

# Machine Learning for Social Change

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[change.org](https://change.org)

the world's largest petition  
platform

[change.org](https://change.org)

# It works

300M signatures

4000 declared victories

Victories in 121 countries

20M users experiencing victory

Smallest winning petition has 2 signatures

Biggest winning petition has 1.3M signatures





**300,000**  
People Say  
Reinstatement Gay  
Scout Leader  
[www.change.org/scouts](http://www.change.org/scouts)



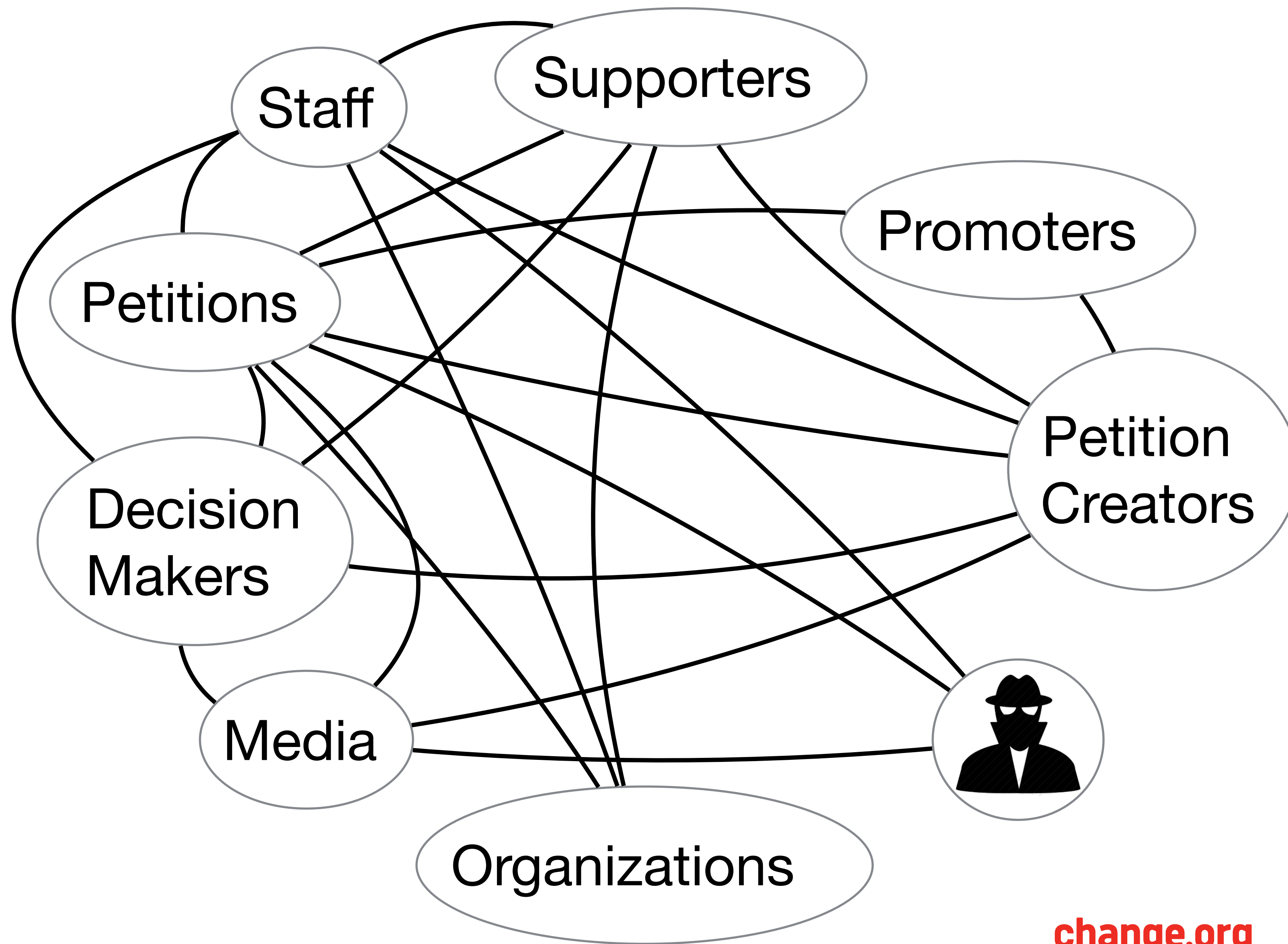
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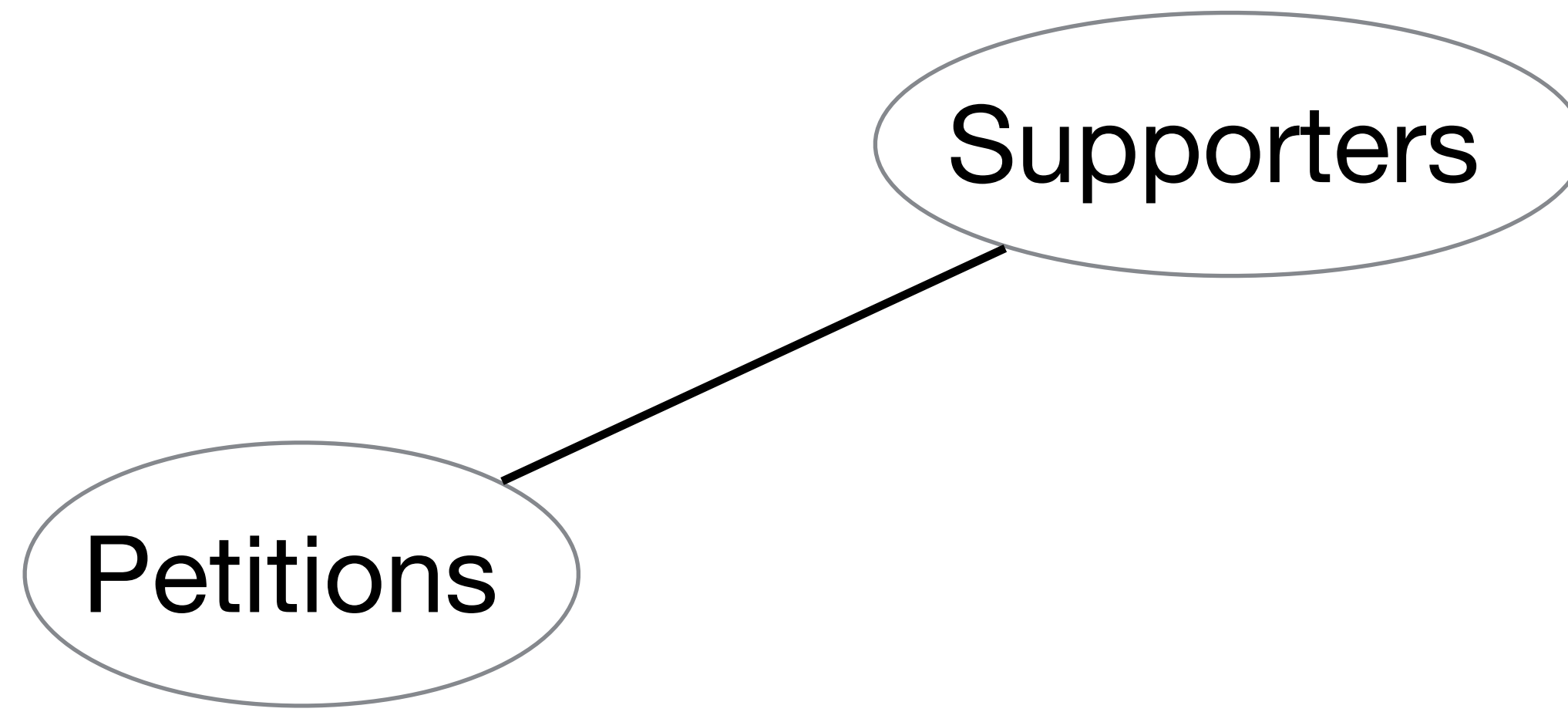


