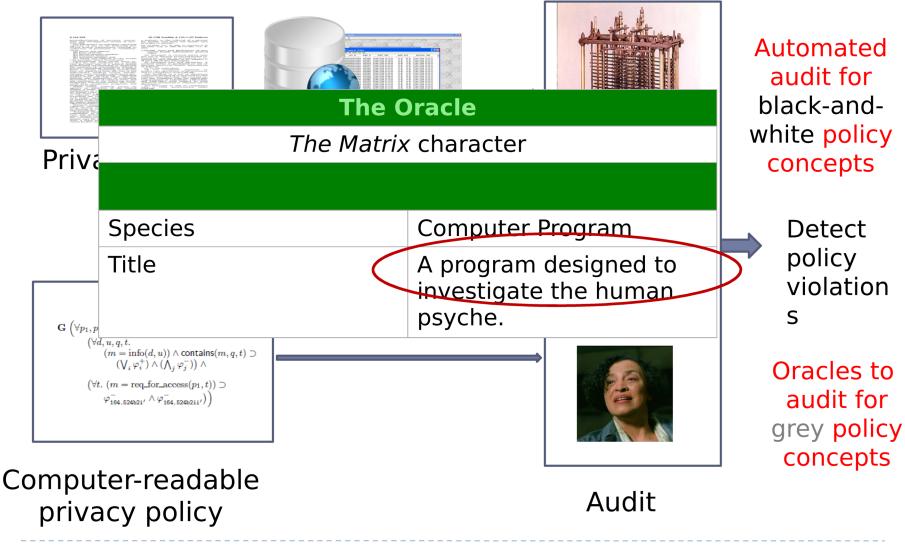
Formalizing and Enforcing Purpose Restrictions in Privacy Policies

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Carnegie Mellon University
18734: Foundations of Privacy
Fall 2017

Detecting Policy Violations



Purpose Restrictions in Privacy Policies



Yahoo!'s practice is **not** to use the content of messages [...] **for** marketing **purposes**.



By providing your personal information, you give [Social Security Administration] consent to use the information **only for** the **purpose** for which it was collected.

Purpose Restrictions are Ubiquitous

- OECD's Privacy Guidelines
- US Privacy Laws
 - HIPAA, GLBA, FERPA, COPPA,...
- EU Privacy Directive
- Organizational Privacy Policies
 - Google, Facebook, Yahoo,...
 - Hospitals, banks, educational institutions, govt
 - Defense: Mission-based information access

Purpose Restrictions on Actions

With M. C. Tschantz (CMU _ Berkeley) and J. M. Wing (CMU _ MSR)

2012 IEEE Symposium on Security & Privacy

Goal

- Give a semantics to
 - "Not for" purpose restrictions
 - "Only for" purpose restrictions that is parametric in the purpose

 Provide automated enforcement of purpose restrictions for that semantics



Send record

No diagnosis by drug company





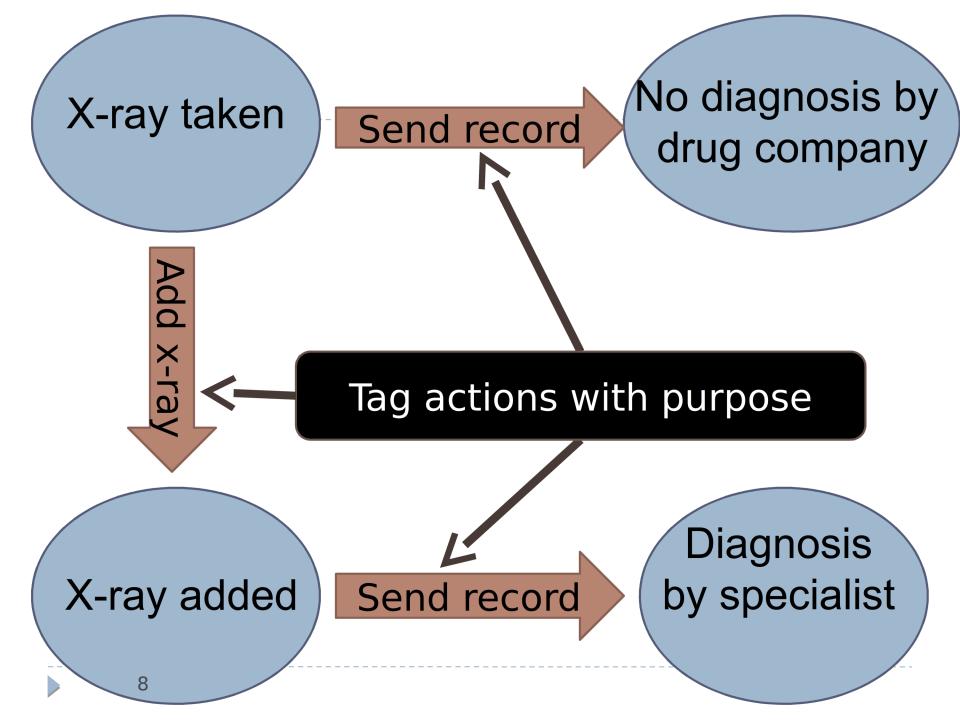
Medical Record Med records used only for

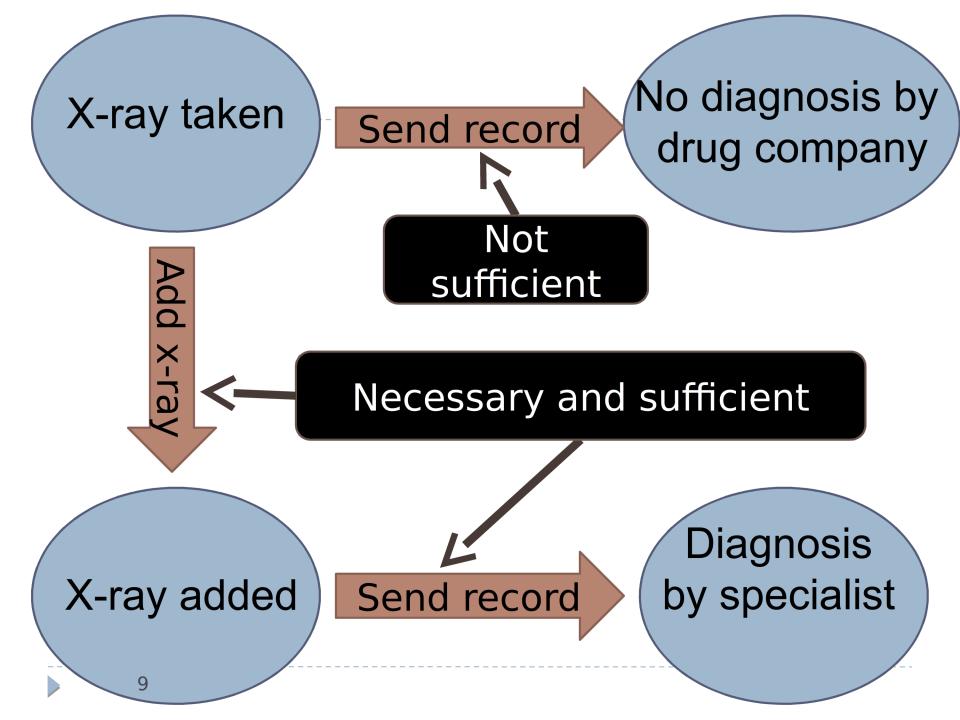


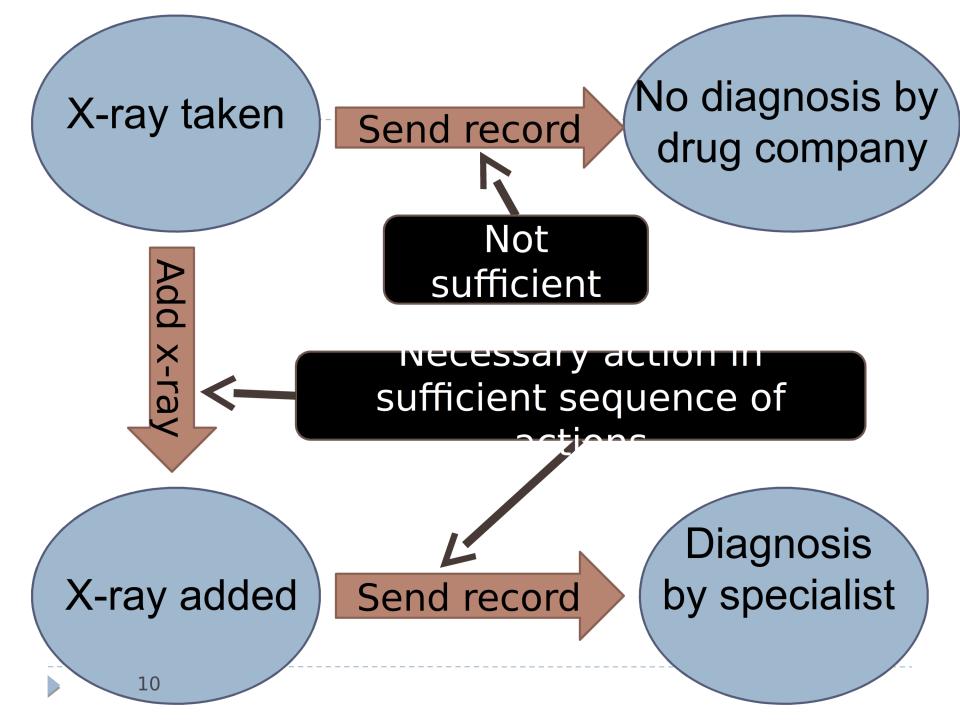
X-ray added

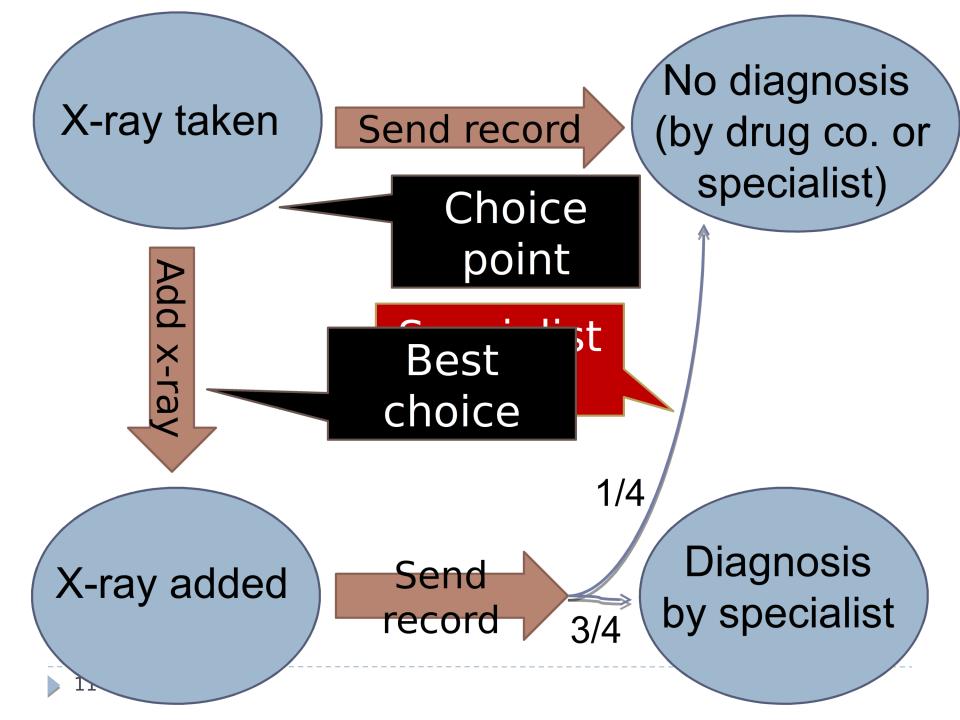
Send record

Diagnosis by specialist









Planning

Thesis: An action is for a purpose iff that action is part of a plan for furthering the purpose

