In [1]:
```
# set tf 1.x for colab
%tensorflow_version 1.x
```

```
UsageError: Line magic function `%tensorflow_version` not found.
```

Generating names with recurrent neural networks

This time you'll find yourself delving into the heart (and other intestines) of recurrent neural networks on a class of toy problems.

Struggle to find a name for the variable? Let's see how you'll come up with a name for your son/daughter. Surely no human has expertize over what is a good child name, so let us train RNN instead;

It's dangerous to go alone, take these:

In [3]:
```
import tensorflow as tf
print(tf.__version__)
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import os
import sys
sys.path.append("..")
import keras_utils
import tqdm_utils
```

```
C:\Users\Xiaowei\Anaconda3\envs\tfspark\lib\site-packages\tensorflow\python\framework\dtypes.py:516: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint8 = np.dtype([("qint8", np.int8, 1)])
C:\Users\Xiaowei\Anaconda3\envs\tfspark\lib\site-packages\tensorflow\python\framework\dtypes.py:517: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint8 = np.dtype([("quint8", np.uint8, 1)])
C:\Users\Xiaowei\Anaconda3\envs\tfspark\lib\site-packages\tensorflow\python\framework\dtypes.py:518: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint16 = np.dtype([("qint16", np.int16, 1)])
C:\Users\Xiaowei\Anaconda3\envs\tfspark\lib\site-packages\tensorflow\python\framework\dtypes.py:519: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint16 = np.dtype([("quint16", np.uint16, 1)])
C:\Users\Xiaowei\Anaconda3\envs\tfspark\lib\site-packages\tensorflow\python\framework\dtypes.py:520: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint32 = np.dtype([("qint32", np.int32, 1)])
C:\Users\Xiaowei\Anaconda3\envs\tfspark\lib\site-packages\tensorflow\python\framework\dtypes.py:525: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  np_resource = np.dtype([("resource", np.ubyte, 1)])
C:\Users\Xiaowei\Anaconda3\envs\tfspark\lib\site-packages\tensorboard\compat\tensorflow_stub\dtypes.py:541: FutureWarning: Passing
```

Load data

The dataset contains ~8k earthling names from different cultures, all in latin transcript.

This notebook has been designed so as to allow you to quickly swap names for something similar: deep learning article titles, IKEA furniture, pokemon names, etc.

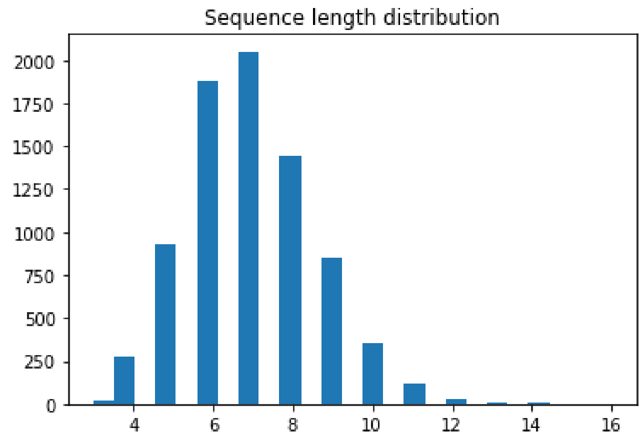
In [4]:
```
start_token = " "  # so that the network knows that we're generating a first token

# this is the token for padding,
# we will add fake pad token at the end of names
# to make them of equal size for further batching
pad_token = "#"

with open("names") as f:
    names = f.read()[:-1].split('\n')
    names = [start_token + name for name in names]
```

In [5]:
```
print('number of samples:', len(names))
for x in names[::1000]:
    print(x)
```

```
number of samples: 7944
 Abagael
 Claresta
 Glory
 Liliane
 Prissie
 Geeta
 Giovanne
 Piggy
```

In [6]:
```python
MAX_LENGTH = max(map(len, names))
print("max length:", MAX_LENGTH)

plt.title('Sequence length distribution')
plt.hist(list(map(len, names)), bins=25);
```

```
max length: 16
```



Text processing

First we need to collect a "vocabulary" of all unique tokens i.e. unique characters. We can then encode inputs as a sequence of character ids.

