CLEF 2022

Notebook for the iDPP Lab on Intelligent Disease Progression Prediction

Baseline Machine Learning Approaches to Predict Amyotrophic Lateral Sclerosis Disease Progression

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iDPP@CLEF 2022 – Aims and methods

Task 1
Rank subjects based on the risk of early occurrence of clinical events for ALS

Task 2
Predict time of occurrence of clinical events for ALS

SURVIVAL ANALYSIS
(model time-to-event directly)

- Cox proportional-hazards model (Cox)
- Survival Support Vector Machines (SSVM)
- Random Survival Forest (RSF)

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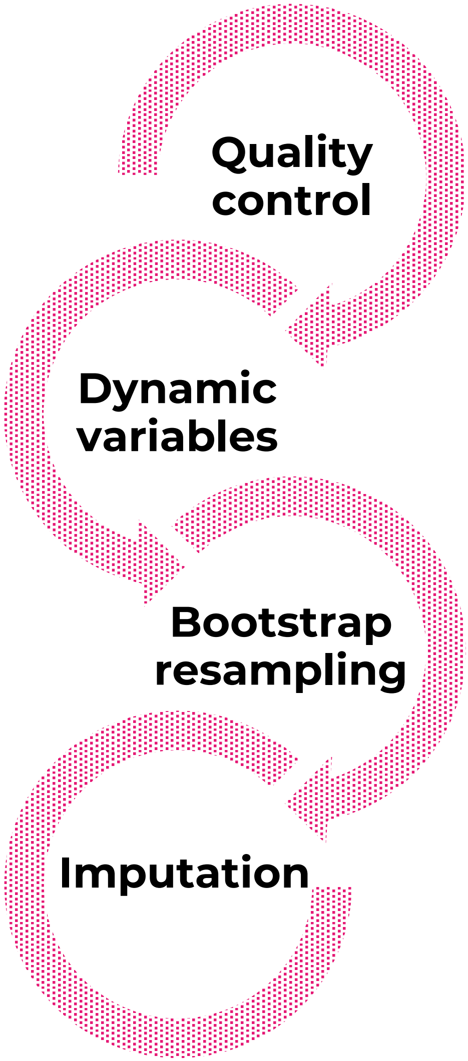
Preprocessing



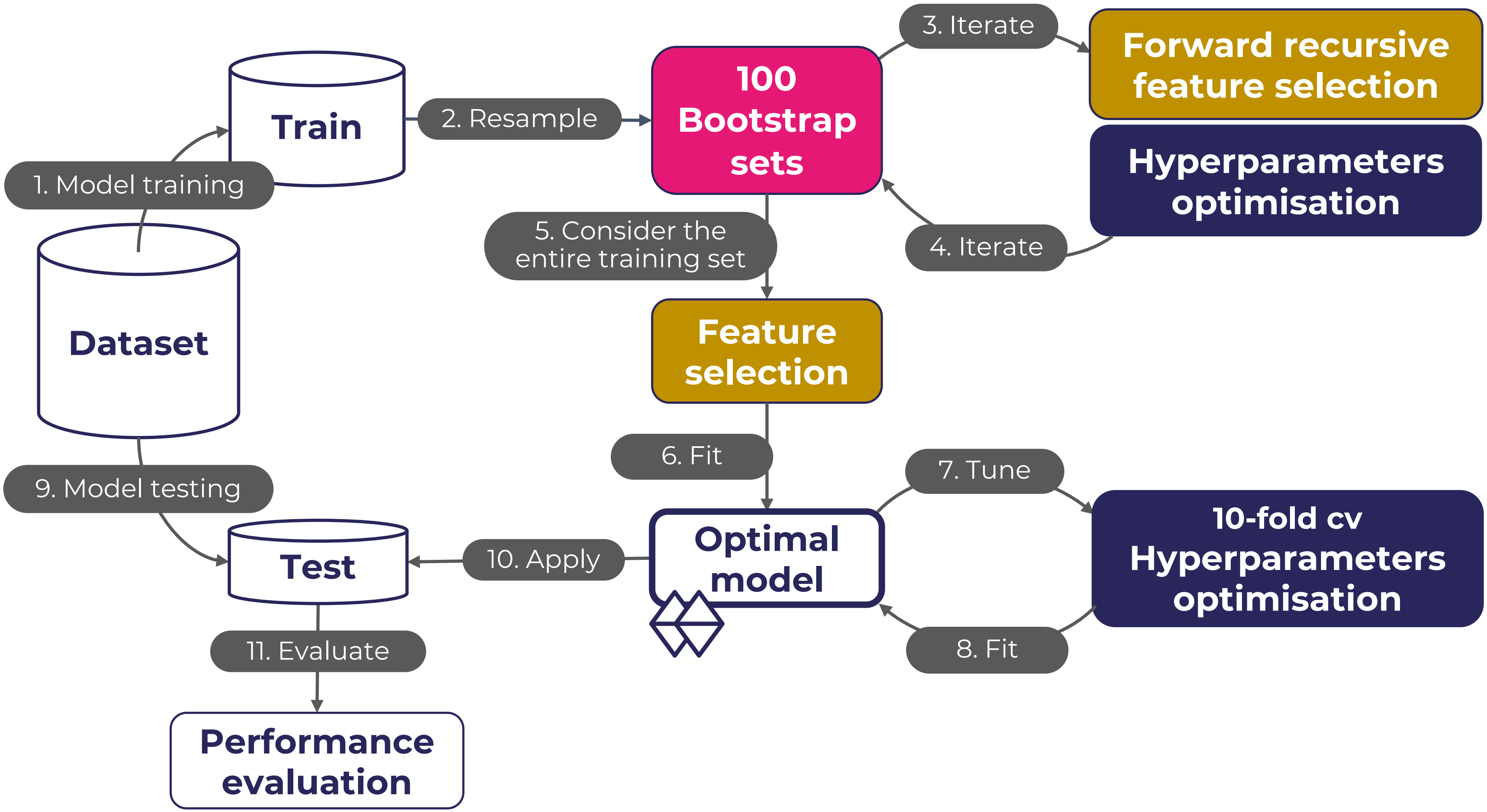
- ▷ No subject with more than 20% missing
- ▷ One subject was removed, positive onset date

- ▷ Considered as slopes to capture the variations over time

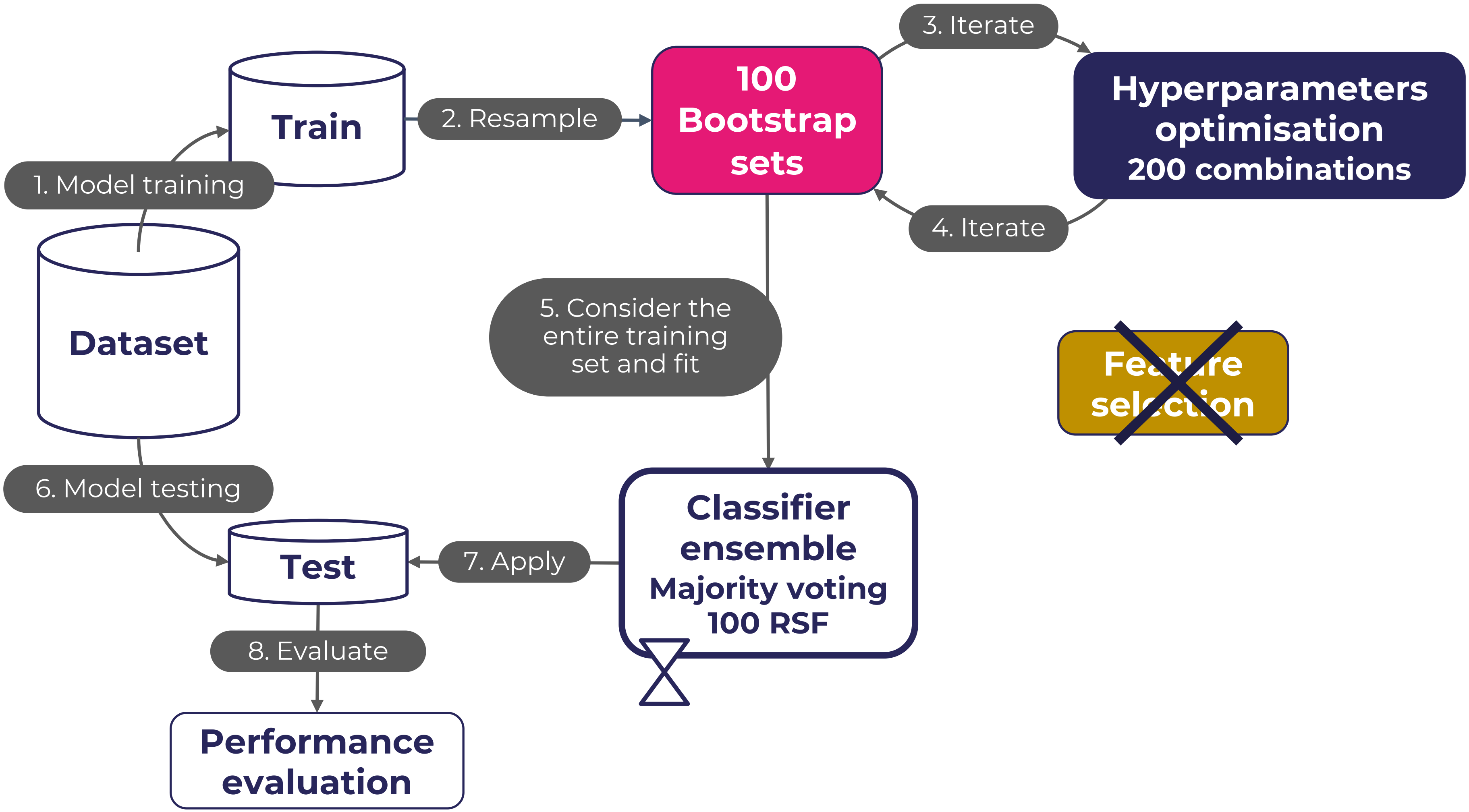
- ▷ Hyperparameters tuning and feature selection
- ▷ 100 sets: internal training set + validation set

- ▷ All variables with more than 70% missing removed
- ▷ 4 variables needed imputation: FVC, instruction level, BMI, weight slope

Cox and SSVM pipeline



RSF pipeline



Model outcome

Cox proportional-hazards model

Survival Support Vector Machines

Random Survival Forest

Model outcome (1 of 2)

Cox proportional-hazards model

- **Model outcome: risk scores**

Survival Support Vector Machines

Random Survival Forest

- **Model outcome: risk scores**

Model outcome (2 of 2)

Cox proportional-hazards model

- Model outcome: risk scores

Survival Support Vector Machines

- **Model outcome: time to event**

Random Survival Forest

- Model outcome: risk scores

Task 1 – Risk prediction

Cox proportional-hazards model

- Model outcome: risk scores

Survival Support Vector Machines

- Model outcome: time to event

Random Survival Forest

- Model outcome: risk scores

Task 1 – Risk prediction

Cox proportional-hazards model

- Model outcome: risk scores
- **Task 1: straightforward from the model**

Survival Support Vector Machines

- Model outcome: time to event

Random Survival Forest

- Model outcome: risk scores
- **Task 1: straightforward from the model**

Task 1 – Risk prediction

Cox proportional-hazards model

- Model outcome: risk scores
- Task 1: straightforward from the model

Survival Support Vector Machines

- Model outcome: time to event
- **Task 1: derived via Platt scaling**

Random Survival Forest

- Model outcome: risk scores
- Task 1: straightforward from the model

Task 2 – Time to event prediction

Cox proportional-hazards model

- Model outcome: risk scores
- Task 1: straightforward from the model

Survival Support Vector Machines

- Model outcome: time to event
- Task 1: derived via Platt scaling

Random Survival Forest

- Model outcome: risk scores
- Task 1: straightforward from the model

Task 2 – Time to event prediction

Cox proportional-hazards model

- Model outcome: risk scores
- Task 1: straightforward from the model
- **Task 2: predicted survival = 0.5**

Survival Support Vector Machines

- Model outcome: time to event
- Task 1: derived via Platt scaling

Random Survival Forest

- Model outcome: risk scores
- Task 1: straightforward from the model
- **Task 2: predicted survival = 0.5**

Task 2 – Time to event prediction

Cox proportional-hazards model

- Model outcome: risk scores
- Task 1: straightforward from the model
- Task 2: predicted survival = 0.5

Survival Support Vector Machines

- Model outcome: time to event
- Task 1: derived via Platt scaling
- **Task 2: straightforward from the model**

Random Survival Forest

- Model outcome: risk scores
- Task 1: straightforward from the model
- Task 2: predicted survival = 0.5

Results

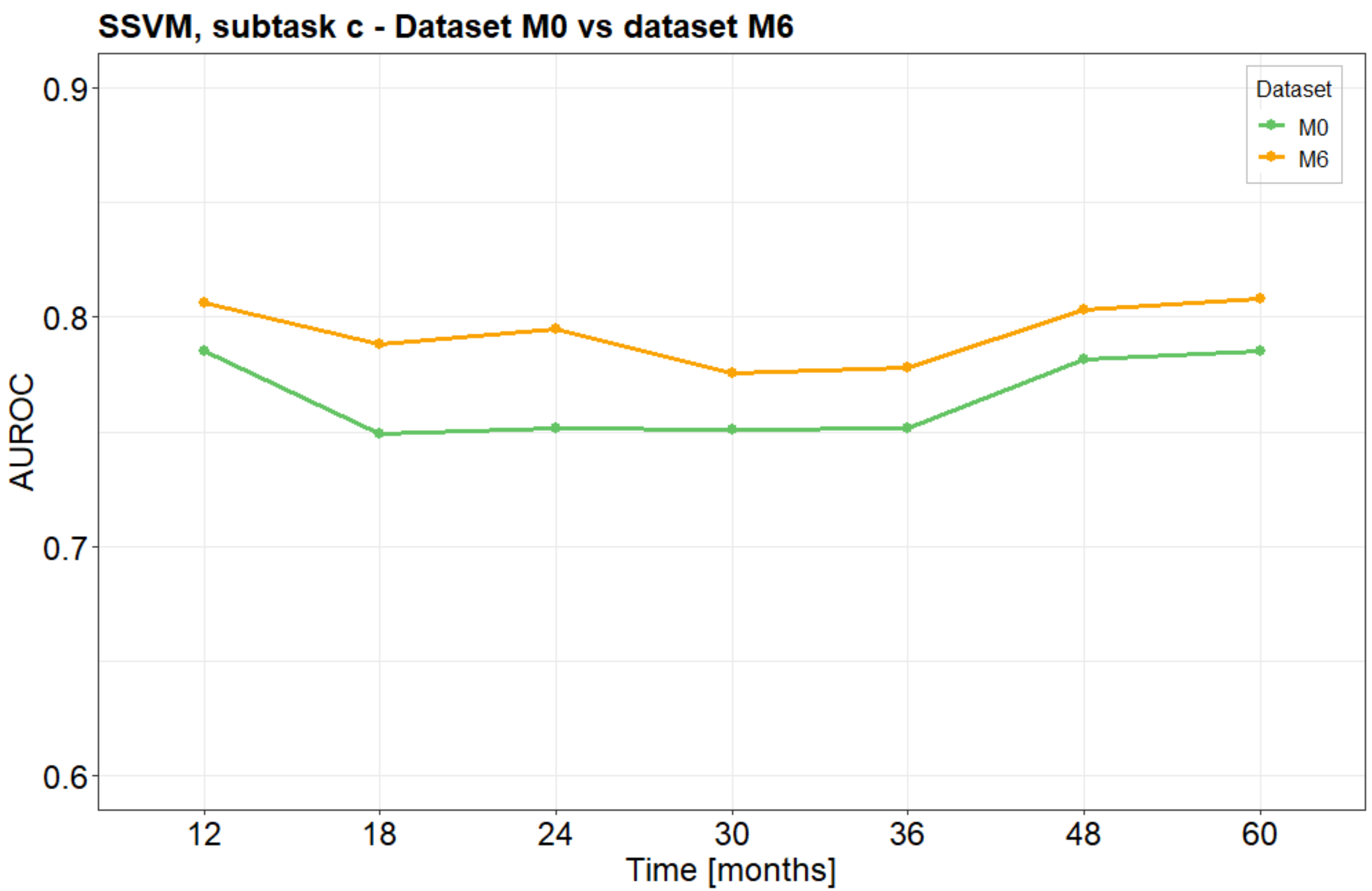
Task 1: submission selection

- For each subtask (a, b, c) and each dataset version (M0 and M6), the two best-performing models according to the average C-index on the 100 bootstrap sets were selected.
- 12 submitted runs for Task 1
  - 3 subtasks
  - 2 dataset versions

	Subtask a: PEG or death		Subtask b: NIV or death		Subtask c: death	
	M0	M6	M0	M6	M0	M6
Cox	0.678 ± 0.009	0.717 ± 0.010	0.684 ± 0.016	0.726 ± 0.015	0.693 ± 0.014	0.726 ± 0.016
SSVM	0.679 ± 0.010	0.715 ± 0.011	0.695 ± 0.013	0.735 ± 0.011	0.698 ± 0.011	0.733 ± 0.012
RSF	0.697 ± 0.020	0.703 ± 0.009	0.690 ± 0.010	0.729 ± 0.008	0.687 ± 0.009	0.722 ± 0.013

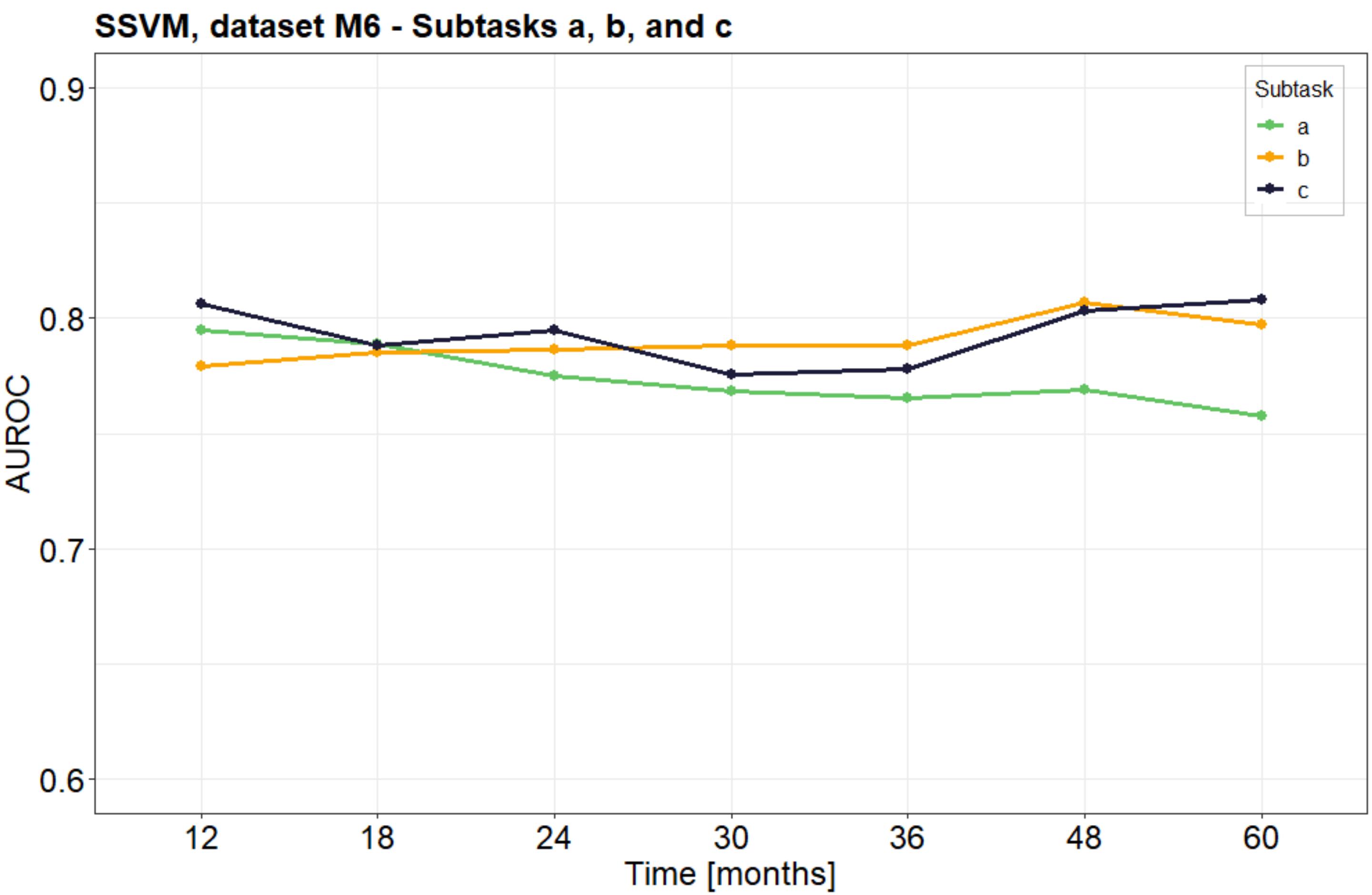
In the table: C-index [mean ± sd]

Model discrimination improves when adding 6 months of data to the baseline (M6 vs. M0)



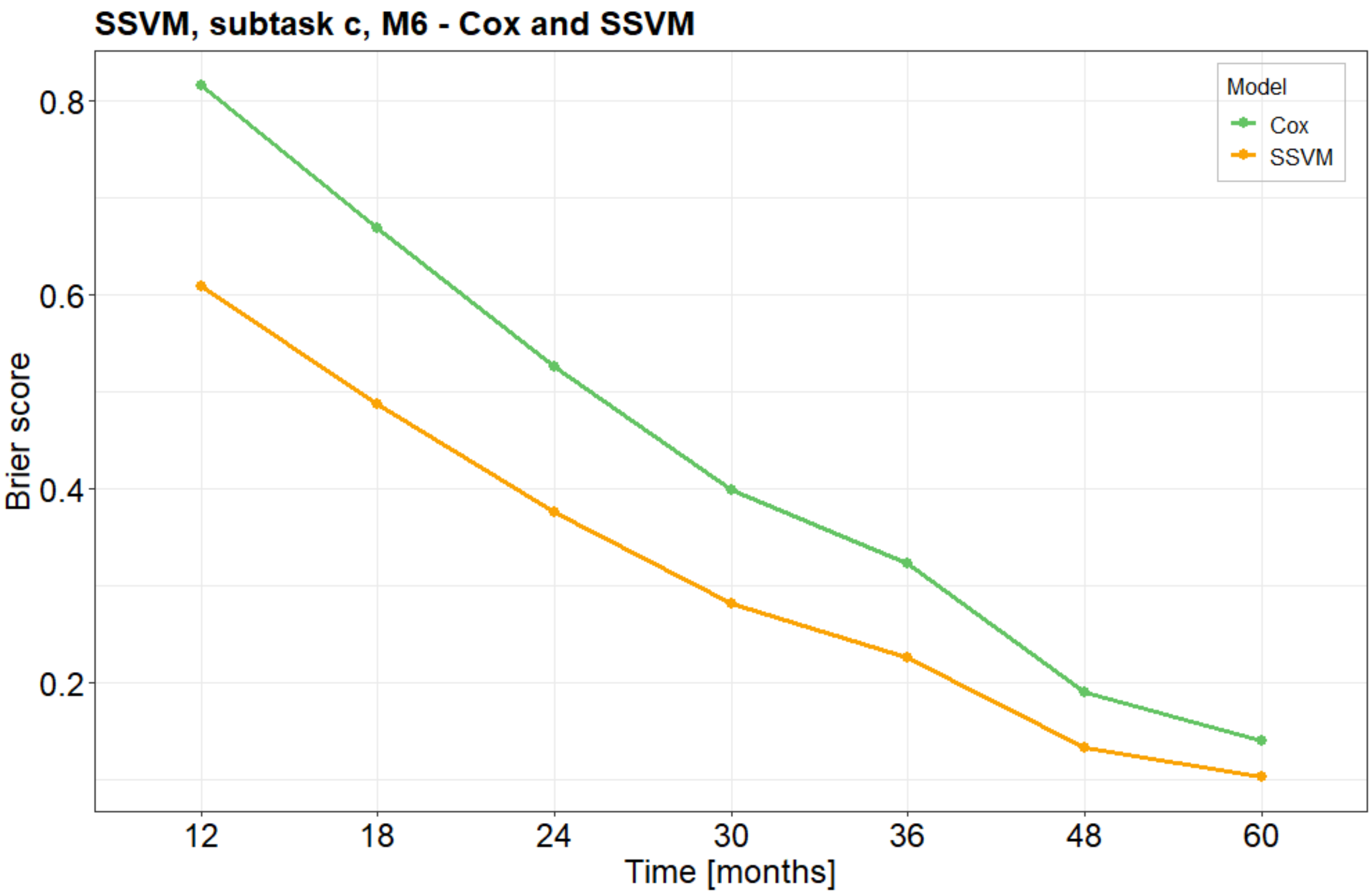
Task 1: results (2 of 3)

Better performance in subtasks b (PEG) and c (death)



Task 1: results (3 of 3)

Better model calibration with longer prediction horizons



Task 2: submission selection

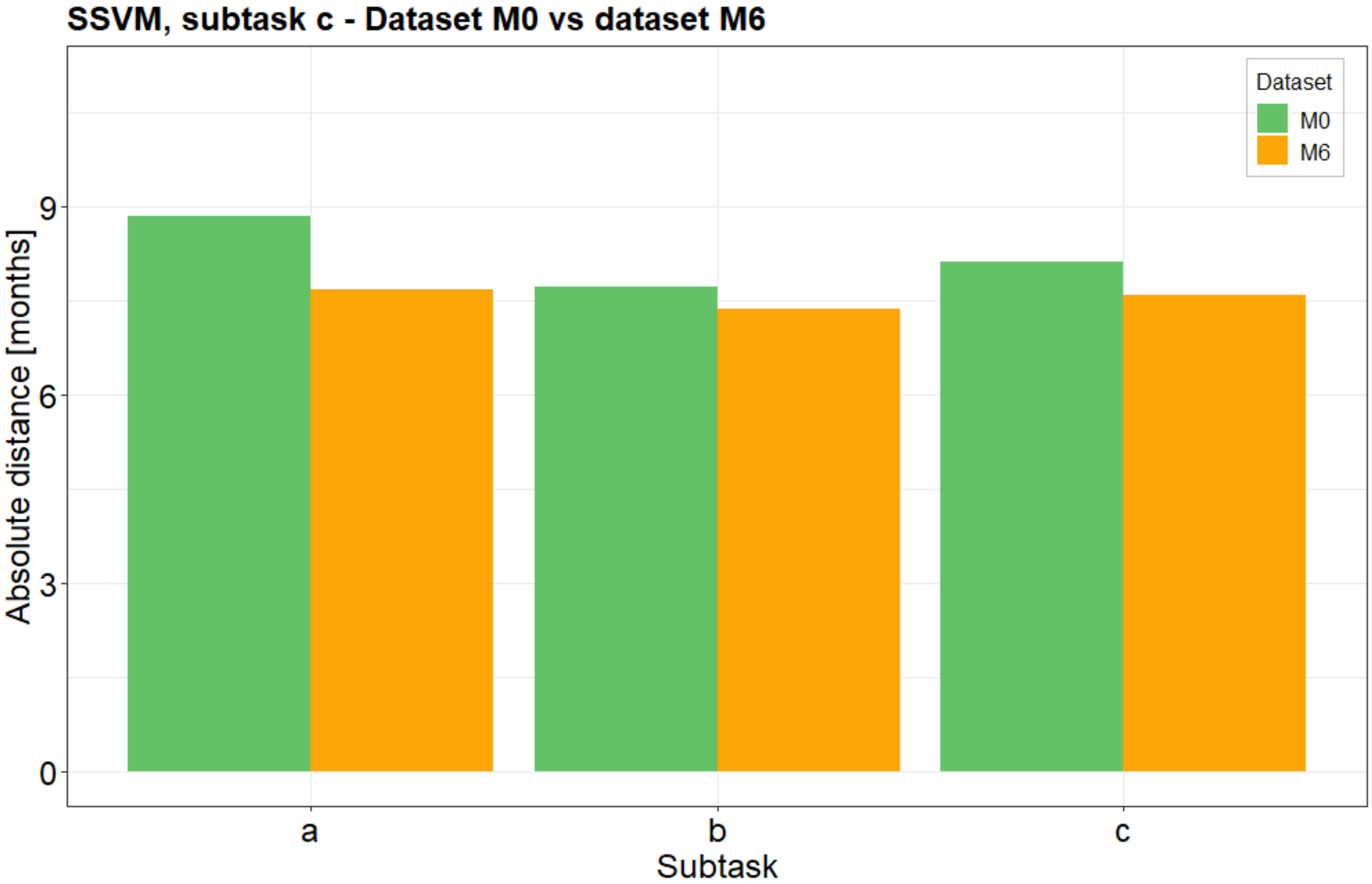
- For each subtask (a, b, c) and each dataset version (M0 and M6), the two best-performing models according to the average C-index on the 100 bootstrap sets were selected.
- 12 submitted runs for Task 2 (same methods as task 1)
  - 3 subtasks
  - 2 dataset versions

	Subtask a: PEG or death		Subtask b: NIV or death		Subtask c: death	
	M0	M6	M0	M6	M0	M6
Cox	--	7.796	--	--	8.187	7.683
SSVM	8.847	7.662	7.714	7.358	8.115	7.582
RSF	8.599	--	7.407	6.857	--	--

In the table: absolute distance [in months]

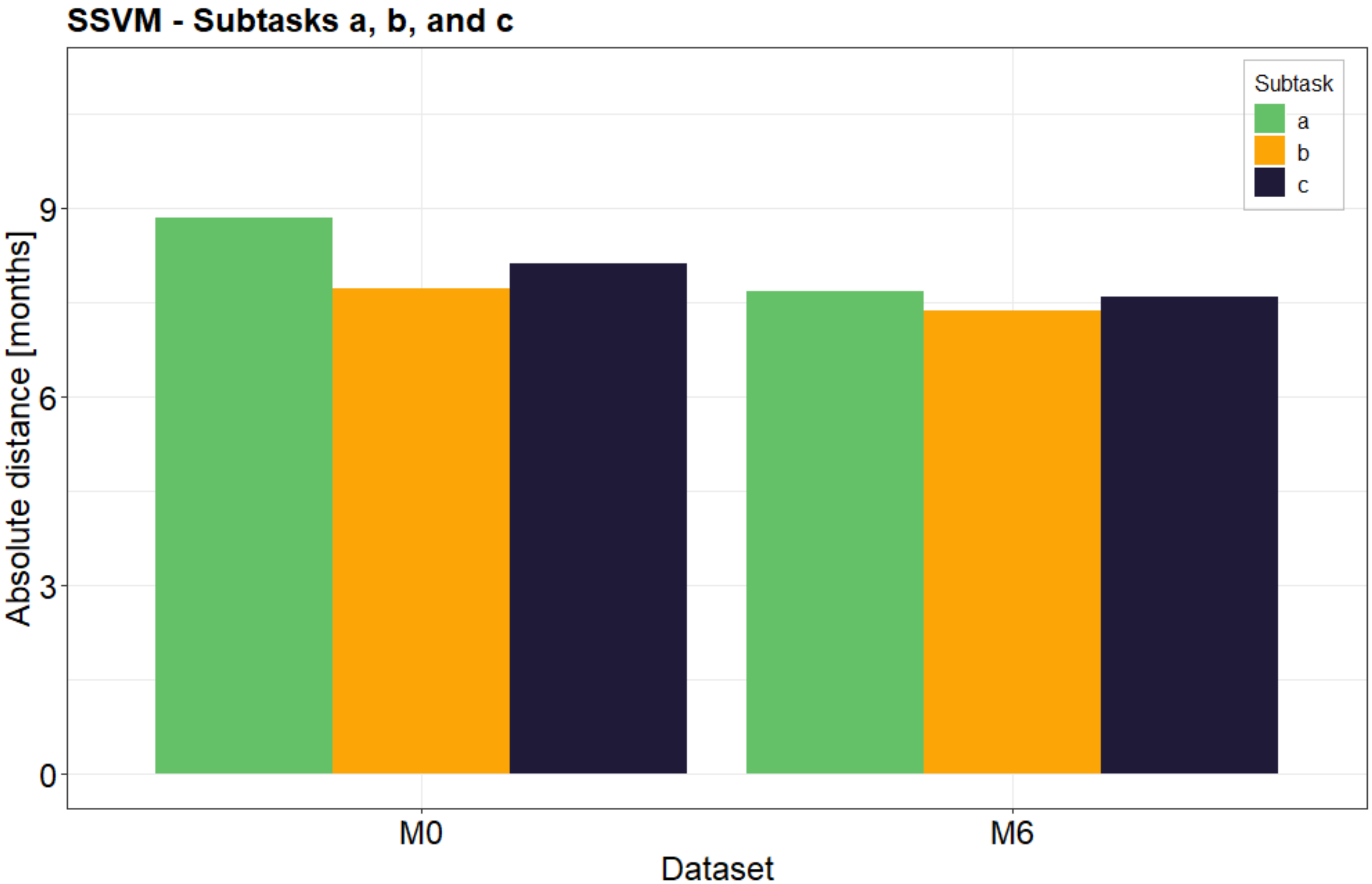
Task 2: results (1 of 3)

Absolute distance between real and predicted times is smaller when adding 6 months of follow-up



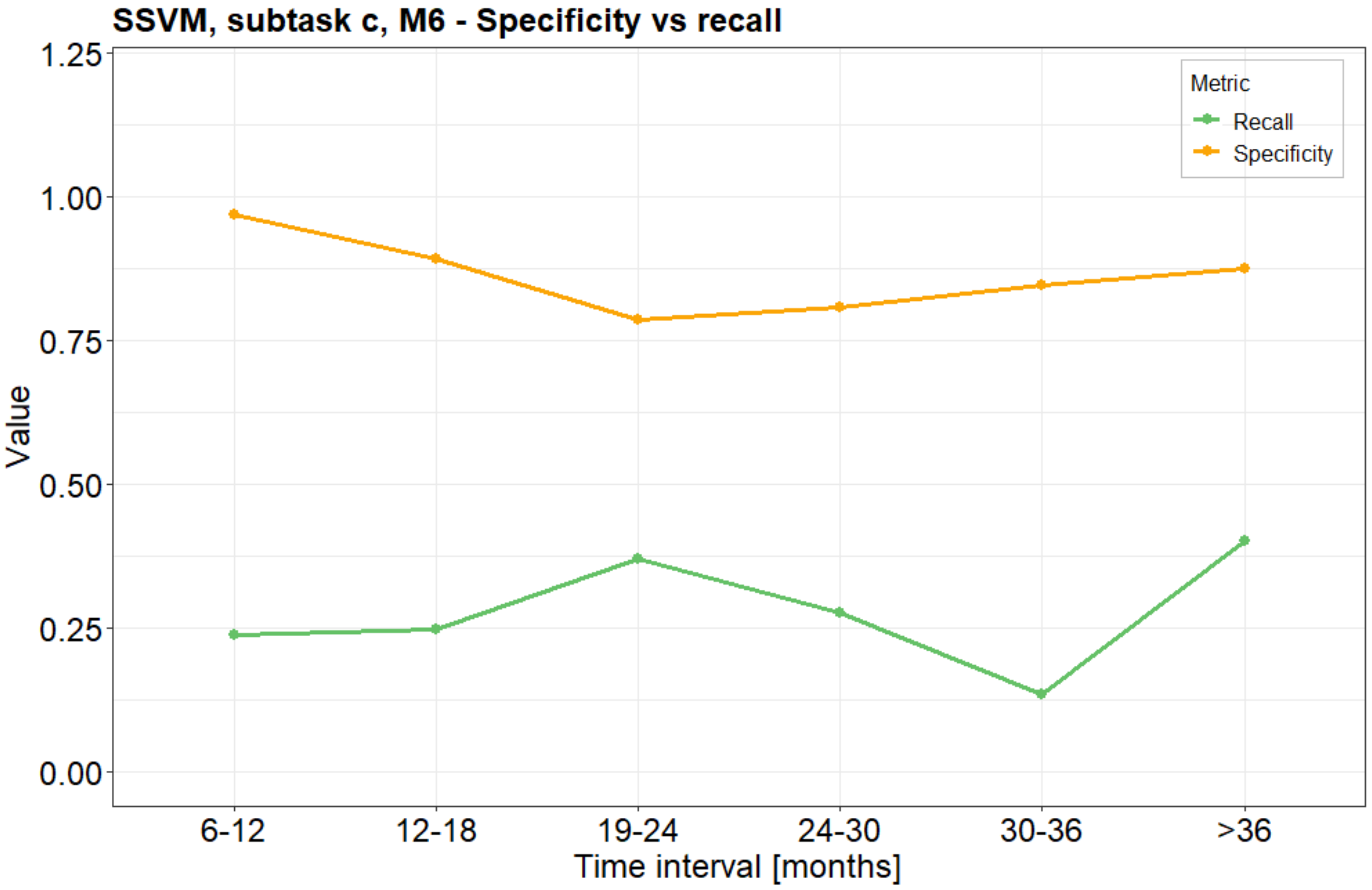
Task 2: results (2 of 3)

Better performance in subtasks b (PEG) and c (death)

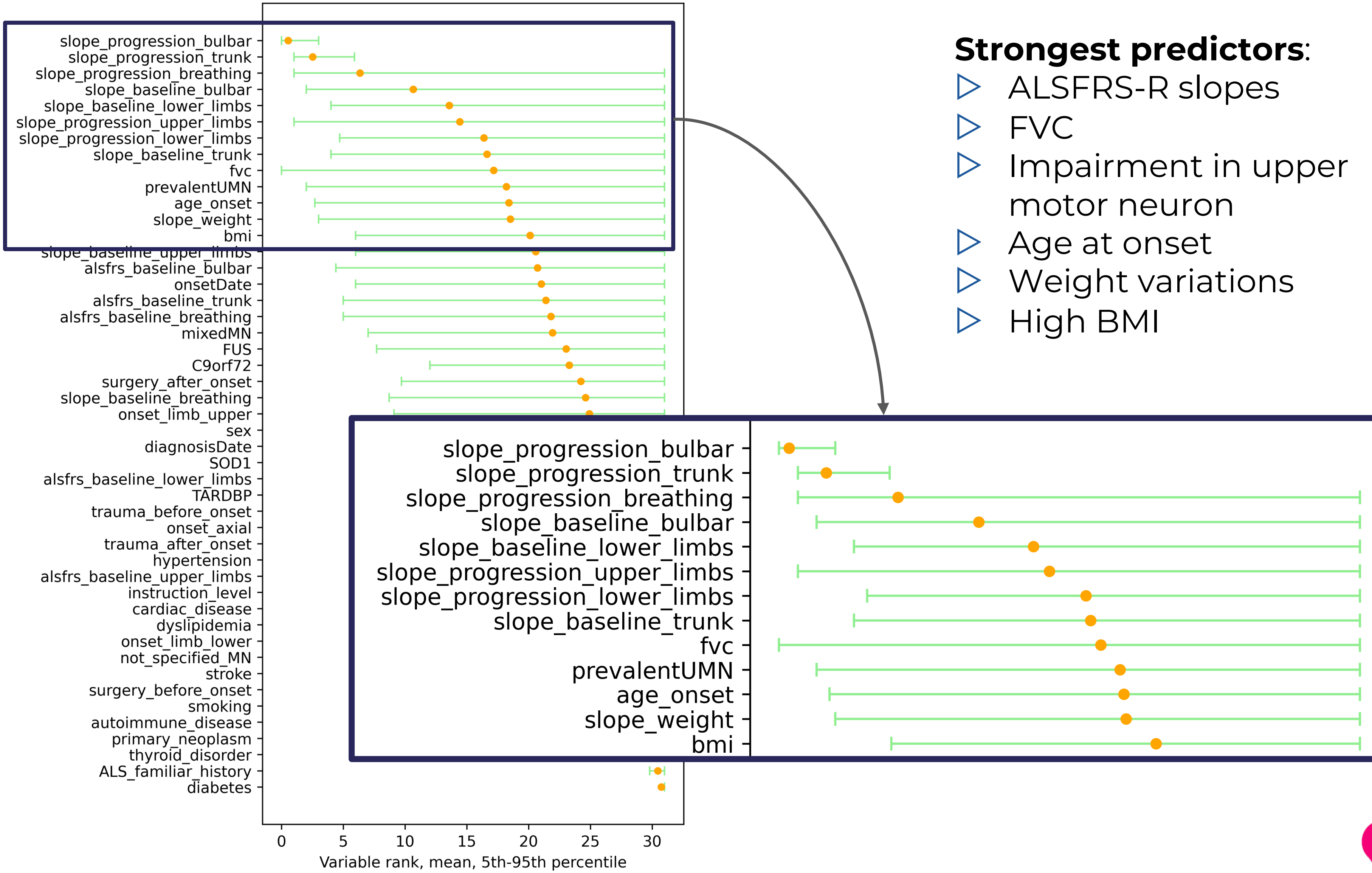


Task 2: results (3 of 3)

High specificity, recall needs to be improved



Variables ranking



Strongest predictors:

- ALSFRS-R slopes
- FVC
- Impairment in upper motor neuron
- Age at onset
- Weight variations
- High BMI

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- For each subtask and model used, performance improved when dynamic features were added as predictors.
- Predicting NIV seems to be more difficult than predicting PEG or death.
- Patient's stratification may lead to more accurate predictions.
- ALSFRS-R slopes, FVC values, and age at onset are among the strongest predictors of ALS clinical events.

Brainteaser

Thank You

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