High load RecSys

Vladislav Goncharenko

Materials by Vadim Kokhtev

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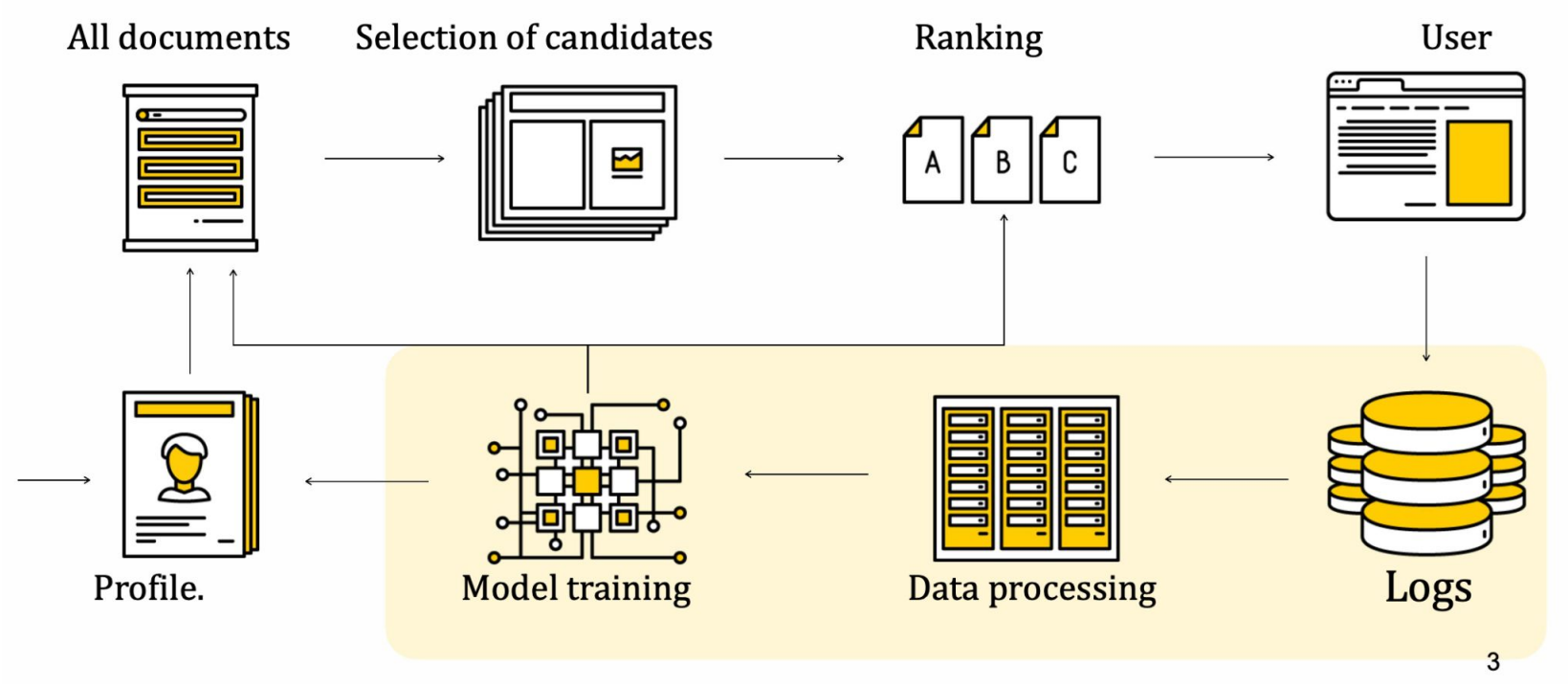
Typical service

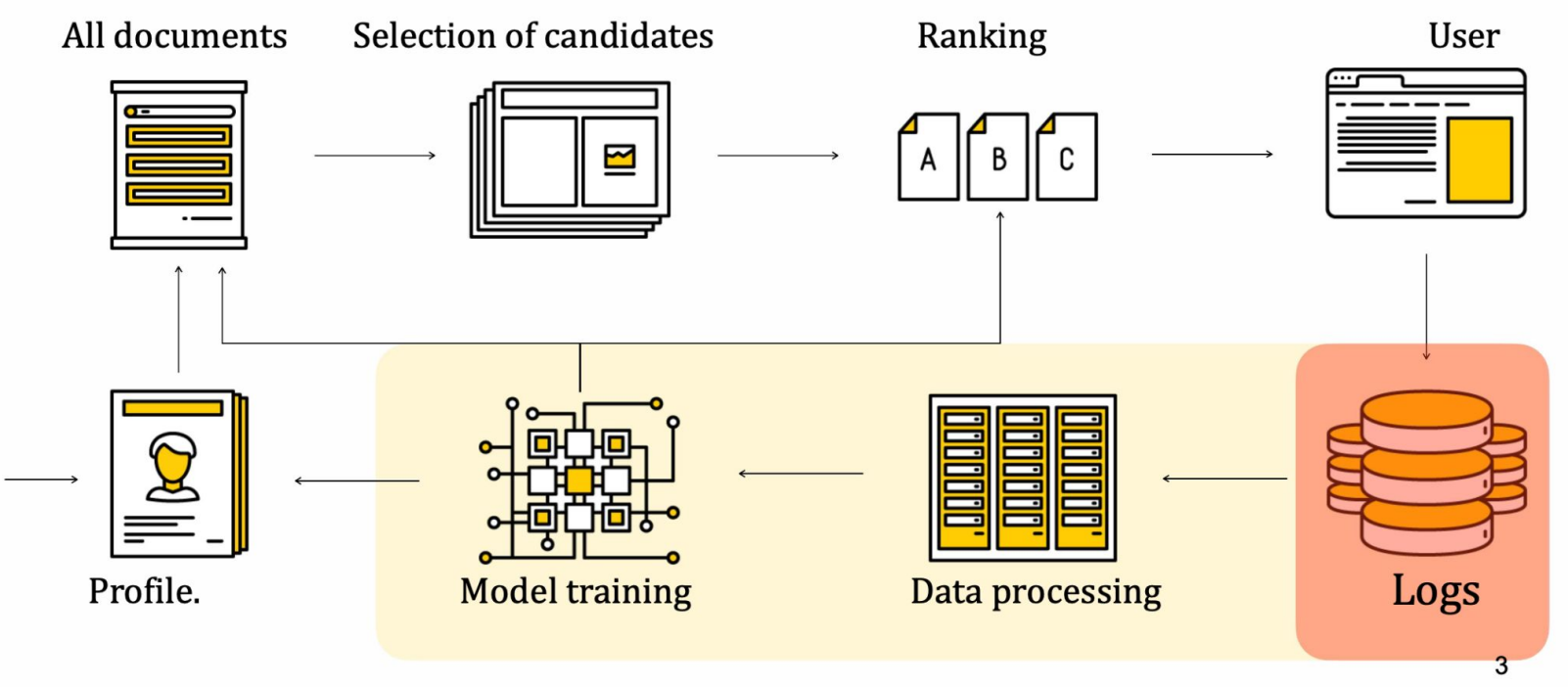
- 10^7 documents
- 10^6 users per day
- 1-10k requests per second (RPS) for recommendations

What could possibly go wrong? 😅

The real system



Logging


All documents
Selection of candidates
Ranking
User
A
B
C
Profile.
Model training
Data processing
Logs

Logging

- To train algorithms, information about user actions is stored in a structured form
- At a minimum, you will need a bundle of "user-item-rating-timestamp"
- Logs should be stored forever because this is unique information about your users

_version	String *optional*
client_info	**Struct** *optional* client_type : String client_version : String
event_id	String *optional*
event_type	String *optional*

Data processing

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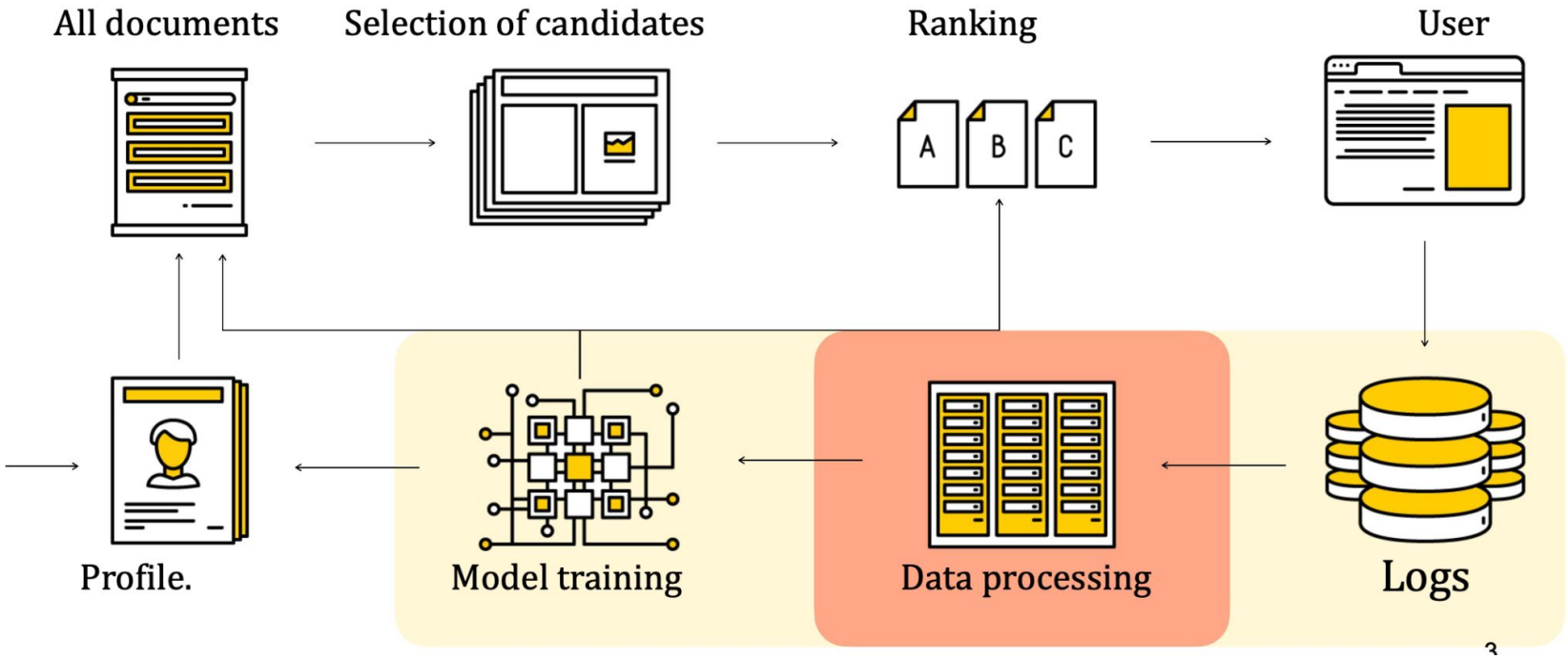
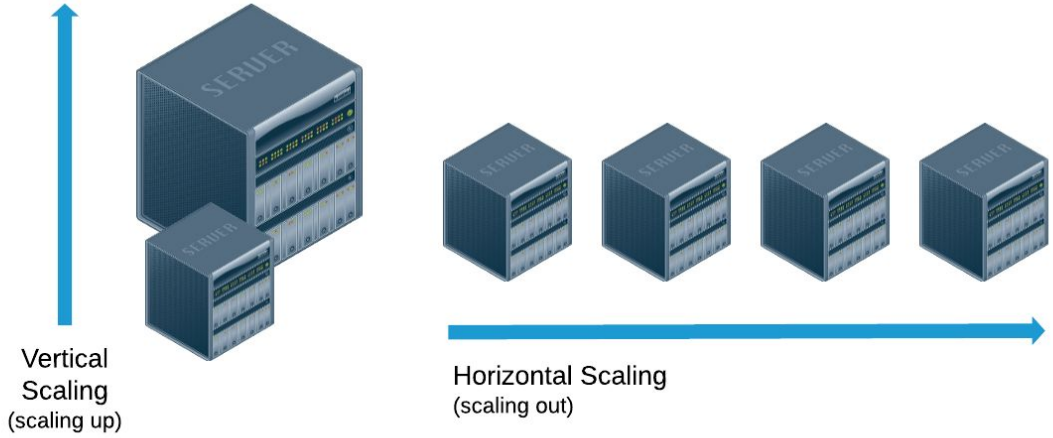
01

Data processing



Scalability

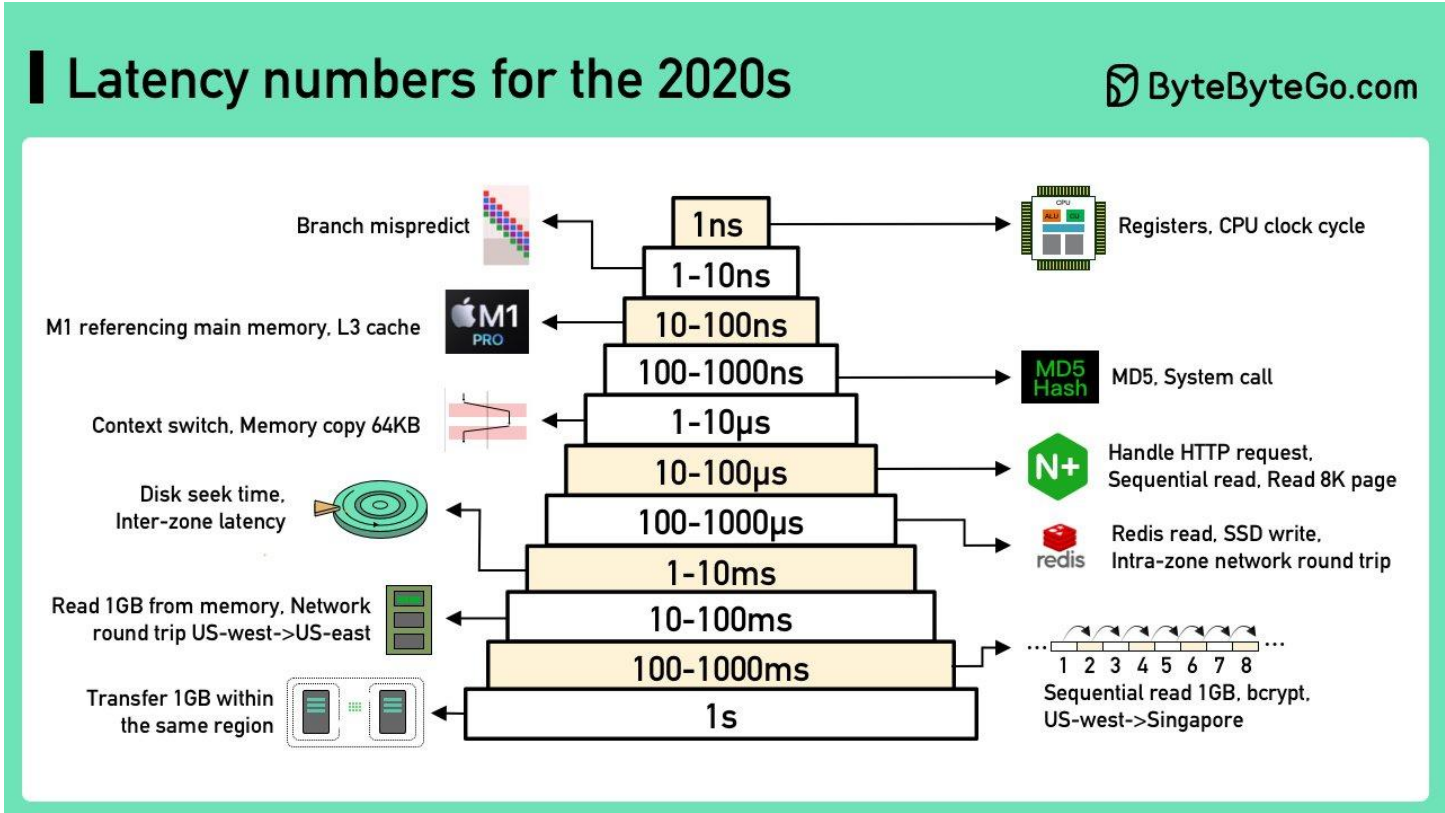
- When there was less data and they were more structured, they could be put into a relational database, having thought out the data schema and a list of possible queries to them in advance
- To speed up processing, we need a more powerful server - **vertical scalability**
- In the MapReduce paradigm, more average servers are needed to speed up processing (**horizontal scalability**), which is much cheaper



Data Locality

Ulrich Drepper, What every programmer should know about memory (2007)

Stackoverflow discussion



Data Locality

- Blocks of a huge file are stored on different machines
- We can process blocks locally on the machines where they are stored
  (fast read from local disk)
- If it is possible to process blocks independently in the task, then it is possible to achieve ideal scalability (embarrassingly parallel)
- For example, the task of filtering file lines scales perfectly. All lines are independently checked by the predicate, the more machines, the faster it will work

MapReduce

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Word frequencies counting problem

Texts from all over the Internet are stored in a distributed system.

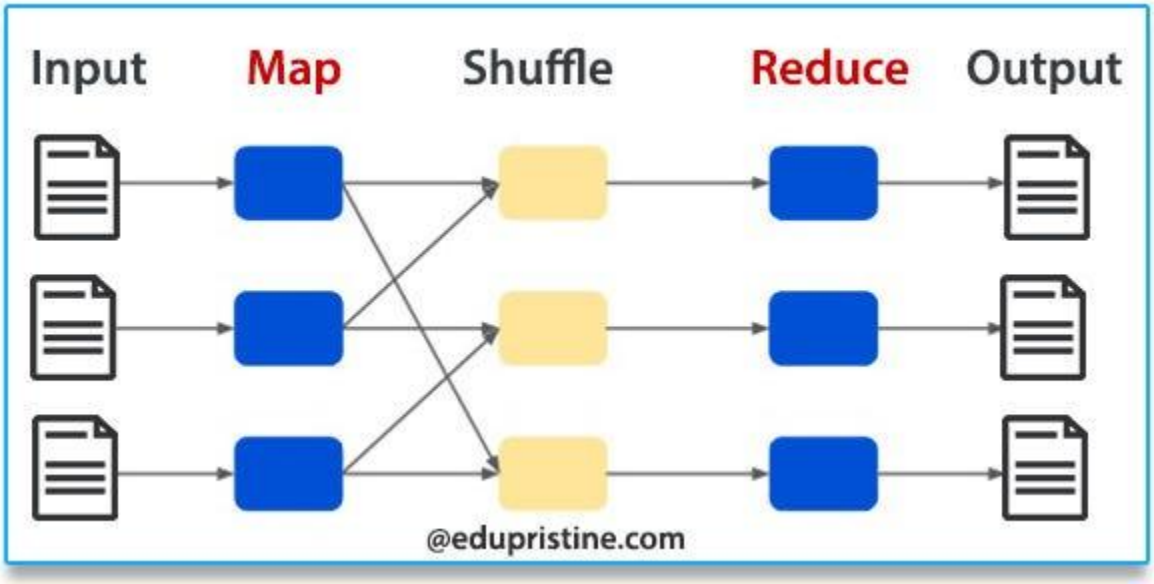
We are interested to know the frequencies of all words (counters for tf-idf).

Solution is MapReduce paradigm

How to solve:

- for each block, we calculate the frequency of words in it (ideally scaled)
- add up the frequencies for all blocks

MapReduce main idea



MapReduce solution

Map:

(K1, V1) ⇨ List(K2, V2)

(line number, “cat sleeps”) ⇨ [(“cat”, 1), (“sleep”, 1)]

Shuffle:

Keys are splitted by **hash(key) % N** on **N** parts

Each parts gets sorted by **key** (independently)

Reduce:

(K2, List(V2)) ⇨ List(K3, V3)

(“cat”, (1, 1, 1)) ⇨ [(“cat”, 3)]

Reliability of operations

- If the mapper is lost, we can restart the task only for its blocks
- If the reducer is lost, we re-collect data from all mappers only for its hash value

Popular track example

UserId	TrackId	AlbumId
11123	4521	842
14322	3593	957
...	...	...

Map: (K1, V1) ⇨ List(K2, V2)

Reduce: (K2, List(V2)) ⇨ List(K3, V3)

Let's take the logs of listening to music.
How do we find the most popular track for each album?

M: #, (user, track, album) ⇨ (album, track), 1

R: (album, track), (1,1,…) ⇨ (album, track), count

M: (album, track), count ⇨ album, (track, count)

R: album, tracks ⇨ album, most popular track

Example:
Item-based CF concurrency

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Example: Item-based CF concurrency

- ***n*** users, ***m*** items, ***n*** ~ 10^6, m ~ 10^7
- It is necessary to calculate in advance the Item-Item similarity

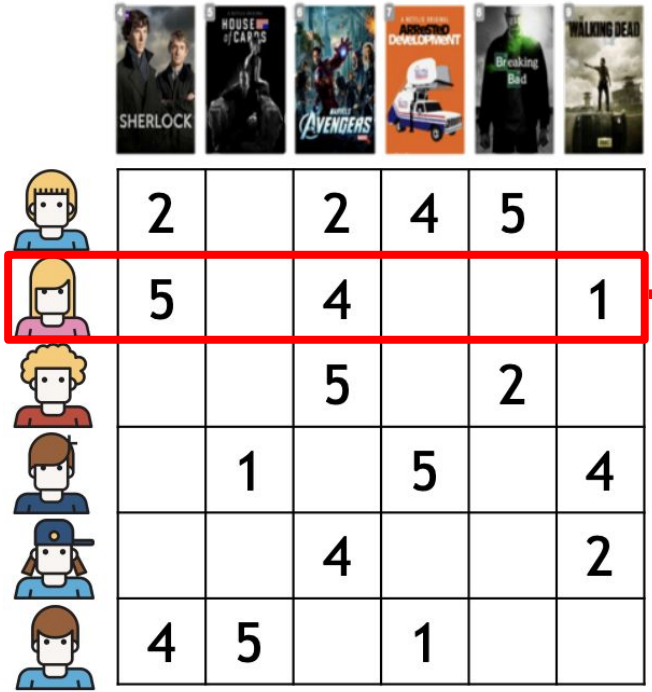
$$s(i,\ j) = \frac{\sum_{u \in U} (r_{ui} - r_u)(r_{uj} - r_u)}{\sqrt{\sum_{u \in U} (r_{ui} - r_u)^2} \sqrt{\sum_{u \in U} (r_{uj} - r_u)^2}}$$

adjusted cosine similarity

- Naive approach – ***O(m²n)***
- The evaluation matrix is very sparse, can it be better?
- The contribution to the similarity of the two products is non-zero only from users who rated both of these products

Inverted index

Update the calculations once a day using the inverted index



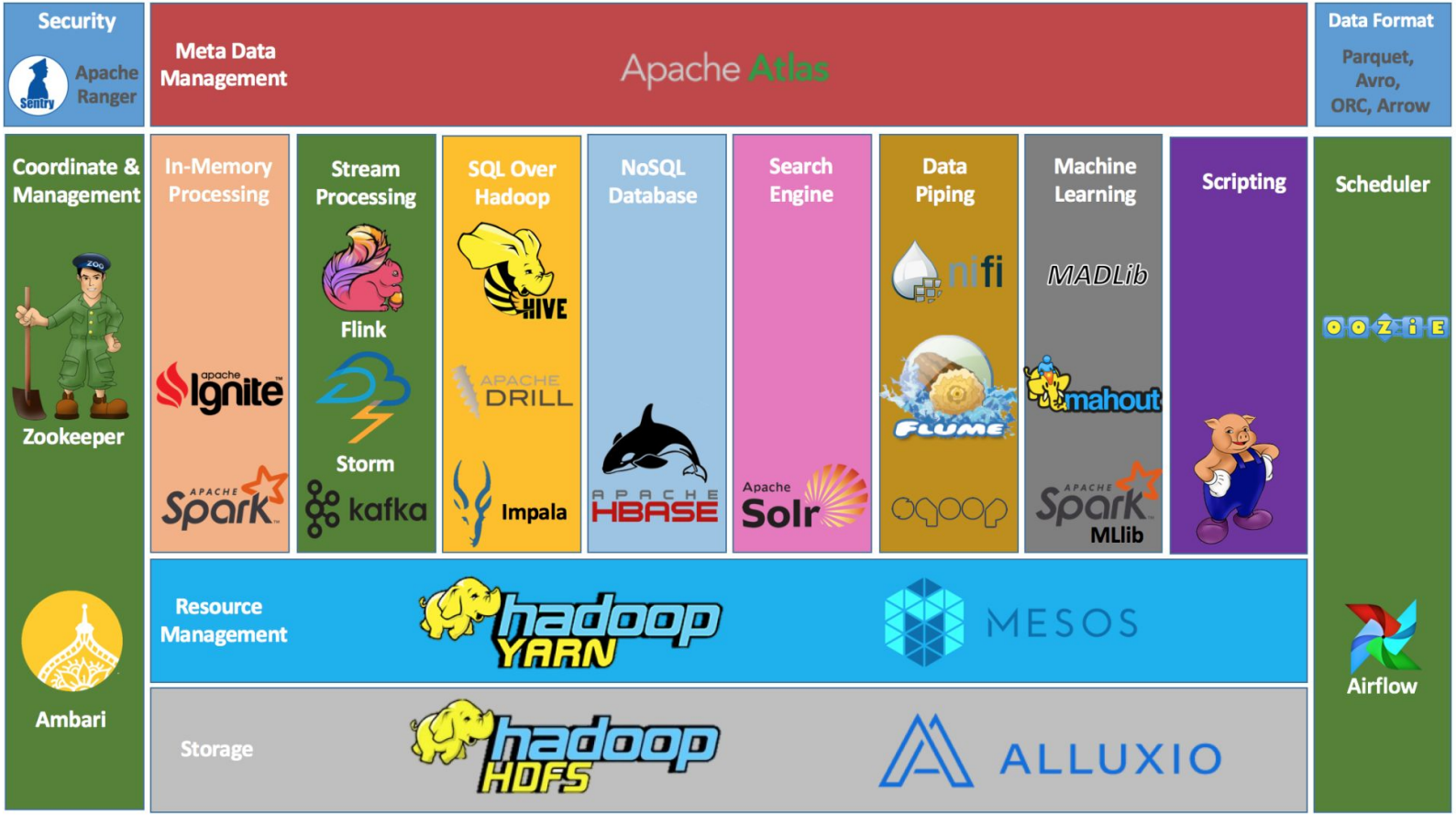
$$s(i,\ j) = \frac{\sum_{u \in U} (r_{ui} - r_u)(r_{uj} - r_u)}{\dots}$$

Map step:

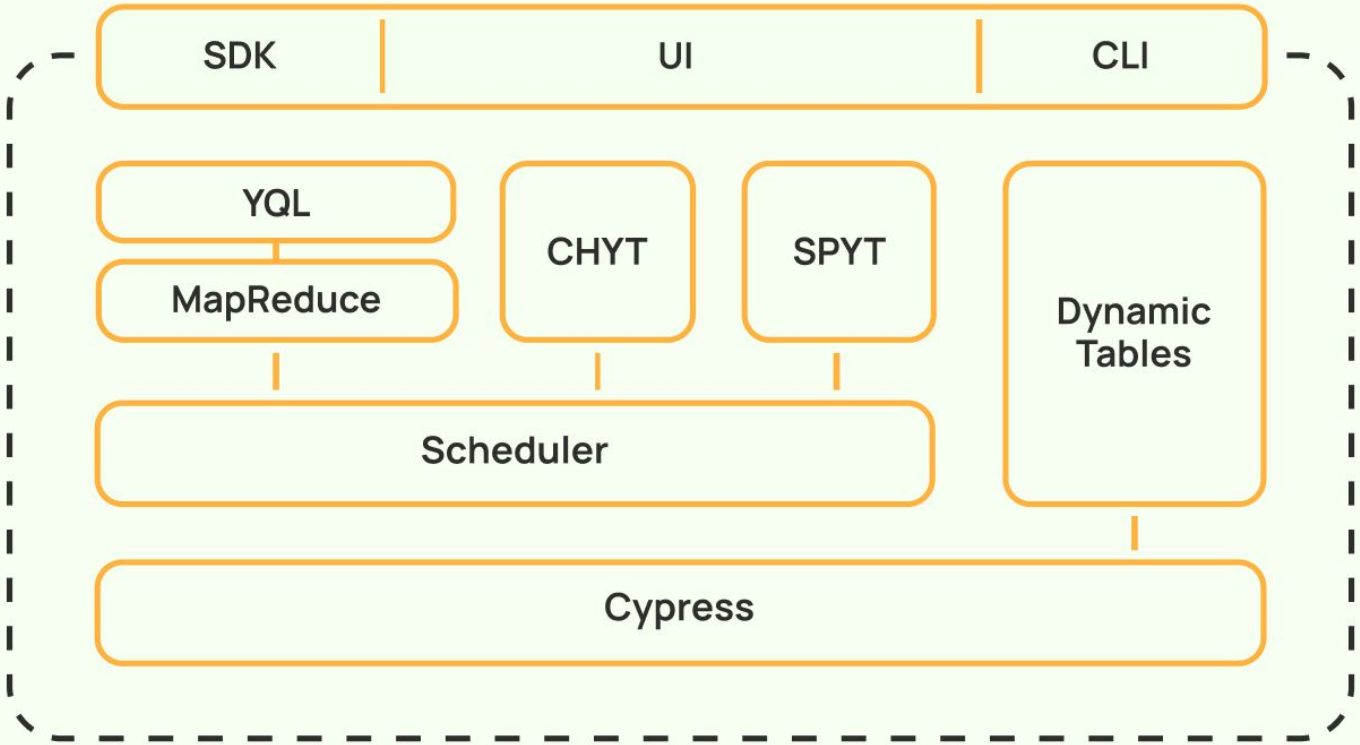
(1, 3) -> (5 - 3.3) * (4 - 3.3)
(1, 6) -> (5 - 3.3) * (1 - 3.3)
(3, 6) -> (4 - 3.3) * (1 - 3.3)

Reduce step: summing up by the key

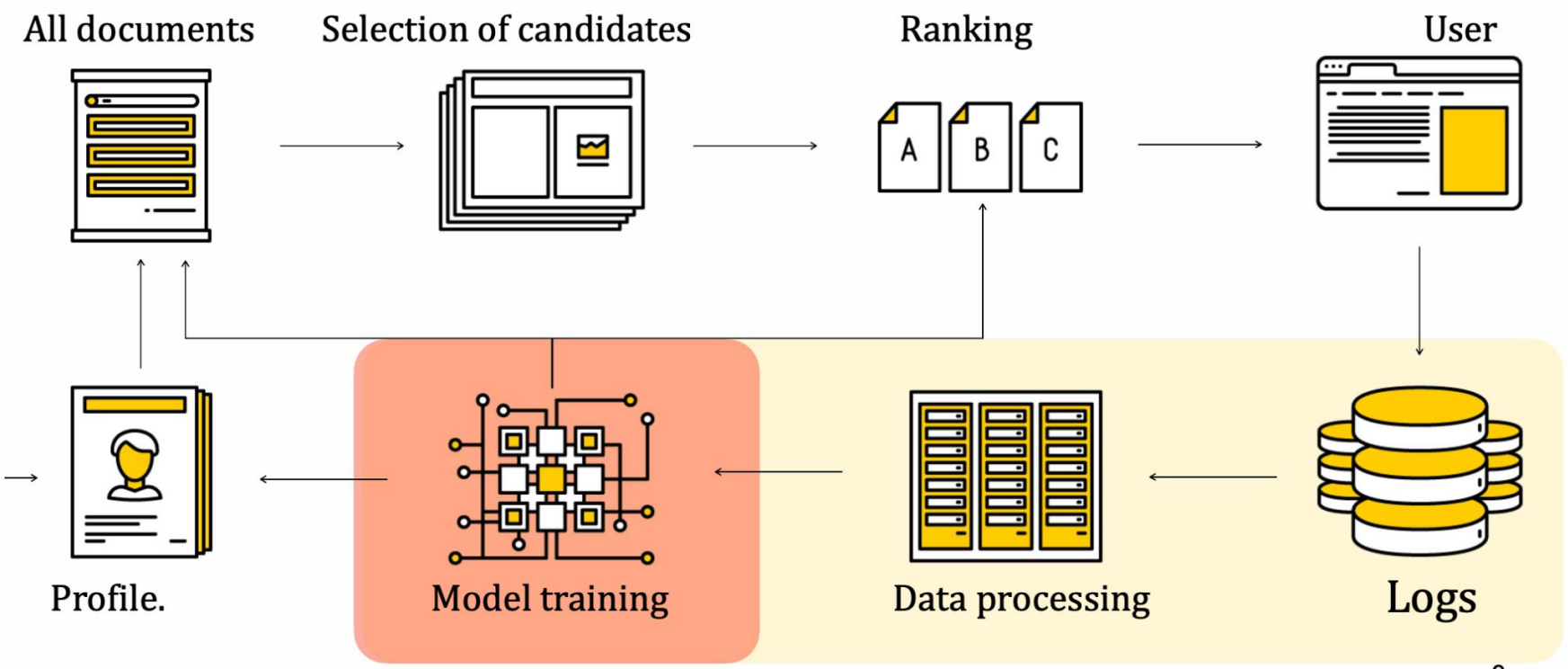
Hadoop: open source MapReduce



YTsaurus: one more MapReduce



Model training



Alternating Least Squares (ALS)

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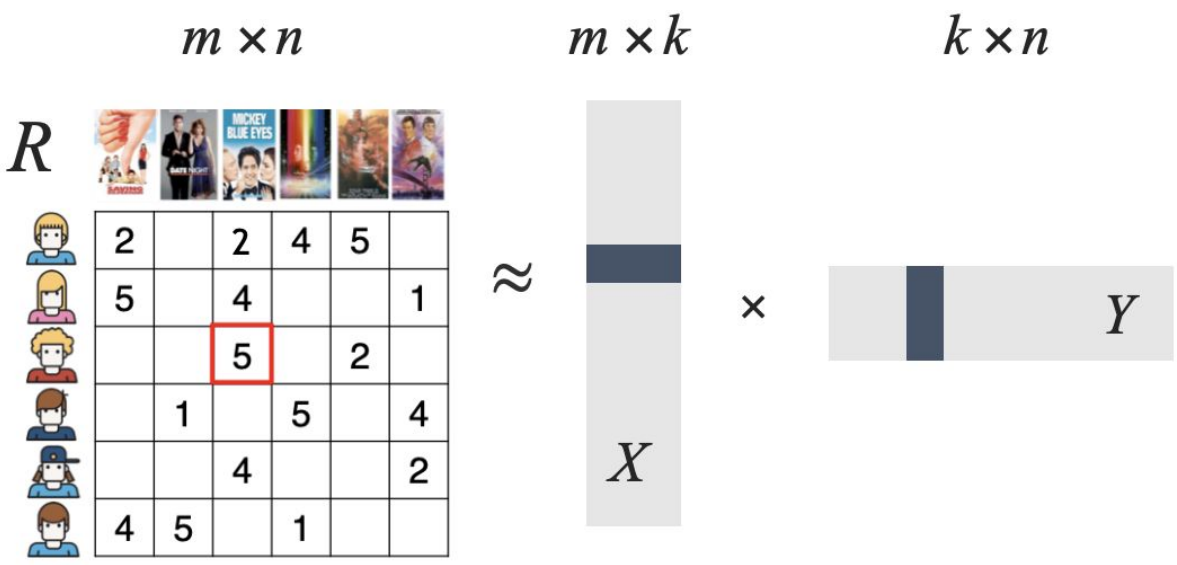
04

Alternating Least Squares (ALS)



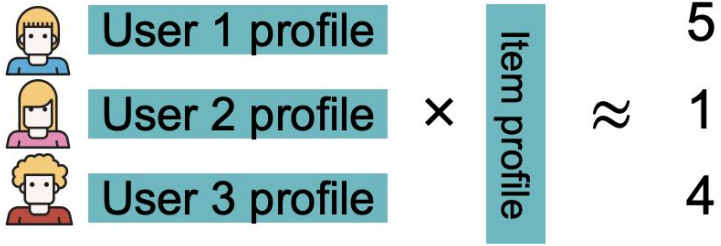
$$\min_{X,\,Y} \sum_{(u,\,i)\in R} \left(r_{ui} - x_u^T y_i\right)^2 + \lambda\left(\|x_u\|^2 + \|y_i\|^2\right)$$

Alternating Least Squares (ALS)

Initialize X and Y with random values

In the loop:

- We fix the matrix Y (products)
- Find the optimal matrix X (solve the ridge regression for each user)



$$\min_{X,Y} \sum_{(u,i)\in R} \left(r_{ui} - x_u^T y_i\right)^2 + \lambda\left(\|x_u\|^2 + \|y_i\|^2\right)$$

$$x_u = \left(\sum_{r_{ui}\in r_{u*}} y_i y_i^T + \lambda I_k\right)^{-1} \sum_{r_{ui}\in r_{u*}} r_{ui} y_i$$

- and vice versa

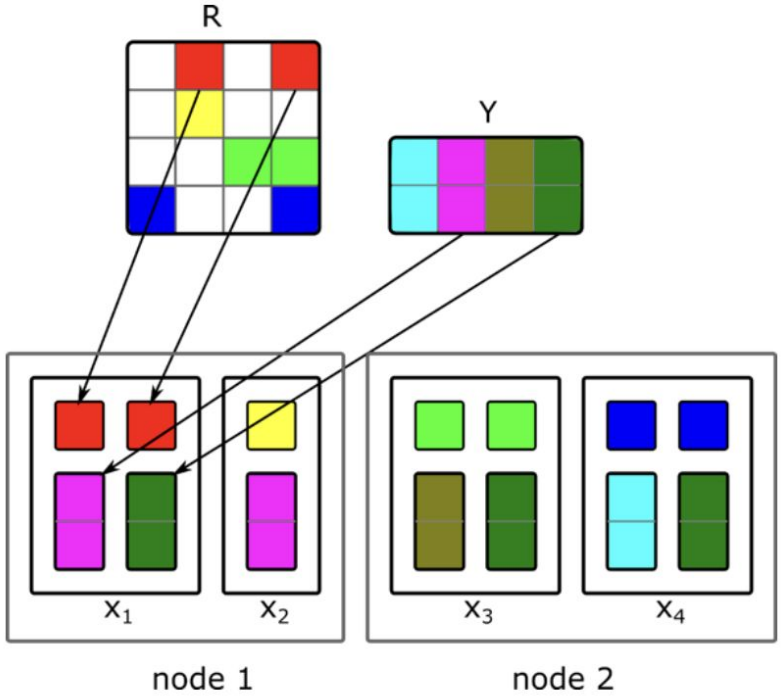
Naive Parallel ALS

- R = X@Y, update X

  Join R and Y by product → $(u,\ r_{ui},\ y_i)$

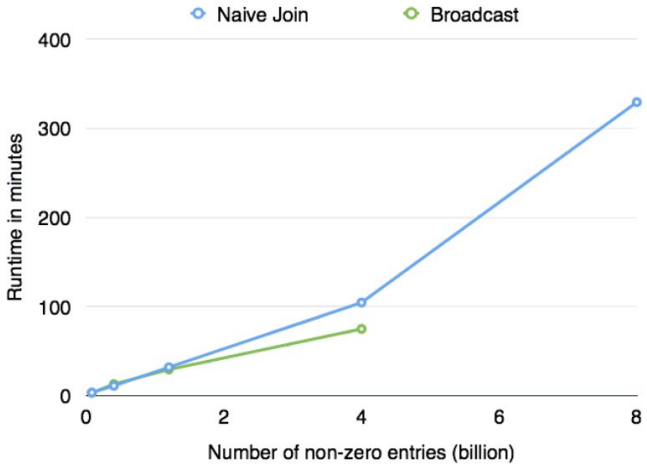
  Grouping by u

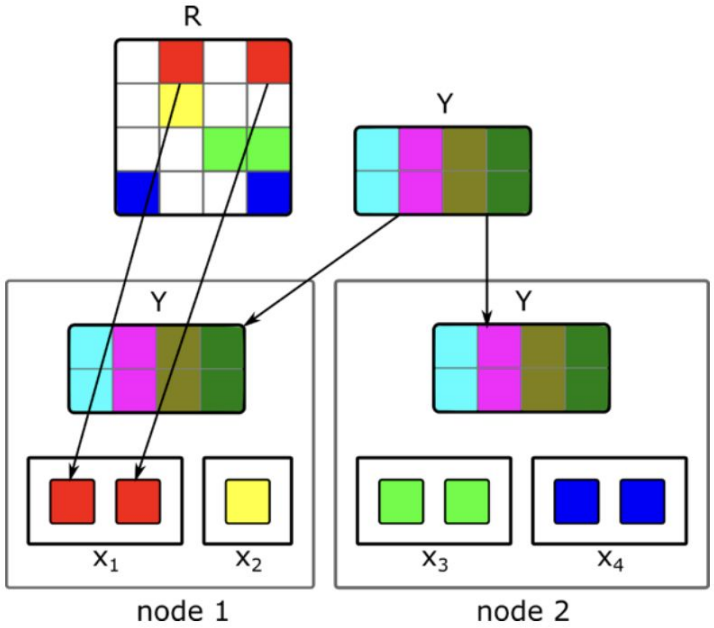
  On each machine we recalculate x_u
- The same vector y_i may be needed by several users on the machine, and will be sent several times



Implementation with broadcast Y

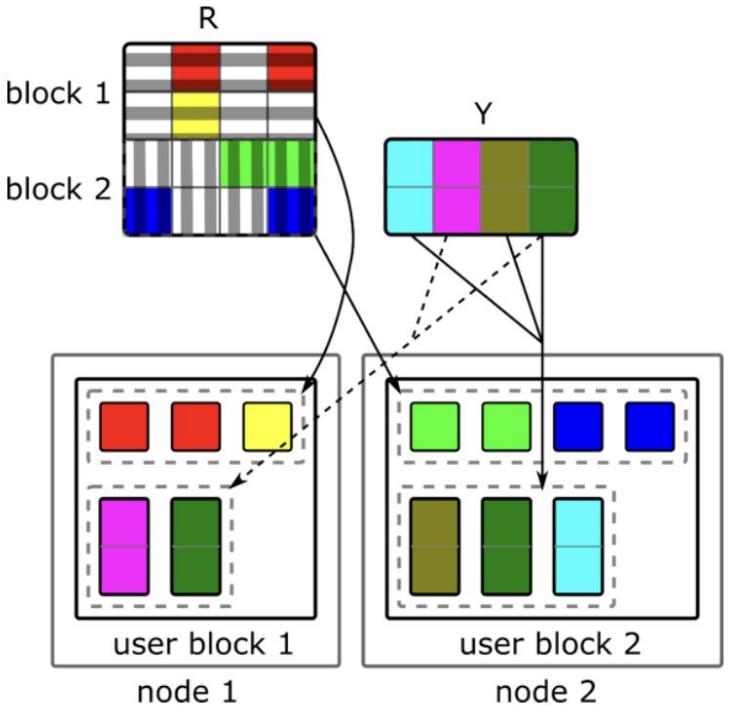
- Faster
- Has a scaling limit (Y must fit into memory)





Block ALS

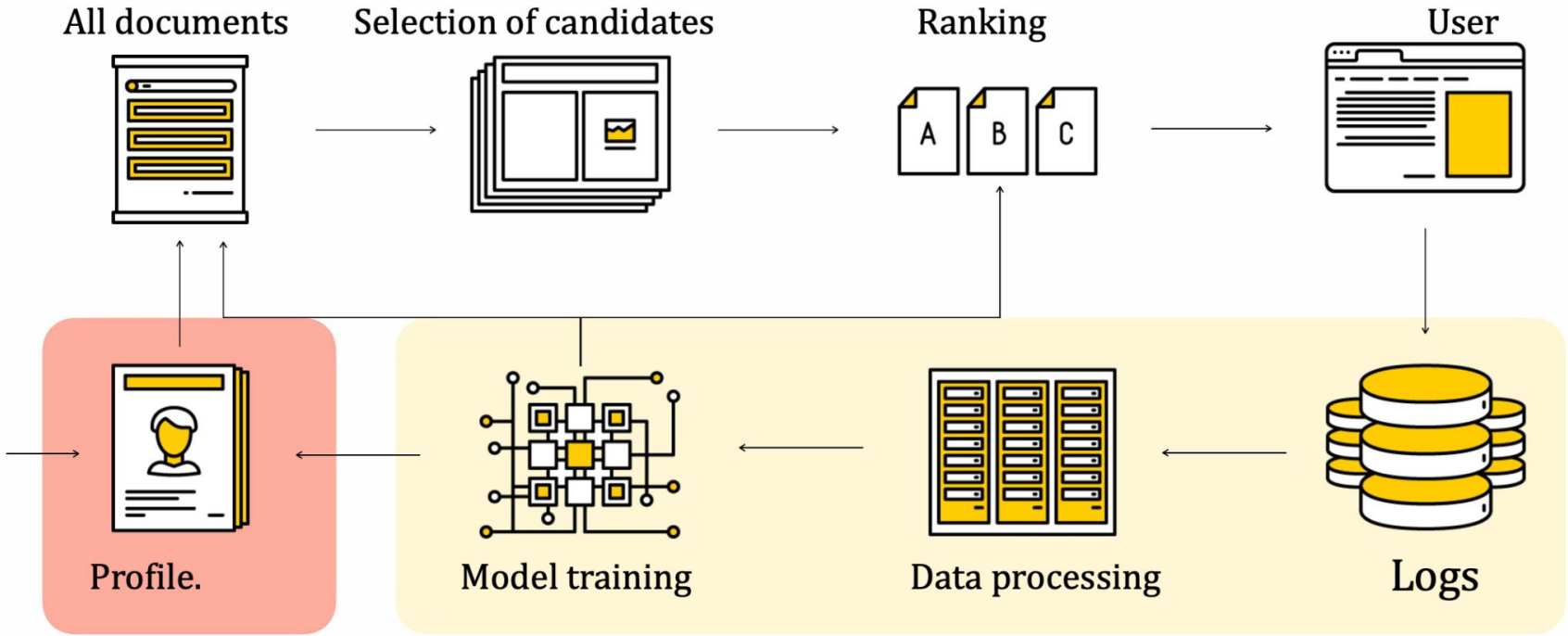
- Implemented in Spark ML
- Users are fighting for blocks, each block is processed on its own machine
- We calculate once what goods will be needed in each block (mapping is stored in memory)
- Only the necessary parts of the matrices in the machine memory are sent



Caching during training

- Recalculate statistics (but not models) of only updating users and objects
- We save the results of third-party services that are difficult to calculate

User Profile



Fast data storage

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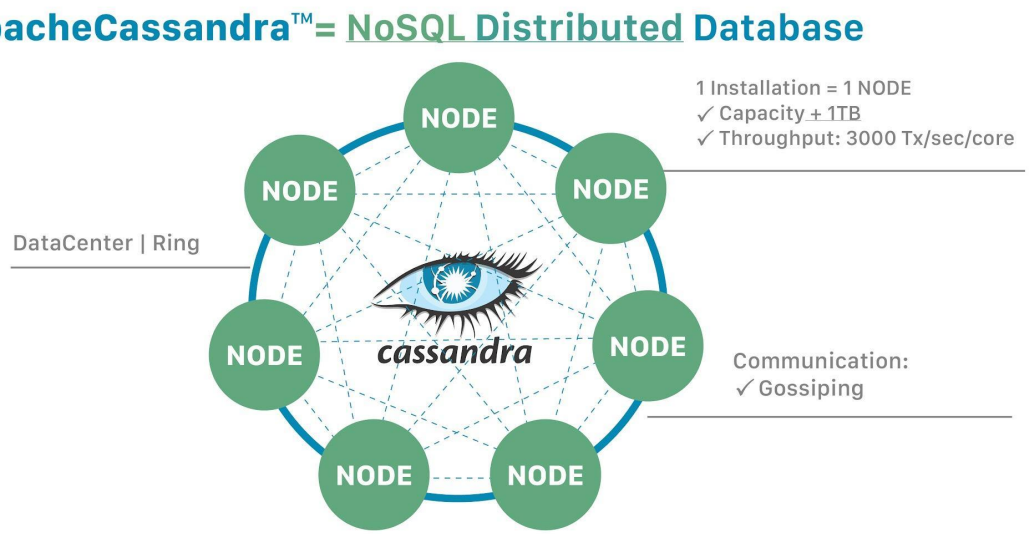
Fast data storage

Key-value

- Reading and writing for O(1)
- Eventual consistency

Examples:

- Apache Cassandra
- Amazon DynamoDB
- Redis

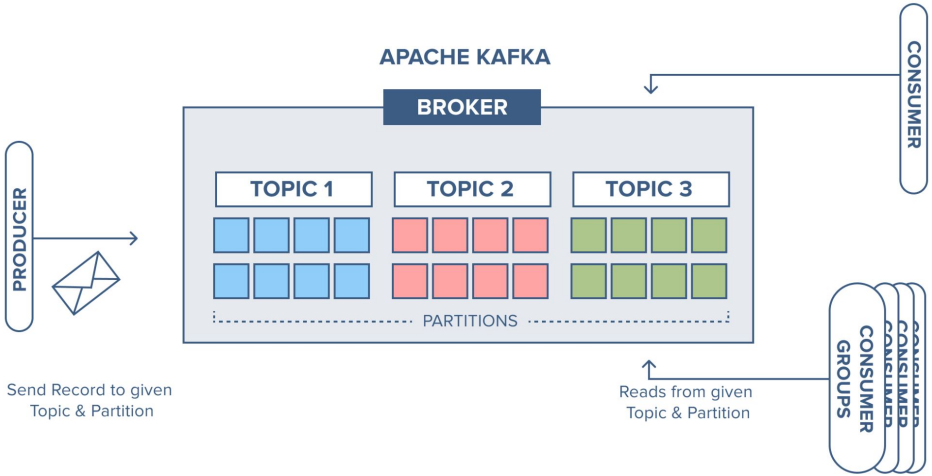


Near-realtime event handling

- We want to update user data as quickly as possible
- We update statistics, model results on the fly, reading updates from event queues

Example: writing user actions in Kafka

1. collect the user profile from the Key-Value response and events from Kafka
2. process statistics and do the ALS step every N minutes



Document storage

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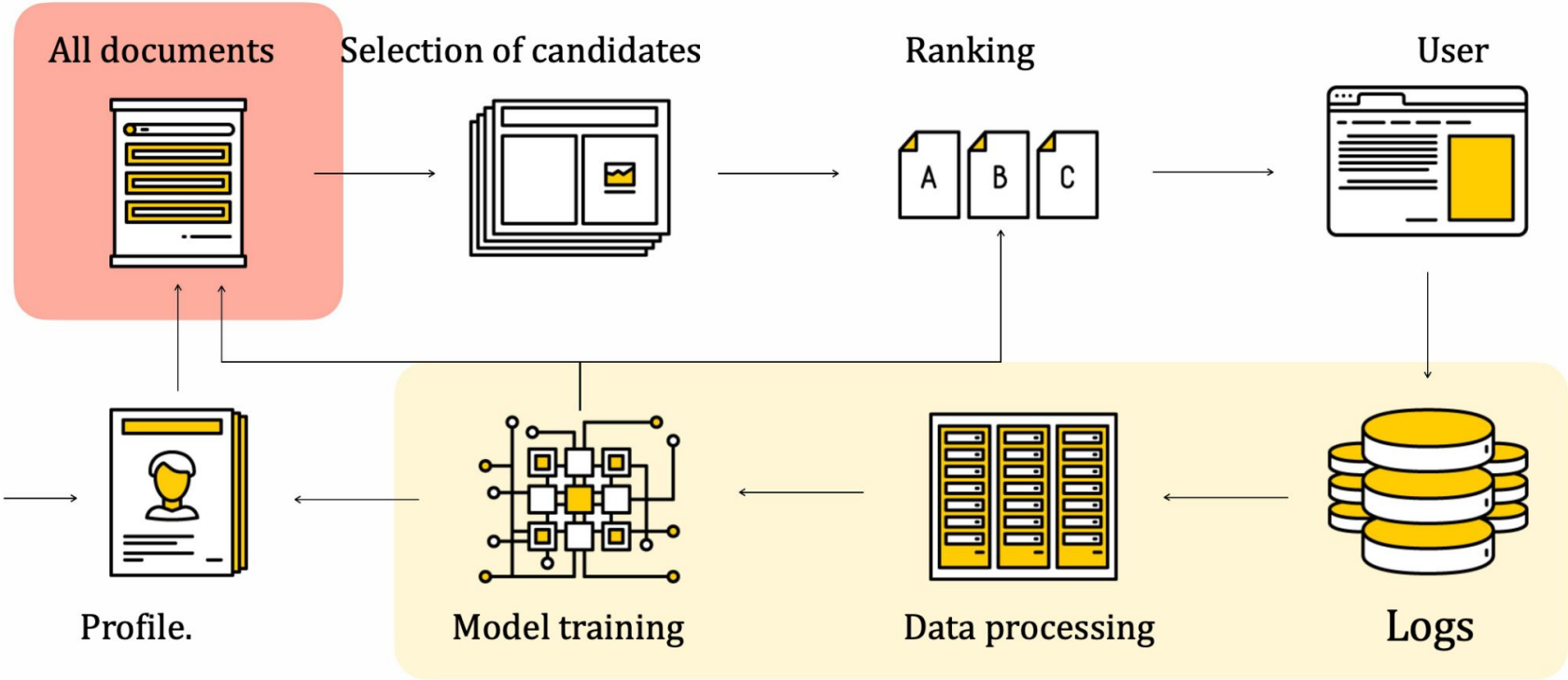
06

