



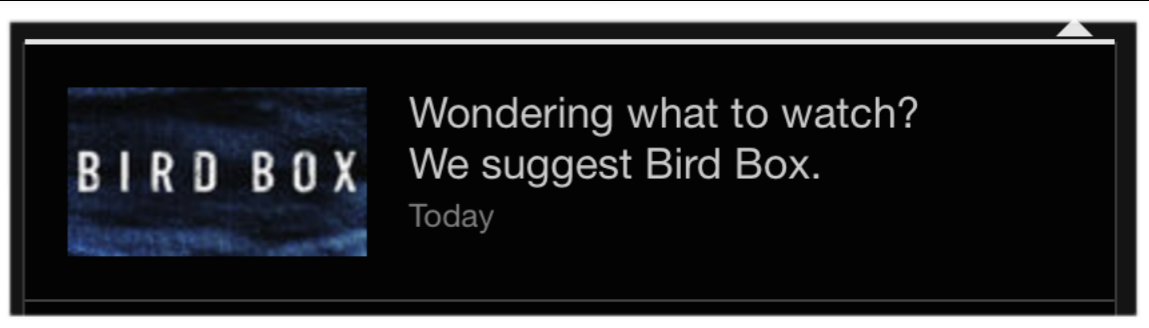
# RECSYS 2019

Peter Gašpar, Miroslav Rác, Michal Kompan

2.10.2019

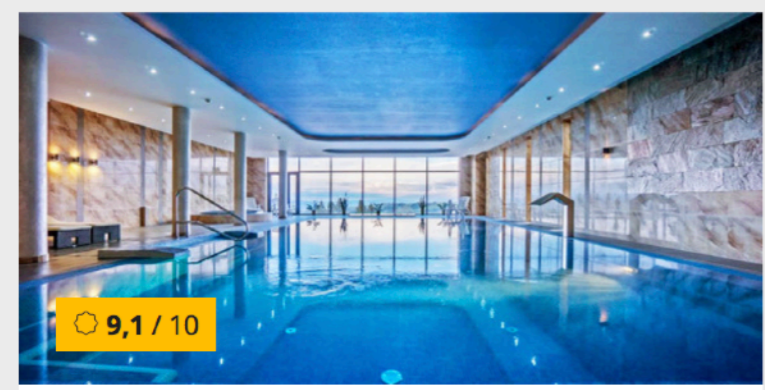
# Odporúčanie

Čo je to odporúčanie?



**BIRD BOX** Wondering what to watch?  
We suggest Bird Box.  
Today

## Zákazníci, ktorí si kúpili túto ponuku, si kúpili tiež



Relax v obľúbenom hoteli Bachledówka



Výborné kúpele Termy Szaflary blízko Zakopaného

📍 Poľsko - Szaflary



Pravý relax na Orave s wellness a zľavou do aquaparkov

📍 Orava

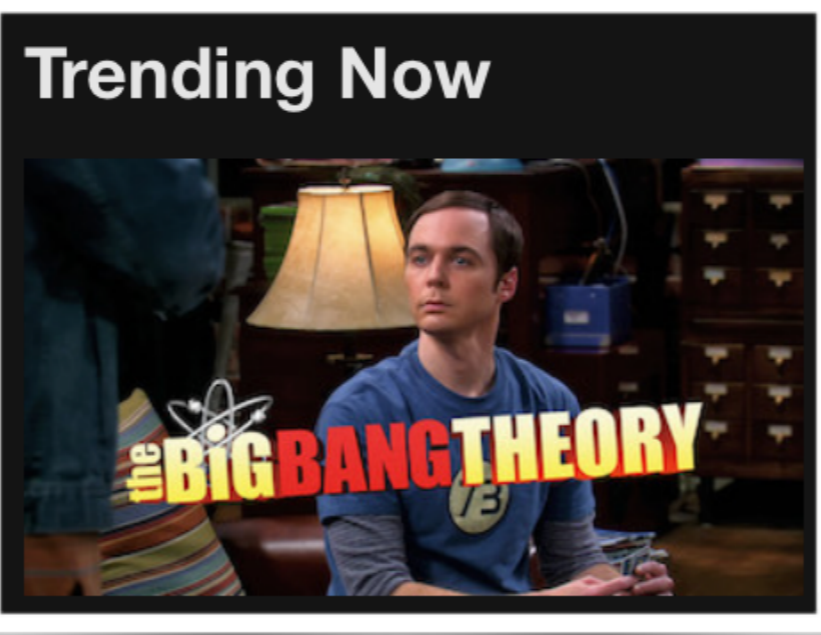
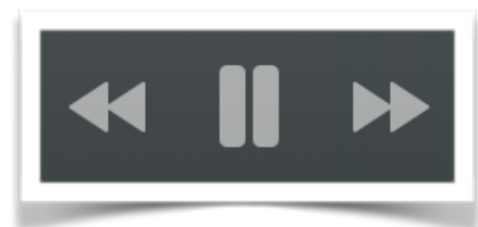
od 99,00 €

> Zobrazíť viac

**Popular filters**

- Breakfast included 100
- Apartments 82
- Hotels 132
- City Centre 63
- Very good: 8+ 138
- Book without credit card 1
- Free cancellation 161
- Free WiFi 217

**Trending Now**

# Odporúčanie

Základný úvod

Aké základné odporúčanie poznáme?

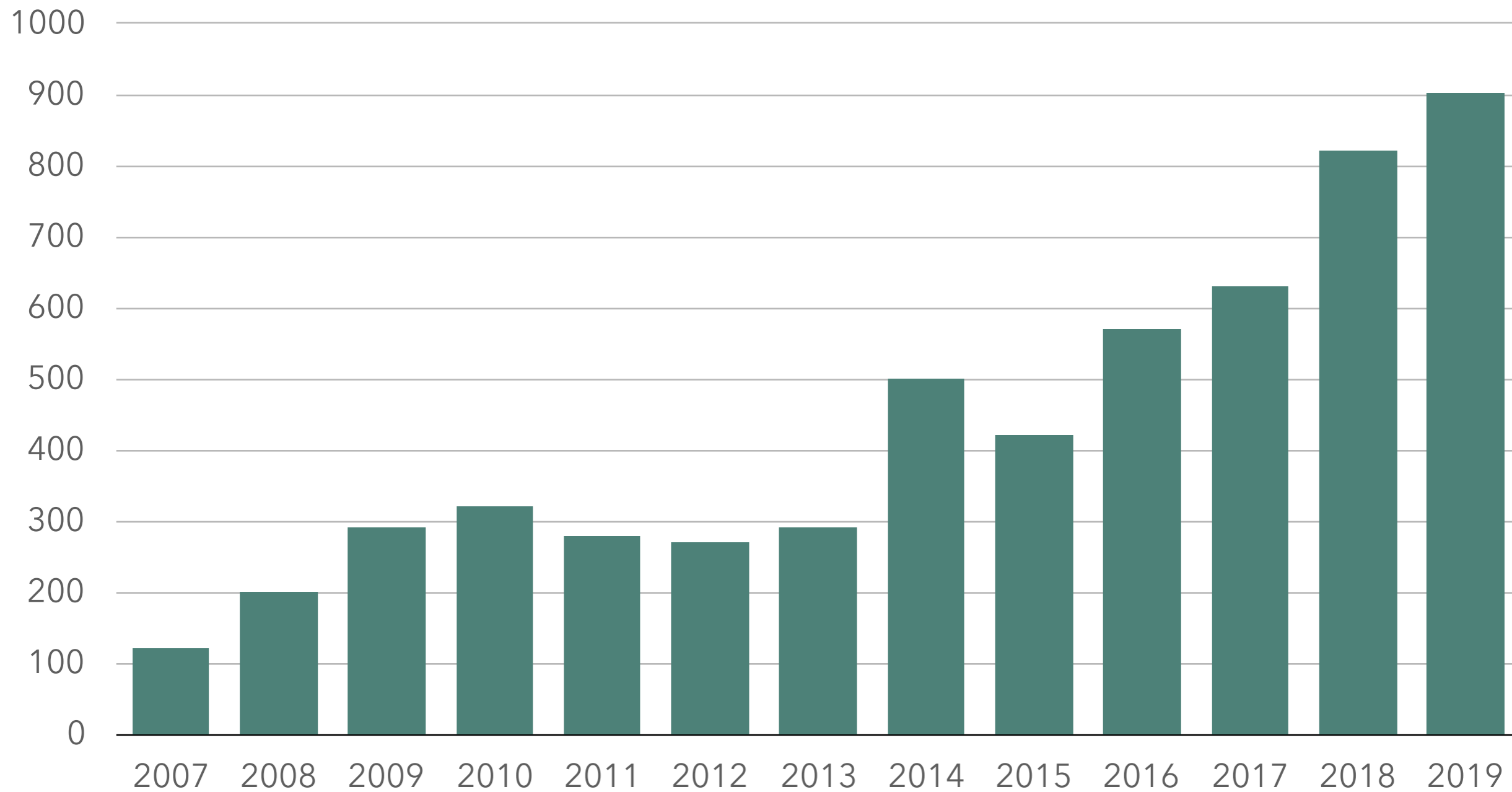
- Kolaboratívne,
- obsahové,
- hybridné.

Skúmame rôzne **metriky**:

presnosť, pokrytie, zotrvanie zákazníka, spokojnosť, ...

# RecSys 2019

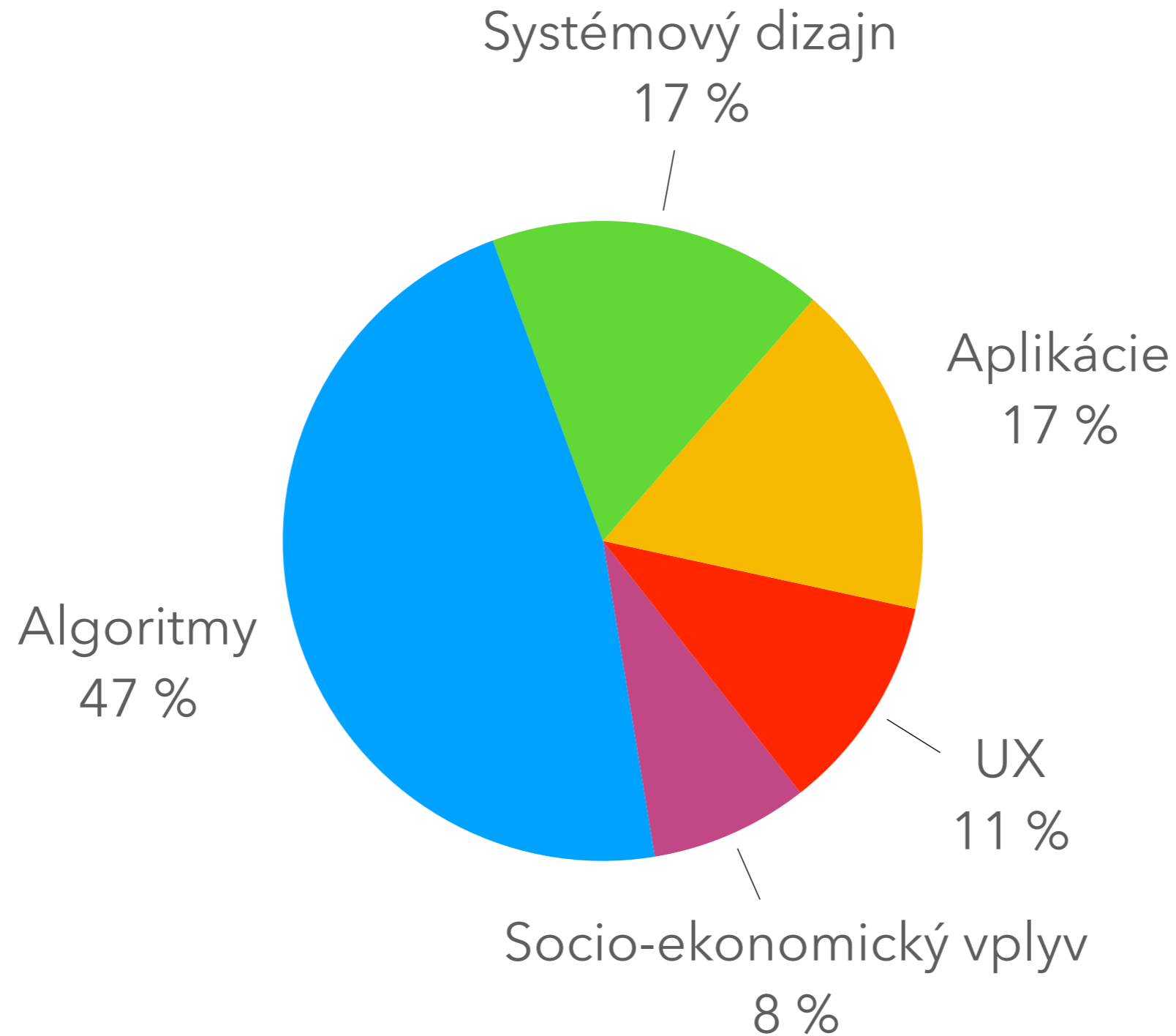
Počet účastníků





# RecSys 2019

## Program





# KEYNOTES



# Keynote 1: Rude Awakenings from Behaviourist Dreams. Methodological Integrity and the GDPR

Mireille Hildebrandt (Vrije Universiteit Brussels, Belgium)

Sú skutočne **personalizované** reklamy účinné?

Často postačuje primerané využitie kontextuálnych informácií namiesto obrovského množstva dát, ktoré dnes zbierajú Facebook a Google.

# Keynote 1: Rude Awakenings from Behaviourist Dreams. Methodological Integrity and the GDPR

Mireille Hildebrandt (Vrije Universiteit Brussels, Belgium)

MOBILE

## When Procter & Gamble Cut \$200 Million in Digital Ad Spend, It Increased Its Reach 10%

Unilever is also reevaluating its budget

By Lauren Johnson | March 1, 2018

 PREMIUM

<https://www.adweek.com/brand-marketing/when-procter-gamble-cut-200-million-in-digital-ad-spend-its-marketing-became-10-more-effective/>



# Keynote 1: Rude Awakenings from Behaviourist Dreams. Methodological Integrity and the GDPR

Mireille Hildebrandt (Vrije Universiteit Brussels, Belgium)

## After GDPR, The New York Times cut off ad exchanges in Europe — and kept growing ad revenue

JANUARY 16, 2019 by [Jessica Davies](#)

When the General Data Protection Regulation arrived last year, The New York Times didn't take any chances.

The publisher blocked all open-exchange ad buying on its European pages, followed swiftly by behavioral targeting. Instead, NYT International focused on contextual and geographical targeting for programmatic guaranteed and private marketplace deals and has not seen ad revenues drop as a result, according to Jean-Christophe Demarta, svp for global advertising at New York Times International.

<https://digiday.com/media/gumgumtest-new-york-times-gdpr-cut-off-ad-exchanges-europe-ad-revenue/>



# Keynote 1: Rude Awakenings from Behaviourist Dreams. Methodological Integrity and the GDPR

Mireille Hildebrandt (Vrije Universiteit Brussels, Belgium)

- Who is paying for recommender systems? Who is profiting from them?
  - Developers?
  - Big tech? Platforms? Publishers? Advertisers?
  - Users?
  
- What is the goal:
  - Mining preferences? Catering to end-users for their own sake?
  - Increasing ad revenue or sales or influencing voting behaviours?
  - **Attention grabbing, holding, hooking** → **promoting addiction**

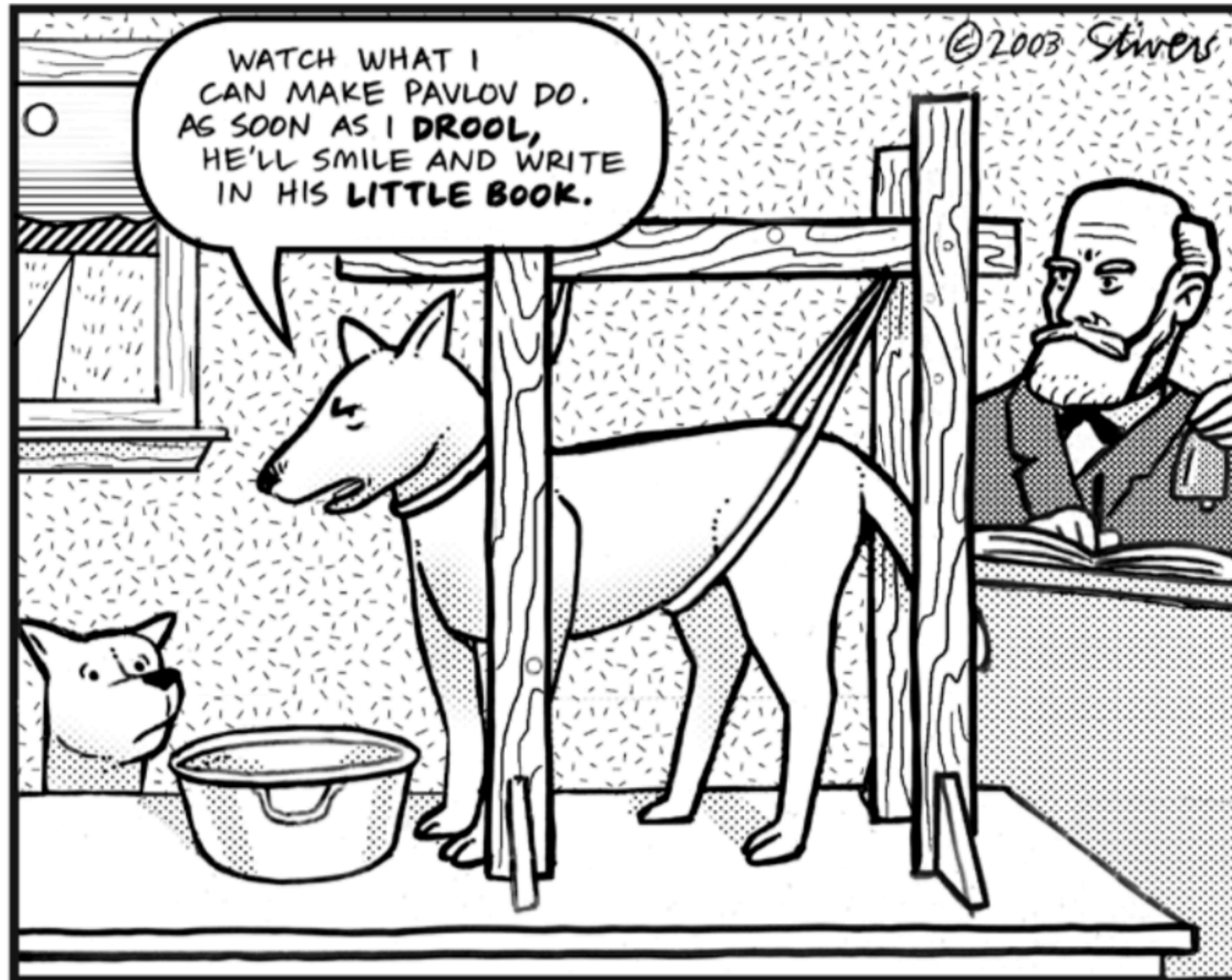
# Keynote 1: Rude Awakenings from Behaviourist Dreams. Methodological Integrity and the GDPR

Mireille Hildebrandt (Vrije Universiteit Brussels, Belgium)

- Data-driven recsys have trained their algorithm (learner) on behavioural data:
  - Online impression, click and conversion behaviours (RTB, AB testing)
  - Purchasing, watching, location (mobility) behaviours (LBS, Amazon, Netflix)
  - Image and voice recognition (Echo, Alexa)
  - All and any (sentiment analysis)
- Behavioural data =
  - Machine readable data (surf behaviour, sensor data, mobility data, etc.)
  - Data is a trace, representation, or imprint of something else
  - Based on the methodological individualism of behaviourism
  - Shares assumptions with rational choice theory and behavioural economics

# Keynote 1: Rude Awakenings from Behaviourist Dreams. Methodological Integrity and the GDPR

Mireille Hildebrandt (Vrije Universiteit Brussels, Belgium)



# Keynote 1: Rude Awakenings from Behaviourist Dreams. Methodological Integrity and the GDPR

Mireille Hildebrandt (Vrije Universiteit Brussels, Belgium)

- **Personal data processing:**
  - Any data relating to an identifiable person (very broad concept)
  - Data subject (natural person)
  - Data processing (from collection to storage to whatever)
  - **Behavioural data that can single out = personal data**
  
- Goal of the GDPR is to enable processing within the Union
  - Based on equivalent protection throughout the Union
  - Mix of public enforcement and private law liability



# Keynote 1: Rude Awakenings from Behaviourist Dreams. Methodological Integrity and the GDPR

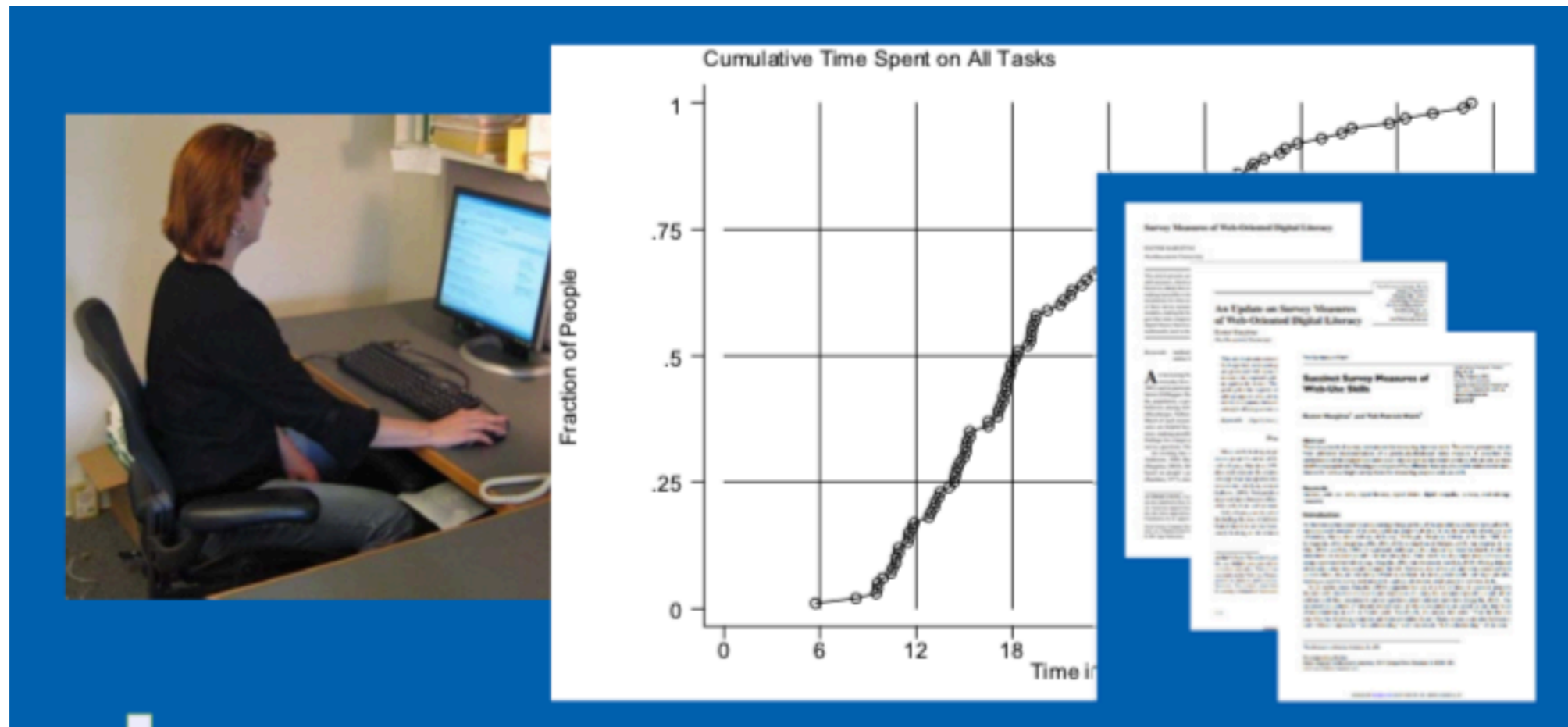
Mireille Hildebrandt (Vrije Universiteit Brussels, Belgium)

Keď príde na trh nový liek, musí prejsť zložitým procesom overovania a registrácie.

Prečo sa to neuplatňuje aj v doméne strojového učenia?

# Keynote 2: Inequality in Online Participation and Why it Matters for Recommendation Systems Research

Eszter Hargittai (University of Zurich, Switzerland)





# Keynote 2: Inequality in Online Participation and Why it Matters for Recommendation Systems Research

Eszter Hargittai (University of Zurich, Switzerland)

Hypotézy:

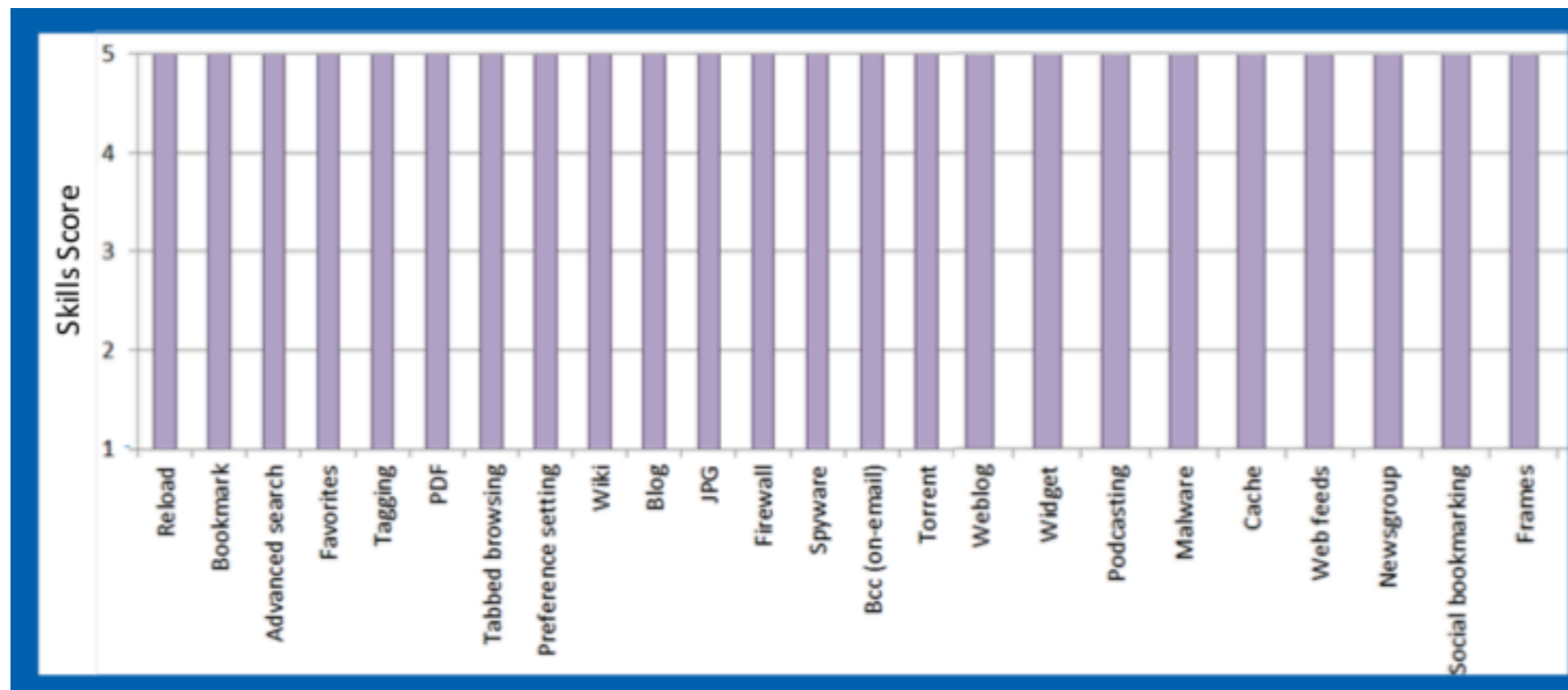
1. Všetci mladí ľudia sú digitálne zdatní.
2. Mladí ľudia sú zdatnejší ako starší ľudia.

# Keynote 2: Inequality in Online Participation and Why it Matters for Recommendation Systems Research

Eszter Hargittai (University of Zurich, Switzerland)

1. Všetci mladí ľudia sú digitálne zdatní.

Očakávaná:

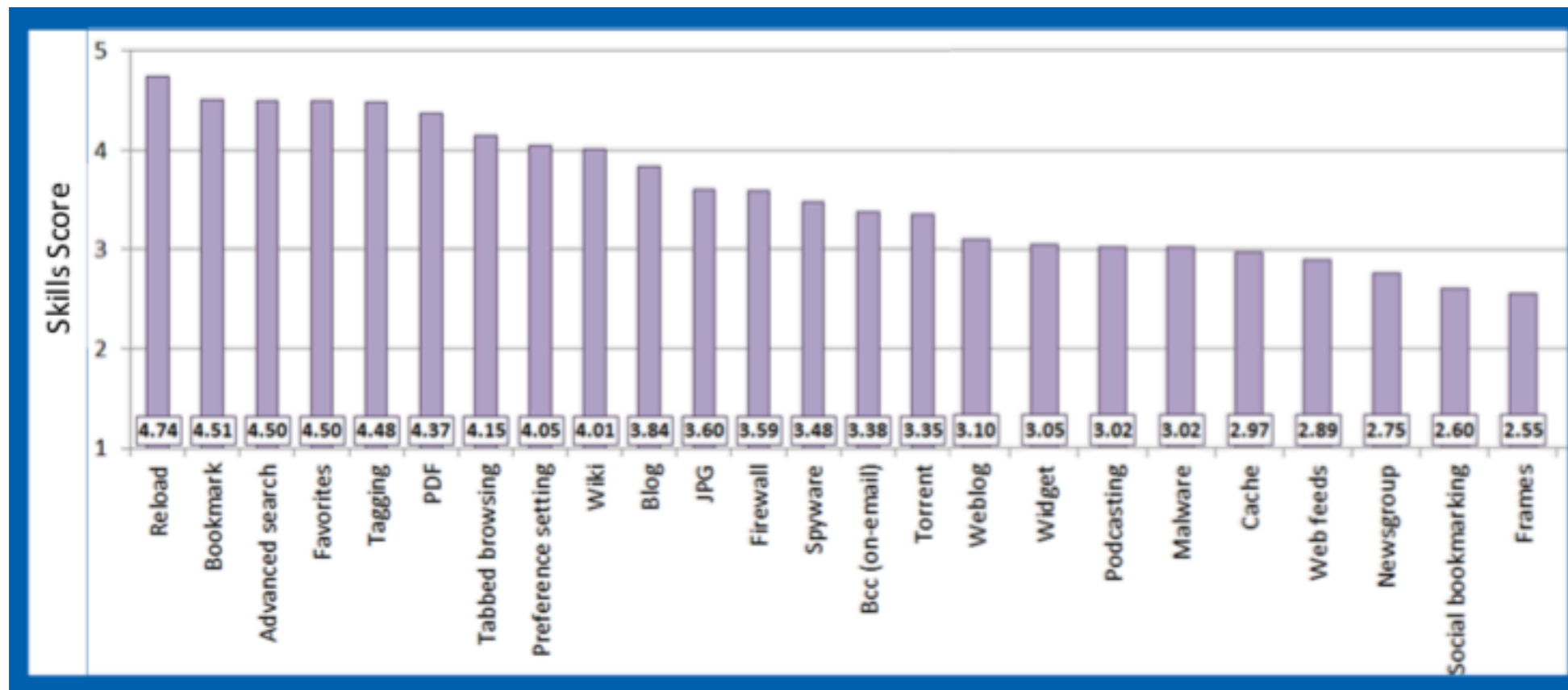


# Keynote 2: Inequality in Online Participation and Why it Matters for Recommendation Systems Research

Eszter Hargittai (University of Zurich, Switzerland)

1. Všetci mladí ľudia sú digitálne zdatní.

Realita:



# Keynote 2: Inequality in Online Participation and Why it Matters for Recommendation Systems Research

Eszter Hargittai (University of Zurich, Switzerland)

Which of the following sites is most likely to be the Web site of a bank called “Bankomat”?

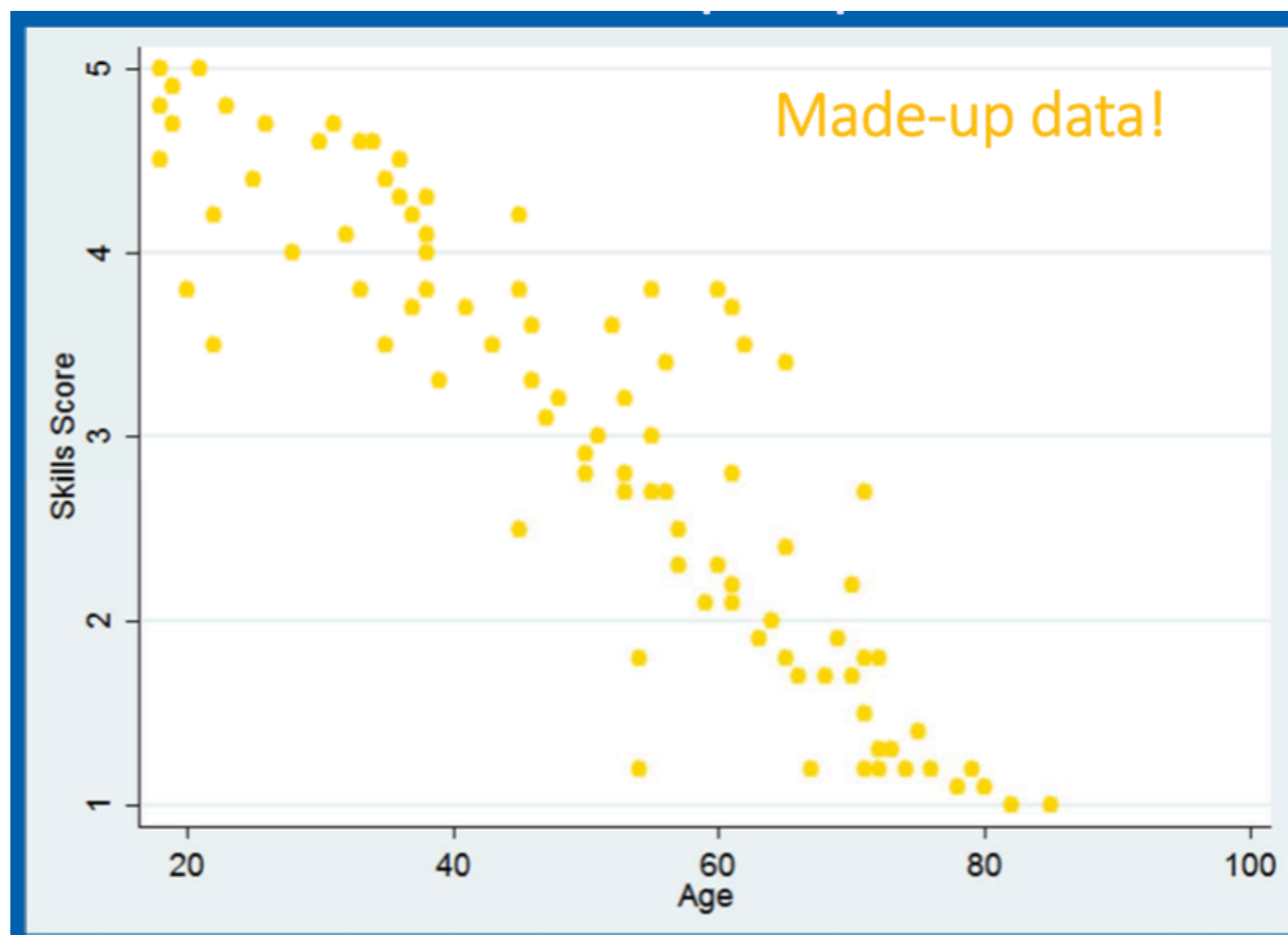
- `www3.da-us.bankomat.com/cgi-bin/citifili/portal/I/I.do` 11%
- `www.bankomat.ve/rify.com` 35%
- `www.us.bankomat.businessportal.ru/bankomat/index.php` 50%
- `www.krezmin.nu/bankomat.com` 4%

# Keynote 2: Inequality in Online Participation and Why it Matters for Recommendation Systems Research

Eszter Hargittai (University of Zurich, Switzerland)

2. Mladí ľudia sú zdatnejší ako starší ľudia.

Očakávaná:

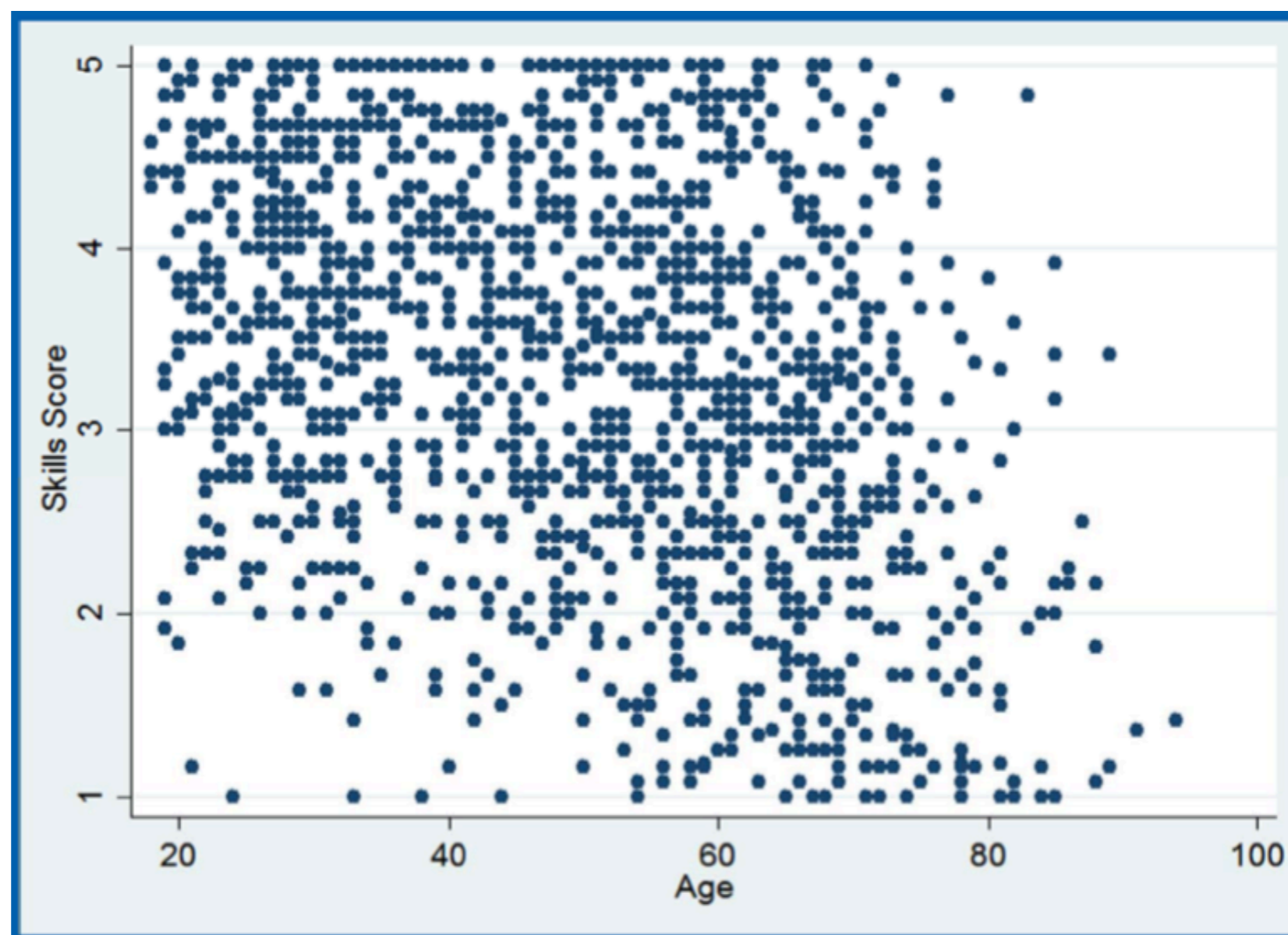


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Eszter Hargittai (University of Zurich, Switzerland)

2. Mladí ľudia sú zdatnejší ako starší ľudia.

Realita:

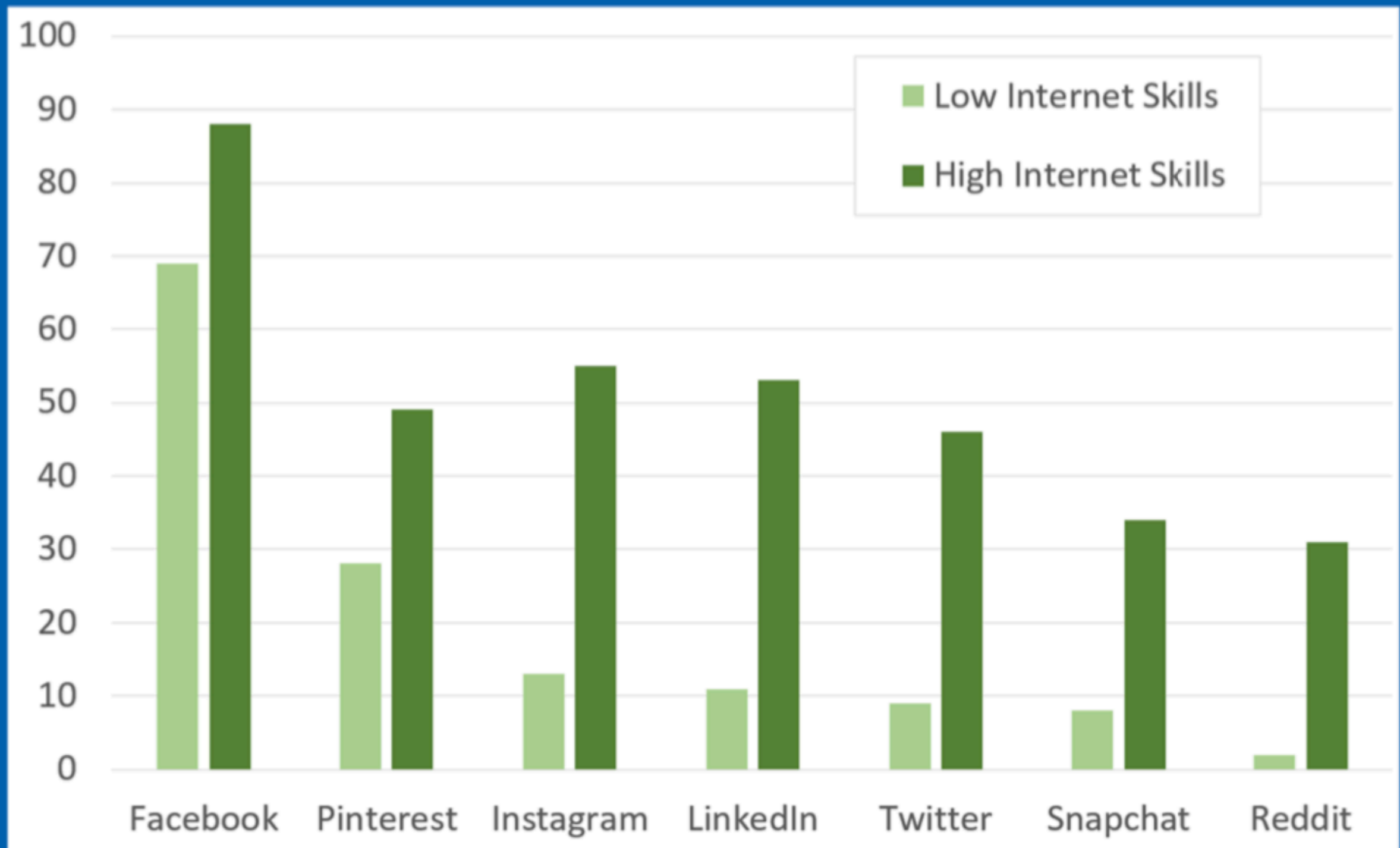




# Keynote 2: Inequality in Online Participation and Why it Matters for Recommendation Systems Research

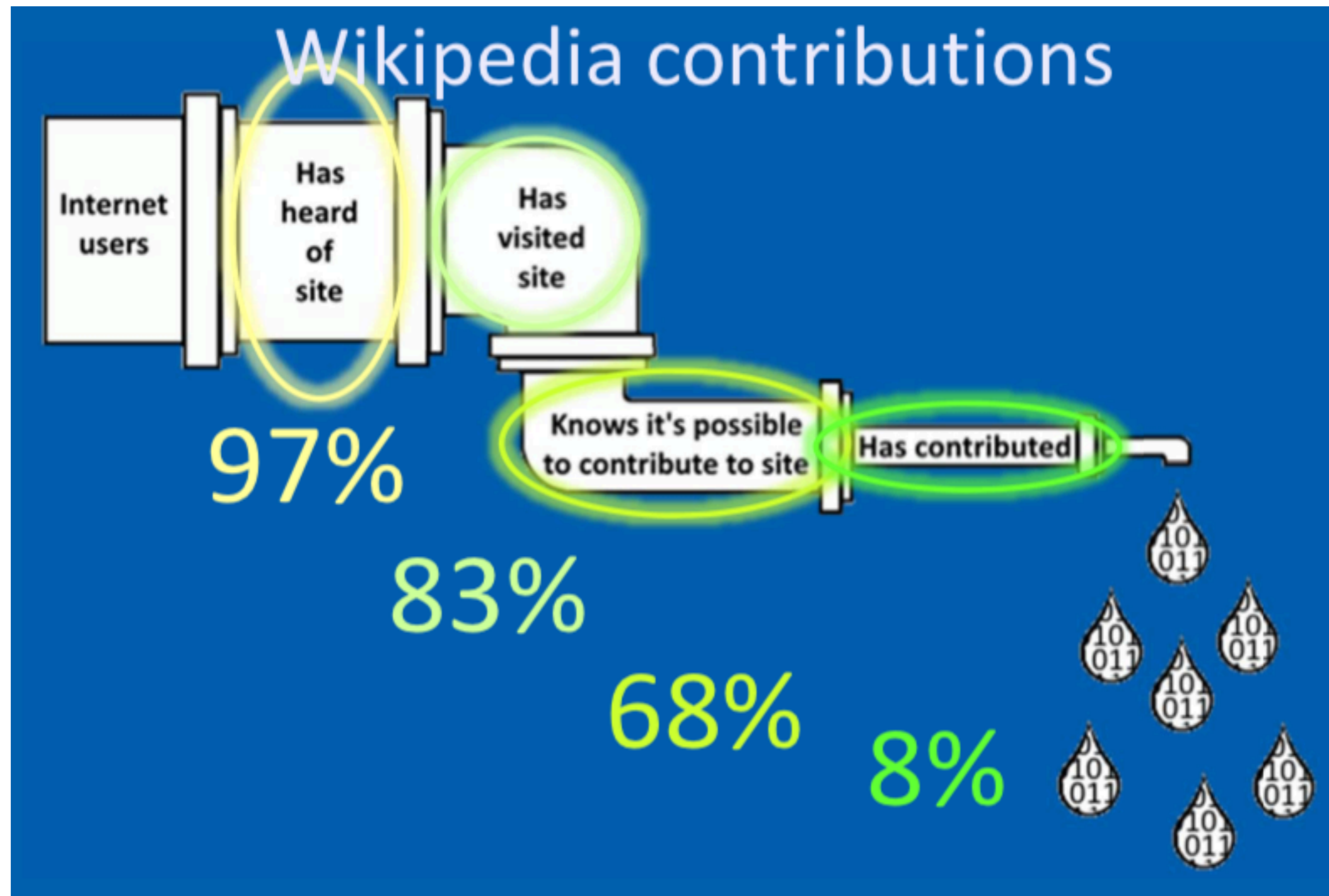
Eszter Hargittai (University of Zurich, Switzerland)

## Use of social network sites by Internet skills, US adults



# Keynote 2: Inequality in Online Participation and Why it Matters for Recommendation Systems Research

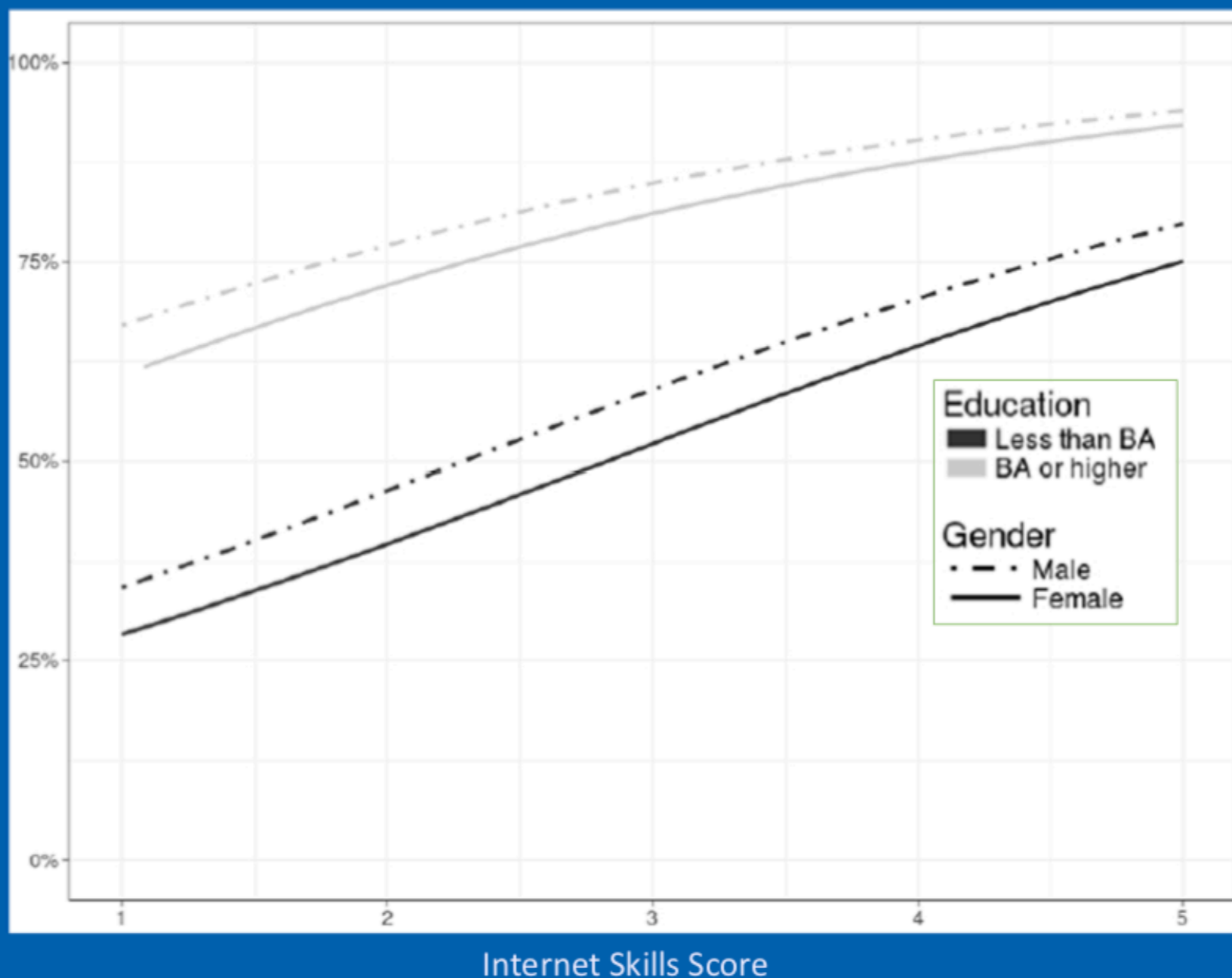
Eszter Hargittai (University of Zurich, Switzerland)



# Keynote 2: Inequality in Online Participation and Why it Matters for Recommendation Systems Research

Eszter Hargittai (University of Zurich, Switzerland)

Predicted probability of **knowing** Wikipedia **can be edited**



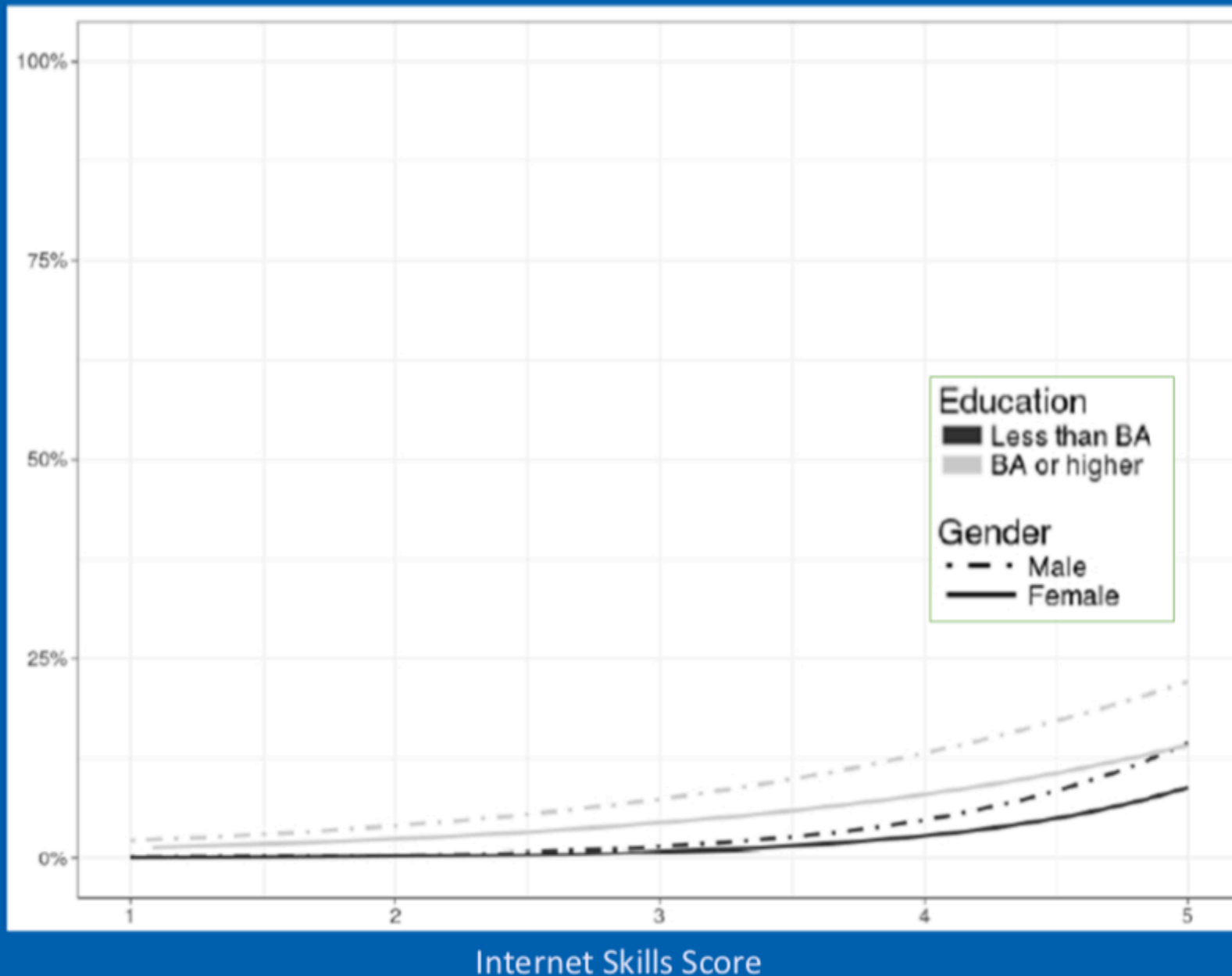
# Keynote 2: Inequality in Online Participation and Why it Matters for Recommendation Systems Research

Eszter Hargittai (University of Zurich, Switzerland)

22. Have you ever edited a Wikipedia page by fixing a mistake or adding new material?

- No  
 Yes

Predicted probability of contributing to Wikipedia



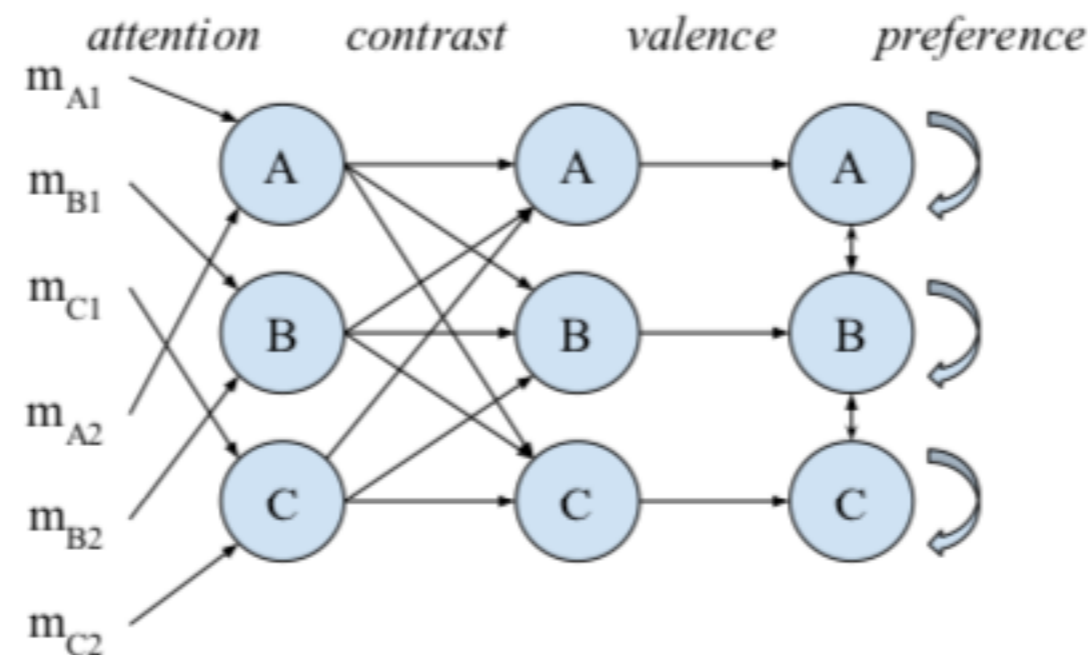
# PAPER SESSIONS



# From preference into decision making: modeling user interactions in recommender systems

Qian Zhao et al. | <https://dl.acm.org/citation.cfm?id=3347065>

Modelovanie správania používateľa: prehliadanie, akcia, neakcia.



The connectionist network representation of DFT  
(Decision Field Theory).



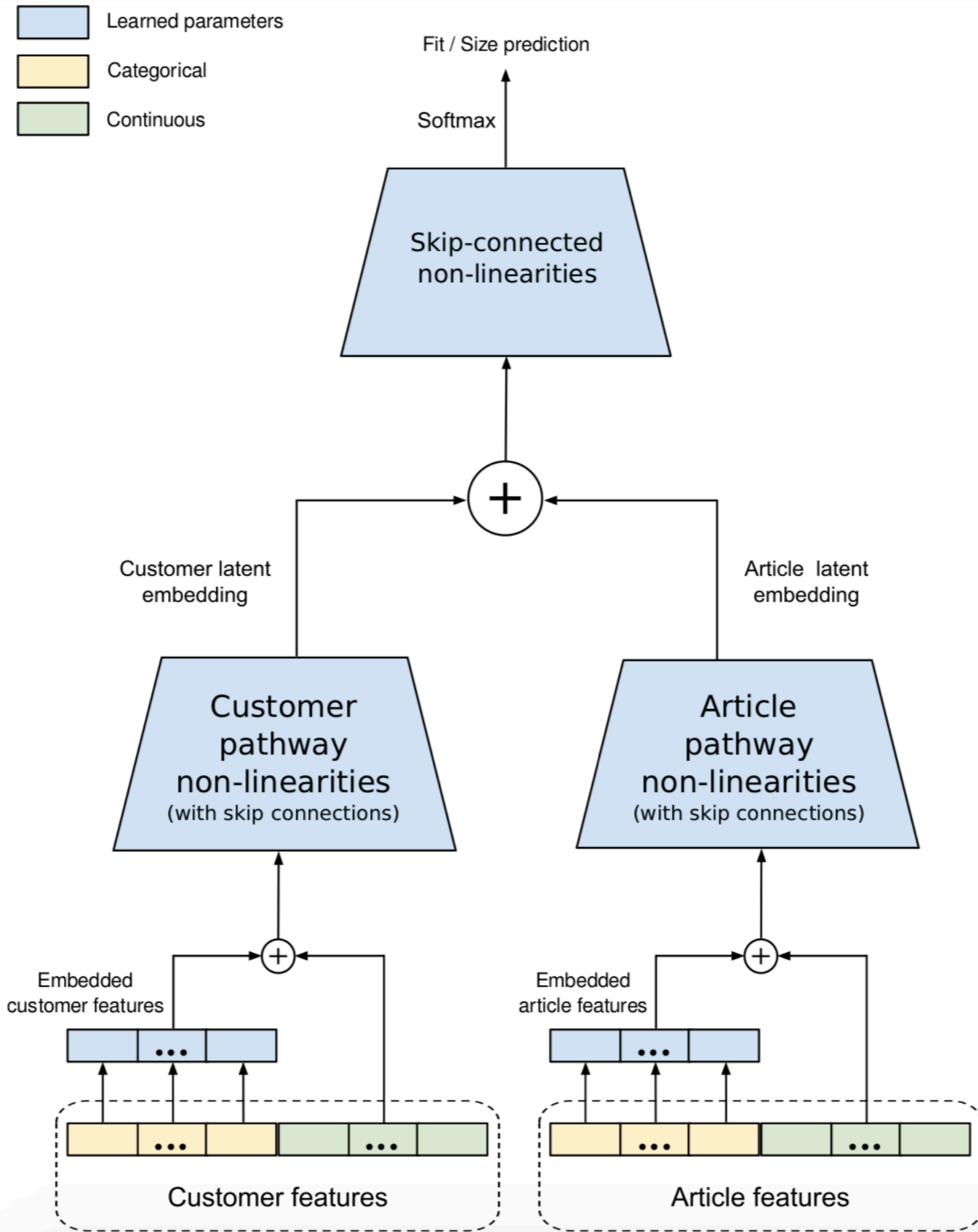
# A deep learning system for predicting size and fit in fashion e-commerce

Abdul-Saboor Sheikh (Zalando) et al. | <https://dl.acm.org/citation.cfm?id=3347006>

## Personalizovaná predpoveď veľkosti oblečenia

- využíva rôzne parametre pre naučenie abstraktnej reprezentácie veľkostí na základe interakcií medzi používateľmi a produktami,
- navyše využili vlastnosti používateľov a produktov.

Features/Dataset	ModCloth	RentTheRunWay
Article	category*, quality, item id*, size	category*, rating, rented for*, item id*, size
Customer	shoe width*, shoe size, waist, bust, cup size, bra size, hips, height, user id*	age, body type*, bust size <sup>+</sup> , height, weight, user id*



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

Maurizio Ferrari Dacrema et al. | <https://dl.acm.org/citation.cfm?id=3347058>

V doméne **odporúčania s využitím hlbokého učenia** sa autori zamerali na dve hlavné oblasti:

- 1. Reprodukovateľnosť výsledkov.** Je výskum zopakovateľný na základe článku?
- 2. Prínos.** Dokážu prezentované prístupy prekonať vyladené základné metódy?

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

Maurizio Ferrari Dacrema et al. | <https://dl.acm.org/citation.cfm?id=3347058>

## Reprodukovatelnost' výsledkov:

- dostupná funkčná verzia zdrojových kódov,
- aspoň 1 dataset z článku je dostupný a možné ho rovnako rozdeliť na train/test.

Conference	Rep. ratio	Reproducible
KDD	3/4 (75%)	[17], [23], [48]
RecSys	1/7 (14%)	[53]
SIGIR	1/3 (30%)	[10]
WWW	2/4 (50%)	[14], [24]
Total	7/18 (39%)	

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

Maurizio Ferrari Dacrema et al. | <https://dl.acm.org/citation.cfm?id=3347058>

## Prínos:

- porovnanie so základnými baselinami, hyper-parameter tuning.

Conference	Rep. ratio	Reproducible
KDD	3/4 (75%)	[17], [23], [48]
RecSys	1/7 (14%)	[53]
SIGIR	1/3 (30%)	[10]
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Total	7/18 (39%)	

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**Table 2: Experimental results for the CMN method using the metrics and cutoffs reported in the original paper. Numbers are printed in bold when they correspond to the best result or when a baseline outperformed CMN.**

	CiteULike-a			
	HR@5	NDCG@5	HR@10	NDCG@10
TopPopular	0.1803	0.1220	0.2783	0.1535
UserKNN	<b>0.8213</b>	<b>0.7033</b>	<b>0.8935</b>	<b>0.7268</b>
ItemKNN	<b>0.8116</b>	<b>0.6939</b>	0.8878	<b>0.7187</b>
$P^3\alpha$	<b>0.8202</b>	<b>0.7061</b>	0.8901	<b>0.7289</b>
$RP^3\beta$	<b>0.8226</b>	<b>0.7114</b>	<b>0.8941</b>	<b>0.7347</b>
CMN	0.8069	0.6666	0.8910	0.6942
	Pinterest			
	HR@5	NDCG@5	HR@10	NDCG@10
TopPopular	0.1668	0.1066	0.2745	0.1411
UserKNN	<b>0.6886</b>	<b>0.4936</b>	0.8527	<b>0.5470</b>
ItemKNN	<b>0.6966</b>	<b>0.4994</b>	<b>0.8647</b>	<b>0.5542</b>
$P^3\alpha$	0.6871	<b>0.4935</b>	0.8449	<b>0.5450</b>
$RP^3\beta$	<b>0.7018</b>	<b>0.5041</b>	<b>0.8644</b>	<b>0.5571</b>
CMN	0.6872	0.4883	0.8549	0.5430
	Epinions			
	HR@5	NDCG@5	HR@10	NDCG@10
TopPopular	<b>0.5429</b>	<b>0.4153</b>	<b>0.6644</b>	<b>0.4547</b>
UserKNN	0.3506	0.2983	0.3922	0.3117
ItemKNN	0.3821	0.3165	0.4372	0.3343
$P^3\alpha$	0.3510	0.2989	0.3891	0.3112
$RP^3\beta$	0.3511	0.2980	0.3892	0.3103
CMN	0.4195	0.3346	0.4953	0.3592

**Table 5: Experimental results for CDL on the dense CiteULike-a dataset.**

	REC@50	REC@100	REC@300
TopPopular	0.0038	0.0073	0.0258
UserKNN	<b>0.0685</b>	0.1028	0.1710
ItemKNN	<b>0.0846</b>	<b>0.1213</b>	0.1861
$P^3\alpha$	<b>0.0718</b>	<b>0.1079</b>	0.1777
$RP^3\beta$	<b>0.0800</b>	<b>0.1167</b>	0.1815
ItemKNN-CBF	<b>0.2135</b>	<b>0.3038</b>	<b>0.4707</b>
ItemKNN-CFCBF	<b>0.1945</b>	<b>0.2896</b>	<b>0.4620</b>
CDL	0.0543	0.1035	0.2627





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

Maurizio Ferrari Dacrema et al. | <https://dl.acm.org/citation.cfm?id=3347058>



**Dagmar Monett** @dmonett · 27. 7.

A "worrying analysis":

"18 [#deeplearning] algorithms ... presented at top-level research conferences ... Only 7 of them could be reproduced w/ reasonable effort ... 6 of them can often be outperformed w/ comparably simple heuristic methods."

Paper:

[Inkd.in/dTaGCTv](https://inkd.in/dTaGCTv)

#AI

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

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Dietmar Jannach  
University of Klagenfurt, Austria  
dietmar.jannach@uau.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 schol-

### 1 INTRODUCTION

Within only a few years, deep learning techniques have started to dominate the landscape of algorithmic research in recommender 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 neu-

02v1 [cs.IR] 16 Jul 2019

47

1,3 tis.

2,6 tis.



<https://twitter.com/dmonett/status/1154876433564655616>



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

Maurizio Ferrari Dacrema et al. | <https://dl.acm.org/citation.cfm?id=3347058>

**Fantómový progres** môže byť spôsobený:

- **výber baselineov** – napr. zvolená neurónová sieť ako baseline (hoci sa ukázalo, že nie je baseline),
- nedostatok informácií o **optimalizácii baselineov**,
- **chyby pri delení** dát a pri implementácii **metriek**,
- množstvo datasetov, metriek, protokolov na delenie dát, ktoré sťažujú jednoduchšie a priame porovnanie.

# Ghosting: Contextualized Inline Query Completion in Large Scale Retail Search

Lakshmi Ramachandran et al. | <https://dl.acm.org/citation.cfm?id=3346995>

wireless bl 	wireless bluetooth headphones 
wireless bluetooth headphones <b>speakers</b> wireless bluetooth wireless bluetooth earbuds wireless bluetooth speakers portable wireless bluetooth mouse wireless bluetooth car kit wireless bluetooth headset wireless bluetooth microphone wireless bluetooth earbuds for iphone wireless bluetooth keyboard	wireless bluetooth headphones <b>speakers</b> wireless bluetooth wireless bluetooth earbuds wireless bluetooth speakers portable wireless bluetooth mouse wireless bluetooth car kit wireless bluetooth headset wireless bluetooth microphone wireless bluetooth earbuds for iphone wireless bluetooth keyboard

# Ghosting: Contextualized Inline Query Completion in Large Scale Retail Search

Lakshmi Ramachandran et al. | <https://dl.acm.org/citation.cfm?id=3346995>

<b>Recently searched query</b>	bose bluetooth headphones	dslr camera	wireless charger
<b>Frequency</b>	<u>jvc</u> headphones	<u>nike</u> socks men	<u>iphone</u> charger
<b>Session context</b>	<u>jvc</u> bluetooth headphones ✓	<u>nikon</u> dslr camera ✓	<u>iphone</u> wireless charger ✓
<b>Recently searched query</b>	dance clothes for women	bike shorts	adidas trail running shoes
<b>Frequency</b>	<u>zumba</u> fitness dvd	<u>bike</u> seat	<u>trash</u> bags
<b>Session context</b>	<u>zumba</u> clothes for women ✓	<u>bike</u> shorts women ✓	<u>trail</u> running shoes men ✓



# Ghosting: Contextualized Inline Query Completion in Large Scale Retail Search

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<b>Session context</b>	<u>zumba</u> clothes for women ✓	<u>bike</u> shorts women ✓	<u>trail</u> running shoes men ✓

**Table 3: Evaluating ghosting on a production system. The better model has a larger positive impact on acceptance, cart-add rate and net sales and larger negative impact on spell-correction rate and avg. prefix length. Statistically significant results are marked with "\*" ( $t$ -test,  $p$ -value < 0.05). The session context model shows improvements on all metrics.**

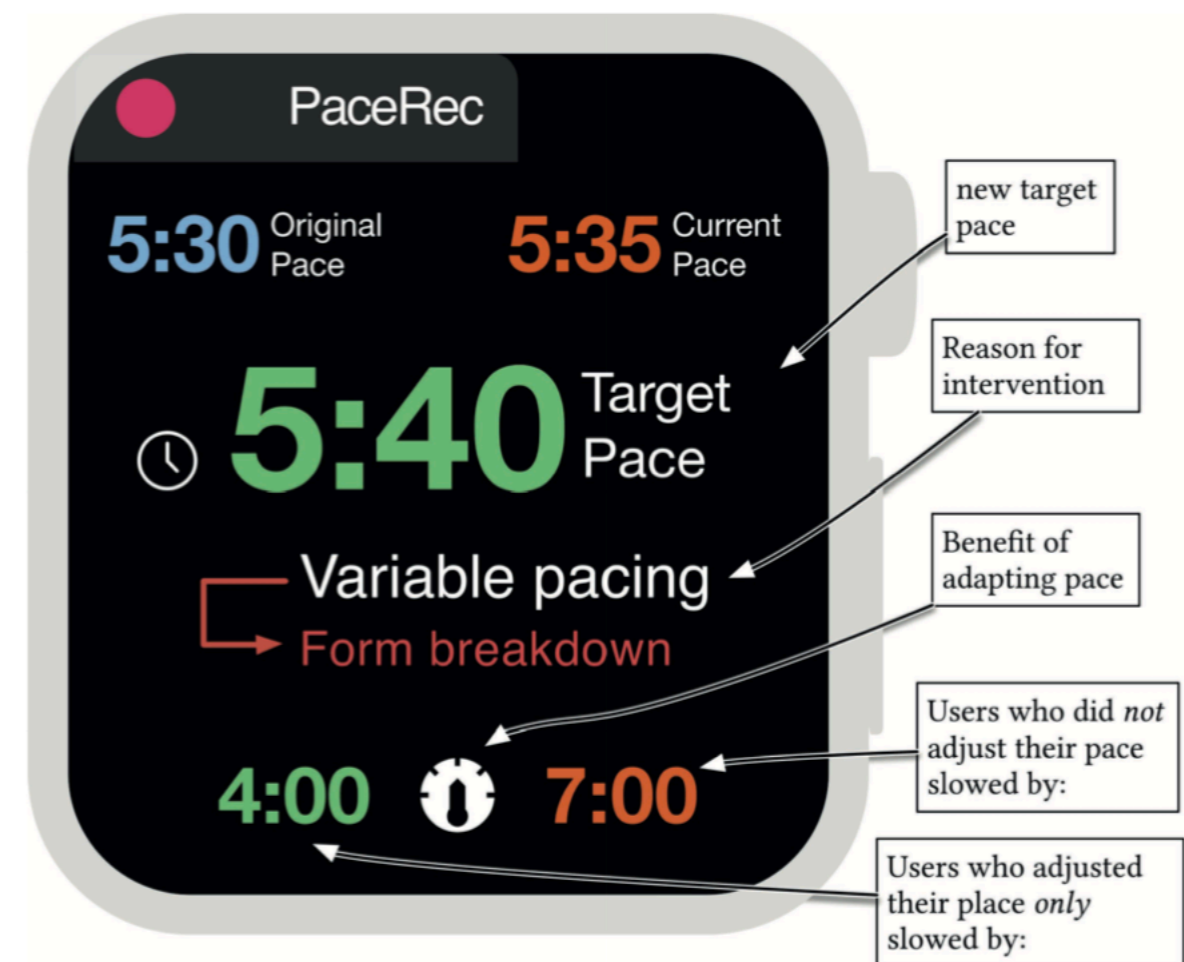
Ghosting model	acceptance	spell-correction rate	average prefix length	cart-add rate	net sales
Frequency	+9.01*	-9.52*	-7.51*	-0.03	-0.15
Session context	+6.18*	-4.42*	-7.12*	+0.04*	+0.14*

# Pace My Race: Recommendations for Marathon Running

Jakim Berndsen et al. | <https://dl.acm.org/citation.cfm?id=3346991>

Predikcia času ukončenia behu použitá na odporúčanie.

- Odporúčanie bežeckej stratégie v rôznych častiach behu.





# INDUSTRY SESSIONS



# IKEA: Designer-Driven Add-to-Cart Algorithms

Sandhya Sachidanandan

Odporúčanie produktov s využitím obrázkov.

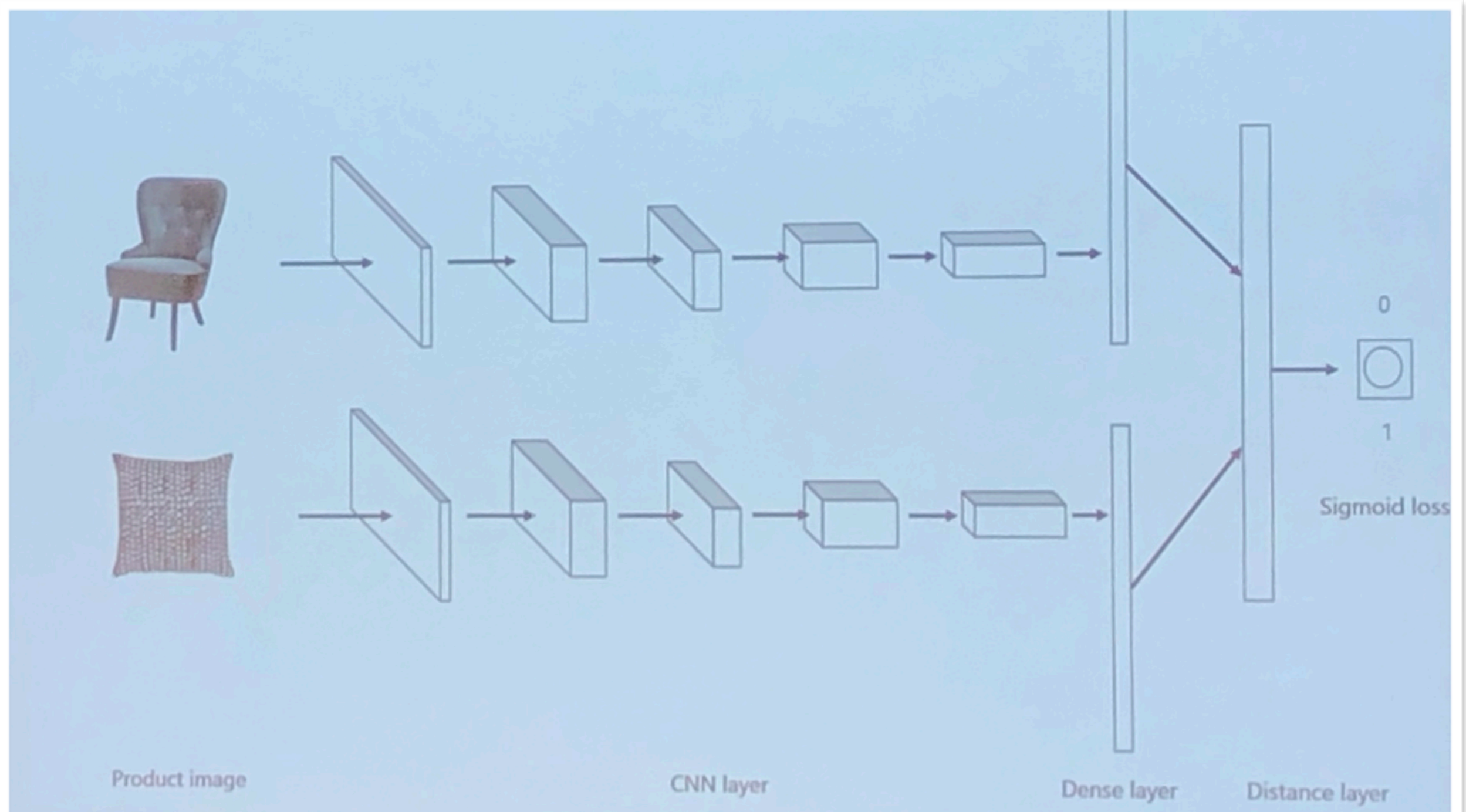
Siamské neurónové siete:

- pozitívne príklady: spolunákupy + expertné pravidlá
- negatívne príklady: rôzne farby, materiály, bez spolunákupov

Cieľ predpovedať: Hodí sa to k sebe?

# IKEA: Designer-Driven Add-to-Cart Algorithms

Sandhya Sachidanandan





# Bosch: Future of In-Vehicle Recommendation Systems

Juergen Luettin, Susanne Rothermel and Mark Andrew

## Examples of In-Vehicle Recommendation Applications



- ▶ Location based services
  - ▶ POIs
  - ▶ Fueling, Charging, Parking
  - ▶ Social network services



- ▶ Infotainment
  - ▶ Music
  - ▶ Communication
  - ▶ Information



- ▶ Navigation
  - ▶ Routing
  - ▶ Shared mobility
  - ▶ Tourism



- ▶ Vehicle control
  - ▶ Seat, mirror, HVAC, windows, ambient light
  - ▶ Driver assistance



- ▶ Vehicle Maintenance
  - ▶ Automatic emergency call
  - ▶ Predictive Diagnostics
  - ▶ Roadside Assistance



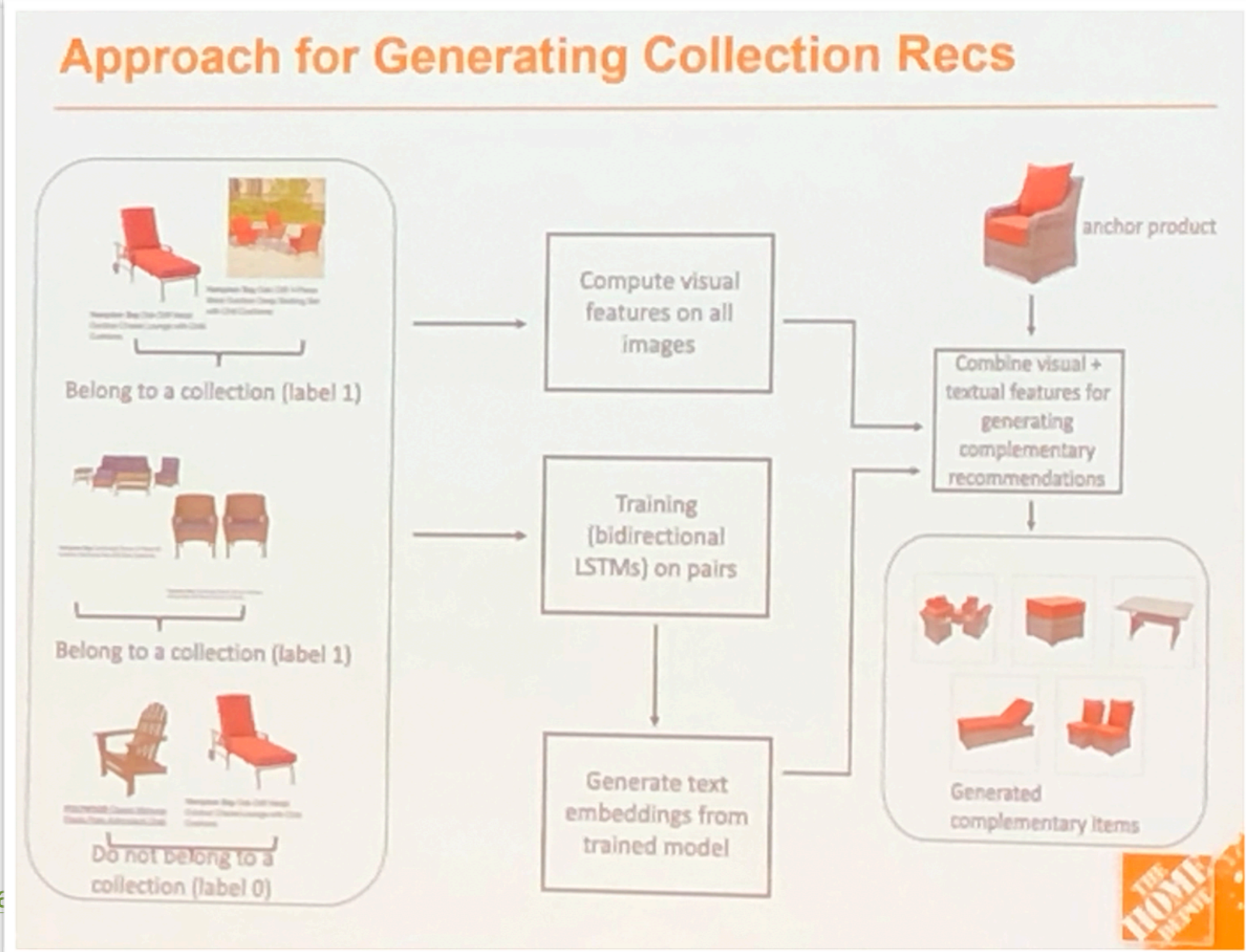
- ▶ Smart Home
  - ▶ Heating
  - ▶ Alarm
  - ▶ Kitchen

Multi-task recommendations need triggering, prioritization and orchestration



# Home Depot: Recommendation in Home Improvement Industry, Challenges and Opportunities

Khalifeh Aljadda





# Pandora: Just Play Something Awesome: The Personalization Powering Voice Interactions at Pandora

Vito Ostuni







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