Adapted from PyTorch tutorial
https://pytorch.org/tutorials/intermediate/char_rnn_generation_tutorial.l
(https://pytorch.org/tutorials/intermediate/char_rnn_generation_tutorial.
originally accessed on 03-28-2023

- The previous task was sequence -> class (classification). This task is class -> sequence (generation).

In [1]:
```
# For tips on running notebooks in Google Colab, see
# https://pytorch.org/tutorials/beginner/colab
%matplotlib inline
```

NLP From Scratch: Generating Names with a Character-Level RNN ¶

Author: Sean Robertson (https://github.com/spro/practical-pytorch)

This is our second of three tutorials on "NLP From Scratch". In the `first tutorial </intermediate/char_rnn_classification_tutorial>` we used a RNN to classify names into their language of origin. This time we'll turn around and generate names from languages.

::

```
> python sample.py Russian RUS
Rovakov
Uantov
Shavakov

> python sample.py German GER
Gerren
Ereng
Rosher

> python sample.py Spanish SPA
Salla
Parer
Allan

> python sample.py Chinese CHI
Chan
Hang
Iun
```

We are still hand-crafting a small RNN with a few linear layers. The big difference is instead of predicting a category after reading in all the letters of a name, we input a category and output one letter at a time. Recurrently predicting characters to form language (this could also be done with words or other higher order constructs) is often referred to as a "language model".

Recommended Reading:

I assume you have at least installed PyTorch, know Python, and understand Tensors:

- https://pytorch.org/ (https://pytorch.org/) For installation instructions
- :doc: `/beginner/deep_learning_60min_blitz` to get started with PyTorch in general
- :doc: `/beginner/pytorch_with_examples` for a wide and deep overview
- :doc: `/beginner/former_torchies_tutorial` if you are former Lua Torch user

It would also be useful to know about RNNs and how they work:

- The Unreasonable Effectiveness of Recurrent Neural Networks (https://karpathy.github.io/2015/05/21/rnn-effectiveness/)_ shows a bunch of real life examples
- Understanding LSTM Networks (https://colah.github.io/posts/2015-08-Understanding-LSTMs/)_ is about LSTMs specifically but also informative about RNNs in general

I also suggest the previous tutorial,
:doc: `/intermediate/char_rnn_classification_tutorial`

Preparing the Data

.. Note:: Download the data from here (https://download.pytorch.org/tutorial/data.zip) and extract it to the current directory.

See the last tutorial for more detail of this process. In short, there are a bunch of plain text files

In [2]:
```
from __future__ import unicode_literals, print_function, division
from io import open
import glob
import os
import unicodedata
import string

all_letters = string.ascii_letters + " .,;'-"
n_letters = len(all_letters) + 1 # Plus EOS marker

def findFiles(path): return glob.glob(path)

# Turn a Unicode string to plain ASCII, thanks to https://stackoverflow.c
def unicodeToAscii(s):
    return ''.join(
        c for c in unicodedata.normalize('NFD', s)
        if unicodedata.category(c) != 'Mn'
        and c in all_letters
    )

# Read a file and split into lines
def readLines(filename):
    with open(filename, encoding='utf-8') as some_file:
        return [unicodeToAscii(line.strip()) for line in some_file]

# Build the category_lines dictionary, a list of lines per category
category_lines = {}
all_categories = []
for filename in findFiles('data/names/*.txt'):
    category = os.path.splitext(os.path.basename(filename))[0]
    all_categories.append(category)
    lines = readLines(filename)
    category_lines[category] = lines

n_categories = len(all_categories)

if n_categories == 0:
    raise RuntimeError('Data not found. Make sure that you downloaded dat
        'from https://download.pytorch.org/tutorial/data.zip and extract
        'the current directory.')

print('# categories:', n_categories, all_categories)
print(unicodeToAscii("O'Néàl"))
```

```
# categories: 18 ['Czech', 'German', 'Arabic', 'Japanese', 'Chinese',
'Vietnamese', 'Russian', 'French', 'Irish', 'English', 'Spanish', 'Gree
k', 'Italian', 'Portuguese', 'Scottish', 'Dutch', 'Korean', 'Polish']
O'Neal
```

Creating the Network

This network extends the last tutorial's RNN_ with an extra argument for the category tensor, which is concatenated along with the others. The category tensor is a one-hot vector just like the letter input.

We will interpret the output as the probability of the next letter. When sampling, the most likely output letter is used as the next input letter.

I added a second linear layer `o2o` (after combining hidden and output) to give it more muscle to work with. There's also a dropout layer, which [randomly zeros parts of its input (https://arxiv.org/abs/1207.0580)_](https://arxiv.org/abs/1207.0580) with a given probability (here 0.1) and is usually used to fuzz inputs to prevent overfitting. Here we're using it towards the end of the network to purposely add some chaos and increase sampling variety.

.. figure:: [https://i.imgur.com/jzVrf7f.png (https://i.imgur.com/jzVrf7f.png)](https://i.imgur.com/jzVrf7f.png) :alt:

In [3]:
```
import torch
import torch.nn as nn

class RNN(nn.Module):
    def __init__(self, input_size, hidden_size, output_size):
        super(RNN, self).__init__()
        self.hidden_size = hidden_size

        self.i2h = nn.Linear(n_categories + input_size + hidden_size, hid
        self.i2o = nn.Linear(n_categories + input_size + hidden_size, out
        self.o2o = nn.Linear(hidden_size + output_size, output_size)
        self.dropout = nn.Dropout(0.1)
        self.softmax = nn.LogSoftmax(dim=1)

    def forward(self, category, input, hidden):
        input_combined = torch.cat((category, input, hidden), 1)
        hidden = self.i2h(input_combined)
        output = self.i2o(input_combined)
        output_combined = torch.cat((hidden, output), 1)
        output = self.o2o(output_combined)
        output = self.dropout(output)
        output = self.softmax(output)
        return output, hidden

    def initHidden(self):
        return torch.zeros(1, self.hidden_size)
```

Training

Preparing for Training

First of all, helper functions to get random pairs of (category, line):

In [4]:
```
import random

# Random item from a list
def randomChoice(l):
    return l[random.randint(0, len(l) - 1)]

# Get a random category and random line from that category
def randomTrainingPair():
    category = randomChoice(all_categories)
    line = randomChoice(category_lines[category])
    return category, line
```

For each timestep (that is, for each letter in a training word) the inputs of the network will be `(category, current letter, hidden state)` and the outputs will be `(next letter, next hidden state)`. So for each training set, we'll need the category, a set of input letters, and a set of output/target letters.

Since we are predicting the next letter from the current letter for each timestep, the letter pairs are groups of consecutive letters from the line - e.g. for `"ABCD<EOS>"` we would create ("A", "B"), ("B", "C"), ("C", "D"), ("D", "EOS").

.. figure:: https://i.imgur.com/JH58tXY.png (https://i.imgur.com/JH58tXY.png) :alt:

The category tensor is a one-hot tensor (https://en.wikipedia.org/wiki/One-hot)_ of size `<1 x n_categories>`. When training we feed it to the network at every timestep - this is a design choice, it could have been included as part of initial hidden state or some other strategy.

In [5]:
```
# One-hot vector for category
def categoryTensor(category):
    li = all_categories.index(category)
    tensor = torch.zeros(1, n_categories)
    tensor[0][li] = 1
    return tensor

# One-hot matrix of first to last letters (not including EOS) for input
def inputTensor(line):
    tensor = torch.zeros(len(line), 1, n_letters)
    for li in range(len(line)):
        letter = line[li]
        tensor[li][0][all_letters.find(letter)] = 1
    return tensor

# LongTensor of second letter to end (EOS) for target
def targetTensor(line):
    letter_indexes = [all_letters.find(line[li]) for li in range(1, len(l
    letter_indexes.append(n_letters - 1) # EOS
    return torch.LongTensor(letter_indexes)
```

For convenience during training we'll make a `randomTrainingExample` function that fetches a random (category, line) pair and turns them into the required (category, input, target) tensors.

In [6]:
```
# Make category, input, and target tensors from a random category, line p
def randomTrainingExample():
    category, line = randomTrainingPair()
    category_tensor = categoryTensor(category)
    input_line_tensor = inputTensor(line)
    target_line_tensor = targetTensor(line)
    return category_tensor, input_line_tensor, target_line_tensor
```

Training the Network

In contrast to classification, where only the last output is used, we are making a prediction at every step, so we are calculating loss at every step.

The magic of autograd allows you to simply sum these losses at each step and call backward at the end.

In [7]:
```
criterion = nn.NLLLoss()

learning_rate = 0.0005

def train(category_tensor, input_line_tensor, target_line_tensor):
    target_line_tensor.unsqueeze_(-1)
    hidden = rnn.initHidden()

    rnn.zero_grad()

    loss = 0

    for i in range(input_line_tensor.size(0)):
        output, hidden = rnn(category_tensor, input_line_tensor[i], hidde
        l = criterion(output, target_line_tensor[i])
        loss += l

    loss.backward()

    for p in rnn.parameters():
        p.data.add_(p.grad.data, alpha=-learning_rate)

    return output, loss.item() / input_line_tensor.size(0)
```

To keep track of how long training takes I am adding a `timeSince(timestamp)` function which returns a human readable string:

In [8]:
```
import time
import math

def timeSince(since):
    now = time.time()
    s = now - since
    m = math.floor(s / 60)
    s -= m * 60
    return '%dm %ds' % (m, s)
```

Training is business as usual - call train a bunch of times and wait a few minutes, printing the current time and loss every `print_every` examples, and keeping store of an average loss per `plot_every` examples in `all_losses` for plotting later.

In [9]:
```
rnn = RNN(n_letters, 128, n_letters)

n_iters = 100000
print_every = 5000
plot_every = 500
all_losses = []
total_loss = 0 # Reset every plot_every iters

start = time.time()

for iter in range(1, n_iters + 1):
    output, loss = train(*randomTrainingExample())
    total_loss += loss

    if iter % print_every == 0:
        print('%s (%d %d%%) %.4f' % (timeSince(start), iter, iter / n_ite

    if iter % plot_every == 0:
        all_losses.append(total_loss / plot_every)
        total_loss = 0
```

```
0m 12s (5000 5%) 2.8813
0m 26s (10000 10%) 2.8088
0m 39s (15000 15%) 2.4395
0m 52s (20000 20%) 2.9785
1m 7s (25000 25%) 2.8687
1m 20s (30000 30%) 2.5995
1m 38s (35000 35%) 2.6571
1m 53s (40000 40%) 3.1403
2m 6s (45000 45%) 2.3654
2m 20s (50000 50%) 2.7594
2m 33s (55000 55%) 2.0739
2m 47s (60000 60%) 1.9114
3m 0s (65000 65%) 2.2673
3m 13s (70000 70%) 2.0595
3m 27s (75000 75%) 1.8569
3m 40s (80000 80%) 2.2200
3m 53s (85000 85%) 3.4743
4m 6s (90000 90%) 2.1851
4m 19s (95000 95%) 2.1491
4m 32s (100000 100%) 2.5035
```

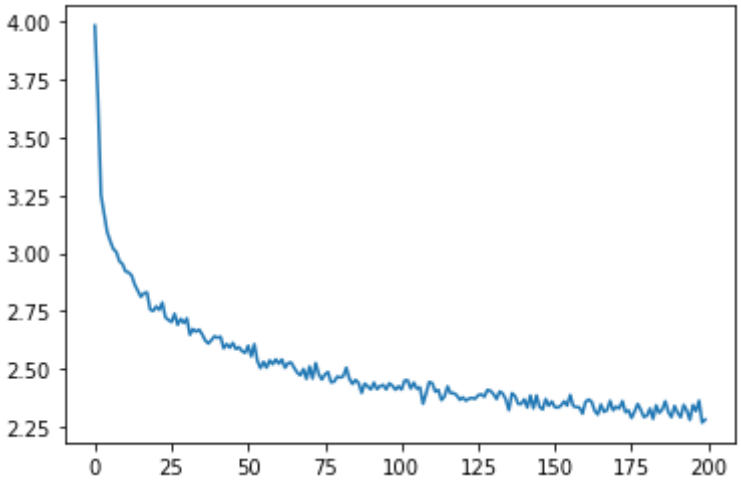
Plotting the Losses

Plotting the historical loss from all_losses shows the network learning:

In [10]:
```
import matplotlib.pyplot as plt

plt.figure()
plt.plot(all_losses)
```

Out[10]:
```
[<matplotlib.lines.Line2D at 0x7fcda8e5e040>]
```



Sampling the Network

To sample we give the network a letter and ask what the next one is, feed that in as the next letter, and repeat until the EOS token.

- Create tensors for input category, starting letter, and empty hidden state
- Create a string `output_name` with the starting letter
- Up to a maximum output length,
  - Feed the current letter to the network
  - Get the next letter from highest output, and next hidden state
  - If the letter is EOS, stop here
  - If a regular letter, add to `output_name` and continue
- Return the final name

.. Note:: Rather than having to give it a starting letter, another strategy would have been to include a "start of string" token in training and have the network choose its own starting letter.

In [11]:
```
max_length = 20

# Sample from a category and starting letter
def sample(category, start_letter='A'):
    with torch.no_grad():  # no need to track history in sampling
        category_tensor = categoryTensor(category)
        input = inputTensor(start_letter)
        hidden = rnn.initHidden()

        output_name = start_letter

        for i in range(max_length):
            output, hidden = rnn(category_tensor, input[0], hidden)
            topv, topi = output.topk(1)
            topi = topi[0][0]
            if topi == n_letters - 1:
                break
            else:
                letter = all_letters[topi]
                output_name += letter
            input = inputTensor(letter)

        return output_name

# Get multiple samples from one category and multiple starting letters
def samples(category, start_letters='ABC'):
    for start_letter in start_letters:
        print(sample(category, start_letter))

samples('Russian', 'RUS')

samples('German', 'GER')

samples('Spanish', 'SPA')

samples('Chinese', 'CHI')
```

```
Rovaki
Uakonov
Sakovov
Gare
Eren
Rour
Sara
Palla
Alara
Cang
Han
Iun
```

Exercises

- Try with a different dataset of category -> line, for example:
  - Fictional series -> Character name
  - Part of speech -> Word

    - Country -> City
- Use a "start of sentence" token so that sampling can be done without choosing a start letter
- Get better results with a bigger and/or better shaped network
    - Try the nn.LSTM and nn.GRU layers
    - Combine multiple of these RNNs as a higher level network