Character Level Language Model

65 million years ago dinosaurs existed on Earth, and now they are back. Leading biology researchers are creating new breeds of dinosaurs and bringing them to life, our job is to give names to these new dinosaurs.

Using a list of current dinosaur names, we will build a neural network to create new dinosaur names. The long short-term memory (LSTM) algorithm will learn the different name patterns, and randomly generate new names. Hopefully, the new names will not make any of the dinosaurs' angry with us!

In [2]:
```
# import our libraries
import sys
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from keras.models import Model
from keras.layers import Input, LSTM, Dense, Dropout, Bidirectional
from keras.callbacks import ModelCheckpoint
from keras.optimizers import Adam
from keras.utils import np_utils

import warnings
warnings.filterwarnings('ignore')
import tensorflow as tf
tf.logging.set_verbosity(tf.logging.ERROR)
```

In [3]:
```
# load the data & convert the text to lower case
data = open('data/dinos.txt', 'r').read()
data= data.lower()
# review the data
chars = list(set(data))
print("Here is list of unique characters: \n" + str(chars))
n_chars, n_vocab = len(data), len(chars)
print("Total characters: ", n_chars)
print("Total vocabulary: ", n_vocab)
```

```
Here is list of unique characters:
['p', 'x', 'g', 'j', 'm', 'f', 'l', 'w', 'd', 'r', 'a', 'y', 'z', 'h',
'c', 't', 'e', 'i', 'b', 'k', 'v', 'q', 'o', 'n', '\n', 'u', 's']
Total characters:  19910
Total vocabulary:  27
```

In [4]:
```
# create python dictionaries mapping chars-to-integers and integers-to
-chars
char_to_ix = { ch:i for i,ch in enumerate(sorted(chars)) }
ix_to_char = { i:ch for i,ch in enumerate(sorted(chars)) }
print(ix_to_char)
print("-----------")
print(char_to_ix)
```

```
{0: '\n', 1: 'a', 2: 'b', 3: 'c', 4: 'd', 5: 'e', 6: 'f', 7: 'g', 8:
'h', 9: 'i', 10: 'j', 11: 'k', 12: 'l', 13: 'm', 14: 'n', 15: 'o', 16:
'p', 17: 'q', 18: 'r', 19: 's', 20: 't', 21: 'u', 22: 'v', 23: 'w', 2
4: 'x', 25: 'y', 26: 'z'}
-----------
{'\n': 0, 'a': 1, 'b': 2, 'c': 3, 'd': 4, 'e': 5, 'f': 6, 'g': 7, 'h':
8, 'i': 9, 'j': 10, 'k': 11, 'l': 12, 'm': 13, 'n': 14, 'o': 15, 'p':
16, 'q': 17, 'r': 18, 's': 19, 't': 20, 'u': 21, 'v': 22, 'w': 23,
'x': 24, 'y': 25, 'z': 26}
```

In [5]:
```
# Build list of all dinosaur names (aka training examples).
with open("data/dinos.txt") as f:
    examples = f.readlines()
examples = [x.lower().strip() for x in examples]
print("A sample name:", examples[25])
```

```
A sample name: aetonyxafromimus
```

In [6]:
```
# determine the average word length of a dinosaur name
avg = sum(len(word) for word in examples) / len(examples)
print("Average word length:", avg)
long = max(examples, key=len)
print("Longest word:", long)
print("Longest word length:", len(long))
```

```
Average word length: 11.962239583333334
Longest word: lisboasauruslliubangosaurus
Longest word length: 26
```

In [7]:
```
# create the training dataset of input / output pairs encoded as integ
ers
seq_length = 60
dataX = []
dataY = []
for i in range(0, n_chars - seq_length, 1):
    seq_in = data[i:i + seq_length]
    seq_out = data[i + seq_length]
    dataX.append([char_to_ix[char] for char in seq_in])
    dataY.append(char_to_ix[seq_out])
n_patterns = len(dataX)
print("Total Patterns: ", n_patterns)
```

```
Total Patterns:  19850
```

In [8]:
```
# reshape input to [samples, time steps, features] for the LSTM cells
X = np.reshape(dataX, (n_patterns, seq_length, 1))
print("Input shape:", X.shape)
# normalize the data
X = X / float(n_vocab)
# one-hot encode the output variable
y = np_utils.to_categorical(dataY)
print("Output shape:", y.shape)
```

```
Input shape: (19850, 60, 1)
Output shape: (19850, 27)
```

In [9]:
```
# define the LSTM model
def lstm_model(X, y):
    inputs = Input(shape=(X.shape[1], X.shape[2]))
    L1 = LSTM(128, return_sequences=True)(inputs)
    L2 = LSTM(128, return_sequences=False)(L1)
    D1 = Dropout(0.25)(L2)
    output = Dense(y.shape[1], activation='softmax')(D1)
    model = Model(inputs=inputs, outputs=output)
    return model
```

In [10]:
```
# create the LSTM model
model = lstm_model(X, y)
model.compile(optimizer='adam', loss='categorical_crossentropy', metri
cs=['acc'])
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         (None, 60, 1)             0
_________________________________________________________________
lstm_1 (LSTM)                (None, 60, 128)           66560
_________________________________________________________________
lstm_2 (LSTM)                (None, 128)               131584
_________________________________________________________________
dropout_1 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_1 (Dense)              (None, 27)                3483
=================================================================
Total params: 201,627
Trainable params: 201,627
Non-trainable params: 0
_________________________________________________________________
```

In [11]:
```
# fit the model
nb_epochs = 200
history = model.fit(X, y, epochs=nb_epochs, batch_size=32, shuffle=True).history
```

```
Epoch 1/200
19850/19850 [==============================] - 76s 4ms/step - loss: 2.
7977 - acc: 0.1331
Epoch 2/200
19850/19850 [==============================] - 73s 4ms/step - loss: 2.
5275 - acc: 0.2517
Epoch 3/200
19850/19850 [==============================] - 73s 4ms/step - loss: 2.
3570 - acc: 0.3111
Epoch 4/200
19850/19850 [==============================] - 73s 4ms/step - loss: 2.
2948 - acc: 0.3262
Epoch 5/200
19850/19850 [==============================] - 73s 4ms/step - loss: 2.
2457 - acc: 0.3376
Epoch 6/200
19850/19850 [==============================] - 73s 4ms/step - loss: 2.
2017 - acc: 0.3502
Epoch 7/200
19850/19850 [==============================] - 73s 4ms/step - loss: 2.
1532 - acc: 0.3689
Epoch 8/200
19850/19850 [==============================] - 75s 4ms/step - loss: 2.
1165 - acc: 0.3826
Epoch 9/200
19850/19850 [==============================] - 73s 4ms/step - loss: 2.
0682 - acc: 0.3940
Epoch 10/200
19850/19850 [==============================] - 73s 4ms/step - loss: 2.
0159 - acc: 0.4088
Epoch 11/200
19850/19850 [==============================] - 73s 4ms/step - loss: 1.
9716 - acc: 0.4168
Epoch 12/200
19850/19850 [==============================] - 73s 4ms/step - loss: 1.
9263 - acc: 0.4336
Epoch 13/200
19850/19850 [==============================] - 73s 4ms/step - loss: 1.
8881 - acc: 0.4450
Epoch 14/200
19850/19850 [==============================] - 73s 4ms/step - loss: 1.
8462 - acc: 0.4515
Epoch 15/200
19850/19850 [==============================] - 73s 4ms/step - loss: 1.
8142 - acc: 0.4641
Epoch 16/200
19850/19850 [==============================] - 73s 4ms/step - loss: 1.
7694 - acc: 0.4767
Epoch 17/200
19850/19850 [==============================] - 73s 4ms/step - loss: 1.
7290 - acc: 0.4859
Epoch 18/200
19850/19850 [==============================] - 73s 4ms/step - loss: 1.
6886 - acc: 0.4973
Epoch 19/200
19850/19850 [==============================] - 73s 4ms/step - loss: 1.
6483 - acc: 0.5098
```

```
Epoch 20/200
19850/19850 [==============================] - 73s 4ms/step - loss: 1.
6124 - acc: 0.5183
Epoch 21/200
19850/19850 [==============================] - 73s 4ms/step - loss: 1.
5714 - acc: 0.5309
Epoch 22/200
19850/19850 [==============================] - 73s 4ms/step - loss: 1.
5277 - acc: 0.5431
Epoch 23/200
19850/19850 [==============================] - 73s 4ms/step - loss: 1.
4948 - acc: 0.5502
Epoch 24/200
19850/19850 [==============================] - 73s 4ms/step - loss: 1.
4464 - acc: 0.5641
Epoch 25/200
19850/19850 [==============================] - 73s 4ms/step - loss: 1.
4135 - acc: 0.5706
Epoch 26/200
19850/19850 [==============================] - 73s 4ms/step - loss: 1.
3724 - acc: 0.5850
Epoch 27/200
19850/19850 [==============================] - 73s 4ms/step - loss: 1.
3334 - acc: 0.5938
Epoch 28/200
19850/19850 [==============================] - 73s 4ms/step - loss: 1.
2938 - acc: 0.6069
Epoch 29/200
19850/19850 [==============================] - 73s 4ms/step - loss: 1.
2546 - acc: 0.6170
Epoch 30/200
19850/19850 [==============================] - 73s 4ms/step - loss: 1.
2219 - acc: 0.6229
Epoch 31/200
19850/19850 [==============================] - 73s 4ms/step - loss: 1.
1774 - acc: 0.6398
Epoch 32/200
19850/19850 [==============================] - 73s 4ms/step - loss: 1.
1490 - acc: 0.6451
Epoch 33/200
19850/19850 [==============================] - 72s 4ms/step - loss: 1.
1091 - acc: 0.6599
Epoch 34/200
19850/19850 [==============================] - 71s 4ms/step - loss: 1.
0782 - acc: 0.6682
Epoch 35/200
19850/19850 [==============================] - 71s 4ms/step - loss: 1.
0431 - acc: 0.6752
Epoch 36/200
19850/19850 [==============================] - 71s 4ms/step - loss: 1.
0063 - acc: 0.6851
Epoch 37/200
19850/19850 [==============================] - 72s 4ms/step - loss: 0.
9848 - acc: 0.6919
Epoch 38/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
9515 - acc: 0.7057
```

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Epoch 39/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
9344 - acc: 0.7054
Epoch 40/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
9044 - acc: 0.7150
Epoch 41/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
8766 - acc: 0.7274
Epoch 42/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
8525 - acc: 0.7330
Epoch 43/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
8167 - acc: 0.7447
Epoch 44/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
8076 - acc: 0.7456
Epoch 45/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
7786 - acc: 0.7510
Epoch 46/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
7619 - acc: 0.7587
Epoch 47/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
7423 - acc: 0.7637
Epoch 48/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
7293 - acc: 0.7640
Epoch 49/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
7053 - acc: 0.7736
Epoch 50/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
6735 - acc: 0.7853
Epoch 51/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
6664 - acc: 0.7844
Epoch 52/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
6699 - acc: 0.7855
Epoch 53/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
6319 - acc: 0.7965
Epoch 54/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
6236 - acc: 0.7964
Epoch 55/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
5992 - acc: 0.8063
Epoch 56/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
5876 - acc: 0.8099
Epoch 57/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
5659 - acc: 0.8164
```

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Epoch 58/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
5583 - acc: 0.8194
Epoch 59/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
5501 - acc: 0.8220
Epoch 60/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
5347 - acc: 0.8233
Epoch 61/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
5192 - acc: 0.8277
Epoch 62/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
5168 - acc: 0.8304
Epoch 63/200
19850/19850 [==============================] - 70s 4ms/step - loss: 0.
5109 - acc: 0.8364
Epoch 64/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
4886 - acc: 0.8413
Epoch 65/200
19850/19850 [==============================] - 70s 4ms/step - loss: 0.
4809 - acc: 0.8423
Epoch 66/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
4714 - acc: 0.8438
Epoch 67/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
4618 - acc: 0.8508
Epoch 68/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
4690 - acc: 0.8444
Epoch 69/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
4540 - acc: 0.8496
Epoch 70/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
4511 - acc: 0.8535
Epoch 71/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
4331 - acc: 0.8583
Epoch 72/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
4223 - acc: 0.8614
Epoch 73/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
4057 - acc: 0.8689
Epoch 74/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
4616 - acc: 0.8469
Epoch 75/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
3823 - acc: 0.8721
Epoch 76/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
3906 - acc: 0.8691
```

```
Epoch 77/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
3858 - acc: 0.8707
Epoch 78/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
3950 - acc: 0.8681
Epoch 79/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
3793 - acc: 0.8735
Epoch 80/200
19850/19850 [==============================] - 70s 4ms/step - loss: 0.
3741 - acc: 0.8792
Epoch 81/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
3727 - acc: 0.8768
Epoch 82/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
3600 - acc: 0.8804
Epoch 83/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
3544 - acc: 0.8810
Epoch 84/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
3585 - acc: 0.8819
Epoch 85/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
3331 - acc: 0.8899
Epoch 86/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
3493 - acc: 0.8830
Epoch 87/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
3425 - acc: 0.8853
Epoch 88/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
3351 - acc: 0.8875
Epoch 89/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
3219 - acc: 0.8944
Epoch 90/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
3194 - acc: 0.8933
Epoch 91/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
3313 - acc: 0.8876
Epoch 92/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
3347 - acc: 0.8893
Epoch 93/200
19850/19850 [==============================] - 71s 4ms/step - loss: 0.
3061 - acc: 0.8992
Epoch 94/200
19850/19850 [==============================] - 72s 4ms/step - loss: 0.
3037 - acc: 0.8989
Epoch 95/200
19850/19850 [==============================] - 49s 2ms/step - loss: 0.
3254 - acc: 0.8906
```

```
Epoch 96/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
3222 - acc: 0.8914
Epoch 97/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
3040 - acc: 0.8980
Epoch 98/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2874 - acc: 0.9043
Epoch 99/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2900 - acc: 0.9046
Epoch 100/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
3370 - acc: 0.8873
Epoch 101/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2854 - acc: 0.9049
Epoch 102/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2788 - acc: 0.9073
Epoch 103/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2843 - acc: 0.9050
Epoch 104/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2823 - acc: 0.9079
Epoch 105/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2826 - acc: 0.9054
Epoch 106/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2686 - acc: 0.9091
Epoch 107/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2788 - acc: 0.9064
Epoch 108/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2692 - acc: 0.9116
Epoch 109/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2795 - acc: 0.9062
Epoch 110/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2888 - acc: 0.9032
Epoch 111/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2595 - acc: 0.9108
Epoch 112/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2628 - acc: 0.9132
Epoch 113/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2767 - acc: 0.9088
Epoch 114/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2560 - acc: 0.9135
```

```
Epoch 115/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2790 - acc: 0.9082
Epoch 116/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2498 - acc: 0.9173
Epoch 117/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2645 - acc: 0.9123
Epoch 118/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2460 - acc: 0.9158
Epoch 119/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2605 - acc: 0.9155
Epoch 120/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2465 - acc: 0.9169
Epoch 121/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2616 - acc: 0.9158
Epoch 122/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2357 - acc: 0.9203
Epoch 123/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2223 - acc: 0.9255
Epoch 124/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2826 - acc: 0.9063
Epoch 125/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2559 - acc: 0.9144
Epoch 126/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2320 - acc: 0.9230
Epoch 127/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2249 - acc: 0.9248
Epoch 128/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2461 - acc: 0.9212
Epoch 129/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2289 - acc: 0.9240
Epoch 130/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2235 - acc: 0.9263
Epoch 131/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2176 - acc: 0.9279
Epoch 132/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2426 - acc: 0.9207
Epoch 133/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2317 - acc: 0.9221
```

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Epoch 134/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2536 - acc: 0.9155
Epoch 135/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2341 - acc: 0.9220
Epoch 136/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2342 - acc: 0.9234
Epoch 137/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2235 - acc: 0.9252
Epoch 138/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2071 - acc: 0.9332
Epoch 139/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2232 - acc: 0.9255
Epoch 140/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2427 - acc: 0.9184
Epoch 141/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2332 - acc: 0.9222
Epoch 142/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2100 - acc: 0.9308
Epoch 143/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2197 - acc: 0.9266
Epoch 144/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2218 - acc: 0.9280
Epoch 145/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2067 - acc: 0.9316
Epoch 146/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2282 - acc: 0.9246
Epoch 147/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2376 - acc: 0.9220
Epoch 148/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2044 - acc: 0.9300
Epoch 149/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
1987 - acc: 0.9350
Epoch 150/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2130 - acc: 0.9283
Epoch 151/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2207 - acc: 0.9278
Epoch 152/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2362 - acc: 0.9216
```

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Epoch 153/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2121 - acc: 0.9286
Epoch 154/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2072 - acc: 0.9317
Epoch 155/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2019 - acc: 0.9336
Epoch 156/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
1982 - acc: 0.9332
Epoch 157/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2059 - acc: 0.9311
Epoch 158/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2208 - acc: 0.9271
Epoch 159/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2431 - acc: 0.9223
Epoch 160/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
1882 - acc: 0.9379
Epoch 161/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2014 - acc: 0.9325
Epoch 162/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2054 - acc: 0.9320
Epoch 163/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2008 - acc: 0.9317
Epoch 164/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
1896 - acc: 0.9362
Epoch 165/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2064 - acc: 0.9316
Epoch 166/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
1827 - acc: 0.9381
Epoch 167/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2136 - acc: 0.9291
Epoch 168/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2050 - acc: 0.9296
Epoch 169/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
1734 - acc: 0.9428
Epoch 170/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
1814 - acc: 0.9392
Epoch 171/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2054 - acc: 0.9313
```

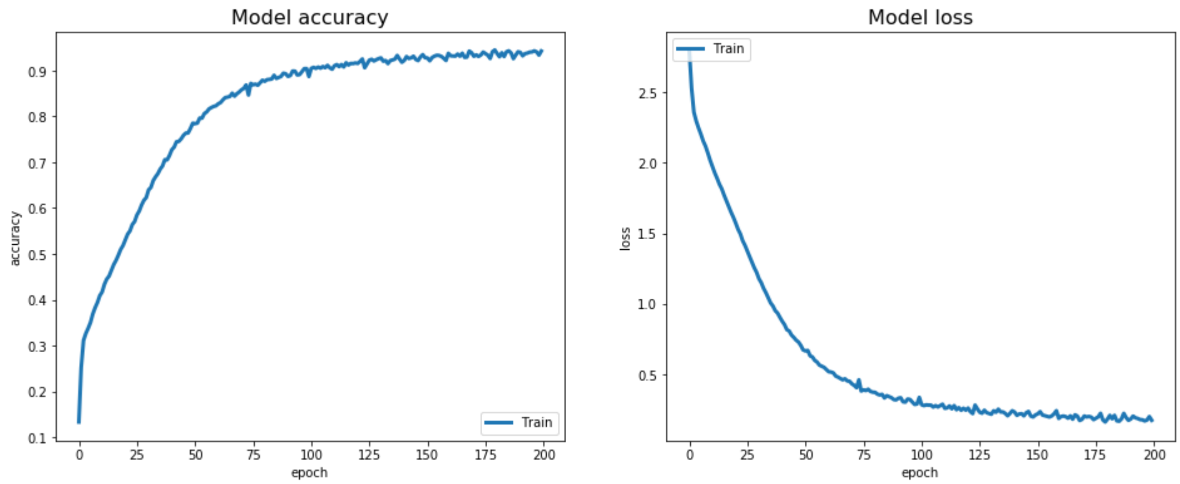
```
Epoch 172/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
1983 - acc: 0.9345
Epoch 173/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2022 - acc: 0.9311
Epoch 174/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
1974 - acc: 0.9343
Epoch 175/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
1796 - acc: 0.9407
Epoch 176/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
1895 - acc: 0.9370
Epoch 177/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
1993 - acc: 0.9338
Epoch 178/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2247 - acc: 0.9265
Epoch 179/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
1776 - acc: 0.9415
Epoch 180/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
1631 - acc: 0.9451
Epoch 181/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
1837 - acc: 0.9374
Epoch 182/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2097 - acc: 0.9303
Epoch 183/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
1857 - acc: 0.9391
Epoch 184/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2100 - acc: 0.9308
Epoch 185/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
1712 - acc: 0.9411
Epoch 186/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
1680 - acc: 0.9433
Epoch 187/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
1848 - acc: 0.9387
Epoch 188/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2242 - acc: 0.9262
Epoch 189/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
1945 - acc: 0.9341
Epoch 190/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
1748 - acc: 0.9413
```

```
Epoch 191/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
1842 - acc: 0.9399
Epoch 192/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2046 - acc: 0.9325
Epoch 193/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
1927 - acc: 0.9371
Epoch 194/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
1878 - acc: 0.9383
Epoch 195/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
1800 - acc: 0.9405
Epoch 196/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
1784 - acc: 0.9409
Epoch 197/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
1705 - acc: 0.9433
Epoch 198/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
1767 - acc: 0.9410
Epoch 199/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
2015 - acc: 0.9340
Epoch 200/200
19850/19850 [==============================] - 32s 2ms/step - loss: 0.
1753 - acc: 0.9428
```

In [12]:
```
# plot the model loss and accuracy
fig, (axis1, axis2) = plt.subplots(nrows=1, ncols=2, figsize=(16,6))

# summarize history for accuracy
axis1.plot(history['acc'], label='Train', linewidth=3)
axis1.set_title('Model accuracy', fontsize=16)
axis1.set_ylabel('accuracy')
axis1.set_xlabel('epoch')
axis1.legend(loc='lower right')

# summarize history for loss
axis2.plot(history['loss'], label='Train', linewidth=3)
axis2.set_title('Model loss', fontsize=16)
axis2.set_ylabel('loss')
axis2.set_xlabel('epoch')
axis2.legend(loc='upper left')
plt.show()
```



In [13]:
```
# pick a random starting sequence as your seed sequence
start = np.random.randint(0, len(dataX)-1)
seed = dataX[start]
print("Seed:")
print("\"",''.join([ix_to_char[value] for value in seed]),"\"")
```

```
Seed:
" eyawati
jianchangosaurus
jiangjunmiaosaurus
jiangjunosaurus
 "
```

In [14]:
```
# generate new dinosaur names
for i in range(1200):
    x = np.reshape(seed, (1, len(seed), 1))
    x = x / float(n_vocab)
    prediction = model.predict(x)
    index = np.argmax(prediction)
    result = ix_to_char[index]
    seq_in = [ix_to_char[value] for value in seed]
    sys.stdout.write(result)
    seed.append(index)
    seed = seed[1:len(seed)]
print("\n Done")
```

```
jiangshanosaurus
jiangxisaurus
jianianhualong
jinfengopteryx
jingshanosaurus
jintasaurus
jinzhnusaurus
jiutaisaurus
jobaria
jubbulpuria
judiceratops
jurapteryx
jurassosaurus
juratyrant
juravenator
kagasaurus
kaijiangia
majnsaurus
kaglapcurosaurus
lanacisataurus
lamtsuchus
laiyangosaurus
lamusposaurus
kartentasaura
latenivenatrix
latirhinus
leaellynasaura
leinkusaus
leiiisaurus
lenurosaurus
kerberosaurus
kesedrosaurus
keseerosaurus
keseerosaurus
kesadrosaurus
kentrosaurus
khaan
keetrossosaurus
mengocrn
signotosaurus
mentosaptor
mertinsaptor
neuquensaurus
nattrrsaurus
narshsaurus
nartossosaurus
maronssaualarosaurus
naramauenatitan
nasutoceratops
natronasaurus
nebulasaurus
nictia
raiolocosaurus
nictosaurus
nicroconlodus
liloernaeln
urus
```

```
uienyanoong
qinjnane
vilcena
tasisaurus
tarootesantoraurus
raptosex
ratchasimasaurus
rativates
rayososaurus
razanandrongobe
rebbachisaurus
regaliceratops
regnosaurus
revueltosaurus
thabdodon
rhadinosaurus
rhinorex
rhodanosaurus
rhoetosaurus
rhopalodon
riabininohadros
richardoestesia
rileya
rileyasuchus
rinchenia
rinconsaurus
rioarribasaurus
riodevasaurus
riojasaurus
riojasuchus
rocasaurus
roccosaurus
rubhosaurus
ruehleia
rugocaudia
rugops
rukwatitan
ru
 Done
```