# Learning the Preferences of Ignorant, Inconsistent Agents

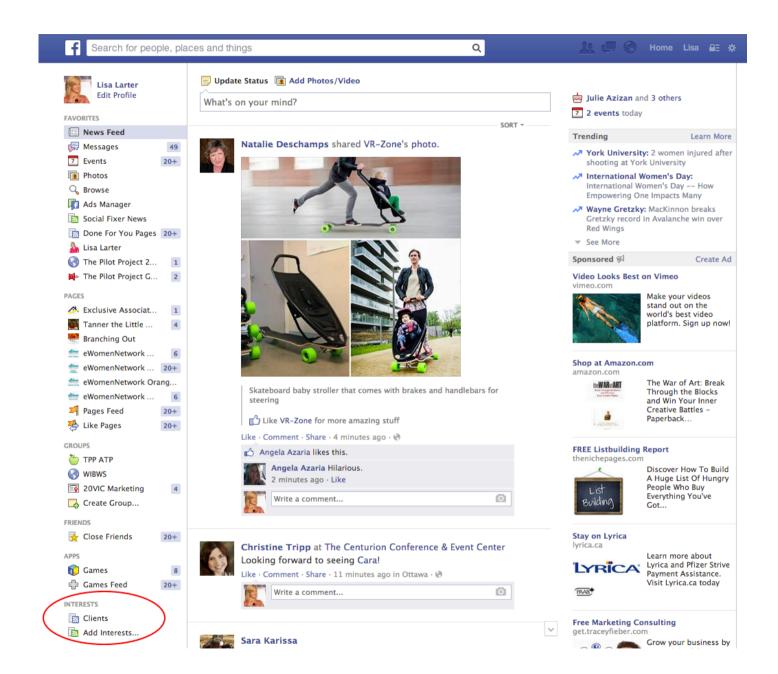
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## 1. Motivation for learning human preferences

- Scientific (economics, psychology): how do people value work vs. leisure, short-term vs. long-term, country vs. friends & family?
- Machine learning (applications): recommendation (movie, job, dating), create tailored content.
- Machine learning (long-term goal): the more systems **understand** our preferences, the more they can help us make **high stakes** decisions in **novel** circumstances.



### 2. Learning preferences with IRL

#### **Inverse Reinforcement Learning (AI) / Structural Estimation (Econ):**

- Unsupervised learning, assumed model is MDP, POMDP, RL.
- Learn from sequences of choices in complex environments (cf. Netflix)
- Learn utility/reward function not policy: enduring cause not contingent effects.
- People act on their preferences without ability to report them quantitatively (driving skill, detailed vacation plan)

### 3. The problem of systematic error

- IRL: infer preferences from observed actions ... assuming human fits (MDP/POMDP) model up to random (softmax) errors.
- But human make **systematic** errors! Person smokes every day but regrets it.
- Behavioral economics (hyperbolic discounting, Prospect Theory)
- Bounded cognition (forgetting, limited computational ability, etc.)

### 4. Learning from ignorant, inconsistent agents

Our approach:

- 1. build flexible generative models to capture a range of biases and cognitive bounds (while maintaining tractability)
- 2. jointly infer **biases** (or lack thereof) and **preferences** from behavior
- 3. if successful, can help humans overcome biases

#### 5. Human bias: Time inconsistency

- Intuition: tonight you want to rise early but tomorrow you want to sleep in.
- Most prominent bias: addiction, procrastination, impulsiveness, willpower / pre-commitment.
- Formally, any non-exponential discounting implies time-inconsistency.

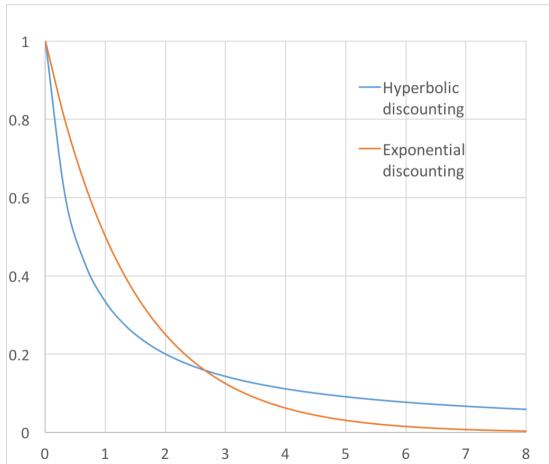
#### 5. Human bias: Time inconsistency

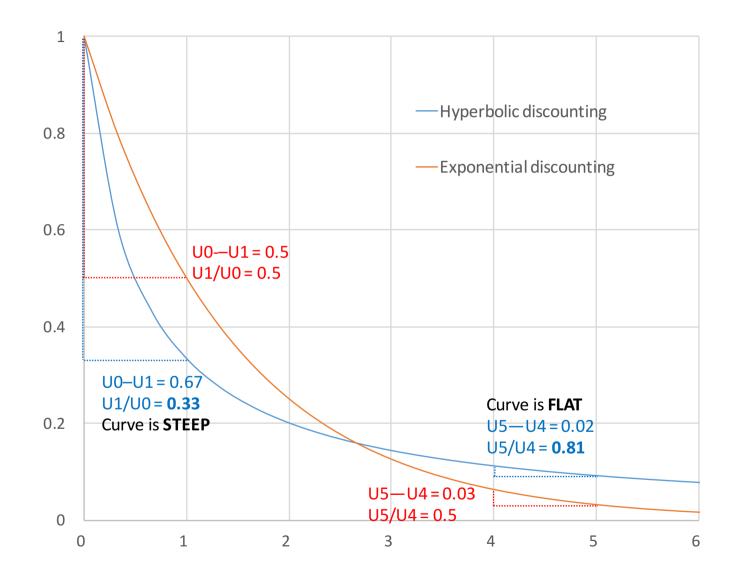
#### Hyperbolic discounting

Discount factor = 1/(1+kt)

At t=0, you prefer \$80 at t=8 to \$70 at t=7 (curve **shallow**)

At t=7, you re-evaluate and prefer \$70 now to \$80 tomorrow (curve **steep)**.





#### 5. Model for biased agent

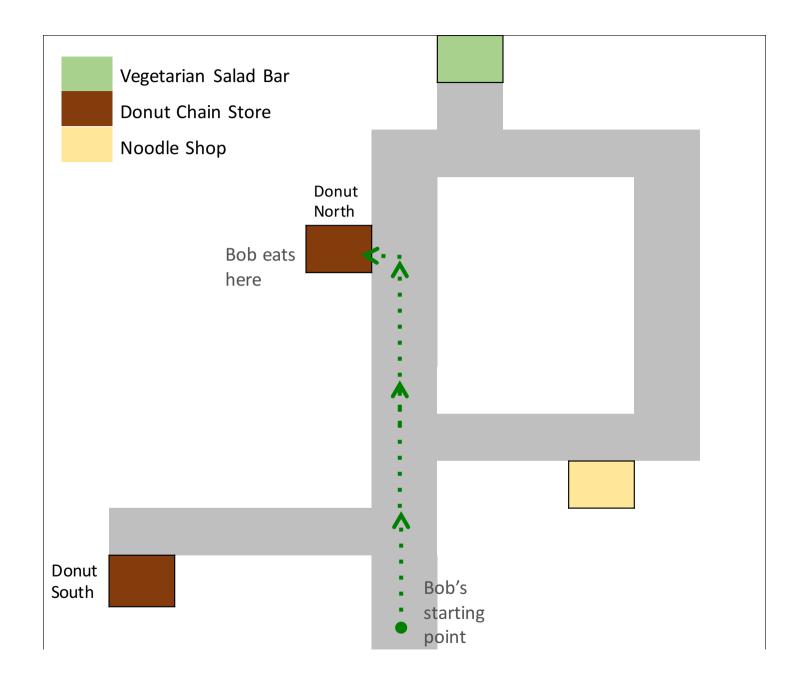
MDP model: 
$$\operatorname{EU}_{s}[a] = U(s, a) + \mathop{\mathbb{E}}_{s', a'} [\operatorname{EU}_{s'}[a']]$$
  
with  $s' \sim T(s, a)$  and  $a' \sim C(s')$ 

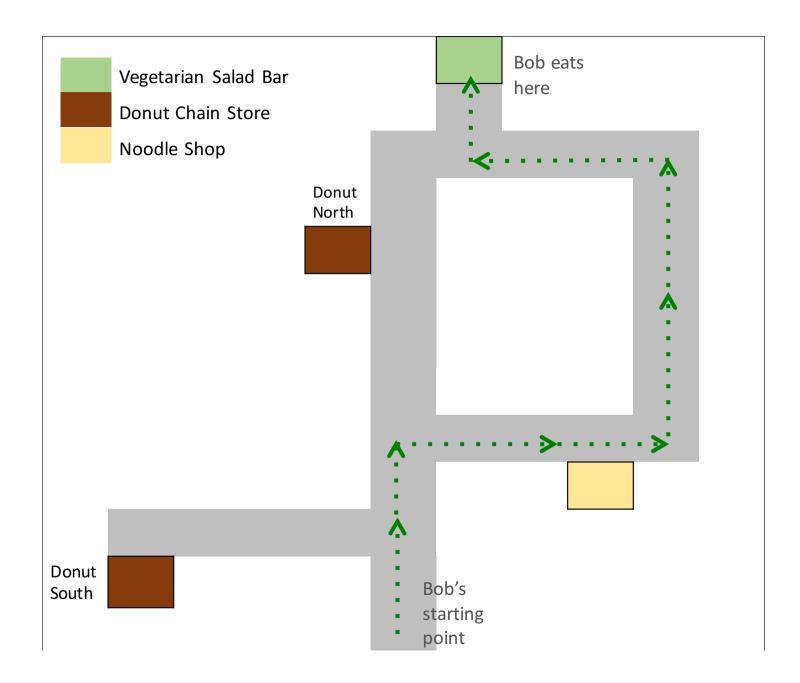
**MDP + Hyberbolic discounting** (variable *d* for "delay" measures how far in the future the action *a* would take place):

$$EU_{s,d}[a] = \frac{1}{1+kd}U(s,a) + \mathop{\mathbb{E}}_{s',a'}[EU_{s',d+1}[a']]$$

#### 6. Goal for examples and experiments

- Show that ignoring biases (assuming optimality) leads to mistakes in learning preferences
- Mistakes occur in simple, uncontrived, everyday scenarios.





#### 5. Model for biased agent - NAIVE

MDP model: 
$$\operatorname{EU}_{s}[a] = U(s, a) + \mathop{\mathbb{E}}_{s', a'} [\operatorname{EU}_{s'}[a']]$$
  
with  $s' \sim T(s, a)$  and  $a' \sim C(s')$ 

**MDP + Hyberbolic discounting** (variable *d* for "delay" measures how far in the future the action *a* would take place):

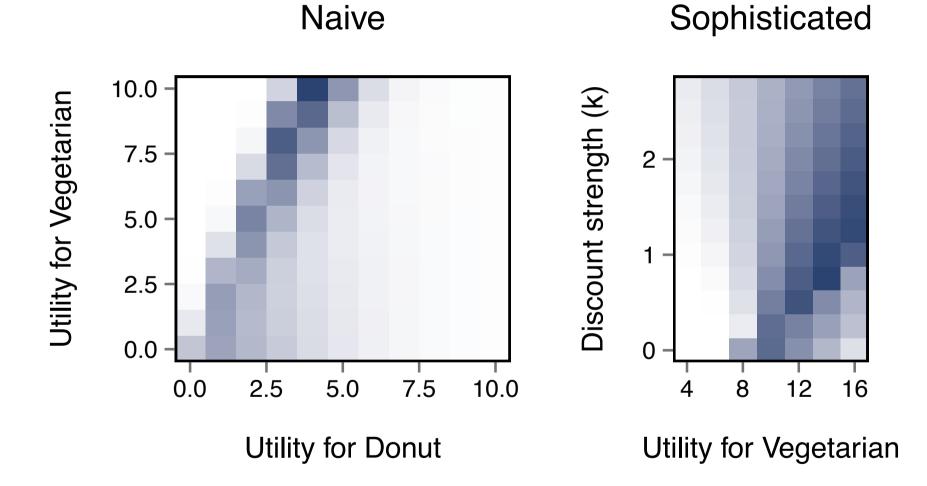
$$EU_{s,d}[a] = \frac{1}{1+kd}U(s,a) + \mathbb{E}_{s',a'}[EU_{s',d+1}[a']]$$
$$a' \sim C(s',d+1)$$

#### 5. Model for biased agent - SOPHISTICATED

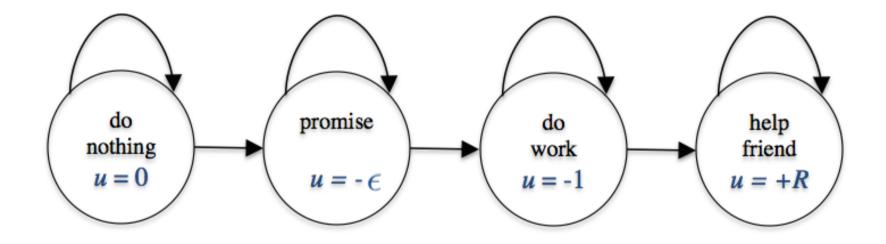
MDP model: 
$$\operatorname{EU}_{s}[a] = U(s, a) + \mathop{\mathbb{E}}_{s', a'} [\operatorname{EU}_{s'}[a']]$$
  
with  $s' \sim T(s, a)$  and  $a' \sim C(s')$ 

**MDP + Hyberbolic discounting** (variable *d* for "delay" measures how far in the future the action *a* would take place):

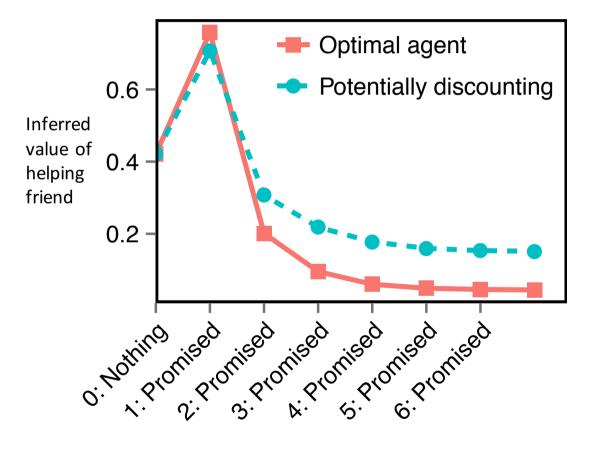
$$EU_{s,d}[a] = \frac{1}{1+kd}U(s,a) + \mathbb{E}_{s',a'}[EU_{s',d+1}[a']]$$
$$a' \sim C(s',0)$$

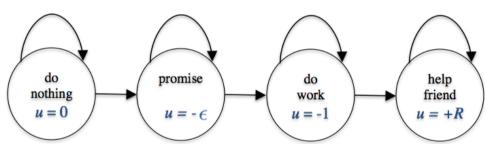


#### 6. Model for biases agent: Procrastination



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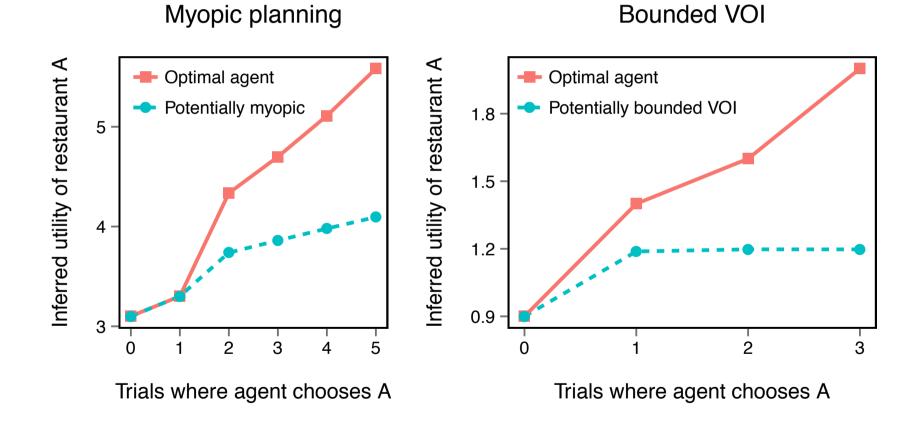
Day and state

#### 7. Model for biased agent: Myopia

- Simple myopia (near sighted): ignore any rewards or costs after time k1 > 0 (even though you'll still be alive).
- **Bounded Value-of-Information:** ignore the value of information gained after time  $k^2 > 0$  (even though you will still get benefits from information).



#### 7. Model for biased agent: Myopia



# agentmodels.org

Interactive, online tutorial and open-source library for constructing this kind of model (Work in progress).

Main sections:

- Agent models for one-player sequential problems (MDPs, POMDPs, RL), where agent can be biased
- Inference (IRL) for a large space of possible agents
- Multi-agent interactions: coordination, group preferences.

Tom's decision rule is to take action a that maximizes utility, i.e., the action

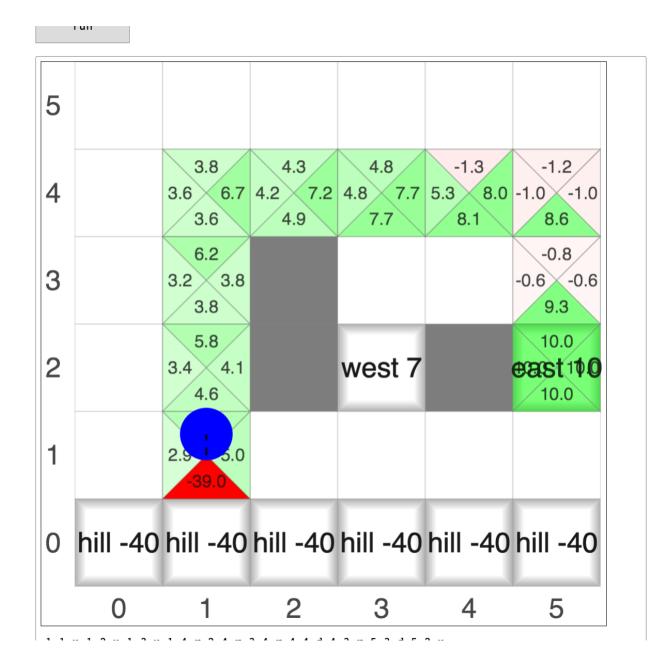
 $rg\max_{a\in A} U(T(s,a))$ 

In WebPPL, we can implement this utility-maximizing agent as a function maxAgent that takes a state  $s \in S$  as input and returns an action. For Tom's choice between restaurants, we assume that the agent starts off in a state "default", denoting whatever Tom does before going off to eat. The program directly translates the decision rule above using the higher-order function argMax.

```
// Choose to eat at the Italian or French restaurants
var actions = ['italian', 'french'];
var transition = function(state, action){
  return (action === 'italian') ? 'pizza' : 'steak frites';
};
var utility = function(state){
  return (state === 'pizza') ? 1 : 0;
};
var maxAgent = function(state){
 return argMax(
    function(action){
      return utility(transition(state, action));
    },
    actions);
};
print("Agent chooses: " + maxAgent("default"));
```

run

Agent chooses: french



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