智能数据挖掘大作业报告

人工智能（图灵）

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1. 电影推荐

1.1 UserCF

算法思想：

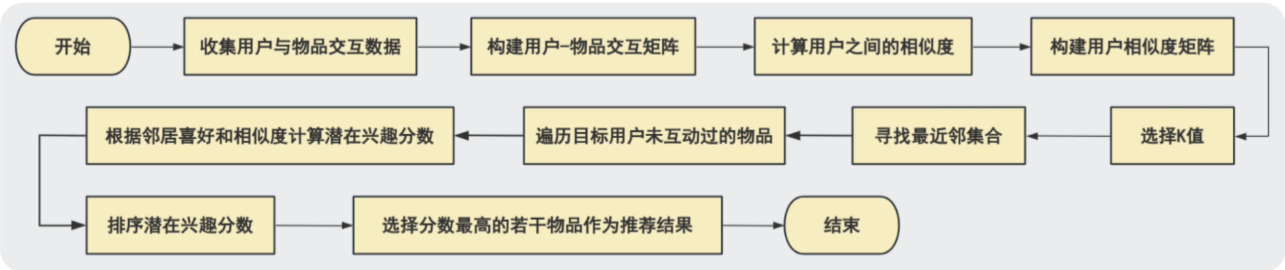
UserCF 的基本假设是具有相似兴趣的用户可能会喜欢相同类型的物品（人以群分）。如果两个用户在过去对某些物品表现出相似的喜好，那么他们未来的行为也可能会相似。因此，当一个用户需要个性化推荐时，可以找到与其兴趣相似的一组用户，然后将这些用户喜欢且目标用户尚未接触过的物品推荐给他。

优势与局限性：

优势：个性化推荐强：能捕捉到用户的独特偏好；适合冷门物品推荐：即使某些电影评分少，只要有用户喜欢，也可能被推荐给相似用户；适合活跃用户：当用户评分较多时，更容易找到相似用户。

局限性：计算复杂度高：随着用户数量增加，用户相似度矩阵的计算代价大；用户兴趣漂移难处理：用户兴趣可能会随时间变化，模型难以及时更新；稀疏性问题敏感：如果用户-物品评分矩阵非常稀疏，用户间相似度计算不准确。

流程图：



代码：

```python
import random
import math
from operator import itemgetter

class UserBasedCF:
    def init(self):
        self.nsimuser = 20
        self.nrecmovie = 10
        self.trainSet = {}
        self.testSet = {}
        self.usersimmatrix = {}
        self.moviecount = 0
        print('Similar user number = %d' % self.nsimuser)
        print('Recommneded movie number = %d' % self.nrecmovie)
    def getdataset(self, filename, pivot=0.75):
        trainSetlen = 0
        testSetlen = 0
        for line in self.loadfile(filename):
            user, movie, rating, timestamp = line.split('::')
            if random.random() < pivot:
                self.trainSet.setdefault(user, {})
                self.trainSet[user][movie] = rating
                trainSetlen += 1
            else:
                self.testSet.setdefault(user, {})
                self.testSet[user][movie] = rating
                testSetlen += 1
        print('Split trainingSet and testSet success!')
        print('TrainSet = %s' % trainSetlen)
        print('TestSet = %s' % testSetlen)
    def loadfile(self, filename):
        with open(filename, 'r') as f:
            for i, line in enumerate(f):
                if i == 0:
                    continue
                yield line.strip('rn')
```

```
        print('Load %s success!' % filename)
    def calcusersim(self):
        print('Building movie-user table ...')
        movieuser = {}
        for user, movies in self.trainSet.items():
            for movie in movies:
                if movie not in movieuser:
                    movieuser[movie] = set()
                movieuser[movie].add(user)
        print('Build movie-user table success!')
        self.moviecount = len(movieuser)
        print('Total movie number = %d' % self.moviecount)
        print('Build user co-rated movies matrix ...')
        for movie, users in movieuser.items():
            for u in users:
                for v in users:
                    if u == v:
                        continue
                    self.usersimmatrix.setdefault(u, {})
                    self.usersimmatrix[u].setdefault(v, 0)
                    self.usersimmatrix[u][v] += 1
        print('Build user co-rated movies matrix success!')
        print('Calculating user similarity matrix ...')
        for u, relatedusers in self.usersimmatrix.items():
            for v, count in relatedusers.items():
                self.usersimmatrix[u][v] = count / math.sqrt(len(self.trainSet[u])  len(self.trainSet[v]))
        print('Calculate user similarity matrix success!')
    def recommend(self, user):
        K = self.nsimuser
        N = self.nrecmovie
        rank = {}
        watchedmovies = self.trainSet[user]
        for v, wuv in sorted(self.usersimmatrix[user].items(), key=itemgetter(1), reverse=True)[0:K]:
            for movie in self.trainSet[v]:
                if movie in watchedmovies:
                    continue
                rank.setdefault(movie, 0)
                rank[movie] += wuv
        return sorted(rank.items(), key=itemgetter(1), reverse=True)[0:N]
    def evaluate(self):
        print("Evaluation start ...")
        N = self.nrecmovie
        hit = 0
        reccount = 0
        testcount = 0
        allrecmovies = set()
        for i, user, in enumerate(self.trainSet):
            testmovies = self.testSet.get(user, {})
            recmovies = self.recommend(user)
            for movie, w in recmovies:
                if movie in testmovies:
                    hit += 1
                allrecmovies.add(movie)
            reccount += N
            testcount += len(testmovies)
        precision = hit / (1.0  reccount)
        recall = hit / (1.0  testcount)
        coverage = len(allrecmovies) / (1.0  self.moviecount)
        print('precisioin=%.4ftrecall=%.4ftcoverage=%.4f' % (precision, recall, coverage))

if name == 'main':
    ratingfile = r'./ratings.dat'
    userCF = UserBasedCF()
    userCF.getdataset(ratingfile)
    userCF.calcusersim()
    userCF.evaluate()
```

运行结果：

```
Similar user number = 20
Recommneded movie number = 10
Load ./ratings.dat success!
Split trainingSet and testSet success!
TrainSet = 749800
TestSet = 250408
Building movie-user table ...
```

```
Build movie-user table success!
Total movie number = 3665
Build user co-rated movies matrix ...
Build user co-rated movies matrix success!
Calculating user similarity matrix ...
Calculate user similarity matrix success!
Evaluation start ...
precisioin=0.3452  recall=0.083  coverage=0.3241
```

1.2 ItemCF

算法思想：

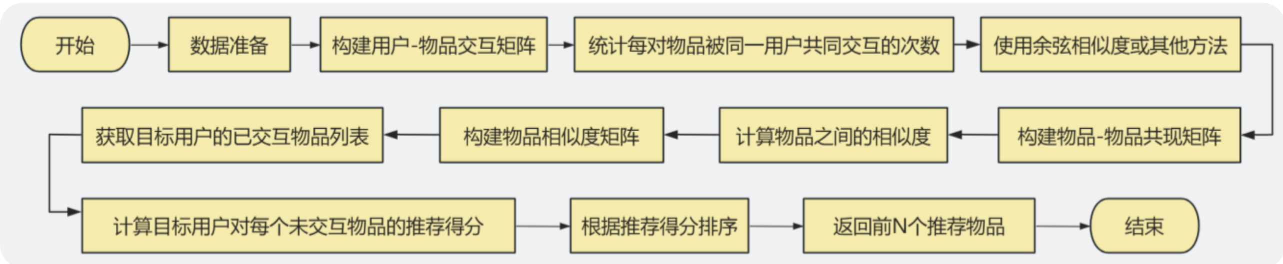
ItemCF 的核心思想是：如果一个用户喜欢某个物品，那么他可能会喜欢与该物品相似的其他物品。因此，算法首先需要计算物品之间的相似度。这个相似度并不是基于物品本身的属性，比如电影的导演、演员或者书籍的作者等信息，而是根据用户的行为数据，例如购买历史、评分或浏览行为来推断。即如果很多用户同时喜欢物品 A 和物品 B，那么我们就认为这两个物品是相似的，并且可以互相作为推荐对象。

优势与局限性：

优势：计算效率更高：物品数量通常远小于用户数量，且物品相似度可以离线计算；推荐结果更稳定：物品特征相对稳定，适合长期推荐；适合实时推荐场景：新用户也能得到推荐，只要他们有少量评分或点击行为，就能够有效得推荐。

局限性：冷门物品推荐能力弱：只有被足够多用户评分过的物品才容易被推荐；新物品冷启动问题严重：新上架的电影由于缺乏评分记录，很难被推荐；推荐多样性差：容易集中在热门或常见类型的电影，缺乏探索性；忽略用户兴趣变化：无法很好地捕捉用户短期兴趣的变化。

流程图：



代码：

```python
import random
import math
from operator import itemgetter
class ItemBasedCF:
    def __init__(self):
        self.n_sim_movie = 20
        self.n_rec_movie = 10
        self.trainSet = {}
        self.testSet = {}
        self.movie_sim_matrix = {}
        self.movie_popular = {}
        self.movie_count = 0
        print('Similar movie number = %d' % self.n_sim_movie)
        print('Recommneded movie number = %d' % self.n_rec_movie)
    def get_dataset(self, filename, pivot=0.75):
        trainSet_len = 0
        testSet_len = 0
        for line in self.load_file(filename):
            user, movie, rating, timestamp = line.split('::')
            if(random.random() < pivot):
                self.trainSet.setdefault(user, {})
                self.trainSet[user][movie] = rating
                trainSet_len += 1
            else:
                self.testSet.setdefault(user, {})
                self.testSet[user][movie] = rating
                testSet_len += 1
        print('Split trainingSet and testSet success!')
```

```python
        print('TrainSet = %s' % trainSet_len)
        print('TestSet = %s' % testSet_len)
    def load_file(self, filename):
        with open(filename, 'r') as f:
            for i, line in enumerate(f):
                if i == 0:
                    continue
                yield line.strip('\r\n')
        print('Load %s success!' % filename)
    def calc_movie_sim(self):
        for user, movies in self.trainSet.items():
            for movie in movies:
                if movie not in self.movie_popular:
                    self.movie_popular[movie] = 0
                self.movie_popular[movie] += 1
        self.movie_count = len(self.movie_popular)
        print("Total movie number = %d" % self.movie_count)
        for user, movies in self.trainSet.items():
            for m1 in movies:
                for m2 in movies:
                    if m1 == m2:
                        continue
                    self.movie_sim_matrix.setdefault(m1, {})
                    self.movie_sim_matrix[m1].setdefault(m2, 0)
                    self.movie_sim_matrix[m1][m2] += 1
        print("Build co-rated users matrix success!")
        print("Calculating movie similarity matrix ...")
        for m1, related_movies in self.movie_sim_matrix.items():
            for m2, count in related_movies.items():
                if self.movie_popular[m1] == 0 or self.movie_popular[m2] == 0:
                    self.movie_sim_matrix[m1][m2] = 0
                else:
                    self.movie_sim_matrix[m1][m2] = \
                        count / math.sqrt(self.movie_popular[m1] * self.movie_popular[m2])
        print('Calculate movie similarity matrix success!')
    def recommend(self, user):
        K = self.n_sim_movie
        N = self.n_rec_movie
        rank = {}
        watched_movies = self.trainSet[user]
        for movie, rating in watched_movies.items():
            for related_movie, w in sorted(self.movie_sim_matrix[movie].items(),
                                           key=itemgetter(1), reverse=True)[:K]:
                if related_movie in watched_movies:
                    continue
                rank.setdefault(related_movie, 0)
                rank[related_movie] += w * float(rating)
        return sorted(rank.items(), key=itemgetter(1), reverse=True)[:N]
    def evaluate(self):
        print('Evaluating start ...')
        N = self.n_rec_movie
        hit = 0
        rec_count = 0
        test_count = 0
        all_rec_movies = set()
        for i, user in enumerate(self.trainSet):
            test_moives = self.testSet.get(user, {})
            rec_movies = self.recommend(user)
            for movie, w in rec_movies:
                if movie in test_moives:
                    hit += 1
                all_rec_movies.add(movie)
            rec_count += N
            test_count += len(test_moives)
        precision = hit / (1.0 * rec_count)
        recall = hit / (1.0 * test_count)
        coverage = len(all_rec_movies) / (1.0 * self.movie_count)
        print('precisioin=%.4f\trecall=%.4f\tcoverage=%.4f' % (precision, recall, coverage))
if __name__ == '__main__':
    rating_file = './ratings.dat'
    itemCF = ItemBasedCF()
    itemCF.get_dataset(rating_file)
    itemCF.calc_movie_sim()
    itemCF.evaluate()
```

运行结果：

```
Similar movie number = 20
Recommneded movie number = 10
Load ./ratings.dat success!
Split trainingSet and testSet success!
TrainSet = 750100
TestSet = 250108
Total movie number = 3666
Build co-rated users matrix success!
Calculating movie similarity matrix ...
Calculate movie similarity matrix success!
Evaluating start ...
precisioin=0.3447  recall=0.0832   coverage=0.1691
```

2. 预测广告点击率

2.1 DeepFM

算法思想：

DeepFM 模型由两大部分组成：一个 FM 部分和一个 DNN 部分。这两个部分共享相同的输入层和嵌入层，这意味着它们使用相同的特征表示进行训练。

FM 部分： FM 部分负责捕捉低阶特征交互，如一阶和二阶特征组合。一阶项是指线性特征权重，而二阶项通过隐向量内积建模特征交叉。具体来说，给定一个特征向量x，其对应的 FM 输出可以表示为：

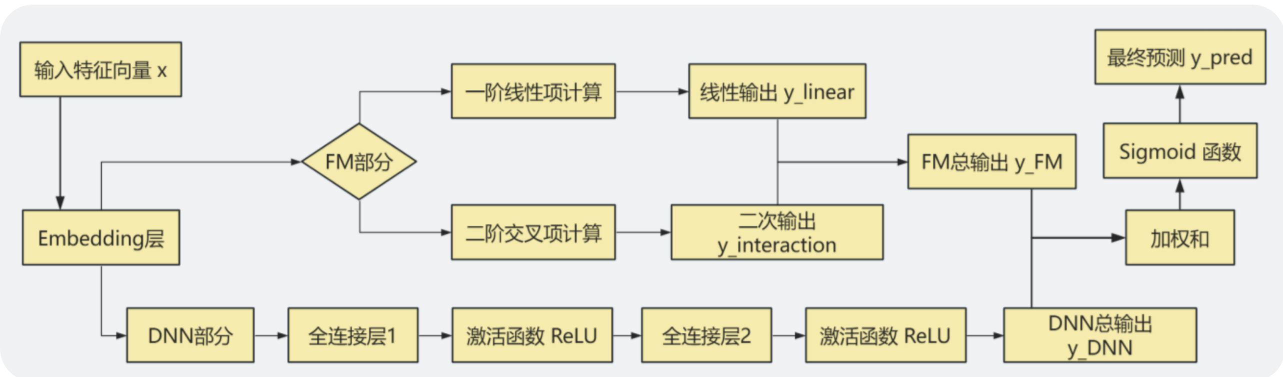
$$y_{FM} = w_0 + \sum_{i=1}^{n} w_i x_i + \sum_{i=1}^{n} \sum_{j=i+1}^{n} \langle v_i, v_j \rangle x_i x_j$$

其中，w_0是全局偏置，w_i是一阶特征权重，$\langle v_i, v_j \rangle$是第i个和第j个特征对应的隐向量的点积，用于计算特征间的交互作用。

DNN 部分： Deep 部分则是一个多层前馈神经网络，它捕捉的是高阶非线性特征交互。特征首先通过嵌入层转换为稠密向量，然后这些向量被拼接起来并输入到全连接网络中。这种结构允许模型自动学习复杂的特征组合模式，而不需要显式的特征工程。在 Deep 部分，原始特征经过嵌入后形成稠密向量，接着通过多个隐藏层进行变换，每一层都应用激活函数，以引入非线性元素，最终输出一个值或向量，代表该部分对目标变量的预测贡献。

模型架构： DeepFM 的架构设计旨在利用 FM 的高效性和 DNN 的强大表达能力。模型的整体预测值是 FM 部分和 Deep 部分输出的加权和，通常会通过 sigmoid 函数将这个总和映射到[0, 1]区间，作为最终的点击概率估计。Embedding 层：将稀疏的离散特征转换成稠密的特征向量，使得不同 field 的向量长度相同，便于后续计算。FM 层：用于计算交叉特征，捕捉低阶特征交互。DNN 部分：捕捉高阶特征交互，通过多层非线性变换提高模型表达力。输出层：融合 FM 层和 DNN 部分的输出得到最终的预测结果。

流程图：



代码:

```
# File: DeepFM.py
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from time import time
class DeepFM(nn.Module):
    def __init__(self, feature_sizes, embedding_size=4,
                 hidden_dims=[32, 32], num_classes=1, dropout=[0.5, 0.5],
                 use_cuda=True, verbose=False):
        """
        Initialize a new network
        Inputs:
        - feature_size: A list of integer giving the size of features for each field.
        - embedding_size: An integer giving size of feature embedding.
        - hidden_dims: A list of integer giving the size of each hidden layer.
        - num_classes: An integer giving the number of classes to predict. For example,
                    someone may rate 1,2,3,4 or 5 stars to a film.
        - batch_size: An integer giving size of instances used in each interation.
        - use_cuda: Bool, Using cuda or not
        - verbose: Bool
        """
        super().__init__()
        self.field_size = len(feature_sizes)
        self.feature_sizes = feature_sizes
        self.embedding_size = embedding_size
        self.hidden_dims = hidden_dims
        self.num_classes = num_classes
        self.dtype = torch.long
        self.bias = torch.nn.Parameter(torch.randn(1))
        # check if use cuda
        if use_cuda and torch.cuda.is_available():
            self.device = torch.device('cuda')
        else:
            self.device = torch.device('cpu')
        # init fm part
        self.fm_first_order_embeddings = nn.ModuleList(
            [nn.Embedding(feature_size, 1) for feature_size in self.feature_sizes])
        self.fm_second_order_embeddings = nn.ModuleList(
            [nn.Embedding(feature_size, self.embedding_size) for feature_size in self.feature_sizes])
        # init deep part
        all_dims = [self.field_size * self.embedding_size] + \
            self.hidden_dims + [self.num_classes]
        for i in range(1, len(hidden_dims) + 1):
            setattr(self, 'linear_'+str(i),
                    nn.Linear(all_dims[i-1], all_dims[i]))
            # nn.init.kaiming_normal_(self.fc1.weight)
            setattr(self, 'batchNorm_' + str(i),
                    nn.BatchNorm1d(all_dims[i]))
            setattr(self, 'dropout_'+str(i),
                    nn.Dropout(dropout[i-1]))
    def forward(self, Xi, Xv):
        """
        Forward process of network.
        Inputs:
        - Xi: A tensor of input's index, shape of (N, field_size, 1)
        - Xv: A tensor of input's value, shape of (N, field_size, 1)
        """
        # fm part
        fm_first_order_emb_arr = [(torch.sum(emb(Xi[:, i, :]), 1).t() * Xv[:, i]).t()
                                  for i, emb in enumerate(self.fm_first_order_embeddings)]
        fm_first_order = torch.cat(fm_first_order_emb_arr, 1)
        fm_second_order_emb_arr = [(torch.sum(emb(Xi[:, i, :]), 1).t() * Xv[:, i]).t()
                                   for i, emb in enumerate(self.fm_second_order_embeddings)]
        fm_sum_second_order_emb = sum(fm_second_order_emb_arr)
        fm_sum_second_order_emb_square = fm_sum_second_order_emb * \
            fm_sum_second_order_emb  # (x+y)^2
        fm_second_order_emb_square = [
            item*item for item in fm_second_order_emb_arr]
        fm_second_order_emb_square_sum = sum(
            fm_second_order_emb_square)  # x^2+y^2
        fm_second_order = (fm_sum_second_order_emb_square -
                           fm_second_order_emb_square_sum) * 0.5
        # deep part
```

```
        deep_emb = torch.cat(fm_second_order_emb_arr, 1)
        deep_out = deep_emb
        for i in range(1, len(self.hidden_dims) + 1):
            deep_out = getattr(self, 'linear_' + str(i))(deep_out)
            deep_out = getattr(self, 'batchNorm_' + str(i))(deep_out)
            deep_out = getattr(self, 'dropout_' + str(i))(deep_out)
        # sum
        total_sum = torch.sum(fm_first_order, 1) + \
                    torch.sum(fm_second_order, 1) + torch.sum(deep_out, 1) + self.bias
        return total_sum
    def fit(self, loader_train, loader_val, optimizer, scheduler, epochs, verbose=False, print_every=100):
        """
        Training a model and valid accuracy.
        Inputs:
        - loader_train: I
        - loader_val: .
        - optimizer: Abstraction of optimizer used in training process.
        - epochs: Integer, number of epochs.
        - verbose: Bool, if print.
        - print_every: Integer, print after every number of iterations.
        """
        # load input data
        model = self.train().to(device=self.device)
        criterion = F.binary_cross_entropy_with_logits
        for _ in range(epochs):
            for t, (xi, xv, y) in enumerate(loader_train):
                xi = xi.to(device=self.device, dtype=self.dtype)
                xv = xv.to(device=self.device, dtype=torch.float)
                y = y.to(device=self.device, dtype=torch.float)
                total = model(xi, xv)
                loss = criterion(total, y)
                optimizer.zero_grad()
                loss.backward()
                optimizer.step()
                scheduler.step()
                if verbose and t % print_every == 0:
                    print('Iteration %d, loss = %.4f' % (t, loss.item()))
                    self.check_accuracy(loader_val, model)
                    print()
    def check_accuracy(self, loader, model):
        if loader.dataset.train:
            print('Checking accuracy on validation set')
        else:
            print('Checking accuracy on test set')
        num_correct = 0
        num_samples = 0
        model.eval()  # set model to evaluation mode
        with torch.no_grad():
            for xi, xv, y in loader:
                xi = xi.to(device=self.device, dtype=self.dtype)  # move to device, e.g. GPU
                xv = xv.to(device=self.device, dtype=torch.float)
                y = y.to(device=self.device, dtype=torch.bool)
                total = model(xi, xv)
                preds = (F.sigmoid(total) > 0.5)
                num_correct += (preds == y).sum()
                num_samples += preds.size(0)
            acc = float(num_correct) / num_samples
            print('Got %d / %d correct (%.2f%%)' % (num_correct, num_samples, 100 * acc))

# File dataset.py
import torch
from torch.utils.data import Dataset
import pandas as pd
import numpy as np
import os
continous_features = 13
class CriteoDataset(Dataset):
    def __init__(self, root, train=True):
        """
        Initialize file path and train/test mode.
        Inputs:
        - root: Path where the processed data file stored.
        - train: Train or test. Required.
        """
        self.root = root
```

```
        self.train = train
        if not self._check_exists():
            raise RuntimeError('Dataset not found.')
        if self.train:
            data = pd.read_csv(os.path.join(root, 'train.txt'))
            self.train_data = data.iloc[:, :-1].values
            self.target = data.iloc[:, -1].values
        else:
            data = pd.read_csv(os.path.join(root, 'test.txt'))
            self.test_data = data.iloc[:, :-1].values

    def __getitem__(self, idx):
        if self.train:
            dataI, targetI = self.train_data[idx, :], self.target[idx]
            # index of continous features are zero
            Xi_coutinous = np.zeros_like(dataI[:continous_features])
            Xi_categorial = dataI[continous_features:]
            Xi = torch.from_numpy(np.concatenate(
                     (Xi_coutinous, Xi_categorial)).astype(np.int32)).unsqueeze(-1)
            # value of categorial features are one (one hot features)
            Xv_categorial = np.ones_like(dataI[continous_features:])
            Xv_coutinous = dataI[:continous_features]
            Xv = torch.from_numpy(np.concatenate((Xv_coutinous, Xv_categorial)).astype(np.int32))
            return Xi, Xv, targetI
        else:
            dataI = self.test_data.iloc[idx, :]
            # index of continous features are one
            Xi_coutinous = np.ones_like(dataI[:continous_features])
            Xi_categorial = dataI[continous_features:]
            Xi = torch.from_numpy(np.concatenate(
                     (Xi_coutinous, Xi_categorial)).astype(np.int32)).unsqueeze(-1)
            # value of categorial features are one (one hot features)
            Xv_categorial = np.ones_like(dataI[continous_features:])
            Xv_coutinous = dataI[:continous_features]
            Xv = torch.from_numpy(np.concatenate((Xv_coutinous, Xv_categorial)).astype(np.int32))
            return Xi, Xv
    def __len__(self):
        if self.train:
            return len(self.train_data)
        else:
            return len(self.test_data)
    def _check_exists(self):
        return os.path.exists(self.root)

# File train.py
import numpy as np
import torch.optim as optim
from torch.utils.data import DataLoader
from torch.utils.data import sampler
from model.DeepFM import DeepFM
from data.dataset import CriteoDataset
# 10000 items for training, 10000 items for valid, of all 20000 items
Num_train = 50
# load data
train_data = CriteoDataset('./data', train=True)
loader_train = DataLoader(train_data, batch_size=200,
                          sampler=sampler.SubsetRandomSampler(range(Num_train)))
val_data = CriteoDataset('./data', train=True)
loader_val = DataLoader(val_data, batch_size=200,
                        sampler=sampler.SubsetRandomSampler(range(Num_train, 100)))
feature_sizes = np.loadtxt('./data/feature_sizes.txt', delimiter=',')
feature_sizes = [int(x) for x in feature_sizes]
print(feature_sizes)
epochs = 1000
model = DeepFM(feature_sizes, use_cuda=True, embedding_size=256,
                     hidden_dims=[256, 256, 256], dropout=[0.2, 0.2, 0.2])
optimizer = optim.AdamW(model.parameters(), lr=3e-4, weight_decay=0.1)
scheduler = optim.lr_scheduler.CosineAnnealingLR(optimizer, T_max=epochs, eta_min=1e-6)
model.fit(loader_train, loader_val, optimizer, scheduler, epochs=epochs, verbose=True, print_every=1000)
```

运行结果：

```
Iteration 0, loss = 69403.1562
Checking accuracy on validation set
Got 40 / 50 correct (80.00%)
```