Recommendation Systems

And applications in social media like twitter.

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But first of all, what are recommendation systems?

- The colossal amount of data available on the internet nowadays poses a series of problems, one of them being that for each user of the internet, **there can only be a set amount of information that can be shown to them**.
- This makes deciding what information to show and when to show it to a certain user critical, furthermore on more "***personalised***" matters, like adverts or what to see next on Netflix.
- To deal with this problem, information **filters** have been created, commonly known as "***recommendation systems***".

But first of all, what are recommendation systems?

- These “filters” **produce suggestions and recommendations** to assists users in many decision-making processes.
- With the help of these, users **are more likely to access appropriate products and services** such as movies, books, music, food, hotels, and restaurants.

Notice the fact that these systems do not imply the user will be interested in a certain item or service, but they guarantee that there is a bigger chance something the user is interested in will be shown to them.

Phases of recommendation process

1. Information collection phase: there are different ways to collect information.

-Explicit feedback: The user has to rate items to give information to the system. The accuracy of the prediction will be improved.

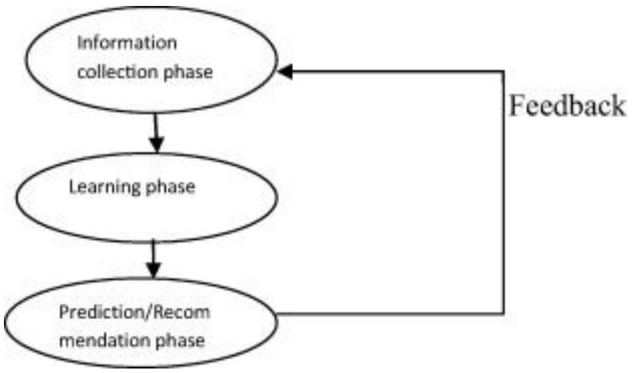
-Implicit feedback: The system automatically deduces the user's preferences watching his history of purchases, his navigation history… The accuracy of the prediction will be smaller.

-Hybrid feedback: The user can give his feedback but the system will also learn by observing his information.

Phases of recommendation process

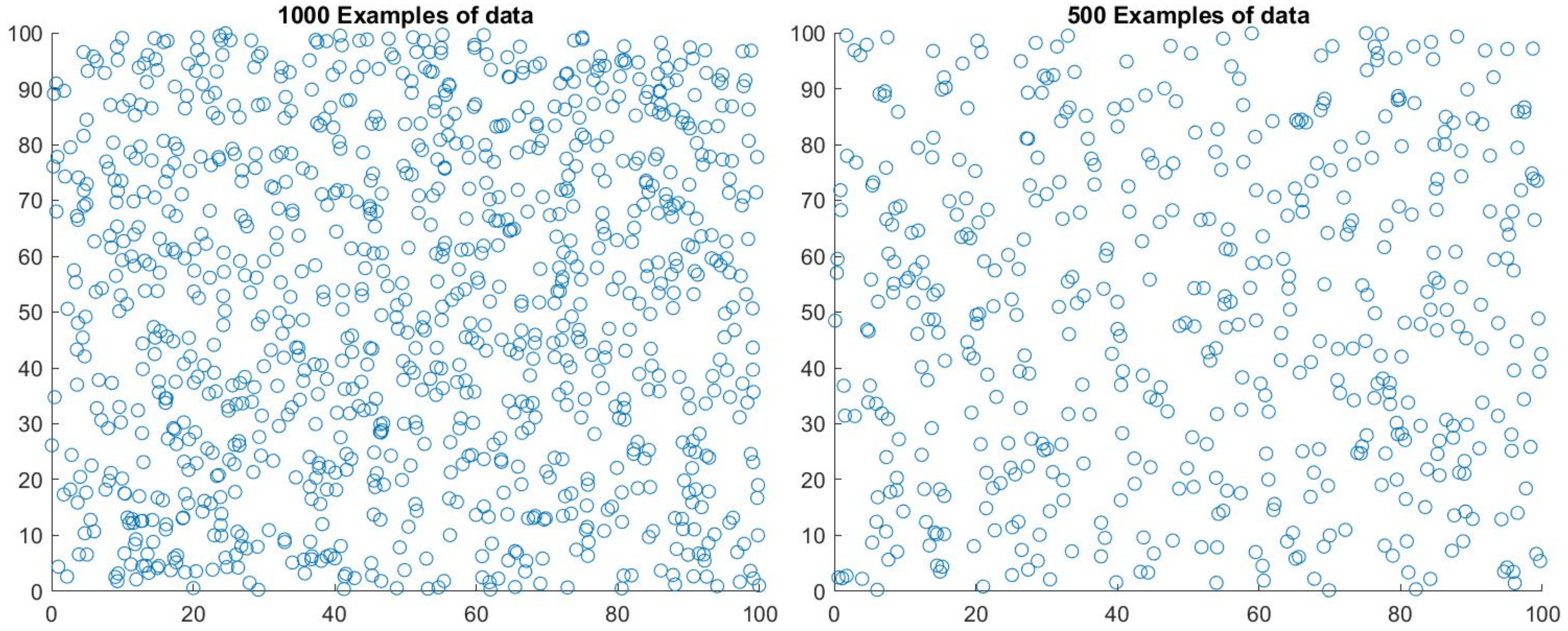
2. Learning phase: The system learns from the collected information.

