ACA-Phoneme-NN

May 5, 2018

1 ACA Phoneme Recognition: Neural Network

Using the MFCC data obtained from TIMIT using MATLAB, we now implement a neural network for classification.

1.1 Loading the Keras package

We begin by loading keras and the other packages

```
In [1]: import keras
```

```
Using TensorFlow backend.
```

```
In [2]: import numpy as np
        import scipy.io
        import matplotlib
        import matplotlib.pyplot as plt
        %matplotlib inline
```

1.2 Load the Data

The MFCC data was processed in MATLAB. Labels have been converted to integers.

```
In [3]: data_dir = 'ACA/'
        train = scipy.io.loadmat(data_dir+'phn_train_scaled.mat')
        test = scipy.io.loadmat(data_dir+'phn_test_scaled.mat')
        train_label = scipy.io.loadmat(data_dir+'phn_train_int_label.mat')
        test_label = scipy.io.loadmat(data_dir+'phn_test_int_label.mat')
        Xtr = train['data'].T
        ytr = train_label['train_label'][0,0].T
        Xts = test['data'].T
        yts = test_label['test_label'][0,0].T
```

- What is the number of training and test samples?
- What is the number of features for each sample?
- How many classes (i.e. instruments) are their per class.

```
In [4]: ntr = Xtr.shape[0]
        nts = Xts.shape[0]
        print('Number of training samples: {0:d}'.format(ntr))
        print('Number of test samples: {0:d}'.format(nts))
        print('Number of features: {0:d}'.format(Xtr.shape[1]))
        print('Number of classes: {0:d}'.format((np.unique(yts)).shape[0]))
```

```
Number of training samples: 177080
Number of test samples: 64145
Number of features: 72
Number of classes: 61
```

1.3 Building a Neural Network Classifier

Clear the keras session.

```
In [5]: from keras.models import Model, Sequential
        from keras.layers import Dense, Activation
```

```
In [6]: import keras.backend as K
        K.clear_session()
```

Create a neural network `model` with: * `nh=256` hidden units * `sigmoid` activation

```
In [7]: nin = Xtr.shape[1]
        nh = 512 # Number of hidden units
        nout = int((np.unique(yts)).shape[0]+1)
        model = Sequential()
        model.add(Dense(nh, input_shape=(nin,), activation='sigmoid', name='hidden'))
        model.add(Dense(nout, activation='softmax', name='output'))
```

Print the model summary.

```
In [8]: model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
hidden (Dense)               (None, 512)               37376
_________________________________________________________________
output (Dense)               (None, 62)                31806
=================================================================
Total params: 69,182
Trainable params: 69,182
Non-trainable params: 0
_________________________________________________________________
```

To keep track of the loss history and validation accuracy, we use a *callback* function as described in Keras callback documentation.

```
In [9]: class LossHistory(keras.callbacks.Callback):
            def on_train_begin(self, logs={}):
                # Create two empty lists, self.loss and self.val_acc
                self.loss = []
                self.val_acc = []

            def on_batch_end(self, batch, logs={}):
                # This is called at the end of each batch.
                # Add the loss in logs.get('loss') to the loss list
                self.loss.append(logs.get('loss'))

            def on_epoch_end(self, epoch, logs):
                # This is called at the end of each epoch.
                # Add the test accuracy in logs.get('val_acc') to the val_acc list
                self.val_acc.append(logs.get('val_acc'))

        # Create an instance of the history callback
        history_cb = LossHistory()
```

Create an optimizer using the Adam optimizer with a learning rate of 0.001. Then, compile the model.

```
In [10]: from keras import optimizers


         opt = optimizers.Adam(lr=0.001)
         model.compile(optimizer=opt,
                       loss='sparse_categorical_crossentropy',
                       metrics=['accuracy'])
```

Fit the model for 25 epochs using the scaled data for both the training and validation. Use a batch size of 100.

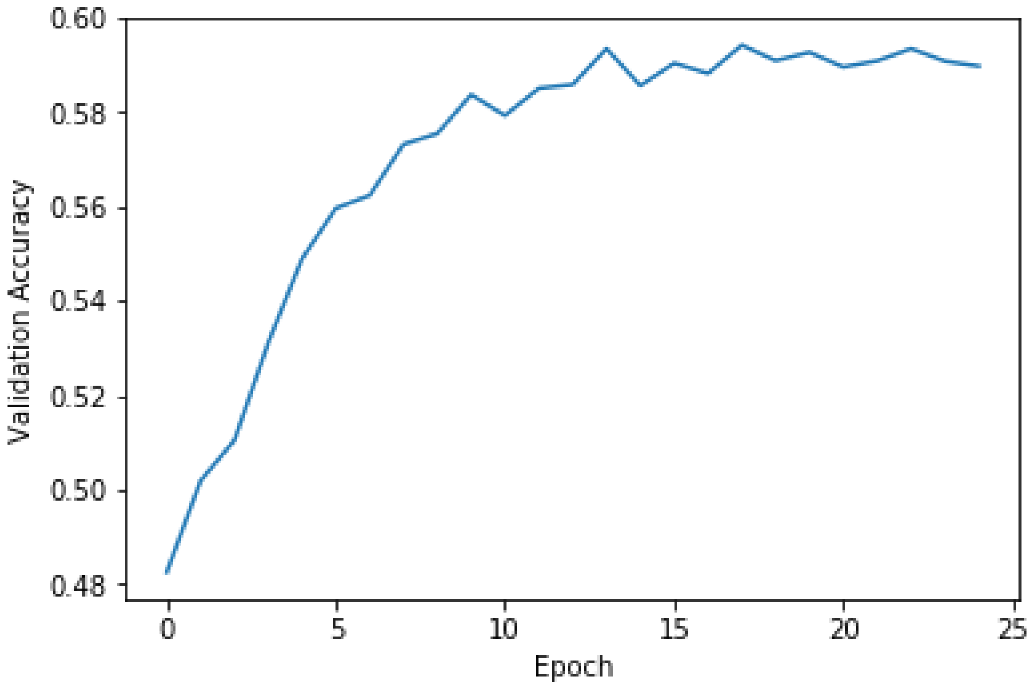
```
In [11]: model.fit(Xtr, ytr, epochs=25, batch_size = 100, validation_data=(Xts,yts), callbacks=

Train on 177080 samples, validate on 64145 samples
Epoch 1/25
177080/177080 [==============================] - 32s - loss: 2.0262 - acc: 0.4290 - val_loss: 
Epoch 2/25
177080/177080 [==============================] - 31s - loss: 1.6584 - acc: 0.4987 - val_loss: 
Epoch 3/25
177080/177080 [==============================] - 31s - loss: 1.5792 - acc: 0.5174 - val_loss: 
Epoch 4/25
177080/177080 [==============================] - 31s - loss: 1.5125 - acc: 0.5345 - val_loss: 
Epoch 5/25
177080/177080 [==============================] - 31s - loss: 1.4497 - acc: 0.5526 - val_loss: 
Epoch 6/25
```

```
177080/177080 [==============================] - 31s - loss: 1.3955 - acc: 0.5659 - val_loss:
Epoch 7/25
177080/177080 [==============================] - 31s - loss: 1.3482 - acc: 0.5794 - val_loss:
Epoch 8/25
177080/177080 [==============================] - 32s - loss: 1.3105 - acc: 0.5896 - val_loss:
Epoch 9/25
177080/177080 [==============================] - 31s - loss: 1.2764 - acc: 0.5980 - val_loss:
Epoch 10/25
177080/177080 [==============================] - 31s - loss: 1.2478 - acc: 0.6060 - val_loss:
Epoch 11/25
177080/177080 [==============================] - 32s - loss: 1.2213 - acc: 0.6141 - val_loss:
Epoch 12/25
177080/177080 [==============================] - 32s - loss: 1.1984 - acc: 0.6199 - val_loss:
Epoch 13/25
177080/177080 [==============================] - 31s - loss: 1.1777 - acc: 0.6255 - val_loss:
Epoch 14/25
177080/177080 [==============================] - 31s - loss: 1.1599 - acc: 0.6300 - val_loss:
Epoch 15/25
177080/177080 [==============================] - 31s - loss: 1.1416 - acc: 0.6366 - val_loss:
Epoch 16/25
177080/177080 [==============================] - 32s - loss: 1.1260 - acc: 0.6397 - val_loss:
Epoch 17/25
177080/177080 [==============================] - 35s - loss: 1.1120 - acc: 0.6436 - val_loss:
Epoch 18/25
177080/177080 [==============================] - 32s - loss: 1.0981 - acc: 0.6471 - val_loss:
Epoch 19/25
177080/177080 [==============================] - 31s - loss: 1.0855 - acc: 0.6512 - val_loss:
Epoch 20/25
177080/177080 [==============================] - 32s - loss: 1.0741 - acc: 0.6542 - val_loss:
Epoch 21/25
177080/177080 [==============================] - 32s - loss: 1.0634 - acc: 0.6566 - val_loss:
Epoch 22/25
177080/177080 [==============================] - 41s - loss: 1.0540 - acc: 0.6605 - val_loss:
Epoch 23/25
177080/177080 [==============================] - 32s - loss: 1.0437 - acc: 0.6631 - val_loss:
Epoch 24/25
177080/177080 [==============================] - 31s - loss: 1.0351 - acc: 0.6649 - val_loss:
Epoch 25/25
177080/177080 [==============================] - 31s - loss: 1.0254 - acc: 0.6687 - val_loss:
```

```
Out[11]: <keras.callbacks.History at 0x2558c109c18>
```

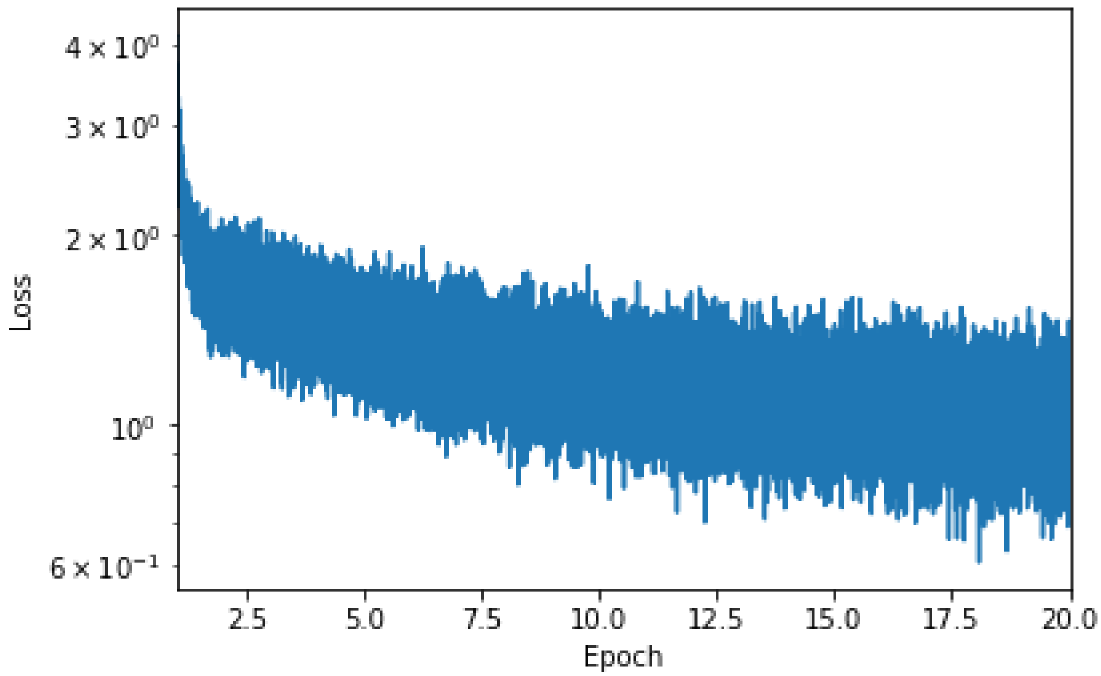
Plot the validation accuracy saved in the `history_cb`. This gives one accuracy value per epoch.

```
In [12]: plt.plot(history_cb.val_acc)
         plt.xlabel('Epoch')
         plt.ylabel('Validation Accuracy')
         plt.show()
```



Plot the loss values saved in the `history_cb` class.

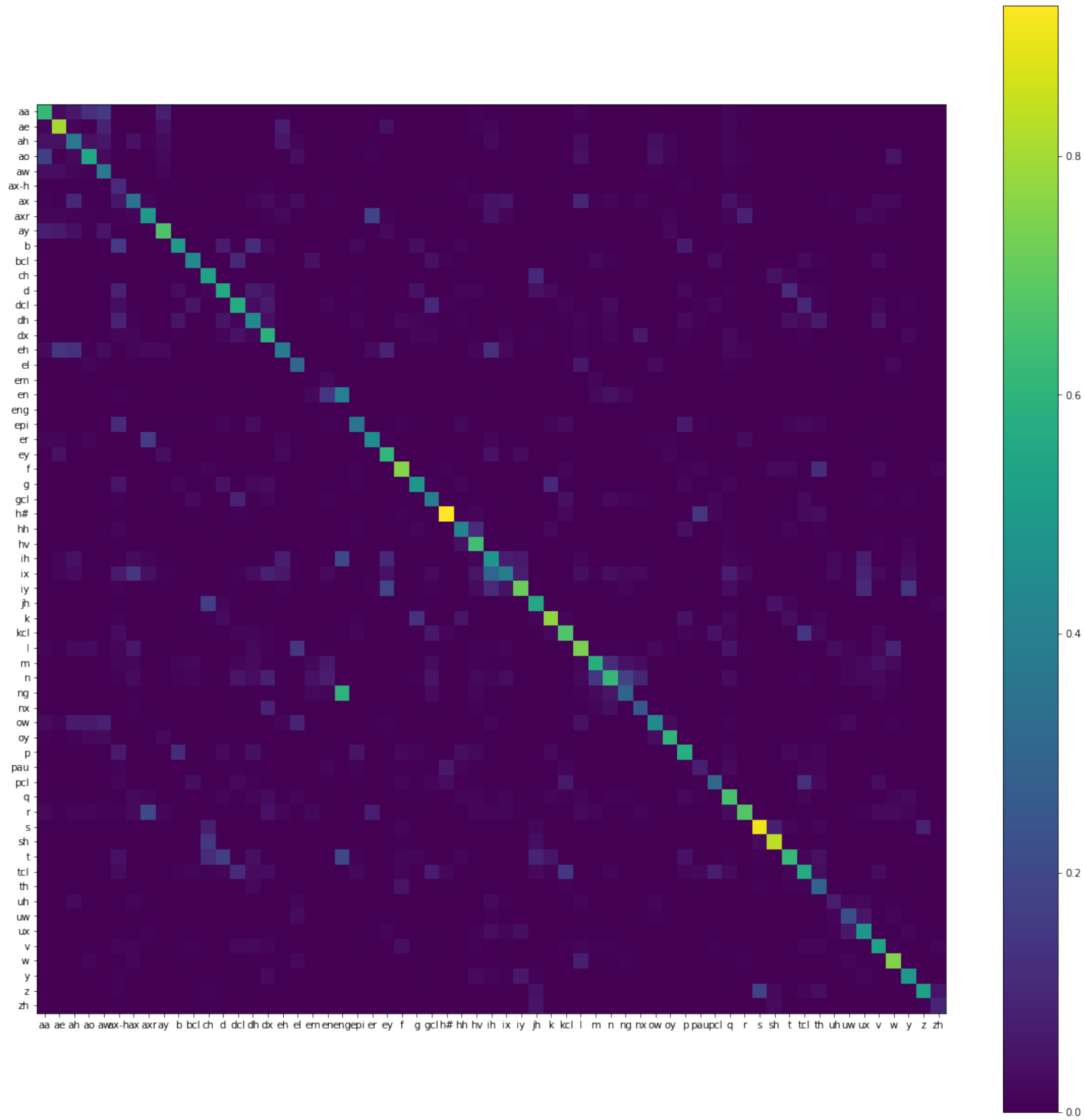
```
In [13]: plt.semilogy(np.linspace(1,20,44275),history_cb.loss)
         plt.xlabel('Epoch')
         plt.xlim([1,20])
         plt.ylabel('Loss')
         plt.show()
```




```
In [14]: yhat_ts = model.predict(Xts,batch_size=100,verbose=1)
         yhat_ts = np.argmax(yhat_ts,axis=1)

         from sklearn.metrics import confusion_matrix
         C = confusion_matrix(yts,yhat_ts)
         Csum = np.sum(C,1)
         C = C/Csum[None,:]
         print(np.array_str(C,precision=3,suppress_small=True))
         fig = plt.figure(figsize = (20,20))
         ax = fig.add_subplot(111)
         im = ax.imshow(C,interpolation='none')
         fig.colorbar(im,ax=ax)
         phn = ('aa', 'ae', 'ah', 'ao', 'aw', 'ax-h', 'ax', 'axr', 'ay', 'b', 'bcl', 'ch', 'd'
         xt=plt.xticks(np.arange(np.unique(yts).shape[0]),phn)
         yt=plt.yticks(np.arange(np.unique(yts).shape[0]),phn)

         fig.savefig('cm-NN-all.png')
```

```
64100/64145 [============================>.] - ETA: 0s[[ 0.615  0.026  0.06   ...,  0.     0.
 [ 0.016  0.802  0.017 ...,  0.     0.     0.   ]
 [ 0.043  0.041  0.367 ...,  0.     0.     0.   ]
 ...,
 [ 0.     0.     0.    ...,  0.492  0.001  0.   ]
 [ 0.     0.     0.    ...,  0.     0.531  0.054]]
```

```
 [ 0.      0.      0.     ...,  0.002   0.01    0.095]]
```



2 Repeat for other class groups

Halberstadt, 6 groups

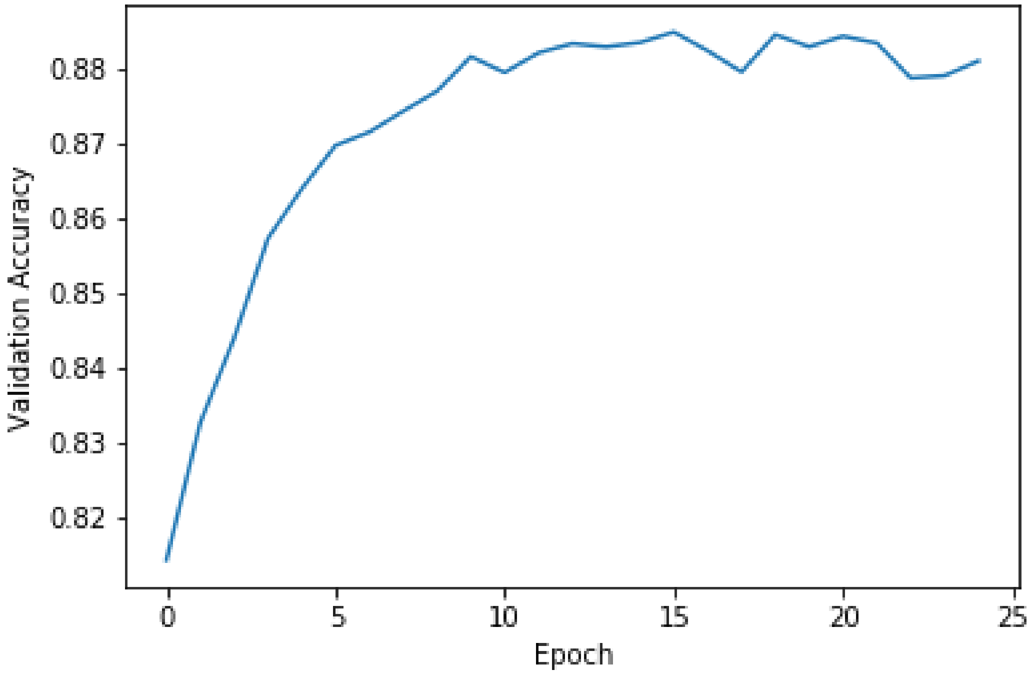
```
In [20]: ytr = train_label['train_label'][0,1].T
         yts = test_label['test_label'][0,1].T
         ntr = Xtr.shape[0]
         nts = Xts.shape[0]
```

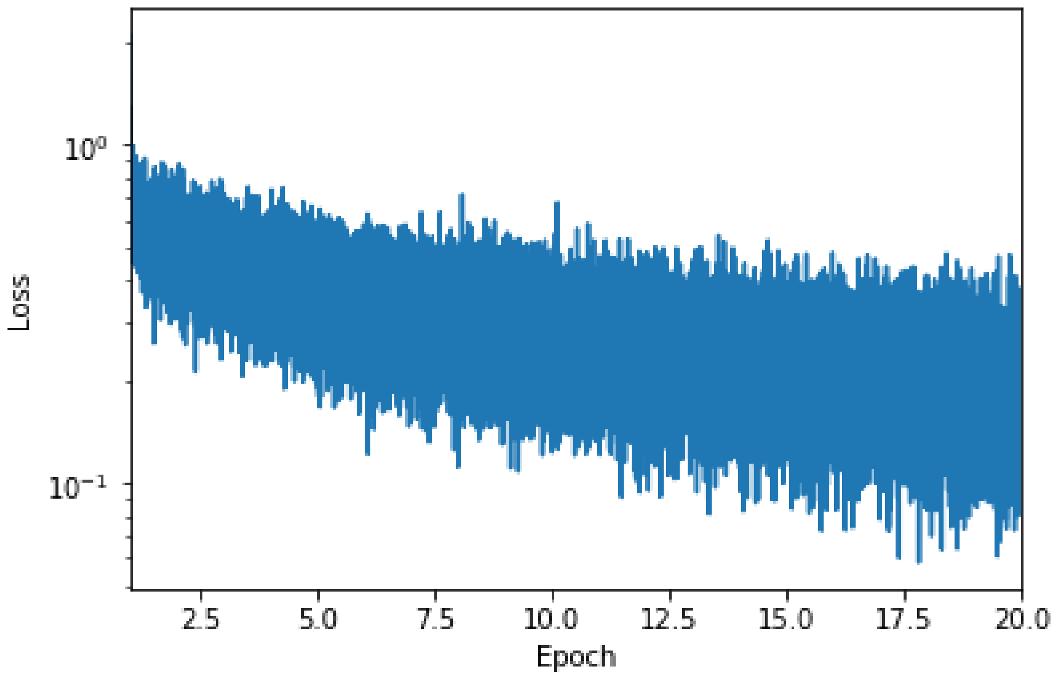
```python
K.clear_session()
nin = Xtr.shape[1]
nh = 512 # Number of hidden units
nout = int((np.unique(yts)).shape[0]+1)
model = Sequential()
model.add(Dense(nh, input_shape=(nin,), activation='sigmoid', name='hidden'))
model.add(Dense(nout, activation='softmax', name='output'))
model.summary()
opt = optimizers.Adam(lr=0.001)
model.compile(optimizer=opt,
             loss='sparse_categorical_crossentropy',
             metrics=['accuracy'])

model.fit(Xtr, ytr, epochs=25, batch_size = 100, validation_data=(Xts,yts), callbacks=
plt.plot(history_cb.val_acc)
plt.xlabel('Epoch')
plt.ylabel('Validation Accuracy')
plt.show()
plt.semilogy(np.linspace(1,20,44275),history_cb.loss)
plt.xlabel('Epoch')
plt.xlim([1,20])
plt.ylabel('Loss')
plt.show()

yhat_ts = model.predict(Xts,batch_size=100,verbose=1)
yhat_ts = np.argmax(yhat_ts,axis=1)

C = confusion_matrix(yts,yhat_ts)
Csum = np.sum(C,1)
C = C/Csum[None,:]
print(np.array_str(C,precision=3,suppress_small=True))
plt.imshow(C,interpolation='none')
plt.colorbar()
plt.xticks(np.arange(np.unique(yts).shape[0]),('VS','NF','SF','WF','ST','CL'))
plt.yticks(np.arange(np.unique(yts).shape[0]),('VS','NF','SF','WF','ST','CL'))

plt.savefig('cm-NN-halb1.png')
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
hidden (Dense)               (None, 512)               37376
_________________________________________________________________
output (Dense)               (None, 7)                 3591
=================================================================
Total params: 40,967
Trainable params: 40,967
```

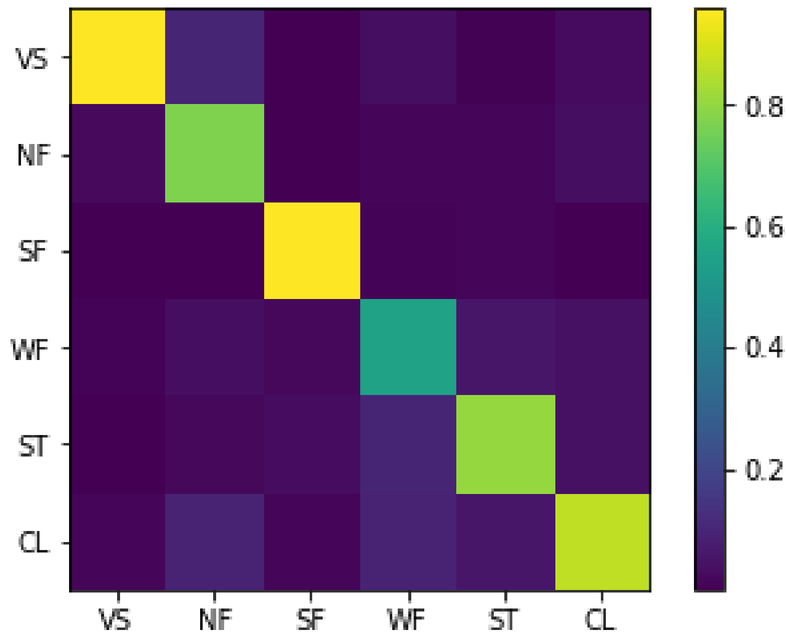
```
Non-trainable params: 0
_________________________________________________________________
Train on 177080 samples, validate on 64145 samples
Epoch 1/25
177080/177080 [==============================] - 22s - loss: 0.6127 - acc: 0.7935 - val_loss: 0
Epoch 2/25
177080/177080 [==============================] - 21s - loss: 0.5136 - acc: 0.8223 - val_loss: 0
Epoch 3/25
177080/177080 [==============================] - 21s - loss: 0.4662 - acc: 0.8380 - val_loss: 0
Epoch 4/25
177080/177080 [==============================] - 20s - loss: 0.4243 - acc: 0.8528 - val_loss: 0
Epoch 5/25
177080/177080 [==============================] - 21s - loss: 0.3918 - acc: 0.8642 - val_loss: 0
Epoch 6/25
177080/177080 [==============================] - 20s - loss: 0.3678 - acc: 0.8716 - val_loss: 0
Epoch 7/25
177080/177080 [==============================] - 20s - loss: 0.3474 - acc: 0.8785 - val_loss: 0
Epoch 8/25
177080/177080 [==============================] - 20s - loss: 0.3310 - acc: 0.8843 - val_loss: 0
Epoch 9/25
177080/177080 [==============================] - 20s - loss: 0.3165 - acc: 0.8893 - val_loss: 0
Epoch 10/25
177080/177080 [==============================] - 20s - loss: 0.3032 - acc: 0.8944 - val_loss: 0
Epoch 11/25
177080/177080 [==============================] - 20s - loss: 0.2921 - acc: 0.8973 - val_loss: 0
Epoch 12/25
177080/177080 [==============================] - 23s - loss: 0.2821 - acc: 0.9018 - val_loss: 0
Epoch 13/25
177080/177080 [==============================] - 22s - loss: 0.2727 - acc: 0.9044 - val_loss: 0
Epoch 14/25
177080/177080 [==============================] - 20s - loss: 0.2643 - acc: 0.9078 - val_loss: 0
Epoch 15/25
177080/177080 [==============================] - 21s - loss: 0.2564 - acc: 0.9105 - val_loss: 0
Epoch 16/25
177080/177080 [==============================] - 20s - loss: 0.2490 - acc: 0.9133 - val_loss: 0
Epoch 17/25
177080/177080 [==============================] - 21s - loss: 0.2422 - acc: 0.9158 - val_loss: 0
Epoch 18/25
177080/177080 [==============================] - 24s - loss: 0.2347 - acc: 0.9182 - val_loss: 0
Epoch 19/25
177080/177080 [==============================] - 21s - loss: 0.2291 - acc: 0.9203 - val_loss: 0
Epoch 20/25
177080/177080 [==============================] - 20s - loss: 0.2229 - acc: 0.9229 - val_loss: 0
Epoch 21/25
177080/177080 [==============================] - 20s - loss: 0.2173 - acc: 0.9245 - val_loss: 0
Epoch 22/25
177080/177080 [==============================] - 20s - loss: 0.2119 - acc: 0.9270 - val_loss: 0
Epoch 23/25
```

```
177080/177080 [==============================] - 21s - loss: 0.2062 - acc: 0.9286 - val_loss: 0
Epoch 24/25
177080/177080 [==============================] - 26s - loss: 0.2015 - acc: 0.9303 - val_loss: 0
Epoch 25/25
177080/177080 [==============================] - 24s - loss: 0.1972 - acc: 0.9320 - val_loss: 0
```






```
63600/64145 [============================>.] - ETA: 0s[[ 0.957  0.101  0.002  0.037  0.008  0.0
 [ 0.026  0.772  0.002  0.019  0.012  0.035]
 [ 0.001  0.001  0.959  0.011  0.015  0.004]
 [ 0.011  0.037  0.02   0.553  0.058  0.042]
 [ 0.002  0.022  0.031  0.101  0.809  0.042]
 [ 0.017  0.092  0.014  0.096  0.058  0.868]]
```



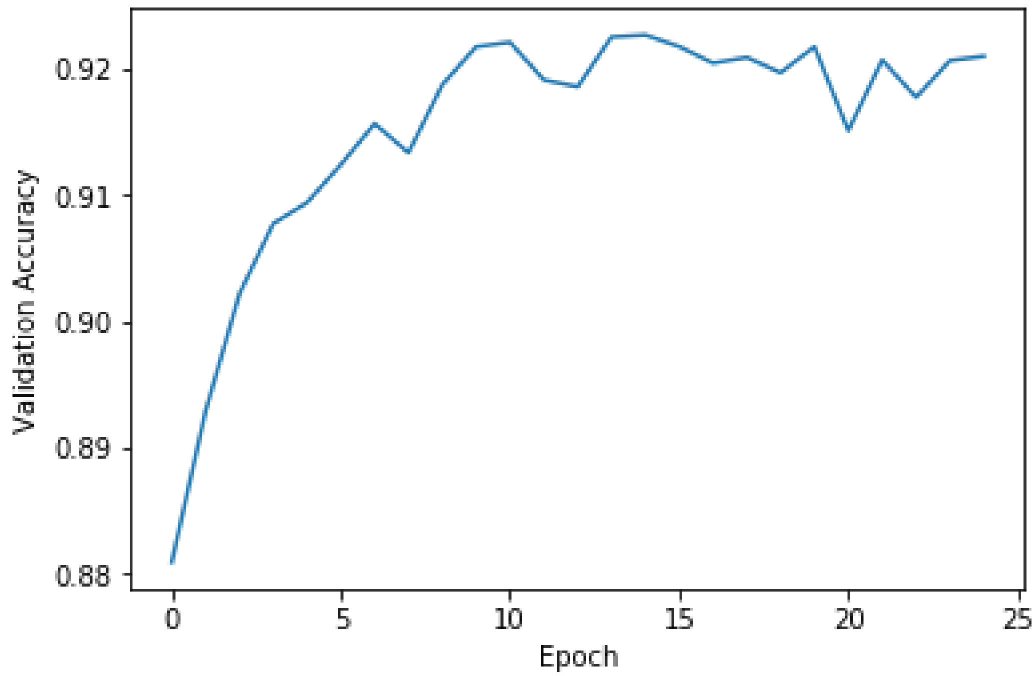
Halberstadt, 3 broader groups

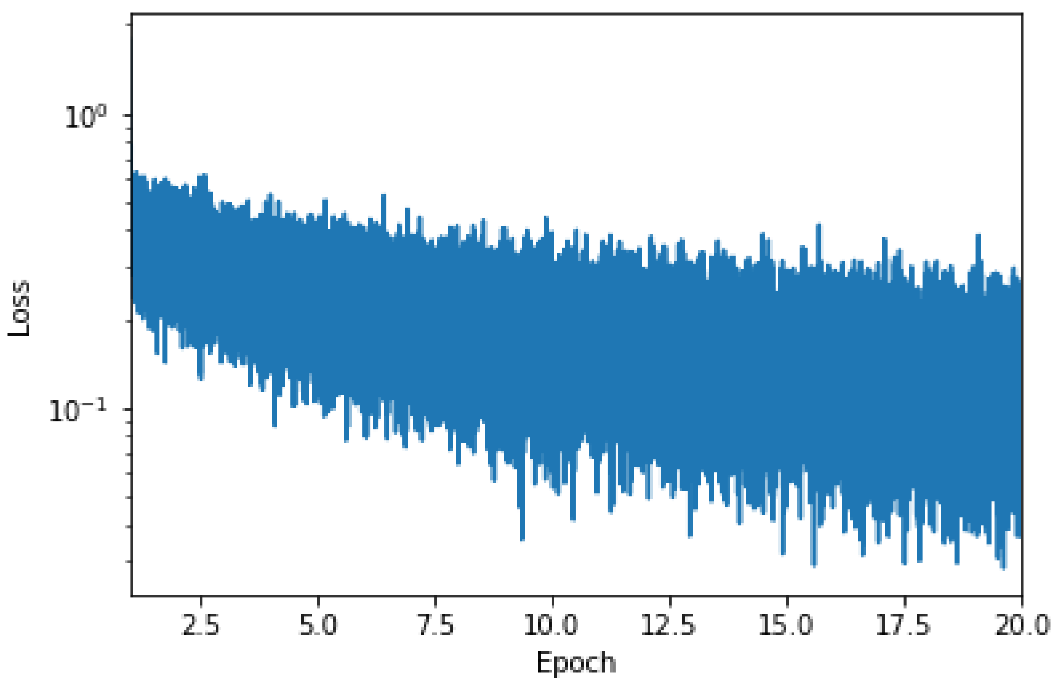
```
In [21]: ytr = train_label['train_label'][0,2].T
         yts = test_label['test_label'][0,2].T
         ntr = Xtr.shape[0]
         nts = Xts.shape[0]

         K.clear_session()
         nin = Xtr.shape[1]
         nh = 512 # Number of hidden units
         nout = int((np.unique(yts)).shape[0]+1)
         model = Sequential()
         model.add(Dense(nh, input_shape=(nin,), activation='sigmoid', name='hidden'))
         model.add(Dense(nout, activation='softmax', name='output'))
         model.summary()
         opt = optimizers.Adam(lr=0.001)
         model.compile(optimizer=opt,
                       loss='sparse_categorical_crossentropy',
                       metrics=['accuracy'])

         model.fit(Xtr, ytr, epochs=25, batch_size = 100, validation_data=(Xts,yts), callbacks=
         plt.plot(history_cb.val_acc)
         plt.xlabel('Epoch')
         plt.ylabel('Validation Accuracy')
         plt.show()
         plt.semilogy(np.linspace(1,20,44275),history_cb.loss)
```

```
plt.xlabel('Epoch')
plt.xlim([1,20])
plt.ylabel('Loss')
plt.show()

yhat_ts = model.predict(Xts,batch_size=100,verbose=1)
yhat_ts = np.argmax(yhat_ts,axis=1)

C = confusion_matrix(yts,yhat_ts)
Csum = np.sum(C,1)
C = C/Csum[None,:]
print(np.array_str(C,precision=3,suppress_small=True))
plt.imshow(C,interpolation='none')
plt.colorbar()
plt.xticks(np.arange(np.unique(yts).shape[0]),('SON','OBS','SIL'))
plt.yticks(np.arange(np.unique(yts).shape[0]),('SON','OBS','SIL'))

plt.savefig('cm-NN-halb2.png')
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
hidden (Dense)               (None, 512)               37376     
_________________________________________________________________
output (Dense)               (None, 4)                 2052      
=================================================================
Total params: 39,428
Trainable params: 39,428
Non-trainable params: 0
_________________________________________________________________
Train on 177080 samples, validate on 64145 samples
Epoch 1/25
177080/177080 [==============================] - 20s - loss: 0.3873 - acc: 0.8645 - val_loss: 0
Epoch 2/25
177080/177080 [==============================] - 19s - loss: 0.3339 - acc: 0.8820 - val_loss: 0
Epoch 3/25
177080/177080 [==============================] - 19s - loss: 0.2991 - acc: 0.8937 - val_loss: 0
Epoch 4/25
177080/177080 [==============================] - 19s - loss: 0.2681 - acc: 0.9040 - val_loss: 0
Epoch 5/25
177080/177080 [==============================] - 19s - loss: 0.2481 - acc: 0.9112 - val_loss: 0
Epoch 6/25
177080/177080 [==============================] - 19s - loss: 0.2343 - acc: 0.9154 - val_loss: 0
Epoch 7/25
177080/177080 [==============================] - 19s - loss: 0.2218 - acc: 0.9203 - val_loss: 0
Epoch 8/25
177080/177080 [==============================] - 20s - loss: 0.2127 - acc: 0.9231 - val_loss: 0
Epoch 9/25
```

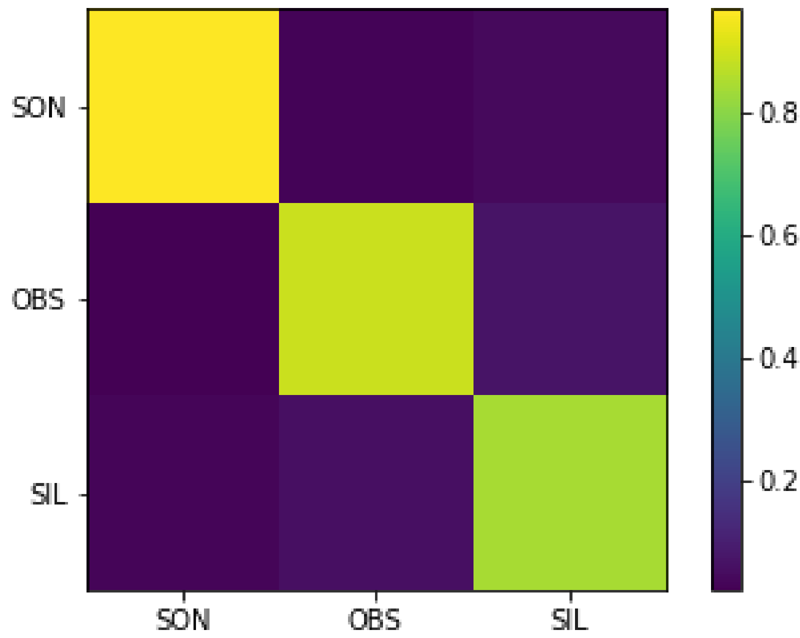
```
177080/177080 [==============================] - 20s - loss: 0.2037 - acc: 0.9260 - val_loss: 0
Epoch 10/25
177080/177080 [==============================] - 21s - loss: 0.1956 - acc: 0.9293 - val_loss: 0
Epoch 11/25
177080/177080 [==============================] - 23s - loss: 0.1881 - acc: 0.9312 - val_loss: 0
Epoch 12/25
177080/177080 [==============================] - 20s - loss: 0.1818 - acc: 0.9344 - val_loss: 0
Epoch 13/25
177080/177080 [==============================] - 21s - loss: 0.1752 - acc: 0.9367 - val_loss: 0
Epoch 14/25
177080/177080 [==============================] - 20s - loss: 0.1694 - acc: 0.9388 - val_loss: 0
Epoch 15/25
177080/177080 [==============================] - 23s - loss: 0.1637 - acc: 0.9407 - val_loss: 0
Epoch 16/25
177080/177080 [==============================] - 22s - loss: 0.1582 - acc: 0.9425 - val_loss: 0
Epoch 17/25
177080/177080 [==============================] - 20s - loss: 0.1531 - acc: 0.9447 - val_loss: 0
Epoch 18/25
177080/177080 [==============================] - 20s - loss: 0.1480 - acc: 0.9471 - val_loss: 0
Epoch 19/25
177080/177080 [==============================] - 20s - loss: 0.1433 - acc: 0.9484 - val_loss: 0
Epoch 20/25
177080/177080 [==============================] - 22s - loss: 0.1389 - acc: 0.9508 - val_loss: 0
Epoch 21/25
177080/177080 [==============================] - 26s - loss: 0.1345 - acc: 0.9521 - val_loss: 0
Epoch 22/25
177080/177080 [==============================] - 21s - loss: 0.1307 - acc: 0.9534 - val_loss: 0
Epoch 23/25
177080/177080 [==============================] - 20s - loss: 0.1265 - acc: 0.9550 - val_loss: 0
Epoch 24/25
177080/177080 [==============================] - 19s - loss: 0.1226 - acc: 0.9566 - val_loss: 0
Epoch 25/25
177080/177080 [==============================] - 20s - loss: 0.1185 - acc: 0.9580 - val_loss: 0
```






```
63800/64145 [============================>.] - ETA: 0s[[ 0.967  0.032  0.044]
 [ 0.021  0.892  0.072]
```

```
[ 0.036  0.061  0.845]]
```



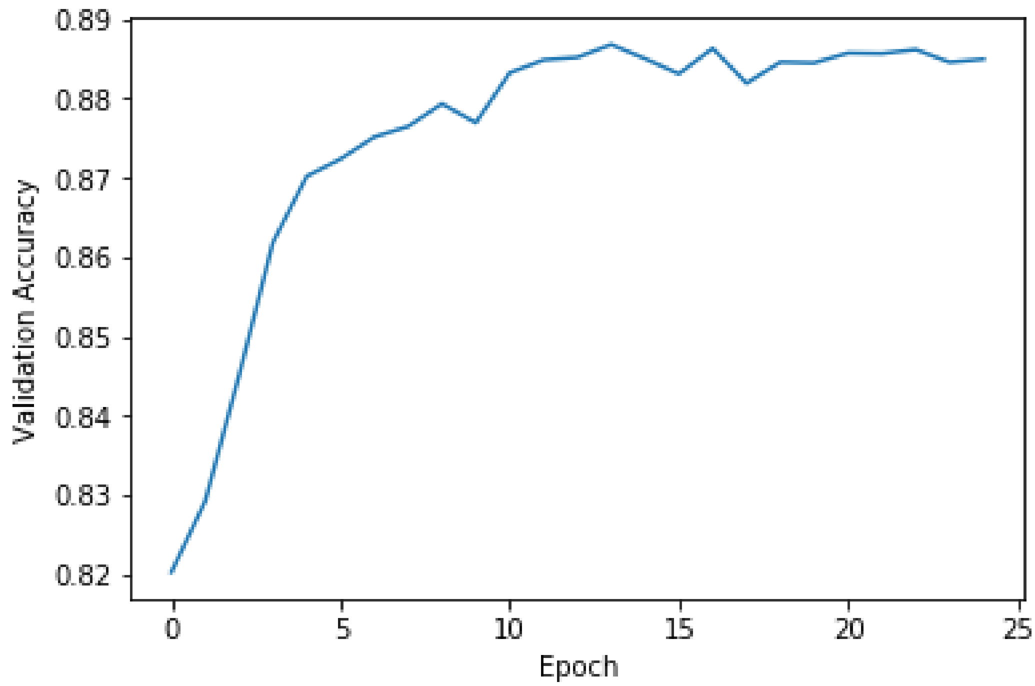
Scanlon

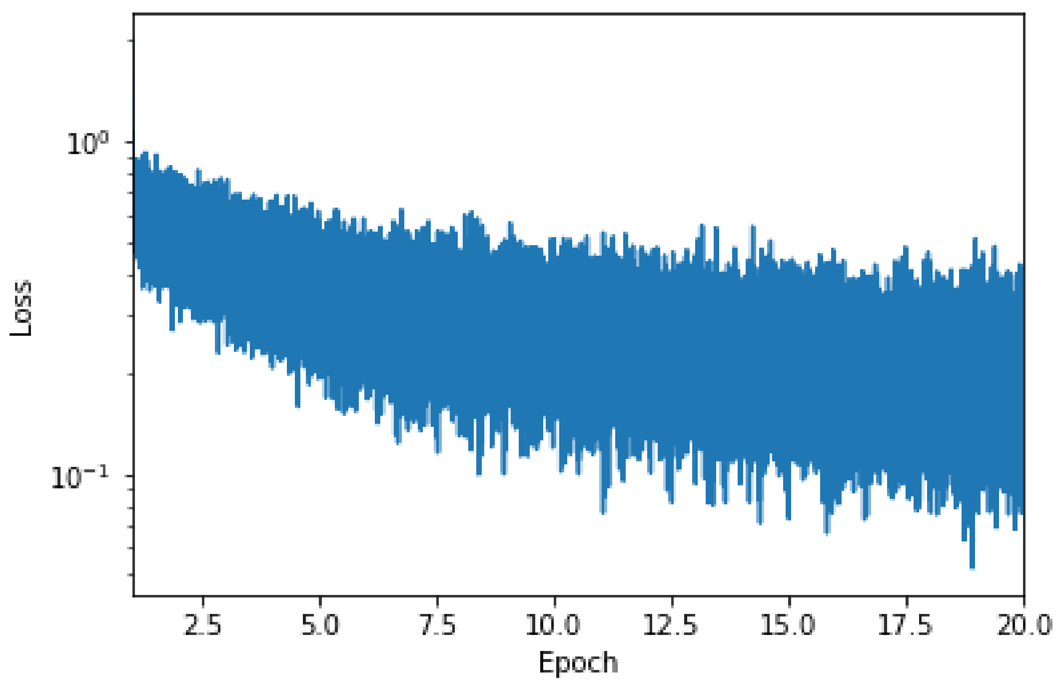
```
In [22]: ytr = train_label['train_label'][0,3].T
         yts = test_label['test_label'][0,3].T
         ntr = Xtr.shape[0]
         nts = Xts.shape[0]

         K.clear_session()
         nin = Xtr.shape[1]
         nh = 512 # Number of hidden units
         nout = int((np.unique(yts)).shape[0]+1)
         model = Sequential()
         model.add(Dense(nh, input_shape=(nin,), activation='sigmoid', name='hidden'))
         model.add(Dense(nout, activation='softmax', name='output'))
         model.summary()
         opt = optimizers.Adam(lr=0.001)
         model.compile(optimizer=opt,
                       loss='sparse_categorical_crossentropy',
                       metrics=['accuracy'])

         model.fit(Xtr, ytr, epochs=25, batch_size = 100, validation_data=(Xts,yts), callbacks=
         plt.plot(history_cb.val_acc)
         plt.xlabel('Epoch')
         plt.ylabel('Validation Accuracy')
```

```
plt.show()
plt.semilogy(np.linspace(1,20,44275),history_cb.loss)
plt.xlabel('Epoch')
plt.xlim([1,20])
plt.ylabel('Loss')
plt.show()

yhat_ts = model.predict(Xts,batch_size=100,verbose=1)
yhat_ts = np.argmax(yhat_ts,axis=1)

C = confusion_matrix(yts,yhat_ts)
Csum = np.sum(C,1)
C = C/Csum[None,:]
print(np.array_str(C,precision=3,suppress_small=True))
plt.imshow(C,interpolation='none')
plt.colorbar()
plt.xticks(np.arange(np.unique(yts).shape[0]),('Vowels','Stops','Fricatives','Nasals'
plt.yticks(np.arange(np.unique(yts).shape[0]),('Vowels','Stops','Fricatives','Nasals'

plt.savefig('cm-NN-s.png')
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
hidden (Dense)               (None, 512)               37376
_________________________________________________________________
output (Dense)               (None, 6)                 3078
=================================================================
Total params: 40,454
Trainable params: 40,454
Non-trainable params: 0
_________________________________________________________________
Train on 177080 samples, validate on 64145 samples
Epoch 1/25
177080/177080 [==============================] - 21s - loss: 0.6024 - acc: 0.7982 - val_loss: (
Epoch 2/25
177080/177080 [==============================] - 20s - loss: 0.5168 - acc: 0.8233 - val_loss: (
Epoch 3/25
177080/177080 [==============================] - 21s - loss: 0.4623 - acc: 0.8399 - val_loss: (
Epoch 4/25
177080/177080 [==============================] - 20s - loss: 0.4113 - acc: 0.8566 - val_loss: (
Epoch 5/25
177080/177080 [==============================] - 20s - loss: 0.3784 - acc: 0.8675 - val_loss: (
Epoch 6/25
177080/177080 [==============================] - 21s - loss: 0.3541 - acc: 0.8763 - val_loss: (
Epoch 7/25
177080/177080 [==============================] - 27s - loss: 0.3359 - acc: 0.8824 - val_loss: (
Epoch 8/25
```

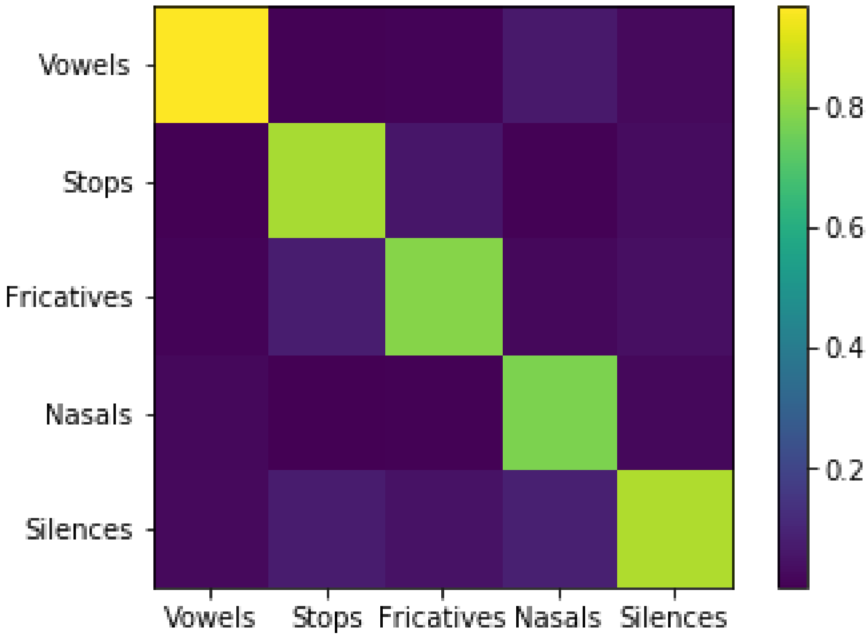
```
177080/177080 [==============================] - 23s - loss: 0.3209 - acc: 0.8868 - val_loss: 
Epoch 9/25
177080/177080 [==============================] - 20s - loss: 0.3079 - acc: 0.8918 - val_loss: 
Epoch 10/25
177080/177080 [==============================] - 20s - loss: 0.2967 - acc: 0.8955 - val_loss: 
Epoch 11/25
177080/177080 [==============================] - 20s - loss: 0.2858 - acc: 0.9000 - val_loss: 
Epoch 12/25
177080/177080 [==============================] - 20s - loss: 0.2769 - acc: 0.9028 - val_loss: 
Epoch 13/25
177080/177080 [==============================] - 20s - loss: 0.2674 - acc: 0.9060 - val_loss: 
Epoch 14/25
177080/177080 [==============================] - 23s - loss: 0.2600 - acc: 0.9090 - val_loss: 
Epoch 15/25
177080/177080 [==============================] - 26s - loss: 0.2521 - acc: 0.9116 - val_loss: 
Epoch 16/25
177080/177080 [==============================] - 21s - loss: 0.2454 - acc: 0.9141 - val_loss: 
Epoch 17/25
177080/177080 [==============================] - 20s - loss: 0.2390 - acc: 0.9159 - val_loss: 
Epoch 18/25
177080/177080 [==============================] - 20s - loss: 0.2326 - acc: 0.9186 - val_loss: 
Epoch 19/25
177080/177080 [==============================] - 21s - loss: 0.2267 - acc: 0.9208 - val_loss: 
Epoch 20/25
177080/177080 [==============================] - 22s - loss: 0.2202 - acc: 0.9233 - val_loss: 
Epoch 21/25
177080/177080 [==============================] - 27s - loss: 0.2154 - acc: 0.9242 - val_loss: 
Epoch 22/25
177080/177080 [==============================] - 22s - loss: 0.2102 - acc: 0.9269 - val_loss: 
Epoch 23/25
177080/177080 [==============================] - 20s - loss: 0.2051 - acc: 0.9287 - val_loss: 
Epoch 24/25
177080/177080 [==============================] - 20s - loss: 0.2005 - acc: 0.9302 - val_loss: 
Epoch 25/25
177080/177080 [==============================] - 20s - loss: 0.1955 - acc: 0.9317 - val_loss: 
```






```
64000/64145 [============================>.] - ETA: 0s[[ 0.964  0.01   0.014  0.071  0.03 ]
 [ 0.004  0.839  0.063  0.008  0.036]
```

```
[ 0.013  0.081  0.791  0.026  0.042]
[ 0.023  0.007  0.009  0.774  0.026]
[ 0.028  0.076  0.049  0.088  0.851]]
```




```
In [ ]:
```