

Feature Hashing

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March 25, 2012
(Post Presentation Version)

Features in Practice: Engineered Features

Hand crafted features, built up iteratively over time, each new feature fixing a discovered problem.

In essence, boosting where humans function as the weak learner.

- ① +Good understanding of what's happening.
- ② +Never fail to learn the obvious.
- ③ +Small RAM usage.
- ④ -Slow at test time. Intuitive features for humans can be hard
- ⑤ -Low Capacity. A poor fit for large datasets. (Boosted)
Decision trees are a good compensation on smaller datasets.
- ⑥ -High persontime.

Use a nonlinear/nonconvex possibly deep learning algorithm.

- ① +Good results in Speech & Vision.
- ② +Fast at test time.
- ③ +High capacity. Useful on large datasets.
- ④ -Slow training. Days to weeks are common.
- ⑤ -Wizardry may be required.

Features in Practice: Count Features

An example: for each (word, ad) pair keep track of empirical expectation of click $\hat{E}[c|(word, ad)]$.

- 1 +High capacity.
- 2 +Fast learning. Counting is easy on map-reduce architectures.
- 3 +fast test time. Lookup some numbers, then compute an easy prediction.
- 4 -High RAM usage. Irrelevant features take RAM.
- 5 -Correlation effects lost. Adding explicit conjunction features takes even more RAM.

Features in Practice: sparse words

Generate a feature for every word, ngram, skipgram, pair of (ad word, query word), etc... and use high dimensional representation.

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- ⑤ -High RAM usage This lecture.

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Perfect hash = overfit decision tree mapping n fixed (and known in advance) strings to integers $\{1, n\}$.

How does feature address parameter?

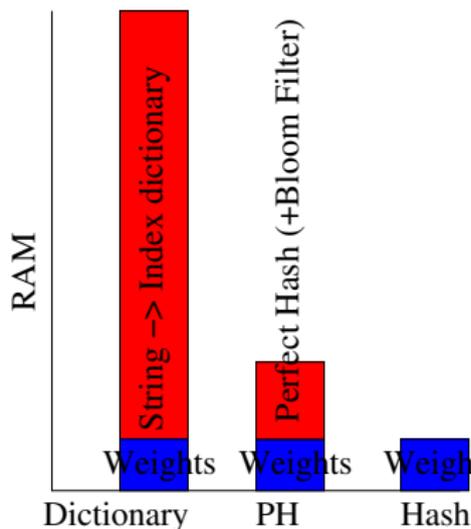
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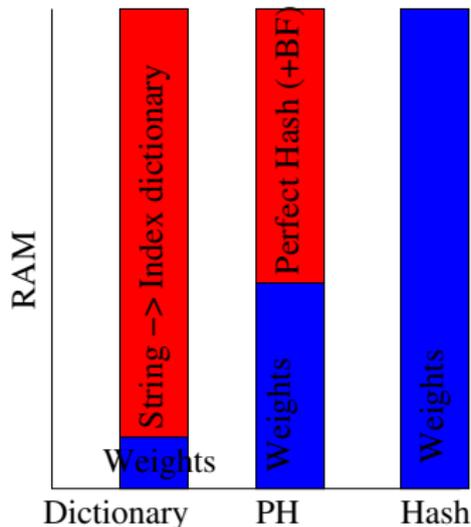
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More weights is better!

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Theorem: If a feature is duplicated $O(\log n)$ times when there are $O(n)$ features, at least one version of the feature is uncollided when hashing with $\log(n \log n)$ bits.

Proof: Similar to Bloom filter proof.

Example 1: CCAT RCV1

1 | tuesday year million short compan vehicl line stat financ commit
exchang plan corp subsid credit issu debt pay gold bureau prelimin
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-1 | econom stock rate month year invest week produc report
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Run:

```
vw -b 24 --loss_function logistic --ngram 2 --skips 4 -c  
rcv1.train.raw.txt --binary
```

to see progressive validation loss **4.5%**: about 0.6% better than
linear on base features.

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Use `-audit` to decode. Or, keep your own dictionary on the side if desirable.

`vw-varinfo rcv1.test.raw.txt.gz` = perl script in VW distribution for automatically decoding and inspecting results.

Use of Hash: Feature Pairing

Once you accept a hash function, certain operations become very easy.

`-q df` pairs every feature in namespaces beginning with `d` with every feature in namespaces beginning with `f`.

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But how?

Feature = (index,weight)

`pair_weight = d_weight * f_weight`

`pair_index = (d_index * magic + f_index) & mask`

This is done *inline* for speed.

Use of Hash: Ngrams

2gram = a feature for every pair of adjacent words.

3gram = a feature for every triple of adjacent words, etc...

ngram = ...

Features computed in the same fashion as for `-q`

(More clever solution = rolling hash, not yet implemented.)

Computed by the `parser` on the fly (since `#features/example` only grows linearly).

In many applications, you must have **multiple predictors**. Hashing allows all these to be mapped into the same array using a different offsets saving gobs of RAM and programming headaches.

-oaa, **-ect**, **-csoaa**, and others.

Example 2: Mass Personalized Spam Filtering

- 1 $3.2 * 10^6$ labeled emails.
- 2 433167 users.
- 3 $\sim 40 * 10^6$ unique tokens.

How do we construct a spam filter which is personalized, yet uses global information?

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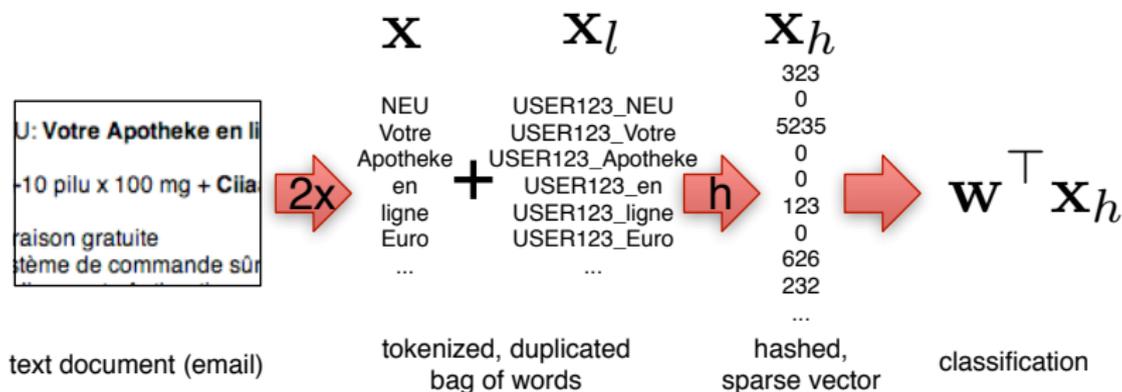
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How do we construct a spam filter which is personalized, yet uses global information?

Bad answer: Construct a global filter + 433167 personalized filters using a conventional hashmap to specify features. This might require $433167 * 40 * 10^6 * 4 \sim 70$ Terabytes of RAM.

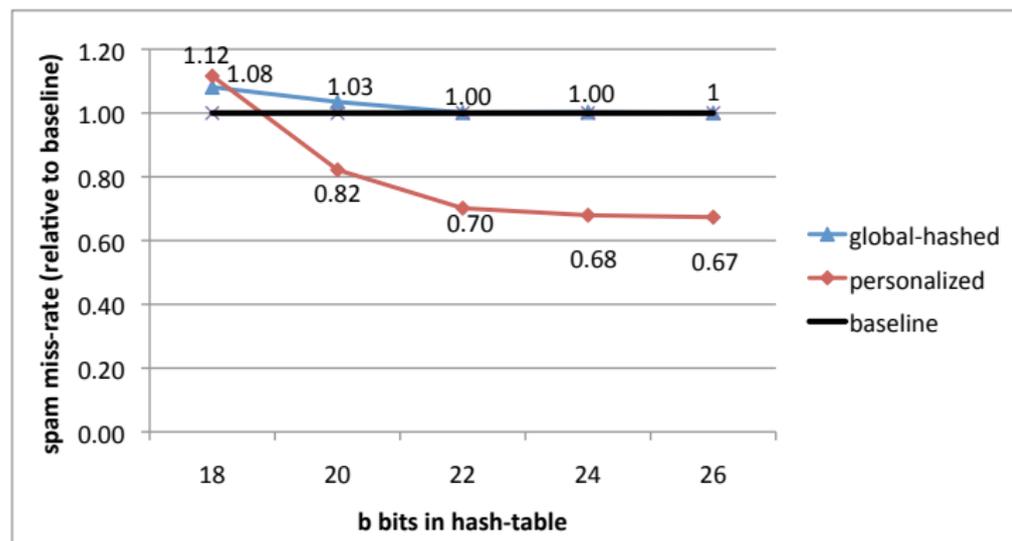
Using Hashing

Use hashing to predict according to: $\langle w, \phi(x) \rangle + \langle w, \phi_u(x) \rangle$



(in VW: specify the userid as a feature and use -q)

Results



2^{26} parameters = 64M parameters = 256MB of RAM.
An **x270K** savings in RAM requirements.

Features sometimes collide, which is scary, but then you love it

Generate a feature for every word, ngram, skipgram, pair of (ad word, query word), etc... and use high dimensional representation.

- ① +High capacity.
- ② +Correlation effects nailed.
- ③ +Fast test time. Compute an easy prediction.
- ④ +Fast Learning (with Online + parallel techniques. See talks.)
- ⑤ +/-Variable RAM usage. Highly problem dependent but fully controlled.

Another cool observation: Online learning + Hashing = learning algorithm with fully controlled memory footprint \Rightarrow Robustness.

- 1 Reinforcement Learning: An Introduction, Richard S. Sutton and Andrew G. Barto, MIT Press, Cambridge, MA, 1998. Chapter 8.3.1 hashes states.
- 2 CRM114 <http://crm114.sourceforge.net/>, 2002. Uses hashing of grams for spam detection.
- 3 Apparently used by others as well, internally.
- 4 Many use hashtables which store the original item or a 64+ bit hash of the original item.

References, “modern” hashing trick

- 1 2007, Langford, Li, Strehl, Vowpal Wabbit released.
- 2 2008, Ganchev & Dredze, ACL workshop: A hash function is as good as a hashmap empirically.
- 3 2008/2009, VW Reimplementation/Reimagination/Integration in Stream (James Patterson & Alex Smola) and Torch (Jason Weston, Olivier Chapelle, Kilian).
- 4 2009, AISTAT Qinfeng Shi et al, Hash kernel definition, Asymptopia Redundancy analysis
- 5 2009, ICML Kilian et al, Unbiased Hash Kernel, Length Deviation Bound, Mass Personalization Example and Multiuse Bound.