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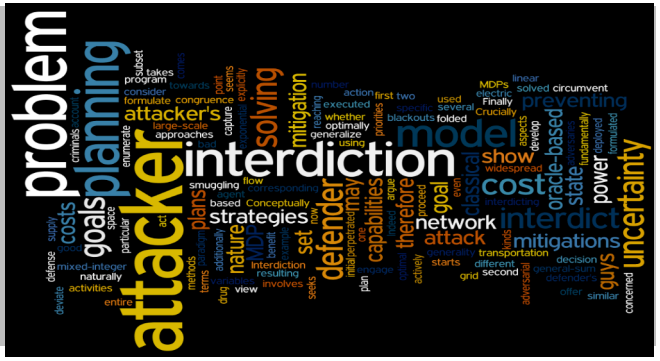

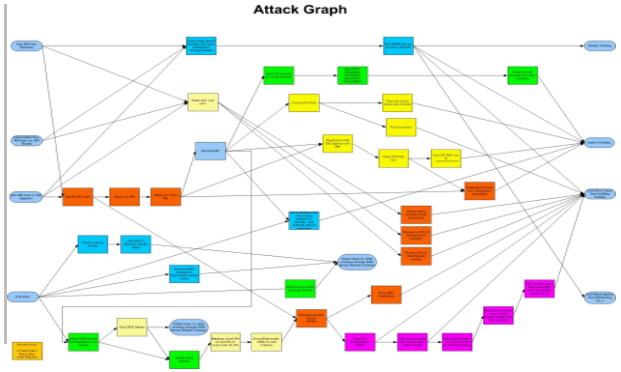

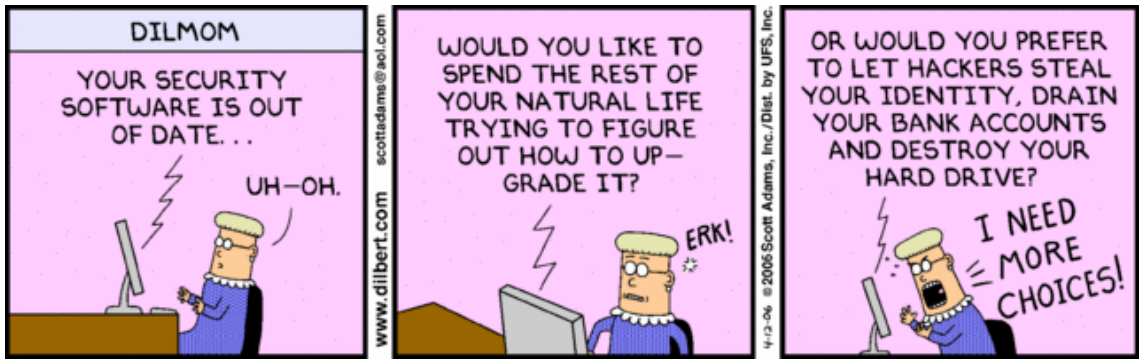

Cyber Games

Yevgeniy [Eugene] Vorobeychik

Sandia National Laboratories

U.S. DEPARTMENT OF ENERGY | NNSA Nuclear Security Administration

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The Cyber threat

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- *Attackers are increasingly sophisticated, often have (direct or tacit) support of a state, very highly rewarded for success, and pay attention to what we are doing!*

- *Stuxnet/conficker*
  - *sophisticated combination of cyber attack tactics, including zero-days*
  - *Stunxnet: cyber-physical attack targeting critical infrastructure*

- *Corporate America loses between $100 billion to $1 trillion / year from theft of proprietary information (The Economist, Babbage blog, May 11, 2012)*

Conficker vs. The World

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- Conficker:
  - an infected machine generates 250 random domain names from 5 TLDs each day, and if one resolves, it is used to download the payload (seeded with date to synchronize)
- The World:
  - block all 250 domain names each day to counteract this
  - anti-virus signature, windows update
- Conficker:
  - increase number of TLDs to 8
  - blocks auto-update
  - attaches to removable media
- The World:
  - Conficker working group continues to shut down the generated domain names
- Conficker:
  - generate 50,000 random domain names from 8 TLDs

Security as Chess

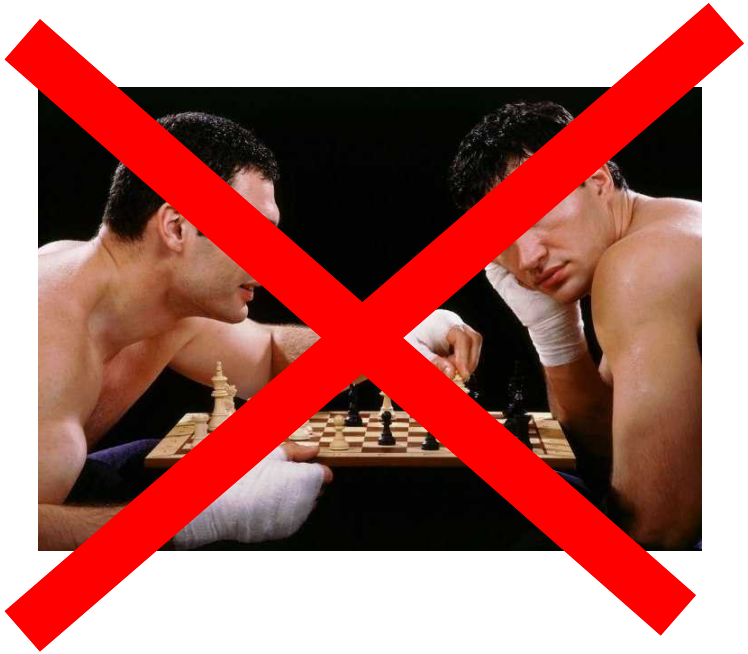
Adversarial: only one winner ("zero-sum")

Opponents must anticipate each other's moves

strategy should account for how the opponent will respond

Extremely complex: impossible to enumerate the set of all states in the game

How is Cyber NOT like Chess?



Chess has *complete information*:
- well-known rules
- clear what the opponent's objective is
  - *Cyber*: attacker' specific objectives are uncertain

Chess has *perfect information*:
- can observe all previous moves
  - *Cyber*: attackers can be difficult to detect

Chess has *no uncertainty* of any kind:
- consequences of moves are deterministic
  - *Cyber*: systems complex, non-deterministic

Chess has *only two players*
  - *Cyber*: many players

Game Theoretic Model

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(Non-Zero-Sum) Stackelberg Game

- *Defender moves first*:
  - *jointly chooses defense policies*
- *Attackers learn about the defenders' decisions*
  - *respond by choosing optimal attack policies*

Outline

- Complexity of Attack Space
  - Model attacker as a planning agent
  - Optimal plan interdiction problem
- Uncertainty about attackers (capabilities, goals); noise
  - Bayesian plan interdiction problem
  - Interdicting an attacker MDP
- Machine learning in adversarial settings

OPTIMAL INTERDICTION OF ATTACK PLANS

Game Theory for Physical Security

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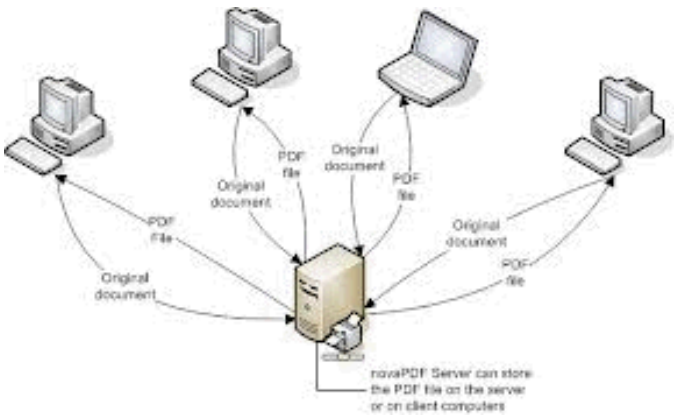
- Defender protects N targets
- Attacker attacks a single target
  - maximizes expected utility given defense decisions

Fielded systems in LAX, US Coast Guard, Federal Air Marshall Service

	#1	#2
Target #1	5, -3	-1, 1
Target #2	-5, 5	2, -1

Game Theory for Cyber Security



targets?

Sophisticated cyber attacks involve complex series of steps towards an attack goal

Cyber attacks (*Boddy et al.*):

1. Attacker sends an email message, spoofed to be from a colleague, with a new screensaver as an attachment.
2. Attachment is an executable that enables remote login, and captures and relays the user's password.
3. Attacker logs into the machine and executes a buffer overflow attack, gaining root (admin) privileges.
4. ...

Threat/Adversary Modeling

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- Basic picture in threat modeling and mitigation:
  - *Attacker*:
    - has a set of capabilities
    - can choose from a collection of "actions" (activities, exploits, attacks)
      - actions can have costs (time, likelihood of detection/capture, etc)
    - has a set of goals
      - goals may have different importance to the attacker/defender
      - may be content to achieve a subset of goals
    - constructs a plan (a sequence of actions) to achieve goals starting with capabilities
  - *Defender*:
    - *mitigations*: can block attack actions, initial capabilities, patch vulnerabilities
      - mitigations can be costly

Typical Approaches: Attack Graphs & Scenarios

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- A common way attacker decision process is modeled in practice (e.g., red teaming) is by using *attack graphs* and/or *scenarios*
- *Attack graphs:* a graph describing possible steps an attacker may take to achieve a goal
- *A scenario:* a sequence of actions that allows the attacker to achieve a goal starting from initial capabilities
  - For example: starting with a set of capabilities, how an attacker can exfiltrate Data X

Shortcomings of Attack Graphs/Scenarios

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- Attack graphs become unwieldy very quickly
  - size exponential in the number of things the attacker can affect
  - 400 variables = 2^{400} states/nodes; age of universe, in seconds < 2^{30}
- Only a few attack scenarios can be crafted by hand; can miss the vast majority of possible attack graph paths

Modeling Attacker as a Planner

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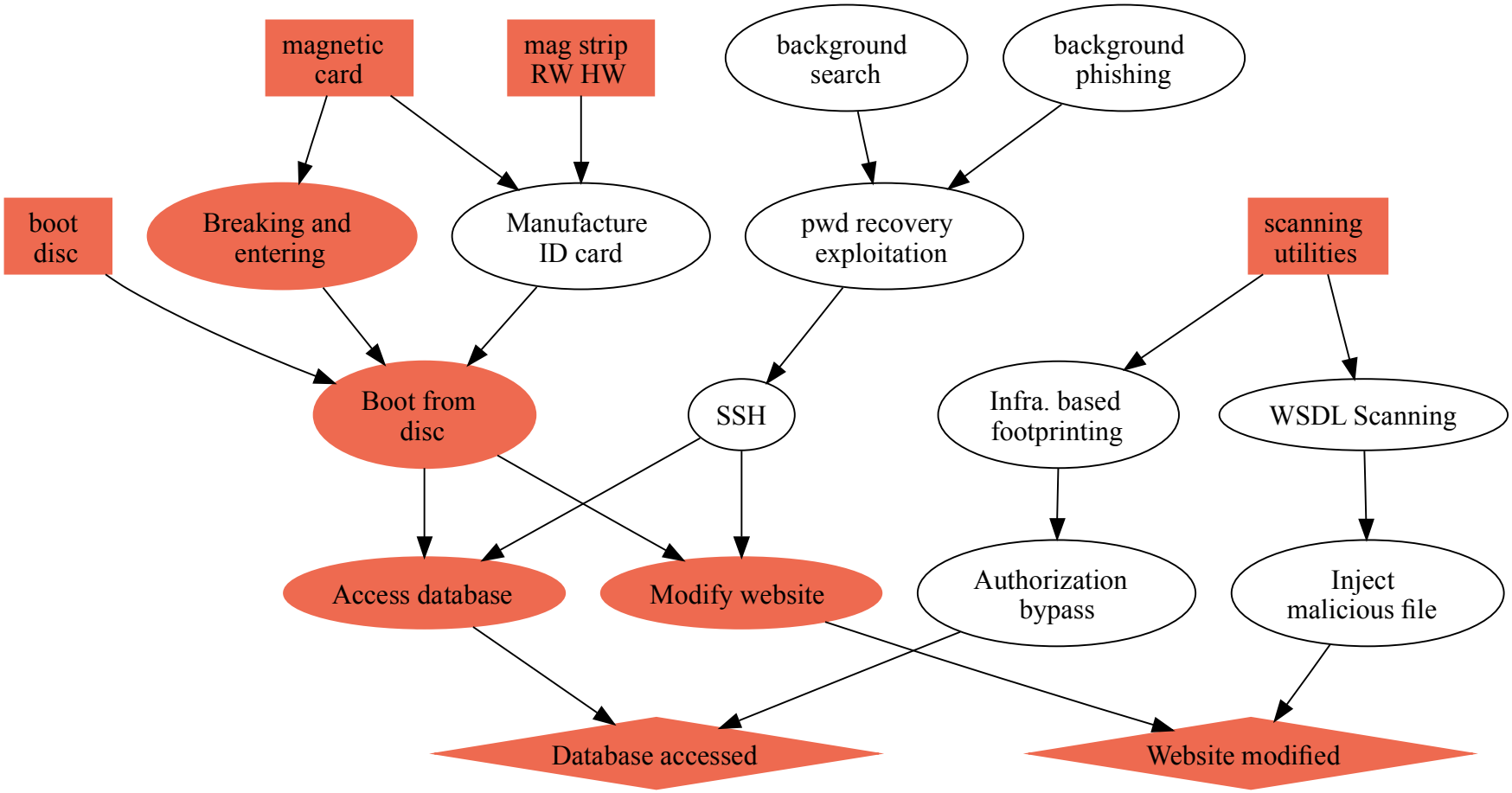
- One of the main branches of AI is (formal/logic-based) planning
  - Model the planning problem using formal logic
  - Numerous heuristic planning tools
- (*Deterministic/Classical*) Planning problem:
  - The world = a set of logical variables = *state* (of the world)
  - Start: initial state of the world (variables that are **true** at time 0)
    - *attacker capabilities, network vulnerabilities*
  - Goal(s): variables (or boolean expressions) that the planner wants to satisfy
    - *attacker's goals (e.g., exfiltrate Data X)*
  - Actions: actions/steps a planner can take towards the goal
    - preconditions: variables that must be true for the action to apply
    - effects: variables that become true/false as a result of the action
  - A plan: a partial order of actions that achieve goals starting from the initial state

("Action") Attack Graph, and an Optimal Plan for an Example Scenario



Deterministic Plan Interdiction Problem

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DPIP: defender chooses an optimal subset of mitigations, accounting for attacker's best response plans

(optimal: maximizing defender's utility)

(utility = Value of goals – cost of mitigations)

Deterministic Plan Interdiction (DPIP)

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- DPIP_DP (deterministic plan interdiction decision problem): can the defender achieve target utility?
- Theorem: DPIP_DP is PSPACE-Complete
- Proof: by reduction from partial satisfaction planning
- Optimization: based on a known Integer Program for computing an optimal partial satisfaction plan (Vossen et al., 1999; Briel et al., 2004)
  - Maximize defender utility
  - subject to:
    - a plan is feasible/legal
    - a plan is the best plan for the attacker (*by comparison to all **feasible** plans*)

DPIP formulation

$$\max_{D_a, D_m, y_{a,t}, \delta_p} \quad \sum_{l \in L} V_l^D s_l - \sum_{m \in M} D_m C_m^D$$

s.t. :

$$\forall_a \quad D_a \leq \sum_m D_m A_{m,a}$$

$$\forall_{m,a} \quad D_a \geq D_m A_{m,a}$$

compute which actions are interdicted

$$\forall_{a,t} \quad y_{a,t} \leq (1 - D_a)$$

attacker cannot choose interdicted actions

$$\forall_{p,a} \quad \delta_p \geq D_a$$

$$\forall_p \quad \delta_p \leq \sum_{a \in p} D_a$$

identify non-interdicted plans

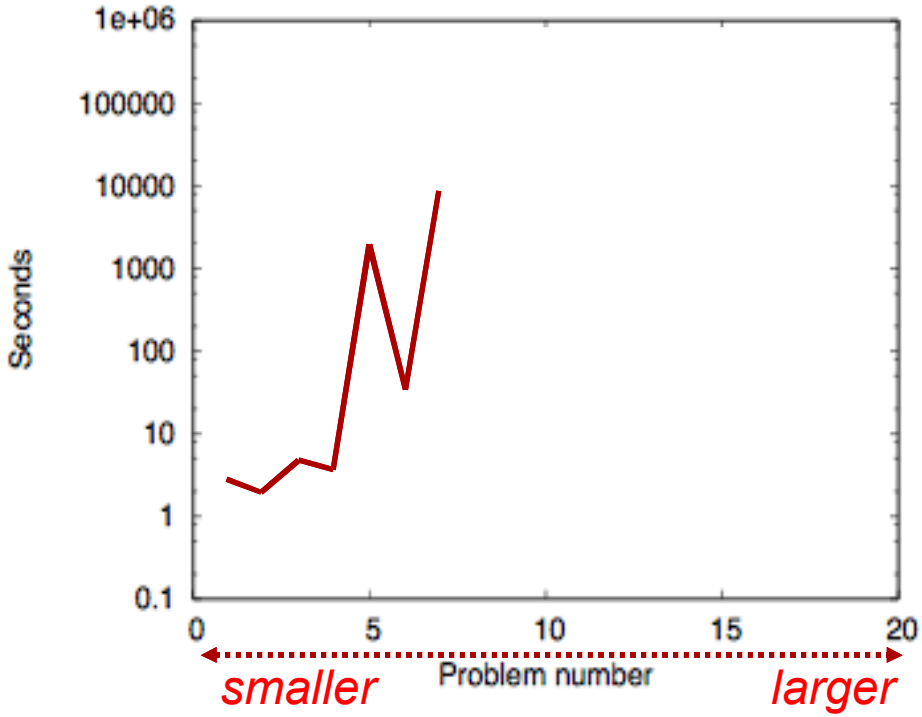
$$\forall_p \quad \sum_{l \in L} V_l^A s_l - \sum_{a,t} C_a^A y_{a,t} \geq U^A(p) - Z\delta_p$$

choose the best non-interdicted attack plan

plan feasibility constraints

DPIP (cont'd)

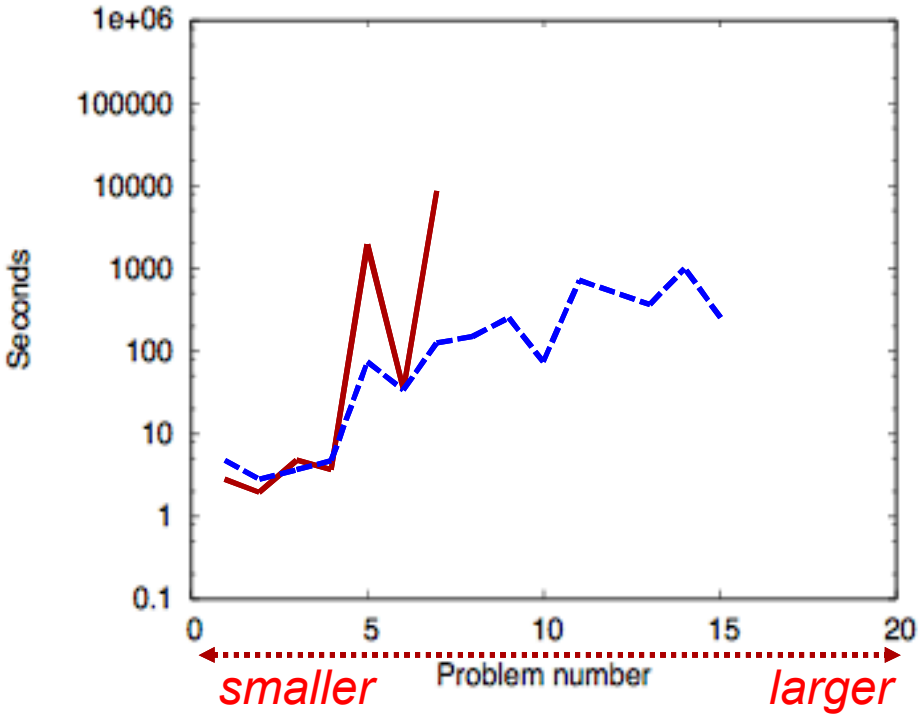
- IP: far too large (lots of feasible plans)
- Solution approach: constraint generation
  - *We "know" how to compute an optimal plan*
  - Iterate:
    - Compute optimal mitigations, given a subset of feasible plans
    - Compute a best response (plan) given mitigations
    - Use best response to generate a new set of constraints
    - Repeat (until convergence)



Problems from IPC

DPIP: Speeding Up

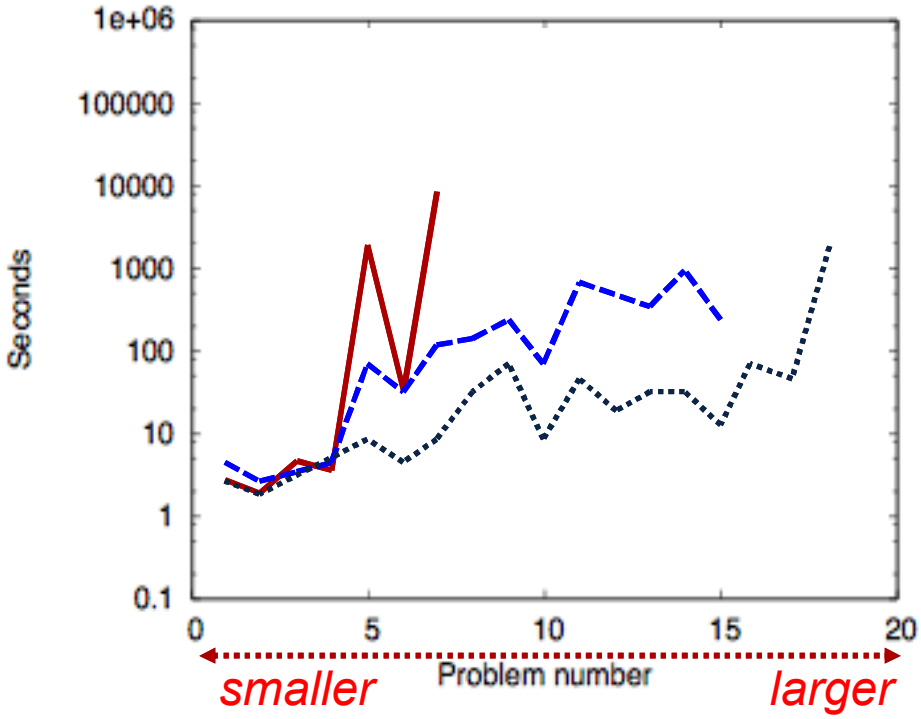
- Computing an *optimal* attack plan is quite hard
- Solution: set a time limit on the IP (usually lots of time is taken up to prove solution optimality)
- Verify optimality only at the very end
  - Still provably optimal solution for the defender



Problems from IPC

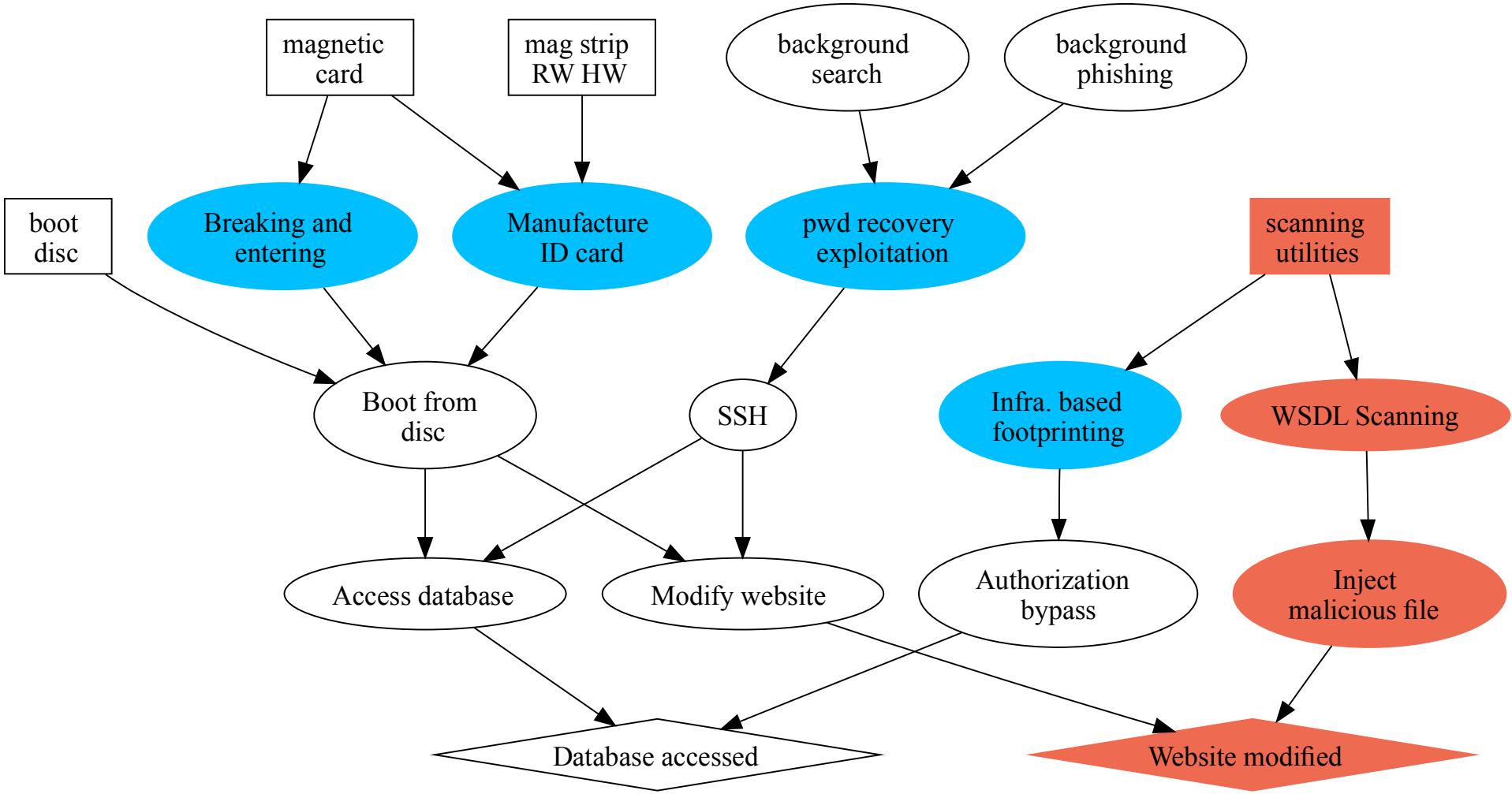
DPIP: speeding up more

- A better idea: leverage best heuristic planning tools from AI research community
  - SGPLAN5: state-of-the-art heuristic partial satisfaction planner; winner of IPC
- Still guarantee optimal solution by running the full IP in the end



Problems from IPC

Optimal Plan Interdiction Example



INCORPORATING UNCERTAINTY

What about uncertainty?

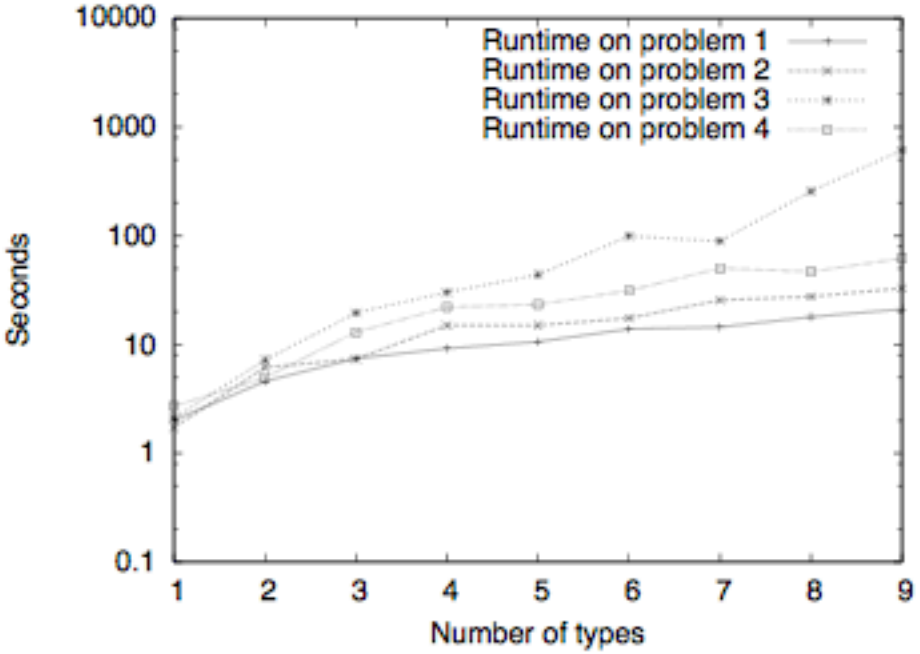
- DPIP assumes everything is certain/deterministic
- Usually uncertain about:
  - Attacker capabilities, goals
  - Execution and effects of actions
  - etc
- Questions:
  - Can we extend DPIP to accommodate all/some of this uncertainty?
  - If not, how should we model it?

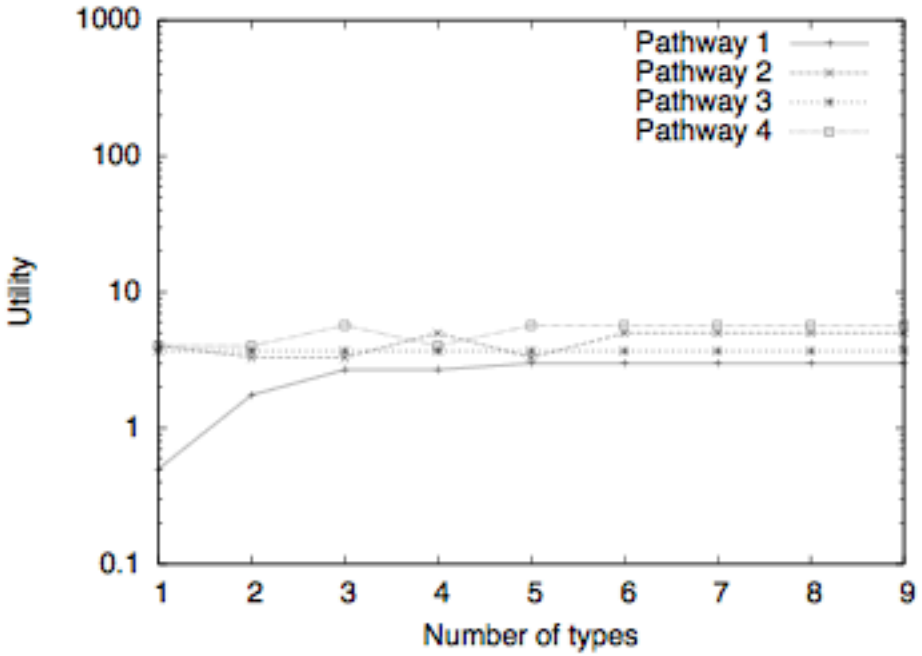
Uncertainty about capabilities/goals

- Can naturally model within the DPIP framework
  - Attacker has multiple types ("personalities"), each type corresponding to a set of capabilities/goals (*Bayesian plan interdiction problem; BPIP*)
  - Each type computes an optimal plan in response to mitigations
  - Objective now to maximize expected defender utility wrt distribution over attacker types

$$\sum_{\theta} \sum_{l \in L} p_{\theta} V^{D}_{\theta,l} s_{\theta,l} - \sum_{m \in M} D_m C^{D}_{m}$$

Experiments: BPIP





- Created an instance with 9 types, and aggregated (abstracted) types into sets to get fewer types
- Scales reasonably well, and only need relatively few types to get near-optimal solutions

Execution Uncertainty

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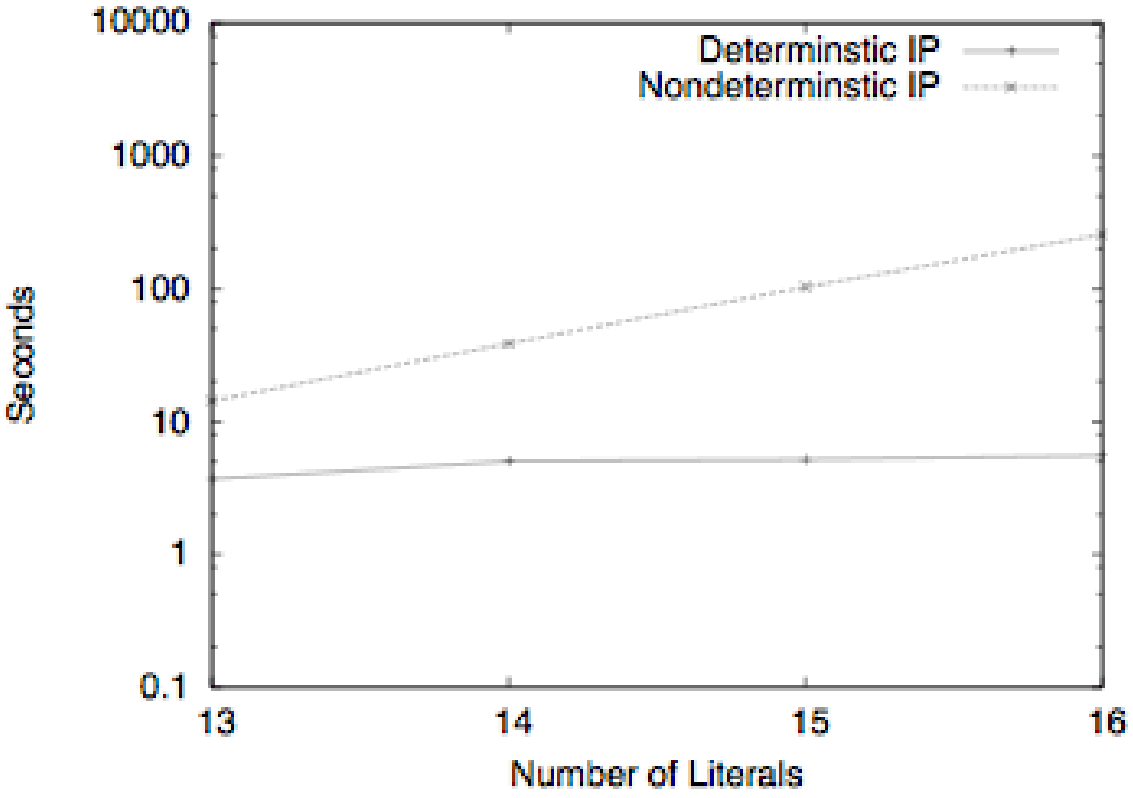
- *Special case*: only uncertain about whether an action succeeds or not, success is observable, and action can be repeated
  - Can be done using DPIP framework by computing expected number of tries for each action
- *Generalizing*: state is observable, but action may have non-deterministic effects
  - Example: “port scan” action (info you get is uncertain)
  - Attack planning problem is an MDP
  - MPD interdiction (MDPIP)
  - Leverage (dual) LP for computing optimal value in an MDP
  - *State space explosion*: must now explicitly represent all states in the system

Experiments with MDPIP



Can't scale beyond 15-20 literals

Much slower / poorer scalability than DPIP

But: far more general

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USING MACHINE LEARNING IN ADVERSARIAL ENVIRONMENTS

Traditional Machine Learning

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- Take a data set $\{(x_1,y_1),\ldots,(x_n,y_n)\}$, $(x,y) \sim \mathcal{D}$
- x is a feature vector
- Train a classifier, f(x) on data
- "Test" by classifying unseen instances $(x',y') \sim \mathcal{D}$
- Key assumption: both training and test data come from (roughly) the same distribution

- Alternative: online learning
- The opposite extreme: no distributional assumptions
- BUT: guarantees are asymptotic (for "large" sequences of x), and very weak; assume that labels y(x) are fixed for a given x

Machine Learning in Adversarial Environments

- Adversary deliberately manipulates features to bypass defensive measures
  - adversary previously (i.e., in $\mathcal{D}$) chose x (f(x) = bad), now chooses x' such that f(x') = good
  - clearly distribution is non-stationary
  - adversary effectively manipulates labels on instances (x' may previously have usually been good)
  - we care about *short-run impact*

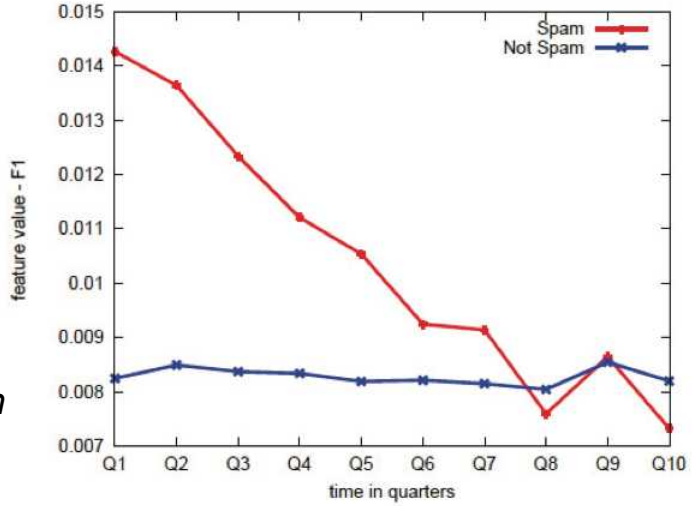

figure due to Rich Colbaugh and Kristin Glass, Sandia National Laboratories

Related Work

- Dalvi et al., 2004, Bruckner and Scheffer, 2009; 2011, Liu and Chawla, 2010, Colbaugh and Glass, 2013, etc
  - Adversary performs a linear transformation of the data (except for Dalvi et al)
  - Adversary aims to maximize total loss

Our Work

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- adversary can choose an arbitrary x
- adversary wishes to maximize expected utility from a successful attack (doesn't care about false positives)
- "defender" cares about false positives, as well as false negatives (Sommer and Paxson, 2010)
  - lost value to users
  - operational constraints: can only "inspect" so many cyber alerts
- many attackers
  - different attackers (or types) reflect different goals; why lump them into one bin?
- revealed preference
  - attacker previously used *x* as an attack; this reveals his preference about the most favorable means of attack
  - choice of *x'* must be as close to *x* as possible (change only a few feature values; similar to Dalvi et al. 2004 and Lowd and Meek, 2005)

Learning in a Box

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- Key insight: separate *learning* [about prediction based on current distribution of attacks] and *operational decisions* [using predictions made by learning and an adversary model]
  - Use learning as a black box to get *p(x)* = probability that *x* is generated by a malicious actor (e.g., use Naïve Bayes probabilities)
  - Optimize operational decisions based on *p(x)* and a *model of adversarial response*

Modeling Adversarial Response

- Let *x* be the preferred attack of some attacker
  - an email (feature vector) that embeds a malicious link
  - a sequence of steps to gain privileged access
- Suppose that *q(x)* is the probability that *x* will be blocked/*inspected*/generate an alert/etc
  - if $q(x) = 1$, *x* is not an effective means of attack
  - perhaps there is some other *x'* that achieves a similar goal, but has $q(x') < 1$?
  - *x' close to x are much more likely to have this property*
- Define $Q(x,x') = \exp\{-\delta \, ||x - x'||\}$
  - $\delta = 0$ => *doesn't matter which x' to use;* δ *large => can only achieve the objective with x*
- Utility of using *x'* is $\mu(x,x'; q) = V(x)\, Q(x,x')\, (1 - q(x'))$

Full model

- Consider two classes of adversaries (special cases of the model)
  - static ($\delta = \infty$), with probability P_S and dynamic ($0 < \delta < \infty$), w.p. P_A
  - static: those reusing already available tools/templates
  - dynamic: actively trying to get into the systems; highly sophisticated
- Defender's objective is to maximize utility, $U_D(q,p,X)$:
  - $U_D(q,p,X) = \Sigma_x (1-q(x))G(x) (1-p(x)) - p(x) (P_S v_S(x;q) + P_A v_A(x;q))$
  - $v_S(x;q) = V(x) (1-q(x))$
  - $v_A(x;q) = max_{x'} \mu(x,x'; q)$

Optimization Problem

$\max_q U_D(q,p,X)$

subject to:

$0 \leq q(x) \leq 1$

$v_S(x;q) = V(x)\ (1-q(x))$
$v_A(x;q) = max_{x'}\ \mu(x,x';\ q)$

Optimization Problem

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operational budget constraint

$\Sigma_x\ q(x) < c|X|$

Optimization Problem

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$\max_q U_D(q,p,X)$

subject to:

$0 \leq q(x) \leq 1$

$v_S(x;q) = V(x)\ (1\text{-}q(x))$
$v_A(x;q) = max_{x'}\ \mu(x,x';\ q)$

operational budget constraint

$\Sigma_x\ q(x) < c|X|$

key assumption: *X* (set of all feature vectors) is finite

Optimization Problem (LP)

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$\max_q U_D(q,p,X)$

subject to:

$0 \le q(x) \le 1$

$v_S(x;q) = V(x)\ (1\text{-}q(x))$
$v_A(x;q) = max_{x'}\ \mu(x,x';\ q)$

operational budget constraint

$\Sigma_x\ q(x) < c|X|$

key assumption: *X* (set of all feature vectors) is finite

(can either use a sample from distribution over x, or batch)

Relationship to “Standard” Learning

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- Typically people use a threshold on *p(x)* to classify good and bad

Relationship to "Standard" Learning

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- Typically people use a threshold on *p(x)* to classify good and bad
- **Proposition**: *suppose that there is no budget constraint and only static attackers. Then a threshold policy is optimal.*

Relationship to "Standard" Learning

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- Typically people use a threshold on *p(x)* to classify good and bad
- **Proposition**: *suppose that there is no budget constraint and only static attackers. Then a threshold policy is optimal.*

- **Proposition**: suppose that there are only static attackers, and a budget constraint. Then the following policy is optimal:
  - rank *x* according to *p(x)*
  - remove all *x* below threshold on *p(x)*
  - set *q(x) = 1* in descending order of *p(x)* until budget is exhausted

Experiments

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- Setup: TREC data set (50% spam, 50% ham), 2005-2008
- *Experiment 1*: train on 2005, test on ’05-’08, using *q(x)*
- *Experiment 2*: simulate utility-maximizing attacker
- *Experiment 3*: suppose our attacker model is wrong

Testing on Spam Data

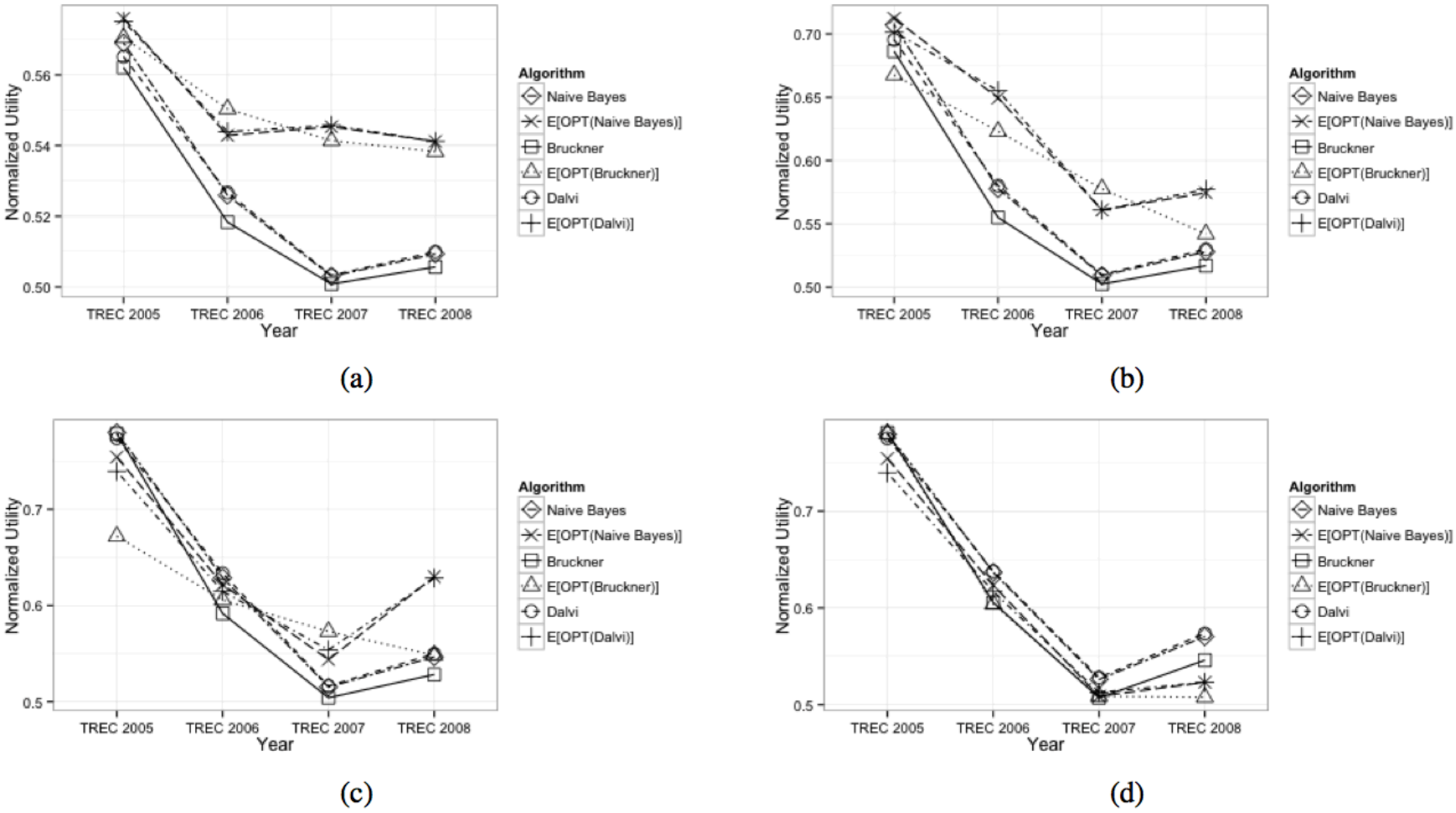
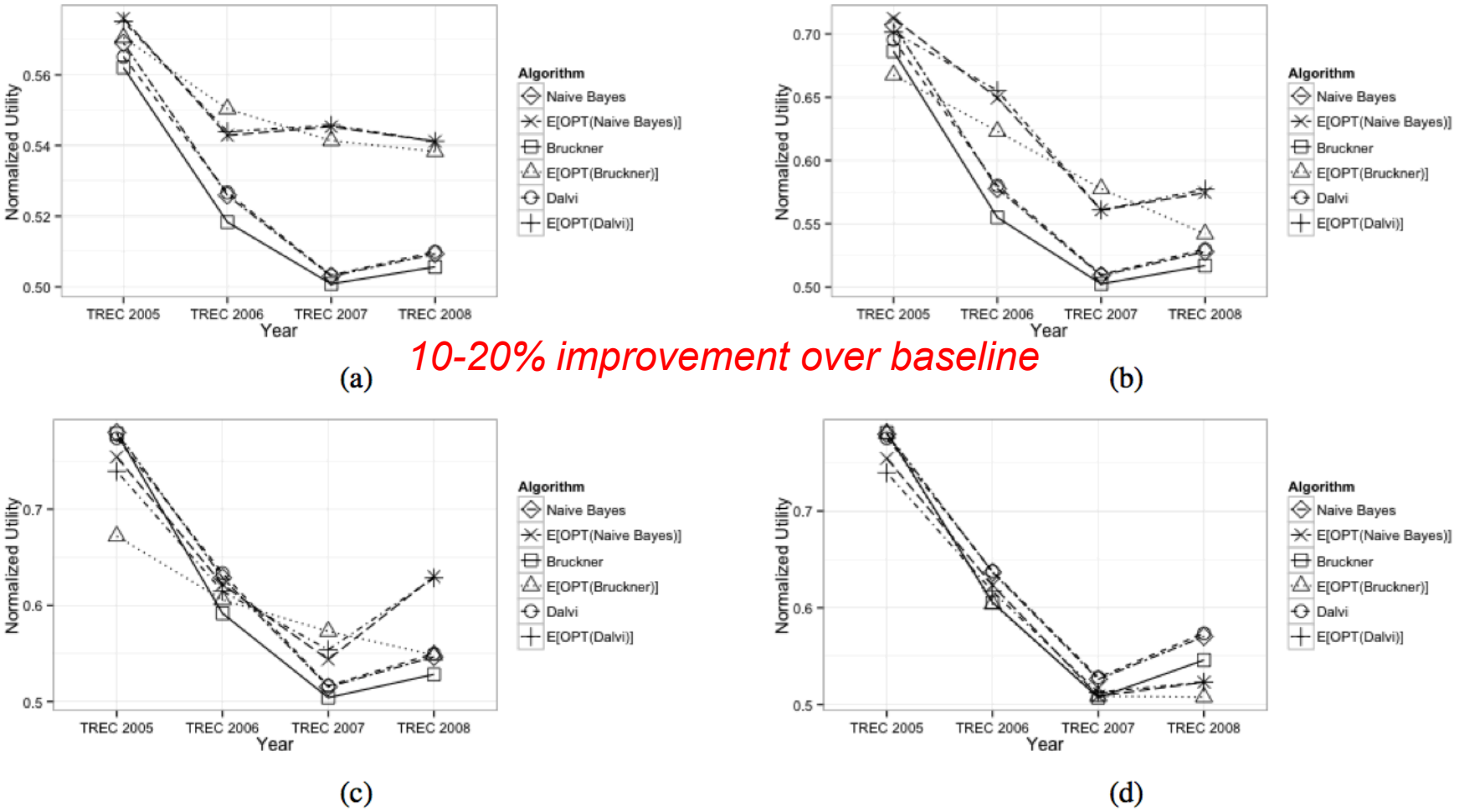


Fig. 2. Comparison of algorithms on TREC data, trained on year 2005, and tested on years 2005-2008. Our approach is labeled as $E[OPT(\cdot)]$, where the parameter is the classifier that serves as our $p(\vec{x})$. We use the following parameters: $\delta = 1$, $V(x) = G(x) = 1, P_A = 0.5$. (a) $c = 0.1$; (b) $c = 0.3$; (c) $c = 0.5$; (d) $c = 0.9$.

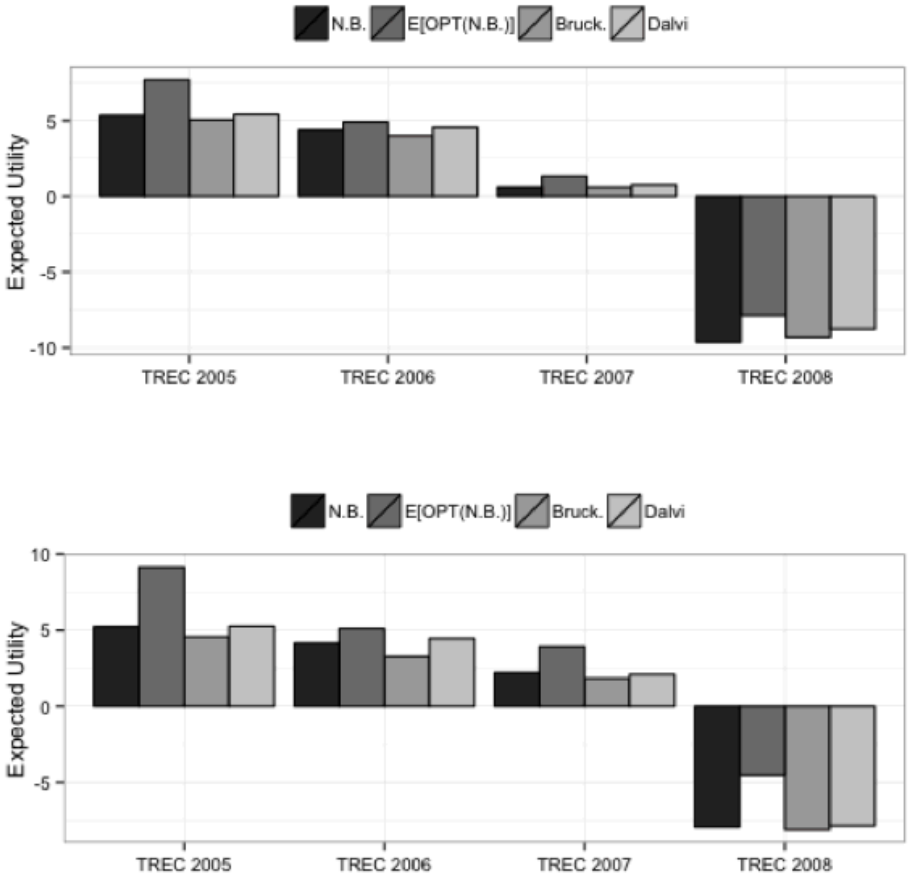
Testing on Spam Data



10-20% improvement over baseline

Fig. 2. Comparison of algorithms on TREC data, trained on year 2005, and tested on years 2005-2008. Our approach is labeled as $E[OPT(\cdot)]$, where the parameter is the classifier that serves as our $p(\vec{x})$. We use the following parameters: $\delta = 1$, $V(x) = G(x) = 1, P_A = 0.5$. (a) $c = 0.1$; (b) $c = 0.3$; (c) $c = 0.5$; (d) $c = 0.9$.

Against a utility-maximizing attacker

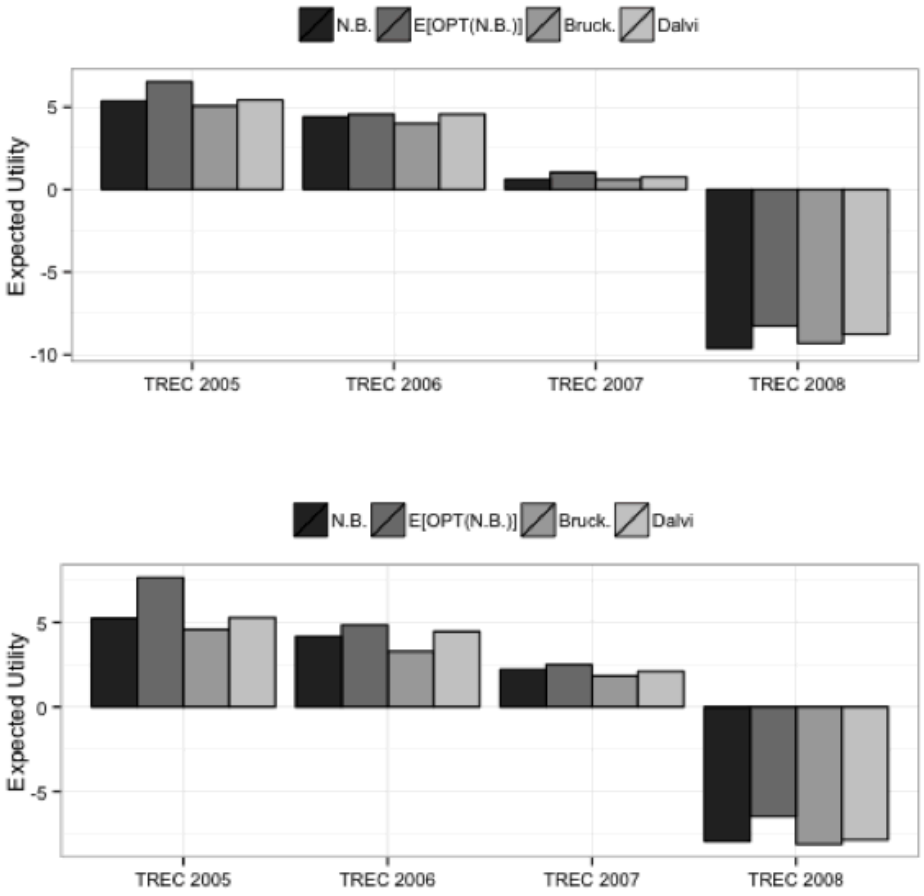


nearly 100% improvement over alternatives in some cases

even only using Naïve Bayes as the "baseline" p(x)

Fig. 5. The expected utilities, assuming $P_A = 1$ and that our attacker model is correct, where $p(x)$ is provided by Naïve Bayes; top: $c = 0.1$; bottom: $c = 0.3$.

Errors in attacker model parameters



assume error ~30%

almost no effect (robust to errors)

Fig. 8. The expected utilities, assuming $P_A = 1$, that our attacker model is correct, but allowing for errors in parameter estimates, and $p(x)$ is provided by Naïve Bayes; top: $c = 0.1$; bottom: $c = 0.3$.

Wrong attacker model

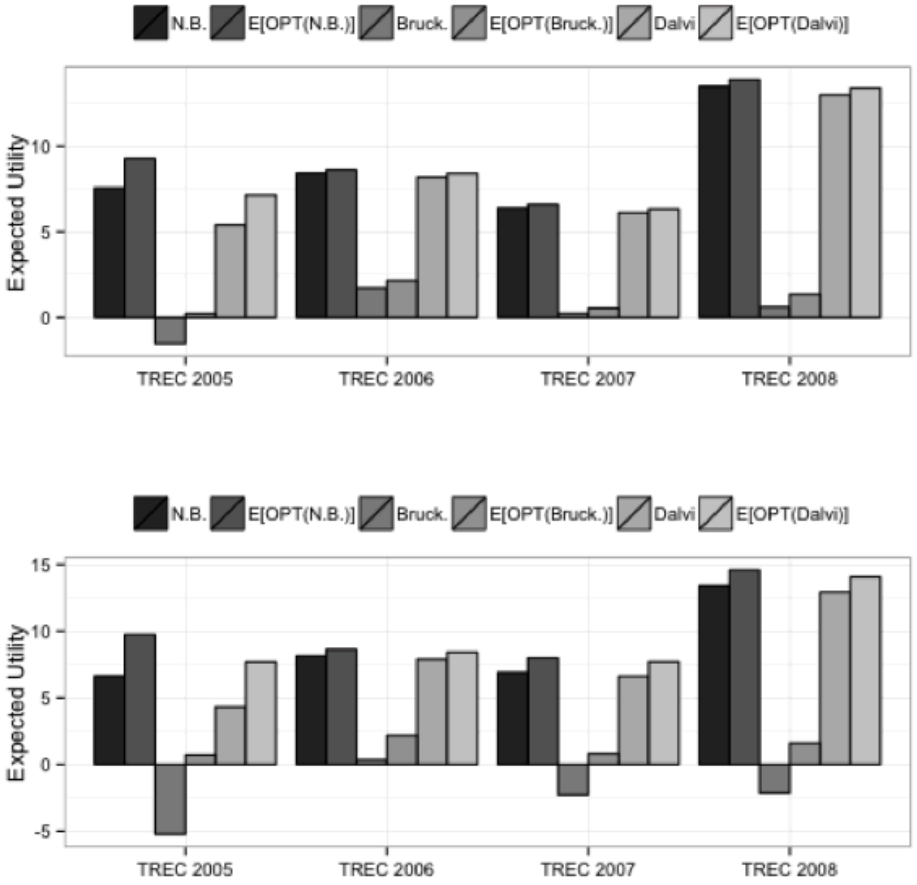


Fig. 10. The expected utilities, assuming $P_A = 1$ and that our attacker utility model is incorrect, and the actual utility decays for non-prefered input vectors according to Equation 8; top: $c = 0.1$; bottom: $c = 0.3$.

suppose actual attacker utility exhibits polynomial decay

almost no effect, still far better than other models

Summary

- Dynamic attacker model: use classical (AI) planning formalism to model an attacker
  - Can solve the plan interdiction problem at scale using Bender's
    - (also tried heuristics, which allow us to get similar scalability, but also use less memory)
  - Extension to uncertainty about attackers direct
  - Extension to execution uncertainty: scalability is a problem
- Adversarial machine learning
  - Model an attacker as a utility maximizer
  - Can compute optimal inspection/filtering policy (under budget constraint) using LP
  - Significantly outperforms alternative approaches

Future work

- Scale MDP interdiction problem (current research; using factored MDP representation, linear value function approximation, and state space abstraction techniques)
- Implement (current research; SANDMAN tool implements the threat model, user interface, and plan generation)
- AML approach: assumption of finite/sampled X problematic
  - look into alternative parametric function classes to approximate *q(x)*
- Relax assumption that the attacker "knows" *q(x)*
  - attacker is learning / reverse engineering the defense policy
  - introduces interesting ML theory questions

Collaborators

- Josh Letchford (formerly Duke University; now Sandia)
- John Ross Wallrabenstein (Purdue)