Session-based Recommendations with Recurrent Neural Networks

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Session-based recommendation

Permanent cold start: where personalized recommendations fail

- **User identification**: Many sites (e.g. classifieds, video services) don't require users to log in. Although some form of identification is possible, it is not reliable.
- **Intent/theme**: Sessions usually have a goal or a specific theme. Different sessions of the same user center around different concepts. The entire user history may not help much in identifying the user's current needs.
- **Never/rarely returning users**: High percentage of the users of webshops come from search engines in search for some products and rarely return.

Workaround in practice

- **Item-to-item recommendations**: Recommend similar or frequently co-occurring items.

We explore item-to-session recommendations. By modeling the whole session, more accurate recommendations can be provided. We propose an RNN-based approach to model the session and provide session-based recommendations.

Gated Recurrent Unit

Hidden state is the mix of the previous hidden state and the current hidden state candidate (controlled by the update gate):

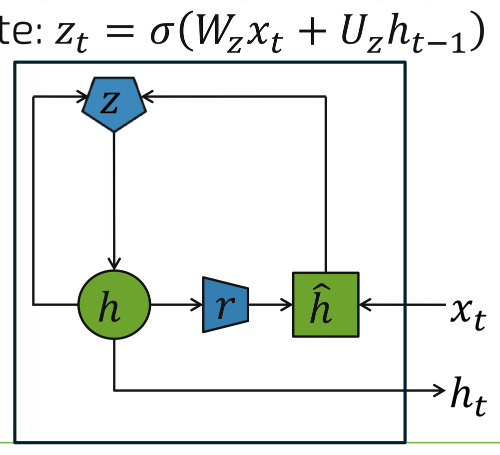
$$h_t = (1 - z_t)h_{t-1} + z_t\hat{h}_t$$

The reset gate controls the contribution of the previous hidden state to the hidden state candidate:

$$\hat{h}_t = \tanh\left(Wx_t + U(r_t \circ h_{t-1})\right)$$

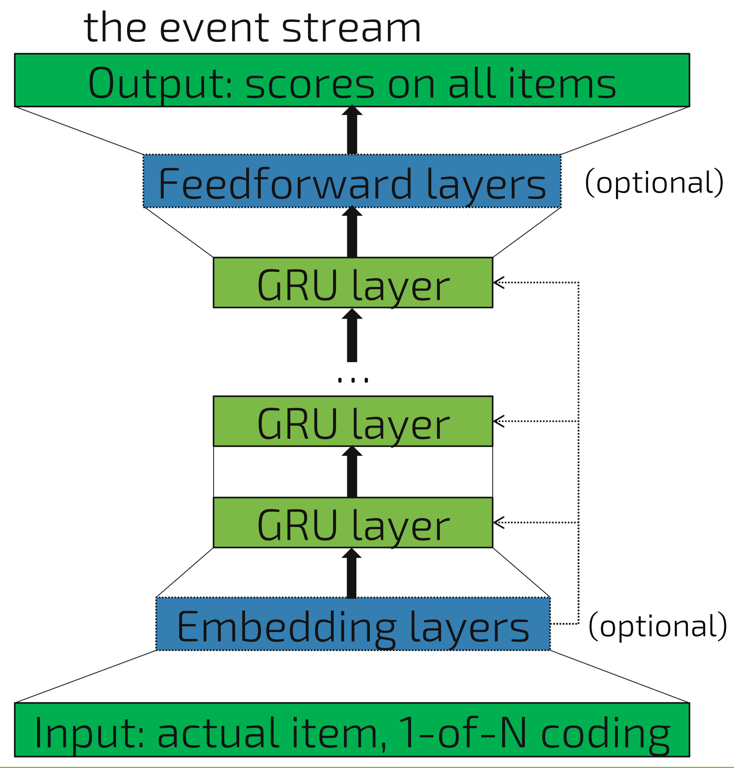
Reset gate: $r_t = \sigma(W_r x_t + U_r h_{t-1})$

Update gate: $z_t = \sigma(W_z x_t + U_z h_{t-1})$



Architecture

- Input: item of the actual event
- Output: likelihood for every item for being the next one in the event stream

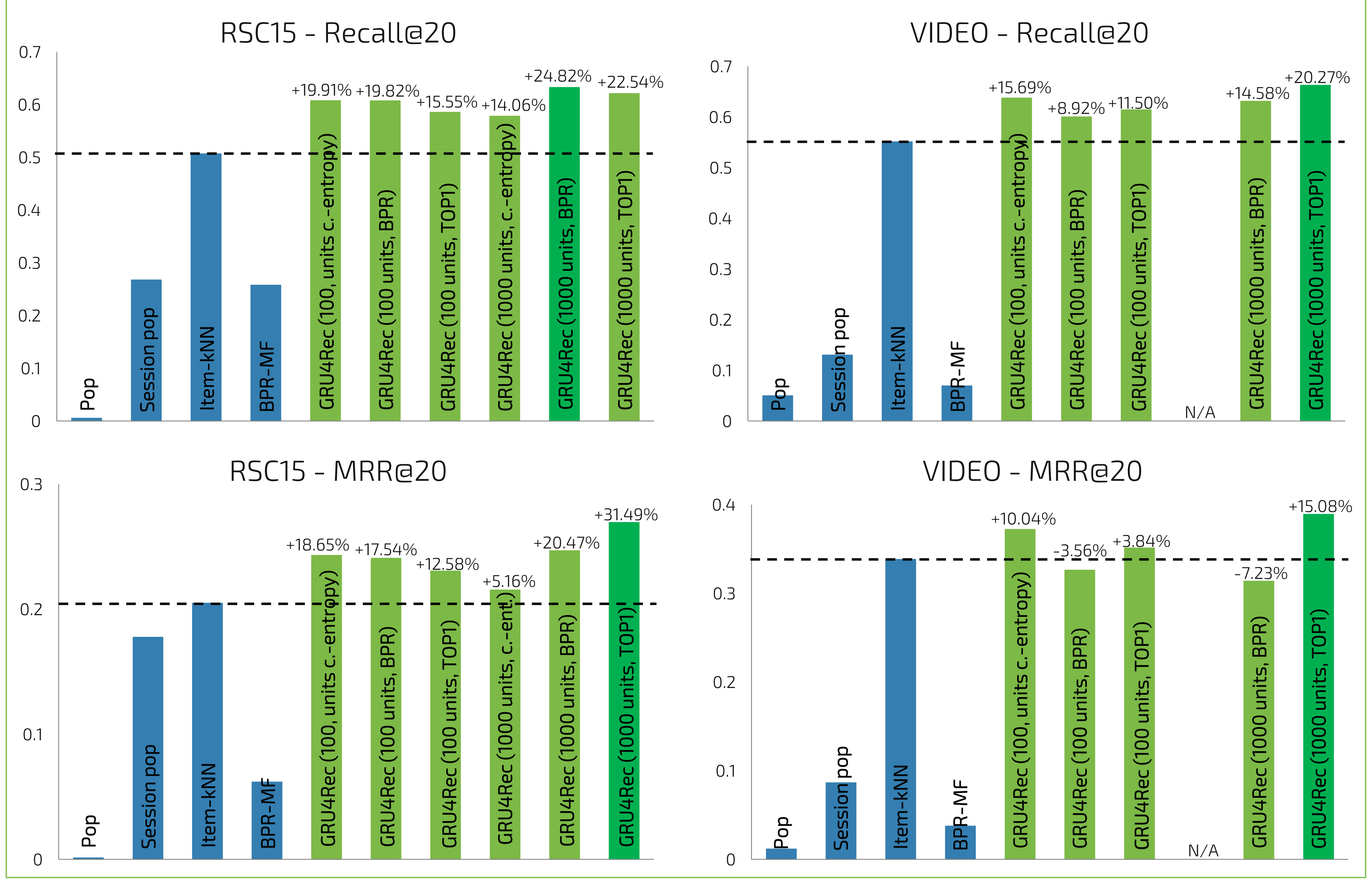


Experiments

Data	Description	Items	Train		Test	
			Sessions	Events	Sessions	Events
RSC15	RecSys Challenge 2015. Clickstream data of a webshop.	37,483	7,966,257	31,637,239	15,324	71,222
VIDEO	Watch events collected from a video service platform.	327,929	2,954,816	13,180,128	48,746	178,637

Findings (Architecture, training & parameters)

- Single layer GRU performs best
- Pre/postprocessing FF layers are not needed
- Adagrad works better than RMSProp
- TOP1 loss is better overall than other losses
- Pointwise losses (e.g. cross-entropy) are unstable
- Feeding the network earlier events of the session (i.e. reminding it) does not improve preformance
- LSTM & RNN are inferior to GRU
- The number of hidden units has the highest impact on performance



Adapting GRU to the RecSys task

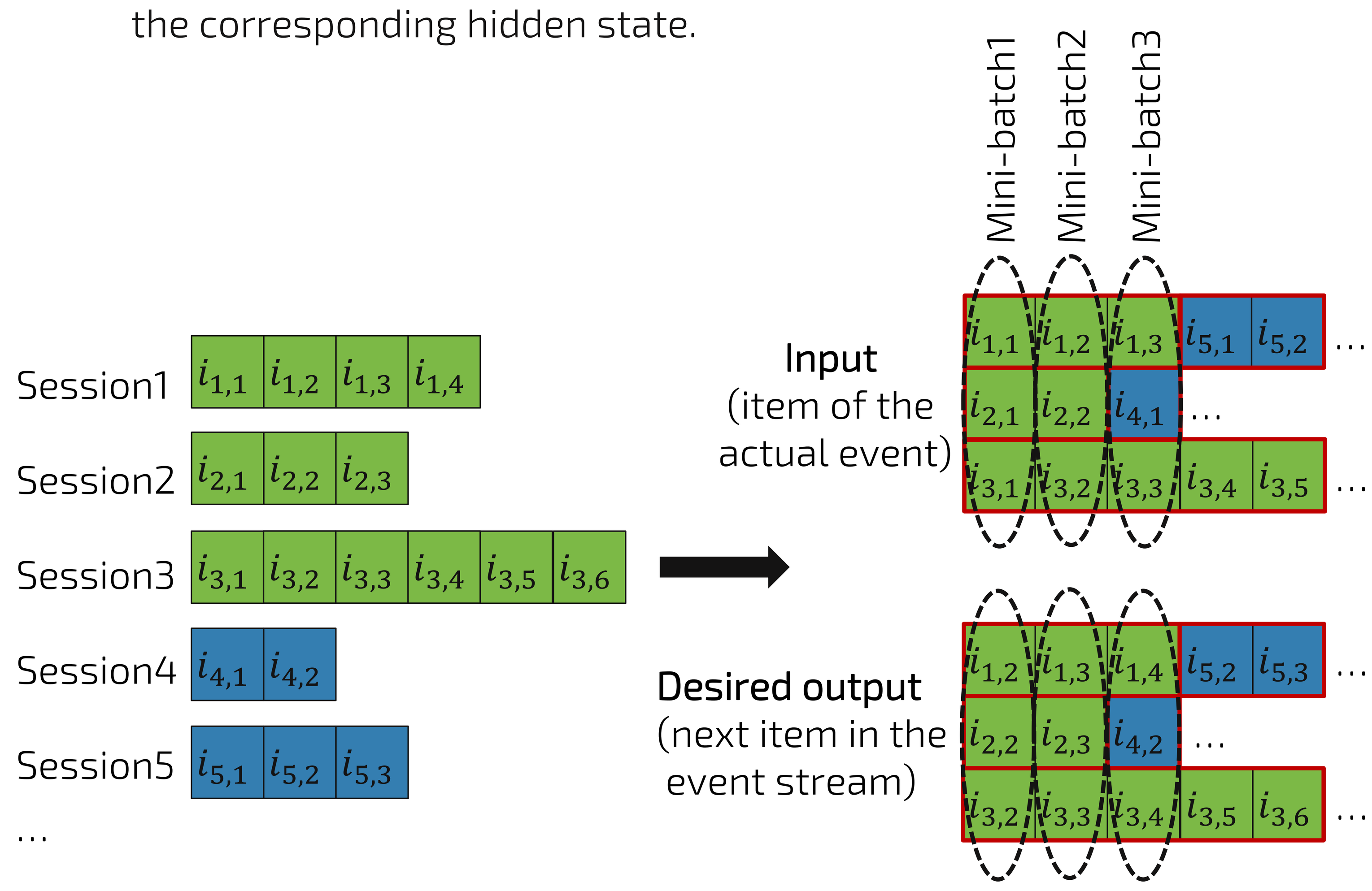
Session-parallel mini-batches

Motivation:

- High variance in the length of the sessions (from 2 to 100s of events)
- The goal is to capture how sessions evolve

Approach:

- Have an ordering of all sessions (e.g. random order or order by time)
- Take the first events of the first X sessions (X – mini-batch size) to form the first input mini-batch.
- The desired output is formed from the second events of the first X sessions.
- The second mini-batch (input) is formed from the second events, etc.
- If a session ends, put the next available session in its place and reset the corresponding hidden state.



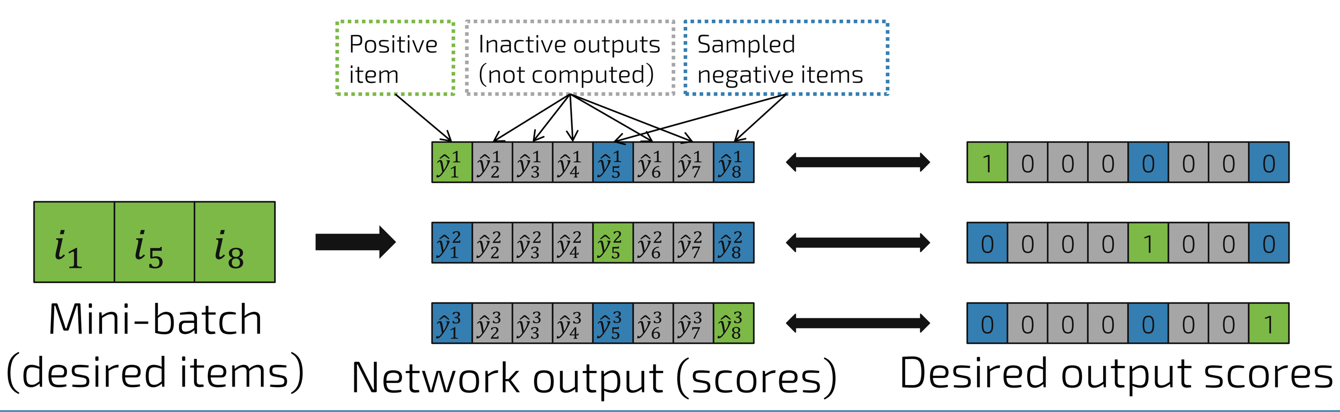
Sampling the output

Motivation:

- The number of items is generally high: 100,000s or even a few millions.
- Training scales with the product of the number of events, hidden units and outputs ($O(N_E H N_I)$). The latter equals to the number of items.
- Models need to be trained frequently to keep up with the changes in the item catalog and user behavior.

Approach:

- For an input, the desired output is a one-hot vector over all items.
- Always compute the score for the coordinate corresponding to the desired item. Sample the others.
- Popularity based sampling: it is more likely that the lack of an event on a more popular item means negative feedback.
- Use the items of the other examples of the mini-batch as the negative examples for each event in the mini-batch. This is a form of popularity based sampling with several practical benefits.



Ranking loss

Motivation:

- The ultimate goal of recommenders is to rank the items.
- Pointwise and pairwise rankings have been applied with great success (listwise ranking is not scalable enough in practice).
- Pairwise ranking (A is preferred over B) often performs better.

Approach:

- **BPR**: Adapt Bayesian Personalized Ranking for multiple negative samples.
  - $L = -\frac{1}{N_S}\sum_{j=1}^{N_S}\log\left(\sigma\left(\hat{r}_{s,i} - \hat{r}_{s,j}\right)\right)$
- **TOP1**: This ranking loss was devised by us for this task. It is the approximation of the relative rank of the desired item. Regularization is added for the sake of stability.
  - $L = \frac{1}{N_S}\sum_{j=1}^{N_S}\sigma\left(\hat{r}_{s,j} - \hat{r}_{s,i}\right) + \sigma\left(\hat{r}_{s,j}^2\right)$

Read the paper: http://arxiv.org/abs/1511.06939
Try the algorithm: https://github.com/hidasib/GRU4Rec

crowdrec