Data Science - Capstone Project Submission

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- Student Pace: **Self Paced**
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- Blog URL: **https://toopster.github.io/ (https://toopster.github.io/)**

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3. Deep Learning Models for Speech Recognition

In [314]:

```
# Import relevant libraries and modules for creating and training neural networks
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import wave
import soundfile as sf
import librosa, librosa.display
import IPython.display as ipd
import os
import json

import tensorflow as tf
from tensorflow.keras.layers.experimental import preprocessing
from tensorflow.keras import layers
from tensorflow.keras import models
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder

import logging
logging.getLogger("tensorflow").setLevel(logging.ERROR)

import pathlib
from pathlib import Path
```

In [315]:

```
# Set seed for reproducibility
seed = 123
tf.random.set_seed(seed)
np.random.seed(seed)
```

3A. Preprocessing - Stage Two

In [64]:

```
# Function to extract Mel Spectrograms and MFCCs to use in the models and store in J
def preprocess_dataset(dataset_path, json_path, feature, num_samples, num_mfcc=13, n
    '''
    Extract Mel Spectrograms and MFCCs to use in the models and store in JSON file

        Params:
            dataset_path (str): Path to dataset containing audio samples
            feature (str): Specific feature requested, accepts either 'MFCCs' or 'me
            json_path (str): Output path to JSON file
            num_samples (int):
            num_mfcc (int):
            n_fft (int):
            hop_length (int):
    '''
    # Dictionary to temporarily store mapping, labels, MFCCs and filenames
    if feature == 'mel_specs':
        data = {
            'mapping': [],
            'labels': [],
            'mel_specs': [],
            'files': []
        }
    else:
         data = {
            'mapping': [],
            'labels': [],
            'MFCCs': [],
            'files': []
        }

    # Loop through all sub directories
    for i, (dirpath, dirnames, filenames) in enumerate(os.walk(dataset_path)):

        # Ensure we're at sub-folder level
        if dirpath is not dataset_path:

            # Save label in the mapping
            label = dirpath.split('/')[-1]
            data['mapping'].append(label)
            print("\nProcessing: '{}'".format(label))

            # Process all audio files in the sub directory and store MFCCs and Mel S
            for f in filenames:
                file_path = os.path.join(dirpath, f)

                # Load audio file and slice it to ensure length consistency among di
                signal, sample_rate = librosa.load(file_path)

                # Drop audio files with less than pre-decided number of samples
                if len(signal) >= num_samples:

                    # Ensure consistency of the length of the signal
                    signal = signal[:num_samples]

                    # Extract MFCCs
                    if feature == 'mel_specs':
                        mel_specs = librosa.feature.melspectrogram(signal,
                                                                   sample_rate,
                                                                   n_fft=n_fft,
```

```
                                                                    hop_length=hop_le
                        data['mel_specs'].append(mel_specs.T.tolist())

                    else:
                        MFCCs = librosa.feature.mfcc(signal,
                                                     sample_rate,
                                                     n_mfcc=num_mfcc,
                                                     n_fft=n_fft,
                                                     hop_length=hop_length)

                        data['MFCCs'].append(MFCCs.T.tolist())

                    # Append data in dictionary
                    data['labels'].append(i-1)
                    data['files'].append(file_path)
                    print("{}: {}".format(file_path, i-1))

    # Save data in JSON file for re-using later
    with open(json_path, 'w') as file_path:
        json.dump(data, file_path, indent=4)
```

In [4]:

```
# Set the parameters for the Speech Commands dataset for preprocessing
sc_dataset_path = 'data/speech_commands_v0.02'
sc_json_path = 'speech_commands_data.json'
num_samples = 22050
```

In [ ]:

```
# Preprocess the Speech Commands dataset
preprocess_dataset(sc_dataset_path, sc_json_path, 'MFCCs', num_samples)
```

In [5]:

```
# Set the parameters for the Ultrasuite dataset for preprocessing
us_dataset_path = 'data/ultrasuite_top35'
us_json_path = 'ultrasuite_top35_data.json'
num_samples = 22050
```

In [ ]:

```
# Preprocess the Ultrasuite dataset
preprocess_dataset(us_dataset_path, us_json_path, 'MFCCs', num_samples)
```

In [7]:

```
def load_data(data_path, feature):
    '''
    Load the data from the JSON file depending on selected feature

        Params:
            data_path (str): Path to json file containing data
            feature (str): Specific feature requested, accepts either 'MFCCs' or 'me

        Returns:
            X (ndarray): Inputs
            y (ndarray): Targets
    '''
    with open(data_path, 'r') as file_path:
        data = json.load(file_path)

    X = np.array(data[feature])
    y = np.array(data['labels'])

    print('Datasets loaded...')

    return X, y
```

In [8]:

```
def create_train_test(data_path, feature, test_size=0.2, val_size=0.2):
    '''
    Splits the data to create training, test and validation datasets

        Params:
            data_path (str): Path to json file containing data
            feature (str): Specific feature requested, accepts either 'MFCCs' or 'me
            test_size (float): Test size percentage
            val_size (float): Validation size percentage

        Returns:
            X_train (ndarray): Inputs for the training dataset
            y_train (ndarray): Targets for the training dataset
            X_val (ndarray): Inputs for the validation dataset
            y_val (ndarray): Targets for the validation dataset
            X_test (ndarray): Inputs for the test dataset
            y_test (ndarray): Targets for the test dataset
    '''
    # Load dataset
    X, y = load_data(data_path, feature)

    # Create train, test and validation splits
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=test_size)
    X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_size=va

    # Increase the dimension of the array for each split
    X_train = X_train[..., np.newaxis]
    X_test = X_test[..., np.newaxis]
    X_val = X_val[..., np.newaxis]

    return X_train, y_train, X_val, y_val, X_test, y_test
```

In [9]:

```
def visualise_results(results):
    '''
    Visualise the results from the model history plotting training / validation accu

        Params:
            results: Model history
    '''
    history = results.history

    plt.figure(figsize=(20,8))
    plt.xticks(fontsize=12)
    plt.yticks(fontsize=12)

    plt.subplot(1, 2, 1)
    plt.plot(history['val_loss'])
    plt.plot(history['loss'])
    plt.legend(['Validation Loss', 'Training Loss'], fontsize=12)
    plt.title('Loss', fontsize=18)
    plt.xlabel('Epochs', fontsize=14)
    plt.ylabel('Loss', fontsize=14)

    plt.subplot(1, 2, 2)
    plt.plot(history['val_acc'])
    plt.plot(history['acc'])
    plt.legend(['Validation Accuracy', 'Training Accuracy'], fontsize=12)
    plt.title('Accuracy', fontsize=18)
    plt.xlabel('Epochs', fontsize=14)
    plt.ylabel('Accuracy', fontsize=14)
    plt.show()
```

In [10]:

```
# Create the train, test and validation datasets for the Speech Commands dataset us
sc_data_path = 'speech_commands_data.json'
sc_X_train, sc_y_train, sc_X_val, sc_y_val, sc_X_test, sc_y_test = create_train_test
```

```
Datasets loaded...
```

In [12]:

```
# Create the train, test and validation datasets for the Ultrasuite Top 35 dataset u
us_data_path = 'ultrasuite_top35_data.json'
us_X_train, us_y_train, us_X_val, us_y_val, us_X_test, us_y_test = create_train_test
```

```
Datasets loaded...
```

In [13]:

```
def check_array_shapes(X_train, y_train, X_val, y_val, X_test, y_test):
    '''
    Output the training, test and validation dataset shapes

        Params:
            X_train (ndarray): Inputs for the training dataset
            y_train (ndarray): Targets for the training dataset
            X_val (ndarray): Inputs for the validation dataset
            y_val (ndarray): Targets for the validation dataset
            X_test (ndarray): Inputs for the test dataset
            y_test (ndarray): Targets for the test dataset
    '''
    print ("Number of training samples: " + str(X_train.shape[0]))
    print ("Number of testing samples: " + str(X_test.shape[0]))
    print ("Number of validation samples: " + str(X_val.shape[0]))
    print ("X_train shape: " + str(X_train.shape))
    print ("y_train shape: " + str(y_train.shape))
    print ("X_test shape: " + str(X_test.shape))
    print ("y_test shape: " + str(y_test.shape))
    print ("X_val shape: " + str(X_val.shape))
    print ("y_val shape: " + str(y_val.shape))
```

In [14]:

```
def reformat_y(y):
    '''
    Reformats / One Hot Encodes targets

        Params:
            y (ndarray): Input targets

        Returns:
            y (ndarray): One hot encoded targets
    '''
    y = LabelEncoder().fit_transform(y)
    y = tf.keras.utils.to_categorical(y)
    return y
```

In [15]:

```
# Check the array shapes for the Ultrasuite dataset
check_array_shapes(us_X_train, us_y_train, us_X_val, us_y_val, us_X_test, us_y_test
```

```
Number of training samples: 3942
Number of testing samples: 1233
Number of validation samples: 986
X_train shape: (3942, 44, 13, 1)
y_train shape: (3942,)
X_test shape: (1233, 44, 13, 1)
y_test shape: (1233,)
X_val shape: (986, 44, 13, 1)
y_val shape: (986,)
```

In [16]:

```
us_y_test[:10]
```

Out[16]:

```
array([23, 31, 19,  6, 22, 10, 14,  3,  6, 11])
```

In [17]:

```
# One-hot encode Ultrasuite Top 35 labels
us_train_y = reformat_y(us_y_train)
us_test_y = reformat_y(us_y_test)
us_val_y = reformat_y(us_y_val)
```

In [18]:

```
us_test_y[:10]
```

Out[18]:

```
array([[0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0.,
        0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0.,
0.,
        0., 0., 0.],
       [0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0.,
        0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
1.,
        0., 0., 0.],
       [0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0.,
        0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0.,
        0., 0., 0.],
       [0., 0., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0.,
0.,
        0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0.,
        0., 0., 0.],
       [0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0.,
        0., 0., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0.,
0.,
        0., 0., 0.],
       [0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 0., 0.,
0.,
        0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0.,
        0., 0., 0.],
       [0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1.,
0.,
        0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0.,
        0., 0., 0.],
       [0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0.,
        0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0.,
        0., 0., 0.],
       [0., 0., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0.,
0.,
        0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0.,
        0., 0., 0.],
       [0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 0.,
0.,
        0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0.,
        0., 0., 0.]], dtype=float32)
```

3B. Model 1: Create a simple baseline model

In [19]:

```
def build_baseline_model(input_shape, output_units, loss_func='categorical_crossentr
    '''
    Build a baseline model

        Params:
            input_shape (tuple): Shape of array representing a sample train
            output_units (int): Number of targets / categories
            loss_func (str): Loss function to use
            learning_rate (float): Learning rate

        Returns:
            baseline_model: Tensorflow model
    '''
    baseline_model = tf.keras.models.Sequential()
    baseline_model.add(tf.keras.layers.InputLayer(input_shape=input_shape))
    baseline_model.add(tf.keras.layers.Flatten())
    baseline_model.add(tf.keras.layers.BatchNormalization())
    baseline_model.add(tf.keras.layers.Dense(output_units, activation='softmax'))

    # Set optimizer and learning rate
    optimiser = tf.optimizers.Adam(learning_rate=learning_rate)

    # Compile the baseline model
    baseline_model.compile(loss=loss_func,
                           optimizer=optimiser,
                           metrics=['acc'])

    # Print summary for model
    baseline_model.summary()

    return baseline_model
```

In [20]:

```
# Function for fitting the model
def fit_model(model, epochs, batch_size, patience, X_train, y_train, X_val, y_val):
    '''
    Fit the model

        Params:
            model : Input Tensorflow model
            epochs (int): Number of training epochs
            batch_size (int): Number of samples per batch
            patience (int): Number of epochs to wait before early stop, if there no
            X_train (ndarray): Inputs for the training dataset
            y_train (ndarray): Targets for the training dataset
            X_val (ndarray): Inputs for the validation dataset
            y_val (ndarray): Targets for the training dataset

        Returns:
            results: Training history
    '''
    # Define early stopping criteria
    early_stopping = tf.keras.callbacks.EarlyStopping(monitor='accuracy', min_delta=

    # Fit the model
    results = model.fit(X_train,
                        y_train,
                        epochs=epochs,
                        batch_size=batch_size,
                        validation_data=(X_val, y_val),
                        callbacks=[early_stopping])
    return results
```

In [21]:

```
# Function to save the model if so required
def save_model(save_model, save_path):
    '''
    Save the model

        Params:
            save_model : Input Tensorflow model
            save_path (str): Path to save model including file extension .h5
    '''
    save_model.save(save_path)
```

Baseline model for the Speech Commands dataset

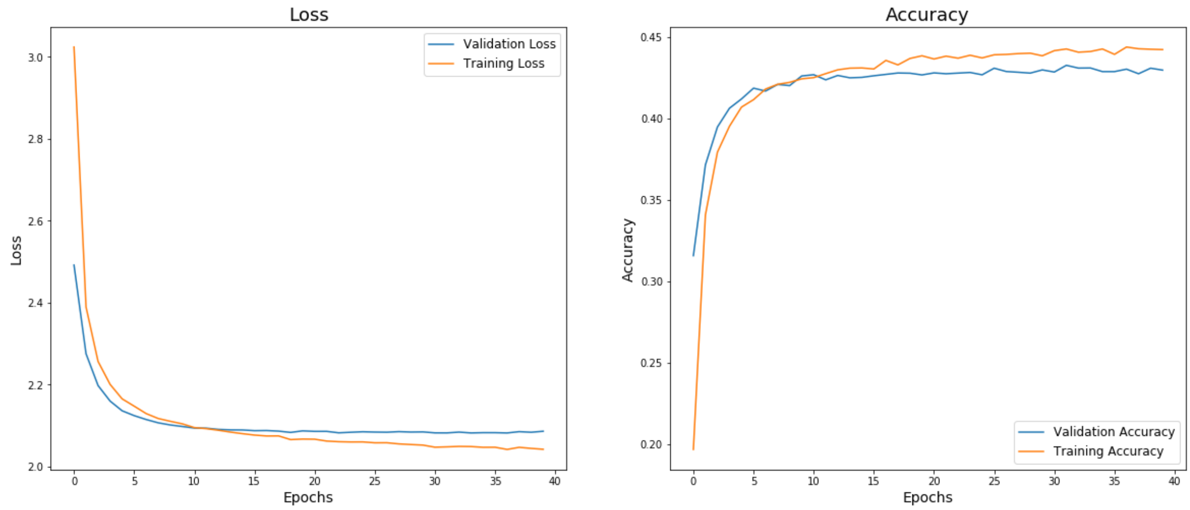
In [25]:

```
# One-hot encode Speech Commands labels
sc_train_y = reformat_y(sc_y_train)
sc_test_y = reformat_y(sc_y_test)
sc_val_y = reformat_y(sc_y_val)

# Create baseline model for Speech Commands dataset
sc_input_shape = (sc_X_train[0].shape)
sc_output_units = 35
sc_baseline_model = build_baseline_model(sc_input_shape, sc_output_units, learning_r

# Fit model
sc_epochs = 40
sc_batch_size = 32
sc_patience = 5
sc_baseline_results = fit_model(sc_baseline_model,
                                sc_epochs,
                                sc_batch_size,
                                sc_patience,
                                sc_X_train,
                                sc_train_y,
                                sc_X_val,
                                sc_val_y)
```

```
_________________________________________________________________
dense_2 (Dense)              (None, 35)                20055
=================================================================
Total params: 22,343
Trainable params: 21,199
Non-trainable params: 1,144
_________________________________________________________________
Epoch 1/40
WARNING: AutoGraph could not transform <function Model.make_train_fun
ction.<locals>.train_function at 0x7fd5713c5dd0> and will run it as-i
s.
Please report this to the TensorFlow team. When filing the bug, set t
he verbosity to 10 (on Linux, `export AUTOGRAPH_VERBOSITY=10`) and at
tach the full output.
Cause: 'arguments' object has no attribute 'posonlyargs'
To silence this warning, decorate the function with @tf.autograph.exp
erimental.do_not_convert
1901/1908 [============================>.] - ETA: 0s - loss: 3.0259 -
acc: 0.1964WARNING: AutoGraph could not transform <function Model.mak
e_test_function.<locals>.test_function at 0x7fd56eefa710> and will ru
```

In [27]:

```
# Visualise the loss and accuracy of the training and validation sets across epochs
visualise_results(sc_baseline_results)
```



In [28]:

```
# Evaluate the training results
sc_baseline_train = sc_baseline_model.evaluate(sc_X_train, sc_train_y)
sc_baseline_train
```

```
1908/1908 [==============================] - 2s 1ms/step - loss: 1.947
8 - acc: 0.4735
```

Out[28]:

```
[1.9478094577789307, 0.4735143780708313]
```

In [29]:

```
# Evaluate the test results
sc_baseline_test = sc_baseline_model.evaluate(sc_X_test, sc_test_y)
sc_baseline_test
```

```
597/597 [==============================] - 1s 1ms/step - loss: 2.0892
- acc: 0.4318
```

Out[29]:

```
[2.0892269611358643, 0.4318360388278961]
```

Baseline model for the Ultrasuite dataset

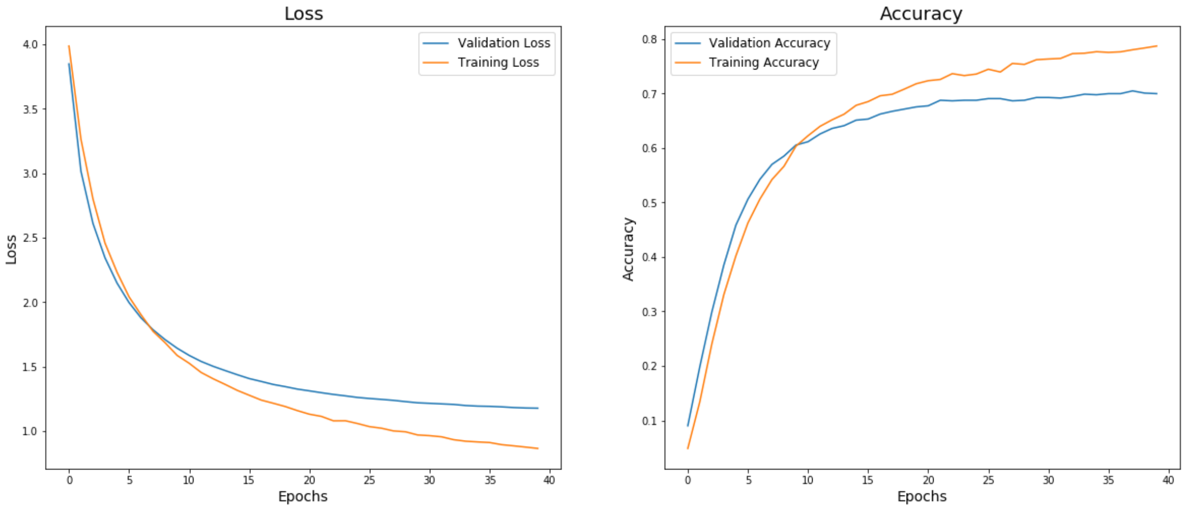
In [31]:

```
# Create baseline model for Ultrasuite dataset
us_input_shape = (us_X_train[0].shape)
us_output_units = 35
us_baseline_model = build_baseline_model(us_input_shape, us_output_units, learning_r

# Fit model
us_epochs = 40
us_batch_size = 32
us_patience = 5
us_baseline_results = fit_model(us_baseline_model,
                                us_epochs,
                                us_batch_size,
                                us_patience,
                                us_X_train,
                                us_train_y,
                                us_X_val,
                                us_val_y)
```

```
Epoch 8/40
124/124 [==============================] - 0s 2ms/step - loss: 1.7744
- acc: 0.5421 - val_loss: 1.7866 - val_acc: 0.5700
Epoch 9/40
124/124 [==============================] - 0s 2ms/step - loss: 1.6861
- acc: 0.5665 - val_loss: 1.7100 - val_acc: 0.5852
Epoch 10/40
124/124 [==============================] - 0s 2ms/step - loss: 1.5879
- acc: 0.6035 - val_loss: 1.6437 - val_acc: 0.6055
Epoch 11/40
124/124 [==============================] - 0s 2ms/step - loss: 1.5269
- acc: 0.6225 - val_loss: 1.5880 - val_acc: 0.6116
Epoch 12/40
124/124 [==============================] - 0s 2ms/step - loss: 1.4555
- acc: 0.6398 - val_loss: 1.5410 - val_acc: 0.6258
Epoch 13/40
124/124 [==============================] - 0s 2ms/step - loss: 1.4066
- acc: 0.6517 - val_loss: 1.5031 - val_acc: 0.6359
Epoch 14/40
124/124 [==============================] - 0s 2ms/step - loss: 1.3627
```

In [32]:

```
# Visualise the loss and accuracy of the training and validation sets across epochs
visualise_results(us_baseline_results)
```



In [33]:

```
# Evaluate the training results
us_baseline_results_train = us_baseline_model.evaluate(us_X_train, us_train_y)
us_baseline_results_train
```

```
124/124 [==============================] - 0s 1ms/step - loss: 0.7920
- acc: 0.8108
```

Out[33]:

```
[0.7920032143592834, 0.8107559680938721]
```

In [34]:

```
# Evaluate the test results
us_baseline_results_test = us_baseline_model.evaluate(us_X_test, us_test_y)
us_baseline_results_test
```

```
39/39 [==============================] - 0s 2ms/step - loss: 1.2501 -
acc: 0.6748
```

Out[34]:

```
[1.2501418590545654, 0.6747769713401794]
```

Conclusion

It's starting point with the training accuracy for the Ultrasuite dataset being 81%. The model is clearly overfitting the training data and is not generalising well when shown unseen data given the validation accuracy of just over 67%.

What is of particular note is the vastly different accuracies when compared to the Speech Commands dataset which are both under 50%.

This could suggest that a more simple model works better for audio samples from children with a speech sound disorder.

3C. Model 2: Baseline model with increased learning rate and batch size

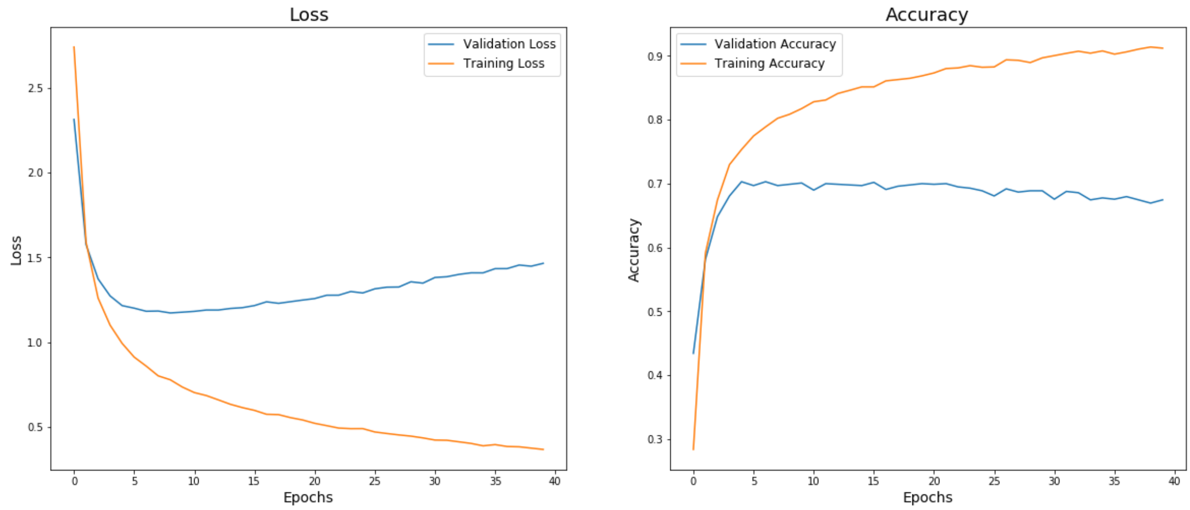
In [36]:

```
# Create second baseline model on Ultrasuite dataset changing the learning rate and
us_input_shape = (us_X_train[0].shape)
us_output_units = 35
us_baseline_model_2 = build_baseline_model(us_input_shape, us_output_units, learning


# Fit model
us_epochs = 40
us_batch_size = 64
us_patience = 5
us_baseline_results_2 = fit_model(us_baseline_model_2,
                      us_epochs,
                      us_batch_size,
                      us_patience,
                      us_X_train,
                      us_train_y,
                      us_X_val,
                      us_val_y)
```

```
acc: 0.8628 - val_loss: 1.2288 - val_acc: 0.6957
Epoch 19/40
62/62 [==============================] - 0s 3ms/step - loss: 0.5542 -
acc: 0.8648 - val_loss: 1.2385 - val_acc: 0.6978
Epoch 20/40
62/62 [==============================] - 0s 3ms/step - loss: 0.5405 -
acc: 0.8686 - val_loss: 1.2481 - val_acc: 0.6998
Epoch 21/40
62/62 [==============================] - 0s 3ms/step - loss: 0.5209 -
acc: 0.8732 - val_loss: 1.2568 - val_acc: 0.6988
Epoch 22/40
62/62 [==============================] - 0s 3ms/step - loss: 0.5070 -
acc: 0.8800 - val_loss: 1.2766 - val_acc: 0.6998
Epoch 23/40

62/62 [==============================] - 0s 3ms/step - loss: 0.4927 -
acc: 0.8810 - val_loss: 1.2768 - val_acc: 0.6947
Epoch 24/40
62/62 [==============================] - 0s 3ms/step - loss: 0.4893 -
acc: 0.8846 - val_loss: 1.2985 - val_acc: 0.6927
```

In [37]:

```
# Visualise the loss and accuracy of the training and validation sets across epochs
visualise_results(us_baseline_results_2)
```



In [38]:

```
# Evaluate the training results
us_baseline_results_2_train = us_baseline_model_2.evaluate(us_X_train, us_train_y)
us_baseline_results_2_train
```

```
124/124 [==============================] - 0s 1ms/step - loss: 0.2870
- acc: 0.9439
```

Out[38]:

```
[0.2869826853275299, 0.9439370632171631]
```

In [39]:

```
# Evaluate the test results
results_3_test = us_baseline_model_2.evaluate(us_X_test, us_test_y)
results_3_test
```

```
39/39 [==============================] - 0s 2ms/step - loss: 1.5570 -
acc: 0.6529
```

Out[39]:

```
[1.5570393800735474, 0.6528791785240173]
```

Conclusion

We have improved the training accuracy of the baseline model, to over 94%, by increasing the learning rate and increasing the batch size but this has only served to exascerbate the issue of overfitting with test accuracy not reducing to 65% and the difference between the two plots being dramatic.

In an effort to deal with the issue of overfitting, we will introduce some regularization layers and see what effect they have on performance.

3D. Model 3: Adding hidden layers to the baseline model, deepening the network

In [95]:

```
# Build a second baseline model
def build_model_2(input_shape, output_units, loss_func='categorical_crossentropy', l

    model_2 = tf.keras.models.Sequential()
    model_2.add(tf.keras.layers.InputLayer(input_shape=input_shape))
    model_2.add(tf.keras.layers.Flatten())
    model_2.add(tf.keras.layers.BatchNormalization())
    model_2.add(tf.keras.layers.Dense(256, activation='relu'))
#     model_2.add(tf.keras.layers.Dropout(0.3))
    model_2.add(tf.keras.layers.Dense(128, activation='relu'))
    model_2.add(tf.keras.layers.Dense(64, activation='relu'))
    model_2.add(tf.keras.layers.Dense(output_units, activation='softmax'))

    # Set optimizer and learning rate
    optimiser = tf.optimizers.Adam(learning_rate=learning_rate)

    # Compile the baseline model
    model_2.compile(loss=loss_func,
                        optimizer=optimiser,
                        metrics=['acc'])

    # Print summary for model
    model_2.summary()

    return model_2
```

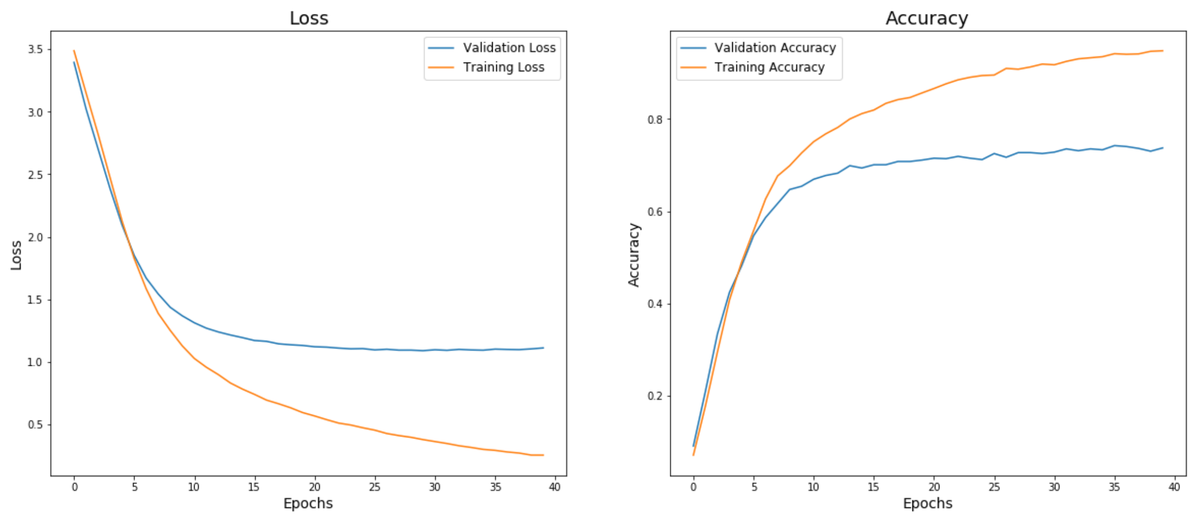
In [96]:

```
# Create baseline model for Ultrasuite dataset
us_input_shape = (us_X_train[0].shape)
us_output_units = 35
us_model_2 = build_model_2(us_input_shape, us_output_units, learning_rate=0.0001)

# Fit model
us_epochs = 40
us_batch_size = 64
us_patience = 3
us_results_3 = fit_model(us_model_2,
                      us_epochs,
                      us_batch_size,
                      us_patience,
                      us_X_train,
                      us_train_y,
                      us_X_val,
                      us_val_y)
```

```
acc: 0.9178 - val_loss: 1.0970 - val_acc: 0.7282
Epoch 32/40
62/62 [==============================] - 0s 5ms/step - loss: 0.3478 -
acc: 0.9252 - val_loss: 1.0928 - val_acc: 0.7353
Epoch 33/40
62/62 [==============================] - 0s 6ms/step - loss: 0.3298 -
acc: 0.9307 - val_loss: 1.1002 - val_acc: 0.7312
Epoch 34/40
62/62 [==============================] - 0s 6ms/step - loss: 0.3165 -
acc: 0.9330 - val_loss: 1.0958 - val_acc: 0.7353
Epoch 35/40
62/62 [==============================] - 0s 5ms/step - loss: 0.3011 -
acc: 0.9353 - val_loss: 1.0936 - val_acc: 0.7333
Epoch 36/40
62/62 [==============================] - 0s 5ms/step - loss: 0.2931 -
acc: 0.9419 - val_loss: 1.1023 - val_acc: 0.7424
Epoch 37/40
62/62 [==============================] - 0s 6ms/step - loss: 0.2804 -
acc: 0.9406 - val_loss: 1.0998 - val_acc: 0.7404
Epoch 38/40
```

In [97]:

```
# Visualise the loss and accuracy of the training and validation sets across epochs
visualise_results(us_results_3)
```



In [98]:

```
# Evaluate the training results
us_results_3_train = us_model_2.evaluate(us_X_train, us_train_y)
us_results_3_train
```

```
124/124 [==============================] - 0s 2ms/step - loss: 0.1969
- acc: 0.9609
```

Out[98]:

```
[0.1969350427389145, 0.9609335064888]
```

In [99]:

```
# Evaluate the test results
results_4_test = us_model_2.evaluate(us_X_test, us_test_y)
results_4_test
```

```
39/39 [==============================] - 0s 2ms/step - loss: 1.0700 -
acc: 0.7137
```

Out[99]:

```
[1.0699917078018188, 0.7137064337730408]
```

3E. Model 4: Convolutional Neural Network

In [325]:

```
# Build a CNN model

def build_cnn_model(input_shape, output_units, loss='categorical_crossentropy', lea

    cnn_model = tf.keras.models.Sequential()

    # 1st convolutional layer
    cnn_model.add(tf.keras.layers.Conv2D(32, (3, 3),
                                         activation='relu',
                                         input_shape=input_shape,
                                         kernel_regularizer=tf.keras.regularizers.l
    cnn_model.add(tf.keras.layers.BatchNormalization())
    cnn_model.add(tf.keras.layers.MaxPooling2D((2, 2), strides=(2,2), padding='same

    # 2nd convolutional layer
    cnn_model.add(tf.keras.layers.Conv2D(32, (4, 4),
                                   activation='relu',
                                   kernel_regularizer=tf.keras.regularizers.l2(0.
    cnn_model.add(tf.keras.layers.BatchNormalization())
    cnn_model.add(tf.keras.layers.MaxPooling2D((3, 3), strides=(2,2), padding='same

    # 3rd convolutional layer
    cnn_model.add(tf.keras.layers.Conv2D(64, (2, 2),
                                         activation='relu',
                                         kernel_regularizer=tf.keras.regularizers.l
    cnn_model.add(tf.keras.layers.BatchNormalization())
    cnn_model.add(tf.keras.layers.MaxPooling2D((2, 2), strides=(2,2), padding='same

    # Flatten output and feed into dense layer
    cnn_model.add(tf.keras.layers.Flatten())
    cnn_model.add(tf.keras.layers.Dense(32, activation='relu'))
    cnn_model.add(tf.keras.layers.Dropout(0.3))

    # Softmax output layer
    cnn_model.add(tf.keras.layers.Dense(output_units, activation='softmax'))

    optimiser = tf.optimizers.Adam(learning_rate=learning_rate)

    # Compile model
    cnn_model.compile(optimizer=optimiser,
                      loss=loss,
                      metrics=['acc'])

    # Print summary for model
    cnn_model.summary()

    return cnn_model
```

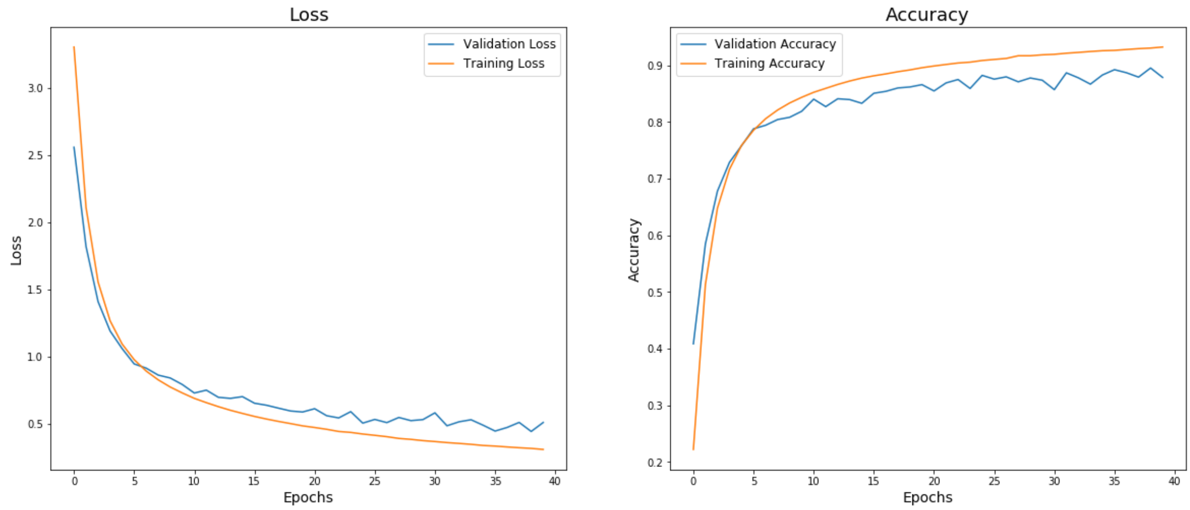
In [50]:

```
# Create CNN model using Speech Commands MFCCs
sc_cnn_input_shape = (sc_X_train.shape[1], sc_X_train.shape[2], 1)
sc_output_units = 35
sc_cnn_model = build_cnn_model(sc_cnn_input_shape, sc_output_units, learning_rate=0.


# Fit model to Speech Commands data
sc_epochs = 40
sc_batch_size = 64
sc_patience = 3
sc_cnn_results = fit_model(sc_cnn_model,
                          sc_epochs,
                          sc_batch_size,
                          sc_patience,
                          sc_X_train,
                          sc_train_y,
                          sc_X_val,
                          sc_val_y)
```

```
954/954 [==============================] - 107s 112ms/step - loss: 0.
3608 - acc: 0.9214 - val_loss: 0.4858 - val_acc: 0.8868
Epoch 33/40
954/954 [==============================] - 97s 102ms/step - loss: 0.3
547 - acc: 0.9229 - val_loss: 0.5154 - val_acc: 0.8779
Epoch 34/40
954/954 [==============================] - 117s 123ms/step - loss: 0.
3479 - acc: 0.9245 - val_loss: 0.5307 - val_acc: 0.8668
Epoch 35/40
954/954 [==============================] - 81s 85ms/step - loss: 0.33
95 - acc: 0.9259 - val_loss: 0.4901 - val_acc: 0.8830
Epoch 36/40
954/954 [==============================] - 66s 70ms/step - loss: 0.33
48 - acc: 0.9265 - val_loss: 0.4465 - val_acc: 0.8924
Epoch 37/40
954/954 [==============================] - 64s 67ms/step - loss: 0.32
84 - acc: 0.9280 - val_loss: 0.4734 - val_acc: 0.8869

Epoch 38/40
954/954 [==============================] - 67s 70ms/step - loss: 0.32
```

In [51]:

```
# Visualise the loss and accuracy of the training and validation sets across epochs
visualise_results(sc_cnn_results)
```



In [52]:

```
# Evaluate the training results
sc_cnn_results_train = sc_cnn_model.evaluate(sc_X_train, sc_train_y)
sc_cnn_results_train
```

```
1908/1908 [==============================] - 17s 9ms/step - loss: 0.34
92 - acc: 0.9178
```

Out[52]:

```
[0.34924957156181335, 0.9178405404090881]
```

In [53]:

```
# Evaluate the test results
sc_cnn_results_test = sc_cnn_model.evaluate(sc_X_test, sc_test_y)
sc_cnn_results_test
```

```
597/597 [==============================] - 5s 9ms/step - loss: 0.5155
- acc: 0.8779
```

Out[53]:

```
[0.5155156254768372, 0.877928614616394]
```

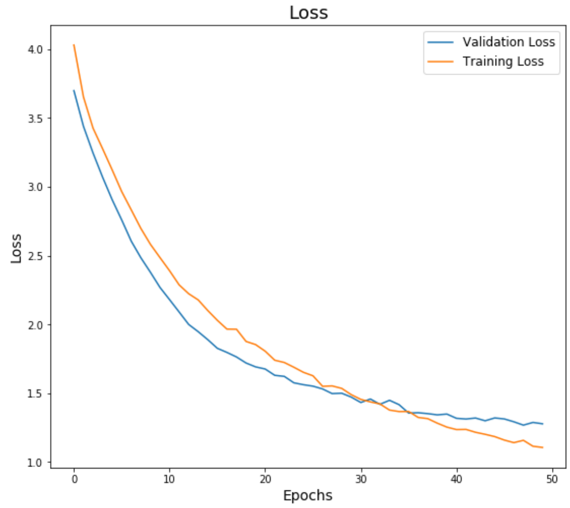
In [358]:

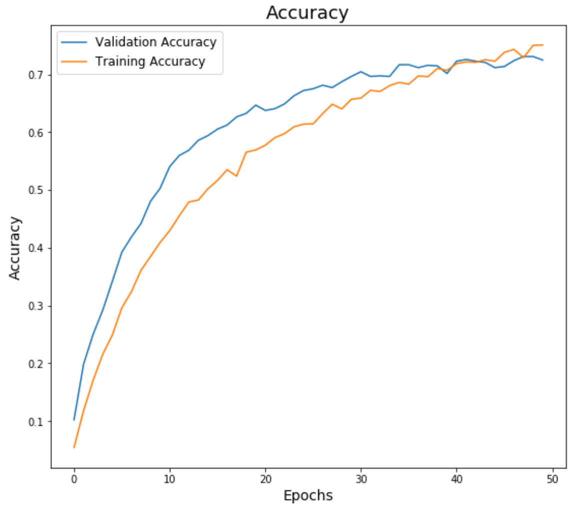
```
# Create CNN model using Ultrasuite MFCCs
us_cnn_input_shape = (us_X_train.shape[1], us_X_train.shape[2], 1)
us_output_units = 35
us_cnn_model = build_cnn_model(us_cnn_input_shape, us_output_units, learning_rate=0.


# Fit model to Ultrasuite data
us_epochs = 50
us_batch_size = 16
us_patience = 3
us_cnn_results = fit_model(us_cnn_model,
                      us_epochs,
                      us_batch_size,
                      us_patience,
                      us_X_train,
                      us_train_y,
                      us_X_val,
                      us_val_y)
```

```
4 - acc: 0.7189 - val_loss: 1.3180 - val_acc: 0.7231
Epoch 42/50
247/247 [==============================] - 4s 15ms/step - loss: 1.237
5 - acc: 0.7220 - val_loss: 1.3131 - val_acc: 0.7262
Epoch 43/50
247/247 [==============================] - 4s 15ms/step - loss: 1.216
6 - acc: 0.7212 - val_loss: 1.3201 - val_acc: 0.7231
Epoch 44/50
247/247 [==============================] - 4s 15ms/step - loss: 1.202
0 - acc: 0.7258 - val_loss: 1.3001 - val_acc: 0.7211
Epoch 45/50
247/247 [==============================] - 4s 15ms/step - loss: 1.185
4 - acc: 0.7230 - val_loss: 1.3207 - val_acc: 0.7120
Epoch 46/50
247/247 [==============================] - 4s 15ms/step - loss: 1.160
2 - acc: 0.7385 - val_loss: 1.3136 - val_acc: 0.7140
Epoch 47/50
247/247 [==============================] - 4s 15ms/step - loss: 1.141
4 - acc: 0.7435 - val_loss: 1.2929 - val_acc: 0.7241
Epoch 48/50
```

In [359]:

```
# Visualise the loss and accuracy of the training and validation sets across epochs
visualise_results(us_cnn_results)
```





In [368]:

```
# Evaluate the training results
us_cnn_results_train = us_cnn_model.evaluate(us_X_train, us_train_y)
us_cnn_results_train
```

```
124/124 [==============================] - 1s 6ms/step - loss: 0.7119
- acc: 0.8965
```

Out[368]:

```
[0.7119315266609192, 0.8964992165565491]
```

In [369]:

```
# Evaluate the test results
us_cnn_results_test = us_cnn_model.evaluate(us_X_test, us_test_y)
us_cnn_results_test
```

```
39/39 [==============================] - 0s 7ms/step - loss: 1.3616 -
acc: 0.7161
```

Out[369]:

```
[1.3616187572479248, 0.7161394953727722]
```

In [364]:

```
save_model(us_cnn_model, 'final_model.h5')
```

Running the models using Mel Spectrograms instead of MFCCs

A thought exercise more than anything else, just to see if there are any performance gains that can be made by using Mel Spectrograms instead of MFCCs.

In [62]:

```
# Set the parameters for the Ultrasuite dataset for preprocessing based on Mel Spec
us_dataset_path = 'data/ultrasuite_top35'
us_melspec_json_path = 'ultrasuite_top35_data_melspec.json'
num_samples = 22050
```

In [ ]:

```
# Preprocess the Ultrasuite dataset
preprocess_dataset(us_dataset_path, us_melspec_json_path, 'mel_specs', num_samples)
```

In [66]:

```
# Create the train, test and validation datasets for the Ultrasuite Top 40 dataset u
us_data_path = 'ultrasuite_top35_data_melspec.json'
X_train_mel, y_train_mel, X_val_mel, y_val_mel, X_test_mel, y_test_mel = create_tra
```

```
Datasets loaded...
```

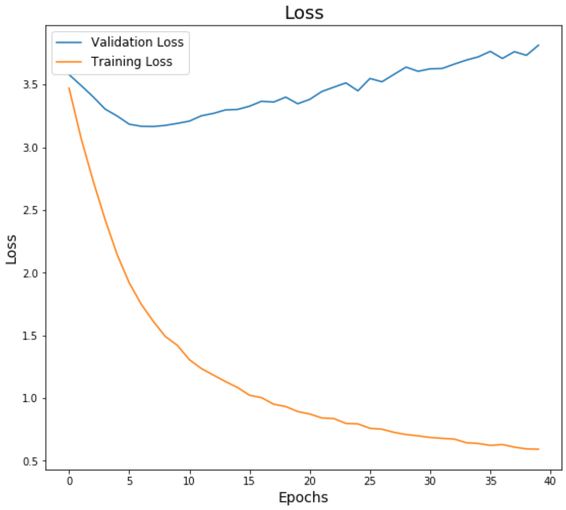
In [67]:

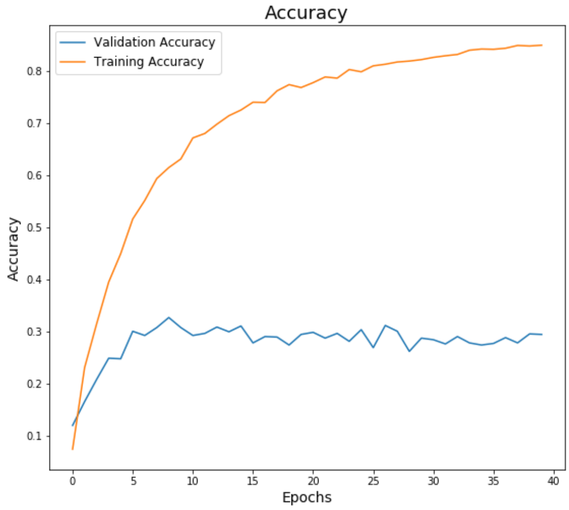
```
# Create CNN model using MFCCs
us_mel_input_shape = (X_train_mel.shape[1], X_train_mel.shape[2], 1)
us_mel_output_units = 35
us_mel_model = build_model_2(us_mel_input_shape, us_mel_output_units, learning_rate=

# One-hot encode Speech Commands labels
mel_train_y = reformat_y(y_train_mel)
mel_test_y = reformat_y(y_test_mel)
mel_val_y = reformat_y(y_val_mel)

# Fit model
us_mel_epochs = 40
us_mel_batch_size = 64
us_mel_patience = 3
us_mel_results = fit_model(us_mel_model, us_mel_epochs, us_mel_batch_size, us_mel_pa
```

```
- acc: 0.7613 - val_loss: 3.3600 - val_acc: 0.2890
Epoch 19/40
62/62 [==============================] - 2s 25ms/step - loss: 0.9322
- acc: 0.7732 - val_loss: 3.3997 - val_acc: 0.2738
Epoch 20/40
62/62 [==============================] - 2s 25ms/step - loss: 0.8926
- acc: 0.7676 - val_loss: 3.3466 - val_acc: 0.2941
Epoch 21/40
62/62 [==============================] - 1s 20ms/step - loss: 0.8727
- acc: 0.7770 - val_loss: 3.3817 - val_acc: 0.2982
Epoch 22/40
62/62 [==============================] - 1s 22ms/step - loss: 0.8412
- acc: 0.7879 - val_loss: 3.4443 - val_acc: 0.2870
Epoch 23/40
62/62 [==============================] - 1s 21ms/step - loss: 0.8364
- acc: 0.7856 - val_loss: 3.4791 - val_acc: 0.2961
Epoch 24/40
62/62 [==============================] - 1s 22ms/step - loss: 0.7977
- acc: 0.8021 - val_loss: 3.5134 - val_acc: 0.2809
Epoch 25/40
```

In [68]:

```
# Visualise the loss and accuracy of the training and validation sets across epochs
visualise_results(us_mel_results)
```





3F. Final Model Performance Evaluation

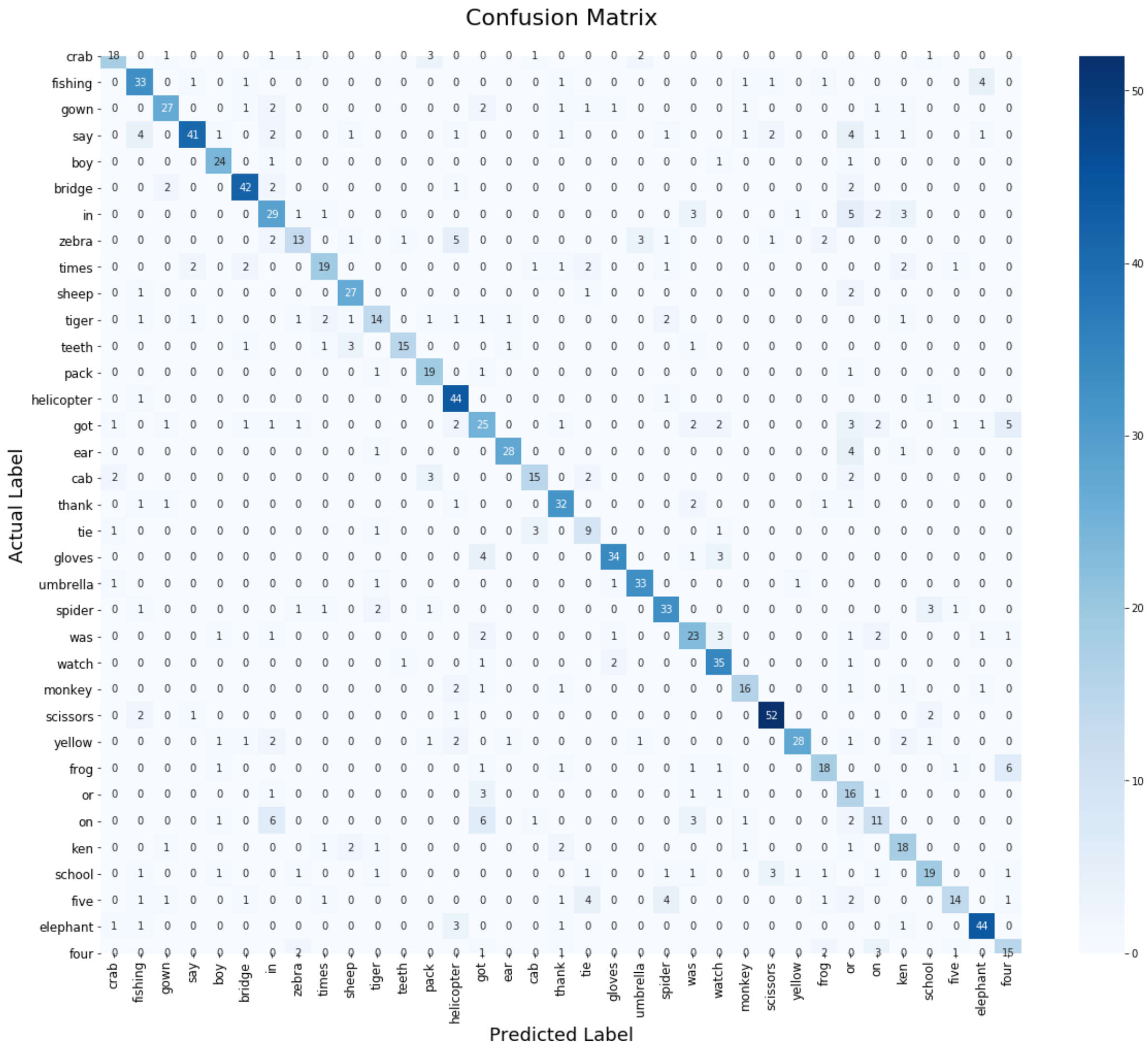
In [362]:

```
# Import necessary libraries for performance evaluation.
from sklearn.metrics import accuracy_score, confusion_matrix

# Create predictions
preds = us_cnn_model.predict(us_X_test)

# Calculate accuracy and confusion matrix
acc = accuracy_score(us_test_y, np.round(preds))*100
cm = confusion_matrix(us_test_y.argmax(axis=1), np.round(preds.argmax(axis=1)))


print('CONFUSION MATRIX ------------------')
print(cm)

print('\nTEST METRICS ----------------------')
print('Loss: {}'.format(us_cnn_results_test[0]))
print('Accuracy: {}%'.format(np.round(us_cnn_results_test[1]*100), 2))

print('\nTRAIN METRICS ----------------------')
print('Loss: {}'.format(us_cnn_results_train[0]))
print('Accuracy: {}%'.format(np.round(us_cnn_results_train[1]*100), 2))
```

```
WARNING: AutoGraph could not transform <function Model.make_predict_fu
nction.<locals>.predict_function at 0x7fd588477dd0> and will run it as
-is.
Please report this to the TensorFlow team. When filing the bug, set th
e verbosity to 10 (on Linux, `export AUTOGRAPH_VERBOSITY=10`) and atta
ch the full output.
Cause: 'arguments' object has no attribute 'posonlyargs'
To silence this warning, decorate the function with @tf.autograph.expe
rimental.do_not_convert
CONFUSION MATRIX ------------------
[[18  0  1 ...  0  0  0]
 [ 0 33  0 ...  0  4  0]
 [ 0  0 27 ...  0  0  0]
 ...
 [ 0  1  1 ... 14  0  1]
 [ 1  1  0 ...  0 44  0]
 [ 0  0  0 ...  1  0 15]]

TEST METRICS ----------------------
Loss: 1.3616187572479248
Accuracy: 72.0%

TRAIN METRICS ----------------------
Loss: 0.7119315266609192
Accuracy: 90.0%
```

In [363]:

```
# Use Seaborn to make the confusion matrix more visually presentable
plt.figure(figsize=(20,16))
ax = plt.subplot()
sns.heatmap(cm, annot=True, ax=ax, fmt='g', cmap='Blues')

us_keywords = [
    'crab',
    'fishing',
    'gown',
    'say',
    'boy',
    'bridge',
    'in',
    'zebra',
    'times',
    'sheep',
    'tiger',
    'teeth',
    'pack',
    'helicopter',
    'got',
    'ear',
    'cab',
    'thank',
    'tie',
    'gloves',
    'umbrella',
    'spider',
    'was',
    'watch',
    'monkey',
    'scissors',
    'yellow',
    'frog',
    'or',
    'on',
    'ken',
    'school',
    'five',
    'elephant',
    'four']

ax.set_title('Confusion Matrix', fontsize=22, pad=30)
ax.set_xlabel('Predicted Label', fontsize=18)
ax.set_ylabel('Actual Label', fontsize=18)
ax.xaxis.set_ticklabels(us_keywords, rotation=90, fontsize=12)
ax.yaxis.set_ticklabels(us_keywords, rotation=0, fontsize=12)
plt.show();
```

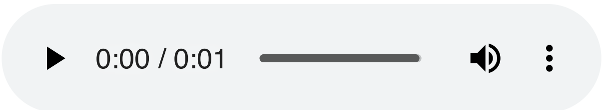


In [365]:

```
# Load the audio sample and preview
target_sample = 'audio/martha-frog.wav'
target_label = 'Frog'
audio_sample, sr = librosa.load(target_sample)
print('Audio sample:', target_label)
ipd.Audio(audio_sample, rate=sr)
```

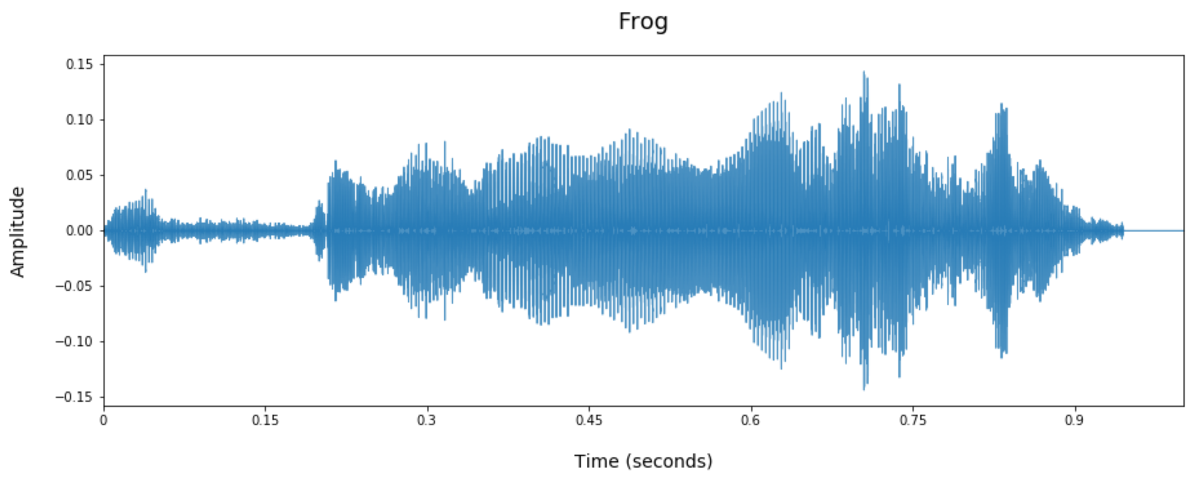
Audio sample: Frog

Out[365]:



In [366]:

```
# Plot the waveform for the specific audio sample
plt.figure(figsize=(15, 5))
plt.title(target_label, fontsize=18, pad=20)
librosa.display.waveplot(audio_sample, sr, alpha=0.8)
plt.xlabel('Time (seconds)', fontsize=14, labelpad=20)
plt.ylabel('Amplitude', fontsize=14, labelpad=20)
plt.show();
```



In [367]:

```
# Run inference on the unseen audio file
mfccs = librosa.feature.mfcc(audio_sample, sr, n_mfcc=13, n_fft=2048, hop_length=512
mfccs = mfccs.T
mfccs = mfccs[np.newaxis, ..., np.newaxis]

prediction = us_cnn_model.predict(mfccs)
predicted_index = np.argmax(prediction)

predicted_keyword = us_keywords[predicted_index]
print('Martha says...',predicted_keyword, '!')
```

```
Martha says... frog !
```

Conclusion

Initial models did not generalise well and tended to overfit the training data. Subsequent changes to parameters significantly improved the training accuracy but, again were overfitting the training data.

Whilst it does not have a high accuracy score, this final model using a Convolutional Neural Network produced the best results classifying over 70% of the “unseen” audio samples whilst minimising the overfitting to training data.

The very nature of speech sound disorders mean that a model that has been simply trained on audio samples of "typical" speech will generally be more accurate than one that has been trained on audio samples of "atypical" speech as demonstrated above with the model comparison between the Speech Commands and Ultrasuite datasets.

Given the eventual usage of this model, it is arguable the app would be more useful if it suggested three potential words in order of likelihood, giving the parent options of what the child might be trying to communicate.

Additional data and further manipulation of the architecture of Convolutional Neural Network could also potentially improve accuracy but also utilising data augmentation techniques such as MixSpeech (https://arxiv.org/abs/2102.12664) that could take a weighted combination of mel-spectrograms and MFCC in order to improve model performance.

Sources / Code adapted from:
* Hands-On Machine Learning with Scikit-Learn, Keras & Tensorflow - Aurélien Géron (https://www.oreilly.com/library/view/hands-on-machine-learning/9781492032632/)
* Simple audio recognition: Recognizing keywords - Tensorflow (https://www.tensorflow.org/tutorials/audio/simple_audio)
* Deep Learning Audio Application from Design to Deployment - Valerio Velardo - The Sound of AI (https://github.com/musikalkemist/Deep-Learning-Audio-Application-From-Design-to-Deployment)

In [ ]:

```

```