Recommendation Systems for Online Advertising

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08/11/2018

FUI Project Calypso

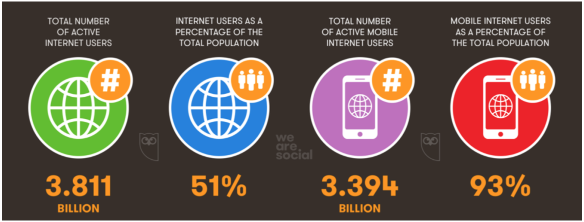
Goal Design of an efficient decision system for online advertising

Participants (not an exhaustive list!)

- **Kelkoo Group**: eCommerce marketing platform
  - Jerome Colin (Program manager)
  - Gilles Vandelle (Chief scientist)
  - André Brois-Crettez (Software Architect / Data Scientist)
- **Purch**: digital publishing and marketplace platform
  - Laurent Metzger (Director of Engineering)
  - Christophe Sebastien (Senior Software Developer)
  - Abderrazagh Mbodj (Data Scientist)
- **LIG**: Laboratory of computer science of Grenoble
  - Massih-Reza Amini (Professor)
  - Charlotte Laclau (Maître de Conférences)
  - Sumit Sidana (Ph.D. student)

Machine learning for online advertising/recommender systems: a huge market

Context: more and more people use internet



Strong economic impact for major companies

More than ...

- 60% of the films seen on **Netflix** are recommended ones
- 35% of sales on **Amazon** are done thanks to recommendation
- 38% of clicks on **Google** are generated over recommended items

The "Recommender problem"

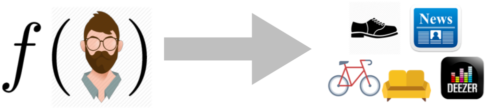
Traditional definition

- Estimate a utility function that automatically predicts how much a user will like an item.

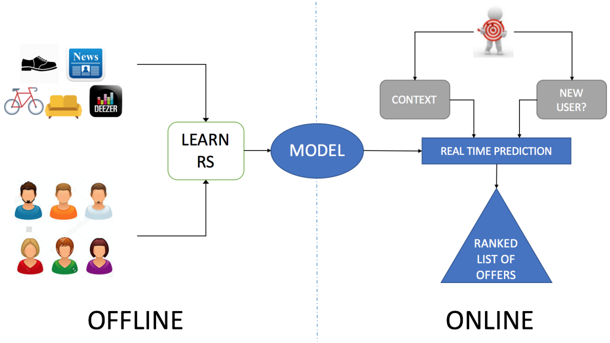
Based on:

- Past behavior
- Relation to other users
- Item similarity
- Context
- ...

What all items will this user like:



Recommendation: A two stage process



- **Stage 1**: gather data and learn a model (offline)
- **Stage 2**: use the model to make prediction (online)

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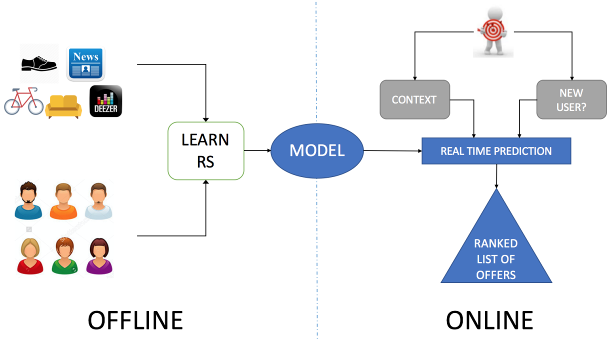

- **Stage 1**: gather data and learn a model (offline)
- **Stage 2**: use the model to make prediction (online)

In this Ph.D., we focus mostly on offline stage

Collaborative filtering

CF: set of techniques ignoring user and item attributes but rather focusing on **user-item interactions.**

Memory-based

- Use the data to establish correlation between users or items
- Recommend from items seen by the similar users
- Do not work well under sparsity constraints or scale very well

Model-based

- Also known as *latent factor models*
- Attempts to build a model to explain the rating patterns

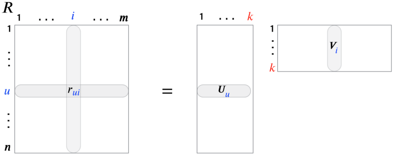

Figure: Principle of Matrix Factorization.

Learning to rank - Overview classification

→ Care to make accurate **ranking** and not **rating** prediction
→ Learning-to-Rank for recommendations is a more realistic problem to solve, as compared to, the rating prediction problem

Pointwise: train a **regressor** to make predictions then rank the results from higher to lower
Pairwise: look at **pair of items** and try to predict relative order for that pair
Listwise: look at the **entire list of items** and try to come up with the optimal ordering of it

Pointwise	Pairwise	Listwise
Matrix Factorization [Koren 2009]	**BPR** [Rendle 2009]	**CofiRank** [Weimer 2007]
Factorisation Machines [Rendle 2009]	**EigenRank** [Liu 2008]	**ListRank** [Shi 2010]
Field-aware FM [Juan 2016]	**LightFM** [Kula 2015]	**WLT** [Volkovs 2012]

Representation Learning (RL) with Embeddings

Embedding as applied to words

- Research in vector representations of words has taken off since the work of [Mikolov et al., 2013], who represent words as embedding vectors.

Representation Learning with Neural Networks

- Sparse datasets represented as low dimensional dense vectors
- Exploiting the sequential nature of user's interactions
  - **Prod2Vec** [Grobovic 2015]: next item prediction
  - **Neural Collaborative Filtering** [He et al., 2017]: A neural architecture combining GMF and MLP
  - **Item2Vec** [Barkan and Koenigstein, 2016a]:
- Exploiting the equivalence between Skip-Gram and MF [Levy 2014]
  - **CoFactor**[Liang et al., 2016]: items embedding as a regularisation term
  - **LightFM** [Kula, 2015a]: neural version of BPR

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None of the previous works focus on learning user/item representation and user-preference for items jointly

Some challenges: Types of feedback

From explicit feedback...

- e.g. 5-star rating
- Pros: good quality
- Cons: scarcity

to implicit feedback

- e.g. clicking, buying
- Pros: available in abundance
- Cons: noisy, no true negatives

Some challenges: Sparsity

- A *catalog* is full database of offers (or items).
- Large number of items available in catalog and shown to the users.
- Users rate or click on only a very limited number of items, compared to what is shown.
- For data extracted from online advertising this phenomenon is even more pronounced (KASANDR and PANDOR).
- Cons: Machine learning models fail on highly sparse datasets as it is difficult to learn anything when no feedback is available from the user.

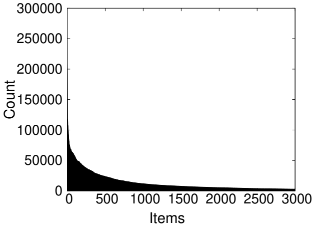
Table: An illustration of sparsity present in the datasets we used.

	# of users	# of items	# of interactions	Sparsity
ML-100K	943	1,682	100,000	**93.685%**
ML-1M	6,040	3,706	1,000,209	**95.530%**
NETFLIX	90,137	3,560	4,188,098	**98.700%**
KASANDR-GER	25,848	1,513,038	9,489,273	**99.976%**
PANDOR	1,918,968	3,755	225,579	**99.997%**

Some challenges: Popularity-Bias, Long Tail and Filter Bubble

- Popularity bias: a situation where a large majority of items have only very few ratings or clicks.

- Can lead to *"rich-get-richer-effect"* [Jannach et al., 2015]
- Limited catalog coverage (concentration bias)
- Cons: Can lead to monotonous recommendations and can harm long term retention of user's interest



- Filter Bubble [Pariser, 2011]: a phenomenon, where people do not get exposed to viewpoints different from their own

- Cons: Media favoring biased view-points for catering to user's interest.

Some challenges: Representation Learning of users and items

- Representation plays an important role in recommender systems.
- Leverage multiple sources of data for rich representation [Sonie et al., 2018].
- Representation of users and items:
  - Transactions (Example. Matrix Factorization)
  - Content: Product description, Reviews, Product image
  - User demography

How to best represent users and items

- How to take into account the transactions and contextual information in order to best represent users and items
- Cons: Bad representation can adversely affect the model's performance

Summing up contributions

- Enhance user and item representation to increase performance
- Take the Popularity bias into account
- Extract temporal topics from user and item descriptions for contextual information
- Large scale datasets containing contextual information
- Model should also:
  - scale to the data
  - work on highly sparse data
  - deal with implicit feedback

Outline

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Recommending with NervE

General idea

Representation learning and pairwise ranking simultaneously using neural networks
joint work with Mikhail Trofimov, Oleg Horodnitskii, Charlotte Laclau, Yury Maximov and Massih-Reza Amini[a]

[a] Work submitted to IPM

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Notations

- $\mathcal{U}$ and $\mathcal{I}$ the set of users and items, respectively.
- **U** and **V** their latent representations
- for each $u \in \mathcal{U}$, we consider two subsets of items $\mathcal{I}_u^+, \mathcal{I}_u^- \subset \mathcal{I}$
  - i) $\mathcal{I}_u^- \neq \varnothing$ and $\mathcal{I}_u^+ \neq \varnothing$,
  - ii) for any pair $(i, i') \in \mathcal{I}_u^+ \times \mathcal{I}_u^-$; u has a preference, symbolized by $\succsim_u$. Hence $i \succsim_u i'$ implies that, user u prefers item i over item i'.

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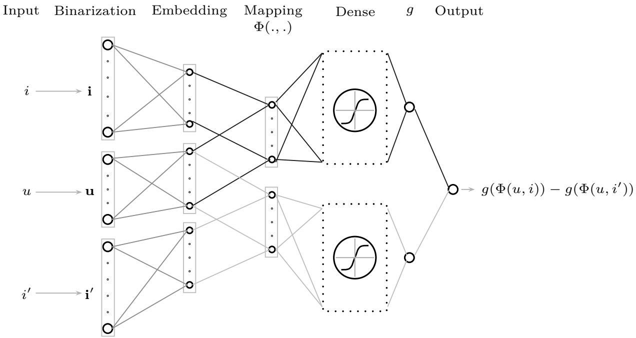
Ground-truth

The desired output $y_{i,u,i'} \in \{-1, +1\}$ is defined over each triplet $(i, u, i') \in \mathcal{I}_u^+ \times \mathcal{U} \times \mathcal{I}_u^-$ as:

$$y_{i,u,i'} = \begin{cases} 1 & \text{if } i \underset{u}{\succ} i', \\ -1 & \text{otherwise.} \end{cases}$$

Graphical representation of NervE



- *Embedding* layer: transforms the sparse binary representations of the user and each of the items to denser real-valued vectors.
- *Mapping* layer: composed of two groups of units each being obtained from the element-wise product of user and item embedding
- *Dense* layer: fully connect each of these units

