Interpretable Click-Through Rate Prediction through Hierarchical Attention

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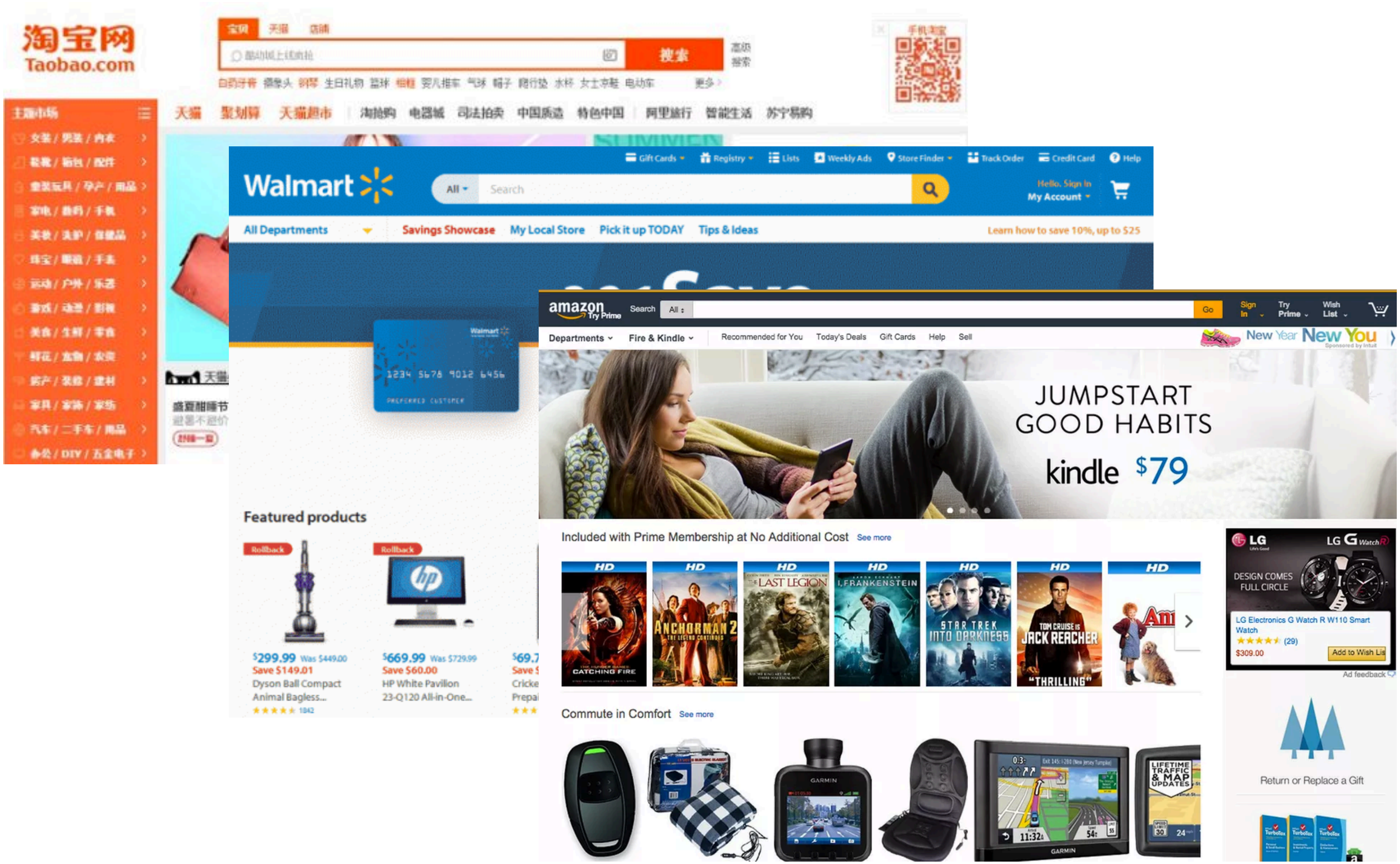
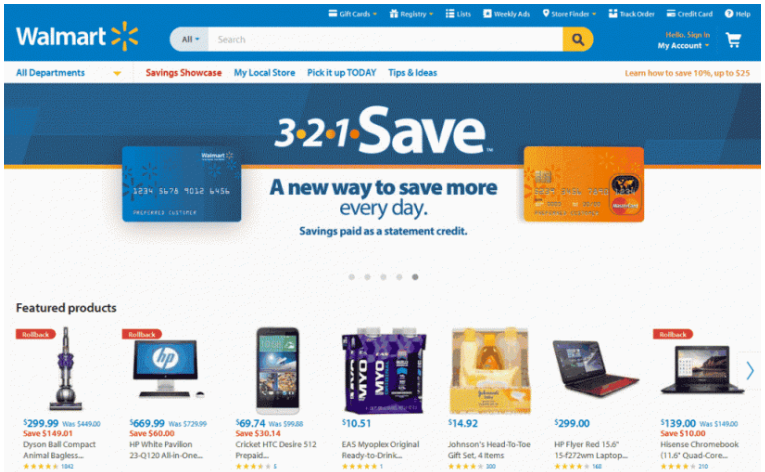
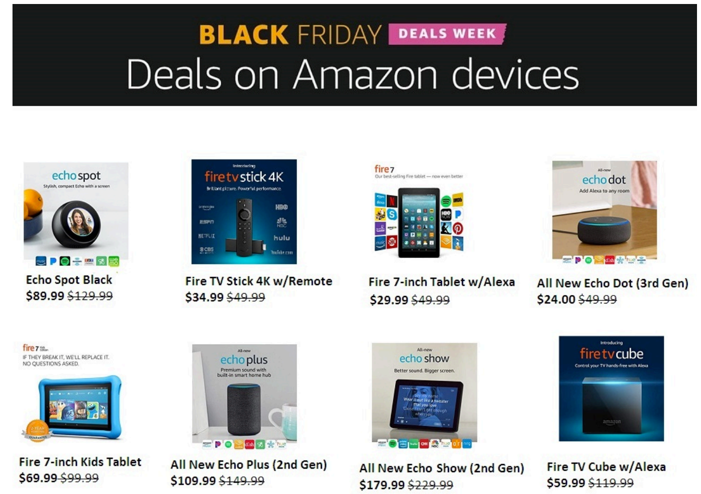
Recommender systems



Click-throughs





Click-throughs

Two natural questions to ask:

1. How many advertisements will be clicked?
2. How many clicks will be purchased?

Click-throughs

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Click-Through Rate Prediction (CTR)

- CTR:
  - Important role in recommendation system
  - Revenue of advertisements

Image: https://www.lyfemarketing.com/blog/average-click-through-rate/

Background

- CTR: *binary prediction*
- Pre-Deep Learning Model
  - FM: Factorization Machine
  - MF: Matrix Factorization
  - LR: Logistic Regression
- Deep learning based CTR model
  - DeepFM = FM module + Deep module
  - xDeepFM = CIN module + Deep module
    - CIN: Compressed Interest Network
  - and more …

SOTA models with DNN

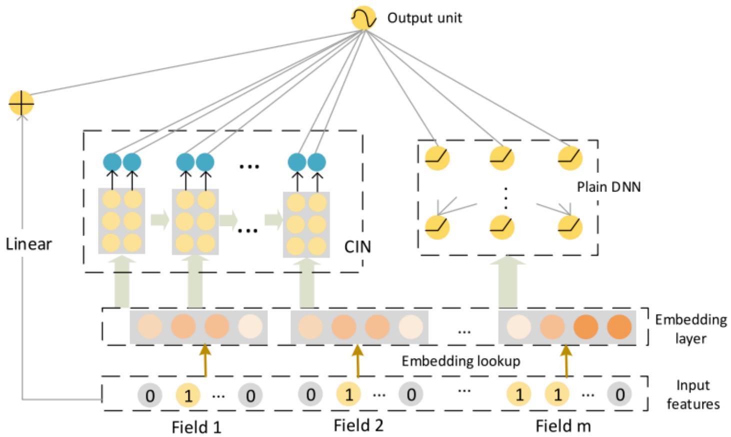


Figure 5: The architecture of xDeepFM.

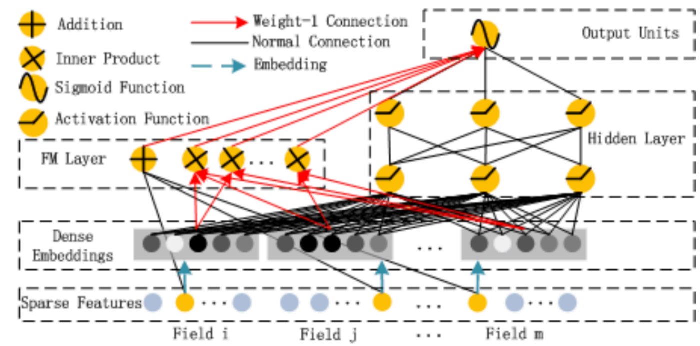
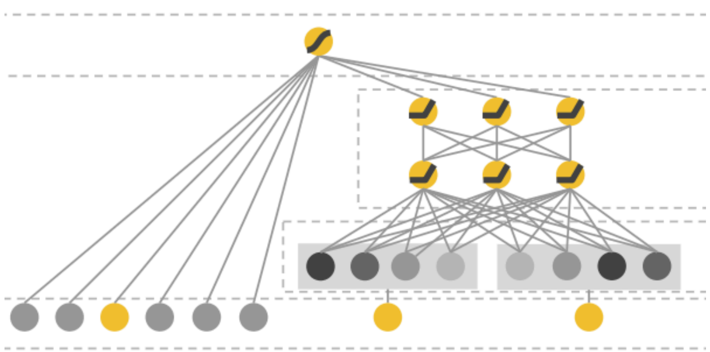


Figure 1: Wide & deep architecture of DeepFM. The wide and deep component share the same input raw feature vector, which enables DeepFM to learn low- and high-order feature interactions simultaneously from the input raw features.

xDeepFM		DeepFM
WDN	DCN	PNN



Wide & Deep Models

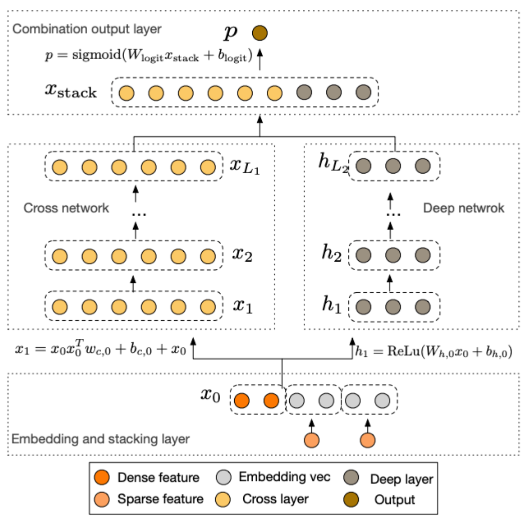
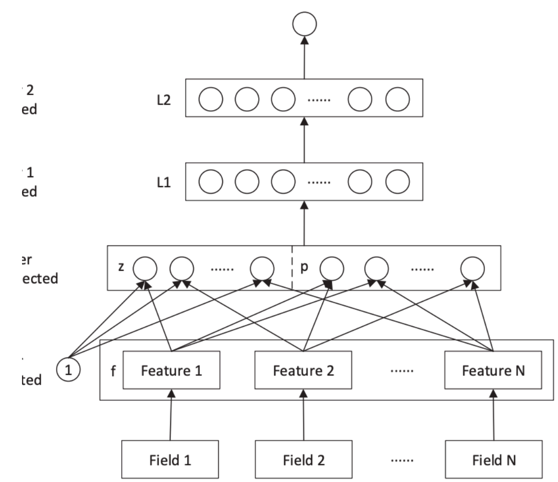
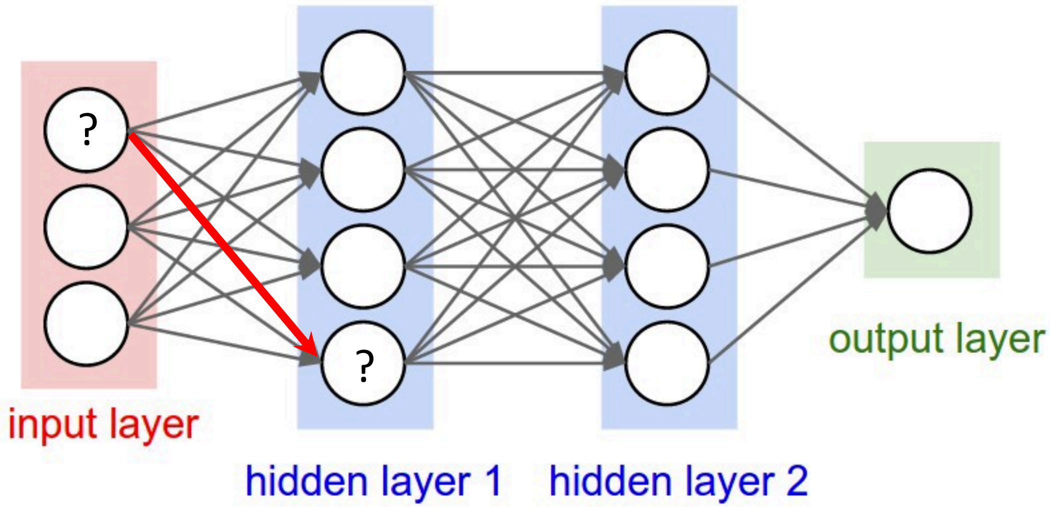


Figure 1: The Deep & Cross Network



Product-based Neural Network Architecture.

Deep neural network (DNN) module

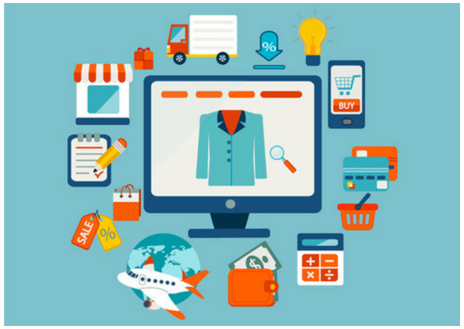


- DNN
  - Widely used in CTR models
  - Unjustifiable element-wise computation within representations of input or hidden features
  - Unaffordable complexity for big feature dim or size

Image: https://hackernoon.com/challenges-in-deep-learning-57bbf6e73bb

Concerns of DNN

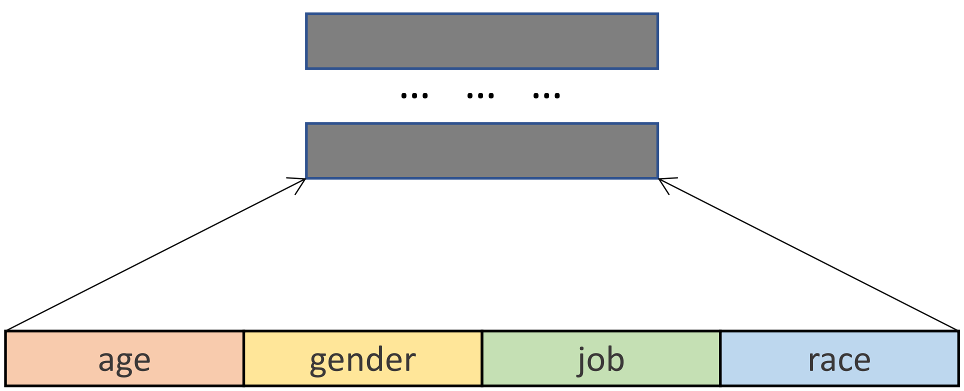
- Okay for online shopping with general purposes
  - Shopping on Amazon ...
- *NOT* okay for:
  - Medicine recommendation
  - Financial service recommendation
- Criteo:
  - 4 billions clicks in 24 hrs

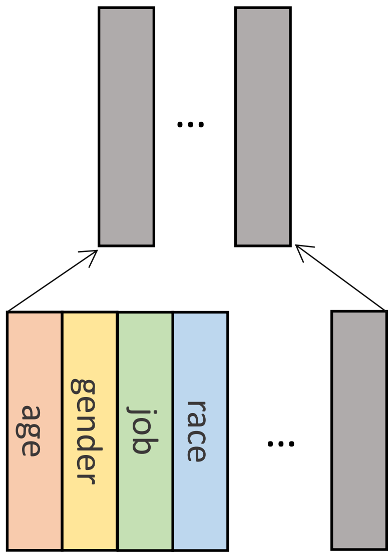


Images: https://www.fajarmag.com/an-increasing-trend-of-online-shopping/; https://www.tes.com/lessons/arP_sMT1GxDxHQ/medicine-by-the-minute; https://www.wealthandfinance-news.com/awards/

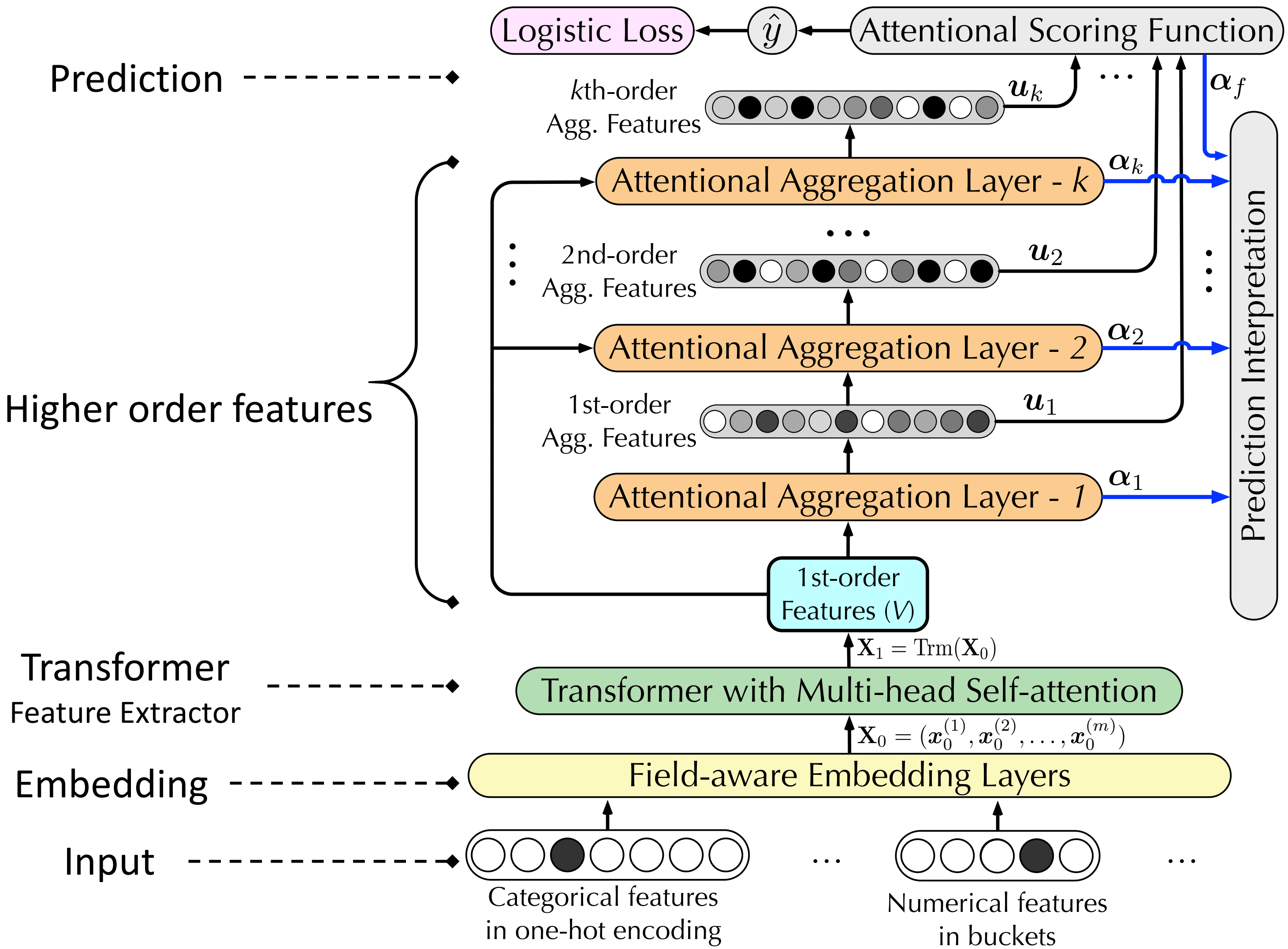
Our idea -- InterHAt

- Interpretability
  - Attention mechanism
  - Avoid flat concatenation of features
  - Avoid DNN and dim-wise computation
- Efficiency
  - Shrunk problem size



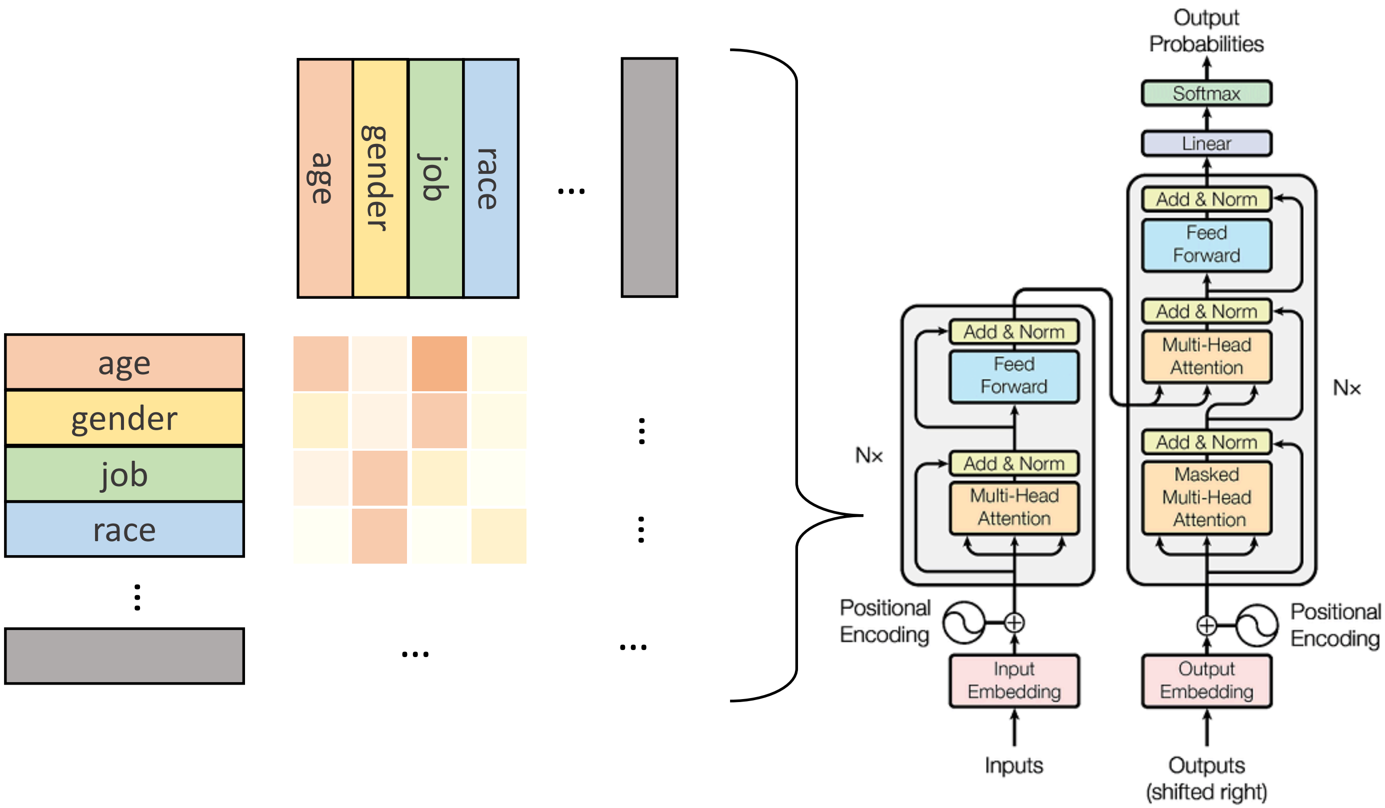


Interpretable CTR via Hierarchical Attention



Polysemy

- Self attention in Transformer



Right Figure: Vaswani, Ashish, et al. "Attention is all you need." Advances in neural information processing systems. 2017.

Hierarchical Attention

- Input: i-th order features:
- Generate aggregated feature:

$$\alpha_i^{(j)} = \frac{\exp\left(\boldsymbol{c}_i^T ReLU(\mathbf{W}_i \boldsymbol{x}_i^{(j)}\right)}{\sum_{j' \in F} \exp\left(\boldsymbol{c}_i^T ReLU(\mathbf{W}_i \boldsymbol{x}_i^{(j')})\right)},$$

$$\boldsymbol{u}_i = \text{AttentionalAgg}(\mathbf{X}_i) = \sum_{j=1}^{m} \alpha_i^{(j)} \boldsymbol{x}_i^{(j)},$$

- Output (i+1)-t order features:

$$\boldsymbol{x}_{i+1}^{(j)} = \boldsymbol{u}_i \circ \boldsymbol{x}_1^{(j)} + \boldsymbol{x}_i^{(j)}, \quad j \in \{1, \ldots, m\},$$

Evaluation

- Datasets
  - Performance evaluation
    - Critio, Avazu, Frappe
  - Interpretability study
    - Movielens-1m dataset (reviews as clicks)

Dataset	Criteo	Avazu	Frappe
#. of features (C + N)	22 + 14	21 + 0	7 + 0
#. of total records	13.8M	12.1M	288K
#. of distinct features	605.7K	23.8K	5,382

- Baselines
  - FM, Wide&Deep, DCN, PNN, DeepFM, xDeepFM
- Metrics
  - Area Under ROC Curve (AUC)
  - Cross Entropy (LogLoss)

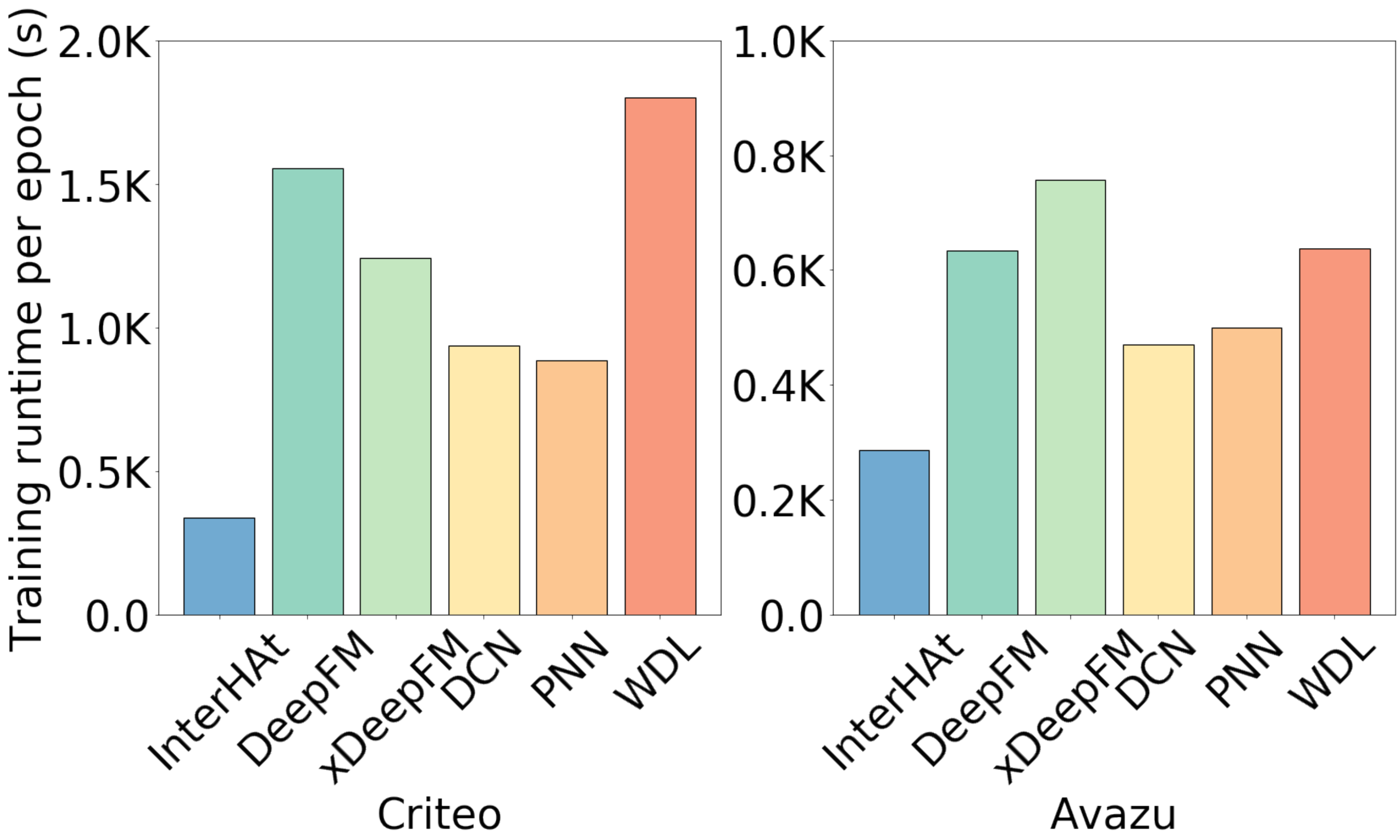
Performance

- Comparable with SOTA models
- Perform better on categorical features
  - SOTA models have close performance
  - Need better ways for encoding numeric features

Dataset	Criteo		Avazu		Frappe	
Metrics	Logloss	AUC	Logloss	AUC	Logloss	AUC
FM	0.4814	0.7525	0.3951	0.7508	0.4480	0.8625
Wide&Deep	0.4577	0.7845	0.3920	0.7564	0.2571	0.9500
DCN	0.4590	0.7826	0.3921	0.7564	0.2335	0.9616
PNN	**0.4547**	**0.7887**	0.3916	0.7569	0.2177	0.9642
DeepFM	0.4560	0.7866	0.3920	0.7561	0.2410	0.9520
xDeepFM	0.4563	0.7874	0.3917	0.7569	0.2043	0.9694
InterHAt-S	0.4608	0.7820	0.3919	0.7577	0.2151	0.9616
InterHAt	0.4577	0.7845	**0.3910**	**0.7582**	**0.2026**	**0.9696**

Efficiency

- InterHAt trains faster than other baselines



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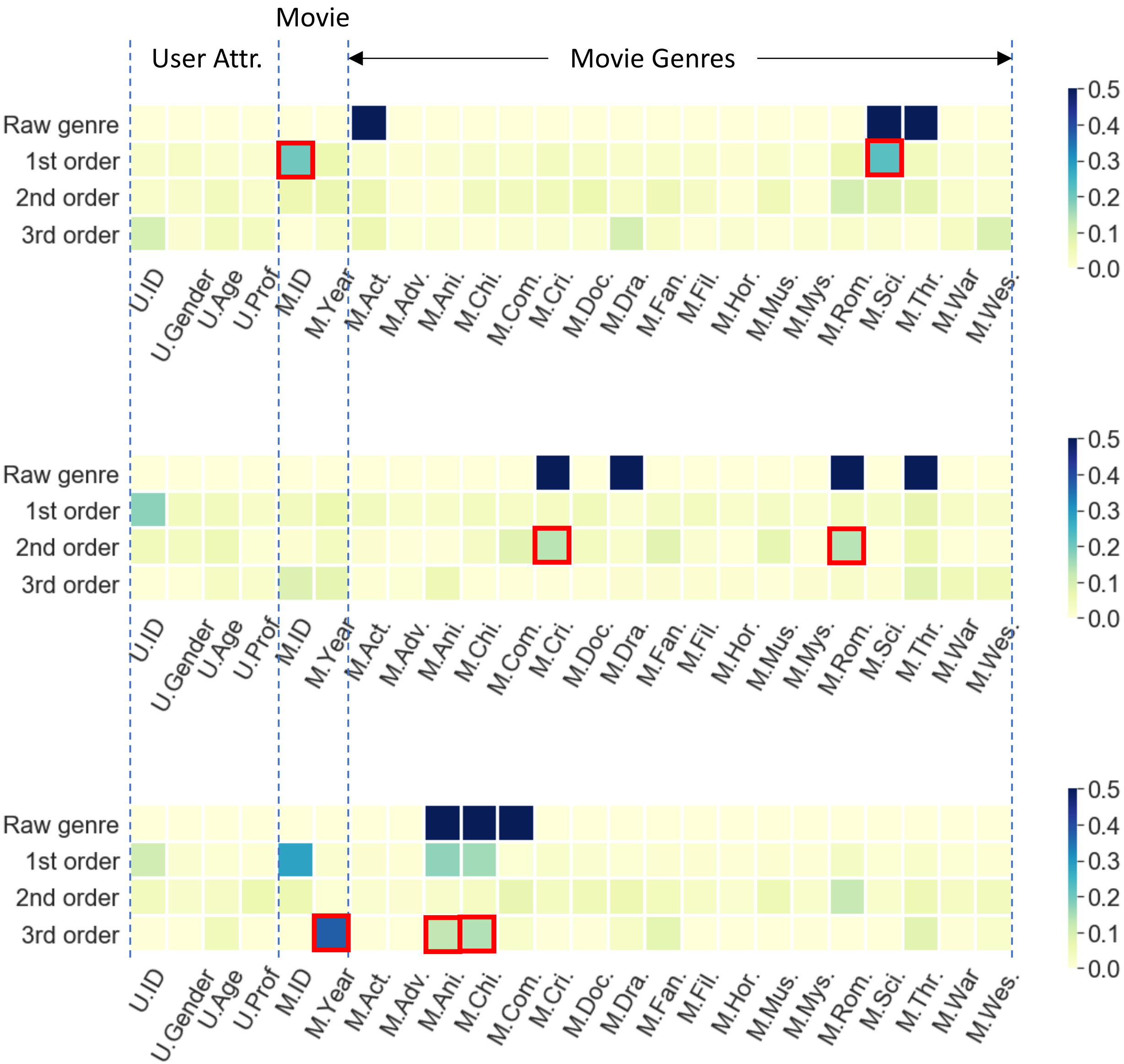
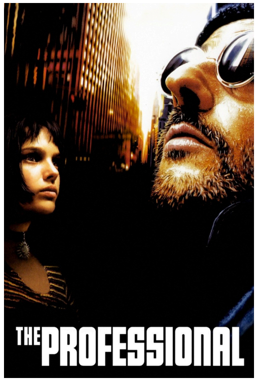
Interpretability





Conclusion

- InterHAt:
  - Efficiency and interpretability issues of CTR task
    - Efficiency:
      - Avoiding **deep** fully connect neural networks
    - Interpretability:
      - Attention mechanism
      - Interpretability v.s. Explanability
  - Nice performances on both aspects!
  - Try it out:
    - **`https://github.com/zyli93/InterHAt`**

Questions?

Wei Cheng

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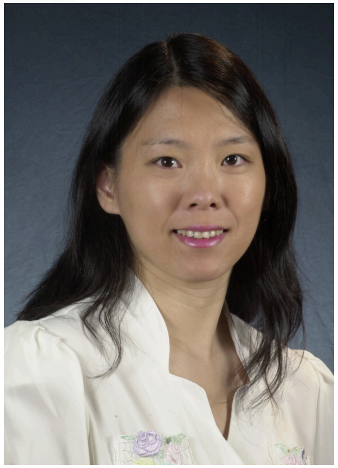
Haifeng Chen



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