根据用户对类目偏好打分训练基于ALS的矩阵分解模型

根据统计的次数 + 打分规则 ==> 偏好打分数据集 ==> 基于ALS的矩阵分解模型

本节目的：为每个用户召集他最感兴趣的3个类别

In [2]:

```
import os
# 配置pyspark和spark driver运行时 使用的python解释器
JAVA_HOME = '/root/bigdata/jdk'
PYSPARK_PYTHON = '/miniconda2/envs/py365/bin/python'
# 当存在多个版本时，不指定很可能会导致出错
os.environ['PYSPARK_PYTHON'] = PYSPARK_PYTHON
os.environ['PYSPARK_DRIVER_PYTHON'] = PYSPARK_PYTHON
os.environ['JAVA_HOME'] = JAVA_HOME
# 配置spark信息
from pyspark import SparkConf
from pyspark.sql import SparkSession

SPARK_APP_NAME = 'createUserCateRatingALSModel'
SPARK_URL = 'spark://192.168.58.100:7077'

conf = SparkConf()    # 创建spark config对象
config = (
    ("spark.app.name", SPARK_APP_NAME),    # 设置启动的spark的app名称，没有提供，将随
    ("spark.executor.memory", "2g"),    # 设置该app启动时占用的内存用量，默认1g
    ("spark.master", SPARK_URL),    # spark master的地址
    ("spark.executor.cores", "2"),    # 设置spark executor使用的CPU核心数
    # 以下三项配置，可以控制执行器数量
    # ("spark.dynamicAllocation.enabled", True),
    # ("spark.dynamicAllocation.initialExecutors", 1),    # 1个执行器
    # ("spark.shuffle.service.enabled", True)
    # ('spark.sql.pivotMaxValues', '99999'),  # 当需要pivot DF，且值很多时，需要修改，
)
# 查看更详细配置及说明：https://spark.apache.org/docs/latest/configuration.html

conf.setAll(config)

# 利用config对象，创建spark session
spark = SparkSession.builder.config(conf=conf).getOrCreate()
```

In [ ]:

```
# spark ml的模型训练是基于内存的，如果数据过大，内存空间小，迭代次数过多的化，可能会造
# 设置Checkpoint的话，会把所有数据落盘，这样如果异常退出，下次重启后，可以接着上次的训
# 但该方法其实指标不治本，因为无法防止内存溢出，所以还是会报错
# 如果数据量大，应考虑的是增加内存、或限制迭代次数和训练数据量级等
spark.sparkContext.setCheckpointDir("checkPoint")
```

In [4]:
```
from pyspark.sql.types import StructType, StructField, StringType, IntegerType, Long
schema = StructType([
    StructField("userId", IntegerType()),
    StructField("cateId", IntegerType()),
    StructField("pv", IntegerType()),
    StructField("fav", IntegerType()),
    StructField("cart", IntegerType()),
    StructField("buy", IntegerType())
])

# 加载上一节存的透视表
# 从hdfs加载CSV文件,这种加载有一个好处：加载出的新df可以指定新的schema
# 我尝试过如果指定，pv到buy的数据类型是bigint(即longtype)，这种类型在下面toDF那步会报
cate_count_df = spark.read.csv("cate_count.csv", header=True, schema=schema)
cate_count_df.printSchema()
cate_count_df.first()
```

```
root
 |-- userId: integer (nullable = true)
 |-- cateId: integer (nullable = true)
 |-- pv: integer (nullable = true)
 |-- fav: integer (nullable = true)
 |-- cart: integer (nullable = true)
 |-- buy: integer (nullable = true)
```

Out[4]:
```
Row(userId=375653, cateId=6341, pv=None, fav=None, cart=None, buy=None)
```

In [73]:
```
# 对比cate_count_df.printSchema()的效果
cate_count_df.printSchema
```

Out[73]:
```
<bound method DataFrame.printSchema of DataFrame[userId: int, cateId: int, pv: int, fa
v: int, cart: int, buy: int]>
```

In [5]:
```
def process_row(r):
    # 注意这里要全部设为浮点数，spark运算时对类型比较敏感，要保持数据类型都一致
    pv_count = r.pv if r.pv else 0.0
    fav_count = r.fav if r.fav else 0.0#浏览次数
    cart_count = r.cart if r.cart else 0.0
    buy_count = r.buy if r.buy else 0.0

    # 该偏好权重比例，次数上限仅供参考，具体数值应根据产品业务场景权衡
    pv_score = 0.2*pv_count if pv_count<=20 else 4.0
    fav_score = 0.4*fav_count if fav_count<=20 else 8.0
    cart_score = 0.6*cart_count if cart_count<=20 else 12.0
    buy_score = 1*buy_count if buy_count<=20 else 20.0

    rating = pv_score + fav_score + cart_score + buy_score
    # 返回用户ID、分类ID、用户对分类的偏好打分
    return r.userId, r.cateId, rating
# toDF不是每个rdd都有的方法，DF->RDD->DF 仅限此处的 rdd
cate_rating_df =cate_count_df.rdd.map(process_row).toDF(["userId", "cateId", "rating"]
```

In [6]:
```
# cate_count_df都死int型，结果运算后变成了long和double型
cate_rating_df
```

Out[6]:
```
DataFrame[userId: bigint, cateId: bigint, rating: double]
```

In [7]:
```
cate_rating_df.show()
```

```
+-------+------+------+
| userId|cateId|rating|
+-------+------+------+
| 375653|  6341|   0.0|
|1095337|  4290|   0.0|
| 689354|  4278|   0.0|
| 773481|  4521|   0.0|
| 279865|  4297|   0.6|
| 876505|  5510|   0.0|
| 182591|  5954|   0.6|
| 149925|  6130|   0.0|
| 799323|  6736|   0.0|
|1096923| 11156|   0.0|
|  58847|  6426|   0.0|
| 462878|  6682|   0.0|
|1012280|  5038|   0.0|
| 790875|  6244|   0.0|
| 506220|  4267|   0.0|
| 222785|  3772|   0.0|
|  95052|  6547|   0.0|
| 369186|    45|   0.0|
| 747755|  6427|   0.0|
| 196296|  7021|   0.0|
+-------+------+------+
only showing top 20 rows
```

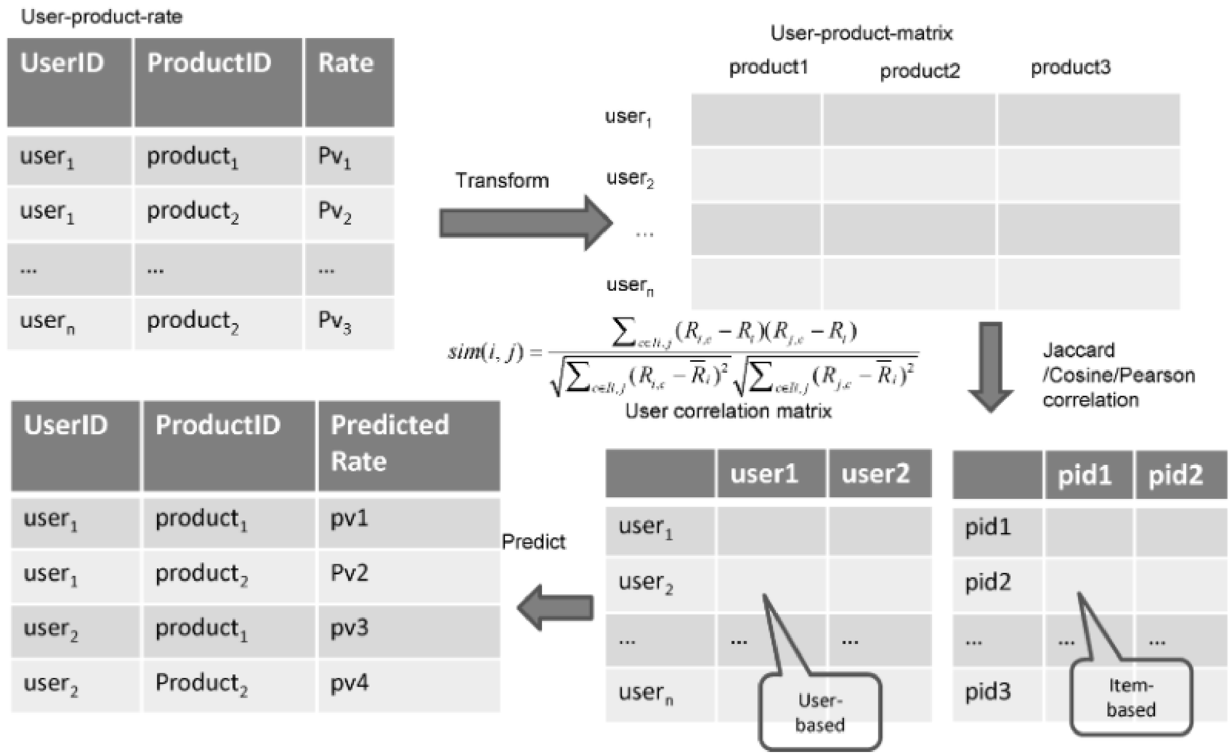
In [ ]:
```
# 可通过该方法获得 user-cate-matrix
# 但由于cateId字段过多，这里运算量比很大，机器内存要求很高才能执行，否则无法完成任务
# 请谨慎使用

# 但好在我们训练ALS模型时，不需要转换为user-cate-matrix，所以这里可以不用运行
# cate_rating_df.groupBy("userId").povit("cateId").min("rating")
```

In [ ]:
```

```

通常如果使用USER-ITEM打分数据应该是通过以下方式进行处理转换为user-cate-matrix



但这里我们将使用Spark的ALS模型进行CF推荐，因此不需要转换矩阵

基于Spark的ALS隐因子模型进行CF评分预测

ALS的意思是交替最小二乘法（Alternating Least Squares），是Spark2.*中加入的进行基于模型的协同过滤（model-based CF）的推荐系统算法。

详细使用方法：[pyspark.ml.recommendation.ALS (https://spark.apache.org/docs/2.2.2/api/python/pyspark.ml.html?highlight=vectors#module-pyspark.ml.recommendation)](https://spark.apache.org/docs/2.2.2/api/python/pyspark.ml.html?highlight=vectors#module-pyspark.ml.recommendation)

注意：由于数据量巨大，因此这里也不考虑基于内存的CF算法

参考：[为什么Spark中只有ALS (https://www.cnblogs.com/mooba/p/6539142.html)](https://www.cnblogs.com/mooba/p/6539142.html)

In [9]:

```
# 使用pyspark中的ALS矩阵分解方法实现CF评分预测
# 文档地址：https://spark.apache.org/docs/2.2.2/api/python/pyspark.ml.html?highlight=
from pyspark.ml.recommendation import ALS
als = ALS(userCol='userId',itemCol='cateId',ratingCol='rating',checkpointInterval=5)
```

In [80]:

```
# 此处训练时间较长
model=als.fit(cate_rating_df)
```

模型训练好后，调用方法进行使用，[具体API查看 (https://spark.apache.org/docs/2.2.2/api/python/pyspark.ml.html?highlight=alsmodel#pyspark.ml.recommendation.ALSModel)](https://spark.apache.org/docs/2.2.2/api/python/pyspark.ml.html?highlight=alsmodel#pyspark.ml.recommendation.ALSModel)

In [82]:

```
# model.recommendForAllUsers(N) 给所有用户推荐TOP-N个物品
ret=model.recommendForAllUsers(3)
# 由于是给所有用户进行推荐，此处运算时间也较长
ret.show()
```

...

In [83]:

```
# 推荐结果存放在recommendations列中，
ret.show(truncate=False)
```

```
+------+-----------------------------------------------------------+
|userId|recommendations                                            |
+------+-----------------------------------------------------------+
|463   |[[2614,3.814289], [1856,3.810282], [6133,2.9419253]]       |
|471   |[[5595,1.3937049], [7777,1.2667428], [4470,1.2655703]]     |
|496   |[[5808,0.21850951], [3280,0.20912437], [6992,0.20885153]]|
|833   |[[650,3.0506895], [11991,2.5738168], [9442,2.444895]]      |
|1088  |[[7777,0.5331895], [5873,0.4836679], [1796,0.4594512]]     |
|1238  |[[2531,3.9033172], [12511,3.4017303], [3015,3.3892038]]    |
|1342  |[[10029,3.5094855], [3601,3.1661687], [3280,3.151603]]     |
|1580  |[[4783,0.3156656], [2356,0.2983618], [2531,0.296698]]      |
|1591  |[[1856,0.5038745], [2614,0.36057153], [1460,0.3232775]]    |
|1645  |[[5595,0.95775396], [9805,0.5424484], [7777,0.5372277]]    |
|1829  |[[5731,1.4036021], [12084,1.3702909], [1796,1.3409215]]    |
|1959  |[[2614,0.70558584], [3280,0.6489351], [4783,0.5592411]]    |
|2142  |[[867,0.9078737], [7777,0.86316544], [7587,0.85665566]]    |
|2659  |[[11410,6.4133377], [2614,5.9658675], [9805,5.8297386]]    |
|3794  |[[2614,0.506202], [9754,0.45685008], [8516,0.41384575]]    |
|3918  |[[5595,0.41725752], [3280,0.2753573], [2531,0.2467127]]    |
|3997  |[[5595,1.3701121], [6375,1.0384352], [4470,1.0379413]]     |
|4519  |[[2614,4.4880323], [3280,4.3875613], [4783,3.9587555]]    |
|4900  |[[650,2.0529048], [4525,1.8256125], [10637,1.786796]]      |
|4935  |[[9442,2.1188283], [8416,1.5195788], [2468,1.4475018]]     |
+------+-----------------------------------------------------------+
only showing top 20 rows
```

In [ ]:

```
# model.recommendForUserSubset 给部分用户推荐TOP-N个物品

# 注意注意注意：recommendForUserSubset API，2.2.2版本中无法使用
dataset = spark.createDataFrame([[1],[2],[3]])
dataset = dataset.withColumnRenamed("_1", "userId")
ret = model.recommendForUserSubset(dataset, 3)

# 只给部分用推荐，运算时间短
ret.show()
ret.collect()    # 注意： collect会将所有数据加载到内存，慎用
```

In [ ]:

```
# transform中提供userId和cateId可以对打分 预测，利用打分结果排序后，同样可以实现TOP-N
# model.transform
# 将模型进行存储
# 已经存过，不用再存
# model.save("models/userCateRatingALSModel.obj")
```

In [10]:

```
from pyspark.ml.recommendation import ALSModel
als_model=ALSModel.load('/models/userCateRatingALSModel.obj')
# model.recommendForAllUsers(N) 给用户推荐TOP-N个物品
# 运行时间较长
result=als_model.recommendForAllUsers(3)
result.show()
```

```
+------+--------------------+
|userId|     recommendations|
+------+--------------------+
|   148|[[5607,8.091523],...|
|   463|[[1610,8.860008],...|
|   471|[[1610,13.1980295...|
|   496|[[3347,6.303711],...|
|   833|[[5607,10.028404]...|
|  1088|[[5731,6.969639],...|
|  1238|[[1610,16.75008],...|
|  1342|[[5607,9.428972],...|
|  1580|[[5579,8.038961],...|
|  1591|[[5607,11.379921]...|
|  1645|[[201,12.506715],...|
|  1829|[[1610,19.828497]...|
|  1959|[[5631,10.744259]...|
|  2122|[[5737,11.620426]...|
|  2142|[[1610,12.57279],...|
|  2366|[[1610,13.826477]...|
|  2659|[[1610,14.002829]...|
|  2866|[[1610,11.263525]...|
|  3175|[[11568,1.8160022...|
|  3749|[[1610,3.5862575]...|
+------+--------------------+
only showing top 20 rows
```

In [90]:

```
result
```

Out[90]:

```
DataFrame[userId: int, recommendations: array<struct<cateId:int,rating:float>>]
```

In [17]:

```
import redis
host = "192.168.58.100"
port = 6379
db = "2"
# 召回到redis
def recall_cate_by_cf(partition):
    # 建立redis 连接池
    pool = redis.ConnectionPool(host=host, port=port, db=db)
    # 建立redis客户端
    client = redis.Redis(connection_pool=pool)
    for row in partition:
        client.hset("recall_cate", row.userId, [i.cateId for i in row.recommendations

# 对每个分片的数据进行处理
# foreachPartition()方法：将f函数应用于此DataFrame的每个分区，这是``df.rdd.foreachPar
result.foreachPartition(recall_cate_by_cf)

# 注意：这里这是召回的是用户最感兴趣的n个类别
# 存储了大半后可能报错，网上说是redis版本太高导致
```

```
---------------------------------------------------------------------------
Py4JJavaError                             Traceback (most recent call last)
<ipython-input-17-819e55a94f29> in <module>
     14 # 对每个分片的数据进行处理
     15 # foreachPartition()方法：将f函数应用于此DataFrame的每个分区，这是``df.rdd.f
oreachPartition（）``的简写。
---> 16 result.foreachPartition(recall_cate_by_cf)
     17
     18 # 注意：这里这是召回的是用户最感兴趣的n个类别

/miniconda2/envs/py365/lib/python3.6/site-packages/pyspark-2.2.2-py3.6.egg/pyspark/sq
l/dataframe.py in foreachPartition(self, f)
    499         >>> df.foreachPartition(f)
    500         """
--> 501         self.rdd.foreachPartition(f)
    502
    503     @since(1.3)

/miniconda2/envs/py365/lib/python3.6/site-packages/pyspark-2.2.2-py3.6.egg/pyspark/rd
```

In [13]:

```
# 总的条目数，查看redis中总的条目数是否一致
result.count()
```

Out[13]: 1136340