Lab_3

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0.1 IST 718 Lab 3

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The research question is can we use algorithms and compute to identify clothing items? Specifically, can we determine which algorithm and compute methodology provides us the most efficient approach for classifying simple fashion images?

- Using the base samples available from Zalando Research:
  - https://github.com/zalandoresearch/fashion-mnist
  - Review the data – clean as appropriate
  - Provide an initial data analysis
- Implement at least two approaches for classifying the digits – examples below:
  - Naïve bayes
  - Neural Networks
  - Keras
  - Azure ML
  - IBM DSX
  - Boosted trees
  - Linear classification
  - Your choice
- Answer the following questions:
  - What is the accuracy of each method?
  - What are the trade-offs of each approach?
  - What is the compute performance of each approach?

Reference links:
https://www.tensorflow.org/tutorials/keras/classification

https://stackoverflow.com/questions/40427435/extract-images-from-idx3-ubyte-file-or-gzip-via-python

http://rasbt.github.io/mlxtend/user_guide/data/loadlocal_mnist/

Datasets: 1. Fashion-MNIST https://github.com/zalandoresearch/fashion-mnist/tree/master/data/fashion

1 Outline:

```
+ Load the dataset
+ Explore the datasets
```

```
    - FASHION-MINST
* Statistical Analysis
* Models
    + Linear classification
    + Logistics regression
    + Support vector
    + Naïve bayes
    + K-Nearest Neighbors
    + Random Forest
    + Keras (ANN - Artificial Neural Network)
    + Keras (CNN - Convolutional Neural Network)
* Final Model
* Questions
* Conclusion
```

2 Load the dataset

[1]:
```
pip install tensorflow-gpu==2.0.0.alpha0
```

```
Collecting tensorflow-gpu==2.0.0.alpha0
  Downloading https://files.pythonhosted.org/packages/1a/66/32cffad0952532
19d53f6b6c2a436637bbe45ac4e7be0244557210dc3918/tensorflow_gpu-2.0.0a0-cp36-cp36m
-manylinux1_x86_64.whl (332.1MB)
     |                 | 332.1MB 52kB/s
Requirement already satisfied: wheel>=0.26 in
/usr/local/lib/python3.6/dist-packages (from tensorflow-gpu==2.0.0.alpha0)
(0.34.2)
Requirement already satisfied: termcolor>=1.1.0 in
/usr/local/lib/python3.6/dist-packages (from tensorflow-gpu==2.0.0.alpha0)
(1.1.0)
Requirement already satisfied: grpcio>=1.8.6 in /usr/local/lib/python3.6/dist-
packages (from tensorflow-gpu==2.0.0.alpha0) (1.27.1)
Requirement already satisfied: keras-applications>=1.0.6 in
/usr/local/lib/python3.6/dist-packages (from tensorflow-gpu==2.0.0.alpha0)
(1.0.8)
Requirement already satisfied: protobuf>=3.6.1 in /usr/local/lib/python3.6/dist-
packages (from tensorflow-gpu==2.0.0.alpha0) (3.10.0)
Requirement already satisfied: astor>=0.6.0 in /usr/local/lib/python3.6/dist-
packages (from tensorflow-gpu==2.0.0.alpha0) (0.8.1)
Requirement already satisfied: absl-py>=0.7.0 in /usr/local/lib/python3.6/dist-
packages (from tensorflow-gpu==2.0.0.alpha0) (0.9.0)
Requirement already satisfied: numpy<2.0,>=1.14.5 in
/usr/local/lib/python3.6/dist-packages (from tensorflow-gpu==2.0.0.alpha0)
(1.17.5)
Requirement already satisfied: six>=1.10.0 in /usr/local/lib/python3.6/dist-
packages (from tensorflow-gpu==2.0.0.alpha0) (1.12.0)
Requirement already satisfied: keras-preprocessing>=1.0.5 in
```

```
/usr/local/lib/python3.6/dist-packages (from tensorflow-gpu==2.0.0.alpha0)
(1.1.0)
Requirement already satisfied: google-pasta>=0.1.2 in
/usr/local/lib/python3.6/dist-packages (from tensorflow-gpu==2.0.0.alpha0)
(0.1.8)
Collecting tb-nightly<1.14.0a20190302,>=1.14.0a20190301
  Downloading https://files.pythonhosted.org/packages/a9/51/aa1d756644bf46
24c03844115e4ac4058eff77acd786b26315f051a4b195/tb_nightly-1.14.0a20190301-py3-no
ne-any.whl (3.0MB)
     |                  | 3.0MB 20.8MB/s
Requirement already satisfied: gast>=0.2.0 in
/usr/local/lib/python3.6/dist-packages (from tensorflow-gpu==2.0.0.alpha0)
(0.2.2)
Collecting tf-estimator-nightly<1.14.0.dev2019030116,>=1.14.0.dev2019030115
  Downloading https://files.pythonhosted.org/packages/13/82/f16063b4eed210
dc2ab057930ac1da4fbe1e91b7b051a6c8370b401e6ae7/tf_estimator_nightly-1.14.0.dev20
19030115-py2.py3-none-any.whl (411kB)
     |                  | 419kB 42.8MB/s
Requirement already satisfied: h5py in /usr/local/lib/python3.6/dist-
packages (from keras-applications>=1.0.6->tensorflow-gpu==2.0.0.alpha0) (2.8.0)
Requirement already satisfied: setuptools in /usr/local/lib/python3.6/dist-
packages (from protobuf>=3.6.1->tensorflow-gpu==2.0.0.alpha0) (45.2.0)
Requirement already satisfied: markdown>=2.6.8 in /usr/local/lib/python3.6/dist-
packages (from tb-nightly<1.14.0a20190302,>=1.14.0a20190301->tensorflow-
gpu==2.0.0.alpha0) (3.2.1)
Requirement already satisfied: werkzeug>=0.11.15 in
/usr/local/lib/python3.6/dist-packages (from tb-
nightly<1.14.0a20190302,>=1.14.0a20190301->tensorflow-gpu==2.0.0.alpha0) (1.0.0)
Installing collected packages: tb-nightly, tf-estimator-nightly, tensorflow-gpu
Successfully installed tb-nightly-1.14.0a20190301 tensorflow-gpu-2.0.0a0 tf-
estimator-nightly-1.14.0.dev2019030115
```

[2]:
```
pip install "numpy<1.17"
```

```
Collecting numpy<1.17
  Downloading https://files.pythonhosted.org/packages/90/b1/ba7e59da253c58
aaf874ea790ae71d6870255a5243010d94688c41618678/numpy-1.16.6-cp36-cp36m-manylinux
1_x86_64.whl (17.4MB)
     |                  | 17.4MB 194kB/s
ERROR: datascience 0.10.6 has requirement folium==0.2.1, but you'll have

folium 0.8.3 which is incompatible.
ERROR: albumentations 0.1.12 has requirement imgaug<0.2.7,>=0.2.5, but

you'll have imgaug 0.2.9 which is incompatible.
Installing collected packages: numpy
  Found existing installation: numpy 1.17.5
    Uninstalling numpy-1.17.5:
      Successfully uninstalled numpy-1.17.5
```

```
Successfully installed numpy-1.16.6
```

[0]:

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import time

pd.set_option('display.max_columns', 50)
pd.set_option('display.max_rows', 300)
```

[4]:

```python
# TensorFlow and tf.keras
import tensorflow as tf
from tensorflow import keras
print(tf.__version__)
```

```
/usr/local/lib/python3.6/dist-
packages/tensorflow/python/framework/dtypes.py:523: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of
numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint8 = np.dtype([("qint8", np.int8, 1)])
/usr/local/lib/python3.6/dist-
packages/tensorflow/python/framework/dtypes.py:524: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of
numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint8 = np.dtype([("quint8", np.uint8, 1)])
/usr/local/lib/python3.6/dist-
packages/tensorflow/python/framework/dtypes.py:525: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of
numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint16 = np.dtype([("qint16", np.int16, 1)])
/usr/local/lib/python3.6/dist-
packages/tensorflow/python/framework/dtypes.py:526: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of
numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint16 = np.dtype([("quint16", np.uint16, 1)])
/usr/local/lib/python3.6/dist-
packages/tensorflow/python/framework/dtypes.py:527: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of
numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint32 = np.dtype([("qint32", np.int32, 1)])
/usr/local/lib/python3.6/dist-
packages/tensorflow/python/framework/dtypes.py:532: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of
numpy, it will be understood as (type, (1,)) / '(1,)type'.
  np_resource = np.dtype([("resource", np.ubyte, 1)])
```

```
2.0.0-alpha0
```

```
/usr/local/lib/python3.6/dist-
packages/tensorboard/compat/tensorflow_stub/dtypes.py:541: FutureWarning:
Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future
version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint8 = np.dtype([("qint8", np.int8, 1)])
/usr/local/lib/python3.6/dist-
packages/tensorboard/compat/tensorflow_stub/dtypes.py:542: FutureWarning:
Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future
version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint8 = np.dtype([("quint8", np.uint8, 1)])
/usr/local/lib/python3.6/dist-
packages/tensorboard/compat/tensorflow_stub/dtypes.py:543: FutureWarning:
Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future
version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint16 = np.dtype([("qint16", np.int16, 1)])
/usr/local/lib/python3.6/dist-
packages/tensorboard/compat/tensorflow_stub/dtypes.py:544: FutureWarning:
Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future
version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint16 = np.dtype([("quint16", np.uint16, 1)])
/usr/local/lib/python3.6/dist-
packages/tensorboard/compat/tensorflow_stub/dtypes.py:545: FutureWarning:
Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future
version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint32 = np.dtype([("qint32", np.int32, 1)])
/usr/local/lib/python3.6/dist-
packages/tensorboard/compat/tensorflow_stub/dtypes.py:550: FutureWarning:
Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future
version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  np_resource = np.dtype([("resource", np.ubyte, 1)])
```

[5]:
```python
# Load the fashion-mnist dataset from keras.datasets library
fashion_mnist = keras.datasets.fashion_mnist
(train_images, train_labels), (test_images, test_labels) = fashion_mnist.
 ↪load_data()
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-
datasets/train-labels-idx1-ubyte.gz
32768/29515 [==================================] - 0s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-
datasets/train-images-idx3-ubyte.gz
26427392/26421880 [==============================] - 1s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-
datasets/t10k-labels-idx1-ubyte.gz
8192/5148 [================================================] - 0s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-
datasets/t10k-images-idx3-ubyte.gz
4423680/4422102 [==============================] - 0s 0us/step
```

2.0.1 Normalizing the images

We need to divide each pixel value of the image in the training and test sets by the maximum number of pixel values (255).

In this way each pixel value will be in the range [0, 1]. By normalizing images it can help make sure that models train faster and perform better.

[0]:
```
# Normalizing the images
train_images = train_images / 255.0
test_images = test_images /255.0
```

2.0.2 Reshaping the dataset

[7]:
```
print('Before reshape:')
# training set shape info
print('Shape of the training set (images): {}'.format(train_images.shape))
print('Shape of the training set (labels): {}'.format(train_labels.shape))

