Detecting Network Effects

Randomizing Over Randomized Experiments

Martin Saveski
(@msaveski)
MIT

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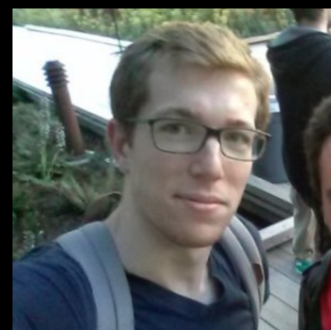


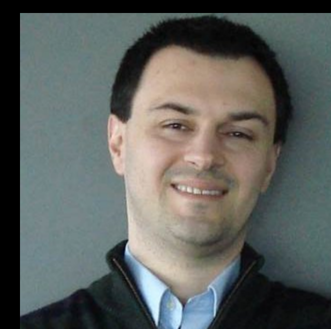
Jean Pouget-Abadie
Harvard

Guillaume Saint-Jacques
MIT

Weitao Duan
LinkedIn

Souvik Ghosh
LinkedIn

Ya Xu
LinkedIn

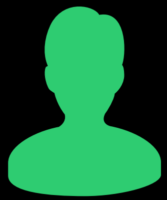


Edo Airoldi
Harvard

Treatment

$$Z_i = 1$$

New Feed
Ranking Algorithm

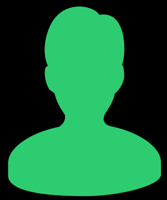


Treatment

$Z_i = 1$

New Feed
Ranking Algorithm

$\downarrow$



Control

$Z_j = 0$

Old Feed
Ranking Algorithm

$\downarrow$

Treatment

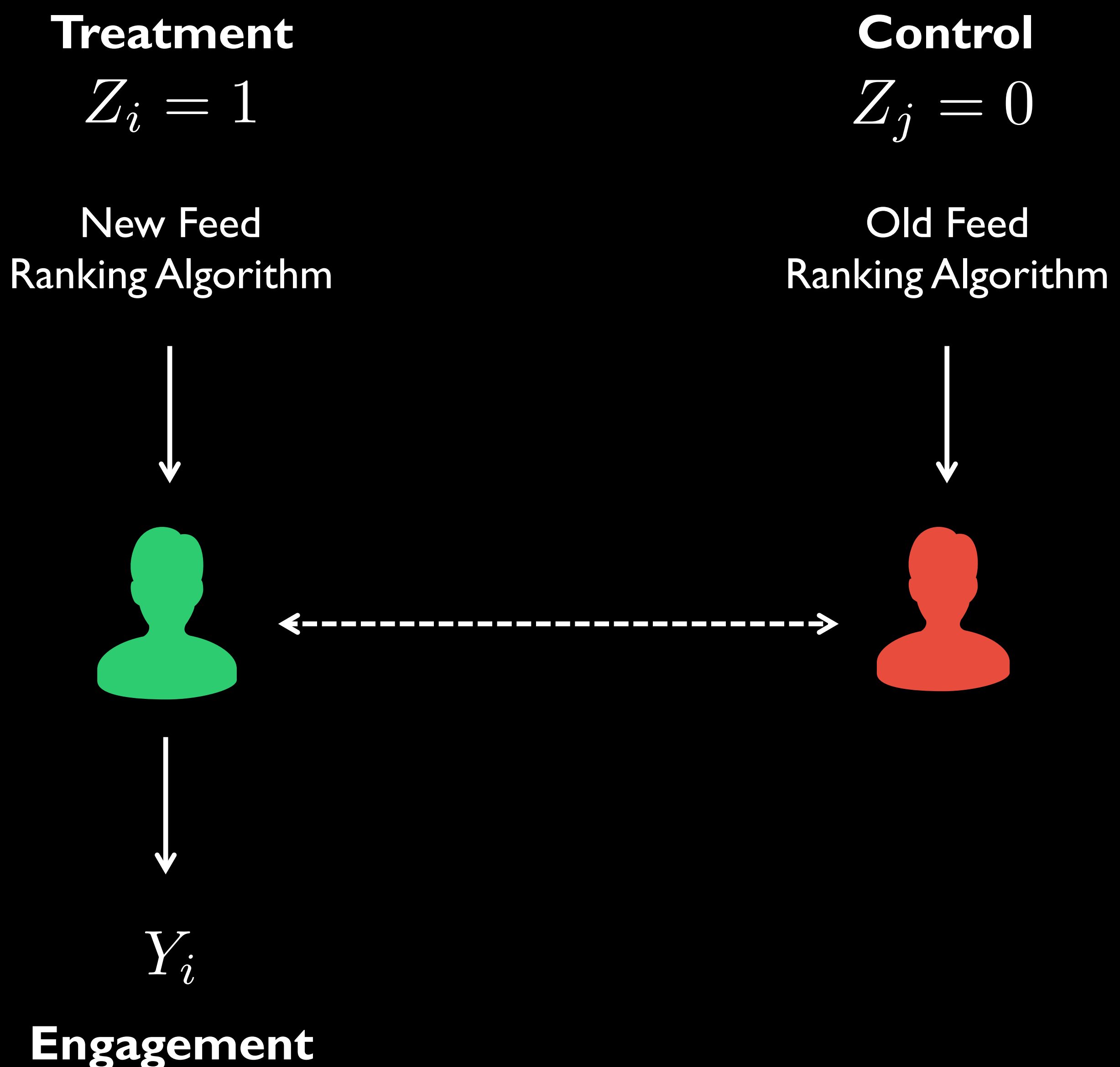
$Z_i = 1$

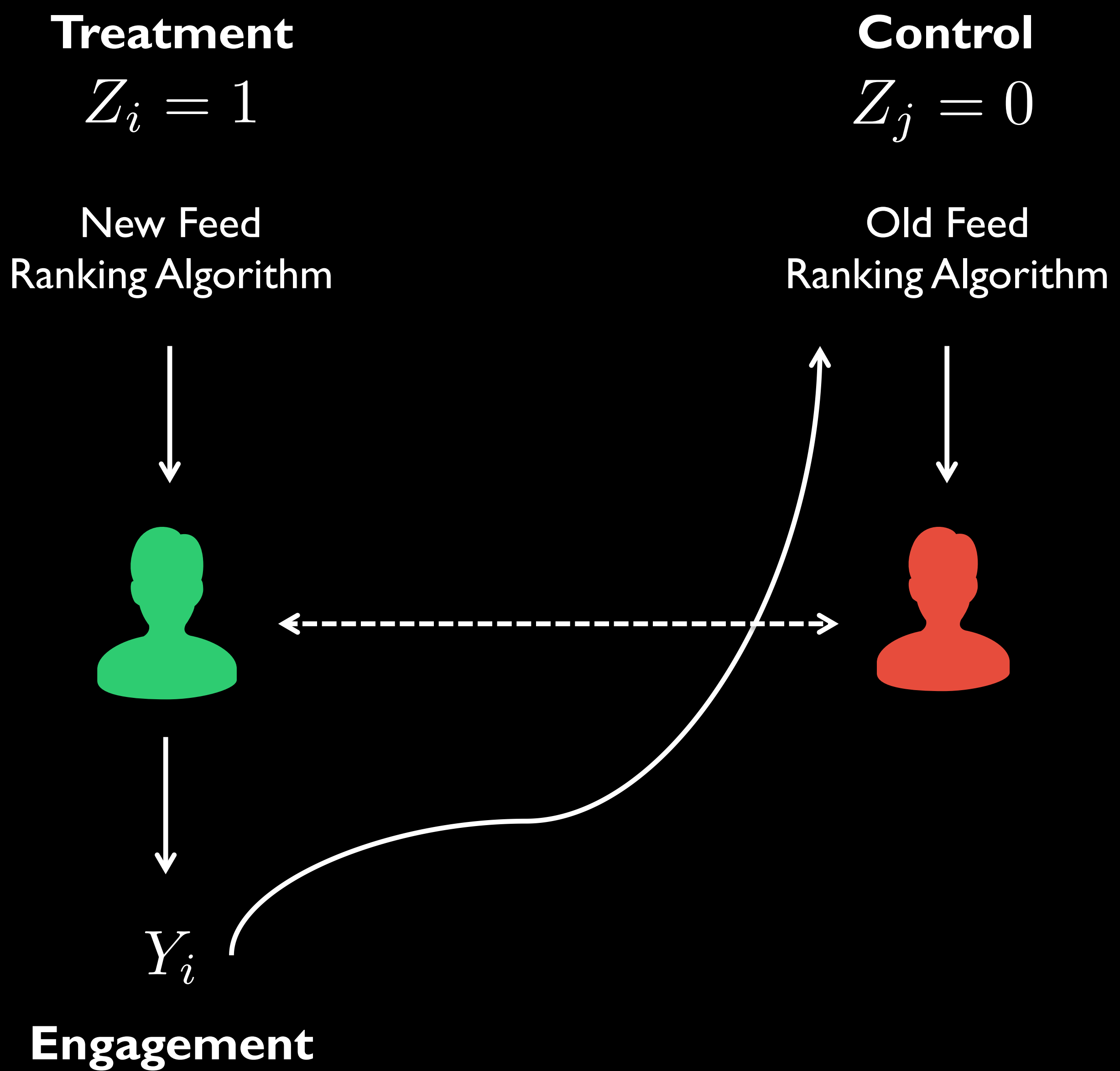
New Feed
Ranking Algorithm

Control

$Z_j = 0$

Old Feed
Ranking Algorithm


Treatment
$Z_i = 1$
New Feed
Ranking Algorithm
Control
$Z_j = 0$
Old Feed
Ranking Algorithm
Y_i
Engagement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$Z_i = 1$
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Engagement
Control
$Z_j = 0$
Old Feed
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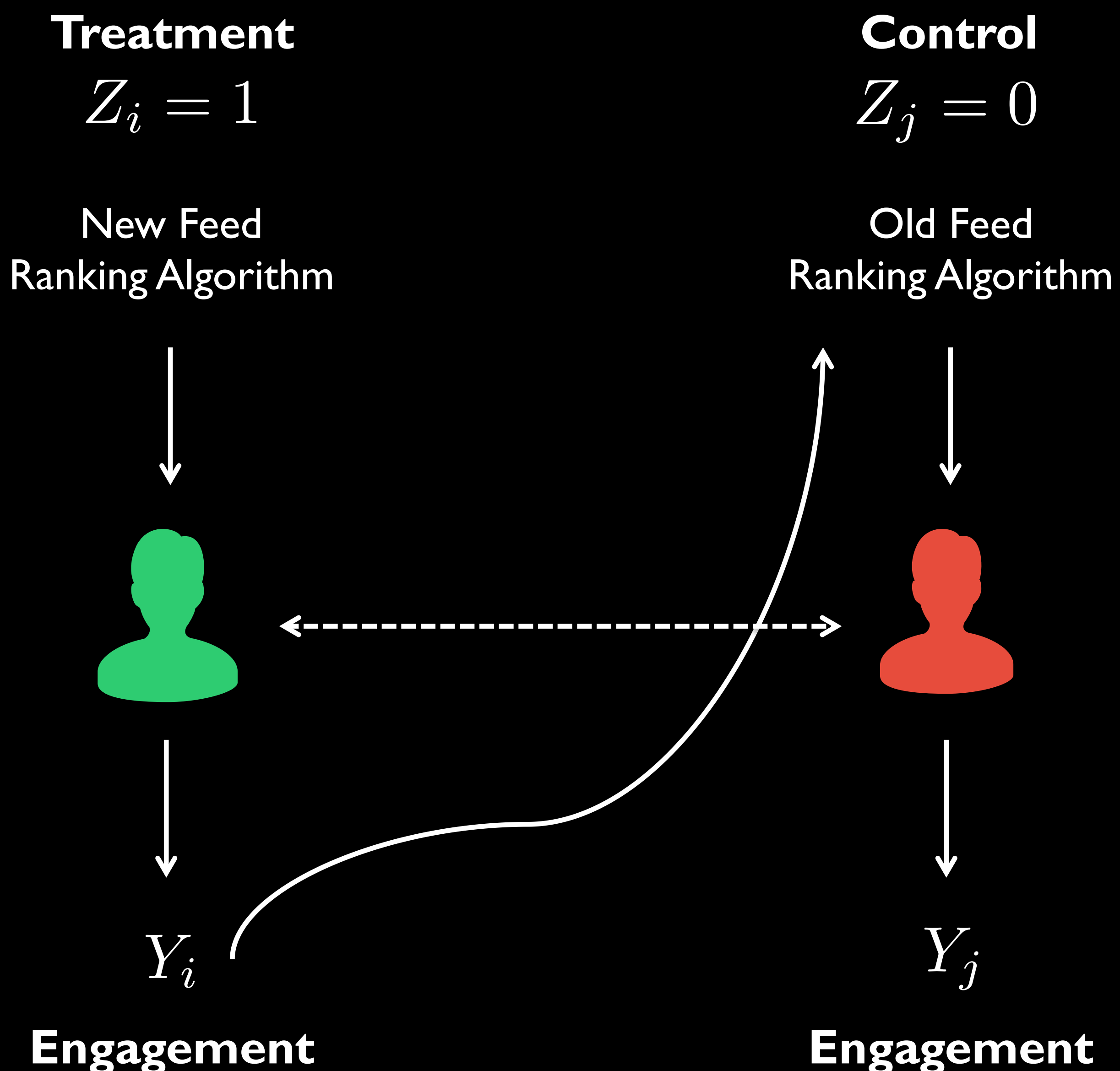
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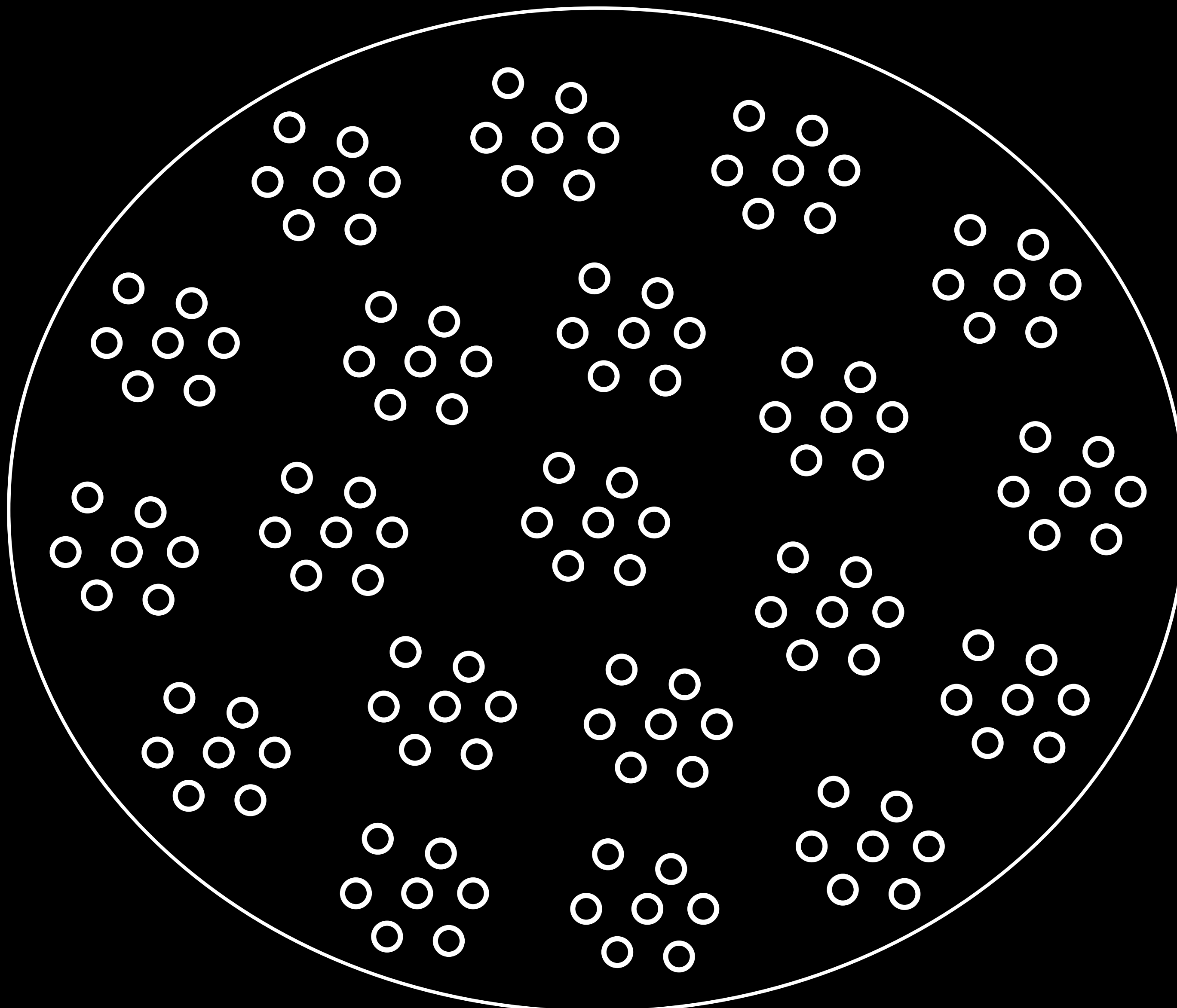
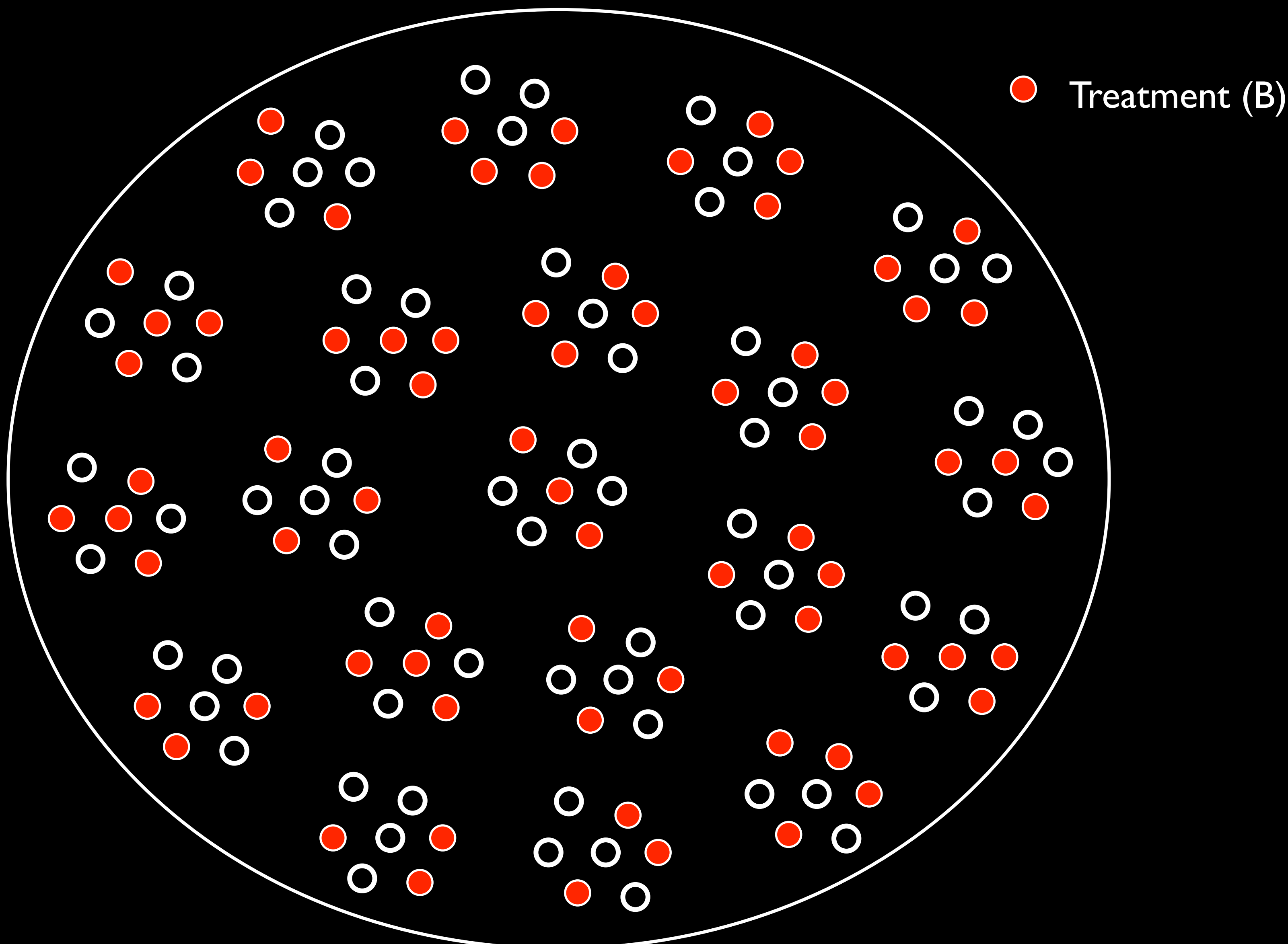
Y_j
Engagement



Completely-randomized Experiment



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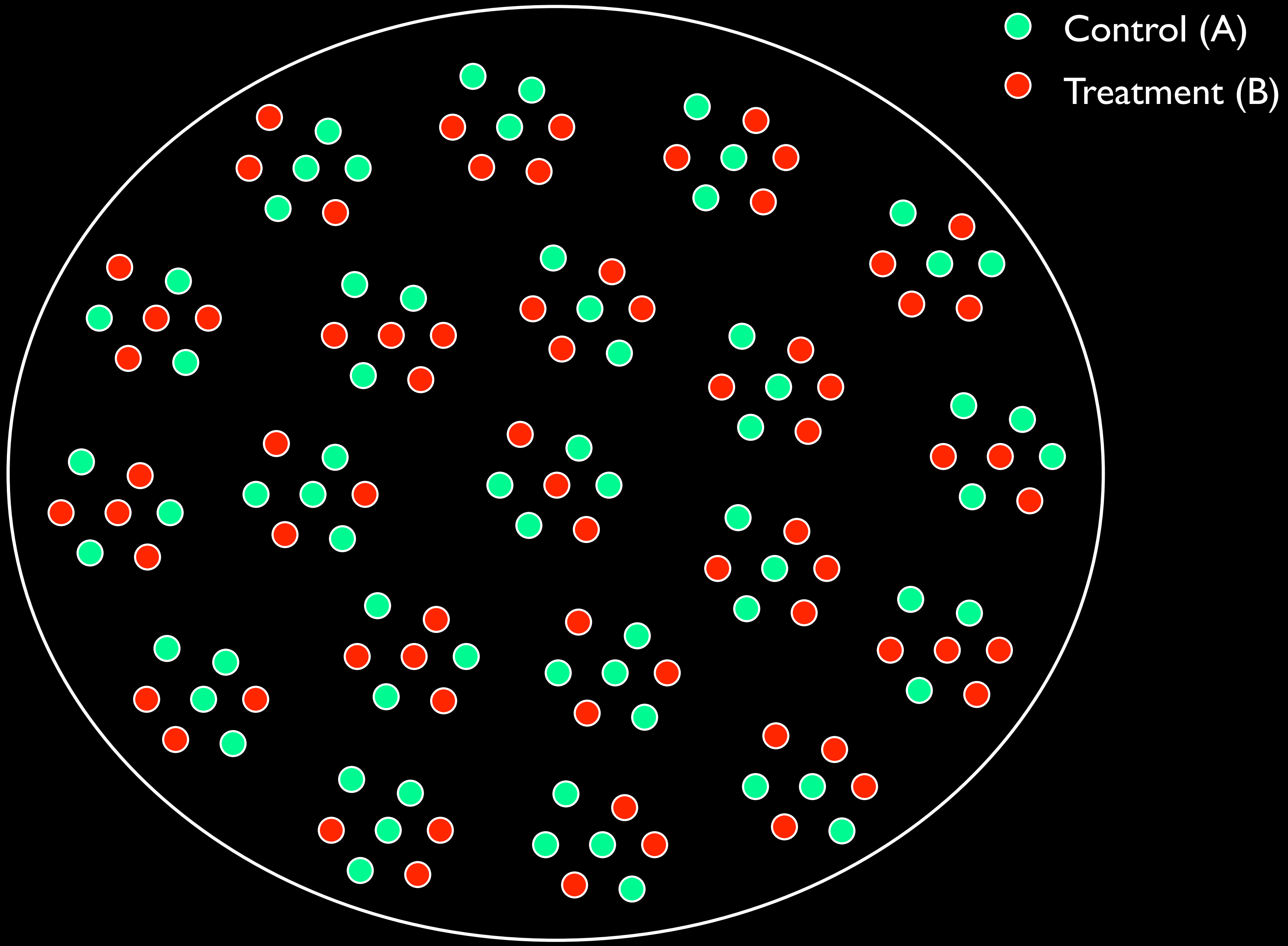
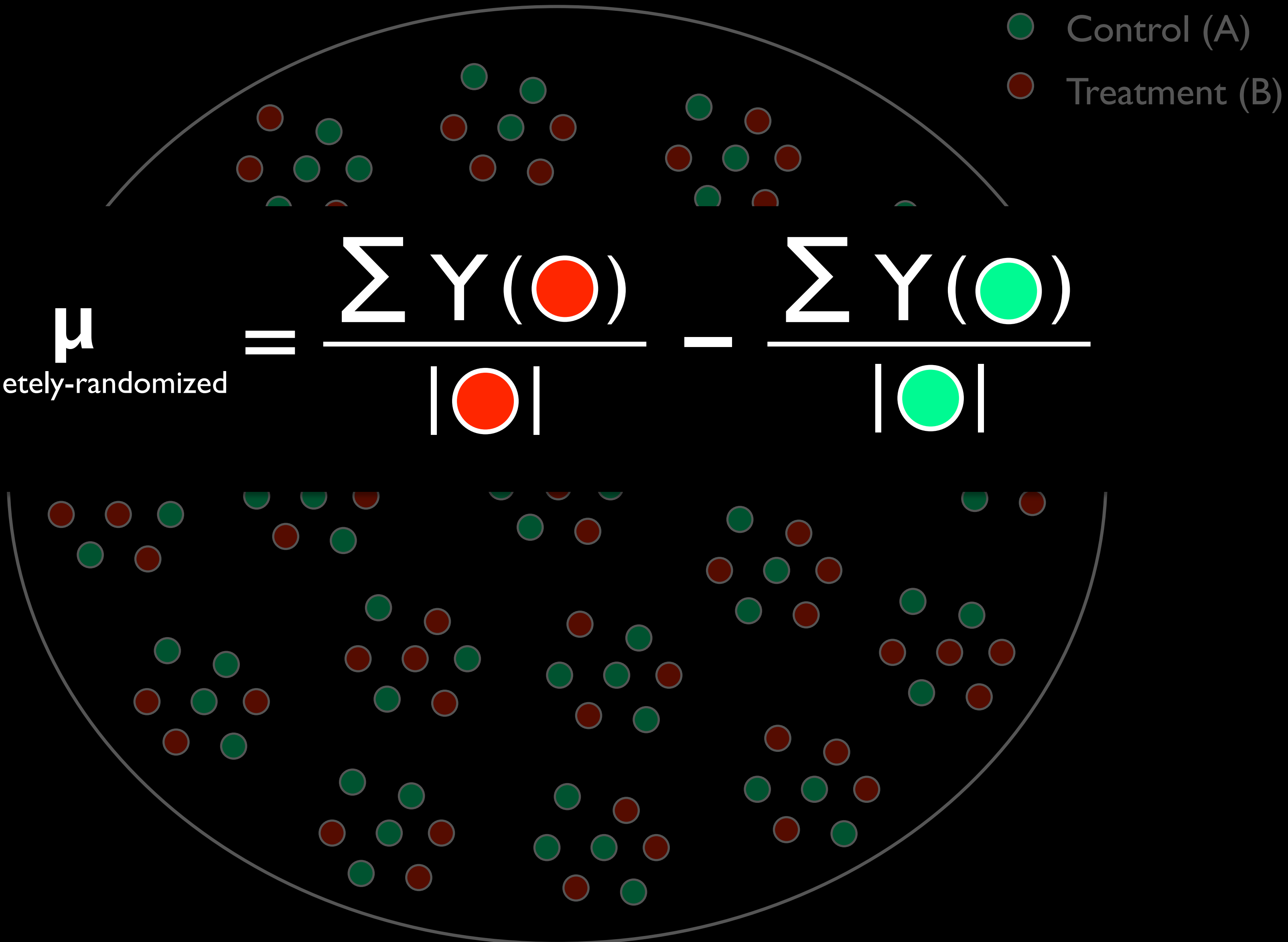


Completely-randomized Experiment



$$\mu_{\text{completely-randomized}} = \frac{\sum Y(\textcolor{red}{\bullet})}{|\textcolor{red}{\bullet}|} - \frac{\sum Y(\textcolor{green}{\bullet})}{|\textcolor{green}{\bullet}|}$$

Completely-randomized Experiment

Control (A)
Treatment (B)

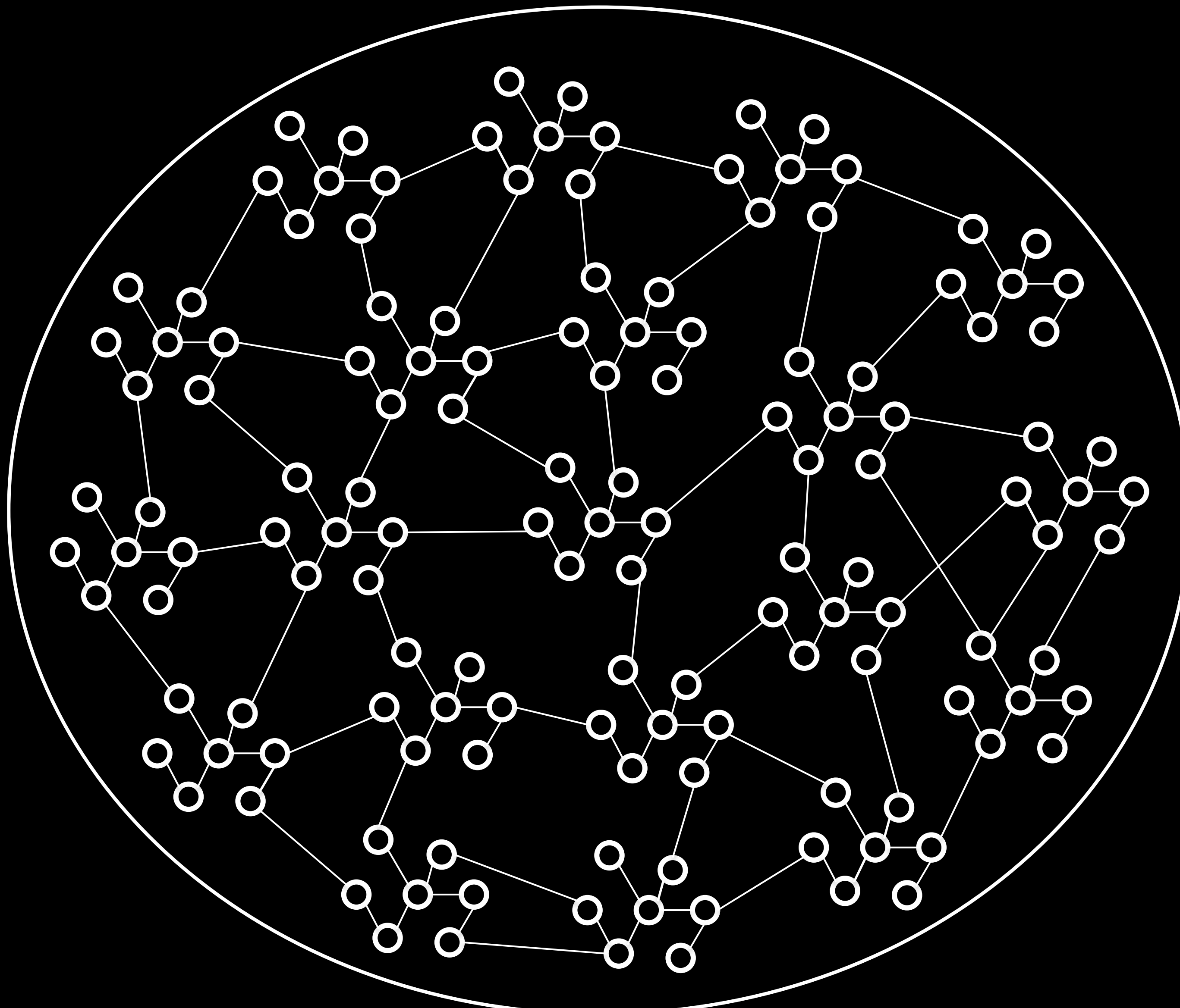
$$\mu_{\text{completely-randomized}} = \frac{\sum Y(\bullet)}{|\bullet|} - \frac{\sum Y(\bullet)}{|\bullet|}$$

