Artificial intelligence for ECG classification and prediction of the risk of death

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Presentation outline

1. The Telehealth Network of Minas Gerais and the CODE group;

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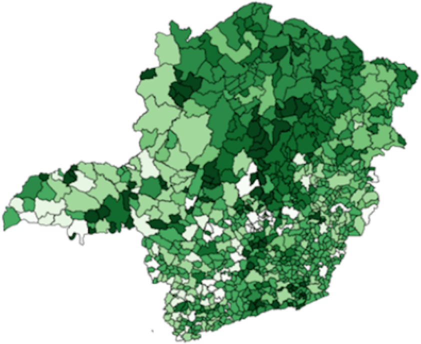
4. Mortality risk from the AI predicted ECG-age.
   E. M. Lima, A. H. Ribeiro, G. M. Paixão, *et al.*, "Deep neural network estimated electrocardiographic-age as a mortality predictor," *medRxiv*, Feb. 2021. DOI: 10.1101/2021.02.19.21251232.

Telehealth Network of Minas Gerais

Year	# Municipalities
2006	82
2007	102
2008	97
2009	328
2011	54
2013	106
2015	42
Total	811



M. B. Alkmim, R. M. Figueira, M. S. Marcolino, *et al.*, "Improving patient access to specialized health care: The Telehealth Network of Minas Gerais, Brazil," *Bulletin of the World Health Organization*, vol. 90, no. 5, pp. 373–378, May 2012, ISSN: 1564-0604. DOI: 10/f3x7px.

The CODE group

Figure: The CODE (*Clinical outcomes in eletrocardiography*) group was created to conduct clinical studies using storical data from the telehealth network.

My first experience with ECG processing

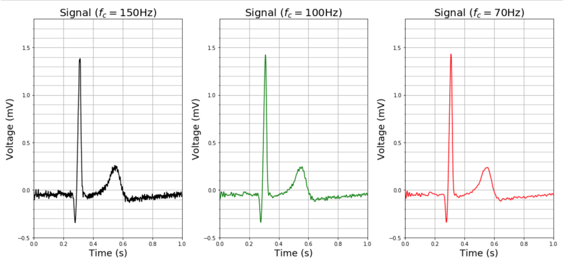
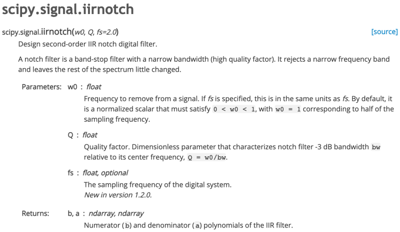


Figure: Filtered ECGs

https://github.com/antonior92/ECG-jupyter-notebook

Removing powerline interference



scipy.signal.iirnotch

scipy.signal.iirnotch(*w0, Q, fs=2.0*) [source]

Design second-order IIR notch digital filter.

A notch filter is a band-stop filter with a narrow bandwidth (high quality factor). It rejects a narrow frequency band and leaves the rest of the spectrum little changed.

Parameters: w0 : *float*

Frequency to remove from a signal. If *fs* is specified, this is in the same units as *fs*. By default, it is a normalized scalar that must satisfy `0 < w0 < 1`, with `w0 = 1` corresponding to half of the sampling frequency.

Q : *float*

Quality factor. Dimensionless parameter that characterizes notch filter -3 dB bandwidth `bw` relative to its center frequency, `Q = w0/bw`.

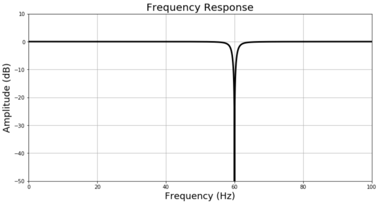
fs : *float, optional*

The sampling frequency of the digital system.
New in version 1.2.0.

Returns: b, a : *ndarray, ndarray*

Numerator (`b`) and denominator (`a`) polynomials of the IIR filter.

(a)



(b)

Figure: The Notch filter: my first contribution to SciPy

My trajectory in SciPy

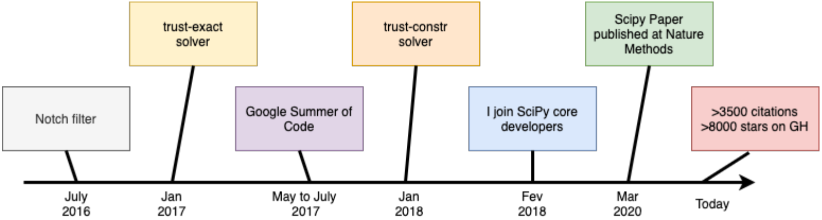
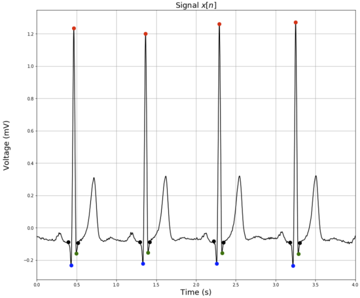


Figure: timeline

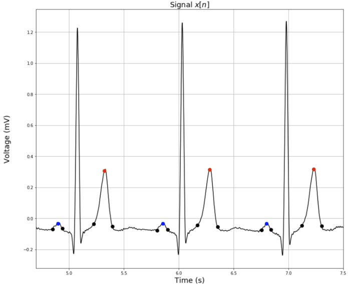
SciPy organization and governance

- Hosted on github;
- Contributors >> Core Developers >> Steering Council >> Benevolent Dictator for Life;

ECG segmentation



(a) QRS complex



(b) T and P waves

Figure: ECG segmented using signal processing

Classical ECG automated analysis

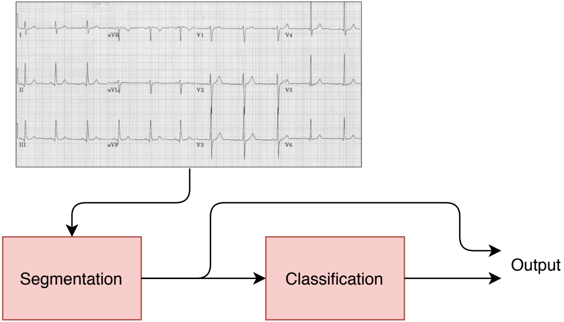
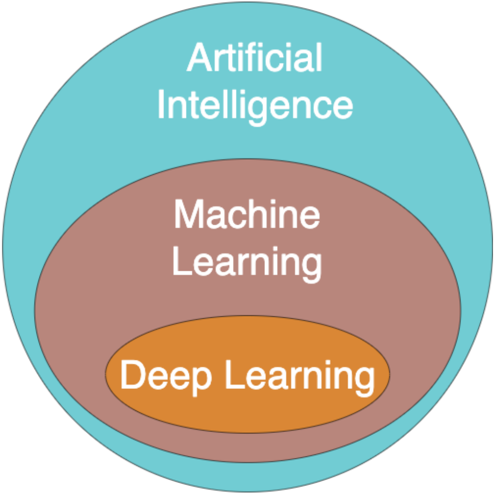


Figure: Two step procedure

P. W. Macfarlane, B. Devine, and E. Clark, "The university of glasgow (Uni-G) ECG analysis program," in *Computers in Cardiology*, 2005, pp. 451–454, ISBN: 0276-6574. DOI: 10.1109/CIC.2005.1588134.

Machine learning and artificial intelligence



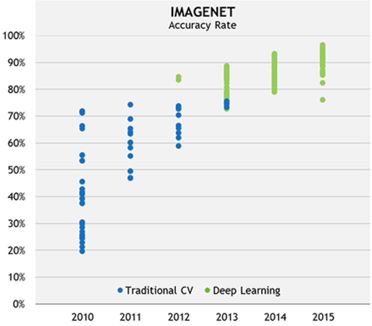
Deep neural networks

Yoshua Bengio, Geoffrey Hinton and Yann LeCun *"for conceptual and engineering breakthroughs that have made* deep neural networks *a critical component of computing."*

– Turing award (2018)

Image classification with deep neural networks

(a) Samples



(b) Accuracy

Figure: The imagenet classification benchmark.

Automatic ECG classification

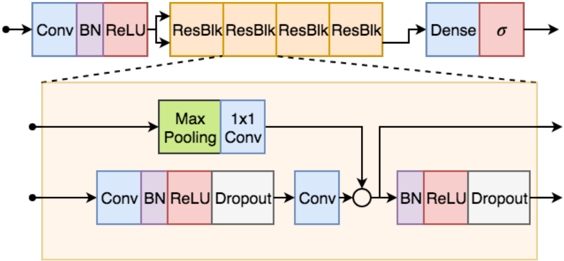


Figure: The uni-dimensional residual neural network architecture used for ECG classification.

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The training dataset

- 2.3 million records 1.6 million distinct patients;
- Annotated by telehealth center cardiologist;
- Refined by comparing with University of Glasgow software results;
- 30 000 exams manually reviewed.

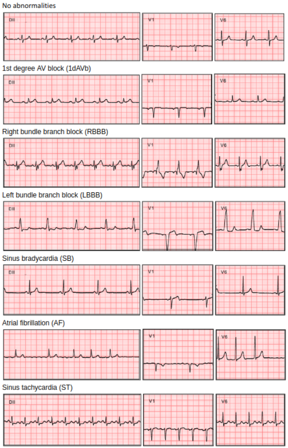


Figure: Abnormalities for the classification problem.

The testing dataset

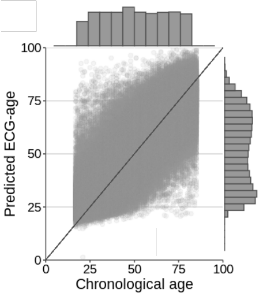
- 827 tracings from distinct patients;
- Annotated by 3 different cardiologists.

Results

	F1 Score			
	DNN	cardio.	emerg.	stud.
1dAVb	**0.897**	0.776	0.719	0.732
RBBB	**0.944**	0.917	0.852	0.928
LBBB	**1.000**	0.947	0.912	0.915
SB	**0.882**	**0.882**	0.848	0.750
AF	**0.870**	0.769	0.696	0.706
ST	**0.960**	0.882	0.946	0.873

Table: Performance indexes

Age-prediction model



Δ age = ECG-age - age

Figure: Predicted vs estimated age in 15% hold-out test set (n = 218,169 patients). Mean absolute error of 8.38 years.

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ECG-age as a mortality predictor

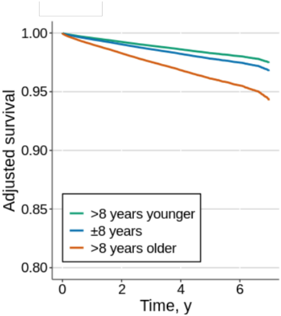

Figure: Kaplan-Meier survival curve (CODE-15%)

Table: Hazard ratio from Cox model

Adjusted by age and sex	
Δ age $<$ - 8 y	0.78
Δ age $>$ 8 y	1.79
Adjusted by age, sex and comorbities	
Δ age $<$ - 8 y	0.78
Δ age $>$ 8 y	1.78

Validation on ELSA-Brasil (and Sami-Trop)

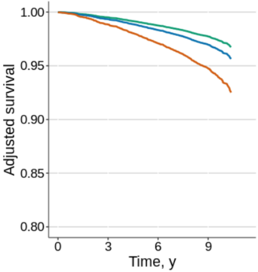

Figure: Kaplan-Meier survival curve (ELSA-Brasil)

Table: Hazard ratio from Cox model

Adjusted by age and sex	
Δ age $<$ - 8 y	0.74
Δ age $>$ 8 y	1.75
Adjusted by age, sex and comorbities	
Δ age $<$ - 8 y	0.82
Δ age $>$ 8 y	1.57

Aquino, E. M. L., Barreto, S.M., Bensenor I.M., et. al. (2020)
Brazilian longitudinal study of adult health (ELSA-Brasil): Objectives and design
American Journal of Epidemiology 175 (4), 315-324.

Analysis on ECGs classified as normal

Table: Hazard ratio from Cox model

	CODE-15%	ELSA-Brasil
Adjusted by age and sex		
Δ age $<$ - 8 y	0.66	0.91
Δ age $>$ 8 y	1.53	1.63
Adjusted by age, sex and comorbities		
Δ age $<$ - 8 y	0.66	0.91
Δ age $>$ 8 y	1.52	1.42

Discussion

- Improved automatic classification using deep learning
  - Potential to improve tele-health service in short/medium term;
  - Screen more important exams;
  - Avoid medical mistakes and improve accuracy.
- AI to extend the potential of ECG for prognosis
  - Capability of identifying patterns that are not obvious for a cardiologist (double-edged aspect of it);
  - Extend ECG role in risk stratification.

Thank you!

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