Deep Learning for Recommender Systems

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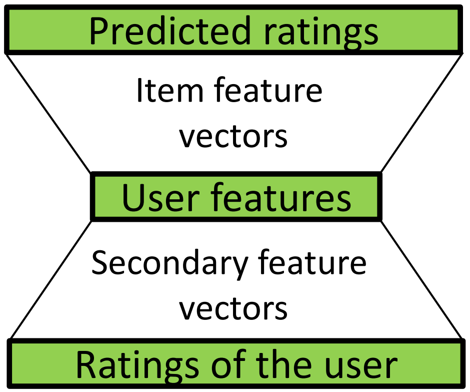
Deep Collaborative Filtering

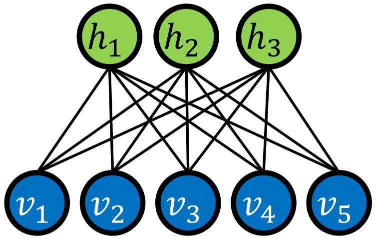
CF with Neural Networks

- Natural application area
- Some exploration during the Netflix prize
- E.g.: NSVD1 [Paterek, 2007]
  - Asymmetric MF
  - The model:
    - Input: sparse vector of interactions
      - Item-NSVD1: ratings given for the item by users
        - » Alternatively: metadata of the item
      - User-NSVD1: ratings given by the user
    - Input to hidden weights: „secondary" feature vectors
    - Hidden layer: item/user feature vector
    - Hidden to output weights: user/item feature vectors
    - Output:
      - Item-NSVD1: predicted ratings on the item by all users
      - User-NSVD1: predicted ratings of the user on all items
  - Training with SGD
  - Implicit counterpart by [Pilászy et. al, 2009]
  - No non-linarities in the model

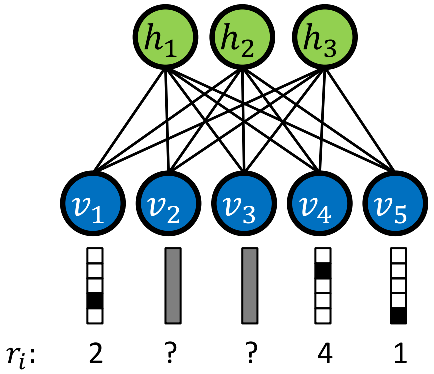


Restricted Boltzmann Machines (RBM) for recommendation

- RBM
  - Generative stochastic neural network
  - Visible & hidden units connected by (symmetric) weights
    - Stochastic binary units
    - Activation probabilities:
      - $p(h_j = 1|v) = \sigma(b_j^h + \sum_{i=1}^{m} w_{i,j} v_i)$
      - $p(v_i = 1|h) = \sigma(b_i^v + \sum_{j=1}^{n} w_{i,j} h_j)$
  - Training
    - Set visible units based on data
    - Sample hidden units
    - Sample visible units
    - Modify weights to approach the configuration of visible units to the data

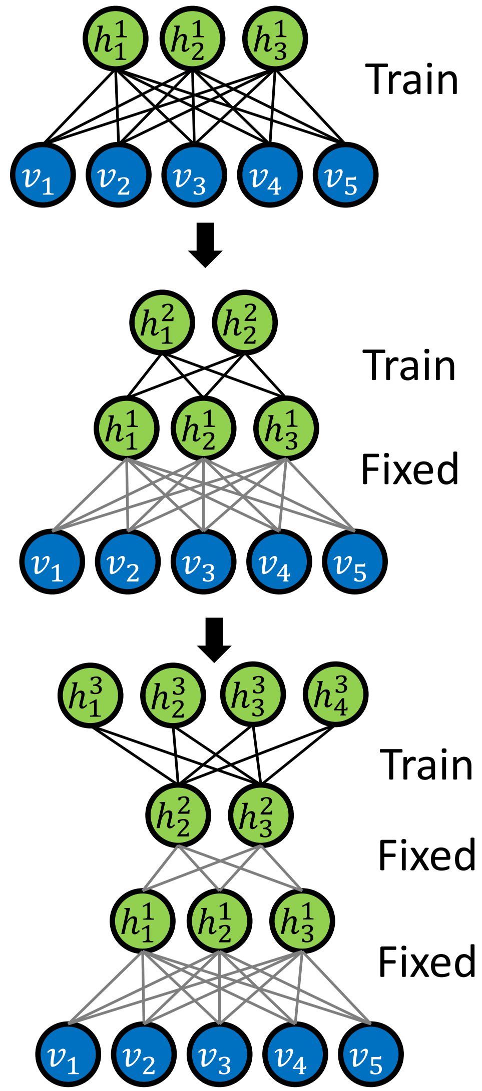


- In recommenders [Salakhutdinov et. al, 2007]
  - Visible units: ratings on the movie
    - Softmax unit
      - Vector of length 5 (for each rating value) in each unit
      - Ratings are one-hot encoded
    - Units correnponding to users who not rated the movie are ignored
  - Hidden binary units



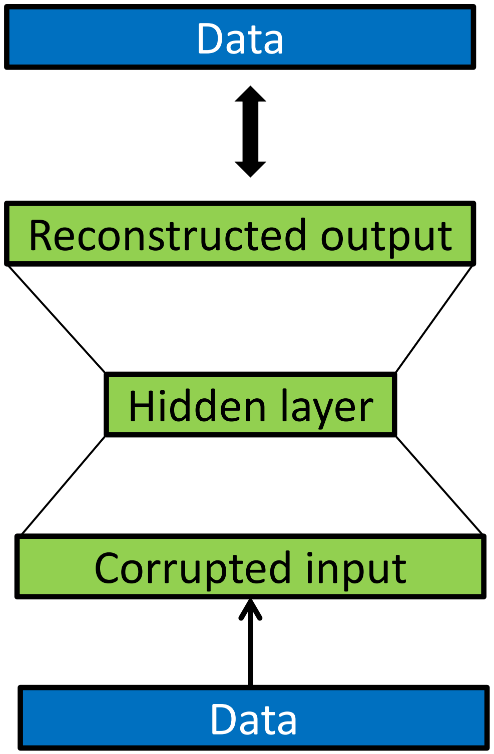
Deep Boltzmann Machines (DBM)

- Layer-wise training
  - Train weights between visible and hidden units in an RBM
  - Add a new layer of hidden units
  - Train weights connecting the new layer to the network
    - All other weights (e.g. visible-hidden weights) are fixed



Autoencoders

- Autoencoder
  - One hidden layer
  - Same number of input and output units
  - Try to reconstruct the input on the output
  - Hidden layer: compressed representation of the data
- Constraining the model: improve generalization
  - Sparse autoencoders
    - Activations of units are limited
    - Activation penalty
    - Requires the whole train set to compute
  - Denoising autoencoders [Vincent et. al, 2008]
    - Corrupt the input (e.g. set random values to zero)
    - Restore the original on the output
- Deep version
  - Stacked autoencoders
  - Layerwise training (historically)
  - End-to-end training (more recently)



Autoencoders for recommendation

- Reconstruct corrupted user interaction vectors
  - CDL [Wang et. al, 2015]

  Collaborative Deep Learning

  Uses Bayesian stacked denoising autoencoders

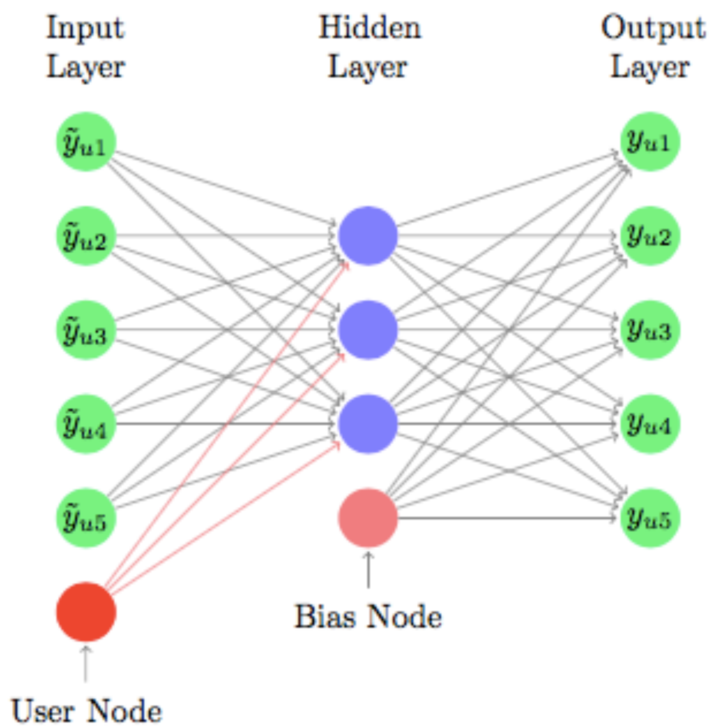
  Uses tags/metadata instead of the item ID

Autoencoders for recommendation

- Reconstruct corrupted user interaction vectors
  - CDAE [Wu et. al, 2016]

  Collaborative Denoising Auto-Encoder

  Additional user node on the input and bias node beside the hidden layer

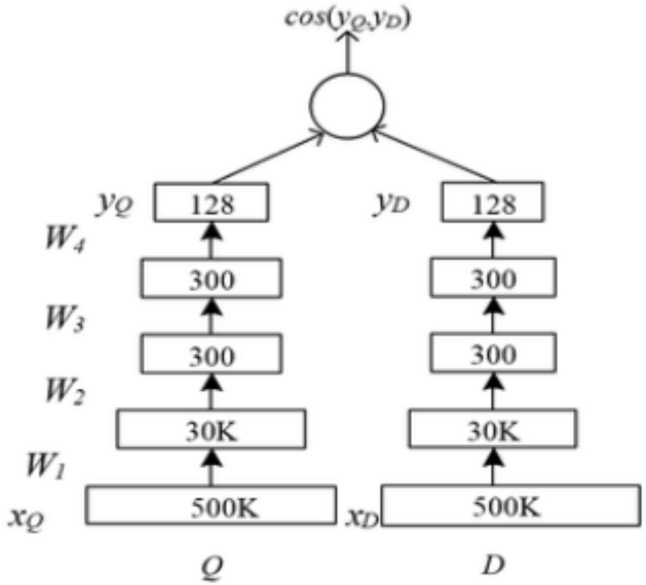


Recurrent autoencoder

- CRAE [Wang et. al, 2016]
  - Collaborative Recurrent Autoencoder
  - Encodes text (e.g. movie plot, review)
  - Autoencoding with RNNs
    - Encoder-decoder architecture
    - The input is corrupted by replacing words with a deisgnated BLANK token
  - CDL model + text encoding simultaneously
    - Joint learning

