Recommendation systems and user representations

Seznam Advertising Systems

Seznam.cz

Agenda

Theoretical part (90 min. + break)

- *practical part prep: notebook #001*
- About us
- About Seznam
- Introduction to recommender systems
- Recommender system at Seznam
- Recommender system infrastructure
- *practical part prep: notebook #003*
- Ranking models
- Cold-start problem

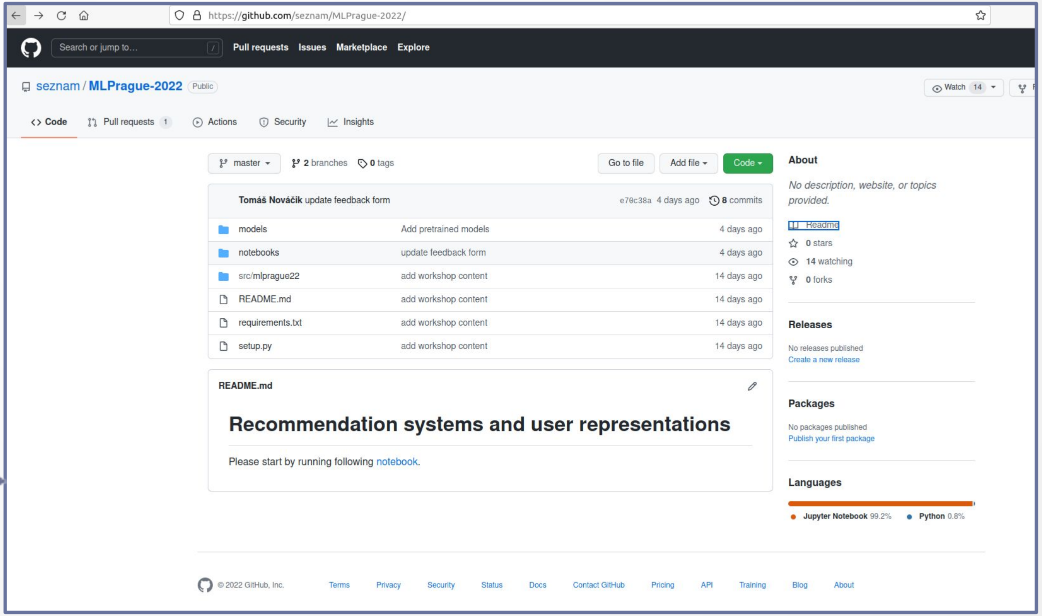
Practical part (90 min.)

- Tools setup and intro
- MIND dataset preparation
- Exploratory data analysis
- Embeddings for user representations
- Train ranking model with user representation

practical part prep: notebook #001

1) go to: https://tinyurl.com/48se6ze5
2) open the initial notebook (as in README.md)
3) open the "*001-prepare-dataset*"
4) copy
5) launch

1.



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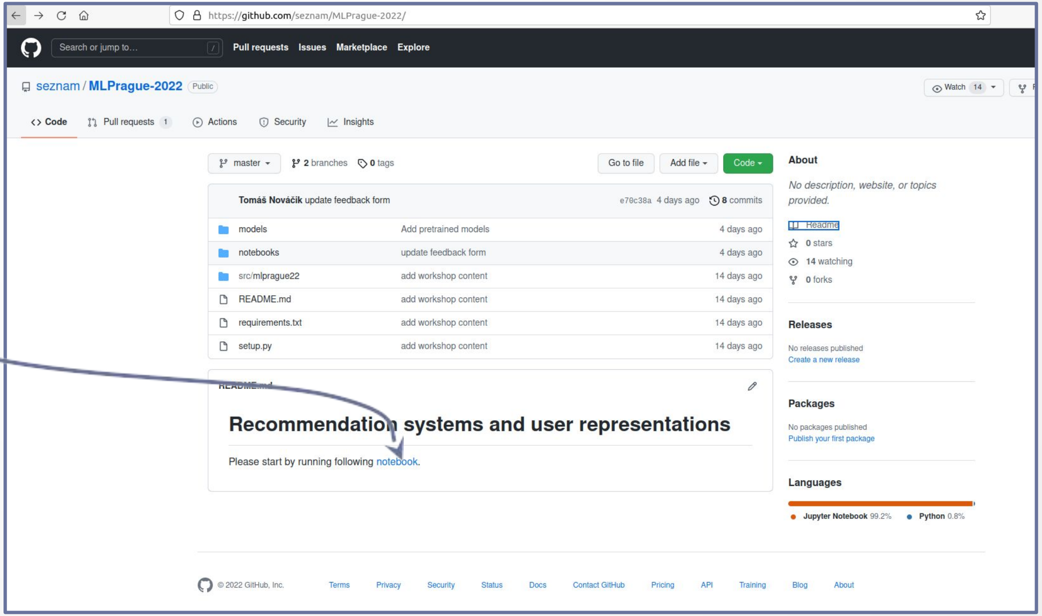

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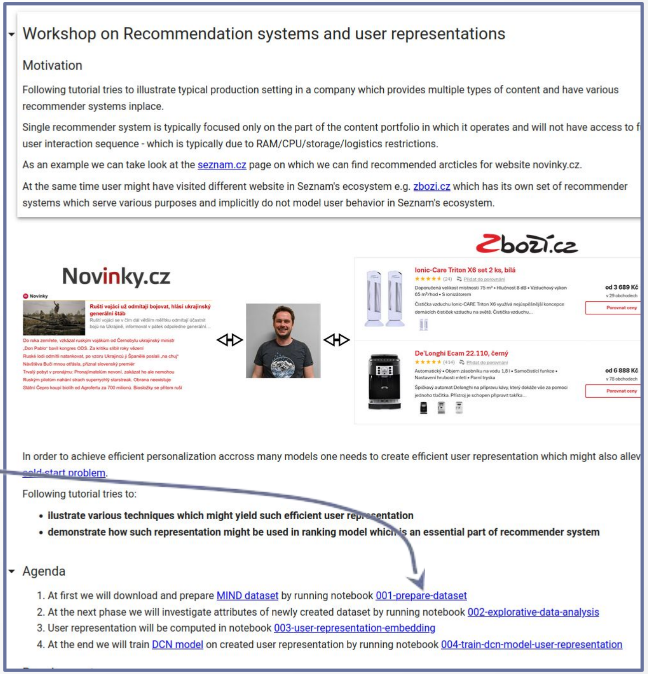

Workshop on Recommendation systems and user representations

Motivation

Following tutorial tries to illustrate typical production setting in a company which provides multiple types of content and have various recommender systems inplace.

Single recommender system is typically focused only on the part of the content portfolio in which it operates and will not have access to f user interaction sequence - which is typically due to RAM/CPU/storage/logistics restrictions.

As an example we can take look at the seznam.cz page on which we can find recommended arcticles for website novinky.cz.

At the same time user might have visited different website in Seznam's ecosystem e.g. zbozi.cz which has its own set of recommender systems which serve various purposes and implicitly do not model user behavior in Seznam's ecosystem.

In order to achieve efficient personalization accross many models one needs to create efficient user representation which might also allev cold-start problem.

Following tutorial tries to:

- **ilustrate various techniques which might yield such efficient user representation**
- **demonstrate how such representation might be used in ranking model which is an essential part of recommender system**

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1. At first we will download and prepare MIND dataset by running notebook 001-prepare-dataset
2. At the next phase we will investigate attributes of newly created dataset by running notebook 002-explorative-data-analysis
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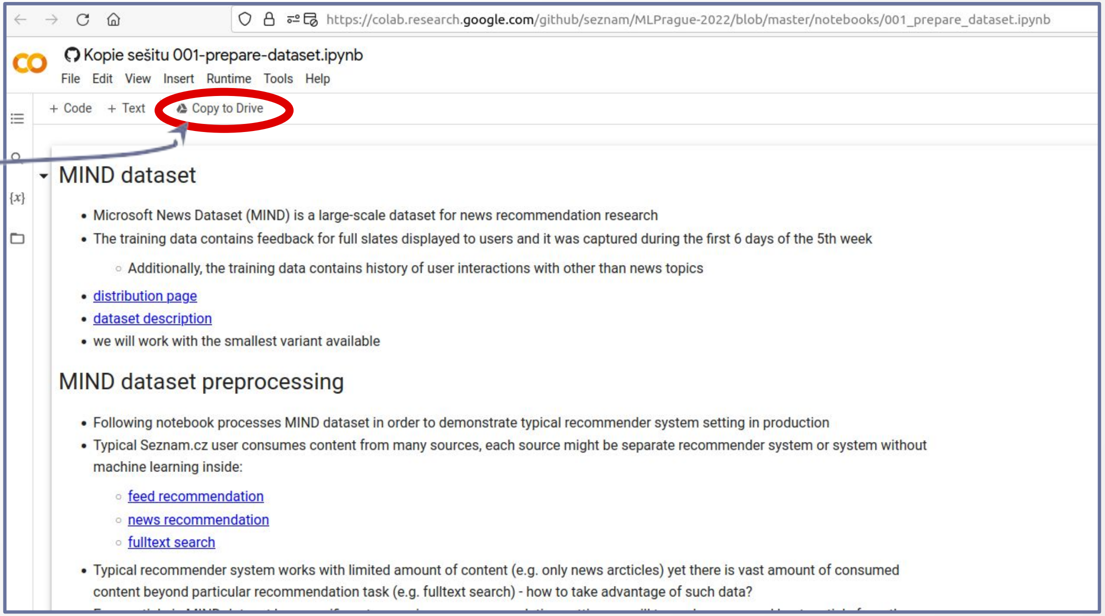

