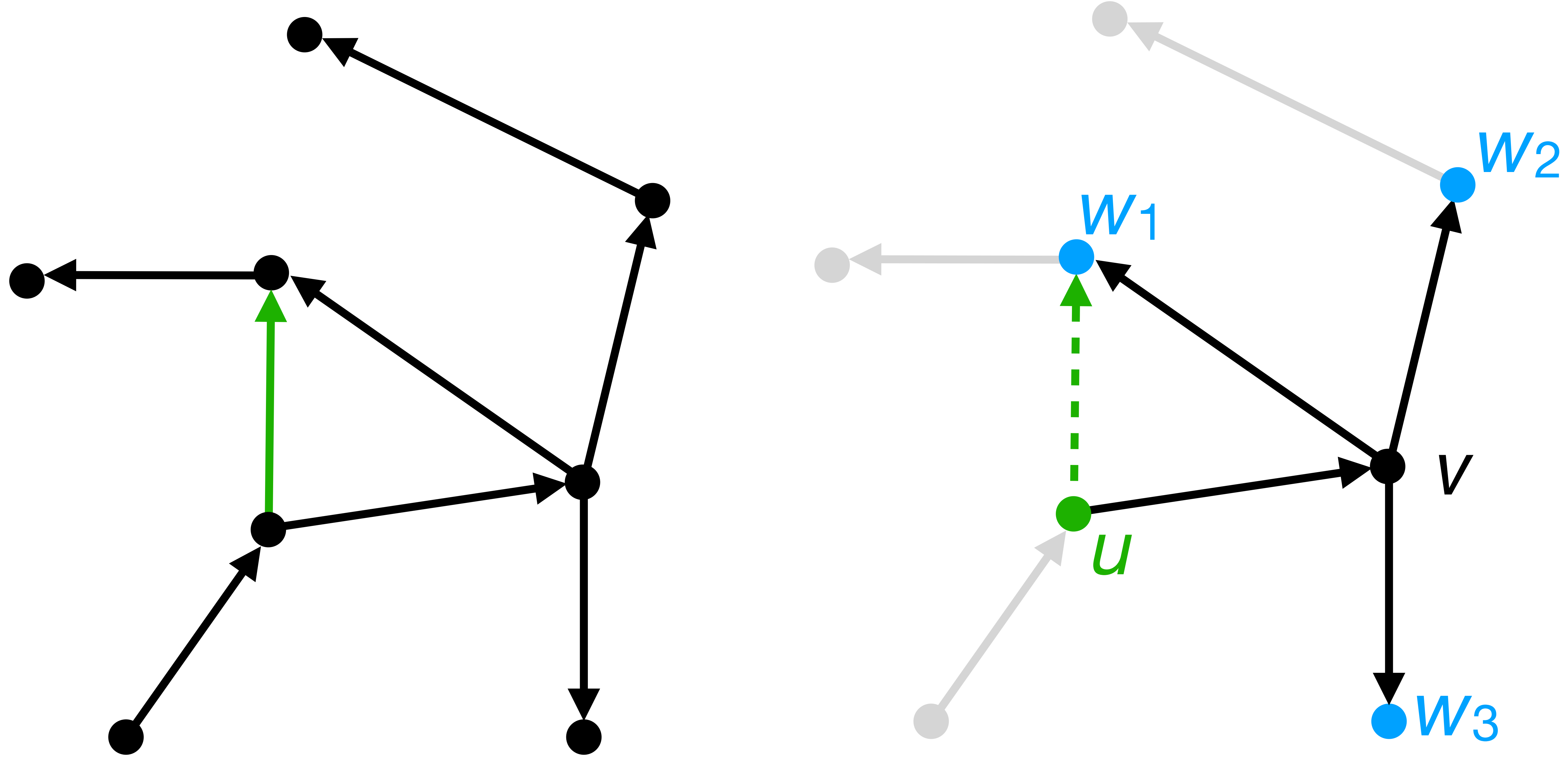

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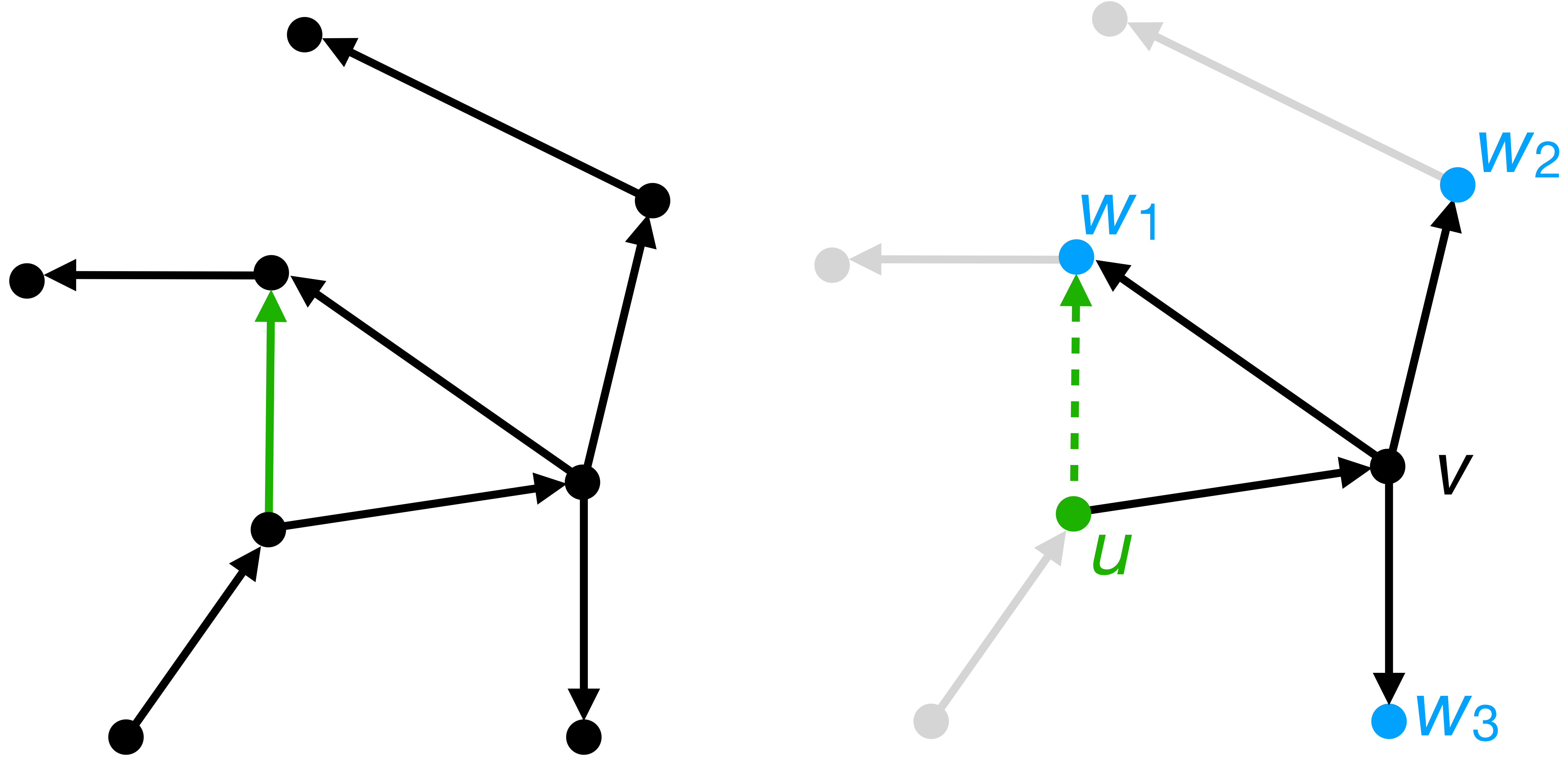
Timestamped edges
(including repeats)



chooser
u

Choosing to close triangles

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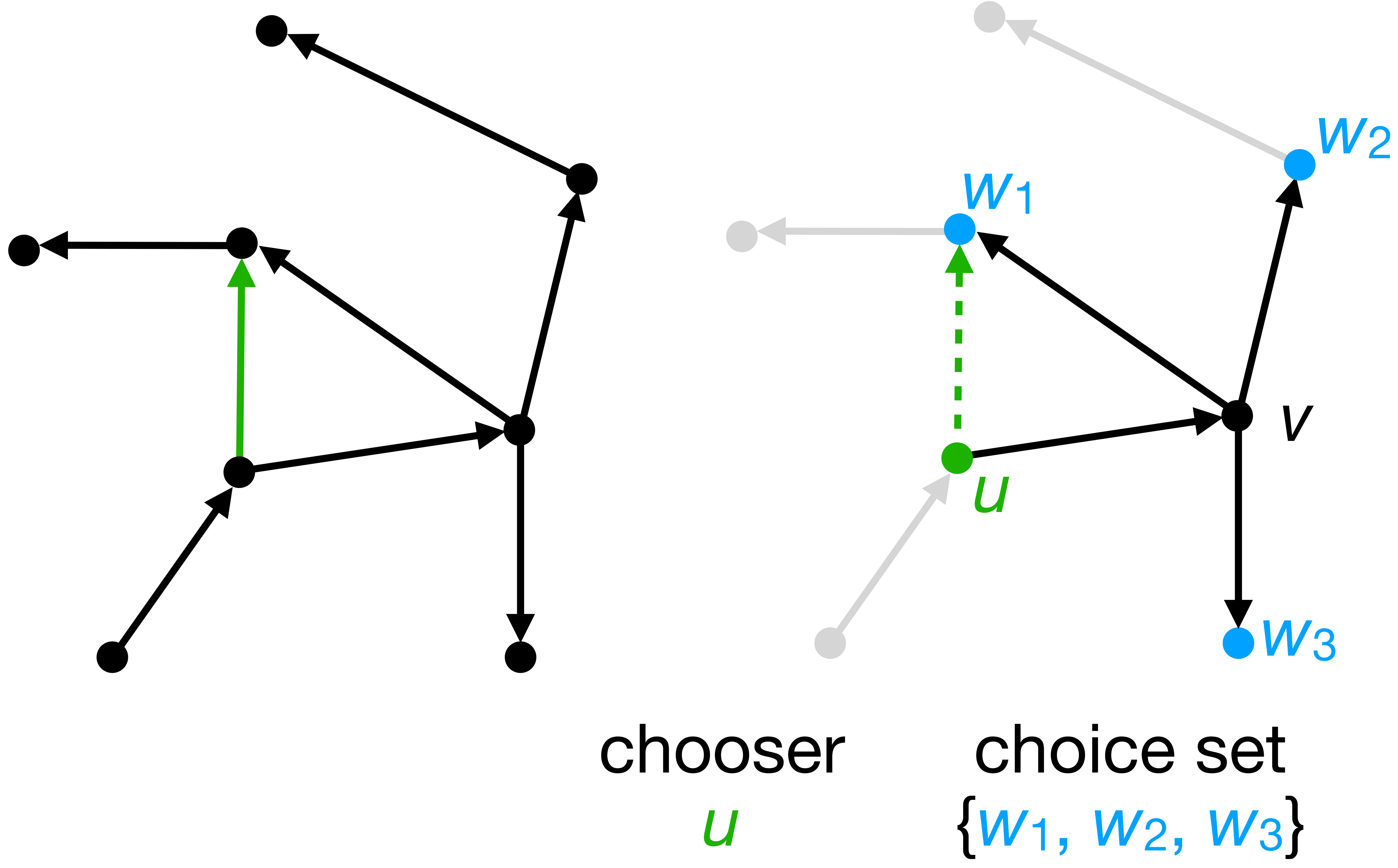
→ tractable inference
→ varied choice sets

Our data
Timestamped edges
(including repeats)



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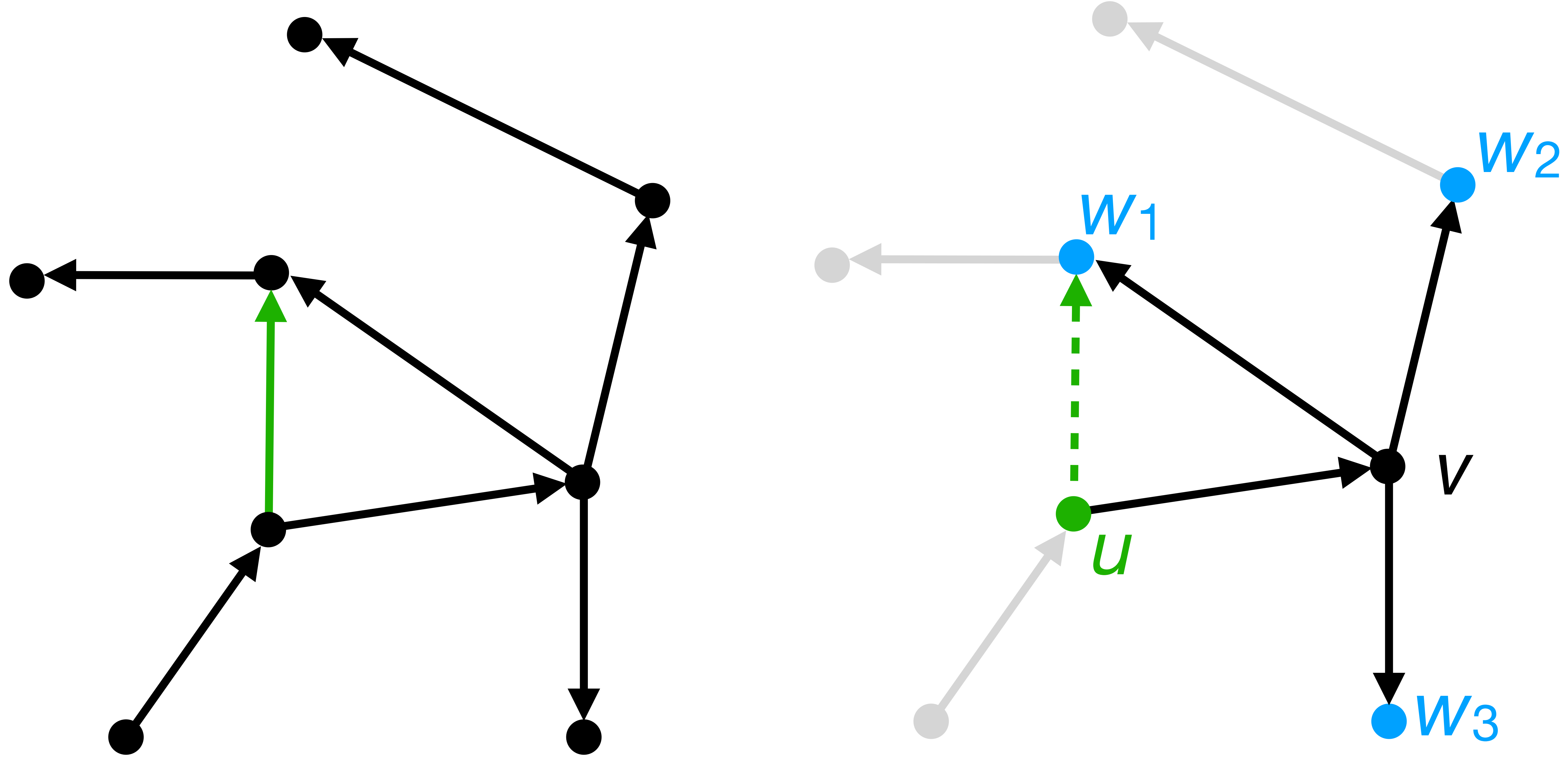

chooser	choice set	choice
u	$\{w_1, w_2, w_3\}$	w_1

Choosing to close triangles

Triadic closure offers small choice sets
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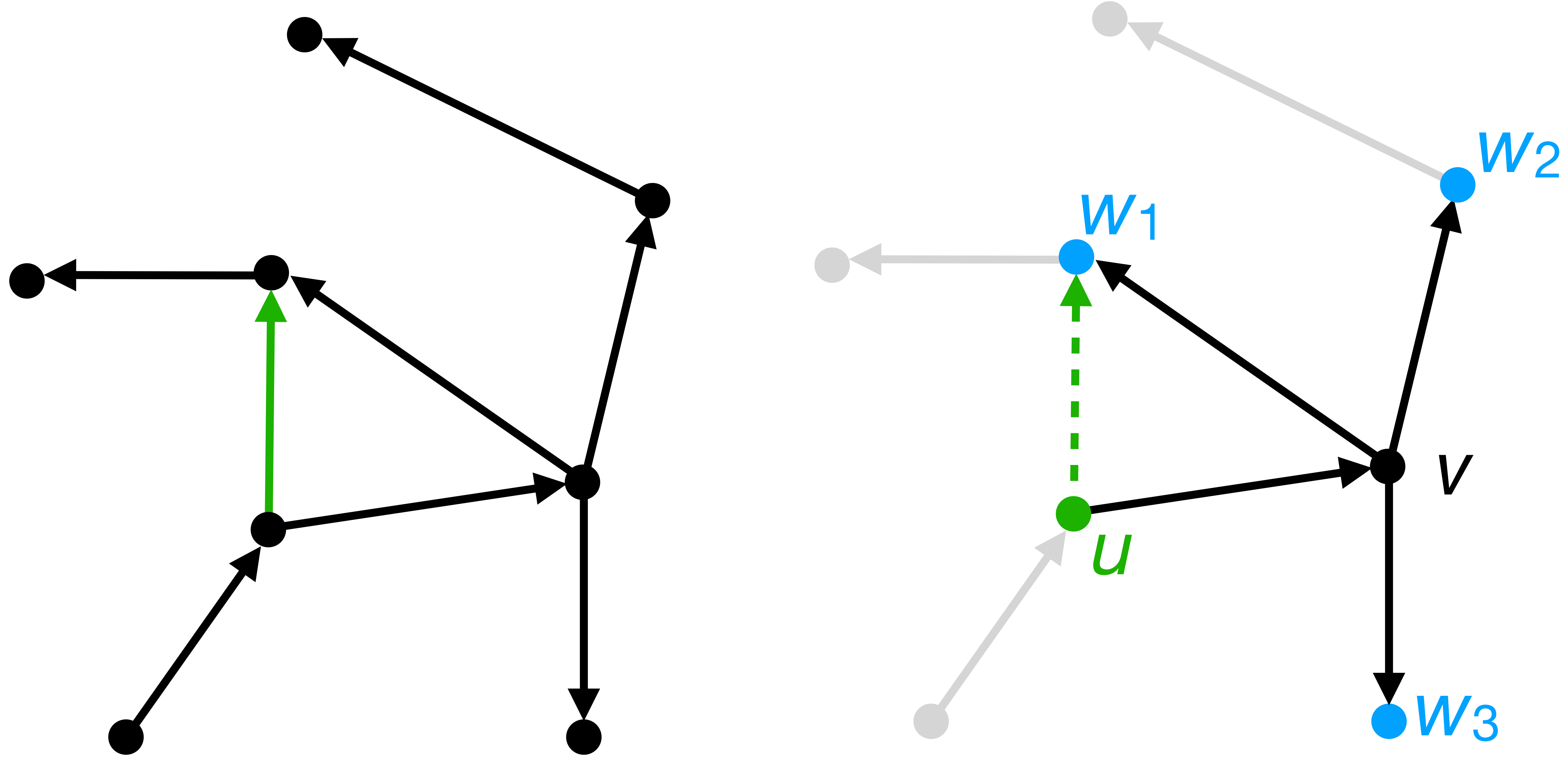
→ varied choice sets

Our data
Timestamped edges
(including repeats)



Node features

1. in-degree of w
2. # shared neighbors of u, w
3. weight of edge $w \to u$
4. time since last edge into w
5. time since last edge out of w
6. time since last $w \to u$ edge

chooser	choice set	choice
u	$\{w_1, w_2, w_3\}$	w_1

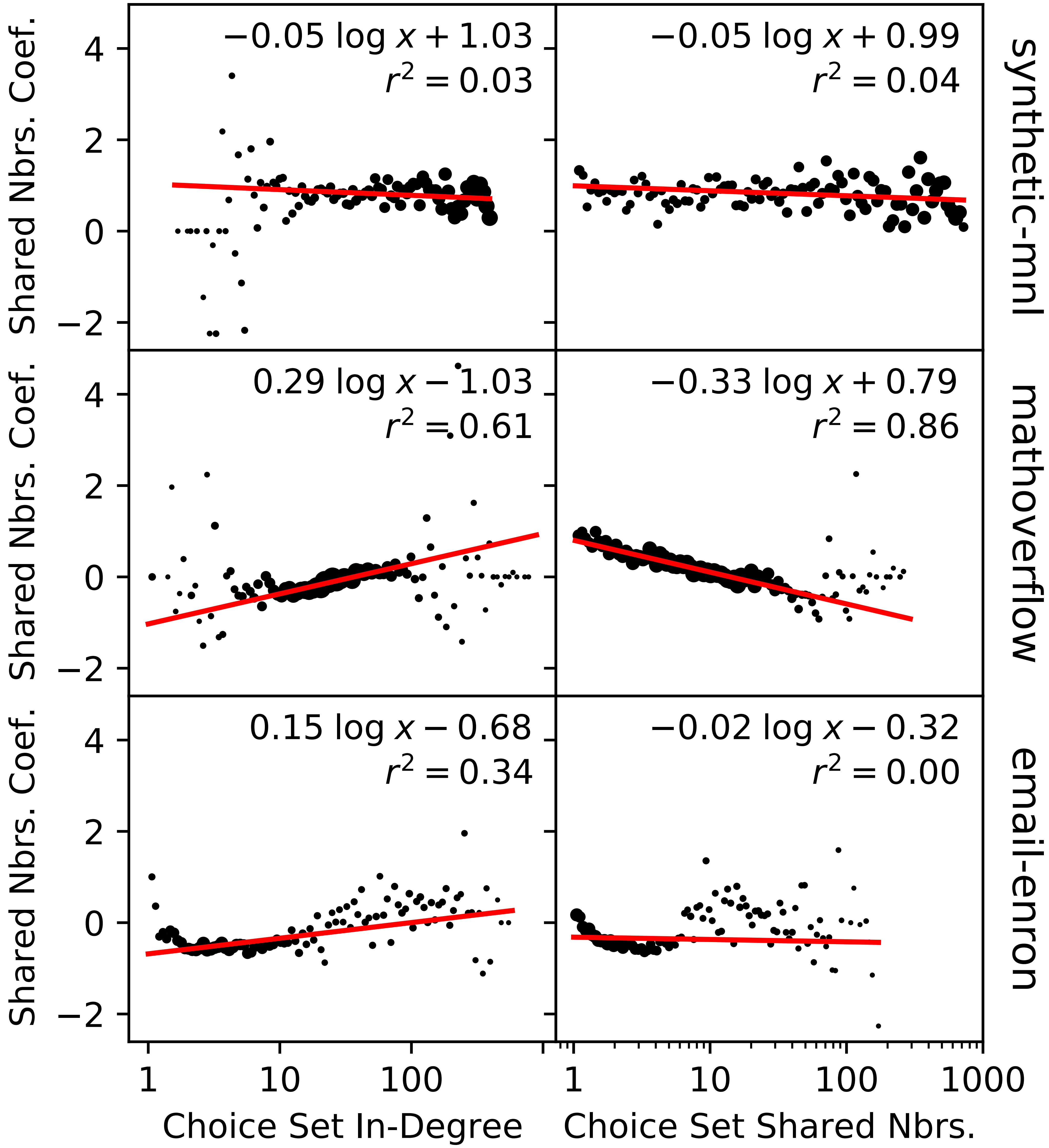
Context matters in triadic closure

Context matters in triadic closure

Datasets
email-enron
email-eu
email-w3c
wiki-talk
reddit-hyperlink
bitcoin-alpha
bitcoin-otc
mathoverflow
college-msg
facebook-wall
sms-a
sms-b
sms-c

bit.ly/lcl-data

Context matters in triadic closure



Datasets

email-enron
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wiki-talk
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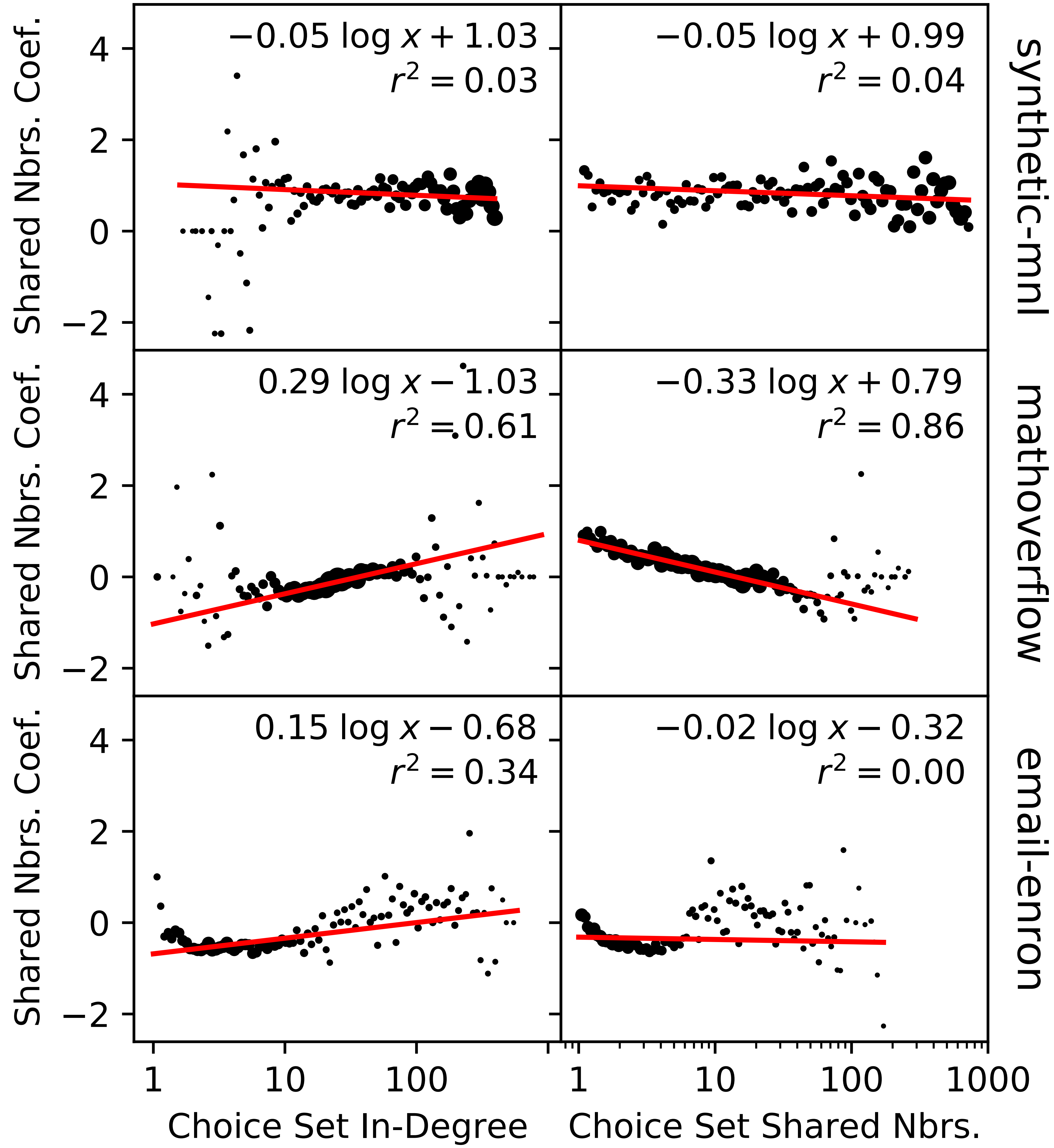

Synthetic data,
no context effects

Datasets
email-enron
email-eu
email-w3c
wiki-talk
reddit-hyperlink
bitcoin-alpha
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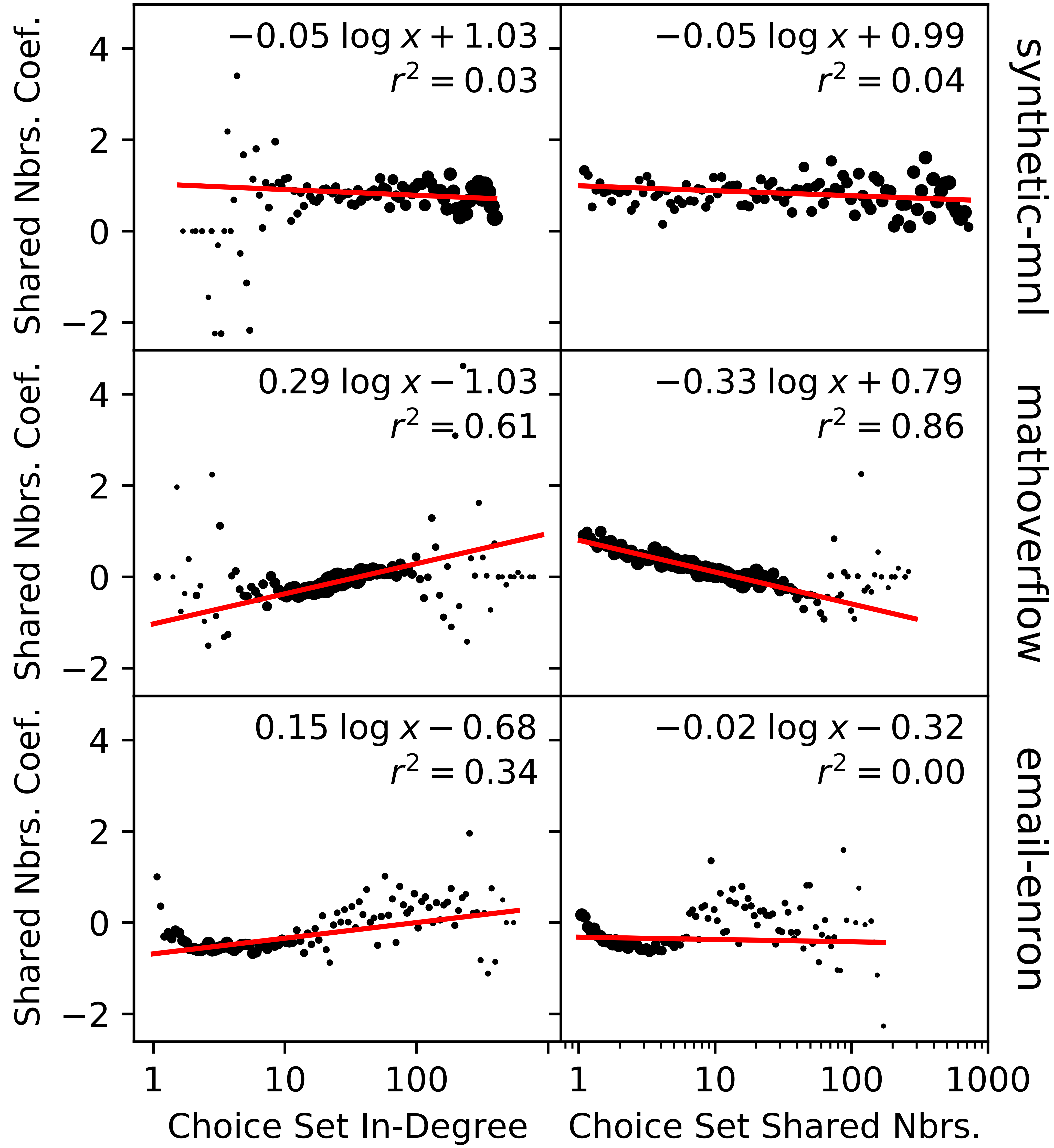

Synthetic data,
no context effects

Commenting network,
linear context effects

Datasets
email-enron
email-eu
email-w3c
wiki-talk
reddit-hyperlink
bitcoin-alpha
bitcoin-otc
mathoverflow
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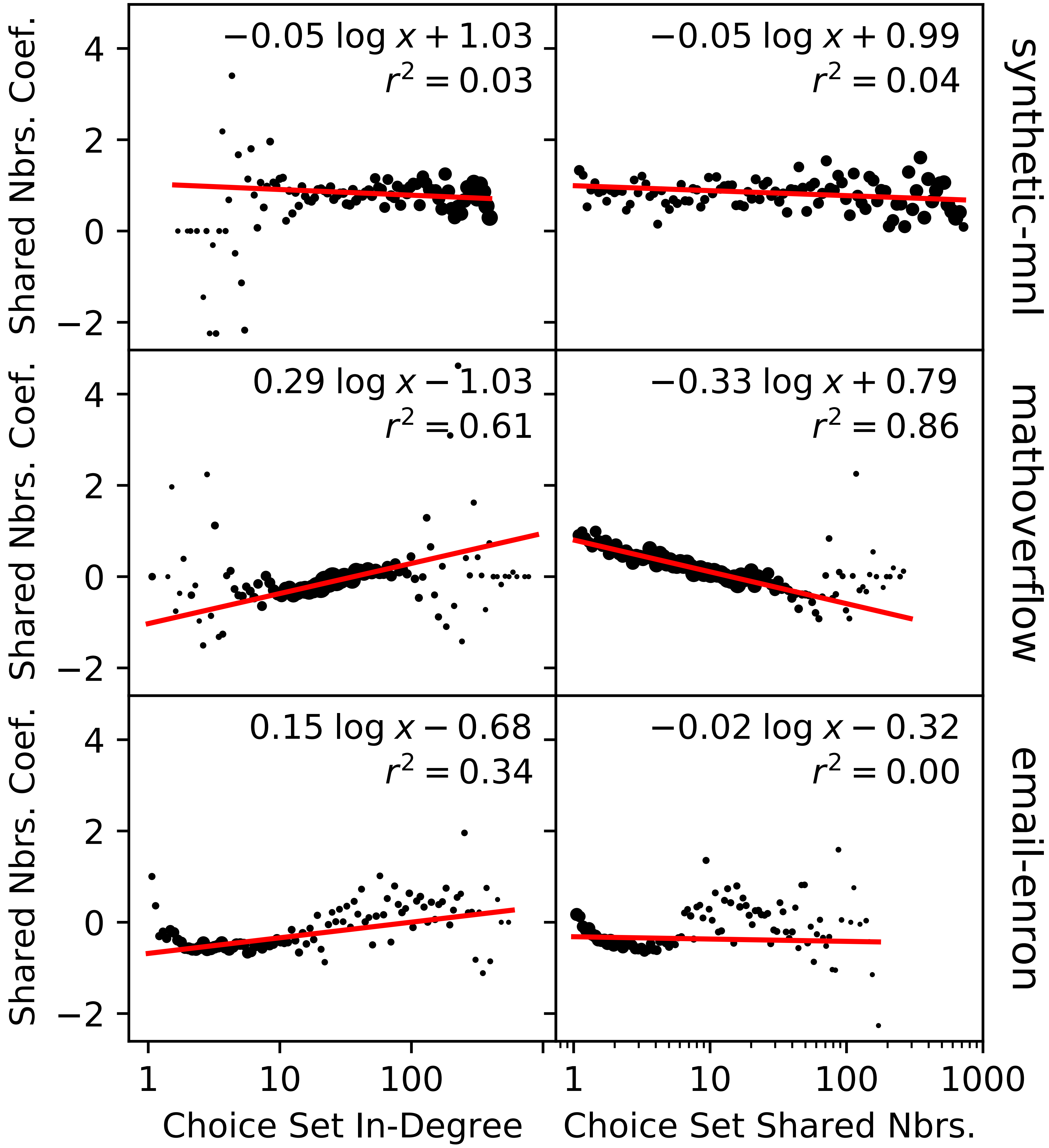
facebook-wall
sms-a
sms-b
sms-c

bit.ly/lcl-data

Context matters in triadic closure



Synthetic data,
no context effects

Commenting network,
linear context effects

Email network,
nonlinear context effects?

Datasets
email-enron
email-eu
email-w3c
wiki-talk
reddit-hyperlink
bitcoin-alpha
bitcoin-otc
mathoverflow
college-msg
facebook-wall
sms-a
sms-b
sms-c

bit.ly/lcl-data

LCL reveals interpretable context effects

LCL reveals interpretable context effects

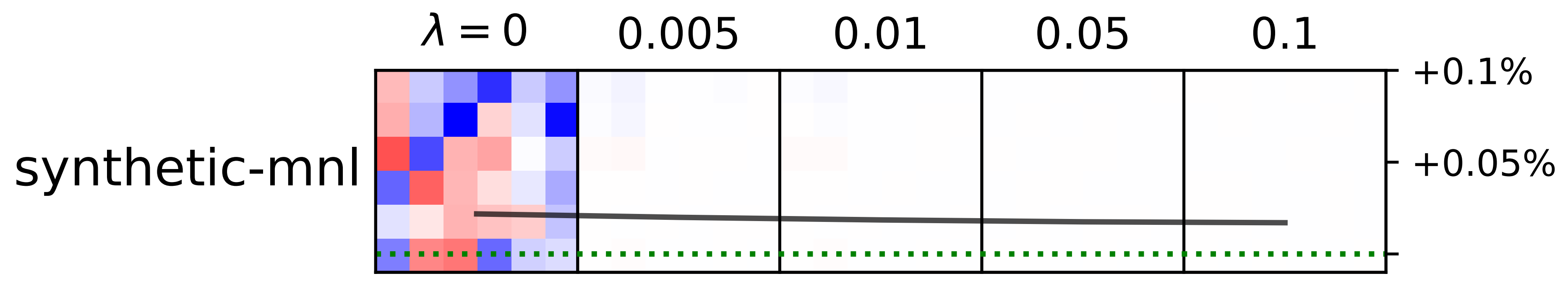
Estimation

MLE to infer LCL

$$\ell(\theta, A; \mathscr{D}) = \sum_{(i,C)\in\mathscr{D}} \left(\theta + Ax_C\right)^T x_i - \log \sum_{j\in C} \exp(\left[\theta + Ax_C\right]^T x_j)$$

(concave)

LCL reveals interpretable context effects



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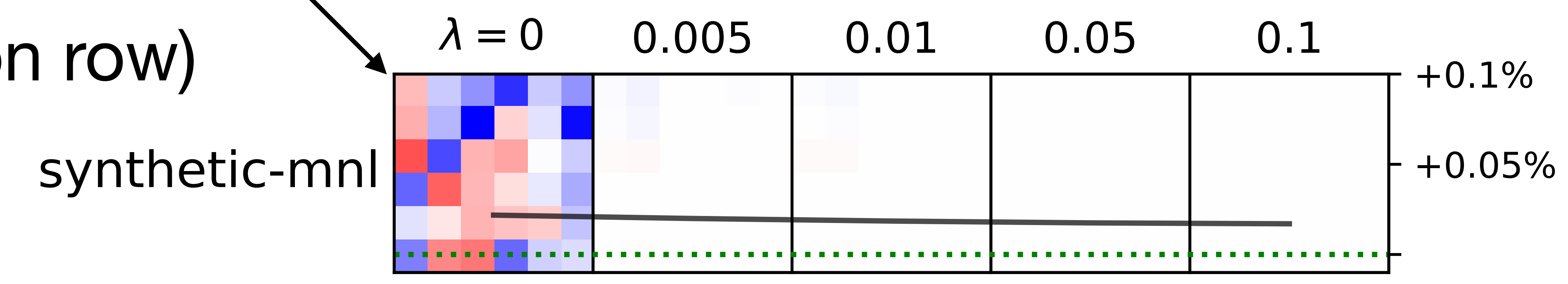
(concave)

LCL reveals interpretable context effects

context effect matrix A
red: +, blue: -, white: 0
(column acts on row)



Node features
(left-right, top-bottom)

1. in-degree
2. shared neighbors
3. reciprocal weight
4. send recency
5. receive recency
6. reciprocal recency

Estimation

MLE to infer LCL

$$\ell(\theta, A; \mathscr{D}) = \sum_{(i,C)\in\mathscr{D}} (\theta + A x_C)^T x_i - \log \sum_{j\in C} \exp([\theta + A x_C]^T x_j)$$

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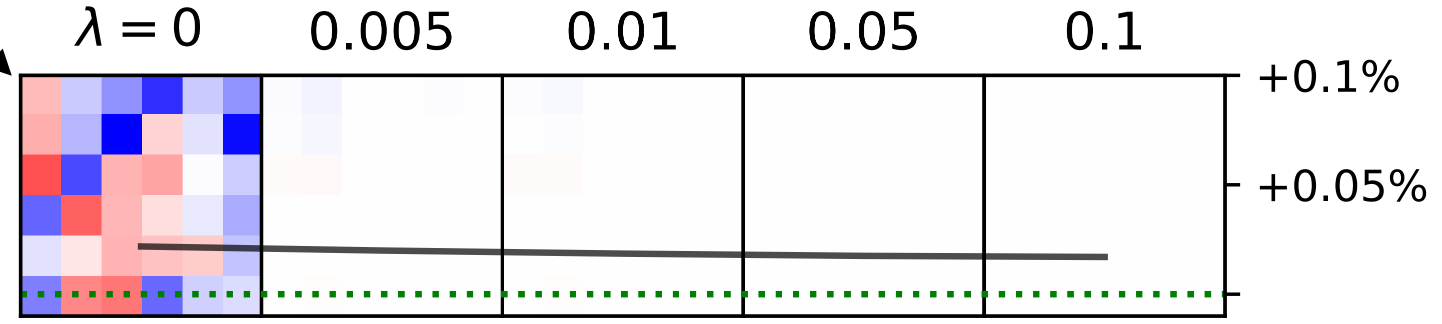
L_1 regularization level



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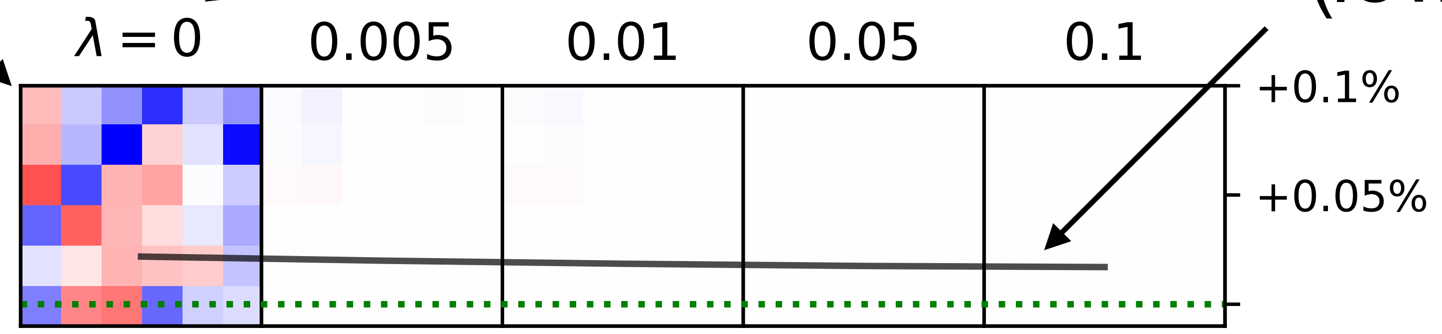
L_1 regularization level

LCL negative log-likelihood
(lower = better)

synthetic-mnl



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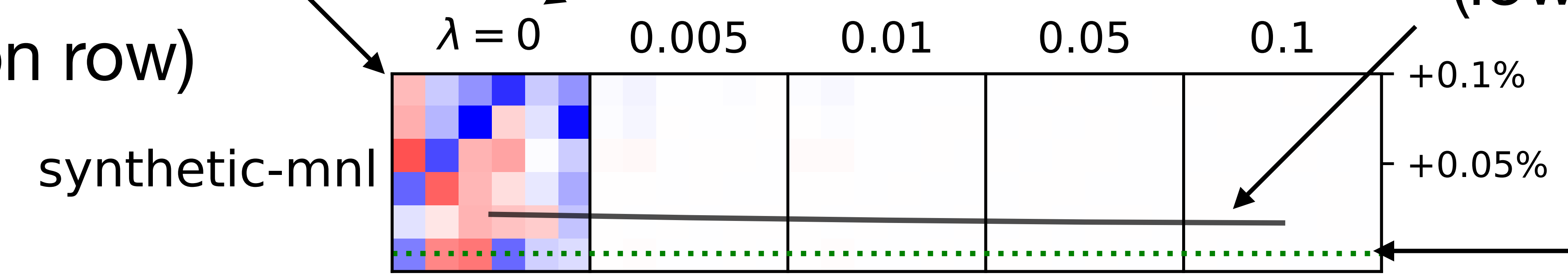

likelihood-ratio test vs MNL
significance threshold
($p < 0.001$)

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MLE to infer LCL

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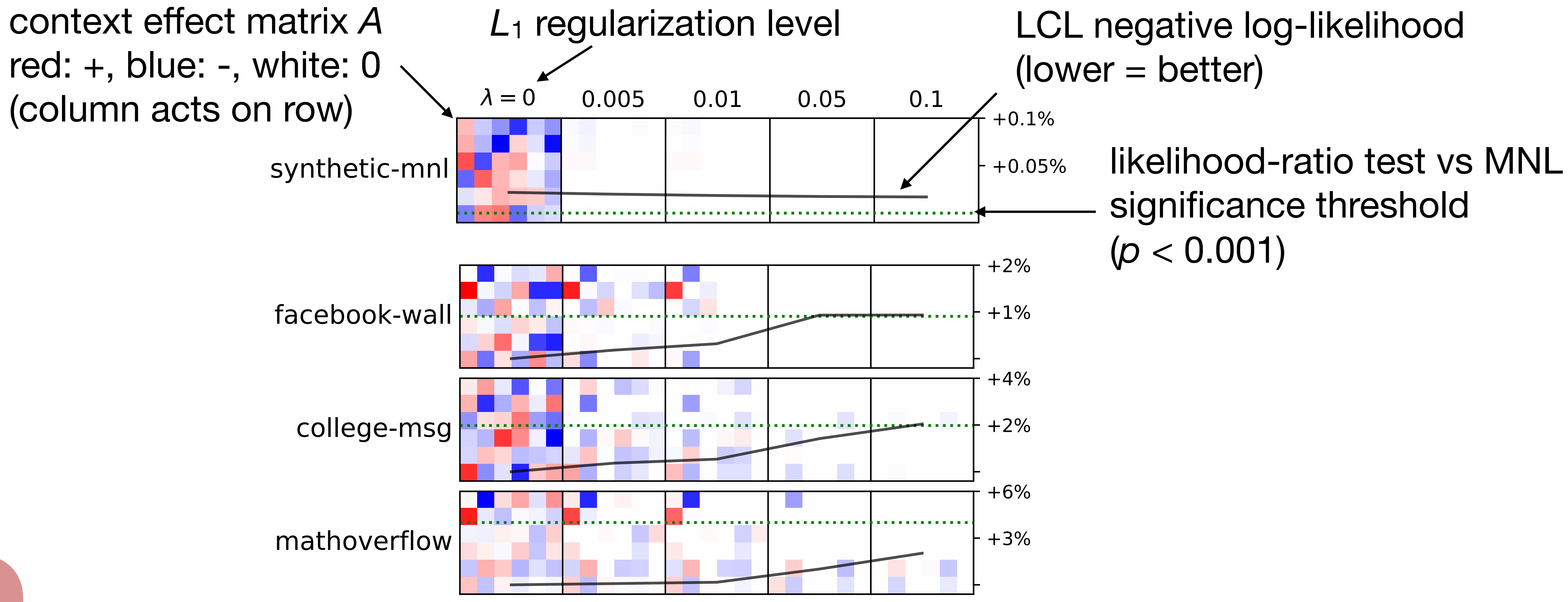

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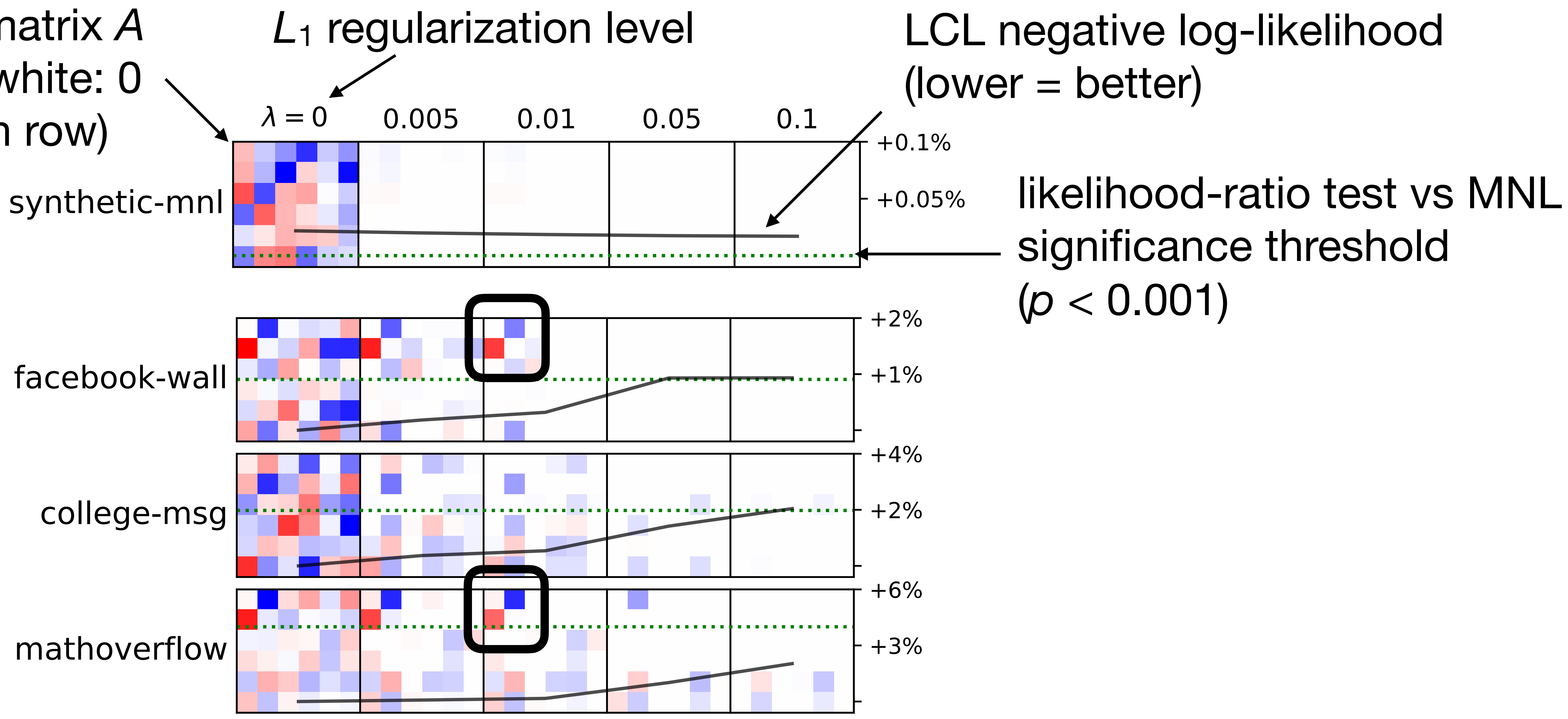

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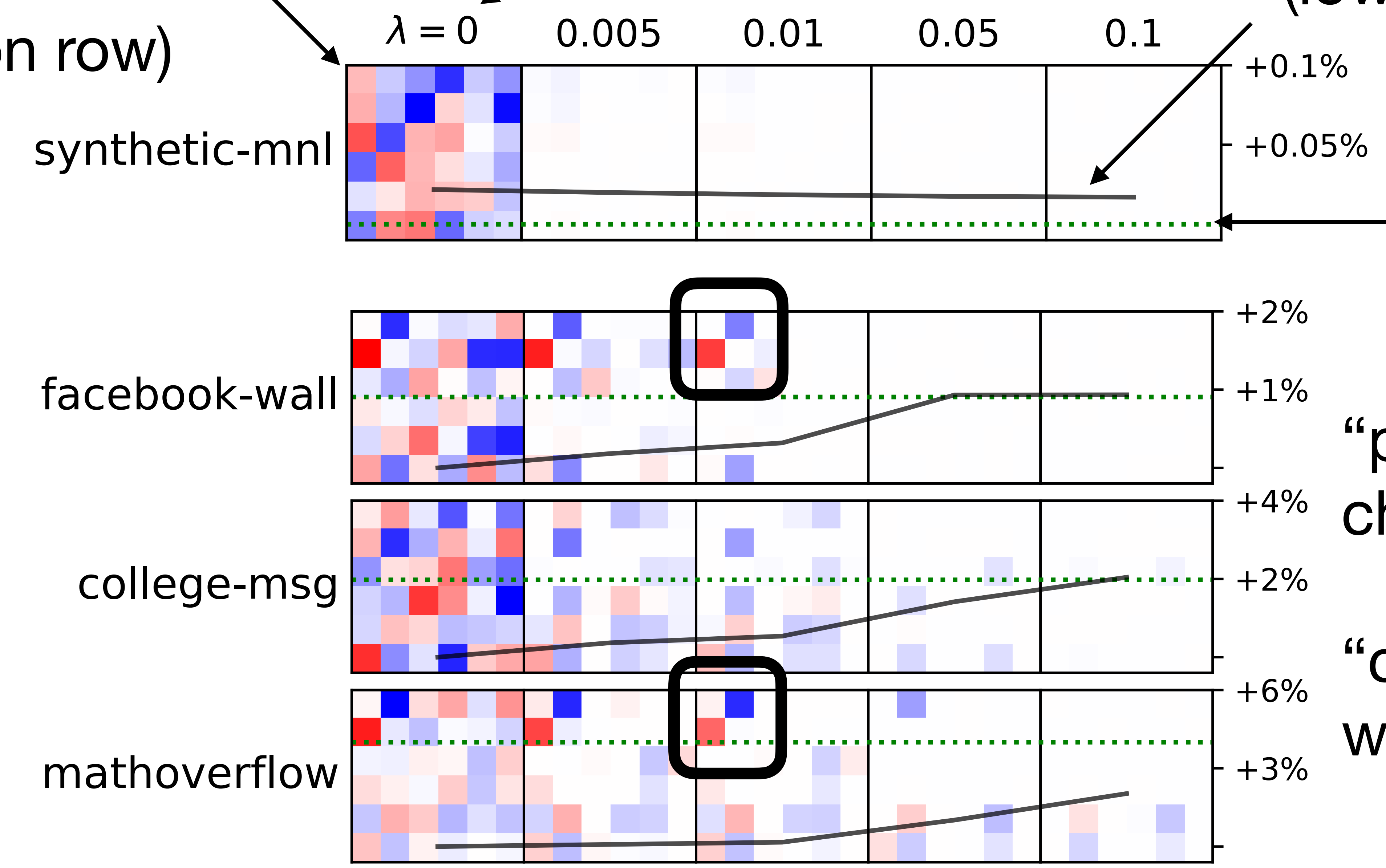

likelihood-ratio test vs MNL
significance threshold
($p < 0.001$)

“popularity matters less when choosing from close connections”

“close connections matter more when choosing from the popular”

LCL reveals interpretable context effects

Node features
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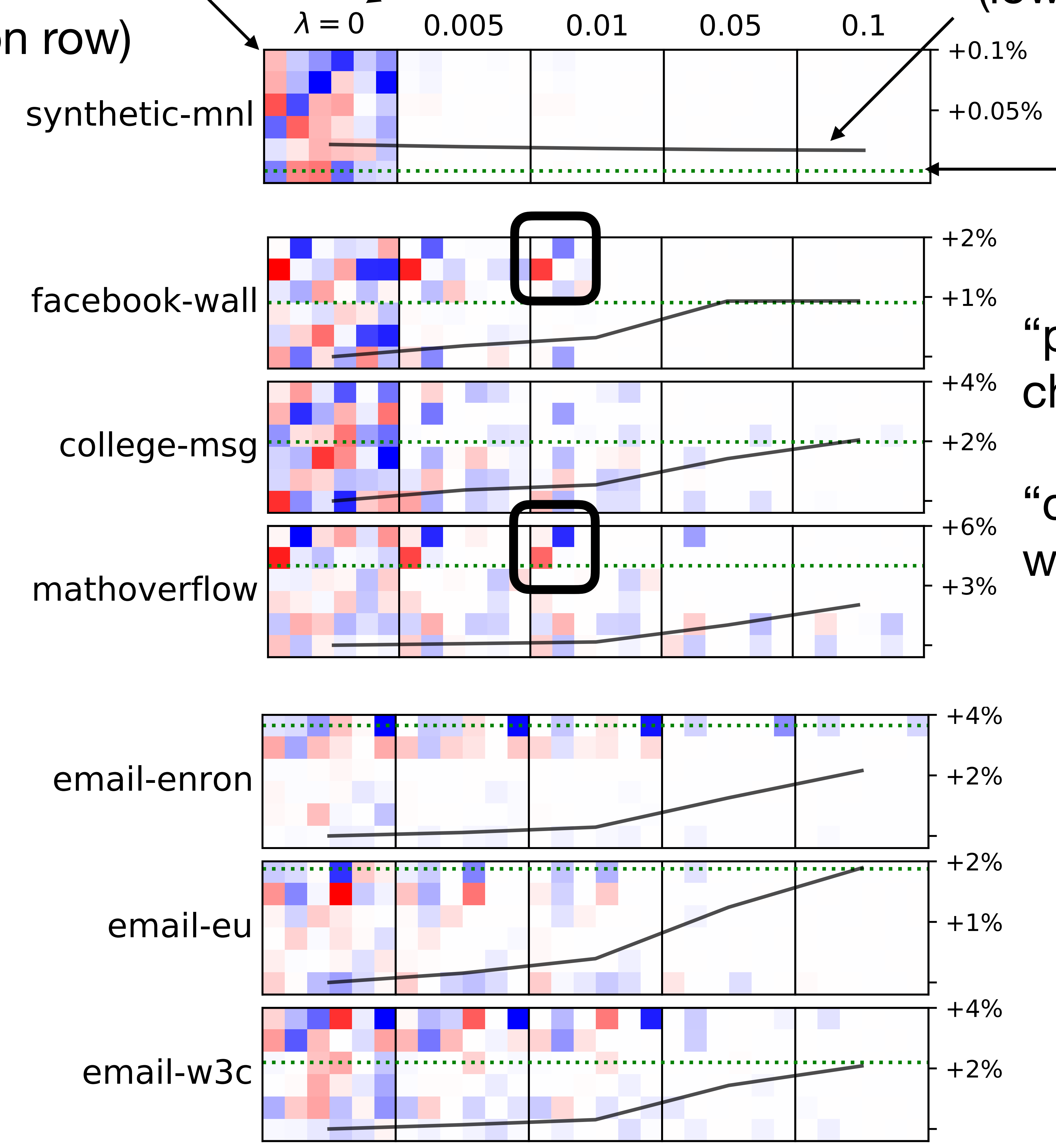

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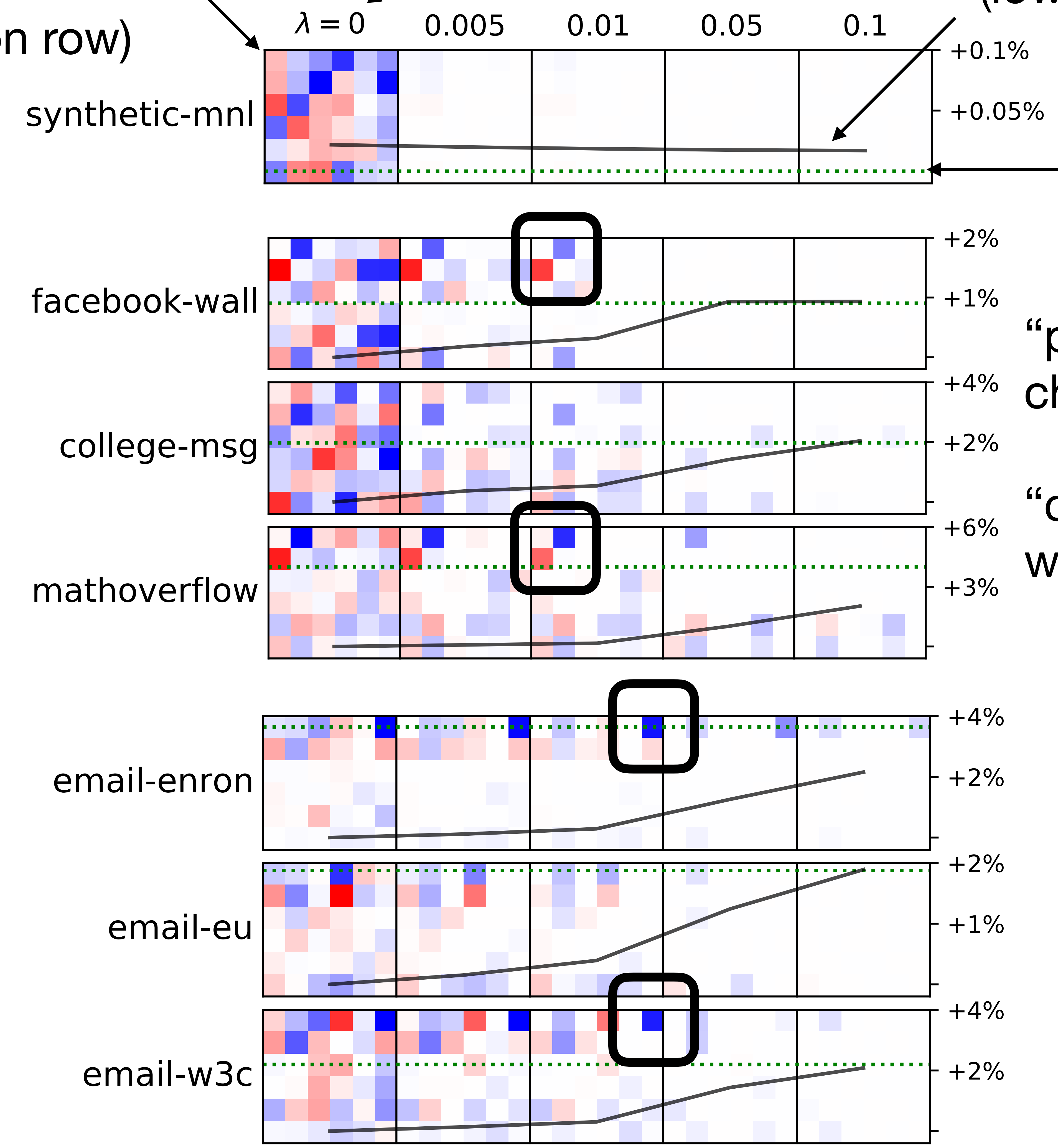

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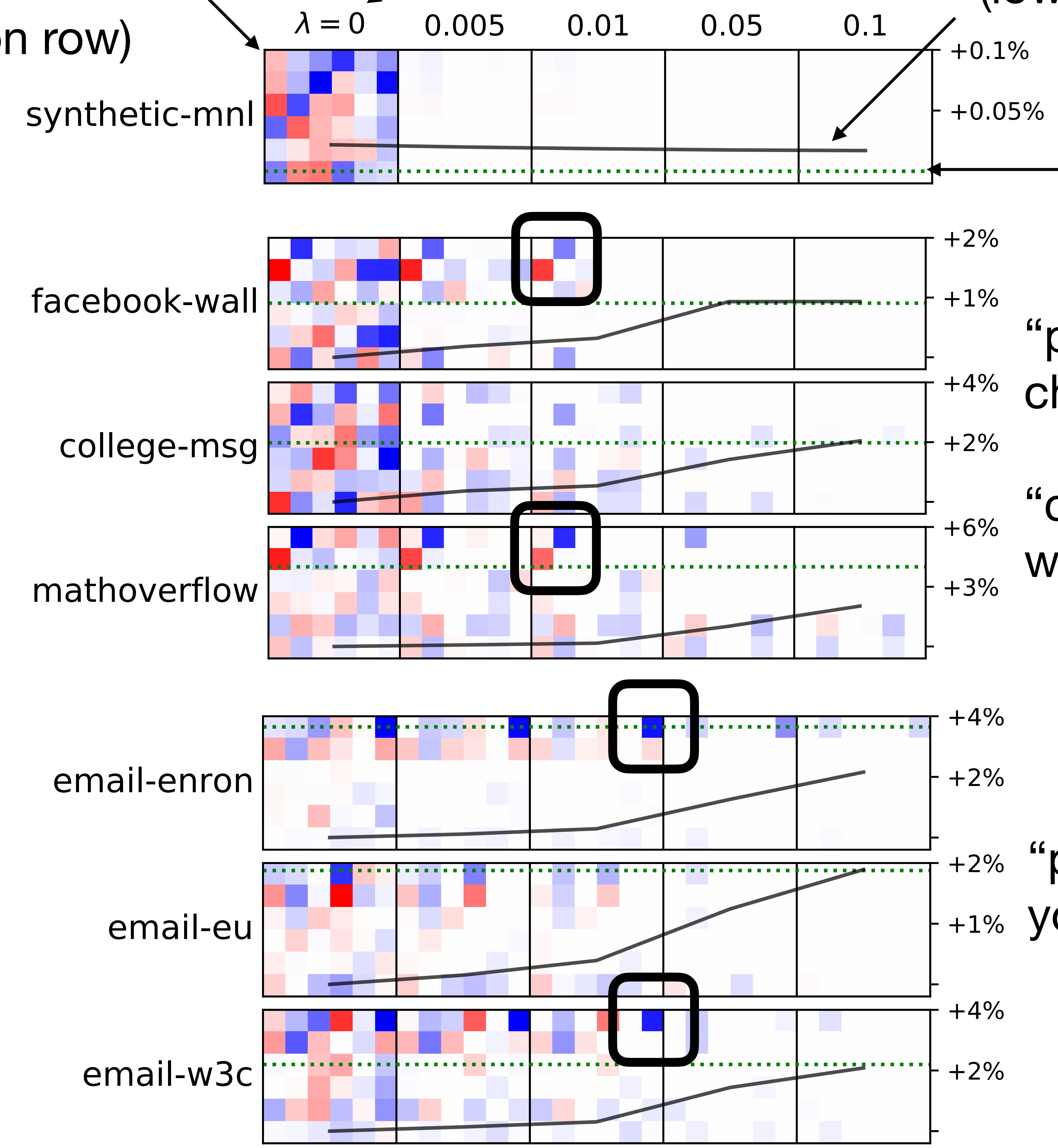

likelihood-ratio test vs MNL significance threshold ($p < 0.001$)

“popularity matters less when choosing from close connections”

“close connections matter more when choosing from the popular”

“popularity matters less when your inbox is full of recent emails”

Estimation

MLE to infer LCL

$$\ell(\theta, A; \mathscr{D}) = \sum_{(i,C)\in\mathscr{D}} (\theta + A x_C)^T x_i - \log \sum_{j\in C} \exp([\theta + A x_C]^T x_j)$$

(concave)

Other things in our paper

Kiran Tomlinson and Austin R. Benson
Learning Interpretable Feature Context Effects in Discrete Choice
arXiv: 2009.03417, September 2020
bit.ly/lcl-paper

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- LCL derivation from simple assumptions

Other things in our paper

$$\Pr(i, C) = \sum_{k=1}^{d} \pi_k \frac{\exp\left([B_k + A_k (x_C)_k]^T x_i\right)}{\sum_{j \in C} \exp\left([B_k + A_k (x_C)_k]^T x_j\right)}$$

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- LCL derivation from simple assumptions
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Theorem 1. A d-feature linear context logit is identifiable from a dataset $\mathcal{D}$ if and only if

$$\operatorname{span}\left\{\begin{bmatrix} x_C \\ 1 \end{bmatrix} \otimes (x_i - x_C) \mid C \in \mathcal{C}_\mathcal{D}, i \in C\right\} = \mathbb{R}^{d^2+d}. \qquad (6)$$

- LCL derivation from simple assumptions
- More flexible model: decomposed LCL
- LCL identifiability condition

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- LCL derivation from simple assumptions
- More flexible model: decomposed LCL
- LCL identifiability condition
- Application to general choice data

$$\Pr(i, C) = \sum_{k=1}^{d} \pi_k \frac{\exp\left([B_k + A_k(x_C)_k]^T x_i\right)}{\sum_{j \in C} \exp\left([B_k + A_k(x_C)_k]^T x_j\right)}$$

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Dataset
DISTRICT
DISTRICT-SMART
SUSHI
EXPEDIA
CAR-A
CAR-B
CAR-ALT

Other things in our paper

$$\Pr(i, C) = \sum_{k=1}^{d} \pi_k \frac{\exp\left([B_k + A_k(x_C)_k]^T x_i\right)}{\sum_{j \in C} \exp\left([B_k + A_k(x_C)_k]^T x_j\right)}$$

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- LCL derivation from simple assumptions
- More flexible model: decomposed LCL
- LCL identifiability condition
- Application to general choice data
- Accounting for context improves prediction

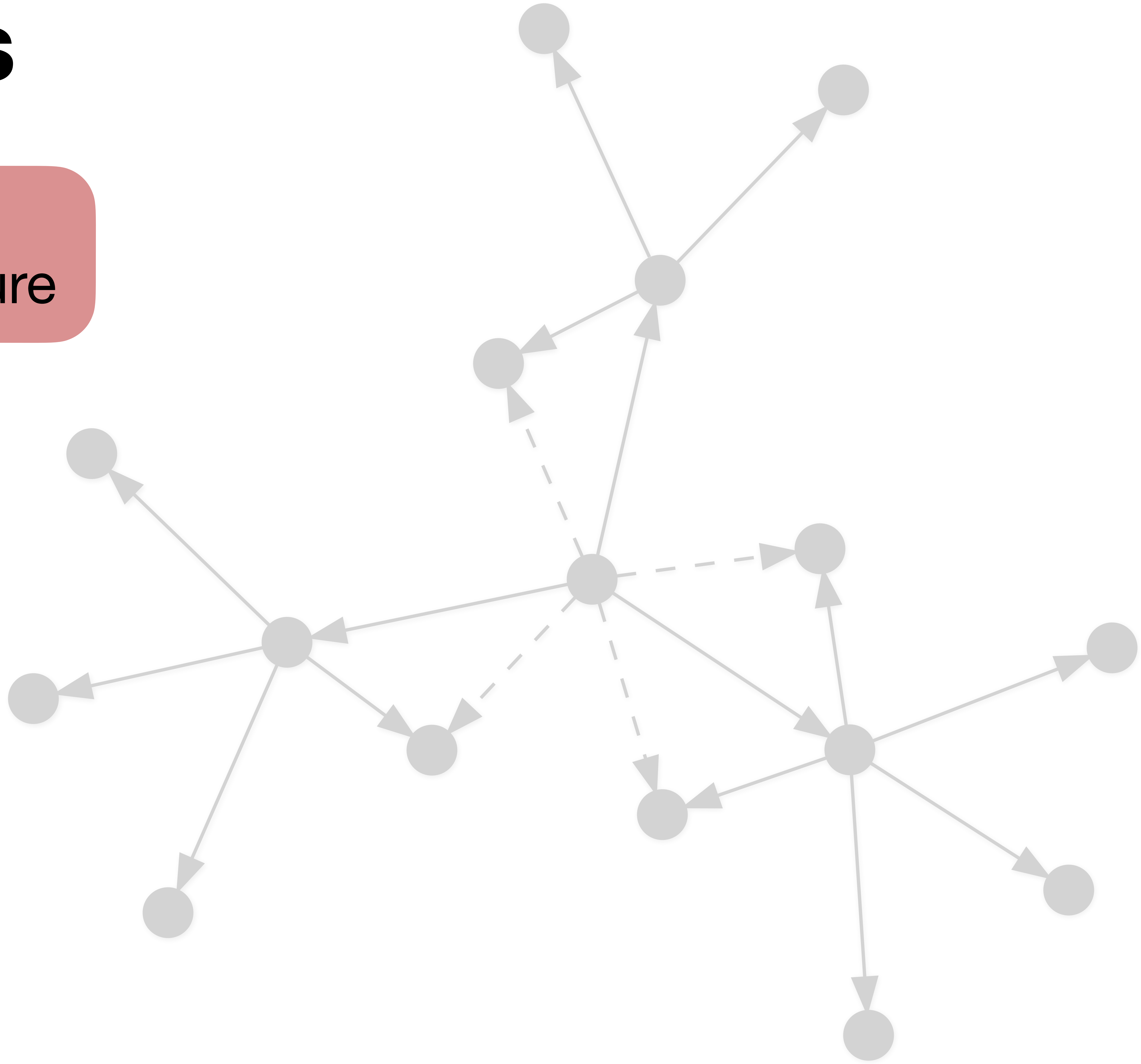
Dataset
DISTRICT
DISTRICT-SMART
SUSHI
EXPEDIA
CAR-A
CAR-B
CAR-ALT

	MNL	**LCL**
DISTRICT	.3680 (.4823)	.3327 (.4712)
DISTRICT-SMART	.4006 (.4900)	.3894 (.4876)
EXPEDIA	.3859 (.2954)	.3696* (.2926)
SUSHI	.2727 (.2751)	.2741 (.2771)
CAR-A	.3570 (.4791)	**.3514** (.4774)
CAR-B	.3326 (.4711)	.3326 (.4711)
CAR-ALT	.2944 (.2875)	**.2650*** (.2804)
SYNTHETIC-MNL	.1513 (.1865)	**.1512** (.1864)
SYNTHETIC-LCL	.1360 (.1684)	**.1357*** (.1683)
WIKI-TALK	.2946 (.2916)	**.2666*** (.2773)
REDDIT-HYPERLINK	.2859 (.2611)	.2761* (.2606)
BITCOIN-ALPHA	.2724 (.3246)	.2591* (.3178)
BITCOIN-OTC	.1891 (.2756)	.1529* (.2468)
SMS-A	.2825 (.3250)	**.2661*** (.3193)
SMS-B	.3045 (.3419)	**.2848*** (.3273)
SMS-C	.3115 (.3455)	**.3070** (.3477)
EMAIL-ENRON	.1265 (.2068)	.1244* (.2115)
EMAIL-EU	.2683 (.3021)	.2665 (.3037)
EMAIL-W3C	.1332 (.2070)	.1210* (.1845)
FACEBOOK-WALL	.2176 (.2895)	.2109* (.2871)
COLLEGE-MSG	.1850 (.2726)	**.1723*** (.2655)
MATHOVERFLOW	.1385 (.2503)	.1153* (.2200)

Concluding thoughts

Key takeaway
Context effects matter in triadic closure

Challenges
Features correlate
Causal context effects?
Handling nonlinearity?
Global edge formation modes?
Missing timestamps?



Concluding thoughts

Slides: bit.ly/lcl-slides
Preprint: bit.ly/lcl-paper
Code: bit.ly/lcl-code
Data: bit.ly/lcl-data

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Missing timestamps?

Thank you!

More questions or ideas?
Email me: kt@cs.cornell.edu

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