Нейросетевые рекомендеры

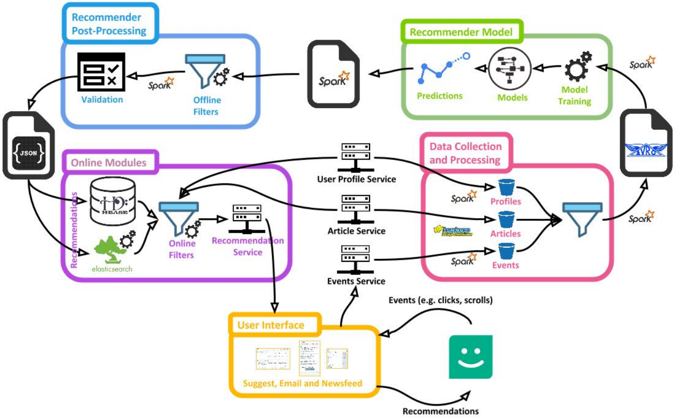
Николай Анохин

21 октября 2021 г.

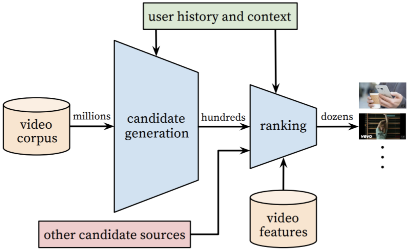
Программа модуля

Дата	Тема	Семинар	Домашка
2021-09-30	Рекомендательные сервисы в продакшене	✓	
2021-10-07	Метрики и базовые подходы	✓	
2021-09-14	Классические алгоритмы рекомендаций	✓	✓
2021-09-21	Нейросетевые рекомендеры	✓	
2021-09-28	Нерешенные проблемы и новые направления	✓	

Контекст


Recommender Post-Processing
Validation
Spark
Offline Filters
Spark
Recommender Model
Predictions
Models
Model Training
Spark
JSON
Online Modules
Recommendations
elasticsearch
Online Filters
Recommendation Service
User Profile Service
Article Service
Events Service
Data Collection and Processing
Spark
Profiles
Articles
Spark
Events
Spark
User Interface
Suggest, Email and Newsfeed
Events (e.g. clicks, scrolls)
Recommendations

Deep Neural Networks for YouTube Recommendations [CAS16]

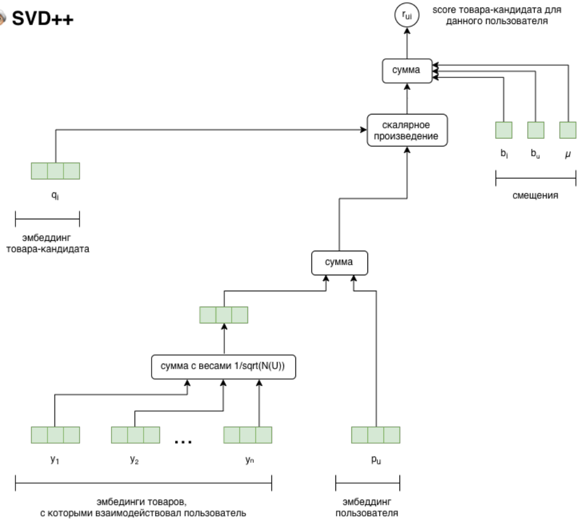


Интересность	⋆⋆⋆⋆⋆
Полезность	⋆⋆⋆⋆⋆

SVD++

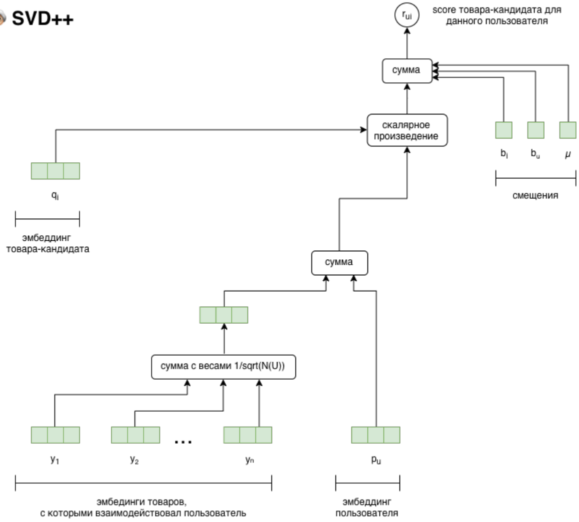
$$\hat{r}_{ui} = \mu + b_u + b_i + q_i^T \left(p_u + \frac{1}{\sqrt{|N(u)|}} \sum_j y_j \right)$$

SVD++



r_{ui}
score товара-кандидата для данного пользователя
сумма
скалярное произведение
b_i
b_u
μ
смещения
q_i
эмбеддинг товара-кандидата
сумма
сумма с весами 1/sqrt(N(U))
y_1
y_2
...
y_n
p_u
эмбеддинги товаров, с которыми взаимодействовал пользователь
эмбеддинг пользователя

SVD++


score товара-кандидата для данного пользователя
r_{ui}
сумма
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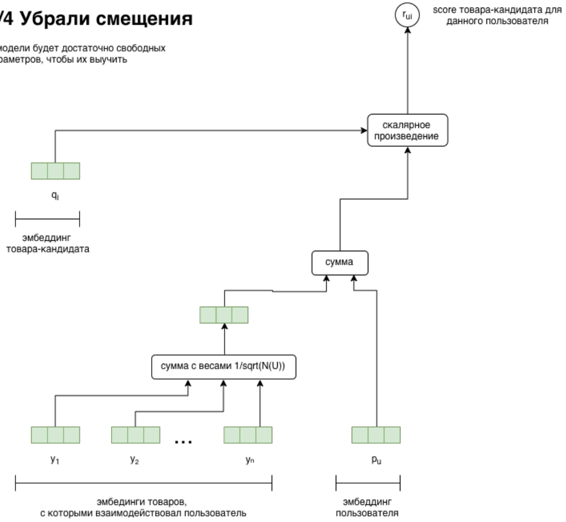
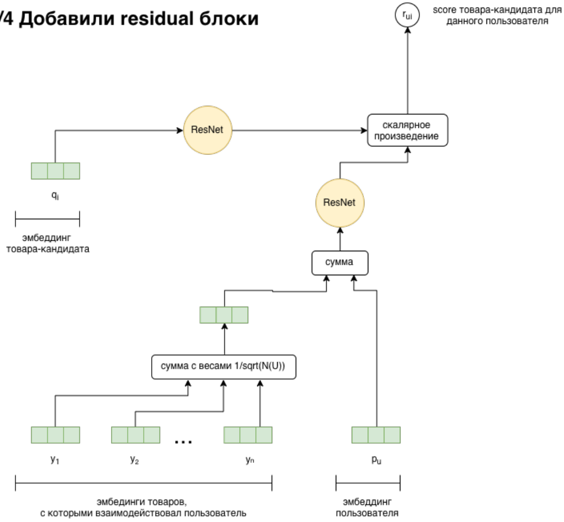
...
y_n
p_u
эмбеддинги товаров, с которыми взаимодействовал пользователь
эмбеддинг пользователя

1/4 Убрали смещения

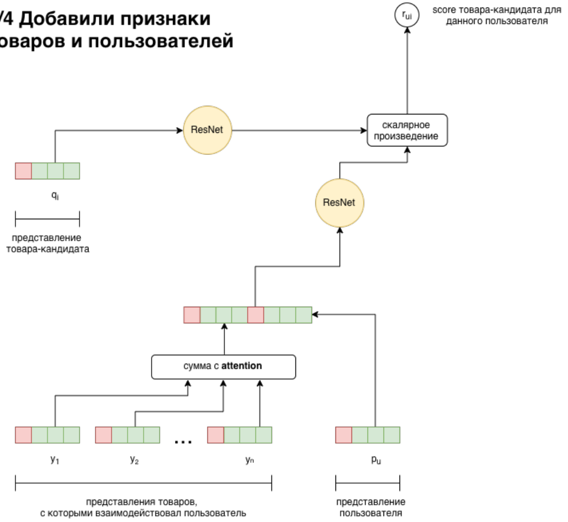
У модели будет достаточно свободных параметров, чтобы их выучить



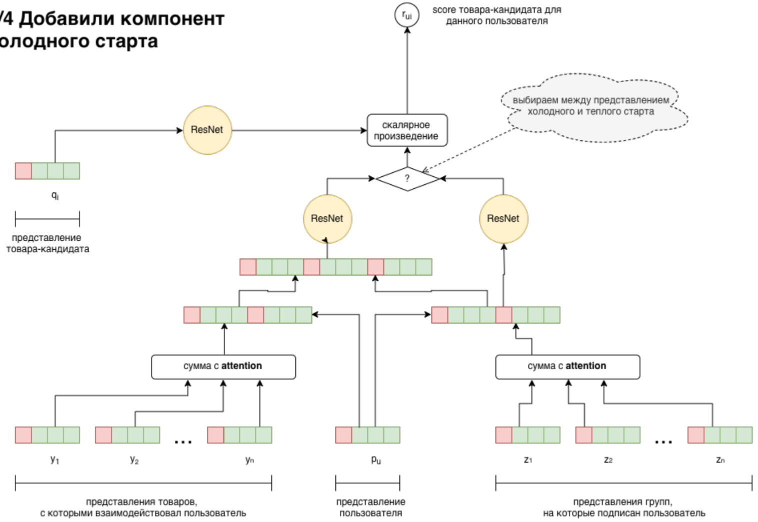
2/4 Добавили residual блоки



3/4 Добавили признаки товаров и пользователей



4/4 Добавили компонент холодного старта

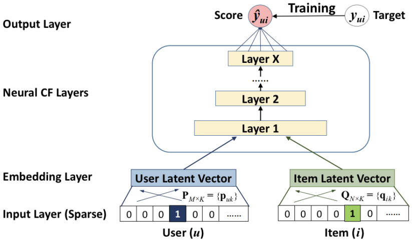


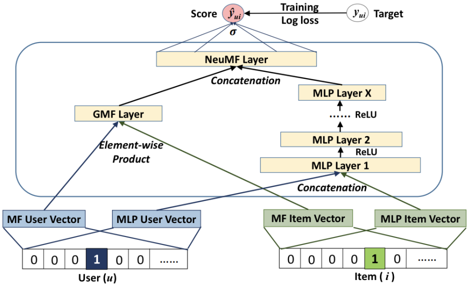
Истории успеха: отбор кандидатов

Как оставить след в науке

- Изобрести или прикрутить хитрый лосс
- Изобрести новый метод семплирования данных
- Заменить скалярное произведение чем-нибудь покруче
- Заменить эмбединги чем-нибудь покруче

Neural Collaborative Filtering [HLZ+17]

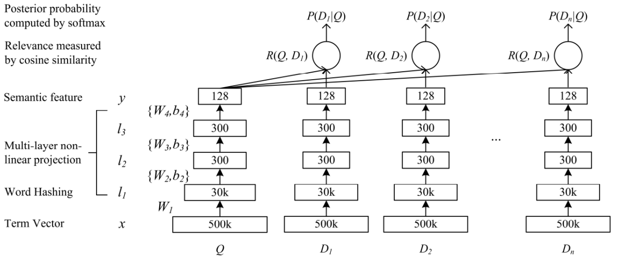




Интересность ⋆⋆⋆

Полезность ⋆⋆⋆

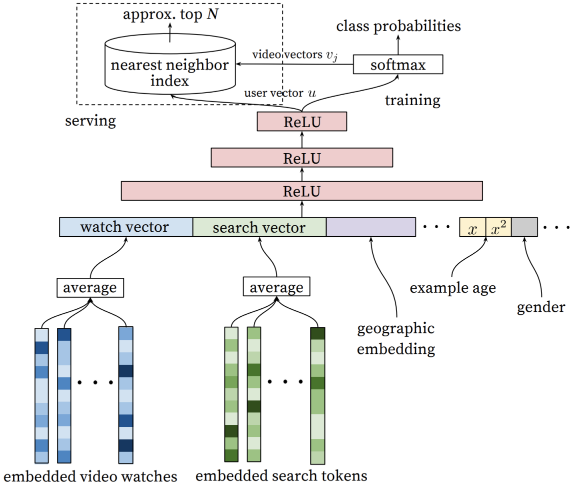
Learning Deep Structured Semantic Models for Web Search using Clickthrough Data [HHG+13]



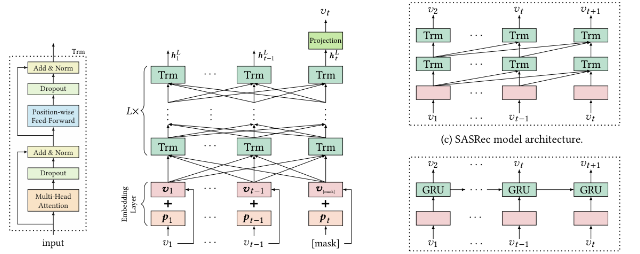
Интересность ⋆ ⋆ ⋆

Полезность ⋆ ⋆ ⋆⋆

YouTube: отбор кандидатов



BERT4Rec: Sequential Recommendation with Bidirectional Encoder Representations from Transformer [SLW+19]



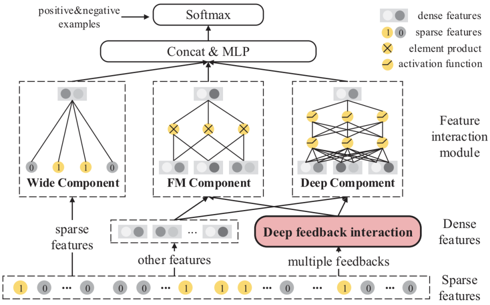
(a) Transformer Layer. (b) BERT4Rec model architecture. (c) SASRec model architecture. (d) RNN based sequential recommendation methods.

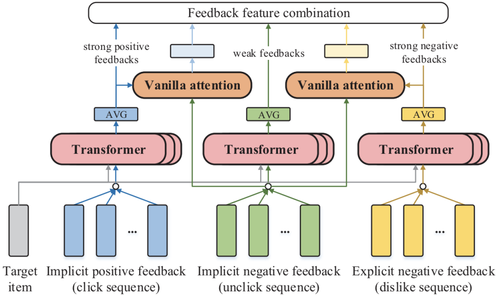
Интересность	⋆⋆
Полезность	⋆

BERT4Rec: эксперименты

Datasets	Metric	POP	BPR-MF	NCF	FPMC	GRU4Rec	GRU4Rec$^+$	Caser	SASRec	BERT4Rec	Improv.
Beauty	HR@1	0.0077	0.0415	0.0407	0.0435	0.0402	0.0551	0.0475	0.0906	**0.0953**	5.19%
	HR@5	0.0392	0.1209	0.1305	0.1387	0.1315	0.1781	0.1625	0.1934	**0.2207**	14.12%
	HR@10	0.0762	0.1992	0.2142	0.2401	0.2343	0.2654	0.2590	0.2653	**0.3025**	14.02%
	NDCG@5	0.0230	0.0814	0.0855	0.0902	0.0812	0.1172	0.1050	0.1436	**0.1599**	11.35%
	NDCG@10	0.0349	0.1064	0.1124	0.1211	0.1074	0.1453	0.1360	0.1633	**0.1862**	14.02%
	MRR	0.0437	0.1006	0.1043	0.1056	0.1023	0.1299	0.1205	0.1536	**0.1701**	10.74%
Steam	HR@1	0.0159	0.0314	0.0246	0.0358	0.0574	0.0812	0.0495	0.0885	**0.0957**	8.14%
	HR@5	0.0805	0.1177	0.1203	0.1517	0.2171	0.2391	0.1766	0.2559	**0.2710**	5.90%
	HR@10	0.1389	0.1993	0.2169	0.2551	0.3313	0.3594	0.2870	0.3783	**0.4013**	6.08%
	NDCG@5	0.0477	0.0744	0.0717	0.0945	0.1370	0.1613	0.1131	0.1727	**0.1842**	6.66%
	NDCG@10	0.0665	0.1005	0.1026	0.1283	0.1802	0.2053	0.1484	0.2147	**0.2261**	5.31%
	MRR	0.0669	0.0942	0.0932	0.1139	0.1420	0.1757	0.1305	0.1874	**0.1949**	4.00%
ML-1m	HR@1	0.0141	0.0914	0.0397	0.1386	0.1583	0.2092	0.2194	0.2351	**0.2863**	21.78%
	HR@5	0.0715	0.2866	0.1932	0.4297	0.4673	0.5103	0.5353	0.5434	**0.5876**	8.13%
	HR@10	0.1358	0.4301	0.3477	0.5946	0.6207	0.6351	0.6692	0.6629	**0.6970**	4.15%
	NDCG@5	0.0416	0.1903	0.1146	0.2885	0.3196	0.3705	0.3832	0.3980	**0.4454**	11.91%
	NDCG@10	0.0621	0.2365	0.1640	0.3439	0.3627	0.4064	0.4268	0.4368	**0.4818**	10.32%
	MRR	0.0627	0.2009	0.1358	0.2891	0.3041	0.3462	0.3648	0.3790	**0.4254**	12.24%
ML-20m	HR@1	0.0221	0.0553	0.0231	0.1079	0.1459	0.2021	0.1232	0.2544	**0.3440**	35.22%
	HR@5	0.0805	0.2128	0.1358	0.3601	0.4657	0.5118	0.3804	0.5727	**0.6323**	10.41%
	HR@10	0.1378	0.3538	0.2922	0.5201	0.5844	0.6524	0.5427	0.7136	**0.7473**	4.72%
	NDCG@5	0.0511	0.1332	0.0771	0.2239	0.3090	0.3630	0.2538	0.4208	**0.4967**	18.04%
	NDCG@10	0.0695	0.1786	0.1271	0.2895	0.3637	0.4087	0.3062	0.4665	**0.5340**	14.47%
	MRR	0.0709	0.1503	0.1072	0.2273	0.2967	0.3476	0.2529	0.4026	**0.4785**	18.85%

Deep Feedback Network for Recommendation [XLW+20]



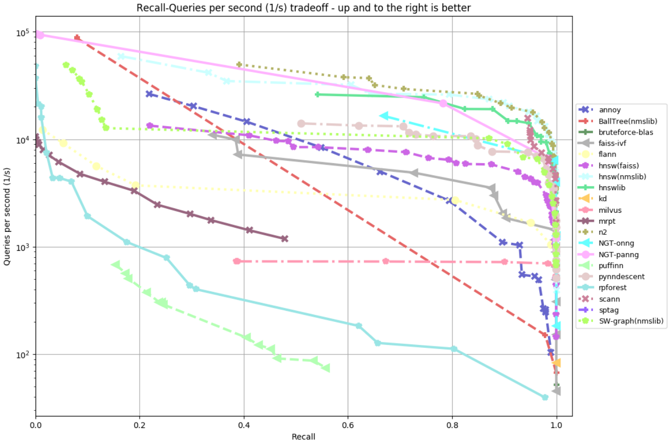


Интересность ⋆⋆⋆

Полезность ⋆

Библиотеки приближенного поиска соседей

https://github.com/erikbern/ann-benchmarks

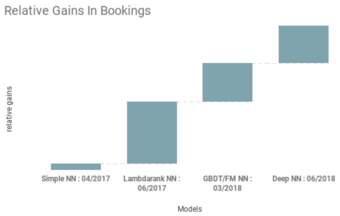


Истории успеха: ранжирование

Как оставить след в науке

- Победить xgboost
- Пофиксить смещения

Applying Deep Learning To Airbnb Search [HAR+19]



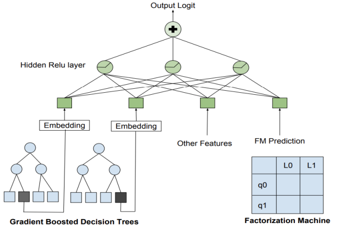
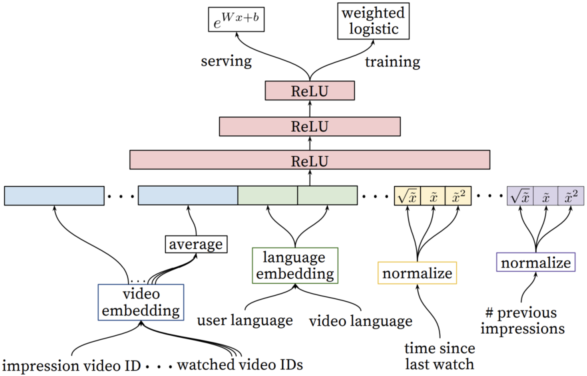


Figure 3: NN with GBDT tree nodes and FM prediction as features

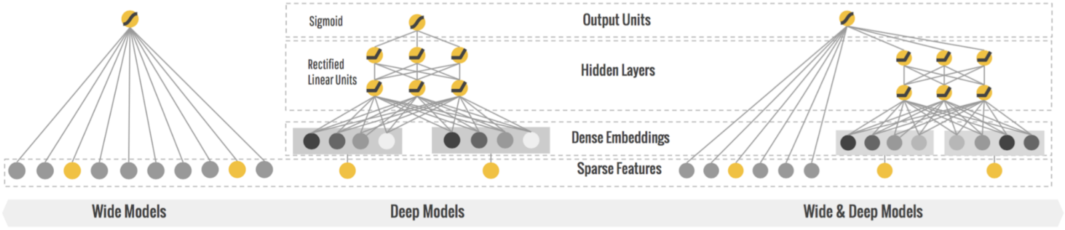
> ...we were able to deprecate all that complexity by simply scaling the training data 10x and moving to a DNN with 2 hidden layers...

Интересность ⋆⋆⋆⋆
Полезность ⋆⋆⋆⋆⋆

YouTube: ранжирование

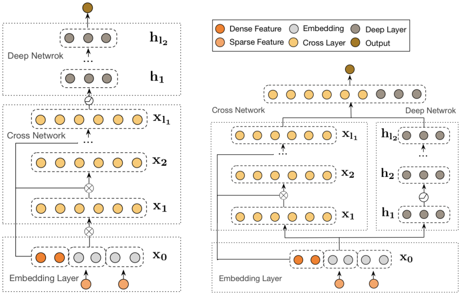


Wide & Deep Learning: Better Together with TensorFlow [Che16]



Интересность ⋆⋆
Полезность ⋆⋆⋆⋆

DCN V2: Improved Deep & Cross Network and Practical Lessons for Web-scale Learning to Rank Systems [WSC+21]



(a) Stacked **(b) Parallel**

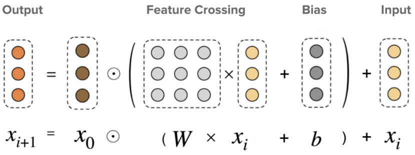
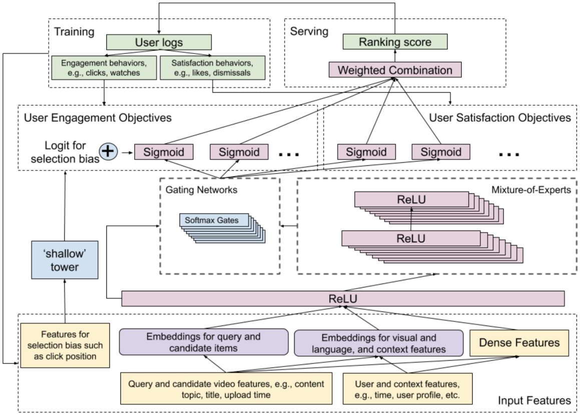


Figure 2: Visualization of a cross layer.

Интересность ⋆⋆⋆

Полезность ⋆⋆⋆⋆

Recommending What Video to Watch Next: A Multitask Ranking System [ZHW+19]



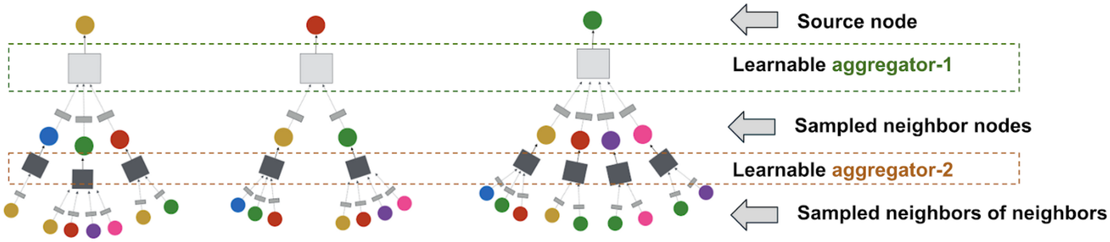
Интересность ⋆⋆⋆⋆⋆
Полезность ⋆⋆

Истории успеха: контент

Как оставить след в науке

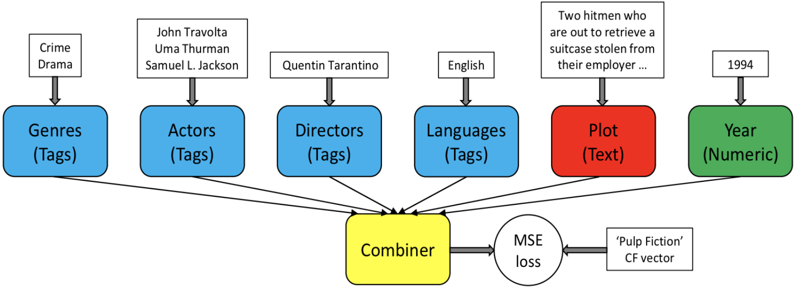
- Решить проблему холодного старта, хитро обучив эмбединги

PinSage: A new graph convolutional neural network for web-scale recommender systems [YHC+18]



Интересность	★★★★★
Полезность	★★★

CB2CF: A Neural Multiview Content-to-Collaborative Filtering Model for Completely Cold Item Recommendations [BKYK19]



Интересность ⋆⋆⋆⋆

Полезность ⋆⋆⋆⋆⋆

Проблема воспроизводимости [DCJ19]

Многие результаты из статей невозможно воспроизвести

Некоторые новые алгоритмы работают хуже, чем затюненные бейзлайны

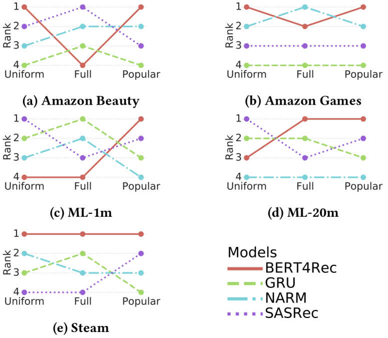
The CMN method was presented at SIGIR 18 and combines memory networks and neural attention mechanisms with latent factor and neighborhood models

Pinterest	HR@5	NDCG@5	HR@10	NDCG@10
TopPopular	0.1668	0.1066	0.2745	0.1411
UserKNN	**0.6886**	**0.4936**	0.8527	**0.5470**
ItemKNN	**0.6966**	**0.4994**	**0.8647**	**0.5542**
$P^3\alpha$	0.6871	**0.4935**	0.8449	**0.5450**
$RP^3\beta$	**0.7018**	**0.5041**	**0.8644**	**0.5571**
CMN	0.6872	0.4883	0.8549	0.5430

Epinions	HR@5	NDCG@5	HR@10	NDCG@10
TopPopular	**0.5429**	**0.4153**	**0.6644**	**0.4547**
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

Проблема сравнений [DZH21]

Результат сравнения может поменяться на обратный в зависимости от того, по какой метрике сравниваютъ



Итоги

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Литература III

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- Po-Sen Huang, Xiaodong He, Jianfeng Gao, Li Deng, Alex Acero, and Larry Heck, *Learning deep structured semantic models for web search using clickthrough data*, Proceedings of the 22nd ACM International Conference on Information and Knowledge Management (New York, NY, USA), CIKM '13, Association for Computing Machinery, 2013, p. 2333–2338.

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Fei Sun, Jun Liu, Jian Wu, Changhua Pei, Xiao Lin, Wenwu Ou, and Peng Jiang, *Bert4rec: Sequential recommendation with bidirectional encoder representations from transformer*, Proceedings of the 28th ACM International Conference on Information and Knowledge Management (New York, NY, USA), CIKM '19, ACM, 2019, pp. 1441–1450.

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- Ruoxi Wang, Rakesh Shivanna, Derek Cheng, Sagar Jain, Dong Lin, Lichan Hong, and Ed Chi, *Dcn v2: Improved deep and cross network and practical lessons for web-scale learning to rank systems*, Proceedings of the Web Conference 2021 (New York, NY, USA), WWW '21, Association for Computing Machinery, 2021, p. 1785–1797.

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- Rex Ying, Ruining He, Kaifeng Chen, Pong Eksombatchai, William L. Hamilton, and Jure Leskovec, *Graph convolutional neural networks for web-scale recommender systems*, Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (New York, NY, USA), KDD '18, Association for Computing Machinery, 2018, p. 974–983.

Литература VI

Zhe Zhao, Lichan Hong, Li Wei, Jilin Chen, Aniruddh Nath, Shawn Andrews, Aditee Kumthekar, Maheswaran Sathiamoorthy, Xinyang Yi, and Ed Chi, *Recommending what video to watch next: A multitask ranking system*, Proceedings of the 13th ACM Conference on Recommender Systems (New York, NY, USA), RecSys '19, Association for Computing Machinery, 2019, p. 43–51.