# test set shape info
print('Shape of the test set (images): {}'.format(test_images.shape))
print('Shape of the test set (labels): {}'.format(test_labels.shape))
```

```
Before reshape:
Shape of the training set (images): (60000, 28, 28)
Shape of the training set (labels): (60000,)
Shape of the test set (images): (10000, 28, 28)
Shape of the test set (labels): (10000,)
```

[0]:
```
# Reshape the training set and the test set to be into the vector format
# Since each image's dimension is 28x28, we reshape the full dataset to [-1␣
↪(all elements), height * width]
train_images = train_images.reshape(-1, 28*28)
test_images = test_images.reshape(-1, 28*28)
```

[9]:
```
print('After reshape:')
# training set shape info
print('Shape of the training set (images): {}'.format(train_images.shape))
print('Shape of the training set (labels): {}'.format(train_labels.shape))

# test set shape info
print('Shape of the test set (images): {}'.format(test_images.shape))
print('Shape of the test set (labels): {}'.format(test_labels.shape))
```

```
After reshape:
Shape of the training set (images): (60000, 784)
Shape of the training set (labels): (60000,)
Shape of the test set (images): (10000, 784)
Shape of the test set (labels): (10000,)
```

2.0.3 Shuffling index

By shuffling the training set, it helps adjust the combination of weights in neural network running in batches.

[0]:
```
shuffle_index = np.random.permutation(60000)
train_images, train_labels = train_images[shuffle_index],␣
↪train_labels[shuffle_index]
```

3 Explore the datasets

[0]:
```
label = ['T-shirt/top', 'Trouser', 'Pullover', 'Dress',
         'Coat', 'Sandal', 'Shirt', 'Sneaker', 'Bag', 'Ankle boo']
label_encode = [0,1,2,3,4,5,6,7,8,9]
```

What the outcomes look like?

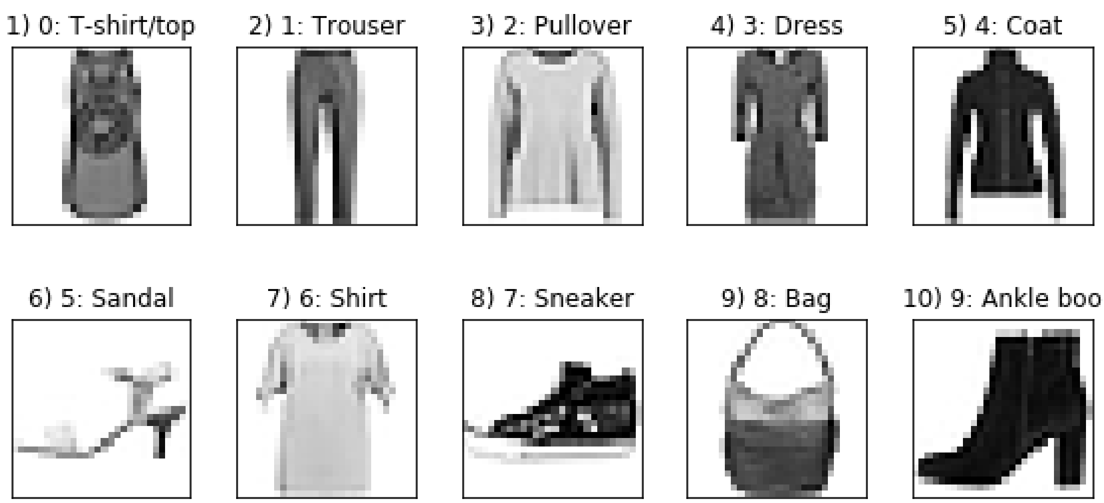
Sinle item

[12]:
```
# Sinle item
cloth = train_images[48765] # select a random number between [0,60000)
# Each image id 28 pixel * 28 pixel;
# thus, the record needs to be reshape to 28*28 to help visualization
cloth_image = cloth.reshape(28,28)
plt.imshow(cloth_image, cmap = plt.cm.binary, interpolation="nearest")
plt.axis("off") # trun off the axises
plt.show()
```

Each of the item

[13]:
```python
# Each of the item
fig, ax = plt.subplots(nrows=2, ncols=5, sharex=True, sharey=True,
                       figsize=(8,4) )
ax = ax.flatten()
for i in range(10):
    img = train_images[train_labels == i][0].reshape(28,28)
    ax[i].imshow(img, cmap='Greys', interpolation='nearest')
    ax[i].set_title('{}) {}: {}'.format(i+1, label_encode[i], label[i]))

ax[0].set_xticks([])
ax[0].set_yticks([])
plt.tight_layout()
plt.savefig('cloth_mnist_all.png', dpi=300)
plt.show()
```



Variation of an item

[14]:
```python
# Variation of an item (Coat)
fig, ax = plt.subplots(nrows=5, ncols=5, sharex=True, sharey=True,
                       figsize=(8,8))
ax = ax.flatten()
for i in range(25):
    img = train_images[train_labels == 4][i].reshape(28, 28)
    ax[i].imshow(img, cmap='Greys', interpolation='nearest')
    ax[i].set_title('Style {}'.format(i+1))

ax[0].set_xticks([])
ax[0].set_yticks([])
plt.suptitle('Coat', fontsize=15)
```

```
plt.tight_layout(rect=[0, 0.03, 1, 0.95])
plt.savefig('cloth_mnist_coat.png', dpi=300)
plt.show()
```

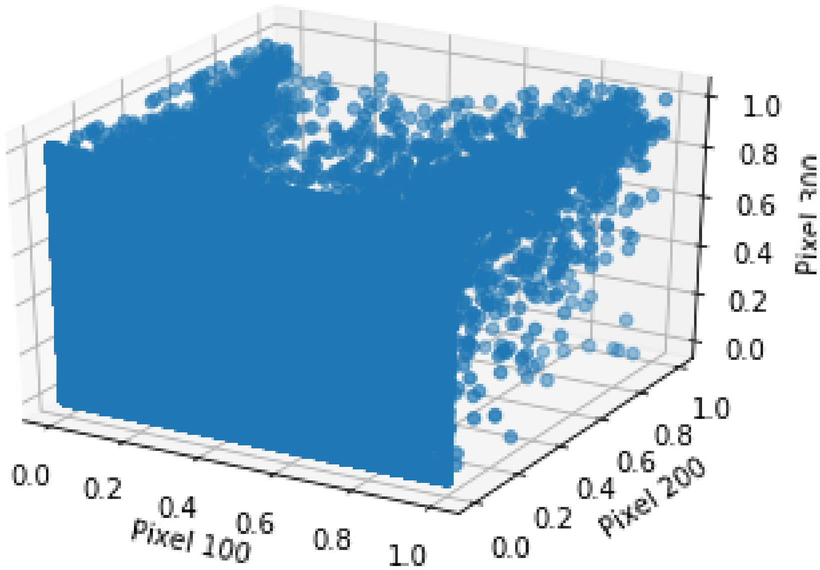
[15]:
```
# portion of 3d plot
from mpl_toolkits.mplot3d import Axes3D
fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')

ax.scatter(train_images[:,99], train_images[:,199], train_images[:,299])

ax.set_xlabel('Pixel 100')
```

```
ax.set_ylabel('Pixel 200')
ax.set_zlabel('Pixel 300')

plt.show()
```



4 Statistical Analysis

4.1 Outcome Distribution

4.1.1 Create lables_df (entire dataset)

[0]:
```
labels_dic = {0:'T-shirt/top', 1:'Trouser', 2:'Pullover', 3:'Dress', 4:'Coat',␣
↪5:'Sandal',
              6:'Shirt', 7:'Sneaker', 8:'Bag', 9:'Ankle boo'}
```

[0]:
```
labels_df = pd.DataFrame(pd.concat([pd.Series(train_labels),pd.
↪Series(test_labels)]) , columns=['outcome'])
labels_df['label'] = labels_df['outcome'].map(labels_dic)
```

[18]:
```
labels_df.head()
```

[18]:

	outcome	label
0	5	Sandal
1	4	Coat
2	6	Shirt
3	7	Sneaker
4	4	Coat

4.1.2 Create label_df_train

[0]:
```
labels_df_train = pd.DataFrame(train_labels , columns=['outcome'])
labels_df_train['label'] = labels_df_train['outcome'].map(labels_dic)
```

4.1.3 Create label_df_test

[0]:
```
labels_df_test = pd.DataFrame(test_labels , columns=['outcome'])
labels_df_test['label'] = labels_df_test['outcome'].map(labels_dic)
```

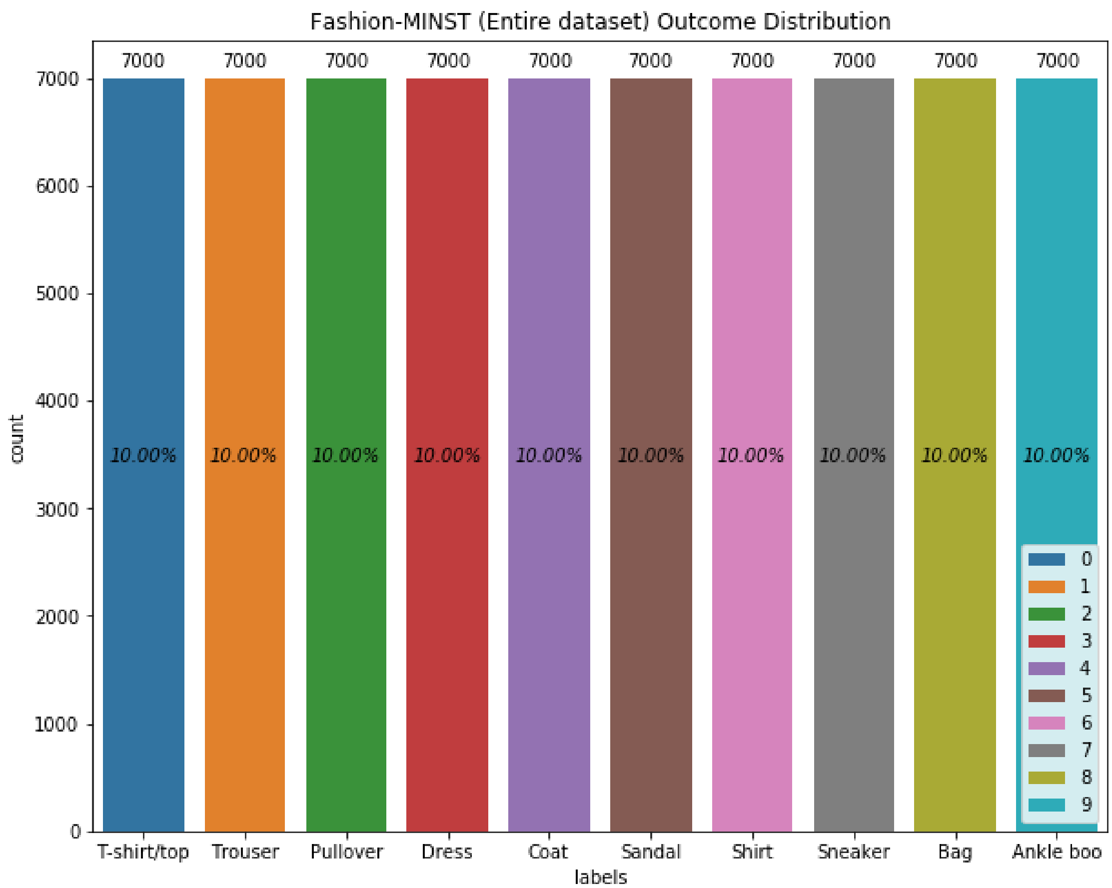
4.1.4 Create plots

[21]:
```
# Control plt figure size
plt.figure(figsize=(10,8))

# Plot the countplot
ax=sns.countplot(x='outcome', hue='outcome',data=labels_df, dodge=False,
                 hue_order=[0,1,2,3,4,5,6,7,8,9] ,
                 order=[0,1,2,3,4,5,6,7,8,9]
                 )

# set title of the plot, x-axis label, xticklabels, and legend
ax.set_title('Fashion-MINST (Entire dataset) Outcome Distribution');
ax.legend(loc='lower right')
ax.set_xticklabels(['T-shirt/top', 'Trouser', 'Pullover', 'Dress',
          'Coat', 'Sandal', 'Shirt', 'Sneaker', 'Bag', 'Ankle boo'])
ax.set_xlabel('labels')

# annotate the count/percentage of each column
total = (labels_df).shape[0]
for p in ax.patches:
    percentage = '{:.2f}%'.format(100 * p.get_height()/total)
    coutns = '{:.0f}'.format(p.get_height())
    x = p.get_x() + p.get_width()/2
    y = p.get_y() + p.get_height()
    ax.annotate(percentage, (x, y/2), ha='center',␣
 ↪va='center_baseline',style='italic')
    ax.annotate(coutns, (x, y+100), ha='center', va='baseline')
```



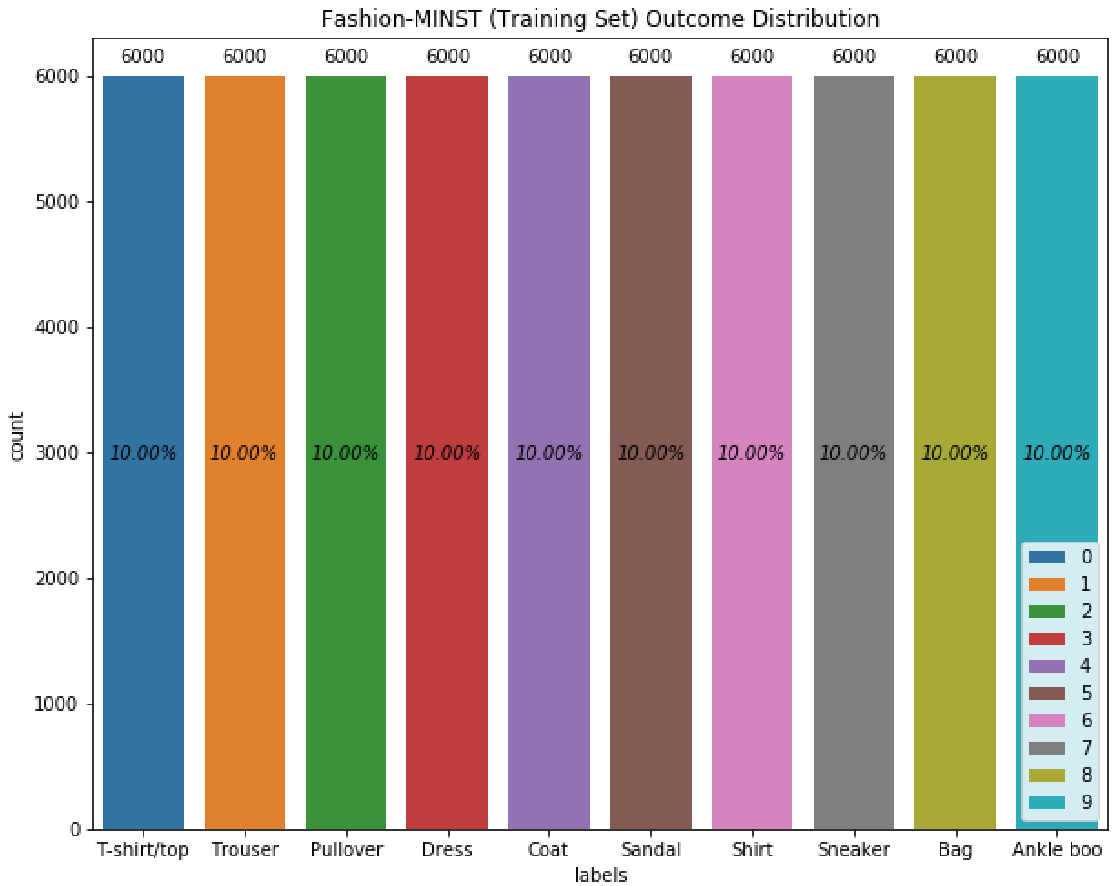
[22]:
```
# Control plt figure size
plt.figure(figsize=(10,8))

# Plot the countplot
ax=sns.countplot(x='outcome', hue='outcome',data=labels_df_train, dodge=False,
                 hue_order=[0,1,2,3,4,5,6,7,8,9]  ,
                 order=[0,1,2,3,4,5,6,7,8,9]
                 )

# set title of the plot, x-axis label, xticklabels, and legend
ax.set_title('Fashion-MINST (Training Set) Outcome Distribution');
ax.legend(loc='lower right')
ax.set_xticklabels(['T-shirt/top', 'Trouser', 'Pullover', 'Dress',
          'Coat', 'Sandal', 'Shirt', 'Sneaker', 'Bag', 'Ankle boo'])
ax.set_xlabel('labels')

# annotate the count/percentage of each column
total = (labels_df_train).shape[0]
for p in ax.patches:
```

```
    percentage = '{:.2f}%'.format(100 * p.get_height()/total)
    coutns = '{:.0f}'.format(p.get_height())
    x = p.get_x() + p.get_width()/2
    y = p.get_y() + p.get_height()
    ax.annotate(percentage, (x, y/2), ha='center',␣
↪va='center_baseline',style='italic')
    ax.annotate(coutns, (x, y+100), ha='center', va='baseline')
```



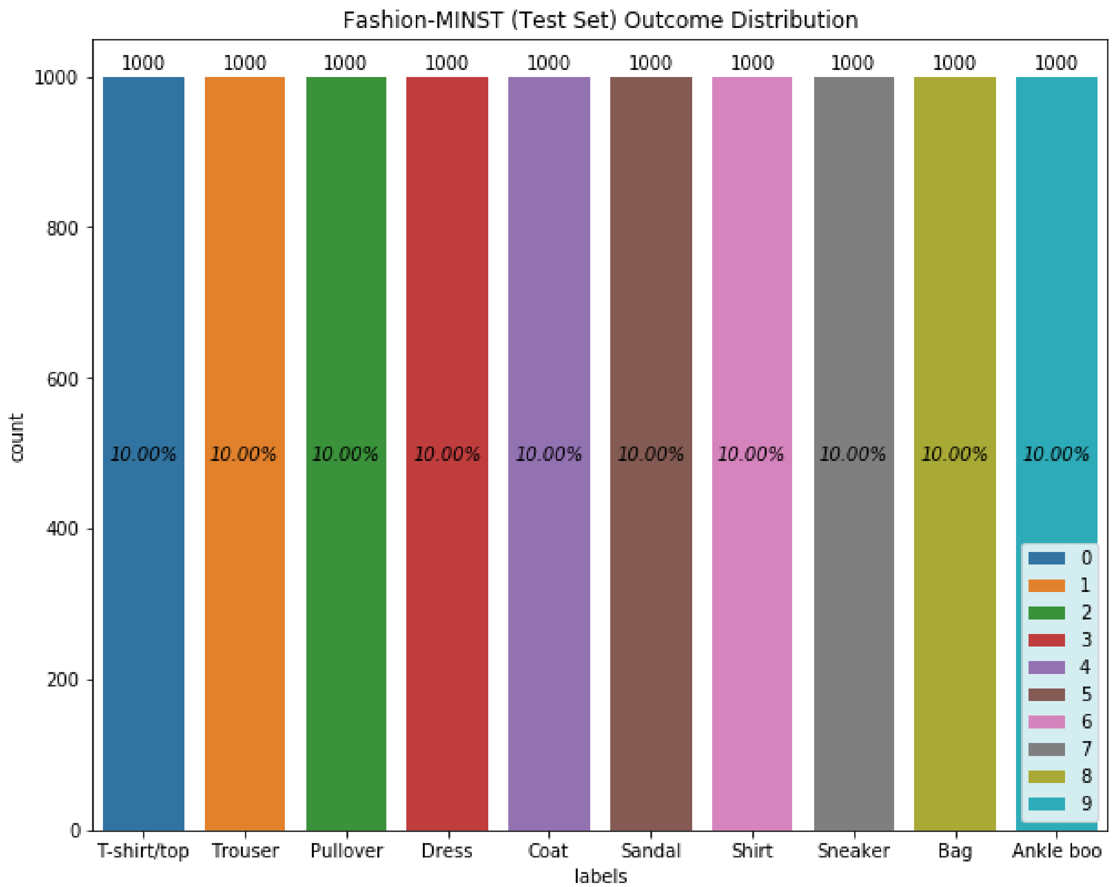
[23]:
```
# Control plt figure size
plt.figure(figsize=(10,8))

# Plot the countplot
ax=sns.countplot(x='outcome', hue='outcome',data=labels_df_test, dodge=False,
                 hue_order=[0,1,2,3,4,5,6,7,8,9] ,
                 order=[0,1,2,3,4,5,6,7,8,9]
                 )

# set title of the plot, x-axis label, xticklabels, and legend
ax.set_title('Fashion-MINST (Test Set) Outcome Distribution');
```

```python
ax.legend(loc='lower right')
ax.set_xticklabels(['T-shirt/top', 'Trouser', 'Pullover', 'Dress',
          'Coat', 'Sandal', 'Shirt', 'Sneaker', 'Bag', 'Ankle boo'])
ax.set_xlabel('labels')

# annotate the count/percentage of each column
total = (labels_df_test).shape[0]
for p in ax.patches:
    percentage = '{:.2f}%'.format(100 * p.get_height()/total)
    coutns = '{:.0f}'.format(p.get_height())
    x = p.get_x() + p.get_width()/2
    y = p.get_y() + p.get_height()
    ax.annotate(percentage, (x, y/2), ha='center',␣
 ↪va='center_baseline',style='italic')
    ax.annotate(coutns, (x, y+10), ha='center', va='baseline')
```



Each category is evenly distributed within the training set and test set.

5 Models

5.1 Linear classification

[0]:
```
from sklearn import linear_model
lclf = linear_model.SGDClassifier(max_iter=1000)
```

[25]:
```
start = time.time()

lclf_fit = lclf.fit(train_images, train_labels)

end = time.time()
final_time = end-start
print('\n')
print('Training time:{}'.format(final_time))
```

```
Training time:31.080594778060913
```

[26]:
```
start = time.time()

lclf_pred = lclf.predict(test_images)

end = time.time()
final_time = end-start
print('\n')
print('Testing time:{}'.format(final_time))
```

```
Testing time:0.035745859146118164
```

[27]:
```
# Confusion Matrix
from sklearn.metrics import confusion_matrix
confusion_matrix = confusion_matrix(test_labels, lclf_pred)
print(confusion_matrix)
```

```
[[770   5  22  19   1   4 168   0  11   0]
 [  4 962   8  17   1   0   5   1   2   0]
 [ 14   3 771   4  56   0 144   1   7   0]
 [ 41  32  27 749   9   0 134   0   8   0]
 [  1   5 179  20 482   0 303   0  10   0]
 [  3   0   2   0   0 919   0  43  11  22]
 [111   2 136  17  37   0 676   0  21   0]
 [  1   0   0   0   0  38   0 913   2  46]
 [  5   1   7   6   1   7  31   3 938   1]
 [  1   1   0   2   0  33   4  35   1 923]]
```

[28]:
```python
# Classification Report
from sklearn.metrics import classification_report
print(classification_report(test_labels, lclf_pred, digits=4))
```

```
              precision    recall  f1-score   support

           0     0.8097    0.7700    0.7893      1000
           1     0.9515    0.9620    0.9567      1000
           2     0.6693    0.7710    0.7165      1000
           3     0.8981    0.7490    0.8168      1000
           4     0.8211    0.4820    0.6074      1000
           5     0.9181    0.9190    0.9185      1000
           6     0.4614    0.6760    0.5485      1000
           7     0.9167    0.9130    0.9148      1000
           8     0.9278    0.9380    0.9329      1000
           9     0.9304    0.9230    0.9267      1000

    accuracy                         0.8103     10000
   macro avg     0.8304    0.8103    0.8128     10000
weighted avg     0.8304    0.8103    0.8128     10000
```

[29]:
```python
from sklearn.metrics import accuracy_score
accuracy_score(test_labels, lclf_pred)
```

[29]: 0.8103

5.2 Logistics regression

[0]:
```python
from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression(solver='lbfgs', max_iter=10000)
```

[31]:
```python
start = time.time()

logreg_fit = logreg.fit(train_images, train_labels)

end = time.time()
final_time = end-start
print('\n')
print('Training time:{}'.format(final_time))
```

```
Training time:751.8370032310486
```

[32]:
```python
start = time.time()
```

```
logreg_pred = logreg.predict(test_images)

end = time.time()
final_time = end-start
print('\n')
print('Testing time:{}'.format(final_time))
```

```
Testing time:0.030037879943847656
```

[33]:
```
# Confusion Matrix
from sklearn.metrics import confusion_matrix
confusion_matrix = confusion_matrix(test_labels, logreg_pred)
print(confusion_matrix)
```

```
[[806   2  11  53   4   2 111   0  11   0]
 [  4 958   3  25   4   0   3   1   2   0]
 [ 24   4 739  10 124   0  86   1  12   0]
 [ 24  17  18 861  30   0  39   0  11   0]
 [  0   2 115  36 763   0  77   0   7   0]
 [  0   0   0   1   0 922   0  48   7  22]
 [143   2 123  38 100   0 571   0  23   0]
 [  0   0   0   0   0  35   0 939   0  26]
 [  7   1   7  14   5   6  21   5 934   0]
 [  0   1   0   0   0  12   1  38   0 948]]
```

[34]:
```
# Classification Report
from sklearn.metrics import classification_report
print(classification_report(test_labels, logreg_pred, digits=4))
```

```
              precision    recall  f1-score   support

           0     0.7996    0.8060    0.8028      1000
           1     0.9706    0.9580    0.9643      1000
           2     0.7274    0.7390    0.7331      1000
           3     0.8295    0.8610    0.8449      1000
           4     0.7408    0.7630    0.7517      1000
           5     0.9437    0.9220    0.9327      1000
           6     0.6282    0.5710    0.5982      1000
           7     0.9099    0.9390    0.9242      1000
           8     0.9275    0.9340    0.9307      1000
           9     0.9518    0.9480    0.9499      1000

    accuracy                         0.8441     10000
   macro avg     0.8429    0.8441    0.8433     10000
weighted avg     0.8429    0.8441    0.8433     10000
```

[35]:
```
from sklearn.metrics import accuracy_score
accuracy_score(test_labels, logreg_pred)
```

[35]:
```
0.8441
```

5.3 Support vector

[0]:
```
from sklearn.svm import SVC
svc= SVC()
```

[37]:
```
start = time.time()

svc_fit = svc.fit(train_images, train_labels)

end = time.time()
final_time = end-start
print('\n')
print('Training time:{}'.format(final_time))
```

```
Training time:579.6898975372314
```

[38]:
```
start = time.time()

svc_pred = svc.predict(test_images)

end = time.time()
final_time = end-start
print('\n')
print('Testing time:{}'.format(final_time))
```

```
Testing time:207.91561722755432
```

[39]:
```
# Confusion Matrix
from sklearn.metrics import confusion_matrix
confusion_matrix = confusion_matrix(test_labels, svc_pred)
print(confusion_matrix)
```

```
[[857   0  16  28   3   2  85   0   9   0]
 [  4 962   2  25   3   0   4   0   0   0]
 [ 11   2 816  16  88   0  65   0   2   0]
 [ 27   3  11 890  33   0  32   0   4   0]
 [  1   1  87  32 815   0  61   0   3   0]
 [  0   0   0   1   0 951   0  33   1  14]
```

```
[135   1 103  27  68   0 655   0  11   0]
[  0   0   0   0   0  21   0 955   0  24]
[  3   1   1   5   2   2   4   5 977   0]
[  0   0   0   0   0  11   1  37   0 951]]
```

[40]:
```
# Classification Report
from sklearn.metrics import classification_report
print(classification_report(test_labels, svc_pred, digits=4))
```

```
              precision    recall  f1-score   support

           0     0.8256    0.8570    0.8410      1000
           1     0.9918    0.9620    0.9766      1000
           2     0.7876    0.8160    0.8016      1000
           3     0.8691    0.8900    0.8794      1000
           4     0.8053    0.8150    0.8101      1000
           5     0.9635    0.9510    0.9572      1000
           6     0.7222    0.6550    0.6869      1000
           7     0.9272    0.9550    0.9409      1000
           8     0.9702    0.9770    0.9736      1000
           9     0.9616    0.9510    0.9563      1000

    accuracy                         0.8829     10000
   macro avg     0.8824    0.8829    0.8824     10000
weighted avg     0.8824    0.8829    0.8824     10000
```

[41]:
```
from sklearn.metrics import accuracy_score
accuracy_score(test_labels, svc_pred)
```

[41]: 0.8829

5.4 Naïve bayes

[0]:
```
from sklearn.naive_bayes import GaussianNB
gnb = GaussianNB()
```

[43]:
```
start = time.time()

gnb_fit = gnb.fit(train_images, train_labels)

end = time.time()
final_time = end-start
print('\n')
print('Training time:{}'.format(final_time))
```

```
Training time:0.6993002891540527
```

[44]:
```python
start = time.time()

gnb_pred = gnb.predict(test_images)

end = time.time()
final_time = end-start
print('\n')
print('Testing time:{}'.format(final_time))
```

```
Testing time:0.5419938564300537
```

[45]:
```python
# Confusion Matrix
from sklearn.metrics import confusion_matrix
confusion_matrix = confusion_matrix(test_labels, gnb_pred)
print(confusion_matrix)
```

```
[[586  64  29 162 110   0  20   0  29   0]
 [  1 939  14  36   7   0   1   0   2   0]
 [  7  14 324  65 545   0  23   0  22   0]
 [  9 387   6 545  43   0   4   0   6   0]
 [  0  34  44 131 779   0   4   0   8   0]
 [  0   0   1   1   0 278   3 660   5  52]
 [117  34 112 200 435   0  40   0  62   0]
 [  0   0   0   0   0   3   0 988   0   9]
 [  0   2  19  85 149   3  27   4 710   1]
 [  0   0   1   1   0  16   3 304   8 667]]
```

[46]:
```python
# Classification Report
from sklearn.metrics import classification_report
print(classification_report(test_labels, gnb_pred, digits=4))
```

```
              precision    recall  f1-score   support

           0     0.8139    0.5860    0.6814      1000
           1     0.6370    0.9390    0.7591      1000
           2     0.5891    0.3240    0.4181      1000
           3     0.4445    0.5450    0.4897      1000
           4     0.3767    0.7790    0.5078      1000
           5     0.9267    0.2780    0.4277      1000
           6     0.3200    0.0400    0.0711      1000
           7     0.5051    0.9880    0.6685      1000
           8     0.8333    0.7100    0.7667      1000
           9     0.9150    0.6670    0.7715      1000
```

```
    accuracy                         0.5856     10000
   macro avg     0.6361    0.5856    0.5562     10000
weighted avg     0.6361    0.5856    0.5562     10000
```

[47]:
```python
from sklearn.metrics import accuracy_score
accuracy_score(test_labels, gnb_pred)
```

[47]:
```
0.5856
```

5.5 K-Nearest Neighbors

[0]:
```python
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=5)
```

[49]:
```python
start = time.time()

knn.fit(train_images, train_labels)

end = time.time()
final_time = end-start
print('\n')
print('Training time:{}'.format(final_time))
```

```
Training time:11.35332727432251
```

[50]:
```python
start = time.time()

knn_pred = knn.predict(test_images)

end = time.time()
final_time = end-start
print('\n')
print('Testing time:{}'.format(final_time))
```

```
Testing time:771.0947904586792
```

[51]:
```python
# Confusion Matrix
from sklearn.metrics import confusion_matrix
confusion_matrix = confusion_matrix(test_labels, knn_pred)
print(confusion_matrix)
```

```
[[855   1  17  16   3   1 100   1   6   0]
 [  8 968   4  12   4   0   3   0   1   0]
```

```
[ 24   2 819  11  75   0  69   0   0   0]
[ 41   8  15 860  39   0  34   0   3   0]
[  2   1 126  26 773   0  71   0   1   0]
[  1   0   0   0   0 822   5  96   1  75]
[176   1 132  23  80   0 575   0  13   0]
[  0   0   0   0   0   3   0 961   0  36]
[  2   0  10   4   7   0  16   7 953   1]
[  0   0   0   0   0   2   1  29   0 968]]
```

[52]:

```
# Classification Report
from sklearn.metrics import classification_report
print(classification_report(test_labels, knn_pred, digits=4))
```

```
              precision    recall  f1-score   support

           0     0.7710    0.8550    0.8108      1000
           1     0.9867    0.9680    0.9773      1000
           2     0.7293    0.8190    0.7715      1000
           3     0.9034    0.8600    0.8811      1000
           4     0.7880    0.7730    0.7804      1000
           5     0.9928    0.8220    0.8993      1000
           6     0.6579    0.5750    0.6137      1000
           7     0.8784    0.9610    0.9179      1000
           8     0.9744    0.9530    0.9636      1000
           9     0.8963    0.9680    0.9308      1000

    accuracy                         0.8554     10000
   macro avg     0.8578    0.8554    0.8546     10000
weighted avg     0.8578    0.8554    0.8546     10000
```

[53]:

```
from sklearn.metrics import accuracy_score
accuracy_score(test_labels, knn_pred)
```

[53]: 0.8554

5.6 Random Forest

[0]:

```
from sklearn.ensemble import RandomForestClassifier
forest = RandomForestClassifier(n_estimators = 100)
```

[55]:

```
start = time.time()

forest.fit(train_images, train_labels)

end = time.time()
final_time = end-start
```

```
print('\n')
print('Training time:{}'.format(final_time))
```

```
Training time:81.60474896430969
```

[56]:

```
start = time.time()

forest_pred = forest.predict(test_images)

end = time.time()
final_time = end-start
print('\n')
print('Testing time:{}'.format(final_time))
```

```
Testing time:0.4056282043457031
```

[57]:

```
# Confusion Matrix
from sklearn.metrics import confusion_matrix
confusion_matrix = confusion_matrix(test_labels, forest_pred)
print(confusion_matrix)
```

```
[[862   0  11  31   2   1  83   0  10   0]
 [  3 961   2  21   5   0   6   0   2   0]
 [ 12   0 803  10 117   0  54   0   4   0]
 [ 18   2  11 909  30   0  28   0   2   0]
 [  1   0  94  33 820   0  50   0   2   0]
 [  0   0   0   1   0 956   0  32   1  10]
 [155   1 117  28  91   0 592   0  16   0]
 [  0   0   0   0   0  17   0 949   0  34]
 [  1   1   6   2   5   2   7   4 972   0]
 [  0   0   0   0   0  11   0  41   3 945]]
```

[58]:

```
# Classification Report
from sklearn.metrics import classification_report
print(classification_report(test_labels, forest_pred, digits=4))
```

```
              precision    recall  f1-score   support

           0     0.8194    0.8620    0.8402      1000
           1     0.9959    0.9610    0.9781      1000
           2     0.7692    0.8030    0.7857      1000
           3     0.8783    0.9090    0.8934      1000
           4     0.7664    0.8200    0.7923      1000
           5     0.9686    0.9560    0.9623      1000
```

```
           6     0.7220    0.5920    0.6505      1000
           7     0.9250    0.9490    0.9368      1000
           8     0.9605    0.9720    0.9662      1000
           9     0.9555    0.9450    0.9502      1000

    accuracy                         0.8769     10000
   macro avg     0.8760    0.8769    0.8756     10000
weighted avg     0.8760    0.8769    0.8756     10000
```

[59]:
```
from sklearn.metrics import accuracy_score
accuracy_score(test_labels, forest_pred)
```

[59]:
```
0.8769
```

5.7 Keras (ANN)

(ANN - Artificial Neural Network)

5.7.1 Defining the model

[0]:
```
# Define an object of the Sequential model
ANN = tf.keras.Sequential()
```

5.7.2 Adding a first fully-connected hidden layer

Layer hyper-parameters: - number of units/neurons: 128 - activation function: ReLU - input_shape: (784,)

[0]:
```
ANN.add(tf.keras.layers.Dense(units=128, activation='relu', input_shape=(784,␣
↪)))
```

5.7.3 Adding a second layer with Dropout

Dropout is a Regularization technique where we randomly set neurons in a layer to zero. That way while training those neurons won't be updated. Because some percentage of neurons won't be updated the whole training process is long and we have less chance for overfitting.

[0]:
```
ANN.add(tf.keras.layers.Dropout(0.2))
```

5.7.4 Adding more layers

[0]:
```
ANN.add(tf.keras.layers.Dense(units=64, activation='relu'))
ANN.add(tf.keras.layers.Dropout(0.2))
ANN.add(tf.keras.layers.Dense(units=64, activation='linear'))
```

5.7.5 Adding the output layer

- units: number of classes (10 in the Fashion MNIST dataset)
- activation: softmax

[0]:
```
ANN.add(tf.keras.layers.Dense(units=10, activation='softmax'))
```

5.7.6 Compiling the model

- Optimizer: Adam
- Loss: Sparse softmax (categorical) crossentropy

[0]:
```
ANN.compile(optimizer='adam', loss='sparse_categorical_crossentropy',
              metrics=['sparse_categorical_accuracy'])
```

[66]:
```
ANN.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 128)               100480
_________________________________________________________________
dropout (Dropout)            (None, 128)               0
_________________________________________________________________
dense_1 (Dense)              (None, 64)                8256
_________________________________________________________________
dropout_1 (Dropout)          (None, 64)                0
_________________________________________________________________
dense_2 (Dense)              (None, 64)                4160
_________________________________________________________________
dense_3 (Dense)              (None, 10)                650
=================================================================
Total params: 113,546
Trainable params: 113,546
Non-trainable params: 0
_________________________________________________________________
```

5.7.7 Training the model

[67]:
```
start = time.time()

ANN.fit(train_images, train_labels, epochs=30)

end = time.time()
final_time = end-start
print('\n')
print('Training time:{}'.format(final_time))
```

```
Epoch 1/30
60000/60000 [==============================] - 12s 197us/sample - loss: 0.5758 -
sparse_categorical_accuracy: 0.7915
Epoch 2/30
60000/60000 [==============================] - 11s 177us/sample - loss: 0.4413 -
sparse_categorical_accuracy: 0.8401
Epoch 3/30
60000/60000 [==============================] - 10s 175us/sample - loss: 0.4027 -
sparse_categorical_accuracy: 0.8542
Epoch 4/30
60000/60000 [==============================] - 11s 176us/sample - loss: 0.3849 -
sparse_categorical_accuracy: 0.8604
Epoch 5/30
60000/60000 [==============================] - 11s 180us/sample - loss: 0.3658 -
sparse_categorical_accuracy: 0.8677
Epoch 6/30
60000/60000 [==============================] - 10s 173us/sample - loss: 0.3537 -
sparse_categorical_accuracy: 0.8707
Epoch 7/30
60000/60000 [==============================] - 10s 173us/sample - loss: 0.3403 -
sparse_categorical_accuracy: 0.8753
Epoch 8/30
60000/60000 [==============================] - 10s 175us/sample - loss: 0.3355 -
sparse_categorical_accuracy: 0.8769
Epoch 9/30
60000/60000 [==============================] - 11s 176us/sample - loss: 0.3267 -
sparse_categorical_accuracy: 0.8796
Epoch 10/30
60000/60000 [==============================] - 11s 178us/sample - loss: 0.3180 -
sparse_categorical_accuracy: 0.8824
Epoch 11/30
60000/60000 [==============================] - 10s 174us/sample - loss: 0.3117 -
sparse_categorical_accuracy: 0.8850
Epoch 12/30
60000/60000 [==============================] - 11s 181us/sample - loss: 0.3107 -
sparse_categorical_accuracy: 0.8853
Epoch 13/30
60000/60000 [==============================] - 10s 174us/sample - loss: 0.3020 -
sparse_categorical_accuracy: 0.8880
Epoch 14/30
60000/60000 [==============================] - 11s 177us/sample - loss: 0.2952 -
sparse_categorical_accuracy: 0.8911
Epoch 15/30
60000/60000 [==============================] - 11s 176us/sample - loss: 0.2925 -
sparse_categorical_accuracy: 0.8912
Epoch 16/30
60000/60000 [==============================] - 11s 177us/sample - loss: 0.2882 -
sparse_categorical_accuracy: 0.8924
```

```
Epoch 17/30
60000/60000 [==============================] - 11s 179us/sample - loss: 0.2865 -
sparse_categorical_accuracy: 0.8928
Epoch 18/30
60000/60000 [==============================] - 10s 172us/sample - loss: 0.2824 -
sparse_categorical_accuracy: 0.8940
Epoch 19/30
60000/60000 [==============================] - 10s 172us/sample - loss: 0.2826 -
sparse_categorical_accuracy: 0.8957
Epoch 20/30
60000/60000 [==============================] - 10s 174us/sample - loss: 0.2765 -
sparse_categorical_accuracy: 0.8980
Epoch 21/30
60000/60000 [==============================] - 11s 177us/sample - loss: 0.2734 -
sparse_categorical_accuracy: 0.8983
Epoch 22/30
60000/60000 [==============================] - 10s 172us/sample - loss: 0.2678 -
sparse_categorical_accuracy: 0.9004
Epoch 23/30
60000/60000 [==============================] - 10s 175us/sample - loss: 0.2678 -
sparse_categorical_accuracy: 0.8995
Epoch 24/30
60000/60000 [==============================] - 11s 176us/sample - loss: 0.2648 -
sparse_categorical_accuracy: 0.9028
Epoch 25/30
60000/60000 [==============================] - 11s 181us/sample - loss: 0.2650 -
sparse_categorical_accuracy: 0.9013
Epoch 26/30
60000/60000 [==============================] - 10s 175us/sample - loss: 0.2600 -
sparse_categorical_accuracy: 0.9023
Epoch 27/30
60000/60000 [==============================] - 11s 177us/sample - loss: 0.2596 -
sparse_categorical_accuracy: 0.9034
Epoch 28/30
60000/60000 [==============================] - 11s 175us/sample - loss: 0.2585 -
sparse_categorical_accuracy: 0.9043
Epoch 29/30
60000/60000 [==============================] - 11s 176us/sample - loss: 0.2478 -
sparse_categorical_accuracy: 0.9064
Epoch 30/30
60000/60000 [==============================] - 10s 171us/sample - loss: 0.2522 -
sparse_categorical_accuracy: 0.9056


Training time:318.2523956298828
```

5.7.8 Model evaluation and prediction

[68]:
```
start = time.time()

ANN_pred= ANN.predict_classes(test_images)

end = time.time()
final_time = end-start
print('\n')
print('Testing time:{}'.format(final_time))
```

```
Testing time:0.4532601833343506
```

[69]:
```
# Confusion Matrix
from sklearn.metrics import confusion_matrix
confusion_matrix = confusion_matrix(test_labels, ANN_pred)
print(confusion_matrix)
```

```
[[789   2   9  52   9   1 129   0   9   0]
 [  0 975   1  17   4   0   2   0   1   0]
 [ 16   2 797  12 111   0  61   0   1   0]
 [ 17   6   8 908  41   0  16   0   4   0]
 [  0   1  81  28 848   0  40   0   2   0]
 [  0   0   0   0   0 959   0  24   1  16]
 [ 78   1  88  46  78   0 698   0  11   0]
 [  0   0   0   0   0  13   0 974   0  13]
 [  1   0   0   6   3   1   7   3 979   0]
 [  0   0   0   0   0   7   1  52   0 940]]
```

[70]:
```
# Classification Report
from sklearn.metrics import classification_report
print(classification_report(test_labels, ANN_pred, digits=4))
```

```
              precision    recall  f1-score   support

           0     0.8757    0.7890    0.8301      1000
           1     0.9878    0.9750    0.9814      1000
           2     0.8100    0.7970    0.8034      1000
           3     0.8494    0.9080    0.8777      1000
           4     0.7751    0.8480    0.8099      1000
           5     0.9776    0.9590    0.9682      1000
           6     0.7317    0.6980    0.7144      1000
           7     0.9250    0.9740    0.9489      1000
           8     0.9712    0.9790    0.9751      1000
           9     0.9701    0.9400    0.9548      1000
```

```
    accuracy                         0.8867     10000
   macro avg     0.8874    0.8867    0.8864     10000
weighted avg     0.8874    0.8867    0.8864     10000
```

[71]:
```python
test_loss, test_accuracy = ANN.evaluate(test_images, test_labels)
```

```
10000/10000 [==============================] - 1s 91us/sample - loss: 0.3291 -
sparse_categorical_accuracy: 0.8867
```

[72]:
```python
print("Test accuracy: {}".format(test_accuracy))
```

```
Test accuracy: 0.8866999745368958
```

5.8 Keras (CNN)

(CNN - Convolutional Neural Network)

5.8.1 Data for CNN

When using a convolutional layer as the first layer to the CNN model, we need to reshape our data to (n_images, x_shape, y_shape, channels). We should set channels to 1 for grayscale images and set channels to 3 when we have a set of RGB-images as input.

Load dataset

[0]:
```python
# Load the fashion-mnist dataset from keras.datasets library
fashion_mnist = keras.datasets.fashion_mnist
(CNN_train_images, CNN_train_labels), (CNN_test_images, CNN_test_labels) =␣
↪fashion_mnist.load_data()
```

Normalizing the images

[0]:
```python
# Normalizing the images
CNN_train_images = CNN_train_images / 255.0
CNN_test_images = CNN_test_images /255.0
```

Reshaping the dataset To feed in the dataset into a convolutional nerual network, the dataset must at least in grayscale.

[75]:
```python
print('Before reshape:')
# training set shape info
print('Shape of the training set (images): {}'.format(CNN_train_images.shape))
print('Shape of the training set (labels): {}'.format(CNN_train_labels.shape))

# test set shape info
print('Shape of the test set (images): {}'.format(CNN_test_images.shape))
print('Shape of the test set (labels): {}'.format(CNN_test_labels.shape))
```

```
Before reshape:
Shape of the training set (images): (60000, 28, 28)
Shape of the training set (labels): (60000,)
Shape of the test set (images): (10000, 28, 28)
Shape of the test set (labels): (10000,)
```

[0]:
```
# Reshape the training set and the test set to be into the vector format
# Since each image's dimension is 28x28, we reshape the full dataset to [-1␣
↪(all elements), height * width]
CNN_train_images = CNN_train_images.reshape(-1, 28,28, 1)
CNN_test_images = CNN_test_images.reshape(-1, 28,28, 1)
```

[77]:
```
print('After reshape:')
# training set shape info
print('Shape of the training set (images): {}'.format(CNN_train_images.shape))
print('Shape of the training set (labels): {}'.format(CNN_train_labels.shape))

# test set shape info
print('Shape of the test set (images): {}'.format(CNN_test_images.shape))
print('Shape of the test set (labels): {}'.format(CNN_test_labels.shape))
```

```
After reshape:
Shape of the training set (images): (60000, 28, 28, 1)
Shape of the training set (labels): (60000,)
Shape of the test set (images): (10000, 28, 28, 1)
Shape of the test set (labels): (10000,)
```

5.8.2 Shuffling index

[0]:
```
shuffle_index = np.random.permutation(60000)
CNN_train_images, CNN_train_labels = CNN_train_images[shuffle_index],␣
↪CNN_train_labels[shuffle_index]
```

5.8.3 Defining the model

[0]:
```
CNN = tf.keras.models.Sequential()
```

5.8.4 Adding the first CNN Layer

CNN layer hyper-parameters:

```
- filters: 32
- kernel_size: (3,3)
- padding: same
- activation: relu
- input_shape: (28, 28, 1)
```

Filters: the number of feauters are going to be used for convolving (filtering) the input
Kernel_size: the size of the filter

Padding='Valid':
* No padding
* Dimensions reduce

Padding='Same':
* Zeros around the edges * Dimensions stay the same

Conv1D is used for input signals which are similar to the voice. By employing them you can find patterns across the signal.
Example: 1 second stereo voice signal sampled at 44100 Hz, shape: (batch_size, 44100, 2)

Conv2D is used for images. This use case is very popular. The convolution method used for this layer is so called convolution over volume. This means you have a two-dimensional image which contains multiple channels, RGB as an example. In this case, each convolutional filter should be a three-dimensional filter to be convolved, cross-correlated actually, with the image to find appropriate patterns across the image.
Example: 32x32 RGB image, shape: (batch_size, 32, 32, 3)

Conv3D is usually used for videos where you have a frame for each time span. These layers usually have more parameters to be learnt than the previous layers. The reason we call them 3D is that other than images for each frame, there is another axis called time containing discrete values, and each of them corresponds to a particular frame.
Example: 1 second video of 32x32 RGB images at 24 fps, shape: (batch_size, 32, 32, 3, 24)

[0]:
```
CNN.add(tf.keras.layers.Conv2D(filters=32, kernel_size=(3,3), padding="same",␣
↪activation="relu", input_shape=[28, 28, 1]))
```

5.8.5 Adding the second CNN Layer and max pool layer

CNN layer hyper-parameters:

```
- filters: 32
- kernel_size: (3,3)
- padding: same
- activation: relu
```

MaxPool layer hyper-parameters:

```
- pool_size: (2,2)
- strides: 2
- padding: valid
```

[0]:
```
CNN.add(tf.keras.layers.Conv2D(filters=32, kernel_size=(3,3), padding="same",␣
↪activation="relu"))
```

[0]:
```
CNN.add(tf.keras.layers.MaxPool2D(pool_size=(2,2), strides=2, padding='valid'))
```

5.8.6 Adding the third CNN Layer

CNN layer hyper-parameters:

```
filters: 64
kernel_size: (3,3)
padding: same
activation: relu
```

[0]:
```
CNN.add(tf.keras.layers.Conv2D(filters=64, kernel_size=(3,3), padding="same",␣
↪activation="relu"))
```

5.8.7 Adding the fourth CNN Layer and max pool layer

CNN layer hyper-parameters:

```
filters: 64
kernel_size: (3,3)
padding: same
activation: relu
```

MaxPool layer hyper-parameters:

```
pool_size: (2,2)
strides: 2
padding: valid
```

[0]:
```
CNN.add(tf.keras.layers.Conv2D(filters=64, kernel_size=(3,3), padding="same",␣
↪activation="relu"))
```

[0]:
```
CNN.add(tf.keras.layers.MaxPool2D(pool_size=(2,2), strides=2, padding='valid'))
```

5.8.8 Adding the Flatten layer

[0]:
```
CNN.add(tf.keras.layers.Flatten())
```

5.8.9 Adding the first Dense layer

Dense layer hyper-parameters: - units/neurons: 128 - activation: relu

[0]:
```
CNN.add(tf.keras.layers.Dense(units=128, activation='relu'))
```

5.8.10 Adding the more Dense layer

[0]:
```
CNN.add(tf.keras.layers.Dropout(0.4))
CNN.add(tf.keras.layers.Dense(units=64, activation='relu'))
CNN.add(tf.keras.layers.Dropout(0.2))
CNN.add(tf.keras.layers.Dense(units=32, activation='relu'))
```

5.8.11 Adding the last Dense layer (output layer)

Dense layer hyper-parameters:

- units/neurons: 10 (number of classes)
- activation: softmax

[0]:
```
CNN.add(tf.keras.layers.Dense(units=10, activation='softmax'))
```

[90]:
```
CNN.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 28, 28, 32)        320
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 28, 28, 32)        9248
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 14, 14, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 14, 14, 64)        18496
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 14, 14, 64)        36928
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 7, 7, 64)          0
_________________________________________________________________
flatten (Flatten)            (None, 3136)              0
_________________________________________________________________
dense_4 (Dense)              (None, 128)               401536
_________________________________________________________________
dropout_2 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_5 (Dense)              (None, 64)                8256
_________________________________________________________________
dropout_3 (Dropout)          (None, 64)                0
_________________________________________________________________
dense_6 (Dense)              (None, 32)                2080
_________________________________________________________________
dense_7 (Dense)              (None, 10)                330
=================================================================
Total params: 477,194
Trainable params: 477,194
Non-trainable params: 0
_________________________________________________________________
```

5.8.12 Compiling the model

sparse_categorical_accuracy sparse_categorical_accuracy checks to see if the maximal true value is equal to the index of the maximal predicted value.

https://stackoverflow.com/questions/44477489/keras-difference-between-categorical-accuracy-and-sparse-categorical-accuracy

[0]:
```
CNN.compile(loss="sparse_categorical_crossentropy",
              optimizer="Adam", metrics=["sparse_categorical_accuracy"])
```

5.8.13 Training the model

[92]:
```
start = time.time()

CNN.fit(CNN_train_images, CNN_train_labels, epochs=30)

end = time.time()
final_time = end-start
print('\n')
print('Training time:{}'.format(final_time))
```

```
Epoch 1/30
60000/60000 [==============================] - 30s 497us/sample - loss: 0.5787 -
sparse_categorical_accuracy: 0.7905
Epoch 2/30
60000/60000 [==============================] - 25s 411us/sample - loss: 0.3433 -
sparse_categorical_accuracy: 0.8794
Epoch 3/30
60000/60000 [==============================] - 25s 422us/sample - loss: 0.2829 -
sparse_categorical_accuracy: 0.9014
Epoch 4/30
60000/60000 [==============================] - 25s 415us/sample - loss: 0.2491 -
sparse_categorical_accuracy: 0.9118
Epoch 5/30
60000/60000 [==============================] - 25s 412us/sample - loss: 0.2247 -
sparse_categorical_accuracy: 0.9190
Epoch 6/30
60000/60000 [==============================] - 25s 411us/sample - loss: 0.2075 -
sparse_categorical_accuracy: 0.9269
Epoch 7/30
60000/60000 [==============================] - 24s 405us/sample - loss: 0.1909 -
sparse_categorical_accuracy: 0.9326
Epoch 8/30
60000/60000 [==============================] - 25s 410us/sample - loss: 0.1789 -
sparse_categorical_accuracy: 0.9379
Epoch 9/30
60000/60000 [==============================] - 25s 411us/sample - loss: 0.1679 -
```

```
sparse_categorical_accuracy: 0.9398
Epoch 10/30
60000/60000 [==============================] - 25s 414us/sample - loss: 0.1568 -
sparse_categorical_accuracy: 0.9448
Epoch 11/30
60000/60000 [==============================] - 25s 422us/sample - loss: 0.1482 -
sparse_categorical_accuracy: 0.9464
Epoch 12/30
60000/60000 [==============================] - 25s 412us/sample - loss: 0.1398 -
sparse_categorical_accuracy: 0.9503
Epoch 13/30
60000/60000 [==============================] - 25s 415us/sample - loss: 0.1338 -
sparse_categorical_accuracy: 0.9530
Epoch 14/30
60000/60000 [==============================] - 24s 408us/sample - loss: 0.1271 -
sparse_categorical_accuracy: 0.9551
Epoch 15/30
60000/60000 [==============================] - 24s 406us/sample - loss: 0.1196 -
sparse_categorical_accuracy: 0.9580
Epoch 16/30
60000/60000 [==============================] - 24s 403us/sample - loss: 0.1140 -
sparse_categorical_accuracy: 0.9598
Epoch 17/30
60000/60000 [==============================] - 25s 413us/sample - loss: 0.1141 -
sparse_categorical_accuracy: 0.9599
Epoch 18/30
60000/60000 [==============================] - 25s 417us/sample - loss: 0.1079 -
sparse_categorical_accuracy: 0.9621
Epoch 19/30
60000/60000 [==============================] - 25s 416us/sample - loss: 0.1014 -
sparse_categorical_accuracy: 0.9647
Epoch 20/30
60000/60000 [==============================] - 25s 418us/sample - loss: 0.0990 -
sparse_categorical_accuracy: 0.9665
Epoch 21/30
60000/60000 [==============================] - 25s 417us/sample - loss: 0.0975 -
sparse_categorical_accuracy: 0.9661
Epoch 22/30
60000/60000 [==============================] - 25s 411us/sample - loss: 0.0928 -
sparse_categorical_accuracy: 0.9683
Epoch 23/30
60000/60000 [==============================] - 26s 426us/sample - loss: 0.0868 -
sparse_categorical_accuracy: 0.9701
Epoch 24/30
60000/60000 [==============================] - 25s 412us/sample - loss: 0.0834 -
sparse_categorical_accuracy: 0.9718
Epoch 25/30
60000/60000 [==============================] - 25s 413us/sample - loss: 0.0858 -
```

```
sparse_categorical_accuracy: 0.9698
Epoch 26/30
60000/60000 [==============================] - 25s 414us/sample - loss: 0.0833 -
sparse_categorical_accuracy: 0.9718
Epoch 27/30
60000/60000 [==============================] - 25s 414us/sample - loss: 0.0737 -
sparse_categorical_accuracy: 0.9743
Epoch 28/30
60000/60000 [==============================] - 25s 421us/sample - loss: 0.0797 -
sparse_categorical_accuracy: 0.9730
Epoch 29/30
60000/60000 [==============================] - 25s 422us/sample - loss: 0.0724 -
sparse_categorical_accuracy: 0.9755
Epoch 30/30
60000/60000 [==============================] - 26s 433us/sample - loss: 0.0720 -
sparse_categorical_accuracy: 0.9756


Training time:752.390468120575
```

5.8.14 Model evaluation and prediction

[93]:
```python
 start = time.time()

CNN_pred= CNN.predict_classes(CNN_test_images)

end = time.time()
final_time = end-start
print('\n')
print('Testing time:{}'.format(final_time))
```

```


Testing time:1.047379493713379
```

[94]:
```python
# Confusion Matrix
from sklearn.metrics import confusion_matrix
confusion_matrix = confusion_matrix(CNN_test_labels, CNN_pred)
print(confusion_matrix)
```

```
[[897   1  14   8   1   0  75   0   4   0]
 [  0 985   0   9   0   0   4   0   2   0]
 [ 18   2 909   8  32   0  30   0   1   0]
 [ 23   0  11 933   9   0  23   0   1   0]
 [  0   0  59  28 871   0  41   0   1   0]
 [  0   0   0   0   0 978   0  13   0   9]
 [118   2  47  22  66   0 740   0   5   0]
 [  0   0   0   0   0   8   0 982   0  10]
```

```
[   1    0    0    4    1    2    1    1  990    0]
[   0    0    0    0    0    5    1   27    0  967]]
```

[95]:
```
# Classification Report
from sklearn.metrics import classification_report
print(classification_report(CNN_test_labels, CNN_pred, digits=4))
```

```
              precision    recall  f1-score   support

           0     0.8486    0.8970    0.8721      1000
           1     0.9949    0.9850    0.9899      1000
           2     0.8740    0.9090    0.8912      1000
           3     0.9219    0.9330    0.9274      1000
           4     0.8888    0.8710    0.8798      1000
           5     0.9849    0.9780    0.9814      1000
           6     0.8087    0.7400    0.7728      1000
           7     0.9599    0.9820    0.9708      1000
           8     0.9861    0.9900    0.9880      1000
           9     0.9807    0.9670    0.9738      1000

    accuracy                         0.9252     10000
   macro avg     0.9249    0.9252    0.9247     10000
weighted avg     0.9249    0.9252    0.9247     10000
```

[96]:
```
test_loss, test_accuracy = CNN.evaluate(CNN_test_images, CNN_test_labels)
```

```
10000/10000 [==============================] - 1s 141us/sample - loss: 0.2955 -
sparse_categorical_accuracy: 0.9252
```

[97]:
```
print("Test accuracy: {}".format(test_accuracy))
```

```
Test accuracy: 0.9251999855041504
```

6 Final Model

[0]:
```
algorithm = ['Linear Classification', 'Logistics Regression', 'Support Vector',␣
 ↪'Naïve Bayes', 'K-Nearest Neighbors', 'Random Forest',
             'ANN (Artificial Neural Network)', 'CNN (Convolutional Neural␣
 ↪Network)']
training = [31.0805, 751.8370, 579.6898, 0.6993, 11.3533, 81.6047,
            318.2523, 752.3904]
testing = [0.0357, 0.0300, 207.9156, 0.5419, 771.0947, 0.4056,
           0.4532, 1.0473]
score = np.array([0.8103, 0.8441, 0.8829, 0.5856, 0.8554, 0.8769,
                  0.8867, 0.9251])*100
```

[0]:
```
performance_df = pd.DataFrame({'Algorithm':algorithm, 'Training':training,␣
↪'Testing':testing, 'Score':score})
performance_df.sort_values(by=['Score'], axis=0, ascending=False, inplace=True)
performance_df['Rank']=(1,2,3,4,5,6,7,8)
```

[6]:
```
# convert the dataframe to long data
df_melt = pd.melt(performance_df, id_vars=['Algorithm','Score','Rank'],␣
↪value_vars=['Training','Testing'],
             var_name='data', value_name='Cost')
df_melt
```

[6]:

	Algorithm	Score	Rank	data	Cost
0	CNN (Convolutional Neural Network)	92.51	1	Training	752.3904
1	ANN (Artificial Neural Network)	88.67	2	Training	318.2523
2	Support Vector	88.29	3	Training	579.6898
3	Random Forest	87.69	4	Training	81.6047
4	K-Nearest Neighbors	85.54	5	Training	11.3533
5	Logistics Regression	84.41	6	Training	751.8370
6	Linear Classification	81.03	7	Training	31.0805
7	Naïve Bayes	58.56	8	Training	0.6993
8	CNN (Convolutional Neural Network)	92.51	1	Testing	1.0473
9	ANN (Artificial Neural Network)	88.67	2	Testing	0.4532
10	Support Vector	88.29	3	Testing	207.9156
11	Random Forest	87.69	4	Testing	0.4056
12	K-Nearest Neighbors	85.54	5	Testing	771.0947
13	Logistics Regression	84.41	6	Testing	0.0300
14	Linear Classification	81.03	7	Testing	0.0357
15	Naïve Bayes	58.56	8	Testing	0.5419

[7]:
```
# add total cost feature
performance_df['Total cost'] = performance_df['Training'] +␣
↪performance_df['Testing']
performance_df
```

[7]:

	Algorithm	Training	Testing	Score	Rank	\
7	CNN (Convolutional Neural Network)	752.3904	1.0473	92.51	1	
6	ANN (Artificial Neural Network)	318.2523	0.4532	88.67	2	
2	Support Vector	579.6898	207.9156	88.29	3	
5	Random Forest	81.6047	0.4056	87.69	4	
4	K-Nearest Neighbors	11.3533	771.0947	85.54	5	
1	Logistics Regression	751.8370	0.0300	84.41	6	
0	Linear Classification	31.0805	0.0357	81.03	7	
3	Naïve Bayes	0.6993	0.5419	58.56	8	

	Total cost
7	753.4377
6	318.7055

```
2    787.6054
5     82.0103
4    782.4480
1    751.8670
0     31.1162
3      1.2412
```

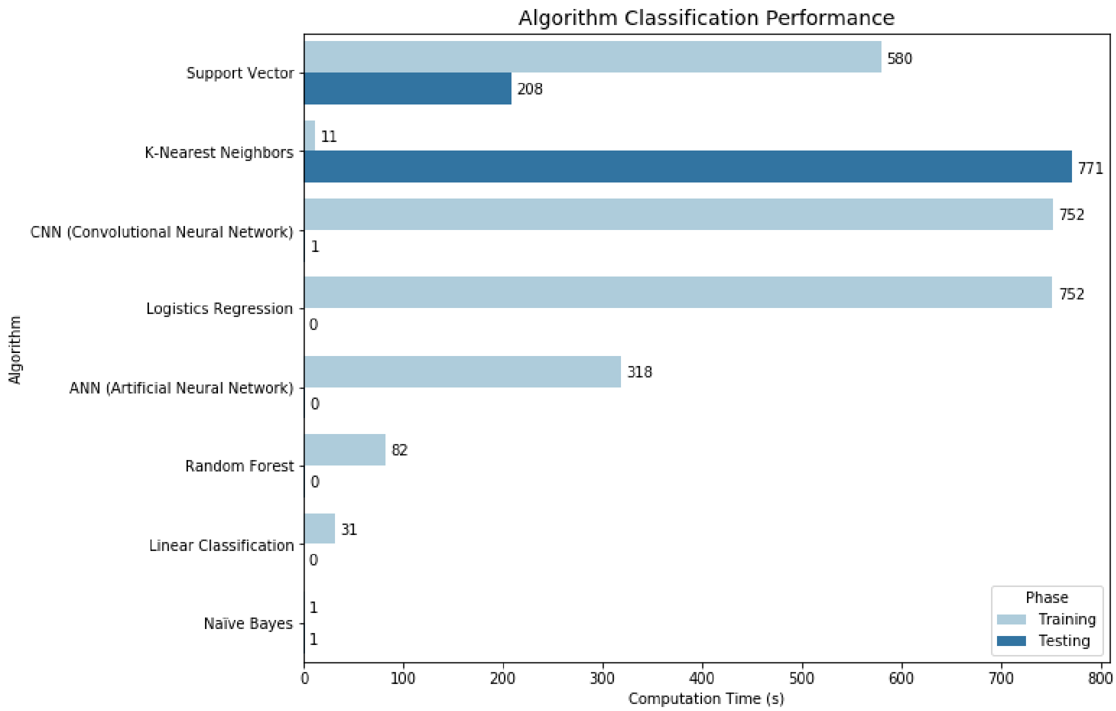
[8]:

```python
# Control plt figure size
plt.figure(figsize=(10,8))

# Plot the countplot
ax=sns.barplot(y='Algorithm', x='Cost', data=df_melt, hue='data', palette=sns.
 ↪color_palette("Paired"), dodge=True
               ,order = performance_df.sort_values(by=['Total cost'], axis=0,␣
 ↪ascending=False)['Algorithm'].values
               )

# set title of the plot, x-axis label, xticklabels, and legend
ax.set_title('Algorithm Classification Performance', fontsize=14);
ax.legend(loc='lower right', title="Phase", fancybox=True)
ax.set_xlabel('Computation Time (s)')

# annotate the time of each column
for p in ax.patches:
    time = '{:.0f}'.format(p.get_width())
    x = p.get_x() + p.get_width()
    y = p.get_y() + p.get_height()/2
    ax.annotate(time, (x+5, y), ha='left', va='center_baseline')
```



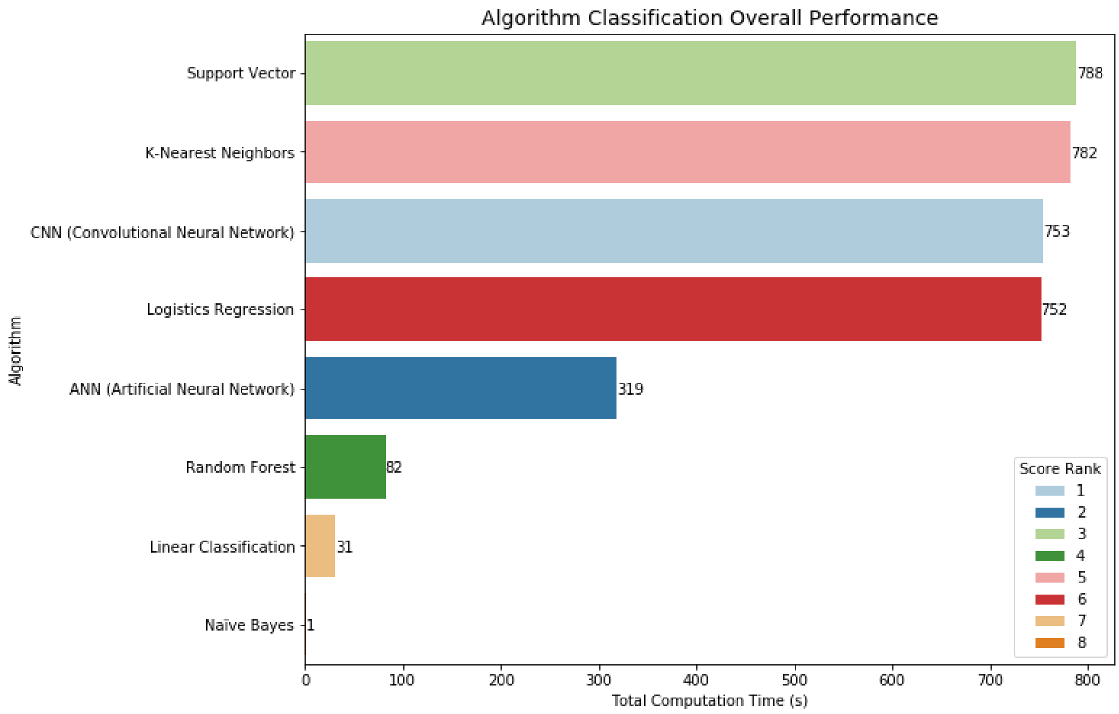
[9]:

```python
# Control plt figure size
plt.figure(figsize=(10,8))

# Plot the countplot
ax=sns.barplot(y='Algorithm', x='Total cost', data=performance_df, hue='Rank',␣
↪palette=sns.color_palette("Paired"), dodge=False,
                 order = performance_df.sort_values(by=['Total cost'], axis=0,␣
↪ascending=False)['Algorithm'].values)

# set title of the plot, x-axis label, xticklabels, and legend
ax.set_title('Algorithm Classification Overall Performance', fontsize=14);
ax.legend(loc='lower right', title="Score Rank", fancybox=True)
ax.set_xlabel('Total Computation Time (s)')

# annotate the time of each column
for p in ax.patches:
    time = '{:.0f}'.format(p.get_width())
    x = p.get_x() + p.get_width()
    y = p.get_y() + p.get_height()/2
    ax.annotate(time, (x, y), ha='left', va='center_baseline')
```

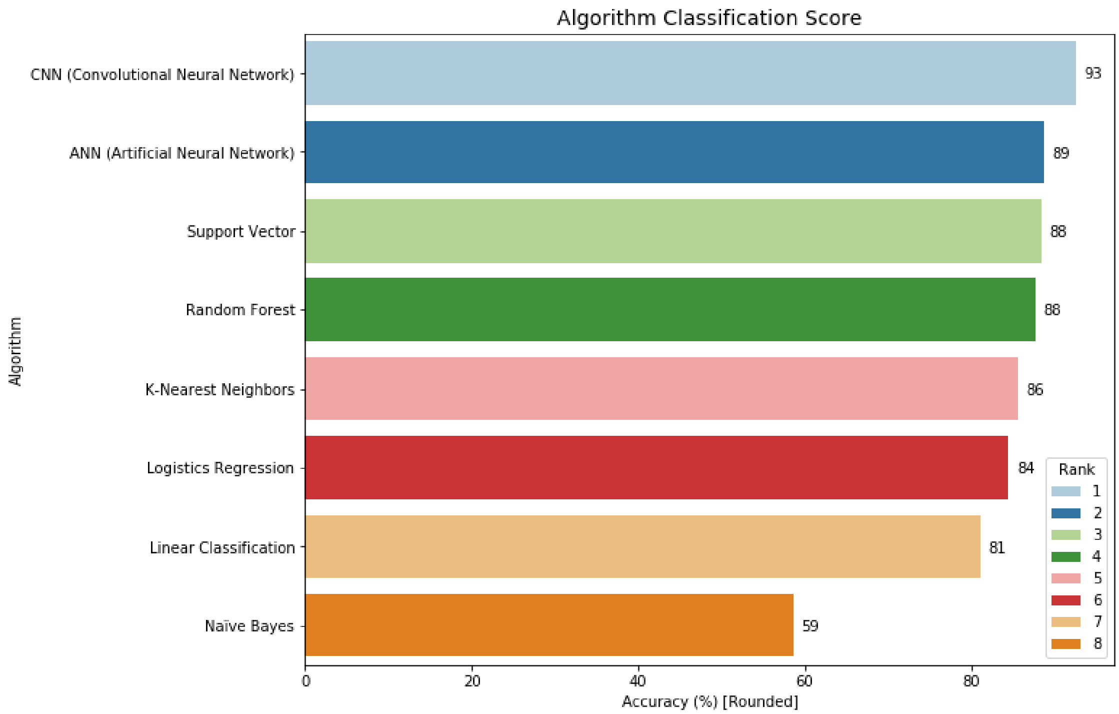


[10]:
```python
# Control plt figure size
plt.figure(figsize=(10,8))

# Plot the countplot
ax=sns.barplot(y='Algorithm', x='Score', data=performance_df, hue='Rank',␣
↪palette=sns.color_palette("Paired"), dodge=False,
                order = performance_df.sort_values(by=['Score'], axis=0,␣
↪ascending=False)['Algorithm'].values)

# set title of the plot, x-axis label, xticklabels, and legend
ax.set_title('Algorithm Classification Score', fontsize=14);
#ax.legend(loc='lower left', title="Score Rank", fancybox=True)
ax.set_xlabel('Accuracy (%) [Rounded]')

# annotate the time of each column
for p in ax.patches:
    time = '{:.0f}'.format(p.get_width())
    x = p.get_x() + p.get_width()
    y = p.get_y() + p.get_height()/2
    ax.annotate(time, (x+1, y), ha='left', va='center_baseline')
```



7 Questions

What is the accuracy of each method?

[11]:
```
performance_df.reset_index(drop=True)[['Algorithm','Score']]
```

[11]:
```
                            Algorithm  Score
0  CNN (Convolutional Neural Network)  92.51
1      ANN (Artificial Neural Network)  88.67
2                      Support Vector  88.29
3                       Random Forest  87.69
4                 K-Nearest Neighbors  85.54
5                Logistics Regression  84.41
6               Linear Classification  81.03
7                         Naïve Bayes  58.56
```

What are the trade-offs of each approach?

Each approach has its own advantage and disadvantage.

Convolutional Neural Network works the best among others. However, it comes with the package that the computation cost on training could be higher depending on how deep the network is. Artificial Neural Network works the same but has less computation cost and slightly off on the accuracy since it cannot detect every aspect of features as Convolutional Neural Network does.

Support Vector Machine (SVM) works effectively in classifying higher dimensional space and saves spaces on memory because it only uses the support vectors to create the optimal line. It is the best classifier when data points are separable. But, SVM performs poorly when the classes are overlapping, such as non-separable data points, and it is limited to small dataset. The bigger the training data, the higher the computation cost. Therefore, in our case, it has higher computation cost and higher accuracy rate.

Random forest has pretty good overall performance. It can handle both linear and non-linear data. But, one thing must be aware of. That is the higher depth of trees could bring the issue of the overfitting.

K-Nearest Neighbors has higher computation cost on predicting It is not good for production since it requires more computation cost in predicting than training.

Logistic regression works fairly and it can be used in practice but it may require more computation cost.

Linear classification works just fine on the fashion-MINST dataset, but its performance is depending on the dataset. Linear classification works better on linear dataset with scaled input.

Naïve Bayes is the simplest approach and known for faster computation compared to more sophisticated methods. When the training data contains continuous attribute, Gaussian Naïve Bayes is the choice. When the feature vectors represent frequencies, Multinomial Naïve Bayes should be implemented. When, the input variables are independent Booleans (binary variables), the Bernoulli Naïve Bayes is the tool to use. Overall, Naïve Bayes can perform will when the input variable is normally distributed and its predictors are independent to each other. But, clearly, it is not the case for our fashion-MINST dataset.

What is the compute performance of each approach?

[12]:
```
performance_df.sort_values(by='Total cost', ascending=False).
↪reset_index(drop=True)[['Algorithm','Training', 'Testing','Total cost']]
```

[12]:

	Algorithm	Training	Testing	Total cost
0	Support Vector	579.6898	207.9156	787.6054
1	K-Nearest Neighbors	11.3533	771.0947	782.4480
2	CNN (Convolutional Neural Network)	752.3904	1.0473	753.4377
3	Logistics Regression	751.8370	0.0300	751.8670
4	ANN (Artificial Neural Network)	318.2523	0.4532	318.7055
5	Random Forest	81.6047	0.4056	82.0103
6	Linear Classification	31.0805	0.0357	31.1162
7	Naïve Bayes	0.6993	0.5419	1.2412

8 Conclusion

The fashion-MINST dataset was used for the eight algorithms. Among the 10 classes, 'T-shirt/top', 'Trouser', 'Pullover', 'Dress', 'Coat', 'Sandal', 'Shirt', 'Sneaker', 'Bag', and 'Ankle boo', it is easy to find that 'Shirt' is the class that is hard to be classified by each of approaches. The reason could be that 'Shirt' shares the similar features with 'T-shirt/top', 'Pullover', and 'Coat'. We can tell that by observing 'T-shirt/top', 'Pullover' and 'Coat' are not the top easy to be classified classes. 'Trouser' and ‘Bag’ are the classes that are easy to be classified because they have the clear features that are clearly different from others. In order to improve the ability of images recognition, the complicated neural network, Convolution Neural Network (CNN), should be built deeper for learning the varies of features with feature detector.

[0]:
```

```