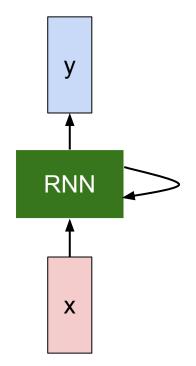


We can process a sequence of vectors **x** by applying a recurrence formula at every time step:

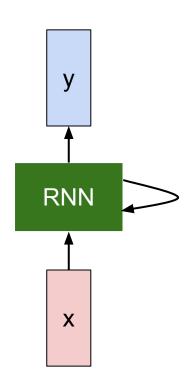
$$h_t = f_W(h_{t-1}, x_t)$$
 new state  $\int$  old state input vector at some time step some function with parameters W



We can process a sequence of vectors **x** by applying a recurrence formula at every time step:

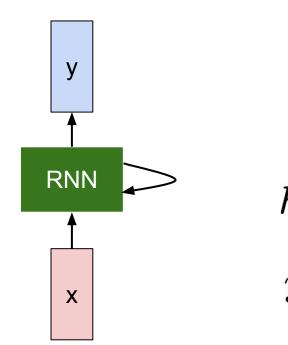
$$h_t = f_W(h_{t-1}, x_t)$$

Notice: the same function and the same set of parameters are used at every time step.



# (Vanilla) Recurrent Neural Network

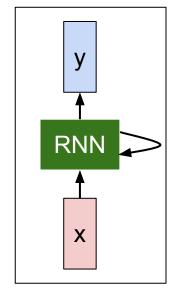
The state consists of a single "hidden" vector h:



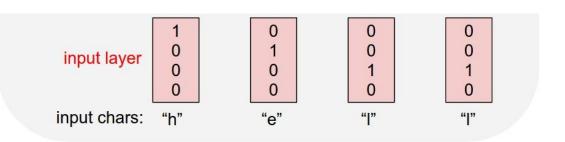
$$h_t = f_W(h_{t-1}, x_t)$$
  $\downarrow$   $h_t = anh(W_{hh}h_{t-1} + W_{xh}x_t)$   $y_t = W_{hu}h_t$ 

$$y_t = W_{hy} h_t$$

Vocabulary: [h,e,l,o]

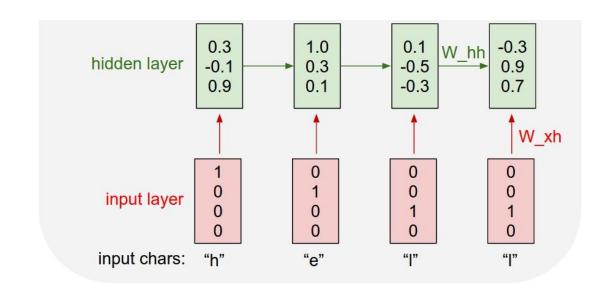


Vocabulary: [h,e,l,o]

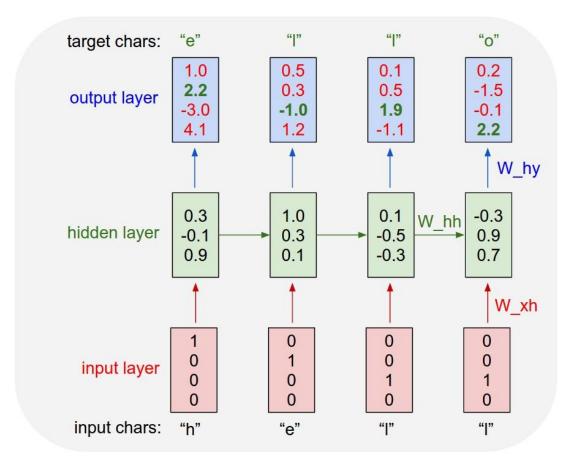


$$h_t = anh(W_{hh}h_{t-1} + W_{xh}x_t)$$

Vocabulary: [h,e,l,o]



Vocabulary: [h,e,l,o]



## min-char-rnn.py gist: 112 lines of Python

```
Minimal character-level Vanilla RNN model. Written by Andrej Karpathy (@karpathy)
 3 BSD License
 5 import numpy as np
 7 # data I/O
 8 data = open('input.txt', 'r').read() # should be simple plain text file
 chars = list(set(data))
data_size, vocab_size = len(data), len(chars)
print 'data has %d characters, %d unique.' % (data_size, vocab_size)
char_to_ix = { ch:i for i,ch in enumerate(chars) }
ix_to_char = { i:ch for i,ch in enumerate(chars) }
16 hidden_size = 100 # size of hidden layer of neurons
17 seg length = 25 # number of steps to uproll the RNN for
18 learning rate = 1e-1
21 Wxh = np.random.randn(hidden_size, vocab_size)*0.01 # input to hidden
22 Whh = np.random.randn(hidden_size, hidden_size)*0.01 # hidden to hidden
23 Why = np.random.rando(vocab size, hidden size)*0.01 # hidden to output
24 bh = np.zeros((hidden_size, 1)) # hidden bias
25 by = np.zeros((vocab_size, 1)) # output bias
27 def lossFun(inputs, targets, hprev):
      inputs, targets are both list of integers.
      hprev is Hx1 array of initial hidden state
      returns the loss, gradients on model parameters, and last hidden state
      xs, hs, ys, ps = {}, {}, {}, {}
      hs[-1] = np.copy(hprev)
      for t in xrange(len(inputs)):
        xs[t] = np.zeros((vocab_size,1)) # encode in 1-of-k representation
        hs[t] = np.tanh(np.dot(Wxh, xs[t]) + np.dot(Whh, hs[t-1]) + bh) # hidden state
        ys[t] = np.dot(Why, hs[t]) + by # unnormalized log probabilities for next chars
        ps[t] = np.exp(ys[t]) / np.sum(np.exp(ys[t])) # probabilities for next chars
        loss += -np.log(ps[t][targets[t],0]) # softmax (cross-entropy loss)
44 # backward pass: compute gradients going backwards
dwxh, dwhh, dwhy = np.zeros_like(wxh), np.zeros_like(whh), np.zeros_like(why)
46 dbh, dby = np.zeros_like(bh), np.zeros_like(by)
      dhnext = np.zeros like(hs[0])
      for t in reversed(xrange(len(inputs))):
        dy = np.copy(ps[t])
        dy[targets[t]] -= 1 # backprop into y
        dWhy += np.dot(dy, hs[t].T)
53 dh = np.dot(Why.T, dy) + dhnext # backprop into h
54 dhraw = (1 - hs[t] * hs[t]) * dh # backprop through tanh nonlinearity
        dwxh += np.dot(dhraw, xs[t].T)
        dWhh += np.dot(dhraw, hs[t-1].T)
        dhnext = np.dot(Whh.T, dhraw)
       for dparam in [dwxh, dwhh, dwhy, dbh, dby]:
        np.clip(dparam, -5, 5, out=dparam) # clip to mitigate exploding gradients
      return loss, dwxh, dwhh, dwhy, dbh, dby, hsflen(inputs)-1]
```

```
63 def sample(h, seed_ix, n):
       sample a sequence of integers from the model
      h is memory state, seed_ix is seed letter for first time step
68 x = np.zeros((vocab_size, 1))
69 x[seed_ix] = 1
78 ixes = []
71 for t in xrange(n):
        h = np.tanh(np.dot(Wxh, x) + np.dot(Whh, h) + bh)
        y = np.dot(Why, h) + by
        p = np.exp(y) / np.sum(np.exp(y))
        ix = np.random.choice(range(vocab_size), p=p.ravel())
        x = np.zeros((vocab_size, 1))
         ixes.append(ix)
82 mWxh. mWhh. mWhy = np.zeros like(Wxh), np.zeros like(Whh), np.zeros like(Why)
83 mbh. mby = np.zeros like(bh), np.zeros like(by) # memory variables for Adagrad
84 smooth_loss = -np.log(1.0/vocab_size)*seq_length # loss at iteration 0
     # prepare inputs (we're sweeping from left to right in steps seq_length long)
       if p+seq length+1 >= len(data) or n == 0:
        horev = np.zeros((hidden size.1)) # reset RNN memory
        p = 0 # go from start of data
       inputs = [char_to_ix[ch] for ch in data[p:p+seq_length]]
       targets = [char_to_ix[ch] for ch in data[p+1:p+seq_length+1]]
93 # sample from the model now and then
94 if n % 100 == 0:
         sample_ix = sample(hprev, inputs[0], 200)
         txt = ''.join(ix_to_char[ix] for ix in sample_ix)
        print '----\n %s \n----' % (txt, )
       # forward seg length characters through the net and fetch gradient
       loss, dWxh, dWhh, dWhy, dbh, dby, hprey = lossFun(inputs, targets, hprey)
       smooth loss = smooth loss * 0.999 + loss * 0.001
      if n % 100 == 0; print 'iter %d, loss: %f' % (n, smooth loss) # print progress
      # perform parameter update with Adagrad
       for param, dparam, mem in zip([Wxh, Whh, Why, bh, by],
                                   [dwxh, dwhh, dwhy, dbh, dby],
                                   [mWxh, mWhh, mWhy, mbh, mby]):
        param += -learning_rate * dparam / np.sqrt(mem + 1e-8) # adagrad update
      p += seq length # move data pointer
      n += 1 # iteration counter
```

(https://gist.github. com/karpathy/d4dee566867f8291f086)

```
Minimal character-level Vanilla RNN model. Written by Andrej Karpathy (@karpathy)
BSD License
import numpy as np
data = open('input.txt', 'r').read() # should be simple plain text file
data size, vocab size = len(data), len(chars)
print 'data has %d characters, %d unique.' % (data_size, vocab_size)
 char_to_ix = { ch:i for i,ch in enumerate(chars) }
ix_to_char = { i:ch for i,ch in enumerate(chars) }
hidden size = 100 # size of hidden layer of neurons
seq_length = 25 # number of steps to unroll the RNN for
wxh = np.random.randn(hidden_size, vocab_size)*0.01 # input to hidden
Whh = np.random.randn(hidden_size, hidden_size)*8.81 # hidden to hidden
why = np.random.randn(vocab_size, hidden_size)*0.01 # hidden to output
by = np.zeros((vocab_size, 1)) # output bias
def lossFun(inputs, targets, hprev):
 inputs, targets are both list of integers.
   hprev is Hx1 array of initial hidden state
  returns the loss, gradients on model parameters, and last hidden state
  xs, hs, ys, ps = {}, {}, {}, {}
  hs[-1] = np.copy(hprev)
  loss = 8
  for t in xrange(len(inputs)):
    xs[t] = np.zeros((vocab_size,1)) # encode in 1-of-k representation
    hs[t] = np.tanh(np.dot(wxh, xs[t]) + np.dot(whh, hs[t-1]) + bh) # hidden state
     valt1 = np.dot(why. halt1) + by = uncormalized log probabilities for next chars
     ps[t] = np.exp(ys[t]) / np.sum(np.exp(ys[t])) + probabilities for next chars
     loss += -mp.log(ps[t][targets[t],0]) # softmax (cross-entropy loss)
   dwxh, dwhh, dwhy = np.zeros_like(wxh), np.zeros_like(whh), np.zeros_like(why)
   dbh, dby = np.zeros_like(bh), np.zeros_like(by)
   dhnext = np.zeros like(hs[p])
   for t in reversed(xrange(len(inputs))):
     dy = np.copy(ps[t])
     dyfragners[r]] .= 1 a backgross into y
     dwhy += np.dot(dy, hs[t].T)
    dh = np.dot(why.T. dy) + dhnext # backgrop into h
     dhraw = (i - hs[t] * hs[t]) * dh # backprop through tanh nonlinearity
     dbh += dhraw
    datch += nn_dot(dbraw, vs[t].T)
     dwhh += np.dot(dhraw, hs[t-1].T)
     dhnext = np.dot(whh.T, dhraw)
 for dparam in [dwxh, dwhh, dwhy, dbh, dby]:
    np.clip(dparam, -5, 5, out=dparam) # clip to mitigate exploding gradients
 return loss, dwxh, dwhh, dwhy, dbh, dby, hs[len(inputs)-1]
def sample(h, seed_ix, n):
 sample a sequence of integers from the model
h is memory state, seed_ix is seed letter for first time step
  x = np.zeros((wocab_size, 1))
  x[seed_ix] = 1
   h = np.tanh(np.dot(wxh, x) + np.dot(whh, h) + bh)
   y = np.dot(Why, h) + by
p = np.exp(y) / np.sum(np.exp(y))
   ix = nn.random.choice(range(vncah size), ncn.ravel())
   x = np.zeros((vocab_size, 1))
x[ix] = 1
   ixes.append(ix)
  return ixes
mixh, mihh, mihy = np.zeros_like(wxh), np.zeros_like(whh), np.zeros_like(why)
with why E on zeros like(bb) on zeros like(by) a memory variables for Adamsa
  mooth_loss = -mp.log(1.0/vocab_size)'seq_length = loss at iteration 0
while True:
   horey = np.zeros((hidden_size, 1)) # reset NNN memory
  p = 0 s go from start of data
inputs = [char_to_ix[ch] for ch in data[p:p+seq_length]]
  targets = [char_to_ix[ch] for ch in data[p+1:p+seq_length+1]]
  # sample from the model now and then
    sample_ix = sample(hprev, inputs[0], 200)
   txt = ''.join(ix to char(ix) for ix in sample ix)
   print '----\n %s \n----' % (txt, )
 loss, dkch, dkh, dkh, dbh, dbh, hepev = loss:mufingutt, targets, hprev)
smooth_loss = smooth_loss * 0.990 + loss * 0.001
if n % 100 = 00 print 'iter %d, loss: %f % (n, smooth_loss) # print progress
                              [mich, mith, mity, mth, mby]);
   param += -learning_rate * dparam / sp.sqrt(mem + ie-8) # adagrad update
```

p += seq\_length # move data pointer

### Data I/O

```
Minimal character-level Vanilla RNN model. Written by Andrej Karpathy (@karpathy)
BSD License
"""
import numpy as np

# data I/O
data = open('input.txt', 'r').read() # should be simple plain text file
chars = list(set(data))
data_size, vocab_size = len(data), len(chars)
print 'data has %d characters, %d unique.' % (data_size, vocab_size)
char_to_ix = { ch:i for i,ch in enumerate(chars) }
ix_to_char = { i:ch for i,ch in enumerate(chars) }
```

```
Minimal character-level vanilla RNN model. Written by Andrej Karpathy (@karpathy)
BSD License
import numpy as np
data = open('input.txt', 'r').read() # should be simple plain text file
data size, vocab size = len(data), len(chars)
print 'data has %d characters, %d unique,' % (data_size, vocab_size)
 char_to_ix = { ch:i for i,ch in enumerate(chars) }
ix_to_char = { i:ch for i,ch in enumerate(chars) }
hidden size = 100 # size of hidden layer of neuron
seq_length = 25 # number of steps to unroll the RNN for
wxh = np.random.randn(hidden_size, vocab_size)*0.01 # input to hidden
Whh = np.random.randn(hidden_size, hidden_size)*8.81 # hidden to hidden
why = np.random.randn(vocab_size, hidden_size)*0.01 # hidden to output
 bh = np.zeros((hidden_size, 1)) # hidden b
by = np.zeros((vocab size, 1)) = output bis
def lossFun(inputs, targets, hprev):
  inputs, targets are both list of integers.
   horey is Hxl array of initial hidden state
   returns the loss, gradients on model parameters, and last hidden state
  xs, hs, ys, ps = {}, {}, {}, {}
  hs[-1] = np.copy(hprev)
  loss = 8
  for t in xrange(len(inputs)):
     xs[t] = np.zeros((vocab_size,1)) # encode in 1-of-k representation
     hs[t] = np.tanh(np.dot(wxh, xs[t]) + np.dot(whh, hs[t-1]) + bh) # hidden state
     vs[t] = np.dot(why. hs[t]) + by = unnormalized log probabilities for next char-
     ps[t] = np.exp(ys[t]) / np.sum(np.exp(ys[t])) + probabilities for next chars
     loss += -mp.log(ps[t][targets[t],0]) # softmax (cross-entropy loss)
   dwxh, dwhh, dwhy = np.zeros_like(wxh), np.zeros_like(whh), np.zeros_like(why)
   dbh, dby = np.zeros_like(bh), np.zeros_like(by)
   dhnext = np.zeros like(hs[p])
   for t in reversed(xrange(len(inputs))):
     dy = np.copy(ps[t])
     dyfragners[r]] .= 1 a backgross into y
     dwhy += np.dot(dy, hs[t].T)
     dh = np.dot(why.T. dy) + dhnext # backgrop into h
     dhraw = (i - hs[t] * hs[t]) * dh # backprop through tanh nonlinearity
     dbh += dhraw
     dayb += no.dot(dbraw. vs[t].T)
     dwhh += np.dot(dhraw, hs[t-1].T)
     dhnext = np.dot(whh.T, dhraw)
  for dparam in [dwxh, dwhh, dwhy, dbh, dby]:
     np.clip(dparam, -5, 5, out=dparam) # clip to mitigate exploding gradients
  return loss, dwxh, dwhh, dwhy, dbh, dby, hs[len(inputs)-1]
def sample(h, seed ix, n):
  sample a sequence of integers from the model h is memory state, seed_ix is seed letter for first time step
  x[seed_ix] = 1
   h = np.tanh(np.dot(wxh, x) + np.dot(whh, h) + bh)
   y = np.dot(Why, h) + by
p = np.exp(y) / np.sum(np.exp(y))
   ix = nn.random.choice(range(vncah size), ncn.ravel())
   x = np.zeros((vocab_size, 1))
x[ix] = 1
    ixes.append(ix)
  return ixes
 maxh, mihh, mihy = np.zeros_like(wxh), np.zeros_like(whh), np.zeros_like(why)
with why E on zeros like(bb) on zeros like(by) a memory variables for Adamsa
  mooth_loss = -mp.log(1.0/vocab_size)'seq_length = loss at iteration 0
while True:
   hprey = np.zeros((hidden_size,1)) # reset MNN memory
  inputs = [char_to_ix[ch] for ch in data[p:p-seq_length]]
  targets = [char_to_ix[ch] for ch in data[p+1:p+seq_length+1]]
  # sample from the model now and then
    sample_ix = sample(hprev, inputs[0], 200)
   txt = ''.join(ix to char(ix) for ix in sample ix)
   print '----\n %s \n----' % (txt, )
  loss, dech, dehh, dehy, deb, day, hprev = loss*indinguts, targets, hprev)
smooth_loss = smooth_loss * 0.000 + loss * 0.001
if n % 100 = 00 print 'iter %d, loss: %d' % (n, smooth_loss) # print progress
```

[mich, mith, mity, mbh, mby]);

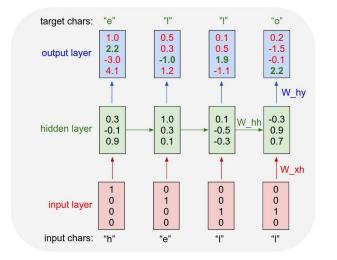
param += -learning\_rate \* dparam / np.sqrt(mem + ie-8) # adagrad update

p += seq\_length # move data pointer

### Initializations

```
# hyperparameters
    hidden_size = 100 # size of hidden layer of neurons
16
     seq_length = 25 # number of steps to unroll the RNN for
     learning_rate = 1e-1
18
19
    # model parameters
    Wxh = np.random.randn(hidden_size, vocab_size)*0.01 # input to hidden
    Whh = np.random.randn(hidden size, hidden size)*0.01 # hidden to hidden
    Why = np.random.randn(vocab size, hidden size)*0.01 # hidden to output
    bh = np.zeros((hidden_size, 1)) # hidden bias
    by = np.zeros((vocab_size, 1)) # output bias
```

## recall:



```
Minimal character-level vanilla RNN model. Written by Andrej Karpathy (@karpathy)
BSD License
import numpy as np
data = open('input.txt', 'r').read() # should be simple plain text file
 chars = list(set(data))
data size, vocab size = len(data), len(chars)
print 'data has %d characters, %d unique.' % (data_size, vocab_size)
 char_to_ix = { ch:i for i,ch in enumerate(chars) }
ix_to_char = { i:ch for i,ch in enumerate(chars) }
hidden size = 100 # size of hidden layer of neurons
seq_length = 25 # number of steps to unroll the RNN for
learning_rate = 1e-1
with = np.random.rando(hidden size, vocab size)*8.81 # input to hidden
Whh = np.random.randn(hidden_size, hidden_size)*8.81 # hidden to hidden
why = np.random.randn(vocab_size, hidden_size)*0.01 # hidden to output
 bh = np.zeros((hidden_size, 1)) # hidden bia
by = np.zeros((vocab_size, 1)) # output bias
def lossFun(inputs, targets, hprey);
 inputs, targets are both list of integers.
   horey is Hx1 array of initial hidden state
  returns the loss, gradients on model parameters, and last hidden state
  xs, hs, ys, ps = {}, {}, {}, {}
  hs[-1] = np.copy(hprev)
  loss = 8
  for t in xrange(len(inputs)):
    xs[t] = np.zeros((vocab_size,1)) # encode in 1-of-k representation
     xs[t][inputs[t]] = 1
     hs[t] = np.tanh(np.dot(wxh, xs[t]) + np.dot(whh, hs[t-1]) + bh) # hidden state
     valt1 = np.dot(why. halt1) + by = uncormalized log probabilities for next chars
     ps[t] = np.exp(ys[t]) / np.sum(np.exp(ys[t])) # probabilities for next chars
     loss += -mp.log(ps[t][targets[t],0]) # softmax (cross-entropy loss)
   dwxh, dwhh, dwhy = np.zeros_like(wxh), np.zeros_like(whh), np.zeros_like(why)
   dbh, dby = np.zeros_like(bh), np.zeros_like(by)
   dhnext = np.zeros like(hs[p])
   for t in reversed(xrange(len(inputs))):
     dy = np.copy(ps[t])
     dyfragners[r]] .= 1 a backgross into y
     dwhy += np.dot(dy, hs[t].T)
     dby += dy
     dh = np.dot(why.T. dy) + dhnext # backgrop into h
     dhraw = (i - hs[t] * hs[t]) * dh # backprop through tanh nonlinearity
     dbh += dhraw
     dayb += no.dot(dbraw. vs[t].T)
     dwhh += np.dot(dhraw, hs[t-1].T)
     dhnext = np.dot(whh.T, dhraw)
  for dparam in [dwxh, dwhh, dwhy, dbh, dby]:
    np.clip(dparam, -5, 5, out=dparam) # clip to mitigate exploding gradients
  return loss, dwxh, dwhh, dwhy, dbh, dby, hs[len(inputs)-1]
def sample(h, seed ix, n):
  sample a sequence of integers from the model h is memory state, seed_ix is seed letter for first time step
 x = np.zeros((vocab_size, 1))
  x[seed_ix] = 1
  ixes = []
for t in xrange(n):
   h = np.tanh(np.dot(wxh, x) + np.dot(whh, h) + bh)
   y = np.dot(Why, h) + by
p = np.exp(y) / np.sum(np.exp(y))
   ix = nn.random.choice(range(vncah size), ncn.ravel())
   x = np.zeros((vocab_size, 1))
x[ix] = 1
    ixes.append(ix)
  return ixes
 maxh, mith, mitry = np.zeros_like(wxh), np.zeros_like(whh), np.zeros_like(why)
mbh. mby = no zeros like(bb), no zeros like(by) a memory variables for adams
  mooth_loss = -mp.log(i.0/vocab_size)*seq_length = loss at iteration 0
while True:
   hprey = np.zeros((hidden_size,1)) # reset MNN memory
  p = 0 s go from start of data
inputs = [char_to_ix[ch] for ch in data[p:p+seq_length]]
  targets = [char_to_ix[ch] for ch in data[p+1:p+seq_length+1]]
   sample_ix = sample(hprev, inputs[0], 200)
   txt = ''.join(ix_to_char[ix] for ix in sample_ix)
print '....\n %5 \n....' % (txt, )
  loss, dech, dehh, dehy, deb, day, hprev = loss*indinguts, targets, hprev)
smooth_loss = smooth_loss * 0.000 + loss * 0.001
if n % 100 = 00 print 'iter %d, loss %d' % (n, smooth_loss) # print progress
  for param, dparam, mem in zip([Wch, Whh, Why, bh, by],
                             [mich, mich, mich, mbh, mby]);
   param += -learning_rate * dparam / sp.sqrt(mem + ie-8) # adagrad update
```

p += seq\_length # move data pointer

```
n, p = 0, 0
    mWxh, mWhh, mWhv = np.zeros like(Wxh), np.zeros like(Whh), np.zeros like(Whv)
    mbh, mby = np.zeros_like(bh), np.zeros_like(by) # memory variables for Adagrad
    smooth_loss = -np.log(1.0/vocab_size)*seq_length # loss at iteration 0
    while True:
      # prepare inputs (we're sweeping from left to right in steps seq_length long)
      if p+seq_length+1 >= len(data) or n == 0:
        hprev = np.zeros((hidden_size,1)) # reset RNN memory
        p = 0 # go from start of data
      inputs = [char_to_ix[ch] for ch in data[p:p+seq_length]]
      targets = [char_to_ix[ch] for ch in data[p+1:p+seq_length+1]]
      # sample from the model now and then
94
      if n % 100 == 0:
        sample_ix = sample(hprev, inputs[0], 200)
        txt = ''.join(ix_to_char[ix] for ix in sample_ix)
        print '----\n %s \n----' % (txt, )
      # forward seq length characters through the net and fetch gradient
      loss, dWxh, dWhh, dWhy, dbh, dby, hprev = lossFun(inputs, targets, hprev)
      smooth loss = smooth loss * 0.999 + loss * 0.001
      if n % 100 == 0: print 'iter %d, loss: %f' % (n, smooth loss) # print progress
      # perform parameter update with Adagrad
      for param, dparam, mem in zip([Wxh, Whh, Why, bh, by],
                                     [dWxh, dWhh, dWhy, dbh, dby],
                                     [mWxh, mWhh, mWhy, mbh, mby]):
        mem += dparam * dparam
        param += -learning rate * dparam / np.sqrt(mem + 1e-8) # adagrad update
      p += seq length # move data pointer
      n += 1 # iteration counter
```

```
Minimal character-level vanilla RNN model. Written by Andrej Karpathy (@karpathy)
BSD License
import numpy as np
data = open('input.txt', 'r').read() # should be simple plain text file
 chars = list(set(data))
data size, vocab size = len(data), len(chars)
print 'data has %d characters, %d unique.' % (data_size, vocab_size)
 char_to_ix = { ch:i for i,ch in enumerate(chars) }
ix_to_char = { i:ch for i,ch in enumerate(chars) }
hidden size = 100 # size of hidden layer of neurons
seq_length = 25 # number of steps to unroll the RNN for
learning_rate = 1e-1
with = np.random.rando(hidden size, vocab size)*8.81 # input to hidden
Whh = np.random.randn(hidden_size, hidden_size)*8.81 # hidden to hidden
why = np.random.randn(vocab_size, hidden_size)*0.01 # hidden to output
 bh = np.zeros((hidden_size, 1)) # hidden bia
by = np.zeros((vocab_size, 1)) # output bias
def lossFun(inputs, targets, hprey);
 inputs, targets are both list of integers.
   horey is Hx1 array of initial hidden state
  returns the loss, gradients on model parameters, and last hidden state
  xs, hs, ys, ps = {}, {}, {}, {}
  hs[-1] = np.copy(hprev)
  loss = 8
  for t in xrange(len(inputs)):
    xs[t] = np.zeros((vocab_size,1)) # encode in 1-of-k representation
     xs[t][inputs[t]] = 1
     hs[t] = np.tanh(np.dot(wxh, xs[t]) + np.dot(whh, hs[t-1]) + bh) # hidden state
     valt1 = np.dot(why. halt1) + by = uncormalized log probabilities for next chars
     ps[t] = np.exp(ys[t]) / np.sum(np.exp(ys[t])) # probabilities for next chars
     loss += -mp.log(ps[t][targets[t],0]) # softmax (cross-entropy loss)
   dwxh, dwhh, dwhy = np.zeros_like(wxh), np.zeros_like(whh), np.zeros_like(why)
   dbh, dby = np.zeros_like(bh), np.zeros_like(by)
   dhnext = np.zeros like(hs[p])
   for t in reversed(xrange(len(inputs))):
     dy = np.copy(ps[t])
     dyfragners[r]] .= 1 a backgross into y
     dwhy += np.dot(dy, hs[t].T)
     dby += dy
     dh = np.dot(why.T. dy) + dhnext # backgrop into h
     dhraw = (i - hs[t] * hs[t]) * dh # backprop through tanh nonlinearity
     dbh += dhraw
     dayb += no.dot(dbraw. vs[t].T)
     dwhh += np.dot(dhraw, hs[t-1].T)
     dhnext = np.dot(whh.T, dhraw)
  for dparam in [dwxh, dwhh, dwhy, dbh, dby]:
    np.clip(dparam, -5, 5, out=dparam) # clip to mitigate exploding gradients
  return loss, dwxh, dwhh, dwhy, dbh, dby, hs[len(inputs)-1]
def sample(h, seed ix, n):
  sample a sequence of integers from the model h is memory state, seed_ix is seed letter for first time step
 x = np.zeros((vocab_size, 1))
  x[seed_ix] = 1
  ixes = []
for t in xrange(n):
   h = np.tanh(np.dot(wxh, x) + np.dot(whh, h) + bh)
   y = np.dot(Why, h) + by
p = np.exp(y) / np.sum(np.exp(y))
   ix = nn.random.choice(range(vncah size), ncn.ravel())
   x = np.zeros((vocab_size, 1))
x[ix] = 1
    ixes.append(ix)
  return ixes
 maxh, mith, mitry = np.zeros_like(wxh), np.zeros_like(whh), np.zeros_like(why)
mbh. mby = no zeros like(bb), no zeros like(by) a memory variables for adams
  mooth_loss = -mp.log(i.0/vocab_size)*seq_length = loss at iteration 0
while True:
   hprey = np.zeros((hidden_size,1)) # reset MNN memory
  p = 0 s go from start of data
inputs = [char_to_ix[ch] for ch in data[p:p+seq_length]]
  targets = [char_to_ix[ch] for ch in data[p+1:p+seq_length+1]]
   sample_ix = sample(hprev, inputs[0], 200)
   txt = ''.join(ix_to_char[ix] for ix in sample_ix)
print '....\n %5 \n....' % (txt, )
  loss, dech, dehh, dehy, deb, day, hprev = loss*indinguts, targets, hprev)
smooth_loss = smooth_loss * 0.000 + loss * 0.001
if n % 100 = 00 print 'iter %d, loss %d' % (n, smooth_loss) # print progress
  for param, dparam, mem in zip([Wch, Whh, Why, bh, by],
                             [mich, mich, mich, mbh, mby]);
   param += -learning_rate * dparam / sp.sqrt(mem + ie-8) # adagrad update
```

p += seq\_length # move data pointer

```
n, p = 0, 0
    mWxh, mWhh, mWhv = np.zeros like(Wxh), np.zeros like(Whh), np.zeros like(Whv)
    mbh, mby = np.zeros_like(bh), np.zeros_like(by) # memory variables for Adagrad
    smooth_loss = -np.log(1.0/vocab_size)*seq_length # loss at iteration 0
    while True:
      # prepare inputs (we're sweeping from left to right in steps seq_length long)
      if p+seq_length+1 >= len(data) or n == 0:
        hprev = np.zeros((hidden_size,1)) # reset RNN memory
        p = 0 # go from start of data
      inputs = [char_to_ix[ch] for ch in data[p:p+seq_length]]
      targets = [char_to_ix[ch] for ch in data[p+1:p+seq_length+1]]
      # sample from the model now and then
94
      if n % 100 == 0:
        sample_ix = sample(hprev, inputs[0], 200)
        txt = ''.join(ix_to_char[ix] for ix in sample_ix)
        print '----\n %s \n----' % (txt, )
      # forward seg length characters through the net and fetch gradient
      loss, dWxh, dWhh, dWhy, dbh, dby, hprev = lossFun(inputs, targets, hprev)
      smooth loss = smooth loss * 0.999 + loss * 0.001
      if n % 100 == 0: print 'iter %d, loss: %f' % (n, smooth loss) # print progress
      # perform parameter update with Adagrad
      for param, dparam, mem in zip([Wxh, Whh, Why, bh, by],
                                     [dWxh, dWhh, dWhy, dbh, dby],
                                     [mWxh, mWhh, mWhy, mbh, mby]):
        mem += dparam * dparam
        param += -learning rate * dparam / np.sqrt(mem + 1e-8) # adagrad update
      p += seq length # move data pointer
      n += 1 # iteration counter
```

```
Minimal character-level vanilla RNN model. Written by Andrej Karpathy (@karpathy)
BSD License
import numpy as np
data = open('input.txt', 'r').read() # should be simple plain text file
 chars = list(set(data))
data size, vocab size = len(data), len(chars)
print 'data has %d characters, %d unique.' % (data_size, vocab_size)
 char_to_ix = { ch:i for i,ch in enumerate(chars) }
ix_to_char = { i:ch for i,ch in enumerate(chars) }
hidden size = 100 # size of hidden layer of neurons
seq_length = 25 # number of steps to unroll the RNN for
learning_rate = 1e-1
with = np.random.rando(hidden size, vocab size)*8.81 # input to hidden
Whh = np.random.randn(hidden_size, hidden_size)*8.81 # hidden to hidden
why = np.random.randn(vocab_size, hidden_size)*0.01 # hidden to output
 bh = np.zeros((hidden_size, 1)) # hidden bia
by = np.zeros((vocab_size, 1)) # output bias
def lossFun(inputs, targets, hprey);
 inputs, targets are both list of integers.
   horey is Hx1 array of initial hidden state
  returns the loss, gradients on model parameters, and last hidden state
  xs, hs, ys, ps = {}, {}, {}, {}
  hs[-1] = np.copy(hprev)
  loss = 8
  for t in xrange(len(inputs)):
    xs[t] = np.zeros((vocab_size,1)) # encode in 1-of-k representation
     xs[t][inputs[t]] = 1
     hs[t] = np.tanh(np.dot(wxh, xs[t]) + np.dot(whh, hs[t-1]) + bh) # hidden state
     valt1 = np.dot(why. halt1) + by = uncormalized log probabilities for next chars
     ps[t] = np.exp(ys[t]) / np.sum(np.exp(ys[t])) # probabilities for next chars
     loss += -mp.log(ps[t][targets[t],0]) # softmax (cross-entropy loss)
   dwxh, dwhh, dwhy = np.zeros_like(wxh), np.zeros_like(whh), np.zeros_like(why)
   dbh, dby = np.zeros_like(bh), np.zeros_like(by)
   dhnext = np.zeros like(hs[p])
   for t in reversed(xrange(len(inputs))):
     dy = np.copy(ps[t])
     dyfragners[r]] .= 1 a backgross into y
     dwhy += np.dot(dy, hs[t].T)
     dby += dy
     dh = np.dot(why.T. dy) + dhnext # backgrop into h
     dhraw = (i - hs[t] * hs[t]) * dh # backprop through tanh nonlinearity
     dbh += dhraw
     dayb += no.dot(dbraw. vs[t].T)
     dwhh += np.dot(dhraw, hs[t-1].T)
     dhnext = np.dot(whh.T, dhraw)
  for dparam in [dwxh, dwhh, dwhy, dbh, dby]:
    np.clip(dparam, -5, 5, out=dparam) # clip to mitigate exploding gradients
  return loss, dwxh, dwhh, dwhy, dbh, dby, hs[len(inputs)-1]
def sample(h, seed ix, n):
  sample a sequence of integers from the model h is memory state, seed_ix is seed letter for first time step
 x = np.zeros((vocab_size, 1))
  x[seed_ix] = 1
  ixes = []
for t in xrange(n):
   h = np.tanh(np.dot(wxh, x) + np.dot(whh, h) + bh)
   y = np.dot(Why, h) + by
p = np.exp(y) / np.sum(np.exp(y))
   ix = nn.random.choice(range(vocah size), ncn.ravel())
   x = np.zeros((vocab_size, 1))
x[ix] = 1
    ixes.append(ix)
  return ixes
 maxh, mith, mitry = np.zeros_like(wxh), np.zeros_like(whh), np.zeros_like(why)
mbh. mby = no zeros like(bb), no zeros like(by) a memory variables for adams
  smooth_loss = -mp.log(i.@/voceb_size)*seq_length # loss at iteration @
while True:
   hprey = np.zeros((hidden_size,1)) # reset MNN memory
  p = 0 s go from start of data
inputs = [char_to_ix[ch] for ch in data[p:p+seq_length]]
  targets = [char_to_ix[ch] for ch in data[p+1:p+seq_length+1]]
   sample_ix = sample(hprev, inputs[0], 200)
   txt = ''.join(ix_to_char[ix] for ix in sample_ix)
print '....\n %5 \n....' % (txt, )
  loss, dech, dehh, dehy, deb, day, hprev = loss*indinguts, targets, hprev)
smooth_loss = smooth_loss * 0.000 + loss * 0.001
if n % 100 = 00 print 'iter %d, loss %d' % (n, smooth_loss) # print progress
  for param, dparam, mem in zip([Wch, Whh, Why, bh, by],
                             [mich, mich, mich, mbh, mby]);
   param += -learning_rate * dparam / sp.sqrt(mem + ie-8) # adagrad update
```

p += seq\_length # move data pointer

```
n, p = 0, 0
mWxh, mWhh, mWhv = np.zeros like(Wxh), np.zeros like(Whh), np.zeros like(Whv)
mbh, mby = np.zeros_like(bh), np.zeros_like(by) # memory variables for Adagrad
smooth_loss = -np.log(1.0/vocab_size)*seq_length # loss at iteration 0
while True:
 # prepare inputs (we're sweeping from left to right in steps seq_length long)
  if p+seq_length+1 >= len(data) or n == 0:
    hprev = np.zeros((hidden_size,1)) # reset RNN memory
    p = 0 # go from start of data
  inputs = [char_to_ix[ch] for ch in data[p:p+seq_length]]
  targets = [char_to_ix[ch] for ch in data[p+1:p+seq_length+1]]
  # sample from the model now and then
  if n % 100 == 0:
    sample_ix = sample(hprev, inputs[0], 200)
    txt = ''.join(ix_to_char[ix] for ix in sample_ix)
    print '----\n %s \n----' % (txt. )
  # forward seq length characters through the net and fetch gradient
  loss, dWxh, dWhh, dWhy, dbh, dby, hprev = lossFun(inputs, targets, hprev)
  smooth loss = smooth loss * 0.999 + loss * 0.001
  if n % 100 == 0: print 'iter %d, loss: %f' % (n, smooth loss) # print progress
  # perform parameter update with Adagrad
  for param, dparam, mem in zip([Wxh, Whh, Why, bh, by],
                                [dWxh, dWhh, dWhy, dbh, dby],
                                [mWxh, mWhh, mWhy, mbh, mby]):
    mem += dparam * dparam
    param += -learning rate * dparam / np.sqrt(mem + 1e-8) # adagrad update
  p += seq length # move data pointer
  n += 1 # iteration counter
```

```
Minimal character-level vanilla RNN model. Written by Andrej Karpathy (@karpathy)
BSD License
import numpy as np
data = open('input.txt', 'r').read() # should be simple plain text file
 chars = list(set(data))
data size, vocab size = len(data), len(chars)
print 'data has %d characters, %d unique.' % (data_size, vocab_size)
 char_to_ix = { ch:i for i,ch in enumerate(chars) }
ix_to_char = { i:ch for i,ch in enumerate(chars) }
hidden size = 100 # size of hidden layer of neurons
seq_length = 25 # number of steps to unroll the RNN for
learning_rate = 1e-1
with = np.random.rando(hidden size, vocab size)*8.81 # input to hidden
Whh = np.random.randn(hidden_size, hidden_size)*8.81 # hidden to hidden
why = np.random.randn(vocab_size, hidden_size)*0.01 # hidden to output
 bh = np.zeros((hidden_size, 1)) # hidden bia
by = np.zeros((vocab_size, 1)) # output bias
def lossFun(inputs, targets, hprey);
 inputs, targets are both list of integers.
   horey is Hx1 array of initial hidden state
  returns the loss, gradients on model parameters, and last hidden state
  xs, hs, ys, ps = {}, {}, {}, {}
  hs[-1] = np.copy(hprev)
  loss = 8
  for t in xrange(len(inputs)):
    xs[t] = np.zeros((vocab_size,1)) # encode in 1-of-k representation
     xs[t][inputs[t]] = 1
     hs[t] = np.tanh(np.dot(wxh, xs[t]) + np.dot(whh, hs[t-1]) + bh) # hidden state
     valt1 = np.dot(why. halt1) + by = uncormalized log probabilities for next chars
     ps[t] = np.exp(ys[t]) / np.sum(np.exp(ys[t])) # probabilities for next chars
     loss += -mp.log(ps[t][targets[t],0]) # softmax (cross-entropy loss)
   dwxh, dwhh, dwhy = np.zeros_like(wxh), np.zeros_like(whh), np.zeros_like(why)
   dbh, dby = np.zeros_like(bh), np.zeros_like(by)
   dhnext = np.zeros like(hs[p])
   for t in reversed(xrange(len(inputs))):
     dy = np.copy(ps[t])
     dyfragners[r]] .= 1 a backgross into y
     dwhy += np.dot(dy, hs[t].T)
     dby += dy
     dh = np.dot(why.T. dy) + dhnext # backgrop into h
     dhraw = (i - hs[t] * hs[t]) * dh # backprop through tanh nonlinearity
     dbh += dhraw
     dayb += no.dot(dbraw. vs[t].T)
     dwhh += np.dot(dhraw, hs[t-1].T)
     dhnext = np.dot(whh.T, dhraw)
  for dparam in [dwxh, dwhh, dwhy, dbh, dby]:
    np.clip(dparam, -5, 5, out=dparam) # clip to mitigate exploding gradients
  return loss, dwxh, dwhh, dwhy, dbh, dby, hs[len(inputs)-1]
def sample(h, seed ix, n):
  sample a sequence of integers from the model h is memory state, seed_ix is seed letter for first time step
 x = np.zeros((vocab_size, 1))
  x[seed_ix] = 1
  ixes = []
for t in xrange(n):
   h = np.tanh(np.dot(wxh, x) + np.dot(whh, h) + bh)
   y = np.dot(Why, h) + by
p = np.exp(y) / np.sum(np.exp(y))
   ix = nn.random.choice(range(vocah size), ncn.ravel())
   x = np.zeros((vocab_size, 1))
x[ix] = 1
    ixes.append(ix)
  return ixes
 maxh, mith, mitry = np.zeros_like(wxh), np.zeros_like(whh), np.zeros_like(why)
mbh. mby = no zeros like(bb), no zeros like(by) a memory variables for adams
  mooth_loss = -mp.log(1.0/voceb_size)'seq_length = loss at iteration 0
while True:
   hprey = np.zeros((hidden_size,1)) # reset MNN memory
  p = 0 s go from start of data
inputs = [char_to_ix[ch] for ch in data[p:p+seq_length]]
  targets = [char_to_ix[ch] for ch in data[p+1:p+seq_length+1]]
   sample_ix = sample(hprev, inputs[0], 200)
   txt = ''.join(ix_to_char[ix] for ix in sample_ix)
print '....\n %5 \n....' % (txt, )
  loss, dech, dehh, dehy, deb, day, hprev = loss*indinguts, targets, hprev)
smooth_loss = smooth_loss * 0.000 + loss * 0.001
if n % 100 = 00 print 'iter %d, loss %d' % (n, smooth_loss) # print progress
  for param, dparam, mem in zip([Wch, Whh, Why, bh, by],
```

[mint, mith, mith, mbh, mbh]):
mem += dparam \* dparam
param += -learning\_rate \* dparam / mp.mgrt(mem + ie-8) # adagrad update

p += seq\_length # move data pointer

```
n, p = 0, 0
    mWxh, mWhh, mWhv = np.zeros like(Wxh), np.zeros like(Whh), np.zeros like(Whv)
    mbh, mby = np.zeros_like(bh), np.zeros_like(by) # memory variables for Adagrad
    smooth_loss = -np.log(1.0/vocab_size)*seq_length # loss at iteration 0
    while True:
      # prepare inputs (we're sweeping from left to right in steps seq_length long)
      if p+seq_length+1 >= len(data) or n == 0:
        hprev = np.zeros((hidden_size,1)) # reset RNN memory
        p = 0 # go from start of data
      inputs = [char_to_ix[ch] for ch in data[p:p+seq_length]]
      targets = [char_to_ix[ch] for ch in data[p+1:p+seq_length+1]]
      # sample from the model now and then
94
      if n % 100 == 0:
        sample_ix = sample(hprev, inputs[0], 200)
        txt = ''.join(ix_to_char[ix] for ix in sample_ix)
        print '----\n %s \n----' % (txt, )
      # forward seq length characters through the net and fetch gradient
      loss, dWxh, dWhh, dWhy, dbh, dby, hprev = lossFun(inputs, targets, hprev)
      smooth loss = smooth loss * 0.999 + loss * 0.001
      if n % 100 == 0: print 'iter %d, loss: %f' % (n, smooth loss) # print progress
      # perform parameter update with Adagrad
      for param, dparam, mem in zip([Wxh, Whh, Why, bh, by],
                                     [dWxh, dWhh, dWhy, dbh, dby],
                                     [mWxh, mWhh, mWhy, mbh, mby]):
        mem += dparam * dparam
        param += -learning rate * dparam / np.sqrt(mem + 1e-8) # adagrad update
      p += seq length # move data pointer
      n += 1 # iteration counter
```

```
Minimal character-level vanilla RNN model. Written by Andrej Karpathy (@karpathy)
BSD License
import numpy as np
data = open('input.txt', 'r').read() # should be simple plain text file
 chars = list(set(data))
data size, vocab size = len(data), len(chars)
print 'data has %d characters, %d unique.' % (data_size, vocab_size)
 char_to_ix = { ch:i for i,ch in enumerate(chars) }
ix_to_char = { i:ch for i,ch in enumerate(chars) }
hidden size = 100 # size of hidden layer of neurons
seq_length = 25 # number of steps to unroll the RNN for
learning_rate = 1e-1
with = np.random.rando(hidden size, vocab size)*8.81 # input to hidden
Whh = np.random.randn(hidden_size, hidden_size)*8.81 # hidden to hidden
why = np.random.randn(vocab_size, hidden_size)*0.01 # hidden to output
 bh = np.zeros((hidden_size, 1)) # hidden bia
by = np.zeros((vocab_size, 1)) # output bias
def lossFun(inputs, targets, hprey);
 inputs, targets are both list of integers.
   horey is Hx1 array of initial hidden state
  returns the loss, gradients on model parameters, and last hidden state
  xs, hs, ys, ps = {}, {}, {}, {}
  hs[-1] = np.copy(hprev)
  loss = 8
  for t in xrange(len(inputs)):
    xs[t] = np.zeros((vocab_size,1)) # encode in 1-of-k representation
     xs[t][inputs[t]] = 1
     hs[t] = np.tanh(np.dot(wxh, xs[t]) + np.dot(whh, hs[t-1]) + bh) # hidden state
     valt1 = np.dot(why. halt1) + by = uncormalized log probabilities for next chars
     ps[t] = np.exp(ys[t]) / np.sum(np.exp(ys[t])) # probabilities for next chars
     loss += -mp.log(ps[t][targets[t],0]) # softmax (cross-entropy loss)
   dwxh, dwhh, dwhy = np.zeros_like(wxh), np.zeros_like(whh), np.zeros_like(why)
   dbh, dby = np.zeros_like(bh), np.zeros_like(by)
   dhnext = np.zeros like(hs[p])
   for t in reversed(xrange(len(inputs))):
     dy = np.copy(ps[t])
     dyfragners[r]] .= 1 a backgross into y
     dwhy += np.dot(dy, hs[t].T)
     dh = np.dot(why.T. dy) + dhnext # backgrop into h
     dhraw = (i - hs[t] * hs[t]) * dh # backprop through tanh nonlinearity
     dbh += dhraw
     dayb += no.dot(dbraw. vs[t].T)
     dwhh += np.dot(dhraw, hs[t-1].T)
     dhnext = np.dot(whh.T, dhraw)
  for dparam in [dwxh, dwhh, dwhy, dbh, dby]:
    np.clip(dparam, -5, 5, out=dparam) # clip to mitigate exploding gradients
  return loss, dwxh, dwhh, dwhy, dbh, dby, hs[len(inputs)-1]
def sample(h, seed ix, n):
  sample a sequence of integers from the model
  h is memory state, seed_ix is seed letter for first time step
 x = np.zeros((vocab_size, 1))
  x[seed_ix] = 1
  ixes = []
for t in xrange(n):
   h = np.tanh(np.dot(wxh, x) + np.dot(whh, h) + bh)
   y = np.dot(Why, h) + by
p = np.exp(y) / np.sum(np.exp(y))
   ix = nn.random.choice(range(vncah size), ncn.ravel())
   x = np.zeros((vocab_size, 1))
x[ix] = 1
    ixes.append(ix)
  return ixes
 maxh, mith, mitry = np.zeros_like(wxh), np.zeros_like(whh), np.zeros_like(why)
mbh. mby = no zeros like(bb), no zeros like(by) a memory variables for adams
  mooth_loss = -mp.log(i.0/vocab_size)*seq_length = loss at iteration 0
while True:
   hprey = np.zeros((hidden_size,1)) # reset MNN memory
  p = 0 s go from start of data
inputs = [char_to_ix[ch] for ch in data[p:p+seq_length]]
  targets = [char_to_ix[ch] for ch in data[p+1:p+seq_length+1]]
   sample_ix = sample(hprev, inputs[0], 200)
   txt = ''.join(ix_to_char[ix] for ix in sample_ix)
print '....\n %5 \n....' % (txt, )
  loss, dech, dehh, dehy, deb, day, hprev = loss*indinguts, targets, hprev)
smooth_loss = smooth_loss * 0.000 + loss * 0.001
if n % 100 = 00 print 'iter %d, loss %d' % (n, smooth_loss) # print progress
  for param, dparam, mem in zip([Wch, Whh, Why, bh, by],
                             [mich, mich, mich, mbh, mby]);
```

param += -learning\_rate \* dparam / sp.sqrt(mem + ie-8) # adagrad update

```
n, p = 0, 0
    mWxh, mWhh, mWhv = np.zeros like(Wxh), np.zeros like(Whh), np.zeros like(Whv)
    mbh, mby = np.zeros_like(bh), np.zeros_like(by) # memory variables for Adagrad
    smooth_loss = -np.log(1.0/vocab_size)*seq_length # loss at iteration 0
    while True:
      # prepare inputs (we're sweeping from left to right in steps seq_length long)
      if p+seq_length+1 >= len(data) or n == 0:
        hprev = np.zeros((hidden_size,1)) # reset RNN memory
        p = 0 # go from start of data
      inputs = [char_to_ix[ch] for ch in data[p:p+seq_length]]
      targets = [char_to_ix[ch] for ch in data[p+1:p+seq_length+1]]
      # sample from the model now and then
94
      if n % 100 == 0:
        sample_ix = sample(hprev, inputs[0], 200)
        txt = ''.join(ix_to_char[ix] for ix in sample_ix)
        print '----\n %s \n----' % (txt, )
      # forward seq length characters through the net and fetch gradient
      loss, dWxh, dWhh, dWhy, dbh, dby, hprev = lossFun(inputs, targets, hprev)
      smooth loss = smooth loss * 0.999 + loss * 0.001
      if n % 100 == 0: print 'iter %d, loss: %f' % (n, smooth_loss) # print progress
      # perform parameter update with Adagrad
      for param, dparam, mem in zip([Wxh, Whh, Why, bh, by],
                                     [dWxh, dWhh, dWhy, dbh, dby],
                                     [mWxh, mWhh, mWhy, mbh, mby]):
        mem += dparam * dparam
        param += -learning rate * dparam / np.sqrt(mem + 1e-8) # adagrad update
      p += seq length # move data pointer
      n += 1 # iteration counter
```

```
Minimal character, level vanilla BNN model. Written by Andrei Karnathy (Akarnathy
BSD License
import numpy as np
data = open('input.txt', 'r').read() # should be simple plain text file
data size, vocab size = len(data), len(chars)
print 'data has %d characters, %d unique,' % (data_size, vocab_size)
 char_to_ix = { ch:i for i,ch in enumerate(chars) }
ix_to_char = { i:ch for i,ch in enumerate(chars) }
hidden size = 100 # size of hidden layer of neurons
seq_length = 25 # number of steps to unroll the RNN for
with = np.random.rando(hidden size, vocab size)*8.81 # input to hidden
Who = no random rando/bidden size bidden size) 10 01 0 bidden to bidden
why = np.random.randn(vocab_size, hidden_size)*0.01 # hidden to output
by = np.zeros((vocab size, 1)) = output bias
def lossFun(inputs, targets, hprev):
  inputs, targets are both list of integers.
  returns the loss, gradients on model parameters, and last hidden state
  hs[-1] = np.copy(hprev)
  for t in xrange(len(inputs)):
    xs[t] = np.zeros((vocab_size,1)) # encode in 1-of-k representation
    hs[t] = np.tanh(np.dot(wxh, xs[t]) + np.dot(whh, hs[t-1]) + bh) # hidden state
    vs[t] = np.dot(why. hs[t]) + by = unnormalized log probabilities for next char-
     ps[t] = np.exp(ys[t]) / np.sum(np.exp(ys[t])) # probabilities for next chars
    loss += -mp.log(ps[t][targets[t],0]) # softmax (cross-entropy loss)
   dayb, daby = nn zeros like(why), nn zeros like(why), nn zeros like(why)
   dbh, dby = np.zeros_like(bh), np.zeros_like(by)
   dhnext = np.zeros like(hs[p])
    dy = np.copy(ps[t])
    dwhy += np.dot(dy, hs[t].T)
    dh = np.dot(why.T. dy) + dhnext # backgrop into h
    dhraw = (1 - hs[t] * hs[t]) * dh # backprop through tanh nonlinearity
    dayb += np.dot(dbraw, vs[t].T)
    dwhh += np.dot(dhraw, hs[t-1].T)
    dhnext = np.dot(Whh.T, dhraw)
  for dparam in [dwxh, dwhh, dwhy, dbh, dby]:
    np.clip(dparam, -5, 5, out=dparam) # clip to mitigate exploding gradients
   return loss, dwxh, dwhh, dwhy, dbh, dby, hs[len(inputs)-1]
  sample a sequence of integers from the model
 x = np.zeros((vocab_size, 1))
  x[seed_ix] = 1
   h = np.tanh(np.dot(wxh, x) + np.dot(whh, h) + bh)
   y = np.dot(Why, h) + by
p = np.exp(y) / np.sum(np.exp(y))
   ix = nn.random.choice(range(vocah size), ncn.ravel())
   x = np.zeros((vocab_size, 1))
x[ix] = 1
    ixes.append(ix)
  return ixes
mbh. mby = no zeros like(bh), no zeros like(by) a memory variables for adams
  mooth_loss = -mp.log(1.0/vocab_size)*seq_length = loss at iteration 0
while True:
   hprey = np.zeros((hidden_size,1)) # reset MNN memory
 p = 0 # go from start of data
inputs = [char to ix[ch] for ch in data[p:p-seq_length]]
  targets = [char_to_ix[ch] for ch in data[p+1:p+seq_length+1]]
    sample_ix = sample(hprev, inputs[0], 200)
   txt = ''.join(ix to char(ix) for ix in sample ix)
  loss, dich, dwh, dwhy, dbh, dby, hprev = lossFun(inputs, targets, hprev) smooth_loss = smooth_loss * 0.000 + loss * 0.001
  if n % 100 == 0; print 'iter %d, loss: %f' % (n, smooth_loss) # print progress
```

[mich. mith. mity. mth. mby]); param += -learning\_rate \* dparam / np.sqrt(mem + ie-8) # adagrad update

### Loss function

- forward pass (compute loss)
- backward pass (compute param gradient)

```
def lossFun(inputs, targets, hprev);
 inputs, targets are both list of integers.
 hprev is Hx1 array of initial hidden state
 returns the loss, gradients on model parameters, and last hidden state
 xs, hs, ys, ps = \{\}, \{\}, \{\}, \{\}
 hs[-1] = np.copy(hprev)
 loss = 0
 # forward pass
 for t in xrange(len(inputs)):
   xs[t] = np.zeros((vocab_size,1)) # encode in 1-of-k representation
   xs[t][inputs[t]] = 1
   hs[t] = np.tanh(np.dot(Wxh, xs[t]) + np.dot(Whh, hs[t-1]) + bh) # hidden state
   ys[t] = np.dot(Why, hs[t]) + by # unnormalized log probabilities for next chars
   ps[t] = np.exp(ys[t]) / np.sum(np.exp(ys[t])) # probabilities for next chars
   loss += -np.log(ps[t][targets[t],0]) # softmax (cross-entropy loss)
 # backward pass: compute gradients going backwards
 dWxh, dWhh, dWhy = np.zeros_like(Wxh), np.zeros_like(Whh), np.zeros_like(Why)
 dbh, dby = np.zeros_like(bh), np.zeros_like(by)
 dhnext = np.zeros_like(hs[0])
 for t in reversed(xrange(len(inputs))):
   dy = np.copy(ps[t])
   dy[targets[t]] -= 1 # backprop into y
   dWhy += np.dot(dy, hs[t].T)
   dby += dy
   dh = np.dot(Why.T, dy) + dhnext # backprop into h
   dhraw = (1 - hs[t] * hs[t]) * dh # backprop through tanh nonlinearity
   dbh += dhraw
   dWxh += np.dot(dhraw, xs[t].T)
   dWhh += np.dot(dhraw, hs[t-1].T)
   dhnext = np.dot(Whh.T, dhraw)
 for dparam in [dWxh, dWhh, dWhy, dbh, dby]:
```

np.clip(dparam, -5, 5, out=dparam) # clip to mitigate exploding gradients

return loss, dWxh, dWhh, dWhy, dbh, dby, hs[len(inputs)-1]

```
min-char-rnn.py gist
                                                                                                                   def lossFun(inputs, targets, hprev):
 Minimal character-level vanilla RNN model. Written by Andrej Karpathy (@karpathy)
 BSD License
 import numpy as np
                                                                                                                       inputs, targets are both list of integers.
 data = open('input.txt', 'r').read() # should be simple plain text file
                                                                                                                       hprev is Hx1 array of initial hidden state
 data size, vocab size = len(data), len(chars)
 print 'data has %d characters, %d unique,' % (data_size, vocab_size)
  char_to_ix = { ch:i for i,ch in enumerate(chars) }
                                                                                                                       returns the loss, gradients on model parameters, and last hidden state
 ix_to_char = { i:ch for i,ch in enumerate(chars) }
 hidden size = 100 # size of hidden layer of neurons
                                                                                                                        11 11 11
 seq_length = 25 # number of steps to unroll the RNN for
                                                                                                                       xs, hs, ys, ps = {}, {}, {}, {}
 with = np.random.rando(hidden size, vocab size)*8.81 # input to hidden
 Whh = np.random.randn(hidden_size, hidden_size)*8.81 # hidden to hidden
 why = np.random.randn(vocab_size, hidden_size)*0.01 # hidden to output
                                                                                                                       hs[-1] = np.copy(hprev)
  bh = np.zeros((hidden_size, 1)) # hidden bia
 by = np.zeros((vocab size, 1)) = output bias
  def lossFun(inputs, targets, hprev)
                                                                                                                        loss = 0
   inputs, targets are both list of integers.
                                                                                                                       # forward pass
   returns the loss, gradients on model parameters, and last hidden state
                                                                                                       37
                                                                                                                       for t in xrange(len(inputs)):
   for t in xrange(len(inputs)):
                                                                                                                            xs[t] = np.zeros((vocab_size,1)) # encode in 1-of-k representation
    xs[t] = np.zeros((vocab_size,1)) # encode in 1-of-k representation
    hs[t] = np.tanh(np.dot(wkh, xs[t]) + np.dot(whh, hs[t-1]) + bh) + hidden state
    vs[t] = np.dot(Why. hs[t]) + by = unp
                                                                                                                            xs[t][inputs[t]] = 1
   dwxh, dwhh, dwhy = np.zeros_like(wxh), np.zeros_like(whh), np.zeros_like(why)
                                                                                                                           hs[t] = np.tanh(np.dot(Wxh, xs[t]) + np.dot(Whh, hs[t-1]) + bh) # hidden state
   dbh, dby = np.zeros_like(bh), np.zeros_like(by)
   dhnext = np.zeros like(hs[p])
   for t in reversed(xrange(len(inputs))):
                                                                                                                          ys[t] = np.dot(Why, hs[t]) + by # unnormalized log probabilities for next chars
                                                                                                       41
    dy = np.copy(ps[t])
    dwhy += np.dot(dy, hs[t].T)
                                                                                                                            ps[t] = np.exp(ys[t]) / np.sum(np.exp(ys[t])) # probabilities for next chars
                                                                                                       42
    dh = np.dot(why.T. dy) + dhnext # backgrop into h
    dhraw = (1 - hs[t] * hs[t]) * dh # backprop through tanh nonlinearity
                                                                                                                            loss += -np.log(ps[t][targets[t],0]) # softmax (cross-entropy loss)
    dayb += np.dot(dbraw, vs[t].T)
    dwhh += np.dot(dhraw, hs[t-1].T)
    dhnext = np.dot(whh.T, dhraw)
   for dparam in [dwxh, dwhh, dwhy, dbh, dby]:
    np.clip(dparam, -5, 5, out=dparam) # clip to mitigate exploding gradients
   return loss, dwxh, dwhh, dwhy, dbh, dby, hs[len(inputs)-1]
  sample a sequence of integers from the model h is memory state, seed_ix is seed letter for first time step
  x = np.zeros((wocab_size, 1))
                                                                             h_t = 	anh(W_{hh}h_{t-1} + W_{xh}x_t)
  x[seed_ix] = 1
   h = np.tanh(np.dot(wxh, x) + np.dot(whh, h) + bh)
   y = np.dot(Why, h) + by
p = np.exp(y) / np.sum(np.exp(y))
   ix = nn.random.choice(range(vncah size), ncn.ravel())
   x = np.zeros((vocab_size, 1))
x[ix] = 1
    ixes.append(ix)
                                                                             y_t = W_{hy}h_t
  return ixes
 mbh mby a no zeros like(bh) no zeros like(by) a memory variables for adamrad
   mooth_loss = -mp.log(1.0/vocab_size)*seq_length = loss at iteration 0
 while True:
   horey = np.zeros((hidden_size, 1)) # reset NNN memory
                                                                                                                                                           Softmax classifier
   inputs = [char_to_ix[ch] for ch in data[p:p-seq_length]]
  targets = [char_to_ix[ch] for ch in data[p+1:p+seq_length+1]]
  # sample from the model now and then
    sample_ix = sample(hprev, inputs[0], 200)
   txt = ''.join(ix to char(ix) for ix in sample ix)
   print '----\n %s \n----' % (txt, )
  loss, dich, dwh, dwhy, dbh, dby, hprev = lossFun(inputs, targets, hprev) smooth_loss = smooth_loss * 0.000 + loss * 0.001
  if n % 100 == 0; print 'iter %d, loss: %f' % (n, smooth_loss) # print progress
```

[mint, mith, mithy, mbh, mby]):
mem += dparam \* dparam
param += -learning\_rate \* dparam / mp.mgrt(mem + ie-8) # adagrad update

p += seq\_length # move data pointer

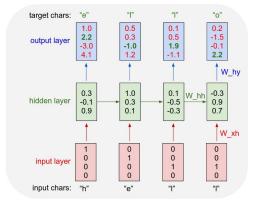
#### min-char-rnn.py gist Minimal character-level vanilla RNN model. Written by Andrej Karpathy (@karpathy) BSD License import numpy as np data = open('input.txt', 'r').read() # should be simple plain text file data size, vocab size = len(data), len(chars) print 'data has %d characters, %d unique,' % (data size, vocab size char\_to\_ix = { ch:i for i,ch in enumerate(chars) } ix\_to\_char = { i:ch for i,ch in enumerate(chars) } hidden size = 100 # size of hidden layer of neurons seq\_length = 25 # number of steps to unroll the RNN for learning\_rate = 1e-1 with = np.random.rando(hidden size, vocab size)\*8.81 # input to hidden Whh = np.random.randn(hidden\_size, hidden\_size)\*8.81 # hidden to hidden why = np.random.randn(vocab\_size, hidden\_size)\*0.01 # hidden to output by = np.zeros((vocab\_size, 1)) # output bias def lossFun(inputs, targets, hprev): inputs, targets are both list of integers. returns the loss, gradients on model parameters, and last hidden state xs, hs, ys, ps = {}, {}, {}, {} hs[-1] = np.copy(hprev) for t in xrange(len(inputs)) xs[t] = np.zeros((vocab\_size,1)) # encode in 1-of-k representation hs[t] = np.tanh(np.dot(wxh, xs[t]) + np.dot(whh, hs[t-1]) + bh) # hidden statevs[t] = np.dot(why. hs[t]) + by = uncormalized log probabilities for next charps[t] = np.exp(ys[t]) / np.sum(np.exp(ys[t])) + probabilities for next charsloss += -mp.log(ps[t][targets[t],0]) # softmax (cross-entropy loss) dbh, dby = np.zeros\_like(bh), np.zeros\_like(by) dhnext = np.zeros like(hs[p]) dy = np.copy(ps[t]) dwhy += np.dot(dy, hs[t].T) dh = np.dot(why.T. dy) + dhnext # backgrop into h dhraw = (1 - hs[t] \* hs[t]) \* dh # backprop through tanh nonlinearity dwh += nn.dot(dbraw, xs[t].T) dwhh += np.dot(dhraw, hs[t-1].T) dhnext = np.dot(Whh.T, dhraw) for doaram in [dwxh, dwhh, dwhy, dbh, dby]; np.clip(dparam, -5, 5, out=dparam) =

```
sample a sequence of integers from the model
  h is memory state, seed_ix is seed letter for first time step
 x = np.zeros((vocab_size, 1))
  x[seed_ix] = 1
   h = np.tanh(np.dot(wxh, x) + np.dot(whh, h) + bh)
    y = np.dot(Why, h) + by
p = np.exp(y) / np.sum(np.exp(y))
    ix = nn.random.choice(range(yncah size), ncn.rayel())
   x = np.zeros((vocab_size, 1))
x[ix] = 1
    ixes.append(ix)
  return ixes
 maxh, mihh, mihy = np.zeros_like(wxh), np.zeros_like(whh), np.zeros_like(why)
mbh. mby = no zeros like(bb), no zeros like(by) a memory variables for adaptas
   mooth_loss = -mp.log(1.0/vocab_size)*seq_length = loss at iteration 0
while True:
    hprey = np.zeros((hidden.size, 1)) # reset MNN memory
   inputs = [char_to_ix[ch] for ch in data[p:p-seq_length]]
  targets = [char_to_ix[ch] for ch in data[p+1:p+seq_length+1]]
   # sample from the model now and then
     sample_ix = sample(hprev, inputs[0], 200)
    txt = ''.join(ix to char(ix) for ix in sample ix)
    print '----\n %s \n----' % (txt, )
  loss, dich, dwh, dwhy, dbh, dby, hprev = lossFun(inputs, targets, hprev) smooth_loss = smooth_loss * 0.000 + loss * 0.001
  if n % 100 == 0; print 'iter %d, loss: %f' % (n, smooth_loss) # print progress
                                  [mich, mith, mity, mbh, mby]);
    param += -learning_rate * dparam / np.sqrt(mem + ie-8) # adagrad update
```

p += seq\_length # move data pointer

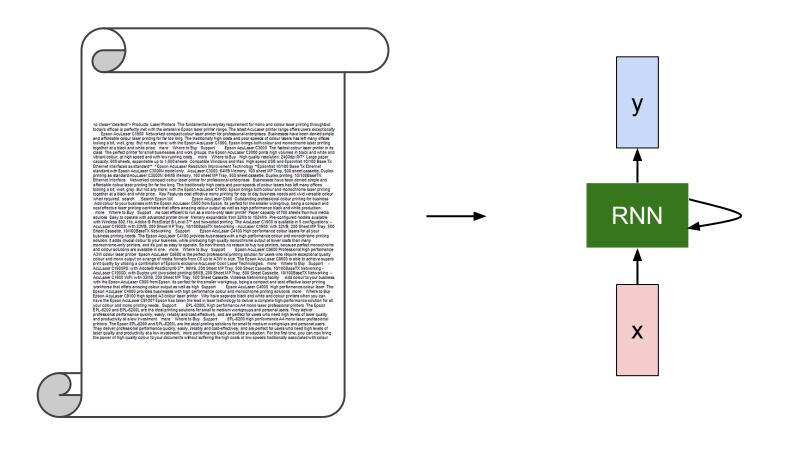
```
# backward pass: compute gradients going backwards
44
       dWxh, dWhh, dWhy = np.zeros_like(Wxh), np.zeros_like(Whh), np.zeros_like(Why)
45
       dbh, dby = np.zeros_like(bh), np.zeros_like(by)
46
       dhnext = np.zeros_like(hs[0])
47
       for t in reversed(xrange(len(inputs))):
48
         dy = np.copy(ps[t])
49
        dy[targets[t]] -= 1 # backprop into y
         dWhy += np.dot(dy, hs[t].T)
         dby += dy
         dh = np.dot(Why.T, dy) + dhnext # backprop into h
         dhraw = (1 - hs[t] * hs[t]) * dh # backprop through tanh nonlinearity
         dbh += dhraw
         dWxh += np.dot(dhraw, xs[t].T)
57
         dWhh += np.dot(dhraw, hs[t-1].T)
         dhnext = np.dot(Whh.T, dhraw)
       for dparam in [dWxh, dWhh, dWhy, dbh, dby]:
         np.clip(dparam, -5, 5, out=dparam) # clip to mitigate exploding gradients
60
       return loss, dWxh, dWhh, dWhy, dbh, dby, hs[len(inputs)-1]
61
```

## recall:



```
Minimal character-level vanilla RNN model. Written by Andrej Karpathy (@karpathy)
BSD License
import numpy as np
data = open('input.txt', 'r').read() # should be simple plain text file
data size, vocab size = len(data), len(chars)
print 'data has %d characters, %d unique.' % (data_size, vocab_size)
 char_to_ix = { ch:i for i,ch in enumerate(chars) }
ix_to_char = { i:ch for i,ch in enumerate(chars) }
hidden size = 100 # size of hidden layer of neurons
seq_length = 25 # number of steps to unroll the RNN for
wxh = np.random.randn(hidden_size, vocab_size)*0.01 # input to hidden
Whh = np.random.randn(hidden_size, hidden_size)*8.81 # hidden to hidden
why = np.random.randn(vocab_size, hidden_size)*0.01 # hidden to output
by = np.zeros((vocab_size, 1)) # output bias
def lossFun(inputs, targets, hprev):
 inputs, targets are both list of integers.
   hprev is Hx1 array of initial hidden state
  returns the loss, gradients on model parameters, and last hidden state
  xs, hs, ys, ps = {}, {}, {}, {}
  hs[-1] = np.copy(hprev)
  loss = 8
  for t in xrange(len(inputs)):
    xs[t] = np.zeros((vocab_size,1)) # encode in 1-of-k representation
    hs[t] = np.tanh(np.dot(wxh, xs[t]) + np.dot(whh, hs[t-1]) + bh) # hidden state
     vs[t] = np.dot(why. hs[t]) + by = unnormalized log probabilities for next char-
     ps[t] = np.exp(ys[t]) / np.sum(np.exp(ys[t])) + probabilities for next chars
     loss += -mp.log(ps[t][targets[t],0]) # softmax (cross-entropy loss)
   dwxh, dwhh, dwhy = np.zeros_like(wxh), np.zeros_like(whh), np.zeros_like(why)
   dbh, dby = np.zeros_like(bh), np.zeros_like(by)
   dhnext = np.zeros like(hs[p])
   for t in reversed(xrange(len(inputs))):
     dy = np.copy(ps[t])
     dyfragners[r]] .= 1 a backgross into y
     dwhy += np.dot(dy, hs[t].T)
     dh = np.dot(why.T. dy) + dhnext # backgrop into h
     dhraw = (i - hs[t] * hs[t]) * dh # backprop through tanh nonlinearity
     dbh += dhraw
    datch += nn_dot(dbraw, vs[t].T)
     dwhh += np.dot(dhraw, hs[t-1].T)
     dhnext = np.dot(whh.T, dhraw)
  for dparam in [dwxh, dwhh, dwhy, dbh, dby]:
    np.clip(dparam, -5, 5, out=dparam) # clip to mitigate exploding gradients
  return loss, dwxh, dwhh, dwhy, dbh, dby, hs[len(inputs)-1]
  sample a sequence of integers from the model h is memory state, seed_ix is seed letter for first time step
  x = np.zeros((vocab_size, 1))
  x[seed_ix] = 1
   h = np.tanh(np.dot(wxh, x) + np.dot(whh, h) + bh)
   y = np.dot(Why, h) + by
p = np.exp(y) / np.sum(np.exp(y))
   ixes.append(ix)
mixh, mikh, mikhy = np.zeros_like(wixh), np.zeros_like(whh), np.zeros_like(why)
with why a so zeros like(bh) on zeros like(by) a memory variables for adapta
  smooth_loss = -mp.log(1.0/voceb_size)*seq_length # loss at iteration 0
   horey = np.zeros((hidden_size, 1)) # reset NNN memory
  p = 0 s go from start of data
inputs = [char_to_ix[ch] for ch in data[p:p+seq_length]]
  targets = [char_to_ix[ch] for ch in data[p+1:p+seq_length+1]]
  # sample from the model now and then
    sample_ix = sample(hprev, inputs[0], 200)
   txt = ''.join(ix to char(ix) for ix in sample ix)
   print '----\n %s \n----' % (txt, )
 loss, dkch, dkh, dkh, dbh, dbh, hepev = loss:mufingutt, targets, hprev)
smooth_loss = smooth_loss * 0.990 + loss * 0.001
if n % 100 = 00 print 'iter %d, loss: %f % (n, smooth_loss) # print progress
                              [mich, mith, mity, mth, mby]);
   param += -learning_rate * dparam / sp.sqrt(mem + ie-8) # adagrad update
  p += seq_length # move data pointer
```

```
def sample(h, seed_ix, n):
64
       sample a sequence of integers from the model
       h is memory state, seed ix is seed letter for first time step
66
       11 11 11
      x = np.zeros((vocab_size, 1))
      x[seed_ix] = 1
69
       ixes = []
       for t in xrange(n):
         h = np.tanh(np.dot(Wxh, x) + np.dot(Whh, h) + bh)
         y = np.dot(Why, h) + by
74
         p = np.exp(y) / np.sum(np.exp(y))
         ix = np.random.choice(range(vocab_size), p=p.ravel())
76
         x = np.zeros((vocab_size, 1))
        x[ix] = 1
         ixes.append(ix)
       return ixes
```



#### Sonnet 116 - Let me not ...

by William Shakespeare

Let me not to the marriage of true minds
 Admit impediments. Love is not love

Which alters when it alteration finds,
 Or bends with the remover to remove:

O no! it is an ever-fixed mark
 That looks on tempests and is never shaken;

It is the star to every wandering bark,
 Whose worth's unknown, although his height be taken.

Love's not Time's fool, though rosy lips and cheeks
 Within his bending sickle's compass come:

Love alters not with his brief hours and weeks,
 But bears it out even to the edge of doom.

If this be error and upon me proved,
 I never writ, nor no man ever loved.

### at first:

tyntd-iafhatawiaoihrdemot lytdws e ,tfti, astai f ogoh eoase rrranbyne 'nhthnee e plia tklrgd t o idoe ns,smtt h ne etie h,hregtrs nigtike,aoaenns lng

#### train more

"Tmont thithey" fomesscerliund Keushey. Thom here sheulke, anmerenith ol sivh I lalterthend Bleipile shuwy fil on aseterlome coaniogennc Phe lism thond hon at. MeiDimorotion in ther thize."

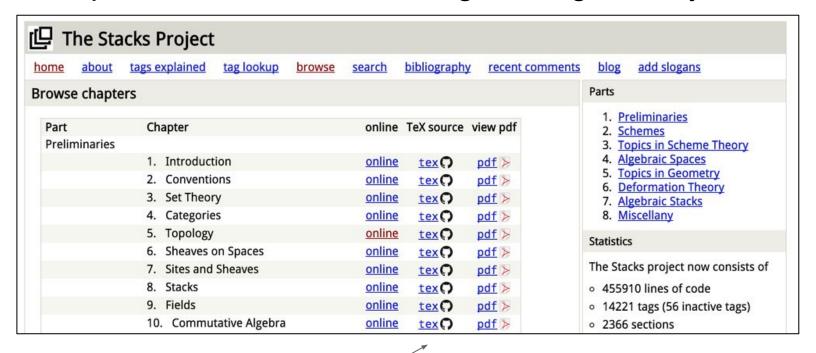
## train more

Aftair fall unsuch that the hall for Prince Velzonski's that me of her hearly, and behs to so arwage fiving were to it beloge, pavu say falling misfort how, and Gogition is so overelical and ofter.

### train more

"Why do what that day," replied Natasha, and wishing to himself the fact the princess, Princess Mary was easier, fed in had oftened him. Pierre aking his soul came to the packs and drove up his father-in-law women.

# open source textbook on algebraic geometry



Latex source

For  $\bigoplus_{n=1,...,m}$  where  $\mathcal{L}_{m_{\bullet}} = 0$ , hence we can find a closed subset  $\mathcal{H}$  in  $\mathcal{H}$  and any sets  $\mathcal{F}$  on X, U is a closed immersion of S, then  $U \to T$  is a separated algebraic space.

Proof. Proof of (1). It also start we get

$$S = \operatorname{Spec}(R) = U \times_X U \times_X U$$

and the comparison in the fibre product covering we have to prove the lemma generated by  $\coprod Z \times_U U \to V$ . Consider the maps M along the set of points  $Sch_{fppf}$  and  $U \to U$  is the fibre category of S in U in Section,  $\ref{School}$  and the fact that any U affine, see Morphisms, Lemma  $\ref{Morphisms}$ . Hence we obtain a scheme S and any open subset  $W \subset U$  in Sh(G) such that  $\operatorname{Spec}(R') \to S$  is smooth or an

$$U = \bigcup U_i \times_{S_i} U_i$$

which has a nonzero morphism we may assume that  $f_i$  is of finite presentation over S. We claim that  $\mathcal{O}_{X,x}$  is a scheme where  $x,x',s''\in S'$  such that  $\mathcal{O}_{X,x'}\to \mathcal{O}'_{X',x'}$  is separated. By Algebra, Lemma ?? we can define a map of complexes  $\mathrm{GL}_{S'}(x'/S'')$  and we win.

To prove study we see that  $\mathcal{F}|_U$  is a covering of  $\mathcal{X}'$ , and  $\mathcal{T}_i$  is an object of  $\mathcal{F}_{X/S}$  for i>0 and  $\mathcal{F}_p$  exists and let  $\mathcal{F}_i$  be a presheaf of  $\mathcal{O}_X$ -modules on  $\mathcal{C}$  as a  $\mathcal{F}$ -module. In particular  $\mathcal{F}=U/\mathcal{F}$  we have to show that

$$\widetilde{M}^{\bullet} = \mathcal{I}^{\bullet} \otimes_{\operatorname{Spec}(k)} \mathcal{O}_{S,s} - i_{X}^{-1} \mathcal{F})$$

is a unique morphism of algebraic stacks. Note that

Arrows = 
$$(Sch/S)_{fppf}^{opp}$$
,  $(Sch/S)_{fppf}$ 

and

$$V = \Gamma(S, \mathcal{O}) \longrightarrow (U, \operatorname{Spec}(A))$$

is an open subset of X. Thus U is affine. This is a continuous map of X is the inverse, the groupoid scheme S.

Proof. See discussion of sheaves of sets.

The result for prove any open covering follows from the less of Example ??. It may replace S by  $X_{spaces, \acute{e}tale}$  which gives an open subspace of X and T equal to  $S_{Zar}$ , see Descent, Lemma ??. Namely, by Lemma ?? we see that R is geometrically regular over S.

**Lemma 0.1.** Assume (3) and (3) by the construction in the description.

Suppose  $X = \lim |X|$  (by the formal open covering X and a single map  $\underline{Proj}_X(A) = \operatorname{Spec}(B)$  over U compatible with the complex

$$Set(A) = \Gamma(X, \mathcal{O}_{X, \mathcal{O}_X}).$$

When in this case of to show that  $Q \to C_{Z/X}$  is stable under the following result in the second conditions of (1), and (3). This finishes the proof. By Definition?? (without element is when the closed subschemes are catenary. If T is surjective we may assume that T is connected with residue fields of S. Moreover there exists a closed subspace  $Z \subset X$  of X where U in X' is proper (some defining as a closed subset of the uniqueness it suffices to check the fact that the following theorem

(1) f is locally of finite type. Since  $S = \operatorname{Spec}(R)$  and  $Y = \operatorname{Spec}(R)$ .

*Proof.* This is form all sheaves of sheaves on X. But given a scheme U and a surjective étale morphism  $U \to X$ . Let  $U \cap U = \coprod_{i=1,\dots,n} U_i$  be the scheme X over S at the schemes  $X_i \to X$  and  $U = \lim_i X_i$ .

The following lemma surjective restrocomposes of this implies that  $\mathcal{F}_{x_0} = \mathcal{F}_{x_0} = \mathcal{F}_{x_0,\dots,0}$ .

**Lemma 0.2.** Let X be a locally Noetherian scheme over S,  $E = \mathcal{F}_{X/S}$ . Set  $\mathcal{I} = \mathcal{J}_1 \subset \mathcal{I}'_n$ . Since  $\mathcal{I}^n \subset \mathcal{I}^n$  are nonzero over  $i_0 \leq \mathfrak{p}$  is a subset of  $\mathcal{J}_{n,0} \circ \overline{A}_2$  works.

**Lemma 0.3.** In Situation ??. Hence we may assume q' = 0.

*Proof.* We will use the property we see that  $\mathfrak p$  is the mext functor (??). On the other hand, by Lemma ?? we see that

$$D(\mathcal{O}_{X'}) = \mathcal{O}_X(D)$$

where K is an F-algebra where  $\delta_{n+1}$  is a scheme over S.

Proof. Omitted.

**Lemma 0.1.** Let C be a set of the construction.

Let C be a gerber covering. Let F be a quasi-coherent sheaves of O-modules. We have to show that

$$\mathcal{O}_{\mathcal{O}_X} = \mathcal{O}_X(\mathcal{L})$$

Proof. This is an algebraic space with the composition of sheaves  $\mathcal{F}$  on  $X_{\acute{e}tale}$  we have

$$\mathcal{O}_X(\mathcal{F}) = \{morph_1 \times_{\mathcal{O}_X} (\mathcal{G}, \mathcal{F})\}$$

where G defines an isomorphism  $F \to F$  of O-modules.

**Lemma 0.2.** This is an integer Z is injective.

Proof. See Spaces, Lemma ??.

**Lemma 0.3.** Let S be a scheme. Let X be a scheme and X is an affine open covering. Let  $\mathcal{U} \subset \mathcal{X}$  be a canonical and locally of finite type. Let X be a scheme. Let X be a scheme which is equal to the formal complex.

The following to the construction of the lemma follows.

Let X be a scheme. Let X be a scheme covering. Let

$$b: X \to Y' \to Y \to Y \to Y' \times_X Y \to X.$$

be a morphism of algebraic spaces over S and Y.

*Proof.* Let X be a nonzero scheme of X. Let X be an algebraic space. Let  $\mathcal{F}$  be a quasi-coherent sheaf of  $\mathcal{O}_X$ -modules. The following are equivalent

- F is an algebraic space over S.
- (2) If X is an affine open covering.

Consider a common structure on X and X the functor  $\mathcal{O}_X(U)$  which is locally of finite type.

This since  $\mathcal{F} \in \mathcal{F}$  and  $x \in \mathcal{G}$  the diagram

8 Feb 2016

gor.

 $Mor_{Sets}$   $d(\mathcal{O}_{X_{YB}}, \mathcal{G})$ 

is a limit. Then  $\mathcal G$  is a finite type and assume S is a flat and  $\mathcal F$  and  $\mathcal G$  is a finite type  $f_*$ . This is of finite type diagrams, and

the composition of G is a regular sequence,

 $\operatorname{Spec}(K_{\psi})$ 

O<sub>X'</sub> is a sheaf of rings.

*Proof.* We have see that  $X = \operatorname{Spec}(R)$  and  $\mathcal{F}$  is a finite type representable by algebraic space. The property  $\mathcal{F}$  is a finite morphism of algebraic stacks. Then the cohomology of X is an open neighbourhood of U.

*Proof.* This is clear that G is a finite presentation, see Lemmas ??.

Lecture 10 - 40

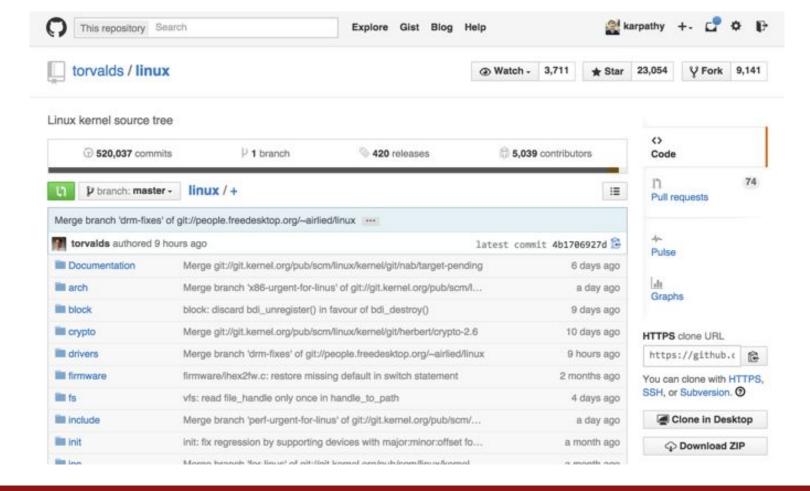
A reduced above we conclude that U is an open covering of C. The functor F is a "field

$$\mathcal{O}_{X,x} \longrightarrow \mathcal{F}_{\overline{x}} -1(\mathcal{O}_{X_{\ell tate}}) \longrightarrow \mathcal{O}_{X_{\ell}}^{-1}\mathcal{O}_{X_{\lambda}}(\mathcal{O}_{X_{n}}^{\overline{v}})$$

is an isomorphism of covering of  $\mathcal{O}_{X_{\ell}}$ . If  $\mathcal{F}$  is the unique element of  $\mathcal{F}$  such that Xis an isomorphism.

The property  $\mathcal{F}$  is a disjoint union of Proposition ?? and we can filtered set of presentations of a scheme  $\mathcal{O}_X$ -algebra with  $\mathcal{F}$  are opens of finite type over S. If  $\mathcal{F}$  is a scheme theoretic image points.

If  $\mathcal{F}$  is a finite direct sum  $\mathcal{O}_X$ , is a closed immersion, see Lemma ??. This is a sequence of  $\mathcal{F}$  is a similar morphism.



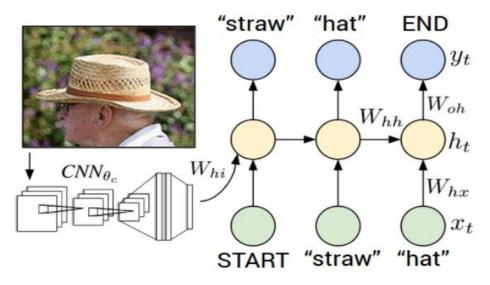
```
static void do command(struct seg file *m, void *v)
 int column = 32 << (cmd[2] & 0x80);
 if (state)
   cmd = (int)(int state ^ (in 8(&ch->ch flags) & Cmd) ? 2 : 1);
 else
   seq = 1;
 for (i = 0; i < 16; i++) {
   if (k & (1 << 1))
      pipe = (in use & UMXTHREAD UNCCA) +
        ((count & 0x0000000fffffff8) & 0x000000f) << 8;
   if (count == 0)
      sub(pid, ppc md.kexec handle, 0x20000000);
   pipe set bytes(i, 0);
 /* Free our user pages pointer to place camera if all dash */
 subsystem info = &of changes[PAGE SIZE];
 rek controls(offset, idx, &soffset);
 /* Now we want to deliberately put it to device */
 control check polarity(&context, val, 0);
 for (i = 0; i < COUNTER; i++)</pre>
   seq puts(s, "policy ");
```

# Generated C code

```
Copyright (c) 2006-2010, Intel Mobile Communications. All rights reserved.
    This program is free software; you can redistribute it and/or modify it
 * under the terms of the GNU General Public License version 2 as published by
 * the Free Software Foundation.
         This program is distributed in the hope that it will be useful,
 * but WITHOUT ANY WARRANTY; without even the implied warranty of
     MERCHANTABILITY or FITNESS FOR A PARTICULAR PURPOSE. See the
    GNU General Public License for more details.
    You should have received a copy of the GNU General Public License
     along with this program; if not, write to the Free Software Foundation,
  Inc., 675 Mass Ave, Cambridge, MA 02139, USA.
#include linux/kexec.h>
#include linux/errno.h>
#include ux/io.h>
#include linux/platform device.h>
#include linux/multi.h>
#include linux/ckevent.h>
#include <asm/io.h>
#include <asm/prom.h>
#include <asm/e820.h>
#include <asm/system info.h>
#include <asm/setew.h>
#include <asm/pgproto.h>
```

```
#include <asm/io.h>
#include <asm/prom.h>
#include <asm/e820.h>
#include <asm/system info.h>
#include <asm/setew.h>
#include <asm/pgproto.h>
#define REG PG vesa slot addr pack
#define PFM NOCOMP AFSR(0, load)
#define STACK DDR(type) (func)
#define SWAP ALLOCATE(nr)
                             (e)
#define emulate sigs() arch get unaligned child()
#define access rw(TST) asm volatile("movd %%esp, %0, %3" : : "r" (0)); \
 if ( type & DO READ)
static void stat PC SEC read mostly offsetof(struct seq argsqueue, \
          pC>[1]);
static void
os prefix(unsigned long sys)
#ifdef CONFIG PREEMPT
 PUT_PARAM_RAID(2, sel) = get_state_state();
  set_pid_sum((unsigned long)state, current_state_str(),
           (unsigned long)-1->lr full; low;
```

## Image Captioning



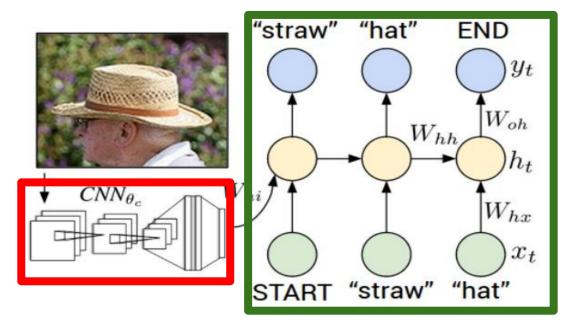
Explain Images with Multimodal Recurrent Neural Networks, Mao et al.

Deep Visual-Semantic Alignments for Generating Image Descriptions, Karpathy and Fei-Fei Show and Tell: A Neural Image Caption Generator, Vinyals et al.

Long-term Recurrent Convolutional Networks for Visual Recognition and Description, Donahue et al.

Learning a Recurrent Visual Representation for Image Caption Generation, Chen and Zitnick

#### **Recurrent Neural Network**



**Convolutional Neural Network** 



test image

image conv-64 conv-64 maxpool conv-128 conv-128 maxpool conv-256 conv-256 maxpool conv-512

conv-512 maxpool

conv-512 conv-512 maxpool

FC-4096 FC-4096 FC-1000 softmax





test image

image conv-64 conv-64 maxpool conv-128 conv-128 maxpool conv-256 conv-256 maxpool conv-512 conv-512 maxpool conv-512 conv-512 maxpool FC-4096 FC-4096 FC 1000 sof wax

## test image



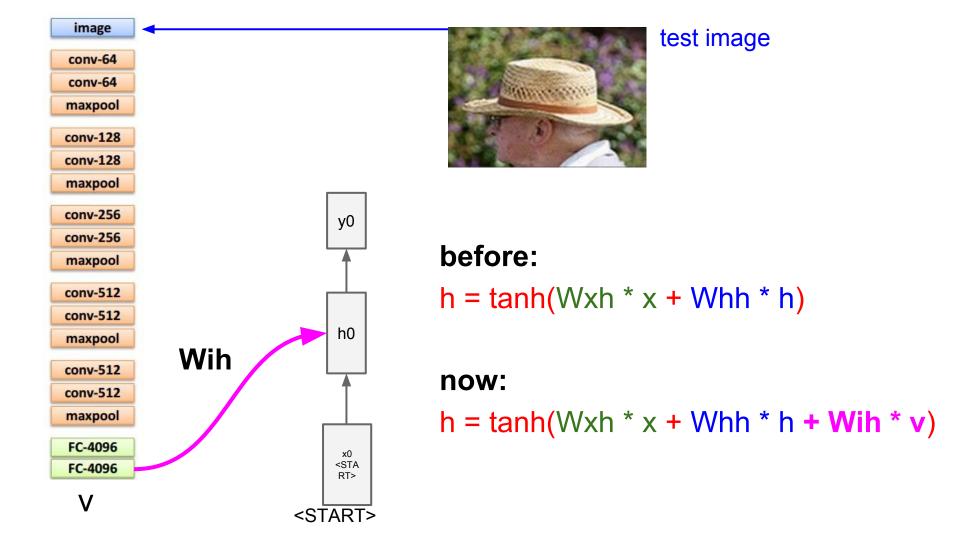
image conv-64 conv-64 maxpool conv-128 conv-128 maxpool conv-256 conv-256 maxpool conv-512 conv-512 maxpool conv-512 conv-512 maxpool FC-4096

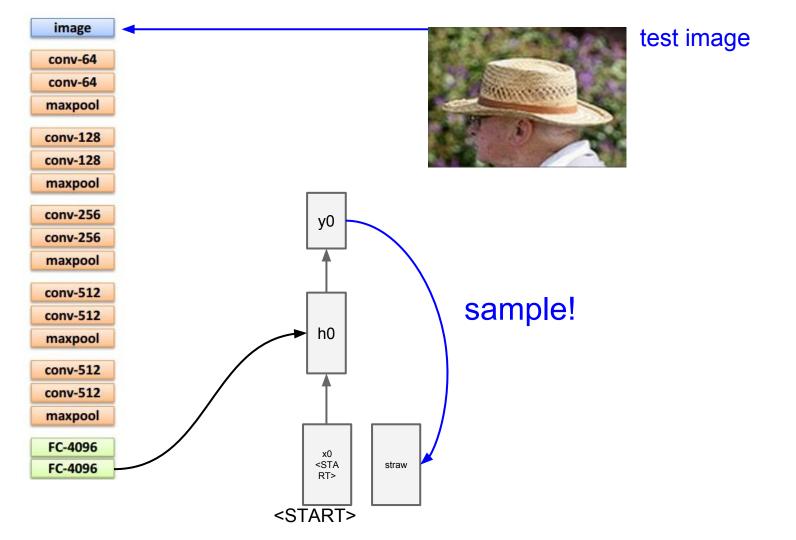
FC-4096

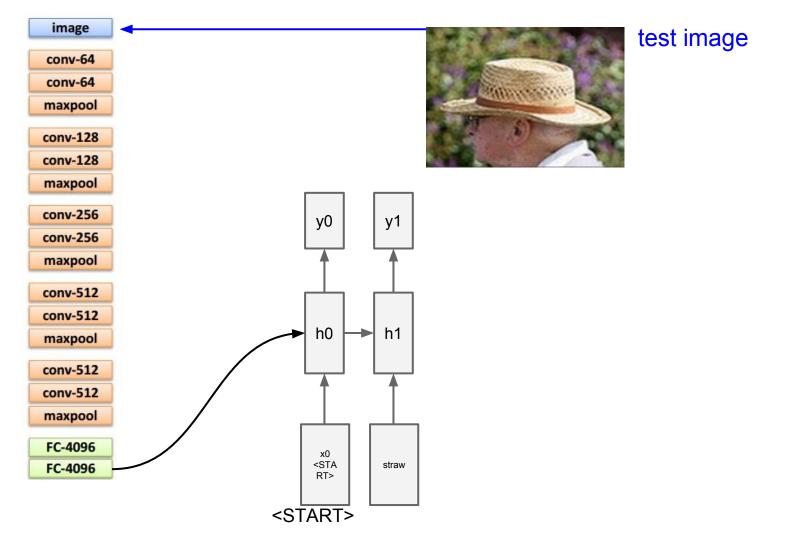


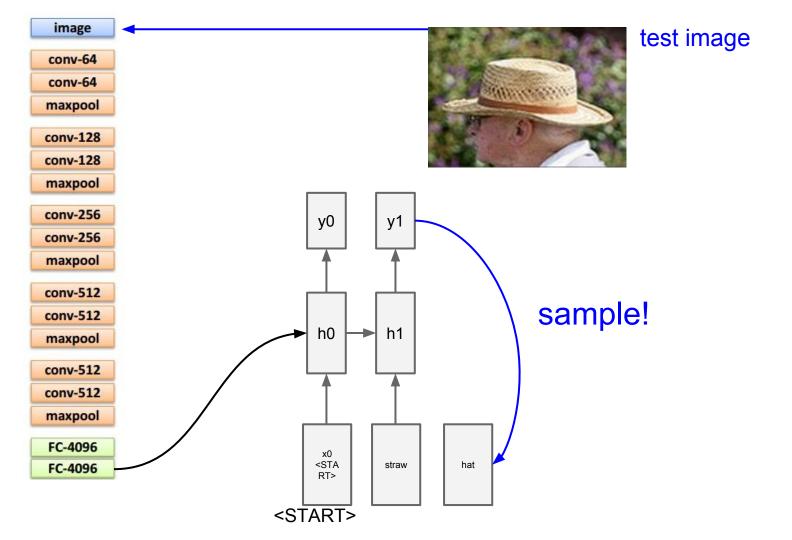
test image

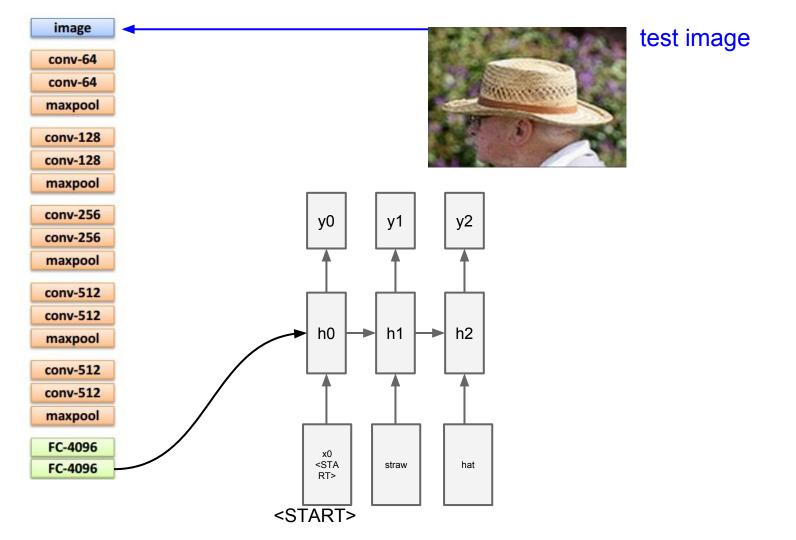


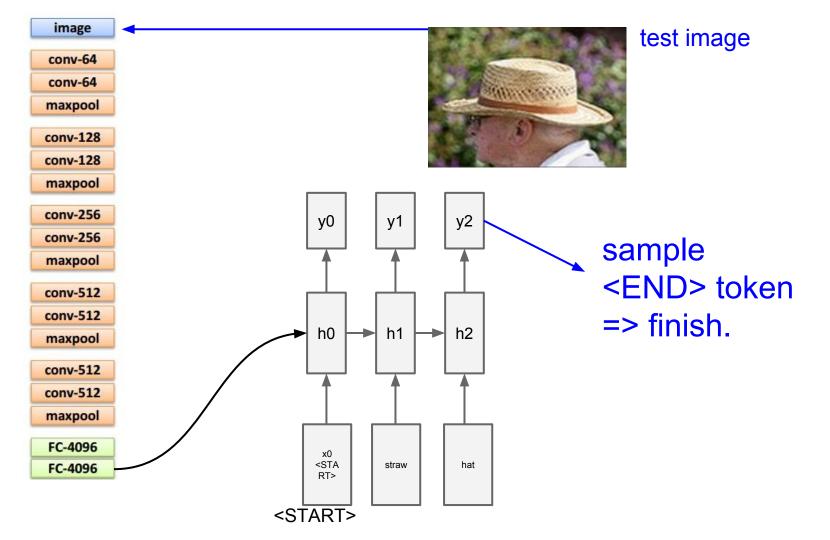












# Image Sentence Datasets

a man riding a bike on a dirt path through a forest. bicyclist raises his fist as he rides on desert dirt trail. this dirt bike rider is smiling and raising his fist in triumph. a man riding a bicycle while pumping his fist in the air. a mountain biker pumps his fist in celebration.



Microsoft COCO
[Tsung-Yi Lin et al. 2014]
mscoco.org

currently:

~120K images

~5 sentences each



"man in black shirt is playing guitar."



"construction worker in orange safety vest is working on road."



"two young girls are playing with lego toy."



"boy is doing backflip on wakeboard."



"man in black shirt is playing



"construction worker in orange safety vest is working on road."



"two young girls are playing with lego toy."



"boy is doing backflip on wakeboard."



"a young boy is holding a baseball bat."



"a cat is sitting on a couch with a remote control."



"a woman holding a teddy bear in front of a mirror."



"a horse is standing in the middle of a road."

