Introduction to RecSys

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- Author of machine learning courses and Masters program at MIPT
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- Open source fan

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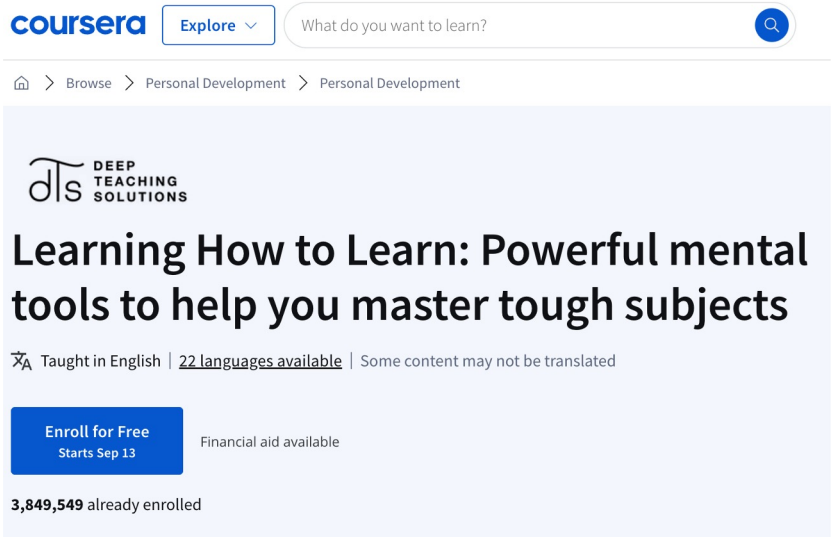
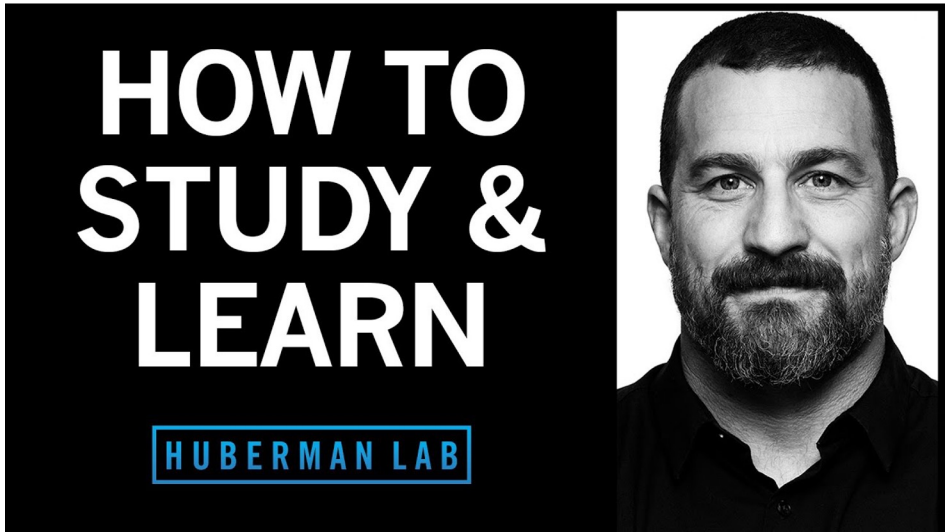
МФТИ

Дзен

Science based learning techniques

- https://www.youtube.com/watch?v=ddq8JIMhz7c
- https://www.coursera.org/learn/learning-how-to-learn





Communication

1. Course channel
2. Course chat
3. Support account @girafeai_support

Teacher will probably not answer to direct messages due to large number of students!

Grading

Для МФК:

- 100% - тесты на занятиях

Для полноценного курса:

- 30% - тесты на занятиях
- 70% - лабораторные работы

Лабораторные работы:

3 шт в течение семестра в виде jupyter notebook-ов

Why recommendation systems are needed

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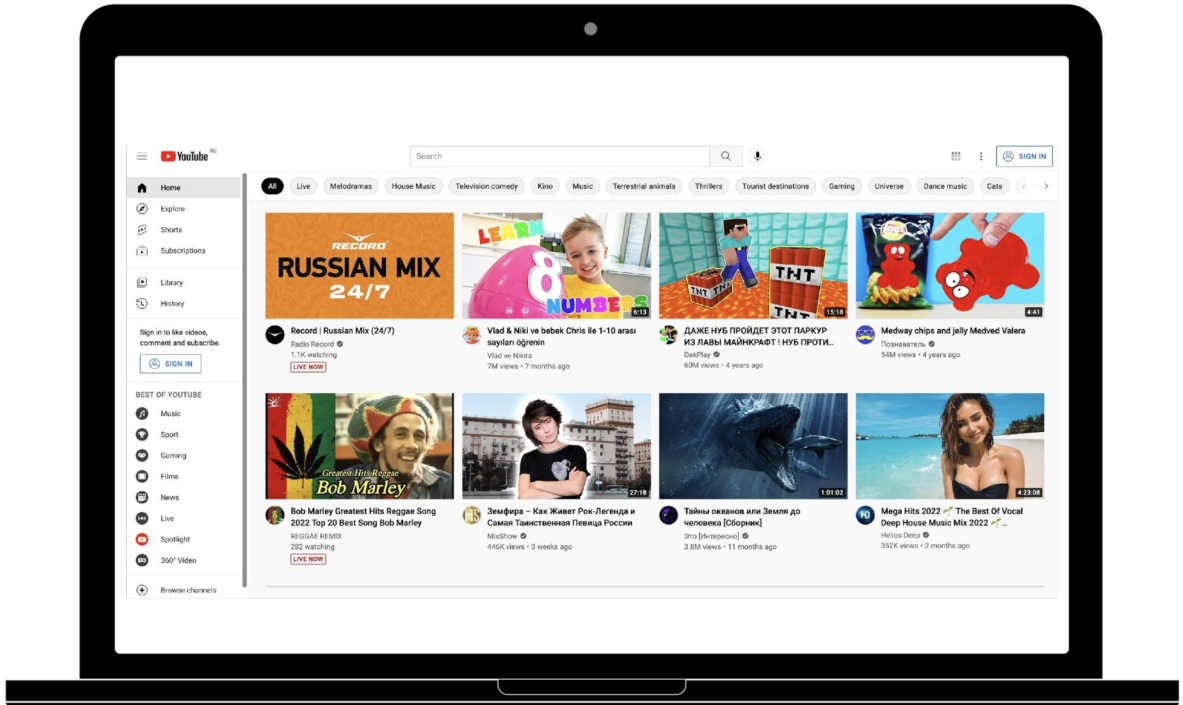
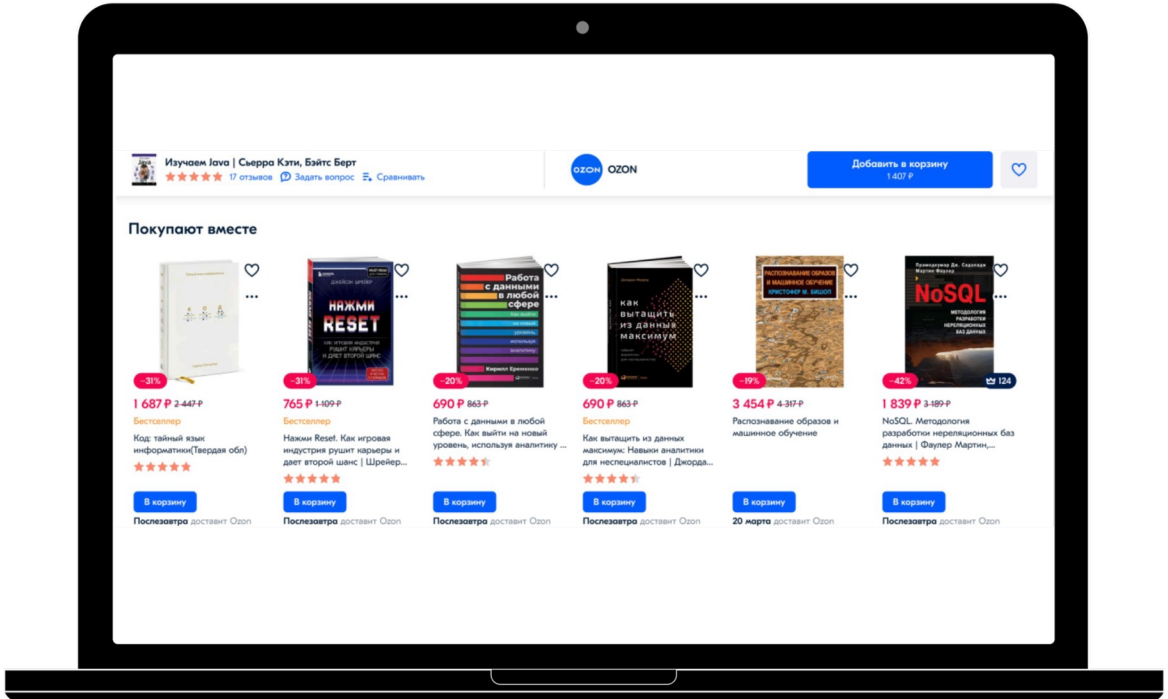
Examples of recommender systems

video recommendations



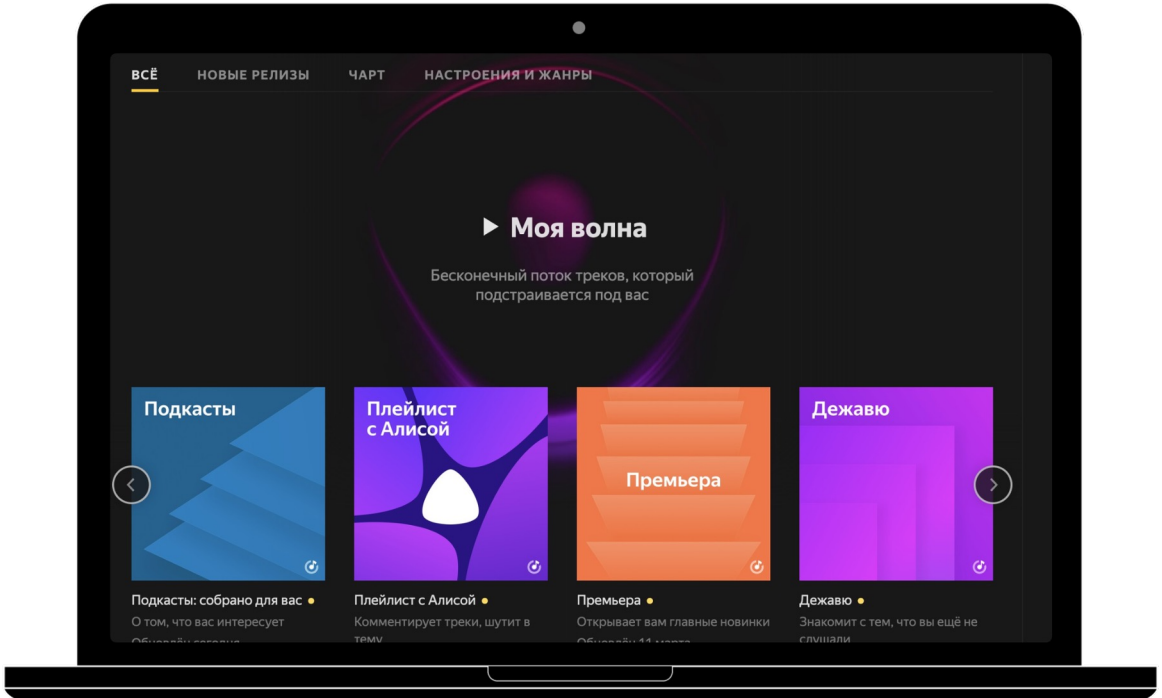
Examples of recommender systems

goods recommendations



Examples of recommender systems

music recommendations



Goals

- Provide best user experience
- Provide business value

Examples of recommender systems

How to convince a person to stay on the video service?

- Suggest watching something else
- The proposed videos should be of interest to the user
- There should be variety in the proposals, so that they are not intrusive
- Etc

This is what recommendation systems do.

Netflix Prize

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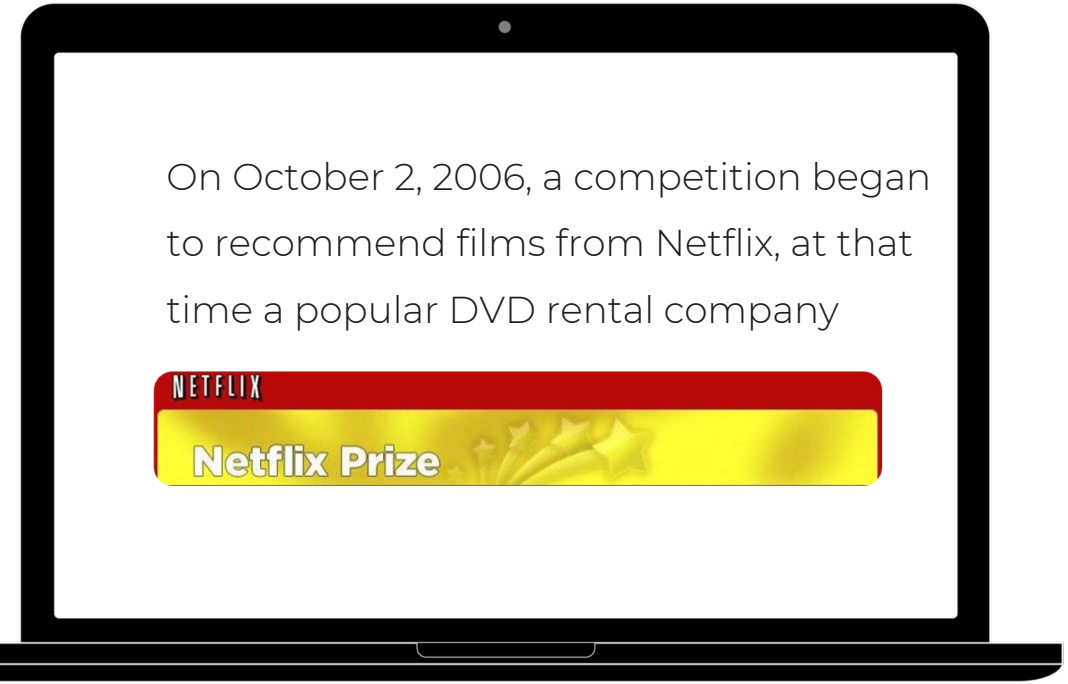
Netflix Prize



- predict the ratings of films from 1 to 5
- RMSE error
- 17700 films
- ~ 480 thousand customers
- ~ 100 million ratings
- prize is $1,000,000
- lasted almost 3 years
- 5100 teams participated

Netflix Prize

★ Results on the train

Rank	Team Name	Best Score	% Improvement	Last Submit Time
1	The Ensemble	0.8553	10.10	2009-07-26 18:38:22
2	BellKor's Pragmatic Chaos	0.8554	10.09	2009-07-26 18:18:28

★ Results on the test

Rank	Team Name	Best Test Score	% Improvement	Best Submit Time
1	BellKor's Pragmatic Chaos	0.8567	10.06	2009-07-26 18:18:28
2	The Ensemble	0.8567	10.06	2009-07-26 18:38:22

The competition gave an impetus to the development of the field of recommendation systems and largely determined the vector of development

Problem statement

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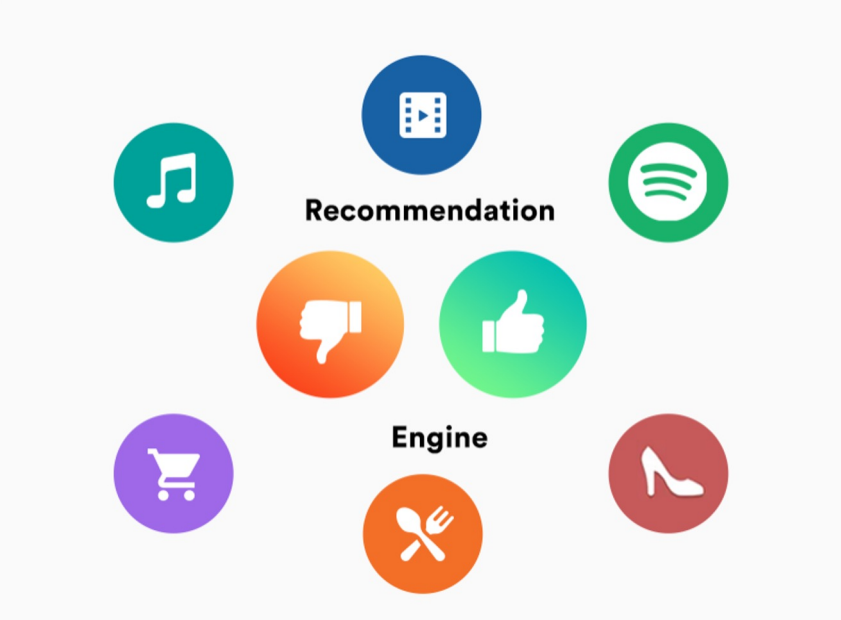
Definition

A recommender system is a subclass of information filtering system that provide suggestions for items that are most pertinent to a particular user.

Recommender systems are particularly useful when an individual needs to choose an item from a potentially overwhelming number of items that a service may offer.

Common knowledge site



Information retrieval subproblems

- Recommender systems
- Search engines
- Advertising

Formal problem statement

- ★ Specified U - set of users, I - set of objects (items), that we recommend
- ★ For each user $u \in U$ his interaction history: he interacted with the items $I_u \subset I,$ to which I gave ratings.

$$R_u = (r_{ui})_{i \in I_u}$$

- ★ Such user ratings are called feedback

The goal is to offer the user new items that would be interesting to the user

How to understand that an item is interesting to the user?

What interesting item is?

We can assess this by the quality of interaction.

For example:

- For the product that it was put in the basket
- For the music that it was listened to to the end
- For the article that it was liked
- For videos that have watched at least half of it
- Etc

Feedback types

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Explicit feedback

Explicit feedback is actions that express the user's explicit attitude to the product.

rating of the film from 1 to 5

like/dislike the track

product review

Implicit feedback

Implicit feedback is any other information, user actions on the site/in the app. It does not reflect its explicit relationship to the product, but can act as a proxy to explicit feedback.

video viewing time

viewing an article

purchase of goods

Features of explicit feedback

- Usually such data is quite small and more difficult to obtain (1-10% of implicit usually)
- Dislike of an article does not mean that such articles should not be recommended to the user. Perhaps he is interested in the subject, but did not like this particular article
- Not all users leave explicit feedback, thus it is highly biased to this subset of users (usually about 10% of users)

There is a funnel of actions from implicit to the most complex ones

Features of implicit feedback

- There is more such data
- As a rule, implicit data can be trusted less, since they express only implicit signals, and not explicit user ratings. For example, a user could buy a product as a gift, but he does not like the product himself
- Since the implicit signal has a different nature, techniques other than explicit feedback are usually used in the recommendation system to optimize it

Collaborative matrix sparsity

Suppose we have 10^7 users and 10^6 items.

User rate 10 items on average. *What is the percentage of filled cells?*

10 * 10^6 / (10^7 * 10^6) = 10^(-6) = **0.0001%**

Types of user representations

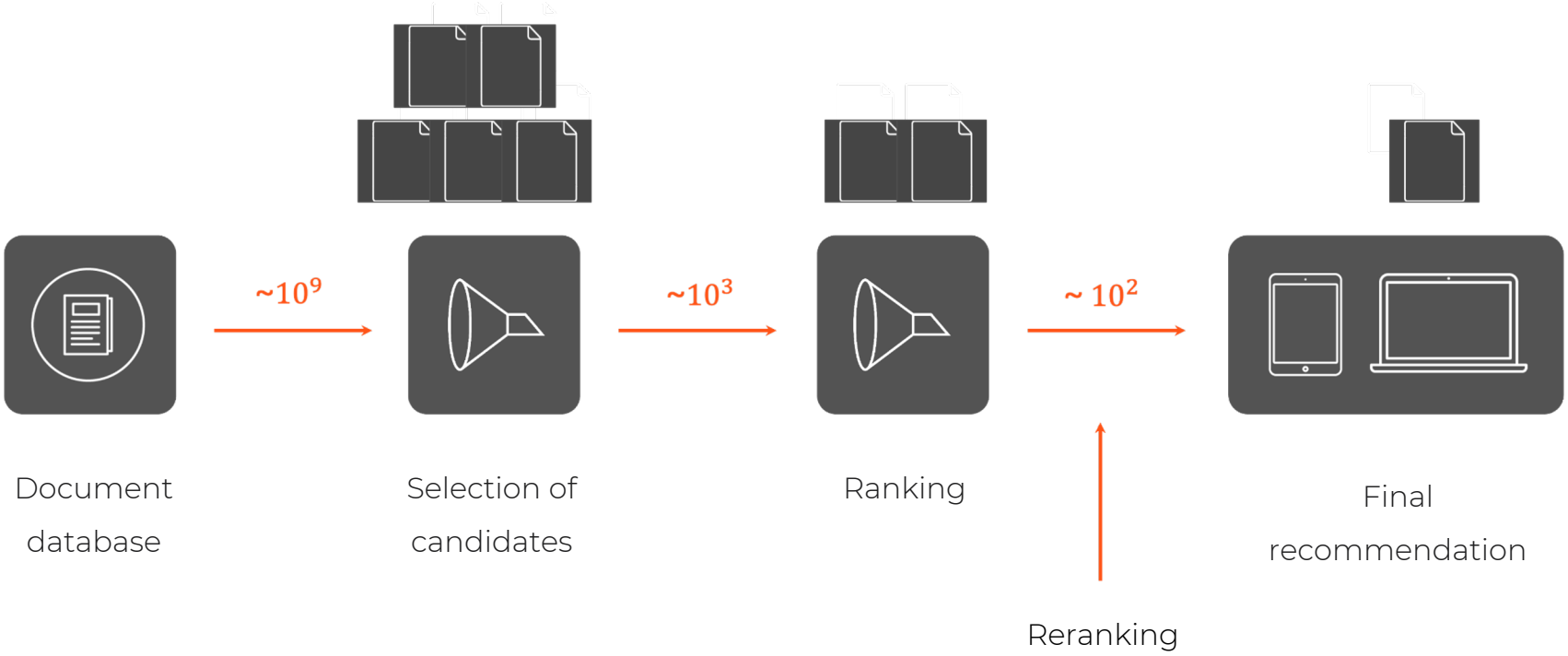
In general, we want to recommend items (music/movie/article/product)
to the user so that the user is happy (we work on long-term metrics)

A typical simplification of a user's happiness is whether a recommendation is liked at the moment.
Or even a bigger simplification —do you like the item as a whole or any item rating
for the user

The user himself can also be represented in different ways

1. As an unordered set of items that the user interacted with
2. As an unordered set of items with ratings
3. As a sequence of items with ratings
4. As a sequence of interactions taking into account the context

General scheme



Course plan

In total, there are 6 lectures in the course:

1. Introduction, main concepts, formal statement
2. Matrix factorizations
3. SLIM, neural networks for recommendations
4. Metrics in RecSys. Learning to rank
5. RecSys in production
6. Case study

Lecture plan

1. Setting the task of recommendation systems

- Basic concepts
- Types of feedback

2. Collaborative filtering

3. Other types of recommendations

- Content models
- Hybrid models

4. Recommendation systems in practice

- Ranking model
- Selection of candidates
- Reranking

5. Properties of recommender systems

Collaborative filtering

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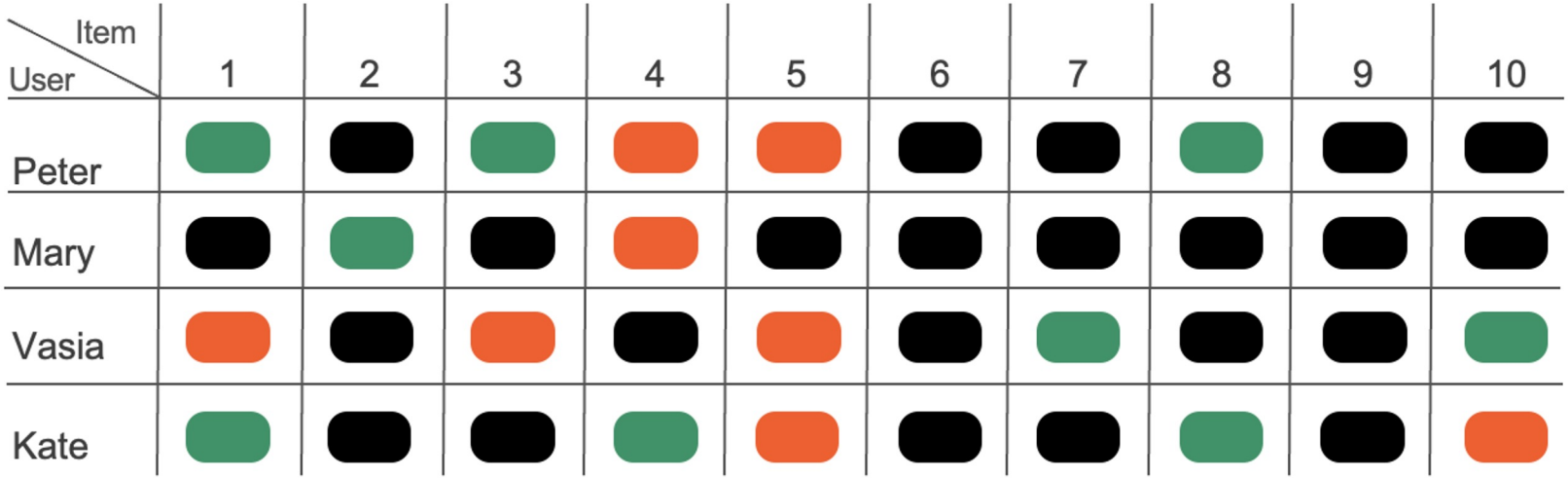
Example

Consider an example. Green cells are likes, red cells are dislikes.



What should I recommend to Kate?

Peter and Kate have similar interactions, so we recommend 3

And what is better not to show to Peter?

It's 10 because it was disliked by Kate

Collaborative filtering

Idea

We want to recommend products to the user that users like him liked

You can act differently. Namely, to recommend items similar to the ones the user liked. Similarities between atoms can be identified by user interaction

Collaborative filtering

Generally it is a family of recommendation methods based on similarities in the history of interaction between users and products

User2User recommendations

- ★ Consider some measure of similarity $s(u, v)$ between users. Then we can consider as neighbors user u and users

$$N(u) = \{v \in U \setminus \{u\} \mid s(u, v) > \alpha\}$$

- ★ We want to offer the user u items that users like him liked. Let's evaluate the user's rating by the rating of neighbors.
- ★ After evaluating the ratings of unseen aitems, recommend a certain number of aitems with the maximum ratingcv
- ★ Denote:

I_u — a lot of items that appreciated

$\bar{r}_u$ — average user rating

User2User formulas

$$\hat{r}_{ui} = \frac{\sum_{v \in N(u)} s(u,v) r_{vi}}{\sum_{v \in N(u)} |s(u,v)|}$$

$$\hat{r}_{ui} = \bar{r}_u + \frac{\sum_{v \in N(u)} s(u,v)(r_{vi} - \bar{r}_v)}{\sum_{v \in N(u)} |s(u,v)|}$$

$$\hat{r}_{ui} = \bar{r}_u + \sigma_u \frac{\sum_{v \in N(u)} s(u,v)(r_{vi} - \bar{r}_v)/\sigma_v}{\sum_{v \in N(u)} |s(u,v)|}$$

$$\sigma_u = \sqrt{\frac{1}{|I_u|} \sum_{i \in I_u} (r_{ui} - \bar{r}_u)^2}$$

User2User recommendations

- Rating score as the average of the neighbors with weights
- Problem: different users put ratings on different scales, so we will make an adjustment for the average user rating
- In addition, estimates from different users may be on a different scale, so we can relate them

User2User similarity

How to choose $s(u, v)$?

- The normalized number of common goods, a measure of Jacquard
- Scalar product of vectors of general ratings
- Pearson correlation between vectors of general ratings
- Pearson correlation between vectors of general ratings adjusted for a small number of general ratings

Similarity formulas

How to choose $s(u,v)$?

$$s(u,v) = \sum_{i \in I_u \cap I_v} r_{ui} r_{vi}$$

$$s(u,v) = \frac{\sum_{i \in I_u \cap I_v} (r_{ui} - \bar{r}_u)(r_{vi} - \bar{r}_v)}{\sqrt{\sum_{i \in I_u \cap I_v} (r_{ui} - \bar{r}_u)^2} \sqrt{\sum_{i \in I_u \cap I_v} (r_{vi} - \bar{r}_v)^2}}$$

$$s(u,v) = \frac{|I_u \cap I_v|}{|I_u \cup I_v|}$$

$$s(u,v) = min\left(\frac{|I_u \cap I_v|}{50}, 1\right) \frac{\sum_{i \in I_u \cap I_v} (r_{ui} - \bar{r}_u)(r_{vi} - \bar{r}_v)}{\sqrt{\sum_{i \in I_u \cap I_v} (r_{ui} - \bar{r}_u)^2} \sqrt{\sum_{i \in I_u \cap I_v} (r_{vi} - \bar{r}_v)^2}}$$

Item2Item recommendations

- Idea: to the products evaluated by the user, we will find the most similar to them and recommend
- The similarity between aitem is defined as a cosine measure adjusted for the average user rating, where U_i — users who rated the aitem i
- Further, using the similarities and the history of user interaction, we similarly evaluate the ratings of unappreciated items

Adjusted pearson correlation

$$s(i,j) = \frac{\sum_{u \in U_i \cap U_j} (r_{ui} - \bar{r}_u)(r_{uj} - \bar{r}_u)}{\sqrt{\sum_{u \in U_i \cap U_j} (r_{ui} - \bar{r}_u)^2} \sqrt{\sum_{u \in U_i \cap U_j} (r_{uj} - \bar{r}_u)^2}}$$

Features of collaborative filtering

- ★ It does not rely on additional information about users and products, collaborative filtering methods are self-sufficient
- ★ They are not applicable for cold users and products, that is, for those with a small history of interactions
- ★ Recommendations are based on the history of interactions in the past, which depends on past recommendations to the user
- ★ More advanced methods will be discussed in Lecture 2

Idea

User2User






2		2	4	5	
5		4			1
		5		2	
	1		5		4
		4			2
4	5		1		






Item2Item

2		2	4	5	
5		4			1
		5		2	
	1		5		4
		4			2
4	5		1		

Choosing between Item2Item and User2User

It strongly depends on the number of ratings per user and per item – the more, the more reliable the similarity.

This also leads to the possibility of pre-calculation: if there are a lot of estimates, then adding a pair of estimates will not change anything. Then you can update once in a while.

The similarities themselves can be used for other tasks (candidate generation, contextual recommendations).

https://www.cs.umd.edu/~samir/498/Amazon-Recommendations.pdf

Content-based recommendations

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Content-based recommendations

Let's go back to the example and look at the items themselves

What should I recommend to Peter?

Peter has a pronounced love for cats, you can show an unproven cat

And what to do with Kate?

Kate has only one interaction with cars, this is not enough,

so we show only cats with whom there were 2 likes

Content approach

they consist in recommendations to users of such items that are similar in content to the ones they liked

Example of content-based recommendations

- Let each item i correspond to an embedding e_i obtained from its content
- Then the user u can be recommended aitems as the proximity ρ between the vectors

  As ρ can be
- Scalar product
- Cosine distance
- Etc

Various methods will be discussed in Lecture 3

Hybrid models

Hybrid models are understood as models of recommendation systems that use both collaborative and content information to build user recommendations at the same time

Ranking model

1. Collaborative and content models have their advantages and disadvantages

2. When making recommendations, I want to use contextual information. For example, user preferences may vary on different days of the week

3. Information about the product would be useful: brand, price, etc.

In practice, as a rule, a ranking model is used, which combines various features

Ranking model

Signs of such a model can be

1. Predictions of basic collaborative, content models
2. User attributes: gender, age, characteristics of the interaction history, etc.
3. Features of the object: price, weight, genre, characteristics of the history of interactions, etc.
4. Contextual information: day of the week, weather, location, etc.

Ranking Model: Model approaches

Tasks for which such a model can be trained

1. Binary classification. The model predicts the presence or absence of a target positive interaction
2. Regression. For example, the model predicts the duration of watching a video, which determines the positivity of the interaction
3. Ranking. There are pairwise and listwise approaches, in which the model learns to correctly arrange a set of objects for the user

As a rule, variations of gradient boosting are used as a model, since at the moment they are better able to cope with tasks on tabular data.

Selection of candidates

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Candidates selection

Problems:

- ★ In a real recommendation system, there can be a huge number of items, about hundreds of millions or billions
- ★ With each user request for new recommendations, it is necessary to conduct all the items through the entire system
- ★ There are complex models that cannot be applied to millions of items
- ★ Solution:
  at the initial stage, select a relatively small number of candidates and apply the next steps only to them.
  Selection of candidates is the first step in the pipeline of recommendations

Candidates selection

When selecting candidates, it is important not to spoil the completeness of suitable products, so that there is nothing to choose from at all.

Possible approaches:

- Heuristic: the most popular products, the most popular among residents of the same city, etc.
- Collaborative: we consider item2item or user2user to be similar
- Content similarities: looking for close embedding; can be quickly identified using data structures HNSW, FAISS, etc.
- Approaches that take into account business logic: fresh, new

Reranking

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Reranking

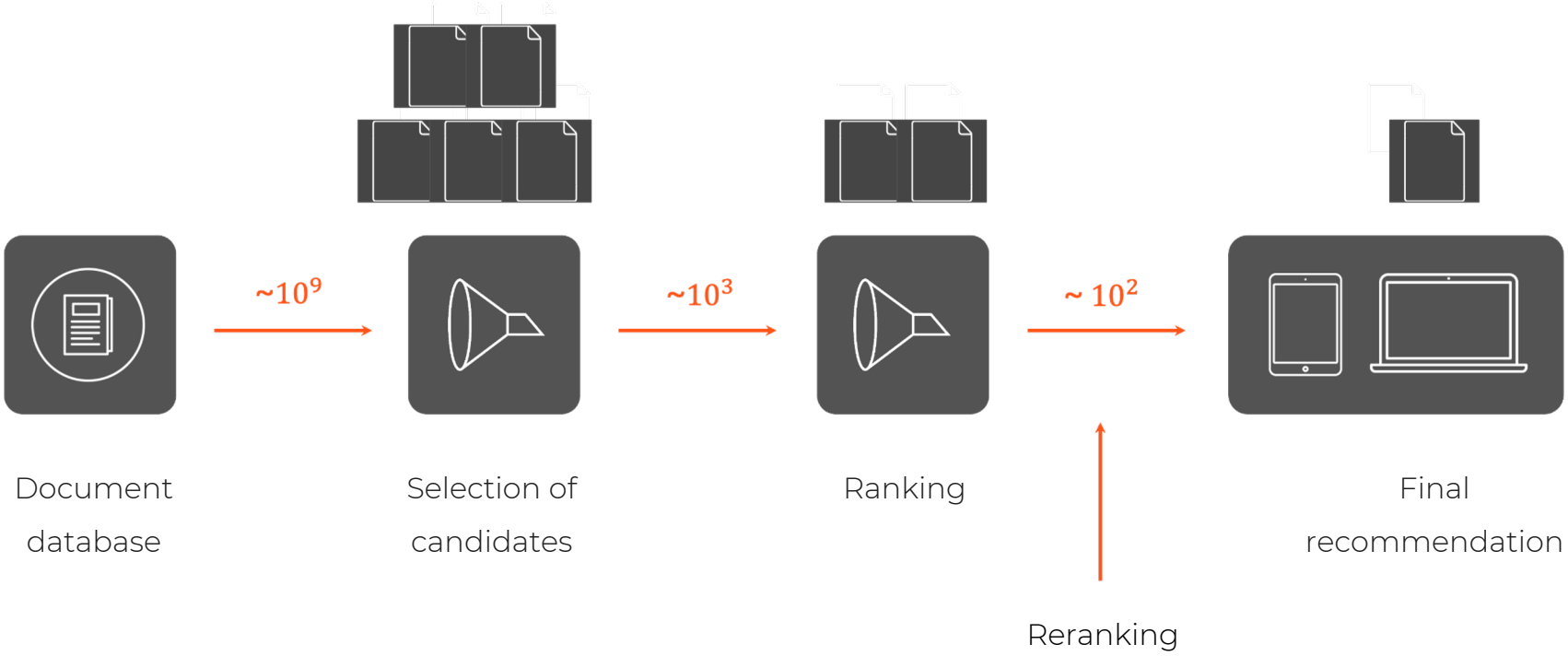
In addition, it is often necessary in practice to take into account different business logic in the recommended objects

For example:

- Limit the number of old or too long videos
- Provide diversity

To do this, after applying the ranking
model, a re-ranking mechanism is used.
The objects (top) arranged by the model are rearranged taking into account the required conditions

The final scheme



The cold start problem

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The cold start problem

1. Problem: how can I recommend something to a new user? How do I know who to show the new product to? How do I start recommending anything at all?

2. New user: try to find out as much information about him as possible, use technical approaches or extend registration, onboarding

3. New product: Recommend using only content models

Feedback loop

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Feedback loop

- The recommendation system learns from a lot of examples that it recommended itself. Because of this, we can get "stuck" in a local optimum, from which it is difficult to get out
- There are also risks that the recommendation system will adapt to a lot of users or products that are currently watching the most
- Simple solutions
    - Recommend fixed percent of random items to each user
    - Stratify training set by user groups or item groups

Thanks for attention!

Questions?

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