FROM NETNEWS TO ETHICS

A HISTORICAL OVERVIEW OF RECOMMENDER SYSTEMS

ALAN SAID
ALANSAID@ACM.ORG

Who am I?

Present: Associate Prof, Uni. of Gothenburg, Sweden

Past:- Recorded Future, SE

- TU Delft, NL
- Centrum Wiskunde & Informatica, NL
- Talis, EN
- TU Berlin (PhD), DE
- Chalmers University of Tech., SE

Research:

- Recommender Systems, Reproducibility, Evaluation, Fairness, Sustainability, Explanations

What I do in RecSys

Present: Chair of ACM RecSys Steering Committee 2023-2026

Past:

- General Chair RecSys 2019
- Creator of RecSys Challenge
- Co-organizer of RecSys Summer School 2019 and 2023


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A HISTORICAL OVERVIEW OF RECOMMENDER SYSTEMS

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- Present
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What is the purpose of recommender systems?

Information overload

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Information overload

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For the album by Alien Sex Fiend, see Information Overload (album).

Information overload (also known as **infobesity**,[1][2] **infoxication**,[3] **information anxiety**,[4] and **information explosion**[5]) is the difficulty in understanding an issue and effectively making decisions when one has **too much information** (TMI) about that issue,[6] and is generally associated with the excessive quantity of daily information. The term "Information overload" was first used in Bertram Gross' 1964 book, *The Managing of Organizations*,[7] and was further popularized by Alvin Toffler in his bestselling 1970 book *Future Shock*.[8] Speier et al. (1999) said that if input exceeds the processing capacity, information overload occurs, which is likely to reduce the quality of the decisions.[9]

In a newer definition, Roetzel (2019) focuses on time and resources aspects. He states that when a decision-maker is given many sets of information, such as complexity, amount, and contradiction, the quality of its decision is decreased because of the individual's limitation of scarce resources to process all the information and optimally make the best decision.[10]

The advent of modern information technology has been a primary driver of information overload on multiple fronts: in quantity produced, ease of dissemination, and breadth of the audience reached. Longstanding technological factors have been further intensified by the rise of social media and the attention economy, which facilitates attention theft.[11][12] In the age of connective digital technologies, informatics, the Internet culture (or the digital culture), information overload is associated with over-exposure, excessive viewing of information, and input abundance of information and data.

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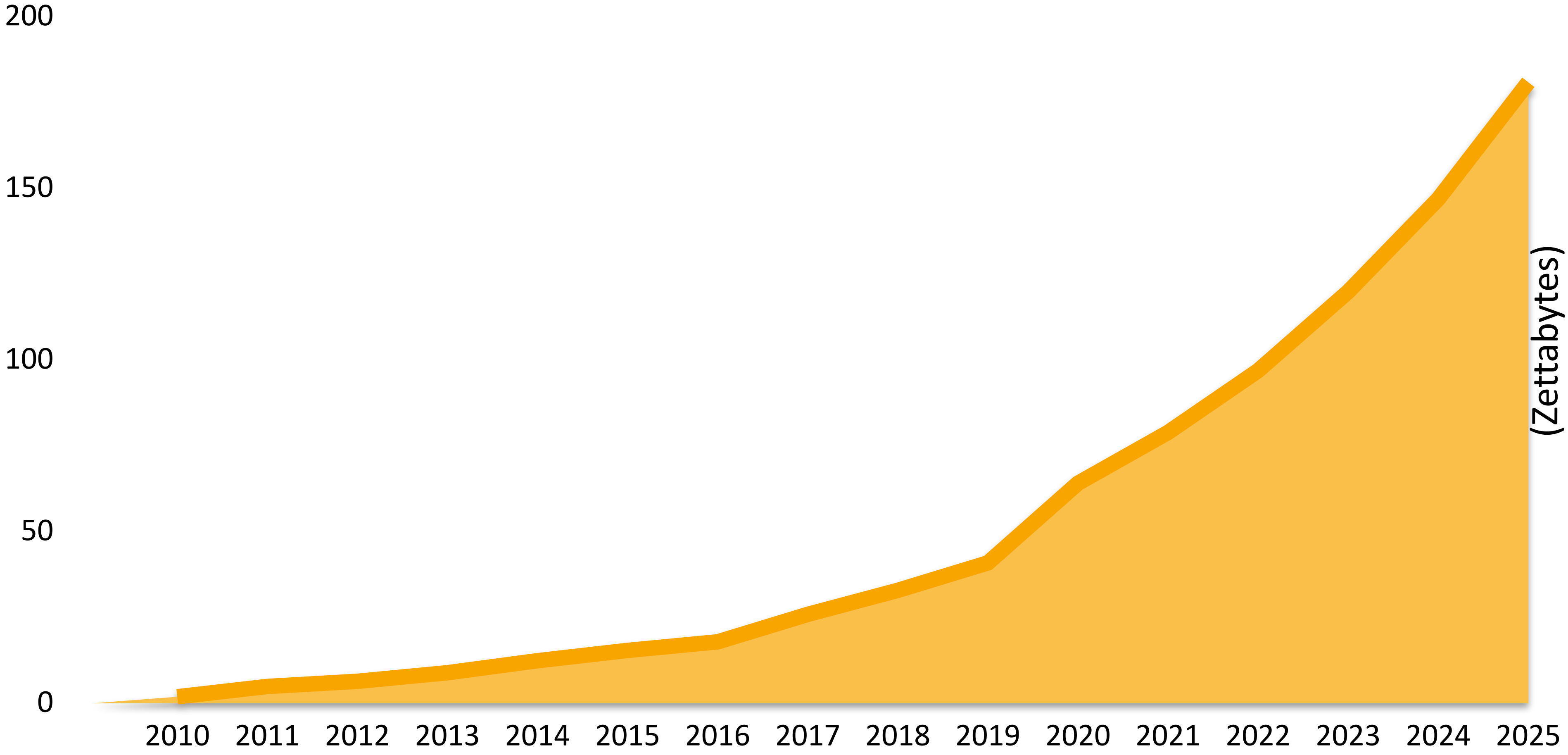

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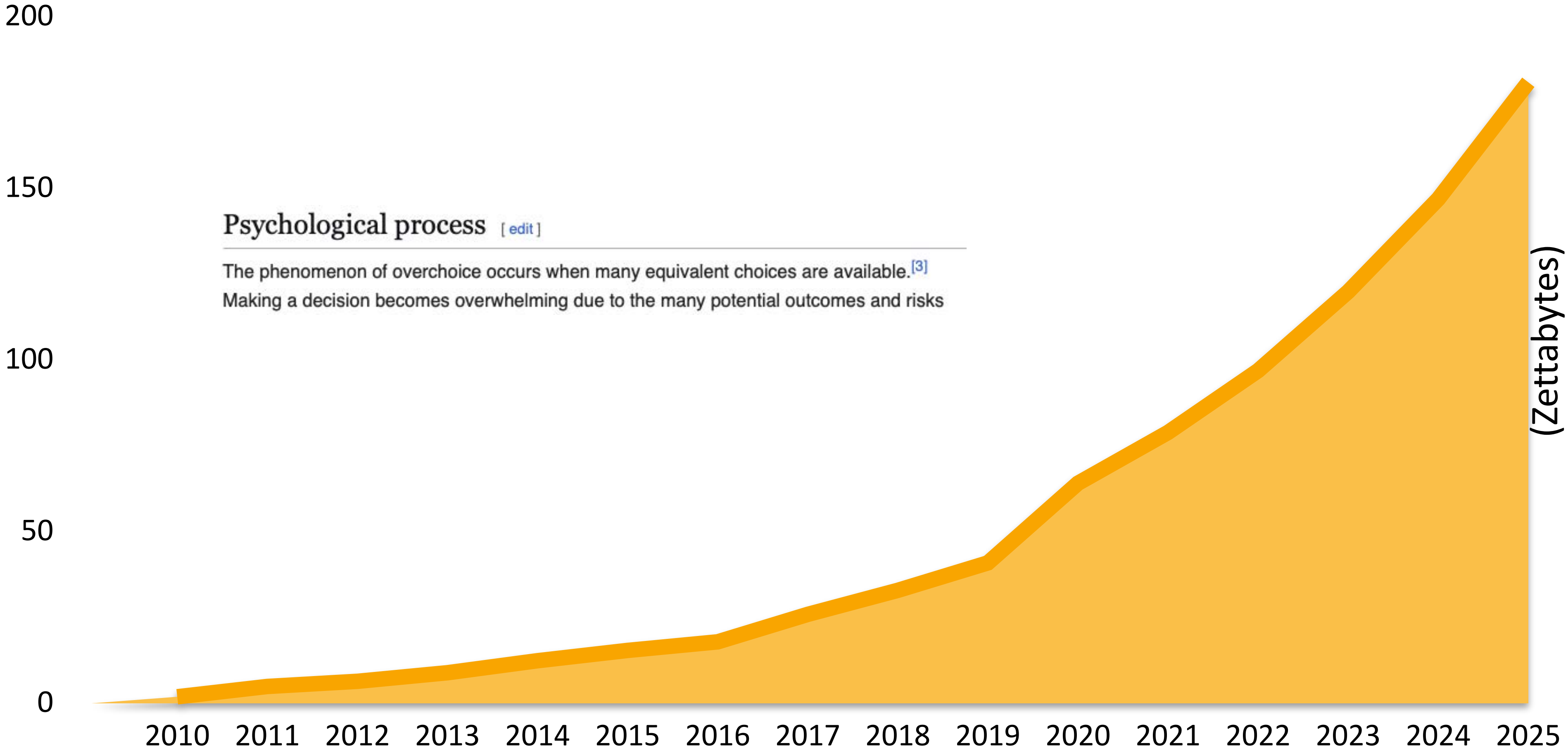

Psychological process [edit]

The phenomenon of overchoice occurs when many equivalent choices are available.[3] Making a decision becomes overwhelming due to the many potential outcomes and risks

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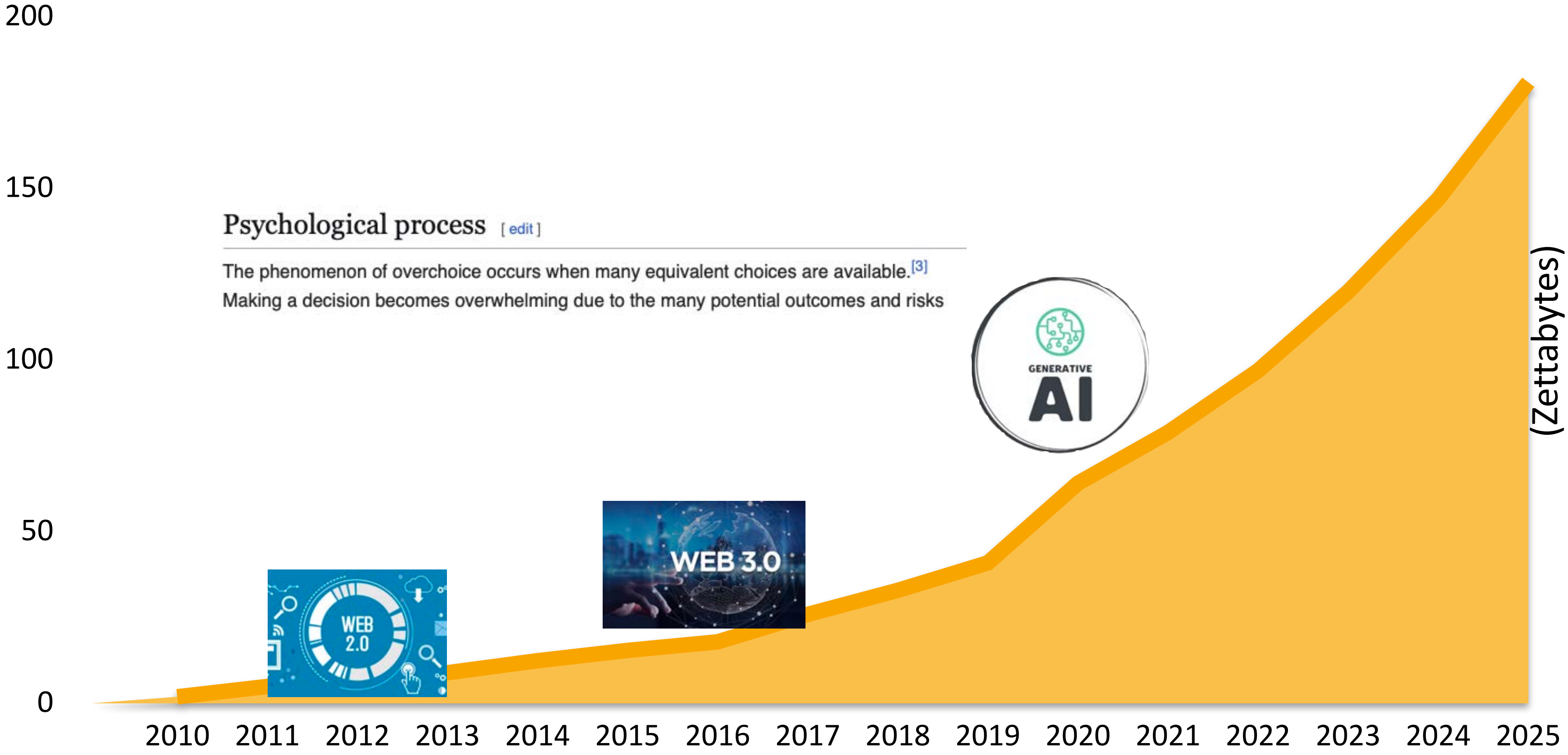

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History of RecSys

recommend

VERB[1]

Factsheet

Etymology

▼ Meaning & use

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- 1. † **transitive. To praise, extol, or commend (a person)...**
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- 3. † transitive (reflexive). To commend (oneself) to (the...
- 4. transitive. To mention or present (a thing, course of...
- 5. transitive. Chiefly of a quality, circumstance, or thing...
- 6. transitive. To defend, speak on behalf of. Obsolete. rare.
- 7. transitive. To offer counsel or advice to someone (to do...

Etymology

Summary

Of multiple origins. Partly a borrowing from French. Partly a borrowing from Latin.

Etymons: French *recommender*; Latin *recommendare*.

Partly < **Anglo-Norman** and **Middle French** *recommender*, variant of *recommander* **recommand** *v.*[1], and partly < **post-classical Latin** *recommendare* to commit, entrust (10th cent.; from 11th cent. in British sources), to praise, commend (from 13th cent. in British sources), to commend in prayer (14th cent. in British sources) < **classical Latin** *re-* **re-** *prefix* + *commendāre* **commend** *v.* Compare **Spanish** *recomendar* (late 13th cent.), **Portuguese** *recomendar* (1387). Compare **recommand** *v.*[1] (and see discussion at that entry).

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Pronunciation

▸ Forms

Frequency

▸ Compounds & derived words

QUOTATIONS

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EARLIER VERSION

recommend, v.[1] in OED Second Edition (1989)

IN OTHER DICTIONARIES

4.a. *transitive*. To mention or present (a thing, course of action) *to* (also *unto*) a person, etc., as being desirable or advisable. Also with indirect object. Cf. sense 7a. **c1460–**

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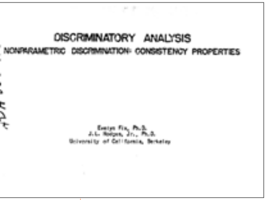
2017


DISCRIMINATORY ANALYSIS

NONPARAMETRIC DISCRIMINATION: CONSISTENCY PROPERTIES

Evelyn Fix, Ph.D.
J.L. Hodges, Jr., Ph.D.
University of California, Berkeley

1951

NONPARAMETRIC DISCRIMINATION: CONSISTENCY PROPERTIES

1. Introduction

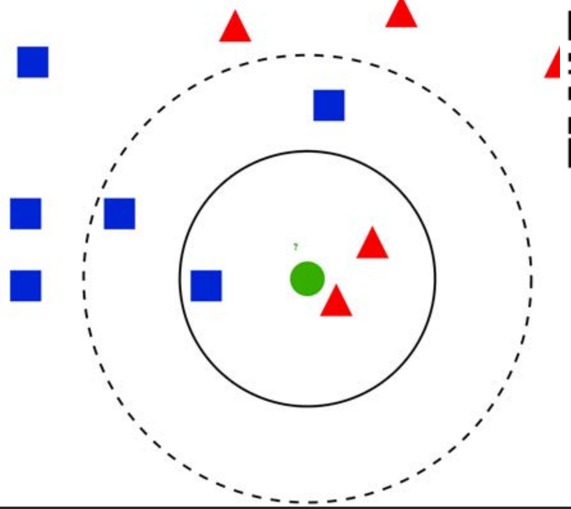
The discrimination problem (two population case) may be defined as follows: a random variable Z, of observed value z, is distributed over some space (say, p-dimensional) either according to distribution F, or according to distribution G. The problem is to decide, on the basis of z, which of the two distributions Z has.

The problem may be classified in various ways into subproblems. One pertinent method of classification is according to the amount of information assumed to be available about F and G. We may distinguish three stages:

(i) F and G are completely known

(ii) F and G are known except for the values of one or more parameters

(iii) F and G are completely unknown, except possibly for assumptions about existence of densities,



An appropriate (positive) constant c is chosen, and the following rule is observed:

If $\frac{f(z)}{g(z)} > c$, we decide in favor of F

If $\frac{f(z)}{g(z)} < c$, we decide in favor of G

If $\frac{f(z)}{g(z)} = c$, the decision may be made in an arbitrary manner

These procedures are known to have optimum properties with regard to control of probability of misclassification (probability of wrong decision). We shall refer to this as the "likelihood ratio procedure," and denote it by L(c).

For simplicity, we shall assume throughout the paper that the borderline case $f(z) = cg(z)$ can be neglected.

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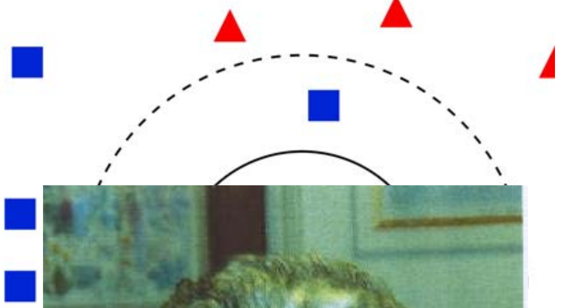

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Nearest Neighbor Pattern Classification

T. M. COVER, MEMBER, IEEE, AND P. E. HART, MEMBER, IEEE

Evelyn Fix, Ph.D.
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University of California, Berkeley

Nearest Neighbor Pattern Classification

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Abstract—**The nearest neighbor decision rule assigns to an unclassified sample point the classification of the nearest of a set of previously classified points. This rule is independent of the underlying joint distribution on the sample points and their classifications, and hence the probability of error R of such a rule must be at least as great as the Bayes probability of error R^*—the minimum probability of error over all decision rules taking underlying probability structure into account. However, in a large sample analysis, we will show in the M-category case that $R^* \leq R \leq R^*(2 - MR^*/(M-1))$, where these bounds are the tightest possible, for all suitably smooth underlying distributions. Thus for any number of categories, the probability of error of the nearest neighbor rule is bounded above by twice the Bayes probability of error. In this sense, it may be said that half the classification information in an infinite sample set is contained in the nearest neighbor.**

I. Introduction

IN THE CLASSIFICATION problem there are two extremes of knowledge which the statistician may possess. Either he may have complete statistical knowledge of the underlying joint distribution of the

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observation x and the true category θ, or he ... no knowledge of the underlying distribution ... which can be inferred from samples. In the fir... a standard Bayes analysis will yield an optim... procedure and the corresponding minimum (... ability of error of classification R^*. In the o... a decision to classify x into category θ is allow... only on a collection of n correctly clas... $(x_1, \theta_1), (x_2, \theta_2), \cdots, (x_n, \theta_n)$, and the deci... is by no means clear. This problem is in ... nonparametric statistics and no optim... procedure exists with respect to all under...

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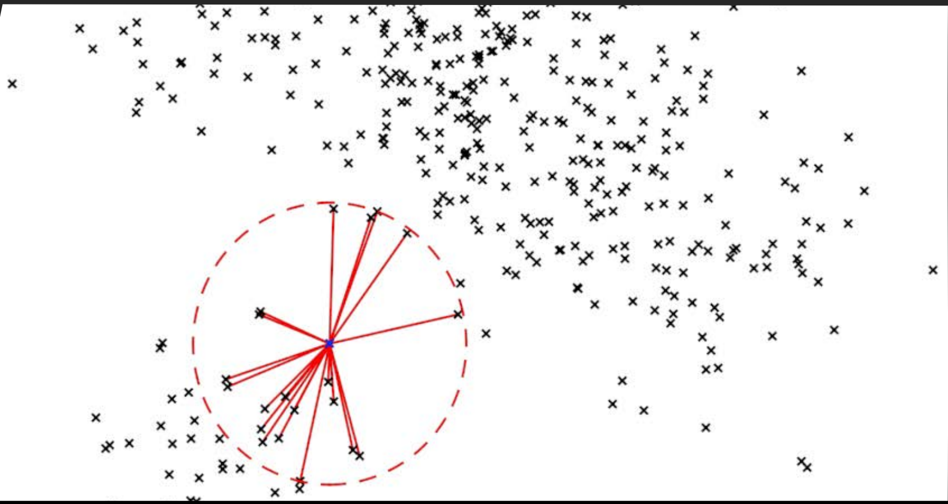
If it is assumed that the classified samples (x_i, θ_i) are *independently identically distributed* according to the distribution of (x, θ), certain heuristic arguments may be made about good decision procedures. For example, it is reasonable to assume that observations which are close together (in some appropriate metric) will have the same classification, or at least will have almost the same posterior probability distributions on their respective classifications. Thus to classify the unknown sample x we may wish to weight the evidence of the nearby x_i's most heavily. Perhaps the simplest nonparametric decision procedure of this form is the *nearest neighbor* (NN) rule, which classifies x in the category of its nearest neighbor.



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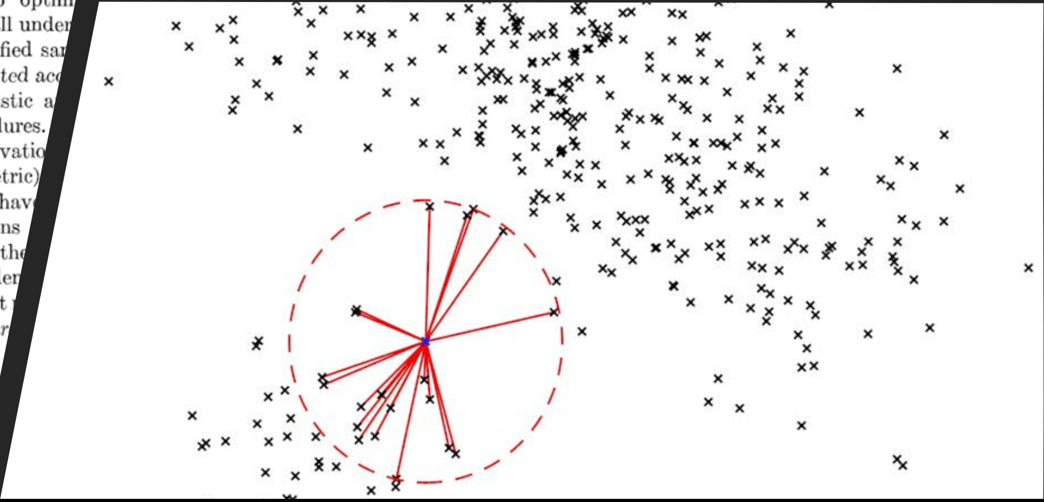

An Algebra for Recommendations

Using Reader Data as a Basis for Measuring Document Proximity

Jussi Karlgren

Department of Computer and Systems Sciences
Stockholm University
Electrum 230
S-164 40 KISTA, Sweden

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jussi@flash.bellcore.com
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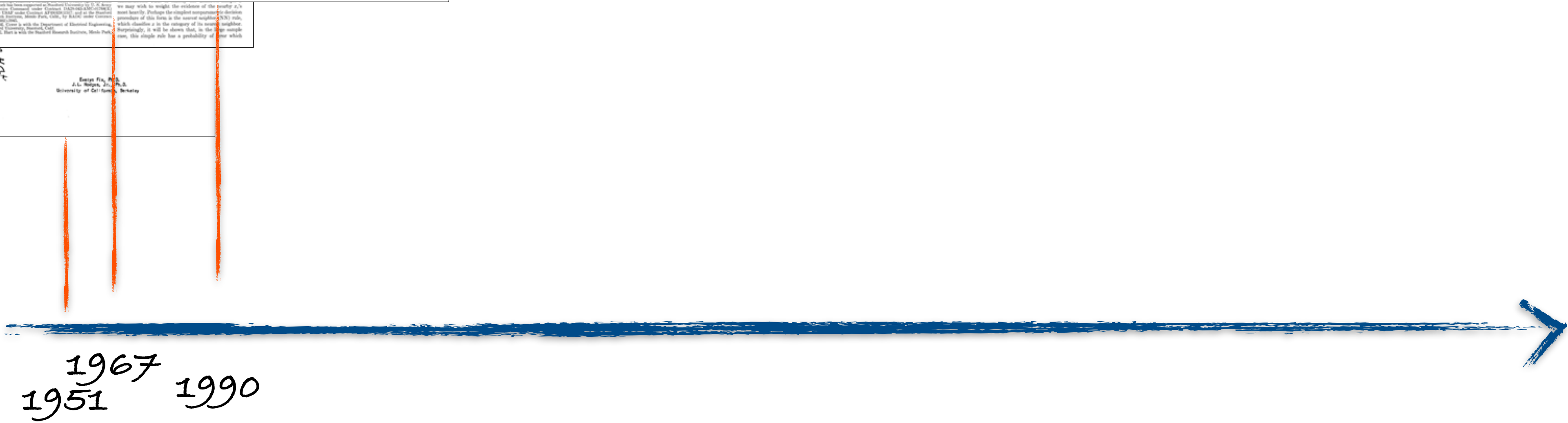

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3. Defining Proximity

Proximity is defined to be a measure of closeness between documents based on the interest readers of the document have shown it. The main idea is, for every pair or set of documents, to use all their readerís interest grades to define relationships from one document to sets of others.

We will do this by first defining recommendation from a document to another, for one reader. This will correspond to the answer a reader gives to the question "I liked book A. Do you believe I will like B?".

3.1 Proximity of One Document to Others

A reader x is represented as a vector

r(x) = [r1, ... ri, ... rn] ,

where

r(x)i = the ith element in r(x),

3.2.1 The Tendency to Give Good or Bad Grades

Another factor which may have to be taken into account when the constants are given numerical values, is the tendency of readers to give good or bad grades. An "Interesting" grade given by someone who only gives it very seldom might be worth more than an "Interesting" grade given by someone who frequently grades documents "Interesting".

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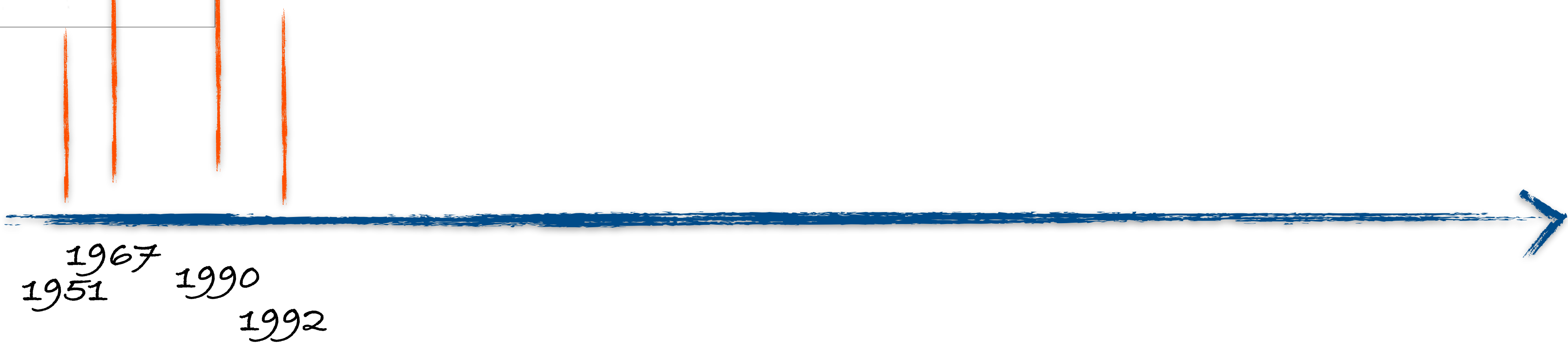
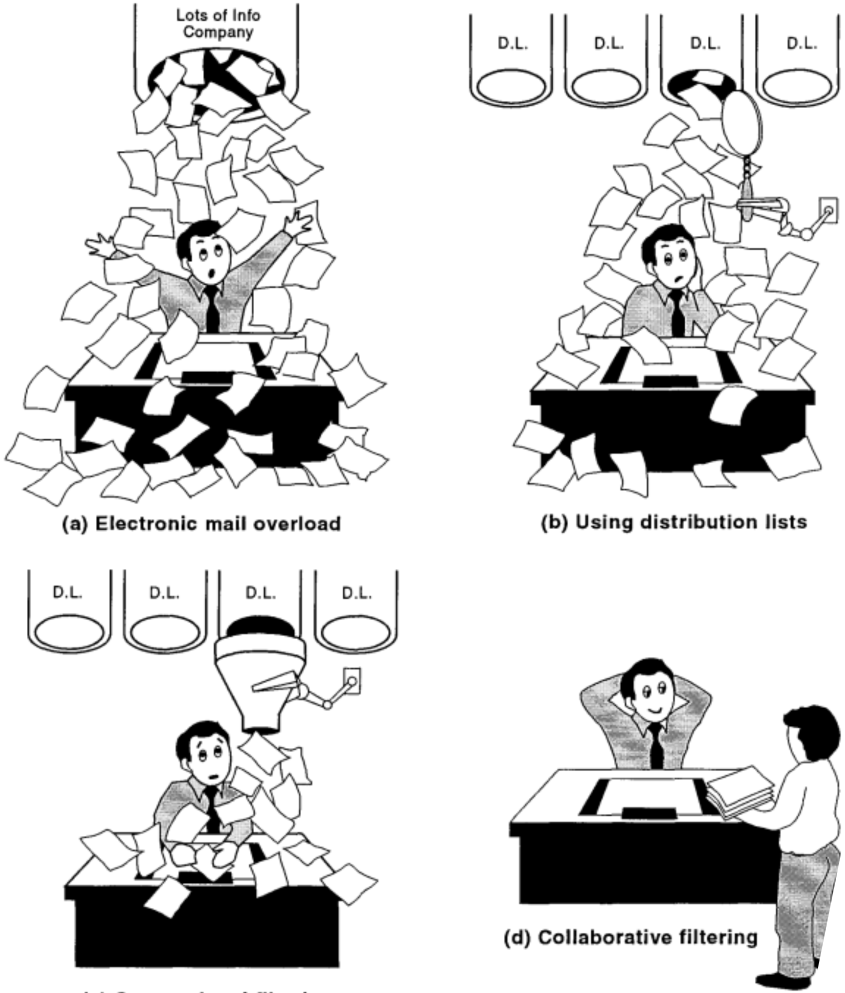
COLLABORATIVE FILTERING
to Weave an Information
TAPESTRY

David Goldberg, David Nichols, Brian M. Oki, and Douglas Terry

Tapestry is an experimental mail system developed at the Xerox Palo Alto Research Center. The motivation for Tapestry comes from the increasing use of electronic mail, which is resulting in users being inundated by a huge stream of incoming documents [2, 7, 12]. One way to handle large volumes of mail is to provide mailing lists, enabling users to subscribe only to those lists of interest to them. However, as illustrated in Figure 1, the set of documents of interest to a particular user rarely map neatly to existing lists. A better solution is for a user to specify a *filter* that scans all lists, selecting interesting documents no matter what list they are in. Several mail systems support filtering based on a document's contents [3, 5, 6, 8]. A basic tenet of the Tapestry work is that more effective filtering can be done by involving humans in the filtering process.

In addition to content-based filtering, the Tapestry system was designed and built to support *collaborative filtering*. Collaborative filtering simply means that people collaborate to help one another perform filtering by recording their reactions to documents they read. Such reactions may be that a document was particularly interesting (or particularly uninteresting). These reactions, more generally called *annotations*, can be accessed by others' filters. One application of annotations is in support of moderated newsgroups.





(a) Electronic mail overload

(b) Using distribution lists

(c) Conventional filtering

(d) Collaborative filtering

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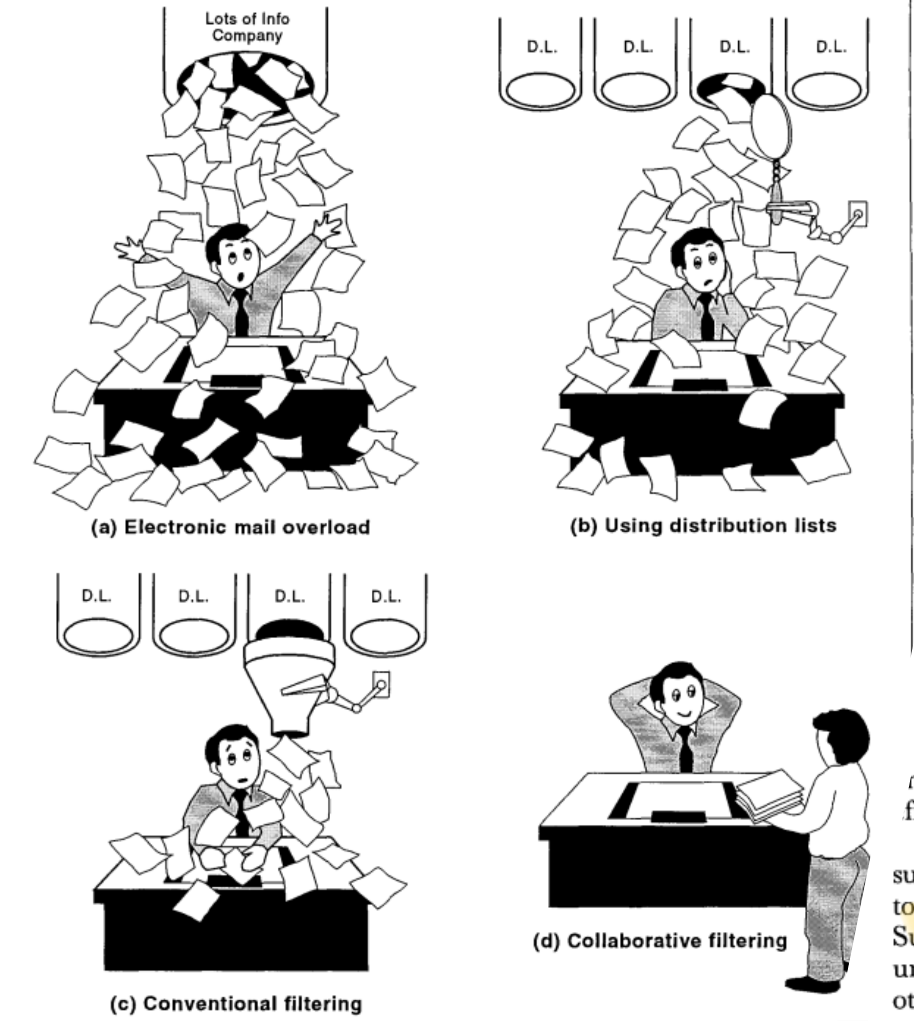

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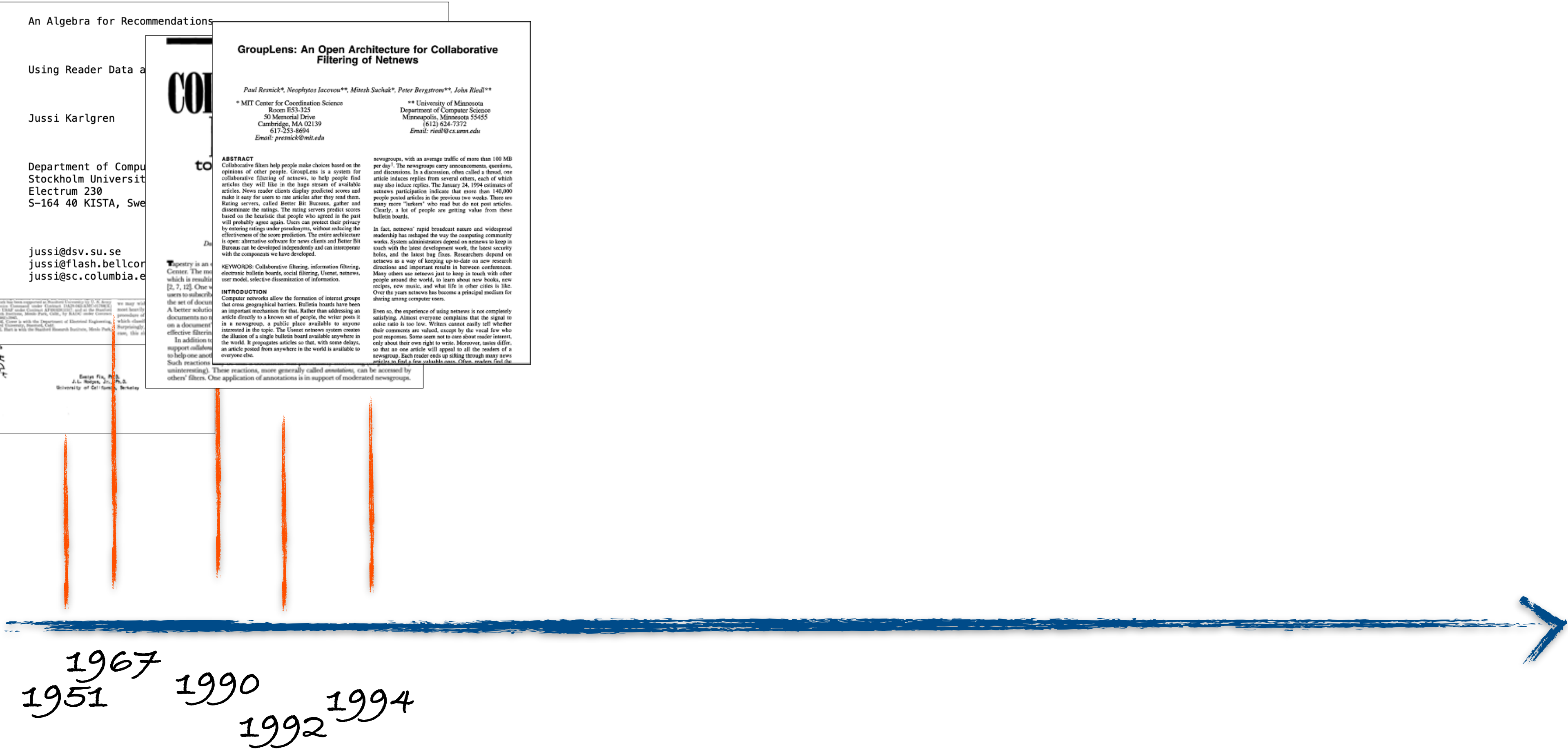

An Algebra for Recommendations
Using Reader Data a
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Department of Compu
Stockholm Universit
Electrum 230
S-164 40 KISTA, Swe
jussi@dsv.su.se
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GroupLens: An Open Architecture for Collaborative Filtering of Netnews
Paul Resnick*, Neophytos Iacovou**, Mitesh Suchak*, Peter Bergstrom**, John Riedl**
* MIT Center for Coordination Science
Room E53-325
50 Memorial Drive
Cambridge, MA 02139
617-253-8694
Email: presnick@mit.edu
** University of Minnesota
Department of Computer Science
Minneapolis, Minnesota 55455
(612) 624-7372
Email: riedl@cs.umn.edu
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Collaborative filters help people make choices based on the opinions of other people. GroupLens is a system for collaborative filtering of netnews, to help people find articles they will like in the huge stream of available articles. News reader clients display predicted scores and make it easy for users to rate articles after they read them. Rating servers, called Better Bit Bureaus, gather and disseminate the ratings. The rating servers predict scores based on the heuristic that people who agreed in the past will probably agree again. Users can protect their privacy by entering ratings under pseudonyms, without reducing the effectiveness of the score prediction. The entire architecture is open: alternative software for news clients and Better Bit Bureaus can be developed independently and can interoperate with the components we have developed.

KEYWORDS: Collaborative filtering, information filtering, electronic bulletin boards, social filtering, Usenet, netnews, user model, selective dissemination of information.

INTRODUCTION
Computer networks allow the formation of interest groups that cross geographical barriers. Bulletin boards have been an important mechanism for that. Rather than addressing an article directly to a known set of people, the writer posts it in a newsgroup, a public place available to anyone interested in the topic. The Usenet netnews system creates the illusion of a single bulletin board available anywhere in the world. It propagates articles so that, with some delays, an article posted from anywhere in the world is available to everyone else.

newsgroups, with an average traffic of more than 100 per day[1]. The newsgroups carry announcements, quest and discussions. In a discussion, often called a thread article induces replies from several others, each of may also induce replies. The January 24, 1994 estim netnews participation indicate that more than 1 people posted articles in the previous two weeks. Th many more "lurkers" who read but do not post Clearly, a lot of people are getting value fro bulletin boards.

In fact, netnews' rapid broadcast nature and w readership has reshaped the way the computing works. System administrators depend on netnew touch with the latest development work, the lat holes, and the latest bug fixes. Researchers netnews as a way of keeping up-to-date on r directions and important results in between Many others use netnews just to keep in tou people around the world, to learn about ne recipes, new music, and what life in other Over the years netnews has become a princi sharing among computer users.

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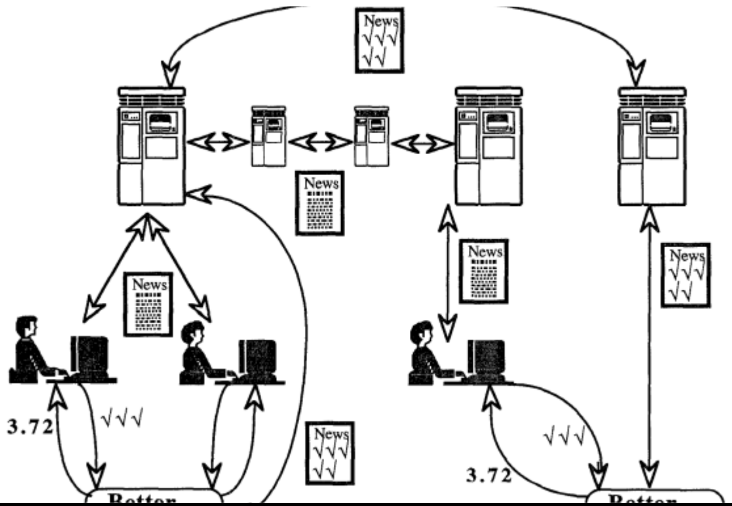

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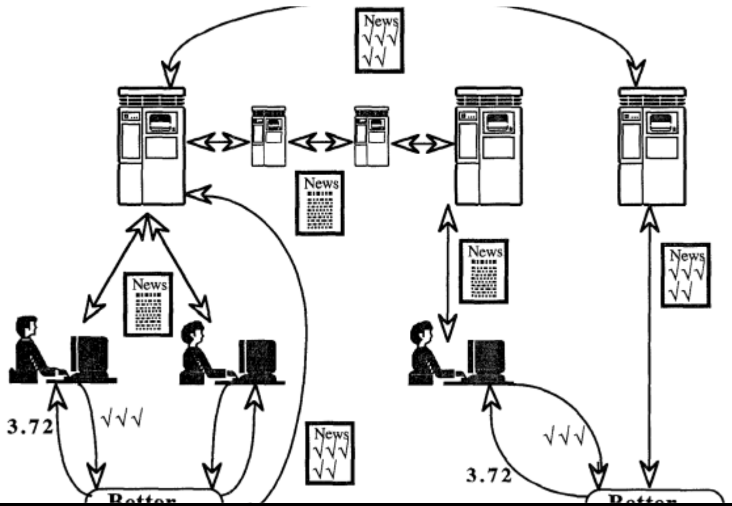


grouplens about datasets publications blog

Social Computing Research at the University of Minnesota

GroupLens advances the theory and practice of social computing by building and understanding systems used by real people

Featured Research

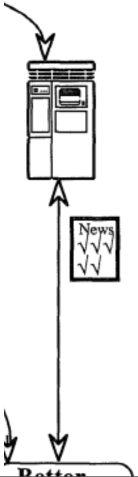
We publish research articles in conferences and journals primarily in the field of computer science, but also in other fields including psychology, sociology, and medicine. See our blog for research highlights and our publications page for a comprehensive view of our research contributions. Here are excerpts from recent articles:

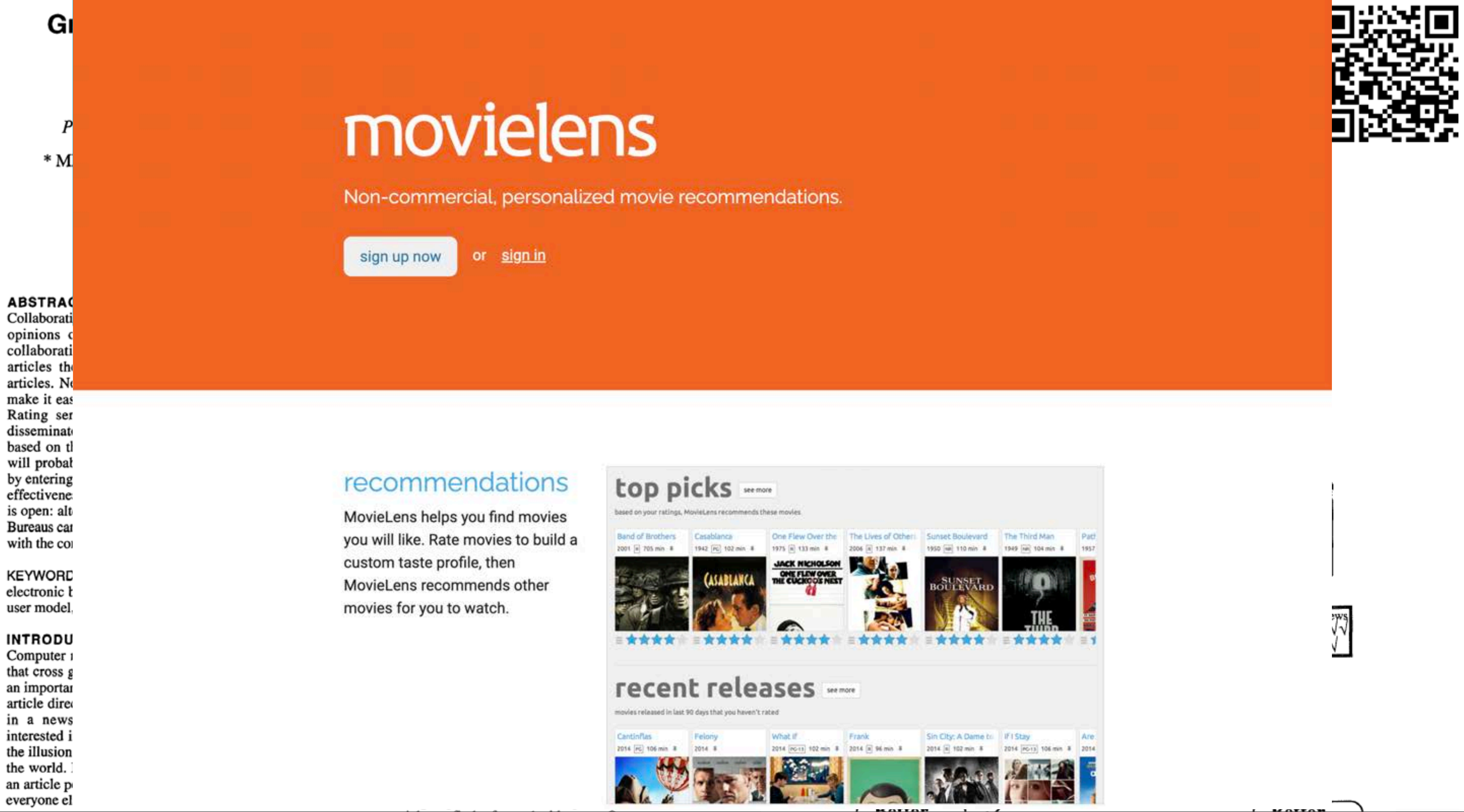
Rethinking Mental Health Interventions: How Crowd-Powered Therapy Can Help Everyone Help Everyone

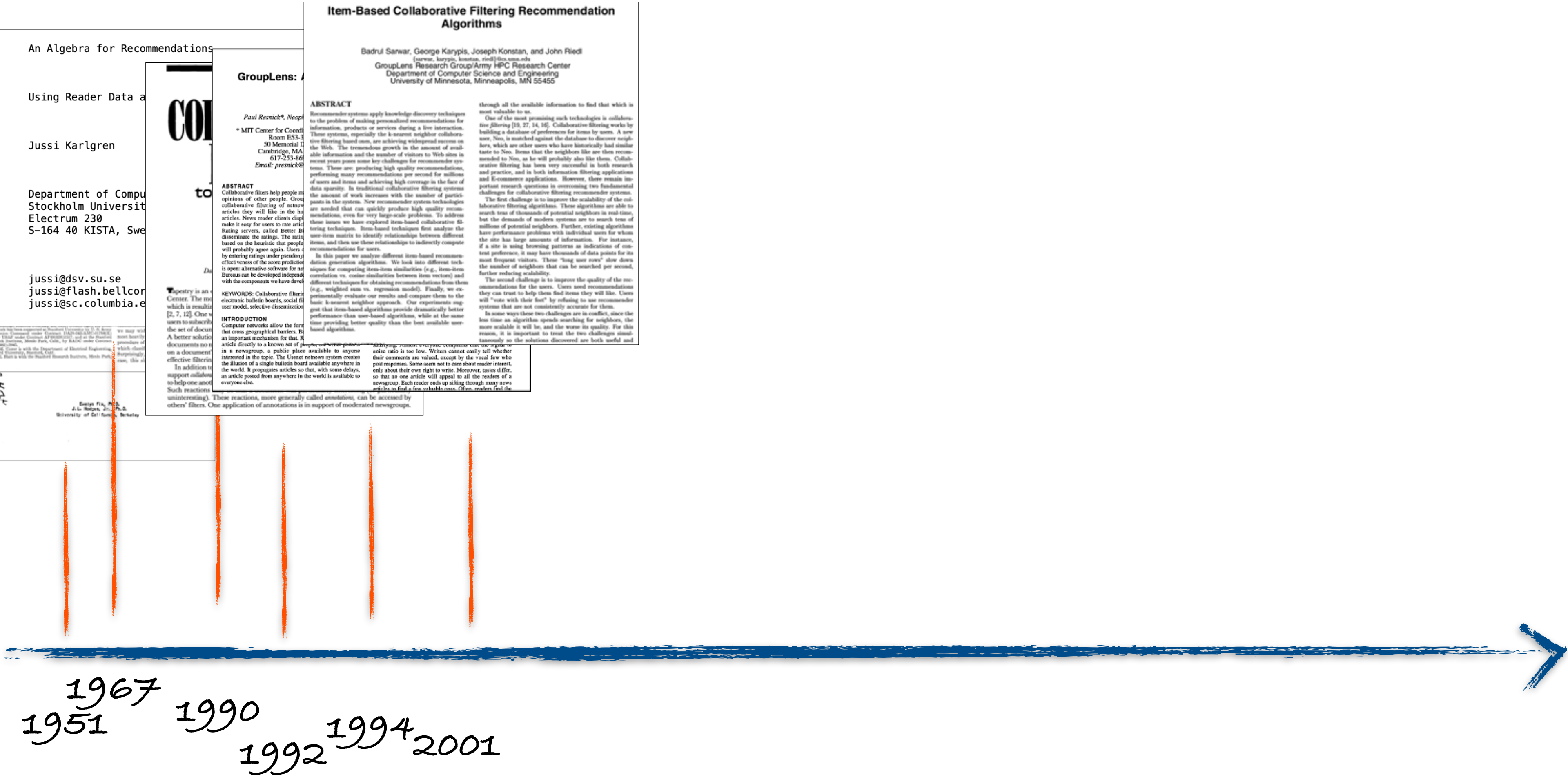
Rates of mental illness continue to rise every year. Yet there are nowhere near enough trained mental health professionals available to meet the need. How can technology create new ways to expand models of delivery for clinically

Are Bots Ravaging Online Encyclopedias?

Wikipedia is the online encyclopedia that anyone can edit. However, you probably didn't know that "bots" also edit Wikipedia! Read this blog about conflict among bots—from the University of Minnesota's "human-centered computing for social good" REU. More...




movielens
Non-commercial, personalized movie recommendations.
sign up now
or
sign in
recommendations
MovieLens helps you find movies you will like. Rate movies to build a custom taste profile, then MovieLens recommends other movies for you to watch.
top picks
see more
based on your ratings, MovieLens recommends these movies
Band of Brothers
Casablanca
One Flew Over the
The Lives of Others
Sunset Boulevard
The Third Man
recent releases
see more
movies released in last 90 days that you haven't rated
Cantinflas
Felony
What If
Frank
Sin City: A Dame to
If I Stay



Item-Based Collaborative Filtering Recommendation Algorithms
Badrul Sarwar, George Karypis, Joseph Konstan, and John Riedl
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ABSTRACT

Recommender systems apply knowledge discovery techniques to the problem of making personalized recommendations for information, products or services during a live interaction. These systems, especially the k-nearest neighbor collaborative filtering based ones, are achieving widespread success on the Web. The tremendous growth in the amount of available information and the number of visitors to Web sites in recent years poses some key challenges for recommender systems. These are: producing high quality recommendations, performing many recommendations per second for millions of users and items and achieving high coverage in the face of data sparsity. In traditional collaborative filtering systems the amount of work increases with the number of participants in the system. New recommender system technologies are needed that can quickly produce high quality recommendations, even for very large-scale problems. To address these issues we have explored item-based collaborative filtering techniques. Item-based techniques first analyze the user-item matrix to identify relationships between different items, and then use these relationships to indirectly compute recommendations for users.

In this paper we analyze different item-based recommendation generation algorithms. We look into different techniques for computing item-item similarities (e.g., item-item correlation vs. cosine similarities between item vectors) and different techniques for obtaining recommendations from them (e.g., weighted sum vs. regression model). Finally, we experimentally evaluate our results and compare them to the basic k-nearest neighbor approach. Our experiments suggest that item-based algorithms provide dramatically better performance than user-based algorithms, while at the same time providing better quality than the best available user-

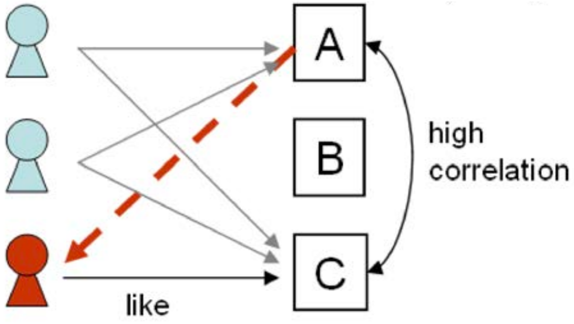
through all the available information to find that whi
most valuable to us.

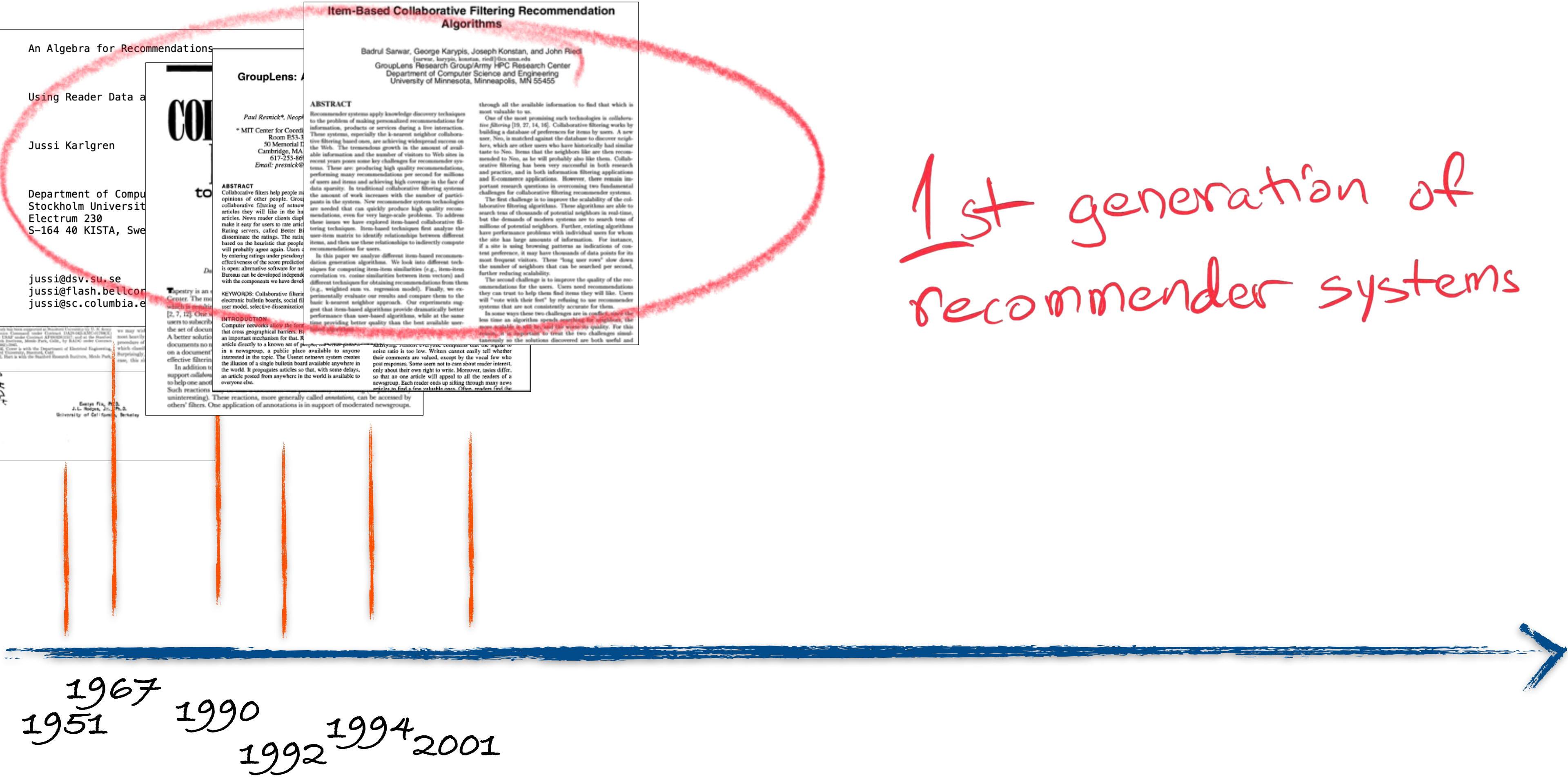
One of the most promising such technologies is *coll*
tive filtering [19, 27, 14, 16]. Collaborative filtering wo
building a database of preferences for items by users.
user, Neo, is matched against the database to discove
bors, which are other users who have historically had
taste to Neo. Items that the neighbors like are the
mended to Neo, as he will probably also like them
orative filtering has been very successful in both
and practice, and in both information filtering ap
and E-commerce applications. However, there r
portant research questions in overcoming two fu
challenges for collaborative filtering recommend

The first challenge is to improve the scalabilit
laborative filtering algorithms. These algorithm
search tens of thousands of potential neighbors
but the demands of modern systems are to s
millions of potential neighbors. Further, exist
have performance problems with individual u
the site has large amounts of information.
if a site is using browsing patterns as ind
tent preference, it may have thousands of d
most frequent visitors. These "long user r
the number of neighbors that can be sear
further reducing scalability.

The second challenge is to improve the
ommendations for the users. Users need
they can trust to help them find items t
will "vote with their feet" by refusing t
systems that are not consistently accur

In some ways these two challenges ar
less time an algorithm spends searchi

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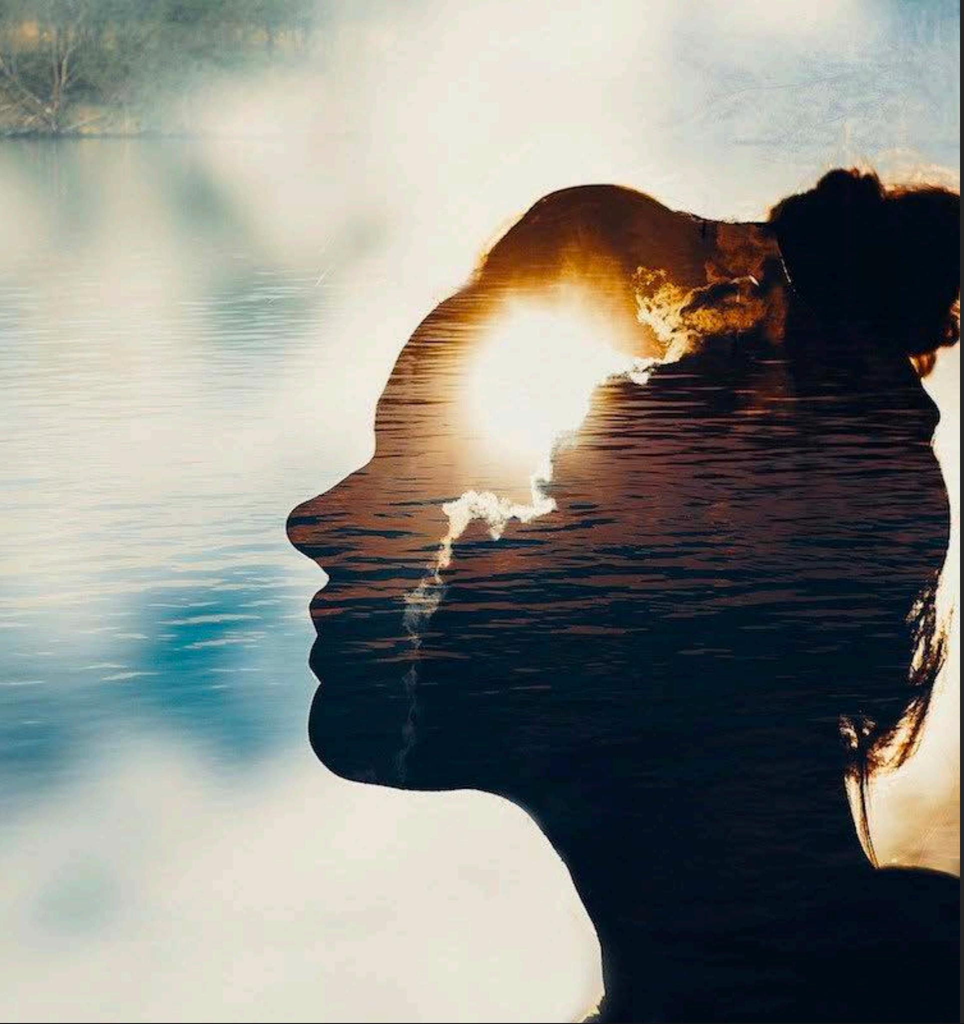
1st generation of recommender systems

- 90s-00s
- User/item-based CF, content-based CF, rule-based, knowledge graph-based
- Intuitive algorithms
- Easy to explain



1st generation of recommender systems

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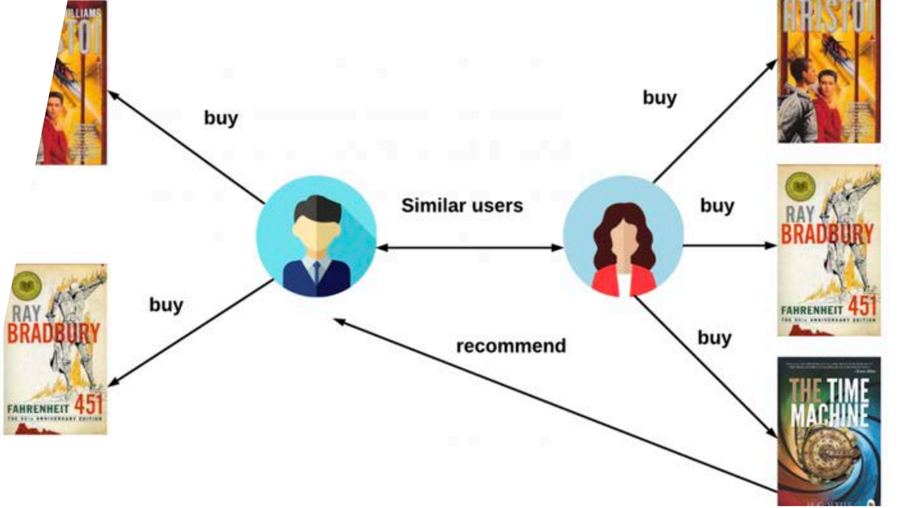
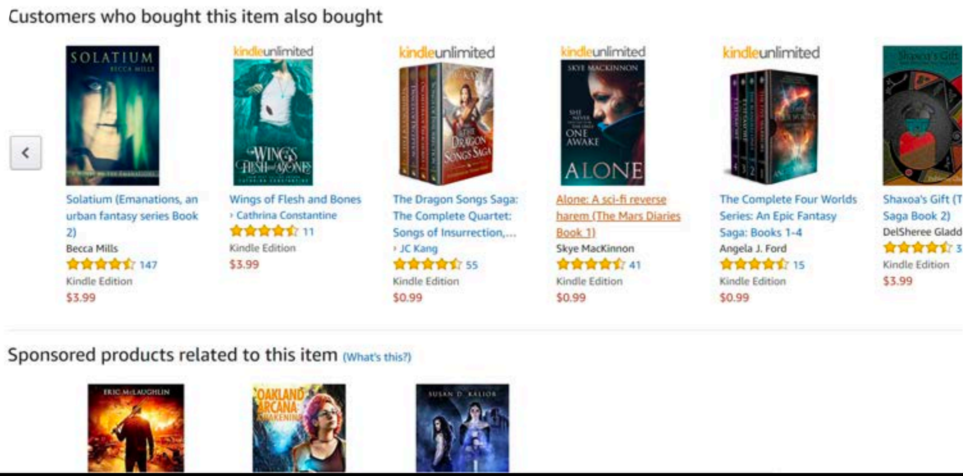
CUSTOMERS WHO BOUGHT THIS ITEM:
MILK
MILK
ALSO BOUGHT:
coffee


buy
buy
Similar users
buy
buy
buy
recommend
RAY BRADBURY
FAHRENHEIT 451
RAY BRADBURY
FAHRENHEIT 451
THE TIME MACHINE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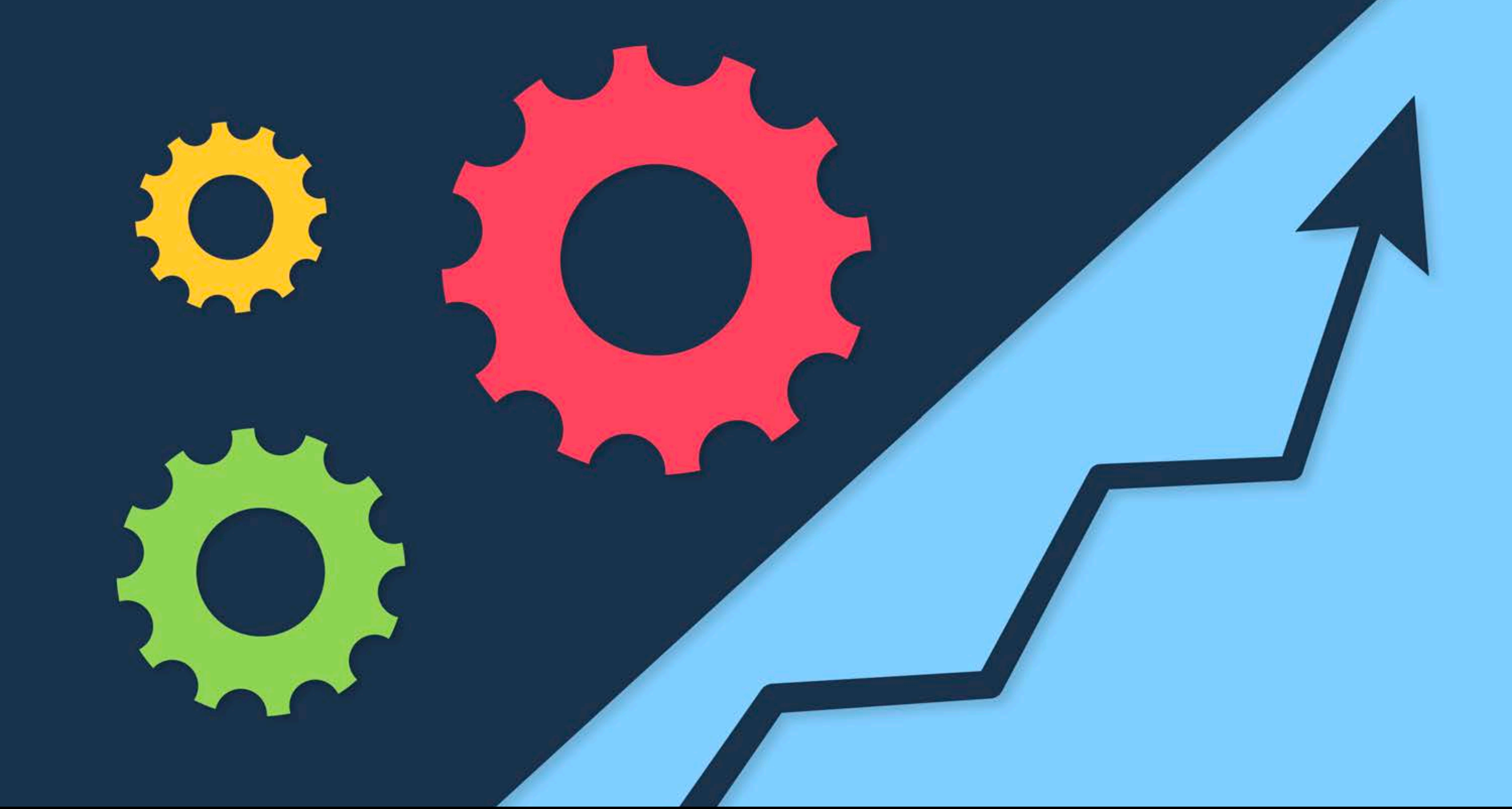