i.e., always makes the best choice for furthering the purpose

X-ray taken

Send record

No diagnosis

No reward

No reward

Markov Decision Process: States, actions, transitions, rewards

X-ray added

No reward

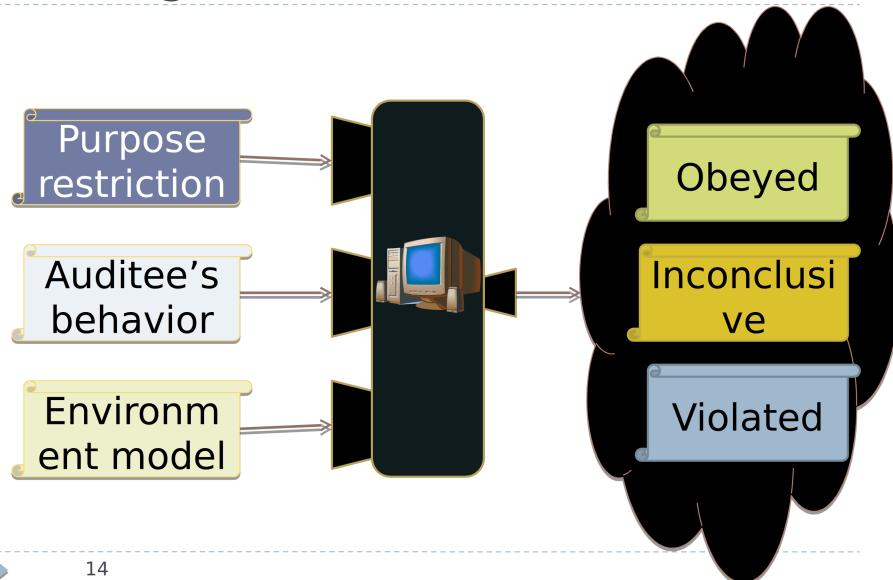
Send record

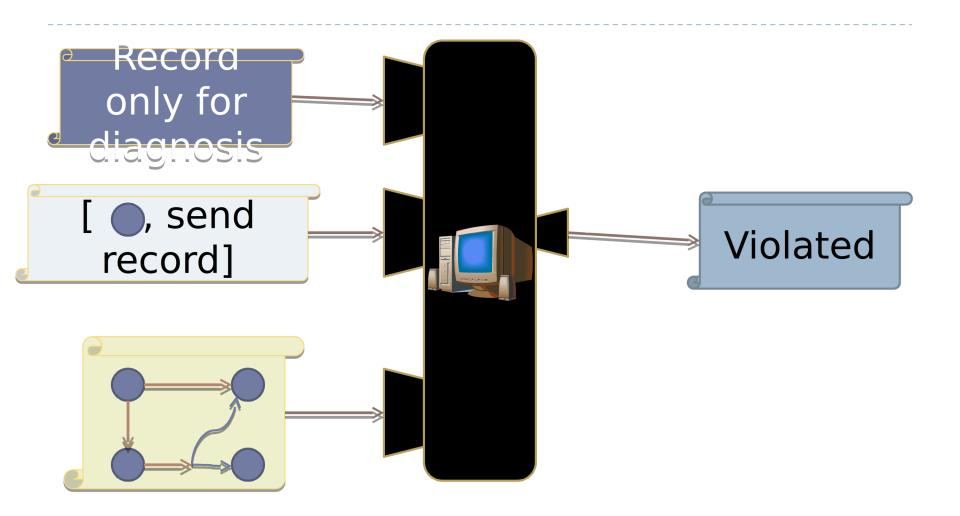
1/4

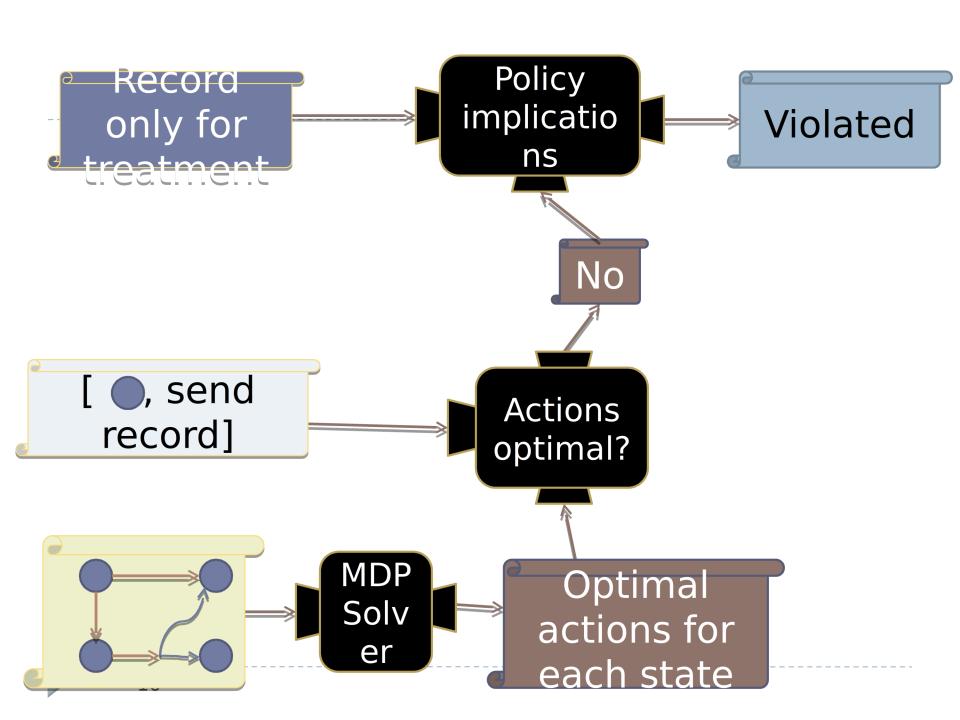
Diagnosis by specialist

Reward!

Auditing







No False Positives

Theorem (Soundness): If the algorithm returns "violation", then the actions recorded in the log are not only for the purpose

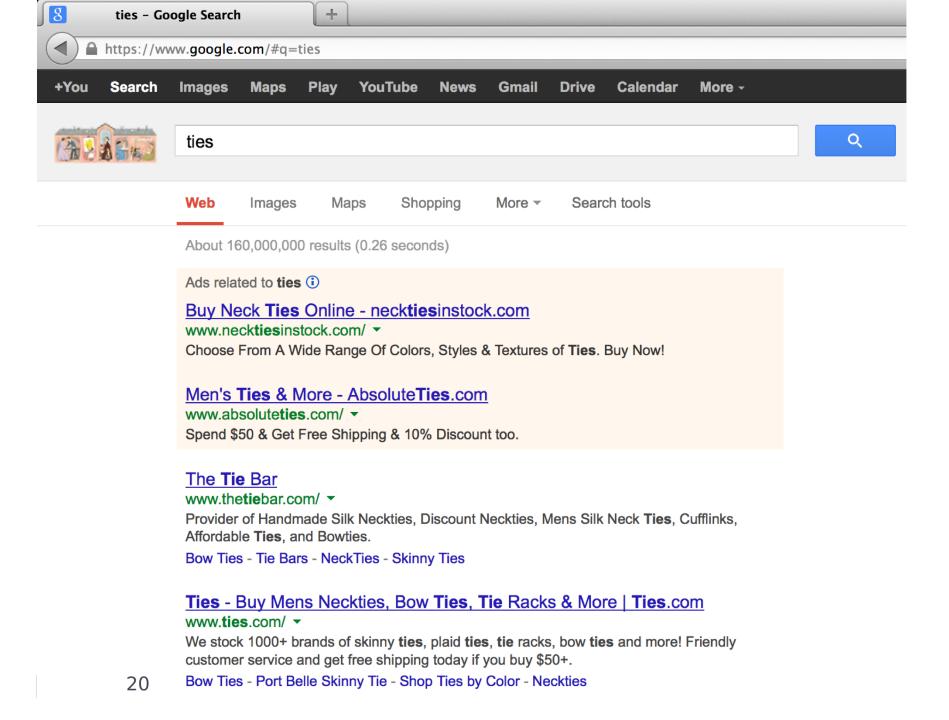
Utility + Privacy

- Learn MDPs from large audit logs
 - E.g., using reinforcement learning techniques
- Compute optimal plans in MDP
 - Improve functional outcomes (e.g, healthcare outcomes, corporate/defense mission)
 - Improve privacy/security (e.g., detect inappropriate accesses to sensitive information by authorized insiders)

Purpose Restrictions on Information Use

With M. C. Tschantz (CMU _ Berkeley) and J. M. Wing (CMU _ MSR)

2013 European Symposium on Research in Computer Security



Antidepressant Medication - Info On An Rx Antidepressant Drug knowmydepression.com/antidepressant ▼
Visit For Treatment Info & Facts.

Party Supplies For Sale - Buy Your Party Supplies Online Now

www.orientaltrading.com/PartySupplies

Free Shipping on Orders Over \$49!

Oriental Trading has 925 followers on Google+

Party Favors Sale

Party Decorations

Birthday Party Supplies

Halloween Party Supplies

Google's Privacy Policy

When showing you tailored ads, we will not associate a cookie or anonymous identifier with sensitive categories, such as those based on race, religion, sexual orientation or health.

Rewards from ads

	Depressed	Not Depressed
Meds	High	Low
Party	Low	High

Show Meds Depressed Ad: None Show Party Reward: None

Depressed

Ad: Meds

Reward: High

Depressed

Ad: Party

Reward: Low

Not Depressed Show Meds

Not Depressed

Ad: Meds

Reward: Low

Ad: None

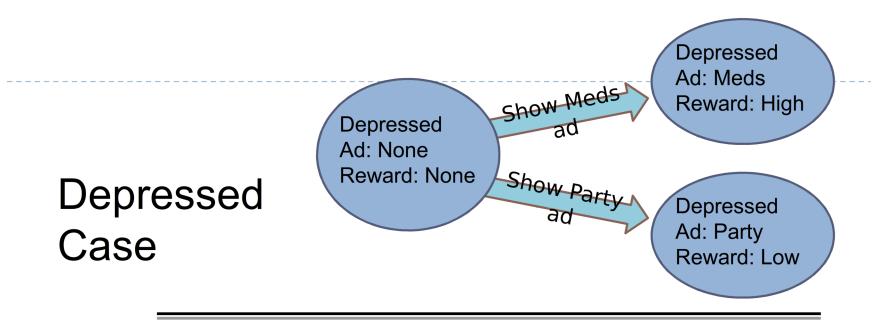
Reward: None

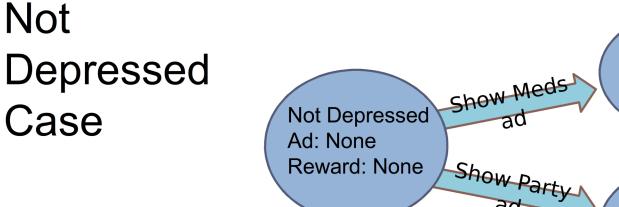
Show Party

Not Depressed

Ad: Party

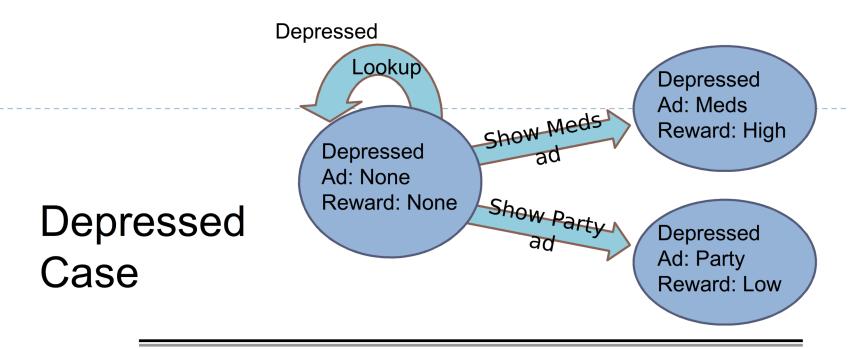
Reward: High



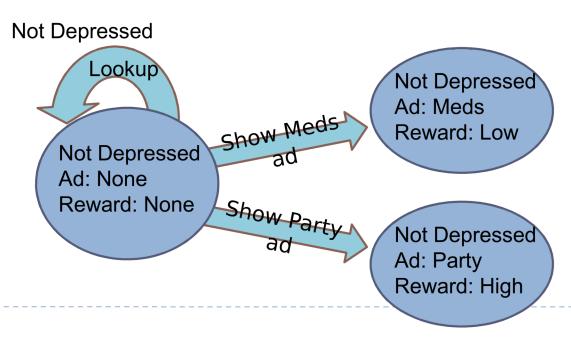


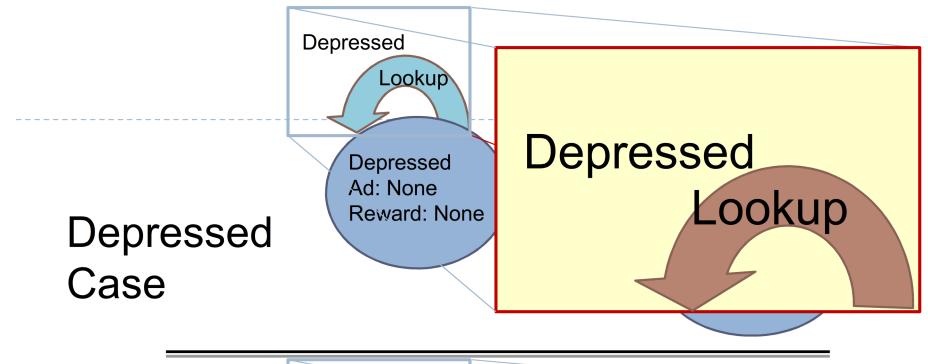
Not Depressed
Ad: Meds
Reward: Low

Not Depressed
Ad: Party
Reward: High



Not Depressed Case



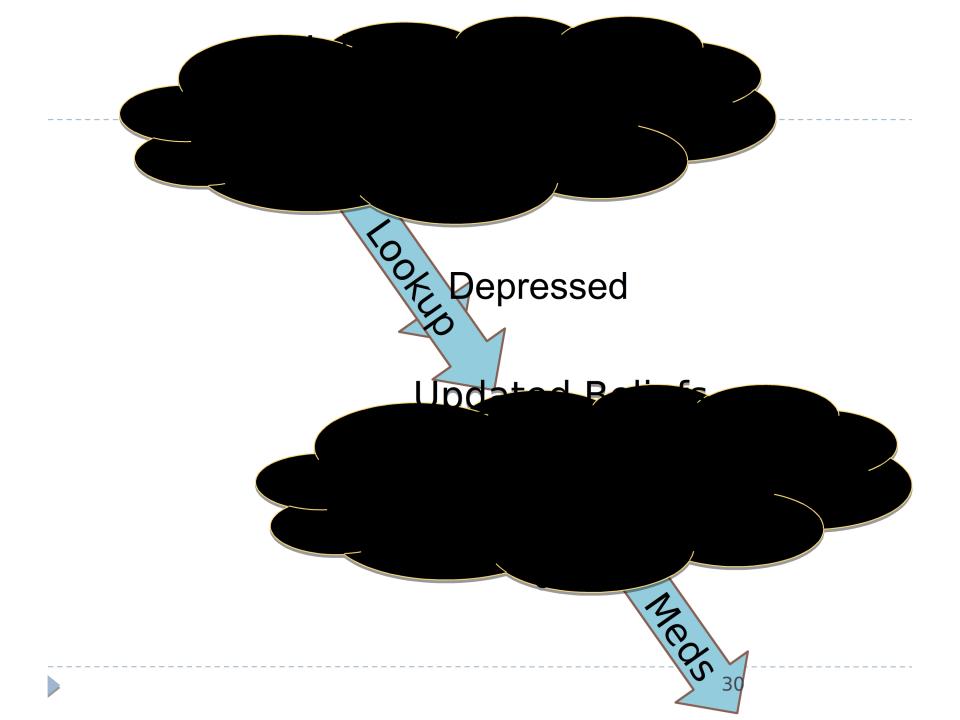


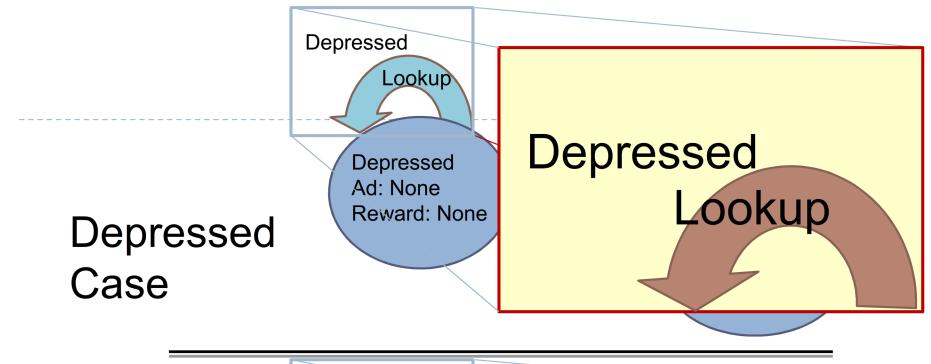
Not Depressed Case

Not Depressed Ad: None Reward: None

Not Depressed

Not Depressed Lookup



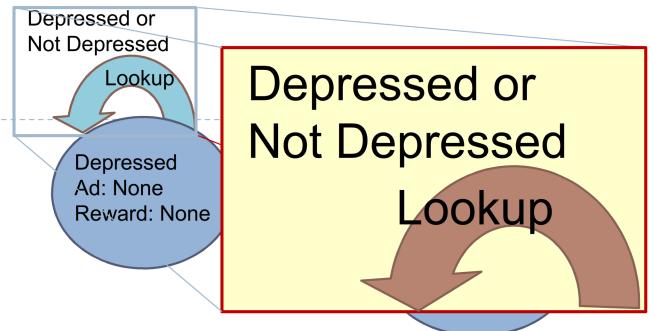


Not Depressed Case

Not Depressed Ad: None Reward: None

Not Depressed

Not Depressed
Lookup



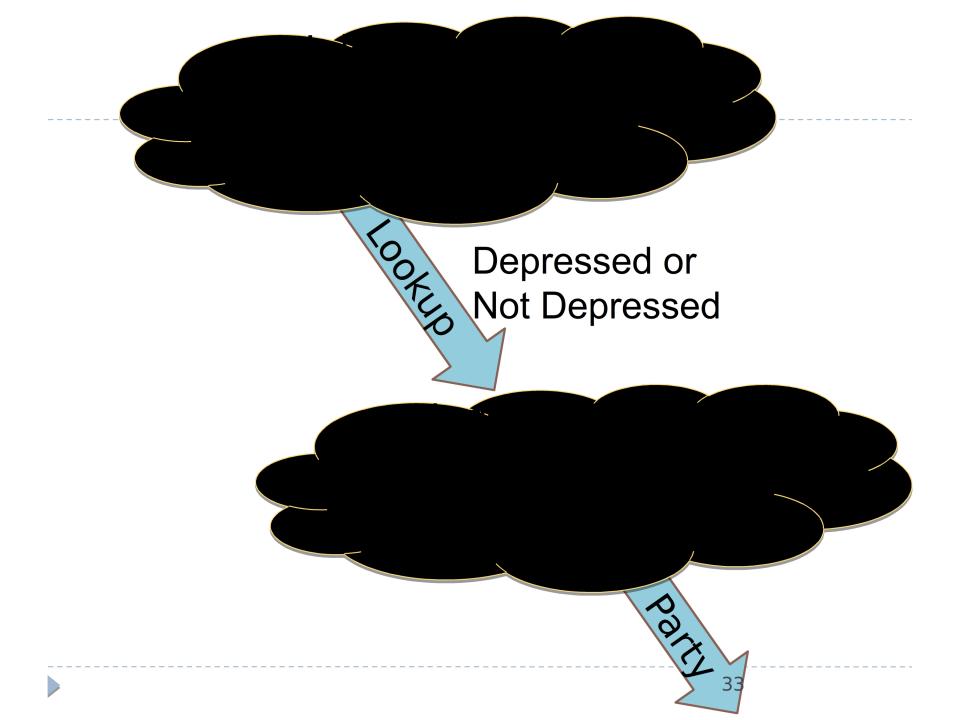
Depressed Case

Not Depressed Case Not Depressed
Lookup

Not Depressed
Ad: None
Reward: None

Depressed or

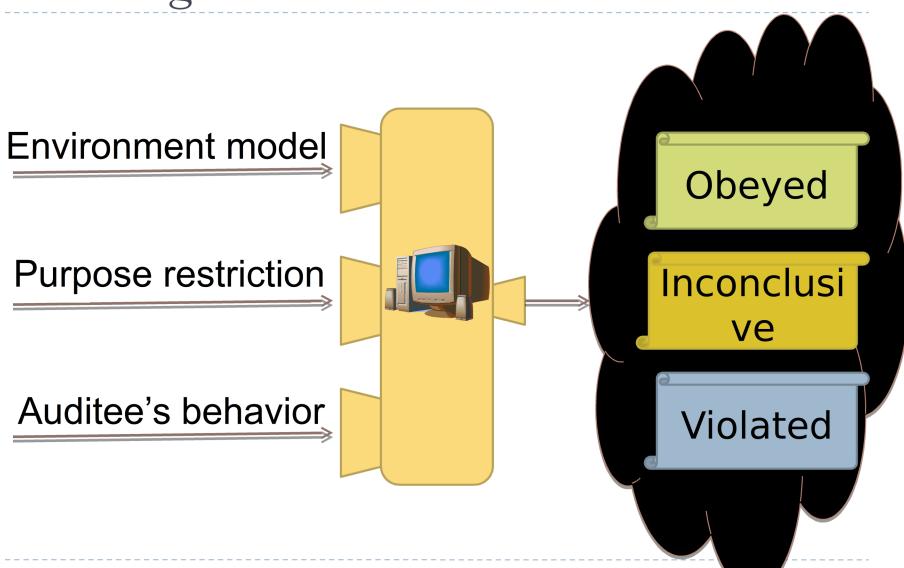
Depressed or Not Depressed Lookup



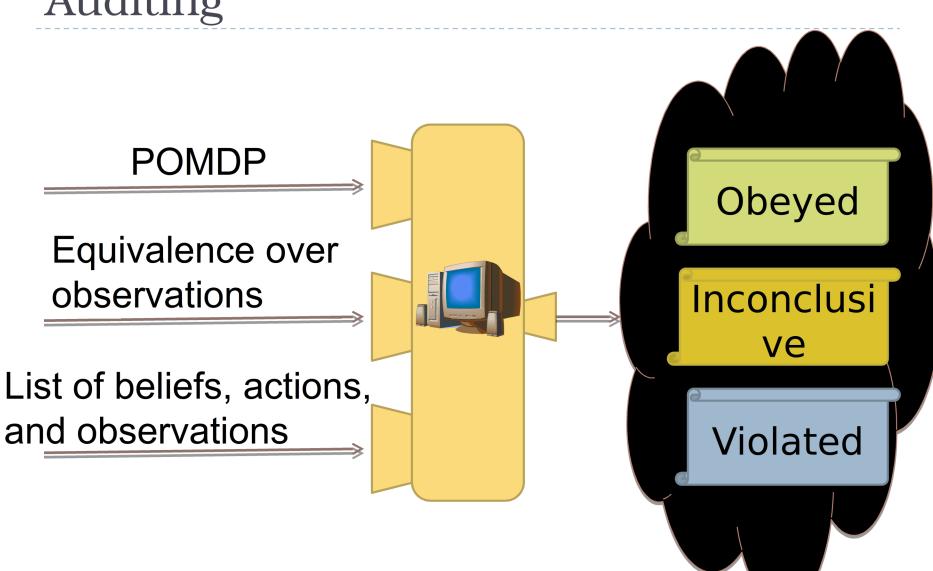
Planning + Information Flow

- Cognitive: Actions are for a purpose without using some information if they came from a plan selected by optimizing a model with disallowed information conflated.
 - Requires mind reading for enforcement
- Behaviorist: Actions are for a purpose without using some information if they are consistent with a plan optimizing a model with disallowed information conflated.
 - Could be consistent by coincidence and actually be for another purpose using the information

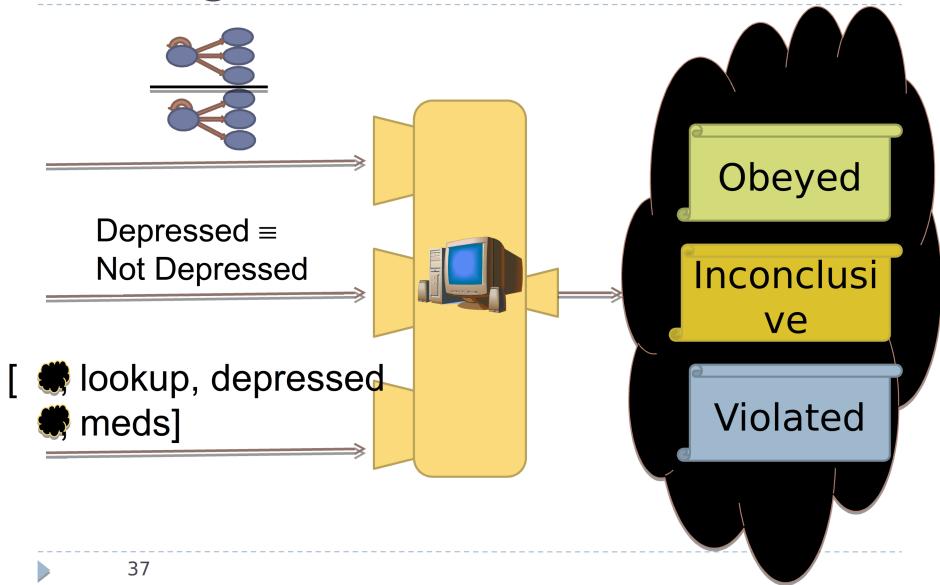
Auditing

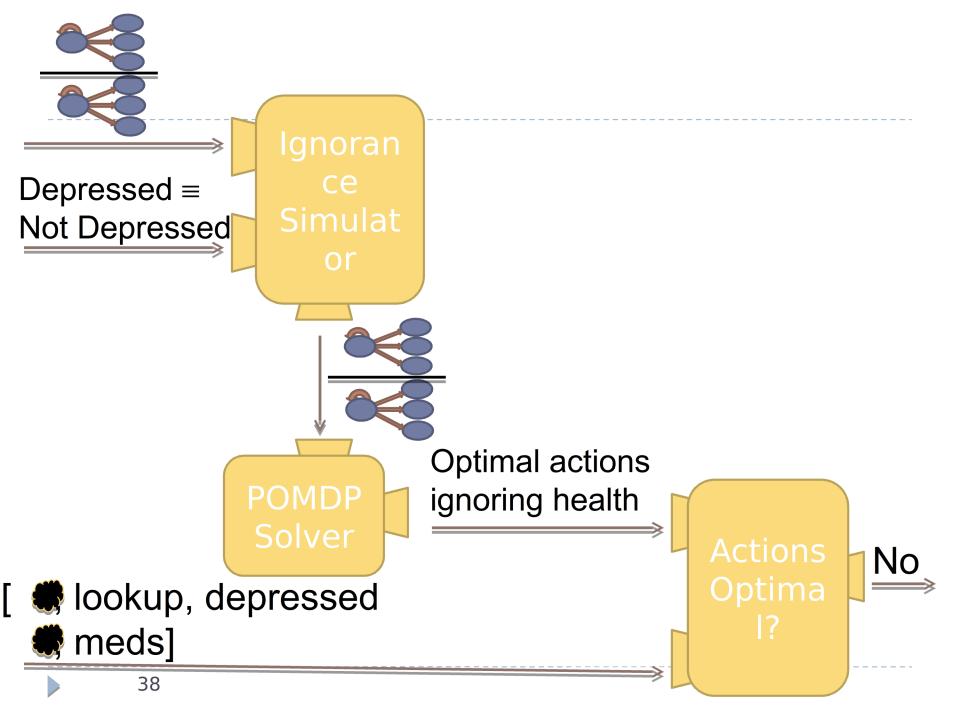


Auditing



Auditing





Implications

- The actions were not for the purpose of marketing without using health data
 - Violates: "marketing without using health data"
- Either (1) used health data for marketing or (2) performed actions for some other purpose
 - In case (1) violates: "health data not for marketing"

Prior Approaches

- Prior approaches:
 - Labeling actions (industry practice)
 - Labeling sequences of actions (Al-Fedaghi 07, Jafari et al. 09)
 - Labeling roles (Byun et al. 05, 08, 10)
 - Labeling code (Hayati and Abadi 05)
- Our work provides a semantic foundation
- Shows the expressiveness of each approach

Interesting Points: only-for rules

- Cannot catch all violations of only-for rules
 - Coincidences provide tenable deniability
- Enforcing only-for rules can improve both privacy and utility
 - Keeps auditees on task

Interesting Point: not-for rules

- Not-for rules restrict very little
 - May still perform actions for very similar purposes
- FIPPs principle on purpose specification tries to address this concern

"The purposes for which personal data are collected should be specified not later than at the time of data collection and the subsequent use limited to the fulfilment of those purposes or such others as are not incompatible with those purposes and as are specified on each occasion of change of purpose."

Future Work

- Improving accuracy
 - Human models of planning
- Furthering practicality
 - Automated creation of environment models
- Applications
 - Minimum necessary disclosure
- Generalizations
 - Multiple purposes

Summary: Audit Approach



Privacy Policy



Organization al audit log



Complete formalization of HIPAA, GLBA

```
\begin{split} \mathbf{G} & \left( \forall p_1, p_2, m. \ \mathsf{send}(p_1, p_2, m) \supset \right. \\ & \left( \forall d, u, q, t. \\ & \left( m = \inf(d, u) \right) \land \mathsf{contains}(m, q, t) \supset \right. \\ & \left( \bigvee_i \varphi_i^+ \right) \land \left( \bigwedge_j \varphi_j^- \right) \right) \land \\ & \left( \forall t. \ \left( m = \mathsf{req\_for\_access}(p_1, t) \right) \supset \right. \\ & \left. \varphi_{\mathsf{164.524b2i'}}^- \land \varphi_{\mathsf{164.524b2ii'}}^- \right) \right) \end{split}
```

Computerreadable privacy policy Environment Model



Automated audit for black-andwhite policy concepts

> Detect policy violatio ns

Oracles to audit for grey policy concepts



Audit

POMDP: Formal Definition

POMDPs. To define POMDPs, let Dist(X) denote the space of all distributions over the set X and let \mathbb{R} be the set of real numbers. A POMDP is a tuple $(Q, A, \tau, \rho, \mathcal{O}, \nu, \gamma)$ where

- Q is a finite state space representing the states of the agent's environment;
- A, a finite set of actions;
- — τ : Q × A → Dist(Q), a transition function from a state and an action to a
 distribution over states representing the possible outcomes of the action;
- − ρ : Q × A → R, a reward function measuring the immediate impact on the satisfaction of the purpose when the agent takes the given action in the given state;
- O, a finite observation space containing any observations the agent may perceive while performing actions;
- ν : A × Q → Dist(O), a distribution over observations given an action and the state resulting from performing that action; and
- $-\gamma$, a discount factor such that $0 \le \gamma < 1$.

POMDP and Purpose

We say that a POMDP models a purpose if ρ measures the degree to which the purpose is satisfied. To select actions for that purpose, the agent should select those that maximizes its expected total discounted reward, $\mathbb{E}\left[\sum_{i=0}^{\infty} \gamma^{i} u_{i}\right]$ where i represents time and u_{i} , the reward from the agent's ith action.

Belief States

This goal is complicated by the agent not knowing a priori which of the possible states of the POMDP is the current state of its environment. Rather it holds beliefs about which state is the current state. In particular, the agent assigns a probability to each state q according to how likely the agent believes that the current state is the state q. A belief state β captures these beliefs as a distribution over states of Q (i.e., $\beta \in \text{Dist}(Q)$). An agent updates its belief state as it performs actions and makes observations. When an agent takes the action a and makes the observation a starting with the beliefs a, the agent develops the new beliefs a where a where a is the probability that a is the next state.

Optimal Strategy

To maximize its expected total discounted reward, the agent does not need to track its history of actions and observations independently of its beliefs as such beliefs are a sufficient statistic. Thus, the agent need only consider for each possible belief β it can have, what action it would perform. That is, the agent can plan by selecting a *strategy*: a function from the space of beliefs Dist(Q) to the space of actions A. (We use the word "strategy" instead of the more common "policy" to avoid confusion with privacy policies.)