IEMS 5780 / IERG 4080 Building and Deploying Scalable Machine Learning Services

Lecture 5 - Recommender Systems

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4th October, 2018

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

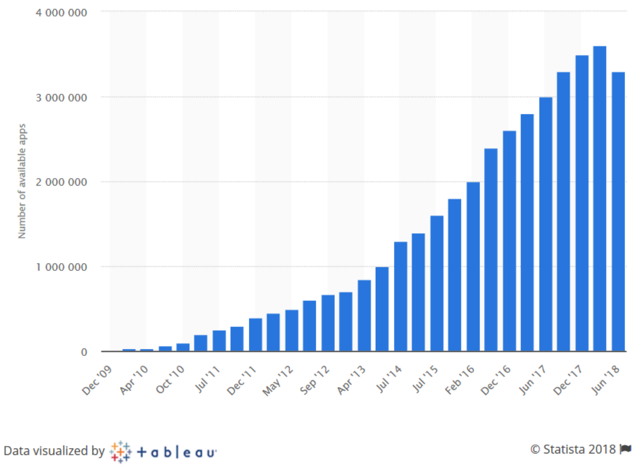
Married (Married)				**Income ($\geq$ \$50K)**			
Coef	Share	n	App name	Coef	Share	n	App name
0.55	67 %	200	Zillow Real Estate & Rentals	0.58	75 %	141	Fitbit
0.44	67 %	622	Walmart	0.45	66 %	205	LinkedIn
0.44	60 %	823	Pinterest	0.41	65 %	41	com.ws.dm
0.44	74 %	39	Gospel Library	0.37	52 %	141	LG Android 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

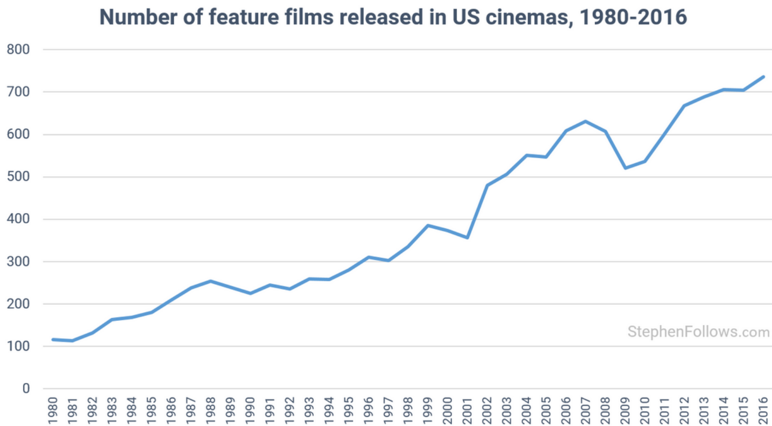
- There are **many** items out there for us to choose
  - Tens of thousands of movies and songs
  - More than 1 million apps in the Android and iPhone app stores
  - Millions of books published every year
- We need more efficient way to **filter information**, and identify items **most relevant** to 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

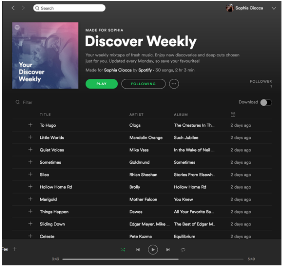


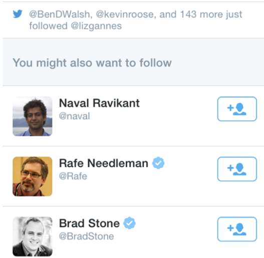
(https://stephenfollows.com/how-many-films-are-released-each-year/)

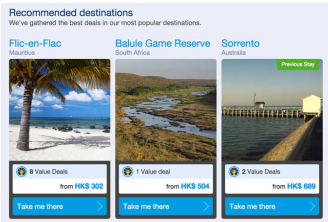
Solution: Recommender Systems

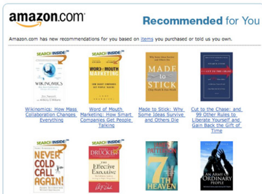
- Use **computers** and **algorithms** to process the huge amount of inforamtion and do the **filtering** for us
- Analyse the **tastes** and **preferences** of different people
- Analyse the **characteristics** of different items/products
- Generate **personalized** recommendation based on users' **past 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
- ...

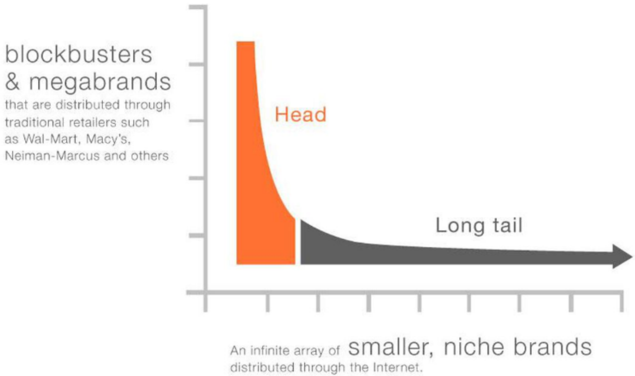
How should recommendations be generated?

https://goo.gl/vz15y9

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

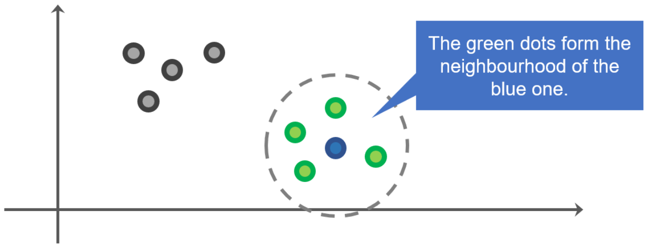
	i_0	i_1	i_2	i_3	i_4	i_5
u_0	-	5	-	-	-	2
u_1	2	-	1	3	-	5
u_2	-	4	-	4	-	5
u_3	4	5	-	-	-	-
u_4	-	-	5	-	1	-
u_5	2	-	-	4	1	-

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

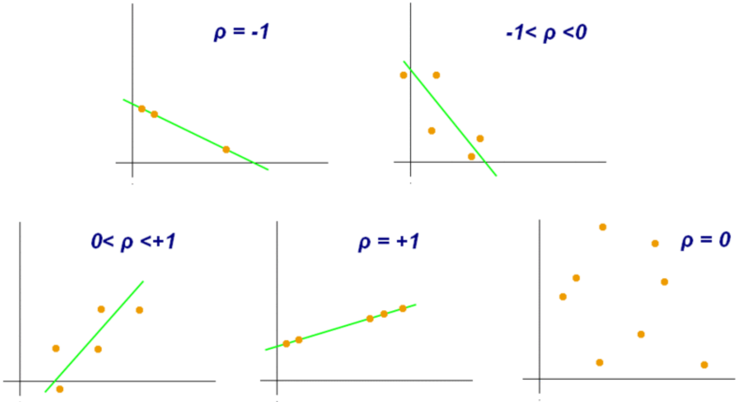
- **Task**: Predict the **extent** to which user u likes item i
- **Procedures**:
  - We have user u, and item i
  - Find a set of users who are similar to u and have rated i
  - Get the **average rating** on i given by this set of users
  - Do this for all items, come up with a **ranking** based on 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
- $\mathrm{sim}(x, y)$ has a value between -1 and 1

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

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)
(-0.59628479399994383, 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

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

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

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

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:

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

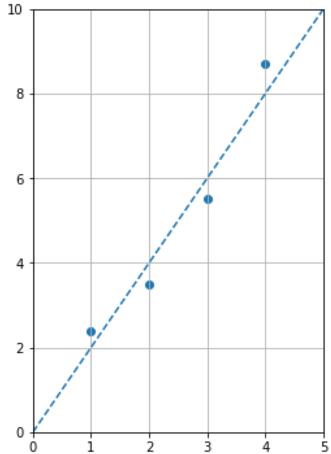
- Each b_i is a parameter of the model
- How exactly do we find the most suitable values of these parameters given the training data?

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:

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

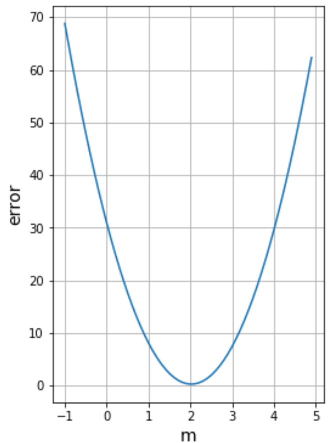
$$= \frac{1}{N}\sum_{i=1}^{N}(y_i - mx_i)^2$$

- 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:

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



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

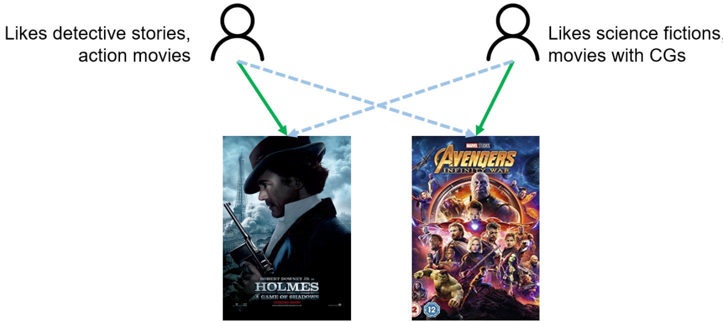
Items

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

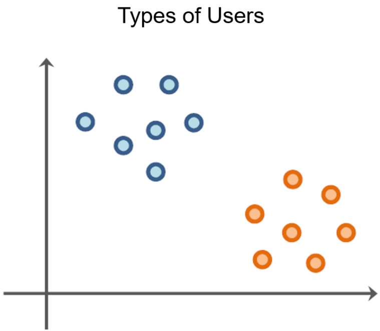
- We assume that users and items can be grouped into different **types**
- Take **movies** as an example:
  - Some users like action movies, while some like romantic movies
  - Some movies are romantic, while some are exciting and full of suspense

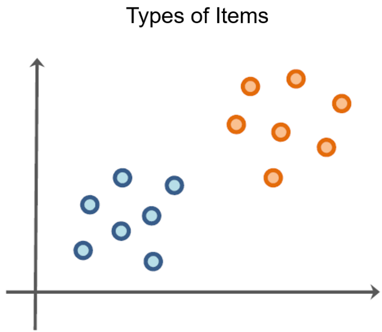


Matrix Factorization

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

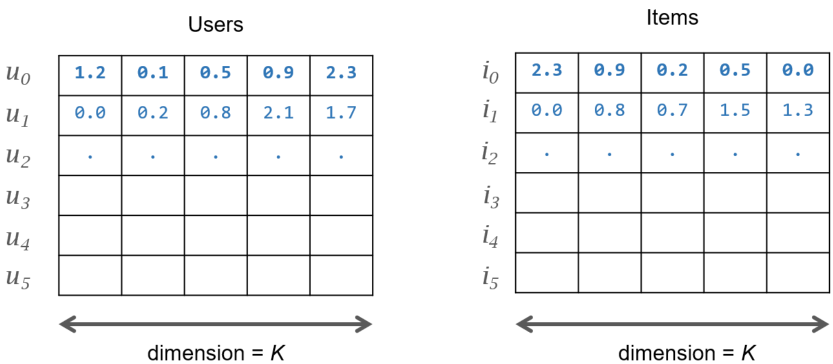
- We can approach this problem differently
- Let's assume in advance that there are K **different types of users and items**
- We use **vectors of length** K to represent users and items
- Each component (**factor**) in a vector represents the **extent** to which the user/item **belongs to that type**

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

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

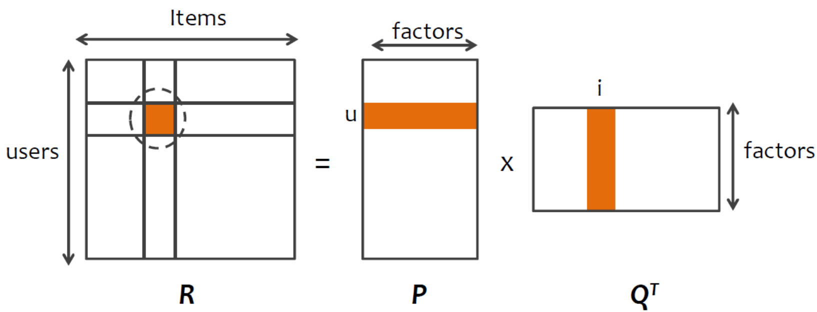
Matrix Factorization

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



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

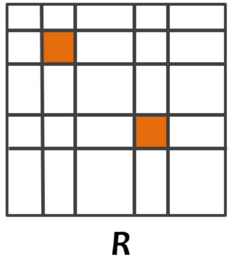
- Usually, we are given the matrix R, **matrix factorization** is the process of finding P and Q such that PxQ^T gives an approximation of R

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

- 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

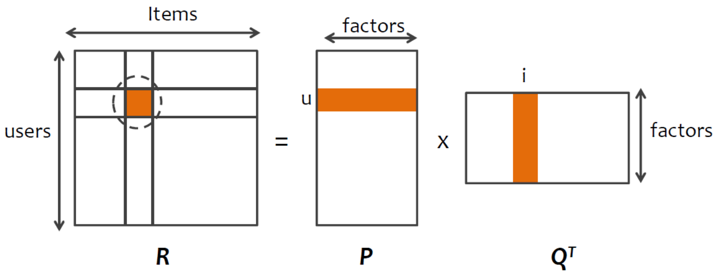
Matrix Factorization

- 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**



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

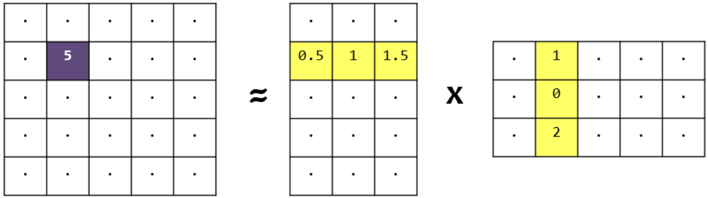
Basic Idea:

- 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 α 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