The project should meet the following guidelines:

- Your project should relate to something related to machine learning. Find a dataset and a topic that you are excited to work on. Who knows, you may take it one further step in the practicum.
- Your project must include data exploration, preferably with visualization and do not be shy to add your own comments to the code and on what you notice from the visualizations
- Your project must include a solid experimental examination. For example, if you implement a classification algorithm, I would expect to see optimization of hyperparameters.
- An evaluation on the training and test data set such as accuracy, MSE, RMSE, precision, recall .. etc for all your trials
- When possible, a brief analysis of the model learned (e.g. looking at the weights of a linear model) or importance of a PCA
- You have to include a baseline model in your trials (either linear or logistic regression) as well as its analysis
- You are encourage to use any external resources you would like including both code and data as long as you cite your resources

Some possible resources and ideas

- Dealing with imbalanced data
- Comparison between random forest, deep learning and baseline
- Bagging and boosting
- Transfer learning

Bonus points

- There will be bonus on working with large datasets … (higher than 20k samples)
- There will be bonus on making your codes run over the cloud

I have selected the following dataset: FashionMNIST: https://www.kaggle.com/zalando-research/fashionmnist (https://www.kaggle.com/zalando-research/fashionmnist)
I believe this dataset will allow me to explore the exciting world of image analysis as well as multiclass classification algorithms for Machine Learning. Also the FashionMNIST dataset has 60000 x 785 dataset for training and 10000 x 785 dataset for testing

```
!pip install keras
```

```
Collecting keras
  Using cached https://files.pythonhosted.org/packages/5e/10/aa32dad071ce52b5502266b5c659451cfd
6ffcbf14e6c8c4f16c0ff5aaab/Keras-2.2.4-py2.py3-none-any.whl
Collecting keras-applications>=1.0.6 (from keras)
  Using cached https://files.pythonhosted.org/packages/71/e3/19762fdfc62877ae9102edf6342d71b28fb
fd9dea3d2f96a882ce099b03f/Keras_Applications-1.0.8-py3-none-any.whl
Requirement already satisfied: h5py in /usr/local/envs/py3env/lib/python3.5/site-packages (from keras)
(2.7.1)
Requirement already satisfied: scipy>=0.14 in /usr/local/envs/py3env/lib/python3.5/site-packages (fro
m keras) (1.0.0)
Collecting keras-preprocessing>=1.0.5 (from keras)
  Using cached https://files.pythonhosted.org/packages/28/6a/8c1f62c37212d9fc441a7e26736df51ce6f
0e38455816445471f10da4f0a/Keras_Preprocessing-1.1.0-py2.py3-none-any.whl
Requirement already satisfied: numpy>=1.9.1 in /usr/local/envs/py3env/lib/python3.5/site-packages (fr
om keras) (1.14.0)
Requirement already satisfied: pyyaml in /usr/local/envs/py3env/lib/python3.5/site-packages (from ker
as) (3.13)
Requirement already satisfied: six>=1.9.0 in /usr/local/envs/py3env/lib/python3.5/site-packages (from
keras) (1.10.0)
Installing collected packages: keras-applications, keras-preprocessing, keras
Successfully installed keras-2.2.4 keras-applications-1.0.8 keras-preprocessing-1.1.0
```

```
# this is unrelated to the project .. It just helps displaying all outputs in a cell instead of just last one
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"
```

```
# Necessary libraries and modules

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
%matplotlib inline
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
import seaborn as sns; sns.set()
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import cross_val_score
from sklearn.decomposition import PCA
from keras.models import Sequential
from keras.layers.normalization import BatchNormalization
from keras.layers.convolutional import Conv2D
from keras.layers.convolutional import MaxPooling2D
from keras.layers.core import Activation
from keras.layers.core import Flatten
from keras.layers.core import Dropout
from keras.layers.core import Dense
from keras import backend as K
from keras.wrappers.scikit_learn import KerasClassifier
from sklearn.model_selection import GridSearchCV
from keras.utils import np_utils
from keras.optimizers import SGD
from keras.optimizers import Adam
from sklearn.ensemble import RandomForestClassifier
```

```
/usr/local/envs/py3env/lib/python3.5/site-packages/h5py/__init__.py:36: FutureWarning: Conversion o
f the second argument of issubdtype from `float` to `np.floating` is deprecated. In future, it will be treat
ed as `np.float64 == np.dtype(float).type`.
  from ._conv import register_converters as _register_converters
Using TensorFlow backend.
```

Loading the data

```
df_train_pd = pd.read_csv('fashion-mnist_train.csv')
df_test_pd = pd.read_csv('fashion-mnist_test.csv')
# df_train_pd=df_train_pd[0:2000]
# df_test_pd=df_test_pd[0:2000]
print(df_train_pd.shape)
print(df_test_pd.shape)
df_train_pd.head(1)
```

```
(60000, 785)
(10000, 785)
```

	label	pixel1	pixel2	pixel3	pixel4	pixel5	pixel6	pixel7	pixel8	pixel9	...	pixel775	pixel'
0	2	0	0	0	0	0	0	0	0	0	...	0	

1 rows × 785 columns

Splitting the data into features and labels.

```
# Converting all columns to float for future processing
df_train = np.array(df_train_pd, dtype='float32')
df_test = np.array(df_test_pd, dtype='float32')

# Splitting training data into X and Y
X_train = df_train[:, 1:]
y_train = df_train[:, 0]

# Splitting test data into X and Y
X_test = df_test[:, 1:]
y_test = df_test[:, 0]
```

Data Exploration

- Display if there are null values.
- Display unique labels.
- Displaying the images to verify the labels.
- PCA of the data to identify possibility of dimensionality reduction

```
print("Null values in Train dataset:", df_train_pd.isna().sum().sum())
print("Null values in Test dataset:", df_test_pd.isna().sum().sum())
```

```
Null values in Train dataset: 0
Null values in Test dataset: 0
```

```
df_combined = np.concatenate((y_train,y_test))
unique_labels = np.unique(df_combined)
print("Unique labels are", unique_labels)
```

```
Unique labels are [0. 1. 2. 3. 4. 5. 6. 7. 8. 9.]
```

The labels shown correspond to the label definition from Kaggle.

Labels

Each training and test example is assigned to one of the following labels:

- **0 T-shirt/top**
- **1 Trouser**
- **2 Pullover**
- **3 Dress**
- **4 Coat**
- **5 Sandal**
- **6 Shirt**
- **7 Sneaker**
- **8 Bag**
- **9 Ankle boot**

```
# Creating an array to map label integer to string

labels=['T-shirt/top', 'Trouser', 'Pullover', 'Dress', 'Coat', 'Sandal', 'Shirt', 'Sneaker', 'Bag', 'Ankle bo
ot']
```

```
# Verifying if items are correctly mapped to labels by picking 20
# random images and displaying their labels along with the image.

np.random.seed(1234)
rand_img = np.random.randint(0,np.size(X_train,0),20)
fig=plt.figure(figsize=(20, 20))
i=1
h=4
w=5
for x in rand_img:
    image = X_train[x, :].reshape((28, 28))
    ax=fig.add_subplot(h, w, i)
    ax.title.set_text("Label: " + str(labels[int(y_train[x])]))
    plt.imshow(image)
    i+=1
plt.show()
```

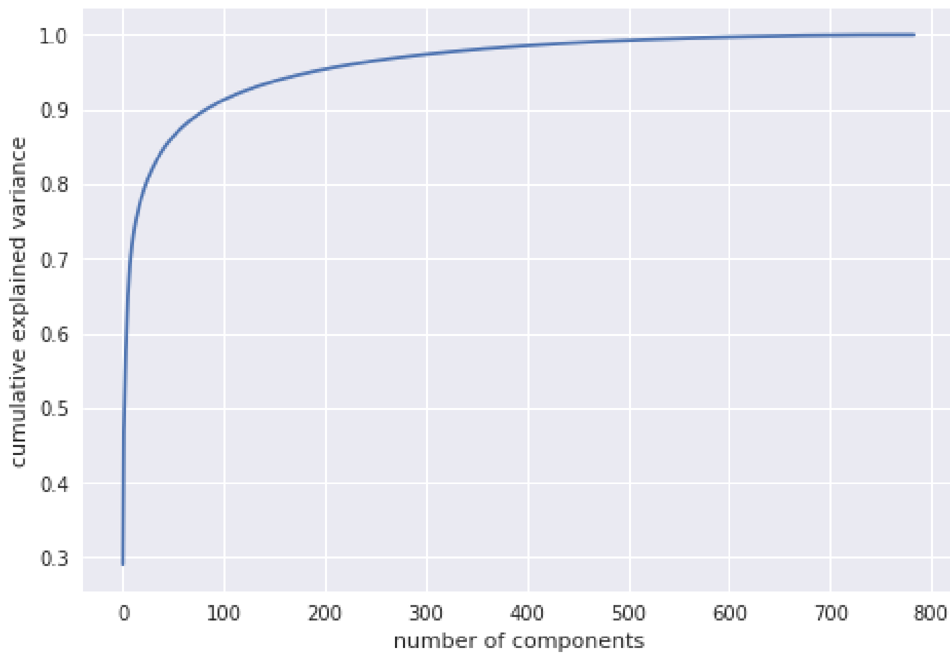
```
<matplotlib.image.AxesImage at 0x7fad36435fd0>

<matplotlib.image.AxesImage at 0x7fad37d383c8>

<matplotlib.image.AxesImage at 0x7fad36094cc0>

<matplotlib.image.AxesImage at 0x7fad3619c5f8>

<matplotlib.image.AxesImage at 0x7fad361bbef0>

<matplotlib.image.AxesImage at 0x7fad36f80748>

<matplotlib.image.AxesImage at 0x7fad36f27080>

<matplotlib.image.AxesImage at 0x7fad36f48978>

<matplotlib.image.AxesImage at 0x7fad36ef1390>

<matplotlib.image.AxesImage at 0x7fad36ef4550>

<matplotlib.image.AxesImage at 0x7fad36eb0e80>

<matplotlib.image.AxesImage at 0x7fad36ed97b8>

<matplotlib.image.AxesImage at 0x7fad36e811d0>

<matplotlib.image.AxesImage at 0x7fad36e1fac8>

<matplotlib.image.AxesImage at 0x7fad36e40d30>

<matplotlib.image.AxesImage at 0x7fad36de9668>

<matplotlib.image.AxesImage at 0x7fad36e0f080>

<matplotlib.image.AxesImage at 0x7fad36daeeb8>

<matplotlib.image.AxesImage at 0x7fad36dd5470>

<matplotlib.image.AxesImage at 0x7fad36d76d68>

/usr/local/envs/py3env/lib/python3.5/site-packages/matplotlib/font_manager.py:1320: UserWarni
ng: findfont: Font family ['sans-serif'] not found. Falling back to DejaVu Sans
  (prop.get_family(), self.defaultFamily[fontext]))
```


Label: Ankle boot
Label: Dress
Label: Coat
Label: Dress
Label: Sandal
Label: Dress
Label: Shirt
Label: Bag
Label: Trouser
Label: T-shirt/top
Label: Dress
Label: Coat
Label: Trouser
Label: Trouser
Label: Pullover
Label: Trouser
Label: Pullover
Label: T-shirt/top
Label: T-shirt/top
Label: Ankle boot

PCA

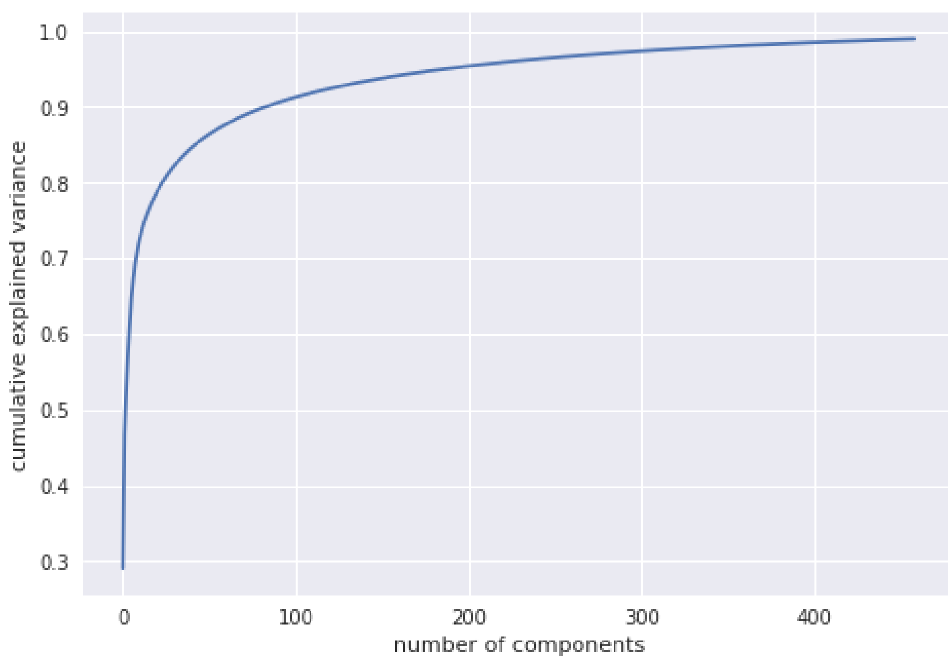
```
# Visualizing the variance of components
pca = PCA().fit(X_train)
plt.plot(np.cumsum(pca.explained_variance_ratio_))
plt.xlabel('number of components')
plt.ylabel('cumulative explained variance');
```

```
/usr/local/envs/py3env/lib/python3.5/site-packages/matplotlib/font_manager.py:1320: UserWarni
ng: findfont: Font family ['sans-serif'] not found. Falling back to DejaVu Sans
  (prop.get_family(), self.defaultFamily[fontext]))
```



```
# Applying image compression for a reduced dataset
pca_reduced=PCA(n_components=0.99)
X_train_reduced=pca_reduced.fit_transform(X_train)
plt.plot(np.cumsum(pca_reduced.explained_variance_ratio_))
plt.xlabel('number of components')
plt.ylabel('cumulative explained variance');

X_test_reduced=pca_reduced.transform(X_test)
```

```
[<matplotlib.lines.Line2D at 0x7fad36b53eb8>]

Text(0.5,0,'number of components')

Text(0,0.5,'cumulative explained variance')

/usr/local/envs/py3env/lib/python3.5/site-packages/matplotlib/font_manager.py:1320: UserWarni
ng: findfont: Font family ['sans-serif'] not found. Falling back to DejaVu Sans
  (prop.get_family(), self.defaultFamily[fontext]))
```



Splitting the data into 3 parts.

- Train
- Validation
- Test

Train and test has been provided.

We will split the train set into 2 more parts. One to train and one to validate. The test data will be used at the end to compare the models we develop based on the train and validate dataset.

Also we will normalize the value per pixel(28x28) to represent a value within 0 and 1.

```
# Max feature value for Train and Test data.

max_train = np.max(X_train)
max_test = np.max(X_test)
max_train_reduced = np.max(X_train_reduced)
max_test_reduced = np.max(X_test_reduced)

# Normalizing data in X_train and X_test

X_train = X_train/max_train
X_test = X_test/max_test

X_train_reduced = X_train_reduced/max_train_reduced
X_test_reduced = X_test_reduced/max_test_reduced
```

```
# Splitting Train set into training and validation set

X_training, X_validate, y_training, y_validate = train_test_split(
    X_train, y_train, test_size=0.2, random_state=1234,
)

X_training_reduced, X_validate_reduced, y_training_reduced, y_validate_reduced = train_test_split(
    X_train_reduced, y_train, test_size=0.2, random_state=1234,
)
```

Defining functions to capture metrics and visualize ROC curves

```
# Function to find accuracy and classification report for a model.
def metrics_generator(model,X,modelName,y_true,y_predictedValue,nn=False,hot_y=[]):
    print("----------------" + modelName + "--------------")
    if nn:
        print("Score is ", model.evaluate(X,hot_y)[1])
    else:
        print("Score is ", model.score(X,y_true))
    print(classification_report(y_true,y_predictedValue,target_names=labels))
    print("----------------------------------------------------")

# Function to draw confusion matrix for a model
def generate_confusion_matrix(y_true,y_pred,labelname):
    cm = confusion_matrix(y_true,y_pred,unique_labels)
    fig, ax = plt.subplots(figsize=(10,10))
    sns.heatmap(cm, square=True, annot=True, fmt='d', cbar=False,
                xticklabels=labels,
                yticklabels=labels,label=labelname,ax=ax)
    plt.xticks(rotation=45)
    plt.yticks(rotation=45)
    plt.ylabel('true label')
    plt.xlabel('predicted label')
    plt.title(labelname)
```

Developing a baseline model: Logistic Regression

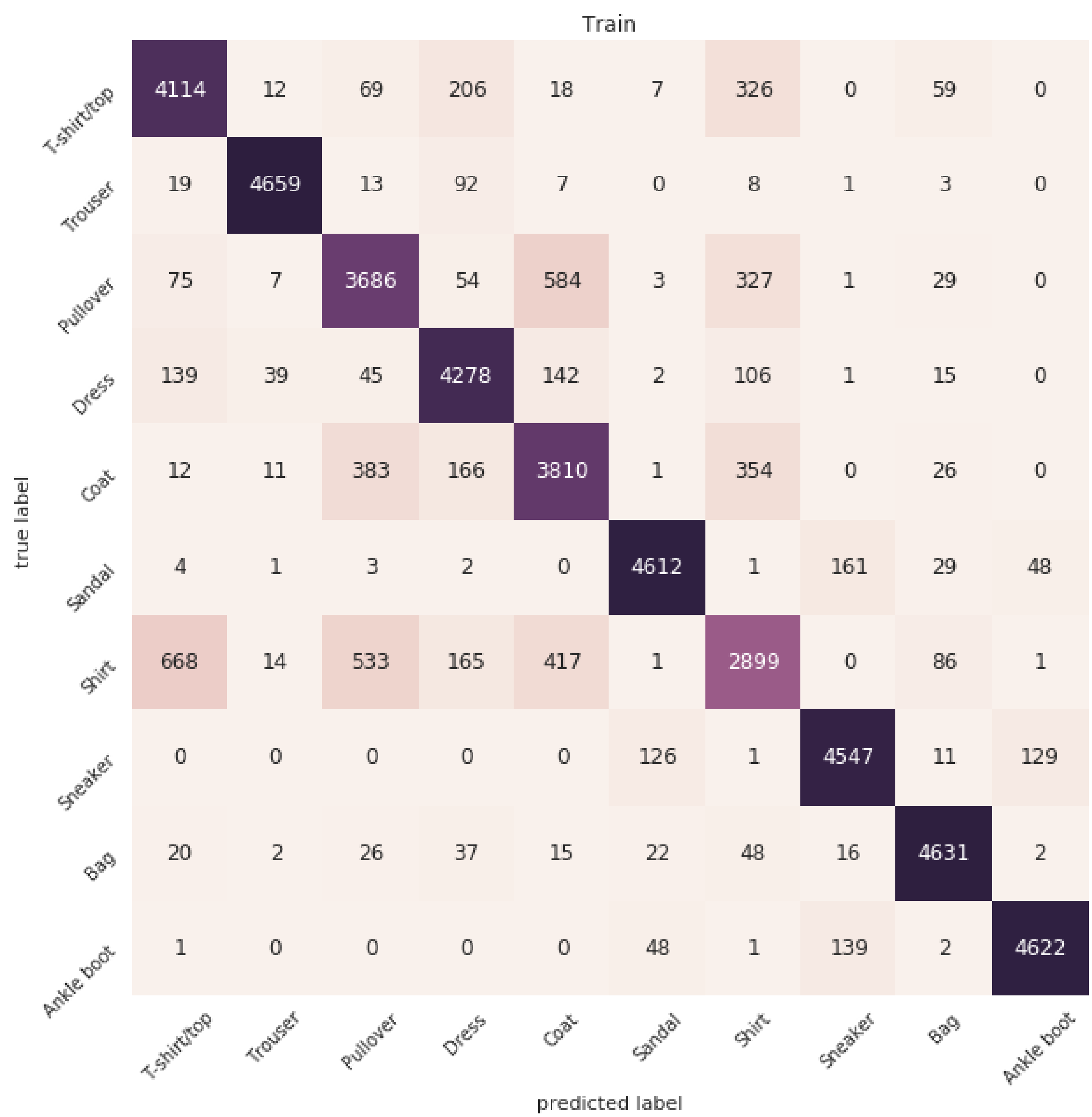
Non PCA data

```
logreg = LogisticRegression(solver = 'saga',multi_class='ovr')
logreg.fit(X_training, y_training)

# Train data
prob_train = logreg.predict(X_training)
metrics_generator(logreg,X_training,"Logistic regression train",y_training,prob_train)

# Test data
prob_test = logreg.predict(X_validate)
metrics_generator(logreg,X_validate,"Logistic regression test",y_validate,prob_test)
```

```
/usr/local/envs/py3env/lib/python3.5/site-packages/sklearn/linear_model/sag.py:326: Convergenc
eWarning: The max_iter was reached which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)

LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='saga', tol=0.0001,
          verbose=0, warm_start=False)

----------------Logistic regression train--------------
Score is  0.8720416666666667
             precision    recall  f1-score   support

T-shirt/top       0.81      0.86      0.83      4811
    Trouser       0.98      0.97      0.98      4802
   Pullover       0.77      0.77      0.77      4766
      Dress       0.86      0.90      0.88      4767
       Coat       0.76      0.80      0.78      4763
     Sandal       0.96      0.95      0.95      4861
      Shirt       0.71      0.61      0.65      4784
    Sneaker       0.93      0.94      0.94      4814
        Bag       0.95      0.96      0.95      4819
 Ankle boot       0.96      0.96      0.96      4813

avg / total       0.87      0.87      0.87     48000

-------------------------------------------------------
----------------Logistic regression test--------------
Score is  0.8550833333333333
             precision    recall  f1-score   support

T-shirt/top       0.79      0.82      0.80      1189
    Trouser       0.98      0.97      0.98      1198
   Pullover       0.77      0.77      0.77      1234
      Dress       0.84      0.89      0.87      1233
       Coat       0.77      0.79      0.78      1237
     Sandal       0.95      0.92      0.94      1139
      Shirt       0.65      0.57      0.61      1216
    Sneaker       0.91      0.95      0.93      1186
        Bag       0.93      0.94      0.94      1181
 Ankle boot       0.96      0.95      0.95      1187

avg / total       0.85      0.86      0.85     12000

-------------------------------------------------------
```

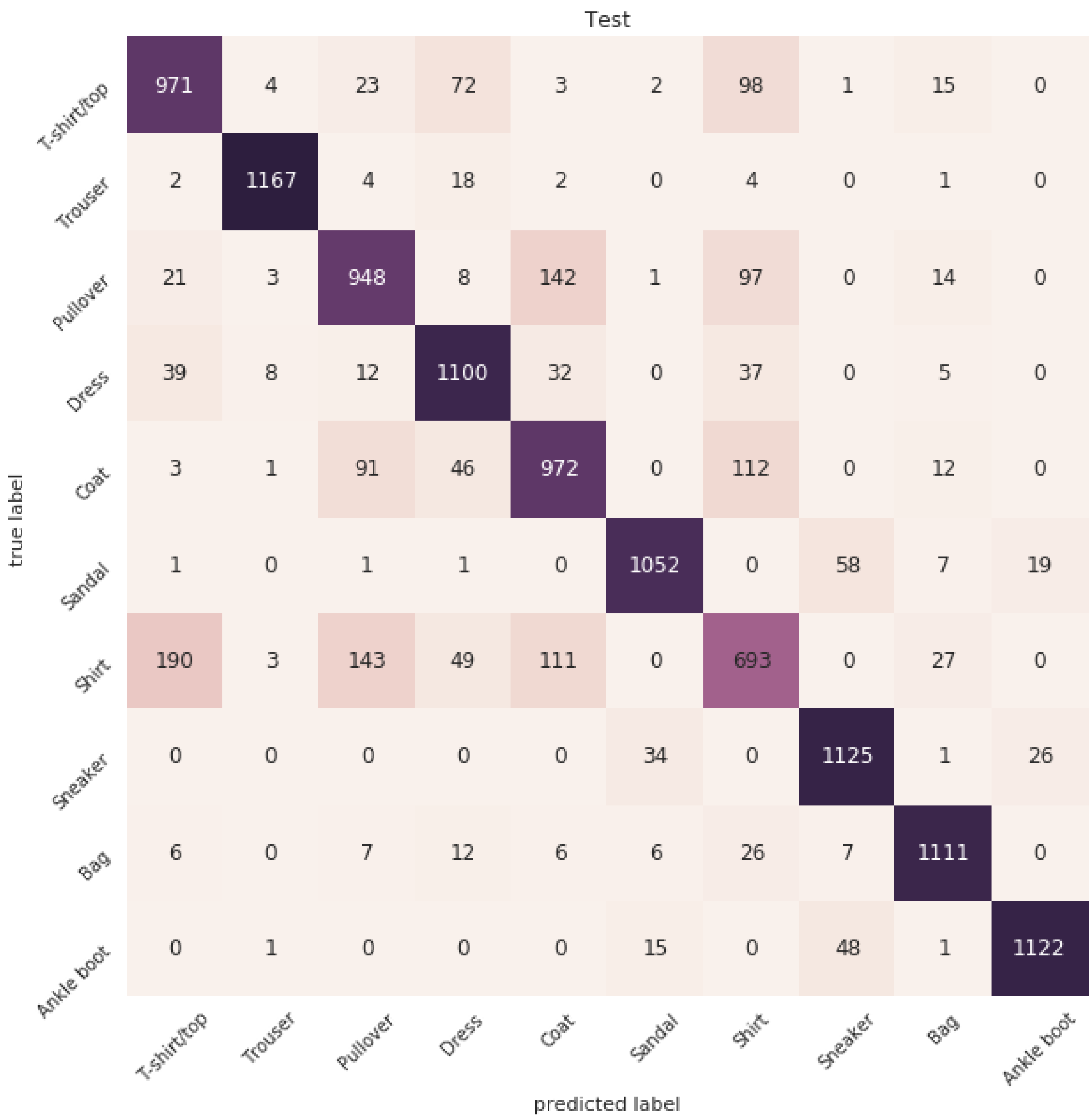
```python
# For train
generate_confusion_matrix(y_training, prob_train,"Train")
```

```
/usr/local/envs/py3env/lib/python3.5/site-packages/matplotlib/font_manager.py:1320: UserWarni
ng: findfont: Font family ['sans-serif'] not found. Falling back to DejaVu Sans
  (prop.get_family(), self.defaultFamily[fontext]))
```



```
# For test
generate_confusion_matrix(y_validate, prob_test,"Test")
```

```
/usr/local/envs/py3env/lib/python3.5/site-packages/matplotlib/font_manager.py:1320: UserWarni
ng: findfont: Font family ['sans-serif'] not found. Falling back to DejaVu Sans
  (prop.get_family(), self.defaultFamily[fontext]))
```



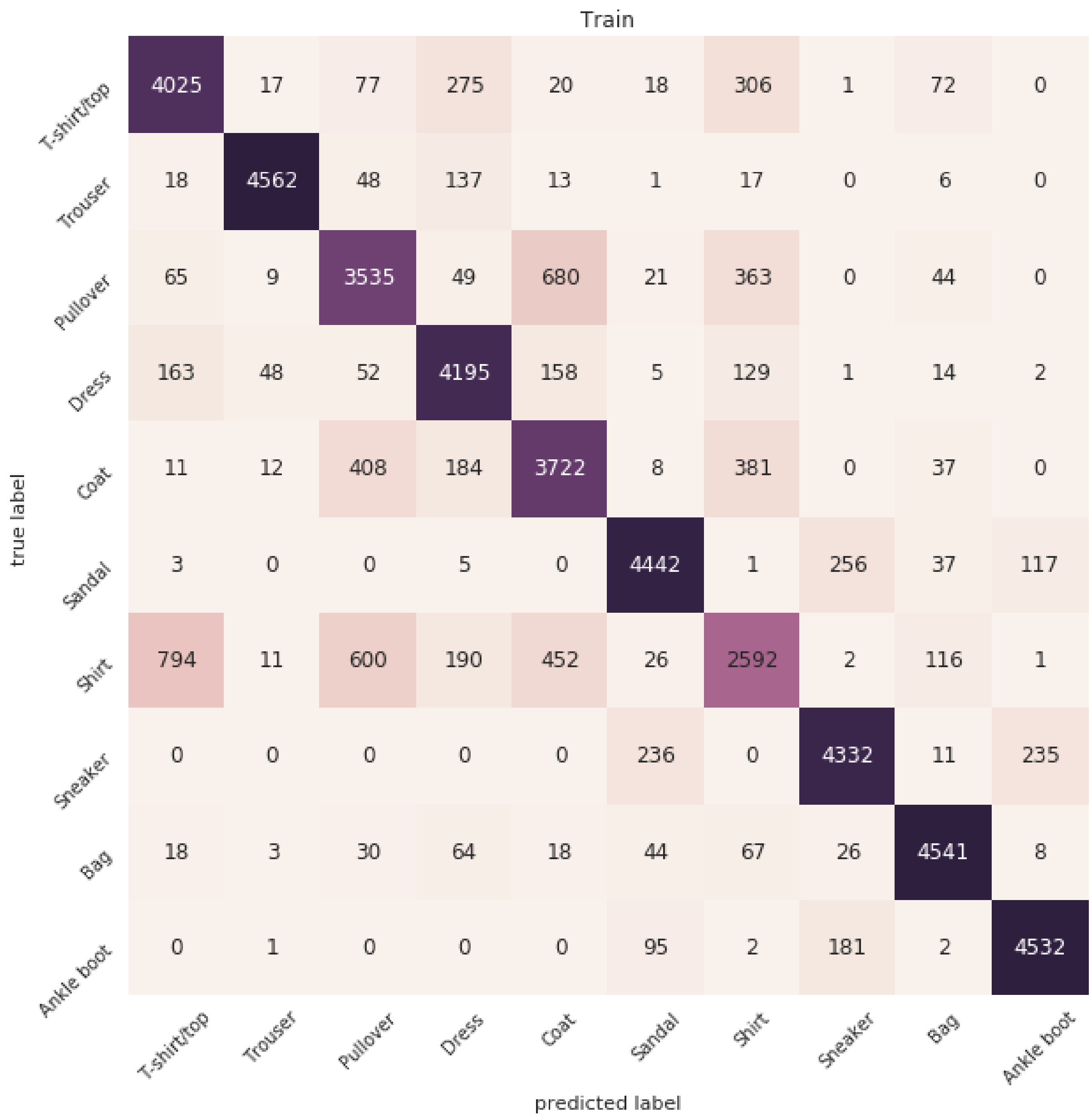
With PCA data

```
logreg_reduced = LogisticRegression(solver = 'saga',multi_class='ovr')
logreg_reduced.fit(X_training_reduced, y_training_reduced)

# Train data
prob_train_reduced = logreg_reduced.predict(X_training_reduced)
metrics_generator(logreg_reduced,X_training_reduced,"PCA Logistic regression train",y_training_re
duced,prob_train_reduced)

# Test data
prob_test_reduced = logreg_reduced.predict(X_validate_reduced)
metrics_generator(logreg_reduced,X_validate_reduced,"PCA Logistic regression test",y_validate_red
uced,prob_test_reduced)
```

```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='saga', tol=0.0001,
          verbose=0, warm_start=False)

----------------PCA Logistic regression train--------------
Score is  0.8432916666666667
             precision    recall  f1-score   support

T-shirt/top       0.79      0.84      0.81      4811
    Trouser       0.98      0.95      0.96      4802
   Pullover       0.74      0.74      0.74      4766
      Dress       0.82      0.88      0.85      4767
       Coat       0.74      0.78      0.76      4763
     Sandal       0.91      0.91      0.91      4861
      Shirt       0.67      0.54      0.60      4784
    Sneaker       0.90      0.90      0.90      4814
        Bag       0.93      0.94      0.94      4819
 Ankle boot       0.93      0.94      0.93      4813

avg / total       0.84      0.84      0.84     48000

-------------------------------------------------------
----------------PCA Logistic regression test--------------
Score is  0.8345
             precision    recall  f1-score   support

T-shirt/top       0.77      0.82      0.80      1189
    Trouser       0.97      0.96      0.97      1198
   Pullover       0.75      0.74      0.75      1234
      Dress       0.82      0.88      0.85      1233
       Coat       0.74      0.77      0.75      1237
     Sandal       0.90      0.89      0.89      1139
      Shirt       0.66      0.52      0.58      1216
    Sneaker       0.88      0.91      0.90      1186
        Bag       0.91      0.93      0.92      1181
 Ankle boot       0.92      0.93      0.93      1187

avg / total       0.83      0.83      0.83     12000

-------------------------------------------------------
```

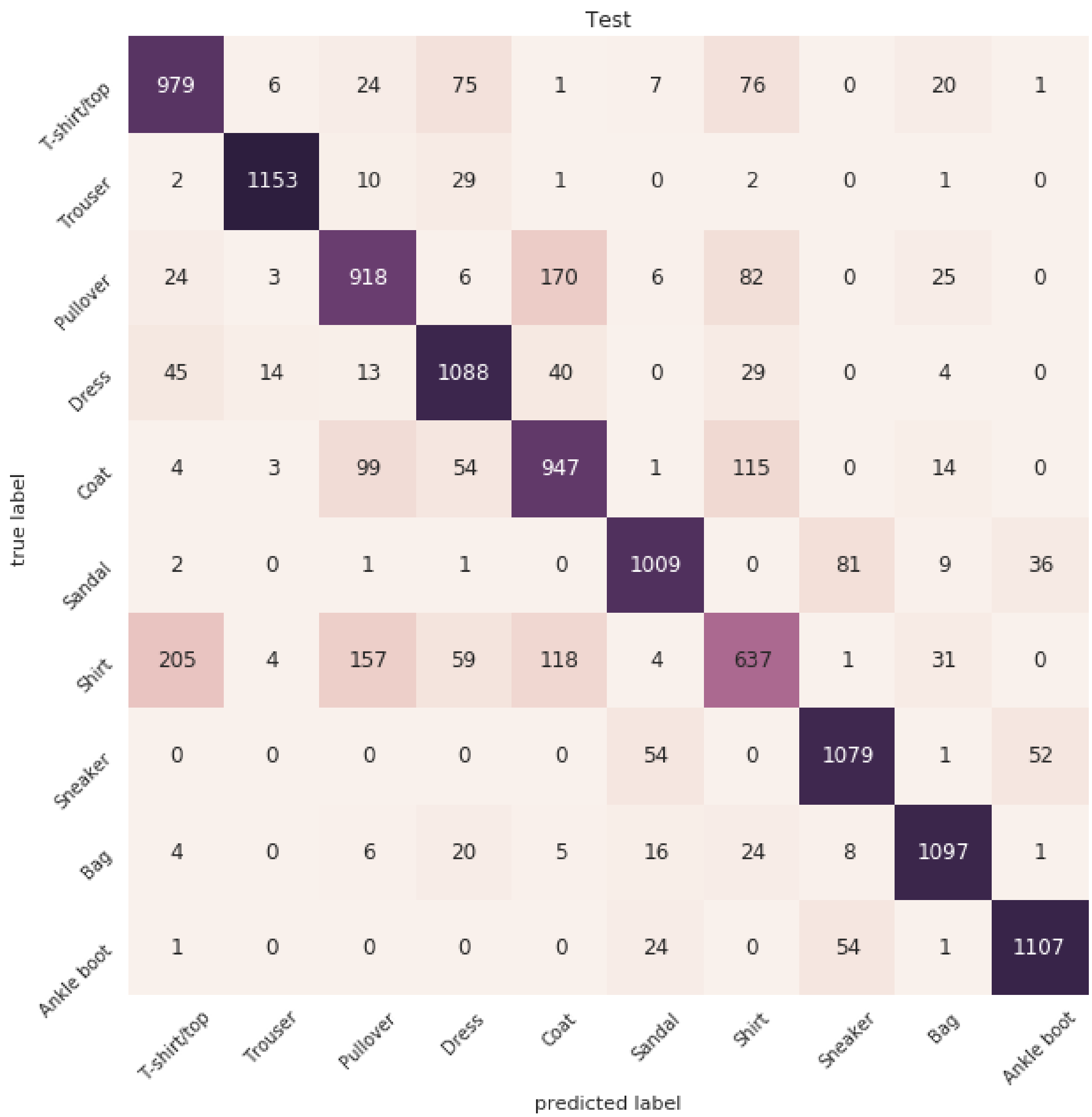
```
# For train
generate_confusion_matrix(y_training_reduced, prob_train_reduced,"Train")
```

```
/usr/local/envs/py3env/lib/python3.5/site-packages/matplotlib/font_manager.py:1320: UserWarni
ng: findfont: Font family ['sans-serif'] not found. Falling back to DejaVu Sans
  (prop.get_family(), self.defaultFamily[fontext]))
```



```
# For test
generate_confusion_matrix(y_validate_reduced, prob_test_reduced,"Test")
```

```
/usr/local/envs/py3env/lib/python3.5/site-packages/matplotlib/font_manager.py:1320: UserWarning: findfont: Font family ['sans-serif'] not found. Falling back to DejaVu Sans
  (prop.get_family(), self.defaultFamily[fontext]))
```



Developing a K-Nearest Neighbour classifier

With Non PCA data

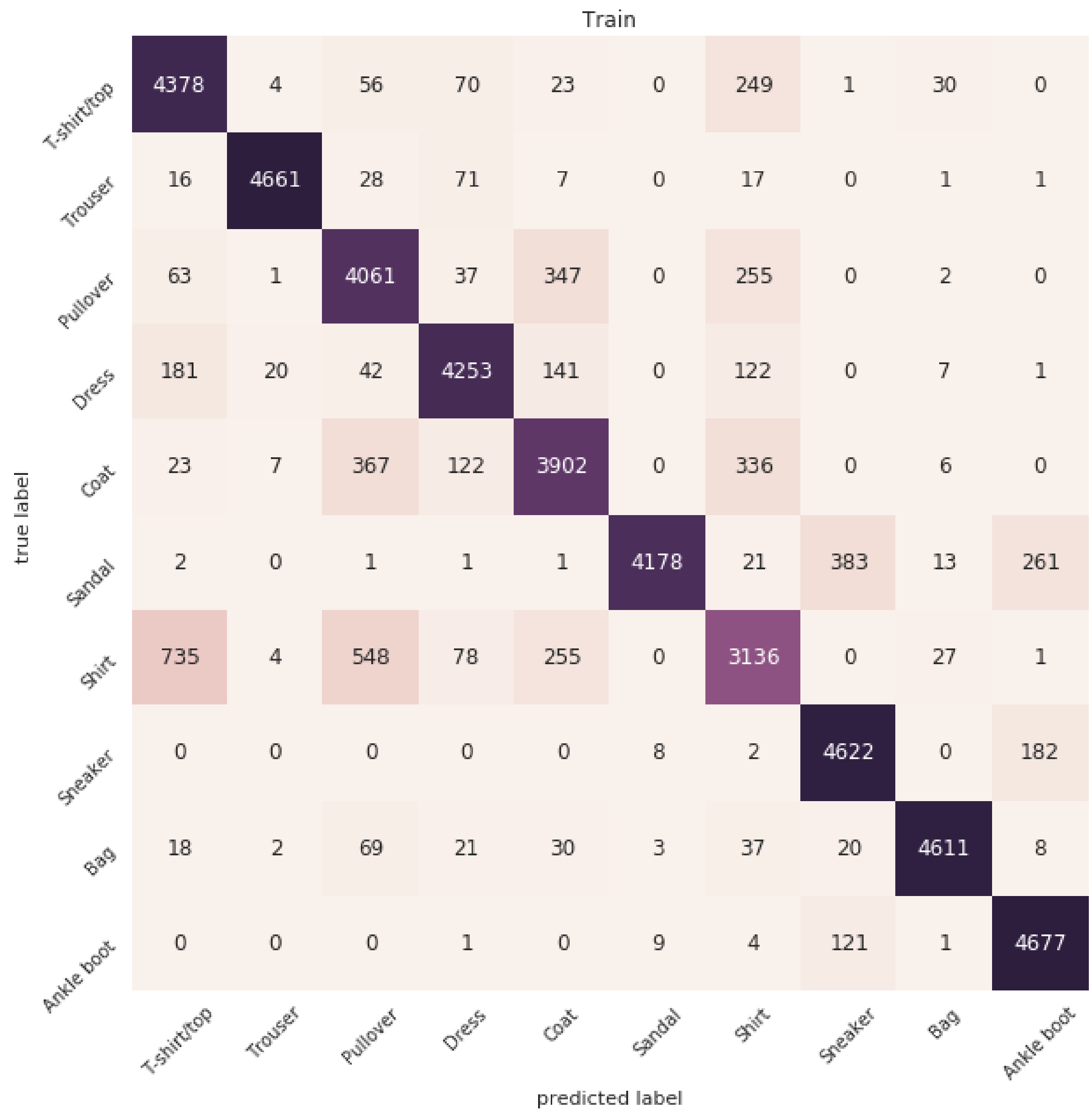
```
# Parameter tuning for an optimum K for KNN
def knnParameterTuning(X,y):
    # Since KNN performs worse as the size of the dataset increases
    # we are going to tune the hyperparameter on a reduced set of data
#     X_reduced = X[0:1000]
#     y_reduced = y[0:1000]
    X_reduced = X
    y_reduced = y
    klist = [3,5,7,10,13,15,17,20,23,25,27,30]

    cv_scores = []

    # performing cross validation
    for k in klist:
        knn_temp = KNeighborsClassifier(n_neighbors=k, n_jobs=-1)
        scores = cross_val_score(knn_temp, X_reduced, y_reduced, cv=10, scoring='accuracy')
        cv_scores.append(scores.mean())

    # changing to misclassification error
    MSE = [1 - x for x in cv_scores]

    # determining best k
    optimal_k = klist[MSE.index(min(MSE))]
    print("The optimal number of neighbors is %d" % optimal_k)

    # plot misclassification error vs k
    plt.plot(klist, MSE)
    plt.xlabel('Number of Neighbors K')
    plt.ylabel('Misclassification Error')
    plt.show()
    return optimal_k

# Calculating optimal_k for KNN
# optimal_k = knnParameterTuning(X_training,y_training)

# Since parameter tuning is a time consuming process, this has been done on my local system. Using valu
es from that run as parameters in cloud.
optimal_k = 7
```

```
knn = KNeighborsClassifier(n_neighbors=optimal_k, n_jobs=-1)
knn.fit(X_training,y_training)

# Train data
prob_train_knn = knn.predict(X_training)
metrics_generator(knn,X_training,"KNN train",y_training,prob_train_knn)

# Test data
prob_test_knn = knn.predict(X_validate)
metrics_generator(knn,X_validate,"KNN test",y_validate,prob_test_knn)
```

```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=-1, n_neighbors=7, p=2,
           weights='uniform')

----------------KNN train--------------
Score is  0.8849791666666667
             precision    recall  f1-score   support

T-shirt/top       0.81      0.91      0.86      4811
    Trouser       0.99      0.97      0.98      4802
   Pullover       0.79      0.85      0.82      4766
      Dress       0.91      0.89      0.90      4767
       Coat       0.83      0.82      0.82      4763
     Sandal       1.00      0.86      0.92      4861
      Shirt       0.75      0.66      0.70      4784
    Sneaker       0.90      0.96      0.93      4814
        Bag       0.98      0.96      0.97      4819
 Ankle boot       0.91      0.97      0.94      4813

avg / total       0.89      0.88      0.88     48000

-----------------------------------------------------
----------------KNN test--------------
Score is  0.8518333333333333
             precision    recall  f1-score   support

T-shirt/top       0.76      0.86      0.81      1189
    Trouser       0.99      0.97      0.98      1198
   Pullover       0.76      0.81      0.78      1234
      Dress       0.90      0.88      0.89      1233
       Coat       0.78      0.75      0.76      1237
     Sandal       1.00      0.80      0.89      1139
      Shirt       0.65      0.59      0.62      1216
    Sneaker       0.87      0.96      0.91      1186
        Bag       0.97      0.94      0.95      1181
 Ankle boot       0.89      0.96      0.93      1187

avg / total       0.85      0.85      0.85     12000

-----------------------------------------------------
```

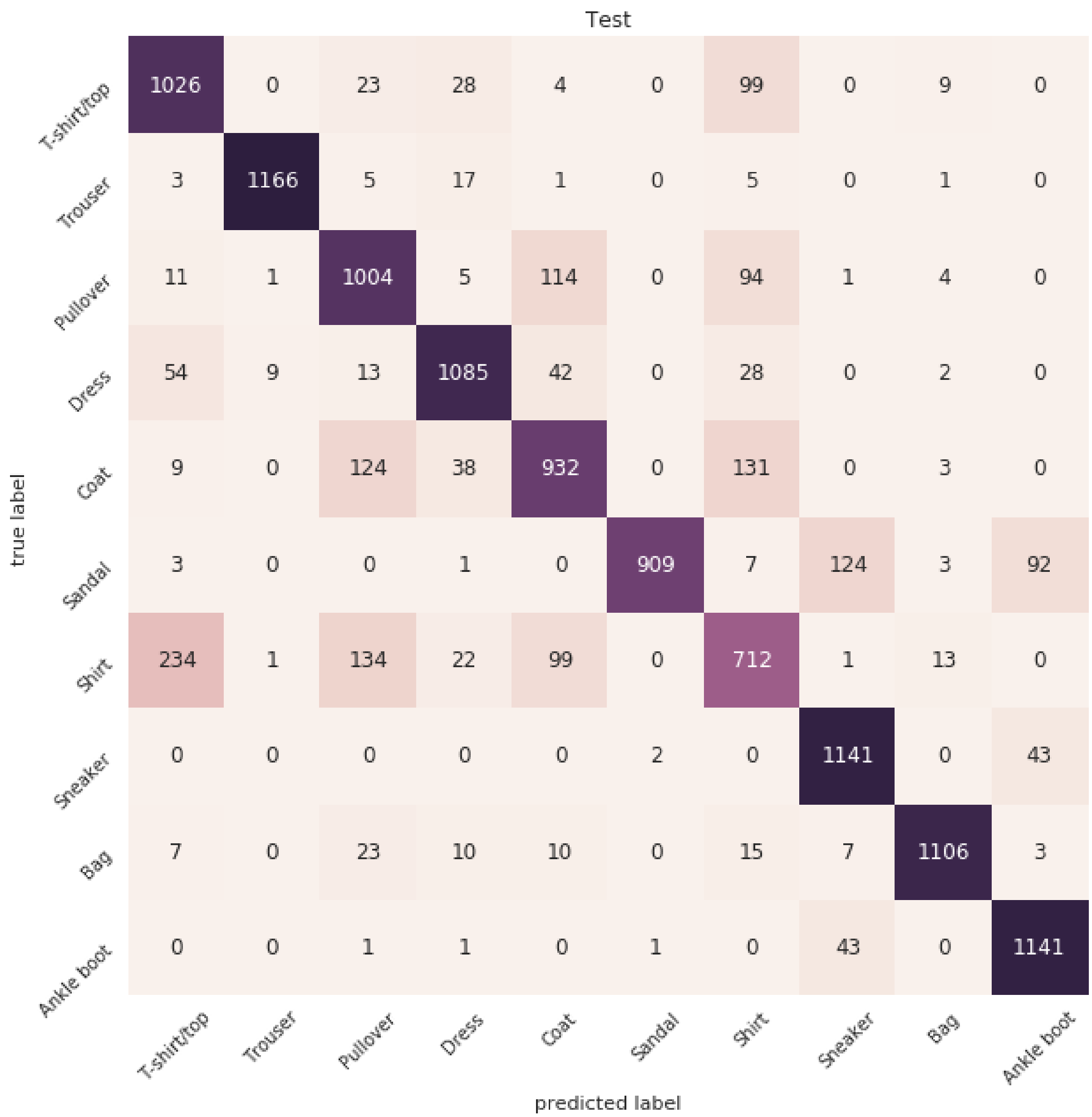
```
# For train
generate_confusion_matrix(y_training, prob_train_knn,"Train")
```

```
/usr/local/envs/py3env/lib/python3.5/site-packages/matplotlib/font_manager.py:1320: UserWarni
ng: findfont: Font family ['sans-serif'] not found. Falling back to DejaVu Sans
  (prop.get_family(), self.defaultFamily[fontext]))
```



```
# For test
generate_confusion_matrix(y_validate, prob_test_knn,"Test")
```

```
/usr/local/envs/py3env/lib/python3.5/site-packages/matplotlib/font_manager.py:1320: UserWarni
ng: findfont: Font family ['sans-serif'] not found. Falling back to DejaVu Sans
  (prop.get_family(), self.defaultFamily[fontext]))
```



With PCA data

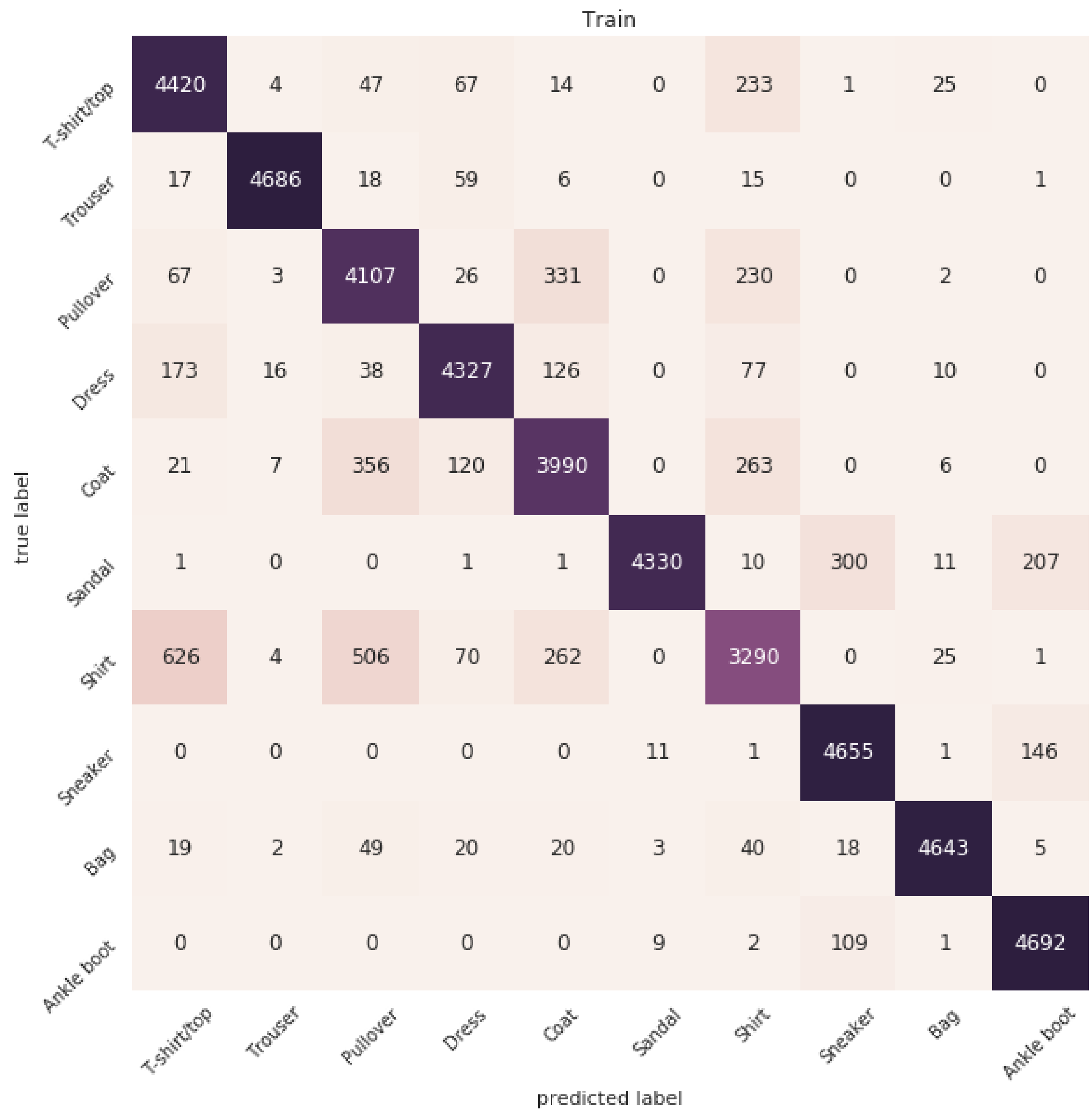
```
# optimal_k = knnParameterTuning(X_training_reduced,y_training_reduced)
# Since parameter tuning is a time consuming process, this has been done on my local system. Using valu
es from that run as parameters in cloud.
optimal_k = 5
```

```
knn_reduced = KNeighborsClassifier(n_neighbors=optimal_k, n_jobs=-1)
knn_reduced.fit(X_training_reduced,y_training_reduced)

# Train data
prob_train_knn_reduced = knn_reduced.predict(X_training_reduced)
metrics_generator(knn_reduced,X_training_reduced,"PCA KNN train",y_training_reduced,prob_tra
in_knn_reduced)

# Test data
prob_test_knn_reduced = knn_reduced.predict(X_validate_reduced)
metrics_generator(knn_reduced,X_validate_reduced,"PCA KNN test",y_validate_reduced,prob_test_
knn_reduced)
```

```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=-1, n_neighbors=5, p=2,
           weights='uniform')

----------------PCA KNN train--------------
Score is  0.89875
             precision    recall  f1-score   support

T-shirt/top       0.83      0.92      0.87      4811
    Trouser       0.99      0.98      0.98      4802
   Pullover       0.80      0.86      0.83      4766
      Dress       0.92      0.91      0.92      4767
       Coat       0.84      0.84      0.84      4763
     Sandal       0.99      0.89      0.94      4861
      Shirt       0.79      0.69      0.74      4784
    Sneaker       0.92      0.97      0.94      4814
        Bag       0.98      0.96      0.97      4819
 Ankle boot       0.93      0.97      0.95      4813

avg / total       0.90      0.90      0.90     48000

-----------------------------------------------------
----------------PCA KNN test--------------
Score is  0.85525
             precision    recall  f1-score   support

T-shirt/top       0.76      0.87      0.81      1189
    Trouser       0.99      0.98      0.98      1198
   Pullover       0.74      0.81      0.78      1234
      Dress       0.90      0.88      0.89      1233
       Coat       0.78      0.75      0.77      1237
     Sandal       1.00      0.82      0.90      1139
      Shirt       0.68      0.59      0.63      1216
    Sneaker       0.87      0.97      0.92      1186
        Bag       0.97      0.94      0.96      1181
 Ankle boot       0.90      0.96      0.93      1187

avg / total       0.86      0.86      0.85     12000

-----------------------------------------------------
```

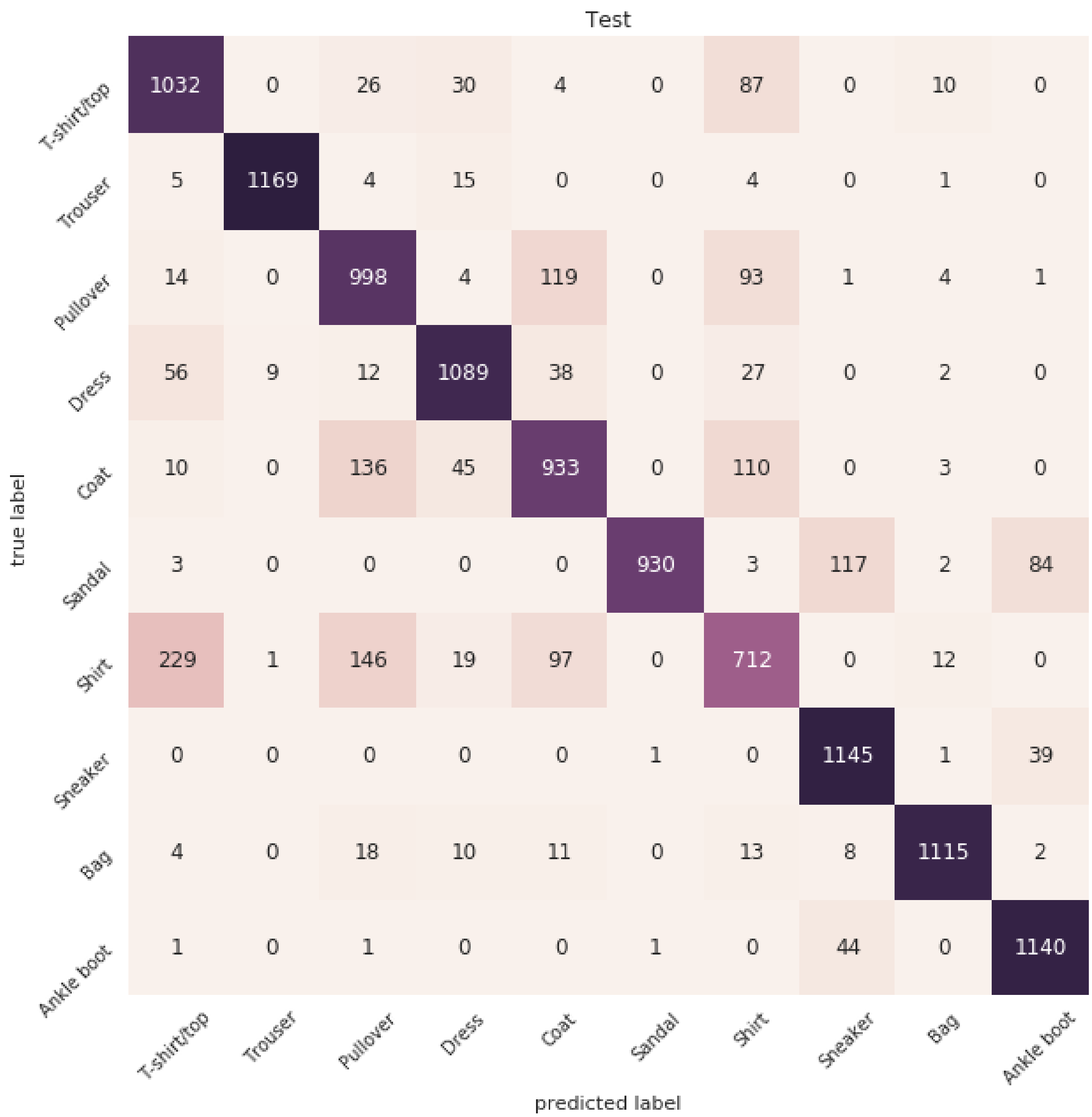
```
# For train
generate_confusion_matrix(y_training_reduced, prob_train_knn_reduced,"Train")
```

```
/usr/local/envs/py3env/lib/python3.5/site-packages/matplotlib/font_manager.py:1320: UserWarni
ng: findfont: Font family ['sans-serif'] not found. Falling back to DejaVu Sans
  (prop.get_family(), self.defaultFamily[fontext]))
```



```
# For test
generate_confusion_matrix(y_validate_reduced, prob_test_knn_reduced,"Test")
```

```
/usr/local/envs/py3env/lib/python3.5/site-packages/matplotlib/font_manager.py:1320: UserWarni
ng: findfont: Font family ['sans-serif'] not found. Falling back to DejaVu Sans
  (prop.get_family(), self.defaultFamily[fontext]))
```



Developing a Convoluted Neural Network classifier

```
# Function to generate the CNN model
def getCNNModel(learning_rate=0.001):
    model = Sequential()
    inputShape = (28, 28, 1)

    model.add(Conv2D(32, kernel_size=(3, 3), activation='relu', input_shape=inputShape))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Dropout(0.25))

    model.add(Conv2D(64, kernel_size=(3, 3), activation='relu'))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Dropout(0.25))

    model.add(Conv2D(128, kernel_size=(3, 3), activation='relu'))
    model.add(Dropout(0.4))

    model.add(Flatten())

    model.add(Dense(128, activation='relu'))
    model.add(Dense(10, activation='softmax'))

    opt = Adam(lr=learning_rate)
    model.compile(loss="categorical_crossentropy", optimizer=opt,metrics=["accuracy"])
    return model


# HyperParmeter search space for grid search
epochs = [30, 60]
learning_rates = [0.01, 0.001]
batches = [128, 256]

# Create hyperparameter dictionary
hyperparameters = dict(epochs=epochs, batch_size=batches, learning_rate=learning_rates)

# Defining default rates
best_result = {
    'learning_rate': 0.001,
    'batch_size': 256,
    'epochs': 60
}
```

```
# Reshape the data
trainX = X_training.reshape((X_training.shape[0], 28, 28, 1))
validateX = X_validate.reshape((X_validate.shape[0], 28, 28, 1))

# one-hot encode the training and testing labels
trainY = np_utils.to_categorical(y_training, len(labels))
validateY = np_utils.to_categorical(y_validate, len(labels))
```

 # # Wrapping Keras model for sklearn modules
 # cnn_sklearn = KerasClassifier(build_fn=getCNNModel, verbose=0)

 # # Performing Grid Search
 # grid = GridSearchCV(estimator=cnn_sklearn, param_grid=hyperparameters, n_jobs=-1, scoring="accuracy")

 # # Fit grid search
 # grid_result = grid.fit(trainX, y_training)

 # # Hyperparameters of best neural network
*# best_result = grid_result.best_params_*

 # print("Best parameters are: ", best_result)

 # Since parameter tuning is a time consuming process, this has been done on my local system. Using values from that run as parameters in cloud.

```
# Get CNN model
cnn = getCNNModel(best_result['learning_rate'])

# Train the CNN
cnn.fit(trainX, trainY,validation_data=(validateX, validateY),batch_size=best_result['batch_size'], ep
ochs=best_result['epochs'])

# Train data
prob_train_cnn = cnn.predict_classes(trainX)
metrics_generator(cnn,trainX,"CNN train",y_training,prob_train_cnn,True,trainY)

# Test data
prob_test_cnn = cnn.predict_classes(validateX)
metrics_generator(cnn,validateX,"CNN test",y_validate,prob_test_cnn,True,validateY)
```

```
Train on 48000 samples, validate on 12000 samples
Epoch 1/60
48000/48000 [==============================] - 118s 2ms/step - loss: 0.8324 - acc: 0.6841
- val_loss: 0.5401 - val_acc: 0.8018
Epoch 2/60
48000/48000 [==============================] - 115s 2ms/step - loss: 0.5202 - acc: 0.8043
- val_loss: 0.4393 - val_acc: 0.8363
Epoch 3/60
48000/48000 [==============================] - 114s 2ms/step - loss: 0.4508 - acc: 0.8341
- val_loss: 0.3801 - val_acc: 0.8577
Epoch 4/60
48000/48000 [==============================] - 114s 2ms/step - loss: 0.4076 - acc: 0.8515
- val_loss: 0.3451 - val_acc: 0.8766
Epoch 5/60
48000/48000 [==============================] - 114s 2ms/step - loss: 0.3739 - acc: 0.8635
- val_loss: 0.3172 - val_acc: 0.8825
Epoch 6/60
48000/48000 [==============================] - 113s 2ms/step - loss: 0.3501 - acc: 0.8733
- val_loss: 0.3024 - val_acc: 0.8893
Epoch 7/60
48000/48000 [==============================] - 113s 2ms/step - loss: 0.3366 - acc: 0.8765
- val_loss: 0.2898 - val_acc: 0.8927
Epoch 8/60
48000/48000 [==============================] - 113s 2ms/step - loss: 0.3226 - acc: 0.8825
- val_loss: 0.2798 - val_acc: 0.8961
Epoch 9/60
48000/48000 [==============================] - 113s 2ms/step - loss: 0.3076 - acc: 0.8866
- val_loss: 0.2740 - val_acc: 0.9001
Epoch 10/60
48000/48000 [==============================] - 114s 2ms/step - loss: 0.2987 - acc: 0.8900
- val_loss: 0.2865 - val_acc: 0.8959
Epoch 11/60
48000/48000 [==============================] - 114s 2ms/step - loss: 0.2897 - acc: 0.8935
- val_loss: 0.2679 - val_acc: 0.8984
Epoch 12/60
48000/48000 [==============================] - 114s 2ms/step - loss: 0.2784 - acc: 0.8977
- val_loss: 0.2544 - val_acc: 0.9045
Epoch 13/60
48000/48000 [==============================] - 114s 2ms/step - loss: 0.2727 - acc: 0.8974
- val_loss: 0.2455 - val_acc: 0.9111
Epoch 14/60
48000/48000 [==============================] - 114s 2ms/step - loss: 0.2677 - acc: 0.9009
- val_loss: 0.2453 - val_acc: 0.9077
Epoch 15/60
48000/48000 [==============================] - 114s 2ms/step - loss: 0.2629 - acc: 0.9025
- val_loss: 0.2452 - val_acc: 0.9092
Epoch 16/60
48000/48000 [==============================] - 114s 2ms/step - loss: 0.2581 - acc: 0.9033
- val_loss: 0.2384 - val_acc: 0.9113
```

Epoch 17/60
48000/48000 [==============================] - 114s 2ms/step - loss: 0.2504 - acc: 0.9071 - val_loss: 0.2446 - val_acc: 0.9078
Epoch 18/60
48000/48000 [==============================] - 114s 2ms/step - loss: 0.2439 - acc: 0.9075 - val_loss: 0.2342 - val_acc: 0.9124
Epoch 19/60
48000/48000 [==============================] - 121s 3ms/step - loss: 0.2423 - acc: 0.9102 - val_loss: 0.2350 - val_acc: 0.9117
Epoch 20/60
48000/48000 [==============================] - 166s 3ms/step - loss: 0.2359 - acc: 0.9118 - val_loss: 0.2313 - val_acc: 0.9148
Epoch 21/60
48000/48000 [==============================] - 115s 2ms/step - loss: 0.2327 - acc: 0.9125 - val_loss: 0.2285 - val_acc: 0.9173
Epoch 22/60
48000/48000 [==============================] - 114s 2ms/step - loss: 0.2288 - acc: 0.9138 - val_loss: 0.2407 - val_acc: 0.9120
Epoch 23/60
48000/48000 [==============================] - 114s 2ms/step - loss: 0.2255 - acc: 0.9147 - val_loss: 0.2304 - val_acc: 0.9153
Epoch 24/60
48000/48000 [==============================] - 114s 2ms/step - loss: 0.2211 - acc: 0.9170 - val_loss: 0.2294 - val_acc: 0.9141
Epoch 25/60
48000/48000 [==============================] - 114s 2ms/step - loss: 0.2161 - acc: 0.9184 - val_loss: 0.2224 - val_acc: 0.9188
Epoch 26/60
48000/48000 [==============================] - 114s 2ms/step - loss: 0.2129 - acc: 0.9210 - val_loss: 0.2213 - val_acc: 0.9185
Epoch 27/60
48000/48000 [==============================] - 115s 2ms/step - loss: 0.2128 - acc: 0.9198 - val_loss: 0.2181 - val_acc: 0.9199
Epoch 28/60
48000/48000 [==============================] - 114s 2ms/step - loss: 0.2079 - acc: 0.9219 - val_loss: 0.2227 - val_acc: 0.9168
Epoch 29/60
48000/48000 [==============================] - 115s 2ms/step - loss: 0.2055 - acc: 0.9230 - val_loss: 0.2184 - val_acc: 0.9205
Epoch 30/60
48000/48000 [==============================] - 114s 2ms/step - loss: 0.2002 - acc: 0.9252 - val_loss: 0.2215 - val_acc: 0.9182
Epoch 31/60
48000/48000 [==============================] - 114s 2ms/step - loss: 0.1980 - acc: 0.9250 - val_loss: 0.2150 - val_acc: 0.9216
Epoch 32/60
48000/48000 [==============================] - 114s 2ms/step - loss: 0.1963 - acc: 0.9264 - val_loss: 0.2171 - val_acc: 0.9221
Epoch 33/60
48000/48000 [==============================] - 114s 2ms/step - loss: 0.1929 - acc: 0.9274

```
- val_loss: 0.2205 - val_acc: 0.9191
Epoch 34/60
48000/48000 [==============================] - 115s 2ms/step - loss: 0.1894 - acc: 0.9290
- val_loss: 0.2174 - val_acc: 0.9205
Epoch 35/60
48000/48000 [==============================] - 114s 2ms/step - loss: 0.1926 - acc: 0.9271
- val_loss: 0.2203 - val_acc: 0.9200
Epoch 36/60
48000/48000 [==============================] - 113s 2ms/step - loss: 0.1886 - acc: 0.9287
- val_loss: 0.2154 - val_acc: 0.9203
Epoch 37/60
48000/48000 [==============================] - 113s 2ms/step - loss: 0.1866 - acc: 0.9298
- val_loss: 0.2099 - val_acc: 0.9233
Epoch 38/60
48000/48000 [==============================] - 113s 2ms/step - loss: 0.1841 - acc: 0.9313
- val_loss: 0.2199 - val_acc: 0.9207
Epoch 39/60
48000/48000 [==============================] - 113s 2ms/step - loss: 0.1791 - acc: 0.9318
- val_loss: 0.2158 - val_acc: 0.9238
Epoch 40/60
48000/48000 [==============================] - 114s 2ms/step - loss: 0.1808 - acc: 0.9309
- val_loss: 0.2148 - val_acc: 0.9223
Epoch 41/60
48000/48000 [==============================] - 114s 2ms/step - loss: 0.1774 - acc: 0.9321
- val_loss: 0.2121 - val_acc: 0.9230
Epoch 42/60
48000/48000 [==============================] - 114s 2ms/step - loss: 0.1735 - acc: 0.9345
- val_loss: 0.2186 - val_acc: 0.9219
Epoch 43/60
48000/48000 [==============================] - 115s 2ms/step - loss: 0.1717 - acc: 0.9350
- val_loss: 0.2147 - val_acc: 0.9237
Epoch 44/60
48000/48000 [==============================] - 115s 2ms/step - loss: 0.1727 - acc: 0.9337
- val_loss: 0.2139 - val_acc: 0.9232
Epoch 45/60
48000/48000 [==============================] - 115s 2ms/step - loss: 0.1693 - acc: 0.9358
- val_loss: 0.2163 - val_acc: 0.9232
Epoch 46/60
48000/48000 [==============================] - 114s 2ms/step - loss: 0.1685 - acc: 0.9352
- val_loss: 0.2272 - val_acc: 0.9208
Epoch 47/60
48000/48000 [==============================] - 115s 2ms/step - loss: 0.1687 - acc: 0.9355
- val_loss: 0.2120 - val_acc: 0.9248
Epoch 48/60
48000/48000 [==============================] - 116s 2ms/step - loss: 0.1645 - acc: 0.9376
- val_loss: 0.2144 - val_acc: 0.9249
Epoch 49/60
48000/48000 [==============================] - 114s 2ms/step - loss: 0.1601 - acc: 0.9387
- val_loss: 0.2196 - val_acc: 0.9222
Epoch 50/60
```

