ECE 511: Biolectric Signals and Systems

Neural Network Based Pattern Recognition and Classification

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Goals

Improve the Detection and Classification of [A or V] vs. [N or L or R or other]

Construct and Train a Network that recognizes ECG heart beats and test for its viability in actual applications

Summary

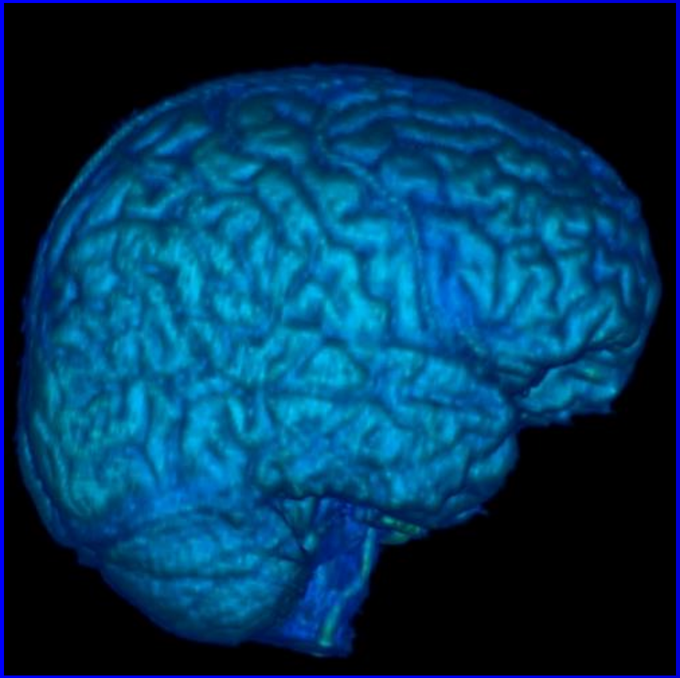
- Introduction
  - Biological foundation and NN principles
- Training the Network
- Testing
- Analysis of Results
- Conclusions

The Biological Foundation of Neural Networks

The Human Nervous System

- Consists of an extremely large number of nerve cells, or neurons
- Operates in parallel to process various types of information throughout the entire body

The Brain



- Neurons – nerve cells

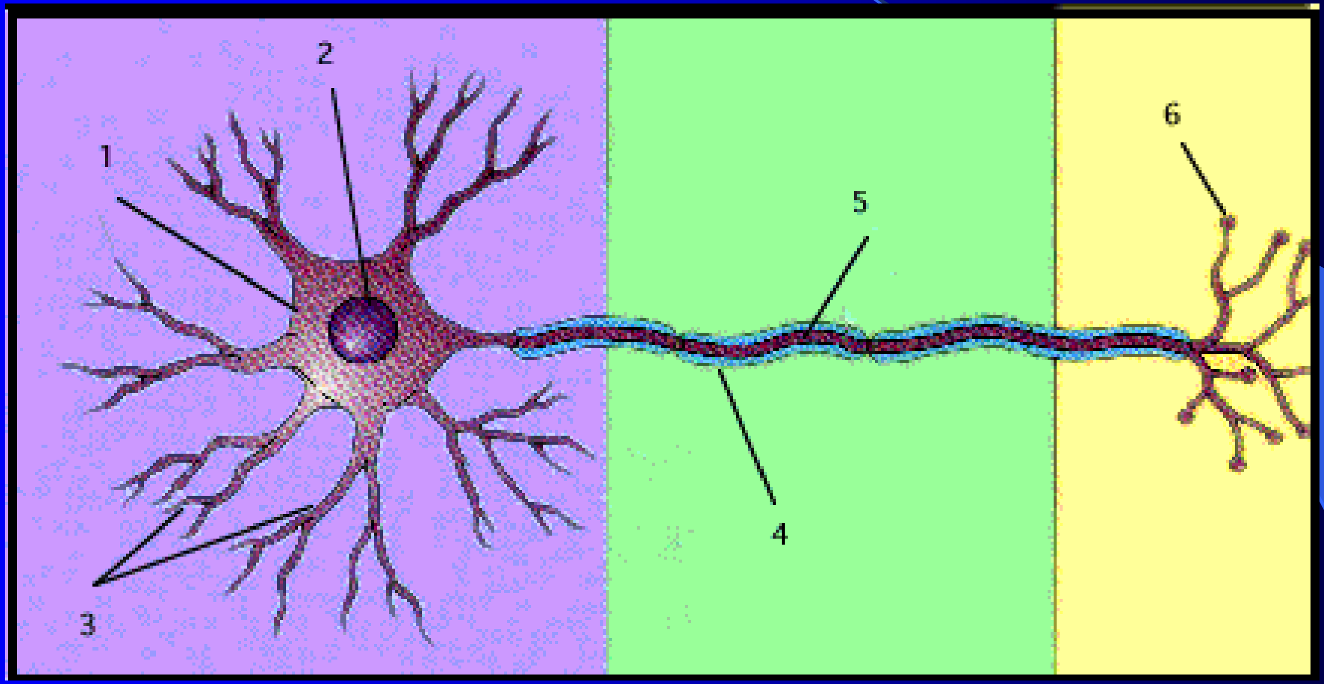
  ~ 100 billion neurons

- Synapses – junction between two neurons

  ~ 10^{15} synapses

If placed end to end, the neurons of one human brain would reach over 250,000 miles!

The Neuron



1 Cell Body (Soma)
2 Nucleus
3 Dendrites
4 Axon
5 Myelin Sheath
6 Axon Terminals

Function of Neurons

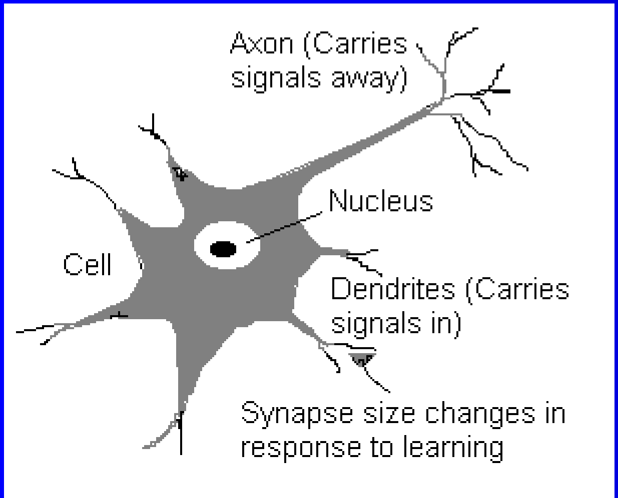
- Receive information
- Process information
- Transmit information

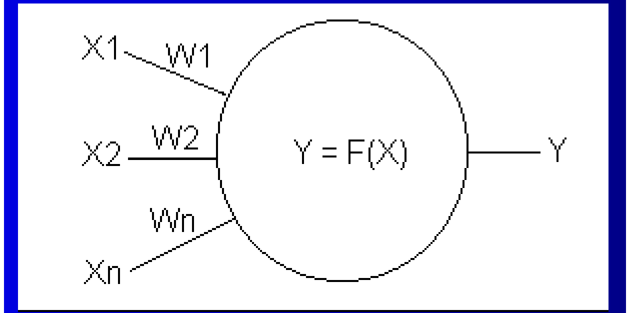
Artificial Neural Networks

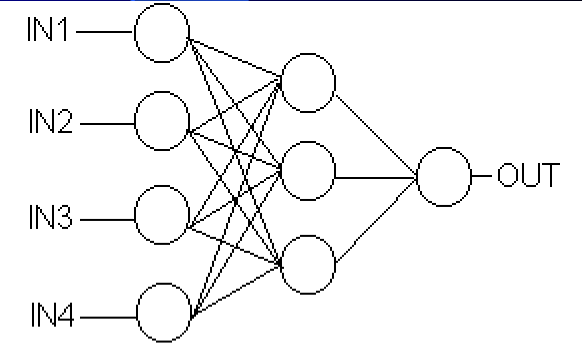
Neural Networks

- NNs are collections of mathematical models with some of the properties of biological nervous systems

A Simplified Mathematical Model

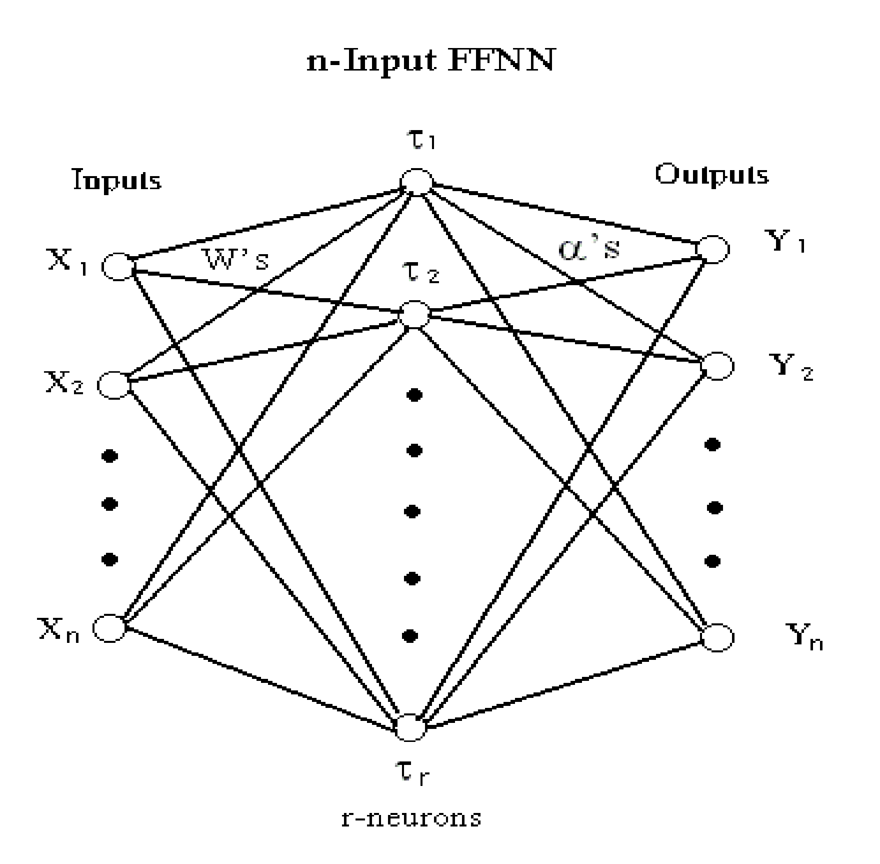






Neuron Cell → Schematic of Neuron → Neural Network

n-Input FFNN


n-Input FFNN
τ1
Inputs
Outputs
X1
W's
τ2
α's
Y1
X2
Y2
Xn
Yn
τr
r-neurons

Biological Connection

- Neurons ~ Interconnected processing elements
- Synapses ~ Weighted connections

Some Properties of NNs

- Learning
- Generalizing
- Decision-making

Learning

- **Biological System** : adjustments in synaptic connections

- **Neural Network** : exposure to I/O data where learning algorithm iteratively adjusts connection weights

Algorithms

Examples of Learning Algorithms:

- The Delta Rule
- Hebb’s Rule
- Hopfield Law
- Kohonen’s Learning Law

Advantages of NNs

- Resilience against distortions in the input data
- Capability of learning
- Can handle complex decision surfaces and multiple interactions among parameters
- Robust when used with many parameters

Areas of Application

- **Prediction** :
  - Use input values to predict some output
- **Classification** :
  - Use input values to determine the classification
- **Data Conceptualization** :
  - Analyze the inputs so that grouping relationships can be inferred
- **Data Association** :
  - Like classification but also recognizes data that contains errors
- **Data Filtering** :
  - Smooth an input signal

Training and Analysis

Training Methods

Software Used: NNCAD for Windows 3.3

- Feed Forward Neural Networks (FFNN)
- For the purposes and simplifications of the lab, our group dealt only with specific variances of parameters to obtain the highest possible f-value.

F-value

Definition: Measure of Network Performance

- Accounts for and weighs all 4 types of classifications

1. Correct Classification	1.0
2. Unclassified	0.2
3. False Positive	0.3
4. False Negative	0.6

Fval = f (1.00*Correct – 0.6*FNeg – 0.2*Unclass – 0.3*FPos)

Choosing the Parameters to Vary

Total: 20 parameters to choose for each training run

Our method: Vary 3 significant parameters

- Number of nodes in the layer
- Maximum number of iterations
- Gamma

Number of Nodes

In this lab: Only single-layer FFNNs were tested. The number of nodes is in the first layer of the neural network.

- Highly interconnected processing element in a neural network

- Represents the neurons in the brain

Maximum Number of Iterations

Definition: The highest number of times that a a training set is allowed to update the weights in the FFNN

- Weight
  - specific neural connection from the input (x_n) to its neuron (τ_n)
  - analogous to the synapse between neurons

Gamma

Determines how far the training set will adjust weights and thresholds at each iteration

Training

December 8th: Ran 5 training runs (SB) on 4 computers

	Number of nodes	Gamma	Maximum number of iterations
Default	15	0.000100	100
Training Run 1	12	0.000100	10,000
Training Run 2	12	0.0000500	75,000
Training Run 3	11	0.000200	50,000
Training Run 4	13	0.000100	100,000
Training Run 5*	**10**	**0.000100**	**150,000**

Training

Ran Training Sets A, B, C, D (10,000 iterations)

	Number of Nodes	Gamma	F-Values
Training Set A	12	0.000100	65.85
Training Set B	12	0.000100	67.36
Training Set C	12	0.000100	45.02
Training Set D	12	0.000100	63.85

Basis for Varying Parameters
Number of Nodes

Default Number of Nodes: 15

- 10-13 nodes for each training set
- Too few nodes would reduce training performance
- Too many nodes would require a higher number of iterations (i.e. more computer time) to see improvement

Basis for Varying Parameters Maximum Number of Iterations

- Maximum Number of Iterations ↑, f-value ↑

- 10,000 iterations
- 50,000 iterations
- 75,000 iterations
- 100,000 iterations
- 150,000 iterations*

- High Maximum Number of Iterations may result in an overtrained set.

Basis for Varying Parameters Gamma

Default Value for Gamma: 0.000100

Small Gamma

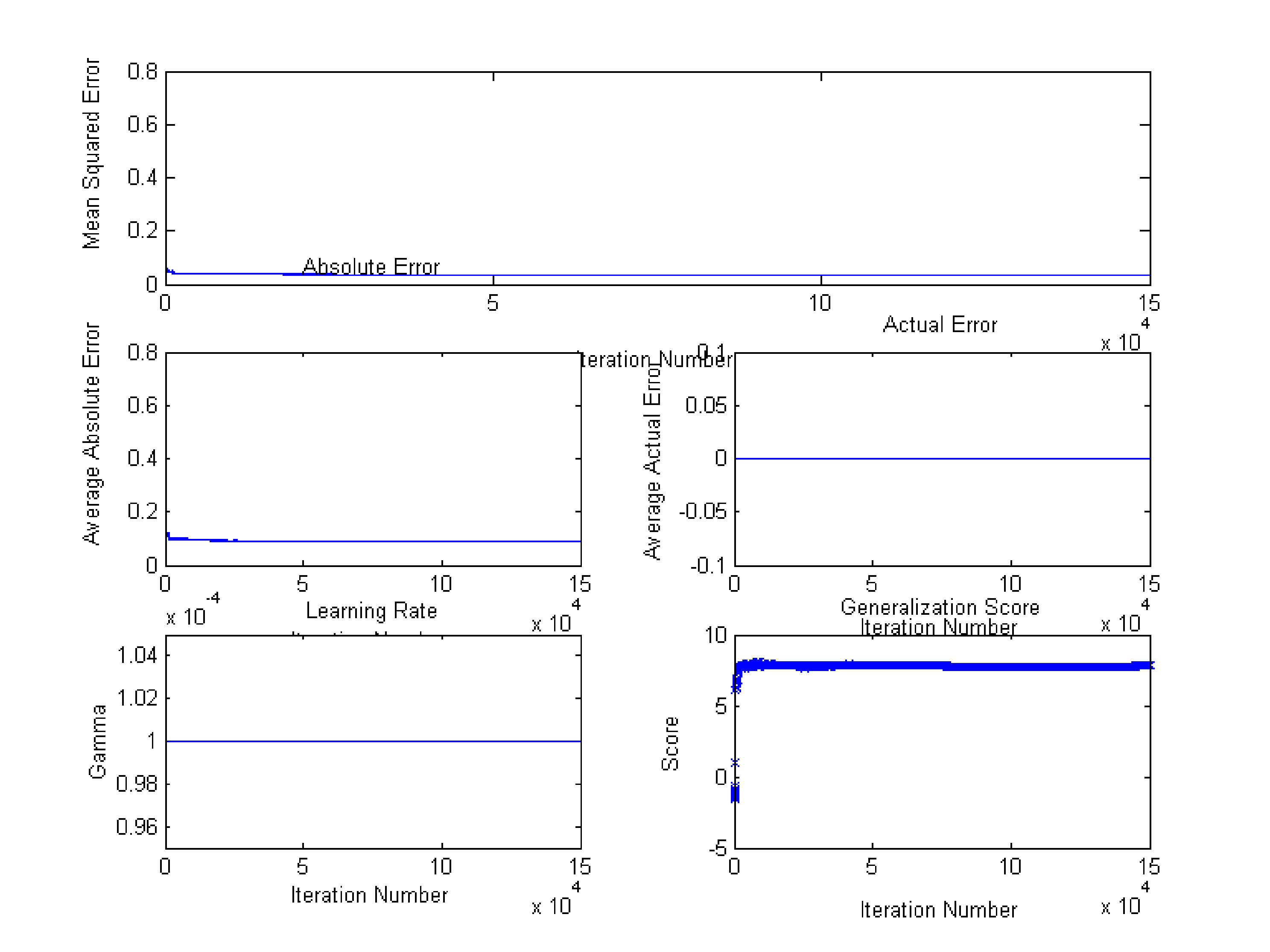
- Minimal training progress
- Local Minimum Error

Large Gamma

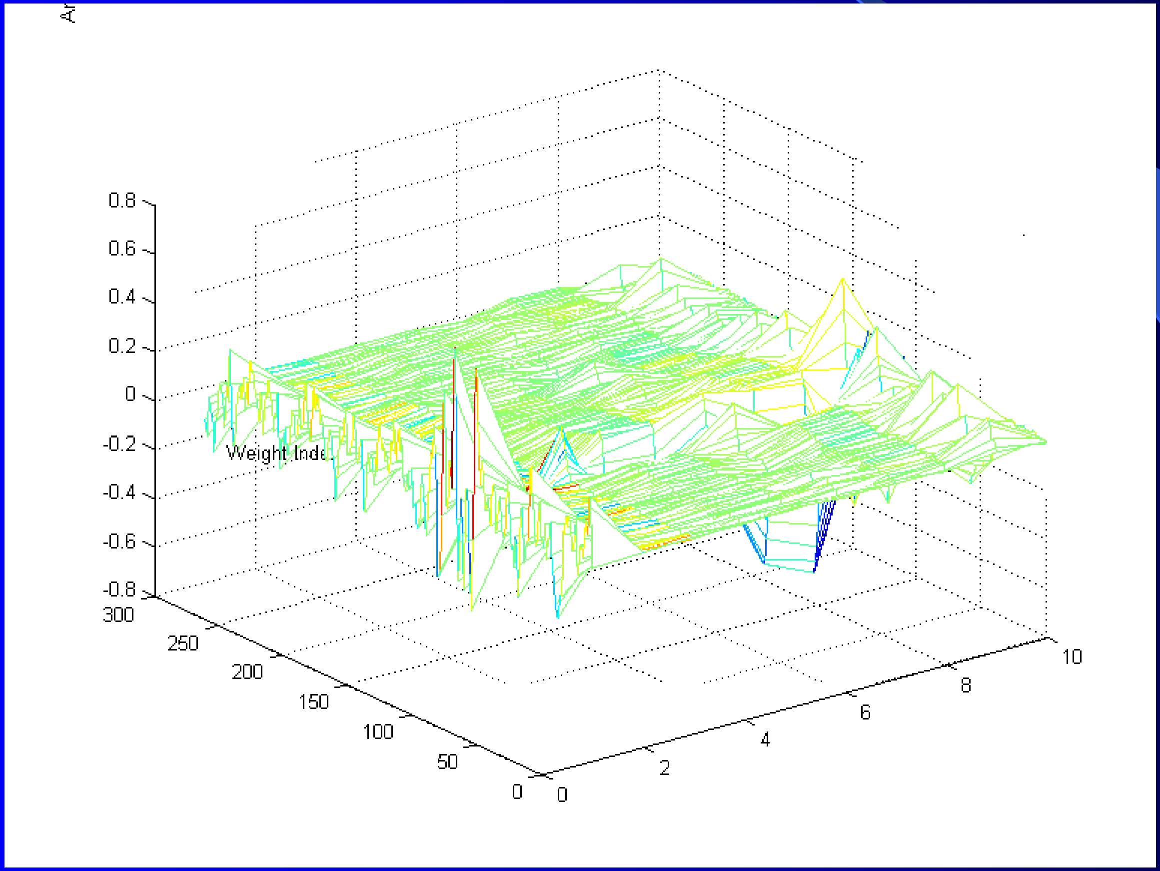
- Unstable updates
- Less refinement of final weight values

Training Results

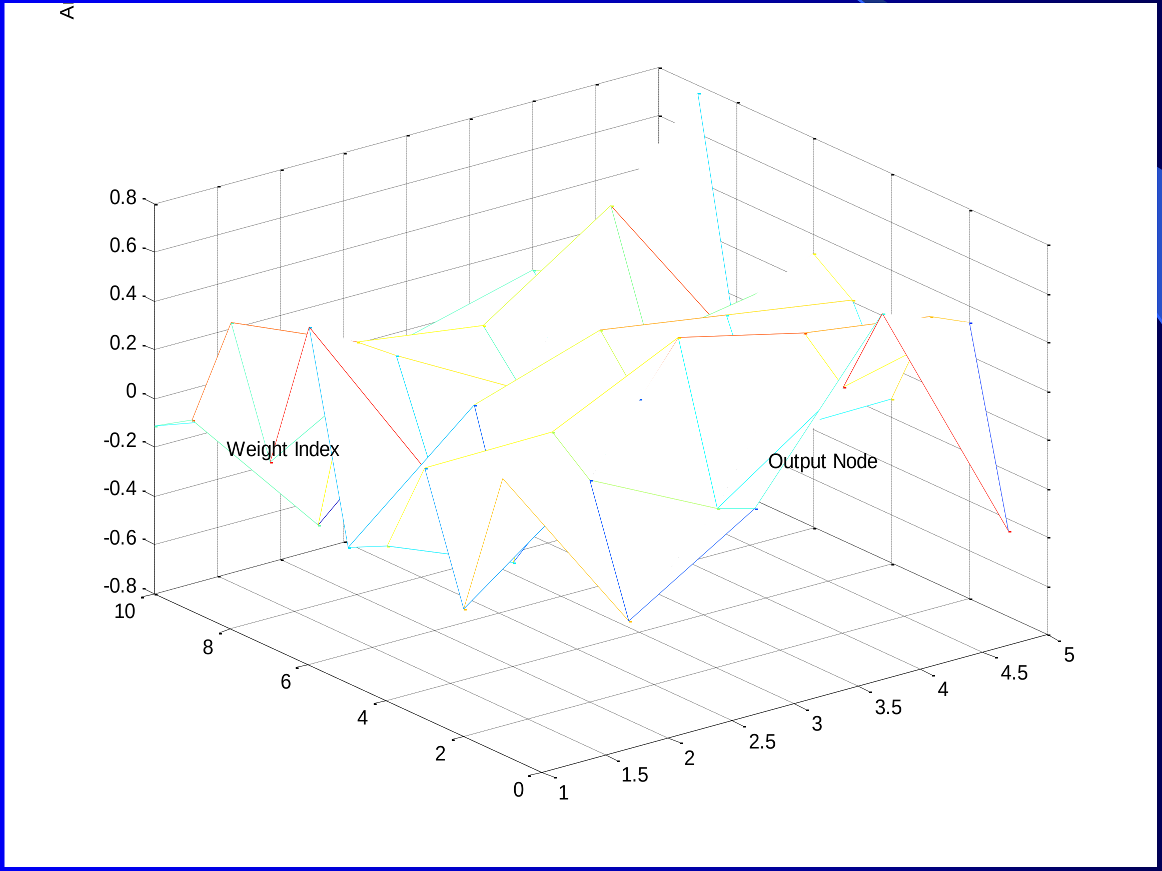
Training Results



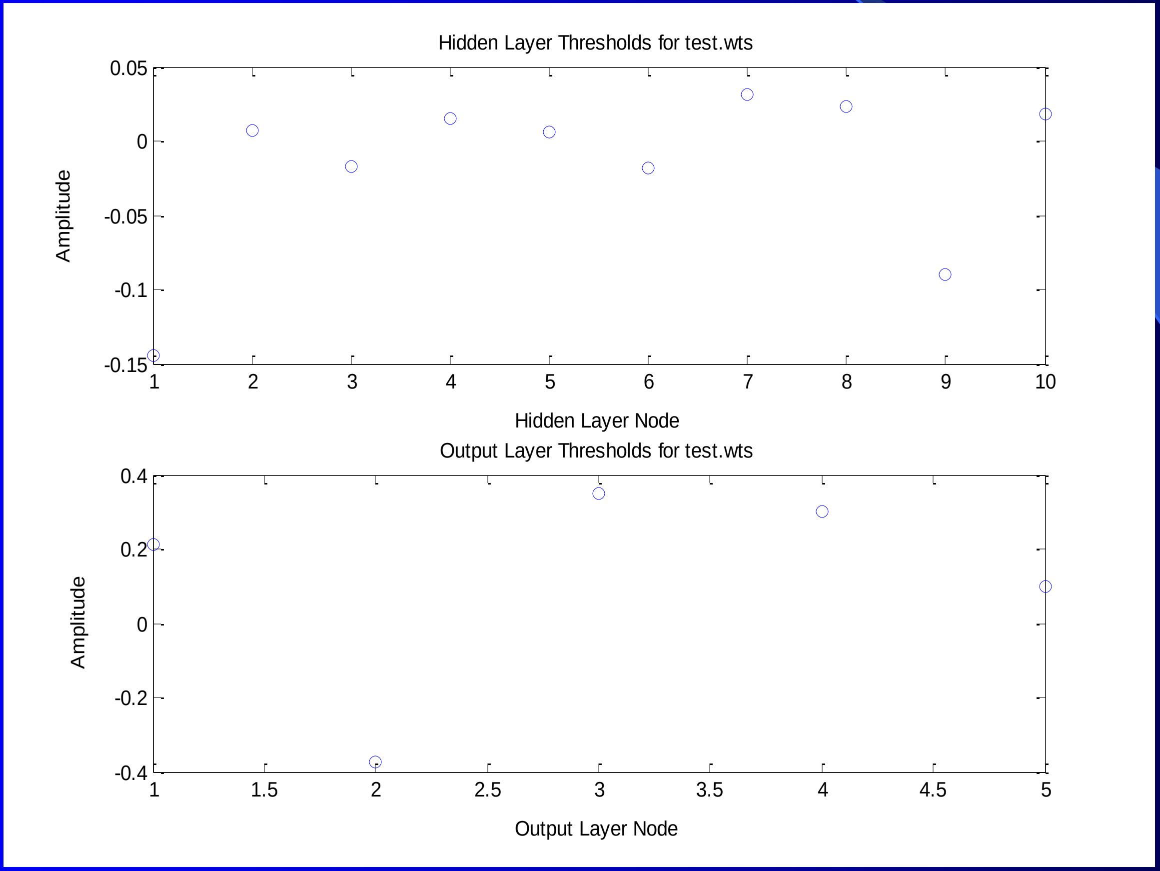
Weight Index Vs. Node (1 layer)



Output Weights Vs. Output Node



Amplitude of Weights in Hidden Layers



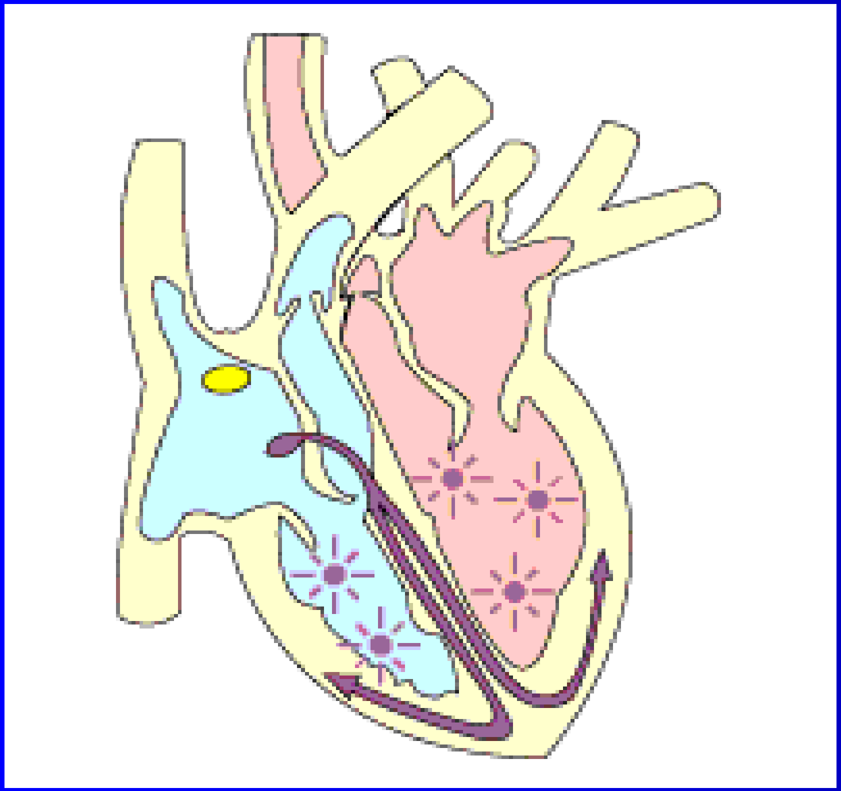
Heart Beats: NAVRL

Classification Scheme and Rationale

- Classification focused on distinguishing between A or V, as well N or L or R. Crucial to determine if anomalous beats originate at the left or the right.

- Premature Beats: Not a main concern, as they are common in normal individuals.
- Their presence alone does not require treatment unless they cause intolerable symptoms.
- Very often, a few changes in lifestyle, such as reducing stress or avoiding caffeine, will be sufficient to regulate the heartbeat

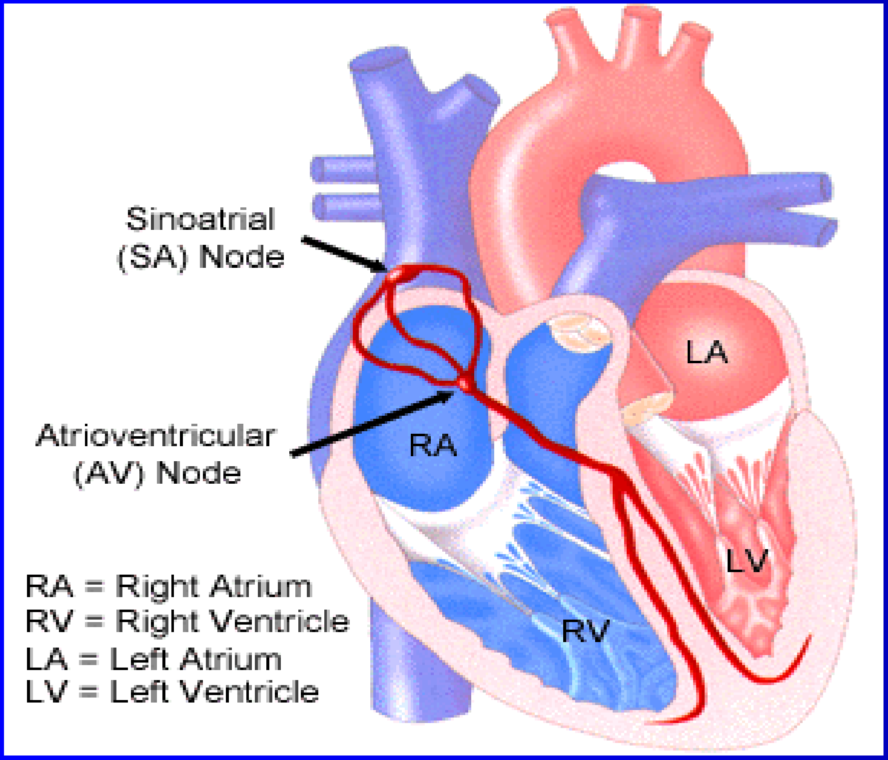
Premature Ventricular Contraction



- PVCs can simply be a normal variation in the heart's healthy operation, or they can mean that there is a serious underlying heart problem

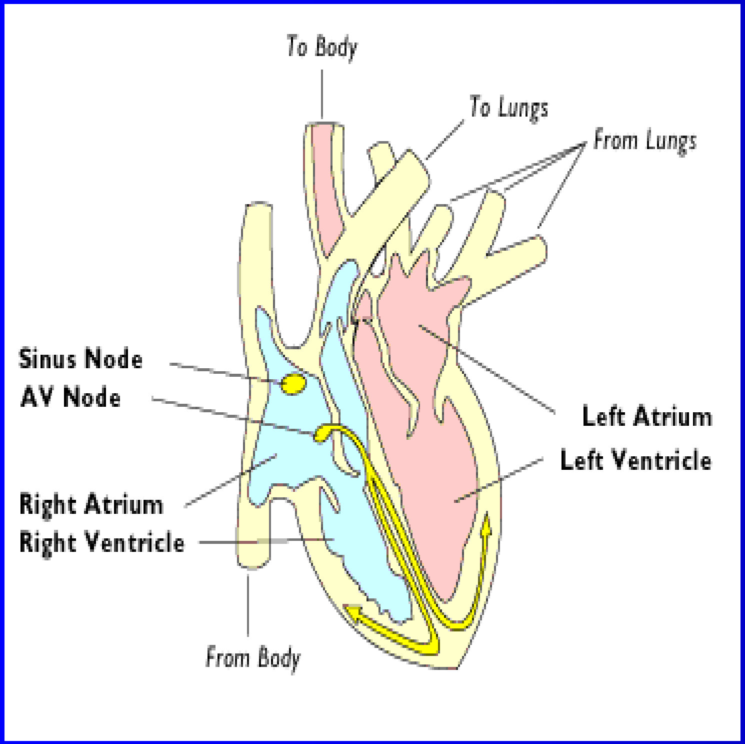
- Two extreme possibilities for classification of V implores distinction from other heartbeat forms

Atrial Premature Beat



- **Premature Atrial Contraction (PAC)** originates within the atrial myocardium but outside the SA node. The PAC occurs before the next expected sinus discharge
- Premature beats are very common in normal children and teenagers — most people have them at some time. Usually no cause can be found and no special treatment is needed. The premature beats may disappear later.

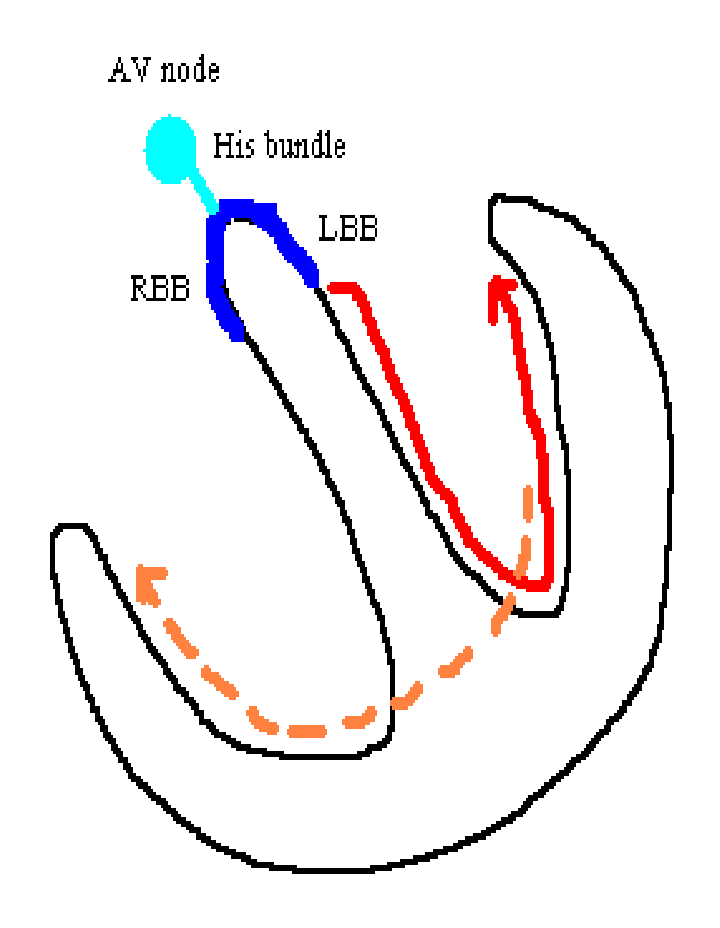
Bundle Branches



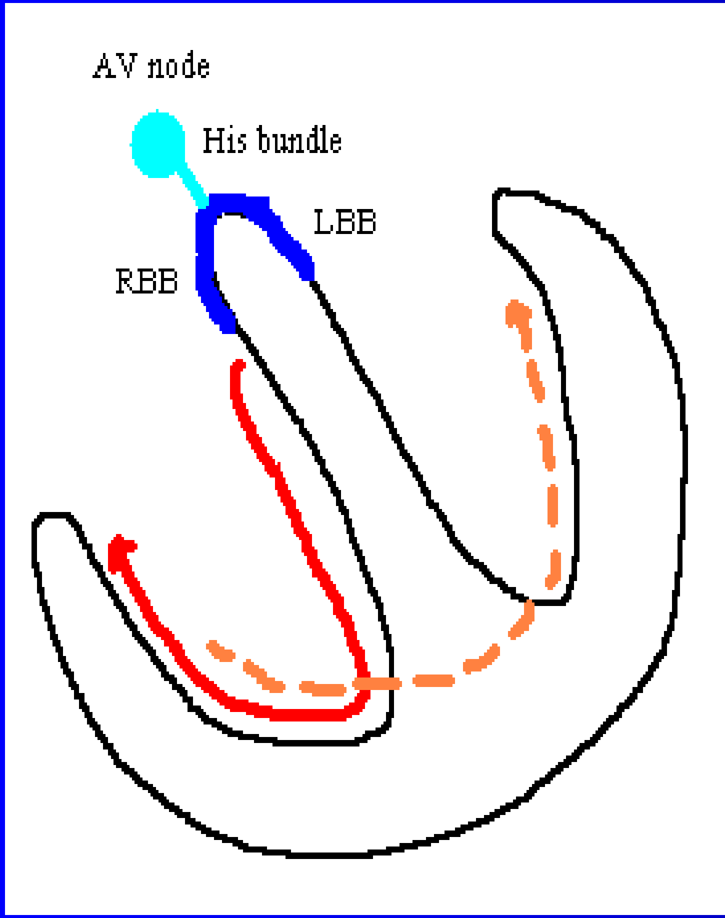
- Electrical impulses normally travel down both the right and left bundles at the same time – thus, left and right ventricles contract simultaneously
- Disrupted conduction of the electrical impulses causes bundle bunch blocking

Right Bundle Branch Block

- Right bundle no longer conducts electricity
- Electric impulse leaves His bundle and enters only LBB, and is carried only to the left ventricle
- Then from left ventricle makes it way to the right ventricle
- As a result, the two ventricles no longer receive stimuli simultaneously
- Commonly occurs in normal, healthy individuals, and screening results no medical problems



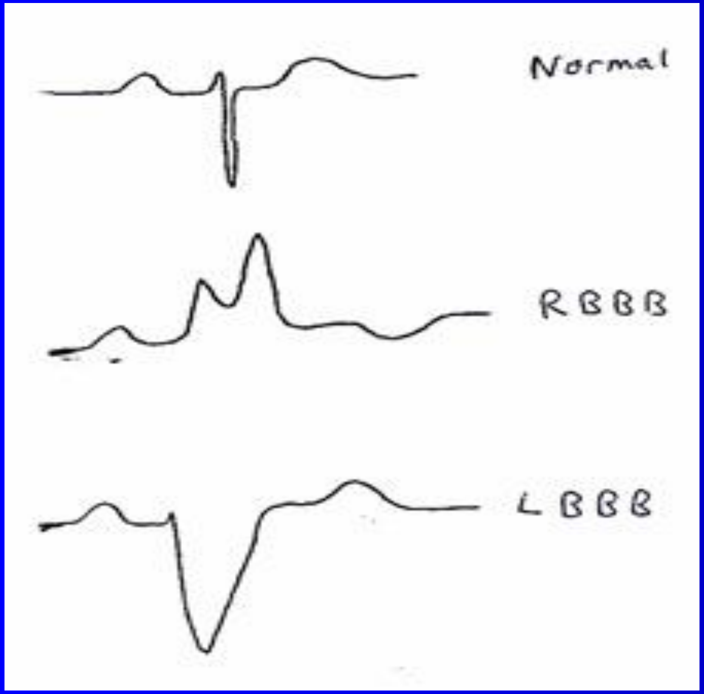
Left Bundle Branch Block



- Similar to RBBB, except the left bundle no longer conducts electricity
- LBBB usually indicates underlying cardiac pathology
- May occur in healthy people, but a thorough research, as opposed to simple screening, should be conducted for underlying cardiac problems

ECG's in BBB

On the ECG, the QRS complex represents the spread of the heart's electrical impulse across the right and left ventricles



- Normal QRS complex
- Wide and misshapen QRS occurring in both
- RBBB and LBBB

TESTING

- Overview of Data
- Choosing Data for Analysis

Review of Data

Sample Number	Classification Overview
100, 101, 103	mostly N, a few V’s and R’s
105	contains set of all types but mostly N’s
106	contains N’s and V’s classified rarely as all types, mostly classified correctly
107	classified almost entirely as others with a few V’s
108	mostly N’s classified as N’s, with a few V’s
109	mostly L’s, classified as L’s
111	L’s classified as L’s, and a few RAVN’s
118	R’s classified as R’s
124	R’s classified as R’s and a few as N’s
207	Diverse classification, almost everything
208	mostly N’s as N’s, and significant no. of V’s as V’s
214	L’s as L’s some as all types
222	N’s classified as N’s, but significantly as A’s and some other types too
231	Sample 231 mostly R’s classified as R’s, and several other diverse classifications

Analysis

Analysis

- Overall the network performed well
- For all frames
  - Correctly classified 86.49%
  - False Negatives 12.49%
  - False Positives 3.12%
  - Unclassified 1.02%
- F value of 75.05

Composite Stats Grid

Network Classification of Frames (StatsGrid)

	L	R	A	V	N	unclassified
L	6843	49	11	978	162	28
R	280	4496	39	12	170	37
A	72	73	104	44	130	32
V	217	29	35	1619	143	51
N	422	251	609	216	14236	173
O	325	90	74	344	2053	20

Performance by Beat Type

Beat TYPE	CORRECT	F/NEG.	F/POS	UNCLASS	TOTAL
L #	6843	1200	991	28	8071
L %	84.79%	14.87%	4.22%	0.35 %	
R #	4496	501	402	37	5032
R %	89.31%	9.95	1.52%	0.74%	
A #	104	319	455	32	694
A %	22.86	70.11%	2.23%	7.03%	
V #	1619	424	1250	51	2094
V %	77.32%	20.25%	4.24%	2.44%	
N #	14236	1498	173	605	15907
N %	89.5%	9.42%	3.86%	1.09%	

F/Pos percentage is the percentage of beats not classified as a particular beat type. For all others, the percentage is of the number of beats that were classified as that type.

Abnormal Beats

- Abnormal Beats include LRAV

Network Classification of Normal Frames (StatsGrid)

	Abnormal	Normal	Unclassified
Abnormal	14901	605	148
Normal	1498	14236	173
Other	833	2053	20

Abnormal Beats

- The most serious error our network could commit would be classifying LAVR beats as normal.
  - Of the 15654 beats classified as L,A,V or R, our network classified the beat as normal 605 times. (3.8%)
  - Since most sick patients have at least a few abnormal beats the network should catch something wrong.

[A or V] vs. [All Other]

Network	F value	Percentage of A or V beats identified as A or V
Competitor 8 node	60.67	86.65 %
Competitor 12 node	66.85	85.7 %
Competitor 20 node	77.53	84.11 %
Group Network	75.05	70.7 %
A/V Network	63.85	87.03%

Composite Stats

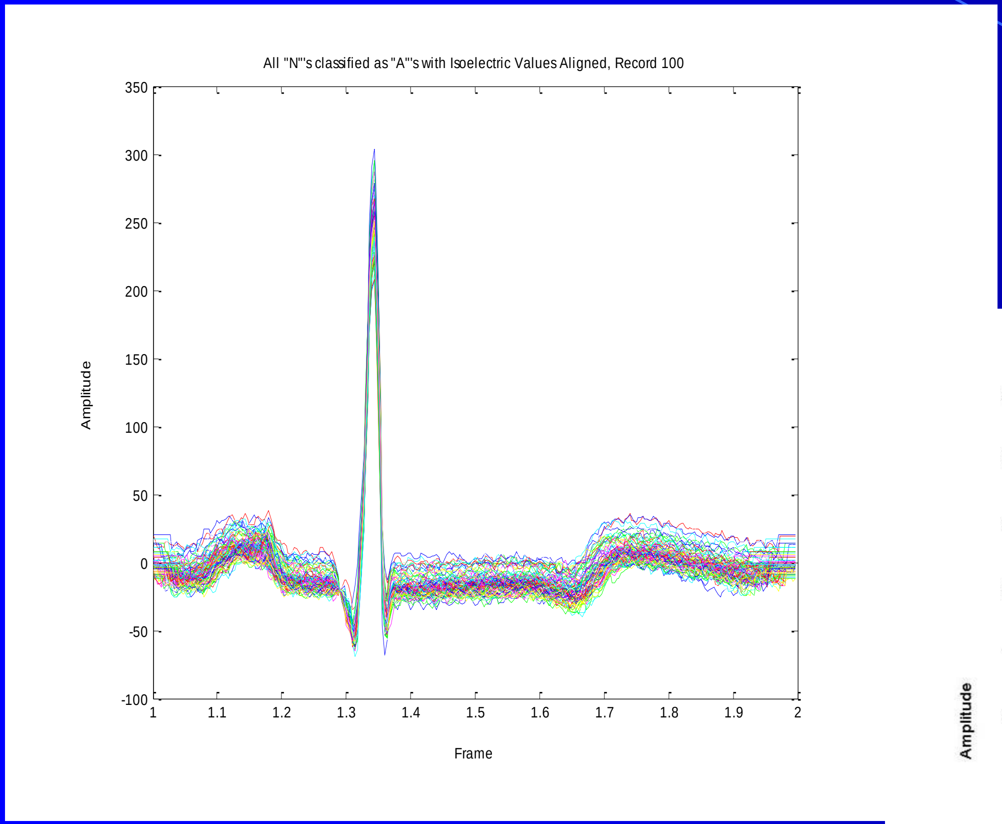
- The network performed very well with two notable exceptions:
  - A and N beats were sometimes confused.
    - Only 3.8% of the N beats were classified as A. However, that represents 69.7 % of all beats classified as A by the network.
    - 28.5 % of the A beats were classified as N beats.
  - L beats were often misclassified as V beats
    - 978/ 8071 L beats (12.1%) were classified as V. This represents 34% of all beats classified as L.

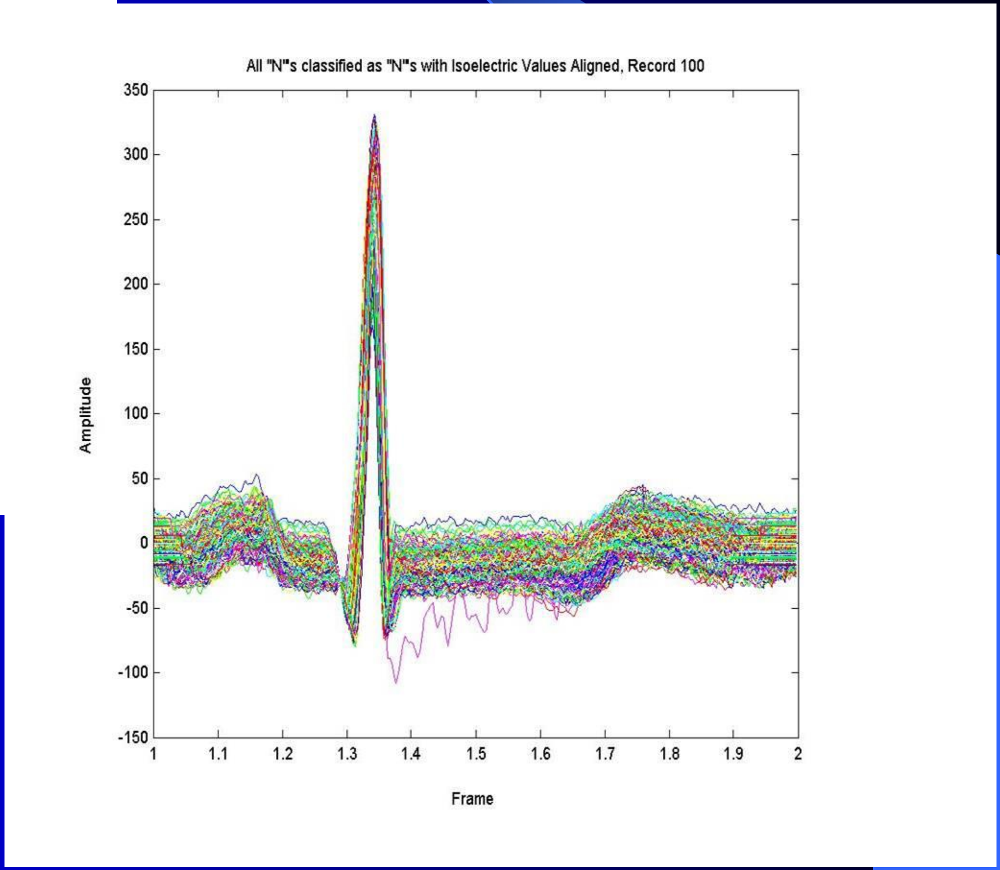
A and V Beat Misclassification

- Although all beats occur with equal frequency in the training set, A and V beats occur infrequently in the testing set.

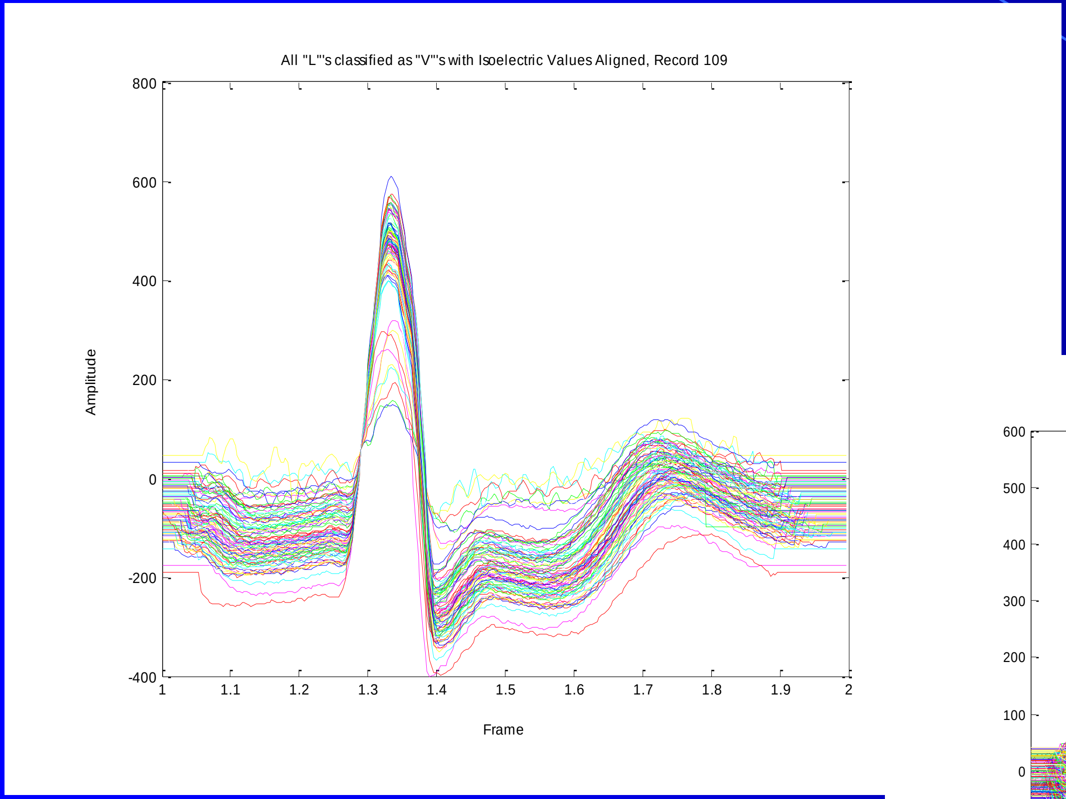
Atrial Beat Misclassification

Record 100 had many N beats classified as A

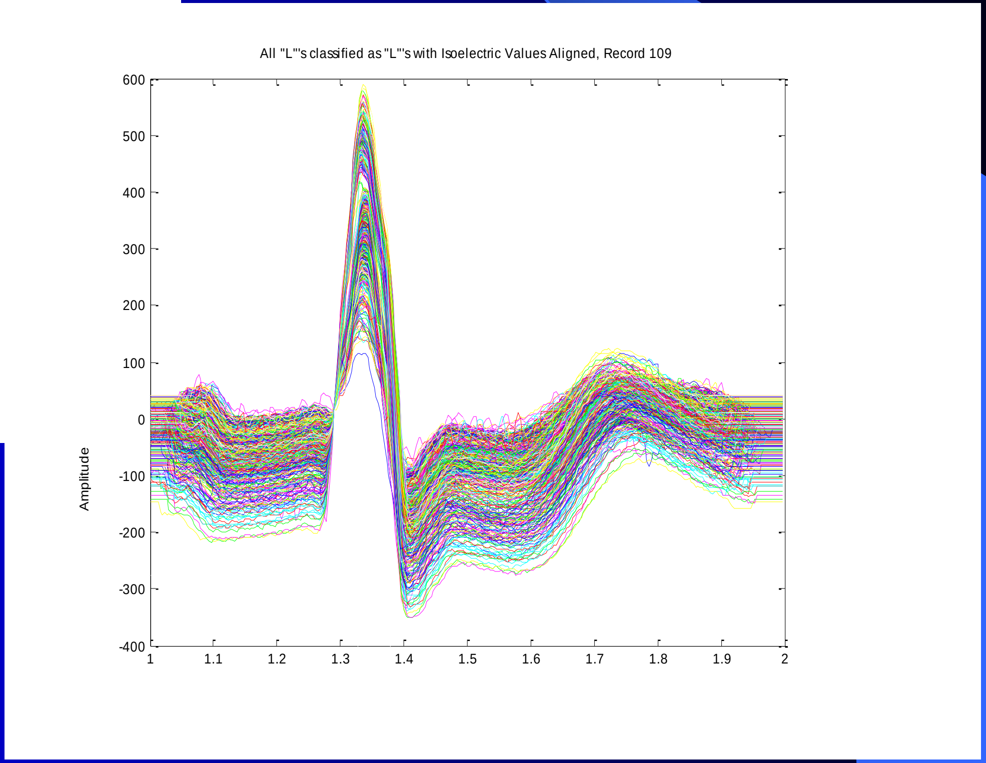




Ventricular Beat Misclassification



Record 109 had many L beats classified as V

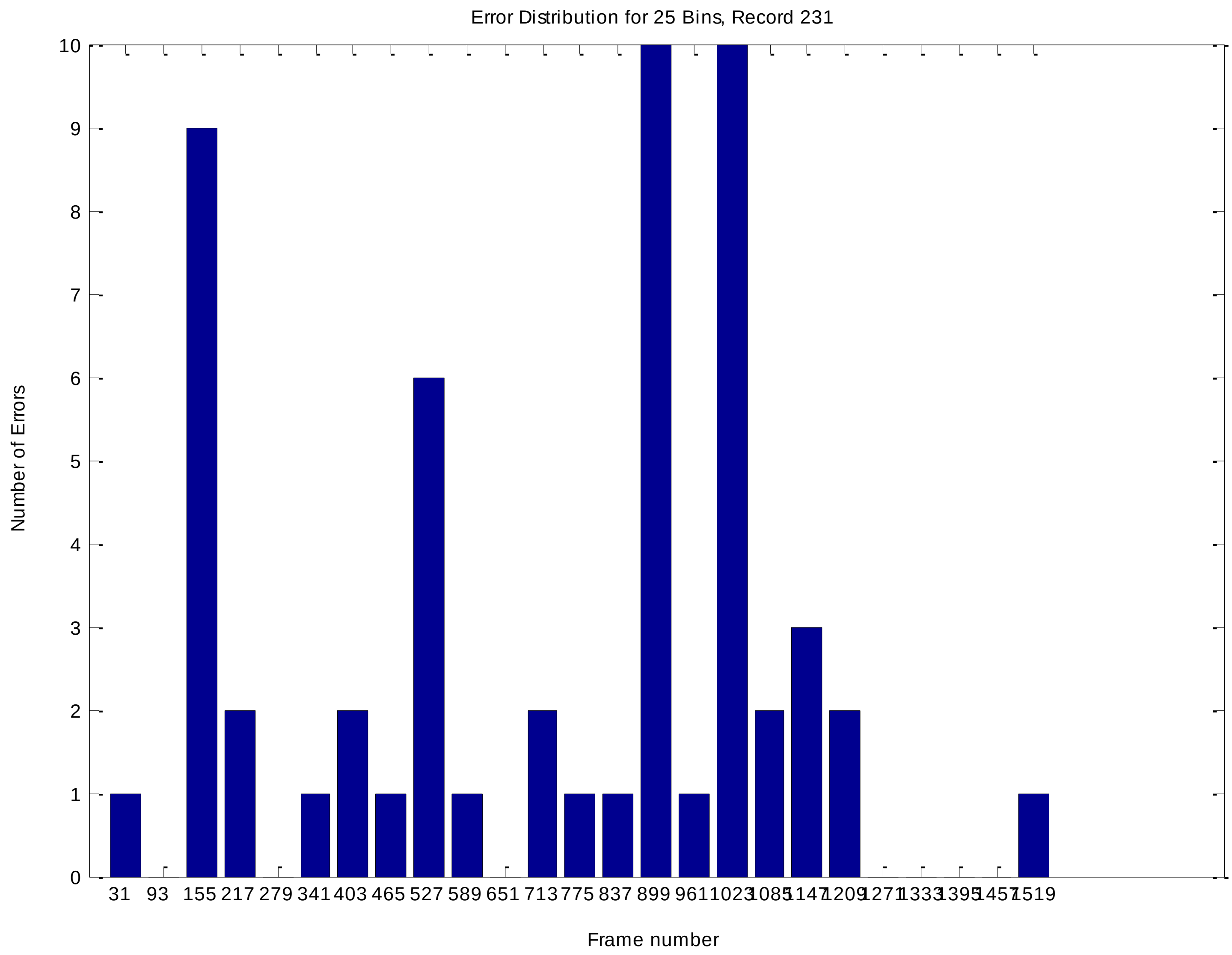


Error Analysis

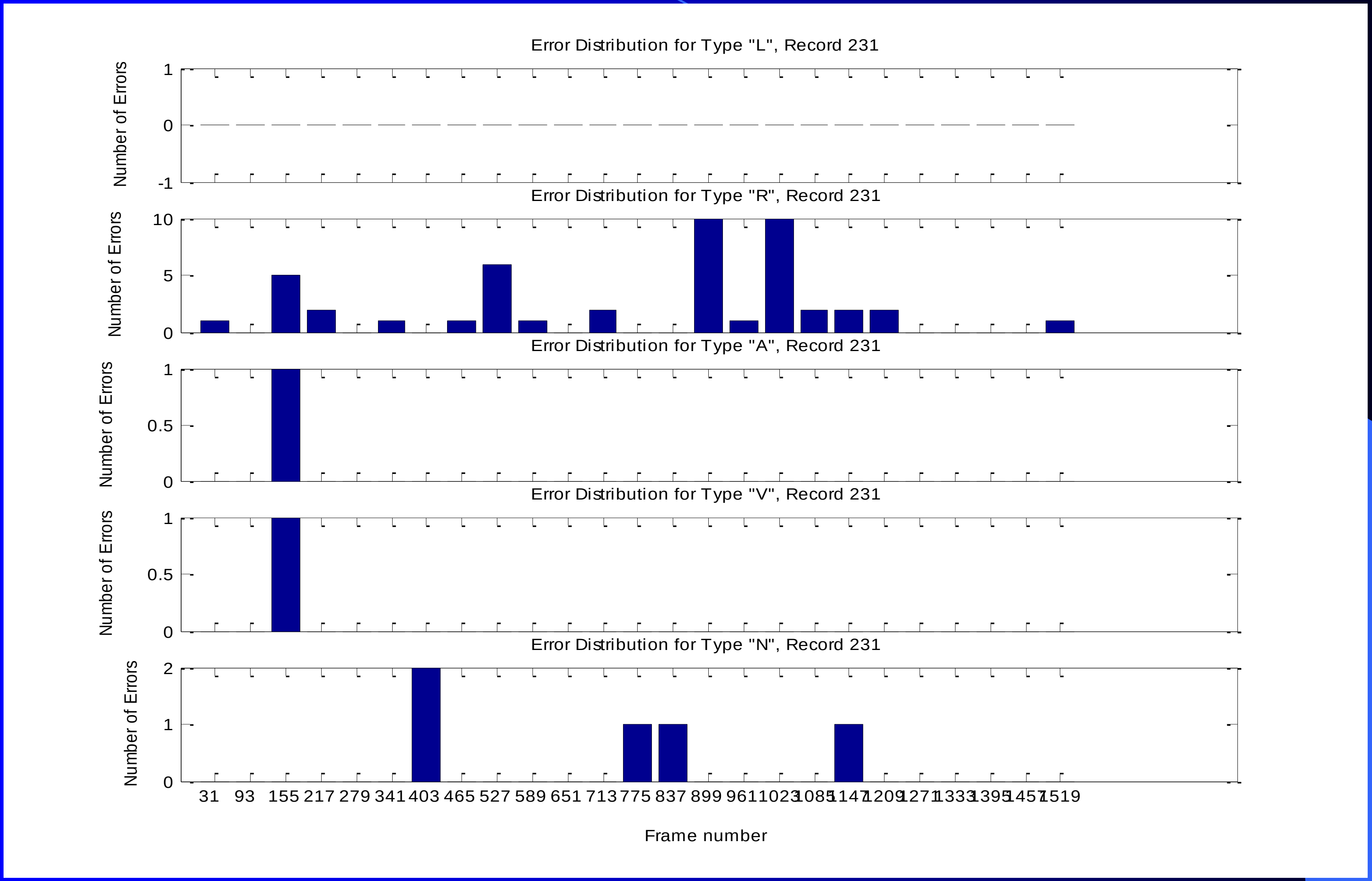
Sample Error Analysis

- EMAP error browser results for record 231.
  - Record 231 provides a decent sampling as it has all beats represented except L

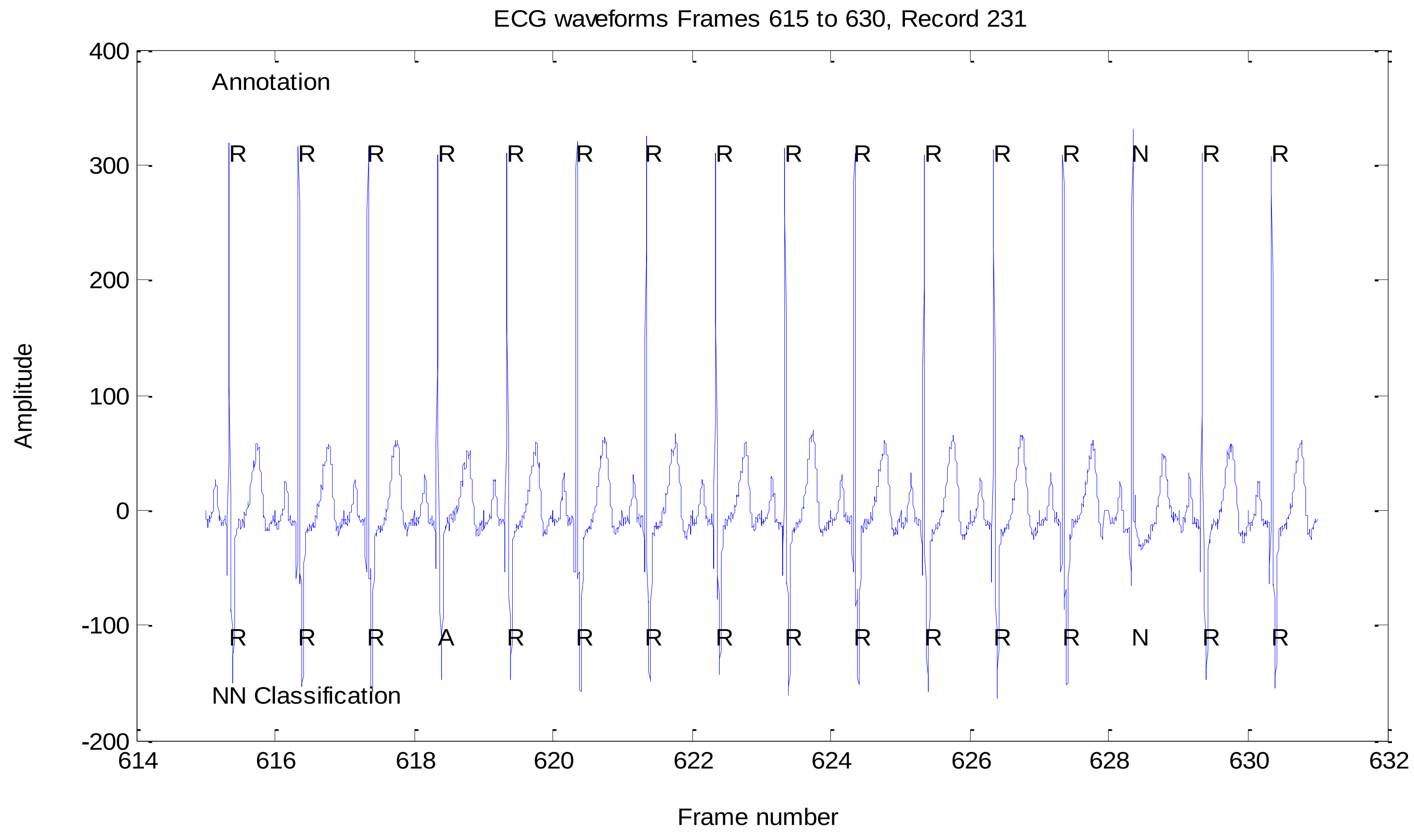
Sample Error Analysis



Sample Error Analysis



Sample Error Analysis



Conclusion

- Our main network performed reasonably well with 86% of all beats classified correctly
- Our A/V Network outperformed our competition
- With more time and computing power we could refine our network

The End

Thank You

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