```
%matplotlib inline
```

Double-click (or enter) to edit

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id=

Enter your authorization code:
··········
Mounted at /content/drive
```

```
import os
os.chdir('/content/drive/My Drive/cs505/char_rnn_tutorial')  #achange dir
!pwd
```

```
/content/drive/My Drive/cs505/char_rnn_tutorial
```

Classifying Names with a Character-Level RNN

Author: `Sean Robertson <https://github.com/spro/practical-pytorch>`_

We will be building and training a basic character-level RNN to classify words. A character-level RNN r
outputting a prediction and "hidden state" at each step, feeding its previous hidden state into each ne
the output, i.e. which class the word belongs to.

Specifically, we'll train on a few thousand surnames from 18 languages of origin, and predict which la
spelling:

::

```
$ python predict.py Hinton
(-0.47) Scottish
(-1.52) English
(-3.57) Irish

$ python predict.py Schmidhuber
(-0.19) German
(-2.48) Czech
(-2.68) Dutch
```

Recommended Reading:

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

- http://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 <http://karpathy.g effectiveness/>` __ shows a bunch of real life examples
- `Understanding LSTM Networks <http://colah.github.io/posts/2015-08-Understandin` but also informative about RNNs in general

Preparing the Data

.. Note:: Download the data from `here <https://download.pytorch.org/tutorial/data.zip>` _ a

Included in the `data/names` directory are 18 text files named as "[Language].txt". Each file contains a mostly romanized (but we still need to convert from Unicode to ASCII).

We'll end up with a dictionary of lists of names per language, `{language: [names ...]}`. The gener language and name in our case) are used for later extensibility.

```
from __future__ import unicode_literals, print_function, division
from io import open
import glob
import os

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

print(findFiles('data/cities_train/*.txt'))

import unicodedata
import string

all_letters = string.ascii_letters + " .,;'"
n_letters = len(all_letters)

# Turn a Unicode string to plain ASCII, thanks to http://stackoverflow.com/a/518232/2
def unicodeToAscii(s):
    return ''.join(
        c for c in unicodedata.normalize('NFD', s)
        if unicodedata.category(c) != 'Mn'
        and c in all_letters
    )

print(unicodeToAscii('Ślusàrski'))

# Build the category lines dictionary, a list of names per language
```

```
# Build the category_lines dictionary, a list of names per language
category_lines = {}
val_category_lines = {}
all_categories = []
val_categories = []

# Read a file and split into lines
def readLines(filename):
    lines = open(filename, encoding="ISO-8859-1").read().split('\n')
    return [unicodeToAscii(line) for line in lines]

for filename in findFiles('data/cities_train/*.txt'):
    category = os.path.splitext(os.path.basename(filename))[0]
    all_categories.append(category)
    lines = readLines(filename)[:-1]
    category_lines[category] = lines

n_categories = len(all_categories)

for filename in findFiles('data/cities_val/*.txt'):
    category = os.path.splitext(os.path.basename(filename))[0]
    val_categories.append(category)
    lines = readLines(filename)[:-1]
    val_category_lines[category] = lines
```

```
['data/cities_train/cn.txt', 'data/cities_train/za.txt', 'data/cities_train/de.t
Slusarski
```

Now we have `category_lines`, a dictionary mapping each category (language) to a list of lines (nan `all_categories` (just a list of languages) and `n_categories` for later reference.

```
print(category_lines['cn'][-5:])
print(val_category_lines['cn'][-5:])
```

```
['cuizongzhuang', 'hetou', 'hulstai', 'shuanglazi', 'tebongori']
['xueguangzhang', 'ian', 'niujiaoxu', 'shuipo', 'daohugou']
```

Turning Names into Tensors

Now that we have all the names organized, we need to turn them into Tensors to make any use of the

To represent a single letter, we use a "one-hot vector" of size `<1 x n_letters>`. A one-hot vector is f current letter, e.g. `"b" = <0 1 0 0 0 ...>`.

To make a word we join a bunch of those into a 2D matrix `<line_length x 1 x n_letters>`.

That extra 1 dimension is because PyTorch assumes everything is in batches - we're just using a batc

```
import torch

# Find letter index from all_letters, e.g. "a" = 0
def letterToIndex(letter):
    return all_letters.find(letter)

# Just for demonstration, turn a letter into a <1 x n_letters> Tensor
def letterToTensor(letter):
    tensor = torch.zeros(1, n_letters)
    tensor[0][letterToIndex(letter)] = 1
    return tensor

# Turn a line into a <line_length x 1 x n_letters>,
# or an array of one-hot letter vectors
def lineToTensor(line):
    tensor = torch.zeros(len(line), 1, n_letters)
    for li, letter in enumerate(line):
        tensor[li][0][letterToIndex(letter)] = 1
    return tensor

print(letterToTensor('J'))

print(lineToTensor('Jones').size())
```

```
tensor([[0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
         0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1.,
         0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
         0., 0., 0.]])
torch.Size([5, 1, 57])
```

Creating the Network

Before autograd, creating a recurrent neural network in Torch involved cloning the parameters of a lay hidden state and gradients which are now entirely handled by the graph itself. This means you can im regular feed-forward layers.

This RNN module (mostly copied from `the PyTorch for Torch users tutorial <http://pytorch.org/tutorials/beginner/former_torchies/ nn_tutorial.html#example-2-` which operate on an input and hidden state, with a LogSoftmax layer after the output.

.. figure:: https://i.imgur.com/Z2xbySO.png :alt:

```
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(input_size + hidden_size, hidden_size)
        self.i2o = nn.Linear(input_size + hidden_size, output_size)
        self.softmax = nn.LogSoftmax(dim=1)

    def forward(self, input, hidden):
        combined = torch.cat((input, hidden), 1)
        hidden = self.i2h(combined)
        output = self.i2o(combined)
        output = self.softmax(output)
        return output, hidden

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

n_hidden = 128
rnn = RNN(n_letters, n_hidden, n_categories)
```

To run a step of this network we need to pass an input (in our case, the Tensor for the current letter) a
initialize as zeros at first). We'll get back the output (probability of each language) and a next hidden s

```
input = letterToTensor('A')
hidden =torch.zeros(1, n_hidden)

output, next_hidden = rnn(input, hidden)
print(output)
```

```
tensor([[-2.2620, -2.1309, -2.1623, -2.1152, -2.1508, -2.2480, -2.2619, -2.2789,
         -2.1812]], grad_fn=<LogSoftmaxBackward>)
```

For the sake of efficiency we don't want to be creating a new Tensor for every step, so we will use `li`
and use slices. This could be further optimized by pre-computing batches of Tensors.

```
input = lineToTensor('Albert')
hidden = torch.zeros(1, n_hidden)

output, next_hidden = rnn(input[0], hidden)
print(output)
```

```
tensor([[-2.2620, -2.1309, -2.1623, -2.1152, -2.1508, -2.2480, -2.2619, -2.2789,
         -2.1812]], grad_fn=<LogSoftmaxBackward>)
```

As you can see the output is a `<1 x n_categories>` Tensor, where every item is the likelihood of tha

Training

Preparing for Training

Before going into training we should make a few helper functions. The first is to interpret the output o
likelihood of each category. We can use `Tensor.topk` to get the index of the greatest value:

```
def categoryFromOutput(output):
    top_n, top_i = output.topk(1)
    category_i = top_i[0].item()
    return all_categories[category_i], category_i

print(categoryFromOutput(output))
```

```
('fr', 3)
```

We will also want a quick way to get a training example (a name and its language):

```
import random

def randomChoice(l):
    return l[random.randint(0, len(l) - 1)]

def randomTrainingExample():
    category = randomChoice(all_categories)
    line = randomChoice(category_lines[category])
    category_tensor = torch.tensor([all_categories.index(category)], dtype=torch.long
    line_tensor = lineToTensor(line)
    return category, line, category_tensor, line_tensor

def randomValidationExample():
    category = randomChoice(val_categories)
    line = randomChoice(val_category_lines[category])
    val_category_tensor = torch.tensor([val_categories.index(category)], dtype=torch.
    val_line_tensor = lineToTensor(line)
    return category, line, val_category_tensor, val_line_tensor

def shuffle_arrs(a,b,c,d):
    combined = list(zip(a, b, c, d))
    random.shuffle(combined)
    a, b, c, d = zip(*combined)
    return a,b,c,d

def genData(category_line_hash, categories_arr):
    x, y, x_tensor, y_tensor = [], [], [], []
    for y_category in category_line_hash.keys():
        for x_line in category_line_hash[y_category]:
            y.append(y_category)
            x.append(x_line)
            y_tensor.append(torch.tensor([categories_arr.index(y_category)], dtype=to
            x_tensor.append(lineToTensor(x_line))
    x, y, x_tensor, y_tensor = shuffle_arrs(x, y, x_tensor, y_tensor)
    return x, y, x_tensor, y_tensor
```

```
        return x, y, x_tensor, y_tensor

    def TrainingData():
        return genData(category_lines, all_categories)
        # y = []
        # x = []
        # for y_category in category_lines.keys():
        #     for x_line in category_lines[y_category]:
        #         y.append(y_category)
        #         x.append(x_line)
        #         y_tensor.append(torch.tensor([val_categories.index(category)], dtype=to
        #         x_tensor.append(lineToTensor(x_line))
        # x, y, x_tensor, y_tensor = shuffle_arrs(x, y, x_tensor, y_tensor)
        # return x, y

    def ValidationData():
        return genData(val_category_lines, val_categories)
        # y = []
        # x = []
        # y_tensor = []
        # x_tensor = []
        # for y_category in val_category_lines.keys():
        #     for x_line in val_category_lines[y_category]:
        #         y.append(y_category)
        #         x.append(x_line)
        #         y_tensor.append(torch.tensor([val_categories.index(category)], dtype=to
        #         x_tensor.append(lineToTensor(x_line))
        # x, y, x_tensor, y_tensor = shuffle_arrs(x, y, x_tensor, y_tensor)
        # return x, y

    print("=== Train ===")
    x,y,x_tensor,y_tensor= TrainingData()
    print(x[:5])
    print(y[:5])
    # print(x_tensor[:1])
    # print(y_tensor[:1])

    print("=== Validation ===")
    x,y,x_tensor,y_tensor = ValidationData()
    print(x[:5])
    print(y[:5])
    # print(x_tensor[:1])
    # print(y_tensor[:1])
```

```
=== Train ===
('dankerode', 'khorkal', 'schaphausen', 'atin', 'leobalde')
('de', 'pk', 'de', 'in', 'de')
=== Validation ===
('qalehye now abraj', 'kofime', 'xaffevillers', 'lujiawobao', 'kottenheide')
('ir', 'fi', 'fr', 'cn', 'de')
```

Training the Network

Now all it takes to train this network is show it a bunch of examples, have it make guesses, and tell it

For the loss function `nn.NLLLoss` is appropriate, since the last layer of the RNN is `nn.LogSoftmax`.

```
criterion = nn.NLLLoss()
```

Each loop of training will:

- Create input and target tensors
- Create a zeroed initial hidden state
- Read each letter in and
  - Keep hidden state for next letter
- Compare final output to target
- Back-propagate
- Return the output and loss

```
learning_rate = 0.001 # If you set this too high, it might explode. If too low, it mi

def train(category_tensor, line_tensor):
    hidden = rnn.initHidden()

    rnn.zero_grad()

    # print("category_tensor={}, line_tensor.size()[0]={}".format(category_tensor, li
    for i in range(line_tensor.size()[0]):
        output, hidden = rnn(line_tensor[i], hidden)

    loss = criterion(output, category_tensor)
    loss.backward()

    # Add parameters' gradients to their values, multiplied by learning rate
    for p in rnn.parameters():
        p.data.add_(-learning_rate, p.grad.data)

    return output, loss.item()

# Just return an output given a line
def evaluate(line_tensor, category_tensor):
    hidden = rnn.initHidden()

    for i in range(line_tensor.size()[0]):
        output, hidden = rnn(line_tensor[i], hidden)
```

```
    loss = criterion(output, category_tensor)

    return output, loss.item()
```

Now we just have to run that with a bunch of examples. Since the `train` function returns both the ou
also keep track of loss for plotting. Since there are 1000s of examples we print only every `print_eve`
loss.

```
import time
import math

print_every = 1000 # total = 27000
plot_every = 1000 # 5000

# Keep track of losses for plotting
current_loss = 0
val_losses = 0.
train_acc_thru_time_aggregate, val_acc_thru_time_aggregate = 0., 0.
train_losses_thru_time = []
val_losses_thru_time = []
train_acc_thru_time = []
val_acc_thru_time = []

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

start = time.time()

print("learning rate = ", learning_rate)

x_train, y_train, x_train_tensor, y_train_tensor = TrainingData()
x_val, y_val, x_val_tensor, y_val_tensor = ValidationData()

x_train_len = len(x_train)
x_val_len = 10 # len(x_val)
print("x_train_len:", x_train_len, ", x_val_len:", x_val_len)

for i in range(x_train_len):
    # category, line, category_tensor, line_tensor = randomTrainingExample()  # TODO:
    category = y_train[i]
    line = x_train[i]
    category_tensor = y_train_tensor[i]
    line_tensor = x_train_tensor[i]

    output, loss = train(category_tensor, line_tensor)
    current_loss += loss
```

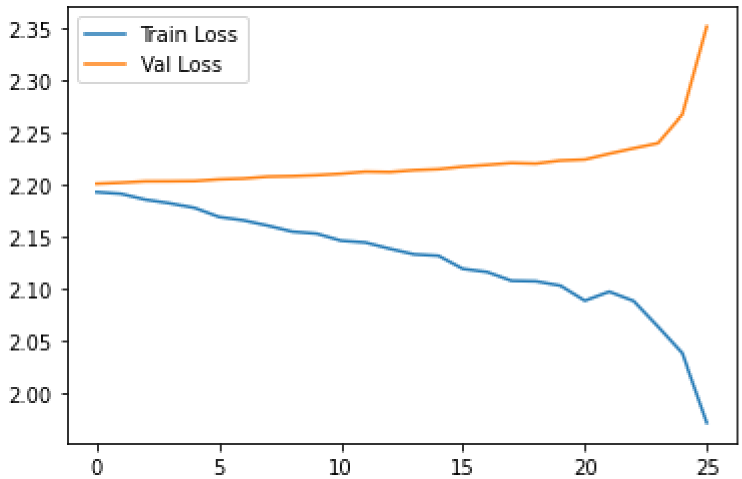
```
        val_loss_per_train_data = 0
        val_correct_guess_count = 0
        train_correct_guess_count = 0
        # for j in range(x_val_len):
        #     val_output, val_loss = evaluate(x_val_tensor[j], y_val_tensor[j])
        #     val_loss_per_train_data += val_loss
        for j in range(x_val_len):
            # Train accuracy calc
            train_category, _, train_category_tensor, train_line_tensor = randomTrainingE
            train_output, train_loss = evaluate(train_line_tensor, train_category_tensor)
            train_guess, _ = categoryFromOutput(train_output)
            train_correct_guess_count += int(train_guess == train_category)

            # Validation accuracy calc
            val_category, _, val_category_tensor, val_line_tensor = randomValidationExamp
            val_output, val_loss = evaluate(val_line_tensor, val_category_tensor)
            val_guess, _ = categoryFromOutput(val_output)
            val_correct_guess_count += int(val_guess == val_category)

            val_loss_per_train_data += val_loss

        # Aggregate accuracy
        train_acc_per_train_data = train_correct_guess_count / x_val_len
        train_acc_thru_time_aggregate += train_acc_per_train_data
        val_acc_per_train_data = val_correct_guess_count / x_val_len
        val_acc_thru_time_aggregate += val_acc_per_train_data

        # Aggregate validation loss
        val_loss_per_train_data_ave = val_loss_per_train_data / x_val_len
        val_losses += val_loss_per_train_data_ave

        # Print iter number, loss, name and guess
        if i % print_every == 0:
            print("iter = {}({:d}%) | time taken = {} | train_loss={:.4f}, val_loss(ave)=
            debug_x, debug_y, debug_x_tensor, debug_y_tensor = [], [], [], []

        # Add current loss avg to list of losses
        if i % plot_every == 0:
            train_losses_thru_time.append(current_loss / plot_every)
            val_losses_thru_time.append(val_losses / plot_every)
            current_loss = 0
            val_losses = 0

            print("iter = {}({:d}%) | time taken = {} | train_acc_thru_time_ave={}, val_a

            train_acc_thru_time.append(train_acc_thru_time_aggregate / plot_every)
            val_acc_thru_time.append(val_acc_thru_time_aggregate / plot_every)
            train_acc_thru_time_aggregate = 0
            val_acc_thru_time_aggregate = 0
```

```
learning rate =  0.001
x_train_len: 27000 , x_val_len: 10
iter = 0(0%) | time taken = 0m 3s | train_loss=2.2668, val_loss(ave)=2.1916 | tra
iter = 0(0%) | time taken = 0m 3s | train_acc_thru_time_ave=0.0002, val_acc_thru_
iter = 1000(3%) | time taken = 0m 23s | train_loss=2.2082, val_loss(ave)=2.1939
iter = 1000(3%) | time taken = 0m 23s | train_acc_thru_time_ave=0.133199999999999
iter = 2000(7%) | time taken = 0m 44s | train_loss=2.1503, val_loss(ave)=2.1937
iter = 2000(7%) | time taken = 0m 44s | train_acc_thru_time_ave=0.139899999999999
iter = 3000(11%) | time taken = 1m 4s | train_loss=2.1270, val_loss(ave)=2.1756
iter = 3000(11%) | time taken = 1m 4s | train_acc_thru_time_ave=0.152099999999999
iter = 4000(14%) | time taken = 1m 25s | train_loss=2.2000, val_loss(ave)=2.2164
iter = 4000(14%) | time taken = 1m 25s | train_acc_thru_time_ave=0.16469999999999
iter = 5000(18%) | time taken = 1m 46s | train_loss=2.1128, val_loss(ave)=2.1962
iter = 5000(18%) | time taken = 1m 46s | train_acc_thru_time_ave=0.18469999999999
iter = 6000(22%) | time taken = 2m 7s | train_loss=2.2378, val_loss(ave)=2.2306
iter = 6000(22%) | time taken = 2m 7s | train_acc_thru_time_ave=0.206799999999999
iter = 7000(25%) | time taken = 2m 27s | train_loss=2.2748, val_loss(ave)=2.1729
iter = 7000(25%) | time taken = 2m 27s | train_acc_thru_time_ave=0.23509999999999
iter = 8000(29%) | time taken = 2m 48s | train_loss=2.0878, val_loss(ave)=2.1948
iter = 8000(29%) | time taken = 2m 48s | train_acc_thru_time_ave=0.25049999999999
iter = 9000(33%) | time taken = 3m 9s | train_loss=2.1558, val_loss(ave)=2.2312
iter = 9000(33%) | time taken = 3m 9s | train_acc_thru_time_ave=0.243699999999999
iter = 10000(37%) | time taken = 3m 30s | train_loss=2.0200, val_loss(ave)=2.216
iter = 10000(37%) | time taken = 3m 30s | train_acc_thru_time_ave=0.2508999999999
iter = 11000(40%) | time taken = 3m 51s | train_loss=2.2084, val_loss(ave)=2.243
iter = 11000(40%) | time taken = 3m 51s | train_acc_thru_time_ave=0.2465999999999
iter = 12000(44%) | time taken = 4m 11s | train_loss=2.2243, val_loss(ave)=2.226
iter = 12000(44%) | time taken = 4m 11s | train_acc_thru_time_ave=0.2440999999999
iter = 13000(48%) | time taken = 4m 32s | train_loss=2.1562, val_loss(ave)=2.206
iter = 13000(48%) | time taken = 4m 32s | train_acc_thru_time_ave=0.2596999999999
iter = 14000(51%) | time taken = 4m 52s | train_loss=2.0937, val_loss(ave)=2.214
iter = 14000(51%) | time taken = 4m 52s | train_acc_thru_time_ave=0.2706000000000
iter = 15000(55%) | time taken = 5m 13s | train_loss=1.9818, val_loss(ave)=2.222
iter = 15000(55%) | time taken = 5m 13s | train_acc_thru_time_ave=0.2814000000000
iter = 16000(59%) | time taken = 5m 34s | train_loss=2.3245, val_loss(ave)=2.213
iter = 16000(59%) | time taken = 5m 34s | train_acc_thru_time_ave=0.2867, val_acc
iter = 17000(62%) | time taken = 5m 55s | train_loss=2.1697, val_loss(ave)=2.213
iter = 17000(62%) | time taken = 5m 55s | train_acc_thru_time_ave=0.2821000000000
iter = 18000(66%) | time taken = 6m 16s | train_loss=2.0872, val_loss(ave)=2.247
iter = 18000(66%) | time taken = 6m 16s | train_acc_thru_time_ave=0.2854000000000
iter = 19000(70%) | time taken = 6m 37s | train_loss=2.4316, val_loss(ave)=2.246
iter = 19000(70%) | time taken = 6m 37s | train_acc_thru_time_ave=0.2919, val_acc
iter = 20000(74%) | time taken = 6m 58s | train_loss=2.2014, val_loss(ave)=2.162
iter = 20000(74%) | time taken = 6m 58s | train_acc_thru_time_ave=0.2990000000000
iter = 21000(77%) | time taken = 7m 19s | train_loss=1.8570, val_loss(ave)=2.163
iter = 21000(77%) | time taken = 7m 19s | train_acc_thru_time_ave=0.3055000000000
iter = 22000(81%) | time taken = 7m 40s | train_loss=2.0498, val_loss(ave)=2.261
iter = 22000(81%) | time taken = 7m 40s | train_acc_thru_time_ave=0.3053000000000
iter = 23000(85%) | time taken = 8m 1s | train_loss=1.9411, val_loss(ave)=2.2629
iter = 23000(85%) | time taken = 8m 1s | train_acc_thru_time_ave=0.31149999999999
iter = 24000(88%) | time taken = 8m 22s | train_loss=1.9037, val_loss(ave)=2.253
iter = 24000(88%) | time taken = 8m 22s | train_acc_thru_time_ave=0.3116000000000
iter = 25000(92%) | time taken = 8m 43s | train_loss=2.1473, val_loss(ave)=2.296
iter = 25000(92%) | time taken = 8m 43s | train_acc_thru_time_ave=0.3192999999999
```

```
import matplotlib.pyplot as plt
```

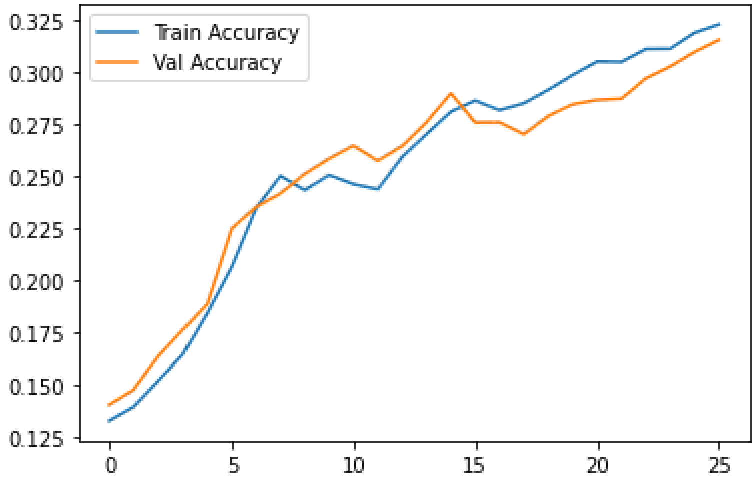
```
import matplotlib.ticker as ticker

plt.figure()
train_loss_plot = plt.plot(train_losses_thru_time[1:], label='Train Loss')
val_loss_plot = plt.plot(val_losses_thru_time[1:], label="Val Loss")
plt.legend()

print("train_losses_thru_time")
print(train_losses_thru_time[1:])
print("val_losses_thru_time")
print(val_losses_thru_time[1:])
```

```
train_losses_thru_time
[2.1931439759731295, 2.191539811849594, 2.1858927879333496, 2.1824070241451263, 
val_losses_thru_time
[2.201238310003283, 2.2022241860389737, 2.203529069900513, 2.2036021126508687, 2.
```




```
import matplotlib.pyplot as plt
import matplotlib.ticker as ticker

plt.figure()
train_acc_plot = plt.plot(train_acc_thru_time[1:], label='Train Accuracy')
val_acc_plot = plt.plot(val_acc_thru_time[1:], label="Val Accuracy")
plt.legend()

print("train_acc_thru_time")
print(train_acc_thru_time[1:])
print("val_acc_thru_time")
print(val_acc_thru_time[1:])
```

```
train_acc_thru_time
[0.13319999999999993, 0.13989999999999927, 0.15209999999999992, 0.1646999999999988
val_acc_thru_time
[0.14089999999999992, 0.14799999999999944, 0.16389999999999902, 0.1765999999999999
```




```
import time
import math

print_every = 1000 # total = 27000
plot_every = 1000 # 5000

# Keep track of losses for plotting
current_loss = 0
val_losses = 0.
train_acc_thru_time_aggregate, val_acc_thru_time_aggregate = 0., 0.
train_losses_thru_time = []
val_losses_thru_time = []
train_acc_thru_time = []
val_acc_thru_time = []

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

start = time.time()

print("learning rate = ", learning_rate)

x_train, y_train, x_train_tensor, y_train_tensor = TrainingData()
x_val, y_val, x_val_tensor, y_val_tensor = ValidationData()

x_train_len = len(x_train)
x_val_len = 10 # len(x_val)
```

```
    print("x_train_len:", x_train_len, ", x_val_len:", x_val_len)

    for i in range(x_train_len):
        # category, line, category_tensor, line_tensor = randomTrainingExample()  # TODO:
        category = y_train[i]
        line = x_train[i]
        category_tensor = y_train_tensor[i]
        line_tensor = x_train_tensor[i]

        output, loss = train(category_tensor, line_tensor)
        current_loss += loss

        val_loss_per_train_data = 0
        val_correct_guess_count = 0
        train_correct_guess_count = 0
        # for j in range(x_val_len):
        #     val_output, val_loss = evaluate(x_val_tensor[j], y_val_tensor[j])
        #     val_loss_per_train_data += val_loss
        for j in range(x_val_len):
            # Train accuracy calc
            train_category, _, train_category_tensor, train_line_tensor = randomTrainingE
            train_output, train_loss = evaluate(train_line_tensor, train_category_tensor)
            train_guess, _ = categoryFromOutput(train_output)
            train_correct_guess_count += int(train_guess == train_category)

            # Validation accuracy calc
            val_category, _, val_category_tensor, val_line_tensor = randomValidationExamp
            val_output, val_loss = evaluate(val_line_tensor, val_category_tensor)
            val_guess, _ = categoryFromOutput(val_output)
            val_correct_guess_count += int(val_guess == val_category)

            val_loss_per_train_data += val_loss

        # Aggregate accuracy
        train_acc_per_train_data = train_correct_guess_count / x_val_len
        train_acc_thru_time_aggregate += train_acc_per_train_data
        val_acc_per_train_data = val_correct_guess_count / x_val_len
        val_acc_thru_time_aggregate += val_acc_per_train_data

        # Aggregate validation loss
        val_loss_per_train_data_ave = val_loss_per_train_data / x_val_len
        val_losses += val_loss_per_train_data_ave

        # Print iter number, loss, name and guess
        if i % print_every == 0:
            print("iter = {}({:d}%) | time taken = {} | train_loss={:.4f}, val_loss(ave)=
            debug_x, debug_y, debug_x_tensor, debug_y_tensor = [], [], [], []

        # Add current loss avg to list of losses
        if i % plot_every == 0:
            train_losses_thru_time.append(current_loss / plot_every)
            val_losses_thru_time.append(val_losses / plot_every)
```

```
        current_loss = 0
        val_losses = 0

        print("iter = {}({:d}%) | train_acc_thru_time_ave={}, val_acc_thru_time_ave={

        train_acc_thru_time.append(train_acc_thru_time_aggregate / plot_every)
        val_acc_thru_time.append(val_acc_thru_time_aggregate / plot_every)
        train_acc_thru_time_aggregate = 0
        val_acc_thru_time_aggregate = 0
```

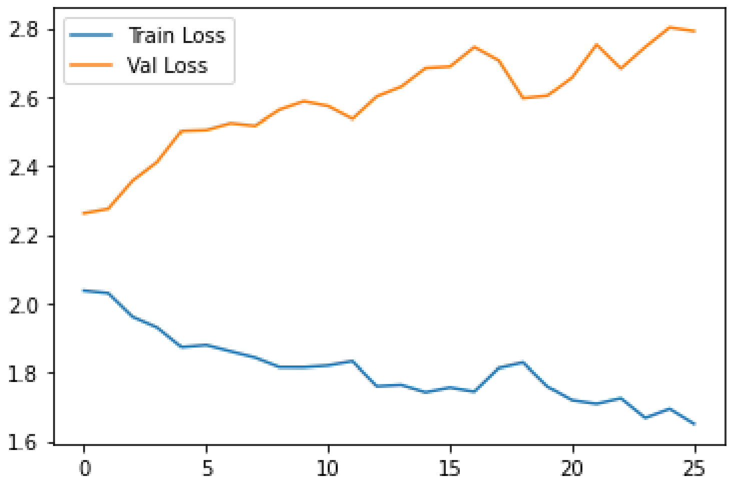
```
learning rate =  0.001
x_train_len: 27000 , x_val_len: 10
iter = 0(0%) | time taken = 0m 3s | train_loss=2.2222, val_loss(ave)=2.3266 | tra
iter = 0(0%) | train_acc_thru_time_ave=0m 3s, val_acc_thru_time_ave=0.0004
iter = 1000(3%) | time taken = 0m 24s | train_loss=1.5628, val_loss(ave)=2.3251
iter = 1000(3%) | train_acc_thru_time_ave=0m 24s, val_acc_thru_time_ave=0.319699
iter = 2000(7%) | time taken = 0m 45s | train_loss=1.8648, val_loss(ave)=2.3004
iter = 2000(7%) | train_acc_thru_time_ave=0m 45s, val_acc_thru_time_ave=0.318900
iter = 3000(11%) | time taken = 1m 6s | train_loss=1.5915, val_loss(ave)=2.7069
iter = 3000(11%) | train_acc_thru_time_ave=1m 6s, val_acc_thru_time_ave=0.329999
iter = 4000(14%) | time taken = 1m 26s | train_loss=1.7824, val_loss(ave)=2.2152
iter = 4000(14%) | train_acc_thru_time_ave=1m 26s, val_acc_thru_time_ave=0.33750
iter = 5000(18%) | time taken = 1m 47s | train_loss=1.9984, val_loss(ave)=2.4863
iter = 5000(18%) | train_acc_thru_time_ave=1m 47s, val_acc_thru_time_ave=0.35010
iter = 6000(22%) | time taken = 2m 7s | train_loss=2.3606, val_loss(ave)=2.5456
iter = 6000(22%) | train_acc_thru_time_ave=2m 7s, val_acc_thru_time_ave=0.346100
iter = 7000(25%) | time taken = 2m 28s | train_loss=1.1203, val_loss(ave)=2.5735
iter = 7000(25%) | train_acc_thru_time_ave=2m 28s, val_acc_thru_time_ave=0.35570
iter = 8000(29%) | time taken = 2m 48s | train_loss=1.5213, val_loss(ave)=2.5407
iter = 8000(29%) | train_acc_thru_time_ave=2m 48s, val_acc_thru_time_ave=0.36710
iter = 9000(33%) | time taken = 3m 9s | train_loss=3.1933, val_loss(ave)=2.7906
iter = 9000(33%) | train_acc_thru_time_ave=3m 9s, val_acc_thru_time_ave=0.361900
iter = 10000(37%) | time taken = 3m 29s | train_loss=1.2495, val_loss(ave)=2.660
iter = 10000(37%) | train_acc_thru_time_ave=3m 29s, val_acc_thru_time_ave=0.3673
iter = 11000(40%) | time taken = 3m 49s | train_loss=1.8335, val_loss(ave)=2.651
iter = 11000(40%) | train_acc_thru_time_ave=3m 49s, val_acc_thru_time_ave=0.3732
iter = 12000(44%) | time taken = 4m 9s | train_loss=1.4305, val_loss(ave)=2.3426
iter = 12000(44%) | train_acc_thru_time_ave=4m 9s, val_acc_thru_time_ave=0.37530
iter = 13000(48%) | time taken = 4m 29s | train_loss=1.6745, val_loss(ave)=2.440
iter = 13000(48%) | train_acc_thru_time_ave=4m 29s, val_acc_thru_time_ave=0.3767
iter = 14000(51%) | time taken = 4m 49s | train_loss=1.8929, val_loss(ave)=2.624
iter = 14000(51%) | train_acc_thru_time_ave=4m 49s, val_acc_thru_time_ave=0.3952
iter = 15000(55%) | time taken = 5m 9s | train_loss=1.5942, val_loss(ave)=2.5534
iter = 15000(55%) | train_acc_thru_time_ave=5m 9s, val_acc_thru_time_ave=0.3896
iter = 16000(59%) | time taken = 5m 29s | train_loss=1.8463, val_loss(ave)=2.698
iter = 16000(59%) | train_acc_thru_time_ave=5m 29s, val_acc_thru_time_ave=0.3893
iter = 17000(62%) | time taken = 5m 48s | train_loss=0.6244, val_loss(ave)=2.683
iter = 17000(62%) | train_acc_thru_time_ave=5m 48s, val_acc_thru_time_ave=0.4026
iter = 18000(66%) | time taken = 6m 8s | train_loss=1.7411, val_loss(ave)=2.9596
iter = 18000(66%) | train_acc_thru_time_ave=6m 8s, val_acc_thru_time_ave=0.35330
iter = 19000(70%) | time taken = 6m 27s | train_loss=1.7421, val_loss(ave)=3.267
iter = 19000(70%) | train_acc_thru_time_ave=6m 27s, val_acc_thru_time_ave=0.3540
iter = 20000(74%) | time taken = 6m 47s | train_loss=1.8878, val_loss(ave)=2.969
iter = 20000(74%) | train_acc_thru_time_ave=6m 47s, val_acc_thru_time_ave=0.3748
iter = 21000(77%) | time taken = 7m 6s | train_loss=0.8556, val_loss(ave)=2.2618
iter = 21000(77%) | train_acc_thru_time_ave=7m 6s, val_acc_thru_time_ave=0.39149
iter = 22000(81%) | time taken = 7m 25s | train_loss=1.6963, val_loss(ave)=2.444
iter = 22000(81%) | train_acc_thru_time_ave=7m 25s, val_acc_thru_time_ave=0.3840
iter = 23000(85%) | time taken = 7m 43s | train_loss=1.9805, val_loss(ave)=1.958
iter = 23000(85%) | train_acc_thru_time_ave=7m 43s, val_acc_thru_time_ave=0.3904
iter = 24000(88%) | time taken = 8m 2s | train_loss=2.0390, val_loss(ave)=3.9155
iter = 24000(88%) | train_acc_thru_time_ave=8m 2s, val_acc_thru_time_ave=0.40660
iter = 25000(92%) | time taken = 8m 21s | train_loss=1.5916, val_loss(ave)=2.801
iter = 25000(92%) | train_acc_thru_time_ave=8m 21s, val_acc_thru_time_ave=0.4297
```

Plotting the Results

Plotting the historical loss from `all_losses` shows the network learning:

```
import matplotlib.pyplot as plt
import matplotlib.ticker as ticker

plt.figure()
train_loss_plot = plt.plot(train_losses_thru_time[1:], label='Train Loss')
val_loss_plot = plt.plot(val_losses_thru_time[1:], label="Val Loss")
plt.legend()

print("train_losses_thru_time")
print(train_losses_thru_time[1:])
print("val_losses_thru_time")
print(val_losses_thru_time[1:])
```

```
train_losses_thru_time
[2.0370060900449753, 2.029802362084389, 1.9607643482089043, 1.9299266896247864, 
val_losses_thru_time
[2.2626027950167646, 2.2753594054341266, 2.3573232454776756, 2.41132256001234, 2
```



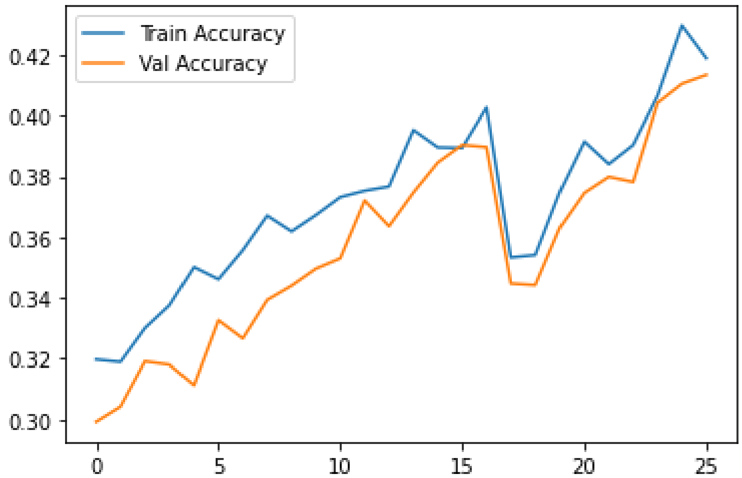

```
train_acc_thru_time_aggregate
```

```
427.19999999999993
```

```
import matplotlib.pyplot as plt
import matplotlib.ticker as ticker

plt.figure()
train_acc_plot = plt.plot(train_acc_thru_time[1:], label='Train Accuracy')
val_acc_plot = plt.plot(val_acc_thru_time[1:], label="Val Accuracy")
plt.legend()

print("train_acc_thru_time")
```

```
print(train_acc_thru_time[1:])
print("val_acc_thru_time")
print(val_acc_thru_time[1:])
```

```
train_acc_thru_time
[0.31969999999999993, 0.3189000000000007, 0.3299999999999998, 0.3375000000000006,
val_acc_thru_time
[0.2992000000000005, 0.3041999999999998, 0.3190999999999999, 0.3180000000000017,
```

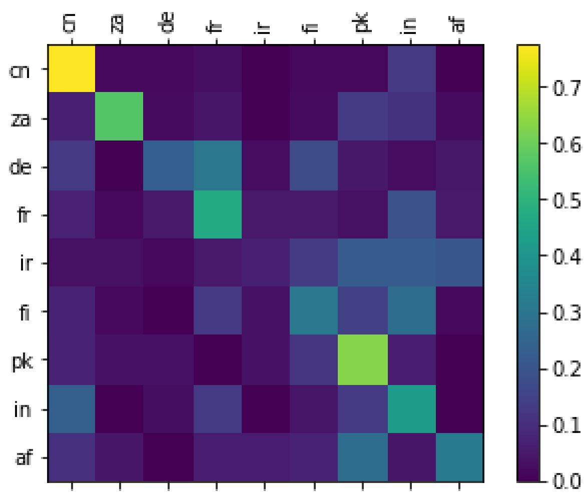


Evaluating the Results

To see how well the network performs on different categories, we will create a confusion matrix, indic
which language the network guesses (columns). To calculate the confusion matrix a bunch of sampl
`evaluate()`, which is the same as `train()` minus the backprop.

```
# Keep track of correct guesses in a confusion matrix
confusion = torch.zeros(n_categories, n_categories)
confusion_no_norm = torch.zeros(n_categories, n_categories)

n_confusion = 500 # 10000

# Go through a bunch of examples and record which are correctly guessed
for i in range(n_confusion):
    category, line, category_tensor, line_tensor = randomTrainingExample()
    output, _ = evaluate(line_tensor, category_tensor)
    guess, guess_i = categoryFromOutput(output)
    category_i = all_categories.index(category)
    confusion[category_i][guess_i] += 1
    confusion_no_norm[category_i][guess_i] += 1

# Normalize by dividing every row by its sum
for i in range(n_categories):
    confusion[i] = confusion[i] / confusion[i].sum()

# Set up plot
```

```
fig = plt.figure()
ax = fig.add_subplot(111)
cax = ax.matshow(confusion.numpy())
fig.colorbar(cax)

# Set up axes
ax.set_xticklabels([''] + all_categories, rotation=90)
ax.set_yticklabels([''] + all_categories)

# Force label at every tick
ax.xaxis.set_major_locator(ticker.MultipleLocator(1))
ax.yaxis.set_major_locator(ticker.MultipleLocator(1))

# sphinx_gallery_thumbnail_number = 2
plt.show()
```




```
print("confusion matrix (no normalization)")
print(confusion_no_norm)

def get_multi_class_accuracy(confusion):
  total = torch.sum(confusion)
  correct = 0
  for guess_i in range(len(confusion)):
    correct += confusion[guess_i][guess_i]
  return correct / total

print("accuracy, multi-class = {}".format(get_multi_class_accuracy(confusion_no_norm)
```

```
    confusion matrix (no normalization)
def get_pos_tp(target_i, confusion):
  pos = torch.sum(confusion[:, target_i])
  tp = confusion[target_i][target_i]
  return pos, tp

def get_multi_class_precision(confusion):
  '''
  multi-class-precision = sum(all tp's across class) / sum(all pos' across class)
  '''
  pos = 0
  tp = 0
  for i in range(len(confusion)):
    target_pos, target_tp = get_pos_tp(i, confusion)
    pos += target_pos
    tp += target_tp

  precision = tp / pos
  return precision

print("precision, multi-class = {}".format(get_multi_class_precision(confusion_no_nor
```

```
precision, multi-class = 0.4259999990463257
```

You can pick out bright spots off the main axis that show which languages it guesses incorrectly, e.g. Italian. It seems to do very well with Greek, and very poorly with English (perhaps because of overlap

Running on User Input

```
# def predict(input_line, n_predictions=3):
#     print('\n> %s' % input_line)
#     with torch.no_grad():
#         output = evaluate(lineToTensor(input_line))

#         # Get top N categories
#         topv, topi = output.topk(n_predictions, 1, True)
#         predictions = []

#         for i in range(n_predictions):
#             value = topv[0][i].item()
#             category_index = topi[0][i].item()
#             print('(%.2f) %s' % (value, all_categories[category_index]))
#             predictions.append([value, all_categories[category_index]])

# predict('Dovesky')
# predict('Jackson')
# predict('Satoshi')
```

The final versions of the scripts `in the Practical PyTorch repo <https://github.com/spro/p rnn-classification>` __ split the above code into a few files:

- `data.py` (loads files)
- `model.py` (defines the RNN)
- `train.py` (runs training)
- `predict.py` (runs `predict()` with command line arguments)
- `server.py` (serve prediction as a JSON API with bottle.py)

Run `train.py` to train and save the network.

Run `predict.py` with a name to view predictions:

::

```
$ python predict.py Hazaki
(-0.42) Japanese
(-1.39) Polish
(-3.51) Czech
```

Run `server.py` and visit http://localhost:5533/Yourname to get JSON output of predictions.

Exercises

- Try with a different dataset of line -> category, for example:
  - Any word -> language
  - First name -> gender
  - Character name -> writer
  - Page title -> blog or subreddit
- Get better results with a bigger and/or better shaped network
  - Add more linear layers
  - Try the `nn.LSTM` and `nn.GRU` layers
  - Combine multiple of these RNNs as a higher level network