Netflix Prize

COMPLETED

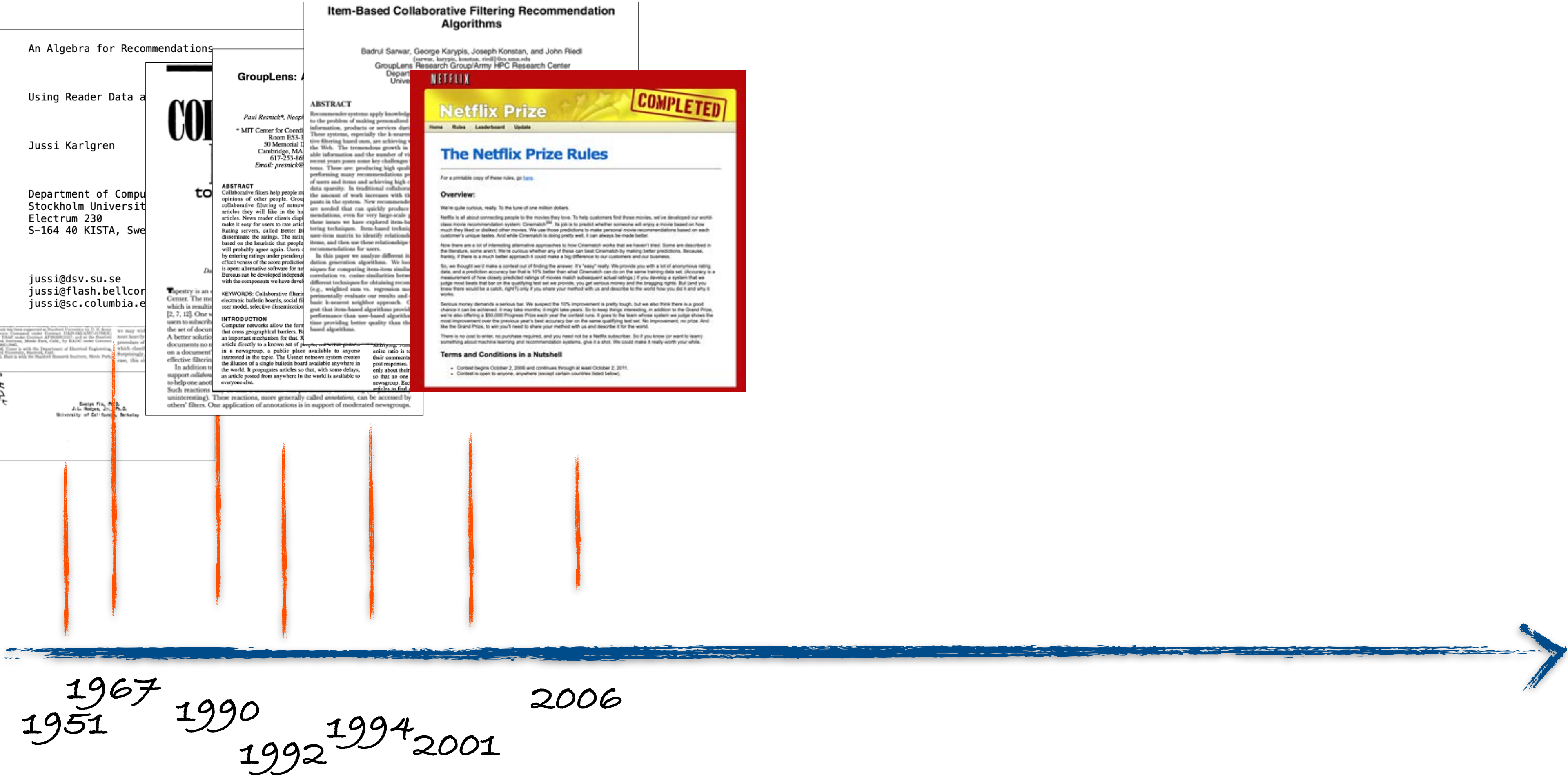
Home | Rules | Leaderboard | Update

Leaderboard

Showing Test Score. Click here to show quiz score

Display top 20 **leaders.**

Rank	Team Name	Best Test Score	% Improvement	Best Submit Time
Grand Prize - RMSE = 0.8567 - Winning Team: BellKor's Pragmatic Chaos				
1	BellKor's Pragmatic Chaos	0.8567	10.06	2009-07-26 18:18:28
2	The Ensemble	0.8567	10.06	2009-07-26 18:38:22
3	Grand Prize Team	0.8582	9.90	2009-07-10 21:24:40
4	Opera Solutions and Vandelay United	0.8588	9.84	2009-07-10 01:12:31
5	Vandelay Industries !	0.8591	9.81	2009-07-10 00:32:20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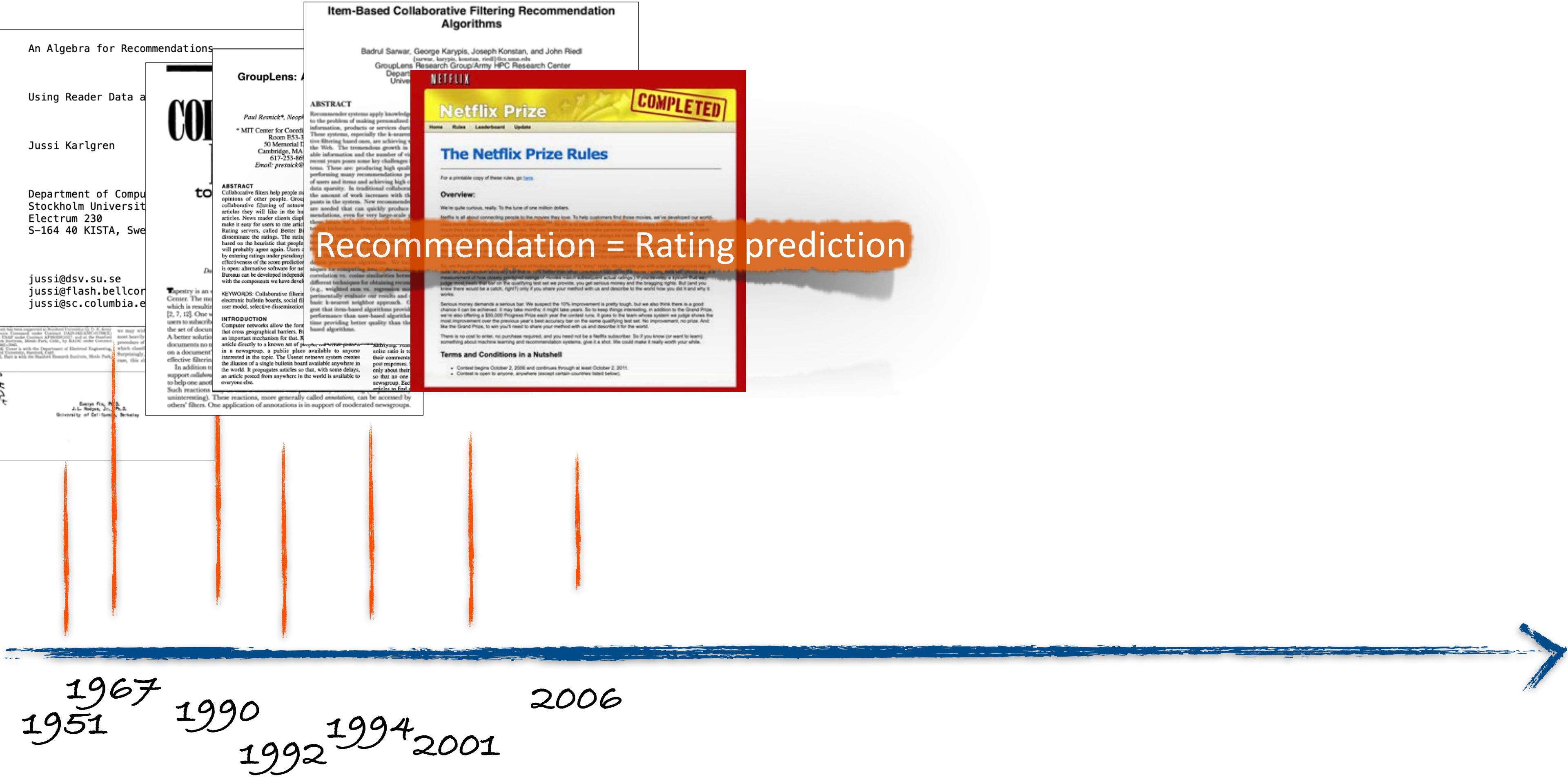

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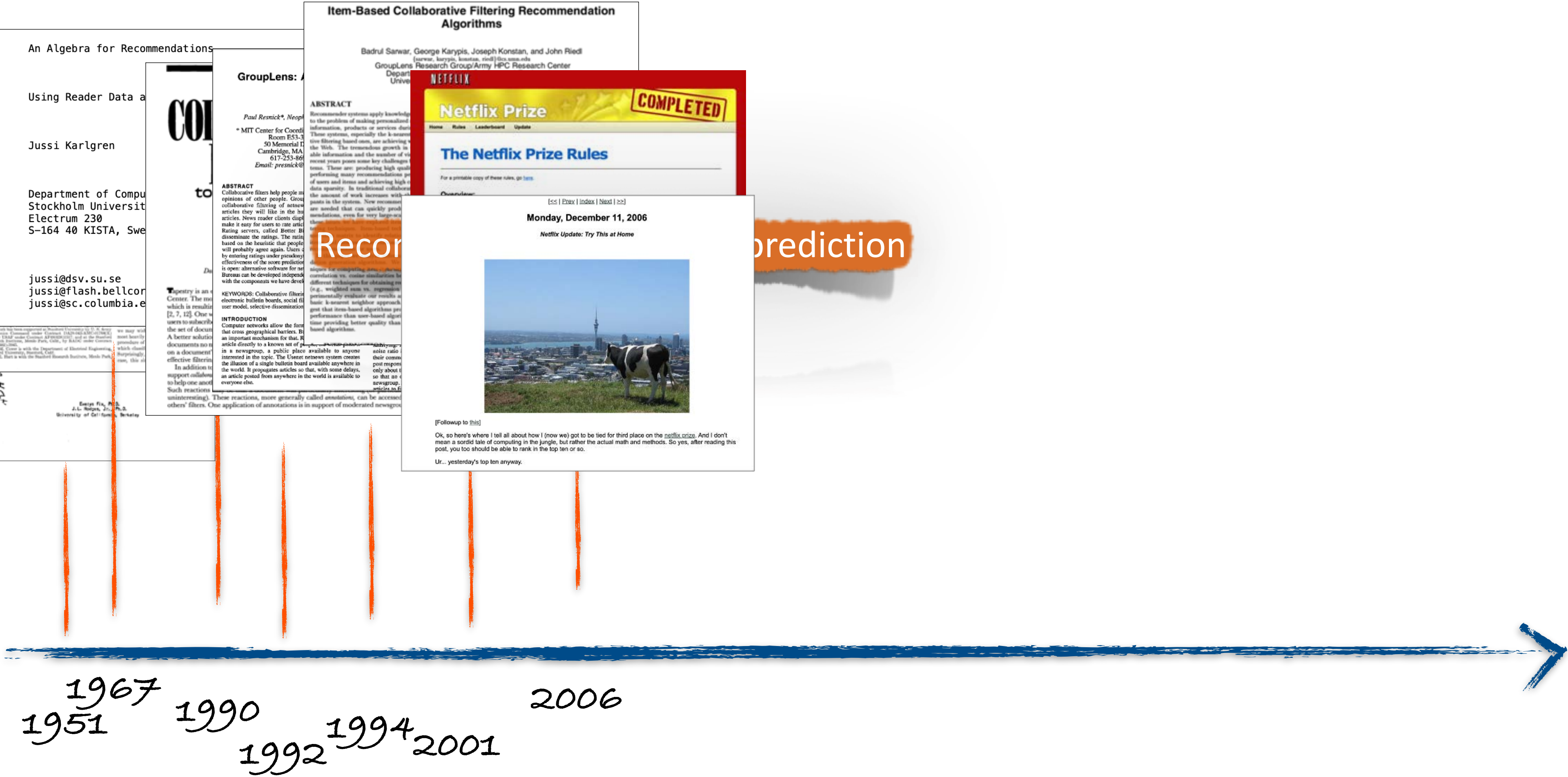
AWESOME
EXCELLENT
GOOD
FORGETTABLE
AWFUL



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Monday, December 11, 2006
Netflix Update: Try This at Home
Recor
prediction
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Monday, December 11, 2006

Netflix Update: Try This at Home

[Followup to this]

Ok, so here's where I tell all about how I (now we) got to be tied for third place on the netflix prize. And I don't mean a sordid tale of computing in the jungle, but rather the actual math and methods. So yes, after reading this post, you too should be able to rank in the top ten or so.

Ur... yesterday's top ten anyway.

My first disclaimer is that our last submission which tied for third place was only actually good enough for ninth place or so. It landed where it did because, just for giggles and grins, we blended results (50/50) with Jetrays who had a similar score to us at the time.

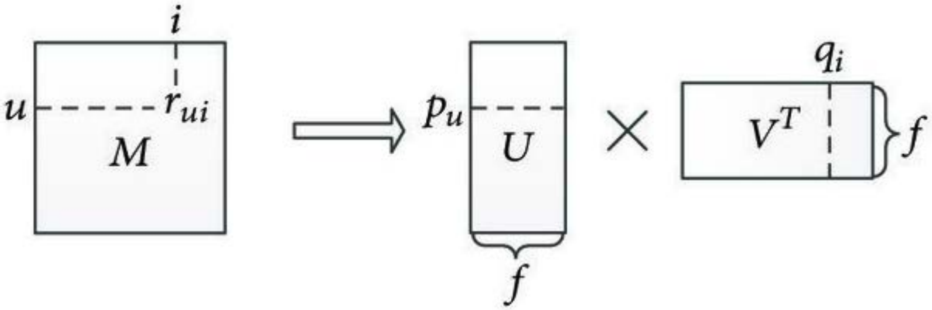
Second, my friend Vincent has been manning the runs on his desktop machines, diligently fine tuning and squeezing out every last bit of performance possible with whatever controls I could give him (not to mention learning python so he could write scripts to blend submissions and whatnot). In short, almost all my progress since my last post has been due to other people. In the meantime I've implemented a handful of failed attempts at improving the performance, plus one or two minorly successful ones which I'll get to.

Now for the method to the mathness, begining with a review of the problem:

Netflix provided 100M ratings (from 1 to 5) of 17K movies by 500K users. These essentially arrive in the form o triplet of numbers: (User,Movie,Rating). E.g., one such entry might be (105932,14002,3). Times 100 million. No go make sense of it. In particular, for (User,Movie,?) not in the database, tell me what the Rating would be--tha is, predict how the given User would rate the given Movie.

I'm tempted to get all philosophical on my soap box here and go into ways of thinking about this stuff and modeling vs function mapping approaches, yadda yadda, but I know you all are just here for the math, so I'll that for the next hapless hosteler who asks me what I do for a living.

Users	User-item interactions matrix	Items
suscribers	rating given by a user to a movie (integer)	movies
readers	time spent by a reader on an article (float)	articles
buyers	product clicked or not when suggested (boolean)	products
	...	

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Department of Compu
Stockholm Universit
Electrum 230
S-164 40 KISTA, Swe
jussi@dsv.su.se
jussi@flash.bellcor
jussi@sc.columbia.e
GroupLens:
ABSTRACT
INTRODUCTION
Item-Based Collaborative Filtering Recommendation Algorithms
Badrul Sarwar, George Karypis, Joseph Konstan, and John Riedl
GroupLens Research Group/Army HPC Research Center
ABSTRACT
NETFLIX
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Recommenders06 - Late Summer School on
The Present and Future of Recommender Systems
On September 12-13, 2006 the Summer School will study the Present and Future of Recommender Systems.
The Summer School will be held in the idyllic setting of the Euskalduna Palace in Bilbao, Spain.
Introduction
Recommender Systems are applications that provide personalized advice to users about products or services they might be interested in. Recommender Systems are playing a major role in the Digital and Social Networking Revolution and becoming a part of everyday life. They are helping people efficiently manage content overload and dive into the long tail of content discovery. The social prevalence of this can be evidenced by the evolution of, and demand for, personalized radio, television, video and on-line shopping.
The Summer School will bring together the concepts and practices of Recommender Systems and is intended for both researchers (including Ph.D. students) and for professionals and managers who want to benefit from the best information on Recommender Systems and personalization advances. An in-depth introduction to Recommender Systems will be provided.
Participation in the Summer School is by acceptance only. Ten scholarships for promising students will be granted.
Lecturers will include:
Chris Anderson, Wired Magazine, US
Todd Beaupre, Yahoo, Inc., US
Jim Bennett, Netflix, Inc., US
Dr. Alexander Felfernig, Klagenfurt University, Austria
Dr. Rick Hangartner, MusicStrands, Inc., US
Prof. Juntae Kim, Dongguk University, Korea
Kaushal Kurapati, Ask.com, US
Paul Lamere, Sun Microsystems Labs, US
Dr. Bamshad Mobasher, DePaul University, US
Mike Mull, Yahoo, Inc., US
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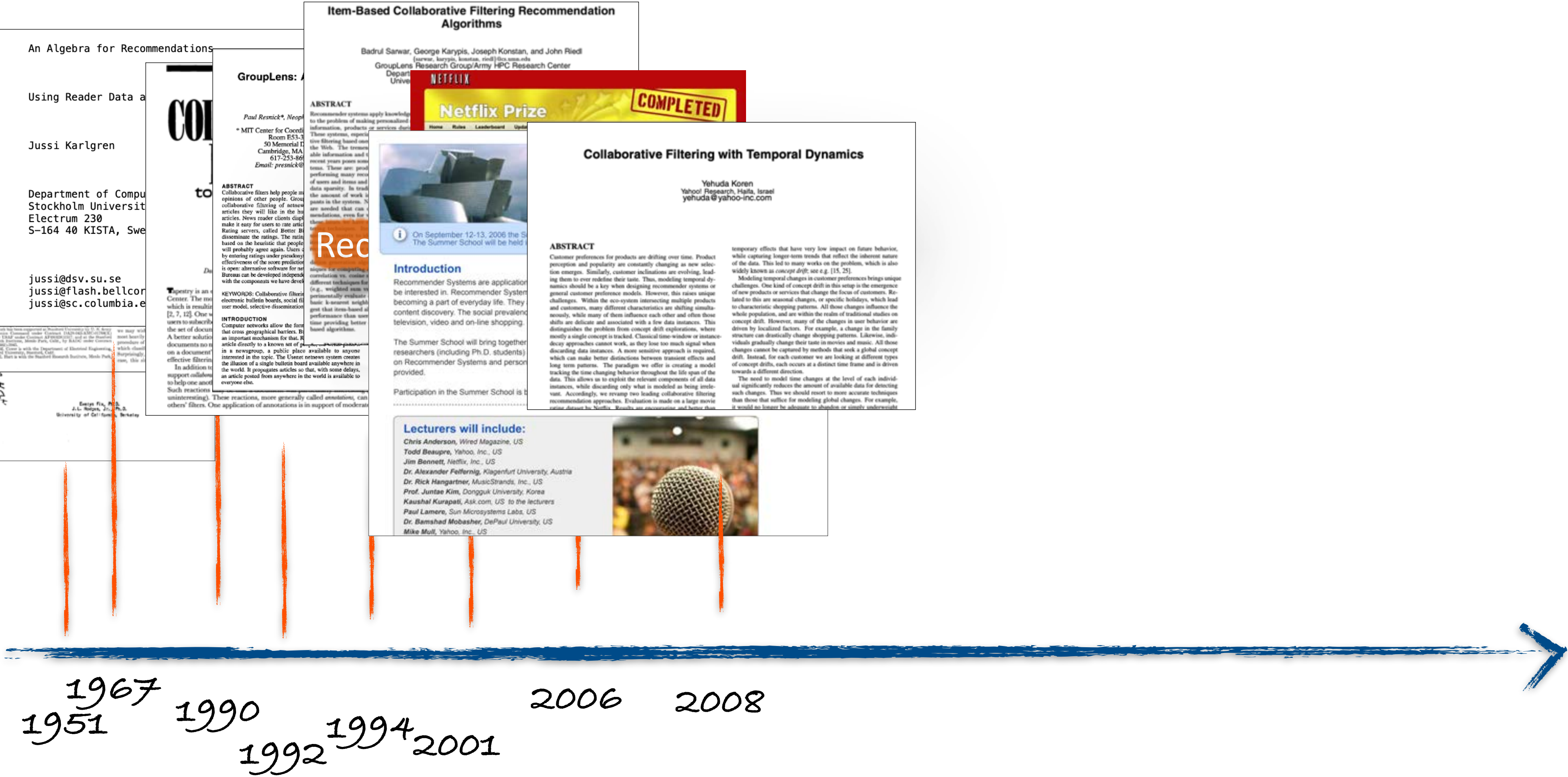
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Mike Mull, Yahoo. Inc., US
Collaborative Filtering with Temporal Dynamics
Yehuda Koren
Yahoo! Research, Haifa, Israel
yehuda@yahoo-inc.com
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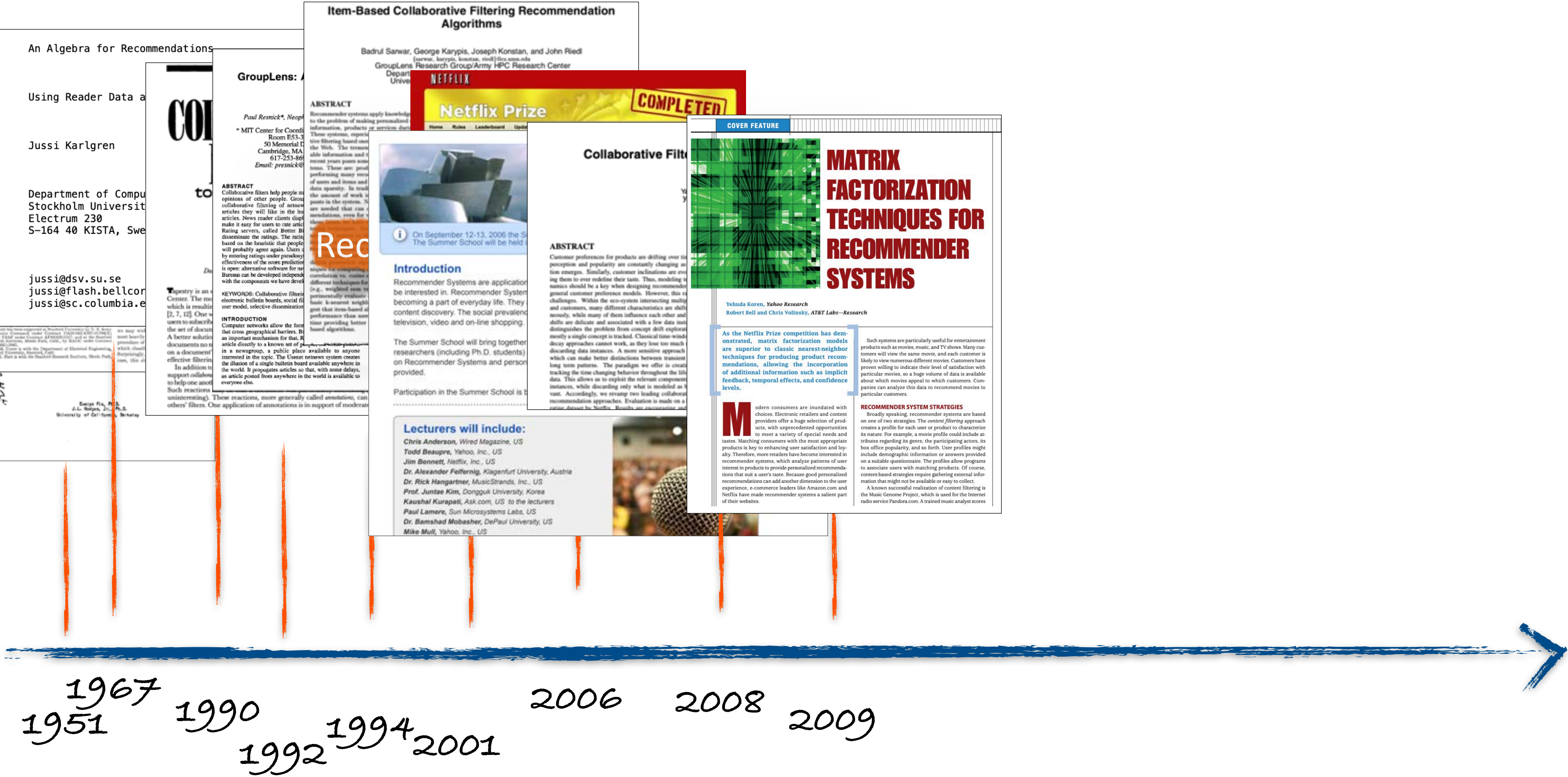

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Robert Bell and Chris Volinsky, AT&T Labs—Research
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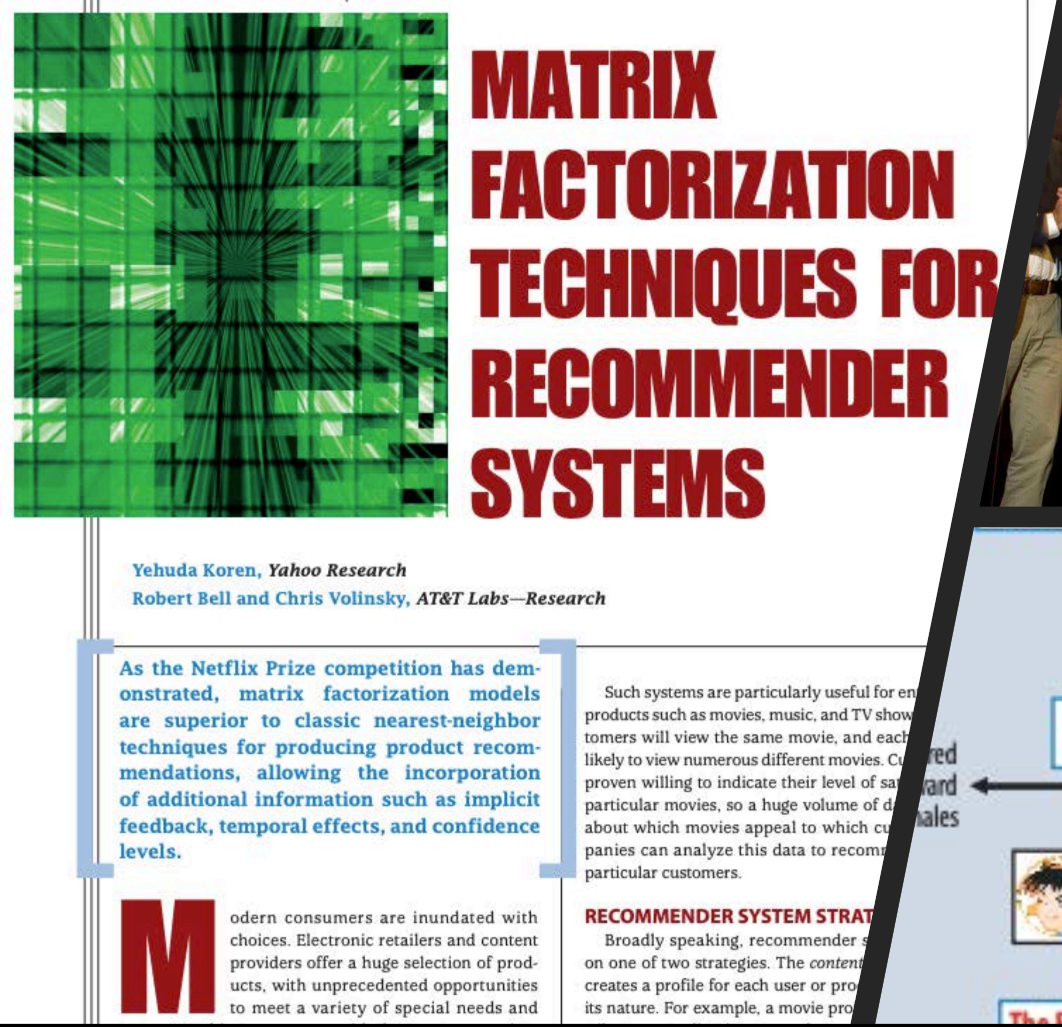


MATRIX FACTORIZATION TECHNIQUES FOR RECOMMENDER SYSTEMS

Yehuda Koren, *Yahoo Research*
Robert Bell and Chris Volinsky, *AT&T Labs—Research*

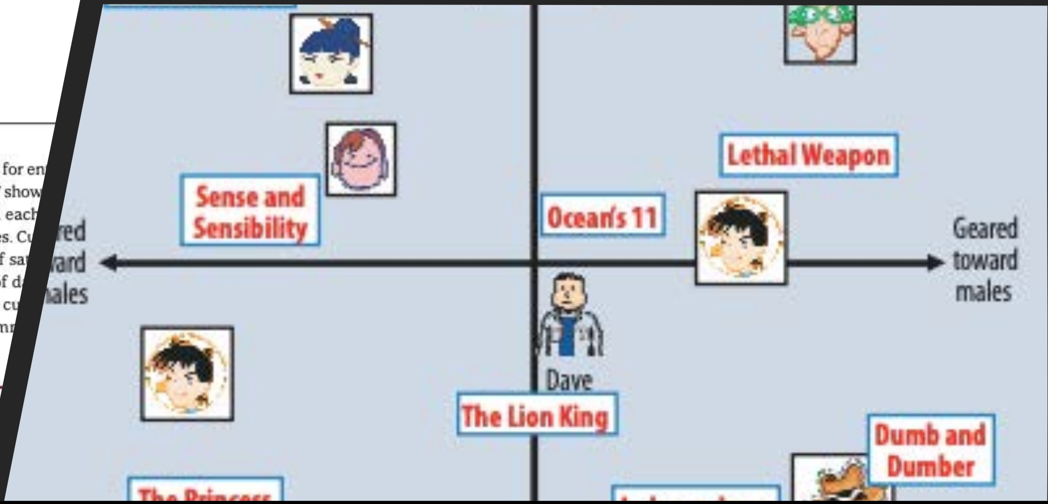
As the Netflix Prize competition has demonstrated, matrix factorization models are superior to classic nearest-neighbor techniques for producing product recommendations, allowing the incorporation of additional information such as implicit feedback, temporal effects, and confidence levels.

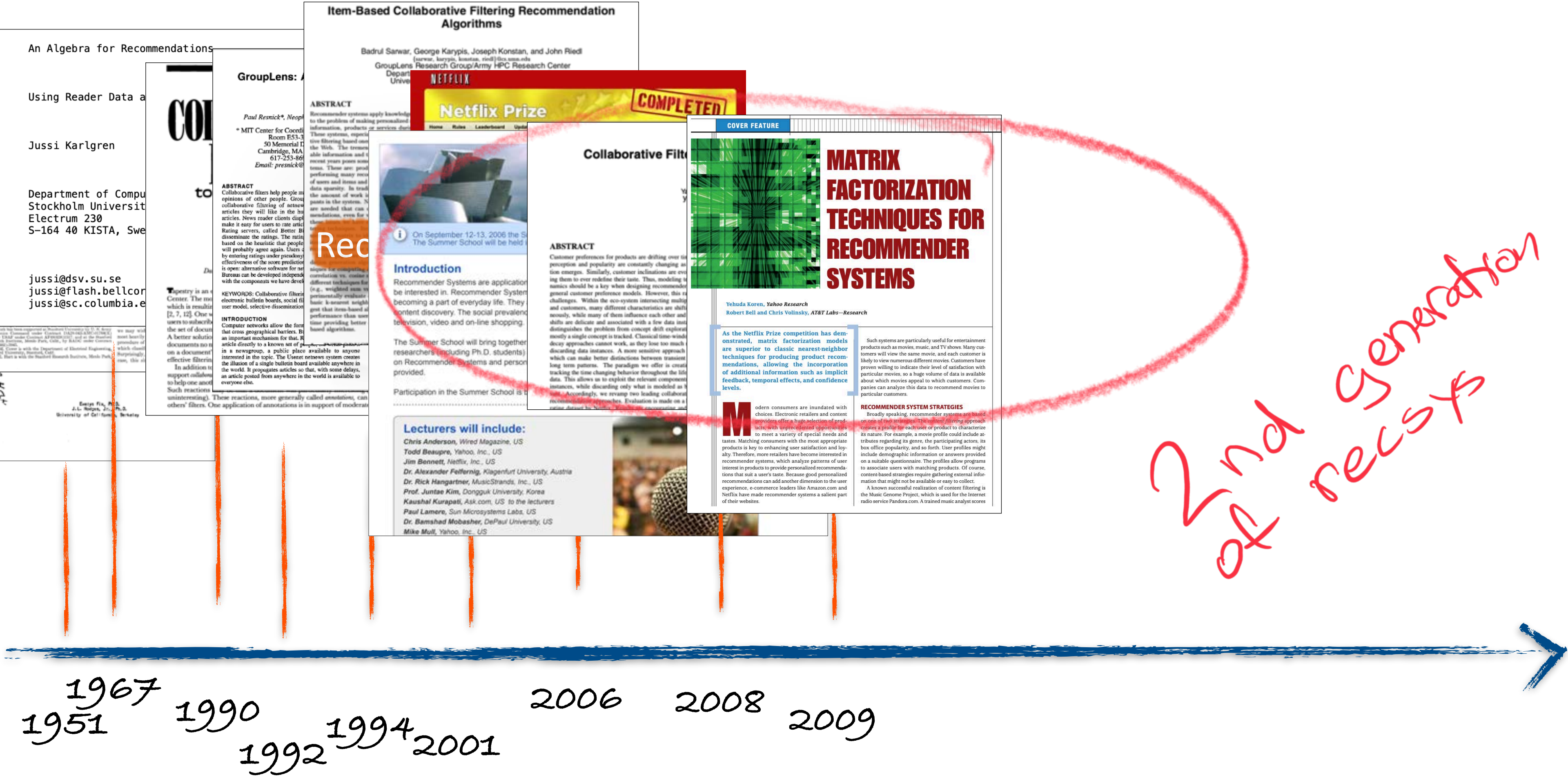
Modern consumers are inundated with choices. Electronic retailers and content providers offer a huge selection of products, with unprecedented opportunities to meet a variety of special needs and

Such systems are particularly useful for en
products such as movies, music, and TV show
tomers will view the same movie, and each
likely to view numerous different movies. Cu
proven willing to indicate their level of sa
particular movies, so a huge volume of d
about which movies appeal to which cu
panies can analyze this data to recomm
particular customers.

RECOMMENDER SYSTEM STRAT

Broadly speaking, recommender s
on one of two strategies. The *content*
creates a profile for each user or pro
its nature. For example, a movie pro

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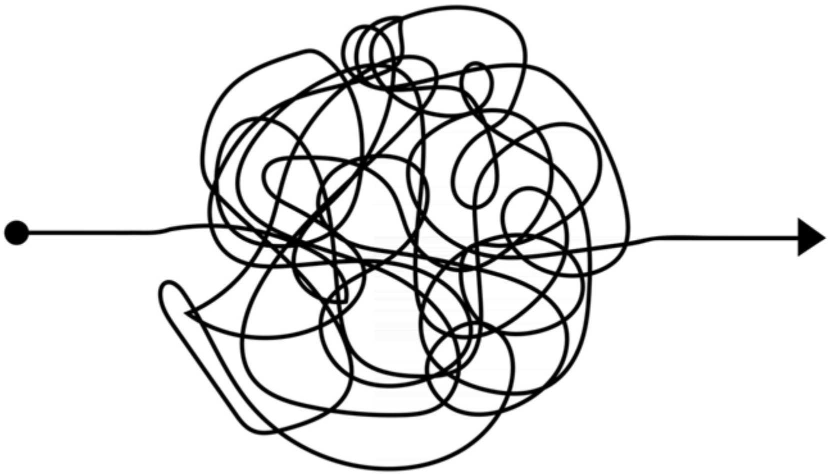
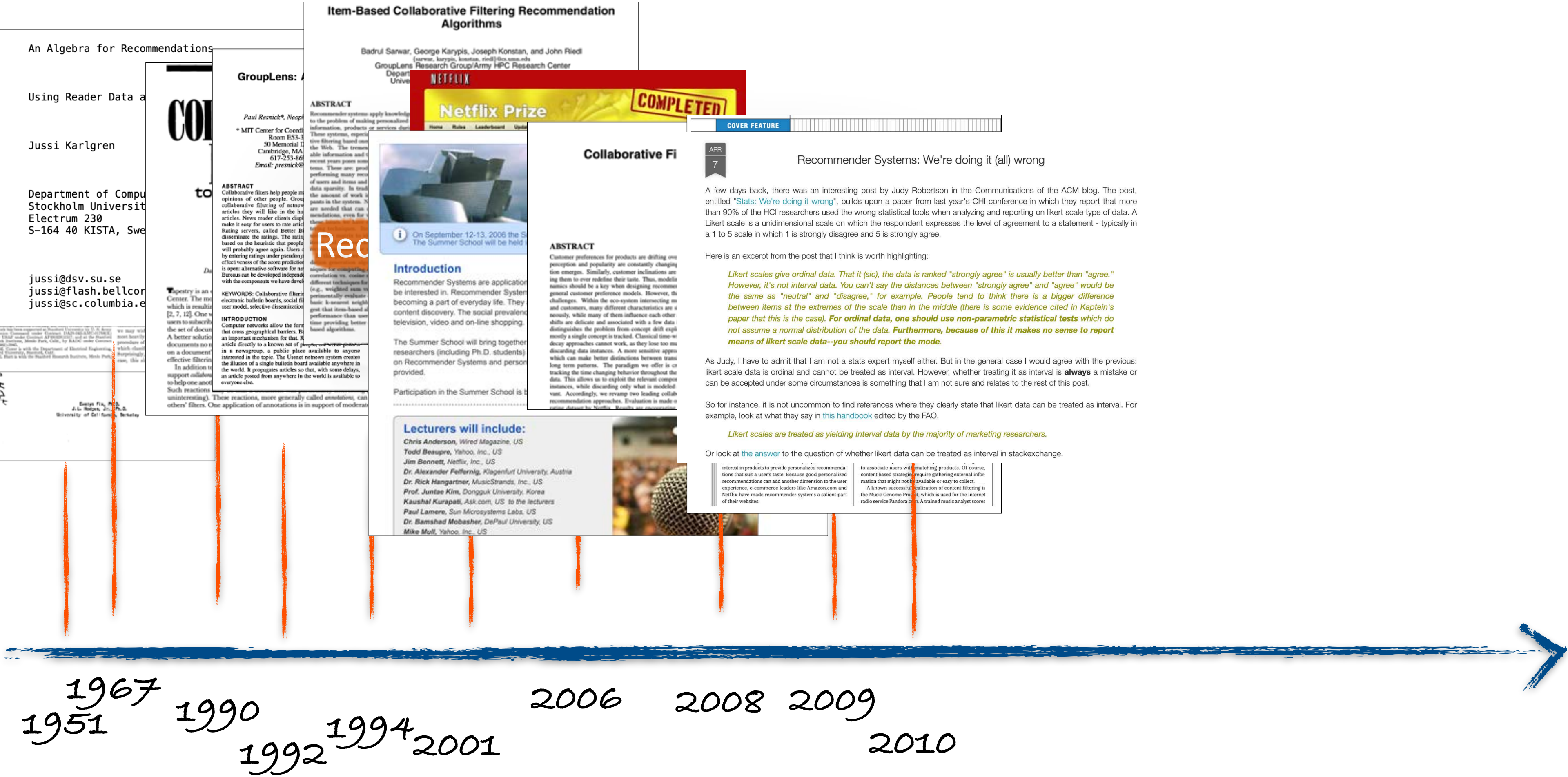


2nd generation of recommender systems

- 00s-10s
- Matrix factorization, latent user/ item representations
- Less intuitive algorithms
- Hard(er) to explain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Recommender Systems: We're doing it (all) wrong
A few days back, there was an interesting post by Judy Robertson in the Communications of the ACM blog. The post, entitled "Stats: We're doing it wrong", builds upon a paper from last year's CHI conference in which they report that more than 90% of the HCI researchers used the wrong statistical tools when analyzing and reporting on likert scale type of data. A Likert scale is a unidimensional scale on which the respondent expresses the level of agreement to a statement - typically in a 1 to 5 scale in which 1 is strongly disagree and 5 is strongly agree.
Here is an excerpt from the post that I think is worth highlighting:
Likert scales give ordinal data. That it (sic), the data is ranked "strongly agree" is usually better than "agree." However, it's not interval data. You can't say the distances between "strongly agree" and "agree" would be the same as "neutral" and "disagree," for example. People tend to think there is a bigger difference between items at the extremes of the scale than in the middle (there is some evidence cited in Kaptein's paper that this is the case). For ordinal data, one should use non-parametric statistical tests which do not assume a normal distribution of the data. Furthermore, because of this it makes no sense to report means of likert scale data--you should report the mode.
As Judy, I have to admit that I am not a stats expert myself either. But in the general case I would agree with the previous: likert scale data is ordinal and cannot be treated as interval. However, whether treating it as interval is always a mistake or can be accepted under some circumstances is something that I am not sure and relates to the rest of this post.
So for instance, it is not uncommon to find references where they clearly state that likert data can be treated as interval. For example, look at what they say in this handbook edited by the FAO.
Likert scales are treated as yielding Interval data by the majority of marketing researchers.
Or look at the answer to the question of whether likert data can be treated as interval in stackexchange.
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Recommender Systems: We're doing it (all) wrong

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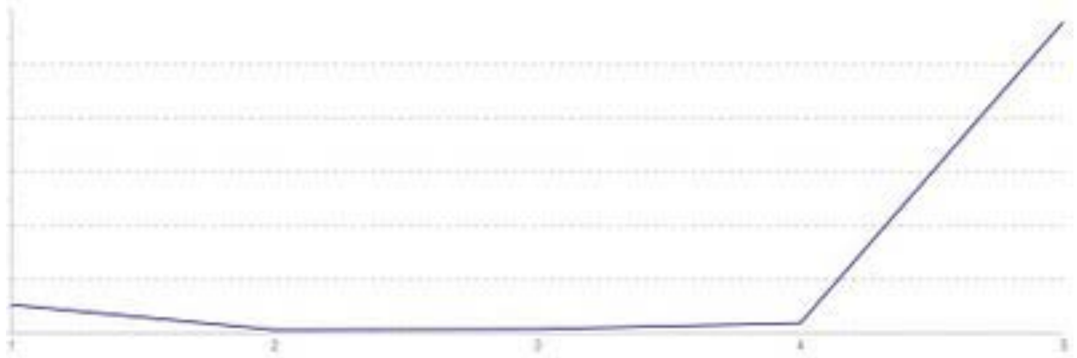
Consequences

At this point, we can safely say that ratings are ordinal but not interval data. However, they are treated as a continuous interval scale in most of the recommender systems research! Let us stop to think a few of the consequences of ratings not being interval data.

Distance Measures: All the neighbor based methods in collaborative filtering are based on the use of some sort of distance measure. The most commonly used are Cosine distance and Pearson Correlation. However, both these distances assume a linear interval scale in their computations! We should conclude that using these distance measures with rating data is wrong. Other measures such as Spearman's rank correlation, do not assume this. But to be honest, I don't remember having read many papers using Spearman.

Error Measures: This is my favorite one... The most commonly accepted measure of success for recommender systems is the Root Mean Squared Error (RMSE). But wait, this measure is explicitly assuming that ratings are also interval data! Similar error measures such as MAE also fall in the same trap... banned! So what could we use? Standard Information Retrieval measures such as Precision and Recall do not necessarily assume interval scale on the ratings, although their mapping to recommendation efficiency may also be questioned. Rank-based measures such as Discounted Cumulative Gain (nDCG) seem like our best bet for now.

https://xkcd.com/1098/



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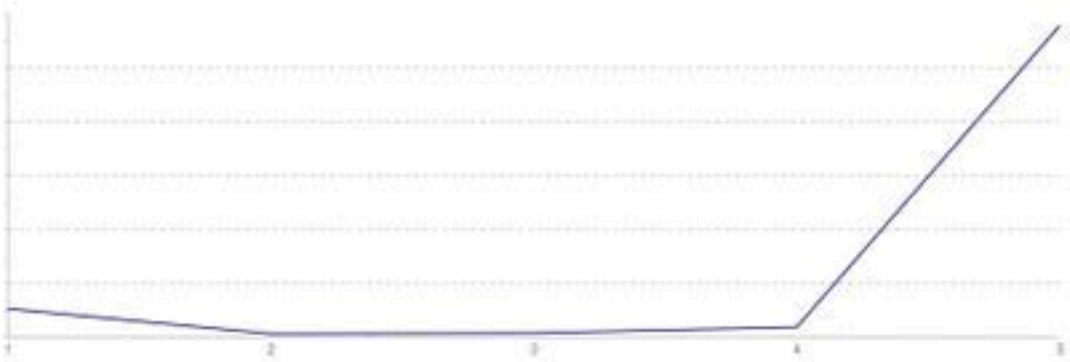
NEWS AND EVENTS

Five Stars Dominate Ratings

By Shiva Rajaraman

Group Product Manager

Sep.22.2009



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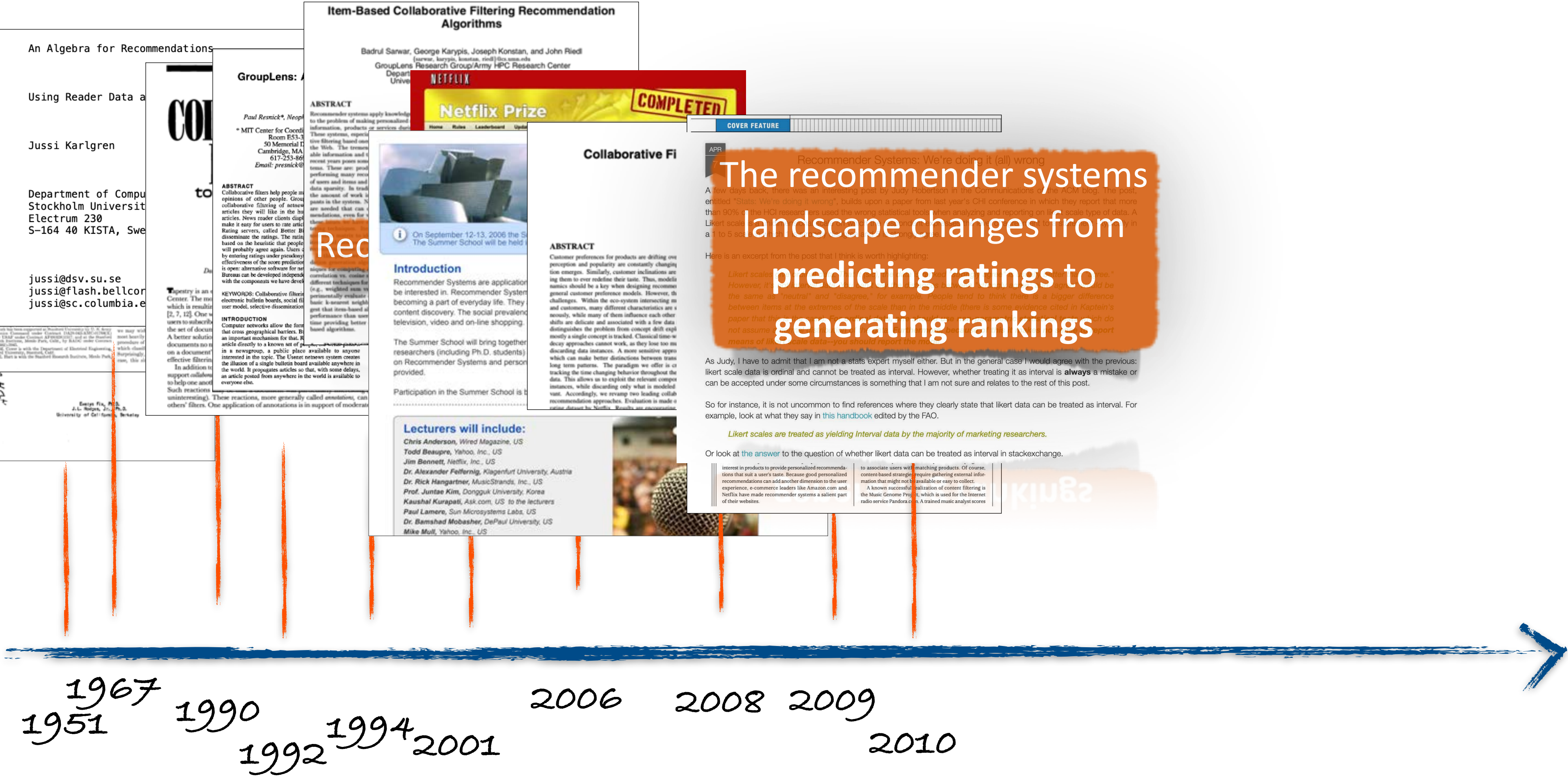
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landscape
1st Workshop on Deep Learning for Recommender Systems
in conjunction with RecSys 2016
15 September 2016, Boston, USA
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Deep Neural Networks for YouTube Recommendations
Paul Covington, Jay Adams, Emre Sargin
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Deep Neural Networks for YouTube Recommendations

Paul Covington, Jay Adams, Emre Sargin
Google
Mountain View, CA
{pcovington, jka, msargin}@google.com

ABSTRACT

YouTube represents one of the largest scale and most sophisticated industrial recommendation systems in existence. In this paper, we describe the system at a high level and focus on the dramatic performance improvements brought by deep learning. The paper is split according to the classic two-stage information retrieval dichotomy: first, we detail a deep candidate generation model and then describe a separate deep ranking model. We also provide practical lessons and insights derived from designing, iterating and maintaining a massive recommendation system with enormous user-facing impact.

Keywords

recommender system; deep learning; scalability

1. INTRODUCTION

YouTube is the world's largest platform for creating, sharing and discovering video content. YouTube recommendations are responsible for helping more than a billion users discover personalized content from an ever-growing corpus of videos. In this paper we will focus on the immense impact deep learning has recently had on the YouTube video recommendations system. Figure 1 illustrates the recommendations on the YouTube mobile app home.

Recommending YouTube videos is extremely challenging from three major perspectives:

- *Scale:* Many existing recommendation algorithms proven to work well on small problems fail to operate on our scale. Highly specialized distributed learning algorithms and efficient serving systems are essential for handling YouTube's massive user base and corpus.
- *Freshness:* YouTube has a very dynamic corpus with

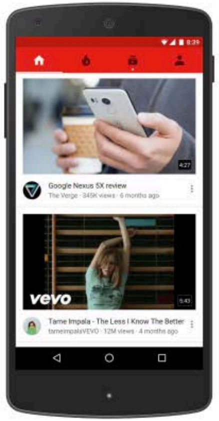
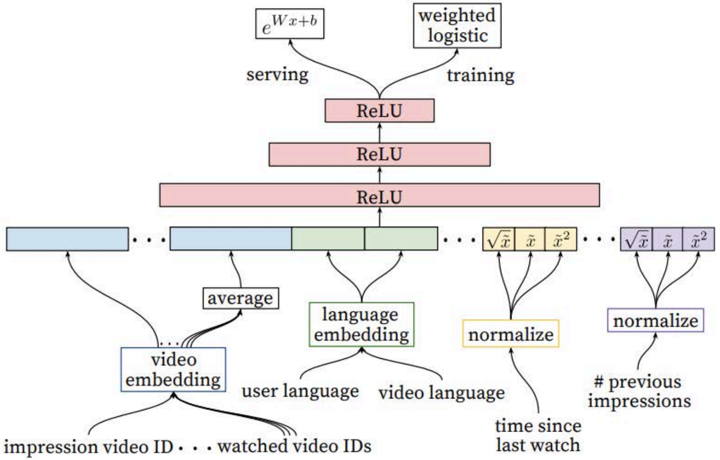
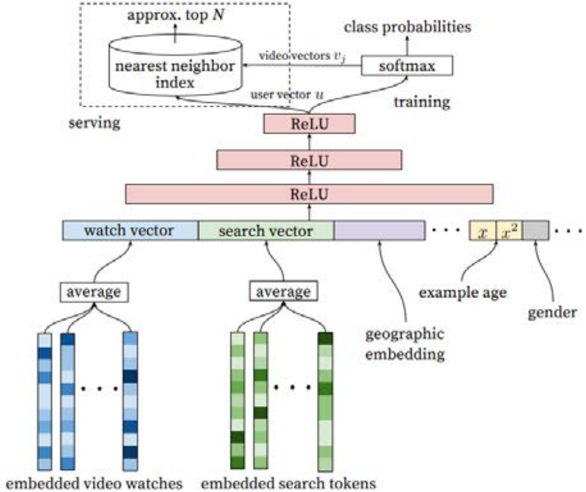


Figure 1: Recommendations displayed mobile app home.

with well-established videos can be an exploration/exploitation perspec

- *Noise:* Historical user behavior on ently difficult to predict due to s ety of unobservable external fact tain the ground truth of user sat model noisy implicit feedback s metadata associated with conter without a well defined ontology



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Published as a conference paper at ICLR 2016
SESSION-BASED RECOMMENDATIONS WITH RECURRENT NEURAL NETWORKS
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Session-based Recommendations with Recurrent Neural Networks

Balázs Hidasi *
Gravity R&D Inc.
Budapest, Hungary
balazs.hidasi@gravityrd.com

Alexandros Karatzoglou
Telefonica Research
Barcelona, Spain
alexk@tid.es

Linas Baltrunas †
Netflix
Los Gatos, CA, USA
lbaltrunas@netflix.com

Domonkos Tikk
Gravity R&D Inc.
Budapest, Hungary
domonkos.tikk@gravityrd.com

Abstract

We apply recurrent neural networks (RNN) on a new domain, namely recommender systems. Real-life recommender systems often face the problem of having to base recommendations only on short session-based data (e.g. a small sportsware website) instead of long user histories (as in the case of Netflix). In this situatior the frequently praised matrix factorization approaches are not accurate. This prob lem is usually overcome in practice by resorting to item-to-item recommendation i.e. recommending similar items. We argue that by modeling the whole sessio more accurate recommendations can be provided. We therefore propose an RN based approach for session-based recommendations. Our approach also consid practical aspects of the task and introduces several modifications to classic RN such as a ranking loss function that make it more viable for this specific prob Experimental results on two data-sets show marked improvements over w used approaches.

1 Introduction

Session-based recommendation is a relatively unappreciated problem in the mac recommender systems community. Many e-commerce recommender systems (

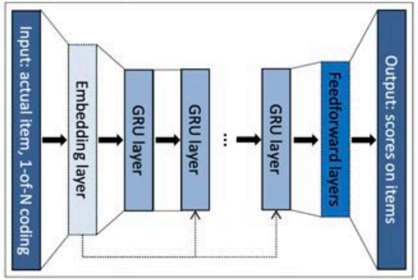

Figure 1: General architecture of the network. Processing of one event of the event stream at once.

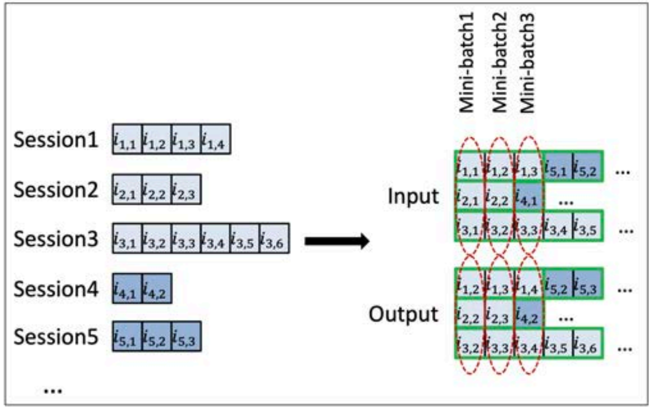

Figure 2: Session-parallel mini-batch creation


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Monolith: Real Time Recommendation System With Collisionless Embedding Table

Zhuoran Liu
Bytedance Inc.

Leqi Zou
Bytedance Inc.

Xuan Zou
Bytedance Inc.

Caihua Wang
Bytedance Inc.

Biao Zhang
Bytedance Inc.

Da Tang
Bytedance Inc.

Bolin Zhu*
Fudan University

Yijie Zhu
Bytedance Inc.

Peng Wu
Bytedance Inc.

Ke Wang
Bytedance Inc.

Youlong Cheng†
Bytedance Inc.
youlong.cheng@bytedance.com

ABSTRACT

Building a scalable and real-time recommendation system is vital for many businesses driven by time-sensitive customer feedback, such as short-videos ranking or online ads. Despite the ubiquitous adoption of production-scale deep learning frameworks like TensorFlow or PyTorch, these general-purpose frameworks fall short of business demands in recommendation scenarios for various reasons: on one hand, tweaking systems based on static parameters and dense computations for recommendation with dynamic and sparse features is detrimental to model quality; on the other hand, such frameworks are designed with batch-training stage and serving stage completely separated, preventing the model from interacting with customer feedback in real-time. These issues led us to reexamine traditional approaches and explore radically different design choices. In this paper, we present **Monolith**[1], a system tailored for online training. Our design has been driven by observations of our application workloads and production environment that reflects a marked departure from other recommendations systems. Our contributions are manifold: first, we crafted a collisionless embedding table with optimizations such as expirable embeddings and frequency filtering to reduce its memory footprint; second, we provide an production-ready online training architecture with high fault-tolerance; finally, we proved that system reliability could be traded-off for real-time learning. Monolith has successfully landed in the BytePlus Recommend[2] product.

ACM Reference Format:
Zhuoran Liu, Leqi Zou, Xuan Zou, Caihua Wang, Biao Zhang, Da Tang, Bolin Zhu, Yijie Zhu, Peng Wu, Ke Wang, and Youlong Cheng. 2022. Monolith: Real Time Recommendation System With Collisionless Embedding Table. In *Proceedings of 5th Workshop on Online Recommender Systems and User Modeling, in conjunction with the 16th ACM Conference on Recommender Systems (ORSUM@ACM RecSys 2022)*. ACM, New York, NY, USA, 10 pages. https://doi.org/XXXXXXX.XXXXXXX

1 INTRODUCTION

The past decade witnessed a boom of businesses powered by recommendation techniques. In pursuit of a better customer experience, delivering personalized content for each individual user as real-time response is a common goal of these business applications. To this end, information from a user's latest interaction is often used as the primary input for training a model, as it would best depict a user's portrait and make predictions of user's interest and future behaviors.

Deep learning have been dominating recommendation models [5, 6, 10, 12, 20, 21] as the gigantic amount of user data is a natural fit for massively data-driven neural models. However, efforts to leverage the power of deep learning in industry-level recommendation systems are constantly encountered with problems arising from the unique characteristics of data derived from real-world user behavior. These data are drastically different from those used

Monolith: Real Time Recommendation System With Collisionless Embedding Table

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Bytedance Inc.

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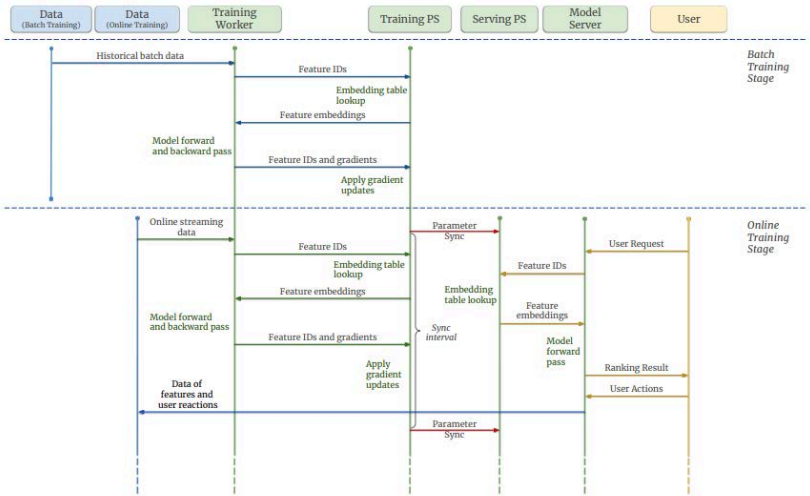

Figure 1: Monolith Online Training Architecture.

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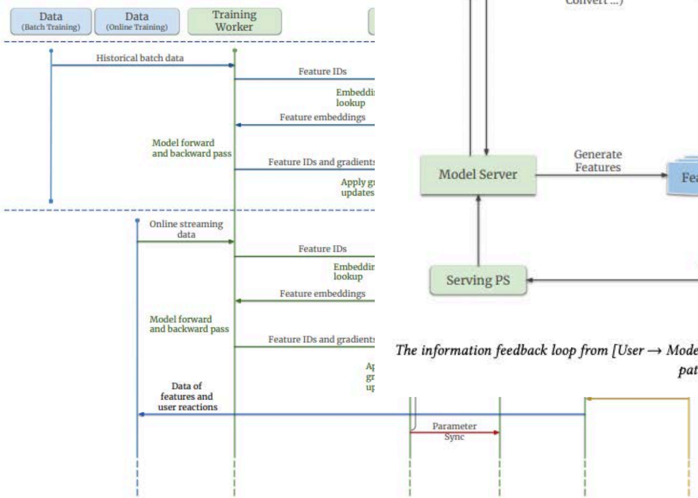

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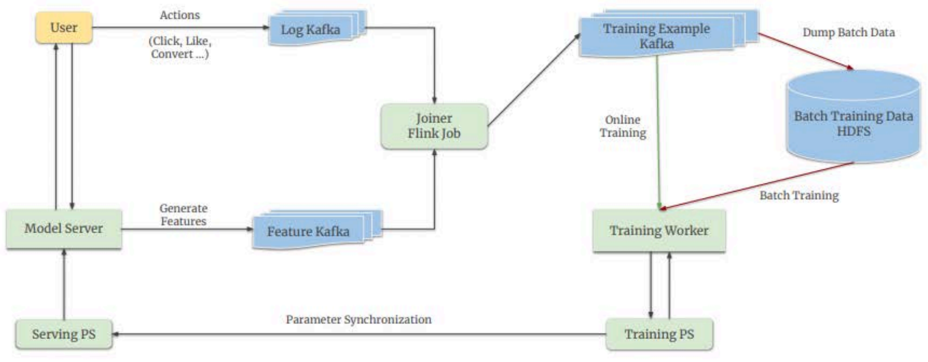

Figure 4: Streaming Engine.

The information feedback loop from [User → Model Server → Training Worker → Model Server → User] would spend a long time when taking the Batch Training path, while the Online Training will close the loop more instantly.

Monolith: Real Time Recommendation System With Collisionless Embedding Table

Zhuoran Liu
Bytedance Inc.

Leqi Zou
Bytedance Inc.

Caihua Wang
Bytedance Inc.

Biao Zhang
Bytedance Inc.

Bolir
Fudan U

ABSTRACT

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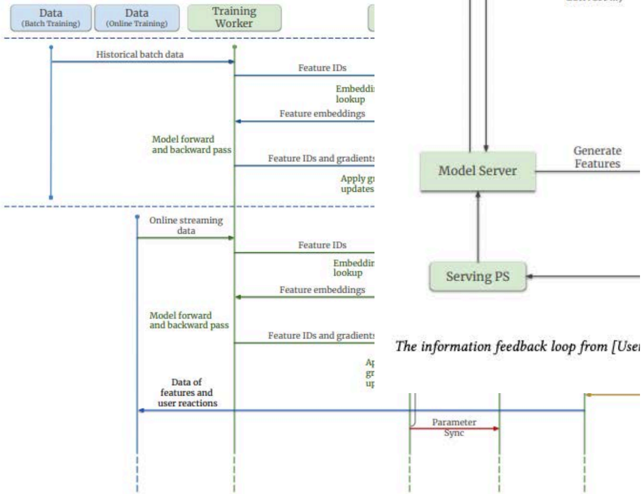
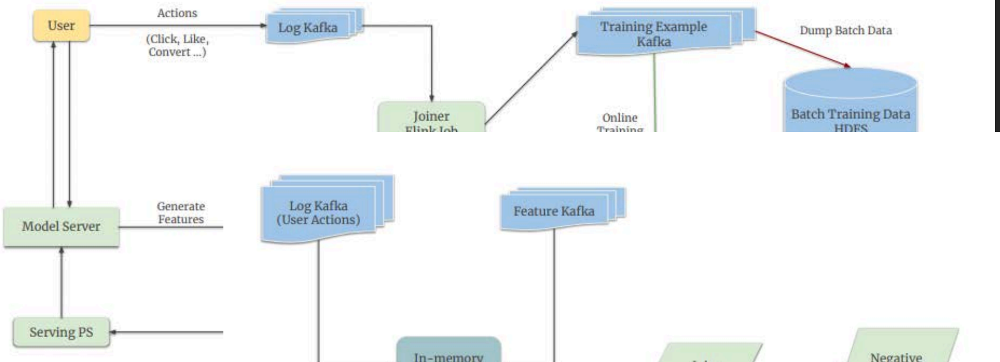


Figure 1: Monolith Online Training Architecture.



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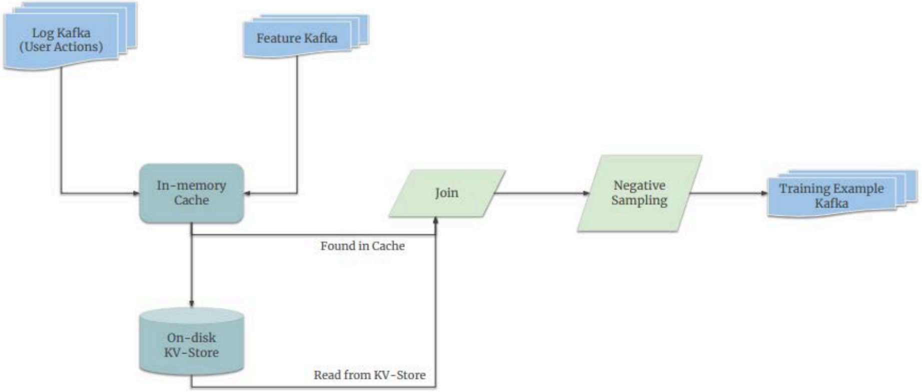

Figure 5: Online Joiner.

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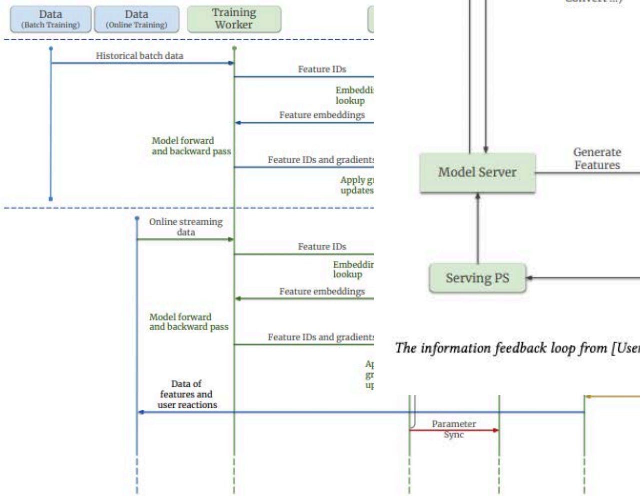

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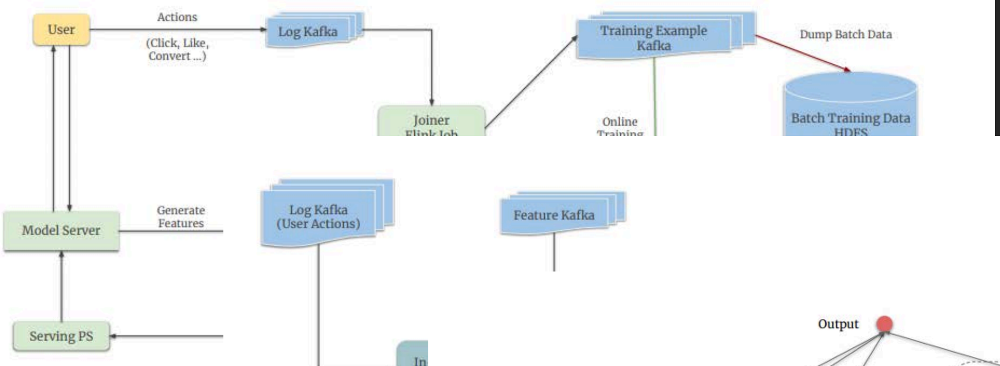

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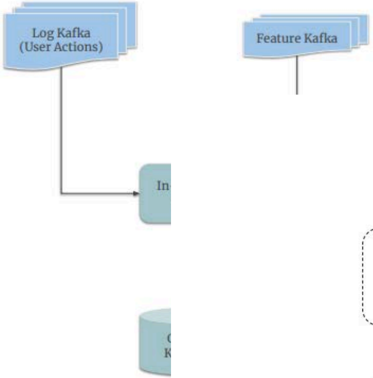


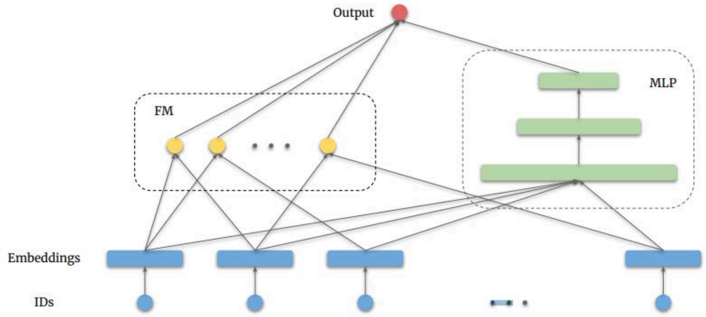
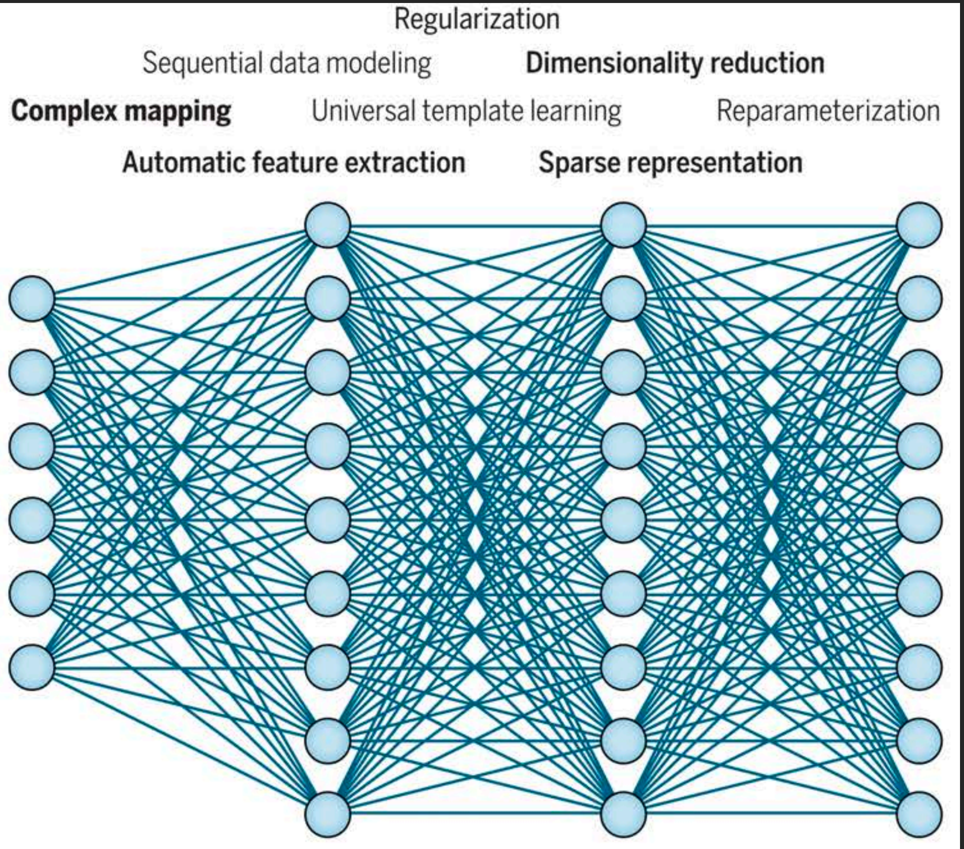


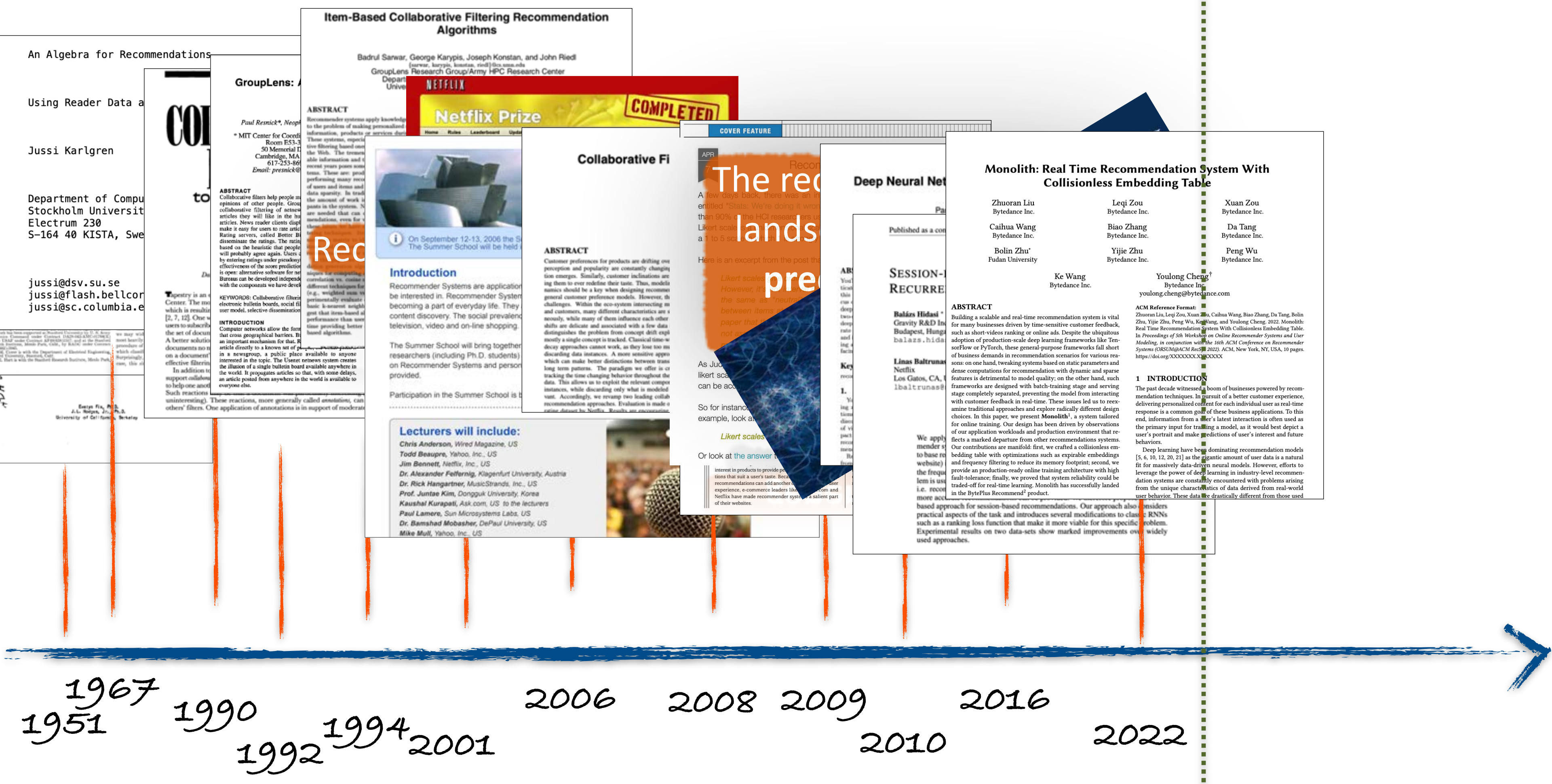
Figure 6: DeepFM model architecture.

3rd generation of recsys



3rd generation of recommender systems

- 10s-20s
- Deep learning, implicit feedback
- Non-intuitive algorithms
- Even harder to explain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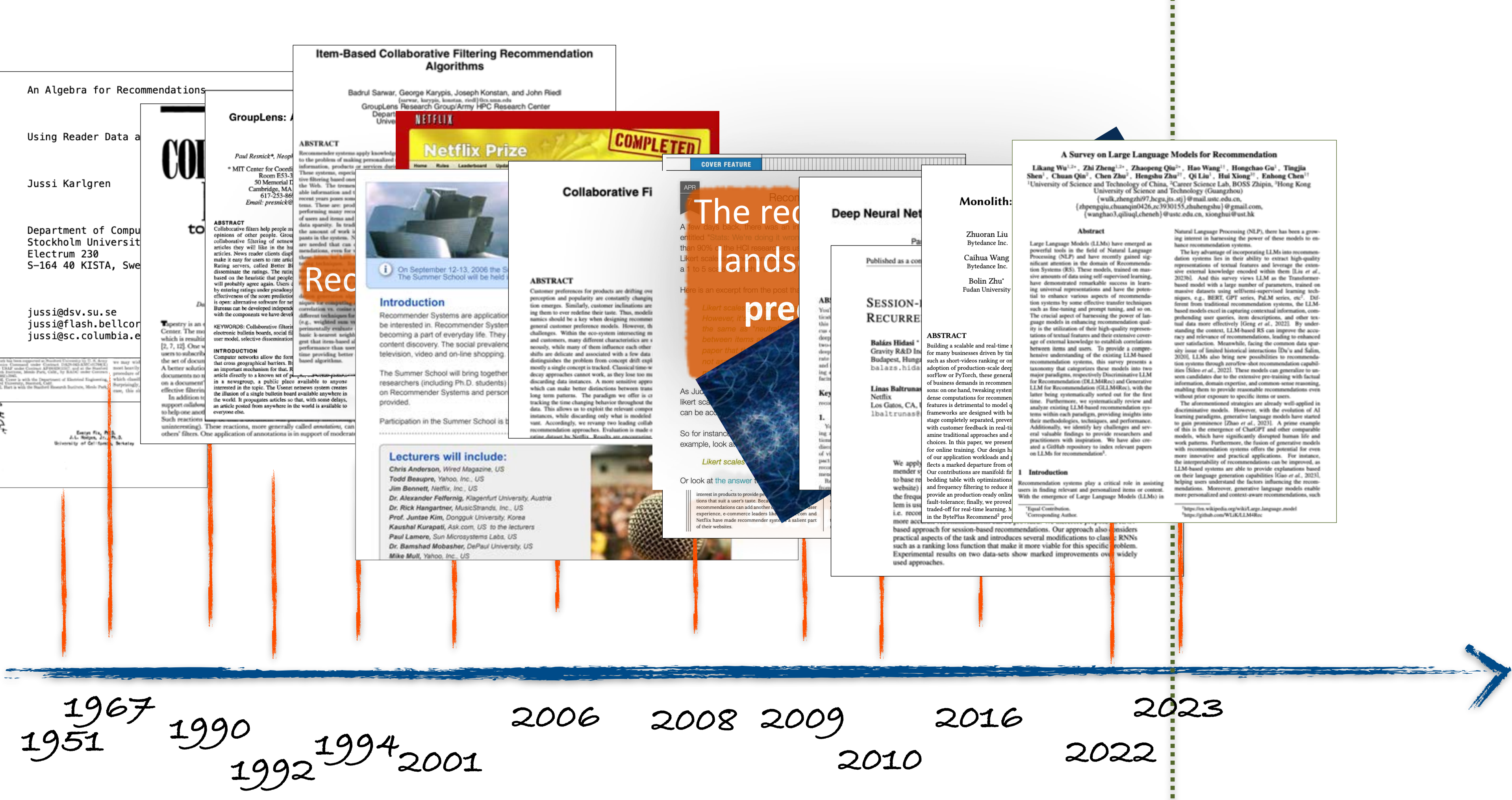
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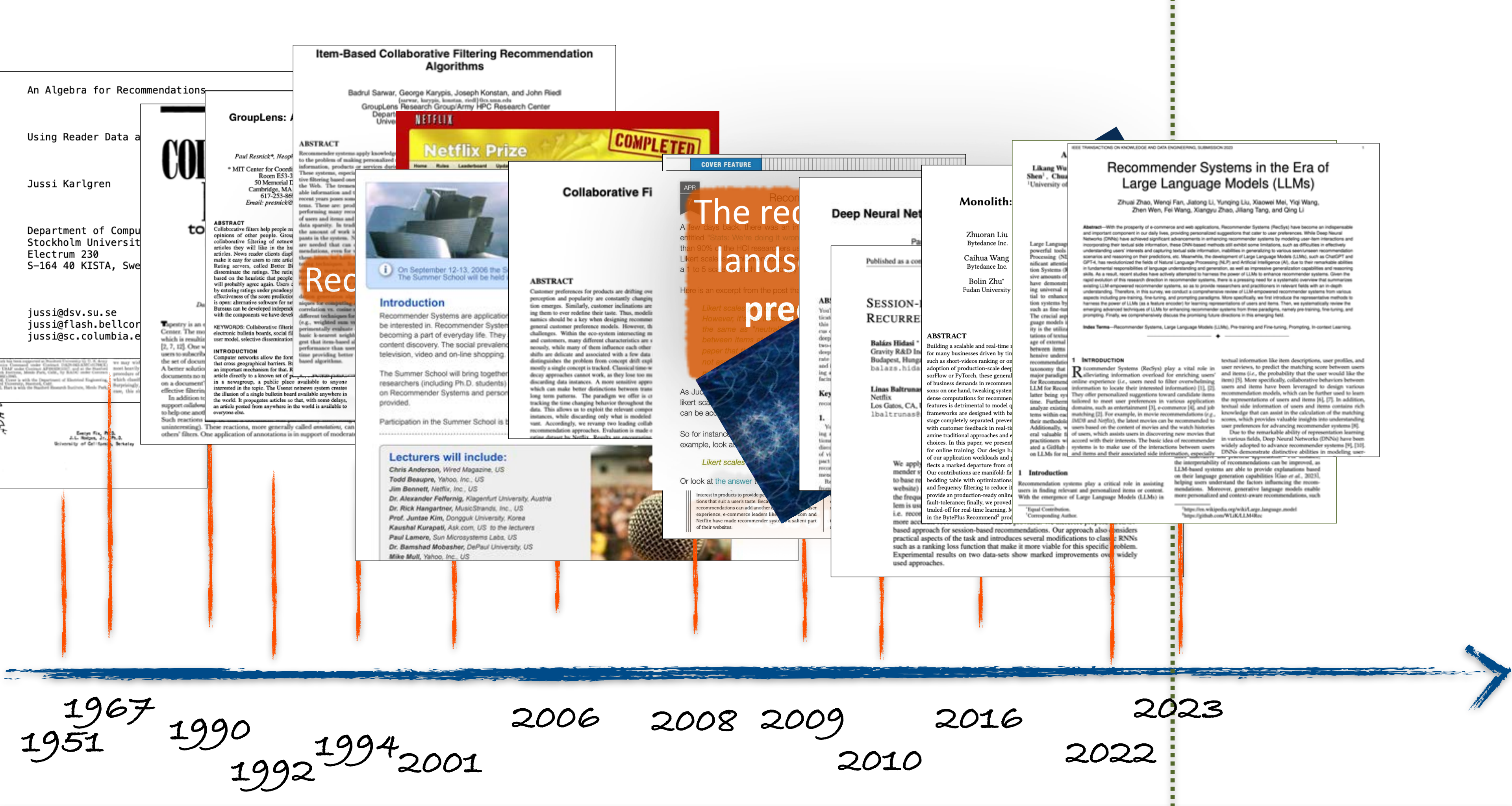
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Jussi Karlgren
Department of Compu
Stockholm Universit
Electrum 230
S-164 40 KISTA, Swe
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jussi@sc.columbia.e
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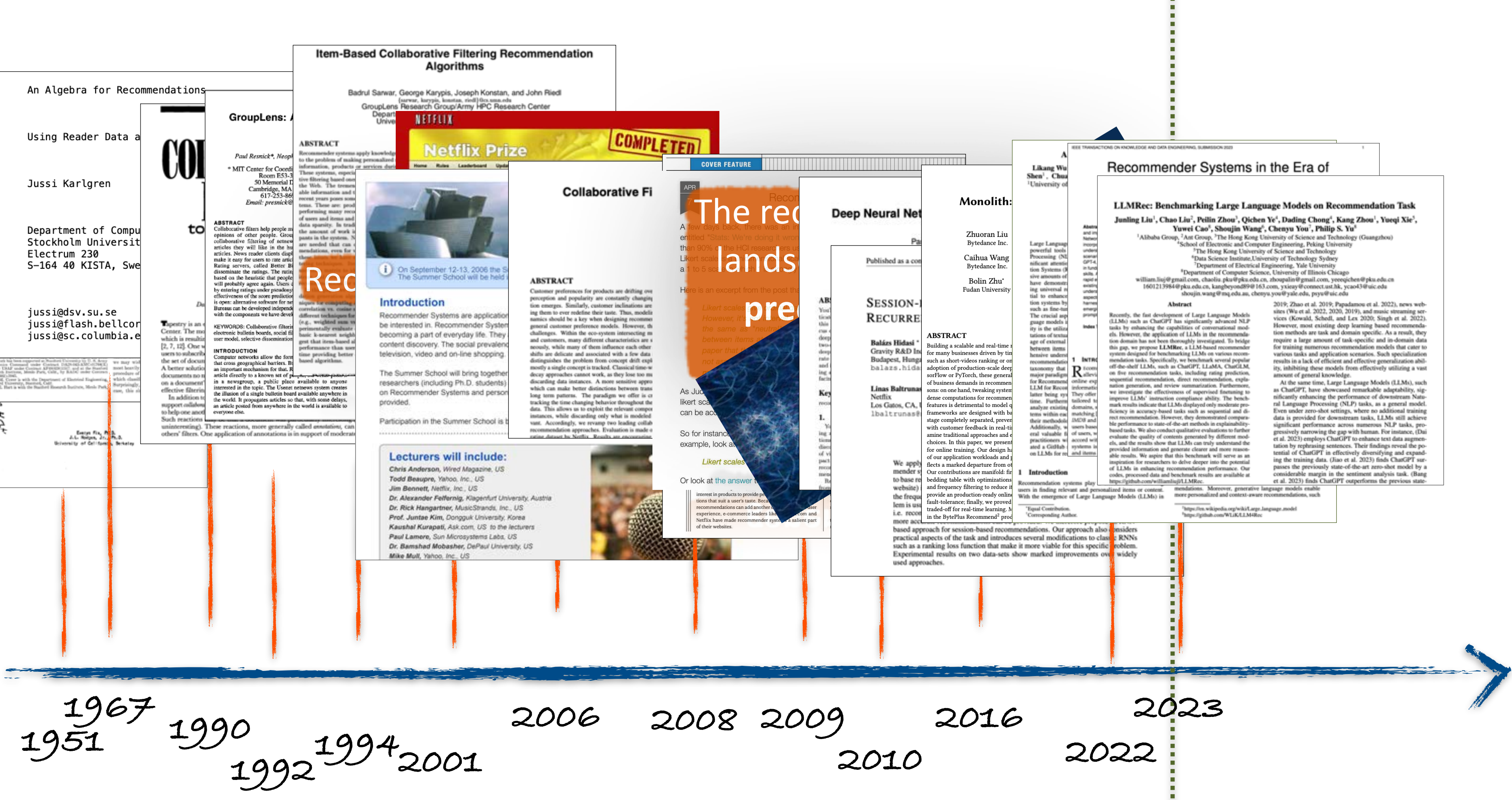
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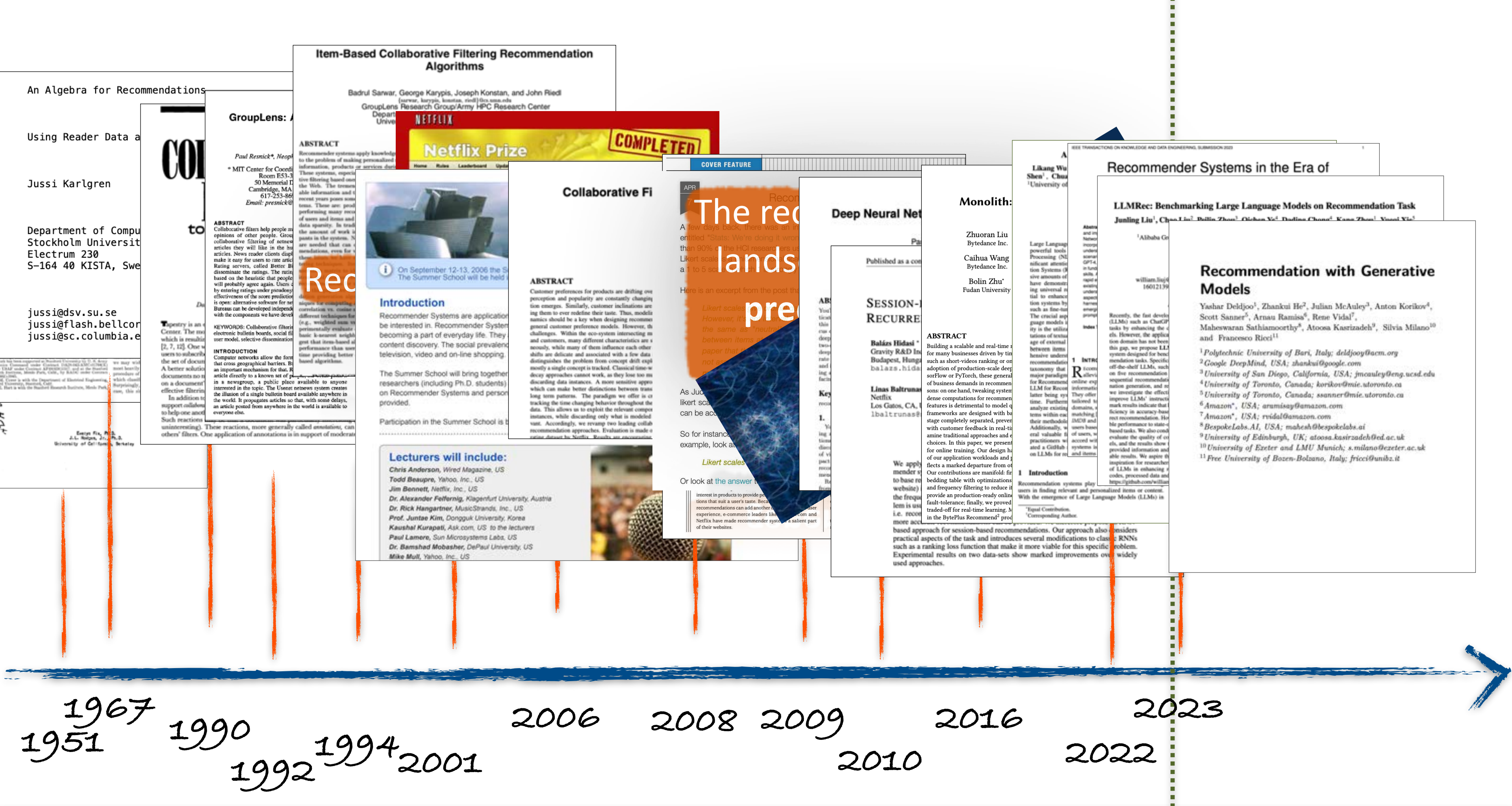
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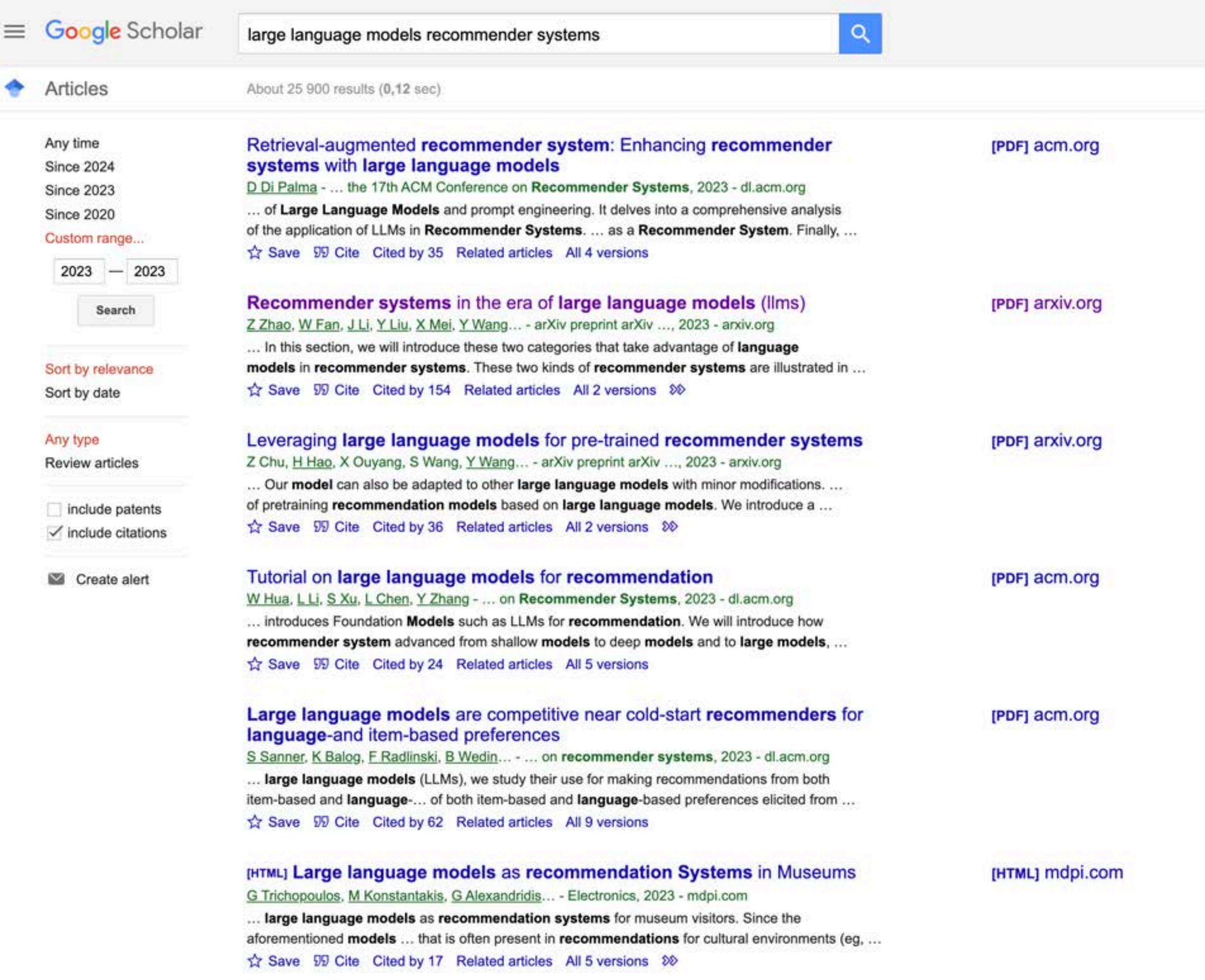
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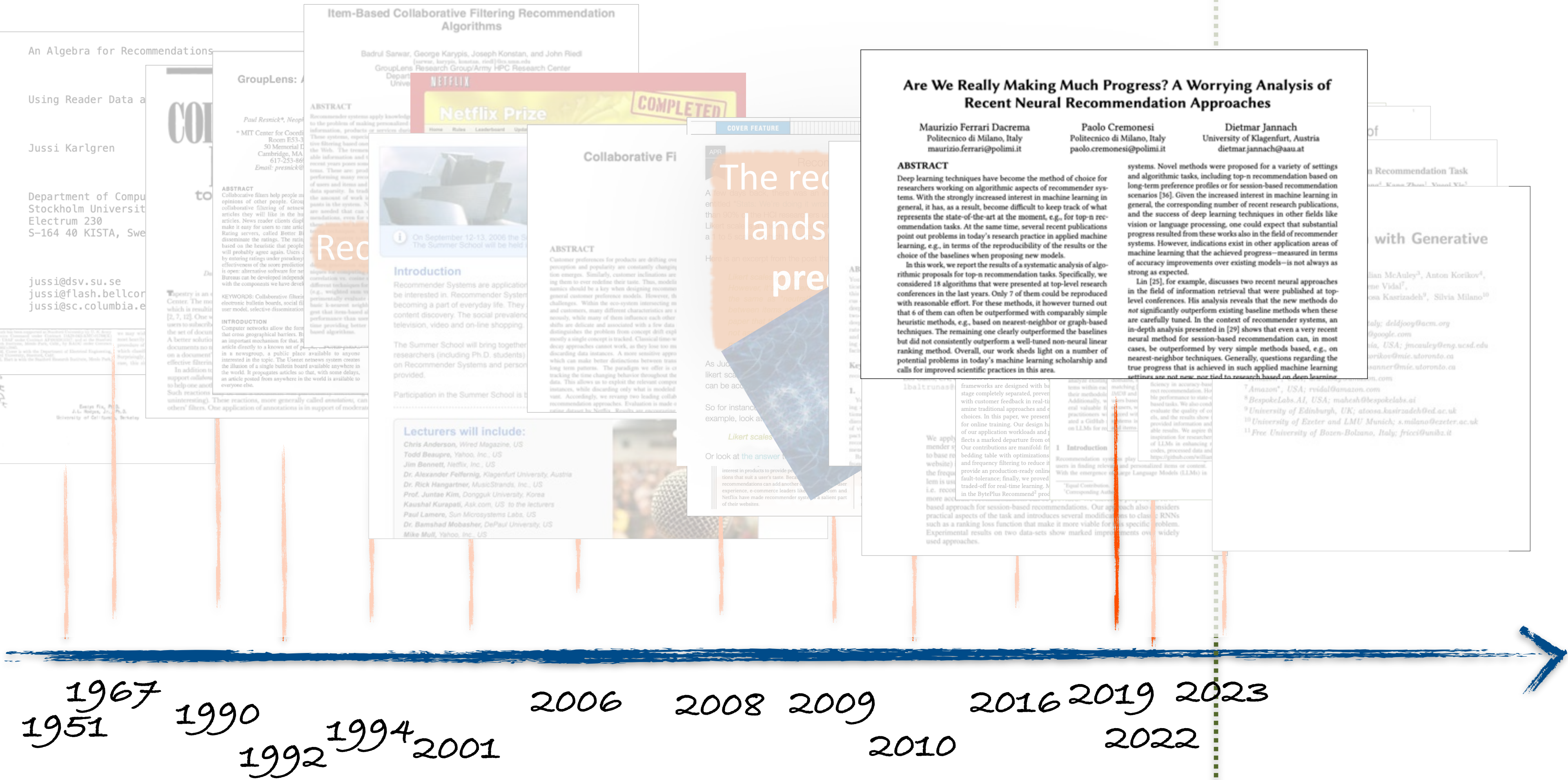
4th generation of recommender systems

- 20s
- LLMs
- Generative recommendations

Hold on…



Are We Really Making Much Progress? A Worrying Analysis of Recent Neural Recommendation Approaches

Maurizio Ferrari Dacrema
Politecnico di Milano, Italy
maurizio.ferrari@polimi.it

Paolo Cremonesi
Politecnico di Milano, Italy
paolo.cremonesi@polimi.it

Dietmar Jannach
University of Klagenfurt, Austria
dietmar.jannach@aau.at

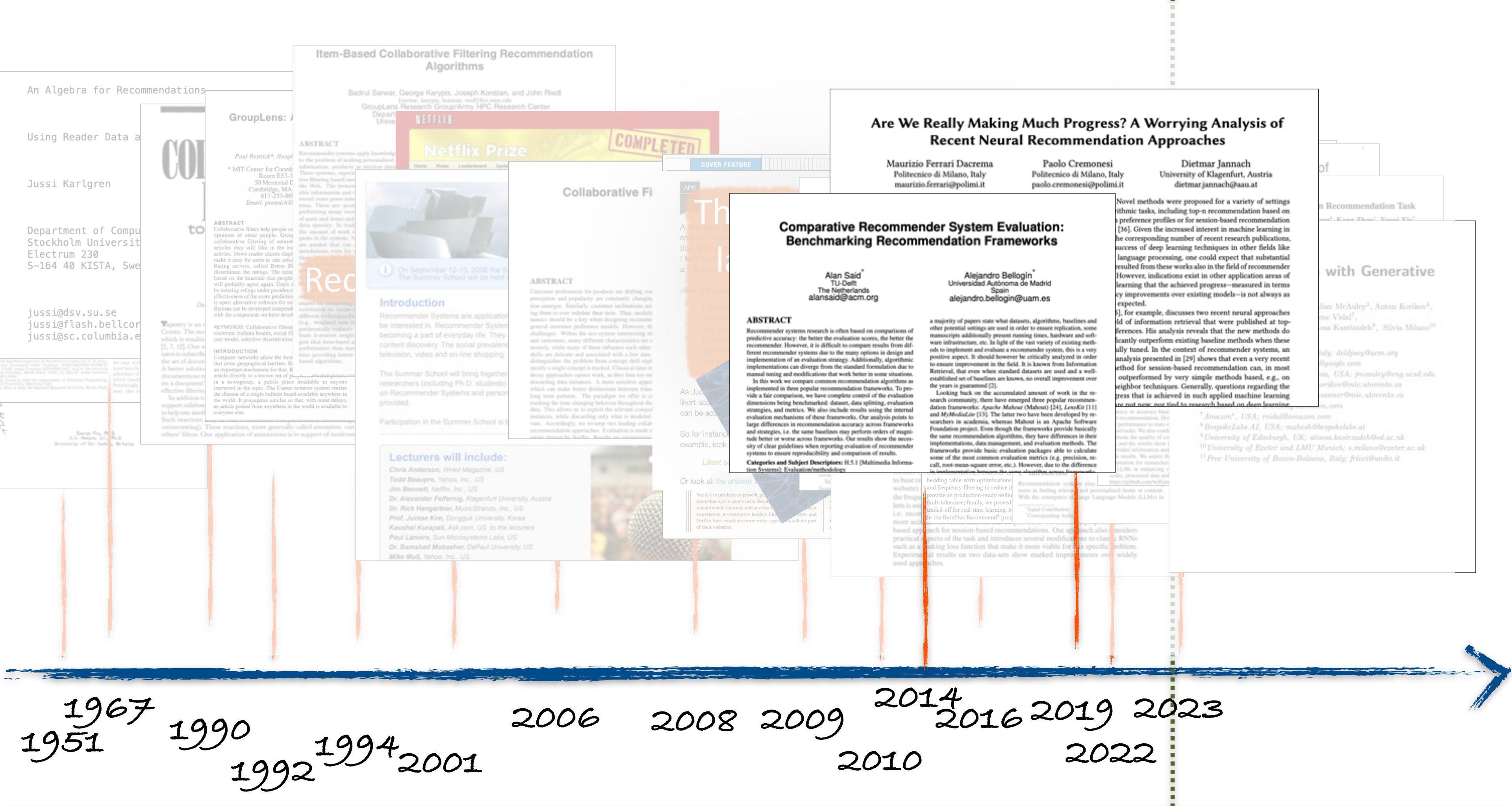
ABSTRACT

Deep learning techniques have become the method of choice for researchers working on algorithmic aspects of recommender systems. With the strongly increased interest in machine learning in general, it has, as a result, become difficult to keep track of what represents the state-of-the-art at the moment, e.g., for top-n recommendation tasks. At the same time, several recent publications point out problems in today's research practice in applied machine learning, e.g., in terms of the reproducibility of the results or the choice of the baselines when proposing new models.

In this work, we report the results of a systematic analysis of algorithmic proposals for top-n recommendation tasks. Specifically, we considered 18 algorithms that were presented at top-level research conferences in the last years. Only 7 of them could be reproduced with reasonable effort. For these methods, it however turned out that 6 of them can often be outperformed with comparably simple heuristic methods, e.g., based on nearest-neighbor or graph-based techniques. The remaining one clearly outperformed the baselines but did not consistently outperform a well-tuned non-neural linear ranking method. Overall, our work sheds light on a number of potential problems in today's machine learning scholarship and calls for improved scientific practices in this area.

systems. Novel methods were proposed for a variety of settings and algorithmic tasks, including top-n recommendation based on long-term preference profiles or for session-based recommendation scenarios [36]. Given the increased interest in machine learning in general, the corresponding number of recent research publications, and the success of deep learning techniques in other fields like vision or language processing, one could expect that substantial progress resulted from these works also in the field of recommender systems. However, indications exist in other application areas of machine learning that the achieved progress—measured in terms of accuracy improvements over existing models—is not always as strong as expected.

Lin [25], for example, discusses two recent neural approaches in the field of information retrieval that were published at top-level conferences. His analysis reveals that the new methods do *not* significantly outperform existing baseline methods when these are carefully tuned. In the context of recommender systems, an in-depth analysis presented in [29] shows that even a very recent neural method for session-based recommendation can, in most cases, be outperformed by very simple methods based, e.g., on nearest-neighbor techniques. Generally, questions regarding the true progress that is achieved in such applied machine learning settings are not new, nor tied to research based on deep learning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University of Klagenfurt, Austria
dietmar.jannach@aau.at
Comparative Recommender System Evaluation: Benchmarking Recommendation Frameworks
Alan Said
TU-Delft
The Netherlands
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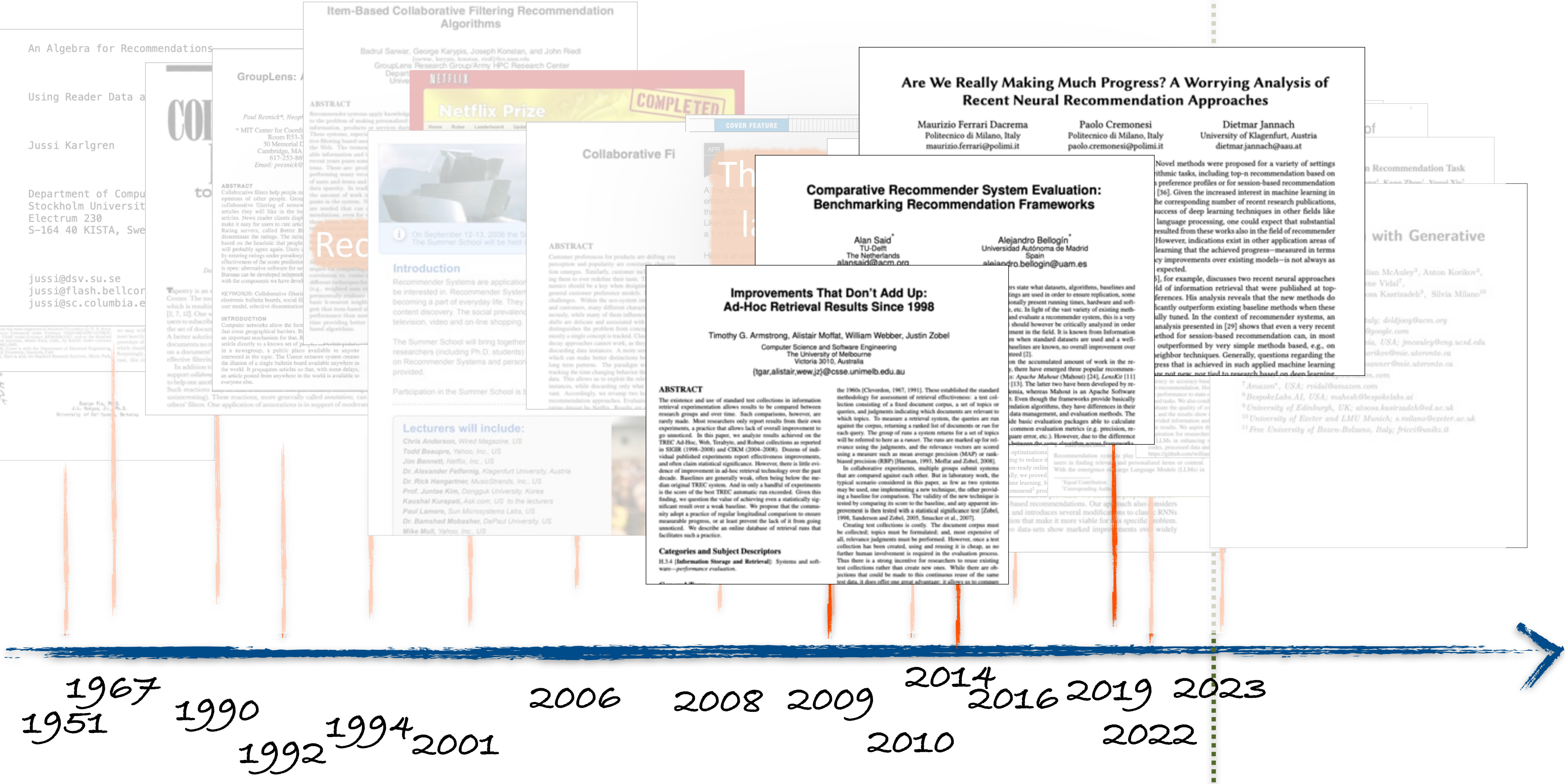
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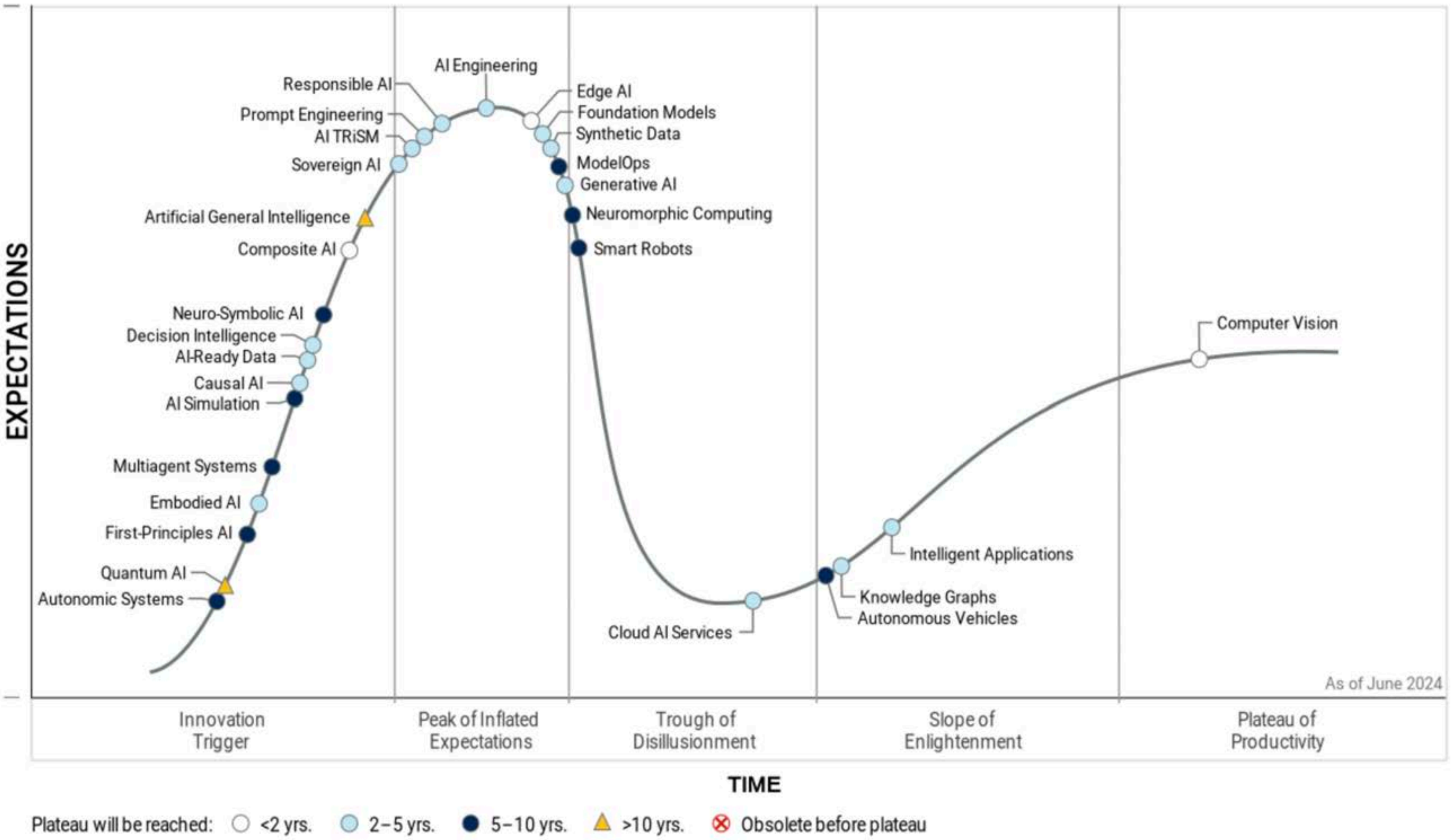

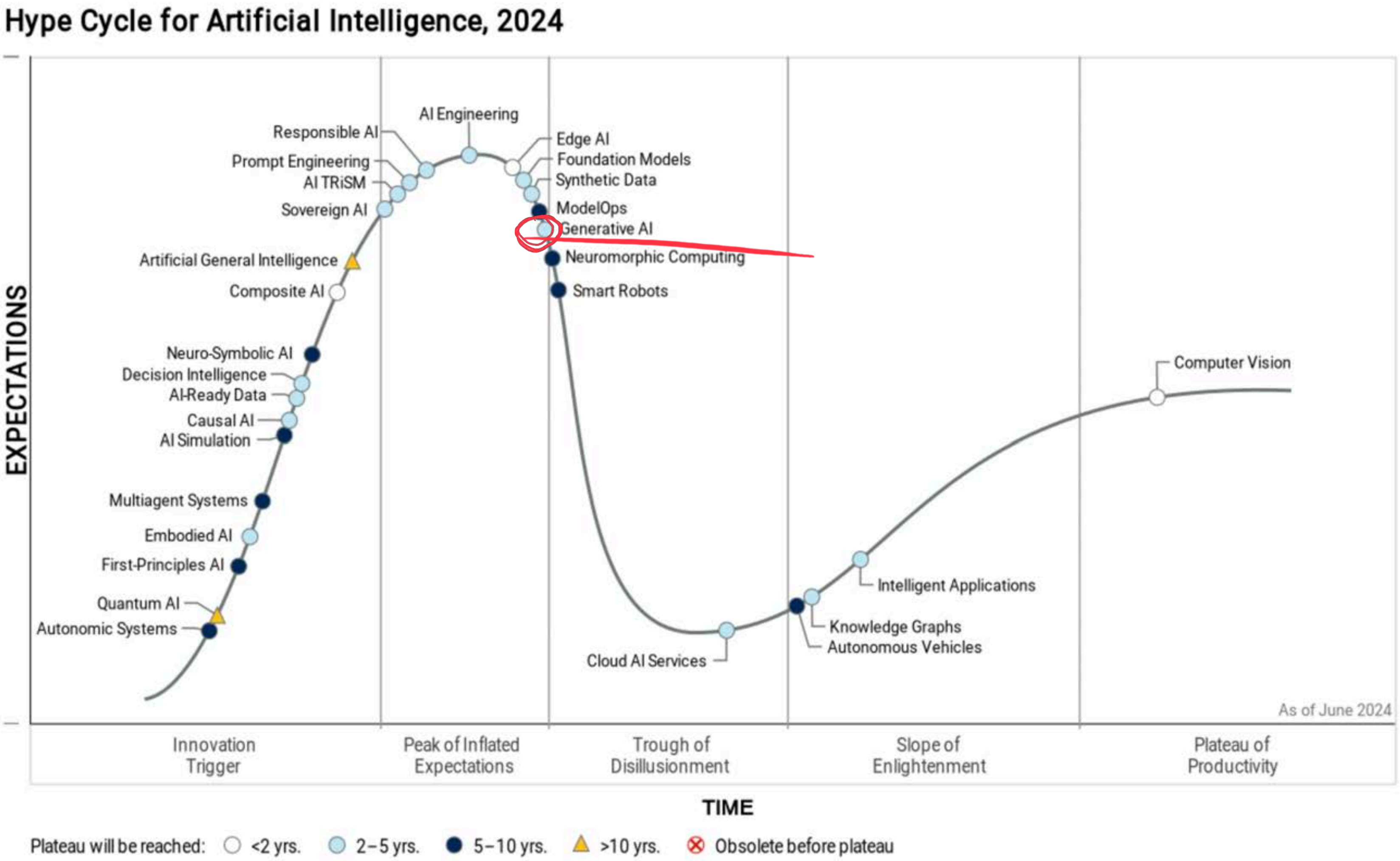
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Neuro-Symbolic AI
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Causal AI
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Quantum AI
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Computer Vision
Intelligent Applications
Knowledge Graphs
Autonomous Vehicles
Cloud AI Services
As of June 2024
Innovation Trigger
Peak of Inflated Expectations
Trough of Disillusionment
Slope of Enlightenment
Plateau of Productivity
TIME
Plateau will be reached: <2 yrs. 2–5 yrs. 5–10 yrs. >10 yrs. Obsolete before plateau

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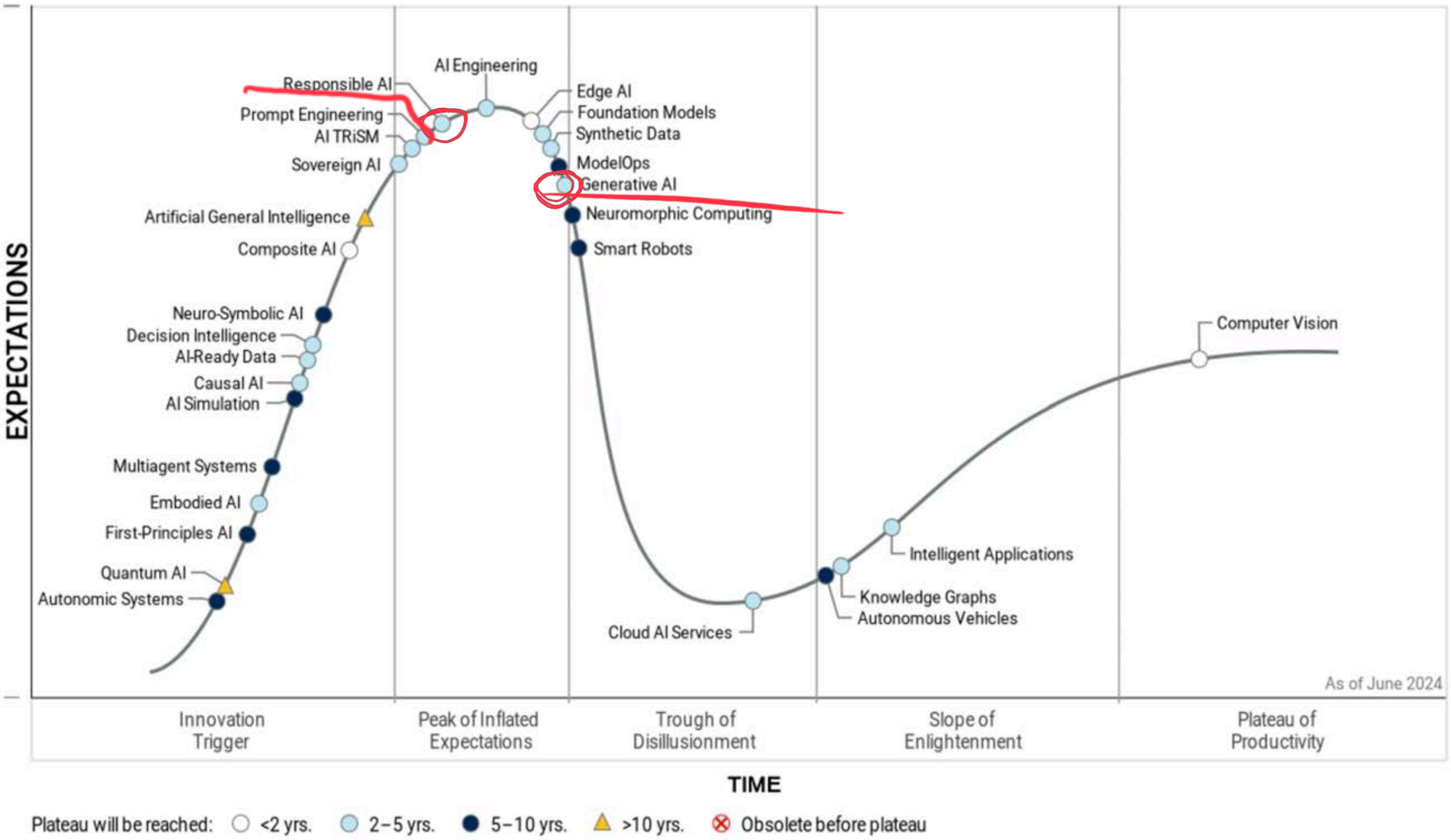

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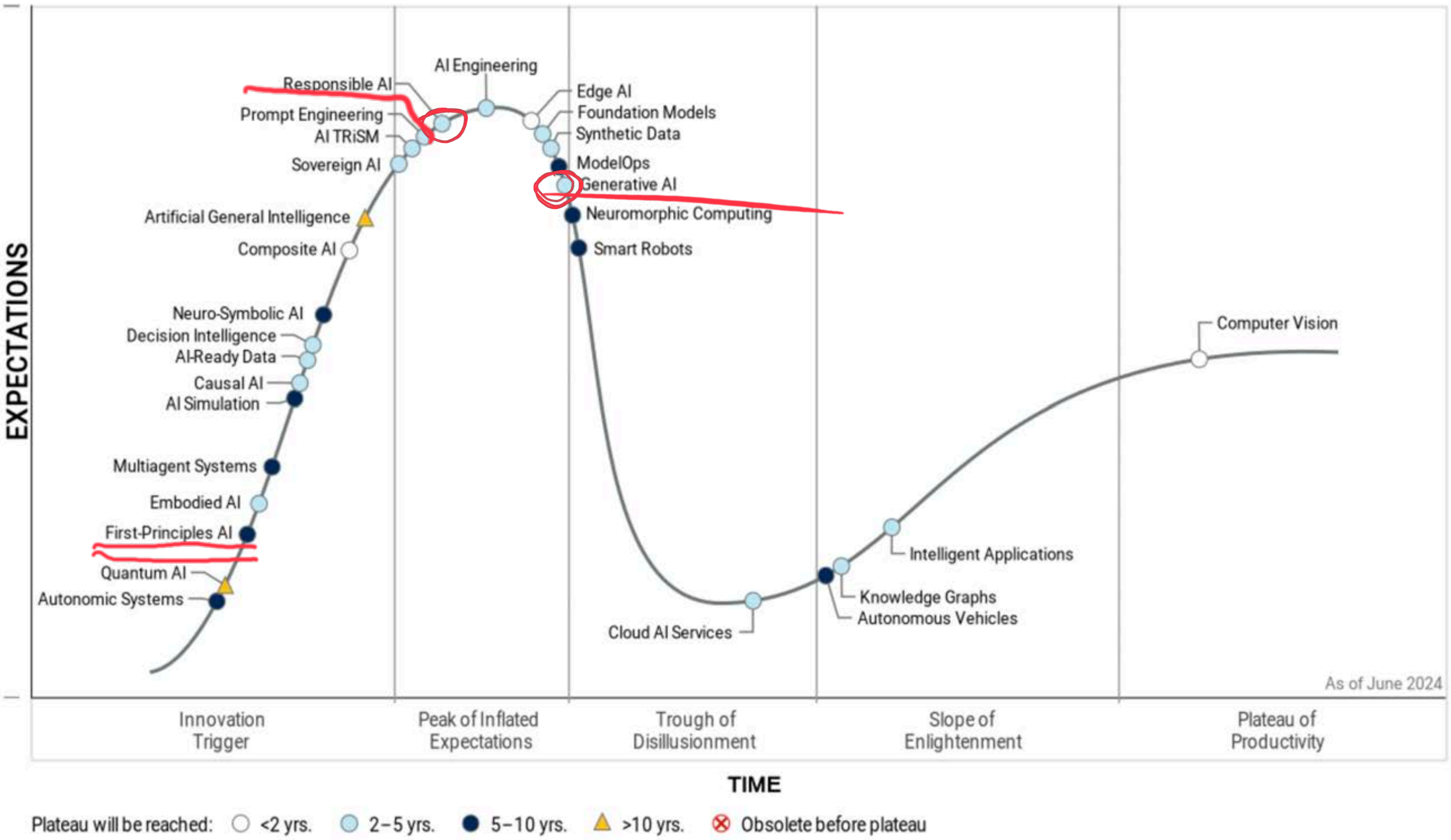

REPORT / STUDY

Ethics guidelines for trustworthy AI

On 8 April 2019, the High-Level Expert Group on AI presented Ethics Guidelines for Trustworthy Artificial Intelligence. This followed the publication of the guidelines' first draft in December 2018 on which more than 500 comments were received through an open consultation.

According to the Guidelines, trustworthy AI should be:

(1) lawful - respecting all applicable laws and regulations

(2) ethical - respecting ethical principles and values

(3) robust - both from a technical perspective while taking into account its social environment

Related topics

Artificial intelligence

Investing in network and technologies

The Guidelines put forward a set of 7 key requirements that AI systems should meet in order to be deemed trustworthy. A specific assessment list aims to help verify the application of each of the key requirements:

- Human agency and oversight: AI systems should empower human beings, allowing them to make informed decisions and fostering their fundamental rights. At the same time, proper oversight mechanisms need to be ensured, which can be achieved through human-in-the-loop, human-on-the-loop, and human-in-command approaches
- Technical Robustness and safety: AI systems need to be resilient and secure. They need to be safe, ensuring a fall back plan in case something goes wrong, as well as being accurate, reliable and reproducible. That is the only way to ensure that also unintentional harm can be minimized and prevented.
- Privacy and data governance: besides ensuring full respect for privacy and data protection, adequate data governance mechanisms must also be ensured, taking into account the quality and integrity of the data, and ensuring legitimised access to data.
- Transparency: the data, system and AI business models should be transparent. Traceability mechanisms can help achieving this. Moreover, AI systems and their decisions should be explained in a manner adapted to the stakeholder concerned. Humans need to be aware that they are interacting with an AI system, and must be informed of the system's capabilities and limitations.
- Diversity, non-discrimination and fairness: Unfair bias must be avoided, as it could could have multiple negative implications, from the marginalization of vulnerable groups, to the exacerbation of prejudice and discrimination. Fostering diversity, AI systems should be accessible to all, regardless of any disability, and involve relevant stakeholders throughout their entire life circle.
- Societal and environmental well-being: AI systems should benefit all human beings, including future generations. It must hence be ensured that they are sustainable and environmentally friendly. Moreover, they should take into account the environment, including other living beings, and their social and societal impact should be carefully considered.
- Accountability: Mechanisms should be put in place to ensure responsibility and accountability for AI systems and their outcomes. Auditability, which enables the assessment of algorithms, data and design processes plays a key role therein, especially in critical applications. Moreover, adequate an accessible redress should be ensured.

Translation: Internet Information Service Algorithmic Recommendation Management Provisions (Opinon-Seeking Draft)

Major new regulations on the use of recommendation algorithms issued for public comment

August 27, 2021 | Rogier Creemers, Helen Toner, Graham Webster

The Cyberspace Administration of China on Aug. 27 released draft "Internet Information Service Algorithmic Recommendation Management Provisions" 《互联网信息服务算法推荐管理规定（征求意见稿）》for public comment, with submissions due Sept. 26.

TRANSLATION

Internet Information Service Algorithmic Recommendation Management Provisions (Opinion-seeking Draft)

5th generation of recommender systems

5th generation of recommender systems

- you decide

Questions?

Human-centered AI

References used in this talk

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