Facial Keypoints Detection (https://www.kaggle.com/c/facial-keypoints-detection)

MIDS W207 Final Project (https://github.com/leiyang-ucb/W207Final)

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Executive Summary:

1. **Baseline Model -- Mean Patch Searching Algorithm:** For our initial submission to Kaggle, we implemented a Mean Patch Searching algorithm. This model is a point-wise, search-based predicting algorithm that compares the neighborhood (patch) of a group of candidate pixels within each test image with the "golden patch" generated from the training data. Using all training images, without any feature engineering, our RMSE score on Kaggle was **5.79**, placing us *42nd* on the Kaggle leaderboard (https://www.kaggle.com/c/facial-keypoints-detection/leaderboard).
2. **Feature Engineering:** We applied 3 different strategies.
   A. **Histogram Stretching:** Histogram stretching rescales each pixel intensity value from an image's original range of [a, b] to [0, 1], where a > 0 and b < 1. Thus, the gray-scale range within the image is "stretched," improving the image's contrast.
   B. **Gaussian Blurring:** Gaussian blurring filters out high-frequency features, thus reducing local noise and making the global pattern more expressive.
   C. **Image Flipping:** We flipped each image horizontally and renamed the left/right keypoints, allowing us to double the size of the training dataset.
   D. **Using Predictions as Training Set:** There were pictures which didn't have all 15 key-points. We used pictures with all the points to train a neural net first, used it to predict on the pictures with missing key-points, then used the predictions to fill in the missing points. Finally we used the whole training set with all(predicted) key-points to re-train yet another neural net.
3. **Cleaning the Data -- Keypoint Grouping:** For this Kaggle competition, the goal is to detect 15 different keypoints on the face, e.g. center of left eye, center of right eye, nose tip. One issue with the training data was that not all images have all 15 keypoints identified. Out of 7049 training images, 7000 images (99%) had at least 4 keypoints identified (center of left eye, center of right eye, nose tip, and center of bottom lip). Only 2140 images (30%) had all 15 keypoints identified. We therefore grouped the data according to which keypoints were available and trained two different models -- one on the 7000 images in the 4-keypoints group and one on the 2140 images in the 15-

keypoints group. Because we also flipped each image, we ended up with training datasets of size 14000 and 4280, respectively. By grouping the training images in this way and building a model for each group, the *geometric constraints among keypoints are implicitly encoded, and the local optimum caused by ambiguity is avoided [Sun et al. 2013] (http://www.cv-foundation.org/openaccess/content_cvpr_2013/papers/Sun_Deep_Convolutional_Network_2013_CVPR_p*

4. **Methodology:** In this work we applied *Convolutional Neural Networks (CNN)* with two distinct structures: one with 3 convolutional layers and 2 neural layers, and the other with 1 convolutional layer and 2 neural layers.
5. **Results:**
    A. **Lasagne Model:** The new *Lasagne* Python library offers functionality to create sophisticated CNNs. It is built on top of Python's *Theano* library. We used Lasagne's NeuralNet class to build a 5-layer CNN that had 3 convolutional layers and 2 hidden, fully-connected neural layers. This model improved our Kaggle score to **3.91**, which ranked us *34th* on the Kaggle leaderboard. We also built a 3-layer CNN with 1 convolutional layer and 2 hidden layers to experiment on different parameters such as our feature engineering, number of epochs, and mini-batch size, etc.
    B. **Theano Model:** Because the Lasagne Model was very slow to train, we went back to raw Theano and built a simpler 3-layer CNN, with only 1 convolutional layer and 2 hidden, fully-connected neural layers. This model trained much faster and gave us our best Kaggle score, **2.92**, which ranked us *13th* on the Kaggle leaderboard.
    C. **Computing Power Constraints:** As mentioned above, the Lasagne Model was prohibitively slow to train, taking roughly 30 minutes per epoch. The Theano Model trained faster, 6 minutes per epoch, but it still wasn't fast enough to allow us to experiment with different parameter settings. Mostly we improved our Theano Model score by allowing the model to run more epochs. To combat this slow training, we attempted to use GPUs instead of CPUs for our computing power. We built a g2.8xlarge EC2 instance to take advantage of AWS's GPU speed and larger memory. We also enabled the use of the GPU's on our laptops by implementing CUDA (http://www.nvidia.com/object/cuda_home_new.html). Yet these attempts were unsuccessful at improving our training speeds. Time constraints prevented us from exploring why GPUs were not able to give us a speed boost.
6. **Error Analysis:** Since "*hand-crafted feature extraction can be advantageously replaced by automatic feature learning that operates directly on pixel images*" *[LeCun 1998] (http://yann.lecun.com/exdb/publis/pdf/lecun-98.pdf)*, our focus was mainly on improving results by experimenting with different network structures and meta-parameters, with various keypoint groupings.
7. **Future Work:**
    A. Extensive structural comparisons, with faster GPU training.
    B. Alternative cost function to improve training with better convergence and prediction.
    C. More image preprocessing to reduce noise and provide better input.

Import Python Packages

In [1]:

```
%matplotlib inline

from lasagne import layers
from lasagne.updates import nesterov_momentum
from nolearn.lasagne import NeuralNet

import os
import time
import csv
import shelve
import pickle
from datetime import datetime

import numpy as np
from pandas.io.parsers import read_csv
from sklearn.utils import shuffle

import matplotlib.pyplot as plt
from matplotlib import cm

import theano
from theano import tensor as T
from theano.sandbox.rng_mrg import MRG_RandomStreams as RandomStreams
from theano.tensor.nnet.conv import conv2d
from theano.tensor.signal.downsample import max_pool_2d
print theano.config.device # We're using CPUs (for now)
print theano.config.floatX # Should be 64 bit for CPUs

np.random.seed(0)
```

```
cpu
float64
```

Data Import, Scaling, and Randomization

In [2]:

```
FTRAIN = './Data/FKD_Train.csv'
FTEST = './Data/FKD_Test.csv'

def load(test=False, cols=None):

    fname = FTEST if test else FTRAIN
    df = read_csv(os.path.expanduser(fname))  # load pandas dataframe

    # The Image column has pixel values separated by space; convert
    # the values to numpy arrays:
    df['Image'] = df['Image'].apply(lambda im: np.fromstring(im, sep=' '))

    if cols:  # get a subset of columns
        df = df[list(cols) + ['Image']]

    X = np.vstack(df['Image'].values) / 255.  # scale pixel values to [0, 1]
    X = X.astype(np.float32)

    if not test:  # only FTRAIN has any target columns
        y = df[df.columns[:-1]].values
        # scale target coordinates to [-1, 1] - need because we don't have bias
on the net
        y = (y - 48) / 48  # 96/2=48
        y = y.astype(np.float32)
        shuffle = np.random.permutation(np.arange(X.shape[0]))
        X, y = X[shuffle], y[shuffle]
    else:
        y = None

    return X, y, np.array(df.columns[:-1])

X, y, y_name = load()
X_t, trash, junk = load(test=True)
print("X.shape == {}; X.min == {:.3f}; X.max == {:.3f}".format(X.shape, X.min(),
X.max()))
print("y.shape == {}; y.min == {:.3f}; y.max == {:.3f}".format(y.shape, y.min(),
y.max()))
print("X_t.shape == {}; X_t.min == {:.3f}; X_t.max == {:.3f}".format(X_t.shape,
X_t.min(), X_t.max()))
ex_x, ex_y = X[666], y[666]
```

```
X.shape == (7049, 9216); X.min == 0.000; X.max == 1.000
y.shape == (7049, 30); y.min == nan; y.max == nan
X_t.shape == (1783, 9216); X_t.min == 0.000; X_t.max == 1.000
```

Baseline: Mean Patch Searching

- *Ref:* http://cs229.stanford.edu/proj2014/Yue%20Wang,Yang%20Song,Facial%20Keypoints%20Detection.pdf (http://cs229.stanford.edu/proj2014/Yue%20Wang,Yang%20Song,Facial%20Keypoints%20Detection.pdf
- Algorithm:
    1. *Training:* For each keypoint, find a center and its square neighborhood (mean patch) based on training data.
    2. *Predicting:* For each key point, find a neighborhood of candidates around the center. Then for each candidate, compare its patch with the mean patch from Step 1. The candidate with the most similar patch is the prediction.
- Score: RMSE = **5.79** (deviation in pixels)
- Implementation: See **Appendix I**

Feature Engineering 1: Histogram Stretching

- a and b are 5 and 95 percentile of the image
- l and u are 0 and 1 respectively for the maximum range
- Histogram stretching transfers any point p of the image to p' such that: $\frac{p-a}{b-a} = \frac{p'-l}{u-l}$
- The transferred image is expected to have better contrast.

In [3]:

```
##### define a helper plotting function #####
def plot2(image1, p1, image2, p2):
    plt.figure(figsize=(16,8))
    plt.subplot(1,2,1)
    plt.imshow(np.reshape(image1,(96,96)), cmap = cm.gray)
    for x, y in np.reshape(p1,(len(p1)/2, 2)):
        plt.plot(x, y, 'r.')
    plt.axis('off')
    plt.subplot(1,2,2)
    plt.imshow(np.reshape(image2,(96,96)), cmap = cm.gray)
    for x, y in np.reshape(p2,(len(p2)/2, 2)):
        plt.plot(x, y, 'r.')
    plt.axis('off')

##### histogram stretching #####
def HistogramStretching(image):
#     a, b = min(image), max(image)
    a, b = np.percentile(image, 5), np.percentile(image, 95)
    l, u = 0, 1
    const = 1.0*(b*l - a*u)/(b - a)
    k = 1.0*(u-l)/(b-a)
    return [k*p+const for p in image]

# plot an example
plot2(ex_x, ex_y*48+48, HistogramStretching(ex_x), ex_y*48+48)

start_time = time.time()
X = [HistogramStretching(x) for x in X]
X_t = [HistogramStretching(x) for x in X_t]
print 'Histogram stretching completed in %.2f seconds' %(time.time()-start_time)
```

```
Histogram stretching completed in 23.95 seconds
```

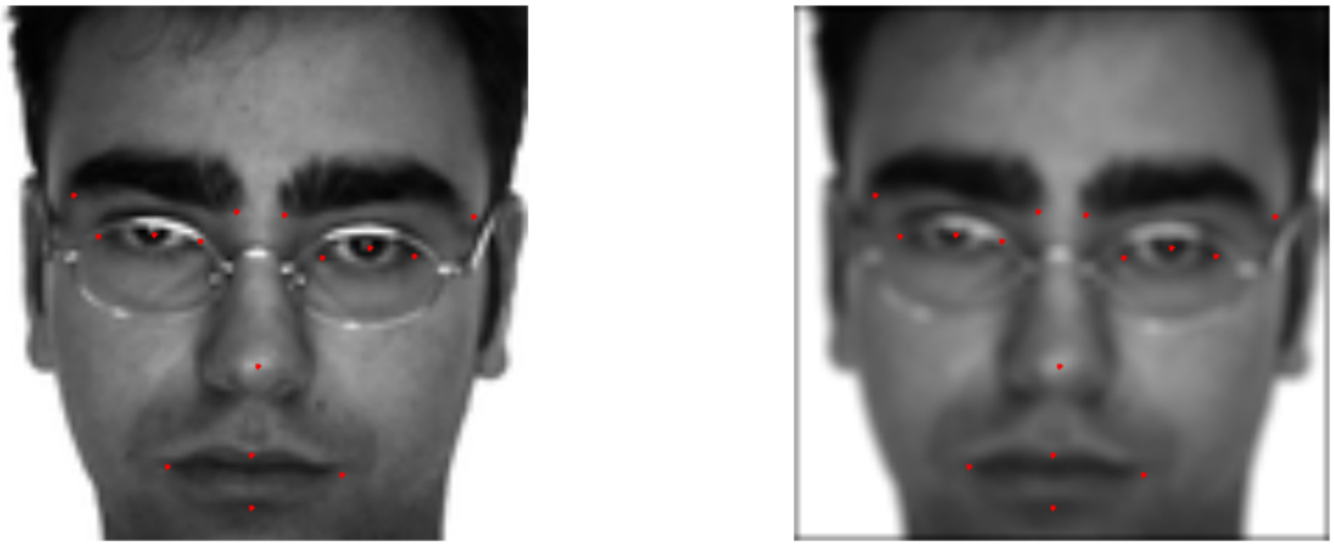
Feature Engineering 2: Gaussian Blurring

- The value of a particular pixel is transformed as the weighted combination of the original value and the values around it.
- The weight of a pixel's influence is determined by a Gaussian function over the distance to the relevant pixel.
- *Gaussian Weight Ref:* [http://www.pixelstech.net/article/1353768112-Gaussian-Blur-Algorithm (http://www.pixelstech.net/article/1353768112-Gaussian-Blur-Algorithm)](http://www.pixelstech.net/article/1353768112-Gaussian-Blur-Algorithm)

In [4]:

```
# define the Gaussian weights of neighbors as constant variable
sigma2 = 1.75**2
neighborIndex = [[i,j] for i in range(-1,2) for j in range(-1,2)]
gaussianWeight = np.array([np.exp(-(i**2+j**2)/(2*sigma2))/(2*np.pi*sigma2) for
i,j in neighborIndex])
gaussianWeight = gaussianWeight / sum(gaussianWeight)

# function to return the index of neighborhood pixels for pixel at n
def getNeighborAndWeight(n, ncolumn, nrow):
    # get row and column id first for index i
    (r, c) = divmod(n, ncolumn)
    # get indices for the neighbors (including self)
    neighbors = [[r+i,c+j] for i,j in neighborIndex]
    # get neighbor index and the associated Gauusian weigth
    neighborWeights = []
    for nb, gw in zip(neighbors, gaussianWeight):  # range(len(neighbors)):
        r,c = nb
        if r>=0 and r<nrow and c>=0 and c<ncolumn:
            neighborWeights.append([r*ncolumn + c, gw])
    return neighborWeights

# apply Gaussian blur to one image
def gaussianBlurOneSample(x):
    y = np.empty(len(x))
    for i in range(len(x)):
        neighbors = getNeighborAndWeight(i,96,96)
        y[i] = sum([x[j[0]]*j[1] for j in neighbors])
    return y

# plot an example
plot2(ex_x, ex_y*48+48, gaussianBlurOneSample(ex_x), ex_y*48+48)

# blur both training and predicting data
start_time = time.time()
X = [gaussianBlurOneSample(x) for x in X]
X_t = [gaussianBlurOneSample(x) for x in X_t]
print 'Gaussian blur completed in %.f seconds!' %(time.time()-start_time)
```

```
Gaussian blur completed in 930 seconds!
```



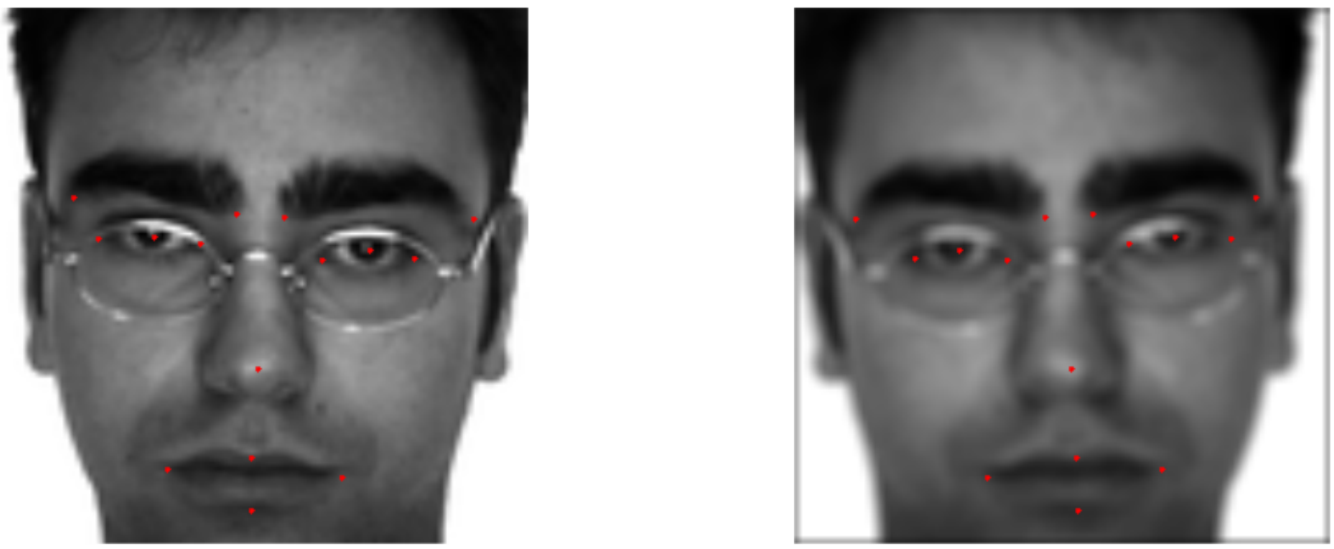
Feature Engineering 3: Image Flipping to Increase Training Sample

- Flip the face horizontally
- Rename x direction features by switching left and right
- To the human eye, the images look similar. Yet they look brand new to the model. Benefit: Increases training dataset with no cost

In [5]:

```
# flip the image
X_flip = np.reshape(np.reshape(X, (-1,1,96,96))[:, :, :, ::-1], (-1, 96*96))

# flip the x coordinate value
multiplier = [-1,1]*(y.shape[1]/2)
y_flip = np.multiply([multiplier,]*y.shape[0], y)

# flip the x coordinates/column name
y_name_flip = []
for name in y_name:
    if 'left' in name.lower():
        y_name_flip.append(name.replace('left','right'))
    elif 'right' in name.lower():
        y_name_flip.append(name.replace('right','left'))
    else:
        y_name_flip.append(name)
y_name_flip=np.array(y_name_flip)
isort = [np.where(y_name_flip==x)[0][0] for x in y_name]

# combine data and align with original column
y = np.concatenate((y, y_flip[:, isort]), axis=0)
X = np.concatenate((X, X_flip), axis=0)
print 'After merge X:%s, y:%s' %(X.shape, y.shape)

plot2(ex_x, ex_y*48+48, X_flip[666], y_flip[666, isort]*48+48)
```

```
After merge X:(14098, 9216), y:(14098, 30)
```



In [ ]:

Cleaning the Data: Group Images By Available Keypoints To Obtain Training Datasets

- Group images with same training keypoints

In [6]:

```
FKP_Count = {}
for x,f in zip(X,y):
    picker = ~np.isnan(f)
    id = str.join(',', y_name[picker])
    if id not in FKP_Count:
        FKP_Count[id] = 0
    FKP_Count[id] += 1

top_feature = np.array(FKP_Count.keys())[np.argsort(FKP_Count.values())[::-1]]

def getTopGroup(fea):
    isort = [np.where(y_name==x)[0][0] for x in fea]
    picker = np.alltrue(~np.isnan(y[:, isort]), axis=1)
    return fea, np.reshape(X[picker], (-1, 1, 96, 96)), np.array(y[picker])[:, i
sort]

feature1, X1, y1 = getTopGroup(top_feature[0].split(','))
feature2, X2, y2 = getTopGroup(top_feature[1].split(','))
x_t = np.reshape(X_t, (-1, 1, 96, 96))

print '1st training set: X1:%s - y1:%s, y1.min:%.3f, y1.max:%.3f' %(str(X1.shape
), str(y1.shape), y1.min(), y1.max())
print '2nd training set: X2:%s - y2:%s, y2.min:%.3f, y2.max:%.3f' %(str(X2.shape
), str(y2.shape), y2.min(), y2.max())
print 'testing set: x_t:%s' %str(x_t.shape)
```

```
1st training set: X1:(14000, 1, 96, 96) - y1:(14000, 8), y1.min:-0.9
86, y1.max:0.996
2nd training set: X2:(4280, 1, 96, 96) - y2:(4280, 30), y2.min:-0.96
4, y2.max:0.996
testing set: x_t:(1783, 1, 96, 96)
```

Model 1: Convolutional Neural Network (https://github.com/dnouri/nolearn/blob/master/nolearn/lasagne/base.py) Using Lasagne

- 3 Convolutional layers (https://github.com/Lasagne/Lasagne/blob/master/lasagne/layers/conv.py) with reception filter: (3x3), (2x2), (2x2) respectively
- Number of layers: 32, 64, 128
- 3 subsampling layers (https://github.com/Lasagne/Lasagne/blob/master/lasagne/layers/pool.py) with filter size (2x2) for each
- Use rectifier activation function for each convolutional layer

In [13]:

```
def getCNN(n_output):
    net = NeuralNet(
        layers=[
            ('input', layers.InputLayer),
            ('conv1', layers.Conv2DLayer),
            ('pool1', layers.MaxPool2DLayer),
            ('conv2', layers.Conv2DLayer),
            ('pool2', layers.MaxPool2DLayer),
            ('conv3', layers.Conv2DLayer),
            ('pool3', layers.MaxPool2DLayer),
            ('hidden4', layers.DenseLayer),
            ('hidden5', layers.DenseLayer),
            ('output', layers.DenseLayer),
            ],
        input_shape=(None, 1, 96, 96),
        # 3 convoluational layer
        conv1_num_filters=32, conv1_filter_size=(3, 3), pool1_pool_size=(2, 2),
        conv2_num_filters=64, conv2_filter_size=(2, 2), pool2_pool_size=(2, 2),
        conv3_num_filters=128, conv3_filter_size=(2, 2), pool3_pool_size=(2, 2),
        # 2 fully connected hidden layer
        hidden4_num_units=500, hidden5_num_units=500,
        # fully connected output layer, no activation function to give continuou
s output
        output_num_units=n_output, output_nonlinearity=None,

        update_learning_rate=0.02,
        update_momentum=0.80,

        regression=True,
        max_epochs=35,
        verbose=1,
        )
    return net

print 'LeNet defined!'
```

```
LeNet defined!
```

Model 2: 3-Layer Convolutional Neural Network Using Theano (http://www.deeplearning.net/software/theano/)

- 1 convolution layer (32 feature maps) with subsampling and 2 globally connected neural layers (600 neurons)
- Because the convergence process was not smooth, we reduced the learning rate to 0.0001 and saved the predictions for the test data whenever the cost was reduced during an epoch.

In [ ]:

```
class FacialDetector():
    # Initialize an instance of the class
```

```
    # initialize an instance of the class.
    def __init__(self, n_output):
        self._getParameters(n_output)
        self._getModel()

    def _getParameters(self, numClasses):
        numHiddenNodes = 600
        patchWidth = 3
        patchHeight = 3
        featureMapsLayer1 = 32
        # Convolution layers.
        w_1 = theano.shared(np.asarray((np.random.randn(*(featureMapsLayer1, 1,
patchWidth, patchHeight))*.01)))
        # Fully connected NN.
        w_4 = theano.shared(np.asarray((np.random.randn(*(featureMapsLayer1 * 49
* 49, numHiddenNodes))*.01)))
        w_5 = theano.shared(np.asarray((np.random.randn(*(numHiddenNodes, numCla
sses))*.01)))
        self.params = [w_1, w_4, w_5]
        self.srng = RandomStreams()

    def _getModel(self):
        theano.config.floatX = 'float64'
        X = T.tensor4() # conv2d works with tensor4 type
        Y = T.matrix()

        w_1, w_4, w_5 = self.params[0], self.params[1], self.params[2]
        y_hat_train = self._model(X, w_1, w_4, w_5, 0.2, 0.5)
        y_hat_predict = self._model(X, w_1, w_4, w_5, 0., 0.)

        self.cost = T.sum(T.sqr(Y - y_hat_train)) #T.sqrt(T.mean(T.sqr(Y - y_hat
_train)))
        update = self._backprop(self.cost, self.params)
        self.train = theano.function(inputs=[X, Y], outputs=self.cost, updates=u
pdate, allow_input_downcast=True)
        self.predict = theano.function(inputs=[X], outputs=y_hat_predict, allow_
input_downcast=True)

    def _model(self, X, w_1, w_4, w_5, p_1, p_2):
        l1 = self._dropout(T.flatten(max_pool_2d(T.maximum(conv2d(X, w_1, border
_mode='full'),0.), (2, 2)), outdim=2), p_1)
        l4 = self._dropout(T.maximum(T.dot(l1, w_4), 0.), p_2)
        return T.dot(l4, w_5)

    def _dropout(self, X, p=0.):
        if p > 0:
            X *= self.srng.binomial(X.shape, p=1 - p)
            X /= 1 - p
        return X

    def _backprop(self, Cost, w, alpha=0.0001, rho=0.66, epsilon=1e-6):
        grads = T.grad(cost=Cost, wrt=w)
        updates = []
        for w1, grad in zip(w, grads):
```

```
            # adding gradient scaling

            acc = theano.shared(w1.get_value() * 0.0)
            acc_new = rho * acc + (1 - rho) * grad ** 2
            gradient_scaling = T.sqrt(acc_new + epsilon)
            grad = grad / gradient_scaling
            updates.append((acc, acc_new))
            updates.append((w1, w1 - grad * alpha))
        return updates

    def _shuffleData(self, p, X, y):
        # shuffle it
        shuffle = np.random.permutation(np.arange(X.shape[0]))
        X, y = X[shuffle], y[shuffle]
        # divide
        n_train = np.round(X.shape[0]*p)
        return X[:n_train], y[:n_train], X[n_train:], y[n_train:]

    def fit_predict(self, X, y, x_t, epochs=1000, miniBatchSize=100):
        filename = 'save_' + datetime.now().strftime("%Y%m%d%H%M%S") + '.txt'
        print '\nepoch#: %d, batch#: %d, training#: %s, file: %s\n' %(epochs, mi
niBatchSize, y.shape, filename)
        start_time = time.time()
        min_test_rmse = 3.5
        # divide data
        train_data, train_labels, test_data, test_labels = self._shuffleData(0.9
, X, y)
        for i in range(epochs):
            epoch_start = time.time()
            # shuffle training data only
            shuffle = np.random.permutation(np.arange(train_data.shape[0]))
            train_data, train_labels = train_data[shuffle], train_labels[shuffle
]
            # run mini-batch gradient descent
            for start, end in zip(range(0, len(train_data), miniBatchSize), rang
e(miniBatchSize, len(train_data), miniBatchSize)):
                self.cost = self.train(train_data[start:end], train_labels[start
:end])
            epoch_time = time.time() - epoch_start
            # rescale labels
            orig_test_labels = test_labels * 48 + 48
            predicted_labels = self.predict(test_data) * 48 + 48
            # predictions are considered accurate if the are off by less than tw
o pixels
            accuracy = np.mean(abs(orig_test_labels - predicted_labels) < 2)
            test_rmse = np.sqrt(np.mean(np.square(predicted_labels - orig_test_l
abels)))
            new_prediction = 'no'
            # if we have a new low test_rmse, save the weights and predictions
            isSaved = ''
            if test_rmse < min_test_rmse:
                min_test_rmse = test_rmse
                new_prediction = 'yes'
                #save new weights - too big
```

```
#                   pickle.dump(self.params, open('kaggle_weights.pkl', 'w'))

                    # save new predictions
                    kaggle_predictions = self.predict(x_t) * 48 + 48
                    np.savetxt(filename, kaggle_predictions)
                    isSaved = '(saved)'
                # print epoch results to screen
                print '%d) trainRMSE = %.4f, accuracy = %.4f, valRMSE = %.4f, trainT
ime = %.2f min, endTime = %s %s' %(i+1, self.cost, accuracy, test_rmse, epoch_ti
me/60, time.strftime("%I:%M:%S"), isSaved)
                if test_rmse < 1.0:
                    print 'RMSE less than 1, good enough!'
                    break
        print '\nTotal train time = %.2f hours' %((time.time() - start_time)/360
0)
        return kaggle_predictions

print 'Model refreshed @ %s' %(time.strftime("%I:%M:%S"))
```

Training, Predicting, and Results

Training Procedures: Best Training Strategy (Appendix III)

1. Train one model (net1) with X1 dataset - 14000 images with 4 key points - 25 minutes/epoch x 69 epochs
2. Train one model (net2) with X2 dataset - 4280 images with all 15 key points - 7.5 minutes/epoch x 38 epochs
3. Each model makes predictions for 1783 testing images, giving predictions only for their available training keypoints (4 or 15).
4. For common keypoints across the two models, we take the weighted mean between the two predictions to generate the final prediction.
5. Shuffle the training data for each epoch. Use RMSE as the cost function. Use a mini-batch size of 10. Use a momentum speed of 0.66. Use a learning rate of 0.0001.
6. Best Score: RMSE = **2.92** (deviation in pixels)

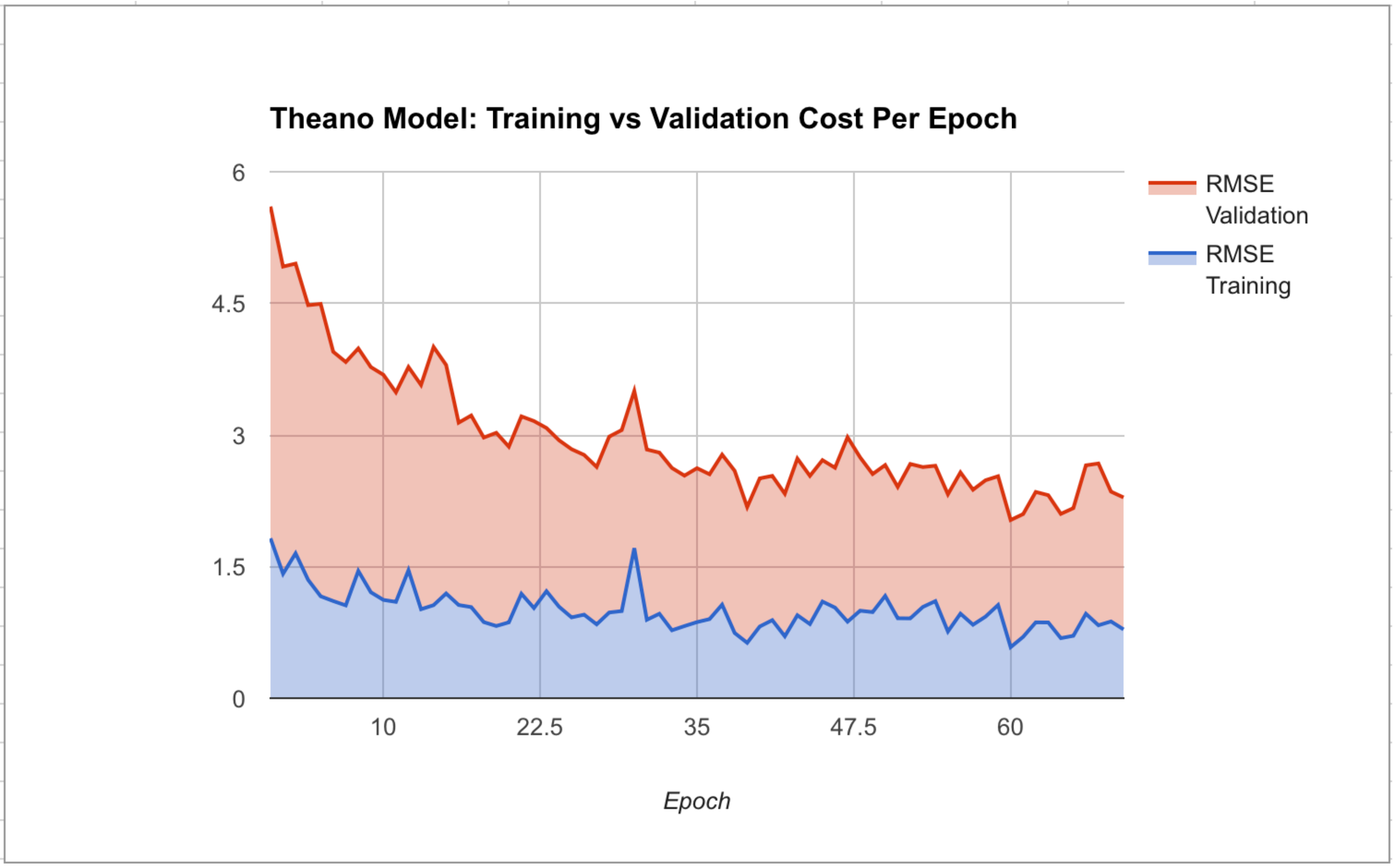
Training Loss Schedule

This shows the cost trend of the Theano Model (net1) while training on dataset X1 for 69 epochs:

In [1]:

```
from IPython.display import Image
Image(filename='CostGraph3.png')
```

Out[1]:



Feature Engineering Benchmark (3-Layer Lasagne Model): Training Time / Accuracy

No.	Method Applied	Train Set Size	# of epochs	mini-batch size	Train Time	RMSE	Improvement
0.	No feature engineering	2140	100	100	96min	3.85	baseline
1.	Histogram Stretching	2140	100	100	125min	3.66	5.0%
2.	#1 + Gaussian Blur	2140	100	100	110min	3.73	3.1%
3.	#1 + Gaussian Blur	2140	100	50	121min	3.52	8.6%
4.	#1 + Gaussian Blur	2140	200	100	244min	3.58	7.0%
5.	#2 + Horizontal Flip	4280	200	100	364min	3.36	12.7%
6.	Predict partial training set and combine with full-point set	14098	200	100	1235min	3.55	7.8%

Lessons Learned:

1. Convergence is not monotonic, despite choosing a smaller learning rate. This is surprising since the cost function, RMSE, is convex.
2. Training takes **a lot** more time with a more complex model structure and/or more training data. A powerful PC using the CPU isn't going to provide the optimal solution.
3. Training time is proportional to the number of epochs and the training dataset size, but reducing mini-batch size didn't increase the training time as much as expected. Reducing the number of layers didn't decrease the training time much. For comparison, the 5-layer neural net took about 7 minutes for one epoch, while the 3-layer neural net took about 6 minutes.
4. Even though we were able to test only two configurations (Nos. 2 and 3 in the table above), mini-batch size seems to have a big impact on accuracy. Halving the mini-batch size increased accuracy better than doubling the number of epochs.
5. At first we assumed that a complex model would always outperform simpler ones. However, the 5-layer neural net was much slower to converge, and given the same number of epochs, resulted in worse RMSE than the 3-layer model. In the end, we learned that the 5-layer model takes many more epochs to configure its weights, and the simpler 3-layer model is much more powerful than we initially thought.
6. Other hyperparameters, such as the number of feature maps, feature detector size, Gaussian blur sigma, and drop out probabilities need more exploration to find the optimal model. With our limited computing power and time constraints, we were not able to conduct all the experiments that we wanted.

Error Analysis

1. Rank Prediction Error on Keypoints and Images
    - Actual [num_test, num_coordinates] - actual keypoint coordinates from testing faces
    - Prediction [num_test, num_coordinates] - predicted keypoint coordinates for testing faces
    - Note: Two inputs must have the same dimensions, and the function is not comparing the absent key points (0) on the face
2. Visualization

In [8]:

```
##### print a rank for predidction RMSE #####
def RankPredictionRMSE(actual, prediction):
    print '\nError Analysis:'
    feaRMSE, keyRMSE = [], []
    # for each feature
    for i in range(len(feature_name)):
        picker = actual[:,i]>0
        feaRMSE.append(np.sqrt(np.mean((actual[picker,i]-prediction[picker,i])**
2)))
    feaRMSE = np.array(feaRMSE)
    feaRank = np.argsort(feaRMSE)

    # for each keypoint
    keypoints = [x[:-2] for x in feature_name]
    indexes = np.unique(keypoints, return_index=True)[1]
    keypoints = np.array([keypoints[i] for i in sorted(indexes)])
    for i in range(len(keypoints)):
        act = actual[:,i*2:(i+1)*2]
        pre = prediction[:,i*2:(i+1)*2]
        picker = act[:,0]>0
        keyRMSE.append(np.sqrt(np.mean((act[picker]-pre[picker])**2)))
    keyRMSE = np.array(keyRMSE)
    keyRank = np.argsort(keyRMSE)
    showKey = np.append(keypoints[keyRank][::-1], np.zeros(shape=(len(keypoints)
,1)))
    showRMSE = np.append(keyRMSE[keyRank][::-1], np.zeros(shape=(len(keypoints),
1)))

    # for each testing image
    imgRMSE = np.array([np.sqrt(np.mean((pre[act>0]-act[act>0])**2)) for pre, ac
t in zip(prediction, actual)])
    imgRank = np.argsort(imgRMSE)

    # print the RMSE ranking results
    template = "{0:35}{1:20}{2:35}{3:10}"
    print template.format("feature name", "RMSE", "keypoint", "RMSE") # header
    for f, r1, k, r2 in zip(feature_name[feaRank][::-1], feaRMSE[feaRank][::-1],
showKey, showRMSE):
        print template.format(f, *['%.3f' %r1, '%s' %(k if k!='0.0' else ''), '%
s' %('%.3f' %r2 if r2!=0 else '')])
```

```
    # plot top 10 badly predicted testing faces
    n_top = np.min([10, actual.shape[0]])
    print '\nTop %d faces with highest RMSE:' %n_top
    plt.figure(figsize=(20, 10))
    i=1
    for iid in imgRank[::-1][:n_top]:
        plt.subplot(2,5,i)
        plt.imshow(np.reshape(dev_faces[iid], (96,96)), cmap = cm.gray)
        picker = actual[iid]>0
        pre = np.reshape(prediction[iid, picker],(sum(picker)/2,2))
        kp = np.reshape(actual[iid, picker], (sum(picker)/2,2))
        for a,p in zip(kp, pre):
            plt.plot(a[0],a[1],'r.')
            plt.plot(p[0],p[1],'c.')
        plt.axis('off')
        plt.title('[%d] RMSE: %.3f' %(iid,imgRMSE[iid]))
        i+=1

##### Visualization #####
def plot(image, points=[], pred=[]):
    # print a picture to see
    plt.figure(figsize=(8, 8))
    if len(image)==96:
        plt.imshow(image, cmap = cm.gray)
    else:
        plt.imshow(np.reshape(image,(96,96)), cmap = cm.gray)
    plt.axis('off')
    if len(points)>0:
        for i in range(len(points)/2):
            plt.plot(points[2*i], points[2*i+1],'r.')
    if len(pred)>0:
        for i in range(len(pred)/2):
            plt.plot(pred[2*i],pred[2*i+1],'c.')
```

Appendix I: Mean Patch Searching Classifier

In [ ]:

```
class MeanPatchSearching:
    # Initialize an instance of the class.
    def __init__(self, patch_size=10, search_size=10, stretch=True):
        self.patch_size = patch_size
        self.search_size = search_size
        self.isStretch = stretch
        self.patch_index = np.array([[i,j] for i in range(-patch_size, patch_siz
e+1)
                                            for j in range(-patch_size, patch_siz
e+1)])
        self.search_index = np.array([[i,j] for i in range(-search_size, search_
size+1)
                                             for j in range(-search_size, search_
```

```
size+1)])


    # train the model
    def fit(self, train_faces, train_coordinates):
        start = datetime.now()
        # stretch input if needed
        if False: #self.isStretch:
            train_faces = np.array([self._histogramStretching(x) for x in train_
faces])
        # number of faces to train
        self.num_examples = train_faces.shape[0]
        print 'number of training faces: %d' %self.num_examples
        # assuming coordinates are (x,y) pairs for each key point
        self.num_keypoints = train_coordinates.shape[1]/2
        # image dimension
        self.ncolumn = np.sqrt(train_faces.shape[1])
        self.nrow = self.ncolumn

        # get patches and their centers for all keypoints
        self.patches, self.patch_centers = [], []
        for i in range(self.num_keypoints):
            # get coordinates of current keypoint
            coordinates = train_coordinates[:,i*2:(i+1)*2]
            # filter zero values (empty from file)
            picker = coordinates[:,0]>0
            # get patch if at least one face has this point
            if sum(picker)>0:
                # get patch for this key point
                self.patches.append(self._getPatch(train_faces[picker], coordina
tes[picker]))
                # get center for this keypoint
                self.patch_centers.append(np.mean(coordinates[picker], axis=0))

        # convert to numpy array
        self.patches = np.array(self.patches)
        self.patch_centers = np.array(self.patch_centers)
        self.num_keypoints = self.patches.shape[0]
        self.training_time = (datetime.now()-start).total_seconds()/60.0
        print 'training patches shape: %s' %str(self.patches.shape)
        print 'training time: %.1f minutes' %self.training_time
        # show training patches
#         self._plotPatches()

    # Make prediction for each test face and return coordinates.
    def predict(self, test_faces):
        start = datetime.now()
        # stretch input if needed
        if self.isStretch:
            test_faces = np.array([self._histogramStretching(x) for x in test_fa
ces])
        self.num_predict = test_faces.shape[0]
        print 'number of predicting faces: %d' %self.num_predict
        predictions = []
```

```
        for i in range(self.num_predict):

            if np.mod((i+1), self.num_predict/10)==0:
                print 'Complete %d%% ...' %(100.0*(i+1)/self.num_predict)
            pred = self._predictOneFace(test_faces[i])
            predictions.append(np.reshape(pred, (1,2*self.num_keypoints))[0])
        self.pred_coor = np.array(predictions)
        self.predict_time = (datetime.now()-start).total_seconds()/60.0
        print 'Done! - Predict time: %.1f minutes' %self.predict_time
        return self.pred_coor

    # calculate total Root Mean Squared Error (RMSE)
    def RMSE(self, actual, pred=[]):
        if len(pred)==0:
            pred = self.pred_coor
        picker = actual>0
        tRMSE = np.sqrt(np.sum((actual[picker]-pred[picker])**2)/np.sum(picker))
        return 'Total RMSE: %.2f, patch size: %d, search size: %d' %(tRMSE, self
.patch_size, self.search_size)

    # save the submission file based on prediction made for test images
    def getSubmission(self, LookupTable, feature_name):
        # create a dictionary for feature name indexing
        feature_index = {x:np.where(feature_name==x)[0][0] for x in feature_name
}
        lookupRow = []
        with open(LookupTable) as csvfile:
            # read the lookup file
            lookupReader = csv.reader(csvfile, delimiter=',')
            lookupRow.append(lookupReader.next())
            for row in lookupReader:
                # get the prediction based on image ID and feature name, and att
ach to the row
                location = self.pred_coor[int(row[1])-1, feature_index[row[2]]]
                lookupRow.append(np.append(row, location))
        lookupRow = np.array(lookupRow)
        # save row ID and location ID columns only to the submission file
        saveFile = 'submission_'+datetime.now().strftime("%Y%m%d%H%M%S")+'.csv'
        with open(saveFile, 'wb') as f:
            writer = csv.writer(f)
            writer.writerows(lookupRow[:,[0,3]])
        print 'Submission file saved as: %s' %saveFile
        return lookupRow

    # get the prediction for one face
    def _predictOneFace(self, face):
        # get prediction for each keypoint available in the model
        pred_coor = []
        for gold_p, center in zip(self.patches, self.patch_centers):
            # get the candidate points based on search size
            candidates = self._getCandidates(center)
            # get a patch for each candidate point
            pred_p = [self._getPatch([face], [x]) for x in candidates]
```

```
            # compare the patches from candidate points with gold_p

            # TODO: use better distance
            dist = [np.sum(np.abs(gold_p-x)) for x in pred_p]
            pred_coor.append(candidates[np.argmin(dist)])
        return pred_coor

    # get the candidate points - return the coordinates
    def _getCandidates(self, center):
        r, c = np.round(center)
        candidates = np.array([[r+i, c+j] for i,j in self.search_index])
        # only keep those within the bound
        picker = (np.sum(candidates>=0,axis=1) + np.sum(candidates<[self.nrow,se
lf.ncolumn],axis=1))==4
        return candidates[picker]

    # get the patch for one keypoint from all faces
    def _getPatch(self, faces, keypoints):
        patches = []
        for face, keypoint in zip(faces, keypoints):
            # get keypoint pixel row and column index
            r, c = np.round(keypoint)
            # get indices for the patch (including self)
            neighbors = np.array([[r+i, c+j] for i,j in self.patch_index])
            if np.sum(neighbors>=0)+np.sum(neighbors<[self.nrow,self.ncolumn]) =
= np.prod(neighbors.shape)*2:
                patches.append(face[[r*self.ncolumn + c for r,c in neighbors]])
#               else:
#                   print 'warning - nonconforming patch'
#           print np.array(patches).shape
        return np.mean(patches, axis=0)

    # histogram stretching pre-processing
    def _histogramStretching(self, image):
        # a, b = min(image), max(image)
        a, b = np.percentile(image, 5), np.percentile(image, 95)
        l, u = 0, 255
        const = 1.0*(b*l - a*u)/(b - a)
        k = 1.0*(u-l)/(b-a)
        return [k*p+const for p in image]

    # plot average patch from training
    def _plotPatches(self):
        n_side = 2*self.patch_size+1
        keypoints = np.reshape([x[:-2] for x in feature_name],(self.num_keypoint
s,2))
        plt.figure(figsize=(16, 8))
        i = 1
        for point, patch in zip(keypoints[:,0], self.patches):
            plt.subplot(3,5,i)
            plt.imshow(np.reshape(patch,(n_side,n_side)), cmap = cm.gray)
            plt.title(point)
            plt.axis('off')
            i += 1
```

```
        plt.show()



##### Get baseline score #####
# training
mps = MeanPatchSearching(patch_size=9, search_size=5, stretch=True)
mps.fit(train_faces[:150], train_coordinates[:150])
# predicting
predictions = mps.predict(test_faces)
mps.getSubmission('./Data/FKD_IdLookupTable.csv', feature_name)
```

Appendix II: 5-Layer CNN Using Theano

In [4]:

```
## (1) Parameters
numHiddenNodes = 600
patchWidth = 3
patchHeight = 3
featureMapsLayer1 = 32
featureMapsLayer2 = 64
featureMapsLayer3 = 128

# For convonets, we will work in 2d rather than 1d.  The facial images are 96x96
in 2d.
imageWidth = 96
# n_train = np.round(X1.shape[0]*0.9)
# train_X, train_y =  X1[:n_train], y1[:n_train]
# test_X, test_y = X1[-n_train:], y1[-n_train:]

n_train = np.round(X2.shape[0]*0.9)
train_X, train_y =  X2[:n_train], y2[:n_train]
test_X, test_y = X2[n_train:], y2[n_train:]

# Convolution layers.
w_1 = theano.shared(np.asarray((np.random.randn(*(featureMapsLayer1, 1, patchWid
th, patchHeight))*.01)))
w_2 = theano.shared(np.asarray((np.random.randn(*(featureMapsLayer2, featureMaps
Layer1, patchWidth-1, patchHeight-1))*.01)))
w_3 = theano.shared(np.asarray((np.random.randn(*(featureMapsLayer3, featureMaps
Layer2, patchWidth-1, patchHeight-1))*.01)))
# Fully connected NN. - 12x12 - dimension of L3 (11) plus bias (1)
w_4 = theano.shared(np.asarray((np.random.randn(*(featureMapsLayer3 * 12 * 12, n
umHiddenNodes))*.01)))
w_5 = theano.shared(np.asarray((np.random.randn(*(numHiddenNodes, train_y.shape[
1]))*.01)))
params = [w_1, w_2, w_3, w_4, w_5]

## (2) Model
theano.config.floatX = 'float64'
X = T.tensor4() # conv2d works with tensor4 type
Y = T.matrix()
```

```
Y = T.matrix()

srng = RandomStreams()
def dropout(X, p=0.):
    if p > 0:
        X *= srng.binomial(X.shape, p=1 - p)
        X /= 1 - p
    return X

# Theano provides built-in support for add convolutional layers
def model(X, w_1, w_2, w_3, w_4, w_5, p_1, p_2):
    l1 = dropout(max_pool_2d(T.maximum(conv2d(X, w_1, border_mode='full'), 0.),
(2, 2)), p_1)
    l2 = dropout(max_pool_2d(T.maximum(conv2d(l1, w_2), 0.), (2, 2)), p_1)
    # flatten to switch back to 1d layers - with "outdim = 2" (2d) output
    l3 = dropout(T.flatten(max_pool_2d(T.maximum(conv2d(l2, w_3), 0.), (2, 2)),
outdim=2), p_1)
    l4 = dropout(T.maximum(T.dot(l3, w_4), 0.), p_2)
    return T.dot(l4, w_5) #T.nnet.softmax(T.dot(l4, w_5))

y_hat_train = model(X, w_1, w_2, w_3, w_4, w_5, 0.2, 0.5)
y_hat_predict = model(X, w_1, w_2, w_3, w_4, w_5, 0., 0.)

## (3) Cost
cost = T.sqrt(T.mean(T.sqr(Y - y_hat_train))) # T.mean(T.nnet.categorical_crosse
ntropy(y_hat_train, Y))

## (4) Minimization.
def backprop(cost, w, alpha=0.01, rho=0.8, epsilon=1e-6):
    grads = T.grad(cost=cost, wrt=w)
    updates = []
    for w1, grad in zip(w, grads):

        # adding gradient scaling
        acc = theano.shared(w1.get_value() * 0.)
        acc_new = rho * acc + (1 - rho) * grad ** 2
        gradient_scaling = T.sqrt(acc_new + epsilon)
        grad = grad / gradient_scaling
        updates.append((acc, acc_new))

        updates.append((w1, w1 - grad * alpha))
    return updates

update = backprop(cost, params)
train = theano.function(inputs=[X, Y], outputs=cost, updates=update, allow_input
_downcast=True)
predict = theano.function(inputs=[X], outputs=y_hat_predict, allow_input_downcas
t=True)

miniBatchSize = 1
def gradientDescentStochastic(epochs):
    print 'Training started @%s, buckle up!' %datetime.now()
    print 'Training set: %s, dev set: %s' %(train_y.shape, test_y.shape)
```

```
    start_time = time.time()

    for i in range(epochs):
        for start, end in zip(range(0, len(train_X), miniBatchSize), range(miniB
atchSize, len(train_X), miniBatchSize)):
            cost = train(train_X[start:end], train_y[start:end])
#               print 'cost: %.3f' %cost
        print '%d) %s: RMSE = %.4f' %(i+1, datetime.now(), np.sqrt(np.mean(np.sq
uare(test_y - predict(test_X)))))
    print 'Total training time = %.2f' %(time.time() - start_time)

# gradientDescentStochastic(10)

# start_time = time.time()
# predict(test_data)
# print 'predict time = %.2f' %(time.time() - start_time)
```

Appendix III: First Training and Predicting Strategy

In [17]:

```
################### Option 1. Lasagne 5-layer Model ###################

##### CNN for X1 training set () ##### #0.00518
net1 = getCNN(y1.shape[1])
net1.fit(X1.astype('float32'), y1.astype('float32'))
start_time = time.time()
y_hat1 = net1.predict(x_t)*48+48
print 'Prediction time: %.2f sec, y_hat1.%s' %(time.time()-start_time, str(y_hat
1.shape))
filename='./Data/mp1_' + datetime.now().strftime("%Y%m%d%H%M%S") + '.pkl'
pickle.dump([y_hat1], open(filename, 'w'))
# release some memory by remove net1
del net1

##### CNN for X2 training set () ##### #0.00421
net2 = getCNN(y2.shape[1])
net2.fit(X2.astype('float32'), y2.astype('float32'))
start_time = time.time()
y_hat2 = net2.predict(x_t)*48+48 # rescale it back
print 'Prediction time: %.2f sec, y_hat2.%s' %(time.time()-start_time, str(y_hat
2.shape))
filename='./Data/mp2_' + datetime.now().strftime("%Y%m%d%H%M%S") + '.pkl'
pickle.dump([y_hat2], open(filename, 'w'))

################### Option 2. Theao 3-layer Model ###################

net2 = FacialDetector(n_output=y2.shape[1])
y2hat = net2.fit_predict(x_t=x_t, X=X2, y=y2, epochs=100, miniBatchSize=10)
del net2 #release some memory

net1 = FacialDetector(n_output=y1.shape[1])
y1hat = net1.fit_predict(x_t=x_t, X=X1, y=y1, epochs=100, miniBatchSize=10)
```

```
y_hat1 = net1.fit_predict(x_t=x_t, X=X1, y=y1, epochs=100, miniBatchSize=10)

################### assebmle results to get submission file ###################
def getSubmission(LookupTable):
    # create a dictionary for feature name indexing
    index2 = {feature2[x]:x for x in range(len(feature2))}
    index1 = {feature1[x]:x for x in range(len(feature1))}
    lookupRow = []
    with open(LookupTable) as csvfile:
        # read the lookup file
        lookupReader = csv.reader(csvfile, delimiter=',')
        lookupRow.append(lookupReader.next())
        for row in lookupReader:
            # get the prediction based on image ID and feature name, and attach
to the row
            image_id, fea = int(row[1])-1, row[2]
            location = y_hat2[image_id, index2[fea]]
            if fea in index1:
                location = (location + y_hat1[image_id, index1[fea]])/2
            lookupRow.append(np.append(row, location))
    lookupRow = np.array(lookupRow)
    # save row ID and location ID columns only to the submission file
    saveFile = 'submission_' + datetime.now().strftime("%Y%m%d%H%M%S") + '.csv'
    with open(saveFile, 'wb') as f:
        writer = csv.writer(f)
        writer.writerows(lookupRow[:,[0,3]])
    print 'Submission file saved as: %s' %saveFile

getSubmission('./Data/FKD_IdLookupTable.csv')
```

```
Submission file saved as: submission_20150806005853.csv
```

Appendix IV: Using Predictions to Fill in Missing Keypoints for Training

In [ ]:

```
### This code is from another ipython notebook we were running and the variable names don't match with other parts of this notebook

# 4. Feature  engineering: histogram stretching + gaussian blur + horizontal flip, partial-point set
train_data_p, train_labels_p = splitSet(train_data_st_bl_fl, train_labels_st_bl_fl, full=False)
test_data_4 = test_data_3
#print '3. Histogram Stretch + Gaussian Blur + Horizontal Flip:  %s - %s' % (train_data_3.shape, train_labels_3.shape)

print 'Predict on partial-point training set and make complete training set'
start_time = time.time()
pred_labels = net_3.predict(train_data_p.astype('float32'))
print 'Partial-point Set Prediction time: %.2fs' %(time.time()-start_time)

## Fill the missing coordinates from prediction
for i in range(0, pred_labels.shape[0]) :
    for j in range(0, pred_labels.shape[1]) :
        if np.isnan(train_labels_p[i,j]) : train_labels_p[i,j] = pred_labels[i,j]

train_data_4 = np.concatenate((train_data_3, train_data_p), axis=0)
train_labels_4 = np.concatenate((train_labels_3, train_labels_p), axis=0)
print '4. Use predictions to fill in the missing keypoints:  %s - %s' % (train_data_4.shape, train_labels_4.shape)

### Final Prediction and Submission
## Now re-train with complete training set and predict on full-point dev data
print 'Training with entire training set'
net_4 = convonet(train_data_4, train_labels_4, 200, 100, 'train_4.pickle')

print 'Predict test set and make submission file'
start_time = time.time()
test_labels_4 = net_4.predict(test_data_4.astype('float32'))
print 'Test Set Prediction time: %.2f min' %((time.time()-start_time)/60.0)

getSubmission(test_labels_4*48+48, './Data/FKD_IdLookupTable.csv')
```