In [5]:
```
from pyspark.sql import SparkSession
```

In [6]:
```
spark = SparkSession.builder.appName('Read CSV File into DataFrame').getOr
```

In [7]:
```
data=spark.read.csv(r"C:\Users\16478\Desktop\BigData\Lab4\Live.csv", sep='
```

In [8]:
```
data.show(5)
```

```
+------------------+----------+---------------+------------+--------
----+----------+---------+---------+--------+---------+--------+---------
-+-------+-------+-------+-------+
|           status_id|status_type|status_published|num_reactions|num_comm
ents|num_shares|num_likes|num_loves|num_wows|num_hahas|num_sads|num_angry
s|Column1|Column2|Column3|Column4|
+------------------+----------+---------------+------------+--------
----+----------+---------+---------+--------+---------+--------+---------
-+-------+-------+-------+-------+
|246675545449582_1...|      video|  4/22/2018 6:00|          529|
512|       262|      432|        92|       3|        1|       1|         0
|   null|   null|   null|   null|
|246675545449582_1...|      photo| 4/21/2018 22:45|          150|
0|         0|      150|         0|       0|        0|       0|         0|
null|   null|   null|   null|
|246675545449582_1...|      video|  4/21/2018 6:17|          227|
236|        57|      204|        21|       1|        1|       0|         0
|   null|   null|   null|   null|
|246675545449582_1...|      photo|  4/21/2018 2:29|          111|
0|         0|      111|         0|       0|        0|       0|         0|
null|   null|   null|   null|
|246675545449582_1...|      photo|  4/18/2018 3:22|          213|
0|         0|      204|         9|       0|        0|       0|         0|
null|   null|   null|   null|
+------------------+----------+---------------+------------+--------
----+----------+---------+---------+--------+---------+--------+---------
-+-------+-------+-------+-------+
only showing top 5 rows
```

In [9]:
```
data.printSchema()
```

```
root
 |-- status_id: string (nullable = true)
 |-- status_type: string (nullable = true)
 |-- status_published: string (nullable = true)
 |-- num_reactions: integer (nullable = true)
 |-- num_comments: integer (nullable = true)
 |-- num_shares: integer (nullable = true)
 |-- num_likes: integer (nullable = true)
 |-- num_loves: integer (nullable = true)
 |-- num_wows: integer (nullable = true)
 |-- num_hahas: integer (nullable = true)
 |-- num_sads: integer (nullable = true)
 |-- num_angrys: integer (nullable = true)
 |-- Column1: string (nullable = true)
 |-- Column2: string (nullable = true)
 |-- Column3: string (nullable = true)
 |-- Column4: string (nullable = true)
```

In [10]:
```
#removing NA Values
```

In [11]:
```
data = data.drop('Column1','Column2','Column3','Column4')
```

In [12]:
```
data
```

Out[12]:
```
DataFrame[status_id: string, status_type: string, status_published: strin
g, num_reactions: int, num_comments: int, num_shares: int, num_likes: in
t, num_loves: int, num_wows: int, num_hahas: int, num_sads: int, num_angr
ys: int]
```

In [13]:
```
#Removing duplicate rows
```

In [14]:
```
data=data.dropDuplicates()
data.show()
```

```
+-------------------+----------+---------------+------------+--------
----+----------+---------+---------+--------+---------+--------+---------
-+
|           status_id|status_type|status_published|num_reactions|num_comm
ents|num_shares|num_likes|num_loves|num_wows|num_hahas|num_sads|num_angry
s|
+-------------------+----------+---------------+------------+--------
----+----------+---------+---------+--------+---------+--------+---------
-+
|246675545449582_1...|      video|   8/8/2017 5:13|         571|
888|       107|      459|      107|       1|        1|       1|         2
|
|246675545449582_1...|      photo|  3/11/2017 8:04|         515|
10|         0|      505|        9|       0|        1|       0|         0|
|246675545449582_1...|      video| 2/10/2017 22:58|          88|
1|         0|       87|        1|       0|        0|       0|         0|
|246675545449582_1...|      photo|   1/6/2017 5:10|         139|
14|         0|      138|        1|       0|        0|       0|         0|
|246675545449582_1...|      photo| 10/10/2016 5:08|         124|
2|         0|      119|        3|       2|        0|       0|         0|
|246675545449582_1...|      photo| 8/21/2016 22:30|         441|
31|         2|      423|       13|       2|        3|       0|         0|
|246675545449582_9...|      photo|  7/8/2016 10:51|          54|
2|         4|       54|        0|       0|        0|       0|         0|
|246675545449582_8...|      photo|  2/7/2016 10:36|         151|
0|         0|      151|        0|       0|        0|       0|         0|
|246675545449582_8...|      photo| 9/20/2015 22:50|        1188|
14|         1|     1188|        0|       0|        0|       0|         0|
|246675545449582_6...|      photo|   1/7/2015 2:03|         366|
28|         5|      366|        0|       0|        0|       0|         0|
|246675545449582_6...|      photo|  1/2/2015 23:16|        1424|
6|         0|     1424|        0|       0|        0|       0|         0|
|246675545449582_4...|      photo|  9/25/2013 3:29|          17|
0|         1|       17|        0|       0|        0|       0|         0|
|246675545449582_2...|      photo| 11/4/2012 10:50|          11|
6|         0|       11|        0|       0|        0|       0|         0|
|134115277150304_2...|      photo|  4/29/2018 9:08|          64|
2|         0|       62|        0|       2|        0|       0|         0|
|134115277150304_2...|      photo|  4/29/2018 6:58|           5|
3|         0|        5|        0|       0|        0|       0|         0|
|134115277150304_2...|      photo|   1/6/2018 7:46|          10|
3|         0|       10|        0|       0|        0|       0|         0|
|134115277150304_1...|      photo| 11/26/2017 2:12|          90|
26|         1|       86|        2|       2|        0|       0|         0|
|848451358648417_8...|      video| 12/18/2017 7:00|           7|
0|         0|        7|        0|       0|        0|       0|         0|
|848451358648417_8...|      video| 11/18/2017 8:26|           8|
0|         0|        8|        0|       0|        0|       0|         0|
|848451358648417_8...|      video|  11/8/2017 6:31|           5|
0|         0|        5|        0|       0|        0|       0|         0|
+-------------------+----------+---------------+------------+--------
----+----------+---------+---------+--------+---------+--------+---------
-+
only showing top 20 rows
```

drop variable columns as it will be not used for clustering

In [15]:
```
data = data.drop('status_id','status_published')
```

In [16]:
```
data.show(1)
```

```
+----------+------------+-----------+----------+---------+---------+--
------+---------+--------+----------+
|status_type|num_reactions|num_comments|num_shares|num_likes|num_loves|nu
m_wows|num_hahas|num_sads|num_angrys|
+----------+------------+-----------+----------+---------+---------+--
------+---------+--------+----------+
|      video|          571|         888|       107|      459|      107|
1|        1|       1|         2|
+----------+------------+-----------+----------+---------+---------+--
------+---------+--------+----------+
only showing top 1 row
```

In [17]:
```
feature_col=['num_reactions','num_comments','num_shares','num_likes','num_
```

In [18]:
```
from pyspark.ml import Pipeline
from pyspark.ml.clustering import GaussianMixture
from pyspark.ml.clustering import KMeans
from pyspark.ml.feature import StringIndexer
from pyspark.ml.feature import VectorAssembler
from pyspark.ml.feature import StandardScaler
from pyspark.ml.evaluation import ClusteringEvaluator
from pyspark.ml.evaluation import MulticlassClassificationEvaluator
from pyspark.sql.functions import col
```

In [19]:
```
indexer = StringIndexer(inputCol='status_type', outputCol='y_target')
i_model=indexer.fit(data)
i_data=i_model.transform(data)
```

In [20]:
```
i_data.show(1)
```

```
+----------+------------+-----------+----------+---------+---------+--
------+---------+--------+----------+--------+
|status_type|num_reactions|num_comments|num_shares|num_likes|num_loves|nu
m_wows|num_hahas|num_sads|num_angrys|y_target|
+----------+------------+-----------+----------+---------+---------+--
------+---------+--------+----------+--------+
|      video|          571|         888|       107|      459|      107|
1|        1|       1|         2|     1.0|
+----------+------------+-----------+----------+---------+---------+--
------+---------+--------+----------+--------+
only showing top 1 row
```

In [21]:
```
assemble=VectorAssembler(inputCols= feature_col, outputCol='features')
#a_data=assemble.transform(i_data)
```

In [22]:
```
scale=StandardScaler(inputCol='features',outputCol='scaled_features',withS
#s_model=scale.fit(a_data)
#s_data=s_model.transform(a_data)
#s_data.show(1)
```

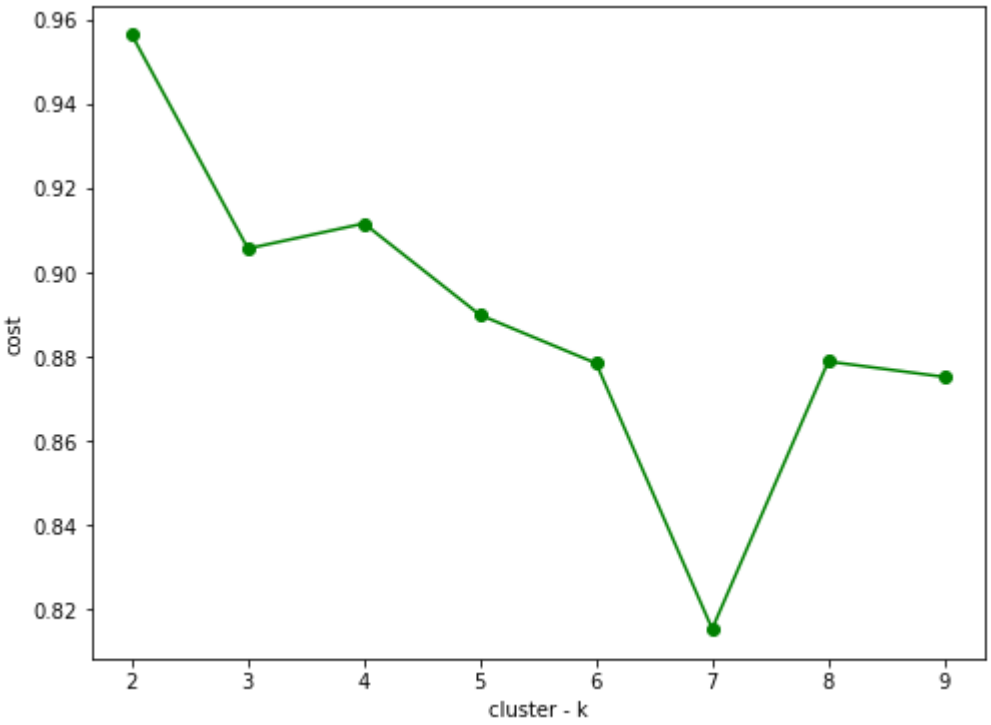
In [23]:

```
silhouette_scores = []
wssse_scores = []
for i in range(2,10):
    kmeans= KMeans(k=i, seed=1)
    pipeline = Pipeline(stages=[assemble,scale,kmeans])
    model = pipeline.fit(i_data)
    predictions = model.transform(i_data)
    evaluator = ClusteringEvaluator()
    silhouette = evaluator.evaluate(predictions)
    silhouette_scores.append(silhouette)
    wssse = model.stages[2].summary.trainingCost
    wssse_scores.append(wssse)
    pred = predictions.withColumn("prediction", col("prediction").cast("do
    #evaluator = MulticlassClassificationEvaluator(predictionCol="predicti
    #accuracy = evaluator.evaluate(pred)
    accuracy= predictions.filter(predictions['prediction'] == predictions[
    print("***"*10)
    print("Silhouette score for k=%d: %f" % (i, silhouette))
    print("wssse score for k=%d: %f" % (i, wssse))
    print("Accuracy for k=%d: %f" % (i, accuracy*100))
    print("***"*10)
```

```
******************************
Silhouette score for k=2: 0.956341
wssse score for k=2: 4839823206.131467
Accuracy for k=2: 62.623232
******************************
******************************
Silhouette score for k=3: 0.905623
wssse score for k=3: 2692041220.507795
Accuracy for k=3: 60.708673
******************************
******************************
Silhouette score for k=4: 0.911592
wssse score for k=4: 2079119591.550163
Accuracy for k=4: 60.865838
******************************
******************************
Silhouette score for k=5: 0.889869
wssse score for k=5: 1462768285.310793
Accuracy for k=5: 58.836977
******************************
******************************
Silhouette score for k=6: 0.878393
wssse score for k=6: 1164758774.117053
Accuracy for k=6: 58.794113
******************************
******************************
Silhouette score for k=7: 0.815348
wssse score for k=7: 1046269037.779072
Accuracy for k=7: 57.779683
******************************
******************************
Silhouette score for k=8: 0.878824
wssse score for k=8: 727786318.716434
Accuracy for k=8: 57.236748
******************************
******************************
Silhouette score for k=9: 0.875152
wssse score for k=9: 640762782.250892
Accuracy for k=9: 57.765395
******************************
```

In [142]:
```
#Visualizing the silhouette scores in a plot
import matplotlib.pyplot as plt
fig, ax = plt.subplots(1,1, figsize =(8,6))
ax.plot(range(2,10),silhouette_scores,marker='o',color='green')
ax.set_xlabel('cluster - k')
ax.set_ylabel('cost')
```

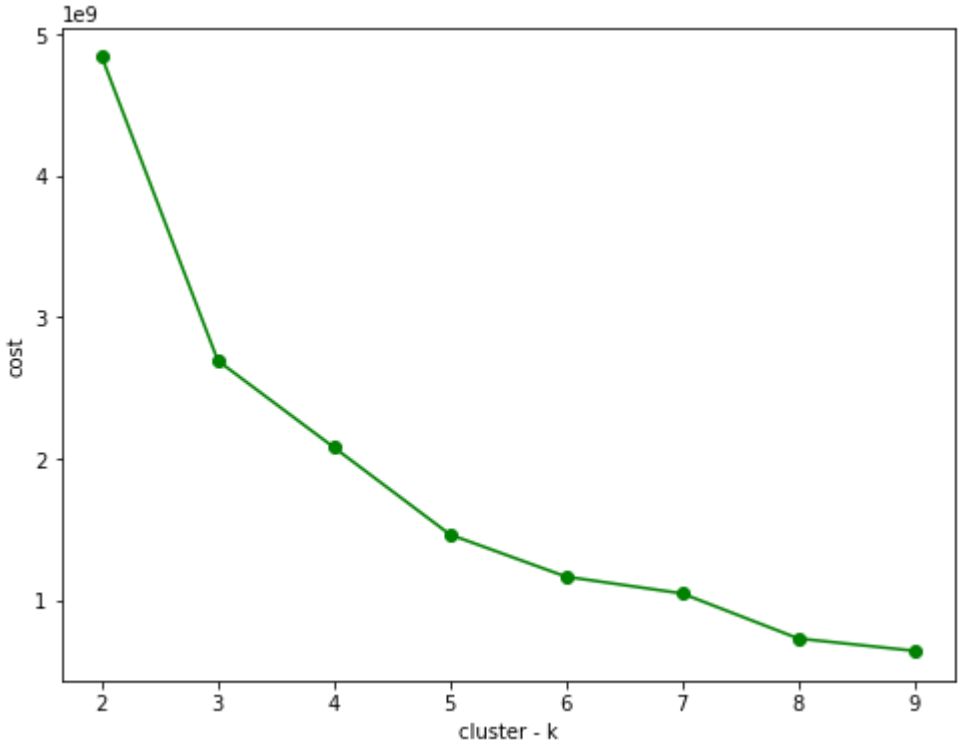
Out[142]:
```
Text(0, 0.5, 'cost')
```



From the above elbow method, we can say that with k = 3 is the optimal number of clusters

In [143]:
```
#Visualizing the wssse scores in a plot
import matplotlib.pyplot as plt
fig, ax = plt.subplots(1,1, figsize =(8,6))
ax.plot(range(2,10),wssse_scores,marker='o',color='green')
ax.set_xlabel('cluster - k')
ax.set_ylabel('cost')
```

Out[143]: Text(0, 0.5, 'cost')



From the above elbow method, we can say that with k = 3 or 5 as the optimal number of clusters

In [100]:
```
label=[row.y_target for row in i_data.select("y_target").collect()]
```

In [174]:
```
#from pyspark.ml.evaluation import MulticlassClassificationEvaluator
#from pyspark.sql.functions import col

#pred = predictions.withColumn("prediction", col("prediction").cast("doubl
#evaluator = MulticlassClassificationEvaluator(predictionCol="prediction",
#accuracy = evaluator.evaluate(pred)

# Print the accuracy
#print("Accuracy = {:.2f}%".format(accuracy * 100))
```

In [24]:

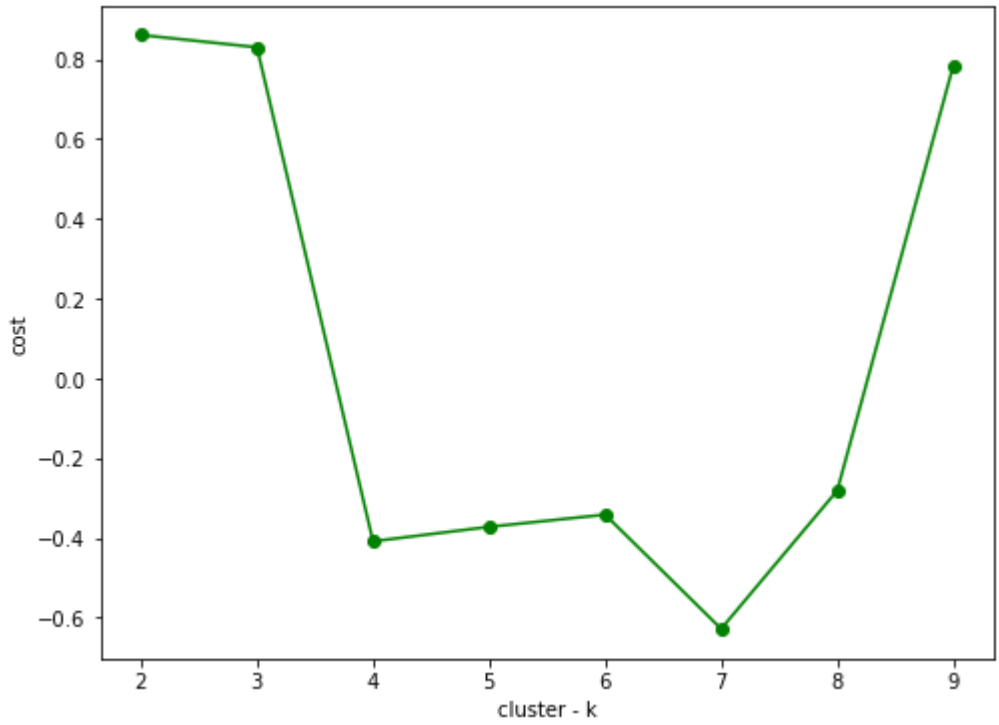
```
gmm_wssse = []
gmm_silhouette = []

for k in range(2, 10):
    gmm = GaussianMixture().setK(k).setSeed(1)
    gmm_pipeline = Pipeline(stages=[assemble,scale,gmm])
    model_gmm = gmm_pipeline.fit(i_data)
    predictions_gmm = model_gmm.transform(i_data)
    evaluator_gmm = ClusteringEvaluator()
    gmm_silhou = evaluator_gmm.evaluate(predictions_gmm)
    gmm_silhouette.append(gmm_silhou)
    gmm_ws = model_gmm.stages[2].summary.logLikelihood
    gmm_wssse.append(gmm_ws)
    pred_gmm = predictions_gmm.withColumn("prediction", col("prediction").
    #evaluator = MulticlassClassificationEvaluator(predictionCol="predicti
    #accuracy = evaluator.evaluate(pred_gmm)
    accuracy= predictions_gmm.filter(predictions_gmm['prediction'] == pred
    print("***"*10)
    print("Silhouette score for k=%d: %f" % (k, gmm_silhou))
    print("wssse score for k=%d: %f" % (k, gmm_ws))
    print("Accuracy for k=%d: %f" % (k, accuracy*100))
    print("***"*10)
```

```
******************************
Silhouette score for k=2: 0.861018
wssse score for k=2: -205116.404800
Accuracy for k=2: 30.718674
******************************
******************************
Silhouette score for k=3: 0.830150
wssse score for k=3: -196866.392619
Accuracy for k=3: 59.165595
******************************
******************************
Silhouette score for k=4: -0.408266
wssse score for k=4: -191123.577946
Accuracy for k=4: 3.471925
******************************
******************************
Silhouette score for k=5: -0.372053
wssse score for k=5: -186719.389573
Accuracy for k=5: 7.343906
******************************
******************************
Silhouette score for k=6: -0.341483
wssse score for k=6: -183133.859694
Accuracy for k=6: 26.432347
******************************
******************************
Silhouette score for k=7: -0.627633
wssse score for k=7: -180102.279532
Accuracy for k=7: 58.051150
******************************
******************************
Silhouette score for k=8: -0.281146
wssse score for k=8: -177476.394219
Accuracy for k=8: 26.332333
******************************
******************************
Silhouette score for k=9: 0.784467
wssse score for k=9: -175159.817225
Accuracy for k=9: 0.371482
******************************
```

In [152]:
```
#Visualizing the silhouette scores in a plot
import matplotlib.pyplot as plt
fig, ax = plt.subplots(1,1, figsize =(8,6))
ax.plot(range(2,10),gmm_silhouette,marker='o',color='green')
ax.set_xlabel('cluster - k')
ax.set_ylabel('cost')
```

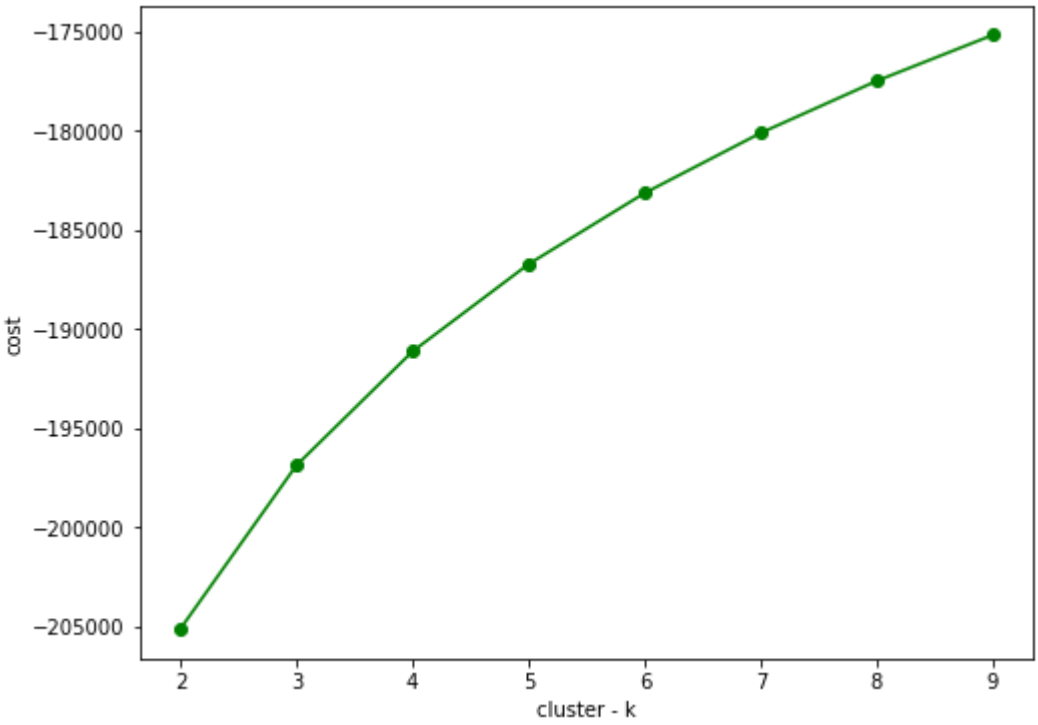
Out[152]:
```
Text(0, 0.5, 'cost')
```



From the above elbow method, we can say that with k = 4 as the optimal number of clusters

In [148]:
```
#Visualizing the WSSSE scores in a plot
import matplotlib.pyplot as plt
fig, ax = plt.subplots(1,1, figsize =(8,6))
ax.plot(range(2,10),gmm_wssse,marker='o',color='green')
ax.set_xlabel('cluster - k')
ax.set_ylabel('cost')
```

Out[148]: Text(0, 0.5, 'cost')



From the above elbow method, we can say that with k = 3 as the optimal number of clusters

#Compare Clustering models

For k-means clustering, the silhouette scores are higher for all values of k, which indicates better clustering quality. The wssse scores also show a decreasing trend as the number of clusters increases, indicating that the clusters are becoming more compact.

For GMM clustering, the silhouette scores are lower for all values of k, indicating that the clusters are less distinct. The wssse scores are negative, which is not a good sign of clustering quality

Overall, k-means clustering seems to have performed better.

In [282]:
```
centroid = model_gmm.stages[-1].gaussiansDF
```

In [28]:
```
distances = model_gmm.stages[-1]('features').rdd \
    .map(lambda x: (x['prediction'], x['features'])) \
    .groupByKey() \
    .flatMap(lambda x: [(x[0], (xi - model.gaussians[x[0]].mean).dot(model
```

```
---------------------------------------------------------------------------
--
TypeError                                 Traceback (most recent call las
t)
Input In [28], in <cell line: 1>()
----> 1 distances = model_gmm.stages[-1]('features').rdd \
      2     .map(lambda x: (x['prediction'], x['features'])) \
      3     .groupByKey() \
      4     .flatMap(lambda x: [(x[0], (xi - model.gaussians[x[0]].mean).
dot(model.gaussians[x[0]].invCov).dot((xi - model.gaussians[x[0]].mean).
T)) for xi in x[1]])

TypeError: 'GaussianMixtureModel' object is not callable
```

In [ ]:
```
spark.stop()
```

In [ ]:

In [ ]:

In [ ]:

In [34]:

In [ ]:

In [59]:

In [ ]:

In [51]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]: