MULTI-OBJECTIVE DEEP LEARNING

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INTRODUCTION

- NLP/Vision challenges have several objectives to be computed simultaneously
- Typical approaches are:
  - Convert all but one into constraint during problem modeling phase
  - Simplifying the problem consideration losing information and requirements along the way
- Multi-output formulation
  - Formulating each objective function separately and giving weights to combined loss function
  - Reveals true nature of the problem without over-simplification

ALGORITHM

- Decompose the network graph into separate branches
- Calculate loss corresponding to each branch end
- Do gradient descent w.r.t. calculated loss as weights

ALGORITHM

define model:

return $branch_1, branch_2 ... branch_n$

$pred_1, pred_2 ... pred_n = model(X)$

$loss_1 = lossfn_1(pred_1, y_1)$

$loss_2 = lossfn_2(pred_2, y_2)$

$loss_n = lossfn_n(pred_n, y_n)$

$$\frac{1}{\alpha_1} = \frac{\frac{1}{loss_1}}{\frac{1}{loss_1} + \frac{1}{loss_2} + \ldots \frac{1}{loss_n}}$$

$$\frac{1}{\alpha_2} = \frac{\frac{1}{loss_2}}{\frac{1}{loss_1} + \frac{1}{loss_2} + \ldots \frac{1}{loss_n}}$$

$$\frac{1}{\alpha_n} = \frac{\frac{1}{loss_n}}{\frac{1}{loss_1} + \frac{1}{loss_2} + \ldots \frac{1}{loss_n}}$$

$optimizer_1.step(\alpha_1)$

$optimizer_2.step(\alpha_2)$

$optimizer_n.step(\alpha_n)$

VISION DATASET CIFAR100

- CIFAR 100 has 2 labels -
  - Coarse labels are 20 in count
  - Fine labels are 100 in count.
- 100 classes containing 600 images each.
- 500 training images and 100 testing images per class. The 100 “fine” classes in the CIFAR-100 are grouped into 20 “coarse” superclasses.

VISION DATASET EXAMPLE

Superclass	Classes
aquatic mammals	beaver, dolphin, otter, seal, whale
fish	aquarium fish, flatfish, ray, shark, trout

NLP DATASET SEMEVAL

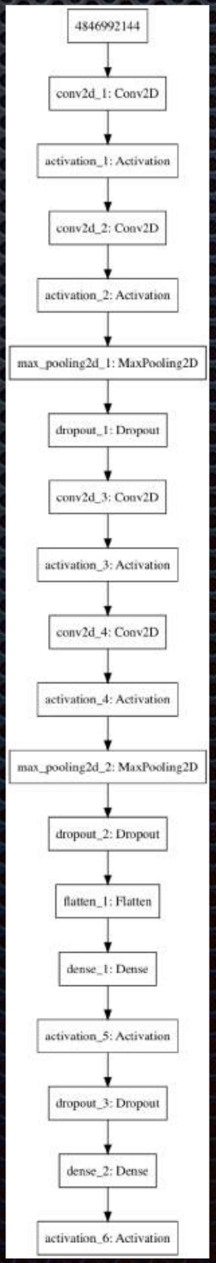
- Tweets have two labels:
  - Binary classification task where the system has to predict whether a tweet is ironic or not.
  - Multiclass classification task where the system has to predict one out of four labels describing i) verbal irony realized through a polarity contrast, ii) verbal irony without such a polarity contrast (i.e., other verbal irony), iii) descriptions of situational irony, iv) non-irony.

NLP DATASET EXAMPLE

- i) verbal irony realized through a polarity contrast,
- *I really love this year's summer; weeks and weeks of awful weather*
- ii) verbal irony without such a polarity contrast (i.e., other verbal irony),
- *Human brains disappear every day. Some of them have never even appeared. http://t.co/Fb0Aq5Frqs |#brain #humanbrain #Sarcasm*
- iii) descriptions of situational irony,
- *Most of us didn't focus in the #ADHD lecture. #irony*
- iv) non-irony.
- *Please dont fuck with me when I first wake up #not a morning person!*

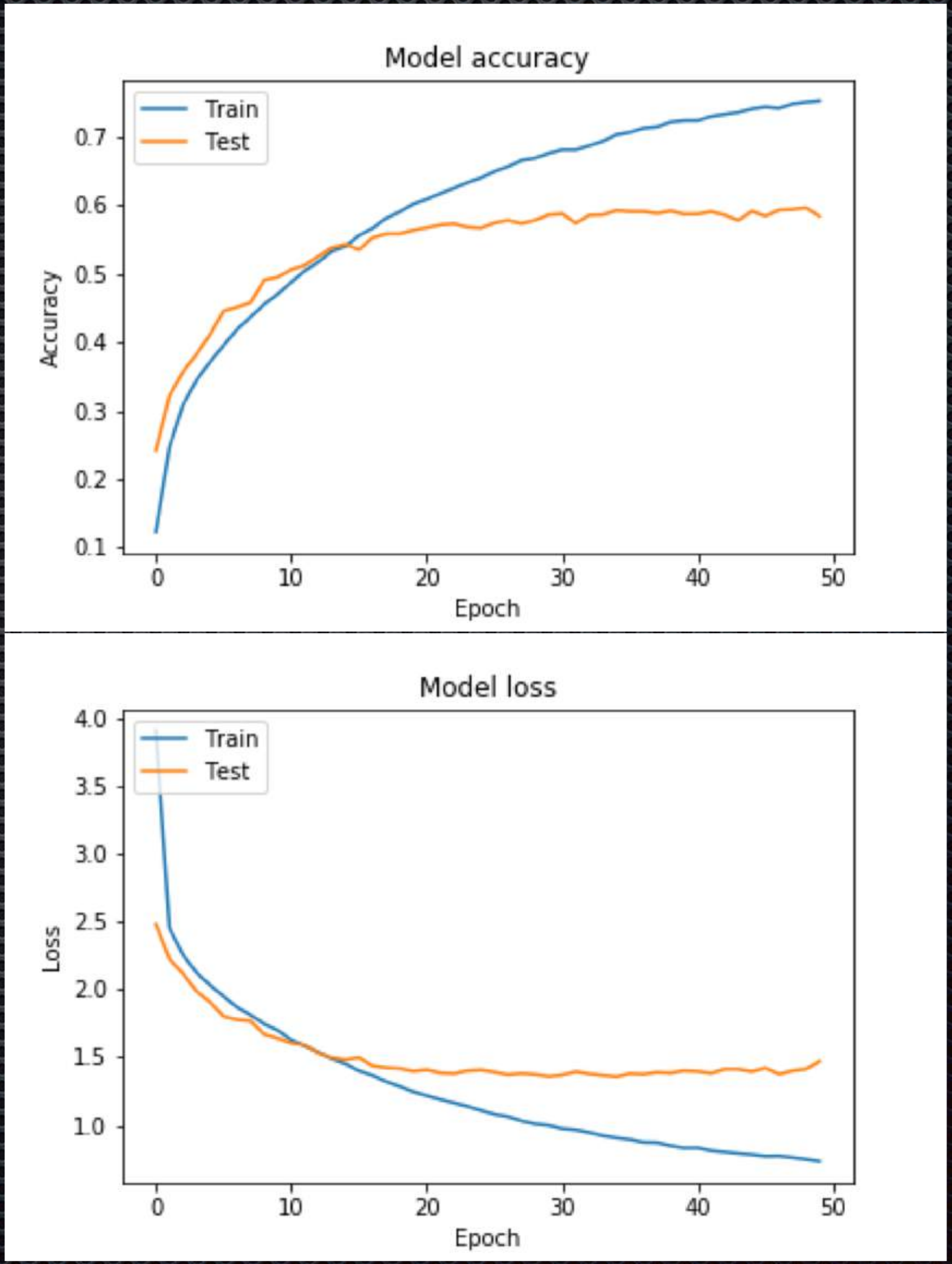
SINGLE NET

- Convolution 2D (32, 3, 3) & RELU Activation x 2
- Max Pool (2x2) & Dropout (0.25)
- Convolution 2D (32, 3, 3) & RELU Activation x 2
- Max Pool (2x2) & Dropout (0.25)
- FC (512) & RELU & Dropout (0.5)
- FC (N) & Softmax [N is 20 for coarse, 100 for fine]



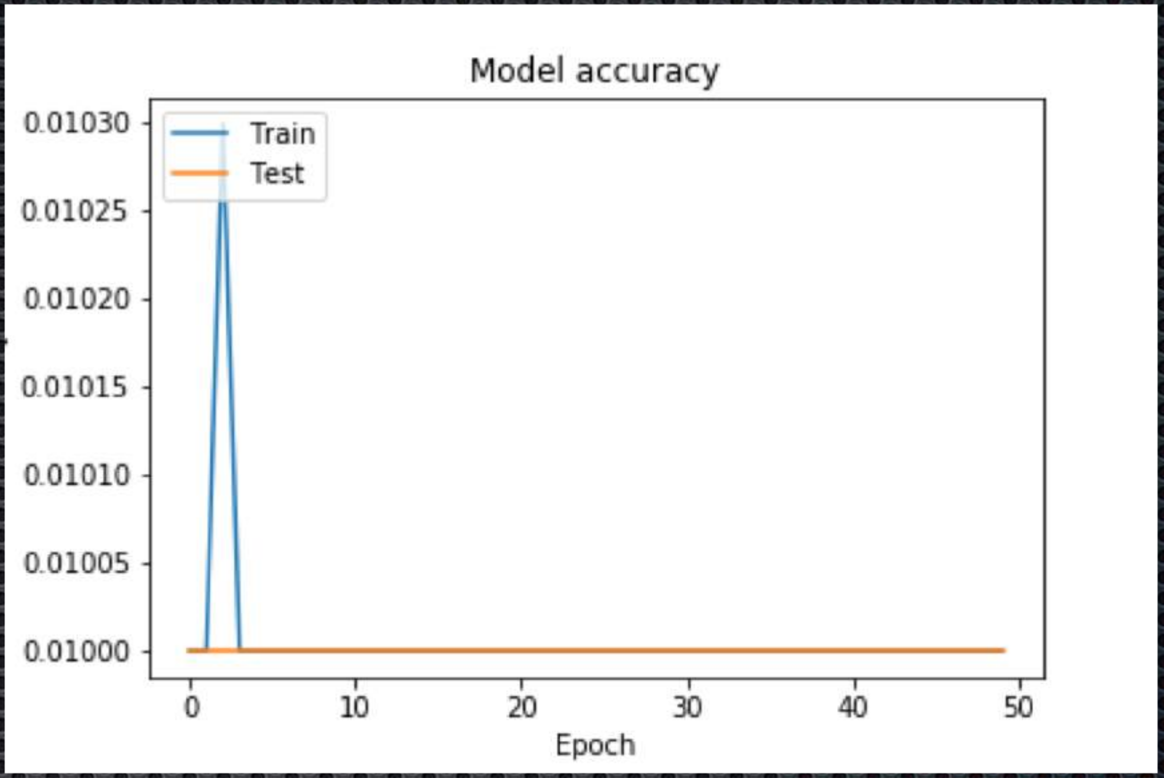
SINGLE NET COARSE RESULTS

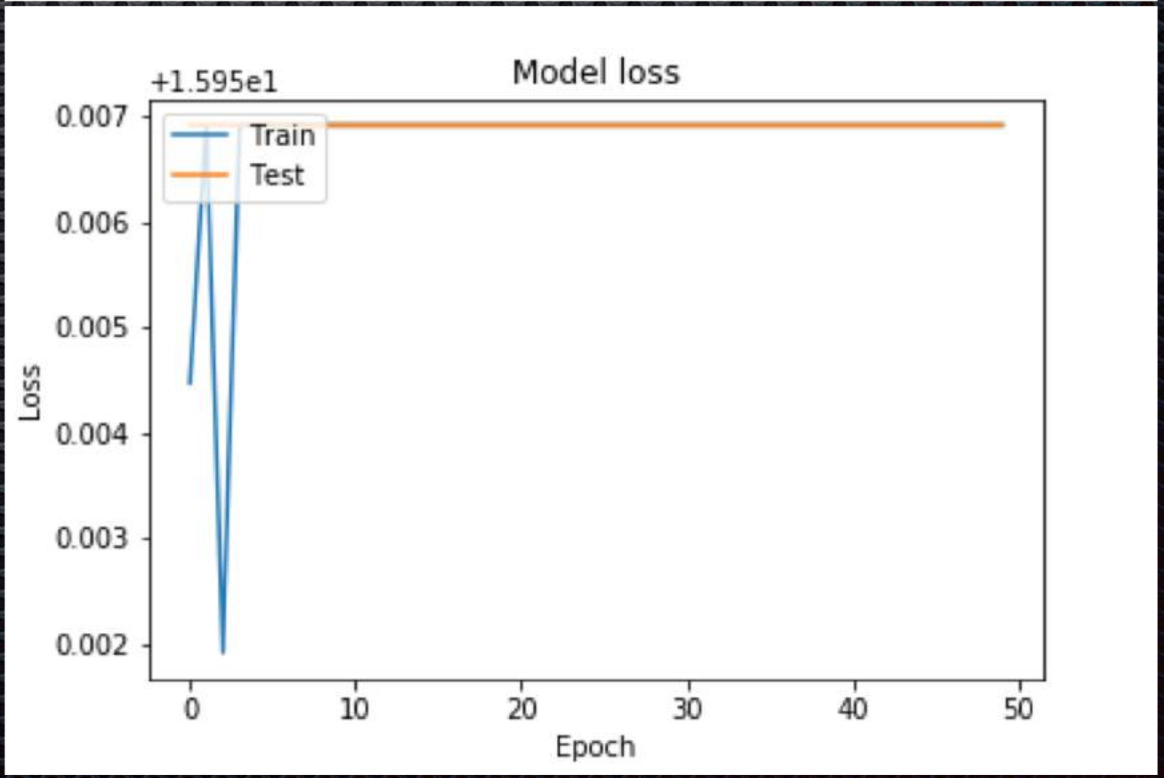
- Total trainable parameters: 1,255,988
- Test loss: 1.469
- Test accuracy: 58.34%



SINGLE NET FINE RESULTS

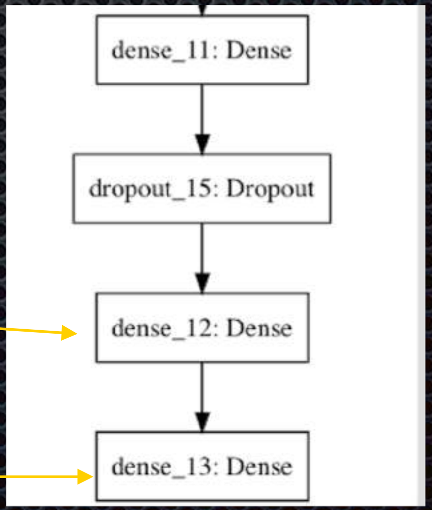
- Total trainable parameters:1,297,028
- Test loss: 15.95
- Test accuracy: 1%
- Average Accuracy for single net models: 28%





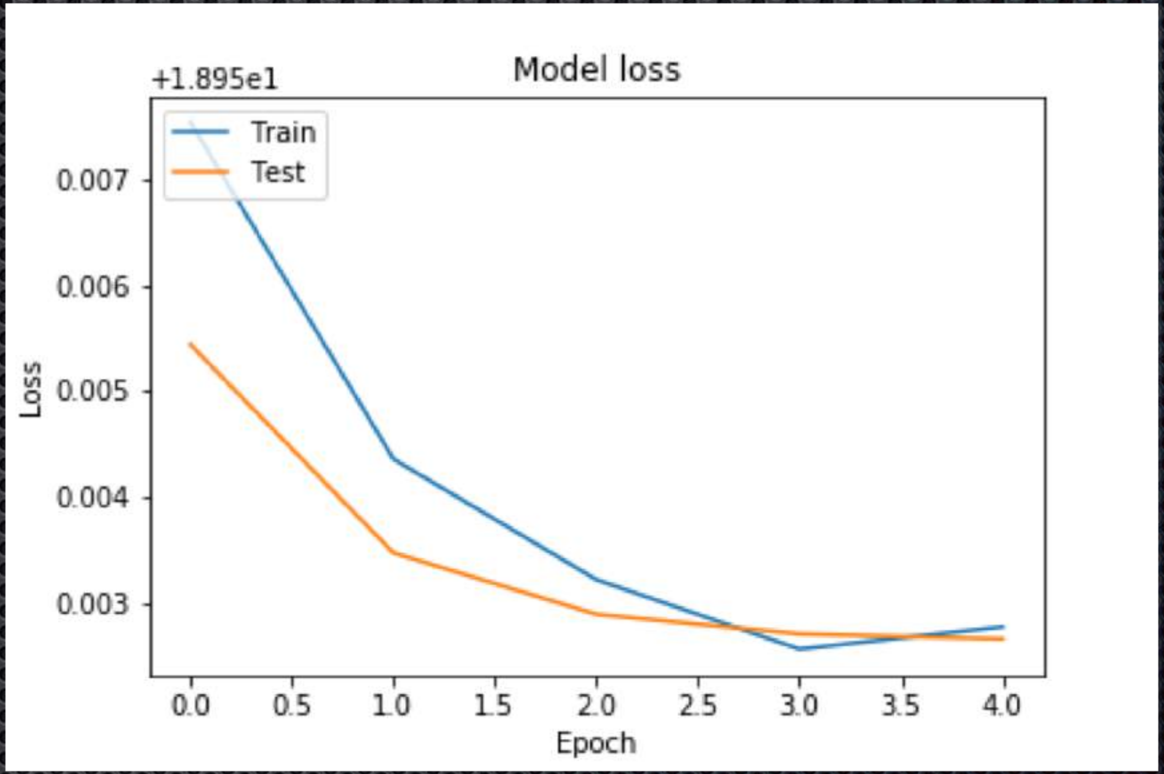
WITHOUT BRANCHING

- Convolution 2D (32, 3, 3) & RELU Activation x 2
- Max Pool (2x2) & Dropout (0.25)
- Convolution 2D (32, 3, 3) & RELU Activation x 2
- Max Pool (2x2) & Dropout (0.25)
- FC (512) & RELU & Dropout (0.5)
- FC (100) & Softmax = **Output 1**
- FC (20) & Softmax = **Output 2**



WITHOUT BRANCHING RESULTS

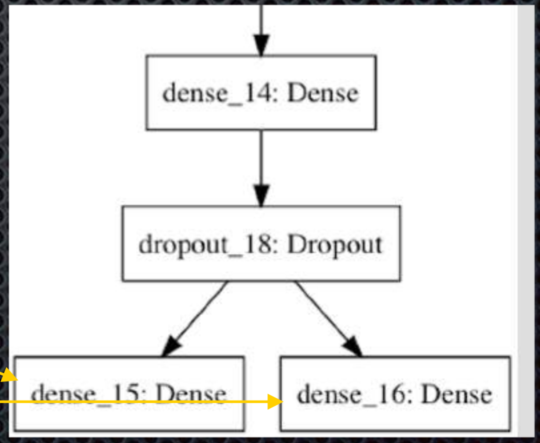
- Total Trainable parameters: 1,299,048
- Test loss: 18.95
- Coarse accuracy: 5%
- Fine accuracy: 1%
- Average accuracy: 3%



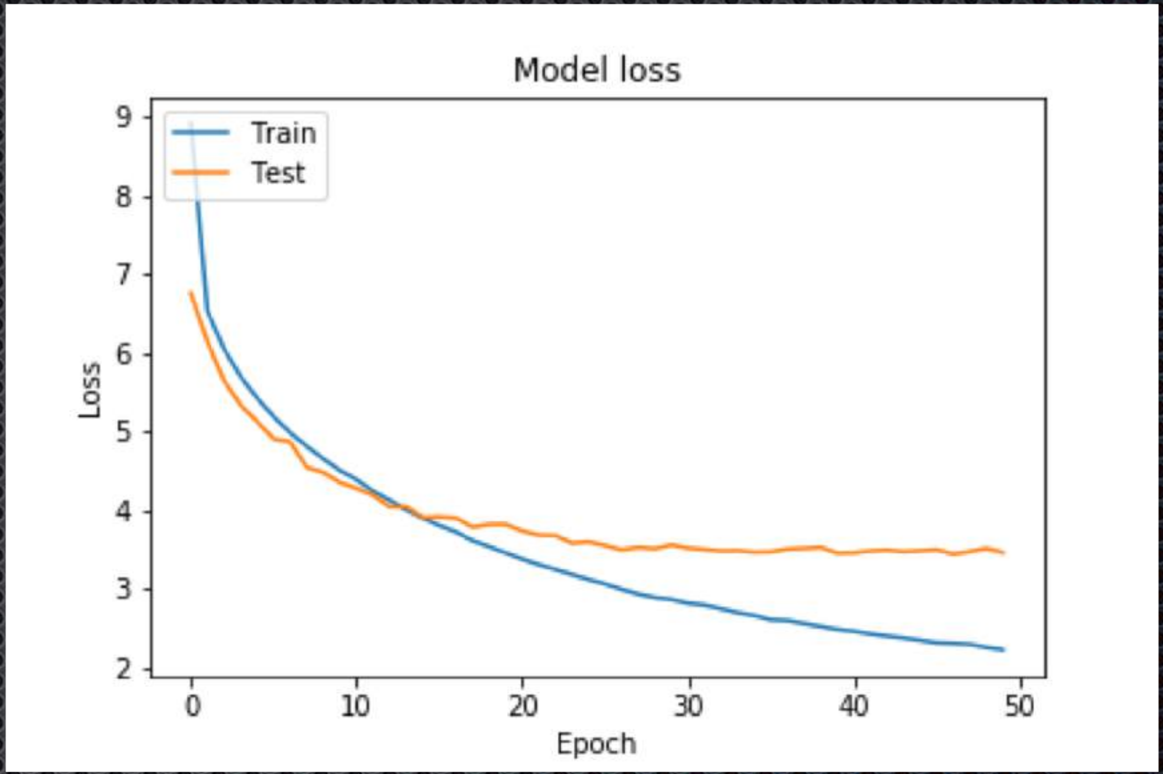
- As we can see, the outputs get stagnant at fixed values because we used single neural net without branching, leading to low accuracy.

MULTI OUTPUT BRANCHED

- Convolution 2D (32, 3, 3) & RELU Activation x 2
- Max Pool (2x2) & Dropout (0.25)
- Convolution 2D (32, 3, 3) & RELU Activation x 2
- Max Pool (2x2) & Dropout (0.25)
- FC (512) & RELU & Dropout (0.5)
- FC (20) & Softmax = **Output 1**
- FC (100) & Softmax = **Output 2**



