Learning signals and systems and its applications to electrocardiography

Antônio Horta Ribeiro

Presented to Aalto community as part of the application for the assistant professor position in AI-Health

Aalto University, Finland (Online)
June 2022

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Figure: Offshore extraction

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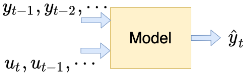

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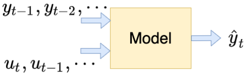

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$$\min \sum_t \text{dist}(\hat{y}_t, y_t)$$

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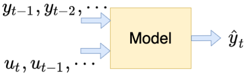

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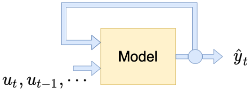
- Long-term predictions:



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Learning recurrent models

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- Noise analysis

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- Optimization analysis

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Contribution: Provide throughout analysis of the tradeo s between extra- exibility and the optimization challenges these model provide.

Outline

Automatic analysis of the electrocardiogram

Robustness and overparametrization

Research vision

The electrocardiogram (ECG) exam

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- leading cause of death globally.
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The ECG is the major diagnostic tool.

- Low-cost, safe and non-invasive
- Can detect: arrhythmias, myocardial infarction, cardiomyopathy...

Left: ECG signal **Right:** Electrode placement.

Computational electrocardiography

Figure: Automated ECG interpretation Glasgow Royal Infirmary (1971).

Macfarlane, P.W.; Kennedy, J. "Automated ECG Interpretation—A Brief History from High Expectations to Deepest Networks." Hearts 2021.

Can we improve on existing automatic tools?

A. H. Ribeiro, M.H. Ribeiro, Paixão, G.M.M., D. M. Oliveira, P. R. Gomes, J. A. Canazart, M. P. S. Ferreira, C. R. Andersson, P. W. Macfarlane, W. Meira Jr., T. B. Schön, A. L. P. Ribeiro "Automatic diagnosis of the 12-lead ECG using a deep neural network," Nature Communications, 2020

Telehealth and automatic tools

- The Telehealth Center of Minas Gerais

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- Better accuracy could enable additional uses

Deep neural networks in computer vision

Imagenet

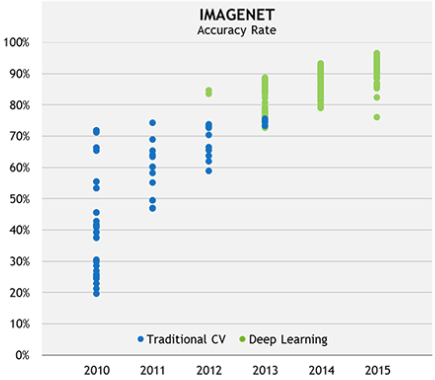

Figure: Models accuracy on ImageNet benchmark. In 2012, LeNet-5 wins ILSVRC.

Deep learning for automatic diagnosis

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  - 2.3 M ECGs from n =1.6M patients
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- Develop and evaluate deep neural network

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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
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Figure: Performance of the deep neural network (DNN) agains experts.

cardio. ! 4th year cardiology residents
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Bootstrapped F1 score values

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- Di erent aspects improved in latter studies
  - Interpretability:

    - W. Meira Jr, A. L. P. Ribeiro, D. M. Oliveira, and A. H. Ribeiro , \Contextualized Interpretable Machine Learning for Medical Diagnosis," Communications of the ACM, 2020
    - D. M. Oliveira, A. H. Ribeiro , J. A. O. Pedrosa, G. M. M. Paixao, A. L. P. Ribeiro, and W. Meira Jr, \Explaining end-to-end ECG automated diagnosis using contextual features," ECML-PKDD, 2020.
  - Use of images instead of signals:

    - V. Sangha, B. J. Mortazavi, A. D. Haimovich, A. H. Ribeiro , C. A. Brandt, D. L. Jacoby, W. L. Schulz, H. M. Krumholz, A. L. P. Ribeiro, Rohan Khera \Automated multilabel diagnosis on electrocardiographic images and signals," Nature Communications, 2022.
  - Use of ensembles:

    A. H. Ribeiro , D. Gedon, D. M. Teixeira, M. H. Ribeiro, A. L P. Ribeiro, T. B Schon, W. Meira Jr \Automatic 12-lead ECG classi cation using a convolutional network ensemble," CinC, 2020.

Deep learning in electrocardiography

- Q1: Can we improve on existing automatic tools?
- Q2: Can we use data-driven methods to detect new conditions?

D. Gedon et al. , S. Gustafsson , E. Lampa, A. H. Ribeiro , M. J. Holzmann, T. B. Schön, J. Sundstrom, "ResNet-based ECG Diagnosis of Myocardial Infarction in the Emergency Department," Workshop at NeurIPS, 2021. Under review

Myocardial Infarction

Can we detect non-STEMI cases from the ECG?

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Diagnosis:

- ST-elevation MI (STEMI)! ECG.
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Left: No MI. Right: STEMI.

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Figure: ROC and precisicion-recall curves
AUROC = 0.82 / 0.74 (STEMI/NSTEMI).

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Data-driven methods to detect new conditions

- Study of bio-markers from ECG to detect mortality

  E. M. Lima , A. H. Ribeiro , G. M. M. Paixão et al., "Deep neural network estimated electrocardiographic-age as a mortality predictor," Nature Communications, vol. 12, 2021 Equal contribution

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Research vision

Neural networks in critical applications

Figure: E ect of adversarial examples on ECG Classi cation.

Source: Han, X., Hu, Y., Foschini, L. et al. Deep learning models for electrocardiograms are susceptible to adversarial attack. Nature Medicine 26, 360{363 (2020).

Overparameterized models

- Double descent

  M. Belkin, D. Hsu, S. Ma, and S. Mandal , \Reconciling modern machine-learning practice and the classical bias{variance trade-o ," PNAS (2019)

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- Example:

Figure: nonlinear ARX mean squared error (MSE).

A. H. Ribeiro , J. N. Hendriks, A. G. Wills, T. B. Schön. \Beyond Occam's Razor in System Identi cation: Double-Descent when Modeling Dynamics". IFAC SYSID 2021. Honorable mention: Young author award

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What is the role of high-dimensionality in model robustness?

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A. H. Ribeiro and T. B. Schön, "Overparameterized Linear Regression under Adversarial Attacks," arXiv:2204.06274. 2022.

Overparameterized models and robustness

Dataset $(x_i; y_i)$, $\dim(x_i) =\ m$:

$$y_i = x_i^T \quad + \quad ; i = 1; \qquad n$$

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- $k\,b\,k_2$ decays with $p \frac{1}{\#\text{ features}}$.
- $k\,b\,k_1$ goes to constant.

Left: `$_2$-norm. Right: `$_1$-norm.

Adversarial attacks

- error = $y - x^T b$

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$$\ell_2 \qquad \ell_1$$

- $E\{\text{error}^2\} + {}^2\|b\|^2 \quad E\{(\text{adv. error})^2\} \quad E\{\text{error}\} + \|b\|^{2}$

Discussion

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- Linear regression: simplest case where both robustness or brittleness can be observed.
- Adversarial training:

  A. H. Ribeiro , D. Zachariah, and T. B. Schön, \Surprises in adversarially-trained linear regression," arXiv:2205.12695, May 2022.

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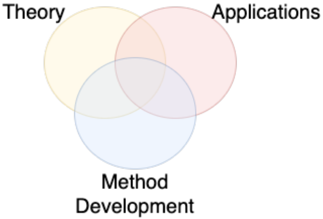
Research vision

Research goals

Build reliable and robust tools that can assist doctors in providing better patient care.

Theory: overparametrization and robustness
Methods: learning from signals and systems
Applications: diagnosis and prognosis of cardiac diseases



Building a research group

Students with applied problems but with theoretical and methodological challenges.

My current students:

- Daniel Gedon (Ph.D.)
  Unsupervised methods for ECG analysis
- Theogene Habineza (M.Sc.)
  AFib risk prediction
- Oscar Larson (M.Sc.)
  Adversarial attacks on the powergrid
- Philipp von Bachmann (M.Sc.)
  Electrolyte concentration prediction

Why I applied to Aalto University

- Top research and education institution
- Ample opportunity to collaboration:
  - Harri Lähdesmäki, Aki Vehtari, Simo Särkkä, Arno Solin, Leo Kärkkäinen
- Interdisciplinary research
  - Department of Computer Science
  - Department of Neuroscience and Biomedical Engineering
  - Department of Electrical Engineering and Automation
- Finnish Center for Artificial Intelligence - AI for health
- Good funding opportunities

My research philosophy

Research should be open, freely available and reproducible

- Contributions SciPy
- Open models and datasets for ECG analysis
  - CODE dset ($n = 1.6$M)
  - CODE-15% dataset ($n > 200\,000$)
  - SaMI-Trop, CODE-test
  - International network collaboration