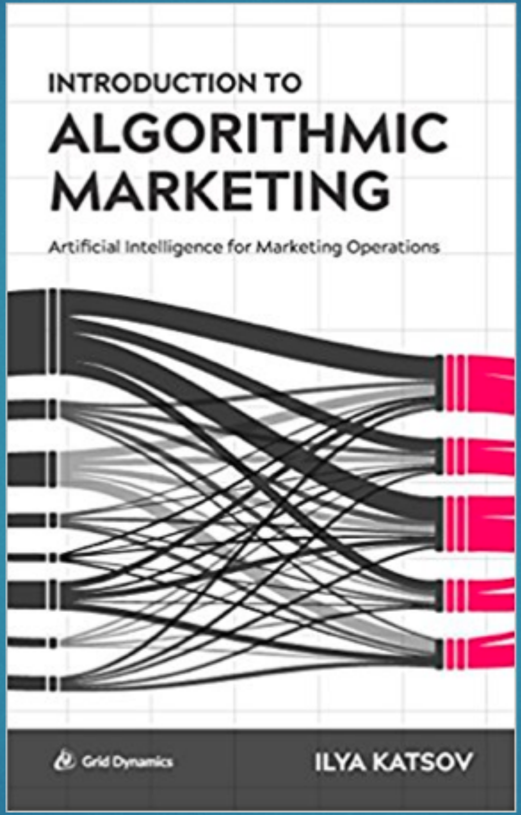
Introduction to Recommender Systems

WILLIAM STEIMEL B1778102
スタイメルウィリアム

Table of Contents

Sources



Chapter 5- Recommendations

This presentation follows this Chapter but is extremely condensed to the depth of the content.

Introduction

- How many times have you went to a website recently and been told that you may be interested in purchasing this item or watching this video or reading this article.
- No matter where you go on the internet nowadays it seems that this is now the norm in our everyday browsing experience.
- This is what is called a recommender system which has become quite popular in the digital age and can be applied to many different business domain areas.

What are Recommender Systems?

- Recommender Systems are information filtering systems that utilize data to provide recommendations to customers or users.
- I would say they are systems that help customers in the digital age have a customized shopping experience based on their interests and/or previous purchase behavior.
- This in turn helps the business create more sales, increase customer satisfaction, and optimizes their marketing strategy.

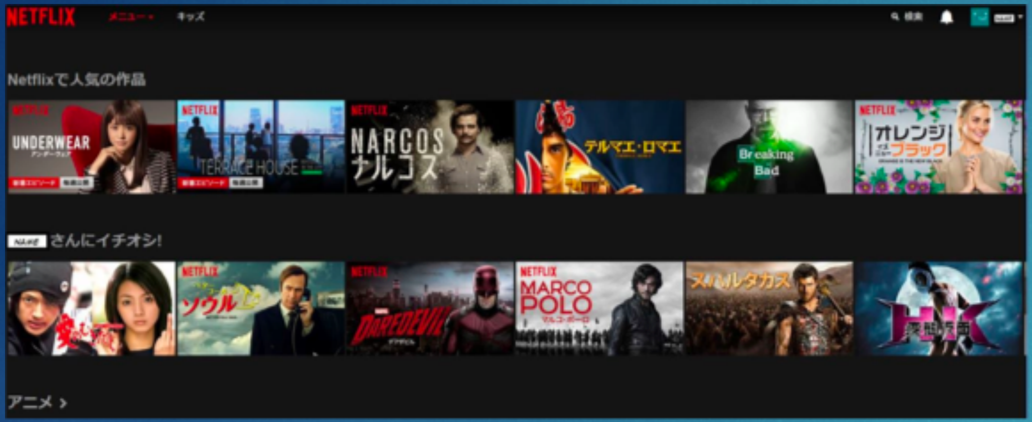
This area of Machine Learning has become very popular lately as businesses continue to desire to maximize their marketing strategy and operations.

What are Recommender Systems?

