let's understand PCA and TSNE technique with MNIST dataset

Data Source: https://www.kaggle.com/c/digit-recognizer/data?select=train.csv

In [51]:

```
import os
import struct
import numpy as np
import matplotlib.image as  img
import matplotlib.pyplot as plt
import pandas as pd
data = pd.read_csv('train.csv')
data.head(5)
```

Out[51]:

	label	pixel0	pixel1	pixel2	pixel3	pixel4	pixel5	pixel6	pixel7	pixel8	...	pixel774	pixel775	pixel776	pixel777	pixel778	pixel77
0	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	
1	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	
2	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	
3	4	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	

5 rows × 785 columns

Observation :

```
    We found 5 rows and 785 column so we can say that we have 785 dimensional data set
```

In [52]:

```
# save the labels to a Pandas series target
l = data['label']
l.shape
```

Out[52]:

```
(42000,)
```

In [53]:

```
# drop the label
d = data.drop('label',axis=1)
d.shape
```

Out[53]:

```
(42000, 784)
```

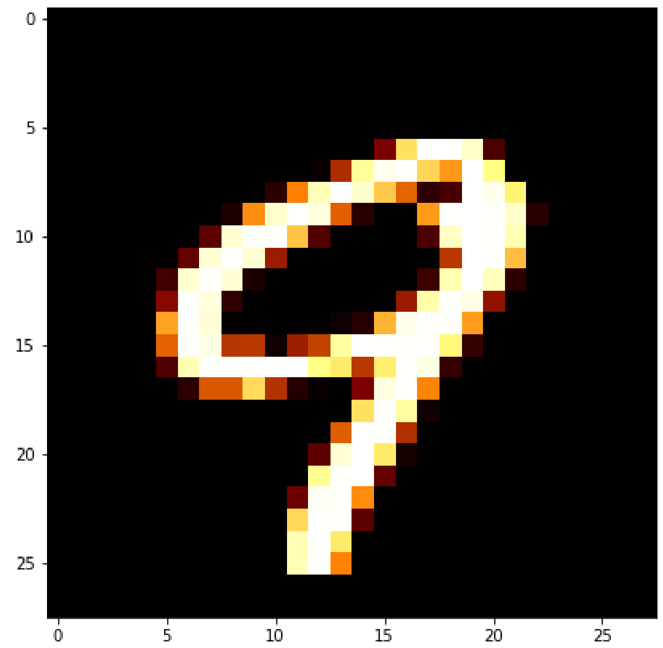
Observation:

```
   We found 42000 rows and 784 column
```

In [54]:

```
# display or plot a number.
plt.figure(figsize=(7,7))
idx = 100

grid_data = d.iloc[idx].to_numpy().reshape(28,28)  # reshape from 1d to 2d pixel array
plt.imshow(grid_data, interpolation = "none", cmap = "afmhot")
```

```
plt.imshow(grid_data, interpolation = "none", cmap = "afmhot")
plt.show()
```



In [55]:

```
labels = l.head(15000)
data = d.head(15000)
```

In [56]:

```
print("the shape of sample data:",data.shape)
```

```
the shape of sample data: (15000, 784)
```

In [57]:

```
#Data Preprocessing : Standardizing the data

from sklearn.preprocessing import StandardScaler
standardized_data = StandardScaler().fit_transform(data)

print(standardized_data.shape)
```

```
(15000, 784)
```

In [58]:

```
# find co-variance matrix which is A^T * A

sample_data = standardized_data

# matrix multiplication using numpy
covar_matrix = np.matmul(sample_data.T,sample_data)
print("Shape of variance matrix",covar_matrix.shape)
```

```
Shape of variance matrix (784, 784)
```

In [59]:

```
# finding  top 2 eigen values and correspoding eigen vector
from scipy.linalg import eigh

# eigh funtion will return eigen values in ascending order
# this code generate only top 2 eigen values
values,vectors = eigh(covar_matrix,eigvals=(782,783))
```

```
values,vectors = eigh(covar_matrix,eigvals=(782,783))

print("Shape of eigen vector:",vectors.shape)
vectors = vectors.T
print("Updated shape of eigen vector:",vectors.shape)

# Here the vectors[1] represent eigen vector corresponding 1st principal eigen vector

#Here the vectors[0] represent eigen vector corresponding to 2nd principal eigen vector
```

```
Shape of eigen vector: (784, 2)
Updated shape of eigen vector: (2, 784)
```

In [60]:

```
import matplotlib.pyplot as plt
new_coordinates = np.matmul(vectors, sample_data.T)

print (" resultant new data points' shape ", vectors.shape, "*", sample_data.T.shape," = ", new_coo
rdinates.shape)
```

```
 resultant new data points' shape  (2, 784) * (784, 15000)  =  (2, 15000)
```

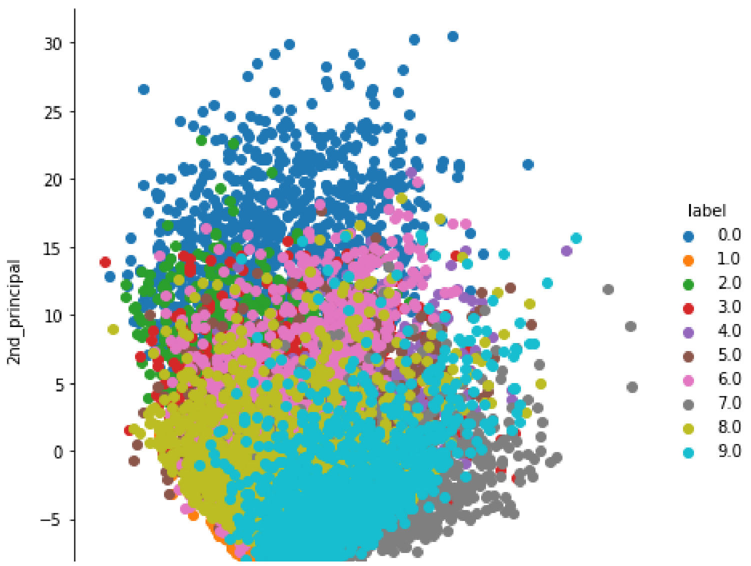
In [62]:

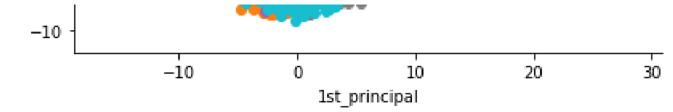
```
# appending label to 2D projected data
new_coordinates = np.vstack((new_coordinates,labels)).T

# creating a new dataframe for plotting the labaled point

dataframe = pd.DataFrame(data = new_coordinates,columns = ("1st_principal","2nd_principal","label"
))
print(dataframe.head())
```

```
   1st_principal  2nd_principal  label
0      -5.558661      -5.043558    1.0
1       6.193635      19.305278    0.0
2      -1.909878      -7.678775    1.0
3       5.525748      -0.464845    4.0
4       6.366527      26.644289    0.0
```

In [63]:

```
# plotting 2D data point with seaborn
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
sns.FacetGrid(dataframe,hue='label',size=6).map(plt.scatter,'1st_principal','2nd_principal').add_le
gend()
plt.show()
```





Implementation of PCA using Sklearn

In [64]:

```
from sklearn import decomposition
pca = decomposition.PCA()
```

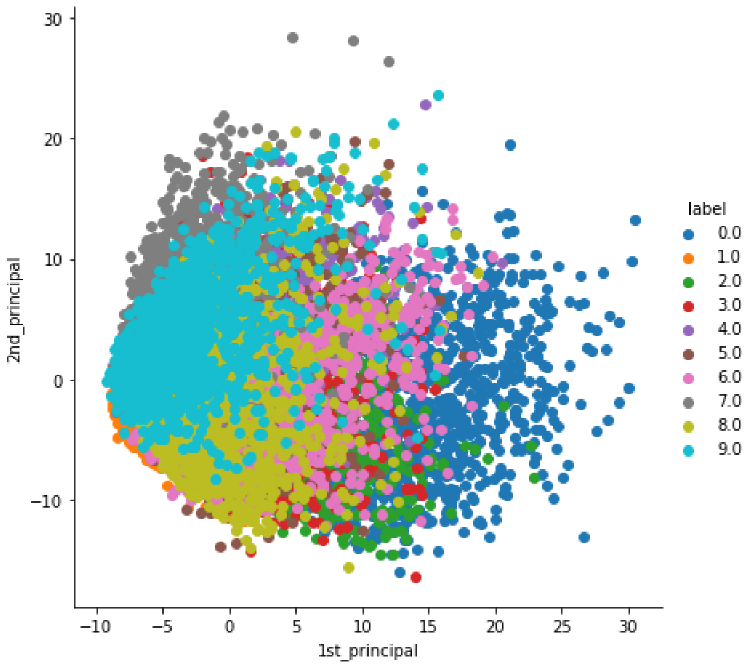
In [65]:

```
# configuring the parameters
#number of components = 2
pca.n_components = 2
pca_data = pca.fit_transform(sample_data) # Fit the model with Sample_data and apply reduction on
sample_data

# pca_reduced will contain 2D projects of sample data

print("Shape of pca_reduced.shape",pca_data.shape)
```

```
Shape of pca_reduced.shape (15000, 2)
```

In [69]:

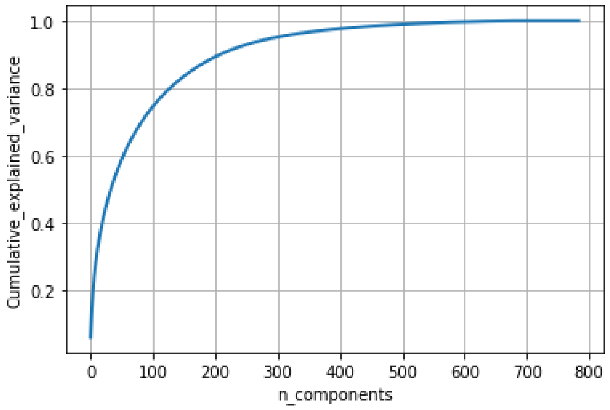
```
#attaching the label for each 2 D data point
pca_data = np.vstack((pca_data.T,labels)).T
pca_df = pd.DataFrame(data = pca_data,columns = ("1st_principal","2nd_principal","label"))
sns.FacetGrid(pca_df,hue = "label",size = 6).map(plt.scatter,'1st_principal','2nd_principal').add_l
egend()
plt.show()
```



In [72]:

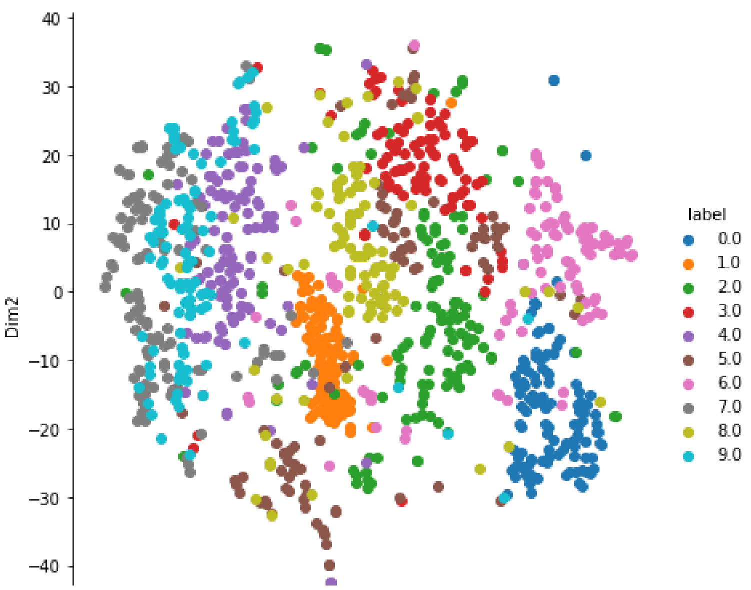
```
# PCA for Dimensionality Reduction (Not Visiualization)
pca.n_components = 784
pca_data = pca.fit_transform(sample_data)

#explained_variance : amount of variance explained by each of selected components
percentage_var_explained = pca.explained_variance_/np.sum(pca.explained_variance_)

cum_var_explained = np.cumsum(percentage_var_explained)
```

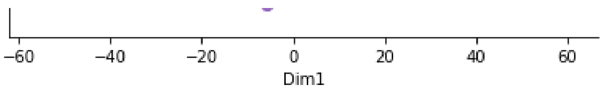
```
cum_var_explained = np.cumsum(percentage_var_explained)

#plot the PCA spectrum

plt.figure(1,figsize = (6,4))
plt.clf()
plt.plot(cum_var_explained,linewidth=2)
plt.axis('tight')
plt.grid()
plt.xlabel('n_components')
plt.ylabel("Cumulative_explained_variance")
plt.show()
```



In [73]:

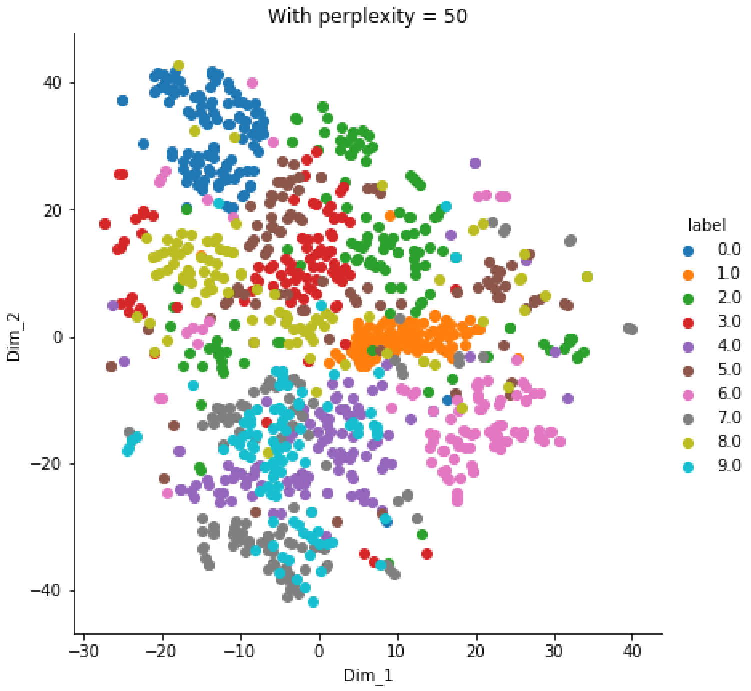
```
from sklearn.manifold import TSNE

# picking 1000 points as TSNE takes lot of time for 15k points

data_1000 = standardized_data[0:1000,:]
labels_1000 = labels[0:1000]

model = TSNE(n_components = 2,random_state = 0)

tsne_data = model.fit_transform(data_1000)

# creating a new dataframe which helps us in plotting the result data

tsne_data = np.vstack((tsne_data.T,labels_1000)).T

tsne_df = pd.DataFrame(data=tsne_data,columns=['Dim1','Dim2','label'])

#plotting the result of tsne

sns.FacetGrid(tsne_df,hue = 'label',size=6).map(plt.scatter,"Dim1","Dim2").add_legend()
plt.show()
```





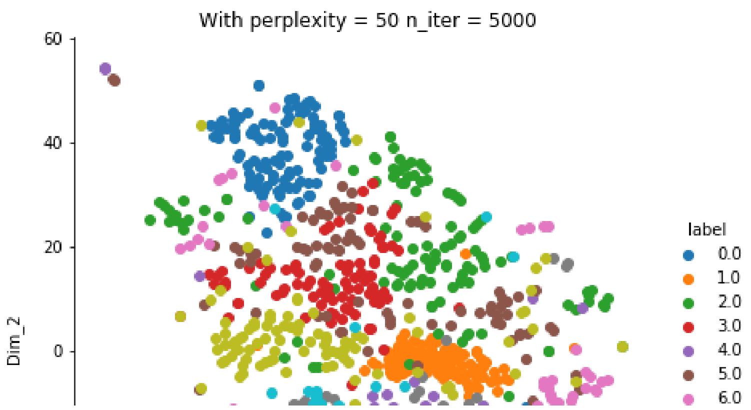
In [76]:

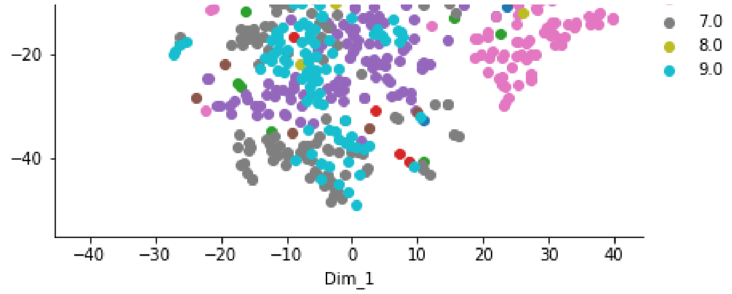
```
model = TSNE(n_components=2, random_state=0, perplexity=50)
tsne_data = model.fit_transform(data_1000)

# creating a new data fram which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, labels_1000)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="label", size=6).map(plt.scatter, 'Dim_1', 'Dim_2').add_legend()
plt.title('With perplexity = 50')
plt.show()
```



In [78]:

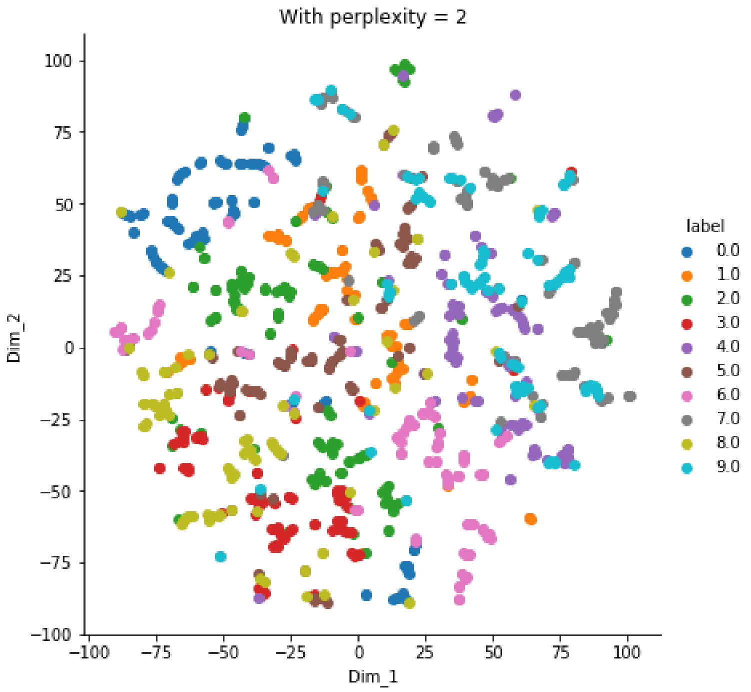
```
model = TSNE(n_components=2, random_state=0, perplexity=50,n_iter=5000)
tsne_data = model.fit_transform(data_1000)

# creating a new data fram which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, labels_1000)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="label", size=6).map(plt.scatter, 'Dim_1', 'Dim_2').add_legend()
plt.title('With perplexity = 50 n_iter = 5000')
plt.show()
```





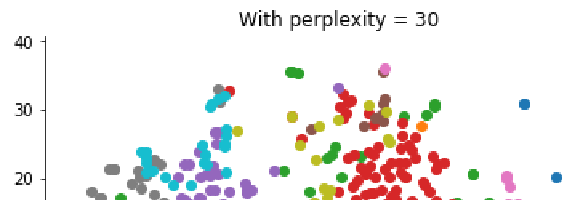
In [79]:

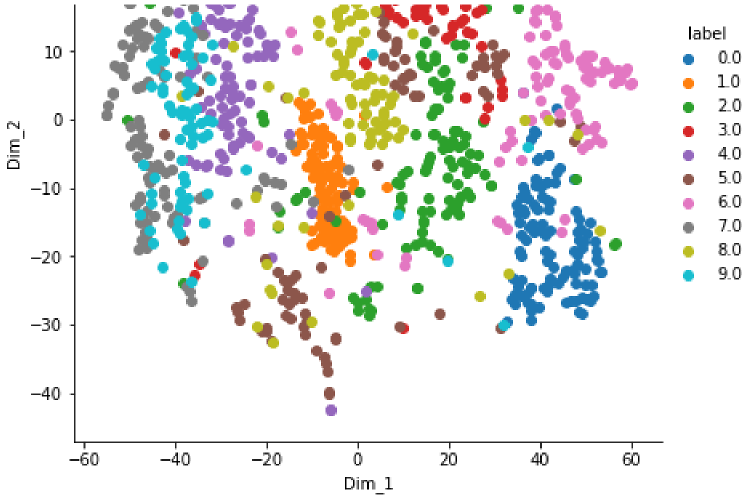
```
model = TSNE(n_components=2, random_state=0, perplexity=2)
tsne_data = model.fit_transform(data_1000)

# creating a new data fram which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, labels_1000)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="label", size=6).map(plt.scatter, 'Dim_1', 'Dim_2').add_legend()
plt.title('With perplexity = 2')
plt.show()
```



In [80]:

```
model = TSNE(n_components=2, random_state=0, perplexity=30)
tsne_data = model.fit_transform(data_1000)

# creating a new data fram which help us in ploting the result data
tsne_data = np.vstack((tsne_data.T, labels_1000)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="label", size=6).map(plt.scatter, 'Dim_1', 'Dim_2').add_legend()
plt.title('With perplexity = 30')
plt.show()
```





label
0.0
1.0
2.0
3.0
4.0
5.0
6.0
7.0
8.0
9.0
Dim_2
Dim_1
10
0
−10
−20
−30
−40
−60
−40
−20
0
20
40
60

In [ ]: