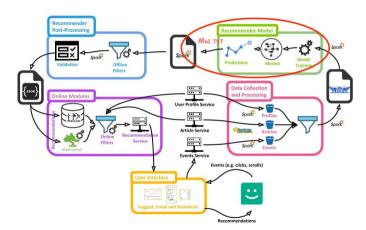
# Нейросетевые рекомендеры

Николай Анохин

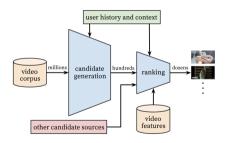
21 марта 2022 г.

#### Контекст



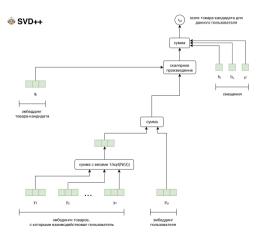
## От классики к нейросетям

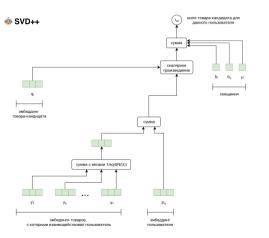
# От классики к нейросетям

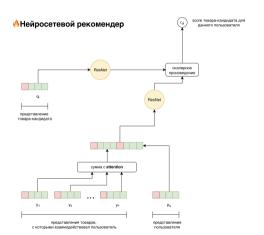


	Классика	Нейросетевые
Отбор кандидатов	MF	NN
Ранжирование	GBM	NN

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







ML = модель + критерий оптимизации + алгоритм оптимизации + данные

ML = модель + критерий оптимизации + алгоритм оптимизации + данные

#### Как оставить след в науке

• Изобрести или прикрутить хитрый лосс

ML = модель + критерий оптимизации + алгоритм оптимизации + данные

- Изобрести или прикрутить хитрый лосс
- Изобрести новый метод семплирования данных

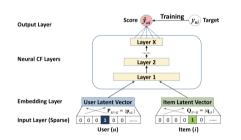
ML = модель + критерий оптимизации + алгоритм оптимизации + данные

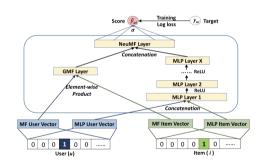
- Изобрести или прикрутить хитрый лосс
- Изобрести новый метод семплирования данных
- Заменить скалярное произведение чем-нибудь покруче

ML = модель + критерий оптимизации + алгоритм оптимизации + данные

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

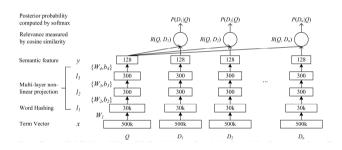
# Neural Collaborative Filtering [HLZ<sup>+</sup>17]





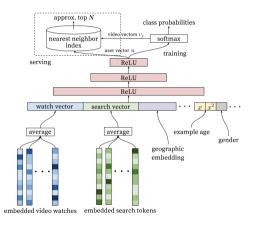
Интересность \* \* \*
Полезность \* \* \*

# Learning Deep Structured Semantic Models for Web Search using Clickthrough Data [HHG<sup>+</sup>13]



Интересность \* \* \* \*
Полезность \* \* \* \*\*

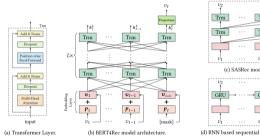
# Deep Neural Networks for YouTube Recommendations [CAS16]



Интересность \* \* \* \* \*
Полезность \* \* \* \* \*



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



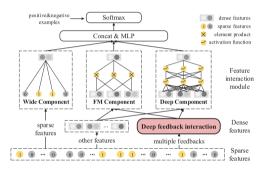
(c) SASRec model architecture.

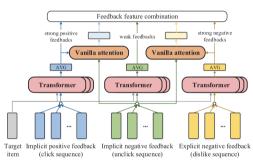
Интересность \*\*
Полезность \*

## BERT4Rec: эксперименты

Datasets	Metric	POP	BPR-MF	NCF	FPMC	GRU4Rec	GRU4Rec <sup>+</sup>	Caser	SASRec	BERT4Rec	Improv.
	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%
Beauty	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%
	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%
Steam	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%
	HR@1	0.0141	0.0914	0.0397	0.1386	0.1583	0.2092	0.2194	0.2351	0.2863	21.78%
ML-1m	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<sup>+</sup>20]





Интересность \*\*\*
Полезность \*

Истории успеха: ранжирование

## Истории успеха: ранжирование

- Победить xgboost
- Пофиксить смещения

# Applying Deep Learning To Airbnb Search [HAR+19]



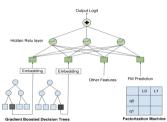


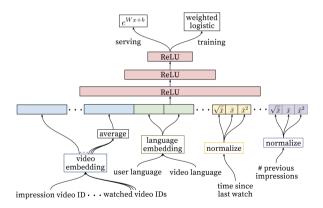
Figure 3: NN with GBDT tree nodes and FM prediction as features

...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

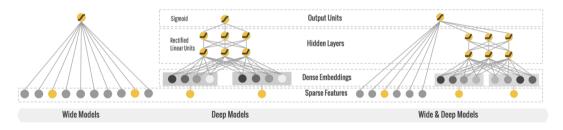


 Интересность
 \*\*\*\*\*

 Полезность
 \*\*\*\*\*



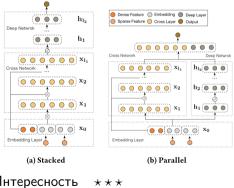
# Wide & Deep Learning: Better Together with TensorFlow [Che16]



 Интересность
 \*\*

 Полезность
 \* \* \*

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



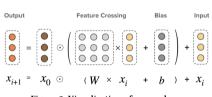
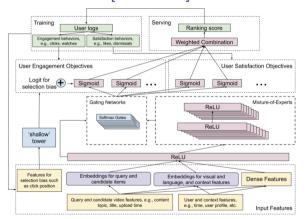


Figure 2: Visualization of a cross layer.

# Recommending What Video to Watch Next: A Multitask Ranking System [ZHW<sup>+</sup>19]



Интересность  $\star \star \star \star \star$ Полезность



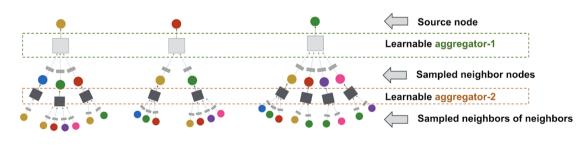
Истории успеха: контент

# Истории успеха: контент

#### Как оставить след в науке

• Решить проблему холодного старта, хитро обучив эмбединги

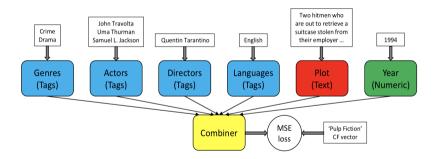
# PinSage: A new graph convolutional neural network for web-scale recommender systems $[YHC^+18]$



 Интересность
 \* \* \* \* \*

 Полезность
 \* \* \*

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



 Интересность
 \* \* \* \*\*

 Полезность
 \* \* \* \* \*

Проблемы нейрорекомендеров

# 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		

## Простые бейзлайны

### SLIM [NK11] / EASE [Ste19]

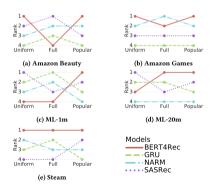
$$\hat{A} = AW$$
,

#### где

- А матрица интеракций
- $\hat{A}$  предсказанные интеракции
- $W_{:,j}$  колонка весов агрегации для j айтема ( $W_{ij} \geq 0$  (SLIM),  $W_{jj} = 0$ ).

# Проблема сравнений [DZH21]

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



### Итоги

#### Итоги

Нейросетевые модели могут заменить любой компонент рекомендательной системы: отборщик кандидатов, ранкер, item2item.

Нейросети помогают добавить inductive bias в рекомендательные модели.

Нейросетевой подход не гарантирует выигрыша – к выбору модели нужно подходить прагматично.

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