Deep Learning for the Real World

Annuli Detection in ultrasound images

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Dataset & Task

 In ultrasound of the heart, detect annuli (rings around the heart valves)

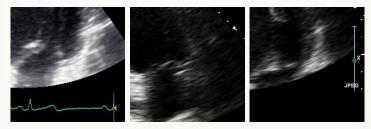
• Examples:



• Annulus roughly at the center of each sample

Preprocessing

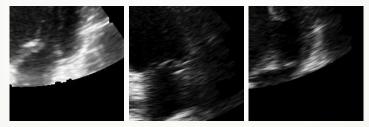
- Images contained artefacts:
 - Scales
 - Lines from ultrasound device



 Fixed by masking colored/purely white pixels; flood fill; image morphology operations (dilation / erosion)

Preprocessing

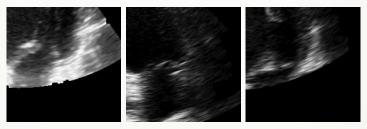
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Preprocessing

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- Standard data normalization: $\tilde{X} = \frac{X-\mu}{\sigma}$

Building the dataset

- Dataset only has 2 classes: left and right annulus
- Training requires 3rd class: no annulus

Building the dataset

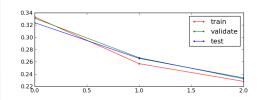
- Dataset only has 2 classes: left and right annulus
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 - Build the dataset from smaller patches in the image $(20 \times 20 \text{px} \text{ or } 60 \times 60 \text{px})$.
 - Take center patches of images as annulus, take surrounding patches as "no annulus".

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 - Shuffle found patches, then split into training/set/validation set (60/20/20).

First approaches

- Standard Feed forward Neural Network
 - 1 Hidden layer, 0.1 learning rate and rmsprop
 - Best result obtained: 17%
- Plots for 2ch 60x60 patch with 2 class



Standard NN with Dropout

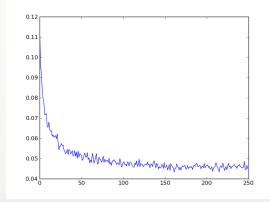
- Implementation Details
 - 1 Hidden layer, with 1200 neurons size
 - 50% dropout on hidden layers,20% dropout on input layer
 - Used theano.binomial to create the mask with given probability
 - Momentum and weight updation is done according to Hinton's paper
 - · decay of learning rate after each epoch

Challenges

- Determination of maximum squared length limit for incoming weights
- Number and dimension of hidden layers
- High dimension for hidden layers like 4200 didn't work so well

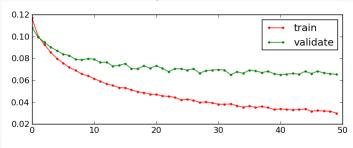
Result with NN Dropout

- Performance improved from standard NN
 - 4% test error for 2 class unbalanced set
 - 6% error for multiclass unbalanced test set
- Plots for 2ch 60x60 patch with 2 class



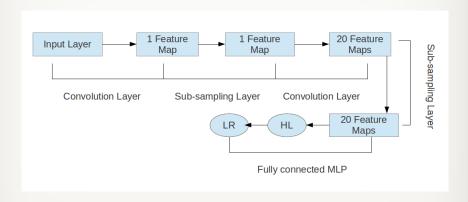
Dropout Result(Continued)

Plots of 2ch 60x60 patch multiclass



- Future Scope
 - Pre-trained DBN with dropout
 - Dropout on last hidden layer of Convolutional Neural Network

Convolutional Neural Network



CNN: Details

- Convolutional Layer 1
 - 20 Filters of 5 x 5
 - Maxpooling by the factor (2, 2)
- Convolutional Layer 2
 - 50 Filters of 5 x 5
 - Maxpooling by the factor (2, 2)
- Hidden Layer
 - Input: (number of Filters of CL2) * (CL2 output size)²
 - Output: 500

CNN: Details

- Logistic Regression Layer
 - Input: 500
 - Output:
 - 2 (Annuli or not) or 3 (left, right or no Annuli) classes
- Hyperparameters: Minibatch Gradient Descent
 - Learning Rate: 0.1
 - Epochs: 20

Additional tricks

 Convolutional Neural Network with rmsprop and Momentum Hyperparameters: RMSPROP

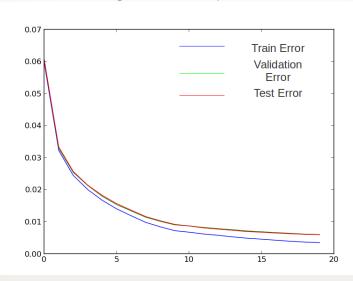
• Learning Rate: 0.0001

• Momentum: 0.7

Neural Network with dropout

Results: CNN-MSGD

2 chamber Images, 20 x 20 patches



Results: CNN-MSGD

Best validation Error: 0.606816 %

Best Test Error: 0.602769 %

Train, validation and test data was balanced, but results were not much different then unbalanced

test set

True Positive(Annuli) 49.9218 %

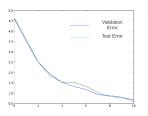
True Negative(Non Annuli) 49.4754 %

False Positive 0.5798 %

False Negative 0.0230 %

Result and Classifier

- Plots of 2ch 60x60 patch with CNN rmsprop
 - Validation Error: 0.676190 %
 - Test Error: 0.600000 %



Classifier

- It takes directory of images
- Do all the preprocessing and create patches from images
- Use previosuly saved weights
- And finally predict whether the image has annulli or not

Questions?

Thank you