Objectives

- Given: a multivariate real-valued function $g(.)$
- The prediction given by NervE for an input (i, u, i') is:

$$f(i, u, i') = g(\Phi(u, i)) - g(\Phi(u, i')).$$

$$\mathcal{L}_c(f, \mathcal{S}) = \frac{1}{|\mathcal{S}|} \sum_{(\mathbf{z}_{i,u,i'}, y_{i,u,i'}) \in \mathcal{S}} \log(1 + e^{y_{i,u,i'}(g(\Phi(u,i')) - g(\Phi(u,i)))}).$$

$$\mathcal{L}_p(\mathbb{U}, \mathbb{V}, \mathcal{S}) = \frac{1}{|\mathcal{S}|} \sum_{(\mathbf{z}_{i,u,i'}, y_{i,u,i'}) \in \mathcal{S}} \Big[\log(1 + e^{y_{i,u,i'} \mathbf{U}_u^\top (\mathbf{V}_{i'} - \mathbf{V}_i)}) + \lambda(\|\mathbf{U}_u\| + \|\mathbf{V}_{i'}\| + \|\mathbf{V}_i\|) \Big]$$

NervE, then minimizes the following objective

$$\mathcal{L}_{c,p}(f, \mathbf{U}, \mathbf{V}, \mathcal{S}) = \alpha \mathcal{L}_c(f, \mathcal{S}) + (1 - \alpha) \mathcal{L}_p(\mathbf{U}, \mathbf{V}, \mathcal{S}),$$

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Why introduce NervE?

$\mathcal{L}_{c,p}$ focuses simultaneously on both relevance of items recommended and representation of users and items
Flexible because α can be tuned to put more weight on either representation learning or preference learning

Learning objective

Scenarios over Losses

- $\mathcal{L}_c(f, \mathcal{S})$ focuses on the ability of the all architecture to respect the relative ordering of items w.r.t. user's preferences
- $\mathcal{L}_p(\mathbf{U}, \mathbf{V}, \mathcal{S})$ reflects the quality of the latent representations to respect this relative order
- $\alpha \in [0, 1]$ is a real-valued parameter to balance between ranking prediction ability and expressiveness of the learned representations
- $\mathcal{S}$ the training set consisting of triplets and ground truth.

Scenarios over α

1. $\alpha = 0$ or $\alpha = 1$
2. $\alpha = 0.5$
3. adapting the value of α at each epoch

Algorithm: Learning phase

Algorithm 1 `NervE.`: Learning phase

Input:

T: maximal number of epochs
A set of users $\mathcal{U} = \{1, \ldots, N\}$
A set of items $\mathcal{I} = \{1, \ldots, M\}$
for $ep = 1, \ldots, T$ **do**
  Randomly sample a mini-batch $\tilde{\mathcal{S}}_n \subseteq \mathcal{S}$ of size n from the original user-item matrix
  for all $((i, u, i'), y_{i,u,i'}) \in \tilde{\mathcal{S}}_n$ **do**
    Propagate (i, u, i') from the input to the output.
  Retro-propagate the pairwise ranking error estimated over $\tilde{\mathcal{S}}_n$.

Output: Users and items latent feature matrices $\mathbb{U}, \mathbb{V}$ and the model weights.

Algorithm: Testing phase

Algorithm 2 `NervE.`: Testing phase

Input:

A user $u \in \mathcal{U}$; A set of items $\mathcal{I} = \{1, \ldots, M\}$;
A set containing the k preferred items in $\mathcal{I}$ by u;
$\mathfrak{N}_{u,k} \leftarrow \varnothing$;
The output of `NervE.` learned over a training set: f
Apply f to the first two items of $\mathcal{I}$ and, note the preferred one i^* and place it at the top of $\mathfrak{N}_{u,k}$;
for $i = 3, \ldots, M$ **do**
  if $g(\Phi(u, i)) > g(\Phi(u, i^*))$ **then**
    Add i to $\mathfrak{N}_{u,k}$ at rank 1
  else
    $j \leftarrow 1$
    while $j \leq k$ AND $g(\Phi(u, i)) < g(\Phi(u, i_g)))$ // where $i_g = \mathfrak{N}_{u,k}(j)$ **do**
      $j \leftarrow j + 1$
    if $j \leq k$ **then**
      Insert i in $\mathfrak{N}_{u,k}$ at rank j

Output: $\mathfrak{N}_{u,k}$;

Introducing diversity

Motivation

- Increase the performance of a RS **on the long-term** [Zhang and Hurley, 2008, McNee et al., 2006].
- Control the **popularity bias** [Abdollahpouri et al., 2017]

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Existing approaches

- **Re-ranking** [Drosou and Pitoura, 2009, Zhang and Hurley, 2008].
- **Clustering** of items [Li and Murata, 2012, Shi, 2013].
- **Multi-function optimization** [Su et al., 2013, Wasilewski and Hurley, 2016].
- Using **structured learning** [Cheng et al., 2017]

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Challenge: finding a trade-off between relevance and diversity and to introduce diversity when there is no meta-information available about items

KL Divergence in $\texttt{NervE}_c$

- $\texttt{NervE}_c$ is the version of $\texttt{NervE}$ with L_c.
- In order to incorporate diversity in $\texttt{NervE}_c$, we introduce KL-Divergence term in $\texttt{NervE}_c$:

$$\mathcal{L}_{\texttt{NervE}_c}(f, U, V, \mathcal{S}) + \boxed{\beta \frac{1}{|U|} \sum_{u \in U} \left(\frac{1}{k(k-1)} \right) \sum_{i,i' \in \mathcal{S}_u^k} KL(\mathbf{V}_i^{\ell_1} || \mathbf{V}_{i'}^{\ell_1})},$$

- $\mathbf{V}_i^{\ell_1}$ (resp. $\mathbf{V}_{i'}^{\ell_1}$) is the ℓ_1-normalized embedding associated with item i (resp. i')
- Embeddings computed using Item2Vec [Barkan and Koenigstein, 2016b]
- β is the diversity inducing regularization parameter
- By inducing diversity in relevance function, we are able to overcome popularity bias (as we will see in experiments section)

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Diversity with no meta-information

Introducing diversity, via embeddings learned from interactions when no meta-information about items is available not addressed by previous works

Summing up

1st Contribution:

- Proposed a NN based collaborative ranking model that learns a hybrid loss function which focuses on both representation learning and pairwise learning-to-rank function.
- NN that paves the way for introducing diversity in a single step of learning process
- Diversity induced in NervE using item embedding
- NN that jointly learns the representation and the ranking of items

What was not presented:

- To take into account contextual features
- Can deal with both item and user cold-start by taking into account contextual features
- Theoretical analysis

Outline

Motivation: Why make use of temporal topics

Prevalence of textual data in RS

- Lot of textual data around; example Amazon reviews, News recommendation systems.
- Topic modeling is a good way to exploit textual data

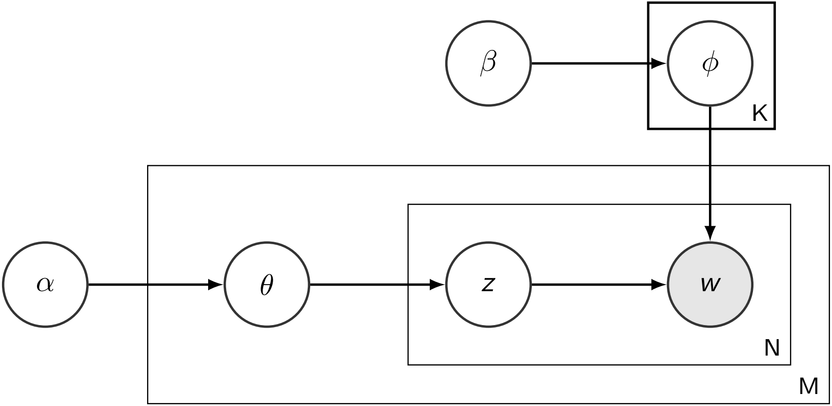
Importance of time

- Recommendations are actions at a moment in time ; Time is a critical aspect in any RS [Basilico and Raimond, 2017]

How to use it?

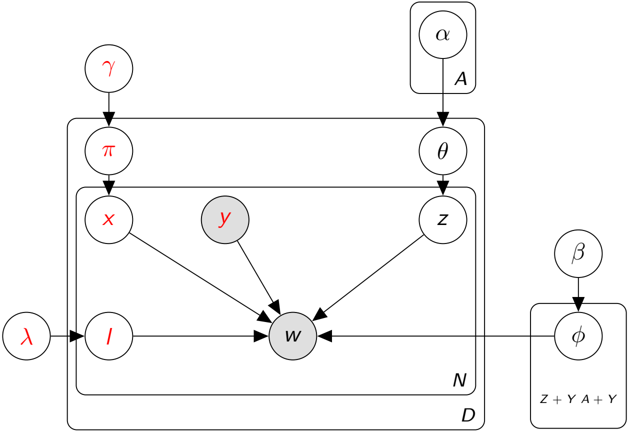
- RS data are usually sparse with users providing very little feedback about their preferences
- **Temporal** topics inferred from text can be used as **supplementary feature** in RS models.
- This contextual information of topics can also be used in content-filtering based RS

General-purpose topic modelling with LDA



- Given a set of documents, the goal of LDA is to come up with underlying topic distributions of the documents

General-purpose topic modelling with TAM



- An *aspect* is defined as a characteristic that spans the document such as an underlying theme.

Time-Aware Topic Aspect Model

→Random variables a and t in TAM[1]

Document level characteristic a

- TAM can then be extended to include a document level characteristic a.
- Document level characteristic could be anything such as *overall sentiment*.
- Sentiment can be positive, negative or could contain more values.

Evolution of sentiment with time

- Sentiment towards topics also evolves with time.
- Taste of users towards various topics keep changing with time.

Introduction of random variable t in TAM

- We introduce a random variable t for time in TAM.
- a (sentiment) is drawn depending on time t.
- Time t itself is drawn from a multinomial distribution ψ.

[1] Sidana et al., IEEE TKDE'18

Plate diagram of time-aware TAM

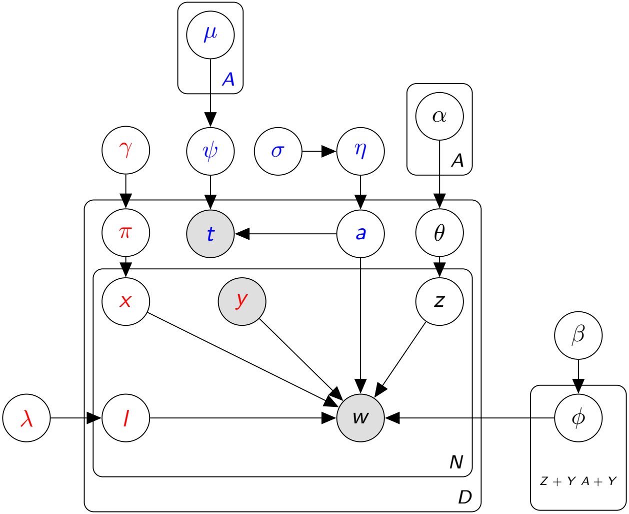


Figure: Time-Aware Topic Aspect Model. Sentiment *a* is time-aware.

