利用Spark分析出租车打车数据

1 数据集简介

本数据集为四川省成都市的出租车GPS记录数据集。该数据集已提前清洗完成，仅提取了原始数据集中某一天的部分数据，并且去除了时间段在 0 点至 6 点之间的较少数据。

数据记录了成都市部分出租车在载客时的GPS位置和时间等信息，数据记录的格式为 CSV 格式。

该数据集中的一条记录如下所示：

1 30.624806 104.136604 211846 对各个字段逐个解释如下：

- TID：出租车的ID。每辆出租车的TID都是唯一的。
- Lat：出租车状态为载客时的纬度。
- Lon：出租车状态为载客时的经度。
- Time：该条记录的时间戳。如 211846 代表 21 点 18 分 46 秒。

2 试验步骤

2.1 首先查看数据：

In [13]:
```
import matplotlib.pyplot as plt
```

In [ ]:
```
//scala

import org.apache.spark._
import org.apache.spark.sql._
import org.apache.spark.sql.types._
import org.apache.spark.sql.functions._
import org.apache.spark.ml.feature.VectorAssembler
import org.apache.spark.ml.clustering.KMeans

val fieldSchema = StructType(Array(
    StructField("TID", StringType, true),
    StructField("Lat", DoubleType, true),
    StructField("Lon", DoubleType, true),
    StructField("Time", StringType, true)
))

val taxiDF = spark.read.format("csv").option("header","false").schema(fieldSchema).load("/sparkml/wei/taxi.csv")
taxiDF.show()
```

```
scala> taxiDF.show()
+---+---------+----------+------+
|TID|      Lat|       Lon|  Time|
+---+---------+----------+------+
|  1|30.624806|104.136604|211846|
|  1|30.624809|104.136612|211815|
|  1|30.624811|104.136587|212017|
|  1|30.624811|104.136596|211916|
|  1|30.624811|104.136619|211744|
|  1|30.624813|104.136589|211946|
|  1|30.624815|104.136585|212118|
|  1|30.624815|104.136587|212048|
|  1|30.624815|104.136639|211714|
|  1|30.624816|104.136569|212250|
|  1|30.624816|104.136574|212219|
|  1|30.624816|104.136577|212149|
|  1|30.624818|104.136564|212320|
|  1|30.624818|104.136621|211542|
|  1| 30.62482|104.136631|211643|
|  1| 30.62482|104.136644|211613|
|  1|30.624823|104.136582|211511|
|  1|30.624826|104.136556|212351|
|  1|30.624828|104.136552|212451|
|  1|30.624828|104.136556|212421|
+---+---------+----------+------+
only showing top 20 rows


scala>
```

2.2 用特征工程提取有用的特征

In [ ]:
```
//scala
val columns = Array("Lat","Lon")
val va = new VectorAssembler().setInputCols(columns).setOutputCol("features")
val taxiDF2 = va.transform(taxiDF)
taxiDF2.show()
```

```
+---+---------+----------+------+------------------+
|TID|      Lat|       Lon|  Time|          features|
+---+---------+----------+------+------------------+
|  1|30.624806|104.136604|211846|[30.624806,104.13...|
|  1|30.624809|104.136612|211815|[30.624809,104.13...|
|  1|30.624811|104.136587|212017|[30.624811,104.13...|
|  1|30.624811|104.136596|211916|[30.624811,104.13...|
|  1|30.624811|104.136619|211744|[30.624811,104.13...|
|  1|30.624813|104.136589|211946|[30.624813,104.13...|
|  1|30.624815|104.136585|212118|[30.624815,104.13...|
|  1|30.624815|104.136587|212048|[30.624815,104.13...|
|  1|30.624815|104.136639|211714|[30.624815,104.13...|
|  1|30.624816|104.136569|212250|[30.624816,104.13...|
|  1|30.624816|104.136574|212219|[30.624816,104.13...|
|  1|30.624816|104.136577|212149|[30.624816,104.13...|
|  1|30.624818|104.136564|212320|[30.624818,104.13...|
|  1|30.624818|104.136621|211542|[30.624818,104.13...|
|  1| 30.62482|104.136631|211643|[30.62482,104.136...|
|  1| 30.62482|104.136644|211613|[30.62482,104.136...|
|  1|30.624823|104.136582|211511|[30.624823,104.13...|
|  1|30.624826|104.136556|212351|[30.624826,104.13...|
|  1|30.624828|104.136552|212451|[30.624828,104.13...|
|  1|30.624828|104.136556|212421|[30.624828,104.13...|
+---+---------+----------+------+------------------+
only showing top 20 rows
```

2.3 使用Kmeans对坐标信息进行聚类

设置聚类数为10，使用features列作为输入

In [ ]:
```
//scala
taxiDF2.cache()
val traintestratio = Array(0.8,0.2)
val Array(traindata,testdata) = taxiDF2.randomSplit(traintestratio,4484)
val km = new KMeans().setK(10).setFeaturesCol("features").setPredictionCol("prediction") .fit(taxiDF2)
val kmresult = km.clusterCenters
val kmRDD1 = spark.sparkContext.parallelize(kmresult)
val kmRDD2 = kmRDD1.map(k=>(k(1),k(0)))
kmRDD2.saveAsTextFile("/sparkml/wei/kmResult")
```

scala> taxiDF2.cache() res3: taxiDF2.type = [TID: string, Lat: double ... 3 more fields]

scala> val traintestratio = Array(0.8,0.2) traintestratio: Array[Double] = Array(0.8, 0.2)

scala> val Array(traindata,testdata) = taxiDF2.randomSplit(traintestratio,4484) traindata: org.apache.spark.sql.Dataset[org.apache.spark.sql.Row] = [TID: string, Lat: double ... 3 more fields] testdata: org.apache.spark.sql.Dataset[org.apache.spark.sql.Row] = [TID: string, Lat: double ... 3 more fields]

scala> val km = new KMeans().setK(10).setFeaturesCol("features").setPredictionCol("prediction") .fit(taxiDF2) 2020-01-07 09:18:34,966 WARN clustering.KMeans: The input data is not directly cached, which may hurt performance if its parent RDDs are also uncached. 2020-01-07 09:18:38,312 WARN netlib.BLAS: Failed to load implementation from: com.github.fommil.netlib.NativeSystemBLAS 2020-01-07 09:18:38,312 WARN netlib.BLAS: Failed to load implementation from: com.github.fommil.netlib.NativeRefBLAS 2020-01-07 09:18:46,240 WARN clustering.KMeans: The input data was not directly cached, which may hurt performance if its parent RDDs are also uncached. km: org.apache.spark.ml.clustering.KMeansModel = kmeans_1b79084981cd

scala> val kmresult = km.clusterCenters kmresult: Array[org.apache.spark.ml.linalg.Vector] = Array([30.673148494635097,104.07578476841387], [30.72412085030872,103.87397208853098], [30.927353901972033,103.62885306030289], [30.59401354785786,103.98592269758088], [30.635381552525054,104.11394199019651], [30.537256303673082,104.05842847715851], [30.753202695449705,104.13250414652543], [30.627461571635052,104.05898271875064], [30.672885436261897,104.01931668552281], [30.56862618296974,104.30709651618582])

scala> val kmRDD1 = spark.sparkContext.parallelize(kmresult) kmRDD1: org.apache.spark.rdd.RDD[org.apache.spark.ml.linalg.Vector] = ParallelCollectionRDD[87] at parallelize at :39

scala> val kmRDD2 = kmRDD1.map(k=>(k(1),k(0))) kmRDD2: org.apache.spark.rdd.RDD[(Double, Double)] = MapPartitionsRDD[88] at map at :39

scala> kmRDD2.saveAsTextFile("/sparkml/wei/kmResult")

2.4 使用sql语句对预测结果进行简单分析

其中hour表示所处时段，prediction表示所处区域（跟前面坐标对应），count表示打车次数

In [ ]:
```
//scala

val prediction = km.transform(testdata)
prediction.createTempView("haha")
val tmpQuery = spark.sql("select substring(Time,0,2) as hour,prediction from haha")
val predictCount = tmpQuery.groupBy("hour","prediction").agg(count("prediction").alias("count")).orderBy(desc("count"))
predictCount.show()
predictCount.write.csv("/sparkml/wei/predictCount.csv")
val busyZones = prediction.groupBy("prediction").count()
busyZones.show()
busyZones.write.csv("/sparkml/wei/busyZones.csv")
```

```
scala> val prediction = km.transform(testdata)
prediction: org.apache.spark.sql.DataFrame = [TID: string, Lat: double ... 4 more fields]

scala> prediction.createTempView("haha")

scala> val tmpQuery = spark.sql("select substring(Time,0,2) as hour,prediction from haha")
2020-01-07 09:21:31,452 WARN metastore.ObjectStore: Version information not found in metastore.
hive.metastore.schema.verification is not enabled so recording the schema version 1.2.0
2020-01-07 09:21:31,892 WARN metastore.ObjectStore: Failed to get database default, returning NoSuchObjectException
2020-01-07 09:21:35,708 WARN metastore.ObjectStore: Failed to get database global_temp, returning NoSuchObjectException
tmpQuery: org.apache.spark.sql.DataFrame = [hour: string, prediction: int]

scala> val predictCount = tmpQuery.groupBy("hour","prediction").agg(count("prediction").alias("count")).orderBy(desc("count"))
predictCount: org.apache.spark.sql.Dataset[org.apache.spark.sql.Row] = [hour: string, prediction: int ... 1 more field]

scala> predictCount.show()
+----+----------+-----+
|hour|prediction|count|
+----+----------+-----+
| 15|         0| 3318|
| 14|         0| 3202|
| 17|         0| 3080|
| 20|         0| 2925|
| 16|         0| 2891|
| 21|         8| 2879|
| 13|         0| 2862|
| 21|         0| 2840|
| 11|         0| 2799|
| 14|         7| 2775|
| 15|         7| 2775|
| 12|         0| 2750|
| 22|         7| 2741|
| 20|         8| 2718|
| 21|         7| 2691|
| 10|         0| 2552|
| 22|         0| 2513|
| 22|         8| 2479|
| 11|         7| 2466|
| 09|         0| 2464|
+----+----------+-----+
only showing top 20 rows


scala> predictCount.write.csv("/sparkml/wei/predictCount.csv")

scala> val busyZones = prediction.groupBy("prediction").count()
busyZones: org.apache.spark.sql.DataFrame = [prediction: int, count: bigint]

scala> busyZones.show()
+----------+-----+
|prediction|count|
+----------+-----+
|         1| 1639|
|         6| 2923|
|         3| 8171|
|         5| 4106|
|         9|  534|
|         4|27974|
|         8|35689|
|         7|36930|
|         2|  705|
|         0|44517|
+----------+-----+


scala> busyZones.write.csv("/sparkml/wei/busyZones.csv")
```

2.5 数据可视化

然后把hdfs上的文件存到本地

hdfs dfs -ls /sparkml/wei

hdfs dfs -get /sparkml/wei/predictCount.csv predictCount.csv

hdfs dfs -get /sparkml/wei/busyZones.csv predictCount.csv

hdfs dfs -getmerge /sparkml/wei/kmResult kmResult.csv

利用正则匹配，将数据变成标准格式：

In [ ]:
```
#bash

sed 's/.$//' kmResult.csv >> kmResult1.csv       #去除行尾括号
sed 's/^.//' kmResult1.csv  kmResult2.csv         #去除行首括号
sed ':a;N;$!ba;s/\n/|/g'  kmResult2.csv >> kmResult3.csv       #将所有换行符\n替换为分隔符|
```

运用python解析百度API返回的地址参数,得到统计图形

In [7]:
```
# !pip install pandas_highcharts
```

In [19]:
```
#python
import pandas as pd
import urllib.request
import json

data = pd.read_csv("busyZones.csv",header=None,names=("area","counts"))
pre = pd.read_csv("kmResult2.csv",header=None,names=("lon","lat"))
pre["area"] = pre.index
df = pd.merge(data,pre,on="area",how="left")
df
```

Out[19]:

	area	counts	lon	lat
0	1	1639	103.873972	30.724121
1	6	2923	104.132504	30.753203
2	3	8171	103.985923	30.594014
3	5	4106	104.058428	30.537256
4	9	534	104.307097	30.568626
5	4	27974	104.113942	30.635382
6	8	35689	104.019317	30.672885
7	7	36930	104.058983	30.627462
8	2	705	103.628853	30.927354
9	0	44517	104.075785	30.673148

In [20]:
```
def foundloc(lon,lat):
    url="http://api.map.baidu.com/geocoder/v2/?location=%f,%f&output=json&ak=Yrf32LVk9DEHOYchZAQlG9nFICRTst5V"%(lat,lon)
    req = urllib.request.urlopen(url)
    res = req.read().decode("utf-8")
    temp = json.loads(res)
    return temp["result"]["formatted_address"]

lon = list(df["lon"])
lat = list(df["lat"])
situation = zip(lon,lat)
situa = []
for i in situation:
    situa.append(foundloc(i[0],i[1])[6:-1])

situa
```

Out[20]:
```
['温江',
'金牛区玉垒',
'武侯区凉港',
'双流县丽景',
'龙泉驿',
'锦江区通盈',
'青羊区华西',
'武侯区二环路南3段-18号-附11',
'都江堰市中大街9',
'青羊区西玉龙街8-1']
```

In [23]:
```
df["name"] = situa
df1 = df[["counts","name"]]
df1 = df1.set_index("name")
df1
```

Out[23]:

name	counts
温江	1639
金牛区玉垒	2923
武侯区凉港	8171
双流县丽景	4106
龙泉驿	534
锦江区通盈	27974
青羊区华西	35689
武侯区二环路南3段-18号-附11	36930
都江堰市中大街9	705
青羊区西玉龙街8-1	44517

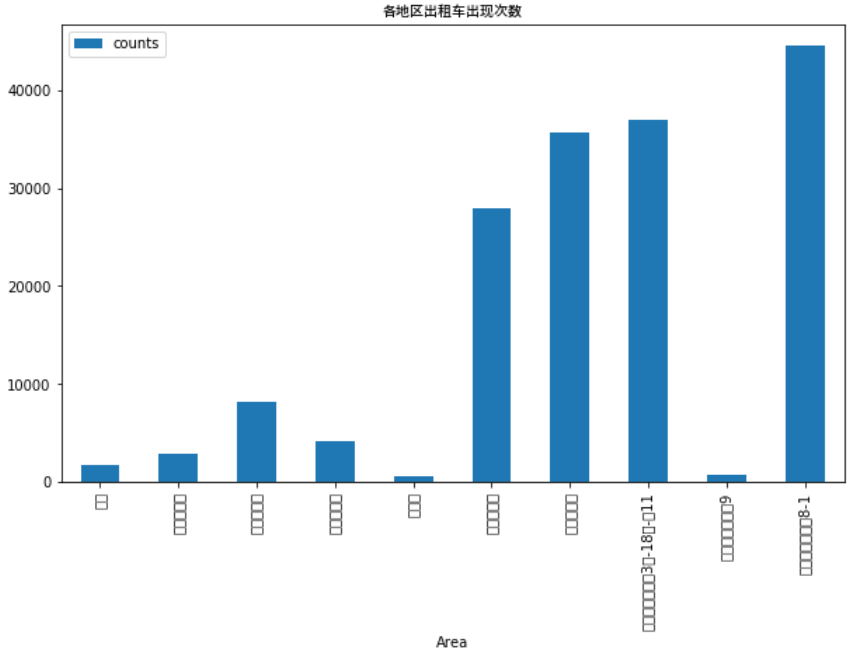
In [63]:
```
#定义自定义字体，中文显示不乱码
import matplotlib
matplotlib.use('qt5agg')
from matplotlib.font_manager import *
import matplotlib.pyplot as plt

myfont = FontProperties(fname='/usr/share/fonts/opentype/noto/NotoSansCJK-Medium.ttc')
```

In [78]:
```
df1.plot(kind='bar', figsize=(10, 6))

plt.xlabel('Area') # add to x-label to the plot
plt.ylabel('')  # add y-label to the plot
plt.title('各地区出租车出现次数',fontproperties=myfont) # add title to the plot

plt.show()
```



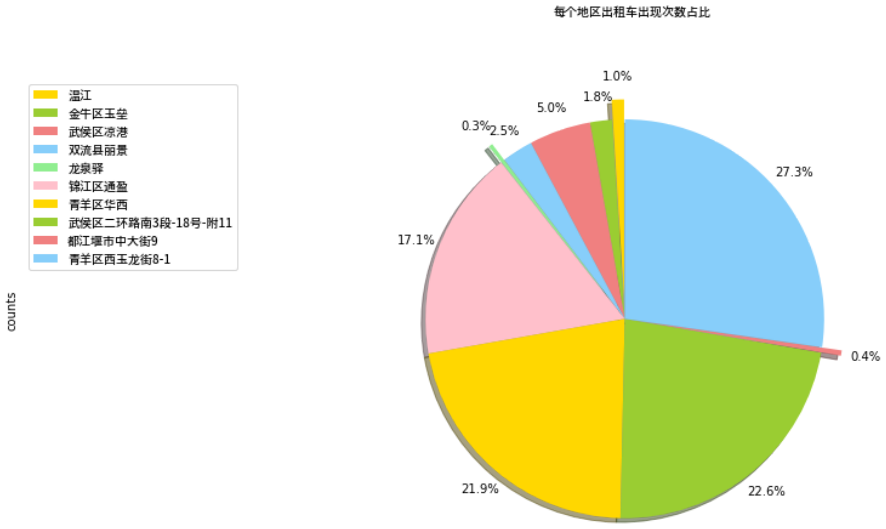
In [64]:
```
colors_list = ['gold', 'yellowgreen', 'lightcoral', 'lightskyblue', 'lightgreen', 'pink']
explode_list = [0.1, 0, 0, 0, 0.1, 0,0, 0, 0.1, 0]          # ratio for each continent with which to offset each wedge.

df1['counts'].plot(
                kind='pie',
                figsize=(18, 7),
                autopct='%1.1f%%',
                startangle=90,
                 shadow=True,
                 labels=None,         # turn off labels on pie chart
                 pctdistance=1.12,    # the ratio between the center of each pie slice and the start of the text generated by autopct
                colors=colors_list,  # add custom colors
                explode=explode_list # 'explode' lowest 3 continents
                        )
# scale the title up by 12% to match pctdistance
plt.title('每个地区出租车出现次数占比', y=1.12,fontproperties=myfont)

plt.axis('equal')

# add legend
plt.legend(labels=df1.index, loc='upper left',prop=myfont)

plt.show()
```



In [ ]: