# IEMS 5780
# Building and Deploying Scalable Machine Learning Services

## Lecture 5 - Recommender Systems

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# Recommender Systems

# Agender

## Recommender Systems

- Introduction
- Content-based Recommendation Systems
- Collaborative Filtering
  - User-based Neighbourhood Model
  - Item-based Neighbourhood Model
  - Matrix Factorization
- Recommendation as Classification

# Recommender Systems

- We make a lot of **decisions** every day
  - Transportation
  - Restaurant reservation
  - Hotel reservation
  - Music
  - Movies
- We usually rely on some **suggestions** or **recommendations**
  - Family and friends
  - Supervisors, teachers, seniors
  - Experts
  - The general public (word-of-mouth)

# Recommender Systems

What are the factors that affect our decisions?

- Our own **preferences** (of the content, the characteristics, the price, etc.)
- What do **most people like**? (which is the blockbuster movie recently?)
- What do **people around us like**? (friends and family)
- What do people **similar to us** like?

# Example: Mobile App User Demographics

| **Gender (Male)** | | | | **Age (33–100)** | | | |
|---|---|---|---|---|---|---|---|
| Coef | Share | $n$ | App name | Coef | Share | $n$ | App name |
| 0.81 | 85 % | 150 | ESPN | 0.53 | 80 % | 42 | Great Clips Online Check-in |
| 0.73 | 80 % | 142 | Geek - Smarter Shopping | 0.48 | 53 % | 1687 | Email |
| 0.63 | 78 % | 277 | Tinder | 0.46 | 58 % | 318 | New Words With Friends |
| 0.59 | 80 % | 172 | Fallout Shelter | 0.44 | 80 % | 65 | BINGO Blitz |
| 0.56 | 86 % | 106 | WatchESPN | 0.43 | 60 % | 380 | iHeartRadio - Music & Radio |
| 0.52 | 72 % | 190 | Clash of Clans | 0.41 | 54 % | 197 | Field Agent |
| 0.52 | 97 % | 41 | Grindr - Gay chat, meet & date | 0.40 | 55 % | 690 | Lookout Security & Antivirus |
| 0.49 | 84 % | 96 | Yahoo Fantasy Football & More | 0.40 | 92 % | 41 | DoubleUCasino |
| **Gender (Female)** | | | | **Age (18–32)** | | | |
| -1.03 | 76 % | 736 | Pinterest | -1.17 | 78 % | 1066 | Snapchat |
| -0.73 | 84 % | 182 | Etsy | -0.52 | 59 % | 113 | Perk Word Search |
| -0.61 | 97 % | 79 | Period Tracker | -0.49 | 64 % | 88 | Summoners War |
| -0.54 | 96 % | 58 | Period Calendar / Tracker | -0.46 | 59 % | 98 | Clash of Kings |
| -0.50 | 76 % | 346 | Cartwheel by Target | -0.45 | 86 % | 90 | iFunny :) |
| -0.49 | 66 % | 258 | Wish - Shopping Made Fun | -0.45 | 81 % | 158 | GroupMe |
| -0.49 | 74 % | 325 | Checkout 51 - Grocery Coupons | -0.42 | 80 % | 68 | GIPHY for Messenger |
| -0.45 | 74 % | 178 | Photo Grid - Collage Maker | -0.42 | 80 % | 183 | Vine |

Ref: You Are What Apps You Use: Demographic Prediction Based on User's Apps

# Example: Mobile App User Demographics

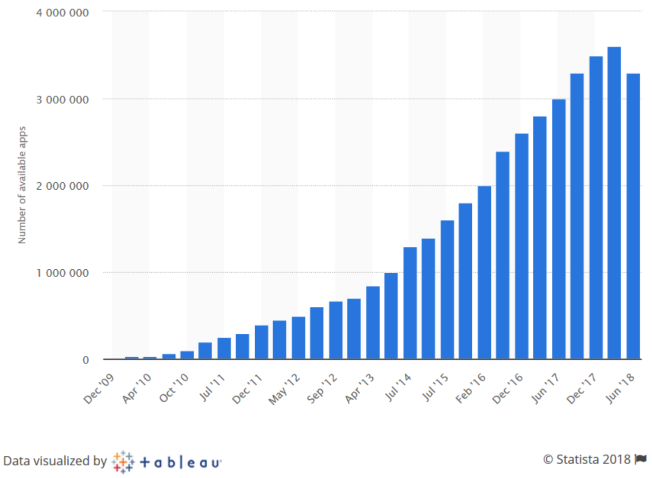
| Married (Married) | | | | Income ($\geq$ \$50K) | | | |
|---|---|---|---|---|---|---|---|
| Coef | Share | $n$ | App name | Coef | Share | $n$ | App name |
| 0.55 | 67 % | 200 | Zillow Real Estate & Rentals | 0.58 | 75 % | 141 | Fitbit |
| 0.44 | 67 % | 622 | Walmart | 0.45 | 66 % | 205 | LinkedIn |
| 0.44 | 60 % | 823 | Pinterest | 0.41 | 65 % | 41 | com.ws.dm |
| 0.44 | 74 % | 39 | Gospel Library | 0.37 | 52 % | 141 | LG Android QuickMemo+ |
| 0.40 | 59 % | 91 | USAA Mobile | 0.37 | 58 % | 191 | Redbox |
| 0.40 | 80 % | 63 | ClassDojo | 0.36 | 72 % | 22 | Like Parent |
| 0.38 | 60 % | 123 | ESPN | 0.34 | 66 % | 63 | Peel Smart Remote |
| 0.37 | 82 % | 28 | Deer Hunter 2014 | 0.34 | 61 % | 220 | Yelp |
| **Married (Single)** | | | | **Income ($\leq$ \$40K)** | | | |
| -0.89 | 70 % | 810 | Snapchat | -0.43 | 66 % | 136 | Job Search |
| -0.78 | 89 % | 114 | POF Free Dating App | -0.43 | 63 % | 97 | Security policy updates |
| -0.73 | 85 % | 219 | Tinder | -0.37 | 78 % | 23 | Solitaire |
| -0.66 | 98 % | 69 | OkCupid Dating | -0.35 | 67 % | 79 | Prize Claw 2 |
| -0.48 | 72 % | 269 | Tumblr | -0.34 | 72 % | 51 | ScreenPay- Get Paid to Unlock |
| -0.42 | 72 % | 205 | SoundCloud - Music & Audio | -0.33 | 78 % | 56 | MeetMe |
| -0.41 | 65 % | 331 | Uber | -0.33 | 62 % | 77 | Foursquare |
| -0.41 | 89 % | 69 | MeetMe | -0.32 | 56 % | 73 | Microsoft Word |

Ref: You Are What Apps You Use: Demographic Prediction Based on User's Apps

# Recommender Systems

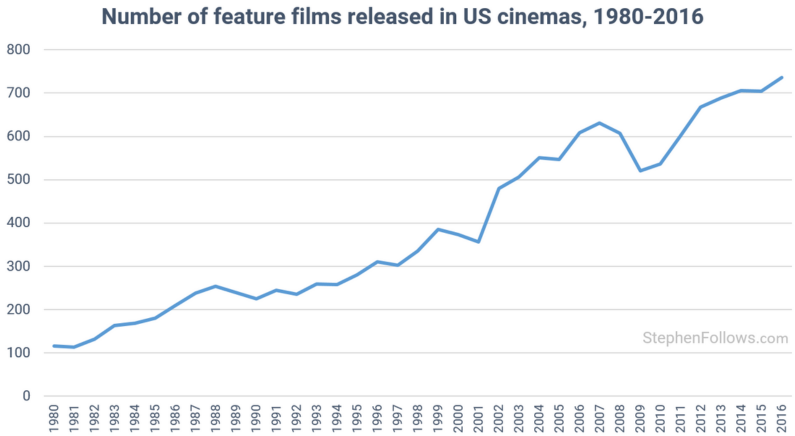
- There are **many** items out there for us to choose
  - Tens of thousands of movies and songs
  - More than 1 million apps in the Android and iPhone app stores
  - Millions of books published every year
- We need more efficient way to **filter information**, and identify items **most relevant** to us
- On the other hand, producers also want to **provide consumers things that they really want** (targetted marketing)

# Mobile Apps




(https://www.statista.com/statistics/266210/number-of-available-applications-in-the-google-play-store/)

# Movies

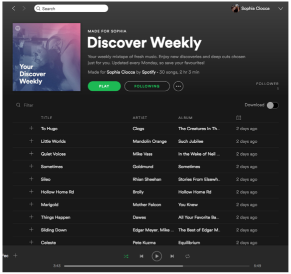


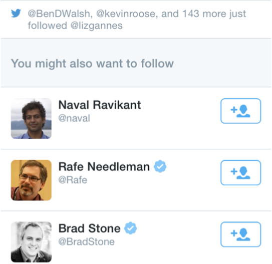

(https://stephenfollows.com/how-many-films-are-released-each-year/)

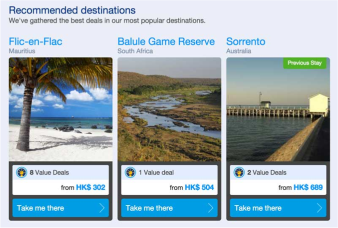
# Solution: Recommender Systems

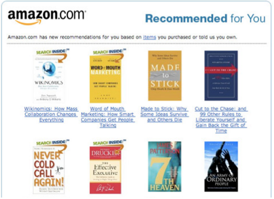
- Use **computers** and **algorithms** to process the huge amount of inforamtion and do the **filtering** for us
- Analyse the **tastes** and **preferences** of different people
- Analyse the **characteristics** of different items/products
- Generate **personalized** recommendation based on users' **past activities** and **feedback**
- Systems performing the above tasks are referred to as **recommender systems** / **recommendation systems**

# Examples of Recommender Systems



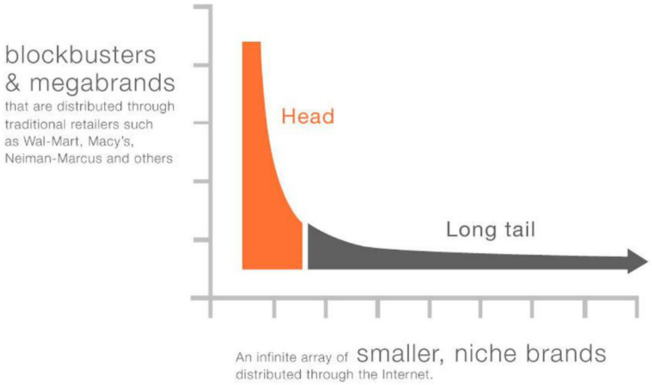




- Music recommendation
- Suggested connections in social networks
- Recommended items in e-commerce Websites
- Recommended travel destinations and accommodations
- ...

# Common Strategies

- **Popularity**
  - Recommend items most people like
- **Item Similarity**
  - Recommend **items that are similar** to what the user has already shown interest
- **User Similarity**
  - Recommend items that are preferred by **users who are similar the the target user** in some ways
- **Diversity**
  - Recommend items that are **least known** to the uuser

# The Long Tail




https://www.forbes.com/sites/robinlewis/2016/05/31/the-long-tail-theory-can-be-reality-for-traditional-megabrands/#2b77afbc6372

# Content-based Recommendation

# Content-based Recommendation

- **Assumptions**
  - Every user has his/her own **interests** / **tastes** / **preferences**
  - Each user's preferences can be represented as **a summary of what he/she has seen/read/watched/liked in the past**
  - A user will prefer something he or she is interested in
- We can compare the **content** or **characteristics** of the items
- Recommend items that are **similar** to what the user has consumed before

# Content-based Recommendation

## Two Steps

1. Learn user **preferences** (what does the user like?)
2. Find items that **match** these preferences

## Problems

1. How do we **learn** user preferences?
2. How do we **represent** user interests?
3. How do we **represent** items?
4. How to measure **similarity**?

# Content-based Recommendation

## Similarity-based

- **Steps**
  - Define features to represent the items (e.g. bag-of-words, author, publish date/time, etc.)
  - Construct **user profile** by the items liked by the user (e.g. average of feature vectors)
  - Calculate **similarity** between user profile and the new items
  - Return a **ranked list** of items
- What is important here is the **user profile**
  - How can we **represent** a user?
  - A user may have **multiple interests**, or his/her interests may **change over time**

# Content-based Recommendation

## Limitations of Content-based Methods

- Content (including meta-data) might not be available or enough in some domains
- It is difficult to represent some items by their 'content' (e.g. movies, books, music)
- Content-based methods tend to return very similar items

# Collaborative Filtering

# Collaborative Filtering

## What is Collaborative Filtering (CF)?

- From Wikipedia:

> *In the newer, narrower sense, collaborative filtering is a method of making automatic predictions (filtering) about the interests of a user by collecting preferences or taste information from many users (collaborating). The underlying assumption of the collaborative filtering approach is that if a person A has the same opinion as a person B on an issue, A is more likely to have B's opinion on a different issue than that of a randomly chosen person.*

# Collaborative Filtering

## Basic Idea

- Instead of relying on the content of the items, we can analyse people's **tastes and preferences**
- Each person is NOT totally different from another
- There are different **kinds** of people, for example:
  - People who like action movies
  - People who read literature
  - People who like spicy food
- By grouping **similar users**, we can recommend similar items to similar users
- This does not require a lot of information about the users and items themselves

# Collaborative Filtering

## Two Types of Collaborative Filtering

1. **Memory-based**
   - Directly use ratings from similar users or items
   - Also called **neighbourhood-based** methods
2. **Model-based**
   - Mathematical models are used to represent users, items and their relations
   - E.g. **matrix factorization**, Bayesian networks, probabilistic models

# Collaborative Filtering

## User-item Interaction

- In the following discussion, we assume that a user may **rate** an item on a **1 to 5** scale

Items

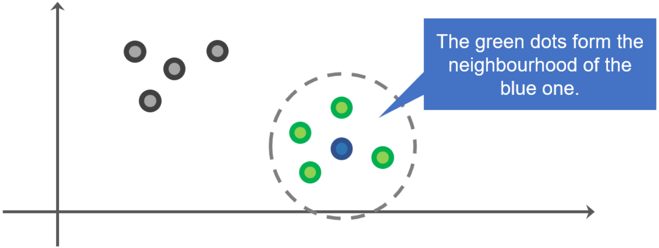
| Users | $i_0$ | $i_1$ | $i_2$ | $i_3$ | $i_4$ | $i_5$ |
|---|---|---|---|---|---|---|
| $u_0$ | - | 5 | - | - | - | 2 |
| $u_1$ | 2 | - | 1 | 3 | - | 5 |
| $u_2$ | - | 4 | - | 4 | - | 5 |
| $u_3$ | 4 | 5 | - | - | - | - |
| $u_4$ | - | - | 5 | - | 1 | - |
| $u_5$ | 2 | - | - | 4 | 1 | - |

# Memory-based Collaborative Filtering

# Neighbourhood

## What is neighbourhood?

- Consider again the **vector space model**
- Users and items can be represented as **vectors** in a high dimensional space
- More similar items/users will appear **closer** to each other



# Neighbourhood Models

## Two Types of Neighbourhood Models

1. **User-based**
   - We consider **similar users**
   - The neighbourhood of a user consists of users who like similar items
2. **Item-based**
   - We consider **similar items**
   - The neighbourhood of an item consists of items that are preferred by similar users

# User-based Collaborative Filtering

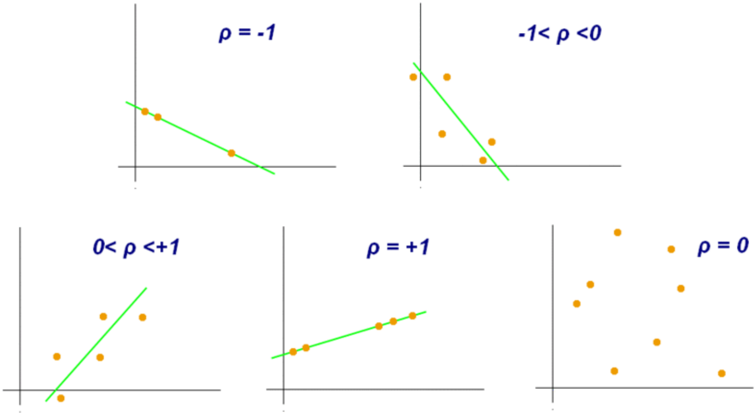
- **Task**: Predict the **extent** to which user $u$ likes item $i$
- **Procedures**:
  - We have user $u$, and item $i$
  - Find a set of users who are similar to $u$ and have rated $i$
  - Get the **average rating** on $i$ given by this set of users
  - Do this for all items, come up with a **ranking** based on the predict rating

# User-based Collaborative Filtering

- In doing **user-based CF**, we made the following **assumptions**:
  - If users had similar tastes in the past, they should have similar tastes in the future
  - User preferences remain **stable and consistent** over time
- Furthermore, we need to define **similarity**
- **Similarity**
  - Should reflect how **close** the tastes and preferences of two users are
  - Similar users should assign **similar ratings** to the same set of items

# Similarity - Pearson Correlation

- One way of computing similarity between two users is to use the **pearson correlation**



# Similarity - Pearson Correlation

- $x$, $y$: users
- $r_{x,i}$: rating assigned to $i$ by $x$
- $I$: the set of items rated by both $x$ and $y$
- $\text{sim}(x, y)$ has a value between -1 and 1

$$\text{sim}(x,y) = \frac{\sum_{i \in I}(r_{x,i} - \overline{r_x})(r_{y,i} - \overline{r_y})}{\sqrt{\sum_{i \in I}(r_{x,i} - \overline{r_x})^2}\sqrt{\sum_{i \in I}(r_{y,i} - \overline{r_y})^2}}$$

# Similarity - Pearson Correlation

- In Python, you can easily compute the correlation using the **`scipy`** module's [pearsonr function]

```
>>> from scipy.stats import pearsonr
>>> a = [5,2,1,4,3,1]
>>> b = [1,5,4,2,1,2]
>>> pearsonr(a,b)
(-0.5962847939999438З, 0.21157899460007421)
>>>
>>> a = [5,2,1,4,3,1]
>>> b = [4,3,1,5,4,2]
>>> pearsonr(a,b)
(0.85978530414910515, 0.028111919656069226)
>>>
```

# Predicting Ratings

- How to **predict** a user's rating for an item?
- Use the equation below:

Similarity between *x* and *u*

Deviation from mean of ratings of user u

$$\text{pred}(x,i) = \overline{r_x} + \frac{\sum_{u \in U} \text{sim}(x,u) \times (r_{u,i} - \overline{r_u})}{\sum_{u \in U} \text{sim}(x,u)}$$

Normalization

- Example: see [l5-user-based-cf.ipynb]

# Limitations

- **Data sparsity**
  - When there are a lot of users and items, very few overlap between users
- **Does not scale**
  - When there are 10 million users, how can you generate all their neighbourhoods?
- Two users may have similar taste in one domain but very different taste in another

# Item-based Collaborative Filtering

## Procedures

- We have user $u$ and item $i$
- Find a set of **items**, which are
  - rated by $u$
  - given **similar ratings** as $i$ by other users
- Get the **average rating** of this set of items given by $u$
- Use that as the predicted rating of $i$ by $u$

