User Profiling in Recommender Systems

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Recommender Systems (RS)

- What are RSs?
- Why are they useful?

Recommender Systems (RS)

- Algorithms that generate personalized content for a user

Commonly used in:

- E-commerce
- Social Networking
- Music
- Video Streaming
- Ad generation

Outline

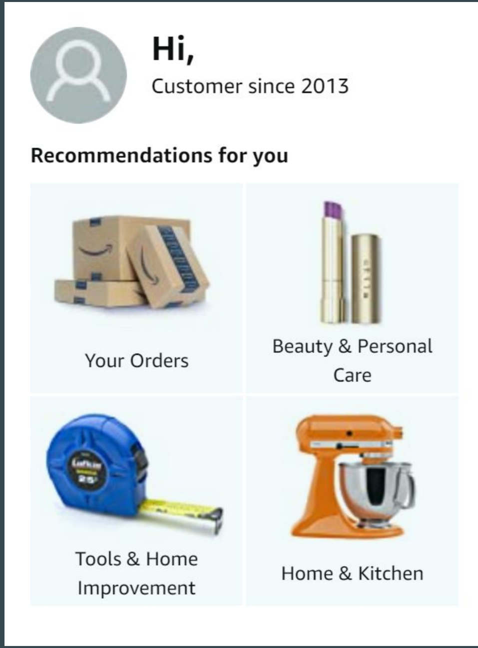
- Background
- Hierarchical User Profiling framework
  - By: Yulong Gu, Zhuoye Ding, Shuaiqiang Wang, Dawei Yin
- Conclusions

Background

- Categories and items
- Neural networks
- Recurrent neural networks
- User profiling

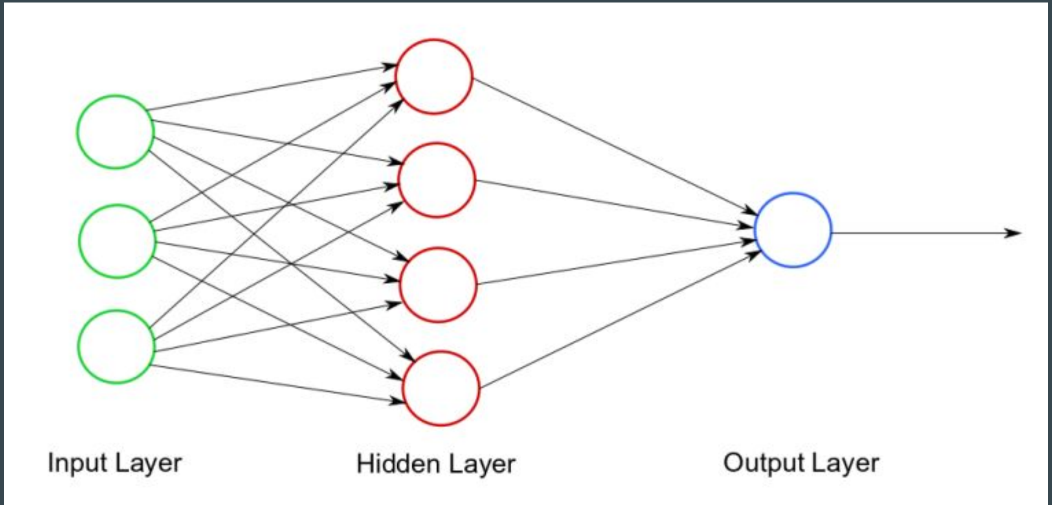
Categories and Items

- Categories contain items
- Items are related to other items



Neural Networks

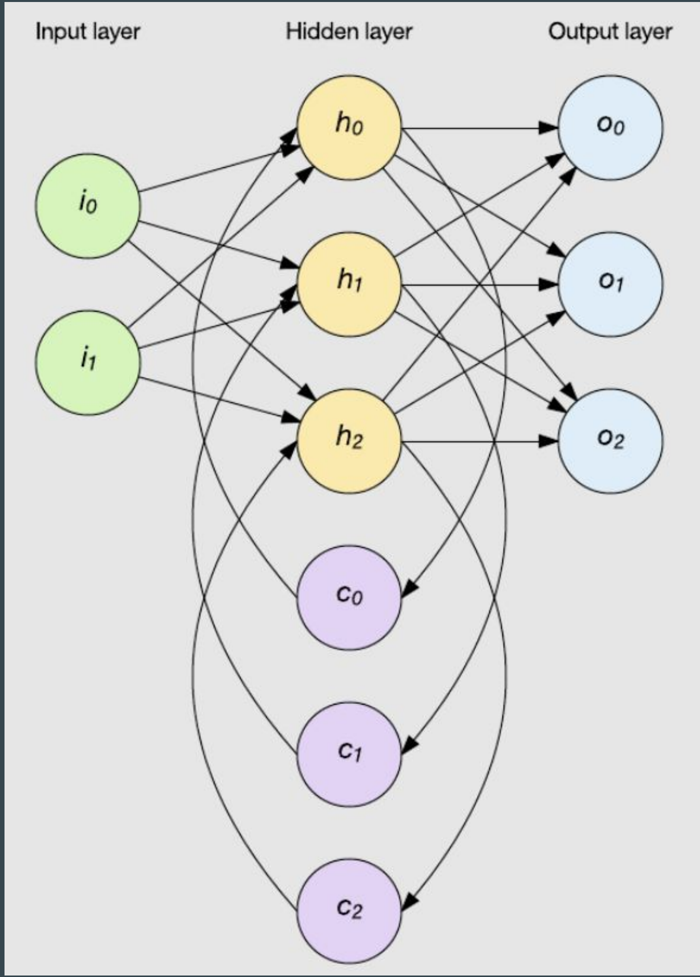
- Neurons
- Connections
  - Weights
- Layers
- Training
  - Iterative process
  - Information passed through
    - Weights adjusted according to results
  - Results in a final set of weights



https://www.kdnuggets.com/2017/10/neural-network-foundations-explained-gradient-descent.html

Recurrent Neural Networks (RNN)

- Memory
- Feedback
- Training



https://developer.ibm.com/articles/cc-cognitive-recurrent-neural-networks/

User Profiling

- Profile vectors (p)

User Profiling

- Profile vectors (p)

Categories user u is interested in (decided by an RNN):

1. Comedy
2. Action
3. Romance

User Profiling

- Profile vectors (p)

Categories user u is interested in (decided by an RNN):

1. Comedy
2. Action
3. Romance

$p_{categories} = \{0, 0, 0, 56, 0, 0, 32, 0, 16\}$

Hierarchical User Profiling (HUP)

Purpose

- Decipher user interests at multiple levels
    - Build a collection of profile vectors that represent multiple levels of granularity
        - Micro-level (fine-grained)
        - Item-level (medium-grained)
        - Category-levels (coarse-grained)
- HUP solves problems that other recommender systems have
    - Not building hierarchical user profile
    - Harvesting limited information

Micro-behaviors (MB)

- A finely-granular action that the user performs
- Used as input for HUP
- Things like:
  - Searching for an item
  - Browsing an item
  - Viewing an item's details
  - Adding to cart
  - Purchasing
  - "Liking" an item

