# On-Line Social Systems with Long-Range Goals 

Jon Kleinberg

Cornell University


Including joint work with Ashton Anderson, Dan Huttenlocher, Jure Leskovec, and Sigal Oren.

## Long-Range Planning



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Growth in on-line systems where users have long visible lifetimes and set long-range goals.

- Reputation, promotion, status, individual achievement.

How should we model individual decision-making in these settings with long-range planning?

## Badges


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Structural framework for analysis: state space of activities.

- User lifetimes correspond to trajectories through state space.
- Effort incurs cost, leads to rewards.

On-line domain: badges and related incentives as reward systems.

- Social-psychological dimensions [Antin-Churchill 2011]
- Game-theoretic [Deterding et al 2011, Easley-Ghosh 2013]
- Contest/auction-based [Cavallo-Jain 12, Chawla-Hartline-Sivan 12]


## Outline

Model the interaction of incentives and long-range planning in state spaces representing actions on site.
(1) Cumulative rewards: milestones for effort [Anderson-Huttenlocher-Kleinberg-Leskovec ]

- A basic model of an individual working toward long-range rewards.
- Exploration of the model on StackOverflow
- Experiments with MOOC forums on Coursera
(2) Incentives and planning with time-inconsistent behavior [Kleinberg-Oren ]
- Start from principles in behavioral economics
[Strotz 1955, Pollak 1968, Akerlof 1991, Laibson 1997]
- Develop a graph-theoretic model to represent planning as path-finding with a behavioral bias.


## First Domain for Analysis: Stack Overflow

## stackoverflow

## Connected components in a graph with 100 million nodes



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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 solution in Python. Many thanks.

## python graph

share | improve this question
asked Jun 13 '12 at 13:48
1.8. user1453508
$27=4$

1 Answer
active oldest votes

SciPy has a connected components algorithm. It expects as input the adjacency matrix of your graph in one of its sparse matrix formats and handles both the directed and undirected cases.

Building a sparse adjacency matrix from a sequence of ( $i, j$ ) pairs adj_list where $i$ and $j$ are (zero-based) indices of nodes can be done with

## Basic Model

A population of users and a site designer.

- Designer wants certain frequency of activites.
- Designer creates badges, which have value to users.

- User trades off preferred activities versus reaching badge.
- This "steers" behavior - balancing activities differently.
- Compare to goal-gradient hypothesis [Kivetz et al 2006]

User's basic trade-off corresponds to path through state space.

## Our Model

- Action types $A_{1}, A_{2}, \ldots, A_{n}$. (ask, answer, vote, off-site, ...)
- User's state is $n$-dimensional.
- User has preferred distribution p over action types.
- User exits system with probability $\delta>0$ each step.

- Each badge $b$ is a monotone subset of the state space; reward $V_{b}$ is conferred when the user enters this subset.
- User can pick distribution $\mathbf{x} \neq \mathbf{p}$ to get badge more quickly; comes at a cost $g(\mathbf{x}, \mathbf{p})$.
- User optimization: Choose $\mathbf{x}_{\mathbf{a}}=\left(\mathbf{x}_{\mathrm{a}}^{1}, \ldots, \mathbf{x}_{\mathrm{a}}^{n}\right)$ in each state $\mathbf{a}$ to optimize utility $U\left(\mathbf{x}_{\mathrm{a}}\right)$.

$$
U\left(\mathbf{x}_{\mathbf{a}}\right)=\sum_{b \text { won }} V_{b}-g\left(\mathbf{x}_{\mathbf{a}}, \mathbf{p}\right)+(1-\delta) \sum_{i=1}^{n} \mathbf{x}_{\mathbf{a}}^{i} \cdot U\left(\mathbf{x}_{\mathbf{a}+\mathbf{e}_{\mathbf{i}}}\right)
$$

## What a Solution Looks Like



## A One-Dimensional Version



Example: Badge at 25 actions of type 1.

- Canonical behavior: user "steers" in $A_{1}$ direction; then resets after receiving the badge.


## Evaluating Qualitative Predictions

Consider two cumulative badges on StackOverflow.

- Civic Duty badge: Vote at least 300 times.
- Electorate: Vote on at least 600 questions (plus some other technical conditions).

5-dimensional state space: (Q, A, Q-vote, A-vote, off-site).



## Badge Placement and Badge Value



## The Badge Placement Problem

- Given $V_{b}$ and a desired action distribution $\mathbf{q}$, how should you define a badge of value $V_{b}$ to create an action distribution as close to $\mathbf{q}$ as possible?
- Special case: If the badge is a milestone on action $i$, and the goal is to maximize amount of action $i$.


## The Feasible Region

Can we characterize the feasible region?

- Which proportions of activities can be implemented with a limited set of badges?


Percentage of $\mathrm{A}_{1}$ actions

## The Feasible Region

Example, with preferred $\mathbf{p}=(.1, .1, .8)$.


## An Experiment on Coursera

Thread byline:

## Connorelly - 2 - 1 - $1 \cdot 2$ months ago $8_{8}$

## Badge ladder:

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.


## An Experiment on Coursera






## Planning and Time-Inconsistency



Tacoma Public School System
Our models thus far:

- Plans are multi-step.
- Agents chooses optimal sequence given costs and benefits.

What could go wrong?

- Costs and benefits are unknown, and/or genuinely changing over time.
- Time-inconsistency.


## Planning and Time-Inconsistency

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## Why did George Akerlof not make it to the post office?

Agent must ship a package sometime in next $n$ days.

- One-time effort cost $c$ to ship it.
- Loss-of-use cost $x$ each day hasn't been shipped.


An optimization problem:

- If shipped on day $t$, cost is $c+t x$.
- Goal: $\min _{1 \leq t \leq n} c+t x$.
- Optimized at $t=1$.

In Akerlof's story, he was the agent, and he procrastinated:

- Each day he planned that he'd do it tomorrow.
- Effect: waiting until day $n$, when it must be shipped, and doing it then, at a significantly higher cumulative cost.


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A model based on present bias [Akerlof 91; cf. Strotz 55, Pollak 68]

- Costs incurred today are more salient: raised by factor $b>1$.

On day $t$ :

- Remaining cost if sent today is $b c$.
- Remaining cost if sent tomorrow is $b x+c$.
- Tomorrow is preferable if $(b-1) c>b x$.

General framework: quasi-hyperbolic discounting [Laibson 1997]

- Cost/reward $c$ realized $t$ units in future has present value $\beta \delta^{t} c$
- Special case: $\delta=1, b=\beta^{-1}$, and agent is naive about bias.
- Can model procrastination, task abandonment [O'Donoghue-Rabin08], and benefits of choice reduction [Ariely and Wertenbroch 02, Kaur-Kremer-Mullainathan 10]


## Cost Ratio



## GYM MEMBERSHIP

Cost ratio:

# Cost incurred by present-biased agent <br> Minimum cost achievable 

Across all stories in which present bias has an effect, what's the worst cost ratio?

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## A Graph-Theoretic Framework



Use graphs as basic structure to represent scenarios.

- Agent plans to follow cheapest path from $s$ to $t$.
- From a given node, immediately outgoing edges have costs multplied by $b>1$.


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## Example: Akerlof's Story as a Graph



Node $v_{i}=$ reaching day $i$ without sending the package.

## Paths with Rewards



Variation: agent only continues on path if cost $\leq$ reward at $t$.

- Can model abandonment: agent stops partway through a completed path.
- Can model benefits of choice reduction: deleting nodes can sometimes make graph become traversable.


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## A More Elaborate Example



Three-week short course with two projects.

- Reward of 16 from finishing the course.
- Effort cost in a given week: 1 from doing no project, 4 from doing one, 9 from doing both.
- $v_{i j}=$ the state in which $i$ weeks of the course are done and the student has completed $j$ projects.


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## Overview


(1) Analyzing present-biased behavior via shortest-path problems.
(2) Characterizing instances with high cost ratios.
(3) Algorithmic problem: optimal choice reduction to help present-biased agents complete tasks.
(9) Heterogeneity: populations with diverse values of $b$.

## A Bad Example for the Cost Ratio



Cost ratio can be roughly $b^{n}$, and this is essentially tight. ( $n=\#$ nodes.)

Can we characterize the instances with exponential cost ratio?

- Goal, informally stated: Must any instance with large cost ratio contain Akerlof's story as a sub-structure?


## Characterizing Bad Instances via Graph Minors



Graph $H$ is a minor of graph $G$ if we can contract connected subsets of $G$ into "super-nodes" so as to produce a copy of $H$.

- In the example: $G$ has a $K_{4}$-minor.


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The $k$-fan $\mathcal{F}_{k}$ : the graph consisting of a $k$-node path, and one more node that all others link to.


## Theorem

For every $\lambda>1$ there exists $\varepsilon>0$ such that if the cost ratio is $>\lambda^{n}$, then the underlying undirected graph of the instance contains an $\mathcal{F}_{k}$-minor for $k=\varepsilon n$.

In subsequent work, tight bound by Tang et al 2015.

## Sketch of the Proof



- The agent traverses a path $P$ as it tries to reach $t$.
- Let the rank of a node on $P$ be the logarithm of its dist. to $t$.
- Show that every time the rank increases by 1 , we can construct a new path to $t$ that avoids the traversed path $P$.


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## Heterogeneity



Heterogeneous population: which paths are possible as we vary $b$ ?

- A kind of parametric shortest path problem.
- How many distinct paths can arise over all $b$ ?
- What kind of parametric shortest path problem is it?

Analogy: $c_{e}(x)=a_{e} x+b_{e}$ leads to super-polynomial \# paths.
[Carstensen 1983, Nikolova et al 2006]

- In our case, at most $O\left(n^{2}\right)$ distinct paths.


## Choice Reduction



Choice reduction problem: Given $G$, not traversable by an agent, is there a subgraph of $G$ that is traversable?

- Our initial idea: if there is a traversable subgraph in $G$, then there is a traversable subgraph that is a path.
- But this is not the case.

Results:

- A characterization of the structure of minimal traversable subgraphs.
- NP-completeness [Feige 2014, Tang et al 2015]
- Open: Approximation by slightly increasing reward and deleting nodes?


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## Further Questions

## foursquare




## Reward systems are a key part of the design space.

- Where does the value reside in rewards for long-range planning? Social, motivational, transactional, ... ?
- How do these different mechanisms for value affect the design? How do we design for a mixture of motivations?
- Computational models incorporating human behavioral biases. Agents that are aware of their biases
[O'Donoghue-Rabin 1999, Kleinberg-Oren-Raghavan 2015].
- Algorithmic ideas will play a crucial role in all these questions.

