UDACITY

‹ Back to Machine Learning Engineer Nanodegree

Creating Customer Segments

REVIEW

CODE REVIEW

HISTORY

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Meets Specifications

This is a very solid analysis here and impressed with your answers. You have an excellent grasp on these unsupervised learning techniques. We don't pass to many on the first attempt, so congrats! Wish you the best of luck in your future!

If you would like to dive in deeper into Machine Learning material, here might be some cool books to check out

- An Introduction to Statistical Learning Code is in R, but great for understanding the topics
- elements of statistical learning More math concepts
- Python Machine Learning Great intuitive ideas and goes through everything in code.

Data Exploration

Three separate samples of the data are chosen and their establishment representations are proposed based on the statistical description of the dataset.

Love the visual here, as this is fine justification. I would suggest explicitly referencing the features. For example (hypothetical)

- Sample 1. Fresh category count is 3.6 times more than the mean. Regarding this category, the value is located in the third quartile (quite a lot), but the count for other categories is considerably below the average. We can conclude that this customer specializes on fresh food trading and a good instance of such an establishment is a organic food supermarket.

Another really cool visualization you could make to analyze the distribution of purchasing behavior of your sample, would be with a Radar Plot

```
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler
%matplotlib inline

scaler = MinMaxScaler()
df = np.round(samples, 1)
index  = df.index[:]
categories = list(df)
df = scaler.fit_transform(df)*100
N = len(categories)
angles = [n / float(N) * 2 * np.pi for n in range(N)]
angles += angles[:1]

plt.figure(figsize=(20, 5))
def Radar(index, title, color):
    ax = plt.subplot(1, 3, index+1, polar=True)
    ax.set_theta_offset(np.pi/2)
    ax.set_theta_direction(-1)
    plt.xticks(angles[:-1], categories, color ='grey', size = 8)
    plt.yticks((25, 50, 75, 100), ("1/4", "1/2", "3/4", "Max"), color = "grey", size = 7)
    values = df[index]
    values = np.append(values, values[:1])
    ax.plot(angles, values, color = color)
    ax.fill(angles, values, color=color, alpha=0.5)
    plt.title('Sample {}'.format(title), y= 1.1)
```

```
for i, n in enumerate(index):
    Radar(index=i, title=n, color='r')
```

A prediction score for the removed feature is accurately reported. Justification is made for whether the removed feature is relevant.

> "I attempted to predict Grocery, which yielded the highest score of 0.681884 among the features, so Grocery can be predicted using the other features and is therefore no necessary feature for identifying customers' spending habits."

Correct. Grocery can be derived from the other features, so not necessary. Thus if we have a high r^2 score(high correlation with other features), this would not be good for identifying customers' spending habits(since the customer would purchase other products along with the one we are predicting, as we could actually derive this feature from the rest of the features). Therefore a negative / low r^2 value would represent the opposite as we could identify the customer's specific behavior just from the one feature.

Maybe also check out with features can derive Grocery

```
import seaborn as sns
sns.barplot(X_train.columns, regressor.feature_importances_)
```

Student identifies features that are correlated and compares these features to the predicted feature. Student further discusses the data distribution for those features.

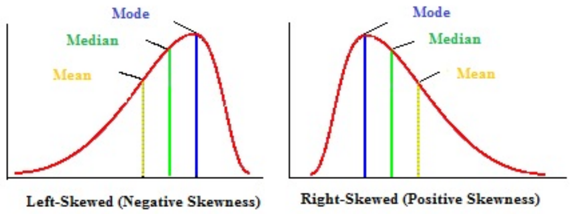
Great job capturing the correlation between features. Can also note that Milk <-> Detergents_Paper, and Milk <-> Grocery are also correlated but not to the same degree. Maybe also add correlation to the plot as well with

```
axes = pd.scatter_matrix(data, alpha = 0.3, figsize = (14,8), diagonal = 'kde')
corr = data.corr().as_matrix()
for i, j in zip(*np.triu_indices_from(axes, k=1)):
axes[i, j].annotate("%.3f" %corr[i,j], (0.8, 0.8), xycoords='axes fraction', ha='center', va='center')
```

And good ideas regarding the data distributions with your comment of

> "The histograms of Detergents_Paper and Grocery below don't look bell-shaped and therefore Detergents_Paper and Grocery are not normally distributed"

Would suggest also mentioning the direction of the skew. Skewed right is correct. Could also mention log normal. As we can actually get an idea of this from the basic stats of the dataset, since the mean is above the median for all features. We typically see this type of distribution when working with sales or income data.



Data Preprocessing

Feature scaling for both the data and the sample data has been properly implemented in code.

Student identifies extreme outliers and discusses whether the outliers should be removed. Justification is made for any data points removed.

Great job discovering the indices of the five data points which are outliers for more than one feature of `[65, 66, 75, 128, 154]`.

Outlier removal is a tender subject, as we definitely don't want to remove too many with this small dataset. But we definitely need to remove some, since outliers can greatly affect distributions, influence a distance based algorithm like clustering and/or PCA! The loss function of the K-means algorithm is defined the terms of sum-of-squared distances, making it sensitive to outliers. In an attempt to reduce the loss function, the algorithm would move a centroid away from the true center of a cluster towards the outlier. This is clearly not the behavior we want.

> " I do not know any criterion that clearly states the conditions under which an outlier should be removed or retained."

There is not clear condition under which an outlier should be removed. One cool thing about unsupervised learning is that we could actually run our future analysis with these data points removed and with these data points included and see how the results change.

(http://www.theanalysisfactor.com/outliers-to-drop-or-not-to-drop/)
(http://graphpad.com/guides/prism/6/statistics/index.htm?stat_checklist_identifying_outliers.htm)

Maybe also examine these duplicate data points further with a heatmap in the original data.

```
# Heatmap using percentiles to display outlier data
import matplotlib.pyplot as plt
import seaborn as sns
percentiles = data.rank(pct=True)
percentiles = percentiles.iloc[[65, 66, 75, 128, 154]]
plt.title('Multiple Outliers Heatmap', fontsize=14)
heat = sns.heatmap(percentiles, annot=True)
display(heat)
```

Feature Transformation

The total variance explained for two and four dimensions of the data from PCA is accurately reported. The first four dimensions are interpreted as a representation of customer spending with justification.

Nice work with the cumulative explained variance for two and four dimensions. Could look into using `np.cumsum(pca.explained_variance_ratio_)`

- As with two dimension we can easily visualize the data(as we do later)
- And with four components we retain much more information(great for new features)

And good analysis of these PCA components. As always remember that the sign of the features in the component really wouldn't matter too much, since if we multiply the entire PCA dimension by -1 it would still be the same PCA component(so in PCA3 Fresh and Deli could be switched!).

To go even further here with the interpretation of the PCA components:

- In terms of customers, since PCA deals with the variance of the data and the correlation between features, the first component would represent that we have some customers who purchase a lot of Milk, Grocery and Detergents_Paper products while other customers purchase very few amounts of Milk, Grocery and Detergents_Paper, hence spread in the data.

PCA has been properly implemented and applied to both the scaled data and scaled sample data for the two-dimensional case in code.

Clustering

The Gaussian Mixture Model and K-Means algorithms have been compared in detail. Student's choice of algorithm is justified based on the characteristics of the algorithm and data.

Good comparison and choice in GMM, as I would choose the same. As we can actually measure the level of uncertainty of our predictions! As the main two differences in these two algorithms are the speed and structural information of each:

Speed:

- K-Mean much faster and much more scalable
- GMM slower since it has to incorporate information about the distributions of the data, thus it has to deal with the co-variance, mean, variance, and prior probabilities of the data, and also has to assign probabilities to belonging to each clusters.

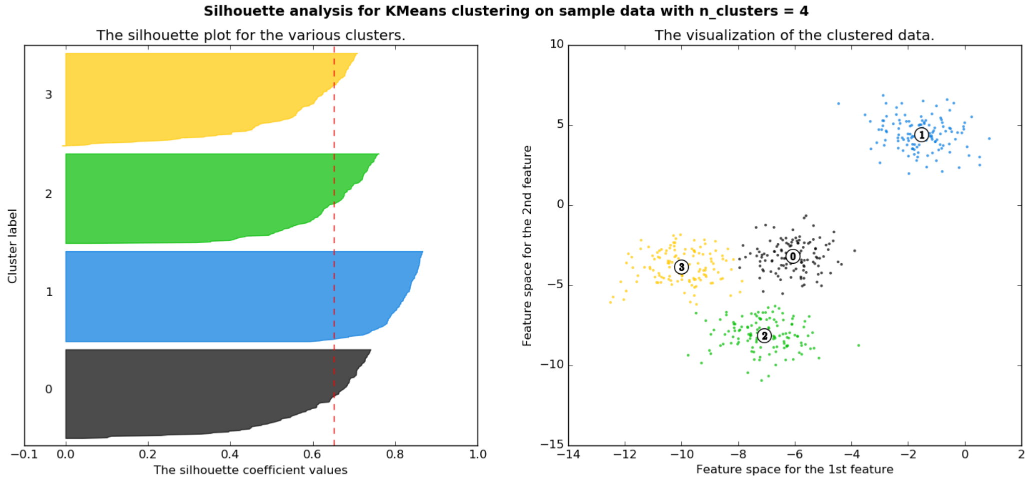
Structure:

- K-Means straight boundaries (hard clustering)
- GMM you get much more structural information, thus you can measure how wide each cluster is, since it works on probabilities (soft clustering)

Several silhouette scores are accurately reported, and the optimal number of clusters is chosen based on the best reported score. The cluster visualization provided produces the optimal number of clusters based on the clustering algorithm chosen.