3. Prediction/recommendation phase: The system makes his recommendation.



Challenges of recommender systems.

- **Lack of Data and the sparsity problem:**
    - The main issue of recommendation systems is that they need immense amounts of data in order to work properly.
    - **The sparsity problem:** The sparsity problem is a particular case of Lack of Data. The sparsity problem occurs when transactional or feedback data is sparse and insufficient for identifying neighbors and it is a major issue limiting the quality of recommendations and the applicability of collaborative filtering in general.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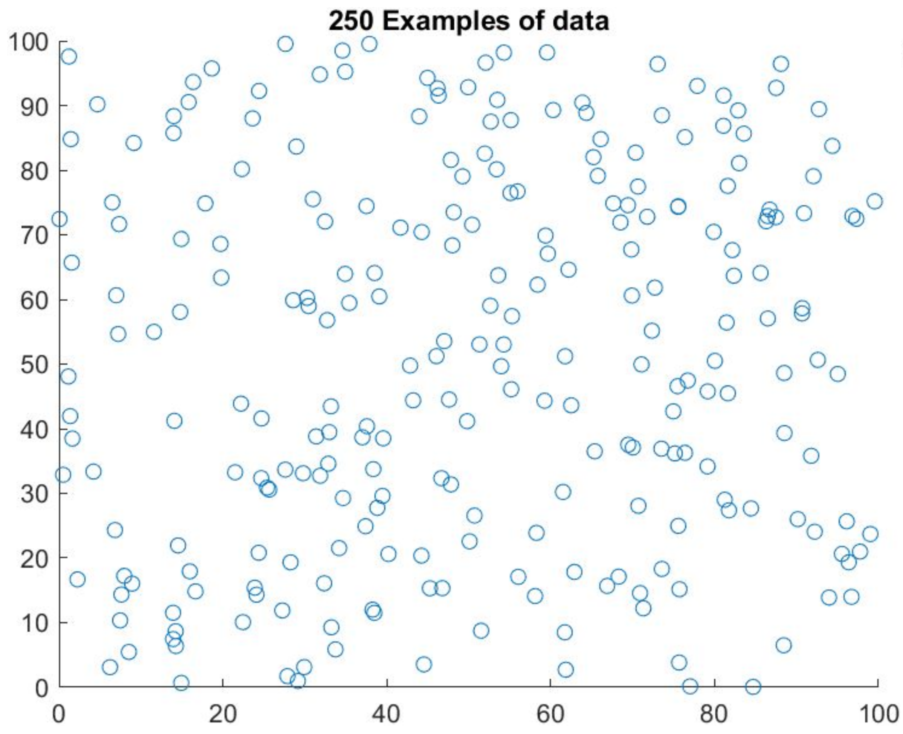
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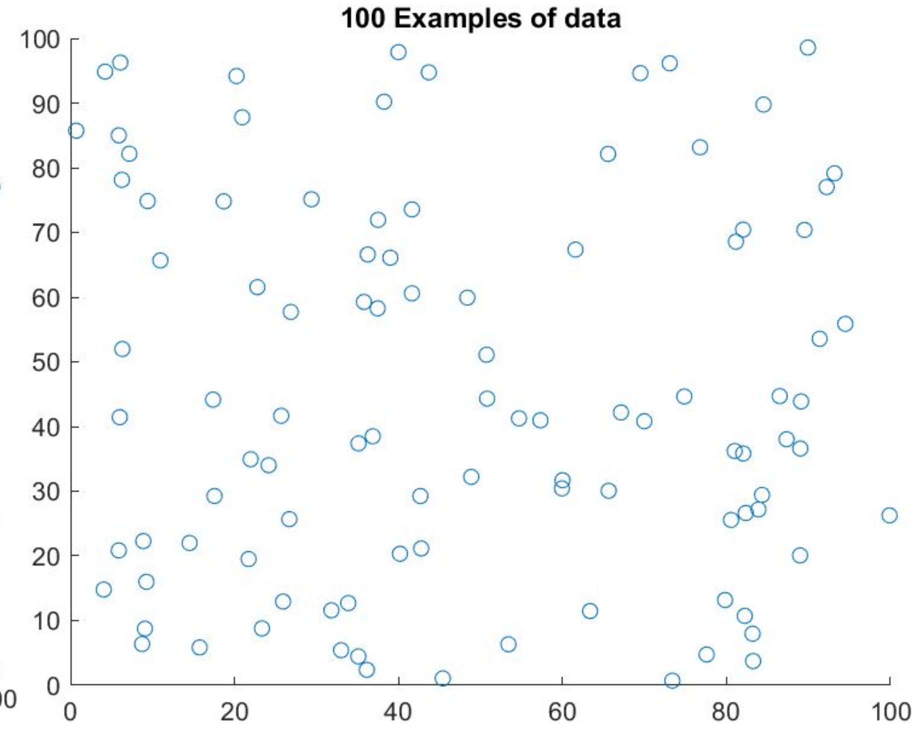
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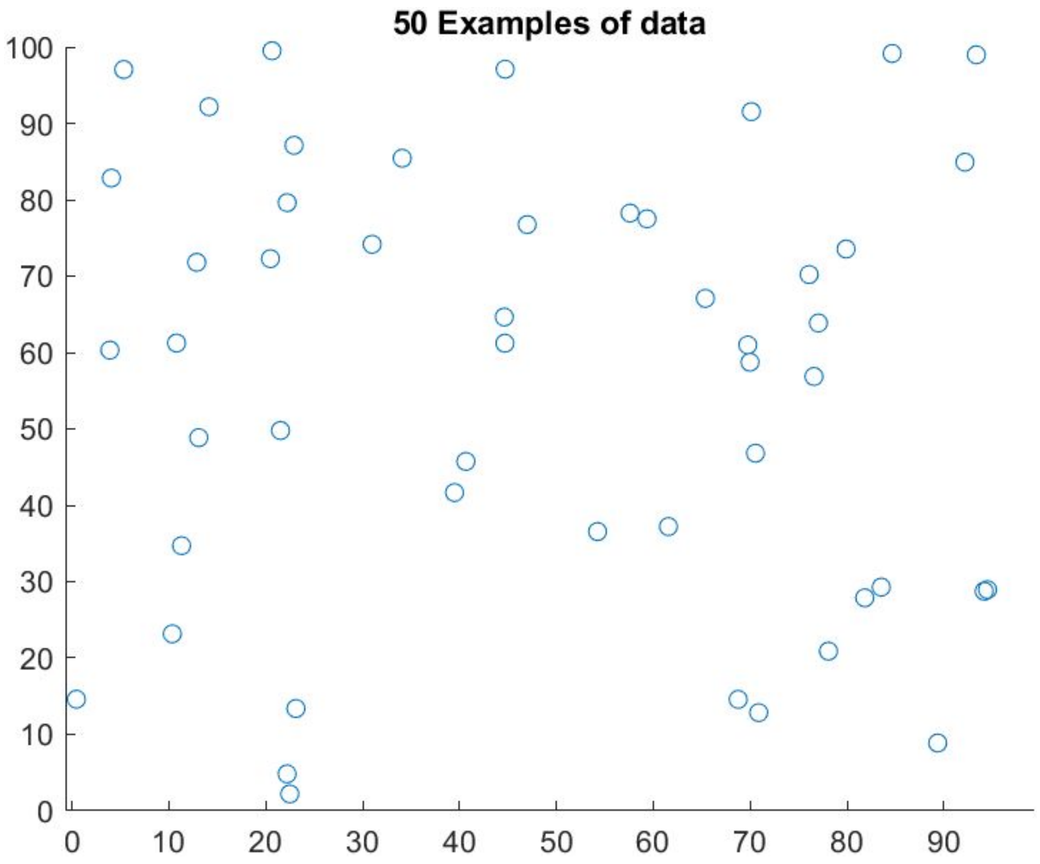
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Challenges of recommender systems.

- **Changing data**: Humans work on trends. Something that can be desired by a lot of people in a certain moment in time might have 0 interest in a future moment.

- **Changes in the users preferences:** Continuing with the human behavior examples, how many times did you actually like, for example, an X item that has this complete opposite Y item, only to change preference and like the Y item more after a while.

Challenges of recommender systems.

- **Unpredictable items:** Similar yet different to the previous problem, some users might be interested in opposite items at the same time, for example, a hard-core metal fan might also be a fan of Julio iglesias, and a system like spotify needs to actually spot these two totally opposite preferences and take them into account.

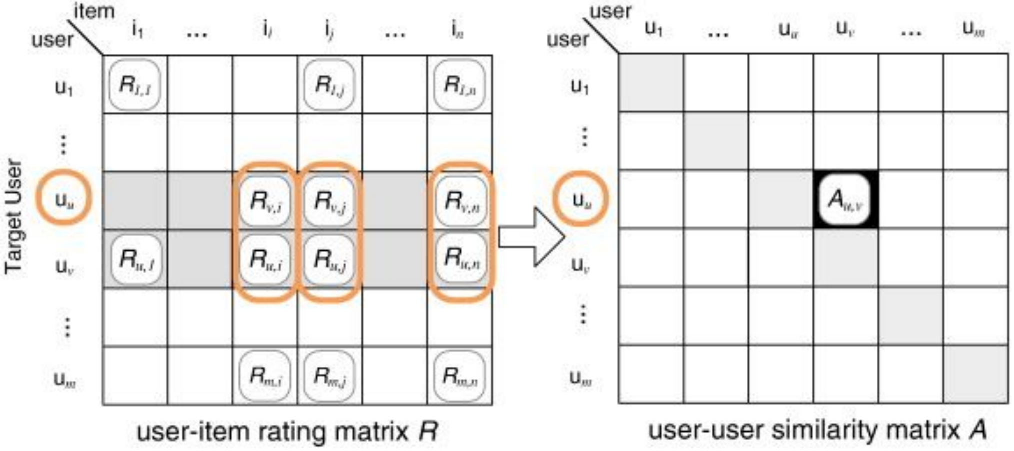
Deep learning within recommender systems.

- Knowing that deep learning is beneficial in analyzing data from multiple sources and discovering hidden features, the researchers have already started to benefit from deep learning techniques in recommender systems. They have utilized deep learning techniques to produce practical solutions to the challenges of recommender systems such **as scalability and sparsity.**

- Advantages of using Deep Learning to produce recommendations are several, **like dimensionality reduction, feature extraction** from different data sources. They can also be used to create or model **user-item preference matrix and side information**.

USER-ITEM Matrix

	I_1	I_2		I_j		I_{m-1}	I_m
U_1			…		…		
U_2			…		…		
	⋮	⋮	⋮	⋮	⋮	⋮	⋮
U_i			…	A_{ij}	…		
	⋮	⋮	⋮	⋮	⋮	⋮	⋮
U_{n-1}			…		…		
U_n			…		…		



Deep learning within recommender systems.

- Deep learning techniques **are not specialized onto a unique recommendation method**; they are utilized in all kinds of recommendation methodologies with different purposes.
- In **content-based filtering**, these techniques are mostly used for extracting features to **generate content-based user/item profile**s (The user/item matrix defined before) from data sources.
- However, in **Collaborative Filtering**, they are often utilized as an approach **to extracting factors on the user-item matrix** (The inverse method, instead of modelling the matrix, making conclusions of such a matrix).
- In **hybrid recommender systems**, deep learning methods are utilized for extracting features from **auxiliary information.** (AKA. side information used to reinforce the model and making better predictions).

Recommendation Systems in Twitter

- The symbol “@” in twitter can be used to mention users
- Previously , they use recents tweets or randomly selected tweets to select a list of names
- The are to many historical tweets so it cannot guarantee the desired results
- Firts tweet encoder is used to represent tweets
- Secondy , a policy gradient is used to select relevant indicator tweets
- User and candidate-mentioned-user tweet selectors are policy grandient agients
- Finally, merge the query-tweet selected by agents.
- To represent query tweet we use a a vector
- Randomly initialize word embbeding matrix is used to represent all words

Conclusion:

Recommendation systems open new opportunities of retrieving personalized information on the Internet. It also helps to alleviate the problem of information overload.

The widespread use of recommendation systems and their advantages on commodity / user based services makes a really important area of current and future research. With their applications on social media still being explored, they have become a staple on services like Netflix, Spotify, Amazon or even Google ads. The introduction of deep learning and multi agent systems, although increasing both the complexity and computational power needed of these recommendation systems, opens a new universe in possibilities and there are a large number of new developing techniques and emerging models each year. With this work we hope to have given the reader the basic insights of recommender systems, a brief explanation of the uses of deep learning recommender systems and their modern applications on social media like twitter.