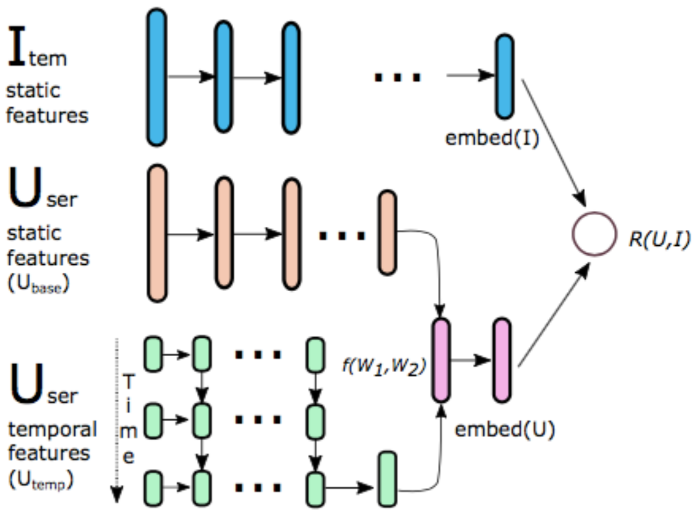
DeepCF methods

- MV-DNN [Elkahky et. al, 2015]
  - Multi-domain recommender
  - Separate feedforward networks for user and items per domain (D+1 networks)
    - Features first are embedded
    - Run through several layers



DeepCF methods

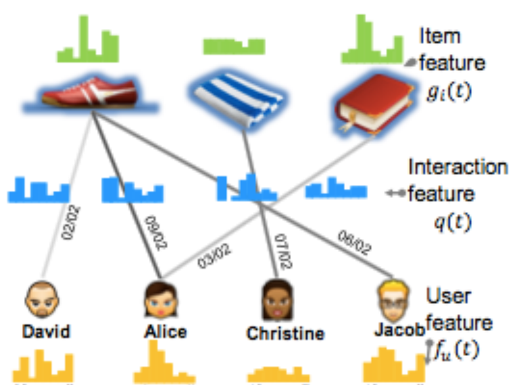
- TDSSM [Song et. al, 2016]
  - Temporal Deep Semantic Structured Model
  - Similar to MV-DNN
  - User features are the combination of a static and a temporal part
  - The time dependent part is modeled by an RNN

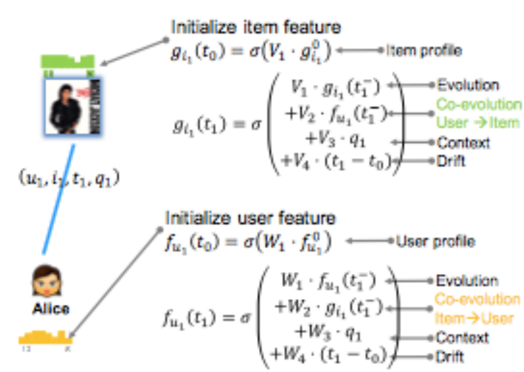


DeepCF methods

- Coevolving features [Dai et. al, 2016]
- Users' taste and items' audiences change over time
- User/item features depend on time and are composed of
    - Time drift vector
    - Self evolution
    - Co-evolution with items/users
    - Interaction vector

  Feature vectors are learned by RNNs





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Feature Extraction from Content

Content features in recommenders

- Hybrid CF+CBF systems
  - Interaction data + metadata
- Model based hybrid solutions
  - Initiliazing
    - Obtain item representation based on metadata
    - Use this representation as initial item features
  - Regularizing
    - Obtain metadata based representations
    - The interaction based representation should be close to the metadata based
    - Add regularizing term to loss of this difference
  - Joining
    - Obtain metadata based representations
    - Have the item feature vector be a concatenation
      - Fixed metadata based part
      - Learned interaction based part

Feature extraction from content

- Deep learning is capable of direct feature extraction
  - Work with content directly
  - Instead (or beside) metadata
- Images
  - E.g.: product pictures, video thumbnails/frames
  - Extraction: convolutional networks
  - Applications (e.g.):
    - Fashion
    - Video
- Text
  - E.g.: product description, content of the product, reviews
  - Extraction
    - RNNs
    - 1D convolution networks
    - Weighted word embeddings
    - Paragraph vectors
  - Applications (e.g.):
    - News
    - Books
    - Publications
- Music/audio
  - Extraction: convolutional networks (or RNNs)

Convolutional Neural Networks (CNN)

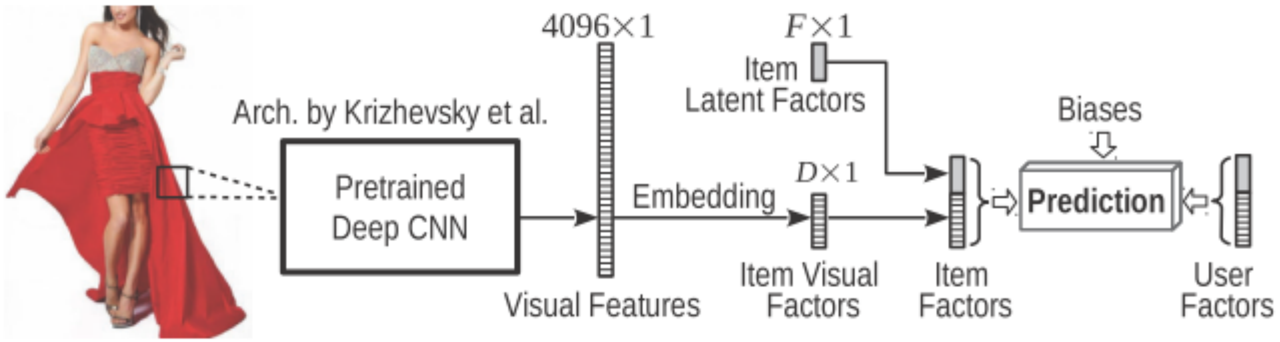
- Speciality of images
  - Huge amount of information
    - 3 channels (RGB)
    - Lots of pixels
    - Number of weights required to fully connect a 320x240 image to 2048 hidden units:
      - 3*320*240*2048 = 471,859,200
  - Locality
    - Objects' presence are independent of their location or orientation
    - Objects are spatially restricted

Images in recommenders

- [McAuley et. Al, 2015]
  - Learns a parameterized distance metric over visual features
    - Visual features are extracted from a pretrained CNN
    - Distance function: Eucledian distance of „embedded” visual features
      - Embedding here: multiplication with a weight matrix to reduce the number of dimensions
  - Personalized distance
    - Reweights the distance with a user specific weight vector
  - Training: maximizing likelihood of an existing relationship with the target item
    - Over uniformly sampled negative items

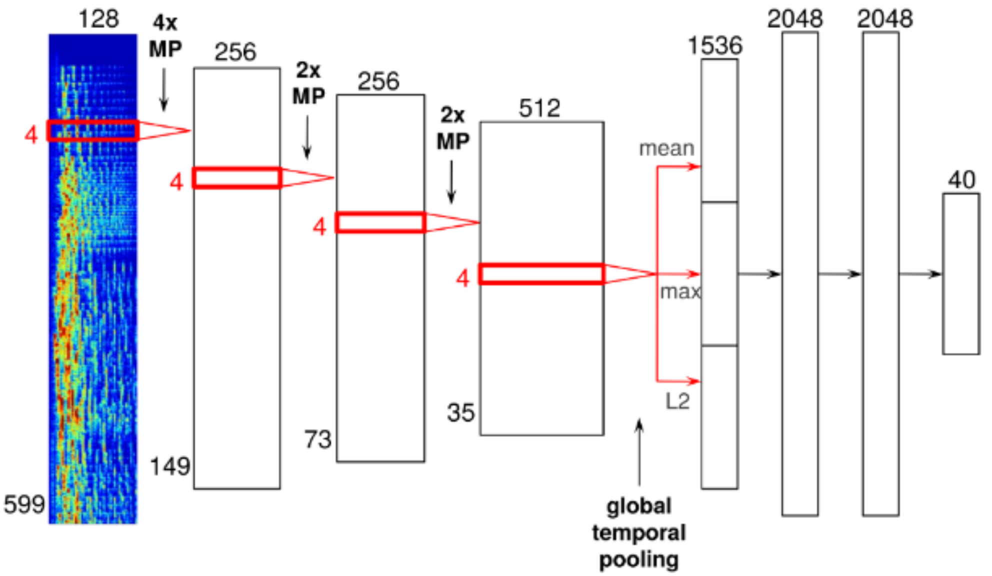
Images in recommenders

- Visual BPR [He & McAuley, 2016]
  - Model composed of
    - Bias terms
    - MF model
    - Visual part
      - Pretrained CNN features
      - Dimension reduction through „embedding”
      - The product of this visual item feature and a learned user feature vector is used in the model
    - Visual bias
      - Product of the pretrained CNN features and a global bias vector over its features
  - BPR loss
  - Tested on clothing datasets (9-25% improvement)



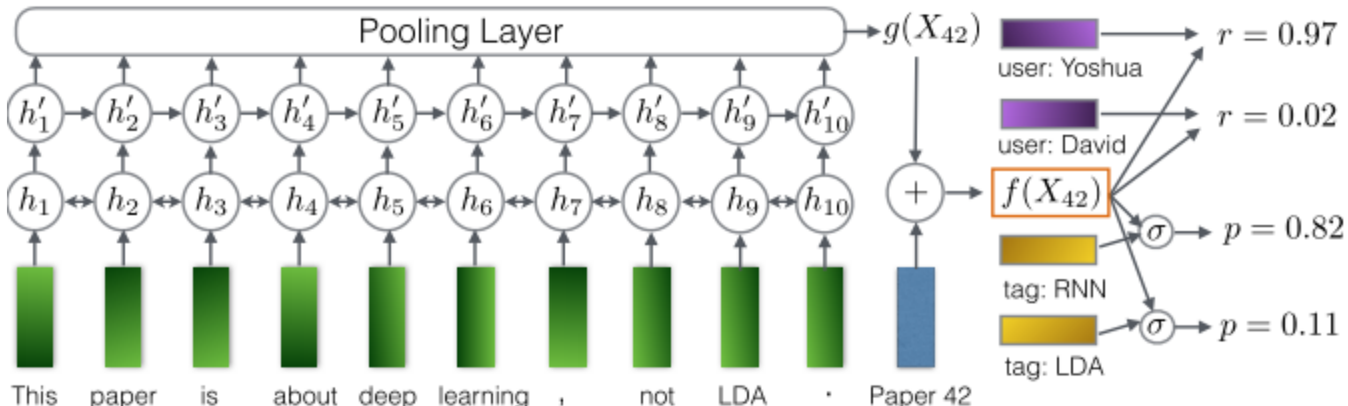
Music representations

- [Oord et. al, 2013]
  - Extends iALS/WMF with audio features
    - To overcome cold-start
  - Music feature extraction
    - Time-frequency representation
    - Applied CNN on 3 second samples
    - Latent factor of the clip: average predictions on consecutive windows of the clip
  - Integration with MF
    - (a) Minimize distance between music features and the MF's feature vectors
    - (b) Replace the item features with the music features (minimize original loss)



Textual information improving recommendations

- [Bansal et. al, 2016]
  - Paper recommendation
  - Item representation
    - Text representation
      - Two layer GRU (RNN): bidirectional layer followed by a unidirectional layer
      - Representation is created by pooling over the hidden states of the sequence
    - ID based representation (item feature vector)
    - Final representation: ID + text added
  - Multi-task learning
    - Predict both user scores
    - And likelihood of tags
  - End-to-end training
    - All parameters are trained simultaneously (no pretraining)
    - Loss
      - User scores: weighted MSE (like in iALS)
      - Tags: weighted log likelihood (unobserved tags are downweighted)



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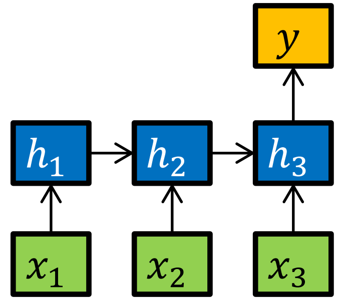
Session-based Recommendations with RNNs

Recurrent Neural Networks

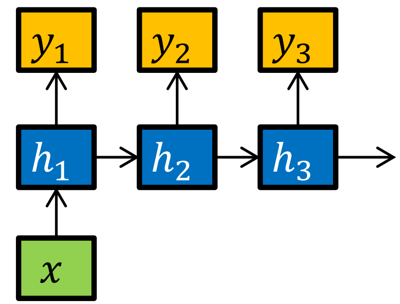
- Input: sequential information ($\{x_t\}_{t=1}^{T}$)
- Hidden state (h_t):
  - representation of the sequence so far
  - influenced by every element of the sequence up to t
- $h_t = f(Wx_t + Uh_{t-1} + b)$

RNN-based machine learning

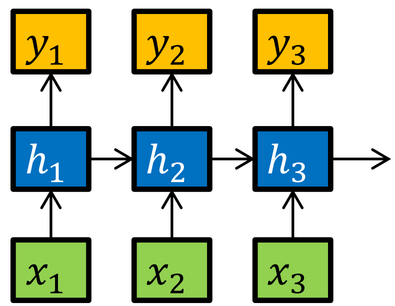
- Sequence to value
  - Encoding, labeling
  - E.g.: time series classification



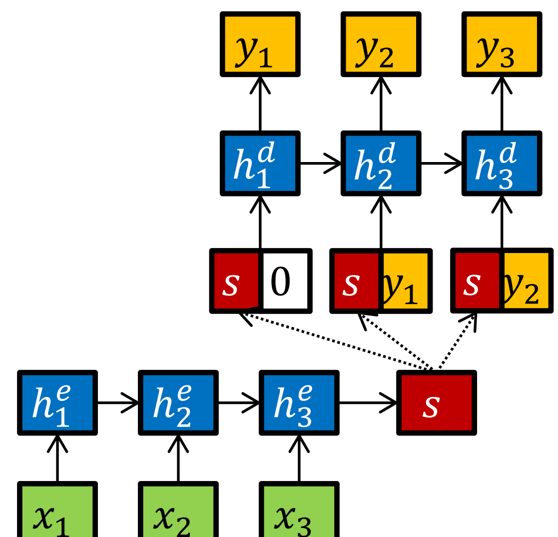
- Value to sequence
  - Decoding, generation
  - E.g.: sequence generation



- Sequence to sequence
  - Simultaneous
    - E.g.: next-click prediction



  - Encoder-decoder architecture
    - E.g.: machine translation
    - Two RNNs (encoder & decoder)
      - Encoder produces a vector describing the sequence
        - » Last hidden state
        - » Combination of hidden states (e.g. mean pooling)
        - » Learned combination of hidden states
      - Decoder receives the summary and generates a new sequence
        - » The generated symbol is usually fed back to the decoder
        - » The summary vector can be used to initialize the decoder
        - » Or can be given as a global context
    - Attention mechanism (optionally)



Exploding/Vanishing gradients

- $h_t = f(Wx_t + Uh_{t-1} + b)$
- Gradient of h_t wrt. x_1
  - Simplification: linear activations
    - In reality: bounded
  - $\frac{\partial h_t}{\partial x_1} = \frac{\partial h_t}{\partial h_{t-1}} \frac{\partial h_{t-1}}{\partial h_{t-2}} \cdots \frac{\partial h_2}{\partial h_1} \frac{\partial h_1}{\partial x_1} = U^{t-1}W$
    - $\|U\|_2 < 1$ → vanishing gradients
      - The effect of values further in the past is neglected
      - The network forgets
    - $\|U\|_2 > 1$ → exploding gradients
      - Gradients become very large on longer sequences
      - The network becomes unstable

Handling exploding gradients

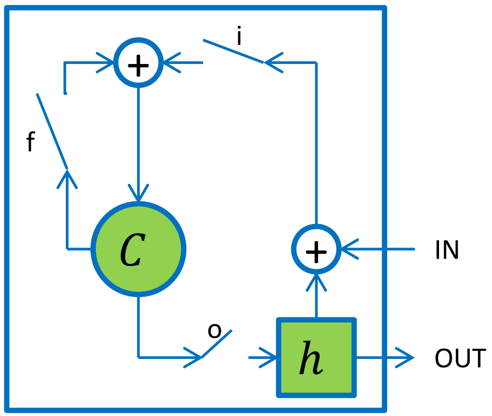
- Gradient clipping
  - If the gradient is larger than a threshold, scale it back to the threshold
  - Updates are not accurate
  - Vanishing gradients are not solved
- Enforce $\|U\|_2 = 1$
  - Unitary RNN
  - Unable to forget
- Gated networks
  - Long-Short Term Memory (LSTM)
  - Gated Recurrent Unit (GRU)
  - (and a some other variants)

Long-Short Term Memory (LSTM)

- [Hochreiter & Schmidhuber, 1999]
- Instead of rewriting the hidden state during update, add a delta
  - $s_t = s_{t-1} + \Delta s_t$
  - Keeps the contribution of earlier inputs relevant
- Information flow is controlled by gates
  - Gates depend on input and the hidden state
  - Between 0 and 1
  - Forget gate (f): 0/1 → reset/keep hidden state
  - Input gate (i): 0/1 → don't/do consider the contribution of the input
  - Output gate (o): how much of the memory is written to the hidden state
- Hidden state is separated into two (read before you write)
  - Memory cell (c): internal state of the LSTM cell
  - Hidden state (h): influences gates, updated from the memory cell

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f)$$
$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i)$$
$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o)$$

$$\tilde{c}_t = \tanh(W x_t + U h_{t-1} + b)$$
$$c_t = f_t \circ c_{t-1} + i_t \circ \tilde{c}_t$$
$$h_t = o_t \circ \tanh(c_t)$$

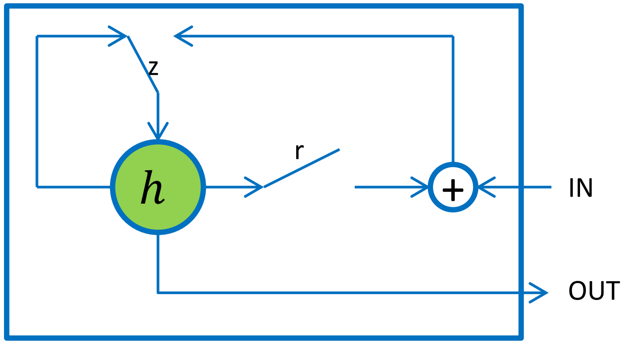


Gated Recurrent Unit (GRU)

- [Cho et. al, 2014]
- Simplified information flow
  - Single hidden state
  - Input and forget gate merged → update gate (z)
  - No output gate
  - Reset gate (r) to break information flow from previous hidden state
- Similar performance to LSTM

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z)$$
$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r)$$

$$\tilde{h}_t = \tanh(W x_t + r_t \circ U h_{t-1} + b)$$
$$h_t = z_t \circ h_t + (1 - z_t) \circ \tilde{h}_t$$

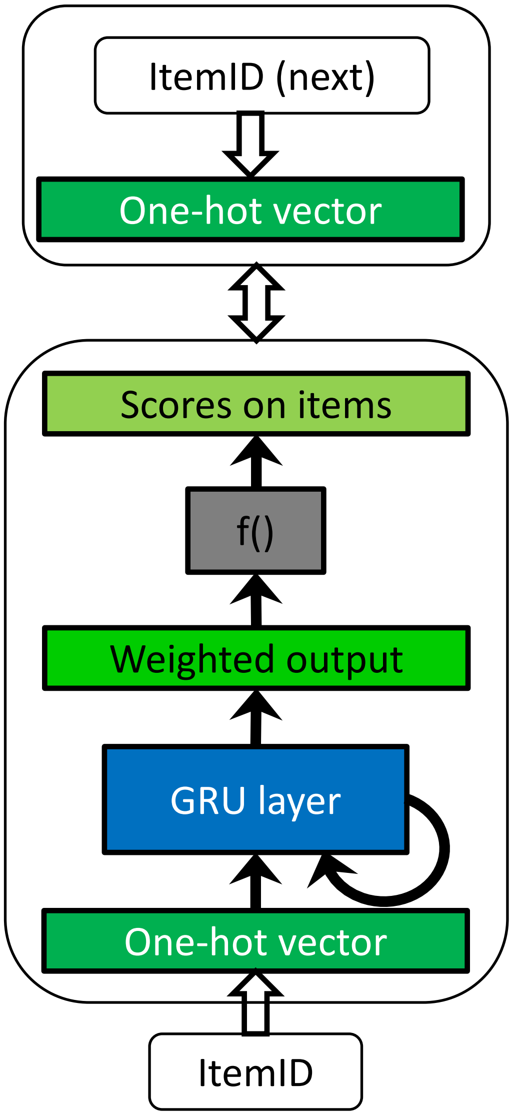


Session-based recommendations

- Sequence of events
  - User identification problem
  - Disjoint sessions (instead of consistent user history)
- Tasks
  - Next click prediction
  - Predicting intent
- Classic algorithms can’t cope with it well
  - Item-to-item recommendations as approximation in live systems
- Area revitalized by RNNs

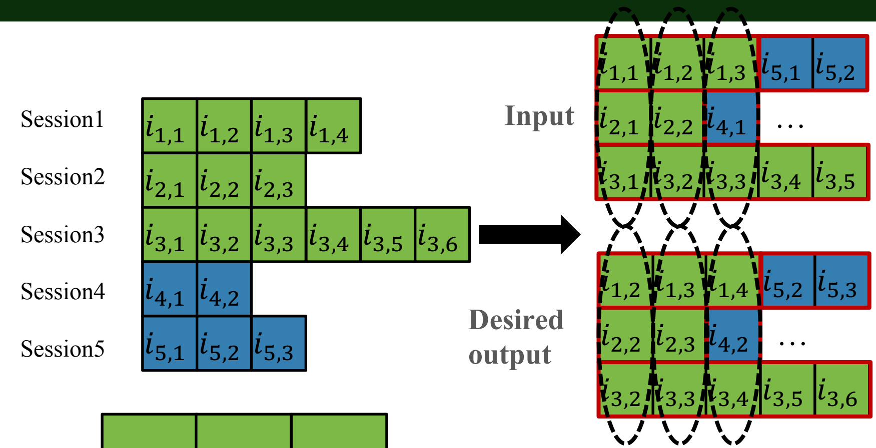
GRU4Rec (1/3)

- [Hidasi et. al, 2015]
- Network structure
  - Input: one hot encoded item ID
  - Optional embedding layer
  - GRU layer(s)
  - Output: scores over all items
  - Target: the next item in the session
- Adapting GRU to session-based recommendations
  - Sessions of (very) different length & lots of short sessions: session-parallel mini-batching
  - Lots of items (inputs, outputs): sampling on the output
  - The goal is ranking: listwise loss functions on pointwise/pairwise scores

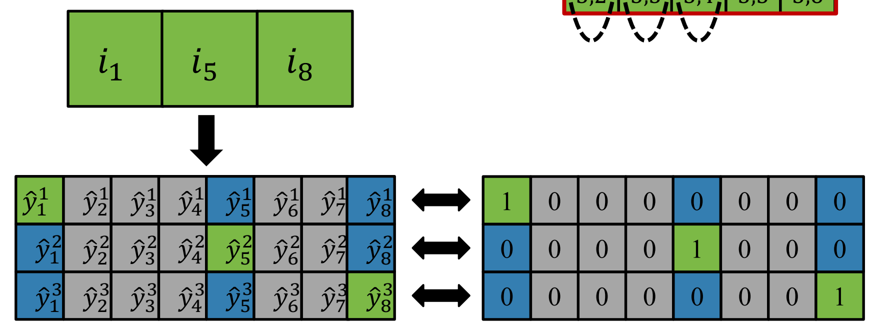


GRU4Rec (2/3)

- Session-parallel mini-batches
  - Mini-batch is defined over sessions
  - Update with one step BPTT
    - Lots of sessions are very short
    - 2D mini-batching, updating on longer sequences (with or without padding) didn't improve accuracy



- Output sampling
  - Computing scores for all items (100K – 1M) in every step is slow
  - One positive item (target) + several samples
  - Fast solution: scores on mini-batch targets
    - Items of the other mini-batch are negative samples for the current mini-batch



- Loss functions
  - Cross-entropy + softmax
  - Average of BPR scores
  - TOP1 score (average of ranking error + regularization over score values)

$$XE = -\log(s_i),\ s_i = \frac{e^{\hat{y}_i}}{\sum_{j=1}^{N_S} e^{\hat{y}_j}}$$

$$BPR = \frac{-\sum_{j=1}^{N_S} \log\left(\sigma\left(\hat{y}_i - \hat{y}_j\right)\right)}{N_S}$$

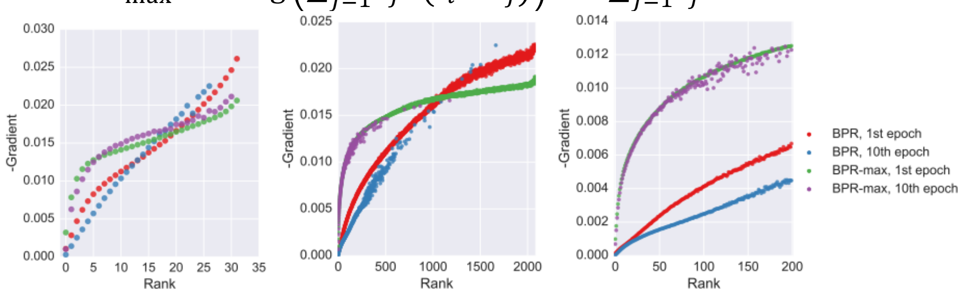
$$TOP1 = \frac{\sum_{j=1}^{N_S} \sigma\left(\hat{y}_j - \hat{y}_i\right) + \sum_{j=1}^{N_S} \sigma\left(\hat{y}_j^2\right)}{N_S}$$

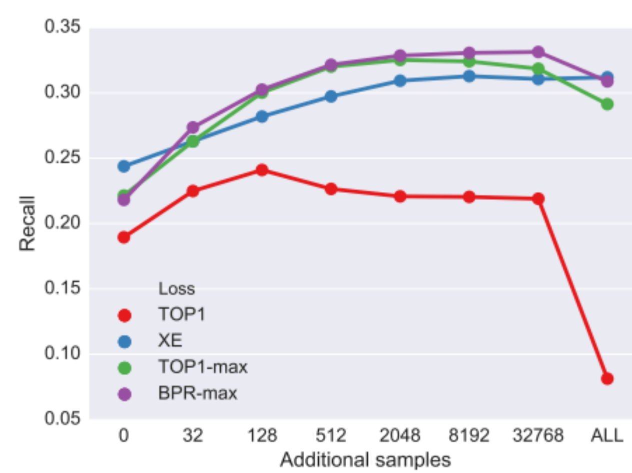
GRU4Rec (3/3)

- Observations
  - Similar accuracy with/without embedding
  - Multiple layers rarely help
    - Sometimes slight improvement with 2 layers
    - Sessions span over short time, no need for multiple time scales
  - Quick conversion: only small changes after 5-10 epochs
  - Upper bound for model capacity
    - No improvement when adding additional units after a certain threshold
    - This threshold can be lowered with some techniques
- Results
  - 20-30% improvement over item-to-item recommendations

Improving GRU4Rec

- Recall@20 on RSC15 by GRU4Rec: **0.6069** (100 units), **0.6322** (1000 units)
- Data augmentation [Tan et. al, 2016]
  - Generate additional sessions by taking every possible sequence starting from the end of a session
  - Randomly remove items from these sequences
  - Long training times
  - Recall@20 on RSC15 (using the full training set for training): ~**0.685** (100 units)
- Bayesian version (ReLeVar) [Chatzis et. al, 2017]
  - Bayesian formulation of the model
  - Basically additional regularization by adding random noise during sampling
  - Recall@20 on RSC15: **0.6507** (1500 units)
- New losses and additional sampling [Hidasi & Karatzoglou, 2017]
  - Use additional samples beside minibatch samples
  - Design better loss functions
    - $\mathrm{BPR}_{\max} = -\log\left(\sum_{j=1}^{N_S} s_j \sigma\left(r_i - r_j\right)\right) + \lambda \sum_{j=1}^{N_S} r_j^2$





  - Recall@20 on RSC15: **0.7119** (100 units)

Extensions

- Multi-modal information (p-RNN model) [Hidasi et. al, 2016]
  – Use image and description besides the item ID
  – One RNN per information source
  – Hidden states concatenated
  – Alternating training
- Item metadata [Twardowski, 2016]
  – Embed item metadata
  – Merge with the hidden layer of the RNN (session representation)
  – Predict compatibility using feedforward layers
- Contextualization [Smirnova & Vasile, 2017]
  – Merging both current and next context
  – Current context on the input module
  – Next context on the output module
  – The RNN cell is redefined to learn context-aware transitions
- Personalizing by inter-session modeling
  – Hierarchical RNNs [Quadrana et. al, 2017], [Ruocco et. al, 2017]
    - One RNN works within the session (next click prediction)
    - The other RNN predicts the transition between the sessions of the user

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Conclusions

- Deep Learning is now in RecSys
- Huge potential, but lot to do
  - E.g. Explore more advanced DL techniques
- Current research directions
  - Item embeddings
  - Deep collaborative filtering
  - Feature extraction from content
  - Session-based recommendations with RNNs
- Scalability should be kept in mind
- Don’t fall for the hype BUT don’t disregard the achievements of DL and its potential for RecSys

Thank you!