2017-07-03

- Initial set up of neural net, based on leNet-5, no signal out, most likely due to using unprocessed data.
- The data is very padded, this has been reduced with the function `cropHeart(inp)`, but I will need to make sure all the files are the same size before they get fed into the CNN.
- I could try normalising the data to get a signal, but will need to get the unpadded data working first.

2017-07-04

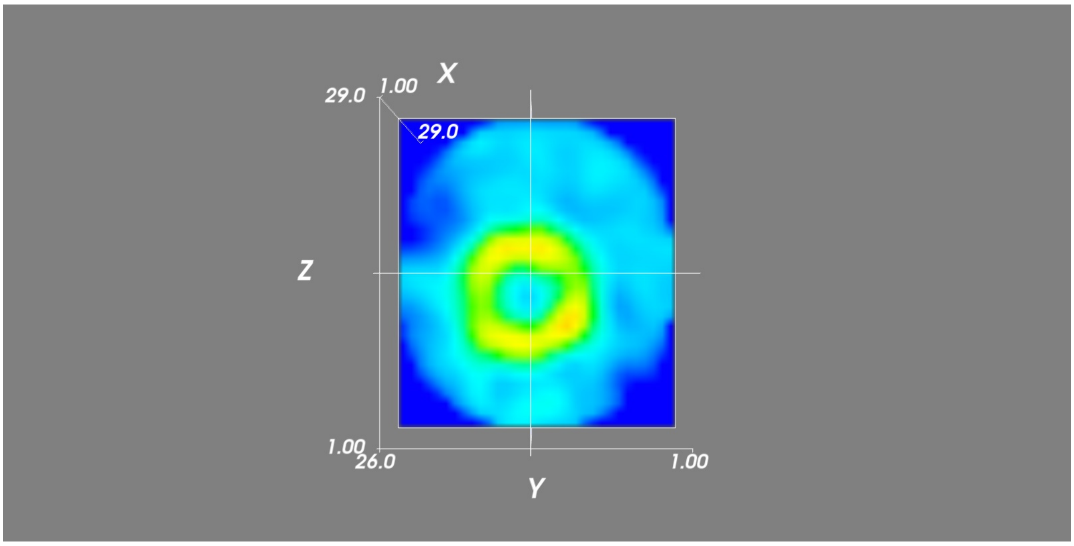
- Wrote a visualisation of the data (`visualisation.py`).
- Still working on repadding the cropped data (It's a bit of a pain).

2017-07-05

- Repadded the cropped data, it is now of size [68,34,34].
- Retrying the CNN with the new data doesn't get a signal. Maybe there isn't enough data to make it work?
- I will fiddle with the hyperparams to see if I can pick something up.
- Maybe normalising the data will help.

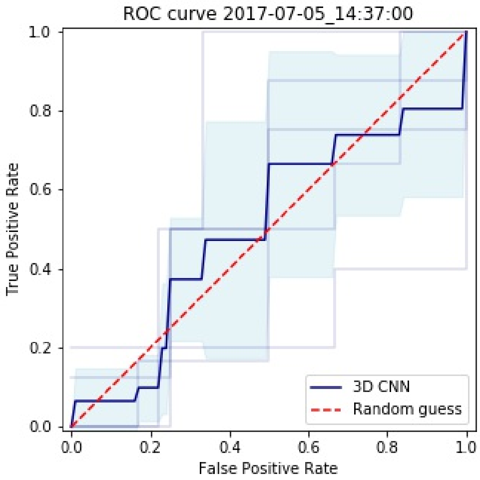
Got some results using 2D slices:

- The 2D slices I used look like:

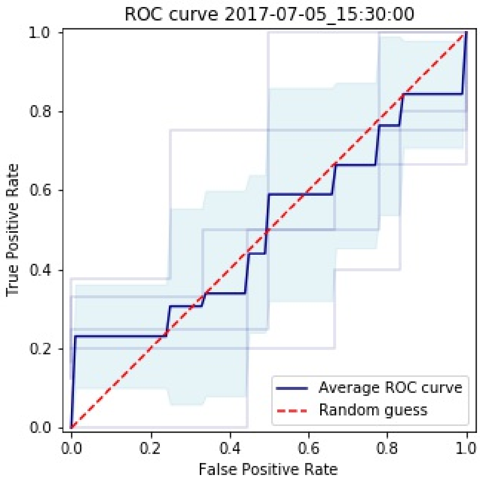


- I have used 2d slices of the data and it works well (halfway through the z-axis). It uses:
    - Slice of rest and slice of stress on z axis. Spacial x and spacial y on x and y axes.
    - LeNet-5 CNN with 3D convolution and subsampling.
    - [2,5,5] filters, pooling 2 with step 2.
    - learning rate of 0.0001, with ADAM optimiser, and batch size of 10.
    - After 50 epochs of 58 images it learns to ~95%.
- I will now apply a k-fold x-validation to it to see if it's not just picking up noise.

- The k=10-fold x-validation shows that the CNN is learning the noise in the data, although this could be due to the small amount of images in each k-fold (only 6!):



- I tried normalising the arrays, with no luck. It stopped overfitting the data, but still hasn't learnt significantly:

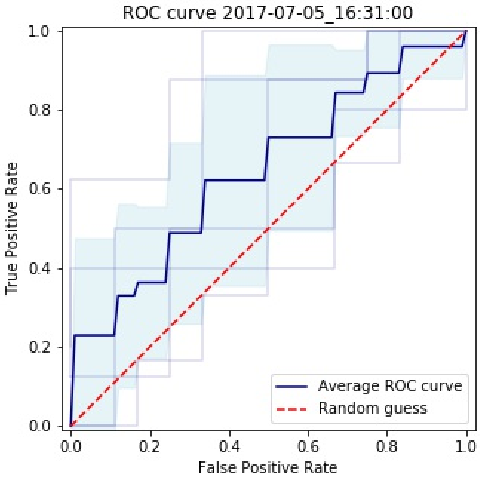


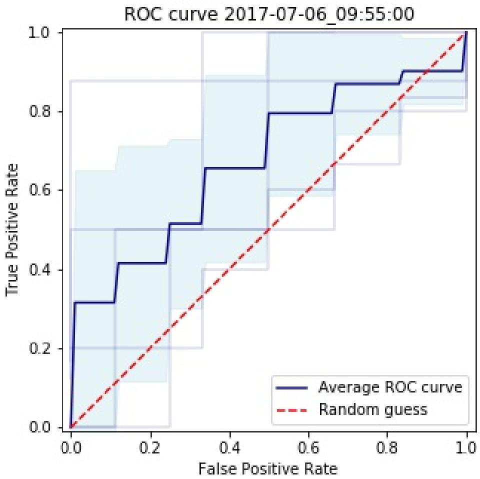
- I think the issue is still the massive amount of blankspace. I should try and scale the arrays so that they are the same size.

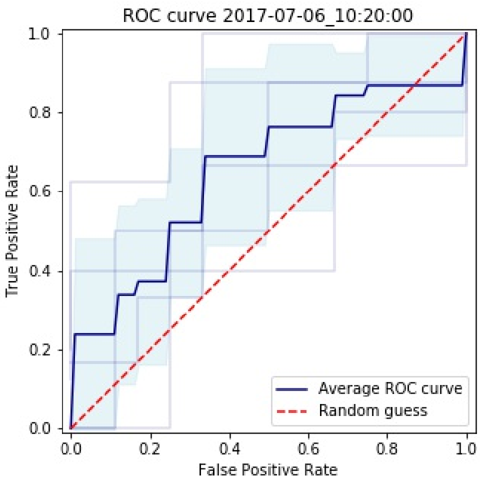
Have a signal!

- I have got a signal with the following CNN:
    - Slice of rest and slice of stress on z axis. Spacial x and spacial y on x and y axes.
    - LeNet-5 CNN with 3D convolution and subsampling.
    - [2,10,10] filters, pooling 2 with step 2.
    - learning rate of 0.0001, with ADAM optimiser, and batch size of 10.
    - 5 k-folds.
    - After 50 epochs of 47 images it learns training data to ~95%.
    - Over three repeats:
        - Avg Spec: 0.583, 0.623, 0.663
        - Avg Sens: 0.633, 0.683, 0.700

- ROC curves:







2017-07-06

- I redid the 2D slice data with three slices along the x, y, and z axes. It will take ~100 mins to finish learning. It's probably time to use some better hardware.

- Found a function (https://docs.scipy.org/doc/scipy-0.14.0/reference/generated/scipy.ndimage.interpolation.zoom.html) which should work well for resizing the images.

- Maybe the reason that the slicing works, and the 3D data doesn't is because the CNN filter only sees one 3D image at a time, and sees both the rest and stress images at the same time in the 2D slice data. I could write a 4D CNN to fix this.

    - mhuen seems to have written a 4D convolution by stacking 3D CNN outputs (https://github.com/mhuen/TFScripts/blob/master/py/tfScripts.py). This might work for what I want to do, and stacking can be used for pooling too.

- I wrote a scaling function hat eliminates most of the whitespace. After training the CNN did not learn significantly.

- Added a ROC AUC calculator to the outputs.

- I'm going to try artificially expanding the data.

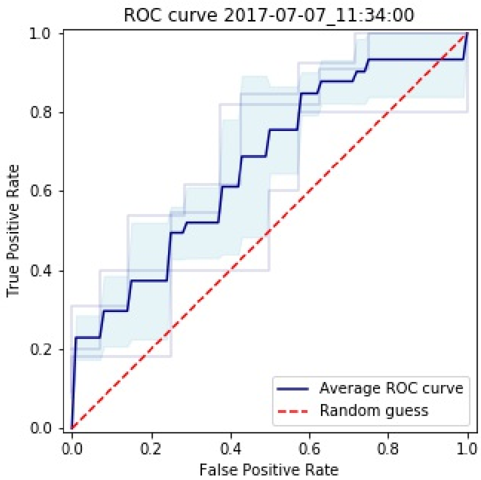
2017-07-07

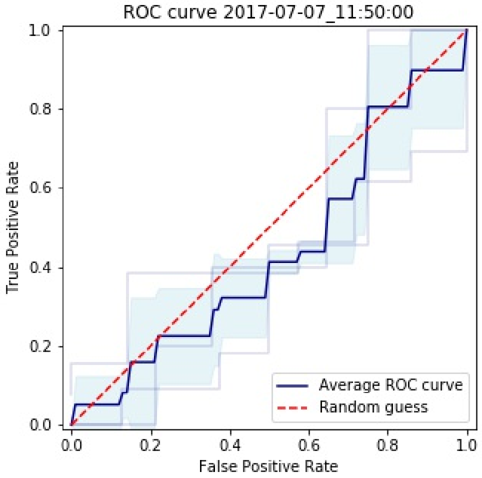
- Because of the overfitting going on when running the CNN, I increased the L2 regularisers' weight decay from 0.001 to 0.01, and added an extra dropout layer between the two FC dense layers.

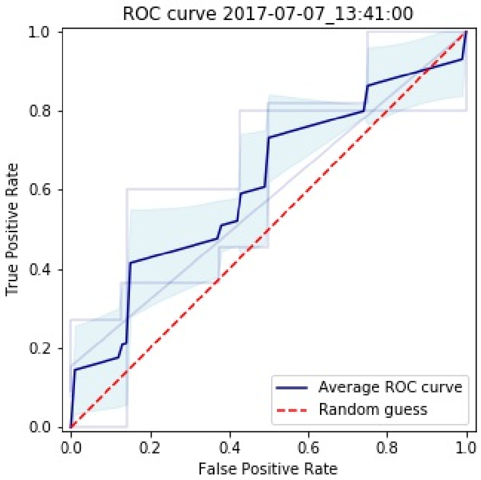
- Can't seem to get any results with a spec/sens over 60%, probably due to the way I'm orgainising the data.

- The CNN appears to train better when using non-scaled data. I can't figure out why. Maybe it's using the image sizes as an aid?

    - Conv filter: [2,15,15]; pool filter: [2,2,2]; 2 FC 1024 neurons, L2 regulisation at weight decay = 0.001, dropout at 0.5 after each FC layer; ADAM optimiser, learning rate = 0.0001, categorical x-entropy loss; batch size = 10 at 38 datum; k = 3 folds.

        - non-scaled: 

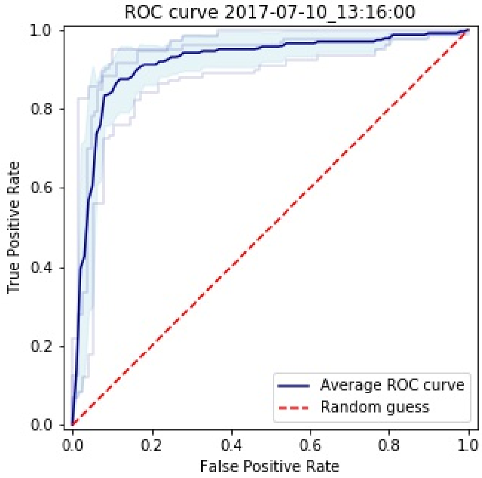
- scaled: 

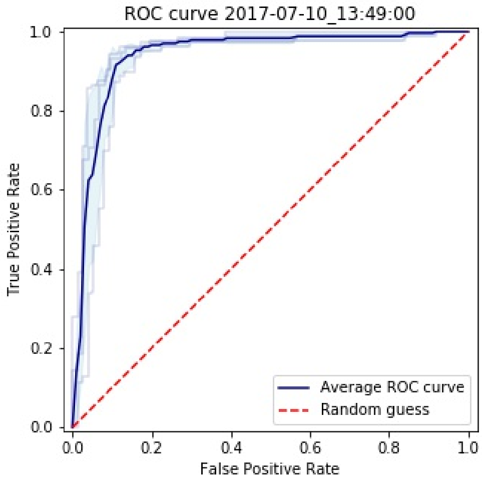
- scaled, not renormalised: 

- As shown in the ROC curves, the only data that is causing consistent learning is the non-scaled one. I don't know why.
- Rewrote heart_data.ipynb so that it can resize the input data.

2017-07-10

- It might be better to use a Siamese CNN instead of a 4D CNN to compare two 3D images, as training will be faster.
  - I have written CNNs using two-channel, and Siamese architectures, along with the OG 3D convolution architecture. The two-channel and Siamese architectures are described here: [(https://arxiv.org/pdf/1504.03641.pdf)](https://arxiv.org/pdf/1504.03641.pdf).
- The use of a very deep NN architecture would reduce linearity, and may be useful.
- Artificially expanding the data seems to have worked. I am getting after k = 3 folds (100 epochs) at 619 datum (two runs):
  - Spec: 0.864, 0.917
  - Sens: 0.888, 0.883
  - ROC AUC: 0.918, 0.940
  - This is with the two-channel architecture. ROC curves:

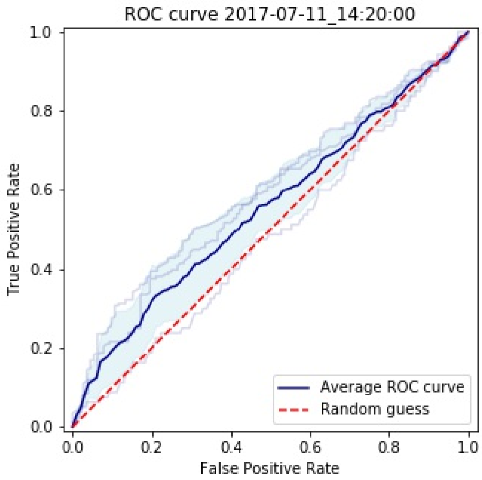
- 

- 

- Haven't got any significant results from the Siamese CNN, but have only trained it to ~30 epochs. It will probably need more training than the two-channel as there are nearly twice as many weights in the Siamese CNN.
- I should try validating the CNN on ppts that it hasn't seen before (like take 10 ppts from the pool before artificial expansion and use these to validate).

2017-07-11

- I have separated ppts into different k-folds before expansion, so each k-fold has unique ppts in it now, even after artificial expansion. We'll see how it performs now... (This is in the 2channel ipynb)
    - It doesn't work very well. Getting ~50% accuracy.

- 

- More data would be helpful to reduce overfitting, but using all three dimensions of the heart data may be enough to get "good enough" results.

- I have written a 2 channel CNN for the 3D data. It should be ready to try on the supercomputer.

2017-07-12

- Testing the 2dSiameseCNN on the supercomputer:
  `$ qsub -q gpu -l nodes=1:ppn=16 -I -X -l walltime=24:00:00`
  It doesn't seem to work. How long is the queue?

- I have found a bug in the 2dsliceCNN that may be causing the lack of learning. The expansion doesn't relabel the expanded data correctly. I have hopefully fixed this.

- Running for 20 epochs @ k = 5 folds to see how it does.

  - Again, ~50% accuracy.

- I have increased the number of conv layers to 4.

  - No change.

- Running the 3D CNN on the hub. It looks like it takes ~20 epochs to train to 100% (I should use validation to see if/when it starts overfitting). It also takes ~12s to train an epoch. To contast it takes my computer ~16mins per epoch, an 80x speedup.

- Added 4(!) new convolution layers to 3D CNN. Since this reduces linearity, we may find something.

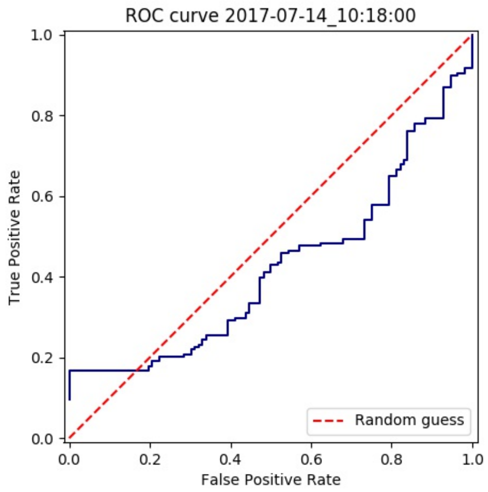
  - Getting some odd results. The CNN comes out with the opposite of what I was expecting (low ROC, accuracy).
  - Look at labelling, try on simpler data (MNIST 0s and 1s?), reintroduce k-folding?

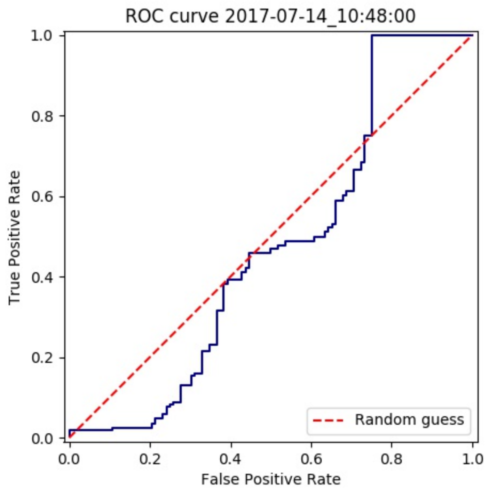
2017-07-14

- Added overall average performance metric to 3dCNN-nokfold.

- I think I have found the cause of the low ROC/accuracy. The random state shuffle is set to 1. If I change it, it may get some more believable results.

- Looks like that was what the issue was. The CNN got lucky with the cubes taken out for testing:

    - 

    - 

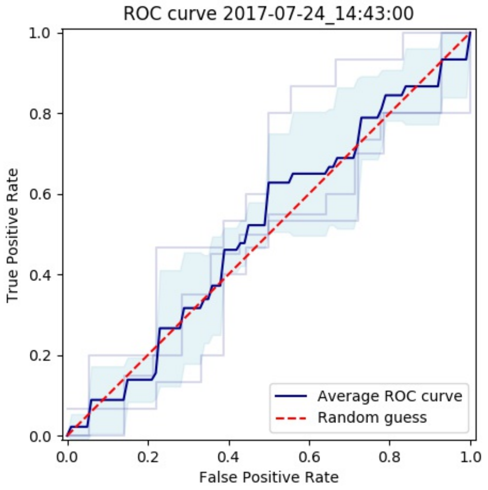
- Using fake data to train a CNN. It's found on `/data/jim/Heart/sims`.

- The CNNs aren't training. For normal/infarction data I have the loss decreasing but the accuracy is static.
[(https://www.reddit.com/r/cs231n/comments/4p12oc/what_does_it_mean_when_the_loss](https://www.reddit.com/r/cs231n/comments/4p12oc/what_does_it_mean_when_the_loss)
< It looks like it is due to the CNN training well on "easy" examples.

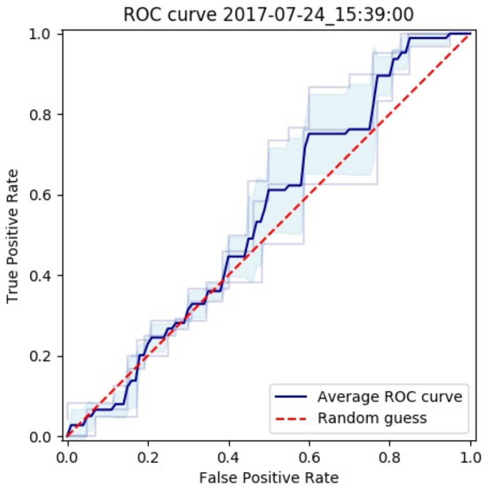
2017-07-24

- Trying a CNN with both heart cubes encoded as one (through matrix multiplication).
- The fake data doesn't seem to be working. I should look for ways to reduce noise in it.
- There was an error in my normalisation function. I'm going to go back and fix it and see if anything happens.
- It's finding something, but it looks like it's getting stuck in local minima. I'll fiddle about with the learning rate.
- Reducing the ppts to 50 healthy 50 unhealthy has got an accuracy of ~70%. This is promising. Maybe the CNN just needs a while to learn?

- Got this:

    - 

- Running again with 400 epochs. Taking ~20 min per k-fold of 100 ppts. I should try this with the full dataset. It will take a long time (~7 hours), so if this works I'll run overnight.
- Got this for 400 epochs:

    - 

- Set up a job for overnight. We'll see how it does tomorrow.

2017-07-25

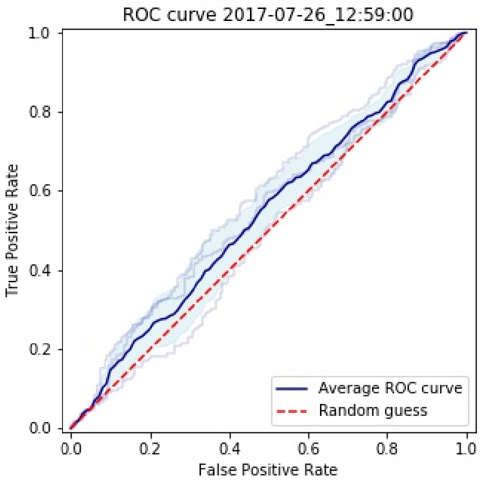
- To run headless on a server I need the following at the top (matplotlib uses X by defualt).

```
import matplotlib
matplotlib.use('Agg')
```

- Rerunning the 400 epoch 1500 ppt CNN...
- There may be an issue with the resizing of the arrays into the zeroArr. I think removing the centring code fixes it, and doesn't affect the CNN. Running a test on the 2D CNN.
    - I can safely remove the centring code.

- It takes a very long time to denoise the heart cubes. Will need to do this on the server.
- OOM error! I will need to rewrite the python script so that each k-fold is considered separately. Looks promising though: ~0.6 accuracy after 400 epochs.

2017-07-26

- The results from the latest run have training accuracy at 55%, with validation accuracy around the same (mean AUC = 0.54). I'll try again with less regularisation (it may be underfitting).
    - 

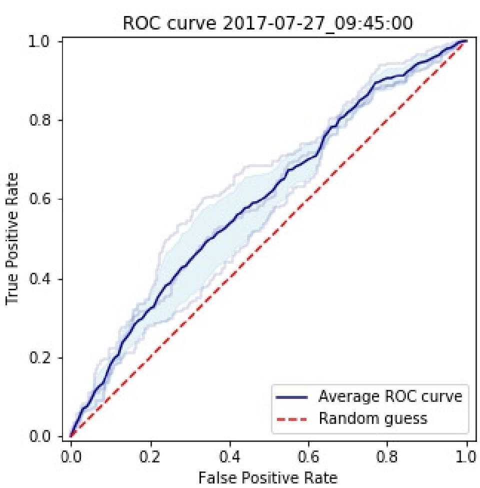
- Rewrote cnn.py so that the logging is more transparent (in plaintext after each k-fold).
- Rerunning the CNN with 500 epochs without dropout. Will be done tomorrow.
- I took out the resizing movement from cnn.py between the 60% and 55% runs. If there is no improvement in the current run I should put it back in:

```
##### There is probably a better way of doing this...
if calm3d.shape[0] != 34:
    startInd = (34 - calm3d.shape[0])/2
    zeroArr0[startInd:calm3d.shape[0]+startInd,:calm3d.shape[1],\
        :calm3d.shape[2]] = calm3d
if calm3d.shape[1] != 34:
    startInd = (34 - calm3d.shape[1])/2
    zeroArr0[:calm3d.shape[0],startInd:calm3d.shape[1]+startInd,\
        :calm3d.shape[2]] = calm3d
if calm3d.shape[2] != 34:
    startInd = (34 - calm3d.shape[2])/2
    zeroArr0[:calm3d.shape[0],:calm3d.shape[1],\
        startInd:calm3d.shape[2]+startInd] = calm3d


if stress3d.shape[0] != 34:
    startInd = (34 - stress3d.shape[0])/2
    zeroArr1[startInd:stress3d.shape[0]+startInd,:stress3d.shape[1],\
        :stress3d.shape[2]] = stress3d
if stress3d.shape[1] != 34:
    startInd = (34 - stress3d.shape[1])/2
    zeroArr1[:stress3d.shape[0],startInd:stress3d.shape[1]+startInd,\
        :stress3d.shape[2]] = stress3d
if stress3d.shape[2] != 34:
    startInd = (34 - stress3d.shape[2])/2
    zeroArr1[:stress3d.shape[0],:stress3d.shape[1],\
        startInd:stress3d.shape[2]+startInd] = stress3d
```

- I have updated cnn.py to start saving the trained CNN models.
- It might also be beneficial to start using the real data as a validation set.
- Processing the log files would be better done in an ipynb.

2017-07-27

- Results from last run have an average specificity of 0.54, and an average sensitivity of 0.62. The AUC average is 0.60.

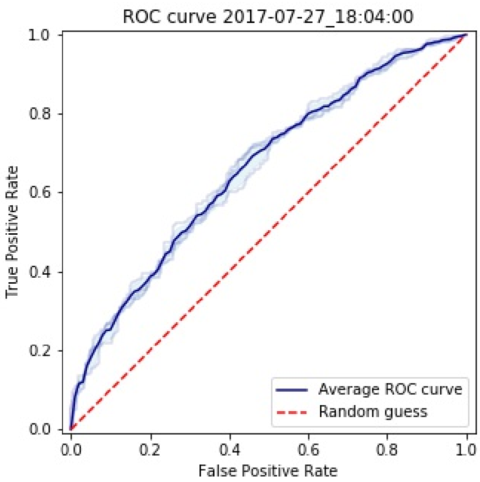


- This is with

```
    # Neural net (two-channel)

    sess = tf.InteractiveSession()
    tf.reset_default_graph()
    tflearn.initializations.normal()

    # Input layer:
    net = tflearn.layers.core.input_data(shape=[None,34,34,34,2])

    # First layer:
    net = tflearn.layers.conv.conv_3d(net, 32, [10,10,10],
activation="leaky_relu")
    net = tflearn.layers.conv.max_pool_3d(net, [2,2,2], strides=[2,2,2])

    # Second layer:
    net = tflearn.layers.conv.conv_3d(net, 64, [5,5,5],
activation="leaky_relu")
    net = tflearn.layers.conv.max_pool_3d(net, [2,2,2], strides=[2,2,2])

    # Fully connected layers
    net = tflearn.layers.core.fully_connected(net, 2048, regularizer="L2",
weight_decay=0.01, activation="leaky_relu")
    #net = tflearn.layers.core.dropout(net, keep_prob=0.5)

    net = tflearn.layers.core.fully_connected(net, 1024, regularizer="L2",
weight_decay=0.01, activation="leaky_relu")
    #net = tflearn.layers.core.dropout(net, keep_prob=0.5)

    net = tflearn.layers.core.fully_connected(net, 512, regularizer="L2",
weight_decay=0.01, activation="leaky_relu")
    #net = tflearn.layers.core.dropout(net, keep_prob=0.5)

    # Output layer:
    net = tflearn.layers.core.fully_connected(net, 2, activation="softmax")

    net = tflearn.layers.estimator.regression(net, optimizer='adam',
learning_rate=0.000001, loss='categorical_crossentropy')
    model = tflearn.DNN(net, tensorboard_verbose=0)

    # Train the model, leaving out the kfold not being used
    dummyData = np.reshape(np.concatenate(kfoldData[:i] + kfoldData[i+1:],
axis=0), [-1,34,34,34,2])
    dummyLabels = np.reshape(np.concatenate(kfoldLabelsOH[:i] +
kfoldLabelsOH[i+1:], axis=0), [-1, 2])
    model.fit(dummyData, dummyLabels, batch_size=100, n_epoch=500,
show_metric=True)
```

- I am convinced that the CNN is finding something. Will push the new cnn.py to github so that we can test the trained nets on real data.
- New CNN further reduces regularisation, and increases learning rate from 0.000001 to

0.0001.

- Writing a python script that finds the part(s) of the cube that the CNN uses for diagnosis.
    - I will need to test it when I have some models, but it looks like it will work. It is saved as `getDiagArea.py`.
- Latest CNN results:
    - AVG spec 0.62, AVG sens 0.61, AVG AUC 0.66. (Over k=3 folds).
    - 

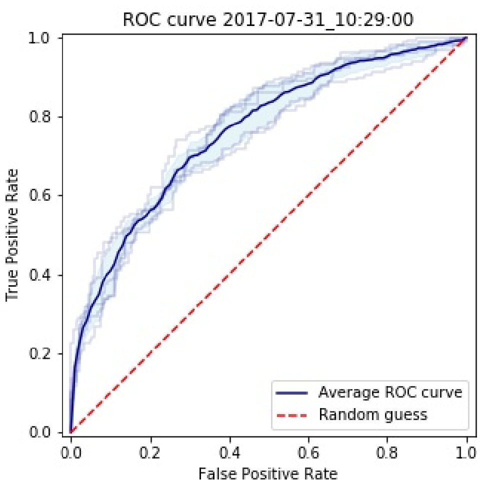
2017-07-31

- Newest results are in with the following CNN:

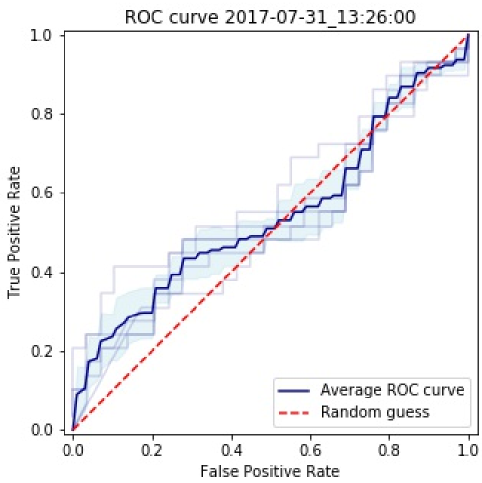
```
    # Neural net (two-channel)

    sess = tf.InteractiveSession()
    tf.reset_default_graph()
    tflearn.initializations.normal()

    # Input layer:
    net = tflearn.layers.core.input_data(shape=[None,34,34,34,2])

    # First layer:
    net = tflearn.layers.conv.conv_3d(net, 32, [10,10,10],
activation="leaky_relu")
    net = tflearn.layers.conv.max_pool_3d(net, [2,2,2], strides=[2,2,2])

    # Second layer:
    net = tflearn.layers.conv.conv_3d(net, 64, [5,5,5],
activation="leaky_relu")
    net = tflearn.layers.conv.max_pool_3d(net, [2,2,2], strides=[2,2,2])

    # Third layer:
    net = tflearn.layers.conv.conv_3d(net, 128, [2,2,2],
activation="leaky_relu") # This was added for CNN 2017-07-28
```

```
    # Fully connected layers
    net = tflearn.layers.core.fully_connected(net, 2048,
activation="leaky_relu") # regularizer="L2", weight_decay=0.01,
    #net = tflearn.layers.core.dropout(net, keep_prob=0.5)

    net = tflearn.layers.core.fully_connected(net, 1024,
activation="leaky_relu") # regularizer="L2", weight_decay=0.01,
    #net = tflearn.layers.core.dropout(net, keep_prob=0.5)

    net = tflearn.layers.core.fully_connected(net, 512,
activation="leaky_relu") # regularizer="L2", weight_decay=0.01,
    #net = tflearn.layers.core.dropout(net, keep_prob=0.5)

    # Output layer:
    net = tflearn.layers.core.fully_connected(net, 2, activation="softmax")

    net = tflearn.layers.estimator.regression(net, optimizer='adam',
learning_rate=0.0001, loss='categorical_crossentropy')
    model = tflearn.DNN(net, tensorboard_verbose=0)

    # Train the model, leaving out the kfold not being used
    dummyData = np.reshape(np.concatenate(kfoldData[:i] + kfoldData[i+1:],
axis=0), [-1,34,34,34,2])
    dummyLabels = np.reshape(np.concatenate(kfoldLabelsOH[:i] +
kfoldLabelsOH[i+1:], axis=0), [-1, 2])
    model.fit(dummyData, dummyLabels, batch_size=100, n_epoch=150,
show_metric=True) # In practice learning stops ~150 epochs.
    dt = str(datetime.datetime.now().replace(second=0,
microsecond=0).isoformat("_"))
    model.save("./models/"+dt+"_3d-2channel-fakedata_"+str(i)+"-of-
"+str(k)+".tflearn")
```

- Avg AUC, spec, sens (over 5 k-folds): 0.762, 0.630, 0.735.

    - 

- Results for the models applied to real data (avg AUC, spec, sens): 0.544, 0.814, 0.207.

    - 

2017-08-01

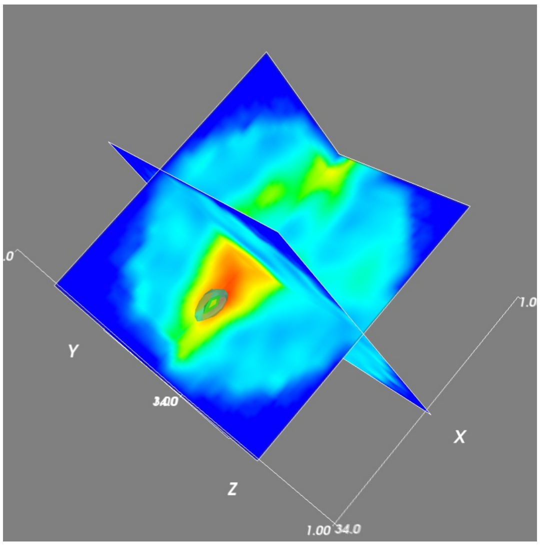
- The visualisation of where the CNN is diagnosing the patient is ready, but it doesn't seem to be looking in the correct places. Maybe the two matrices aren't aligned properly?

2017-08-02

- Adding another conv layer to the CNN doesn't improve things. Moving back to previous CNN...
- Wrote a standalone visualisation for the loss cubes.
- I will tinker around with the CNN and see if I can get any more performance out of it.
- Added another FC layer to the CNN. We'll see how it does.
- Tried using a larger filter in the getDiagArea.py file. Running now, will take a while because the GPU is busy with the new CNN.
    - Looking at the STDOUT it seems like the filter may be too large. I should try a smaller one next time (4?).
- The new CNN doesn't seem to have improved on the previous either. Maybe I need to change the learning rate or the number of epochs?
- It might be helpful to write a GAN so that we can see what the CNN decides a heart cube looks like.
- I have found this: [(https://arxiv.org/pdf/1512.03385v1.pdf)](https://arxiv.org/pdf/1512.03385v1.pdf). When the latest CNN is done training I'll use a very deep cnn to see if we can do any better than 70% acc.

2017-08-03

- OOM when running prediction on new cnn. It is only getting ~0.63 accuracy on the validation dataset so no big loss. Reverting to previous cnn...
- Looks like the OOM error is due to using 2000 training samples in the data.
- The CNN is looking in the "wrong place" to find the problems... I don't know why. It is diagnosing the images correctly regardless of this.

- 

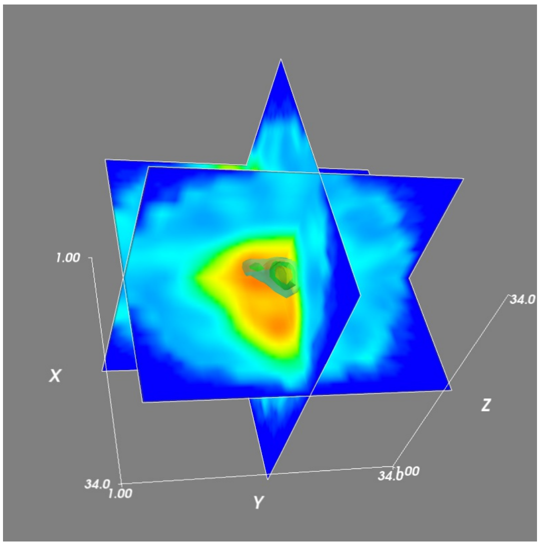
- I could try using the average of the k-folds to see where the diagnostic part is, instead of just one k-fold. I will need to do this after vDeepCNN has finished training.

```
    ### vDeepCNN: ###
    # Input layer:
    net = tflearn.layers.core.input_data(shape=[None,34,34,34,2])

    net = tflearn.layers.conv.conv_3d(net, 32, 7, activation="leaky_relu")
    net = tflearn.layers.conv.max_pool_3d(net, 2, strides=2)
    # Keep running into OOM errors with this...
    net = tflearn.layers.conv.conv_3d(net, 32, 3,  activation="leaky_relu")
    net = tflearn.layers.conv.conv_3d(net, 32, 3,  activation="leaky_relu")
    net = tflearn.layers.conv.conv_3d(net, 32, 3,  activation="leaky_relu")

    net = tflearn.layers.conv.conv_3d(net, 32, 3,  activation="leaky_relu")
    net = tflearn.layers.conv.conv_3d(net, 32, 3,  activation="leaky_relu")
    net = tflearn.layers.conv.conv_3d(net, 32, 3,  activation="leaky_relu")
    net = tflearn.layers.conv.max_pool_3d(net, 2, strides=2)

    net = tflearn.layers.conv.conv_3d(net, 64, 3,  activation="leaky_relu")
    net = tflearn.layers.conv.conv_3d(net, 64, 3,  activation="leaky_relu")
    net = tflearn.layers.conv.conv_3d(net, 64, 3,  activation="leaky_relu")

    net = tflearn.layers.conv.avg_pool_3d(net, [9,9,9], padding='valid')

    # Output layer:
    net = tflearn.layers.core.fully_connected(net, 2, activation="softmax")

    net = tflearn.layers.estimator.regression(net, optimizer='adam',
learning_rate=0.000001, loss='categorical_crossentropy')
    model = tflearn.DNN(net, tensorboard_verbose=0)

    # Train the model, leaving out the kfold not being used
    dummyData = np.reshape(np.concatenate(kfoldData[:i] + kfoldData[i+1:],
axis=0), [-1,34,34,34,2])
    dummyLabels = np.reshape(np.concatenate(kfoldLabelsOH[:i] +
kfoldLabelsOH[i+1:], axis=0), [-1, 2])
    model.fit(dummyData, dummyLabels, batch_size=100, n_epoch=600,
show_metric=True) # In practice learning stops ??? epochs.
```

- k-folded getDiagArea is gtg when gpu is free.

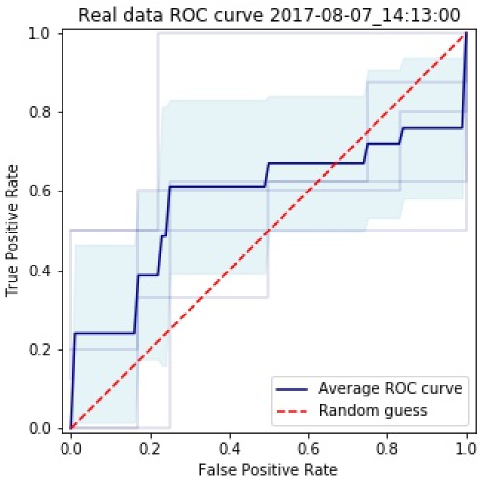
2017-08-04

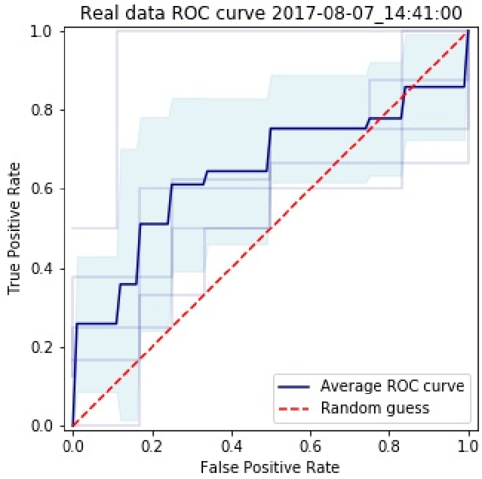
- vDeepCNN with average pooling at the end doesn't seem to work. It does seem to work with FC layers. I'll set that running before I leave.
- Running the getDiagArea k-folding doesn't seem to show anything new... Why is the CNN looking at where it is?

    - 

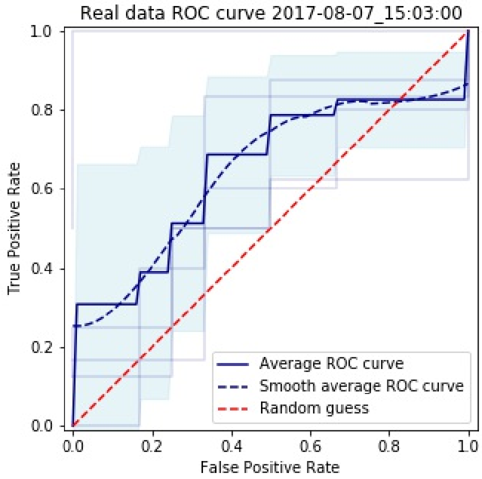
- It seems like the CNN is looking at the denser bits of the heatmap.
- I could try training the CNN on the simulated data and then fine-tuning the CNN on the real data...

2017-08-07

- Only using the real data doesn't find anything.
- Finetuning model with cnnFinetune.py
- It works well!
    - 

- 

- Trying with learning rate = 0.00001, 50 epochs:

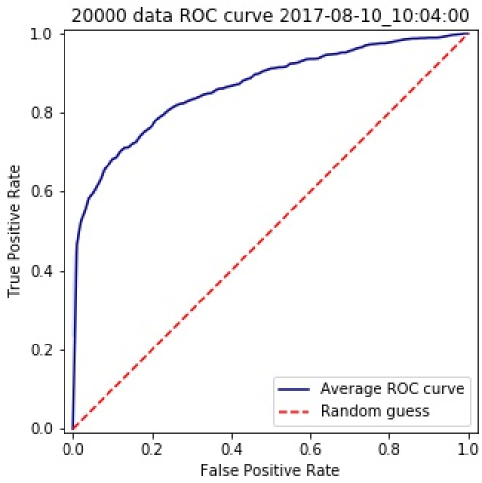
    - 

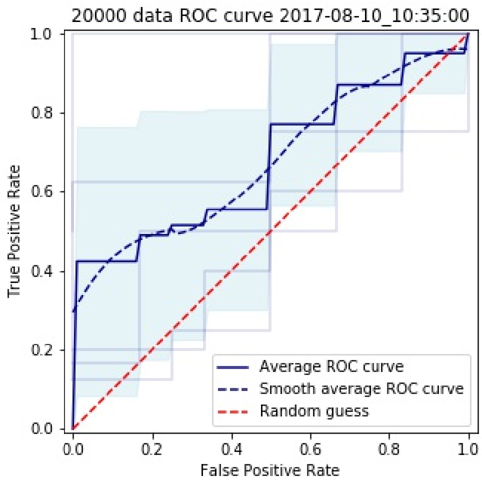
- Getting better results with the fake data would probably correspond to better results in the finetuned CNN with real data.
- Since we have an unlimited amount of fake data I should find a way to get it working without an OOM error.
- I am rewriting the CNN to handle the data via HDF5.

2017-08-08

- HDF5 CNN is up and running. The tflearn.predict class is a bit of a pita as it loads all the input data into vram before usage.
  I have reduced the input data to 500 ppts to counteract this but there is probably a smarter way to do it (feed_dicts?).
    - Fixed the issue by running each heartcube through tflearn.predict via a for loop. The HDF5 file then only fetches one heartcube at a time into ram.
- Running cnnH5.py on the CNN used in 2017-07-28.

2017-08-10

- Running the CNN with 19000 samples gives a validation accuracy of ~0.8.
- ROC curve:
    - 

- The ROC curve for the real data is ok:
    - 

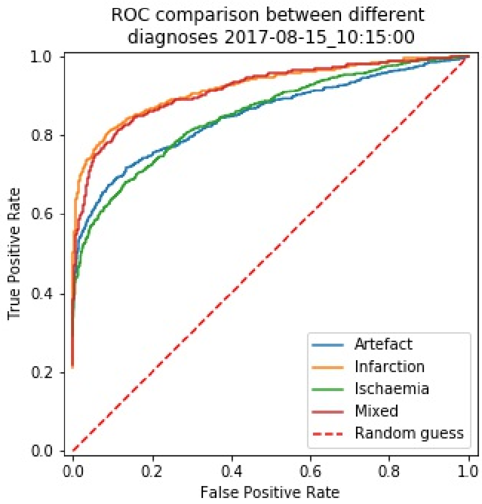
- There isn't a lot of carryover between the sets. It would be better to train the CNN from scratch on real data. It might also be better to use some more realistic fake data.

2017-08-14

- Running the CNN on mixed, infarction, ischaemic, artefact, and healthy patients pairwise. Only using 20 epochs of 10000 examples of ill/healthy.
- It takes ages putting the hearts into *.h5...

2017-08-15

- Here are the ROC curves for the pairwise data (20 epochs, 10000 ill/10000 healthy). The ROC curve should begin at `[fpr,tpr] == [0,0]` but I forgot to manually add that index.

- 

- I am going to run a CNN for categorising 10000 infarcted, ischaemic, mixed, artefact, and healthy hearts. I cannot use ROC curves for this because it is no longer binary, but I can get the overall accuracy, along with some other related ops. I think ~60 epochs will be enough. I will use validation to see where learning stops.
- There is a problem with my install of mayavi, and the diagnosisCubes won't show any more. Idky...
- cnnAll.py should take ~20 hours.

2017-08-16

- We get a validation and test accuracy of ~0.471, and a training accuracy of 0.99. I will turn on some regularisation to stop the overfitting.
    - Accuracies for each cube type: Normal 0.583; Ischaemia 0.614; Infarction 0.298; Mixed 0.274; Artefact 0.583.
- I'll set the epochs to ~30 so that it doesn't take an age..
- Separating the healthy and categorising all the other cubes as ill would allow us to make an ROC cube.
    - Written cnnAll with the new ROC/auc curve algorithm.
- Regularisation atm is way too high. Changed the weighting to 0.0001.

2017-08-18

- The regularisation of 0.0001 has achieved a ~2% increase in accuracy. Although this might be within the margin of error.

2017-08-21

- There are a load of bugs in the ROC generation in cnnAll.py. Fixing...
- I think I have fixed all the bugs now. Running the ROC generator.

2017-08-22

- We are getting an AUC score of ~0.81. I will run the cnnAll again and see if we can

finally get an ROC curve from this.
- Passing each heartcube through tf.predict is not very efficient... If this becomes an issue I can try passing slices instead.

2017-08-23

- Looks like the supercomputer is having trouble processing the code. Splitting the CNN training and ROC/AUC evaluation into
  separate `*.pys`, and linking them with a shell script may help.
- I can probably remove all the cruft and leave the diagnosis cube, and `cnnAll.py` since cnnAll implements the 3D CNN to all
  types of heart, and has a solid evaluation output (ROC, acc for each illness, etc.).

2017-08-24

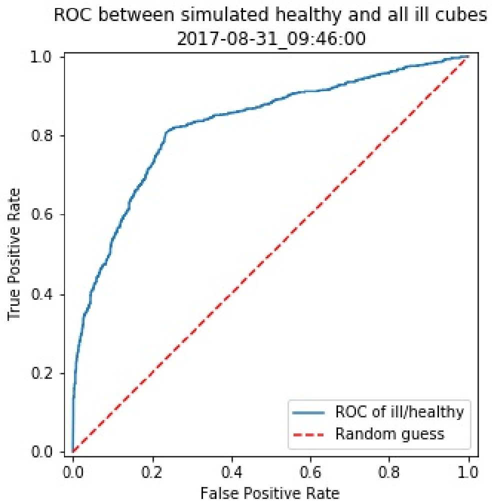
- The computer timed out... :(
- I think the GPU is slowing because it is nearly OOM... Maybe split the diagnostics and model building?
- I could probably also generate ROC curves for each ill/healthy pair, but this would take a long time on the computer we have.

2017-08-28

- Fixed the slowing problem. The masking of the inData_test array was performed for each prediction, meaning each masked array was
  stored in memory. Moving the mask outside the for loop fixed this.
- I've changed the weight decay to 0.00001 on all FC layers. This might fix the overfitting (and low performance) problem with cnnAll.py.

2017-08-29

- The overfitting is still a problem... I have removed one of the FC layers, and upped the regularisation on the remaining layers.
- Latest results
  Normal: [0.452]
  Ischaemic: [0.50599999]
  Infarcted: [0.37099999]
  Mixed: [0.47299998]
  Artefact: [0.51699997]
  Overall accuracy: [0.46379998]
  ROC AUC: [0.826947]


ROC between simulated healthy and all ill cubes
2017-08-31_09:46:00
True Positive Rate
False Positive Rate
ROC of ill/healthy
Random guess