Two Fun Topics + Quick Overview

CS224W: Social and Information Network Analysis Jure Leskovec, Stanford University

http://cs224w.stanford.edu



Users & Online Communities





















Online Communities:

- Understanding the co-evolution of users and communities
- Steering user behavior











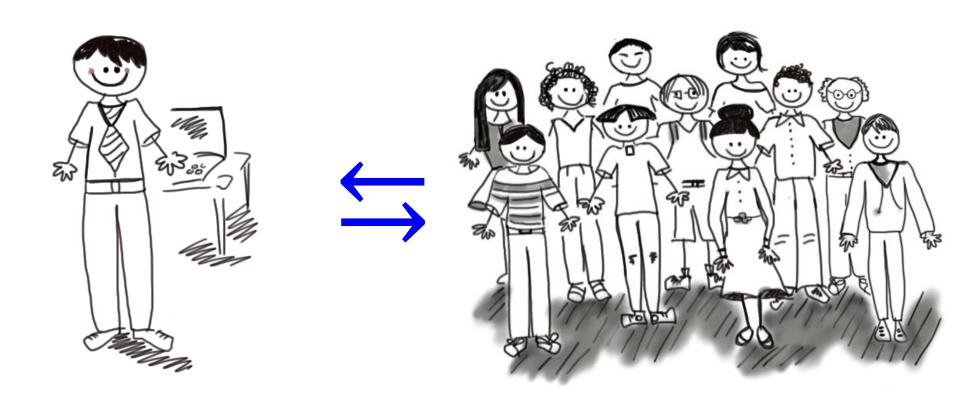








Online Communities



Modeling the relation between a user and a community

Users and Communities

Questions:

- How does a user become member of a community?
- How do user and community practices co-evolve?
- Can we predict when a user will leave the community?

Insight: Linguistic Change

- Language practices (norms, etiquette, ...)
 - build collective identity
 - foster individual expression
- Linguistic change captures the relation between users and communities
 - Framework for tracking linguistic change
 - Measures of user reaction to linguistic change
 - Predict when user will leave the community

Online Communities

People discuss beer:



Tballz420

4/5 rDev +1.8% look: 3 | smell: 4 | taste: 4 | feel: 3.5 | overall: 4.5

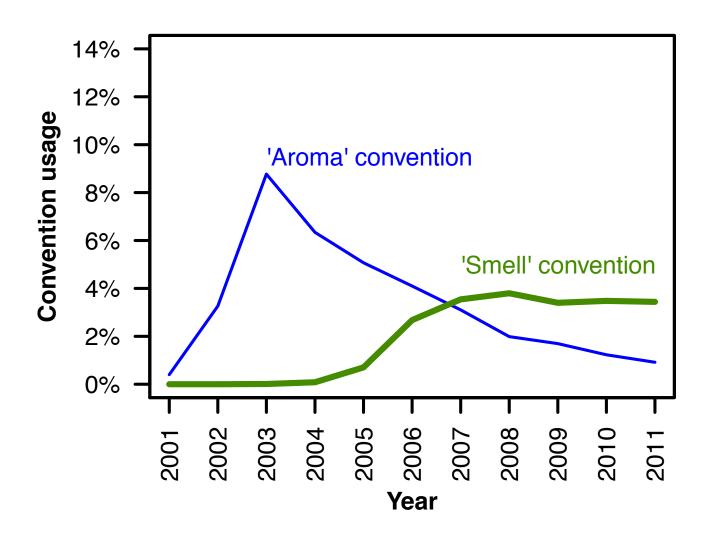


Clear copper colored brew, medium cream colored head. Floral hop nose, caramel malt. Caramel malt front dominated by a nice floral hop backround. Grapefruit tones. Very tasty hops run the show with this brew. Thin to medium mouth. Not a bad choice if you're looking for a nice hop treat.

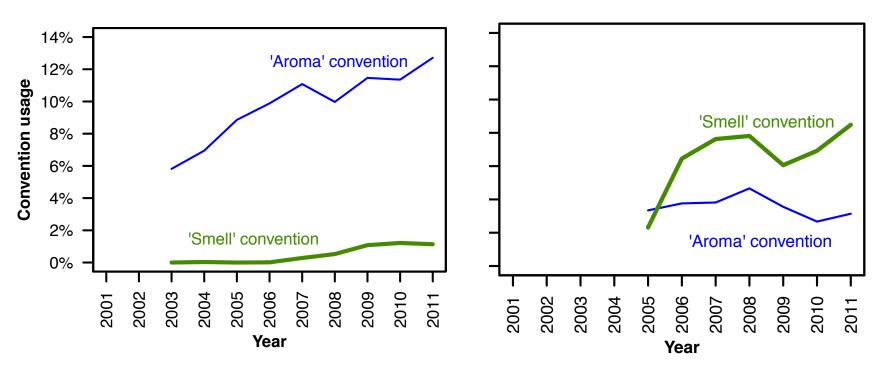


- 10 years of complete linguistic data
 - RateBeer: 3M posts, 30k users
 - BeerAdvocate: 1.6M posts, 33k users

"Aroma" vs. "Smell"



Young Adopt Innovations



Users who joined in 2003 Users who joined in 2005

New users are more likely to use "smell" than users who have been part of the community for a long time.

Community / User Change

User:



"life stage"

Community:



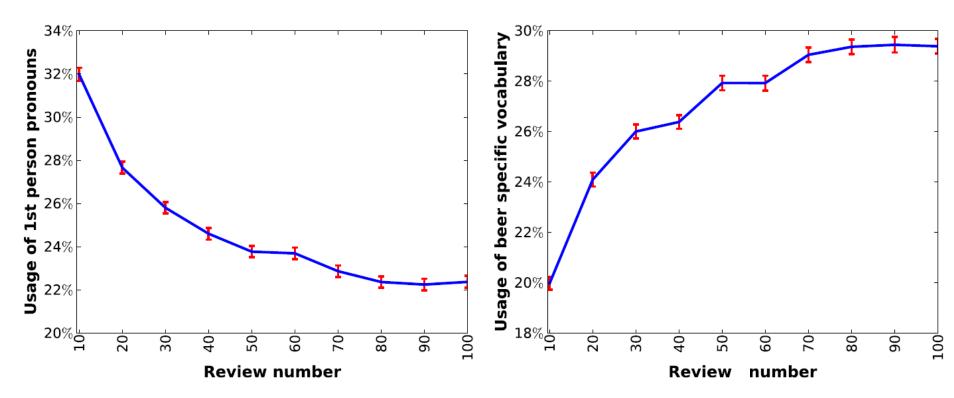




2001

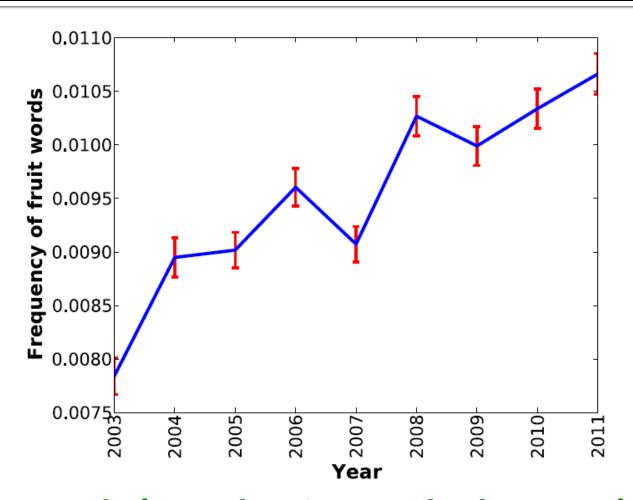
2011

User Language Change

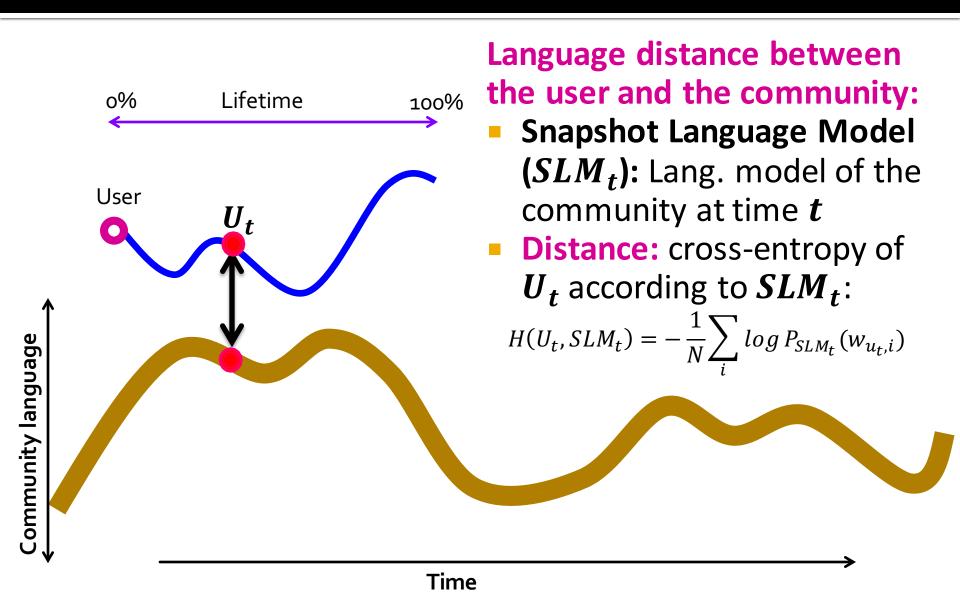


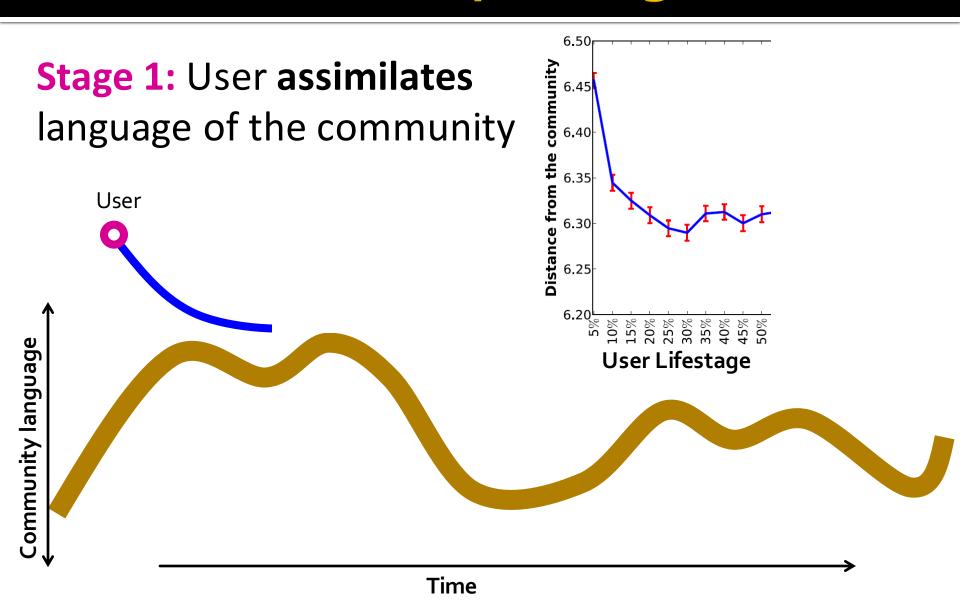
- (a) First person sing. pronouns
- (b) Beer specific vocabulary
- A sign of increasing identification with the community [Pennebaker 2007; Sherblom 2009]

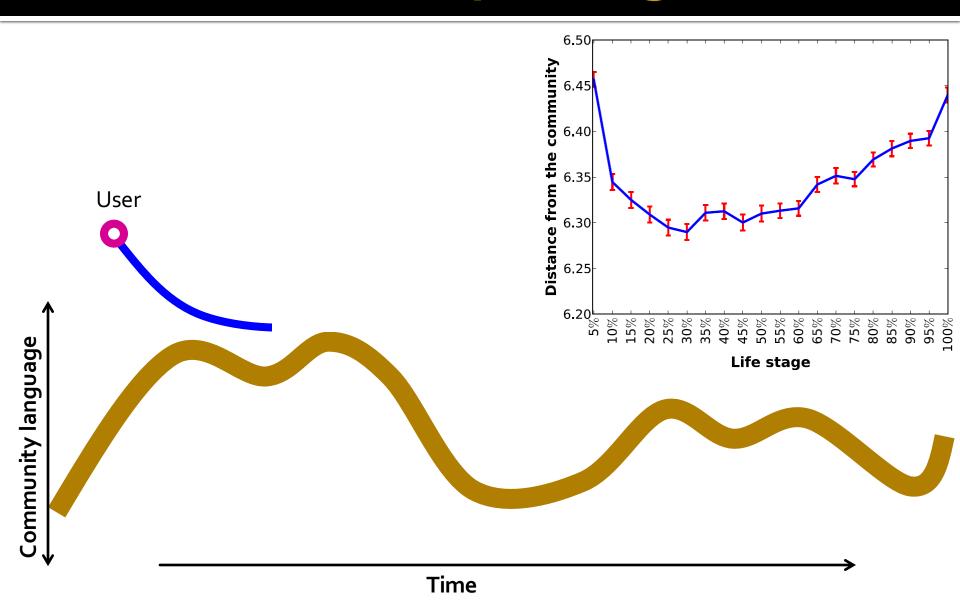
Community Language Change

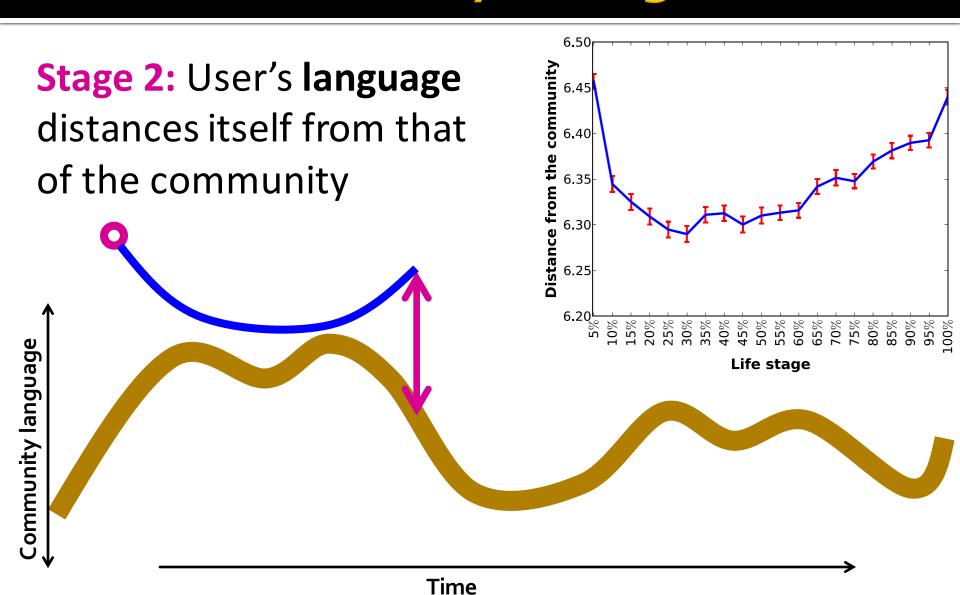


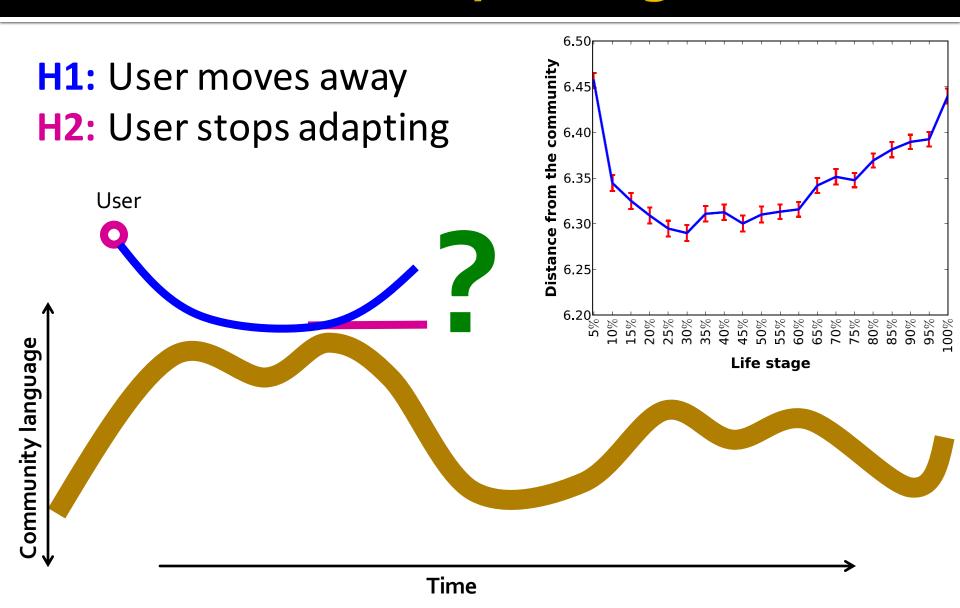
Fruit words (peach, pineapple, berry, ...)
 are getting ever more popular

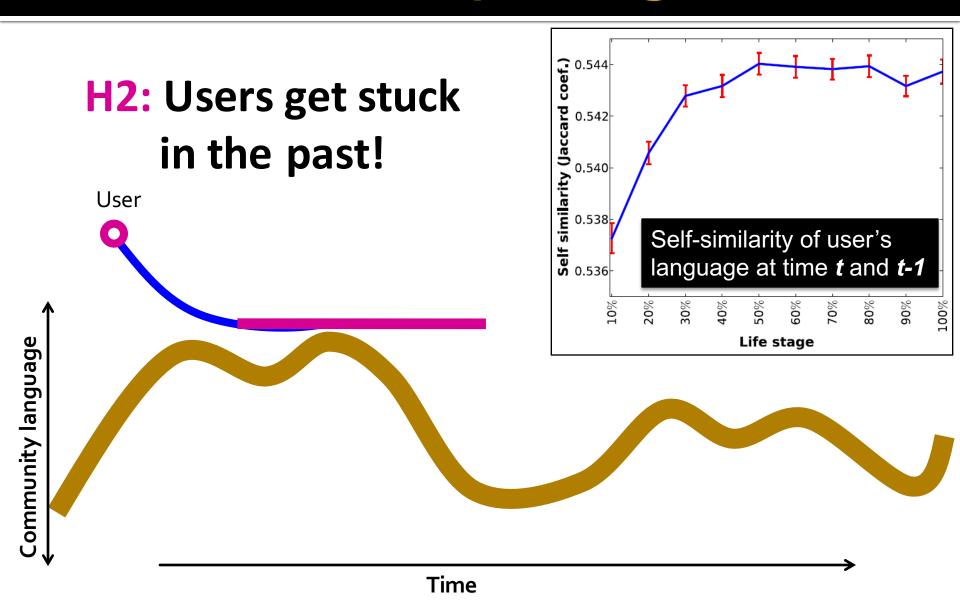






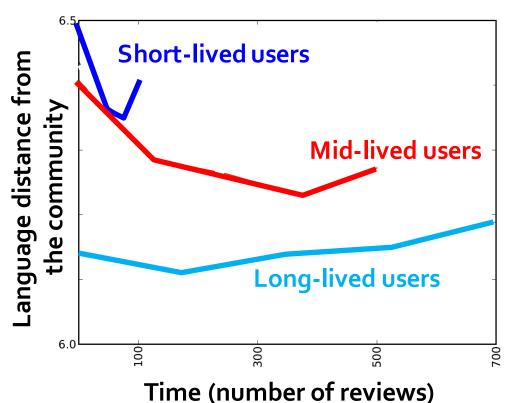






Elastic Lifecycle

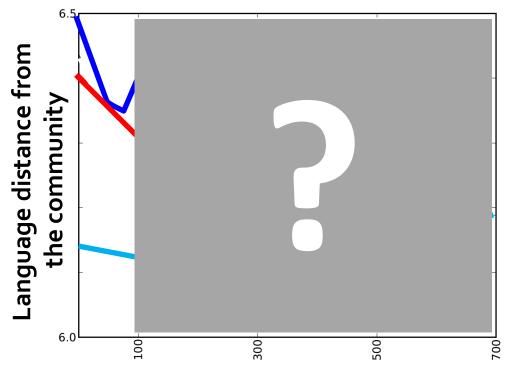
- So far we stretched lifetimes to 0-100%
- What about user's absolute lifetime?



- → Similar lifecycle in spite of different lifespans
 - "All users die old"
- → End of the adaptation phase is a function of the ultimate lifespan
- → Level of receptivity is related to the ultimate lifespan

Elastic Lifecycle

- So far we stretched lifetimes to 0-100%
- What about user's absolute lifetime?



- → Similar lifecycle in spite of different lifespans
 "All users die old"
- → End of the adaptation phase is a function of the <u>ultimate</u> <u>lifespan</u>
- → Level of receptivity is related to the <u>ultimate lifespan</u>

Predict user's ultimate lifespan

How do we influence social systems?

People work amazingly hard to earn badges

"Give me enough medals and I'll win you any war."

Napoleon











Meteorite badges are common and easy to earn when just getting started.



Moon badges are uncommon and represent an investment in learning.



Earth badges are rare.

They require a significant amount of learning.



BADGE TYPES



Sun badges are epic. Earning them is a true challenge, and they require impressive dedication.

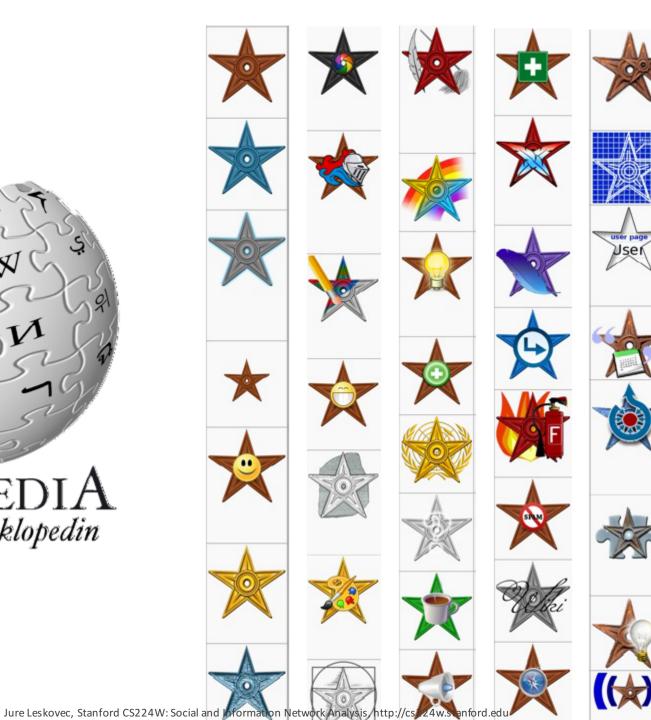


Black Hole badges are legendary and unknown. They are the most unique Khan Academy awards.



Challenge Patches a special awards for completing topic challer





foursquare®



stackoverflow



Badges

• Multiple roles of badges:

- Can recognize a wide range of activities:
 - Total effort, Single high-impact contribution, ...
- Serve both as credentials and incentives
- Incentive aspects of badges:
 - Trend toward gamification [Deterding et al. '11]
 - Customer loyalty programs [Kopalle-Neslin '03]
 - Simple for users to understand, and less based on competition with others

Badges & Behavior Change

How do badges translate into effects on user behavior?

Need lots of data to tease out the effects and build a mathematical model

Badges on Stack
Overflow Q&A site:
2M people
5M questions
10M votes

How to format a JSON date?



I'm taking my first crack at Ajax with jQuery. I'm getting my data onto my page, but I'm trouble with the JSON data that is returned for Date data types. Basically, I'm getting looks like this:



/Date(1224043200000)/

From someone totally new to JSON - How do I format this to a short date format? Sho handled somewhere in the jQuery code? I've tried the jQuery.UI.datepicker p \$.datepicker.formatDate() without any success.

FYI: Here's the solution I came up with using a combination of the answers here:

This solution got my object from the callback method and displayed the dates of date format library.



link edit flag



Badges on StackOverflow





Tags

Users

Badges

Unanswered

Connected components in a graph with 100 million nodes



I am trying to get the list of connected components in a graph with 100 million nodes. For smaller graphs, I usually use the connected components function of the Networkx module in Python which does exactly that. However, loading a graph with 100 million nodes (and their edges) into memory with this module would require ca. 110GB of memory, which I don't have. An alternative would be to use a graph database which has a connected components function but I haven't found any in Python. It would seem that Dex (API: Java, .NET, C++) has this functionality but I'm not 100% sure. Ideally I'm looking for a



python graph

share improve this question

solution in Python. Many thanks.

asked Jun 13 '12 at 13:48 user1453508 27 04

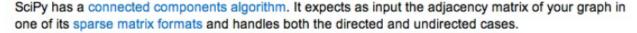
1 Answer

active

oldest

votes







Building a sparse adjacency matrix from a sequence of (i, j) pairs adj_list where i and j



Newbie: Congrats on your 1st answer

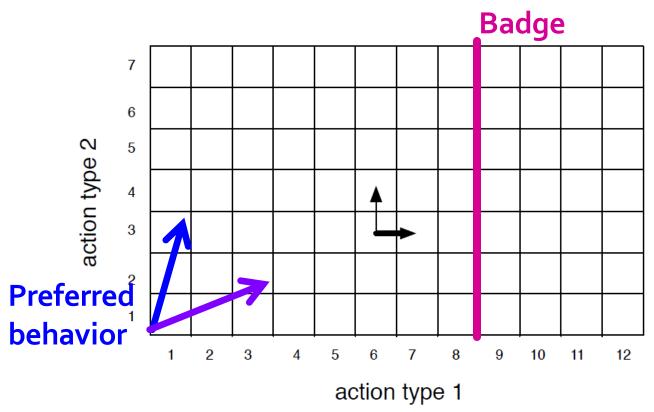


Superstar: You answered 10 questions

Jure Leskoyec, Stanford CS224W: Social and Information Network Analysis, http://cs224w.stanford.edu

- Approach: Utility based model of badges
 - User trades off between her preferred mix of activities and the goal of reaching the badge

- Effects on both engagement and steering
 - Engagement: Increased user site activity
 - Steering: Users change the actions they do



- 2 parts to the model:
 - User gains value from obtaining a badge
 - But it "costs" user to change behavior

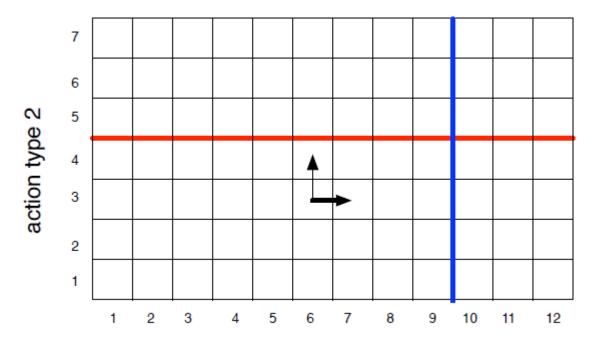
- User's optimization problem:
 Choose actions to maximize utility
 - User balances between achieving badges quickly and keeping cost low
- At each point x_a in time:
 - lacktriangle Receive utility ${m V}_{m b}$ of badges already won
 - Get penalized for deviating from preferred behavior $m{p}$ according to loss function $m{g}(m{p}, m{x})$
 - **Exit** the site with probability $\boldsymbol{\theta}$

$$U(\mathbf{x_a}) = \sum_{b \in B} I_b(\mathbf{a}) V_b + \theta \sum_{i=1}^{n+1} \mathbf{x_a^i} \cdot U(\mathbf{x_{a+e_i}}) - g(\mathbf{x_a}, \mathbf{p})$$
Utility Discounted future utility for action $\mathbf{e_i}$ Cost for deviating from \mathbf{p}

- ullet $U(x_a)...$ total utility for a user with action distribution x_a
- a ... user's actions so far (count of actions)
- $I_b(a)$... given user's actions a, did she get badge b (0/1)
- V_b ... value of badge b
- $\boldsymbol{\theta}$... prob. of exiting the site
- x_a^i ... user's prob. of taking action i
- $U(x_{a+e_i})$... future utility after taking action i
- $g(x_a,p)=\sum_i (x_a^i-p_i)^2$... cost for deviating from p
- p... preferred action distribution

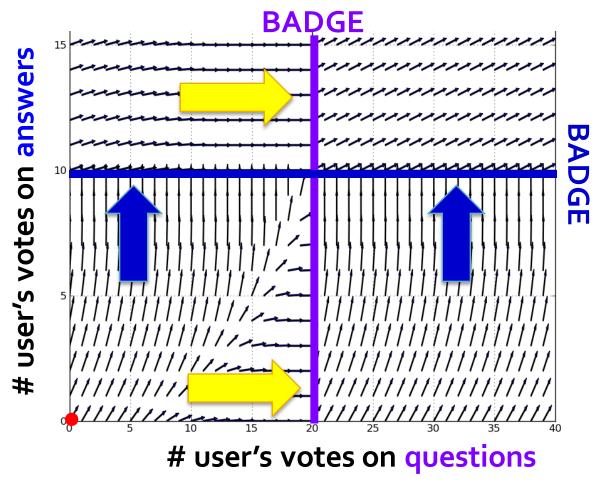
Solving the Model

- Solve arg max $U(\mathbf{x_a}) = \sum_{b \in B} I_b(\mathbf{a}) V_b + \theta \sum_{i=1}^{n+1} \mathbf{x_a}^i \cdot U(\mathbf{x_{a+e_i}}) g(\mathbf{x_a}, \mathbf{p})$
 - Partition space based on badge boundaries
 - Inductively solve regions in order from large coordinates to small

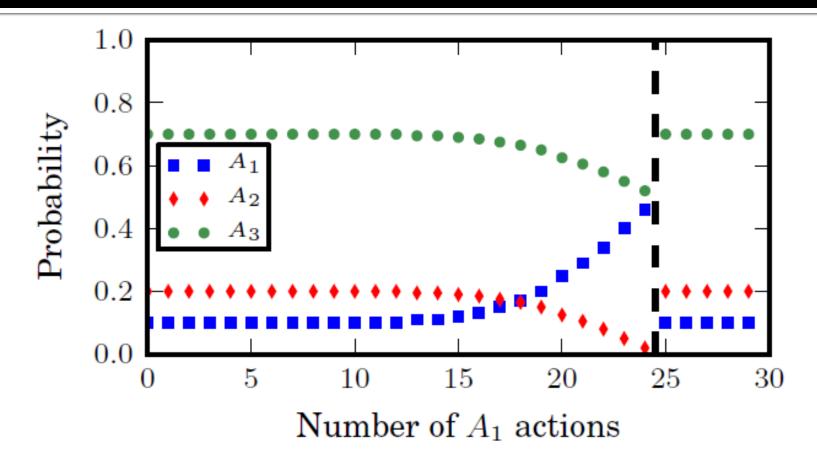


Example: 2 Badges

Influencing user behavior:



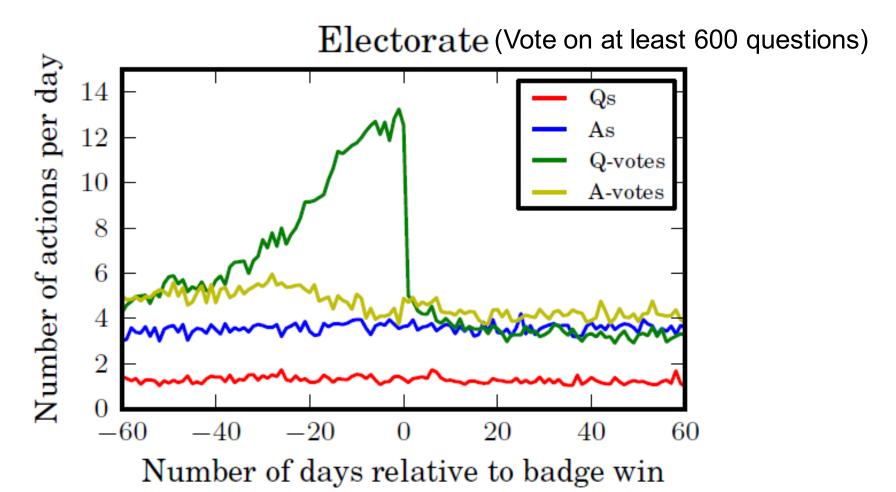
Example: 1 Badge



- Example: Badge at 25 actions of type A₁
 - User steers in A₁ direction as she approaches the badge boundary; then resets after receiving it

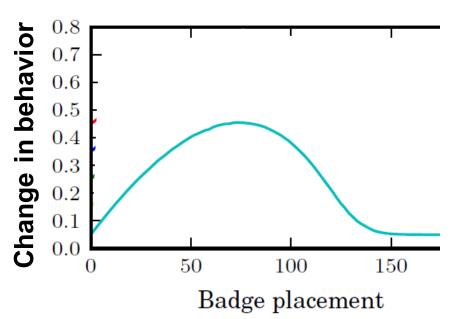
Model vs. Data

Model predicts qualitative behavior



Badge Placement Problem

- Question: How should you "place" badges to achieve desired effects?
- Our model allows for optimizing the badge placement for optimal behavior steering:



Badges on Coursera

Badge Series (2 earned)

The Reader

To earn the next badge (Silver), you must read 30 threads from your classmates.

The Supporter

To earn the next badge (Silver), you must vote on 15 posts that you find interesting or useful.

The Contributor

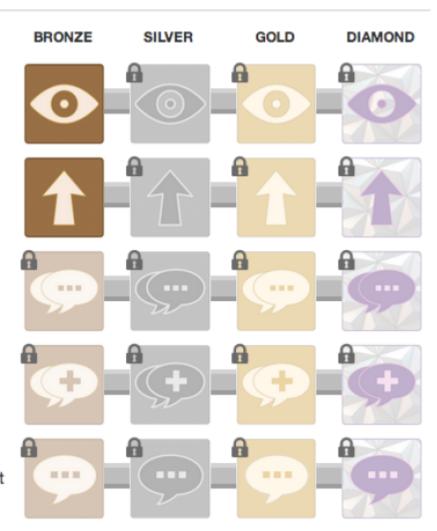
To earn the next badge (Bronze), you must post 3 replies that your classmates find interesting.

The Conversation Starter

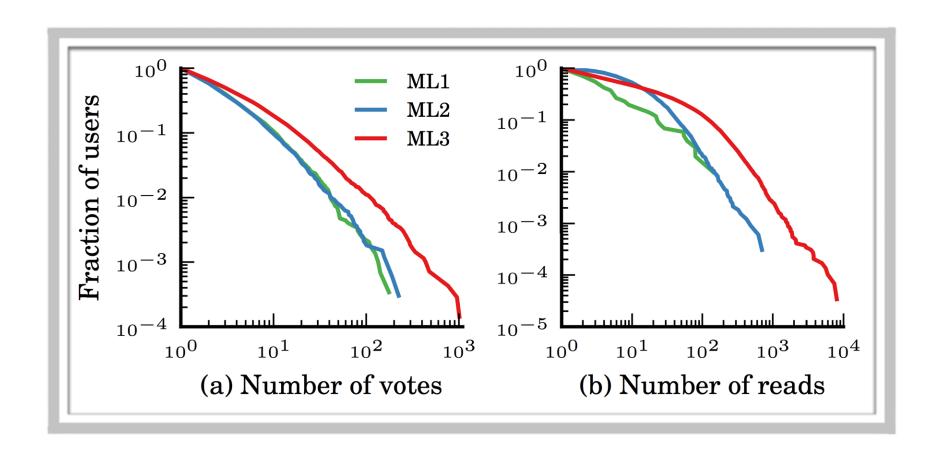
To earn the next badge (Bronze), you must start 3 threads that your classmates find interesting.

Top Posts

To earn the next badge (Bronze), you must write a post that gets 5 upvotes from your classmates.

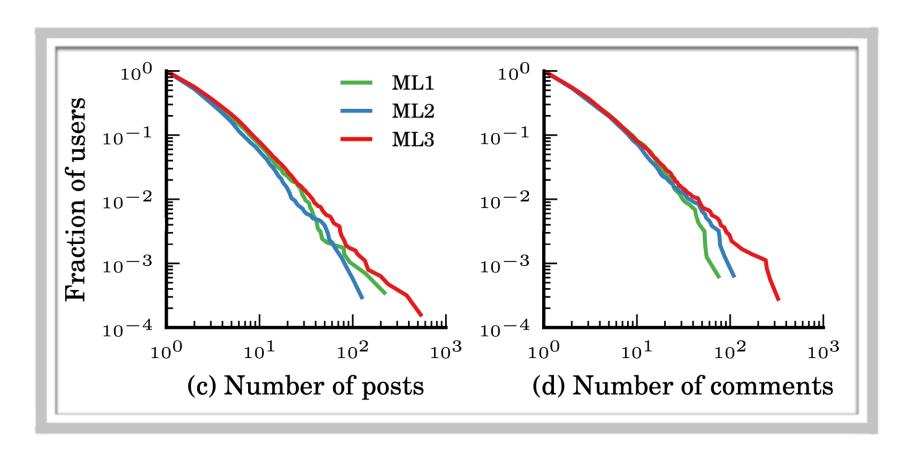


Experiment: ML Class



5x more likely to get to 100 votes/reads!

Experiment: ML Class



No qualitative difference in posts/comments

No badges on these actions!

Badges: Further questions

- Many questions, both within this framework and extending it:
 - Where does the value of a badge come from? Internal, social, transactional, ...
 - How does achievement-seeking interact with competition and scarcity?
 - How far can we develop analogies with off-line domains?

Social and Information Networks: Review of Key Concepts

Networks



How do we reason about networks?

Reasoning About Networks

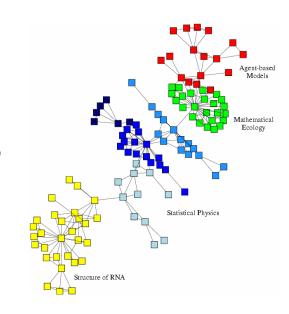
How do we reason about networks?

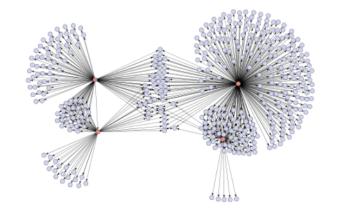
- Empirical: Study network data to find organizational principles
- Mathematical models: Probabilistic, graph theory
- Algorithms: Methods for analyzing graphs

Networks: Structure & Process

What do we study in networks?

- Structure and evolution:
 - What is the structure of a network?
 - Why and how did it become to have such structure?
- Processes and dynamics:
 - Networks provide "skeleton" for spreading of information, behavior, diseases





What We Have Covered

- Network diameter
- Edge clustering
- Scale-free networks
- Strength of weak ties
- Core-periphery structure
- Densification power law
- Shrinking diameters
- Structural Balance
- Status Theory
- Memetracking
- Small-world model
- Erdös-Renyi model
- Preferential attachment
- Network cascades

- Independent cascade model
- Decentralized search
- PageRank
- Hubs and authorities
- Girvan-Newman
- Modularity
- Clique percolation
- Supervised random walks
- Influence maximization
- Outbreak detection
- Linear Influence Model
- Network Inference
- Kronecker Graphs
- Bow-tie structure

How It All Fits Together

Properties

Small diameter, Edge clustering

Scale-free

Strength of weak ties, Core-periphery

Densification power law, Shrinking diameters

Patterns of signed edge creation

Information virality, Memetracking

Models

Small-world model, Erdös-Renyi model

Preferential attachment,
Copying model

Kronecker Graphs

Microscopic model of evolving networks

Structural balance, Theory of status

Independent cascade model, Game theoretic model

Algorithms

Decentralized search

PageRank, Hubs and authorities

Community detection: Girvan-Newman, Modularity

Link prediction, Supervised random walks

Models for predicting edge signs

Influence maximization, Outbreak detection, LIM

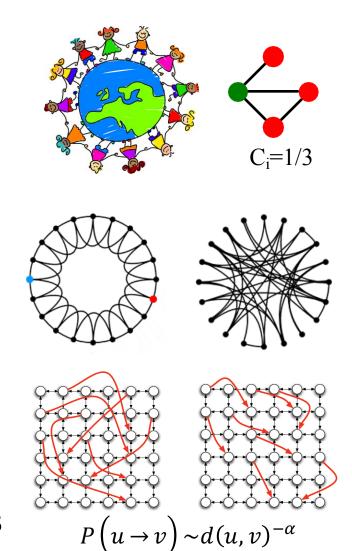
Small-World Phenomena

Properties:

- Six degrees of separation
 - Networks have small diameters
- Edges in the networks cluster
 - Large clustering coefficient

Models:

- Erdös-Renyi model
 - Baseline model for networks
- The Small-World model
 - Small diameter and clustered edges
- Algorithms:
 - Decentralized search in networks
 - Kleinberg's model and algorithm



Scale-Free Networks

Properties:

- Power-law degrees
 - Degrees are heavily skewed



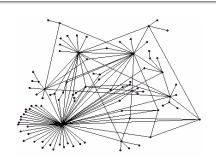
Networks are resilient to random attacks

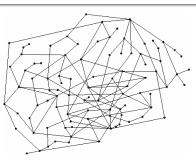
Models:

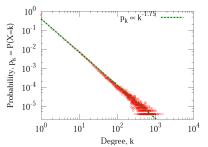
- Preferential attachment
 - Rich get richer

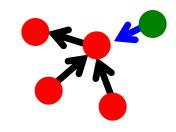
Algorithms:

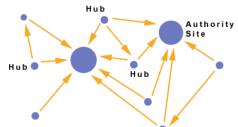
- Hubs and Authorities
 - Recursive: $a_i = \sum_{j \to i} h_j$, $h_i = \sum_{i \to j} a_j$
- PageRank
 - Recursive formulation, Random jumps





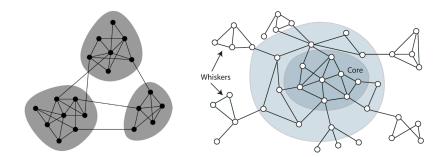


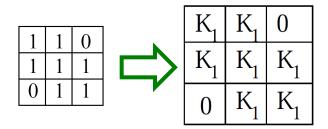


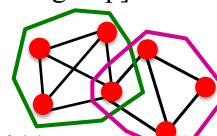


Community Detection

- Strength of weak ties
- Core-periphery structure
- Models:
 - Kronecker graphs model
- Algorithms:
 - Spectral Clustering
 - Girvan-Newman (Betweeness centrality)
 - **Modularity:** #edges within group E[#edges within group]
 - Clique Percolation Method
 - Overlapping communities





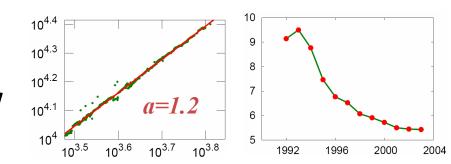


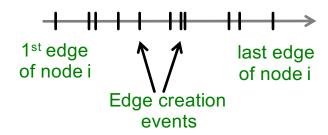
Network Evolution

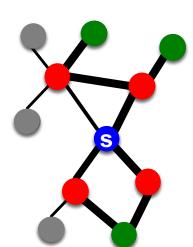
- Densification Power Law
 - $\bullet E(t) \propto N(t)^a$
- Shrinking Diameter
- Models:



- Exponential life-times, Evolving sleeping times
- Random-Random edge attachment
- Algorithms:
 - Link prediction

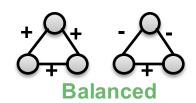


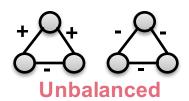


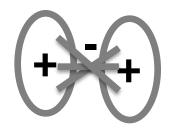


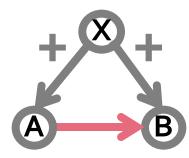
Signed Networks

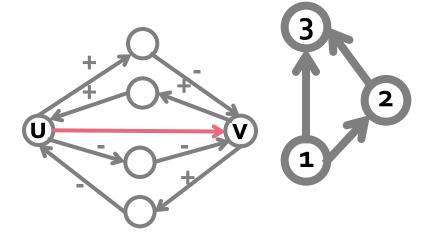
- Signed link creation
- +links are more embedded
- Models:
 - Structural Balance
 - Coalition structure of networks
 - Status Theory
 - Global node status ordering
- Algorithms:
 - Predicting edge signs





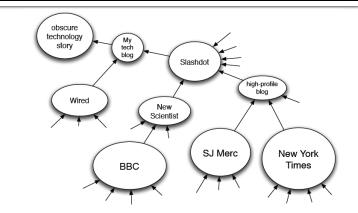


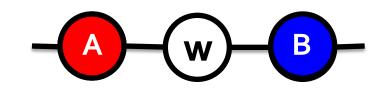




Network Diffusion (1)

- Meme-tracking
 - Blogs trail mass media
- Models:
 - Game theoretic model:
 - Payoffs, Competing products
 - Independent Cascade Model
 - Each node infects a neighbor with some probability

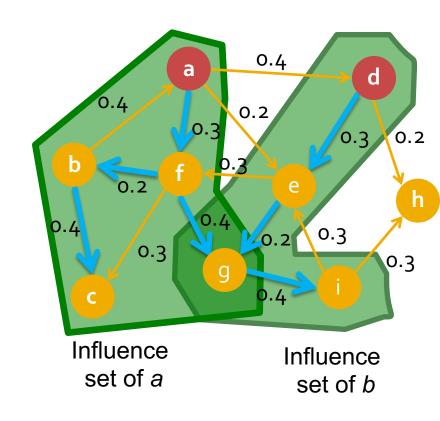




Network Diffusion (2)

Algorithms:

- Influence Maximization
 - Set of k nodes producing largest expected cascade size if activated
 - Submodularity
 - Greedy hill-climbing
- Outbreak Detection
- Network Inference
 - Infer networks based on information diffusion data



Map of Superpowers

Properties

Small diameter, Edge clustering

Scale-free

Strength of weak ties, Core-periphery

Densification power law,
Shrinking diameters

Patterns of signed edge creation

Viral Marketing, Blogosphere, Memetracking

Models

Small-world model, Erdös-Renyi model

Preferential attachment, Copying model

Kronecker Graphs

Microscopic model of evolving networks

Structural balance, Theory of status

Independent cascade model, Game theoretic model

Algorithms

Decentralized search

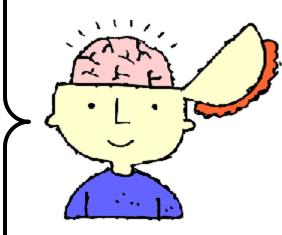
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Community detection: Girvan-Newman, Modularity

Link prediction, Supervised random walks

Models for predicting edge signs

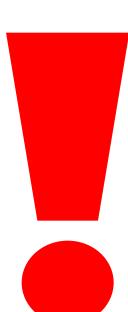
Influence maximization, Outbreak detection, LIM



What Next?

Project write-ups:

- Sun Dec 11 Midnight (11:59PM) Pacific Time No late days!
 - 1 team member uploads PDF to Gradescope
 - See course website for more info
- Poster session:
 - Tue Dec 13 from 3 6pm in Gates
 - All groups with at least one non-SCPD member must present
 - There should be 1 person at the poster at all times
 - Prepare a 2-minute elevator pitch of your poster
 - More instructions to follow



What Next? Seminars

Seminars:

- InfoSeminar: http://i.stanford.edu/infoseminar
 - Can be taken for credit (CS545, also on SCPD)
 - Great industry/academia speakers on Fridays
- Conferences / Journals:
 - WWW: ACM World Wide Web Conference
 - WSDM: ACM Web search and Data Mining
 - ICWSM: AAAI Int. Conf. on Web-blogs & Social Media
 - KDD: Conf. on Knowledge Discovery & Data Mining
 - Journal of Network Science
 - Journal of Complex Networks

What Next? Courses

- CS246: Mining Massive Datasets (Winter 2017)
 - Data Mining & Machine Learning for big data
 - (big==does' fit in memory/single machine), MapReduce
- CS341: Project in Data Mining (Spring 2017)
 - Groups do a research project on big data
 - We provide interesting data, projects and access to the Amazon computing infrastructure
 - Nice way to finish up CS224W project & publish it!

What Next? Courses

Other relevant courses:

- MS&E 231: Computational Social Science
- MS&E334: The Structure of Social Data
- CS276: Information Retrieval and Web Search
- CS229: Machine Learning
- CS245: Database System Principles
- CS347: Transaction Processing & Databases

In Closing...

- You Have Done a Lot!!!
- And (hopefully) learned a lot!!!
 - Answered questions and proved many interesting results
 - Implemented a number of methods
 - And are doing excellently on the class project!

Thank You for the Hard Work!!!

