

Online Recommender Systems

CS 780/880

Outline

- ▶ Content-based offer recommendations

- ▶ Collaborative filtering
 - ▶ Recommender systems
 - ▶ Online travel recommendations
 - ▶ Collaborative filtering
 - ▶ Matrix factorization and completion

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Example recommender systems

- ▶ Movie recommendations (Netflix)
- ▶ Personalized music (Pandora)
- ▶ Relevant product recommendations (Amazon)
- ▶ Online advertising (Facebook)
- ▶ Online dating (OK Cupid)
- ▶ Special offers, coupons, and discounts (Stores)

Google Play recommendations

The screenshot displays the Google Play Entertainment interface. At the top, there is a search bar and navigation icons for Mark, notifications, and profile. A left sidebar lists categories: Entertainment (selected), Apps, Movies & TV, Music, Books, Newsstand, and Devices. Below the sidebar, the 'Recommended for You' section features a grid of 12 items:

Image	Title	Author/Artist	Price	Description
	7 Years	Lukas Graham	\$0.49	Popular in Pop genre
	The Three-Body Problem	Cixin Liu	\$9.99	Popular with similar readers
	The Amazing Spider-Man 2	Action & Adventure	\$2.99	It's great to be Spider-Man (Andrew Garfield). For Peter Parker, there's no feeling quite like swinging between... Pavel Chermakov 5 stars
	Me, Myself & I	G-Eazy	\$1.29	Popular with similar listeners
	13 Hours: The Inside Account of What Happened in Benghazi	Mitchell Zuckoff	\$11.99	NOW A MAJOR MOTION PICTURE Top book
	A Million Ways to Die in the West	Comedy	\$2.99	Seth MacFarlane stretches the boundaries of comedy and propriety as writer, producer, director, and... Popular with similar viewers
	You're Beautiful	James Blunt	\$1.29	More from James Blunt
	Twelve Years a Slave	Solomon Northup	\$0.99	NOW A NEW YORK TIMES Popular with similar readers
	Blended	Comedy	\$2.99	Reuniting Adam Sandler, Drew Barrymore and director Frank Coraco — the trifecta behind New Line Popular with similar viewers

Amazon recommendations



You Save: **\$7.39 (71%)**

In Stock.

Want it tomorrow, April 19? Add it to a qualifying order within **22 hrs 46 mins** and choose Same-Day Delivery at checkout. [Details](#)
Ships from and sold by Amazon.com. Gift-wrap available.

Size: **8-Inches**

6-Inches \$6.34	7-Inches \$6.39	8-Inches \$7.39
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- Great for photos, papers, crafts
- Comes in 6", 7", 8" sizes
- High quality, durable stainless steel blades
- Soft grip handles
- 10 Year Limited Warranty

Add-on item

This item is available because of the Add-on program

The Add-on program allows Amazon to offer thousands of low-priced items that would be cost-prohibitive to ship on their own. These items ship with qualifying orders over \$25. [Details](#)

\$3.00 from **\$2.00** 1 used from **\$1.00**



Save 52%
on the SINGER 3232
Simple Sewing Machine [Learn more](#)



Roll over image to zoom in

Customers Who Bought This Item Also Bought

Page 1 of 12

								
Scotch Desk Tape Dispenser, 1in. Core, Black ★★★★★: 538 \$3.97	Scotch Desktop Tape Dispenser Silvertech, Two-Tone (C80-ST) ★★★★★: 442 \$3.00	Swingline Stapler 3-in-1 S+L Includes Stapler, Stapler Remover and 5000 Count Staples... ★★★★★: 211 \$6.00 vPrime	Swingline Light Duty Standard Staples 20 Sheets, Black (S7040501) ★★★★★: 167 \$3.09	Scotch Magic Tape 3/65, 3/4 x 300 Inches, Pack of 3 ★★★★★: 718 \$4.05	Sharpie Accent Tank-Style Highlighters, 6 Colored Highlighters (25076) ★★★★★: 965 \$3.78	Scotch Classic Desktop Tape Dispenser, Pink, for 1-Inch Core Tapes (C-38-P) ★★★★★: 968 \$3.00	Sparco 8000 Staple Remover, Color May Vary ★★★★★: 195 \$1.00 Deal of the Day (in Staple Removers) \$2.50	BIC Round Stic, Ink Life Ball Pen, Medium Point (1.0 mm), Black, 60-Count ★★★★★: 2,593 \$4.70

IBM travel recommendations

The Leisure Sailing Company

[Home](#) [Shop](#) [Compare](#) [About Us](#)



Shop

Bozburun Yacht Charter



Region: Mediterranean
Country: Turkey
Total Sallors: 2
Duration: 5 Days

[Check Availability](#)

Bustling town of Gocek on Turkey's Lycian coast is ideally situated for a bareboat sailing vacation in one of the least crowded and most beautiful cruising grounds in the Eastern Mediterranean. A Gocek yacht charter allows you to explore the mountainous pine-forested shores, ancient ruins and peaceful anchorages that adorn Turkey's Turquoise Coast at your own pace.

Secluded coves and bays offer fantastic swimming, snorkeling and sunbathing opportunities, and there are glorious beaches just waiting for you to laze upon them. The picturesque harbors where you can moor up for the night are invariably home to a good restaurant or three.

- ✓ Amazing mountainous backdrop
- ✓ Secluded anchorages
- ✓ Beautiful crystal-clear waters
- ✓ Unrivaled historical setting

Other recommended destinations:

Mediterranean • Croatia
Zlarin Yacht Charter



- ✓ Historic towns
- ✓ Beautiful islands
- ✓ Breathtaking natural wonders
- ✓ Secluded white sand bays

[Explore Zlarin](#)

Indian-Ocean • Seychelles
Mahe Flotilla Sailing



- ✓ Superb white sand beaches
- ✓ Surrounded by reefs and shipwrecks
- ✓ Tropical paradise
- ✓ Relaxed tradewind sailing

[Explore Abaco](#)

Mediterranean • Greece
Sporades Flotilla Sailing



- ✓ Stunning natural beauty
- ✓ Perfect family choice
- ✓ Club Flotilla options
- ✓ Rustic Greece at its best

[Explore Sporades](#)

- ▶ Recommend relevant products on website of a tour operator

Travel recommendation steps

Unknown customer



Travel recommendation steps

Unknown customer



Browsing history (trips)



Travel recommendation steps

Unknown customer



Browsing history (trips)



Best guess



Travel recommendation steps

Unknown customer



Browsing history (trips)



Best guess



Recommended trips



Benefits of online recommendations

- ▶ What are the benefits?
- ▶ For users/customer:
 1. Find the right product or information
 2. See only relevant advertising
 3. Discover diverse products or information sources
- ▶ For businesses/websites:
 1. Increase user satisfaction
 2. Sell more products and right products
 3. Discriminate between customers
 4. Predict and understand customer preferences

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Types of recommender systems

- ▶ By delivery:
 - ▶ **Item-to-item** recommendations: e.g. Amazon products
 - ▶ **User-to-item** recommendations: e.g. Netflix, Google Play

- ▶ By information used:
 - ▶ **Content-based**: Use item description and user profile
 - ▶ Use when rich user profile and content information is available
 - ▶ **Collaborative filtering**: Use preferences of other users
 - ▶ When rich interaction history is available
 - ▶ **Hybrid**: Combination

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Content-based or collaborative filtering?

Unknown customer



Browsing history (trips)



Best guess



Recommended trips



Content-based recommender systems

- ▶ Learn user preference model based on attributes
- ▶ Use historical user preference data

User		Movie		
Gender	Age	Genre	Year	Rating
Male	16	Comedy	1998	1
Male	98	Horror	1912	5
Female	43	Action	2016	3

- ▶ Use supervised learning methods

Collaborative-filtering recommender systems

- ▶ Very flexible: no need to know content or user profiles
- ▶ Simple and powerful methods
- ▶ **Training data:** Partial user-item preferences

	item									
user	3	?	?	1	3	1	1	5	?	5
	?	2	3	?	3	?	2	?	?	?
	?	5	?	?	1	?	?	2	?	4
	4	3	?	3	?	?	?	?	?	?
	2	3	5	2	?	?	?	5	?	4
	?	?	1	2	5	3	4	?	?	?

- ▶ **Making recommendations:** Fill in the blanks (?)

Nearest neighbors: Use similar users

- ▶ Infer preferences from similar users

- ▶ **Other users:**

	item										
user	3	?	?	1	3	1	1	5	?	5	
	4	3	?	3	?	?	?	?	5	?	

- ▶ **Current user:**

user	?	3	3	3	?	?	1	5	?	?	
------	---	---	---	---	---	---	---	---	---	---	--

- ▶ Basic algorithm:

1. Find similar user (e.g. 2 ratings same)
2. Infer unknown preferences

- ▶ Why does this fail?

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user	3	?	?	1	3	1	1	5	?	5
	4	3	?	3	?	?	?	?	5	?

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user	4	3	3	3	?	?	1	5	5	?
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	4	3	?	3	?	?	?	?	5	?

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user	4	3	3	3	?	?	1	5	5	?
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user	4	3	3	3	?	?	1	5	5	?
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- ▶ Basic algorithm:

1. Find similar user (e.g. 2 ratings same)
2. Infer unknown preferences

- ▶ Why does this fail? **Conflicting preferences!**

Matrix factorization

- ▶ Better model for addressing incompatible preferences
- ▶ **Assumption:** Latent (unobserved) customer type, e.g.
 1. Adventure seeking
 2. Luxury oriented
- ▶ Low-rank matrix decomposition:

$$\begin{array}{c} \text{user} \\ \left(\begin{array}{ccccc} & \text{item} & & & \\ 2 & 3 & 3 & 1 & 1 \\ 2 & 3 & 3 & 1 & 1 \\ 4 & 3 & 1 & 1 & 3 \\ 4 & 3 & 1 & 1 & 3 \\ 4 & 3 & 1 & 1 & 3 \end{array} \right) \\ \underbrace{\hspace{10em}} \\ D \end{array} = \begin{array}{c} \text{user} \\ \left(\begin{array}{cc} & \text{type} \\ 0 & 1 \\ 0 & 1 \\ 1 & 0 \\ 1 & 0 \\ 1 & 0 \end{array} \right) \\ \underbrace{\hspace{10em}} \\ U \end{array} \begin{array}{c} \text{item} \\ \left(\begin{array}{ccccc} 4 & 3 & 1 & 1 & 3 \\ 2 & 3 & 3 & 1 & 1 \end{array} \right) \\ \underbrace{\hspace{10em}} \\ Q^T \end{array} \begin{array}{c} \text{type} \end{array}$$

- ▶ $D_{11} = U_1 Q_1^T$
- ▶ Not integral in general!

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Computing matrix factorization

- ▶ Given a **small** constant k
- ▶ How to compute the best factorization U, Q ?

$$D \stackrel{?}{=} UQ^T \text{ s.t. } \text{rank}(U) = \text{rank}(Q) = k$$

- ▶ Solve optimization problem:

$$\min_{U, Q} \|D - UQ^T\|_F^2 \text{ s.t. } \text{rank}(U) = \text{rank}(Q) = k$$

- ▶ Frobenius norm: $\|A\|_F^2 = \sum_{i,j} A_{ij}^2 = \sum_i \sigma_i^2$
- ▶ Solve optimally by SVD when D is complete
- ▶ NP-hard when D is incomplete
- ▶ Simple, practical, and effective method
 1. Fix U and solve: $\min_Q \|D - UQ^T\|_F^2$ s.t. $\text{rank}(Q) = k$
 2. Fix Q and solve: $\min_U \|D - UQ^T\|_F^2$ s.t. $\text{rank}(U) = k$

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Matrix factorization: Results

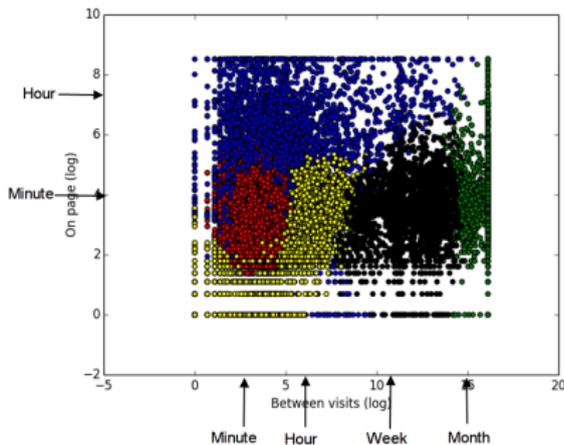
- ▶ One year worth of website click-stream data
- ▶ Dependence on number of previously visited sites
- ▶ Matrix factorization (green) vs baseline (blue)



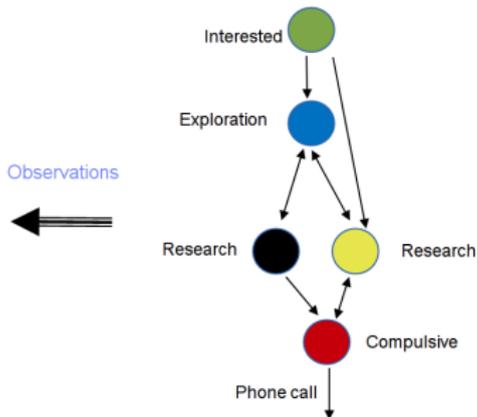
Beyond simple models: Dynamic user behavior

► Hidden Markov Model

Customer Behavior in Hidden States



Hidden Markov Model States



- Strategic recommendations: optimal in long run (conversion/satisfaction)

Recommendations on social media (Twitter)



► Challenges

1. Large volume: (6000 t/s)
2. Short (cryptic) text:
“Cruise with me on this wild ride”

► Approach:

1. Use language models to identify travel intent
2. Matrix factorization to match catalog descriptions with tweets

► Positive engagement: 15%