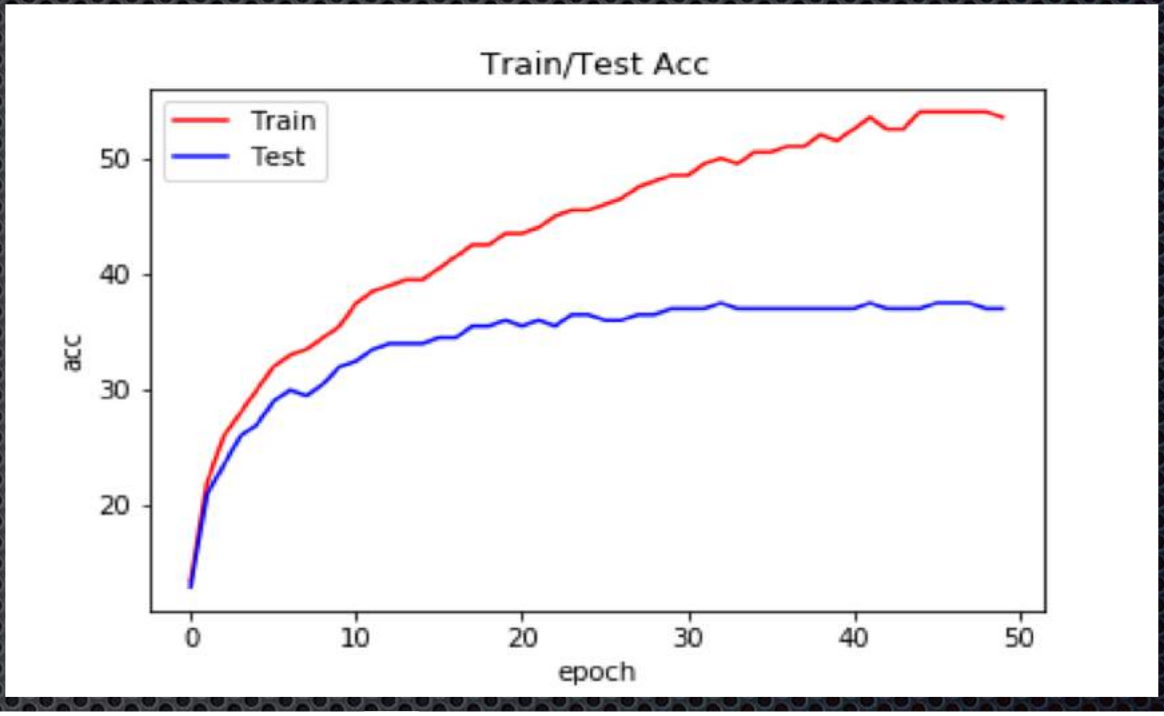
MULTI OUTPUT BRANCHED RESULTS

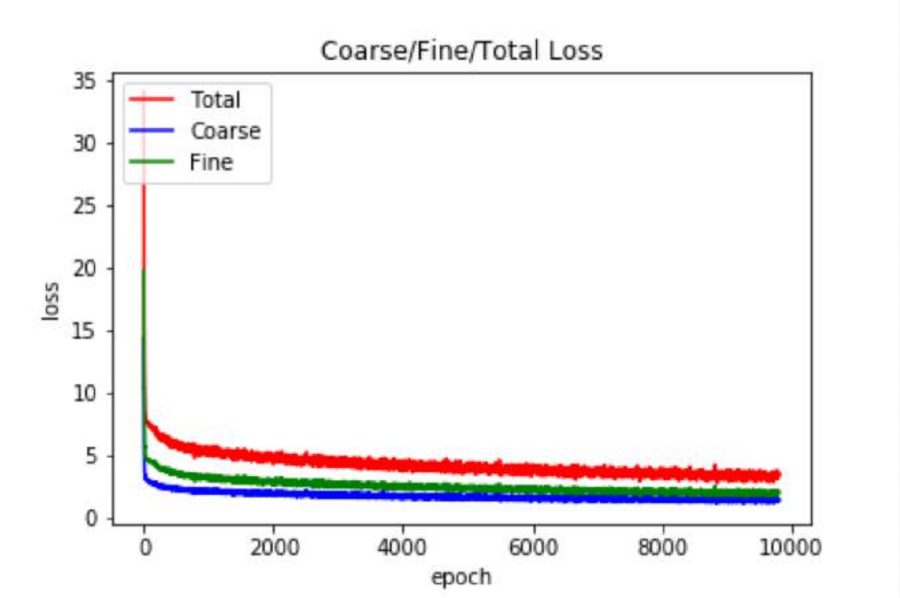


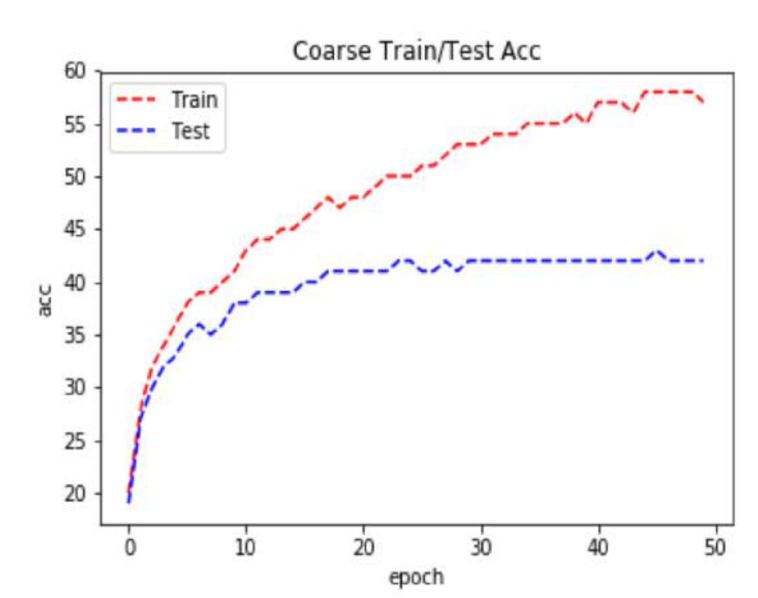
- Total Trainable parameters: 1,307,288
- Test loss: 3.465
- Coarse accuracy: 59.2%
- Fine accuracy: 46.13%
- Average accuracy: 52.665%
- The average accuracy is 52.66% for coarse and fine label based single multi-output neural net model, which is more than single output models by more than 20%.

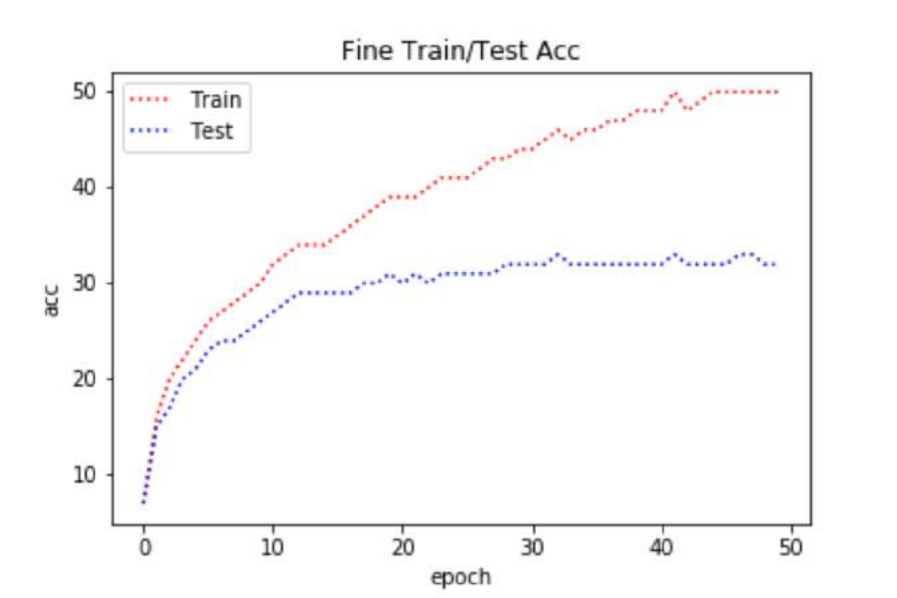
MULTI OUTPUT WEIGHTED BRANCHED

- Test loss: 4.21
- Coarse accuracy: 42%
- Fine accuracy: 32%
- Average accuracy: 37%



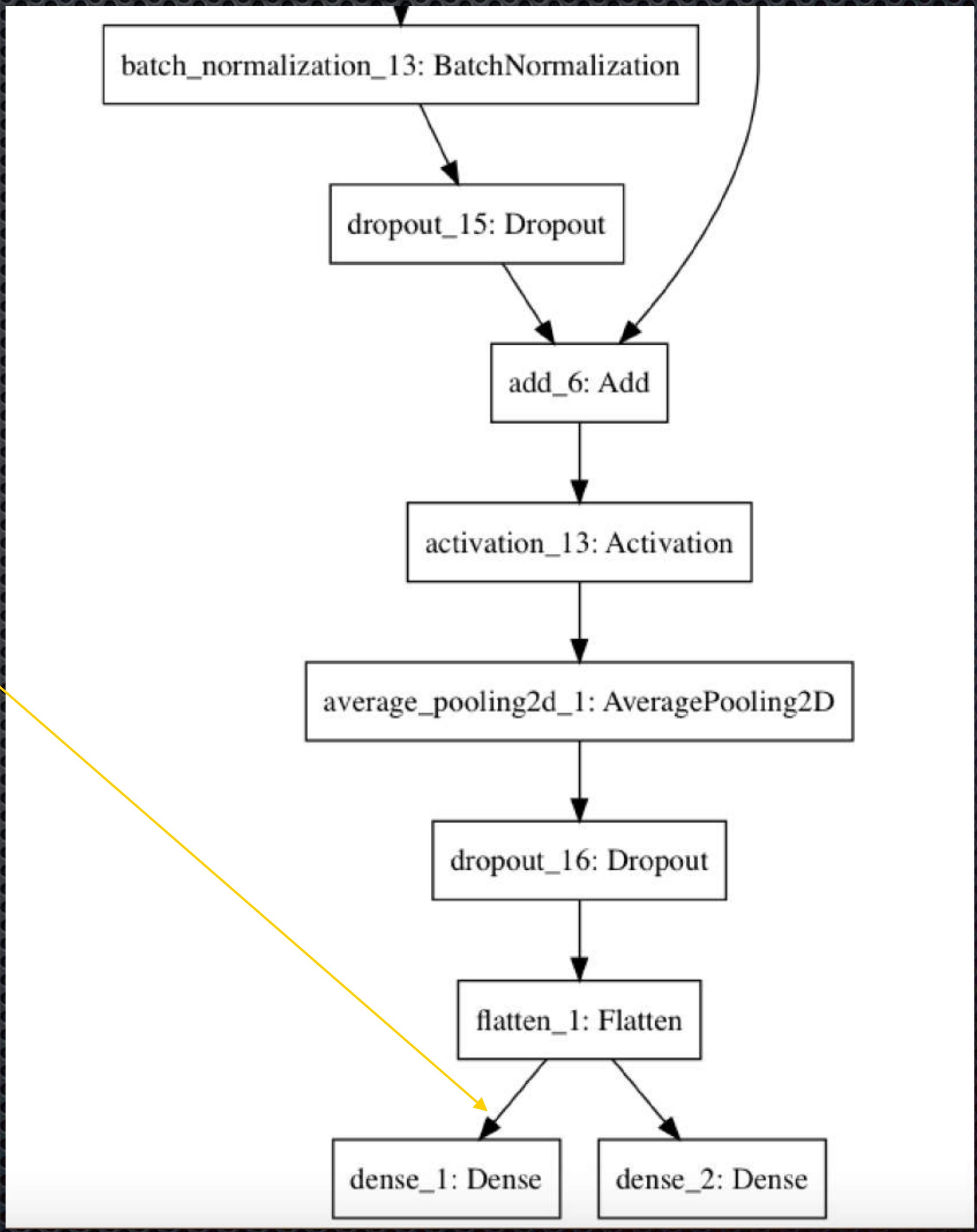






MULTI OUTPUT RESNET

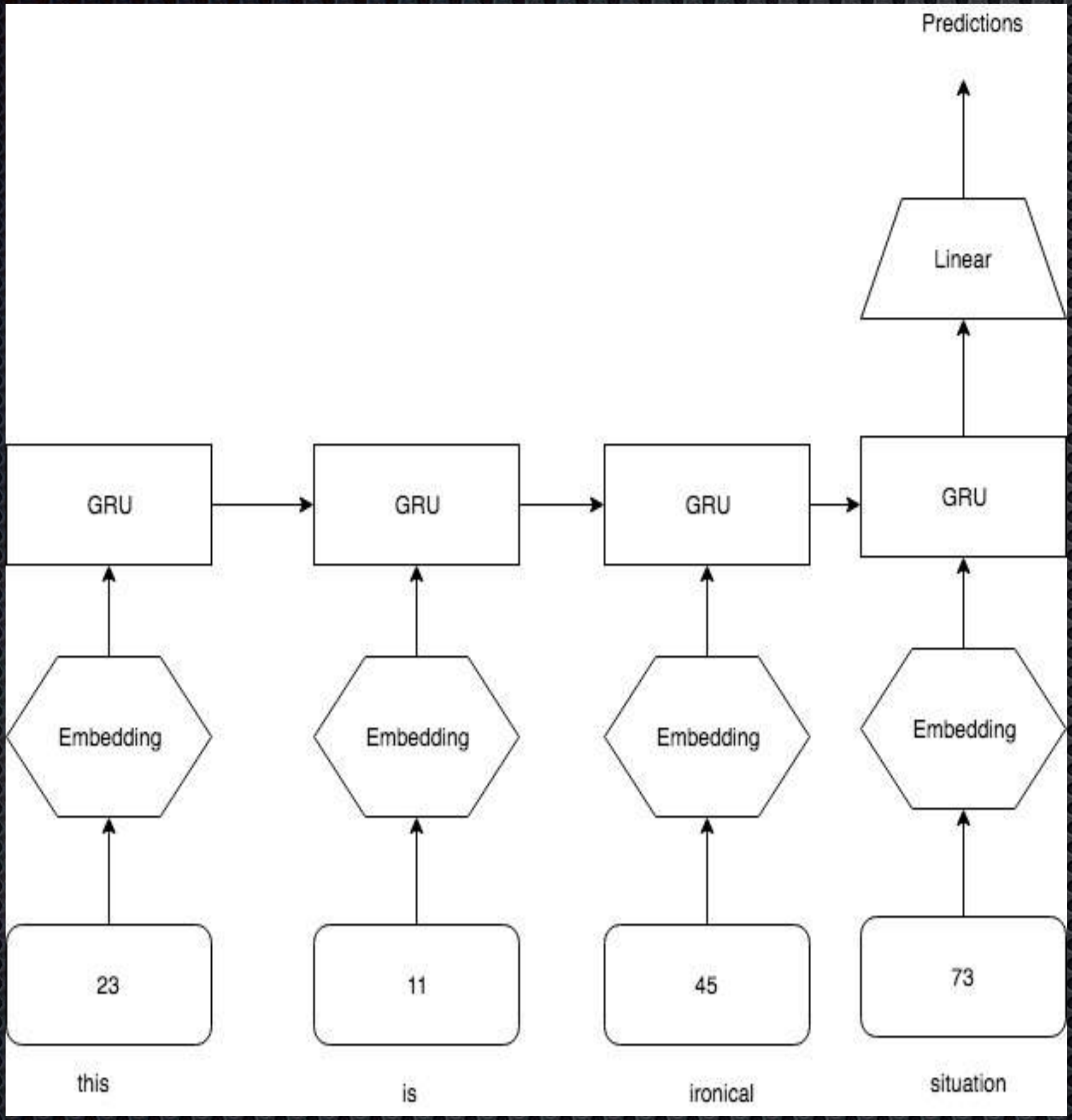
- Resnet with depth 32
- Branching at last level
- 5 Resnet layers
- Total parameters: 477,368
- Trainable parameters: 475,096
- Non-trainable parameters: 2,272

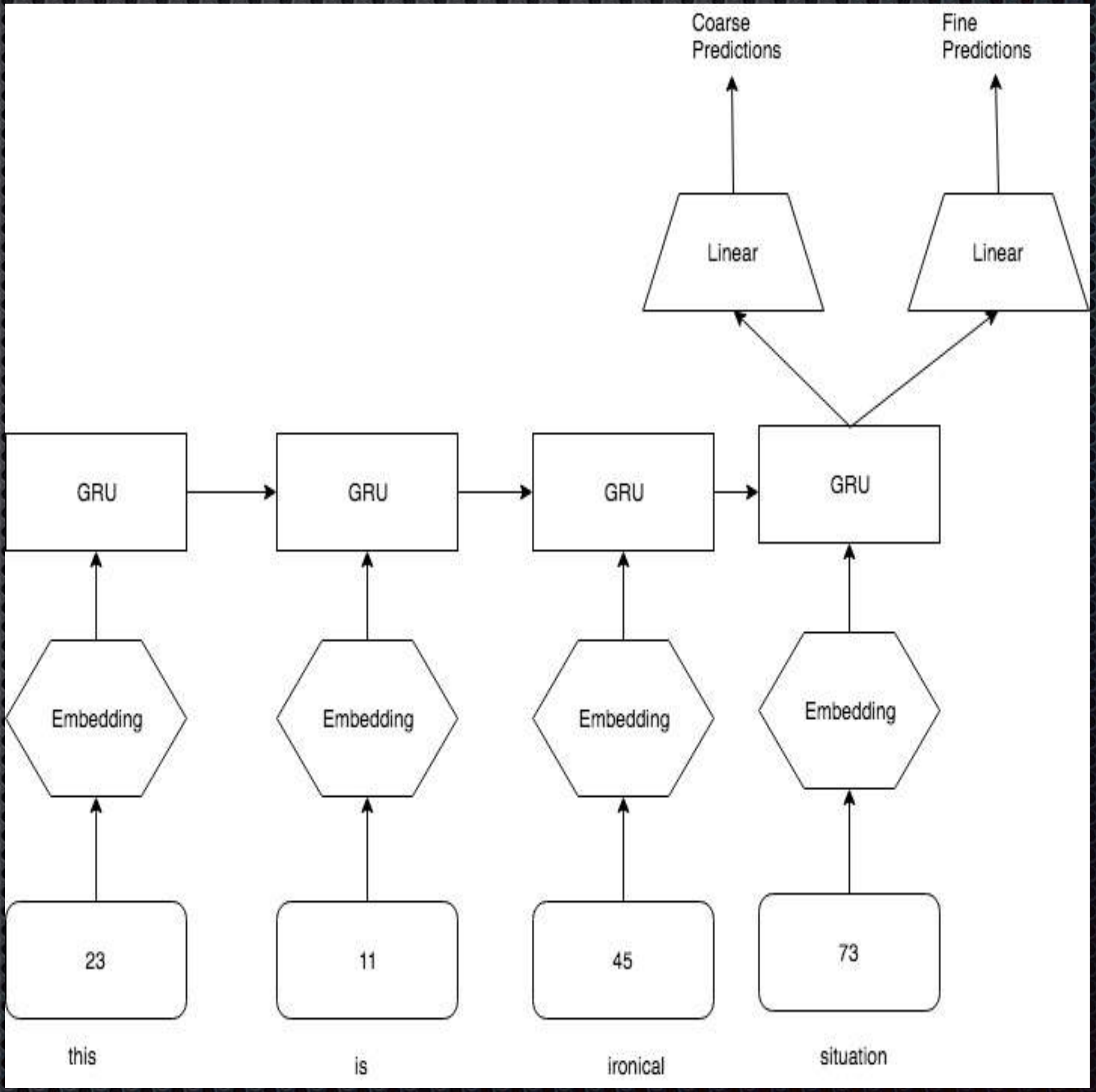


MULTI OUTPUT RESNET RESULTS

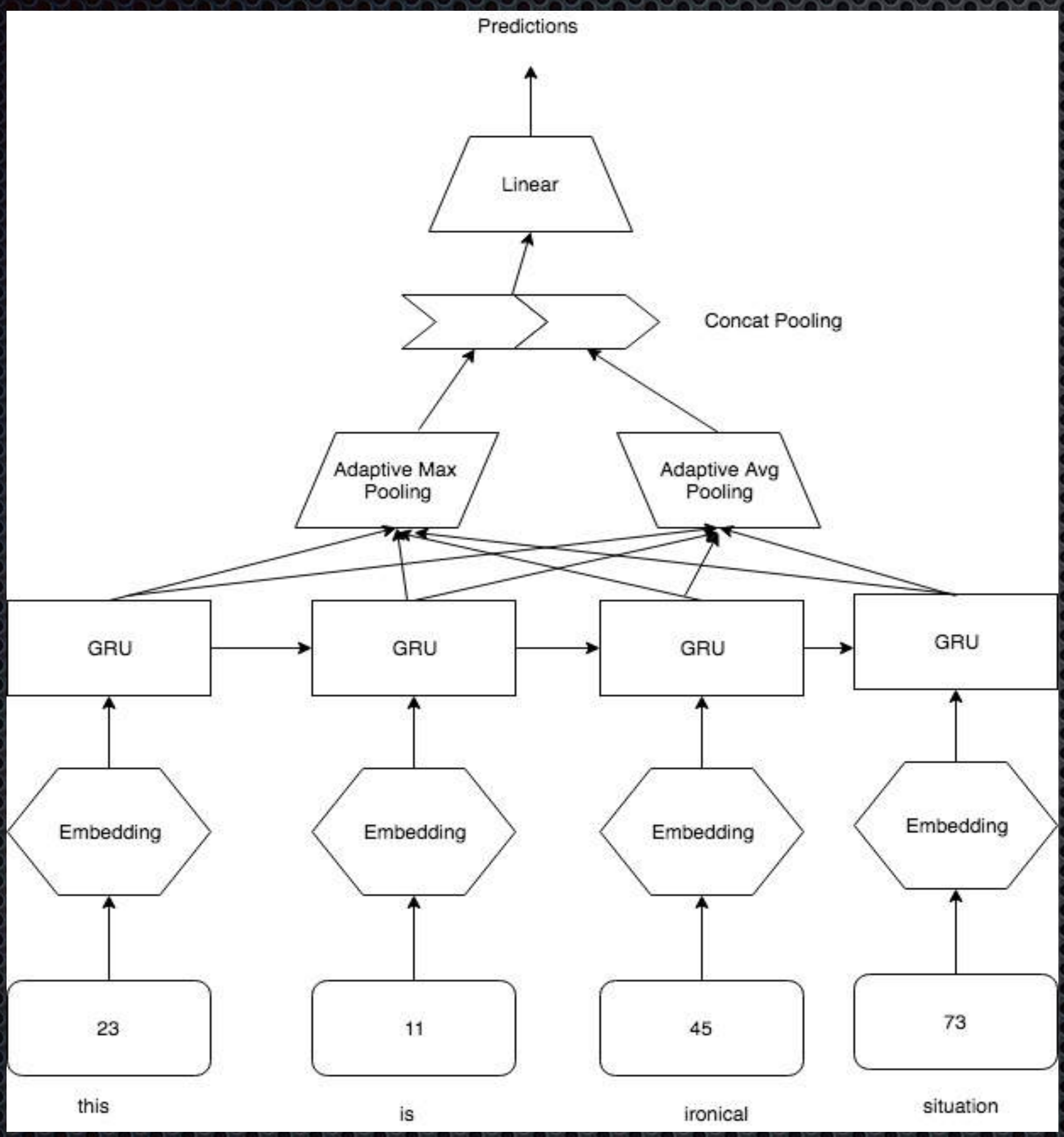
- Test loss: 3.108
- Coarse accuracy: 69.19%
- Fine accuracy: 53.68%
- Average accuracy: 61.435%

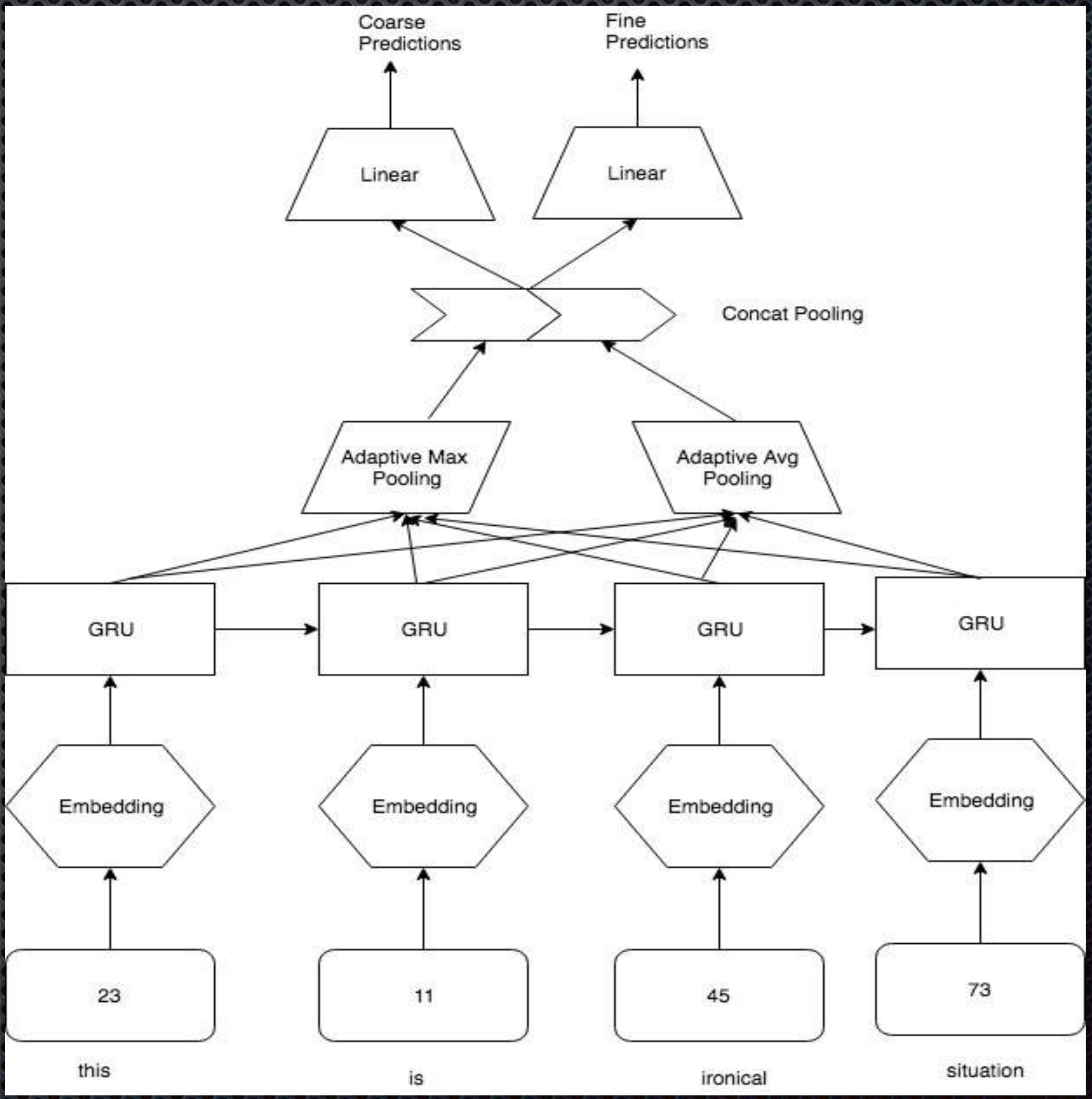
NLP GRU Model





NLP Concat Pooling GRU





SINGLE NET GRU RESULTS

- Coarse Test Loss : .7425
- Coarse Test Accuracy : 63.28%
- Fine Test Loss : 8.9158
- Fine Test Accuracy : 53.39%
- Average Test Accuracy : 58.33%

SINGLE NET CONCAT POOL GRU RESULTS

- Coarse Test Loss : 1.1083
- Coarse Test Accuracy : 67.19%
- Fine Test Loss : 6.0426
- Fine Test Accuracy : 53.39%
- Average Test Accuracy : 60.29%

MULTI-OUTPUT

- Average GRU Test Loss: 1.55
- Average GRU Test Accuracy: 65.62%
- Average Concat Pool GRU Test Loss: 1.5366
- Average Concat Pool GRU Test Accuracy: 64.58%

MULTI-OUTPUT WEIGHTED

- Average GRU Test Loss: 1.52
- Average GRU Test Accuracy: 66.28%
- Average Concat Pool GRU Test Loss: 1.4834
- Average Concat Pool GRU Test Accuracy: 67.06%

Thank You

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