# Item-based Collaborative Filtering

- In doing **item-based CF**, we made the following **assumptions**:
  - If two items are given similar ratings by the users, they should have **similar characteristics**
- Consider **movies**:
  - Movies of the same genre, by the same director, or feature the same actor/actress will be assigned similar ratings
- Ref: Amazon.com Recommendations: Item-to-Item Collaborative Filtering

# Predicting Ratings

- One way to implement item-based CF is to compute a **weighted combination of ratings** given by $u$ to other items

Similarity between two items

Rating given by the user to other items

$$\text{pred}(u, j) = \frac{\sum_{i \in I} \text{sim}(j, i) \times r_{u,i}}{\sum_{i \in I} \text{sim}(j, i)}$$

Normalization

# Neighbourhood-based Collaborative Filtering

- Neighbourhood and recommended items are usually calculated **offline**
- In order to reduce the amount of computation needed, the size of the neighbourhood is usually **limited**
- Previous research shows that a neighbourhood size of **20-50** is quite enough
- Ref: Empirical Analysis of Design Choices in Neighborhood-based Collaborative Filtering Algorithms, Herlocker et al., 2002.

# Food for Thought

TED Talk

How Algorithms Shape Our World

**TEDGlobal 2011, By Kevin Slavin**

http://www.ted.com/talks/kevin_slavin_how_algorithms_shape_our_world.html

# Model-based Collaborative Filtering

# Model-based Collaborative Filtering

- What we have discussed so far are called **memory-based** collaborative filtering
- We have not **trained** any model that can be used to describe the relationship between inputs and outputs
- Memory-based models are **easy to implement**, but usually are NOT very accurate and NOT **scalable**
- Instead, we can consider a **machine learning approach** to the task of recommendation:
  - Create a model that explains how **ratings are generated**, or how **items are ranked**
  - Use past data to **train/optimize** the parameters of the model

# Model-based Collaborative Filtering

We can roughly categorize model-based CF into two types:

- **Matrix Factorization Approach**
  - Assume that there are **latent factors** that determine how users rate items
  - Decompose the user-item matrix using matrix factorization techniques
- **Classification Approach**
  - Consider the task of recommendation as a **classification** problem
  - For each given pair of user and item, we determine whether the user will be interested in the item (binary classification)
  - Can take into account **contextual information** and **implicit feedbacks**

# Gradient Descent

# Parameter Optimization

- Training machine learning models usually means **optimizing parameters** in the model using the **training data**
- Each model is characterized by a set of **parameters**
- Consider linear regression as an example:

$$y = b_0 + b_1 x_1 + b_2 x_2 + \ldots + b_n x_n$$

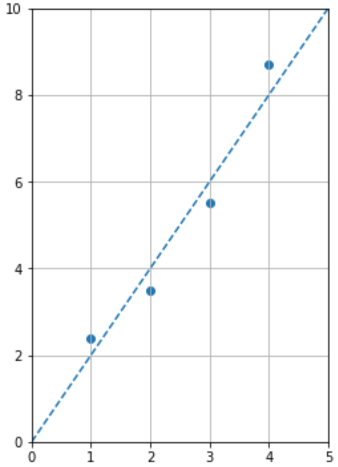
- Each $b_i$ is a parameter of the model
- How exactly do we find the most suitable values of these parameters given the training data?

# Parameter Optimization

- In some cases, we can find a solution **analytically**
  - The solution can be represented by a equation
  - The best parameters can be obtained by substituting the training data $X$ and $y$ into the equation
- However, in many cases, the model is complicated and we cannot do that analytically
- Another approach: **trial and error**
  1. **Initialize** the paraemeters randomly
  2. Use the model to **generate predictions** for the training data
  3. Computer the **error** of the predictions
  4. Use the error to **adjust** the parameters
  5. Go to Step 1 if model is not good enough

# Gradient Descent

- Let's consider a very simple example
- We want to learn a linear model $y = mx$
- Our training data:
  - `X = (1, 2, 3, 4)`
  - `y = (2.4, 3.5, 5.5, 8.7)`
- Obviously the value of $m$ can be determined analytically
- Let's try our **gradient descent** on this example



# Gradient Descent

- To perform gradient descent, we need to first have an **error function** that allows us to understand how much error we are making using current values of the parameters (also called **objective function** or **loss function**)
- Our error function:

$$error = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

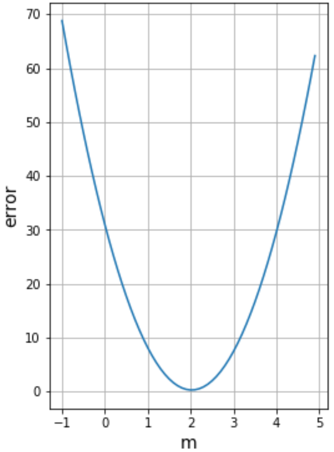
$$= \frac{1}{N}\sum_{i=1}^{N}(y_i - mx_i)^2$$

- where N is number of training samples
- (note that we use the **mean squared error** in this case)

# Gradient Descent

- The objective is to **adjust** the value of our parameter $m$ such that next time the error will be **smaller**
- By **adjusting** we mean either **increase** or **decrease** its value
- To know to which direction we should adjust $m$, we need to know the **gradient** of the error
- In our case:

$$\frac{\partial e}{\partial m} = \frac{1}{N}\sum_{i=1}^{N}(-2x_i y_i + 2mx_i^2)$$



# Gradient Descent

- Once we know the gradient, we know how to adjust $m$
- If gradient is **positive**, we need to **reduce** $m$
- If gradient is **negative**, we need to **increase** $m$
- We use a **hyperparameter** called the **learning rate** to determine **how much** do we adjust $m$ each time
  - If we change the value too much, we may **miss** the optimal value
  - If we cahnge the value too little, we may never arrive at the optimal value
- Implementation in Python: [l5-gradient-descent-example.ipynb]

# Matrix Factorization

# Model-based Collaborative Filtering

- Recall that in recommender systems, we usually deal with a matrix of **user-item ratings**
- In **memory-based methods**, we directly compute a prediction based on the other ratings
- In **model-based methods**, we come up with a **model** of how ratings are **generated**
- **Matrix factorization** is a commonly used model-based methods in recommendations

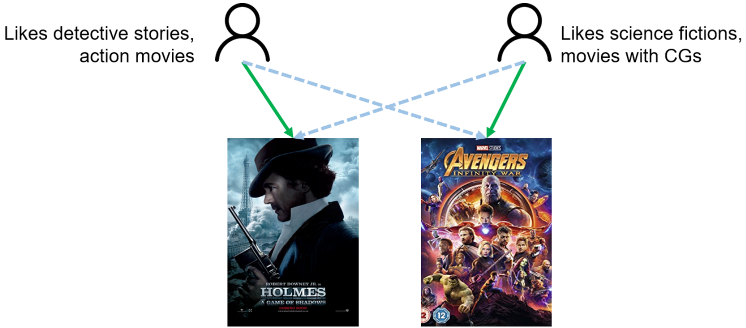
Items

Users

| | $i_0$ | $i_1$ | $i_2$ | $i_3$ | $i_4$ | $i_5$ |
|---|---|---|---|---|---|---|
| $u_0$ | - | 5 | - | - | - | 2 |
| $u_1$ | 2 | - | 1 | 3 | - | 5 |
| $u_2$ | - | 4 | - | 4 | - | 5 |
| $u_3$ | 4 | 5 | - | - | - | - |
| $u_4$ | - | - | 5 | - | 1 | - |
| $u_5$ | 2 | - | - | 4 | 1 | - |

# Matrix Factorization - Basic Idea

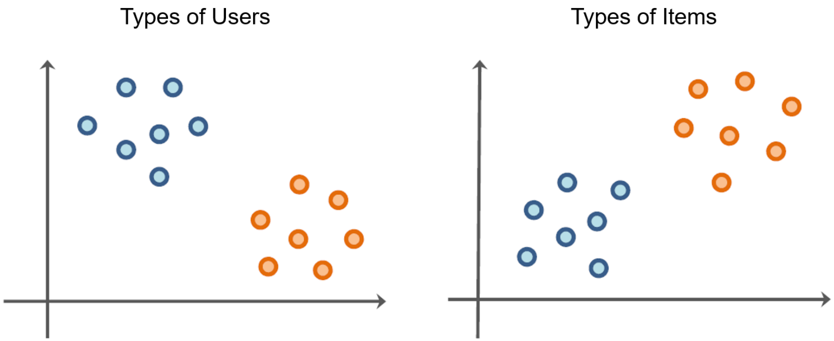
- We assume that users and items can be grouped into different **types**
- Take **movies** as an example:
  - Some users like action movies, while some like romantic movies
  - Some movies are romantic, while some are exciting and full of suspense



# Matrix Factorization

## Challenge

- How can we discover **types** of users and items from our data?
- **Clustering**?



# Matrix Factorization

- Clustering users and items separately **does NOT** work well
  - We need to **manually inspect** the meaning of each group (cluster)
  - We do not know which user groups correspond to which item groups
  - There is no guarantee that we will obtain exact **correspondence** between user groups and item groups
  - E.g. there might be a group of users who like animations, but animations might be grouped under different clusters according to their content

# Matrix Factorization

- We can approach this problem differently
- Let's assume in advance that there are $K$ **different types of users and items**
- We use **vectors of length** $K$ to represent users and items
- Each component (**factor**) in a vector represents the **extent** to which the user/item **belongs to that type**

$$\begin{aligned} \text{user}_1 &= (0.0, 0.1, 0.2, 1.2, 2.3) \\ \text{user}_2 &= (3.1, 0.0, 0.1, 0.2, 0.4) \end{aligned}$$

$$\begin{aligned} \text{item}_1 &= (0.2, 0.9, 1.5, 0.2, 0.8) \\ \text{item}_2 &= (1.5, 2.3, 0.0, 0.9, 0.0) \end{aligned}$$

# Matrix Factorization

- If we consider all the **users** and **items** in our recommender system, we can represent all of them using two different **matrices**

Users

| | | | | | |
|---|---|---|---|---|---|
| $u_0$ | 1.2 | 0.1 | 0.5 | 0.9 | 2.3 |
| $u_1$ | 0.0 | 0.2 | 0.8 | 2.1 | 1.7 |
| $u_2$ | . | . | . | . | . |
| $u_3$ | | | | | |
| $u_4$ | | | | | |
| $u_5$ | | | | | |

dimension = $K$

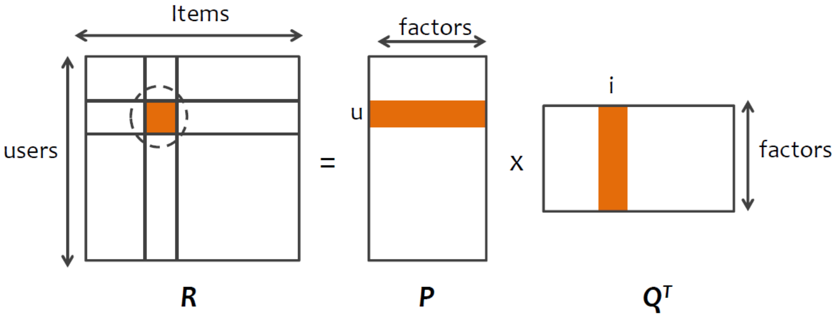
Items

| | | | | | |
|---|---|---|---|---|---|
| $i_0$ | 2.3 | 0.9 | 0.2 | 0.5 | 0.0 |
| $i_1$ | 0.0 | 0.8 | 0.7 | 1.5 | 1.3 |
| $i_2$ | . | . | . | . | . |
| $i_3$ | | | | | |
| $i_4$ | | | | | |
| $i_5$ | | | | | |

dimension = $K$

# Matrix Factorization

- In such a model, the rating on item $i$ given by user $u$ is generated by computing the **dot product** of the corresponding user and item **vectors**
- This is equivalent to multiplying the (transpose of) the item matrix with the user matrix



# Matrix Factorization

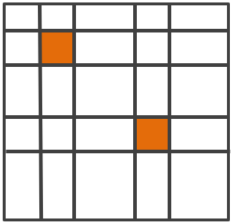
- Usually, we are given the matrix $R$, **matrix factorization** is the process of finding $P$ and $Q$ such that $PxQ^T$ gives an approximation of $R$

$$P \times Q^T = \hat{R} \approx R$$

- Very often $R$ is **incomplete** (e.g. 99% of the cells are empty),
- Therefore, we have to estimate the values in $P$ and $Q$, instead of solving for exact values • The number of factors $K$ reflects the complexity of our model

# Matrix Factorization

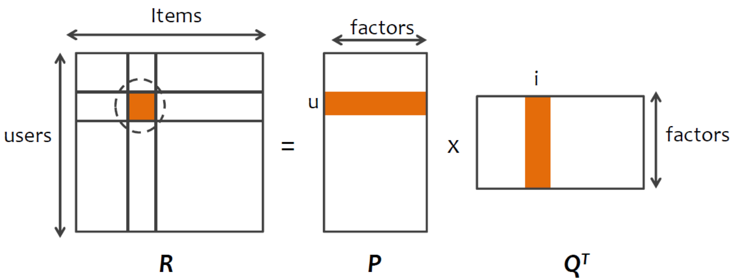
- In matrix factorization, our target is to come up with $P$ and $Q$, the two **factor matrices** whose product approximates the user-item rating matrix $R$
- When we say approximate, we are talking about the **known values** in $R$
- If we can approximate the known values well, our **predictions** of the unknown values will be **accurate**



*R*

# Matrix Factorization

- Let's focus on **one rating** at a time




$$\hat{r}_{ui} = \sum_{k=1}^{K} p_{uk} q_{ki}$$

# Matrix Factorization

- Our goal is to find all $p_{ik}$ and $q_{kj}$ such that

$$\sum_{k=1}^{K} p_{uk} q_{ki} \approx r_{ui}$$

- Our data only contain the values of **some** $r_{ij}$
- How can we determine the values of all $p_{ik}$ and $q_{kj}$?

