Recommendation Systems Part I

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Outline

Introduction

Background

Recommendation systems: why and what?

Example datasets

Problem statement

Recommendation systems: a prediction problem

Model: from caricature to extremely complex

Hands-on

Understanding data

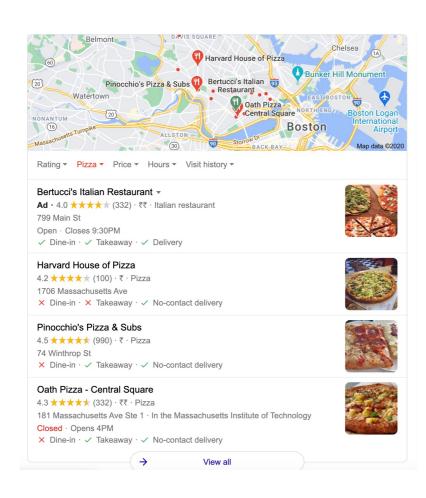
Background

What is it, really?

What food should you eat today?

Why not just search?

Want to eat Pizza, search for Pizza places near you



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Uber Eats | Your order left at your door | UberEats.com

Your order can now be delivered straight to your doorstep. Use "Leave at door" at checkout. Because food brings **us** together—even when we're apart. Order Via Uber Eats. Service you love. High quality cuisine. Morning caffeine kicks. 100+ local foodie spots. Online menus.

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Enjoy 2 Large Signature **Pizzas** plus salad & rolls for \$36. Available for Dine in, Curbside, or Delivery. Order Now. Now Taking Reservations. ToGo & Delivery Available. Brick Oven **Pizza**. Order Bertucci's 2Go · Outdoor Patio Seating · Catering · Join the Bertucci's eClub

But

Which of these *many* options should you be *recommended?*

Which of these *many* be *advertised?*

What is it, really?

What food should you eat today?

Which activities should you plan for the upcoming weekend?

Where should you plan your holidays?

Whom should you date (and marry)?

What are the professional connections of your interest?

Which advertisements should you be subjected to?

What content on YouTube or music on Spotify will fancy you?

0 0 0 0

May be data can help. What data?

May be data can help. What data?

Example: Yelp data

Businesses: attributes (locations, category), hours

Users: attributes, friends

Reviews: rating, description, time

Check-ins: time

Tip

Exercise: go to link below, explore data and reproduce statistics reported

Businesses: 209393 (~200k) in total

	address	attributes	business_id	categories	city	hours	is_open	latitude	longitude	name	postal_code	review_count	stars	state
0	10913 Bailey Rd	{u'BusinessParking': u'{'garage': False, 'stre	f9NumwFMBDn751xgFiRbNA	Active Life, Gun/Rifle Ranges, Guns & Ammo, Sh	Cornelius	{u'Monday': u'10:0- 18:0', u'Tuesday': u'11:0-2	1	35.462724	-80.852612	The Range At Lake Norman	28031	36	3.5	NC
1	8880 E Via Linda, Ste 107	{u'GoodForKids': u'True', u'ByAppointmentOnly'	Yzvjg0SayhoZgCljUJRF9Q	Health & Medical, Fitness & Instruction, Yoga,	Scottsdale	None	1	33.569404	-111.890264	Carlos Santo, NMD	85258	4	5.0	AZ
2	3554 Rue Notre- Dame O	None	XNoUzKckATkOD1hP6vghZg	Pets, Pet Services, Pet Groomers	Montreal	None	1	45.479984	-73.580070	Felinus	H4C 1P4	5	5.0	QC
3	1015 Sharp Cir	{u'DogsAllowed': u'True', u'BusinessParking':	6OAZjbxqM5ol29BuHsil3w	Hardware Stores, Home Services, Building Suppl	North Las Vegas	{u'Friday': u'7:0-16:0', u'Tuesday': u'7:0-16:	0	36.219728	-115.127725	Nevada House of Hose	89030	3	2.5	NV
4	4827 E Downing Cir	{u'BusinessAcceptsCreditCards': u'True', u'ByA	51M2Kk903DFYl6gnB5l6SQ	Home Services, Plumbing, Electricians, Handyma	Mesa	{u'Friday': u'9:0-16:0', u'Tuesday': u'9:0-16:	1	33.428065	-111.726648	USE MY GUY SERVICES LLC	85205	26	4.5	AZ

Data URL:

Users: 1968703 (~2M) in total

	average_stars	compliment_cool	compliment_cute	compliment_funny	compliment_hot	compliment_list	compliment_more	compliment_note	(
0	3.57	22	0	22	3	1	2	11	
1	3.84	63	2	63	36	1	4	33	
2	3.44	17	1	17	9	0	6	3	
3	3.08	7	0	7	2	0	1	7	
4	4.37	31	1	31	8	1	9	22	

	elite	fans	friends	funny	name	review_count	useful	user_id	yelping_since
		14	oeMvJh94PiGQnx_6GlndPQ, wm1z1PaJKvHgSDRKfwhfDg	225	Rafael	553	628	ntlvfPzc8eglqvk92iDIAw	2007-07-06 03:27:11
2008,2009,2010,2011,2012	2,2013	27	ly7EnE8leJmyqyePVYFlug, pRlR63iDytsnnniPb3AOug	316	Michelle	564	790	FOBRPIBHa3WPHFB5qYDIVg	2008-04-28 01:29:25
	2010	5	Uwlk0txjQBPw_JhHsQnyeg, Ybxr1tSCkv3lYA0l1qmnPQ	125	Martin	60	151	zZUnPeh2hEp0WydbAZEOOg	2008-08-28 23:40:05
	2009	6	iog3Nyg1i4jeumiTVG_BSA, M92xWY2Vr9w0xoH8bPplfQ	160	John	206	233	QaELAmRcDc5TfJEylaaP8g	2008-09-20 00:08:14
2009,2010,2011,2012,2014,2015,2016,2017	,2018	78	3W3ZMSthojCUirKEqAwGNw, eTlbuu23j9tOgmla9POyLQ	400	Anne	485	1265	xvu8G900tezTzbbfqmTKvA	2008-08-09 00:30:27

Data URL:

Reviews: 8021122 (~8M) in total

	business_id	cool	date	funny	review_id	stars	text	useful	user_id
0	-MhfebM0QlsKt87iDN-FNw	0	2015-04-15 05:21:16	0	xQY8N_XvtGbearJ5X4QryQ	2.0	As someone who has worked with many museums, I	5	OwjRMXRC0KyPrllcjaXeFQ
1	lbrU8StCq3yDfr-QMnGrmQ	0	2013-12-07 03:16:52	1	UmFMZ8PyXZTY2QcwzsfQYA	1.0	I am actually horrified this place is still in	1	nIJD_7ZXHq-FX8byPMOkMQ
2	HQI28KMwrEKHqhFrrDqVNQ	0	2015-12-05 03:18:11	0	LG2ZaYiOgpr2DK_90pYjNw	5.0	I love Deagan's. I do. I really do. The atmosp	1	V34qejxNsCbcgD8C0HVk-Q
3	5JxlZaqCnk1MnbgRirs40Q	0	2011-05-27 05:30:52	0	i6g_oA9Yf9Y31qt0wibXpw	1.0	Dismal, lukewarm, defrosted- tasting "TexMex" g	0	ofKDkJKXSKZXu5xJNGiiBQ
4	IS4cv902ykd8wj1TR0N3-A	0	2017-01-14 21:56:57	0	6TdNDKywdbjoTkizeMce8A	4.0	Oh happy day, finally have a Canes near my cas	0	UgMW8bLE0QMJDCkQ1Ax5Mg

Data URL:

Check-ins: 175187 (~175k) in total

	business_id	date
0	1UhMGODdWsrMastO9DZw	2016-04-26 19:49:16, 2016-08-30 18:36:57, 2016
1	6MefnULPED_I942VcFNA	2011-06-04 18:22:23, 2011-07-23 23:51:33, 2012
2	7zmmkVg-IMGaXbuVd0SQ	2014-12-29 19:25:50, 2015-01-17 01:49:14, 2015
3	8LPVSo5i0Oo61X01sV9A	2016-07-08 16:43:30
4	9QQLMTbFzLJ_oT-ON3Xw	2010-06-26 17:39:07, 2010-08-01 20:06:21, 2010

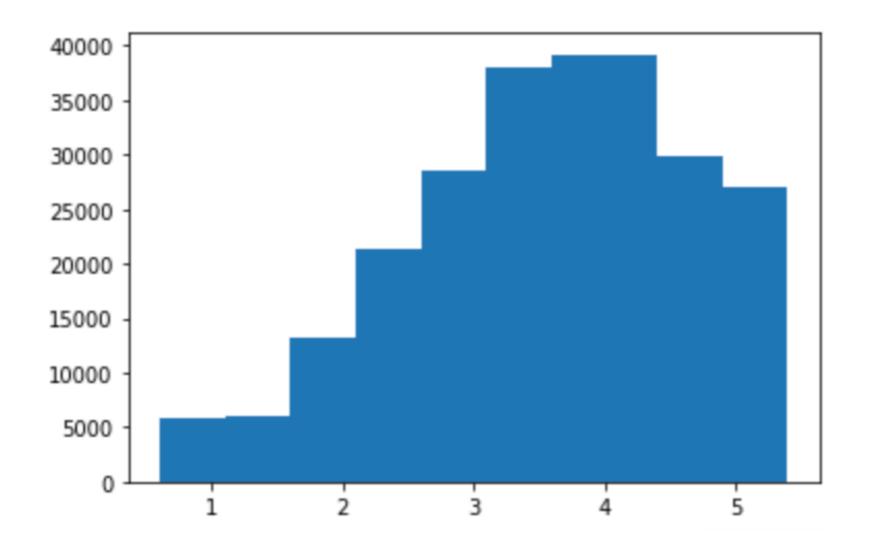
Data URL:

Tip: 1320761 (~1.3M) total

	business_id	compliment_count	date	text	user_id
0	UYX5zL_Xj9WEc_Wp-FrqHw	0	2013-11-26 18:20:08	Here for a quick mtg	hf27xTME3EiCp6NL6VtWZQ
1	Ch3HkwQYv1YKw_FO06vBWA	0	2014-06-15 22:26:45	Cucumber strawberry refresher	uEvusDwoSymbJJ0auR3muQ
2	rDoT-MgxGRiYqCmi0bG10g	0	2016-07-18 22:03:42	Very nice good service good food	AY-lalws3S7YXNI_f_D6rQ
3	OHXnDV01gLokiX1ELaQufA	0	2014-06-06 01:10:34	It's a small place. The staff is friendly.	Ue_7yUlkEbX4AhnYdUfL7g
4	GMrwDXRIAZU2zj5nH6l4vQ	0	2011-04-08 18:12:01	8 sandwiches, \$24 totalwhat a bargain!!! An	LltbT_fUMqZ-ZJP-vJ84IQ

Data URL:

(Aggregate) Star Rating Distribution



Data URL:

What fraction of reviews are known?

Users = $^{\sim}2M$

Businesses = $^{\sim}200k$

Total possible reviews = $^{\sim}2M \times ^{\sim}200k = ^{\sim}0.4T$

Known reviews = 8 M

Fraction known = $^{8}M / 0.4 T = 2 \times 10^{-5}$

i.e. 2 in every 100k reviews is known, rest are unknown

Finding these *unknown* reviews is the primary goal of Rec Sys

Data URL:

MovieLens Data

Movies: attributes including title, release date, genre, actors, director

Users: demographics including age, gender, occupation, zip code

Reviews: ratings, timestamp

Exercise: go to link below, explore data and reproduce statistics reported

Reviews: 100000 (100k) in total

	userld	movield	rating	timestamp
0	1	31	2.5	1260759144
1	1	1029	3.0	1260759179
2	1	1061	3.0	1260759182
3	1	1129	2.0	1260759185
4	1	1172	4.0	1260759205

Data URL:

```
Users: 1682 (~1.7k) in total
```

```
user id | age | gender | occupation | zip code

1|24|M|technician|85711
2|53|F|other|94043
3|23|M|writer|32067
4|24|M|technician|43537
5|33|F|other|15213
6|42|M|executive|98101
7|57|M|administrator|91344
8|36|M|administrator|05201
9|29|M|student|01002
10|53|M|lawyer|90703
```

Data URL:

Movies: 943 (~1k) in total

```
movie id
          movie title
                       release date
                                      video release date
IMDb URL
          unknown
                    Action
                             Adventure
                                        Animation
Children's
                    Crime
                             Documentary | Drama | Fantasy
          Comedy
           Horror | Musical | Mystery | Romance | Sci-Fi
Film-Noir
Thriller |
          War | Western
```

```
1|Toy Story (1995)|01-Jan-1995||http://us.imdb.com/M/title-exact?Toy%20Story%20(1995)|0|0|0|1|1|1|0|0|0|0|0|0|0|0|0|0|0
2|GoldenEye (1995)|01-Jan-1995||http://us.imdb.com/M/title-exact?GoldenEye%20(1995)|0|1|1|0|0|0|0|0|0|0|0|0|0|0|1|0|0
3|Four Rooms (1995)|01-Jan-1995||http://us.imdb.com/M/title-exact?Four%20Rooms%20(1995)|0|0|0|0|0|0|0|0|0|0|0|0|0|0|0|1|0|0
4|Get Shorty (1995)|01-Jan-1995||http://us.imdb.com/M/title-exact?Get%20Shorty%20(1995)|0|1|0|0|1|0|0|1|0|0|0|0|0|0|0|0|0|0
5|Copycat (1995)|01-Jan-1995||http://us.imdb.com/M/title-exact?Copycat%20(1995)|0|0|0|0|0|1|0|1|0|1|0|0|0|0|1|0|0
6|Shanghai Triad (Yao a yao yao dao waipo qiao) (1995)|01-Jan-1995||http://us.imdb.com/Title?Yao+a+yao+yao+dao+waipo+qiao+(1995)|0|0|0|0|0|0|0|1|0|
7|Twelve Monkeys (1995)|01-Jan-1995||http://us.imdb.com/M/title-exact?Twelve%20Monkeys%20(1995)|0|0|0|0|0|0|0|0|0|0|0|0|0|0|1|0|0|0
8|Babe (1995)|01-Jan-1995||http://us.imdb.com/M/title-exact?Babe%20(1995)|0|0|0|1|1|0|0|1|0|0|0|0|0|0|0|0|0
10|Richard III (1995)|22-Jan-1996||http://us.imdb.com/M/title-exact?Richard%20III%20(1995)|0|0|0|0|0|0|0|0|1|0|0|0|0|0|0|1|0
11|Seven (Se7en) (1995)|01-Jan-1995||http://us.imdb.com/M/title-exact?Se7en%20(1995)|0|0|0|0|0|0|0|0|0|0|0|0|0|1|0|0
12|Usual Suspects, The (1995)|14-Aug-1995||http://us.imdb.com/M/title-exact?Usual%20Suspects,%20The%20(1995)|0|0|0|0|0|0|1|0|0|0|0|0|0|0|0|1|0|0
17|From Dusk Till Dawn (1996)|05-Feb-1996||http://us.imdb.com/M/title-exact?From%20Dusk%20Till%20Dawn%20(1996)|0|1|0|0|0|1|1|0|0|0|1|0|0|0|1|0|0
```

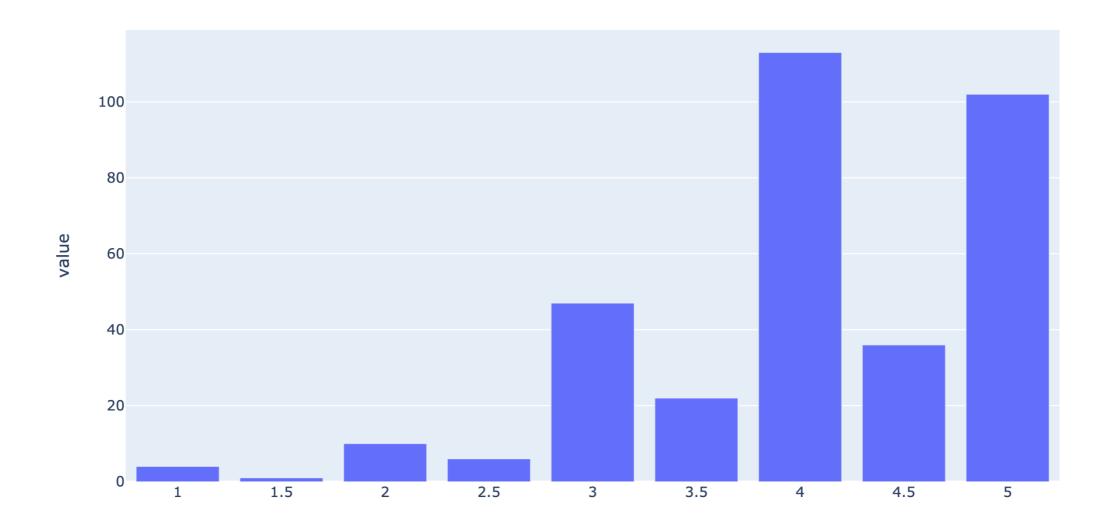
Data URL:

Top rated movies

```
rating['movieId'].value_counts()
           341
356
296
           324
318
           311
593
           304
260
           291
480
           274
           259
2571
           247
527
           244
589
           237
1196
           234
```

Data URL:

Distribution of top-rated movie (356)



Data URL:

What fraction of reviews are known?

Users = $^{\sim}1.7$ k

Movies = $^{\sim}1k$

Total possible reviews = $^{\sim}1.7k \times ^{\sim}1k = ^{\sim}1.7M$

Known reviews = $^{\sim}100k$

Fraction known = $^{\sim}100k / 1.7M = ^{\sim}0.058$ or $^{\sim}6\%$

i.e. 6 in every 100 reviews is known, rest are unknown

Finding these unknown reviews is the primary goal of Rec Sys

Data URL:

Problem Statement

What does Yelp want to do?

Provide list of businesses
that satisfy your search criteria

ordered as per

user's interest or preference list at that moment advertisement revenue considerations

so that ultimately *matching* happens within *few* clicks that provides instant gratification to both user and Yelp and continues bringing user back to Yelp

What about?

Linked In: connect people professionally

Facebook: filter friends' feed

Poshmark, Etsy: organize content of display

Amazon, Retail: display products and sellers

Tinder, Match: find suitable partner

Netflix, YouTube, Spotify: entertainment of interest

0 0 0 0

So that ultimately *matching* happens within *few* clicks providing instant gratification to *user, provider* and *platform* and *users* and *providers* continue engaging with the *platform*

Prediction problem

what is the likelihood of *matching*

user

provider

at a given time

in a given *context*

Accurate solution to this prediction problem

provides essential ingredient for connecting users, providers on the platform

while respecting interests of users, providers and the platform

Prediction problem

N users

M providers or items (or other users)

Given user *i* and item *j*

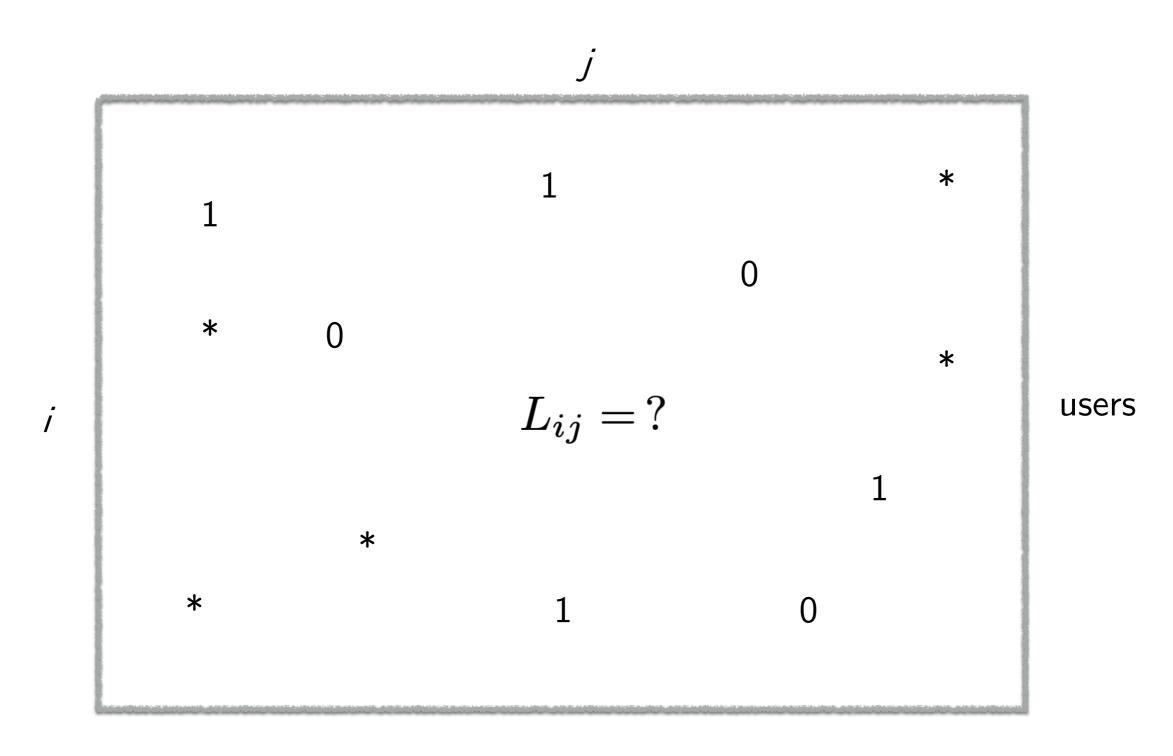
find the likelihood of *i* matching with *j*

$$L_{ij} = ?$$

Using data

Historical matchings or preferences

Prediction problem: complete the matrix



Complete the matrix

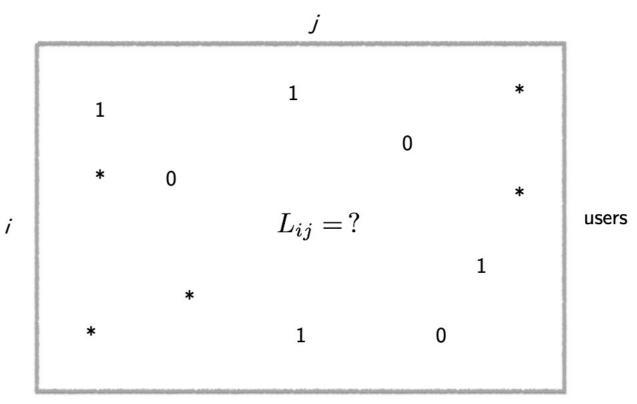
Observations: Y_{ij} over i in users, j in items

$$E[Y_{ij}] = L_{ij}$$

If (i, j) is *not* observed

$$Y_{ij} = \star \text{ or } ?$$

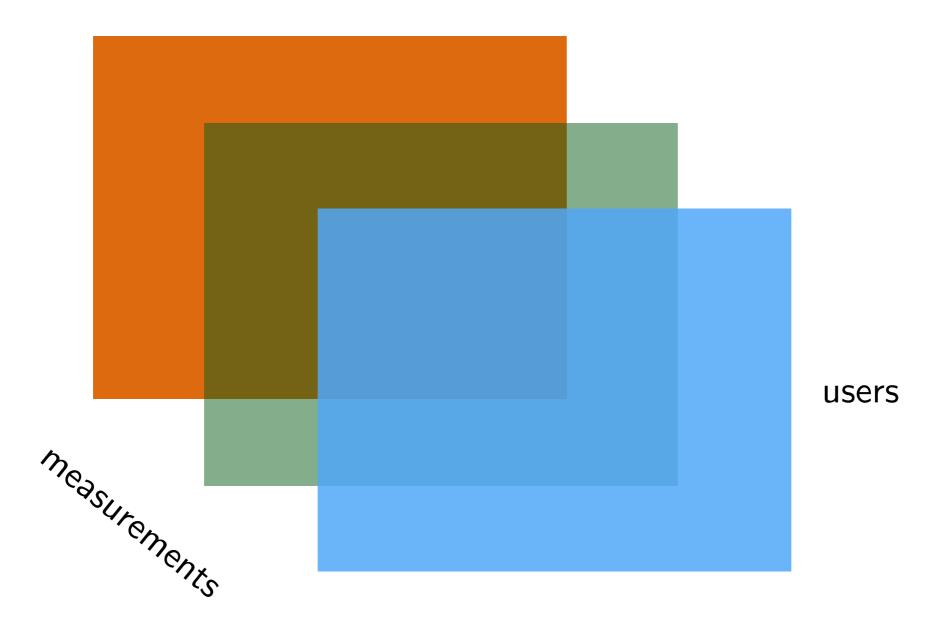
Goal: produce estimation \widehat{L}_{ij} for all i, j



items / providers

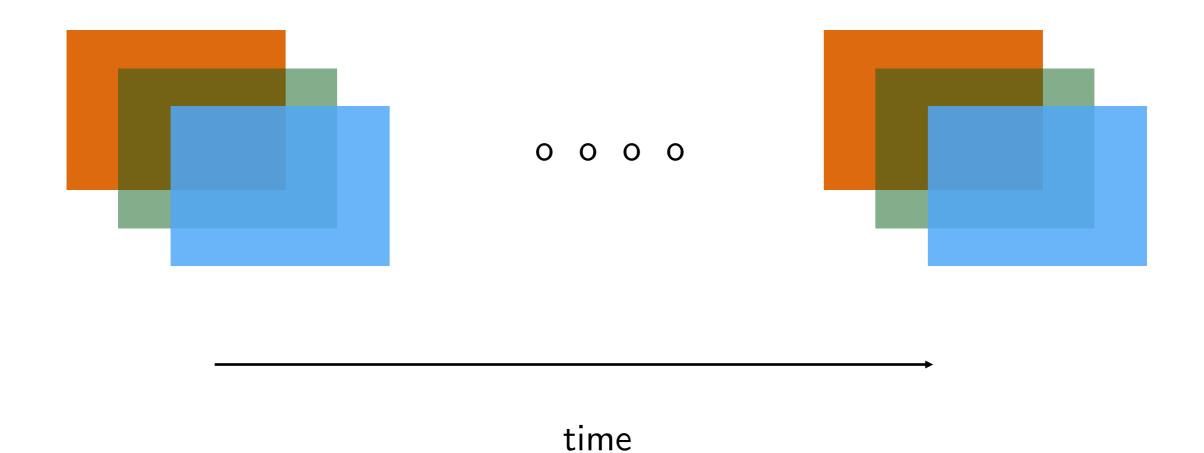
so that $\hat{L}_{ij} \approx L_{ij}$ for all i, j

Prediction problem: complete the tensor



items / providers

Prediction problem: complete the time varying tensor



Challenges that we will not discuss

user provided data

not generated at random

can be strategic

can be driven by innate preference

provider / item

can be systematically manipulated

convenient location

strategically modified content

Challenges that we will not discuss

Side effects of recommendation systems

Information bubble

Feedback loops

Too powerful platforms

Regulation of platforms

Interplay with recommendation systems