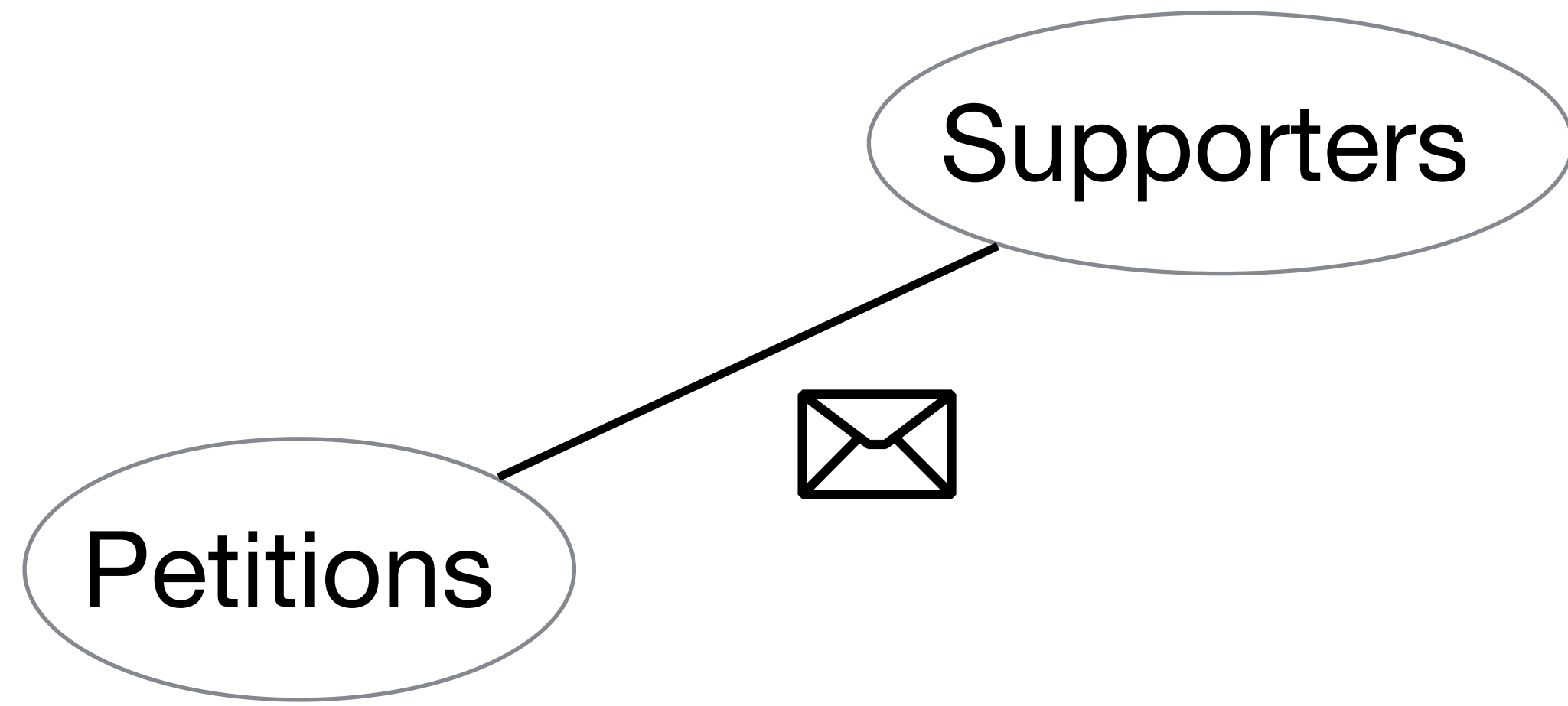
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$$\max_f \left[ f \left( \sum_{x \in \text{globe}} \Delta_x \right) \right]$$









# of Signatures

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Petitions

**change.org**

4.4M signatures

# of Signatures

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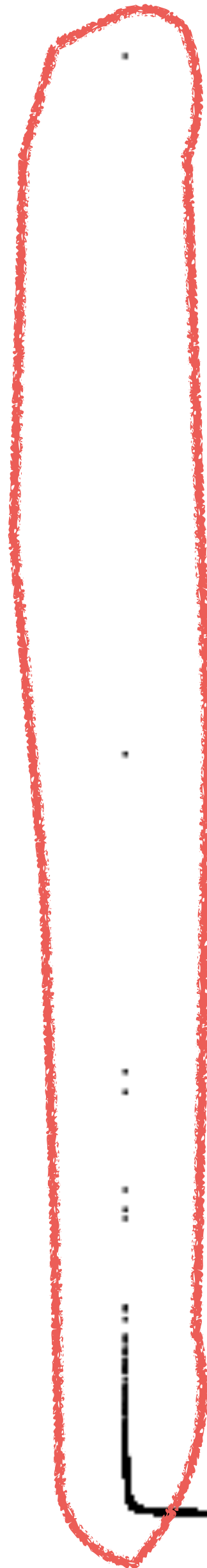
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Petitions

**change.org**



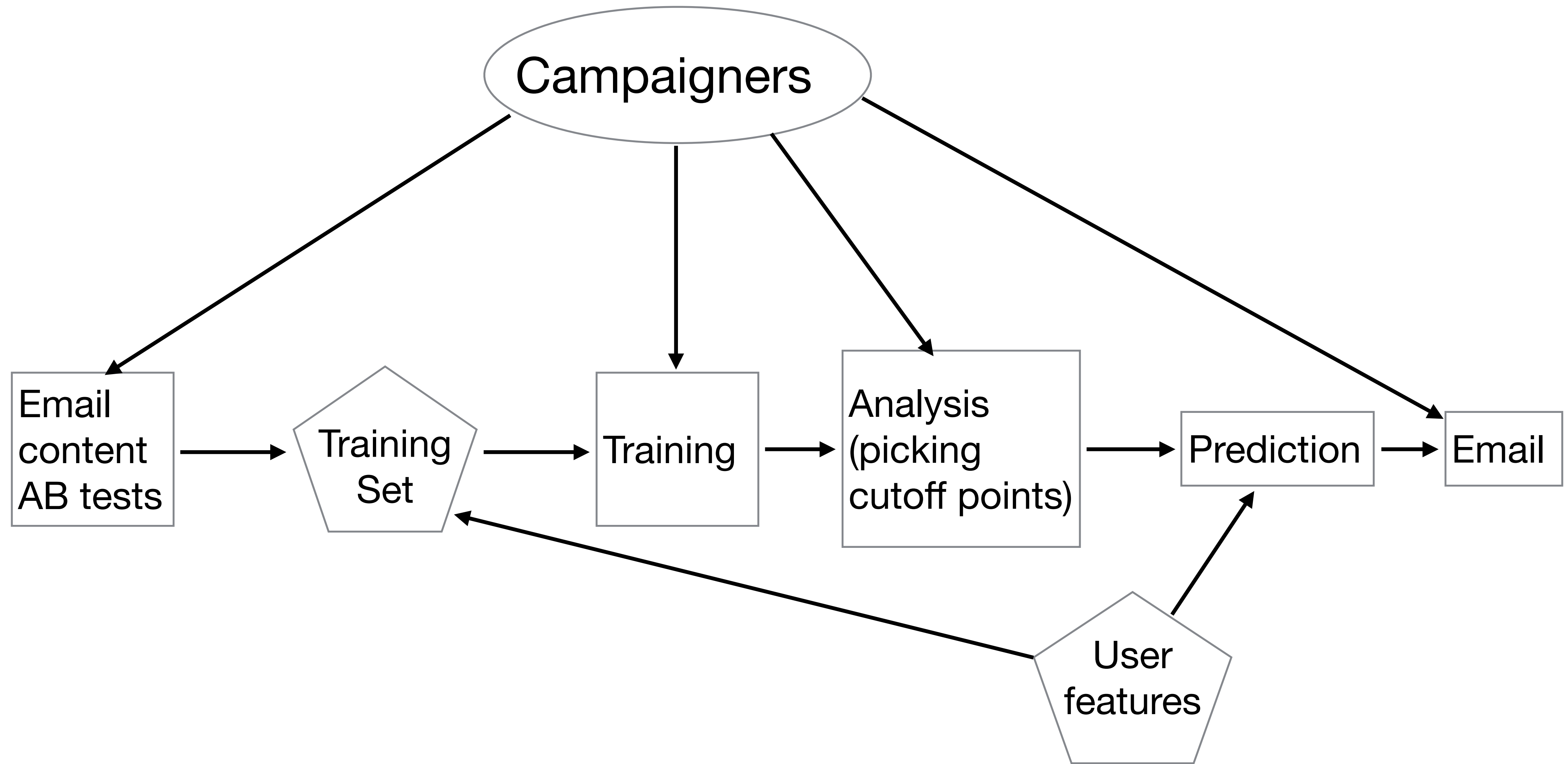
**change.org**

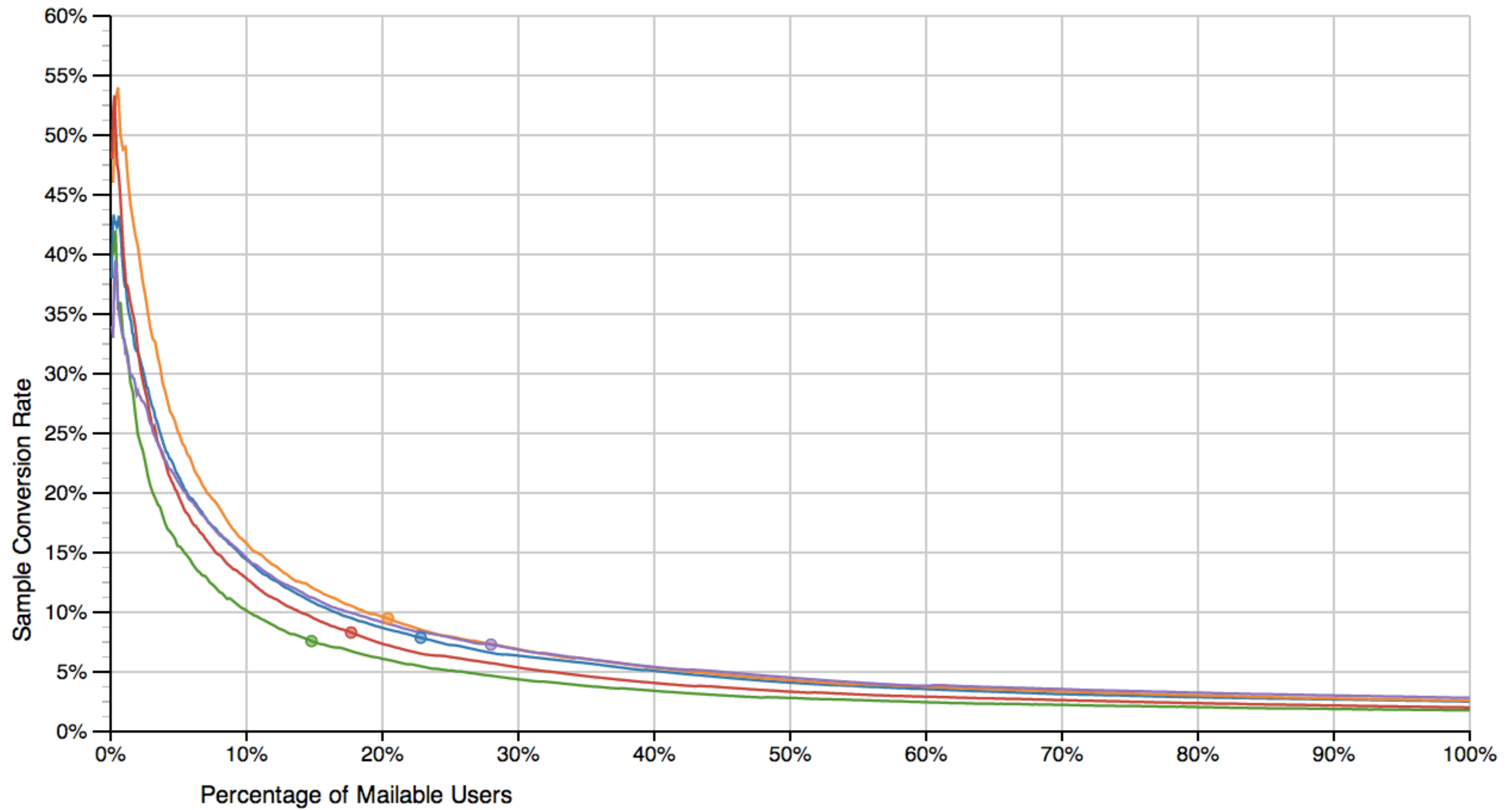
10s of petitions



10Ms of users

*~daily*





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# Learnings

Behavioral data trumps demographics & third party data sources.

Make all your features binary (via bucketing) to have flexibility on which algorithm to pick.

Random Forests work well for imbalanced (~2% positives) data.

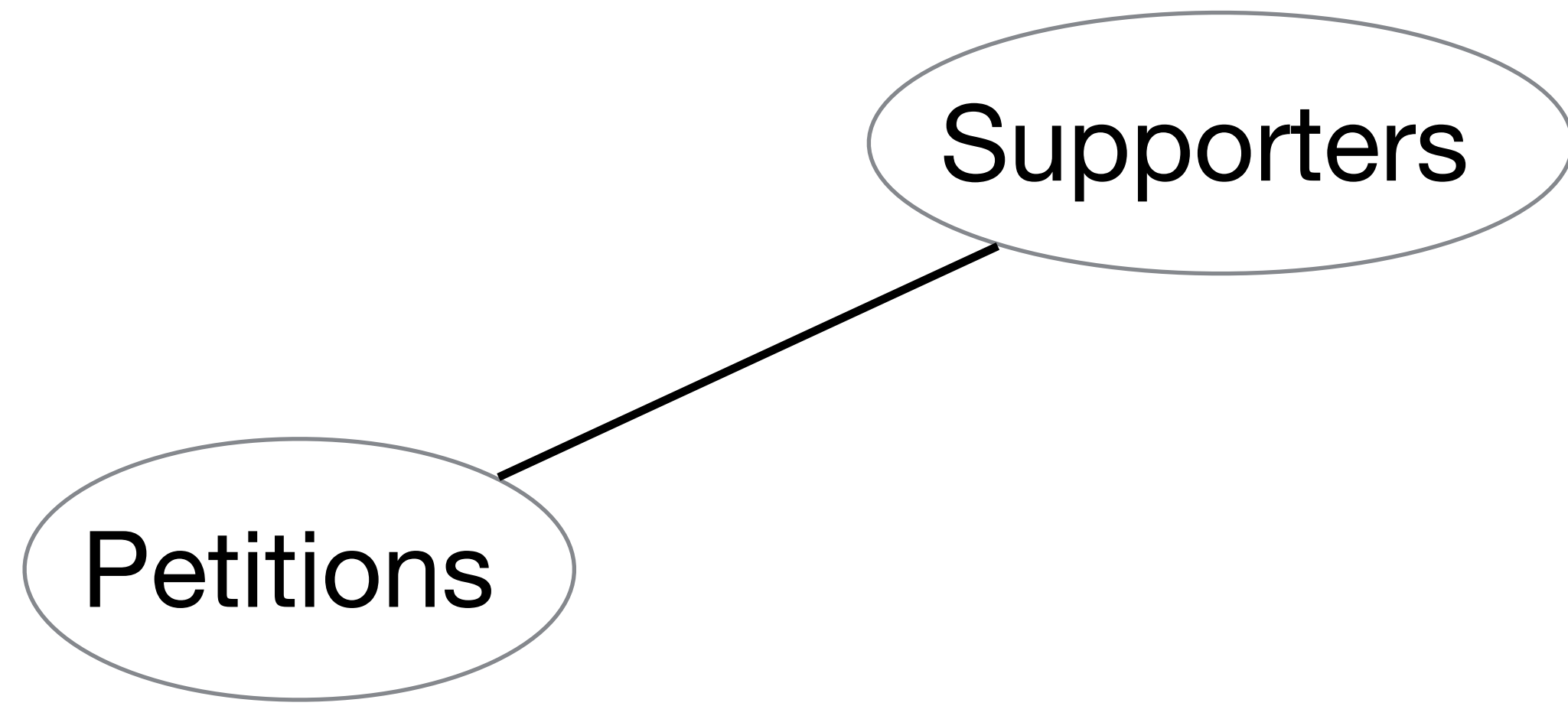
Performance was not the main criteria when choosing the learning model, use case and flexibility were way more important.