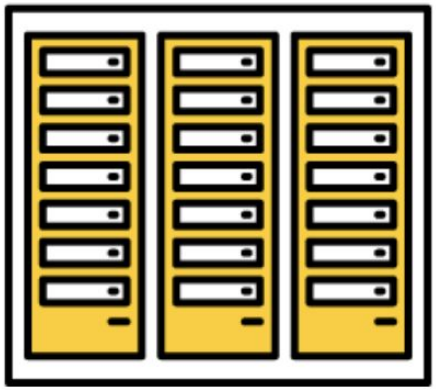
Document storage



Sharding

- One server has a limit on the number of documents stored
- Let's store disjoint sets of documents on different servers, and combine the results of responses

One shard



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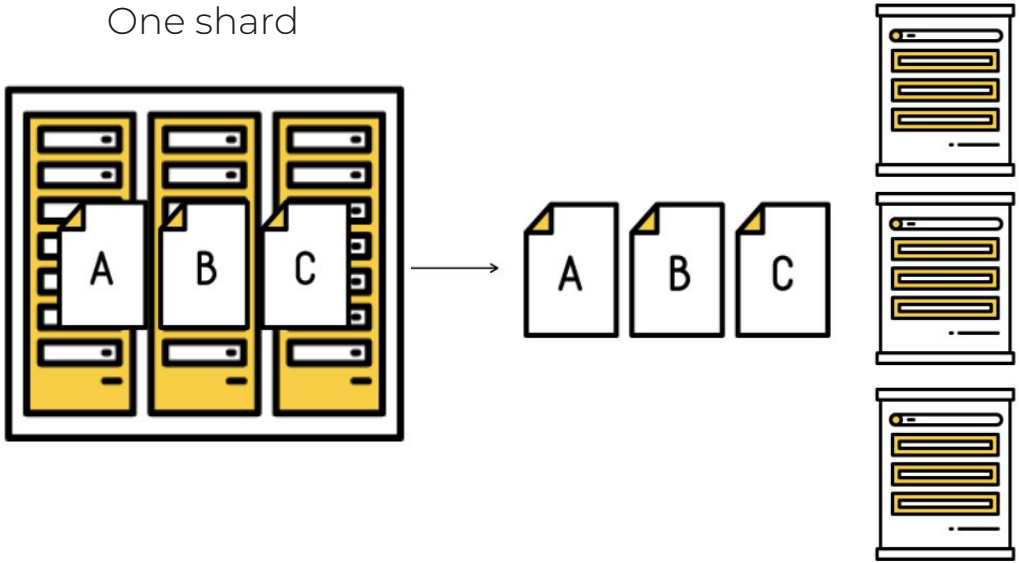
One shard

Multiple shards



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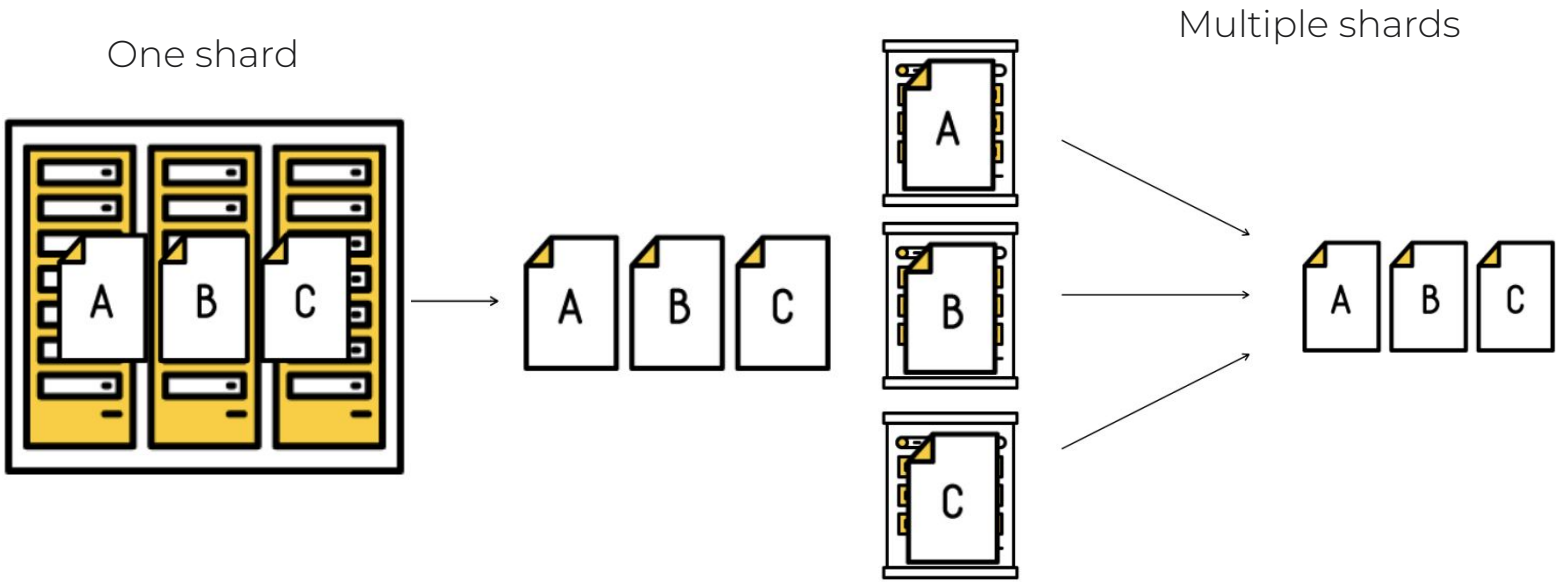
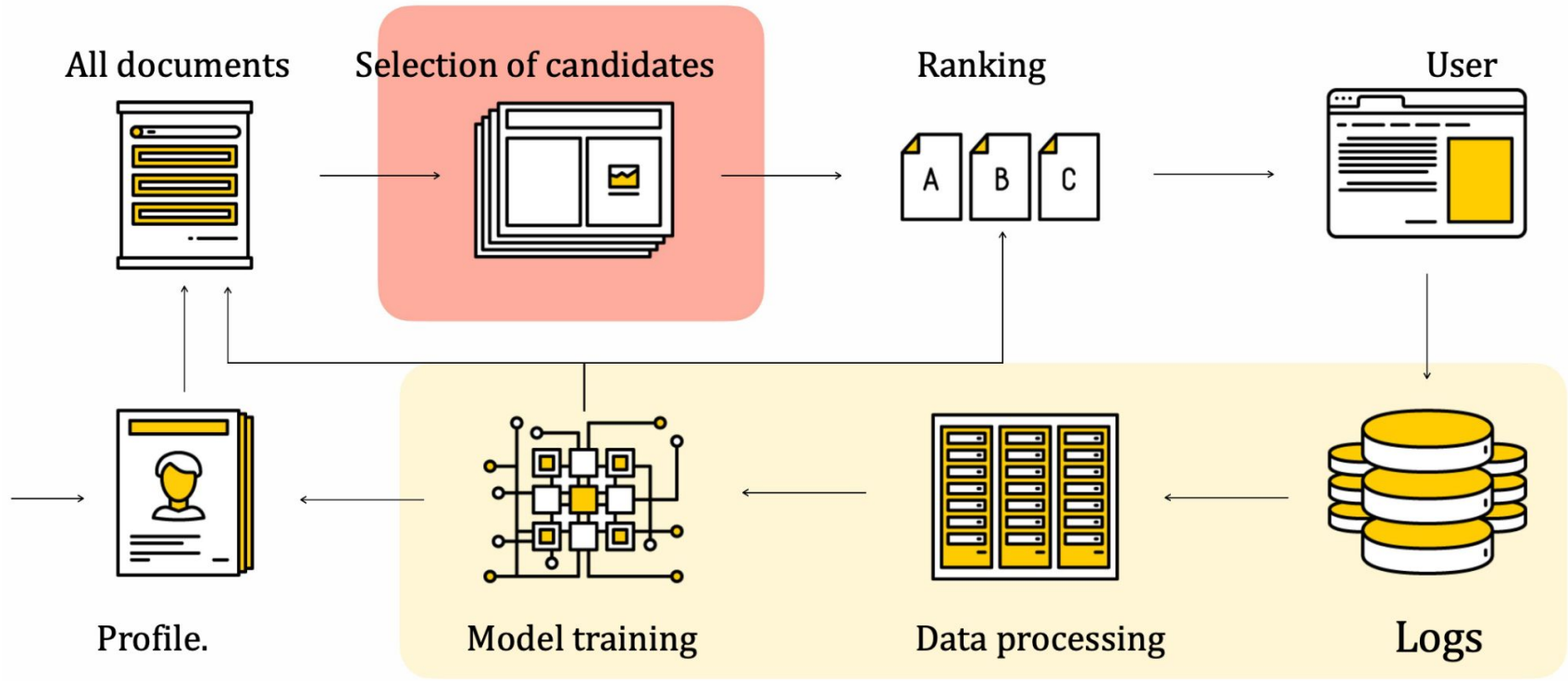


Selection of candidates



Example: Item-based CF

- We will calculate for each product offline 1000 of the most similar to it, add it to the Key-Value storage (for example, Redis)
- Online, let's take the products evaluated by the user (the last 100) and go to Key-Value for similar ones for them

kNN indexes

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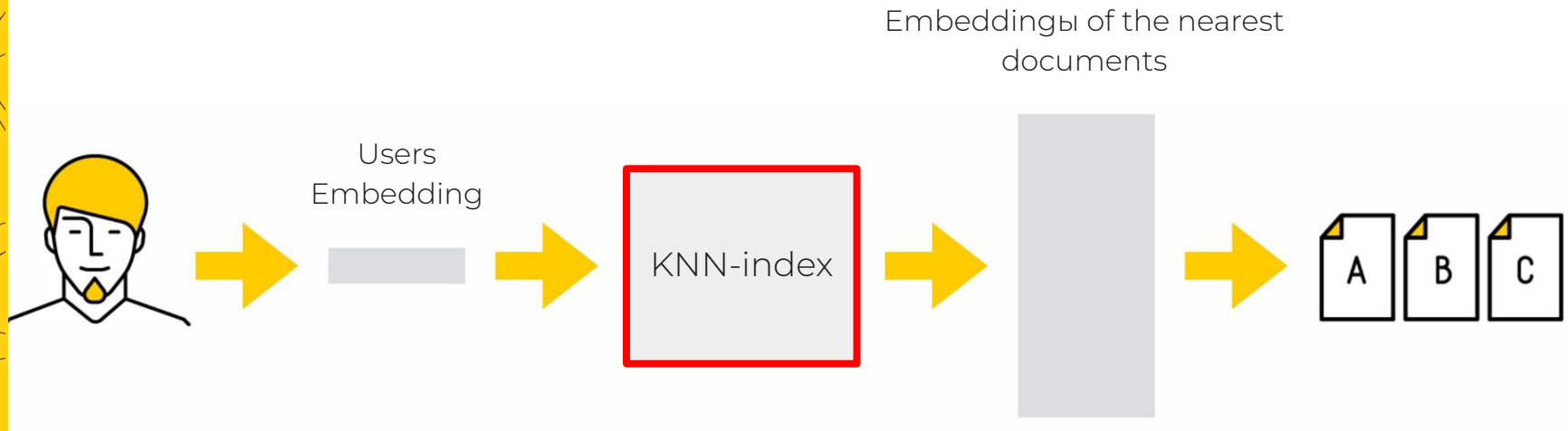
07

kNN index

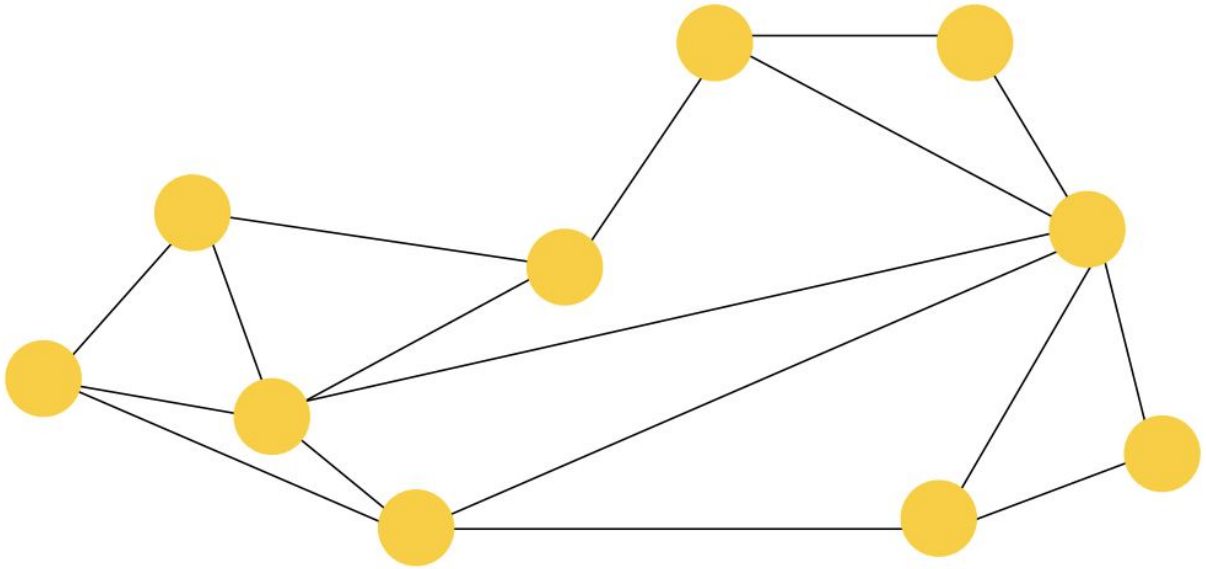
KNN index is a data structure
that allows you to quickly find the N nearest vectors for a given vector



Navigable Small World

- A graph where vertices are embeddings, edges are distances
- Adding nearby and remote vertices as edges
- We start from a random vertex, count the distances and move along the graph closer to the query point

NSW (Navigable Small World)



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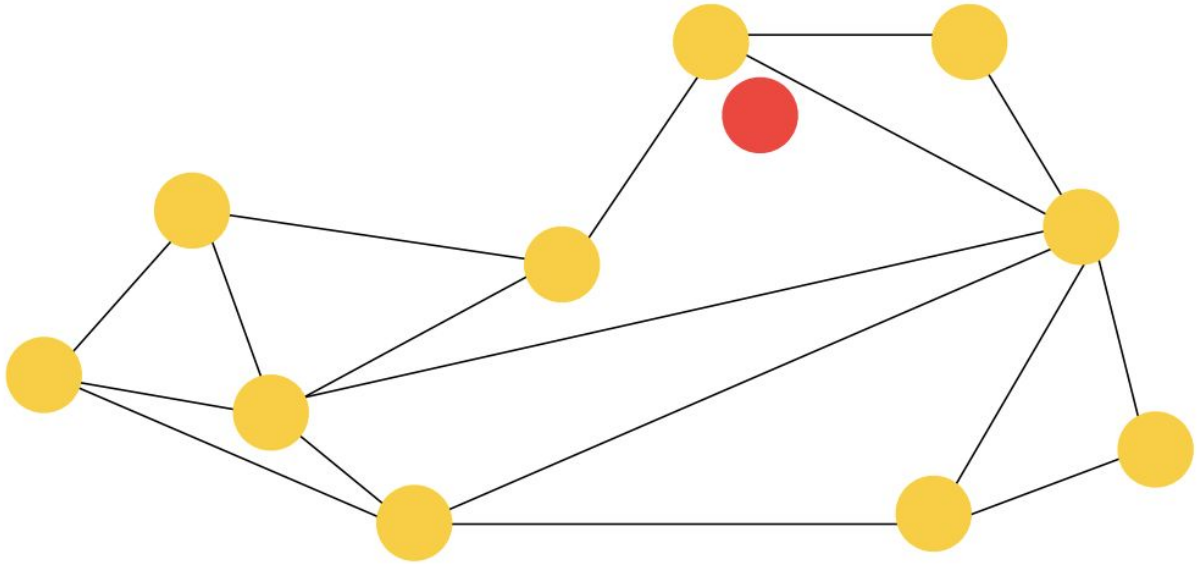

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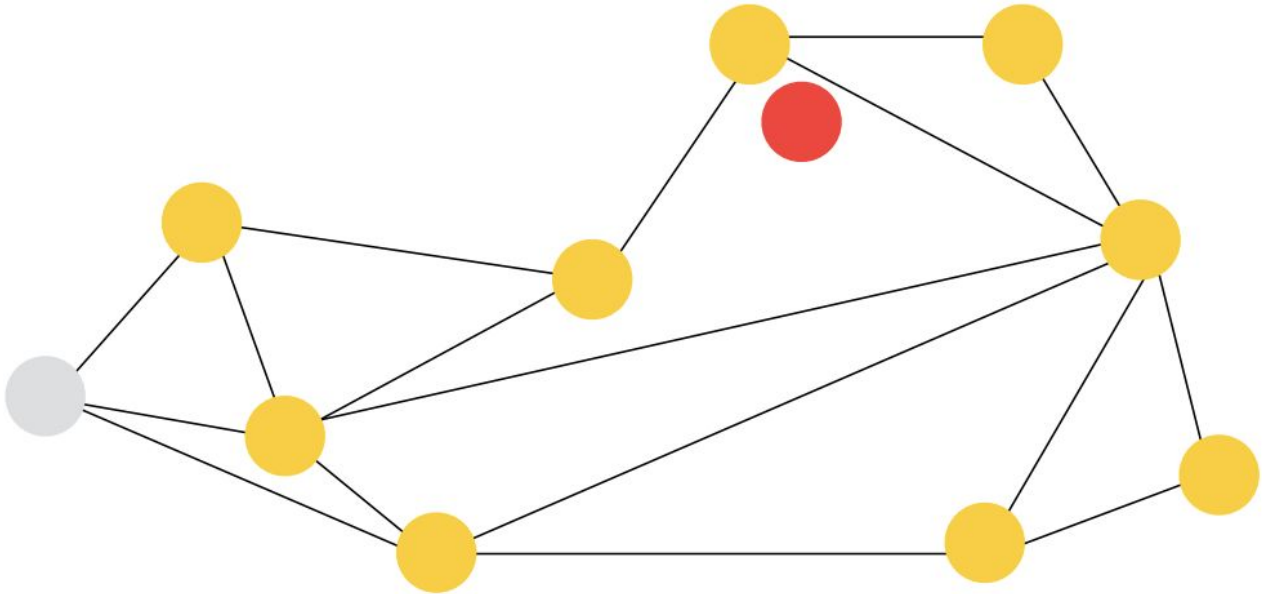

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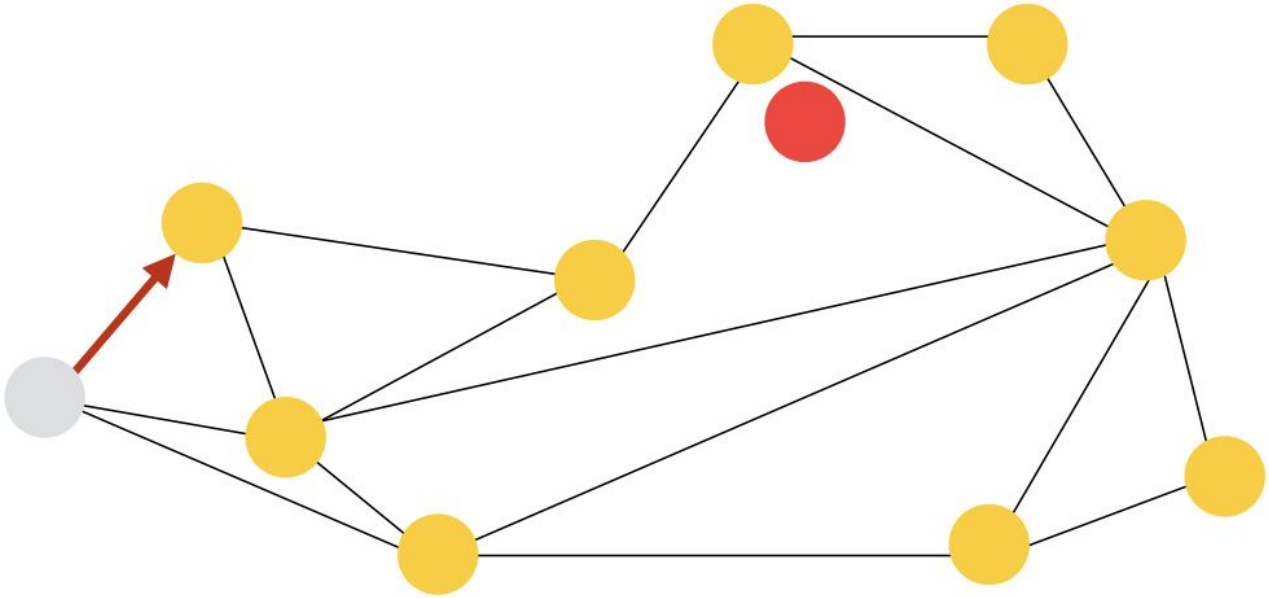

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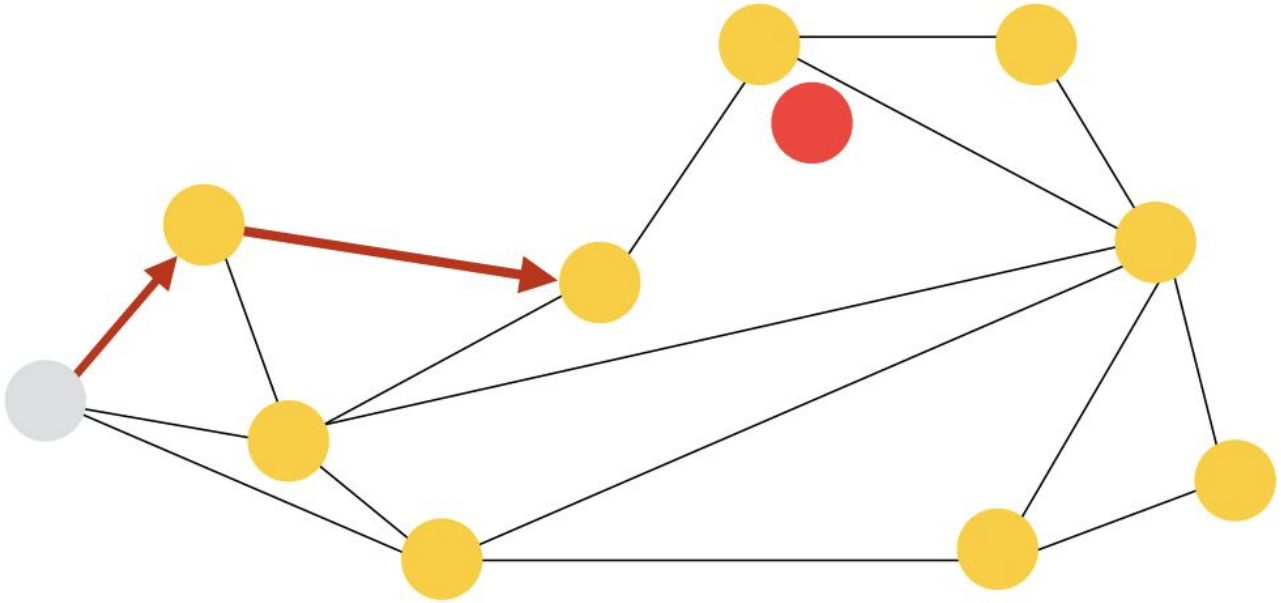
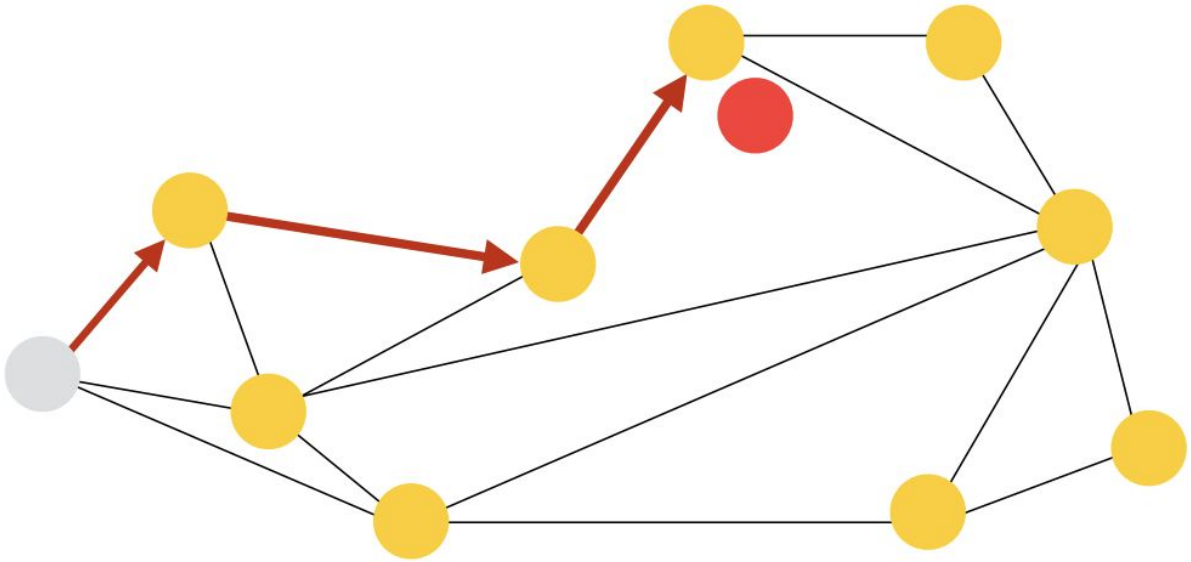


NSW (Navigable Small World)



Hierarchical Navigable Small World (HNSW)

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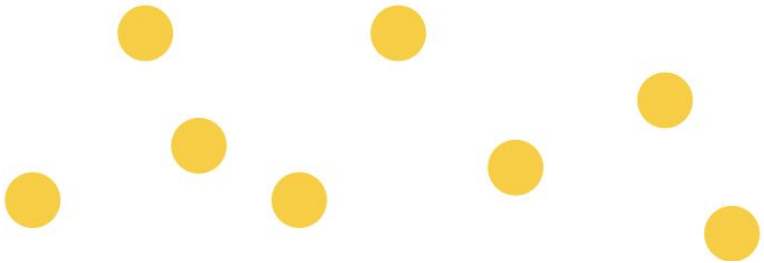
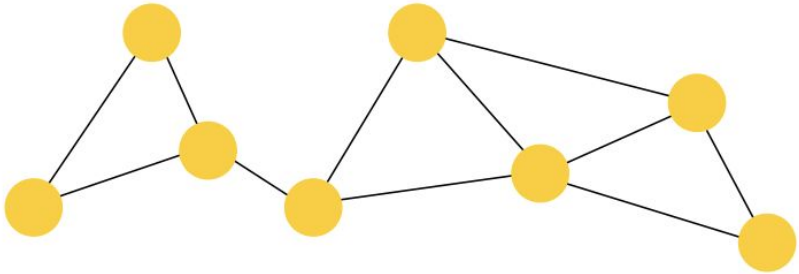
08

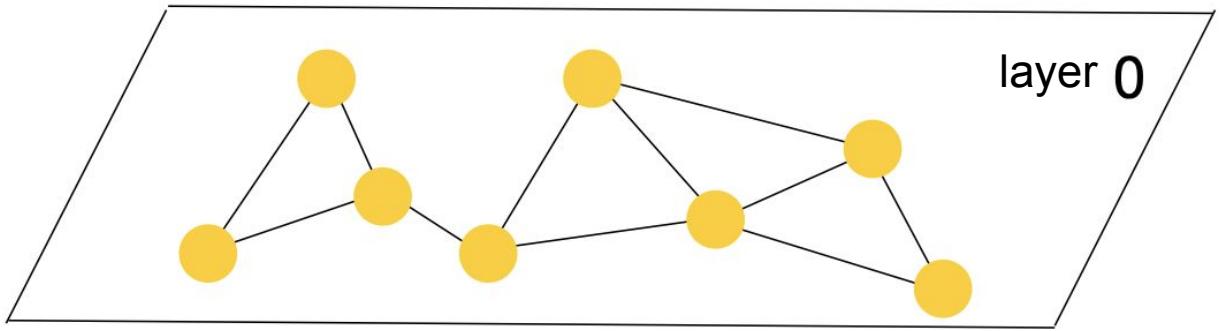
HNSW



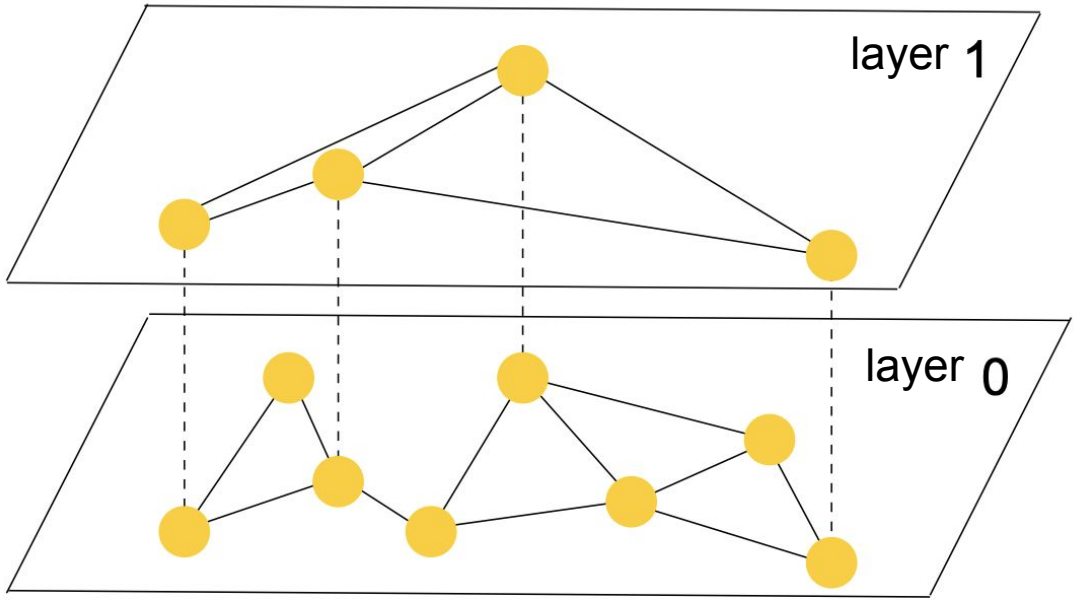
HNSW



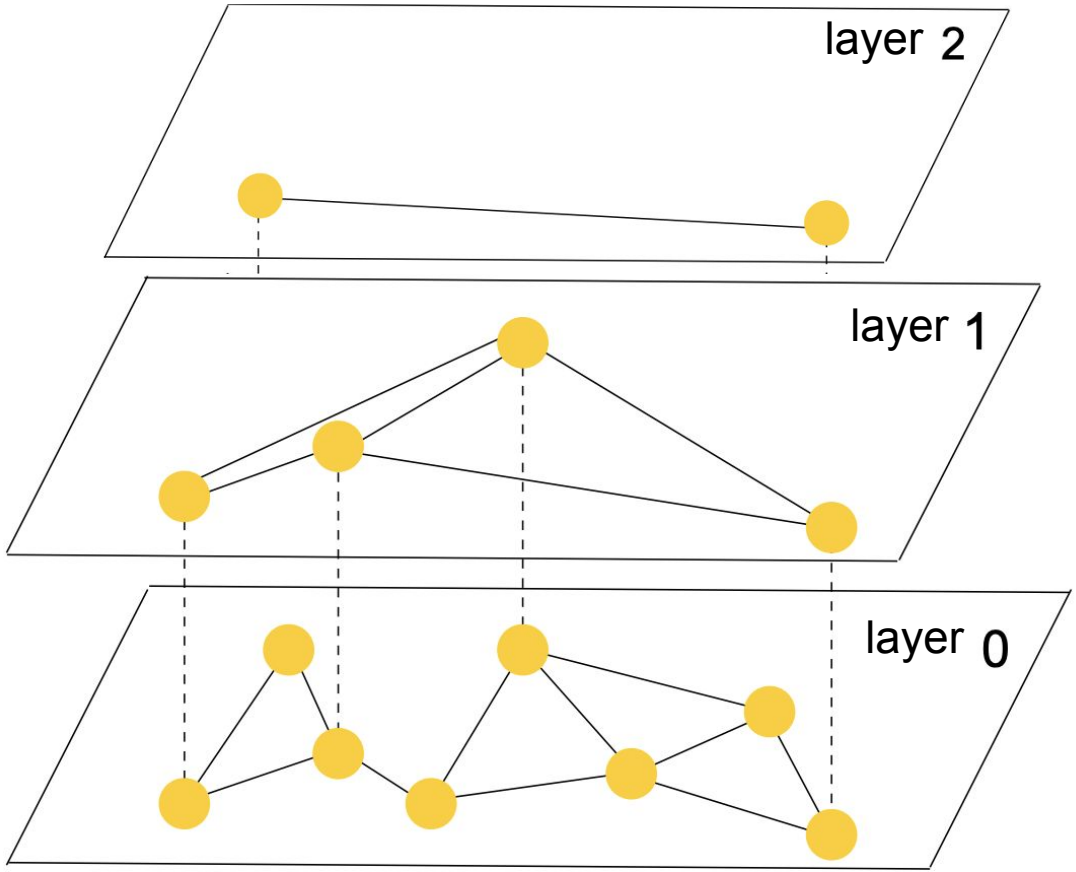
HNSW



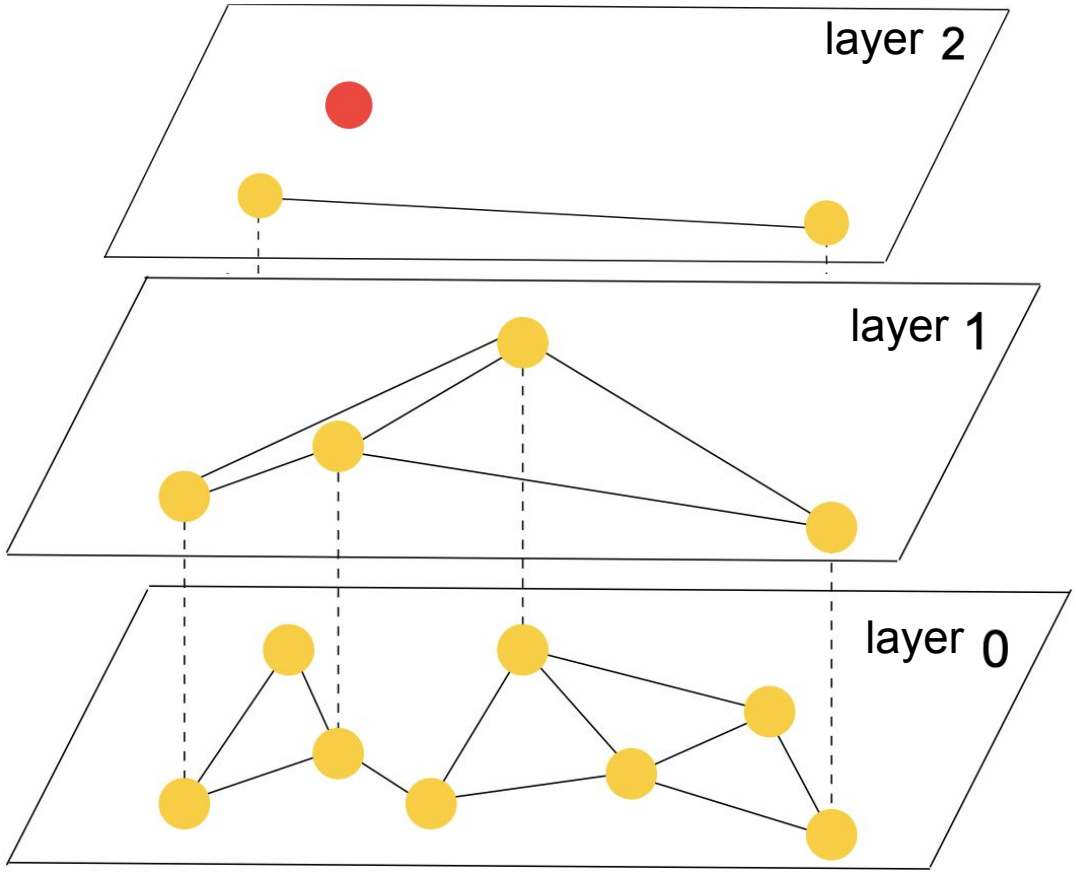
HNSW



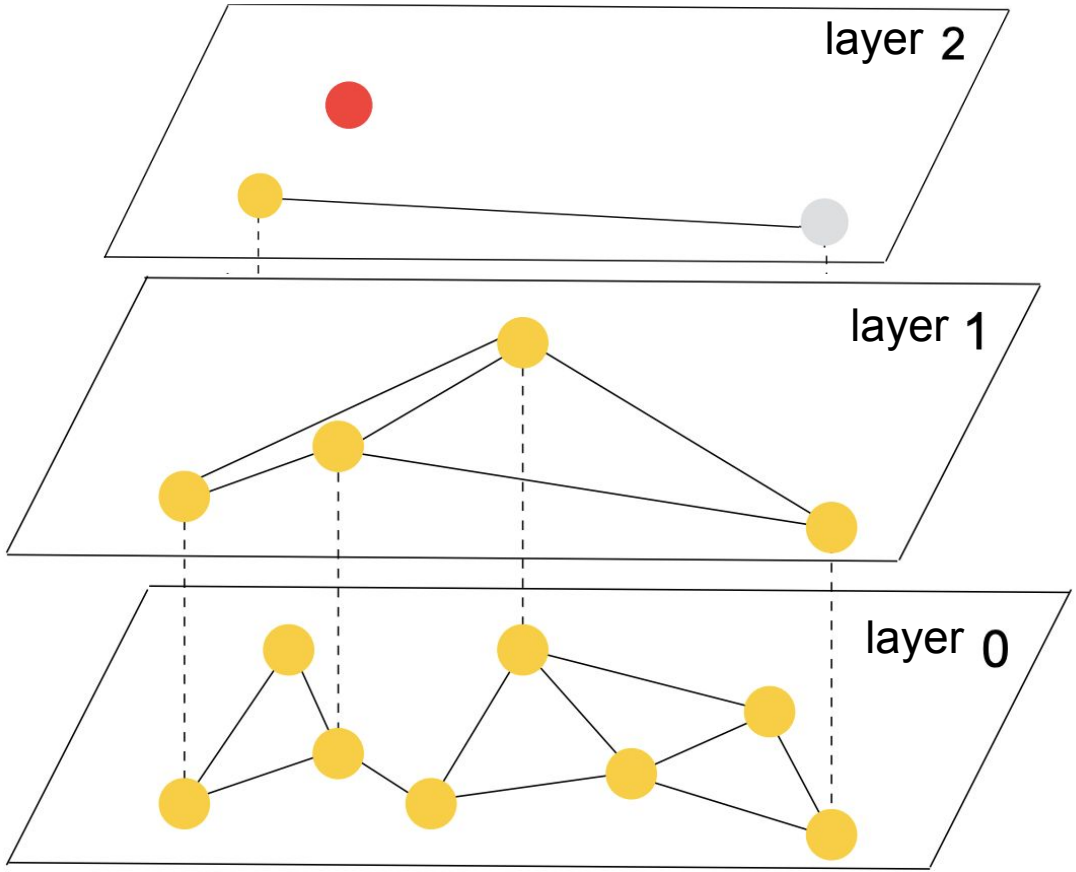
HNSW



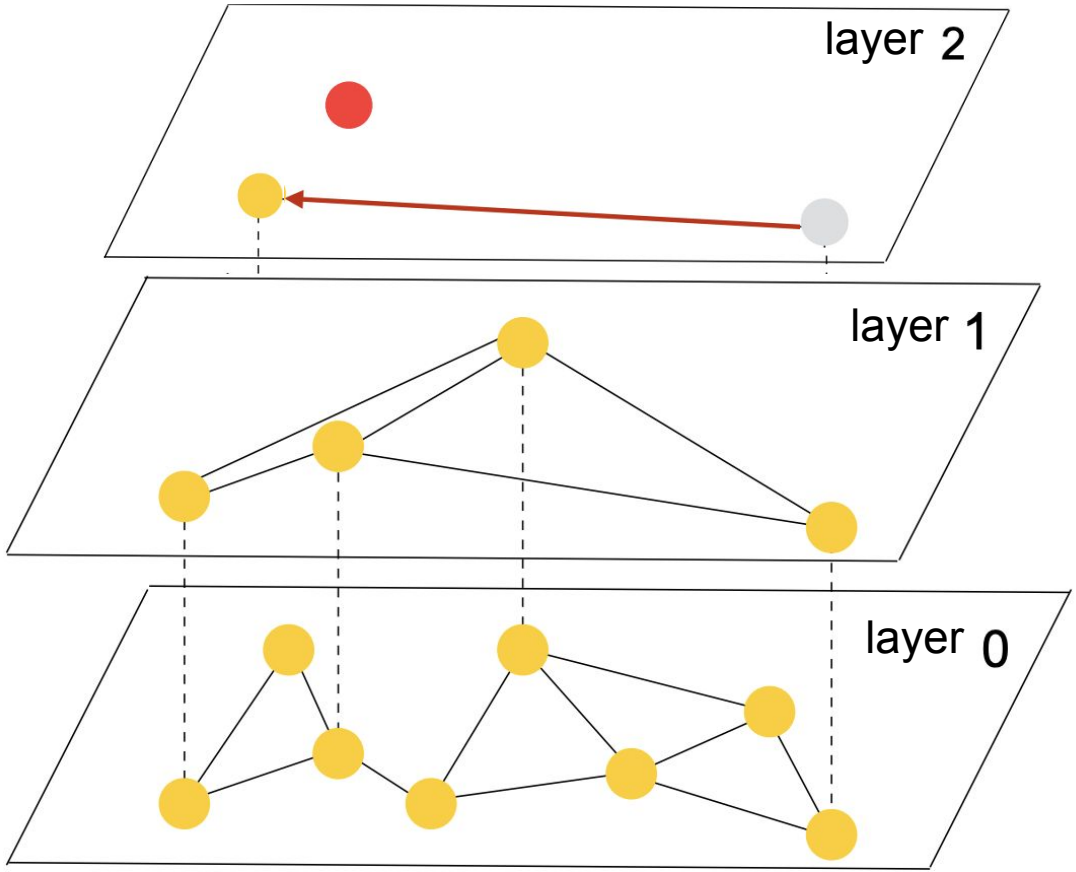
HNSW



HNSW



HNSW



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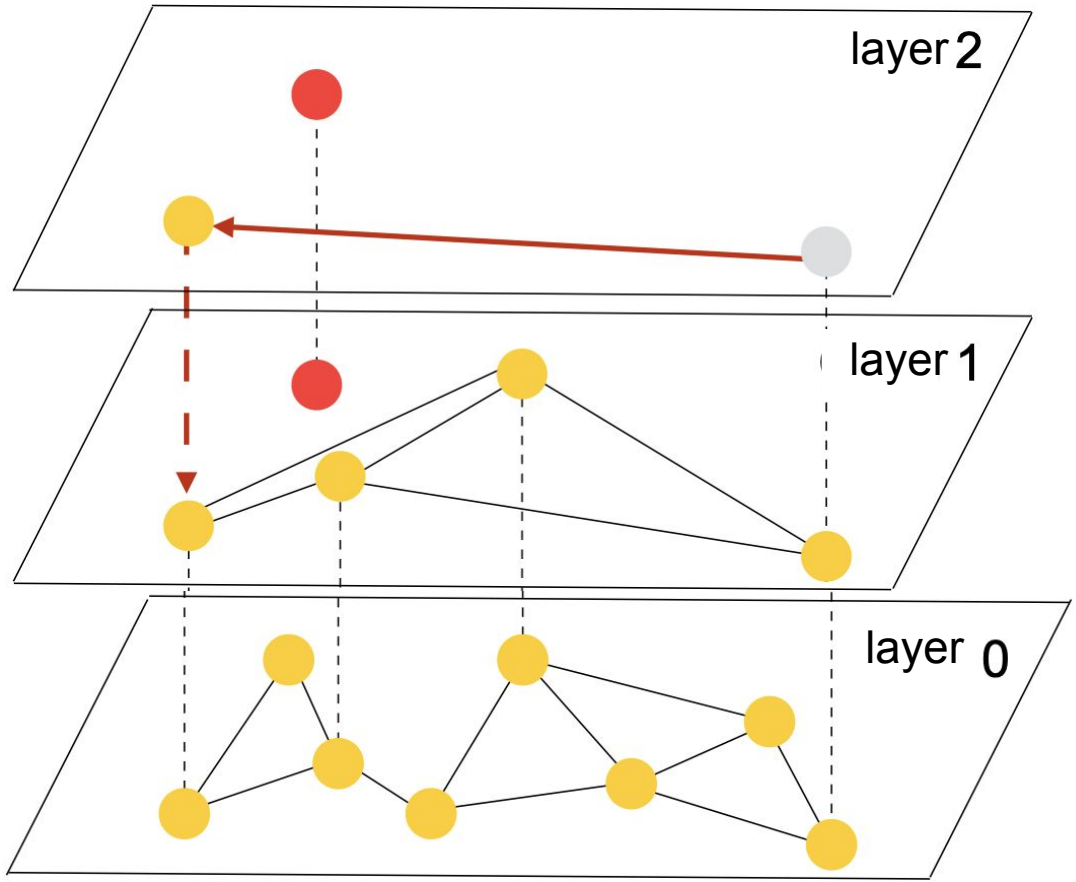
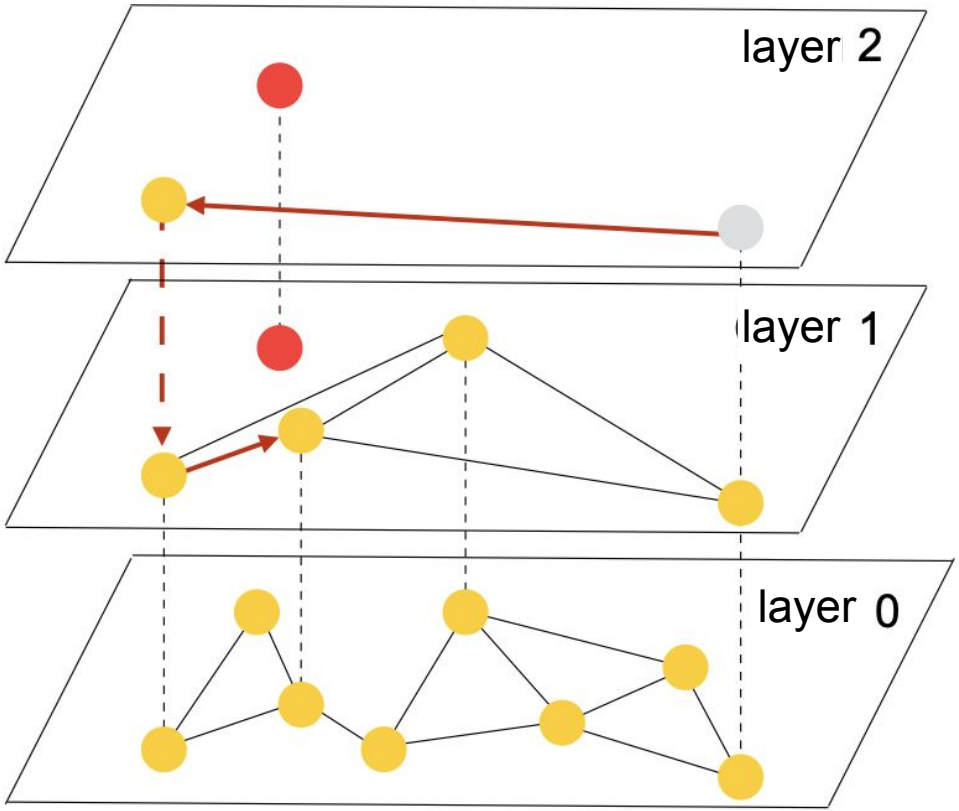
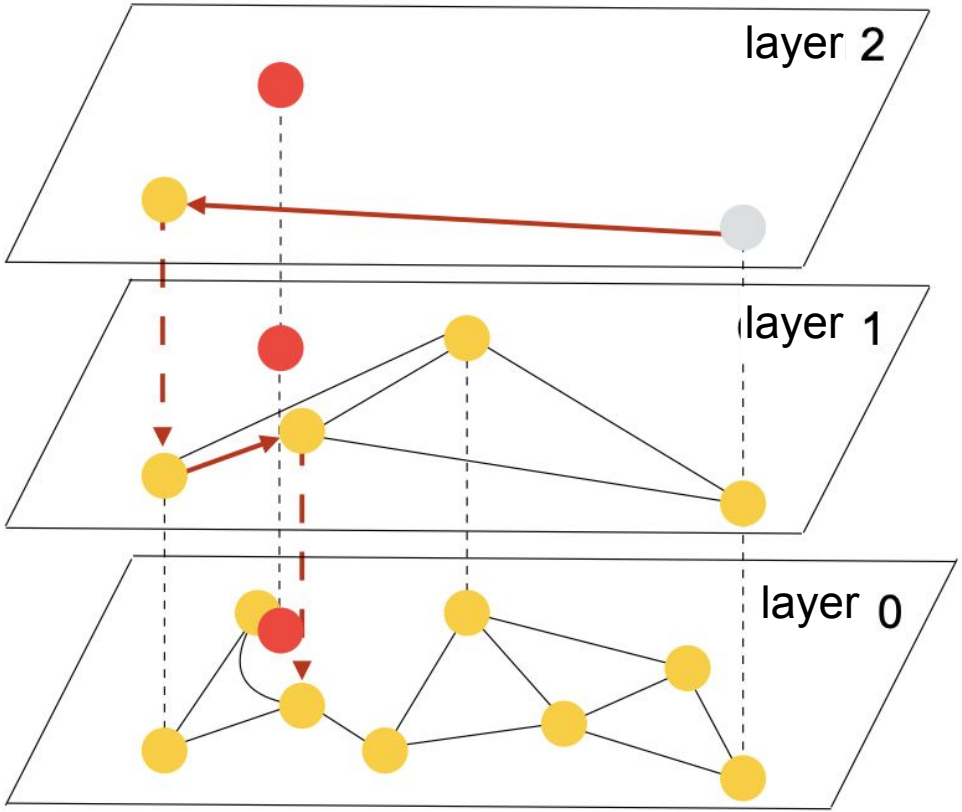


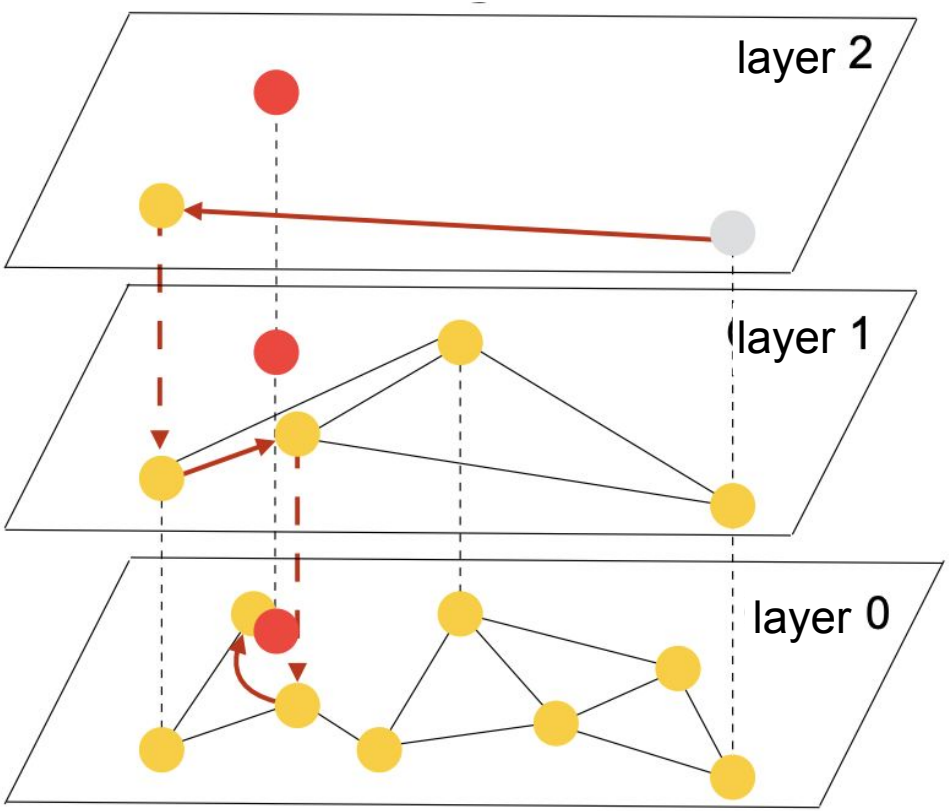
HNSW



HNSW

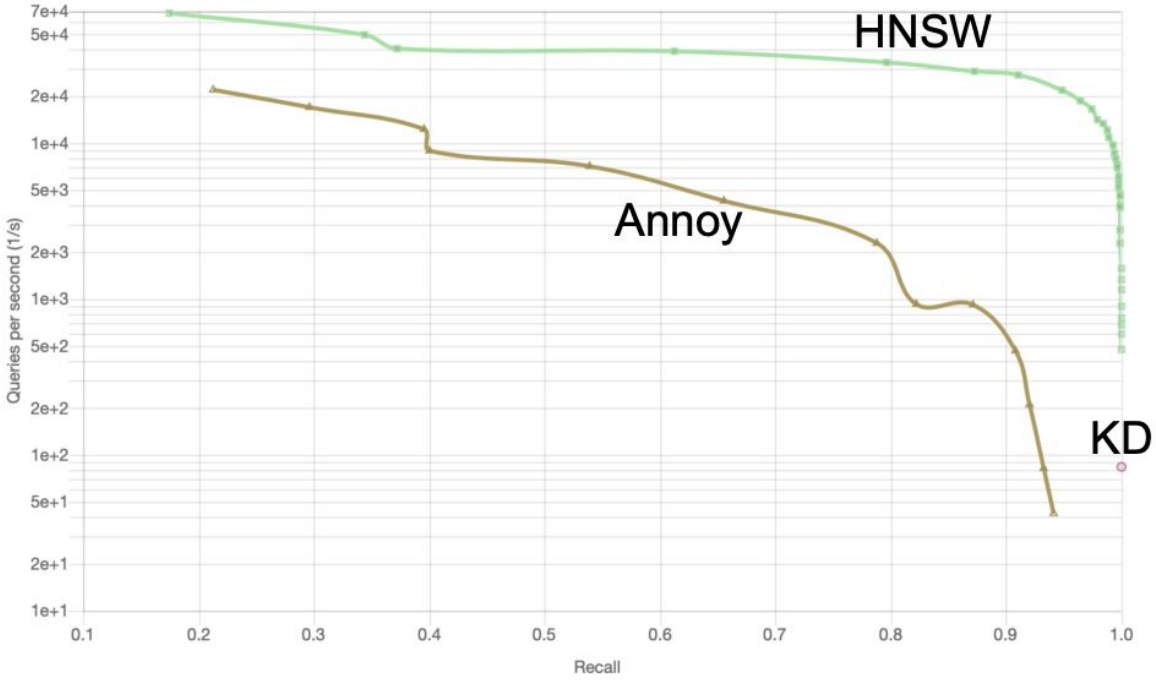


HNSW



Accuracy of approximate search

- In addition to speed, you need to find accurate nearby objects
- Comparison on ALS embedding last fm-64-dot, 360K



kNN index implemenataions

- https://github.com/facebookresearch/faiss
- https://github.com/nmslib/nmslib
- https://github.com/flann-lib/flann
- https://github.com/spotify/annoy
- https://lucene.apache.org/core/9_1_0/core/org/apache/lucene/util/hnsw/package-summary.html

Also list of vector databases from openAI
https://platform.openai.com/docs/guides/embeddings/how-can-i-retrieve-k-nearest-embedding-vectors-quickly

Ready for production solution https://github.com/qdrant/qdrant

Quantization

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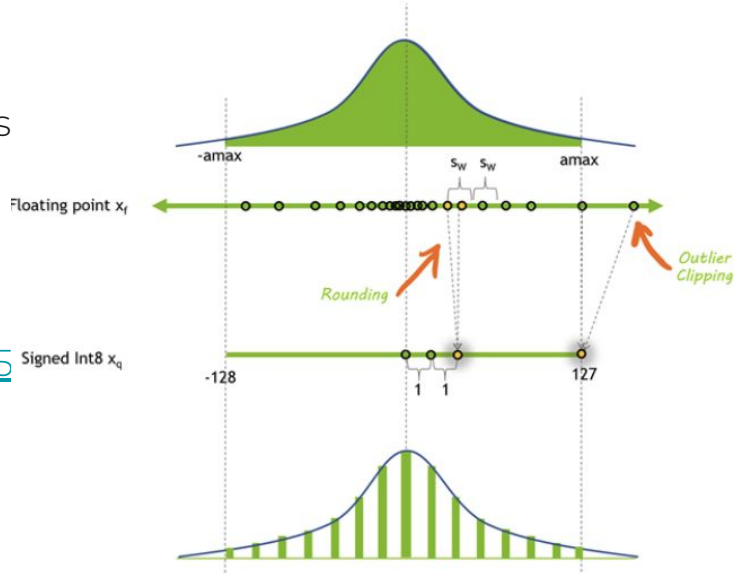
09

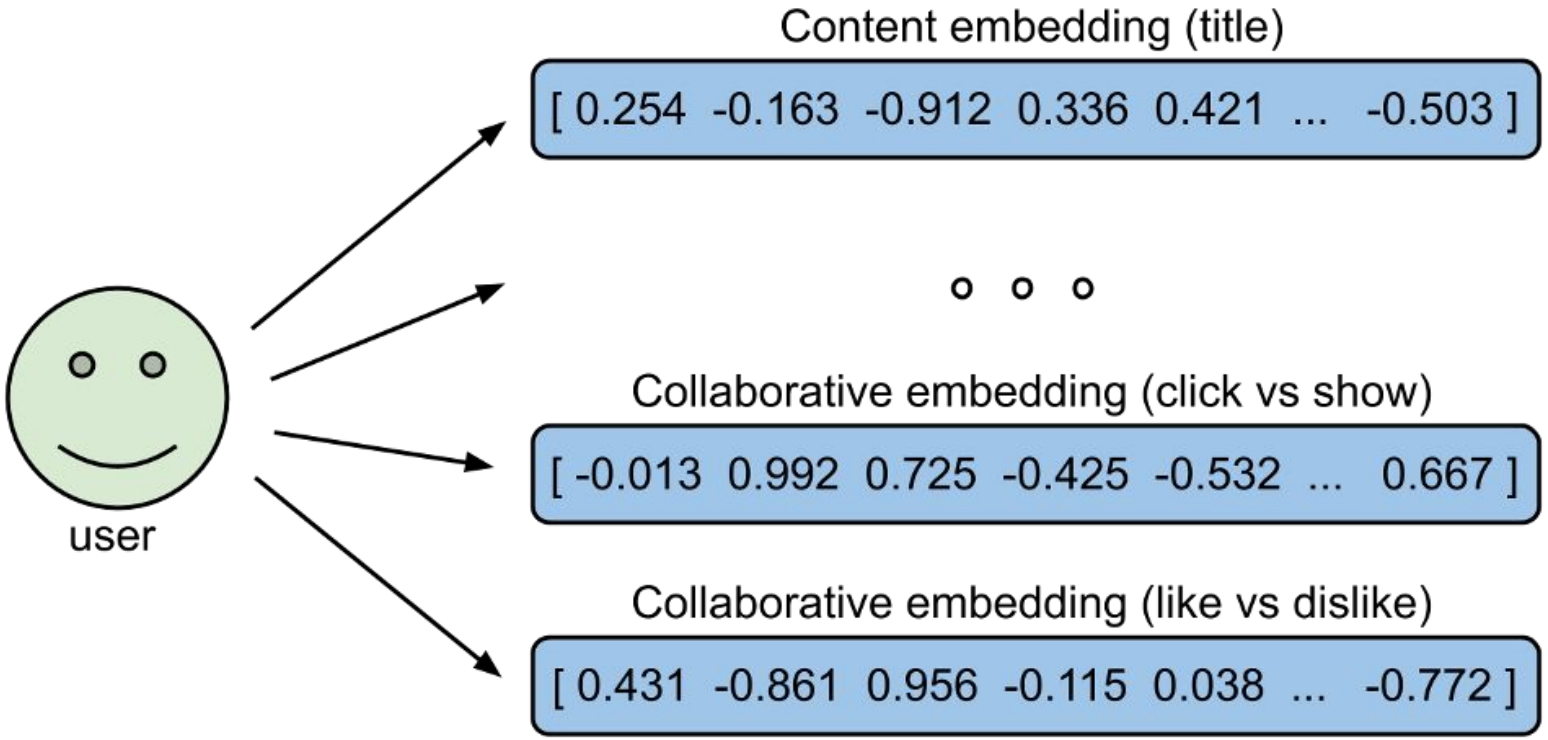
Quantization

- Embedding elements — float32
- How much will a 100-dimensional vector take in bytes?
  - 400 bites
- And if you replace it with int8?
  - 100 bites
- So let's break down the values by quantiles

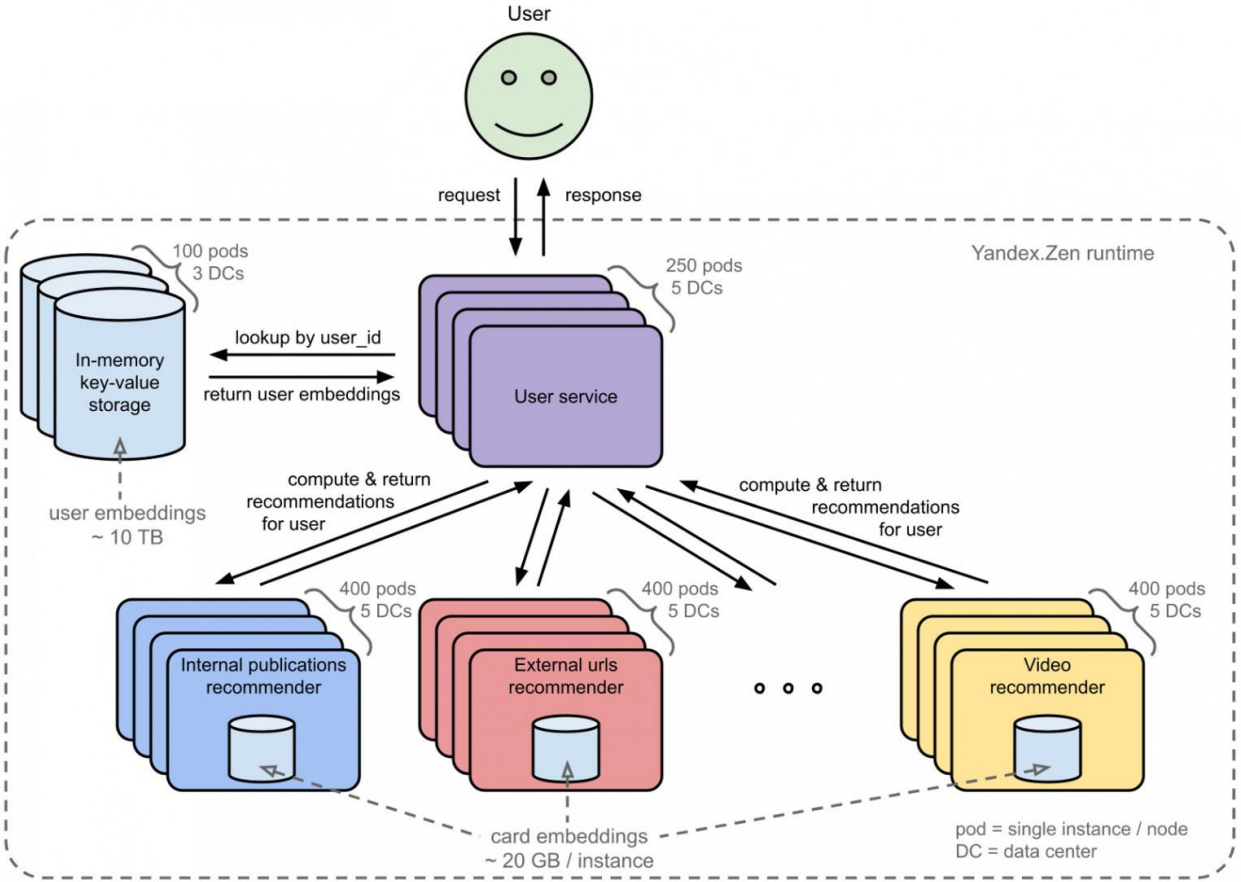
Dzen experience in quantization (ru)
https://habr.com/ru/companies/yandex/articles/5



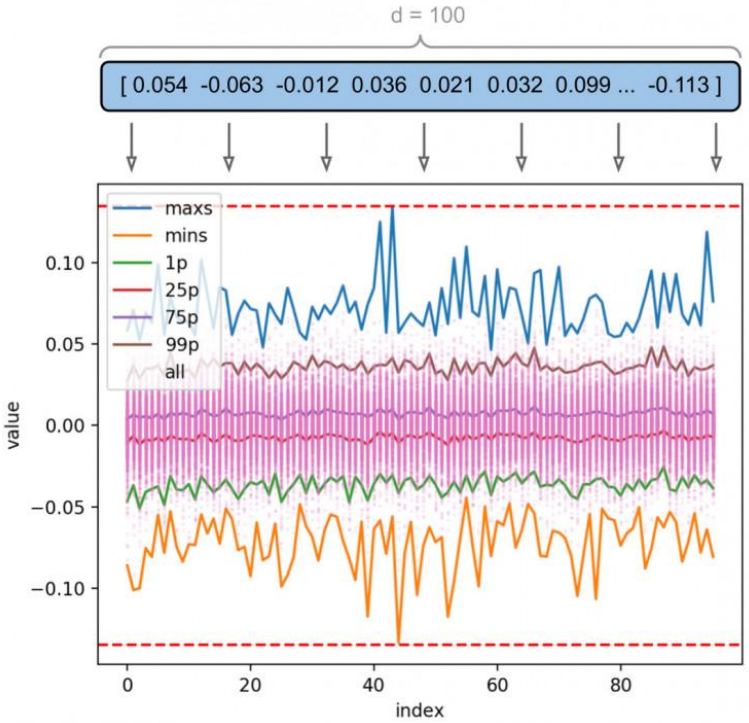
Quantization

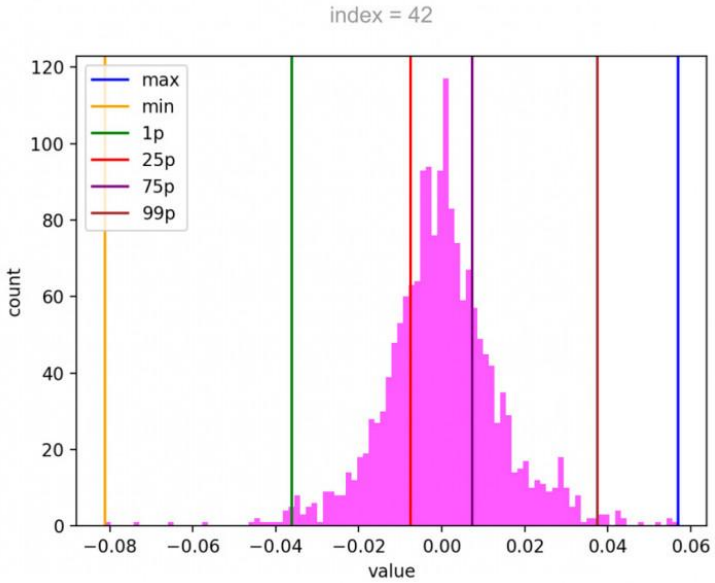


Quantization

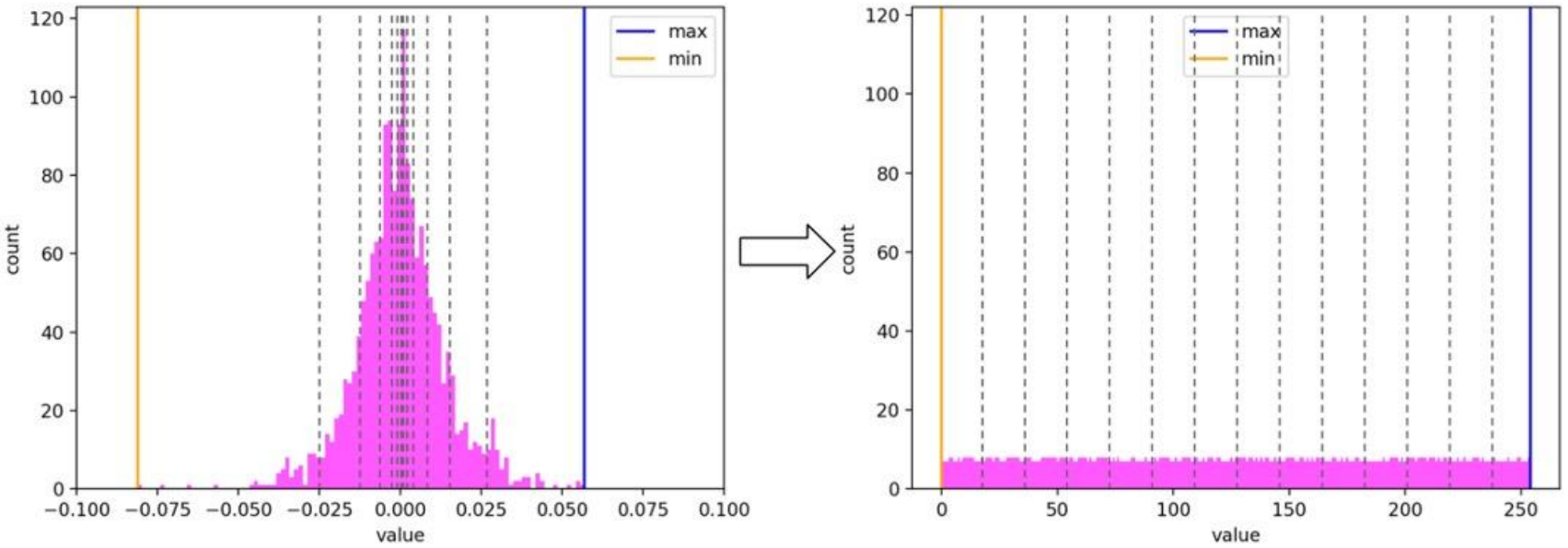


Quantization

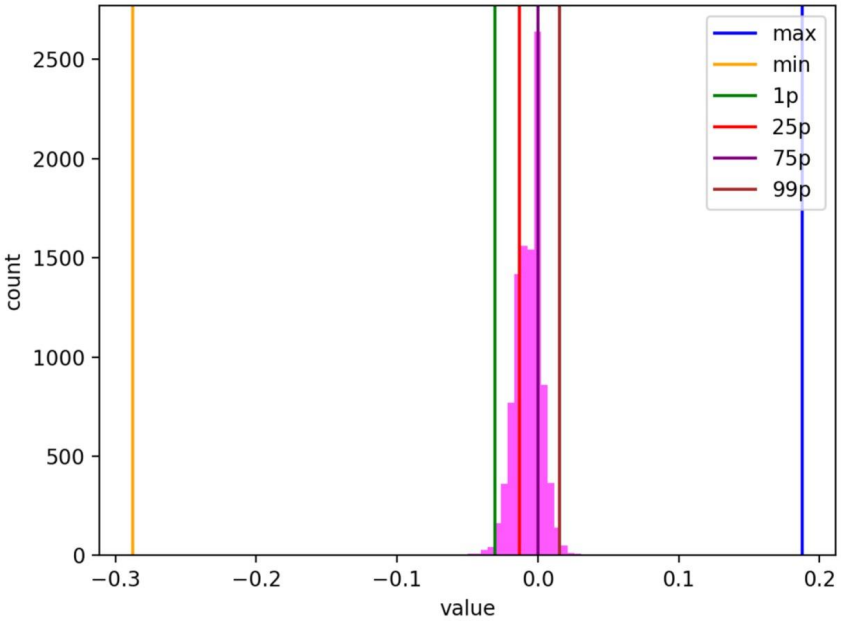




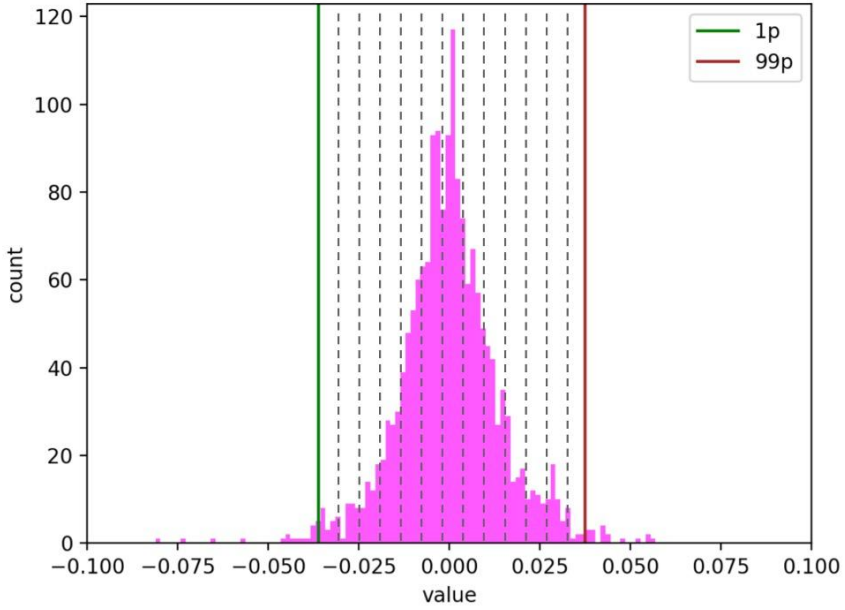
Quantization



Quantization

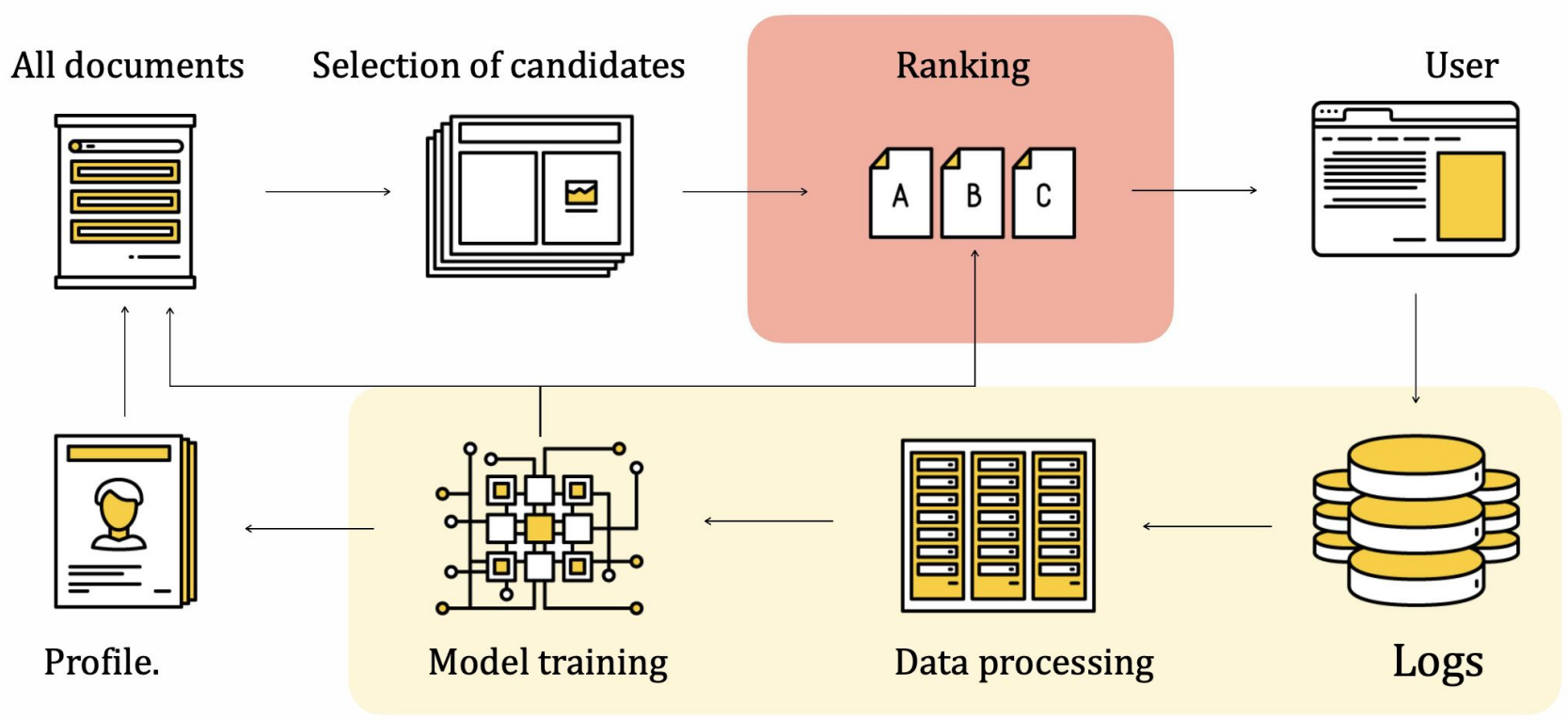


min-max distribution



1-99 percentiles distribution

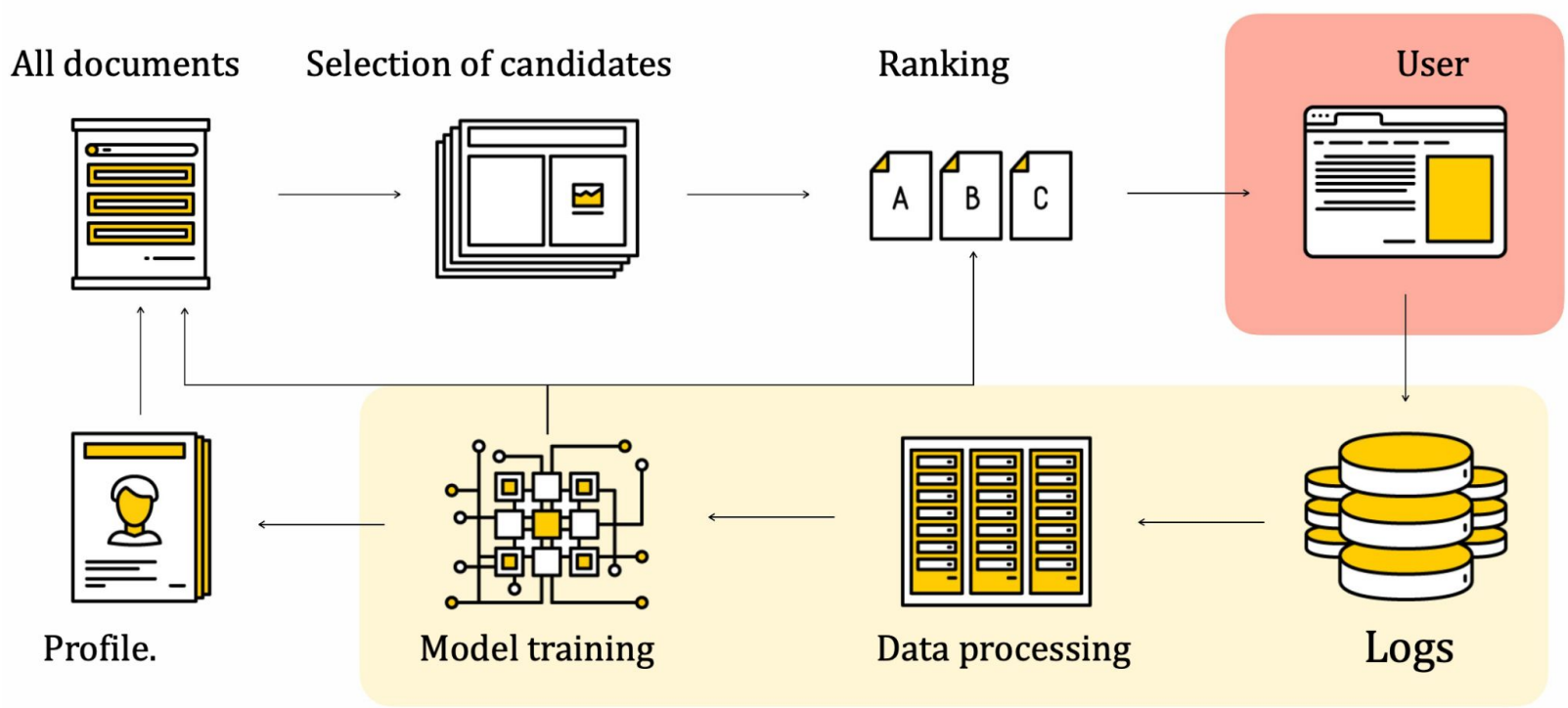
Ranking


All documents
Selection of candidates
Ranking
User
A
B
C
Profile.
Model training
Data processing
Logs

Ranking

In practice, several ranking models can be used, each of which is applied to the top of the documents selected by the previous one; gradient boosting is most often used as models. And almost always the response of the model is transformed using business rules: diversity, history of interaction with the document, freshness, time of day, etc.

Load from users



Caching during serving

- We get the results from the cache, reduce the load on the main service

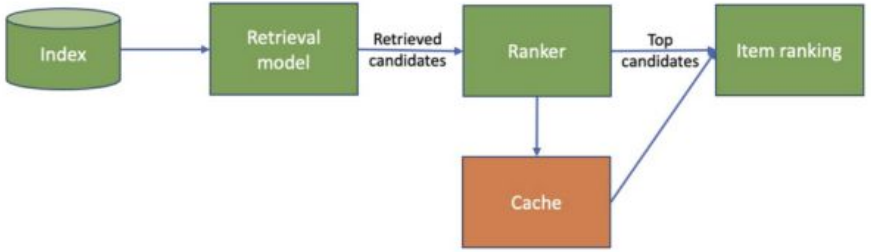


Figure 1: A Delivery Flow of Recommendation Systems with Simple Caching Strategy

- Adding a model that predicts cache usage

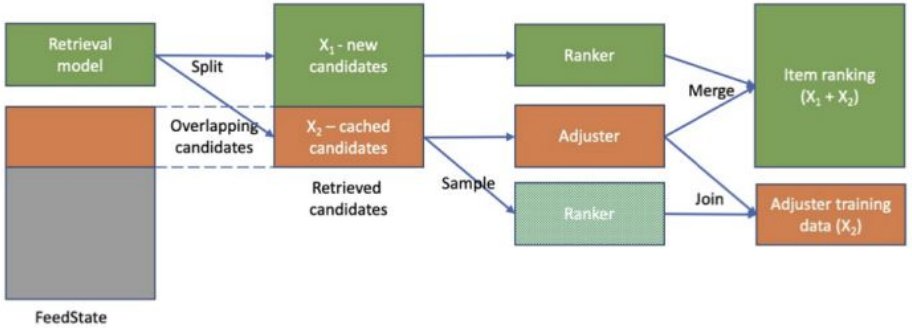


Figure 2: A Delivery Flow with Smart Cache

Recommendation system lifecycle

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12

Features logging

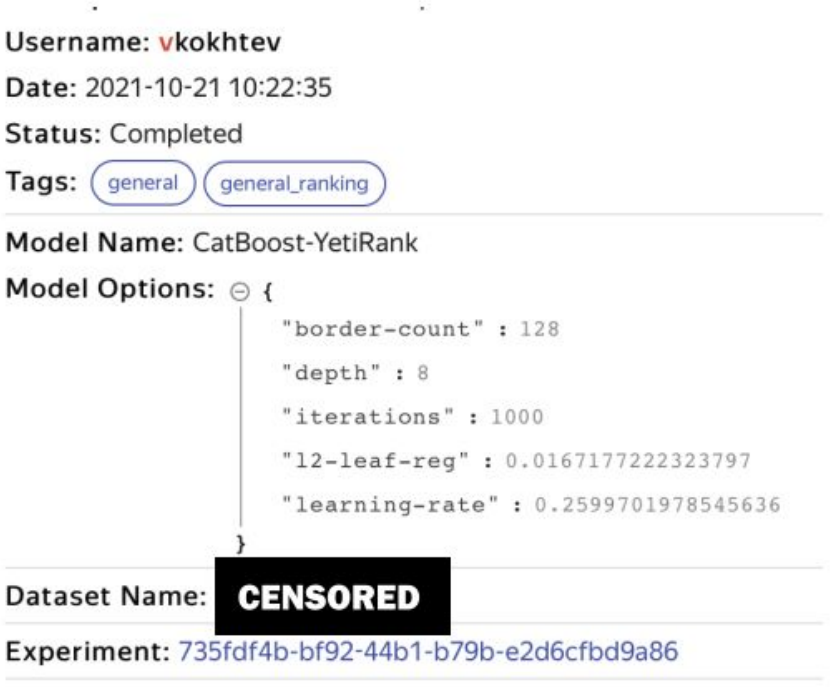
- It is necessary to train the model on the data recorded during the operation of the real system
- Collecting data on historical casts is guaranteed to lead to a discrepancy in values when training and applying models
- Errors in calculations will give rise to incorrect signs with leaks of the target variable ("face")

Reproducible learning

Always versioning your experiments

- Data
- Parameters of models and training
- Executable code

- And of course fix Random Seed (I advise 42)



Metrics monitoring

- Metrics from the last lecture must be constantly monitored
- Model quality metrics

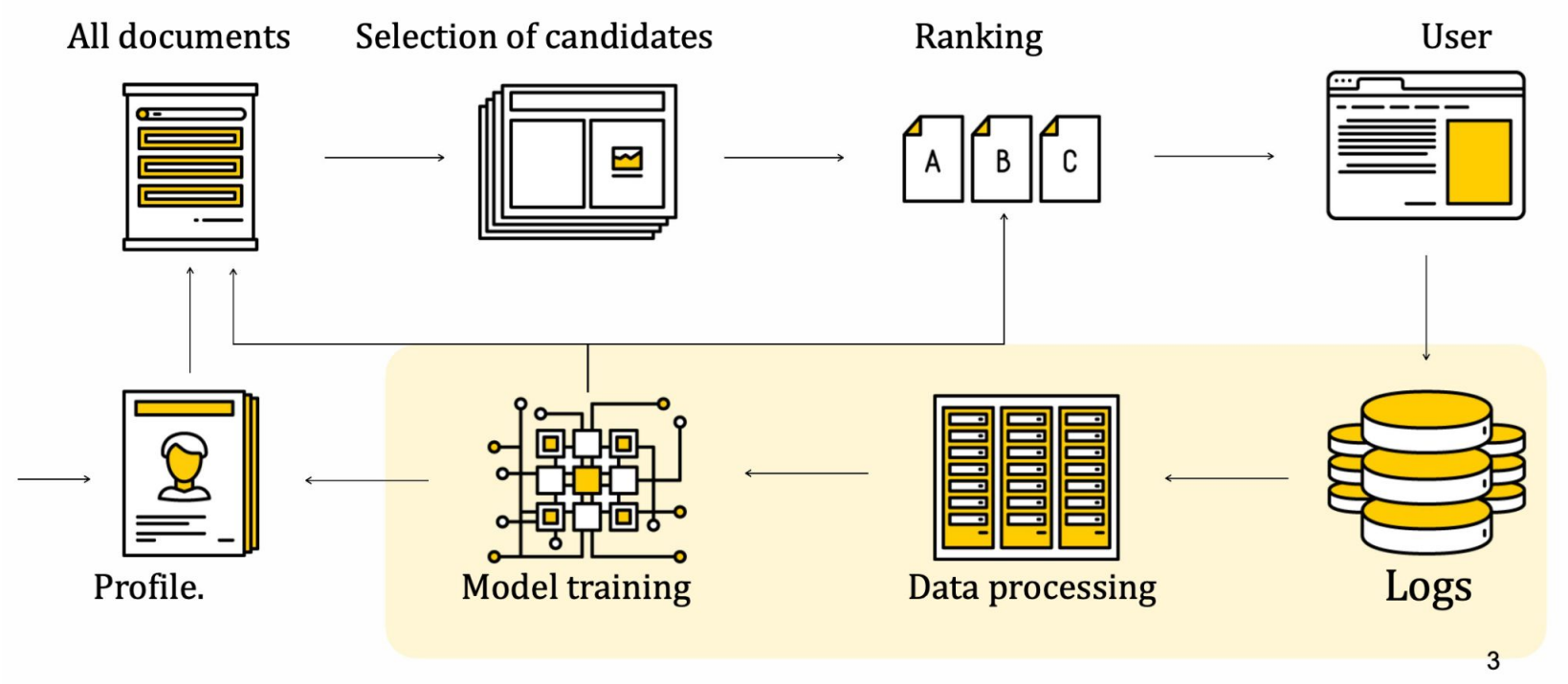
Technical

- Number of requests, response time
- Values of features and responses of models

Regular models retraining

- Even if you have received a good recommendation model once, it will become outdated over time. Therefore, it is necessary to periodically train/retrain models on fresh data
- You can trust automation and run each regular model in an A/B experiment, and if the main metrics are stable or improved, include them for all users

Resume


All documents
Selection of candidates
Ranking
User
A
B
C
Profile.
Model training
Data processing
Logs
3

Thanks for attention!

Questions?

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girafe
ai