In [1]:	Let's build a name generator using LSTM. Topic is Dinosaurus name!!!  # IMPORTANT: if set return_seq=True attr of LSTM will return a tensor of shape (batch_size, seq_len, feature)  # otherwise, shape = (batch_size, feature)
In [2]:	Import necessary libraries  import numpy as np import os
	<pre>import json  from tqdm import tqdm  %matplotlib inline import matplotlib.pyplot as plt  import tensorflow as tf import tensorflow.keras.layers as layers import tensorflow.keras.utils as utils</pre>
In [3]:	# Download dinosaurus name dataset twgetno-check-certificate 'https://drive.google.com/uc?export=download&id=1t1XTlM8cOMqD3uicQ7dpLLnwbKOH6FoU' -0 dino.txt 2024-03-23 11:25:04 https://drive.google.com/uc?export=download&id=1t1XTlM8cOMqD3uicQ7dpLLnwbKOH6FoU Resolving drive.google.com (drive.google.com) 74.125.196.100, 74.125.196.101, 74.125.196.113,  Connecting to drive.google.com (drive.google.com) 74.125.196.100 :443 connected.  HTTP request sent, awaiting response 303 See Other Location: https://drive.usercontent.google.com/download?id=1t1XTlM8cOMqD3uicQ7dpLLnwbKOH6FoU&export=download [following]2024-03-23 11:25:04 https://drive.usercontent.google.com/download?id=1t1XTlM8cOMqD3uicQ7dpLLnwbKOH6FoU&export=download Resolving drive.usercontent.google.com (drive.usercontent.google.com) 108.177.13.132, 2607:F8b0:400c:c09::84 Connecting to drive.usercontent.google.com (drive.usercontent.google.com) 108.177.13.132 :443 connected.  HTTP request sent, awaiting response 200 OK Length: 19909 (19K) [application/octet-stream] Saving to: 'dino.txt'
In [267	dino.txt 100%[===========] 19.44KKB/s in 0s  2024-03-23 11:25:05 (86.1 MB/s) - 'dino.txt' saved [19909/19909]  # Model params and hyperpaprams  BUFFER_SIZE = 1024  BATCH_SIZE = 64
In [5]:	embedding_size = 256 hidden_units = 128  Inspect the data  # Read data
	<pre>with open("dino.txt", "r") as f:     raw = f.read().lower()  vocab = ['\n', 'a', 'b', 'c', 'd', 'e', 'f', 'g', 'h', 'i', 'j', 'k', 'l', 'm', 'n', 'o', 'p', 'q', 'r', 's', 't', 'u',</pre>
	<pre>context = [] target = []  for name in raw.split("\n"):     context.append(name)     target.append(name[1:] + "\n")  # Let's take a look at the dataset. Notice that the end token is "\n"</pre>
III [/].	for i in range(10):     print("{:24s}
	abelisaurus belisaurus abrictosaurus brictosaurus abrosaurus brosaurus abydosaurus bydosaurus
	achelousaurus chelousaurus  acheroraptor cheroraptor  Since the number of samples in dinosaurus name dataset is small, only 1536 samples, another dataset on Latin name of Vertebrate class will be used as the context dataset. The dataset is downloaded from gitHub.
In [8]:	!git clone https://github.com/species-names/dataset.git  Cloning into 'dataset' remote: Enumerating objects: 5591, done. remote: Counting objects: 100% (1613/1613), done. remote: Compressing objects: 100% (1240/1240), done. remote: Total 5591 (delta 1442), reused 502 (delta 364), pack-reused 3978 Receiving objects: 100% (5591/5591), 3.17 MiB   12.10 MiB/s, done.
In [9]:	Resolving deltas: 100% (4865/4865), done.  This dataset is organized as JSON files. Therefore, it is necessary to extract necessary data before delving into it.  data_path = "/content/dataset/data/Vertebrata" animal_classes = os.listdir(data_path)  pretrain_context = [] pretrain_target = []
	<pre>for cls in animal_classes:     cls_path = os.path.join(data_path, cls)     species = os.listdir(cls_path)  for s in species:     species_path = os.path.join(cls_path, s)      with open(species_path, "r") as f:         data = json.load(f)</pre>
In [10]:	<pre>for obj in data:     pretrain_context.append(obj["scientific_name"])     pretrain_target.append(obj["scientific_name"][1:] + "\n")  # Let's take a look at the pretrain dataset. Notice that the end token is "\n" for i in range(10):     print("{:28s} {:28s}".format(pretrain_context[i], pretrain_target[i]))</pre>
	Phasmatonycteris phiomensis hasmatonycteris phiomensis  Phasmatonycteris butleri hasmatonycteris butleri  Mammut giganteus ammut giganteus  Mammut americanus ammut americanus  Rucervus schomburgk ucervus schomburgk
	Rucervus duvaucelii ucervus duvaucelii Moschus moschiferus oschus moschiferus Moschus leucogaster oschus leucogaster Moschus fuscus oschus fuscus
In [11]:	Moschus cupreus  src_len = [len(i) for i in sorted(context, key=len)] time_periods = range(1, len(src_len) + 1)  fig, axs = plt.subplots(1, 1, figsize=(10, 4)) # Adjust figsize as needed  # Create the second bar plot
	<pre>axs.bar(time_periods, src_len, alpha=0.7, edgecolor='black') axs.set_title('Length of names in dataset') axs.set_xlabel('ith') axs.set_ylabel('Length')  # Adjust spacing between subplots plt.tight_layout()  # Show the subplots plt.show()</pre>
	Length of names in dataset  25 - 20 -
	10 -
In [13]:	5 - 0 200 400 600 800 1000 1200 1400 1600 ith  src_len = [len(i) for i in sorted(pretrain_context, key=len)]
	<pre>time_periods = range(1, len(src_len) + 1) fig, axs = plt.subplots(1, 1, figsize=(10, 4)) # Adjust figsize as needed # Create the second bar plot axs.bar(time_periods, src_len, alpha=0.7, edgecolor='black') axs.set_title('Length of names in pretrain dataset') axs.set_xlabel('ith') axs.set_ylabel('Length')</pre>
	# Adjust spacing between subplots plt.tight_layout()  # Show the subplots plt.show()  Length of names in pretrain dataset
	35 - 30 - 25 - 4bu 20 -
	15 - 10 - 5 - 0
	Tokenization  As computer cannot handle text, we need to convert them to numeric representation. In the case of Dinosaurus Name Generation, we will use the character-based tokenization.
In [12]: In [13]:	<pre>tokenizer = layers.StringLookup(vocabulary=list(vocab)) chars_from_ids = layers.StringLookup(     vocabulary=list(vocab), invert=True)  def tokenize_by_character(dataset):     return list(map(lambda x: tokenizer(list(x)), dataset))  tokenized_context = tokenize_by_character(context)</pre>
In [14]:	<pre>tokenized_target = tokenize_by_character(target) tokenized_pretrain_context = tokenize_by_character(pretrain_context) tokenized_pretrain_target = tokenize_by_character(pretrain_target)  # Padding max_len_dataset = max(len(i) for i in tokenized_context) max_len_pretrain = max(len(i) for i in tokenized_pretrain_context)  padded_context = utils.pad_sequences(tokenized_context, max_len_dataset, padding="post")</pre>
	<pre>padded_target = utils.pad_sequences(tokenized_target, max_len_dataset, padding="post") padded_pretrain_context = utils.pad_sequences(tokenized_context, max_len_pretrain, padding="post") padded_pretrain_target = utils.pad_sequences(tokenized_target, max_len_pretrain, padding="post")  # Convert dataset to tf.data.Dataset dataset = (     tf.data.Dataset     .from_tensor_slices((padded_context, padded_target))     .shuffle(BUFFER_SIZE)</pre>
	<pre>.batch(BATCH_SIZE, drop_remainder=True) .prefetch(tf.data.experimental.AUTOTUNE) )  pretrain_dataset = (     tf.data.Dataset     .from_tensor_slices((padded_pretrain_context, padded_pretrain_target))     .shuffle(BUFFER_SIZE)     .batch(BATCH_SIZE, drop_remainder=True)</pre>
	.prefetch(tf.data.experimental.AUTOTUNE)  Model  This name generator model uses LSTM which predicts next character from previous inputs.
In [317	<pre>@tf.keras.utils.register_keras_serializable() class Generator(tf.keras.Model):     @classmethod     def add_method(cls, fun):         setattr(cls, funname, fun)         return fun  definit(self,</pre>
	embedding_size, hidden_units):  Define the Text Generator instance.  :param vocab_size: number of unique characters in vocabulary :param embedding_size: dimensionality of embedding layer :param hidden_units: dimensionality of the output """
	<pre>super(Generator, self)init() self.embedding_size = embedding_size self.hidden_units = hidden_units self.embedding = layers.Embedding(input_dim=vocab_size + 1,</pre>
	<pre>self.dense = layers.Dense(units=vocab_size)  def call(self,</pre>
	<pre>:param inputs: inputs """  x = self.embedding(x) states, h, c = self.lstm(x, training=training,</pre>
-	<pre>else:     return states  @Generator.add_method def get_initial_state(self, batch_size=1):     zeros_tensor = tf.ones((1, self.hidden_units))     return self.lstm.get_initial_state(zeros_tensor)  @tf.function</pre>
In [319	<pre>def train_step(x, y,</pre>
In [320	<pre>grads = tape.gradient(loss_value, model.trainable_weights)   optimizer.apply_gradients(zip(grads, model.trainable_weights))  return loss_value  def train(model,</pre>
	<pre>optimizer,     epochs=40):  """  for epoch in range(epochs):     loss = 0     for step, (x, y) in enumerate(tqdm(dataset)):         loss_value = train_step(x, y,</pre>
In [321	<pre>model,</pre>
	<pre>next_char,</pre>
	<pre>return next_idx  next_char = list(next_char) result = next_char.copy() h, c = self.get_initial_state()  for i in range(maxlen):     if next_char != "\n":</pre>
	<pre>next_char = tokenizer(next_char) while np.ndim(next_char) != 2:     next_char = tf.expand_dims(next_char, axis=0)  states, h, c = self(next_char,</pre>
	<pre># Only take the last state from inner LSTM next_idx = sampling(states[:, -1]) next_char = chars_from_ids(next_idx)  if next_char == "[UNK]":     continue  # Retrieve value from tensor and decode from byte to ASCII result.append(next_char.numpy().decode('ascii'))</pre>
In [322	<pre>else:     break  result = "".join(result)  return result  loss_fn = tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True) optimizer = tf.keras.optimizers.Adam()</pre>
In [323 In [324	g = Generator(vocab_size, embedding_size, hidden_units)  # Pretraining on the pretrain dataset train(g, pretrain_dataset, loss_fn, optimizer, epochs=40)  100%
	100% 24/24 [00:00<00:00, 179.25it/s] 100% 24/24 [00:00<00:00, 180.20it/s] 100% 24/24 [00:00<00:00, 162.60it/s] 100% 24/24 [00:00<00:00, 162.60it/s] 100% 24/24 [00:00<00:00, 108.13it/s] 100% 24/24 [00:00<00:00, 179.25it/s] 100% 24/24 [00:00<00:00, 179.25it/s] 100% 24/24 [00:00<00:00, 179.25it/s] 100% 24/24 [00:00<00:00, 172.11it/s] Epoch: 10, loss = 40.45672607421875  100% 24/24 [00:00<00:00, 179.46it/s]
	100%   24/24 [00:00<00:00, 182.55it/s]   100%   24/24 [00:00<00:00, 168.76it/s]   100%   24/24 [00:00<00:00, 185.22it/s]   100%   24/24 [00:00<00:00, 172.01it/s]   100%   24/24 [00:00<00:00, 172.01it/s]   100%   24/24 [00:00<00:00, 171.79it/s]   100%   24/24 [00:00<00:00, 172.42it/s]   100%   24/24 [00:00<00:00, 172.42it/s]   100%   24/24 [00:00<00:00, 163.34it/s]   100%   24/24 [00:00<00:00, 179.07it/s]   100%   24/24 [00:00<00:00, 163.90it/s]   100%   10
	Epoch: 20, loss = 35.133216857910156  100%  24/24 [00:00<00:00, 177.18it/s] 100%  24/24 [00:00<00:00, 181.83it/s] 100%  24/24 [00:00<00:00, 176.00it/s] 100%  24/24 [00:00<00:00, 179.06it/s] 100%  24/24 [00:00<00:00, 174.16it/s] 100%  24/24 [00:00<00:00, 182.17it/s] 100%  24/24 [00:00<00:00, 165.40it/s] 100%  24/24 [00:00<00:00, 174.71it/s]
	100%  24/24 [00:00<00:00, 174.68it/s] 100%  24/24 [00:00<00:00, 172.97it/s] Epoch: 30, loss = 31.369417190551758  100%  24/24 [00:00<00:00, 168.10it/s] 100%  24/24 [00:00<00:00, 180.61it/s] 100%  24/24 [00:00<00:00, 180.61it/s] 100%  24/24 [00:00<00:00, 189.25it/s] 100%  24/24 [00:00<00:00, 169.36it/s] 100%  24/24 [00:00<00:00, 180.32it/s] 100%  24/24 [00:00<00:00, 173.26it/s]
In [325	100% 24/24 [00:00<00:00, 172.76it/s] 100% 24/24 [00:00<00:00, 174.13it/s] 100% 24/24 [00:00<00:00, 167.37it/s] 100% 24/24 [00:00<00:00, 167.37it/s] 100% 24/24 [00:00<00:00, 178.12it/s] Epoch: 40, loss = 27.889951705932617  train(g, dataset, loss_fn, optimizer, epochs=40)  100% 24/24 [00:01<00:00, 14.13it/s]
	100% 24/24 [00:00<00:00, 172.89it/s] 100% 24/24 [00:00<00:00, 177.70it/s] 100% 24/24 [00:00<00:00, 79.44it/s] 100% 24/24 [00:00<00:00, 79.44it/s] 100% 24/24 [00:00<00:00, 113.75it/s] 100% 24/24 [00:00<00:00, 126.51it/s] 100% 24/24 [00:00<00:00, 119.23it/s] 100% 24/24 [00:00<00:00, 121.32it/s] 100% 24/24 [00:00<00:00, 121.32it/s] 100% 24/24 [00:00<00:00, 116.47it/s] 100% 24/24 [00:00<00:00, 114.36it/s]
	Epoch: 10, loss = 24.584348678588867  100%  24/24 [00:00<00:00, 103.58it/s] 100%  24/24 [00:00<00:00, 125.45it/s] 100%  24/24 [00:00<00:00, 176.10it/s] 100%  24/24 [00:00<00:00, 170.24it/s] 100%  24/24 [00:00<00:00, 176.53it/s] 100%  24/24 [00:00<00:00, 179.15it/s] 100%  24/24 [00:00<00:00, 179.15it/s] 100%  24/24 [00:00<00:00, 174.46it/s]
	100% 24/24 [00:00<00:00, 177.78it/s] 100% 24/24 [00:00<00:00, 178.38it/s] 100% 24/24 [00:00<00:00, 178.38it/s] 100% 24/24 [00:00<00:00, 177.42it/s] Epoch: 20, loss = 21.648019790649414  100% 24/24 [00:00<00:00, 162.74it/s] 100% 24/24 [00:00<00:00, 178.67it/s] 100% 24/24 [00:00<00:00, 172.30it/s] 100% 24/24 [00:00<00:00, 172.30it/s] 100% 24/24 [00:00<00:00, 172.39it/s] 100% 24/24 [00:00<00:00, 170.74it/s]
	100%  24/24 [00:00<00:00, 178.47it/s] 100%  24/24 [00:00<00:00, 174.25it/s] 100%  24/24 [00:00<00:00, 154.71it/s] 100%  24/24 [00:00<00:00, 154.71it/s] 100%  24/24 [00:00<00:00, 170.28it/s] 100%  24/24 [00:00<00:00, 164.49it/s] Epoch: 30, loss = 19.080230712890625  100%  24/24 [00:00<00:00, 165.50it/s] 100%  24/24 [00:00<00:00, 175.62it/s] 100%  24/24 [00:00<00:00, 175.62it/s] 100%  24/24 [00:00<00:00, 176.08it/s]
	100%  24/24 [00:00<00:00, 163.29it/s] 100%  24/24 [00:00<00:00, 165.51it/s] 100%  24/24 [00:00<00:00, 17.92it/s] 100%  24/24 [00:00<00:00, 17.92it/s] 100%  24/24 [00:00<00:00, 175.08it/s] 100%  24/24 [00:00<00:00, 178.73it/s] 100%  24/24 [00:00<00:00, 178.73it/s] 100%  24/24 [00:00<00:00, 170.33it/s] 100%  24/24 [00:00<00:00, 176.88it/s] 100%  24/24 [00:00<00:00, 176.88it/s] 100%  24/24 [00:00<00:00, 176.88it/s] 100%  24/24 [00:00<00:00, 176.88it/s]
In [332 In [327 Out[327]: In [328	g.save("model_v2.keras")
In [342	<pre>h = tf.keras.models.load_model("model_v2.keras")  i = Generator(vocab_size, embedding_size, hidden_units) i.predict("x") i.load_weights("model_v2.h5")  i.predict("a")  'apaceaurus\n'</pre>
Out[342]:	'anaosaurus\n'