Assignment - 10.c (Apply DBSCAN on Amazon Fine Food Reviews)

September 12, 2018

1 OBJECTIVE :- Apply DBSCAN on Amazon Fine Food Reviews

```
In [2]: # Importing libraries
        import warnings
        warnings.filterwarnings("ignore")

        import sqlite3
        import pandas as pd
        import numpy as np
        import nltk
        import string
        import matplotlib.pyplot as plt
        %matplotlib inline
        import seaborn as sns
        from sklearn.feature_extraction.text import TfidfTransformer
        from sklearn.feature_extraction.text import TfidfVectorizer

        from sklearn.feature_extraction.text import CountVectorizer
        from nltk.stem.porter import PorterStemmer

        import re

        import string
        from nltk.corpus import stopwords
        from nltk.stem import PorterStemmer
        from nltk.stem.wordnet import WordNetLemmatizer

        from gensim.models import Word2Vec
        from gensim.models import KeyedVectors
        import pickle
```

2 Loading Data

```
In [3]: # using the SQLite Table to read data.
        con1 = sqlite3.connect('database.sqlite')
```

```
# Eliminating neutral reviews i.e. those reviews with Score = 3
filtered_data = pd.read_sql_query(" SELECT * FROM Reviews WHERE Score != 3 ", con1)

# Give reviews with Score>3 a positive rating, and reviews with a score<3 a negative r
def polarity(x):
    if x < 3:
        return 'negative'
    return 'positive'

# Applying polarity function on Score column of filtered_data
filtered_data['Score'] = filtered_data['Score'].map(polarity)

print(filtered_data.shape)
filtered_data.head()
```

```
(525814, 10)
```

```
Out[3]:    Id   ProductId          UserId                      ProfileName  \
        0   1  B001E4KFG0  A3SGXH7AUHU8GW                       delmartian
        1   2  B00813GRG4  A1D87F6ZCVE5NK                           dll pa
        2   3  B000LQOCH0   ABXLMWJIXXAIN  Natalia Corres "Natalia Corres"
        3   4  B000UA0QIQ  A395BORC6FGVXV                             Karl
        4   5  B006K2ZZ7K  A1UQRSCLF8GW1T    Michael D. Bigham "M. Wassir"

           HelpfulnessNumerator  HelpfulnessDenominator     Score        Time  \
        0                     1                       1  positive  1303862400
        1                     0                       0  negative  1346976000
        2                     1                       1  positive  1219017600
        3                     3                       3  negative  1307923200
        4                     0                       0  positive  1350777600

                         Summary                                              Text
        0  Good Quality Dog Food  I have bought several of the Vitality canned d...
        1      Not as Advertised  Product arrived labeled as Jumbo Salted Peanut...
        2  "Delight" says it all  This is a confection that has been around a fe...
        3         Cough Medicine  If you are looking for the secret ingredient i...
        4            Great taffy  Great taffy at a great price.  There was a wid...
```

3 Data Cleaning: Deduplication

```
In [4]: #Sorting data according to ProductId in ascending order
        sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=Fals

        #Deduplication of entries
        final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep=
        print(final.shape)
```

```
#Checking to see how much % of data still remains
((final.shape[0]*1.0)/(filtered_data.shape[0]*1.0)*100)
```

```
(364173, 10)
```

Out[4]: 69.25890143662969

In [5]:
```
# Removing rows where HelpfulnessNumerator is greater than HelpfulnessDenominator
final = final[final.HelpfulnessNumerator <= final.HelpfulnessDenominator]

print(final.shape)
final[30:50]
```

```
(364171, 10)
```

Out[5]:
```
            Id   ProductId          UserId  \
138683  150501  0006641040   AJ46FKXOVC7NR
138676  150493  0006641040   AMX0PJKV4PPNJ
138682  150500  0006641040  A1IJKK6Q1GTEAY
138681  150499  0006641040  A3E7R866M94L0C
476617  515426  141278509X   AB1A5EGHHVA9M
22621    24751  2734888454  A1C298ITT645B6
22620    24750  2734888454  A13ISQV0U9GZIC
284375  308077  2841233731  A3QD68O22M2XHQ
157850  171161  7310172001   AFXMWPNS1BLU4
157849  171160  7310172001   A74C7IARQEM1R
157833  171144  7310172001  A1V5MY8V9AWUQB
157832  171143  7310172001  A2SW060IW01VPX
157837  171148  7310172001  A3TFTWTG2CC1GA
157831  171142  7310172001  A2Z01AYFVQYG44
157830  171141  7310172001   AZ40270J4JBZN
157829  171140  7310172001   ADXXVGRCGQQUO
157828  171139  7310172001  A13MS1JQG2ADOJ
157827  171138  7310172001  A13LAE0YTXA11B
157848  171159  7310172001  A16GY2RCF410DT
157834  171145  7310172001  A1L8DNQYY69L2Z

                                  ProfileName  \
138683                     Nicholas A Mesiano
138676            E. R. Bird "Ramseelbird"
138682                             A Customer
138681                 L. Barker "simienwolf"
476617                                CHelmic
22621                       Hugh G. Pritchard
22620                               Sandikaye
284375                                LABRNTH
```

157850	H. Sandler
157849	stucker
157833	Cheryl Sapper "champagne girl"
157832	Sam
157837	J. Umphress
157831	Cindy Rellie "Rellie"
157830	Zhinka Chunmee "gamer from way back in the 70's"
157829	Richard Pearlstein
157828	C. Perrone
157827	Dita Vyslouzilova "dita"
157848	LB
157834	R. Flores

	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time \
138683	2	2	positive	940809600
138676	71	72	positive	1096416000
138682	2	2	positive	1009324800
138681	2	2	positive	1065830400
476617	1	1	positive	1332547200
22621	0	0	positive	1195948800
22620	1	1	negative	1192060800
284375	0	0	positive	1345852800
157850	0	0	positive	1229385600
157849	0	0	positive	1230076800
157833	0	0	positive	1244764800
157832	0	0	positive	1252022400
157837	0	0	positive	1240272000
157831	0	0	positive	1254960000
157830	0	0	positive	1264291200
157829	0	0	positive	1264377600
157828	0	0	positive	1265760000
157827	0	0	positive	1269216000
157848	0	0	positive	1231718400
157834	0	0	positive	1243728000

	Summary \
138683	This whole series is great way to spend time w...
138676	Read it once. Read it twice. Reading Chicken S...
138682	It Was a favorite!
138681	Can't explain why
476617	The best drink mix
22621	Dog Lover Delites
22620	made in china
284375	Great recipe book for my babycook
157850	Excellent treats
157849	Sophie's Treats
157833	THE BEST healthy dog treat!
157832	My Alaskan Malamute Loves Them!!

```
157837                                          Best treat ever!
157831          my 12 year old maltese has always loved these
157830                      Dogs, Cats, Ferrets all love this
157829                                                5 snouts!
157828                                       Best dog treat ever
157827                                Great for puppy training
157848                                                   Great!
157834                                          Terrific Treats

                                                           Text
138683  I can remember seeing the show when it aired o...
138676  These days, when a person says, "chicken soup"...
138682  This was a favorite book of mine when I was a ...
138681  This book has been a favorite of mine since I ...
476617  This product by Archer Farms is the best drink...
22621   Our dogs just love them.  I saw them in a pet ...
22620   My dogs loves this chicken but its a product f...
284375  This book is easy to read and the ingredients ...
157850  I have been feeding my greyhounds these treats...
157849  This is one product that my welsh terrier can ...
157833  This is the ONLY dog treat that my Lhasa Apso ...
157832  These liver treas are phenomenal. When i recei...
157837  This was the only treat my dog liked during ob...
157831  No waste , even if she is having a  day when s...
157830  I wanted a treat that was accepted and well li...
157829  My Westie loves these things!  She loves anyth...
157828  This is the only dog treat that my terrier wil...
157827  New puppy loves this, only treat he will pay a...
157848  My dog loves these treats!  We started using t...
157834  This is a great treat which all three of my do...
```

OBSERVATION :- Here books with ProductId - 0006641040 and 2841233731 are also there so we have to remove all these rows with these ProductIds from the data

In [6]:
```
final = final[final['ProductId'] != '2841233731']
final = final[final['ProductId'] != '0006641040']
final.shape
```

Out[6]:
```
(364136, 10)
```

4 Text Preprocessing: Stemming, stop-word removal and Lemmatization.

In [7]:
```
#set of stopwords in English
from nltk.corpus import stopwords
stop = set(stopwords.words('english'))
words_to_keep = set(('not'))
```

```
stop -= words_to_keep
#initialising the snowball stemmer
sno = nltk.stem.SnowballStemmer('english')

 #function to clean the word of any html-tags
def cleanhtml(sentence):
    cleanr = re.compile('<.*?>')
    cleantext = re.sub(cleanr, ' ', sentence)
    return cleantext

#function to clean the word of any punctuation or special characters
def cleanpunc(sentence):
    cleaned = re.sub(r'[?|!|\'|"|#]',r'',sentence)
    cleaned = re.sub(r'[.|,|)|(|\|/]',r' ',cleaned)
    return  cleaned
```

In [8]:
```
#Code for removing HTML tags , punctuations . Code for removing stopwords . Code for c
# also greater than 2 . Code for stemmimg and also to convert them to lowercase letter
i=0
str1=' '
final_string=[]
all_positive_words=[] # store words from +ve reviews here
all_negative_words=[] # store words from -ve reviews here.
s=''
for sent in final['Text'].values:
    filtered_sentence=[]
    #print(sent);
    sent=cleanhtml(sent) # remove HTMl tags
    for w in sent.split():
        for cleaned_words in cleanpunc(w).split():
            if((cleaned_words.isalpha()) & (len(cleaned_words)>2)):
                if(cleaned_words.lower() not in stop):
                    s=(sno.stem(cleaned_words.lower())).encode('utf8')
                    filtered_sentence.append(s)
                    if (final['Score'].values)[i] == 'positive':
                        all_positive_words.append(s) #list of all words used to descri
                    if(final['Score'].values)[i] == 'negative':
                        all_negative_words.append(s) #list of all words used to descri
                else:
                    continue
            else:
                continue

    str1 = b" ".join(filtered_sentence) #final string of cleaned words


    final_string.append(str1)
    i+=1
```

```
In [9]: #adding a column of CleanedText which displays the data after pre-processing of the re
        final['CleanedText']=final_string
        final['CleanedText']=final['CleanedText'].str.decode("utf-8")
        #below the processed review can be seen in the CleanedText Column
        print('Shape of final',final.shape)
        final.head()
```

```
Shape of final (364136, 11)
```

```
Out[9]:             Id   ProductId          UserId        ProfileName  \
        476617  515426  141278509X   AB1A5EGHHVA9M             CHelmic
        22621    24751  2734888454  A1C298ITT645B6  Hugh G. Pritchard
        22620    24750  2734888454  A13ISQV0U9GZIC           Sandikaye
        157850  171161  7310172001   AFXMWPNS1BLU4         H. Sandler
        157849  171160  7310172001   A74C7IARQEM1R            stucker

                HelpfulnessNumerator  HelpfulnessDenominator     Score        Time  \
        476617                     1                       1  positive  1332547200
        22621                      0                       0  positive  1195948800
        22620                      1                       1  negative  1192060800
        157850                     0                       0  positive  1229385600
        157849                     0                       0  positive  1230076800

                           Summary                                               Text  \
        476617  The best drink mix  This product by Archer Farms is the best drink...
        22621    Dog Lover Delites  Our dogs just love them.  I saw them in a pet ...
        22620        made in china  My dogs loves this chicken but its a product f...
        157850    Excellent treats  I have been feeding my greyhounds these treats...
        157849     Sophie's Treats  This is one product that my welsh terrier can ...

                                                      CleanedText
        476617  product archer farm best drink mix ever mix fl...
        22621   dog love saw pet store tag attach regard made ...
        22620   dog love chicken product china wont buy anymor...
        157850  feed greyhound treat year hound littl finicki ...
        157849  one product welsh terrier eat sophi food alerg...
```

5 NOTE :- My laptop got hang badly even with 40K datapoints . So I am performing this assignment only on 10K datapoints . My laptop has only 8GB RAM and unable to perform it with whole dataset . But I will complete all the tasks as was asked in the assignment

RANDOMLY SAMPLING 10K POINTS OUT OF WHOLE DATASET

```
In [10]: ##Sorting data according to Time in ascending order for Time Based Splitting
         time_sorted_data = final.sort_values('Time', axis=0, ascending=True, inplace=False, k
```

```
# We will collect different 10K rows without repetition from time_sorted_data datafra
my_final = time_sorted_data.take(np.random.permutation(len(final))[:10000])

x = my_final['CleanedText'].values
```

6 (1). Bag of Words (BoW)

```
In [11]: #BoW
         count_vect = CountVectorizer(min_df = 500)
         data_vec = count_vect.fit_transform(x)
         print("the type of count vectorizer :",type(data_vec))
         print("the shape of out text BOW vectorizer : ",data_vec.get_shape())
         print("the number of unique words :", data_vec.get_shape()[1])

         # Converting sparse matrix to dense matrix
         data_dense = data_vec.toarray()

         # Standardising the data
         import warnings
         warnings.filterwarnings('ignore')
         from sklearn.preprocessing import StandardScaler
         data = StandardScaler().fit_transform(data_dense)
```

```
the type of count vectorizer : <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer :  (10000, 116)
the number of unique words : 116
```

7 Function To Compute Distance of nth-nearesr neighbour

```
In [12]: # function to determinethe distance of nth-nearest neighbour to all points in a multi
         def n_neighbour(vectors , n):
             distance = []
             for point in vectors:
                 temp = np.sort(np.sum((vectors-point)**2,axis=1),axis=None)
                 distance.append(temp[n])
             return np.sqrt(np.array(distance))
```

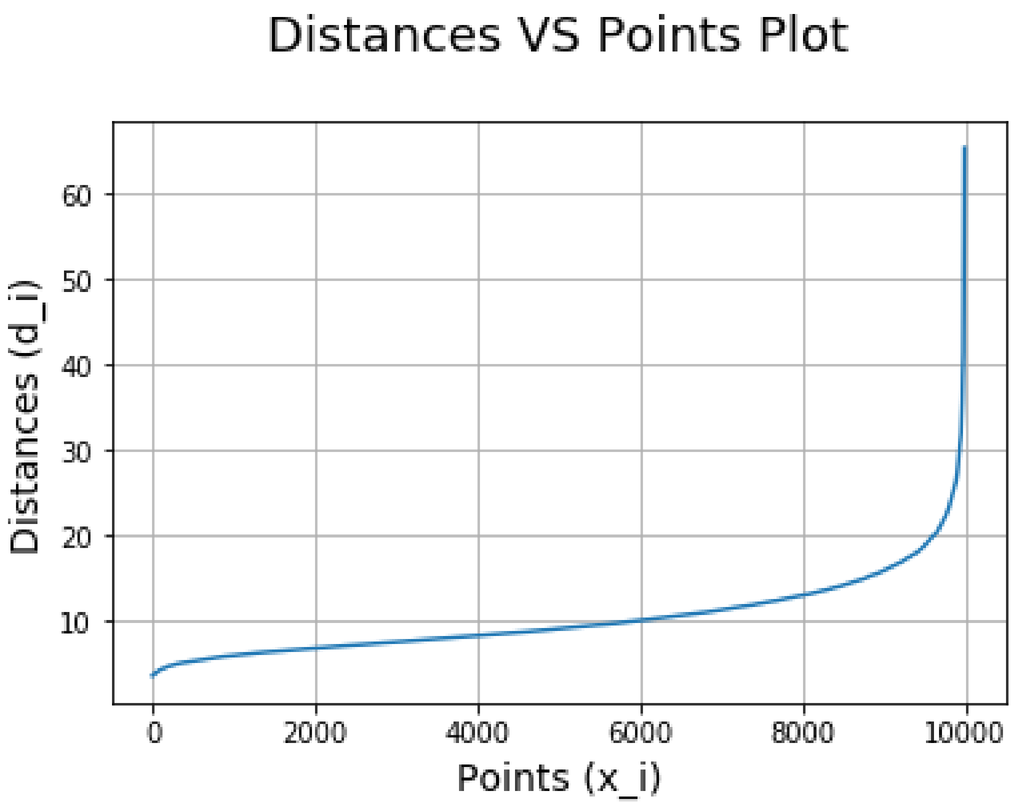
8 Function to call DBSCAN

```
In [16]: # Function definition for implementing DBSCAN
         def dbscan(epsilon, samples, Data):
             from sklearn.cluster import DBSCAN
             db = DBSCAN(eps=epsilon, min_samples=samples, n_jobs=-1).fit(Data)
```

```
    # Number of clusters in labels, ignoring noise(-1) if present.
    n_clusters = len(set(db.labels_))
    print("Number of clusters for MinPts = %d and Epsilon = %f is : %d "%(samples,eps
    print("Labels(-1 is for Noise) : ",set(db.labels_))
    print()
    return db
```

ELBOW METHOD TO FIND RIGHT EPSILON :

```
In [17]: min_points = 2*data.shape[1]

         # Computing distances of nth-nearest neighbours
         distances = n_neighbour(data,min_points)
         sorted_distance = np.sort(distances)
         points = [i for i in range(data.shape[0])]

         # Draw distances(d_i) VS points(x_i) plot
         plt.plot(points, sorted_distance)
         plt.xlabel('Points (x_i)',size=14)
         plt.ylabel('Distances (d_i)',size=14)
         plt.title('Distances VS Points Plot\n',size=18)
         plt.grid()
         plt.show()
```



OBSERVATION :- From above we can see that the right value of Epsilon is 16 because after that there is sharp rise in the value of distances (d_i's)

9 DBSCAN Implementation

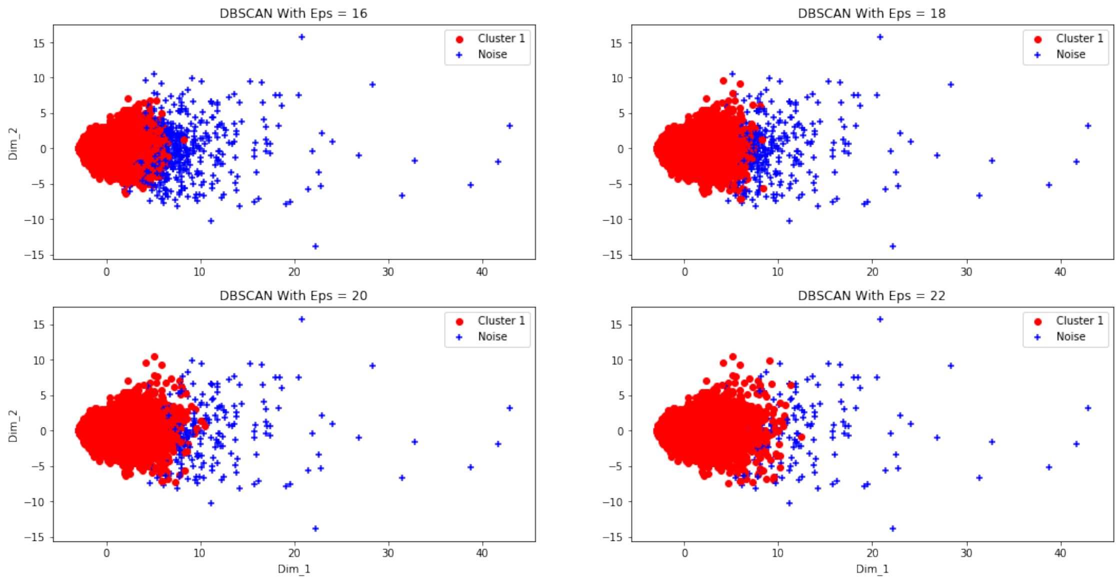
In [18]:
```
optimal_eps = 16
# Clustering with right epsilon
db1 = dbscan(optimal_eps, min_points, data)


# Clustering with  epsilon = 18
db2 = dbscan(18, min_points, data)


# Clustering with epsilon = 20
db3 = dbscan(20, min_points, data)


# Clustering with epsilon = 22
db4 = dbscan(22, min_points, data)
```

```
Number of clusters for MinPts = 232 and Epsilon = 16.000000 is : 2
Labels(-1 is for Noise) :  {0, -1}

Number of clusters for MinPts = 232 and Epsilon = 18.000000 is : 2
Labels(-1 is for Noise) :  {0, -1}

Number of clusters for MinPts = 232 and Epsilon = 20.000000 is : 2
Labels(-1 is for Noise) :  {0, -1}

Number of clusters for MinPts = 232 and Epsilon = 22.000000 is : 2
Labels(-1 is for Noise) :  {0, -1}
```

10 Visualizing The Clusters :

In [28]:
```
from sklearn.decomposition import PCA
pca_2d = PCA(n_components=2).fit_transform(data)

# Scatter plot for DBSCAN with Eps = 16
plt.figure(figsize=(18,9))
plt.subplot(221)
for i in range(0, pca_2d.shape[0]):
    if db1.labels_[i] == 0:
        c1 = plt.scatter(pca_2d[i,0],pca_2d[i,1],c='r',marker='o')
    elif db1.labels_[i] == -1:
```

```
        c2 = plt.scatter(pca_2d[i,0],pca_2d[i,1],c='b',marker='+')
plt.legend([c1, c2], ['Cluster 1', 'Noise'])
plt.title('DBSCAN With Eps = 16')
plt.ylabel('Dim_2')

# Scatter plot for DBSCAN with Eps = 18
plt.subplot(222)
for i in range(0, pca_2d.shape[0]):
    if db2.labels_[i] == 0:
        c1 = plt.scatter(pca_2d[i,0],pca_2d[i,1],c='r',marker='o')
    elif db2.labels_[i] == -1:
        c2 = plt.scatter(pca_2d[i,0],pca_2d[i,1],c='b',marker='+')
plt.legend([c1, c2], ['Cluster 1', 'Noise'])
plt.title('DBSCAN With Eps = 18')

# Scatter plot for DBSCAN with Eps = 20
plt.subplot(223)
for i in range(0, pca_2d.shape[0]):
    if db3.labels_[i] == 0:
        c1 = plt.scatter(pca_2d[i,0],pca_2d[i,1],c='r',marker='o')
    elif db3.labels_[i] == -1:
        c2 = plt.scatter(pca_2d[i,0],pca_2d[i,1],c='b',marker='+')
plt.legend([c1, c2], ['Cluster 1', 'Noise'])
plt.title('DBSCAN With Eps = 20')
plt.ylabel('Dim_2')
plt.xlabel('Dim_1')

# Scatter plot for DBSCAN with Eps = 22
plt.subplot(224)
for i in range(0, pca_2d.shape[0]):
    if db4.labels_[i] == 0:
        c1 = plt.scatter(pca_2d[i,0],pca_2d[i,1],c='r',marker='o')
    elif db4.labels_[i] == -1:
        c2 = plt.scatter(pca_2d[i,0],pca_2d[i,1],c='b',marker='+')
plt.legend([c1, c2], ['Cluster 1', 'Noise'])
plt.title('DBSCAN With Eps = 22')
plt.xlabel('Dim_1')

plt.show()
```



11 (2) TFIDF

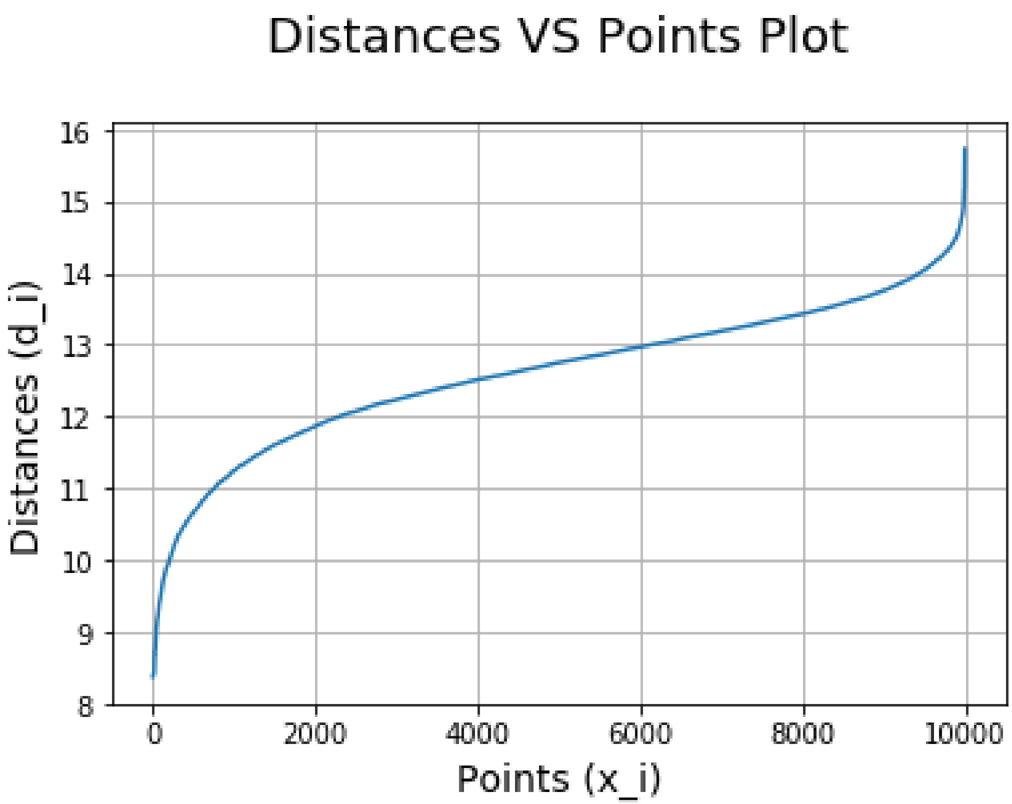
In [29]:
```
tf_idf_vect = TfidfVectorizer(min_df=500)
data_vec = tf_idf_vect.fit_transform(x)
print("the type of count vectorizer :",type(data_vec))
print("the shape of out text BOW vectorizer : ",data_vec.get_shape())
print("the number of unique words :", data_vec.get_shape()[1])

# Converting sparse matrix to dense matrix
data_dense = data_vec.toarray()

# Standardising the data
data = StandardScaler().fit_transform(data_dense)
```

```
the type of count vectorizer : <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer :  (10000, 116)
the number of unique words : 116
```

ELBOW METHOD TO FIND RIGHT EPSILON :

In [30]:
```
min_points = 2*data.shape[1]

# Computing distances of nth-nearest neighbours
distances = n_neighbour(data,min_points)
sorted_distance = np.sort(distances)
points = [i for i in range(data.shape[0])]
```

```
# Draw distances(d_i) VS points(x_i) plot
plt.plot(points, sorted_distance)
plt.xlabel('Points (x_i)',size=14)
plt.ylabel('Distances (d_i)',size=14)
plt.title('Distances VS Points Plot\n',size=18)
plt.grid()
plt.show()
```



OBSERVATION :- From above we can see that the right value of Epsilon is 9 because after that there is sharp rise in the value of distances (d_i's)

12 DBSCAN Implementation

```
In [35]: optimal_eps = 9
         # Clustering with right epsilon
         db1 = dbscan(optimal_eps, min_points, data)


         # Clustering with  epsilon = 10
         db2 = dbscan(10, min_points, data)
```

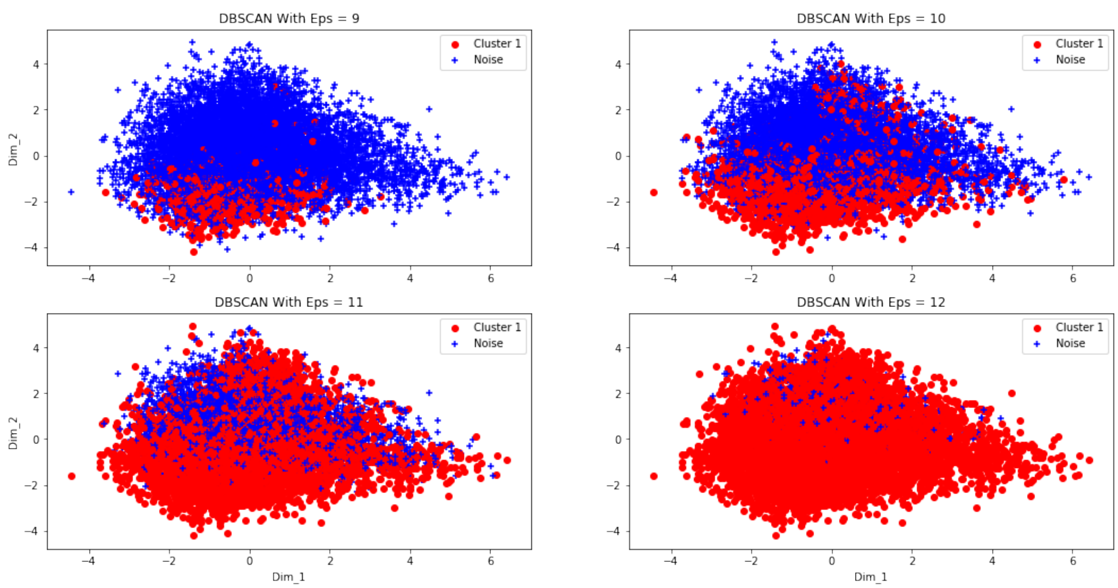
```
# Clustering with epsilon = 11
db3 = dbscan(11, min_points, data)


# Clustering with epsilon = 12
db4 = dbscan(12, min_points, data)
```

```
Number of clusters for MinPts = 232 and Epsilon = 9.000000 is : 2
Labels(-1 is for Noise) :  {0, -1}

Number of clusters for MinPts = 232 and Epsilon = 10.000000 is : 2
Labels(-1 is for Noise) :  {0, -1}

Number of clusters for MinPts = 232 and Epsilon = 11.000000 is : 2
Labels(-1 is for Noise) :  {0, -1}

Number of clusters for MinPts = 232 and Epsilon = 12.000000 is : 2
Labels(-1 is for Noise) :  {0, -1}
```

13 Visualizing The Clusters :

In [36]:
```
pca_2d = PCA(n_components=2).fit_transform(data)

# Scatter plot for DBSCAN with Eps = 9
plt.figure(figsize=(18,9))
plt.subplot(221)
for i in range(0, pca_2d.shape[0]):
    if db1.labels_[i] == 0:
        c1 = plt.scatter(pca_2d[i,0],pca_2d[i,1],c='r',marker='o')
    elif db1.labels_[i] == -1:
        c2 = plt.scatter(pca_2d[i,0],pca_2d[i,1],c='b',marker='+')
plt.legend([c1, c2], ['Cluster 1', 'Noise'])
plt.title('DBSCAN With Eps = 9')
plt.ylabel('Dim_2')

# Scatter plot for DBSCAN with Eps = 10
plt.subplot(222)
for i in range(0, pca_2d.shape[0]):
    if db2.labels_[i] == 0:
        c1 = plt.scatter(pca_2d[i,0],pca_2d[i,1],c='r',marker='o')
    elif db2.labels_[i] == -1:
        c2 = plt.scatter(pca_2d[i,0],pca_2d[i,1],c='b',marker='+')
plt.legend([c1, c2], ['Cluster 1', 'Noise'])
plt.title('DBSCAN With Eps = 10')
```

```python
# Scatter plot for DBSCAN with Eps = 11
plt.subplot(223)
for i in range(0, pca_2d.shape[0]):
    if db3.labels_[i] == 0:
        c1 = plt.scatter(pca_2d[i,0],pca_2d[i,1],c='r',marker='o')
    elif db3.labels_[i] == -1:
        c2 = plt.scatter(pca_2d[i,0],pca_2d[i,1],c='b',marker='+')
plt.legend([c1, c2], ['Cluster 1', 'Noise'])
plt.title('DBSCAN With Eps = 11')
plt.ylabel('Dim_2')
plt.xlabel('Dim_1')

# Scatter plot for DBSCAN with Eps = 12
plt.subplot(224)
for i in range(0, pca_2d.shape[0]):
    if db4.labels_[i] == 0:
        c1 = plt.scatter(pca_2d[i,0],pca_2d[i,1],c='r',marker='o')
    elif db4.labels_[i] == -1:
        c2 = plt.scatter(pca_2d[i,0],pca_2d[i,1],c='b',marker='+')
plt.legend([c1,c2], ['Cluster 1','Noise'])
plt.title('DBSCAN With Eps = 12')
plt.xlabel('Dim_1')

plt.show()
```



14 Word2Vec

In [37]:
```
# List of sentence in X_train text
sent_x = []
for sent in x :
    sent_x.append(sent.split())


# Train your own Word2Vec model using your own train text corpus
# min_count = 5 considers only words that occured atleast 5 times
w2v_model=Word2Vec(sent_x,min_count=5,size=100, workers=4)

w2v_words = list(w2v_model.wv.vocab)
print("number of words that occured minimum 5 times ",len(w2v_words))
```

```
number of words that occured minimum 5 times  4563
```

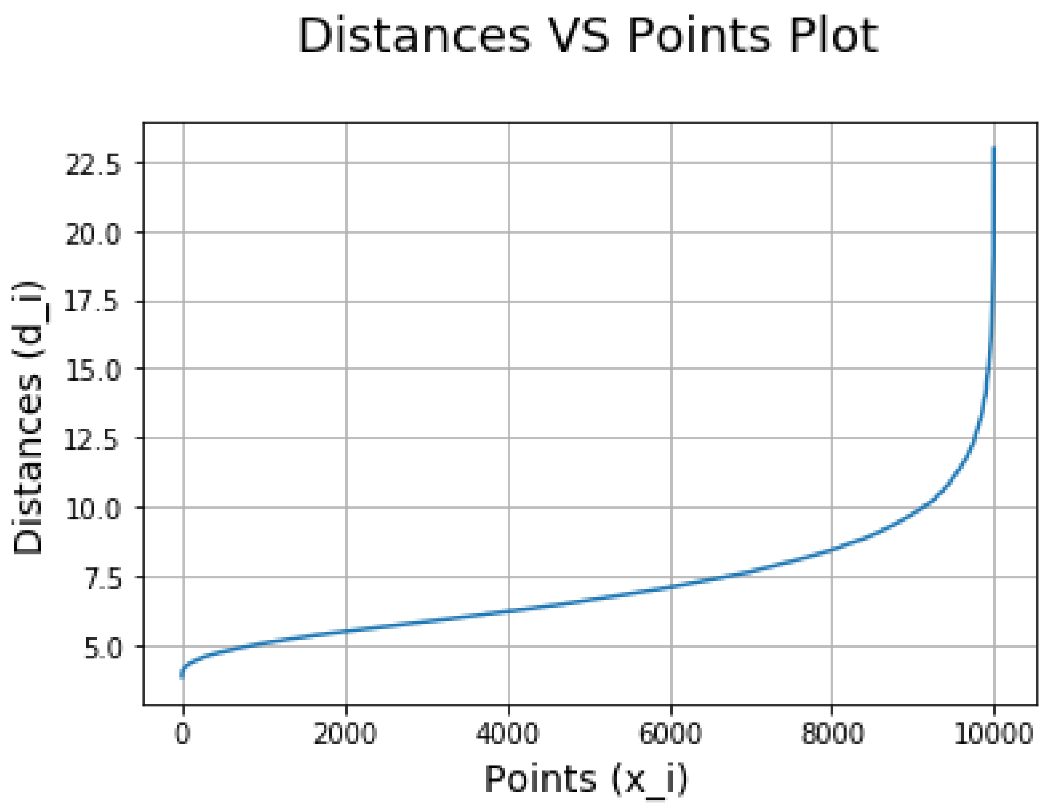
15 (3). Avg Word2Vec

In [38]:
```
# compute average word2vec for each review for sent_x .
train_vectors = [];
for sent in sent_x:
    sent_vec = np.zeros(100)
    cnt_words =0;
    for word in sent: #
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    train_vectors.append(sent_vec)

#Standardising the data
data = StandardScaler().fit_transform(train_vectors)
```

ELBOW METHOD TO FIND RIGHT EPSILON :

In [39]:
```
min_points = 2*data.shape[1]

# Computing distances of nth-nearest neighbours
distances = n_neighbour(data,min_points)
sorted_distance = np.sort(distances)
points = [i for i in range(data.shape[0])]

# Draw distances(d_i) VS points(x_i) plot
plt.plot(points, sorted_distance)
```

```
plt.xlabel('Points (x_i)',size=14)
plt.ylabel('Distances (d_i)',size=14)
plt.title('Distances VS Points Plot\n',size=18)
plt.grid()
plt.show()
```



OBSERVATION :- From above we can see that the right value of Epsilon is 10 because after that there is sharp rise in the value of distances (d_i's)

16 DBSCAN Implementation

In [40]:
```
optimal_eps = 10
# Clustering with right epsilon
db1 = dbscan(optimal_eps, min_points, data)


# Clustering with  epsilon = 11
db2 = dbscan(11, min_points, data)


# Clustering with epsilon = 12
db3 = dbscan(12, min_points, data)
```

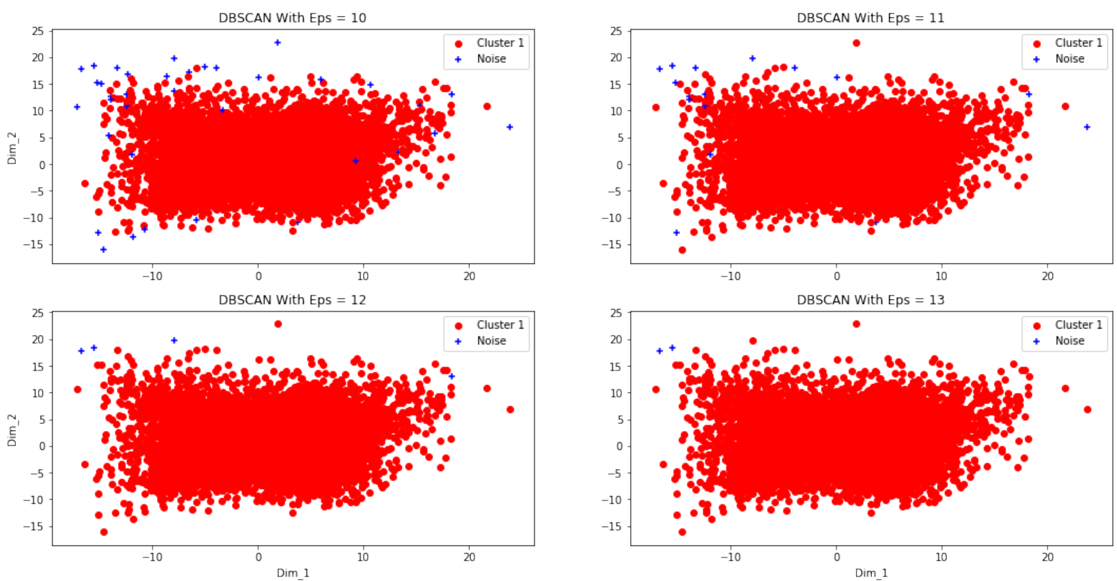
```
# Clustering with epsilon = 13
db4 = dbscan(13, min_points, data)
```

```
Number of clusters for MinPts = 200 and Epsilon = 10.000000 is : 2
Labels(-1 is for Noise) :  {0, -1}

Number of clusters for MinPts = 200 and Epsilon = 11.000000 is : 2
Labels(-1 is for Noise) :  {0, -1}

Number of clusters for MinPts = 200 and Epsilon = 12.000000 is : 2
Labels(-1 is for Noise) :  {0, -1}

Number of clusters for MinPts = 200 and Epsilon = 13.000000 is : 2
Labels(-1 is for Noise) :  {0, -1}
```

17 Visualizing The Clusters :

In [41]:
```
pca_2d = PCA(n_components=2).fit_transform(data)

# Scatter plot for DBSCAN with Eps = 10
plt.figure(figsize=(18,9))
plt.subplot(221)
for i in range(0, pca_2d.shape[0]):
    if db1.labels_[i] == 0:
        c1 = plt.scatter(pca_2d[i,0],pca_2d[i,1],c='r',marker='o')
    elif db1.labels_[i] == -1:
        c2 = plt.scatter(pca_2d[i,0],pca_2d[i,1],c='b',marker='+')
plt.legend([c1, c2], ['Cluster 1', 'Noise'])
plt.title('DBSCAN With Eps = 10')
plt.ylabel('Dim_2')

# Scatter plot for DBSCAN with Eps = 11
plt.subplot(222)
for i in range(0, pca_2d.shape[0]):
    if db2.labels_[i] == 0:
        c1 = plt.scatter(pca_2d[i,0],pca_2d[i,1],c='r',marker='o')
    elif db2.labels_[i] == -1:
        c2 = plt.scatter(pca_2d[i,0],pca_2d[i,1],c='b',marker='+')
plt.legend([c1, c2], ['Cluster 1', 'Noise'])
plt.title('DBSCAN With Eps = 11')

# Scatter plot for DBSCAN with Eps = 12
plt.subplot(223)
```

```
for i in range(0, pca_2d.shape[0]):
    if db3.labels_[i] == 0:
        c1 = plt.scatter(pca_2d[i,0],pca_2d[i,1],c='r',marker='o')
    elif db3.labels_[i] == -1:
        c2 = plt.scatter(pca_2d[i,0],pca_2d[i,1],c='b',marker='+')
plt.legend([c1, c2], ['Cluster 1', 'Noise'])
plt.title('DBSCAN With Eps = 12')
plt.ylabel('Dim_2')
plt.xlabel('Dim_1')

# Scatter plot for DBSCAN with Eps = 13
plt.subplot(224)
for i in range(0, pca_2d.shape[0]):
    if db4.labels_[i] == 0:
        c1 = plt.scatter(pca_2d[i,0],pca_2d[i,1],c='r',marker='o')
    elif db4.labels_[i] == -1:
        c2 = plt.scatter(pca_2d[i,0],pca_2d[i,1],c='b',marker='+')
plt.legend([c1,c2], ['Cluster 1','Noise'])
plt.title('DBSCAN With Eps = 13')
plt.xlabel('Dim_1')

plt.show()
```



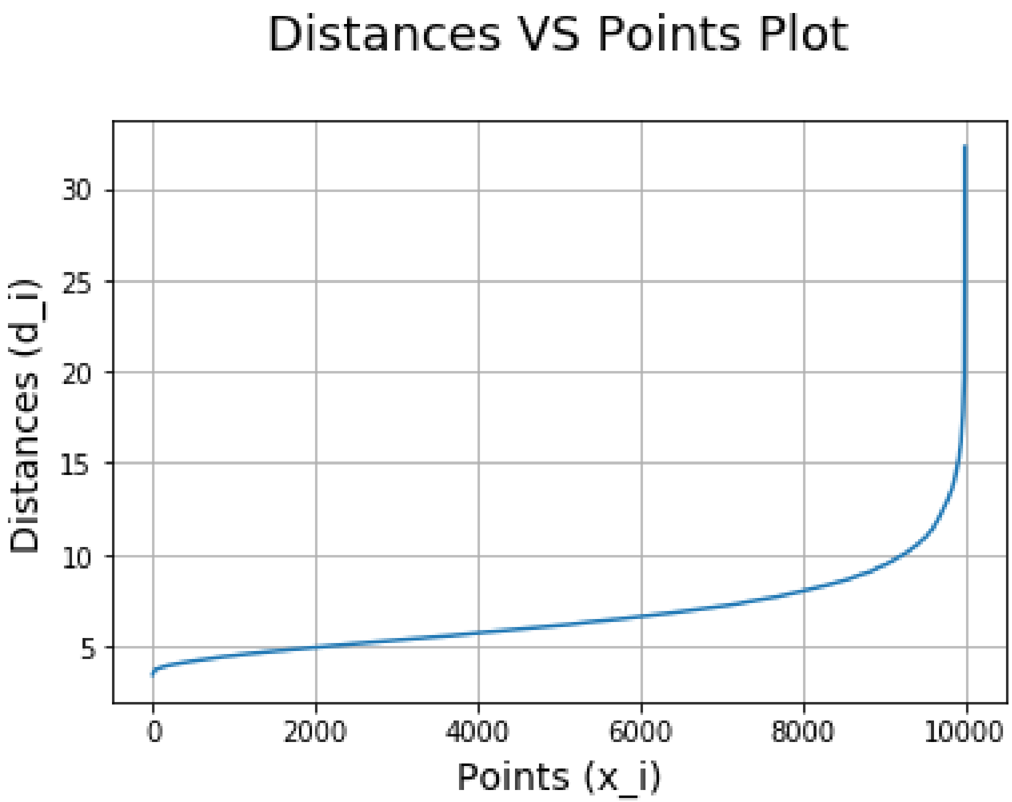
18 (4). TFIDF-Word2Vec

```
In [42]: # TF-IDF weighted Word2Vec
         tf_idf_vect = TfidfVectorizer()
```

```
# final_tf_idf1 is the sparse matrix with row= sentence, col=word and cell_val = tfid
final_tf_idf1 = tf_idf_vect.fit_transform(x)

# tfidf words/col-names
tfidf_feat = tf_idf_vect.get_feature_names()

# compute TFIDF Weighted Word2Vec for each review for sent_x .
tfidf_vectors = [];
row=0;
for sent in sent_x:
    sent_vec = np.zeros(100)
    weight_sum =0;
    for word in sent:
        if word in w2v_words:
            vec = w2v_model.wv[word]
            # obtain the tf_idfidf of a word in a sentence/review
            tf_idf = final_tf_idf1[row, tfidf_feat.index(word)]
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_vectors.append(sent_vec)
    row += 1

#Standardising the data
data = StandardScaler().fit_transform(tfidf_vectors)
```

ELBOW METHOD TO FIND RIGHT EPSILON :

In [43]:
```
min_points = 2*data.shape[1]

# Computing distances of nth-nearest neighbours
distances = n_neighbour(data,min_points)
sorted_distance = np.sort(distances)
points = [i for i in range(data.shape[0])]

# Draw distances(d_i) VS points(x_i) plot
plt.plot(points, sorted_distance)
plt.xlabel('Points (x_i)',size=14)
plt.ylabel('Distances (d_i)',size=14)
plt.title('Distances VS Points Plot\n',size=18)
plt.grid()
plt.show()
```



OBSERVATION :- From above we can see that the right value of Epsilon is 10 because after that there is sharp rise in the value of distances (d_i's)

19 DBSCAN Implementation

```
In [44]: optimal_eps = 10
         # Clustering with right epsilon
         db1 = dbscan(optimal_eps, min_points, data)


         # Clustering with  epsilon = 11
         db2 = dbscan(11, min_points, data)


         # Clustering with epsilon = 12
         db3 = dbscan(12, min_points, data)


         # Clustering with epsilon = 13
         db4 = dbscan(13, min_points, data)
```

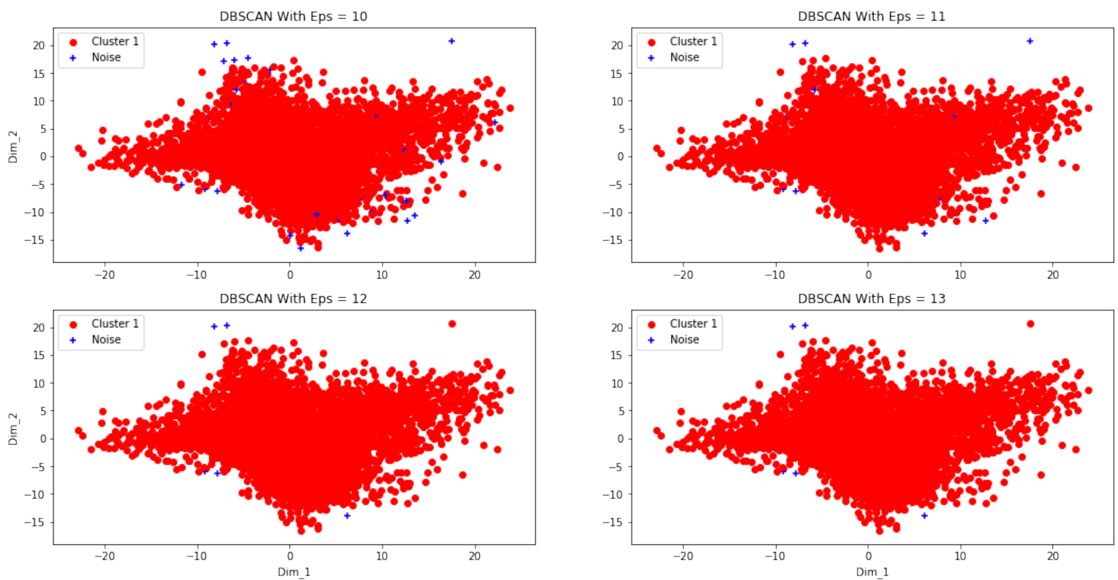
```
Number of clusters for MinPts = 200 and Epsilon = 10.000000 is : 2
```

```
Labels(-1 is for Noise) :  {0, -1}

Number of clusters for MinPts = 200 and Epsilon = 11.000000 is : 2
Labels(-1 is for Noise) :  {0, -1}

Number of clusters for MinPts = 200 and Epsilon = 12.000000 is : 2
Labels(-1 is for Noise) :  {0, -1}

Number of clusters for MinPts = 200 and Epsilon = 13.000000 is : 2
Labels(-1 is for Noise) :  {0, -1}
```

20 Visualizing The Clusters :

In [45]:
```
pca_2d = PCA(n_components=2).fit_transform(data)

# Scatter plot for DBSCAN with Eps = 10
plt.figure(figsize=(18,9))
plt.subplot(221)
for i in range(0, pca_2d.shape[0]):
    if db1.labels_[i] == 0:
        c1 = plt.scatter(pca_2d[i,0],pca_2d[i,1],c='r',marker='o')
    elif db1.labels_[i] == -1:
        c2 = plt.scatter(pca_2d[i,0],pca_2d[i,1],c='b',marker='+')
plt.legend([c1, c2], ['Cluster 1', 'Noise'])
plt.title('DBSCAN With Eps = 10')
plt.ylabel('Dim_2')

# Scatter plot for DBSCAN with Eps = 11
plt.subplot(222)
for i in range(0, pca_2d.shape[0]):
    if db2.labels_[i] == 0:
        c1 = plt.scatter(pca_2d[i,0],pca_2d[i,1],c='r',marker='o')
    elif db2.labels_[i] == -1:
        c2 = plt.scatter(pca_2d[i,0],pca_2d[i,1],c='b',marker='+')
plt.legend([c1, c2], ['Cluster 1', 'Noise'])
plt.title('DBSCAN With Eps = 11')

# Scatter plot for DBSCAN with Eps = 12
plt.subplot(223)
for i in range(0, pca_2d.shape[0]):
    if db3.labels_[i] == 0:
        c1 = plt.scatter(pca_2d[i,0],pca_2d[i,1],c='r',marker='o')
    elif db3.labels_[i] == -1:
        c2 = plt.scatter(pca_2d[i,0],pca_2d[i,1],c='b',marker='+')
plt.legend([c1, c2], ['Cluster 1', 'Noise'])
```

```
plt.title('DBSCAN With Eps = 12')
plt.ylabel('Dim_2')
plt.xlabel('Dim_1')

# Scatter plot for DBSCAN with Eps = 13
plt.subplot(224)
for i in range(0, pca_2d.shape[0]):
    if db4.labels_[i] == 0:
        c1 = plt.scatter(pca_2d[i,0],pca_2d[i,1],c='r',marker='o')
    elif db4.labels_[i] == -1:
        c2 = plt.scatter(pca_2d[i,0],pca_2d[i,1],c='b',marker='+')
plt.legend([c1,c2], ['Cluster 1','Noise'])
plt.title('DBSCAN With Eps = 13')
plt.xlabel('Dim_1')

plt.show()
```



21 CONCLUSION :-

22 Procedure Followed :

STEP 1 :- Text Preprocessing

STEP 2 :- Taking all text data and ignoring class variable .

STEP 3:- Training the vectorizer on text_data and later applying same vectorizer on text_data to transform it into vectors

STEP 4:- Standardizing the vectorized data

STEP 5:- Applying the Elbow Method in order to find the right value of Epsilon

STEP 6:- Draw distances VS points plot

STEP 7:- Implementing DBSCAN with various values of Epsilon including the optimal value of Epsilon

STEP 8:- Draw Scatter plots for DBSCAN with various Epsilon values

Repeat from STEP 3 to STEP 8 for each of these four vectorizers : Bag Of Words(BoW), TFIDF, Avg Word2Vec and TFIDF Word2Vec