DeepCTR-Torch Documentation

Release 0.2.9

Weichen Shen

Oct 21, 2022

Home:

DeepCTR-Torch is a **Easy-to-use** , **Modular** and **Extendible** package of deep-learning based CTR models along with lots of core components layer which can be used to build your own custom model easily.It is compatible with **PyTorch**.You can use any complex model with `model.fit()` and `model.predict()`.

Let's Get Started! (Chinese Introduction)

You can read the latest code at https://github.com/shenweichen/DeepCTR-Torch and DeepCTR for tensorflow version.

CHAPTER 1

News

10/22/2022 : Add multi-task models: SharedBottom, ESMM, MMOE, PLE. Changelog

06/19/2022 : Fix some bugs. Changelog

06/14/2021 : Add AFN and fix some bugs. Changelog

CHAPTER 2

DisscussionGroup

wechat ID: **deepctrbot**

Discussions

公众号

学习小组

2.1 Quick-Start

2.1.1 Installation Guide

`deepctr-torch` depends on torch>=1.2.0, you can specify to install it through `pip`.

```
$ pip install -U deepctr-torch
```

2.1.2 Getting started: 4 steps to DeepCTR-Torch

Step 1: Import model

```
import pandas as pd
import torch
from sklearn.metrics import log_loss, roc_auc_score
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, MinMaxScaler

from deepctr_torch.inputs import SparseFeat, DenseFeat, get_feature_names

data = pd.read_csv('./criteo_sample.txt')

sparse_features = ['C' + str(i) for i in range(1, 27)]
dense_features = ['I' + str(i) for i in range(1, 14)]

data[sparse_features] = data[sparse_features].fillna('-1', )
data[dense_features] = data[dense_features].fillna(0, )
target = ['label']
```

Step 2: Simple preprocessing

Usually there are two simple way to encode the sparse categorical feature for embedding

- Label Encoding: map the features to integer value from 0 ~ len(#unique) - 1

```
for feat in sparse_features:
    lbe = LabelEncoder()
    data[feat] = lbe.fit_transform(data[feat])
```

- Hash Encoding: Currently not supported.

And for dense numerical features,they are usually discretized to buckets,here we use normalization.

```
mms = MinMaxScaler(feature_range=(0,1))
data[dense_features] = mms.fit_transform(data[dense_features])
```

Step 3: Generate feature columns

For sparse features, we transform them into dense vectors by embedding techniques. For dense numerical features, we concatenate them to the input tensors of fully connected layer.

- Label Encoding

```
fixlen_feature_columns = [SparseFeat(feat, vocabulary_size=data[feat].nunique(),
↪embedding_dim=4)
                       for i,feat in enumerate(sparse_features)] + [DenseFeat(feat, 1,
↪)
                      for feat in dense_features]
```

- Feature Hashing on the flycurrently not supported

```
fixlen_feature_columns = [SparseFeat(feat, vocabulary_size=1e6,embedding_dim=4, use_
↪hash=True, dtype='string')  # since the input is string
                              for feat in sparse_features] + [DenseFeat(feat, 1, )
                          for feat in dense_features]
```

- generate feature columns

```
dnn_feature_columns = sparse_feature_columns + dense_feature_columns
linear_feature_columns = sparse_feature_columns + dense_feature_columns

feature_names = get_feature_names(linear_feature_columns + dnn_feature_columns)
```

Step 4: Generate the training samples and train the model

```
train, test = train_test_split(data, test_size=0.2)
train_model_input = {name:train[name] for name in feature_names}

test_model_input = {name:test[name] for name in feature_names}


device = 'cpu'
use_cuda = True
if use_cuda and torch.cuda.is_available():
    print('cuda ready...')
    device = 'cuda:0'

model = DeepFM(linear_feature_columns,dnn_feature_columns,task='binary',device=device)
model.compile("adam", "binary_crossentropy",
              metrics=['binary_crossentropy'], )

history = model.fit(train_model_input,train[target].values,batch_size=256,epochs=10,
↪verbose=2,validation_split=0.2)
pred_ans = model.predict(test_model_input, batch_size=256)
```

You can check the full code here.

2.2 Features

2.2.1 Overview

With the great success of deep learning,DNN-based techniques have been widely used in CTR estimation task.

DNN based CTR estimation models consists of the following 4 modules: `Input,Embedding, Low-order&High-order Feature Extractor,Prediction`

- Input&Embedding

  The data in CTR estimation task usually includes high sparse,high cardinality categorical features and some dense numerical features.

  Since DNN are good at handling dense numerical features,we usually map the sparse categorical features to dense numerical through `embedding technique`.

  For numerical features,we usually apply `discretization` or `normalization` on them.

- Feature Extractor

  Low-order Extractor learns feature interaction through product between vectors.Factorization-Machine and it's variants are widely used to learn the low-order feature interaction.

  High-order Extractor learns feature combination through complex neural network functions like MLP,Cross Net,etc.

2.2.2 Feature Columns

SparseFeat

`SparseFeat` is a namedtuple with signature `SparseFeat(name, vocabulary_size, embedding_dim, use_hash, dtype,embedding_name, group_name)`

- name : feature name
- vocabulary_size : number of unique feature values for sprase feature or hashing space when `use_hash=True`
- embedding_dim : embedding dimension
- use_hash : defualt `False`.If `True` the input will be hashed to space of size `vocabulary_size`.
- dtype : default `float32`.dtype of input tensor.
- embedding_name : default `None`. If None, the embedding_name will be same as `name`.
- group_name : feature group of this feature.

DenseFeat

`DenseFeat` is a namedtuple with signature `DenseFeat(name, dimension, dtype)`

- name : feature name
- dimension : dimension of dense feature vector.
- dtype : default `float32`.dtype of input tensor.

VarLenSparseFeat

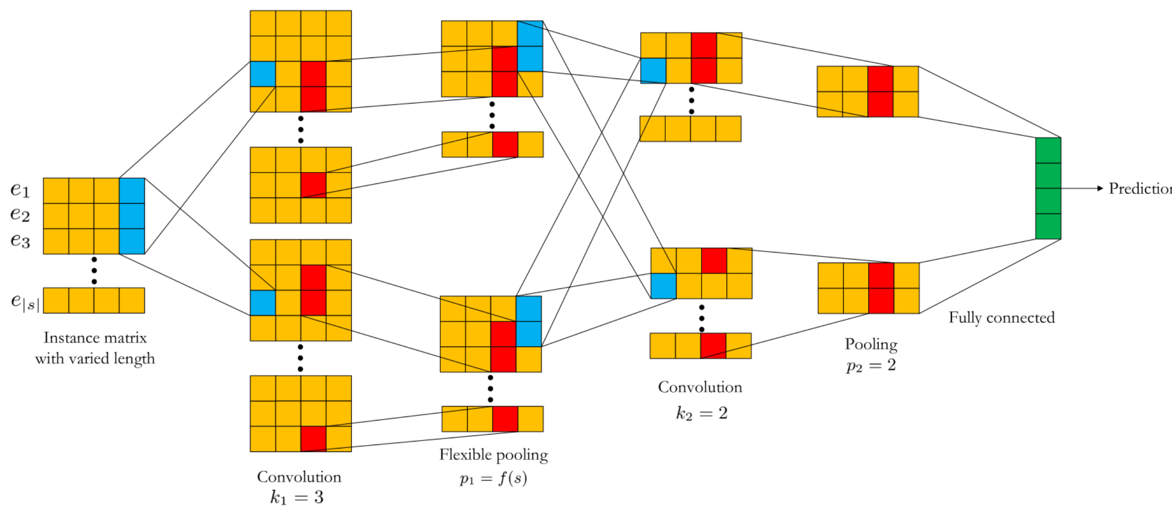
`VarLenSparseFeat` is a namedtuple with signature `VarLenSparseFeat(sparsefeat, maxlen, combiner, length_name)`

- sparsefeat : a instance of `SparseFeat`
- maxlen : maximum length of this feature for all samples
- combiner : pooling method,can be `sum`,`mean` or `max`
- length_name : feature length name,if `None`, value 0 in feature is for padding.

2.2.3 Models

CCPM (Convolutional Click Prediction Model)

CCPM can extract local-global key features from an input instance with varied elements, which can be implemented for not only single ad impression but also sequential ad impression.



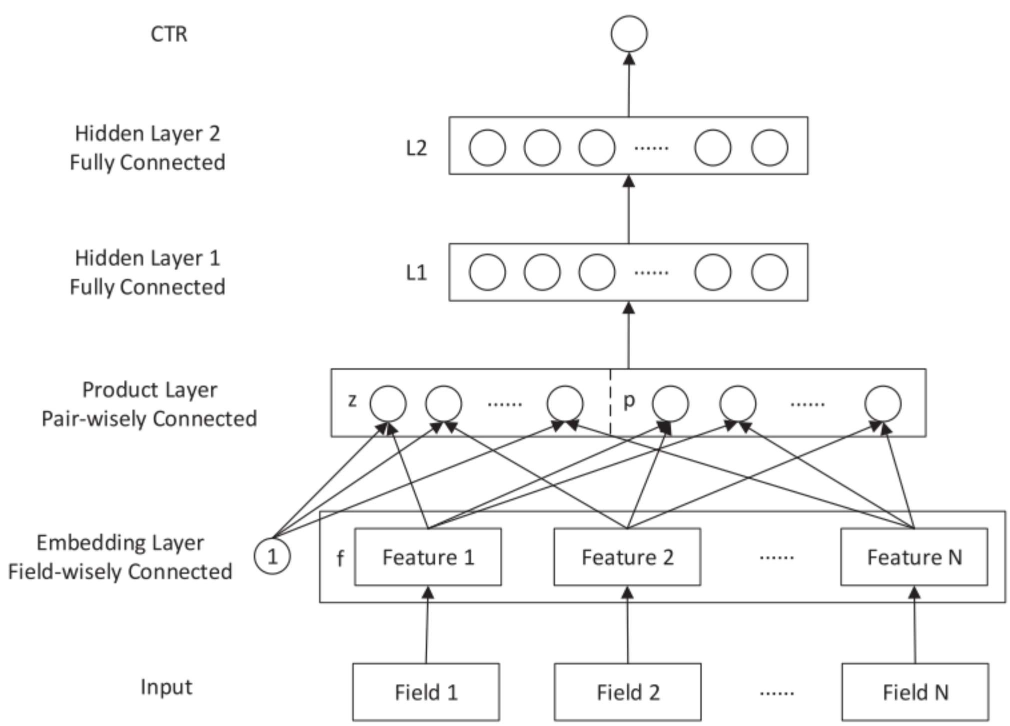
CCPM Model API

Liu Q, Yu F, Wu S, et al. A convolutional click prediction model[C]//Proceedings of the 24th ACM International on Conference on Information and Knowledge Management. ACM, 2015: 1743-1746.

PNN (Product-based Neural Network)

PNN concatenates sparse feature embeddings and the product between embedding vectors as the input of MLP.

PNN Model API



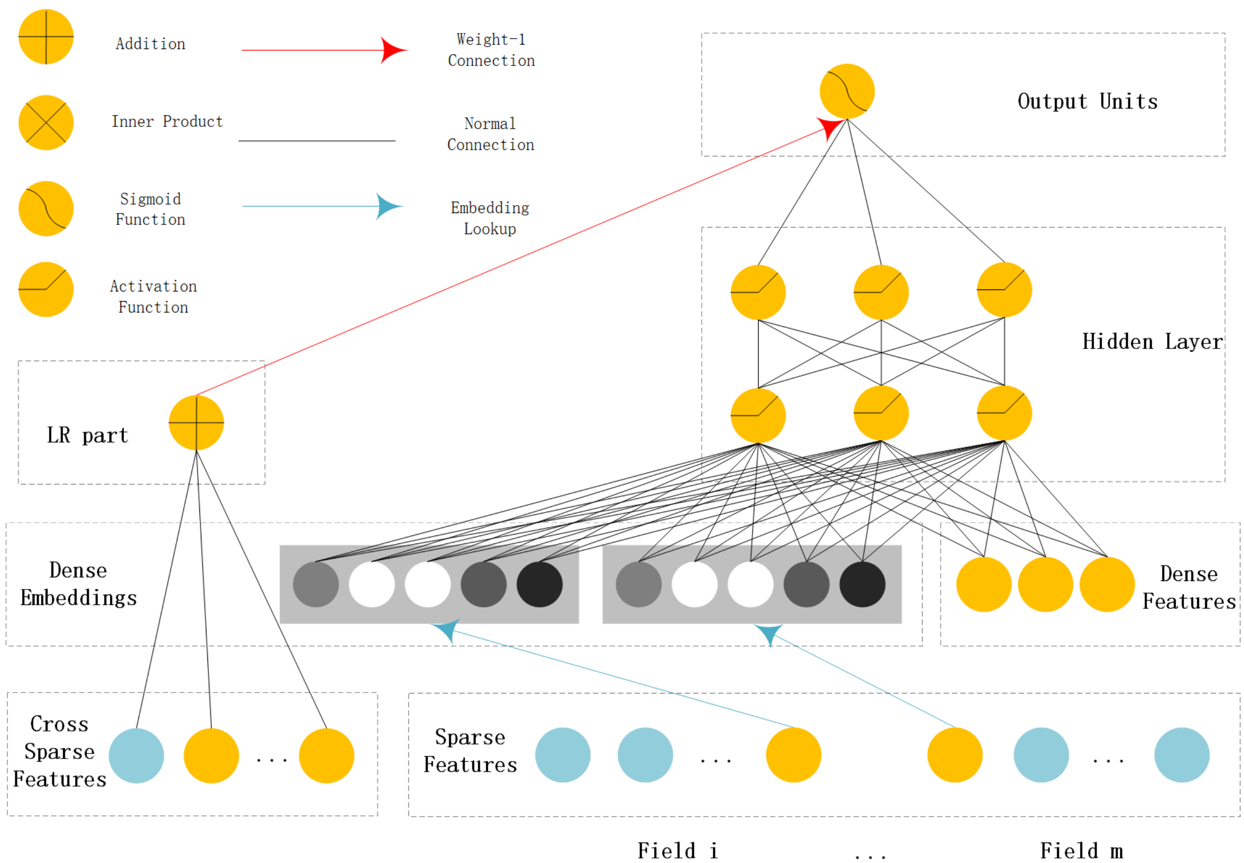
PNN

Qu Y, Cai H, Ren K, et al. Product-based neural networks for user response prediction[C]//Data Mining (ICDM), 2016 IEEE 16th International Conference on. IEEE, 2016: 1149-1154.

Wide & Deep

WDL's deep part concatenates sparse feature embeddings as the input of MLP,the wide part use handcrafted feature as input. The logits of deep part and wide part are added to get the prediction probability.

WDL Model API



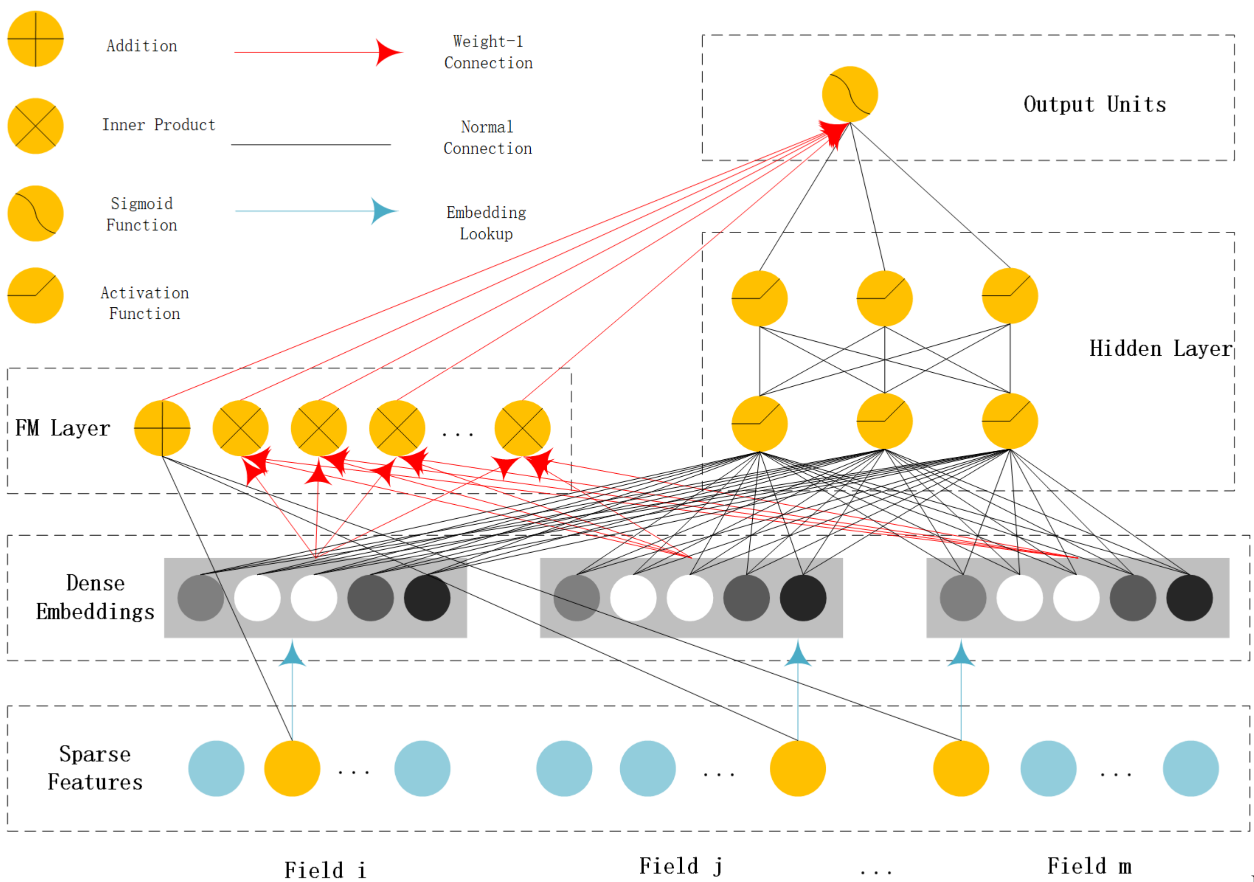
WDL

Cheng H T, Koc L, Harmsen J, et al. Wide & deep learning for recommender systems[C]//Proceedings of the 1st Workshop on Deep Learning for Recommender Systems. ACM, 2016: 7-10.

DeepFM

DeepFM can be seen as an improvement of WDL and FNN.Compared with WDL,DeepFM use FM instead of LR in the wide part and use concatenation of embedding vectors as the input of MLP in the deep part. Compared with FNN,the embedding vector of FM and input to MLP are same. And they do not need a FM pretrained vector to initialiaze,they are learned end2end.

DeepFM Model API



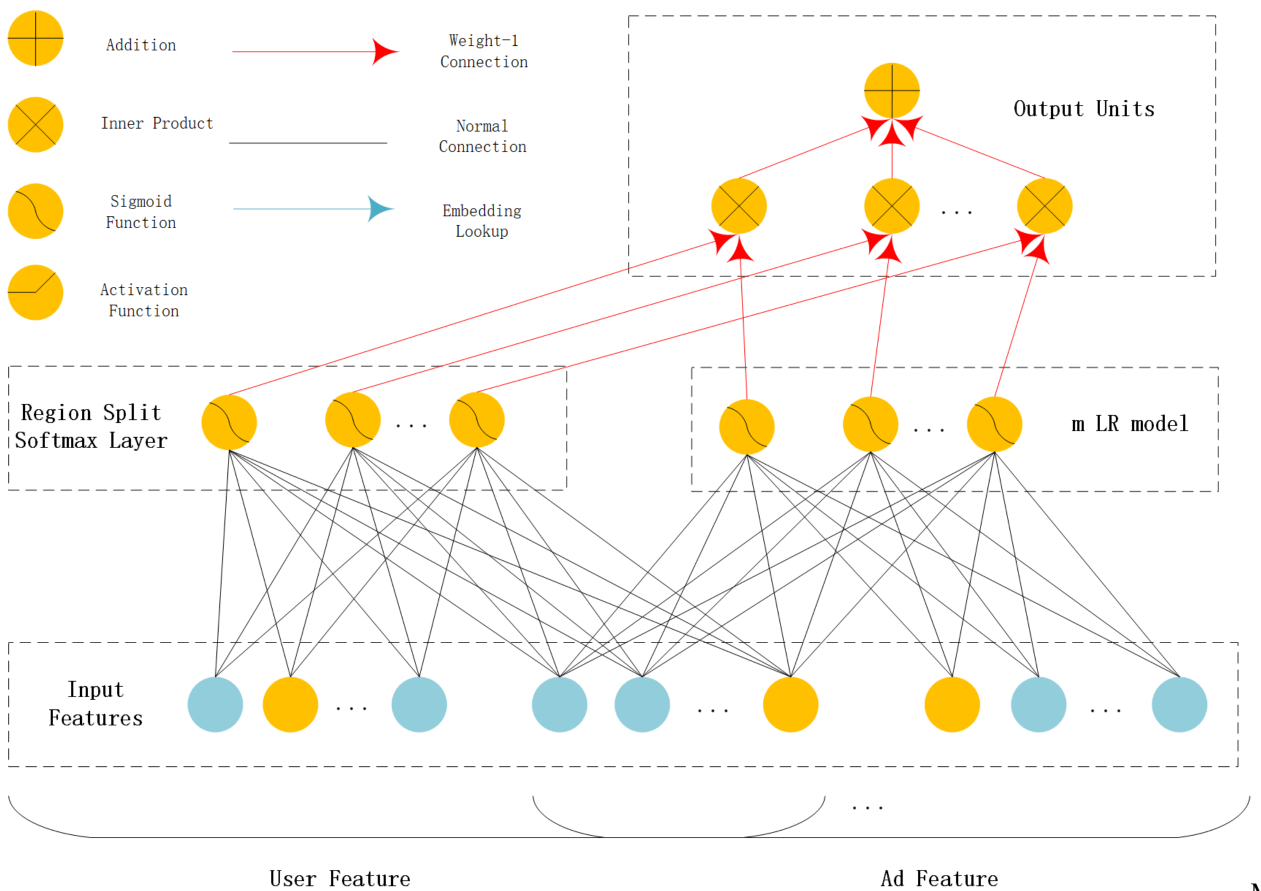
DeepFM

Guo H, Tang R, Ye Y, et al. Deepfm: a factorization-machine based neural network for ctr prediction[J]. arXiv preprint arXiv:1703.04247, 2017.

MLR(Mixed Logistic Regression/Piece-wise Linear Model)

MLR can be viewed as a combination of $2m$ LR model, m is the piece(region) number. m LR model learns the weight that the sample belong to each region,another m LR model learn sample's click probability in the region. Finally,the sample's CTR is a weighted sum of each region's click probability.Notice the weight is normalized weight.

MLR Model API



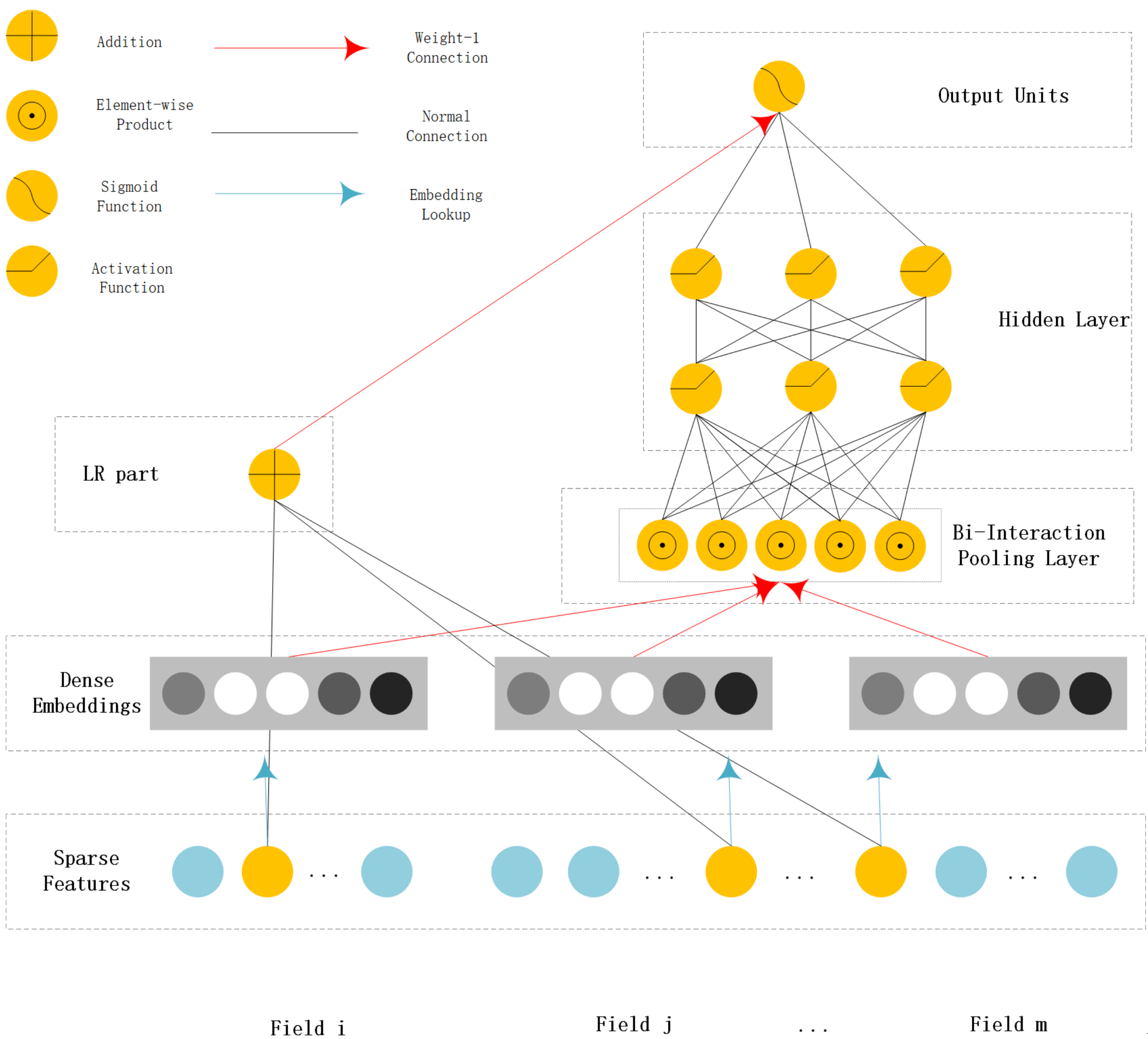
MLR

Gai K, Zhu X, Li H, et al. Learning Piece-wise Linear Models from Large Scale Data for Ad Click Prediction[J]. arXiv preprint arXiv:1704.05194, 2017.

NFM (Neural Factorization Machine)

NFM use a bi-interaction pooling layer to learn feature interaction between embedding vectors and compress the result into a singe vector which has the same size as a single embedding vector. And then fed it into a MLP.The output logit of MLP and the output logit of linear part are added to get the prediction probability.

NFM Model API



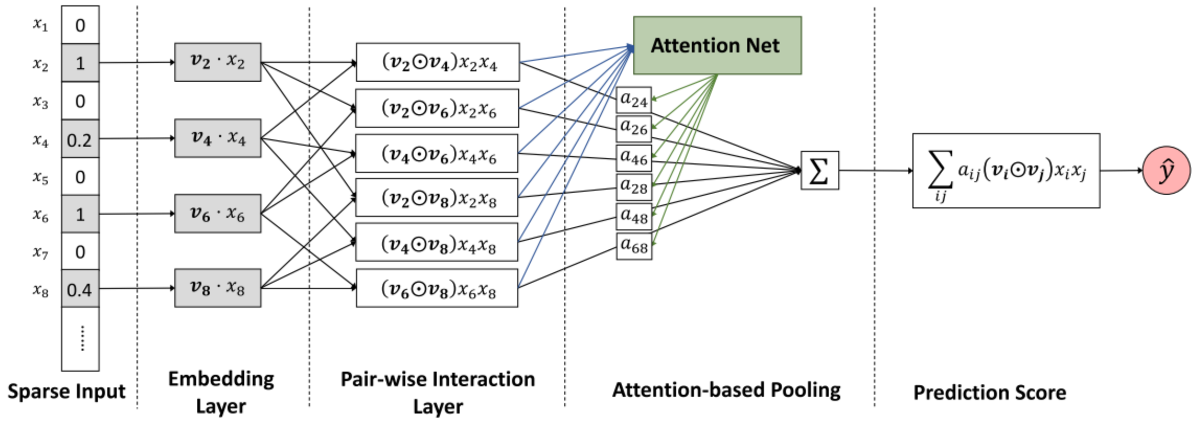
NFM

He X, Chua T S. Neural factorization machines for sparse predictive analytics[C]//Proceedings of the 40th International ACM SIGIR conference on Research and Development in Information Retrieval. ACM, 2017: 355-364.

AFM (Attentional Factorization Machine)

AFM is a variant of FM,tradional FM sums the inner product of embedding vector uniformly. AFM can be seen as weighted sum of feature interactions.The weight is learned by a small MLP.

AFM Model API



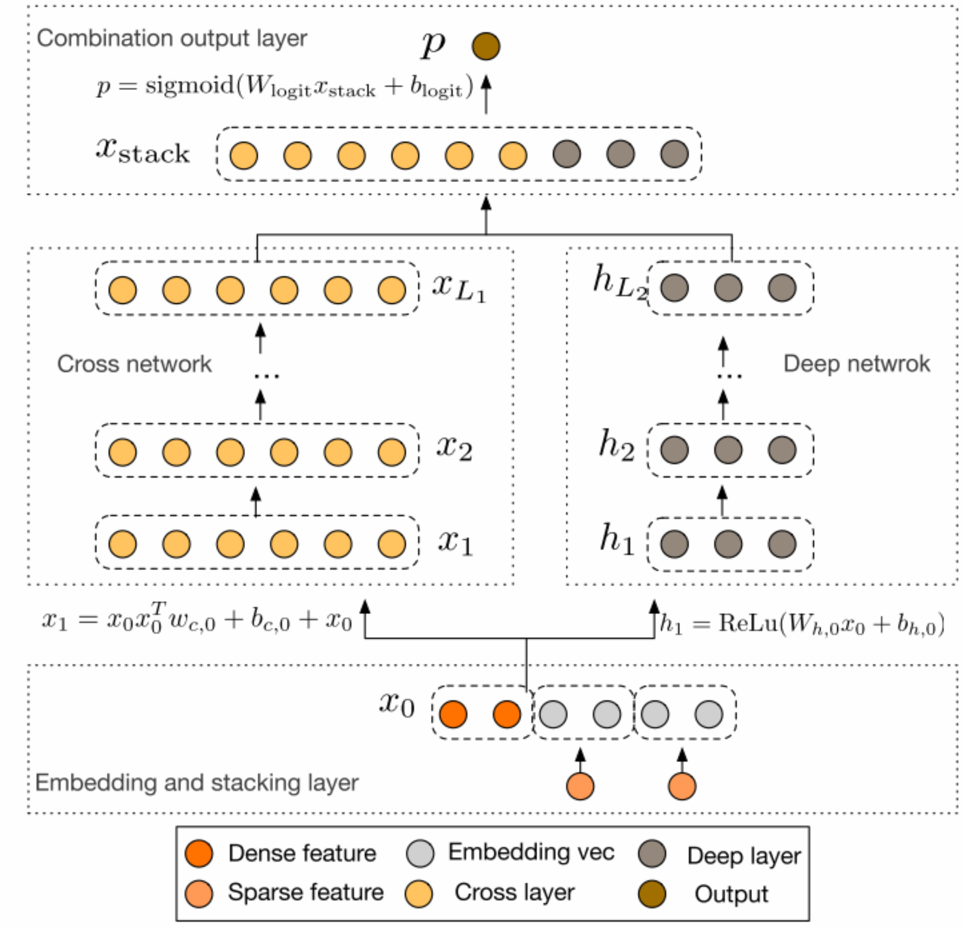
AFM

Xiao J, Ye H, He X, et al. Attentional factorization machines: Learning the weight of feature interactions via attention networks[J]. arXiv preprint arXiv:1708.04617, 2017.

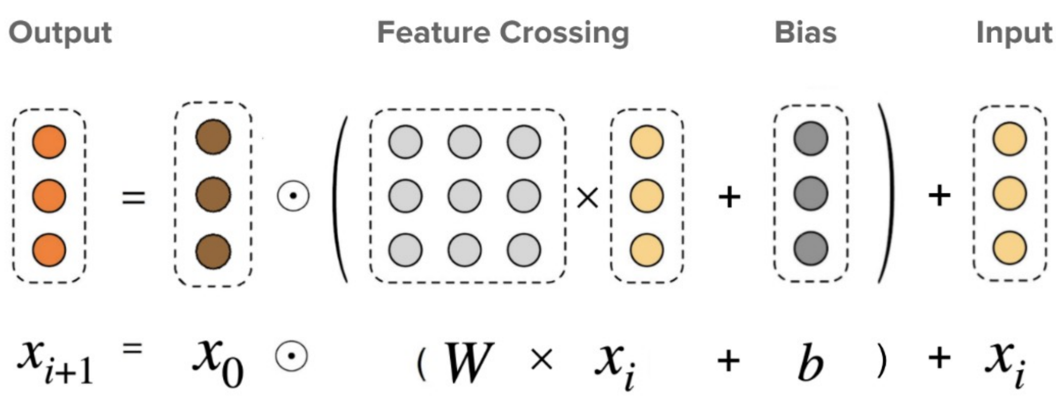
DCN (Deep & Cross Network)

DCN use a Cross Net to learn both low and high order feature interaction explicitly,and use a MLP to learn feature interaction implicitly. The output of Cross Net and MLP are concatenated.The concatenated vector are feed into one fully connected layer to get the prediction probability.

DCN Model API



DCN



Cross

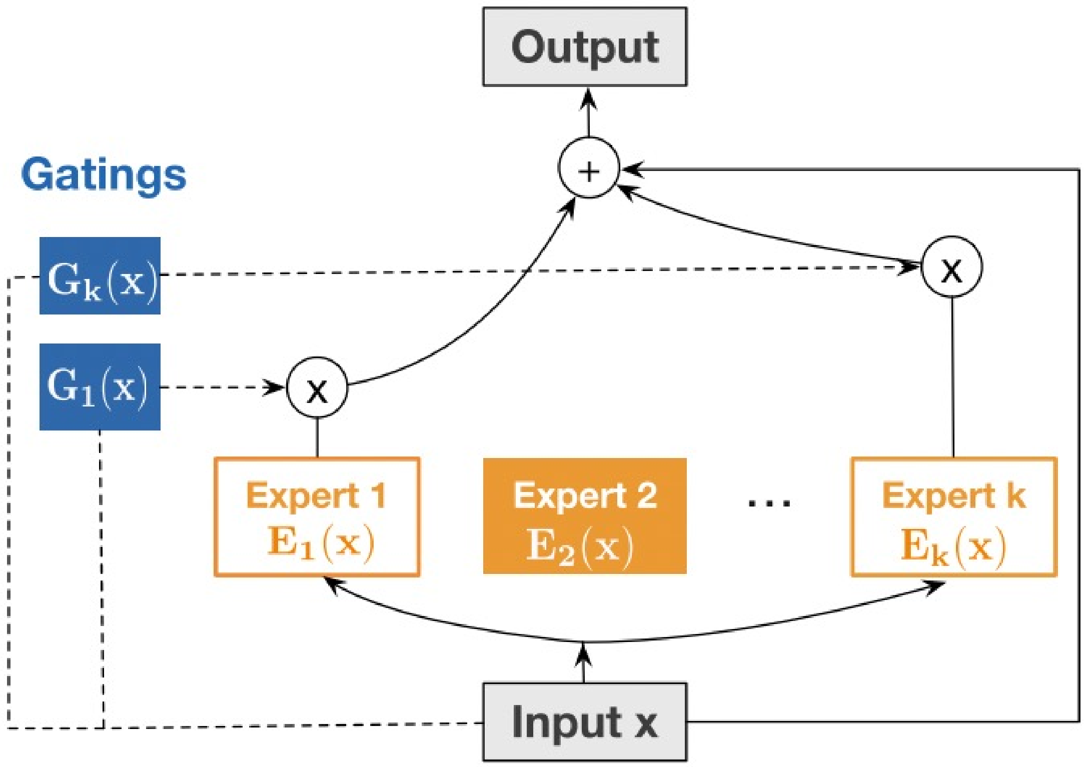
Net in DCN-M

Wang R, Fu B, Fu G, et al. Deep & cross network for ad click predictions[C]//Proceedings of the ADKDD'17. ACM, 2017: 12.

DCN-Mix (Improved Deep & Cross Network with mix of experts and matrix kernel)

DCN-Mix uses a matrix kernel instead of vector kernel in CrossNet compared with DCN,and it uses mixture of experts to learn feature interactions.

DCN-Mix Model API



DCN-Mix

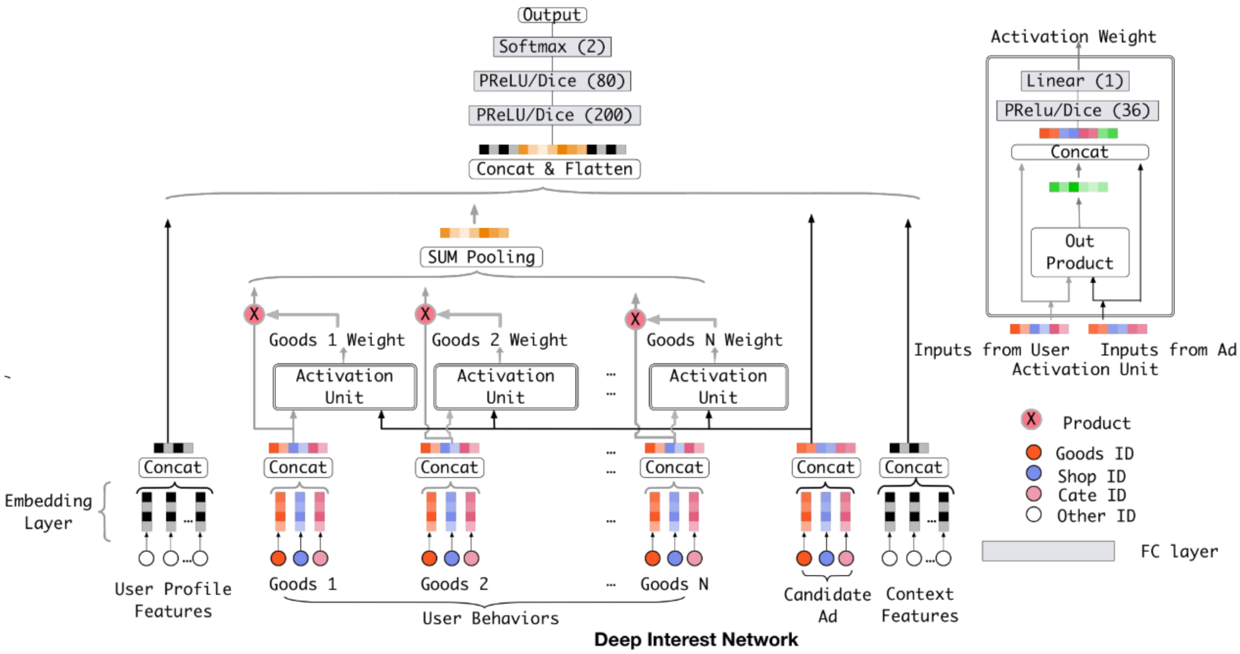
Wang R, Shivanna R, Cheng D Z, et al. DCN-M: Improved Deep & Cross Network for Feature Cross Learning in Web-scale Learning to Rank Systems[J]. arXiv preprint arXiv:2008.13535, 2020.

DIN (Deep Interest Network)

DIN introduce a attention method to learn from sequence(multi-valued) feature. Tradional method usually use sum/mean pooling on sequence feature. DIN use a local activation unit to get the activation score between candidate item and history items. User's interest are represented by weighted sum of user behaviors. user's interest vector and other embedding vectors are concatenated and fed into a MLP to get the prediction.

DIN Model API

DIN example



DIN

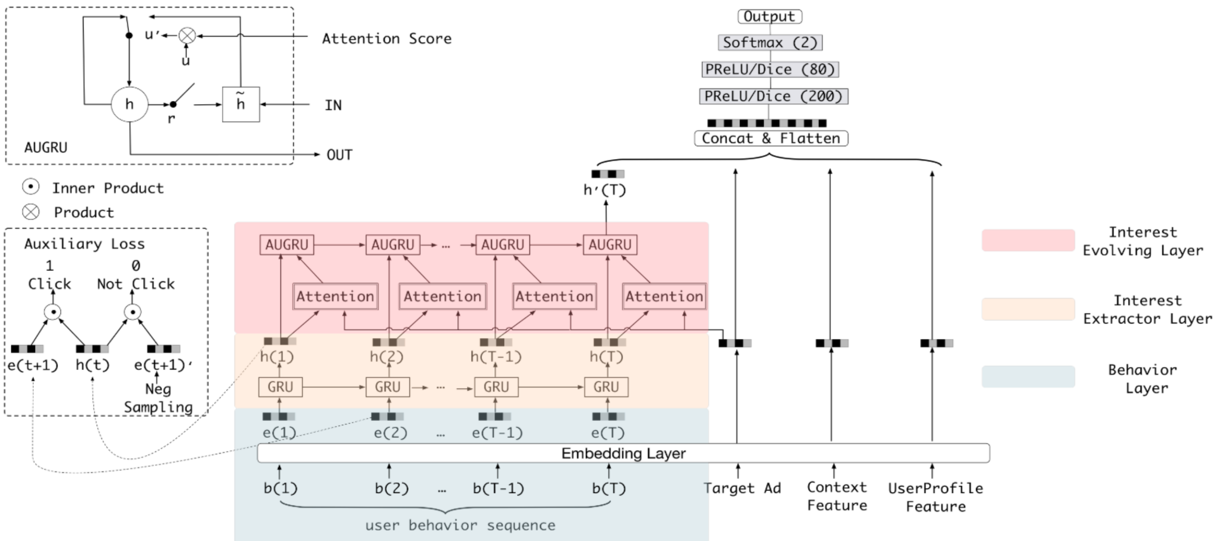
Zhou G, Zhu X, Song C, et al. Deep interest network for click-through rate prediction[C]//Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. ACM, 2018: 1059-1068.

DIEN (Deep Interest Evolution Network)

Deep Interest Evolution Network (DIEN) uses interest extractor layer to capture temporal interests from history behavior sequence. At this layer, an auxiliary loss is proposed to supervise interest extracting at each step. As user interests are diverse, especially in the e-commerce system, interest evolving layer is proposed to capture interest evolving process that is relative to the target item. At interest evolving layer, attention mechanism is embedded into the sequential structure novelly, and the effects of relative interests are strengthened during interest evolution.

DIEN Model API

DIEN example



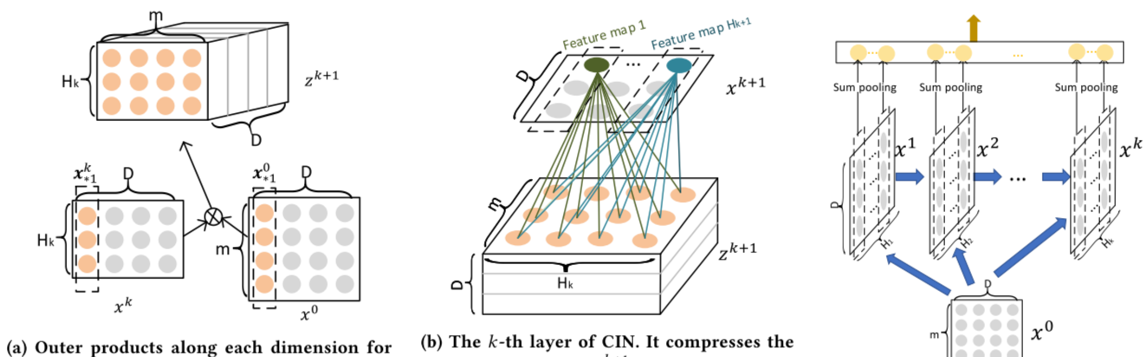
DIEN

Zhou G, Mou N, Fan Y, et al. Deep Interest Evolution Network for Click-Through Rate Prediction[J]. arXiv preprint arXiv:1809.03672, 2018.

xDeepFM

xDeepFM use a Compressed Interaction Network (CIN) to learn both low and high order feature interaction explicitly,and use a MLP to learn feature interaction implicitly. In each layer of CIN,first compute outer products between x^k and x_0 to get a tensor Z_{k+1},then use a 1DConv to learn feature maps H_{k+1} on this tensor. Finally,apply sum pooling on all the feature maps H_k to get one vector.The vector is used to compute the logit that CIN contributes.

xDeepFM Model API



(a) Outer products along each dimension for feature interactions. The tensor Z^{k+1} is an intermediate result for further learning.

(b) The k-th layer of CIN. It compresses the intermediate tensor Z^{k+1} to H_{k+1} embedding vectors (aslo known as *feature maps*).

(c) An overview of the CIN architecture.

Figure 4: Components and architecture of the Compressed Interaction Network (CIN).

CIN

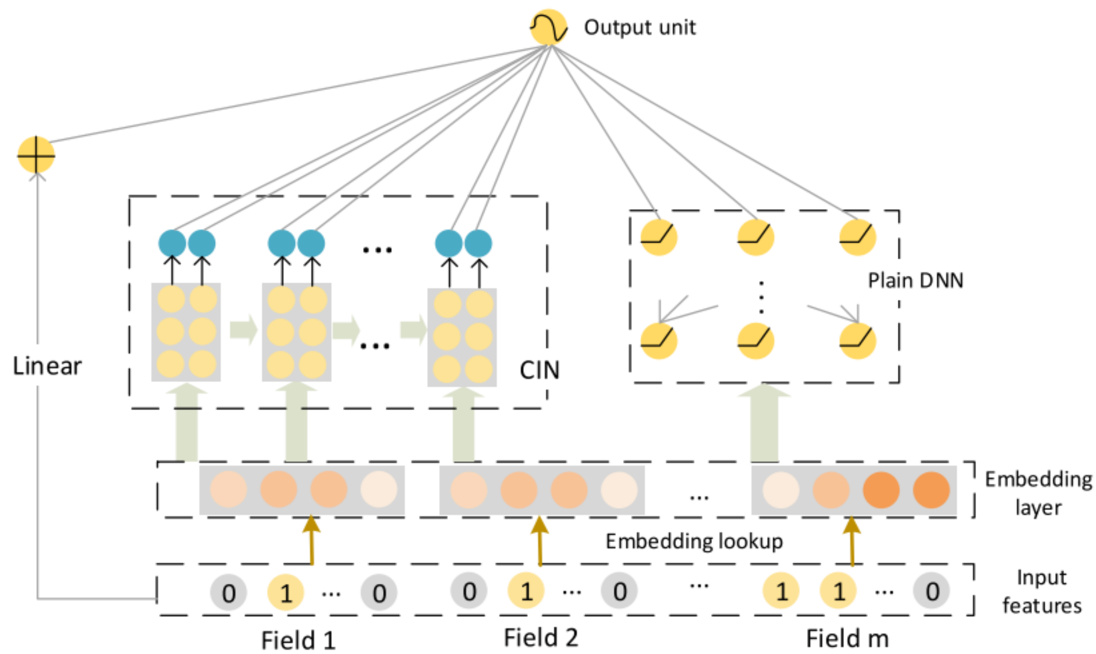


Figure 5: The architecture of xDeepFM.

xDeepFM

Lian J, Zhou X, Zhang F, et al. xDeepFM: Combining Explicit and Implicit Feature Interactions for Recommender Systems[J]. arXiv preprint arXiv:1803.05170, 2018.

AutoInt(Automatic Feature Interaction)

AutoInt use a interacting layer to model the interactions between different features. Within each interacting layer, each feature is allowed to interact with all the other features and is able to automatically identify relevant features to form meaningful higher-order features via the multi-head attention mechanism. By stacking multiple interacting layers,AutoInt is able to model different orders of feature interactions.

AutoInt Model API

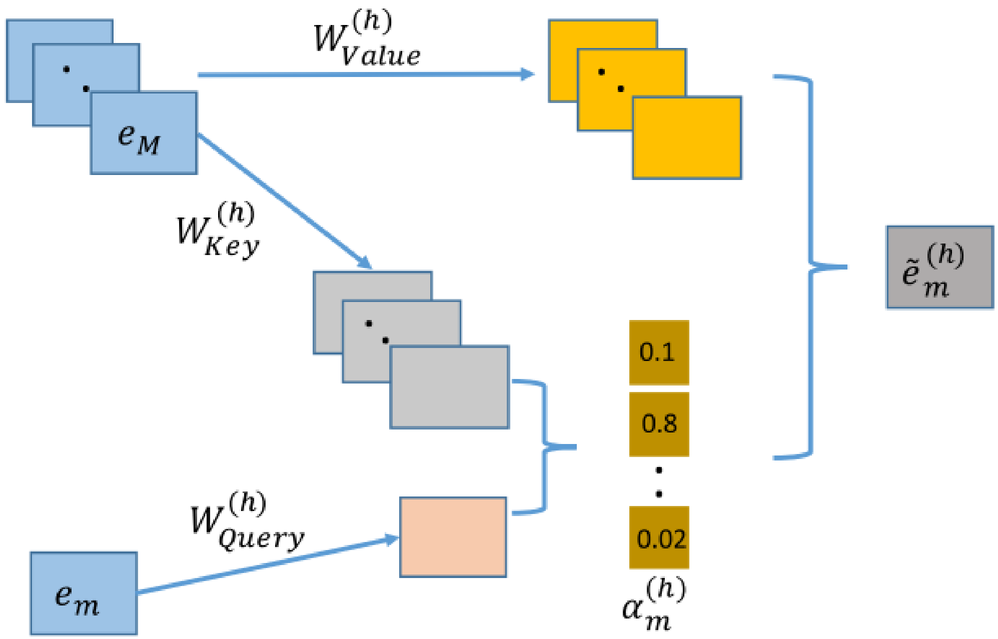


Figure 3: The architecture of interacting layer. Combinatorial features are conditioned on attention weights, i.e., $\alpha_m^{(h)}$.

InteractingLayer

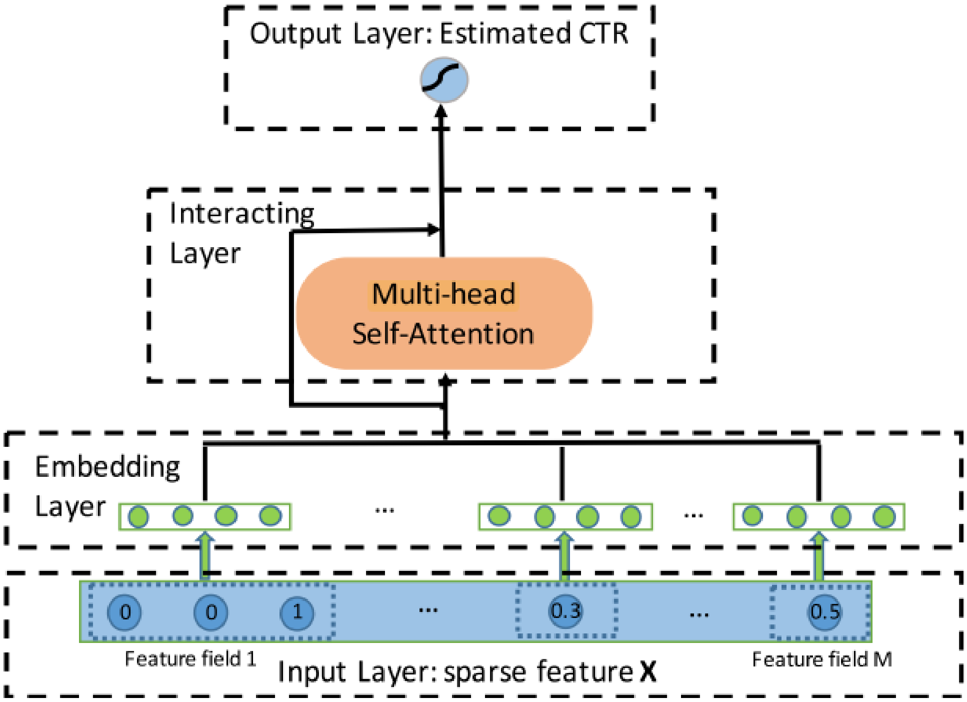


Figure 1: Overview of our proposed model AutoInt. The details of embedding layer and interacting layer are illustrated in Figure 2 and Figure 3 respectively.

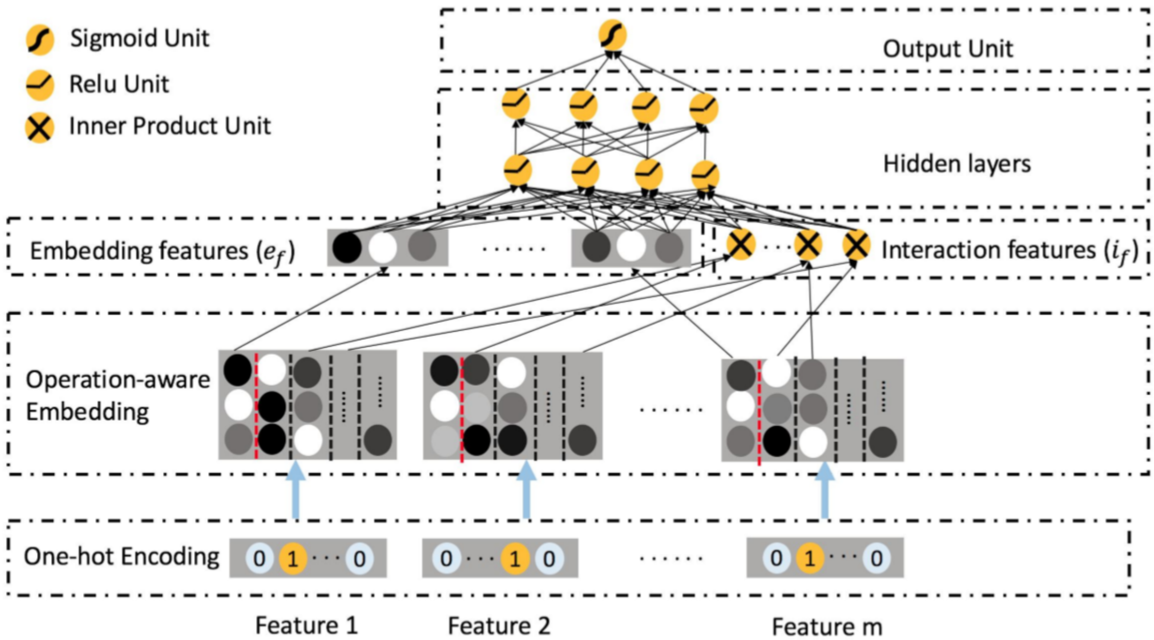
AutoInt

Song W, Shi C, Xiao Z, et al. AutoInt: Automatic Feature Interaction Learning via Self-Attentive Neural Networks[J]. arXiv preprint arXiv:1810.11921, 2018.

ONN(Operation-aware Neural Networks for User Response Prediction)

ONN models second order feature interactions like like FFM and preserves second-order interaction information as much as possible.Further more,deep neural network is used to learn higher-ordered feature interactions.

ONN Model API



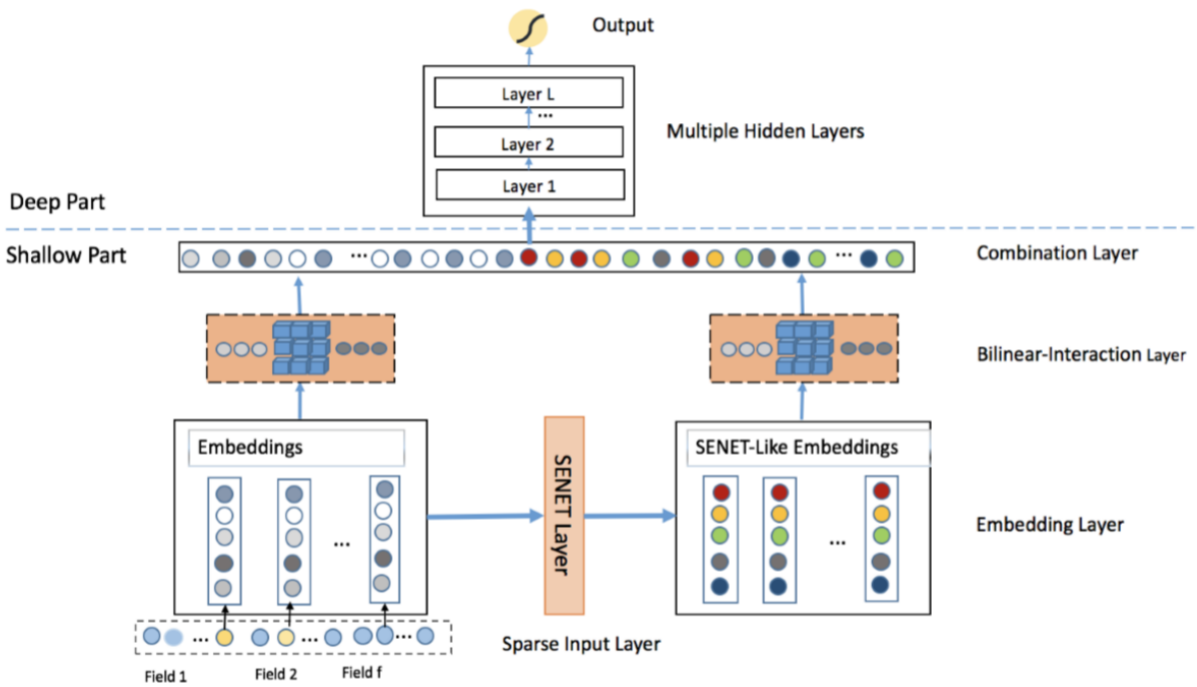
ONN

Yang Y, Xu B, Shen F, et al. Operation-aware Neural Networks for User Response Prediction[J]. arXiv preprint arXiv:1904.12579, 2019.

FiBiNET(Feature Importance and Bilinear feature Interaction NETwork)

Feature Importance and Bilinear feature Interaction NETwork is proposed to dynamically learn the feature importance and fine-grained feature interactions. On the one hand, the FiBiNET can dynamically learn the importance of features via the Squeeze-Excitation network (SENET) mechanism; on the other hand, it is able to effectively learn the feature interactions via bilinear function.

FiBiNET Model API



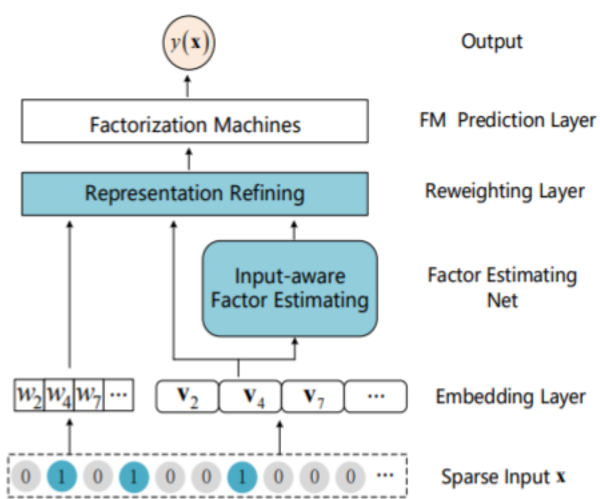
FiBiNET

Huang T, Zhang Z, Zhang J. FiBiNET: Combining Feature Importance and Bilinear feature Interaction for Click-Through Rate Prediction[J]. arXiv preprint arXiv:1905.09433, 2019.

IFM(Input-aware Factorization Machine)

Input-aware Factorization Machine (IFM) learns a unique input-aware factor for the same feature in different instances via a neural network.

IFM Model API



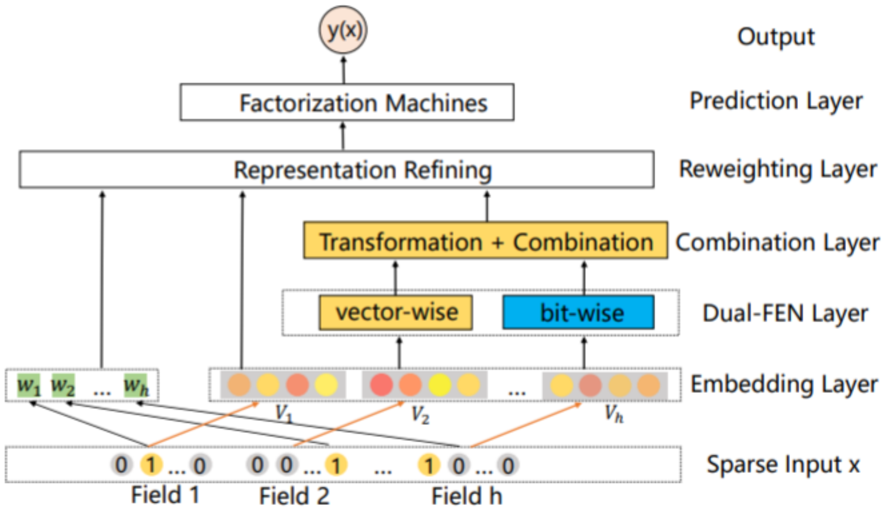
IFM

Yu Y, Wang Z, Yuan B. An Input-aware Factorization Machine for Sparse Prediction[C]//IJCAI. 2019: 1466-1472.

DIFM(Dual Input-aware Factorization Machine)

Dual Inputaware Factorization Machines (DIFM) can adaptively reweight the original feature representations at the bit-wise and vector-wise levels simultaneously.Furthermore, DIFMs strategically integrate various components including Multi-Head Self-Attention, Residual Networks and DNNs into a unified end-to-end model.

DFM Model API

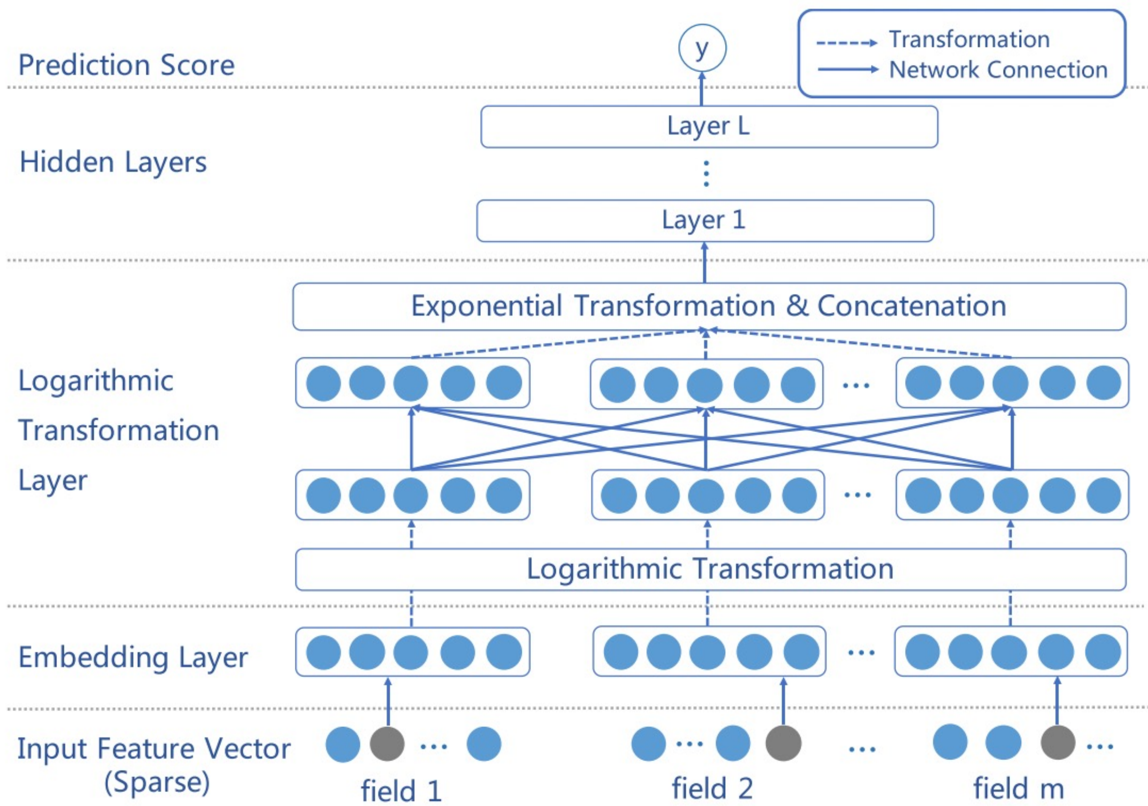


DIFM

Lu W, Yu Y, Chang Y, et al. A Dual Input-aware Factorization Machine for CTR Prediction[C]//IJCAI. 2020: 3139-3145.

AFN(Adaptive Factorization Network: Learning Adaptive-Order Feature Interactions)

Adaptive Factorization Network (AFN) can learn arbitrary-order cross features adaptively from data. The core of AFN is a logarith- mic transformation layer to convert the power of each feature in a feature combination into the coefficient to be learned. **AFN Model API**



AFN

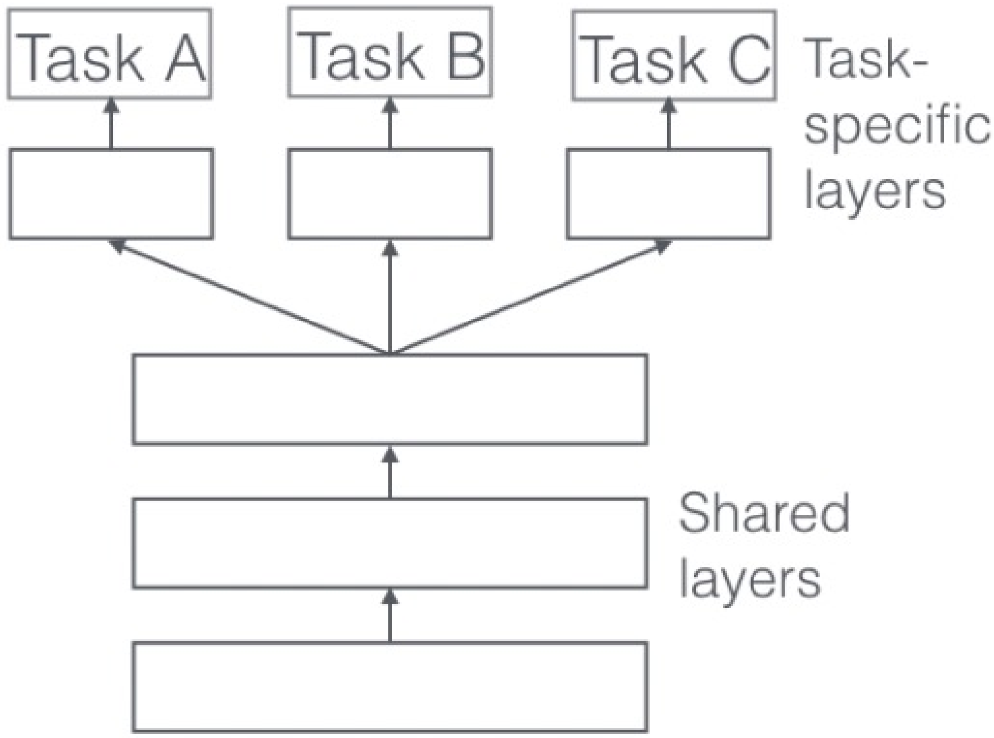
Cheng, W., Shen, Y. and Huang, L. 2020. Adaptive Factorization Network: Learning Adaptive-Order Feature Interactions. Proceedings of the AAAI Conference on Artificial Intelligence. 34, 04 (Apr. 2020), 3609-3616.

2.2.4 MultiTask Models

SharedBottom

Hard parameter sharing is the most commonly used approach to MTL in neural networks. It is generally applied by sharing the hidden layers between all tasks, while keeping several task-specific output layers.

SharedBottom Model API



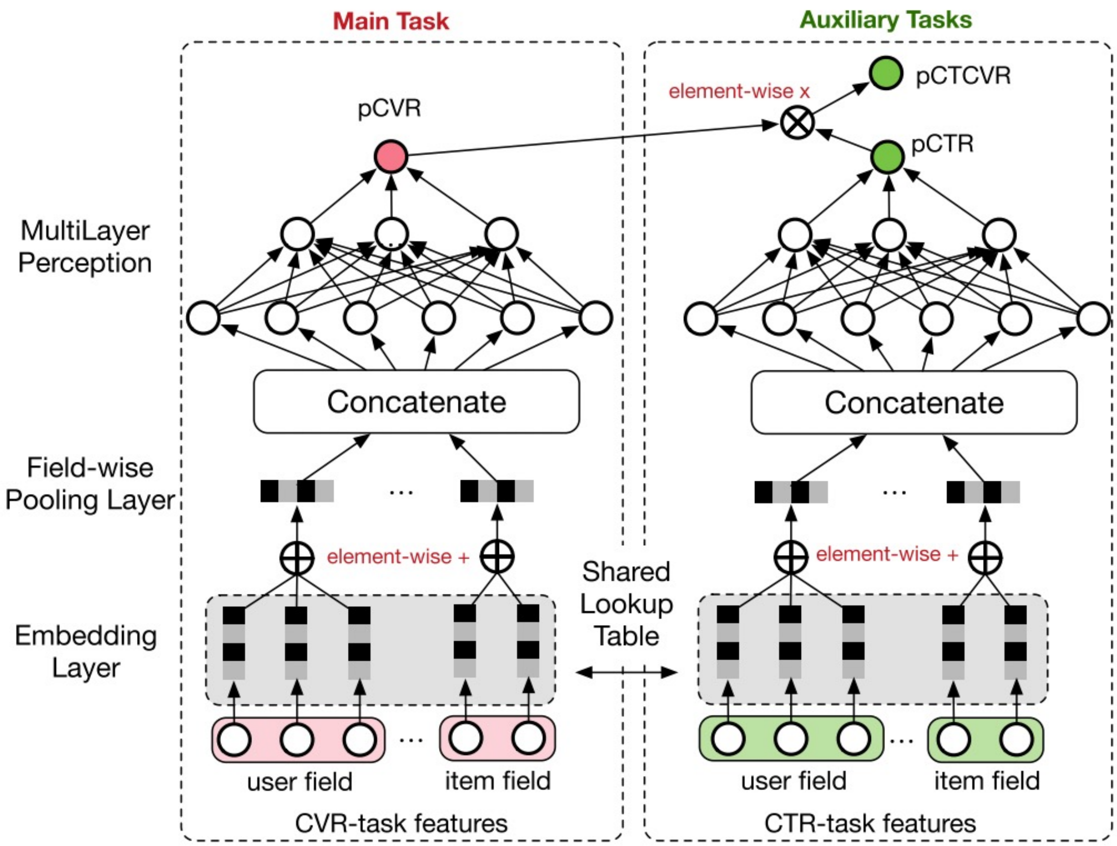
SharedBottom

Ruder S. An overview of multi-task learning in deep neural networks[J]. arXiv preprint arXiv:1706.05098, 2017.

ESMM(Entire Space Multi-task Model)

ESMM models CVR in a brand-new perspective by making good use of sequential pattern of user actions, i.e., impression $\rightarrow$ click $\rightarrow$ conversion. The proposed Entire Space Multi-task Model (ESMM) can eliminate the two problems simultaneously by i) modeling CVR directly over the entire space, ii) employing a feature representation transfer learning strategy.

ESMM Model API



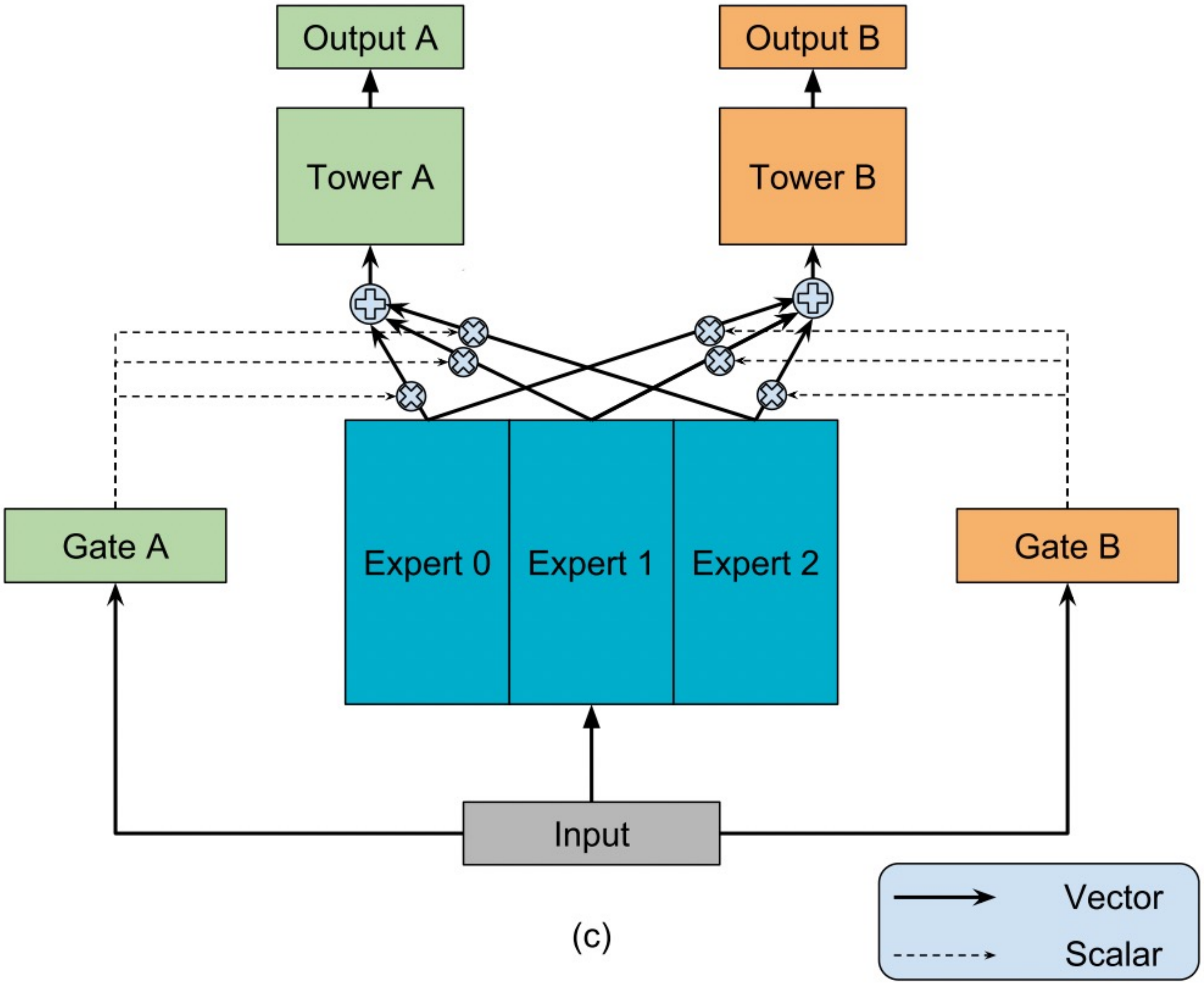
ESMM

Ma X, Zhao L, Huang G, et al. Entire space multi-task model: An effective approach for estimating post-click conversion rate[C]//The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval. 2018.

MMOE(Multi-gate Mixture-of-Experts)

Multi-gate Mixture-of-Experts (MMoE) explicitly learns to model task relationships from data. We adapt the Mixture-of- Experts (MoE) structure to multi-task learning by sharing the expert submodels across all tasks, while also having a gating network trained to optimize each task.

MMOE Model API



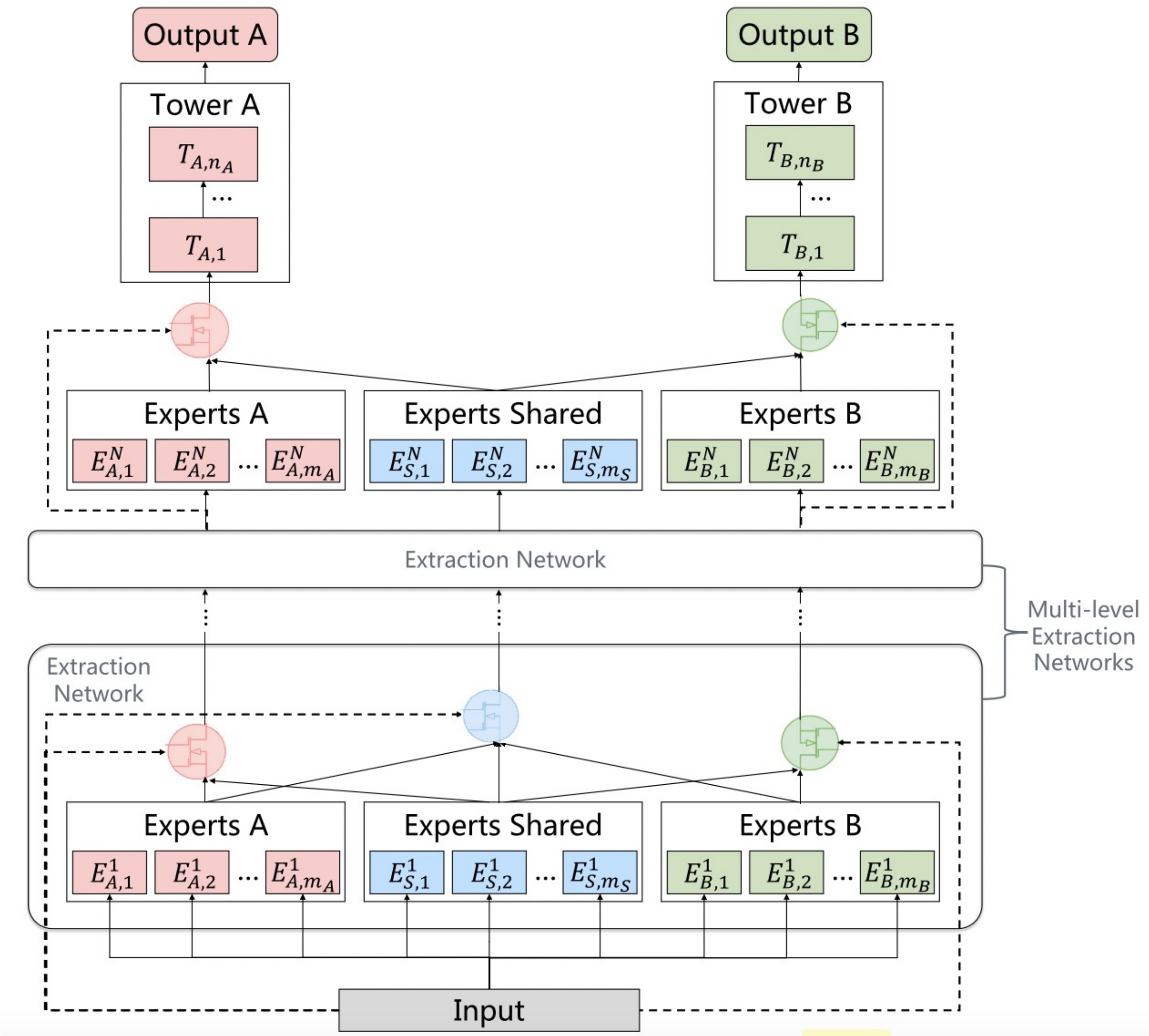
MMOE

Ma J, Zhao Z, Yi X, et al. Modeling task relationships in multi-task learning with multi-gate mixture-of-experts[C]//Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. 2018.

PLE(Progressive Layered Extraction)

PLE separates shared components and task-specific components explicitly and adopts a progressive rout- ing mechanism to extract and separate deeper semantic knowledge gradually, improving efficiency of joint representation learning and information routing across tasks in a general setup.

PLE Model API



PLE

Tang H, Liu J, Zhao M, et al. Progressive layered extraction (ple): A novel multi-task learning (mtl) model for personalized recommendations[C]//Fourteenth ACM Conference on Recommender Systems. 2020.

2.2.5 Layers

The models of deepctr are modular, so you can use different modules to build your own models.

You can see layers API in Layers

2.3 Examples

2.3.1 Classification: Criteo

The Criteo Display Ads dataset is for the purpose of predicting ads click-through rate. It has 13 integer features and 26 categorical features where each category has a high cardinality.

	label	I1	I2	I3	I4	I5	I6	I7	I8	I9	...	C17	C18	C19	C20	C21	C22	C23	C24
0	0	NaN	3	260.0	NaN	17668.0	NaN	NaN	33.0	NaN	...	e5ba7672	87c6f83c	NaN	NaN	0429f84b	NaN	3a171ecb	c0d61a5c
1	0	NaN	-1	19.0	35.0	30251.0	247.0	1.0	35.0	160.0	...	d4bb7bd8	6fc84bfb	NaN	NaN	5155d8a3	NaN	be7c41b4	ded4aac9
2	0	0.0	0	2.0	12.0	2013.0	164.0	6.0	35.0	523.0	...	e5ba7672	675c9258	NaN	NaN	2e01979f	NaN	bcdee96c	6d5d1302
3	0	NaN	13	1.0	4.0	16836.0	200.0	5.0	4.0	29.0	...	e5ba7672	52e44668	NaN	NaN	e587c466	NaN	32c7478e	3b183c5c
4	0	0.0	0	104.0	27.0	1990.0	142.0	4.0	32.0	37.0	...	e5ba7672	25c88e42	21ddcdc9	b1252a9d	0e8585d2	NaN	32c7478e	0d4a6d1a

image

In this example,we simply normailize the dense feature between 0 and 1,you can try other transformation technique like log normalization or discretization.Then we use SparseFeat and DenseFeat to generate feature columns for sparse features and dense features.

This example shows how to use `DeepFM` to solve a simple binary classification task. You can get the demo data criteo_sample.txt and run the following codes.

```
import pandas as pd
import torch
from sklearn.metrics import log_loss, roc_auc_score
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, MinMaxScaler

from deepctr_torch.inputs import SparseFeat, DenseFeat, get_feature_names
from deepctr_torch.models import *

if __name__ == "__main__":
    data = pd.read_csv('./criteo_sample.txt')

    sparse_features = ['C' + str(i) for i in range(1, 27)]
    dense_features = ['I' + str(i) for i in range(1, 14)]

    data[sparse_features] = data[sparse_features].fillna('-1', )
    data[dense_features] = data[dense_features].fillna(0, )
    target = ['label']

    # 1.Label Encoding for sparse features,and do simple Transformation for dense␣
↪features
    for feat in sparse_features:
        lbe = LabelEncoder()
        data[feat] = lbe.fit_transform(data[feat])
    mms = MinMaxScaler(feature_range=(0, 1))
    data[dense_features] = mms.fit_transform(data[dense_features])

    # 2.count #unique features for each sparse field,and record dense feature field␣
↪name

    fixlen_feature_columns = [SparseFeat(feat, data[feat].nunique())
                              for feat in sparse_features] + [DenseFeat(feat, 1, )
                                                              for feat in dense_
↪features]

    dnn_feature_columns = fixlen_feature_columns
    linear_feature_columns = fixlen_feature_columns

    feature_names = get_feature_names(
        linear_feature_columns + dnn_feature_columns)

    # 3.generate input data for model
```

(continues on next page)

(continued from previous page)

```
    train, test = train_test_split(data, test_size=0.2)

    train_model_input = {name: train[name] for name in feature_names}
    test_model_input = {name: test[name] for name in feature_names}

    # 4.Define Model,train,predict and evaluate

    device = 'cpu'
    use_cuda = True
    if use_cuda and torch.cuda.is_available():
        print('cuda ready...')
        device = 'cuda:0'

    model = DeepFM(linear_feature_columns=linear_feature_columns, dnn_feature_
↪columns=dnn_feature_columns,
                   task='binary',
                   l2_reg_embedding=1e-5, device=device)

    model.compile("adagrad", "binary_crossentropy",
                  metrics=["binary_crossentropy", "auc"], )
    model.fit(train_model_input,train[target].values,batch_size=32,epochs=10,
↪verbose=2,validation_split=0.0)

    pred_ans = model.predict(test_model_input, 256)
    print("")
    print("test LogLoss", round(log_loss(test[target].values, pred_ans), 4))
    print("test AUC", round(roc_auc_score(test[target].values, pred_ans), 4))
```

2.3.2 Regression: Movielens

The MovieLens data has been used for personalized tag recommendation,which contains 668, 953 tag applications of users on movies. Here is a small fraction of data include only sparse field.

	movie_id	user_id	gender	age	occupation	zip	rating
254181	2944	1545	M	25	20	20009	4
481546	2208	2962	M	35	3	94109	3
166949	3629	1062	M	50	19	59457	5
536371	569	3308	F	18	20	15701-1348	2
117094	2763	754	M	35	7	38024	4

image

This example shows how to use `DeepFM` to solve a simple binary regression task. You can get the demo data movielens_sample.txt and run the following codes.

```
import pandas as pd
import torch
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder

from deepctr_torch.inputs import SparseFeat, get_feature_names
```

(continues on next page)

(continued from previous page)

```python
from deepctr_torch.models import DeepFM

if __name__ == "__main__":

    data = pd.read_csv("./movielens_sample.txt")
    sparse_features = ["movie_id", "user_id",
                       "gender", "age", "occupation", "zip"]
    target = ['rating']

    # 1.Label Encoding for sparse features,and do simple Transformation for dense␣
↪features
    for feat in sparse_features:
        lbe = LabelEncoder()
        data[feat] = lbe.fit_transform(data[feat])
    # 2.count #unique features for each sparse field
    fixlen_feature_columns = [SparseFeat(feat, data[feat].nunique())
                              for feat in sparse_features]
    linear_feature_columns = fixlen_feature_columns
    dnn_feature_columns = fixlen_feature_columns
    feature_names = get_feature_names(linear_feature_columns + dnn_feature_columns)

    # 3.generate input data for model
    train, test = train_test_split(data, test_size=0.2)
    train_model_input = {name: train[name] for name in feature_names}
    test_model_input = {name: test[name] for name in feature_names}
    # 4.Define Model,train,predict and evaluate

    device = 'cpu'
    use_cuda = True
    if use_cuda and torch.cuda.is_available():
        print('cuda ready...')
        device = 'cuda:0'

    model = DeepFM(linear_feature_columns, dnn_feature_columns, task='regression',␣
↪device=device)
    model.compile("adam", "mse", metrics=['mse'], )

    history = model.fit(train_model_input,train[target].values,batch_size=256,
↪epochs=10,verbose=2,validation_split=0.2)
    pred_ans = model.predict(test_model_input, batch_size=256)
    print("test MSE", round(mean_squared_error(
        test[target].values, pred_ans), 4))
```

2.3.3 Multi-value Input : Movielens

The MovieLens data has been used for personalized tag recommendation,which contains 668, 953 tag applications of users on movies. Here is a small fraction of data include sparse fields and a multivalent field.

	movie_id	user_id	gender	age	occupation	zip	genres	rating
0	12	107	0	2	4	35	Comedy|Drama	4
1	169	123	1	1	4	118	Action|Thriller	3
2	6	12	0	2	13	99	Drama|Romance	4
3	112	21	1	1	18	55	Action|Adventure	3
4	45	187	1	5	19	41	Comedy|Drama	5

image

There are 2 additional steps to use DeepCTR with sequence feature input.

1. Generate the paded and encoded sequence feature of sequence input feature(**value 0 is for padding**).
2. Generate config of sequence feature with VarLenSparseFeat

This example shows how to use `DeepFM` with sequence(multi-value) feature. You can get the demo data movielens_sample.txt and run the following codes.

```
import numpy as np
import pandas as pd
import torch
from sklearn.preprocessing import LabelEncoder
from tensorflow.python.keras.preprocessing.sequence import pad_sequences

from deepctr_torch.inputs import SparseFeat, VarLenSparseFeat, get_feature_names
from deepctr_torch.models import DeepFM


def split(x):
    key_ans = x.split('|')
    for key in key_ans:
        if key not in key2index:
            # Notice : input value 0 is a special "padding",so we do not use 0 to␣
↪encode valid feature for sequence input
            key2index[key] = len(key2index) + 1
    return list(map(lambda x: key2index[x], key_ans))


if __name__ == "__main__":
    data = pd.read_csv("./movielens_sample.txt")
    sparse_features = ["movie_id", "user_id",
                       "gender", "age", "occupation", "zip", ]
    target = ['rating']

    # 1.Label Encoding for sparse features,and process sequence features
    for feat in sparse_features:
        lbe = LabelEncoder()
        data[feat] = lbe.fit_transform(data[feat])
    # preprocess the sequence feature

    key2index = {}
    genres_list = list(map(split, data['genres'].values))
    genres_length = np.array(list(map(len, genres_list)))
```

(continues on next page)

(continued from previous page)

```
    max_len = max(genres_length)
    # Notice : padding=`post`
    genres_list = pad_sequences(genres_list, maxlen=max_len, padding='post', )

    # 2.count #unique features for each sparse field and generate feature config for␣
↪sequence feature

    fixlen_feature_columns = [SparseFeat(feat, data[feat].nunique(), embedding_dim=4)
                              for feat in sparse_features]

    varlen_feature_columns = [VarLenSparseFeat(SparseFeat('genres', vocabulary_
↪size=len(
        key2index) + 1, embedding_dim=4), maxlen=max_len, combiner='mean')]   # Notice␣
↪: value 0 is for padding for sequence input feature

    linear_feature_columns = fixlen_feature_columns + varlen_feature_columns
    dnn_feature_columns = fixlen_feature_columns + varlen_feature_columns

    feature_names = get_feature_names(linear_feature_columns + dnn_feature_columns)

    # 3.generate input data for model
    model_input = {name: data[name] for name in sparse_features}  #
    model_input["genres"] = genres_list

    # 4.Define Model,compile and train

    device = 'cpu'
    use_cuda = True
    if use_cuda and torch.cuda.is_available():
        print('cuda ready...')
        device = 'cuda:0'

    model = DeepFM(linear_feature_columns, dnn_feature_columns, task='regression',␣
↪device=device)

    model.compile("adam", "mse", metrics=['mse'], )
    history = model.fit(model_input,data[target].values,batch_size=256,epochs=10,
↪verbose=2,validation_split=0.2)
```

2.3.4 MultiTask Learning:MMOE

This example shows how to use MMOE to solve a multi task learning problem. You can get the demo data byterec_sample.txt and run the following codes.

```
import pandas as pd
import torch
from sklearn.metrics import log_loss, roc_auc_score
from sklearn.preprocessing import LabelEncoder, MinMaxScaler

from deepctr_torch.inputs import SparseFeat, DenseFeat, get_feature_names
from deepctr_torch.models import *

if __name__ == "__main__":
    # data description can be found in https://www.biendata.xyz/competition/
↪icmechallenge2019/
```

(continues on next page)

(continued from previous page)

```
    data = pd.read_csv('./byterec_sample.txt', sep='\t',
                       names=["uid", "user_city", "item_id", "author_id", "item_city",
↪ "channel", "finish", "like",
                              "music_id", "device", "time", "duration_time"])

    sparse_features = ["uid", "user_city", "item_id", "author_id", "item_city",
↪"channel", "music_id", "device"]
    dense_features = ["duration_time"]

    target = ['finish', 'like']

    # 1.Label Encoding for sparse features,and do simple Transformation for dense␣
↪features
    for feat in sparse_features:
        lbe = LabelEncoder()
        data[feat] = lbe.fit_transform(data[feat])
    mms = MinMaxScaler(feature_range=(0, 1))
    data[dense_features] = mms.fit_transform(data[dense_features])

    # 2.count #unique features for each sparse field,and record dense feature field␣
↪name

    fixlen_feature_columns = [SparseFeat(feat, vocabulary_size=data[feat].max() + 1,␣
↪embedding_dim=4)
                              for feat in sparse_features] + [DenseFeat(feat, 1, )
                                                              for feat in dense_
↪features]

    dnn_feature_columns = fixlen_feature_columns
    linear_feature_columns = fixlen_feature_columns

    feature_names = get_feature_names(
        linear_feature_columns + dnn_feature_columns)

    # 3.generate input data for model

    split_boundary = int(data.shape[0] * 0.8)
    train, test = data[:split_boundary], data[split_boundary:]
    train_model_input = {name: train[name] for name in feature_names}
    test_model_input = {name: test[name] for name in feature_names}

    # 4.Define Model,train,predict and evaluate
    device = 'cpu'
    use_cuda = True
    if use_cuda and torch.cuda.is_available():
        print('cuda ready...')
        device = 'cuda:0'

    model = MMOE(dnn_feature_columns, task_types=['binary', 'binary'],
                 l2_reg_embedding=1e-5, task_names=target, device=device)
    model.compile("adagrad", loss=["binary_crossentropy", "binary_crossentropy"],
                  metrics=['binary_crossentropy'], )

    history = model.fit(train_model_input, train[target].values, batch_size=32,␣
↪epochs=10, verbose=2)
    pred_ans = model.predict(test_model_input, 256)
    print("")
```

(continues on next page)

(continued from previous page)

```
    for i, target_name in enumerate(target):
        print("%s test LogLoss" % target_name, round(log_loss(test[target[i]].values,␣
↪pred_ans[:, i]), 4))
        print("%s test AUC" % target_name, round(roc_auc_score(test[target[i]].values,
↪ pred_ans[:, i]), 4))
```

2.4 FAQ

2.4.1 1. Save or load weights/models

To save/load weights:

```
import torch
model = DeepFM(...)
torch.save(model.state_dict(), 'DeepFM_weights.h5')
model.load_state_dict(torch.load('DeepFM_weights.h5'))
```

To save/load models:

```
import torch
model = DeepFM(...)
torch.save(model, 'DeepFM.h5')
model = torch.load('DeepFM.h5')
```

2.4.2 2. Set learning rate and use earlystopping

Here is a example of how to set learning rate and earlystopping:

```
from torch.optim import Adagrad
from deepctr_torch.models import DeepFM
from deepctr_torch.callbacks import EarlyStopping, ModelCheckpoint

model = DeepFM(linear_feature_columns,dnn_feature_columns)
model.compile(Adagrad(model.parameters(),0.1024),'binary_crossentropy',metrics=[
↪'binary_crossentropy'])

es = EarlyStopping(monitor='val_binary_crossentropy', min_delta=0, verbose=1,␣
↪patience=0, mode='min')
mdckpt = ModelCheckpoint(filepath='model.ckpt', monitor='val_binary_crossentropy',␣
↪verbose=1, save_best_only=True, mode='min')
history = model.fit(model_input,data[target].values,batch_size=256,epochs=10,
↪verbose=2,validation_split=0.2,callbacks=[es,mdckpt])
print(history)
```

2.4.3 3. How to add a long dense feature vector as a input to the model?

```
from deepctr_torch.models import DeepFM
from deepctr_torch.inputs import DenseFeat,SparseFeat,get_feature_names
import numpy as np

feature_columns = [SparseFeat('user_id',120,),SparseFeat('item_id',60,),DenseFeat(
↪"pic_vec",5)]
fixlen_feature_names = get_feature_names(feature_columns)

user_id = np.array([[1],[0],[1]])
item_id = np.array([[30],[20],[10]])
pic_vec = np.array([[0.1,0.5,0.4,0.3,0.2],[0.1,0.5,0.4,0.3,0.2],[0.1,0.5,0.4,0.3,0.
↪2]])
label = np.array([1,0,1])

model_input = {'user_id':user_id,'item_id':item_id,'pic_vec':pic_vec}

model = DeepFM(feature_columns,feature_columns)
model.compile('adagrad','binary_crossentropy')
model.fit(model_input,label)
```

2.4.4 4. How to run the demo with GPU ?

```
import torch
device = 'cpu'
use_cuda = True
if use_cuda and torch.cuda.is_available():
    print('cuda ready...')
    device = 'cuda:0'

model = DeepFM(...,device=device)
```

2.4.5 5. How to run the demo with multiple GPUs ?

```
model = DeepFM(..., device=device, gpus=[0, 1])
```

2.5 History

- 10/22/2022 : v0.2.9 released.Add multi-task models: SharedBottom, ESMM, MMOE, PLE.
- 06/19/2022 : v0.2.8 released.Fix some bugs.
- 06/14/2021 : v0.2.7 released.Add AFN and fix some bugs.
- 04/04/2021 : v0.2.6 released.Add IFM and DIFM;Support multi-gpus running(example).
- 02/12/2021 : v0.2.5 released.Fix bug in DCN-M.
- 12/05/2020 : v0.2.4 released.Imporve compatibility & fix issues.Add History callback.(example).
- 10/18/2020 : v0.2.3 released.Add DCN-M&DCN-Mix.Add EarlyStopping and ModelCheckpoint callbacks(example).
- 10/09/2020 : v0.2.2 released.Improve the reproducibility & fix some bugs.

- 03/27/2020 : v0.2.1 released.Add DIN and DIEN .
- 01/31/2020 : v0.2.0 released.Refactor feature columns.Support to use double precision in metric calculation.
- 10/03/2019 : v0.1.3 released.Simplify the input logic.
- 09/28/2019 : v0.1.2 released.Add sequence(multi-value) input support.
- 09/24/2019 : v0.1.1 released. Add CCPM.
- 09/22/2019 : DeepCTR-Torch first version v0.1.0 is released on PyPi

2.6 DeepCTR-Torch Models API

2.6.1 deepctr_torch.models.basemodel module

Author: Weichen Shen,weichenswc@163.com zanshuxun, zanshuxun@aliyun.com

class deepctr_torch.models.basemodel.**BaseModel**(*linear_feature_columns*, *dnn_feature_columns*, *l2_reg_linear=1e-05*, *l2_reg_embedding=1e-05*, *init_std=0.0001*, *seed=1024*, *task='binary'*, *device='cpu'*, *gpus=None*)

compile(*optimizer*, *loss=None*, *metrics=None*)

Parameters

- **optimizer** – String (name of optimizer) or optimizer instance. See [optimizers](https://pytorch.org/docs/stable/optim.html).
- **loss** – String (name of objective function) or objective function. See [losses](https://pytorch.org/docs/stable/nn.functional.html#loss-functions).
- **metrics** – List of metrics to be evaluated by the model during training and testing. Typically you will use *metrics=['accuracy']*.

evaluate(*x*, *y*, *batch_size=256*)

Parameters

- **x** – Numpy array of test data (if the model has a single input), or list of Numpy arrays (if the model has multiple inputs).
- **y** – Numpy array of target (label) data (if the model has a single output), or list of Numpy arrays (if the model has multiple outputs).
- **batch_size** – Integer or *None*. Number of samples per evaluation step. If unspecified, *batch_size* will default to 256.

Returns Dict contains metric names and metric values.

fit(*x=None*, *y=None*, *batch_size=None*, *epochs=1*, *verbose=1*, *initial_epoch=0*, *validation_split=0.0*, *validation_data=None*, *shuffle=True*, *callbacks=None*)

Parameters

- **x** – Numpy array of training data (if the model has a single input), or list of Numpy arrays (if the model has multiple inputs).If input layers in the model are named, you can also pass a dictionary mapping input names to Numpy arrays.

- **y** – Numpy array of target (label) data (if the model has a single output), or list of Numpy arrays (if the model has multiple outputs).
- **batch_size** – Integer or *None*. Number of samples per gradient update. If unspecified, *batch_size* will default to 256.
- **epochs** – Integer. Number of epochs to train the model. An epoch is an iteration over the entire *x* and *y* data provided. Note that in conjunction with *initial_epoch*, *epochs* is to be understood as "final epoch". The model is not trained for a number of iterations given by *epochs*, but merely until the epoch of index *epochs* is reached.
- **verbose** – Integer. 0, 1, or 2. Verbosity mode. 0 = silent, 1 = progress bar, 2 = one line per epoch.
- **initial_epoch** – Integer. Epoch at which to start training (useful for resuming a previous training run).
- **validation_split** – Float between 0 and 1. Fraction of the training data to be used as validation data. The model will set apart this fraction of the training data, will not train on it, and will evaluate the loss and any model metrics on this data at the end of each epoch. The validation data is selected from the last samples in the *x* and *y* data provided, before shuffling.
- **validation_data** – tuple *(x_val, y_val)* or tuple *(x_val, y_val, val_sample_weights)* on which to evaluate the loss and any model metrics at the end of each epoch. The model will not be trained on this data. *validation_data* will override *validation_split*.
- **shuffle** – Boolean. Whether to shuffle the order of the batches at the beginning of each epoch.
- **callbacks** – List of *deepctr_torch.callbacks.Callback* instances. List of callbacks to apply during training and validation (if). See [callbacks](https://tensorflow.google.cn/api_docs/python/tf/keras/callbacks). Now available: *EarlyStopping* , *ModelCheckpoint*

Returns A *History* object. Its *History.history* attribute is a record of training loss values and metrics values at successive epochs, as well as validation loss values and validation metrics values (if applicable).

predict (*x*, *batch_size=256*)

Parameters

- **x** – The input data, as a Numpy array (or list of Numpy arrays if the model has multiple inputs).
- **batch_size** – Integer. If unspecified, it will default to 256.

Returns Numpy array(s) of predictions.

2.6.2 deepctr_torch.models.ccpm module

Author: Zeng Kai,kk163mail@126.com

Reference: [1] Liu Q, Yu F, Wu S, et al. A convolutional click prediction model[C]//Proceedings of the 24th ACM International on Conference on Information and Knowledge Management. ACM, 2015: 1743-1746. (http://ir.ia.ac.cn/bitstream/173211/12337/1/A%20Convolutional%20Click%20Prediction%20Model.pdf)

class deepctr_torch.models.ccpm.**CCPM**(*linear_feature_columns*, *dnn_feature_columns*, *conv_kernel_width=(6, 5)*, *conv_filters=(4, 4)*, *dnn_hidden_units=(256,)*, *l2_reg_linear=1e-05*, *l2_reg_embedding=1e-05*, *l2_reg_dnn=0*, *dnn_dropout=0*, *init_std=0.0001*, *seed=1024*, *task='binary'*, *device='cpu'*, *dnn_use_bn=False*, *dnn_activation='relu'*, *gpus=None*)

Instantiates the Convolutional Click Prediction Model architecture.

Parameters

- **linear_feature_columns** – An iterable containing all the features used by linear part of the model.
- **dnn_feature_columns** – An iterable containing all the features used by deep part of the model.
- **conv_kernel_width** – list,list of positive integer or empty list,the width of filter in each conv layer.
- **conv_filters** – list,list of positive integer or empty list,the number of filters in each conv layer.
- **dnn_hidden_units** – list,list of positive integer or empty list, the layer number and units in each layer of DNN.
- **l2_reg_linear** – float. L2 regularizer strength applied to linear part
- **l2_reg_embedding** – float. L2 regularizer strength applied to embedding vector
- **l2_reg_dnn** – float. L2 regularizer strength applied to DNN
- **dnn_dropout** – float in [0,1), the probability we will drop out a given DNN coordinate.
- **init_std** – float,to use as the initialize std of embedding vector
- **seed** – integer ,to use as random seed.
- **task** – str, `"binary"` for binary logloss or `"regression"` for regression loss
- **device** – str, `"cpu"` or `"cuda:0"`
- **gpus** – list of int or torch.device for multiple gpus. If None, run on *device*. *gpus[0]* should be the same gpu with *device*.

Returns A PyTorch model instance.

forward(*X*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

2.6.3 deepctr_torch.models.pnn module

Author: Weichen Shen,weichenswc@163.com

Reference: [1] Qu Y, Cai H, Ren K, et al. Product-based neural networks for user response prediction[C]//Data Mining (ICDM), 2016 IEEE 16th International Conference on. IEEE, 2016: 1149-1154.(https://arxiv.org/pdf/1611.00144.pdf)

class deepctr_torch.models.pnn.**PNN**(*dnn_feature_columns*, *dnn_hidden_units=(128, 128)*, *l2_reg_embedding=1e-05*, *l2_reg_dnn=0*, *init_std=0.0001*, *seed=1024*, *dnn_dropout=0*, *dnn_activation='relu'*, *use_inner=True*, *use_outter=False*, *kernel_type='mat'*, *task='binary'*, *device='cpu'*, *gpus=None*)

Instantiates the Product-based Neural Network architecture.

Parameters

- **dnn_feature_columns** – An iterable containing all the features used by deep part of the model.
- **dnn_hidden_units** – list,list of positive integer or empty list, the layer number and units in each layer of deep net
- **l2_reg_embedding** – float . L2 regularizer strength applied to embedding vector
- **l2_reg_dnn** – float. L2 regularizer strength applied to DNN
- **init_std** – float,to use as the initialize std of embedding vector
- **seed** – integer ,to use as random seed.
- **dnn_dropout** – float in [0,1), the probability we will drop out a given DNN coordinate.
- **dnn_activation** – Activation function to use in DNN
- **use_inner** – bool,whether use inner-product or not.
- **use_outter** – bool,whether use outter-product or not.
- **kernel_type** – str,kernel_type used in outter-product,can be `'mat'` , `'vec'` or `'num'`
- **task** – str, `"binary"` for binary logloss or `"regression"` for regression loss
- **device** – str, `"cpu"` or `"cuda:0"`
- **gpus** – list of int or torch.device for multiple gpus. If None, run on *device*. *gpus[0]* should be the same gpu with *device*.

Returns A PyTorch model instance.

forward(*X*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

2.6.4 deepctr_torch.models.wdl module

Author: Weichen Shen,weichenswc@163.com

Reference: [1] Cheng H T, Koc L, Harmsen J, et al. Wide & deep learning for recommender systems[C]//Proceedings of the 1st Workshop on Deep Learning for Recommender Systems. ACM, 2016: 7-10.(https://arxiv.org/pdf/1606.07792.pdf)

class deepctr_torch.models.wdl.**WDL**(*linear_feature_columns*, *dnn_feature_columns*, *dnn_hidden_units=(256, 128)*, *l2_reg_linear=1e-05*, *l2_reg_embedding=1e-05*, *l2_reg_dnn=0*, *init_std=0.0001*, *seed=1024*, *dnn_dropout=0*, *dnn_activation='relu'*, *dnn_use_bn=False*, *task='binary'*, *device='cpu'*, *gpus=None*)

Instantiates the Wide&Deep Learning architecture.

Parameters

- **linear_feature_columns** – An iterable containing all the features used by linear part of the model.
- **dnn_feature_columns** – An iterable containing all the features used by deep part of the model.
- **dnn_hidden_units** – list,list of positive integer or empty list, the layer number and units in each layer of DNN
- **l2_reg_linear** – float. L2 regularizer strength applied to wide part
- **l2_reg_embedding** – float. L2 regularizer strength applied to embedding vector
- **l2_reg_dnn** – float. L2 regularizer strength applied to DNN
- **init_std** – float,to use as the initialize std of embedding vector
- **seed** – integer ,to use as random seed.
- **dnn_dropout** – float in [0,1), the probability we will drop out a given DNN coordinate.
- **dnn_activation** – Activation function to use in DNN
- **task** – str, "binary" for binary logloss or "regression" for regression loss
- **device** – str, "cpu" or "cuda:0"
- **gpus** – list of int or torch.device for multiple gpus. If None, run on *device*. *gpus[0]* should be the same gpu with *device*.

Returns A PyTorch model instance.

forward(*X*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

2.6.5 deepctr_torch.models.deepfm module

Author: Weichen Shen,weichenswc@163.com

Reference: [1] Guo H, Tang R, Ye Y, et al. Deepfm: a factorization-machine based neural network for ctr prediction[J]. arXiv preprint arXiv:1703.04247, 2017.(https://arxiv.org/abs/1703.04247)

class deepctr_torch.models.deepfm.**DeepFM**(*linear_feature_columns*, *dnn_feature_columns*, *use_fm=True*, *dnn_hidden_units=(256, 128)*, *l2_reg_linear=1e-05*, *l2_reg_embedding=1e-05*, *l2_reg_dnn=0*, *init_std=0.0001*, *seed=1024*, *dnn_dropout=0*, *dnn_activation='relu'*, *dnn_use_bn=False*, *task='binary'*, *device='cpu'*, *gpus=None*)

Instantiates the DeepFM Network architecture.

Parameters

- **linear_feature_columns** – An iterable containing all the features used by linear part of the model.
- **dnn_feature_columns** – An iterable containing all the features used by deep part of the model.
- **use_fm** – bool,use FM part or not
- **dnn_hidden_units** – list,list of positive integer or empty list, the layer number and units in each layer of DNN
- **l2_reg_linear** – float. L2 regularizer strength applied to linear part
- **l2_reg_embedding** – float. L2 regularizer strength applied to embedding vector
- **l2_reg_dnn** – float. L2 regularizer strength applied to DNN
- **init_std** – float,to use as the initialize std of embedding vector
- **seed** – integer ,to use as random seed.
- **dnn_dropout** – float in [0,1), the probability we will drop out a given DNN coordinate.
- **dnn_activation** – Activation function to use in DNN
- **dnn_use_bn** – bool. Whether use BatchNormalization before activation or not in DNN
- **task** – str, `"binary"` for binary logloss or `"regression"` for regression loss
- **device** – str, `"cpu"` or `"cuda:0"`
- **gpus** – list of int or torch.device for multiple gpus. If None, run on *device*. *gpus[0]* should be the same gpu with *device*.

Returns A PyTorch model instance.

forward(*X*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

2.6.6 deepctr_torch.models.mlr module

Author: Wutong Zhang Weichen Shen,weichenswc@163.com

Reference: [1] Gai K, Zhu X, Li H, et al. Learning Piece-wise Linear Models from Large Scale Data for Ad Click Prediction[J]. arXiv preprint arXiv:1704.05194, 2017.(https://arxiv.org/abs/1704.05194)

class deepctr_torch.models.mlr.**MLR**(*region_feature_columns*, *base_feature_columns=None*, *bias_feature_columns=None*, *region_num=4*, *l2_reg_linear=1e-05*, *init_std=0.0001*, *seed=1024*, *task='binary'*, *device='cpu'*, *gpus=None*)

Instantiates the Mixed Logistic Regression/Piece-wise Linear Model.

Parameters

- **region_feature_columns** – An iterable containing all the features used by region part of the model.
- **base_feature_columns** – An iterable containing all the features used by base part of the model.
- **region_num** – integer > 1,indicate the piece number
- **l2_reg_linear** – float. L2 regularizer strength applied to weight
- **init_std** – float,to use as the initialize std of embedding vector
- **seed** – integer ,to use as random seed.
- **task** – str, `"binary"` for binary logloss or `"regression"` for regression loss
- **bias_feature_columns** – An iterable containing all the features used by bias part of the model.
- **device** – str, `"cpu"` or `"cuda:0"`
- **gpus** – list of int or torch.device for multiple gpus. If None, run on *device*. *gpus[0]* should be the same gpu with *device*.

Returns A PyTorch model instance.

forward(*X*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

2.6.7 deepctr_torch.models.nfm module

Author: Weichen Shen,weichenswc@163.com

Reference: [1] He X, Chua T S. Neural factorization machines for sparse predictive analytics[C]//Proceedings of the 40th International ACM SIGIR conference on Research and Development in Information Retrieval. ACM, 2017: 355-364. (https://arxiv.org/abs/1708.05027)

class deepctr_torch.models.nfm.**NFM**(*linear_feature_columns*, *dnn_feature_columns*, *dnn_hidden_units=(128, 128)*, *l2_reg_embedding=1e-05*, *l2_reg_linear=1e-05*, *l2_reg_dnn=0*, *init_std=0.0001*, *seed=1024*, *bi_dropout=0*, *dnn_dropout=0*, *dnn_activation='relu'*, *task='binary'*, *device='cpu'*, *gpus=None*)

Instantiates the NFM Network architecture.

Parameters

- **linear_feature_columns** – An iterable containing all the features used by linear part of the model.
- **dnn_feature_columns** – An iterable containing all the features used by deep part of the model.
- **dnn_hidden_units** – list,list of positive integer or empty list, the layer number and units in each layer of deep net
- **l2_reg_embedding** – float. L2 regularizer strength applied to embedding vector
- **l2_reg_linear** – float. L2 regularizer strength applied to linear part.
- **l2_reg_dnn** – float . L2 regularizer strength applied to DNN
- **init_std** – float,to use as the initialize std of embedding vector
- **seed** – integer ,to use as random seed.
- **biout_dropout** – When not `None`, the probability we will drop out the output of BiInteractionPooling Layer.
- **dnn_dropout** – float in [0,1), the probability we will drop out a given DNN coordinate.
- **dnn_activation** – Activation function to use in deep net
- **task** – str, `"binary"` for binary logloss or `"regression"` for regression loss
- **device** – str, `"cpu"` or `"cuda:0"`
- **gpus** – list of int or torch.device for multiple gpus. If None, run on *device*. *gpus[0]* should be the same gpu with *device*.

Returns A PyTorch model instance.

forward(*X*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

2.6.8 deepctr_torch.models.afm module

Author: Weichen Shen,weichenswc@163.com

Reference: [1] Xiao J, Ye H, He X, et al. Attentional factorization machines: Learning the weight of feature interactions via attention networks[J]. arXiv preprint arXiv:1708.04617, 2017. (https://arxiv.org/abs/1708.04617)

class deepctr_torch.models.afm.**AFM**(*linear_feature_columns*, *dnn_feature_columns*, *use_attention=True*, *attention_factor=8*, *l2_reg_linear=1e-05*, *l2_reg_embedding=1e-05*, *l2_reg_att=1e-05*, *afm_dropout=0*, *init_std=0.0001*, *seed=1024*, *task='binary'*, *device='cpu'*, *gpus=None*)

Instantiates the Attentional Factorization Machine architecture.

Parameters

- **linear_feature_columns** – An iterable containing all the features used by linear part of the model.

- **dnn_feature_columns** – An iterable containing all the features used by deep part of the model.
- **use_attention** – bool,whether use attention or not,if set to `False`.it is the same as **standard Factorization Machine**
- **attention_factor** – positive integer,units in attention net
- **l2_reg_linear** – float. L2 regularizer strength applied to linear part
- **l2_reg_embedding** – float. L2 regularizer strength applied to embedding vector
- **l2_reg_att** – float. L2 regularizer strength applied to attention net
- **afm_dropout** – float in [0,1), Fraction of the attention net output units to dropout.
- **init_std** – float,to use as the initialize std of embedding vector
- **seed** – integer ,to use as random seed.
- **task** – str, `"binary"` for binary logloss or `"regression"` for regression loss
- **device** – str, `"cpu"` or `"cuda:0"`
- **gpus** – list of int or torch.device for multiple gpus. If None, run on *device*. *gpus[0]* should be the same gpu with *device*.

Returns A PyTorch model instance.

forward(*X*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

2.6.9 deepctr_torch.models.dcn module

Author: chen_kkkk, bgasdo36977@gmail.com

zanshuxun, zanshuxun@aliyun.com

Reference: [1] Wang R, Fu B, Fu G, et al. Deep & cross network for ad click predictions[C]//Proceedings of the ADKDD'17. ACM, 2017: 12. (https://arxiv.org/abs/1708.05123)

[2] Wang R, Shivanna R, Cheng D Z, et al. DCN-M: Improved Deep & Cross Network for Feature Cross Learning in Web-scale Learning to Rank Systems[J]. 2020. (https://arxiv.org/abs/2008.13535)

class deepctr_torch.models.dcn.**DCN**(*linear_feature_columns, dnn_feature_columns, cross_num=2, cross_parameterization='vector', dnn_hidden_units=(128, 128), l2_reg_linear=1e-05, l2_reg_embedding=1e-05, l2_reg_cross=1e-05, l2_reg_dnn=0, init_std=0.0001, seed=1024, dnn_dropout=0, dnn_activation='relu', dnn_use_bn=False, task='binary', device='cpu', gpus=None*)

Instantiates the Deep&Cross Network architecture. Including DCN-V (parameterization='vector') and DCN-M (parameterization='matrix').

Parameters

- **linear_feature_columns** – An iterable containing all the features used by linear part of the model.
- **dnn_feature_columns** – An iterable containing all the features used by deep part of the model.
- **cross_num** – positive integet,cross layer number
- **cross_parameterization** – str, `"vector"` or `"matrix"`, how to parameterize the cross network.
- **dnn_hidden_units** – list,list of positive integer or empty list, the layer number and units in each layer of DNN
- **l2_reg_embedding** – float. L2 regularizer strength applied to embedding vector
- **l2_reg_cross** – float. L2 regularizer strength applied to cross net
- **l2_reg_dnn** – float. L2 regularizer strength applied to DNN
- **init_std** – float,to use as the initialize std of embedding vector
- **seed** – integer ,to use as random seed.
- **dnn_dropout** – float in [0,1), the probability we will drop out a given DNN coordinate.
- **dnn_use_bn** – bool. Whether use BatchNormalization before activation or not DNN
- **dnn_activation** – Activation function to use in DNN
- **task** – str, `"binary"` for binary logloss or `"regression"` for regression loss
- **device** – str, `"cpu"` or `"cuda:0"`
- **gpus** – list of int or torch.device for multiple gpus. If None, run on *device*. *gpus[0]* should be the same gpu with *device*.

Returns A PyTorch model instance.

forward(*X*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

2.6.10 deepctr_torch.models.dcnmix module

Author: chen_kkkk, bgasdo36977@gmail.com

zanshuxun, zanshuxun@aliyun.com

Reference: [1] Wang R, Fu B, Fu G, et al. Deep & cross network for ad click predictions[C]//Proceedings of the ADKDD'17. ACM, 2017: 12. (https://arxiv.org/abs/1708.05123)

[2] Wang R, Shivanna R, Cheng D Z, et al. DCN-M: Improved Deep & Cross Network for Feature Cross Learning in Web-scale Learning to Rank Systems[J]. 2020. (https://arxiv.org/abs/2008.13535)

class deepctr_torch.models.dcnmix.**DCNMix**(*linear_feature_columns*, *dnn_feature_columns*, *cross_num=2*, *dnn_hidden_units=(128, 128)*, *l2_reg_linear=1e-05*, *l2_reg_embedding=1e-05*, *l2_reg_cross=1e-05*, *l2_reg_dnn=0*, *init_std=0.0001*, *seed=1024*, *dnn_dropout=0*, *low_rank=32*, *num_experts=4*, *dnn_activation='relu'*, *dnn_use_bn=False*, *task='binary'*, *device='cpu'*, *gpus=None*)

Instantiates the DCN-Mix model.

Parameters

- **linear_feature_columns** – An iterable containing all the features used by linear part of the model.
- **dnn_feature_columns** – An iterable containing all the features used by deep part of the model.
- **cross_num** – positive integet,cross layer number
- **dnn_hidden_units** – list,list of positive integer or empty list, the layer number and units in each layer of DNN
- **l2_reg_embedding** – float. L2 regularizer strength applied to embedding vector
- **l2_reg_cross** – float. L2 regularizer strength applied to cross net
- **l2_reg_dnn** – float. L2 regularizer strength applied to DNN
- **init_std** – float,to use as the initialize std of embedding vector
- **seed** – integer ,to use as random seed.
- **dnn_dropout** – float in [0,1), the probability we will drop out a given DNN coordinate.
- **dnn_use_bn** – bool. Whether use BatchNormalization before activation or not DNN
- **dnn_activation** – Activation function to use in DNN
- **low_rank** – Positive integer, dimensionality of low-rank sapce.
- **num_experts** – Positive integer, number of experts.
- **task** – str, `"binary"` for binary logloss or `"regression"` for regression loss
- **device** – str, `"cpu"` or `"cuda:0"`
- **gpus** – list of int or torch.device for multiple gpus. If None, run on *device*. *gpus[0]* should be the same gpu with *device*.

Returns A PyTorch model instance.

forward(*X*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

2.6.11 deepctr_torch.models.din module

Author: Yuef Zhang

Reference: [1] Zhou G, Zhu X, Song C, et al. Deep interest network for click-through rate prediction[C]//Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. ACM, 2018: 1059-1068. (https://arxiv.org/pdf/1706.06978.pdf)

class deepctr_torch.models.din.**DIN**(*dnn_feature_columns*, *history_feature_list*, *dnn_use_bn=False*, *dnn_hidden_units=(256, 128)*, *dnn_activation='relu'*, *att_hidden_size=(64, 16)*, *att_activation='Dice'*, *att_weight_normalization=False*, *l2_reg_dnn=0.0*, *l2_reg_embedding=1e-06*, *dnn_dropout=0*, *init_std=0.0001*, *seed=1024*, *task='binary'*, *device='cpu'*, *gpus=None*)

Instantiates the Deep Interest Network architecture.

Parameters

- **dnn_feature_columns** – An iterable containing all the features used by deep part of the model.
- **history_feature_list** – list,to indicate sequence sparse field
- **dnn_use_bn** – bool. Whether use BatchNormalization before activation or not in deep net
- **dnn_hidden_units** – list,list of positive integer or empty list, the layer number and units in each layer of deep net
- **dnn_activation** – Activation function to use in deep net
- **att_hidden_size** – list,list of positive integer , the layer number and units in each layer of attention net
- **att_activation** – Activation function to use in attention net
- **att_weight_normalization** – bool. Whether normalize the attention score of local activation unit.
- **l2_reg_dnn** – float. L2 regularizer strength applied to DNN
- **l2_reg_embedding** – float. L2 regularizer strength applied to embedding vector
- **dnn_dropout** – float in [0,1), the probability we will drop out a given DNN coordinate.
- **init_std** – float,to use as the initialize std of embedding vector
- **seed** – integer ,to use as random seed.
- **task** – str, `"binary"` for binary logloss or `"regression"` for regression loss
- **device** – str, `"cpu"` or `"cuda:0"`
- **gpus** – list of int or torch.device for multiple gpus. If None, run on *device*. *gpus[0]* should be the same gpu with *device*.

Returns A PyTorch model instance.

forward(*X*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

2.6.12 deepctr_torch.models.dien module

Author: Ze Wang, wangze0801@126.com

Reference: [1] Zhou G, Mou N, Fan Y, et al. Deep Interest Evolution Network for Click-Through Rate Prediction[J]. arXiv preprint arXiv:1809.03672, 2018. (https://arxiv.org/pdf/1809.03672.pdf)

class deepctr_torch.models.dien.**DIEN**(*dnn_feature_columns*, *history_feature_list*, *gru_type='GRU'*, *use_negsampling=False*, *alpha=1.0*, *use_bn=False*, *dnn_hidden_units=(256, 128)*, *dnn_activation='relu'*, *att_hidden_units=(64, 16)*, *att_activation='relu'*, *att_weight_normalization=True*, *l2_reg_dnn=0*, *l2_reg_embedding=1e-06*, *dnn_dropout=0*, *init_std=0.0001*, *seed=1024*, *task='binary'*, *device='cpu'*, *gpus=None*)

Instantiates the Deep Interest Evolution Network architecture.

Parameters

- **dnn_feature_columns** – An iterable containing all the features used by deep part of the model.
- **history_feature_list** – list,to indicate sequence sparse field
- **gru_type** – str,can be GRU AIGRU AUGRU AGRU
- **use_negsampling** – bool, whether or not use negtive sampling
- **alpha** – float ,weight of auxiliary_loss
- **use_bn** – bool. Whether use BatchNormalization before activation or not in deep net
- **dnn_hidden_units** – list,list of positive integer or empty list, the layer number and units in each layer of DNN
- **dnn_activation** – Activation function to use in DNN
- **att_hidden_units** – list,list of positive integer , the layer number and units in each layer of attention net
- **att_activation** – Activation function to use in attention net
- **att_weight_normalization** – bool.Whether normalize the attention score of local activation unit.
- **l2_reg_dnn** – float. L2 regularizer strength applied to DNN
- **l2_reg_embedding** – float. L2 regularizer strength applied to embedding vector
- **dnn_dropout** – float in [0,1), the probability we will drop out a given DNN coordinate.
- **init_std** – float,to use as the initialize std of embedding vector
- **seed** – integer ,to use as random seed.
- **task** – str, `"binary"` for binary logloss or `"regression"` for regression loss
- **device** – str, `"cpu"` or `"cuda:0"`

- **gpus** – list of int or torch.device for multiple gpus. If None, run on *device*. *gpus[0]* should be the same gpu with *device*.

Returns A PyTorch model instance.

forward(*X*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

---

class deepctr_torch.models.dien.**InterestEvolving**(*input_size*, *gru_type='GRU'*, *use_neg=False*, *init_std=0.001*, *att_hidden_size=(64, 16)*, *att_activation='sigmoid'*, *att_weight_normalization=False*)

forward(*query*, *keys*, *keys_length*, *mask=None*)

query: 2D tensor, [B, H] keys: (masked_interests), 3D tensor, [b, T, H] keys_length: 1D tensor, [B]

outputs: 2D tensor, [B, H]

class deepctr_torch.models.dien.**InterestExtractor**(*input_size*, *use_neg=False*, *init_std=0.001*, *device='cpu'*)

forward(*keys*, *keys_length*, *neg_keys=None*)

keys: 3D tensor, [B, T, H] keys_length: 1D tensor, [B] neg_keys: 3D tensor, [B, T, H]

masked_interests: 2D tensor, [b, H] aux_loss: [1]

2.6.13 deepctr_torch.models.xdeepfm module

Author: Wutong Zhang

Reference: [1] Guo H, Tang R, Ye Y, et al. Deepfm: a factorization-machine based neural network for ctr prediction[J]. arXiv preprint arXiv:1703.04247, 2017.(https://arxiv.org/abs/1703.04247)

class deepctr_torch.models.xdeepfm.**xDeepFM**(*linear_feature_columns*, *dnn_feature_columns*, *dnn_hidden_units=(256, 256)*, *cin_layer_size=(256, 128)*, *cin_split_half=True*, *cin_activation='relu'*, *l2_reg_linear=1e-05*, *l2_reg_embedding=1e-05*, *l2_reg_dnn=0*, *l2_reg_cin=0*, *init_std=0.0001*, *seed=1024*, *dnn_dropout=0*, *dnn_activation='relu'*, *dnn_use_bn=False*, *task='binary'*, *device='cpu'*, *gpus=None*)

Instantiates the xDeepFM architecture.

Parameters

- **linear_feature_columns** – An iterable containing all the features used by linear part of the model.

- **dnn_feature_columns** – An iterable containing all the features used by deep part of the model.
- **dnn_hidden_units** – list,list of positive integer or empty list, the layer number and units in each layer of deep net
- **cin_layer_size** – list,list of positive integer or empty list, the feature maps in each hidden layer of Compressed Interaction Network
- **cin_split_half** – bool.if set to True, half of the feature maps in each hidden will connect to output unit
- **cin_activation** – activation function used on feature maps
- **l2_reg_linear** – float. L2 regularizer strength applied to linear part
- **l2_reg_embedding** – L2 regularizer strength applied to embedding vector
- **l2_reg_dnn** – L2 regularizer strength applied to deep net
- **l2_reg_cin** – L2 regularizer strength applied to CIN.
- **init_std** – float,to use as the initialize std of embedding vector
- **seed** – integer ,to use as random seed.
- **dnn_dropout** – float in [0,1), the probability we will drop out a given DNN coordinate.
- **dnn_activation** – Activation function to use in DNN
- **dnn_use_bn** – bool. Whether use BatchNormalization before activation or not in DNN
- **task** – str, `"binary"` for binary logloss or `"regression"` for regression loss
- **device** – str, `"cpu"` or `"cuda:0"`
- **gpus** – list of int or torch.device for multiple gpus. If None, run on *device*. *gpus[0]* should be the same gpu with *device*.

Returns A PyTorch model instance.

forward(*X*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

2.6.14 deepctr_torch.models.autoint module

Author: Weichen Shen,weichenswc@163.com

Reference: [1] Song W, Shi C, Xiao Z, et al. AutoInt: Automatic Feature Interaction Learning via Self-Attentive Neural Networks[J]. arXiv preprint arXiv:1810.11921, 2018.(https://arxiv.org/abs/1810.11921)

class deepctr_torch.models.autoint.**AutoInt**(*linear_feature_columns*, *dnn_feature_columns*, *att_layer_num=3*, *att_head_num=2*, *att_res=True*, *dnn_hidden_units=(256*, *128)*, *dnn_activation='relu'*, *l2_reg_dnn=0*, *l2_reg_embedding=1e-05*, *dnn_use_bn=False*, *dnn_dropout=0*, *init_std=0.0001*, *seed=1024*, *task='binary'*, *device='cpu'*, *gpus=None*)

Instantiates the AutoInt Network architecture.

Parameters

- **linear_feature_columns** – An iterable containing all the features used by linear part of the model.
- **dnn_feature_columns** – An iterable containing all the features used by deep part of the model.
- **att_layer_num** – int.The InteractingLayer number to be used.
- **att_head_num** – int.The head number in multi-head self-attention network.
- **att_res** – bool.Whether or not use standard residual connections before output.
- **dnn_hidden_units** – list,list of positive integer or empty list, the layer number and units in each layer of DNN
- **dnn_activation** – Activation function to use in DNN
- **l2_reg_dnn** – float. L2 regularizer strength applied to DNN
- **l2_reg_embedding** – float. L2 regularizer strength applied to embedding vector
- **dnn_use_bn** – bool. Whether use BatchNormalization before activation or not in DNN
- **dnn_dropout** – float in [0,1), the probability we will drop out a given DNN coordinate.
- **init_std** – float,to use as the initialize std of embedding vector
- **seed** – integer ,to use as random seed.
- **task** – str, `"binary"` for binary logloss or `"regression"` for regression loss
- **device** – str, `"cpu"` or `"cuda:0"`
- **gpus** – list of int or torch.device for multiple gpus. If None, run on *device*. *gpus[0]* should be the same gpu with *device*.

Returns A PyTorch model instance.

forward(*X*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

2.6.15 deepctr_torch.models.onn module

Author: Junyi Huo

Reference: [1] Yang Y, Xu B, Shen F, et al. Operation-aware Neural Networks for User Response Prediction[J]. arXiv preprint arXiv:1904.12579, 2019. https://arxiv.org/pdf/1904.12579

class `deepctr_torch.models.onn.`**`ONN`**(*linear_feature_columns*, *dnn_feature_columns*, *dnn_hidden_units=(128*, *128)*, *l2_reg_embedding=1e-05*, *l2_reg_linear=1e-05*, *l2_reg_dnn=0*, *dnn_dropout=0*, *init_std=0.0001*, *seed=1024*, *dnn_use_bn=False*, *dnn_activation='relu'*, *task='binary'*, *device='cpu'*, *gpus=None*)

Instantiates the Operation-aware Neural Networks architecture.

Parameters

- **linear_feature_columns** – An iterable containing all the features used by linear part of the model.
- **dnn_feature_columns** – An iterable containing all the features used by deep part of the model.
- **dnn_hidden_units** – list,list of positive integer or empty list, the layer number and units in each layer of deep net
- **l2_reg_embedding** – float. L2 regularizer strength applied to embedding vector
- **l2_reg_linear** – float. L2 regularizer strength applied to linear part.
- **l2_reg_dnn** – float . L2 regularizer strength applied to DNN
- **init_std** – float,to use as the initialize std of embedding vector
- **seed** – integer ,to use as random seed.
- **dnn_dropout** – float in [0,1), the probability we will drop out a given DNN coordinate.
- **use_bn** – bool,whether use bn after ffm out or not
- **reduce_sum** – bool,whether apply reduce_sum on cross vector
- **task** – str, `"binary"` for binary logloss or `"regression"` for regression loss
- **device** – str, `"cpu"` or `"cuda:0"`
- **gpus** – list of int or torch.device for multiple gpus. If None, run on *device*. *gpus[0]* should be the same gpu with *device*.

Returns A PyTorch model instance.

`forward`(*X*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

2.6.16 deepctr_torch.models.fibinet module

Author: Wutong Zhang

Reference: [1] Huang T, Zhang Z, Zhang J. FiBiNET: Combining Feature Importance and Bilinear feature Interaction for Click-Through Rate Prediction[J]. arXiv preprint arXiv:1905.09433, 2019.

class `deepctr_torch.models.fibinet.`**`FiBiNET`**(*linear_feature_columns, dnn_feature_columns, bilinear_type='interaction', reduction_ratio=3, dnn_hidden_units=(128, 128), l2_reg_linear=1e-05, l2_reg_embedding=1e-05, l2_reg_dnn=0, init_std=0.0001, seed=1024, dnn_dropout=0, dnn_activation='relu', task='binary', device='cpu', gpus=None*)

Instantiates the Feature Importance and Bilinear feature Interaction NETwork architecture.

Parameters

- **linear_feature_columns** – An iterable containing all the features used by linear part of the model.
- **dnn_feature_columns** – An iterable containing all the features used by deep part of the model.
- **bilinear_type** – str,bilinear function type used in Bilinear Interaction Layer,can be `'all'` , `'each'` or `'interaction'`
- **reduction_ratio** – integer in [1,inf), reduction ratio used in SENET Layer
- **dnn_hidden_units** – list,list of positive integer or empty list, the layer number and units in each layer of DNN
- **l2_reg_linear** – float. L2 regularizer strength applied to wide part
- **l2_reg_embedding** – float. L2 regularizer strength applied to embedding vector
- **l2_reg_dnn** – float. L2 regularizer strength applied to DNN
- **init_std** – float,to use as the initialize std of embedding vector
- **seed** – integer ,to use as random seed.
- **dnn_dropout** – float in [0,1), the probability we will drop out a given DNN coordinate.
- **dnn_activation** – Activation function to use in DNN
- **task** – str, `"binary"` for binary logloss or `"regression"` for regression loss
- **device** – str, `"cpu"` or `"cuda:0"`
- **gpus** – list of int or torch.device for multiple gpus. If None, run on *device*. *gpus[0]* should be the same gpu with *device*.

Returns A PyTorch model instance.

forward(*X*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

2.6.17 deepctr_torch.models.ifm module

Author: zanshuxun, zanshuxun@aliyun.com

Reference: [1] Yu Y, Wang Z, Yuan B. An Input-aware Factorization Machine for Sparse Prediction[C]//IJCAI. 2019: 1466-1472.(https://www.ijcai.org/Proceedings/2019/0203.pdf)

class deepctr_torch.models.ifm.**IFM**(*linear_feature_columns*, *dnn_feature_columns*, *dnn_hidden_units=(256, 128)*, *l2_reg_linear=1e-05*, *l2_reg_embedding=1e-05*, *l2_reg_dnn=0*, *init_std=0.0001*, *seed=1024*, *dnn_dropout=0*, *dnn_activation='relu'*, *dnn_use_bn=False*, *task='binary'*, *device='cpu'*, *gpus=None*)

Instantiates the IFM Network architecture.

Parameters

- **linear_feature_columns** – An iterable containing all the features used by linear part of the model.
- **dnn_feature_columns** – An iterable containing all the features used by deep part of the model.
- **dnn_hidden_units** – list,list of positive integer or empty list, the layer number and units in each layer of DNN
- **l2_reg_linear** – float. L2 regularizer strength applied to linear part
- **l2_reg_embedding** – float. L2 regularizer strength applied to embedding vector
- **l2_reg_dnn** – float. L2 regularizer strength applied to DNN
- **init_std** – float,to use as the initialize std of embedding vector
- **seed** – integer ,to use as random seed.
- **dnn_dropout** – float in [0,1), the probability we will drop out a given DNN coordinate.
- **dnn_activation** – Activation function to use in DNN
- **dnn_use_bn** – bool. Whether use BatchNormalization before activation or not in DNN
- **task** – str, `"binary"` for binary logloss or `"regression"` for regression loss
- **device** – str, `"cpu"` or `"cuda:0"`
- **gpus** – list of int or torch.device for multiple gpus. If None, run on `device` . `gpus[0]` should be the same gpu with `device` .

Returns A PyTorch model instance.

forward(*X*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

2.6.18 deepctr_torch.models.difm module

Author: zanshuxun, zanshuxun@aliyun.com

Reference: [1] Lu W, Yu Y, Chang Y, et al. A Dual Input-aware Factorization Machine for CTR Prediction[C]//IJCAI. 2020: 3139-3145.(https://www.ijcai.org/Proceedings/2020/0434.pdf)

class `deepctr_torch.models.difm.`**`DIFM`**(*linear_feature_columns*, *dnn_feature_columns*, *att_head_num=4*, *att_res=True*, *dnn_hidden_units=(256, 128)*, *l2_reg_linear=1e-05*, *l2_reg_embedding=1e-05*, *l2_reg_dnn=0*, *init_std=0.0001*, *seed=1024*, *dnn_dropout=0*, *dnn_activation='relu'*, *dnn_use_bn=False*, *task='binary'*, *device='cpu'*, *gpus=None*)

Instantiates the DIFM Network architecture.

Parameters

- **`linear_feature_columns`** – An iterable containing all the features used by linear part of the model.
- **`dnn_feature_columns`** – An iterable containing all the features used by deep part of the model.
- **`att_head_num`** – int. The head number in multi-head self-attention network.
- **`att_res`** – bool. Whether or not use standard residual connections before output.
- **`dnn_hidden_units`** – list,list of positive integer or empty list, the layer number and units in each layer of DNN
- **`l2_reg_linear`** – float. L2 regularizer strength applied to linear part
- **`l2_reg_embedding`** – float. L2 regularizer strength applied to embedding vector
- **`l2_reg_dnn`** – float. L2 regularizer strength applied to DNN
- **`init_std`** – float,to use as the initialize std of embedding vector
- **`seed`** – integer ,to use as random seed.
- **`dnn_dropout`** – float in [0,1), the probability we will drop out a given DNN coordinate.
- **`dnn_activation`** – Activation function to use in DNN
- **`dnn_use_bn`** – bool. Whether use BatchNormalization before activation or not in DNN
- **`task`** – str, `"binary"` for binary logloss or `"regression"` for regression loss
- **`device`** – str, `"cpu"` or `"cuda:0"`
- **`gpus`** – list of int or torch.device for multiple gpus. If None, run on `device` . `gpus[0]` should be the same gpu with `device` .

Returns A PyTorch model instance.

forward(*X*)
Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

2.6.19 deepctr_torch.models.multitask.sharedbottom module

Author: zanshuxun, zanshuxun@aliyun.com

Reference: [1] Ruder S. An overview of multi-task learning in deep neural networks[J]. arXiv preprint arXiv:1706.05098, 2017.(https://arxiv.org/pdf/1706.05098.pdf)

class deepctr_torch.models.multitask.sharedbottom.**SharedBottom**(*dnn_feature_columns, bottom_dnn_hidden_units=(256, 128), tower_dnn_hidden_units=(64,), l2_reg_linear=1e-05, l2_reg_embedding=1e-05, l2_reg_dnn=0, init_std=0.0001, seed=1024, dnn_dropout=0, dnn_activation='relu', dnn_use_bn=False, task_types=('binary', 'binary'), task_names=('ctr', 'ctcvr'), device='cpu', gpus=None*)

Instantiates the SharedBottom multi-task learning Network architecture.

Parameters

- **dnn_feature_columns** – An iterable containing all the features used by deep part of the model.
- **bottom_dnn_hidden_units** – list, list of positive integer or empty list, the layer number and units in each layer of shared bottom DNN.
- **tower_dnn_hidden_units** – list, list of positive integer or empty list, the layer number and units in each layer of task-specific DNN.
- **l2_reg_linear** – float, L2 regularizer strength applied to linear part
- **l2_reg_embedding** – float, L2 regularizer strength applied to embedding vector
- **l2_reg_dnn** – float, L2 regularizer strength applied to DNN

- **init_std** – float, to use as the initialize std of embedding vector
- **seed** – integer, to use as random seed.
- **dnn_dropout** – float in [0,1), the probability we will drop out a given DNN coordinate.
- **dnn_activation** – Activation function to use in DNN
- **dnn_use_bn** – bool, Whether use BatchNormalization before activation or not in DNN
- **task_types** – list of str, indicating the loss of each tasks, `"binary"` for binary logloss or `"regression"` for regression loss. e.g. ['binary', 'regression']
- **task_names** – list of str, indicating the predict target of each tasks
- **device** – str, `"cpu"` or `"cuda:0"`
- **gpus** – list of int or torch.device for multiple gpus. If None, run on *device*. *gpus[0]* should be the same gpu with *device*.

Returns A PyTorch model instance.

forward(*X*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

2.6.20 deepctr_torch.models.multitask.esmm module

Author: zanshuxun, zanshuxun@aliyun.com

Reference: [1] Ma X, Zhao L, Huang G, et al. Entire space multi-task model: An effective approach for estimating post-click conversion rate[C]//The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval. 2018.(https://dl.acm.org/doi/10.1145/3209978.3210104)

class deepctr_torch.models.multitask.esmm.**ESMM**(*dnn_feature_columns, tower_dnn_hidden_units=(256, 128), l2_reg_linear=1e-05, l2_reg_embedding=1e-05, l2_reg_dnn=0, init_std=0.0001, seed=1024, dnn_dropout=0, dnn_activation='relu', dnn_use_bn=False, task_types=('binary', 'binary'), task_names=('ctr', 'ctcvr'), device='cpu', gpus=None*)

Instantiates the Entire Space Multi-Task Model architecture.

Parameters

- **dnn_feature_columns** – An iterable containing all the features used by deep part of the model.
- **tower_dnn_hidden_units** – list, list of positive integer or empty list, the layer number and units in each layer of task-specific DNN.

- **l2_reg_linear** – float, L2 regularizer strength applied to linear part.
- **l2_reg_embedding** – float, L2 regularizer strength applied to embedding vector.
- **l2_reg_dnn** – float, L2 regularizer strength applied to DNN.
- **init_std** – float, to use as the initialize std of embedding vector.
- **seed** – integer, to use as random seed.
- **dnn_dropout** – float in [0,1), the probability we will drop out a given DNN coordinate.
- **dnn_activation** – Activation function to use in DNN.
- **dnn_use_bn** – bool, Whether use BatchNormalization before activation or not in DNN.
- **task_types** – list of str, indicating the loss of each tasks, `"binary"` for binary logloss or `"regression"` for regression loss. e.g. ['binary', 'regression'].
- **task_names** – list of str, indicating the predict target of each tasks.
- **device** – str, `"cpu"` or `"cuda:0"`.
- **gpus** – list of int or torch.device for multiple gpus. If None, run on *device*. *gpus[0]* should be the same gpu with *device*.

Returns A PyTorch model instance.

forward(*X*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

2.6.21 deepctr_torch.models.multitask.mmoe module

Author: zanshuxun, zanshuxun@aliyun.com

Reference: [1] Jiaqi Ma, Zhe Zhao, Xinyang Yi, et al. Modeling Task Relationships in Multi-task Learning with Multi-gate Mixture-of-Experts[C] (https://dl.acm.org/doi/10.1145/3219819.3220007)

class deepctr_torch.models.multitask.mmoe.**MMOE**(*dnn_feature_columns, num_experts=3, expert_dnn_hidden_units=(256, 128), gate_dnn_hidden_units=(64,), tower_dnn_hidden_units=(64,), l2_reg_linear=1e-05, l2_reg_embedding=1e-05, l2_reg_dnn=0, init_std=0.0001, seed=1024, dnn_dropout=0, dnn_activation='relu', dnn_use_bn=False, task_types=('binary', 'binary'), task_names=('ctr', 'ctcvr'), device='cpu', gpus=None*)

Instantiates the Multi-gate Mixture-of-Experts architecture.

Parameters

- **dnn_feature_columns** – An iterable containing all the features used by deep part of the model.
- **num_experts** – integer, number of experts.
- **expert_dnn_hidden_units** – list, list of positive integer or empty list, the layer number and units in each layer of expert DNN.
- **gate_dnn_hidden_units** – list, list of positive integer or empty list, the layer number and units in each layer of gate DNN.
- **tower_dnn_hidden_units** – list, list of positive integer or empty list, the layer number and units in each layer of task-specific DNN.
- **l2_reg_linear** – float, L2 regularizer strength applied to linear part.
- **l2_reg_embedding** – float, L2 regularizer strength applied to embedding vector.
- **l2_reg_dnn** – float, L2 regularizer strength applied to DNN.
- **init_std** – float, to use as the initialize std of embedding vector.
- **seed** – integer, to use as random seed.
- **dnn_dropout** – float in [0,1), the probability we will drop out a given DNN coordinate.
- **dnn_activation** – Activation function to use in DNN.
- **dnn_use_bn** – bool, Whether use BatchNormalization before activation or not in DNN.
- **task_types** – list of str, indicating the loss of each tasks, `"binary"` for binary logloss, `"regression"` for regression loss. e.g. ['binary', 'regression'].
- **task_names** – list of str, indicating the predict target of each tasks.
- **device** – str, `"cpu"` or `"cuda:0"`.
- **gpus** – list of int or torch.device for multiple gpus. If None, run on *device*. *gpus[0]* should be the same gpu with *device*.

Returns A PyTorch model instance.

forward(*X*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

2.6.22 deepctr_torch.models.multitask.ple module

Author: zanshuxun, zanshuxun@aliyun.com

Reference: [1] Tang H, Liu J, Zhao M, et al. Progressive layered extraction (ple): A novel multi-task learning (mtl) model for personalized recommendations[C]//Fourteenth ACM Conference on Recommender Systems. 2020.(https://dl.acm.org/doi/10.1145/3383313.3412236)

class `deepctr_torch.models.multitask.ple.`**`PLE`**(*dnn_feature_columns, shared_expert_num=1, specific_expert_num=1, num_levels=2, expert_dnn_hidden_units=(256, 128), gate_dnn_hidden_units=(64,), tower_dnn_hidden_units=(64,), l2_reg_linear=1e-05, l2_reg_embedding=1e-05, l2_reg_dnn=0, init_std=0.0001, seed=1024, dnn_dropout=0, dnn_activation='relu', dnn_use_bn=False, task_types=('binary', 'binary'), task_names=('ctr', 'ctcvr'), device='cpu', gpus=None*)

Instantiates the multi level of Customized Gate Control of Progressive Layered Extraction architecture.

Parameters

- **dnn_feature_columns** – An iterable containing all the features used by deep part of the model.
- **shared_expert_num** – integer, number of task-shared experts.
- **specific_expert_num** – integer, number of task-specific experts.
- **num_levels** – integer, number of CGC levels.
- **expert_dnn_hidden_units** – list, list of positive integer or empty list, the layer number and units in each layer of expert DNN.
- **gate_dnn_hidden_units** – list, list of positive integer or empty list, the layer number and units in each layer of gate DNN.
- **tower_dnn_hidden_units** – list, list of positive integer or empty list, the layer number and units in each layer of task-specific DNN.
- **l2_reg_linear** – float, L2 regularizer strength applied to linear part.
- **l2_reg_embedding** – float, L2 regularizer strength applied to embedding vector.
- **l2_reg_dnn** – float, L2 regularizer strength applied to DNN.
- **init_std** – float, to use as the initialize std of embedding vector.
- **seed** – integer, to use as random seed.
- **dnn_dropout** – float in [0,1), the probability we will drop out a given DNN coordinate.
- **dnn_activation** – Activation function to use in DNN.
- **dnn_use_bn** – bool, Whether use BatchNormalization before activation or not in DNN.
- **task_types** – list of str, indicating the loss of each tasks, `"binary"` for binary logloss, `"regression"` for regression loss. e.g. ['binary', 'regression']
- **task_names** – list of str, indicating the predict target of each tasks.
- **device** – str, `"cpu"` or `"cuda:0"`.
- **gpus** – list of int or torch.device for multiple gpus. If None, run on *device*. *gpus[0]* should be the same gpu with *device*.

Returns A PyTorch model instance.

forward(*X*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

2.7 DeepCTR-Torch Layers API

2.7.1 deepctr_torch.layers.core module

class `deepctr_torch.layers.core.`**`Conv2dSame`**(*in_channels*, *out_channels*, *kernel_size*, *stride=1*, *padding=0*, *dilation=1*, *groups=1*, *bias=True*)

Tensorflow like 'SAME' convolution wrapper for 2D convolutions

`forward`(*x*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

class `deepctr_torch.layers.core.`**`DNN`**(*inputs_dim*, *hidden_units*, *activation='relu'*, *l2_reg=0*, *dropout_rate=0*, *use_bn=False*, *init_std=0.0001*, *dice_dim=3*, *seed=1024*, *device='cpu'*)

The Multi Layer Percetron

Input shape

- nD tensor with shape: `(batch_size, ..., input_dim)`. The most common situation would be a 2D input with shape `(batch_size, input_dim)`.

Output shape

- nD tensor with shape: `(batch_size, ..., hidden_size[-1])`. For instance, for a 2D input with shape `(batch_size, input_dim)`, the output would have shape `(batch_size, hidden_size[-1])`.

Arguments

- **inputs_dim**: input feature dimension.
- **hidden_units**:list of positive integer, the layer number and units in each layer.
- **activation**: Activation function to use.
- **l2_reg**: float between 0 and 1. L2 regularizer strength applied to the kernel weights matrix.
- **dropout_rate**: float in [0,1). Fraction of the units to dropout.
- **use_bn**: bool. Whether use BatchNormalization before activation or not.
- **seed**: A Python integer to use as random seed.

forward(*inputs*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

---

class `deepctr_torch.layers.core.`**LocalActivationUnit**(*hidden_units=(64, 32)*, *embedding_dim=4*, *activation='sigmoid'*, *dropout_rate=0*, *dice_dim=3*, *l2_reg=0*, *use_bn=False*)

The LocalActivationUnit used in DIN with which the representation of user interests varies adaptively given different candidate items.

Input shape

- A list of two 3D tensor with shape: `(batch_size, 1, embedding_size)` and `(batch_size, T, embedding_size)`

Output shape

- 3D tensor with shape: `(batch_size, T, 1)`.

Arguments

- **hidden_units**:list of positive integer, the attention net layer number and units in each layer.
- **activation**: Activation function to use in attention net.
- **l2_reg**: float between 0 and 1. L2 regularizer strength applied to the kernel weights matrix of attention net.
- **dropout_rate**: float in [0,1). Fraction of the units to dropout in attention net.
- **use_bn**: bool. Whether use BatchNormalization before activation or not in attention net.
- **seed**: A Python integer to use as random seed.

References

- [Zhou G, Zhu X, Song C, et al. Deep interest network for click-through rate prediction[C]//Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. ACM, 2018: 1059-1068.](https://arxiv.org/pdf/1706.06978.pdf)

forward(*query*, *user_behavior*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

---

class `deepctr_torch.layers.core.`**PredictionLayer**(*task='binary'*, *use_bias=True*, ***kwargs*)

Arguments

- **task**: str, `"binary"` for binary logloss or `"regression"` for regression loss
- **use_bias**: bool.Whether add bias term or not.

forward(*X*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

2.7.2 deepctr_torch.layers.interaction module

class deepctr_torch.layers.interaction.**AFMLayer**(*in_features*, *attention_factor=4*, *l2_reg_w=0*, *dropout_rate=0*, *seed=1024*, *device='cpu'*)

Attentonal Factorization Machine models pairwise (order-2) feature interactions without linear term and bias.

Input shape

- A list of 3D tensor with shape: `(batch_size,1,embedding_size)`.

Output shape

- 2D tensor with shape: `(batch_size, 1)`.

Arguments

- **in_features** : Positive integer, dimensionality of input features.
- **attention_factor** : Positive integer, dimensionality of the

  attention network output space.

- **l2_reg_w** : float between 0 and 1. L2 regularizer strength

  applied to attention network.

- **dropout_rate** : float between in [0,1). Fraction of the attention net output units to dropout.
- **seed** : A Python integer to use as random seed.

References

- [Attentional Factorization Machines : Learning the Weight of Feature

Interactions via Attention Networks](https://arxiv.org/pdf/1708.04617.pdf)

forward(*inputs*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

---

class `deepctr_torch.layers.interaction.`**`BiInteractionPooling`**

Bi-Interaction Layer used in Neural FM,compress the pairwise element-wise product of features into one single vector.

Input shape

- A 3D tensor with shape: `(batch_size,field_size,embedding_size)`.

Output shape

- 3D tensor with shape: `(batch_size,1,embedding_size)`.

References

- [He X, Chua T S. Neural factorization machines for sparse predictive analytics[C]//Proceedings of the 40th International ACM SIGIR conference on Research and Development in Information Retrieval. ACM, 2017: 355-364.](http://arxiv.org/abs/1708.05027)

`forward`(*inputs*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

---

class `deepctr_torch.layers.interaction.`**`BilinearInteraction`**(*filed_size, embedding_size, bilinear_type='interaction', seed=1024, device='cpu'*)

BilinearInteraction Layer used in FiBiNET.

Input shape

- A list of 3D tensor with shape: `(batch_size,filed_size, embedding_size)`.

Output shape

- 3D tensor with shape: `(batch_size,filed_size*(filed_size-1)/2, embedding_size)`.

Arguments

- **filed_size** : Positive integer, number of feature groups.
- **embedding_size** : Positive integer, embedding size of sparse features.
- **bilinear_type** : String, types of bilinear functions used in this layer.
- **seed** : A Python integer to use as random seed.

References

- [FiBiNET: Combining Feature Importance and Bilinear feature Interaction for Click-Through Rate Prediction

Tongwen](https://arxiv.org/pdf/1905.09433.pdf)

forward(*inputs*)
Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

---

class `deepctr_torch.layers.interaction.`**CIN**(*field_size*, *layer_size=(128, 128)*, *activation='relu'*, *split_half=True*, *l2_reg=1e-05*, *seed=1024*, *device='cpu'*)

Compressed Interaction Network used in xDeepFM. Input shape

- 3D tensor with shape: `(batch_size,field_size,embedding_size)`.

Output shape

- 2D tensor with shape: `(batch_size, featuremap_num)` `featuremap_num = sum(self.layer_size[:-1]) // 2 + self.layer_size[-1]` if `split_half=True`,else `sum(layer_size)` .

Arguments

- **filed_size** : Positive integer, number of feature groups.
- **layer_size** : list of int.Feature maps in each layer.
- **activation** : activation function name used on feature maps.
- **split_half** : bool.if set to False, half of the feature maps in each hidden will connect to output unit.
- **seed** : A Python integer to use as random seed.

References

- [Lian J, Zhou X, Zhang F, et al. xDeepFM: Combining Explicit and Implicit Feature Interactions for Recommender Systems[J]. arXiv preprint arXiv:1803.05170, 2018.] (https://arxiv.org/pdf/1803.05170.pdf)

forward(*inputs*)
Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

---

class `deepctr_torch.layers.interaction.`**ConvLayer**(*field_size*, *conv_kernel_width*, *conv_filters*, *device='cpu'*)

Conv Layer used in CCPM.

Input shape

- A list of N 3D tensor with shape: `(batch_size,1,filed_size,embedding_size)`.

Output shape

- A list of N 3D tensor with shape: `(batch_size,last_filters,pooling_size, embedding_size)`.

Arguments

- **filed_size** : Positive integer, number of feature groups.
- **conv_kernel_width**: list. list of positive integer or empty list,the width of filter in each conv layer.
- **conv_filters**: list. list of positive integer or empty list,the number of filters in each conv layer.

Reference:

- Liu Q, Yu F, Wu S, et al. A convolutional click prediction model[C]//Proceedings of the 24th ACM International on Conference on Information and Knowledge Management. ACM, 2015: 1743-1746.(http://ir.ia.ac.cn/bitstream/173211/12337/1/A%20Convolutional%20Click%20Prediction%20Model.pdf)

forward(*inputs*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

---

class deepctr_torch.layers.interaction.**CrossNet**(*in_features*, *layer_num=2*, *parameterization='vector'*, *seed=1024*, *device='cpu'*)

The Cross Network part of Deep&Cross Network model, which leans both low and high degree cross feature.

Input shape

- 2D tensor with shape: `(batch_size, units)`.

Output shape

- 2D tensor with shape: `(batch_size, units)`.

Arguments

- **in_features** : Positive integer, dimensionality of input features.
- **input_feature_num**: Positive integer, shape(Input tensor)[-1]
- **layer_num**: Positive integer, the cross layer number
- **parameterization**: string, `"vector"` or `"matrix"` , way to parameterize the cross network.
- **l2_reg**: float between 0 and 1. L2 regularizer strength applied to the kernel weights matrix
- **seed**: A Python integer to use as random seed.

References

- [Wang R, Fu B, Fu G, et al. Deep & cross network for ad click predictions[C]//Proceedings of the ADKDD'17. ACM, 2017: 12.](https://arxiv.org/abs/1708.05123)
- [Wang R, Shivanna R, Cheng D Z, et al. DCN-M: Improved Deep & Cross Network for Feature Cross Learning in Web-scale Learning to Rank Systems[J]. 2020.](https://arxiv.org/abs/2008.13535)

forward (*inputs*)
Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

---

class `deepctr_torch.layers.interaction.`**CrossNetMix** (*in_features*, *low_rank=32*, *num_experts=4*, *layer_num=2*, *device='cpu'*)
The Cross Network part of DCN-Mix model, which improves DCN-M by: 1 add MOE to learn feature interactions in different subspaces 2 add nonlinear transformations in low-dimensional space Input shape

- 2D tensor with shape: `(batch_size, units)`.

Output shape

- 2D tensor with shape: `(batch_size, units)`.

Arguments

- **in_features** : Positive integer, dimensionality of input features.
- **low_rank** : Positive integer, dimensionality of low-rank sapce.
- **num_experts** : Positive integer, number of experts.
- **layer_num**: Positive integer, the cross layer number
- **device**: str, e.g. `"cpu"` or `"cuda:0"`

References

- [Wang R, Shivanna R, Cheng D Z, et al. DCN-M: Improved Deep & Cross Network for Feature Cross Learning in Web-scale Learning to Rank Systems[J]. 2020.](https://arxiv.org/abs/2008.13535)

forward (*inputs*)
Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

---

class `deepctr_torch.layers.interaction.`**FM**
Factorization Machine models pairwise (order-2) feature interactions without linear term and bias.

Input shape

- 3D tensor with shape: `(batch_size,field_size,embedding_size)`.

Output shape

- 2D tensor with shape: `(batch_size, 1)`.

References

- [Factorization Machines](https://www.csie.ntu.edu.tw/~b97053/paper/Rendle2010FM.pdf)

forward(*inputs*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

---

class deepctr_torch.layers.interaction.**InnerProductLayer**(*reduce_sum=True*, *device='cpu'*)

InnerProduct Layer used in PNN that compute the element-wise product or inner product between feature vectors.

Input shape

- a list of 3D tensor with shape: `(batch_size,1,embedding_size)`.

Output shape

- 3D tensor with shape: `(batch_size, N*(N-1)/2 ,1)` if use reduce_sum. or 3D tensor with shape:

`(batch_size, N*(N-1)/2, embedding_size )` if not use reduce_sum.

Arguments

- **reduce_sum**: bool. Whether return inner product or element-wise product

References

- [Qu Y, Cai H, Ren K, et al. Product-based neural networks for user response prediction[C]//

Data Mining (ICDM), 2016 IEEE 16th International Conference on. IEEE, 2016: 1149-1154.] (https://arxiv.org/pdf/1611.00144.pdf)

forward(*inputs*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

---

class deepctr_torch.layers.interaction.**InteractingLayer**(*embedding_size*, *head_num=2*, *use_res=True*, *scaling=False*, *seed=1024*, *device='cpu'*)

A Layer used in AutoInt that model the correlations between different feature fields by multi-head self-attention mechanism. Input shape

- A 3D tensor with shape: `(batch_size,field_size,embedding_size)`.

Output shape

- 3D tensor with shape: `(batch_size,field_size,embedding_size)`.

Arguments

- **in_features** : Positive integer, dimensionality of input features.
- **head_num**: int.The head number in multi-head self-attention network.
- **use_res**: bool.Whether or not use standard residual connections before output.
- **seed**: A Python integer to use as random seed.

References

- [Song W, Shi C, Xiao Z, et al. AutoInt: Automatic Feature Interaction Learning via Self-Attentive Neural Networks[J]. arXiv preprint arXiv:1810.11921, 2018.](https://arxiv.org/abs/1810.11921)

forward(*inputs*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

---

class deepctr_torch.layers.interaction.**LogTransformLayer**(*field_size*, *embedding_size*, *ltl_hidden_size*)

Logarithmic Transformation Layer in Adaptive factorization network, which models arbitrary-order cross features.

Input shape

- 3D tensor with shape: `(batch_size, field_size, embedding_size)`.

Output shape

- 2D tensor with shape: `(batch_size, ltl_hidden_size*embedding_size)`.

Arguments

- **field_size** : positive integer, number of feature groups
- **embedding_size** : positive integer, embedding size of sparse features
- **ltl_hidden_size** : integer, the number of logarithmic neurons in AFN

References

- Cheng, W., Shen, Y. and Huang, L. 2020. Adaptive Factorization Network: Learning Adaptive-Order Feature

  Interactions. Proceedings of the AAAI Conference on Artificial Intelligence. 34, 04 (Apr. 2020), 3609-3616.

forward(*inputs*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

---

class `deepctr_torch.layers.interaction.`**`OutterProductLayer`**(*field_size*, *embedding_size*, *kernel_type='mat'*, *seed=1024*, *device='cpu'*)

OutterProduct Layer used in PNN.This implemention is adapted from code that the author of the paper published on https://github.com/Atomu2014/product-nets.

Input shape

- A list of N 3D tensor with shape: `(batch_size,1,embedding_size)`.

Output shape

- 2D tensor with shape: `(batch_size,N*(N-1)/2 )`.

Arguments

- **filed_size** : Positive integer, number of feature groups.
- **kernel_type**: str. The kernel weight matrix type to use,can be mat,vec or num
- **seed**: A Python integer to use as random seed.

References

- [Qu Y, Cai H, Ren K, et al. Product-based neural networks for user response prediction[C]//Data Mining (ICDM), 2016 IEEE 16th International Conference on. IEEE, 2016: 1149-1154.](https://arxiv.org/pdf/1611.00144.pdf)

`forward`(*inputs*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

class `deepctr_torch.layers.interaction.`**`SENETLayer`**(*filed_size*, *reduction_ratio=3*, *seed=1024*, *device='cpu'*)

SENETLayer used in FiBiNET.

Input shape

- A list of 3D tensor with shape: `(batch_size,filed_size,embedding_size)`.

Output shape

- A list of 3D tensor with shape: `(batch_size,filed_size,embedding_size)`.

Arguments

- **filed_size** : Positive integer, number of feature groups.
- **reduction_ratio** : Positive integer, dimensionality of the

  attention network output space.
- **seed** : A Python integer to use as random seed.

References

- [FiBiNET: Combining Feature Importance and Bilinear feature Interaction for Click-Through Rate Prediction

Tongwen](https://arxiv.org/pdf/1905.09433.pdf)

forward(*inputs*)
Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

2.7.3 deepctr_torch.layers.sequence module

class deepctr_torch.layers.sequence.**AGRUCell**(*input_size*, *hidden_size*, *bias=True*)
Attention based GRU (AGRU)

Reference: - Deep Interest Evolution Network for Click-Through Rate Prediction[J]. arXiv preprint arXiv:1809.03672, 2018.

forward(*inputs*, *hx*, *att_score*)
Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

class deepctr_torch.layers.sequence.**AUGRUCell**(*input_size*, *hidden_size*, *bias=True*)
Effect of GRU with attentional update gate (AUGRU)

Reference: - Deep Interest Evolution Network for Click-Through Rate Prediction[J]. arXiv preprint arXiv:1809.03672, 2018.

forward(*inputs*, *hx*, *att_score*)
Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

class `deepctr_torch.layers.sequence.`**`AttentionSequencePoolingLayer`**(*att_hidden_units=(80, 40)*, *att_activation='sigmoid'*, *weight_normalization=False*, *return_score=False*, *supports_masking=False*, *embedding_dim=4*, ***kwargs*)

The Attentional sequence pooling operation used in DIN & DIEN.

Arguments

- **att_hidden_units**:list of positive integer, the attention net layer number and units in each layer.
- **att_activation**: Activation function to use in attention net.
- **weight_normalization**: bool.Whether normalize the attention score of local activation unit.
- **supports_masking**:If True,the input need to support masking.

References

- [Zhou G, Zhu X, Song C, et al. Deep interest network for click-through rate prediction[C]//Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. ACM, 2018: 1059-1068.](https://arxiv.org/pdf/1706.06978.pdf)

`forward`(*query*, *keys*, *keys_length*, *mask=None*)

Input shape

- A list of three tensor: [query,keys,keys_length]
- query is a 3D tensor with shape: `(batch_size, 1, embedding_size)`
- keys is a 3D tensor with shape: `(batch_size, T, embedding_size)`
- keys_length is a 2D tensor with shape: `(batch_size, 1)`

Output shape

- 3D tensor with shape: `(batch_size, 1, embedding_size)`.

class `deepctr_torch.layers.sequence.`**`DynamicGRU`**(*input_size*, *hidden_size*, *bias=True*, *gru_type='AGRU'*)

`forward`(*inputs*, *att_scores=None*, *hx=None*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

class `deepctr_torch.layers.sequence.`**`KMaxPooling`**(*k*, *axis*, *device='cpu'*)

K Max pooling that selects the k biggest value along the specific axis.

Input shape

- nD tensor with shape: `(batch_size, ..., input_dim)`.

Output shape

- nD tensor with shape: `(batch_size, ..., output_dim)`.

Arguments

- **k**: positive integer, number of top elements to look for along the `axis` dimension.
- **axis**: positive integer, the dimension to look for elements.

forward(*inputs*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

class deepctr_torch.layers.sequence.**SequencePoolingLayer**(*mode='mean'*, *supports_masking=False*, *device='cpu'*)

The SequencePoolingLayer is used to apply pooling operation(sum,mean,max) on variable-length sequence feature/multi-value feature.

Input shape

- A list of two tensor [seq_value,seq_len]
- seq_value is a 3D tensor with shape: `(batch_size, T, embedding_size)`
- seq_len is a 2D tensor with shape : `(batch_size, 1)`,indicate valid length of each sequence.

Output shape

- 3D tensor with shape: `(batch_size, 1, embedding_size)`.

Arguments

- **mode**:str.Pooling operation to be used,can be sum,mean or max.

forward(*seq_value_len_list*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

2.8 deepctr_torch.callbacks module

class deepctr_torch.callbacks.**ModelCheckpoint**(*filepath*, *monitor='val_loss'*, *verbose=0*, *save_best_only=False*, *save_weights_only=False*, *mode='auto'*, *save_freq='epoch'*, *options=None*, ***kwargs*)

Save the model after every epoch.

filepath can contain named formatting options, which will be filled the value of *epoch* and keys in *logs* (passed in *on_epoch_end*).

For example: if *filepath* is *weights.{epoch:02d}-{val_loss:.2f}.hdf5*, then the model checkpoints will be saved with the epoch number and the validation loss in the filename.

Arguments: filepath: string, path to save the model file. monitor: quantity to monitor. verbose: verbosity mode, 0 or 1. save_best_only: if *save_best_only=True*,

the latest best model according to the quantity monitored will not be overwritten.

mode: one of {auto, min, max}. If *save_best_only=True*, the decision to overwrite the current save file is made based on either the maximization or the minimization of the monitored quantity. For *val_acc*, this should be *max*, for *val_loss* this should be *min*, etc. In *auto* mode, the direction is automatically inferred from the name of the monitored quantity.

save_weights_only: if True, then only the model's weights will be saved (*model.save_weights(filepath)*), else the full model is saved (*model.save(filepath)*).

period: Interval (number of epochs) between checkpoints.

`on_epoch_end`(*epoch*, *logs=None*)

Called at the end of an epoch.

Subclasses should override for any actions to run. This function should only be called during TRAIN mode.

Args: epoch: Integer, index of epoch. logs: Dict, metric results for this training epoch, and for the

validation epoch if validation is performed. Validation result keys are prefixed with *val_*. For training epoch, the values of the

***Model*'s metrics are returned. Example** [‘{‘loss’: 0.2, ‘accuracy’:] 0.7}‘.

CHAPTER 3

Indices and tables

- genindex
- modindex
- search

Python Module Index

d

Index

F

I