

# Multivariate Symbolic Aggregate Approximation for ECG Analysis

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# Outline

1 Introduction

2 Methods

3 Preliminary Results

# Introduction

# What is an ECG?

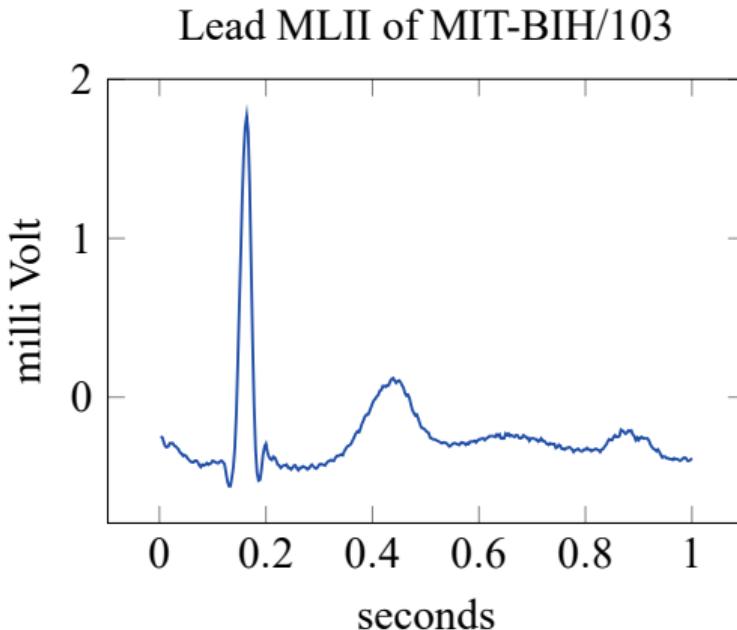


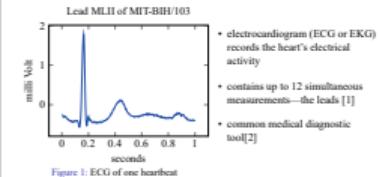
Figure 1: ECG of one heartbeat

- electrocardiogram (ECG or EKG) records the heart's electrical activity
- contains up to 12 simultaneous measurements—the leads [1]
- common medical diagnostic tool[2]

# MSAX for ECG Analysis

- └ Introduction
  - └ ECG Basics
    - └ What is an ECG?

## What is an ECG?



- muscle contractions caused by electric pulses
- electric pulse can be measured on the skin
- the measuring things are called electrodes
- electrodes form leads (need 2 to measure anything)
- they have specific positions and names
- 12 leads is the modern standard
- most types of heart disease can be detected
- diagnosis and analysis is performed by trained cardiologists
- **datasets available online; contain 2 or more leads (the most significant ones)**
- **I will be using online datasets for my analysis**
- heart diseases are some of the most deadly ones, thus ECG are really important

## Lead MLII of MIT-BIH/103

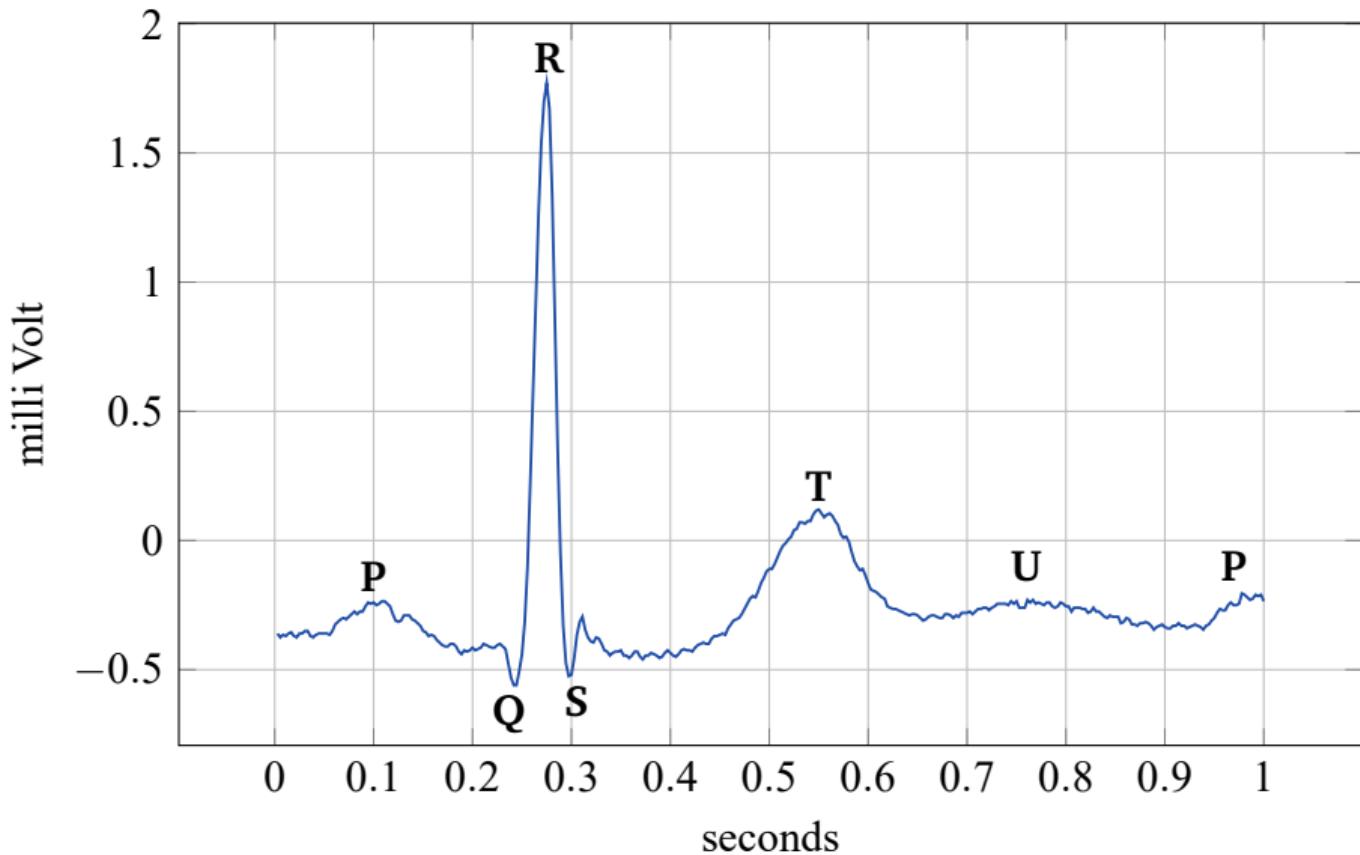
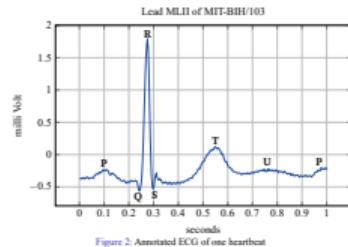


Figure 2: Annotated ECG of one heartbeat

# MSAX for ECG Analysis

- └ Introduction
  - └ ECG Basics



- P wave: atria depolarizing / blood entering the heart
- QRS complex: ventricular depolarization / heart contraction pumping blood
- T: return of ventricle to polarized state
- U: present in 25%, maybe some feedback
- P wave: atria depolarizing / blood entering the heart
- ST-segment: significant, depression, elevation, slope show ischaemia
- R-R interval: shows rhythm and thus arrhythmia etc

# ECGs as Time Series

## Definition

A discrete time series is an ordered sequence that, at discrete points in time, has  $n$  values each. If  $n = 1$ , the series is univariate and if  $n > 1$ , it is multivariate.

- digital ECGs are discrete multivariate time series: [3]
  - have  $> 1$  value at each point, often  $n = 12$
  - recorded at discrete, evenly spaced time points
- time series analysis methods can be applied to ECGs

# MSAX for ECG Analysis

## └ Introduction

### └ ECG Basics

#### └ ECGs as Time Series

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- modern ECGs have at least 2, most have 12
- digital ones have set sampling frequencies, even the machines have set frequencies
- multivariate: measure more than 1 lead per time point
- discrete: set sample frequency in the machines
- discrete: because measured at discrete moments in time
- time series: they are data measured at equal time intervals
- $n$  measurements per point in time (i.e. leads)
- $n = 1$  is univariate,  $n > 1$  is multivariate

# ECG Analysis

- standard method: manual analysis by cardiologist
- recently: automated or computer-assisted ECG analysis
- multiple stages: [4](1) signal acquisition; (2) data transformation, processing, filtering; (3) waveform recognition, feature extraction; (4) classification
- current research focus: artificial neural networks...[5]
- relatively new methods are SAX, MSAX, and HOT SAX

# MSAX for ECG Analysis

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- relatively new methods are SAX, MSAX, and HOTSAX

- is relatively slow; time is of the essence
- lots of training required
- error prone
- maybe not feasible for long ECGs
- can speed up process
- can pick up details humans miss
- digitizing paper ECGs or recording digital ones
- filtering to remove various types of noise
- reduce complexity of the data
- select important features and neglect irrelevant ones to ease analysis
- often added, figure out if there is some disease present or not
- balance between accuracy and complexity needed
- ann: hand all the steps discussed to a NN; use as good classifier too

# SAX, MSAX, and HOT SAX

- Lin *et al.* (2003): Symbolic Aggregate Approximation (SAX)—simplified, symbolic representation [6] [7]
- Anacleto *et al.* (2020): Multivariate SAX (MSAX)—expands SAX to multivariate time series [3]
- Keogh *et al.* (2005): Heuristically Ordered Time series using Symbolic Aggregate Approximation (HOT SAX)—discord discovery algorithm for SAX

# MSAX for ECG Analysis

## └ Introduction

### └ ECG Analysis

#### └ SAX, MSAX, and HOTSAX

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- ecg as letters that mean same thing as original
- guaranteed to behave like the original data
- works on univariate time series
- has been used on ECGs
- takes the correlation between ecg leads into account
- cov mat: covariance between each lead and variance on diag
- uses sax representation to make the finding of discords easier
- can use MSAX just as well

# Time Series Discords

## Definition

A time series discord is the subsequence of a time series that is most different from all other subsequences.

$k$  time series discords are the  $k$  most different subsequences.

- discords represent anomalies in an ECG
- can be found by comparing all subsequences to all other subsequences; does not scale well [8]
- HOT SAX makes this process faster

# MSAX for ECG Analysis

## └ Introduction

### └ ECG Analysis

#### └ Time Series Discords

- these can be diseases, noise, etc
- the discord does not discern
- this is not feasible because of complexity

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# Hypothesis

HOTSAX with MSAX will increase the number of relevant discords detected compared to HOTSAX with SAX.

Accuracy can be judged with the help of annotated ECGs from online databases.

# MSAX for ECG Analysis

- └ Introduction
  - └ Hypothesis
    - └ Hypothesis

## Hypothesis

HOTSAX with MSAX will increase the number of relevant discords detected compared to HOTSAX with SAX.  
Accuracy can be judged with the help of annotated ECGs from online databases.

- mention that MSAX to ECGs in particular is new
- mention that HOTSAX with MSAX is new
- results will not be great as HOTSAX is not a real classifier; this is about finding out if MSAX adds more useful information
- THIS METHOD WILL NOT BE SUPER ACCURATE; MANY ECG changes are relatively small and would get lost in the SAX process
- THE METHOD HAS NO AWARENESS OF MEDICAL RELEVANCE OR ANY OF THAT
- NOVEL: MSAX IS SUPER NEW; HAS NOT BEEN APPLIED TO ECGs IN THIS WAY; ALSO NOT USED WITH HOTSAX

# Methods

# Step 1: Z-Normalization

## Assumption

The time series values are normally distributed.

### SAX

- normalize univariate time series
- uses scalar mean and variance

### MSAX

- normalize multivariate time series
- uses vector mean and covariance matrix

# MSAX for ECG Analysis

## └ Methods

### └ SAX and MSAX

#### └ Step 1: Z-Normalization

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##### Assumption

The time series values are normally distributed.

##### SAX

- normalize univariate time series
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- normalize multivariate time series
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- say that the process is the same as MSAX based on SAX
- this is assumed and this worked for other people who applied SAX to ECGs
- to compare time series, normalization is the accepted step
- what is this
- takes into account the correlation between leads

## Step 2: Dimensionality Reduction

### PAA

Piecewise Aggregate Approximation (PAA) takes  $T$  time series points, splits it into  $w$  ( $w < T$ ) segments, and averages each of them.

### SAX

- apply PAA to time series

### MSAX

- apply PAA to each of the time series individually

# MSAX for ECG Analysis

## └ Methods

### └ SAX and MSAX

#### └ Step 2: Dimensionality Reduction

- this reduces complexity
- PAA form of time series is shorter and simpler
- it still somewhat corresponds to the original

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## SAX PAA of lead MLII of MIT- BIH/103

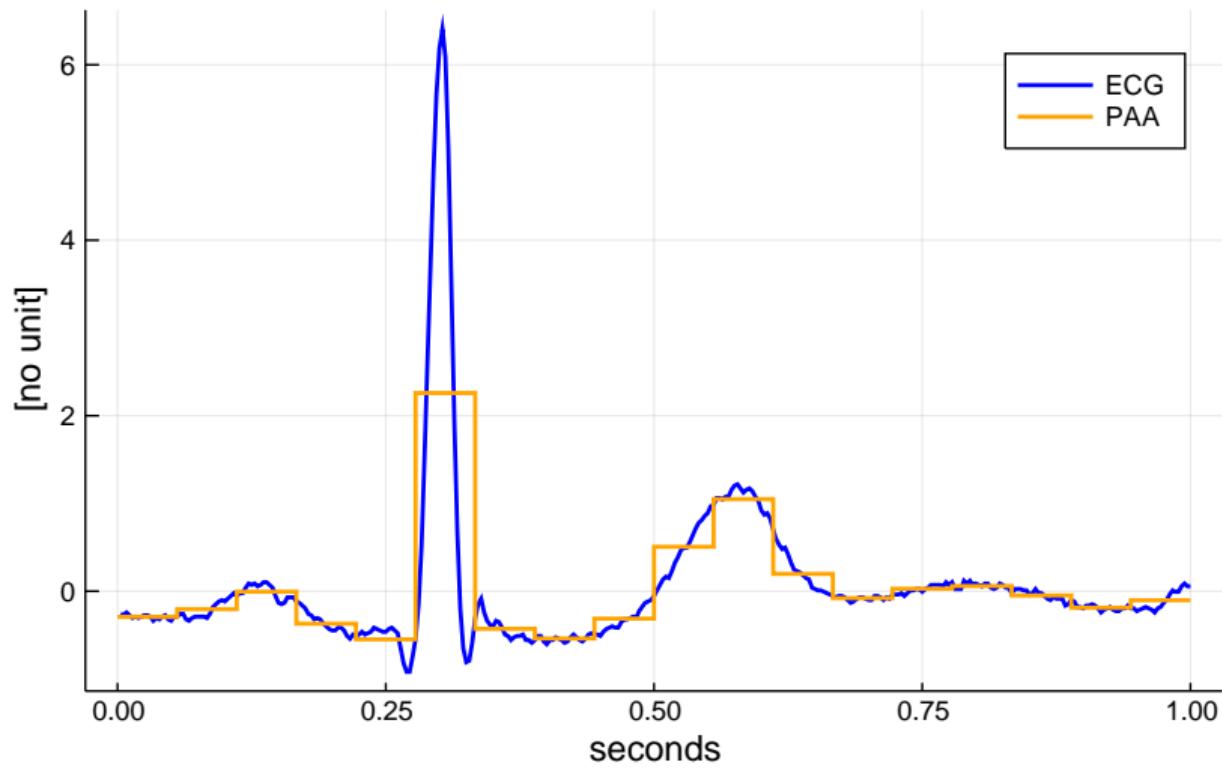


Figure 3: ECG with PAA (MITBIH/100,  $w = 18$ ,  $T = 360$ )

# Step 3: Discretization

## SAX Discretization

Find breakpoints splitting  $\mathcal{N}(0, 1)$  into  $B$  equiprobable segments.

Assign a letter to each area:  $a$  to most-negative,  $b$  to the next biggest...

PAA segments get letters based on which area they are in.

### SAX

- discretize the time series
- results in one word

### MSAX

- discretize each time series individually
- results in one word, one letter per time series

# MSAX for ECG Analysis

## └ Methods

### └ SAX and MSAX

#### └ Step 3: Discretization

- result is called word
- $N$  is the alphabet size
- big thing here is that this gives defined probability to each letter; makes no sense for real numbers (like PAA values)
- simplifies time series even more
- creates discrete categories, can be more useful

#### Step 3: Discretization

##### SAX Discretization

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## SAX of lead MLII of MIT- BIH/103

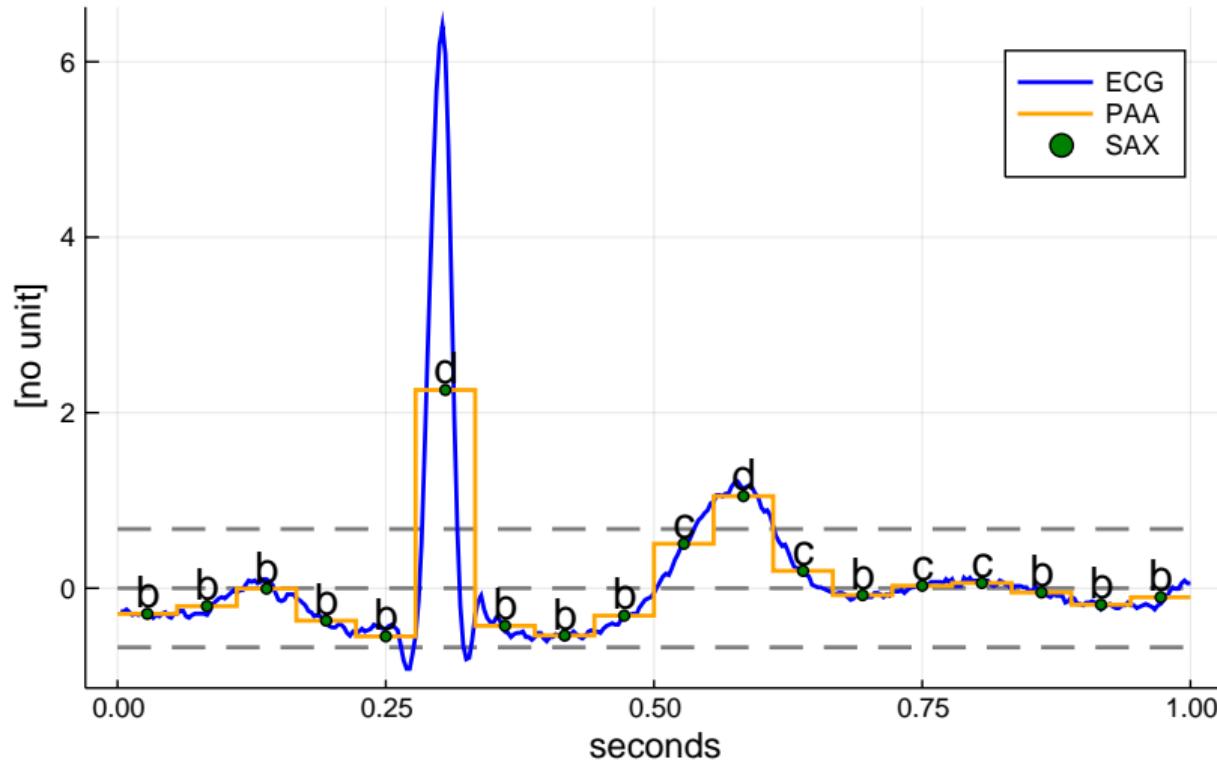


Figure 4: SAX (MITBIH/100,  $w = 18, T = 360, B = 4$ )

## Step 4: Distance Measure

### MINDIST

A distance measure is defined to compare two SAX words. Distance is defined for a pair of letters: 0 if they are neighbors; absolute difference of breakpoint values otherwise.

#### SAX

$$\sqrt{\frac{T}{w}} \sqrt{\sum_{i=1}^w (\text{dist}(\hat{q}[i], \hat{c}[i]))^2}$$

#### MSAX

$$\sqrt{\frac{T}{w}} \sqrt{\sum_{i=1}^w \left( \sum_{j=1}^n (\text{dist}(\hat{q}_j[i], \hat{c}_j[i]))^2 \right)}$$

# MSAX for ECG Analysis

## └ Methods

### └ SAX and MSAX

#### └ Step 4: Distance Measure

- $n$  – length of original time series
- $w$  – length of word
- this lower-bounds the euclidean distance, meaning that results in SAX should hold true for the real data too

**MINDIST**

A distance measure is defined to compare two SAX words. Distance is defined for a pair of letters: 0 if they are neighbors; absolute difference of breakpoint values otherwise.

$$\sqrt{\frac{T}{w} \sum_{i=1}^w (\text{dist}(q[i], c[i]))^2}$$

$$\left| \sqrt{\frac{T}{w} \sum_{i=1}^w \left( \sum_{j=1}^s (\text{dist}(\hat{q}[i], \hat{c}_j[i]))^2 \right)} \right|$$

# Difference Matrix

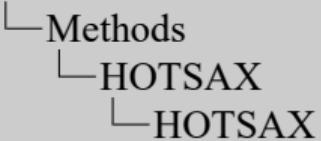
Table 1: Difference matrix for  $B = 4$

	a	b	c	d
a	0	0	0.67449	1.34898
b	0	0	0	0.67449
c	0.67449	0	0	0
d	1.34898	0.67449	0	0

# HOTSAX

- “brute-force” discord discovery is slow, needs  $T^2$  operations
- HOTSAX speeds up discord discovery by considering that
  - discords are rare, start with rarest segment
  - similar segments have similar distances, consider together
- HOTSAX detects anomalies, it is not a classifier
- it uses SAX and MSAX for dimensionality reduction

# MSAX for ECG Analysis



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- this is the basic idea that can speed up the process
- it is not guaranteed to do so, but it does not decrease efficiency
- this speeds up the process even more as we have fewer elements
- because of lower bounding, it still gives accurate results

# Results

# Implementation

- SAX, MSAX, HOT SAX implemented in Julia, a scientific programming language
- used annotated digital ECGs from the MIT-BIH arrhythmia database [1]
- HOT SAX performed for different  $w, B$ , subsequence lengths
- results exported to CSV file and analyzed using the R programming language

# MSAX for ECG Analysis

- └ Preliminary Results
  - └ Implementation
    - └ Implementation

- fast, type support, great libraries, JIT compilation
- ecgs have all heart beats annotated
- know which are normal, diseases, noise, etc
- 48 recordings of 30 minutes
- $w$  - paa segments;  $B$  - alphabet size; subsequence length for HOTSAX

- SAX, MSAX, HOTSAX implemented in Julia, a scientific programming language
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# Preliminary Results

- focus on comparing SAX and MSAX with the top  $k = 80$  discords
- to analyze the relevance of results, recall (sensitivity) is used
- analyzed total of 816 results for different parameters (SAX and MSAX for each)
- recall for MSAX is higher compared to SAX
- if SAX is applied to 2 leads and the results combined, it slightly outperforms MSAX

# MSAX for ECG Analysis

## └ Preliminary Results

### └ Preliminary Results

#### └ Preliminary Results

- how many relevant items are selected
- recall = true positive / (true positive + false negative)
- this is done because for medical things it is more useful to look at a couple too many segments than not enough

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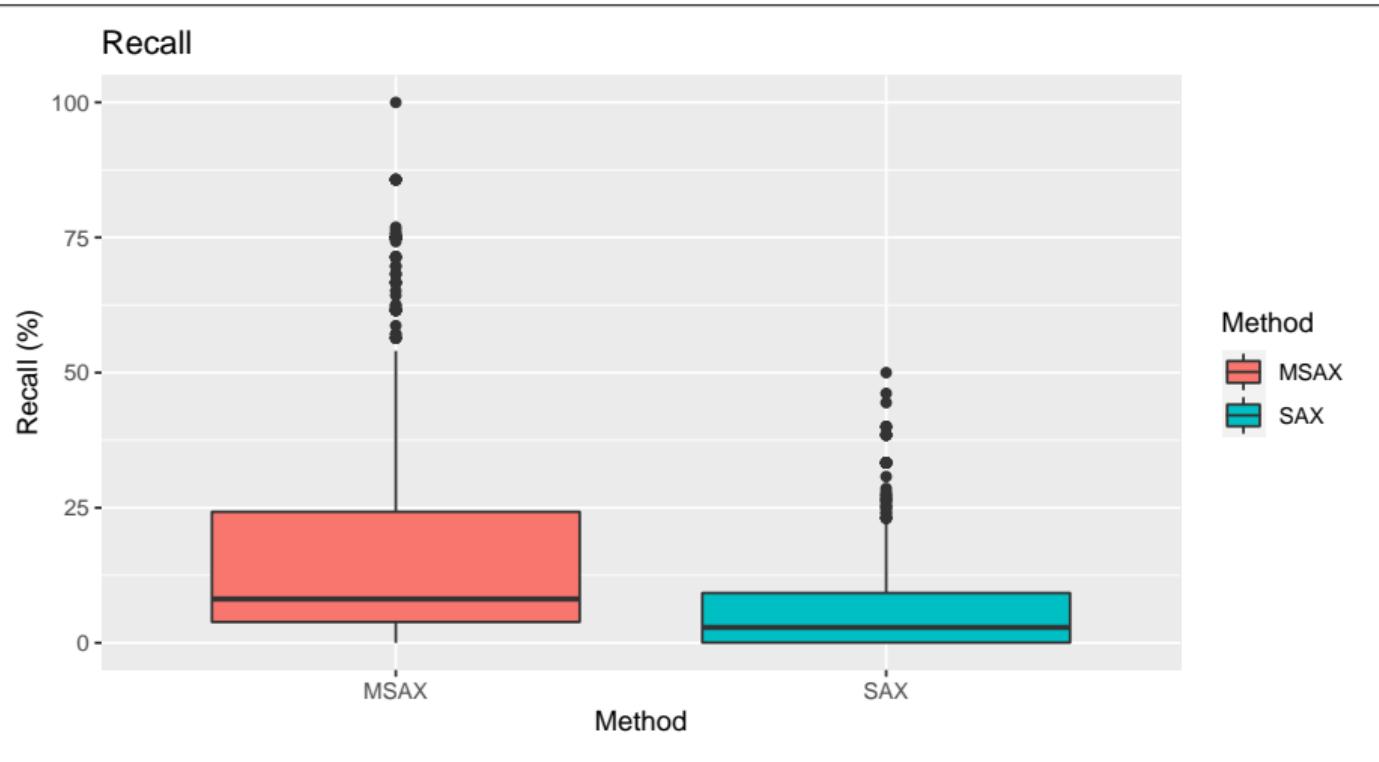


Figure 5: Boxplot comparing Recall for MSAX and single-lead SAX

# MSAX for ECG Analysis

## └ Preliminary Results

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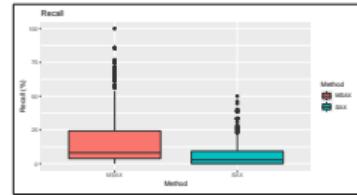


Figure 5: Boxplot comparing Recall for MSAX and single-lead SAX

- msax: average = 17.5%
- sax: average = 6.4%

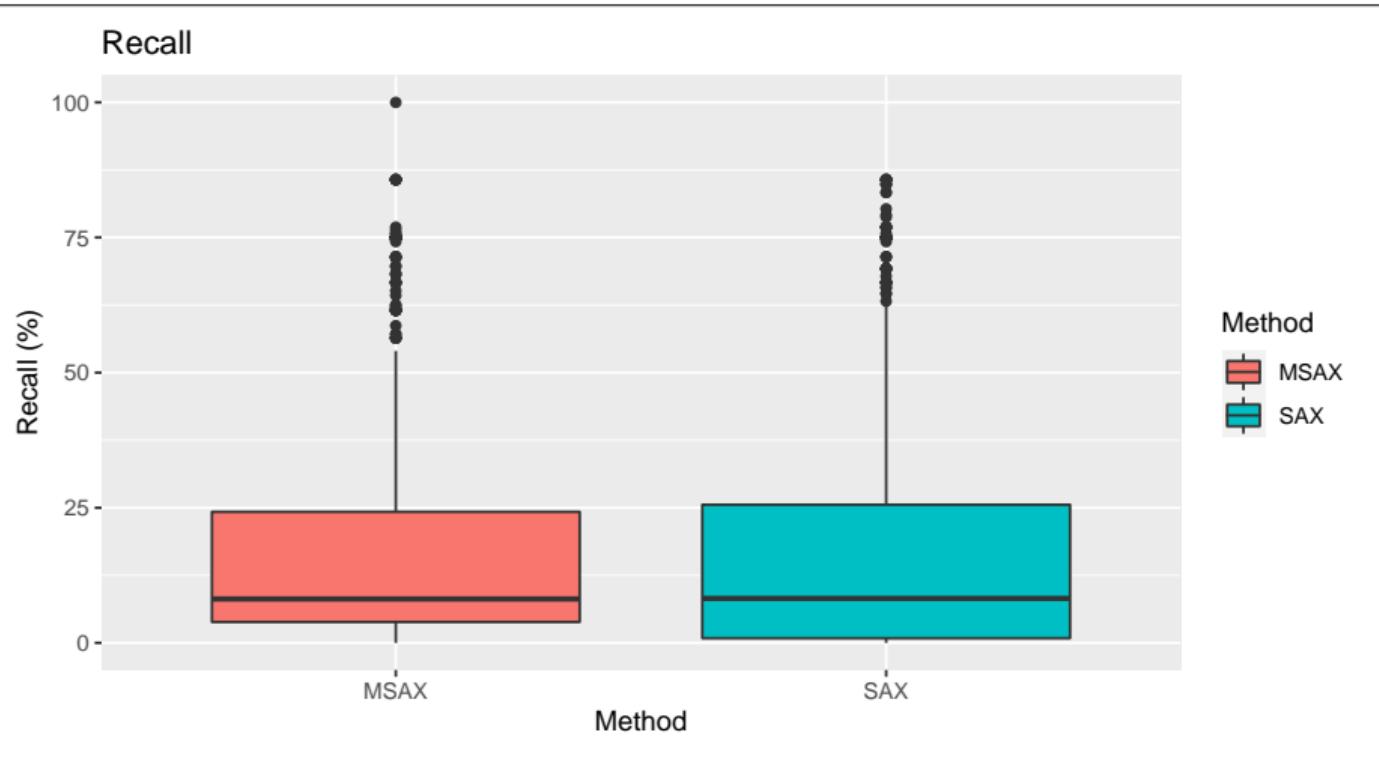


Figure 6: Boxplot comparing Recall for MSAX and dual-lead SAX

# MSAX for ECG Analysis

## └ Preliminary Results

### └ Preliminary Results

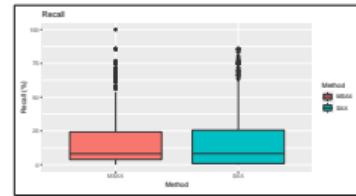


Figure 6: Boxplot comparing Recall for MSAX and dual-lead SAX

- msax: average = 17.5%
- sax: average = 18.5%

# Outlook

- perform statistical tests for significance of the result
- analyze the outliers visible in the boxplots
- more tests with different sets of parameters
- explore the influence of parameters on the result
- use the 12-lead INCART ECG database to investigate the influence of larger numbers of leads

# MSAX for ECG Analysis

## └ Preliminary Results

### └ Outlook

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- for example t-test, biserial correlation

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Thank You!

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