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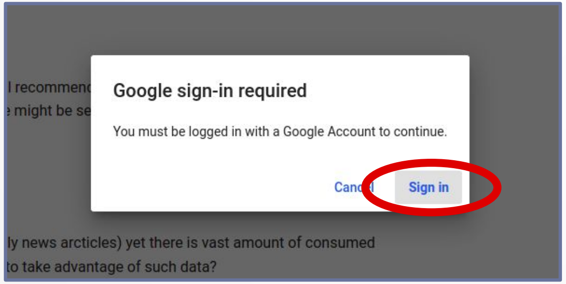

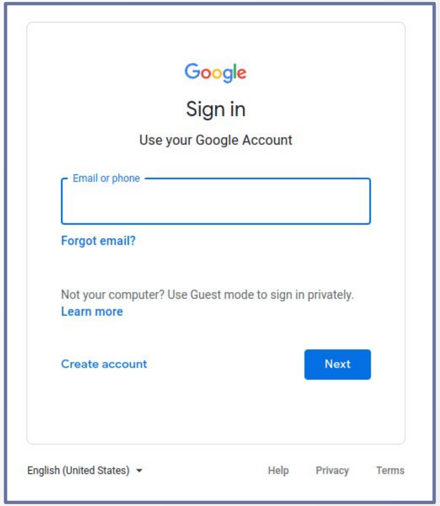

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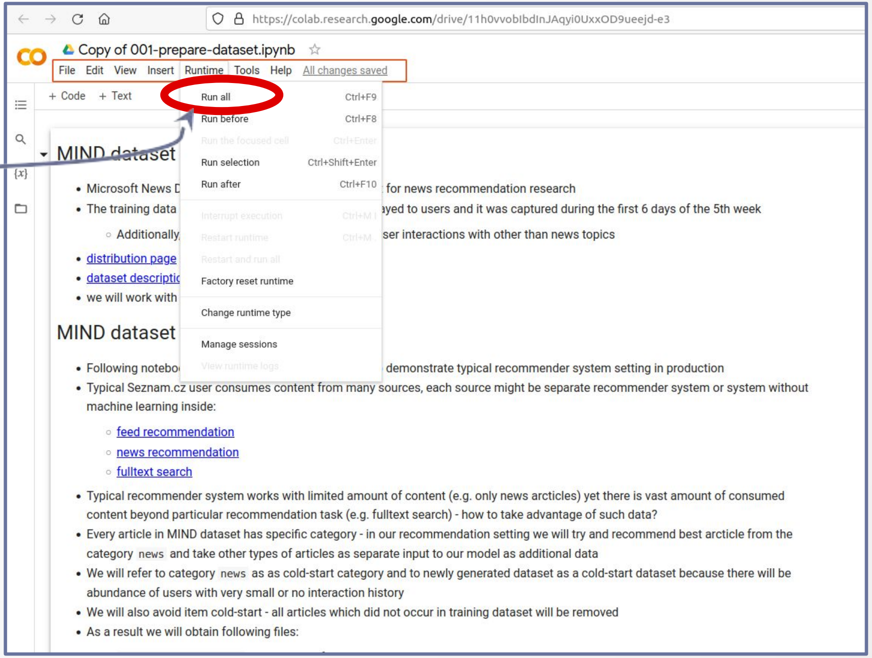

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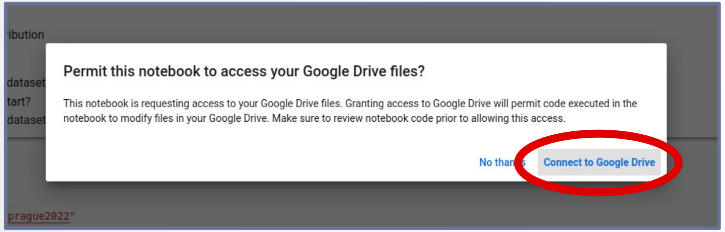

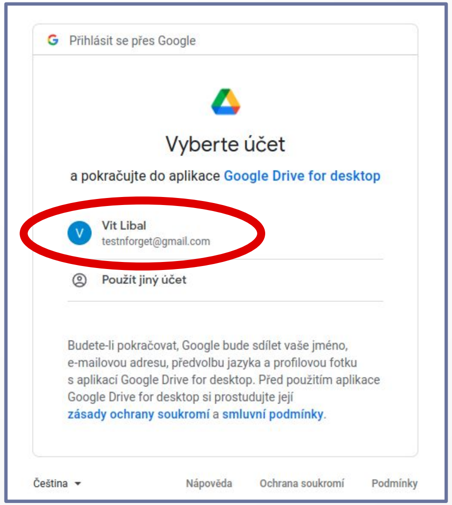

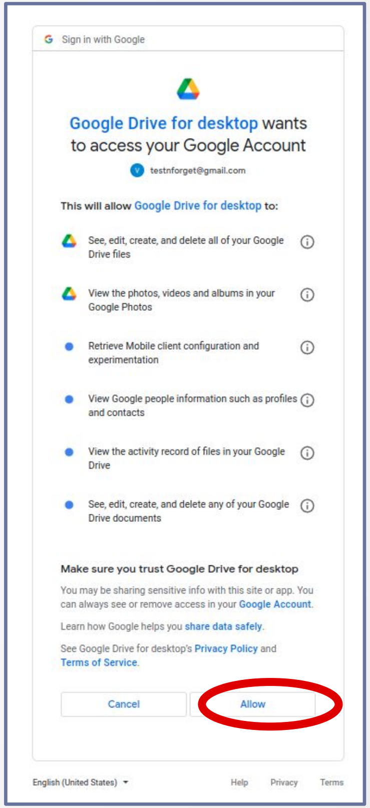

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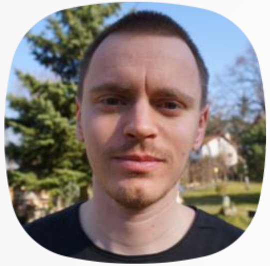
Authors

Václav Blahut

Recommender Systems



Radek Tomšů

Recommender Systems

Tomáš Nováčik

Targeting & personalization

Adam Jurčík

Targeting & personalization

Vít Líbal

Relevance in display advertising

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About Seznam.cz

- Technological company and media house
- The product portfolio consists of highly popular online services such:

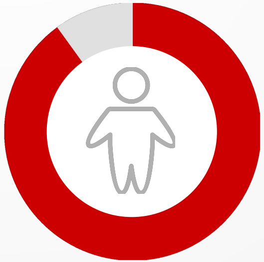
Seznam.cz
Mapy.cz
Sreality.cz
Email
Firmy.cz
stream
Zboží.cz
Sauto.cz
Televize Seznam

About Seznam.cz

- **Most visited content websites** on Czech Internet
- About **7.3 million unique users** visit Seznam.cz services every month

PROŽENY.CZ Novinky.cz Seznam Zprávy GARÁŽ.CZ

SUPER.CZ SPORT.CZ



95 %

Monthly reach of the Czech online population

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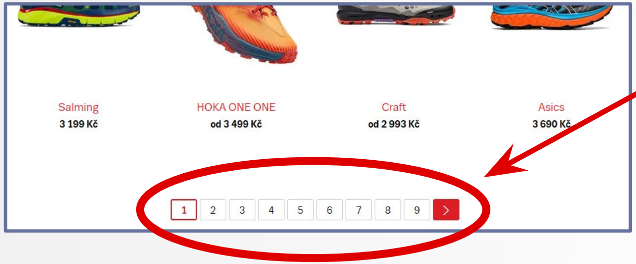
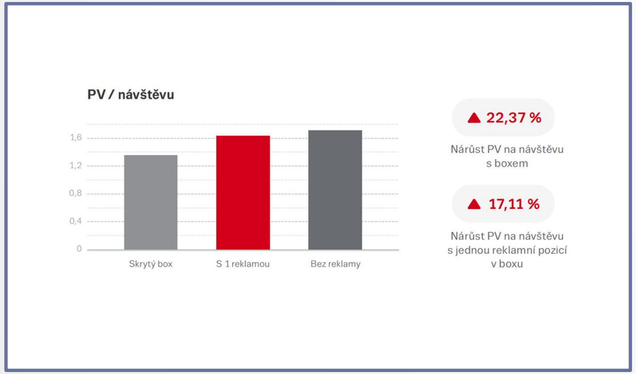
Why are Recommendation Systems important?



- **“Tyranny of choices”:**
  - too many options = user’s discomfort
- **Ecommerce growth:**
  - order of magnitude per decade
  - (5.7→42 Bln in global sales 2010 to 2020)



- 35% of Amazon purchases from recommendations
- 75% of Netflix watched contents from recommendations
- Seznam 2019 case study: 22% readability increase with RS

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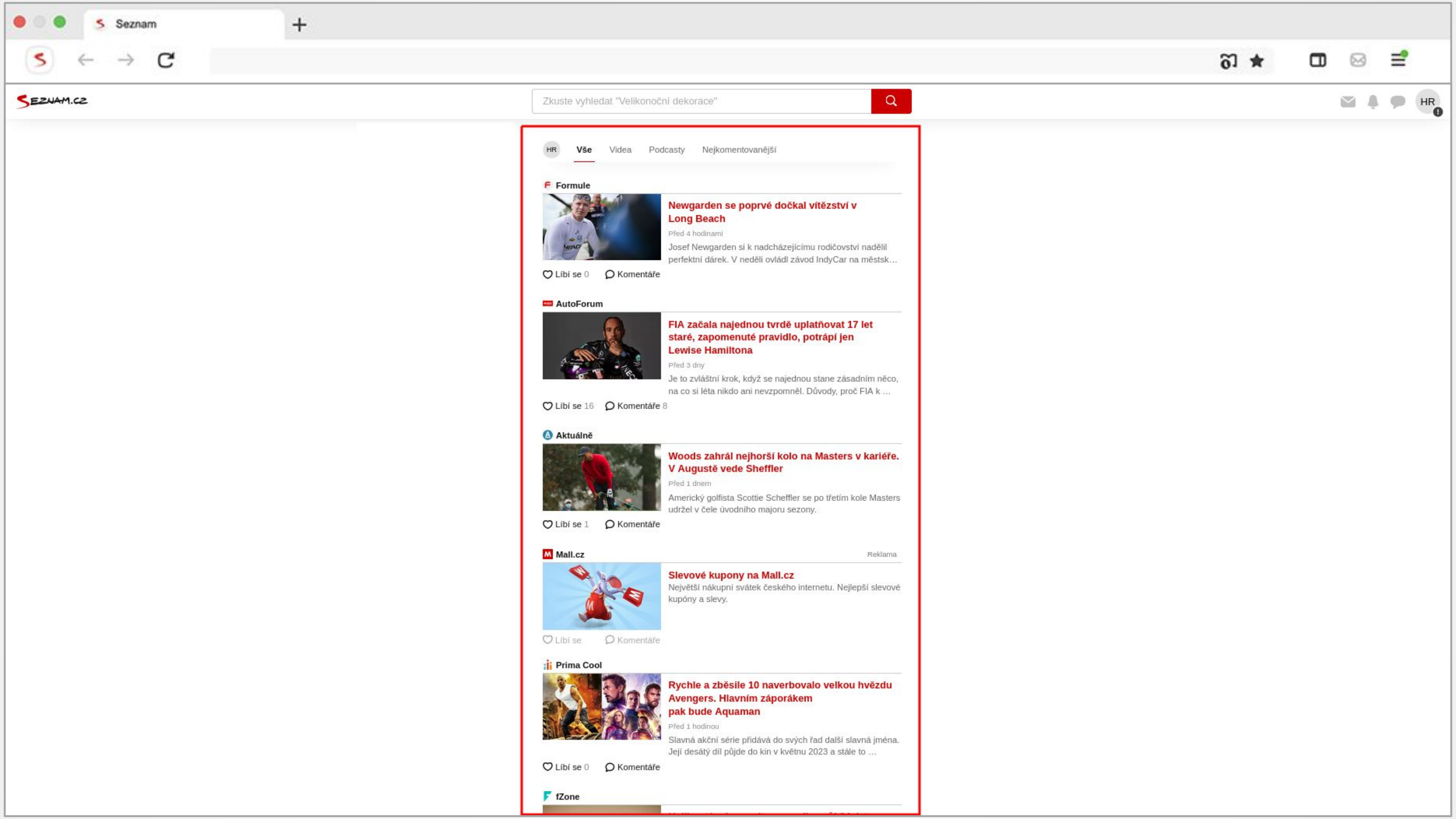
Seznam
Internet Firmy Mapy Zboží Obrázky Slovník Jízdní řády Video
SEZNAM.CZ
Zkuste vyhledat "Křížové cesty"
Vyhledat
Právě se hledá: Počasí Velikonoce 2022 Brzobohatý a Písařovicová Pašijový týden Nehoda na D5
Sauto Kupi Obrázky Volná místa Zboží Slovník Recepty Deníky Sdovolená Hry Mobilní aplikace Podcasty Pohádky Prohlížeč
Seznam Zprávy • Pondělí 11. dubna. Svátek má Izabela.
Nákupy v Česku podražily o 12,7 %. Bude ještě hůř, varují ekonomové
Inflace v Česku dosáhla 12,7 procenta. Mohou za to především vysoké ceny energií a pohonných…
Naštvaní stážisti: Nechceme dotovat předsednictví EU z našich brigád
Ukrajinské děti v pasti. Dopoledne česká výuka, potom distanční z Ukrajiny
Concorde: Velký nadzvukový švindl
Sport
Šílenství v cíli. Emoce bouchly po závodě, piloti šli do sebe pěstmi
Emoce po závodě pořádně probublaly. Zatímco vítězství v posledním díle slavného okruhového…
Sedmdesátiny brankářského gentlemana. NHL legendu stále mrzí
Ronaldův zkrat! Hvězda zaútočila na malého fanouška, pak se omlouvala
Fantastický Krejčí! Český basketbalista v NBA vylepšil rekord
Garáž
Za volant od 17, vyšší tresty za hraní s mobilem. Ministerstvo dopravy chystá změny
Rozdávat nižší tresty za malichernosti, ale přísněji trest větší hříšníky. Tak by měl podle ministra…
Podobné auto na silnici nepotkáte: BMW iX má z budoucnosti design, techniku i cenu
Novinky
ŽIVĚ Bude až 20 stupňů, na Velikonoce se ale citelně ochladí
Nevyzpytatelnost dubnového počasí se naplno projeví i o velikonočním týdnu, který právě startu…
Už dva týdny se s námi nikdo nespojil, stěžuje si pluk Azov v Mariupolu
Drahé energie a pohonné hmoty vyhnaly inflaci na 12,7 procenta
Údaje o spotřebě tepla dostanou lidé každý měsíc
Nejštíhlejší mrakodrap na světě je hotov. První nájemníci se začínají stěhovat
Časté známky nízkého sebevědomí a sebeúcty
Zabavené jachty oligarchů polykají miliardy. Kdo to bude platit?
Uzavřenou Šanghaj ovládl hlad. Z oken zní zoufalý nářek obyvatel
Stream
Takhle jste ji ve Tváři ještě neviděli. Z vystoupení Nesvačilové vám bude běhat mráz po zádech Tvoje tvář má známý hlas
Denisa Nesvačilová měla v show Tvoje tvář má známý hlas štěstí zejména na sexy popové divy.…
Nejlepší velikonoční nádivka, která se vám zaručeně povede Lukáš Mozek
Jak ulevit od bolesti v bedrech: pět jednoduchých cviků, které byste měli cvičit pravidelně Proženy
I pejsci umí žárlit. Huskymu se nelíbí „příchod miminka" Tady virál
Válka na Ukrajině • Українські новини
09:16 Banka Société Générale chystá odchod z Ruska. Dohodla se na prodeji svého podílu v Rosbank a dceřiných pojišťovacích firmách tohoto…
08:54 Německá armáda vypravila v pondělí speciální letoun pro přepravu
Super
Prsa jí vypadávala z dekoltu: S výstřihem do pasu se Aneta Vignerová nebála ani tančit
Rovnou z módního mola na Fashion Weeku přišla v modelu Michaela Kováčika na Český ples…
Bez make-upu, filtrů i dobrého nasvícení: Takhle vypadá Jennifer Lopez po ránu
Leoš Mareš se pochlubil rozkošnou dcerou: Malá Alex oslavila první měsíc na světě a je celý táta
Proženy
Jak ulevit od bolesti v bedrech: pět jednoduchých cviků, které byste měli cvičit pravidelně
Jak si ulevit od bolesti zad? Odložte mobil a počítač, natáhněte se na podložku a pročtivě…
Pro velká prsa i drobnější postavu: nejhezčí jarní šaty, které teď koupíte v kolekcích
Nalepená prsa i vyšší čelo: Jak se Lily James proměnila v Pamelu Anderson
Týdenní horoskop: Střelce popadne „lenora", Panny, pozor na sňatkového podvodníka
Koronavirus
Pozitivní případy +2 648 Reinfekce: 397
V nemocnici -181 1 258
Úmrtí +8 39 880
• Aktuální opatření
• Cestování
Díváte se na včerejší data, dnešní vydá MZČR okolo 08:30


Seznam
Zkuste vyhledat "Velikonoční dekorace"
HR
HR
Vše
Videa
Podcasty
Nejkomentovanější
Formule
Newgarden se poprvé dočkal vítězství v Long Beach
Před 4 hodinami
Josef Newgarden si k nadcházejícímu rodičovství nadělil perfektní dárek. V neděli ovládl závod IndyCar na městsk…
Líbí se 0
Komentáře
AutoForum
FIA začala najednou tvrdě uplatňovat 17 let staré, zapomenuté pravidlo, potrápí jen Lewise Hamiltona
Před 3 dny
Je to zvláštní krok, když se najednou stane zásadním něco, na co si léta nikdo ani nevzpomněl. Důvody, proč FIA k …
Líbí se 16
Komentáře 8
Aktuálně
Woods zahrál nejhorší kolo na Masters v kariéře. V Augustě vede Sheffler
Před 1 dnem
Americký golfista Scottie Scheffler se po třetím kole Masters udržel v čele úvodního majoru sezony.
Líbí se 1
Komentáře
Mall.cz
Reklama
Slevové kupony na Mall.cz
Největší nákupní svátek českého internetu. Nejlepší slevové kupóny a slevy.
Líbí se
Komentáře
Prima Cool
Rychle a zběsile 10 naverbovalo velkou hvězdu Avengers. Hlavním záporákem pak bude Aquaman
Před 1 hodinou
Slavná akční série přidává do svých řad další slavná jména. Její desátý díl půjde do kin v květnu 2023 a stále to …
Líbí se 0
Komentáře
fZone

Finsko má propracovaný plán pro případ ruské invaze

TOMÁŠ TRNĚNÝ

Příslušníci finských aktivních záloh během cvičení v jihovýchodním Finsku v březnu 2022.

10:05

Po desítky let se Finsko, které má s Ruskem hranici dlouhou přes 1 300 kilometrů, připravuje na konflikt se svým sousedem. Ruská invaze na Ukrajinu pak obavy Finů z útoku ještě zvýšila. Země ale hlásí, že je připravena.

Zásoby, evakuační prostory, bojeschopná a početná armáda. Na těchto třech pilířích stojí finská obrana před možnou ruskou agresí. Země má ze svého východního souseda, nejprve Sovětského svazu a později Ruska, obavy už přes 80 let a po celou dobu se připravuje na nejhorší. Může být Finsko inspirací i pro ostatní evropské země?

STALO SE

10:24
Ukrajina varuje před ruskými provokacemi v Podněstří

10:01
Africe hrozí, že se stane světovou popelnicí na plastový odpad

10:00
Nový žebříček Top 50 v českém fotbale: Za Křetínským došlo k povstání trenérů

DALŠÍ ČLÁNKY

DOPORUČOVANÉ

Concorde: Velký nadzvukový švindl

VČERA 19:21

Naštvaní stážisti: Nechceme dotovat předsednictví EU z našich brigád

7:45

Glosa: Čeká nás biblických 7 hubených let. Není na výběr

VČERA 12:00

„Sex je jako komunismus." Objevili jsme soubor erotických povídek Petra Fialy

8:00

Seznam Native

Proč z české krajiny mizí ovocné stromy?

Recommender system at Seznam

2014

First experiments

Combining articles with targeting categories from Targeting & user personalization team

2015

Started works on a retrieval model

Collaborative Filtering (ALS)

2016

Started works on a ranking model

Logistic Regression (Vowpal Wabbit)
Neural networks (Too slow at the time)

2017

Fully working models

Both retrieval and ranking models give solid performance

2018

Improving current models and data pipelines

Elastic search integration
Diversification
New interactions - remove, like

2019

Automation and TF

Started with Tensorflow
AB test evaluation improvements
Offline Evaluation attempts

2020

Automation and new models

Spent time models
First tensorflow models
FastText for article embeddings
Automation of AB testing

2021

Automation and new models v2

New retrieval model
Started works on a new ranking model
New content models

Recommender system at Seznam

~10M
Clicks per day

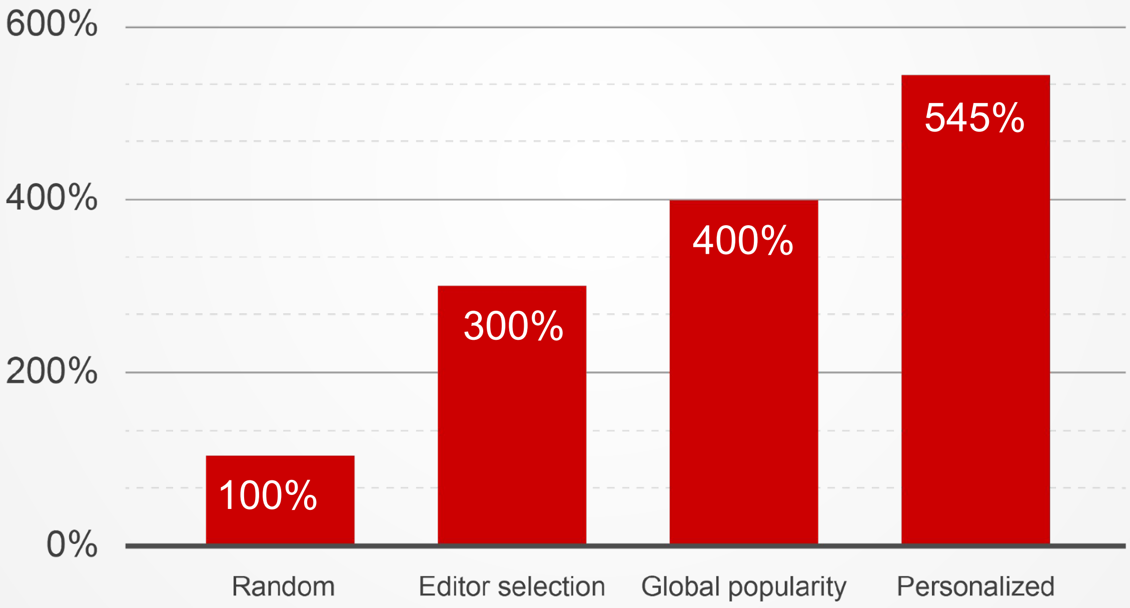
~10K
Requests per second

~1K
New items per day

~1K
Experiments per year

Algorithm performance

Click-through-rate



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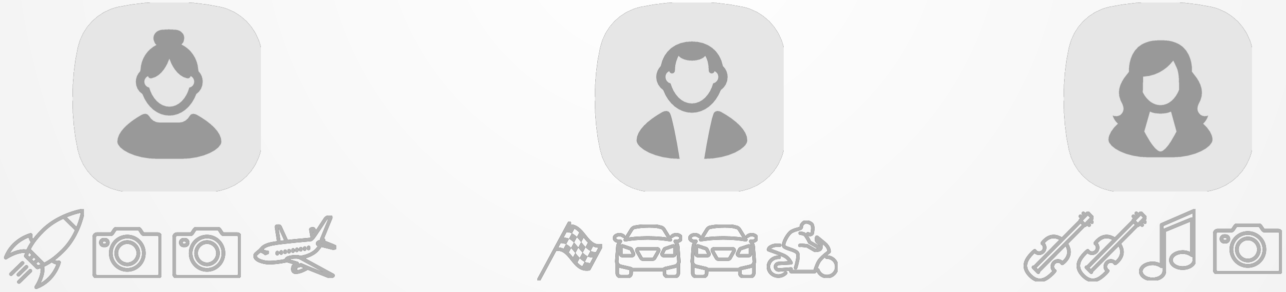
Recommender systems

- Set of users, Set of items
- # of items >> # of items a user is able to read through
- The majority of items might be irrelevant for a user
- The goal: recommend only the items relevant to a user



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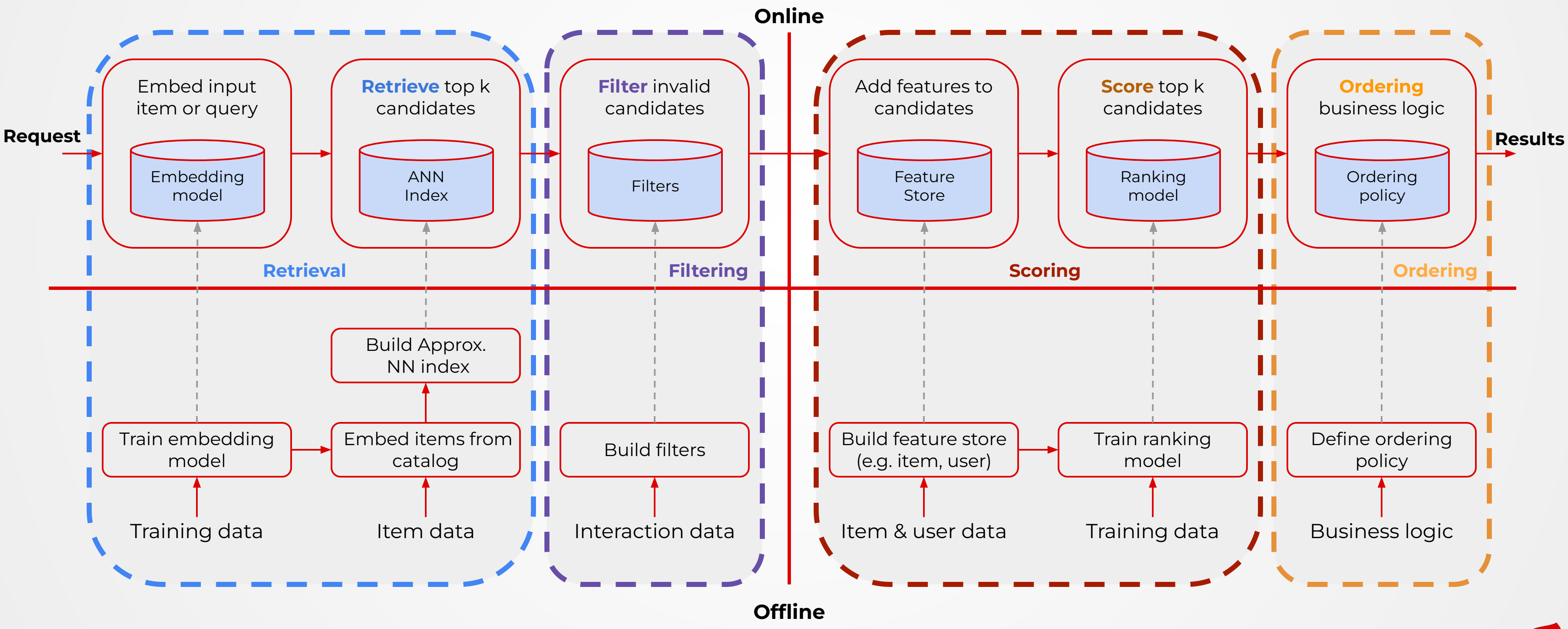
Recommender systems infrastructure



Based on "**Moving Beyond Recommender Models**" by Even Oldridge and Karl Byleen-Higley (NVIDIA), https://www.youtube.com/watch?v=5qjiY-kLwFY

practical part prep: notebook #003

6) go open the “*003_user_representation_embedding*”

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6.

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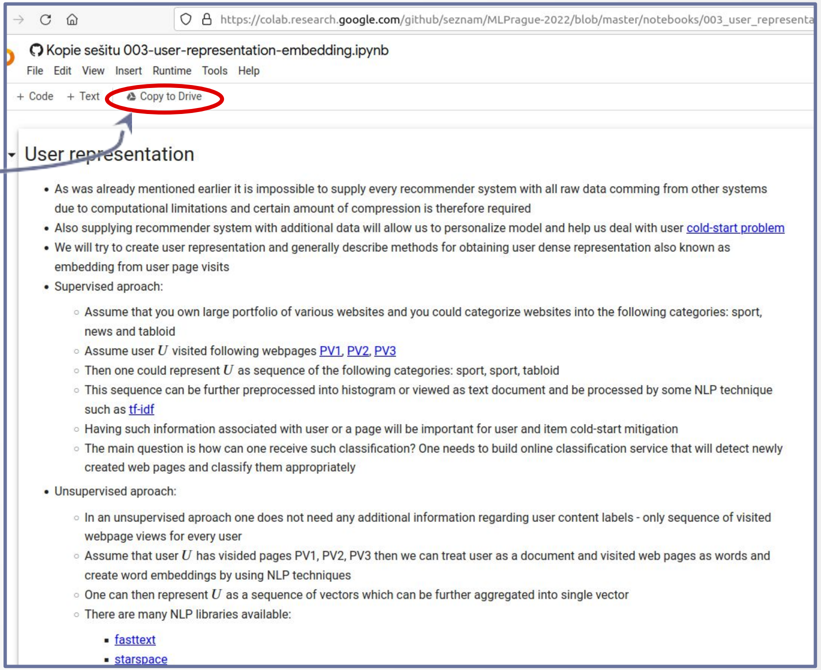

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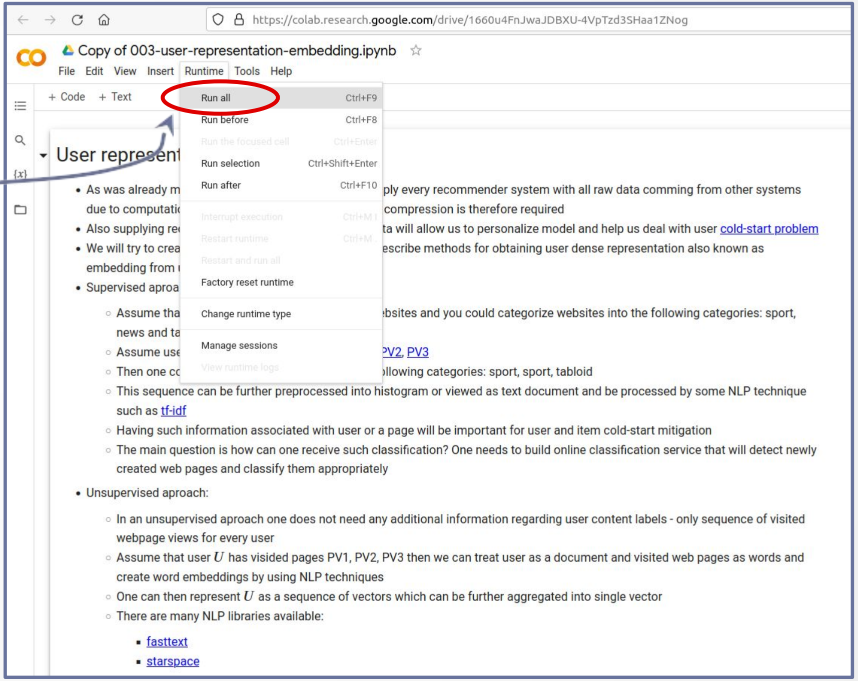

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- Recommender system at Seznam
- Recommender system infrastructure
- **Ranking models**
- Cold-start problem

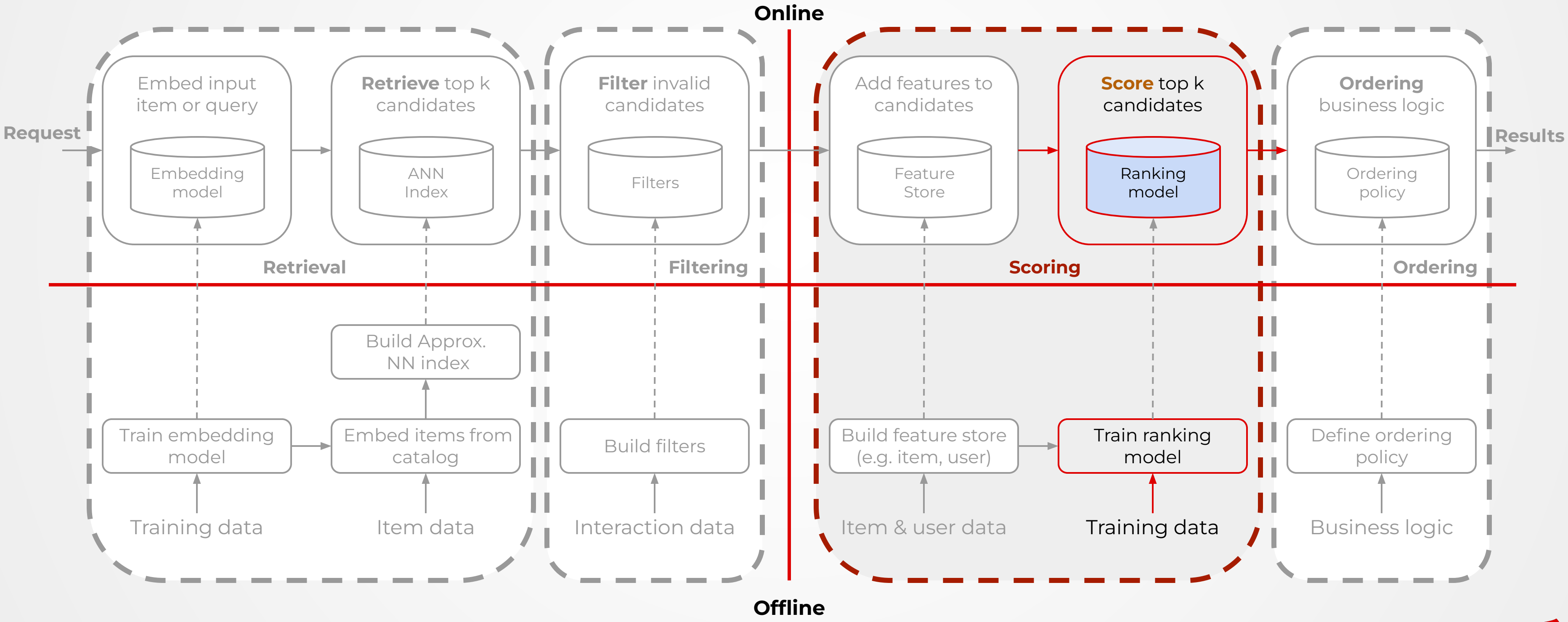
Practical part

- Tools setup and intro
- MIND dataset preparation
- Exploratory data analysis
- Embeddings for user representations
- Train ranking model with user representation

Practical part

- ✔ visit following link: https://tinyurl.com/48se6ze5
- ✔ open notebook according to instructions in README.md
- ✔ run notebook with prefix 003*

Ranking models



Based on "**Moving Beyond Recommender Models**" by Even Oldridge and Karl Byleen-Higley (NVIDIA), https://www.youtube.com/watch?v=5qjiY-kLwFY

Ranking models input - user features

Gender: Male

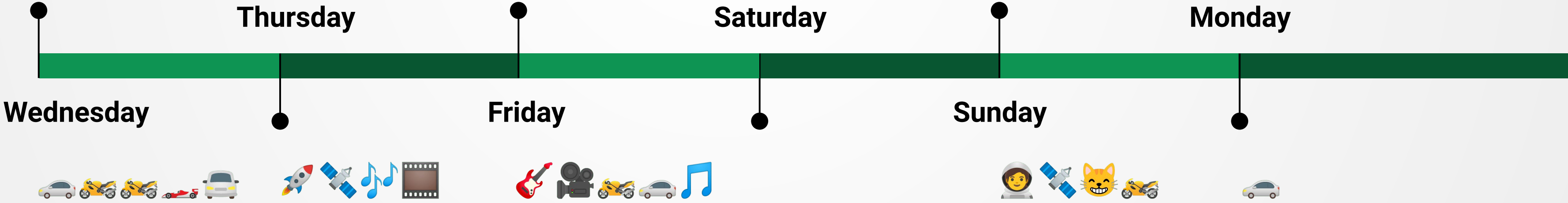
Age: 30s

Location: Prague

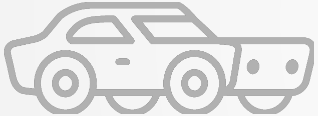
Device: Android Smartphone

…

Ranking models input - user interaction history



Ranking models input - item features



Title: Jeden z posledních Wartburgů: Svezli jsme se v autě z roku 1990. Pořád je to starý pohodlný Hans, jen už tak „neprdí“

Publisher: Garáž.cz

Published: 15 hours ago

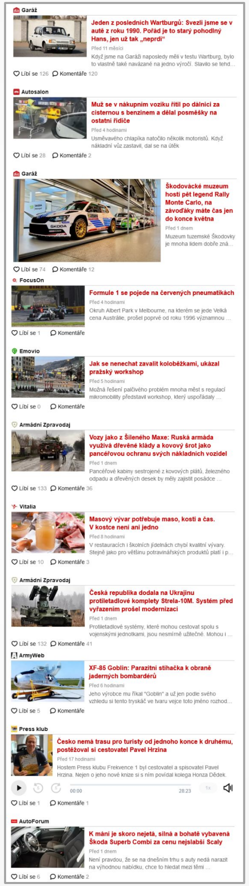
Tags: Cars, Oldtimers, Germany

…

Ranking models input - contextual features

- currently displayed item features
- current time of day/day of week
- time since last interaction
- current section
- …

Ranking models output - label



7 min

2 min

10 min = 35 %

Recommender systems evolution

Collaborative filtering methods

- Based only on user-item rating matrix
- Examples
  - User-based, Item-based
  - Matrix Factorization
  - …

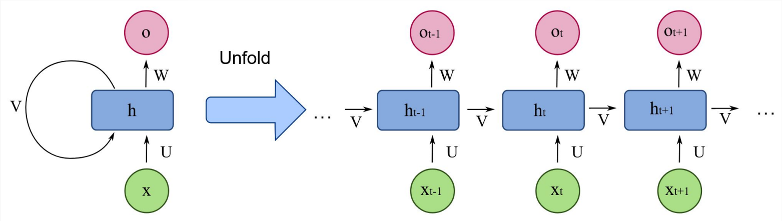
Recommendation as binary classification

- Based on any features available
- Incl. content-based
- Examples
  - Logistic regression (Vowpal Wabbit)
  - Simple NN
  - Factorization Machines
  - …

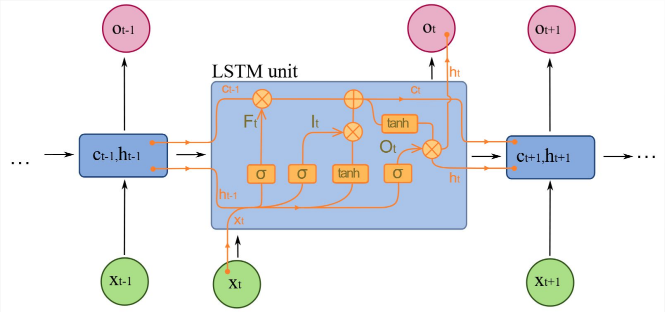
Advanced neural network models

Ranking models - preliminaries

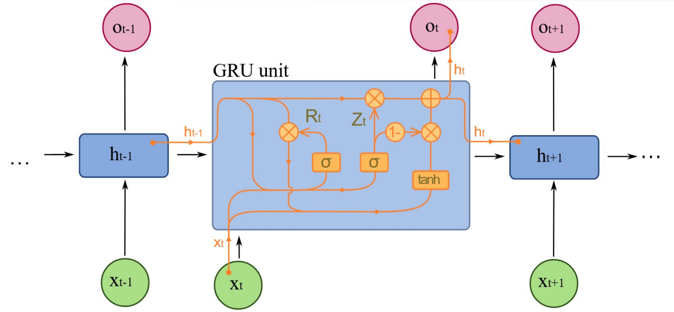
RNN - Recurrent Neural Network



LSTM - Long Short-Term Memory



GRU - Gated Recurrent Unit



New ranking model selection method

Gathering SOTA, reading & pre-selection

Experimental implementation

Offline metrics reality-check

Internal user testing I & II

Production implementation

Online AB tests

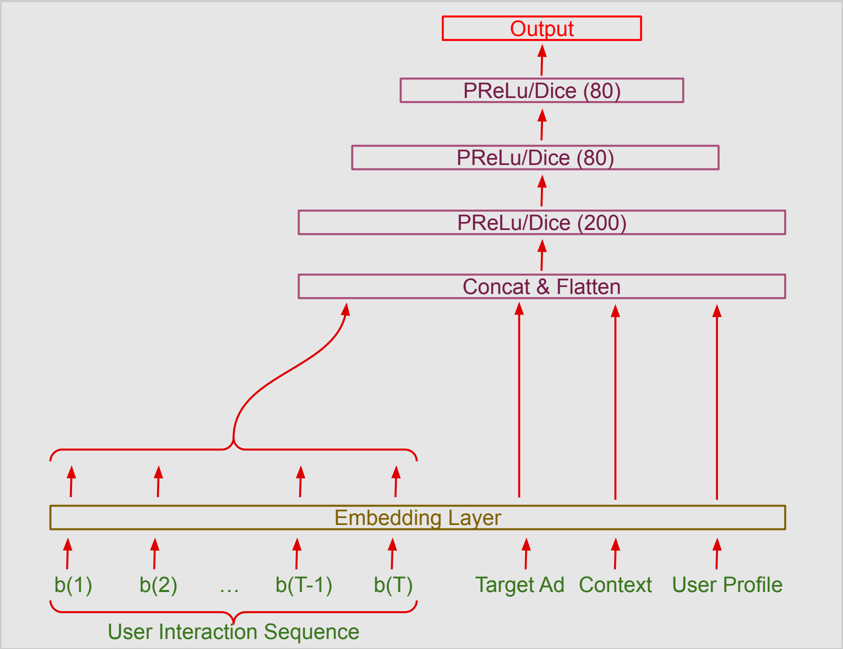
?

