Recommendation Systems

Deep Learning, part 2

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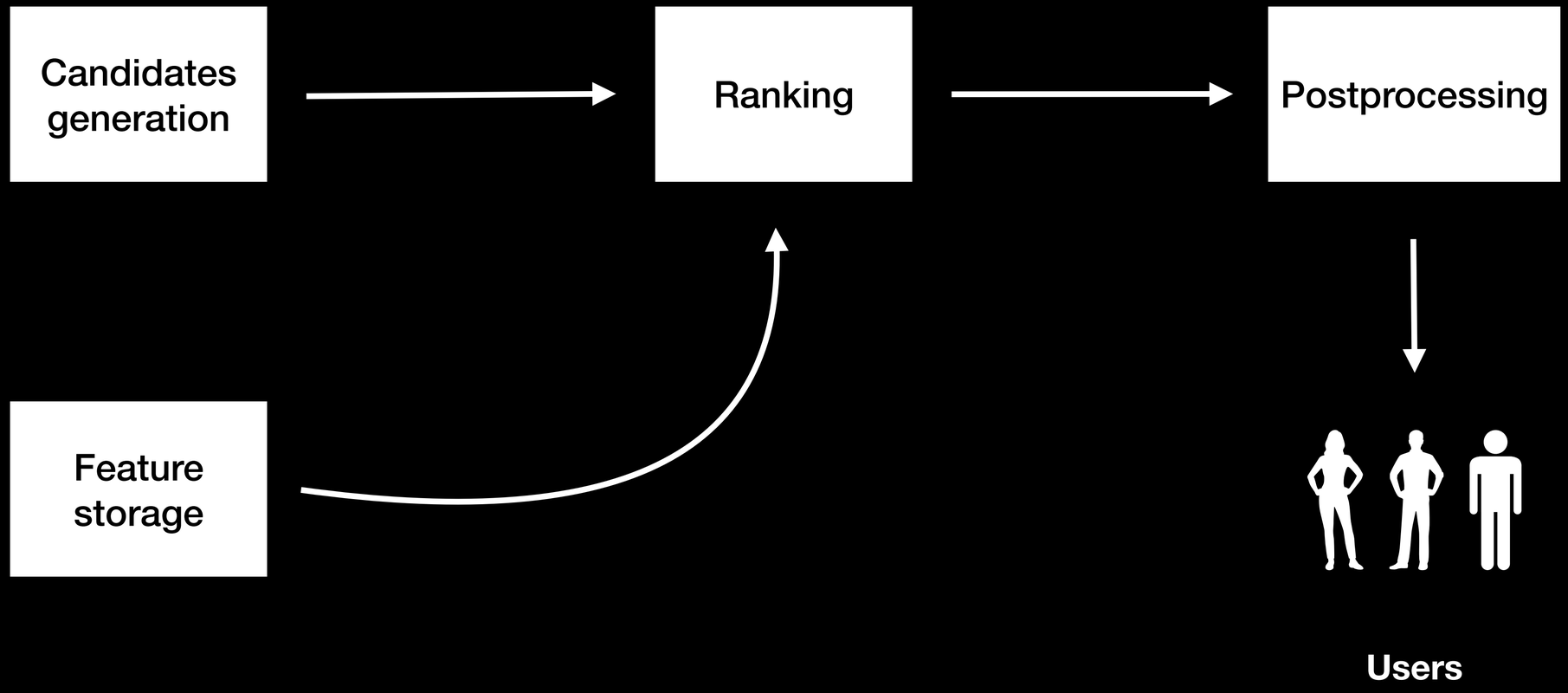
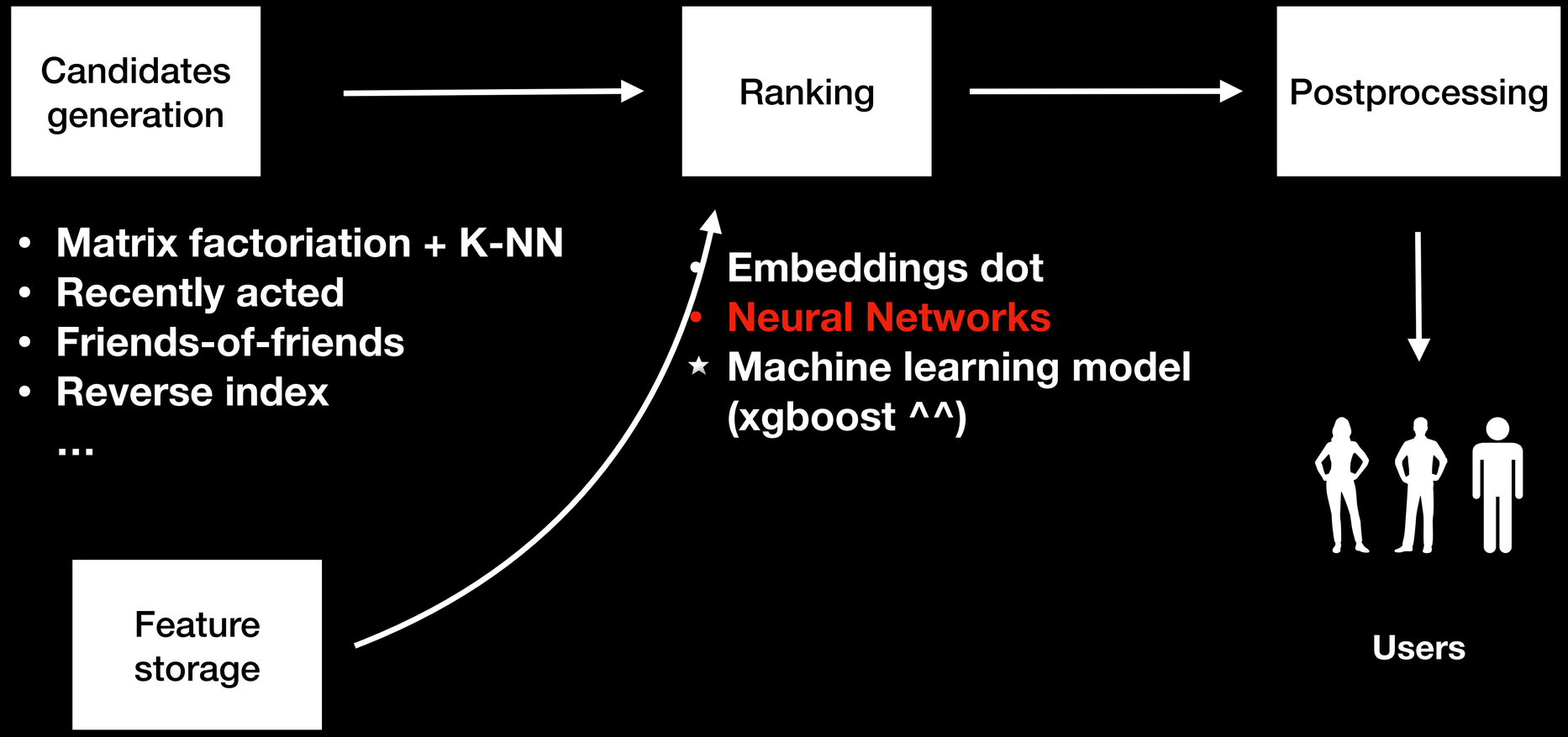
Recommendations pipeline:



Recommendations pipeline:

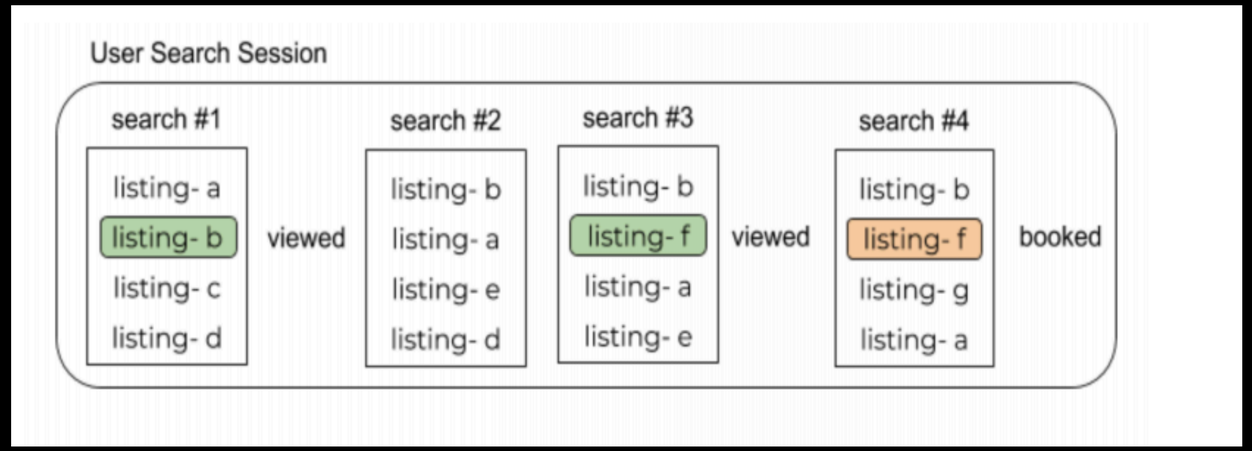


Neural networks as ranking:

- Task: airbnb search.

  Stop, what? We are about recsys. Are you **mad?** Nope. Have you seen airbnb search? It's totally about ranking and search is only «name» , no normal textual questions, all query is built from simple geo and price ranges so yes, it's **more recommender system then search.** They use ranking objectives, measures NDCG and got strong correlations between NDCG- and bookings- gains (offline-online correlation) that's why it's more recommendation then search

- Dataset: **booked vs viewed**.
  Offline quality: **NDCG**.
  Baseline: **GBDT**.
  Online metric: **bookings**.



Source: Applying Deep Learning To Airbnb Search

Ch1. Do not be a heroes:

Custom super-designed architecture.

The same GBDT features.

L2-loss with 1 as positives, 0 as negatives.

Awful results.

WHY?

Source: Applying Deep Learning To Airbnb Search

Ch1. Do not be a heroes:

Simple NN with 32-units hidden layer.

The same GBDT features.

L2-loss with 1 as positives, 0 as negatives.

Awful results.

WHY?

Source: Applying Deep Learning To Airbnb Search

Ch1. Do not be a heroes:

Simple NN with 32-units hidden layer. The same GBDT features. L2-loss with 1 as positives, 0 as negatives. Awful results.

- Feature normalisation:
  - Normal distribution: $(f\_val - \mu)/\sigma$
  - Power law distr: $log(\frac{1 + f\_val}{1 + median})$

Source: Applying Deep Learning To Airbnb Search

Ch1. Do not be a heroes:

Simple NN with 32-units hidden layer. The same GBDT features. L2-loss with 1 as positives, 0 as negatives. Awful results.

- Smooth distributions:
  - Spotting bugs
  - Facilitating generalization

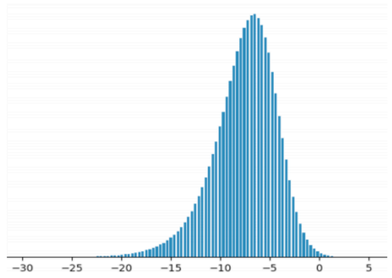


Figure 8: Distribution of output layer.

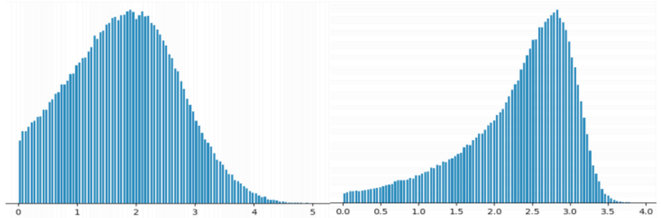


Figure 9: Example distributions from second hidden layer.

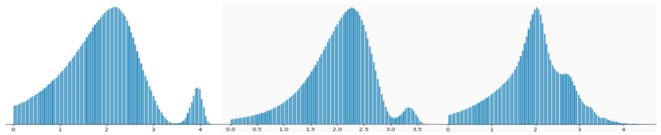


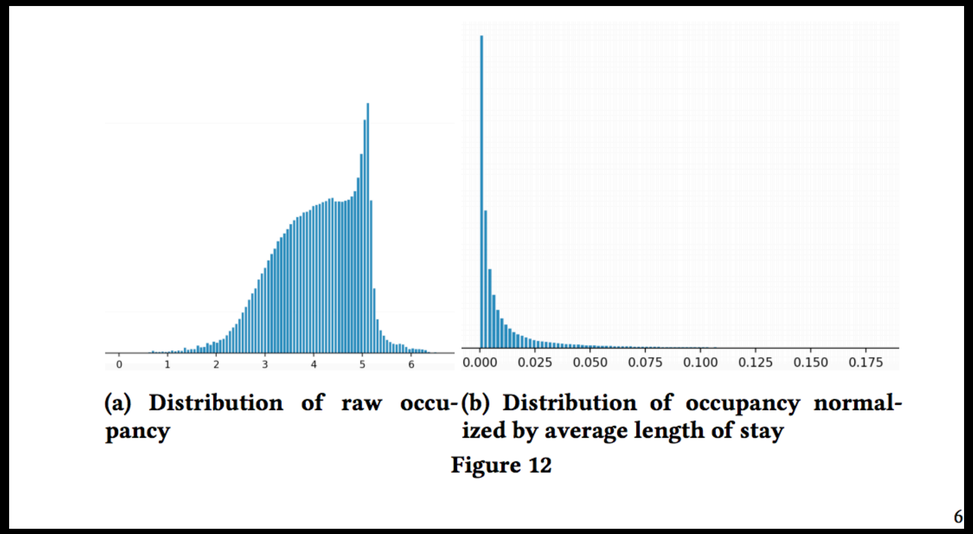
Figure 10: Example distributions from first hidden layer.

Source: Applying Deep Learning To Airbnb Search

Ch1. Do not be a heroes:

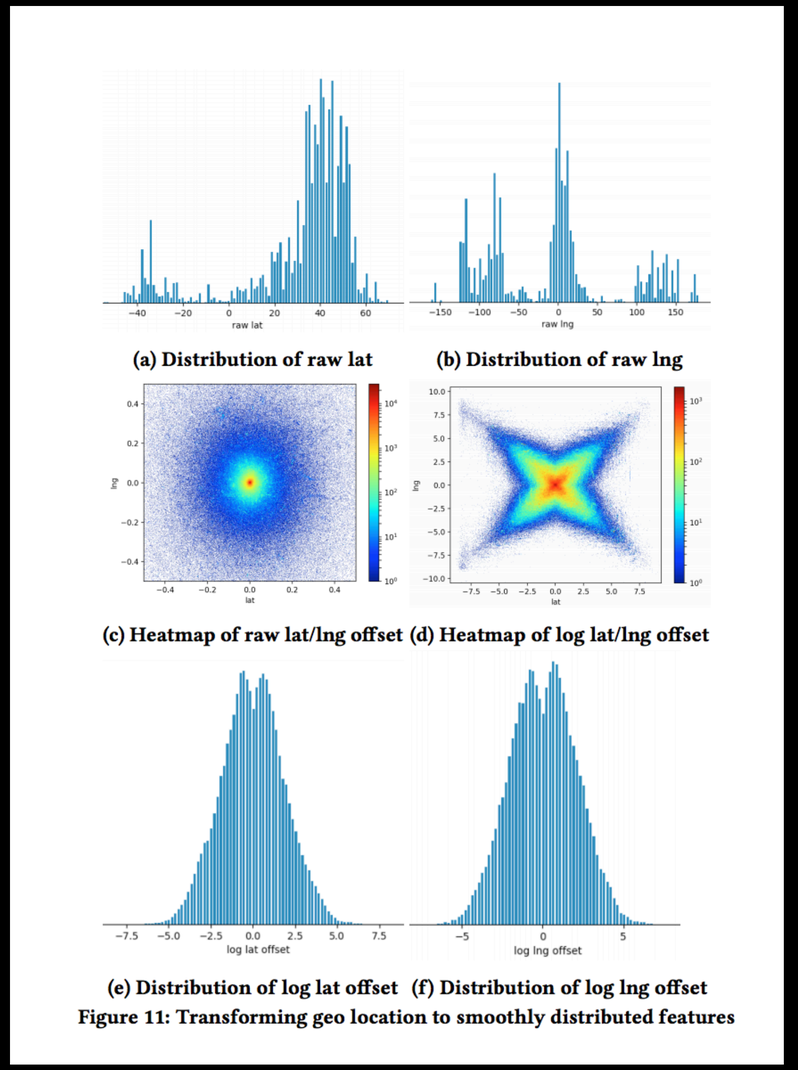
Simple NN with 32-units hidden layer. The same GBDT features. L2-loss with 1 as positives, 0 as negatives. Awful results.

- Special features mapping. Lat/lng to offset wrt users screen centered.
- Completness of features: occupancy



(a) Distribution of raw occupancy (b) Distribution of occupancy normalized by average length of stay

Figure 12



(a) Distribution of raw lat (b) Distribution of raw lng

(c) Heatmap of raw lat/lng offset (d) Heatmap of log lat/lng offset

(e) Distribution of log lat offset (f) Distribution of log lng offset

Figure 11: Transforming geo location to smoothly distributed features

Ch1. Do not be a heroes:

Simple NN with 32-units hidden layer.

Features are normalized and validated.

L2-loss with 1 as positives, 0 as negatives.

Normal results.

Source: Applying Deep Learning To Airbnb Search

Ch2. Main character runs up a stairway:

LambdaRank in NN:

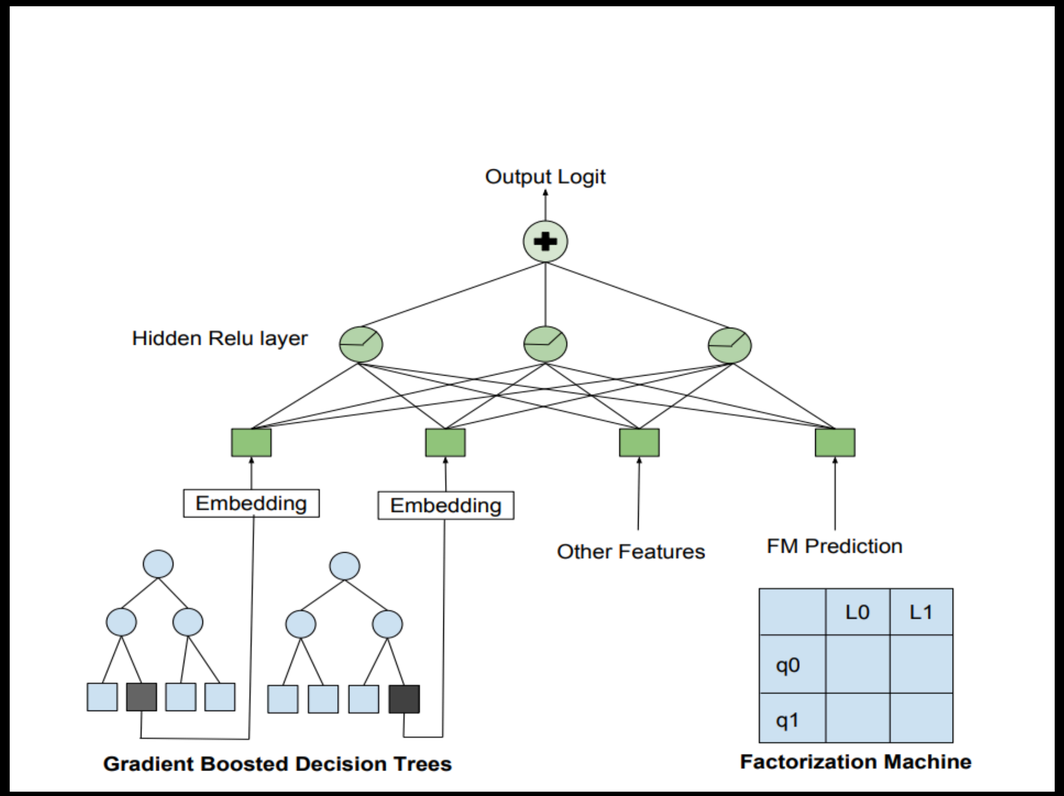
- Pairwise dataset. {positive_list, negative_list} sampled from the same session logs. CE loss between listed and not-listed
- Scaled at NDCG change of swapping pairs.
- ^^ Prioritizes 1 to 0 ranking over 125 to 124.

Ch2. Main character runs up a stairway:

GBDT-NN-shtein:

- GBDT up-ranks different samples.
- FM-machines with their embeddings.
- NN with pretty smooth generalisation and/or interactions

Frankenshtein to combine them all ->



Ch2. Main character runs up a stairway:

Frankenshtein to combine them all -> was overperformed by this network and 10x data.

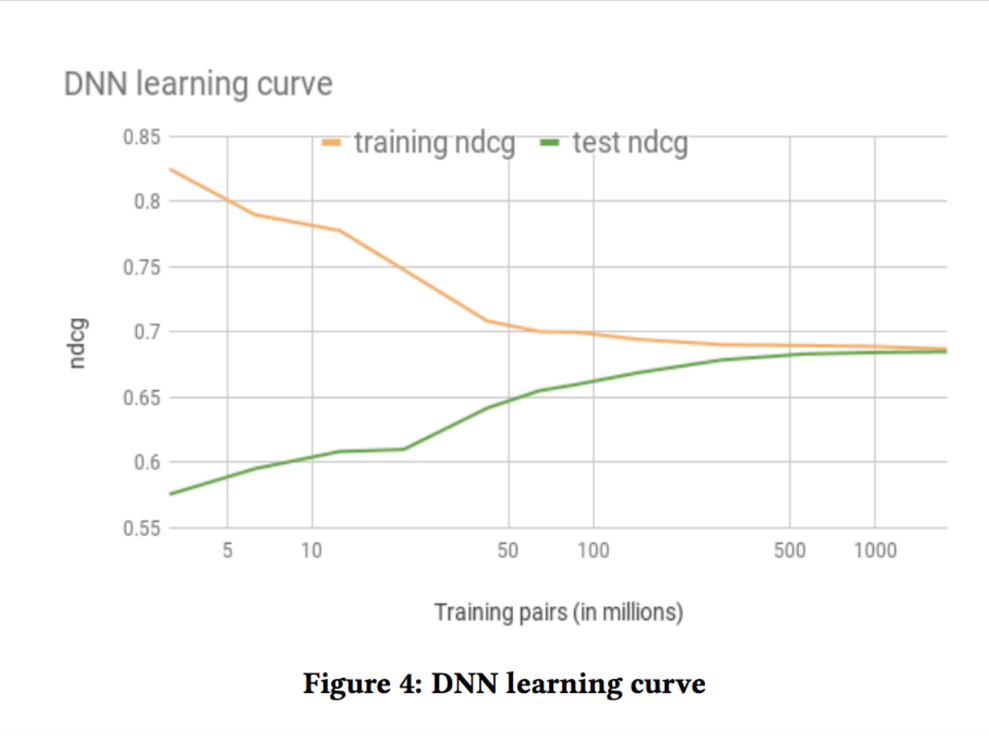
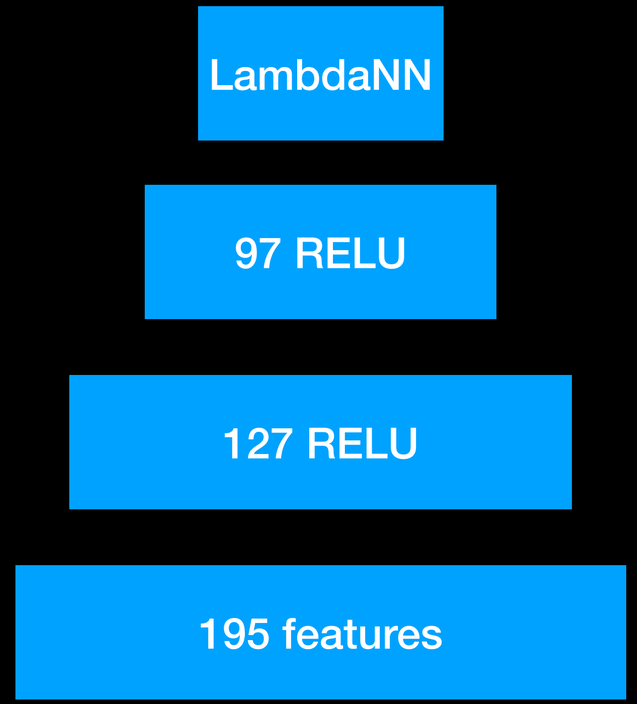


Figure 4: DNN learning curve



Ch2. Main character runs up a stairway:

- «General» embeddings (but location preferences)

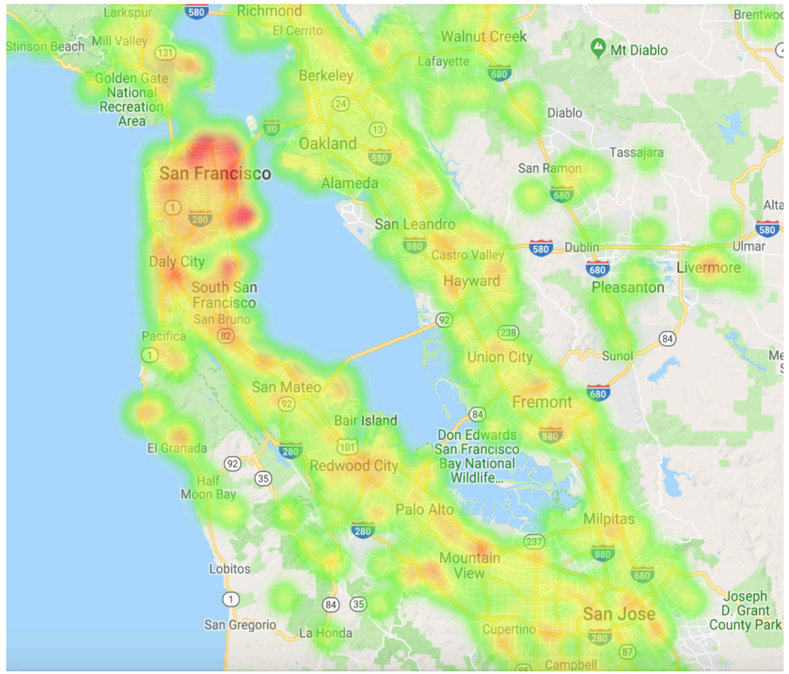


Figure 13: Location preference learnt for the query "San Francisco"

- {"San Francisco", 539058204} → 71829521 (hash of **query** and map S2 cell)

Ch3. Failed strikes:

- MOAR layers
- «Modern attention architectures»
- Direct entities embeddings
- …

Vol.2 Hero strikes back

Fig. 1. X-axis shows how the price of the booked listing offsets from the median price of search results for a guest. Y-axis is the number of users corresponding to a price offset.

Source: Improving Deep Learning For Airbnb Search

Ch1: Naive

$$DNN_\theta(u, q, l_{noPrice}) + (-tanh(w * P + b)$$

$$P = log(\frac{1 + price}{1 + price_{median}})$$

- -5.7% avg price in booking, -1.5% of bookings

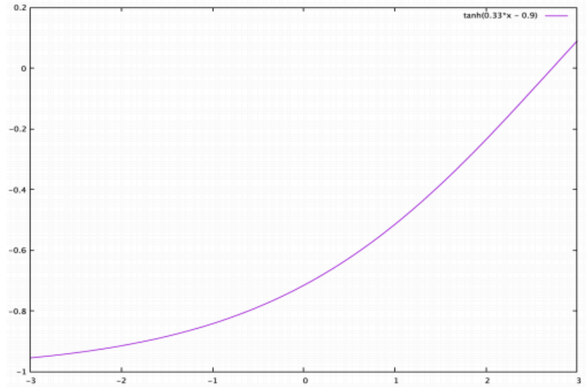


Fig. 2. X-axis is normalized price feature. Y-axis is the value of the $tanh$ term in Equation 1.

Ch1: Less naive

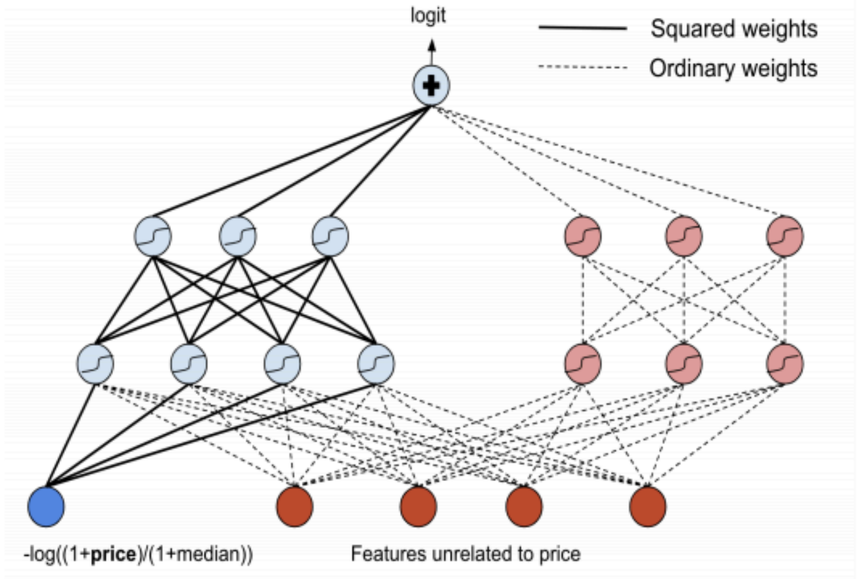
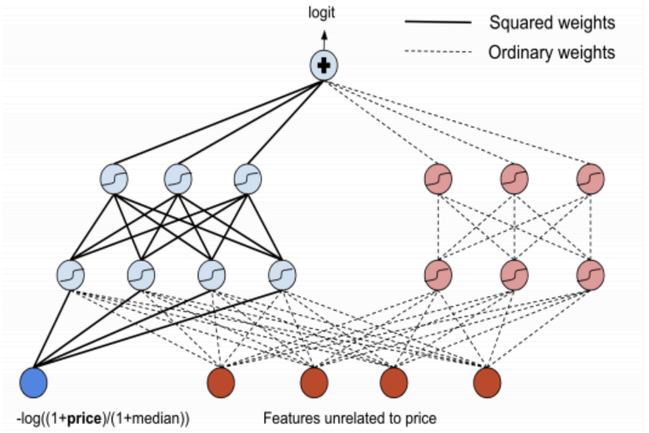


Fig. 3. DNN architecture partially monotonic w.r.t price. Bold solid lines indicate weights that are squared, dashed lines indicate ordinary weights.

Ch1: Less naive

- **-1.4% of bookings**
- Tried even additional loss component - nothing.



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Ch2: I - interpretability

- Individual conditional expectation (ICE) plots

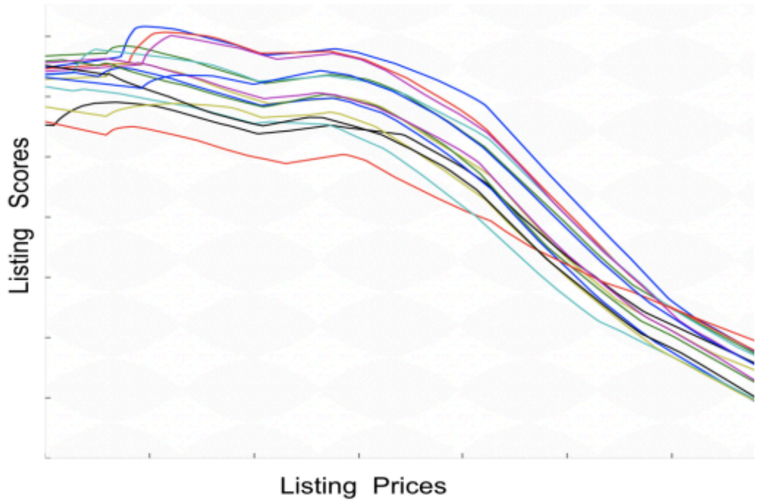

Fig. 4. ICE plot of listing scores (y-axis) vs listing prices (x-axis). Each curve represents a listing in the search result.

Ch2: I - interpretability

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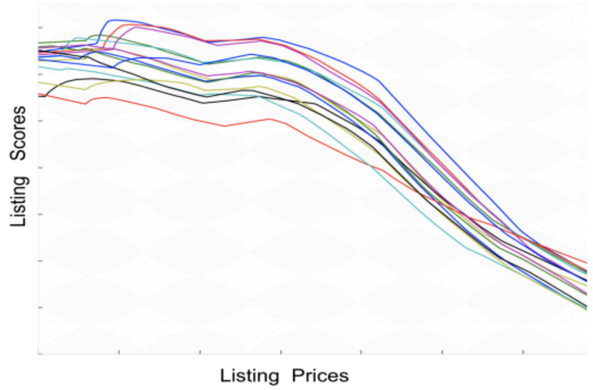

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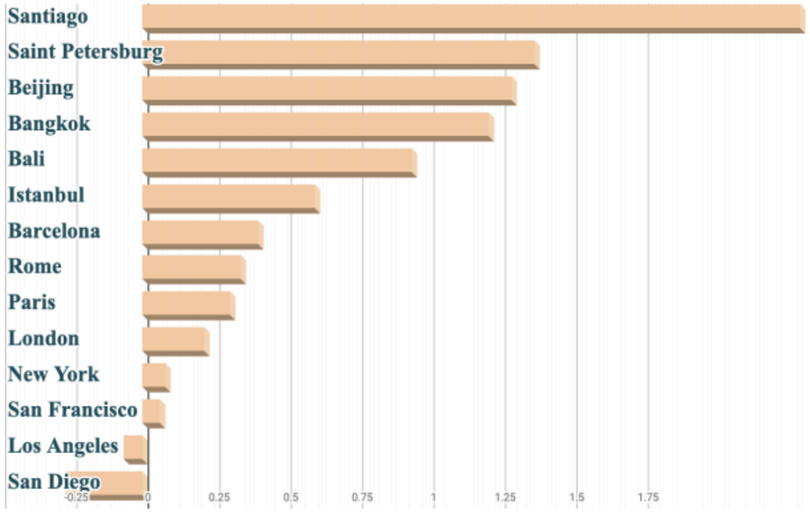


Fig. 5. Average difference between the median price of search results for a guest and the price of the booked listing, split by cities

Ch2: I - interpretability

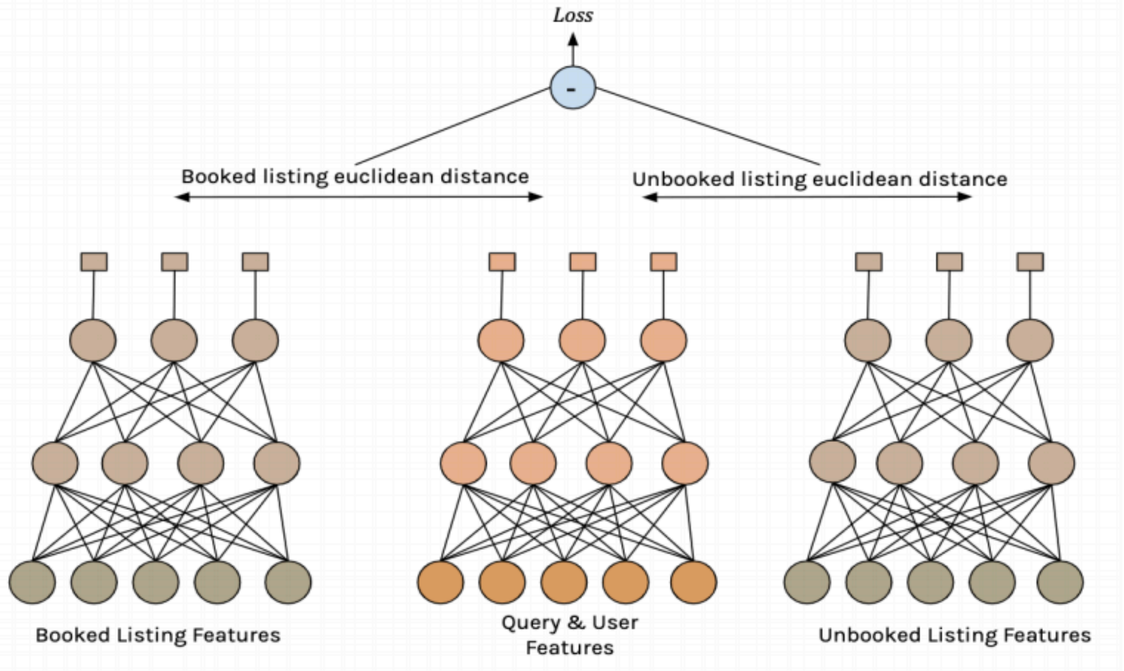


Fig. 6. Pairwise loss computation for training the two tower architecture.

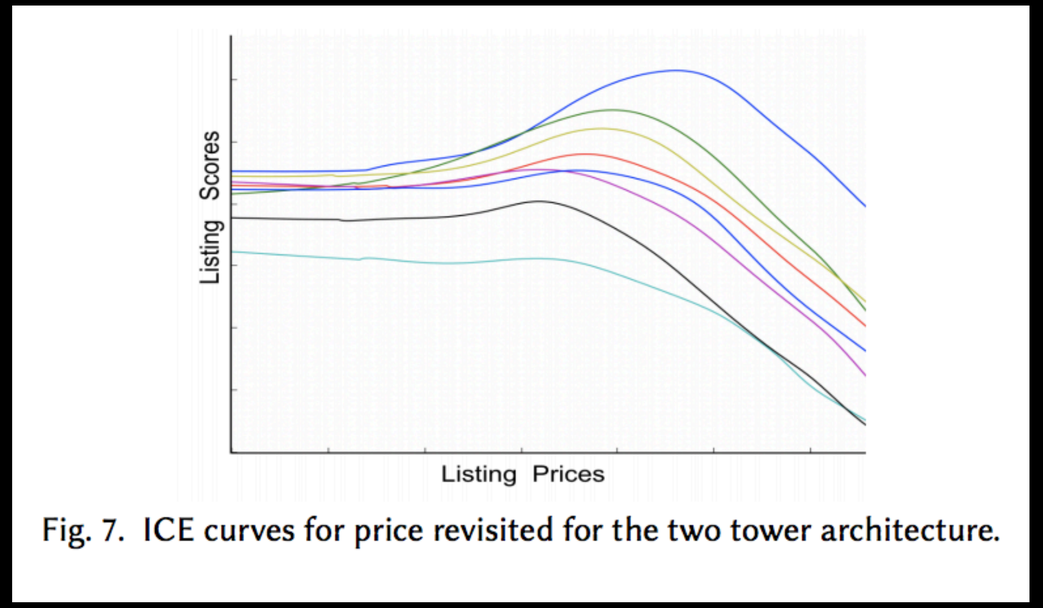
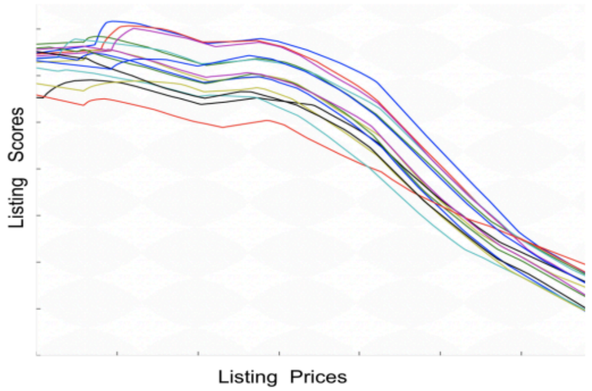


Fig. 7. ICE curves for price revisited for the two tower architecture.

- **-2.3% of bookings, +0.75% revenue**
- -33% peak latency(!)

Ch2: I - interpretability



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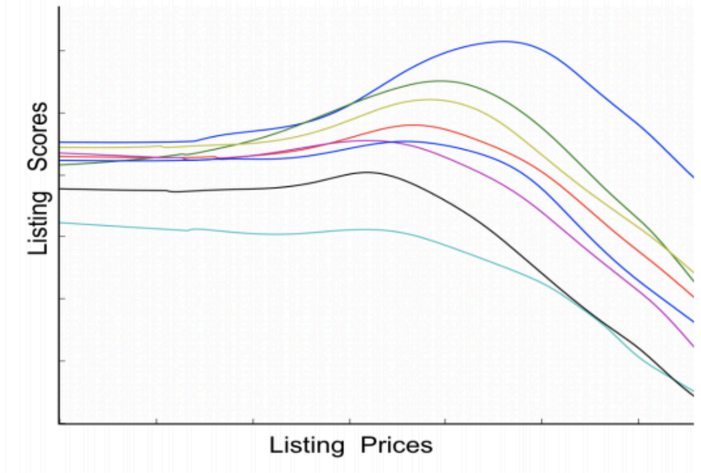


Fig. 7. ICE curves for price revisited for the two tower architecture.

Ch3: Lessons learned

- Users lead - model follows.
- Modern architectures highly tied with applications
- Architecture engineering, not complifications.
- NN requires more work but promise higher results.
- Read moar:
  - Cold start
  - Positional bias
  - Improving Deep Learning For Airbnb Search (c)

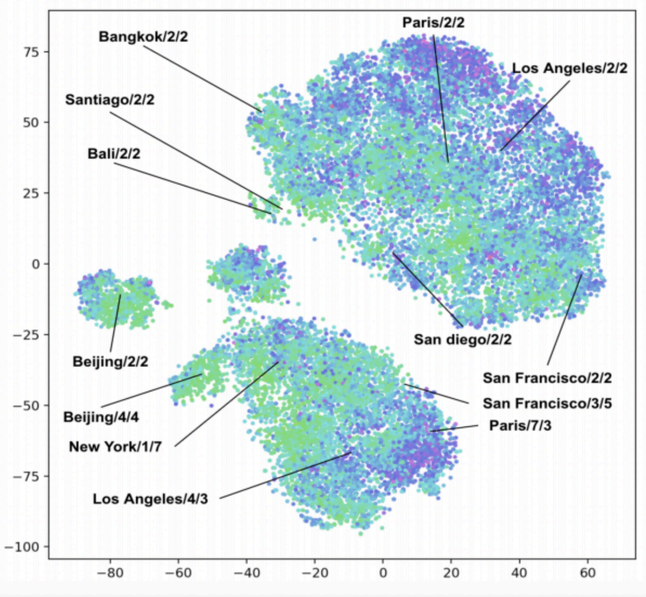


Fig. 8. t-SNE plot for output of query tower mapped to 2-d. Each dot represents a query. Some of the queries are labeled in the *city/guest-count/trip-length* format. Color of the dots indicate price of the listing booked for the query, cheaper towards green, expensive towards blue.

Modern architectures are like:

RecSys

The rest of DL

YT(youtube) recommender:

- Loss: $P(w_t = i \mid U, C) = \frac{e^{v_i u}}{\sum_{j \in J} e^{v_j u}}$

  Problems?

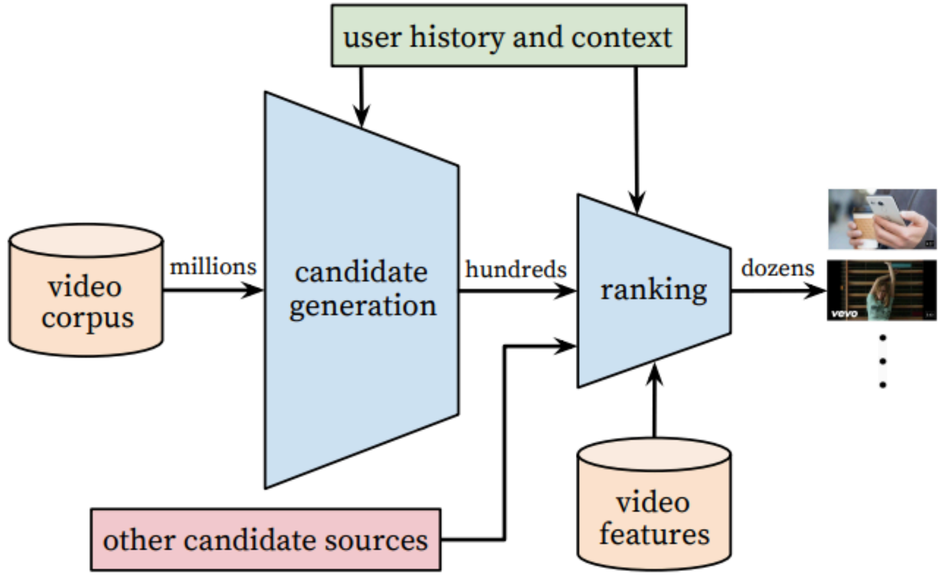
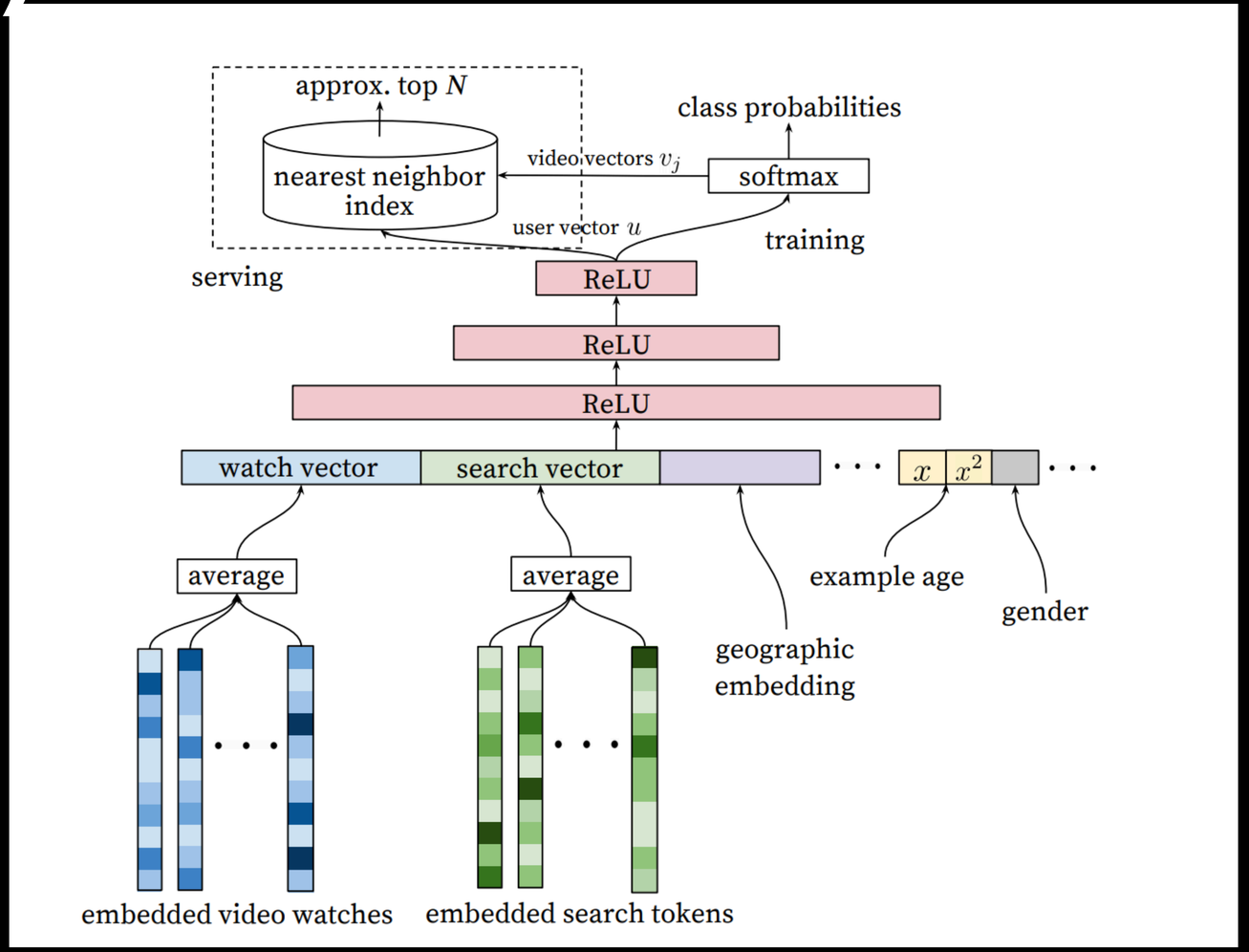


Figure 2: Recommendation system architecture demonstrating the "funnel" where candidate videos are retrieved and ranked before presenting only a few to the user.

YT(youtube) recommender:



- Loss:

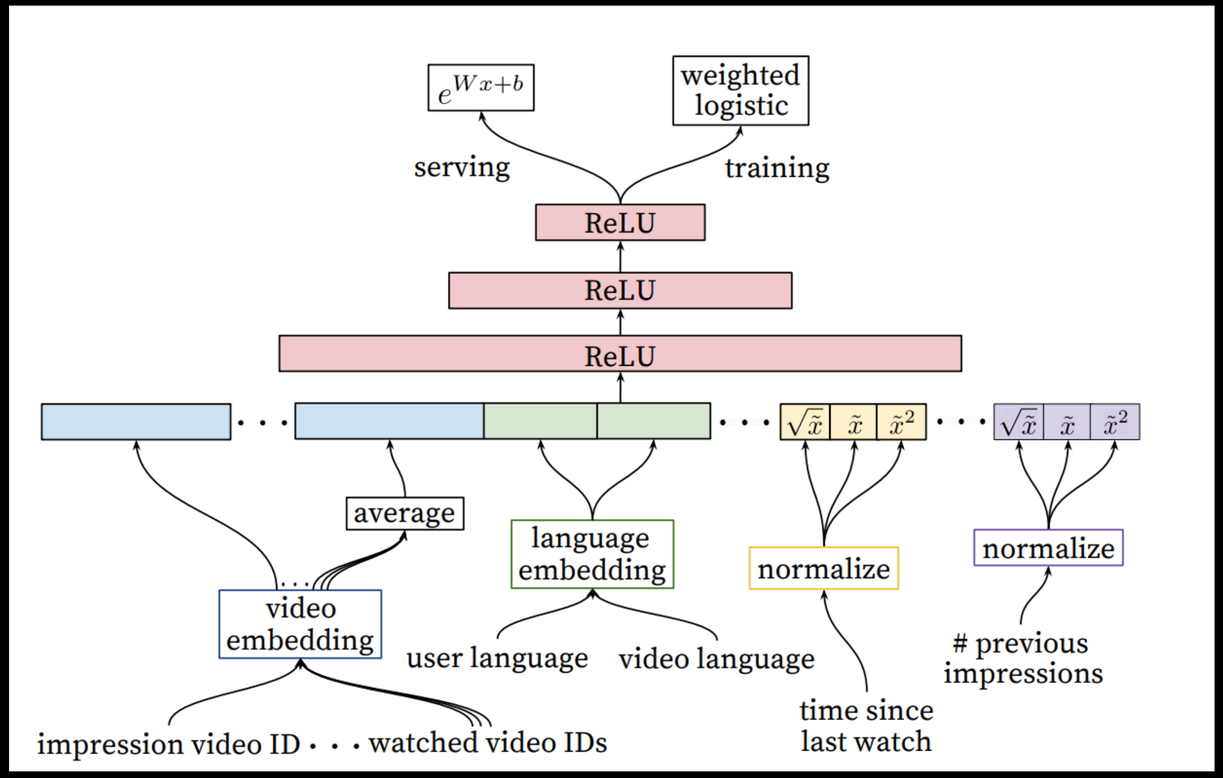
$$P(w_t = i \mid U, C) = \frac{e^{v_i u}}{\sum_{j \in J} e^{v_j u}}$$

Yep, neg sampling

- Better with additional sources then recommended
- ANN in serve time

YT(youtube) recommender:

- Tips and tricks:
  - Continuous normalisation
  - Shared embedding (last video ID, current video ID, searched video ID)
  - Weighted log regr.
    For watch time:
    Positive weighted to T_i watch time
    Negatives unit
    odds ~ $\frac{\sum T_i}{N-k}$,
    learned odds ~ $E[T](1+P)$
    (P is small)



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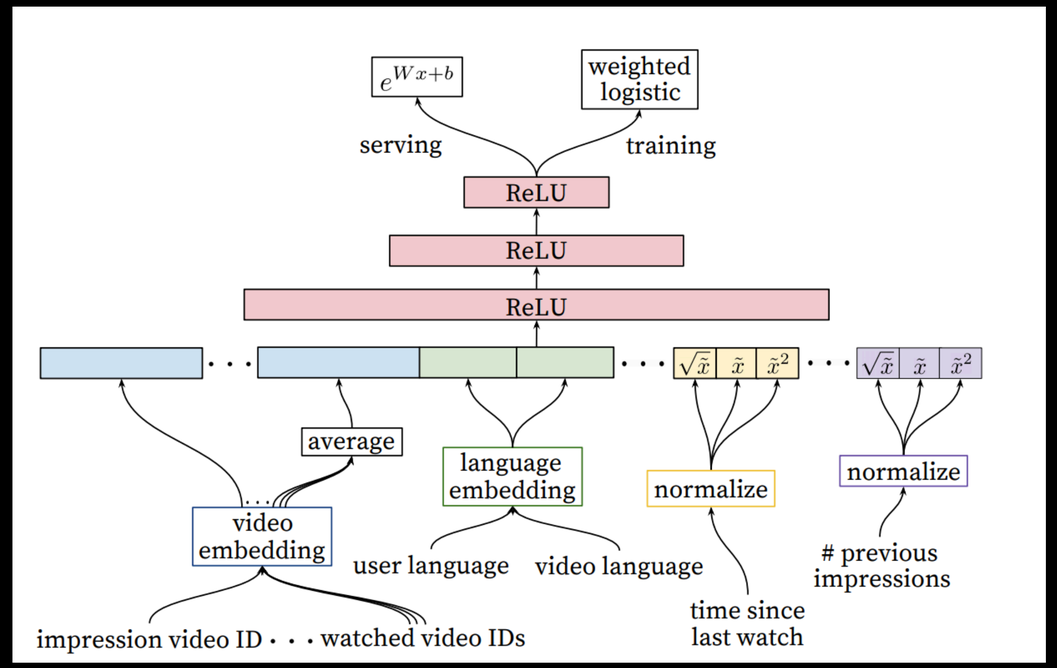
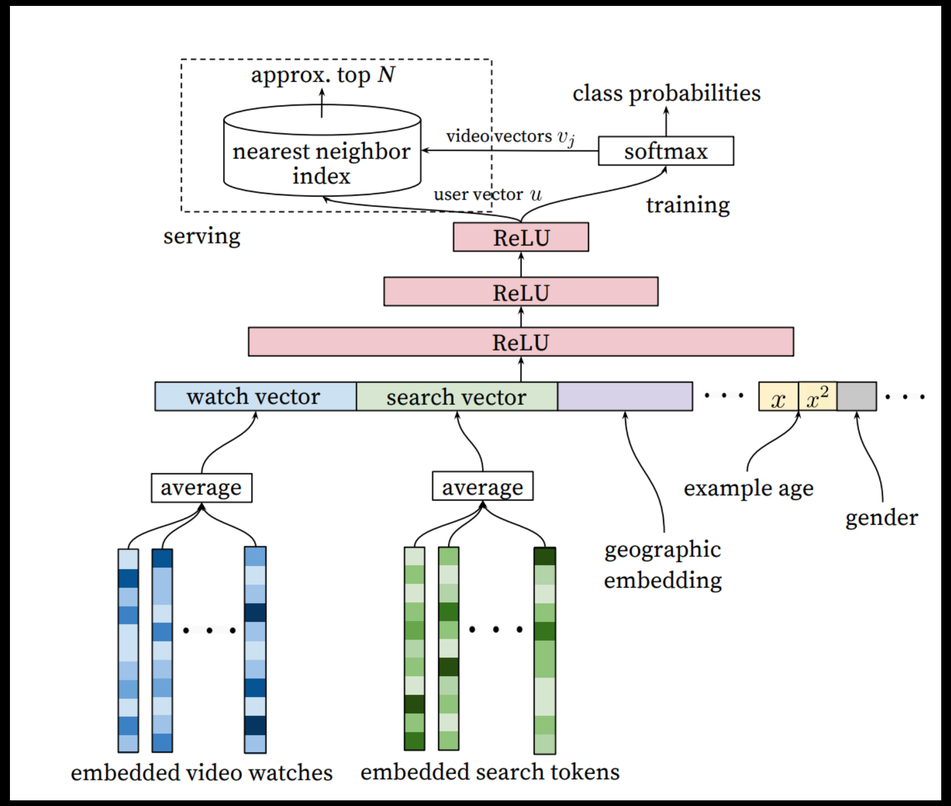
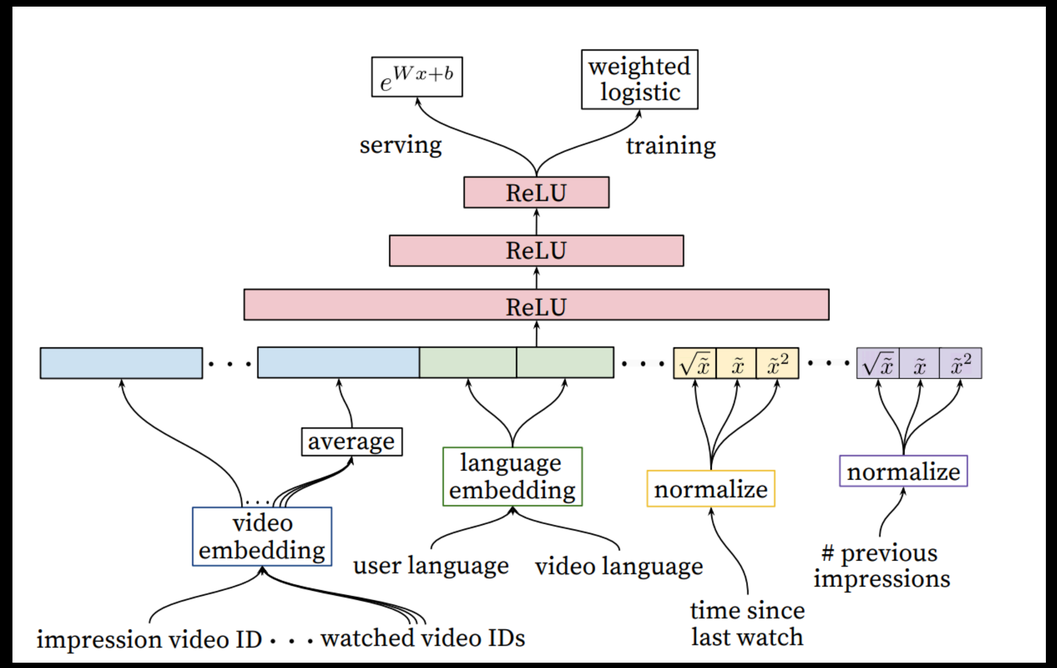
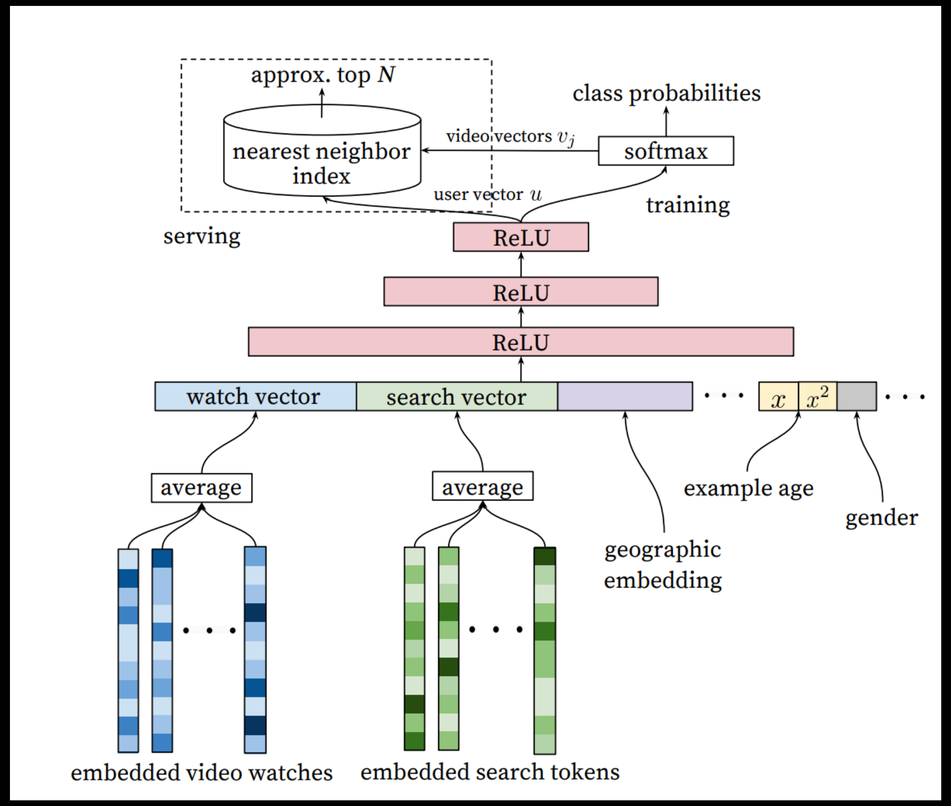




Problems?

YT(youtube) recommender:





Problems?

- New items (not users)
- New feedback

- New features
- Time-dependent features

Recurrent neural networks:

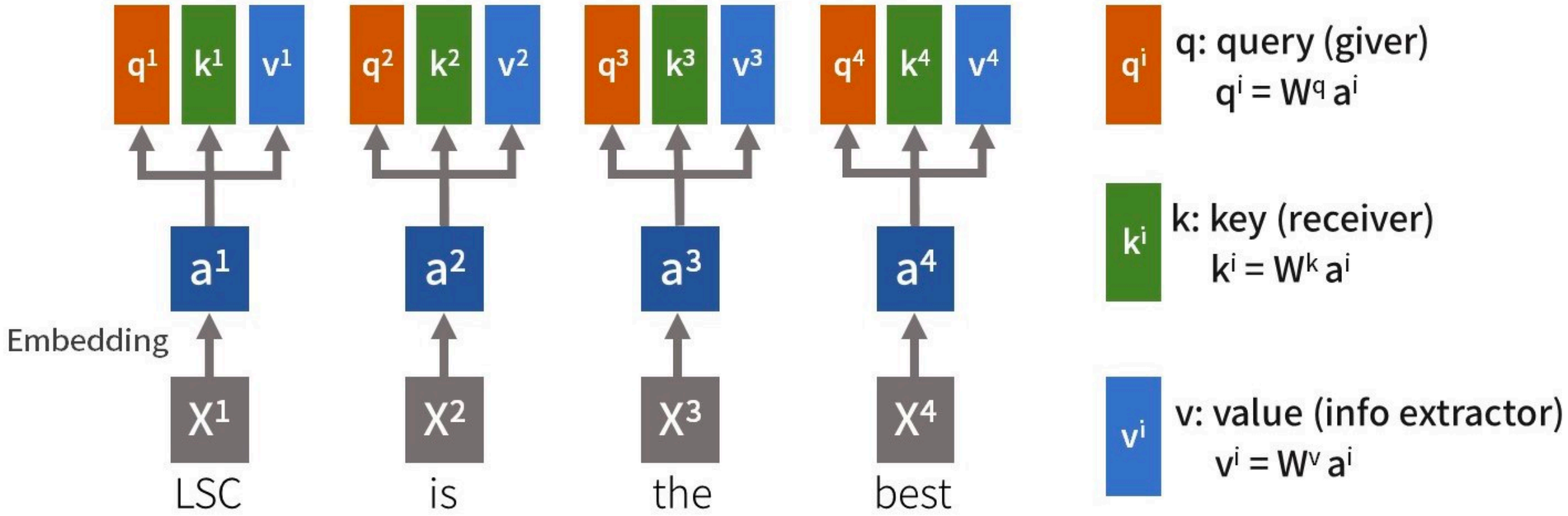
Ну не заводятся и не заводятся

Attention: query-key-value

- **Ability of parallel computing** (compares to RNN)
- **No need of deep network to look for long sentence** (compares to CNN)

Attention — is a neural network technique to **sum vectors** with **learnable weights** from **sequence** w.r.t. it's **meaning.**

Attention: query-key-value

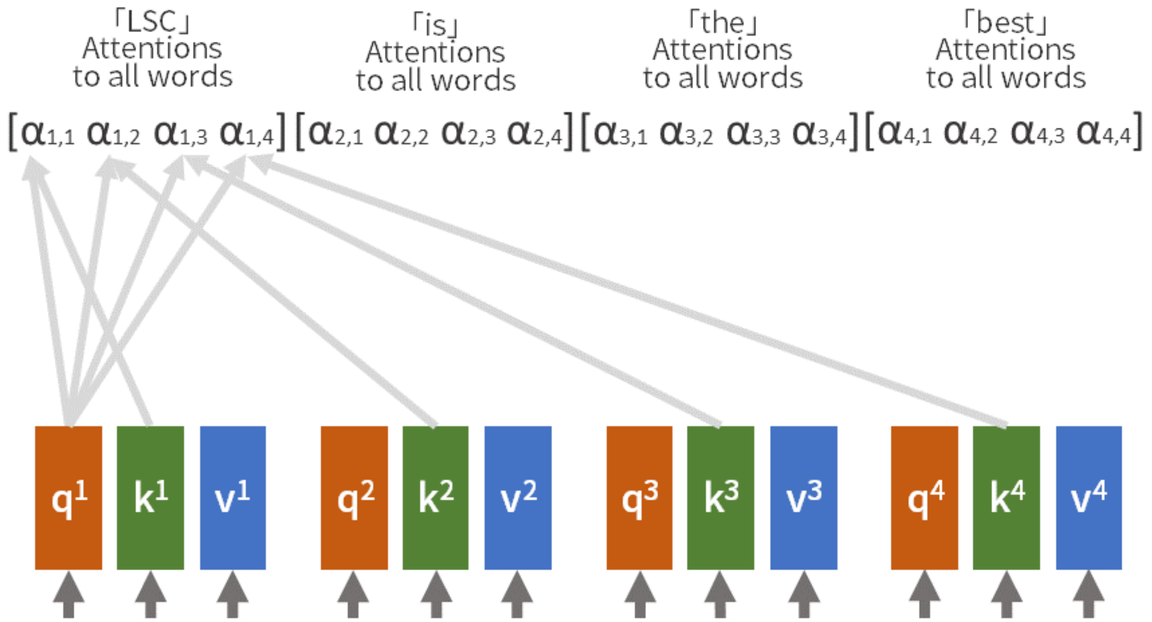


Input: LSC is the best!

- q^i (Query) $= W^q a^i$
- k^i (Key) $= W^k a^i$
- v^i (Value) $= W^v a^i$

LCS, Emb(LCS) -> $a^1 \in R^n$, $W^q[l \times n] * a^1 = q^1 \in R^n$

Attention: query-key-value



$$\alpha_{i,j} = \frac{q^i \cdot k^j}{\sqrt{d}}$$

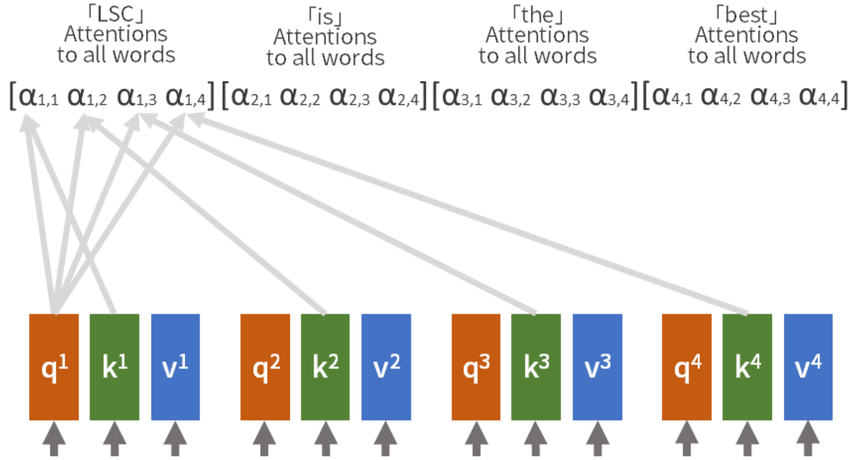
d: dimension of q, k

$$A = \begin{bmatrix} \alpha_{1,1} & \alpha_{1,2} & \alpha_{1,3} & \alpha_{1,4} \\ \alpha_{2,1} & \alpha_{2,2} & \alpha_{2,3} & \alpha_{2,4} \\ \alpha_{3,1} & \alpha_{3,2} & \alpha_{3,3} & \alpha_{3,4} \\ \alpha_{4,1} & \alpha_{4,2} & \alpha_{4,3} & \alpha_{4,4} \end{bmatrix}$$

Attention Matrix

Attention: query-key-value

- **Attentions** α are **defined** as **inner product** of **Query**(giver) and **Key**(receiver) divided by square root of its dimensions.
- **Every word** create **its attention toward all words** by providing Query to match Key which is target word of attention.
- Since longer sentence (more words) results in bigger number of inner products, **the square root** here **act** as a **variance balance**.



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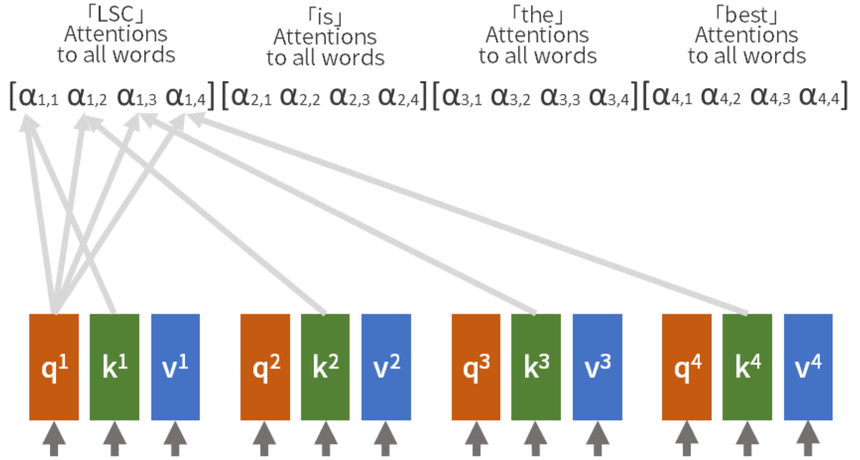
- $\mathrm{r\_1} = \sum_{i=1}^{4} a_{1i} * v_i$



$$\alpha_{i,j} = \frac{q^i \cdot k^j}{\sqrt{d}}$$

d: dimension of q, k

$$A = \begin{bmatrix} \alpha_{1,1} & \alpha_{1,2} & \alpha_{1,3} & \alpha_{1,4} \\ \alpha_{2,1} & \alpha_{2,2} & \alpha_{2,3} & \alpha_{2,4} \\ \alpha_{3,1} & \alpha_{3,2} & \alpha_{3,3} & \alpha_{3,4} \\ \alpha_{4,1} & \alpha_{4,2} & \alpha_{4,3} & \alpha_{4,4} \end{bmatrix}$$

Attention Matrix

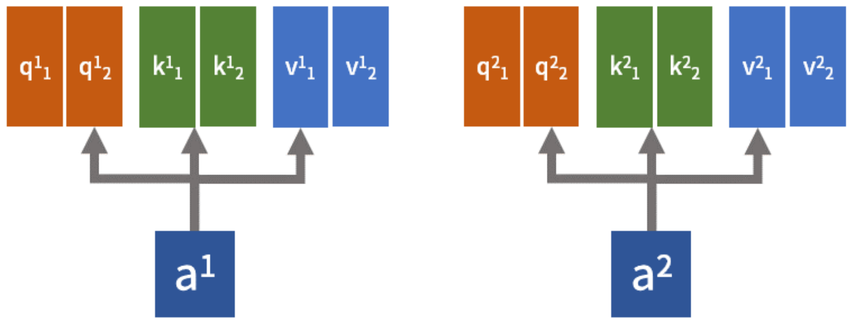
https://medium.com/lsc-psd/introduction-of-self-attention-layer-in-transformer-fc7bff63f3bc

Attention: Multi-head

- In these two sentences, the relation between **“LSC”** and **“best”** is quite difference, they shouldn’t be treated the same in attentions. And also, distance between words should considered by attentions too.

“LSC is the best!”

“It’s the best of LSC.”



$$A^1 = \begin{bmatrix} \alpha^1_{1,1} & \alpha^1_{1,2} \\ \alpha^1_{2,1} & \alpha^1_{2,2} \end{bmatrix}$$

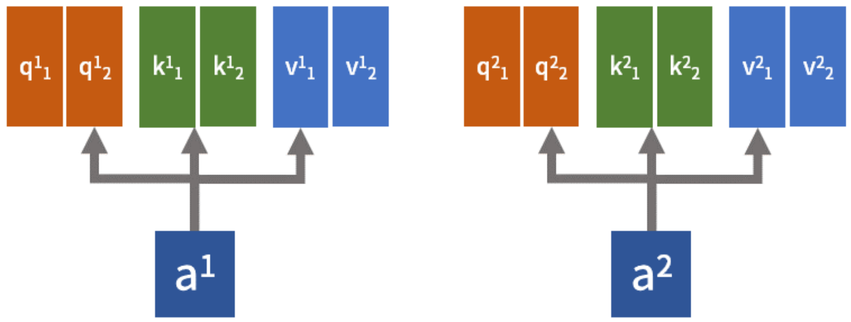
Attention Matrix 1

$$A^2 = \begin{bmatrix} \alpha^2_{1,1} & \alpha^2_{1,2} \\ \alpha^2_{2,1} & \alpha^2_{2,2} \end{bmatrix}$$

Attention Matrix 2

Attention: Multi-head

- Multi-Head is features that can create multiple Attentions Matrix in one layer. By simply double the Query, Key and Value combinations in Self-Attention Layer, and independently calculates Attention Matrix.
- With Multiple-Head, the Self-Attention Layer would create multiple outputs. Therefore, there will be another trainable weights W^o, so that $\boldsymbol{O = W^o B}$ where B is outputs of different Attentions.



$$\underset{\text{Attention Matrix 1}}{A^1} = \begin{bmatrix} \alpha^1_{1,1} & \alpha^1_{1,2} \\ \alpha^1_{2,1} & \alpha^1_{2,2} \end{bmatrix}$$

$$\underset{\text{Attention Matrix 2}}{A^2} = \begin{bmatrix} \alpha^2_{1,1} & \alpha^2_{1,2} \\ \alpha^2_{2,1} & \alpha^2_{2,2} \end{bmatrix}$$

Attention: summary

- Attention — is a neural network **technique** to **sum vectors** with **learnable weights** from **sequence w.r.t.** it's **meaning**.

- Attention is build with **Query, Key** and **Value** fashion.
  Query and **Key determine** the **weight** in final result, **Value** is a **payload** which is sum with weights.

- It showed great performance firstly in NLP and furthermore in various applications.

- Allows us either catch **sequence dependency** but **keep away** from **costly** RNN and/or **uncapable** CNN
  - Self-Attention: **$O(length^2 \cdot dim)$**
  - RNN(LSTM): $O(length \cdot dim^2)$
  - Convolution: $O(length \cdot dim^2 \cdot kernel\text{-}width)$

Controllable Multi-Interest Framework for Recommendation:

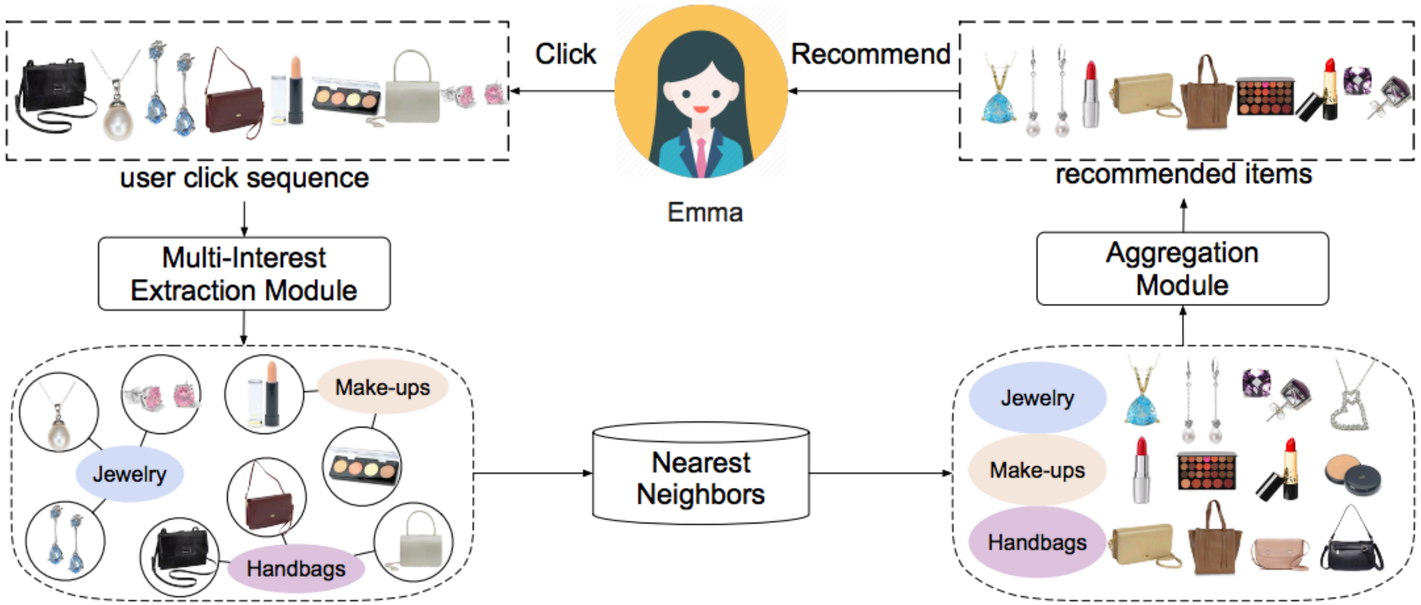
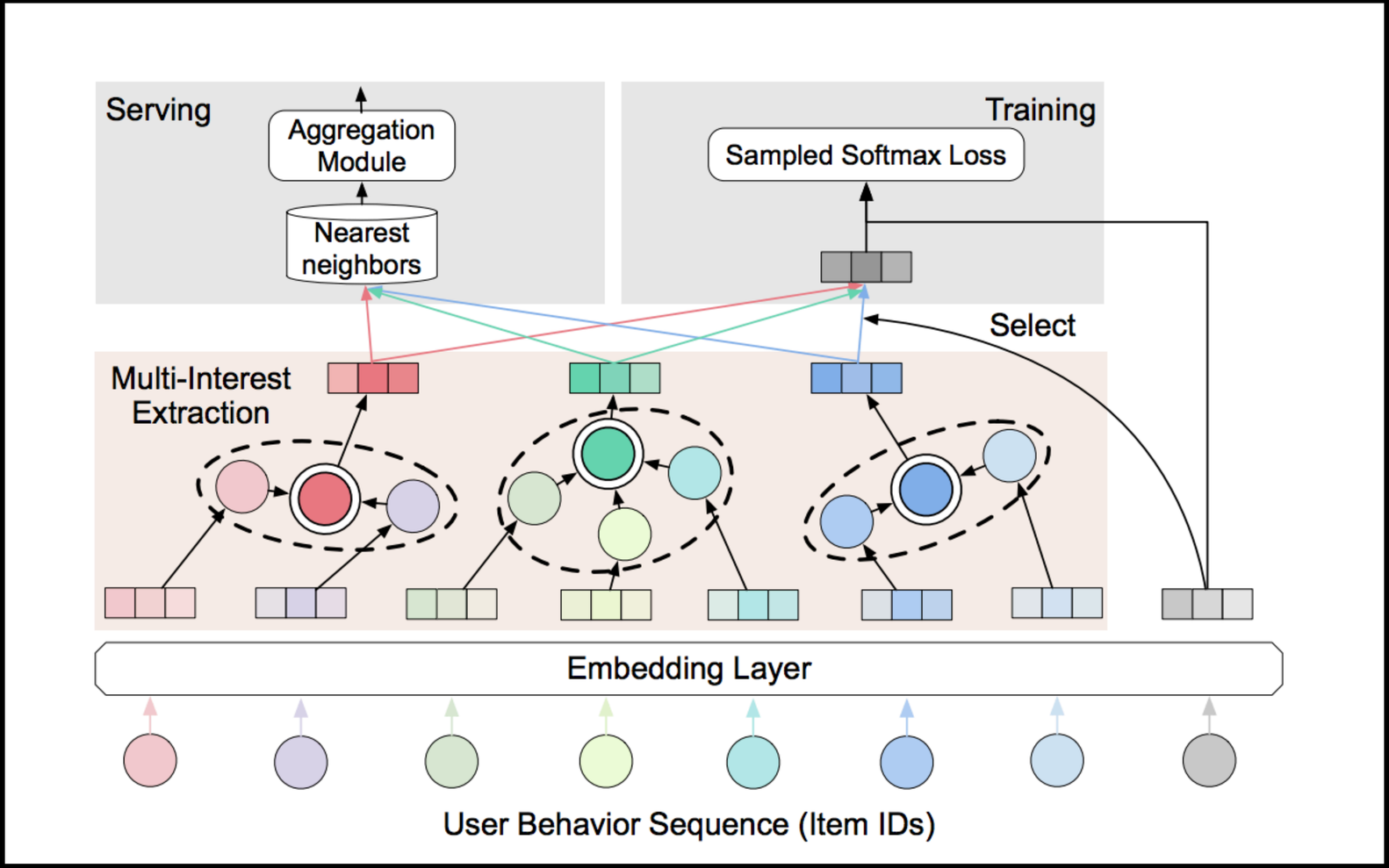


Figure 1: A motivating example of our proposed framework. An e-commerce platform user, Emma, has multiple interests including jewelry, handbags, and make-ups. Our multi-interest extraction module can capture these three interests from her click sequence. Each interest retrieves items from the large-scale item pool based on the interest embedding independently. An aggregation module combines items from different interests and outputs the overall top-N recommended items for Emma.

Source: Controllable Multi-Interest Framework for Recommendation

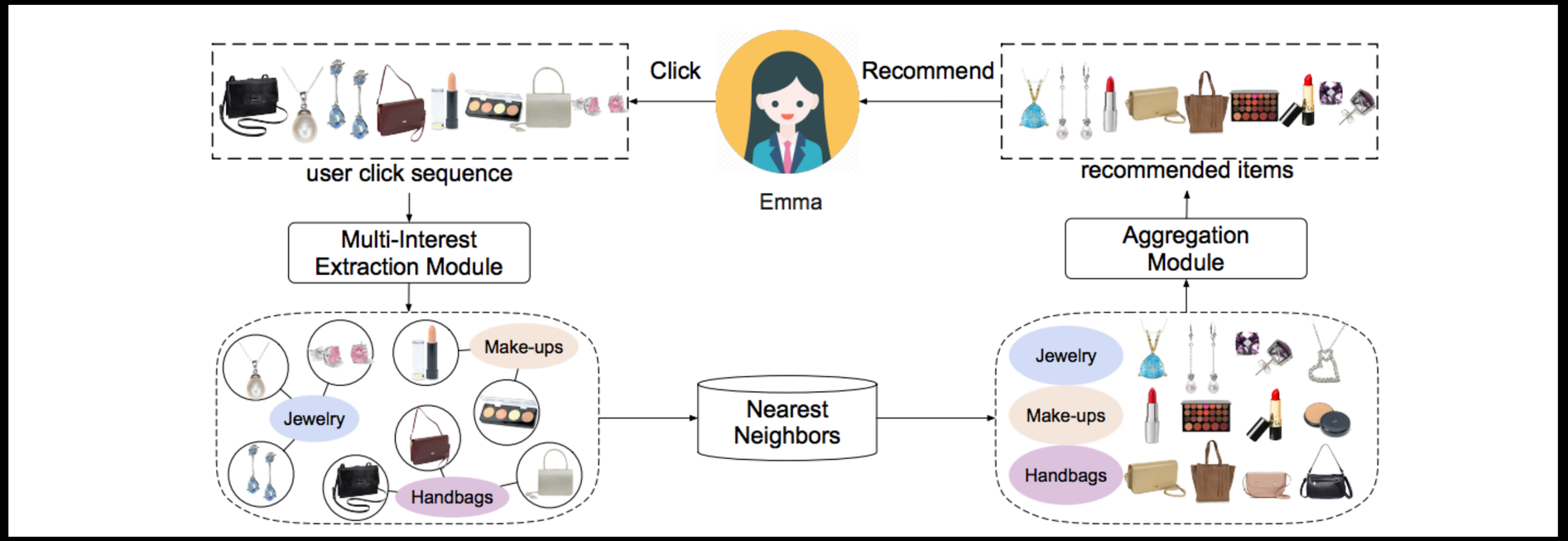
Controllable Multi-Interest Framework for Recommendation:



Controllable Multi-Interest Framework for Recommendation:

- Attention:
  - $A = softmax(W_2^T tanh(W_1 H^T))$, where H^T - prev embeddings matrix, $H = [d\ x\ n], A = n\ x\ att\_heads$
    d — ebb size
    n — history size
    att_heads — num heads

- Attention:
  - $V_U = HA;$
    V_u — user interests matrix, d x att_heads



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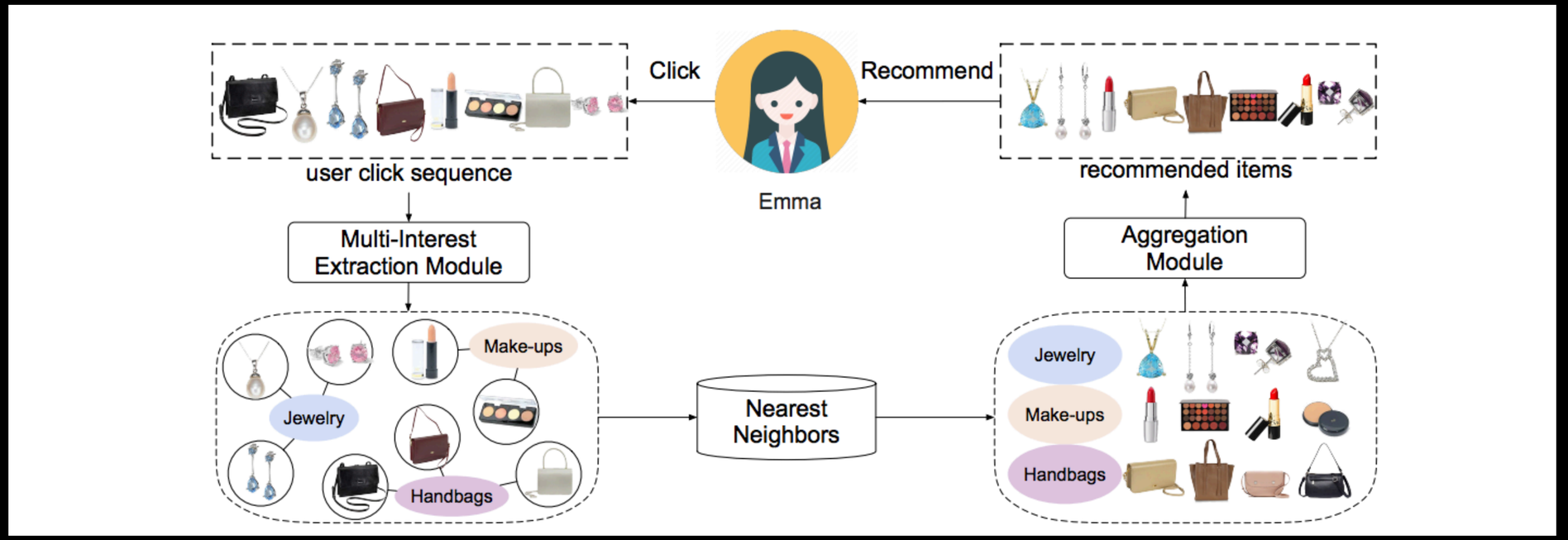
- Model training:
  $v_u = V_u[:, argmax(V_u^T e_i)]$
  Sampled softmax



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- Aggregation model:

$$f(u,i) = max_k(e_i^T, v_u^k)$$

$$Q(u,S) = \sum_{i \in S} f(u,i) + \lambda \sum_{i \in S} \sum_{j \in S} g(i,j)$$

$$g(i,j) = 1\ if\ CATE(i) \neq CATE(j)$$

- Model training:

$$v_u = V_u[:, argmax(V_u^T e_i)]$$

Sampled softmax

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PRBLMS?

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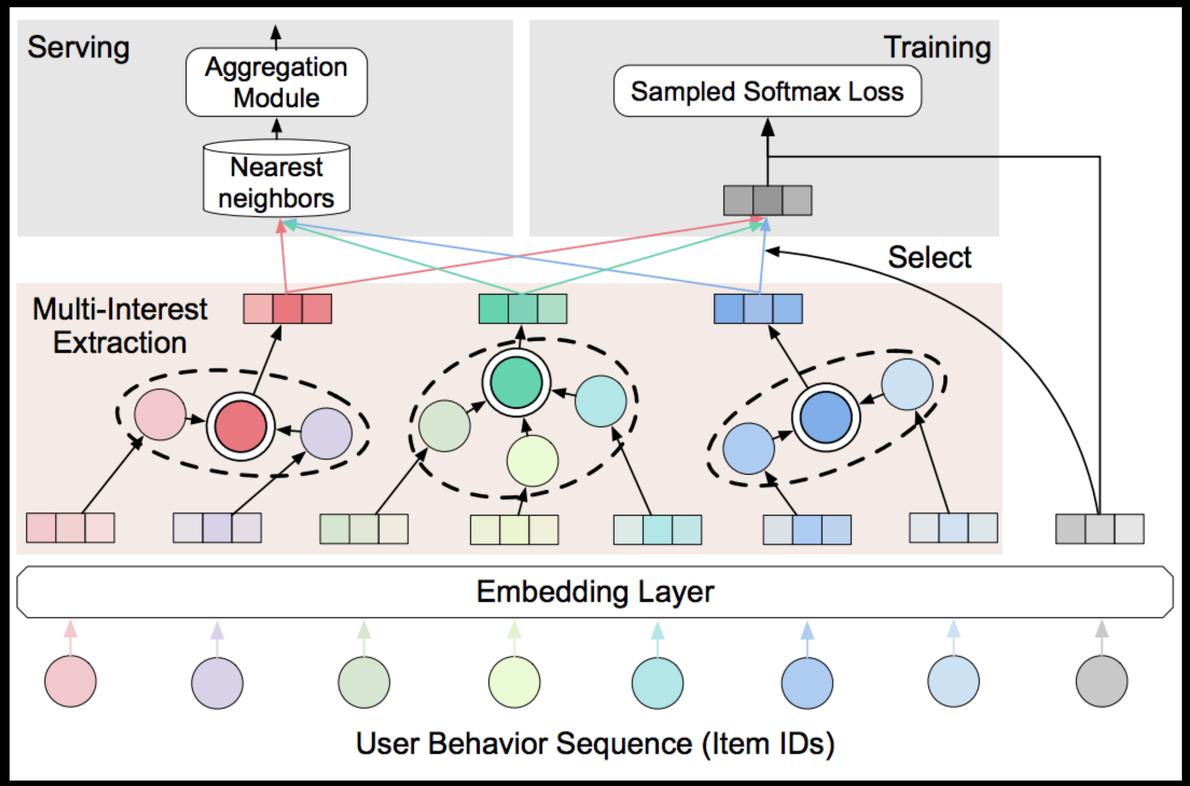
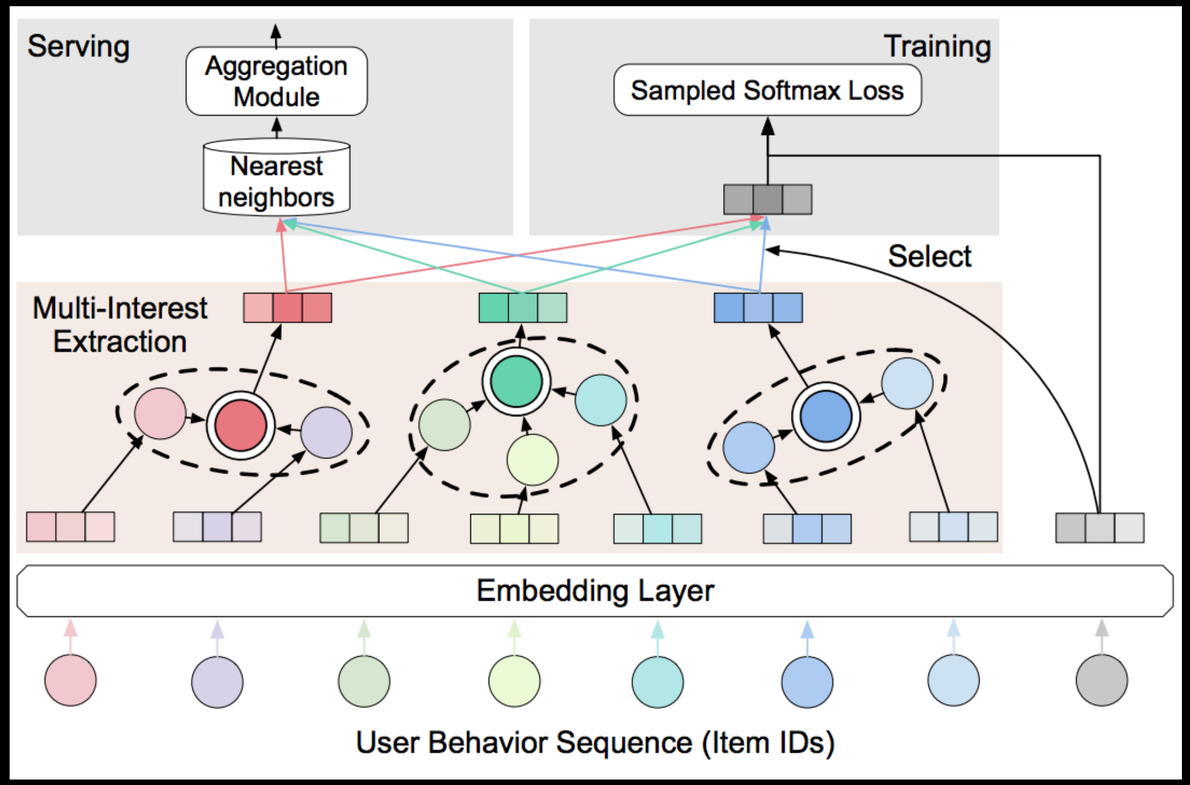
Sampled softmax



Controllable Multi-Interest Framework for Recommendation:

PRBLMS?

- Model training:
  $v_u = V_u[:, argmax(V_u^T e_i)]$ — same heads
- Pre-setted num of interests
- Over-confident heads
- No feature used



Controllable Multi-Interest Framework for Recommendation:

PRBLMS?

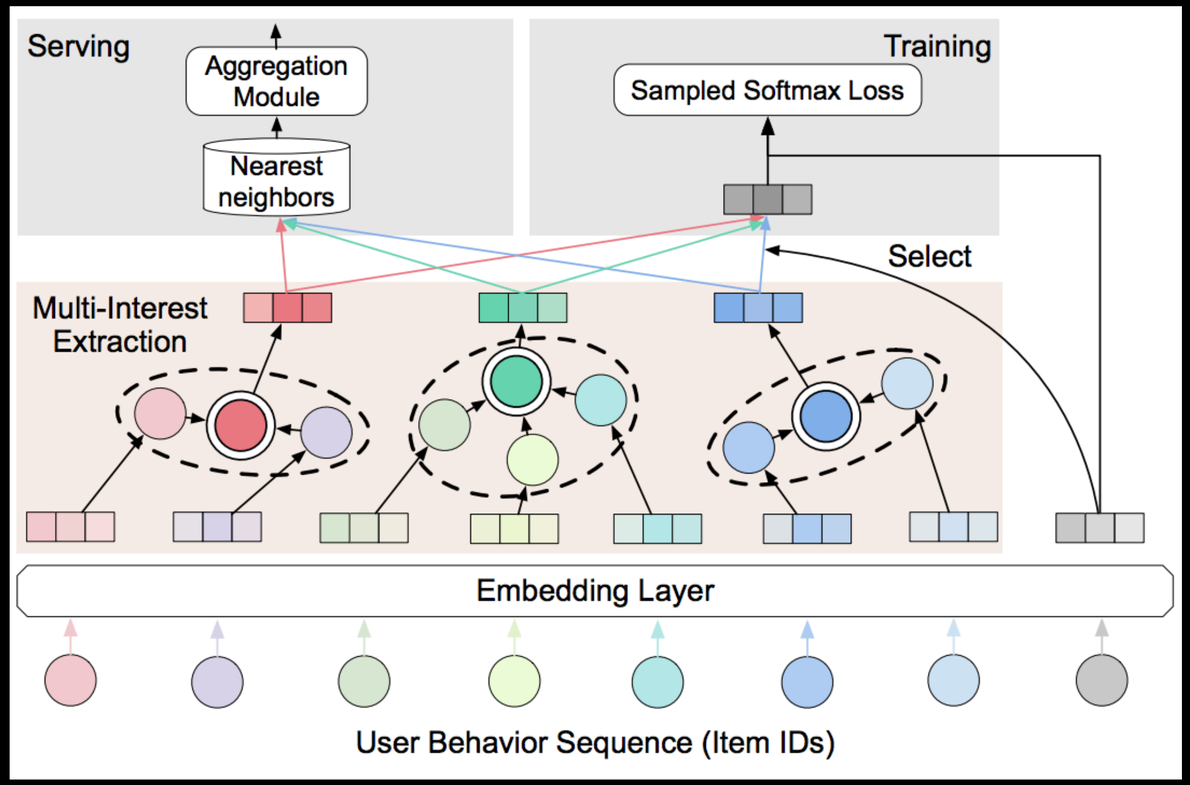
- Model training:
  $v_u = V_u[:, argmax(V_u^T e_i)]$ — same heads

  Additive component to loss:
  $loss = loss + \alpha * (1 - max\_pair\_dot)$

- Pre-setted num of interests
  …

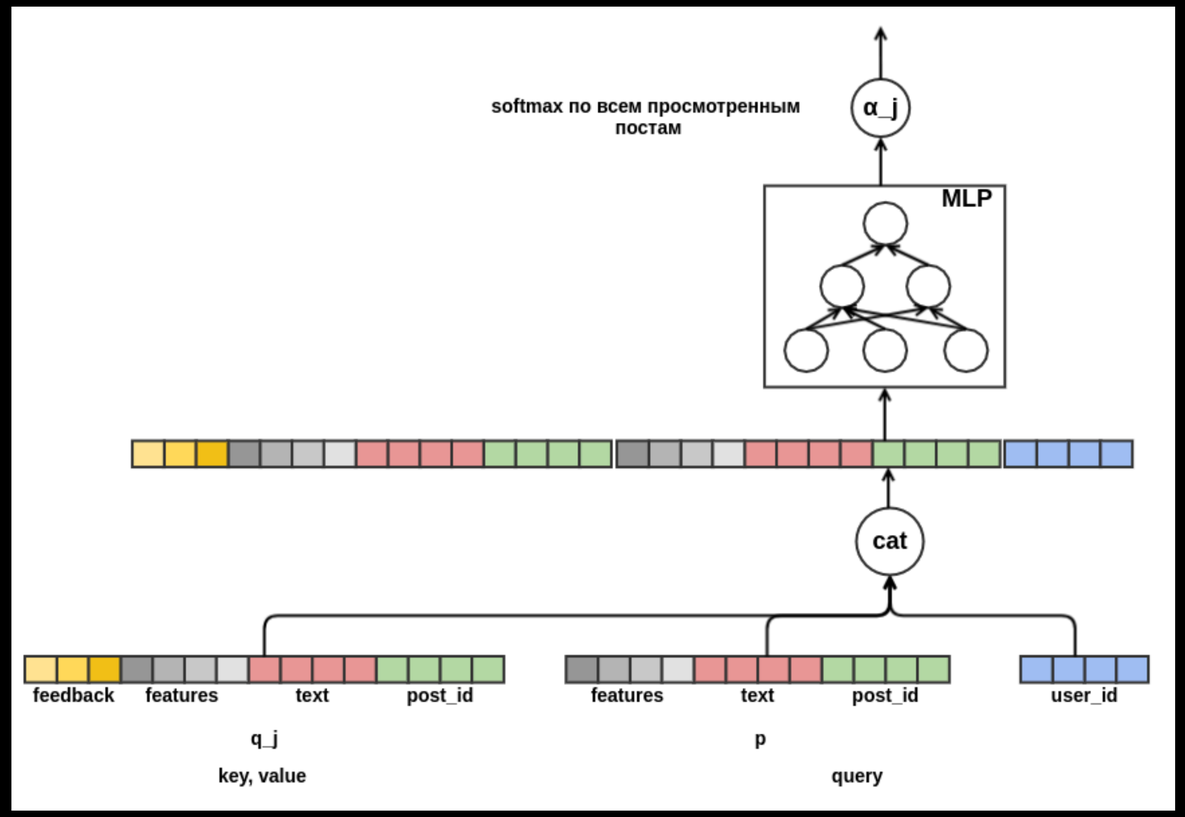
- Over-confident heads
  Temperature, label smooth, dropout

- No feature used
  Add some features, it's attention ;)



Controllable Multi-Interest Framework for Recommendation:

- **No feature used**
  Add some features, it's attention ;)



https://habr.com/ru/company/mailru/blog/445348/

MEANTIME: Mixture of Attention Mechanisms with Multi-temporal Embeddings for Sequential Recommendation:

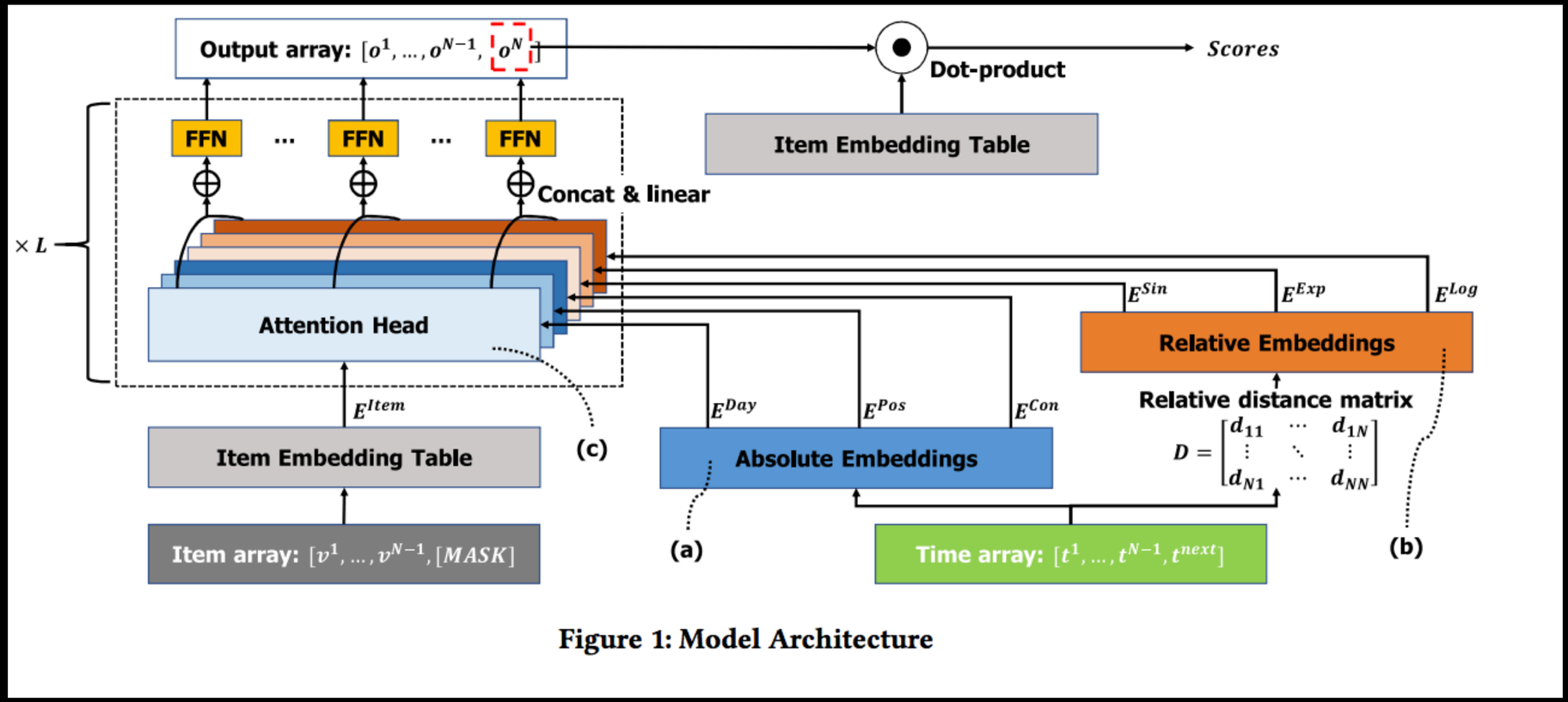


Figure 1: Model Architecture

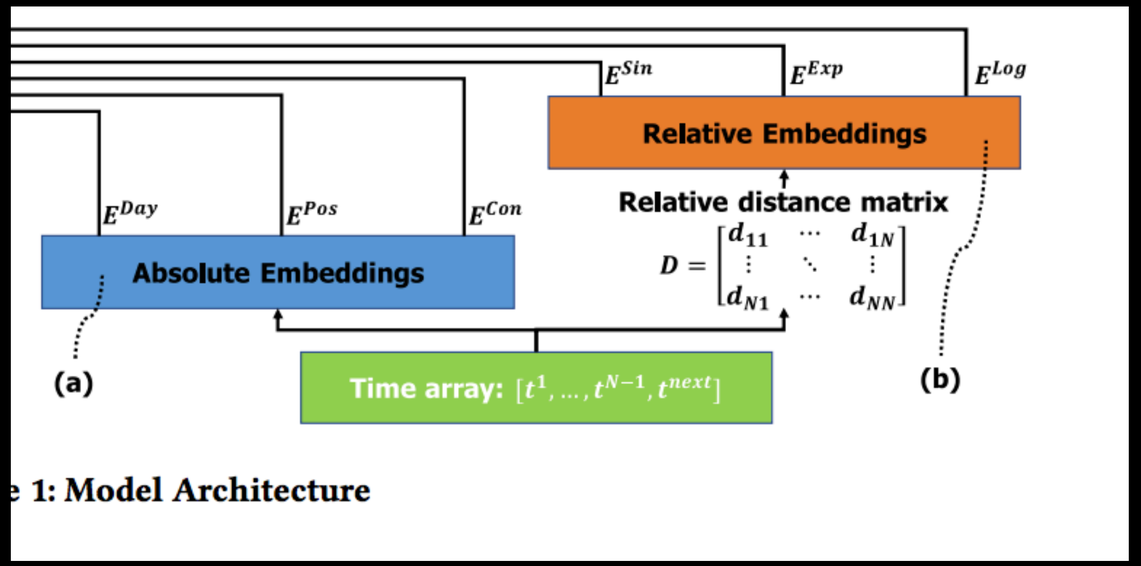
Source: MEANTIME: Mixture of Attention Mechanisms with Multi-temporal Embeddings for Sequential Recommendation:

MEANTIME: Mixture of Attention Mechanisms with Multi-temporal Embeddings for Sequential Recommendation:

- E^{pos} — relative positional embedding.
  To learn sequential patterns.

- E^{day} — embedding of a day (problems?)
  confine the attention scope within the same (or similar) day

- E^{con} — stack of repeated vectors (?) to eliminate positional bias



e 1: Model Architecture

following equation:

$$\vec{\theta}_{ab,2c} = sin(\frac{d_{ab}}{freq^{\frac{2c}{h}}}) \qquad \vec{\theta}_{ab,2c+1} = cos(\frac{d_{ab}}{freq^{\frac{2c}{h}}}) \qquad (1)$$

where $\vec{\theta}_{ab,c}$ is the c^{th} value of the vector $\vec{\theta}_{ab}$ and $freq$ is an adjustable parameter. Likewise, **Exp** encoder and **Log** encoder converts d_{ab} to $\vec{e}_{ab}$ and $\vec{l}_{ab}$ respectively by applying the following equations:

$$\vec{e}_{ab,c} = exp(\frac{-|d_{ab}|}{freq^{\frac{c}{h}}}) \qquad \vec{l}_{ab,c} = log(1 + \frac{|d_{ab}|}{freq^{\frac{c}{h}}}) \qquad (2)$$

- Sin captures periodic occurrences.
- Larger time gap is either quickly decayed to zero in **Exp**
- or manageably increased in **Log**.

Source: MEANTIME: Mixture of Attention Mechanisms with Multi-temporal Embeddings for Sequential Recommendation:

Conclusions:

- NN for rank:

  Accurate feature analysis.
  Good generalization but lack of interpretability.
  Not architecture but data analysis.

- It’s all about embeddings, but embeddings overfits easily

- Not user embedding, but user embedding as function of items.

- Bag of tricks to make things works: label smooth, time encoders, additives losses and etc.

Source: MEANTIME: Mixture of Attention Mechanisms with Multi-temporal Embeddings for Sequential Recommendation: