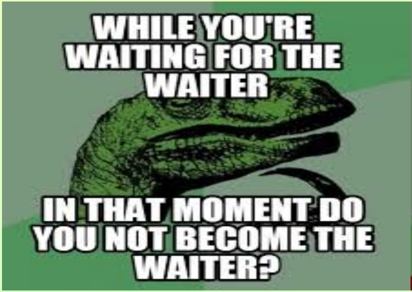
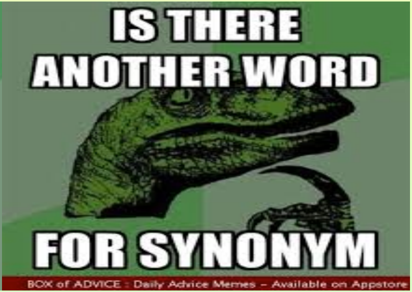
Fast Detection of Near Duplicates

Sambuddha Roy, LinkedIn

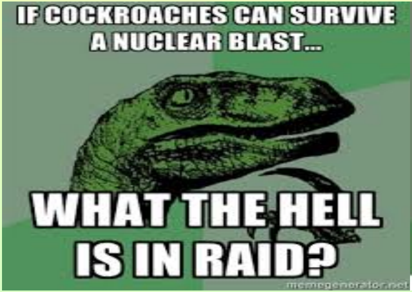
March 16, 2016

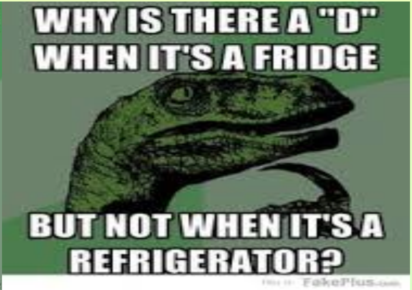
Motivation.


WHILE YOU'RE WAITING FOR THE WAITER
IN THAT MOMENT DO YOU NOT BECOME THE WAITER?


IS THERE ANOTHER WORD
FOR SYNONYM
BOX of ADVICE : Daily Advice Memes – Available on Appstore

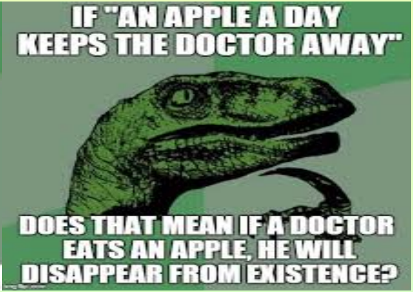
and some more...





and more...


IF TIME IS MONEY...
ARE ATM'S TIME MACHINES?
ohgag.info


IF "AN APPLE A DAY KEEPS THE DOCTOR AWAY"
DOES THAT MEAN IF A DOCTOR EATS AN APPLE, HE WILL DISAPPEAR FROM EXISTENCE?

The duplicate detection problem.

- Why are duplicates problematic?

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  - Someone copies the cat video that *you* uploaded!

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- Youtube had multiple copies of each video!
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- Duplicate content confuses search engines.
  - What happens to the pageRank of the page?

How do you catch duplicates?

- Some form of hashing...
- Different items go to different hashes (collision resistant).
- Group by hashes - each group corresponds to a distinct element.

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- Identity theft!

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- Identity theft!
- Other use cases: plagiarism, etc.

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- ...and a query q arrives.
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- Often, we just want the k nearest neighbors (k-NN problem).

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- So, similarity measures between objects/items...
- i.e. *featurize* items as vectors $\in \mathbb{R}^n$ or in $\{0, 1\}^n$.
- And consider some distance/similarity measure between these vectors.

Typical Distance/Similarity Measures

- Jaccard similarity: $J(A, B) = \frac{|A \cap B|}{|A \cup B|}$

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- Hamming Distance
- ℓ_p for $p \in (0, 2]$.
- Tanimoto distance, Mahalanobis distance, etc.
- It's typical to relate the distance and similarity measures as $\mathrm{dist}(a, b) = 1 - \mathrm{sim}(a, b)$.

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- A search by pairwise comparisons between q and all the items in the database may become too costly.

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- (Aside: what does this even mean? It may be for a threshold τ and points a, b, c that $\mathrm{dist}(a, b) \leqslant \kappa$ and $\mathrm{dist}(b, c) \leqslant \kappa$ but $\mathrm{dist}(a, c) > \kappa$ i.e. similarity is not “transitive”).

Similarity is not transitive

- A more meaningful formulation can be: we want all *pairs* of items a, b such that $\mathrm{sim}(a, b) \geqslant \tau$ for some $\tau \in [0, 1]$ (sufficiently similar items).

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- If we make $\tau = 0$ we are asking for all of the $\binom{n}{2}$ pairs of items (for n items in the database).
- Imagine if the number of items n were 1 million... 1 billion...!

Alternate Formulation/Relaxations

- We really do not want all pairs for the similarity threshold, τ really small; in fact, typical use-cases will consider $\tau > 0.8$ or so (sufficiently similar).
- Let's also relax the all in the above too; replace that by most.

Refining what we want

- Find near-duplicates of query items.
- Some mistakes will be allowed (both false positives, false negatives).
- Time! Querying should be fast. The clustering variant should take $O(n)$ time instead of $O(n^2)$.

Hashing to the rescue

- Can we hash items so that “nearby” items are in same hash-buckets?
- Note that this is counter to the usual notion of hashing, where collisions are taboo.
- Here, we would like collisions - but only between *nearby* items.

Enter LSH

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  - Introduced min-wise permutations.
  - LSH for Jaccard similarity.
- SimHash - by Charikar, 2002.
  - Demonstrated connections between randomized rounding and LSH
  - LSH for cosine similarity (angular distance).

Formal Definition

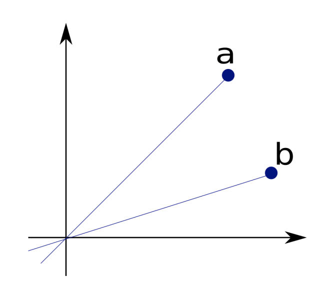
- A family of hash functions $\mathcal{F}$ is a LSH if for *any* x, y the following holds:

$$\mathsf{Pr}_{h\in\mathcal{F}}\left[h(x) = h(y)\right] = \mathrm{sim}(x, y)$$

  where $\mathrm{sim}(x, y)$ is a similarity measure.
- Read as: items that are “highly” similar land in the same hash-bucket with “high” probability, and items that are dissimilar land in the same hash bucket with “low” probability.

LSH *for angular distance*

- Given two vectors a, b, construct a hash function that maps these to the same bucket if the angle θ between them is *small*.
- Idea: use a random hyperplane (random projection).



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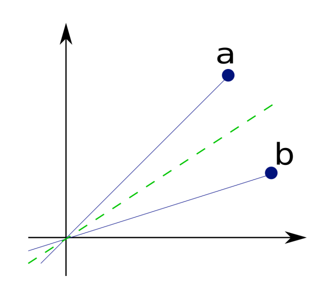

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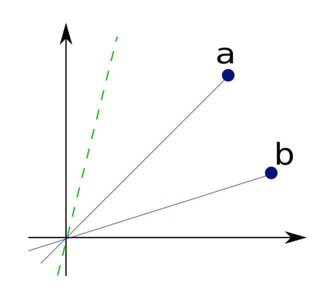
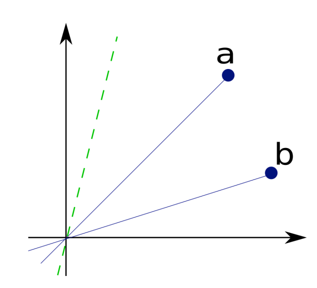


LSH *for angular distance*

- This random hyperplane is a hash function $h : \mathbb{R}^n \rightarrow \{0, 1\}$.
- It maps a vector v to $\{0, 1\}$, depending on whether the vector v is to the top/bottom of the hyperplane (essentially, checking for the sign of the inner product).

Probability calculation

- Probability that vectors a, b map to the same output, i.e. $\Pr[h(a) = h(b)]$?



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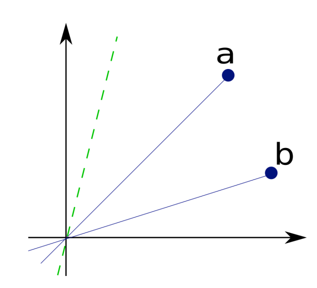

- If θ be the angle between a, b, then this equals $\left[1 - \frac{\theta}{\pi}\right]$.

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- With a single hash function *h*, the precision may be quite low; the recall quite high.
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- With a single hash function h, the precision may be quite low; the recall quite high.
- Just one hash may not be able to detect vectors that are indeed close by. So...
- Several (independent) copies of the hash function h; call these $h_1, h_2, \cdots, h_k$.

Precision? Recall?

- With k hash functions, we have a k-bit binary string, corresponding to a vector v.
- Call this the *hashcode* corresponding to the vector v (denoted as $\mathrm{hashcode}(v)$).
- For two vectors a, b: if $\mathrm{hashcode}(a) = \mathrm{hashcode}(b)$ bit-by-bit, then surely a and b are close.

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- This would help in improving precision. But recall may suffer.

Precision? Recall? Two extremes

- Given the hashcodes of the vectors, we can ask for a full bit-by-bit match to declare near duplicates. High precision, low recall.
- Given the hashcodes, we can ask for a *single* bit match to declare near duplicates. High recall, low precision.

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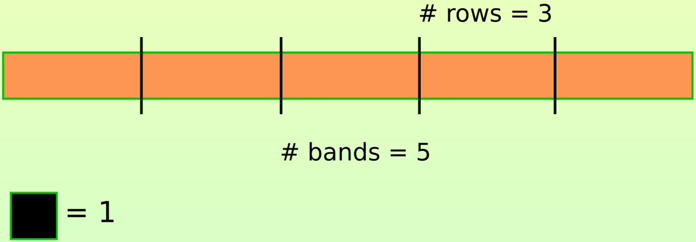
- Given the hashcodes, we can ask for a *single* bit match to declare near duplicates. High recall, low precision.
- Mix the two: Banding. In the parlance of complexity theory, gap amplification.

Banding

- An example with $k = 15$ hashes, where $\mathrm{rows} = 3$ and $\mathrm{bands} = 5$.



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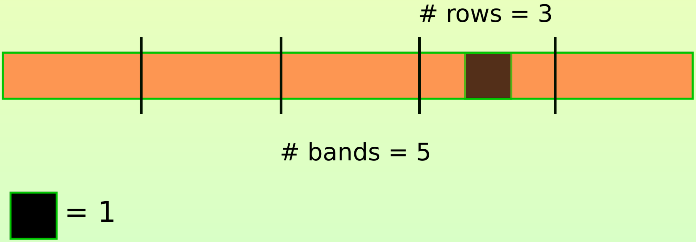

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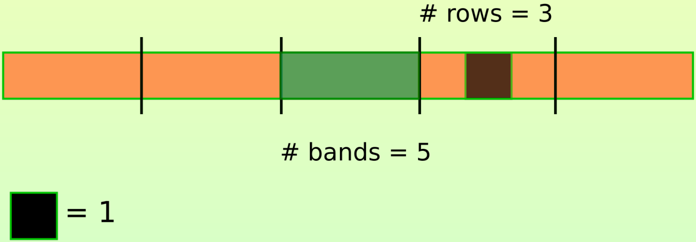
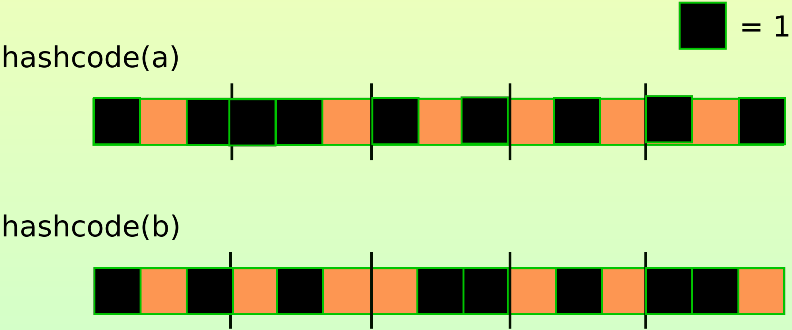


Are a and b near-duplicates?

- We show the hashcode's for *a* and *b*:



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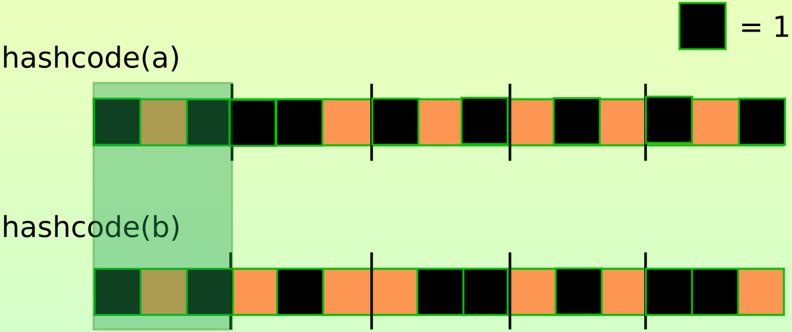

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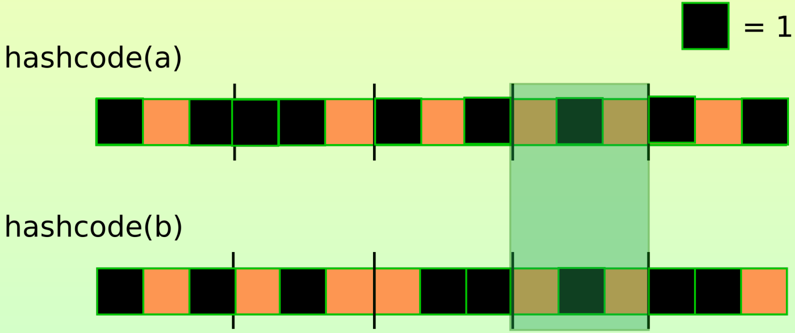

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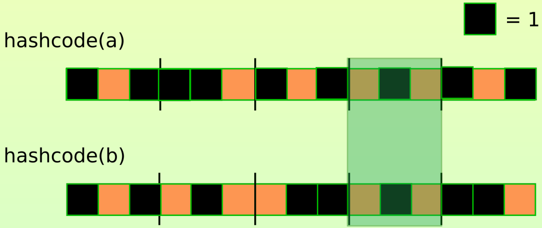

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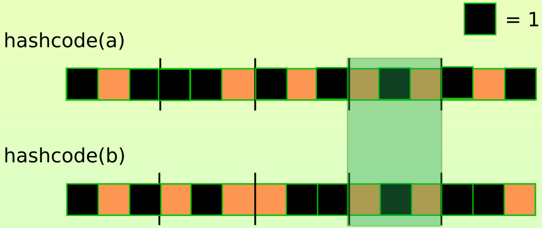

- To increase precision, increase the number of rows. To increase recall, increase number of bands.

Still a flourishing/active area of research

- Various considerations:
  - Engineering aspects: hash table construction time, query times, etc.
  - Engineering aspects: Maintain hashbuckets, update hashes. Bloom filters for hash buckets, etc.
  - How much randomness do I need?
  - How do I improve recall while maintaining precision.
  - Deep Hashing techniques?
  - Which similarity measures work best for different content: text, images, video.

Still a flourishing/active area of research

- Improve *recall* of LSH
  - covering LSH (only for Hamming space), (Pham-Pagh16)
  - other similarity measures wide open.
- Develop LSH's for other similarity measures.
  - Inner product (Neyshabur-Srebro15, Li-Shrivastava14)
  - Also gave rise to Assymetric LSH.
- Improve training and query times based on data:
  - Data Dependent Hashing (Andoni-Razenshteyn15)
  - Learning to hash

LinkedIn's interest in finding near-duplicates

- Do we like memes on our LinkedIn page? Puzzles?

- Spam Filtering: spammers often use the same text repeatedly to *spam* members.

Thank You!

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Questions?

Formal definition of LSH

- A hash is said to be a (S, cS, p_1, p_2)-LSH for a similarity function sim over the space $\mathcal{X}$ if for any $x, y \in \mathcal{X}$:
  - if $\mathrm{sim}(x, y) \geqslant S$ then $\Pr[h(x) = h(y)] \geqslant p_1$.
  - if $\mathrm{sim}(x, y) \leqslant cS$ then $\Pr[h(x) = h(y)] \leqslant p_2$.

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- Read as: items that are "highly" similar land in the same hash-bucket with "high" probability, and items that are dissimilar land in the same hash bucket with "low" probability.
- Ideally we want: $p_1 = 1$, and $p_2 = 0$. These probabilities "mirror" the similarity function $\mathrm{sim}(\cdot, \cdot)$.