# Learnings

Big RAM/CPU instances are cheap, sparse binary datasets are small. If you can do in memory training, do it.

Use statistical distributions and basic time series analysis to verify data in your ETL pipeline.





~100 signatures



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# Recommendation & Discovery as a coherent Product

## The data landscape

Featured Petitions  
Social graph  
Geography  
Similar petitions  
Similar users  
Followed topics  
Followed users



## Delivery Channels

Online feed  
Online contextual (like  
after signing)  
Email push  
Email digest  
Mobile Push  
Facebook

# Recommendation & Discovery as a Product

Tons of input sources to try.

Tons of possible UXs.

Exploration vs Exploitation.

AB testing must as cheap as possible. For algorithms and features.

Which metric do you want to optimize?

Picking the right metric is the hardest part.

# Similar petitions via Collaborative Filtering

Thanks for signing

[^ Back to petition](#)



ASO (Amaury Sports Organization): Allow female professional cycling teams to race the Tour de France

by Kathryn Bertine · 21,430 supporters

[f Share on Facebook](#)

[t Tweet](#)

[✉ Email](#)

Recommended for you



EA Sports: Include Women Players in your Soccer Games

[46,826 signatures](#) · by [Rebekah Araujo](#)



UCI Cyclocross Commission: Include each nation's top 3 ranked women riders in World Championship

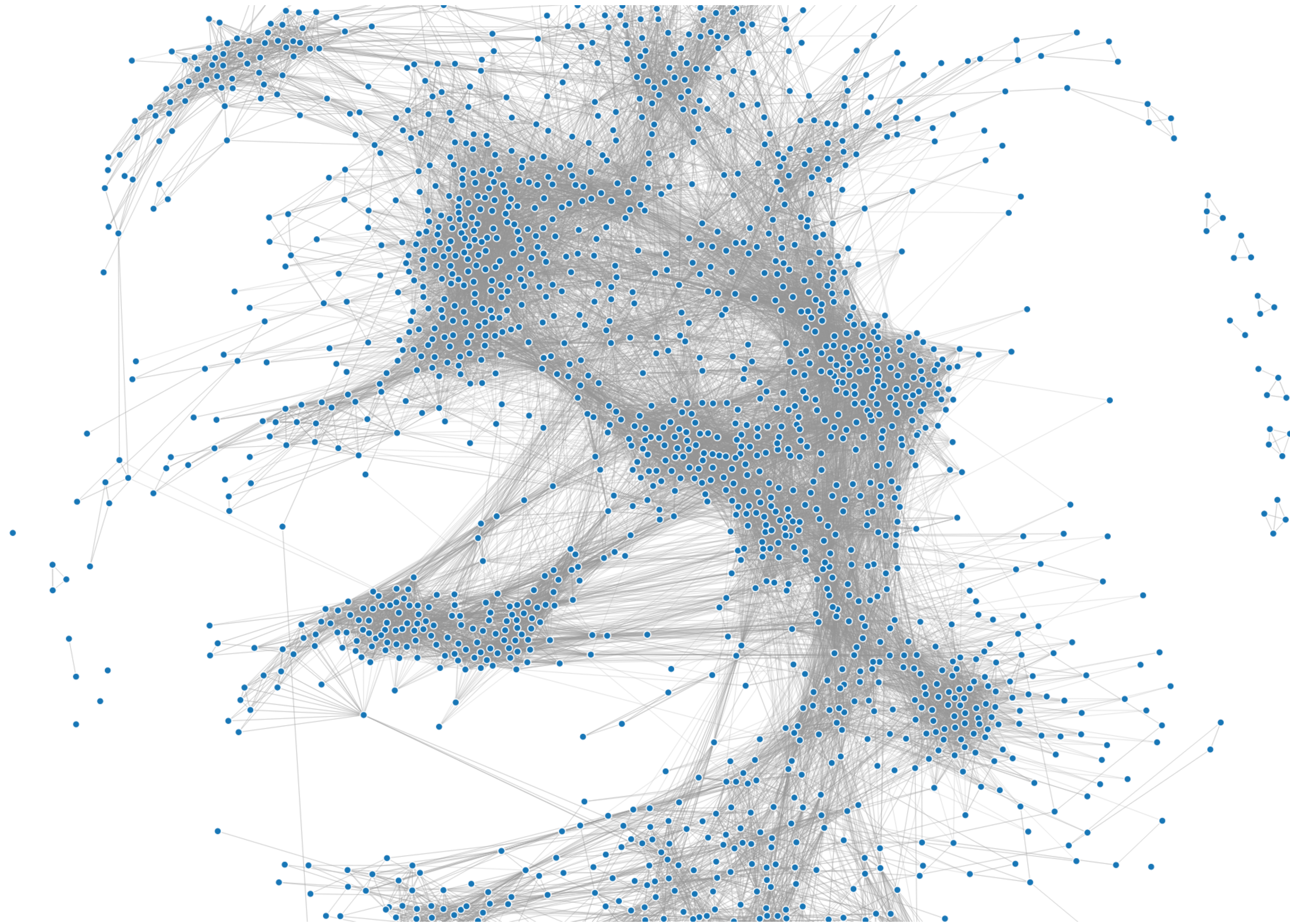
[1,842 signatures](#) · by [Michelle Lee](#)