Good work with the functions and for loop! As we can clearly see that K = 2 gives the highest silhouette score. Another cool interpretation method for Silhouette score is like this

(http://scikit-learn.org/stable/auto_examples/cluster/plot_kmeans_silhouette_analysis.html)



The establishments represented by each customer segment are proposed based on the statistical description of the dataset. The inverse transformation and inverse scaling has been properly implemented and applied to the cluster centers in code.

Good justification for your cluster centroids by comparing the cluster centers with dataset mean values. You could also examine the reduce PCA plot. Anything interesting about dimension 1 and how the clusters are split?

We can also add the mean values from the data and very easily visualize the cluster centroids with a pandas bar plot

```
true_centers = true_centers.append(data.describe().ix['mean'])
true_centers.plot(kind = 'bar', figsize = (16, 4))
```

Sample points are correctly identified by customer segment, and the predicted cluster for each sample point is discussed.

Excellent justification for your predictions by comparing the purchasing behavior of the sample to the cluster centroid!

Could also check out the distance to each cluster centroid for justification

```
for i, pred in enumerate(sample_preds):
    print("Sample point", i, "predicted to be in Cluster", pred)
    print('The distance between sample point {} and center of cluster {}:'.format(i, pred))
    print((samples.iloc[i] - true_centers.iloc[pred]))
```

Conclusion

Student correctly identifies how an A/B test can be performed on customers after a change in the wholesale distributor's service.

> "Maybe a test could be performed like this: Take n customers belonging to cluster 0 and another n customers belonging to cluster 1. Expose all of them to a change in delivery service from currently 5 days a week to 3 days a week. For each of the two clusters, count how many of the n customers of that cluster react positively on that change by not canceling deliveries. If this number is above a predefined threshold then enroll that change in delivery for all customers of that cluster."

Exactly! The key takeaway here is that we should run separate A/B tests for each cluster independently. As if we were to use all of our customers we would essentially have multiple variables(different delivery methods and different purchasing behaviors).
https://en.wikipedia.org/wiki/A/B_testing#Segmentation_and_targeting
https://stats.stackexchange.com/questions/192752/clustering-and-a-b-testing

The two clusters that we have in our model reveal two different consumer profiles that can be tested via A/B test. To better assess the impact of the changes on the delivery service, we would have to split the segment 0 and segment 1 into subgroups measuring its consequences within a delta time. Hypothetically we can raise a scenario where the segment 0 is A/B tested. For this we divide the segment 0 (can also be implemented in segment 1) into two sub-groups of establishments where only one of them would suffer the implementation of the new delivery period of three days a week, and the another would remain as a control with five days a week as usual. After a certain period of time, we could, through the consumption levels of the establishments, come to some conclusions, such as: whether the new frequency of deliveries is sufficient or not for a buyer. Where a sensible increase in overall consumption of all products may indicate the need for the establishment to maintain a storage because of the decreasing delivery frequency; or if it negatively affects the consumption profile of certain products, like groups of costumers who have greater buying fresh produce that can be negatively impacted, precisely because of the demand for fresh products with a higher delivery frequency. We can not say that the change in frequency will affect equally all customers because of the different consumption profiles that are part of the two segments. There will therefore consumers that will be affected, and possibly groups of buyers who will not undergo any change.

Student discusses with justification how the clustering data can be used in a supervised learner for new predictions.

Nice idea to use the cluster assignment as new labels. Another cool idea would be to use a subset of the newly engineered PCA components as new features(great for curing the curse of dimensionality). PCA is really cool and seem almost like magic at time. Just wait till you work with hundreds of features and you can reduce them down into just a handful. This technique becomes very handy especially with images. There is actually a handwritten digits dataset, using the "famous MNIST data" where you do just this and can get around a 98% classification accuracy after doing so. This is a kaggle competition and if you want to learn more check it out here KAGGLE

Comparison is made between customer segments and customer 'Channel' data. Discussion of customer segments being identified by 'Channel' data is provided, including whether this representation is consistent with previous results.

Real world data is really never perfectly linearly separable but it seems as our GMM algorithm did a decent job.

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Student FAQ