Deep Learning based Recommender System

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Overview

1. DEEP LEARNING BASED RECOMMENDATION
   - MLP based Recommendation
   - Autoencoder based Recommendation
   - CNN based Recommendation
   - RNN based Recommendation
   - RBM based Recommendation
   - Neural Attention based Recommendation
   - Neural AutoRegressive based Recommendation
   - Deep Reinforcement Learning for Recommendation
   - GAN based Recommendation
2. Summary

Outline

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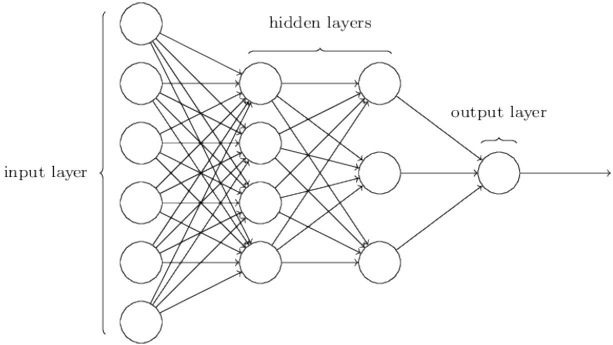
2. Summary

Multilayer Perceptron based Recommendation

1. What is Multilayer Perceptron(MLP)
2. Neural Extension of Traditional Recommendation Methods.
3. Feature Representation Learning with MLP

What is Multilayer Perceptron(MLP)

- MLP is a feed-forward neural network with multiple hidden layers

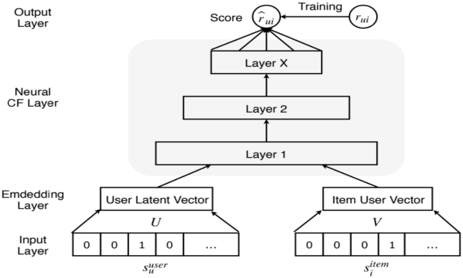


,

$$y_l = \phi(W_2 * \phi(W_1 * x))$$

Neural Extension of Traditional Methods

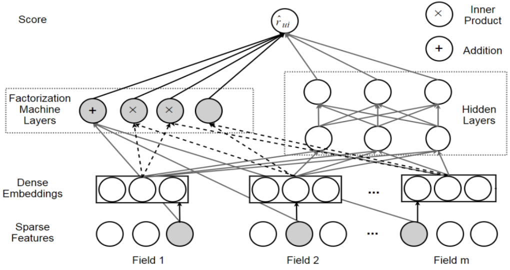
- Neural Collaborative Filtering (NCF)



$$\hat{r}_{ui} = f(U^T \cdot s_u^{user}, V^T \cdot s_i^{item} | U, V, \theta)$$

Feature Representation

- Deep Factorization Machine(DeepFM)
  - FM: linear and pairwise low-order interactions between features.
  - MLP leverages the non-linear activations and deep structure to model the high-order interactions.



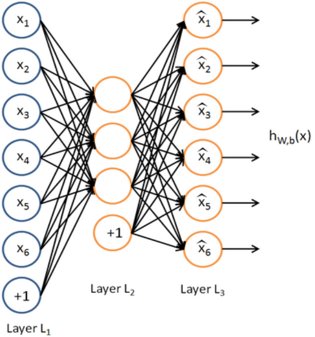
$$\hat{r}_{ui} = \sigma(y_{FM}(x) + y_{MLP}(x) + bias)$$

Autoencoder based Recommendation

- What is Autoencoder
- Autoencoder based Collaborative Filtering.
- Feature Representation Learning with Autoencoder

What is Autoencoder

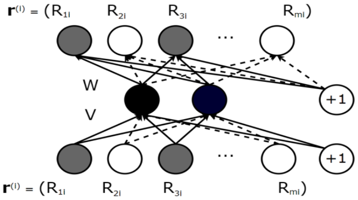
- An autoencoder neural network is an unsupervised learning algorithm, tring to learn a function $h_{W,b}(x) \approx x$.



  - filling the blanks of the interaction matrix directly in the reconstruction layer.
  - using autoencoder to learn lower-dimensional feature representations at the bottleneck layer;

Autoencoder based Collaborative Filtering.

- AutoRec
  - takes user partial vectors $r^{(u)}$ or item partial vectors $r^{(i)}$ as input, and aims to reconstruct them in the output layer.
  - Two variants: item-based AutoRec (I-AutoRec) and user-based AutoRec

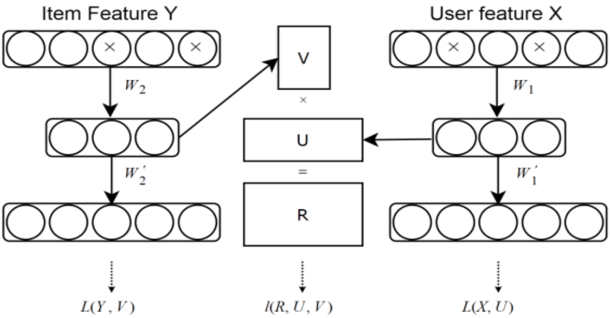


$$argmin_\theta = \sum_{i=1}^{N} \left\| r^i - h(r^i;\theta) \right\|_O^2 + \lambda \times reg$$

here $\|\cdot\|_O^2$ means that it only considers observed ratings

Feature Representation Learning with Autoencoder

- general framework to build hybrid collaborative models.



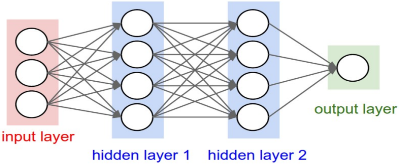
$$arg_{U,V} min\ l(R,U,V) + \beta(U^2 + V^2) + \gamma L(X,U) + \delta L(Y,V)$$

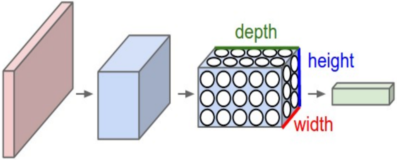
Convolutional Neural Networks based Recommendation

- What is Convolutional Neural Networks(CNN)
- Feature Representation Learning with CNNs.
- CNNs based Collaborative filtering.
- Graph CNNs for Recommendation.

What is Convolutional Neural Networks(CNN)

- a special kind of feed-forward neural network with convolution layers and pooling operations.





  - 默认输入是图像，把特定的性质编码入网络结构，使前馈函数更加有效率，并减少了大量参数。
  - CNNs are powerful in processing unstructured multimedia data with convolution and pool operations.

Feature Representation Learning with CNNs

- Most of the CNNs based recommendation models utilize CNNs for feature extraction.
  - Image Feature Extraction.
  - Text Feature Extraction
    - model user behaviors and item properties from review texts
    - alleviates the sparsity problem and enhances the model interpretability
  - Audio and Video Feature Extraction.
    - content based model can alleviate the cold start problem (music has not been consumed)

CNNs based Collaborative filtering

- ConvNCF
  - use outer product instead of dot product to model the user item interaction patterns.
  - CNNs are applied over the result of outer product and could capture the high-order correlations among embeddings dimensions.

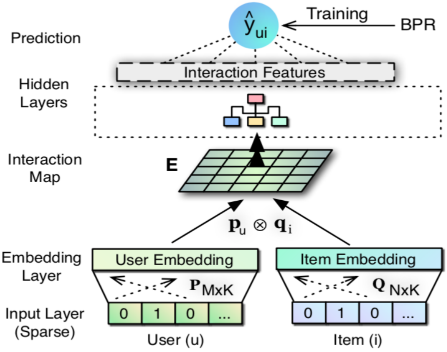


Figure 1: Outer Product-based NCF framework

CNNs based Collaborative filtering

- ConvNCF
  - 外积：交互矩阵融合了每个维度下特征之间的关系（传统 CF ：主对角线求和），能刻画特征维度之间的高阶关系。
  - 卷积：后一层的每一个元素都是由前一层的 4 个元素计算得来的，可以认为是一个 4 阶关系的刻画。直到最后的输出层，降到 1×1 后，即包含了特征每一个维度之间的交互信息。CNN 比 MLP 更容易泛化和建立更深的网络。

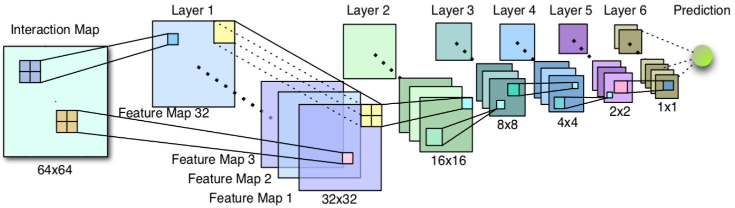


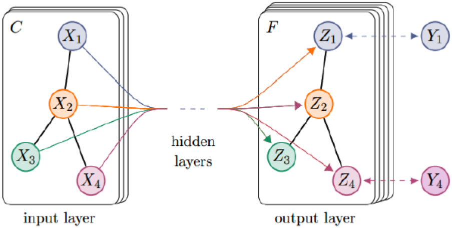
Figure 2: An example of the architecture of our ConvNCF model that has 6 convolution layers with embedding size 64.

Graph CNNs for Recommendation.

- Interactions in recommendation area can also be viewed as bipartite graph,thus the recommendation problem can be considered as a link prediction task with graph CNNs.

- GCN: Graph Convolution Network
  - Set $K = 2$ and view the center node as one of its neighbor, resulting in only one free parameter for each convolution filter
  - Offer an explanation of feature diffusion over graph

$$H^{(l+1)} = \sigma\left(\tilde{D}^{-\frac{1}{2}}\tilde{A}\tilde{D}^{-\frac{1}{2}}H^{(l)}W^{(l)}\right) \qquad H^{(0)} = X$$

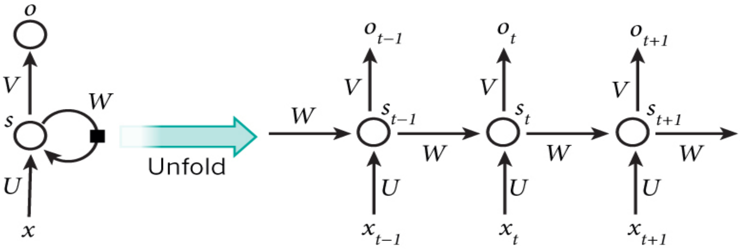


Recurrent Neural Networks based Recommendation

- What is Recurrent Neural Networks(RNN)
- Session-based Recommendation without User Identifier
- Sequential Recommendation with User Identifier
- Feature Representation Learning with RNNs

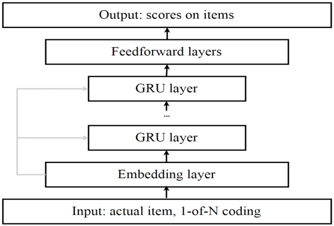
What is Recurrent Neural Networks(RNN)

- RNN is suitable for modelling sequential data. Unlike feedforward neural network, there are loops and memories in RNN to remember former computations.
- RNN 的结构不同于 MLP，输入层与来自序列中上一元素隐层的信号共同作用到当前的隐藏层



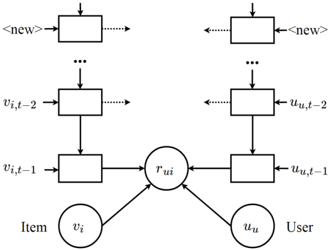
Session-based Recommendation without User Identifier

- GRU4Rec
  1. 输入:用户的行为序列: $[x_1, x_2, x_3, .., x_N]$(1-of-N encoding,或者再过一个Embedding层)
  2. 过若干层的GRU(核心的序列化建模)
  3. Feedforward网络转换
  4. 对下一个目标x_{N+1}进行预测



Sequential Recommendation with User Identifier

- Recurrent Recommender Network (RRN)
  - modelling the seasonal evolution of items and changes of user preferences over time
  - uses two LSTM networks to model dynamic user state u_{ut} and item state v_{it} .
  - incorporates stationary latent attributes such as user long-term interests and item static features: u_u and v_i.



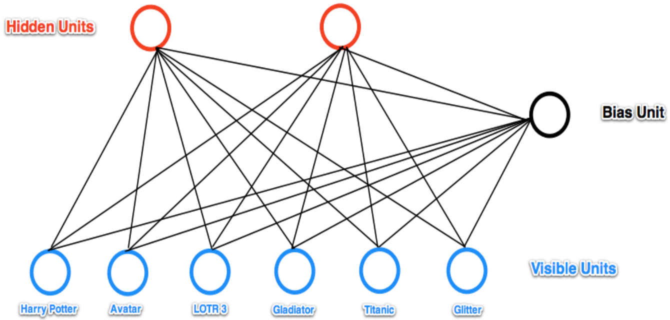
$$\hat{r}_{ui|t} = f(u_{ut}, v_{it}, u_u, v_i)$$

Feature Representation Learning with RNNs

- For side information with sequential patterns
  - learn representations of evolution and co-evolution of user and item features.
  - encode the text sequences into latent factor model.
  - learn more expressive aggregation for user browsing history
  - predicting ratings as well as generating textual tips for users simultaneously
  - two sub-networks to modelling user static features (with MLP) and user temporal features (with RNNs).

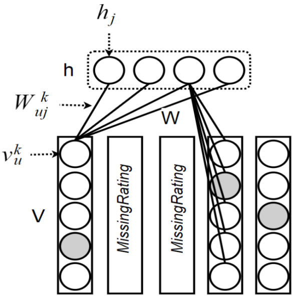
- What is Restricted Boltzmann Machine(RBM)
- Restricted Boltzmann Machine based Recommendation

- RBM is a two layer neural network consisting of a visible layer and a hidden layer.
  - 限制在同一层的神经元之间不会相互连接，而不在同一层的神经元之间会相互连接，连接是双向的以及对称的。这意味着在网络进行训练以及使用时信息会在两个方向上流动，而且两个方向上的权值是相同的。
  - 可见变量和隐藏变量都是二元变量，亦即其状态取0,1



Restricted Boltzmann Machine based Recommendation

- RBM-CF
  - the first recommendation model that built on neural networks.
  - user/item-based RBM-CF :given user’ s/item’s rating is clamped on the visible layer.
  - 假设有m个电影, 则使用m个softmax单元来作为可见单元来构造RBM.如果一个用户没有对第j个电影评分, 则该用户的RBM中不存在第j个softmax单元.



Algorithm 4.4 RBM - Making recommendations

Inputs: a user u, an movie i

Outputs: an estimation of $R(u, i)$

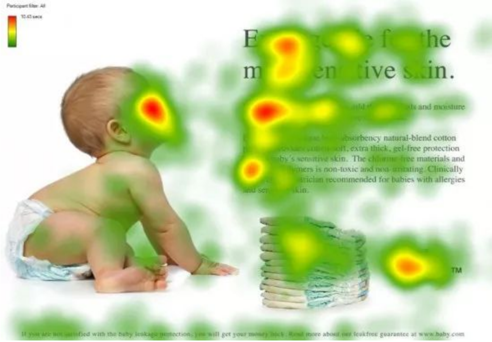
1. Clamp the ratings of u over the softmax units of the RBM.
2. Compute $\boxed{\hat{p}_j = p(h_j = 1|V)}$ for all hidden units j.
3. Compute $\boxed{p(v_i^k = 1|\hat{p}) = \frac{\exp(b_i^k + \sum_{j=1}^{F} \hat{p}_j W_{ij}^k)}{\sum_{l=1}^{K} \exp(b_i^l + \sum_{j=1}^{F} \hat{p}_j W_{ij}^l)} \text{ for } k = 1, ..., K.}$
4. Take the expectation as the prediction, i.e., $R(u, i) = \sum_{k=1}^{K} p(v_i^k = 1|\hat{p})k$.

Neural Attention based Recommendation

- What is Neural Attention.
- Recommendation with Vanilla Attention
- Recommendation with Co-Attention

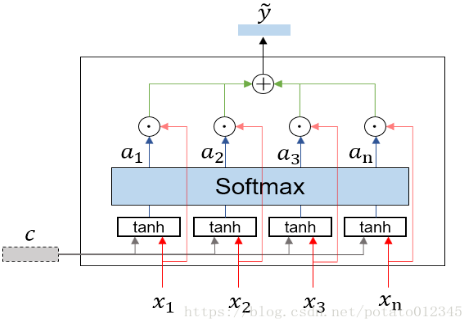
What is Neural Attention

- Attention mechanism is motivated by human visual attention.
- 核心目标:从众多信息中选择出对当前任务目标更关键的信息。

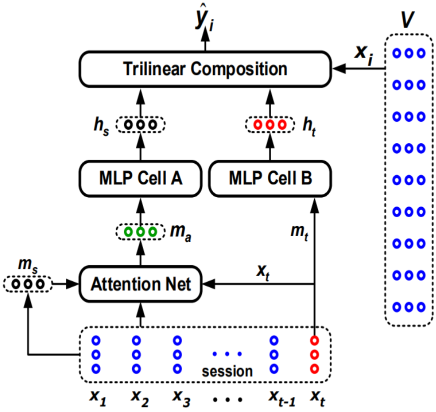


What is Neural Attention

- attention model learns to attend to the input with attention scores (the heart of neural attention models).

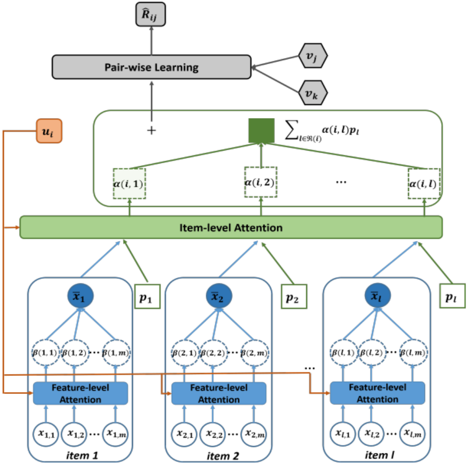


- 基于记忆优先级的短序列推荐
  - 对session内前n-1个全局商品用attention建模得到一个全局表达，并输入MLP



Recommendation with Vanilla Attention

- Attentive Collaborative Filtering(ACF)
  - select items from implicit that are representative to user preferences and then aggregate them to characterize users.



- item-level attention

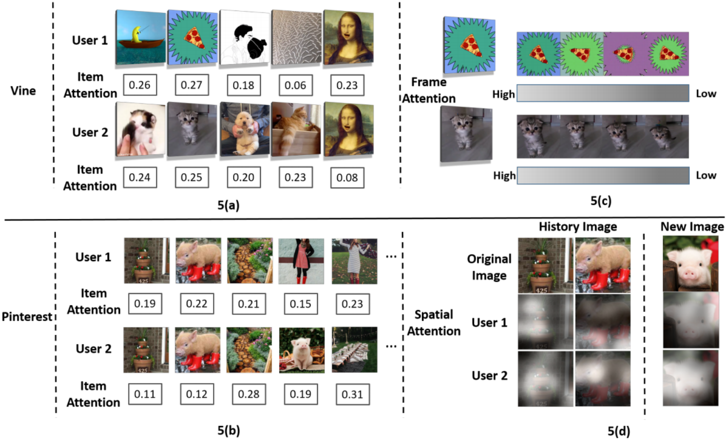
$$u_i + \sum_{l \in R(i)} \alpha(i,l) p_l$$

- component-level attention

$$\bar{x}_l = \sum_{m=1}^{|\{x_{l*}\}|} \beta(i,l,m) \cdot x_{lm}$$

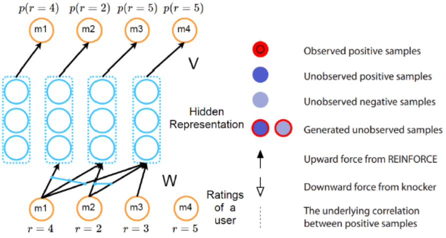
Recommendation with Vanilla Attention

- Attentive Collaborative Filtering(ACF)
  - Attention Visualization



Neural AutoRegressive based Recommendation

- tractable的分布估计器，它是RBM的理想的替代品
- NADE based collaborative filtering model (CF-NADE)
  - models the distribution of user ratings.
  - 有4部电影：m1（评分为4），m2（评分为2），m3（评分为3），m4（评分为5）。 CF-NADE利用链式法则得到的评分向量r的联合概率



(a)

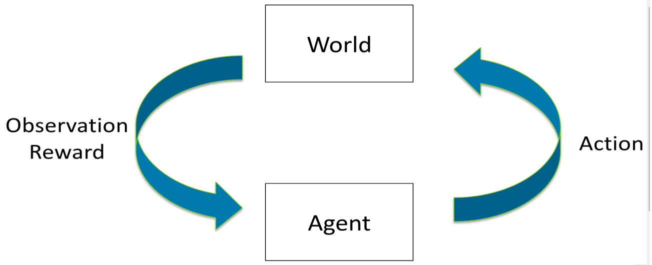
$$p(r) = \Sigma_{i=1}^{4} p(r_{m_i} | r_{m_{<i}})$$

Deep Reinforcement Learning for Recommendation

- What is Deep Reinforcement Learning (DRL)
- Deep Reinforcement Learning for Recommendation

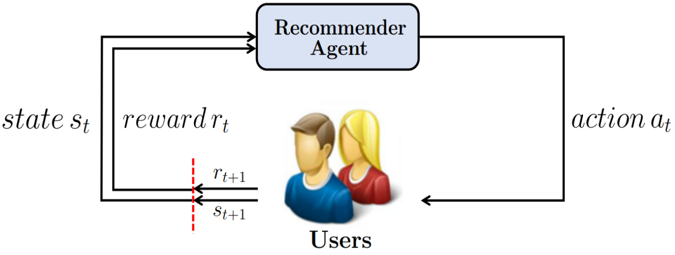
What is Deep Reinforcement Learning (DRL)

- Reinforcement Learning:Learn to make good sequences of decisions
  - Repeated Interactions with World
  - Reward for Sequence of Decisions
  - Repeated Interactions with World
- trial-and-error paradigm
- components: agents, environments, states, actions and rewards.



Deep Reinforcement Learning for Recommendation

- recommender agent (RA) interacts with environment E (or users) by sequentially choosing recommendation items over a sequence of time steps, so as to maximize its cumulative reward.



Adversarial Network based Recommendation

- What is Adversarial Network (AN)
- Adversarial Network based Recommendation

What is Adversarial Network (AN)

- Adversarial Networks (AN) is a generative neural network which consists of a discriminator and a generator.
- They trained simultaneously by competing with each other in a min-max game framework.

Adversarial Network based Recommendation

- IRGAN
  - 在信息检索上有两个思维方式，即生成式检索和判别式检索:
  - Generative retrieval assumes that there is an underlying generative process between documents and queries, and retrieval tasks can be achieved by generating relevant document given a query.
  - Discriminative retrieval learns to predict the relevance score given labelled relevant query-document pairs.
  - minimax game : generative retrieval aims to generate relevant documents similar to ground truth to fool the discriminative retrieval model.

Outline

1 DEEP LEARNING BASED RECOMMENDATION

2 Summary

Why Deep Neural Networks for Recommendation

- Nonlinear Transformation
  - 捕获非线性和非平凡的用户-物品关系
- Representation Learning
  - 捕获数据本身的复杂联系(上下文，文本和视觉信息)
- Sequence Modelling
- Flexibility

The End