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COMP20008 Elements of Data Processing

Semester 2 2018

Lecture 5: Recommender Systems

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Plan today

- Complete section on outlier detection
- Recommender systems and collaborative filtering
- Types of similarity for imputation of missing values
  - Item-Item
  - User-User
  - Matrix factorisation
- Question to consider during lecture: Are we doing cleaning or prediction?

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Recommender systems: missing data

- Movie Recommender systems

Person	Star Wars	Batman	Jurassic World	The Martian	The Revenant	Lego Movie	Selma	….
James	3	2	-	-	-	1	-	
John	-	-	1	2	-	-	-	
Jill	1	-	-	3	2	1	-	

Users and movies
Each user only rates a few movies (say 1%)
Netflix wants to predict the missing ratings for each user

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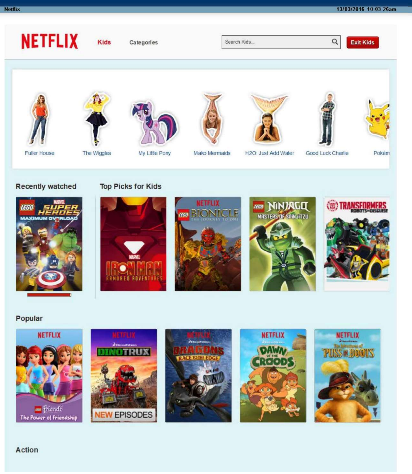
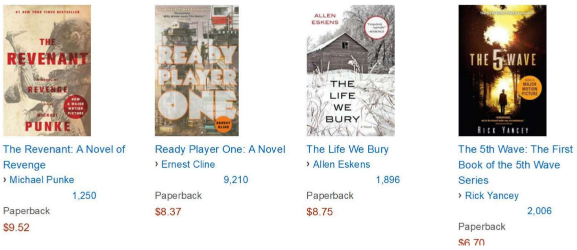
Netflix



Amazon.com: Customers who bought this item also bought …..



The Revenant: A Novel of Revenge
› Michael Punke
1,250
Paperback
$9.52

Ready Player One: A Novel
› Ernest Cline
9,210
Paperback
$8.37

The Life We Bury
› Allen Eskens
1,896
Paperback
$8.75

The 5th Wave: The First Book of the 5th Wave Series
› Rick Yancey
2,006
Paperback
$6.70

- "75% of what people watch is from some sort of recommendation" (Netflix)
- "If I have 3 million customers on the web, I should have 3 million stores on the web." (Amazon CEO)

Other examples of recommender systems

- IMDb
- Online dating
- Twitter: "Who to Follow", what to retweet
- Spotify, youtube: music recommendation
- LinkedIn/Facebook: who to add as a contact, jobs of interest, news of interest
- Tourist attraction apps

- University subjects … ? Subject discussion forums … ?

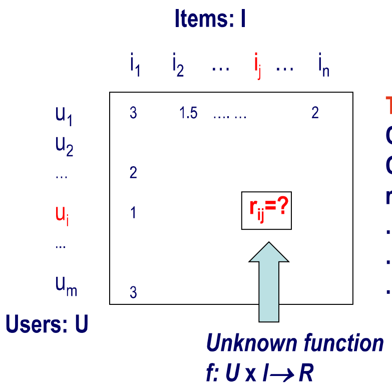
How it works

- Each user has a profile
- Users rate items
  - Explicitly: Give a score
  - Implicitly: web usage mining
    - Time spent in viewing the item
    - Navigation path
    - Etc…
- System does the rest, How?

Collaborative filtering

- *Collaborative Filtering: Make predictions about a user’s missing data according to the behaviour of many other users*
  - Look at users collective behavior
  - Look at the active user history
  - Combine!

Collaborative filtering: A framework



The task:
Q1: Find Unknown ratings?
Q2: Which items should we recommend to this user?
.
.
.

Collaborative filtering approaches

- User based methods
  - Identify like-minded users
- Item based methods
  - Identify similar items
- Model (matrix) based methods
  - Solve an optimization problem and identify latent factors

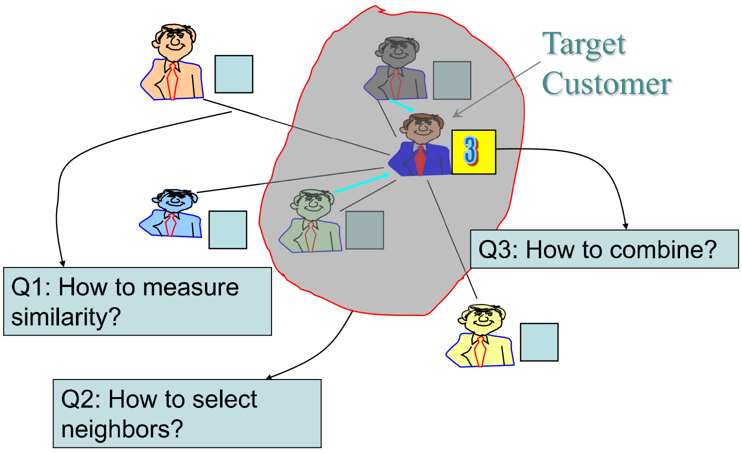
Ratings of items by users: Fill in cell ????

Items

Users

	Item1	Item2	Item3	Item4	Item5	Item6
User1	17	-	20	18	17	18.5
User2	8	-	????	17	14	17.5
User3	-	-	17	18	18.5	17.5
User4	-	-	-	18	17.5	18
User5	17	-	18	19	15.5	-
User6	-	-	17.5	-	16	-
User7	15	17.5	-	17	-	17
User8	18	-	-	-	17	16.5
User9	18	17	-	-	18.5	17
User10	19	17	-	-	-	16.5
User11	17	18.5	19	19	-	-
User12	14	19	17	-	-	15.5
User13	-	16	-	-	17	-
User14	20	18.5	-	18	-	18

User-user similarity: Intuition



Target Customer

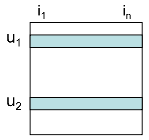
Q1: How to measure similarity?

Q2: How to select neighbors?

Q3: How to combine?

How to measure similarity? Method 1

U1	17	-	20	18	17	18.5
U2	8	-	-	17	14	17.5

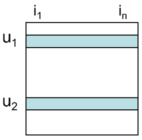


$$SIM(U1,U2) =$$
$$((17-8)^2 + (18.1-14.1)^2 + (20-14.1)^2 + (18-17)^2 + (17-14)^2 + (18.5-17.5)^2$$

- Compute mean value for User1’s missing values (18.1)
- Compute mean value for User2’s missing values (14.1)
- Compute squared Euclidean distance between resulting vectors

How to measure similarity? Method 2

User1	17	-	20	18	17	18.5
User2	8	-	-	17	14	17.5



$$Sim(User1,User2) = \frac{6}{6-2}((17-8)^2 + (18-17)^2 + (17-14)^2 + (18.5-17.5)^2$$

•Compute squared Euclidean distance between vectors, summing only pairs without missing values
•2 out of the 6 pairs have at least one missing value
•Scale the result, according to percentage of pairs with a missing value

Practice example

User1	12	2.5	20	-	17	-	3.5
User2	13	-	-	17	14	17.5	4.5

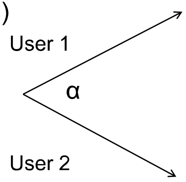
Using Method 2, SIM(User1,User2)=?

$$\text{SIM(User1,User2)} = \frac{7}{3}(|12-13|^2 + |17-14|^2 + |3.5-4.5|^2)$$

$$= \frac{7}{3}(1+9+1) = 25.66$$

User-user similarity: Other measures

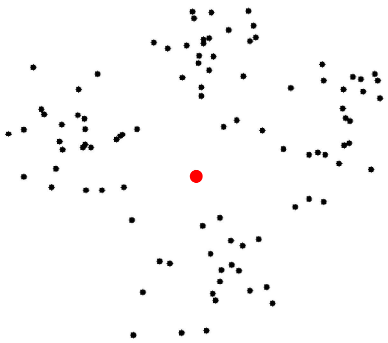
- Instead of Euclidean distance can also use other measures to assess similarity, e.g.
  - Correlation (we will look at later in subject)
  - Cosine similarity (angle between user profile vectors)



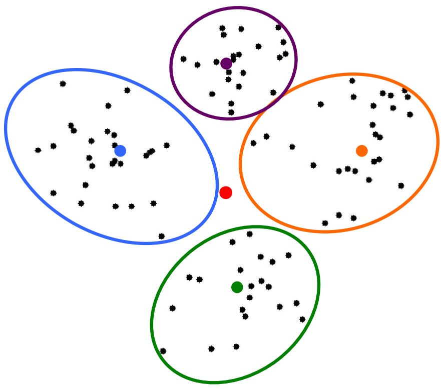
Selecting neighbors and making prediction

- At runtime
  - Need to *select* users to compare to
  - Could choose the top-k most similar users
  - *Combining*: Prediction of rating is the (weighted) average of the values from the top-k similar users
- Can make more efficient by computing clusters of users offline
  - At runtime find nearest cluster and use the centre of the cluster as the rating prediction
  - Faster (more scalable) but a little less accurate

User-user similarity



User-user similarity



User based methods summary

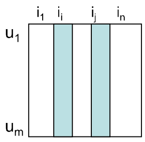
- Achieve good quality in practice
- The more processing we push offline, the better the method scale
- However:
  - User preference is dynamic
    - High update frequency of offline-calculated information
  - No recommendation for new users
    - We don't know much about them yet

Item based methods: Intuition

- Search for similarities among items
- All computations can be done offline
- Item-Item similarity is more stable than user-user similarity
  - No need for frequent updates:

Item based methods

- Same as in user-user similarity but on item vectors
  - Find similar items to the one whose rating is missing
  - E.g. For item i_i compute its similarity to each other item i_j



Item based methods

- Offline phase. For each item
  - Determine its k-most similar items
  - Can use same type of similarity as for user-based
- Online phase:
  - Predict rating r_{aj} for a given user-item pair as a weighted sum over k-most similar items that they rated

$$r_{aj} = \frac{\sum_{i \in \text{k-similar items}} sim(i,j) \times r_{ai}}{\sum_{\in \text{k-similar items}} sim(i,j)}$$

User a	**8**		**r_{aj}**		**9**	**15**

Item j

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Practice example

Users	Titanic	Batman	Inception	Superman	The Martian	Jurassic World
Michelle	2.5		3	3.5	2.5	3
Tom	3	3.5		5	3	3.5
Lao	2.5	3		3.5		4
Chan		3.5	3	4	2.5	
Mary		4	2	3	2	3
Tim	3	4	?	5	3.5	3
John		4.5		4	1	

Item j: Inception
User a: Tim

Offline phase: we calculate k-most similar items for item j. Let's say $k = 3$.

Similarity	Titanic	Batman	Superman	The Martian	Jurassic World
Inception-Method 1	1.06	3.28	3.95	2.04	2.02
Inception-Method 2	3.5	7.22	3.5	1.65	3.5

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Practice example cont.

Users	Titanic	Batman	Inception	Superman	The Martian	Jurassic World
Michelle	2.5		3	3.5	2.5	3
Tom	3	3.5		5	3	3.5
Lao	2.5	3		3.5		4
Chan		3.5	3	4	2.5	
Mary		4	2	3	2	3
Tim	3	4	?	5	3.5	3
John		4.5		4	1	

Item j: Inception
User a: Tim

$$r_{aj} = \frac{\sum_{i \in \text{k-similar items}} sim(i,j) \times r_{ai}}{\sum_{\in \text{k-similar items}} sim(i,j)}$$

Similarity	Superman	The Martian	Jurassic World
$Sim\ (i,j)$	3.5	1.65	3.5

Online phase:

$$r_{aj} = \frac{3.5\ x\ 5 + 1.65\ x\ 3.5 + 3.5\ x\ 3}{3.5 + 1.65 + 3.5} = 3.9$$

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Matrix based techniques

- Treat the User-Item Rating table R as a matrix
  - Use matrix factorisation of this Rating Table

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Matrix based techniques: Rating table R

Items

Users

	Item1	Item2	Item3	Item4	Item5	Item6
User1	17	-	20	18	17	18.5
User2	8	-	-	17	14	17.5
User3	-	-	17	18	18.5	17.5
User4	-	-	-	18	17.5	18
User5	17	-	18	19	15.5	-
User6	-	-	17.5	-	16	-
User7	15	17.5	-	17	-	17
User8	18	-	-	-	17	16.5
User9	18	17	-	-	18.5	17
User10	19	17	-	-	-	16.5
User11	17	18.5	19	19	-	-
User12	14	19	17	-	-	15.5
User13	-	16	-	-	17	-
User14	20	18.5	-	18	-	18

Factorisation

- We are familiar with factorisation of numbers

  15=3*5

  99=3*33

  1000=10*100

  We can also do approximate factorisation

  17 ≈ 6*2.8 (RHS= 16.8, an error of 0.2)

  167 ≈ 17*9.8 (RHD=166.6, an error of 0.4)

Matrix factorization

Given a matrix R, we can find matrices U and V such that when U and V are multiplied together

$$R \approx UV$$

•R is m×n, U is m×k and V is k×n

- k is the “number of latent factors”

For example, suppose R is a 4 × 4 matrix

$$R = \begin{bmatrix} 5 & 2 & 3 & 6 \\ 4 & 4 & 6 & 11 \\ 3 & 19 & 2 & 7 \\ 3 & 8.5 & 4 & 2 \end{bmatrix}$$

Example: m=4, n=4, k=2

$$\begin{bmatrix} 5 & 2 & 3 & 6 \\ 4 & 4 & 6 & 11 \\ 3 & 19 & 2 & 7 \\ 3 & 8.5 & 4 & 2 \end{bmatrix} \approx \begin{bmatrix} 0.34776 & 1.97802 \\ 0.71609 & 3.13615 \\ 4.27876 & 0.58287 \\ 1.88074 & 0.56923 \end{bmatrix} \begin{bmatrix} 0.58367 & 4.40189 & 0.44605 & 1.04492 \\ 1.52915 & 0.26346 & 1.75046 & 3.09976 \end{bmatrix}$$

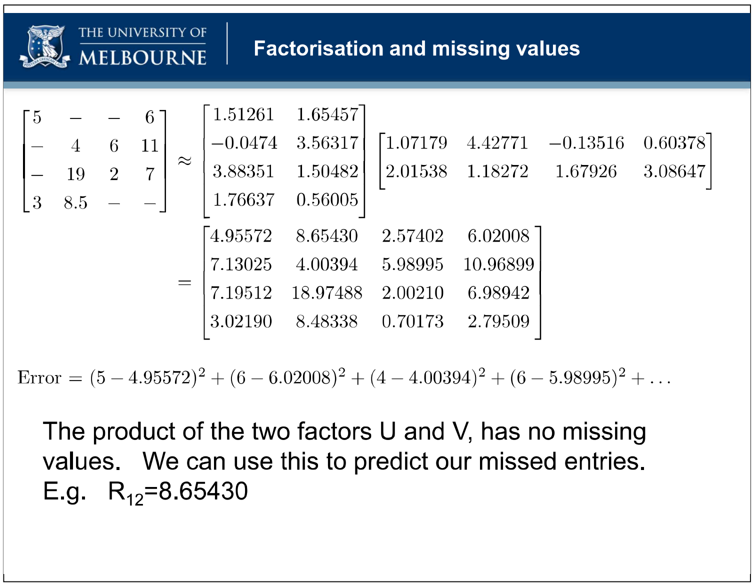
$$= \begin{bmatrix} 3.22769 & 2.05196 & 3.61758 & 6.49480 \\ 5.21363 & 3.97844 & 5.80912 & 10.46959 \\ 3.3887 & 18.98823 & 2.92886 & 6.27777 \\ 1.96819 & 8.42882 & 1.83534 & 3.72973 \end{bmatrix}$$

We can compute the error (squared distance between R and UV). The smaller it is, the better the fit of the factorisation.

$$(5-3.22769)^2 + (2-2.05196)^2 + (3-3.61758)^2 + \ldots$$
$$(4-1.83534)^2 + (2-3.72973)^2$$

How to factorise

- *Details of how to compute the matrix factorisation are beyond the scope of our study.*
- Intuitively, factorisation algorithms search over lots of choices for U and V, with the aim of making the error as low as possible
- If there are missing values in R, ignore these when computing the error.



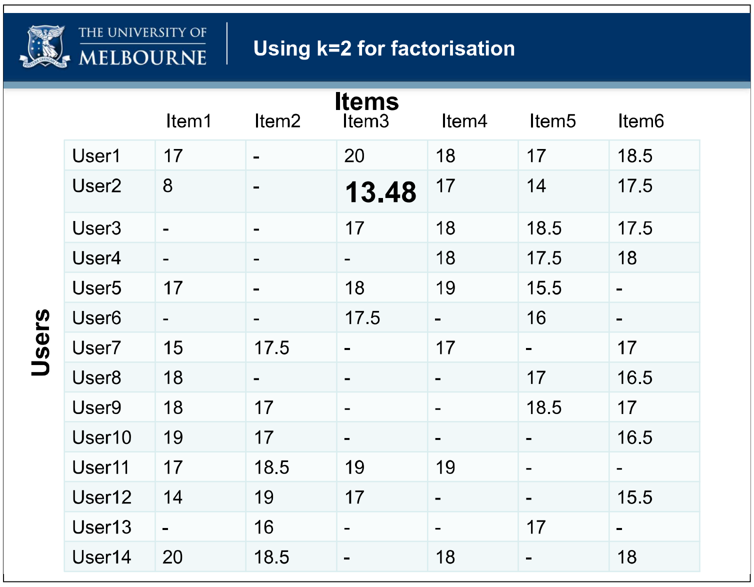
Factorisation and missing values

$$\begin{bmatrix} 5 & - & - & 6 \\ - & 4 & 6 & 11 \\ - & 19 & 2 & 7 \\ 3 & 8.5 & - & - \end{bmatrix} \approx \begin{bmatrix} 1.51261 & 1.65457 \\ -0.0474 & 3.56317 \\ 3.88351 & 1.50482 \\ 1.76637 & 0.56005 \end{bmatrix} \begin{bmatrix} 1.07179 & 4.42771 & -0.13516 & 0.60378 \\ 2.01538 & 1.18272 & 1.67926 & 3.08647 \end{bmatrix}$$

$$= \begin{bmatrix} 4.95572 & 8.65430 & 2.57402 & 6.02008 \\ 7.13025 & 4.00394 & 5.98995 & 10.96899 \\ 7.19512 & 18.97488 & 2.00210 & 6.98942 \\ 3.02190 & 8.48338 & 0.70173 & 2.79509 \end{bmatrix}$$

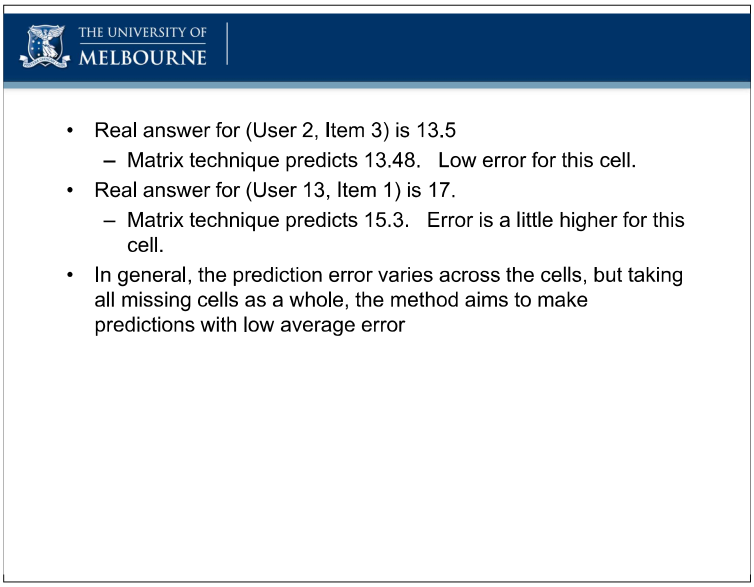
$$\text{Error} = (5 - 4.95572)^2 + (6 - 6.02008)^2 + (4 - 4.00394)^2 + (6 - 5.98995)^2 + \dots$$

The product of the two factors U and V, has no missing values. We can use this to predict our missed entries. E.g. R_{12}=8.65430

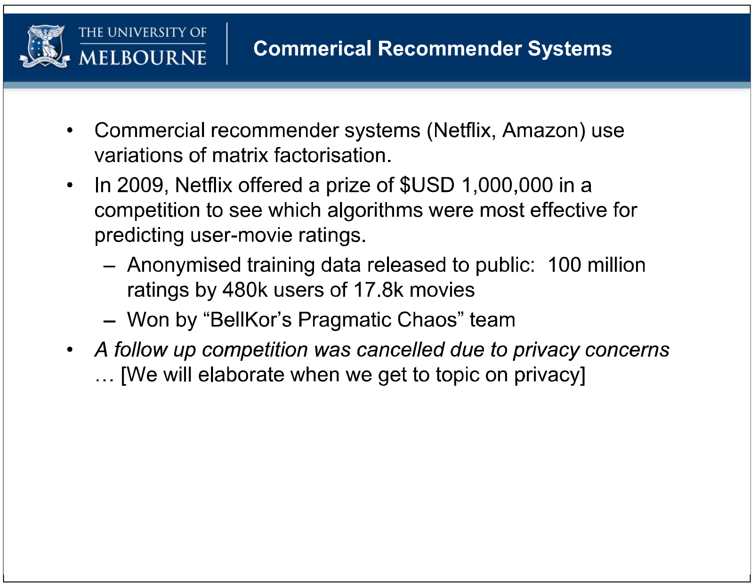


Using k=2 for factorisation

			Items			
Users	Item1	Item2	Item3	Item4	Item5	Item6
User1	17	-	20	18	17	18.5
User2	8	-	**13.48**	17	14	17.5
User3	-	-	17	18	18.5	17.5
User4	-	-	-	18	17.5	18
User5	17	-	18	19	15.5	-
User6	-	-	17.5	-	16	-
User7	15	17.5	-	17	-	17
User8	18	-	-	-	17	16.5
User9	18	17	-	-	18.5	17
User10	19	17	-	-	-	16.5
User11	17	18.5	19	19	-	-
User12	14	19	17	-	-	15.5
User13	-	16	-	-	17	-
User14	20	18.5	-	18	-	18



- Real answer for (User 2, Item 3) is 13.5
  - Matrix technique predicts 13.48. Low error for this cell.
- Real answer for (User 13, Item 1) is 17.
  - Matrix technique predicts 15.3. Error is a little higher for this cell.
- In general, the prediction error varies across the cells, but taking all missing cells as a whole, the method aims to make predictions with low average error



Commerical Recommender Systems

- Commercial recommender systems (Netflix, Amazon) use variations of matrix factorisation.
- In 2009, Netflix offered a prize of $USD 1,000,000 in a competition to see which algorithms were most effective for predicting user-movie ratings.
  - Anonymised training data released to public: 100 million ratings by 480k users of 17.8k movies
  - Won by “BellKor’s Pragmatic Chaos” team
- *A follow up competition was cancelled due to privacy concerns* … [We will elaborate when we get to topic on privacy]

Other issues

- Many challenging issues in deployment of recommendations
  - Interpretability of recommendations?
  - How to be fair to rare items?
  - How to avoid only recommending popular items?
  - How to handle new users?

References

- See
  - Matrix Factorization Techniques for Recommender Systems. Koren, Bell and Volinsky. IEEE Xplore, Vol 42, 2009. Available on the LMS in Week 3 section.

- Some slides based on “Data Mining Concepts and Techniques”, Han et al, 2nd edition 2006.