### 关联规则挖掘报告

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### 一、对数据集进行处理

本次作业选用数据集 NFL Play by Play 2009-2017 (v4),利用 Python 中的 pandas 库进行 csv 数据文件的读取,对数据集进行处理,转换成适合关联规则挖掘的形式:

```
df = pd.read_csv('NFL Play by Play 2009-2017 (v4).csv', dtype=str)

for col in df:
    df_counts = df[col].value_counts()
    num = df_counts.max()
    name = df_counts.idxmax()
    if pd.isnull(name) or name == 'None' or num < len(df)/2_or num > len(df)*0.99:
        df.drop(col, axis=1, inplace=True)

df.fillna(method='ffill')
```

对于数据集中存在过多 "NA"和 "None"的字段进行剔除,众数小于文件长度一半的字段进行剔除,并且,对于大多数值都为同一个的字段(例如,对于 PlayAttempted 属性,它的值全为 1),我们认为其没有研究意义,应将其剔除。然后用 ffill 方法对缺失值进行简单的填充处理

# 二、找出频繁项集

Apriori 算法的两个输入参数分别是最小支持度和数据集。该算法首先会生成所有单个数据字段值的项集列表。接着扫描每行数据来查看哪些项集满足最小支持度要求,那些不满足最小支持度的集合会被去掉。然后,对剩下来的集合进行组合以生成包含两个元素的项集。接下来,再重新扫描每行记录,去掉不满足最小支持度的项集。该过程重复进行直到所有项集都被去掉。

# 2.1 生成候选项集

```
# 生成初始候选频繁项集C1
def createC1(dataSet):
    C1 = []
    for transaction in dataSet:
        for item in transaction:
            if [item] not in C1:
                C1.append([item])
    C1.sort()
    return list(map(frozenset, C1))
def scanD(D, Ck, minSupport):
    ssCnt = {}
    for tid in D:
        for can in Ck:
           if can.issubset(tid):
                ssCnt[can] = ssCnt.get(can, 0) + 1
    numItems = len(D)
    retList = []
    supportData = {}
    for key in ssCnt:
        support = ssCnt[key] / numItems
        if support >= minSupport:
           retList.append(key)
            supportData[key] = support
    return retList, supportData
```

# 2.2 生成频繁项集

生成频繁项级算法的伪代码如下:

当集合中项的个数大于0时

构建一个k个项组成的候选项集的列表

检查数据以确认每个项集都是频繁的

保留频繁项集并构建 k+1 项组成的候选项集的列表

具体相关方法如下:

```
def aprioriGen(Lk, k):
    retList = []
    lenLk = len(Lk)
    for i in range(lenLk):
        for j in range(i+1, lenLk):
           L1 = list(Lk[i]); L2 = list(Lk[j])
           L1.sort(); L2.sort()
            if L1[:k-2] == L2[:k-2]:
               c = Lk[i] \mid Lk[j]
                if has_infrequent_subset(set(c), Lk): continue
                else: retList.append(c)
    return retList
def apriori(dataSet, minSupport=0.5):
   C1 = createC1(dataSet)
   D = list(map(set, dataSet))
   L1, supportData = scanD(D, C1, minSupport)
   L = [L1]
   k = 7
   while len(L[k-2]) > 0:
       Ck = aprioriGen(L[k-2], k)
        Lk, supK = scanD(D, Ck, minSupport)
        supportData.update(supK)
       L.append(Lk)
       k += 1
   return L, supportData
```

函数最后返回的是频繁项集列表以及每个频繁项的支持度。

## 三、导出关联规则, 计算置信度和提升度

根据频繁集学习关联规则,针对规则右部的元素个数进行分级,导出关联规则,并计算 关联规则的提升度和置信度:

```
def calcConf(freqSet, H, supportData, br1, minConf=0.7):
    prunedH = []
    for conseq in H:
        conf = supportData[freqSet] / supportData[freqSet-conseq]
        lift = conf / suppData[conseq]
        if conf >= minConf:
            print(freqSet-conseq, '-->', conseq, 'conf:', conf)
            print(freqSet-conseq, '-->', conseq, 'lift:', lift)
            br1.append((freqSet-conseq, conseq, conf))
            prunedH.append(conseq)
    return prunedH
```

### 四、规则挖掘结果及评价

下图为部分规则挖掘结果及使用 Lift 评价的结果:

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根据这些挖掘到的规则的置信度结果和提升度 (Lift) 结果,可知置信度较高,且提升度均大于1,则可认为这些规则有用。