Indexing and Machine Learning

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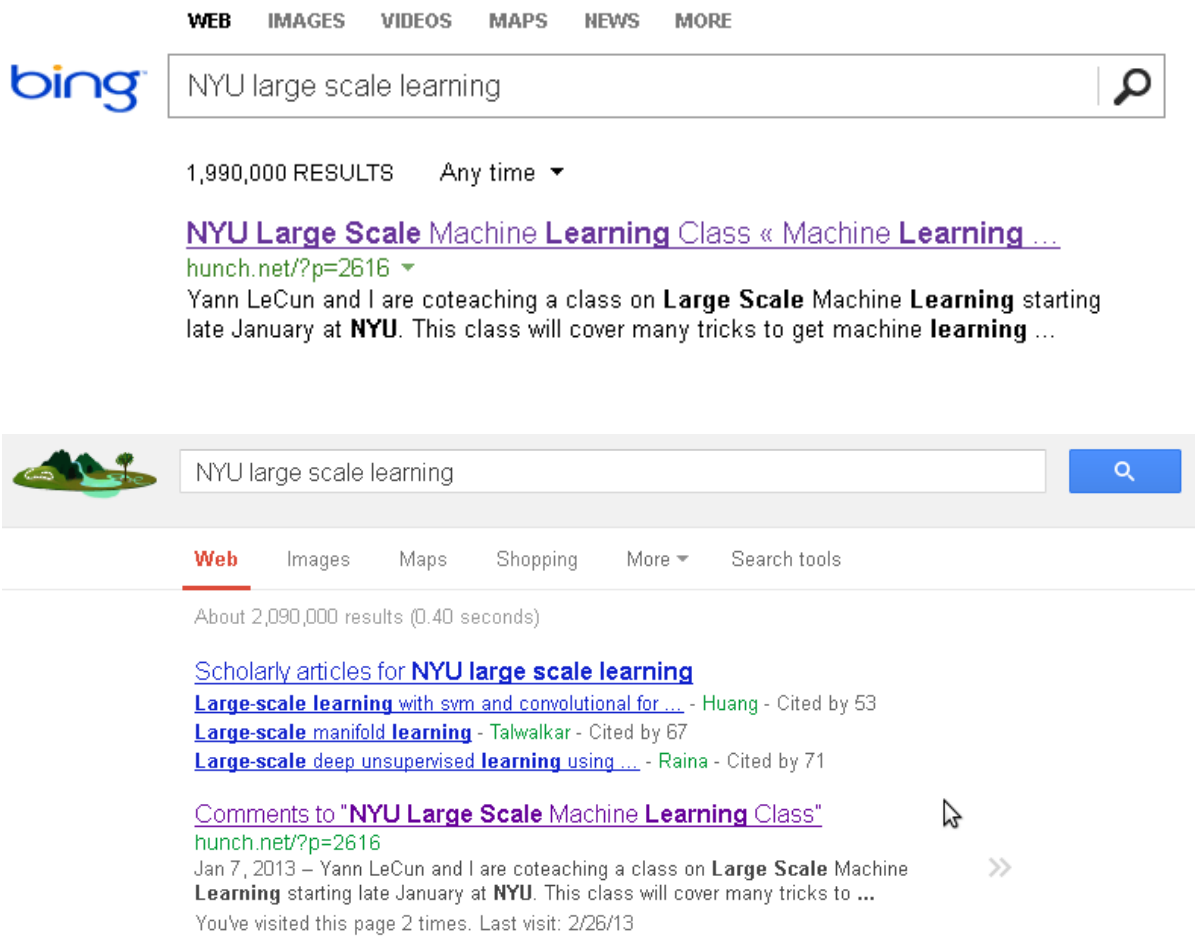
NYU Large Scale Learning Class, April 23

A Scenario

You have 10^{10} webpages and want to return the best result in 100ms.



How do you do it?

Method 1: Linear Scan

"Best" is defined by some (learned) quality score $s(q, r)$ where q is the query and r is the result.
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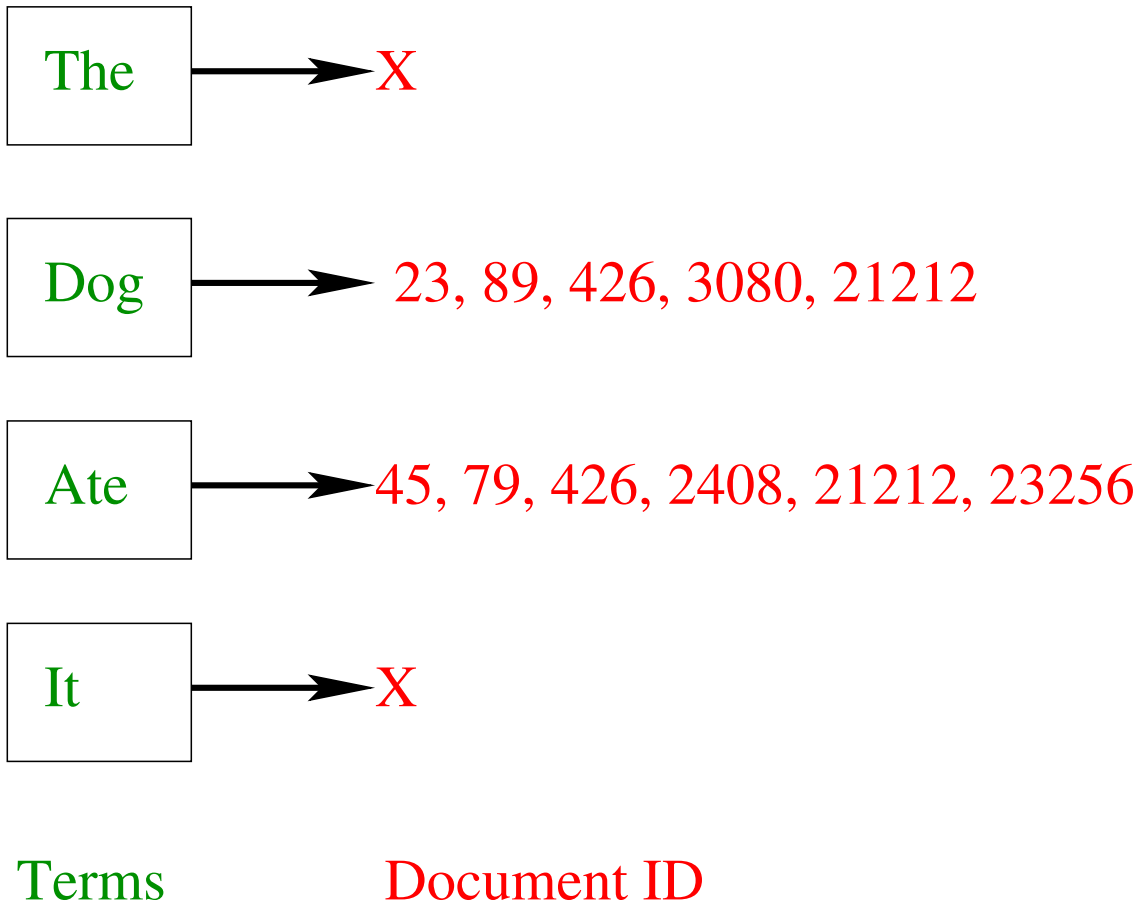
Need perhaps $10^{13}(?)$ cores. Luckily, there are other approaches.

Method 2: Inverted index

Inverted index = lookup table of documents containing a word.
[variants]



"Stop words" are unindexed (index too large).

Inverted Index Ops

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Problem remaining: $s(q, r)$ isn't a simple boolean of sets.
Induced Machine Learning Problem: How do you reformat/canonicalize queries so they pull up the right results?

Method 3: Weighted AND (WAND)

A generalization of an inverted index.

WAND $= \sum_i w_i I_i \geq \theta$ where $w_i > 0, \theta > 0$ and $I_i = 1$ if a term is present and 0 otherwise.

A WAND query can be evaluated efficiently by a clever algorithm using upper bounds and monotonicity.

The ML perspective: Closer to a learned rule, but still quite limited.

Method 4: Locality Sensitive Hashing

Precompute b random vectors $z_1, ..., z_b$
Represent each item with a vector x.
Compute a b-bit hash for each item where bit i satisfies $h_i(x) = I(x \cdot z_i > 0)$.
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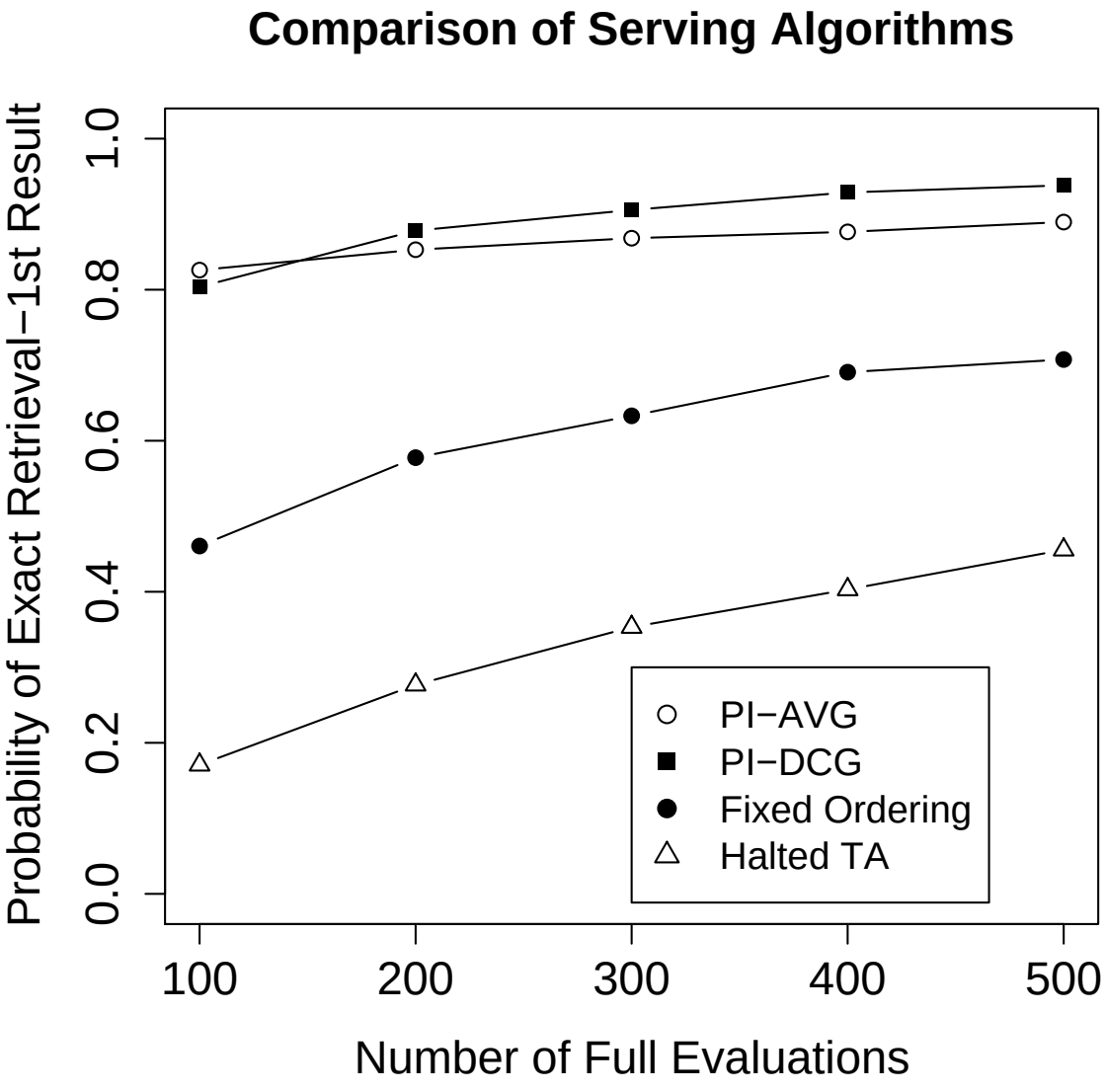
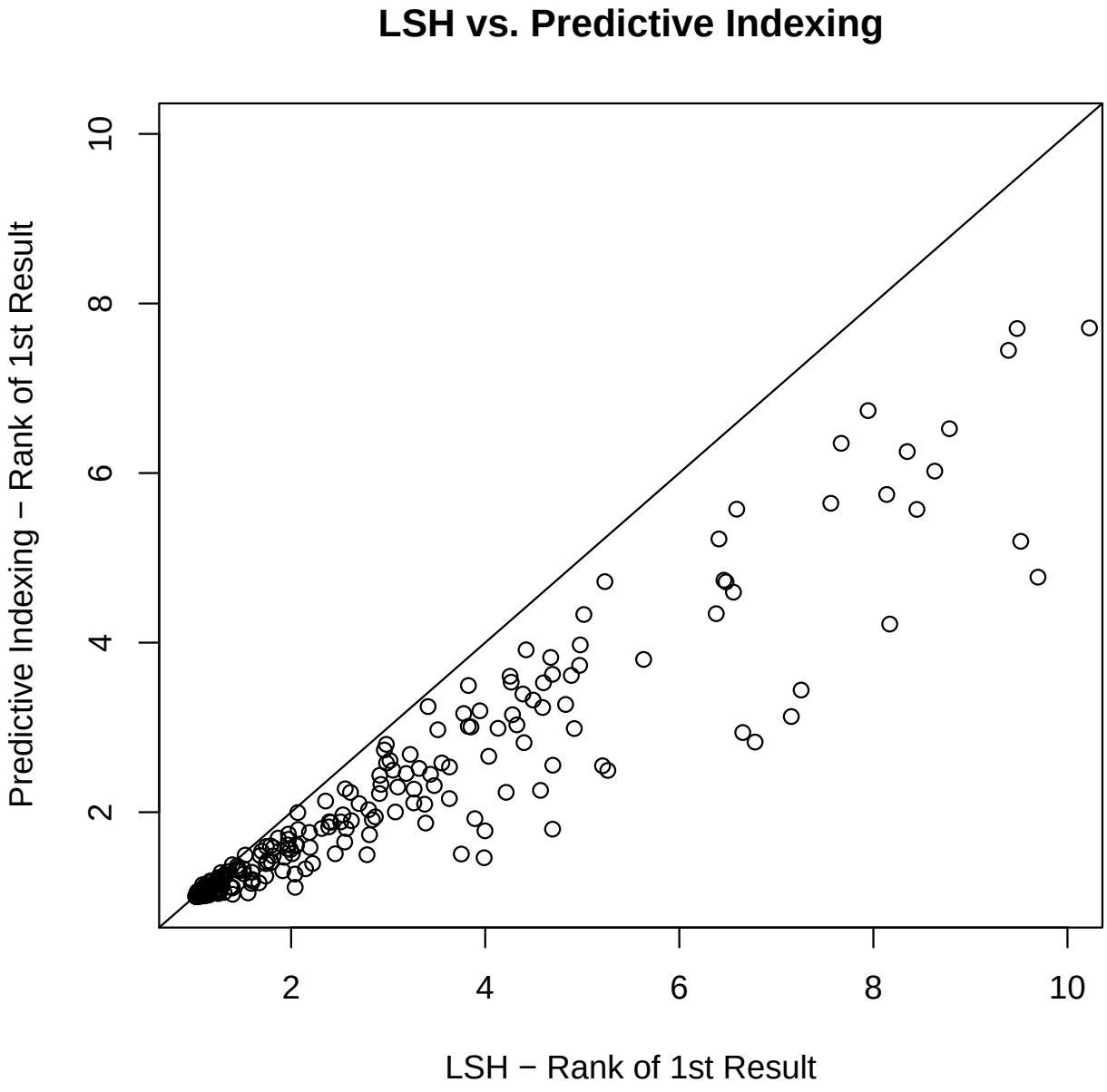
The ML perspective: scoring directly drives datastructure (good!). Still imperfect—you would prefer the learning algorithm directly learns how to return results efficiently.

Predictive Indexing for an Ad problem



Halted TA = ordering by per-feature score in a linear predictor.



Averaged over many datasets with same random projections used for each.

State of Indexing

Computational efficiency is key here—this is a primary hardware cost.

1. New algorithms can make a big $ difference.
2. Efficient implementations win! FPGAs are tempting.
3. The transition from indexing to scoring is often messy.
4. Data-dependent datastructures are a key improvement.
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What is an algorithmically clean and coherent way to learn to index and score simultaneously?

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