

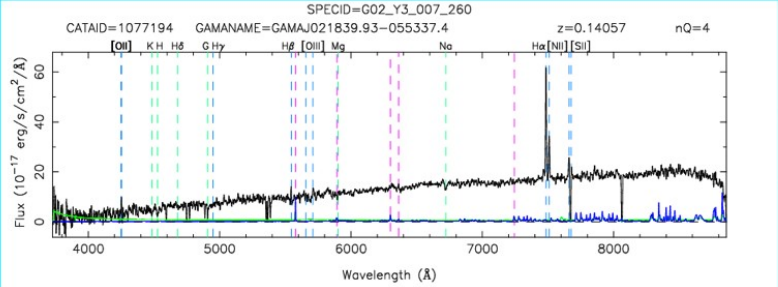
JULIA ZIEGLER

CLASSIFICATION OF GALAXY SPECTRA WITH ARTIFICIAL NEURAL NETWORKS

Bachelor Thesis Defense

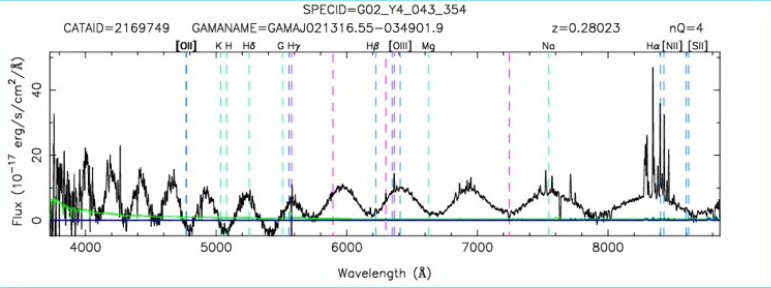
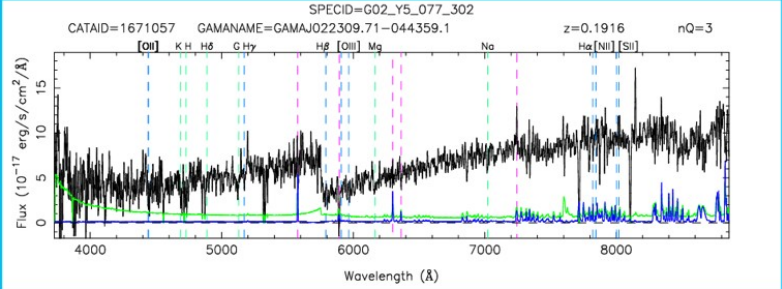
CLASSIFICATION OF GALAXY SPECTRA

- GAMA Spectroscopic survey
- 300,000 spectra
- AAOmega spectrograph on 3.9m Anglo Australian Telescope
- From 2008 to 2014
- Down to magnitude $r < 19.8$ mag



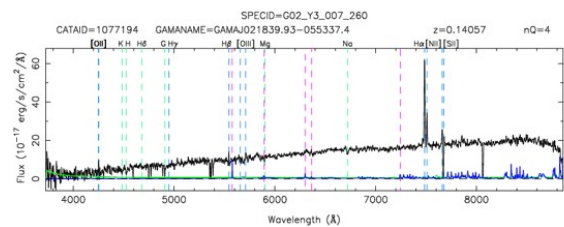
No Problem

Bad Splice

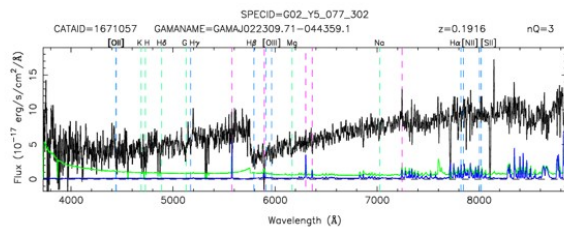


Fringed

GALAXY CLASSIFICATION WITH ARTIFICIAL NEURAL NETWORKS, BACHELOR THESIS DEFENSE



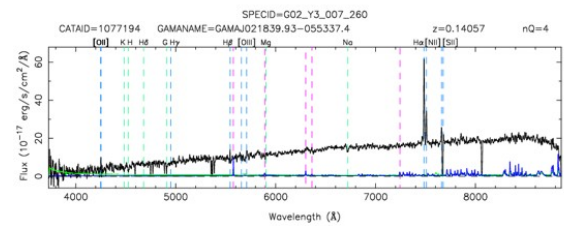
CLASS 0



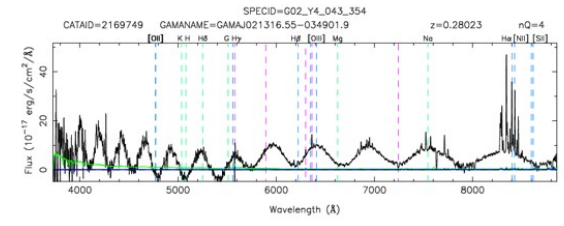
CLASS 1



CLASSIFIER 1



CLASS 0



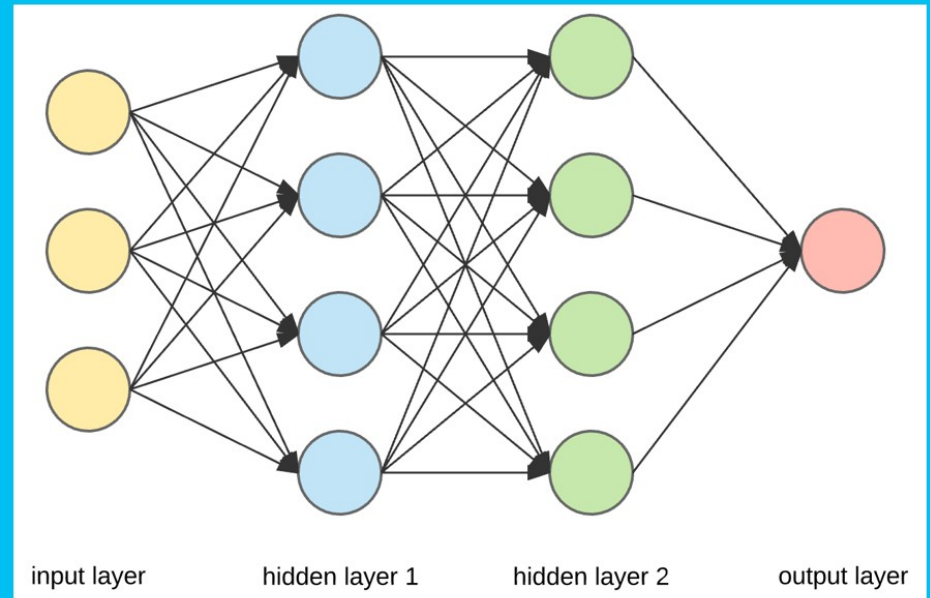
CLASS 1



CLASSIFIER 2

ARTIFICIAL NEURAL NETWORKS (ANN)

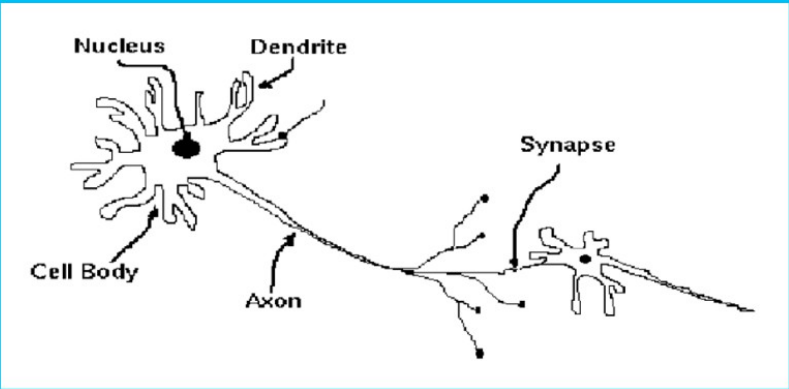
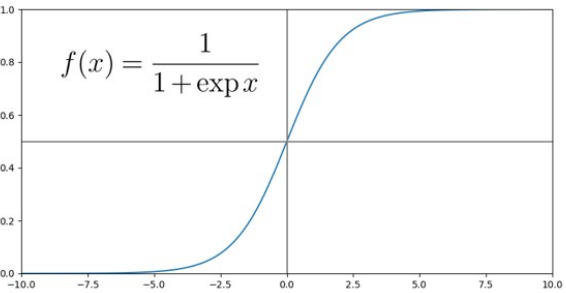
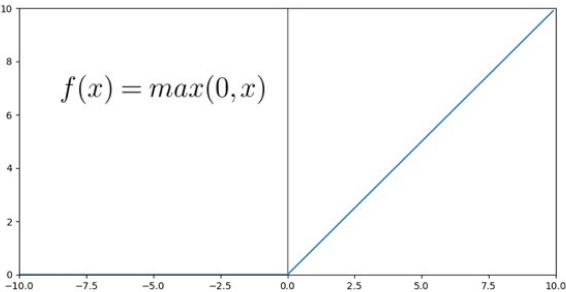
- Inspired by biological neural Networks
- Ability to learn
- Ability to handle probabilistic information
- Often used for: Image recognition, classification



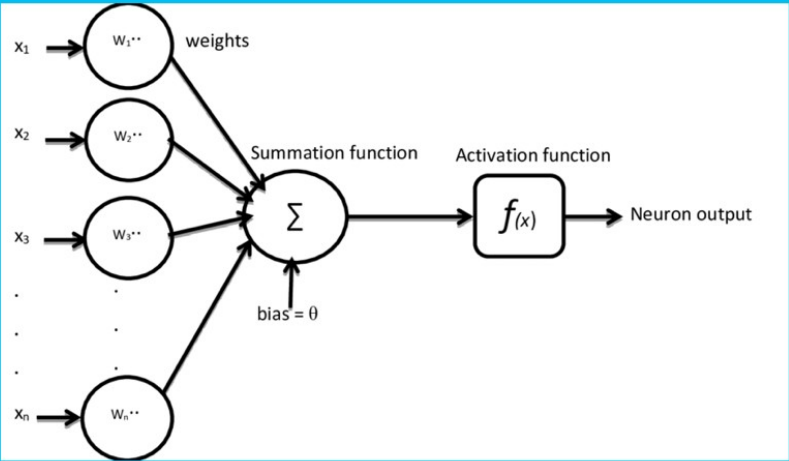
<https://towardsdatascience.com/applied-deep-learning-part-1-artificial-neural-networks-078a6e2a6e88>

NEURON

Activation Functions:



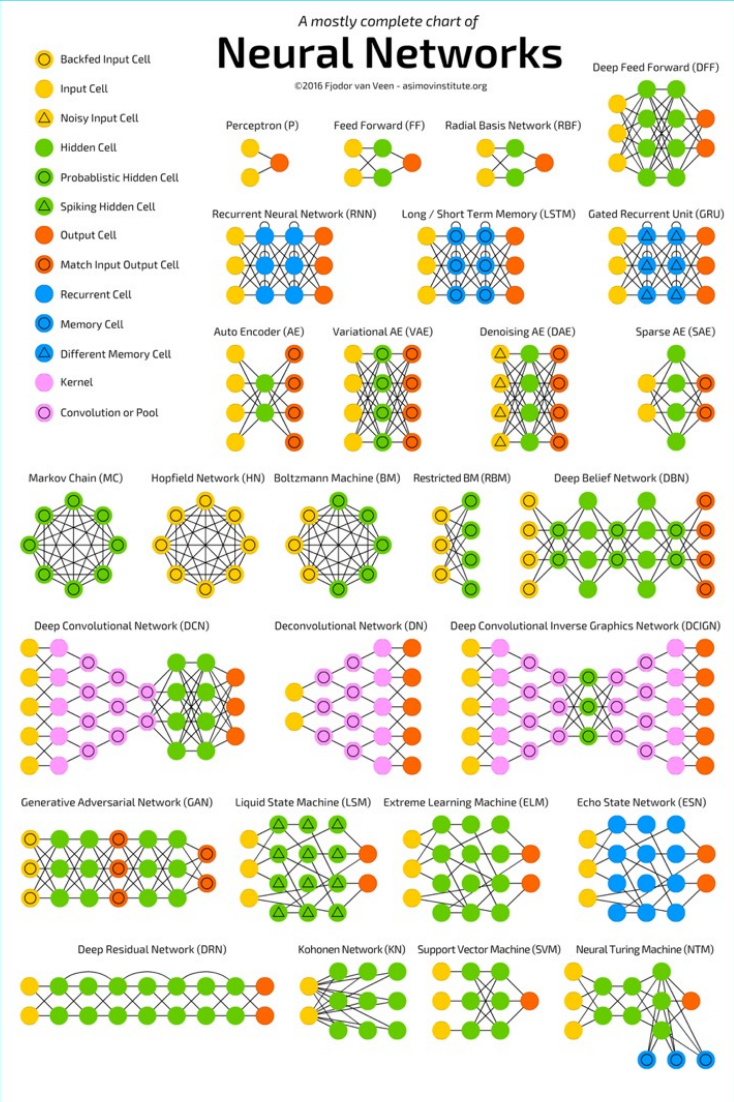
ANDRIES P. ENGELBRECHT. COMPUTATIONAL INTELLIGENCE: AN INTRODUCTION. JOHN WILEY SONS LTD, 2007.



JOSEPH YACIM AND DOUW BOSHOF. IMPACT OF ARTIFICIAL NEURAL NETWORKS TRAINING ALGORITHMS ON ACCURATE PREDICTION OF PROPERTY VALUES. JOURNAL OF REAL ESTATE RESEARCH, 40:375–418, 11 2018.

NEURAL NETWORKS

- Supervised Training
- Minimize Loss
- By adjusting weights



EVALUATING ANN

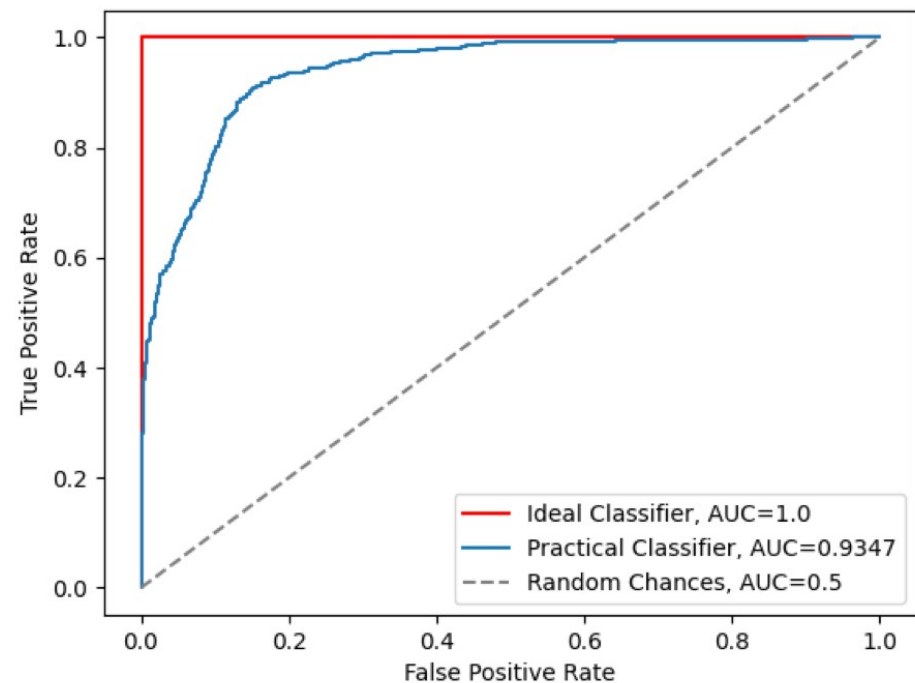
$$ACC = \frac{TP + TN}{TP + FP + TN + FN}$$

$$PRE = \frac{TP}{TP + FP}$$

$$REC = \frac{TP}{TP + FN}$$

$$F1 = \frac{2 \cdot PRE \cdot REC}{PRE + REC}$$

ROC curve



UNBALANCED DATA PROBLEM

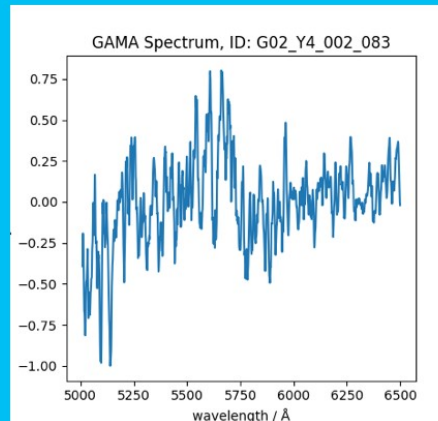
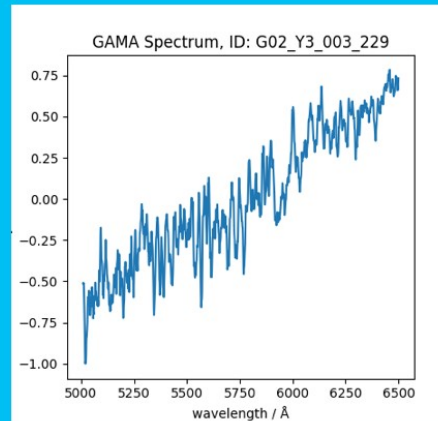
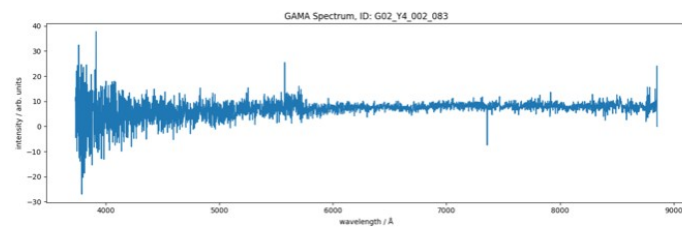
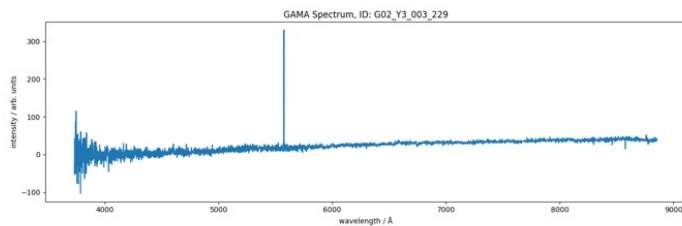
- ANNs perform best on balanced data

SOLUTION

- Random under sampling
- Training Set:
 - - Classifier 1: 800/800 (other/bad splice)
 - - Classifier 2: 400/400 (other/fringed)
- Test Set:
 - - 3,213 (364 bad splice (11%), 92 fringed (3%), 2,757 other (86%))

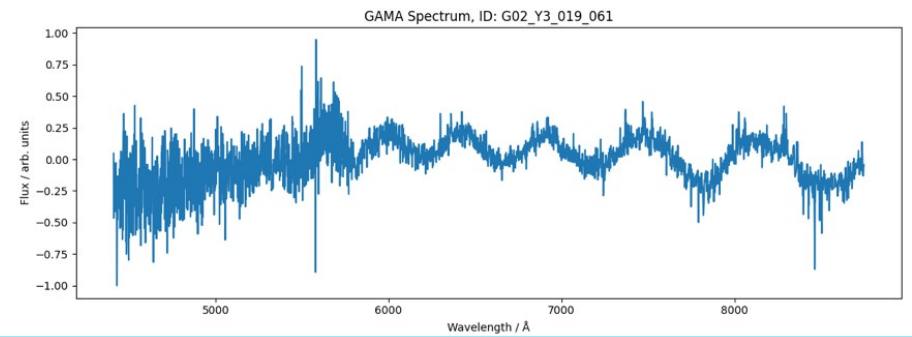
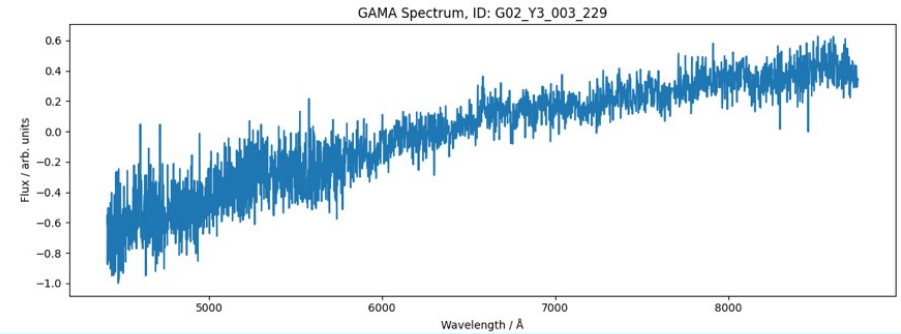
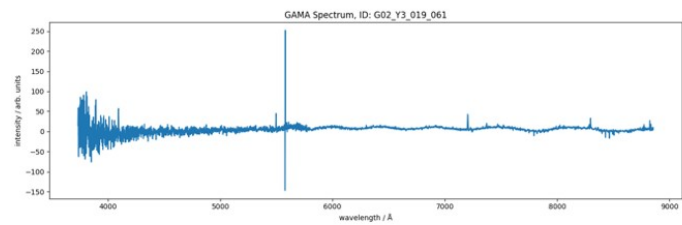
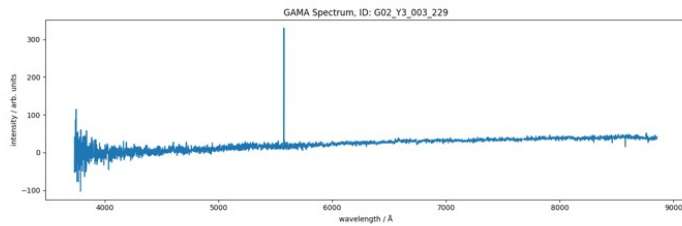
DATA PREPARATION

CLASSIFIER 1



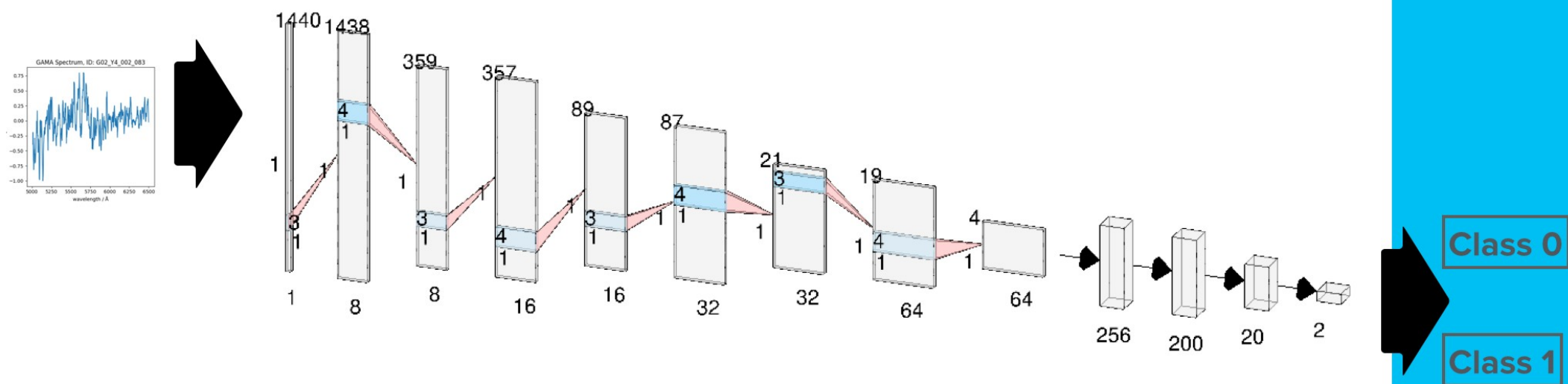
DATA PREPARATION

CLASSIFIER 2



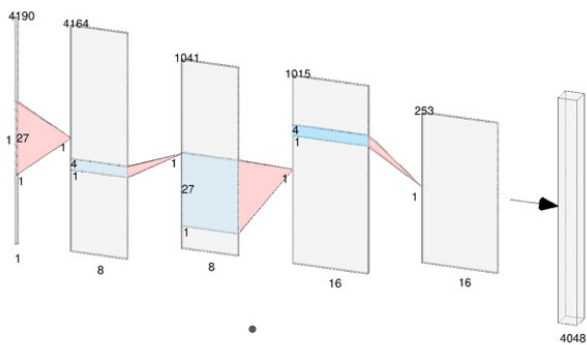
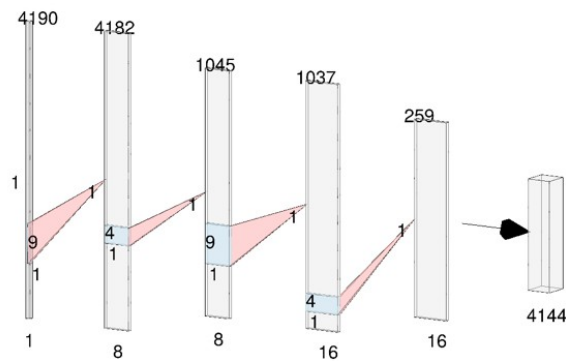
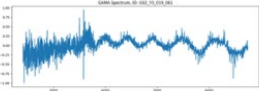
ANN ARCHITECTURE

CLASSIFIER 1

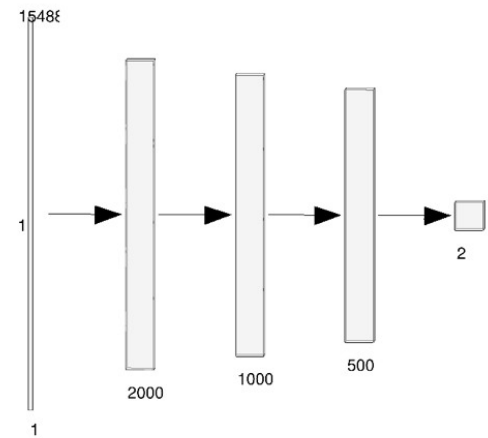


ANN ARCHITECTURE

CLASSIFIER 2

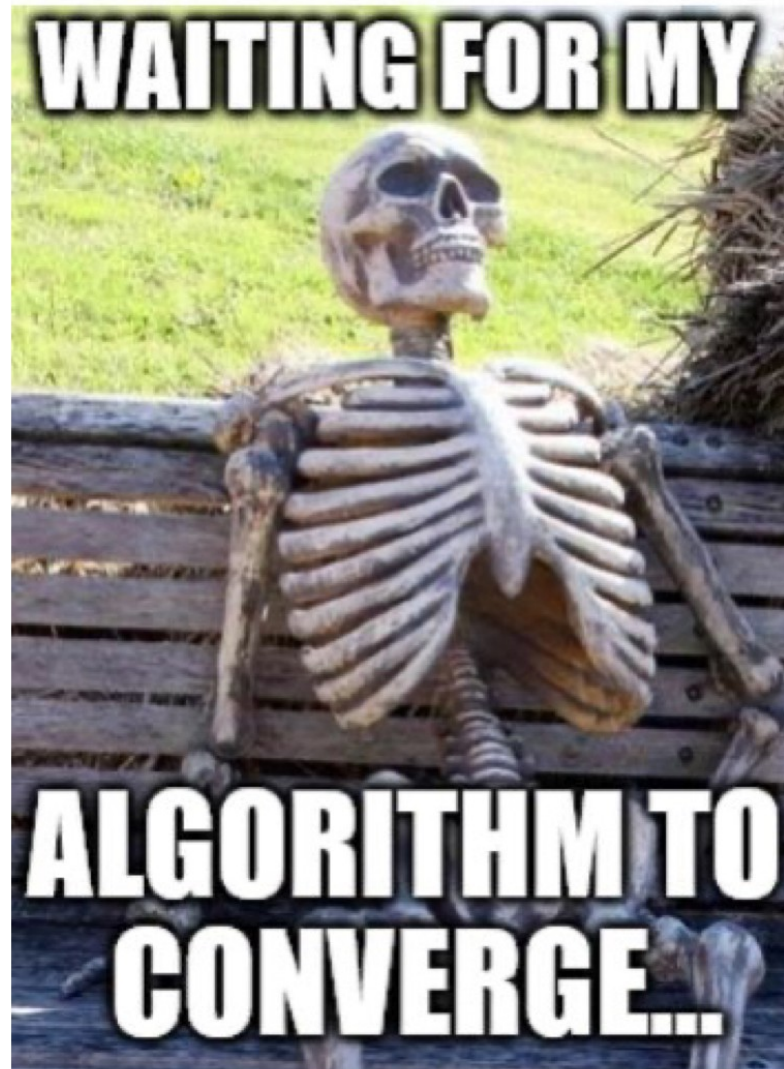


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•
•



Class 0

Class 1



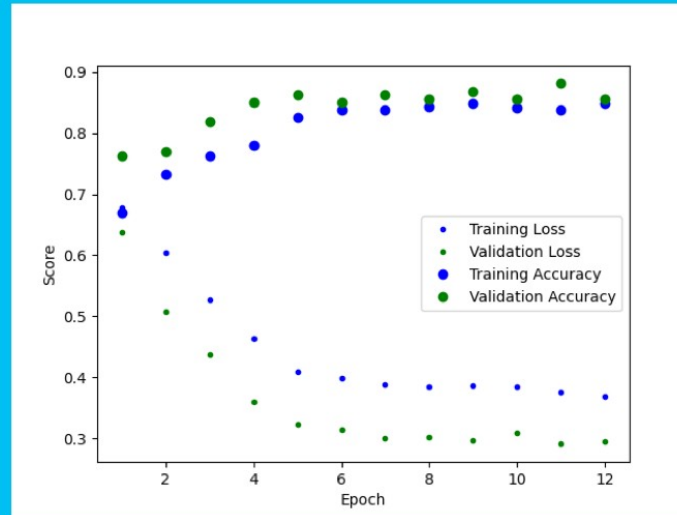
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RESULTS

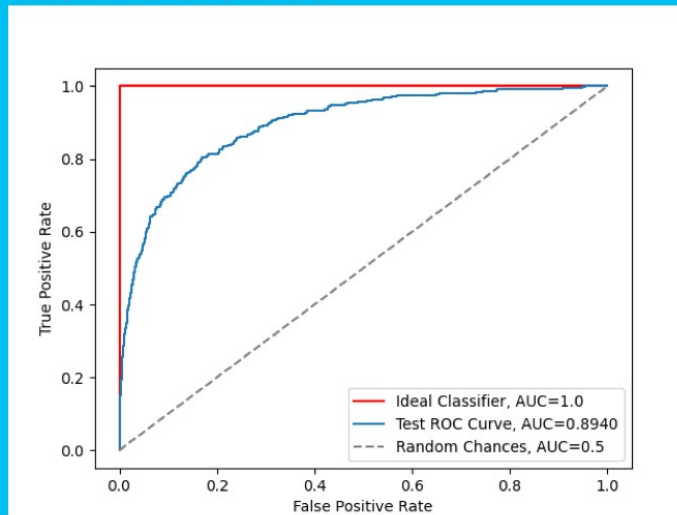
CLASSIFIER 1

- Test Results:
- ACC: 0.8880
- F1_class_0: 0.9353
- F1_class_1: 0.5765

Losscurve



Test ROC curve

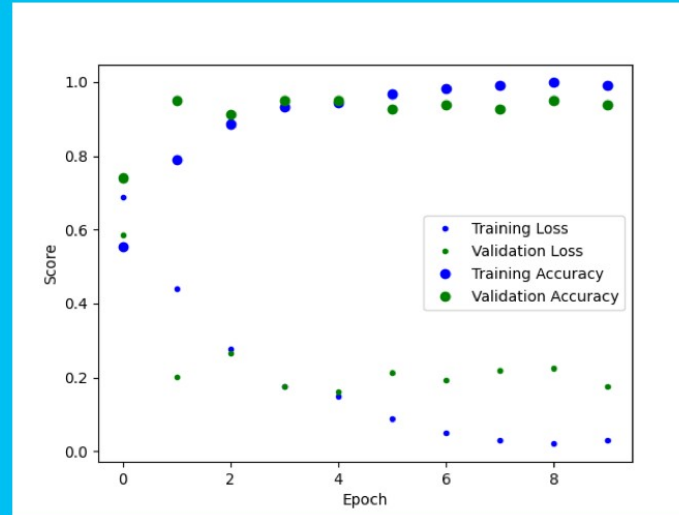


RESULTS

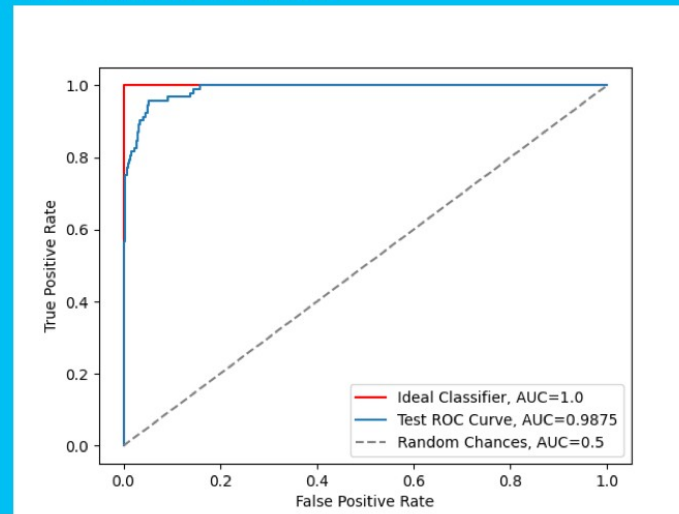
CLASSIFIER 2

- Test Results:
- ACC: 0.9788
- F1_class_0: 0.9890
- F1_class_1: 0.6937

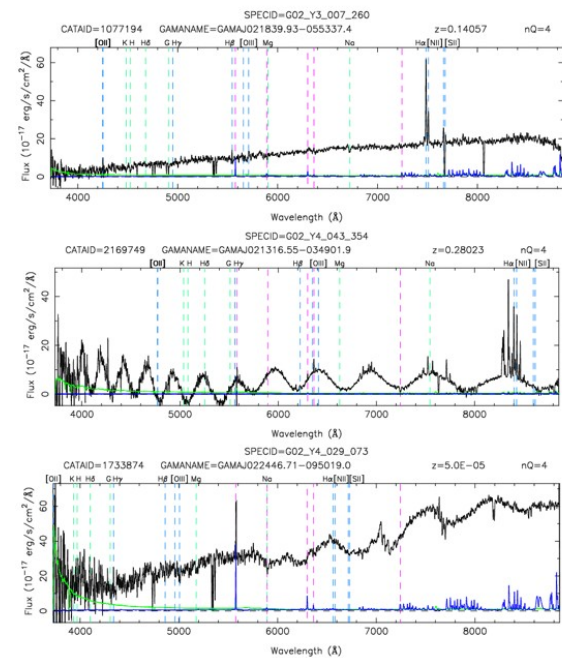
Losscurve



Test ROC curve



IMPROVING CLASSIFIER 2



CLASS 0



CLASS 1



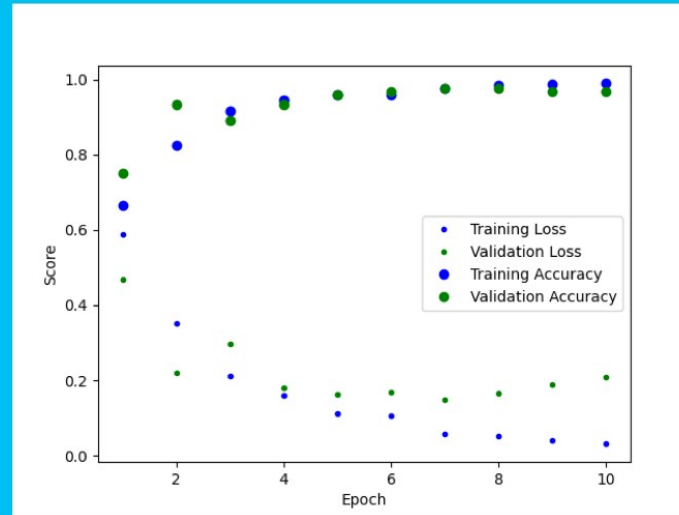
CLASS 2

RESULTS

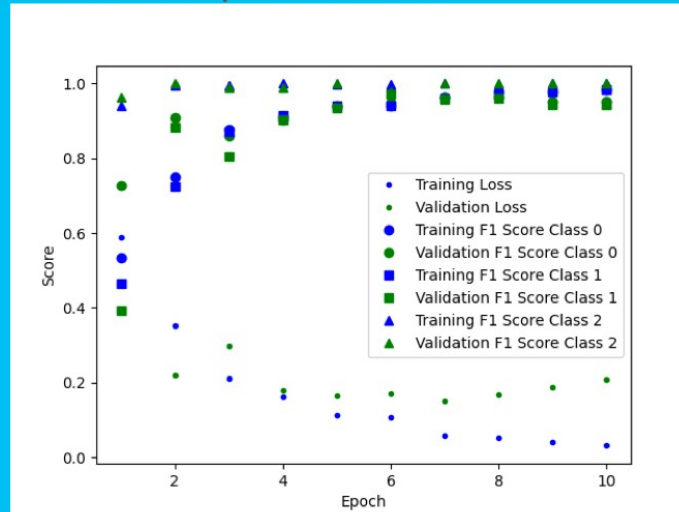
CLASSIFIER 2

- Test Results:
- ACC: 0.99667
- F1_class_0: 0.9813
- F1_class_1: 0.6312
- F1_class_2: 0.8966

Losscurve



Losscurve, F1 scores

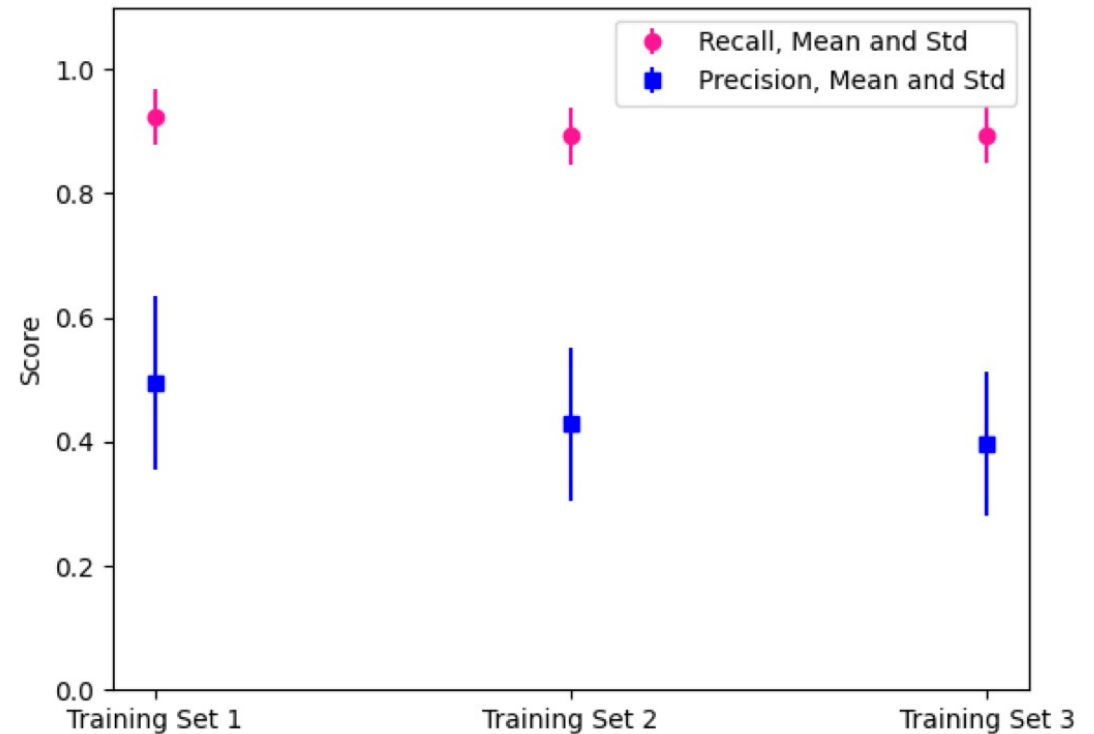


RESULTS

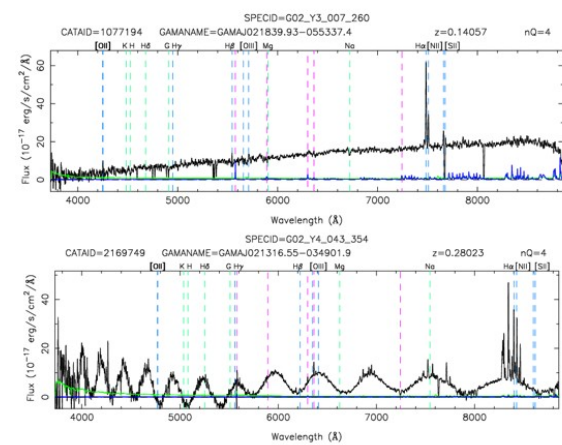
CLASSIFIER 2

- Training Set 1: 400/400/400 (other/fringed/M-star)
- Training Set 2: 400/400 (other/fringed)
- Training Set 3: 400/400 (other(containing 2% M-stars)/fringed)

Test Recall and Precision, Class 1



IMPROVING CLASSIFIER 2



CLASS 0

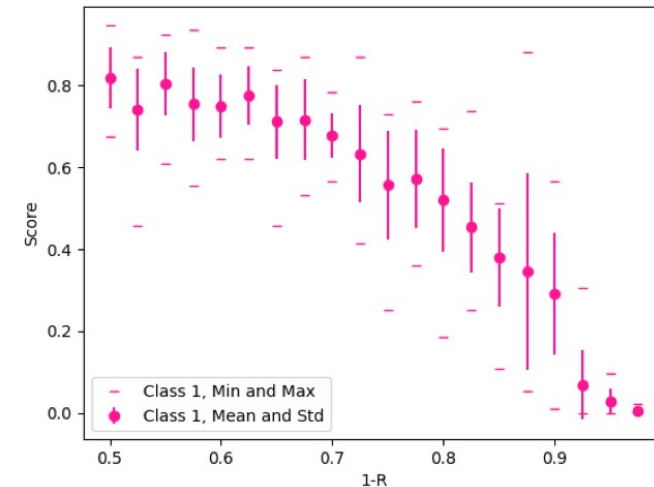


CLASS 1

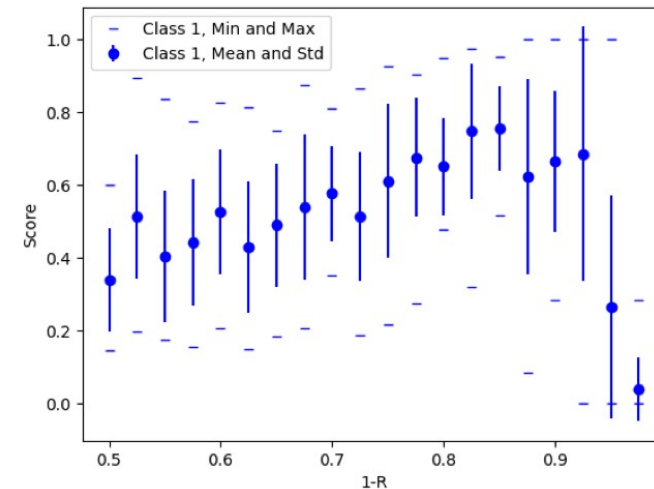
RESULTS

- Change Ratio of class 1 in training set
- Total set size: 400 (other and fringed)

Test Recall, Class 1



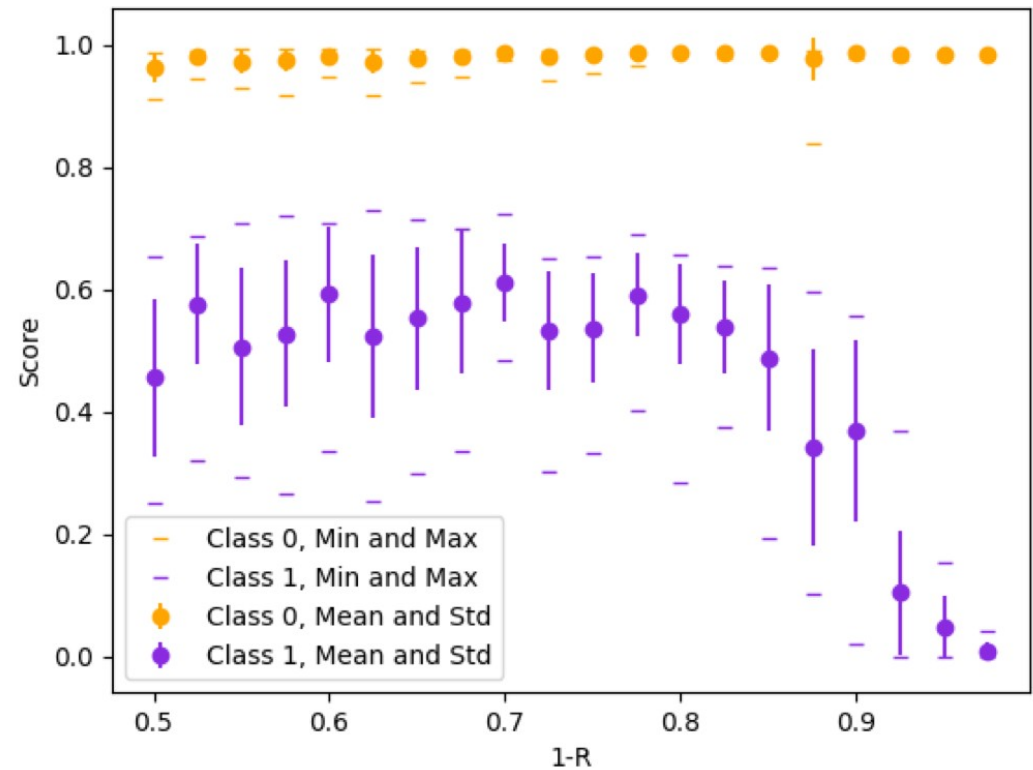
Test Precision, Class 1



RESULTS

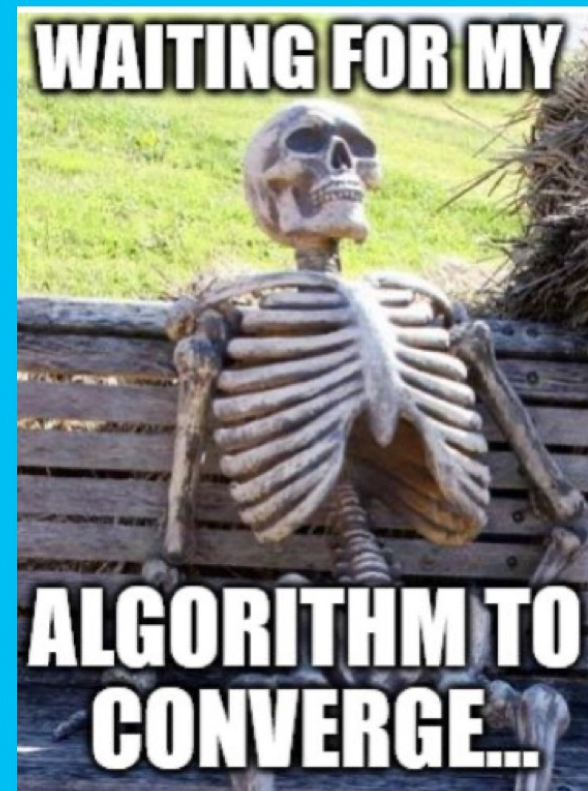
- Change Ratio of class 1 in training set
- Total set size: 400 (other and fringed)

Test F1 scores, Class 0 and 1



FINAL RESULTS

- Unbalance in training set could improve precision
- Highest scores for balanced training:
 - - splicing: $AUC=0.8880$
 - - fringing: $AUC=0.9875$



[HTTPS://I.PINIMG.COM/736X/F6/D6/19/F6D6191DF7B4239DE8C5DC76CA121D33.JPG](https://i.pinimg.com/736x/f6/d6/19/f6d6191df7b4239de8c5dc76ca121d33.jpg)

ROC CURVE

Y

N

True class

p

n

True Positives

False Positives

False Negatives

True Negatives

$fp\ rate = \frac{FP}{N}$

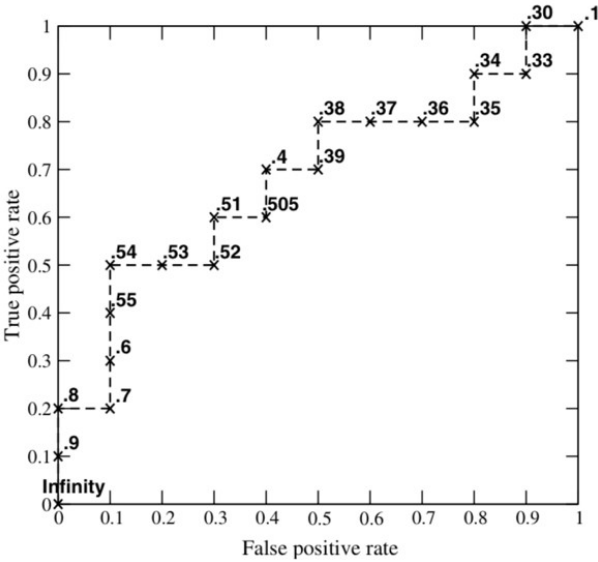
$tp\ rate = \frac{TP}{P}$

$precision = \frac{TP}{TP+FP}$

$recall = \frac{TP}{P}$

$accuracy = \frac{TP+TN}{P+N}$

Inst#	Class	Score	Inst#	Class	Score
1	p	.9	11	p	.4
2	p	.8	12	n	.39
3	n	.7	13	p	.38
4	p	.6	14	n	.37
5	p	.55	15	n	.36
6	p	.54	16	n	.35
7	n	.53	17	p	.34
8	n	.52	18	n	.33
9	p	.51	19	p	.30
10	n	.505	20	n	.1



TOM FAWCETT. AN INTRODUCTION TO ROC ANALYSIS. PATTERN RECOGNITION LETTERS, 27(8):861 – 874, 2006. ROC ANALYSIS IN PATTERN RECOGNITION.