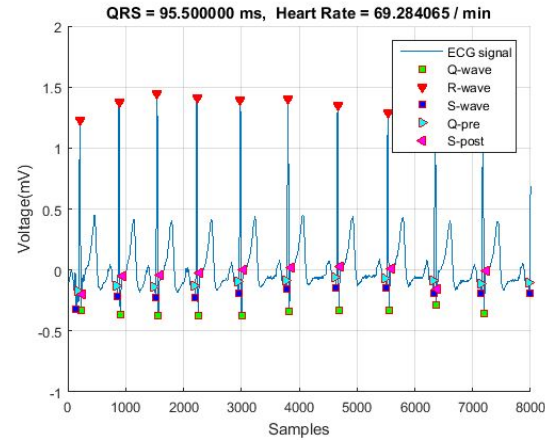


# The Application of Deep Convolutional Networks for the Classification of ECG Signal



Edward Mina  
Professor Byron Wallace Ph.D.  
Northeastern University College of Engineering  
Boston MA

# ECG Heartbeat Classification: A Deep Transferable Representation

Mohammad Kachuee, Shayan Fazeli, Majid Sarrafzadeh  
University of California, Los Angeles (UCLA)  
Los Angeles, USA

Work	Approach	Average Accuracy (%)
<b>This Paper</b>	<b>Deep residual CNN</b>	<b>93.4</b>
Acharya <i>et al.</i> [23]	Augmentation + CNN	93.5
Martis <i>et al.</i> [24]	DWT + SVM	93.8
Li <i>et al.</i> [25]	DWT + random forest	94.6



- Performs Very Poorly with a more appropriately split dataset!
- 80/20 or 75/25

< 4% of data

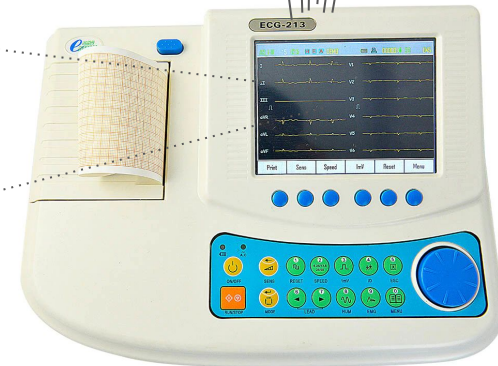
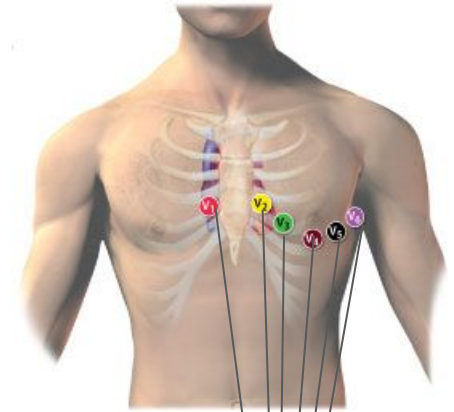
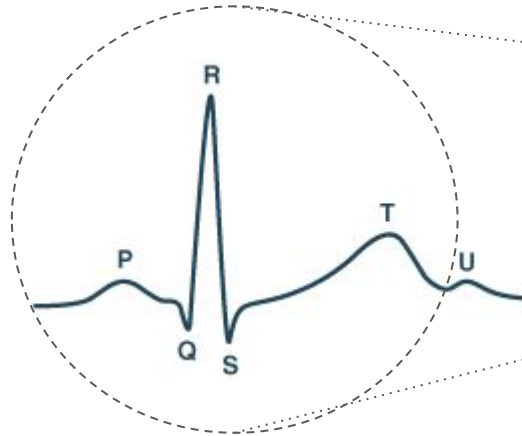
## IV. RESULTS

### A. Arrhythmia Classification and learning the representation

We evaluated the arrhythmia classifier of Section III-B on **4079 heartbeats** (about 819 from each class) that are not used

# What is a heart beat?

- Measured Electrocardiogram (ECG)
- P wave = depolarization of the atria
- QRS = depolarization of ventricles
- T = T wave, which indicates Ventricular repolarization



# Data

- ECG recordings of 48 patients at Beth-Israel Hospital.
- 30 minutes at 360 sample/sec
  - 650k pts per patient

Labeled Heart Beats				Signal Data	
sample_num	type	aux		signal	
0	18	+	(N	0	955
1	111	L	NaN	1	955
2	343	L	NaN	2	955
3	571	L	NaN	3	955
4	807	L	NaN	4	955

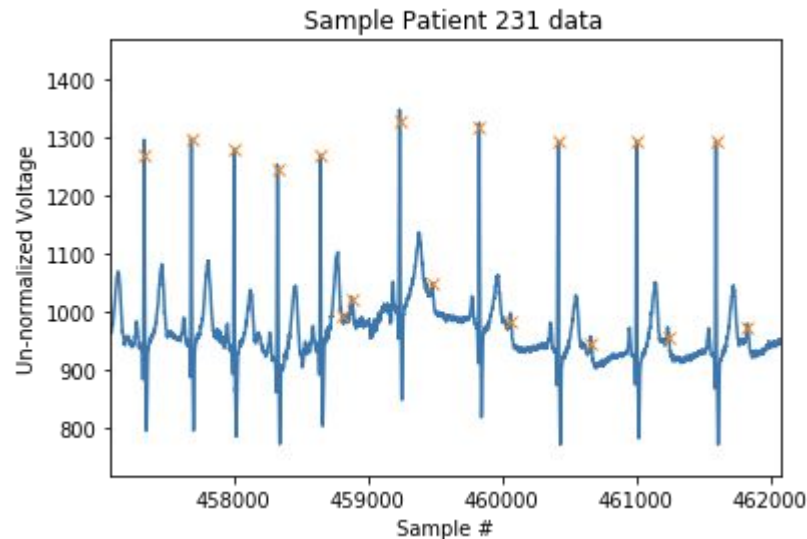


Figure 1: Raw ECG data for patient 231 with labelled peaks with respect to sample number and unnormalized voltage recording.

## MIT-BIH ARRHYTHMIA DATABASE

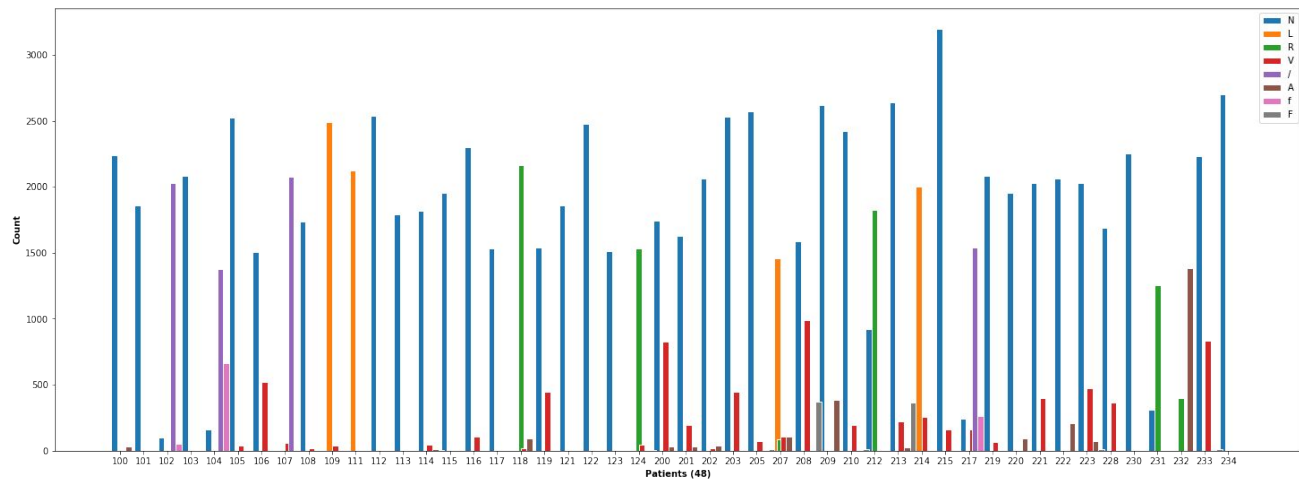
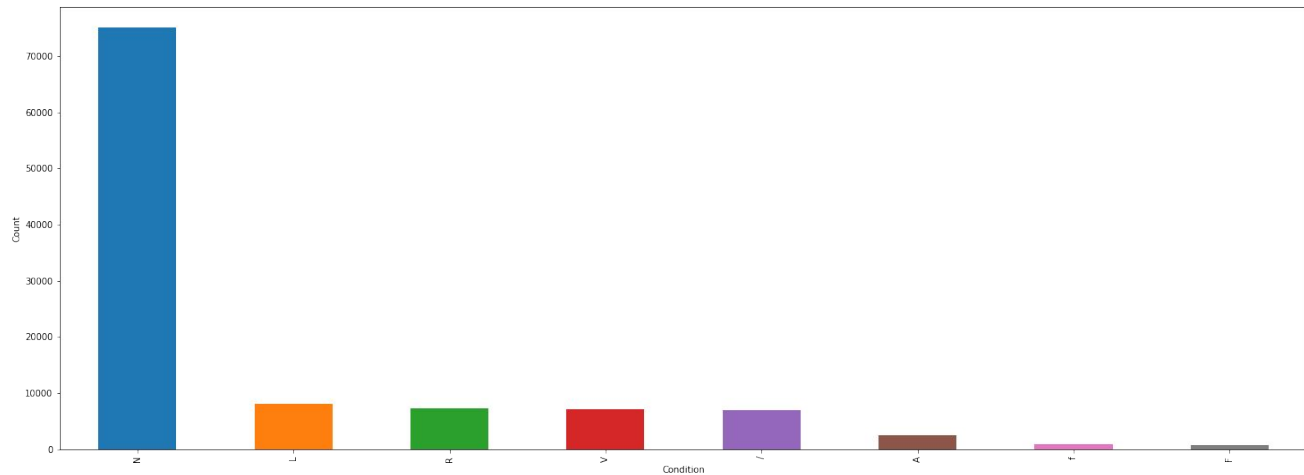
This database is described in

Moody GB, Mark RG. The impact of the MIT-BIH Arrhythmia Database. *IEEE Eng in Med and Biol* 20(3):45-50 (May-June 2001). (PMID: 11446209)

Please cite this publication when referencing this material, and also include the standard citation for PhysioNet:

Goldberger AL, Amaral LAN, Glass L, Hausdorff JM, Ivanov PCh, Mark RG, Mietus JE, Moody GB, Peng C-K, Stanley HE. PhysioBank, PhysioToolkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic Signals. *Circulation* 101(23):e215-e220 [Circulation Electronic Pages; <http://circ.ahajournals.org/content/101/23/e215.full>]; 2000 (June 13).

# Class Imbalance



# Class Simplification and Reduction

```
{'N': 'Normal beat',  
'L': 'Left bundle branch block beat',  
'R': 'Right bundle branch block beat',  
'A': 'Atrial premature beat',  
'a': 'Aberrated atrial premature beat',  
'J': 'Nodal (junctional) premature beat',  
'S': 'Supraventricular premature beat',  
'V': 'Premature ventricular contraction',  
'F': 'Fusion of ventricular and normal beat',  
['': 'Start of ventricular flutter/fibrillation',  
!': 'Ventricular flutter wave',  
]': 'End of ventricular flutter/fibrillation',  
'e': 'Atrial escape beat',  
'j': 'Nodal (junctional) escape beat',  
'E': 'Ventricular escape beat',  
'/' : 'Paced beat',  
'f': 'Fusion of paced and normal beat',  
'x': 'Non-conducted P-wave (blocked APB)',  
'Q': 'Unclassifiable beat',  
|': 'Isolated QRS-like artifact'}
```



```
For class: N (Normal beat)  
  (N) Normal beat  
  (L) Left bundle branch block beat  
  (R) Right bundle branch block beat  
  (e) Atrial escape beat  
  (j) Nodal (junctional) escape beat  
For class: S (Supraventricular premature beat)  
  (S) Supraventricular premature beat  
  (A) Atrial premature beat  
  (a) Aberrated atrial premature beat  
  (J) Nodal (junctional) premature beat  
For class: V (Premature ventricular contraction)  
  (V) Premature ventricular contraction  
  (E) Ventricular escape beat  
For class: F (Fusion of ventricular and normal beat)  
  (F) Fusion of ventricular and normal beat  
For class: Q (Unclassifiable beat)  
  (/) Paced beat  
  (Q) Unclassifiable beat  
  (f) Fusion of paced and normal beat
```

# Normalization

PATIENT: 207

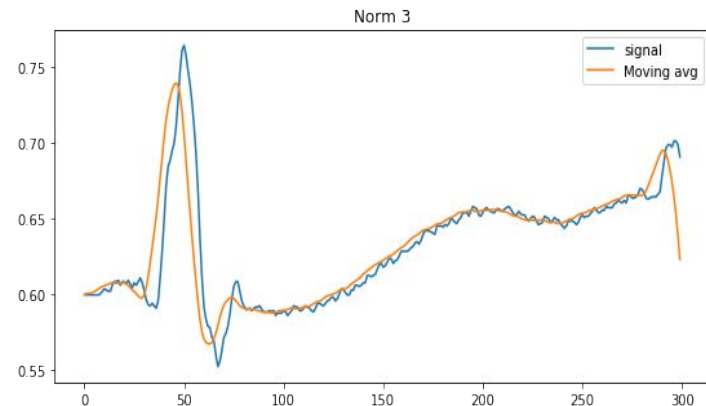
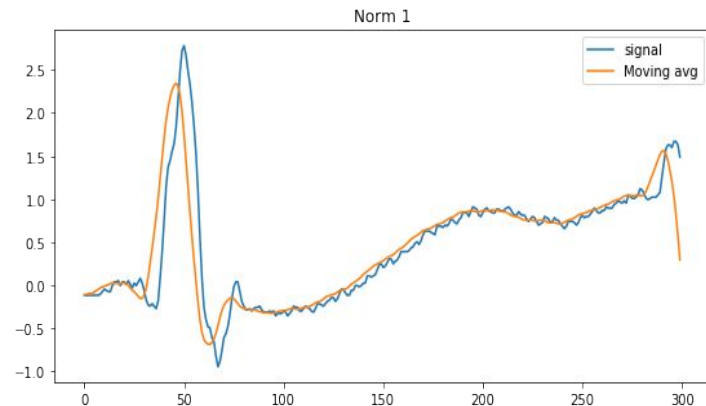
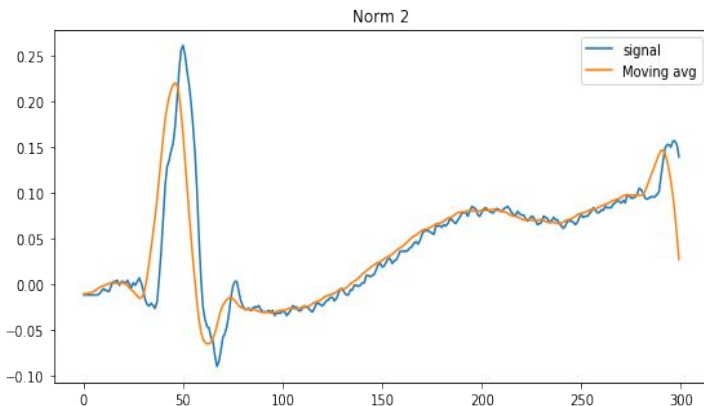
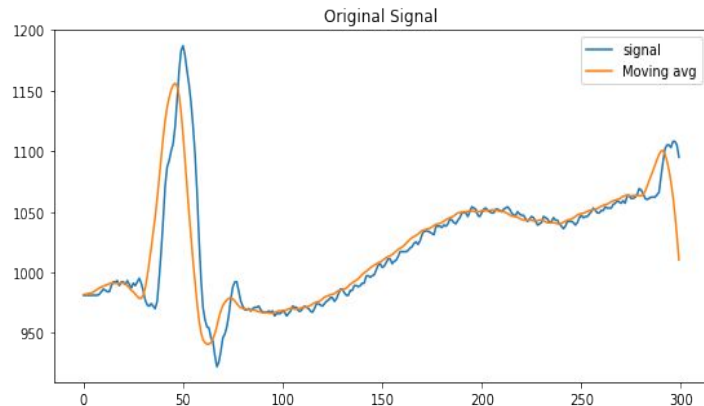
**Norm 1:** Creates a mean of 0, and a std of 1

**Norm 2:** Creates a mean of 0, and y range from [-1 1]

**Norm 3:** Creates a y range from [0 1]

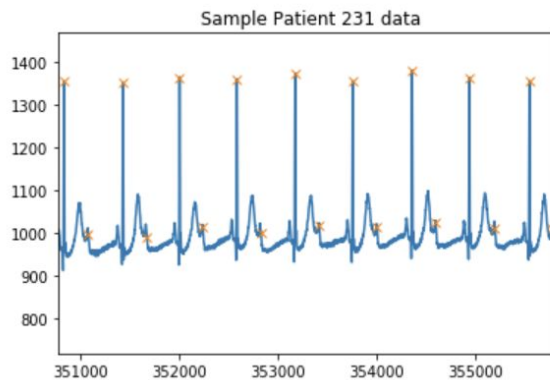
Selected Norm = 3

$$z_i = \frac{x_i - \min(x)}{\max(x) - \min(x)}$$

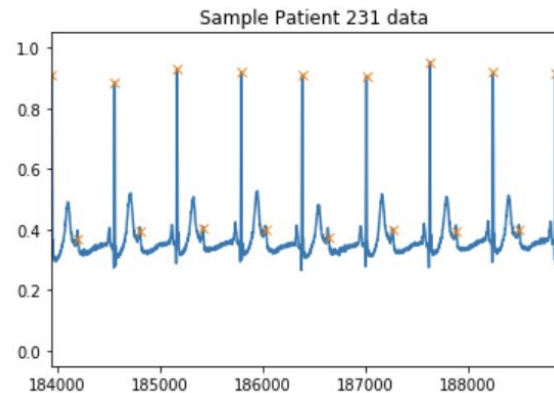


# Effect of Normalization

```
1 hb.get_patient_data(patient=231,norm=False,sample_plot=True)
```



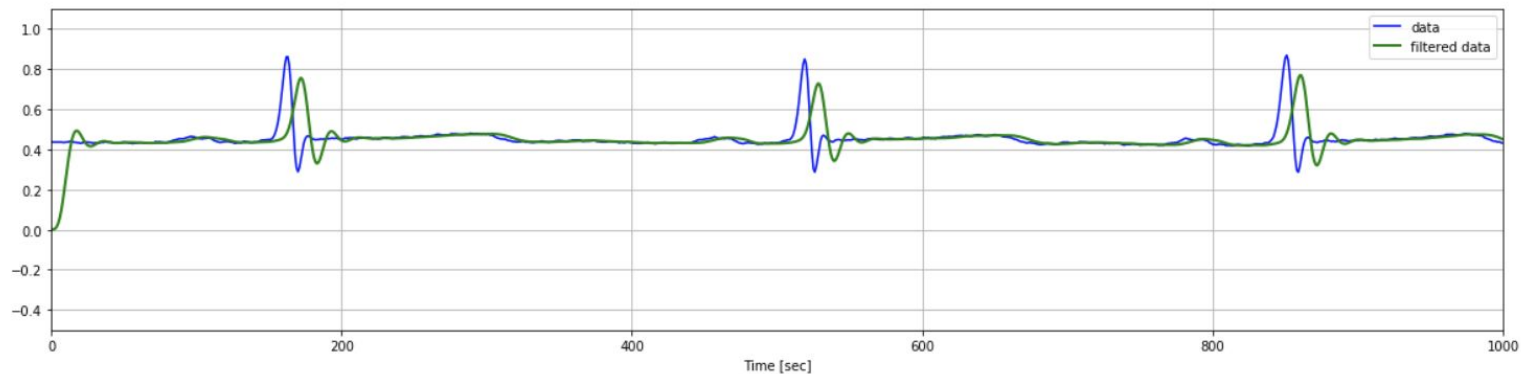
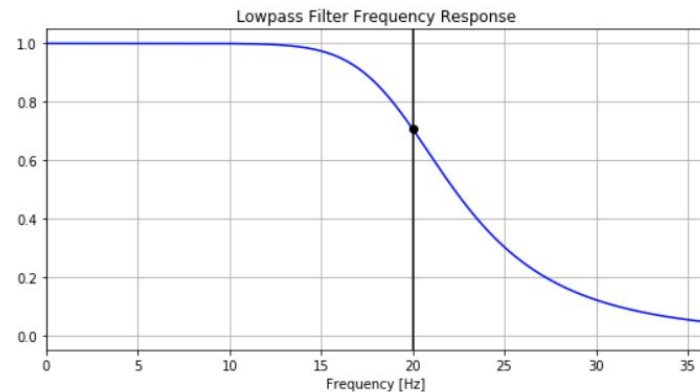
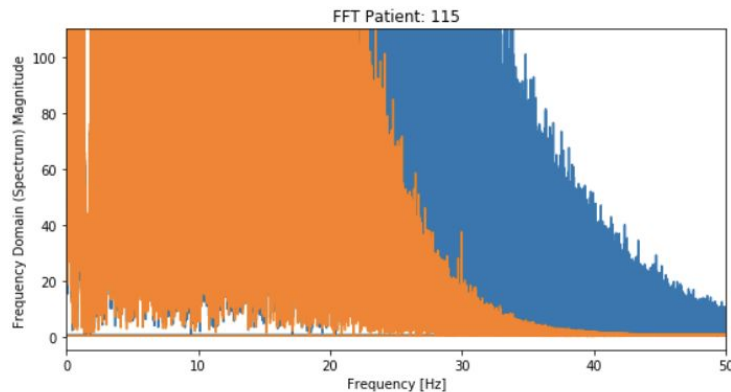
```
1 hb.get_patient_data(patient=231,norm=True,sample_plot=True)
```





# Further Signal Processing...

```
1 from normalizer import filt #class of various filtration functions
2 patient= random.choice(hb.all_patients())
3 filt().low_pass_filter_plot(patient=patient,cutoff=20,fs=360)
```



Given Ecg Signal:

$$Beat_i = \text{signal} \left[ p_i - \frac{p_i - p_{i-1}}{2} : p_i + \frac{p_{i+1} - p_i}{2} \right], \text{ where } p = \text{peak}$$

Zero\_pad w/r max len

```
1 #isolation algorithm heart beat data
2 X,y,isolated_beat= hb.isolate_patient_data(patients=hb.all_patients(),classes=classes,
3                                             classes_further=hb.classes_further, classes_reducer=classes_reducer,
4                                             min_HR= 40,max_HR= 140,fs=360,verbose=False,plot_figs=True)
```

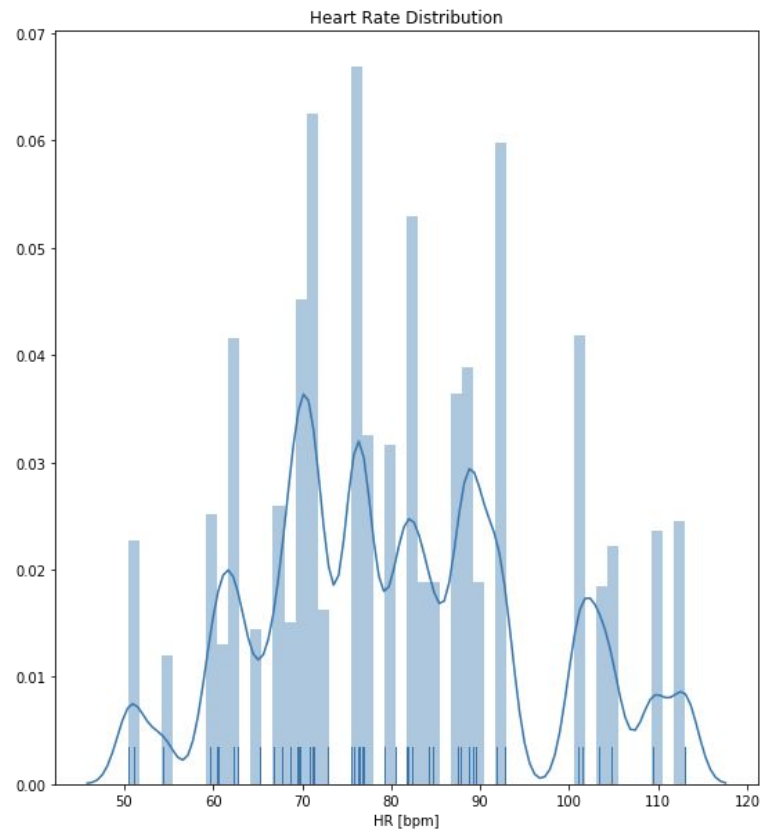
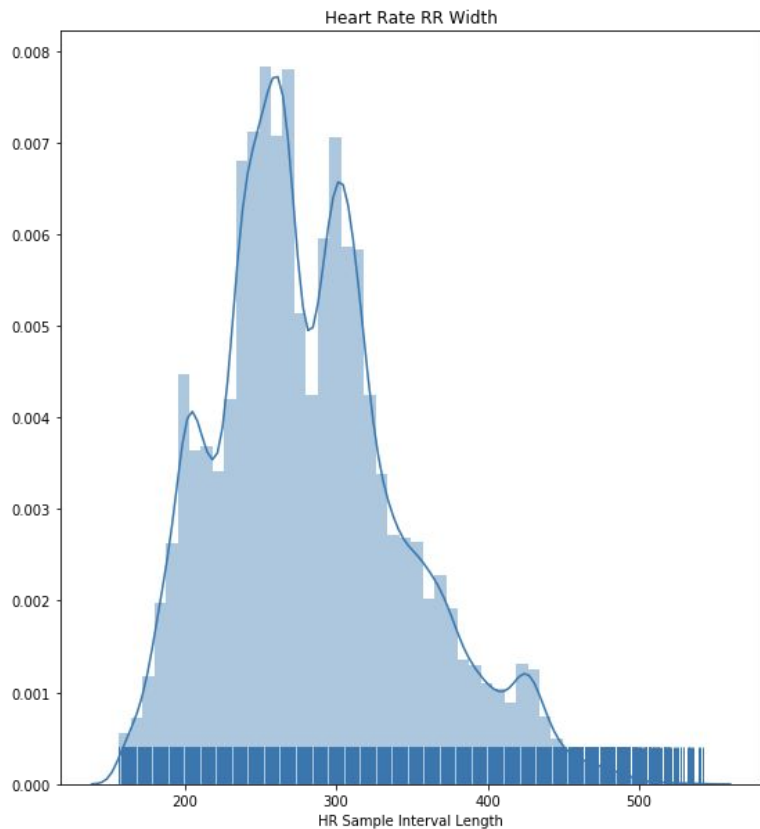
[illegible]

Average HR Sample Len: 284.39 samples (0.79s per beat)  
Average HR: 80.61 bpm

```
1 print("X shape:", X.shape)
2 print("y shape:", y.shape)
3 print("sample y vals:: [patient#, HR, Condition Class]:", y[0])
```

X shape: (107726, 539)  
y shape: (107726, 3)  
sample y vals:: [patient#, HR, Condition Class]: ['100' '75.536676138855' 'N']

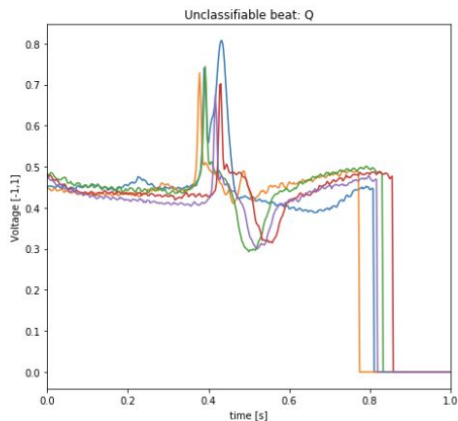
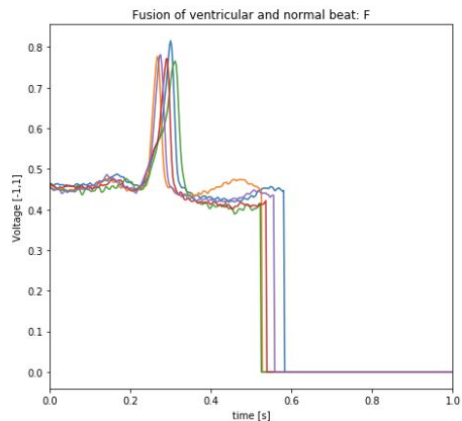
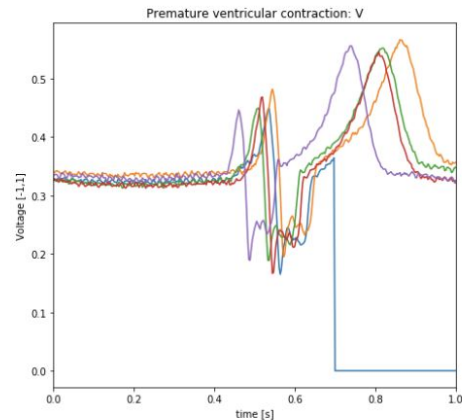
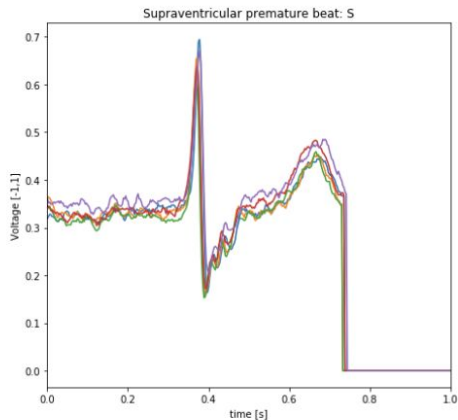
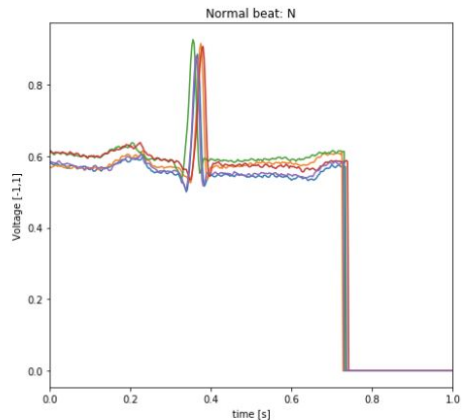
# Isolated HB Distribution



# Heart Beat Classes

```
1 hb.show_sample_plots(X=X,y=y,classes=classes,classes_further=hb.classes_further,plot_xlim=1,dims=[2,3])
```

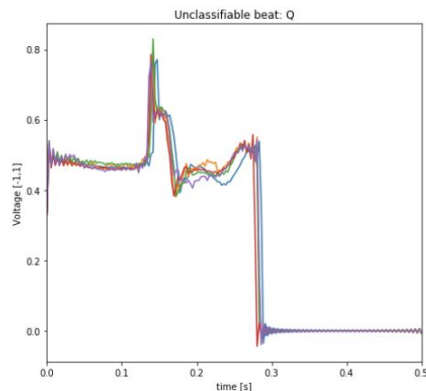
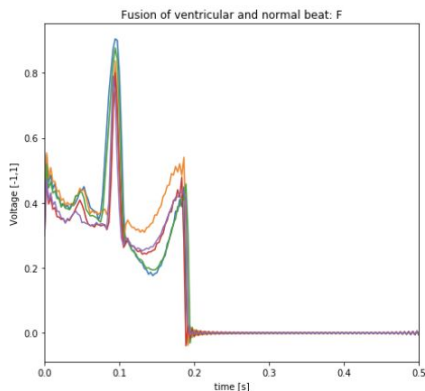
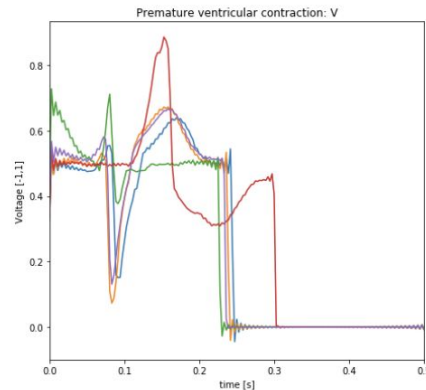
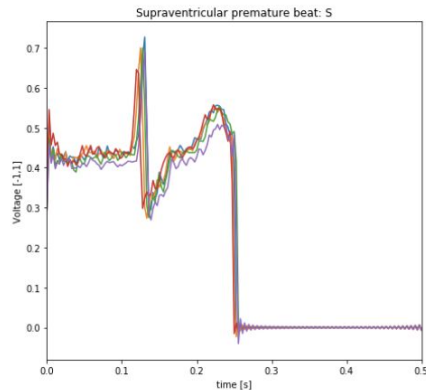
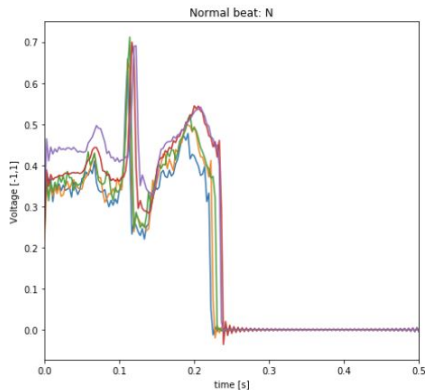
MAX HB TIME: 1.497222222222222



# Resampling 360Hz $\rightarrow$ 125Hz ~65% Reduction

```
1 hb.show_sample_plots(X=X_resamp,y=y,classes=classes,classes_further=hb.classes_further,  
2 plot_xlim=.5,dims=[2,3])
```

MAX HB TIME: 0.5194444444444445



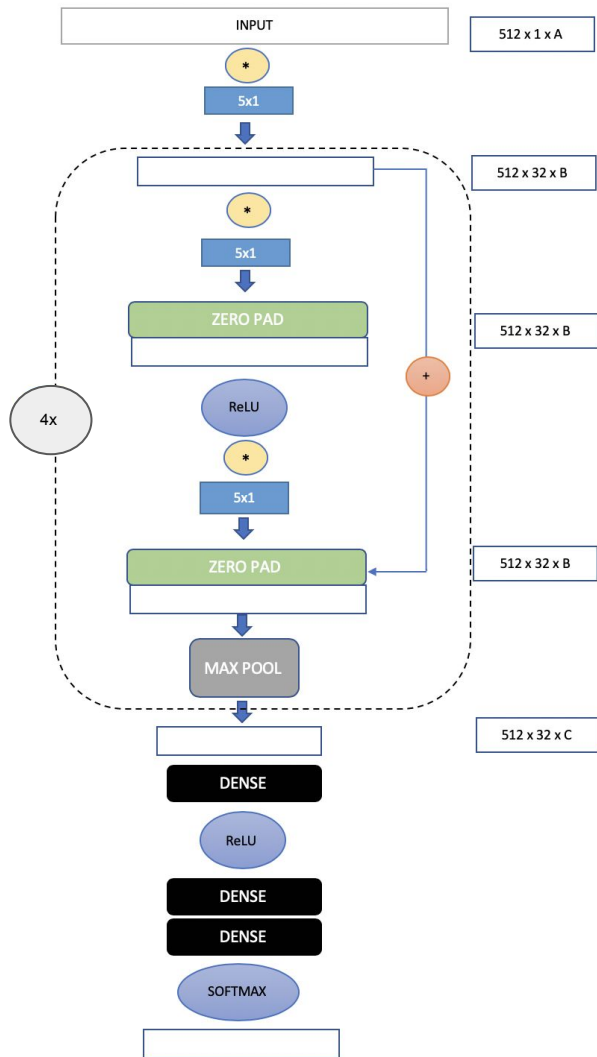
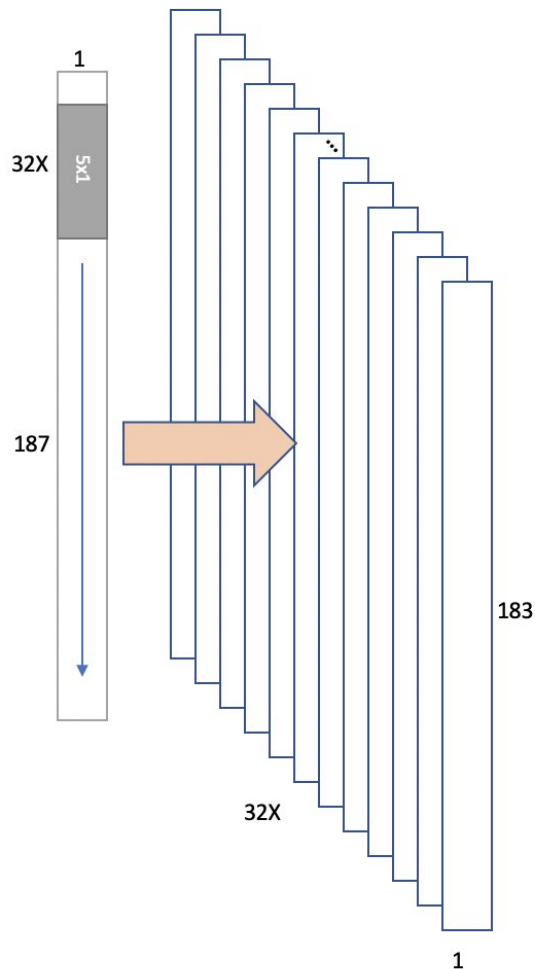
```
1 # Cut Roughly in Half  
2 print('Resampling...\n')  
3 X_resamp=hb.resample_vals(X,samp_len=187)  
4 print("X_resamp shape:", X_resamp.shape)  
5 print("y shape:", y.shape)
```

Resampling...

X\_resamp shape: (107726, 187)  
y shape: (107726, 3)

# 1D CNN

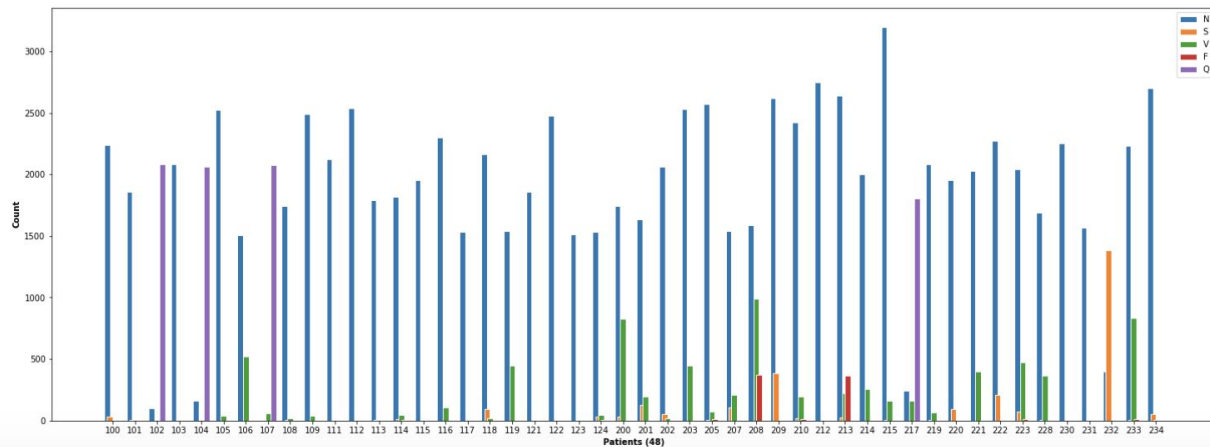
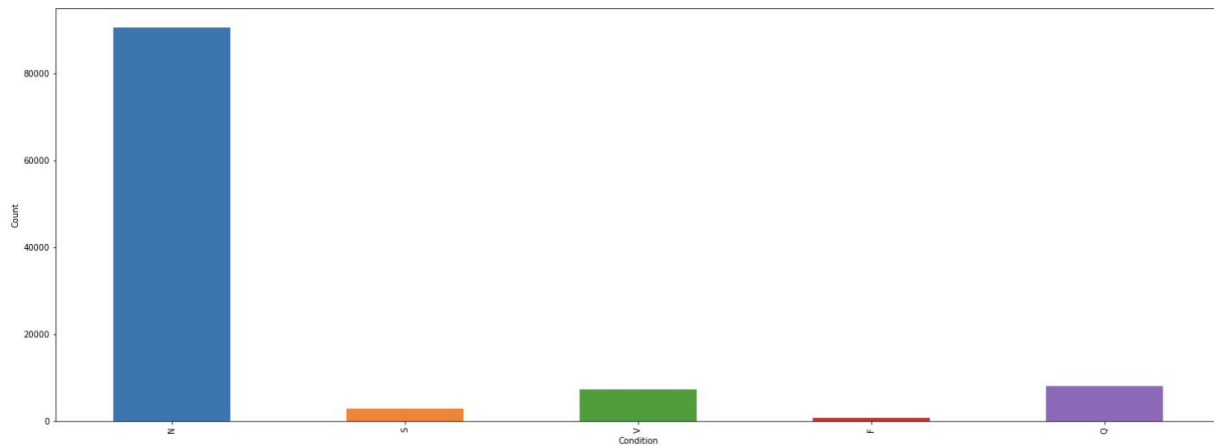
- Effective when examining features from shorter (fixed-length) segments of the data
- 75% Training + 5% Validation
- 20% Test
  - Forced to have all classes present



# Classes Still Unbalanced...

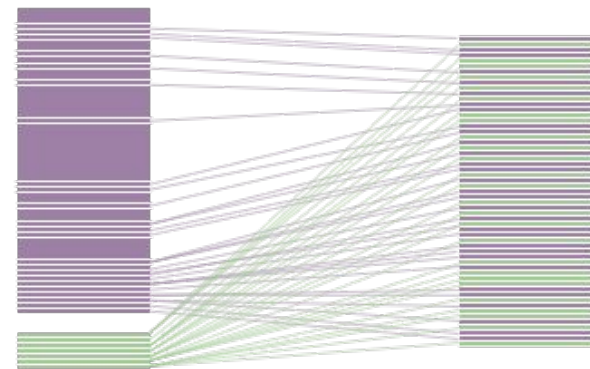
```
1 patient_dic=hb.distribution_bar(patients=hb.all_patients(),classes=classes,  
2                               classes_reducer=classes_reducer)
```

Generating\_plot(s)...



# 80% Improvement With Unbalanced Class Methods

ImbalancedDatasetSampler



original dataset

data augmentation

```
[135] 1 for hb,labels in dataloader['train']:  
      2     for hb_index,label in enumerate(labels):  
      3         print(hb_index,hb[hb_index].size(),label.cpu().numpy().shape,Counter(label.cpu().
```

```
0 torch.Size([512, 187]) (512,) Counter({0: 106, 4: 105, 2: 104, 1: 102, 3: 95})  
1 torch.Size([512, 187]) (512,) Counter({3: 110, 2: 106, 4: 104, 1: 97, 0: 95})  
2 torch.Size([512, 187]) (512,) Counter({4: 114, 3: 108, 2: 106, 1: 93, 0: 91})  
3 torch.Size([512, 187]) (512,) Counter({4: 118, 2: 102, 3: 98, 1: 97, 0: 97})  
4 torch.Size([512, 187]) (512,) Counter({1: 110, 4: 102, 2: 102, 0: 101, 3: 97})  
5 torch.Size([512, 187]) (512,) Counter({0: 121, 2: 113, 1: 96, 3: 95, 4: 87})  
6 torch.Size([512, 187]) (512,) Counter({0: 123, 2: 114, 4: 95, 3: 93, 1: 87})  
7 torch.Size([512, 187]) (512,) Counter({4: 115, 3: 110, 0: 99, 2: 95, 1: 93})  
8 torch.Size([512, 187]) (512,) Counter({0: 118, 1: 101, 4: 100, 3: 97, 2: 96})  
9 torch.Size([512, 187]) (512,) Counter({4: 114, 1: 109, 3: 100, 2: 98, 0: 91})  
10 torch.Size([512, 187]) (512,) Counter({0: 112, 2: 109, 4: 98, 3: 97, 1: 96})  
11 torch.Size([512, 187]) (512,) Counter({1: 112, 0: 103, 3: 102, 4: 101, 2: 94})
```

```
[160] 1 for hb,labels in dataloader['val']:  
      2     for hb_index,label in enumerate(labels):  
      3         print(hb_index,hb[hb_index].size(),label.cpu().numpy().shape,Counter(label.cpu().
```

```
0 torch.Size([512, 187]) (512,) Counter({0: 455, 4: 28, 2: 25, 1: 4})  
1 torch.Size([512, 187]) (512,) Counter({0: 473, 4: 18, 2: 18, 1: 3})  
2 torch.Size([512, 187]) (512,) Counter({0: 458, 2: 28, 4: 20, 1: 6})  
3 torch.Size([512, 187]) (512,) Counter({0: 459, 4: 24, 2: 24, 1: 5})  
4 torch.Size([512, 187]) (512,) Counter({0: 472, 2: 21, 4: 17, 1: 2})  
5 torch.Size([512, 187]) (512,) Counter({0: 466, 4: 26, 2: 19, 1: 1})
```

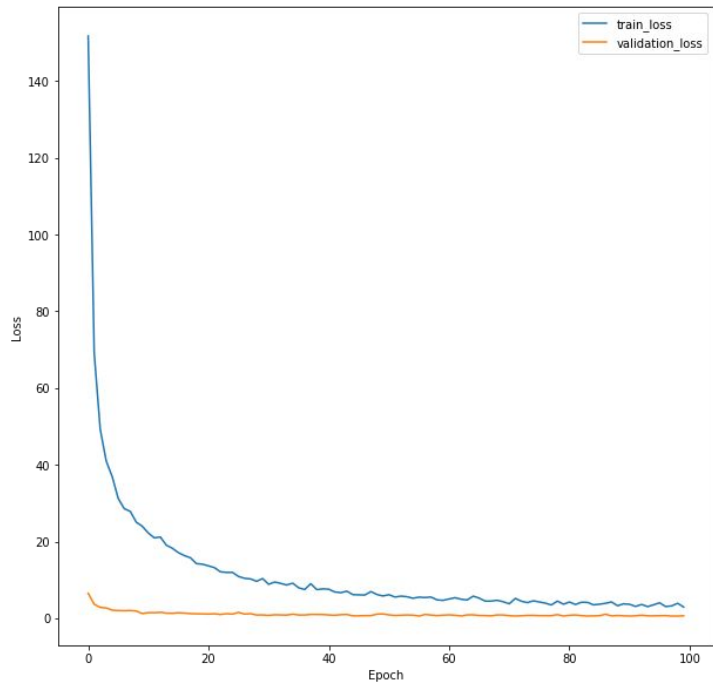


# General Observations

- Best filter size  $32 \times 5 \times 1$ 
  - Larger Values let to validation overfitting
- Best number of “blocks” 4 ~ 5
  - Relatively ineffective after 4
  - If  $<$ , lower performance
- Number of Epochs ~ 100
- Batch 512 (as per specified in the paper)
  - Poor loss behavior  $128 < \& < 1024$
- Lesser Performance with Drop Out



# Results

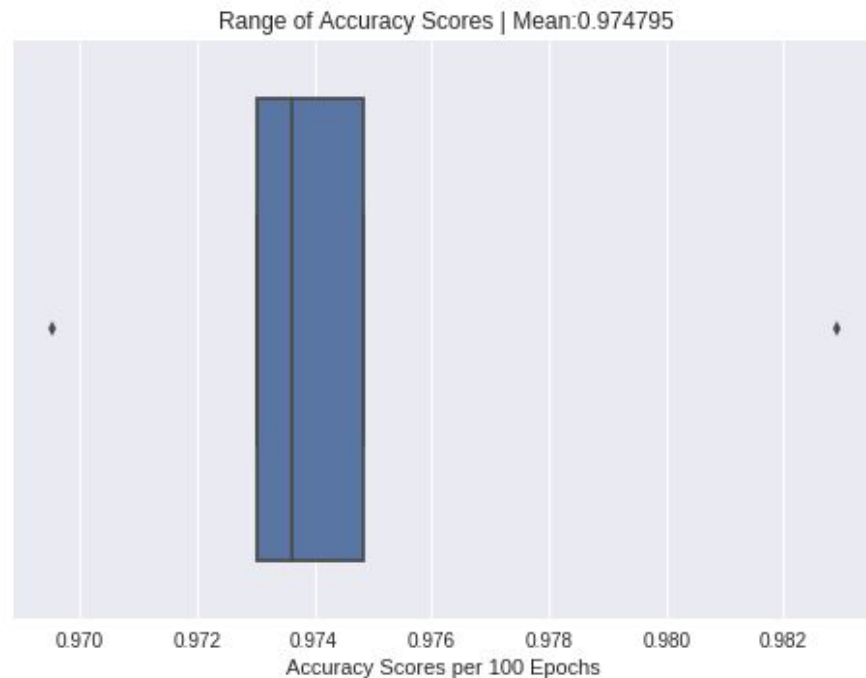
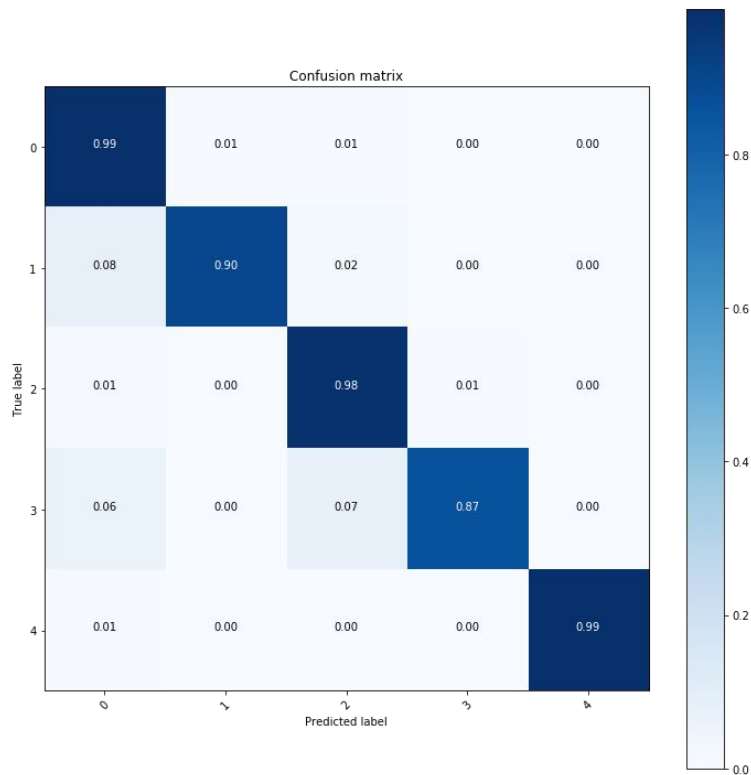


Evaluating....

TEST ACC: 0.9831499791115443

	precision	recall	f1-score	support
0	1.00	0.99	0.99	17939
1	0.82	0.90	0.85	477
2	0.90	0.98	0.94	1365
3	0.76	0.87	0.81	157
4	0.99	0.99	0.99	1605
micro avg	0.98	0.98	0.98	21543
macro avg	0.89	0.94	0.92	21543
weighted avg	0.98	0.98	0.98	21543

# Results Continued...





- Different Possible Combinations of Classes
- Examination RNN's
- Using bpm as a reference
- Isolate beats different or looking at Signal as whole
- Different Processing Methodology
  - Butterworth with different cutoffs
  - Signal smooth techniques
  - Normalizing methods

Questions?