

You are who you know: Inferring user profiles in online social networks

Alan Mislove^{†‡§} Bimal Viswanath[†] Krishna P. Gummadi[†] Peter Druschel[†]

[§] *Northeastern University*

[†] *MPI-SWS*

[‡] *Rice University*

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Facebook and personal data

Users upload information to sites like Facebook

Profile information

Status updates

Photos, videos

The Facebook logo, consisting of the word "facebook" in white lowercase letters on a blue rectangular background.

Privacy model for data

Choose what to reveal

And **what to keep private**

+



When reasoning about privacy

Don't often **consider implicit data**

What our friends reveal about ourselves

What is implicit data?

Example: MIT's Project Gaydar

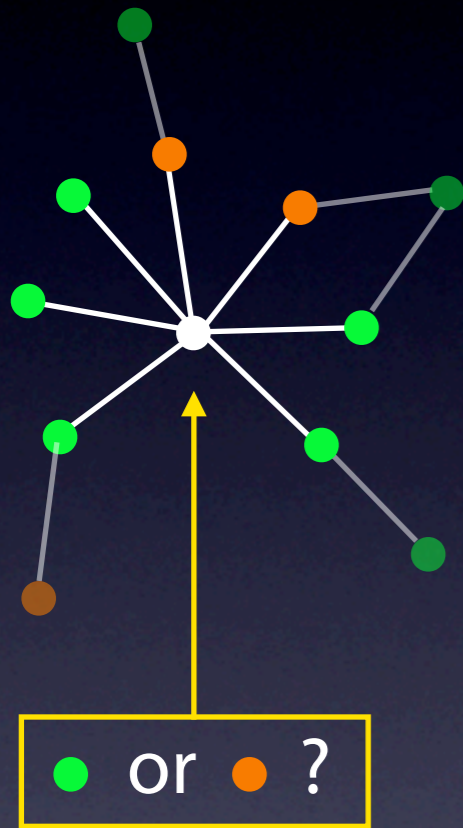
Predict sexual orientation based on friends

Exploiting *homophily*

People **associate with others like them**

What about other attributes?

Using friends-of-friends?



This talk

Explore *how much implicit data exists on online social networks?*

Or, **how much information can be inferred?**

How much data is needed to be able to infer?

Focus on one source: social network

Develop **methodology to infer user attributes**

Test on real-world network data

Roadmap

1. Idea: Use communities to infer attributes
2. Collect fine-grained community data
3. Do attribute-based communities exist?
4. How well can we infer user attributes?

Idea: Use communities

Project Gaydar used 1-hop friends

Using >1 hop friends is challenging

Exponential growth in size

Unclear relationship to source

Look for **groupings of users**

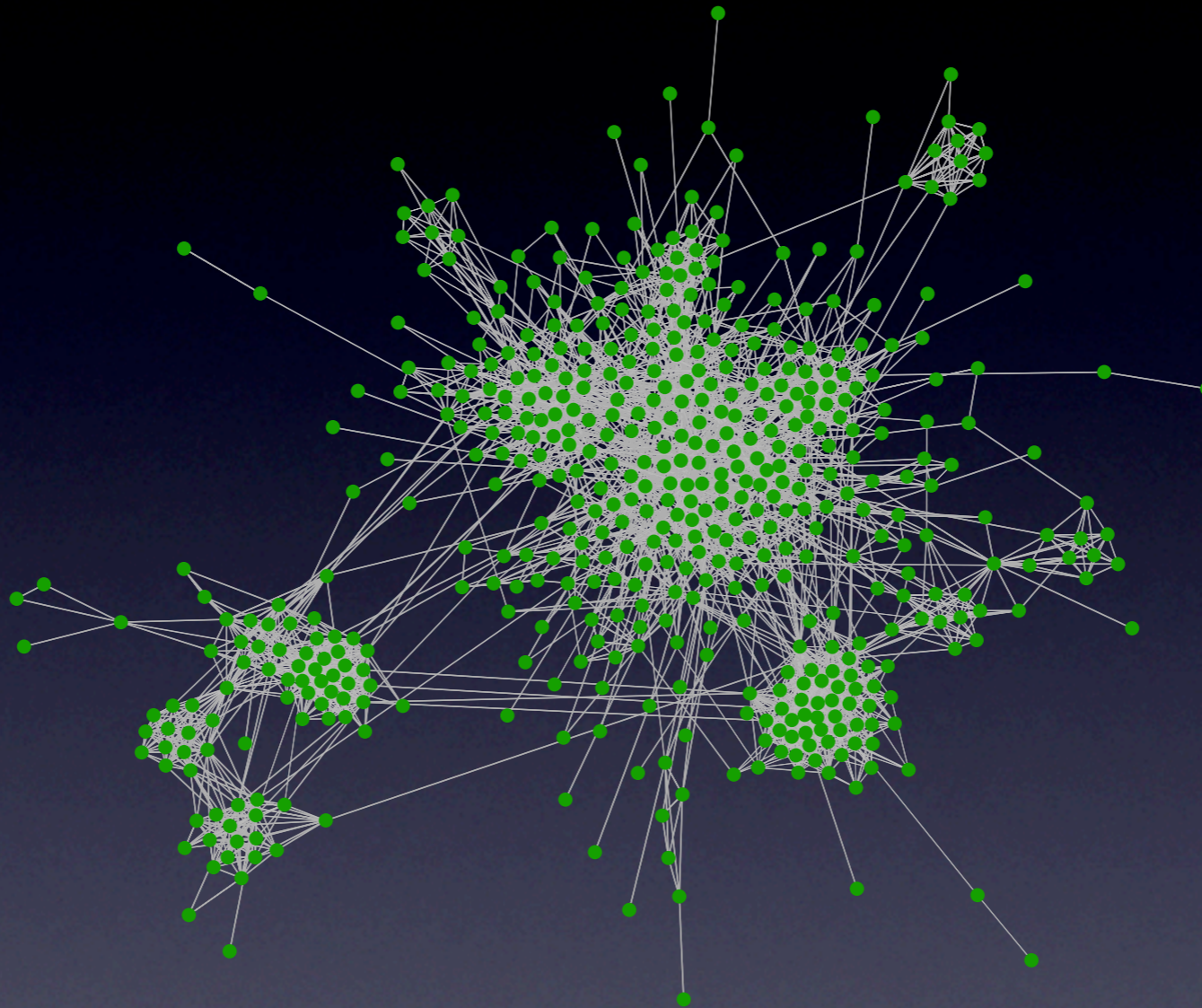
Called *communities*

Potentially share attributes

Leverage literature in community detection



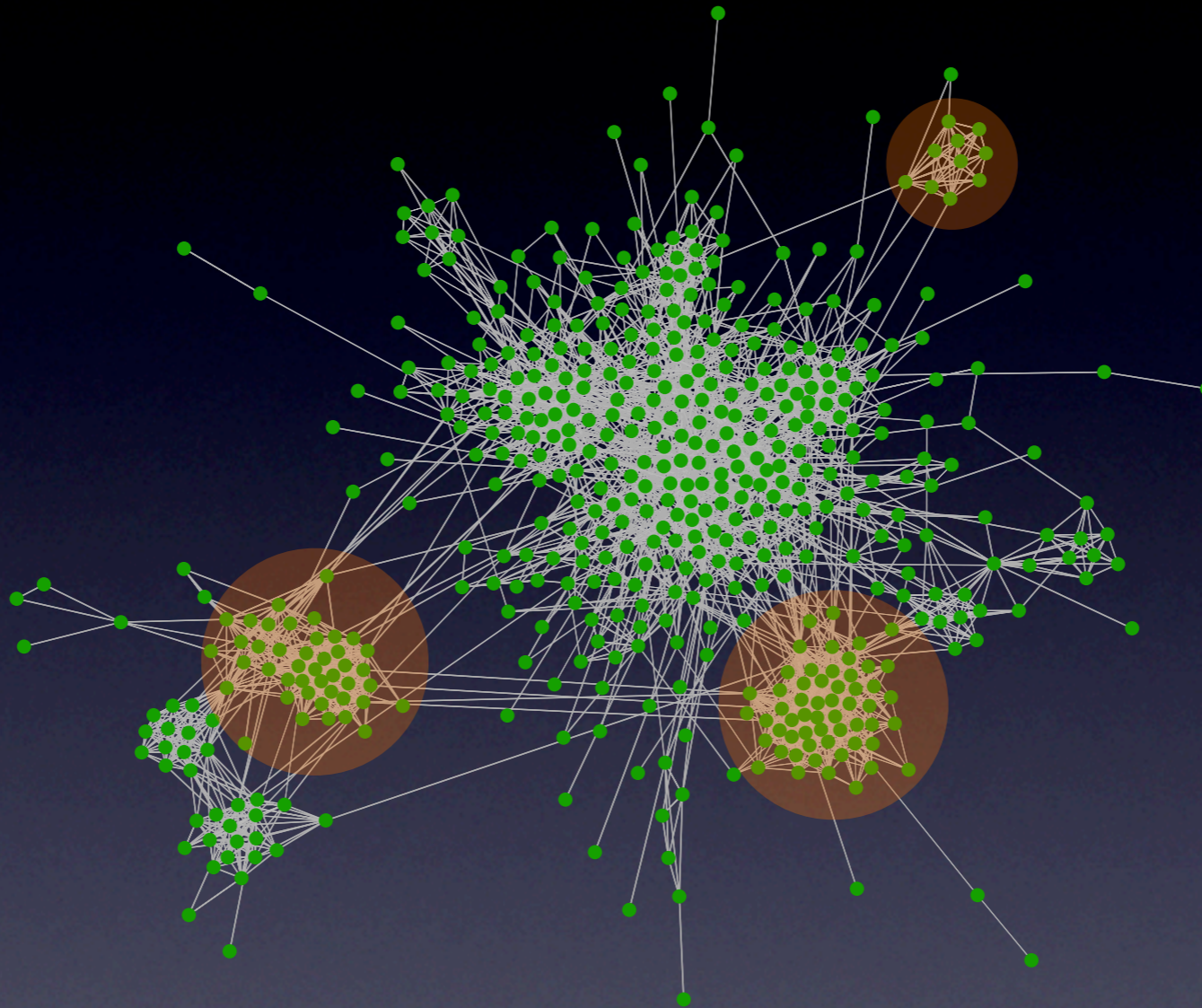
What do we mean by *communities*?



Group: Users who share a common attribute

Community: Users **more densely connected** than overall graph

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Social network data

Crawled two Facebook networks

Rice University (university)

New Orleans (regional)

| | Users | Avg. Degree |
|-------------|-------|-------------|
| Rice ugrad | | |
| Rice grad | | |
| New Orleans | | |

Picked known seed user

Crawled all of his friends, added new users to list

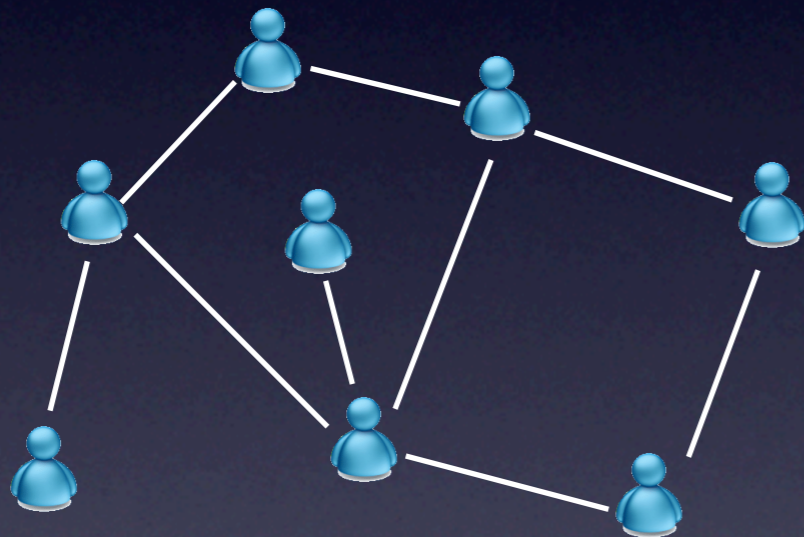
Effectively **performed a BFS of graph**

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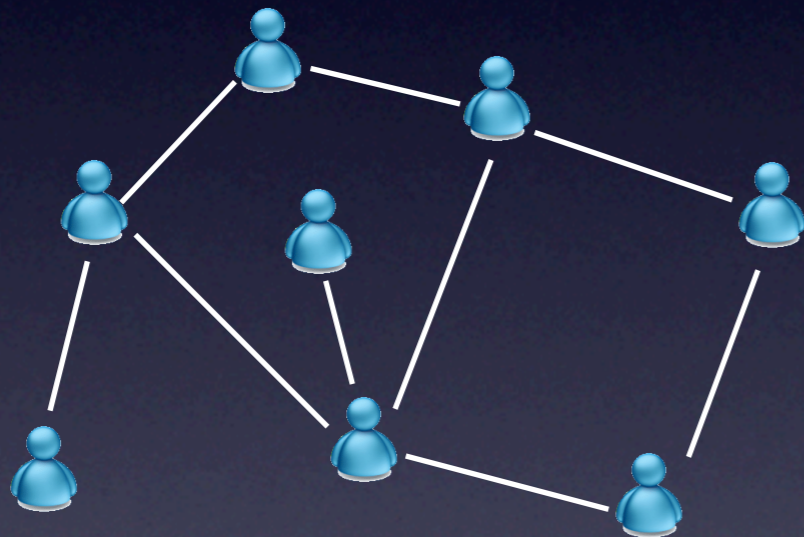
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Social network data

Crawled two Facebook networks

Rice University (university)

New Orleans (regional)



| | Users | Avg. Degree |
|-------------|--------|-------------|
| Rice ugrad | 1,220 | 35.4 |
| Rice grad | 501 | 6.5 |
| New Orleans | 63,731 | 24.2 |

Picked known seed user

Crawled all of his friends, added new users to list

Effectively **performed a BFS of graph**

Collecting attributes

Obtained **authoritative information**

Queried student directory

College (dormitory), major(s), year



Could not collect Facebook profiles

Collected Facebook profiles

The Facebook logo, consisting of the word "facebook" in white lowercase letters on a blue rectangular background, with "new orleans" in white lowercase letters below it.

facebook
new orleans

Extracted all attributes

E.g., high school, groups, gender

Attributes are **freeform text**

Roadmap

1. ~~Idea: Use communities to infer attributes~~
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Do attributes define communities?

Put users into groups based on attributes
Determine if these are communities

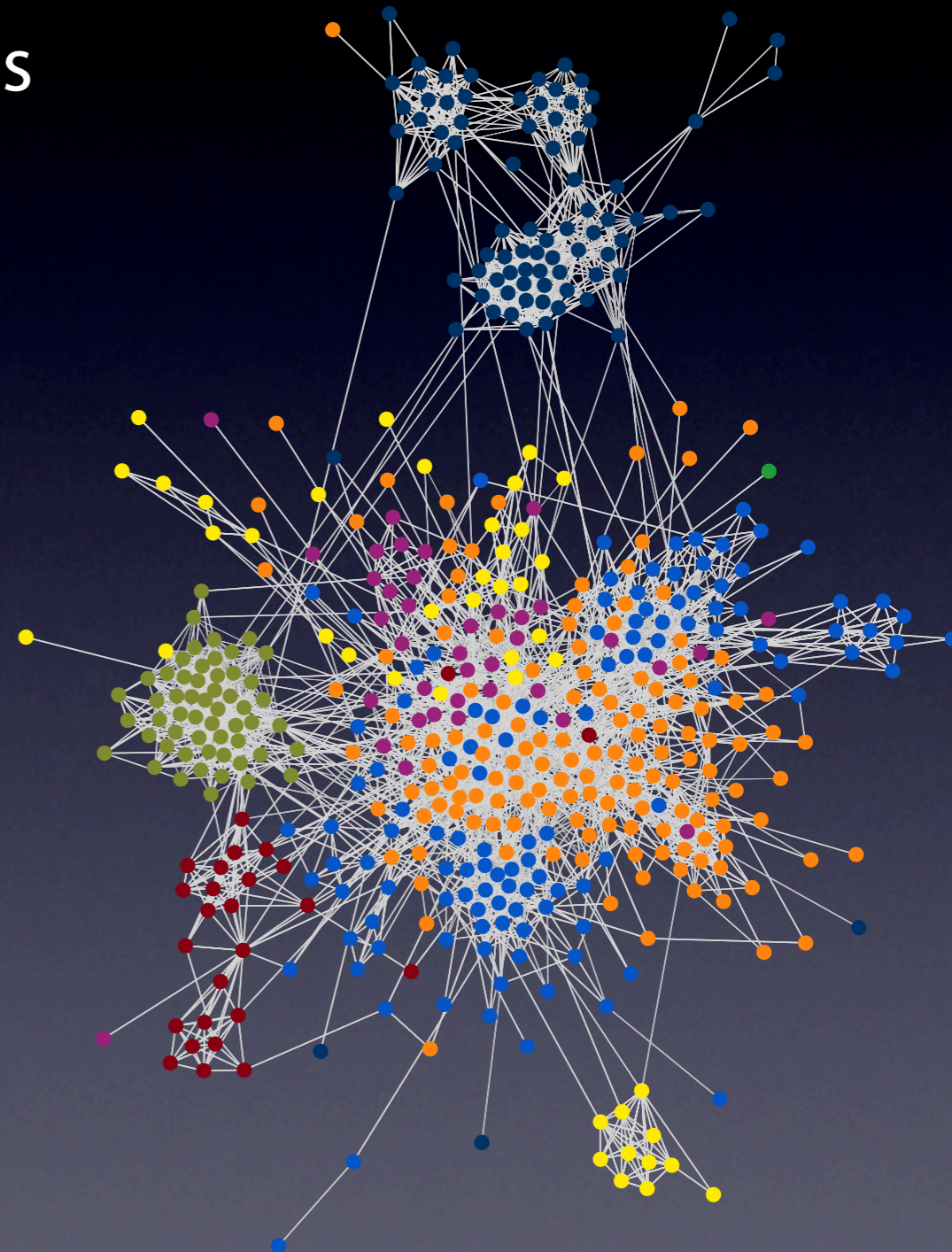
Need metric to rate communities

Modularity rates community strength

Range $[-1,1]$

0 represents expected in random graph

≥ 0.25 represents community structure



Attribute communities for Rice undergrads

| | Communities | Community Size | | | Modularity |
|---------------------|-------------|----------------|-----|-----|------------|
| | | Min | Avg | Max | |
| major | 65 | 1 | 23 | 105 | 0.004 |
| matriculation year | 4 | 95 | 305 | 398 | 0.259 |
| residential college | 9 | 130 | 135 | 142 | 0.385 |

Communities based on shared college or year
Multiple, overlapping community structures

Roadmap

1. ~~Idea: Use communities to infer attributes~~
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Using communities to infer attributes

Can we detect a single attribute community?

Given **a few users in the community**

Previous approaches proposed (local community detection)

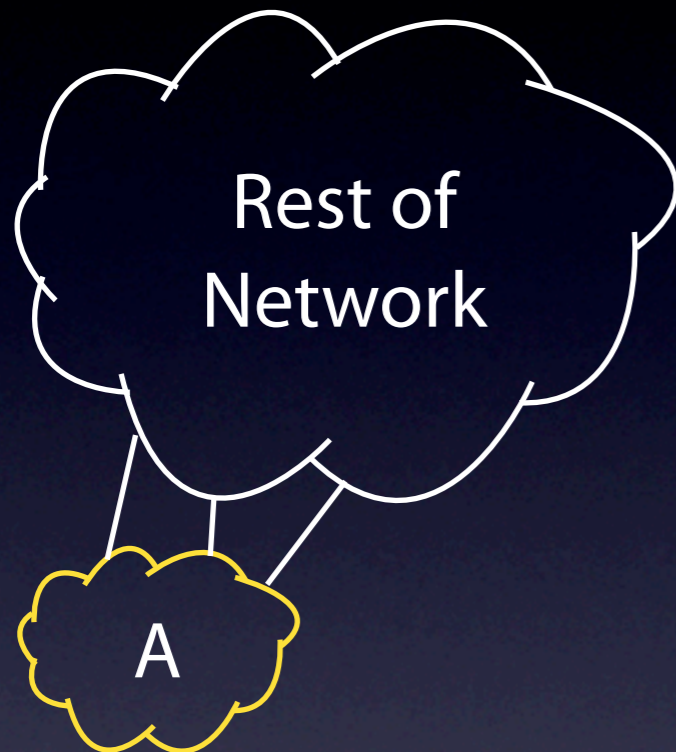
Not designed for social networks

Never evaluated on a large-scale social network

Propose a **new algorithm to detect a specific community**

Problem: How to evaluate community *strength*?

Normalized Conductance



How *strong* is a particular community *A*?

Conductance previously proposed

But, biased towards large communities

Metric: Normalized conductance C

Fraction of *A*'s links within *A*

Relative to a random graph

Range is $[-1,1]$

0 represents no stronger than random

$$C = \frac{e_{AA}}{e_{AA} + e_{AB}} - \frac{e_A e_A}{e_A e_A + e_A e_B}$$

Algorithm

Given seed users, find a community by

Adding users

Stopping at some point

At each step, add user who **increases normalized conductance** by the most

Stop when **no user increases normalized conductance**



How to evaluate?

Evaluate performance *using precision and recall*

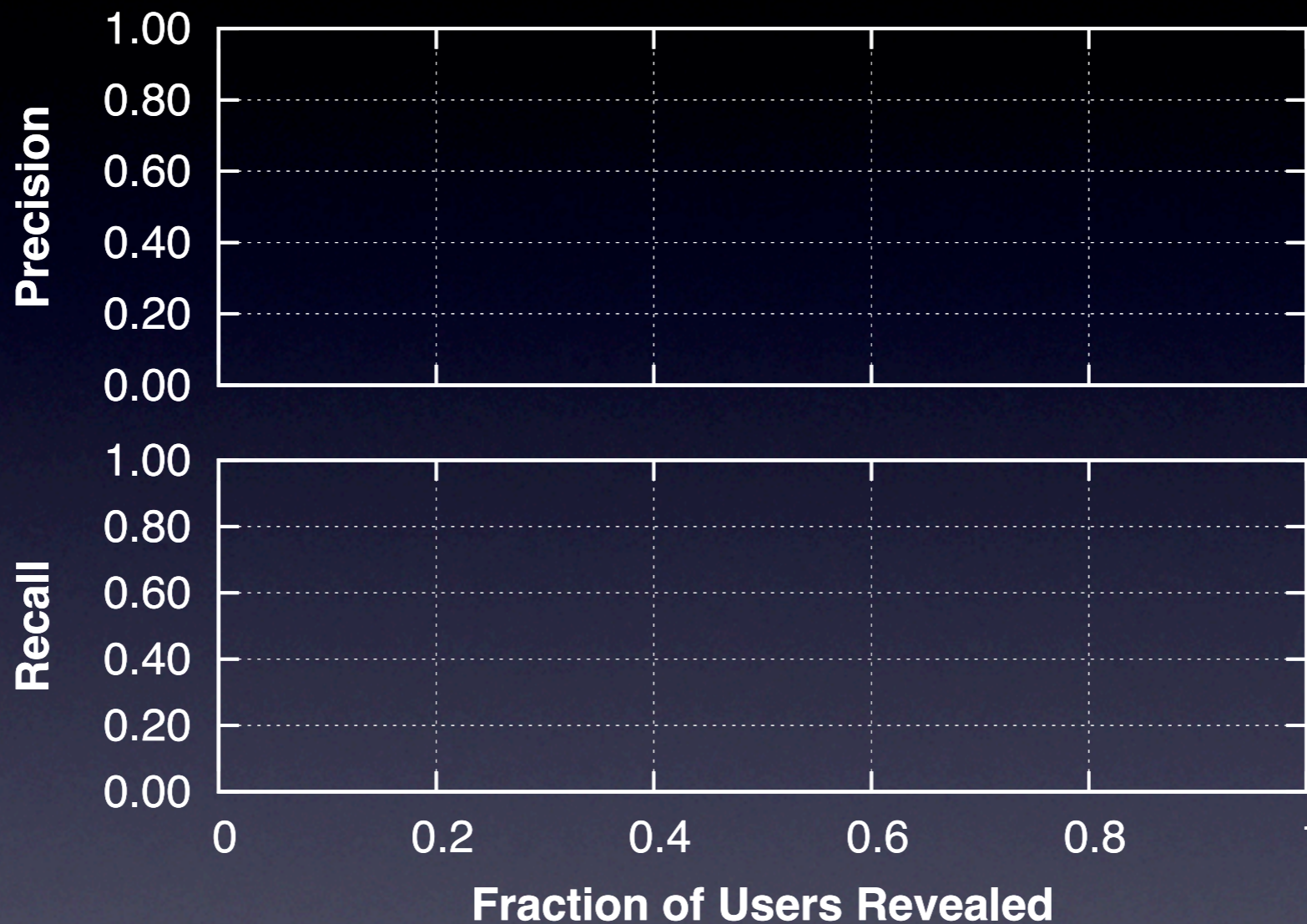
Algorithm takes in fraction sharing attribute

recall = fraction of remaining attribute-sharing users identified

precision = fraction of identified users that share attribute

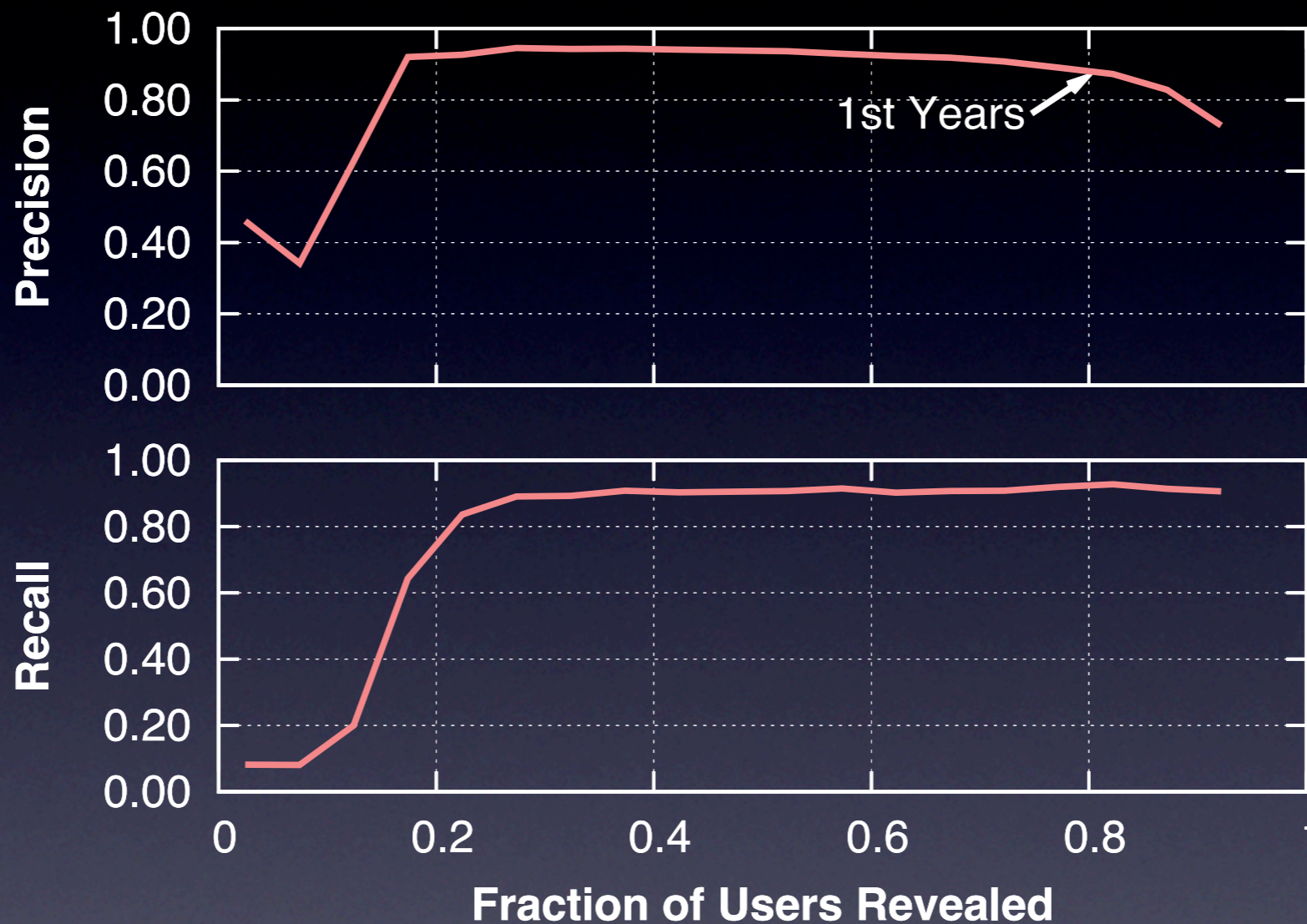
Ideally want a precision and recall of 1.0

Can we infer Rice undergrad classes?



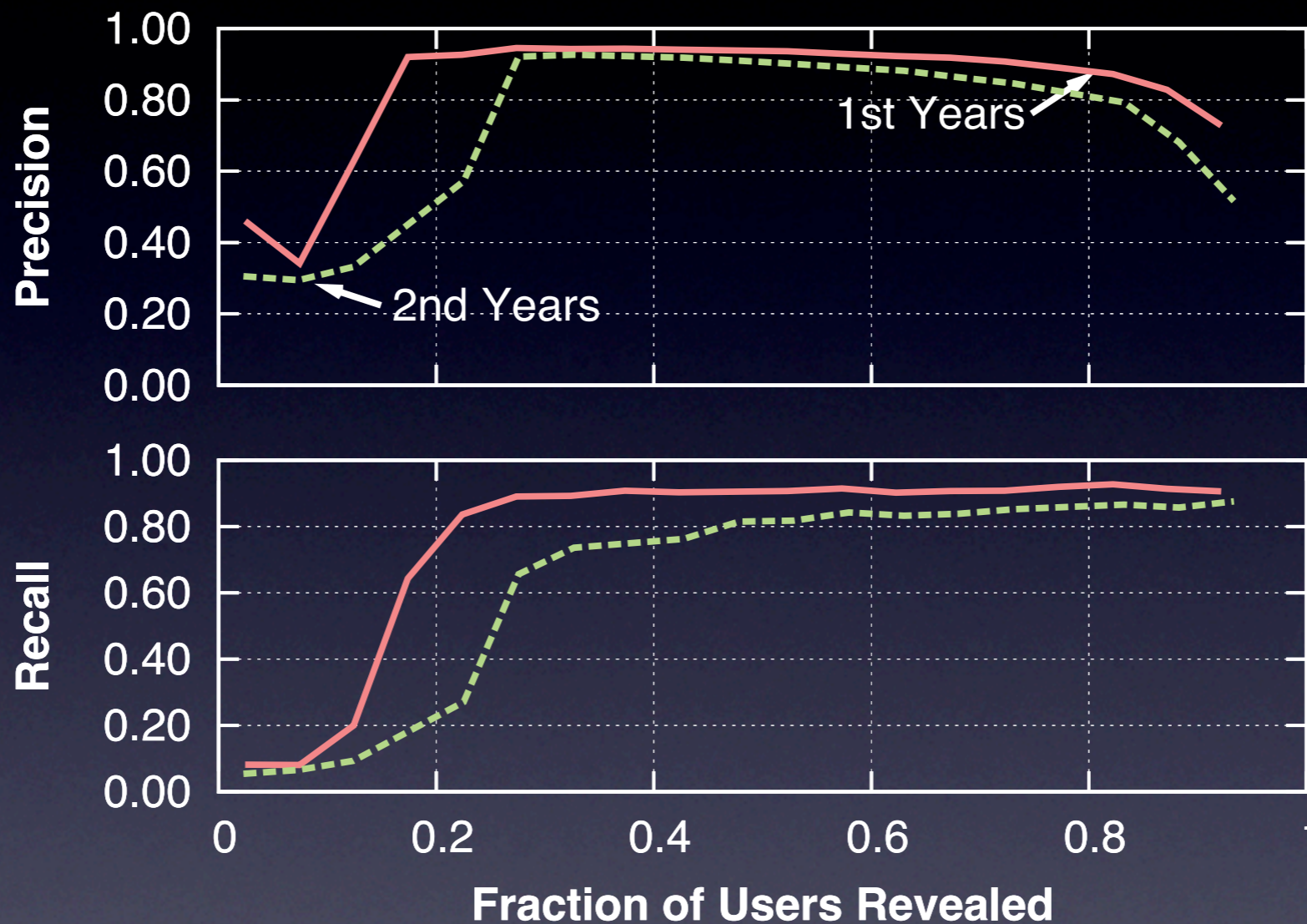
Yes; different communities show different characteristics
In next graphs, average across all groups

Can we infer Rice undergrad classes?



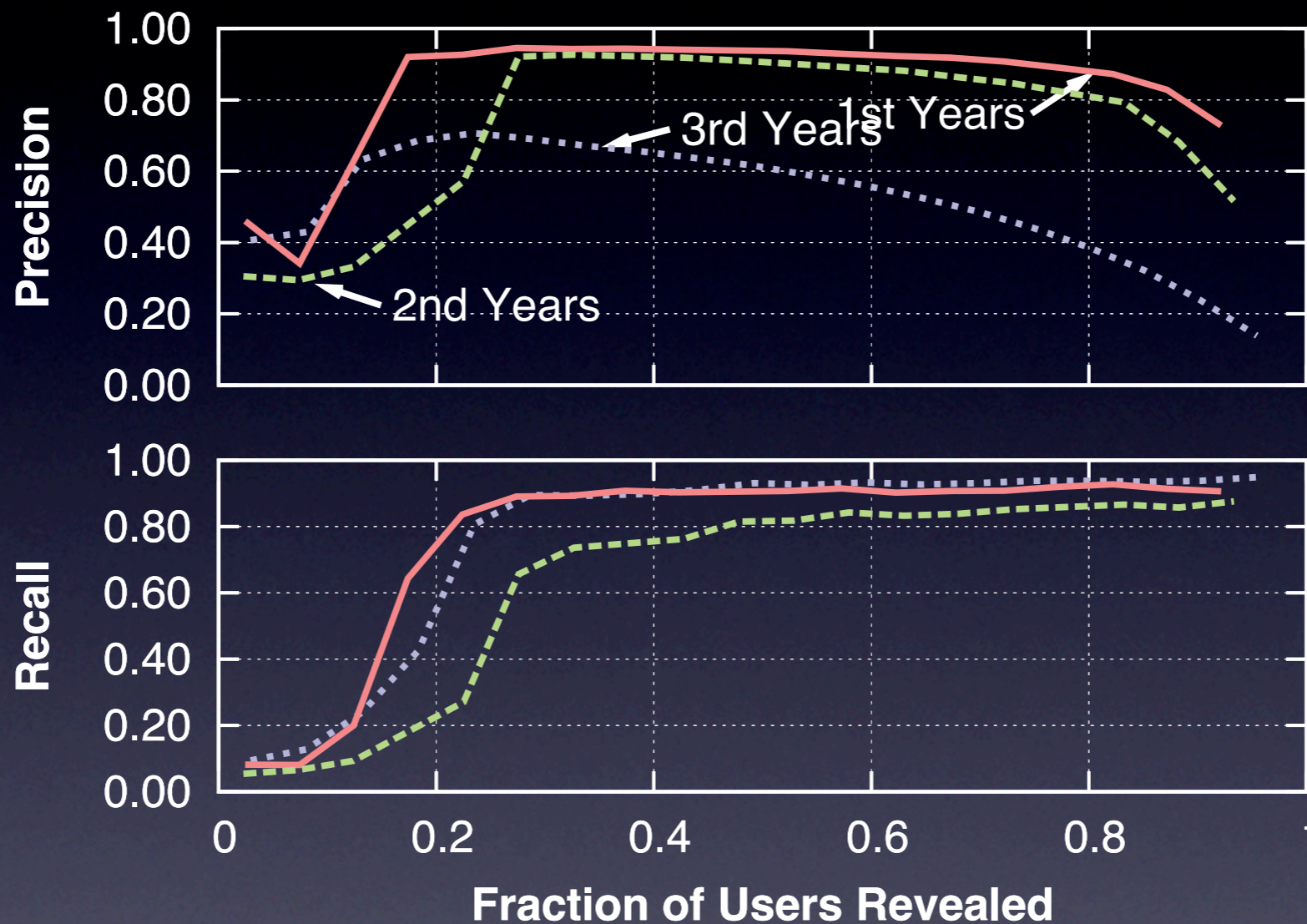
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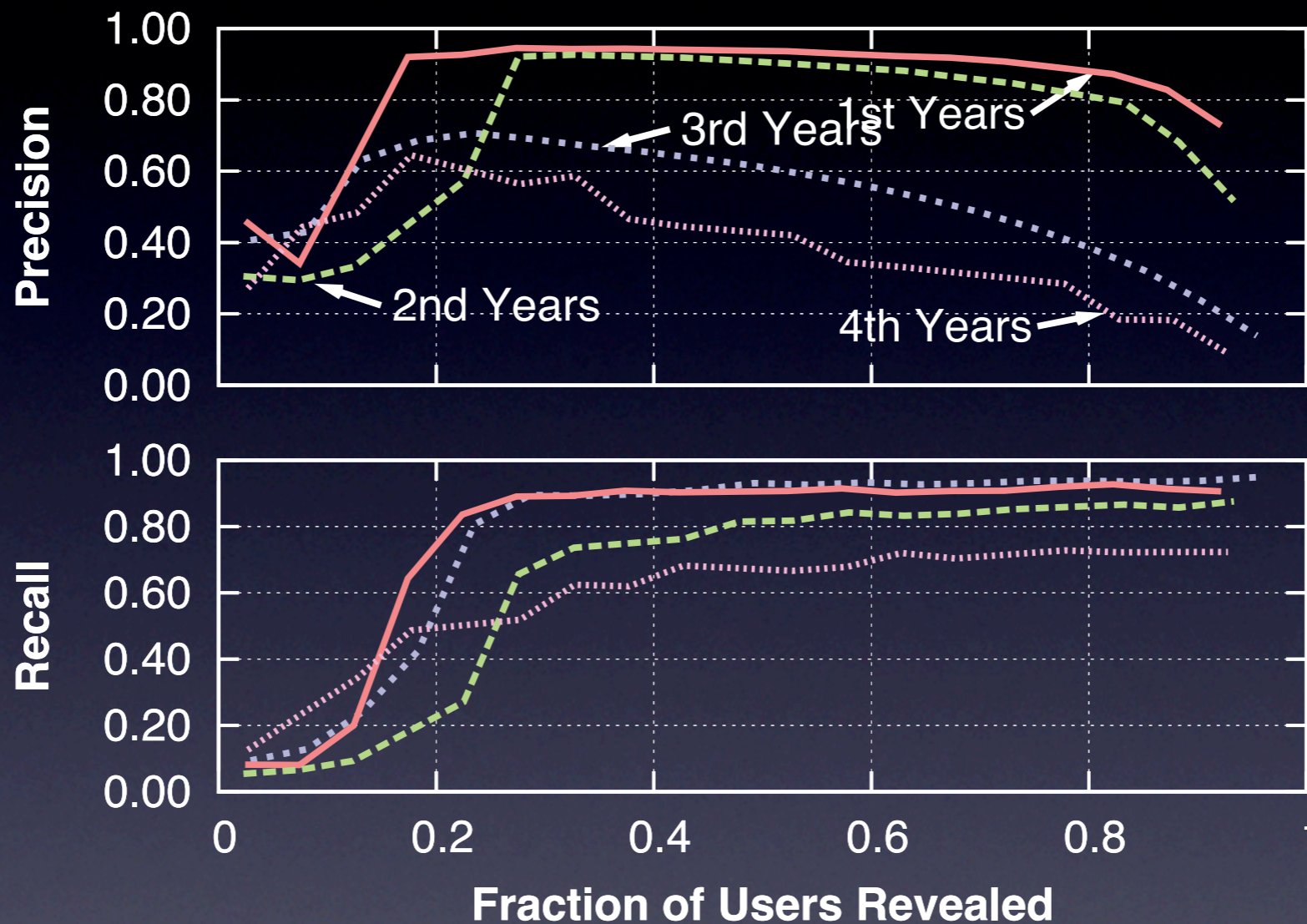
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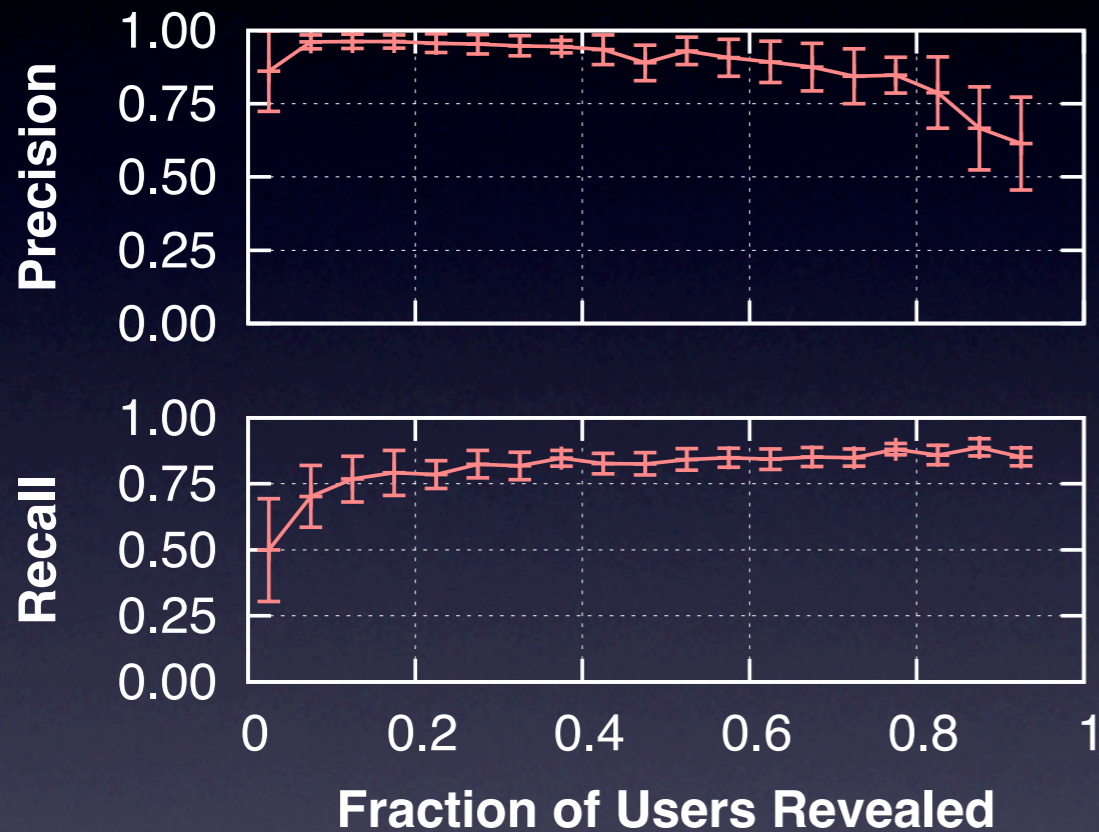
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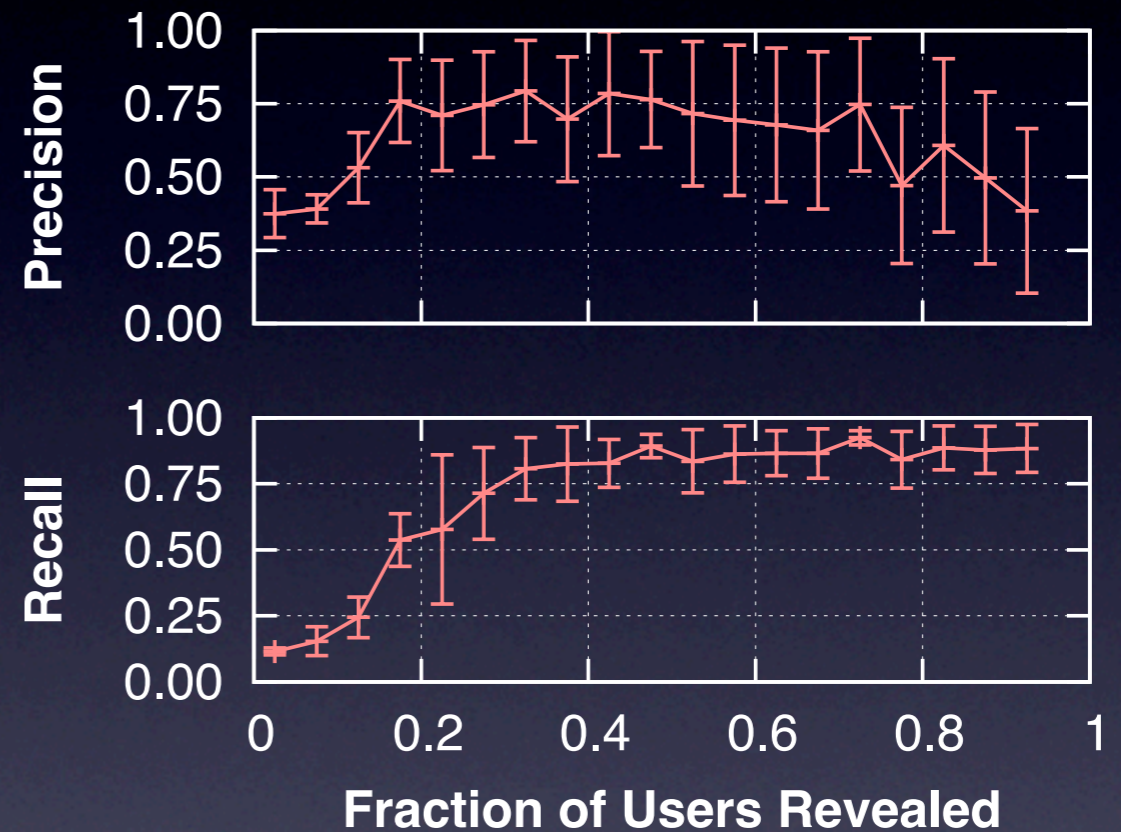


Yes; different communities show different characteristics
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Inferring other attributes

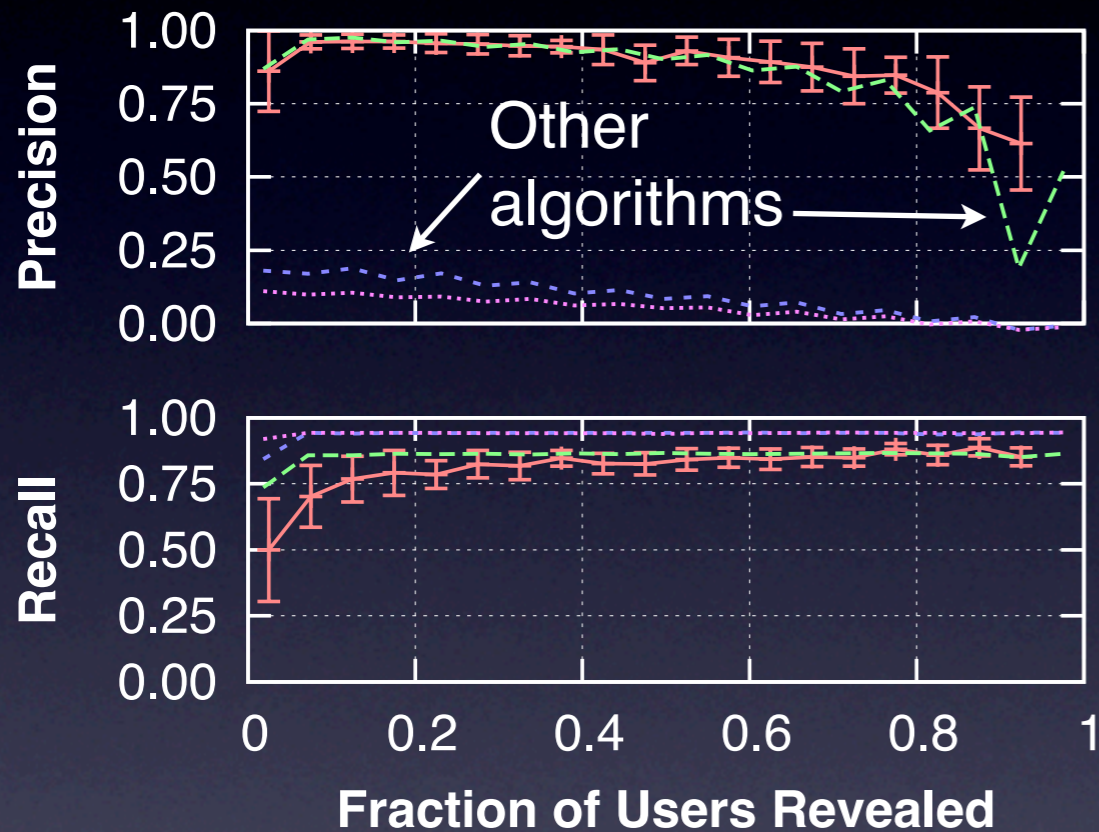


Dormitory

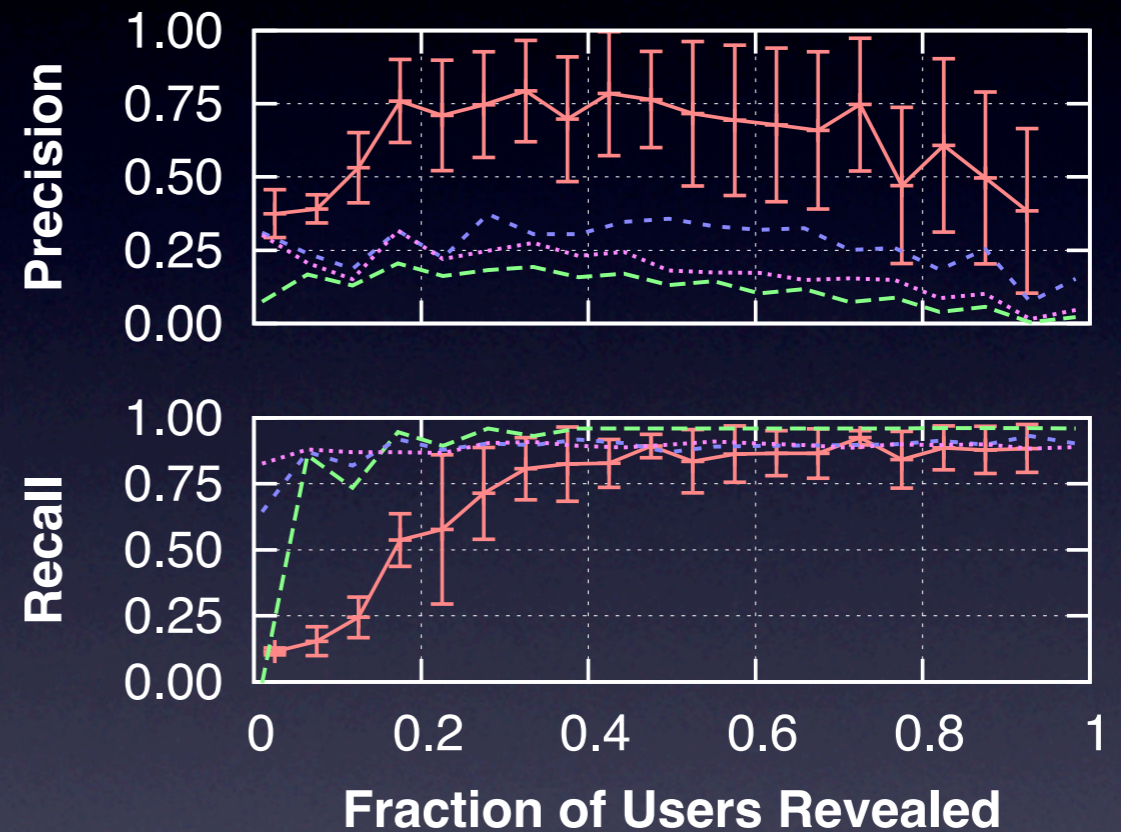


Matriculation year

Inferring other attributes

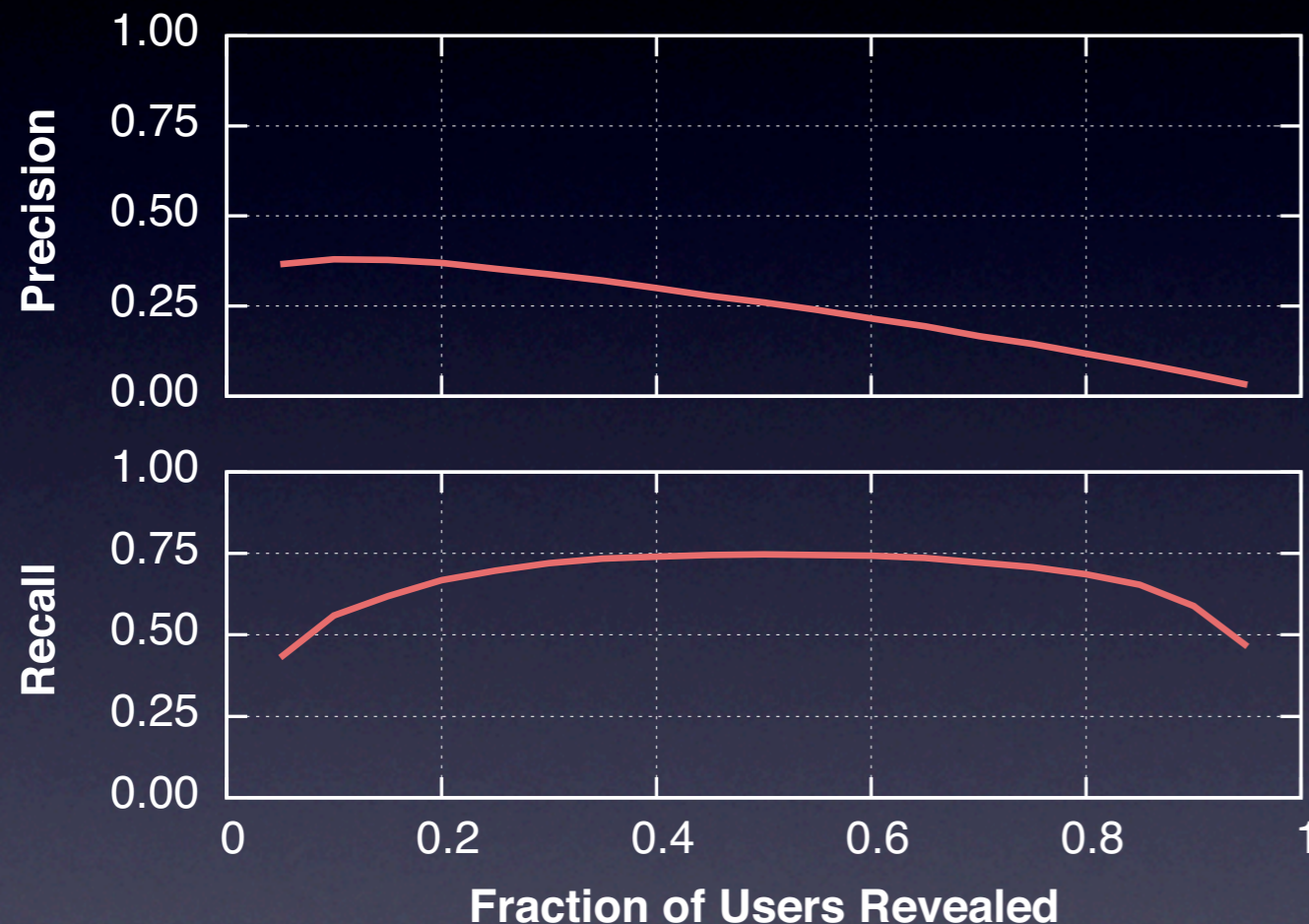


Dormitory



Matriculation year

Can we infer user-provided attributes?



Use New Orleans data

Much more challenging

Freeform text

Non-authoritative attributes

Missing data

Most not communities
(gender, birthday, etc)

Results for 92 groups

With conductance > 0.2

Summary

Ongoing online social network **privacy debate**

Focuses mainly on *explicitly provided* attributes

Demonstrated that many attributes can be inferred

Even if user didn't provide them

Good interpretation: Can reduce burden on users

Don't have to fill in entire profile

Bad interpretation: Can figure out attributes users don't reveal

Privacy is a function of what friends reveal

Questions?

Backup slides

Facebook privacy debate

Debate over **privacy model** and defaults

Who can see users' attributes, status, friends

Scale, intensity of debate illustrates importance

The Facebook logo, consisting of the word "facebook" in white lowercase letters on a blue rectangular background.

So far, focused on **explicit data**

Things the user uploaded or provided

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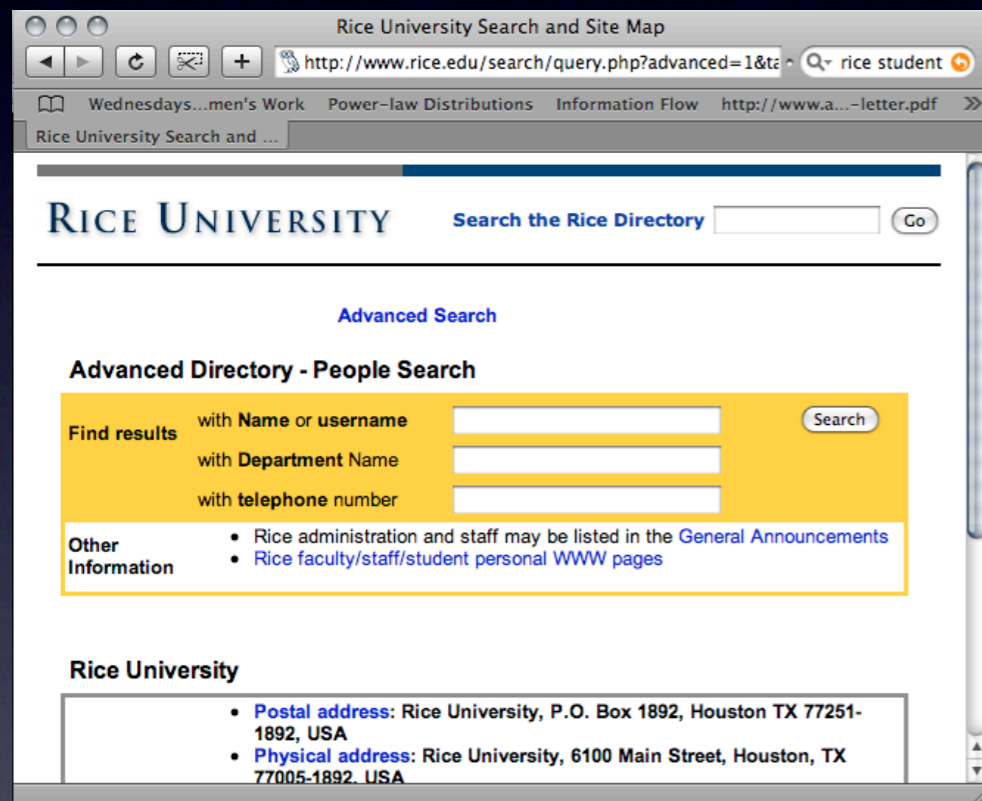


What about *implicit* data?

Data users didn't *explicitly* reveal?

Obtaining authoritative information

Additional information from **student directory** and **alumni directory**



Found matches for

1,233 (20.0%) undergraduates

548 (8.9%) graduate students

2,093 (33.9%) alumni

Focus on **undergraduate network**

Obtained college, major(s), year

Similar results for others

Modularity

How *good* is a community division?



Metric: Modularity Q

Fraction of links within communities

Relative to a random graph

Range is $[-1, 1]$

0 represents no more community structure than random

$$Q = \sum_i (e_{ii} - a_i^2)$$
$$= \text{Tr } \mathbf{e} - \|\mathbf{e}^2\|$$

Modularity > 0.25 indicates strong communities

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