Contextual Bandits Overview

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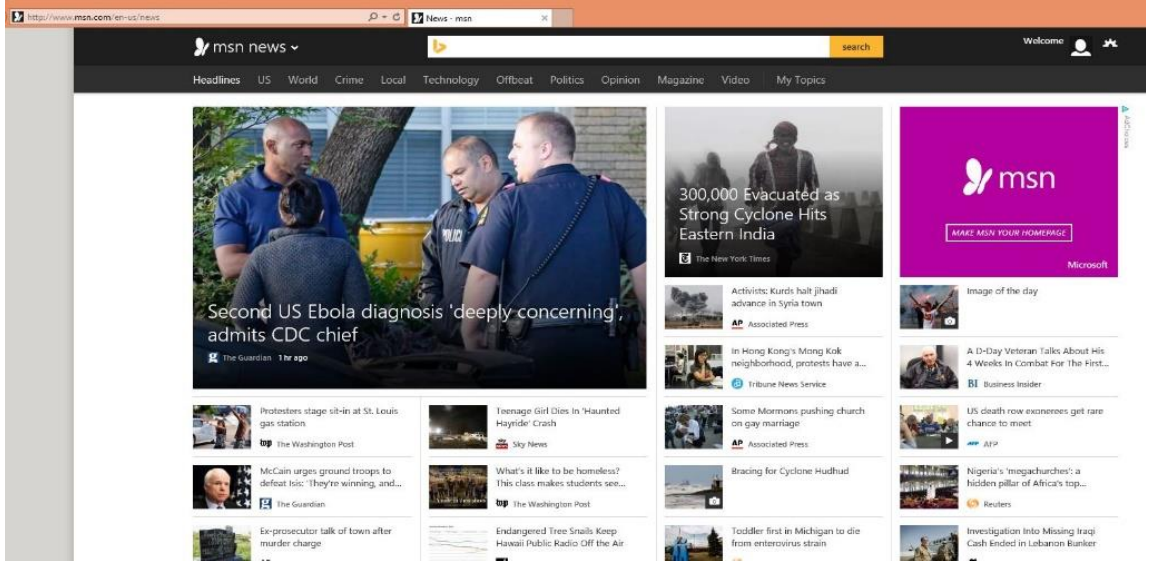
Personalized news?



Repeatedly:

1. Observe features of user+articles
2. Choose a news article.
3. Observe click-or-not

Goal: Maximize fraction of clicks

Health advice?

Repeatedly:

1. Observe features of user+advice
2. Choose an advice.
3. Observe steps walked

Goal: Healthy behaviors (e.g. step count)

Other Real-world Applications

News Rec: [LCLS ‘10]

Ad Choice: [BPQCCPRSS ‘12]

Ad Format: [TRSA ‘13]

Education: [MLLBP ‘14]

Music Rec: [WWHW ‘14]

Robotics: [PG ‘16]

Wellness/Health: [ZKZ ’09, SLLSPM ’11, NSTWCSM ’14, PGCRRH ’14, NHS ’15, KHSBATM ‘15, HFKMTY ’16]

Contextual Bandits (CB)

For $t = 1,2,\dots,T$:

1. Observe features $x_{\mathrm{t}} \sim D_t$
2. Choose action $a_{\mathrm{t}} \in A$
3. Observe reward $r_{\mathrm{t}} \sim D_t(\cdot|x_t)$

Goal: Maximize net reward

$$\boldsymbol{E_{D_t}\left[\sum_{t=1}^{T} r_t\right]}$$

- $|A| = K, \; r_t \in [0,1]$

Adversarial and i.i.d.

i.i.d.

For $t = 1,2,\ldots,T$:

1. Observe features $x_{\mathrm{t}} \sim D$
2. Choose action $a_{\mathrm{t}} \in A$
3. Observe reward $r_{\mathrm{t}} \sim D(\cdot|x_t)$

Goal: Maximize net reward

$$\boldsymbol{E\sum_{t=1}^{T} r_t}$$

Adversarial

For $t = 1,2,\ldots,T$:

1. Observe features x_{t}
2. Simultaneously adversary picks $r_t \in [0,1]^K$
3. Choose action $a_{\mathrm{t}} \in A$
4. Observe reward $r_{\mathrm{t}}(a_t)$

Goal: Maximize net reward

$$\boldsymbol{E_{D_t}\left[\sum_{t=1}^{T} r_t(a_t)\right]}$$

How much reward is good?

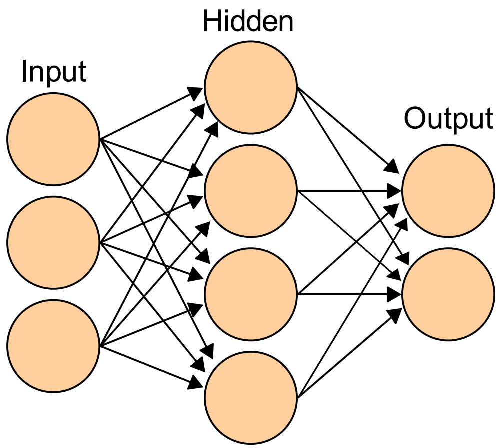
- Need a benchmark for comparison to our cumulative rewards

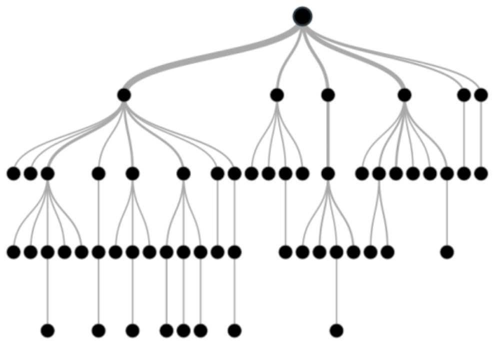
- **MAB:** Compare with the best fixed action in hindsight
  - **Tacit assumption:** A fixed action gets high rewards across all contexts
  - *e.g. same treatment to each patient, irrespective of their symptoms!*

- **EXP4:** Comparison with best expert
  - Good benchmark if we have a good expert

Policies

Policy maps features to actions.





Policy = Classifier that ***acts*.**

- chosen action = prediction of a classifier on the context

Use policies to pick actions in CB

How much reward is good?

- **CB:** Compare with the best fixed policy in a policy class
    - **Tacit assumption:** There is a policy which attains high reward in the class

- Pick an expressive class of policies to capture complex behaviors
- Allows taking different good actions on different contexts

- Limiting to a class restricts complexity for learning, like a hypothesis/concept class in supervised learning

Regret

$$Regret_T = \sum_{t=1}^{T} r_t - \sum_{t}^{T} \max_{\pi \in \Pi} r_t(\pi(x_t))$$

Best policy in hindsight

Connection to other learning settings

- MAB: Different benchmark makes CB harder and more useful
- Supervised learning: Wait for next lecture
- Reinforcement learning: Actions do not have long-term consequences on future contexts and rewards in CB.

Contextual Bandits(ish) Applications

News: Lihong Li, Wei Chu, John Langford, Robert E. Schapire: A contextual-bandit approach to personalized news article recommendation. WWW 2010.

Robotics: Lerrel Pinto, Abhinav Gupta: Supersizing self-supervision: Learning to grasp from 50K tries and 700 robot hours. ICRA 2016: 3406-3413.

Music: Xinxi Wang, Yi Wang, David Hsu, Ye Wang: Exploration in Interactive Personalized Music Recommendation: A Reinforcement Learning Approach. TOMCCAP 11(1): 7:1-7:22 (2014).

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Ad Format: Liang Tang, Rómer Rosales, Ajit Singh, Deepak Agarwal: Automatic ad format selection via contextual bandits. CIKM 2013: 1587-1594.

Ad Choice: Léon Bottou, Jonas Peters, Joaquin Quiñonero-Candela, Denis X. Charles, D. Max Chickering, Elon Portugaly, Dipankar Ray, Patrice Simard, Ed Snelson: Counterfactual reasoning and learning systems: the example of computational advertising. JMLR 14(1): 3207-3260 (2013).

Wellness Contextual Bandits Work

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Y. Zhao, M. R. Kosorok and D. Zeng, "Reinforcement learning design for cancer clinical trials," Statistics in medicine, vol. 28, no. 26, p. 3294, 2009.