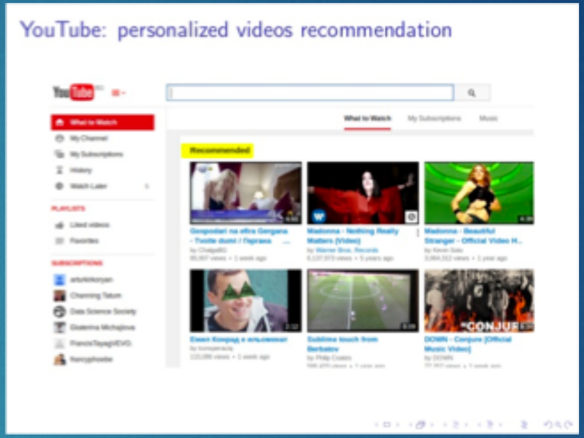
- Modern Uses for Recommender Systems
  - Product Recommendations
  - Movie Recommendations
  - Music Recommendations
  - News recommendations
  - Video Recommendations
  - Many more

Who Uses Recommender Systems?

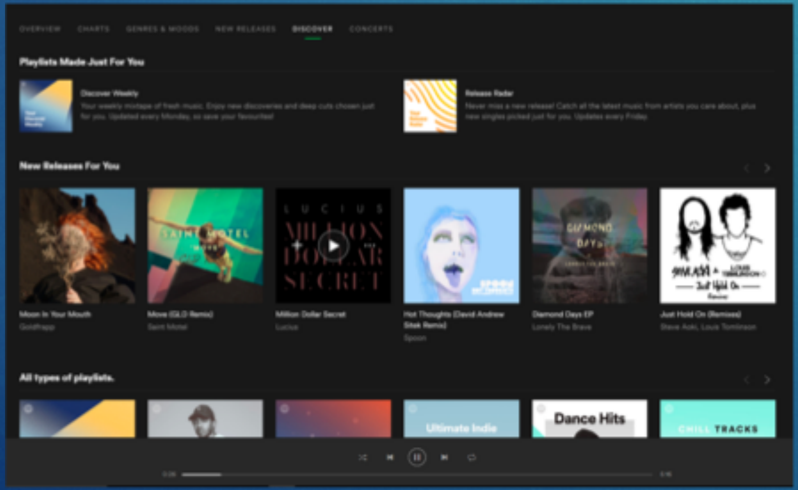
Netflix (Movies)



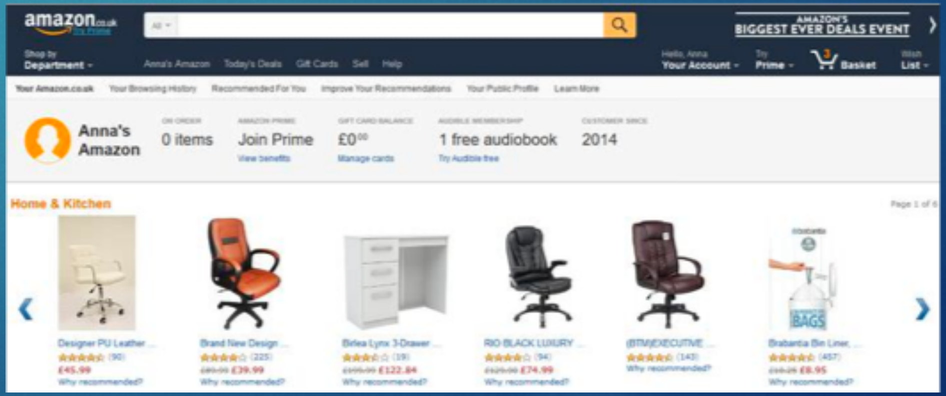
Youtube (Videos)



Spotify (Music)



Amazon (Shopping)



How are recommendations formulated?

- Recommender Systems need to guess the purchase intent based on indirect information like product ratings and customer purchase history.
- This information can be then used to calculate different similarity metrics to find recommendations.

- Three Types of Similarities
  - User Similarities – Purchasing Intent based on past behavior of similar customers
  - Product Similarities - Interactions and purchases of previous items can be used to find relevant products
  - Context Similarities- Contextual Information that also contributes to purchase intent (Seasonal Purchases)

Environment

- Recommender Systems are similar to search services as the main purpose is to provide a ranked list of items
- Customer Ratings are often the most utilized information for recommender systems.
- Two Types of Feedback for Recommender Systems
  - Customer Ratings (Explicit Feedback)
  - Customer Actions – Click, View, Purchase History (Implicit Feedback)

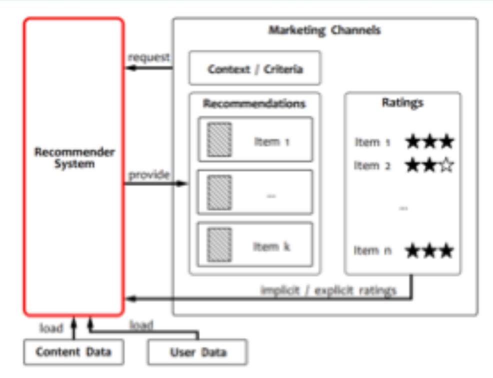


Figure 5.2: The main concepts of the recommendation service environment.

Business Objectives of Recommender Systems

- Relevance- Recommendations suggested to a user should be relevant – meaning a user will likely purchase and rate them highly
- Novelty- Recommendations should be provided that are already not known to the user. (It’s not useful to get recommendations for items a user may already know of as these are useless.)
- Serendipity – Should help users find products that are unexpected/surprising
- Diversity- Recommendations should be diverse to increase chance of sales conversion

Evaluation Methods

- Like all Machine Learning Problems – It is important to have evaluation metrics to determine how well the model is performing or recommending.

This section will cover the below methods for Recommender Evaluation:

  - Prediction Accuracy
  - Ranking Accuracy
  - Novelty
  - Serendipity
  - Diversity
  - Coverage

Prediction Accuracy

- Treats Recommender Problem as a Regression Problem by attempting to predicting how a customer would rate an item.
- This book defines error as : $$e_{uj} = \hat{r}_{uj} - r_{uj} \quad (5.4)$$
- MSE- $$\text{MSE} = \frac{1}{|T|} \sum_{(u,j) \in T} e_{uj}^2 \quad (5.5)$$
- RMSE- $$\text{RMSE} = \sqrt{\text{MSE}} \quad (5.6)$$
- NRMSE- $$\text{NRMSE} = \frac{\text{RMSE}}{r_{max} - r_{min}} \quad (5.7)$$

Legend:
^ruj – Predicted Rating
ruj – Actual Rating
T – indicates Test data set

Ranking Accuracy

Ranking Accuracy Metrics can be used to measure the quality of top (K) recommendations:

- Precision – Percentage of relevant recommendations in list
- Recall – amount of items from the set of available relevant items

$$\text{precision}(K) = \frac{|Y_u(K) \cap I_u|}{|Y_u(K)|} \quad (5.8)$$

$$\text{recall}(K) = \frac{|Y_u(K) \cap I_u|}{|I_u|} \quad (5.9)$$

Legend:

Iu- Subset of positively Rated Items in test set by user U
Yu(K) – the list of top K items recommended to that user
K – Total Recommendations

Ranking Accuracy

- DCG (Discounted Cumulative Gain) – Ranking Quality Metric
  - Metric often used by Web Search Companies to retrieve most relevant documents

$$\mathrm{DCG} = \frac{1}{m} \sum_{u=1}^{m} \sum_{\substack{i \in I_u \\ R_{ui} \leqslant K}} \frac{2^{r_{ui}} - 1}{\log_2 (R_{ui} + 1)} \qquad (5.11)$$

Legend:

<u>Iu-</u> Subset of positively Rated Items in test set by user u
<u>m</u>- total users
<u>K</u>- Top K Recommendations
<u>Rui-</u> the rank of item I in the list of recommendations for user u
<u>rui-</u> the rating from set T provided by user u for item I

Novelty

- Recommendations are considered novel if the user does not know of the recommendations at the time of recommendation.
- Therefore, the lower time that has passed between recommendation and consumption the more it is assumed that the user already knew about the item
- The novelty metric uses time weighted scores to boost long term accurate predictions

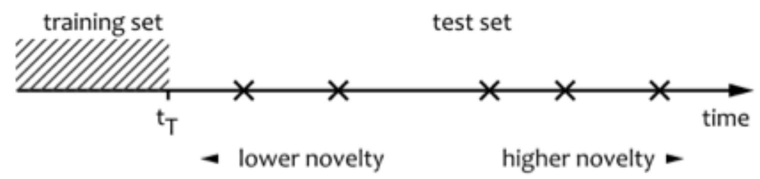


Figure 5.3: Evaluating the novelty of recommendations.

