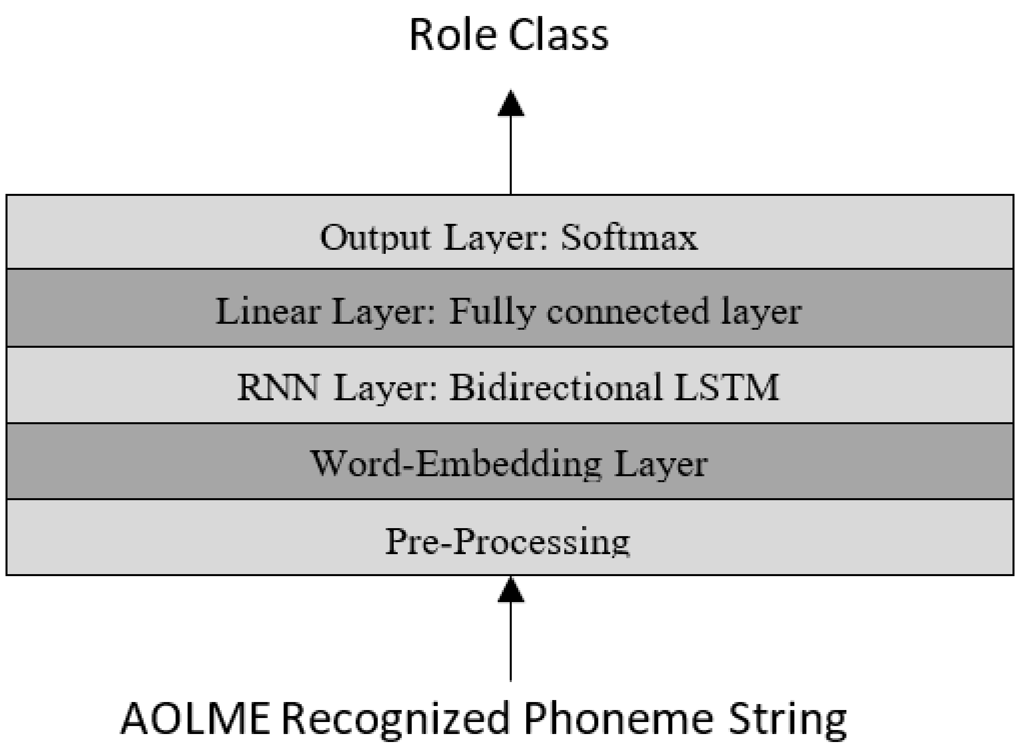
# Roles Classifier

The model implemented here follows the following architecture diagram:




We start with the import declarations:

In [16]:
```
from collections import Counter
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
from torch.utils.data import Dataset, DataLoader
from BiLstmClassifier import BiLstmFixedLength, BiLstmVariableLength, BiLstmGlove

import numpy as np
import pandas as pd
import spacy
import torch
import torch.nn.functional as F
```

## 0. Hyper Parameters Definition

Defining the correct hyper-parameters to refine the performance of the model is very important. We must consider some situations around the values to be assigned.

### 0.1 Epochs

We must define a correct number of epochs to allow the model to learn from the dataset. If this is to few, the model will not learn anything, if the value is too high, we can fall into over-fitting or wasting processing time where the model can't learn anymore.

### 0.2 Batch Size

It defines the amount of data for each batch to be used on each training epoch. Because we have no much data, the value here is small.

### 0.3 Embedded Layer Dimension

Word embeddings are always around 50 and 300 in length, longer embedding vectors don't add enough information and smaller ones don't represent the semantics well enough. For this model, we are using small sentences for most of the cases.

### 0.4 Hidden Layer Dimension

This parameter represents how complex is the language used in the conversations. For example, if the sentences belong to a literature book from Shakespeare, it probably will use a sophisticated language, and we can assign a value of 70. On the other hand, if the sentences belong to simple chat talking about movies, it is maybe simpler, and we can assign a value of 30.

In [17]:
```
EPOCHS = 100
BATCH_SIZE = 1  # Small batches because the dataset is not bigger than 500 rows
HIDDEN_LAYER_DIM = 60  # AOLME is not too complex language, it represents the lar
EMBEDDED_LAYER_DIM = 50
```

## 1. Load dataset

We are going to use the dataset generated by the Jupyter Notebook "AOLME Datasets Generator" (main.ipynb)

In [18]:
```
roles = pd.read_csv('output/balanced_372.csv')
print(f'Dataset Size: {roles.shape}\n')
print(roles.head())
```

```
Dataset Size: (372, 2)

      Role                            Text
0  Student           you like how its like
1  Student  its like youre obsessed with
2  Student                    and this one
3  Student                              no
4  Student            i dont like summary
```

## 2. Pre-Processing

### 2.1. Mapping 'Roles' labels to numbers for vectorization

In [19]:
```
mapping = {'Student': 0, 'Co-Facilitator': 1, 'Facilitator': 2}
roles['Role'] = roles['Role'].apply(lambda x: mapping[x])
roles.head()


# Load English words model package
tok = spacy.load('en')


def tokenize(text: str):
    """
    This method tokenizes a sentence, considering the text is already lowered,
    ASCII, and  punctuation has been removed
    :param text: The sentence to be tokenized
    :return: A list containing each word of the sentence
    """
    return [token.text for token in tok.tokenizer(text)]
```

## 2.2. Dataset cleaning and Sentence Vectorizing

In [20]:
```
# Count number of occurrences of each word
counts = Counter()
for index, row in roles.iterrows():
    counts.update(tokenize(row['Text']))

# Deletes words appearing only once
print(f'Number of Words before cleaning: {len(counts.keys())}')
for word in list(counts):
    if counts[word] < 2:
        del counts[word]
print(f'Number of Words after cleaning: {len(counts.keys())}\n')

# Creates vocabulary
vocab2index = {'': 0, 'UNK': 1}
words = ['', 'UNK']
for word in counts:
    vocab2index[word] = len(words)
    words.append(word)


def encode_sentence(text, vocabulary_map, n=70):
    """
    Encodes the sentence into a numerical vector, based on the vocabulary map
    :param text: The sentence
    :param vocabulary_map: A map assigning a number to each word in the vocabular
    :param n: Required vector size
    :return: Vectorized sentence and length
    """
    tokenized = tokenize(text)
    vectorized = np.zeros(n, dtype=int)
    enc1 = np.array([vocabulary_map.get(w, vocabulary_map["UNK"]) for w in tokeni
    length = min(n, len(enc1))
    vectorized[:length] = enc1[:length]
    return vectorized, length


# Creates a new column into Dataset: each sentence expressed as a numeric vector
roles['Vectorized'] = roles['Text'].apply(lambda x: np.array(encode_sentence(x, v
print(roles.head())
```

```
Number of Words before cleaning: 662
Number of Words after cleaning: 347

   Role                           Text  \
0     0          you like how its like
1     0  its like youre obsessed with
2     0                       and this one
3     0                                 no
4     0           i dont like summary

                                          Vectorized
0  [[2, 3, 4, 5, 3, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,...
1  [[5, 3, 2, 1, 1, 6, 0, 0, 0, 0, 0, 0, 0, 0, 0,...
2  [[7, 8, 9, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,...
3  [[10, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
4  [[11, 12, 13, 3, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,...
```

```
<ipython-input-20-5b2887f873d4>:38: VisibleDeprecationWarning: Creating an ndar
ray from ragged nested sequences (which is a list-or-tuple of lists-or-tuples-o
r ndarrays with different lengths or shapes) is deprecated. If you meant to do
this, you must specify 'dtype=object' when creating the ndarray
  roles['Vectorized'] = roles['Text'].apply(lambda x: np.array(encode_sentence
(x, vocab2index)))
```

Check if the dataset is balanced

In [21]:
```
Counter(roles['Role'])
```

Out[21]:
```
Counter({0: 124, 1: 124, 2: 124})
```

## 2.3 Split into training and validation partitions

In [22]:
```
X = list(roles['Vectorized'])
y = list(roles['Role'])
X_train, X_valid, y_train, y_valid = train_test_split(X, y, test_size=0.2)


class RolesDataset(Dataset):
    """
    Simple PyTorch Dataset wrapper defined by an array of vectorized sentences (X
    """
    def __init__(self, input_x, input_y):
        self.X = input_x
        self.y = input_y

    def __len__(self):
        return len(self.y)

    def __getitem__(self, idx):
        return torch.from_numpy(self.X[idx][0].astype(np.int32)), self.y[idx], se


training_ds = RolesDataset(X_train, y_train)
validation_ds = RolesDataset(X_valid, y_valid)
```

## 2.4 Training and Validation Functions

In [23]:
```
def train_model(input_model, epochs=10, lr=0.001, verbose=True):
    """
    Trains the input model
    :param verbose: Prints each batch iteration
    :param input_model: Input Model
    :param epochs: The number of training epochs
    :param lr: Learning Rate
    :return: training loss, validation loss, validation accuracy, and validation
    """
    parameters = filter(lambda p: p.requires_grad, input_model.parameters())
    optimizer = torch.optim.Adam(parameters, lr=lr)

    for i in range(epochs):
        input_model.train()
        sum_loss = 0.0
        total = 0

        # Iterates on Training DataLoader
        for x, y, l in training_dl:
            x = x.long()
            y = y.long()
            y_pred = input_model(x, l)
            optimizer.zero_grad()
            loss = F.cross_entropy(y_pred, y)
            loss.backward()
            optimizer.step()
            sum_loss += loss.item() * y.shape[0]
            total += y.shape[0]

        val_loss, val_acc, val_rmse = get_metrics(input_model, validation_dl)

        if verbose and (i + 1) % 20 == 1:
            print(f"Epoch {i}: training loss %.3f, valid. loss %.3f, valid. accur
                sum_loss / total, val_loss, val_acc, val_rmse))

    print(f"FINAL: training loss %.3f, valid. loss %.3f, valid. accuracy %.3f, ar
        sum_loss / total, val_loss, val_acc, val_rmse))

    return sum_loss / total, val_loss, val_acc, val_rmse


def get_metrics(input_model, valid_dl):
    """
    Obtains current validation metrics
    :param input_model: Input Model
    :param valid_dl: Validation PyTorch DataLoader
    :return:
    """
    input_model.eval()
    correct = 0
    total = 0
    sum_loss = 0.0
    sum_rmse = 0.0

    # PyTorch uses CrossEntropy function to implement Softmax on the same functic
    for x, y, l in valid_dl:
```

```
        x = x.long()
        y = y.long()
        y_hat = input_model(x, l)
        loss = F.cross_entropy(y_hat, y)
        pred = torch.max(y_hat, 1)[1]
        correct += (pred == y).float().sum()
        total += y.shape[0]
        sum_loss += loss.item() * y.shape[0]
        sum_rmse += np.sqrt(mean_squared_error(pred, y.unsqueeze(-1))) * y.shape[
    return sum_loss / total, correct / total, sum_rmse / total
```

In [24]:
```
vocab_size = len(words)
training_dl = DataLoader(training_ds, batch_size=BATCH_SIZE, shuffle=True)
validation_dl = DataLoader(validation_ds, batch_size=BATCH_SIZE)
```

## BiLSTM - Fixed Length Input

We can see the implemented model class in BiLstmClassifier class (BiLstmClassifier.py).

**BiLstmFixedLength** has the following features:

- Word-Embedding Layer. # Embeddings: Vocabulary Size, Embeddings size: 50
- Bi-directional LSTM Layer. Input size: 50, Hidden size: 60
- Linear Layer. Fully connected layer, Input size: 60, 3 output features (roles)
- Dropout: 0.7
- Fixed Length Input (see encode_sentence function)

In [25]:
```
model_fixed = BiLstmFixedLength(vocab_size, EMBEDDED_LAYER_DIM, HIDDEN_LAYER_DIM)

print(f'\nBiLSTM - Fixed Length: {EPOCHS} epochs, Learning Rate: 0.1')
print('==============================================================')
train_model(model_fixed, epochs=EPOCHS, lr=0.1)
print(f'\nBiLSTM - Fixed Length: {EPOCHS} epochs, Learning Rate: 0.05')
print('==============================================================')
train_model(model_fixed, epochs=EPOCHS, lr=0.05)
print(f'\nBiLSTM - Fixed Length: {EPOCHS} epochs, Learning Rate: 0.01')
print('==============================================================')
train_model(model_fixed, epochs=EPOCHS, lr=0.01)
```

```
BiLSTM - Fixed Length: 100 epochs, Learning Rate: 0.1
==============================================================
Epoch 0: training loss 2.488, valid. loss 2.888, valid. accuracy 0.320, and val
id. RMSE 0.987
Epoch 20: training loss 2.746, valid. loss 2.432, valid. accuracy 0.400, and va
lid. RMSE 0.867
Epoch 40: training loss 2.707, valid. loss 3.495, valid. accuracy 0.280, and va
lid. RMSE 1.013
Epoch 60: training loss 2.768, valid. loss 2.927, valid. accuracy 0.333, and va
lid. RMSE 0.853
Epoch 80: training loss 2.781, valid. loss 2.523, valid. accuracy 0.400, and va
lid. RMSE 0.867
FINAL: training loss 2.972, valid. loss 2.360, valid. accuracy 0.427, and vali
d. RMSE 0.800

BiLSTM - Fixed Length: 100 epochs, Learning Rate: 0.05
==============================================================
Epoch 0: training loss 2.304, valid. loss 1.861, valid. accuracy 0.333, and val
id. RMSE 0.920
Epoch 20: training loss 1.765, valid. loss 1.376, valid. accuracy 0.507, and va
lid. RMSE 0.653
Epoch 40: training loss 1.707, valid. loss 1.800, valid. accuracy 0.293, and va
lid. RMSE 0.987
Epoch 60: training loss 1.742, valid. loss 1.446, valid. accuracy 0.440, and va
lid. RMSE 0.813
Epoch 80: training loss 1.667, valid. loss 1.809, valid. accuracy 0.360, and va
lid. RMSE 0.920
FINAL: training loss 1.738, valid. loss 1.892, valid. accuracy 0.333, and vali
d. RMSE 0.867

BiLSTM - Fixed Length: 100 epochs, Learning Rate: 0.01
==============================================================
Epoch 0: training loss 1.589, valid. loss 1.549, valid. accuracy 0.307, and val
id. RMSE 0.933
Epoch 20: training loss 1.215, valid. loss 1.092, valid. accuracy 0.453, and va
lid. RMSE 0.720
Epoch 40: training loss 1.127, valid. loss 1.170, valid. accuracy 0.427, and va
lid. RMSE 0.747
Epoch 60: training loss 1.129, valid. loss 1.183, valid. accuracy 0.320, and va
lid. RMSE 0.867
Epoch 80: training loss 1.169, valid. loss 1.254, valid. accuracy 0.347, and va
lid. RMSE 0.853
FINAL: training loss 1.129, valid. loss 1.116, valid. accuracy 0.440, and vali
d. RMSE 0.773
```

Out[25]:
```
(1.1289081848430313, 1.1163920362790425, tensor(0.4400), 0.7733333333333333)
```

# BiLSTM - Variable Length Input

We can see the implemented model class in BiLstmClassifier class (BiLstmClassifier.py).

**BiLstmVariableLength** has the following features:

- Word-Embedding Layer. # Embeddings: Vocabulary Size, Embeddings size: 50
- Bi-directional LSTM Layer. Input size: 50, Hidden size: 60
- Linear Layer. Fully connected layer, Input size: 60, 3 output features (roles)
- Dropout: 0.7
- Variable Length Input. Uses PyTorch's pack_padded_sequence (https://pytorch.org/docs/stable/generated/torch.nn.utils.rnn.pack_padded_sequence.html) to create sequences of variable length.

In [26]:
```
model = BiLstmVariableLength(vocab_size, EMBEDDED_LAYER_DIM, HIDDEN_LAYER_DIM)

print(f'\nBiLSTM - Variable Length: {EPOCHS} epochs, Learning Rate: 0.1')
print('=============================================================')
train_model(model, epochs=EPOCHS, lr=0.1)
print(f'\nBiLSTM - Variable Length: {EPOCHS} epochs, Learning Rate: 0.05')
print('=============================================================')
train_model(model, epochs=EPOCHS, lr=0.05)
print(f'\nBiLSTM - Variable Length: {EPOCHS} epochs, Learning Rate: 0.01')
print('=============================================================')
train_model(model, epochs=EPOCHS, lr=0.01)
```

```
BiLSTM - Variable Length: 100 epochs, Learning Rate: 0.1
=============================================================
Epoch 0: training loss 2.520, valid. loss 3.256, valid. accuracy 0.267, and val
id. RMSE 0.907
Epoch 20: training loss 2.867, valid. loss 2.397, valid. accuracy 0.293, and va
lid. RMSE 0.960
Epoch 40: training loss 2.677, valid. loss 3.081, valid. accuracy 0.227, and va
lid. RMSE 1.053
Epoch 60: training loss 2.942, valid. loss 3.176, valid. accuracy 0.320, and va
lid. RMSE 0.947
Epoch 80: training loss 2.754, valid. loss 2.178, valid. accuracy 0.413, and va
lid. RMSE 0.800
FINAL: training loss 2.753, valid. loss 2.943, valid. accuracy 0.280, and vali
d. RMSE 0.933

BiLSTM - Variable Length: 100 epochs, Learning Rate: 0.05
=============================================================
Epoch 0: training loss 2.108, valid. loss 1.730, valid. accuracy 0.320, and val
id. RMSE 0.933
Epoch 20: training loss 1.728, valid. loss 1.579, valid. accuracy 0.413, and va
lid. RMSE 0.853
Epoch 40: training loss 1.733, valid. loss 1.640, valid. accuracy 0.360, and va
lid. RMSE 0.867
Epoch 60: training loss 1.825, valid. loss 1.580, valid. accuracy 0.373, and va
lid. RMSE 0.920
Epoch 80: training loss 1.718, valid. loss 1.433, valid. accuracy 0.400, and va
lid. RMSE 0.867
FINAL: training loss 1.827, valid. loss 1.424, valid. accuracy 0.413, and vali
d. RMSE 0.787

BiLSTM - Variable Length: 100 epochs, Learning Rate: 0.01
=============================================================
Epoch 0: training loss 1.603, valid. loss 1.181, valid. accuracy 0.453, and val
id. RMSE 0.760
Epoch 20: training loss 1.196, valid. loss 1.068, valid. accuracy 0.400, and va
lid. RMSE 0.787
Epoch 40: training loss 1.187, valid. loss 1.238, valid. accuracy 0.307, and va
lid. RMSE 0.867
Epoch 60: training loss 1.182, valid. loss 1.161, valid. accuracy 0.320, and va
lid. RMSE 0.840
Epoch 80: training loss 1.205, valid. loss 1.129, valid. accuracy 0.413, and va
lid. RMSE 0.880
FINAL: training loss 1.161, valid. loss 1.081, valid. accuracy 0.400, and vali
d. RMSE 0.813
```

Out[26]:
```
(1.160707650010032, 1.0812374369303386, tensor(0.4000), 0.8133333333333334)
```

# BiLSTM - with pretrained GloVe Word Embeddings

We can see the implemented model class in [BiLstmClassifier class (BiLstmClassifier.py)](BiLstmClassifier.py).

**BiLstmGloveVector** has the following features:

- Word-Embedding Layer. # Embeddings: Vocabulary Size, Embeddings size: 50
- Bi-directional LSTM Layer. Input size: 50, Hidden size: 60
- Linear Layer. Fully connected layer, Input size: 60, 3 output features (roles)
- Dropout: 0.7
- Uses pretrained GloVe Word Embeddings to initialize weights based on its vocabulary.

In [27]:
```python
def load_glove_vectors():
    """Load the glove Global Vectors for Word Representation"""
    word_vectors = {}

    with open("./glove/glove.6B.50d.txt", encoding="utf8") as f:
        for line in f:
            split = line.split()
            word_vectors[split[0]] = np.array([float(x) for x in split[1:]])
    return word_vectors


def get_embedding_matrix(word_counts, emb_size=50):
    """ Creates embedding matrix from word vectors"""
    vocab_size = len(word_counts) + 2
    vocab_to_idx = {}
    vocab = ["", "UNK"]
    W = np.zeros((vocab_size, emb_size), dtype="float32")
    W[0] = np.zeros(emb_size, dtype='float32')  # adding a vector for padding
    W[1] = np.random.uniform(-0.25, 0.25, emb_size)  # adding a vector for unknow
    vocab_to_idx["UNK"] = 1
    i = 2

    for word in word_counts:
        if word in word_vecs:
            W[i] = word_vecs[word]
        else:
            W[i] = np.random.uniform(-0.25, 0.25, emb_size)
        vocab_to_idx[word] = i
        vocab.append(word)
        i += 1
    return W, np.array(vocab), vocab_to_idx
```

In [28]:
```
word_vecs = load_glove_vectors()
pretrained_weights, vocab, vocab2index = get_embedding_matrix(counts, EMBEDDED_LA

model = BiLstmGloveVector(vocab_size, EMBEDDED_LAYER_DIM, HIDDEN_LAYER_DIM, pretr

print(f'\nBiLSTM - with pretrained GloVe Word Embeddings: {EPOCHS} epochs, Learni
print('==========================================================================
train_model(model, epochs=EPOCHS, lr=0.1)
print(f'\nBiLSTM - with pretrained GloVe Word Embeddings: {EPOCHS} epochs, Learni
print('==========================================================================
train_model(model, epochs=EPOCHS, lr=0.05)
print(f'\nBiLSTM - with pretrained GloVe Word Embeddings: {EPOCHS} epochs, Learni
print('==========================================================================
train_model(model, epochs=EPOCHS, lr=0.01)
```

```
BiLSTM - with pretrained GloVe Word Embeddings: 100 epochs, Learning Rate: 0.
1
=============================================================================
=======
Epoch 0: training loss 1.963, valid. loss 2.220, valid. accuracy 0.267, and v
alid. RMSE 0.733
Epoch 20: training loss 2.092, valid. loss 2.080, valid. accuracy 0.347, and
valid. RMSE 0.960
Epoch 40: training loss 2.260, valid. loss 2.004, valid. accuracy 0.253, and
valid. RMSE 0.880
Epoch 60: training loss 2.470, valid. loss 1.646, valid. accuracy 0.387, and
valid. RMSE 0.867
Epoch 80: training loss 2.277, valid. loss 1.299, valid. accuracy 0.467, and
valid. RMSE 0.720
FINAL: training loss 2.279, valid. loss 2.117, valid. accuracy 0.387, and val
id. RMSE 0.893

BiLSTM - with pretrained GloVe Word Embeddings: 100 epochs, Learning Rate: 0.
05
=============================================================================
=======
Epoch 0: training loss 1.917, valid. loss 1.425, valid. accuracy 0.360, and v
alid. RMSE 0.920
Epoch 20: training loss 1.586, valid. loss 1.339, valid. accuracy 0.400, and
valid. RMSE 0.867
Epoch 40: training loss 1.599, valid. loss 1.219, valid. accuracy 0.467, and
valid. RMSE 0.747
Epoch 60: training loss 1.520, valid. loss 1.297, valid. accuracy 0.453, and
valid. RMSE 0.813
Epoch 80: training loss 1.593, valid. loss 1.305, valid. accuracy 0.480, and
valid. RMSE 0.760
FINAL: training loss 1.580, valid. loss 1.366, valid. accuracy 0.373, and val
id. RMSE 0.813

BiLSTM - with pretrained GloVe Word Embeddings: 100 epochs, Learning Rate: 0.
01
=============================================================================
=======
Epoch 0: training loss 1.461, valid. loss 1.166, valid. accuracy 0.387, and v
alid. RMSE 0.827
Epoch 20: training loss 1.130, valid. loss 1.101, valid. accuracy 0.400, and
```

```
valid. RMSE 0.787
Epoch 40: training loss 1.070, valid. loss 1.143, valid. accuracy 0.453, and
valid. RMSE 0.840
Epoch 60: training loss 1.127, valid. loss 1.214, valid. accuracy 0.307, and
valid. RMSE 0.840
Epoch 80: training loss 1.121, valid. loss 1.109, valid. accuracy 0.427, and
valid. RMSE 0.773
FINAL: training loss 1.127, valid. loss 1.138, valid. accuracy 0.307, and val
id. RMSE 0.787
```

Out[28]:
```
(1.1273477321572176, 1.1376529622077942, tensor(0.3067), 0.7866666666666666)
```

## Testing Several Files

In [29]:
```
@torch.no_grad()
def get_all_preds(model, loader):
    all_preds = torch.tensor([])
    for batch in loader:
        images, labels = batch

        preds = model(images)
        all_preds = torch.cat(
            (all_preds, preds)
            ,dim=0
        )
    return all_preds

def get_num_correct(preds, labels):
    return preds.argmax(dim=1).eq(labels).sum().item()

file_size = [150, 200, 250, 300, 350, 400, 450, 500, 550, 600, 645]
accuracy_fixed = []
accuracy_variable = []
accuracy_glove = []

for i in file_size:
    # BATCH_SIZE = int(i * 0.5)
    file_name = f'output/balanced_{i}.csv'
    roles = pd.read_csv(file_name)
    mapping = {'Student': 0, 'Co-Facilitator': 1, 'Facilitator': 2}
    roles['Role'] = roles['Role'].apply(lambda x: mapping[x])
    counts = Counter()

    for index, row in roles.iterrows():
        counts.update(tokenize(row['Text']))

    for word in list(counts):
        if counts[word] < 2:
            del counts[word]

    vocab2index = {'': 0, 'UNK': 1}
    words = ['', 'UNK']
    for word in counts:
        vocab2index[word] = len(words)
        words.append(word)

    roles['Vectorized'] = roles['Text'].apply(lambda x: np.array(encode_sentence(

    X = list(roles['Vectorized'])
    y = list(roles['Role'])
    X_train, X_valid, y_train, y_valid = train_test_split(X, y, test_size=0.2)

    training_ds = RolesDataset(X_train, y_train)
    validation_ds = RolesDataset(X_valid, y_valid)

    vocab_size = len(words)
    training_dl = DataLoader(training_ds, batch_size=BATCH_SIZE, shuffle=True)
    validation_dl = DataLoader(validation_ds, batch_size=BATCH_SIZE)

    print('\n********************************************')
```

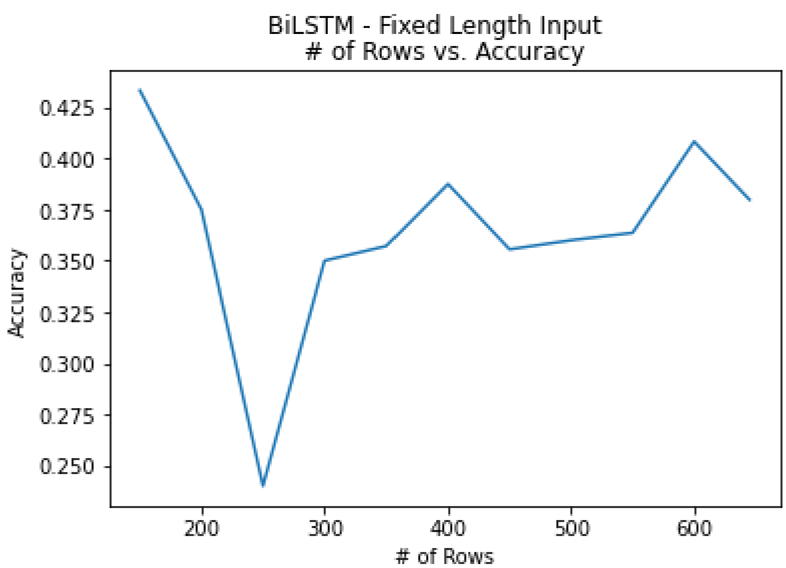
```
    print(f'* Processing file: {file_name} *')
    print('*********************************************')

    print(f'\nBiLSTM - Fixed Length Input')
    print('===========================')
    model_fixed = BiLstmFixedLength(vocab_size, EMBEDDED_LAYER_DIM, HIDDEN_LAYER_
    train_model(model_fixed, epochs=EPOCHS, lr=0.1, verbose=False)
    train_model(model_fixed, epochs=EPOCHS, lr=0.05, verbose=False)
    _, _, validation_accuracy, _ = train_model(model_fixed, epochs=EPOCHS, lr=0.0
    accuracy_fixed.append(validation_accuracy)

    print(f'\nBiLSTM - Variable Length Input')
    print('==============================')
    model_varaiable = BiLstmVariableLength(vocab_size, EMBEDDED_LAYER_DIM, HIDDEN
    train_model(model_varaiable, epochs=EPOCHS, lr=0.1, verbose=False)
    train_model(model_varaiable, epochs=EPOCHS, lr=0.05, verbose=False)
    _, _, validation_accuracy, _ = train_model(model_varaiable, epochs=EPOCHS, lr
    accuracy_variable.append(validation_accuracy)

    print(f'\nBiLSTM - with pretrained GloVe Word Embeddings')
    print('==============================================')
    word_vecs = load_glove_vectors()
    pretrained_weights, vocab, vocab2index = get_embedding_matrix(counts, EMBEDDE
    model = BiLstmGloveVector(vocab_size, EMBEDDED_LAYER_DIM, HIDDEN_LAYER_DIM, p
    train_model(model, epochs=EPOCHS, lr=0.1, verbose=False)
    train_model(model, epochs=EPOCHS, lr=0.05, verbose=False)
    _, _, validation_accuracy, _ = train_model(model, epochs=EPOCHS, lr=0.01, ver
    accuracy_glove.append(validation_accuracy)
```

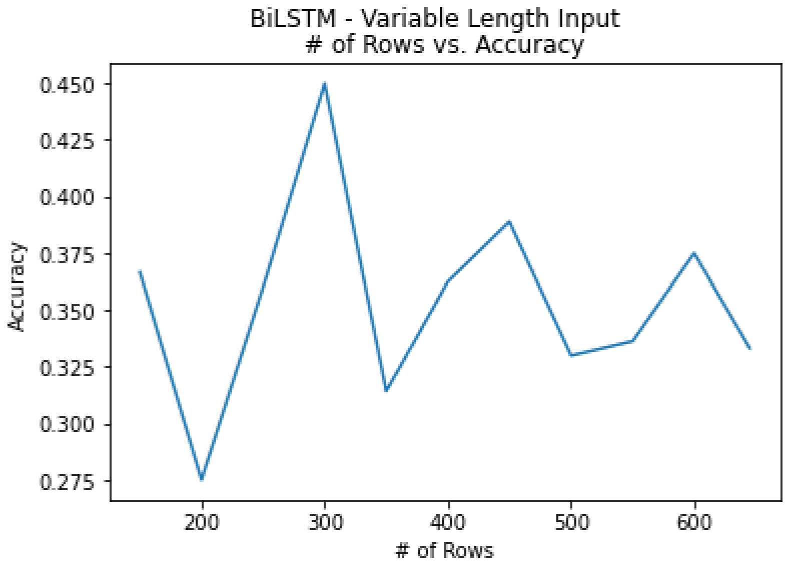
```
id. RMSE 0.906
FINAL: training loss 1.547, valid. loss 1.530, valid. accuracy 0.322, and val
id. RMSE 0.922
FINAL: training loss 1.142, valid. loss 1.088, valid. accuracy 0.322, and val
id. RMSE 0.911

********************************************
* Processing file: output/balanced_500.csv *
********************************************

BiLSTM - Fixed Length Input
===========================

<ipython-input-29-903bf98d7a0c>:43: VisibleDeprecationWarning: Creating an nd
array from ragged nested sequences (which is a list-or-tuple of lists-or-tupl
es-or ndarrays with different lengths or shapes) is deprecated. If you meant
to do this, you must specify 'dtype=object' when creating the ndarray
  roles['Vectorized'] = roles['Text'].apply(lambda x: np.array(encode_sentenc
e(x, vocab2index)))
```

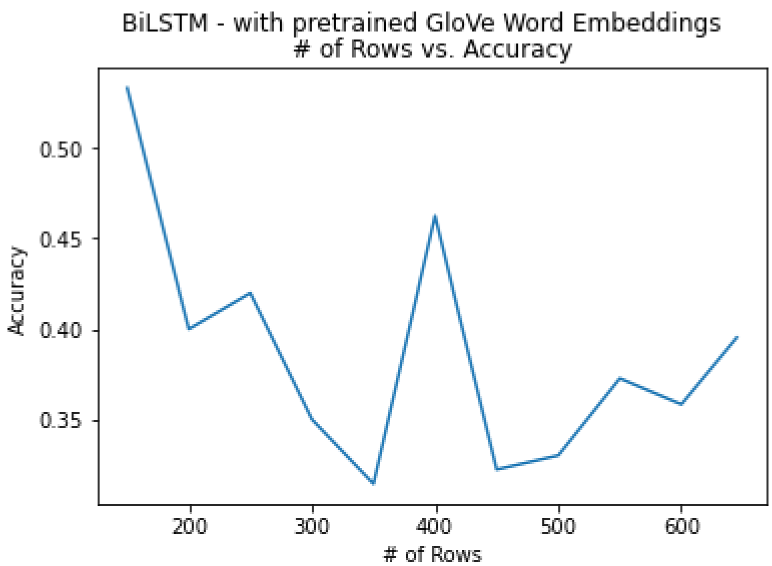
## Graphical Performance Analysis

In the following plots we can see the how the model behaves when it is trained with different amounts of data.

In [30]:
```
%matplotlib inline

import matplotlib.pyplot as plt

plt.plot(file_size, accuracy_fixed)
plt.title('# of Rows vs. Accuracy')
plt.suptitle('BiLSTM - Fixed Length Input')
plt.xlabel('# of Rows')
plt.ylabel('Accuracy')
plt.show()

plt.plot(file_size, accuracy_variable)
plt.title('# of Rows vs. Accuracy')
plt.suptitle('BiLSTM - Variable Length Input')
plt.xlabel('# of Rows')
plt.ylabel('Accuracy')
plt.show()

plt.plot(file_size, accuracy_glove)
plt.title('# of Rows vs. Accuracy')
plt.suptitle('BiLSTM - with pretrained GloVe Word Embeddings')
plt.xlabel('# of Rows')
plt.ylabel('Accuracy')
plt.show()
```






# Conclusions

- The model with the best performance is **BiLSTM - with pretrained GloVe Word Embeddings**, as we can see that it has a most stable performance as the model is trained with more data.
- The model reaches an approximated Accuracy of 60% for the selected model, and it will probably improve when it is trained with a bigger dataset.
- It is important to see that the first iteration with the smallest dataset with 150 rows reaches a high accuracy. This is happening because over-fitting caused by too few rows, but the accuracy starts to show a more real behavior with bigger datasets.

In [ ]:

In [ ]:

In [ ]:

In [ ]: