Sequence-Aware Recommender Systems

Tutorial at TheWebConf 2019, San Francisco

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Agenda

- 09:00 – 09:45 Introduction & Problem Definition
- 09:45 – 10:30 Algorithms I
- 10:30 – 11:00 Coffee break
- 11:00 – 11:30 Algorithms II
- 11:30 – 12:00 Evaluation
- 12:00 – 12:20 Hands-on
- 12:20 – 12:30 Conclusion / Questions

Algorithms

Taxonomy

- Sequence Learning
  - Frequent Pattern Mining
  - Sequence Modeling
  - Distributed Item Representations
  - Supervised Models with Sliding Window
- Sequence-aware Matrix Factorization
- Hybrids
  - Factorized Markov Chains
  - LDA/Clustering + sequence learning
- Others
  - Graph-based, Discrete-optimization

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Sequence Learning (SL)

- Useful in application domains where input data has an inherent sequential nature
  - Natural Language Processing
  - Time-series prediction
  - DNA modelling
  - **Sequence-Aware Recommendation**

Frequent Pattern Mining (FPM)

1. Discover **user consumption patterns**
   - Association rules, (Contiguous) Sequential Patterns
2. Look for patterns matching partial transactions
3. Rank items by confidence of matched rules

Size 1	Size 2	Size 3
$< A > (5)$	$< A, B > (4)$	$< A, B, E > (4)$
$< B > (6)$	$< A, C > (4)$	$< A, E, C > (4)$
$< C > (4)$	$< A, E > (4)$	
$< E > (5)$	$< B, C > (4)$	
	$< B, E > (5)$	
	$< C, E > (4)$	

Table 3: Frequent Sequential Patterns

Credits (Nakagawa and Mobasher, 2003)

Applications

- Page prefetching and recommendations
- Personalized FPM for next-item recommendation
- Next-app prediction

FPM

- Association Rule Mining
  - items co-occurring within the same sessions
    - no check on order
    - if you like A and B, you also like C (aka: learning to rank)
- Sequential Pattern Mining
  - Items co-occurring in the same order
    - no check on distance
    - If you watch A and **later** watch B, you will **later** watch C
- Contiguous Sequential Pattern Mining
  - Item co-occurring in the same order and distance
    - If you watch A and B **one after the other**, if **now** watch C

[Mobasher et al] **Using sequential and non-sequential patterns in predictive web usage mining tasks**. ICDM '02

FPM

- Two steps approach
  1. Offline: rule mining
  2. Online: rule matching (with current user session)

- Rules have
  - Support: number of examples (main parameter)
  - Confidence: conditional probability

- Lower thresholds -> fewer rules
  - few rules: difficult to find rules matching a session
  - many rules: noisy rules (low quality)

Frequent Pattern Mining (FPM)

- Pros
  - Easy to implement
  - Explainable predictions

- Cons
  - Choice of the minimum support/confidence thresholds
  - Data sparsity
  - Limited scalability

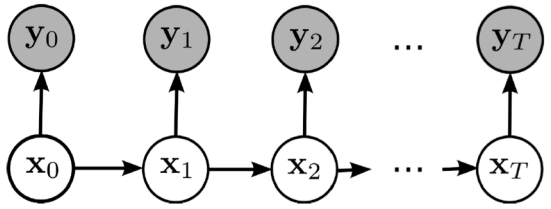
[C. Lu et al] **Mining mobile application sequential patterns for usage prediction**. GrC '14
[Nakagawa and Mobasher] **Impact of site characteristics on recommendation models based on association rules and sequential patterns**. IJCAI '03
[Yap et al.] **Effective next-items recommendation via personalized sequential pattern mining**. DASFAA '12
[Zhou et al.] **An intelligent recommender system using sequential web access patterns**. CIS '04

Sequence Modeling

- Sequences of past user actions as time series with **discrete** observations
  - Timestamps used only to **order** user actions (optionally to model time intervals)
- Aim to learn models from past observations to predict future ones
- Categories of SM models
  - Markov Models
  - Reinforcement Learning
  - Recurrent Neural Networks

Markov Models

- Stochastic processes over **discrete random variables**
  - Finite history (= order of the model)
    → user actions depend on a limited # of most recent actions
  - Extensions: Variable Order MM / Context Trees, HMMs



HMM (Harvard University, Source)

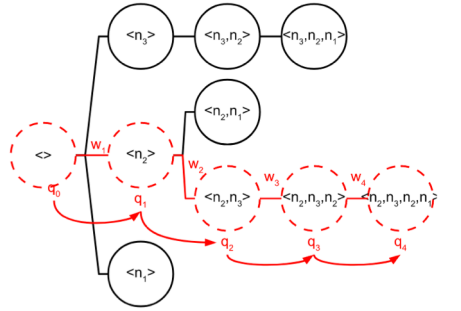


Figure 2: VMM context tree for the sequence $s = \langle n_1, n_2, n_3, n_2 \rangle$. Nodes in red-dashed are active experts $\mu \in A(s)$.

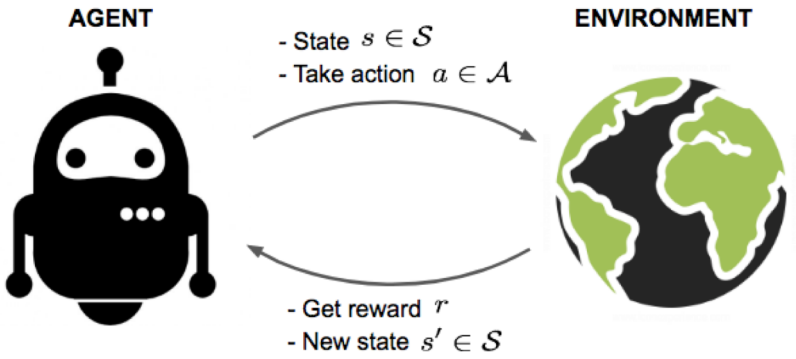
Credits (Garcin et al, 2013)

- Applications
  - Online shops
  - Playlist generation
  - **Variable Order Markov Models** for news recommendation
  - **Hidden Markov Models** for contextual next-track prediction

[Garcin et al.] **Personalized news recommendation with context trees**. RecSys '13,
[He et al.] **Web query recommendation via sequential query prediction**. ICDE '09
[Hosseinzadeh Aghdam et al.] **Adapting recommendations to contextual changes using hierarchical hidden markov models**. RecSys '15
[McFee and Lanckriet] **The natural language of playlists**. ISMIR '11
[Shani et al.] **An MDP-based recommender system**. J. Mach. Learn. Res. 2005.

Reinforcement Learning

- Learn by **sequential interactions** with the **environment**
- Generate recommendations (**actions**) and collect user feedback (**reward**)
- Markov Decisions Processes (MDPs)



Credits lilianweng.github.io

- Applications
  - Online e-commerce services
  - Sequential relationships between the attributes of items explored in a user session

[Moling et al.] **Optimal radio channel recommendations with explicit and implicit feedback**. RecSys '12
[Shani et al.] **An MDP-based recommender system**. J. Mach. Learn. Res. 2005.
[Tavakol and Brefeld] **Factored mdps for detecting topics of user sessions**. RecSys '14

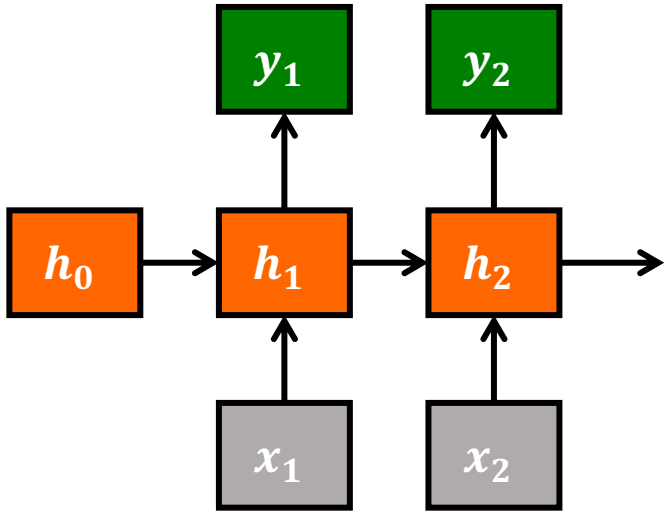
Recurrent Neural Networks (RNN)

- Distributed real-valued hidden state models with non-linear dynamics
  - Hidden state: latent representation of user state within/across sessions
  - Update the hidden state on the current input and its previous value, then use it to predict the probability for the next action

- Applications
  - Next-click prediction with RNNs
  - Session-based recommendation
  - Long-term/short-term user modeling

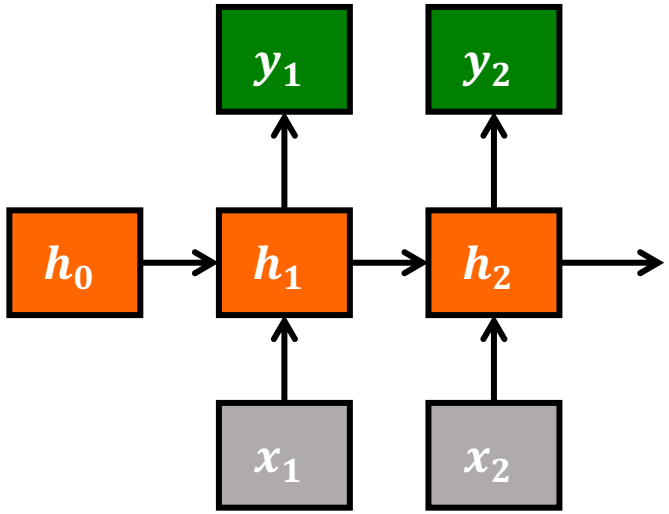
Simple Recurrent Neural Network

- Hidden state → used to predict the output
  - Computed from next input and previous hidden state



Simple Recurrent Neural Network

- Hidden state → used to predict the output
  - Computed from next input and previous hidden state
- Three weight matrices
  - $h_t = f(x^T W_x + h_{t-1}^T W_h + b_h)$
  - $y_t = f(h_t^T W_y)$



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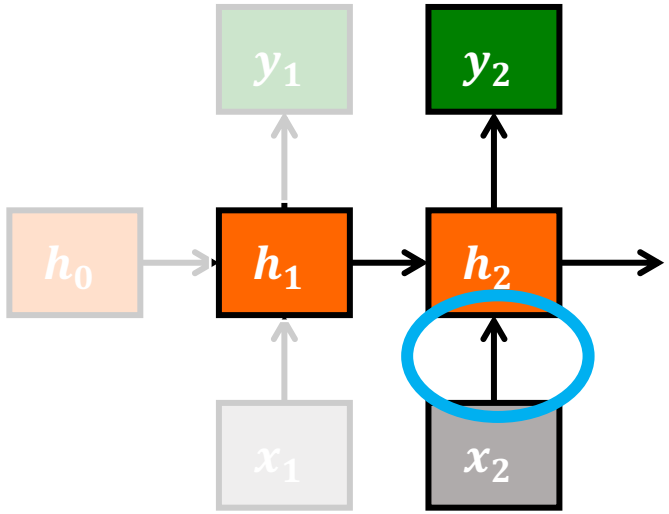

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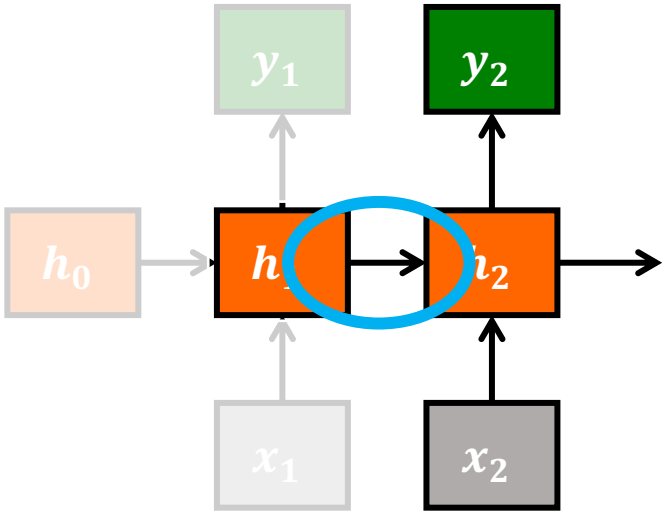

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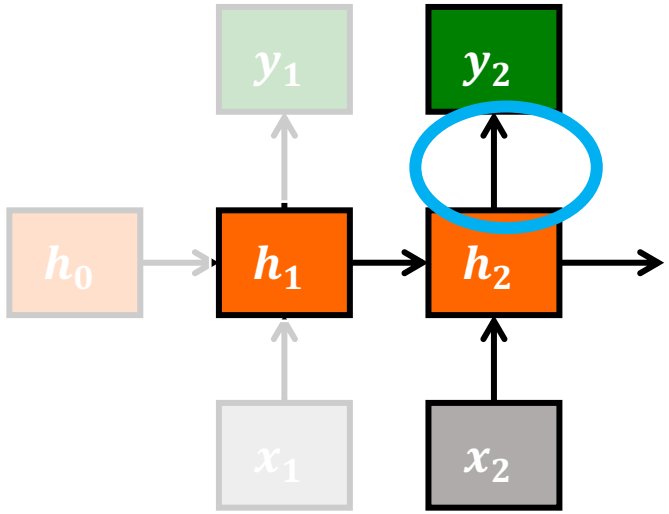


