fashion_mnist

July 2, 2019

1 Fashion MNIST

An MNIST-like dataset of 70,000 28x28 labeled fashion images
Photo by Artificial Photography

1.1 Context

Fashion-MNIST is a dataset of Zalando's article images—consisting of a training set of 60,000 examples and a test set of 10,000 examples. Each example is a 28x28 grayscale image, associated with a label from 10 classes. Zalando intends Fashion-MNIST to serve as a direct drop-in replacement for the original MNIST dataset for benchmarking machine learning algorithms. It shares the same image size and structure of training and testing splits.

1.2 Content

- Each row is a separate image of 28 pixels in height and 28 pixels in width
- Column 1 is the class label.
- Remaining columns are pixel numbers (784 total).
- Each value is the darkness of the pixel (1 to 255) with higher numbers meaning darker
- The first column consists of the class labels (see below), and represents the article of clothing. The rest of the columns contain the pixel-values of the associated image.

1.3 Goal

Use a neural network on a simple classification task (classifaction of clothes' images into 10 classes). For learning purpose i'll use a Multi Layer Perceptron, but **there might be better type of NN such as CNN**.

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2 Data exploration

```
In [22]: import numpy as np
         import pandas as pd
         import matplotlib.pyplot as plt
         import seaborn as sns
```

```
In [23]: from tensorflow.keras.utils import to_categorical

         from tensorflow.keras.models import Sequential
         from tensorflow.keras.layers import Dense
```

```
In [24]: from sklearn.decomposition import PCA
         from sklearn.preprocessing import StandardScaler
```

```
In [25]: X_train = pd.read_csv('../input/fashion-mnist_train.csv')
         X_test = pd.read_csv('../input/fashion-mnist_test.csv')

         X_train.shape, X_test.shape
```

```
Out[25]: ((60000, 785), (10000, 785))
```

```
In [26]: X_train.head()
```

```
Out[26]:    label  pixel1  pixel2  pixel3  pixel4  pixel5  pixel6  pixel7  pixel8  \
         0      2       0       0       0       0       0       0       0       0
         1      9       0       0       0       0       0       0       0       0
         2      6       0       0       0       0       0       0       0       5
         3      0       0       0       0       1       2       0       0       0
         4      3       0       0       0       0       0       0       0       0

            pixel9    ...     pixel775  pixel776  pixel777  pixel778  pixel779  \
         0       0    ...            0         0         0         0         0
         1       0    ...            0         0         0         0         0
         2       0    ...            0         0         0        30        43
         3       0    ...            3         0         0         0         0
         4       0    ...            0         0         0         0         0

            pixel780  pixel781  pixel782  pixel783  pixel784
         0         0         0         0         0         0
         1         0         0         0         0         0
         2         0         0         0         0         0
         3         1         0         0         0         0
         4         0         0         0         0         0

         [5 rows x 785 columns]
```

Splitting features and targets

```
In [27]: y_train, y_test = X_train['label'], X_test['label']
         X_train, X_test = X_train.iloc[:, 1:], X_test.iloc[:, 1:]
         X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

```
Out[27]: ((60000, 784), (10000, 784), (60000,), (10000,))
```

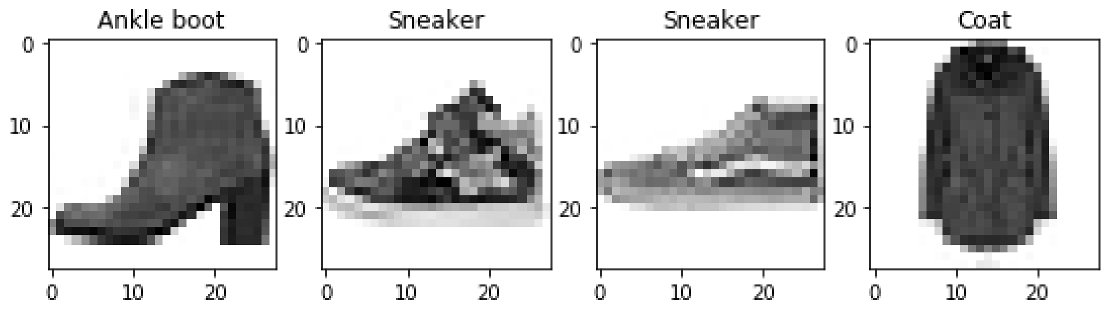
```
In [28]: X_train, X_test = np.array(X_train), np.array(X_test)
         type(X_train)
```

```
Out[28]: numpy.ndarray
```

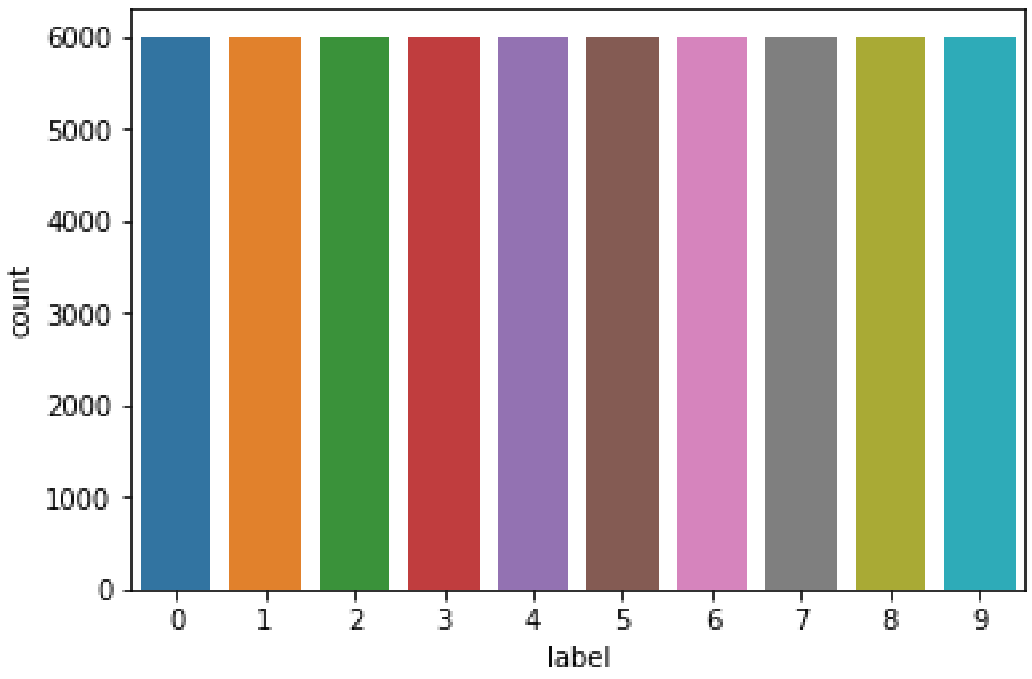
This dataset contains 10 classes: * 0: T-shirt/top * 1: Trouser * 2: Pullover * 3: Dress * 4: Coat * 5: Sandal * 6: Shirt * 7: Sneaker * 8: Bag * 9: Ankle boot

```
In [29]: class_names = ['T-shirt/top','Trouser','Pullover','Dress','Coat','Sandal','Shirt','Sne
```

```
In [30]: # display 5 randomly choosen clothes
         plt.figure(figsize=(12, 5))

         for i in range(1, 5):
             plt.subplot(1, 5, i)
             num = np.random.randint(X_train.shape[0])
             plt.imshow(X_train[num].reshape(28, 28), cmap='gray_r')
             plt.title(class_names[y_train[num]])

         plt.show()
```



```
In [31]: # number of clothes for each class
         sns.countplot(y_train)

Out[31]: <matplotlib.axes._subplots.AxesSubplot at 0x7f11ae64d7b8>
```



There isn't any imbalaced class. All have the same number of objects.

---

3 Data preparation

Scaling data

```
In [32]: X_train = X_train/255
         X_test = X_test/255
         X_train.mean(), X_test.mean()
```

```
Out[32]: (0.2861052180872351, 0.2869051175470186)
```

No need to resape 28 x 28 images since the already come as flatten np.array of dimension 784.

Let's make categories of the different classes (similar to the label encoding in sklearn but using the Keras function `to_categorical`)

```
In [33]: nb_class = len(class_names)

         y_train_cat = to_categorical(y_train, num_classes=nb_class, dtype='float32')
         y_test_cat  = to_categorical(y_test , num_classes=nb_class, dtype='float32')

         y_train.shape, y_train_cat.shape, y_test.shape, y_test_cat.shape
```

```
Out[33]: ((60000,), (60000, 10), (10000,), (10000, 10))
```

---

4 Model creation, training and results

4.1 MLP theory

Source: deepai.org

The Perceptron consists of an input layer and an output layer which are fully connected. MLPs have the same input and output layers but may have multiple hidden layers in between the aforementioned layers, as seen below.

The algorithm for the MLP is as follows:

- Just as with the perceptron, the inputs are pushed forward through the MLP by taking the dot product of the input with the weights that exist between the input layer and the hidden layer (W■H). This dot product yields a value at the hidden layer. We do not push this value forward as we would with a perceptron though.
- MLPs utilize activation functions at each of their calculated layers. There are many activation functions to discuss: rectified linear units (ReLU), sigmoid function, tanh. Push the calculated output at the current layer through any of these activation functions.
- Once the calculated output at the hidden layer has been pushed through the activation function, push it to the next layer in the MLP by taking the dot product with the corresponding weights.
- Repeat steps two and three until the output layer is reached.
- At the output layer, the calculations will either be used for a backpropagation algorithm that corresponds to the activation function that was selected for the MLP (in the case of training) or a decision will be made based on the output (in the case of testing).

MLPs form the basis for all neural networks and have greatly improved the power of computers when applied to classification and regression problems. Computers are no longer limited by XOR cases and can learn rich and complex models thanks to the multilayer perceptron.

4.2 Architecture

Let's build our neural network architecture with Keras. We start with a one.

```
In [34]: feat_nb = X_train.shape[1]
```

```
In [35]: def create_model(nb_hidden_layers, nb_units):
             model = Sequential()

             # 1st layer non hidden
             model.add(Dense(nb_units, input_dim=feat_nb, activation='sigmoid'))

             # all hidden layer
             for _ in range(nb_hidden_layers):
                 model.add(Dense(nb_units, activation='sigmoid'))

             # using softmax for the activiation of the last layer since this is a multi class
```

```
            model.add(Dense(nb_class, activation='softmax'))

            print(model.summary())
            return model
```

```
In [36]: # creation of a MLP with 2 hidden layers, all layers have 10 units
         mlp = create_model(2, 10)
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_4 (Dense)              (None, 10)                7850
_________________________________________________________________
dense_5 (Dense)              (None, 10)                110
_________________________________________________________________
dense_6 (Dense)              (None, 10)                110
_________________________________________________________________
dense_7 (Dense)              (None, 10)                110
=================================================================
Total params: 8,180
Trainable params: 8,180
Non-trainable params: 0
_________________________________________________________________
None
```

4.3 Compilation and training

Now compile and fit the model on the training data. Since this is a multiclass classification, the loss is `categorical_crossentropy`.

```
In [37]: # Compile model
         mlp.compile(optimizer='SGD', loss='categorical_crossentropy', metrics=['accuracy'])
```

```
In [42]: # Fit model
         mlp.fit(X_train, y_train_cat, validation_data=(X_test, y_test_cat), epochs=60, batch_s
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 3s 51us/sample - loss: 0.7420 - acc: 0.7304 - va
Epoch 2/20
60000/60000 [==============================] - 3s 52us/sample - loss: 0.7304 - acc: 0.7337 - va
Epoch 3/20
60000/60000 [==============================] - 3s 52us/sample - loss: 0.7195 - acc: 0.7390 - va
Epoch 4/20
60000/60000 [==============================] - 3s 53us/sample - loss: 0.7085 - acc: 0.7428 - va
Epoch 5/20
60000/60000 [==============================] - 3s 53us/sample - loss: 0.6978 - acc: 0.7466 - va
Epoch 6/20
```

```
60000/60000 [==============================] - 3s 53us/sample - loss: 0.6868 - acc: 0.7514 - va
Epoch 7/20
60000/60000 [==============================] - 3s 54us/sample - loss: 0.6759 - acc: 0.7565 - va
Epoch 8/20
60000/60000 [==============================] - 3s 54us/sample - loss: 0.6652 - acc: 0.7610 - va
Epoch 9/20
60000/60000 [==============================] - 3s 55us/sample - loss: 0.6536 - acc: 0.7682 - va
Epoch 10/20
60000/60000 [==============================] - 3s 55us/sample - loss: 0.6423 - acc: 0.7732 - va
Epoch 11/20
60000/60000 [==============================] - 4s 59us/sample - loss: 0.6309 - acc: 0.7803 - va
Epoch 12/20
60000/60000 [==============================] - 3s 54us/sample - loss: 0.6196 - acc: 0.7871 - va
Epoch 13/20
60000/60000 [==============================] - 3s 56us/sample - loss: 0.6082 - acc: 0.7922 - va
Epoch 14/20
60000/60000 [==============================] - 3s 58us/sample - loss: 0.5977 - acc: 0.7982 - va
Epoch 15/20
60000/60000 [==============================] - 3s 47us/sample - loss: 0.5874 - acc: 0.8033 - va
Epoch 16/20
60000/60000 [==============================] - 3s 51us/sample - loss: 0.5774 - acc: 0.8074 - va
Epoch 17/20
60000/60000 [==============================] - 3s 52us/sample - loss: 0.5681 - acc: 0.8113 - va
Epoch 18/20
60000/60000 [==============================] - 3s 54us/sample - loss: 0.5597 - acc: 0.8150 - va
Epoch 19/20
60000/60000 [==============================] - 3s 53us/sample - loss: 0.5514 - acc: 0.8185 - va
Epoch 20/20
60000/60000 [==============================] - 3s 58us/sample - loss: 0.5436 - acc: 0.8216 - va
```

```
Out[42]: <tensorflow.python.keras.callbacks.History at 0x7f11b1e0f438>
```

4.4 Results

Once our model is trained, let's compute the accuracy on the train and test datasets.

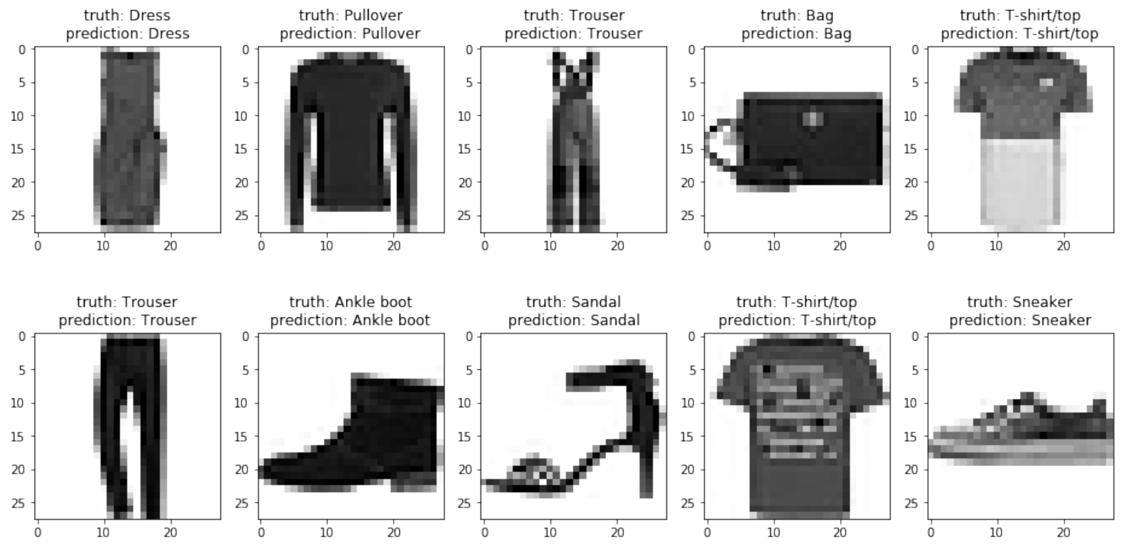
Beware, Keras returns softmax output (so an array of 10 values between 0 and 1, for which the sum is equal to 1). To compute correctly the accuracy, you have to convert that array into a categorical array with zeros and a 1.

```
In [43]: loss, accuracy = mlp.evaluate(X_test, y_test_cat)
         loss, accuracy
```

```
10000/10000 [==============================] - 0s 20us/sample - loss: 0.5519 - acc: 0.8166
```

```
Out[43]: (0.5519142246246338, 0.8166)
```

```
In [44]: y_pred = mlp.predict(X_test)
         y_pred = y_pred.argmax(axis=1)
         y_pred

Out[44]: array([0, 1, 2, ..., 8, 8, 0])

In [45]: # display 10 randomly choosen clothes with predicted labels and ground truth
         plt.figure(figsize=(16, 8))

         for i in range(1, 11):
             plt.subplot(2, 5, i)
             num = np.random.randint(X_test.shape[0])
             plt.imshow(X_test[num].reshape(28, 28), cmap='gray_r')
             title = 'truth: ' + class_names[y_test[num]] + '\nprediction: ' + class_names[y_p
             plt.title(title)

         plt.show()
```



```
In [ ]:
```