CREATE A CHATBOT IN PYTHON

Phase-2 Project (Innovation Submission)

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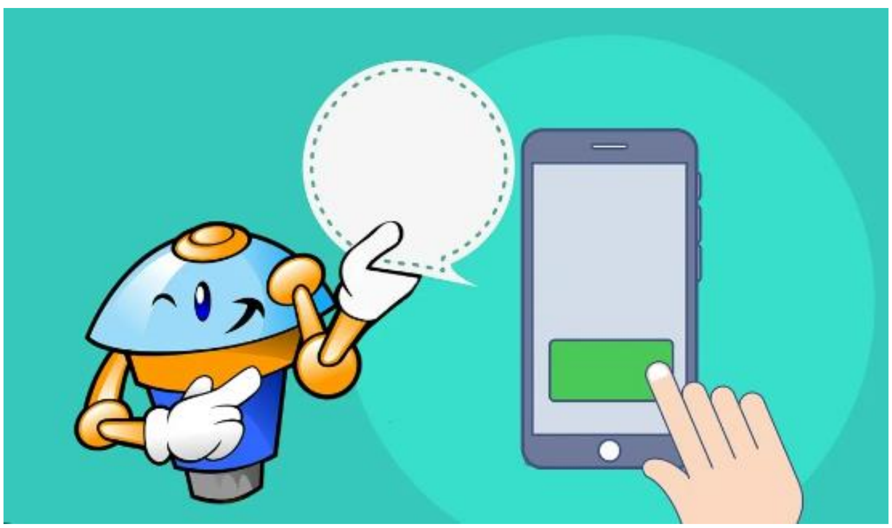
Project title : Chatbot in python



CREATE A CHATBOT IN PYTHON

Introduction:

Chatbot have become an integral part of modern communication, assisting users with various tasks, answering questions, and providing information.

Traditional chatbots focus on natural language processing (NLP) for conversation generation, incorporating advanced regression techniques can enable chatbots to make data-driven predictions and provide personalized responses.

In this project, we will explore how to build a chatbot using Python and leverage advanced regression algorithms such as Random Forest Regression and Gradient Boosting Regression to enhance it's capabilities.

Content for project phase 2:

consider more advanced methods like Random Forest Regression or Gradient Boosting Regression.

Data source:

Data is the lifeblood of a chatbot. It's the source of knowledge, the key to understanding, and the fuel for intelligent conversations.

Dataset:

Link: https://www.kaggle.com/datasets/grafstor/simple-dialogs-for-chatbot

Collect and Prepare Data:

Gather the dataset that contains the data you want to use for regression. Ensure that the data is clean and suitable for regression analysis. In your case, it might be related to chatbot performance metrics or user feedback.

Feature Engineering:

Identify the relevant features (independent variables) from your dataset that you believe will impact the regression task. These features can include chatbot-related metrics, user behavior data, or any other relevant data points.

Split Data:

Split your dataset into training and testing sets. The training set will be used to train your regression model, while the testing set will be used to evaluate its performance.

Choose a Regression Algorithm:

Select a regression algorithm that is appropriate for your specific problem. Common regression techniques include Linear Regression, Ridge Regression, Lasso Regression, Decision Tree Regression, and more. You may also consider more advanced methods like Random Forest Regression or Gradient Boosting Regression.

Advanced Regression Techniques:

Support Vector Regression (SVR):

SVR is a regression technique that extends Support Vector Machines (SVM) to perform regression tasks.

It can handle both linear and non-linear regression problems.

SVR aims to find a hyperplane that best fits the data while minimizing the margin violations.

Random Forest Regression:

Random Forest Regression is an ensemble learning method that combines multiple decision trees to make predictions.

It is robust against overfitting and can handle both numerical and categorical data.

Random Forests can capture complex relationships in the data.

Gradient Boosting Regression:

Gradient Boosting is another ensemble method that builds a strong predictive model by combining the predictions of multiple weak learners (usually decision trees).

Algorithms like XGBoost, LightGBM, and CatBoost are popular implementations of Gradient Boosting for regression tasks.

Lasso Regression:

Lasso (Least Absolute Shrinkage and Selection Operator) is a linear regression technique that adds a penalty term to the cost function to encourage sparsity in the feature coefficients.

It can be used for feature selection and regularization, making it useful when dealing with high-dimensional data.

Elastic Net Regression:

Elastic Net is a hybrid regression technique that combines the penalties of both L1 (Lasso) and L2 (Ridge) regularization.

It addresses some of the limitations of Lasso and Ridge regression, providing a balance between feature selection and coefficient shrinkage.

Train the Model:

Use the training data to train your regression model. Provide the selected features as input and the target variable (the variable you want to predict) as the output.

Evaluate the Model:

Use the testing dataset to evaluate the performance of your regression model. Common evaluation metrics for regression tasks include Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R2).

Tune Hyperparameters:

Depending on the algorithm you choose, you may need to fine-tune hyperparameters to optimize your model's performance. Techniques like cross-validation can help in this process.

Predictions:

Once your regression model is trained and evaluated, you can use it to make predictions on new data or use it to analyze chatbot performance based on the collected data.

PYTHON PROGRAM:

Chatbot Using Python

PYTHON PROGRAM:

Import Libraries

In [1]:

```
import tensorflow as tf
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from tensorflow.keras.layers import TextVectorization
import re,string
from tensorflow.keras.layers import
LSTM,Dense,Embedding,Dropout,LayerNormalization
```

In [2]:

```
df=pd.read_csv('/kaggle/input/simple-dialogs-for-
chatbot/dialogs.txt',sep='\t',names=['question','answer'])
print(f'Dataframe size: {len(df)}')
df.head()
Dataframe size: 3725
```

Out[2]:

	Question	answer
0	hi, how are you doing?	i'm fine. how about yourself?
1	i'm fine. how about yourself?	i'm pretty good. thanks for asking.

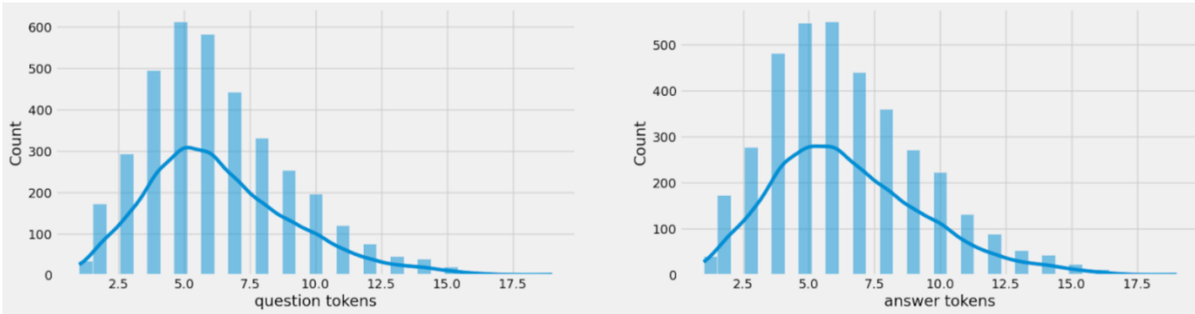
	Question	answer
2	i'm pretty good. thanks for asking.	no problem. so how have you been?
3	no problem. so how have you been?	i've been great. what about you?
4	i've been great. what about you?	i've been good. i'm in school right now.

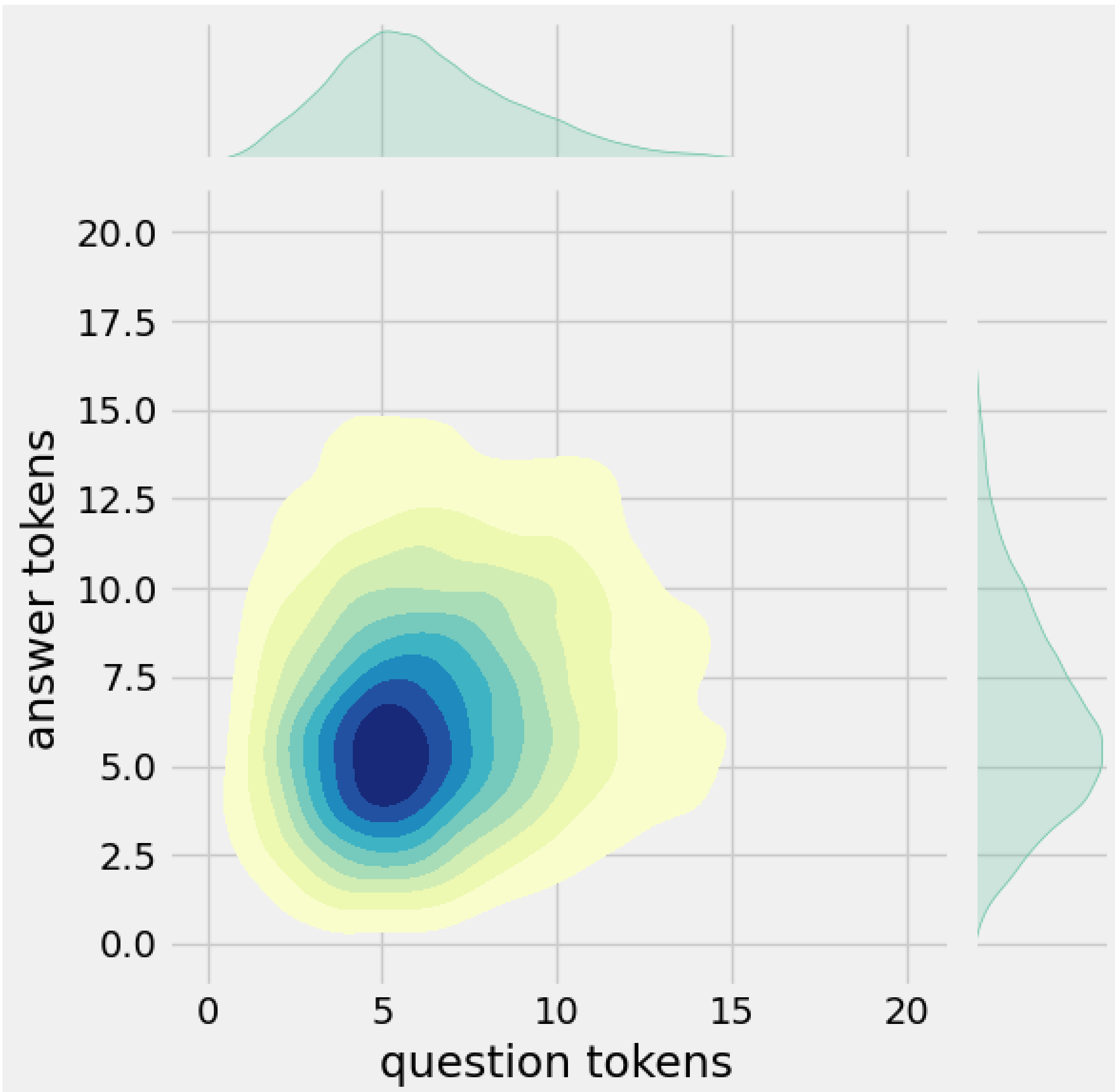
Data Preprocessing

Data Visualization

In [3]:

```
df['question tokens']=df['question'].apply(lambda x:len(x.split()))
df['answer tokens']=df['answer'].apply(lambda x:len(x.split()))

plt.style.use('fivethirtyeight')
fig,ax=plt.subplots(nrows=1,ncols=2,figsize=(20,5))

sns.set_palette('Set2')
sns.histplot(x=df['question tokens'],data=df,kde=True,ax=ax[0])

sns.histplot(x=df['answer tokens'],data=df,kde=True,ax=ax[1])

sns.jointplot(x='question tokens',y='answer
tokens',data=df,kind='kde',fill=True,cmap='YlGnBu')

plt.show()
```





