Assessing Multiple Imputation of Missing Values for Robust Analysis of Telehealth Kiosk Data

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IA et santé : approches interdisciplinaires
June, 29th 2022

Introduction

- **Telehealth** allows the distribution of health-related services.
- Promising avenue for **prevention,** and **remote diagnosis** and **monitoring** of diseases.
- Can be a solution when **access** to care is **restricted.**

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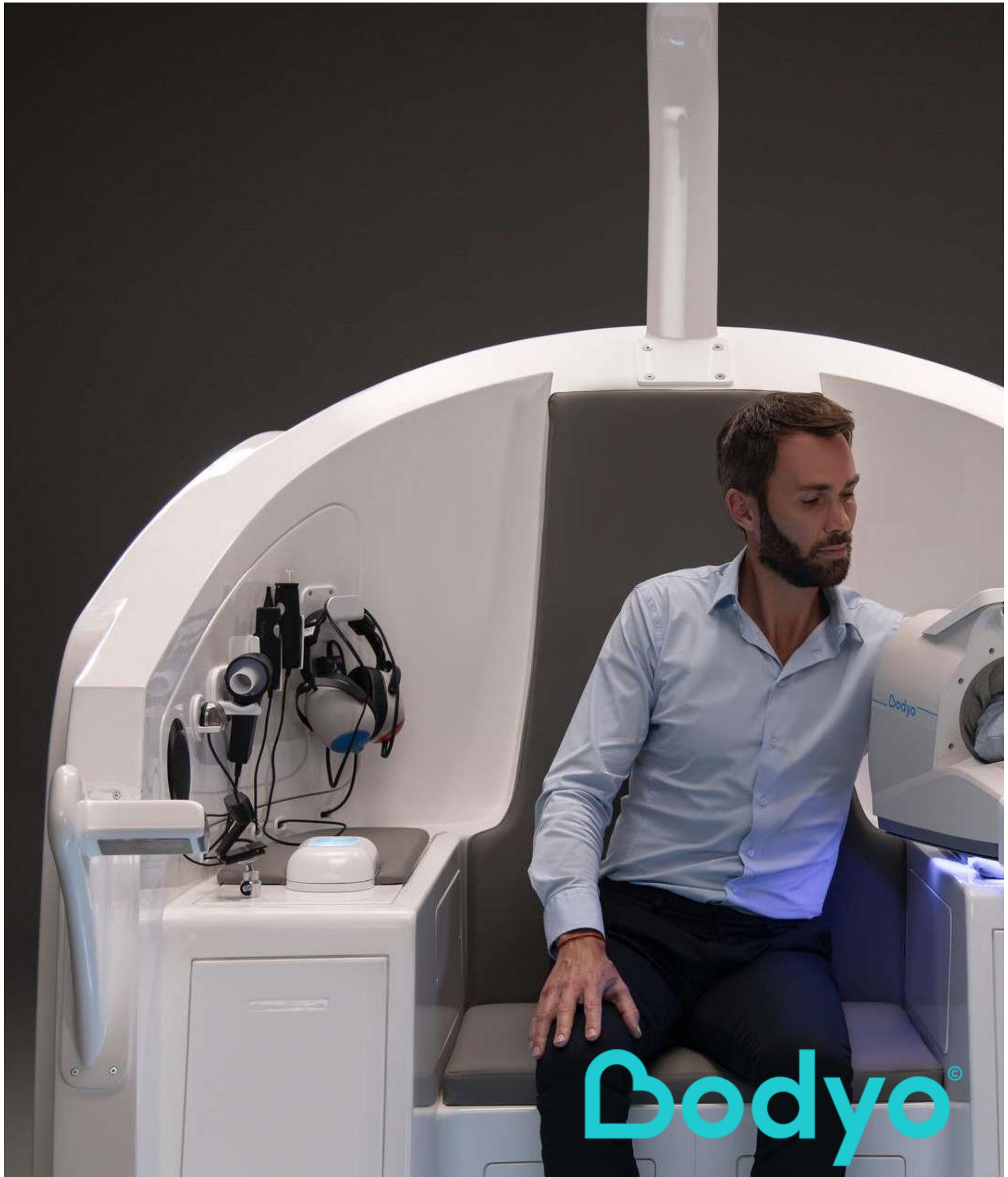

Bodyo AiPod

- Stand-alone **telehealth** kiosk.
- Measures **27 health indicators** in 6 minutes.
- 4 **sensors** collect information :
  - a **scale**
  - a **body composition** sensor
  - an **oximeter**
  - a **blood pressure** sensor

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Deploying the AiPod

- In non-clinical contexts **sensors may fail**, leading to incomplete data.
- If one sensor fails **all measures** collected by the sensor go missing.
- We cannot afford to **discard** incomplete observations.

Problem:

How to deal with missing data?

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Working with missing data

- We investigate two ways to deal with missing data:
  - **Imputation schemes** to fill the missing values.
  - A **set approach** that avoids **imputation.**

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Imputation of missing values

Imputation schemes

- We still want to **keep observations** with missing values.
- Imputation schemes allow to **fill** missing values.
- Imputation needs to **preserve the integrity** of the original data.

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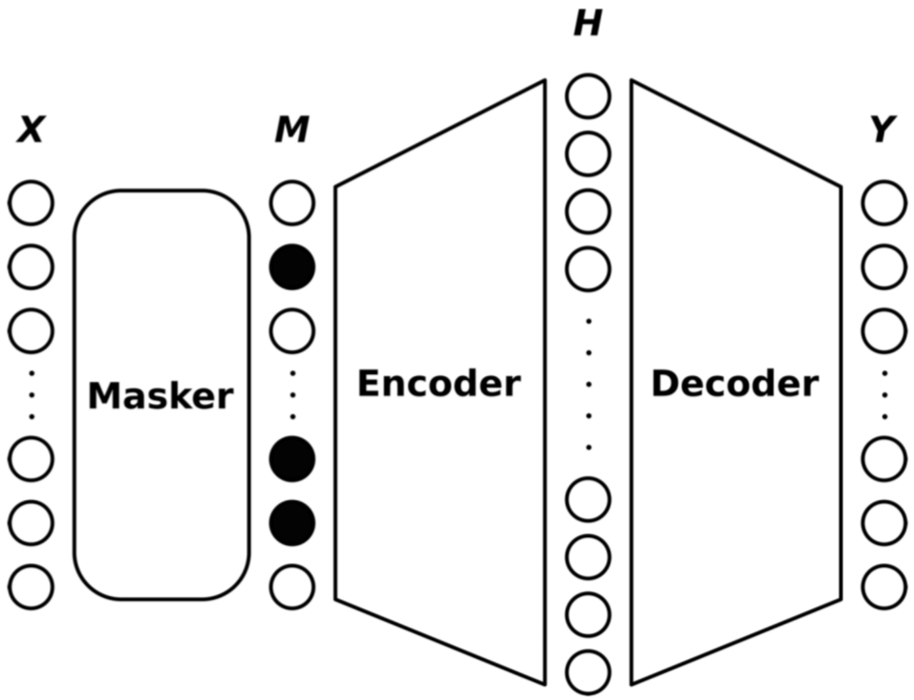
Multiple Imputation with Denoising Autoencoders (MIDA)

- The MIDA architecture[1] **imputes** missing values.
- Based on a **denoising** autoencoder.
- MIDA masker **not suitable** for our problem.



Our Approach:
Modify the masker to imitate the pattern of a failing sensor.

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[1] Gondara, L., & Wang, K. (2018, June). Mida: Multiple imputation using denoising autoencoders. In *Pacific-Asia conference on knowledge discovery and data mining* (pp. 260-272). Springer, Cham.

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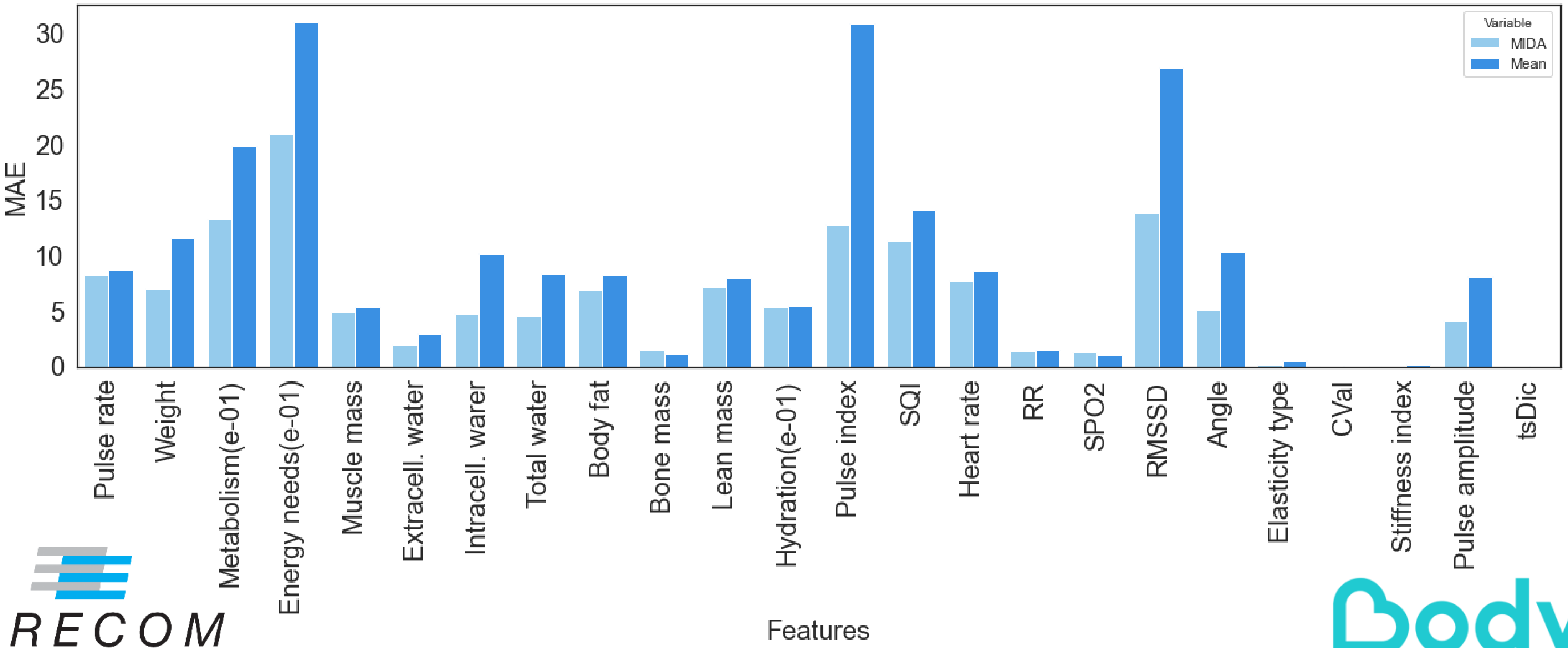
Evaluation : feature reconstruction error

Average Mida MAE = 15.893

Mean MAE = 40.249



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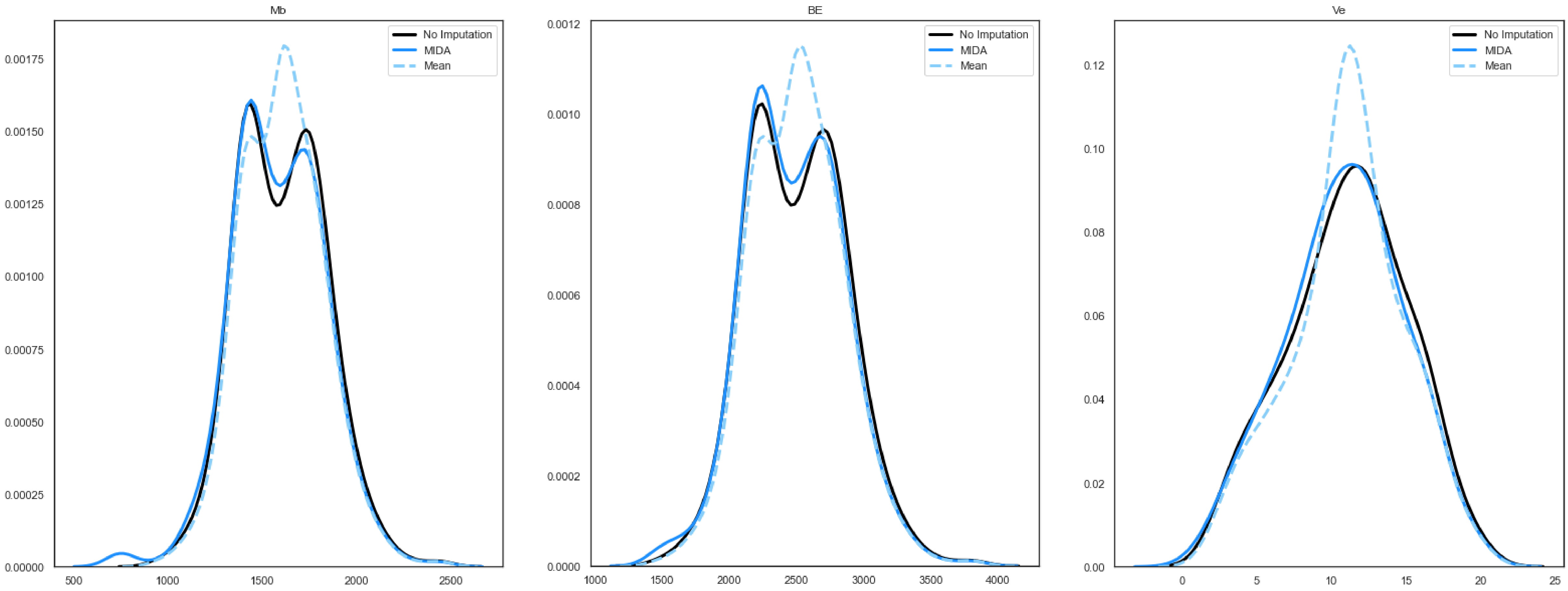
Evaluation : feature distribution



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Evaluation : blood pressure classification

- Dataset: **329 samples** with **24 features.**
- Data from at least one of the sensors is missing for **48 samples.**
- **Use case:** assess if imputation improves the binary classification of BP categories according to 2 categories.

	Accuracy	F1-score	Precision	Sensitivity
None	0.67	0.65	0.62	0.69
Mean	0.64	0.67	0.59	**0.77**
Our method	**0.71**	**0.71**	**0.65**	**0.77**

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Limitations of imputation

- There may be additional information, not collected by the sensors.
- In our dataset, only **105 samples** (out of 329) have no missing values.
- Imputation of poorly represented information can introduce **significant biases** in the learning process.

Set approach to learn with missing values

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Set models

- Most classical machine learning models require **fixed-dimensional** inputs.
- **Sets** allow to overcome this limitation.
- Good **alternative** to learn with missing values.

Set models

- **Idea:** use **permutation invariant** neural networks.
- **Permutation invariant function:** indifferent to the ordering of its input.

Theorem 1. *A function f operating on a set X having elements in a countable universe, is a valid set function iff there are functions $\varphi : R \to Z$ and $\rho : Z \to R$ such that*

$$f(X) = \rho\Big(\sum_{x \in X} \varphi(x)\Big) \tag{1}$$

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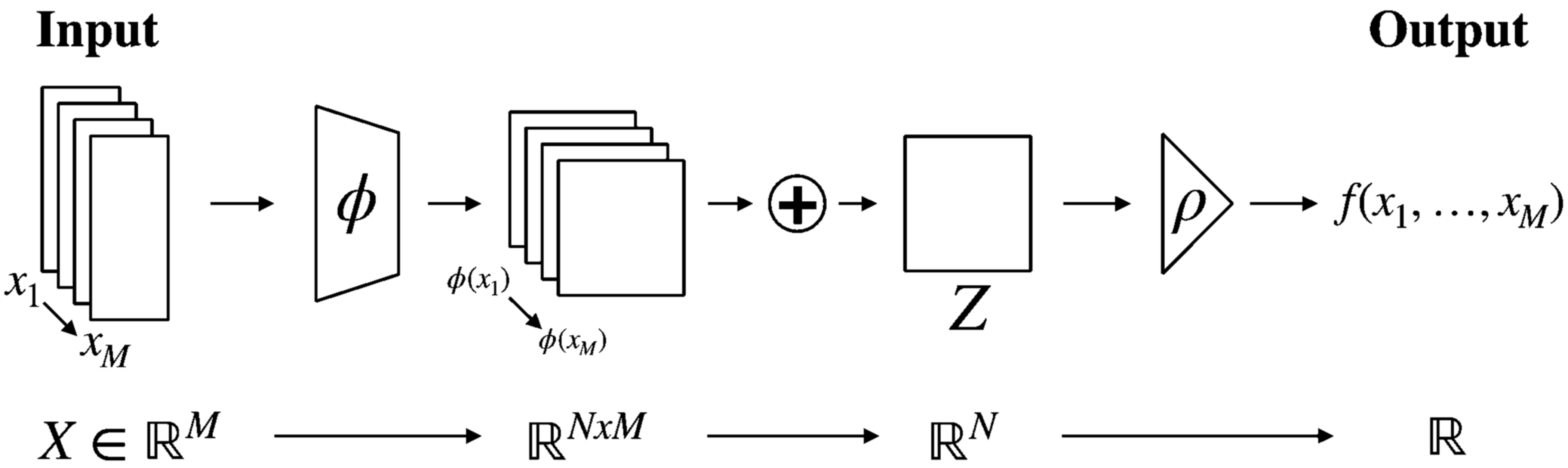
Deep Sets architecture



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[2] Zaheer, M., Kottur, S., Ravanbakhsh, S., Poczos, B., Salakhutdinov, R. R., & Smola, A. J. (2017). Deep sets. *Advances in neural information processing systems*, *30*.

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Our approach

- Each input vector X_i is **encoded as a set** of permutation invariant observations x_j.
- Each x_j is represented as a **tuple** (v_j, m_j) such that :

$$X_i := \{(v_1, m_1),\ldots,(v_p, m_p)\}$$

- The whole dataset can then be described as:

$$D := \{(X_1, y_1),\ldots,(X_n, y_n)\}$$

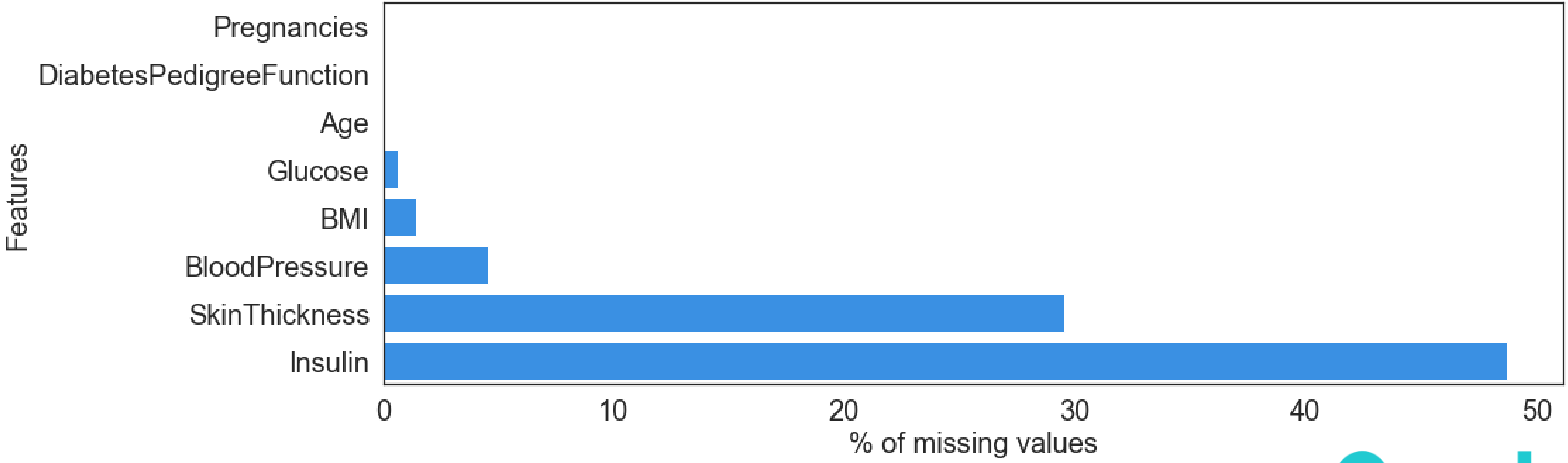
Our Approach:

Allows us to deal with missing values.

Paper in writting.

Evaluation: diabetes classification

- The **Pima Indians Diabetes**[3] database is composed of **768 samples** and **8 features.**
- Up to **374 samples** have missing values across 5 features.



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[3] https://www.kaggle.com/competitions/diabetes-classification/data

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Evaluation : benchmark

- **Benchmark:** Logistic regression, Random Forests and Gradient Boosting.
- Missing values need to be **imputed** first for the benchmark.

	Accuracy	F1-score	Precision	Sensitivity
Mean imp. + LR	0.753	0.61	**0.70**	0.52
Mean imp. + RF	0.772	0.65	0.71	0.59
Mean imp. + GB	0.727	0.59	0.62	0.56
Our method	**0.792**	**0.71**	0.68	**0.74**

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Concluding remarks

- The problem of missing values is a **particularly sensitive** issue in the medical field.
- We proposed two **simple** yet **robust** models that yield good performances.
- Imputation methods should be used **sparingly** to avoid biases in the learning.

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Ongoing work

- Develop a way to compute a **weighted aggregation.**
- Test the method on the **AiPod data.**
- Investigate the **combination** of the two approaches.

Thank you!

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