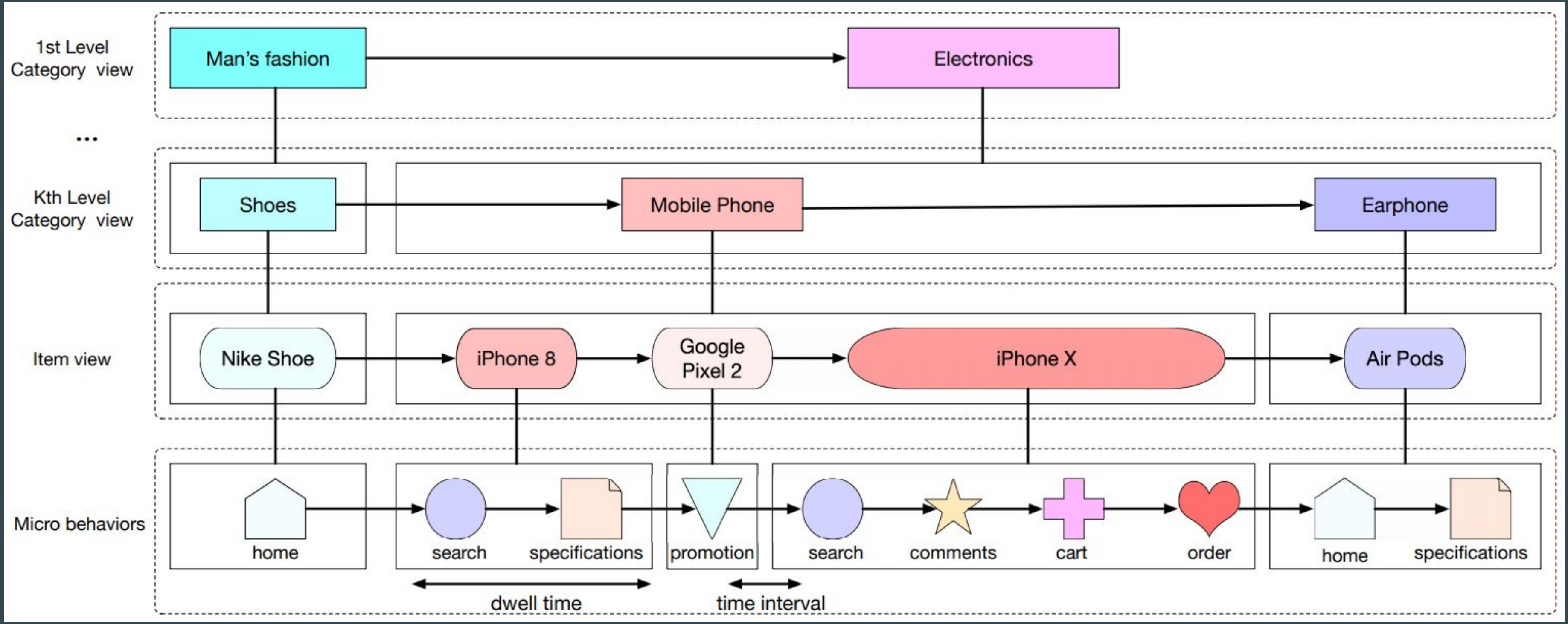


Image taken from [1]

Layered Approach

- Pyramid Recurrent Neural Network (PRNN)
  - A series of RNNs that are layered on top of each other
    - Micro-level RNN
    - Item-level RNN
    - Category-levels RNN
- This results in a hierarchical user profile
  - A collection of profile vectors

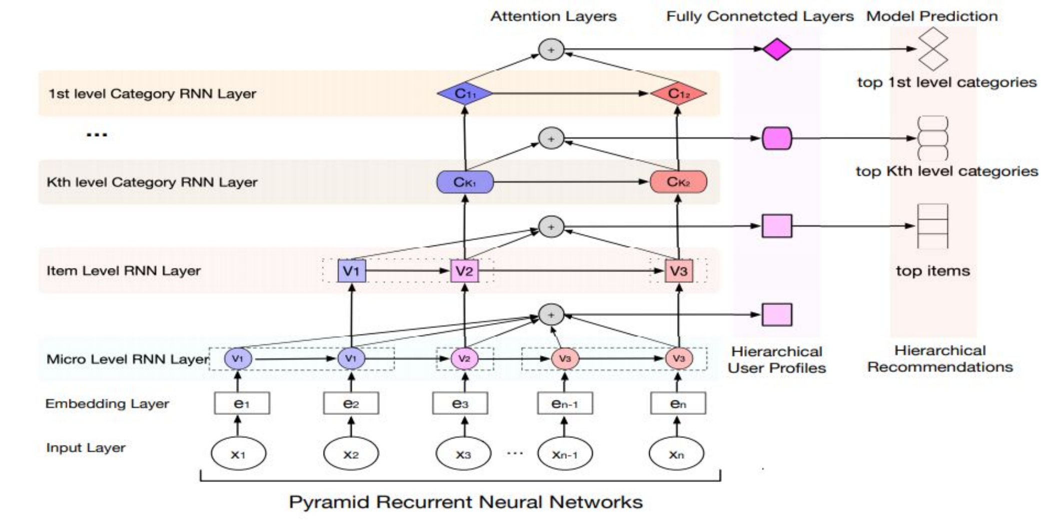
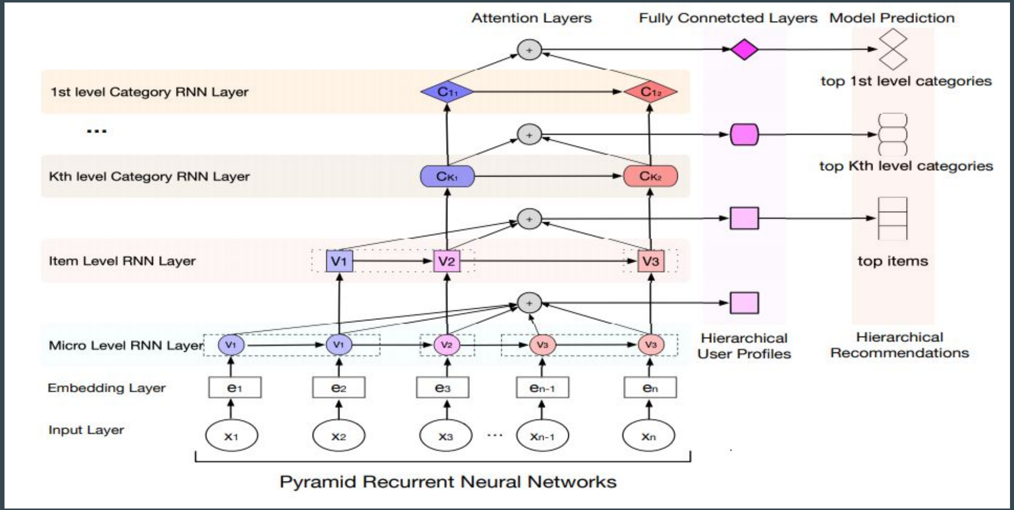


Image taken from [1]

Input and Embedding Layer

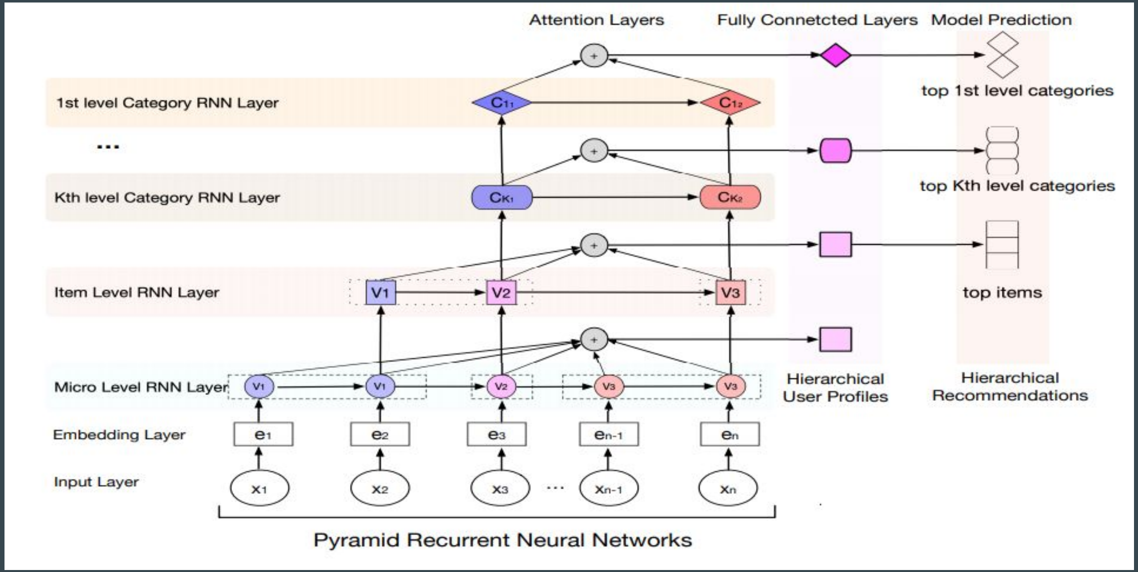


- Micro-behaviors are used as input
  - $X = \{x_1, x_2, \ldots, x_n\}$
- Each micro-behavior is a sextuple
  - $x_i = (t_i, v_i, c_i, b_i, d_i, g_i)$
    - t_i : Time MB occured
    - v_i : Item MB was performed on
    - c_i : Categories that v_i belongs to
    - b_i : MB type
    - d_i : Dwell time
    - g_i : Time between this MB and the next
- v_i , c_i , b_i , d_i , g_i are transformed into embedding vectors: $(e_{v_i}, e_{c_i}, e_{b_i}, e_{d_i}, e_{g_i})$
  - Those vectors are concatenated into a single imbedding vector e_i

Subsequent Layers

Micro-level RNN layer

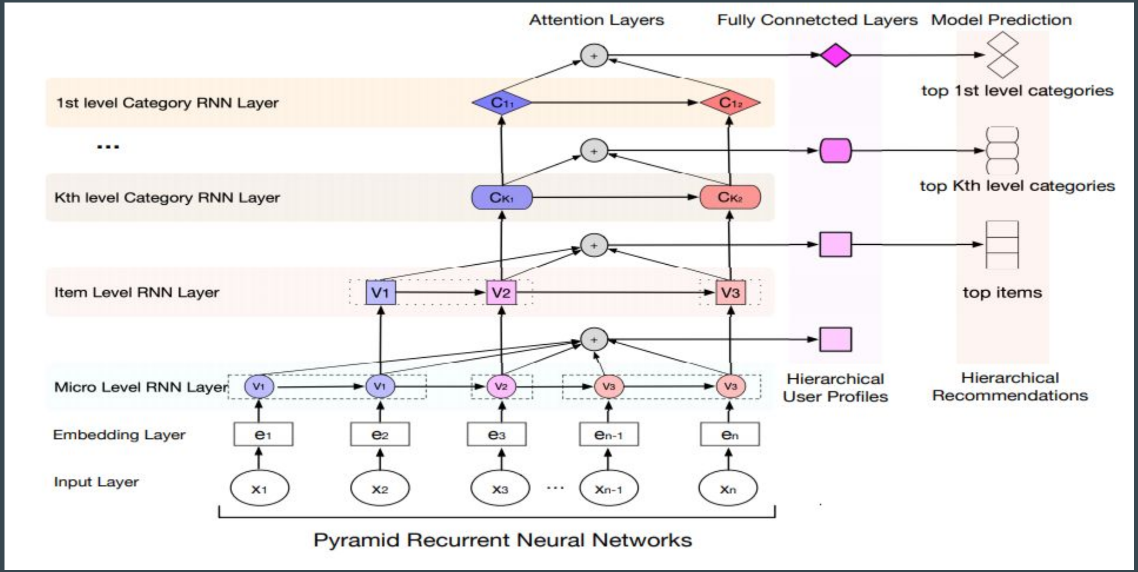
- Shows most granular interests
- Takes e_i as input
- Generates p_{micro}



Subsequent Layers

Item-level RNN layer

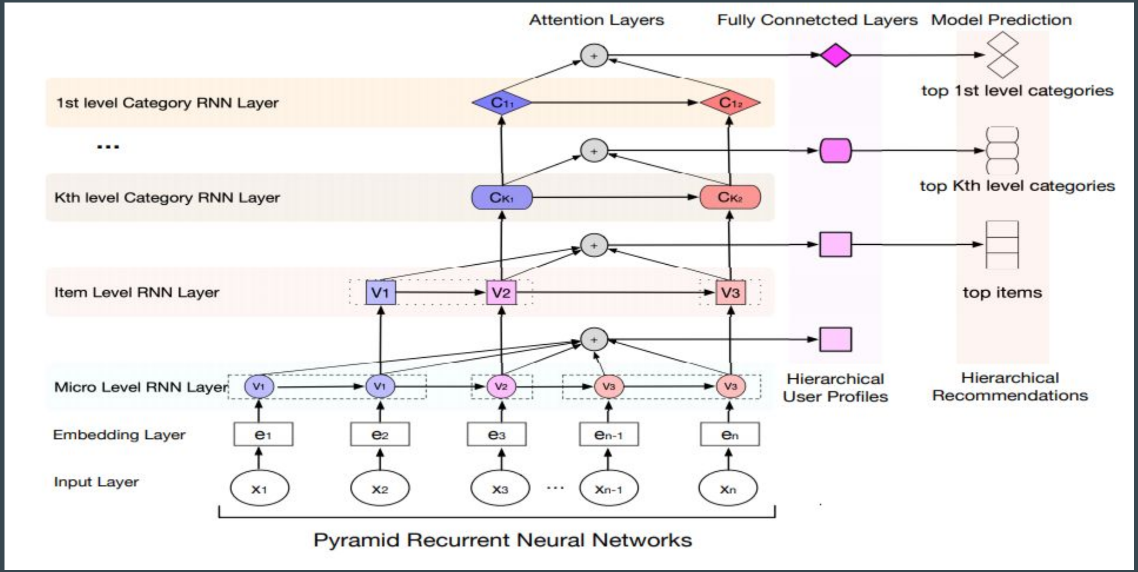
- Shows interest in items
- Uses the concatenation of e_{v_i} and the micro-level layer output as input.
- Generates p_{items}



Subsequent Layers

Categories-level RNN layer

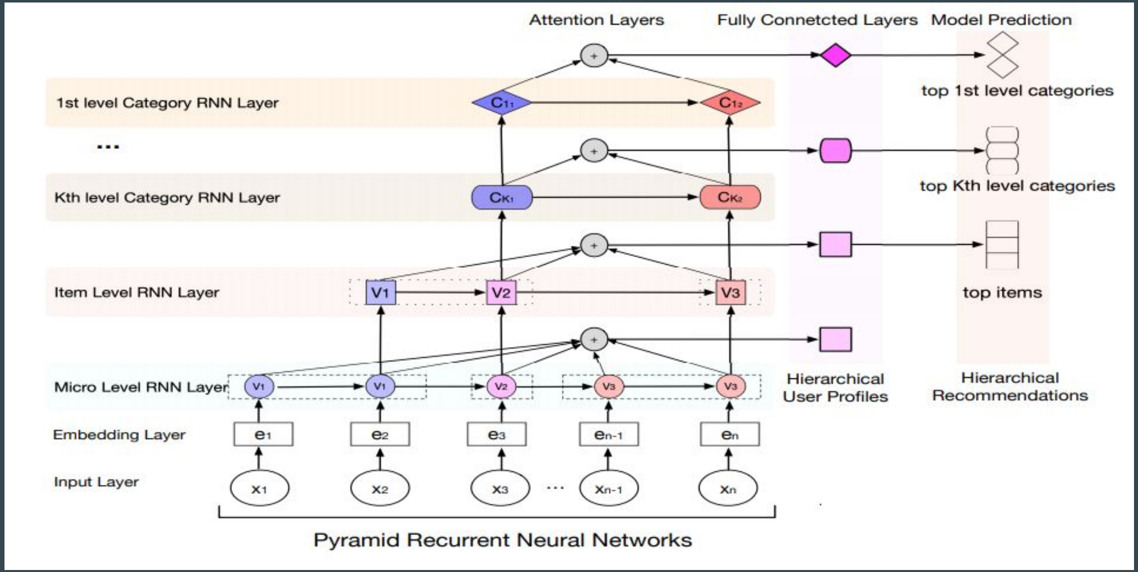
- Multiple category layers
- Kth level has finest granularity
- 1st level is the most general



Subsequent Layers

Categories-level RNN layer

- Shows interest in categories at different levels
- Uses the concatenation of $e_{c_i}^{(k)}$ and the item-level output as input
- Generates K profile vectors $p_{category}^{(k)}$



Long Short-Term Memory Cells

What is an LSTM?

- A component of an RNN that excels at making predictions
- LSTMs deal with an RNN training problem
- LSTMs include gates
    - Forget gate
    - Input gate
    - Output gate

Behavior-LSTM

- Designed to include micro-behavior type and dwell time
- Includes two additional components
  - Time gate
  - Behavior gate
- Time gate
  - Captures time intervals between each MB and decides how much information will be given to the next cell state.
- Behavior gate
  - Calculates the importance of each MB using its type and dwell time information.

Recommendation Generation

1. HUP generates a set profile vectors
2. Candidate items are selected
3. The similarity between each candidate embedding and the item-level profile vector is calculated
4. Assign each candidate a ranking score
5. Select top ranked candidates for recommendation

Category recommendations are done in the same way

Experimentation Setting

- HUP has been tested by generating recommendations at the item and categories levels
- Test data comes from the JD Micro Behaviors Datasets
    - Collected from a large e-commerce website
    - Contains user MB data for Appliances and Computers
- Tested against 8 baseline methods
    - Including 3 RNN-based methods
- Two popular metrics Recall@K and MRR@K were used to compare results

Recall@K

K = 4

User	Recommendations	Number of relevant	Recall@4
A	goat, **ferret**, ants, **toad**	2	2 / 4 = .5
B	**newt**, **horse**, bird, **turtle**	3	3 / 4 = .75

MRR@K

Mean reciprocal rank

K = 3

User	Recommendations	First Relevant	Rank	Reciprocal Rank
A	rabbit, toad, **mouse**	mouse	3	⅓
B	horse, **spider**, dog	spider	2	½
C	**cat**, gerbil, goat	cat	1	1

MRR = (⅓ + ½ + 1) / 3 = .611

Experimentation Results

- HUP outperforms all baseline methods in both item and category recommendation
- Category performance gains are smaller

Model	Applicances				Computers			
	Item Rec		Category Rec		Item Rec		Category Rec	
	Recall@20	*MRR@20*	*Recall@5*	*MRR@5*	*Recall@20*	*MRR@20*	*Recall@5*	*MRR@5*
POP	3.1	0.5	45.0	24.0	3.4	1.0	44.0	28.6
BPR-MF	13.1	3.1	55.4	35.0	11.3	3.0	70.1	42.9
Item-KNN	42.9	9.6	87.0	43.1	*29.8*	6.8	68.8	32.7
Word2vec	38.5	8.8	91.1	90.6	28.4	6.2	84.1	81.6
Word2vec-avg	38.7	13.1	86.7	80.0	24.4	7.1	81.0	71.5
RIB	47.6	14.3	92.9	91.2	28.6	7.6	88.0	83.0
Time-LSTM	49.4	18.9	93.4	91.3	32.8	10.9	88.7	83.9
S-HRNN	49.8	19.2	92.6	90.4	33.0	11.0	88.2	82.9
HUP	**51.5***	**20.5***	**93.8***	**91.6***	**35.0***	**12.0***	**89.2***	**84.4***

Image taken from [1]

Conclusions

- HUP is flexible and has a wide range of possible usages
- MB are an effective way of interpreting a user’s interests
- Hierarchical user profiles carry more information
- Granularity is important in RSs
- HUP has shown statistically significant improvements over other frameworks

Questions

References

[1] Y. Gu, Z. Ding, S. Wang, and D. Yin. Hierarchical user profiling for e-commerce recommender systems. In Proceedings of the 13th International Conference on Web Search and Data Mining, WSDM ’20, page 223–231, New York, NY, USA, 2020. Association for Computing Machinery

[2] M. Zhou, Z. Ding, J. Tang, and D. Yin. Micro behaviors: A new perspective in e-commerce recommender systems. In Proceedings of the Eleventh ACM International Conference on Web Search and Data Mining, WSDM ’18, page 727–735, New York, NY, USA, 2018. Association for Computing Machinery.