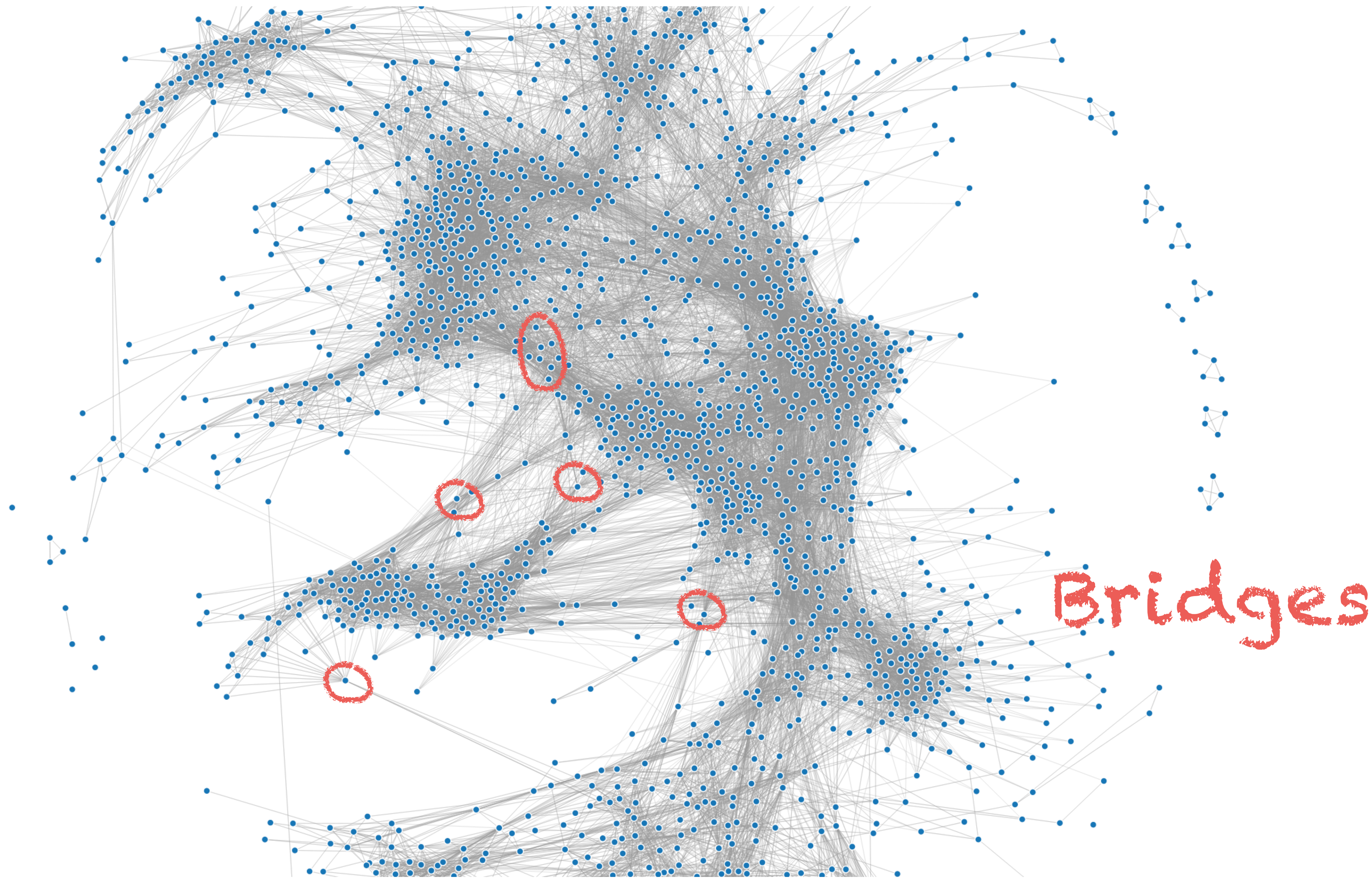
NCAA: Name the Women's College Basketball Championship Trophy After My Hero, Pat Summitt

[39,251 signatures](#) · by [Megan Netland](#)

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# Similar petitions via Collaborative Filtering

3x increase over baseline in additional signatures.

30% increase in overall signatures.

Always start with the simplest models such as basic similarity metrics.

Computing  $n^2$  pairs is a lot, use company data insights and Locality Sensitive Hashing to drastically reduce that number.

# Recommendation & Discovery as a Product

A more complicated model with a meager 5% improvement is usually not worth it.

Finding the right UX flow is the hardest part.

Better recommendations means less focus on the rest of the page (such as sharing).

# Learnings

Recommendations' performance is highly variable depending on *context*.

A user's sensitivity to different data inputs changes drastically over time.

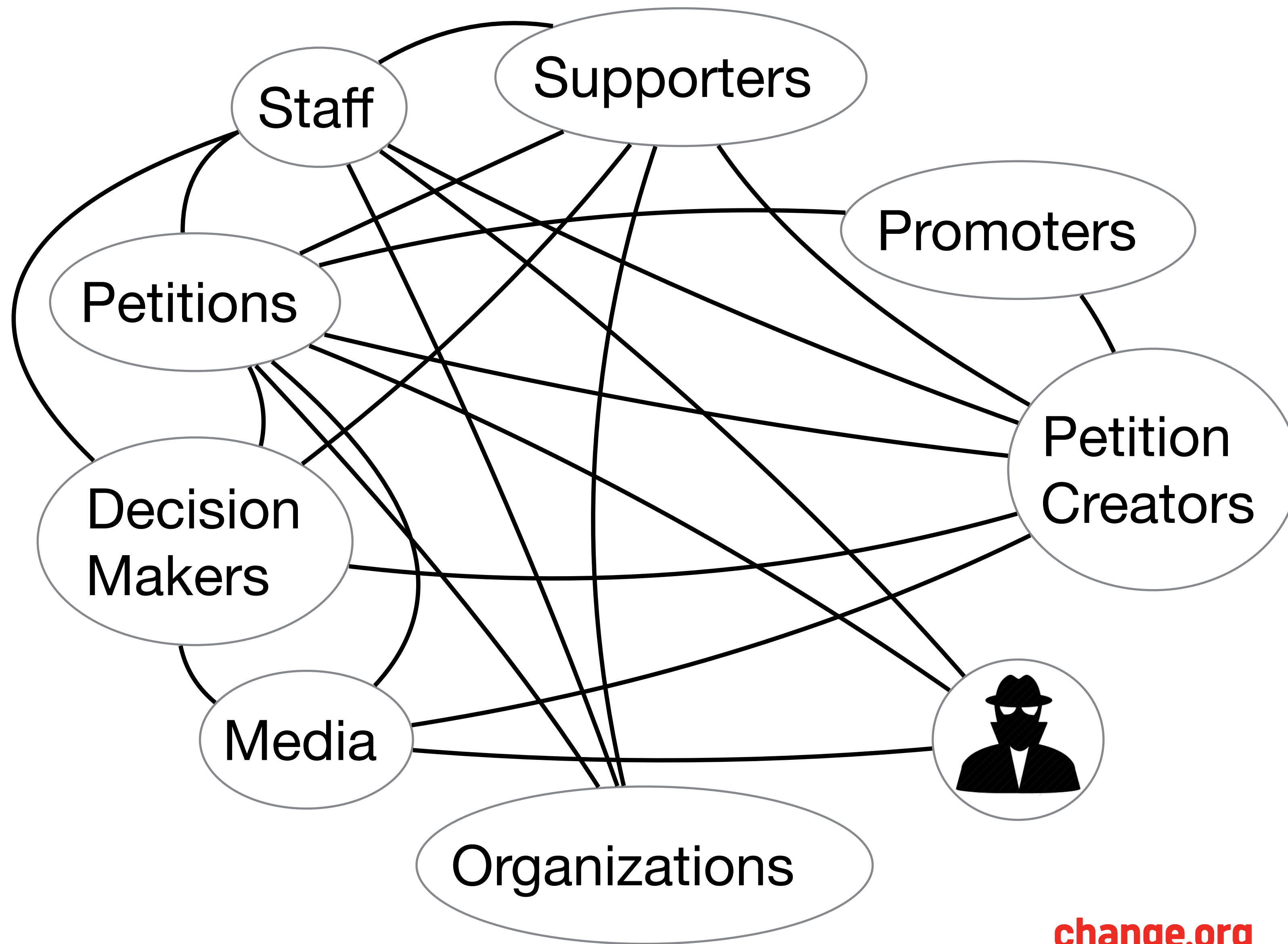
New users are not interested in similar petitions but highly sensitive to what their friends are signing.

# Learnings

Cold starting users is not the biggest problem.

Getting data about a user is not enough. You must first show the user the value of engaging with the platform.

Social graph partitioning is hard and incompatible with cohort analyses.



Supporters

Organizations

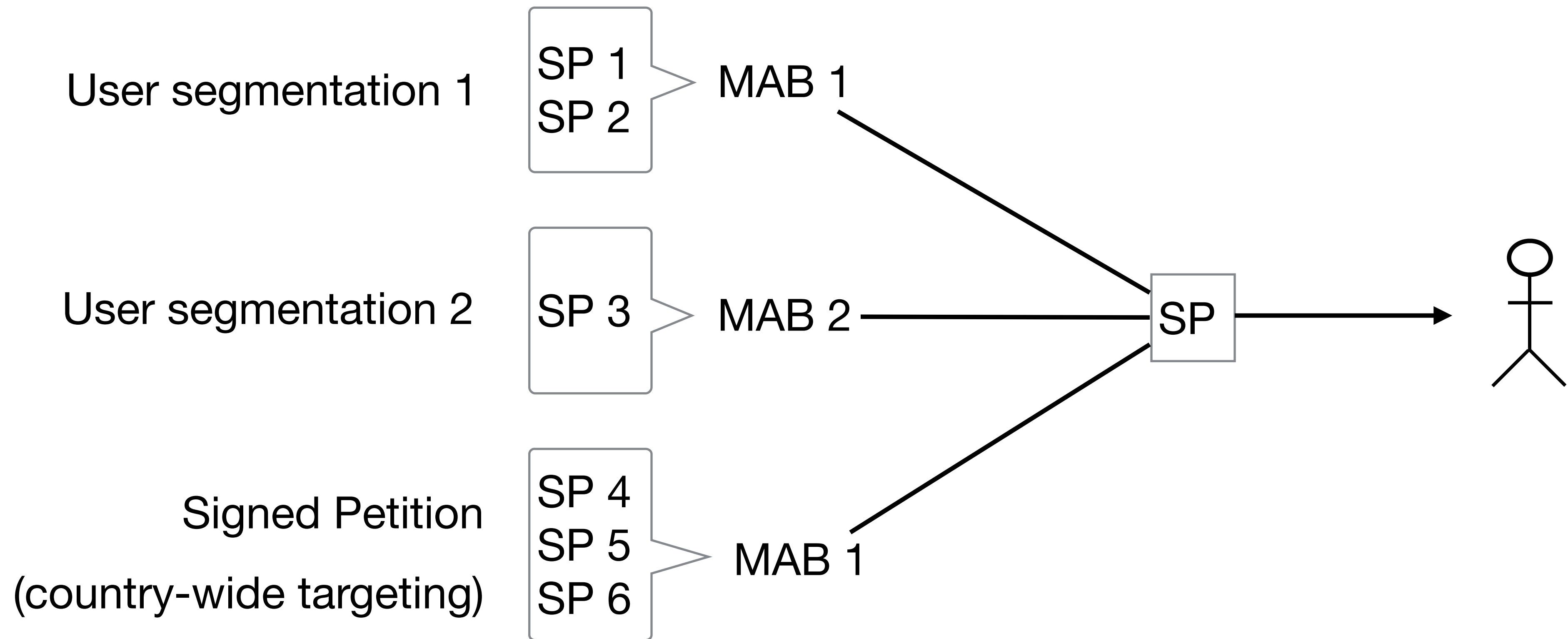
**change.org**

# Sponsored petition (SP) targeting

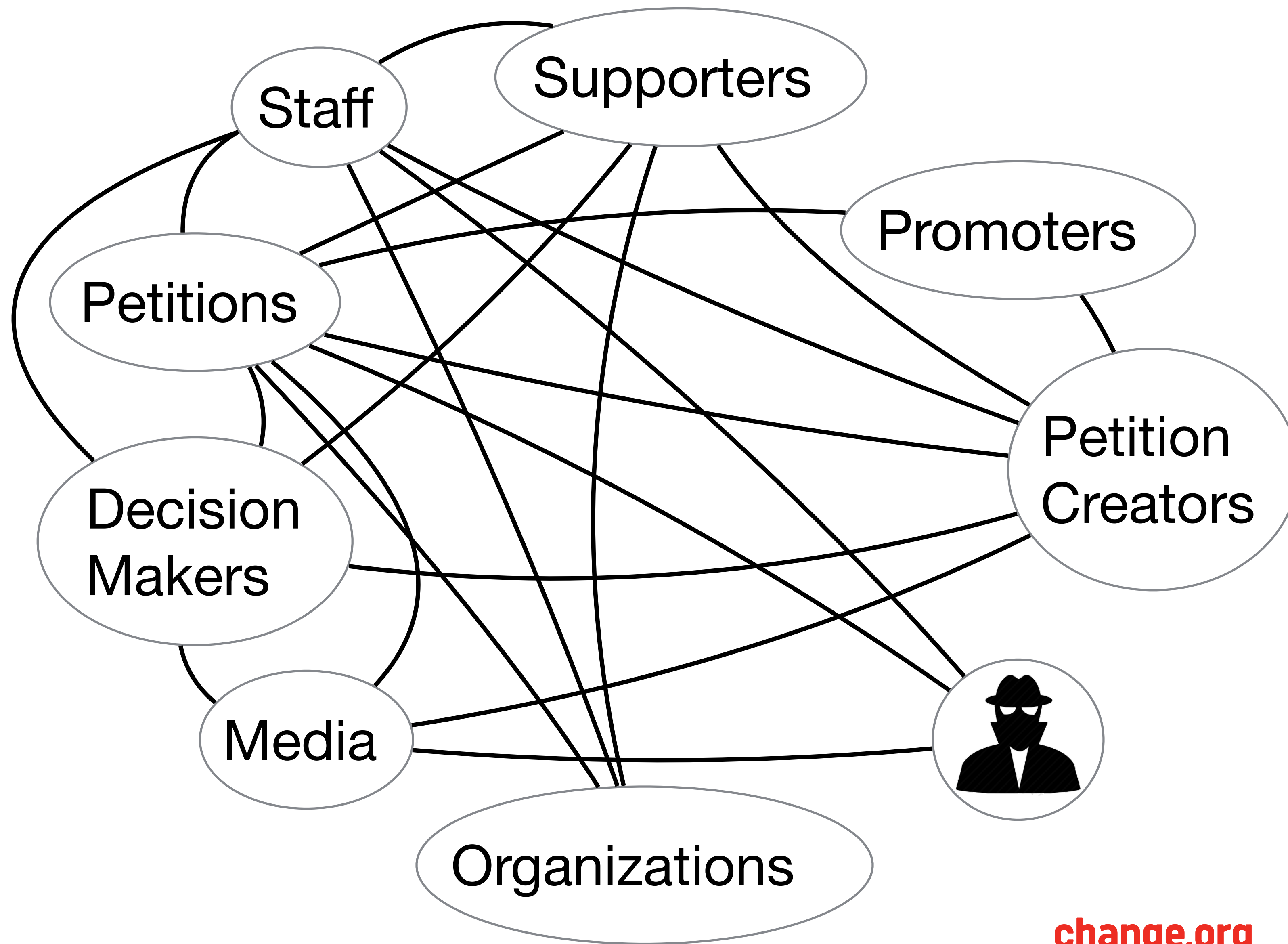
Contextualized Multi-Armed Bandits (MAB)  $\max_i (price_i \cdot CTR_i)$

# Sponsored petition (SP) targeting

Contextualized Multi-Armed Bandits (MAB)  $\max_i (price_i \cdot CTR_i)$









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# We're hiring!

[change.org/careers](https://change.org/careers)

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