Vowpal Wabbit 2017 Update

John Langford

http://hunch.net/~vw/

git clone
git://github.com/JohnLangford/vowpal_wabbit.git

What is Vowpal Wabbit

1. Large Scale linear regression (*)
2. Online Learning (*)
3. Active Learning (*)
4. Learning Reduction (*)

(*) Old stuff

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11. JSON/Decision Service (Markus)

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Community

1. BSD license.

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Step 2: vw -t --sparse_weights <test set>

(memory footprint is 100MB)

Baseline and Contextual Bandits

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Baseline

Setting: **online regression**

- **Problem**: range of targets (e.g. offset) is unknown
- Bias term (weight for "constant" features) can be slow to learn
- Hurts performance of learning / exploration algorithms

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Goal: adapt quickly and automatically to the range of targets

Baseline

Solution:

- Learn baseline regressor separately from rest
  - From constant features on example --baseline
  - Or separate global constant example --baseline --global_only

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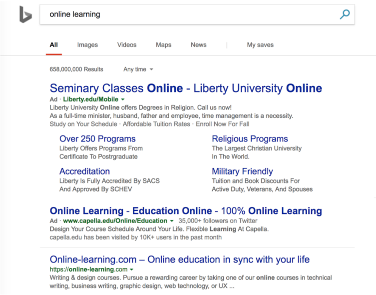
Note: learning rate multiplied by max label to converge faster than other normalized updates

Contextual Bandits

Repeat:

- Get some **context** x
  - Search query, user info, user's interests
- Choose **action** a
  - Advertisement
  - News story
  - Medical treatment
- Observe **reward/loss** r(a)
  - Click/no click
  - Revenue
  - Treatment outcome



Goal: maximize **cumulative reward**

How? Balance **exploration/exploitation**

Baseline: example for cb loss estimates

Reward/loss estimation is key (e.g. doubly robust)

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```
> vw ds.txt --cbify 10 --cb_explore_adf --cb_type dr --epsilon 0.05
0.682315
> vw ... --loss0 9 --loss1 10
0.787594
> vw ... --loss0 9 --loss1 10 --baseline
0.710636
> vw ... --loss0 9 --loss1 10 --baseline --global_only
0.636140
```

Contextual bandits: bagging

Bagging: "bootstrapped Thompson sampling"

- Each update is performed *Poisson*(1) times
- For only one policy, **greedy** performs better (always update once)

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- Each update is performed *Poisson*(1) times
- For only one policy, **greedy** performs better (always update once)
- --bag n --greedify treats first policy like greedy
- Often works better, especially for small n

Contextual bandits: cover

Cover: maintains set of diverse policies good for explore/exploit

- New parameterization: --cover n [--psi 0.01] [--nounif]
  - ψ controls diversity cost for training policies ($\psi = 0 \rightarrow$ all ERM policies)
  - $\epsilon_t = 1/\sqrt{Kt}$ always
  - --nounif disables exploration on ϵ actions (not chosen by any policy)

Contextual bandits: miscellaneous

- Most changes are only in the **ADF** code
- --cbify K --cb_explore_adf for using ADF code in cbify
  - --loss0 [0] –loss1 [1] to specify different loss encodings
- **Cover + MTR** uses MTR for the first (ERM) policy, DR for the rest
- **Upcoming**: reduce uniform ϵ exploration in ϵ-greedy using disagreement test (from active learning)