# Matrix Factorization

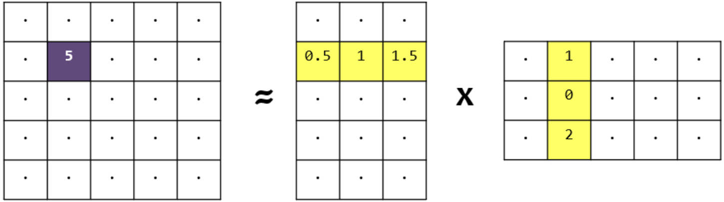
## Basic Idea:

- We first initialize $P$ and $Q$ with some **random values**
- We measure our **error**, i.e. how far we are from the **true** values in R
- We update the values in $P$ and $Q$ based on the error we computed
- **Repeat** the steps above until the error is sufficiently small

- In other words, we can use **gradient descent**

# Matrix Factorization

- Example:




- The **dot product** of the user vector and the item vector is:

$$0.5 \times 1 + 1 \times 0 + 1.5 \times 2 = 3.5$$

- We can then compute our **error**

# Matrix Factorization

- Error is give by:

$$e_{ui} = r_{ui} - \hat{r}_{ui} = r_{ui} - \sum_{k=1}^{K} p_{uk} q_{ki}$$

- Squared error:

$$e_{ui}^2 = (r_{ui} - \hat{r}_{ui})^2 = (r_{ui} - \sum_{k=1}^{K} p_{uk} q_{ki})^2$$

- The **machine learning** problem here is to optimize all $p$'s and $q$'s such that $e_{ui}^2$ is **minimized**

# Matrix Factorization

## Gradient Descent

$$e_{ui}^2 = (r_{ui} - \hat{r}_{ui})^2 = (r_{ui} - \sum_{k=1}^{K} p_{uk} q_{ki})^2$$

$$\frac{\partial e_{ui}^2}{\partial p_{uk}} = -2(r_{ui} - \sum_{k=1}^{K} p_{uk} q_{ki}) q_{ki} = -2 e_{ui} q_{ki}$$

$$\frac{\partial e_{ui}^2}{\partial q_{ki}} = -2(r_{ui} - \sum_{k=1}^{K} p_{uk} q_{ki}) p_{uk} = -2 e_{ui} p_{uk}$$

# Matrix Factorization

- Having obtained the gradients, we can construct our **update rules** as follows:

$$p'_{uk} = p_{uk} - \alpha(-2e_{ui}q_{ki}) = p_{uk} + 2\alpha e_{ui}q_{ki}$$

$$q'_{ki} = q_{ki} - \alpha(-2e_{ui}p_{uk}) = q_{ki} + 2\alpha e_{ui}p_{uk}$$

- where $\alpha$ is the **learning rate**
- $p'_{uk}$ and $q'_{ki}$ are the **new values**

# Matrix Factorization

## Training Data

- Note that we only optimize $P$ and $Q$ using the **known values** in the matrix $R$
- We can consider transforming the user-item rating matrix into a list of **tuples**: (user, item, rating):

| | | | | |
|---|---|---|---|---|
| . | . | . | 3 | . |
| . | 5 | . | . | 2 |
| 4 | 1 | . | 2 | . |
| . | . | 3 | . | . |
| . | . | 4 | . | 5 |

```
(u0, i3, 3)
(u1, i1, 5)
(u1, i4, 2)
...
...
(u4, i4, 5)
```

# Beyond Rating Predictions

- In many other cases, we do NOT always have **ratings (explicit feedback)** from the users
- Instead, we would have **implicit feedback** from the users on the items
  - The user purchased an item
  - The user clicked on an advertisement
  - The user viewed the details of an item
- Implicit feedbacks can also be considered as **(weaker) indications** that the user is interested in the items
- We can still populate a user-item matrix using implicit feedbacks
- Ref: Collaborative Filtering for Implicit Feedback Datasets (Hu et al. 2008)

# Recommendation as Classification

# Recommendation as Classification

- Besides rating prediction using matrix factorization, recommendation can also be considered as a **classification task**
- Ultimately, we want to determine the **probability that a user is interested / likes / wants to purchase an item**
- Besides the explicit/implicit feedbacks, there are actually a lot of things we can consider as **features**
  - date/time when the users visit the Website
  - the browsing history of the users
  - the various characteristics of the items (e.g. actors/actresses in a movie, storyline of a fiction)
  - Whether the user is using a PC or a smartphone
  - **interactions** between user and item features

# Recommendation as Classification

- Recommendation can be considered as a **binary classification** problem
  - Whether the user will **click** on an advertisement
  - Whether the user will **purchase** the item
  - Whether the user will **download** the mobile app
- **Common classification models** can be used
  - Logistic regression
  - Support vector machines
  - Decision trees / Random forests
- The most important things in this approach are the **features** --> **Feature Engineering**

# Recommendation as Classification

- To train a classifier, you need both **positive** and **negative** samples
- However, very often you don't know what the user **DOES NOT** like
- A user hasn't interacted with an item DOES NOT mean that he/she is not interested in an item
- **Negative sampling**
  - For each positive feedback you have, **randomly sample** items that the user has not interacted with
  - Use these items as **negative** samples
  - Can also weight each sample differently (how?)

End of Lecture 5