48000/48000 [==============================] - 113s 2ms/step - loss: 0.1601 - acc: 0.9395 - val_loss: 0.2180 - val_acc: 0.9246
Epoch 51/60
48000/48000 [==============================] - 114s 2ms/step - loss: 0.1622 - acc: 0.9380 - val_loss: 0.2214 - val_acc: 0.9242
Epoch 52/60
48000/48000 [==============================] - 113s 2ms/step - loss: 0.1606 - acc: 0.9389 - val_loss: 0.2234 - val_acc: 0.9227
Epoch 53/60
48000/48000 [==============================] - 114s 2ms/step - loss: 0.1604 - acc: 0.9387 - val_loss: 0.2119 - val_acc: 0.9254
Epoch 54/60
48000/48000 [==============================] - 115s 2ms/step - loss: 0.1530 - acc: 0.9417 - val_loss: 0.2236 - val_acc: 0.9217
Epoch 55/60
48000/48000 [==============================] - 114s 2ms/step - loss: 0.1552 - acc: 0.9405 - val_loss: 0.2234 - val_acc: 0.9217
Epoch 56/60
48000/48000 [==============================] - 171s 4ms/step - loss: 0.1539 - acc: 0.9416 - val_loss: 0.2150 - val_acc: 0.9249
Epoch 57/60
48000/48000 [==============================] - 113s 2ms/step - loss: 0.1517 - acc: 0.9409 - val_loss: 0.2281 - val_acc: 0.9213
Epoch 58/60
48000/48000 [==============================] - 113s 2ms/step - loss: 0.1517 - acc: 0.9425 - val_loss: 0.2248 - val_acc: 0.9222
Epoch 59/60
48000/48000 [==============================] - 113s 2ms/step - loss: 0.1485 - acc: 0.9422 - val_loss: 0.2140 - val_acc: 0.9272
Epoch 60/60
48000/48000 [==============================] - 114s 2ms/step - loss: 0.1532 - acc: 0.9420 - val_loss: 0.2170 - val_acc: 0.9264

<keras.callbacks.History at 0x7fad365e9358>

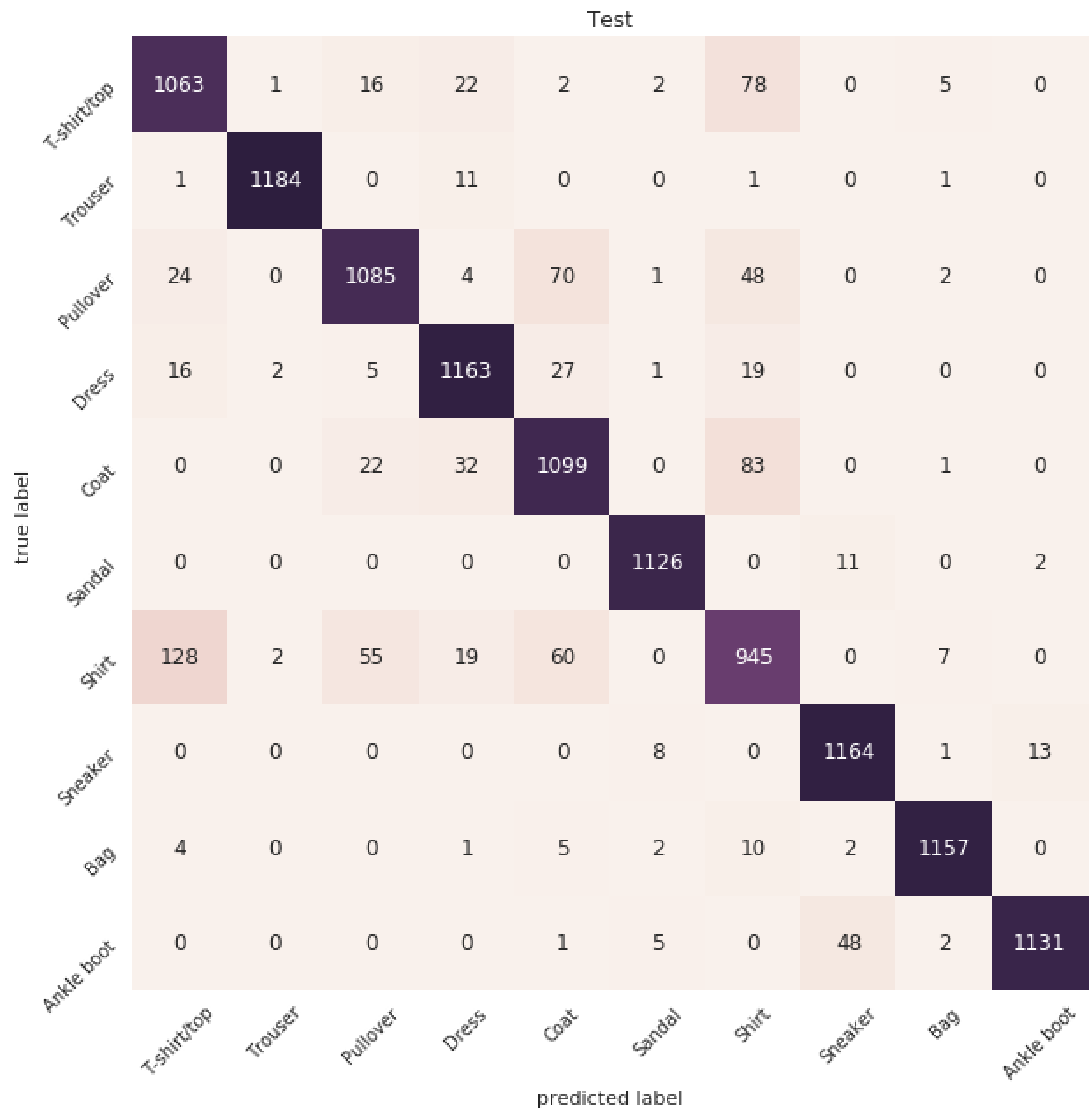
```
----------------CNN train--------------
48000/48000 [==============================] - 30s 624us/step
Score is  0.972625
             precision    recall  f1-score   support

T-shirt/top       0.94      0.96      0.95      4811
    Trouser       1.00      1.00      1.00      4802
   Pullover       0.97      0.93      0.95      4766
      Dress       0.98      0.98      0.98      4767
       Coat       0.93      0.97      0.95      4763
     Sandal       1.00      1.00      1.00      4861
      Shirt       0.92      0.91      0.91      4784
    Sneaker       0.98      1.00      0.99      4814
        Bag       1.00      1.00      1.00      4819
 Ankle boot       1.00      0.98      0.99      4813

avg / total       0.97      0.97      0.97     48000

----------------------------------------------------
----------------CNN test-------------
12000/12000 [==============================] - 8s 625us/step
Score is  0.9264166666666667
             precision    recall  f1-score   support

T-shirt/top       0.86      0.89      0.88      1189
    Trouser       1.00      0.99      0.99      1198
   Pullover       0.92      0.88      0.90      1234
      Dress       0.93      0.94      0.94      1233
       Coat       0.87      0.89      0.88      1237
     Sandal       0.98      0.99      0.99      1139
      Shirt       0.80      0.78      0.79      1216
    Sneaker       0.95      0.98      0.97      1186
        Bag       0.98      0.98      0.98      1181
 Ankle boot       0.99      0.95      0.97      1187

avg / total       0.93      0.93      0.93     12000

----------------------------------------------------
```

```
# For train
generate_confusion_matrix(y_training, prob_train_cnn,"Train")
```

```
/usr/local/envs/py3env/lib/python3.5/site-packages/matplotlib/font_manager.py:1320: UserWarni
ng: findfont: Font family ['sans-serif'] not found. Falling back to DejaVu Sans
  (prop.get_family(), self.defaultFamily[fontext]))
```

```
# For test
generate_confusion_matrix(y_validate, prob_test_cnn,"Test")
```

```
/usr/local/envs/py3env/lib/python3.5/site-packages/matplotlib/font_manager.py:1320: UserWarning: findfont: Font family ['sans-serif'] not found. Falling back to DejaVu Sans
  (prop.get_family(), self.defaultFamily[fontext]))
```



Developing a Random Forest classifier

With Non PCA data

```
# HyperParmeter search space for grid search
estimators = [50, 100, 150]
depth = [20, 50 ,70]

# Create hyperparameter dictionary
hyperparameters = dict(n_estimators=estimators, max_depth=depth)

# Defining default rates
# best_result = {
#     'n_estimators': 100,
#     'max_depth': 50
# }
# Since parameter tuning is a time consuming process, this has been done on my local system. Using valu
es from that run as parameters in cloud.
best_result = {
    'n_estimators': 150,
    'max_depth': 70
}
```

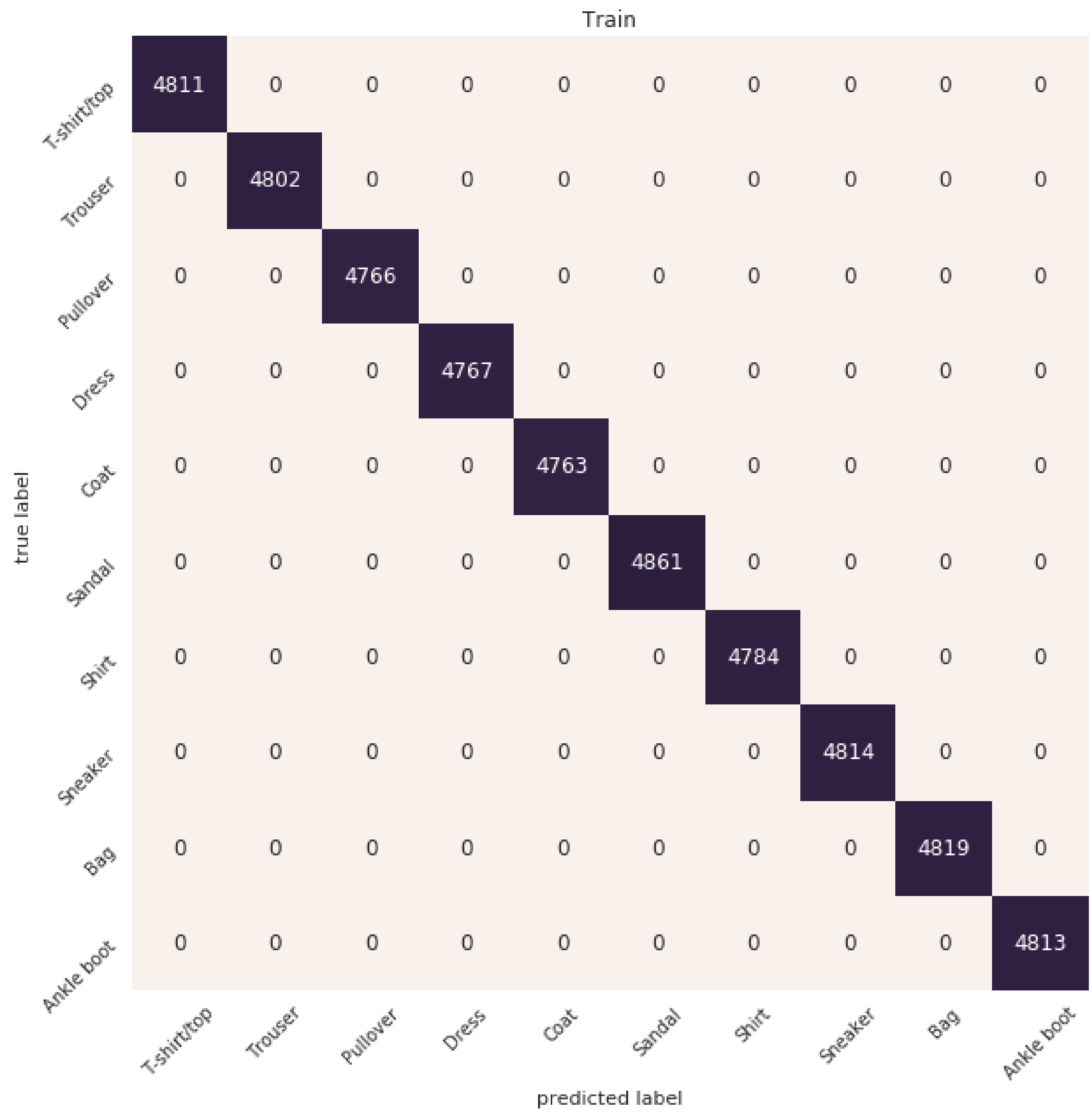
```
# rfc = RandomForestClassifier()

# # Performing Grid Search
# grid = GridSearchCV(estimator=rfc, param_grid=hyperparameters, n_jobs=-1, scoring="accuracy")

# # Fit grid search
# grid_result = grid.fit(X_training, y_training)

# # Hyperparameters of best neural network
# best_result = grid_result.best_params_

# print("Best parameters are: ", best_result)

# Since parameter tuning is a time consuming process, this has been done on my local system. Using valu
es from that run as parameters in cloud.
```

```
# Create RN
rnd_clf = RandomForestClassifier(n_estimators=best_result['n_estimators'], max_depth=best_result[
'max_depth'])

# Train the RN
rnd_clf.fit(X_training, y_training)

# Train data
prob_train_rf = rnd_clf.predict(X_training)
metrics_generator(rnd_clf,X_training,"RF train",y_training,prob_train_rf)

# Test data
prob_test_rf = rnd_clf.predict(X_validate)
metrics_generator(rnd_clf,X_validate,"RF test",y_validate,prob_test_rf)
```

```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=70, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=150, n_jobs=1,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False)

----------------RF train--------------
Score is  1.0
             precision    recall  f1-score   support

T-shirt/top       1.00      1.00      1.00      4811
    Trouser       1.00      1.00      1.00      4802
   Pullover       1.00      1.00      1.00      4766
      Dress       1.00      1.00      1.00      4767
       Coat       1.00      1.00      1.00      4763
     Sandal       1.00      1.00      1.00      4861
      Shirt       1.00      1.00      1.00      4784
    Sneaker       1.00      1.00      1.00      4814
        Bag       1.00      1.00      1.00      4819
 Ankle boot       1.00      1.00      1.00      4813

avg / total       1.00      1.00      1.00     48000

-----------------------------------------------------
----------------RF test--------------
Score is  0.8805833333333334
             precision    recall  f1-score   support

T-shirt/top       0.81      0.86      0.83      1189
    Trouser       1.00      0.97      0.98      1198
   Pullover       0.79      0.82      0.81      1234
      Dress       0.88      0.93      0.90      1233
       Coat       0.78      0.84      0.81      1237
     Sandal       0.97      0.96      0.96      1139
      Shirt       0.74      0.57      0.64      1216
    Sneaker       0.93      0.95      0.94      1186
        Bag       0.95      0.97      0.96      1181
 Ankle boot       0.96      0.95      0.95      1187

avg / total       0.88      0.88      0.88     12000

-----------------------------------------------------
```

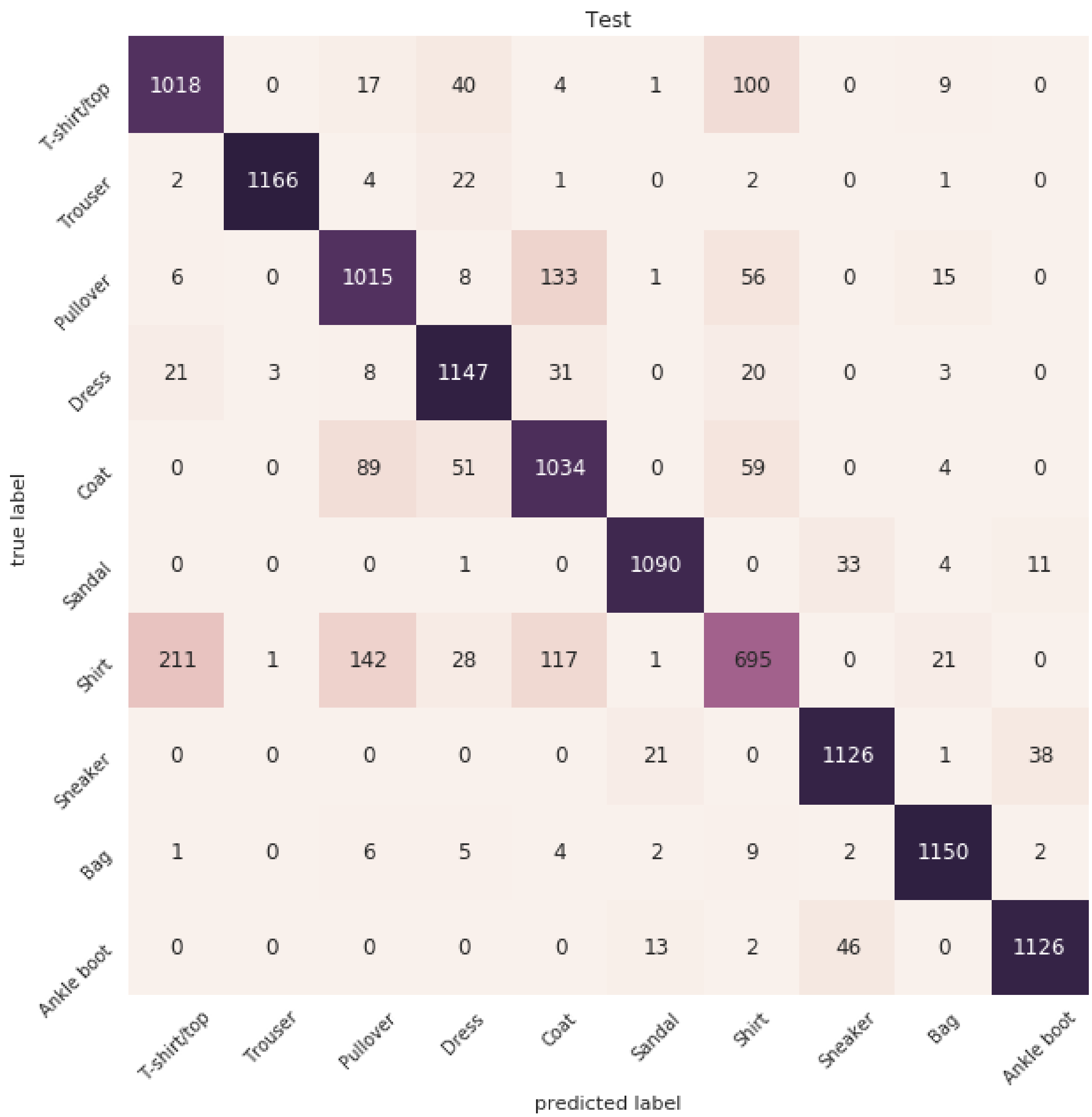
```
# For train
generate_confusion_matrix(y_training, prob_train_rf,"Train")
```

```
/usr/local/envs/py3env/lib/python3.5/site-packages/matplotlib/font_manager.py:1320: UserWarni
ng: findfont: Font family ['sans-serif'] not found. Falling back to DejaVu Sans
  (prop.get_family(), self.defaultFamily[fontext]))
```



```
# For test
generate_confusion_matrix(y_validate, prob_test_rf,"Test")
```

```
/usr/local/envs/py3env/lib/python3.5/site-packages/matplotlib/font_manager.py:1320: UserWarni
ng: findfont: Font family ['sans-serif'] not found. Falling back to DejaVu Sans
  (prop.get_family(), self.defaultFamily[fontext]))
```



With PCA Data

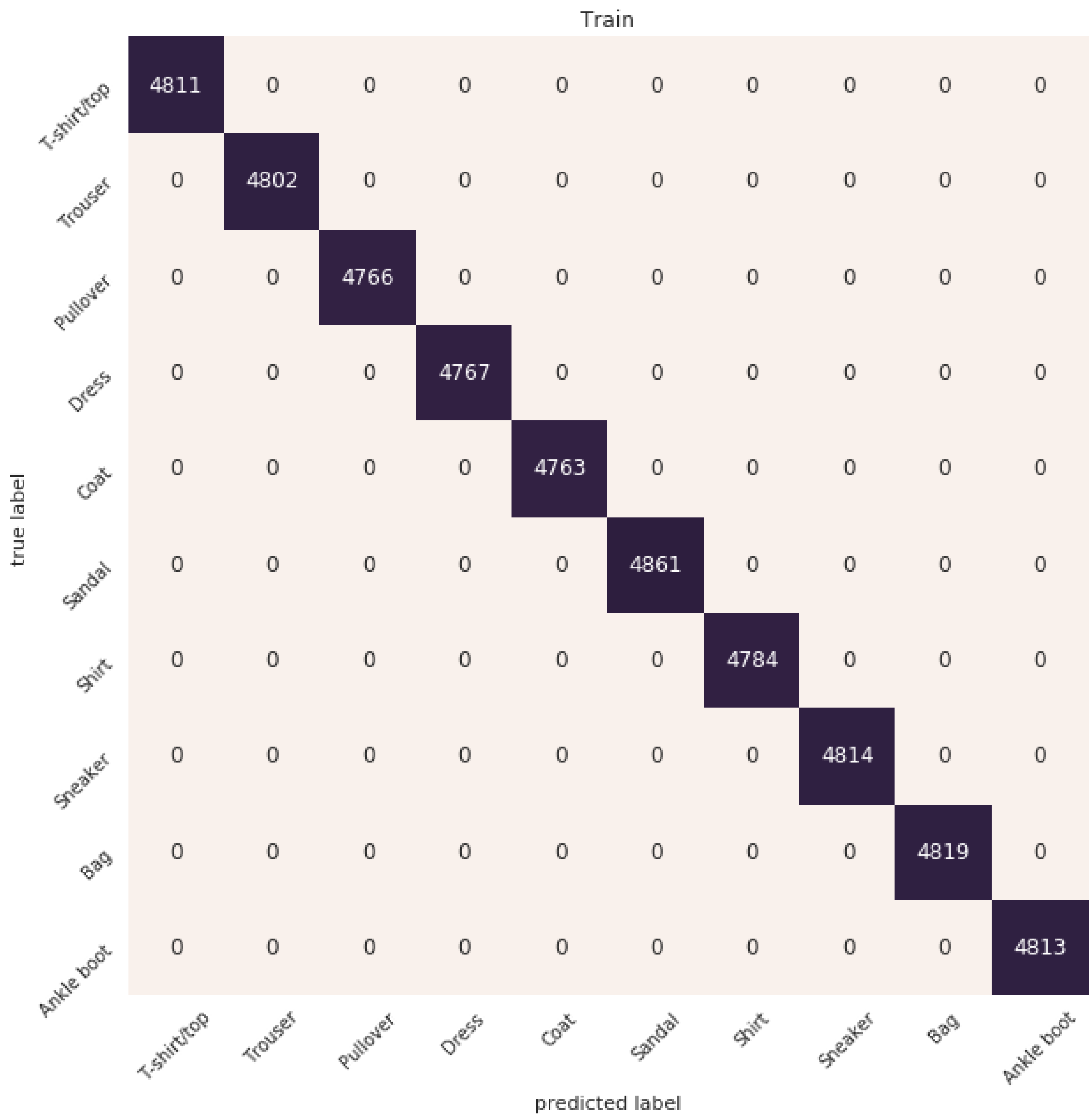
```
# rfc = RandomForestClassifier()

# # Performing Grid Search
# grid = GridSearchCV(estimator=rfc, param_grid=hyperparameters, n_jobs=-1, scoring="accuracy")

# # Fit grid search
# grid_result = grid.fit(X_training_reduced, y_training_reduced)

# # Hyperparameters of best neural network
# best_result = grid_result.best_params_

# print("Best parameters are: ", best_result)

# Since parameter tuning is a time consuming process, this has been done on my local system. Using valu
es from that run as parameters in cloud.
best_result = {
    'n_estimators': 150,
    'max_depth': 50
}
```

```
# Create RN
rnd_clf_reduced = RandomForestClassifier(n_estimators=best_result['n_estimators'], max_depth=bes
t_result['max_depth'])

# Train the RN
rnd_clf_reduced.fit(X_training_reduced, y_training_reduced)

# Train data
prob_train_rf_reduced = rnd_clf_reduced.predict(X_training_reduced)
metrics_generator(rnd_clf_reduced,X_training_reduced,"PCA RF train",y_training,prob_train_rf_re
duced)

# Test data
prob_test_rf_reduced = rnd_clf_reduced.predict(X_validate_reduced)
metrics_generator(rnd_clf_reduced,X_validate_reduced,"PCA RF test",y_validate,prob_test_rf_redu
ced)
```

```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=50, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=150, n_jobs=1,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False)

----------------PCA RF train--------------
Score is  1.0
             precision    recall  f1-score   support

T-shirt/top       1.00      1.00      1.00      4811
    Trouser       1.00      1.00      1.00      4802
   Pullover       1.00      1.00      1.00      4766
      Dress       1.00      1.00      1.00      4767
       Coat       1.00      1.00      1.00      4763
     Sandal       1.00      1.00      1.00      4861
      Shirt       1.00      1.00      1.00      4784
    Sneaker       1.00      1.00      1.00      4814
        Bag       1.00      1.00      1.00      4819
 Ankle boot       1.00      1.00      1.00      4813

avg / total       1.00      1.00      1.00     48000

------------------------------------------------------
----------------PCA RF test--------------
Score is  0.8525833333333334
             precision    recall  f1-score   support

T-shirt/top       0.77      0.84      0.80      1189
    Trouser       1.00      0.96      0.98      1198
   Pullover       0.78      0.81      0.79      1234
      Dress       0.85      0.91      0.88      1233
       Coat       0.77      0.79      0.78      1237
     Sandal       0.91      0.91      0.91      1139
      Shirt       0.70      0.53      0.60      1216
    Sneaker       0.92      0.91      0.92      1186
        Bag       0.90      0.94      0.92      1181
 Ankle boot       0.93      0.94      0.93      1187

avg / total       0.85      0.85      0.85     12000

------------------------------------------------------
```

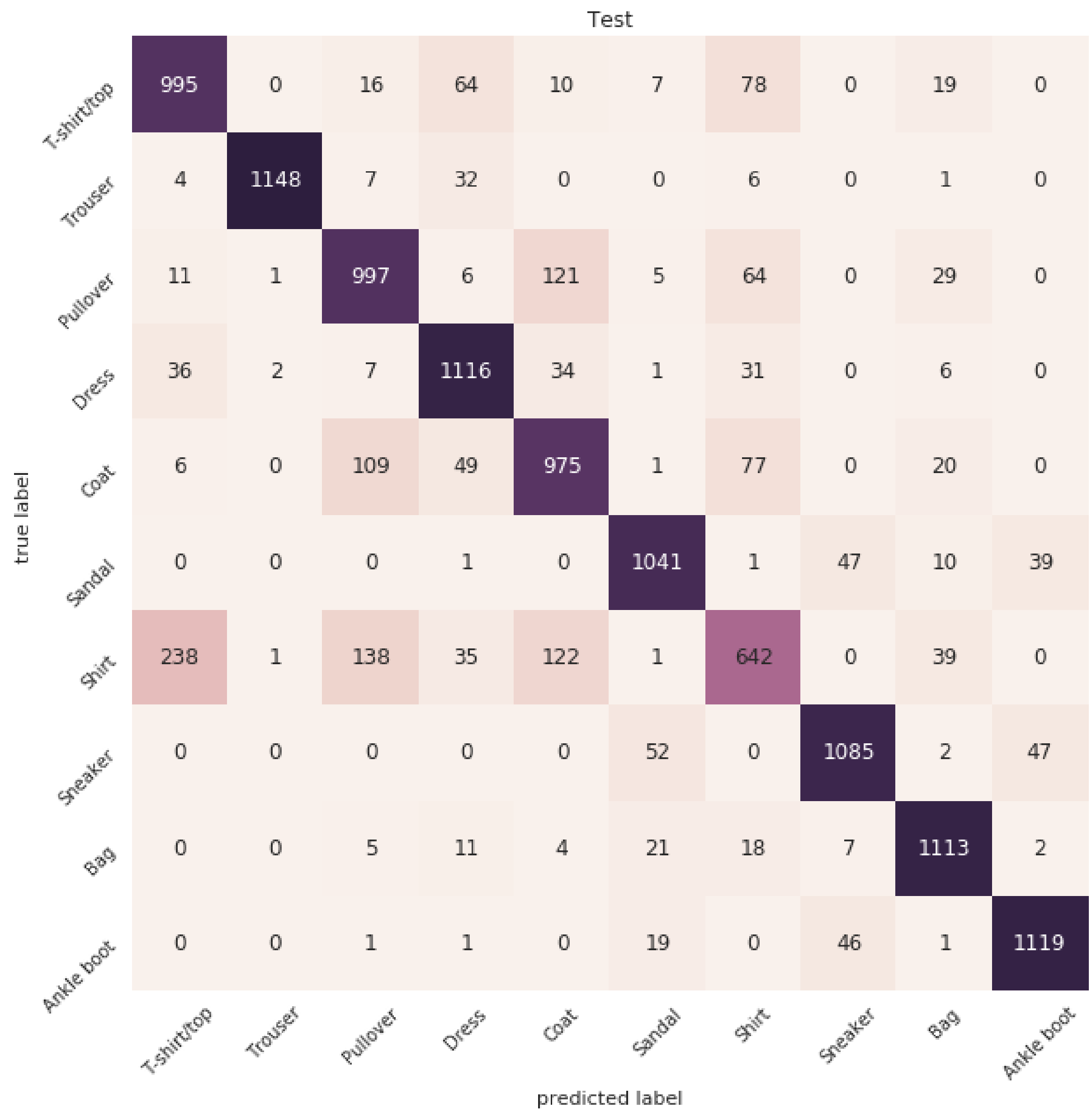
```
# For train
generate_confusion_matrix(y_training_reduced, prob_train_rf_reduced,"Train")
```

```
/usr/local/envs/py3env/lib/python3.5/site-packages/matplotlib/font_manager.py:1320: UserWarni
ng: findfont: Font family ['sans-serif'] not found. Falling back to DejaVu Sans
  (prop.get_family(), self.defaultFamily[fontext]))
```



```
# For test
generate_confusion_matrix(y_validate_reduced, prob_test_rf_reduced,"Test")
```

```
/usr/local/envs/py3env/lib/python3.5/site-packages/matplotlib/font_manager.py:1320: UserWarni
ng: findfont: Font family ['sans-serif'] not found. Falling back to DejaVu Sans
  (prop.get_family(), self.defaultFamily[fontext]))
```



Testing all generated model against the Test data set and comparing their performance.

1. **Logistic Regression without PCA.**
2. **Logistic Regression with PCA.**
3. **KNN without PCA(Hyperparameter tuned).**
4. **KNN with PCA(Hyperparameter tuned).**
5. **3 layer CNN(Hyperparameter tuned using Grid Search).**
6. **Random Forest without PCA(Hyperparameter tuned using Grid Search).**
7. **Random Forest with PCA(Hyperparameter tuned using Grid Search).**

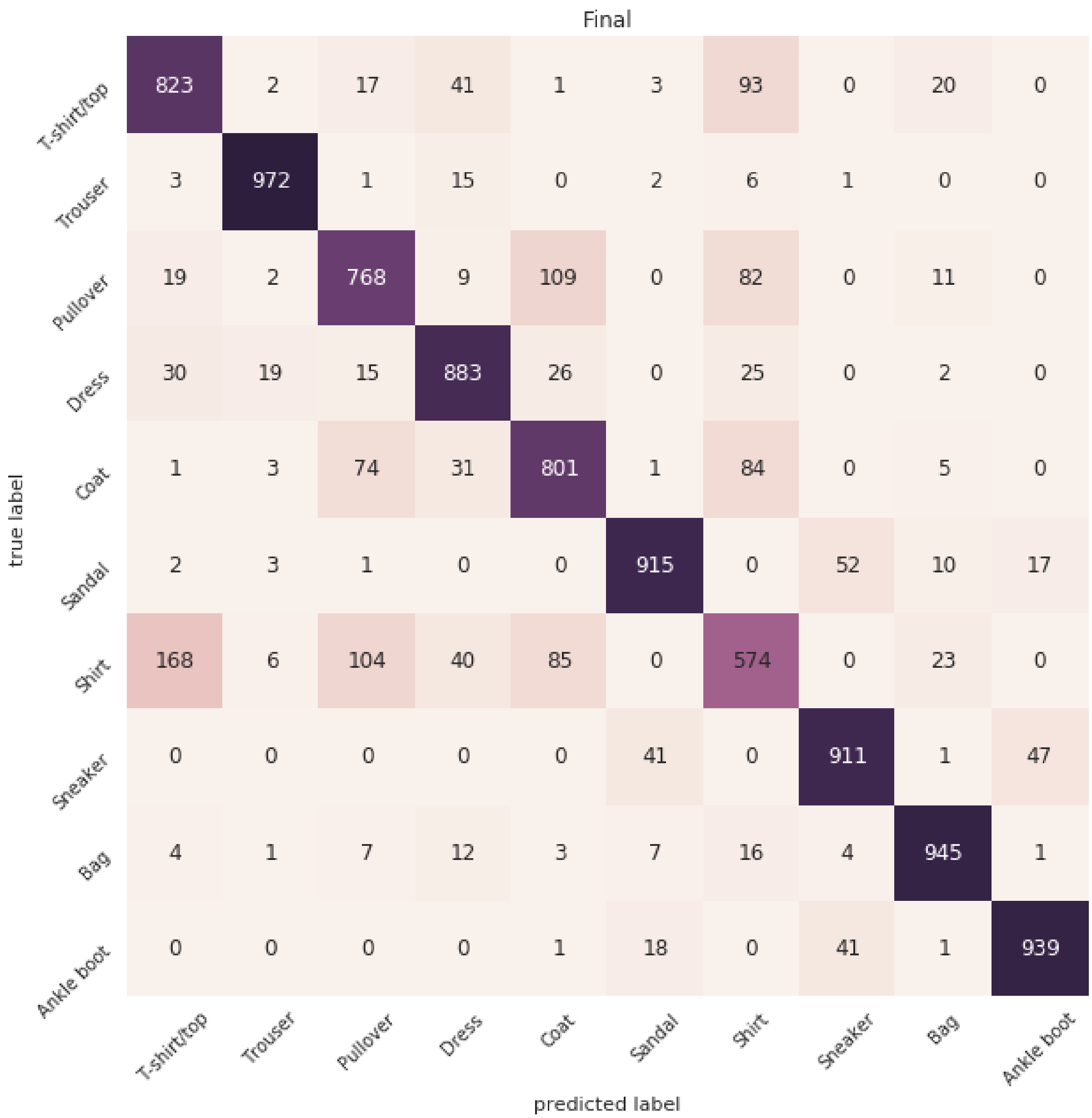
Logistic Regression without PCA

```
prob_final = logreg.predict(X_test)
metrics_generator(logreg,X_test,"Logistic regression final",y_test,prob_final)
```

```
----------------Logistic regression final--------------
Score is  0.8531
             precision    recall  f1-score   support

T-shirt/top       0.78      0.82      0.80      1000
    Trouser       0.96      0.97      0.97      1000
   Pullover       0.78      0.77      0.77      1000
      Dress       0.86      0.88      0.87      1000
       Coat       0.78      0.80      0.79      1000
     Sandal       0.93      0.92      0.92      1000
      Shirt       0.65      0.57      0.61      1000
    Sneaker       0.90      0.91      0.91      1000
        Bag       0.93      0.94      0.94      1000
 Ankle boot       0.94      0.94      0.94      1000

avg / total       0.85      0.85      0.85     10000

-------------------------------------------------------
```

```
# For train
generate_confusion_matrix(y_test, prob_final,"Final")
```

```
/usr/local/envs/py3env/lib/python3.5/site-packages/matplotlib/font_manager.py:1320: UserWarning: findfont: Font family ['sans-serif'] not found. Falling back to DejaVu Sans
  (prop.get_family(), self.defaultFamily[fontext]))
```



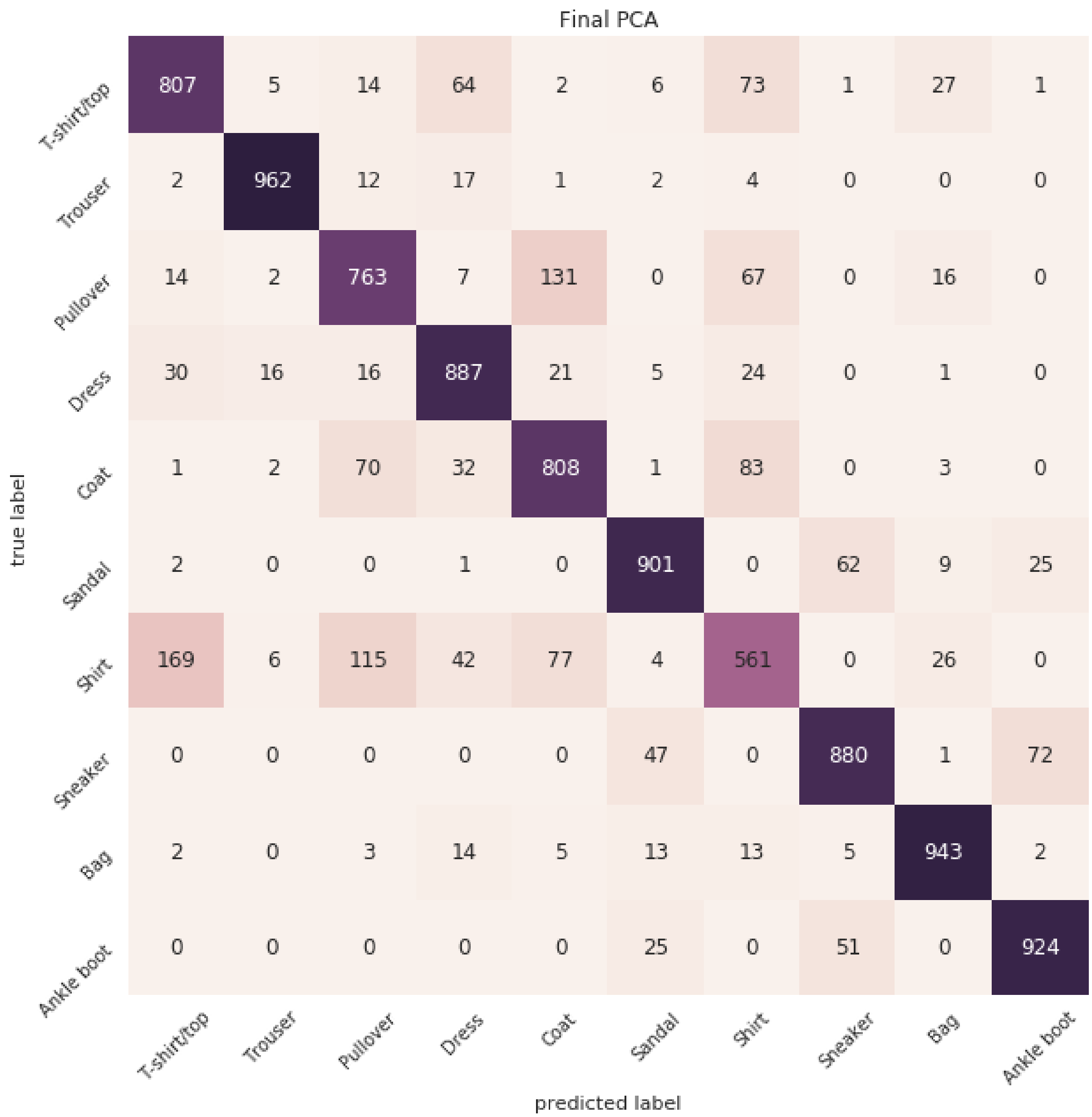
Logistic Regression with PCA

```
# Test data
prob_final_reduced = logreg_reduced.predict(X_test_reduced)
metrics_generator(logreg_reduced,X_test_reduced,"PCA Logistic regression final",y_test,prob_final_
reduced)
```

```
----------------PCA Logistic regression final--------------
Score is  0.8436
             precision    recall  f1-score   support

T-shirt/top       0.79      0.81      0.80      1000
    Trouser       0.97      0.96      0.97      1000
   Pullover       0.77      0.76      0.77      1000
      Dress       0.83      0.89      0.86      1000
       Coat       0.77      0.81      0.79      1000
     Sandal       0.90      0.90      0.90      1000
      Shirt       0.68      0.56      0.61      1000
    Sneaker       0.88      0.88      0.88      1000
        Bag       0.92      0.94      0.93      1000
 Ankle boot       0.90      0.92      0.91      1000

avg / total       0.84      0.84      0.84     10000

-------------------------------------------------------
```

```
# For final
generate_confusion_matrix(y_test, prob_final_reduced,"Final PCA")
```

```
/usr/local/envs/py3env/lib/python3.5/site-packages/matplotlib/font_manager.py:1320: UserWarni
ng: findfont: Font family ['sans-serif'] not found. Falling back to DejaVu Sans
  (prop.get_family(), self.defaultFamily[fontext]))
```



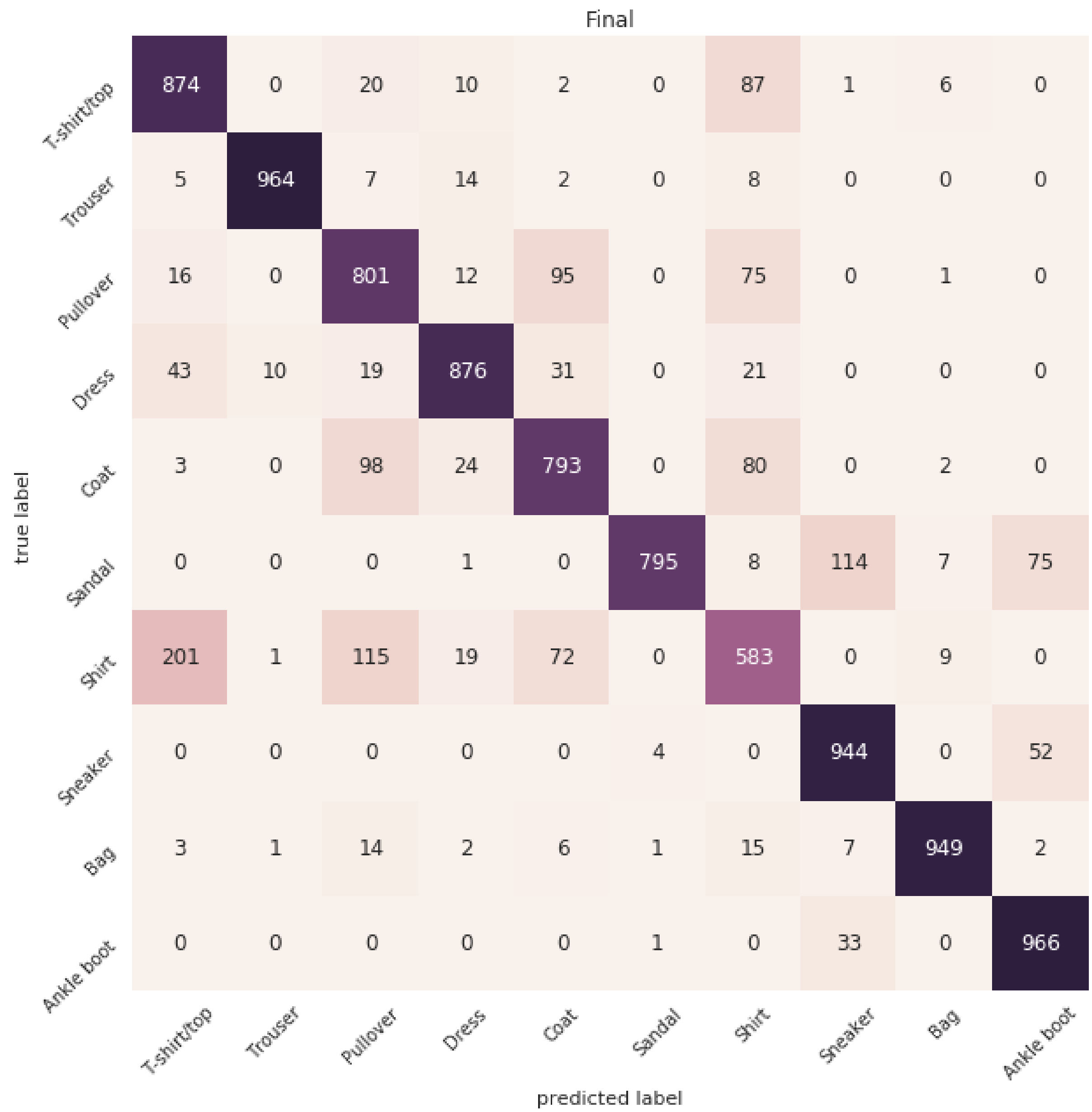
KNN without PCA(Hyperparameter tuned)

```
# Test data
prob_final_knn = knn.predict(X_test)
metrics_generator(knn,X_test,"KNN final",y_test,prob_final_knn)
```

```
----------------KNN final--------------
Score is  0.8545
             precision    recall  f1-score   support

T-shirt/top       0.76      0.87      0.81      1000
    Trouser       0.99      0.96      0.98      1000
   Pullover       0.75      0.80      0.77      1000
      Dress       0.91      0.88      0.89      1000
       Coat       0.79      0.79      0.79      1000
     Sandal       0.99      0.80      0.88      1000
      Shirt       0.66      0.58      0.62      1000
    Sneaker       0.86      0.94      0.90      1000
        Bag       0.97      0.95      0.96      1000
 Ankle boot       0.88      0.97      0.92      1000

avg / total       0.86      0.85      0.85     10000

----------------------------------------------------
```

```
# For final
generate_confusion_matrix(y_test, prob_final_knn,"Final")
```

```
/usr/local/envs/py3env/lib/python3.5/site-packages/matplotlib/font_manager.py:1320: UserWarni
ng: findfont: Font family ['sans-serif'] not found. Falling back to DejaVu Sans
  (prop.get_family(), self.defaultFamily[fontext]))
```



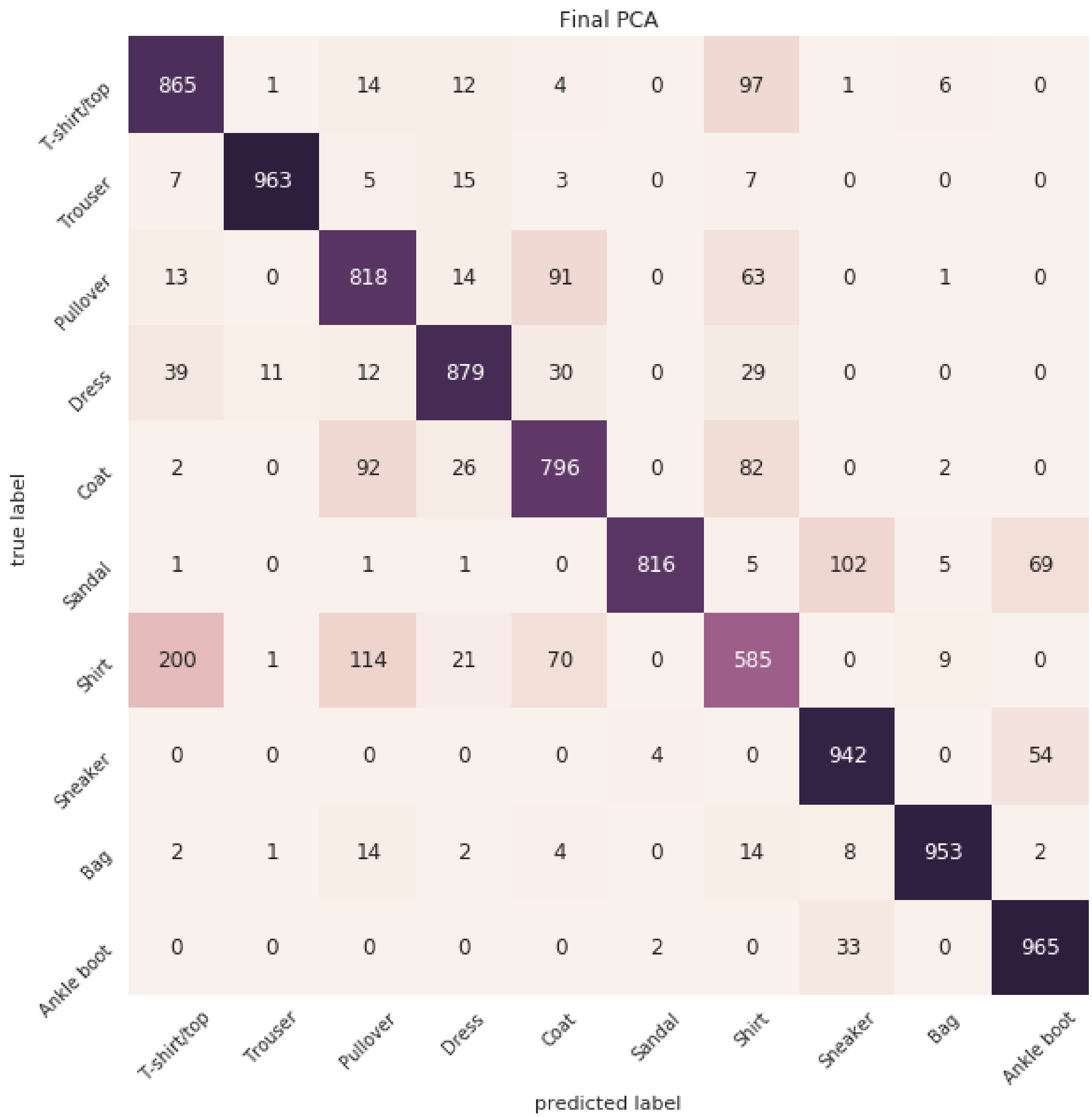
KNN with PCA(Hyperparameter tuned)

```
# Test data
prob_final_knn_reduced = knn_reduced.predict(X_test_reduced)
metrics_generator(knn_reduced,X_test_reduced,"PCA KNN final",y_test,prob_final_knn_reduced)
```

```
----------------PCA KNN final--------------
Score is  0.8582
             precision    recall  f1-score   support

T-shirt/top       0.77      0.86      0.81      1000
    Trouser       0.99      0.96      0.97      1000
   Pullover       0.76      0.82      0.79      1000
      Dress       0.91      0.88      0.89      1000
       Coat       0.80      0.80      0.80      1000
     Sandal       0.99      0.82      0.90      1000
      Shirt       0.66      0.58      0.62      1000
    Sneaker       0.87      0.94      0.90      1000
        Bag       0.98      0.95      0.96      1000
 Ankle boot       0.89      0.96      0.92      1000

avg / total       0.86      0.86      0.86     10000

--------------------------------------------------------
```

```python
# For final
generate_confusion_matrix(y_test, prob_final_knn_reduced,"Final PCA")
```

```
/usr/local/envs/py3env/lib/python3.5/site-packages/matplotlib/font_manager.py:1320: UserWarni
ng: findfont: Font family ['sans-serif'] not found. Falling back to DejaVu Sans
  (prop.get_family(), self.defaultFamily[fontext]))
```



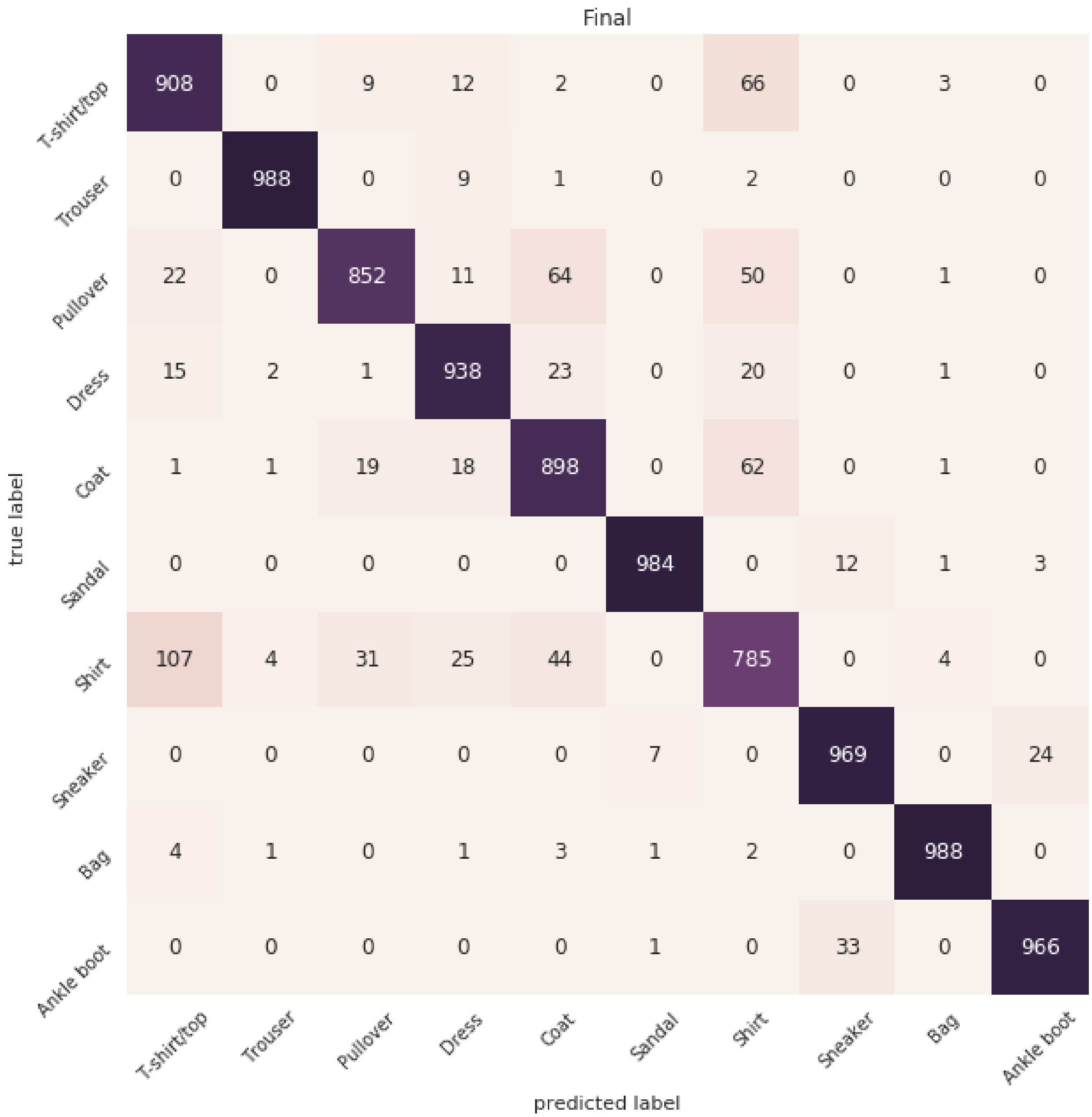
3 layer CNN(Hyperparameter tuned using Grid Search)

```
# Reshape the data
testX = X_test.reshape((X_test.shape[0], 28, 28, 1))

# one-hot encode the training and testing labels
testY = np_utils.to_categorical(y_test, len(labels))

# Test data
prob_final_cnn = cnn.predict_classes(testX)
metrics_generator(cnn,testX,"CNN final",y_test,prob_final_cnn,True,testY)
```

```
----------------CNN final--------------
10000/10000 [==============================] - 6s 626us/step
Score is  0.9276
             precision    recall  f1-score   support

T-shirt/top       0.86      0.91      0.88      1000
    Trouser       0.99      0.99      0.99      1000
   Pullover       0.93      0.85      0.89      1000
      Dress       0.93      0.94      0.93      1000
       Coat       0.87      0.90      0.88      1000
     Sandal       0.99      0.98      0.99      1000
      Shirt       0.80      0.79      0.79      1000
    Sneaker       0.96      0.97      0.96      1000
        Bag       0.99      0.99      0.99      1000
 Ankle boot       0.97      0.97      0.97      1000

avg / total       0.93      0.93      0.93     10000

-------------------------------------------------------
```

```
# For final
generate_confusion_matrix(y_test, prob_final_cnn,"Final")
```

```
/usr/local/envs/py3env/lib/python3.5/site-packages/matplotlib/font_manager.py:1320: UserWarni
ng: findfont: Font family ['sans-serif'] not found. Falling back to DejaVu Sans
  (prop.get_family(), self.defaultFamily[fontext]))
```



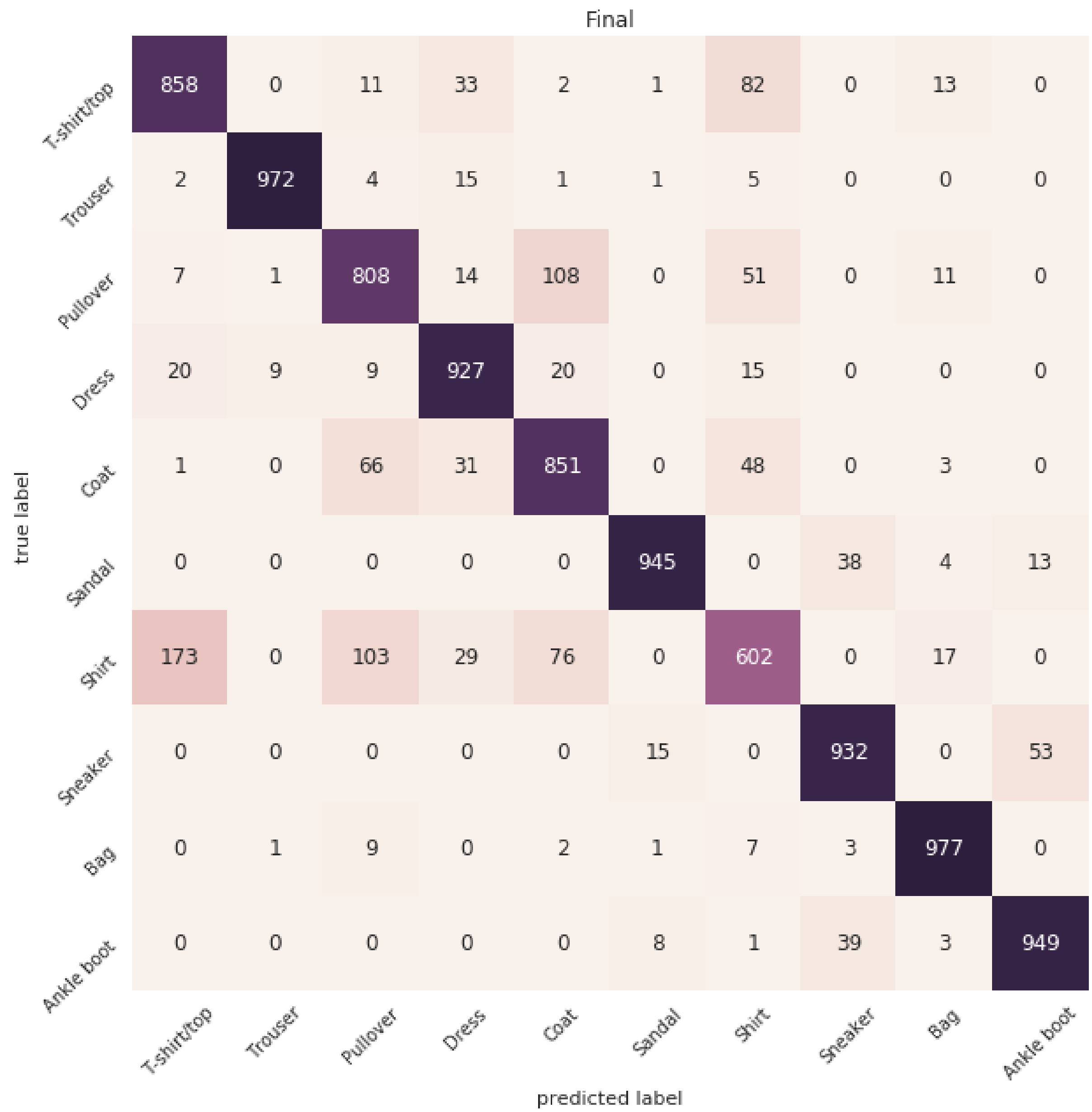
Random Forest without PCA(Hyperparameter tuned using Grid Search)

```
# Test data
prob_final_rf = rnd_clf.predict(X_test)
metrics_generator(rnd_clf,X_test,"RF final",y_test,prob_final_rf)
```

```
----------------RF final--------------
Score is  0.8821
             precision    recall  f1-score   support

T-shirt/top       0.81      0.86      0.83      1000
    Trouser       0.99      0.97      0.98      1000
   Pullover       0.80      0.81      0.80      1000
      Dress       0.88      0.93      0.90      1000
       Coat       0.80      0.85      0.83      1000
     Sandal       0.97      0.94      0.96      1000
      Shirt       0.74      0.60      0.66      1000
    Sneaker       0.92      0.93      0.93      1000
        Bag       0.95      0.98      0.96      1000
 Ankle boot       0.93      0.95      0.94      1000

avg / total       0.88      0.88      0.88     10000

----------------------------------------------------
```

```
# For final
generate_confusion_matrix(y_test, prob_final_rf,"Final")
```

```
/usr/local/envs/py3env/lib/python3.5/site-packages/matplotlib/font_manager.py:1320: UserWarni
ng: findfont: Font family ['sans-serif'] not found. Falling back to DejaVu Sans
  (prop.get_family(), self.defaultFamily[fontext]))
```



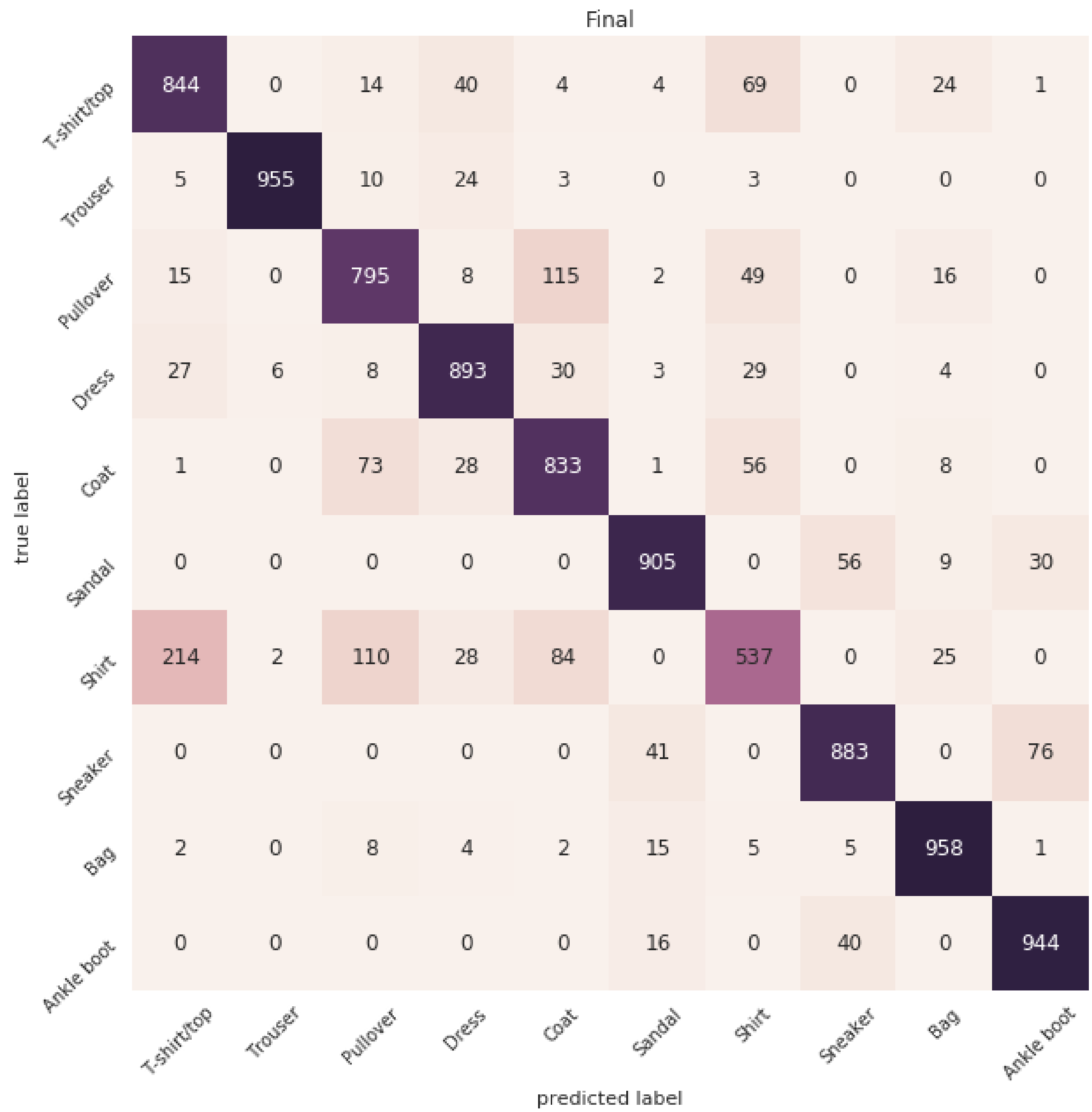
Random Forest with PCA(Hyperparameter tuned using Grid Search)

```
# Test data
prob_final_rf_reduced = rnd_clf_reduced.predict(X_test_reduced)
metrics_generator(rnd_clf_reduced,X_test_reduced,"PCA RF final",y_test,prob_final_rf_reduced)
```

```
----------------PCA RF final--------------
Score is  0.8547
             precision    recall  f1-score   support

T-shirt/top       0.76      0.84      0.80      1000
    Trouser       0.99      0.95      0.97      1000
   Pullover       0.78      0.80      0.79      1000
      Dress       0.87      0.89      0.88      1000
       Coat       0.78      0.83      0.80      1000
     Sandal       0.92      0.91      0.91      1000
      Shirt       0.72      0.54      0.61      1000
    Sneaker       0.90      0.88      0.89      1000
        Bag       0.92      0.96      0.94      1000
 Ankle boot       0.90      0.94      0.92      1000

avg / total       0.85      0.85      0.85     10000

---------------------------------------------------
```

```
# For final
generate_confusion_matrix(y_test, prob_final_rf_reduced,"Final")
```

```
/usr/local/envs/py3env/lib/python3.5/site-packages/matplotlib/font_manager.py:1320: UserWarni
ng: findfont: Font family ['sans-serif'] not found. Falling back to DejaVu Sans
  (prop.get_family(), self.defaultFamily[fontext]))
```



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7. https://chrisalbon.com/deep_learning/keras/tuning_neural_network_hyperparameters/ (https://chrisalbon.com/deep_learning/keras/tuning_neural_network_hyperparameters/)