Recommendation Systems for Décathlon - Discussion

Machine Learning I
MATH60629

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Presentation of the case

Q1: Which model(s) for a recommendation system would the data science team need to choose, and why?

Item-based vs. User-based

- |Users| >> |Items|
- Item-based
  - (+) Stability
  - (+) Better performance (not always)
  - (+) Explainability
- User-based
  - (+) Diversity

Plan

- Choose the right model for a recommendation task
- Models chosen by Décathlon
  - Basic models, as reference
  - Model 1: Based on similarity between product images
  - Model 2: Collaborative filtering based on products
  - Model 3: Matrix factorization
  - Model 4: Recurrent neural networks
  - Chosen metrics
  - Results and final choice
- Limits of the current models and the next steps being considered by Décathlon

How to Choose the Right Model?

- Somewhat subjective task
- Imperative: the model must be able to process a large amount of data
- Started with simpler models and then moved on to more complex ones
- Final choice according to performance on chosen metrics and logistical considerations
- 4 models have been selected

(Basic) Model 0: Reference Point

- Random recommendation
- Recommending the same 10 most popular items to every user

Model 1: Based on Similarity Between Product Images

Take the vector that represents the image of each product (representation from a CNN model)

1. **For each user, a list of all the products with which they have *interacted* is extracted.**

2. **For each *interacted product*, the 10 most "similar" products are chosen, based on the cosine distance between their image vectors.**

3. **The most similar product gets 10 "points", the second one gets 9, and so on. Points are added up, and the 5 products with the highest scores get recommended.**

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User A has interacted in the past with items **3** and **5**

For each item, we identify the 10 items in the rest of the catalog that are most similar. We give 10 pts to the most similar one, 9 pts to the second most, and so on

3	5	
7	11	10 pts
12	7	9 pts
37	22	8 pts
11	30	7 pts
22	1	6 pts
6	26	5 pts
1	27	4 pts
28	12	3 pts
29	15	2 pts
30	9	1 pts

We sum all the scores, and recommend the top five items to our user

Recommendations to user **A**:

Item **7** (19 pts)
Item **11** (17 pts)
Item **22** (14 pts)
Item **12** (12 pts)
Item **1** (10 pts)

 

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Pros and Cons

- (+) Even new or unpopular products can get recommended
- (+) Explanations can be offered (*because you bought product X, you could find these products interesting*)
- (+) Easy to implement

- (-) The recommended products are very similar to previously purchased items
- (-) *Cold-start* problem for the users

Model 2: Collaborative Filtering Based on Products

Very similar model to the previous one. Instead of calculating the similarity of image vectors, similarity is calculated according to a user-product interaction matrix.

1. For each user, a list of all the products with which they have interacted is extracted.

2. For each product, the 10 most “similar” products are chosen, based on a cosine distance between their respective lines in the user-product interaction matrix.

3. The final score is similar to the one produced by model 1. However, instead of attributing arbitrary points (10 pts for the 1st, 9 for the 2nd, etc.), the similarity scores are used directly. Points are added, and the 5 products with the highest scores get recommended.

Example: similarity between two products

- In this matrix, lines represent users and columns represent products. A value of 1 indicates an interest, and 0 means no interaction.
  - For example, the first column shows that only User 4 has interacted with Product 1.
- The cosine similarity between the first (a =[0 0 0 1]) and the second product (b=[0 1 0 0]) would be 0. No user has interacted with both products.
- The similarity between the third (c=[1 0 1 0]) and the fifth product (e=[1 0 1 1]) is 0.82. The closer the value is to 1, the greater the similarity between the products.

Products

```
[0, 0, 1, 0, 1, 0]
[0, 1, 0, 0, 0, 0]
[0, 0, 1, 0, 1, 0]
[1, 0, 0, 0, 1, 0]
```

Users

Pros and Cons

- (+) Explanations can be offered (because you bought product X, you could find these products interesting)

- (+) Easy and quick to implement

- (+) Collaborative filtering usually yields good results

- (-) Cold-start problem for the users and the products

Model 3 : Matrix Factorization

- Completion of the user-product interaction matrix through matrix factorization
  - Several methodologies have been used, like Singular Value Decomposition and Non-Negative Matrix Factorization.
- It predicts the probability of an interaction with each product. Recommended products are the ones with the highest probabilities of interaction.

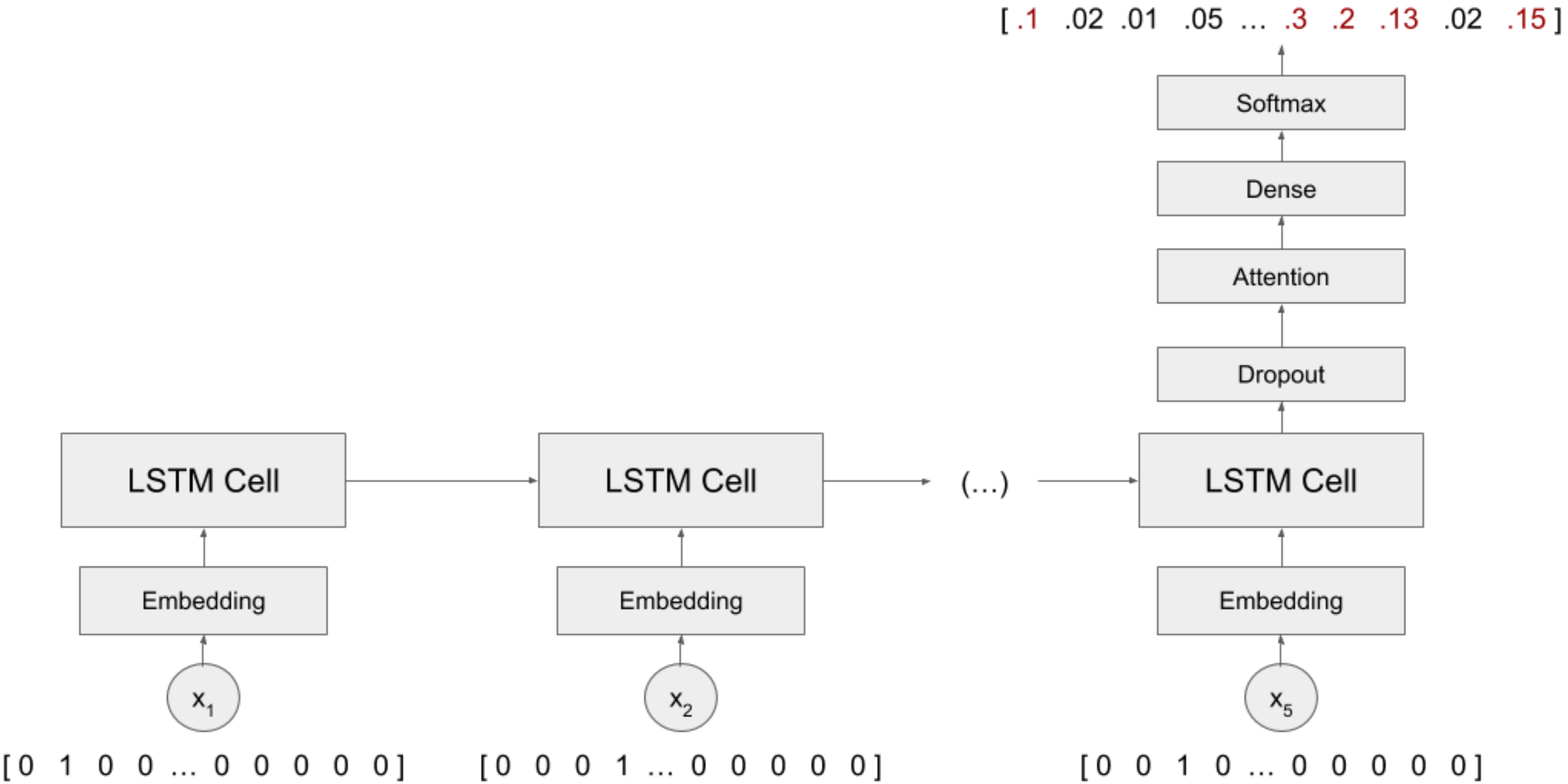
Pros and Cons

- (+) Matrix factorization usually yields good results
- (+) It can reveal interesting underlying characteristics

- (-) Cold-start problem for the users and the products
- (-) Important computational costs
- (-) Deploying the models requires a more complex virtual infrastructure*

Model 4: Recurrent Neural Networks

- This model tackles the problem as a sequence of products with which the user interacts, and tries to predict what the next one could be.
  - Each product is represented by a one-hot vector.
    - Products are entered into the network sequentially, and the network predicts the next one.
  - The network then outputs a probability distribution for every product in the catalogue.
  - Long Short-Term Memory (LSTM) neurons are used, with dropout-type regularization and attention principles.


[.1 .02 .01 .05 … .3 .2 .13 .02 .15]
Softmax
Dense
Attention
Dropout
LSTM Cell
LSTM Cell
(…)
LSTM Cell
Embedding
Embedding
Embedding
x_1
x_2
x_5
[0 1 0 0 … 0 0 0 0 0]
[0 0 0 1 … 0 0 0 0 0]
[0 0 1 0 … 0 0 0 0 0]

Pros and Cons

- (+) New users can be easily added
- (+) Recurrent networks usually give very good results

- (-) Cold-start problem for the products
- (-) Works better if a user has interacted with several products

Metrics

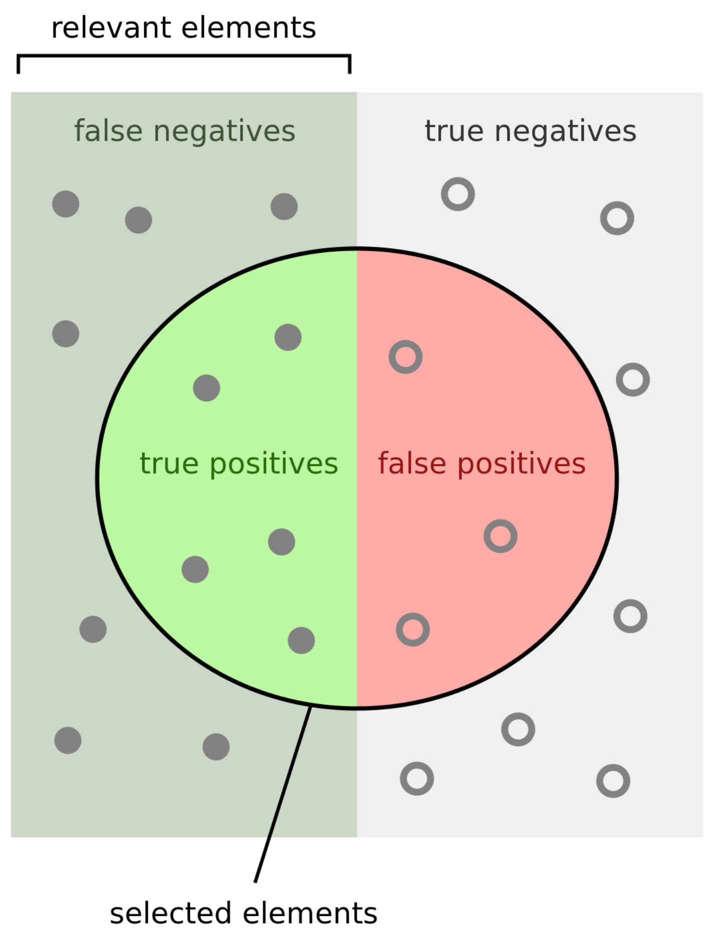
Only off-line metrics: the team does not have access to on-line evaluation or user studies

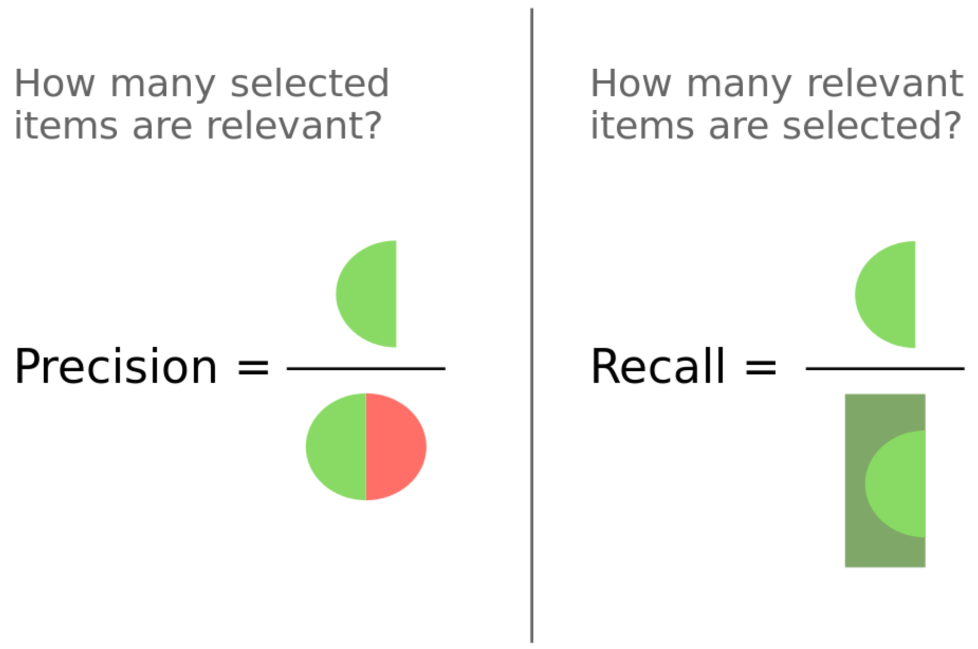
A. **Accuracy:** proportion of the recommended products that actually get bought by the users

B. **Recall:** proportion of products that were actually bought which were recommended

C. **Coverage:** proportion of products that were recommended to at least 1 user

Option to not consider diversity or serendipity

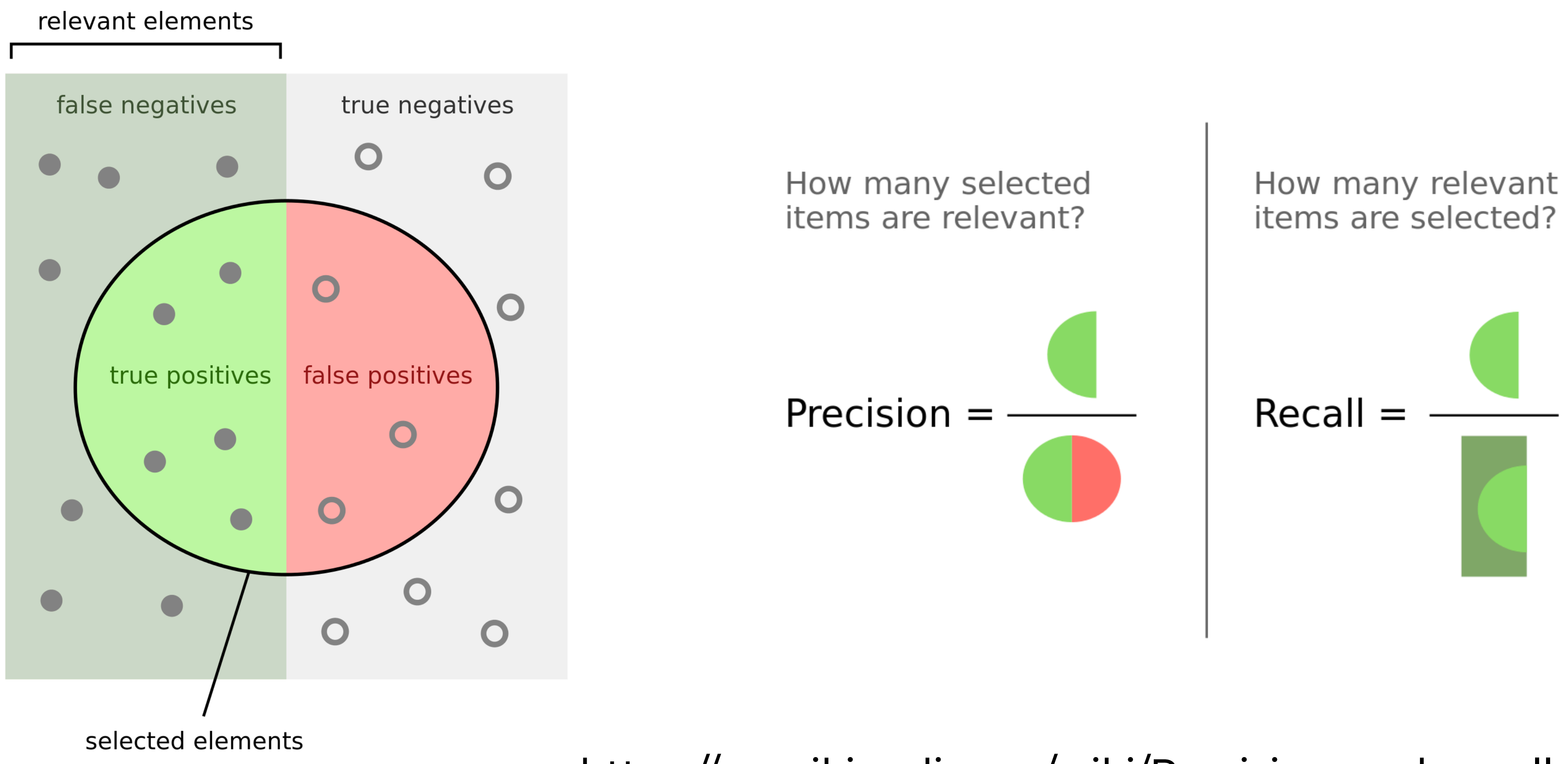




https://en.wikipedia.org/wiki/Precision_and_recall

Results

Model	Random	Most popular	1. Visual Similarity	2. Collaborative, based on products	3. Matrix factorization	4. Recurrent Neural Networks (RNNs)
Precision	0,06%	1,5%	1,9%	3,4%	3,9%	4%
Recall	0,07%	1,8%	2,3%	4,1%	5,3%	5,7%
Coverage	91%	0,07%	37,1%	74%	69%	57%



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