RECOMMENDER SYSTEMS

WHAT, WHY, HOW

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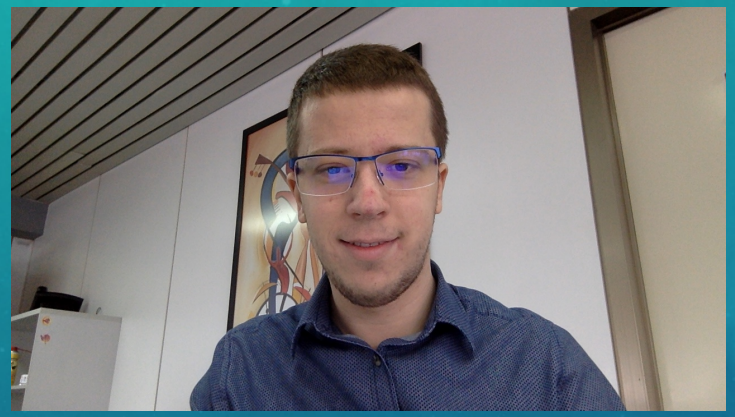
Who am I



- Software Engineer working in the field of Data Science
- **3 years** of experience in working on data platforms, and applications that take advantage of machine learning techniques

What I’ll talk about

- **What** is a Recommender System (Engine)
- Brief history
- **Why** do we need one
- **How** do we build one
- How do we know we’ve build a **good** one

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  - Use these models to **improve** and **enrich the user experience**
  - Create a **personalized environment** for the user, on the system
  - **Adjust that model** by analyzing the user-system interactions and by "**learning",** by means of incorporating **user feedback**

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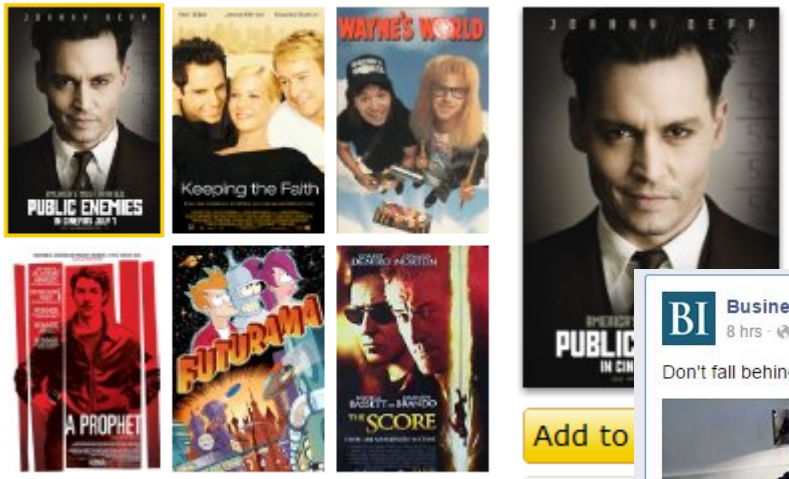

Public Enemies (2009)
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7.0/10
The Feds try to take down notorious American gangsters John Dillinger, Baby Face Nelson and Pretty Boy Floyd during a booming crime wave in the 1930s.

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Why do **we need** Recommender Systems?

- In the eyes of the **service provider**
  - ⇒ **Helps in deciding what kind of offerings should be made to the user**
  - ⇒ **Helps in guiding user attention**
  - ⇒ **Helps in presenting the user with the desired customization**

