Batch normalisation

November 11, 2020

1 Batch normalisation layers

In this reading we will look at incorporating batch normalisation into our models and look at an example of how we do this in practice.

As usual, let's first import tensorflow.

```
In [1]: import tensorflow as tf
        print(tf.__version__)
```

```
2.0.0
```

We will be working with the diabetes dataset that we have been using in this week's screencasts.

Let's load and pre-process the dataset.

```
In [2]: # Load the dataset

        from sklearn.datasets import load_diabetes
        diabetes_dataset = load_diabetes()
```

```
In [3]: # Save the input and target variables

        from sklearn.model_selection import train_test_split

        data = diabetes_dataset['data']
        targets = diabetes_dataset['target']
```

```
In [4]: # Normalise the target data (this will make clearer training curves)

        targets = (targets - targets.mean(axis=0)) / (targets.std())
```

```
In [5]: # Split the dataset into training and test datasets

        train_data, test_data, train_targets, test_targets = train_test_split(data, targets, te
```

1.0.1 Batch normalisation - defining the model

We can implement batch normalisation into our model by adding it in the same way as any other layer.

```
In [6]: from tensorflow.keras.models import Sequential
        from tensorflow.keras.layers import Flatten, Dense, Conv2D, MaxPooling2D, BatchNormali
```

```
In [7]: # Build the model

        model = Sequential([
            Dense(64, input_shape=[train_data.shape[1],], activation="relu"),
            BatchNormalization(),  # <- Batch normalisation layer
            Dropout(0.5),
            BatchNormalization(),  # <- Batch normalisation layer
            Dropout(0.5),
            Dense(256, activation='relu'),
        ])

        # NB: We have not added the output layer because we still have more layers to add!
```

```
In [8]: # Print the model summary

        model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 64)                704
_________________________________________________________________
batch_normalization (BatchNo (None, 64)                256
_________________________________________________________________
dropout (Dropout)            (None, 64)                0
_________________________________________________________________
batch_normalization_1 (Batch (None, 64)                256
_________________________________________________________________
dropout_1 (Dropout)          (None, 64)                0
_________________________________________________________________
dense_1 (Dense)              (None, 256)               16640
=================================================================
Total params: 17,856
Trainable params: 17,600
Non-trainable params: 256
_________________________________________________________________
```

Recall that there are some parameters and hyperparameters associated with batch normalisation.

- The hyperparameter **momentum** is the weighting given to the previous running mean when re-computing it with an extra minibatch. By **default**, it is set to 0.99.
- The hyperparameter ϵ is used for numeric stability when performing the normalisation over the minibatch. By **default** it is set to 0.001.
- The parameters β and γ are used to implement an affine transformation after normalisation. By **default**, β is an all-zeros vector, and γ is an all-ones vector.

1.0.2 Customising parameters

These can all be changed (along with various other properties) by adding optional arguments to `tf.keras.layers.BatchNormalization()`.

We can also specify the axis for batch normalisation. By default, it is set as -1.

Let's see an example.

```
In [9]: # Add a customised batch normalisation layer

        model.add(tf.keras.layers.BatchNormalization(
            momentum=0.95,
            epsilon=0.005,
            axis = -1,
            beta_initializer=tf.keras.initializers.RandomNormal(mean=0.0, stddev=0.05),
            gamma_initializer=tf.keras.initializers.Constant(value=0.9)
        ))
```

```
In [10]: # Add the output layer

         model.add(Dense(1))
```

1.1 Compile and fit the model

Let's now compile and fit our model with batch normalisation, and track the progress on training and validation sets.

First we compile our model.

```
In [11]: # Compile the model

         model.compile(optimizer='adam',
                       loss='mse',
                       metrics=['mae'])
```

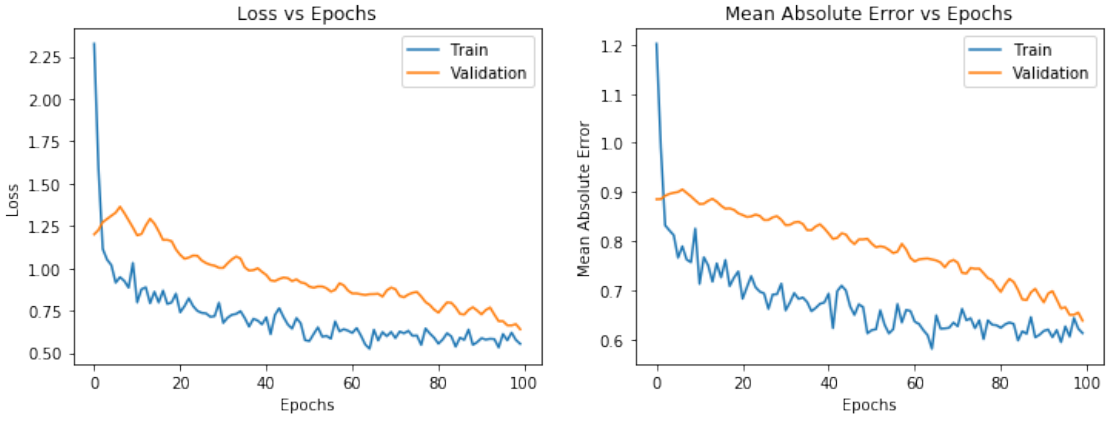
Now we fit the model to the data.

```
In [12]: # Train the model

         history = model.fit(train_data, train_targets, epochs=100, validation_split=0.15, bat
```

Finally, we plot training and validation loss and accuracy to observe how the accuracy of our model improves over time.

In [13]:
```
# Plot the learning curves

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline

frame = pd.DataFrame(history.history)
epochs = np.arange(len(frame))

fig = plt.figure(figsize=(12,4))

# Loss plot
ax = fig.add_subplot(121)
ax.plot(epochs, frame['loss'], label="Train")
ax.plot(epochs, frame['val_loss'], label="Validation")
ax.set_xlabel("Epochs")
ax.set_ylabel("Loss")
ax.set_title("Loss vs Epochs")
ax.legend()

# Accuracy plot
ax = fig.add_subplot(122)
ax.plot(epochs, frame['mae'], label="Train")
ax.plot(epochs, frame['val_mae'], label="Validation")
ax.set_xlabel("Epochs")
ax.set_ylabel("Mean Absolute Error")
ax.set_title("Mean Absolute Error vs Epochs")
ax.legend()
```

Out[13]:
```
<matplotlib.legend.Legend at 0x7fadc45427f0>
```



1.2 Further reading and resources

- https://keras.io/layers/normalization/
- https://www.tensorflow.org/versions/r2.0/api_docs/python/tf/keras/layers/BatchNormalization