In [2]:

```
from google.colab import drive
drive.mount('/content/gdrive')
import os
os.chdir("gdrive/My Drive/MP2")
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id=947318989803-6bn6
qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redirect_uri=urn%3Aietf%3Awg%3Aoauth%3A2.0%
b&scope=email%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2Fwww.googleapis.
2Fauth%2Fdrive%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive.photos.readonly%20https%3A%2F%2Fww
ogleapis.com%2Fauth%2Fpeopleapi.readonly&response_type=code

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

In [0]:

```
import numpy as np
import matplotlib.pyplot as plt

from utils.data_process import get_CIFAR10_data
from models.neural_net import NeuralNetwork
from kaggle_submission import output_submission_csv

%matplotlib inline
plt.rcParams['figure.figsize'] = (10.0, 8.0) # set default size of plots
plt.rcParams['image.interpolation'] = 'nearest'
plt.rcParams['image.cmap'] = 'gray'

# for auto-reloading external modules
# see http://stackoverflow.com/questions/1907993/autoreload-of-modules-in-ipython
%load_ext autoreload
%autoreload 2
```

Loading CIFAR-10

Now that you have implemented a neural network that passes gradient checks and works on toy data, you will test your network on the CIFAR-10 dataset.

In [0]:

```
# You can change these numbers for experimentation
# For submission be sure they are set to the default values
TRAIN_IMAGES = 49000
VAL_IMAGES = 1000
TEST_IMAGES = 5000

data = get_CIFAR10_data(TRAIN_IMAGES, VAL_IMAGES, TEST_IMAGES)
X_train, y_train = data['X_train'], data['y_train']
X_val, y_val = data['X_val'], data['y_val']
X_test, y_test = data['X_test'], data['y_test']
```

Train a network

To train our network we will use SGD. In addition, we will adjust the learning rate with an exponential learning rate schedule as optimization proceeds; after each epoch, we will reduce the learning rate by multiplying it by a decay rate.

You can try different numbers of layers and also the different activation functions that you implemented on the CIFAR-10 dataset below.

In [6]:

```
input_size = 32 * 32 * 3
num_layers = 3
```

```
hidden_size = 120
hidden_sizes = [hidden_size]*(num_layers-1)
num_classes = 10
net = NeuralNetwork(input_size, hidden_sizes, num_classes, num_layers, nonlinearity='relu')

# Train the network
stats = net.train(X_train, y_train, X_val, y_val,
            num_iters=6000, batch_size=200,
            learning_rate=0.01, learning_rate_decay=0.95,
            reg=0.05, verbose=True)

# Predict on the validation set
val_acc = (net.predict(X_val) == y_val).mean()
print('Validation accuracy: ', val_acc)
```

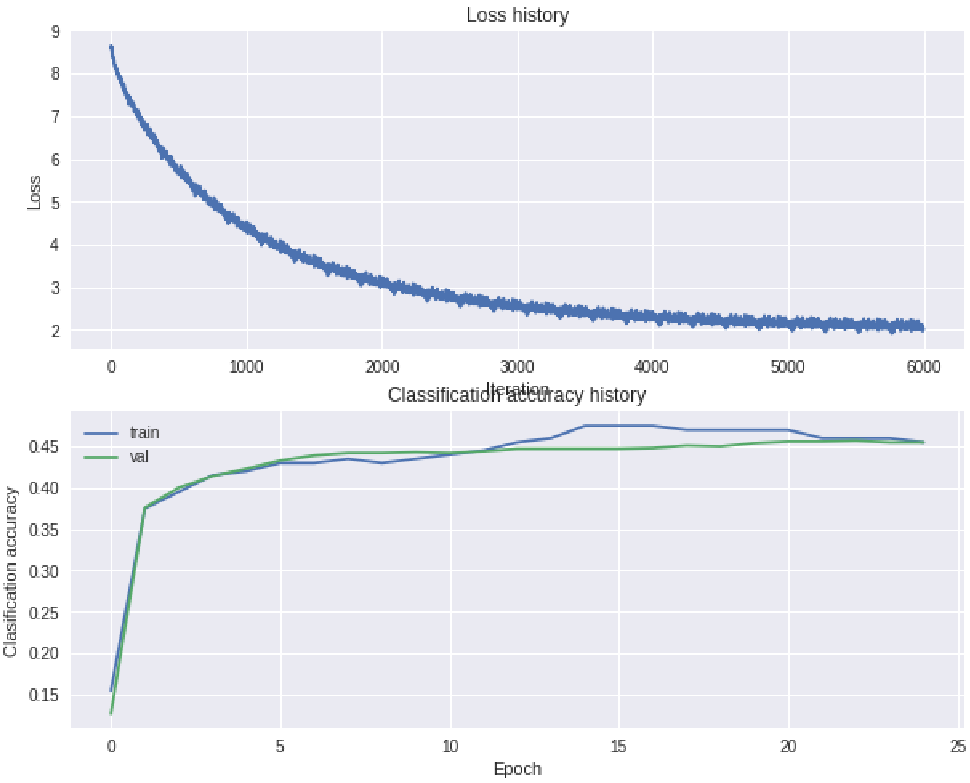
```
iteration 0 / 6000: loss 8.623294
iteration 100 / 6000: loss 7.624793
iteration 200 / 6000: loss 7.007365
iteration 300 / 6000: loss 6.561170
iteration 400 / 6000: loss 6.145479
iteration 500 / 6000: loss 5.713850
iteration 600 / 6000: loss 5.381783
iteration 700 / 6000: loss 5.176224
iteration 800 / 6000: loss 4.903490
iteration 900 / 6000: loss 4.607177
iteration 1000 / 6000: loss 4.424954
iteration 1100 / 6000: loss 4.071642
iteration 1200 / 6000: loss 4.037194
iteration 1300 / 6000: loss 3.995987
iteration 1400 / 6000: loss 3.716058
iteration 1500 / 6000: loss 3.550575
iteration 1600 / 6000: loss 3.275966
iteration 1700 / 6000: loss 3.285899
iteration 1800 / 6000: loss 3.329315
iteration 1900 / 6000: loss 3.216086
iteration 2000 / 6000: loss 3.043292
iteration 2100 / 6000: loss 3.103232
iteration 2200 / 6000: loss 3.031614
iteration 2300 / 6000: loss 2.844690
iteration 2400 / 6000: loss 2.786778
iteration 2500 / 6000: loss 2.800072
iteration 2600 / 6000: loss 2.699306
iteration 2700 / 6000: loss 2.621647
iteration 2800 / 6000: loss 2.594212
iteration 2900 / 6000: loss 2.667463
iteration 3000 / 6000: loss 2.566874
iteration 3100 / 6000: loss 2.488588
iteration 3200 / 6000: loss 2.520321
iteration 3300 / 6000: loss 2.439049
iteration 3400 / 6000: loss 2.410874
iteration 3500 / 6000: loss 2.447506
iteration 3600 / 6000: loss 2.327603
iteration 3700 / 6000: loss 2.515776
iteration 3800 / 6000: loss 2.291620
iteration 3900 / 6000: loss 2.235403
iteration 4000 / 6000: loss 2.241397
iteration 4100 / 6000: loss 2.321118
iteration 4200 / 6000: loss 2.218556
iteration 4300 / 6000: loss 2.269966
iteration 4400 / 6000: loss 2.230498
iteration 4500 / 6000: loss 2.229157
iteration 4600 / 6000: loss 2.285227
iteration 4700 / 6000: loss 2.200305
iteration 4800 / 6000: loss 2.215362
iteration 4900 / 6000: loss 2.185761
iteration 5000 / 6000: loss 2.132130
iteration 5100 / 6000: loss 2.121165
iteration 5200 / 6000: loss 2.182811
iteration 5300 / 6000: loss 2.148229
iteration 5400 / 6000: loss 2.115442
iteration 5500 / 6000: loss 2.103571
iteration 5600 / 6000: loss 2.201662
iteration 5700 / 6000: loss 2.178688
iteration 5800 / 6000: loss 2.112546
iteration 5900 / 6000: loss 2.154492
Validation accuracy:  0.455
```

Graph loss and train/val accuracies

Examining the loss graph along with the train and val accuracy graphs should help you gain some intuition for the hyperparameters you should try in the hyperparameter tuning below. It should also help with debugging any issues you might have with your network.

In [7]:

```
# Plot the loss function and train / validation accuracies
plt.subplot(2, 1, 1)
plt.plot(stats['loss_history'])
plt.title('Loss history')
plt.xlabel('Iteration')
plt.ylabel('Loss')

plt.subplot(2, 1, 2)
plt.plot(stats['train_acc_history'], label='train')
plt.plot(stats['val_acc_history'], label='val')
plt.title('Classification accuracy history')
plt.xlabel('Epoch')
plt.ylabel('Clasification accuracy')
plt.legend()
plt.show()
```



Hyperparameter tuning

Once you have successfully trained a network you can tune your hyparameters to increase your accuracy.

Based on the graphs of the loss function above you should be able to develop some intuition about what hyperparameter adjustments may be necessary. A very noisy loss implies that the learning rate might be too high, while a linearly decreasing loss would suggest that the learning rate may be too low. A large gap between training and validation accuracy would suggest overfitting due to large model without much regularization. No gap between training and validation accuracy would indicate low model capacity.

You will compare networks of two and three layers using the different activation functions you implemented.

The different hyperparameters you can experiment with are:

- **Batch size**: We recommend you leave this at 200 initially which is the batch size we used.
- **Number of iterations**: You can gain an intuition for how many iterations to run by checking when the validation accuracy plateaus in your train/val accuracy graph.
- **Initialization** Weight initialization is very important for neural networks. We used the initialization `W =`

np.random.randn(n) / sqrt(n) where n is the input dimension for layer corresponding to W. We recommend you stick with the given initializations, but you may explore modifying these. Typical initialization practices: http://cs231n.github.io/neural-networks-2/#init

- **Learning rate**: Generally from around 1e-4 to 1e-1 is a good range to explore according to our implementation.
- **Learning rate decay**: We recommend a 0.95 decay to start.
- **Hidden layer size**: You should explore up to around 120 units per layer. For three-layer network, we fixed the two hidden layers to be the same size when obtaining the target numbers. However, you may experiment with having different size hidden layers.
- **Regularization coefficient**: We recommend trying values in the range 0 to 0.1.

Hints:

- After getting a sense of the parameters by trying a few values yourself, you will likely want to write a few for loops to traverse over a set of hyperparameters.
- If you find that your train loss is decreasing, but your train and val accuracy start to decrease rather than increase, your model likely started minimizing the regularization term. To prevent this you will need to decrease the regularization coefficient.

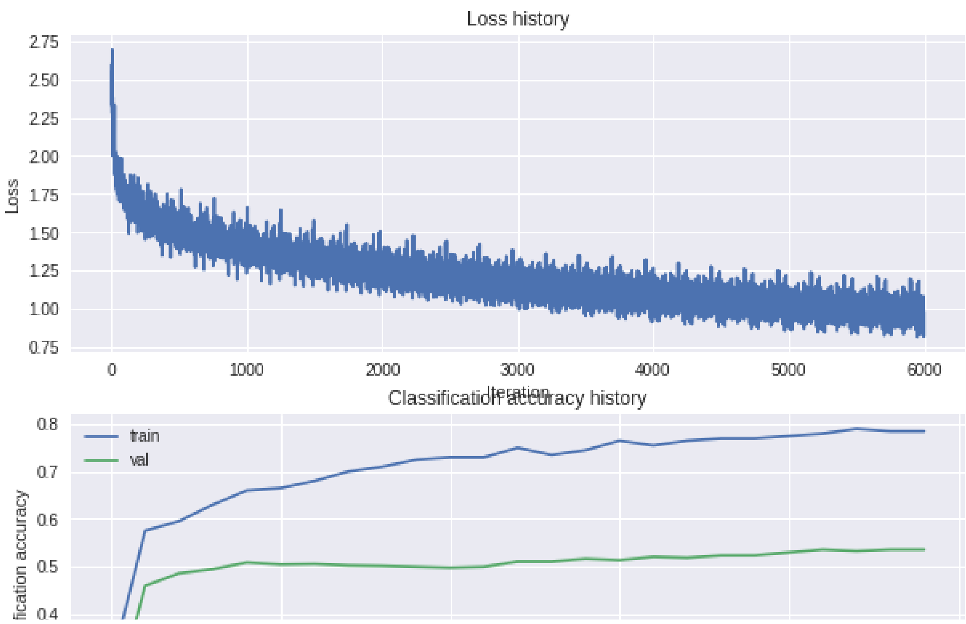
Two-layer Relu Activation Network

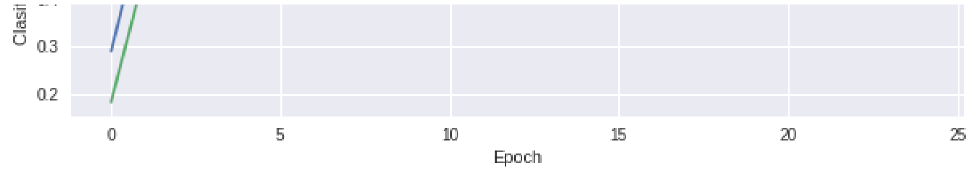
In [8]:

```
best_2layer_relu = None # store the best model into this

################################################################################
# TODO: Tune hyperparameters using the validation set. Store your best trained  #
# model in best_2layer_relu.                                                   #
################################################################################


input_size = 32 * 32 * 3
num_layers = 2
hidden_size = 100
hidden_sizes = [hidden_size]*(num_layers-1)
num_classes = 10
best_2layer_relu = NeuralNetwork(input_size, hidden_sizes, num_classes, num_layers, nonlinearity='r
elu')

# Train the network
stats = best_2layer_relu.train(X_train, y_train, X_val, y_val,
            num_iters=6000, batch_size=200,
            learning_rate=0.1, learning_rate_decay=0.95,
            reg=0.001, verbose=True)

# Predict on the validation set
val_acc = (best_2layer_relu.predict(X_val) == y_val).mean()
print('Validation accuracy: ', val_acc)

# Plot the loss function and train / validation accuracies
plt.subplot(2, 1, 1)
plt.plot(stats['loss_history'])
plt.title('Loss history')
plt.xlabel('Iteration')
plt.ylabel('Loss')

plt.subplot(2, 1, 2)
plt.plot(stats['train_acc_history'], label='train')
plt.plot(stats['val_acc_history'], label='val')
plt.title('Classification accuracy history')
plt.xlabel('Epoch')
plt.ylabel('Clasification accuracy')
plt.legend()
plt.show()
```

```
iteration 0 / 6000: loss 2.549643
iteration 100 / 6000: loss 1.711890
iteration 200 / 6000: loss 1.552029
iteration 300 / 6000: loss 1.655969
iteration 400 / 6000: loss 1.524730
iteration 500 / 6000: loss 1.475860
iteration 600 / 6000: loss 1.435754
iteration 700 / 6000: loss 1.467770
```

```
iteration 800 / 6000: loss 1.597663
iteration 900 / 6000: loss 1.368106
iteration 1000 / 6000: loss 1.548073
iteration 1100 / 6000: loss 1.306682
iteration 1200 / 6000: loss 1.379399
iteration 1300 / 6000: loss 1.421897
iteration 1400 / 6000: loss 1.229473
iteration 1500 / 6000: loss 1.279348
iteration 1600 / 6000: loss 1.121228
iteration 1700 / 6000: loss 1.223697
iteration 1800 / 6000: loss 1.211885
iteration 1900 / 6000: loss 1.221579
iteration 2000 / 6000: loss 1.196658
iteration 2100 / 6000: loss 1.247361
iteration 2200 / 6000: loss 1.316933
iteration 2300 / 6000: loss 1.253595
iteration 2400 / 6000: loss 1.123926
iteration 2500 / 6000: loss 1.141823
iteration 2600 / 6000: loss 1.269110
iteration 2700 / 6000: loss 1.060291
iteration 2800 / 6000: loss 1.026120
iteration 2900 / 6000: loss 1.197140
iteration 3000 / 6000: loss 1.133363
iteration 3100 / 6000: loss 1.158075
iteration 3200 / 6000: loss 1.356377
iteration 3300 / 6000: loss 0.998082
iteration 3400 / 6000: loss 1.144018
iteration 3500 / 6000: loss 1.210452
iteration 3600 / 6000: loss 0.978705
iteration 3700 / 6000: loss 1.331457
iteration 3800 / 6000: loss 1.063691
iteration 3900 / 6000: loss 1.064310
iteration 4000 / 6000: loss 1.019892
iteration 4100 / 6000: loss 0.988694
iteration 4200 / 6000: loss 1.036523
iteration 4300 / 6000: loss 1.013786
iteration 4400 / 6000: loss 0.989018
iteration 4500 / 6000: loss 1.113542
iteration 4600 / 6000: loss 1.047252
iteration 4700 / 6000: loss 1.048787
iteration 4800 / 6000: loss 1.165356
iteration 4900 / 6000: loss 0.982900
iteration 5000 / 6000: loss 0.997222
iteration 5100 / 6000: loss 0.952293
iteration 5200 / 6000: loss 1.150586
iteration 5300 / 6000: loss 0.974310
iteration 5400 / 6000: loss 1.058002
iteration 5500 / 6000: loss 0.944292
iteration 5600 / 6000: loss 1.078271
iteration 5700 / 6000: loss 0.985080
iteration 5800 / 6000: loss 0.926518
iteration 5900 / 6000: loss 1.128232
Validation accuracy:  0.535
```





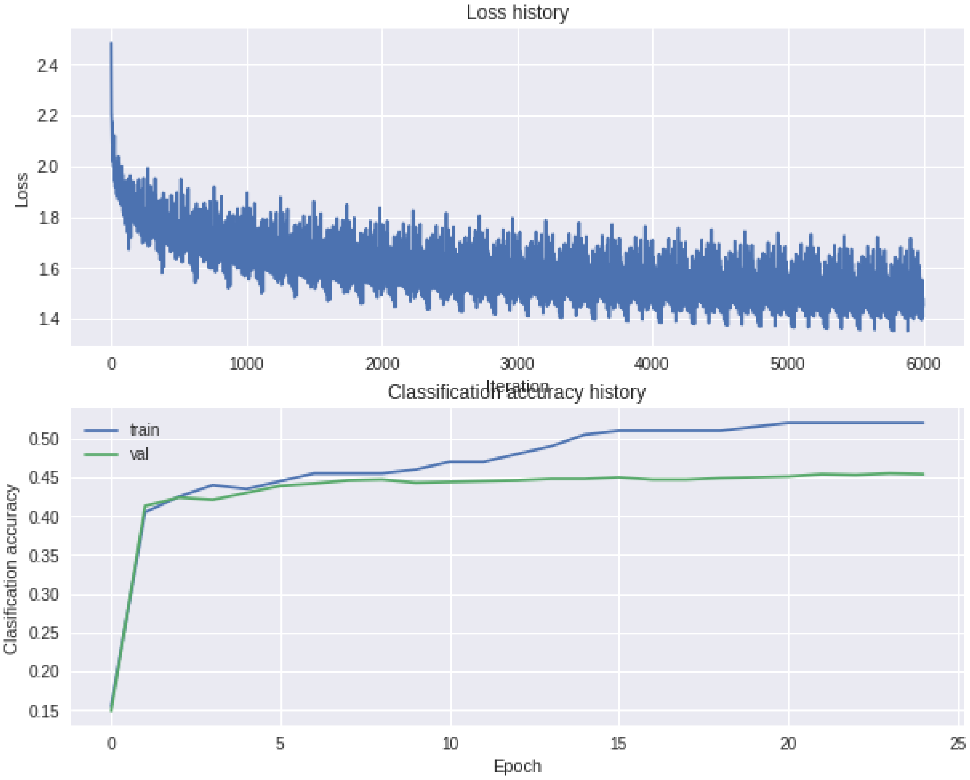
Two-layer Sigmoid Activation Network

In [5]:

```
best_2layer_sigmoid = None # store the best model into this

################################################################################
# TODO: Tune hyperparameters using the validation set. Store your best trained  #
# model in best_2layer_sigmoid.                                                 #
################################################################################

input_size = 32 * 32 * 3
num_layers = 2
hidden_size = 75
hidden_sizes = [hidden_size]*(num_layers-1)
num_classes = 10
best_2layer_sigmoid = NeuralNetwork(input_size, hidden_sizes, num_classes, num_layers, nonlinearity
='sigmoid')

# Train the network
stats = best_2layer_sigmoid.train(X_train, y_train, X_val, y_val,
            num_iters=6000, batch_size=200,
            learning_rate=0.1, learning_rate_decay=0.95,
            reg=0.001, verbose=True)

# Predict on the validation set
val_acc = (best_2layer_sigmoid.predict(X_val) == y_val).mean()
print('Validation accuracy: ', val_acc)

# Plot the loss function and train / validation accuracies
plt.subplot(2, 1, 1)
plt.plot(stats['loss_history'])
plt.title('Loss history')
plt.xlabel('Iteration')
plt.ylabel('Loss')

plt.subplot(2, 1, 2)
plt.plot(stats['train_acc_history'], label='train')
plt.plot(stats['val_acc_history'], label='val')
plt.title('Classification accuracy history')
plt.xlabel('Epoch')
plt.ylabel('Clasification accuracy')
plt.legend()
plt.show()
```

```
iteration 0 / 6000: loss 2.485217
iteration 100 / 6000: loss 1.886669
iteration 200 / 6000: loss 1.770255
iteration 300 / 6000: loss 1.825179
iteration 400 / 6000: loss 1.755104
iteration 500 / 6000: loss 1.754354
iteration 600 / 6000: loss 1.729260
iteration 700 / 6000: loss 1.722969
iteration 800 / 6000: loss 1.806475
iteration 900 / 6000: loss 1.660771
iteration 1000 / 6000: loss 1.706508
iteration 1100 / 6000: loss 1.580174
iteration 1200 / 6000: loss 1.692823
iteration 1300 / 6000: loss 1.783303
iteration 1400 / 6000: loss 1.658060
iteration 1500 / 6000: loss 1.554598
iteration 1600 / 6000: loss 1.470168
iteration 1700 / 6000: loss 1.523412
iteration 1800 / 6000: loss 1.682142
iteration 1900 / 6000: loss 1.540981
iteration 2000 / 6000: loss 1.503621
iteration 2100 / 6000: loss 1.716288
```

```
iteration 2200 / 6000: loss 1.765474
iteration 2300 / 6000: loss 1.611653
iteration 2400 / 6000: loss 1.614624
iteration 2500 / 6000: loss 1.646002
iteration 2600 / 6000: loss 1.580198
iteration 2700 / 6000: loss 1.441989
iteration 2800 / 6000: loss 1.622855
iteration 2900 / 6000: loss 1.664798
iteration 3000 / 6000: loss 1.598877
iteration 3100 / 6000: loss 1.546145
iteration 3200 / 6000: loss 1.624585
iteration 3300 / 6000: loss 1.473458
iteration 3400 / 6000: loss 1.531767
iteration 3500 / 6000: loss 1.668960
iteration 3600 / 6000: loss 1.490231
iteration 3700 / 6000: loss 1.770527
iteration 3800 / 6000: loss 1.461618
iteration 3900 / 6000: loss 1.470215
iteration 4000 / 6000: loss 1.454184
iteration 4100 / 6000: loss 1.561896
iteration 4200 / 6000: loss 1.428947
iteration 4300 / 6000: loss 1.559826
iteration 4400 / 6000: loss 1.558264
iteration 4500 / 6000: loss 1.593494
iteration 4600 / 6000: loss 1.579472
iteration 4700 / 6000: loss 1.577197
iteration 4800 / 6000: loss 1.585435
iteration 4900 / 6000: loss 1.526494
iteration 5000 / 6000: loss 1.554234
iteration 5100 / 6000: loss 1.444624
iteration 5200 / 6000: loss 1.535791
iteration 5300 / 6000: loss 1.480393
iteration 5400 / 6000: loss 1.553149
iteration 5500 / 6000: loss 1.556520
iteration 5600 / 6000: loss 1.532543
iteration 5700 / 6000: loss 1.578596
iteration 5800 / 6000: loss 1.455511
iteration 5900 / 6000: loss 1.585498
Validation accuracy:  0.455
```



Three-layer Relu Activation Network

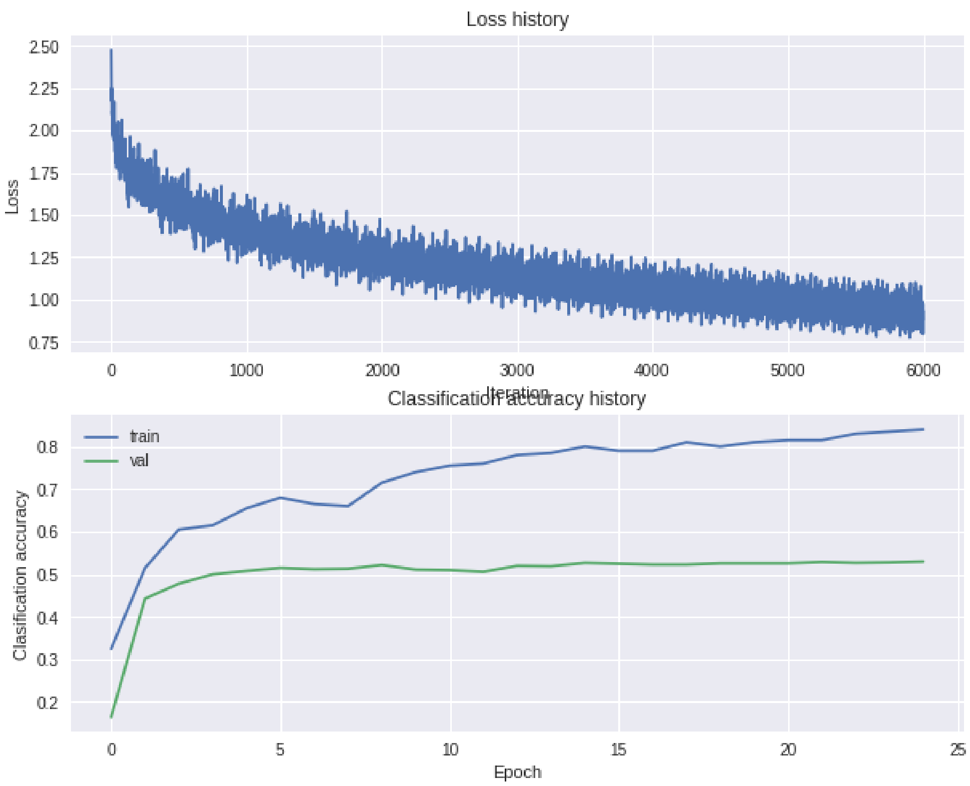
In [16]:

```
best_3layer_relu = None # store the best model into this
```

```
################################################################################
# TODO: Tune hyperparameters using the validation set. Store your best trained  #
# model in best_3layer_relu.                                                    #
################################################################################

input_size = 32 * 32 * 3
num_layers = 3
hidden_size = 100
hidden_sizes = [hidden_size]*(num_layers-1)
num_classes = 10
best_3layer_relu = NeuralNetwork(input_size, hidden_sizes, num_classes, num_layers, nonlinearity='r
elu')

# Train the network
stats = best_3layer_relu.train(X_train, y_train, X_val, y_val,
            num_iters=6000, batch_size=200,
            learning_rate=0.1, learning_rate_decay=0.95,
            reg=0.001, verbose=True)

# Predict on the validation set
val_acc = (best_3layer_relu.predict(X_val) == y_val).mean()
print('Validation accuracy: ', val_acc)

# Plot the loss function and train / validation accuracies
plt.subplot(2, 1, 1)
plt.plot(stats['loss_history'])
plt.title('Loss history')
plt.xlabel('Iteration')
plt.ylabel('Loss')

plt.subplot(2, 1, 2)
plt.plot(stats['train_acc_history'], label='train')
plt.plot(stats['val_acc_history'], label='val')
plt.title('Classification accuracy history')
plt.xlabel('Epoch')
plt.ylabel('Clasification accuracy')
plt.legend()
plt.show()
```

```
iteration 0 / 6000: loss 2.475691
iteration 100 / 6000: loss 1.764272
iteration 200 / 6000: loss 1.654223
iteration 300 / 6000: loss 1.696301
iteration 400 / 6000: loss 1.555327
iteration 500 / 6000: loss 1.499311
iteration 600 / 6000: loss 1.432283
iteration 700 / 6000: loss 1.524094
iteration 800 / 6000: loss 1.568074
iteration 900 / 6000: loss 1.420128
iteration 1000 / 6000: loss 1.564693
iteration 1100 / 6000: loss 1.307564
iteration 1200 / 6000: loss 1.386859
iteration 1300 / 6000: loss 1.405273
iteration 1400 / 6000: loss 1.204928
iteration 1500 / 6000: loss 1.279257
iteration 1600 / 6000: loss 1.141498
iteration 1700 / 6000: loss 1.209147
iteration 1800 / 6000: loss 1.248685
iteration 1900 / 6000: loss 1.283459
iteration 2000 / 6000: loss 1.153768
iteration 2100 / 6000: loss 1.202659
iteration 2200 / 6000: loss 1.316008
iteration 2300 / 6000: loss 1.236621
iteration 2400 / 6000: loss 1.171352
iteration 2500 / 6000: loss 1.072927
iteration 2600 / 6000: loss 1.159680
iteration 2700 / 6000: loss 1.078613
iteration 2800 / 6000: loss 1.118330
iteration 2900 / 6000: loss 1.233056
iteration 3000 / 6000: loss 1.196726
iteration 3100 / 6000: loss 1.110757
iteration 3200 / 6000: loss 1.270563
iteration 3300 / 6000: loss 1.069221
iteration 3400 / 6000: loss 1.050064
iteration 3500 / 6000: loss 1.109117
iteration 3600 / 6000: loss 1.039743
```

```
iteration 3600 / 6000: loss 1.039745
iteration 3700 / 6000: loss 1.263386
iteration 3800 / 6000: loss 1.038930
iteration 3900 / 6000: loss 0.990149
iteration 4000 / 6000: loss 0.950503
iteration 4100 / 6000: loss 1.055442
iteration 4200 / 6000: loss 1.061673
iteration 4300 / 6000: loss 1.084307
iteration 4400 / 6000: loss 0.945031
iteration 4500 / 6000: loss 1.046912
iteration 4600 / 6000: loss 1.117180
iteration 4700 / 6000: loss 1.032014
iteration 4800 / 6000: loss 1.075054
iteration 4900 / 6000: loss 0.976106
iteration 5000 / 6000: loss 1.014381
iteration 5100 / 6000: loss 0.861074
iteration 5200 / 6000: loss 1.114183
iteration 5300 / 6000: loss 0.878180
iteration 5400 / 6000: loss 0.942297
iteration 5500 / 6000: loss 0.960983
iteration 5600 / 6000: loss 1.012750
iteration 5700 / 6000: loss 0.928692
iteration 5800 / 6000: loss 0.960595
iteration 5900 / 6000: loss 1.014051
Validation accuracy:  0.535
```



Three-layer Sigmoid Activation Network

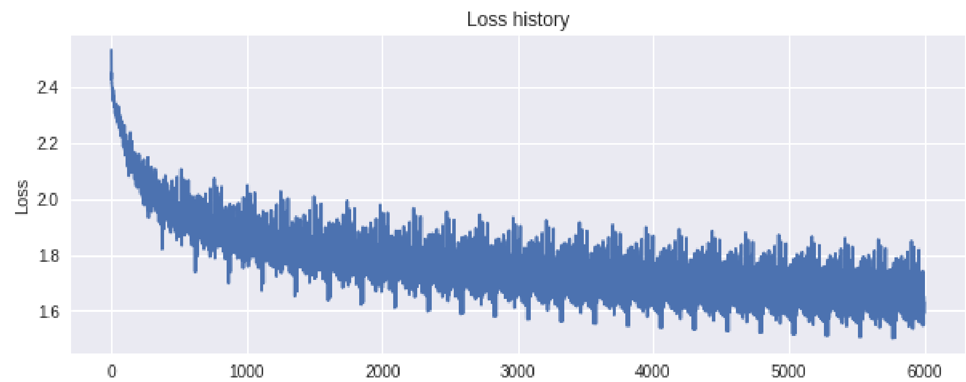
In [19]:

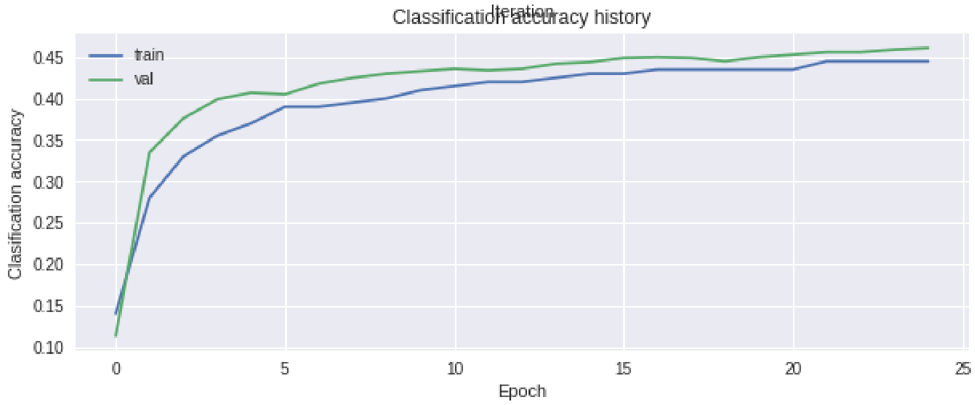
```
best_3layer_sigmoid = None # store the best model into this

################################################################################
# TODO: Tune hyperparameters using the validation set. Store your best trained  #
# model in best_3layer_sigmoid.                                                 #
################################################################################


input_size = 32 * 32 * 3
num_layers = 3
hidden_size = 110
hidden_sizes = [hidden_size]*(num_layers-1)
num_classes = 10
best_3layer_sigmoid = NeuralNetwork(input_size, hidden_sizes, num_classes, num_layers, nonlinearity
='sigmoid')
```

```
# Train the network
stats = best_3layer_sigmoid.train(X_train, y_train, X_val, y_val,
            num_iters=6000, batch_size=200,
            learning_rate=0.1, learning_rate_decay=0.95,
            reg=0.001, verbose=True)

# Predict on the validation set
val_acc = (best_3layer_sigmoid.predict(X_val) == y_val).mean()
print('Validation accuracy: ', val_acc)

# Plot the loss function and train / validation accuracies
plt.subplot(2, 1, 1)
plt.plot(stats['loss_history'])
plt.title('Loss history')
plt.xlabel('Iteration')
plt.ylabel('Loss')

plt.subplot(2, 1, 2)
plt.plot(stats['train_acc_history'], label='train')
plt.plot(stats['val_acc_history'], label='val')
plt.title('Classification accuracy history')
plt.xlabel('Epoch')
plt.ylabel('Clasification accuracy')
plt.legend()
plt.show()
```

```
iteration 0 / 6000: loss 2.531084
iteration 100 / 6000: loss 2.195611
iteration 200 / 6000: loss 2.055366
iteration 300 / 6000: loss 2.043408
iteration 400 / 6000: loss 2.008482
iteration 500 / 6000: loss 1.958543
iteration 600 / 6000: loss 1.901821
iteration 700 / 6000: loss 1.963669
iteration 800 / 6000: loss 1.965079
iteration 900 / 6000: loss 1.863145
iteration 1000 / 6000: loss 1.850691
iteration 1100 / 6000: loss 1.762979
iteration 1200 / 6000: loss 1.863939
iteration 1300 / 6000: loss 1.954997
iteration 1400 / 6000: loss 1.838234
iteration 1500 / 6000: loss 1.716060
iteration 1600 / 6000: loss 1.636654
iteration 1700 / 6000: loss 1.712133
iteration 1800 / 6000: loss 1.853666
iteration 1900 / 6000: loss 1.728602
iteration 2000 / 6000: loss 1.682664
iteration 2100 / 6000: loss 1.885598
iteration 2200 / 6000: loss 1.916390
iteration 2300 / 6000: loss 1.753766
iteration 2400 / 6000: loss 1.764626
iteration 2500 / 6000: loss 1.852087
iteration 2600 / 6000: loss 1.717984
iteration 2700 / 6000: loss 1.650005
iteration 2800 / 6000: loss 1.772208
iteration 2900 / 6000: loss 1.831469
iteration 3000 / 6000: loss 1.733928
iteration 3100 / 6000: loss 1.713857
iteration 3200 / 6000: loss 1.784363
iteration 3300 / 6000: loss 1.638435
iteration 3400 / 6000: loss 1.670683
iteration 3500 / 6000: loss 1.773170
iteration 3600 / 6000: loss 1.661285
iteration 3700 / 6000: loss 1.906647
iteration 3800 / 6000: loss 1.609312
iteration 3900 / 6000: loss 1.637768
iteration 4000 / 6000: loss 1.615226
iteration 4100 / 6000: loss 1.720222
iteration 4200 / 6000: loss 1.571343
iteration 4300 / 6000: loss 1.725032
iteration 4400 / 6000: loss 1.714243
iteration 4500 / 6000: loss 1.711844
iteration 4600 / 6000: loss 1.747247
iteration 4700 / 6000: loss 1.732537
iteration 4800 / 6000: loss 1.752463
iteration 4900 / 6000: loss 1.698488
```

```
iteration 5000 / 6000: loss 1.704025
iteration 5100 / 6000: loss 1.623612
iteration 5200 / 6000: loss 1.719650
iteration 5300 / 6000: loss 1.640177
iteration 5400 / 6000: loss 1.718803
iteration 5500 / 6000: loss 1.695298
iteration 5600 / 6000: loss 1.702356
iteration 5700 / 6000: loss 1.770083
iteration 5800 / 6000: loss 1.602809
iteration 5900 / 6000: loss 1.731287
Validation accuracy:  0.455
```





Run on the test set

When you are done experimenting, you should evaluate your final trained networks on the test set.

In [9]:

```
print('Two-layer relu')
test_acc = (best_2layer_relu.predict(X_test) == y_test).mean()
print('Test accuracy: ', test_acc)
```

```
Two-layer relu
Test accuracy:  0.524
```

In [6]:

```
print('Two-layer sigmoid')
test_acc = (best_2layer_sigmoid.predict(X_test) == y_test).mean()
print('Test accuracy: ', test_acc)
```

```
Two-layer sigmoid
Test accuracy:  0.4686
```

In [17]:

```
print('Three-layer relu')
test_acc = (best_3layer_relu.predict(X_test) == y_test).mean()
print('Test accuracy: ', test_acc)
```

Three-layer relu
Test accuracy: 0.531

In [20]:

```
print('Three-layer sigmoid')
test_acc = (best_3layer_sigmoid.predict(X_test) == y_test).mean()
print('Test accuracy: ', test_acc)
```

Three-layer sigmoid
Test accuracy: 0.456

Kaggle output

Once you are satisfied with your solution and test accuracy output a file to submit your test set predictions to the Kaggle for Assignment 2 Neural Network. Use the following code to do so:

In [0]:

```
output_submission_csv('nn_2layer_relu_submission.csv', best_2layer_relu.predict(X_test))
```

In [0]:

```
output_submission_csv('nn_2layer_sigmoid_submission.csv', best_2layer_sigmoid.predict(X_test))
```

In [0]:

```
output_submission_csv('nn_3layer_relu_submission.csv', best_3layer_relu.predict(X_test))
```

In [0]:

```
output_submission_csv('nn_3layer_sigmoid_submission.csv', best_3layer_sigmoid.predict(X_test))
```