Serendipity

- “Serendipity is a measure of the extent to which recommendations are both attractive and surprising to the user” [Herlocker et al., 2004].
- It is hard to measure Serendipity as it is largely subjective, but serendipity essentially measures the fraction of non-trivial and relevant items in a recommendation list.
- One method to calculate Serendipity:

$$\text{serendipity} = \frac{1}{m \cdot K} \sum_{u=1}^{m} \sum_{i \in I_u} \mathbb{I}\left(i \in \left(Y_u \setminus Y_u^0\right)\right) \tag{5.12}$$

Legend:

m- number of users
Iu- set of items in test set positively rated by user
K- number of recommendations in the list
Yu – set of items recommended to user by algorithm under evaluation
Y0u- set recommended by baseline algorithm that is known to suggest non-serendipitous items
II- indicator function that equals true if the item belongs to the set Yu but not to Y0u

Diversity

- Diversity is the ability for the recommender to produce a list of recommendations that are not similar.
- Typically Distance metrics like cosine distances based on product descriptions can be used to determine how diverse a recommender is.

Coverage

- Coverage is the percentage of users or items which the system can make recommendations for.
- Number of items that appear in at least 1 recommendation list.

$$\text{catalog coverage} = \frac{1}{n}\left|\bigcup_{u=1}^{m} Y_u\right| \qquad (5.13)$$

Legend:

n- total number of items in the catalog

U- Union of recommendation lists over all users in the system

Types of Recommender Systems

- Collaborative Filtering
- Content-Based Filtering
- Hybrid (Combination of Content/Collaborative)
- Non-Personalized

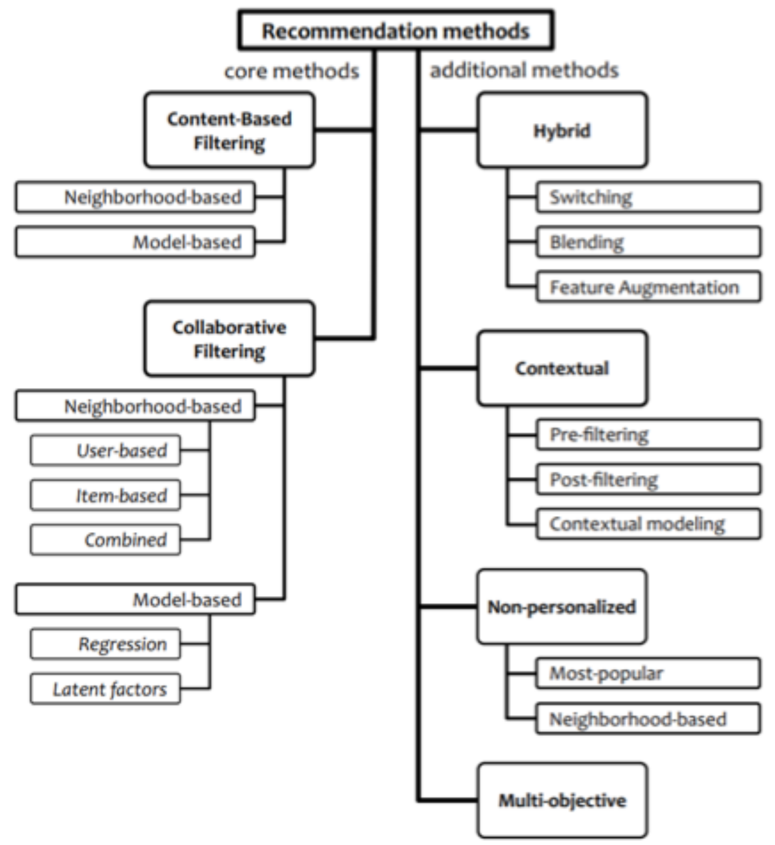
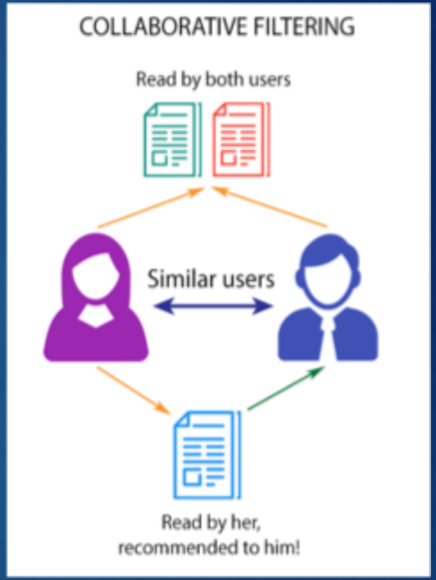


Figure 5.4: Classification of recommendation methods from the algorithmic perspective.

Collaborative Filtering

- A recommender system that is based on user community actions as a whole.
- This form of recommendation system is more based on your personality and interest.
- The system attempts to recommend things to you based on what others with similar interests/personality profiles have liked.
- Companies nowadays have a lot of data on your purchases including age, country, city, items purchased, items liked/dislikes, and demographic information that can be matched up with other similar users in a collaborative filtering system to create recommendations.

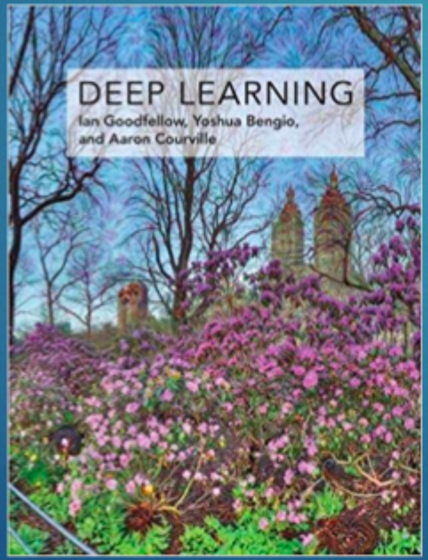


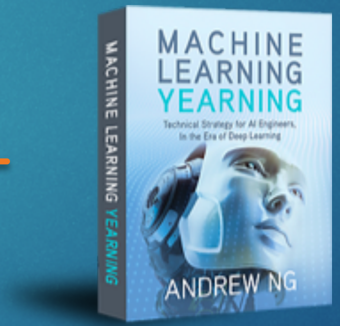
Collaborative Filtering

- Collaborative filtering is strong as it can personalize recommendations but its weakness is that you will often need data and users to produce recommendations.
- If you are a new user there will often be a lack of data to make the associated recommendations from the get go. (Cold Start Problem)
- Two Types of Collaborative Filtering:
  - Item Based Collaborative Filtering
  - User Based Collaborative Filtering

Collaborative Filtering

- Item Based Collaborative Filtering
- Example: Recommending books similar to Deep Learning when browsing on Amazon based on similar users past behavior. (Item Based)





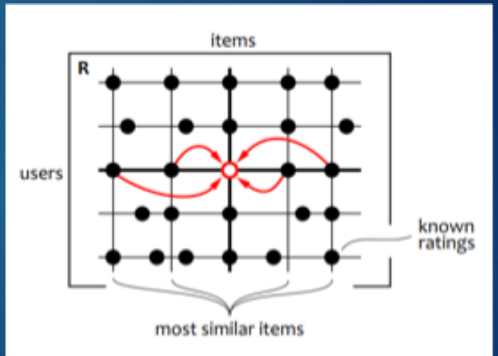


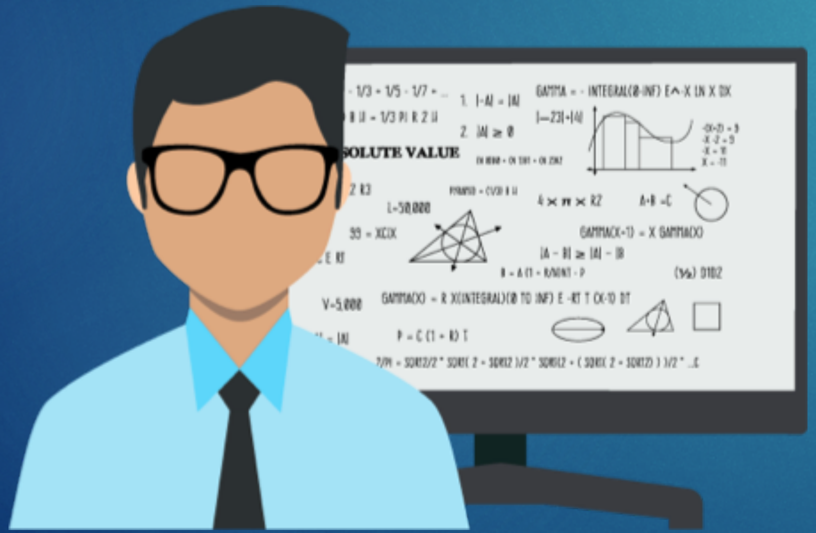
Figure 5.9: Item-based collaborative filtering.

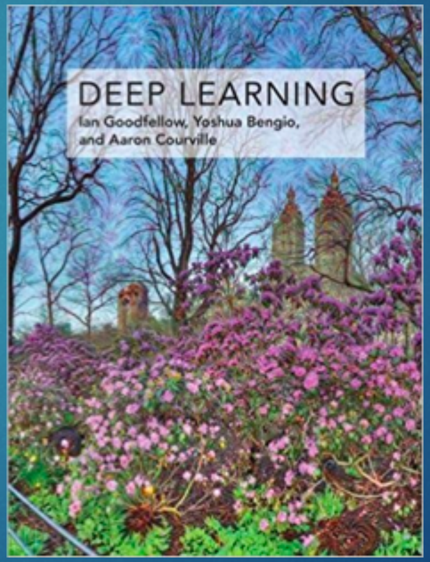
Similar Items to Deep Learning by Ian Goodfellow, Yoshua Bengio, and Aaron Courville

Collaborative Filtering

- User Based Collaborative Filtering
- Example: Recommending items to a specific user on Amazon based on similar users past behavior. (User Based)

宮本先生





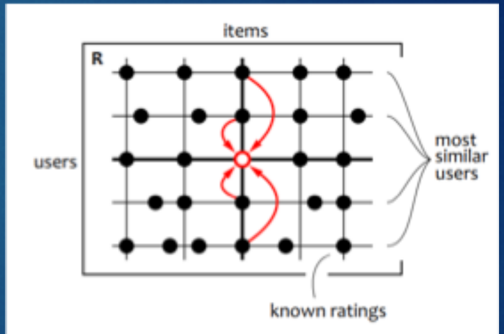


Figure 5.8: User-based collaborative filtering.

Img Source: https://imarticus.org/what-a-data-scientist-could-do/

Items Recommended to Professor Miyamoto

Collaborative Filtering

Some Sample Approaches

- Clustering- KNN Neighborhood Based Collaborative Filtering
- Matrix Factorization
- Deep Learning

Content-Based Filtering

- "Content-based filtering attempts to approximate user tastes and judgements by a similarity measure between the contents of catalog items"
- A Recommender system that is more based on your historical choices and items of similar nature.
  - Example: If you told a book store you liked sci-fi books it would be natural for someone to recommend books of a similar genre and content.
- In simple terms, A content based approach would look at the characteristics of your previously liked items and try to recommend items that are similar to those.
  - Other Approaches include NLP for content based recommendation
- Another example of this would be a recommender system that recommends me machine learning books of similar nature after knowing that I have previous purchases with high ratings.

Content-Based Filtering

- Sample Approaches:
  - Nearest Neighbor Approach –Each document field is represented as a vector of words and the similarity/distance is calculated to other document fields
  - Naïve Bayes Classifier – Text Classification
    - Bag of words through use of fields like summary, customer reviews, title, category (probabilities for all combinations of words)

Hybrid

- Hybrid-approaches seek to combine multiple types of recommender systems approaches.
  - "The hybrid approach attempts to create superior recommendation systems by combining several basic algorithms together"
- There are a few methods for Hybrid-Recommenders but I will discuss mainly Switching and Blending.
- Switching- Switching between models based on a condition
  - Ex: Choosing between a collaborative and content based system based on number of ratings

$$\hat{r}_{ui} = \begin{cases} \hat{r}_{ui}^{(\text{collaborative})}, & \text{if } |U_i| > 20 \\ \hat{r}_{ui}^{(\text{content})}, & \text{otherwise} \end{cases} \tag{5.121}$$

- Blending/Stacking- The combination of several Recommendation Models to produce a final estimate

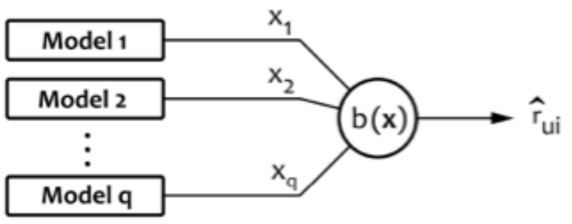


Figure 5.17: A blending recommender.

Non-Personalized Recommendations

- Popular Items- Top Sellers
- Trending Items- Items that are trending upwards
- New Releases- Newly Released Items
- Similar Items- Items similar in terms of content/category
- Frequent Patterns- Leverage small amount of Sales/Purchase history to recommend frequent patterns

Recommender Systems Architecture

The Diagram on the right describes a typical Recommender Systems Architecture

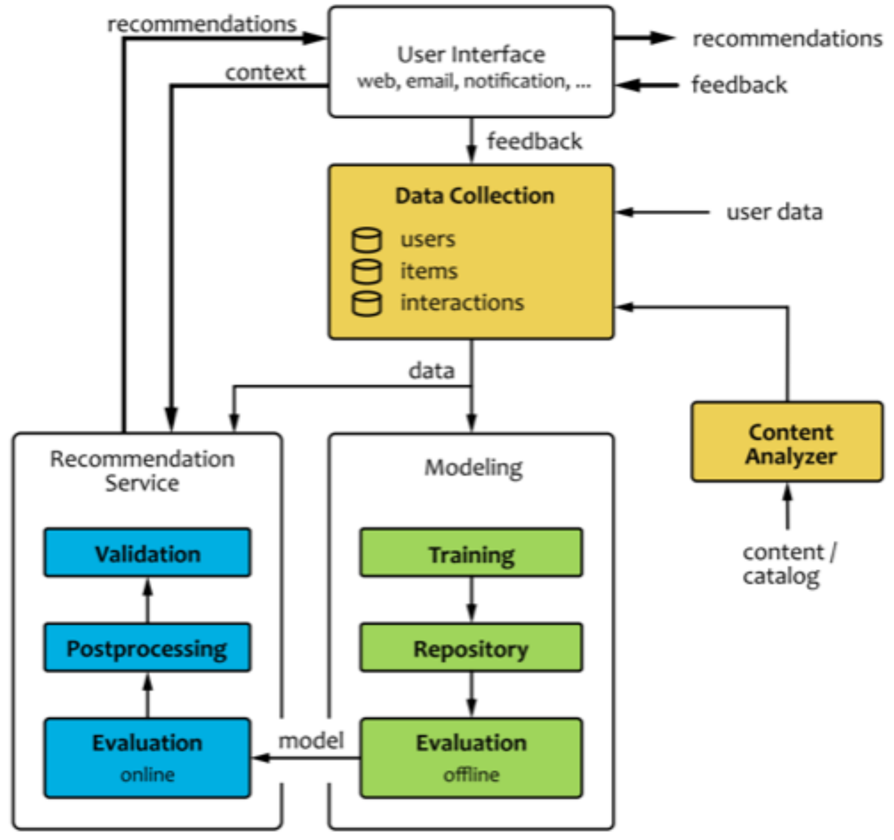


Figure 5.26: High-level architecture of a recommender system.

Implementation of Recommender System

Anime Recommendations Database

Datasets for practice

- Movielens (https://grouplens.org/datasets/movielens/) - Movies Data
- Jester (http://eigentaste.berkeley.edu/dataset/) - Jokes Data
- Book-Crossing (http://www2.informatik.uni-freiburg.de/~cziegler/BX/) - Books Data
- Last-Fm (https://grouplens.org/datasets/hetrec-2011/) - Music Data
- Wikipedia (https://en.wikipedia.org/wiki/Wikipedia:Database_download#English-language_Wikipedia) - Wikipedia Data
- Open Street Map (http://planet.openstreetmap.org/planet/full-history/) - Maps Data

Additional References

- **Please also reference the attached research on collaborative recommender systems if you are interested in learning more:**
- **Amazon**
  - http://www.cs.umd.edu/~samir/498/Amazon-Recommendations.pdf
- **Collaborative Filtering**
  - http://www.ra.ethz.ch/cdstore/www10/papers/pdf/p519.pdf