Simple Recurrent Neural Network

- Item subject to user interaction as **1-of-N** coded vector

- Example:
  - Output: item 4

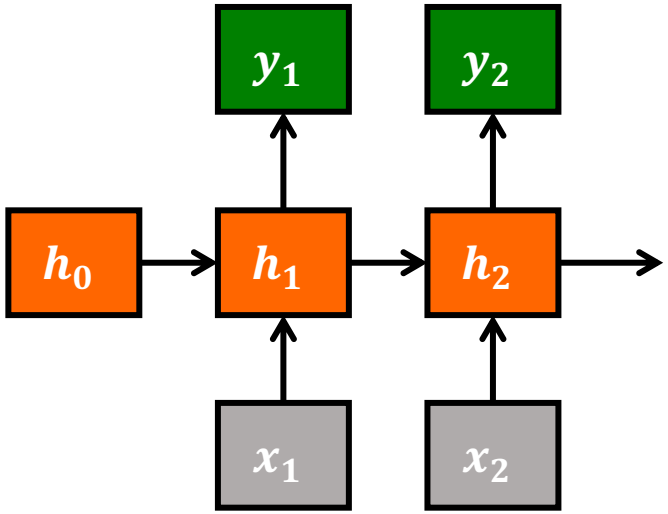
y_2 =

0	0	0	1	0

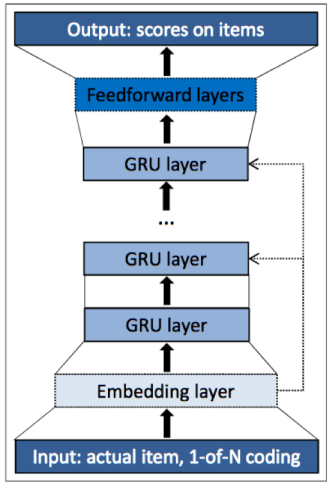
  - Input: item 3

x_2 =

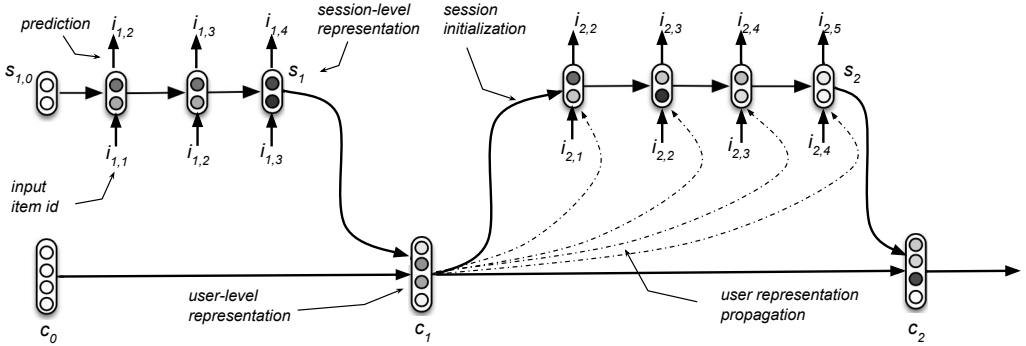
0	0	1	0	0



RNNs for Session-based Recommendation



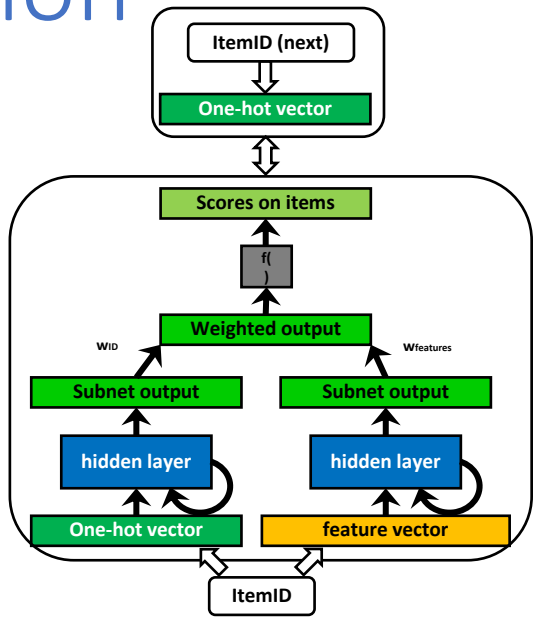
- GRU4Rec/GRU4Rec+ [Hidasi, 2018]
  - Gated Recurrent Units (GRU), 1-hot item encoding, parallel mini-batching
  - Optimized **negative item sampling** and **ranking loss function**
- HGRURec [Quadrana, 2017]
  - Hierarchical RNN, **long+short-term** user profiling, **personalized** in-session recommendations
  - Bonus: **Time intervals** between sessions with Point Processes [Vassøy, 2019]



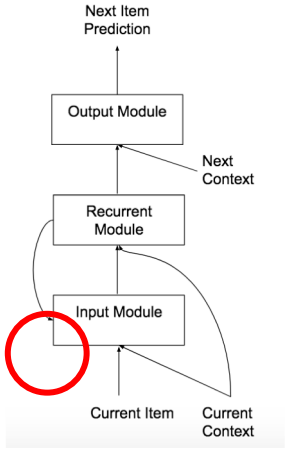
[Quadrana et al.] **Personalizing session-based recommendations with hierarchical recurrent neural networks**. RecSys '17
[Hidasi and Karatzoglou] **Recurrent Neural Networks with Top-k Gains for Session-based Recommendations**. CIKM '18
[Vassøy et al.] **Time is of the Essence: a Joint Hierarchical RNN and Point Process Model for Time and Item Predictions**. WSDM '19

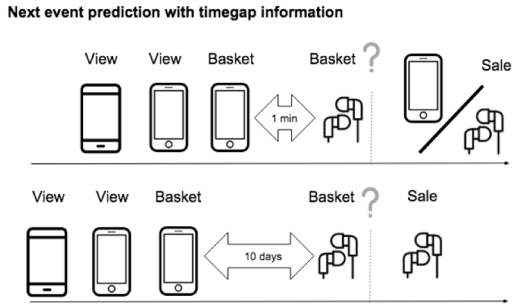
RNNs for Session-based Recommendation

- Parallel RNNs [Hidasi, 2016]
  - Jointly modelling **item features** and **identifiers**
  - **Alternated training** procedure to learn robust feature representations
  - Experiments with product **images** and **descriptions**



- Contextual Sequence Modeling [Smirnova, 2016]
  - Temporal ctx, action type, etc.
  - Concatenation $[x_t; c_t]$
  - Mult. interaction $x_t \odot Cc_t$
  - Combined $[x_t \odot Cc_t; c_t]$

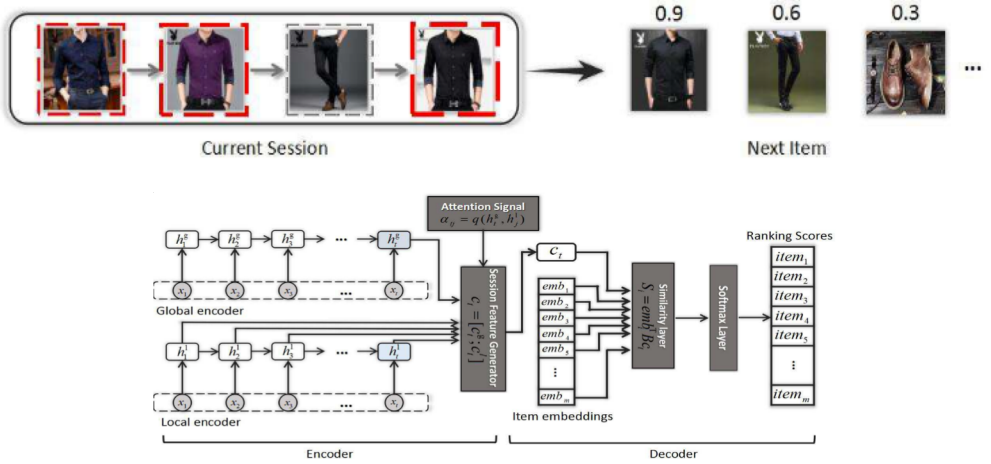




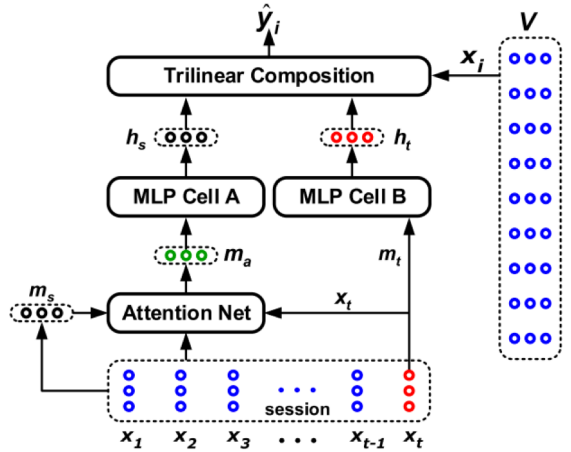
[Liu et al.] **Predicting the next location: A recurrent model with spatial and temporal contexts**. AAAI '16
[Smirnova and Vasile] **Contextual RNNs for Recommendation**. DLRS 2017

RNNs for Session-based Recommendation

- Neural Attention Networks [Liu, 2017]
  - Standard RNN → **global** session repr.
  - Attention RNN → **main purpose** of the session
  - Combine local/global features with bi-linear matching scheme



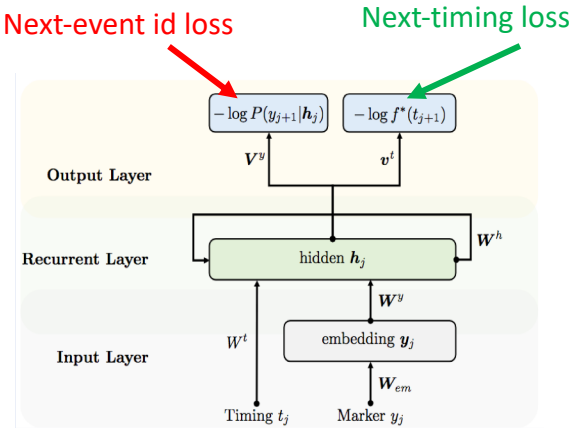
- Attentive memory networks [Liu, 2018]
  - Replace RNN with **attention/memory module**
  - Memory retains short-term user interests
  - **Weighted attention** to memory
  - Only Feed-forward networks!



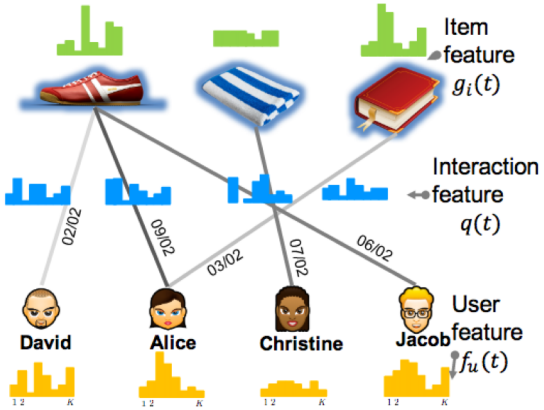
[Li et al.] Neural Attentive Session-based Recommendation. CIKM 2017
[Liu et al.] STAMP: Short-Term Attention/Memory Priority Model for Session-based Recommendation. KDD 2018

Other RNN Applications

- Recurrent Marked Temporal Point Process (RNN) [Du, 2016]
  - Joint learning **next target item** and **its timing** with a combination of Hawkes process + RNNs
  - Predict **when and what** event will likely occur next



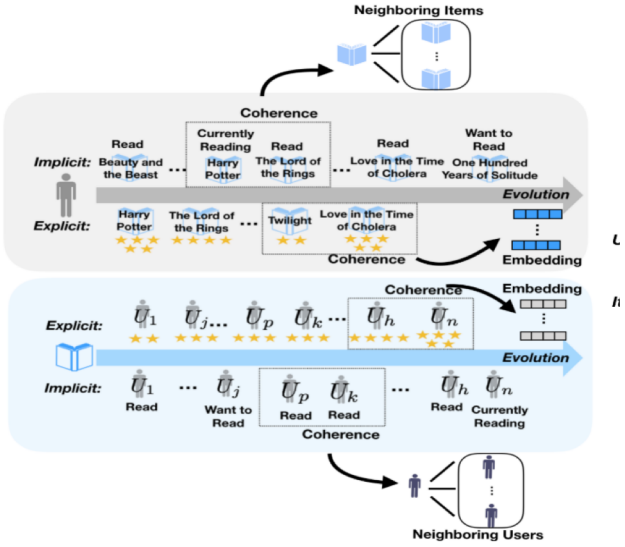
- Deep Co-evolutionary networks [Dai, 2016]
  - Jointly model **user-item feature co-evolution** and **influence each-other** over time

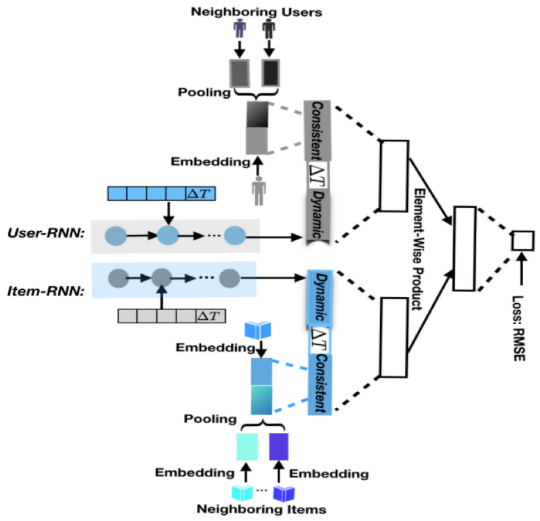


[Du et al.] **Recurrent Marked Temporal Point Processes: Embedding Event History to Vector**. KDD 2016
[Dai et al.] **Deep Coevolutionary Network: Embedding User and Item Features for Recommendation**. DLRS 2016

Other RNN Applications

- Recurrent Recommendation with Local Coherence
  - Short-term user/item neighborhood are coherent (users who rate or read the same book in a shorter time period are more similar)
  - Coherence-based neighbors with skip-grams
  - Dynamic latent-factors with parallel user/item RNN

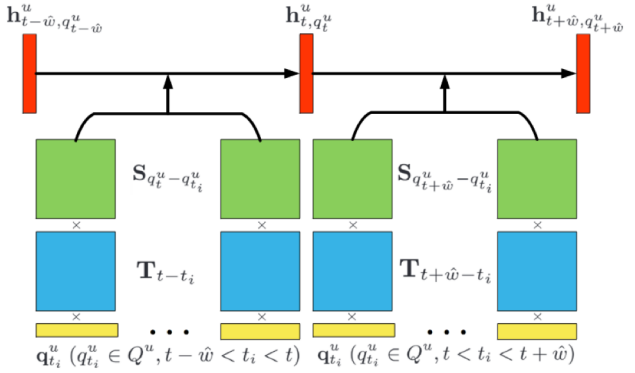




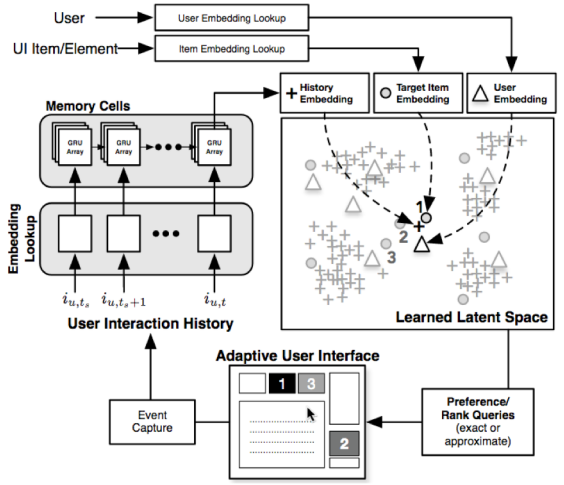
[Wang and Caverlee, 2019] Recurrent Recommendation with Local Coherence. WSDM '19

Other RNN Applications

- Spatio-Temporal RNN (ST-RNN) [Liu, 2016]
  - Next-location prediction with custom Spatial and Temporal hidden-to-hidden transition matrices



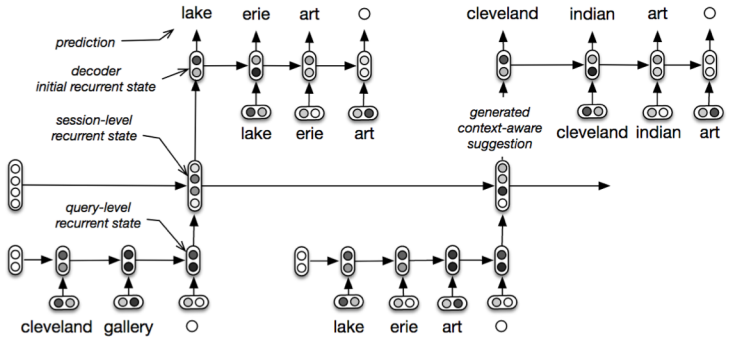
- Sequential recommendation for dynamic adaptation of user interfaces [Sho, 2017]



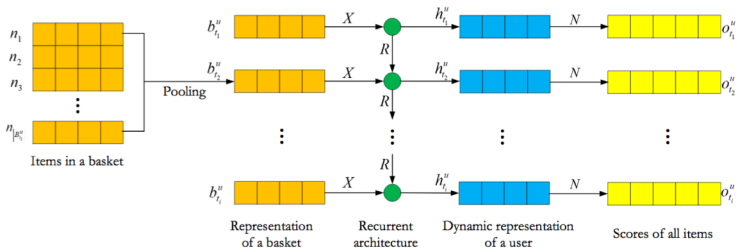
[Liu et al.] **Predicting the next location: A recurrent model with spatial and temporal contexts**. AAAI '16, 2016.
[Soh et al.] **Deep sequential recommendation for personalized adaptive user interfaces**. IUI '17

Other RNN Applications

- Generative context-aware next-query recommendation [Sordoni, 2015]
  - Hierarchical RNN to model query-level + session-level features



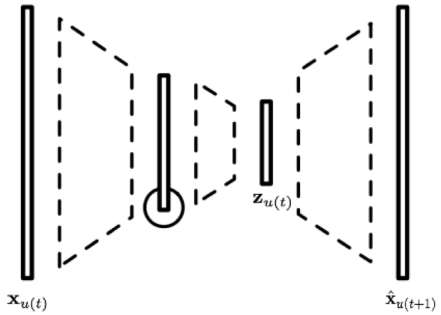
- Dynamic REcurrent bAsket Model (DREAM) [Yu, 2016]
  - Pooling to generate basket representations



[Sordoni et al.] A hierarchical recurrent encoder-decoder for generative context-aware query suggestion. CIKM '15
[Yu et al.] A dynamic recurrent model for next basket recommendation. SIGIR '16

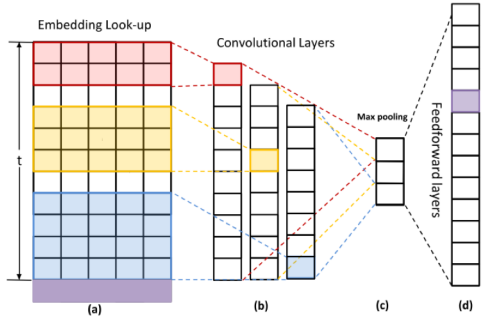
Other DL approaches

- Sequential Variational Autoencoders [Sachdeva, 2019]
  - VAE with recurrent dependency on the latent representation *z*.

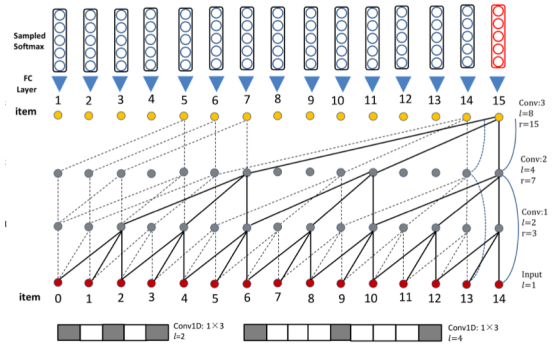


(c) SVAE

- CNN-based methods
  - CASER [Tang and Wang, 2018]
    - Embedding, 1d conv, max pooling and FFD layers



  - NextItNet [Yuan, 2019]
    - Dilated convolutions



[Sachdeva, 2019] **Sequential Variational Autoencoders for Collaborative Filtering**. WSDM '19
[Tang and Wang, 2018] **Personalized Top-N Sequential Recommendation via Convolutional Sequence Embedding**. WSDM '18
[Yuan et al., 2019] **A Simple Convolutional Generative Network for Next Item Recommendation**. WSDM '19

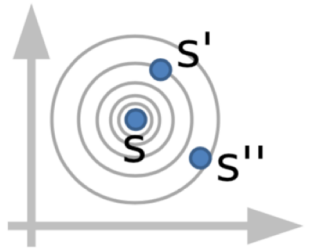
Distributed Item Representations

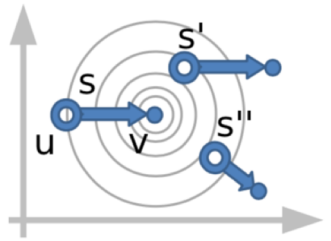
- Dense, lower-dimensional representations of items
  - derived from sequences of events
  - preserve the sequential relationships between items
- Similar to latent factor models
  - “similar” items are projected to similar vectors
  - every item is associated with a real-valued embedding vector
  - its projection into a lower-dimensional space
  - certain item transition properties are preserved
    - e.g., co-occurrence of items in similar contexts
- Different approaches are possible
  - Latent Markov Embedding (LME)
  - Prod2Vec

Latent Markov Embeddings

- Transition probability related with the **Euclidean distance** between the **embeddings** of **subsequent** items

$$\Pr(p^{[i]}|p^{[i-1]}) = \frac{e^{-||X(p^{[i]})-X(p^{[i-1]})||_2^2}}{\sum_{j=1}^{|S|} e^{-||X(s_j)-X(p^{[i-1]})||_2^2}}$$





  - Symmetric transitions → **single-point model**
  - Asymmetric transitions → **dual-point model**
  - MLE over the existing sequences
  - Recommendation through **sampling**
- Applications:
  - Playlist generation
  - POI recommendation

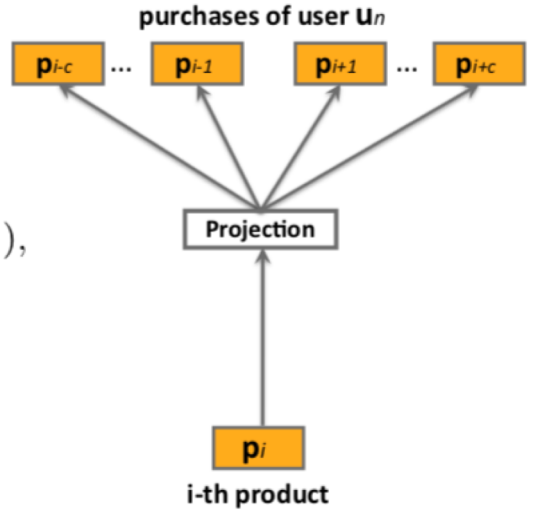
[Chen et al.] **Playlist prediction via metric embedding**. KDD '12 **Multi-space probabilistic sequence modeling**. KDD '13
[Feng et al.] **Personalized ranking metric embedding for next new POI recommendation**. IJCAI '15
[Wu et al.] **Personalized next-song recommendation in online karaokes**. RecSys '13

Prod2Vec

- Transition probability related to the **dot product** between the **embeddings** of items within the **context window**

$$\mathbb{P}(p_{i+j}|p_i) = \frac{\exp(\mathbf{v}_{p_i}^\top \mathbf{v}'_{p_{i+j}})}{\sum_{p=1}^{P} \exp(\mathbf{v}_{p_i}^\top \mathbf{v}'_p)},$$

$$\mathcal{L} = \sum_{s \in \mathcal{S}} \sum_{p_i \in s} \sum_{-c \leq j \leq c, j \neq 0} \log \mathbb{P}(p_{i+j}|p_i),$$

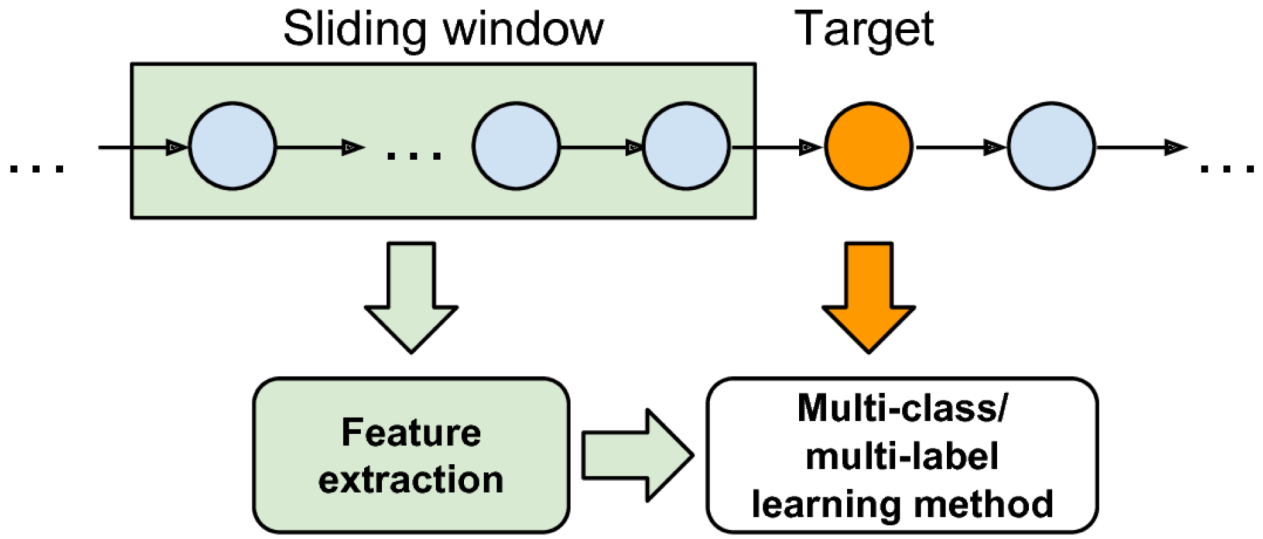


  - MLE + **Skip-gram**
  - Recommendation with (decayed) **KNN**
- Variants
  - Bagged-prod2vec [Grbovic, 2015]
  - Meta-prod2vec [Vasile, 2016]
  - User representation with paragraph vectors [Tagami,2015][Grbovic,2015]
- Applications
  - E-commerce, music, pretrained embeddings for other sequence models

[Grbovic et al.] **E-commerce in your inbox: Product recommendations at scale**. KDD '15
[Tagami et al.] **Modeling user activities on the web using paragraph vector**. WWW '15
[Vasile et al.] **Meta-prod2vec: Product embeddings using side-information for recommendation**. RecSys '16

Supervised Learning w/ Sliding Windows

- Frame sequential recommendation as a classification problem



[Baeza-Yates et al.] **Predicting the next app that you are going to use**. WSDM '15
[Zimdars et al.] **Using temporal data for making recommendations**. UAI '01

Taxonomy

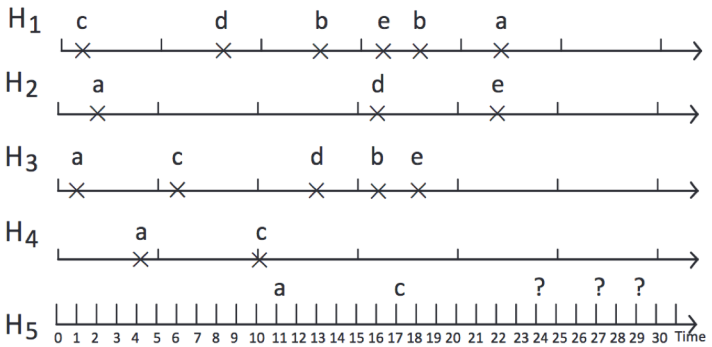
- Sequence Learning
  - Frequent Pattern Mining
  - Sequence Modeling
  - Distributed Item Representations
  - Supervised Models with Sliding Window
- Sequence-aware Matrix Factorization
- Hybrids
  - Factorized Markov Chains
  - LDA/Clustering + sequence learning
- Others
  - Graph-based, Discrete-optimization

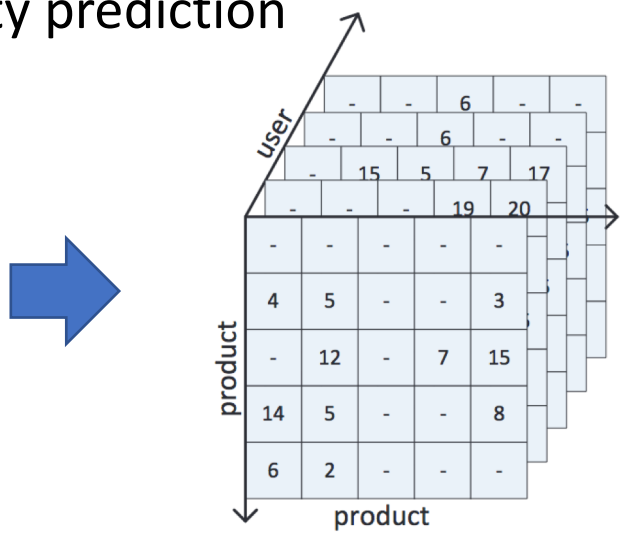
Sequence-aware Matrix Factorization

- Sequence information usually derived from timestamps

  → Time-aware recommender systems

- Purchase sequences → personalized purchase interval prediction
  - Framed as factorized (SVD) maximum utility prediction





[Zhao et al.] **Increasing temporal diversity with purchase intervals**. SIGIR '12
[Zhao et al.] **Utilizing purchase intervals in latent clusters for product recommendation**. SNAKDD '14

Taxonomy

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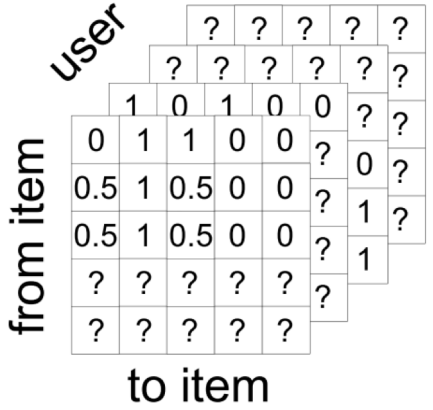
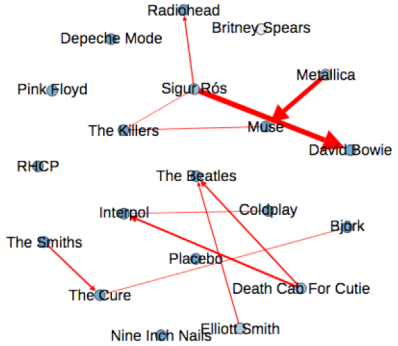
Hybrid Methods

- Sequence Learning + Matrix Completion (CF or CBF)
  - Factored Personalized Markov Chains (FPMC) [Rendle, 2010]
    - Transition cube factorization with Pairwise Loss



- Topic modelling/clustering → sequence learning
  - **LDA** on sequences → **FPM** on topic sequences [Hariri, 2012]
  - Clustering over order-1 Markov transition matrices (**behavioural clustering**) → personalized Page-rank [Natarajan, 2013]

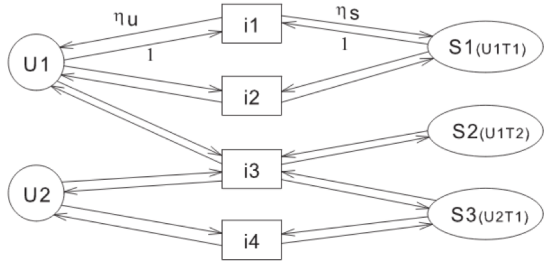


(a) Cluster 1.

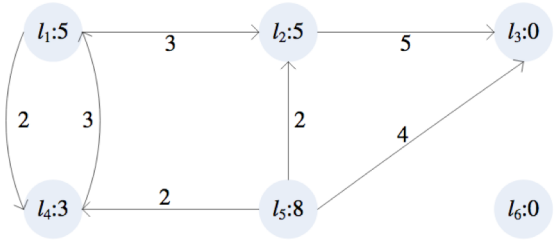
[Rendle et al.] **Factorizing personalized markov chains for next-basket recommendation**. WWW '10
[Hariri et al.] **Context-aware music recommendation based on latent topic sequential patterns**. RecSys '12
[Natarajan et al.] **Which app will you use next?: Collaborative filtering with interactional context**. RecSys '13

Other approaches

- Graph-based
  - Session-based Transition Graph [Xiang, 2010]



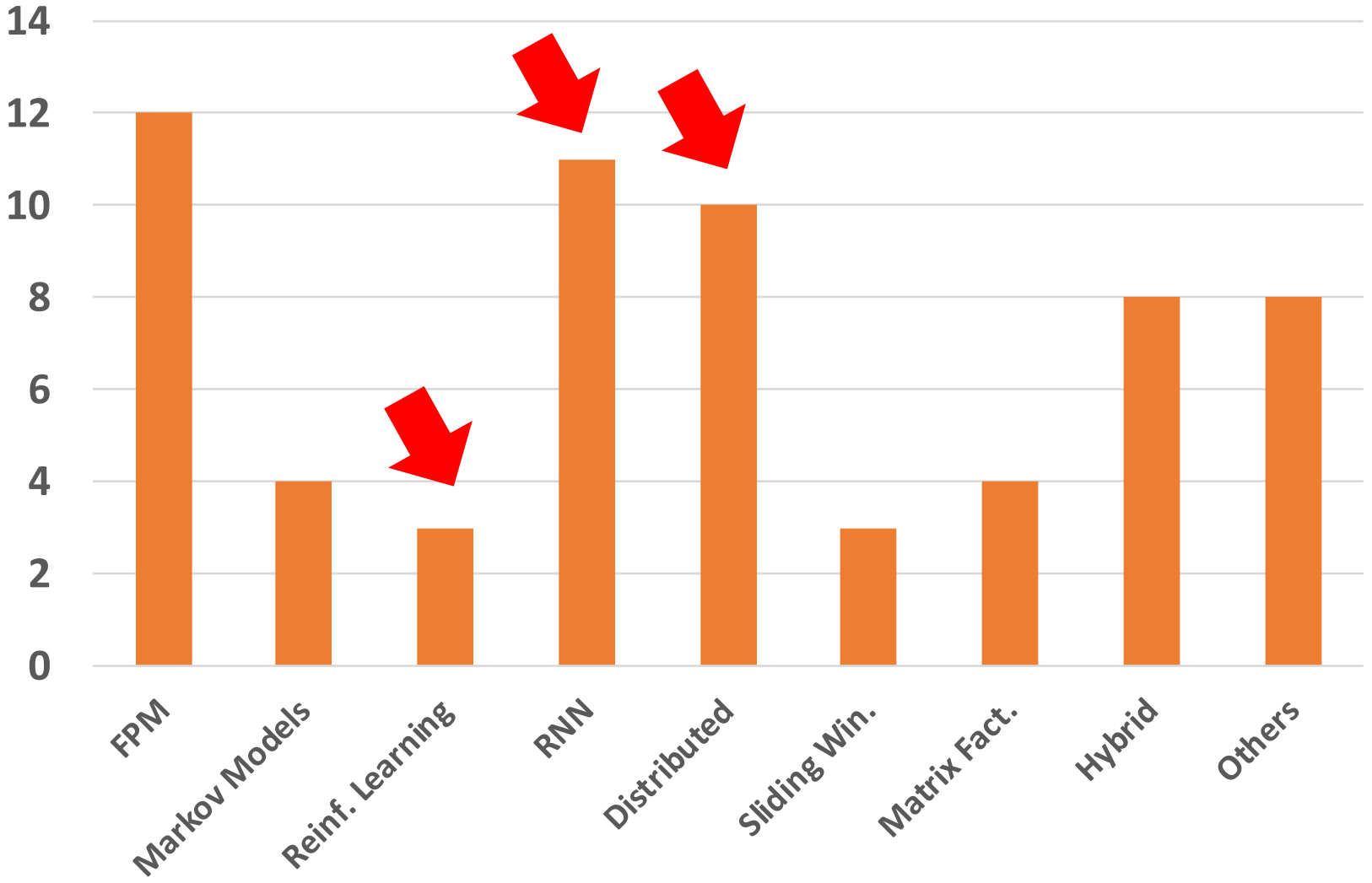
  - Location-location Transition Graph [Zhang, 2014]



- Discrete optimization via constraint satisfaction [Jannach, 2015][Paws, 2006][Xu, 2016]

[Xiang et al.] **Temporal recommendation on graphs via long- and short-term preference fusion**. KDD ’10
[Zhang et al.] **Lore: Exploiting sequential influence for location recommendations**. SIGSPATIAL ’14
[Jannach et al.] **Beyond "hitting the hits": Generating coherent music playlist continuations with the right tracks**. RecSys ’15
[Pauws et al.] **Fast generation of optimal music playlists using local search**. ISMIR ’06
[Xu et al.] **Personalized course sequence recommendations**. IEEE Trans. Signal Process. 2016.

Statistics


14
12
10
8
6
4
2
0
FPM
Markov Models
Reinf. Learning
RNN
Distributed
Sliding Win.
Matrix Fact.
Hybrid
Others

Algorithm Summary

Algorithm	Main idea	Pros	Cons
FPM	Discover patterns in user action sequences	• Easy implementation • Explainable results	• Complex configuration • Suffers from data sparsity • Limited scalability
MC	Compute transition probabilities over fixed-length sequences	• Explainable results	• Fixed transition order • Suffers from data sparsity • Limited scalability
VMM	Compute transition probabilities over variable-length sequences	• Variable transition orders • Explainable results	• Suffers from data sparsity
HMM	Model the causal factors in user sequences as transitions between *discrete* hidden states	• Learns from variable-length inputs • Robust to data sparsity	• Limited explainability • Huge number of discrete parameters
RL	Directly maximize the customer and seller reward over time	• Dynamically adapt recommendations to future (unknown) rewards • Under active research	• MDP-based approaches have same issues as MCs • Limited explainability
RNN	Model the causal factors in user sequences with *non-linear* transitions between *continuous* hidden states	• Learns from variable-length inputs • Learns long-term dependencies • Robust to data sparsity • Compact hidden states • Under active research	• Complex configuration • Limited explainability • Benefits not fully clear in some domains
EMB	Embed items into latent spaces that preserves sequential transition properties	• Robust to data sparsity • Visually interpetable embeddings • Under active research	• Need auxiliary methods to make recommendations • Limited explainability
SL	Use supervised learning over features extracted from fixed-size sliding windows over sequences	• Easy implementation • Use off-the-shelf supervised algorithms	• Explainability depends on the chosen supervised method • Feature engineering
MF	Define new inputs and loss functions for MF to handle sequences	• Extensive literature available • Robust to data sparsity	• Non-trivial input and loss design • Concerns regarding scalability

Algorithm: FPM: Frequent Pattern Mining, MC: Markov Chains, VMM: Variable-order Markov Models, HMM: Hidden Markov Models, RL: Reinforcement Learning, RNN: Recurrent Neural Networks, EMB: Distributed Item Representations, SL: Supervised Learning w/ Sliding Windows, MF: Matrix Factorization