In [7]:
```python
### YOUR CODE HERE: all unique characters go here, padding included!
tokens = sorted(set(''.join(names + [start_token, pad_token])))

tokens = list(tokens)
n_tokens = len(tokens)
print ('n_tokens:', n_tokens)

assert 50 < n_tokens < 60
```

```
n_tokens: 56
```

Cast everything from symbols into identifiers

Tensorflow string manipulation is a bit tricky, so we'll work around it. We'll feed our recurrent neural network with ids of characters from our dictionary.

To create such dictionary, let's assign `token_to_id`

In [8]:
```python
### YOUR CODE HERE: create a dictionary of {symbol -> its  index in tokens}
token_to_id = {v:k for k, v in enumerate(tokens)}

assert len(tokens) == len(token_to_id), "dictionaries must have same size"
```

In [9]:
```python
token_to_id
```

Out[9]:
```
{' ': 0,
 '#': 1,
 "'": 2,
 '-': 3,
 'A': 4,
 'B': 5,
 'C': 6,
 'D': 7,
 'E': 8,
 'F': 9,
 'G': 10,
 'H': 11,
 'I': 12,
 'J': 13,
 'K': 14,
 'L': 15,
 'M': 16,
 'N': 17,
 'O': 18,
```

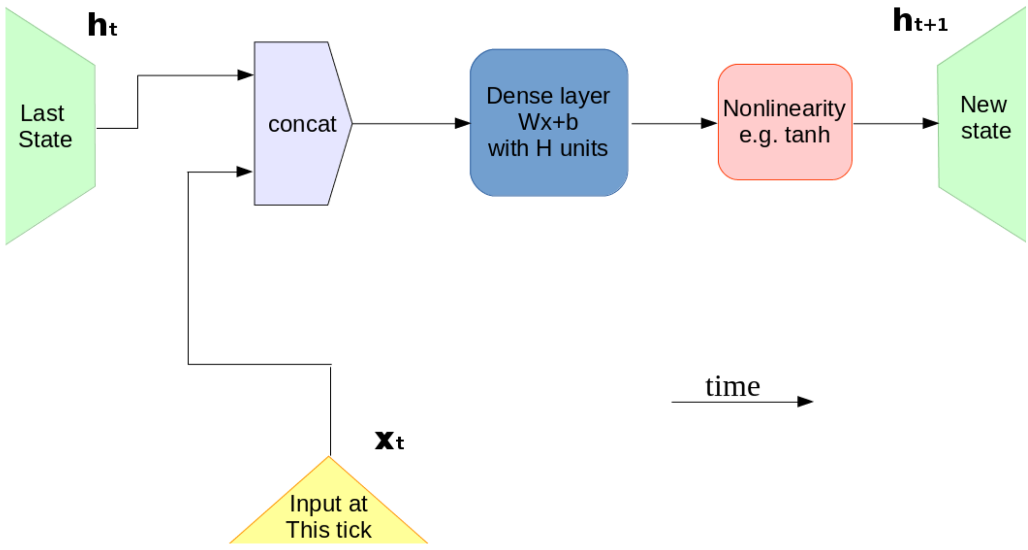
In [10]:
```python
def to_matrix(names, max_len=None, pad=token_to_id[pad_token], dtype=np.int32):
    """Casts a list of names into rnn-digestable padded matrix"""

    max_len = max_len or max(map(len, names))
    names_ix = np.zeros([len(names), max_len], dtype) + pad

    for i in range(len(names)):
        name_ix = list(map(token_to_id.get, names[i]))
        names_ix[i, :len(name_ix)] = name_ix

    return names_ix
```

In [11]:
```
# Example: cast 4 random names to padded matrices (so that we can easily batch them)
print('\n'.join(names[::2000]))
print(to_matrix(names[:2000]))
```

```
 Abagael
 Glory
 Prissie
 Giovanne
[[ 0  4 31 ...  1  1  1]
 [ 0  4 31 ...  1  1  1]
 [ 0  4 31 ...  1  1  1]
 ...
 [ 0 10 41 ...  1  1  1]
 [ 0 10 41 ...  1  1  1]
 [ 0 10 41 ...  1  1  1]]
```

Defining a recurrent neural network

We can rewrite recurrent neural network as a consecutive application of dense layer to input x_t and previous rnn state h_t. This is exactly what we're gonna do now.



Since we're training a language model, there should also be:

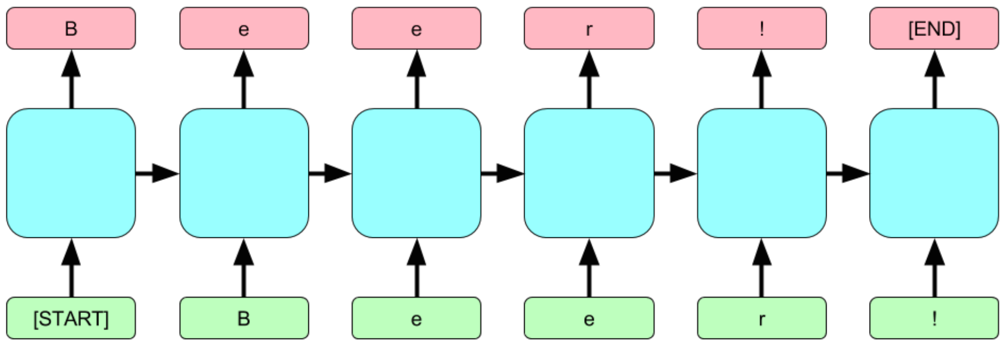
- An embedding layer that converts character id x_t to a vector.
- An output layer that predicts probabilities of next phoneme based on h_t+1

In [12]:
```
# remember to reset your session if you change your graph!
s = keras_utils.reset_tf_session()
```

```
WARNING:tensorflow:From ..\keras_utils.py:68: The name tf.get_default_session is deprecated. Please use tf.compat.v1.get_default_session instead.

WARNING:tensorflow:From C:\Users\Xiaowei\Anaconda3\envs\tfspark\lib\site-packages\keras\backend\tensorflow_backend.py:95: The name tf.reset_default_graph is deprecated. Please use tf.compat.v1.reset_default_graph instead.

WARNING:tensorflow:From C:\Users\Xiaowei\Anaconda3\envs\tfspark\lib\site-packages\keras\backend\tensorflow_backend.py:98: The name tf.placeholder_with_default is deprecated. Please use tf.compat.v1.placeholder_with_default instead.

WARNING:tensorflow:From C:\Users\Xiaowei\Anaconda3\envs\tfspark\lib\site-packages\keras\backend\tensorflow_backend.py:102: The name tf.get_default_graph is deprecated. Please use tf.compat.v1.get_default_graph instead.

WARNING:tensorflow:From ..\keras_utils.py:75: The name tf.ConfigProto is deprecated. Please use tf.compat.v1.ConfigProto instead.
```

In [13]:
```
import keras
from keras.layers import concatenate, Dense, Embedding

rnn_num_units = 64  # size of hidden state
embedding_size = 16  # for characters

# Let's create layers for our recurrent network
# Note: we create layers but we don't "apply" them yet (this is a "functional API" of Keras)
# Note: set the correct activation (from keras.activations) to Dense layers!

# an embedding layer that converts character ids into embeddings
embed_x = Embedding(n_tokens, embedding_size)

# a dense layer that maps input and previous state to new hidden state, [x_t,h_t]->h_t+1
### YOUR CODE HERE
get_h_next = Dense(rnn_num_units, activation='tanh')

# a dense layer that maps current hidden state to probabilities of characters [h_t+1]->P(x_t+1|h_t+1)
### YOUR CODE HERE
get_probas = Dense(n_tokens, activation='softmax')
```

We will generate names character by character starting with `start_token` :



In [14]:
```
def rnn_one_step(x_t, h_t):
    """
    Recurrent neural network step that produces
    probabilities for next token x_t+1 and next state h_t+1
    given current input x_t and previous state h_t.
    We'll call this method repeatedly to produce the whole sequence.

    You're supposed to "apply" above layers to produce new tensors.
    Follow inline instructions to complete the function.
    """
    # convert character id into embedding
    x_t_emb = embed_x(tf.reshape(x_t, [-1, 1]))[:, 0]

    # concatenate x_t embedding and previous h_t state
    ### YOUR CODE HERE
    x_and_h = concatenate([x_t_emb, h_t], axis=-1)

    # compute next state given x_and_h
    ### YOUR CODE HERE
    h_next = get_h_next(x_and_h)

    # get probabilities for language model P(x_next|h_next)
    ### YOUR CODE HERE
    output_probas = get_probas(h_next)

    return output_probas, h_next
```

RNN: loop

Once `rnn_one_step` is ready, let's apply it in a loop over name characters to get predictions.

Let's assume that all names are at most length-16 for now, so we can simply iterate over them in a for loop.

In [15]:
```
input_sequence = tf.placeholder(tf.int32, (None, MAX_LENGTH))  # batch of token ids
batch_size = tf.shape(input_sequence)[0]

predicted_probas = []
h_prev = tf.zeros([batch_size, rnn_num_units])  # initial hidden state

for t in range(MAX_LENGTH):
    x_t = input_sequence[:, t]  # column t
    probas_next, h_next = rnn_one_step(x_t, h_prev)

    h_prev = h_next
    predicted_probas.append(probas_next)

# combine predicted_probas into [batch, time, n_tokens] tensor
predicted_probas = tf.transpose(tf.stack(predicted_probas), [1, 0, 2])

# next to last token prediction is not needed
predicted_probas = predicted_probas[:, :-1, :]
```

RNN: loss and gradients

Let's gather a matrix of predictions for $P(x_{next}|h)$ and the corresponding correct answers.

We will flatten our matrices to shape [None, n_tokens] to make it easier.

Our network can then be trained by minimizing crossentropy between predicted probabilities and those answers.

In [16]:
```
# flatten predictions to [batch*time, n_tokens]
predictions_matrix = tf.reshape(predicted_probas, [-1, n_tokens])

# flatten answers (next tokens) and one-hot encode them
answers_matrix = tf.one_hot(tf.reshape(input_sequence[:, 1:], [-1]), n_tokens)
```

Usually it's a good idea to ignore gradients of loss for padding token predictions.

Because we don't care about further prediction after the pad_token is predicted for the first time, so it doesn't make sense to punish our network after the pad_token is predicted.

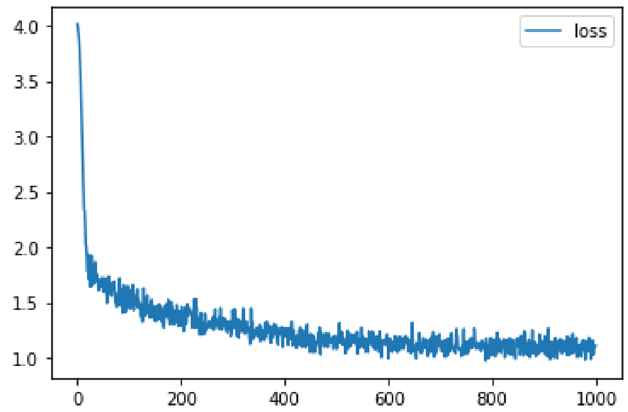
For simplicity you can ignore this comment, it's up to you.

In [17]:
```
# Define the loss as categorical cross-entropy (e.g. from keras.losses).
# Mind that predictions are probabilities and NOT logits!
# Remember to apply tf.reduce_mean to get a scalar loss!
### YOUR CODE HERE
loss = tf.reduce_mean(tf.keras.losses.categorical_crossentropy(answers_matrix, predictions_matrix))

optimize = tf.train.AdamOptimizer().minimize(loss)
```

```
WARNING:tensorflow:From C:\Users\Xiaowei\Anaconda3\envs\tfspark\lib\site-packages\tensorflow\python\ops\math_grad.py:1250: add_disp
atch_support.<locals>.wrapper (from tensorflow.python.ops.array_ops) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where
```

RNN: training

In [18]:
```
from IPython.display import clear_output
from random import sample

s.run(tf.global_variables_initializer())

batch_size = 32
history = []

for i in range(1000):
    batch = to_matrix(sample(names, batch_size), max_len=MAX_LENGTH)
    loss_i, _ = s.run([loss, optimize], {input_sequence: batch})

    history.append(loss_i)

    if (i + 1) % 100 == 0:
        clear_output(True)
        plt.plot(history, label='loss')
        plt.legend()
        plt.show()

assert np.mean(history[:10]) > np.mean(history[-10:]), "RNN didn't converge"
```



RNN: sampling

Once we've trained our network a bit, let's get to actually generating stuff. All we need is the `rnn_one_step` function you have written above.

In [19]:
```
x_t = tf.placeholder(tf.int32, (1,))
h_t = tf.Variable(np.zeros([1, rnn_num_units], np.float32))  # we will update hidden state in this variable

# For sampling we need to define `rnn_one_step` tensors only once in our graph.
# We reuse all parameters thanks to functional API usage.
# Then we can feed appropriate tensor values using feed_dict in a loop.
# Note how different it is from training stage, where we had to unroll the whole sequence for backprop.
next_probs, next_h = rnn_one_step(x_t, h_t)
```

In [20]:
```
def generate_sample(seed_phrase=start_token, max_length=MAX_LENGTH):
    '''
    This function generates text given a `seed_phrase` as a seed.
    Remember to include start_token in seed phrase!
    Parameter `max_length` is used to set the number of characters in prediction.
    '''
    x_sequence = [token_to_id[token] for token in seed_phrase]
    s.run(tf.assign(h_t, h_t.initial_value))

    # feed the seed phrase, if any
    for ix in x_sequence[:-1]:
         s.run(tf.assign(h_t, next_h), {x_t: [ix]})

    # start generating
    for _ in range(max_length-len(seed_phrase)):
        x_probs,_ = s.run([next_probs, tf.assign(h_t, next_h)], {x_t: [x_sequence[-1]]})
        x_sequence.append(np.random.choice(n_tokens, p=x_probs[0]))

    return ''.join([tokens[ix] for ix in x_sequence if tokens[ix] != pad_token])
```

In [21]:
```
# without prefix
for _ in range(10):
    print(generate_sample())
```

```
Dglila
Kerlli
Laynte
Boel
Kherka
Cyrdac
Mirly
Parha
Golli
Mannser
```

In [22]:
```
# with prefix conditioning
for _ in range(10):
    print(generate_sample(' Trump'))
```

```
Trump
Trump
Trumpa
Trumpa
Trump
Trumpera
Trumpisty
Trumpila
Trumpa
Trumpulo
```

Submit to Coursera

In [23]:
```
# token expires every 30 min
COURSERA_TOKEN = "e2f2dGXhTPjAMzyJ"
COURSERA_EMAIL = "lxwvictor@gmail.com"
```

In [24]:
```
from submit import submit_char_rnn
samples = [generate_sample(' Al') for i in tqdm_utils.tqdm_notebook_failsafe(range(25))]
submission = (history, samples)
submit_char_rnn(submission, COURSERA_EMAIL, COURSERA_TOKEN)
```

A Jupyter widget could not be displayed because the widget state could not be found. This could happen if the kernel storing the widget is no longer available, or if the widget state was not saved in the notebook. You may be able to create the widget by running the appropriate cells.

```
Submitted to Coursera platform. See results on assignment page!
```

Try it out!

Disclaimer: This part of assignment is entirely optional. You won't receive bonus points for it. However, it's a fun thing to do. Please share your results on course forums.

You've just implemented a recurrent language model that can be tasked with generating any kind of sequence, so there's plenty of data you can try it on:

- Novels/poems/songs of your favorite author
- News titles/clickbait titles
- Source code of Linux or Tensorflow
- Molecules in [smiles (https://en.wikipedia.org/wiki/Simplified_molecular-input_line-entry_system)](https://en.wikipedia.org/wiki/Simplified_molecular-input_line-entry_system) format
- Melody in notes/chords format
- IKEA catalog titles
- Pokemon names
- Cards from Magic, the Gathering / Hearthstone

If you're willing to give it a try, here's what you wanna look at:

- Current data format is a sequence of lines, so a novel can be formatted as a list of sentences. Alternatively, you can change data preprocessing altogether.
- While some datasets are readily available, others can only be scraped from the web. Try `Selenium` or `Scrapy` for that.
- Make sure MAX_LENGTH is adjusted for longer datasets. There's also a bonus section about dynamic RNNs at the bottom.
- More complex tasks require larger RNN architecture, try more neurons or several layers. It would also require more training iterations.
- Long-term dependencies in music, novels or molecules are better handled with LSTM or GRU

Good hunting!

Bonus level: dynamic RNNs

Apart from Keras, there's also a friendly TensorFlow API for recurrent neural nets. It's based around the symbolic loop function (aka [tf.scan (https://www.tensorflow.org/api_docs/python/tf/scan)](https://www.tensorflow.org/api_docs/python/tf/scan)).

RNN loop that we implemented for training can be replaced with single TensorFlow instruction: [tf.nn.dynamic_rnn (https://www.tensorflow.org/api_docs/python/tf/nn/dynamic_rnn)](https://www.tensorflow.org/api_docs/python/tf/nn/dynamic_rnn). This interface allows for dynamic sequence length and comes with some pre-implemented architectures.

Take a look at [tf.nn.rnn_cell.BasicRNNCell (https://www.tensorflow.org/api_docs/python/tf/contrib/rnn/BasicRNNCell)](https://www.tensorflow.org/api_docs/python/tf/contrib/rnn/BasicRNNCell).

In [ ]:

```
    def call(self, input, state):
        # from docs:
        # Returns:
        # Output: A 2-D tensor with shape [batch_size, self.output_size].
        # New state: Either a single 2-D tensor, or a tuple of tensors matching the arity and shapes of state.
        return rnn_one_step(input[:, 0], state)

    @property
    def output_size(self):
        return n_tokens

cell = CustomRNN(rnn_num_units)

input_sequence = tf.placeholder(tf.int32, (None, None))

predicted_probas, last_state = tf.nn.dynamic_rnn(cell, input_sequence[:, :, None], dtype=tf.float32)

print('LSTM outputs for each step [batch,time,n_tokens]:')
print(predicted_probas.eval({input_sequence: to_matrix(names[:10], max_len=50)}).shape)
```

Note that we never used MAX_LENGTH in the code above: TF will iterate over however many time-steps you gave it.

You can also use any pre-implemented RNN cell:

In [ ]:

```
for obj in dir(tf.nn.rnn_cell) + dir(tf.contrib.rnn):
    if obj.endswith('Cell'):
        print(obj, end="\t")
```

In [ ]:

```
input_sequence = tf.placeholder(tf.int32, (None, None))

inputs_embedded = embed_x(input_sequence)

# standard cell returns hidden state as output!
cell = tf.nn.rnn_cell.LSTMCell(rnn_num_units)

state_sequence, last_state = tf.nn.dynamic_rnn(cell, inputs_embedded, dtype=tf.float32)

s.run(tf.global_variables_initializer())

print('LSTM hidden state for each step [batch,time,rnn_num_units]:')
print(state_sequence.eval({input_sequence: to_matrix(names[:10], max_len=50)}).shape)
```

In [ ]:

```

```