Ranking models - SOTA

- Mainly focused on the core, usually accompanied by standard DNN
- Ordered from least to most successful attempts:
    - DIEN
    - SLi-Rec
    - SUM
    - **DCN**

Deep Interest Evolution Network (DIEN)

Embeddings
+ Interest Extractor
+ Interest Evolution Model
+ MLP

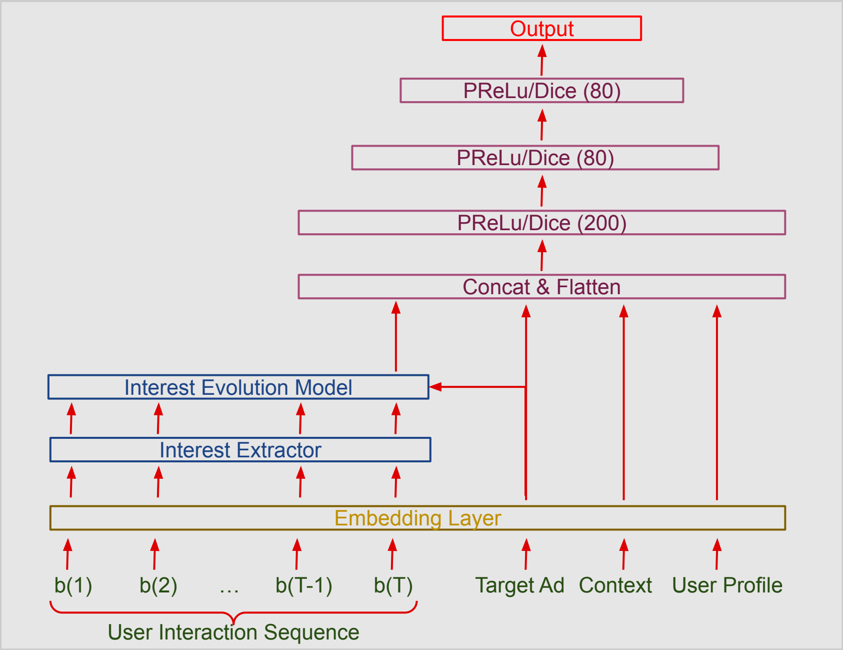


Deep Interest Evolution Network (DIEN)

Embeddings
+ Interest Extractor
+ Interest Evolution Model
+ MLP

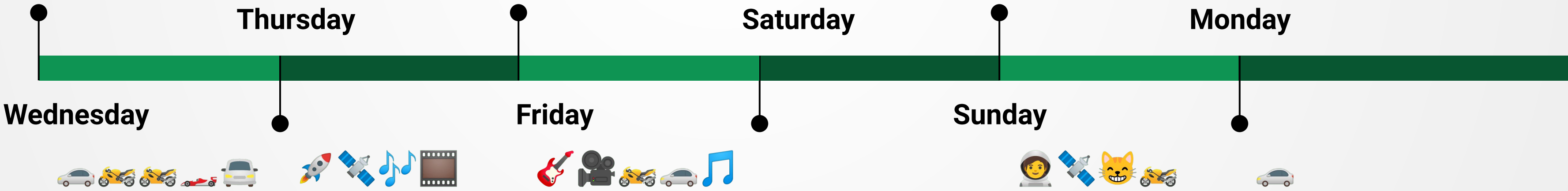
Interest Extraction + Interest Evolution Model:

- GRU based (Gate Recurrent Units) representation of latent temporal interest + sequence model
- 20% online improvement over baseline model
- Did not show good results @ Seznam RS



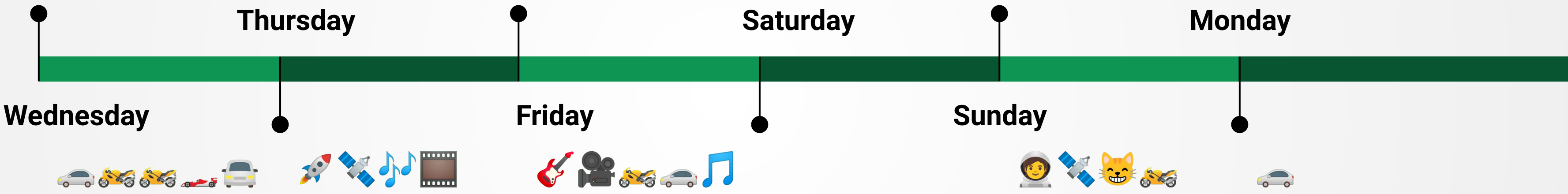
SLi-Rec - Short-term and Long-term preference Integrated RECommender system

- Advanced sequential RNN for user preference modelling
- Short-term preference modelling
  - Upgraded LSTM
  - Time-aware controller - capture temporal distance between interactions
  - Intent-aware controller - contextual attentive mechanism to suppress deviations



SLi-Rec - Short-term and Long-term preference Integrated REcommender system

- Long-term preference modelling
- Attentive mechanism to adaptively combine short-term and long-term components based on context



Pros

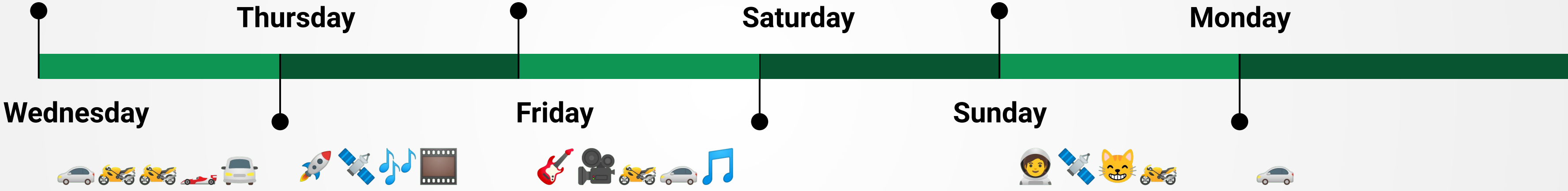
- Clear intuition of what model does
- SOTA performance

Cons

- No real-world results presented
- Too slow and expensive in SZN practice
- Requires time-stamped data

SUM - Sequential User Matrix

- Multi-channel memory network for NRT large-scale RS
- User representations can be stored and updated incrementally



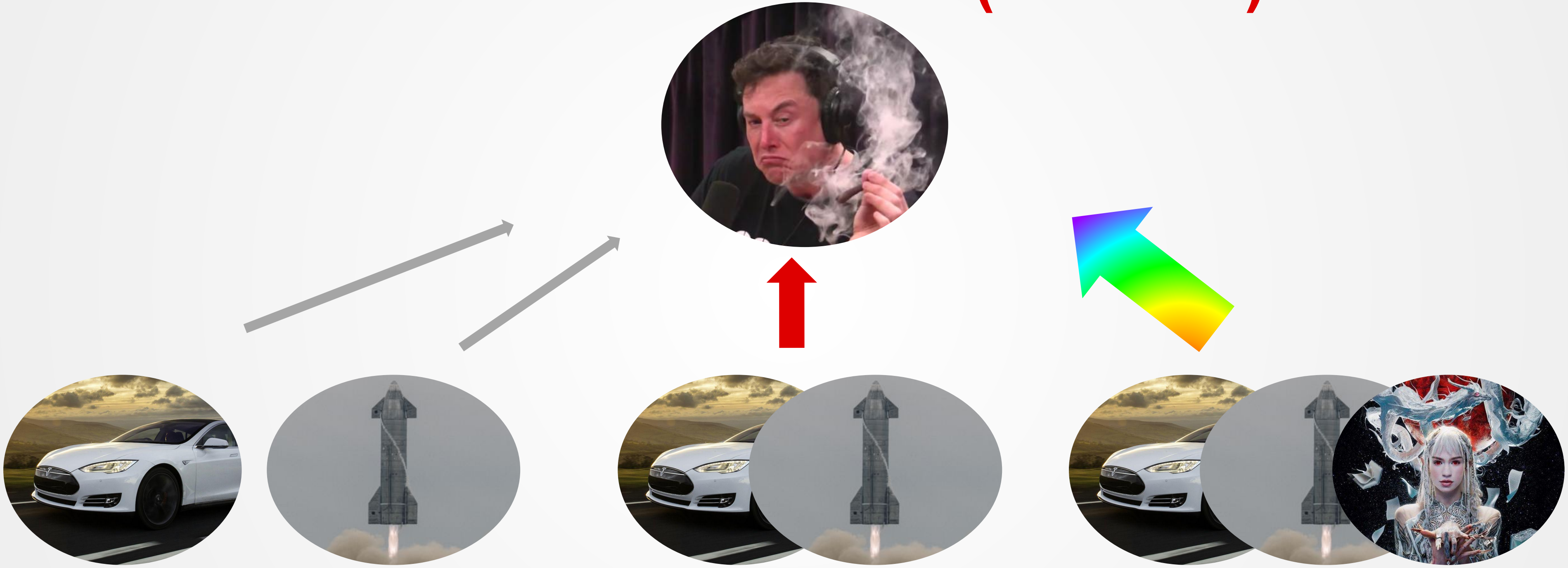
Pros

- Scalable, industry-level approach
- Online experiment results available

Cons

- Less intuitive architecture
- Unable to make it work well enough at SZN (yet)

DCN - Feature interactions (crosses)



Single features

Quadratic interactions

Cubic interactions

DCN - Deep & Cross Network v2

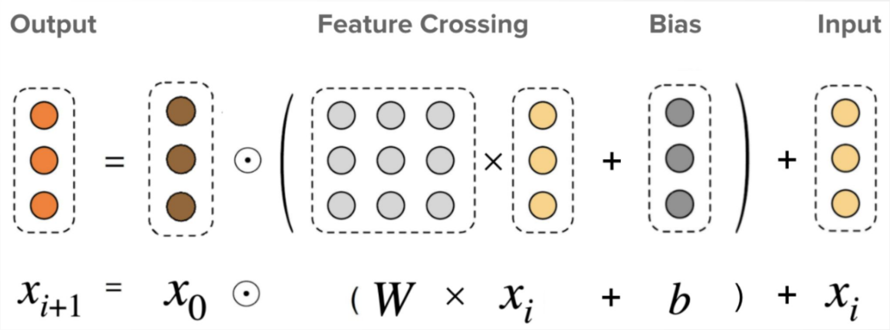
- Implicit f.i. modelled by DNN are not efficient
- Explicit f.i. were formerly hand-designed, now created by cross-layers
- Each cross-layer adds an order of f.i.

Pros

- Avoids need of manual feature crossing
- Simple, elegant, general solution
- Further optimizable, scalable,
  industry-level approach
- Tested at SZN, looking good

Cons

- Not sequential



Agenda

Theoretical part

- Advance the notebooks
- About us
- About Seznam
- Introduction to recommender systems
- Recommender system at Seznam
- Recommender system infrastructure
- Ranking models
- **Cold start problem**

Practical part

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Cold-start

Missing interaction history?

Cold-start

Missing interaction history = likely poor recommendation

- Not optimal performance yet

Cold-start

Missing interaction history

= likely poor recommendation

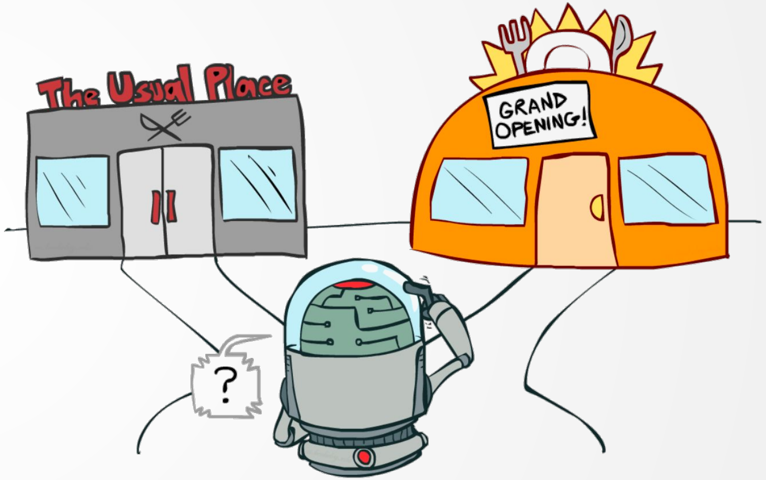
- Not optimal performance yet
- Item cold-start
    - New article, product = no or little interaction with users
    - Unable to kick-off promising items, user engagement loss
- User cold-start
    - New user, weak user identity (3p cookies) = no or little interaction with items
    - Unable to acquire new users

Cold-start mitigation

How to cope with cold-start?

Cold-start mitigtion

- Item cold-start
  - Popularity model - already known users
  - Metadata - cohort/segment
  - External behavior - social media
- User cold-start
  - Exploration - multi-armed bandit
  - Metadata - category/topic
  - Content-based features - hybrid approach



Zdroj:
https://lilianweng.github.io/posts/2018-01-23-multi-armed-bandit/

Extra user features

- User profile - provided metadata
- Other domain behaviour
  - User history - search queries
  - Classification, segmentation – interests
- Encoding
  - One-hot - sparse, unsuitable for NNs
  - Histogram - denser, but not optimal
  - Embedding
    - Dense - 10s-100s dimensions
    - Items retain similarity
    - Automatic compression/transformation

One-hot

																		
	I	II	…	VIII	IX	I	II	III	I	II	…	VI	VII	I	II	…	VIII	IX
A	✔	✔	…	✔	✔	✔	✔	✔	✔		…			✔	✔	…	✔	✔
B	✔		…			✔	✔	✔	✔	✔	…	✔	✔	✔		…		
C			…	✔	✔	✔	✔	✔			…			✔	✔	…	✔	✔

Histogram

				
A	8	3	1	7
B	1	3	7	1
C	3	3	0	9

Embedding

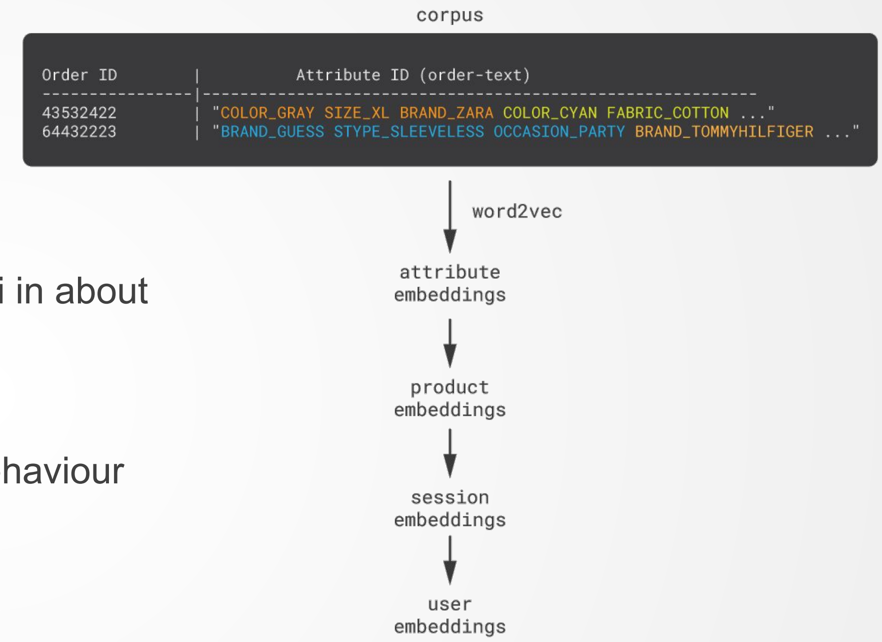
A (0.3, -0.7, 0.1)

B (1.1, 0.2, -0.3)

C (0.2, -0.4, 0.6)

User embedding

- Embedding (NLP)
    - Classification, translation
    - Word similarity ⇔ vector similarity
    - Very efficient - can process english wiki in about a day
- User history ⇔ Text document
    - Model user similarity using common behaviour
        - User actions ⇔ words
        - Users / sessions ⇔ Documents
    - User vector
        - Combine action vectors - average, sum
        - word2vec, fastText



Zdroj: https://blog.griddynamics.com/customer2vec-representation-learning-and-automl-for-customer-analytics-and-personalization/

Summary

- ✔ Introduction to recommender systems
- ✔ Complexity/performance tradeoff in SOTA models
- ✔ Cold-start problem can be tackled by using additional data
- ✔ Feature embedding is the way to go

Thank you!

Questions & inquiries

vit.libal@firma.seznam.cz

We are hiring!

https://kariera.seznam.cz

- **Relevance in display advertising:**
  - https://kariera.seznam.cz/402701-vyzkumnik-v-oblasti-machine-learning/
  - ML models to predict clicks in display advertising, exploration & exploitation, bandits.
- **Online auction Bidding Automation:**
  - https://kariera.seznam.cz/403956-machine-learning-vyzkumnik-automatizace-bidovani
  - Reinforcement learning a control theory for bidding strategy automatizaci, ML models to predict ad conversions.
- **Relevance in search advertising:**
  - https://kariera.seznam.cz/403972-machine-learning-vyzkumnik-relevance-reklamy-ve-vyhledavani/
  - ML modely predikce prokliku reklamy ve vyhledávání včetně NLP technologií.
- **Targeting and personalization:**
  - https://kariera.seznam.cz/400105-vyzkumnik-strojoveho-uceni-pro-cileni-reklamy-a-personalizaci/
  - ML models to estimate user profile and interests.
- **Recommendation systems:**
  - https://kariera.seznam.cz/395074-machine-learning-vyzkumnik-pro-doporucovaci-systemy/
  - ML models to recommend content
- **Operational research:**
  - https://kariera.seznam.cz/405314-operacni-vyzkum-data-scientist/
  - Discrete optimization, ML modeling of online auctions, game theory for design of ad systems and its logic.

References

Motivation:

https://redstagfulfillment.com/2010s-ecommerce-growth-decade/
https://faculty.washington.edu/jdb/345/345%20Articles/Iyengar%20%26%20Lepper%20(2000).pdf
https://blog.seznam.cz/2020/07/pripadova-studie-zvyste-pocet-zhlednutych-stranek-a-sve-vynosy-diky-seznam-doporucuje/
https://www.mckinsey.com/industries/retail/our-insights/how-retailers-can-keep-up-with-consumers

DIEN:

https://arxiv.org/abs/1809.03672
https://github.com/mouna99/dien

SLi-Rec:

https://www.microsoft.com/en-us/research/uploads/prod/2019/07/IJCAI19-ready_v1.pdf

SUM:

https://arxiv.org/abs/2102.09211

DCN:

https://arxiv.org/abs/2008.13535

User Embedding:

https://jalammar.github.io/illustrated-word2vec/
https://fasttext.cc/
https://medium.com/wisio/a-gentle-introduction-to-doc2vec-db3e8c0cce5e
https://ai.facebook.com/tools/starspace/

Please leave us your feedback:

https://forms.gle/s3cEEDV1hoQ16fLEA