Practical Guide Of Unsupervised Learning Algorithms and Reinforcement learning

What is Unsupervised Learning?

In unsupervised learning, the model learns from unlabeled data without proper supervision.

Unsupervised learning uses machine learning techniques to cluster unlabeled data based on similarities and differences. The unsupervised algorithms discover hidden patterns in data without human supervision. Unsupervised learning aims to arrange the raw data into new features or groups together with similar patterns of data.

For instance, to predict the churn rate, we provide unlabeled data to our model for prediction. There is no information given that customers have churned or not. The model will analyze the data and find hidden patterns to categorize into two clusters: churned and non-churned customers.

Unsupervised Learning Approaches

Unsupervised algorithms can be used for three tasks—clustering, dimensionality reduction, and association. Below, we will highlight some commonly used clustering and association algorithms.

Clustering Techniques

Clustering, or cluster analysis, is a popular data mining technique for unsupervised learning. The clustering approach works to group non-labeled data based on similarities and differences. Unlike supervised learning, clustering algorithms discover natural groupings in data.

A **good clustering** method produces high-quality clusters having high intra-class similarity (similar data within a cluster) and less intra-class similarity (cluster data is dissimilar to other clusters).

It can be defined as the grouping of data points into various clusters containing similar data points. The same objects remain in the group that has fewer similarities with other groups. Here, we will discuss two popular clustering techniques: K-Means clustering and DBScan Clustering.

- **K-Means Clustering**

K-Means is the simplest unsupervised technique used to solve clustering problems. It groups the unlabeled data into various clusters. The K value defines the number of clusters you need to tell the system how many to create.

K-Means is a centroid-based algorithm in which each cluster is associated with the centroid. The goal is to minimize the sum of the distances between the data points and their corresponding clusters.

It is an iterative approach that breaks down the unlabeled data into different clusters so that each data point belongs to a group with similar characteristics.

K-means clustering performs two tasks:

1. Using an iterative process to create the best value of K.
2. Each data point is assigned to its closest k-center. The data point that is closer to the particular k-center makes a cluster.

An illustration of K-means clustering. Image source

- DBScan Clustering

“DBScan” stands for “Density-based spatial clustering of applications with noise.” There are three main words in DBscan: density, clustering, and noise.

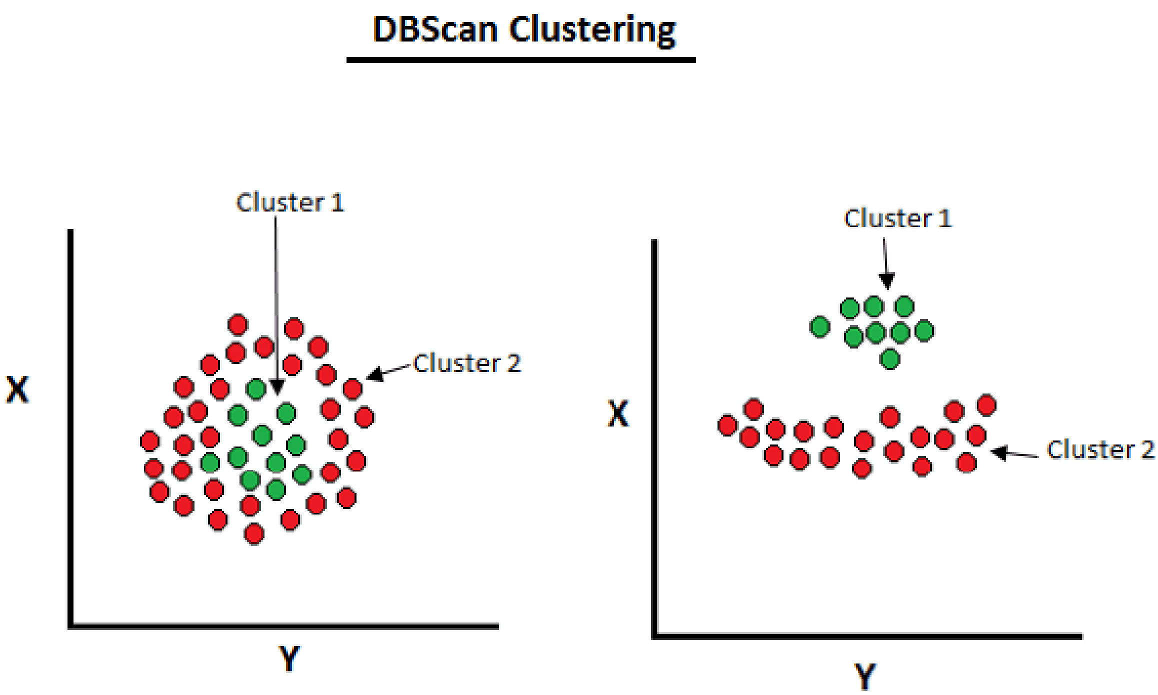
Therefore, this algorithm uses the notion of density-based clustering to form clusters and detect the noise.

Clusters are usually dense regions that are separated by lower density regions. Unlike the k-means algorithm, which works only on well-separated clusters, DBscan has a wider scope and can create clusters within the cluster. It discovers clusters of various shapes and sizes from a large set of data, which consists of noise and outliers.

There are two parameters in the DBScan algorithm:

minPts: The threshold, or the minimum number of points grouped together for a region considered as a dense region.

eps(ε): The distance measure used to locate the points in the neighborhood.



An illustration of density-based clustering. Image Source

ASSOCIATION RULE MINING

An association rule mining is a popular data mining technique. It finds interesting correlations in large numbers of data items. This rule shows how frequently items occur in a transaction.

Market Basket Analysis is a typical example of an association rule mining that finds relationships between items in the grocery store. It enables retailers to identify and analyze the associations between items that people frequently buy.

Important terminology used in association rules:

Support: It tells us about the combination of items bought frequently or frequently bought items.

Confidence: It tells us how often the items A and B occur together, given the number of times A occurs.

Lift: The lift indicates the strength of a rule over the random occurrence of A and B. For instance, A->B, the life value is 5. It means that if you buy A, the occurrence of buying B is five times.

The Apriori algorithm is a well-known association rule based technique.

- Apriori algorithm

The Apriori algorithm was proposed by R. Agarwal and R. Srikant in 1994 to find the frequent items in the dataset. The algorithm's name is based on the fact that it uses prior knowledge of frequently occurring things.

The Apriori algorithm finds frequently occurring items with minimum support.

It consists of two steps:

- Generation of candidate itemsets.
- Removing items that are infrequent and don't fulfill the criteria of minimum support.

Practical Implementation of Unsupervised Algorithms

In this tutorial, you will learn about the implementation of various unsupervised algorithms in Python. Scikit-learn is a powerful Python library widely used for various unsupervised learning tasks. It is an open-source library that provides numerous robust algorithms, which include classification, dimensionality reduction, clustering techniques, and association rules.

Let's begin!

1. K-MEANS ALGORITHM

Now let's dive deep into the implementation of the K-Means algorithm in Python. We'll break down each code snippet so that you can understand it easily.

Import libraries

First of all, we will import the required libraries and get access to the functions.

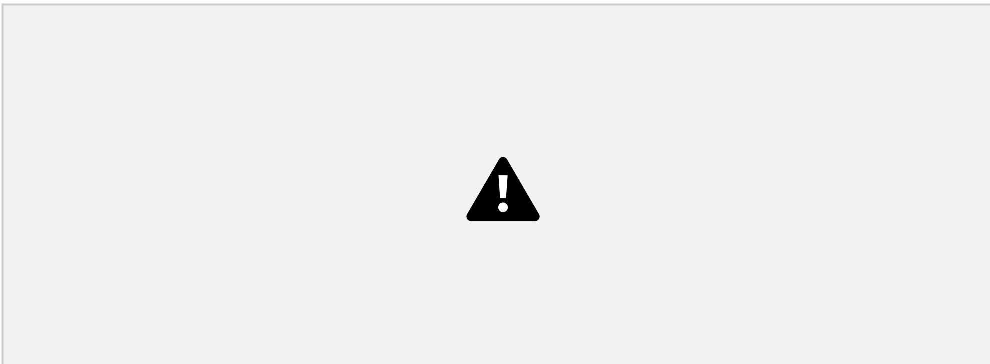
```
#Let's import the required libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

import seaborn as sns
```

Loading the dataset

The dataset is taken from the kaggle website. You can easily download it from the given link. To load the dataset, we use the **pd.read_csv()** function. **head()** returns the first five rows of the dataset.

```
my_data = pd.read_csv('Customers_Mall.csv.')
```

```
my_data.head()
```



The dataset contains five columns: customer ID, gender, age, annual income in (K$), and spending score from 1-100.

Data Preprocessing

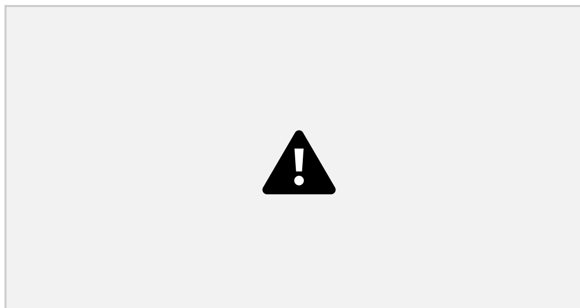
The **info()** function is used to get quick information about the dataset. It shows the number of entries, columns, total non-null values, memory usage, and datatypes.

```
my_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 5 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   CustomerID              200 non-null    int64
 1   Gender                  200 non-null    object
 2   Age                     200 non-null    int64
 3   Annual Income (k$)      200 non-null    int64
 4   Spending Score (1-100)  200 non-null    int64
dtypes: int64(4), object(1)
memory usage: 7.9+ KB
```

To check the missing values in the dataset, we use **isnull().sum(), which** returns the total number of null values.

```
#Check missing values

my_data.isnull().sum()
```



The **box plot** or **whisker plot** is used to detect outliers in the dataset. It also shows a statistical five number summary, which includes the minimum, first quartile, median (2nd quartile), third quartile, and maximum.

```
my_data.boxplot(figsize=(8,4))
```

Using Box Plot, we’ve detected an outlier in the annual income column. Now we will try to remove it before training our model.

```
#let's remove outlier from data
med =61
my_data["Annual Income (k$)"] = np.where(my_data["Annual Income (k$)"] >
 120,med,my_data['Annual Income (k$)'])
```

The outlier in the annual income column has been removed now to confirm we used the box plot again.

```
my_data.boxplot(figsize=(8,5))
```

Data Visualization

A histogram is used to illustrate the important features of the distribution of data. The **hist()** function is used to show the distribution of data in each numerical column.

```
my_data.hist(figsize=(6,6))
```

The correlation heatmap is used to find the potential relationships between variables in the data and to display the strength of those relationships. To display the heatmap, we have used the **seaborn** plotting library.

```
plt.figure(figsize=(10,6))
sns.heatmap(my_data.corr(), annot=True, cmap='icefire').set_title('seaborn')
plt.show()
```

Choosing the Best K Value

The **iloc()** function is used to select a particular cell of the data. It enables us to select a value that belongs to a specific row or column. Here, we’ve chosen the annual income and spending score columns.

```
X_val = my_data.iloc[:, 3:].values

X_val
```

```
# Loading Kmeans Library

from sklearn.cluster import KMeans
```

Now we will select the best value for K using the **Elbow's method.** It is used to determine the optimal number of clusters in K-means clustering.

```
my_val = []

for i in range(1,11):

    kmeans = KMeans(n_clusters = i, init='k-means++', random_state = 123)

    kmeans.fit(X_val)

    my_val.append(kmeans.inertia_)
```

The **sklearn.cluster.KMeans()** is used to choose the number of clusters along with the initialization of other parameters. To display the result, just call the variable.

```
my_val
```

```
#Visualization of clusters using elbow's method

plt.plot(range(1,11),my_val)

plt.xlabel('The No of clusters')

plt.ylabel('Outcome')
```

```
plt.title('The Elbow Method')

plt.show()
```

Through Elbow's Method, when the graph looks like an arm, then the elbow on the arm is the best value of K. In this case, we've taken K=3, which is the optimal value for K.

```
kmeans = KMeans(n_clusters = 3, init='k-means++')

kmeans.fit(X_val)

#To show centroids of clusters

kmeans.cluster_centers_


#Prediction of K-Means clustering

y_kmeans = kmeans.fit_predict(X_val)

y_kmeans
```

Splitting the dataset into three clusters

The scatter graph is used to plot the classification results of our dataset into three clusters.

```
plt.scatter(X_val[y_kmeans == 0,0], X_val[y_kmeans == 0,1], c='red',s=100)

plt.scatter(X_val[y_kmeans == 1,0], X_val[y_kmeans == 1,1], c='green',s=100)

plt.scatter(X_val[y_kmeans == 2,0], X_val[y_kmeans == 2,1], c='orange',s=100)
```

```
plt.scatter(kmeans.cluster_centers_[:,0], kmeans.cluster_centers_[:,1], s=300,
c='brown')

plt.title('K-Means Unsupervised Learning')

plt.show()
```

2. APRIORI ALGORITHM

To implement the apriori algorithm, we will utilize “The Bread Basket” dataset. The dataset is available on Kaggle and you can download it from the link. This algorithm suggests products based on the user’s purchase history. Walmart has greatly utilized the algorithm to recommend relevant items to its users.

Let’s implement the Apriori algorithm in Python.

Import libraries

To implement the algorithm, we need to import some important libraries.

```
import pandas as pd

import matplotlib.pyplot as plt

import numpy as np


import seaborn as sns
```

Loading the dataset

The dataset contains five columns and 20507 entries. The **data_time** is a prominent column and we can extract many vital insights from it.

```
my_data= pd.read_csv("bread basket.csv")
```

```
my_data.head()
```

Data Preprocessing

Convert the **data_time** into an appropriate format.

```
my_data['date_time'] = pd.to_datetime(my_data['date_time'])

#Total No of unique customers

my_data['Transaction'].nunique()
```

Now we want to extract new columns from the **data_time** to extract meaningful information from the data.

```
#Let's extract date

my_data['date'] = my_data['date_time'].dt.date

#Let's extract time

my_data['time'] = my_data['date_time'].dt.time

#Extract month and replacing it with String

my_data['month'] = my_data['date_time'].dt.month

my_data['month'] = my_data['month'].replace((1,2,3,4,5,6,7,8,9,10,11,12),

('Jan','Feb','Mar','Apr','May','Jun','Jul','Aug',

                                          'Sep','Oct','Nov','Dec'))
```

```
#Extract hour

my_data['hour'] = my_data['date_time'].dt.hour

# Replacing hours with text

# Replacing hours with text

hr_num = (1,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23)

hr_obj = ('1-2','7-8','8-9','9-10','10-11','11-12','12-13','13-14','14-15',

          '15-16','16-17','17-18','18-19','19-20','20-21','21-22','22-23','23-24')

my_data['hour'] = my_data['hour'].replace(hr_num, hr_obj)

# Extracting weekday and replacing it with String

my_data['weekday'] = my_data['date_time'].dt.weekday

my_data['weekday'] = my_data['weekday'].replace((0,1,2,3,4,5,6),

                                   ('Mon','Tues','Wed','Thur','Fri','Sat','Sun'))

#Now drop date_time column

my_data.drop('date_time', axis = 1, inplace = True)
```

After extracting the date, time, month, and hour columns, we dropped the **data_time** column.

Now to display, we simply use the head() function to see the changes in the dataset.

my_data.head()

 # cleaning the item column

my_data['Item'] = my_data['Item'].str.strip()

my_data['Item'] = my_data['Item'].str.lower()

my_data.head()

Data Visualization

To display the top 10 items purchased by customers, we used a **barplot()** of the **seaborn** library.

```
plt.figure(figsize=(10,5))

sns.barplot(x=my_data.Item.value_counts().head(10).index,
y=my_data.Item.value_counts().head(10).values,palette='RdYlGn')

plt.xlabel('No of Items', size = 17)

plt.xticks(rotation=45)

plt.ylabel('Total Items', size = 18)

plt.title('Top 10 Items purchased', color = 'blue', size = 23)
```

```
plt.show()
```

From the graph, coffee is the top item purchased by the customers, followed by bread.

Now, to display the number of orders received each month, the **groupby()** function is used along with **barplot()** to visually show the results.

```
mon_Tran =my_data.groupby('month')['Transaction'].count().reset_index()

mon_Tran.loc[:,"mon_order"] =[4,8,12,2,1,7,6,3,5,11,10,9]

mon_Tran.sort_values("mon_order",inplace=True)

plt.figure(figsize=(12,5))

sns.barplot(data = mon_Tran, x = "month", y = "Transaction")

plt.xlabel('Months', size = 14)

plt.ylabel('Monthly Orders', size = 14)

plt.title('No of orders received each month', color = 'blue', size = 18)

plt.show()
```

To show the number of orders received each day, we applied **groupby()** to the weekday column.

```
wk_Tran = my_data.groupby('weekday')['Transaction'].count().reset_index()

wk_Tran.loc[:,"wk_ord"] = [4,0,5,6,3,1,2]
```

```
wk_Tran.sort_values("wk_ord",inplace=True)

plt.figure(figsize=(11,4))

sns.barplot(data = wk_Tran, x = "weekday", y = "Transaction",palette='RdYlGn')

plt.xlabel('Week Day', size = 14)

plt.ylabel('Per day orders', size = 14)

plt.title('Orders received per day', color = 'blue', size = 18)

plt.show()
```

Implementation of the Apriori Algorithm

We import the **mlxtend** library to implement the association rules and count the number of items.

```
from mlxtend.frequent_patterns import association_rules, apriori

tran_str= my_data.groupby(['Transaction',
'Item'])['Item'].count().reset_index(name ='Count')

tran_str.head(8)
```

Now we'll make a mxn matrix where m=transaction and n=items, and each row represents whether the item was in the transaction or not.

```
Mar_baskt = tran_str.pivot_table(index='Transaction', columns='Item',
values='Count', aggfunc='sum').fillna(0)

Mar_baskt.head()
```

We want to make a function that returns 0 and 1. 0 means that the item wasn't present in the transaction, while 1 means the item exists.

```
def encode(val):

    if val<=0:

        return 0

    if val>=1:

        return 1

#Let's apply the function to the dataset

Basket=Mar_baskt.applymap(encode)

Basket.head()


#using apriori algorithm to set min_support 0.01 means 1%

freq_items = apriori(Basket, min_support = 0.01,use_colnames = True)

freq_items.head()
```

Using the association_rules() function to generate the most frequent items from the dataset.

```
App_rule= association_rules(freq_items, metric = "lift", min_threshold = 1)

App_rule.sort_values('confidence', ascending = False, inplace = True)

App_rule.head()
```

From the above implementation, the most frequent items are coffee and toast, both having a lift value of 1.47 and a confidence value of 0.70.

3. PRINCIPAL COMPONENT ANALYSIS

Principal component analysis (PCA) is one of the most widely used unsupervised learning techniques. It can be used for various tasks, including dimensionality reduction, information compression, exploratory data analysis and Data de-noising.

Let's use the PCA algorithm!

First we import the required libraries to implement this algorithm.

```
import numpy as np

import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns

%matplotlib inline

from sklearn.decomposition import PCA


from sklearn.datasets import load_digits
```

Loading the Dataset

To implement the PCA algorithm the load_digits dataset of Scikit-learn is used which can easily be loaded using the below command. The dataset contains images data which include 1797 entries and 64 columns.

```
#Load the dataset

my_data= load_digits()

#Creating features

X_value = my_data.data

#Creating target

#Let's check the shape of X_value


X_value.shape

#Each image is 8x8 pixels therefore 64px

my_data.images[10]


#Let's display the image

plt.gray()

plt.matshow(my_data.images[34])


plt.show()
```

Now let's project data from 64 columns to 16 to show how 16 dimensions classify the data.

```
X_val = my_data.data

y_val = my_data.target

my_pca = PCA(16)

X_projection = my_pca.fit_transform(X_val)

print(X_val.shape)

print(X_projection.shape)
```

Using colormap we visualize that with only ten dimensions we can classify the data points. Now we'll select the optimal number of dimensions (principal components) by which data can be reduced into lower dimensions.

```
plt.scatter(X_projection[:, 0], X_projection[:, 1], c=y_val,
edgecolor='white',

            cmap=plt.cm.get_cmap("gist_heat",12))

plt.colorbar();



pca=PCA().fit(X_val)

plt.plot(np.cumsum(my_pca.explained_variance_ratio_))

plt.xlabel('Principal components')

plt.ylabel('Explained variance')
```

Based on the below graph, only 12 components are required to explain more than 80% of the variance which is still better than computing all the 64 features. Thus, we've reduced the large number of dimensions into 12 dimensions to avoid the dimensionality curse.

```
pca=PCA().fit(X_val)

plt.plot(np.cumsum(pca.explained_variance_ratio_))

plt.xlabel('Principal components')

plt.ylabel('Explained variance')



#Let's visualize how it looks like

Unsupervised_pca = PCA(12)

X_pro = Unsupervised_pca.fit_transform(X_val)

print("New Data Shape is =>",X_pro.shape)
```

```
#Let's Create a scatter plot

plt.scatter(X_pro[:, 0], X_pro[:, 1], c=y_val, edgecolor='white',

            cmap=plt.cm.get_cmap("nipy_spectral",10))

plt.colorbar();
```

Reinforcement Algorithms

Model-free RL

Policy Gradient (PG)

Material to refer:

https://medium.com/free-code-camp/an-introduction-to-policy-gradients-with-cartpole-and-doom-495b5ef2207f

Asynchronous Advantage Actor-Critic (A3C)

Material to refer:

https://medium.com/emergent-future/simple-reinforcement-learning-with-tensorflow-part-8-asynchronous-actor-critic-agents-a3c-c88f72a5e9f2

Deep Q Neural Network (DQN)

Material to refer:

https://www.freecodecamp.org/news/an-introduction-to-deep-q-learning-lets-play-doom-54d02d8017d8

Distributional Reinforcement Learning with Quantile Regression (QR-DQN)

Material to refer:

https://github.com/senya-ashukha/quantile-regression-dqn-pytorch

Hindsight Experience Replay (HER)

Material to refer:

https://becominghuman.ai/learning-from-mistakes-with-hindsight-experience-replay-547fce2b3305

Hybrid

Materials to refer:

Deep Deterministic Policy Gradients (DDPG): paper and code,

Soft Actor -Critic (SAC): paper and code.

Twin Delayed Deep Deterministic Policy Gradients (TD3) paper and code

Model-based RL

Learn the Model

- World models: paper and code.
- Imagination-Augmented Agents (I2A): Paper and implementation.
- Model-Based Priors for Model-Free Reinforcement Learning (MBMF): paper and code.
- Model-Based Value Expansion (MBVE): paper