In [2]:
```
import numpy as np

import random
from tqdm import tqdm

import matplotlib.pyplot as plt


import json
import pickle
import os


from sklearn.model_selection import train_test_split
from tensorflow import keras
import tensorflow as tf
import tensorflow_addons as tfa
import matplotlib.pyplot as plt
```

In [3]:
```
tf.__version__
```

Out[3]:
```
'2.3.1'
```

In [4]:
```
def load_file(file_path: str):
    """ A helper functions that loads the file into a list

    :param file_path: path to the data file
    :return parse data into a list
    """
    data = open(file_path, "r").readlines()
    return [line.rstrip() for line in data]
```

In [5]:
```
def parse_equations(equations):
    """ A helper functions that parse equations list into a list of tupl
es.
        each tuple contains lhs and rhs of the equation

    :param ARRAY of equations
    :return factors: (LHS) inputs to the model
            expansions: (RHS) group truth
    """
    factors, expansions = zip(*[line.strip().split("=") for line in equa
tions])
    return factors, expansions
```

Load the train set and parse each line. For each line, separate LHS and RHS of the equation

In [6]:
```
equations = load_file('train.txt')
np.random.shuffle(equations)
lhses, rhses = parse_equations(equations)
```

Using keras Tokenizer, covert the equations to token at character level

```
In [7]: tokenizer = keras.preprocessing.text.Tokenizer(char_level=True)
        tokenizer.fit_on_texts(equations + ['abcdefghijklmnopqrstuvwxyzABCDEFGHI
        JKLMNOPQRSTUVWXYZ0123456789+-*)('])
```

eg: equation "4*a**2+67*a-399" is converted to token [9, 1, 21, 1, 1, 3, 7, 11, 14, 1, 21, 2, 10, 19, 19]

```
In [8]: tokenizer.texts_to_sequences(['4*a**2+67*a-399'])

Out[8]: [[9, 1, 21, 1, 1, 3, 7, 11, 14, 1, 21, 2, 10, 19, 19]]
```

```
In [9]: tokenizer.sequences_to_texts([[9, 1, 21, 1, 1, 3, 7, 11, 14, 1, 21, 2, 1
        0, 19, 19]])

Out[9]: ['4 * a * * 2 + 6 7 * a - 3 9 9']
```

```
In [10]: dataset_size = tokenizer.document_count
```

```
In [11]: "total number of equations in the dataset {}".format(dataset_size)

Out[11]: 'total number of equations in the dataset 1000001'
```

Save the tokenizer to file to use later during inferencing

```
In [12]: with open('saved_model/tokenizer.pickle', 'wb') as handle:
             pickle.dump(tokenizer, handle, protocol=pickle.HIGHEST_PROTOCOL)
```

character to token map

In [13]:
```
tokenizer.word_index
```

Out[13]:
```
{'*': 1,
 '-': 2,
 '2': 3,
 '(': 4,
 ')': 5,
 '1': 6,
 '+': 7,
 '=': 8,
 '4': 9,
 '3': 10,
 '6': 11,
 '5': 12,
 '8': 13,
 '7': 14,
 '0': 15,
 's': 16,
 'n': 17,
 'i': 18,
 '9': 19,
 't': 20,
 'a': 21,
 'c': 22,
 'o': 23,
 'y': 24,
 'z': 25,
 'k': 26,
 'h': 27,
 'j': 28,
 'x': 29,
 'b': 30,
 'd': 31,
 'e': 32,
 'f': 33,
 'g': 34,
 'l': 35,
 'm': 36,
 'p': 37,
 'q': 38,
 'r': 39,
 'u': 40,
 'v': 41,
 'w': 42}
```

Let's divide the dataset into train (95%), validation (2.5%) and test (2.5%)

In [14]:
```
train_size = int(dataset_size * 0.95)
```

In [15]:
```
valid_size = int(dataset_size *0.025)
```

In [16]:
```
test_size = int(dataset_size *0.025)
```

In [69]:
```
print('train size - {} \nvalidation size - {} \ntest size - {}'.format(t
rain_size, valid_size, test_size))
```

```
train size - 950000
validation size - 25000
test size - 25000
```

In [70]:
```
train_size + valid_size + test_size
```

Out[70]:
```
1000000
```

Prepare dataset by considering "lhs" as source sequence and "rhs" as target sequence. A similar strategy is followed for all the three sets i.e. train, test and valid

In [19]:
```
train_lhs, train_rhs = lhses[0:train_size], rhses[0:train_size]
valid_lhs, valid_rhs = lhses[train_size:train_size + valid_size], rhses[
train_size:train_size + valid_size]
test_lhs, test_rhs = lhses[train_size + valid_size:], rhses[train_size +
valid_size:]
```

In [20]:
```
train_lhs[0]
```

Out[20]:
```
'n*(n-13)'
```

In [21]:
```
train_rhs[0]
```

Out[21]:
```
'n**2-13*n'
```

Convert the sequence to list of tokens using Tokenizer

In [22]:
```
encoded_train_lhs = tokenizer.texts_to_sequences(train_lhs)
encoded_valid_lhs = tokenizer.texts_to_sequences(valid_lhs)
encoded_test_lhs = tokenizer.texts_to_sequences(test_lhs)
```

In [23]:
```
encoded_train_rhs = tokenizer.texts_to_sequences(train_rhs)
encoded_valid_rhs = tokenizer.texts_to_sequences(valid_rhs)
encoded_test_rhs = tokenizer.texts_to_sequences(test_rhs)
```

In [24]:
```
encoded_test_lhs[0]
```

Out[24]:
```
[2, 9, 1, 16, 1, 4, 6, 13, 2, 12, 1, 16, 5]
```

In [25]:
```
encoded_test_rhs[0]
```

Out[25]:
```
[3, 15, 1, 16, 1, 1, 3, 2, 14, 3, 1, 16]
```

Let's convert the list of tokens to ragged tensors to make it easy to store and process data with non-uniform shapes

In [26]:
```
def ragged_tensor(mat):
    return tf.ragged.constant(np.array(mat)).to_tensor()
```

In [27]:
```
X_train = ragged_tensor(encoded_train_lhs)
Y_train = ragged_tensor(encoded_train_rhs)

X_valid = ragged_tensor(encoded_valid_lhs)
Y_valid = ragged_tensor(encoded_valid_rhs)

X_test = ragged_tensor(encoded_test_lhs)
Y_test = ragged_tensor(encoded_test_rhs)
```

In [28]:
```
X_train
```

Out[28]:
```
<tf.Tensor: shape=(950000, 29), dtype=int32, numpy=
array([[17,  1,  4, ...,  0,  0,  0],
       [ 4,  3,  6, ...,  0,  0,  0],
       [ 4,  2, 12, ...,  0,  0,  0],
       ...,
       [ 4,  3,  1, ...,  0,  0,  0],
       [ 4, 10,  1, ...,  0,  0,  0],
       [ 4,  3,  6, ...,  0,  0,  0]], dtype=int32)>
```

In [29]:
```
X_valid
```

Out[29]:
```
<tf.Tensor: shape=(25000, 29), dtype=int32, numpy=
array([[12,  1, 25, ...,  0,  0,  0],
       [ 4,  3, 12, ...,  0,  0,  0],
       [ 4,  6, 14, ...,  0,  0,  0],
       ...,
       [11,  1, 22, ...,  0,  0,  0],
       [ 4,  2,  3, ...,  0,  0,  0],
       [ 4,  2, 10, ...,  0,  0,  0]], dtype=int32)>
```

In [30]:
```
Y_train
```

Out[30]:
```
<tf.Tensor: shape=(950000, 28), dtype=int32, numpy=
array([[17,  1,  1, ...,  0,  0,  0],
       [ 3,  1, 20, ...,  0,  0,  0],
       [ 2, 12,  1, ...,  0,  0,  0],
       ...,
       [ 6, 15,  1, ...,  0,  0,  0],
       [ 6,  3,  1, ...,  0,  0,  0],
       [ 2,  6, 13, ...,  0,  0,  0]], dtype=int32)>
```

In [31]:
```
print("shape of X train {}".format(X_train.shape))
print("shape of Y train {}".format(Y_train.shape))
print("shape of X valid {}".format(X_valid.shape))
print("shape of Y valid {}".format(Y_valid.shape))
print("shape of X test {}".format(X_test.shape))
print("shape of Y test {}".format(Y_test.shape))
```

```
shape of X train (950000, 29)
shape of Y train (950000, 28)
shape of X valid (25000, 29)
shape of Y valid (25000, 28)
shape of X test (25000, 29)
shape of Y test (25000, 28)
```

In [32]:
```
vocab_length = max(tokenizer.word_index.values())
```

In [33]:
```
vocab_length
```

Out[33]:
```
42
```

numbers from 1 to 42 are attached to one of the character, we can use number 43 indicate start of the sequence

In [34]:
```
sos_id = vocab_length + 1
```

In [35]:
```
total_vocab_length = vocab_length + 1
```

In [36]:
```
total_vocab_length
```

Out[36]:
```
43
```

The plan is to build a seq2seq model by processing the input sequence (LHS) and predicting the output sequence (LHS). Instead of predicting the output sequence from the final hidden state of the encoder, we feed the output sequence shifted by one to the right. Using this strategy, at each time step decoder gets two inputs 1) encoder output vector and 2) the previous target charatcer

So model would require two inputs, input sequence (X_train) and new input (Shifted Output Vector). Let's build the output vector

Once we move the output sequence to right, we need to fill the left most empty position with some identifier, and we can use the sos_id (30) for indicating the start of sequence

In [37]:
```
def shift_sequence(Y, sos_id = sos_id):
    """ A helper functions to right shift a Tensor and fill the left mos
t place with sos_id

    :param Tensor
    :return Tensor with sos_id concatenated to the left
    """
    sos_tokens = tf.fill(dims=(len(Y), 1), value=sos_id)
    return tf.concat([sos_tokens, Y[:, :-1]], axis=1)
```

In [38]:
```
X_train_decoder = shift_sequence(Y_train)
X_valid_decoder = shift_sequence(Y_valid)
```

In [39]:
```
X_train_decoder
```

Out[39]:
```
<tf.Tensor: shape=(950000, 28), dtype=int32, numpy=
array([[43, 17,  1, ...,  0,  0,  0],
       [43,  3,  1, ...,  0,  0,  0],
       [43,  2, 12, ...,  0,  0,  0],
       ...,
       [43,  6, 15, ...,  0,  0,  0],
       [43,  6,  3, ...,  0,  0,  0],
       [43,  2,  6, ...,  0,  0,  0]], dtype=int32)>
```

In [71]:
```
X_valid_decoder
```

Out[71]:
```
<tf.Tensor: shape=(25000, 28), dtype=int32, numpy=
array([[43,  2, 12, ...,  0,  0,  0],
       [43,  2,  3, ...,  0,  0,  0],
       [43,  6, 11, ...,  0,  0,  0],
       ...,
       [43,  6,  3, ...,  0,  0,  0],
       [43,  2,  6, ...,  0,  0,  0],
       [43,  2, 10, ...,  0,  0,  0]], dtype=int32)>
```

X_train_decoder is Y_train with a value 43 (sos_id) prepended to each sequence, which increased the shape of the each sequence from 27 to 28

In [72]:
```
max_output_length = Y_train.shape[1]
```

In [73]:
```
max_output_length
```

Out[73]:
```
28
```

At each step, the decoder outputs a score for each character in the output vocabulary, and then the softmax layer turns these scores into probabilities

attention mechanisms. As their name suggests, these are neural network components that learn to select the part of the inputs that the rest of the model should focus on at each time step

In [74]:
```
BATCH_SIZE = 32
```

In [43]:
```
class EquationSolver(keras.models.Model):
    def __init__(self, units=128, encoder_embedding_size=32, decoder_emb
edding_size=32, input_dim=42, sos_id=43, **kwargs):
        super().__init__(**kwargs)

        # embedding for encoder

        self.sos_id = sos_id
        self.input_dim = input_dim
        """
        The first layer is an Embedding layer, which will convert charac
ter IDs into embeddings.
        The embedding matrix needs to have one row per char ID and one c
olumn per embedding dimension
        Here we are using embedding dimension of 32
        Whereas the inputs of the model will be 2D tensors of shape [bat
ch size, time steps] i.e. [None, 31],
        the output of the Embedding layer will be a 3D tensor of shape
 [batch size, time steps, embedding size] ie. [None, 31, 32]
        """
        self.encoder_embedding = keras.layers.Embedding(input_dim= input
_dim + 1, output_dim=encoder_embedding_size)

        """
        encoder is LSTM with 128 units
        return_state=True when creating the LSTM layer so that we can ge
t its final hidden state and
        pass it to the decoder. Note: LSTM cell has two hidden states (s
hort term and long term)
        """
        self.encoder = keras.layers.LSTM(units, return_sequences=True, r
eturn_state=True)

        """
        similar to encoder embedding input [batch_size, time steps] o/p
 [batch_size, time steps, embedding dimension]
        """
        self.decoder_embedding = keras.layers.Embedding(input_dim=input_
dim + 2, output_dim=decoder_embedding_size)

        """
        simply wrap the decoder cell in an AttentionWrapper,
        we provide the desired attention mechanism, we are using Luong a
ttention for this task
        """
        decoder_cell = keras.layers.LSTMCell(units)
        self.luong_attention = tfa.seq2seq.LuongAttention(units)
        self.decoder_cell = tfa.seq2seq.AttentionWrapper(cell=decoder_ce
ll, attention_mechanism=self.luong_attention)

        # output is Dense Layer with input_dim + 1 units
        output_layer = keras.layers.Dense(input_dim + 1)
        # decoder while training
        self.decoder_training_sampler = tfa.seq2seq.sampler.TrainingSamp
ler()
        self.decoder = tfa.seq2seq.BasicDecoder(cell=self.decoder_cell,
```

```
sampler=self.decoder_training_sampler,
                                                        output_layer=output_laye
r,
                                                        batch_size= BATCH_SIZE)

        """
        decoder while inference,
        almost similar to training decoder except we use GreedyEmbedding
Sampler and need to provide maximum_iterations.
        GreedyEmbeddingSampler:
            computes the argmax of the decoder's outputs and the winner
 is passed through the decoder_embedding
            Then it is feed to decoder at the next time step
        maximum_iterations: for this task it is set to maximum length of
the output sequence in the dataset (29)
        """
        self.decoder_inference_sampler = tfa.seq2seq.sampler.GreedyEmbed
dingSampler(embedding_fn=self.decoder_embedding)
        self.inference_decoder = tfa.seq2seq.BasicDecoder(cell=self.deco
der_cell,
                                                                    sampler=self.d
ecoder_inference_sampler,
                                                                    output_layer=o
utput_layer, maximum_iterations=input_dim)

    def call(self, inputs, training=None, **kwargs):
        encoder_input, shifted_decoder_inputs = inputs
        encoder_embeddings = self.encoder_embedding(encoder_input)
        # Note: LSTM cell has two hidden states (short term and long ter
m)
        encoder_outputs, encoder_state_h, encoder_state_c = self.encoder
(
            encoder_embeddings,
            training=training)

        encoder_state = [encoder_state_h, encoder_state_c]

        self.luong_attention(encoder_outputs,
                             setup_memory=True)

        decoder_embeddings = self.decoder_embedding(shifted_decoder_inpu
ts)

        decoder_initial_state = self.decoder_cell.get_initial_state(
            decoder_embeddings, batch_size = self.input_dim)
        decoder_initial_state = decoder_initial_state.clone(
            cell_state=encoder_state)

        if training:
            decoder_outputs, _, _ = self.decoder(
                decoder_embeddings,
                initial_state=decoder_initial_state,
                training=training
                )
        else:
            start_tokens = tf.zeros_like(encoder_input[:, 0]) + self.sos
_id
```

```
            decoder_outputs, _, _ = self.inference_decoder(
                decoder_embeddings,
                initial_state=decoder_initial_state,
                start_tokens=start_tokens,
                end_token=0)

        """
        The decoder outputs (scores) are passed through a softmax
        """
        return tf.nn.softmax(decoder_outputs.rnn_output)
```

In [122]:
```
model.summary()
```

```
Model: "equation_solver"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding (Embedding)        multiple                  1376
_________________________________________________________________
lstm (LSTM)                  multiple                  82432
_________________________________________________________________
embedding_1 (Embedding)      multiple                  1408
_________________________________________________________________
LuongAttention (LuongAttenti multiple                  16384
_________________________________________________________________
attention_wrapper (Attention multiple                  164352
_________________________________________________________________
basic_decoder (BasicDecoder) multiple                  169899
_________________________________________________________________
basic_decoder_1 (BasicDecode multiple                  169899
=================================================================
Total params: 255,115
Trainable params: 255,115
Non-trainable params: 0
_________________________________________________________________
```

we compile this model using the "sparse_categorical_crossentropy" loss and Nadam optimizer. Changing optimizer from Adam to Nadam gave a performace boost

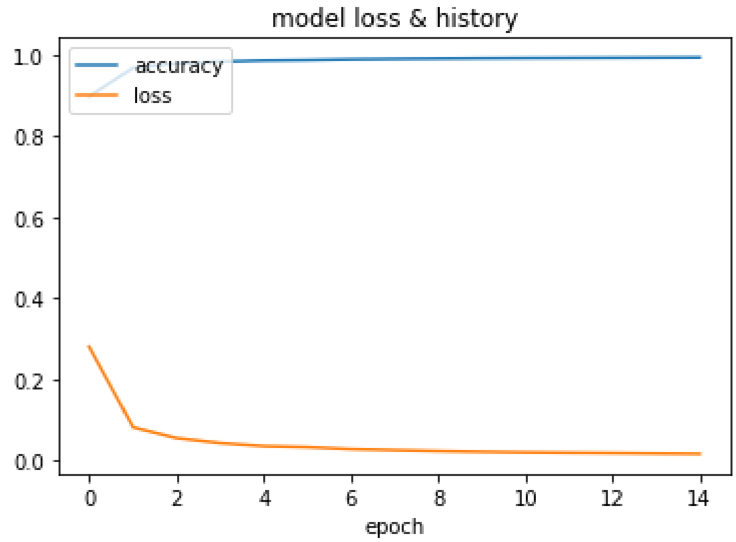
In [44]:
```
model = EquationSolver()
optimizer = keras.optimizers.Nadam()
model.compile(loss="sparse_categorical_crossentropy", optimizer=optimize
r,
              metrics=["accuracy"])
```

In [45]:
```
history = model.fit([X_train, X_train_decoder], Y_train, epochs=15)
```

```
Epoch 1/15
29688/29688 [==============================] - 1146s 39ms/step - loss:
0.2803 - accuracy: 0.8973
Epoch 2/15
29688/29688 [==============================] - 1255s 42ms/step - loss:
0.0823 - accuracy: 0.9679
Epoch 3/15
29688/29688 [==============================] - 1277s 43ms/step - loss:
0.0556 - accuracy: 0.9787
Epoch 4/15
29688/29688 [==============================] - 1288s 43ms/step - loss:
0.0435 - accuracy: 0.9835
Epoch 5/15
29688/29688 [==============================] - 1284s 43ms/step - loss:
0.0359 - accuracy: 0.9863
Epoch 6/15
29688/29688 [==============================] - 1329s 45ms/step - loss:
0.0334 - accuracy: 0.9874
Epoch 7/15
29688/29688 [==============================] - 1360s 46ms/step - loss:
0.0284 - accuracy: 0.9892
Epoch 8/15
29688/29688 [==============================] - 1300s 44ms/step - loss:
0.0259 - accuracy: 0.9903
Epoch 9/15
29688/29688 [==============================] - 1299s 44ms/step - loss:
0.0237 - accuracy: 0.9911
Epoch 10/15
29688/29688 [==============================] - 1338s 45ms/step - loss:
0.0218 - accuracy: 0.9918
Epoch 11/15
29688/29688 [==============================] - 2244s 76ms/step - loss:
0.0205 - accuracy: 0.9923
Epoch 12/15
29688/29688 [==============================] - 1305s 44ms/step - loss:
0.0195 - accuracy: 0.9927
Epoch 13/15
29688/29688 [==============================] - 1395s 47ms/step - loss:
0.0188 - accuracy: 0.9931
Epoch 14/15
29688/29688 [==============================] - 1412s 48ms/step - loss:
0.0178 - accuracy: 0.9934
Epoch 15/15
29688/29688 [==============================] - 1352s 46ms/step - loss:
0.0168 - accuracy: 0.9938
```

In [ ]:
```
# save_weights to tuned weights to use later during inferencing
```

In [127]:
```
plt.plot(history.history['accuracy'])
plt.plot(history.history['loss'])
plt.title('model loss & history')
plt.xlabel('epoch')
plt.legend(['accuracy', 'loss'], loc='upper left')
plt.show()
```



In [46]:
```
model.save_weights(
    'saved_model/equ_model_2', overwrite=True, save_format=None, options
=None)
```

In [ ]:
```
# model.load_weights('saved_model/equ_model_2')
```

In [47]:
```
max_input_length = X_train.shape[1]
```

In [98]:
```
def prepare_new_sequences(factors, max_input_length = 29, max_output_len
gth = 28):
    seqs = tokenizer.texts_to_sequences(factors)
    X_new = ragged_tensor(seqs)

    if X_new.shape[1] < max_input_length:
        X_new = tf.pad(X_new, [[0, 0], [0, max_input_length - X_new.shap
e[1]]])
    X_decoder = tf.zeros(shape=(len(X_new), max_output_length), dtype=tf
.int32)
    return X_new, X_decoder
```

In [99]:
```
def predict_seqs(factors):
    X_new, X_decoder = prepare_new_sequences(factors)
    Y_probas = model.predict([X_new, X_decoder])

    Y_pred = tf.argmax(Y_probas, axis=-1)
    return Y_pred
```

In [100]:
```
def chunks(lst, n):
    for i in range(0, len(lst), n):
        yield lst[i:i+n]
```

In [ ]:
```

```

In [94]:
```
test_set = [test_lhs, test_rhs]
```

In [68]:
```
with open('test.txt', 'w') as f:
    for l, r in zip(test_lhs, test_rhs):
        f.write("%s=%s\n" % (l, r))
```

In [116]:
```
results = []
for e in chunks(test_set[0], 32):
    ids = predict_seqs(e)
    results.append(tokenizer.sequences_to_texts(ids.numpy().tolist()))
```

In [117]:
```
def process_result(r):
    return r.replace(' ', '')
```

In [118]:
```
def score(true_expansion: str, pred_expansion: str) -> int:
    """ the scoring function - this is how the model will be evaluated

    :param true_expansion: group truth string
    :param pred_expansion: predicted string
    :return:
    """
    return int(true_expansion == pred_expansion)
```

In [119]:
```
import itertools
results = list(itertools.chain(*results))
results = list(map(process_result, results))
```

In [120]:
```
expected = test_set[1]
count = len(expected)
correct_count = 0

for a, b in zip(results, expected):
    correct_count += score(a, b)
```

In [121]:
```
"total score on test set {}".format(correct_count/count)
```

Out[121]:
```
'total score on test set 0.8388'
```

references:

https://www.tensorflow.org/addons/api_docs/python/tfa/seq2seq/BasicDecoder (https://www.tensorflow.org/addons/api_docs/python/tfa/seq2seq/BasicDecoder)

https://www.tensorflow.org/addons/tutorials/networks_seq2seq_nmt (https://www.tensorflow.org/addons/tutorials/networks_seq2seq_nmt)

https://www.tensorflow.org/addons/api_docs/python/tfa/seq2seq/LuongAttention (https://www.tensorflow.org/addons/api_docs/python/tfa/seq2seq/LuongAttention)