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

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Uppsala University, Sweden

AIMLab group meeting
Technion, 2021
1. The Telehealth Network of Minas Gerais and the CODE group;
Presentation outline

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2. Open source and SciPy;
3. Automatic classification of ECGs using deep learning
4. Mortality risk from the AI predicted ECG-age.
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4. Mortality risk from the AI predicted ECG-age.
Telehealth Network of Minas Gerais

<table>
<thead>
<tr>
<th>Year</th>
<th># Municipalities</th>
</tr>
</thead>
<tbody>
<tr>
<td>2006</td>
<td>82</td>
</tr>
<tr>
<td>2007</td>
<td>102</td>
</tr>
<tr>
<td>2008</td>
<td>97</td>
</tr>
<tr>
<td>2009</td>
<td>328</td>
</tr>
<tr>
<td>2011</td>
<td>54</td>
</tr>
<tr>
<td>2013</td>
<td>106</td>
</tr>
<tr>
<td>2015</td>
<td>42</td>
</tr>
<tr>
<td>Total</td>
<td>811</td>
</tr>
</tbody>
</table>

The CODE group

Figure: The CODE (Clinical outcomes in electrocardiography) 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)

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 as relative to its center frequency, \( Q = \frac{w0}{\text{bw}} \).
- 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.

Figure: The Notch filter: my first contribution to SciPy
My trajectory in SciPy

Figure: timeline

- Notch filter: July 2016
- trust-exact solver: Jan 2017
- Google Summer of Code: May to July 2017
- trust-constr solver: Jan 2018
- I join SciPy core developers: Fev 2018
- Scipy Paper published at Nature Methods: Mar 2020
- >3500 citations >8000 stars on GH: Today
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

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.

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

<table>
<thead>
<tr>
<th></th>
<th>F1 Score</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DNN</td>
</tr>
<tr>
<td>1dAVb</td>
<td>0.897</td>
</tr>
<tr>
<td>RBBB</td>
<td>0.944</td>
</tr>
<tr>
<td>LBBB</td>
<td>1.000</td>
</tr>
<tr>
<td>SB</td>
<td>0.882</td>
</tr>
<tr>
<td>AF</td>
<td>0.870</td>
</tr>
<tr>
<td>ST</td>
<td>0.960</td>
</tr>
</tbody>
</table>

**Table:** Performance indexes
Age-prediction model

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

\[ \Delta \text{age} = \text{ECG-age} - \text{age} \]

ECG-age as a mortality predictor

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

Table: Hazard ratio from Cox model

<table>
<thead>
<tr>
<th></th>
<th>Adjusted by age and sex</th>
<th>Adjusted by age, sex and comorbidities</th>
</tr>
</thead>
<tbody>
<tr>
<td>Δ age &lt; 8 y</td>
<td>0.78</td>
<td>0.78</td>
</tr>
<tr>
<td>Δ age &gt; 8 y</td>
<td>1.79</td>
<td>1.78</td>
</tr>
</tbody>
</table>
Validation on ELSA-Brasil (and Sami-Trop)

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

Table: Hazard ratio from Cox model

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<thead>
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<tbody>
<tr>
<td>Δ age &lt; - 8 y</td>
<td>0.74</td>
</tr>
<tr>
<td>Δ age &gt; 8 y</td>
<td>1.75</td>
</tr>
</tbody>
</table>

<table>
<thead>
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<th>Adjusted by age, sex and comorbidities</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Δ age &lt; - 8 y</td>
<td>0.82</td>
</tr>
<tr>
<td>Δ age &gt; 8 y</td>
<td>1.57</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
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<th>CODE-15%</th>
<th>ELSA-Brasil</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Adjusted by age and sex</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Δ age &lt; - 8 y</td>
<td>0.66</td>
<td>0.91</td>
</tr>
<tr>
<td>Δ age &gt; 8 y</td>
<td>1.53</td>
<td>1.63</td>
</tr>
<tr>
<td><strong>Adjusted by age, sex and comorbidities</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Δ age &lt; - 8 y</td>
<td>0.66</td>
<td>0.91</td>
</tr>
<tr>
<td>Δ age &gt; 8 y</td>
<td>1.52</td>
<td>1.42</td>
</tr>
</tbody>
</table>
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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