The colored text is unique to each paper, the plain text is the same.
This is a quick analysis, which could be fooled by rephrasing etc.

SIGIR paper

phrase-level sentiment analysis for identifying "topics" that are correlated with user ratings. Deep Cooperative Neural Networks (DeepCoNN) [51] model user-item interactions based on review texts by utilizing a factorization machine model [38] on top of two convolutional neural networks [24]. The TransNets model [3] extends the DeepCoNN model by introducing an additional layer that is regularized by the latent representation of review texts.

Recently, sequence-to-sequence (seq2seq) deep neural network

The user review decoder utilizes a single decoder GRU that iteratively generates reviews word by word. At time step t, the decoder GRU first embeds the output word $y_{i,t-1}$ at the previous time step into the corresponding word vector $x_{i,t-1} \in \mathcal{R}^k$, and then concatenates it with the user textual feature vector $\widetilde{U_i}$, i.e., $x'_{i,t} = \left[x_{i,t-1}, \widetilde{U_i}\right]$. The concatenated vector is provided as input into the decoder GRU to obtain the hidden activation h_t. Then the hidden activation is multiplied by an output projection matrix and passed through a softmax over all the words in the vocabulary to represent the probability of each word given the current context. The output word $y_{i,t}$ at time step t is sampled from the multinomial distribution given by the softmax. Note that, at each time step, the

with, each word in the review is mapped to the corresponding word vector, which is then concatenated with a user-specific vector that identifies user information. The user-specific vectors are learned together with other parameters during training. The concatenated vector representations are then processed by a convolutional layer, followed by a max-pooling layer and a fully-connected projection layer. The final output unit is a sigmoid non-linearity, which squashes the probability into the [0, 1] interval.

gradient ascent. The training objective of the discriminator is to minimize the probability of classifying adversarial samples to be authentic, while maximizing the probability of assigning correct labels to ground-truth reviews. The training objective can thus be

RecSys paper

collaborative filtering for ratings and deep representation learning for the textual information. The Deep Cooperative Neural Networks (DeepCoNN) [20] model user-item interactions based on review texts by utilizing a factorization machine model on top of two convolutional neural networks. The TNET model [3] extends the DeepCoNN model by introducing an additional layer that is regularized by the latent representation of reviews, enforcing the regularized representation to be similar to the embedding of the

with length l. The decoder employs a single GRU that iteratively produces reviews word by word. In particular, at time step t the GRU first maps the output representation z_{ut-1} of the previous time step into a k-dimensional vector y_{ut-1} and concatenates it with $\overline{U}_u$ to generate a new vector y_{ut}. Finally, y_{ut} is fed to the GRU to obtain the hidden representation h_t, and then h_t is multiplied by an output projection matrix and passed through a softmax over all the words in the vocabulary of the document to represent the probability of each word. The output word z_{ut} at time step t is sampled from the multinomial distribution given by the softmax.

CNN. Each word of the review r is mapped to the corresponding word vector, which is then concatenated with a user-specific vector. Notice that the user-specific vectors are learned together with the parameters of the discriminator D_θ in the adversarial training of Section 2.3. The concatenated vector representations are then processed by a convolutional layer, followed by a max-pooling layer and a fully-connected projection layer. The final output of the CNN

by minimizing the probability of classifying adversarial (machine-generated) reviews to be authentic, while maximizing the probability of classifying users' groundtruth reviews as authentic ones.