Clash of the Contagions: Cooperation and Competition in Information Diffusion

Seth Myers
Jure Leskovec

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- Users are constantly exposed to new pieces of information by their neighbors
- Most models assume different pieces of information spread from user to user independently
- But can one piece of information promote or suppress the spread of another piece of information?

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- Upon exposure to a contagion, a user will adopt the contagion with certain probability.

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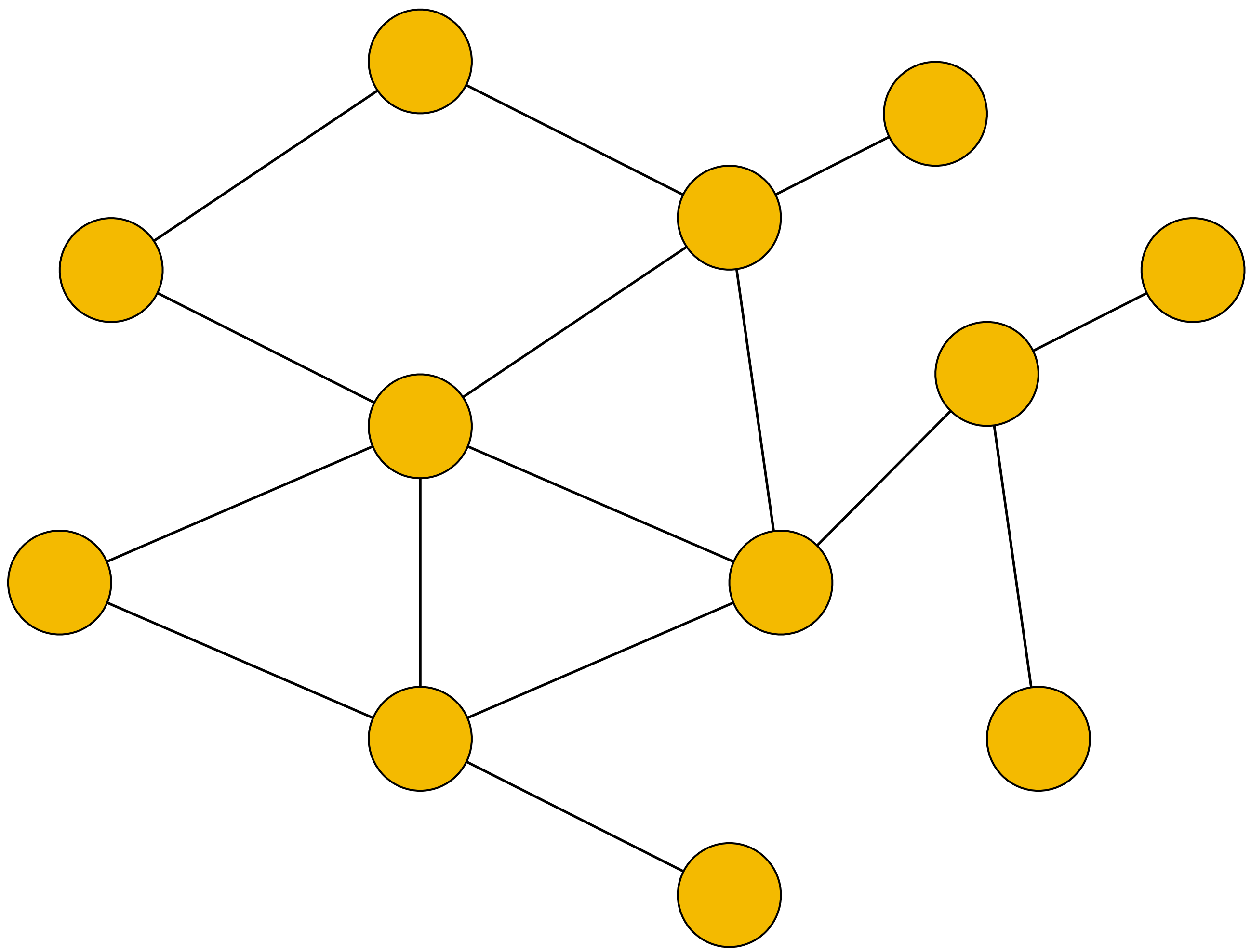

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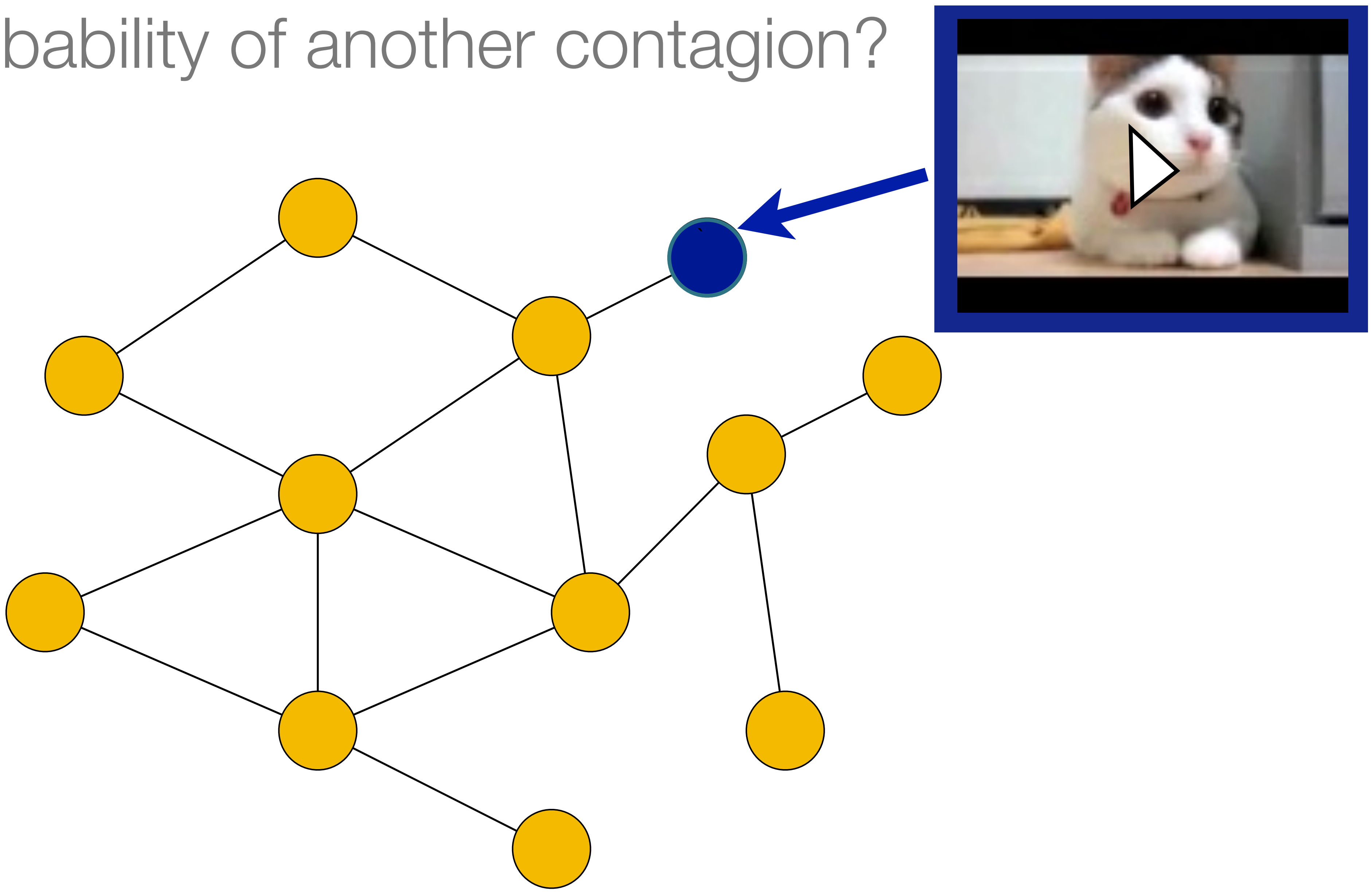

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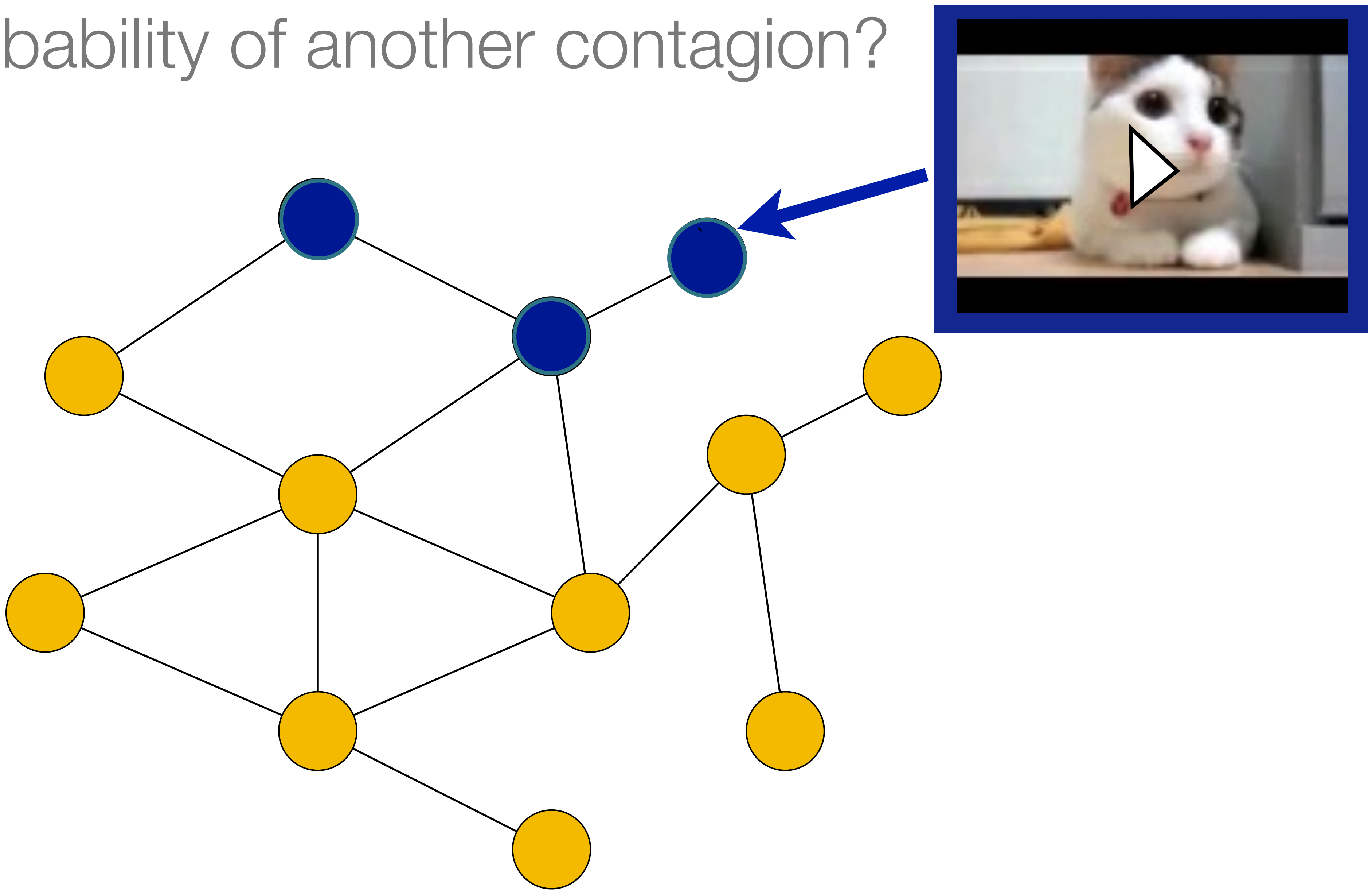

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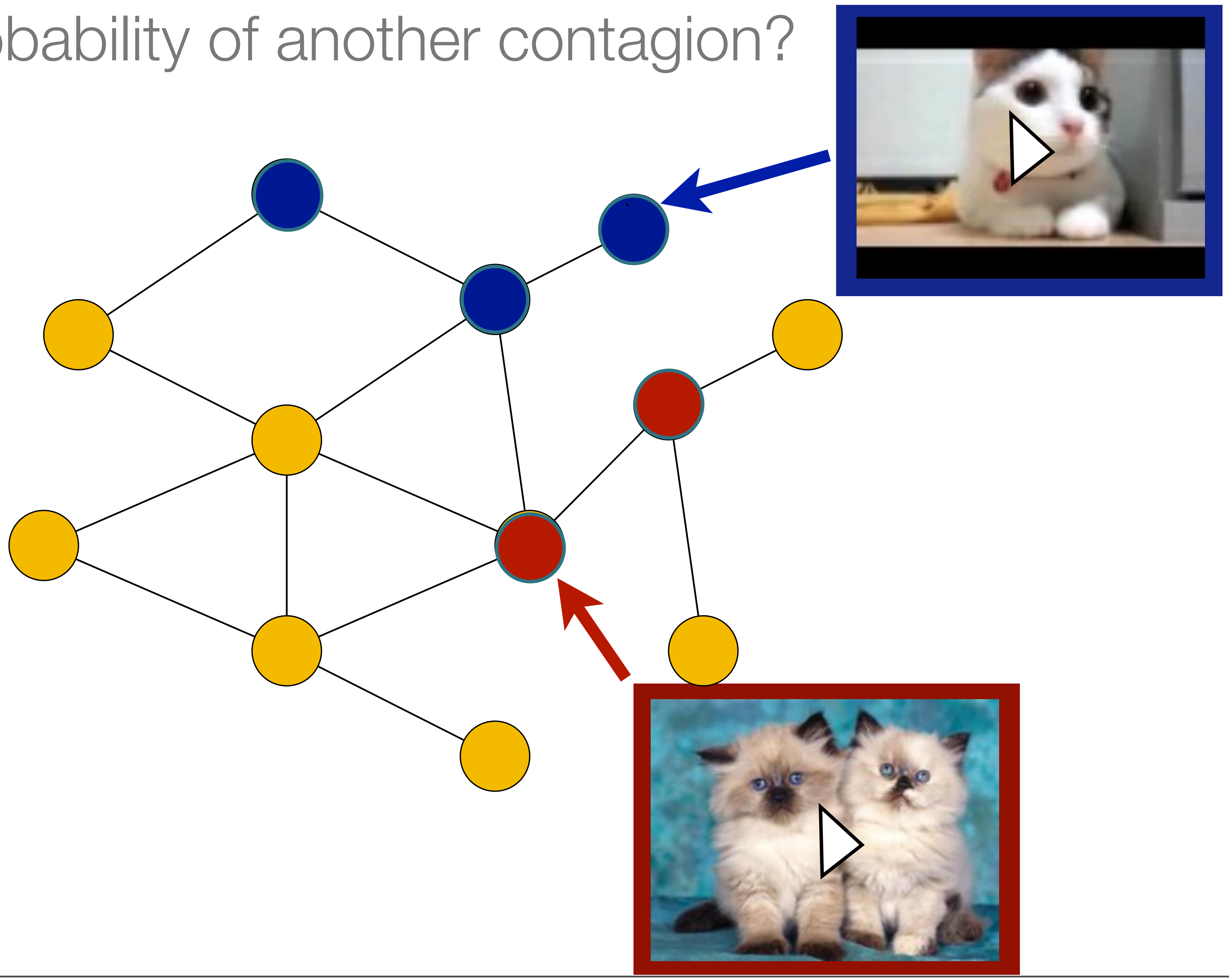

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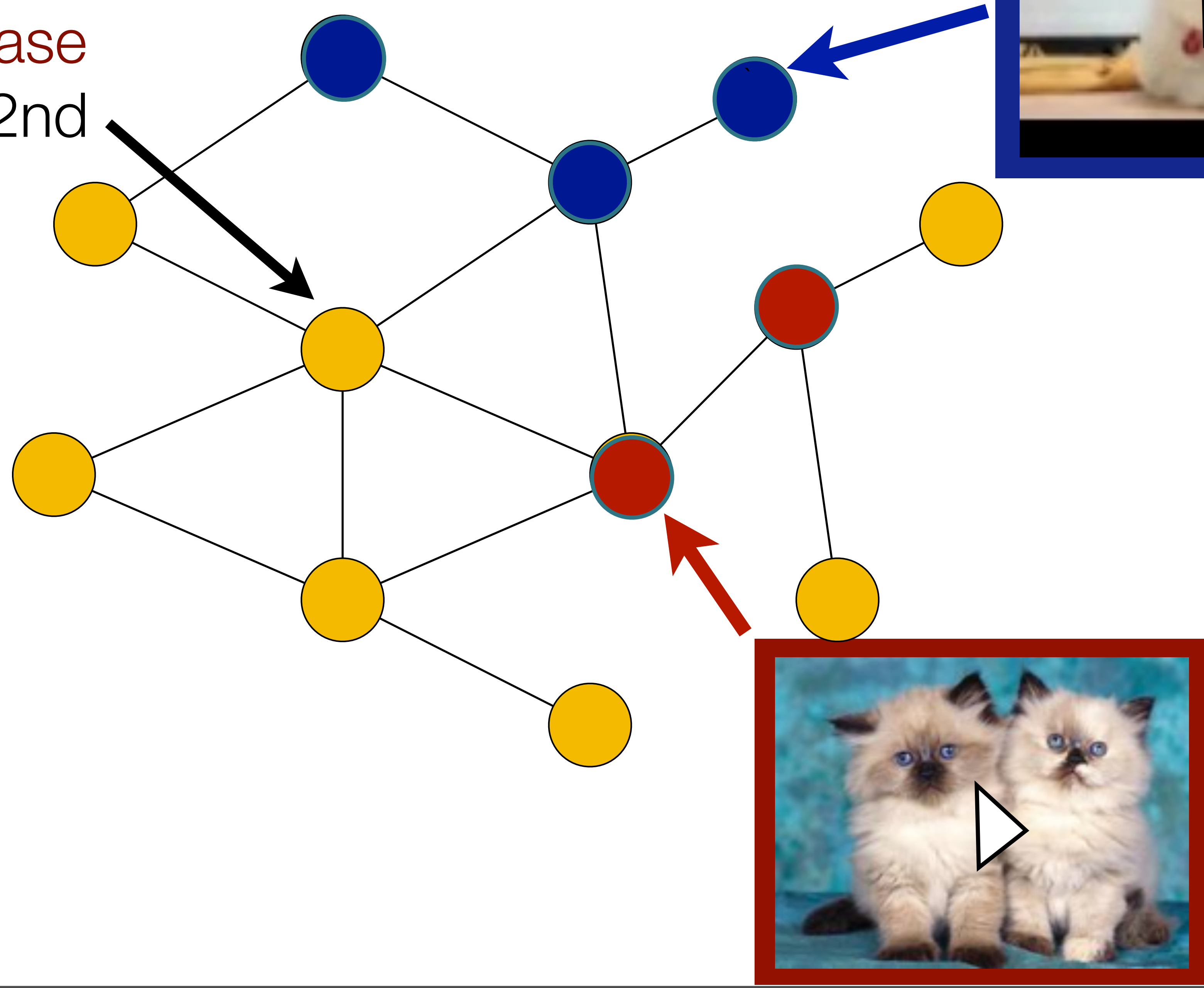

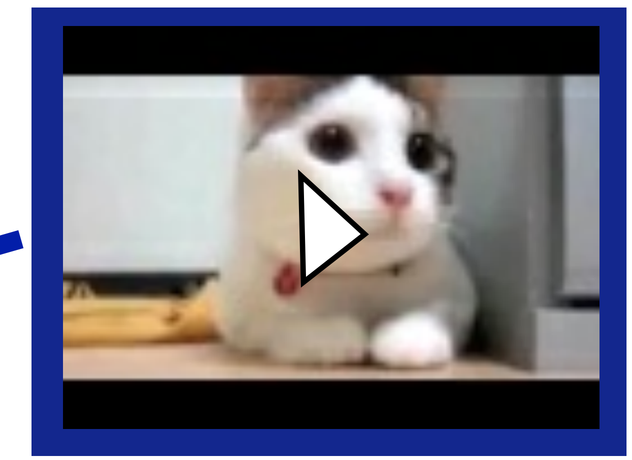

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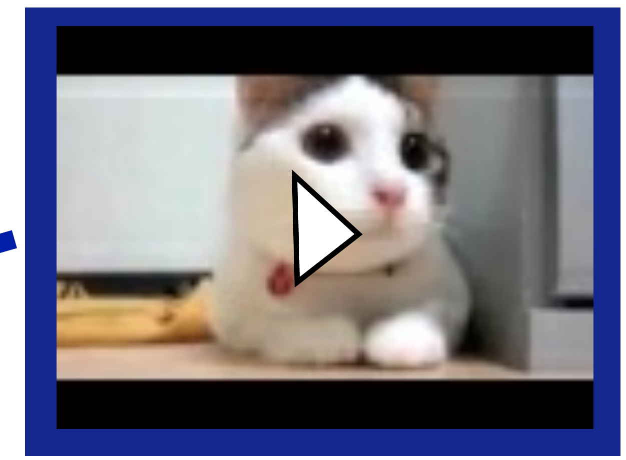

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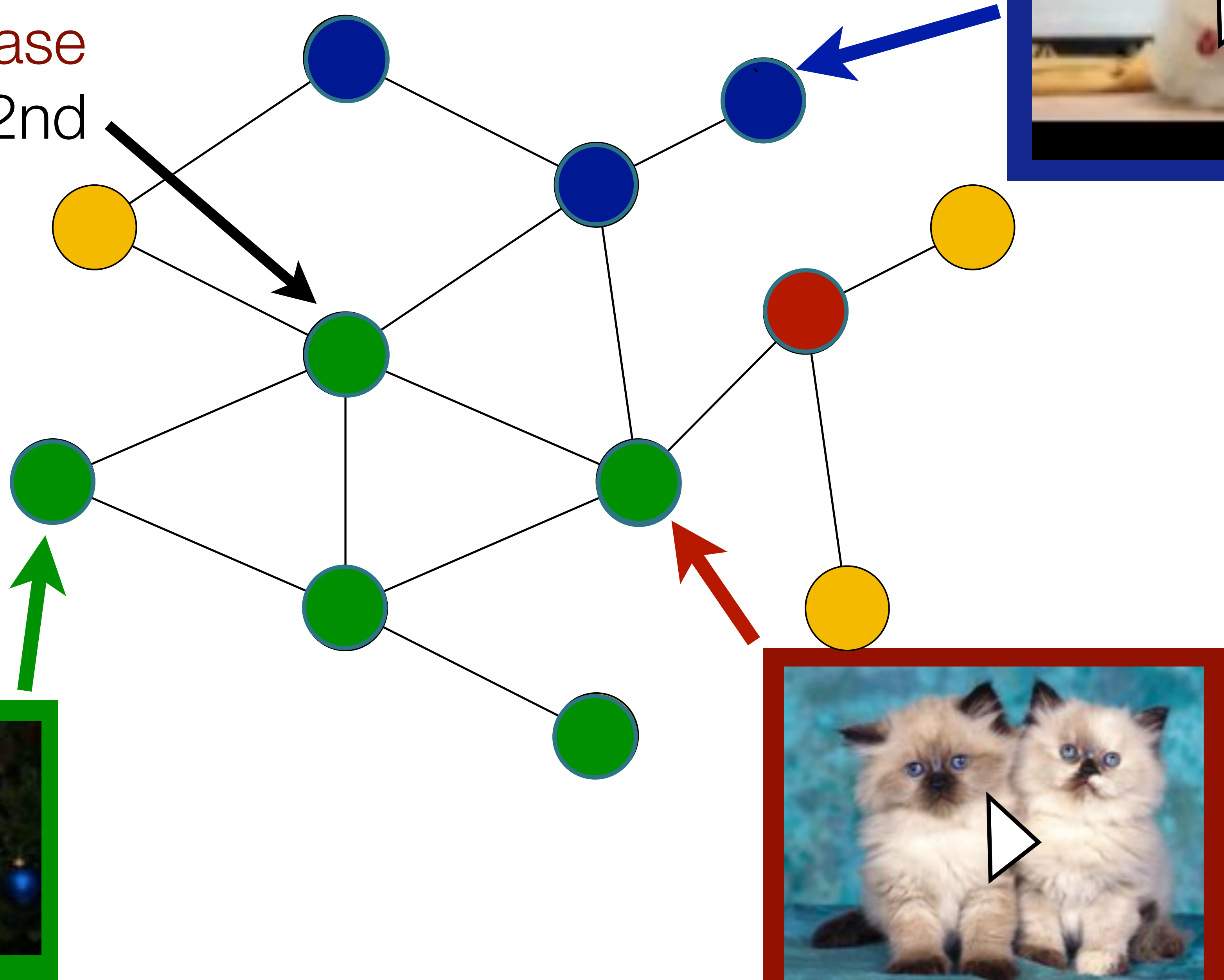

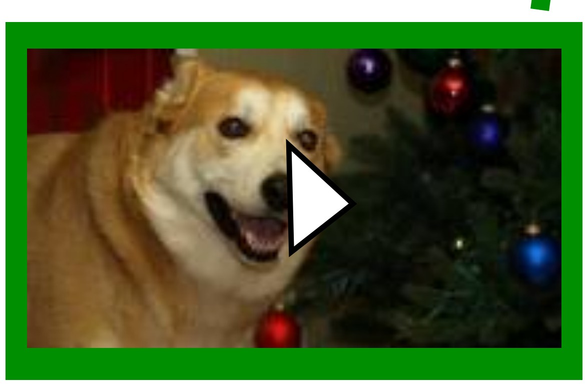

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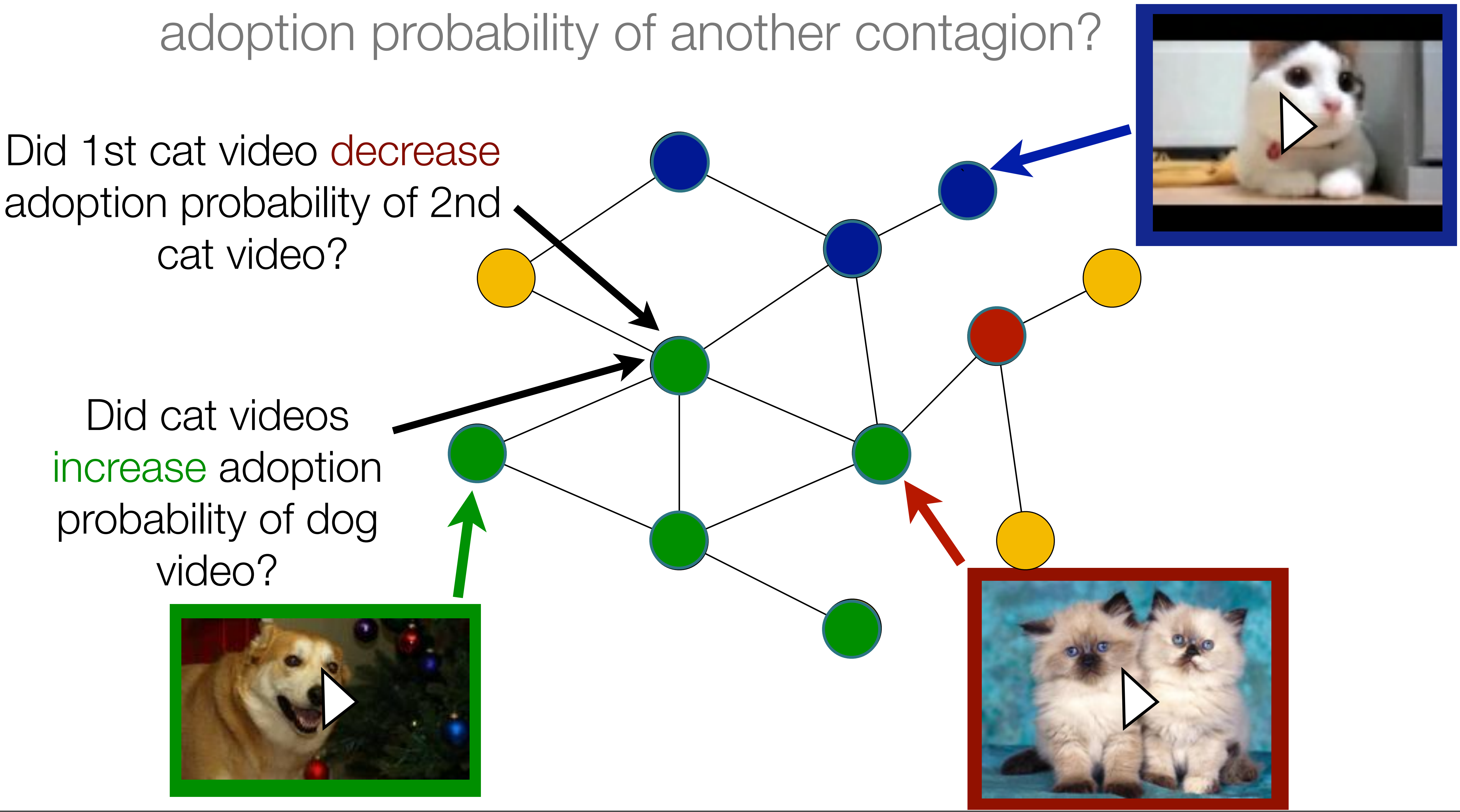

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- In general, this leads to a more accurate diffusion model

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- The ordering of contagion exposures matters
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- The sampling of all possible interactions and exposure sequences is sparse.

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1. Presentation of Model

2. Experiments of Model on real-world data

3. Insights gained from Model

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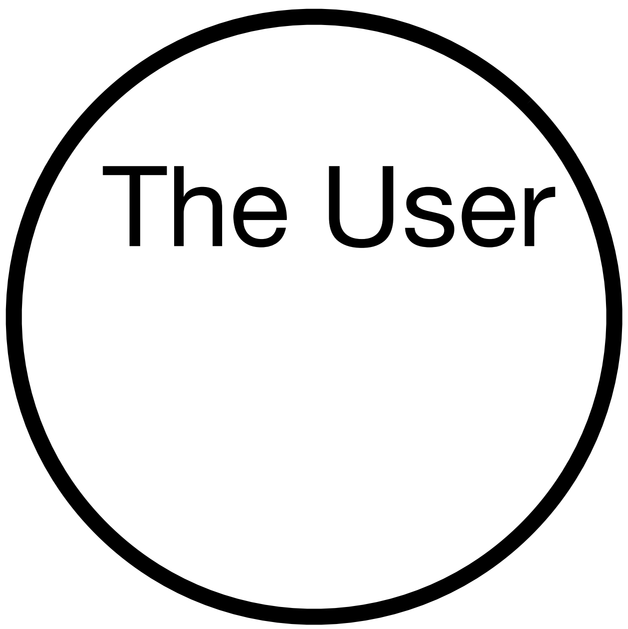

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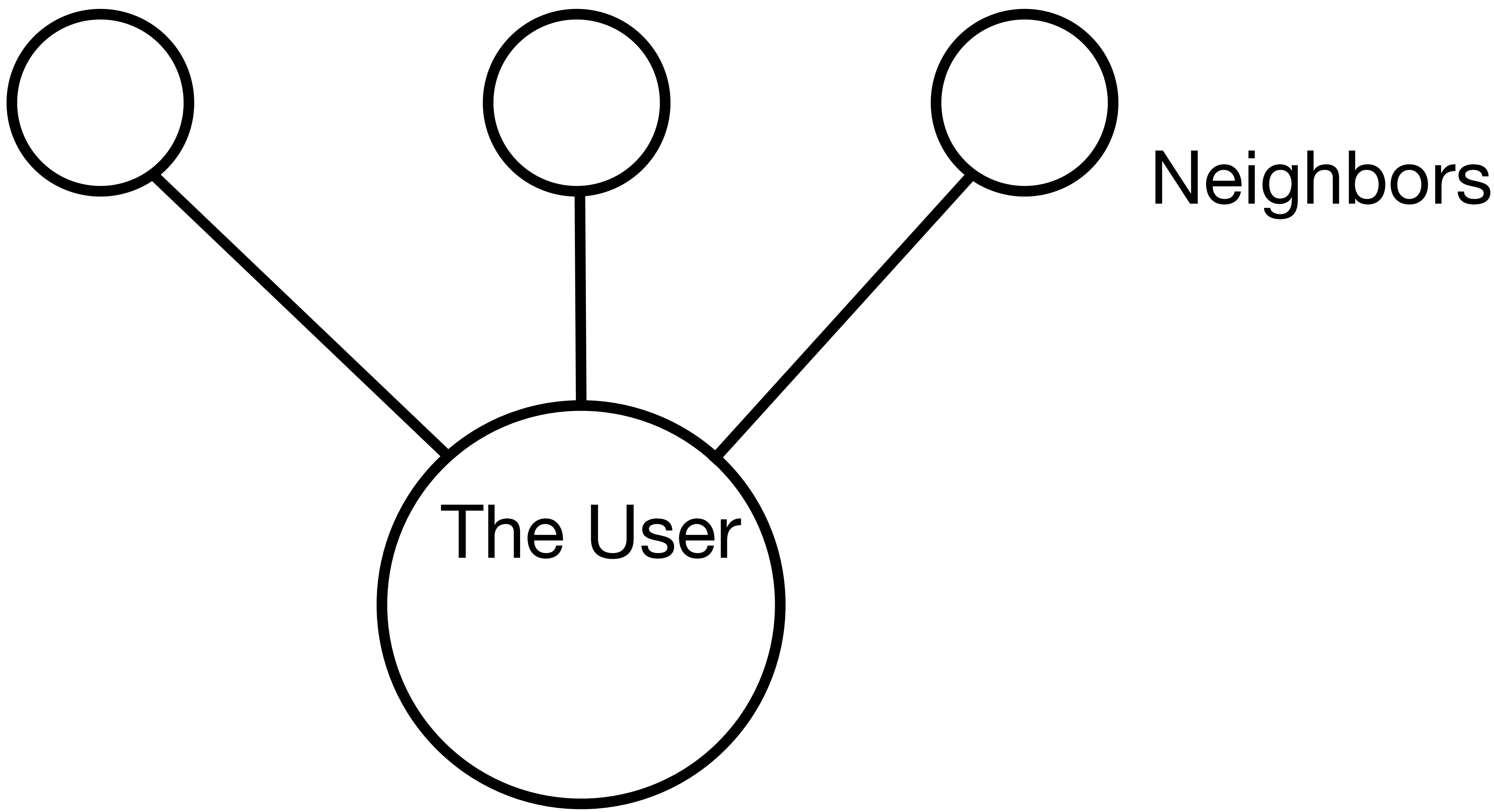

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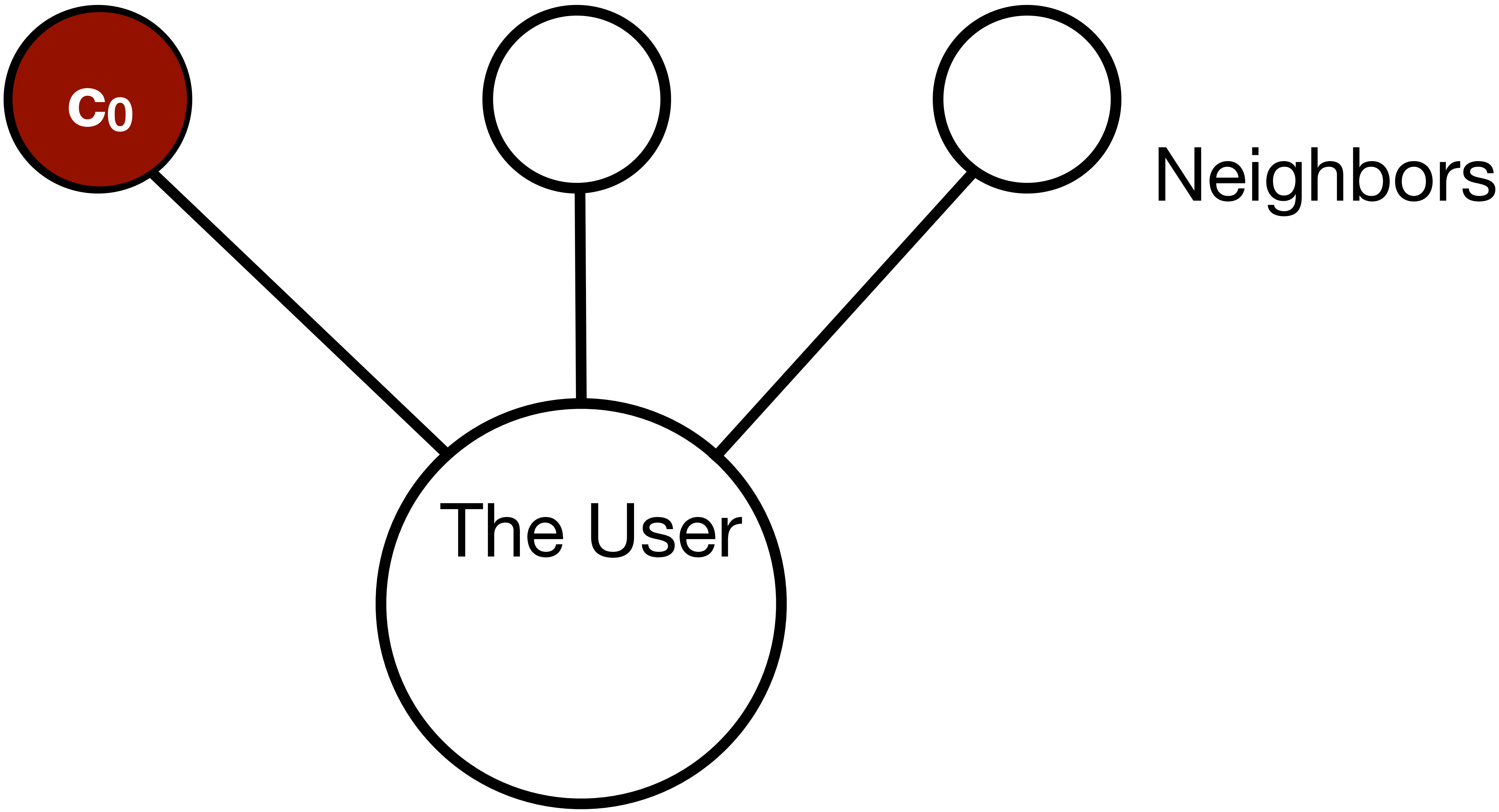

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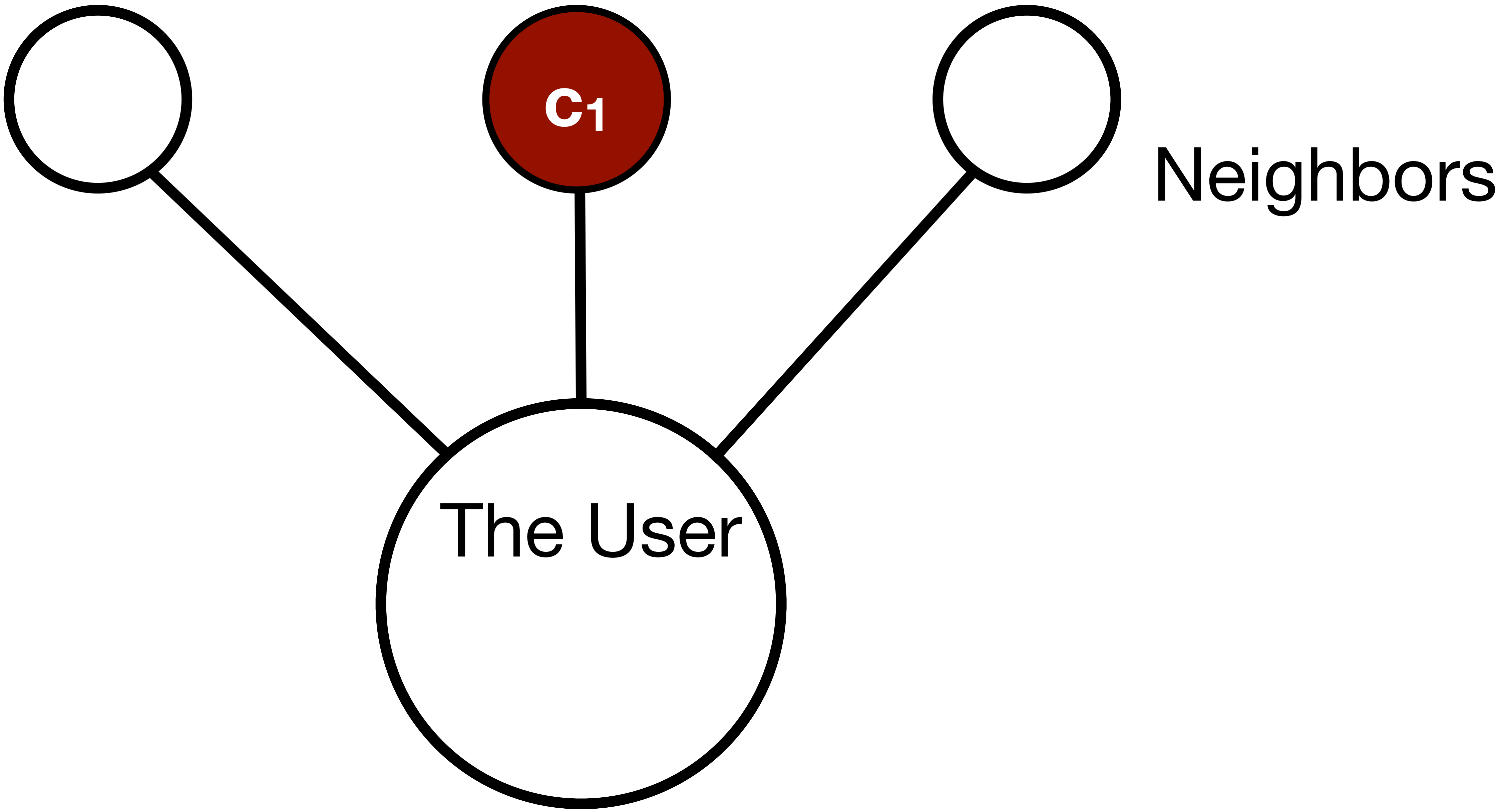

$P(\text{adopt } c_1 \mid \text{exposed } to\ c_0)$

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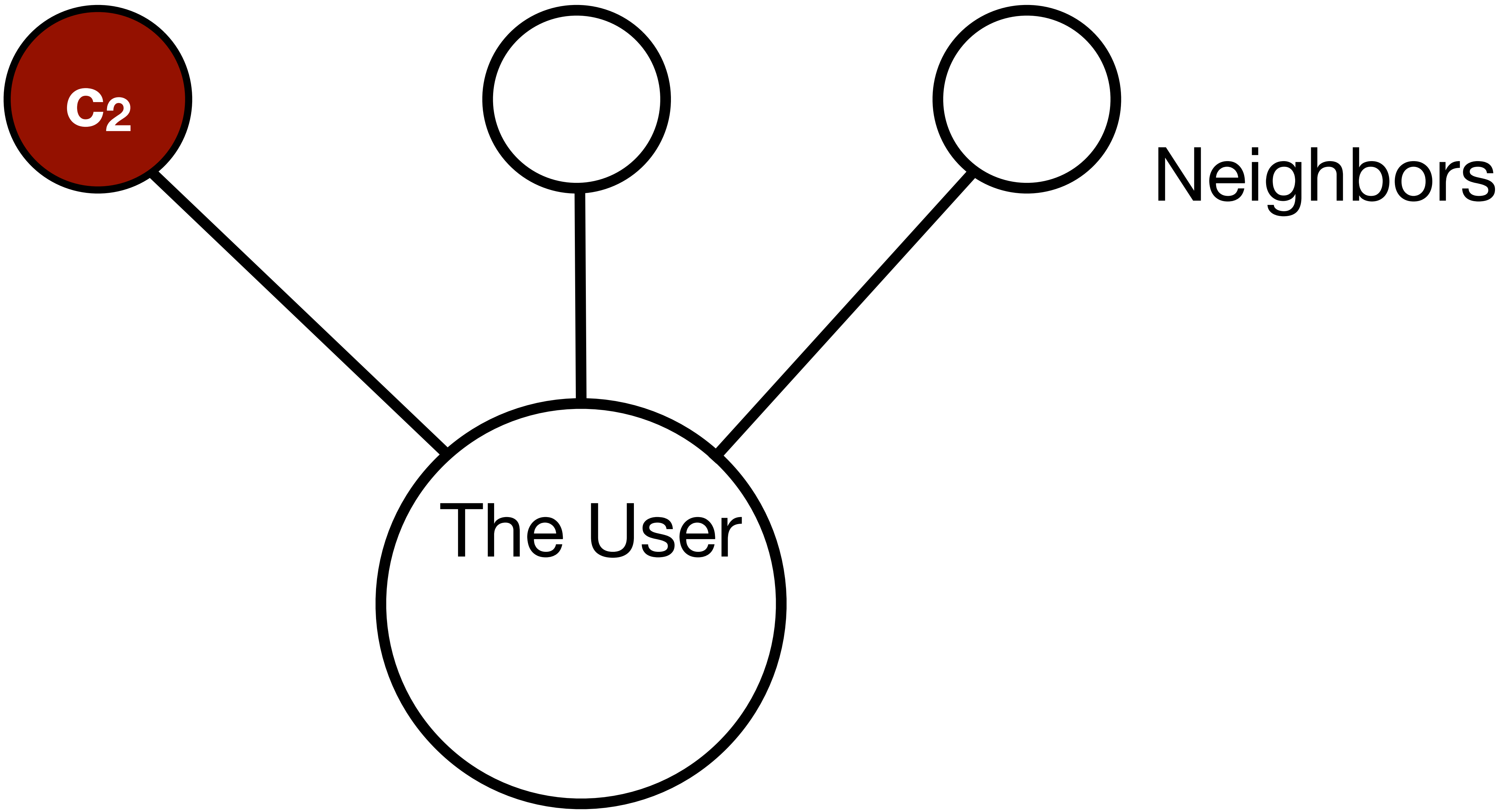

P(adopt c_2 | exposed *to* c_1 , c_0)

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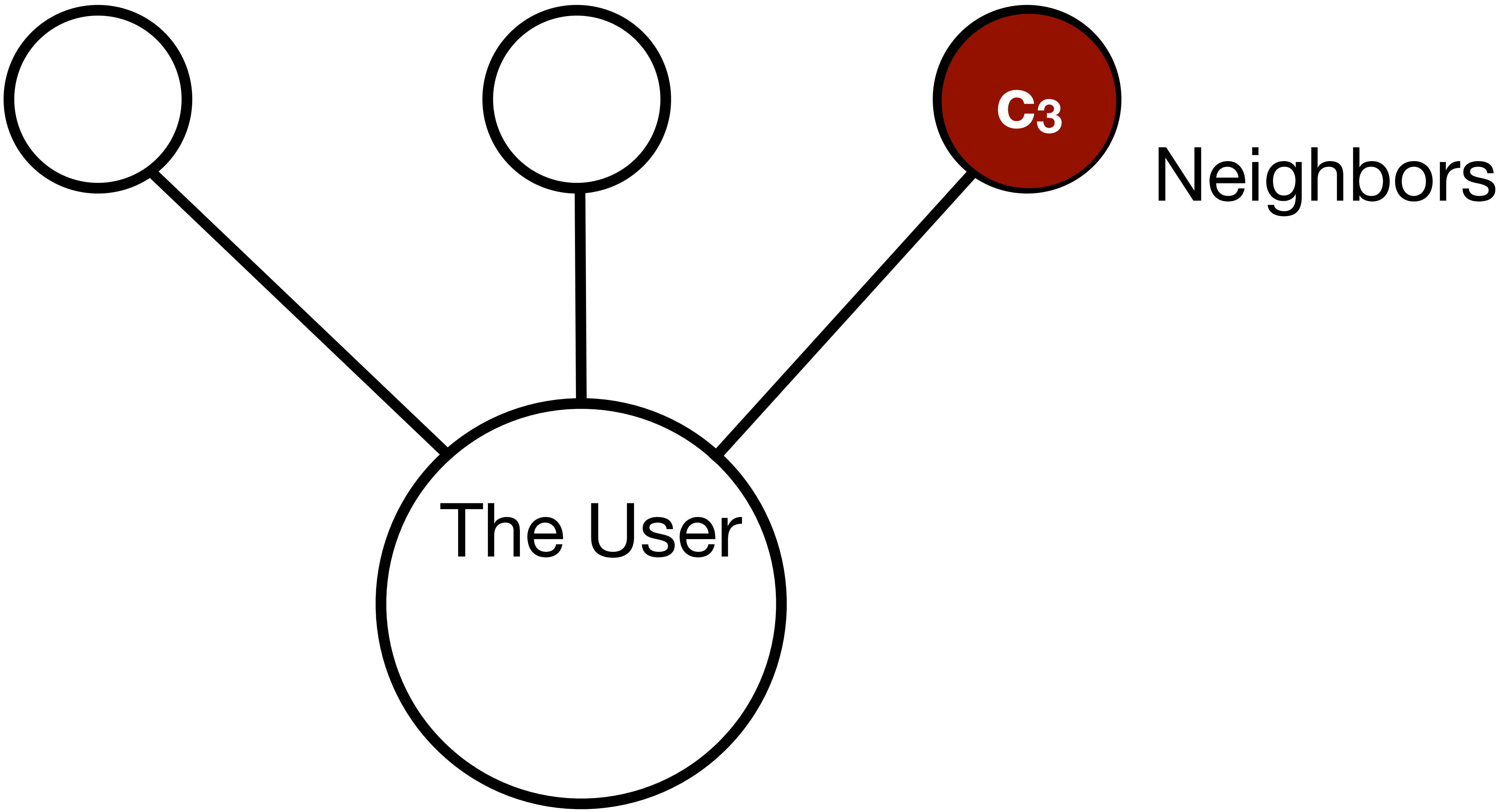

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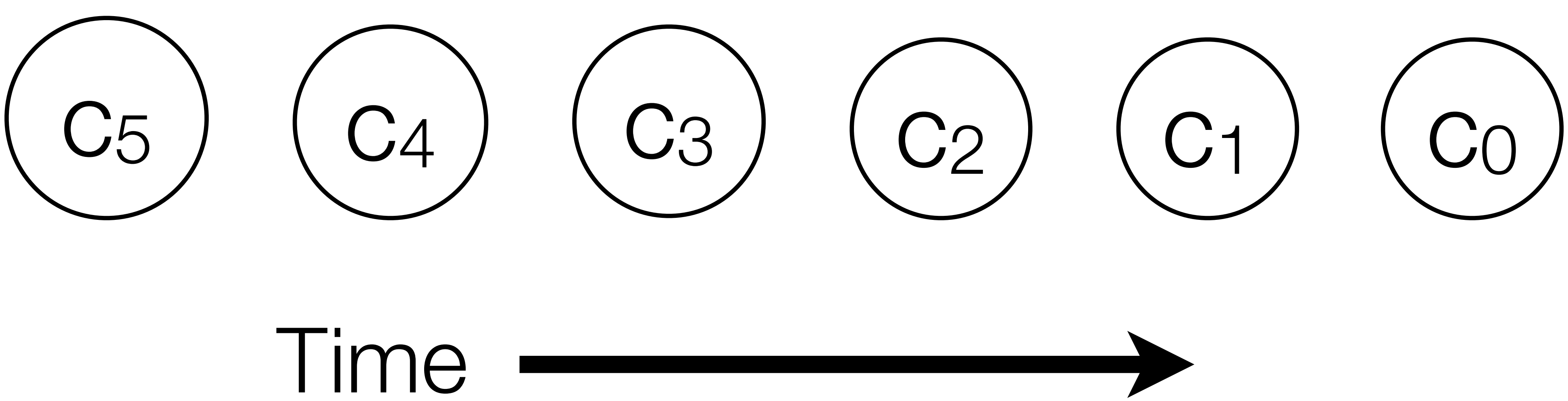

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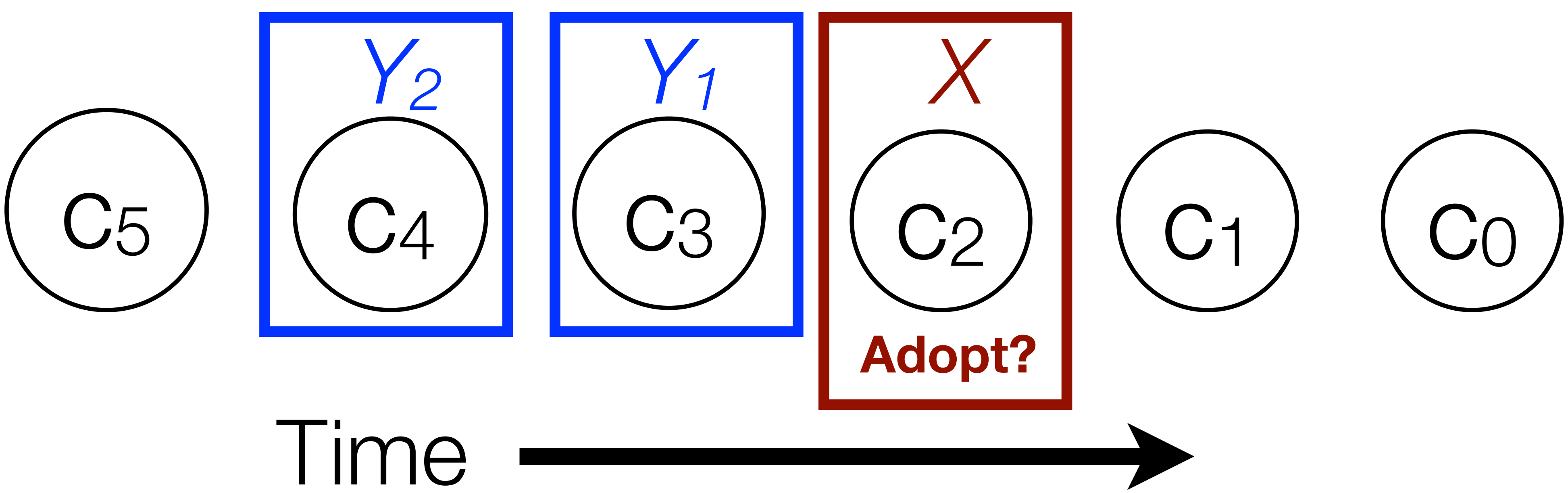

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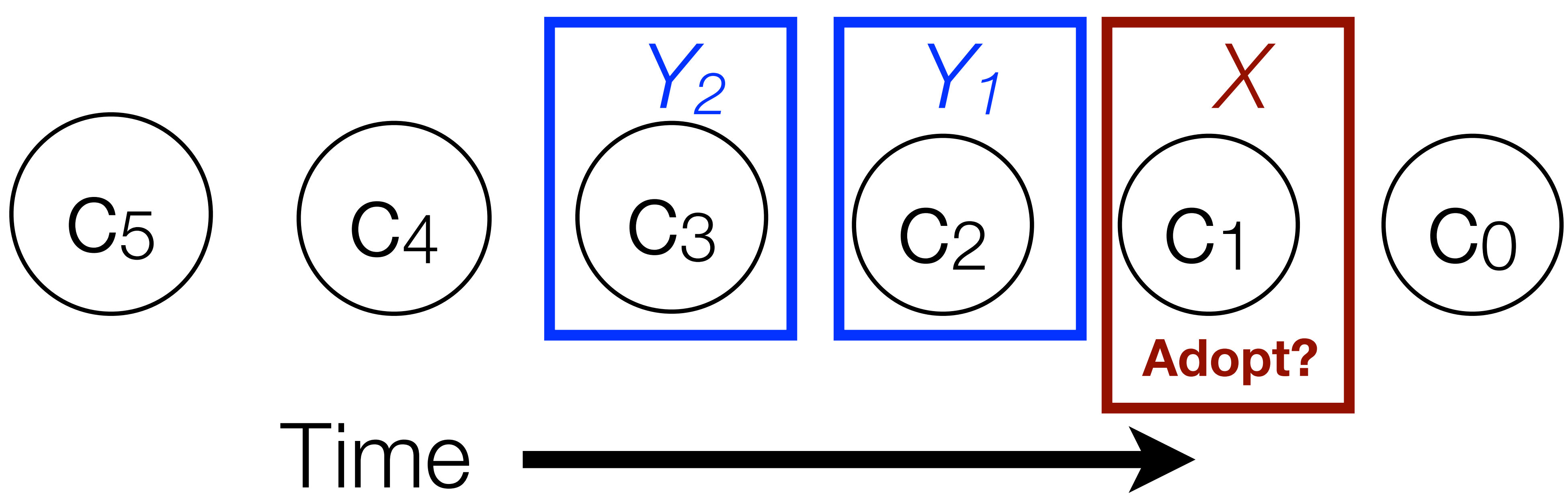

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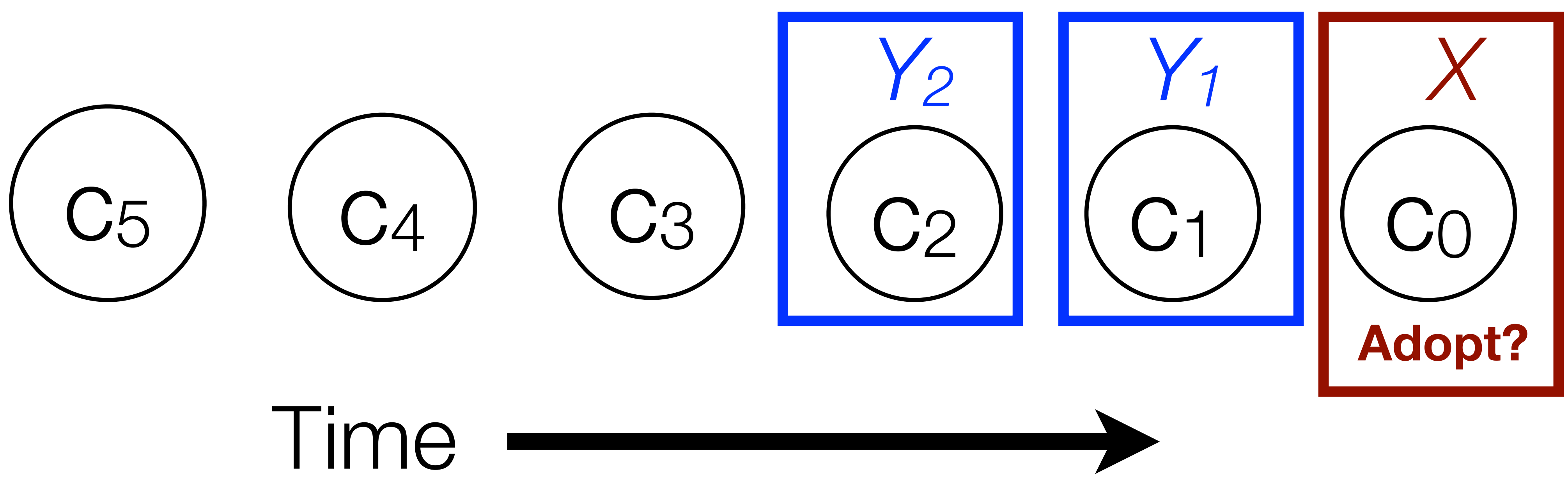

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Easily measured empirically

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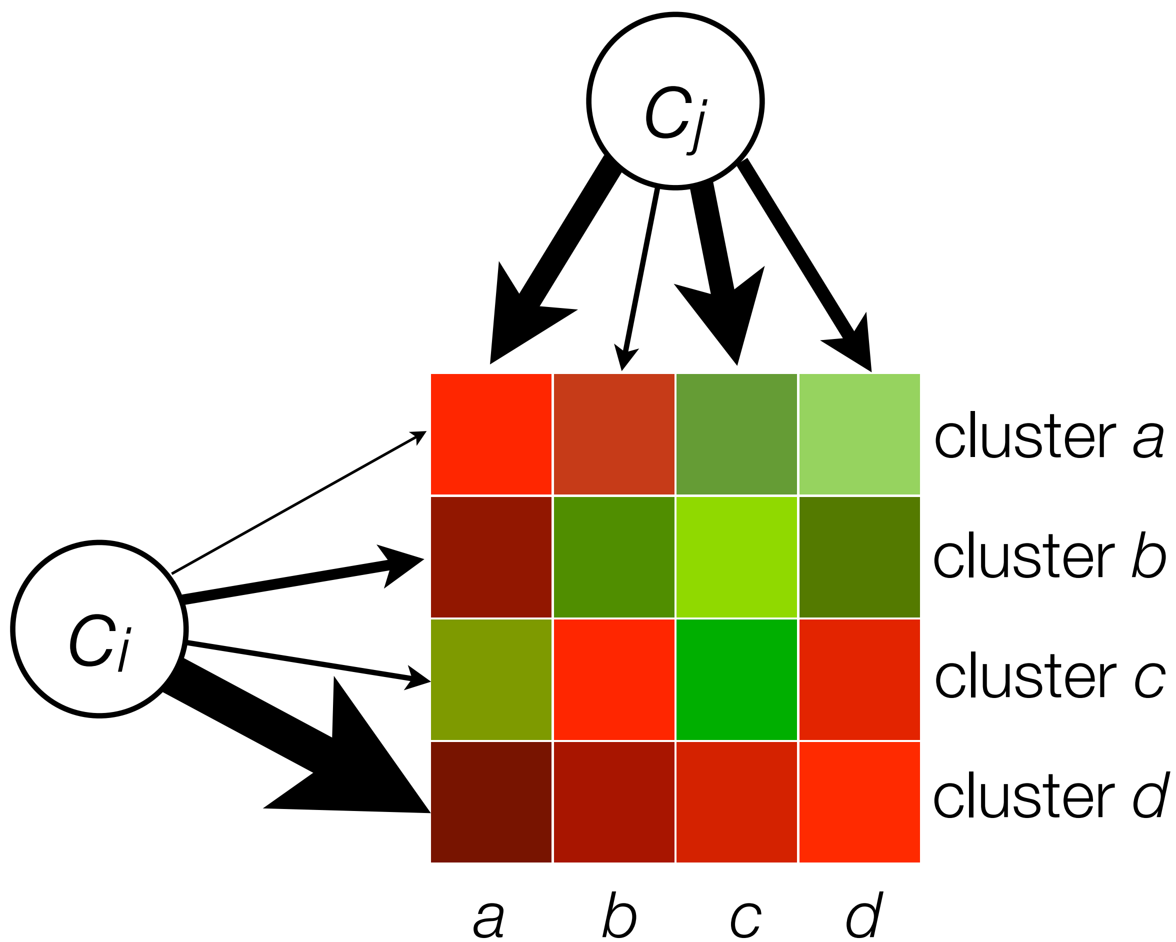

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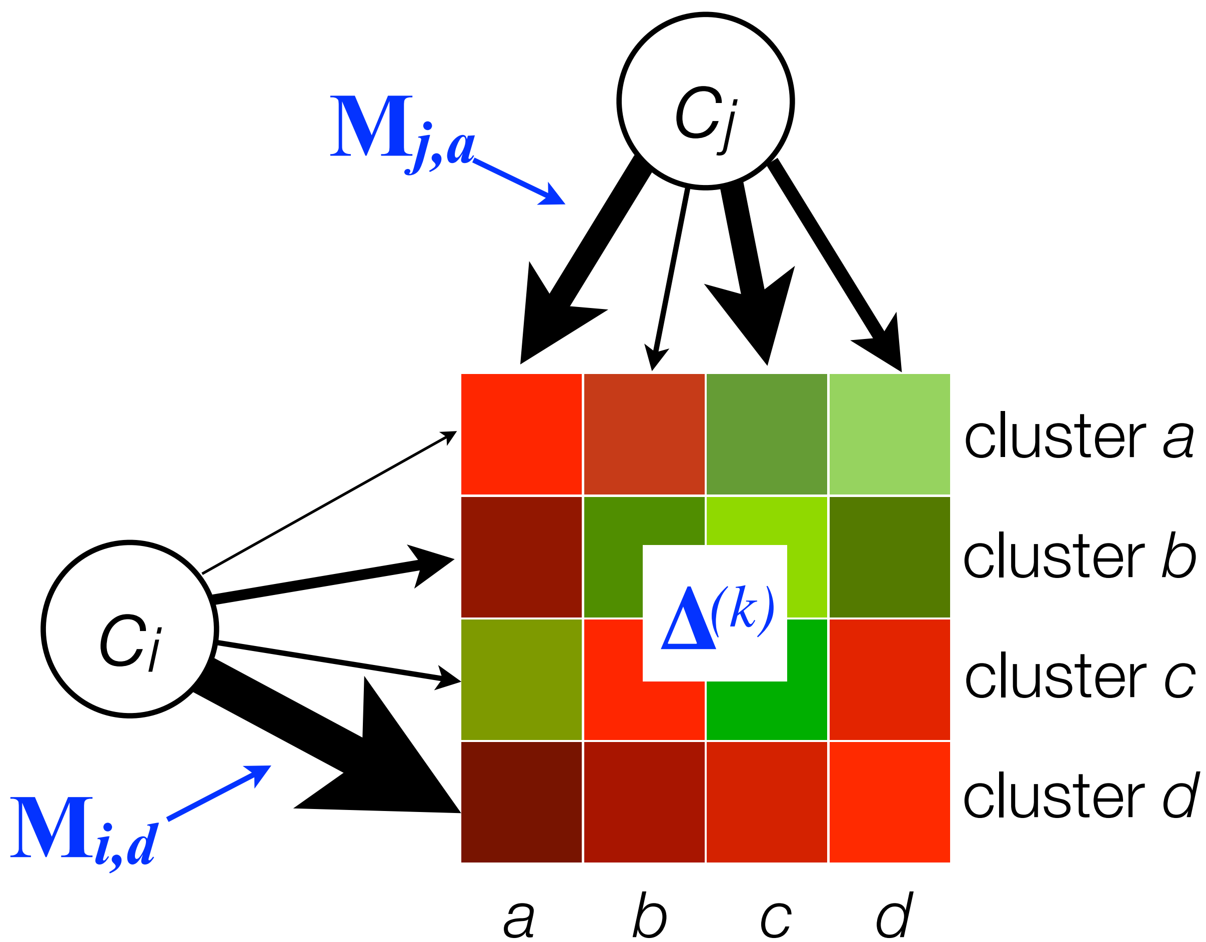

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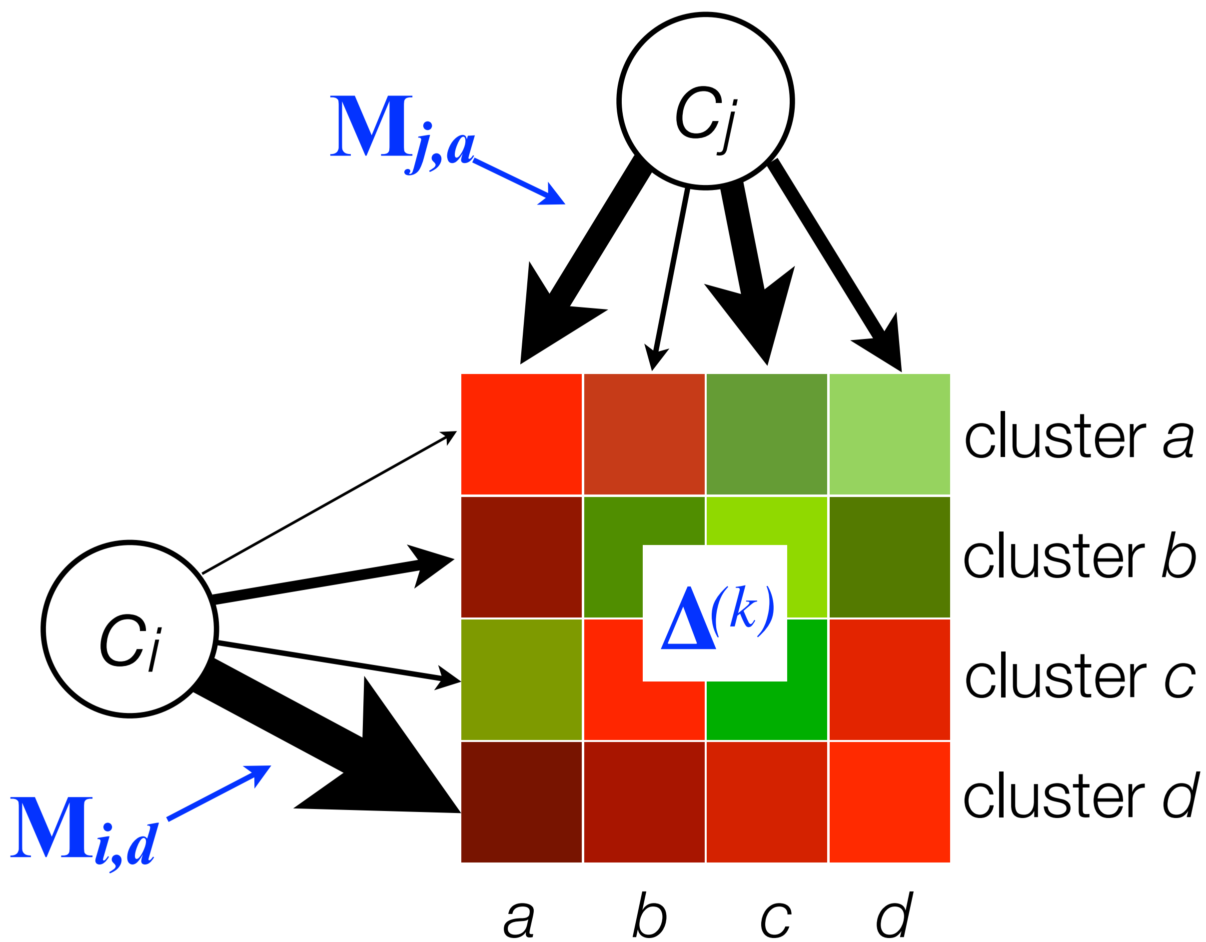

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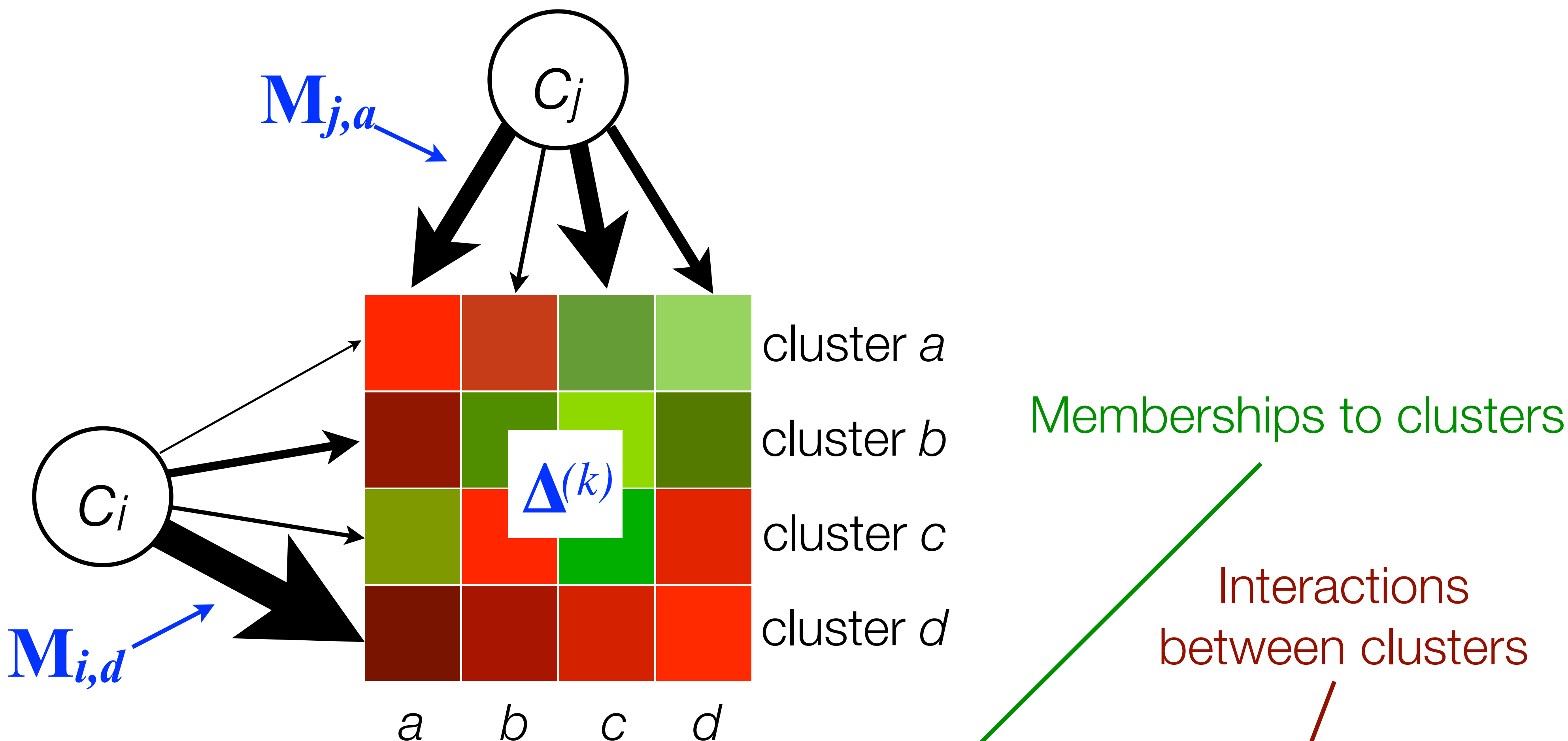

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$P(X \mid Y_k)$ negatively sampled

Optimizing the Objective Function

- We fit $\mathbf{M}$ and $\mathbf{\Delta}^{(k)}$ to the observed data using stochastic gradient descent:
- A small subset of the p^k_{ij} and n^k_{ij} values (terms in the objective function) are chosen randomly.
- The parameters are fit to this subset using gradient descent.
- After ~20 iterations, the p^k_{ij} and n^k_{ij} values are resampled.
- This continues until no improvement can be achieved.

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- We iterated through every tweet sent on Twitter in January 2011, and we extracted tweeted URLs:
  - 18,186 high-volume URLs
  - 1,087,033 users with 103,112,438 follower edges
  - URLs tweeted 2,664,207 times
  - 810,884,361 exposures to URLs.
- Each URL is a different contagion
- A user adopts a URL contagion by tweeting it.

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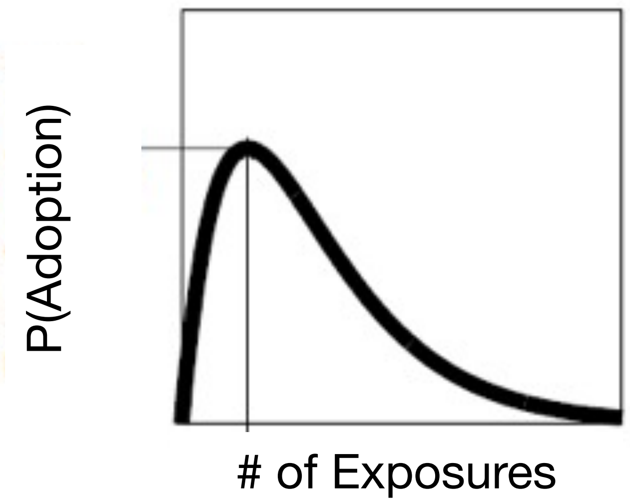
  - Exposure Curve [Romero et al 2011, Myers et al 2012]: Adoption probability of X as a function of exposure count.



Experiments - Results

	Log-Like.	Area under PR	max F_1
Prior Adoption Probability	-335,550.39	0.0157	0.0157
Prior+User Bias	-338,821.54	0.0123	0.0112
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Including a user bias parameter offered no improvement in performance.

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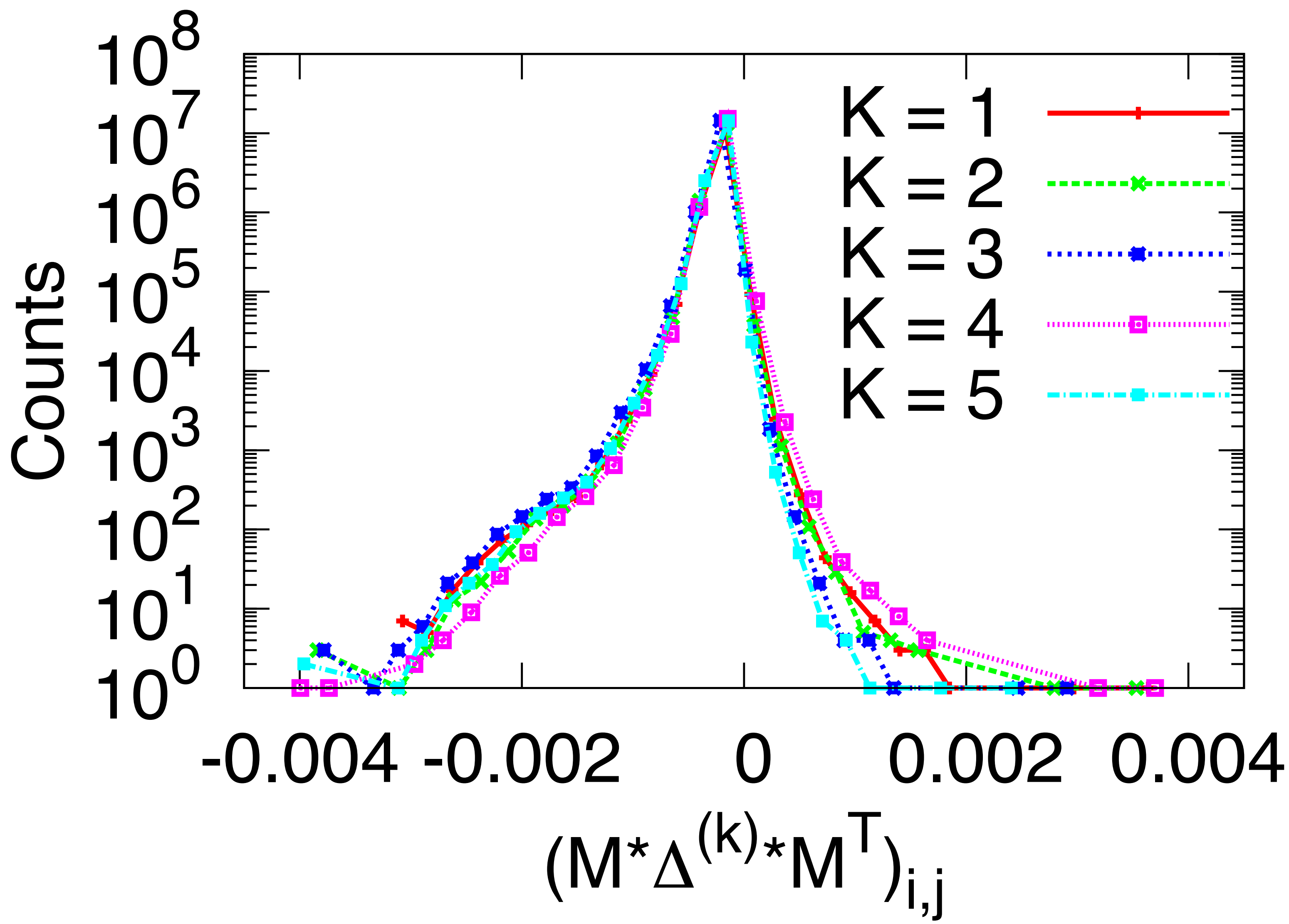

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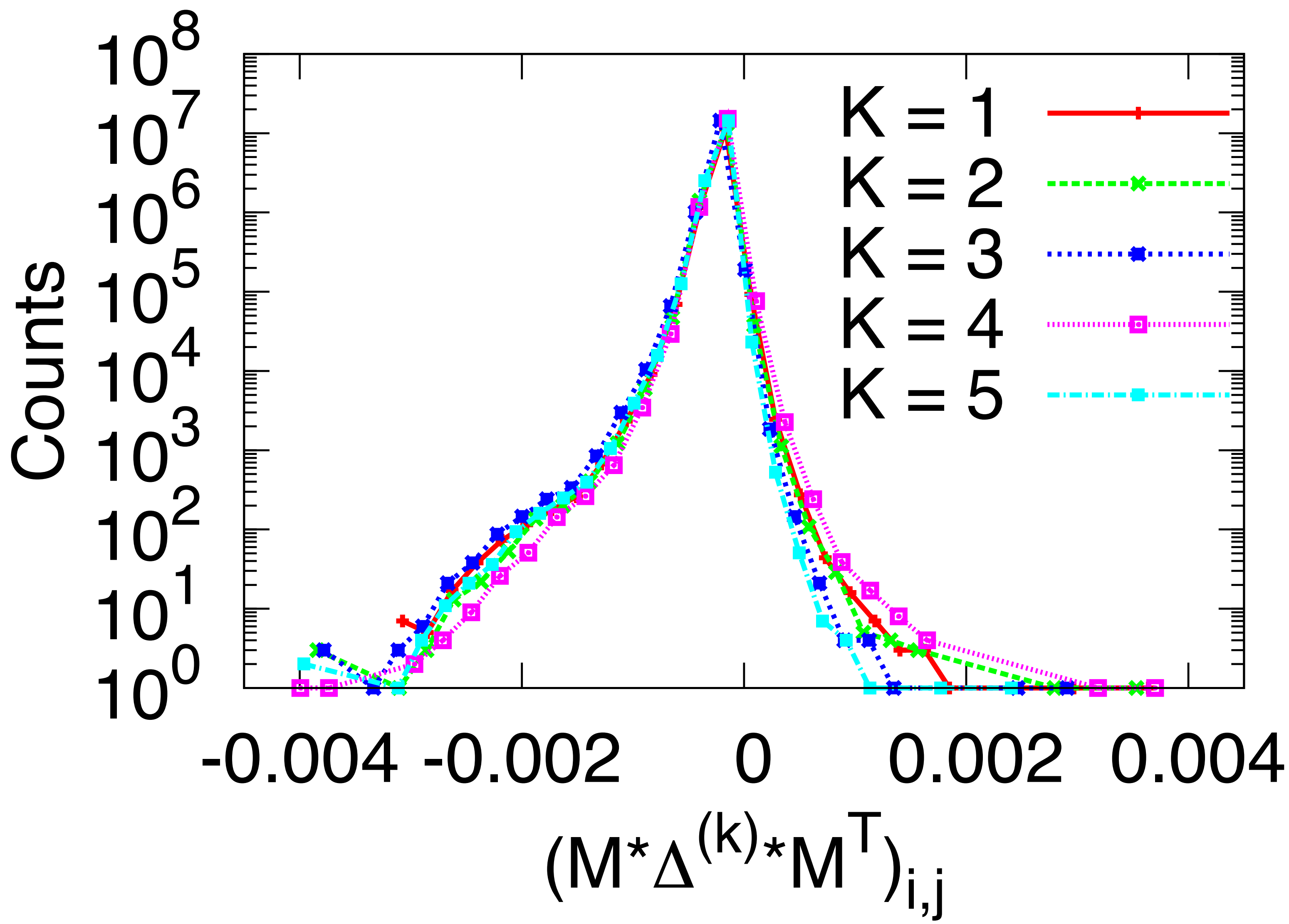

- In all, interactions between other contagions change adoption probability by *71% on average!*

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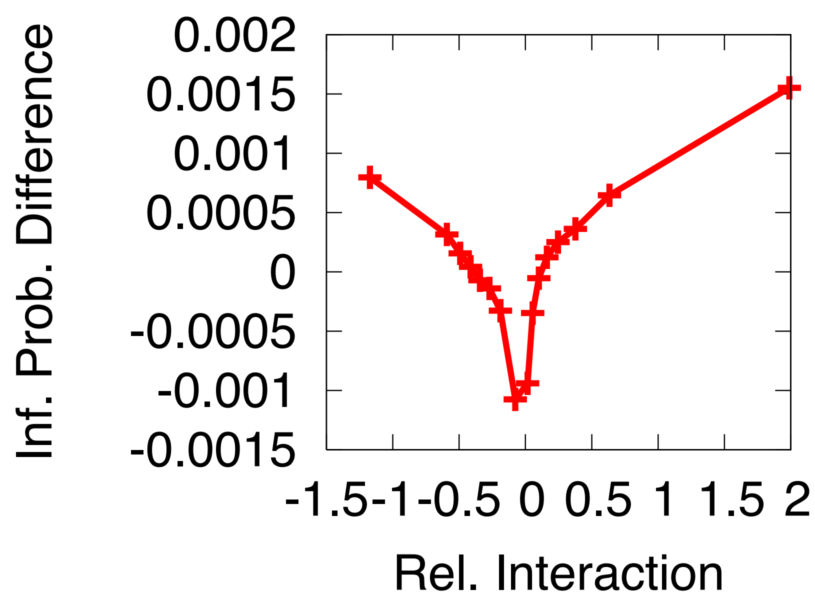

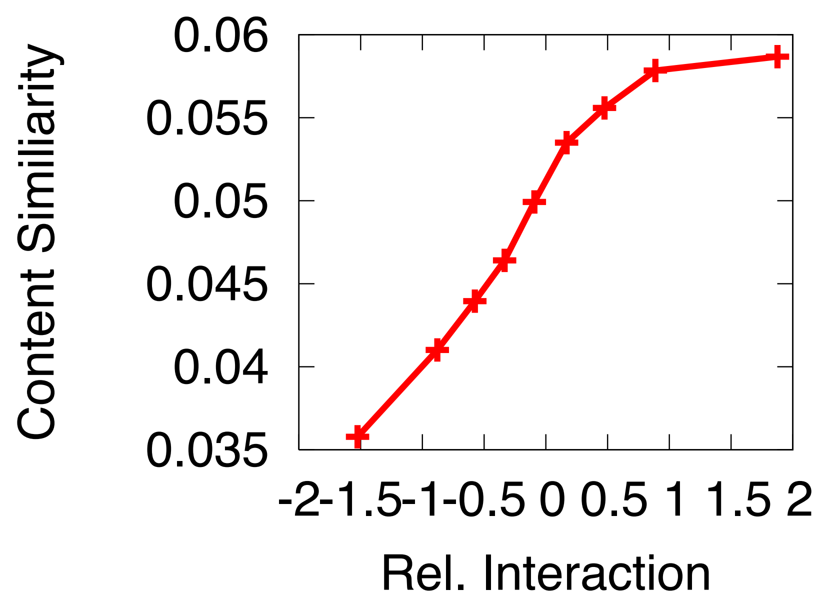

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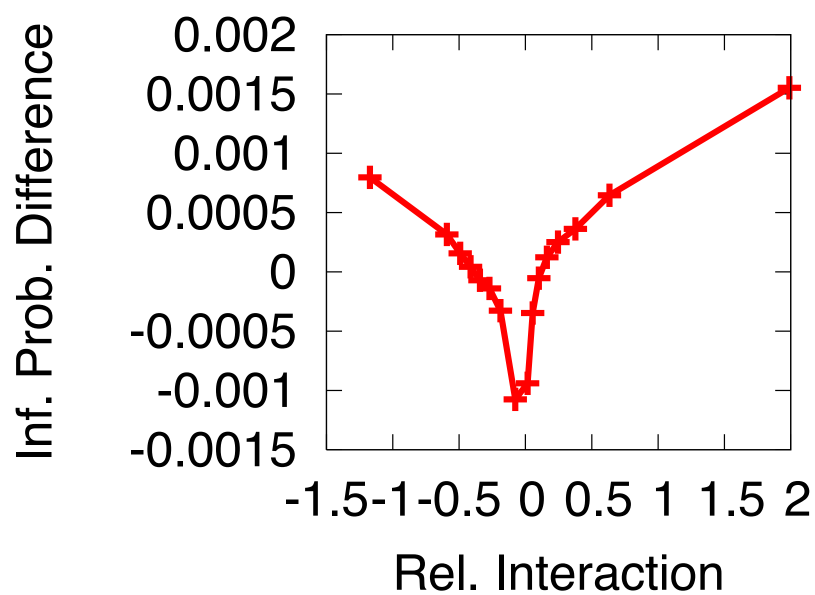
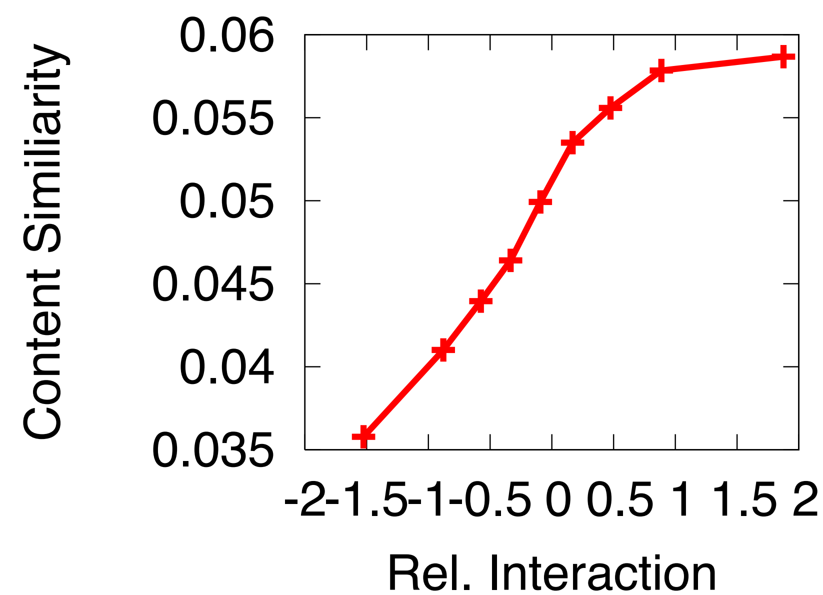


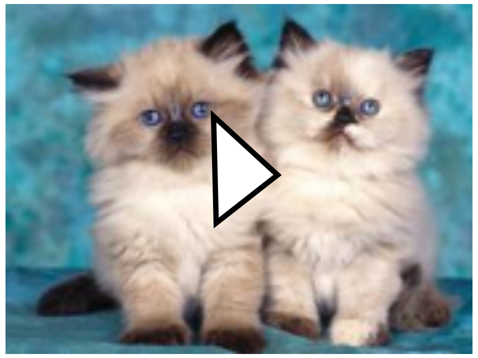


- This is evidence of an underlying process of interactions...

The Interaction Process - An example

“Paint continues to dry without incident.”

Golf.



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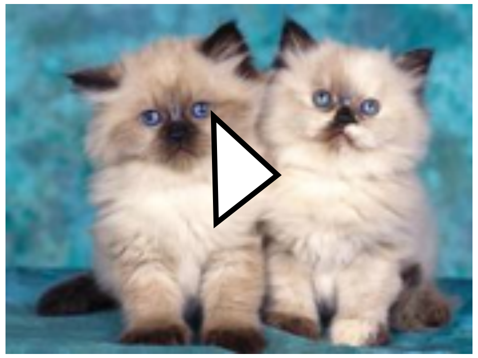

Boring...

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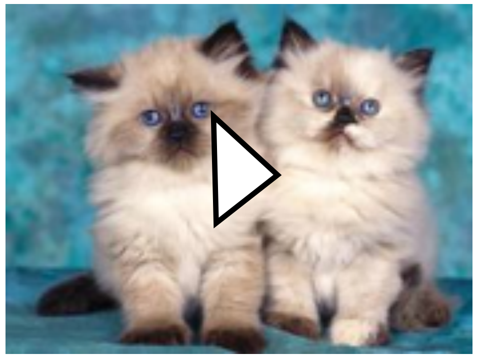
[yawn]



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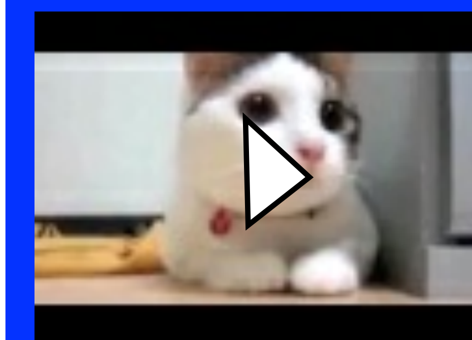
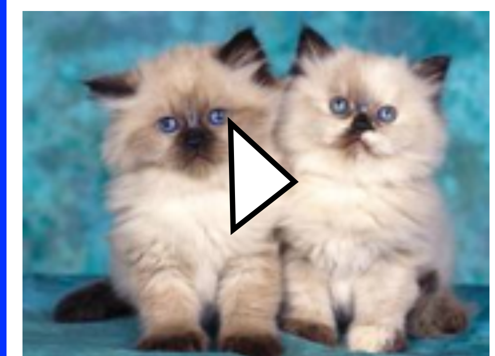


I love cat videos!



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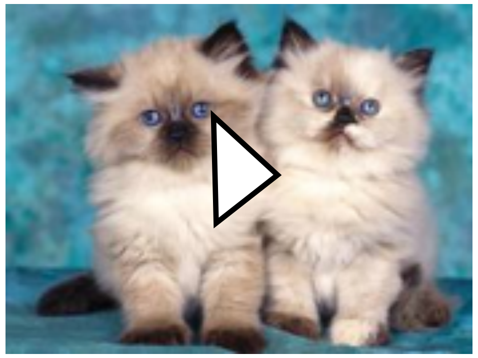

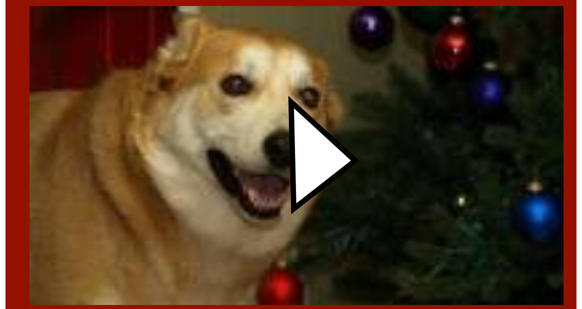

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Best time for a Cat Food Ad.

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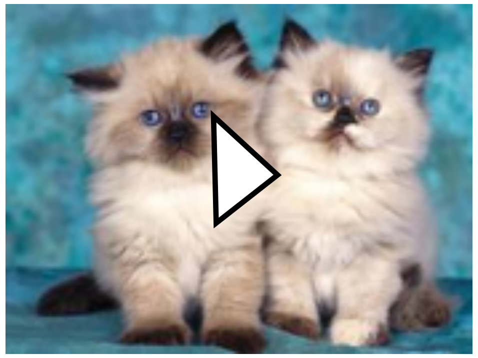

Best time for a Car Ad.

Best time for a Cat Food Ad.

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- Our model provides insight into the process of interactions between spreading contagions.