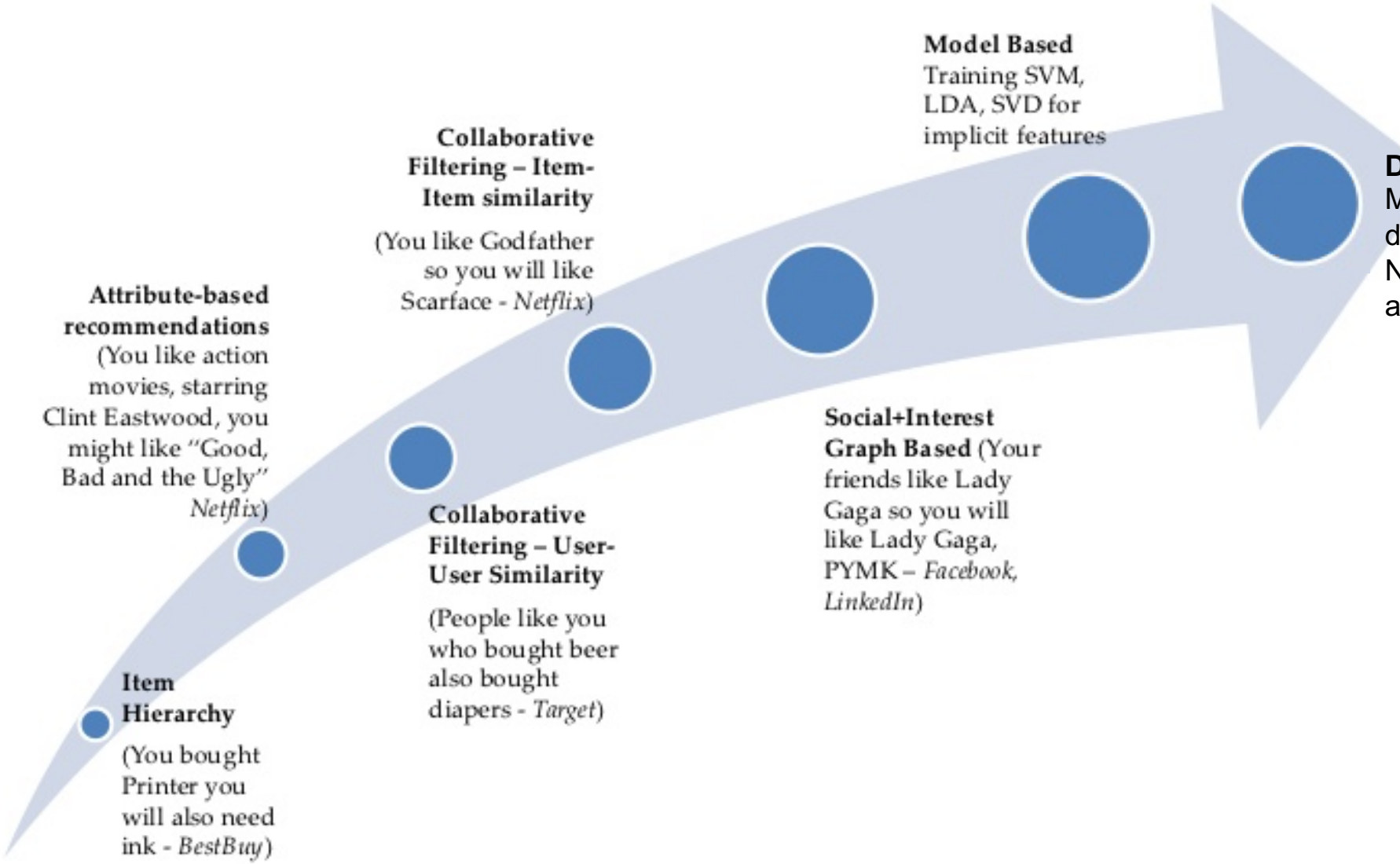
- In the eyes of the **user**
  - ⇒ **Helps in finding a particular item**
  - ⇒ **Helps in comparing / choosing among a large number of items**

Personalized / Non-Personalized

- Is this item important / attractive **in general**?
  - Top N overall, Trending now, Association rules

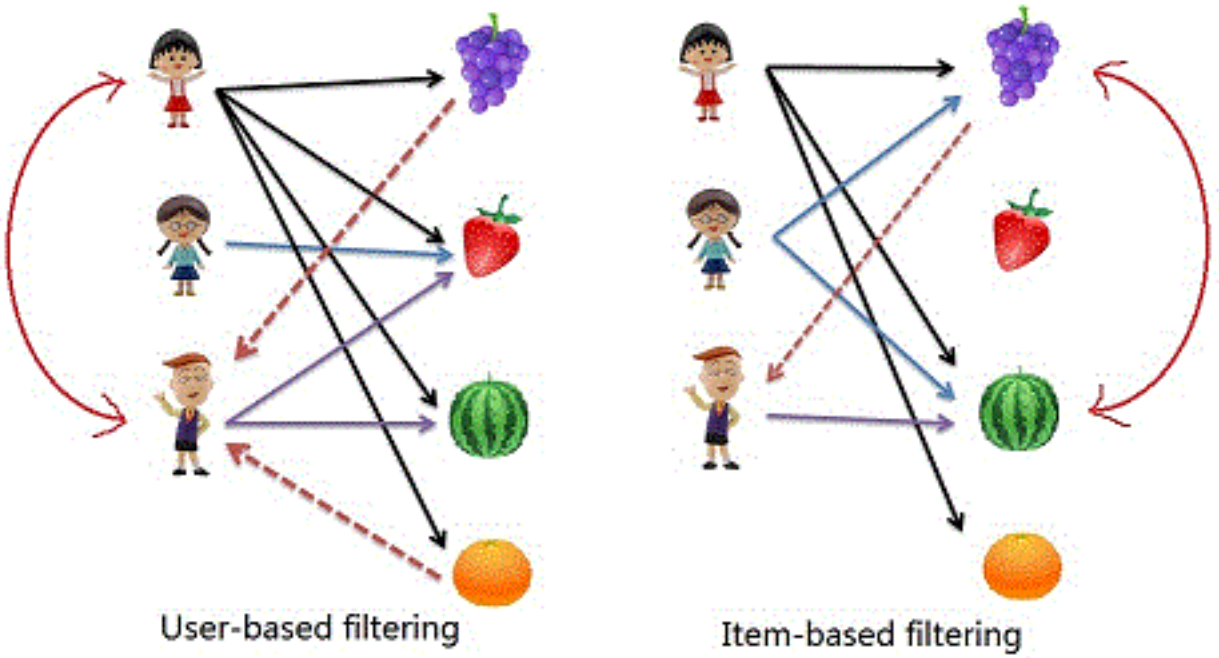
- Is this item important / attractive **for this user**?
  - Because you liked that, you might like this
  - Because your friend liked that, you might like this
  - Because this is similar to something you liked

Recommender Approaches



Most common approaches

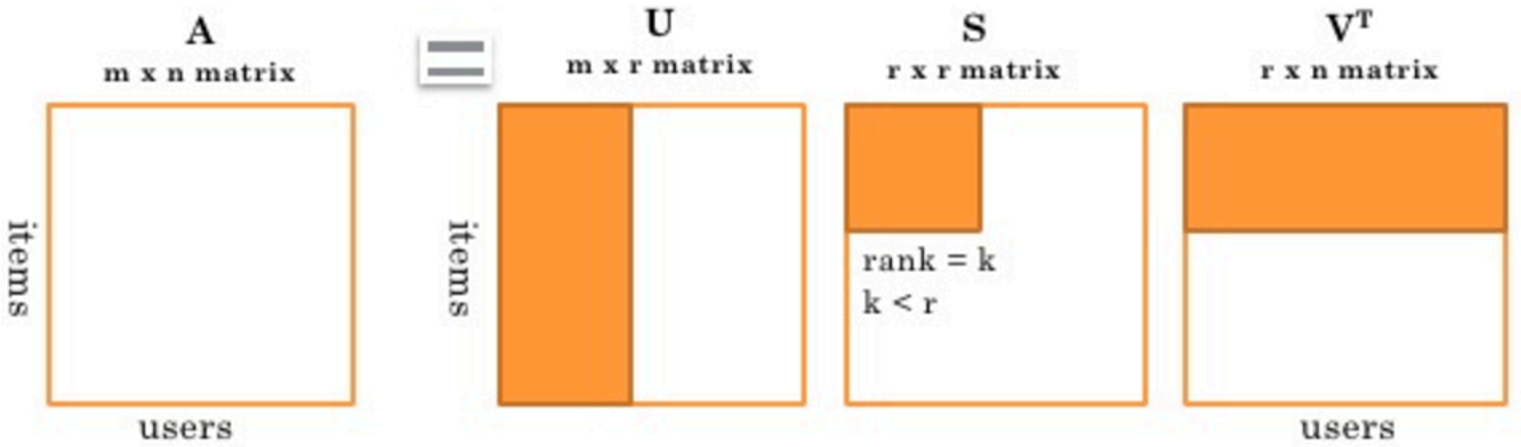
- **Statistical methods**
- **Collaborative filtering techniques**
  - **Item – Item based**
  - **User – User based**
  - **Hybrid** combination
- **Matrix Factorization techniques (SVD, Deep Learning)**



Credits:
http://www.salemmarafi.com/wp-content/uploads/2014/04/collaborativeFiltering-960x540.jpg

Singular Value Decomposition (SVD)

$$A = U \times S \times V^T$$



$$A_k = U_k \times S_k \times V_k^T$$

- Low rank approx. Item profile is $U_k * \sqrt{S_k}$
- Low rank approx. User profile is $\sqrt{S_k} * V_k^T$
- Low rank approx. Item-User matrix is $U_k * \sqrt{S_k} * \sqrt{S_k} * V_k^T$

Credits:
https://image.slidesharecdn.com/4772391/95/building-a-recommendation-engine-an-example-of-a-product-recommendation-engine-21-728.jpg

How do we **build** one?

Data

- Users
- Events
- Actions

Features

- Feature Engineering
- Entity relationships

ML alg.

- Choose wisely for the use-cases

Predictions

- Generate predictions (ranking…)

Validate

- Test the system in the wild
- Incorporate user feedback


data
mining
Data
information
analysis
software
warehousing
relationships
knowledge
different
determine
advances
organizations
databases
companies
patterns
Information
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grocery
example
Thursdays
supermarket
used
sales
enables
analyze
transactional
retail
Knowledge
computer
power
storage
diapers
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many
bought
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Saturdays
increase
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First, we get the **data**!

In order to recommend an item to a user or a group of users, you need to have:

- an offering of items, and
- users to which to recommend those items

Step 1:

Aggregate, structure and analyze the data that the system holds. Some visualizations might point to particular trends, and the size and volume of data might give clue to what algorithm is most appropriate.

Define the features

- **Decide on:**
  - What is known for the user entity?
  - What is known for the item entity?
  - What actions does the system track, that might offer useful information?
  - What is known for the relationship between the entities?

Step 2:

Define the features of the entities and the features of the relationship between the users, items and actions in the system. Make the features as descriptive as possible. Sometimes a mixture of attributes can be a feature also.

Choose an Algorithm

- **Research, experiment and decide:**
  - Whether the recommender system will be personalized / non personalized
  - Whether it will use collaborative filtering, or factorization techniques
  - Which machine algorithm will be leveraged (supervised / unsupervised learning) ?

Step 3:

Build on the shoulders of giants. See what has been used before, to solve a similar problem. Research and experiment with different algorithms, and techniques.

Build models and generate predictions

- **Use the features / algorithm decision and implement a model**
- **Use the data to train the model**
- **Use the model to generate predictions**
- **Check the performance of the model**

Step 4:

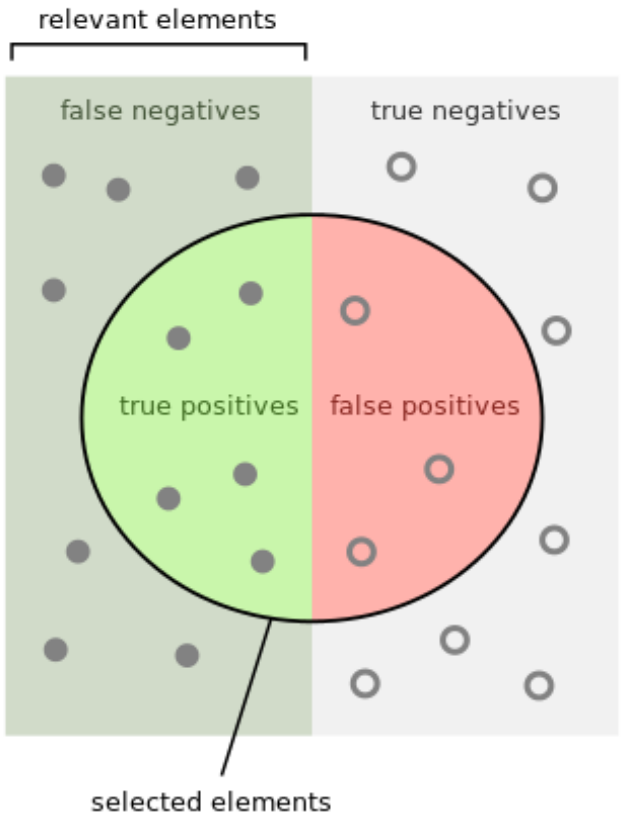
Build and train a model. Build more than one model. Compare the predictions and evaluate the models.

Test / Validate the models

- **Use the built models, to show predictions (recommendations) to real users**
- **Monitor the response / actions of the users**
- **Make sure to provide as much options as possible for the users to provide feedback**

Step 5:

Test the built models with real users. Start off with something small like a “what you might like” section. Incorporate user feedback in order to improve model performance.



How many selected items are relevant?

$$\text{Precision} = \frac{\text{true positives}}{\text{true positives} + \text{false positives}}$$

How many relevant items are selected?

$$\text{Recall} = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}}$$

$$F_1 = 2 \cdot \frac{\mathrm{precision} \cdot \mathrm{recall}}{\mathrm{precision} + \mathrm{recall}}$$

The cold start problem…

- What if there is no sufficient data for users / items in the system?

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⇒ Provide quick and easy ways for users to let you know more about them

Offer ways for the user to give **feedback**

- Like / dislike
- Rate
- Swipe to remove / hide (don’t show me items like this)
- Was this helpful?

- **Track implicit feedback, as well as explicit…**

=> If the user was presented with 5 recommendations, and the user choose the third one, maybe the first two deserve a bad mark...

Gotchas…

- Uneven rankings from different people (one mans' 3 can mean the same as other mans' 5, on a 1-5 scale)
- Temporal data (what is relevant today, may not be as relevant tomorrow)
- What scale best captures your items nature 0-1 (like, no like), 1-5, 1-10, 0-100?
- Are user ratings reliable? Would the same user rate the same item with the same grade today, as it did 1 week/month/year ago?

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=> Implement a weight cost function which puts accent on newest actions

It’s the little things…

- “We recommend” vs “what you might like”
- This product has a 4.3 star rating. Out of HOW MANY ratings?
- We recommend this item… Why?