SUTVA: Stable Unit Treatment Value Assumption

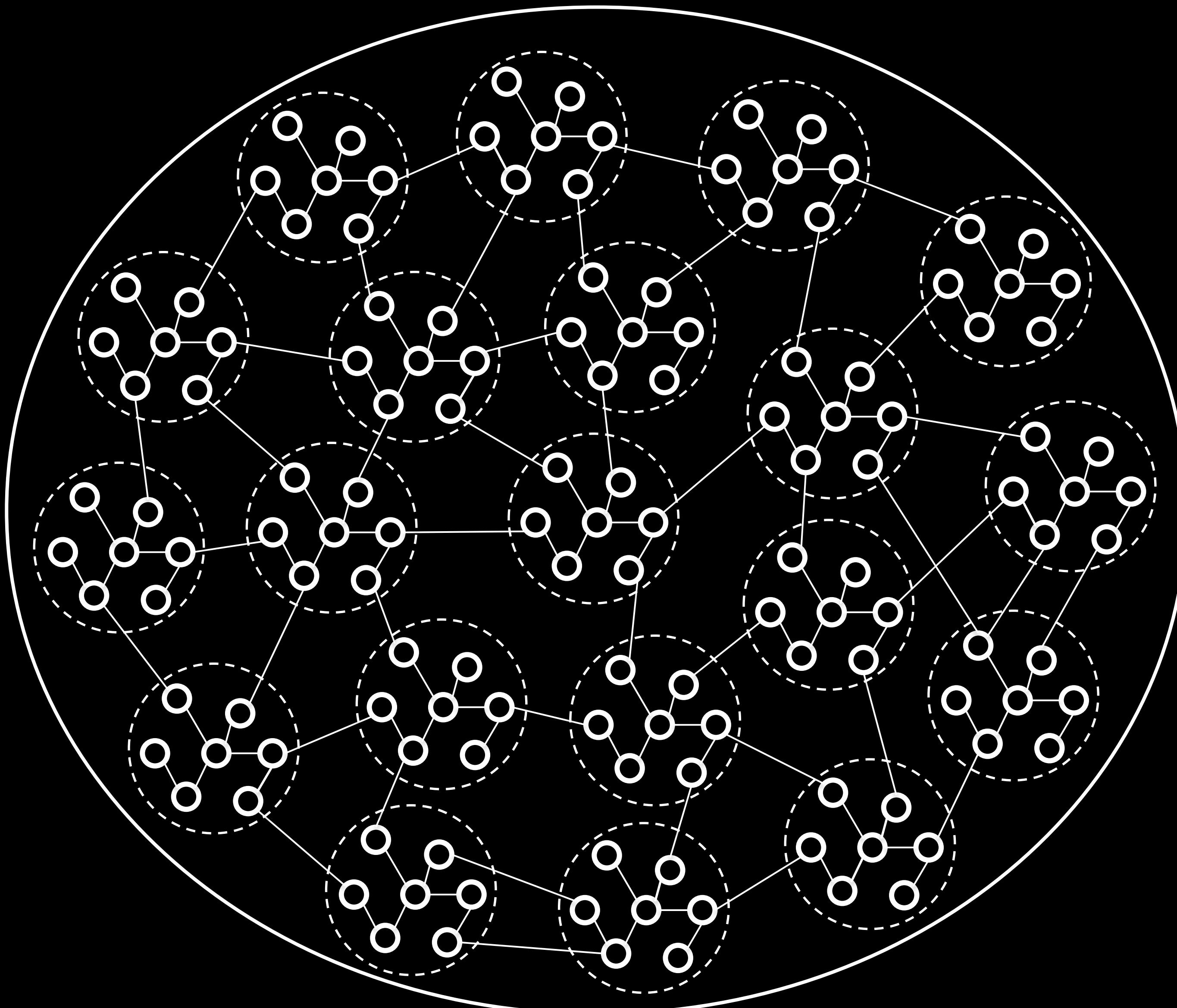
Every user's behavior is affected only by their treatment and NOT by the treatment of any other user

Completely-randomized Experiment

Cluster-based Randomized Experiment



Cluster-based Randomized Experiment



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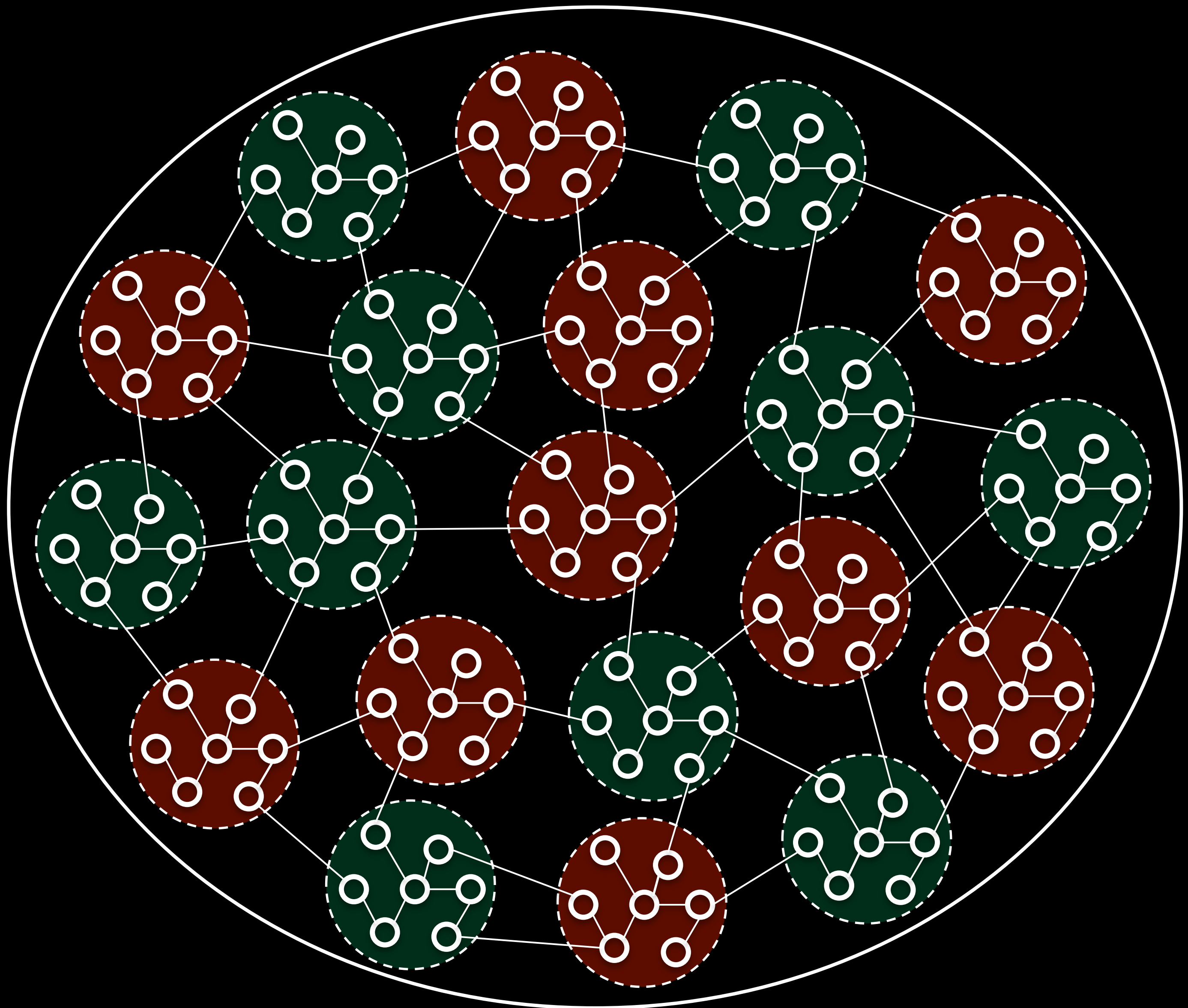

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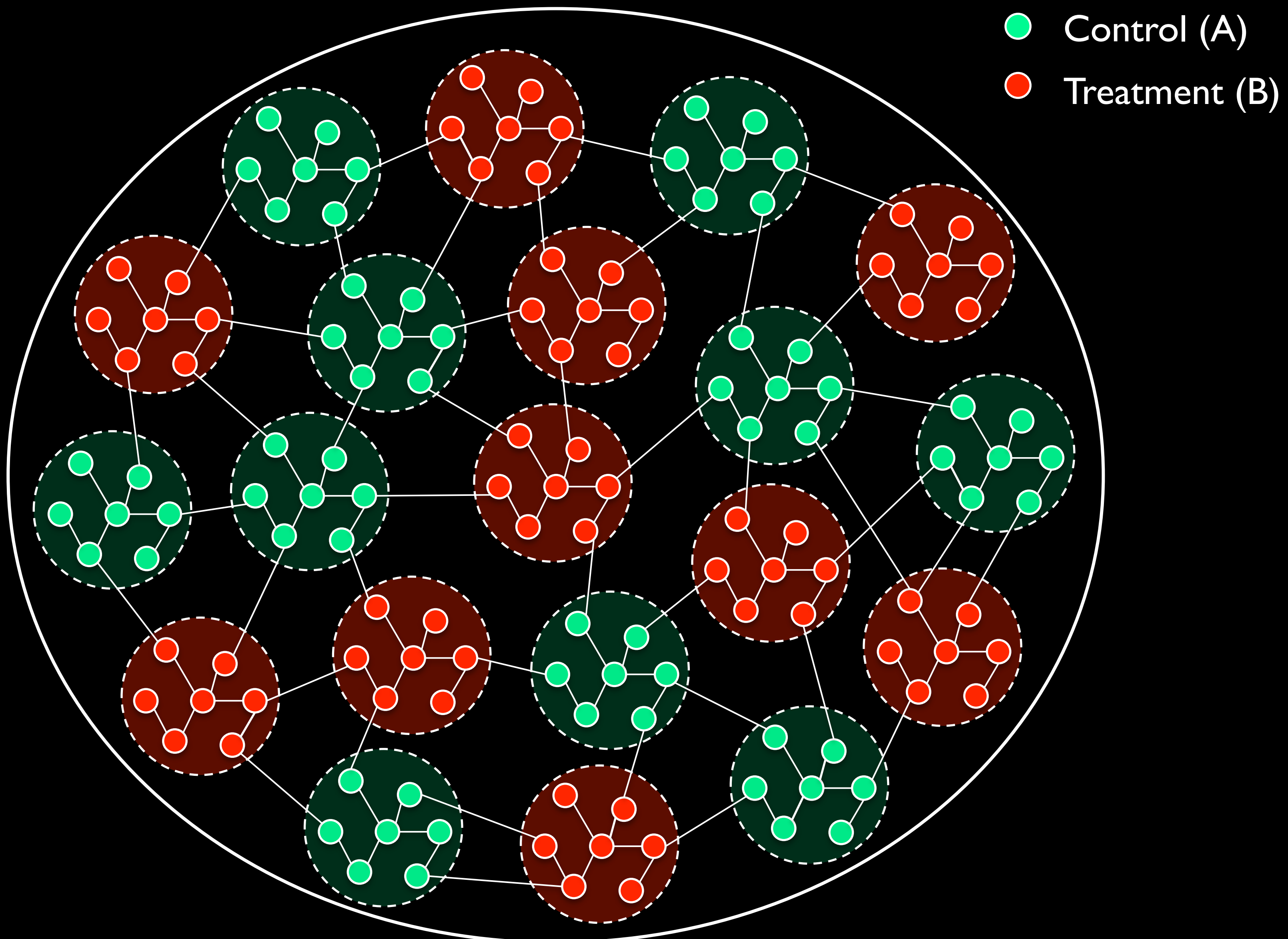
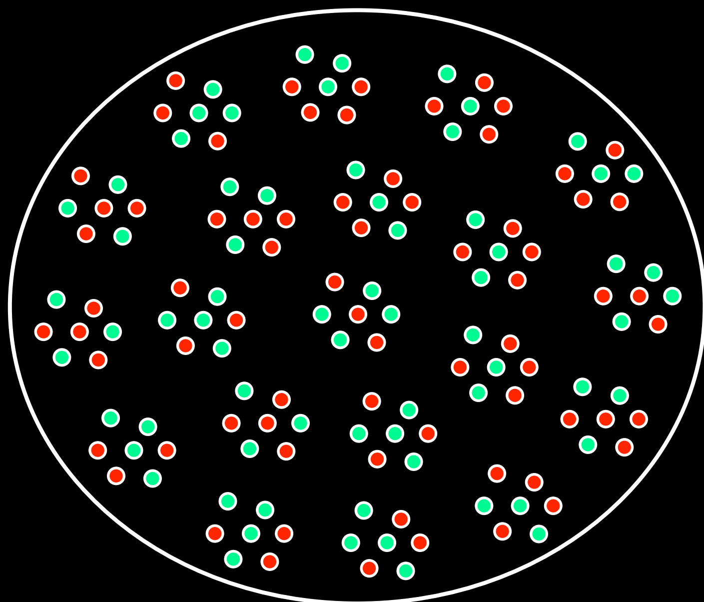


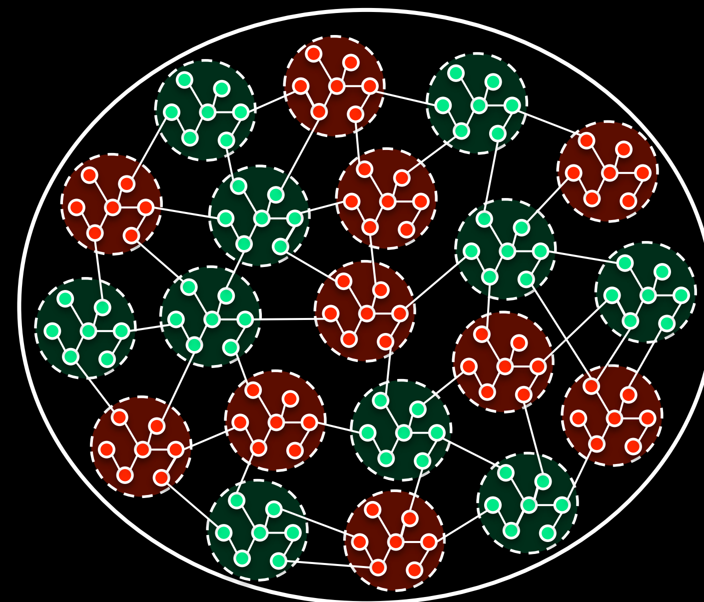
Cluster-based Randomized Experiment

Completely-randomized Experiment

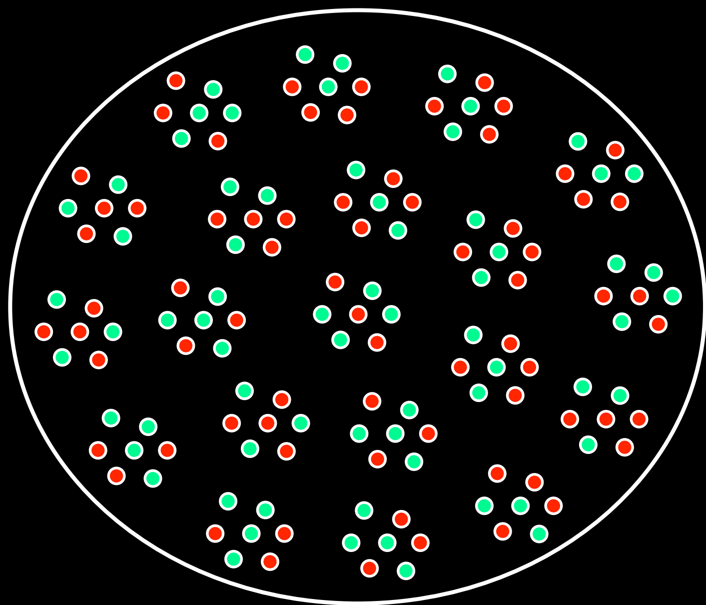


OR

Cluster-based Randomized Experiment

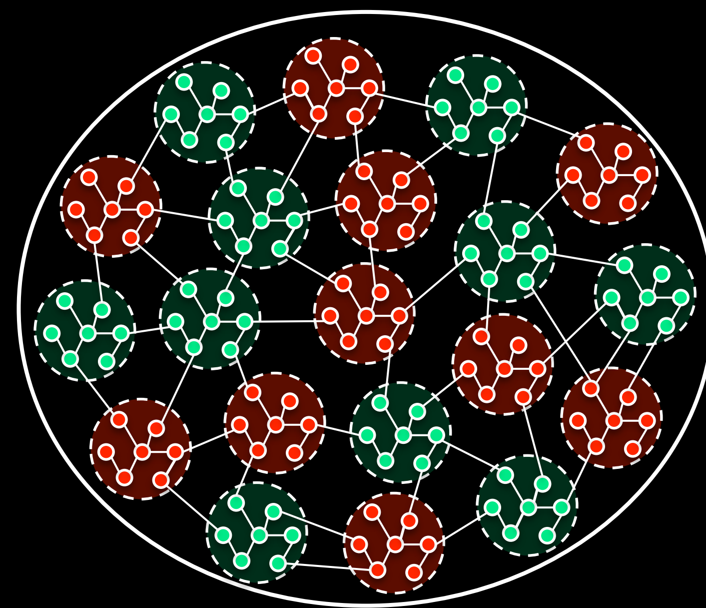


Completely-randomized Experiment



OR

Cluster-based Randomized Experiment



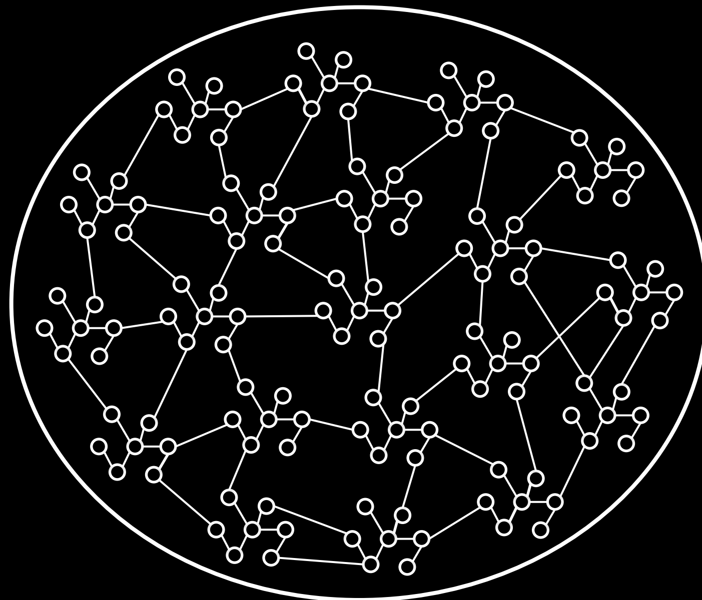
More Spillovers

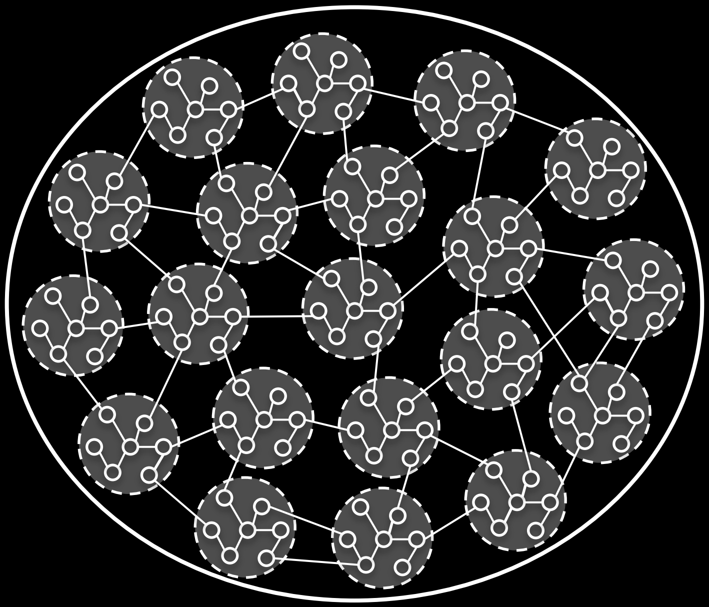
Lower Variance

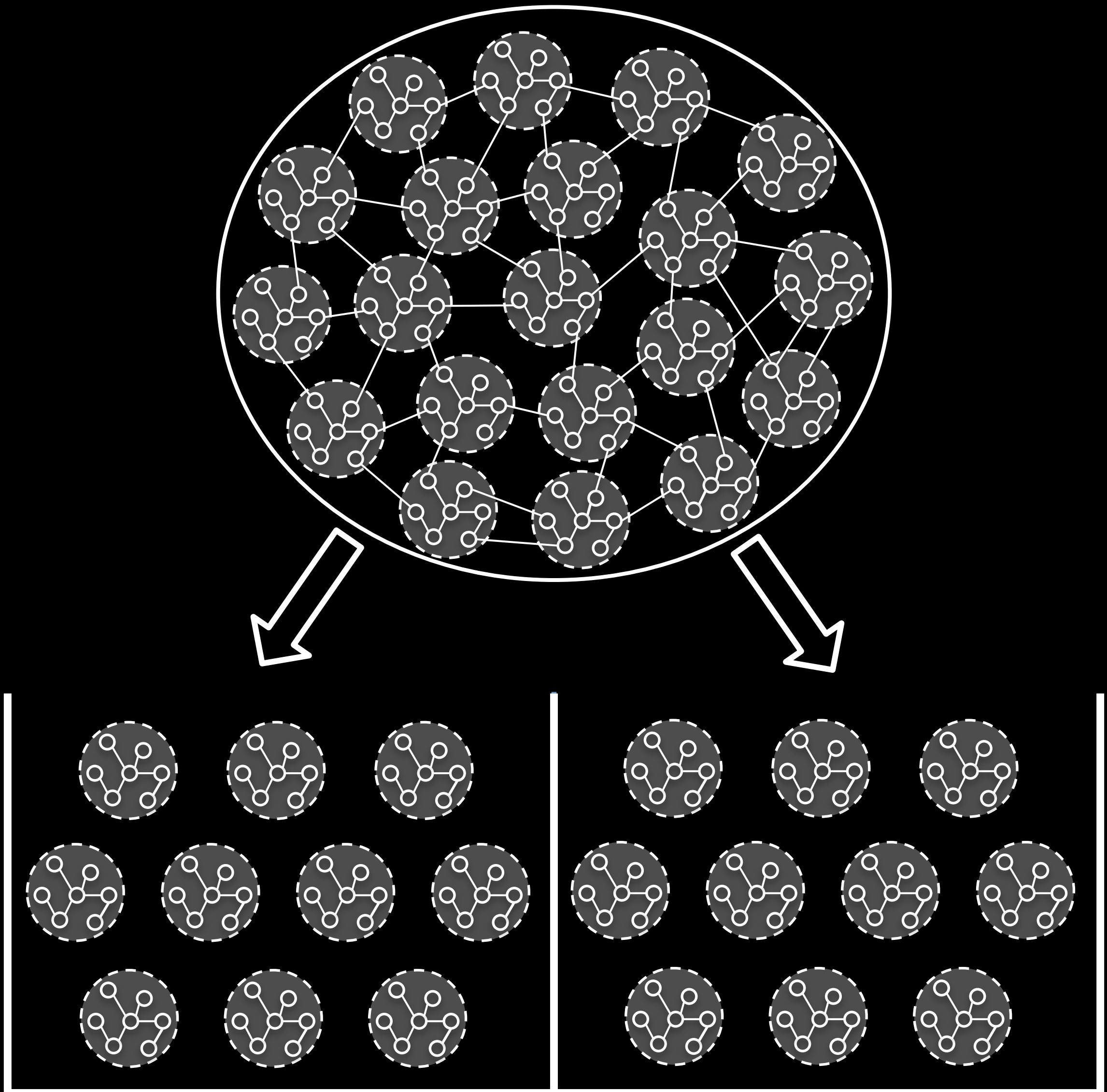
Less Spillovers

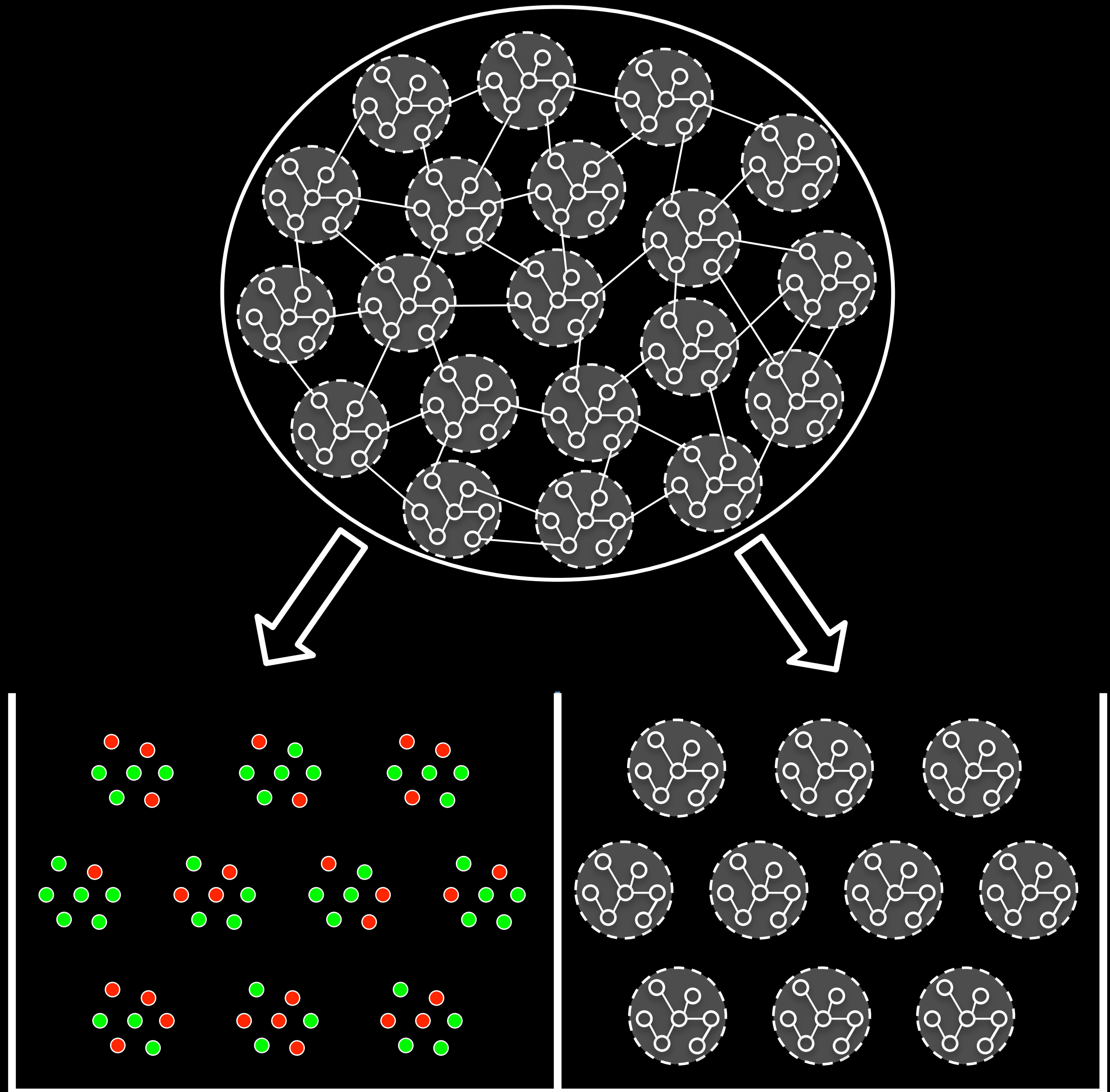
Higher Variance

Design for Detecting Network Effects

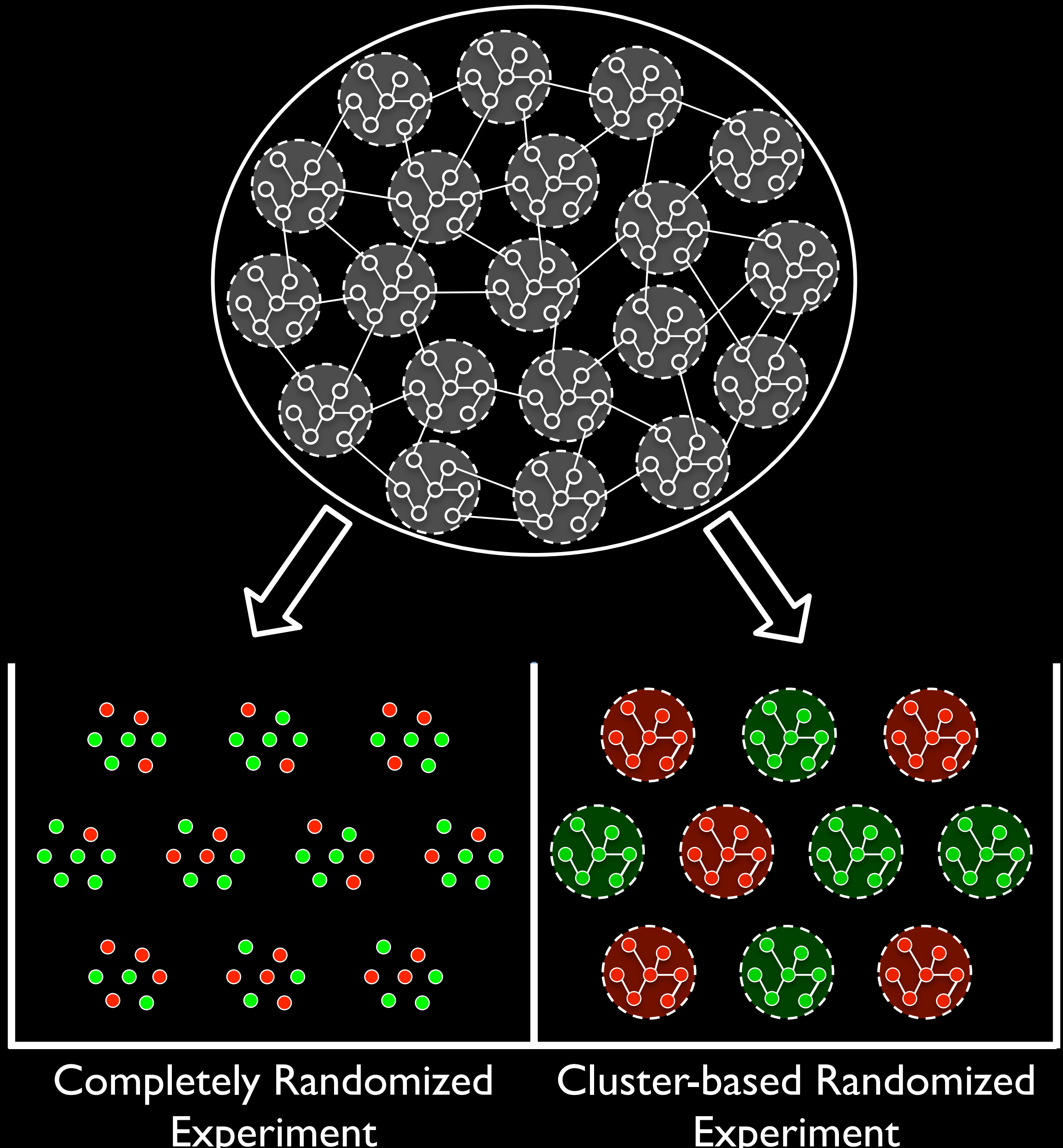


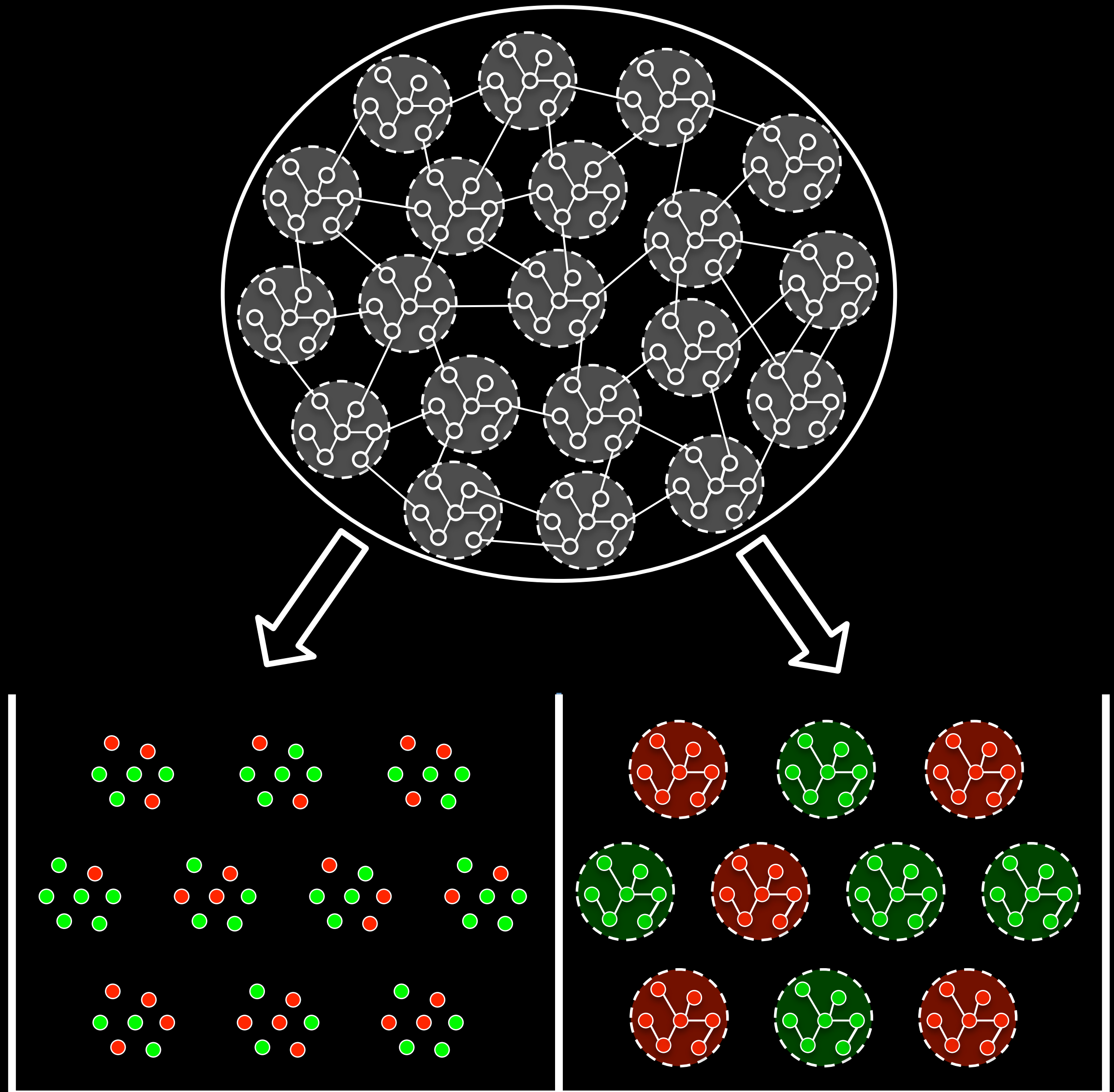






Completely Randomized
Experiment


Completely Randomized
Experiment
Cluster-based Randomized
Experiment



Completely Randomized Experiment

Cluster-based Randomized Experiment

$$\mu_{\text{completely-randomized}} \stackrel{?}{=} \mu_{\text{cluster-based}}$$

Hypothesis Test

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H_0: SUTVA Holds

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$$E_{\mathbf{w},\mathbf{z}}\left[\hat{\mu}_{cbr} - \hat{\mu}_{cr}\right] = 0$$

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Reject the null when:

Hypothesis Test

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Reject the null when:

$$\boxed{\frac{|\hat{\mu}_{cr} - \hat{\mu}_{cbr}|}{\sqrt{\hat{\sigma}^2}} \geq \frac{1}{\sqrt{\alpha}}}$$

Hypothesis Test

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Type I error is no greater than α

Nuts and Bolts of Running Cluster-based Randomized Experiments

Why Balanced Clustering?

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- Theoretical Motivation
  - Constants VS random variables

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- Practical Motivations

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- Practical Motivations
  - Variance reduction

Why Balanced Clustering?

- Theoretical Motivation
  - Constants VS random variables
- Practical Motivations
  - Variance reduction
  - Balance on pre-treatment covariates
    (homophily => large homogenous clusters)

Algorithms for Balanced Clustering

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Most clustering methods find skewed distributions of cluster sizes
(Leskovec, 2009; Fortunato, 2010)

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=> Algorithms that enforce equal cluster sizes

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Restreaming Linear Deterministic Greedy
(Nishimura & Ugander, 2013)

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Most clustering methods find skewed distributions of cluster sizes
(Leskovec, 2009; Fortunato, 2010)

=> Algorithms that enforce equal cluster sizes

Restreaming Linear Deterministic Greedy
(Nishimura & Ugander, 2013)

- Streaming
- Parallelizable
- Stable

Clustering the LinkedIn Graph

- Graph: >100M nodes, >10B edges
- 350 Hadoop nodes
- 1% leniency

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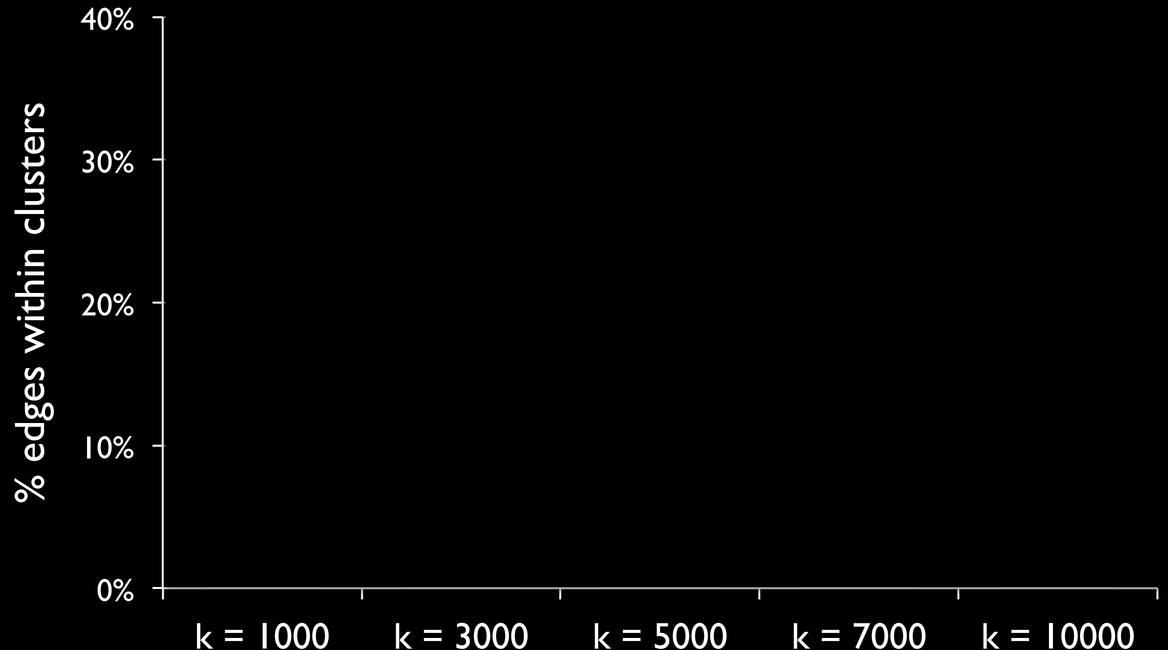

Clustering the LinkedIn Graph

- Graph: >100M nodes, >10B edges
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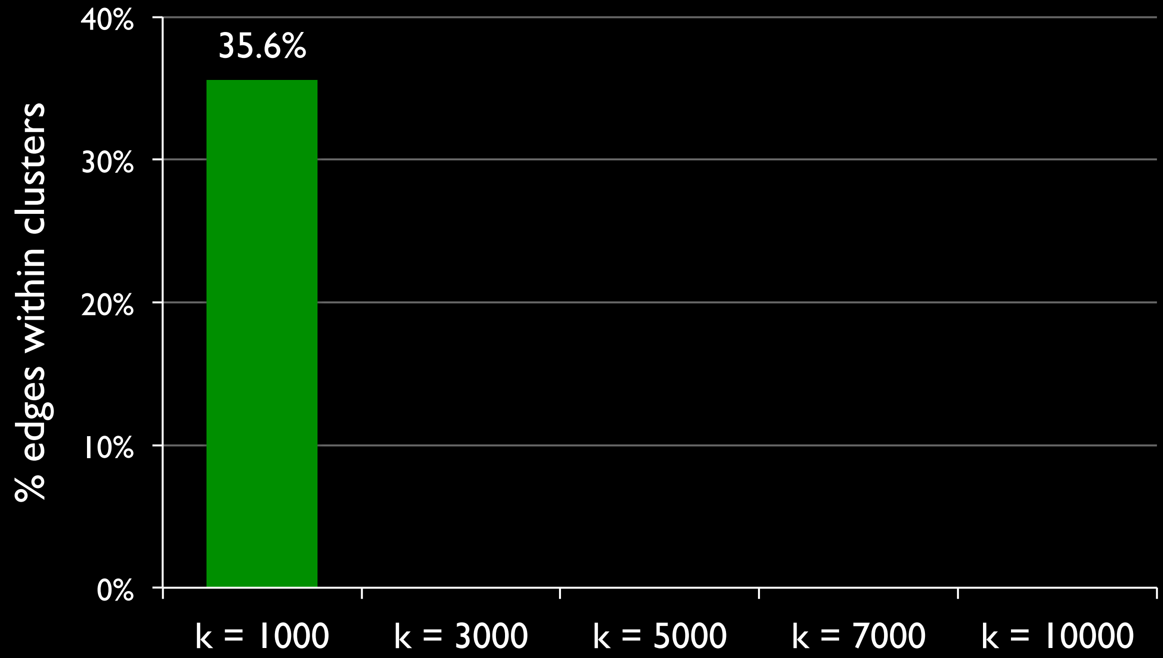

Clustering the LinkedIn Graph

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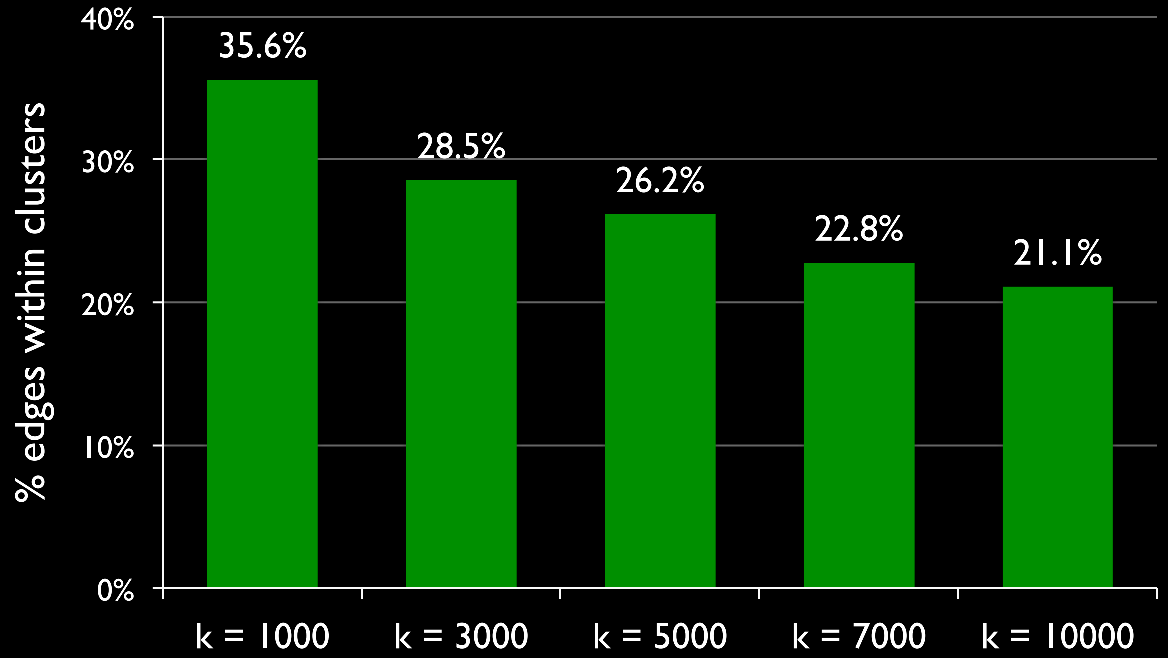

Choosing the Number of Clusters

Choosing the Number of Clusters

small *k* large *k*

Choosing the Number of Clusters

small k — large k

large clusters — small clusters

Choosing the Number of Clusters

small *k*

large *k*

large clusters

small clusters

large network effect

small network effect

large variance

small variance

Choosing the Number of Clusters

Understanding the Type II error

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Assuming an interference model

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Understanding the Type II error

Assuming an interference model

$$Y_i = \beta_0 + \beta_1 Z_i + \beta_2 \rho_i + \epsilon_i$$

ρ_i : fraction of treated friends

Choosing the Number of Clusters

Understanding the Type II error

Assuming an interference model

$$Y_i = \beta_0 + \beta_1 Z_i + \beta_2 \rho_i + \epsilon_i$$

ρ_i : fraction of treated friends

$$E\left[\hat{\mu}_{cbr} - \hat{\mu}_{cr}\right] \approx \rho \cdot \beta_2$$

ρ : average fraction of a unit's neighbors contained in the cluster

Choosing the Number of Clusters

Understanding the Type II error

Assuming an interference model

$$Y_i = \beta_0 + \beta_1 Z_i + \beta_2 \rho_i + \epsilon_i$$

ρ_i : fraction of treated friends

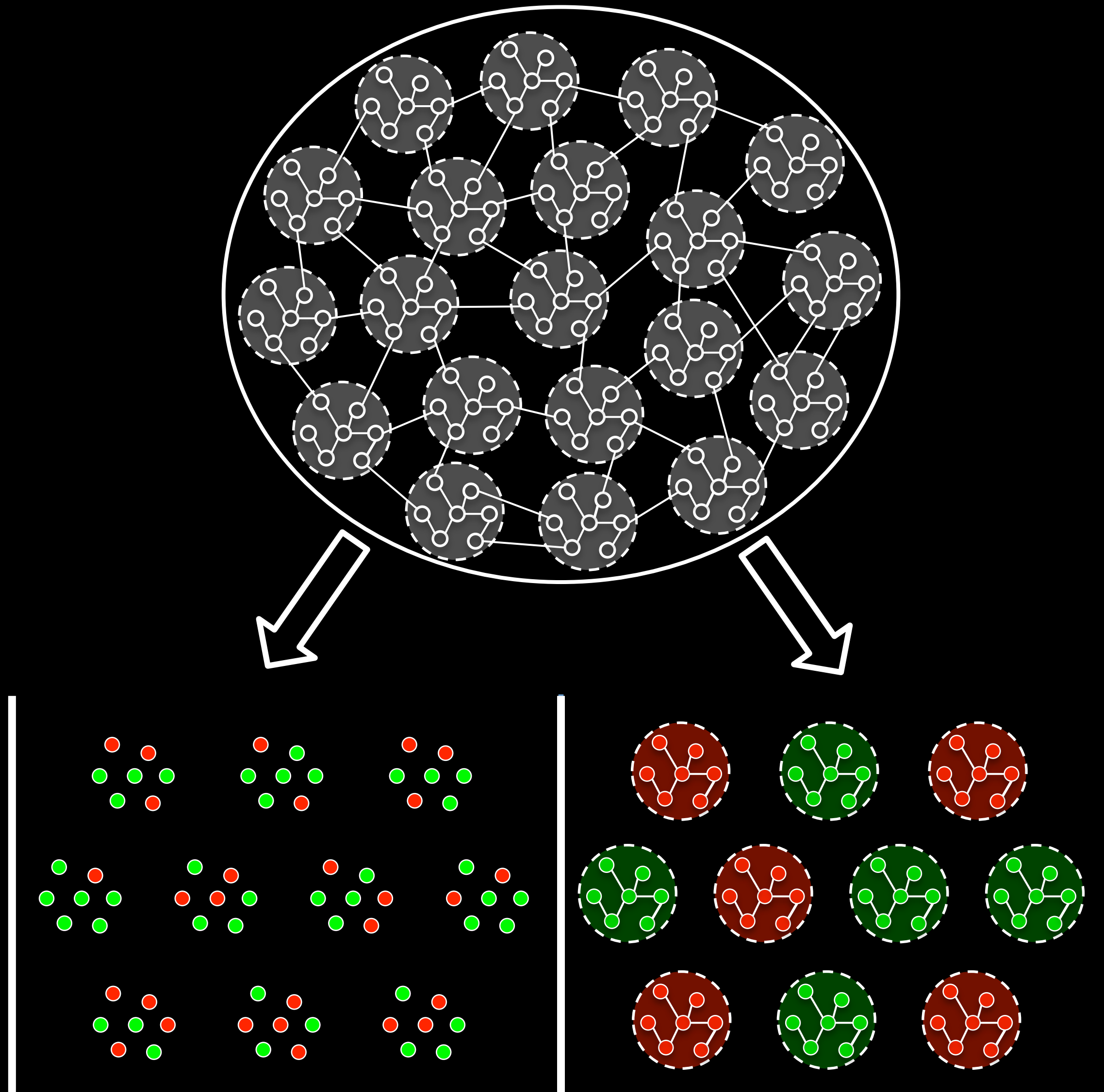
$$E\left[\hat{\mu}_{cbr} - \hat{\mu}_{cr}\right] \approx \rho \cdot \beta_2$$

ρ : average fraction of a unit's neighbors contained in the cluster

Choose number of clusters M and clustering C such that

$$\max_{M,C} \frac{\rho}{\sqrt{\hat{\sigma}_C^2}}$$

Experiments on LinkedIn



Completely Randomized Experiment

Cluster-based Randomized Experiment

Bernoulli Randomized Experiment

$(\mu_{\text{bernoulli}})$

$$\mu_{\text{completely-randomized}} \stackrel{?}{=} \mu_{\text{cluster-based}}$$

Experiment 1

Experiment 1

- Population: 20% of all LinkedIn users [Bernoulli: 10%, Cluster-based: 10%]

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	Treatment effect	Standard Deviation
Bernoulli Randomization (BR)		
Cluster-based Randomization (CBR)		
Delta (CBR – BR)		

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	Treatment effect	Standard Deviation
Bernoulli Randomization (BR)	0.0559	0.0050
Cluster-based Randomization (CBR)		
Delta (CBR – BR)		

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- Time period: 2 weeks
- Number of clusters: k = 3,000
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	Treatment effect	Standard Deviation
Bernoulli Randomization (BR)	0.0559	0.0050
Cluster-based Randomization (CBR)	0.0771	0.0260
Delta (CBR – BR)		

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	Treatment effect	Standard Deviation
Bernoulli Randomization (BR)	0.0559	0.0050
Cluster-based Randomization (CBR)	0.0771	0.0260
Delta (CBR – BR)	-0.0211	0.0265

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- Population: 20% of all LinkedIn users [Bernoulli: 10%, Cluster-based: 10%]
- Time period: 2 weeks
- Number of clusters: k = 3,000
- Outcome: feed engagement

	Treatment effect	Standard Deviation
Bernoulli Randomization (BR)	0.0559	0.0050
Cluster-based Randomization (CBR)	0.0771	0.0260
Delta (CBR – BR)	-0.0211	0.0265

p-value: 0.4246

Experiment 2

Experiment 2

– Population: 36% of all LinkedIn users [Bernoulli: 20%, Cluster-based: 16%]

Experiment 2

- Population: 36% of all LinkedIn users [Bernoulli: 20%, Cluster-based: 16%]
- Time period: 4 weeks

Experiment 2

- Population: 36% of all LinkedIn users [Bernoulli: 20%, Cluster-based: 16%]
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	Treatment effect	Standard Deviation
Bernoulli Randomization (BR)	0.2108	0.2911
Cluster-based Randomization (CBR)		
Delta (CBR – BR)		

Experiment 2

- Population: 36% of all LinkedIn users [Bernoulli: 20%, Cluster-based: 16%]
- Time period: 4 weeks
- Number of clusters: k = 10,000
- Outcome: feed engagement

	Treatment effect	Standard Deviation
Bernoulli Randomization (BR)	0.2108	0.2911
Cluster-based Randomization (CBR)	0.5390	0.5613
Delta (CBR – BR)		

Experiment 2

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- Number of clusters: k = 10,000
- Outcome: feed engagement

	Treatment effect	Standard Deviation
Bernoulli Randomization (BR)	0.2108	0.2911
Cluster-based Randomization (CBR)	0.5390	0.5613
Delta (CBR – BR)	-0.3281	0.5712

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	Treatment effect	Standard Deviation
Bernoulli Randomization (BR)	0.2108	0.2911
Cluster-based Randomization (CBR)	0.5390	0.5613
Delta (CBR – BR)	-0.3281	0.5712

p-value: 0.0483

Test SUTVA null

Test SUTVA null

reject

Test SUTVA null

reject

Use cluster-based experiment to estimate treatment effects

Test SUTVA null

reject

Use cluster-based experiment to estimate treatment effects

(higher variance)

Test SUTVA null

reject

fail to reject

Use cluster-based experiment to estimate treatment effects

(higher variance)

Test SUTVA null

reject

fail to reject

Use cluster-based experiment to estimate treatment effects

(higher variance)

Use Bernoulli experiment to estimate treatment effects

Test SUTVA null

reject

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(higher variance)

fail to reject

Use Bernoulli experiment to estimate treatment effects

(lower variance)

Papers available online

KDD'17

Arxiv

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