

# Real World Reinforcement Learning

John Langford

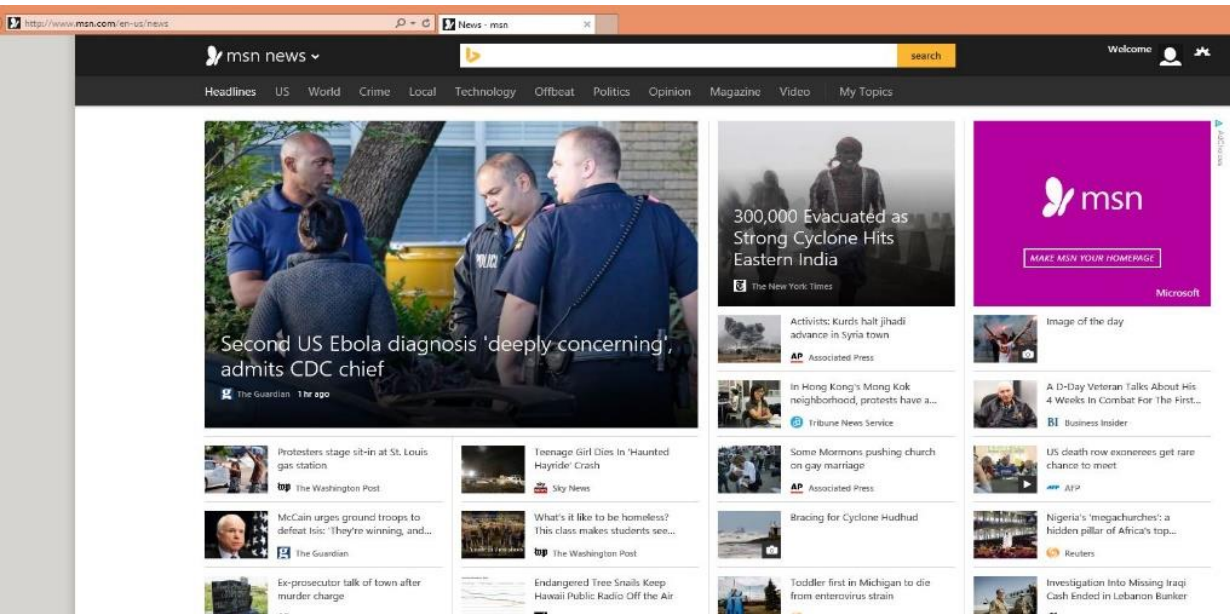


AI Nextcon, NYC, July 23

+ Workshop July 25, 9-12

<https://vowpalwabbit.github.io/workshop/>

# Which News? Why?



28% lift

# Which Game?



40% lift

# workshop

## Real World Reinforcement Learning Workshop

### AI NEXTCon 2019

Thursday July 24, 2019  
9:00AM - 12:00PM

### Abstract

Microsoft recently announced the Azure Cognitive Service, Personalizer, aimed at democratizing real world reinforcement learning for content personalization. Its goal is to make reinforcement learning accessible to everyone, not just machine learning experts. Personalizer is the result of a successful partnership between Microsoft Research and Azure Cognitive Services aimed at rapid technology transfer and innovation.

In this workshop you will learn the theory behind contextual bandits and how this applies to content personalization. We will walk you through setting up the service, writing your first application, and optimizing the policy using offline optimization.



Home / Services / Cognitive Services / Personalizer

# Personalizer PREVIEW

An AI service that delivers a personalized user experience

Try Personalizer >

Product overview Features More >



Dismiss

Join GitHub today

GitHub is home to over 36 million developers working together to host and review code, manage projects, and build software together.

Sign up

Vowpal Wabbit is a machine learning system which pushes the frontier of machine learning with techniques such as online, hashing, allreduce, reductions, learning2search, active, and interactive learning. <http://hunch.net/~vw/>

- c-plus-plus
- machine-learning
- online-learning
- contextual-bandits
- reinforcement-learning
- active-learning
- learning-to-search
- cpp

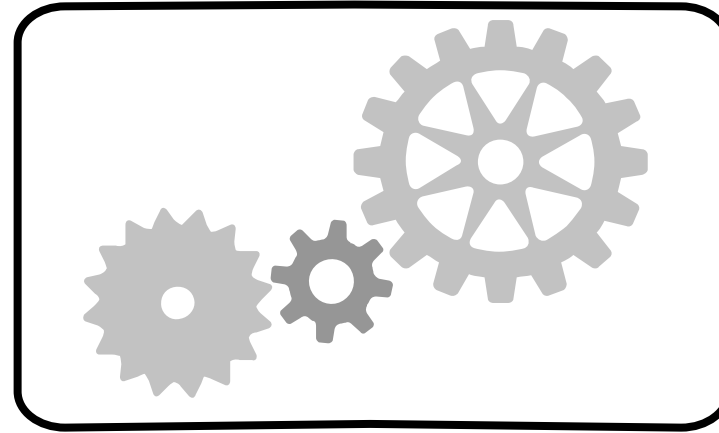
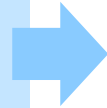
# The Baseline: Supervised Learning

1 1 5 4 3  
7 5 3 5 3  
5 5 9 0 6  
3 5 2 0 0

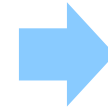
Training examples

1	1	5	4	3
7	5	3	5	3
5	5	9	0	6
3	5	2	0	0

Training labels



Supervised Learner



Accurate digit  
classifier

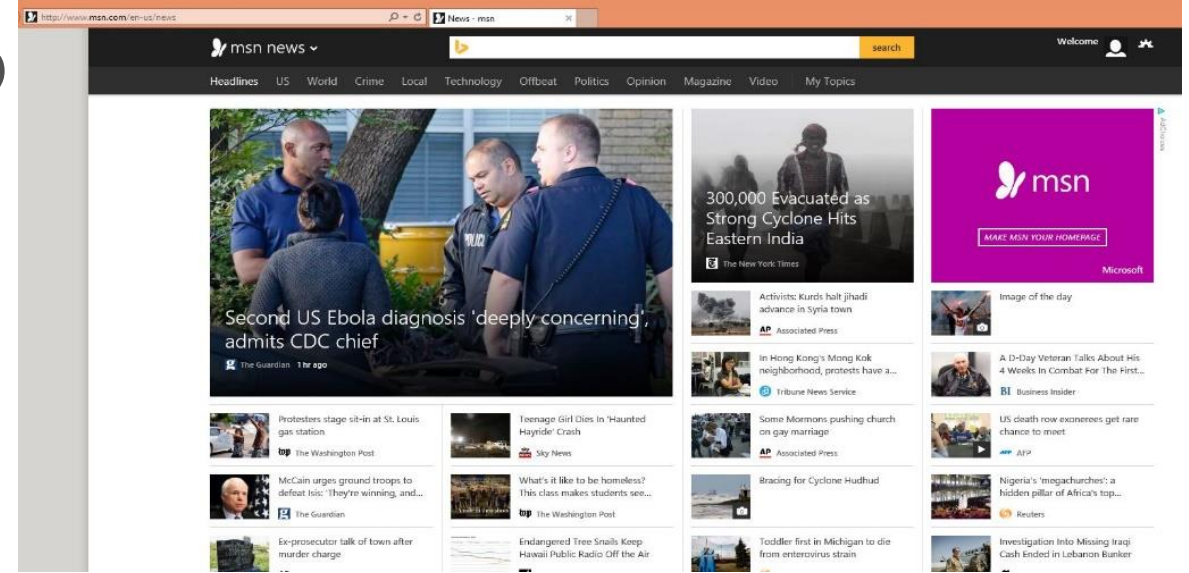
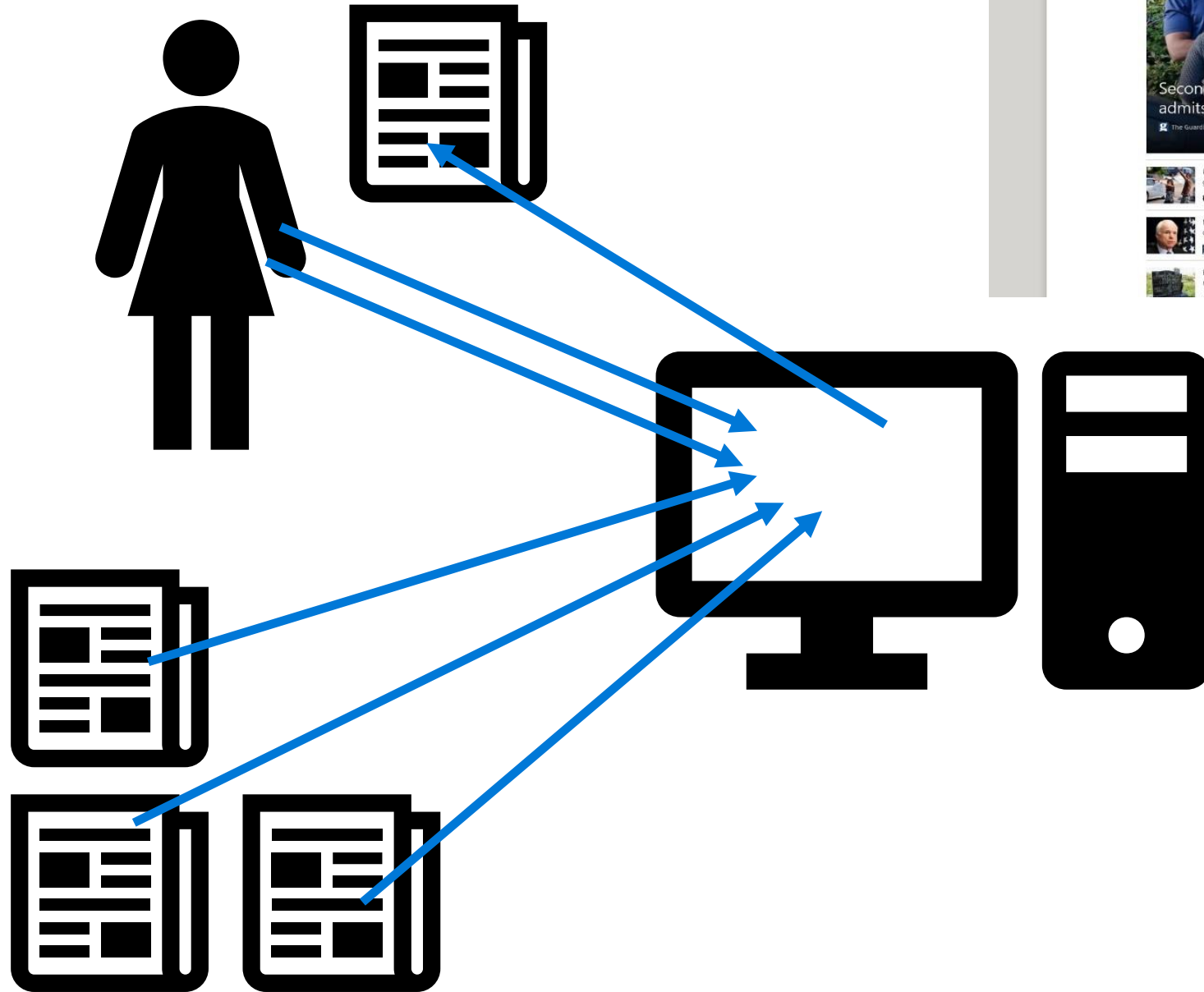
2

# Supervised Learning is cool





# How about news?





# A standard pipeline

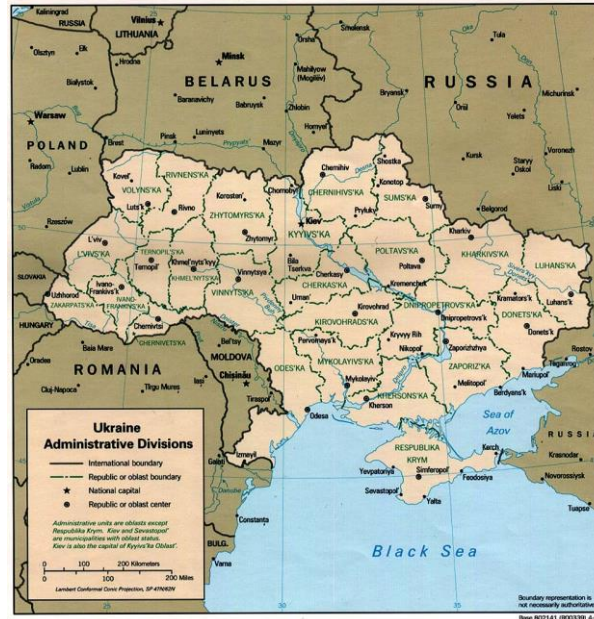
1. Collect *(user, article)* information.
2. Hire editor to judge *relevance(user, article)*
3. Learn  $\widehat{relevance}(user, article)$
4. Act with best *article* from  $\widehat{relevance}(user, article)$
5. Deploy in A/B test for 2 weeks
6. A/B test fails 😞

# A standard pipeline

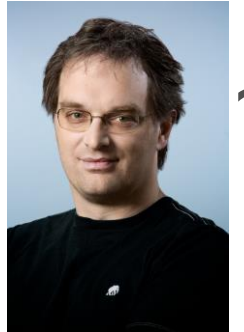
1. Collect  $(user, article, click)$  information.
2. Learn  $\hat{P}(click|user, article)$
3. Act with best  $article$  from  $\hat{P}(click|user, article)$
4. Deploy in A/B test for 2 weeks
5. A/B test fails 😞 Why?

# Q: What goes wrong?

Is Ukraine



interesting to John



?

# A: Need Right Signal for Right Answer

# What goes wrong?

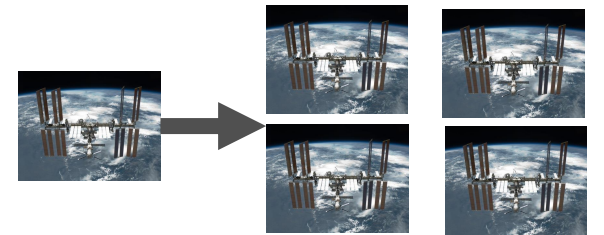
What is the probability of click on a food article



If you only display a space article?

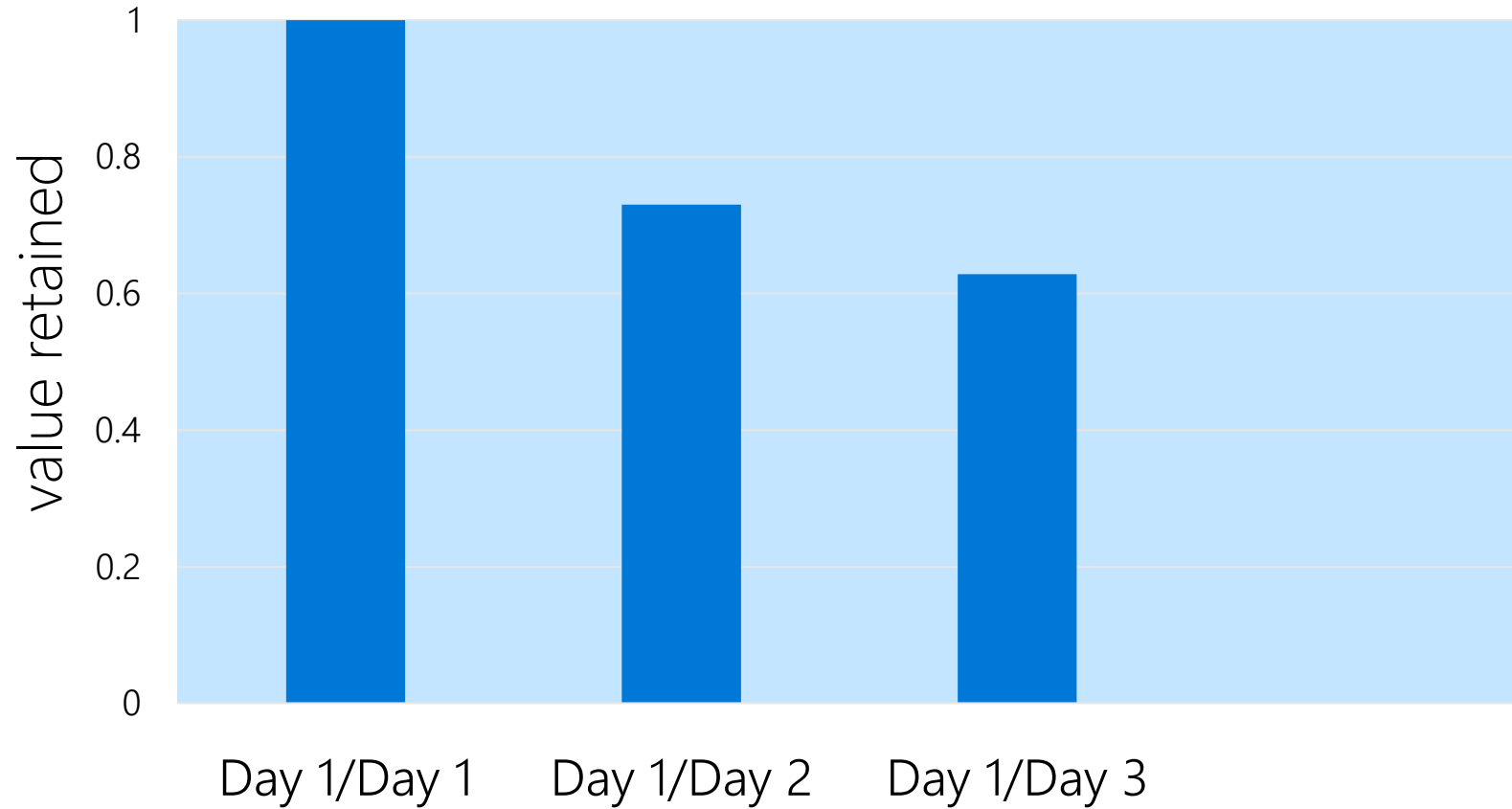


We must avoid “self-fulfilling prophecy”





# What else goes wrong?



The world changes!

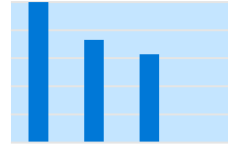
# Can we optimize for best outcome?

Amongst a given set of choices?

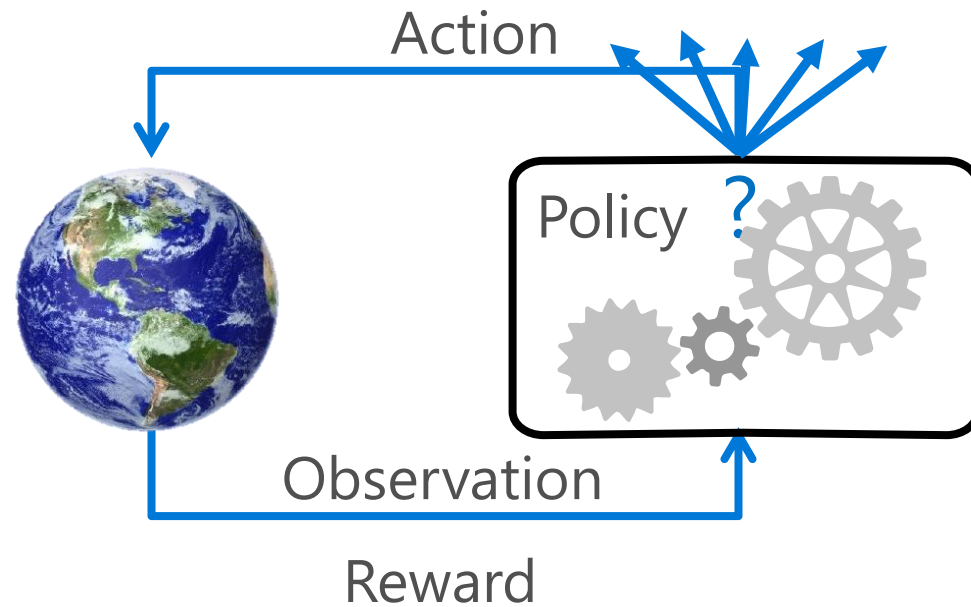
For what matters to individuals?

Without self-fulfilling prophecies?

With real-time learning?

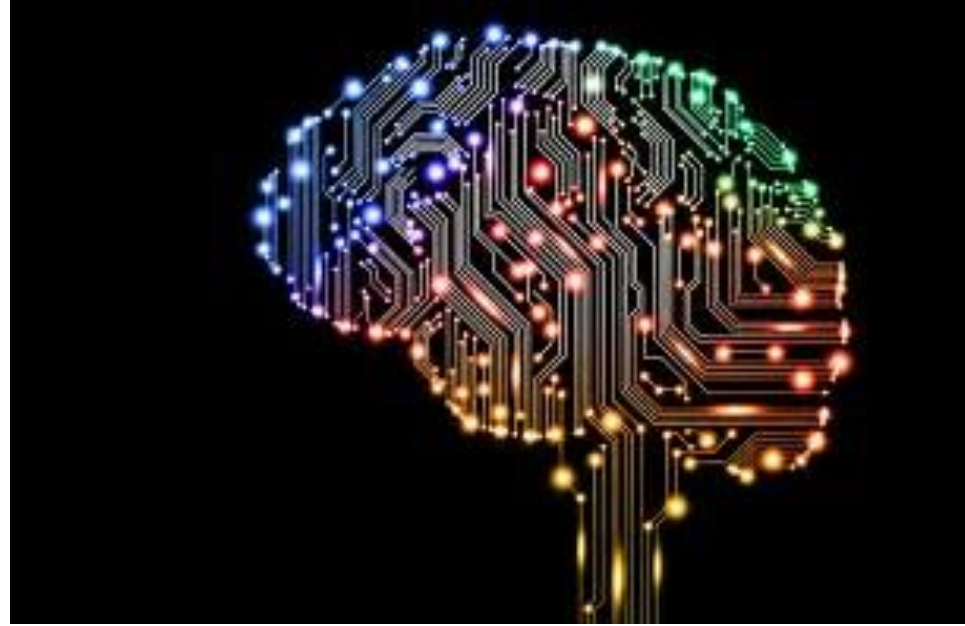


# Reinforcement Learning can do this!



Goal: Find a policy maximizing the sum of rewards

Q: One last Why...



~~AI: A function programmed with data~~

AI: An economically viable digital agent that explores, learns, and acts

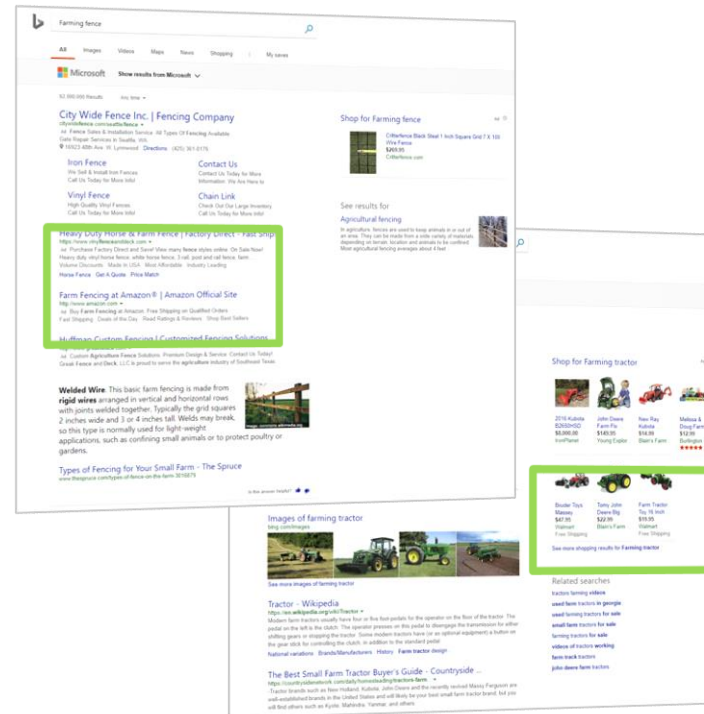


# Content

# Layout

# Creative

“Book Your Vacation to Hawaii”



# Wellness

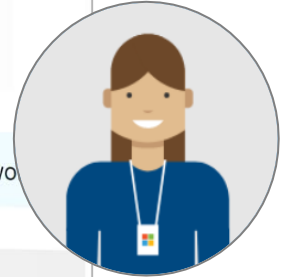


[ZKZ '09, SLLSPM '11, NSTWCSM '14,  
PGCRRH '14, NHS '15, KHSBATM '15,  
HFKMTY '16]

# Bots

I'm Microsoft's Virtual Agent. I'd love to help you. You can also ask to talk to a person at any time. Please briefly describe your issue below.

My printer isn't wo



## Check power and connection

If you are unable to print or connect to your printer in Windows 10, first try this:

1. Make sure that your printer is plugged into the power supply and turned on.
2. Check the USB connection (for wired printers) or the wireless connection (for wireless printers).

Did that solve the problem?

Yes

No, show solution 2 of 5

# Other Real-world Applications

Ad Choice: [BPQCCPRSS '12]

Ad Format: [TRSA '13]

Education: [MLLBP '14]

Music Rec: [WWHW '14]

Robotics: [PG '16]

# Formalism: Contextual Bandits

Repeatedly:

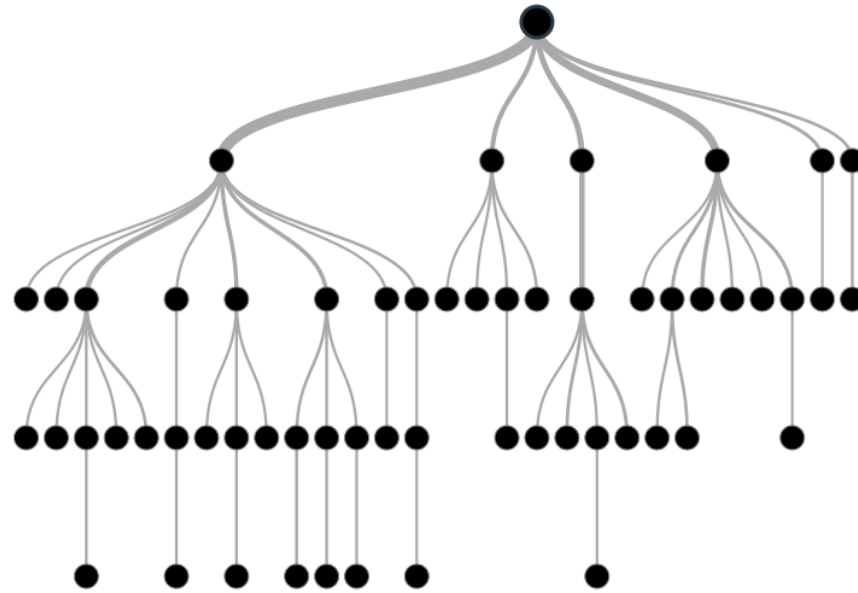
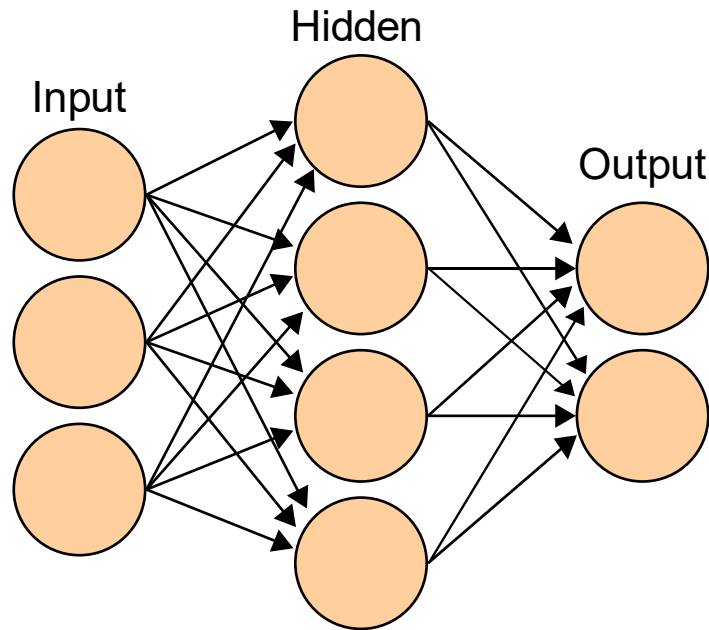
1. Observe features  $x$
2. Choose action  $a \in A$
3. Observe reward  $r$

Goal: Maximize expected reward



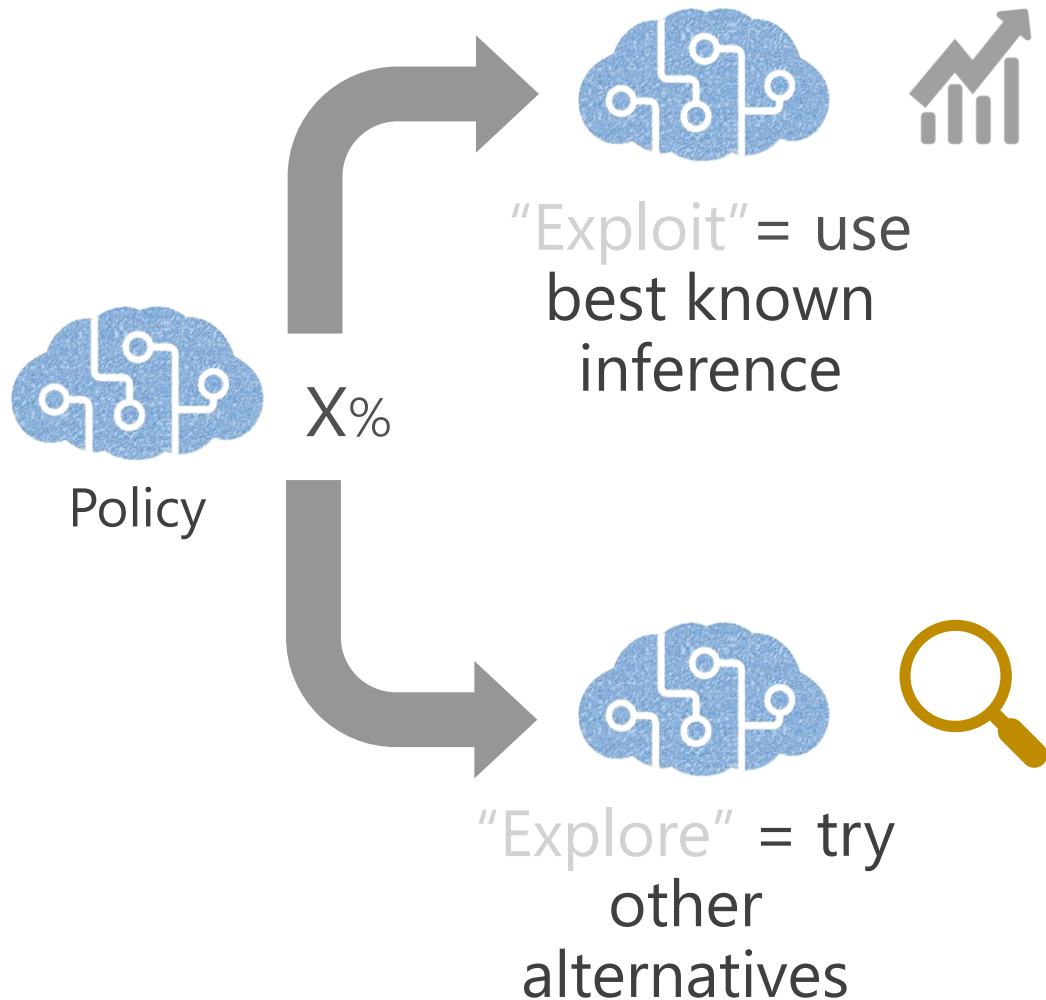
# Policies

Policy maps features to actions.



Policy = Classifier that *acts*.

# Why does it work?



"Exploit" = use  
best known  
inference

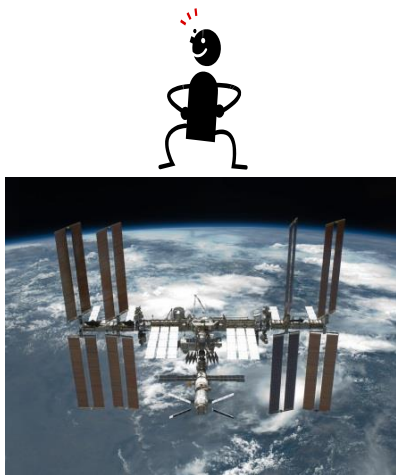
Exploit for  
performance

"How much should I  
explore to discover  
how to best perform?"

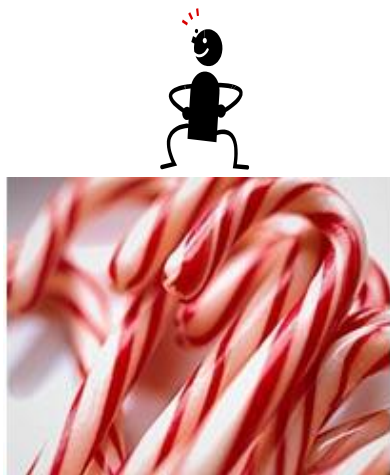
"Explore" = try  
other  
alternatives

Explore to  
discover new  
things

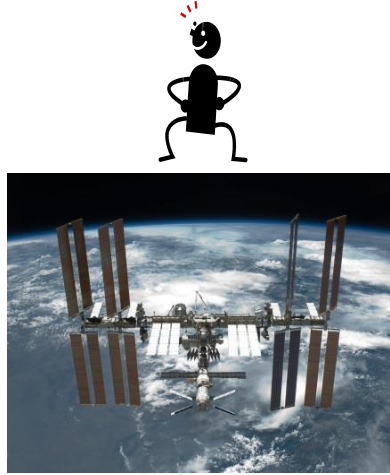
# Counterfactual Evaluation



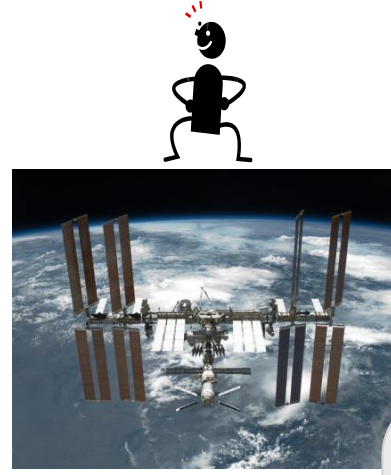
Read



Read



Ignored



Read

...

Tests can use the same events!

Later evaluate Location rule:

Teacher

Texas

Engineer

Seattle

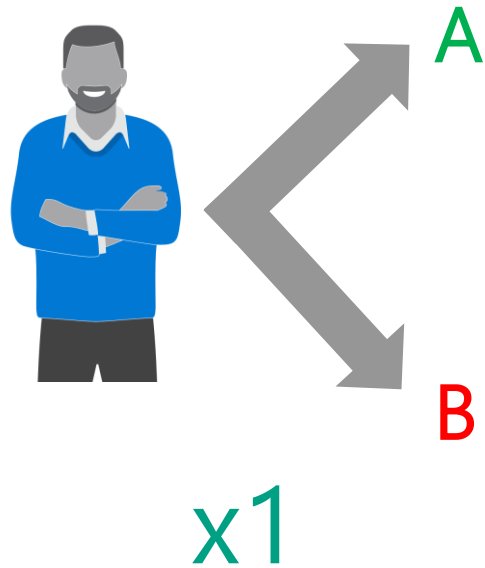
Engineer

Seattle

Engineer

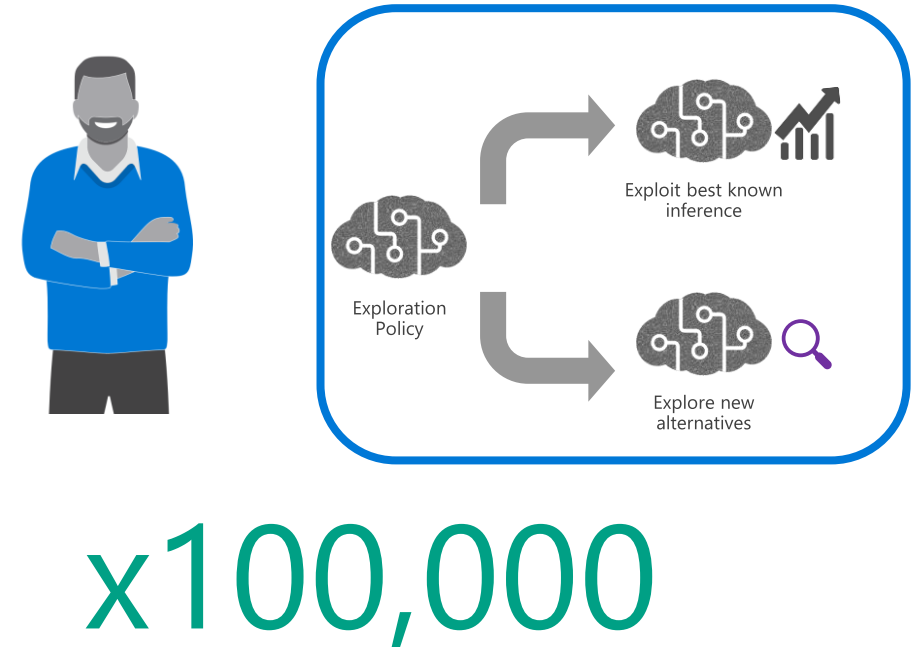
Texas

# A/B vs. Counterfactual



A/B Test:

1. Design the Right Experiment,
2. Test online once
3. Start over




Offline Experiment:

1. Use models that exploit and explore
2. Record User Interaction
3. Find the policy and model that fits reality



# Inverse Propensity Score (IPS)

Given experience  $\{(x, a, p, r)\}$  and a policy  $\pi: x \rightarrow a$ , how good is  $\pi$ ?

$$V_{\text{IPS}}(\pi) = \frac{1}{n} \sum_{(x,a,p,r)} \frac{r I(\pi(x) = a)}{p}$$


Propensity Score

# What do we know about IPS?

Theorem: For all  $\pi$ , for all  $D(x, \vec{r})$

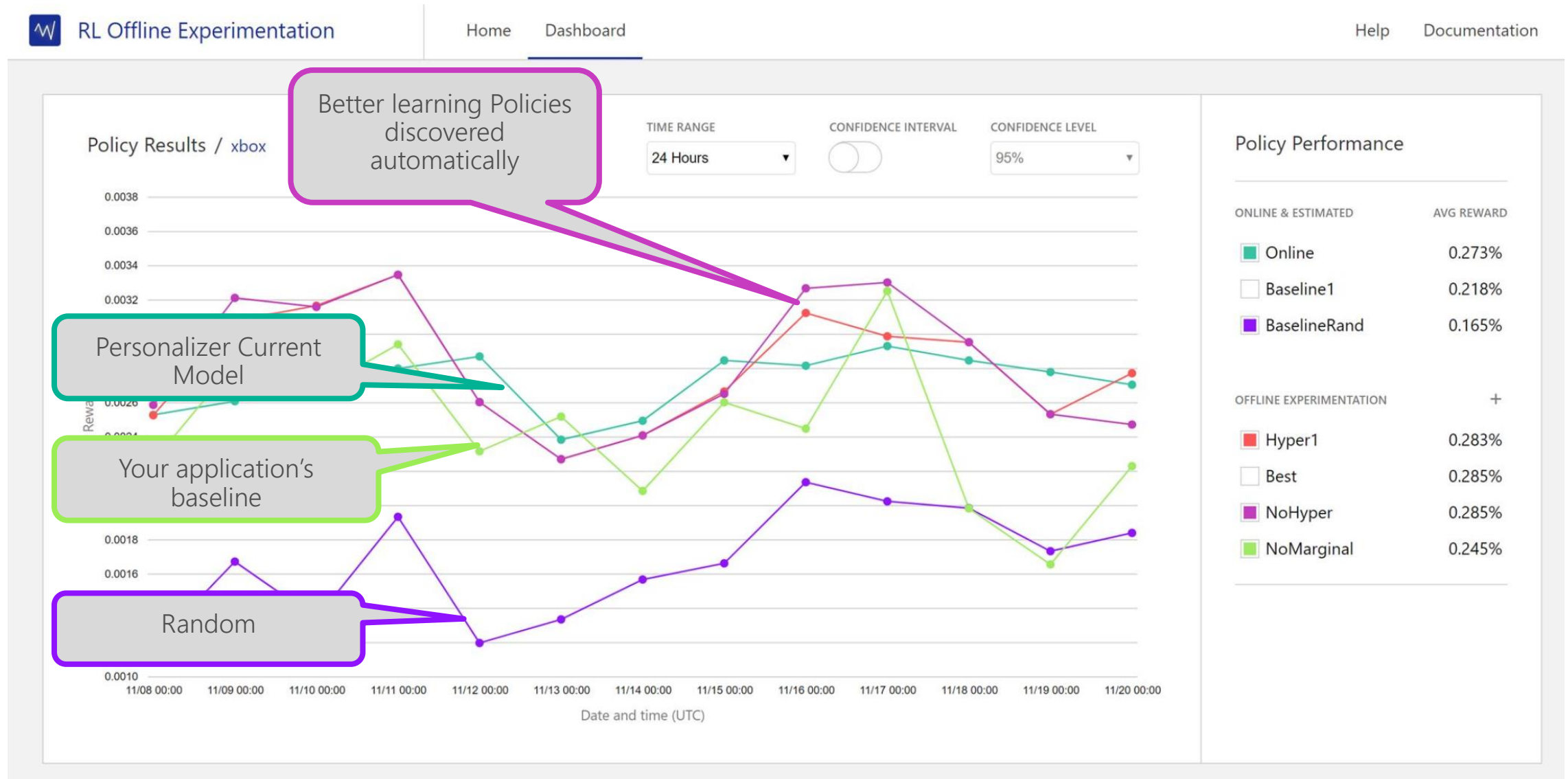
$$\mathbb{E} \left[ r_{\pi(x)} \right] = \mathbb{E}[V_{\text{IPS}}(\pi)] = \mathbb{E} \left[ \frac{1}{n} \sum_{(x,a,p,r)} \frac{r I(\pi(x)=a)}{p} \right]$$

Proof: For all  $(x, \vec{r})$ ,  $E_{a \sim \vec{p}} \left[ \frac{r_a I(\pi(x)=a)}{p_a} \right]$

$$= \sum_a p_a \frac{r_a I(\pi(x)=a)}{p_a}$$

$$= r_{\pi(x)}$$

# Why Explore? You can do learning



# Better Evaluation Techniques

Double Robust: [DLL '11]

Weighted IPS: [K '92, SJ '15]

Clipping: [BL '08]

Empirical Likelihood: [MKL '19]

# Learning from Exploration

Given Data  $\{(x, a, p, r)\}$  how to maximize  $E[r_{\pi(x)}]$ ?

Maximize  $E[V_{IPS}(\pi)]$  instead!

$$r_a = \begin{cases} r/p & \text{if } \pi(x) = a \\ 0 & \text{otherwise} \end{cases}$$

Equivalent to:

$$r'_a = \begin{cases} 1 & \text{if } \pi(x) = a \\ 0 & \text{otherwise} \end{cases}$$

with importance weight  $\frac{r}{p}$

Importance weighted multiclass classification!

# Better Learning from Exploration

Policy Gradient: [W '92]

Offset Tree: [BL '09]

Double Robust for learning: [DLL '11]

Multitask Regression: [BAL '18]

Weighted IPS for learning: [SJ '15]



# Evaluating Online Learning

Problem: How do you evaluate an online learning algorithm  
**Offline?**

Answer: Use Progressive Validation [BKL '99, CCG '04]



Theorem:

- 1) Expected PV value = Uniform expected policy value.
- 2) Trust like a **test set error**.

# How do you do Exploration?

Simplest Algorithm:  $\epsilon$ -greedy.

With probability  $\epsilon$  act uniform random

With probability  $1 - \epsilon$  act greedily

# Better Exploration Algorithms

Better algorithms maintain ensemble and explore amongst actions of this ensemble.

Thompson Sampling: [T '33]

EXP4: [ACFS '02]

Epoch Greedy: [LZ '07]

Polytime: [DHKKLRZ '11]

Cover&Bag: [AHKLLS '14]

Bootstrap: [EK '14]

# Evaluating Exploration Algorithms

Problem: How do you take the choice of examples acquired by an exploration algorithm into account?

Answer: Rejection Sample from history. [DELL '12]



Theorem: Realized history is unbiased up to length observed.

Better versions: [DELL '14]

# More Details!

AI Nextcon Workshop, July 25 9-12

<https://vowpalwabbit.github.io/workshop/>

Personalizer Service: <http://aka.ms/personalizer>

Vowpal Wabbit: <http://vowpalwabbit.org>

ICML tutorial: <http://hunch.net/~rwil>