Deep And Shallow Learning In Recommendation Systems

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Outline

Problem setup

Challenges

Modeling

Case study

Problem Setup

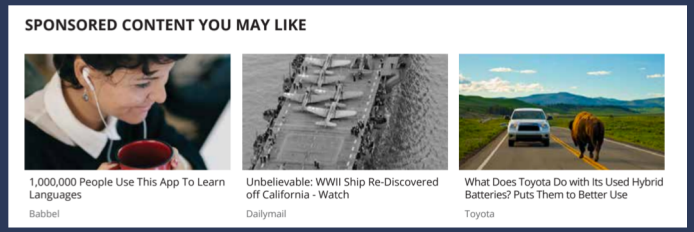
Millions of Possible Recommendations

Rank N recommendations by *CTR * CPC * f(Post-Click Engagement)*

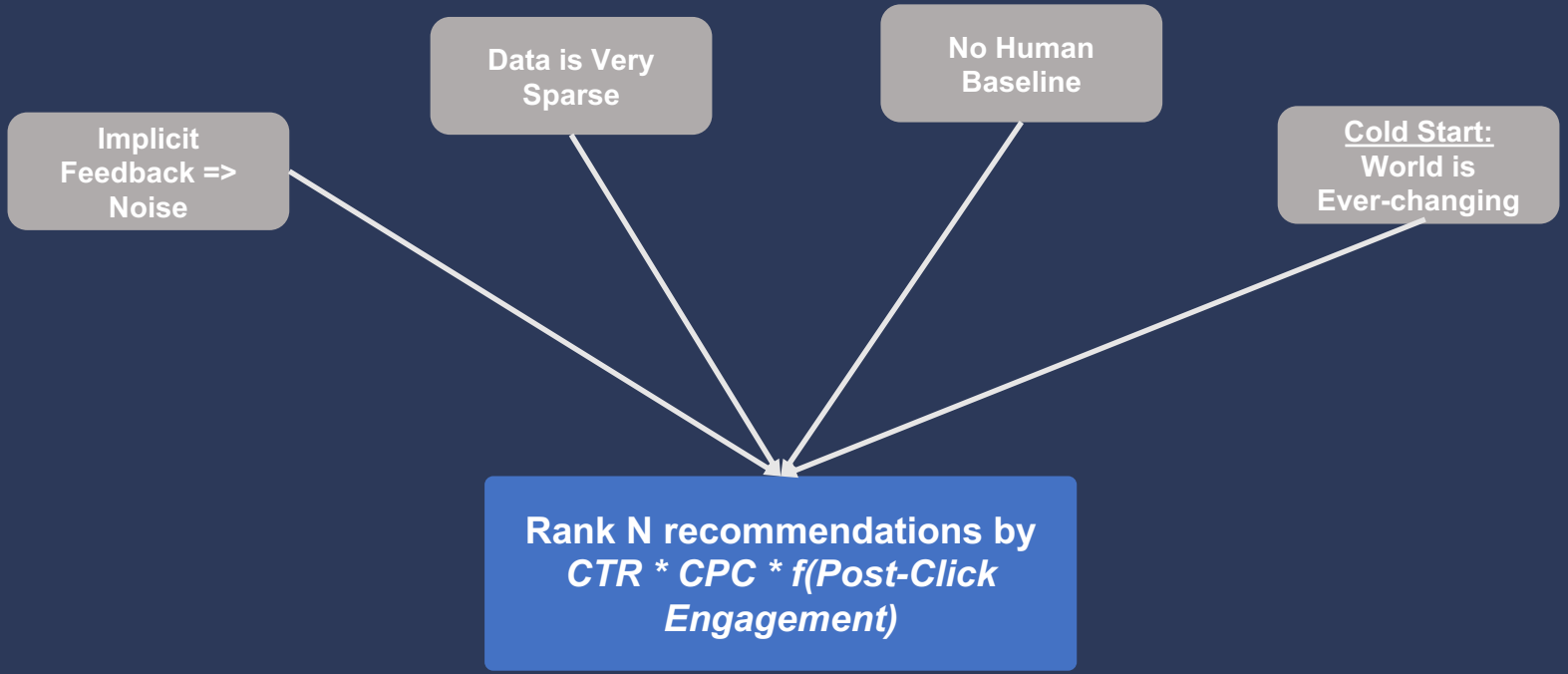
Context Metadata

Location Region-based Information

User Historical Data



Machine Learning + Recommendations = Hard



The Cold Start Problem

- Hard cold start: introduction of a new entity
- Soft cold start: existing entity in a new situation
- In Taboola, both issues are common
  - Borrow strength from similar informative situations

Matrix Factorization

$$loss = \frac{1}{n}\sum_{i,j\ \epsilon\ D}\left(r_{ij} - \overrightarrow{u_i}\overrightarrow{m_j}\right)^2 + reg_{trem}$$

	User 1	User 2	User 3	User 4	User 5
Movie 1	7.5	2.2	?	?	8.2
Movie 2	?	?	8.3	?	7
Movie 3	?	7.9	0.3	?	?
Movie 4	9.9	?	?	10	?
Movie 5	?	8.2	3.4	?	6.5

Matrix Factorization

Item

User

	W	X	Y	Z
A		4.5	2.0	
B	4.0		3.5	
C		5.0		2.0
D		3.5	4.0	1.0

Rating Matrix

=

A	*1.2*	*0.8*
B	*1.4*	*0.9*
C	*1.5*	*1.0*
D	*1.2*	*0.8*

User Matrix

X

W	X	Y	Z
1.5	*1.2*	*1.0*	*0.8*
1.7	*0.6*	*1.1*	*0.4*

Item Matrix

Limitation of Matrix Factorization

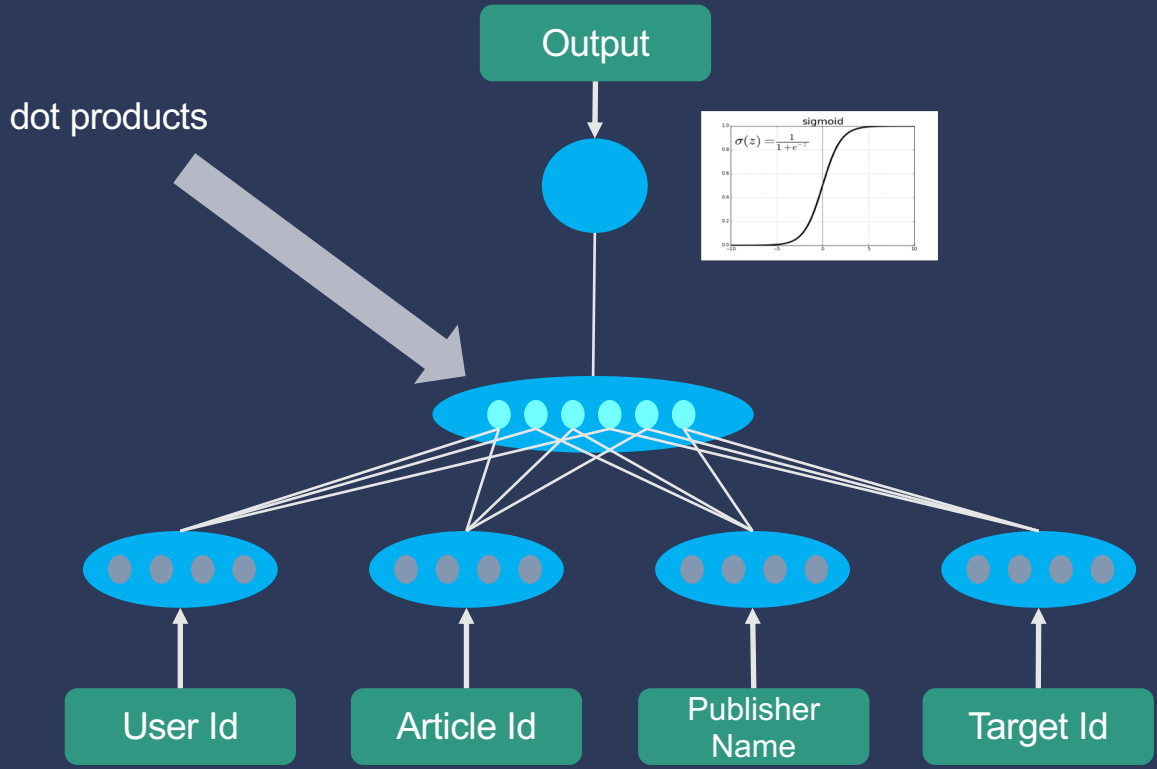
Or why the Netflix solution doesn't work for Taboola

- It doesn't handle cold start very well
  - For instance, input is sparse
- Input is complex and diverse
  - Could be sequential, textual, media, etc.
- In the Netflix challenge, feedback is explicit
- Need for additional generalizing features

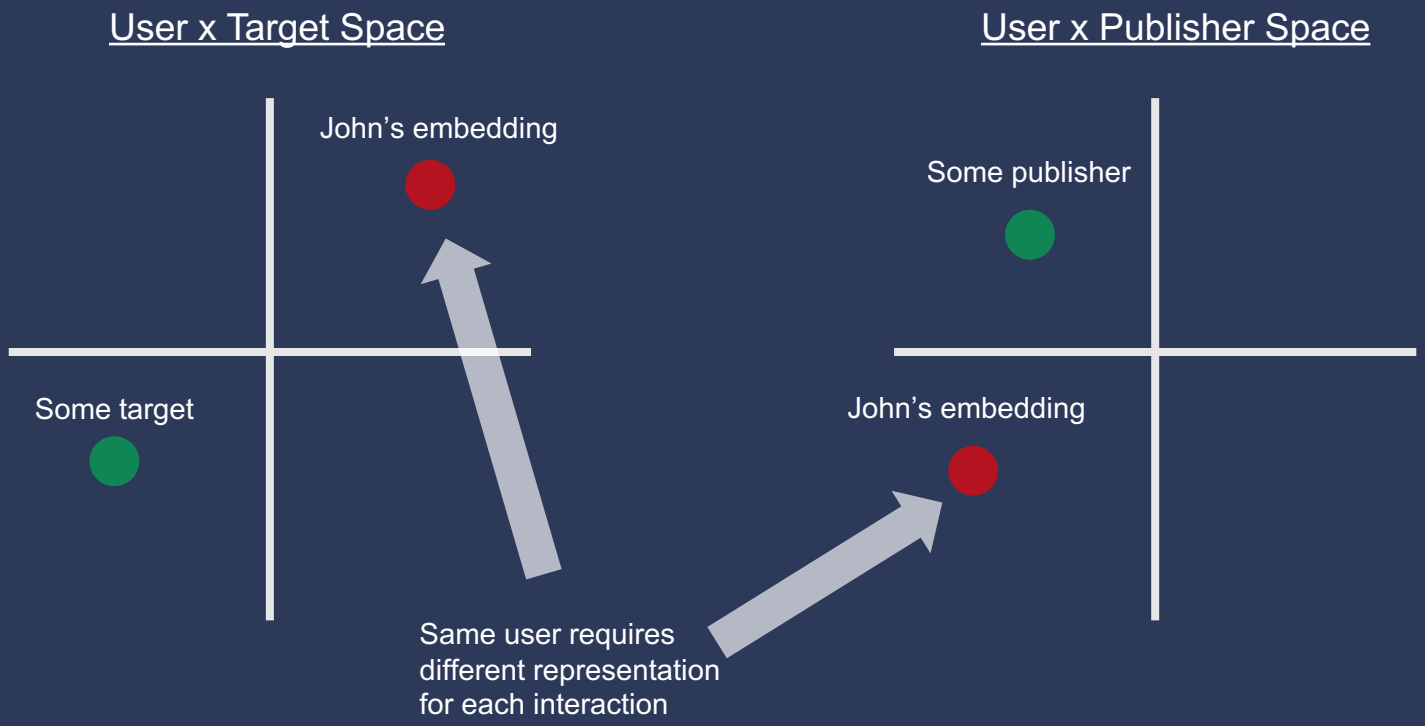
Factorization Machines

- Can factorize many pairs (i.e. features)
- Each feature gets embedding (its latent representation)
- $\emptyset_{FM}(w, x) = \sum_{i,j \in x} w_i \cdot w_j$
- n = number of features, k = latent feature vector length
- Works with any loss

Factorization Machines



Limitation of Factorization Machines



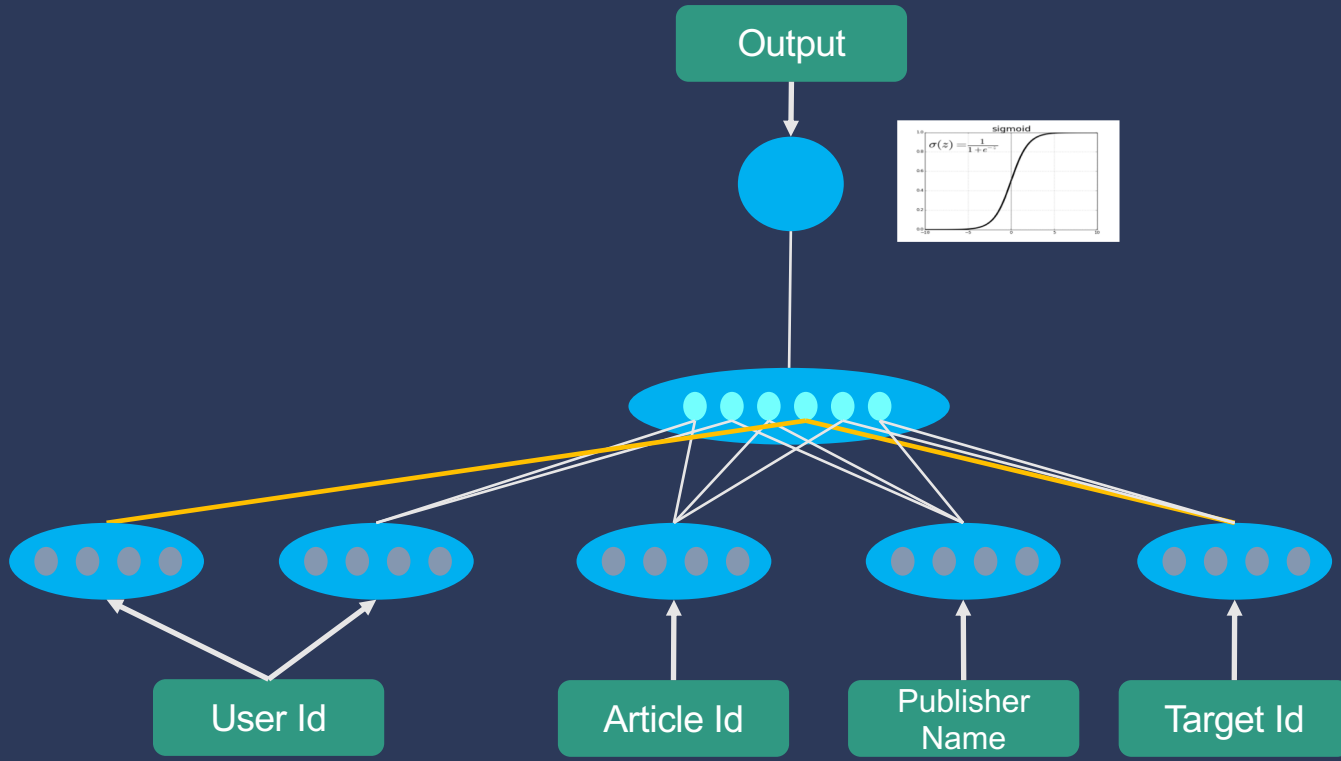
Field-aware Factorization Machines (FFM)

- Separate embedding for different interactions
- $Nike * usatoday.com \; vs \; Nike' * User_j$
- $K_{ffm} \ll K_{fm}$

$$\phi_{\text{FFM}}(\boldsymbol{w}, \boldsymbol{x}) = \sum_{j_1=1}^{n} \sum_{j_2=j_1+1}^{n} (\boldsymbol{w}_{j_1,f_2} \cdot \boldsymbol{w}_{j_2,f_1}) x_{j_1} x_{j_2}$$

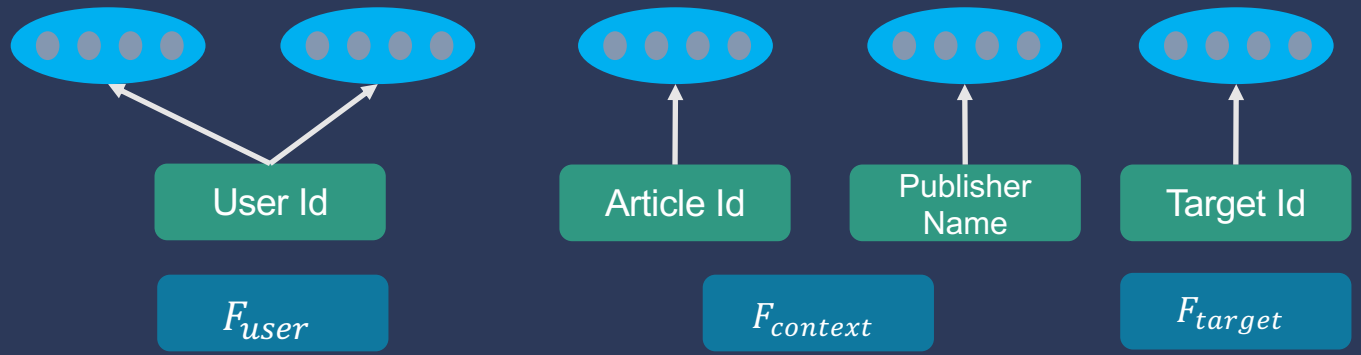
Field-aware Factorization Machines for CTR Prediction, RecSys 2016

Factorization Machines



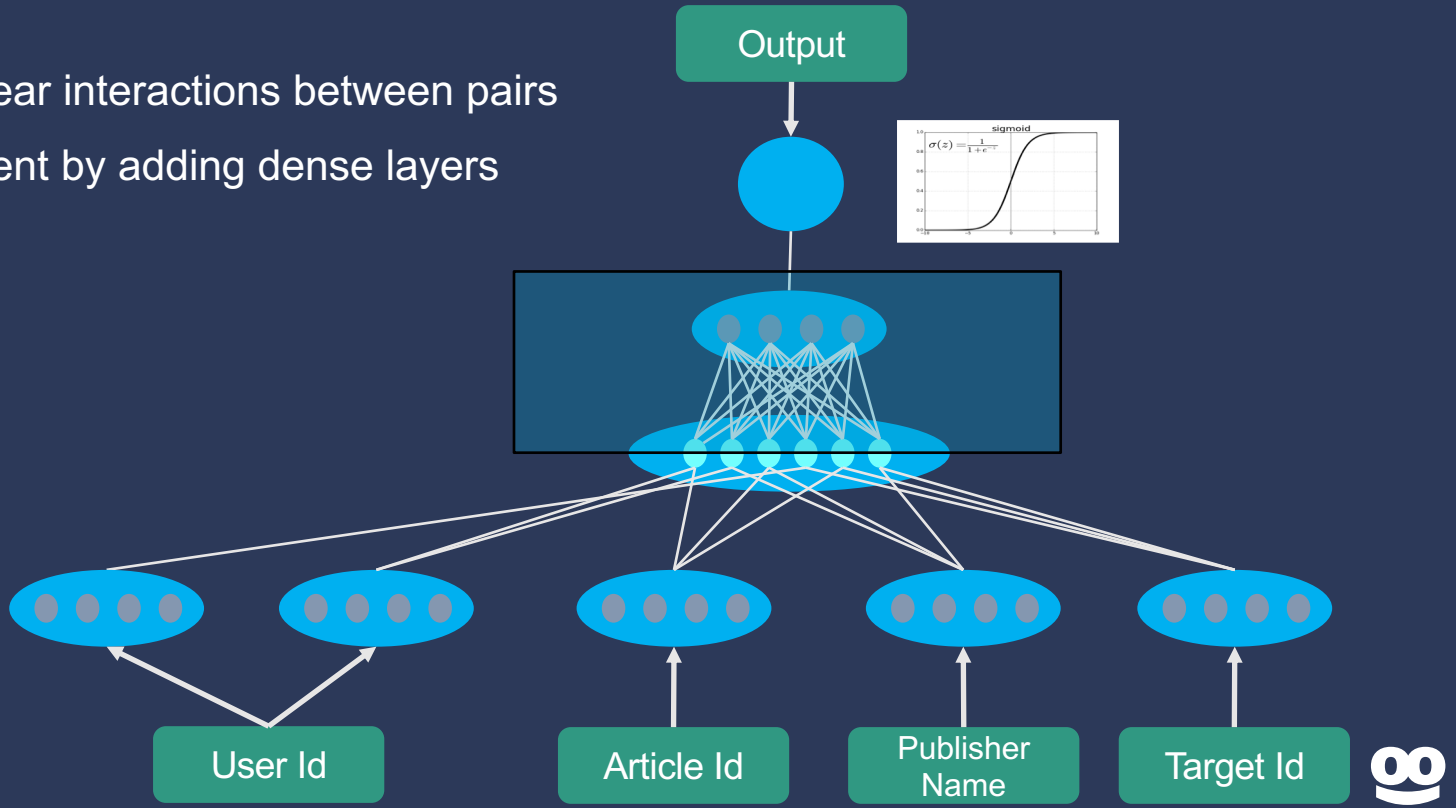
What's a Field in FFM?

- Number of variables $n * f * k$
- $f = number\ of\ fields$
- Determine feature families, e.g. Target, User, Context
- f Embedding for each feature
- $Nike_{user}, Nike_{context}, Nike_{target}$



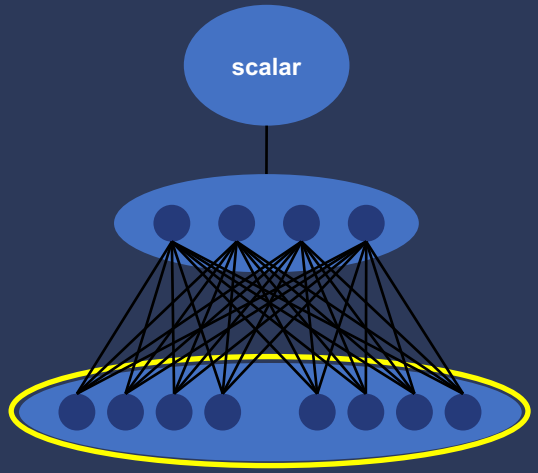
Representing additional relations in FFM

- Capture non-linear interactions between pairs
- Easy to implement by adding dense layers

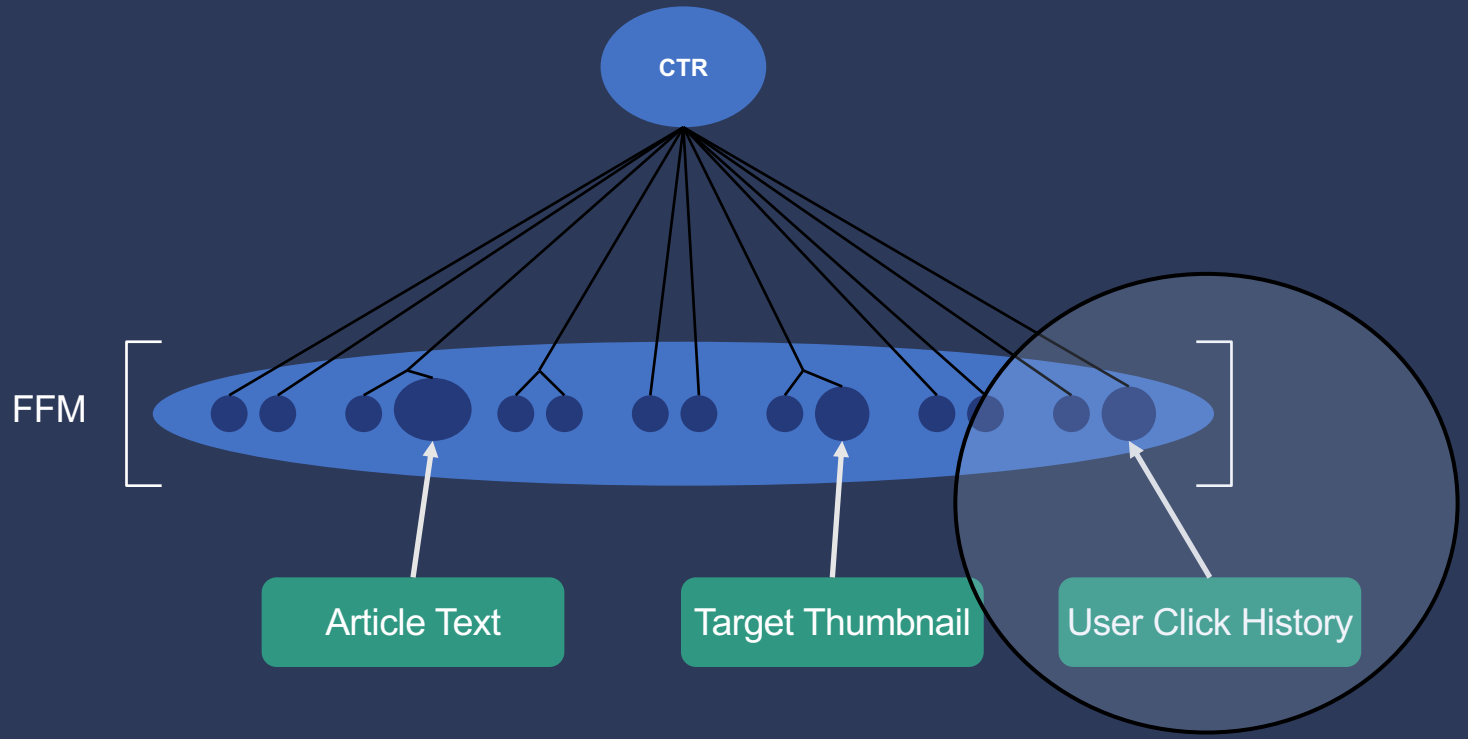


Handling numerical feature in FFM

- Option 1: Bucketing (not a trivial task)
- Option 2: Vectorization via small deep net

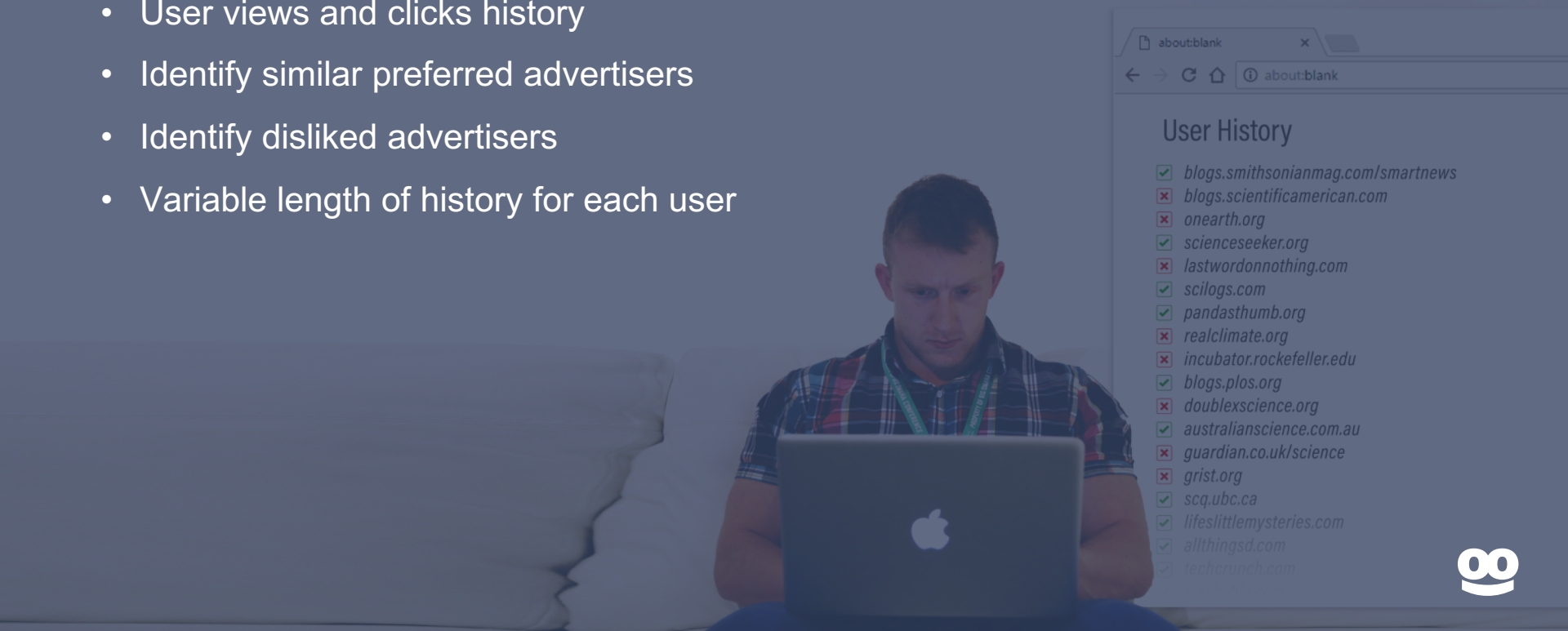


Deep & Shallow Learning



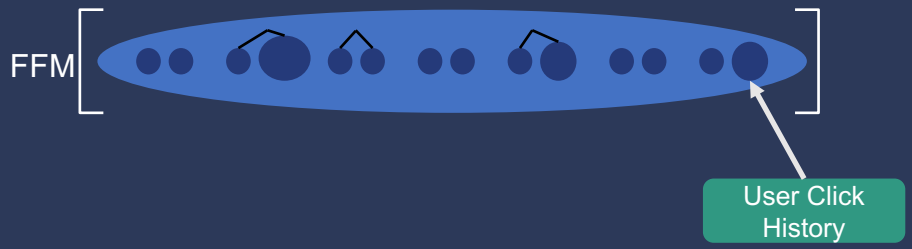
Case study – user advertiser history

- User views and clicks history
- Identify similar preferred advertisers
- Identify disliked advertisers
- Variable length of history for each user



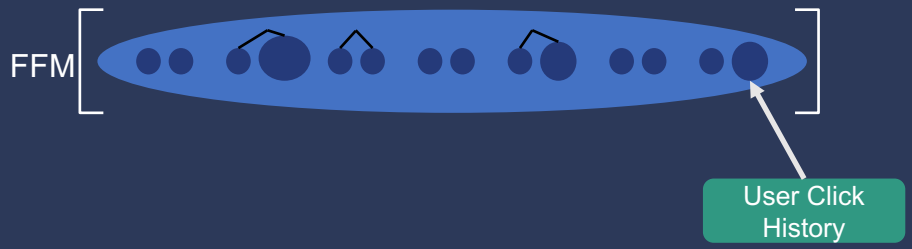
Case study - input

- $[a_1, a_2, \ldots . . a_n]$ - Nike, coca cola
- $[c_1, c_1, \ldots . . c_n]$ – Number of clicks
- $[v_1, v_2, \ldots . . v_n]$ – Number of views



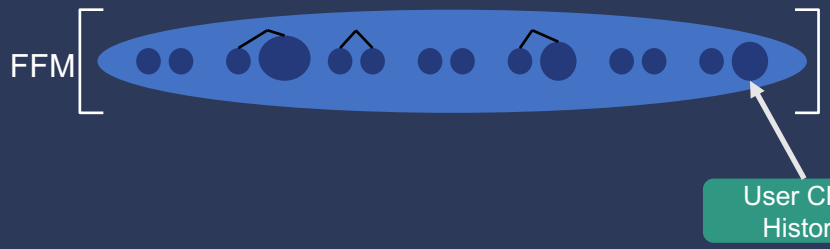
We could one hot encode…

- $[1,0,1,0,\ldots\ldots,1]$ - ids
- $[2,0,0,0,\ldots\ldots,1]$ – clicks
- $[23,0,3,0,\ldots\ldots,5]$ - views



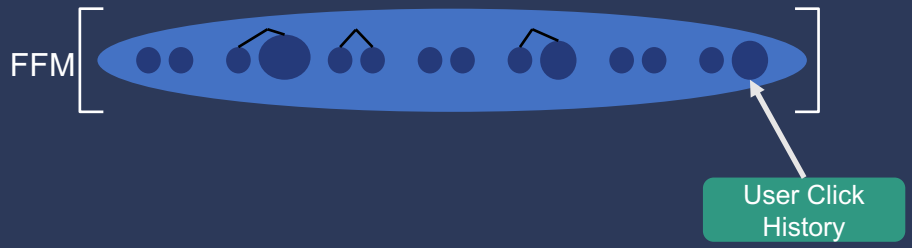
Embedding to the rescue (BoW style)

- $[a_1, \ldots a_n]$ => $[\overrightarrow{a_1}, \ldots . \overrightarrow{a_n}]$
- $res = \frac{1}{n}\sum_1^n A_i$
- Filter non-clicks, filter OOV
- $sign_i = c_i > 0 \,?\, 1 : -1$
- $res = \frac{1}{n}\sum_1^n sign_i * A_i$



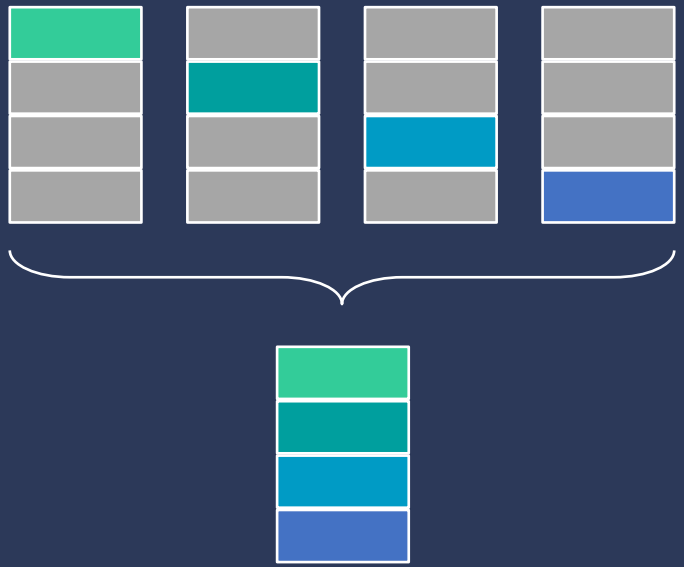
Integrating clicks & views

- $[a_1, \dots a_n]$ => $[\overrightarrow{a_1}, \dots . \overrightarrow{a_n}]$
- $[c_1, \dots c_n], [v_1, \dots v_n]$
- $res = \sum_1^n \frac{Ci}{V_i} * A_i \ * norm_{factor}$
- Integrating priors $p_c, p_v \ - network\ weights$
- $res = \sum_1^n \frac{Ci+p_c}{V_{i+p_v}} * A_i \ * norm_{factor}$



Max pooling

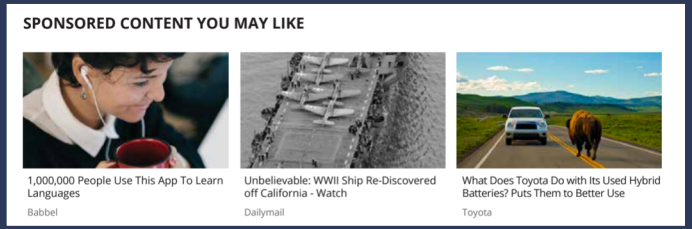
- Extract the max from each dimension of the latent vector



And Many Other Ways..

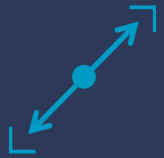
- Using an attention layer (learn a weighted average)
- Using an RNN (if time matters)
- Take user's favorite embedding

- Could model text/image/video input
  - Using your deep subnet of your choice



Summary

Recommendation system in a dynamic environment

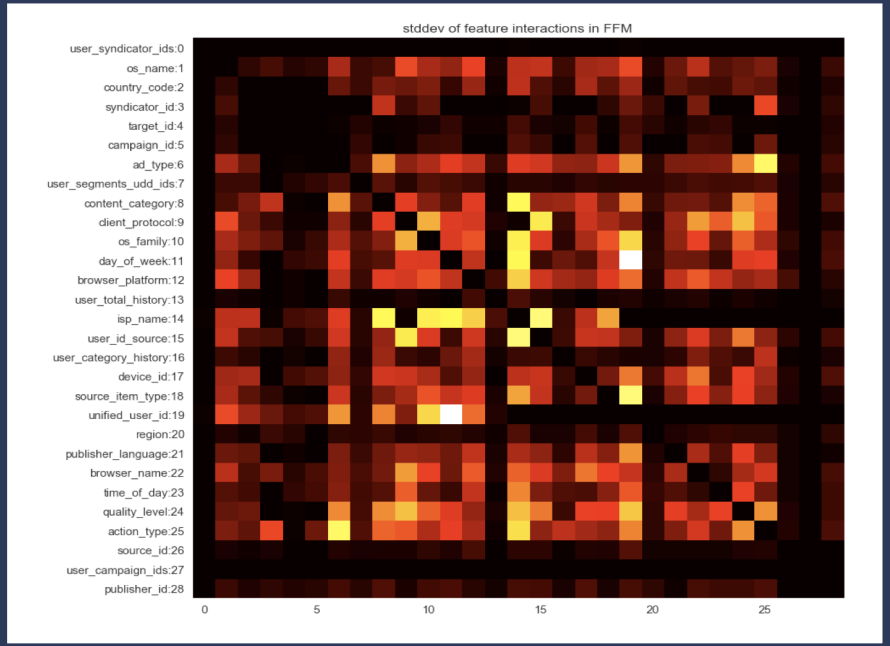


Deep learning – not one size fit all

Modeling matters – modularity is king

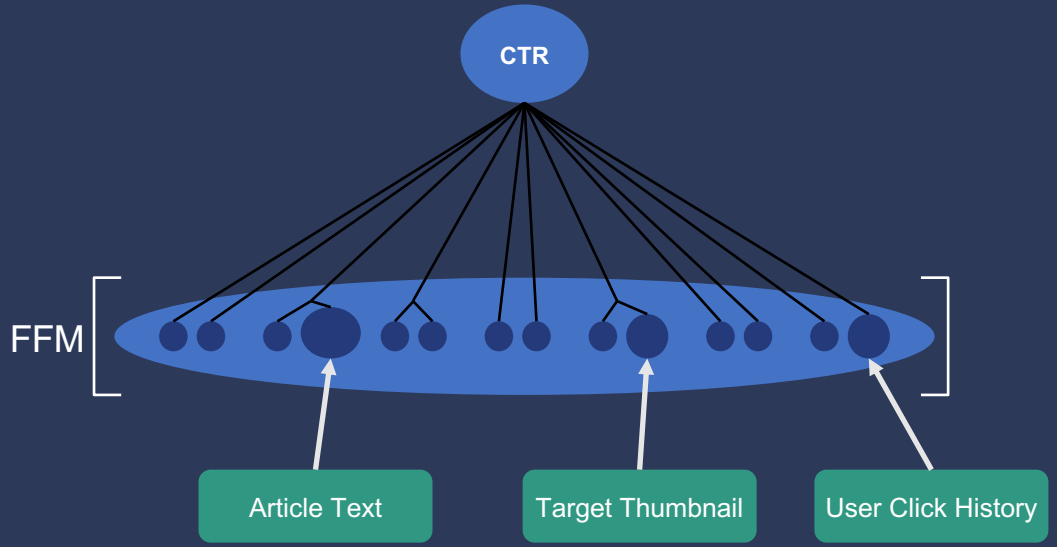
Interpretable FFM

- Using a simplified model for analysis
  - Without intermediate dense layers
- TensorFlow makes it easy…



Additional Architecture

- Plain fully connected deep network
- Deep FM
- Wide and Deep



Thank You!

Questions?

Where is this used in Taboola

- Dataset of ~40M rows
- Goals: CTR and CVR prediction
- Tensorflow over GPU for training
- Tensorflow Serving for serving
- 1T estimations per day