Recommender Systems

Lecture 1

Required knowledge / skills

Necessary

Linear Algebra

Coding:

- Python
- Pandas
- Numpy/Scipy
- Jupyter Notebook / VS Code

Will be helpful

Optimization

Machine Learning

Statistics

Source Control

Kaggle competitions

Course grading

1. home assignments – 25%
2. ongoing online competition – 25%
   - results below baseline (provided) – 0 pts
   - max point depends on relative position in the leaderboard
3. Mid-term exam – 25%
4. Final group project – 25%

Other requirements

Expectations:

- properly annotated charts and graphs in reports
- following python code style guides (e.g., PEP-8)
- vectorized code where possible

Grading:

- too inefficient code affects boundary decisions (not in a student's favor)
- code plagiarism is forbidden, will be strictly penalized

Course Instructors

Instructor

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Course Communications

Channels of communication:

- LMS at HSE (?)
- Telegram Channel

Join Telegram Group:

https://t.me/+bZjyf_59I1RkMTgy

Reading

Main book:

- **Personalized Machine Learning**, Julian McAuley, 2022 (in press);
  https://cseweb.ucsd.edu/~jmcauley/pml/pml_book.pdf

Additional reading (in no particular order):

- **Recommender Systems. The Textbook**, 2016; Charu C. Aggarwal
- **Recommender Systems: An Introduction**, 2010; D. Jannach, M. Zanker, A. Felfernig, G. Friedrich
- **Mining Massive Datasets**, Stanford University, http://www.mmds.org
- **Collaborative Recommendations: Algorithms, Practical Challenges and Applications**;
  S. Berkovsky, I. Cantador and D. Tikk; 2019.
- **Recommender Systems Handbook,** 2022, 3rd edition; F. Ricci, L. Rokach, B. Shapira
- **Statistical Methods for Recommender Systems**, 2016; Deepak K. Agarwal, Bee-Chung Chen
- **Programming Collective Intelligence,** 2007; Toby Segaran

Helpful resources

Courses

- Julian McAuley's course at UCSD, cse258 class
  (visit https://cseweb.ucsd.edu/~jmcauley/)
- Coursera https://www.coursera.org/specializations/recommender-systems

Video tutorials

- Machine Learning Summer School 2014 (by X. Amatriain and D. Agarwal)
  https://www.youtube.com/playlist?list=PLZSO_6-bSqHQCIYxE3ycGLXHMjK3XV7Iz
- Introduction to Machine Learning 10-701 CMU 2015 (by A. Smola)
  https://www.youtube.com/watch?v=gCaOa3W9kM0

Online resources

- RecSys wiki: http://recsyswiki.com
- Fresh RecSys news https://recommender-systems.com
- Dive Into Deep Learning – Recommender Systems
  https://d2l.ai/chapter_recommender-systems/index.html
- Blog: A Practical Guide to Building Recommender Systems
  https://buildingrecommenders.wordpress.com
- Telegram channel (ex-Slack ODS), #recommender_systems (Russian language)
  https://t.me/ods_recommender_systems

Other sources

Conferences

- ACM RecSys
- CIKM
- UMAP
- WWW
- KDD
- WSDM
- IJCAI
- ...

Competitions

- RecSys Challenge
- CIKM challenge

Sometimes other conferences, too

- Kaggle
- ...

(Some) Frameworks and Libraries

Polara (*Disclaimer*: I'm the author)
https://github.com/evfro/polara
RecTools (MTS)
https://github.com/MobileTeleSystems/RecTools
RePlay (Sber AI Lab)
https://github.com/sberbank-ai-lab/RePlay
Surprise
https://github.com/NicolasHug/Surprise
Turi Create (acquired by Apple)
https://turi.com/learn/userguide/recommender/introduction.html
TorchRec
https://github.com/pytorch/torchrec
Microsoft Azure
https://github.com/Microsoft/Recommenders
Google
https://www.tensorflow.org/recommenders
Recbole (modern, PyTorch-based)
https://recbole.io

Collaborative Filtering for Implicit Feedback Datasets (iALS /WRMF)
https://github.com/benfred/implicit (fastest)
https://github.com/quora/qmf (by Quora)

Factorization Machines
https://github.com/srendle/libfm
https://github.com/coreylynch/pyFM

Other libraries

- Neural Networks
  https://github.com/maciejkula/spotlight
  https://github.com/MrChrisJohnson/deep-mf
  https://github.com/songgc/TF-recomm
  https://github.com/Netflix/vectorflow (by Netflix)
- Bilinear models
  https://github.com/lyst/lightfm/
  http://www.recsyswiki.com/wiki/SVDFeature
- MyMediaLite (used to be popular)
  http://www.mymedialite.net
- Many latent factor models
  https://github.com/zhangsi/CisRec
- Logistic-MF (ex-Spotify)
  https://github.com/MrChrisJohnson/logistic-mf
- Simple content-based recommendation engine
  https://github.com/groveco/content-engine
- Hermes (Supports Spark)
  https://github.com/Lab41/hermes

Recommender Systems Datasets
https://darel13712.github.io/rs_datasets/
Recmetrics – Basic analysis and evaluation
https://github.com/statisticianinstilettos/recmetrics

What this course is about

Systematic overview of basic RecSys concepts.

Collection of hints for conducting research and trying ideas.

Practical recipes for using popular recommendation algorithms.

Basic algorithms’ implementation and their quality evaluation.

Learning by doing!

Avoid answering wrong questions and solving wrong problems.

"He points out that one of the really tough things is figuring out what questions to ask... Once you figure out the question, then the answer is relatively easy.”

Elon Mask’s reflections on the “The Hitchhiker's Guide to the Galaxy”, by Douglas Adams.

What this course is NOT about

- Building complex RS models (including elaborate Deep Learning solutions) and ensembles
- Distributed systems, map-reduce
- Production-level architectures and pipelines
- Hypothesis verification and user studies

Doesn’t mean we won’t touch some of these topics.

High-level course structure

Basic concepts:
- General problem formulation and basic recommendation techniques.
- Evaluation of recommender systems.

Standard methods:
- Collaborative filtering: memory-based and model-based approaches.
- Matrix factorization techniques (a lot of focus on this topic!).

Special methods for collaborative filtering:
- Beyond standard MF techniques.
- Closed-form solutions.
- Ranking objectives.

Beyond standard collaborative filtering:
- Cold start and hybrid recommender systems.
- Context-aware recommender systems.
- Sequence-aware recommendations.

Artificial neural networks in recommender systems.

What is a recommender system?

Examples:
- Amazon
- Netflix
- Pandora
- Spotify
- Social platforms
- etc.

Many different areas: e-commerce, news, tourism, entertainment, education...

Goal: predict user preferences given some prior information on user behavior.

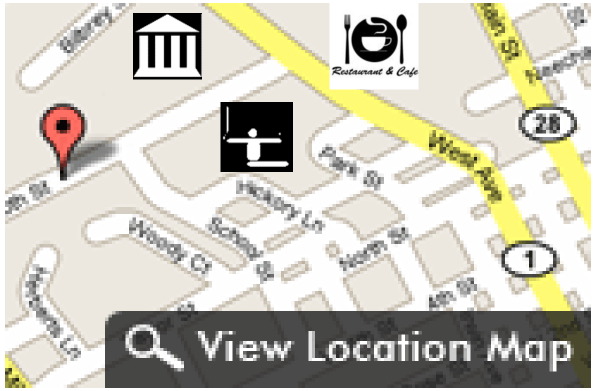
In a more general sense

Recommender Systems aim to recover partially observed relations between two or more entities.

Sequential data:
item → next item
(order matters)

Social Networks:
user ↔ user

Ternary relations:
user → action → location



Material Discovery and Recommender Systems

Finding *chemically relevant compositions* and atomic arrangements of *inorganic compounds* using information from inorganic crystal structure databases.

(a)

$$
\boldsymbol{X} = \begin{array}{c c}
\begin{array}{ccccccccccc}
\text{Li,O (1,1,1)} & \text{Li,O (1,1,2)} & \text{Li,O (1,2,2)} & \text{Li,O (1,3,3)} & \text{Li,O (1,4,3)} & & \text{In,O (1,1,2)} & \text{In,O (1,1,3)} & \text{In,O (1,2,4)} & \text{In,O (2,2,5)} & \text{In,O (3,3,8)}
\end{array} & \\
\begin{pmatrix}
0 & 0 & 0 & 0 & 0 & \cdots & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & \cdots & 0 & 0 & 1 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 & 0 \\
\vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \vdots \\
1 & 1 & 1 & 1 & 0 & \cdots & 1 & 0 & 1 & 1 & 1 \\
0 & 0 & 0 & 0 & 1 & \cdots & 0 & 0 & 1 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & \cdots & 0 & 1 & 0 & 0 & 0
\end{pmatrix} & \begin{array}{l} \text{Na} \\ \text{Mg} \\ \text{Al} \\ \\ \text{Cu} \\ \text{Zn} \\ \text{Ga} \end{array}
\end{array}
$$

(b)

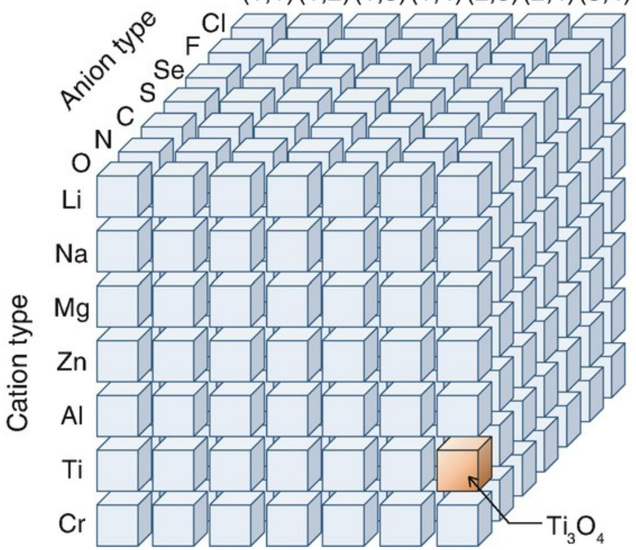


Image Source
Seko, Atsuto, Hiroyuki Hayashi, Hisashi Kashima, and Isao Tanaka. "Recommender Systems for Materials Discovery." In Machine Learning Meets Quantum Physics, pp. 427-443. Springer, Cham, 2020.

Discovered compounds and their stability

Composition	Predicted rating	Stability
$RbInO_2$	1.01	○
Rb_3InO_3	0.64	○
$RbIn_5O_8$	0.20	–
$NaGaS_2$	0.98	○
$NaGa_5S_8$	0.21	–
$KPbCl_3$	0.97	–
Ca_2TiO_4	0.95	○
$CaTi_3O_7$	0.29	–
Ca_3TiO_5	0.21	–
$BaAs_2O_6$	0.93	○
$CsZnCl_3$	0.92	○
$CsZn_2Cl_5$	0.25	○
$RbInF_4$	0.91	○
Rb_3SbO_3	0.91	○
CsY_2F_7	0.87	○
Cs_2YF_5	0.44	○
$CsYF_4$	0.38	–
$CsYS_2$	0.87	○
$Ba_2Ga_2O_5$	0.85	○
$BaGa_4O_7$	0.55	–
$RbZnCl_3$	0.85	○
$RbZn_2Cl_5$	0.23	–

Drug Discovery and Recommender Systems

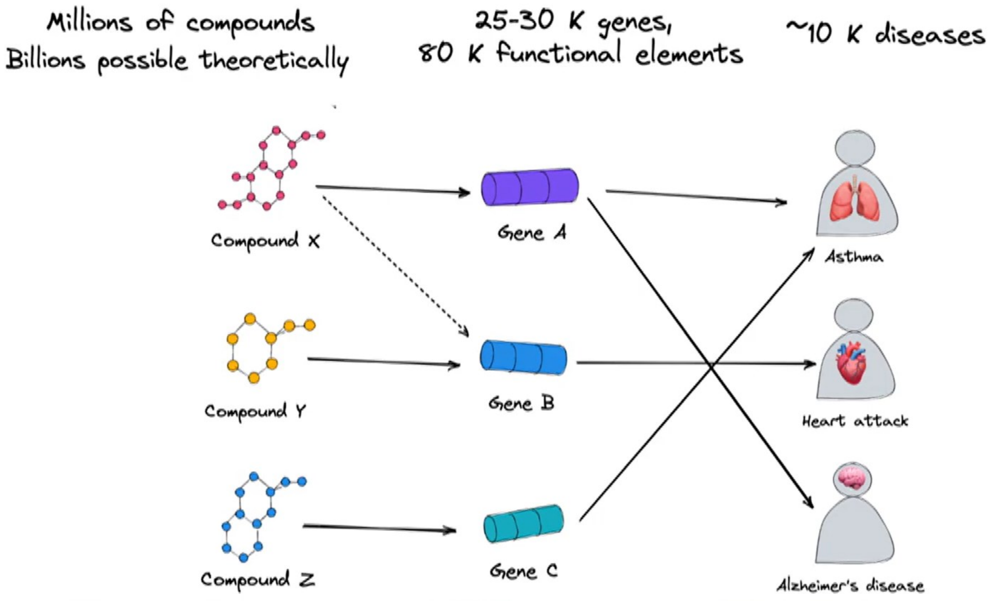


Image Source:
Gogleva, Anna, Eliseo Papa, Erik Jansson, and Greet De Baets. "Drug Discovery as a Recommendation Problem: Challenges and Complexities in Biological Decisions." In *Fifteenth ACM Conference on Recommender Systems*, pp. 548-550. 2021.

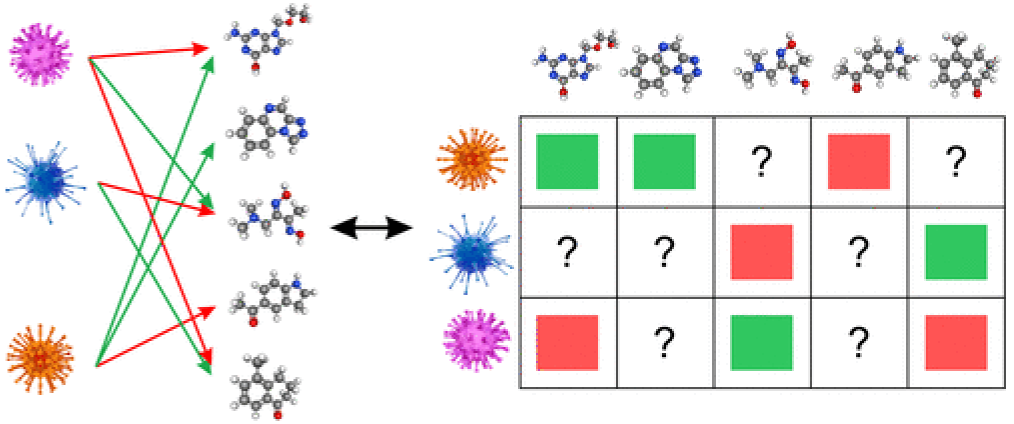
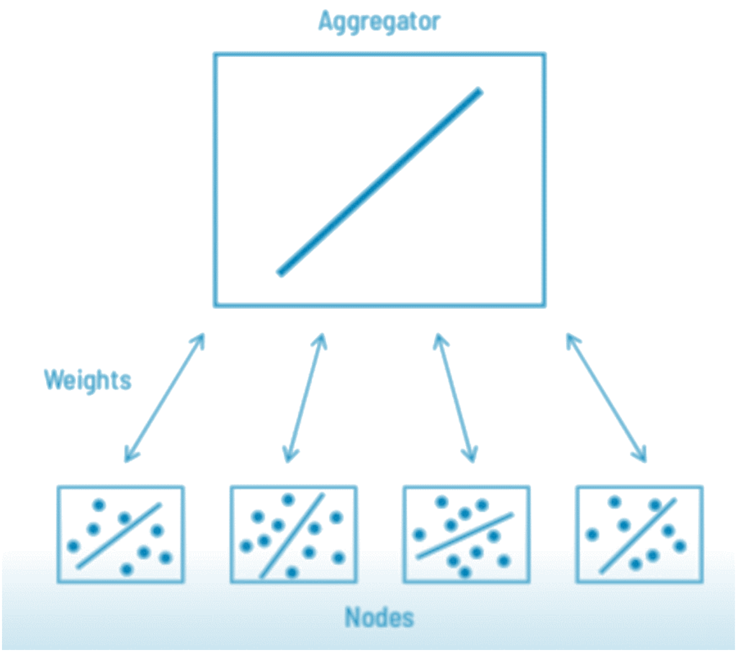


Image Source:
Sosnina, Ekaterina A., Sergey Sosnin, Anastasia A. Nikitina, Ivan Nazarov, Dmitry I. Osolodkin, and Maxim V. Fedorov. "Recommender systems in antiviral drug discovery." *ACS omega* 5, no. 25 (2020): 15039-15051.

Projects @Skoltech RecSys Group

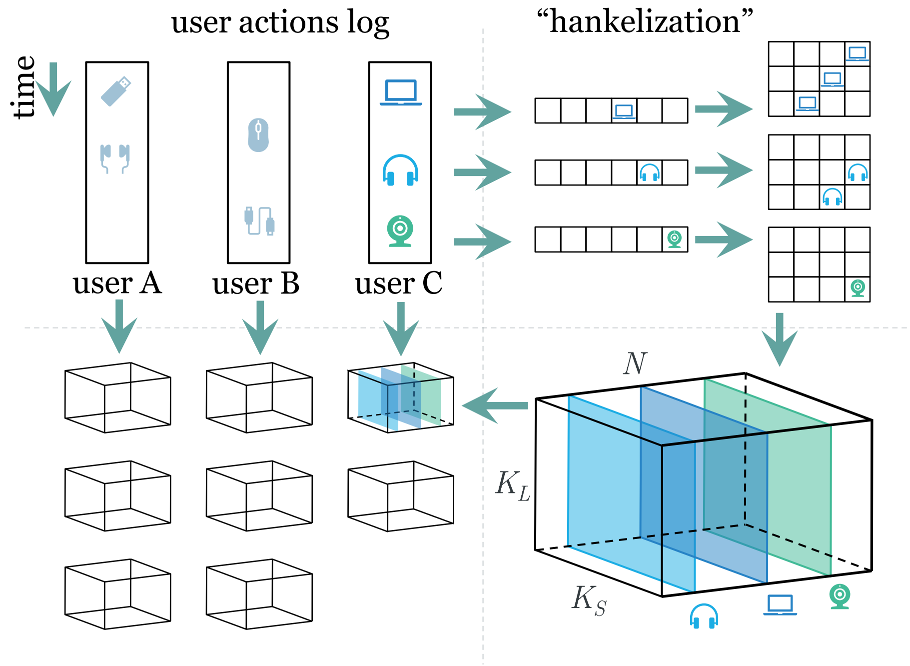
Privacy-preserving Federated Learning in Collaborative Filtering



Accurate Recommendations with Hyperbolic Geometry

(a) M. C. Eschers Circle Limit III, 1959

Next Item Predictions with Sequential Tensor Networks



Role of personalized services

+$2.93 billion to revenue after integration of recommendations[1]

80% of what people watch comes from recommendations; results in $1 billion savings[2]

personalized "Just For You" listings:

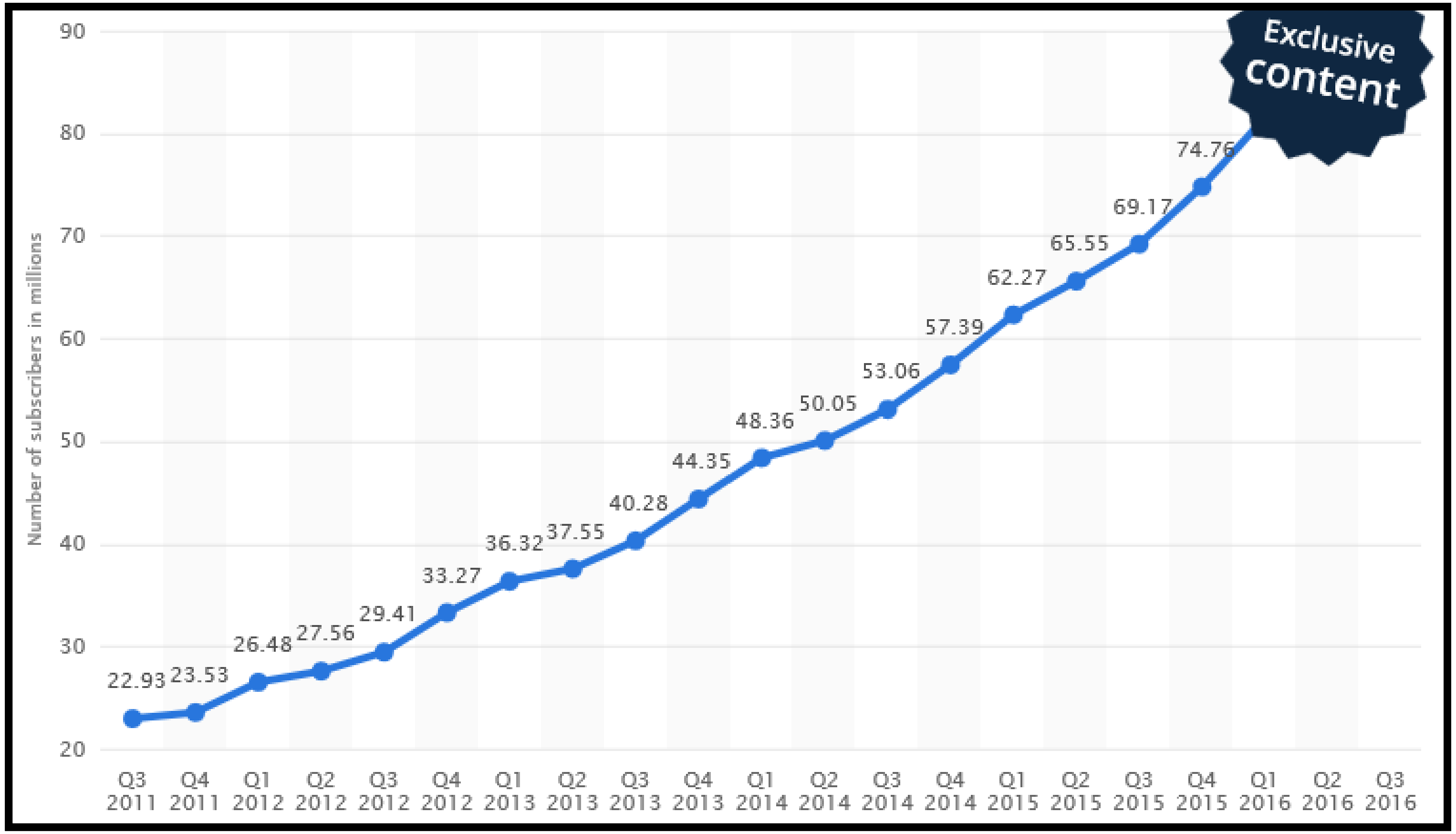
"want to be every user's personalized travel guide"[3]

"younger travelers … prefer hotel searches closely tailored to their profiles", CEO Darren Huston

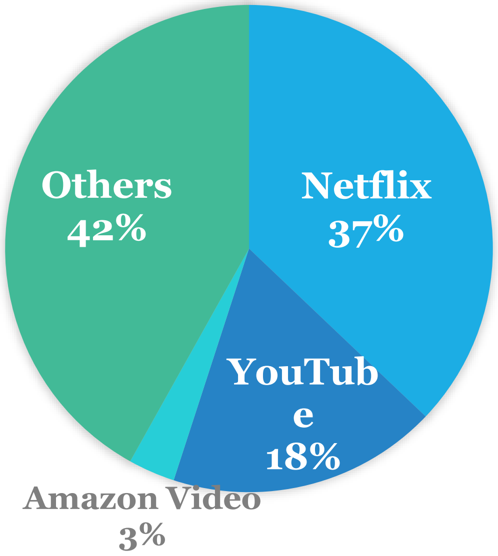
[1] http://fortune.com/2012/07/30/amazons-recommendation-secret/
[2] http://dl.acm.org/citation.cfm?id=2843948
[3] TripAdvisor's annual report, april 2015

Example 1

Netflix's audience



Internet video traffic share



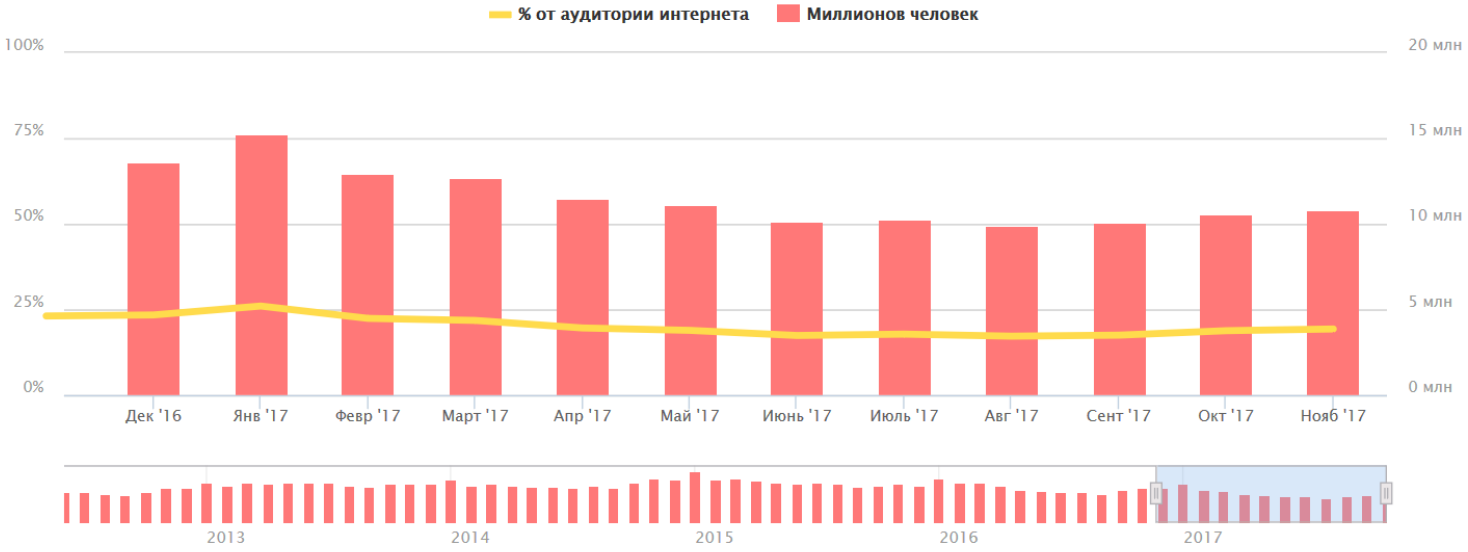
Data sources:
http://www.internetphenomena.com/tag/amazon-video/
https://www.statista.com/statistics/250934/quarterly-number-of-netflix-streaming-subscribers-worldwide/

Example 2

Kinopoisk

Aggregates many other content providers: ivi.ru, Megogo, Tvzavr, etc.

Auidience stats



Yandex Projects in Russia

December 2021

Project	Monthly audience	Daily audience	Average time	Mobile app	
Yandex	107 978 699	57 907 413	12 h 47 m	69 %	i
Portal	87 756 057	38 770 316	4 h 44 m	55 %	1
Yandex Zen	62 354 465	22 347 220	5 h 46 m	58 %	2
Yandex.Maps	44 368 313	7 590 836	1 h 4 m	40 %	3
News	33 515 427	9 014 109	53 m 3 s	0 %	4
Yandex.Weather	33 053 430	8 618 296	12 m 34 s	12 %	5
KinoPoisk	24 955 179	2 450 322	13 m 35 s	20 %	6

Revenue: $2,3M in 2012

https://radar.yandex.ru/yandex?month=2021-12

Source: https://stat.yandex.ru/Russia/Kinopoisk

Competition example in entertainment

B2C:
https://www.rottentomatoes.com
http://www.metacritic.com
https://www.criticker.com
http://veboli.com
http://www.taste.io
http://www.gyde.tv
https://www.tastekid.com
http://www.cinesift.com
http://itcher.com
http://chickflix.net
http://letterboxd.com

B2B:
http://www.jinni.com
http://www.tvgenius.net
http://www.loomia.com
http://www.thefilter.com
http://www.baynote.com
http://www.contentwise.tv

Local:
http://imhonet.ru – **closed**
https://www.kinopoisk.ru
http://megogo.net
http://www.ivi.ru

And more…

- Suggest Me Movie - Movie Recomme...
- agoodmovietowatch - The Good Mo...
- Movies Like Drive Human Movie Rec...
- Foundd Doesn't Just Recommend Go...
- Movli A Personalized Movie Recomm...
- And Chill
- Drive - Flickathon
- Movienr - Coming Soon
- Rinema Your Movies & The Next!
- Tank Top TV A philosophy of recom...
- Filmster Find the best films online
- About Movie Pilot
- Moviee Monk Best Movie Recomme...
- Jaman Movie Discovery
- Find Me Similar
- Smate Find people with similar movi...
- TOP250 The movies and TV shows rec...
- Similar movies like Drive (2011)
- Social Movie Picks FlikPiks
- TasteMonster - Movie Recommendati...
- Film School Rejects
- TOP 100 - The Ultimate Site
- Crowdwyse - The Social Rating Netw...
- Listal - List the stuff you love! Movies,...
- What to Rent! - Great DVD-Movie Ren...
- Goodshows is like Goodreads but for ...
- Partigi - movie premieres, DVD y Blu-...
- Televisor
- Ayush Ghai is building a Tech Startup ...

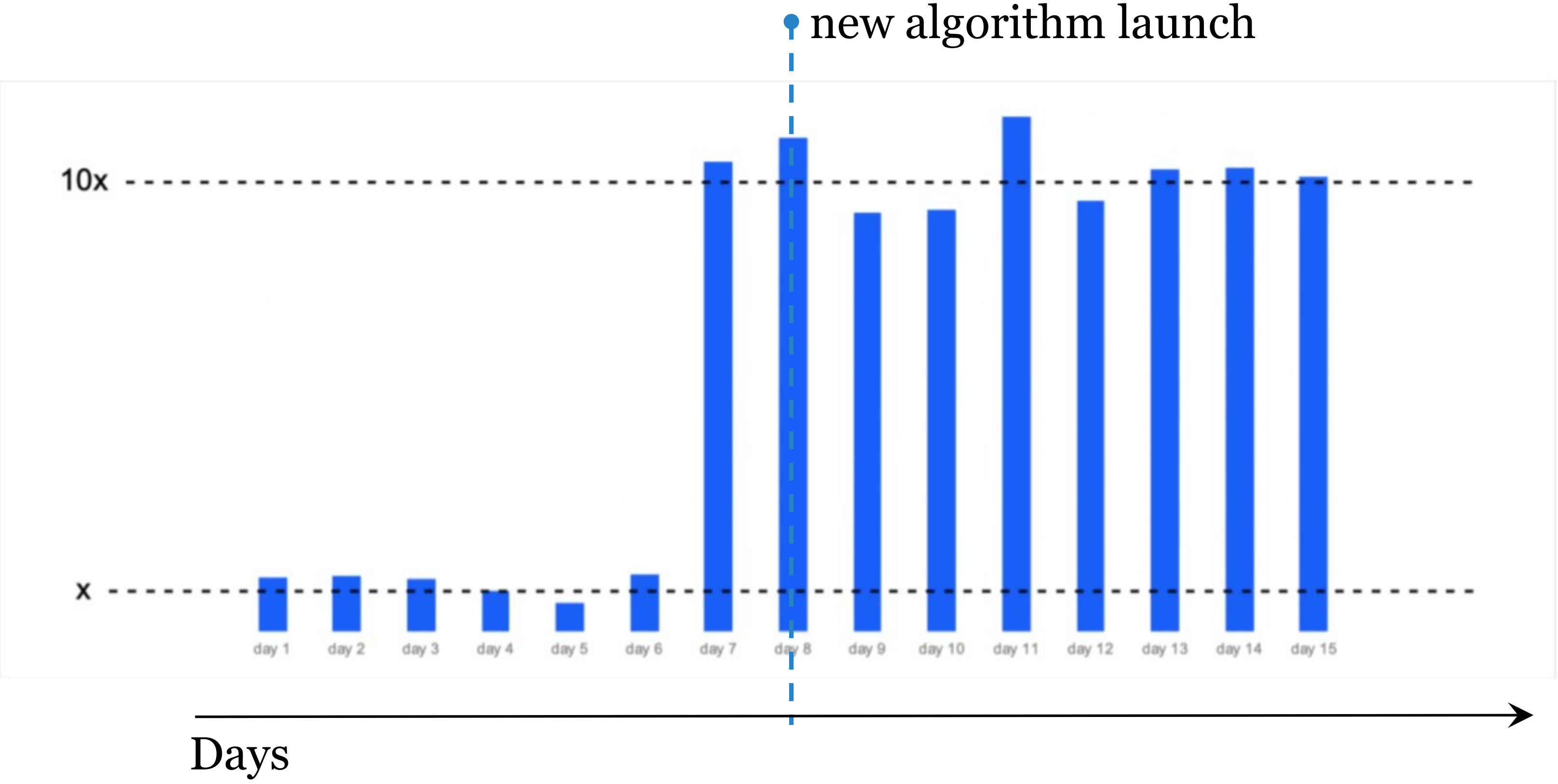
Example 3 - IKEA

Selling«**inspirational shopping experience**» based on intelligent matching of products within a common design style.

Paper: Designer-driven add-to-cart recommendations
https://dl.acm.org/doi/10.1145/3298689.3346959

taken from RecSys'19 conference

Example 4 - Ozon



Ozon tries promoting complement products. *“Harry Potter” problem*.

Main target – low CTR products.

Source (in Russian) [Дзен-митап: Рекомендательные системы изнутри] June 28, 2019

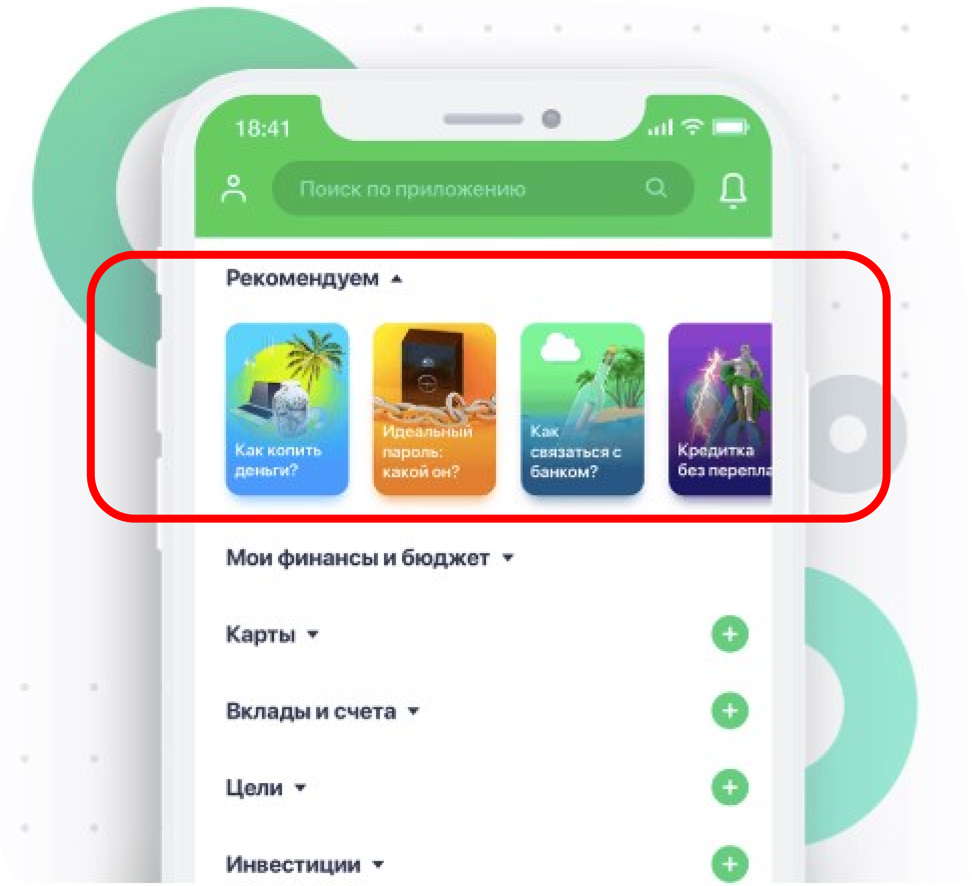
Example 5 – Finance sector

- Individual recommendations of banking products
  - User transactions can be used to guess possible interests, such as:
  - Visit a shopping mall nearby to buy certain products

- What it gives:
  - increases attachment to banking services
  - allows a convenient way of describing possible interests of users
  - improves the connectivity and reliability of the accumulated information about users
  - gives new insights for making business decisions and forming marketing strategy

Such strategies increase revenue in the long-term.

Sberbank Stories Case



Task: displaying relevant “stories” cards.

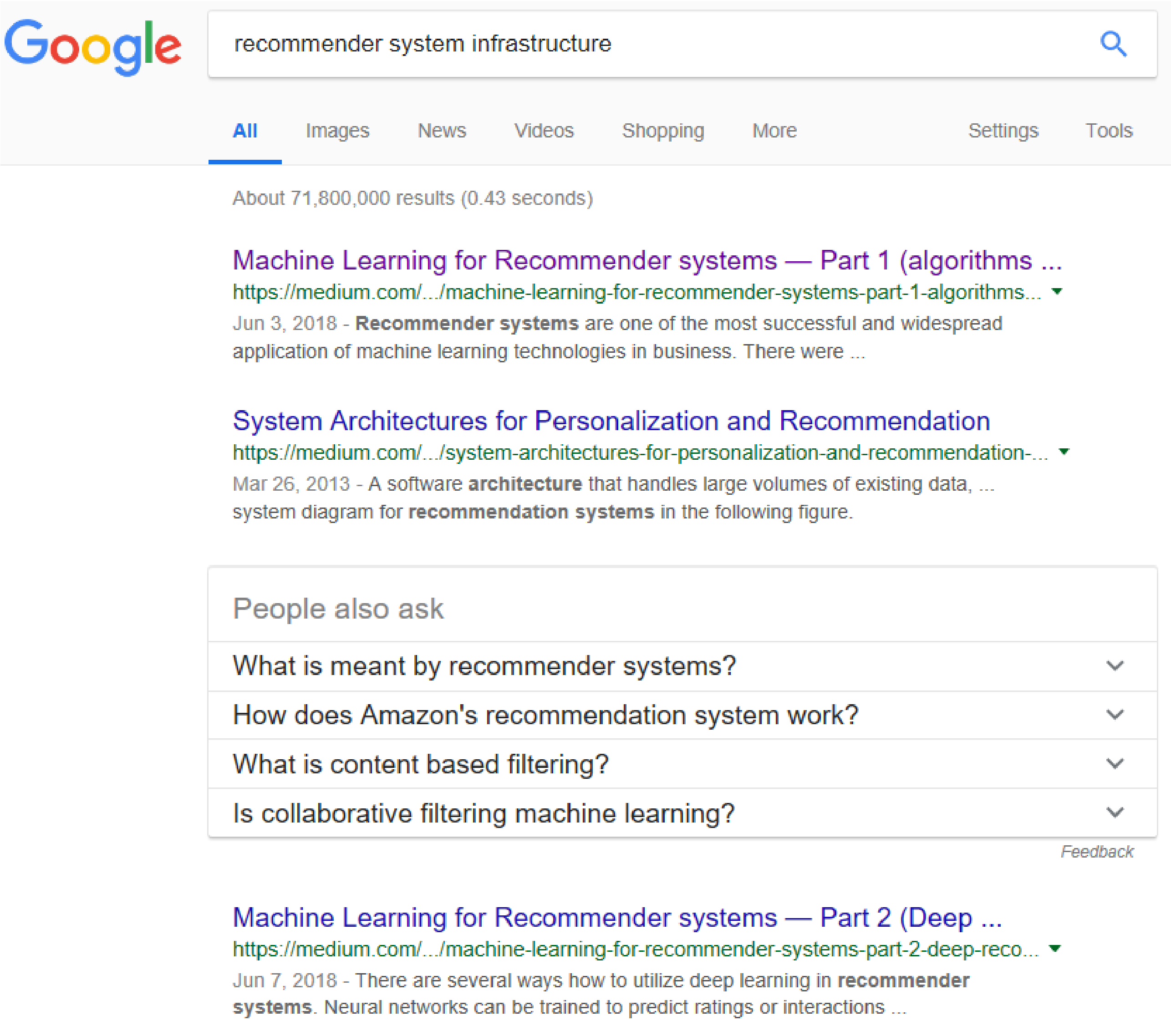
If users actually click them may help with:

- promoting bank's services and products
- spreading news about special offers
  - e.g. with large bonuses / discounts
- stimulating card transactions
  - e.g., ticket sales for movie premieres)

Recommenders Systems vs Search

Search is a query-driven recommender system.

Recommender system is a “query-less” search.



Academia vs. Industry

Academia	Industry
New, sophisticated, top-performer algorithms	Good, stable, well-known algorithms
Complexity is not an issue	Complexity vs maintenance
“Small” datasets	Almost unlimited data
Data-driven verification	User-driven verification
Focus on one specific part	General view
Focus on accuracy	Balance of various aspects

Trick for productionizing research: read current 3-5 pubs and note the stupid simple thing they all claim to beat, implement that.

Source: https://twitter.com/jaykreps/status/219977241839411200

Demo

Simple recommendation engine in 3 lines of python code.

Task for recommender systems

Predict user preferences given some prior information on user behavior.

- What are user preferences?
  - ratings, likes/dislikes, clicks/views
- What is prior information?
  - full user profile, anonymous sessions
- What kind of behavior?
  - short-term, contextual, sequential
- How many users to take into account?
- What kind of prediction is the most appropriate?
  - explanation
  - predicted relevance

- No unified approach (but there're are a few popular ones)
- Many hand-crafted rules and concepts
- Requires creativity
- Requires domain expertise
- A lot depends on user studies
- Good math is preferable but not always required

And...is it really about users in the end?

Personalization levels

- Generic / non-personalized
- Stereotypic
  - Matches by grouping users into certain stereotype categories (e.g., targeting, ads).
- Circumstantial
  - Based on current activity, typically short-term.
- Long-term
  - True personalization based on user history.

It is not just for marketing…

> "The best minds of my generation are thinking about how to make people click ads“

Jeffrey Hammerbacher
Founder of Cloudera

Source: https://www.bloomberg.com/news/articles/2011-04-14/this-tech-bubble-is-different

A bit of philosophy…

Life is the best recommender and the person is the Query

https://www.youtube.com/watch?v=8eBpR9-7swk

So what is the main question?

- user satisfaction
- company revenue

- does user satisfaction correlate with revenue?
- what is mathematical formulation?
- how to measure it?

Business goals vs. user satisfaction

Mark Zuckerberg Facebook newsfeed change cost

All Images **News** Videos Shopping More Settings Tools

All news ▾ **Past week** ▾ Sorted by relevance ▾ Clear

Mark Zuckerberg Has Lost This Much Money for **Changing** ...
Fortune - 14 hours ago
Facebook stock took a hit after the social network announced massive **changes** to its **news feed**. And no one felt that hit more than **Mark Zuckerberg**. The founder and CEO of **Facebook** owns over 400 million shares of the company, meaning stock fluctuations hit him the hardest. The trick is figuring out exactly how hard ...

Mark Zuckerberg Lost $3.3 Billion After Announcing **Changes** To ...
HuffPost Canada - Jan 14, 2018

Mark Zuckerberg loses $3.3bn of personal fortune after **Facebook** ...
Citifmonline - 21 hours ago

Facebook News Feed changes might **cost** the company nearly $23 ...
BGR India - Jan 14, 2018

I mentored **Mark Zuckerberg**. Here's my road map for fixing **Facebook**.
Opinion - Washington Post - Jan 14, 2018

Facebook's bid to stop fake news could hurt real news outlets
In-Depth - OregonLive.com - 13 hours ago

Over the next few weeks, Facebook’s news feed will start showing fewer news articles, and less marketing content and ads, Zuckerberg wrote on Thursday.
http://fortune.com/2018/01/12/facebook-news-feed-change/

Typical problems and challenges

cold-start	• recommendation uncertainty • representative items
missing values	• 99.99…% of unknowns • subject to biases, Missing Not at Random (MNAR)
short head / long tail	• 5% of items may hold 40% of all interactions) • niche products
evaluation	• metric choice • offline evaluation vs. AB-tests
complex models	• incorporating content information • including context information
performance	• quick model computation • real-time recommendations

Long tail

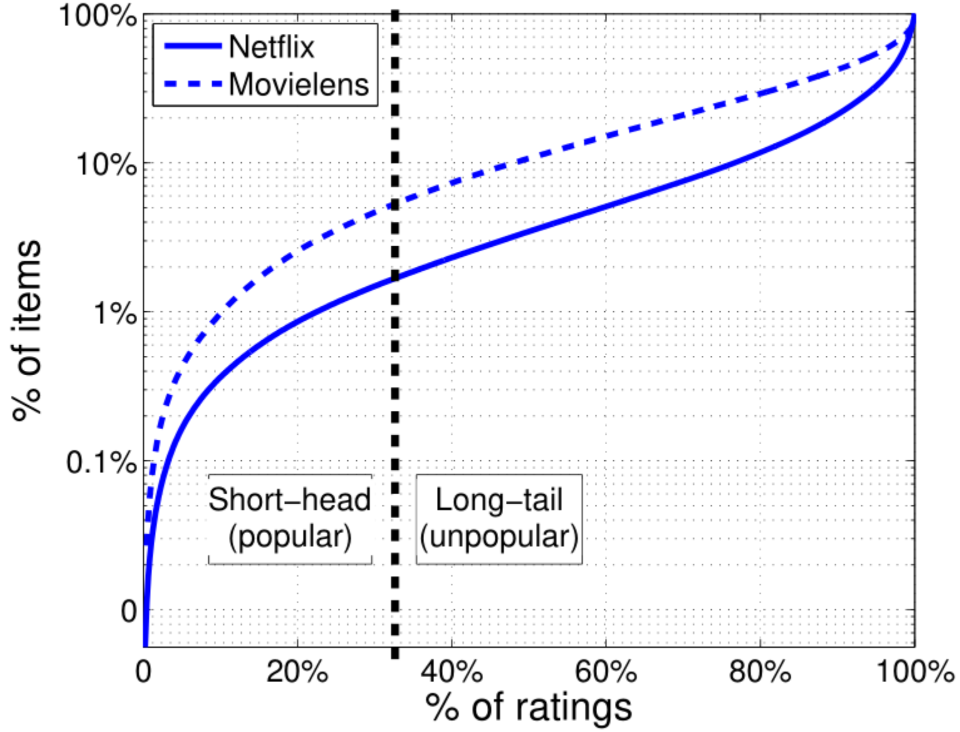


Figure 1: Rating distribution for Netflix (solid line) and Movielens (dashed line). Items are ordered according to popularity (most popular at the bottom).

Image credit: *"Performance of Recommender Algorithms on Top-N Recommendation Tasks"*, Paolo Cremonesi, Yehuda Koren, Roberto Turrin; ACM RecSys *2010*

Missing values

Missing not at random data - MNAR

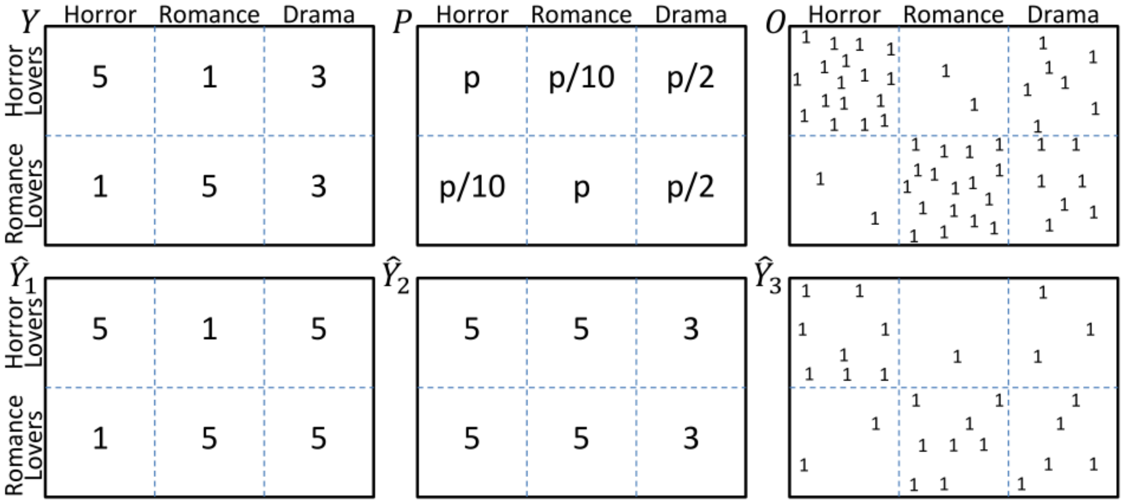


Figure 1. Movie-Lovers toy example. Top row: true rating matrix Y, propensity matrix P, observation indicator matrix O. Bottom row: two rating prediction matrices $\hat{Y}_1$ and $\hat{Y}_2$, and intervention indicator matrix $\hat{Y}_3$.

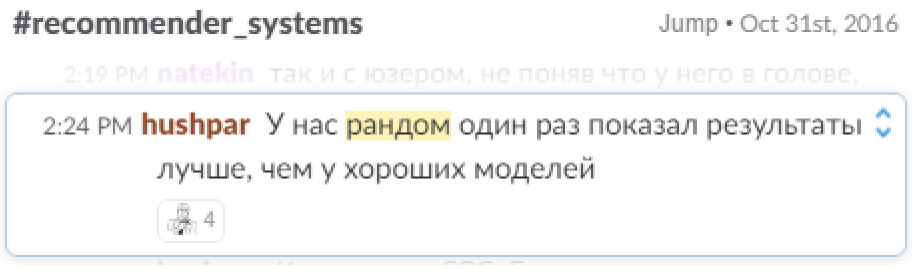
Which one is better: $\hat{Y}_1$ or $\hat{Y}_2$ w.r.t to original data Y?

Image credit: *"Recommendations as Treatments: Debiasing Learning and Evaluation",* T. Schnabel, A. Swaminathan, A. Singh, N. Chandak, T. Joachims, 2016

Evaluation difficulties

there're various metrics, but for many of them there's no convenient math formulation

From practical experience:
even when objective's defined, there's still no guarantee that the result will correspond to real RS performance

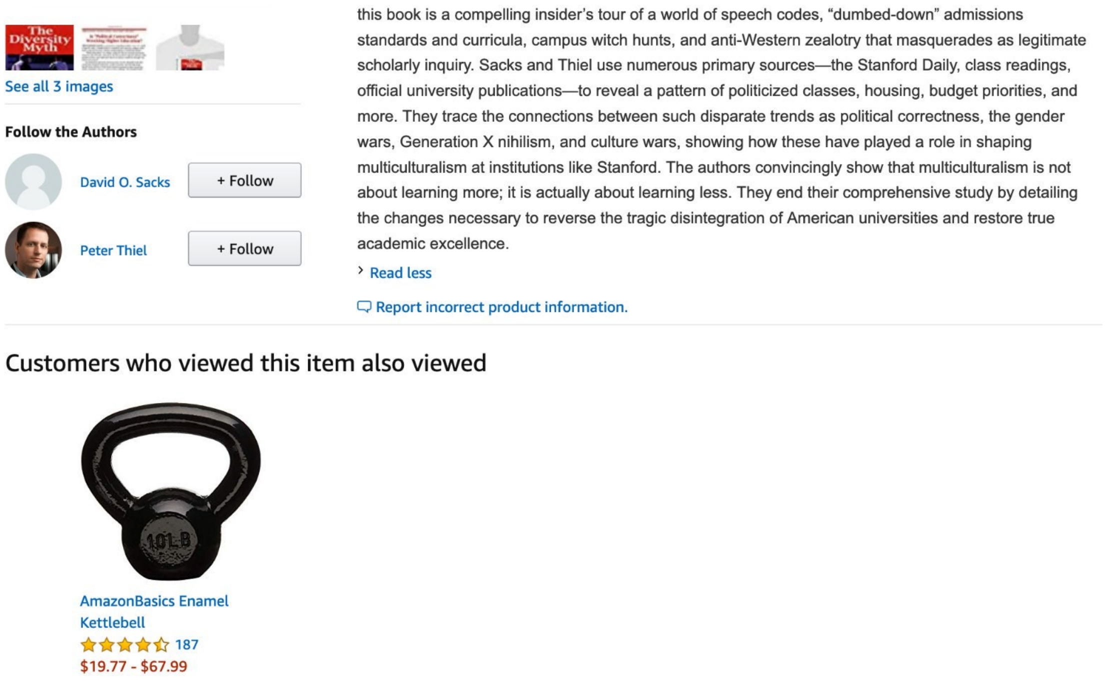


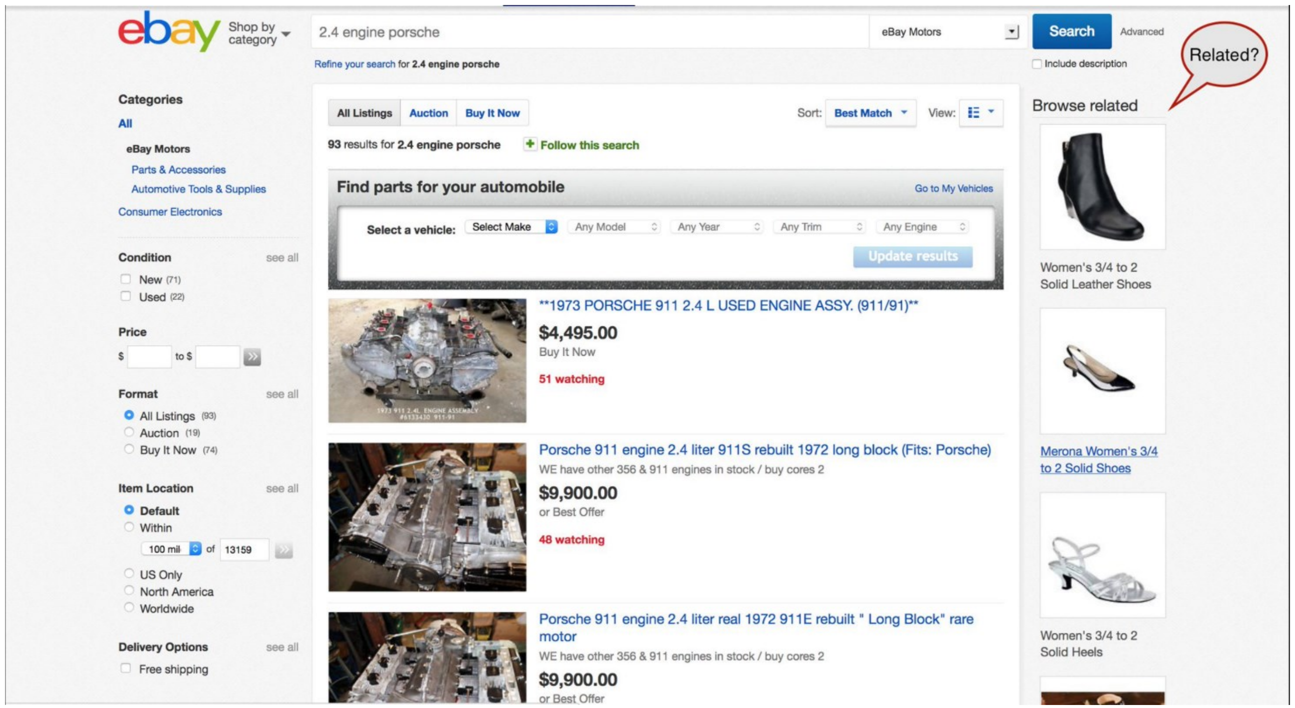
Translation: Once we had random recommendations outperform our fine-tuned models.

Funny fails

“If you like *The Diversity Myth* book by Peter Thiel you may also like a kettlebell.”

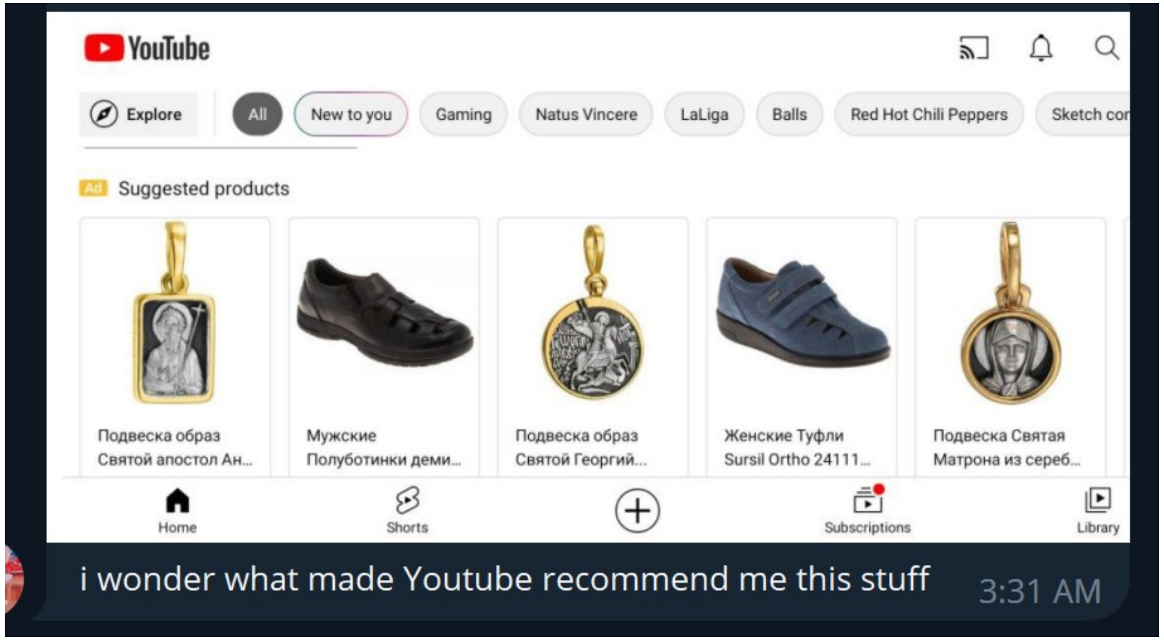
“Need engine parts?
You may find these women shoes relevant.”





Funny fails

From the previous year course participants:

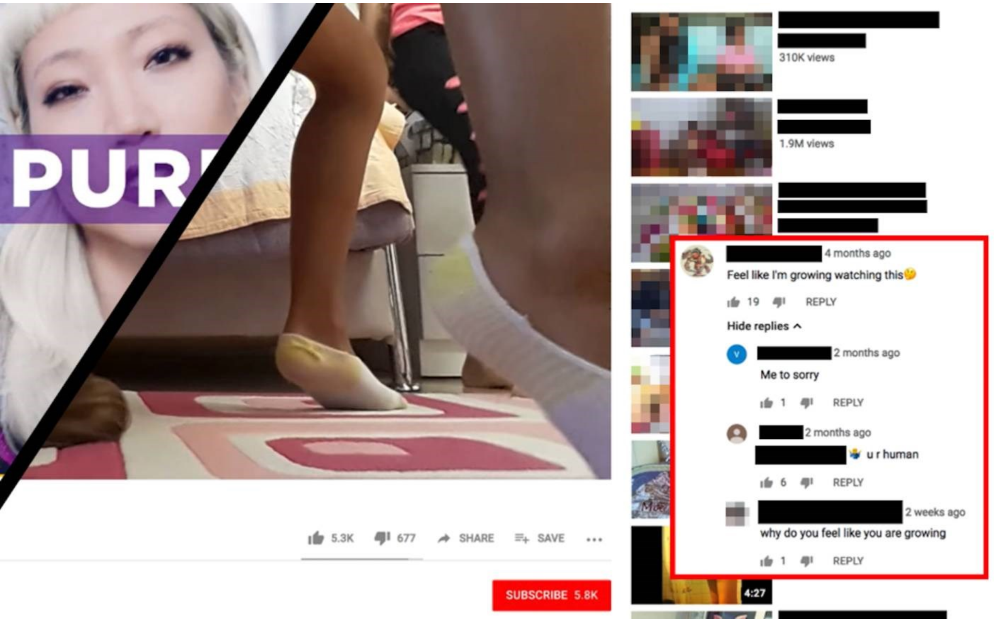


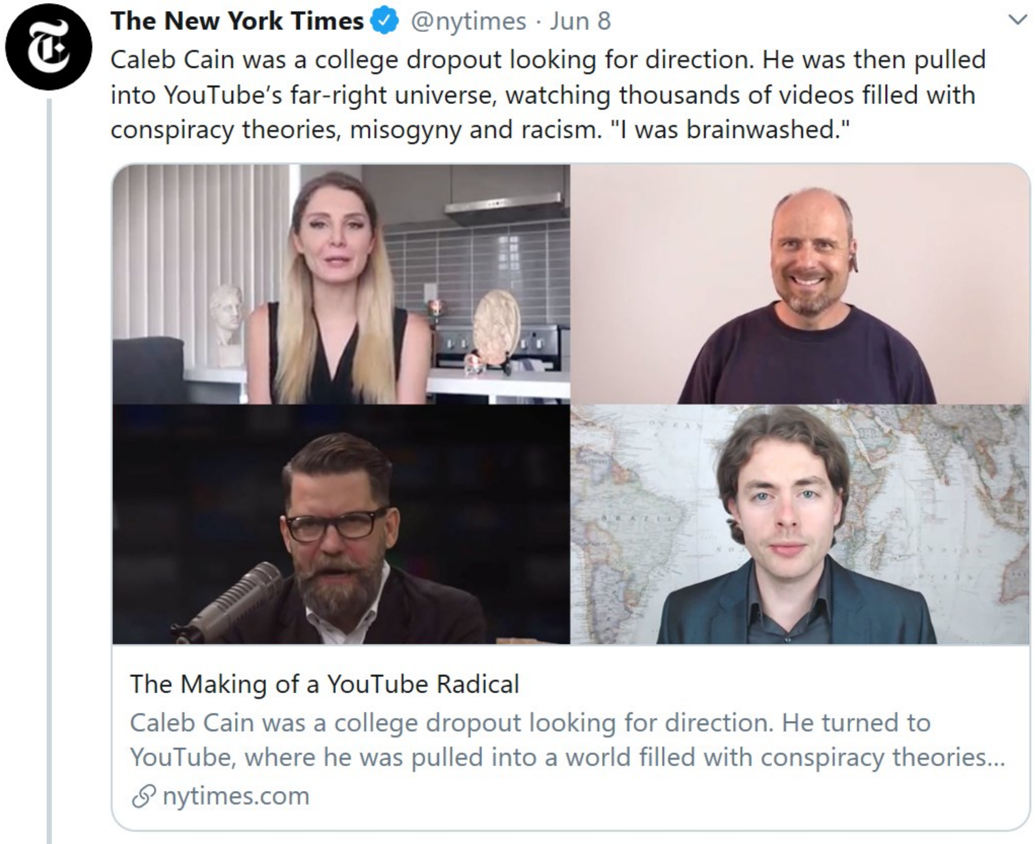
Not funny fails

Unprotected minors and families

Feedback loops

Political radicalization of users





https://www.newsweek.com/youtube-cp-algorithm-ban-mattswhatitis-algorithm-1334873

https://blog.youtube/news-and-events/an-update-on-our-efforts-to-protect

https://www.nytimes.com/interactive/2019/06/08/technology/youtube-radical.html

Algorithms can be biased on variables that aren't part of the dataset. https://www.fast.ai/2019/05/28/google-nyt-mohan/

Feedback loops and intervention

Is there a difference between TikTok in the U.S. and China? A social media analyst compares it to opium and spinach

Although they're owned by the same company, China's version of TikTok offers a child-friendly version, with educational videos and a time limit, that isn't offered in the U.S.

https://www.deseret.com/2022/11/24/23467181/difference-between-tik-tok-in-china-and-the-us

Related **The content on Chinese Douyin is better than American TikTok. Is this true?**

Yes.

My Tik tok feed (South East Asia) is filled with teenagers doing stupid things.

My Dou yin feed is filled with self improvement, photography, travel, calligraphy, life hacks, trivia, interesting new products, and of course, cute dog/cat videos.

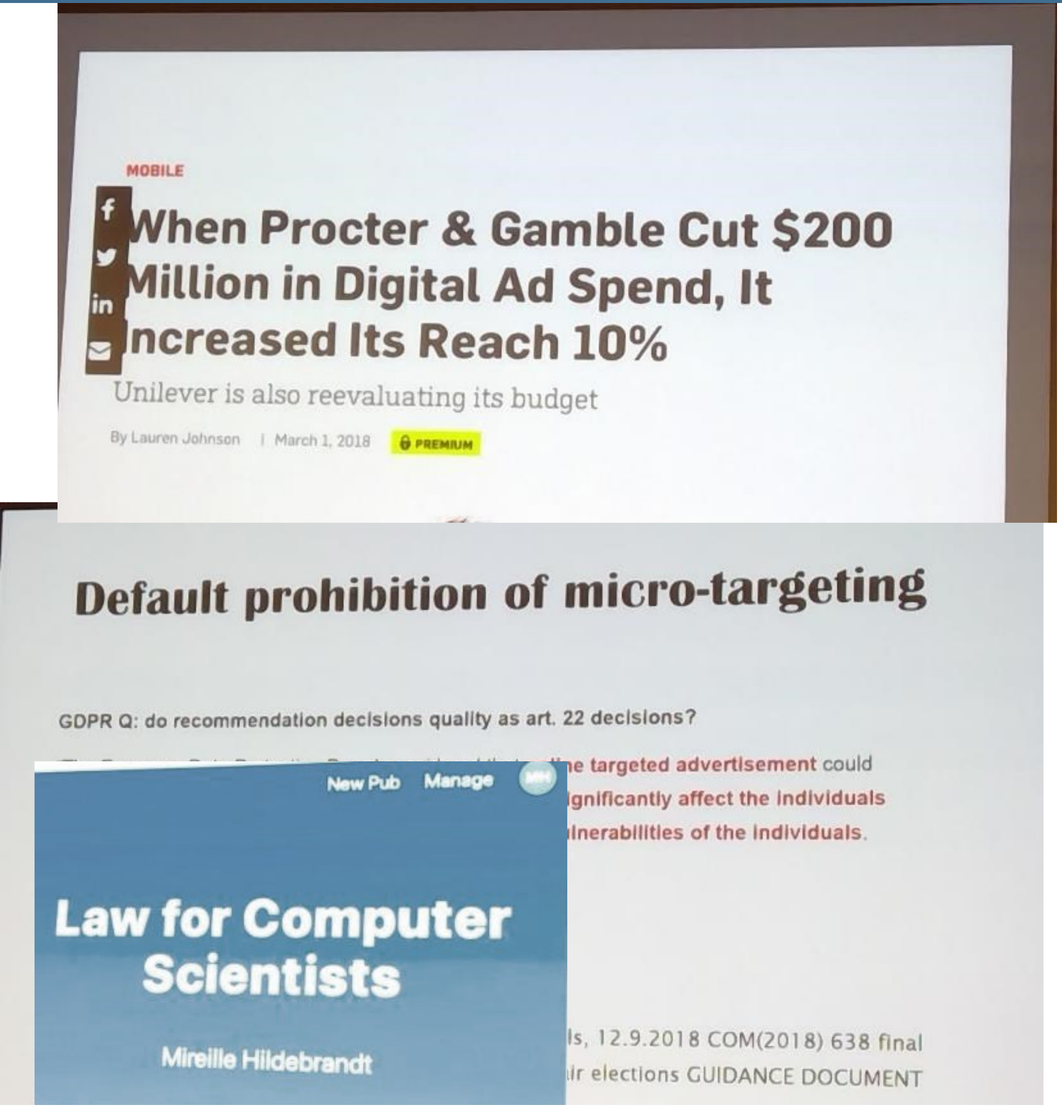
The production quality of douyin videos is generally higher too.

47 1

https://www.quora.com/Is-it-true-that-TikTok-algorithm-promotes-dance-and-lip-sync-videos-in-the-world-but-scientific-and-engineering-content-in-China

Suggest possible explanation to these observations.

GDPR – "Rude Awakening"



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https://measurementnow.net/when-procter-gamble-cut-200-million-in-digital-ad-spend-it-increased-its-reach-10/

https://www.cohubicol.com

The slides are available at: Opening Keynote, Rude Awakenings from Behaviourists Dreams. GDPR and the Methodological Integrity and the GDPR.

Other topics

- Multi-task learning
- Causality
- Federated learning and privacy
- Fairness and debiasing
- Reinforcement learning
- Conversational Recommenders, critiquing