Objective:

```
->Dataset from kaggle contains images, each image is of size 28*28 p
ixels

->Each image is of 784 dimesnions

->Reducing the dimensionality by using dimensionality reduction tech
niques like PCA,t-SNE
```

In [3]:

```
#MNIST dataset from kaggle

#Importing required libraries

import numpy as np
import pandas as pd
import matplotlib.pyplot as mp
```

loading the data

In [4]:

```
data = pd.read_csv("train.csv")
```

Analyzing the data features

In [5]:

```
print(data.shape)
print(data.columns)
print(data.ndim)
print(data.head(5))
```

```
(42000, 785)
Index(['label', 'pixel0', 'pixel1', 'pixel2', 'pixel3', 'pixel4', 'pixel5',
       'pixel6', 'pixel7', 'pixel8',
       ...
       'pixel774', 'pixel775', 'pixel776', 'pixel777', 'pixel778', 'pixel77
9',
       'pixel780', 'pixel781', 'pixel782', 'pixel783'],
      dtype='object', length=785)
2
   label  pixel0  pixel1  pixel2  pixel3  pixel4  pixel5  pixel6  pixel7  \
0      1       0       0       0       0       0       0       0       0
1      0       0       0       0       0       0       0       0       0
2      1       0       0       0       0       0       0       0       0
3      4       0       0       0       0       0       0       0       0
4      0       0       0       0       0       0       0       0       0

   pixel8    ...     pixel774  pixel775  pixel776  pixel777  pixel778  \
0       0    ...            0         0         0         0         0
1       0                   0         0         0         0         0
```

```
1        0    ...        0        0        0        0        0
2        0    ...        0        0        0        0        0
3        0    ...        0        0        0        0        0
4        0    ...        0        0        0        0        0

   pixel779  pixel780  pixel781  pixel782  pixel783
0         0         0         0         0         0
1         0         0         0         0         0
2         0         0         0         0         0
3         0         0         0         0         0
4         0         0         0         0         0

[5 rows x 785 columns]
```

Observations:

```
->The dataset contains of 42000 images each of 784 dimesnions

->Label is the class type to which the image belongs to

->So we have to seperate the label data and continue with the proces
s
```

Taking the label from the data frame and removing the label feature from the dataframe

In [8]:

```
l = data['label']
data = data.drop('label',axis=1)
print(l.shape)
print(data.shape)
```

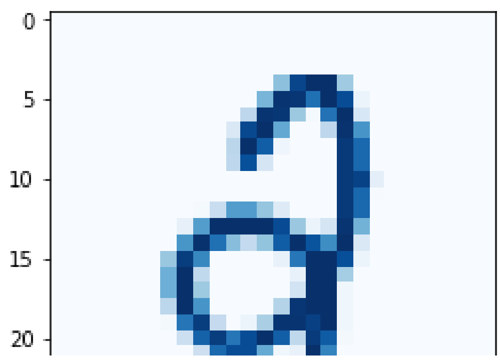
```
(42000,)
(42000, 784)
```

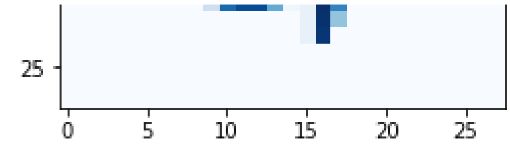
->To plot the image we have to convert the datapoint which is an array from 1-d to 2-d

->At the same time we can check with the label for accuracy

In [10]:

```
index = 10000
grid_data = data.iloc[index].as_matrix().reshape(28,28)
mp.imshow(grid_data,interpolation='none',cmap='Blues')
mp.show()
print(l[index])
```






```
2
```

2D Visualization using PCA without Scikit-Learn

->Keeping in consideration about the RAM and time efficiency, taking the subset of data

In [11]:

```
label = l.head(20000)
dataframe = data.head(20000)
print(label.shape)
print(dataframe.shape)
print(l.shape)
print(data.shape)
```

```
(20000,)
(20000, 784)
(42000,)
(42000, 784)
```

Note:

```
->Using sklearn is a simple process, but without sklearn we need to
process bunch of steps:

    ->Data-preprocessing-Standardizing of data is mandatory(mean=0 a
nd variance=1)

    ->Computing the co-variance matrix

    ->Generating the top two eigen vectors to plot on the 2-dimensio
n plane,this can be done
      using eigh from scipy.linalg

    ->This will return the eigen values in the ascending order, Sinc
e we are doing on 2-d we
      can take top two values
```

In [12]:

```
from sklearn.preprocessing import StandardScaler
standarad_data = StandardScaler().fit_transform(dataframe)
print(standarad_data.shape)
```

```
(20000, 784)
```

In [13]:

```
standarad_data_1 = standarad_data
co_var_matrix = np.matmul(standarad_data_1.T,standarad_data_1)
print(co_var_matrix.shape)
```

```
print(co_var_matrix.shape)
```

```
(784, 784)
```

In [17]:

```
from scipy.linalg import eigh
value,vector = eigh(co_var_matrix,eigvals=(782,783))
vector = vector.T
new_cord = np.matmul(vector,standarad_data_1.T)
print(vector.shape)
print(standarad_data_1.T.shape)
```

```
(2, 784)
(784, 20000)
```

In [15]:

```
new_cord.shape
```

Out[15]:

```
(2, 20000)
```

Appending the label data to plot

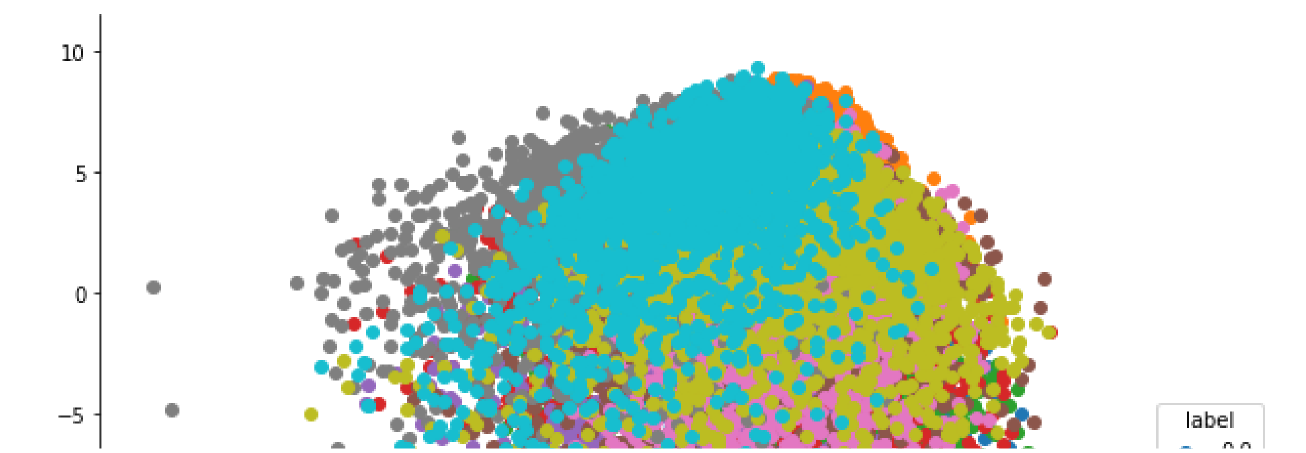
In [18]:

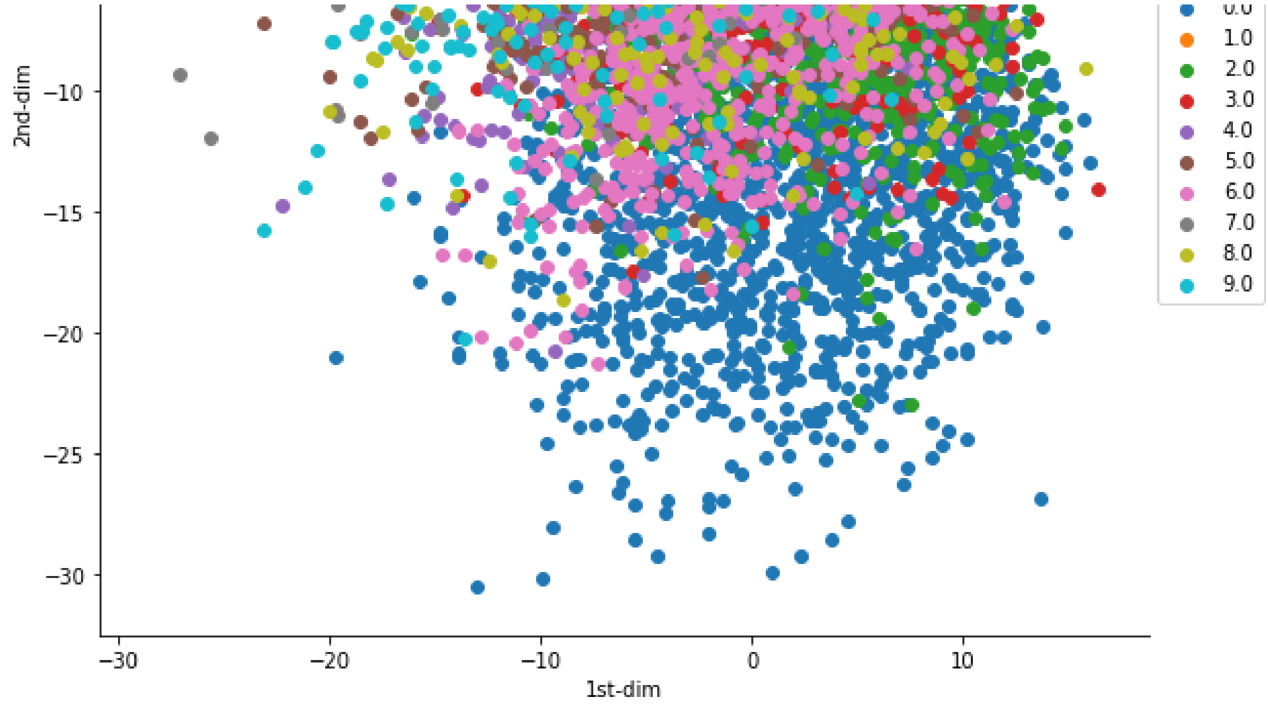
```
new_cord = np.vstack((new_cord,label)).T
```

In [21]:

```
df = pd.DataFrame(data=new_cord,columns=('1st-dim','2nd-dim','label'))
print(df.shape)
print(df.head(6))
import seaborn as s
s.FacetGrid(df,hue='label',size=8).map(mp.scatter,'1st-dim','2nd-dim').add_
legend()
mp.show()
```

```
(20000, 3)
     1st-dim    2nd-dim  label
0   5.430697   5.060862    1.0
1  -6.242999 -19.293148    0.0
2   1.828611   7.684498    1.0
3  -5.585495   0.440132    4.0
4  -6.333250 -26.597773    0.0
5   0.659000  -1.280238    0.0
```





PCA Using Scikit-Learn

-> It becomes very easy when using Scikit-Learn library

->We just need to inform the number of dimesnions and then we need to add the labels to the data

->Should create a dataframe to plot as just as we done on above

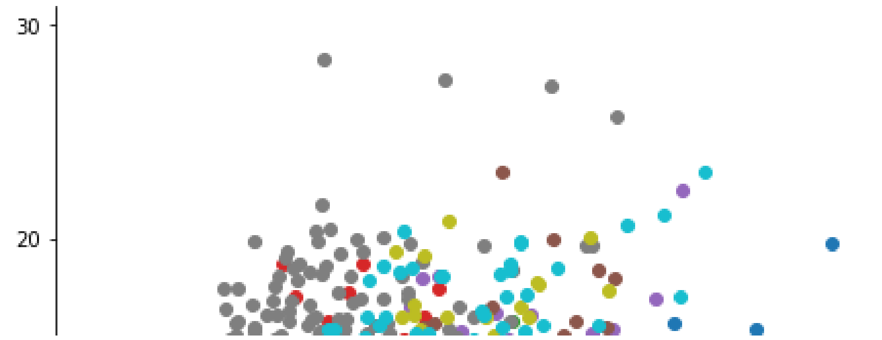
In [23]:

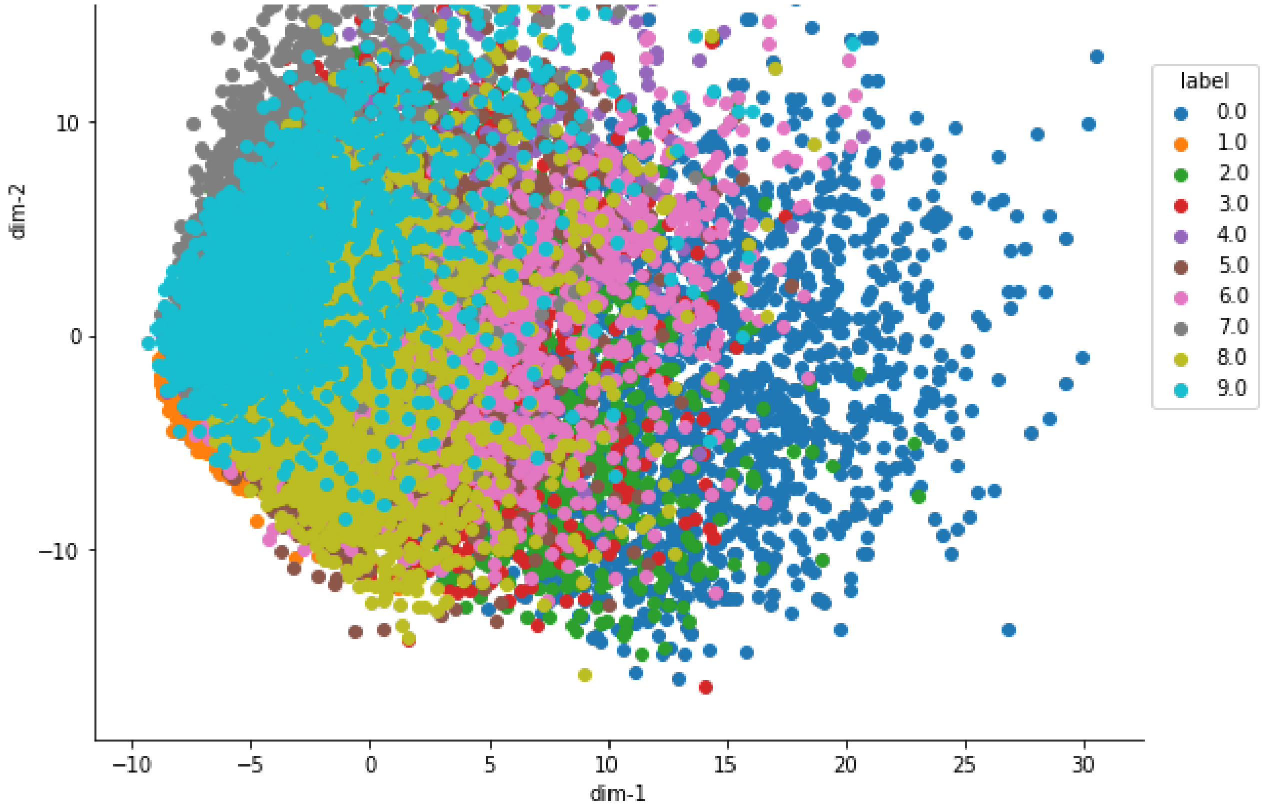
```
from sklearn import decomposition
pca = decomposition.PCA()
pca.n_components=2
pca_data = pca.fit_transform(standarad_data_1)
print(standarad_data_1.shape)
pca_data = np.vstack((pca_data.T,label)).T
print(pca_data.shape)
```

```
(20000, 784)
(20000, 3)
```

In [24]:

```
pca_data_df = pd.DataFrame(data=pca_data,columns=('dim-1','dim-2','label'))
s.FacetGrid(pca_data_df,hue='label',size=8).map(mp.scatter,'dim-1','dim-2')
.add_legend()
mp.show()
```





Note:

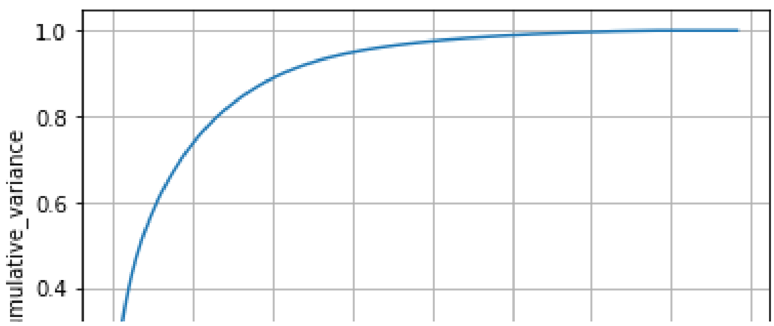
```
->We can use PCA not only for dimensionality reduction but also for
picking the most useful dimensions

->When the dimension were 2 or 3 then it is for visualization

->Based on the application we can reduce our dimensions
```

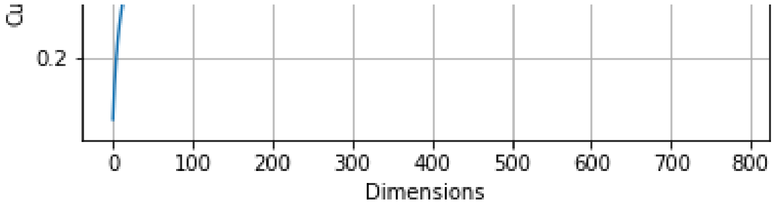
In [26]:

```
pca.n_components = 784
pca_data = pca.fit_transform(standarad_data_1)
variance_percentage =
pca.explained_variance_/np.sum(pca.explained_variance_)
cumulative_variance = np.cumsum(variance_percentage)
mp.plot(cumulative_variance)
mp.grid()
mp.xlabel('Dimensions')
mp.ylabel('Cumulative_variance')
```

Out[26]:

```
Text(0,0.5,'Cumulative_variance')
```





Observation:

```
->Based on the application requirement we can go for dimensionality
reduction

->If we go for 100-dimensions then 77 percent of data spread is used
.

->If we want 90 of data to be used then we have to choose 200-dimens
ions
```

t-SNE using Scikit-Learn:

```
             ->We just need to mention the number of components
required

             ->Perplexity to understand complexity which gives better i
n the range from 30 to 50

             ->Number of Iterations for optimaztion

             -> We train the model with 2 components and then fit our
data to that model

             ->Then we add our label to the modeled data and then we c
reate our normal dataframe
                with column names

             ->By using seaborn we can plot our tsne results
```

In [28]:

```python
from sklearn.manifold import TSNE
print(standarad_data_1.shape)
print(label.shape)
```

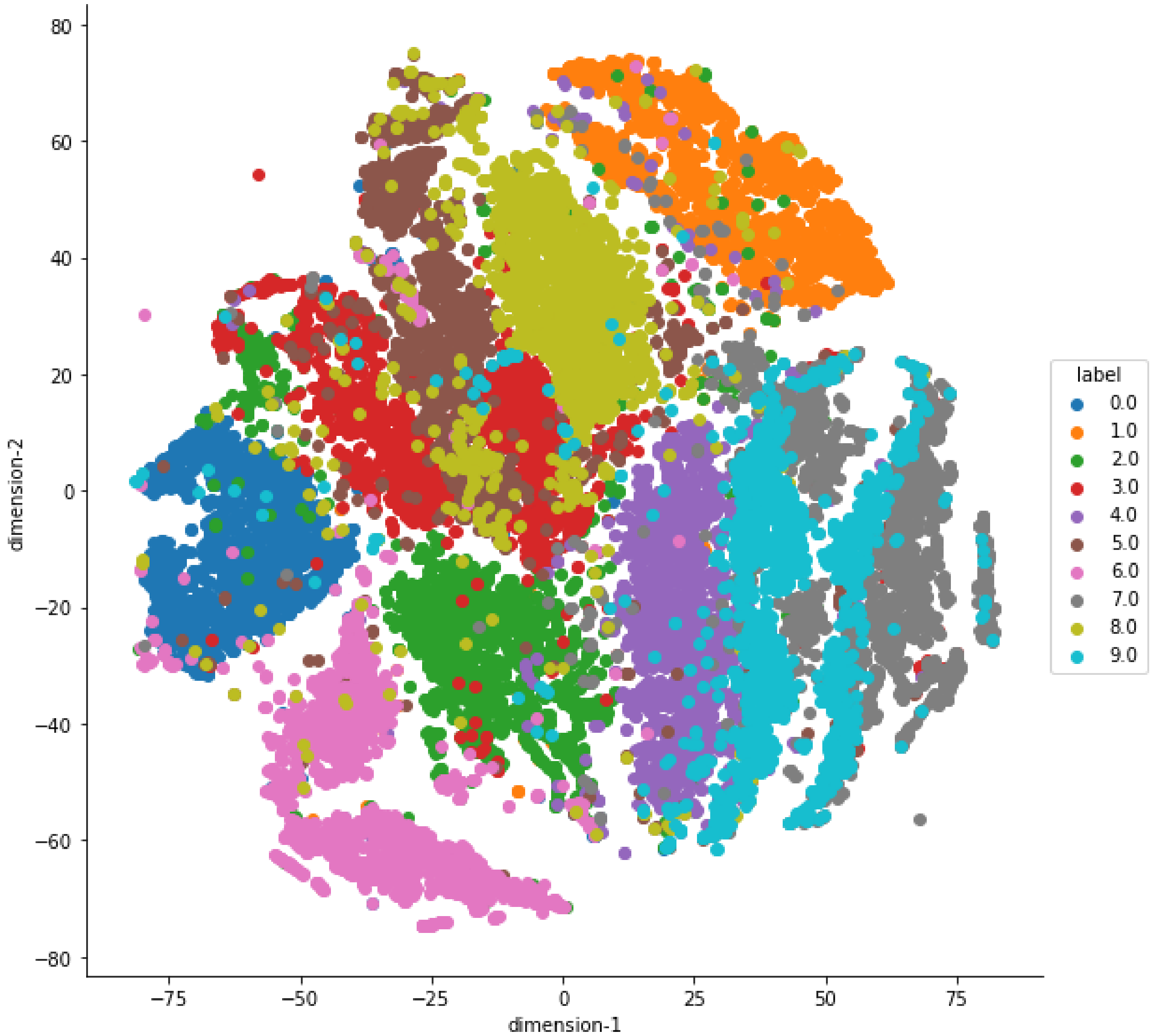
```
(20000, 784)
(20000,)
```

In [36]:

```python
model = TSNE(n_components=2)
tsne_data = model.fit_transform(standarad_data_1)
print(tsne_data.shape)
print(label.shape)
tsne_data_model = np.vstack((tsne_data.T,label)).T
```

```
tsne_data_model = np.vstack((tsne_data.T,label)).T
print(tsne_data_model.shape)
tsne_model_df = pd.DataFrame(data=tsne_data_model,columns=('dimension-1','d
imension-2','label'))
s.FacetGrid(tsne_model_df,hue='label',size=8).map(mp.scatter,'dimension-1',
'dimension-2').add_legend()
mp.show()
```

```
(20000, 2)
(20000,)
(20000, 3)
```



Note:

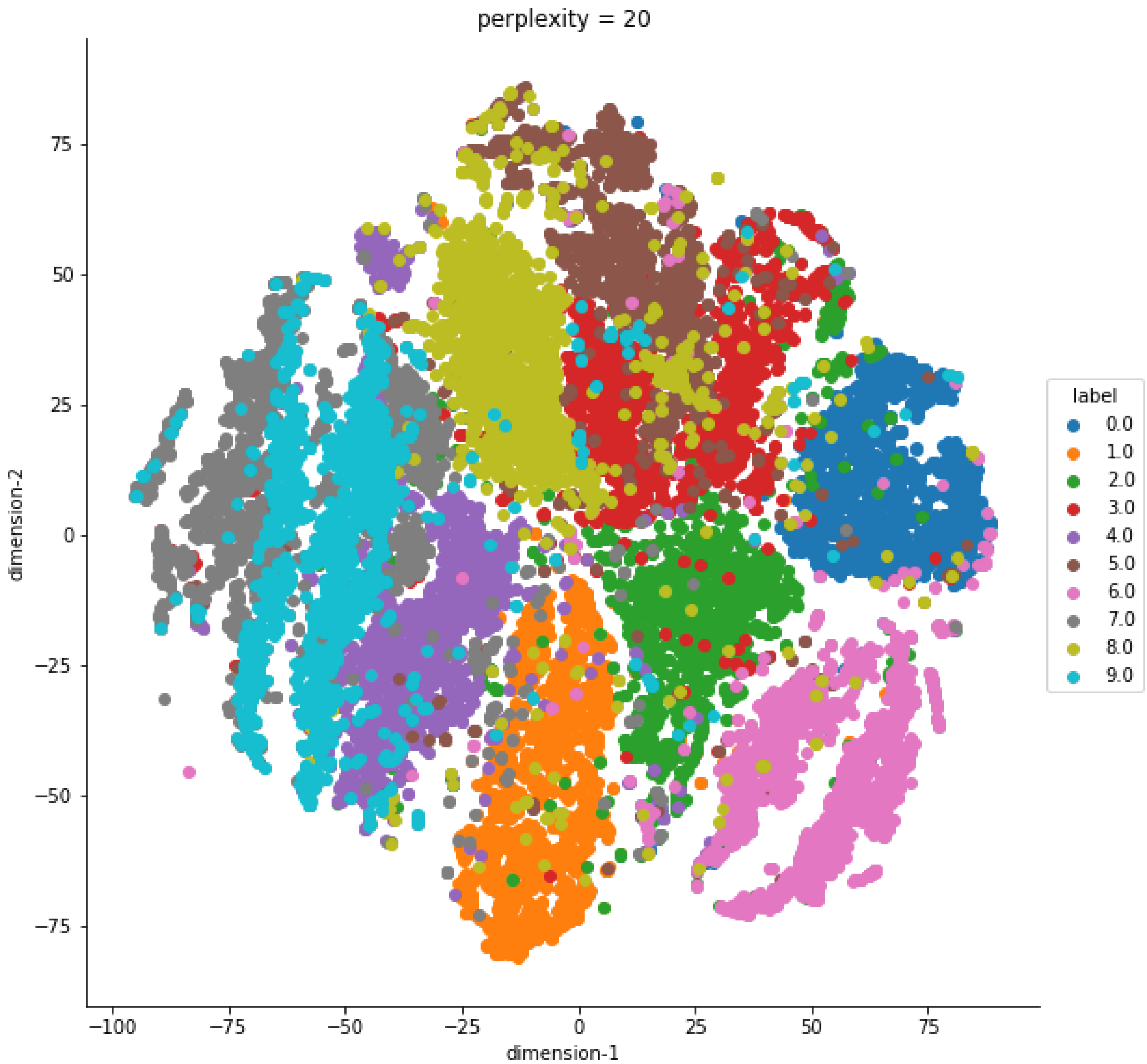
```
->We have to try this same model for different perplexity values and
number of iterations

->Getting the best from t-SNE mean that by analyzing multiple graphs
with different perplexity values
```

t-SNE with perplexity of 20

In [37]:

```
model = TSNE(n_components=2,random_state=998,perplexity=20)
tsne_model = model.fit_transform(standarad_data_1)
tsne_model = np.vstack((tsne_model.T,label)).T
print(tsne_model.shape)
tsne_model_df = pd.DataFrame(data=tsne_model,columns=('dimension-1','dimens
ion-2','label'))
s.FacetGrid(tsne_model_df,hue='label',size=8).map(mp.scatter,'dimension-1',
'dimension-2').add_legend()
mp.title('perplexity = 20')
mp.show()
```

```
(20000, 3)
```



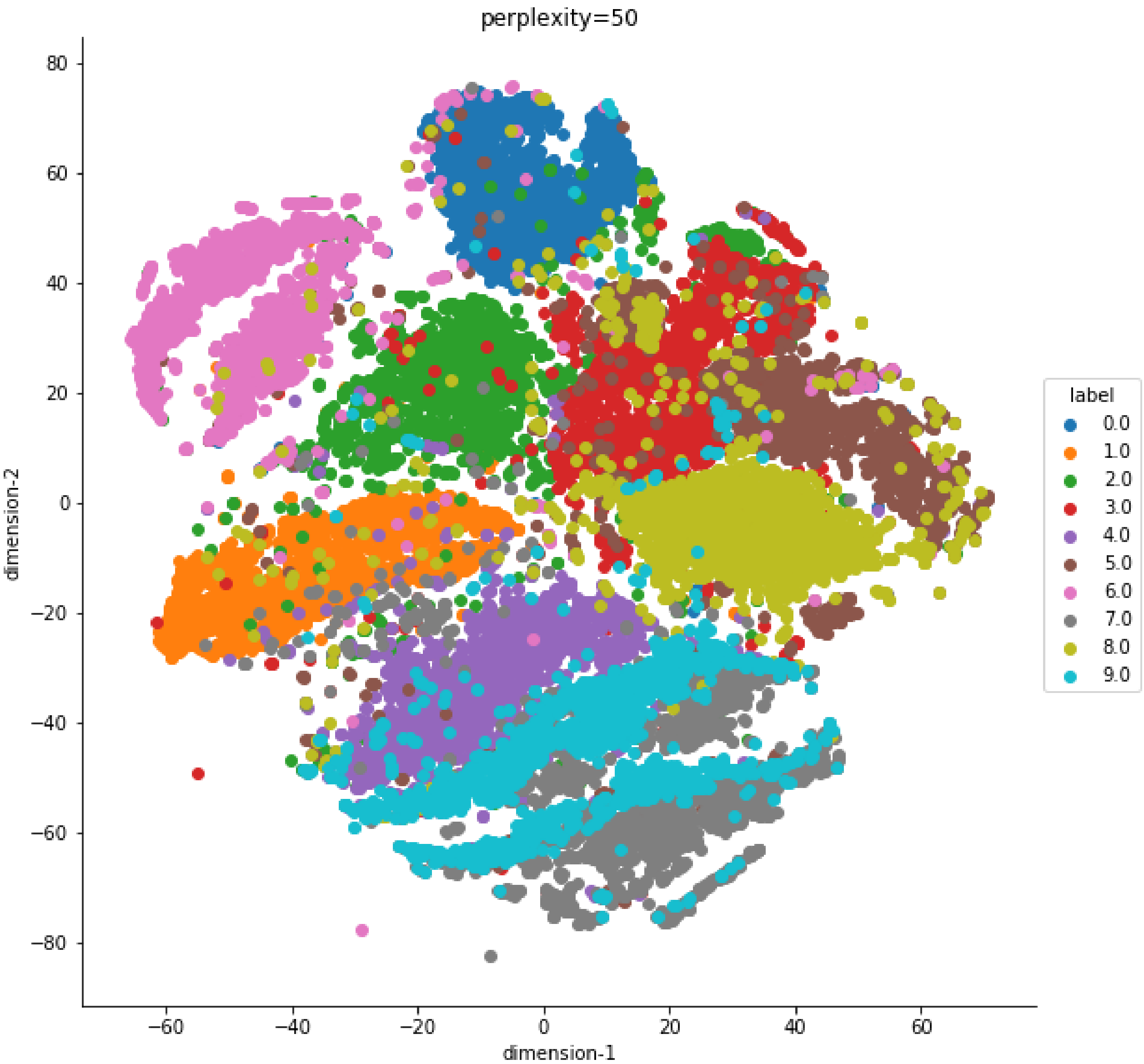
t-SNE with perplexity of 50

In [38]:

```
model = TSNE(n_components=2,random_state=997,perplexity=50)
tsne_model = model.fit_transform(standarad_data_1)
tsne_model = np.vstack((tsne_model.T,label)).T
print(tsne_model.shape)
tsne_model_df = pd.DataFrame(data=tsne_model,columns=('dimension-1','dimens
ion-2','label'))
s.FacetGrid(tsne_model_df,hue='label',size=8).map(mp.scatter,'dimension-1',
'dimension-2').add_legend()
```

```
mp.title("perplexity=50")
mp.show()
```

(20000, 3)



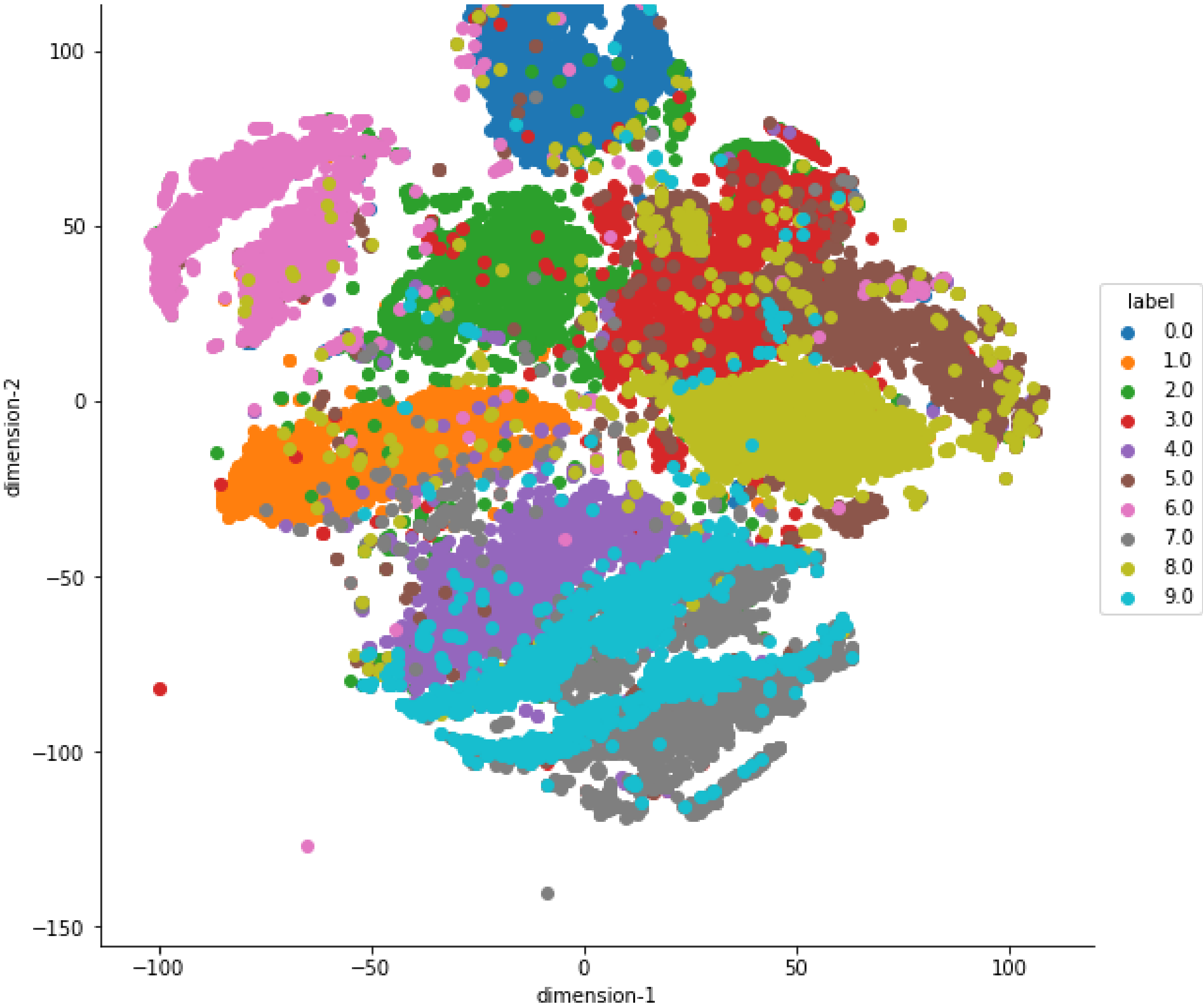
t-SNE with perplexity 50 and number of iterations as 2000

In [39]:

```
model = TSNE(n_components=2,random_state=997,perplexity=50,n_iter=2000)
tsne_model = model.fit_transform(standarad_data_1)
tsne_model = np.vstack((tsne_model.T,label)).T
print(tsne_model.shape)
tsne_model_df = pd.DataFrame(data=tsne_model,columns=('dimension-1','dimens
ion-2','label'))
s.FacetGrid(tsne_model_df,hue='label',size=8).map(mp.scatter,'dimension-1',
'dimension-2').add_legend()
mp.title("perplexity=50 and iterations=2000")
mp.show()
```

(20000, 3)

perplexity=50 and iterations=2000



Conclusion:

```
-> PCA will tries to preserve the global shape of the data

-> t-SNE will tries to preserve the local shape of the data and it t
ries to preserve the
   global shape of the data

-> t-SNE tries to embed the points from high dimensionality to low d
imesnionality by
   preserving the distance of local clusters
```