Foundations of Data Mining: Assignment 4

- Group: 20
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In [10]:

```
%matplotlib inline
from preamble import *
plt.rcParams['savefig.dpi'] = 100 # This controls the size of your figures
# Comment out and restart notebook if you only want the last output of each cell.
InteractiveShell.ast_node_interactivity = "all"
```

Backpropagation (3 points)

Solution

- We choose Loss function:
  - $L(x, y; w) = \frac{1}{2}(o_\theta - y)^2$
- ϕ is ReLU=max(q,0) here
- Forward 1:

$$r = \phi(q_0) = \phi(w_0 x_0) = 1$$

$$o = \phi(q_1) = \phi(w_1 r) = 2$$

- Backward 1:

$$w_1 = w_1 - \alpha \frac{\partial L}{\partial w_1} = w_1 - \alpha \frac{\partial L}{\partial o}\frac{\partial o}{\partial q_1}\frac{\partial q_1}{\partial w_1} = w_1 - \alpha \cdot x_0(o - y_0) = 2 - 0.1 * 1 * 0 = 2$$

$$w_0 = w_0 - \alpha \frac{\partial L}{\partial w_0} = w_0 - \alpha \frac{\partial L}{\partial o}\frac{\partial o}{\partial w_0} = w_0 - 0 = 1$$

Since $o_\theta = y$ for first point, weights don't update.

- Forward 2:

$$r = \phi(q_0) = \phi(w_0 x_1) = 2$$

$$o = \phi(q_1) = \phi(w_1 r) = 4$$

- Backward 2:

$$\frac{\partial L}{\partial w_1} \qquad \frac{\partial L}{\partial o}\frac{\partial o}{\partial q_1}\frac{\partial q_1}{\partial w_1}$$

$$w_1 = w_1 - \alpha \cdots = w_1 - \alpha \cdots = w_1 - \alpha \cdot x_1(o - y_1) = 2 - 0.1 * 2 * 1 = 1.8$$

$$w_0 = w_0 - \alpha \frac{\partial L}{\partial w_1}\frac{\partial w_1}{\partial w_0} = w_0 - \alpha \frac{\partial L}{\partial q_1}\frac{\partial q_1}{\partial r}\frac{\partial r}{\partial q_0}\frac{\partial q_0}{\partial w_0} = w_0 - \alpha * x_1 * w_1(o - y_1) = 0.6$$

$o_\theta \neq y$ for second point, so weights update after backpropa.

Training Deep Models (3 points)

The model in the example code below performs poorly as its depth increases. Train this model on the MNIST digit detection task.

Examine its training performance by gradually increasing its depth:

- Set the depth to 1 hidden layer
- Set the depth to 2 hidden layers
- Set the depth to 3 hidden layers

Modify the model such that you improve its performance when its depth increases. Train the new model again for the different depths:

- Set the depth to 1 hidden layer
- Set the depth to 2 hidden layers
- Set the depth to 3 hidden layers

Submit an explanation for the limitation of the original model. Explain your modification. Submit your code and 6 plots (can be overlaid) for the training performance of both models with different depths.

In [11]:

```
# (You don't need to change this part of the code)
from __future__ import print_function
import numpy as np
np.random.seed(1234)

from keras.datasets import mnist
from keras.models import Sequential
from keras.layers.core import Dense, Dropout, Activation
from keras.optimizers import SGD
from keras.utils import np_utils


import matplotlib.pyplot as plt

batch_size = 128
nb_classes = 10
nb_epoch = 10
```

In [12]:

```
# (You don't need to change this part of the code)
# the data, shuffled and split between train and test sets
(X_train, y_train), (X_test, y_test) = mnist.load_data()

X_train = X_train.reshape(60000, 784)
X_test = X_test.reshape(10000, 784)
```

```
X_train = X_train.astype('float32')
X_test = X_test.astype('float32')
X_train /= 255
X_test /= 255
print(X_train.shape[0], 'train samples')
print(X_test.shape[0], 'test samples')

# convert class vectors to binary class matrices
Y_train = np_utils.to_categorical(y_train, nb_classes)
Y_test = np_utils.to_categorical(y_test, nb_classes)
```

```
60000 train samples
10000 test samples
```

In [13]:

```
# Use this parameter to change the depth of the model
number_hidden_layers = 3  # Number of hidden layers
```

In [4]:

```
def train_model(number_hidden_layers, activation):
    model = Sequential()
    model.add(Dense(512, input_shape=(784,), activation=activation))
    model.add(Dropout(0.2))

    while number_hidden_layers > 1:
        model.add(Dense(512))
        model.add(Activation(activation))
        model.add(Dropout(0.2))
        number_hidden_layers -= 1

    model.add(Dense(10))
    model.add(Activation('softmax'))
    model.summary()

    model.compile(loss='categorical_crossentropy',
                  optimizer=SGD(),
                  metrics=['accuracy'])

    history = model.fit(X_train, Y_train,
                        batch_size=batch_size, nb_epoch=nb_epoch,
                        verbose=0, validation_data=(X_test, Y_test))
    score = model.evaluate(X_test, Y_test, verbose=0)

    return score[0], score[1], history

def run_model(activation):
    for num_layer in [1, 2, 3]:
        test_score, test_accuracy, history =
train_model(num_layer,activation)
        print('Depth:', num_layer)
        print('Test score:', test_score)
        print('Test accuracy:', test_accuracy)

        plt.subplot(1, 3, num_layer)
        plt.plot(history.history['acc'])
        plt.plot(history.history['val_acc'])
        plt.title('model accuracy with depth: %d' % (num_layer))
        plt.ylabel('accuracy')
```

```
        plt.ylabel('accuracy')
        plt.xlabel('epoch')
        plt.legend(['train', 'test'], loc='upper left')
```

In [5]:

```
plt.figure(figsize=(12, 4))
plt.suptitle('Sigmoid Activation')
run_model('sigmoid')
plt.show()
```

Out[5]:

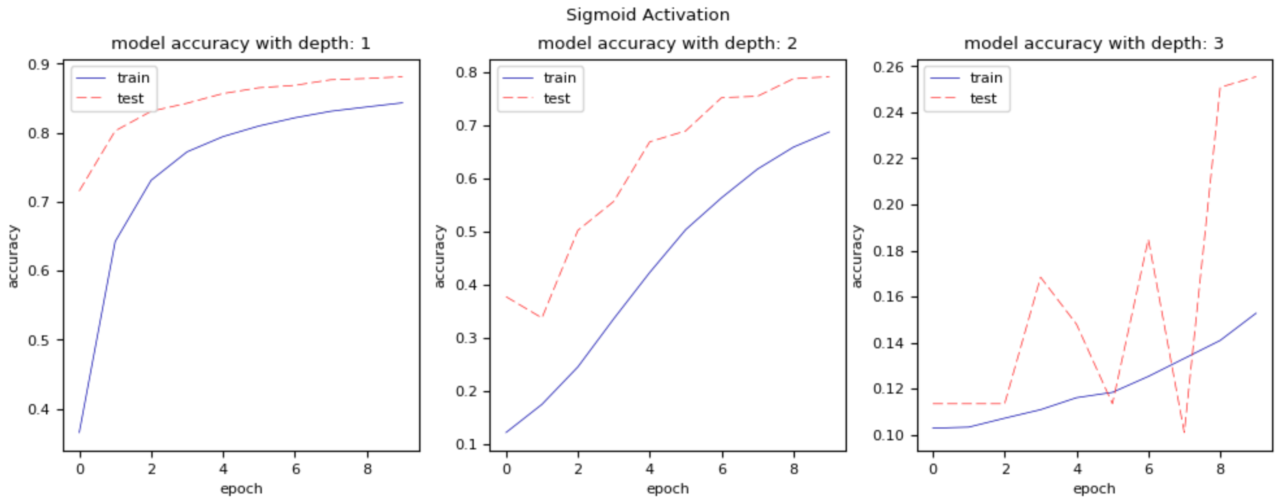
```
<matplotlib.figure.Figure at 0x116b693c8>
```

Out[5]:

```
<matplotlib.text.Text at 0x116b3f940>
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_1 (Dense)              (None, 512)               401920    
_________________________________________________________________
dropout_1 (Dropout)          (None, 512)               0         
_________________________________________________________________
dense_2 (Dense)              (None, 10)                5130      
_________________________________________________________________
activation_1 (Activation)    (None, 10)                0         
=================================================================
Total params: 407,050.0
Trainable params: 407,050.0
Non-trainable params: 0.0
_________________________________________________________________
Depth: 1
Test score: 0.466248050857
Test accuracy: 0.8811
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_3 (Dense)              (None, 512)               401920    
_________________________________________________________________
dropout_2 (Dropout)          (None, 512)               0         
_________________________________________________________________
dense_4 (Dense)              (None, 512)               262656    
_________________________________________________________________
activation_2 (Activation)    (None, 512)               0         
_________________________________________________________________
dropout_3 (Dropout)          (None, 512)               0         
_________________________________________________________________
dense_5 (Dense)              (None, 10)                5130      
_________________________________________________________________
activation_3 (Activation)    (None, 10)                0         
=================================================================
Total params: 669,706.0
Trainable params: 669,706.0
Non-trainable params: 0.0
_________________________________________________________________
Depth: 2
Test score: 0.869930342674
Test accuracy: 0.7908
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
```

```
Layer (type)                 Output Shape              Param #
=================================================================
dense_6 (Dense)              (None, 512)               401920
_________________________________________________________________
dropout_4 (Dropout)          (None, 512)               0
_________________________________________________________________
dense_7 (Dense)              (None, 512)               262656
_________________________________________________________________
activation_4 (Activation)    (None, 512)               0
_________________________________________________________________
dropout_5 (Dropout)          (None, 512)               0
_________________________________________________________________
dense_8 (Dense)              (None, 512)               262656
_________________________________________________________________
activation_5 (Activation)    (None, 512)               0
_________________________________________________________________
dropout_6 (Dropout)          (None, 512)               0
_________________________________________________________________
dense_9 (Dense)              (None, 10)                5130
_________________________________________________________________
activation_6 (Activation)    (None, 10)                0
=================================================================
Total params: 932,362.0
Trainable params: 932,362.0
Non-trainable params: 0.0
_________________________________________________________________
Depth: 3
Test score: 2.23485740509
Test accuracy: 0.2554
```



In [20]:

```python
plt.figure(figsize=(12, 4))
plt.suptitle('ReLU Activation')
run_model('relu')
plt.show()
```

Out[20]:

```
<matplotlib.figure.Figure at 0x1316d2518>
```

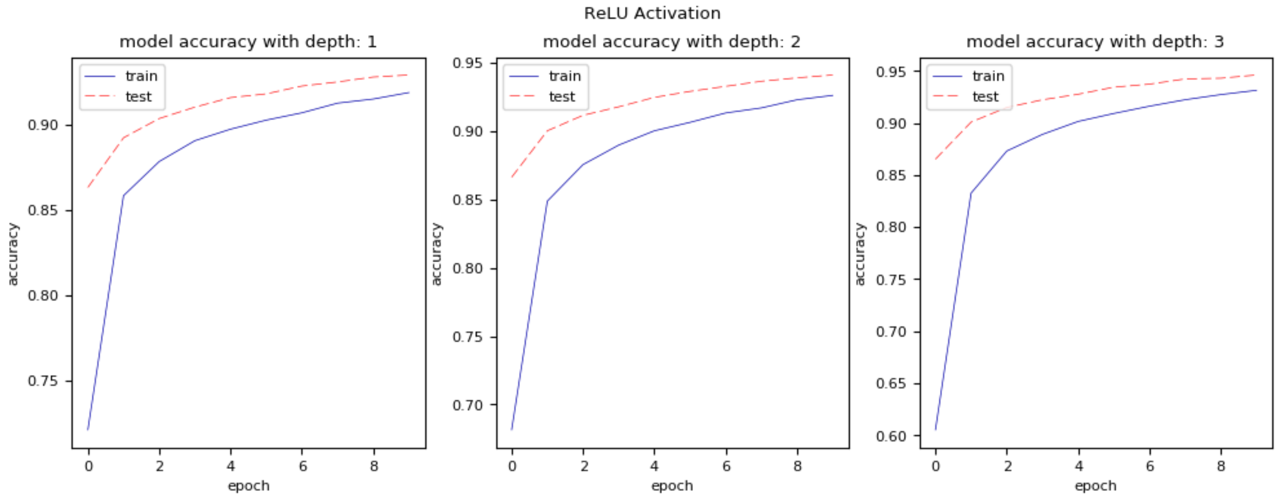
Out[20]:

```
<matplotlib.text.Text at 0x1316d2358>
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
```

```
=================================================================
dense_30 (Dense)             (None, 512)               401920
_________________________________________________________________
dropout_20 (Dropout)         (None, 512)               0
_________________________________________________________________
dense_31 (Dense)             (None, 10)                5130
_________________________________________________________________
activation_20 (Activation)   (None, 10)                0
=================================================================
Total params: 407,050.0
Trainable params: 407,050.0
Non-trainable params: 0.0
_________________________________________________________________
Depth: 1
Test score: 0.256563024029
Test accuracy: 0.9293
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_32 (Dense)             (None, 512)               401920
_________________________________________________________________
dropout_21 (Dropout)         (None, 512)               0
_________________________________________________________________
dense_33 (Dense)             (None, 512)               262656
_________________________________________________________________
activation_21 (Activation)   (None, 512)               0
_________________________________________________________________
dropout_22 (Dropout)         (None, 512)               0
_________________________________________________________________
dense_34 (Dense)             (None, 10)                5130
_________________________________________________________________
activation_22 (Activation)   (None, 10)                0
=================================================================
Total params: 669,706.0
Trainable params: 669,706.0
Non-trainable params: 0.0
_________________________________________________________________
Depth: 2
Test score: 0.207567299627
Test accuracy: 0.941
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_35 (Dense)             (None, 512)               401920
_________________________________________________________________
dropout_23 (Dropout)         (None, 512)               0
_________________________________________________________________
dense_36 (Dense)             (None, 512)               262656
_________________________________________________________________
activation_23 (Activation)   (None, 512)               0
_________________________________________________________________
dropout_24 (Dropout)         (None, 512)               0
_________________________________________________________________
dense_37 (Dense)             (None, 512)               262656
_________________________________________________________________
activation_24 (Activation)   (None, 512)               0
_________________________________________________________________
dropout_25 (Dropout)         (None, 512)               0
_________________________________________________________________
dense_38 (Dense)             (None, 10)                5130
```

```
________________________________________________________________
activation_25 (Activation)    (None, 10)                0
================================================================
Total params: 932,362.0
Trainable params: 932,362.0
Non-trainable params: 0.0
________________________________________________________________
Depth: 3
Test score: 0.180363421577
Test accuracy: 0.946
```



Solution

We can conclude from figures above that changing the activation 'sigmoid' to 'ReLU' can modify the results a lot.

Sigmoid activation function is $\frac{1}{1+e^{-w^T x}}$, so the gradient calculation of it would be complex. Although it seems good when number of hidden_layer is 1 but when we add more layers, the gradient would vanish or explode thus makes little or too heavy contribution to the network and result in low and unstable accuracy.

On the contrary, the ReLU is a max function: max{0,x}, so we only have gradient 0 or 1, which is simple to computate. And without the gradient vanishing and exploding problems, the accuracy will be higher with the number of layers increasing.

Convolutional Neural Networks for Filtering (2 points)

Solution

We define the number of layer as 3. Which includes the input layer, the sepia combine Gaussian blurring layer and the output layer.

The image consists of 128×128 pixels. The color of each point is defined by a 3D vector, and the value of each axis of the vector represents the RGB value repectively. The middle layer is achieved by a $3 \times Conv. \times 5 \times 5 \times 3$ convolution. The neuron computes the RGB values respectively with both sepia effect and Gaussian blurring effect.

As a discretized version of the filter is given, which can be represent by a matrix like below:

$$Gus = 1/273 \times \begin{bmatrix} 1 & 4 & 7 & 4 & 1 \\ 4 & 16 & 26 & 16 & 4 \\ 7 & 26 & 41 & 26 & 7 \\ 4 & 16 & 26 & 16 & 4 \\ 1 & 4 & 7 & 4 & 1 \end{bmatrix}$$

Below shows how to apply both effects to the R value:

$R'(i,j) = \sum_{m=1}^{5}\sum_{n=1}^{5}((R_{(i+m-1,j+n-1)} * .393) + (G_{(i+m-1,j+n-1)} * .769) + (B_{(i+m-1,j+n-1)} * .189)) \times Gus(m,$
i, j is from 1 to 124.

Do the similar steps to G and B values. we can get an output image of size $124 \times 124 \times 3$.

$G'(i,j) = \sum_{m=1}^{5}\sum_{n=1}^{5}((R_{(i+m-1,j+n-1)} * .349) + (G_{(i+m-1,j+n-1)} * .686) + (B_{(i+m-1,j+n-1)} * .168)) \times Gus(m,$
i, j is from 1 to 124.

$B'(i,j) = \sum_{m=1}^{5}\sum_{n=1}^{5}((R_{(i+m-1,j+n-1)} * .272) + (G_{(i+m-1,j+n-1)} * .534) + (B_{(i+m-1,j+n-1)} * .131)) \times Gus(m,$
i, j is from 1 to 124.

- The definition of the architecture of the CNN:
  - Number of the layers: The number of layers is 3, which includes the input layer, the middle layer and output layer.
  - Number of filters of middle layer is 3
  - Shape of filter : $5 \times 5 \times 3$
- Padding size: 0, Stride: 1
- Dimension of the output image: $124 \times 124 \times 3$

Model Design (2 Points)

Solution

Our model consists of a vision CNN followed by a language generating RNN. Inspired by paper [Show and Tell: A Neural Image Caption Generator], we learnt that the natural way to do image captioning is using a CNN as an image “encoder”, by first pre-training it for an image classification task and using the last hidden layer as an input to the RNN decoder that generates sentences. Which we could refer, as the task is to learn a short caption for a video clip.

So the idea here is based on that the contents of frames in a short video clip may not differ a lot, then we could learn common objects or even motion and generate a caption for this bunch of pictures. Thus we combine the captions of images by CNN encoder and use them as the input of RNN decoder to generate a whole sentence for the video clip. We identify the most likely discription for a video is by maximizing the probability

$$\log p(S|V) = \sum_{t=0}^{N} log p(S_t|V, S_0, \ldots, S_{t-1})$$

Thus, the sentence is learnt by an input video and the words learnt sequentially before.

To avoid overfitting we use dropout to regularize the model. With each state h_t decided by h_{t-1} and h_t^{l-1}, where t represents the time and l represents the layer, we choose to apply dropout on h_t^{l-1} part, which refered from RECURRENT NEURAL NETWORK REGULARIZATION.

- Input data format: a short video clip consisting several frames.
- Number of layers: 4
- Type of layer: Input layer (3D), Convolutional layer (3D), Recurrent layer (2 LSTM layers each is 1D), and Output layer (1D vector).
- Regularization: dropout
- loss function: cross entropy

MNIST Calculator (5 points)

In [35]:

```
from __future__ import print_function
from keras.models import Sequential
from keras.engine.training import _slice_arrays
from keras.layers import Activation, TimeDistributed, Dense, RepeatVector,
recurrent
import numpy as np
from six.moves import range
from keras.datasets import mnist
from keras.layers import Dense, Dropout, Flatten
from keras.layers import Conv2D, MaxPooling2D
from keras import backend as K


DIGITS = 3
MAXLEN = DIGITS + 1 + DIGITS
chars = '0123456789+ '
RNN = recurrent.LSTM
HIDDEN_SIZE = 256
BATCH_SIZE = 512
LAYERS = 2
TRAINING_SIZE = 50000

class CharacterTable(object):
    def __init__(self, chars, maxlen):
        self.chars = sorted(set(chars))
        self.char_indices = dict((c, i) for i, c in enumerate(self.chars))
        self.indices_char = dict((i, c) for i, c in enumerate(self.chars))
        self.maxlen = maxlen

    def encode(self, C, maxlen=None):
        maxlen = maxlen if maxlen else self.maxlen
        X = np.zeros((maxlen, len(self.chars)))
        for i, c in enumerate(C):
            X[i, self.char_indices[c]] = 1
        return X

    def decode(self, X, calc_argmax=True):
        if calc_argmax:
            X = X.argmax(axis=-1)
        return ''.join(self.indices_char[x] for x in X)

class colors:
```

```
    ok = '\033[92m'
    fail = '\033[91m'
    close = '\033[0m'
```

In [36]:

```
ctable = CharacterTable(chars, MAXLEN)
```

In [37]:

```
img_rows = img_cols = 28

(x_train, y_train), (x_test, y_test) = mnist.load_data()

if K.image_data_format() == 'channels_first':
    x_train = x_train.reshape(x_train.shape[0], 1, img_rows, img_cols)
    x_test = x_test.reshape(x_test.shape[0], 1, img_rows, img_cols)
    input_shape = (1, img_rows, img_cols)
else:
    x_train = x_train.reshape(x_train.shape[0], img_rows, img_cols, 1)
    x_test = x_test.reshape(x_test.shape[0], img_rows, img_cols, 1)
    input_shape = (img_rows, img_cols, 1)
y_train1 = y_train
```

In [40]:

```
def random_question():
    f = lambda: int(''.join(np.random.choice(list('0123456789')) for i in ra
nge(np.random.randint(1, DIGITS + 1))))
    a, b = f(), f()

    query = '{}+{}'.format(a, b)
    ans = str(a + b)

    query += ' ' * (MAXLEN - len(query))
    ans += ' ' * (DIGITS + 1 - len(ans))

    return query, ans

def encode_question(question, output=None):
    if output is None:
        i = 0
        output = np.zeros([1, MAXLEN] + list(input_shape), dtype=x_train.dty
pe)
        for j, char in enumerate(question):
            if char in '0123456789':
                orin = None
                while orin is None:
                    num = np.random.choice(y_train1.shape[0])
                    if y_train1[num] == int(char):
                        orin = x_train[num]
            else:
                orin = 255 * np.random.random(input_shape)

            output[i,j] = orin
    else:
        for j, char in enumerate(question):
            if char in '0123456789':
                orin = None
                while orin is None:
```

```
                    num = np.random.choice(y_train1.shape[0])
                    if y_train1[num] == int(char):
                        orin = x_train[num]
            else:
                orin = 255 * np.random.random(input_shape)

            output[j] = orin
    return output
```

In [41]:

```
X = np.zeros([TRAINING_SIZE, MAXLEN] + list(input_shape), dtype=x_train.dty
pe)
y = np.zeros((TRAINING_SIZE, DIGITS + 1, len(chars)), dtype=np.bool)


for i in range(TRAINING_SIZE):
    question, answer = random_question()
    y[i] = ctable.encode(answer, maxlen=DIGITS + 1)
    X[i] = encode_question(question, X[i])

# Shuffle (X, y) in unison as the later parts of X will almost all be large
r digits
indices = np.arange(len(y))
np.random.shuffle(indices)
X = X[indices]
y = y[indices]

split_at = int(X.shape[0] * 0.9)
(X_train, X_val) = (_slice_arrays(X, 0, split_at), _slice_arrays(X, split_at
))
(y_train, y_val) = (y[:split_at], y[split_at:])
```

In [42]:

```
model = Sequential()
model.add(TimeDistributed(Conv2D(32, kernel_size=(5, 5),
                 activation='relu',strides=(3,3)),
                 input_shape=X_train.shape[1:]))
model.add(TimeDistributed(MaxPooling2D(pool_size=(2, 2))))
model.add(Dropout(0.25))
model.add(TimeDistributed(Conv2D(64, (3, 3), activation='relu',strides=(1,1)
)))
model.add(TimeDistributed(MaxPooling2D(pool_size=(2, 2))))
model.add(Dropout(0.5))
model.add(TimeDistributed(Flatten()))
model.add(TimeDistributed(Dense(128, activation='relu')))

model.add(RNN(HIDDEN_SIZE))
model.add(RepeatVector(DIGITS + 1))
for _ in range(LAYERS):
    model.add(RNN(HIDDEN_SIZE, return_sequences=True))

# For each of step of the output sequence, decide which character should be
chosen
model.add(TimeDistributed(Dense(len(chars))))
model.add(Activation('softmax'))

model.compile(loss='categorical_crossentropy',
```

```
                  optimizer='adam',
                  metrics=['accuracy'])
```

In [43]:

```
for iteration in range(1, 10):
    print()
    print('-' * 50)
    print('Iteration', iteration)
    model.fit(X_train, y_train, validation_data=(X_val, y_val),
              batch_size=BATCH_SIZE, epochs=5, verbose=2)

    for i in range(10):
        question, answer = random_question()
        out = encode_question(question)
        preds = model.predict_classes(out, verbose=0)
        guess = ctable.decode(preds[0], calc_argmax=False)
        print('Q', question)
        print('T', answer)
        print(colors.ok + '☑' + colors.close if answer == guess else colors.
fail + '☒' + colors.close, guess)
        print('---')
```

```
--------------------------------------------------
Iteration 1
Train on 45000 samples, validate on 5000 samples
Epoch 1/5
111s - loss: 1.7623 - acc: 0.4094 - val_loss: 1.5621 - val_acc: 0.4361
Epoch 2/5
108s - loss: 1.5418 - acc: 0.4505 - val_loss: 1.5156 - val_acc: 0.4544
Epoch 3/5
113s - loss: 1.5180 - acc: 0.4525 - val_loss: 1.4950 - val_acc: 0.4581
Epoch 4/5
114s - loss: 1.5008 - acc: 0.4571 - val_loss: 1.4631 - val_acc: 0.4666
Epoch 5/5
117s - loss: 1.4619 - acc: 0.4663 - val_loss: 1.3843 - val_acc: 0.4885
```

Out[43]:

```
<keras.callbacks.History at 0x144953550>
```

```
Q 8+9
T 17
☒ 13
---
Q 2+69
T 71
☒ 68
---
Q 500+53
T 553
☒ 558
---
Q 9+4
T 13
☒ 15
---
Q 778+77
T 855
☒ 908
---
```

```
Q 114+877
T 991
☒ 111
---
Q 99+12
T 111
☒ 12
---
Q 6+4
T 10
☒ 1
---
Q 5+995
T 1000
☒ 908
---
Q 2+4
T 6
☒ 1
---

--------------------------------------------------
Iteration 2
Train on 45000 samples, validate on 5000 samples
Epoch 1/5
112s - loss: 1.3808 - acc: 0.4906 - val_loss: 1.2925 - val_acc: 0.5095
Epoch 2/5
109s - loss: 1.3092 - acc: 0.5132 - val_loss: 1.1946 - val_acc: 0.5571
Epoch 3/5
109s - loss: 1.1999 - acc: 0.5530 - val_loss: 1.0114 - val_acc: 0.6270
Epoch 4/5
108s - loss: 1.0816 - acc: 0.6063 - val_loss: 0.8796 - val_acc: 0.6932
Epoch 5/5
109s - loss: 0.9815 - acc: 0.6535 - val_loss: 0.7769 - val_acc: 0.7422
```

Out[43]:

```
<keras.callbacks.History at 0x14544d710>
```

```
Q 36+5
T 41
☒ 50
---
Q 952+69
T 1021
☒ 1011
---
Q 104+4
T 108
☒ 118
---
Q 412+423
T 835
☒ 645
---
Q 29+7
T 36
☑ 36
---
Q 0+48
T 48
```

```
☒ 58
---
Q 6+8
T 14
☑ 14
---
Q 534+0
T 534
☒ 434
---
Q 2+40
T 42
☑ 42
---
Q 98+12
T 110
☒ 100
---

--------------------------------------------------
Iteration 3
Train on 45000 samples, validate on 5000 samples
Epoch 1/5
113s - loss: 0.8899 - acc: 0.7014 - val_loss: 0.6701 - val_acc: 0.7941
Epoch 2/5
757s - loss: 0.7994 - acc: 0.7408 - val_loss: 0.5679 - val_acc: 0.8357
Epoch 3/5
113s - loss: 0.7312 - acc: 0.7680 - val_loss: 0.5123 - val_acc: 0.8515
Epoch 4/5
115s - loss: 0.6747 - acc: 0.7899 - val_loss: 0.4494 - val_acc: 0.8702
Epoch 5/5
114s - loss: 0.6237 - acc: 0.8073 - val_loss: 0.4324 - val_acc: 0.8698
```

Out[43]:

```
<keras.callbacks.History at 0x14548c668>
```

```
Q 18+53
T 71
☑ 71
---
Q 82+78
T 160
☑ 160
---
Q 11+2
T 13
☑ 13
---
Q 435+69
T 504
☒ 404
---
Q 2+1
T 3
☒ 2
---
Q 73+2
T 75
☑ 75
---
```

```
Q 48+794
T 842
☒ 830
---
Q 31+11
T 42
☑ 42
---
Q 169+543
T 712
☒ 8022
---
Q 943+392
T 1335
☒ 1315
---

--------------------------------------------------
Iteration 4
Train on 45000 samples, validate on 5000 samples
Epoch 1/5
115s - loss: 0.5910 - acc: 0.8202 - val_loss: 0.3852 - val_acc: 0.8902
Epoch 2/5
117s - loss: 0.5602 - acc: 0.8309 - val_loss: 0.3631 - val_acc: 0.8930
Epoch 3/5
121s - loss: 0.5280 - acc: 0.8418 - val_loss: 0.3308 - val_acc: 0.9056
Epoch 4/5
125s - loss: 0.5058 - acc: 0.8493 - val_loss: 0.3167 - val_acc: 0.9117
Epoch 5/5
126s - loss: 0.4895 - acc: 0.8552 - val_loss: 0.3136 - val_acc: 0.9130
```

Out[43]:

```
<keras.callbacks.History at 0x14548c710>
```

```
Q 8+20
T 28
☑ 28
---
Q 266+493
T 759
☒ 749
---
Q 478+66
T 544
☑ 544
---
Q 3+763
T 766
☑ 766
---
Q 932+74
T 1006
☒ 100
---
Q 73+15
T 88
☑ 88
---
Q 97+187
T 284
☒ 254
```

```
---
Q 4+648
T 652
☑ 652
---
Q 50+611
T 661
☑ 661
---
Q 991+9
T 1000
☑ 1000
---

--------------------------------------------------
Iteration 5
Train on 45000 samples, validate on 5000 samples
Epoch 1/5
119s - loss: 0.4715 - acc: 0.8621 - val_loss: 0.2944 - val_acc: 0.9171
Epoch 2/5
117s - loss: 0.4613 - acc: 0.8655 - val_loss: 0.2739 - val_acc: 0.9216
Epoch 3/5
115s - loss: 0.4422 - acc: 0.8712 - val_loss: 0.2785 - val_acc: 0.9203
Epoch 4/5
117s - loss: 0.4322 - acc: 0.8744 - val_loss: 0.2659 - val_acc: 0.9254
Epoch 5/5
116s - loss: 0.4224 - acc: 0.8777 - val_loss: 0.2678 - val_acc: 0.9277
```

Out[43]:

```
<keras.callbacks.History at 0x14490f908>
```

```
Q 53+626
T 679
☒ 678
---
Q 599+1
T 600
☑ 600
---
Q 5+3
T 8
☑ 8
---
Q 25+956
T 981
☑ 981
---
Q 7+78
T 85
☑ 85
---
Q 44+90
T 134
☒ 14
---
Q 381+55
T 436
☑ 436
---
Q 15+91
```

```
T 106
☑ 106
---
Q 0+91
T 91
☑ 91
---
Q 7+6
T 13
☑ 13
---

--------------------------------------------------
Iteration 6
Train on 45000 samples, validate on 5000 samples
Epoch 1/5
118s - loss: 0.4133 - acc: 0.8814 - val_loss: 0.2539 - val_acc: 0.9301
Epoch 2/5
120s - loss: 0.4051 - acc: 0.8837 - val_loss: 0.2462 - val_acc: 0.9310
Epoch 3/5
116s - loss: 0.3953 - acc: 0.8873 - val_loss: 0.2383 - val_acc: 0.9353
Epoch 4/5
117s - loss: 0.3881 - acc: 0.8892 - val_loss: 0.2441 - val_acc: 0.9331
Epoch 5/5
125s - loss: 0.3840 - acc: 0.8902 - val_loss: 0.2290 - val_acc: 0.9357
```

Out[43]:

```
<keras.callbacks.History at 0x13c6ba320>
```

```
Q 12+587
T 599
☒ 699
---
Q 3+8
T 11
☑ 11
---
Q 934+794
T 1728
☑ 1728
---
Q 0+7
T 7
☑ 7
---
Q 1+6
T 7
☑ 7
---
Q 50+54
T 104
☑ 104
---
Q 42+922
T 964
☑ 964
---
Q 719+59
T 778
☑ 778
```

```
---
Q 377+155
T 532
☒ 432
---
Q 78+5
T 83
☒ 13
---

--------------------------------------------------
Iteration 7
Train on 45000 samples, validate on 5000 samples
Epoch 1/5
119s - loss: 0.3750 - acc: 0.8936 - val_loss: 0.2273 - val_acc: 0.9394
Epoch 2/5
117s - loss: 0.3733 - acc: 0.8946 - val_loss: 0.2287 - val_acc: 0.9368
Epoch 3/5
115s - loss: 0.3637 - acc: 0.8969 - val_loss: 0.2147 - val_acc: 0.9407
Epoch 4/5
115s - loss: 0.3568 - acc: 0.8993 - val_loss: 0.2130 - val_acc: 0.9438
Epoch 5/5
115s - loss: 0.3544 - acc: 0.8995 - val_loss: 0.2221 - val_acc: 0.9406
```

Out[43]:

```
<keras.callbacks.History at 0x14548ca58>
```

```
Q 6+7
T 13
☑ 13
---
Q 667+6
T 673
☑ 673
---
Q 787+17
T 804
☒ 704
---
Q 8+62
T 70
☑ 70
---
Q 625+6
T 631
☑ 631
---
Q 35+0
T 35
☑ 35
---
Q 357+9
T 366
☒ 361
---
Q 86+748
T 834
☑ 834
---
Q 98+251
T 349
```

```
☑ 349
---
Q 3+300
T 303
☑ 303
---

--------------------------------------------------
Iteration 8
Train on 45000 samples, validate on 5000 samples
Epoch 1/5
119s - loss: 0.3478 - acc: 0.9019 - val_loss: 0.2143 - val_acc: 0.9437
Epoch 2/5
119s - loss: 0.3396 - acc: 0.9044 - val_loss: 0.2142 - val_acc: 0.9439
Epoch 3/5
126s - loss: 0.3418 - acc: 0.9032 - val_loss: 0.2033 - val_acc: 0.9456
Epoch 4/5
122s - loss: 0.3320 - acc: 0.9059 - val_loss: 0.2095 - val_acc: 0.9429
Epoch 5/5
117s - loss: 0.3329 - acc: 0.9050 - val_loss: 0.1952 - val_acc: 0.9467
```

Out[43]:

```
<keras.callbacks.History at 0x14548c5c0>
```

```
Q 55+8
T 63
☑ 63
---
Q 1+485
T 486
☑ 486
---
Q 578+53
T 631
☑ 631
---
Q 1+888
T 889
☑ 889
---
Q 18+308
T 326
☑ 326
---
Q 2+971
T 973
☑ 973
---
Q 927+55
T 982
☑ 982
---
Q 89+3
T 92
☒ 83
---
Q 995+80
T 1075
☒ 1065
---
```

```
Q 9+84
T 93
☑ 93
---

--------------------------------------------------
Iteration 9
Train on 45000 samples, validate on 5000 samples
Epoch 1/5
123s - loss: 0.3280 - acc: 0.9080 - val_loss: 0.1959 - val_acc: 0.9484
Epoch 2/5
117s - loss: 0.3259 - acc: 0.9083 - val_loss: 0.1978 - val_acc: 0.9467
Epoch 3/5
121s - loss: 0.3224 - acc: 0.9084 - val_loss: 0.2238 - val_acc: 0.9414
Epoch 4/5
123s - loss: 0.3196 - acc: 0.9096 - val_loss: 0.2033 - val_acc: 0.9468
Epoch 5/5
125s - loss: 0.3151 - acc: 0.9114 - val_loss: 0.1930 - val_acc: 0.9482
```

Out[43]:

```
<keras.callbacks.History at 0x14548c9e8>
```

```
Q 89+92
T 181
☑ 181
---
Q 92+91
T 183
☑ 183
---
Q 7+24
T 31
☑ 31
---
Q 97+1
T 98
☑ 98
---
Q 87+83
T 170
☑ 170
---
Q 43+28
T 71
☒ 62
---
Q 89+62
T 151
☑ 151
---
Q 6+39
T 45
☑ 45
---
Q 934+760
T 1694
☑ 1694
---
Q 1+3
T 4
☑ 4
```

☑ 4

In [ ]: