# Hierarchical Modelling For ALS Prognosis: Predicting The Progression Towards Critical Events

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# AMYOTROPHIC LATERAL SCLEROSIS

- Patients experience progressive loss of motor and cognitive capacities.

- Mechanisms poorly understood, meaning no available cure.

- Prognosis becomes fundamental to improve quality of life in patients.

# ALS PROGNOSIS



- Need for researching new care treatments that prolong survival and improve the quality of ALS patients' life.
- People with ALS have a few interdisciplinary demands.
- They benefit from individualised rehabilitation programs to improve independence, function, and safety.
- Patients with ALS and their family benefit from regular patient follow-up in anticipating and preparing for death

- Task 2: Predicting Time of Impairment
- Goal: Predict when specific impairments will occur (i.e. in the correct time-window).
  - Task2a: NIV (Non-Invasive Ventilation) or (competing event) Death, whichever occurs first;
  - Task2b: PEG (Percutaneous Endoscopic Gastrostomy) or (competing event) Death, whichever occurs first;
  - Task2c: Death.

# DATA PREPROCESSING

- Two different types of visit assessments - ALSFRS and Spirometry

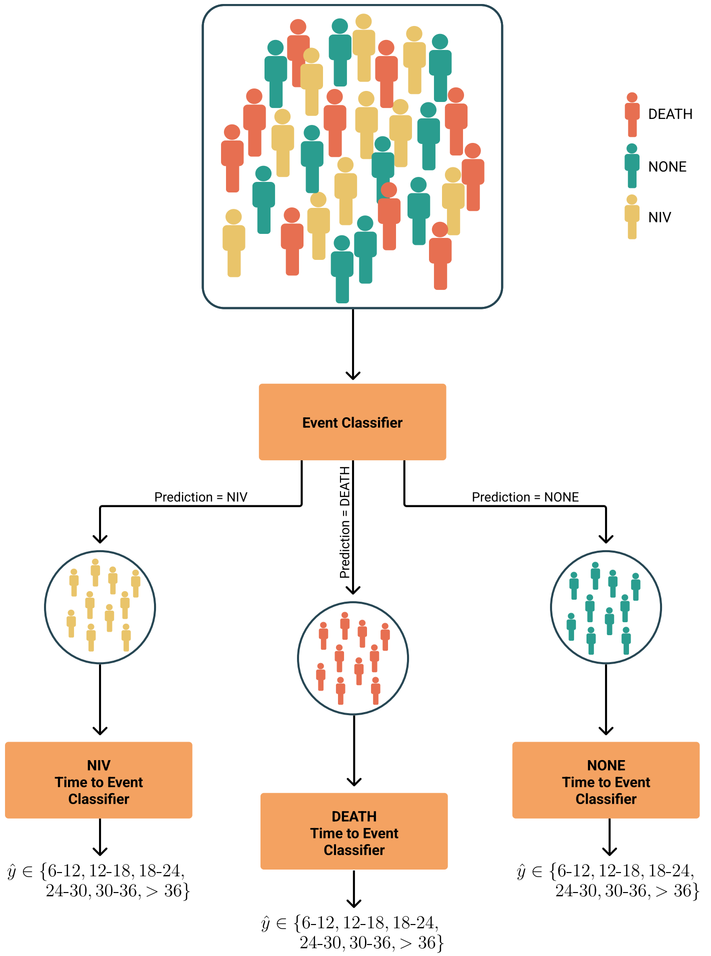
- Temporal data (Visits) were grouped in snapshots following the an aglomerative strategy proposed by Carreiro et al.

- Snapshots only group visits in which patients performed different tests

# HIERARCHICAL PROGNOSIS: OVERVIEW

- Stage I: Predict the **Event**
  - NIV (2a), NONE or DEATH
  - PEG (2b), NONE or DEATH
  - DEATH (2c) or NONE

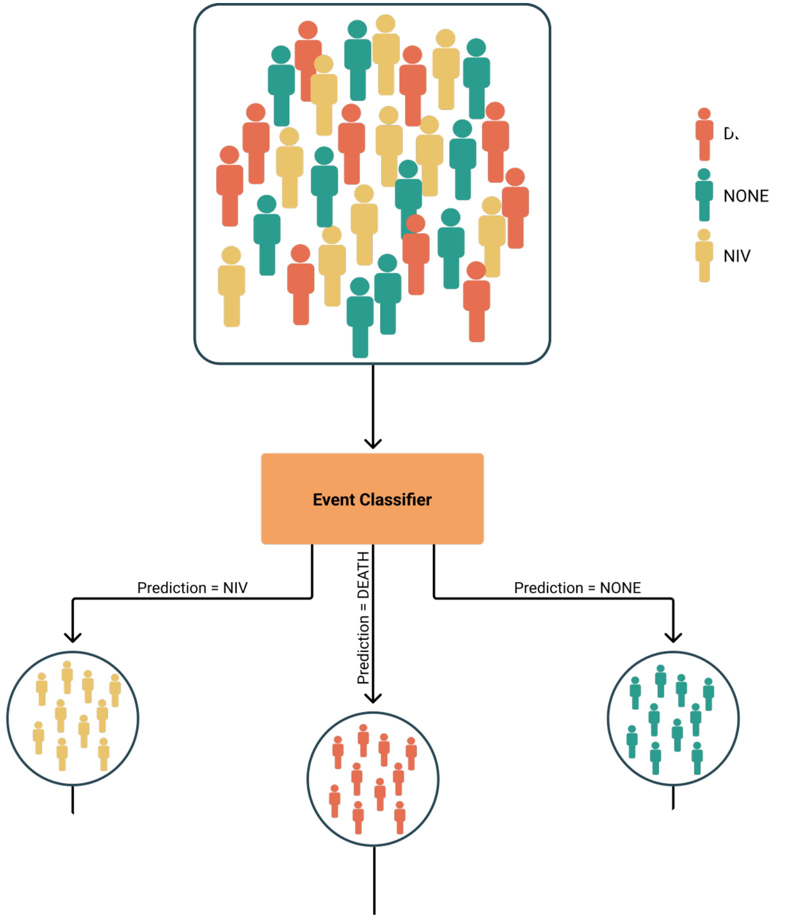
- Stage II: Predict the **Time to event**
  - 6-12 months
  - 12-18 months
  - 18-24 months
  - 24-30 months
  - 30-36 months
  - >36 months



# HIERARCHICAL PROGNOSIS: STAGE I

- Event Classifier

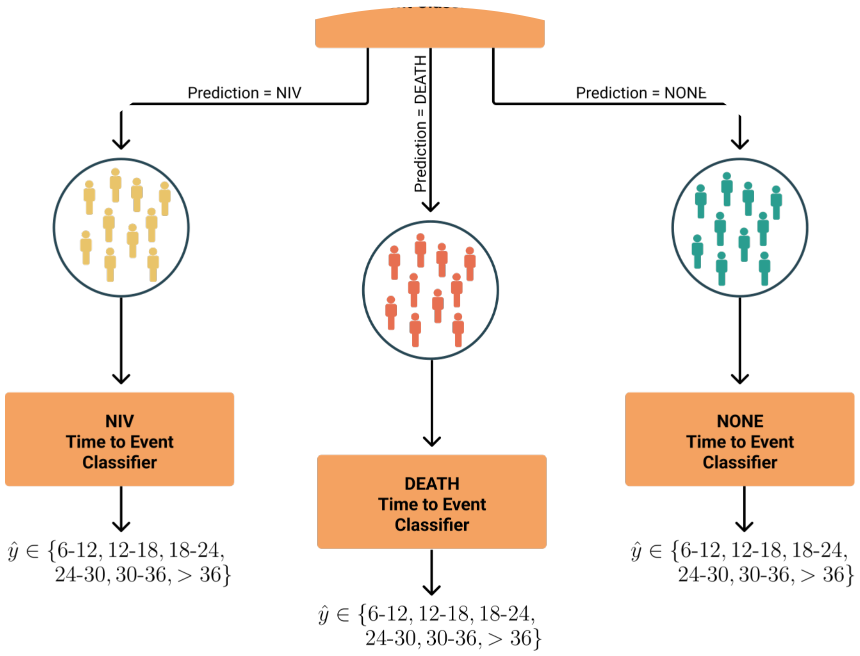
  - Employing pattern mining algorithms and using occurrence of extracted patterns as features
  - Similarity matrices between patient's data and patterns as learning examples



# HIERARCHICAL PROGNOSIS: STAGE II



- Time to event classifier
  - The dataset is split by event type, creating different populations composed of patients with the same event type.
  - For each event type, a classifier is trained to predict, based on the patients' features, one of the possible time windows (in months): 6-12, 12-18, 18-24, 24-30, 30-36, >36
- Output: *(event, time to event) tuple*



# RESULTS PREDICTING THE EVENT

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| Subtask | Data | Macro-Recall | Macro-Specificity |
|---|---|---|---|
| A | M0 | 0.498 | 0.749 |
| A | M0 | **0.513** | **0.757** |
| A | M6 | 0.484 | 0.742 |
| A | M6 | 0.498 | 0.749 |
| A | M6 | 0.500 | 0.750 |
| B | M0 | 0.503 | 0.752 |
| B | M0 | **0.554** | **0.777** |
| B | M6 | 0.502 | 0.751 |
| B | M6 | 0.494 | 0.748 |
| B | M6 | 0.502 | 0.751 |
| C | M0 | **0.904** | **0.968** |
| C | M0 | 0.896 | 0.965 |
| C | M6 | 0.887 | 0.962 |
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| C | M6 | 0.887 | 0.962 |

- Regarding the prediction of the event (regardless of the time window) we could confirm that our method achieved good results, particularly in subtask C, when considering only the first month of data (M0)

- Event can be better distinguished with M0, hinting at the possibility that at the first visit(s) the patients already show clear signs regarding the event to come.

- Static features more important

# RESULTS PREDICTING TIME TO EVENT

data and systems intelligence

| Subtask | Data | Macro-Recall | Macro-Specificity |
|---|---|---|---|
| A | M0 | **0.203** | **0.904** |
| A | M0 | **0.203** | 0.902 |
| A | M6 | 0.202 | 0.902 |
| A | M6 | 0.202 | 0.903 |
| A | M6 | 0.202 | 0.902 |
| B | M0 | 0.239 | 0.889 |
| B | M0 | 0.239 | 0.889 |
| B | M6 | **0.245** | 0.895 |
| B | M6 | 0.244 | **0.896** |
| B | M6 | 0.234 | 0.886 |
| C | M0 | 0.405 | 0.852 |
| C | M0 | 0.404 | 0.850 |
| C | M6 | 0.412 | 0.857 |
| C | M6 | **0.413** | 0.858 |
| C | M6 | 0.412 | **0.860** |

- Concerning the time to event prediction, as expected by the F1 scores obtained with the trained data (see Table 2), the recall value was low. These values were somewhat expected given the high number of classes considered (16 classes, resulting from the product between events and time windows).

- M6 was overall better (temporality matters, obviously.

- Further analysis: performance worsens as the time window to predict is larger in terms of months. This could be due to data imbalance and/or patterns are more evident the shorter the time window is.

# TAKE-AWAYS

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- The use of snapshots allows for a consistent description of patients conditions.
- Pattern mining techniques for event prediction, allowed to use the entire patient medical history into consideration. Additionally, the patterns itself, used for classification, have a interpretability advantage, which is of particular importance in healthcare.
- The hierarchical nature of our classification approach allowed for reducing class imbalance within event data subsets and less heterogeneity across the patient population improving predictions for the less frequent (event, time window) pairs.



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# THANK YOU!



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