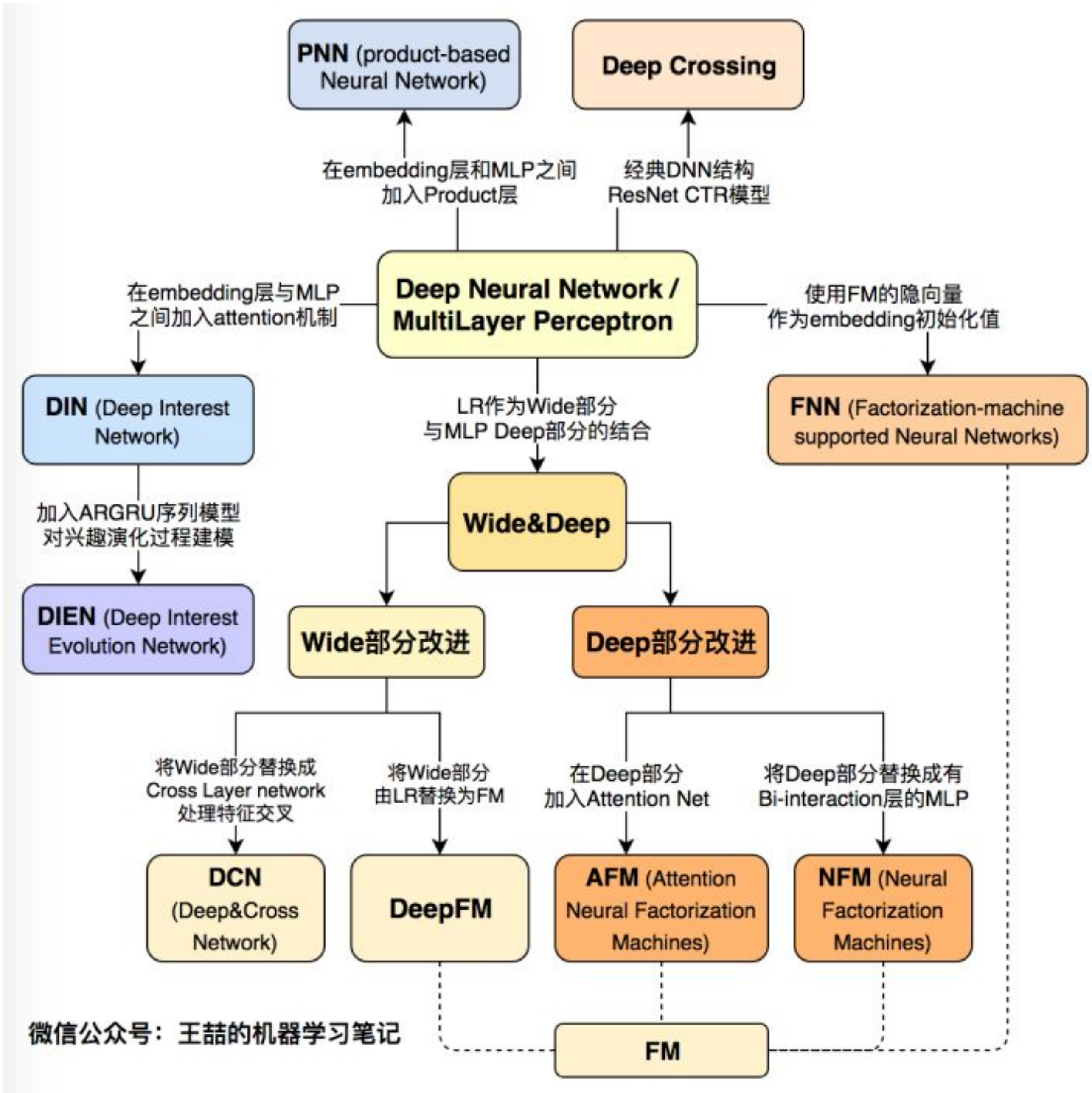
paper reading

开局一张图：



微软Deep Crossing（2016年）： Deep Crossing - Web-Scale Modeling without Manually Crafted Combinatorial Features

Feature name	Type	Dimension
Query	Text	49,292
Keyword	Text	49,292
Title	Text	49,292
MatchType	Category	4
CampaignID	ID	10,001
CampaignIDCount	Numerical	5

Table 1: Examples of individual features

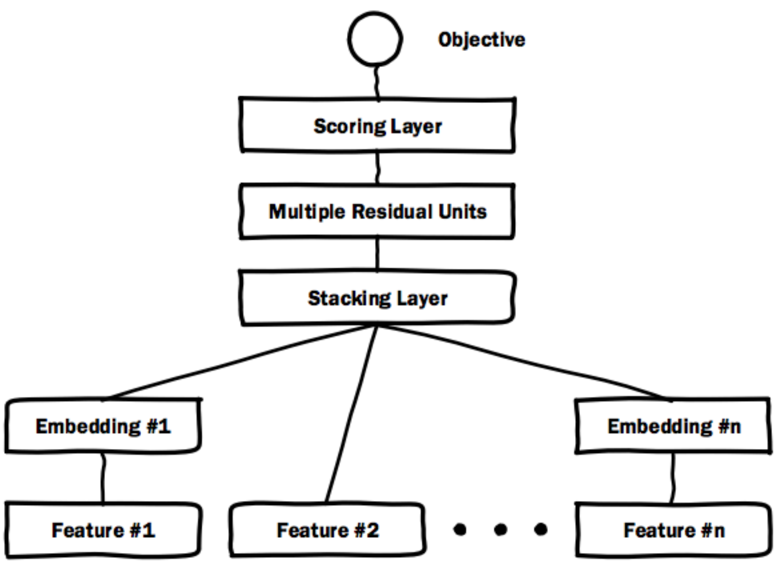


Figure 1: Deep Crossing Model Architecture

embedding layer

$$X_j^O = \max(\mathbf{0}, \mathbf{W}_j X_j^I + \mathbf{b}_j),$$

这里的stacking layer其实就是concat layer

Residual Units， 与图像领域的不同是，没用卷积核

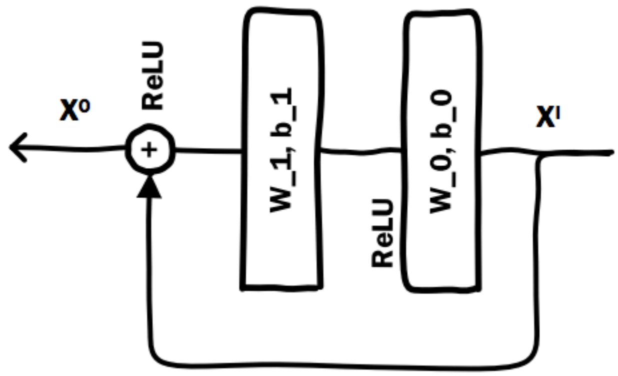


Figure 2: A Residual Unit

$$X^O = \mathcal{F}(X^I, \{\mathbf{W}_0, \mathbf{W}_1\}, \{\mathbf{b}_0, \mathbf{b}_1\}) + X^I,$$

FNN（2016年）：Deep Learning over Multi-field Categorical Data– A Case Study on User Response Prediction

Factorisation-machine supported Neural Networks (FNN)

主要是为了解决，最近的一些 方法在feature计算上计算量过重（The former loses the ability of exploring feature interactions, while the latter results in a heavy computation in the large feature space）
给出了三种feature transformation 方法，FM，RBMs，DAEs

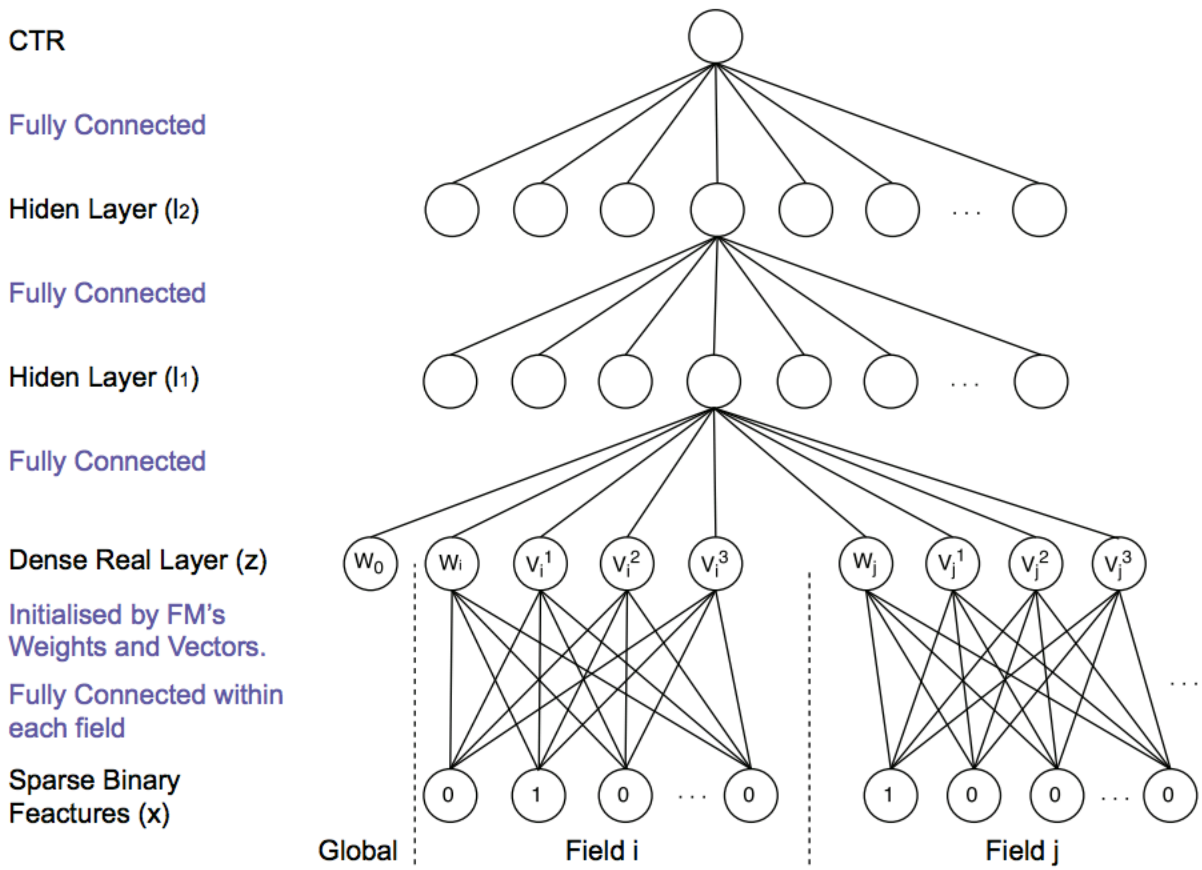


Fig. 1. A 4-layer FNN model structure.

$$y_{\mathrm{FM}}(\boldsymbol{x}) := \mathrm{sigmoid}\left(w_0 + \sum_{i=1}^{N} w_i x_i + \sum_{i=1}^{N} \sum_{j=i+1}^{N} \langle \boldsymbol{v}_i, \boldsymbol{v}_j \rangle x_i x_j\right),$$

PNN（2016年）： Product-based Neural Networks for User ResponsePrediction

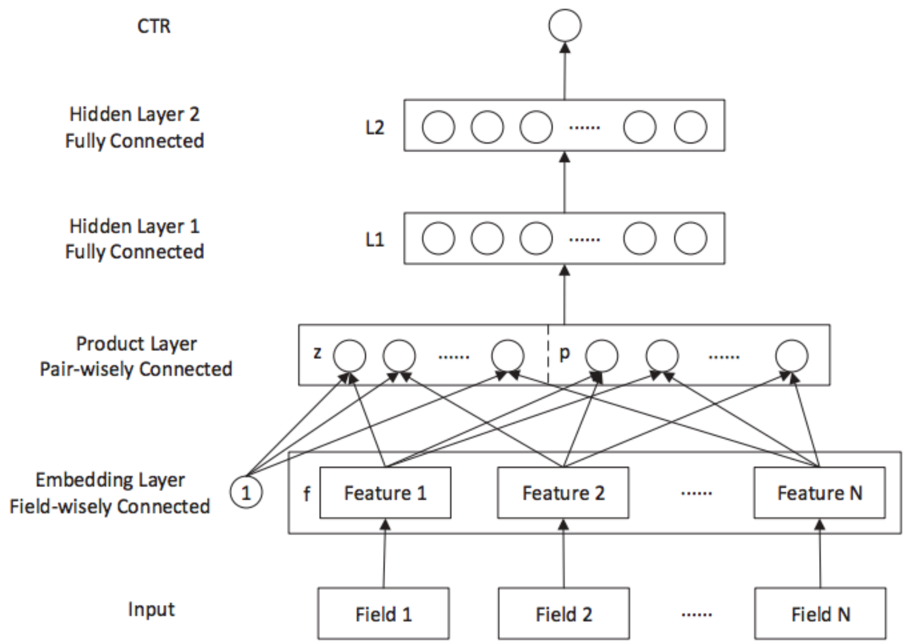
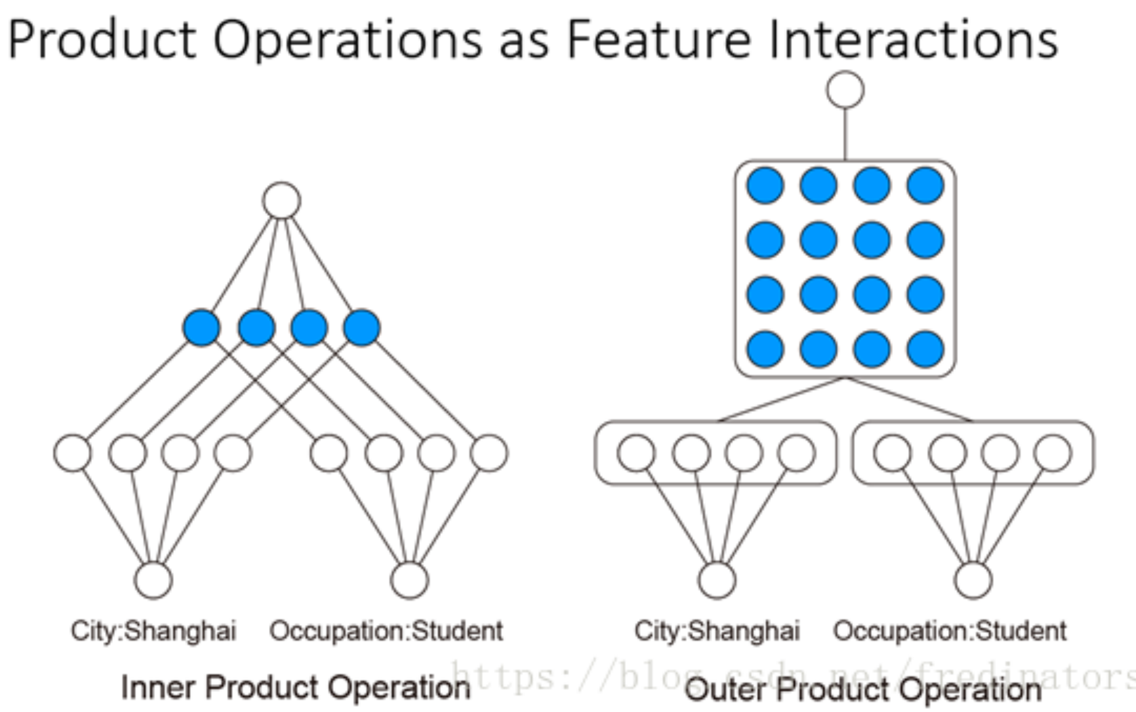


Fig. 1: Product-based Neural Network Architecture.



Google Wide&Deep（2016年）：Wide & Deep Learning for Recommender Systems

华为 DeepFM (2017年)： DeepFM: A Factorization-Machine based Neural Network for CTR Prediction

Google Deep&Cross（2017年）： Deep & Cross Network for Ad Click Predictions

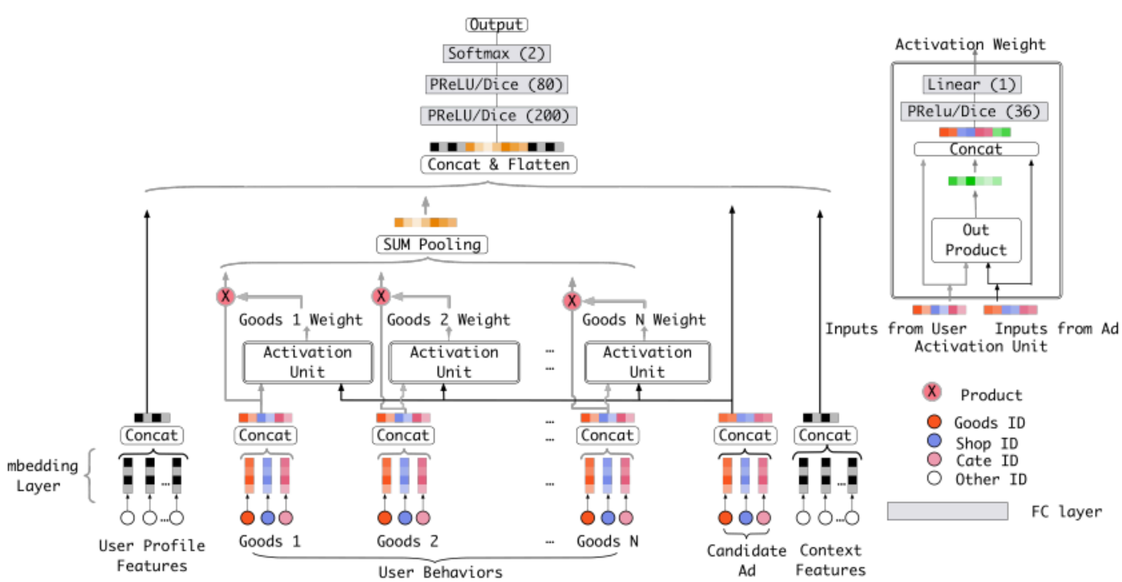
NFM（2017年）： Neural Factorization Machines for Sparse Predictive Analytics*

AFM（2017年）引入Attention机制的FM： Attentional Factorization Machines:Learning the Weight of Feature Interactions via Attention Networks

阿里DIN（2018年）： Deep Interest Network for Click-Through Rate Prediction

主要是加入了attention
对比为普通的dnn模型，还包括wide&deep

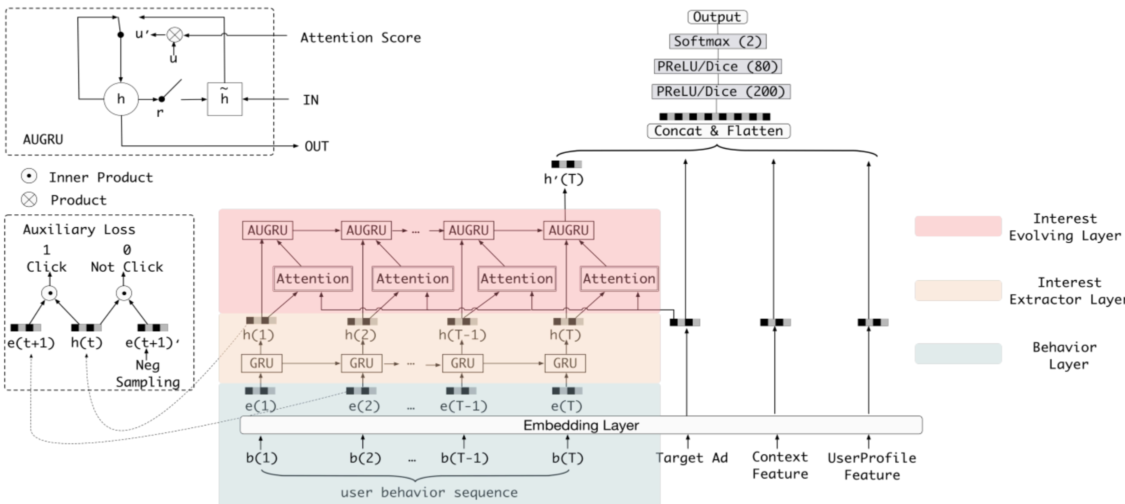
特征为one-hot直接embedding，multi-hot是sum(embedding)



Deep Interest Network

论文里还提了一个正则化方法，能够大幅减小计算量

阿里DIEN（2018年）：Deep Interest Evolution Network for Click-Through Rate Prediction



1、综述论文：Deep Learning based Recommender System: A Survey and New Perspectives
Key contribute:
(1) We conduct a systematic review for recommendation models based on deep learning techniques and propose a classification scheme to position and organize the current work;
(2) We provide an overview and summary for the state-of-the-arts.
(3) We discuss the challenges and open issues, and identify the new trends and future directions in this research field to share the vision and expand the horizons of deep learning based recommender system research.

1、方法梳理
Recommendation models are usually classified into three categories:
a) collaborative filtering
b) content based
c) hybrid recommender system

列举了主流的DL技术方向：

Multilayer Perceptron (MLP) , Autoencoder(AE) ,   Convolutional Neural Network (CNN) ,
Recurrent Neural Network (RNN) ,   Restricted Boltzmann Machine (RBM) ,   Neural Autoregressive Distribution Estimation (NADE)
Adversarial Networks (AN) ,   Attentional Models (AM) ,   DeepReinforcementLearning(DRL)

DL的吸引点：
(1) end-to-end differentiable and (2) provide suitable inductive biases catered to the input data type

DL所擅长的点：
a) Nonlinear Transformation
b) Representation Learning：减少特征工程，引入图片文本等高阶特征
c) Sequence Modelling
d) Flexibility

DL的限制
a) Interpretability：可解释性不足
b) Data Requirement ：数据规模要求较高
c) Extensive Hyperparameter Tuning ：