TM–LDA

- Modeling evolution of topics of dynamic collection of documents over time.
- At the heart of the algorithm lies the following equation.

$$\theta_i \approx \frac{\theta_{i-1}.M}{\|\theta_{i-1}.M\|_{\ell_1}} \quad (1)$$

- M is a $k \times k$ matrix, called the transition matrix, and k is the number of topics.
- Solution:

$$M = \arg\min_X \|A.X - B\|_F \quad (2)$$

- TM–LDA is quite elegant in modeling general purpose topics over time
- Cons: Huge amount of postprocessing to model transition matrices

Summing up

What was presented:

- General purpose topic models like LDA and TAM
- Introduction of two random variables in TAM: t and a
- An existing temporal topic model TM–LDA, which we will use later to enrich feature set in order to improvise recommendations

What was not presented:

- Application of TAM with random variables t and a on health-monitoring social-media dataset

Outline

KASANDR: Collection of the data

KASANDR[a] (Kelkoo lArge ScAle juNe Data for Recommendation)

[a]Sidana et al., *KASANDR: A Large-Scale Dataset with Implicit Feedback for Recommendation*, SIGIR'17

- Records interactions of Kelkoo's customers from 20 countries in June
- 4 services: Ads, Kelkoo's Website, Partners, Kelkoo Feed System

Different scenarios in which the database gets populated

- User visits Kelkoo's website and enters a search keyword
- User browsing through Kelkoo's or partner's website is shown an ad
- User enters search keywords in Kelkoo's partner's website

What is new about KASANDR

- Rich set of contextual feautres (users and items)
- First implicit feedback recommender dataset of this size contributed and made public by any research lab (Uncompressed size: 950 GB.)

KASANDR: Description

General Statistics

- KASANDR comes with meta-information about offers and users
  - Users : country code
  - Items : product category, price, query string

# of users	# of unique offers	# of offers shown	# of clicks	Sparsity
123,529,420	56,667,919	3,210,050,267	16,107,227	99.9999997848%

- Users are shown **26 offers** in average
- Average number of clicks is only **1.71**, for users with at least one click

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Time-granularity and Cold Start

- Few number of users return to the system.
- Significance of taking *time-granularity*
- Significance of handling user cold-start

Week Number	# New Users	# Returning Users
23	36,932,009	165,951
24	26,736,201	199,467
25	22,358,876	185,749
26	13,908,242	135,303

PANDOR: Collection of the data

PANDOR (Purch dAta for oNline recommeDation and cOld-staRt) [a]

[a]Sidana et al., *Learning to recommend diverse items over implicit feedback on PANDOR*, RecSys'18

- User's traffic collected from Tom's hardware website
- User browsing through Purch's websites is shown an ad
- Another implicit feedback recommender system data set belonging to Purch's one month click logs made public

What is new about PANDOR?

- First dataset to contain actual English text words and information about page text and offer text
- Page text on which offer was displayed
- No previous datasets contain actual text words

PANDOR basic statistics

- Overall Dataset Statistics, for 1 month.

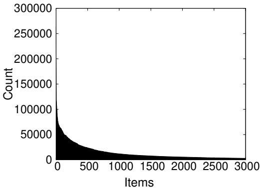
# of users	# of unique offers	# of offers shown	# of clicks	Sparsity
5,894,431	14,716	48,754,927	337,511	99.99961

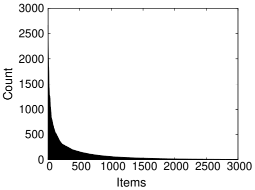
- PANDOR provides a rich set of textual information
  - offer text
  - page text
  - keywords

Page text vocabulary size	9,111
Product text vocabulary size	6,016
Keyword vocabulary size	543
# Offers which have at least 1 text word	2,701 (27.4%)
# Pages which have at least 1 text word	1,990 (28.1%)

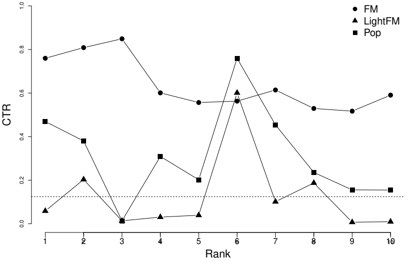
PANDOR popularity bias

- **Long tail item** : number of time an item is recommended and clicked.





- **Rank** of items as a function of **CTR**
- Strong ML approaches recommend
  - popular items
  - items with high CTR
- Why? Current RS system at Purch is based on **popularity**



Outline

Evaluation: Expected Intra List Diversity

→ Relevance Evaluation: Mean Average Precision@different ranks

- Intra-List distance of any list $L(s)$ of items recommended to a particular user is given by:

$$ILD(L_u) = \frac{1}{N(N-1)} \sum_{i,j \in L(s)} d(i,j) \tag{3}$$

- EILD is then given by averaging over all users:

$$EILD = \frac{1}{|U|} \sum_{u \in U} ILD \tag{4}$$

- Distance $d(i,j)$ between two items i and j is computed using meta-data of items suchas item-genre, item-category or item-embeddings.
- High value of EILD indicates high diversity.

Evaluation Baselines

Non-Machine Learning

- The random rule (Rand)
- The popularity rule (Pop)
- The past interaction technique (PastI)

Classification-Based

- Matrix Factorization (MF) [Koren et al., 2009].
- Factorization Machines (FM) [Rendle, 2010].
- Field-Aware Factorization Machines (FFM) [Juan et al., 2016]

Ranking-Based

- Rank-ALS [Takács and Tikk, 2012]
- Bayesian Personalized Ranking (BPR) [Rendle et al., 2009]
- LightFM [Kula, 2015b],
- `Co-Factor` [Liang et al., 2016] co-occurrence counts.
- $\texttt{NervE}_{c,p}$ uses a linear combination of $\mathcal{L}_p$ and $\mathcal{L}_c$.
- $\texttt{NervE}_p$ focuses on the quality of the latent representation of users and items
- $\texttt{NervE}_c$ focuses on the accuracy of the score at the output of the framework

Datasets

- We use following datasets to evaluate the performance of `NervE`
  - ML-100K
  - ML-1M
  - NETFLIX
  - KASANDR-GER

	# of users	# of items	# of interactions	Sparsity
ML-100K	943	1,682	100,000	93.685%
ML-1M	6,040	3,706	1,000,209	95.530%
NETFLIX	90,137	3,560	4,188,098	98.700%
KASANDR-GER	25,848	1,513,038	9,489,273	99.976%

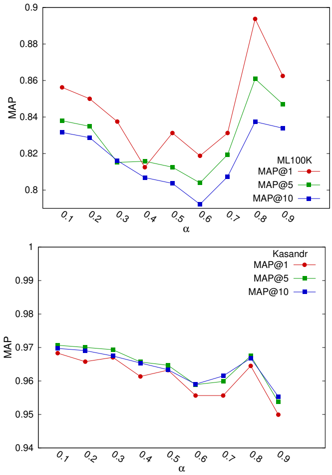
- Statistics of various collections used in our experiments after preprocessing.
- KASANDR-GER is the only true implicit feedback, others are synthetically made implicit

Evaluation Settings

- We consider two settings w.r.t. to the set of items selected for the prediction.
  - Item recommendation only relies on past interacted offers (shown + clicked) ; arguably the most common in academic research
  - Item recommendation only relies on all offers ; reflects this real-world scenario as, at the time of making the recommendation, the notion of shown items is not available
- We use Mean Average Precision (MAP) for evaluating relevance of recommended list of offers
- For all datasets, we only keep users who have rated at least five movies and remove users who gave the same rating for all movies.
- In addition, for NETFLIX, we take a subset of the original data and randomly sample 20% of the users and 20% of the items.

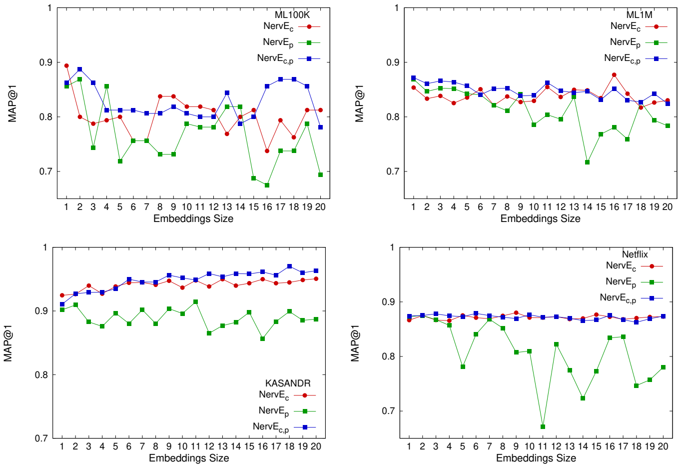
NervE performance with changing the α parameter

- α is the tradeoff between representation learning and preference score learning



NervE performance with changing the embeddings

- Best MAP@1 results are generally obtained with small sizes of item and user embedded vector spaces k



Parameter Tuning

	ML-100K			ML-1M			Netflix			Kasandr-Ger		
	NervE_c	NervE_p	$\mathrm{NervE}_{c,p}$	NervE_c	NervE_p	$\mathrm{NervE}_{c,p}$	NervE_c	NervE_p	$\mathrm{NervE}_{c,p}$	NervE_c	NervE_p	$\mathrm{NervE}_{c,p}$
k	1	2	2	16	1	1	9	2	6	19	1	18
λ	0.05	0.005	0.005	0.05	0.0001	0.001	0.05	0.01	0.05	0.0001	0.05	0.005
# units	32	64	16	32	16	32	64	16	16	64	16	64

- Best parameters for NervE_p, NervE_c and $\mathrm{NervE}_{c,p}$ when prediction is done on only shown offers.
- k denotes the dimension of embeddings.
- λ the regularization parameter.
- We also report the number of hidden units per layer.

	ML-100K			ML-1M			Netflix			Kasandr-Ger		
	NervE_c	NervE_p	$\mathrm{NervE}_{c,p}$	NervE_c	NervE_p	$\mathrm{NervE}_{c,p}$	NervE_c	NervE_p	$\mathrm{NervE}_{c,p}$	NervE_c	NervE_p	$\mathrm{NervE}_{c,p}$
k	15	5	8	2	11	2	3	13	1	4	16	14
λ	0.001	0.001	0.001	0.05	0.0001	0.001	0.0001	0.001	0.001	0.001	0.0001	0.05
# units	32	16	16	32	64	32	32	64	64	32	64	64

- Best parameters for NervE_p, NervE_c and $\mathrm{NervE}_{c,p}$ when prediction is done on all offers.

Results on Interacted Offers

	ML-100K		ML-1M		NETFLIX		KASANDR-GER	
	MAP@1	MAP@10	MAP@1	MAP@10	MAP@1	MAP@10	MAP@1	MAP@10
BPR-MF	0.613$^{\downarrow}$	0.608$^{\downarrow}$	0.788$^{\downarrow}$	0.748$^{\downarrow}$	**0.909**	0.842$^{\downarrow}$	0.857$^{\downarrow}$	0.857$^{\downarrow}$
LightFM	0.772$^{\downarrow}$	0.770$^{\downarrow}$	0.832$^{\downarrow}$	0.795$^{\downarrow}$	0.800$^{\downarrow}$	0.793$^{\downarrow}$	0.937$^{\downarrow}$	0.936$^{\downarrow}$
CoFactor	0.718$^{\downarrow}$	0.716$^{\downarrow}$	0.783$^{\downarrow}$	0.741$^{\downarrow}$	0.693$^{\downarrow}$	0.705$^{\downarrow}$	0.925$^{\downarrow}$	0.918$^{\downarrow}$
NervE$_c$	**0.894**	**0.848**	0.877$^{\downarrow}$	0.835	0.880$^{\downarrow}$	**0.847**	0.958$^{\downarrow}$	0.963$^{\downarrow}$
NervE$_p$	0.881$^{\downarrow}$	0.846	0.876$^{\downarrow}$	**0.839**	0.875$^{\downarrow}$	0.844	0.915$^{\downarrow}$	0.923$^{\downarrow}$
NervE$_{c,p}$	0.888$^{\downarrow}$	0.842	**0.884**	**0.839**	0.879$^{\downarrow}$	**0.847**	**0.970**	**0.973**

- Prediction is done only on offers shown to users. The best result is in bold.
- Beats all the other algorithms on KASANDR-GER, ML-100K and ML-1M.
- On NETFLIX, BPR-MF outperforms our approach in terms of MAP@1.

Results on All Offers

	ML-100K		ML-1M		NETFLIX		KASANDR-GER	
	MAP@1	MAP@10	MAP@1	MAP@10	MAP@1	MAP@10	MAP@1	MAP@10
BPR-MF	0.140$^{\downarrow}$	**0.261**	0.048$^{\downarrow}$	0.097$^{\downarrow}$	0.035$^{\downarrow}$	0.072$^{\downarrow}$	0.016$^{\downarrow}$	0.024$^{\downarrow}$
LightFM	0.144$^{\downarrow}$	0.173$^{\downarrow}$	0.028$^{\downarrow}$	0.096$^{\downarrow}$	0.006$^{\downarrow}$	0.032$^{\downarrow}$	0.002$^{\downarrow}$	0.003$^{\downarrow}$
CoFactor	0.056$^{\downarrow}$	0.031$^{\downarrow}$	0.089$^{\downarrow}$	0.033$^{\downarrow}$	0.049$^{\downarrow}$	0.030$^{\downarrow}$	0.002$^{\downarrow}$	0.001$^{\downarrow}$
$\texttt{NervE}_c$	0.106$^{\downarrow}$	0.137$^{\downarrow}$	0.067$^{\downarrow}$	0.093$^{\downarrow}$	0.032$^{\downarrow}$	0.048$^{\downarrow}$	0.049$^{\downarrow}$	0.059$^{\downarrow}$
$\texttt{NervE}_p$	**0.239**	0.249	**0.209**	**0.220**	**0.080**	**0.089**	0.100$^{\downarrow}$	0.100$^{\downarrow}$
$\texttt{NervE}_{c,p}$	0.111$^{\downarrow}$	0.134$^{\downarrow}$	0.098$^{\downarrow}$	0.119$^{\downarrow}$	0.066$^{\downarrow}$	0.087	**0.269**	**0.284**

- Prediction is done on all offers. The best result is in bold
- All the algorithms encounter an extreme drop of their performance in terms of MAP
- NervE framework significantly outperforms all other algorithms
- This difference is all the more important on KASANDR-GER

Comparison between NervE versions

	ML-100K		ML-1M		Netflix		Kasandr-Ger	
	MAP@1	MAP@10	MAP@1	MAP@10	MAP@1	MAP@10	MAP@1	MAP@10
$\texttt{NervE}_c$	0.106$^\downarrow$	0.137$^\downarrow$	0.067$^\downarrow$	0.093$^\downarrow$	0.032$^\downarrow$	0.048$^\downarrow$	0.049$^\downarrow$	0.059$^\downarrow$
$\texttt{NervE}_p$	**0.239**	0.249	**0.209**	**0.220**	**0.080**	**0.089**	0.100$^\downarrow$	0.100$^\downarrow$
$\texttt{NervE}_{c,p}$	0.111$^\downarrow$	0.134$^\downarrow$	0.098$^\downarrow$	0.119$^\downarrow$	0.066$^\downarrow$	0.087	**0.269**	**0.284**

	ML-100K		ML-1M		Netflix		Kasandr-Ger	
	MAP@1	MAP@10	MAP@1	MAP@10	MAP@1	MAP@10	MAP@1	MAP@10
$\texttt{NervE}_c$	**0.894**	**0.848**	0.877$^\downarrow$	0.835	0.880$^\downarrow$	**0.847**	0.958$^\downarrow$	0.963$^\downarrow$
$\texttt{NervE}_p$	0.881$^\downarrow$	0.846	0.876$^\downarrow$	**0.839**	0.875$^\downarrow$	0.844	0.915$^\downarrow$	0.923$^\downarrow$
$\texttt{NervE}_{c,p}$	0.888$^\downarrow$	0.842	**0.884**	**0.839**	0.879$^\downarrow$	**0.847**	**0.970**	**0.973**

- ($\texttt{NervE}_{c,p}$) increases the quality of overall recommendations
- ($\texttt{NervE}_{c,p}$) outperforms ($\texttt{NervE}_p$) and ($\texttt{NervE}_c$) on ML-1M, Kasandr-Ger and Netflix (interacted offers setting).
- ($\texttt{NervE}_{c,p}$) outperforms ($\texttt{NervE}_p$) and ($\texttt{NervE}_c$) on Kasandr-Ger.
- Optimizing both losses simultaneously is beneficial in case of true implicit feedback datasets such as Kasandr-Ger(all offers setting)
- In case of interacted offers setting, optimizing ranking and embedding loss simultaneously boosts performance on all datasets.

Outline

Evaluation Setting on PANDOR

Data preprocessing

- 1,767,589 interactions from 119,536 unique users on 2,840 unique items.
- Sort all interactions according to time; filter out users without a single click; take the first 70% interactions for training and the remaining 30% for testing.

Prediction settings

- We consider both settings w.r.t. to the set of items selected for the prediction.
- For the first setting, the prediction is done over 20.653 items on average
- For the second one, the prediction is over 2840 items.

Baselines

- Baselines: Rank-ALS, BPR-MF, FM, LightFM
- As PANDOR suffers from popularity bias, we show diversity results.

Results on PANDOR

	MAP@1	MAP@5	MAP@10	EILD@10
Random	0.135	0.157	0.161	0.172
Popularity	0.249	0.262	0.266	0.080
FM (SGD)	0.244	0.269	0.273	**0.191**
BPR-MF	0.222	0.240	0.229	0.173
LightFM	**0.479**	**0.526**	**0.535**	0.099
$\texttt{NervE}_C$	0.251	0.292	0.299	0.115
Rank-ALS	0.256	0.261	0.261	0.008

- MAP@k obtained for all compared approaches on interacted items on PANDOR. The best results are in bold.

	MAP@1	MAP@5	MAP@10	EILD@10
Random	9.934e-05	0.0001	0.0001	0.536
Popularity	**0.007**	**0.009**	**0.011**	0.396
FM (SGD)	0.001	0.002	0.003	0.534
BPR-MF	0.005	0.008	0.010	0.493
LightFM	0.0002	0.0008	0.002	0.287
$\texttt{NervE}_C$	0.006	0.008	0.010	**0.560**
Rank-ALS	0.002	0.002	0.003	0.564

- MAP@k obtained for all compared approaches on all items on PANDOR.

Introduction of Diversity on PANDOR

- We explore the ability of diversity in RS to overcome the strong bias induced by popular items.
- we focus only on the setting in which we test on all items as most approaches fail to provide good results on such setting.
- Two approaches tested:
  - $\texttt{NervE}_c$
  - RankALS [Wasilewski and Hurley, 2016]
- The first one was initially proposed by [Wasilewski and Hurley, 2016]
- We compute item embeddings, with Gensim based Skip-Gram implementation of Word2Vec
- Dimension of embeddings: 20 and the context window: 3.

Diversity Results on PANDOR

Metric Maximized	β	MAP@10	EILD@10
MAP@10	0.0001	0.010	0.633
EILD	0.1	0.001	0.666
HM(MAP@10,EILD)	0.0001	0.010	0.633
HM(MAP@10,EILD) while maximizing diversity	-0.75	0.006	0.635

- Results of $\texttt{NervE}_c$ coupled with diversity.

Metric Maximized	*regularizer*	MAP@10	EILD@10
MAP@10	PLapDQ-min	0.018	0.552
EILD	No-Regularizer	0.0002	0.692
HM(MAP@10,EILD)	PLapDQ-min	0.018	0.552
HM(MAP@10,EILD) while maximizing diversity	DQ-max	0.016	0.553

- Results of RankALS coupled with diversity.

	Before Diversity				After Diversity			
	MAP@1	MAP@5	MAP@10	EILD@10	MAP@1	MAP@5	MAP@10	EILD@10
$\texttt{NervE}_C$	0.006	0.008	0.010	0.561	0.009	0.009	0.010	0.633
RankALS	0.002	0.002	0.003	0.564	0.010	0.014	0.016	0.553

- By Introducing diversity we are able to increase both relevance of the items and diversity of items

Topic-Modelling application to RS on PANDOR

Model and features used

- We use one of the topic models, namely TM–LDA, and feed the topics derived from it, as contextual information to Factorization Machines.
- We use PANDOR page textual information because pages, which users are browsing on, depict the interest of the user

Data Preprocessing

- We first sort the dataset temporally and remove all the users who did not do a single click
- We, then, take first 80% for training and remaining 20% for testing.

- MAP@k improves after putting TM–LDA-based topics as contextual information in Factorization Machines on interacted items on PANDOR.

	MAP@1	MAP@5	MAP@10
Random	0.135	0.157	0.161
Popularity	0.249	0.262	0.266
Factorization Machines (FM)	0.244	0.269	0.273
TM–LDA-Based FM using Page Text	**0.385**(57.7%↑)	**0.390**(45%↑)	**0.389**(42.5%↑)

Outline

Main contributions

- A neural network, named `NervE` to learn user preference and representation for implicit feedback simultaneously
- An enormous data set, named KASANDR, consisting of clicks containing rich meta information
- A data set, named PANDOR, consisting of rich text and affected by popularity bias facilitating research on algorithms, which help overcome the same.
- Introduction of diversity in loss function of $\texttt{NervE}_c$ using KL-Divergence and item embeddings
- Introduction of 2 novel topic models to make use of contextual information in recommender algorithms

Future directions

- Use contextual information (meta-information), topics in `NervE`.
- Use time-aware topic models to do content-based recommendations.
- Do online evaluation and A/B testing of `NervE` and time-aware topic models.
- Learning automatically α in `NervE`.
- Taking into account the imbalance between types of feedback.

Thank you for your attention!

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