# ECE271B Project: Amazon Fine Foods Recommender to Customers

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# **Problem Statement & Dataset Introduction**

#### **Motivations**

- Amazon is the NO.1 most popular shopping App in the United States
- Over 89% customers trust Amazon
- The recommendation from Amazon to customer is important



# **Objective and Methodology**

- Objective:
  - Predict the ratings of customers to products.
  - Decide which product to recommend.

- Methodology
  - Collaborative Filter
  - Latent factor model

#### **Dataset**

- Consists of reviews of fine foods from Amazon. (from Oct 1999 Oct 2012)
  - 568,454 reviews
  - 256,059 users
  - 74,258 products
  - 260 users with > 50 reviews
  - 10 columns

	ld	Productid	Userld	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary	Text
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	5	1303862400	Good Quality Dog Food	I have bought several of the Vitality canned d
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	1	1346976000	Not as Advertised	Product arrived labeled as Jumbo Salted Peanut
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	4	1219017600	"Delight" says it all	This is a confection that has been around a fe

J. McAuley and J. Leskovec. From amateurs to connoisseurs: modeling the evolution of user expertise through online reviews. WWW, 2013.

### **Dataset Manipulations**

- Drop columns
  - Unrelated columns (Id, ProfileName, Time)
  - Text columns (Text, Summary)
  - Helpfulness columns (major missing values)
- Drop rows
  - Ignore users who have < 20 reviews</li>



68,015 rows, 3 columns

	Productid	Userld	Score
0	B001GVISJM	A18ECVX2RJ7HUE	4
1	B001GVISJM	A2MUGFV2TDQ47K	5
2	B001GVISJM	A2A9X58G2GTBLP	5
3	B001EO5QW8	A2G7B7FKP2O2PU	5
4	B001E05QW8	AQLL2R1PPR46X	5
5	B0059WXJKM	A25VFHVGI4CFTP	1
6	B001REEG6C	AY12DBB0U420B	5
7	B001GVISJW	A2YIO225BTKVPU	4
8	B001GVISJW	A1Z54EM24Y40LL	5
9	B001GVISJW	A281387UUS2IN5	3
10	B000ITVLE2	A3NID9D9WMIV01	5

# **Rating Predictions**

## **Problem Formulation**

- Complete data is typically not available.
- Fill the blanks using the known data.

	Product 1	Product 2	Product 3	Product 4
User A	5.0		4.0	3.4
User B	3.0	3.6	3.5	
User C		4.6		4.8
User D	5.0		3.5	

# **Set up and Baseline**

- Randomly divide the dataset into:
  - 80% training.
  - 20% testing.

- Baseline:
  - Prediction by average.
  - The MSE is around 1.37 on the test set.

# **Method 1: Collaborative Filter**

# Similarity-based Model

#### Two steps:

- Look for users similar to the active user.
- Predict the rating using weighted ratings from the similar users.

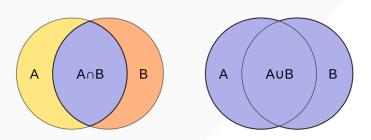
$$r(u,i) = \frac{1}{Z} \sum_{v \in U_i \setminus \{u\}} r_{v,i} \cdot \operatorname{sim}(u,v)$$

- $r_{u,j}$ : rating of user u to product j
- sim(u, v): similarity between user u and v
- $Z = \sum_{v \in U_i \setminus \{u\}} sim(u, v)$ : normalization constant

# **Similarity Rules**

Jaccard similarity

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A| + |B| - |A - B|}$$



Cosine similarity

$$C(x,y) = \cos(\vec{x}, \vec{y}) = \frac{\vec{x} \cdot \vec{y}}{\|\vec{x}\| \|\vec{y}\|} = \frac{\sum_{i \in I_{xy}} r_{x,i} r_{y,i}}{\sqrt{\sum_{i \in I_{xy}} r_{x,i}^2} \sqrt{\sum_{i \in I_{xy}} r_{y,i}^2}}$$

# Results

- Similarity-based Collaborative filtering: MSE = 0.742 on test set.
- Much better than the baseline.

# **Method 2: Latent Factor Model**

# **Matrix Factorization**



	Product 1	Product 2	Product 3	Product 4
Factor X	1.0	0.4	0.5	0.2
Factor Y	0.0	0.6	0.5	0.8



	Factor X	Factor Y
User A	5	3
User B	3	4
User C	4	5
User D	5	2



	Product 1	Product 2	Product 3	Product 4
User A	5.0	3.8	4.0	3.4
User B	3.0	3.6	3.5	3.8
User C	4.0	4.6	4.5	4.8
User D	5.0	3.2	3.5	2.6

# **Latent Factor Model & Optimization**

Latent Factor Model

$$f(u,i) = \alpha + \beta_u + \beta_i$$

$$\begin{cases} \alpha: \text{ global average} \\ \beta_u: \text{ how much does the user tend to rate above mean} \\ \beta_i: \text{ does this item tend to receive high ratings} \end{cases}$$

The optimization problem

$$\arg\min_{\alpha,\beta} \underbrace{\sum_{u,i} \left(\alpha + \beta_u + \beta_i - R_{u,i}\right)^2}_{\text{error}} + \underbrace{\lambda \left[\sum_{u} \beta_u^2 + i \sum_{i} \beta_i^2\right]}_{\text{regularization}}$$

# **Update Parameters**

• The Update Rules:

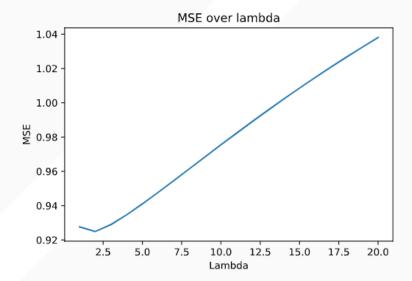
$$\alpha = \frac{\sum_{u,i} R_{u,i} - (\beta_u + \beta_i)}{N_{\text{train}}}$$

$$\beta_u = \frac{\sum_{i \in I_u} R_{u,i} - (\alpha + \beta_i)}{\lambda + |I_u|}$$

$$\beta_i = \frac{\sum_{u \in U_i} R_{u,i} - (\alpha + \beta_u)}{\lambda + |U_i|}$$

# Results

- Latent Factor Model: MSE = 0.92 when  $\lambda$  is 2
- Slightly worse than the first method



# **Conclusion**

### **Final results**

- Similarity-based Collaborative filtering: MSE = 0.742 on test set.
- Latent Factor Model: MSE = 0.92 when λ is 2

#### **Future work**

• Apply different models.

• Tune or add parameters.

• Generate recommendations for each user.

#### Reference

https://www.oberlo.com/blog/amazon-statistics

https://www.kaggle.com/snap/amazon-fine-food-reviews

https://cseweb.ucsd.edu/classes/fa20/cse258-a/slides/recommendation\_clean.pdf

J. McAuley and J. Leskovec. From amateurs to connoisseurs: modeling the evolution of user expertise through online reviews. WWW, 2013.