Text Cleaning

In [4]:

```
def clean_text(text):
    text=re.sub('-',' ',text.lower())
    text=re.sub('[.]',' . ',text)
```

```
    text=re.sub('[1]',' 1 ',text)
    text=re.sub('[2]',' 2 ',text)
    text=re.sub('[3]',' 3 ',text)
    text=re.sub('[4]',' 4 ',text)
    text=re.sub('[5]',' 5 ',text)
    text=re.sub('[6]',' 6 ',text)
    text=re.sub('[7]',' 7 ',text)
    text=re.sub('[8]',' 8 ',text)
    text=re.sub('[9]',' 9 ',text)
    text=re.sub('[0]',' 0 ',text)
    text=re.sub('[,]',' , ',text)
    text=re.sub('[?]',' ? ',text)
    text=re.sub('[!]',' ! ',text)
    text=re.sub('[$]',' $ ',text)
    text=re.sub('[&]',' & ',text)
    text=re.sub('[/]',' / ',text)
    text=re.sub('[:]',' : ',text)
    text=re.sub('[;]',' ; ',text)
    text=re.sub('[*]',' * ',text)
    text=re.sub('[\']',' \' ',text)
    text=re.sub('[\"]',' \" ',text)
    text=re.sub('\t',' ',text)
    return text

df.drop(columns=['answer tokens','question tokens'],axis=1,inplace=True)
df['encoder_inputs']=df['question'].apply(clean_text)
df['decoder_targets']=df['answer'].apply(clean_text)+' <end>'
df['decoder_inputs']='<start> '+df['answer'].apply(clean_text)+' <end>'

df.head(10)
```

Out[4]:

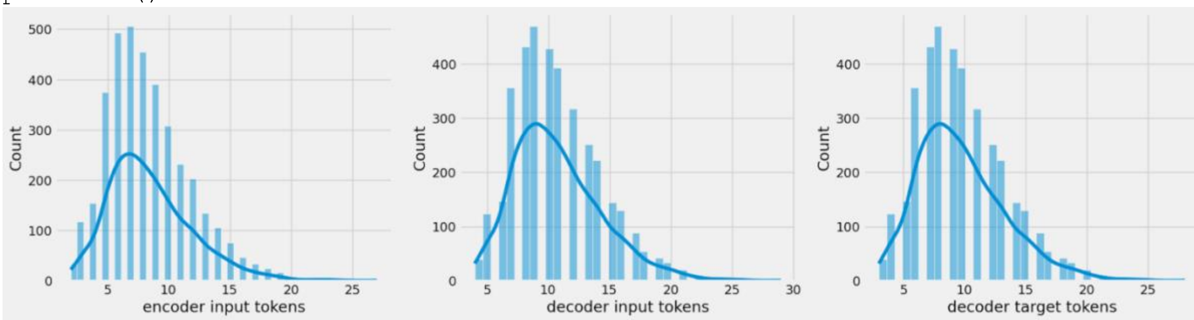
	question	answer	encoder_inputs	decoder_targets	decoder_inputs
0	hi, how are you doing?	i'm fine. how about yourself?	hi , how are you doing ?	i ' m fine . how about yourself ? <end>	<start> i ' m fine . how about yourself ? <end>
1	i'm fine. how about yourself?	i'm pretty good. thanks for asking.	i ' m fine . how about yourself ?	i ' m pretty good . thanks for asking . <end>	<start> i ' m pretty good . thanks for asking...
2	i'm pretty good. thanks for asking.	no problem. so how have you been?	i ' m pretty good . thanks for asking .	no problem . so how have you been ? <end>	<start> no problem . so how have you been ? ...

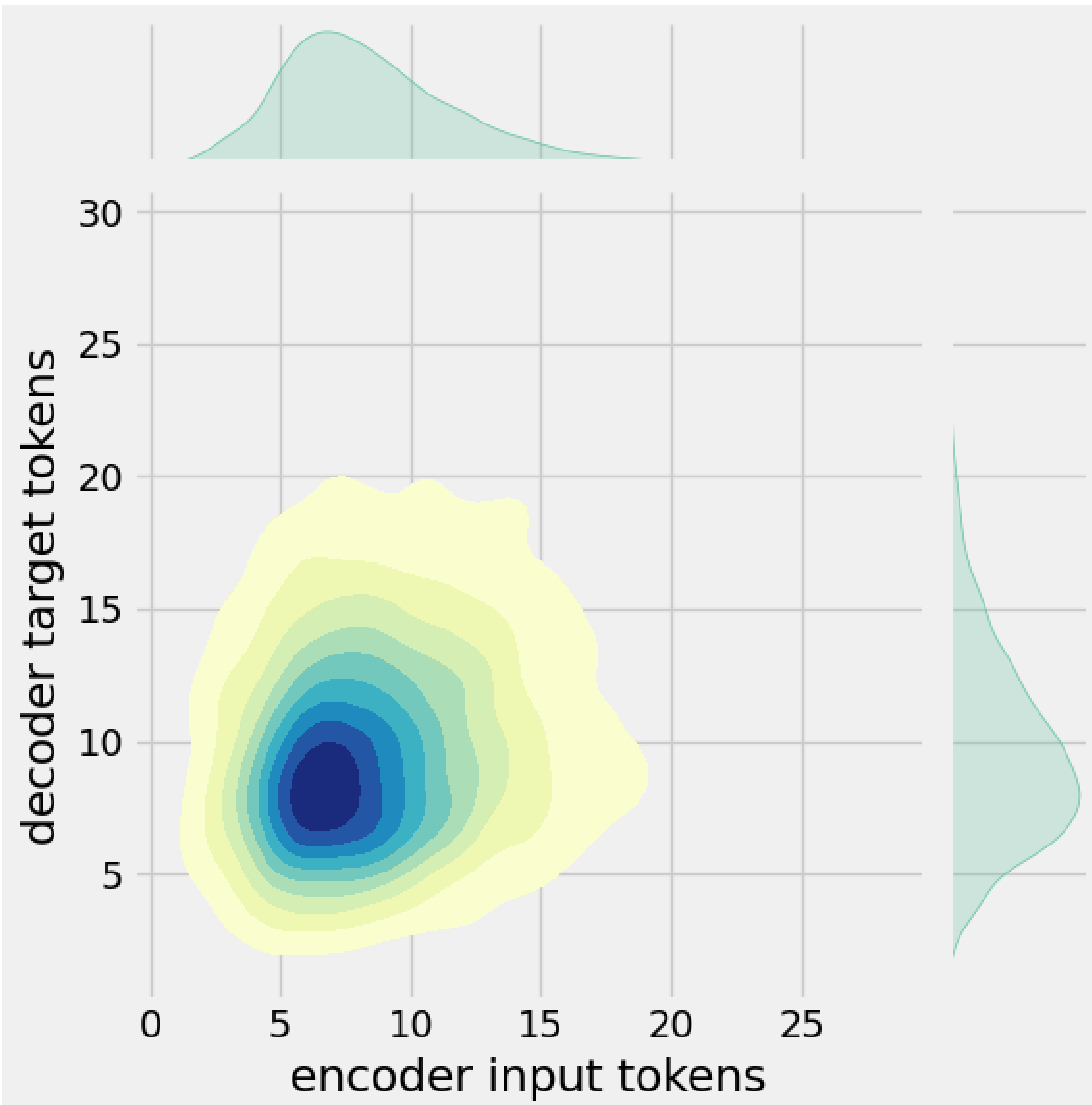
	question	answer	encoder_inputs	decoder_targets	decoder_inputs
3	no problem. so how have you been?	i've been great. what about you?	no problem . so how have you been ?	i ' ve been great . what about you ? <end>	<start> i ' ve been great . what about you ? ...
4	i've been great. what about you?	i've been good. i'm in school right now.	i ' ve been great . what about you ?	i ' ve been good . i ' m in school right now ...	<start> i ' ve been good . i ' m in school ri...
5	i've been good. i'm in school right now.	what school do you go to?	i ' ve been good . i ' m in school right now .	what school do you go to ? <end>	<start> what school do you go to ? <end>
6	what school do you go to?	i go to pcc.	what school do you go to ?	i go to pcc . <end>	<start> i go to pcc . <end>
7	i go to pcc.	do you like it there?	i go to pcc .	do you like it there ? <end>	<start> do you like it there ? <end>
8	do you like it there?	it's okay. it's a really big campus.	do you like it there ?	it ' s okay . it ' s a really big campus . <...	<start> it ' s okay . it ' s a really big cam...
9	it's okay. it's a really big campus.	good luck with school.	it ' s okay . it ' s a really big campus .	good luck with school . <end>	<start> good luck with school . <end>

In [5]:

```
df['encoder input tokens']=df['encoder_inputs'].apply(lambda
x:len(x.split()))
df['decoder input tokens']=df['decoder_inputs'].apply(lambda
x:len(x.split()))
df['decoder target tokens']=df['decoder_targets'].apply(lambda
x:len(x.split()))
plt.style.use('fivethirtyeight')
fig,ax=plt.subplots(nrows=1,ncols=3,figsize=(20,5))
sns.set_palette('Set2')
sns.histplot(x=df['encoder input tokens'],data=df,kde=True,ax=ax[0])
sns.histplot(x=df['decoder input tokens'],data=df,kde=True,ax=ax[1])
sns.histplot(x=df['decoder target tokens'],data=df,kde=True,ax=ax[2])
```

```
sns.jointplot(x='encoder input tokens',y='decoder target
tokens',data=df,kind='kde',fill=True,cmap='YlGnBu')
plt.show()
```





In [6]:

```python
print(f"After preprocessing: {' '.join(df[df['encoder input tokens'].max()==df['encoder input tokens']]['encoder_inputs'].values.tolist())}")
print(f"Max encoder input length: {df['encoder input tokens'].max()}")
print(f"Max decoder input length: {df['decoder input tokens'].max()}")
print(f"Max decoder target length: {df['decoder target tokens'].max()}")

df.drop(columns=['question','answer','encoder input tokens','decoder input tokens','decoder target tokens'],axis=1,inplace=True)
params={
    "vocab_size":2500,
    "max_sequence_length":30,
    "learning_rate":0.008,
    "batch_size":149,
    "lstm_cells":256,
    "embedding_dim":256,
    "buffer_size":10000
}
learning_rate=params['learning_rate']
batch_size=params['batch_size']
embedding_dim=params['embedding_dim']
lstm_cells=params['lstm_cells']
vocab_size=params['vocab_size']
buffer_size=params['buffer_size']
max_sequence_length=params['max_sequence_length']
df.head(10)
```

```
After preprocessing: for example ,  if your birth date is
january  1  2  ,   1  9  8  7  ,  write  0  1  /  1  2  /  8  7  .
Max encoder input length: 27
Max decoder input length: 29
Max decoder target length: 28
```

Out[6]:

	encoder_inputs	decoder_targets	decoder_inputs
0	hi , how are you doing ?	i ' m fine . how about yourself ? <end>	<start> i ' m fine . how about yourself ? <end>
1	i ' m fine . how about yourself ?	i ' m pretty good . thanks for asking . <end>	<start> i ' m pretty good . thanks for asking...
2	i ' m pretty good . thanks for asking .	no problem . so how have you been ? <end>	<start> no problem . so how have you been ? ...
3	no problem . so how have you been	i ' ve been great . what about you ?	<start> i ' ve been great . what about you

	encoder_inputs	decoder_targets	decoder_inputs
	?	<end>	? ...
4	i ' ve been great . what about you ?	i ' ve been good . i ' m in school right now ...	<start> i ' ve been good . i ' m in school ri...
5	i ' ve been good . i ' m in school right now .	what school do you go to ? <end>	<start> what school do you go to ? <end>
6	what school do you go to ?	i go to pcc . <end>	<start> i go to pcc . <end>
7	i go to pcc .	do you like it there ? <end>	<start> do you like it there ? <end>
8	do you like it there ?	it ' s okay . it ' s a really big campus . <...	<start> it ' s okay . it ' s a really big cam...
9	it ' s okay . it ' s a really big campus .	good luck with school . <end>	<start> good luck with school . <end>

Tokenization

In [7]:

```
vectorize_layer=TextVectorization(
    max_tokens=vocab_size,
    standardize=None,
    output_mode='int',
    output_sequence_length=max_sequence_length
)
vectorize_layer.adapt(df['encoder_inputs']+' '+df['decoder_targets']+' <start> <end>')
vocab_size=len(vectorize_layer.get_vocabulary())
print(f'Vocab size: {len(vectorize_layer.get_vocabulary())}')
print(f'{vectorize_layer.get_vocabulary()[:12]}')
Vocab size: 2443
['', '[UNK]', '<end>', '.', '<start>', "'", 'i', '?', 'you', ',', 'the', 'to']
```

In [8]:

```
def sequences2ids(sequence):
    return vectorize_layer(sequence)
```

```
def ids2sequences(ids):
    decode=''
    if type(ids)==int:
        ids=[ids]
    for id in ids:
        decode+=vectorize_layer.get_vocabulary()[id]+' '
    return decode

x=sequences2ids(df['encoder_inputs'])
yd=sequences2ids(df['decoder_inputs'])
y=sequences2ids(df['decoder_targets'])

print(f'Question sentence: hi , how are you ?')
print(f'Question to tokens: {sequences2ids("hi , how are you ?")[:10]}')
print(f'Encoder input shape: {x.shape}')
print(f'Decoder input shape: {yd.shape}')
print(f'Decoder target shape: {y.shape}')
```

```
Question sentence: hi , how are you ?
Question to tokens: [1971    9   45   24    8    7    0    0    0    0]
Encoder input shape: (3725, 30)
Decoder input shape: (3725, 30)
Decoder target shape: (3725, 30)
```

In [9]:

```
print(f'Encoder input: {x[0][:12]} ...')
print(f'Decoder input: {yd[0][:12]} ...')    # shifted by one time step of
the target as input to decoder is the output of the previous timestep
print(f'Decoder target: {y[0][:12]} ...')
```

```
Encoder input:
[1971    9   45   24    8  194    7    0    0    0    0    0] ...
Decoder input: [  4    6    5   38 646    3   45   41 563    7    2    0] ...
Decoder target: [  6    5   38 646    3   45   41 563    7    2    0    0] ...
```

In [10]:

```
data=tf.data.Dataset.from_tensor_slices((x,yd,y))
data=data.shuffle(buffer_size)

train_data=data.take(int(.9*len(data)))
train_data=train_data.cache()
train_data=train_data.shuffle(buffer_size)
train_data=train_data.batch(batch_size)
train_data=train_data.prefetch(tf.data.AUTOTUNE)
train_data_iterator=train_data.as_numpy_iterator()

val_data=data.skip(int(.9*len(data))).take(int(.1*len(data)))
val_data=val_data.batch(batch_size)
val_data=val_data.prefetch(tf.data.AUTOTUNE)

_=train_data_iterator.next()
print(f'Number of train batches: {len(train_data)}')
print(f'Number of training data: {len(train_data)*batch_size}')
print(f'Number of validation batches: {len(val_data)}')
print(f'Number of validation data: {len(val_data)*batch_size}')
print(f'Encoder Input shape (with batches): {_[0].shape}')
print(f'Decoder Input shape (with batches): {_[1].shape}')
```

```
print(f'Target Output shape (with batches): {_[2].shape}')
```

```
Number of train batches: 23
Number of training data: 3427
Number of validation batches: 3
Number of validation data: 447
Encoder Input shape (with batches): (149, 30)
Decoder Input shape (with batches): (149, 30)
Target Output shape (with batches): (149, 30)
```

Build Models

Build Encoder

In [ ]:

In [11]:

```
class Encoder(tf.keras.models.Model):
    def __init__(self,units,embedding_dim,vocab_size,*args,**kwargs) -> None:
        super().__init__(*args,**kwargs)
        self.units=units
        self.vocab_size=vocab_size
        self.embedding_dim=embedding_dim
        self.embedding=Embedding(
            vocab_size,
            embedding_dim,
            name='encoder_embedding',
            mask_zero=True,
            embeddings_initializer=tf.keras.initializers.GlorotNormal()
        )
        self.normalize=LayerNormalization()
        self.lstm=LSTM(
            units,
            dropout=.4,
            return_state=True,
            return_sequences=True,
            name='encoder_lstm',
            kernel_initializer=tf.keras.initializers.GlorotNormal()
        )

    def call(self,encoder_inputs):
        self.inputs=encoder_inputs
        x=self.embedding(encoder_inputs)
        x=self.normalize(x)
        x=Dropout(.4)(x)
        encoder_outputs,encoder_state_h,encoder_state_c=self.lstm(x)
        self.outputs=[encoder_state_h,encoder_state_c]
        return encoder_state_h,encoder_state_c

encoder=Encoder(lstm_cells,embedding_dim,vocab_size,name='encoder')
encoder.call(_[0])
```

Out[11]:

```
(<tf.Tensor: shape=(149, 256), dtype=float32, numpy=
 array([[ 0.16966951, -0.10419625, -0.12700348, ..., -0.12251794,
          0.10568858,  0.14841646],
        [ 0.08443093,  0.08849293, -0.09065959, ..., -0.00959182,
          0.10152507, -0.12077457],
```

```
        [ 0.03628462, -0.02653611, -0.11506603, ..., -0.14669597,
          0.10292757,  0.13625325],
        ...,
        [-0.14210635, -0.12942064, -0.03288083, ...,  0.0568463 ,
         -0.02598592, -0.22455114],
        [ 0.20819993,  0.01196991, -0.09635217, ..., -0.18782297,
          0.10233591,  0.20114912],
        [ 0.1164271 , -0.07769038, -0.06414707, ..., -0.06539135,
         -0.05518465,  0.25142196]], dtype=float32)>,
 <tf.Tensor: shape=(149, 256), dtype=float32, numpy=
 array([[ 0.34589   , -0.30134732, -0.43572   , ..., -0.3102559 ,
          0.34630865,  0.2613009 ],
        [ 0.14154069,  0.17045322, -0.17749965, ..., -0.02712595,
          0.17292541, -0.2922624 ],
        [ 0.07106856, -0.0739173 , -0.3641197 , ..., -0.3794833 ,
          0.36470377,  0.23766585],
        ...,
        [-0.2582597 , -0.25323495, -0.06649272, ...,  0.16527973,
         -0.04292646, -0.58768904],
        [ 0.43155715,  0.03135502, -0.33463806, ..., -0.47625306,
          0.33486888,  0.35035062],
        [ 0.23173636, -0.20141824, -0.22034441, ..., -0.16035017,
         -0.17478186,  0.48899865]], dtype=float32)>)
```

Build Encoder## Build Decoder

In [12]:

```python
class Decoder(tf.keras.models.Model):
    def __init__(self,units,embedding_dim,vocab_size,*args,**kwargs) -> None:
        super().__init__(*args,**kwargs)
        self.units=units
        self.embedding_dim=embedding_dim
        self.vocab_size=vocab_size
        self.embedding=Embedding(
            vocab_size,
            embedding_dim,
            name='decoder_embedding',
            mask_zero=True,
            embeddings_initializer=tf.keras.initializers.HeNormal()
        )
        self.normalize=LayerNormalization()
        self.lstm=LSTM(
            units,
            dropout=.4,
            return_state=True,
            return_sequences=True,
            name='decoder_lstm',
            kernel_initializer=tf.keras.initializers.HeNormal()
        )
        self.fc=Dense(
            vocab_size,
            activation='softmax',
            name='decoder_dense',
            kernel_initializer=tf.keras.initializers.HeNormal()
        )

    def call(self,decoder_inputs,encoder_states):
```

```
        x=self.embedding(decoder_inputs)
        x=self.normalize(x)
        x=Dropout(.4)(x)
        x,decoder_state_h,decoder_state_c=self.lstm(x,initial_state=encoder_s
tates)
        x=self.normalize(x)
        x=Dropout(.4)(x)
        return self.fc(x)

decoder=Decoder(lstm_cells,embedding_dim,vocab_size,name='decoder')
decoder(_[1][:1],encoder(_[0][:1]))
```

Out[12]:

```
<tf.Tensor: shape=(1, 30, 2443), dtype=float32, numpy=
array([[[3.4059247e-04, 5.7348556e-05, 2.1294907e-05, ...,
         7.2067953e-05, 1.5453645e-03, 2.3599296e-04],
        [1.4662130e-03, 8.0250365e-06, 5.4062020e-05, ...,
         1.9187471e-05, 9.7244098e-05, 7.6433855e-05],
        [9.6929165e-05, 2.7441782e-05, 1.3761305e-03, ...,
         3.6009602e-05, 1.5537882e-04, 1.8397317e-04],
        ...,
        [1.9002777e-03, 6.9266016e-04, 1.4346189e-04, ...,
         1.9552530e-04, 1.7106640e-05, 1.0252406e-04],
        [1.9002777e-03, 6.9266016e-04, 1.4346189e-04, ...,
         1.9552530e-04, 1.7106640e-05, 1.0252406e-04],
        [1.9002777e-03, 6.9266016e-04, 1.4346189e-04, ...,
         1.9552530e-04, 1.7106640e-05, 1.0252406e-04]]], dtype=float32)>
```

Build Training Model

In [13]:

```
class ChatBotTrainer(tf.keras.models.Model):
    def __init__(self,encoder,decoder,*args,**kwargs):
        super().__init__(*args,**kwargs)
        self.encoder=encoder
        self.decoder=decoder

    def loss_fn(self,y_true,y_pred):
        loss=self.loss(y_true,y_pred)
        mask=tf.math.logical_not(tf.math.equal(y_true,0))
        mask=tf.cast(mask,dtype=loss.dtype)
        loss*=mask
        return tf.reduce_mean(loss)

    def accuracy_fn(self,y_true,y_pred):
        pred_values = tf.cast(tf.argmax(y_pred, axis=-1), dtype='int64')
        correct = tf.cast(tf.equal(y_true, pred_values), dtype='float64')
        mask = tf.cast(tf.greater(y_true, 0), dtype='float64')
        n_correct = tf.keras.backend.sum(mask * correct)
        n_total = tf.keras.backend.sum(mask)
        return n_correct / n_total

    def call(self,inputs):
        encoder_inputs,decoder_inputs=inputs
        encoder_states=self.encoder(encoder_inputs)
        return self.decoder(decoder_inputs,encoder_states)
```

```
    def train_step(self,batch):
        encoder_inputs,decoder_inputs,y=batch
        with tf.GradientTape() as tape:
            encoder_states=self.encoder(encoder_inputs,training=True)
            y_pred=self.decoder(decoder_inputs,encoder_states,training=True)
            loss=self.loss_fn(y,y_pred)
            acc=self.accuracy_fn(y,y_pred)

        variables=self.encoder.trainable_variables+self.decoder.trainable_var
iables
        grads=tape.gradient(loss,variables)
        self.optimizer.apply_gradients(zip(grads,variables))
        metrics={'loss':loss,'accuracy':acc}
        return metrics

    def test_step(self,batch):
        encoder_inputs,decoder_inputs,y=batch
        encoder_states=self.encoder(encoder_inputs,training=True)
        y_pred=self.decoder(decoder_inputs,encoder_states,training=True)
        loss=self.loss_fn(y,y_pred)
        acc=self.accuracy_fn(y,y_pred)
        metrics={'loss':loss,'accuracy':acc}
        return metrics
```

In [14]:

```
model=ChatBotTrainer(encoder,decoder,name='chatbot_trainer')
model.compile(
    loss=tf.keras.losses.SparseCategoricalCrossentropy(),
    optimizer=tf.keras.optimizers.Adam(learning_rate=learning_rate),
    weighted_metrics=['loss','accuracy']
)
model(_[:2])
```

Out[14]:

```
<tf.Tensor: shape=(149, 30, 2443), dtype=float32, numpy=
array([[[3.40592262e-04, 5.73484940e-05, 2.12948853e-05, ...,
          7.20679745e-05, 1.54536311e-03, 2.35993255e-04],
         [1.46621116e-03, 8.02504110e-06, 5.40619949e-05, ...,
          1.91874733e-05, 9.72440175e-05, 7.64339056e-05],
         [9.69291723e-05, 2.74417835e-05, 1.37613132e-03, ...,
          3.60095728e-05, 1.55378671e-04, 1.83973272e-04],
         ...,
         [1.90027885e-03, 6.92659756e-04, 1.43461803e-04, ...,
          1.95525470e-04, 1.71066222e-05, 1.02524005e-04],
         [1.90027885e-03, 6.92659756e-04, 1.43461803e-04, ...,
          1.95525470e-04, 1.71066222e-05, 1.02524005e-04],
         [1.90027885e-03, 6.92659756e-04, 1.43461803e-04, ...,
          1.95525470e-04, 1.71066222e-05, 1.02524005e-04]],

        [[9.24730921e-05, 3.46553512e-04, 2.07866033e-05, ...,
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         [8.46863186e-05, 3.65541164e-05, 2.54740953e-05, ...,
          7.12379551e-05, 3.62201303e-04, 4.16714087e-04],
         [2.30146630e-04, 3.91469621e-06, 2.72463716e-04, ...,
          9.26126595e-05, 1.03836363e-04, 1.40792166e-04],
```

```
 ...,
 [6.84961735e-04, 9.07644513e-04, 2.86691647e-04, ...,
  3.87946144e-04, 6.09236558e-05, 1.12995331e-05],
 [6.84961735e-04, 9.07644513e-04, 2.86691647e-04, ...,
  3.87946144e-04, 6.09236558e-05, 1.12995331e-05],
 [6.84961735e-04, 9.07644513e-04, 2.86691647e-04, ...,
  3.87946144e-04, 6.09236558e-05, 1.12995322e-05]],

[[1.19036995e-03, 8.10516722e-05, 2.42324077e-05, ...,
  4.99442758e-05, 6.67208573e-04, 9.55566764e-04],
 [1.53046989e-04, 9.76863957e-05, 4.96972689e-06, ...,
  3.24743196e-05, 2.12563842e-04, 1.18708890e-03],
 [9.40205529e-04, 1.80782794e-04, 7.26205144e-06, ...,
  1.96355060e-04, 8.16940737e-05, 1.38416886e-03],
 ...,
 [3.52622545e-03, 1.26781175e-03, 1.02695449e-04, ...,
  2.35450850e-03, 3.25187625e-06, 9.46984728e-05],
 [3.52622545e-03, 1.26781175e-03, 1.02695449e-04, ...,
  2.35450850e-03, 3.25187625e-06, 9.46984728e-05],
 [3.52622545e-03, 1.26781175e-03, 1.02695449e-04, ...,
  2.35450850e-03, 3.25187625e-06, 9.46984728e-05]],

...,

[[9.03617911e-05, 1.57651404e-04, 1.02747028e-04, ...,
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 [1.55469708e-04, 1.53608169e-04, 1.14945491e-04, ...,
  1.88878359e-04, 5.11967926e-04, 5.13108505e-04],
 [8.27641197e-05, 2.83437112e-05, 6.29429938e-04, ...,
  2.15980137e-04, 3.02832137e-04, 1.77760507e-04],
 ...,
 [2.41102395e-03, 1.29279669e-03, 9.11735406e-05, ...,
  4.06600971e-04, 7.58682154e-06, 6.05909081e-05],
 [2.41102395e-03, 1.29279669e-03, 9.11735406e-05, ...,
  4.06600971e-04, 7.58682154e-06, 6.05909081e-05],
 [2.41102395e-03, 1.29279669e-03, 9.11735406e-05, ...,
  4.06600971e-04, 7.58682154e-06, 6.05909081e-05]],

[[3.99837241e-04, 2.36026899e-05, 6.89777007e-05, ...,
  5.94239136e-05, 4.32556757e-04, 4.60232928e-04],
 [3.88111075e-04, 8.31133584e-05, 1.11861555e-04, ...,
  3.03280340e-05, 2.54765386e-04, 2.82170397e-04],
 [2.12516752e-03, 7.19837190e-05, 1.88700986e-04, ...,
  1.86366087e-04, 7.02239413e-05, 2.54370330e-04],
 ...,
 [4.56329063e-03, 2.23812275e-03, 2.37343236e-04, ...,
  2.64523784e-04, 4.05454011e-05, 1.55662783e-04],
 [4.56329063e-03, 2.23812275e-03, 2.37343236e-04, ...,
  2.64523784e-04, 4.05454011e-05, 1.55662783e-04],
 [4.56329063e-03, 2.23812275e-03, 2.37343236e-04, ...,
  2.64523784e-04, 4.05454011e-05, 1.55662783e-04]],

[[3.24600202e-04, 9.31067043e-05, 4.60048941e-05, ...,
```

```
          6.66230699e-05, 5.76460850e-04, 1.52416309e-04],
         [7.51478728e-05, 7.63997741e-05, 2.09082973e-05, ...,
          2.55555002e-04, 2.28998848e-04, 4.37303359e-04],
         [1.03114333e-04, 1.55743372e-04, 9.97955431e-06, ...,
          1.12485175e-03, 4.80950950e-03, 6.83143327e-04],
         ...,
         [5.20280097e-03, 3.23211338e-04, 2.47709468e-05, ...,
          3.07609705e-04, 6.09844255e-06, 8.61325825e-05],
         [5.20280097e-03, 3.23211338e-04, 2.47709468e-05, ...,
          3.07609705e-04, 6.09844255e-06, 8.61325825e-05],
         [5.20280097e-03, 3.23211338e-04, 2.47709468e-05, ...,
          3.07609705e-04, 6.09844255e-06, 8.61325825e-05]]],
dtype=float32)>
```

Train Model

In [15]:

```
history=model.fit(
    train_data,
    epochs=100,
    validation_data=val_data,
    callbacks=[
        tf.keras.callbacks.TensorBoard(log_dir='logs'),
        tf.keras.callbacks.ModelCheckpoint('ckpt',verbose=1,save_best_only=Tr
ue)
    ]
)
```

```
Epoch 1/100
23/23 [==============================] - ETA: 0s - loss: 1.6590 -
accuracy: 0.2180
Epoch 1: val_loss improved from inf to 1.21875, saving model to ckpt
23/23 [==============================] - 68s 3s/step - loss: 1.6515 -
accuracy: 0.2198 - val_loss: 1.2187 - val_accuracy: 0.3072
Epoch 2/100
23/23 [==============================] - ETA: 0s - loss: 1.2327 -
accuracy: 0.3087
Epoch 2: val_loss improved from 1.21875 to 1.10877, saving model to ckpt
23/23 [==============================] - 53s 2s/step - loss: 1.2287 -
accuracy: 0.3092 - val_loss: 1.1088 - val_accuracy: 0.3415
Epoch 3/100
23/23 [==============================] - ETA: 0s - loss: 1.1008 -
accuracy: 0.3368
Epoch 3: val_loss did not improve from 1.10877
23/23 [==============================] - 22s 973ms/step - loss: 1.0984 -
accuracy: 0.3370 - val_loss: 1.1161 - val_accuracy: 0.3315
Epoch 4/100
23/23 [==============================] - ETA: 0s - loss: 1.0209 -
accuracy: 0.3536
Epoch 4: val_loss improved from 1.10877 to 0.95189, saving model to ckpt
23/23 [==============================] - 53s 2s/step - loss: 1.0186 -
accuracy: 0.3540 - val_loss: 0.9519 - val_accuracy: 0.3718
Epoch 5/100
23/23 [==============================] - ETA: 0s - loss: 0.9622 -
accuracy: 0.3673
Epoch 5: val_loss did not improve from 0.95189
```

```
23/23 [==============================] - 23s 979ms/step - loss: 0.9672 -
accuracy: 0.3670 - val_loss: 0.9642 - val_accuracy: 0.3666
Epoch 6/100
23/23 [==============================] - ETA: 0s - loss: 0.9159 -
accuracy: 0.3801
Epoch 6: val_loss improved from 0.95189 to 0.94015, saving model to ckpt
23/23 [==============================] - 53s 2s/step - loss: 0.9182 -
accuracy: 0.3796 - val_loss: 0.9401 - val_accuracy: 0.3598
Epoch 7/100
23/23 [==============================] - ETA: 0s - loss: 0.8737 -
accuracy: 0.3908
Epoch 7: val_loss improved from 0.94015 to 0.83293, saving model to ckpt
23/23 [==============================] - 52s 2s/step - loss: 0.8746 -
accuracy: 0.3900 - val_loss: 0.8329 - val_accuracy: 0.4180
Epoch 8/100
23/23 [==============================] - ETA: 0s - loss: 0.8389 -
accuracy: 0.4013
Epoch 8: val_loss improved from 0.83293 to 0.77748, saving model to ckpt
23/23 [==============================] - 53s 2s/step - loss: 0.8395 -
accuracy: 0.4013 - val_loss: 0.7775 - val_accuracy: 0.4305
Epoch 9/100
23/23 [==============================] - ETA: 0s - loss: 0.8148 -
accuracy: 0.4094
Epoch 9: val_loss did not improve from 0.77748
23/23 [==============================] - 23s 983ms/step - loss: 0.8187 -
accuracy: 0.4084 - val_loss: 0.8608 - val_accuracy: 0.3830
Epoch 10/100
23/23 [==============================] - ETA: 0s - loss: 0.7889 -
accuracy: 0.4200
Epoch 10: val_loss improved from 0.77748 to 0.73131, saving model to ckpt
23/23 [==============================] - 53s 2s/step - loss: 0.7923 -
accuracy: 0.4188 - val_loss: 0.7313 - val_accuracy: 0.4515
Epoch 11/100
23/23 [==============================] - ETA: 0s - loss: 0.7624 -
accuracy: 0.4284
Epoch 11: val_loss did not improve from 0.73131
23/23 [==============================] - 22s 965ms/step - loss: 0.7615 -
accuracy: 0.4282 - val_loss: 0.8036 - val_accuracy: 0.4472
Epoch 12/100
23/23 [==============================] - ETA: 0s - loss: 0.7433 -
accuracy: 0.4361
Epoch 12: val_loss did not improve from 0.73131
23/23 [==============================] - 23s 984ms/step - loss: 0.7452 -
accuracy: 0.4354 - val_loss: 0.7384 - val_accuracy: 0.4623
Epoch 13/100
23/23 [==============================] - ETA: 0s - loss: 0.7246 -
accuracy: 0.4493
Epoch 13: val_loss did not improve from 0.73131
23/23 [==============================] - 23s 988ms/step - loss: 0.7281 -
accuracy: 0.4488 - val_loss: 0.8017 - val_accuracy: 0.4449
Epoch 14/100
23/23 [==============================] - ETA: 0s - loss: 0.7080 -
accuracy: 0.4513
Epoch 14: val_loss did not improve from 0.73131
```

```
23/23 [==============================] - 23s 995ms/step - loss: 0.7080 -
accuracy: 0.4509 - val_loss: 0.7568 - val_accuracy: 0.4259
Epoch 15/100
23/23 [==============================] - ETA: 0s - loss: 0.6853 -
accuracy: 0.4620
Epoch 15: val_loss did not improve from 0.73131
23/23 [==============================] - 22s 974ms/step - loss: 0.6826 -
accuracy: 0.4616 - val_loss: 0.7376 - val_accuracy: 0.4502
Epoch 16/100
23/23 [==============================] - ETA: 0s - loss: 0.6731 -
accuracy: 0.4673
Epoch 16: val_loss did not improve from 0.73131
23/23 [==============================] - 23s 983ms/step - loss: 0.6733 -
accuracy: 0.4672 - val_loss: 0.7646 - val_accuracy: 0.4538
Epoch 17/100
23/23 [==============================] - ETA: 0s - loss: 0.6576 -
accuracy: 0.4732
Epoch 17: val_loss improved from 0.73131 to 0.66131, saving model to ckpt
23/23 [==============================] - 52s 2s/step - loss: 0.6539 -
accuracy: 0.4738 - val_loss: 0.6613 - val_accuracy: 0.4714
Epoch 18/100
23/23 [==============================] - ETA: 0s - loss: 0.6468 -
accuracy: 0.4807
Epoch 18: val_loss improved from 0.66131 to 0.65303, saving model to ckpt
23/23 [==============================] - 53s 2s/step - loss: 0.6458 -
accuracy: 0.4805 - val_loss: 0.6530 - val_accuracy: 0.4993
Epoch 19/100
23/23 [==============================] - ETA: 0s - loss: 0.6353 -
accuracy: 0.4881
Epoch 19: val_loss did not improve from 0.65303
23/23 [==============================] - 23s 994ms/step - loss: 0.6357 -
accuracy: 0.4876 - val_loss: 0.7331 - val_accuracy: 0.4677
Epoch 20/100
23/23 [==============================] - ETA: 0s - loss: 0.6194 -
accuracy: 0.4968
Epoch 20: val_loss improved from 0.65303 to 0.55054, saving model to ckpt
23/23 [==============================] - 54s 2s/step - loss: 0.6188 -
accuracy: 0.4967 - val_loss: 0.5505 - val_accuracy: 0.5221
Epoch 21/100
23/23 [==============================] - ETA: 0s - loss: 0.6160 -
accuracy: 0.4978
Epoch 21: val_loss did not improve from 0.55054
23/23 [==============================] - 23s 987ms/step - loss: 0.6182 -
accuracy: 0.4965 - val_loss: 0.6790 - val_accuracy: 0.4979
Epoch 22/100
23/23 [==============================] - ETA: 0s - loss: 0.6011 -
accuracy: 0.5052
Epoch 22: val_loss did not improve from 0.55054
23/23 [==============================] - 23s 996ms/step - loss: 0.6011 -
accuracy: 0.5051 - val_loss: 0.6221 - val_accuracy: 0.5277
Epoch 23/100
23/23 [==============================] - ETA: 0s - loss: 0.5950 -
accuracy: 0.5079
Epoch 23: val_loss did not improve from 0.55054
```

```
23/23 [==============================] - 23s 987ms/step - loss: 0.5934 -
accuracy: 0.5081 - val_loss: 0.6142 - val_accuracy: 0.5198
Epoch 24/100
23/23 [==============================] - ETA: 0s - loss: 0.5810 -
accuracy: 0.5160
Epoch 24: val_loss did not improve from 0.55054
23/23 [==============================] - 22s 971ms/step - loss: 0.5803 -
accuracy: 0.5170 - val_loss: 0.5759 - val_accuracy: 0.5137
Epoch 25/100
23/23 [==============================] - ETA: 0s - loss: 0.5716 -
accuracy: 0.5227
Epoch 25: val_loss did not improve from 0.55054
23/23 [==============================] - 23s 986ms/step - loss: 0.5733 -
accuracy: 0.5229 - val_loss: 0.6344 - val_accuracy: 0.5169
Epoch 26/100
23/23 [==============================] - ETA: 0s - loss: 0.5676 -
accuracy: 0.5225
Epoch 26: val_loss did not improve from 0.55054
23/23 [==============================] - 22s 963ms/step - loss: 0.5708 -
accuracy: 0.5210 - val_loss: 0.6254 - val_accuracy: 0.4882
Epoch 27/100
23/23 [==============================] - ETA: 0s - loss: 0.5616 -
accuracy: 0.5291
Epoch 27: val_loss did not improve from 0.55054
23/23 [==============================] - 23s 988ms/step - loss: 0.5624 -
accuracy: 0.5280 - val_loss: 0.6774 - val_accuracy: 0.5379
Epoch 28/100
23/23 [==============================] - ETA: 0s - loss: 0.5531 -
accuracy: 0.5318
Epoch 28: val_loss did not improve from 0.55054
23/23 [==============================] - 22s 949ms/step - loss: 0.5543 -
accuracy: 0.5310 - val_loss: 0.7284 - val_accuracy: 0.5302
Epoch 29/100
23/23 [==============================] - ETA: 0s - loss: 0.5398 -
accuracy: 0.5389
Epoch 29: val_loss did not improve from 0.55054
23/23 [==============================] - 23s 1s/step - loss: 0.5391 -
accuracy: 0.5398 - val_loss: 0.7385 - val_accuracy: 0.5193
Epoch 30/100
23/23 [==============================] - ETA: 0s - loss: 0.5375 -
accuracy: 0.5416
Epoch 30: val_loss improved from 0.55054 to 0.50346, saving model to ckpt
23/23 [==============================] - 53s 2s/step - loss: 0.5384 -
accuracy: 0.5417 - val_loss: 0.5035 - val_accuracy: 0.5411
Epoch 31/100
23/23 [==============================] - ETA: 0s - loss: 0.5270 -
accuracy: 0.5481
Epoch 31: val_loss did not improve from 0.50346
23/23 [==============================] - 22s 958ms/step - loss: 0.5262 -
accuracy: 0.5477 - val_loss: 0.5805 - val_accuracy: 0.5457
Epoch 32/100
23/23 [==============================] - ETA: 0s - loss: 0.5304 -
accuracy: 0.5447
Epoch 32: val_loss did not improve from 0.50346
```

```
23/23 [==============================] - 22s 963ms/step - loss: 0.5329 - accuracy: 0.5435 - val_loss: 0.5374 - val_accuracy: 0.5725
Epoch 33/100
23/23 [==============================] - ETA: 0s - loss: 0.5196 - accuracy: 0.5520
Epoch 33: val_loss did not improve from 0.50346
23/23 [==============================] - 23s 975ms/step - loss: 0.5211 - accuracy: 0.5518 - val_loss: 0.6217 - val_accuracy: 0.5066
Epoch 34/100
23/23 [==============================] - ETA: 0s - loss: 0.5129 - accuracy: 0.5558
Epoch 34: val_loss did not improve from 0.50346
23/23 [==============================] - 23s 1000ms/step - loss: 0.5129 - accuracy: 0.5556 - val_loss: 0.6070 - val_accuracy: 0.5653
Epoch 35/100
23/23 [==============================] - ETA: 0s - loss: 0.5059 - accuracy: 0.5620
Epoch 35: val_loss did not improve from 0.50346
23/23 [==============================] - 22s 966ms/step - loss: 0.5081 - accuracy: 0.5614 - val_loss: 0.6153 - val_accuracy: 0.5452
Epoch 36/100
23/23 [==============================] - ETA: 0s - loss: 0.5037 - accuracy: 0.5619
Epoch 36: val_loss did not improve from 0.50346
23/23 [==============================] - 23s 980ms/step - loss: 0.5063 - accuracy: 0.5617 - val_loss: 0.5328 - val_accuracy: 0.5873
Epoch 37/100
23/23 [==============================] - ETA: 0s - loss: 0.4977 - accuracy: 0.5682
Epoch 37: val_loss did not improve from 0.50346
23/23 [==============================] - 22s 969ms/step - loss: 0.4980 - accuracy: 0.5682 - val_loss: 0.5976 - val_accuracy: 0.5693
Epoch 38/100
23/23 [==============================] - ETA: 0s - loss: 0.4939 - accuracy: 0.5704
Epoch 38: val_loss did not improve from 0.50346
23/23 [==============================] - 23s 993ms/step - loss: 0.4953 - accuracy: 0.5687 - val_loss: 0.5937 - val_accuracy: 0.5236
Epoch 39/100
23/23 [==============================] - ETA: 0s - loss: 0.4860 - accuracy: 0.5758
Epoch 39: val_loss did not improve from 0.50346
23/23 [==============================] - 23s 986ms/step - loss: 0.4868 - accuracy: 0.5746 - val_loss: 0.6155 - val_accuracy: 0.5457
Epoch 40/100
23/23 [==============================] - ETA: 0s - loss: 0.4809 - accuracy: 0.5778
Epoch 40: val_loss did not improve from 0.50346
23/23 [==============================] - 23s 1s/step - loss: 0.4821 - accuracy: 0.5760 - val_loss: 0.5046 - val_accuracy: 0.5662
Epoch 41/100
23/23 [==============================] - ETA: 0s - loss: 0.4781 - accuracy: 0.5817
Epoch 41: val_loss did not improve from 0.50346
```

```
23/23 [==============================] - 23s 990ms/step - loss: 0.4782 -
accuracy: 0.5821 - val_loss: 0.5256 - val_accuracy: 0.5907
Epoch 42/100
23/23 [==============================] - ETA: 0s - loss: 0.4713 -
accuracy: 0.5836
Epoch 42: val_loss did not improve from 0.50346
23/23 [==============================] - 23s 982ms/step - loss: 0.4729 -
accuracy: 0.5824 - val_loss: 0.6387 - val_accuracy: 0.5456
Epoch 43/100
23/23 [==============================] - ETA: 0s - loss: 0.4641 -
accuracy: 0.5904
Epoch 43: val_loss did not improve from 0.50346
23/23 [==============================] - 23s 1s/step - loss: 0.4627 -
accuracy: 0.5908 - val_loss: 0.5668 - val_accuracy: 0.5741
Epoch 44/100
23/23 [==============================] - ETA: 0s - loss: 0.4608 -
accuracy: 0.5921
Epoch 44: val_loss improved from 0.50346 to 0.49920, saving model to ckpt
23/23 [==============================] - 53s 2s/step - loss: 0.4618 -
accuracy: 0.5920 - val_loss: 0.4992 - val_accuracy: 0.5768
Epoch 45/100
23/23 [==============================] - ETA: 0s - loss: 0.4592 -
accuracy: 0.5902
Epoch 45: val_loss did not improve from 0.49920
23/23 [==============================] - 22s 970ms/step - loss: 0.4599 -
accuracy: 0.5887 - val_loss: 0.5423 - val_accuracy: 0.5854
Epoch 46/100
23/23 [==============================] - ETA: 0s - loss: 0.4535 -
accuracy: 0.5978
Epoch 46: val_loss improved from 0.49920 to 0.48429, saving model to ckpt
23/23 [==============================] - 53s 2s/step - loss: 0.4552 -
accuracy: 0.5966 - val_loss: 0.4843 - val_accuracy: 0.6049
Epoch 47/100
23/23 [==============================] - ETA: 0s - loss: 0.4528 -
accuracy: 0.5987
Epoch 47: val_loss improved from 0.48429 to 0.47868, saving model to ckpt
23/23 [==============================] - 54s 2s/step - loss: 0.4537 -
accuracy: 0.5990 - val_loss: 0.4787 - val_accuracy: 0.5906
Epoch 48/100
23/23 [==============================] - ETA: 0s - loss: 0.4441 -
accuracy: 0.6016
Epoch 48: val_loss did not improve from 0.47868
23/23 [==============================] - 23s 982ms/step - loss: 0.4439 -
accuracy: 0.6025 - val_loss: 0.5746 - val_accuracy: 0.5542
Epoch 49/100
23/23 [==============================] - ETA: 0s - loss: 0.4436 -
accuracy: 0.6041
Epoch 49: val_loss did not improve from 0.47868
23/23 [==============================] - 22s 951ms/step - loss: 0.4432 -
accuracy: 0.6045 - val_loss: 0.5058 - val_accuracy: 0.5753
Epoch 50/100
23/23 [==============================] - ETA: 0s - loss: 0.4435 -
accuracy: 0.6033
Epoch 50: val_loss did not improve from 0.47868
```

```
23/23 [==============================] - 22s 949ms/step - loss: 0.4441 -
accuracy: 0.6043 - val_loss: 0.6037 - val_accuracy: 0.5473
Epoch 51/100
23/23 [==============================] - ETA: 0s - loss: 0.4382 -
accuracy: 0.6069
Epoch 51: val_loss did not improve from 0.47868
23/23 [==============================] - 22s 957ms/step - loss: 0.4383 -
accuracy: 0.6067 - val_loss: 0.5206 - val_accuracy: 0.6154
Epoch 52/100
23/23 [==============================] - ETA: 0s - loss: 0.4293 -
accuracy: 0.6125
Epoch 52: val_loss did not improve from 0.47868
23/23 [==============================] - 23s 971ms/step - loss: 0.4284 -
accuracy: 0.6123 - val_loss: 0.4997 - val_accuracy: 0.5840
Epoch 53/100
23/23 [==============================] - ETA: 0s - loss: 0.4309 -
accuracy: 0.6109
Epoch 53: val_loss improved from 0.47868 to 0.42987, saving model to ckpt
23/23 [==============================] - 52s 2s/step - loss: 0.4317 -
accuracy: 0.6094 - val_loss: 0.4299 - val_accuracy: 0.6062
Epoch 54/100
23/23 [==============================] - ETA: 0s - loss: 0.4292 -
accuracy: 0.6120
Epoch 54: val_loss did not improve from 0.42987
23/23 [==============================] - 22s 980ms/step - loss: 0.4309 -
accuracy: 0.6115 - val_loss: 0.6996 - val_accuracy: 0.5592
Epoch 55/100
23/23 [==============================] - ETA: 0s - loss: 0.4225 -
accuracy: 0.6115
Epoch 55: val_loss did not improve from 0.42987
23/23 [==============================] - 22s 976ms/step - loss: 0.4224 -
accuracy: 0.6102 - val_loss: 0.5500 - val_accuracy: 0.5769
Epoch 56/100
23/23 [==============================] - ETA: 0s - loss: 0.4220 -
accuracy: 0.6180
Epoch 56: val_loss did not improve from 0.42987
23/23 [==============================] - 23s 995ms/step - loss: 0.4236 -
accuracy: 0.6169 - val_loss: 0.5689 - val_accuracy: 0.5817
Epoch 57/100
23/23 [==============================] - ETA: 0s - loss: 0.4173 -
accuracy: 0.6210
Epoch 57: val_loss did not improve from 0.42987
23/23 [==============================] - 22s 976ms/step - loss: 0.4161 -
accuracy: 0.6217 - val_loss: 0.4614 - val_accuracy: 0.6048
Epoch 58/100
23/23 [==============================] - ETA: 0s - loss: 0.4183 -
accuracy: 0.6198
Epoch 58: val_loss did not improve from 0.42987
23/23 [==============================] - 23s 1s/step - loss: 0.4183 -
accuracy: 0.6201 - val_loss: 0.4372 - val_accuracy: 0.6067
Epoch 59/100
23/23 [==============================] - ETA: 0s - loss: 0.4120 -
accuracy: 0.6251
Epoch 59: val_loss did not improve from 0.42987
```

```
23/23 [==============================] - 23s 994ms/step - loss: 0.4136 -
accuracy: 0.6237 - val_loss: 0.6183 - val_accuracy: 0.5948
Epoch 60/100
23/23 [==============================] - ETA: 0s - loss: 0.4090 -
accuracy: 0.6239
Epoch 60: val_loss did not improve from 0.42987
23/23 [==============================] - 23s 980ms/step - loss: 0.4101 -
accuracy: 0.6225 - val_loss: 0.5042 - val_accuracy: 0.6161
Epoch 61/100
23/23 [==============================] - ETA: 0s - loss: 0.4051 -
accuracy: 0.6314
Epoch 61: val_loss did not improve from 0.42987
23/23 [==============================] - 23s 1s/step - loss: 0.4077 -
accuracy: 0.6296 - val_loss: 0.5100 - val_accuracy: 0.6128
Epoch 62/100
23/23 [==============================] - ETA: 0s - loss: 0.4016 -
accuracy: 0.6326
Epoch 62: val_loss did not improve from 0.42987
23/23 [==============================] - 24s 1s/step - loss: 0.4029 -
accuracy: 0.6322 - val_loss: 0.5295 - val_accuracy: 0.6005
Epoch 63/100
23/23 [==============================] - ETA: 0s - loss: 0.4049 -
accuracy: 0.6323
Epoch 63: val_loss did not improve from 0.42987
23/23 [==============================] - 23s 981ms/step - loss: 0.4069 -
accuracy: 0.6316 - val_loss: 0.5103 - val_accuracy: 0.6088
Epoch 64/100
23/23 [==============================] - ETA: 0s - loss: 0.3951 -
accuracy: 0.6335
Epoch 64: val_loss did not improve from 0.42987
23/23 [==============================] - 22s 981ms/step - loss: 0.3943 -
accuracy: 0.6341 - val_loss: 0.5366 - val_accuracy: 0.5869
Epoch 65/100
23/23 [==============================] - ETA: 0s - loss: 0.3967 -
accuracy: 0.6344
Epoch 65: val_loss improved from 0.42987 to 0.40702, saving model to ckpt
23/23 [==============================] - 53s 2s/step - loss: 0.3972 -
accuracy: 0.6352 - val_loss: 0.4070 - val_accuracy: 0.6452
Epoch 66/100
23/23 [==============================] - ETA: 0s - loss: 0.3942 -
accuracy: 0.6351
Epoch 66: val_loss did not improve from 0.40702
23/23 [==============================] - 22s 961ms/step - loss: 0.3954 -
accuracy: 0.6337 - val_loss: 0.4963 - val_accuracy: 0.6039
Epoch 67/100
23/23 [==============================] - ETA: 0s - loss: 0.3884 -
accuracy: 0.6409
Epoch 67: val_loss did not improve from 0.40702
23/23 [==============================] - 22s 951ms/step - loss: 0.3879 -
accuracy: 0.6424 - val_loss: 0.4651 - val_accuracy: 0.6276
Epoch 68/100
23/23 [==============================] - ETA: 0s - loss: 0.3876 -
accuracy: 0.6398
Epoch 68: val_loss improved from 0.40702 to 0.38016, saving model to ckpt
```

```
23/23 [==============================] - 52s 2s/step - loss: 0.3870 -
accuracy: 0.6388 - val_loss: 0.3802 - val_accuracy: 0.6614
Epoch 69/100
23/23 [==============================] - ETA: 0s - loss: 0.3897 -
accuracy: 0.6394
Epoch 69: val_loss did not improve from 0.38016
23/23 [==============================] - 22s 961ms/step - loss: 0.3895 -
accuracy: 0.6395 - val_loss: 0.4046 - val_accuracy: 0.6587
Epoch 70/100
23/23 [==============================] - ETA: 0s - loss: 0.3855 -
accuracy: 0.6433
Epoch 70: val_loss did not improve from 0.38016
23/23 [==============================] - 22s 967ms/step - loss: 0.3870 -
accuracy: 0.6432 - val_loss: 0.4162 - val_accuracy: 0.6475
Epoch 71/100
23/23 [==============================] - ETA: 0s - loss: 0.3828 -
accuracy: 0.6422
Epoch 71: val_loss did not improve from 0.38016
23/23 [==============================] - 23s 986ms/step - loss: 0.3828 -
accuracy: 0.6423 - val_loss: 0.4099 - val_accuracy: 0.6612
Epoch 72/100
23/23 [==============================] - ETA: 0s - loss: 0.3825 -
accuracy: 0.6460
Epoch 72: val_loss did not improve from 0.38016
23/23 [==============================] - 24s 1s/step - loss: 0.3831 -
accuracy: 0.6449 - val_loss: 0.5160 - val_accuracy: 0.6117
Epoch 73/100
23/23 [==============================] - ETA: 0s - loss: 0.3795 -
accuracy: 0.6451
Epoch 73: val_loss did not improve from 0.38016
23/23 [==============================] - 23s 1s/step - loss: 0.3797 -
accuracy: 0.6448 - val_loss: 0.4963 - val_accuracy: 0.6231
Epoch 74/100
23/23 [==============================] - ETA: 0s - loss: 0.3769 -
accuracy: 0.6479
Epoch 74: val_loss did not improve from 0.38016
23/23 [==============================] - 22s 975ms/step - loss: 0.3783 -
accuracy: 0.6459 - val_loss: 0.4888 - val_accuracy: 0.6084
Epoch 75/100
23/23 [==============================] - ETA: 0s - loss: 0.3719 -
accuracy: 0.6541
Epoch 75: val_loss did not improve from 0.38016
23/23 [==============================] - 22s 971ms/step - loss: 0.3724 -
accuracy: 0.6538 - val_loss: 0.5175 - val_accuracy: 0.6032
Epoch 76/100
23/23 [==============================] - ETA: 0s - loss: 0.3697 -
accuracy: 0.6555
Epoch 76: val_loss did not improve from 0.38016
23/23 [==============================] - 23s 1s/step - loss: 0.3687 -
accuracy: 0.6548 - val_loss: 0.4598 - val_accuracy: 0.6059
Epoch 77/100
23/23 [==============================] - ETA: 0s - loss: 0.3702 -
accuracy: 0.6552
Epoch 77: val_loss did not improve from 0.38016
```

```
23/23 [==============================] - 22s 954ms/step - loss: 0.3713 -
accuracy: 0.6540 - val_loss: 0.5650 - val_accuracy: 0.5824
Epoch 78/100
23/23 [==============================] - ETA: 0s - loss: 0.3685 -
accuracy: 0.6548
Epoch 78: val_loss did not improve from 0.38016
23/23 [==============================] - 23s 982ms/step - loss: 0.3675 -
accuracy: 0.6557 - val_loss: 0.4115 - val_accuracy: 0.6292
Epoch 79/100
23/23 [==============================] - ETA: 0s - loss: 0.3659 -
accuracy: 0.6584
Epoch 79: val_loss did not improve from 0.38016
23/23 [==============================] - 22s 970ms/step - loss: 0.3662 -
accuracy: 0.6577 - val_loss: 0.3868 - val_accuracy: 0.6516
Epoch 80/100
23/23 [==============================] - ETA: 0s - loss: 0.3626 -
accuracy: 0.6628
Epoch 80: val_loss did not improve from 0.38016
23/23 [==============================] - 23s 994ms/step - loss: 0.3627 -
accuracy: 0.6638 - val_loss: 0.4733 - val_accuracy: 0.6388
Epoch 81/100
23/23 [==============================] - ETA: 0s - loss: 0.3623 -
accuracy: 0.6578
Epoch 81: val_loss did not improve from 0.38016
23/23 [==============================] - 22s 970ms/step - loss: 0.3621 -
accuracy: 0.6577 - val_loss: 0.5189 - val_accuracy: 0.5979
Epoch 82/100
23/23 [==============================] - ETA: 0s - loss: 0.3603 -
accuracy: 0.6612
Epoch 82: val_loss did not improve from 0.38016
23/23 [==============================] - 23s 982ms/step - loss: 0.3600 -
accuracy: 0.6614 - val_loss: 0.4210 - val_accuracy: 0.6280
Epoch 83/100
23/23 [==============================] - ETA: 0s - loss: 0.3608 -
accuracy: 0.6604
Epoch 83: val_loss did not improve from 0.38016
23/23 [==============================] - 23s 1s/step - loss: 0.3627 -
accuracy: 0.6592 - val_loss: 0.5621 - val_accuracy: 0.6082
Epoch 84/100
23/23 [==============================] - ETA: 0s - loss: 0.3605 -
accuracy: 0.6640
Epoch 84: val_loss did not improve from 0.38016
23/23 [==============================] - 23s 998ms/step - loss: 0.3628 -
accuracy: 0.6634 - val_loss: 0.4241 - val_accuracy: 0.6462
Epoch 85/100
23/23 [==============================] - ETA: 0s - loss: 0.3498 -
accuracy: 0.6713
Epoch 85: val_loss did not improve from 0.38016
23/23 [==============================] - 23s 976ms/step - loss: 0.3484 -
accuracy: 0.6713 - val_loss: 0.4425 - val_accuracy: 0.6489
Epoch 86/100
23/23 [==============================] - ETA: 0s - loss: 0.3537 -
accuracy: 0.6663
Epoch 86: val_loss did not improve from 0.38016
```

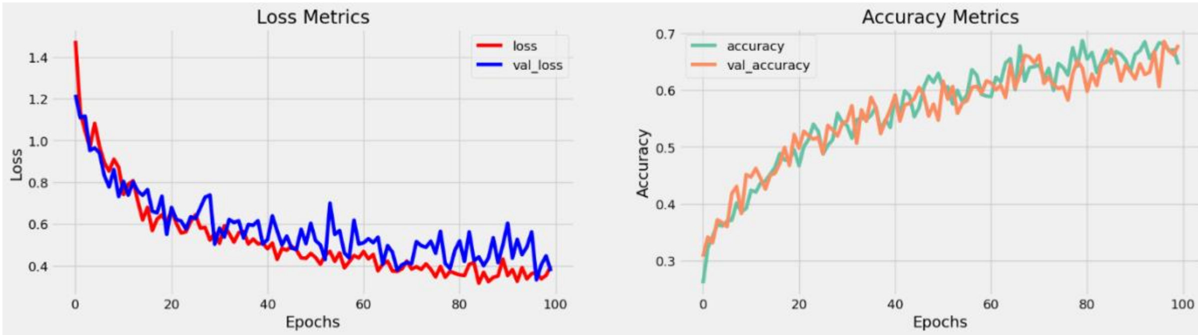
```
23/23 [==============================] - 23s 1s/step - loss: 0.3543 -
accuracy: 0.6656 - val_loss: 0.4006 - val_accuracy: 0.6716
Epoch 87/100
23/23 [==============================] - ETA: 0s - loss: 0.3503 -
accuracy: 0.6698
Epoch 87: val_loss did not improve from 0.38016
23/23 [==============================] - 23s 987ms/step - loss: 0.3493 -
accuracy: 0.6697 - val_loss: 0.4375 - val_accuracy: 0.6527
Epoch 88/100
23/23 [==============================] - ETA: 0s - loss: 0.3497 -
accuracy: 0.6714
Epoch 88: val_loss did not improve from 0.38016
23/23 [==============================] - 23s 986ms/step - loss: 0.3495 -
accuracy: 0.6710 - val_loss: 0.5339 - val_accuracy: 0.6160
Epoch 89/100
23/23 [==============================] - ETA: 0s - loss: 0.3500 -
accuracy: 0.6671
Epoch 89: val_loss did not improve from 0.38016
23/23 [==============================] - 22s 970ms/step - loss: 0.3501 -
accuracy: 0.6666 - val_loss: 0.4148 - val_accuracy: 0.6438
Epoch 90/100
23/23 [==============================] - ETA: 0s - loss: 0.3494 -
accuracy: 0.6661
Epoch 90: val_loss did not improve from 0.38016
23/23 [==============================] - 23s 995ms/step - loss: 0.3529 -
accuracy: 0.6647 - val_loss: 0.4992 - val_accuracy: 0.6324
Epoch 91/100
23/23 [==============================] - ETA: 0s - loss: 0.3479 -
accuracy: 0.6718
Epoch 91: val_loss did not improve from 0.38016
23/23 [==============================] - 23s 986ms/step - loss: 0.3482 -
accuracy: 0.6715 - val_loss: 0.6037 - val_accuracy: 0.6195
Epoch 92/100
23/23 [==============================] - ETA: 0s - loss: 0.3436 -
accuracy: 0.6767
Epoch 92: val_loss did not improve from 0.38016
23/23 [==============================] - 22s 964ms/step - loss: 0.3452 -
accuracy: 0.6764 - val_loss: 0.4368 - val_accuracy: 0.6462
Epoch 93/100
23/23 [==============================] - ETA: 0s - loss: 0.3377 -
accuracy: 0.6793
Epoch 93: val_loss did not improve from 0.38016
23/23 [==============================] - 23s 984ms/step - loss: 0.3372 -
accuracy: 0.6795 - val_loss: 0.5267 - val_accuracy: 0.6275
Epoch 94/100
23/23 [==============================] - ETA: 0s - loss: 0.3433 -
accuracy: 0.6743
Epoch 94: val_loss did not improve from 0.38016
23/23 [==============================] - 22s 964ms/step - loss: 0.3453 -
accuracy: 0.6736 - val_loss: 0.4532 - val_accuracy: 0.6314
Epoch 95/100
23/23 [==============================] - ETA: 0s - loss: 0.3409 -
accuracy: 0.6780
Epoch 95: val_loss did not improve from 0.38016
```

```
23/23 [==============================] - 23s 987ms/step - loss: 0.3407 -
accuracy: 0.6775 - val_loss: 0.4901 - val_accuracy: 0.6680
Epoch 96/100
23/23 [==============================] - ETA: 0s - loss: 0.3378 -
accuracy: 0.6791
Epoch 96: val_loss did not improve from 0.38016
23/23 [==============================] - 23s 991ms/step - loss: 0.3388 -
accuracy: 0.6793 - val_loss: 0.5620 - val_accuracy: 0.6063
Epoch 97/100
23/23 [==============================] - ETA: 0s - loss: 0.3389 -
accuracy: 0.6763
Epoch 97: val_loss improved from 0.38016 to 0.33265, saving model to ckpt
23/23 [==============================] - 53s 2s/step - loss: 0.3402 -
accuracy: 0.6765 - val_loss: 0.3327 - val_accuracy: 0.6854
Epoch 98/100
23/23 [==============================] - ETA: 0s - loss: 0.3408 -
accuracy: 0.6768
Epoch 98: val_loss did not improve from 0.33265
23/23 [==============================] - 22s 974ms/step - loss: 0.3407 -
accuracy: 0.6766 - val_loss: 0.4046 - val_accuracy: 0.6695
Epoch 99/100
23/23 [==============================] - ETA: 0s - loss: 0.3388 -
accuracy: 0.6795
Epoch 99: val_loss did not improve from 0.33265
23/23 [==============================] - 23s 985ms/step - loss: 0.3394 -
accuracy: 0.6791 - val_loss: 0.4475 - val_accuracy: 0.6622
Epoch 100/100
23/23 [==============================] - ETA: 0s - loss: 0.3358 -
accuracy: 0.6787
Epoch 100: val_loss did not improve from 0.33265
23/23 [==============================] - 22s 968ms/step - loss: 0.3385 -
accuracy: 0.6773 - val_loss: 0.3742 - val_accuracy: 0.6796
```

Visualize Metrics

In [16]:

```
fig,ax=plt.subplots(nrows=1,ncols=2,figsize=(20,5))
ax[0].plot(history.history['loss'],label='loss',c='red')
ax[0].plot(history.history['val_loss'],label='val_loss',c = 'blue')
ax[0].set_xlabel('Epochs')
ax[1].set_xlabel('Epochs')
ax[0].set_ylabel('Loss')
ax[1].set_ylabel('Accuracy')
ax[0].set_title('Loss Metrics')
ax[1].set_title('Accuracy Metrics')
ax[1].plot(history.history['accuracy'],label='accuracy')
ax[1].plot(history.history['val_accuracy'],label='val_accuracy')
ax[0].legend()
ax[1].legend()
plt.show()
```



Save Model

In [17]:

```
model.load_weights('ckpt')
model.save('models',save_format='tf')
```

In [18]:

```
for idx,i in enumerate(model.layers):
    print('Encoder layers:' if idx==0 else 'Decoder layers: ')
    for j in i.layers:
        print(j)
    print('----------------------')
Encoder layers:
<keras.layers.core.embedding.Embedding object at 0x782084b9d190>
<keras.layers.normalization.layer_normalization.LayerNormalization object
at 0x7820e56f1b90>
<keras.layers.rnn.lstm.LSTM object at 0x7820841bd650>
----------------------
Decoder layers:
<keras.layers.core.embedding.Embedding object at 0x78207c258590>
<keras.layers.normalization.layer_normalization.LayerNormalization object
at 0x78207c78bd10>
<keras.layers.rnn.lstm.LSTM object at 0x78207c258a10>
<keras.layers.core.dense.Dense object at 0x78207c2636d0>
----------------------
```

Create Inference Model

In [19]:

```
class ChatBot(tf.keras.models.Model):
    def __init__(self,base_encoder,base_decoder,*args,**kwargs):
        super().__init__(*args,**kwargs)
        self.encoder,self.decoder=self.build_inference_model(base_encoder,bas
e_decoder)

    def build_inference_model(self,base_encoder,base_decoder):
        encoder_inputs=tf.keras.Input(shape=(None,))
        x=base_encoder.layers[0](encoder_inputs)
        x=base_encoder.layers[1](x)
        x,encoder_state_h,encoder_state_c=base_encoder.layers[2](x)
        encoder=tf.keras.models.Model(inputs=encoder_inputs,outputs=[encoder_
state_h,encoder_state_c],name='chatbot_encoder')

        decoder_input_state_h=tf.keras.Input(shape=(lstm_cells,))
```

```
        decoder_input_state_c=tf.keras.Input(shape=(lstm_cells,))
        decoder_inputs=tf.keras.Input(shape=(None,))
        x=base_decoder.layers[0](decoder_inputs)
        x=base_encoder.layers[1](x)
        x,decoder_state_h,decoder_state_c=base_decoder.layers[2](x,initial_st
ate=[decoder_input_state_h,decoder_input_state_c])
        decoder_outputs=base_decoder.layers[-1](x)
        decoder=tf.keras.models.Model(
            inputs=[decoder_inputs,[decoder_input_state_h,decoder_input_state
_c]],
            outputs=[decoder_outputs,[decoder_state_h,decoder_state_c]],name=
'chatbot_decoder'
        )
        return encoder,decoder

    def summary(self):
        self.encoder.summary()
        self.decoder.summary()

    def softmax(self,z):
        return np.exp(z)/sum(np.exp(z))

    def sample(self,conditional_probability,temperature=0.5):
        conditional_probability =
np.asarray(conditional_probability).astype("float64")
        conditional_probability = np.log(conditional_probability) /
temperature
        reweighted_conditional_probability =
self.softmax(conditional_probability)
        probas = np.random.multinomial(1, reweighted_conditional_probability,
1)
        return np.argmax(probas)

    def preprocess(self,text):
        text=clean_text(text)
        seq=np.zeros((1,max_sequence_length),dtype=np.int32)
        for i,word in enumerate(text.split()):
            seq[:,i]=sequences2ids(word).numpy()[0]
        return seq

    def postprocess(self,text):
        text=re.sub(' - ','-',text.lower())
        text=re.sub(' [.] ','. ',text)
        text=re.sub(' [1] ','1',text)
        text=re.sub(' [2] ','2',text)
        text=re.sub(' [3] ','3',text)
        text=re.sub(' [4] ','4',text)
        text=re.sub(' [5] ','5',text)
        text=re.sub(' [6] ','6',text)
        text=re.sub(' [7] ','7',text)
        text=re.sub(' [8] ','8',text)
        text=re.sub(' [9] ','9',text)
        text=re.sub(' [0] ','0',text)
        text=re.sub(' [,] ',', ',text)
        text=re.sub(' [?] ','? ',text)
        text=re.sub(' [!] ','! ',text)
```

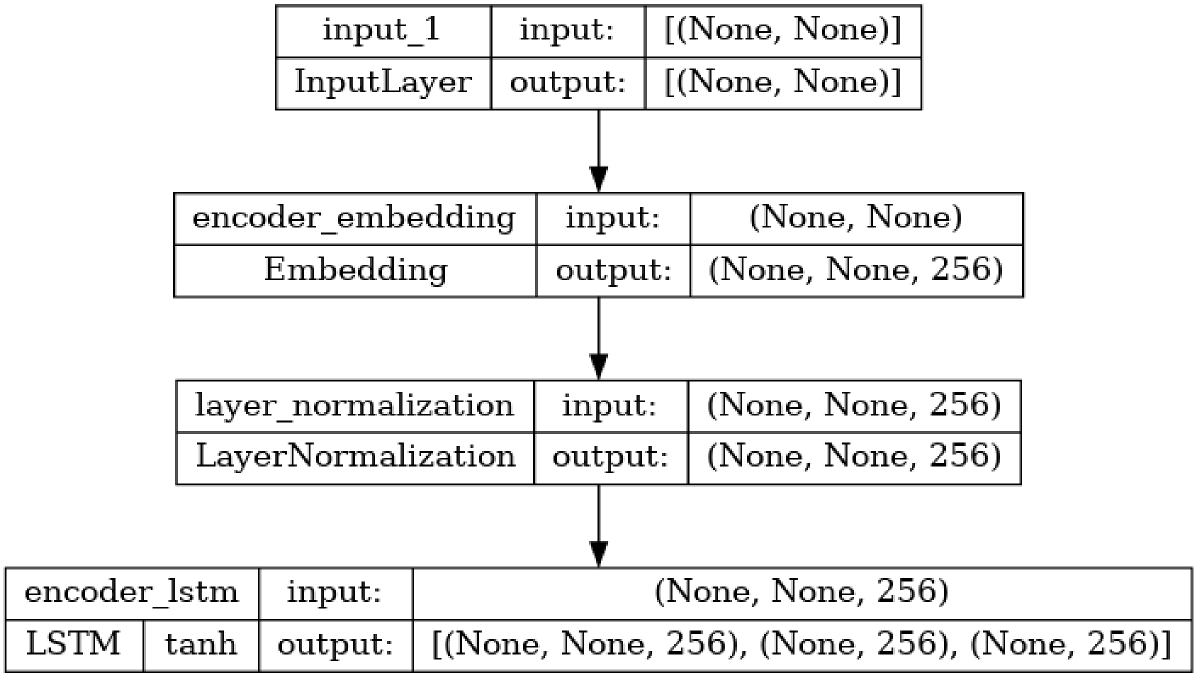
```
        text=re.sub(' [$] ','$ ',text)
        text=re.sub(' [&] ','& ',text)
        text=re.sub(' [/] ','/ ',text)
        text=re.sub(' [:] ',': ',text)
        text=re.sub(' [;] ','; ',text)
        text=re.sub(' [*] ','* ',text)
        text=re.sub(' [\'] ','\'',text)
        text=re.sub(' [\"] ','\"',text)
        return text

    def call(self,text,config=None):
        input_seq=self.preprocess(text)
        states=self.encoder(input_seq,training=False)
        target_seq=np.zeros((1,1))
        target_seq[:,:]=sequences2ids(['<start>']).numpy()[0][0]
        stop_condition=False
        decoded=[]
        while not stop_condition:
            decoder_outputs,new_states=self.decoder([target_seq,states],train
ing=False)
#             index=tf.argmax(decoder_outputs[:,-1,:],axis=-1).numpy().item()
            index=self.sample(decoder_outputs[0,0,:]).item()
            word=ids2sequences([index])
            if word=='<end> ' or len(decoded)>=max_sequence_length:
                stop_condition=True
            else:
                decoded.append(index)
                target_seq=np.zeros((1,1))
                target_seq[:,:]=index
                states=new_states
        return self.postprocess(ids2sequences(decoded))

chatbot=ChatBot(model.encoder,model.decoder,name='chatbot')
chatbot.summary()
Model: "chatbot_encoder"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, None)]            0

 encoder_embedding (Embeddin  (None, None, 256)        625408
 g)

 layer_normalization (LayerN  (None, None, 256)        512
 ormalization)

 encoder_lstm (LSTM)         [(None, None, 256),       525312
                              (None, 256),
                              (None, 256)]

=================================================================
Total params: 1,151,232
Trainable params: 1,151,232
Non-trainable params: 0
_________________________________________________________________
```

```
Model: "chatbot_decoder"
________________________________________________________________________________________________________
 Layer (type)                    Output Shape          Param #     Connected
to
========================================================================================================
 input_4 (InputLayer)           [(None,
None)]        0             []


 decoder_embedding (Embedding)  (None, None,
256)    625408      ['input_4[0][0]']


 layer_normalization (LayerNorm  (None, None,
256)   512          ['decoder_embedding[0][0]']
 alization)



 input_2 (InputLayer)           [(None,
256)]        0             []


 input_3 (InputLayer)           [(None,
256)]        0             []


 decoder_lstm (LSTM)            [(None, None,
256),  525312      ['layer_normalization[1][0]',
                                 (None,
256),                        'input_2[0][0]',
                                 (None,
256)]                        'input_3[0][0]']


 decoder_dense (Dense)          (None, None,
2443)   627851      ['decoder_lstm[0][0]']


========================================================================================================
Total params: 1,779,083
Trainable params: 1,779,083
Non-trainable params: 0
________________________________________________________________________________________________________
```

In [20]:

```python
tf.keras.utils.plot_model(chatbot.encoder,to_file='encoder.png',show_shapes=True,show_layer_activations=True)
```

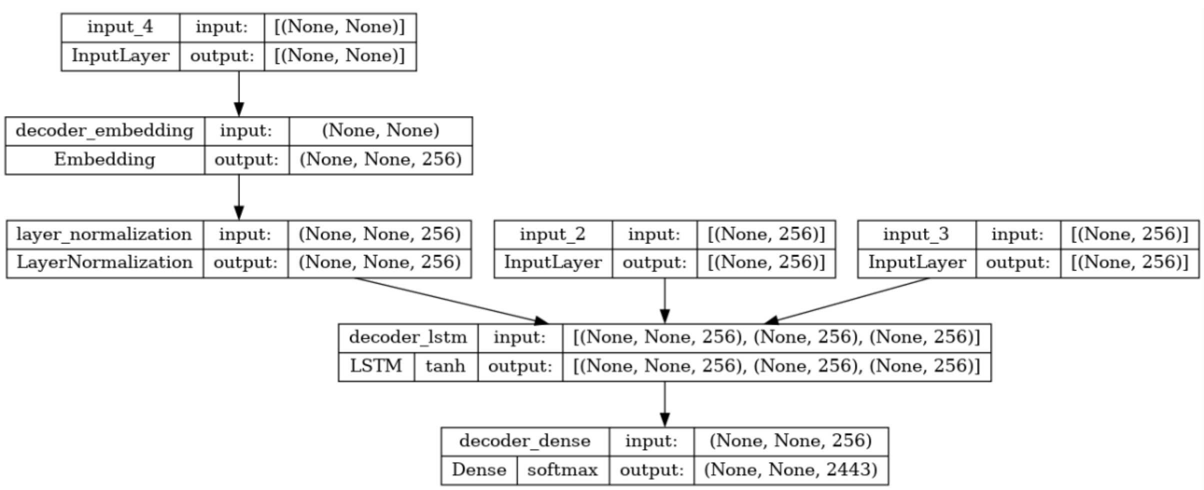
Out[20]:



In [21]:

```
tf.keras.utils.plot_model(chatbot.decoder,to_file='decoder.png',show_shapes=True,show_layer_activations=True)
```

Out[21]:



Time to Chat

In [22]:

```
def print_conversation(texts):
    for text in texts:
        print(f'You: {text}')
        print(f'Bot: {chatbot(text)}')
        print('========================')
```

In [23]:

```
print_conversation([
```

```
    'hi',
    'do yo know me?',
    'what is your name?',
    'you are bot?',
    'hi, how are you doing?',
    "i'm pretty good. thanks for asking.",
    "Don't ever be in a hurry",
    '''I'm gonna put some dirt in your eye ''',
    '''You're trash ''',
    '''I've read all your research on nano-technology ''',
    '''You want forgiveness? Get religion''',
    '''While you're using the bathroom, i'll order some food.''',
    '''Wow! that's terrible.''',
    '''We'll be here forever.''',
    '''I need something that's reliable.''',
    '''A speeding car ran a red light, killing the girl.''',
    '''Tomorrow we'll have rice and fish for lunch.''',
    '''I like this restaurant because they give you free bread.'''
])
You: hi
Bot: i have to go to the bathroom.
========================
You: do you know me?
Bot: yes, it's too close to the other.
========================
You: what is your name?
Bot: i have to walk the house.
========================
You: you are bot?
Bot: no, i have. all my life.
========================
You: hi, how are you doing?
Bot: i'm going to be a teacher.
========================
You: i'm pretty good. thanks for asking.
Bot: no problem. i'll have to give you the english assignments from my
mind.
========================
You: Don't ever be in a hurry
Bot: it's not a great.
========================
You: I'm gonna put some dirt in your eye
Bot: that's a good idea.
========================
You: You're trash
Bot: the tv news is reporting a bank robbery.
========================
You: I've read all your research on nano-technology
Bot: it's the weather. i've gone around the world.
========================
You: You want forgiveness? Get religion
Bot: no, i'll be my.
========================
You: While you're using the bathroom, i'll order some food.
Bot: don't order for me. i've been a cheater.
```

```
========================
You: Wow! that's terrible.
Bot: never park your car under the house.
========================
You: We'll be here forever.
Bot: we'll be there in half an hour.
========================
You: I need something that's reliable.
Bot: you need a car with low mileage.
========================
You: A speeding car ran a red light, killing the girl.
Bot: what happened?
========================
You: Tomorrow we'll have rice and fish for lunch.
Bot: i'll make a sandwich.
========================
You: I like this restaurant because they give you free bread.
Bot: well, i think that's a good idea.
```

NEXT STEPS:

In Phase 3 of the project, we will proceed with the following tasks:

Implementing Tensorflow & Keras – ANN,Convolutional Neural Networks and OpenCV

CONCLUSION:

In phase 2 conclusion we have summarized the key findings and insights from the advanced regression techniques. Data wrangling techniques are employed.