Нерешенные проблемы и новые направления

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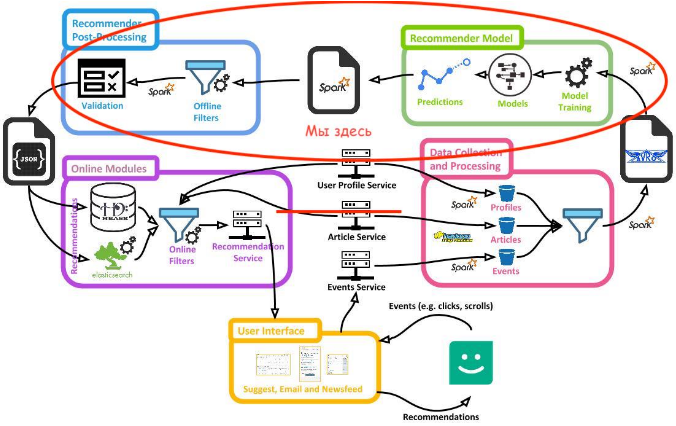
Контекст


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

Что мы уже умеем

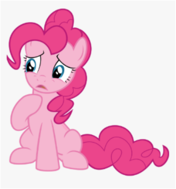
$$\hat{r}_{ui} = f_\theta(x_u, x_i, x_c)$$

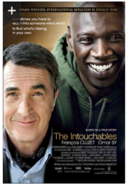
Проблемы

1. Оцениваем айтемы по-отдельности, а показываем по несколько (лентой)
2. Смещение между распределениями на обучении и применении
3. Модель не объясняет, почему именно эти айтемы подходят пользователю
4. Не учитывается долгострочный эффект рекомендаций

Смещения

Удачные рекомендации





Смещения в рекомендациях [CDW+21]

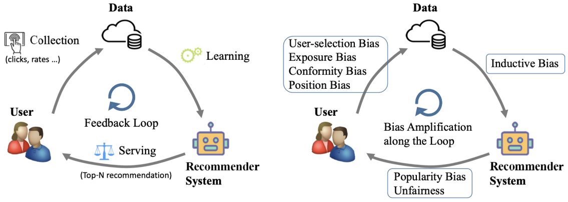


Fig. 2. Feedback loop in recommendation, where biases occur in different stages.

Table 1. The characteristics of seven types of biases in recommendation and the bias amplification in loop.

Types	Stages in Loop	Cause	Effect	Major solutions
Selection Bias	User→Data	Users' self-selection	Skewed observed rating distribution	Data Imputation; Propensity Score; Joint Generative Model; Doubly Robust Model
Exposure Bias	User→Data	Item Popularity; Intervened by systems; User behavior and background	Unobserved interactions do not mean negative	Giving confidence weights by heuristic, sampling or exposure-based model; Propensity Score; Causality-based Model
Conformity Bias	User→Data	Conformity	Skewed interaction labels	Modeling social or popularity effect
Position Bias	User→Data	Trust top of lists; Exposed to top of lists	Unreliable positive data	Click models; Propensity Score; Trust-aware Model
Inductive Bias	Data→Model	Added by researchers or engineers	Better generalization, lower variance or Faster recommendation	-
Popularity Bias	Model→User	Algorithm and unbalanced data	Matthew effect	Regularization; Adversarial Learning; Causal Graph
Unfairness	Model→User	Algorithm and unbalanced data	Unfairness for some groups	Rebalancing; Regularization; Adversarial Learning; Causal Modeling
Bias amplification in Loop	All	Feedback loop	Enhance and spread bias	Break the loop by collecting random data or using reinforcement learning

Пример self-selection bias

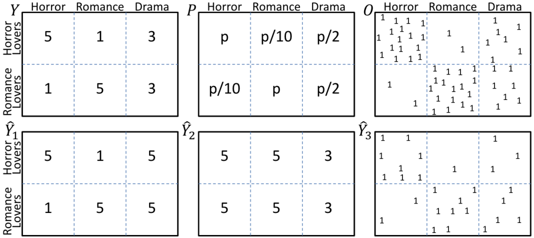


Figure 1. Movie-Lovers toy example. Top row: true rating matrix Y, propensity matrix P, observation indicator matrix O. Bottom row: two rating prediction matrices $\hat{Y}_1$ and $\hat{Y}_2$, and intervention indicator matrix $\hat{Y}_3$.

$$R(\hat{Y}) = \frac{1}{UI}\sum_u \sum_i \delta_{ui}(Y, \hat{Y}), \quad R_{naive}(\hat{Y}) = \frac{1}{N}\sum_{(u,i)\in D} \delta_{ui}(Y, \hat{Y})$$

Inverse Propensity Scored Estimator [SSS+16]

$P_{ui} = P((u,i) \in D)$ – вероятность, что пользователь u поставит оценку айтему i

$$R_{IPS}(\hat{Y}|P) = \frac{1}{UI} \sum_{(u,i)\in D} \frac{\delta_{ui}(Y,\hat{Y})}{P_{ui}}$$

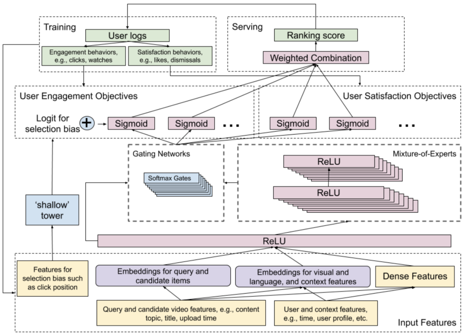
$$E_D[R_{IPS}(\hat{Y}|P)] = \frac{1}{UI} \sum_u \sum_i E_D\left[\frac{\delta_{ui}(Y,\hat{Y})}{P_{ui}} \mathbb{I}\{(u,i) \in D\}\right] =$$

$$= \frac{1}{UI} \sum_u \sum_i \delta_{ui}(Y,\hat{Y}) = R(\hat{Y})$$

IPS Estimator: проблемы

1. Когда P_{ui} неизвестно, его приходится оценивать
2. Большая дисперсия при оценке P_{ui}
3. Непонятно, как быть с рекомендациями списков

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



Идея. При обучении модель "видит" признак-позицию айтема, а при инференсе признак зануляется.

Sampling-Bias-Corrected Neural Modeling for Large Corpus Item Recommendations [YYH+19]

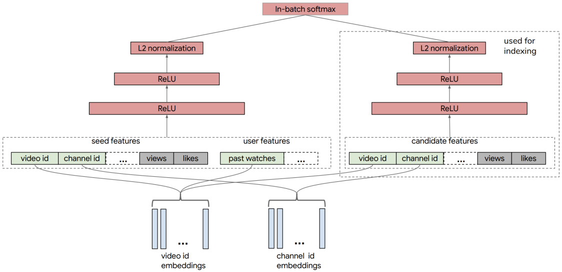


Figure 2: Illustration of the Neural Retrieval Model for YouTube.

Идея. Скорректировать смещение от in-batch негативных с помощью logQ поправки.

Mixed Negative Sampling for Learning Two-tower Neural Networks in Recommendations [YYC+20]

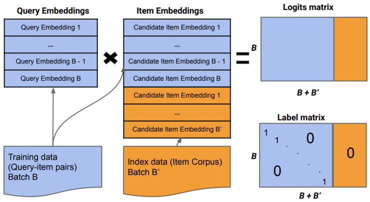


Figure 3: Illustration of MNS for training two-tower DNN model.

Идея. Уменьшаем selection bias, добавляя к in-batch негативным случайно сэмплированные айтемы.

Из-за специфики сбора данных рекомендации подвержены смещениям.

Существуют техники для корректировки, но они несовершенны.

Объяснение рекомендаций

Объяснения

???


Disney · PIXAR
WALL·E
JUNE 27


PALME D'OR
"ONE OF THE BEST FILMS OF THE DECADE."
PARASITE
A FILM BY BONG JOON HO


WELCOME TO A WORLD WITHOUT RULES.
BALE CAINE LEDGER OLDMAN ECKHART GYLLENHAAL FREEMAN
THE DARK KNIGHT
JULY 18

Объяснения

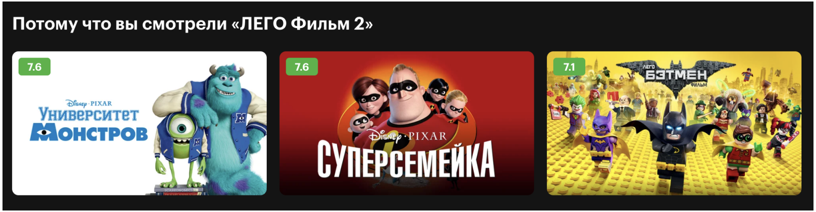

Потому что вы оценили Toy Story
Потому что вам нравятся комедии
Популярное
WALL·E
JUNE 27
PARASITE
THE DARK KNIGHT
JULY 18

Зачем объяснять рекомендации?

1. Прозрачность: объяснить пользователю, как работает система
2. Контролируемость: позволить пользователю исправить ошибки
3. Доверие: убедить пользователя, что система работает правильно
4. Убеждение: мотивировать пользователя к покупке

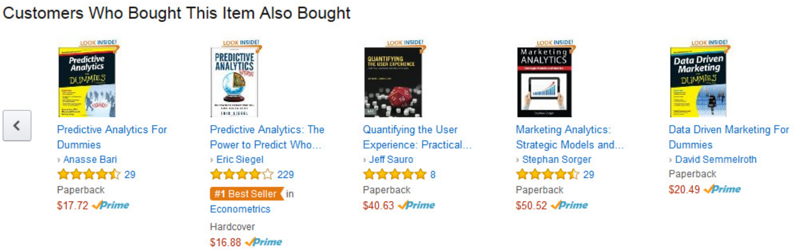
Case-based

Because you have selected or highly rated: Movie A



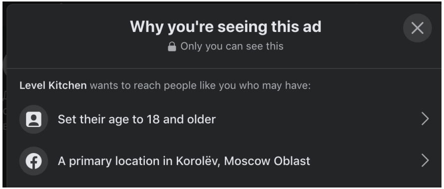
Collaborative

Customers Who Bought This Item Also Bought A



Content-based

Recommended because you said liked science fiction



Knowledge-based

Less Memory and Lower Resolution and Cheaper

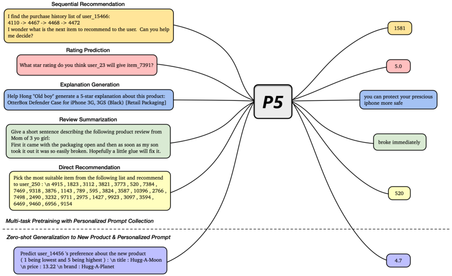
	This item			
	This item Lenovo IdeaPad 3 14" Laptop, Intel Core i3-1005G1 Processor, 4GB DDR4 RAM, 128GB M.2 SSD Storage, 14.0" FHD (1920 x 1080) Display, Integrated Graphics, Windows 10 S, 81WD010QUS, Platinum Grey #1 Best Seller Add to Cart	Lenovo IdeaPad 3 14 Laptop, AMD Ryzen 5 5500U Processor, 8GB DDR4 RAM, 256GB NVMe TLC SSD Storage, 14.0" FHD (1920 x 1080) Display, AMD Radeon 7 Graphics, Windows 10 Home, 82KT00AMUS, Abyss Blue Add to Cart	Lenovo IdeaPad 1 14 14.0" Laptop, 14.0" HD (1366 x 768) Display, Intel Celeron N4020 Processor, 4GB DDR4 RAM, 64 GB SSD Storage, Intel UHD Graphics 600, Win 10 in S Mode, 81VU0079US, Ice Blue Add to Cart	Lenovo IdeaPad Gaming 3 15 15.6" Laptop, 15.6" FHD (1920 x 1080) Display, AMD Ryzen 5 5600H Processor, NVIDIA GeForce GTX 1650, 8GB DDR4 RAM, 256GB SSD Storage, Windows 10H, 82K20015US, Shadow Black Add to Cart
Customer Rating	(32)	(118)	(590)	(134)
Price	$399.00	$539.00	$266.42	$769.22
Sold By	eSales Plus	Xocean	Mohawk Shop	ETRON INC - ELECTRONICS SUPPLIER
Computer Memory Size	128 GB	8	4	8
CPU Model Manufacturer	Intel	AMD	Intel	AMD
CPU Speed	1.2 GHz	2.1	1.1	3.3

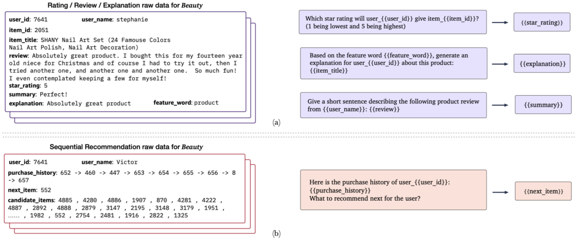
Explore, Exploit, and Explain: Personalizing Explainable Recommendations with Bandits [MLH+18]

Explanation	# Impressions
Because it's [day of week]	140.3K
Inspired by [user]'s recent listening	138.4K
Because it's a new release	140.5K
Because [user] likes [genre]	130.7K
Because it's popular	140.5K
Mood	140.7K
Focus	140.5K

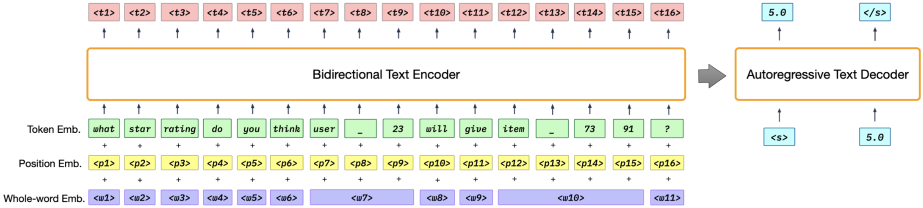
$$r(j, e, x) = \sigma(\theta_{global} + \theta_j \times 1_j + \theta_e \times 1_e + \theta_x \times 1_x)$$

Recommendation as Language Processing (RLP): A Unified Pretrain, Personalized Prompt and Predict Paradigm (P5) [GLF+22]





Recommendation as Language Processing (RLP): A Unified Pretrain, Personalized Prompt and Predict Paradigm (P5) [GLF+22]



Cross-entropy Loss

$$\mathcal{L}_{\theta}^{\mathrm{P5}} = -\sum_{j=1}^{|\mathbf{y}|} \log P_{\theta}\left(\mathbf{y}_j \mid \mathbf{y}_{<j}, \mathbf{x}\right)$$

Если хотим делать объяснения рекомендаций, нужно ответить на вопросы:

- Какую цель мы достигнем объяснениями?
- Какие объяснения можно получить из модели?
- Как правильно представить объяснения пользователю?

Итоги

Итоги

При построении моделей мы делаем упрощающие предположения. Из-за этих предположений в продакшен системах могут возникать негативные эффекты. Эти эффекты нужно учитывать и пытаться исправить.

https://t.me/mlvok

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