EIVIA 2025: Deep Learning for Time Series and Applications to Healthcare

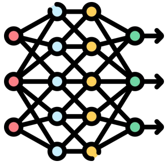
Gonzalo Uribarri
KTH Royal Institute of Technology & SciLifeLab

@gonzauri

About me

Argentina (Phd)

Gabo Mindlin



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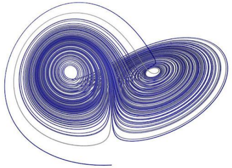

Dynamical Systems

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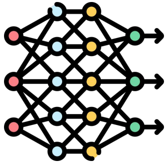
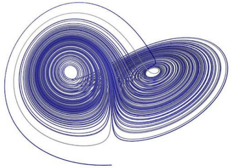


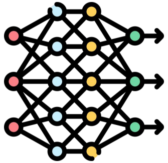
Machine Learning



Dynamical Systems

Sweden (Postdoc)

Erik Fransén



Machine Learning

Biomedical Data

About the course

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The goal of the course is for you to learn:

- ❏ An Overview of Time Series Classification Methods
- ❏ Opportunities and Challenges of Applications in Healthcare

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Things we will **not cover** in the course:

- ❑ An Introduction to ML Fundamentals
- ❑ Details about the Technical Implementation of the Models

Course Plan

1/ INTRODUCTION

- Challenges of ML for healthcare
- Introduction to ML for time series

2/ TIME SERIES:
Standard Algorithms

- Basic ML for TS Classification
- Deep Learning for TS Classification

3/ TIMES SERIES:
State-of -the-art

- SOTA TS Classification models
- ROCKET and InceptionTime

4/ APPLICATIONS

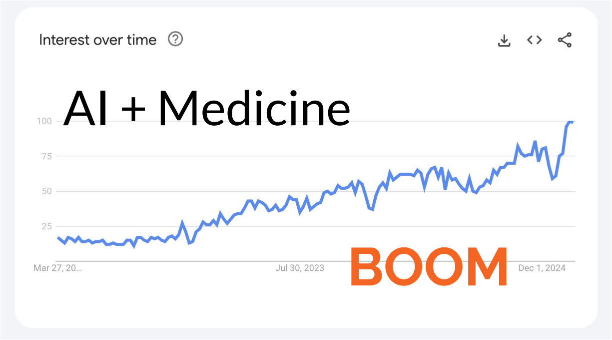
- Case studies in healthcare: Eye-tracking and EEG data
- Proper Evaluation

5/ LARGE MODELS

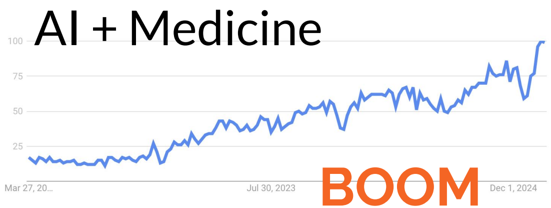
- TS models for large datasets
- Transfer learning: Foundational models for TS?

ML for Healthcare

ML for Healthcare



ML for Healthcare



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Charlie Tran, Kai Shen, Kang Liu, Akshay Ashok, Adolfo Ramirez-Zamora, Jinghua Chen, Yulin Li & Ruogu Fang

Scientific Reports 14, Article number: 3637 (2024) | Cite this article

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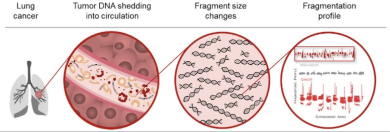
06/06/2024



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A pathology foundation model for cancer diagnosis and prognosis prediction

Xiyue Wang, Junhan Zhao, Eliana Marostica, Wei Yuan, Jietian Jin, Jiayu Zhang, Ruijiang Li, Hongping Tang, Kanran Wang, Yu Li, Fang Wang, Yulong Peng, Junyou Zhu, Jing Zhang, Christopher R. Jackson, Jun Zhang, Deborah Dillon, Nancy U. Lin, Lynette Sholl, Thomas Denize, David Meredith, Keith L. Ligon, Sabina Signoretti, Shuji Ogino, ... Kun-Hsing Yu + Show authors

Nature 634, 970–978 (2024) | Cite this article

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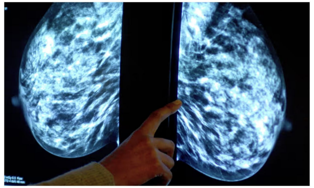
NHS to launch world's biggest trial of AI breast cancer diagnosis

If successful, the scheme could speed up testing and reduce radiologists' workload by around half



At present, the NHS uses a 'second reader' system where two radiologists check mammograms for signs of breast cancer. Photograph: Rui Vieira/PA

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ML for Healthcare

Why is there a boom?

- Data Availability
- Better Models
- Hype

ML for Healthcare

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But… CHALLENGES

- Data Privacy
- Interpretability / Explainability
- Generalization (Bias, Fairness)
- Deployment to Clinics

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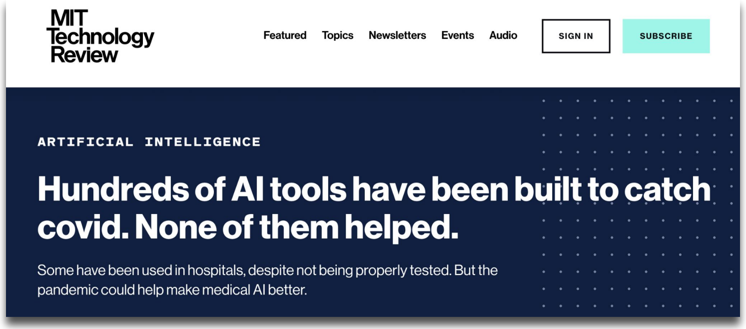
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ARTIFICIAL INTELLIGENCE

Hundreds of AI tools have been built to catch covid. None of them helped.

Some have been used in hospitals, despite not being properly tested. But the pandemic could help make medical AI better.

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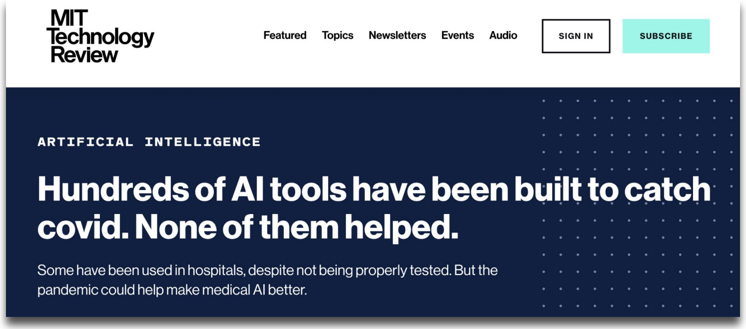
Ethical / Technical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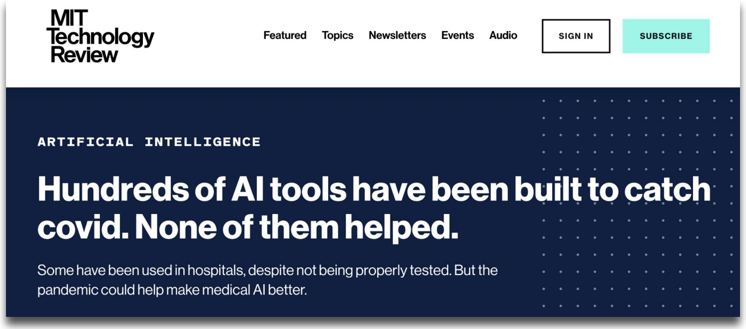

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Ethical / $\boxed{\text{Technical}}$

Challenge in Clinical Datasets

Ideal Classification Setting

Subjects

Condition (Label)

A B

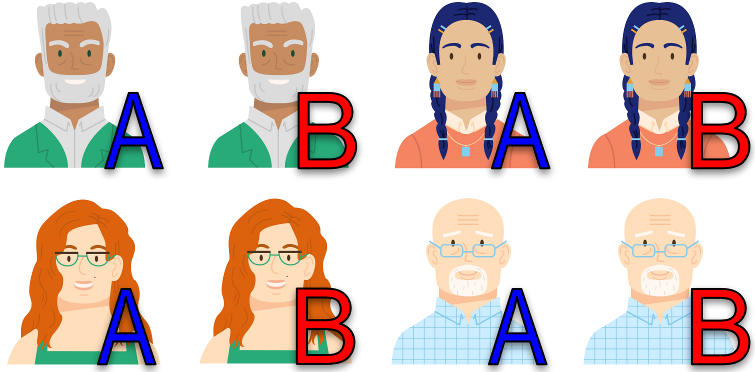
Ideal Classification Setting

Subjects

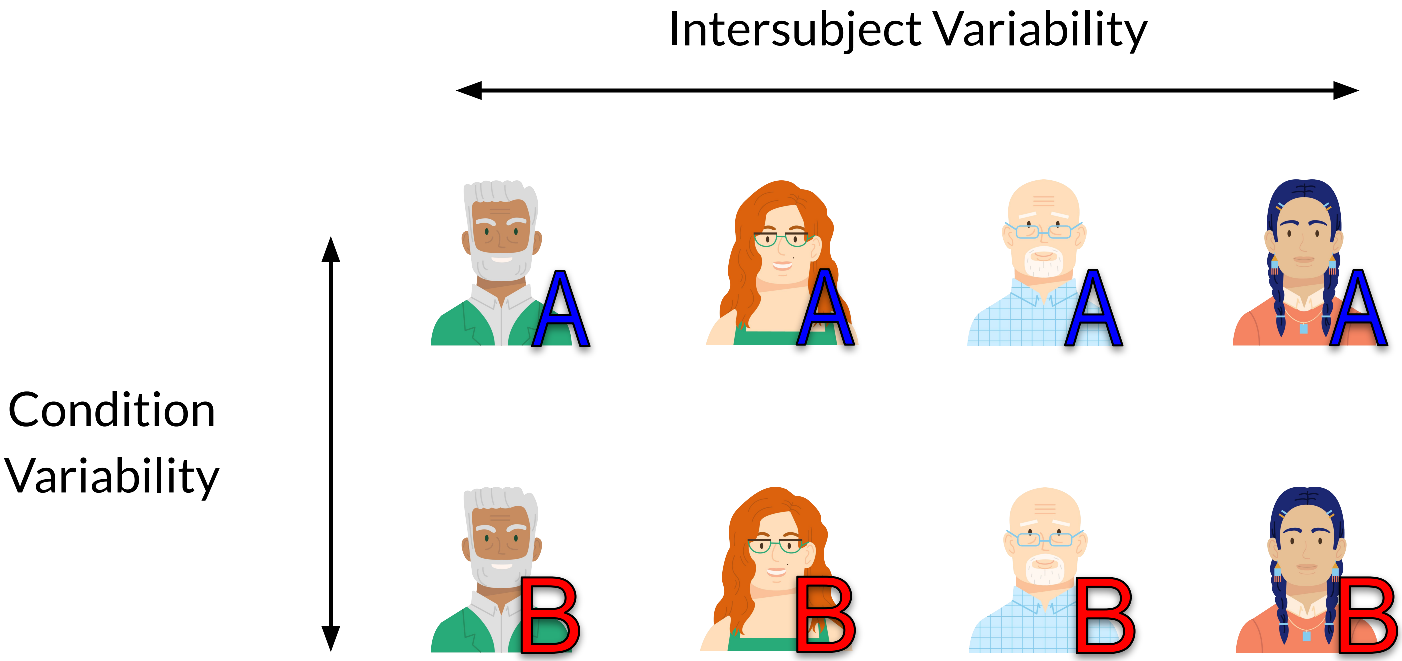
Condition (Label)

A B

Ideal dataset (8 trials)



Ideal Classification Setting



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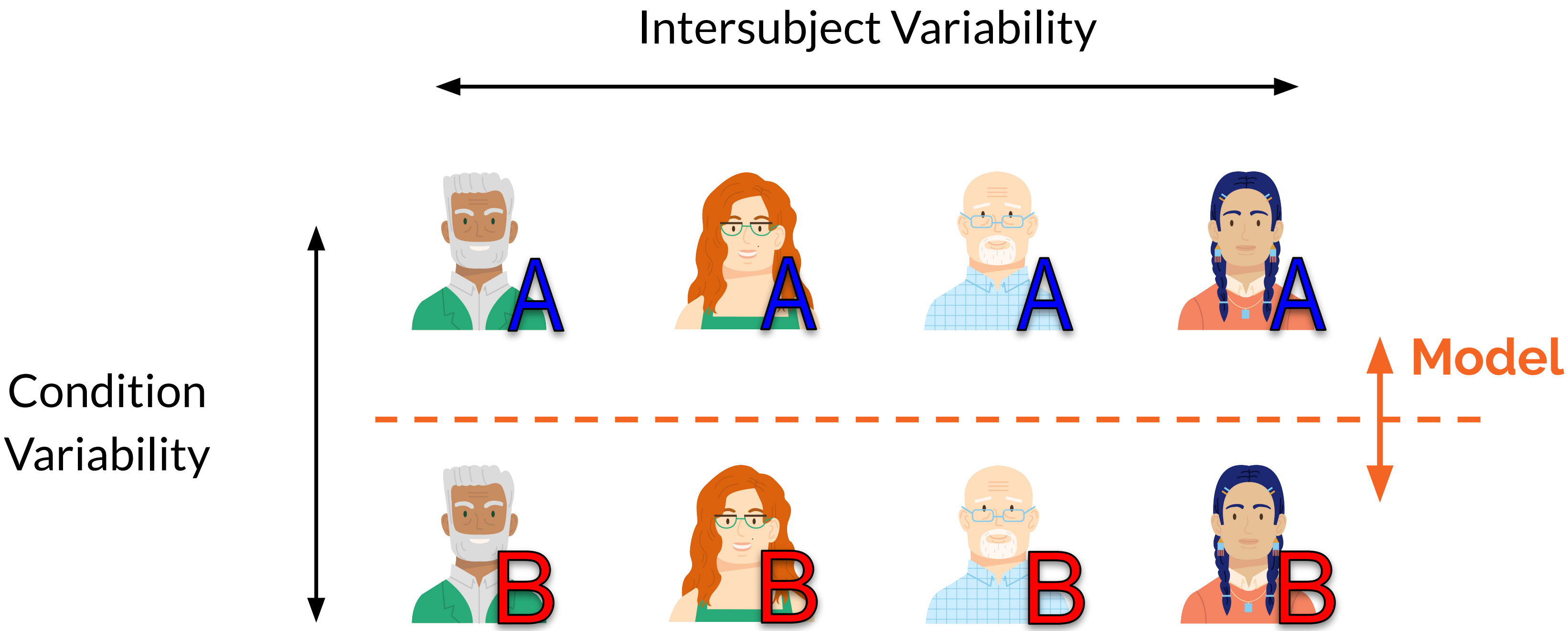


Challenging Classification Setting

Subjects

Condition (Label)

A B

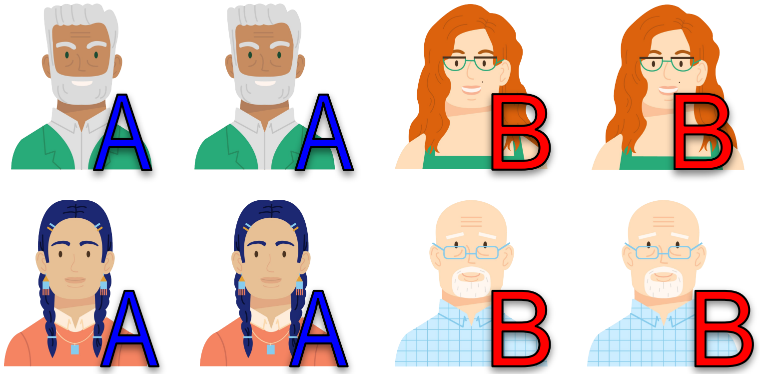
Challenging Classification Setting

Subjects

Condition (Label)

A B

Neurodegenerative disease Dataset



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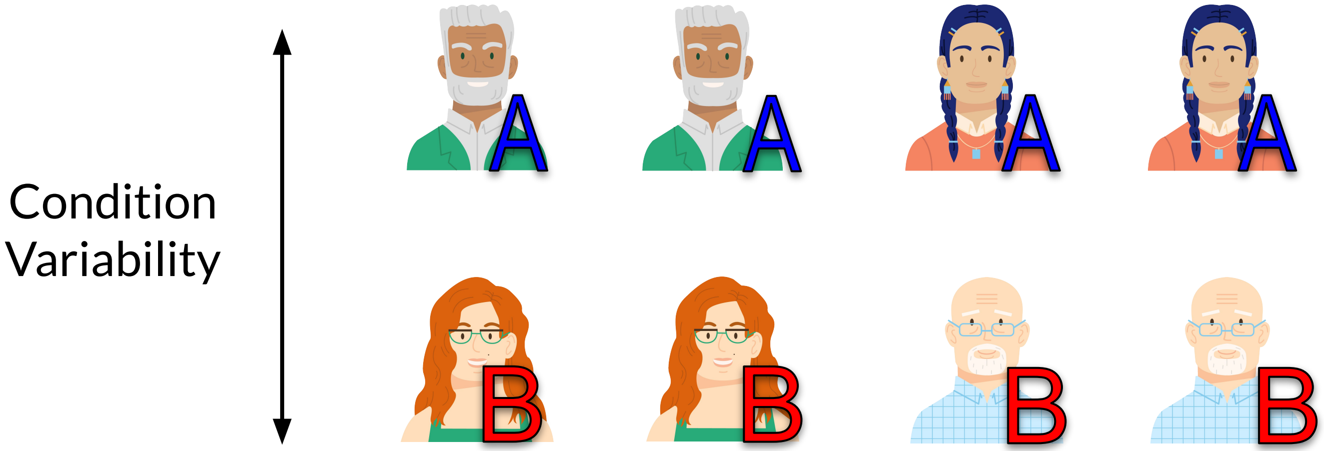
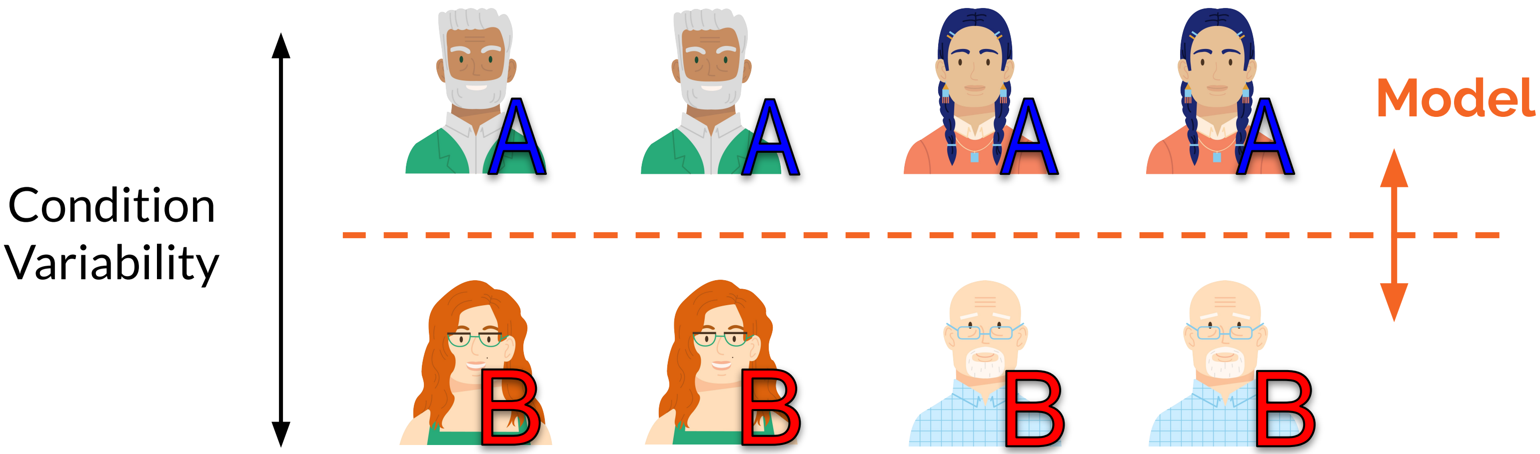
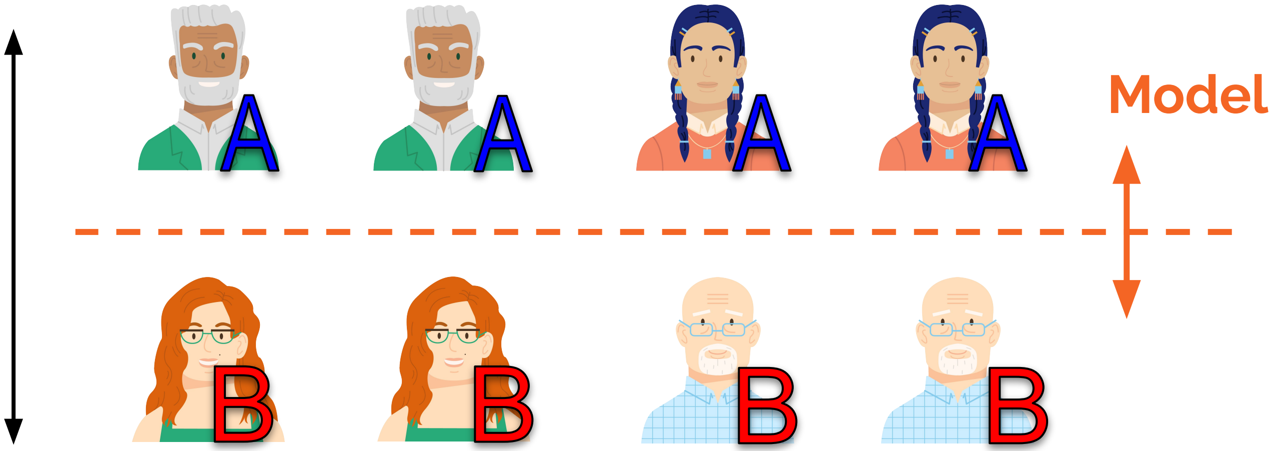


Challenging Classification Setting



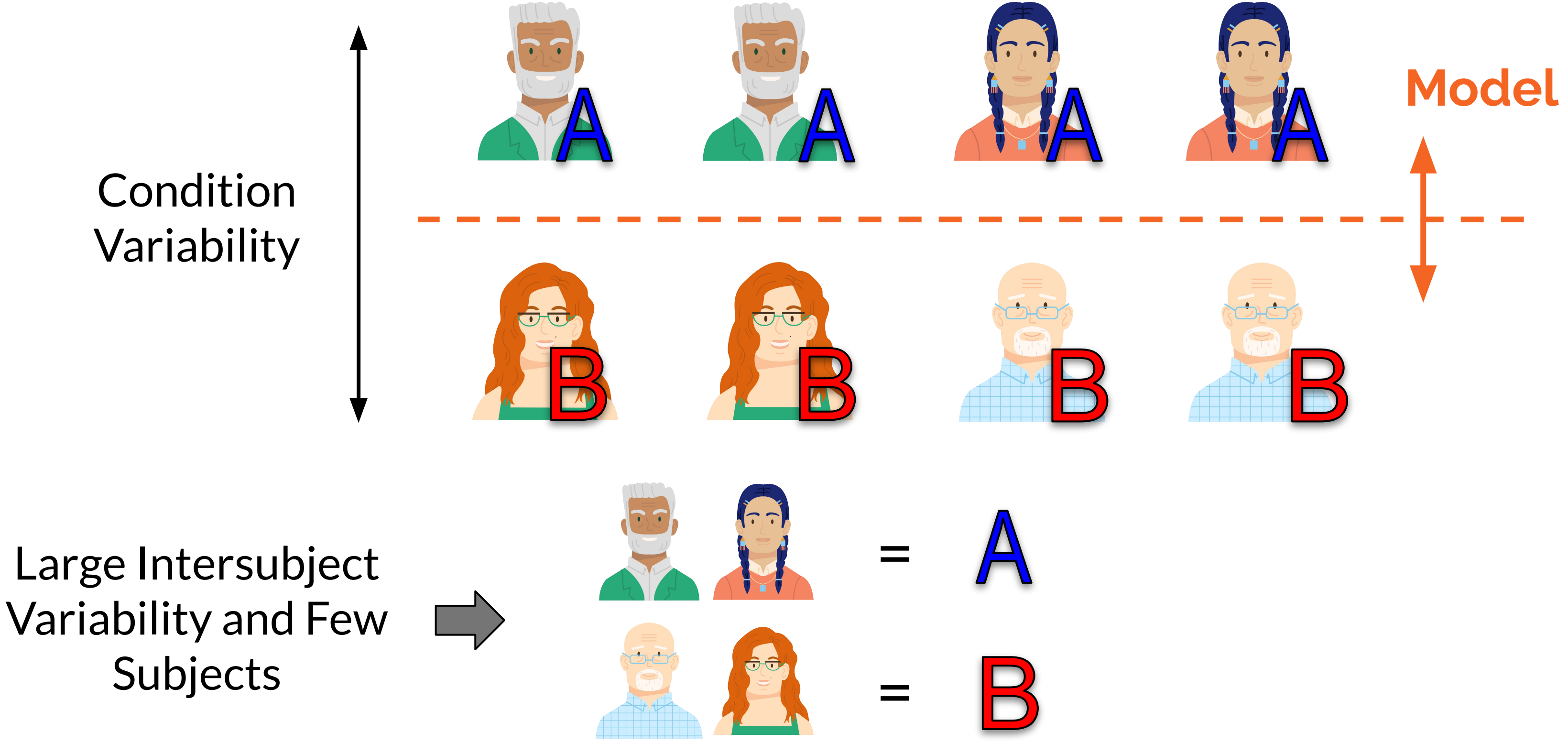
Challenging Classification Setting

Condition Variability



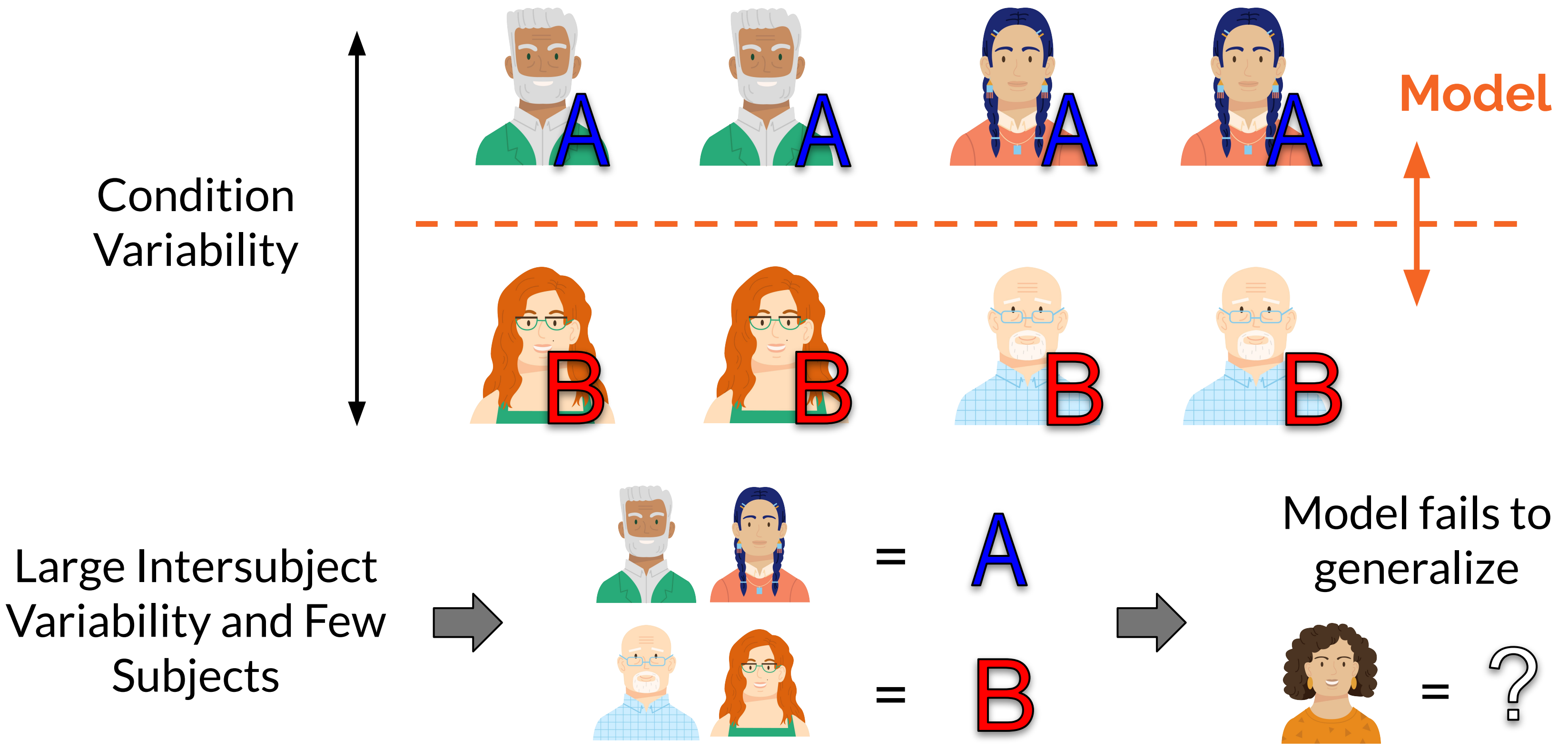
Large Intersubject Variability and Few Subjects

Challenging Classification Setting



Comment on individual variability (useful up to some point)

Challenging Classification Setting



Overcoming the Generalization Problem

Possible solutions:

1) **Increase Number of Participants**

Overcoming the Generalization Problem

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4) **Machine Learning Framework Design:** Do feature engineering and/or impose a particular inductive bias on the ML model.

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Overcoming the Generalization Problem

Possible solutions:

Experimental Design

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2) **Longitudinal Study**:

3) **Data Specificity:** Select an experimental task and data modality where the condition variability is large.

This is where we work

4) **Machine Learning Framework Design:** Do feature engineering and/or impose a particular inductive bias on the ML model.

Real World Example (preview)

The Dataset

- The dataset consists of **84** subjects in total:
  - **54** patients with Parkinson's disease
  - **30** Healthy controls

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Time Series
  - ❑ MEG (Magnetoencephalography)
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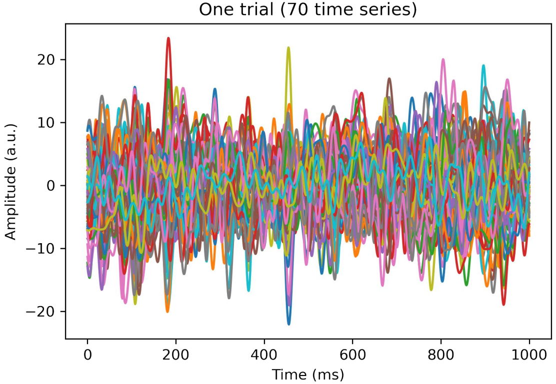
Task

Brain activity recording (1 trial)

Multichannel Data
(High-dimensional)



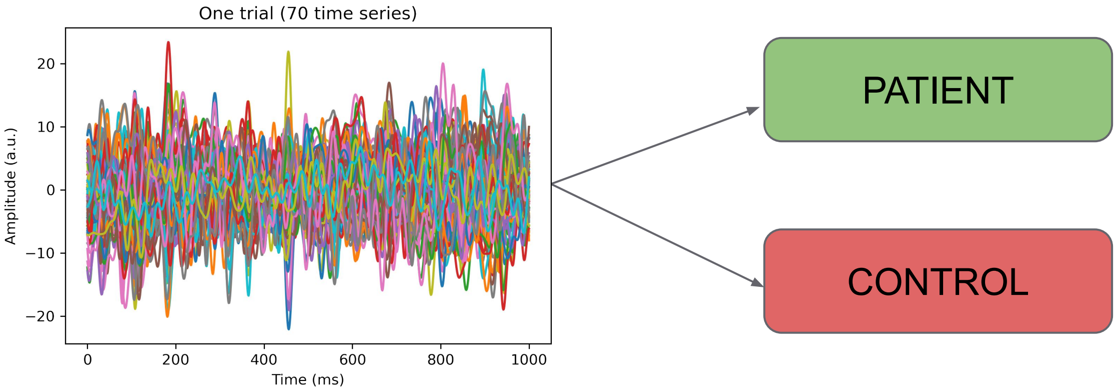
1s of recording

Task

Brain activity recording (1 trial)

Can we classify?
(Diagnosis task)

Multichannel Data
(High-dimensional)



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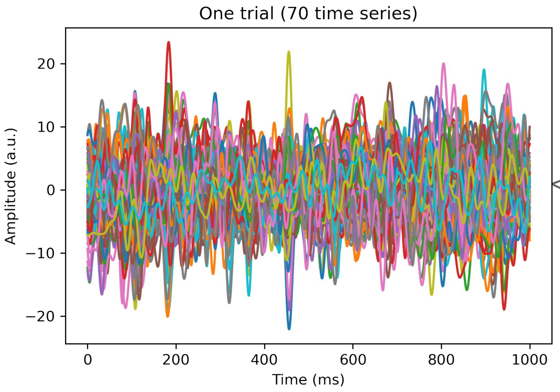


1s of recording

PATIENT

CONTROL

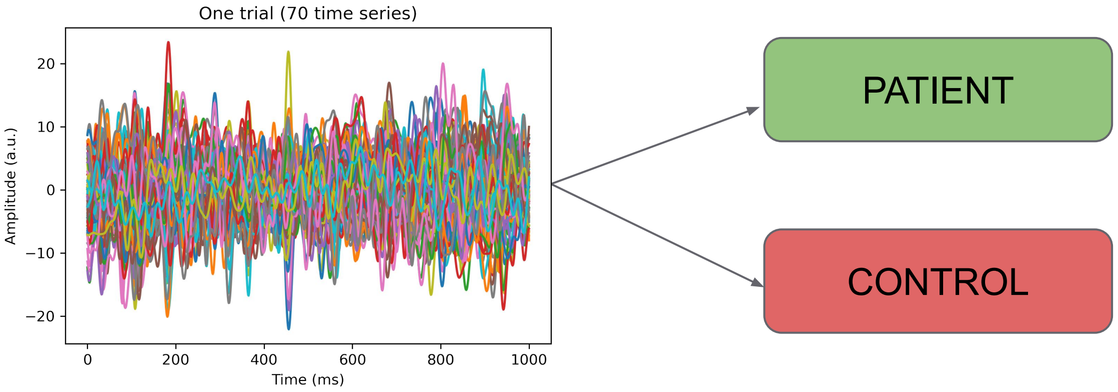
We have **8400** trials…
but only **84** subjects.

Task

Brain activity recording (1 trial)

Can we classify?
(Diagnosis task)

Multichannel Data
(High-dimensional)

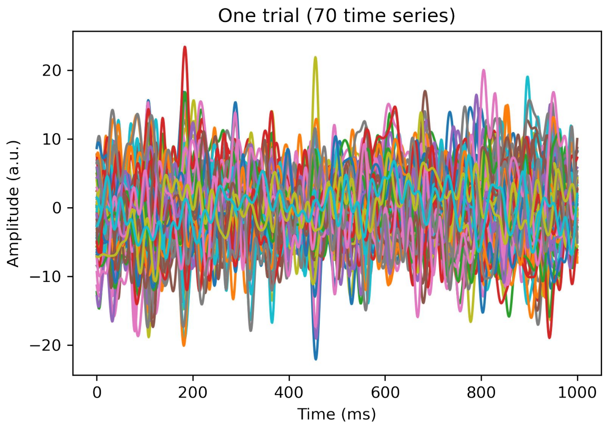


1s of recording

We have **8400** trials...
but only **84** subjects.

It is **really challenging** to generalize tu new subjects

Our Goal



We have **8400** high-dimensional trials and only **84** subjects.

We need to **carefully design** ML models that can deal with this **high-dimensional data** and **generalize**.

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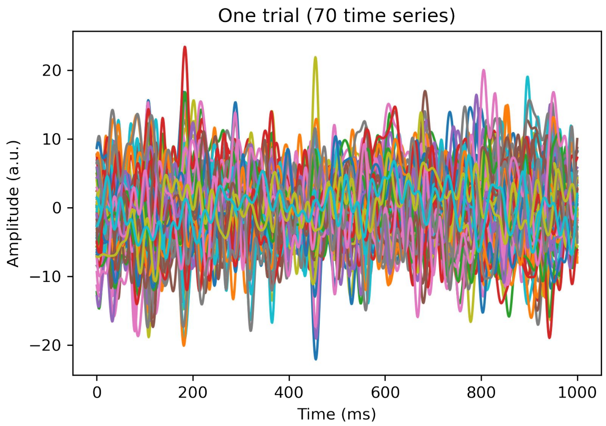

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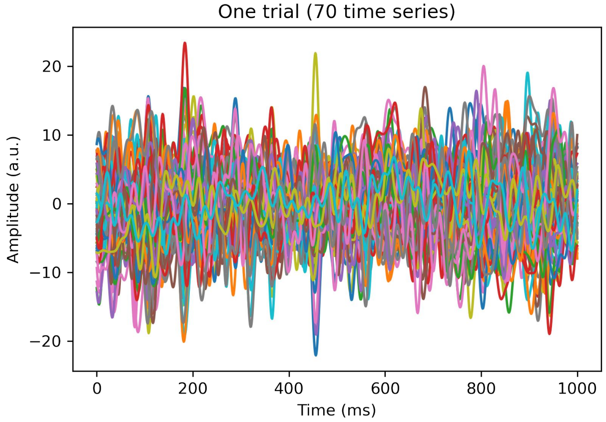

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We are going to explore how can we do this for Time Series Data

Machine Learning for Time Series

Sequential data

Sequential data is data arranged in sequences where order matters. Data points are conditioned on other data points in the sequence.

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Sequential Data

Discrete Sequences	Time Series
Series of discrete tokens where order matters, but there is no explicit time variable	Quasi-continuous numerical values that evolve as a function of time.
E.g., Text, DNA, List of events	**E.g., ECG, Sound, Temperature**

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Sequential Data

Transformers

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Linear RNNs: xLSTM, Mamba, RWKV

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Focus

Tasks for Time Series Data

Machine Learning for Time Series

Supervised

- Classification
- Extrinsic Regression
- Forecasting

Unsupervised

- Clustering
- Compression
- Generative
- Outlier Detection

Tasks for Time Series Data

Machine Learning for Time Series

Supervised

Focus
- Classification
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Unsupervised

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ML for Time Series Classification

There are two standard archives for benchmarking:

- ❏ UCR

  142 Univariate Time Series Datasets

- ❏ UEA

  30 Multivariate Time Series Datasets

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- UCR

  142 Univariate Time Series Datasets

- UEA

  30 Multivariate Time Series Datasets

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Hands-on Time:
Notebook 1