A Joint Survival-Longitudinal Modelling Approach for the Dynamic Prediction of Rehospitalization in Telemonitored Chronic Heart Failure Patients

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Chronic Heart Failure

- Inability of heart to pump enough for body needs.
- Compensatory mechanisms.
- Problems (decompensation).

Rehospitalization and Telemonitoring

- Rehospitalization rates high.
- Remote monitoring after discharge.
- Predict rehospitalization.

Data

- Chronic heart failure (CHF) study.
- Focus on 80 patients telemonitored for 6 months.
- Daily measurements.

Data Continued

- Diastolic, and Systolic Blood Pressure,
- Heart Rate, and Weight.
- Day when patient rehospitalized.

- Various methods based on cut-offs.
- Predict rehospitalizations using whole history?
- Performance of the predictions?

Step 1:

- Joint model for time-to-rehospitalization and marker.
- Model for hazard, given marker.
- Time-varying covariate.

Challenges

- Longitudinal not at every event time.
- Censoring.
- Longitudinal with error.

Step 2:

- Conditional survival probabilities.
- $\text{Prob}(T_i^* \geq t + \Delta t | T_i^* > t)$ e.g. $t + \Delta t = 20 + 5$
- Equivalently, $\text{Prob}\{T_i^* \epsilon (t, t + \Delta t] | T_i^* > t\}$

Step 2 Continued:

- Confidence intervals for these estimates.
- Additional information for intervention decisions.

Step 3 Continued:

- Quantify predictive performance.
- Based on Area Under ROC curve (AUC) ideas.

Step 3 Continued:

- For given t and given Δt (AUC(t)).
- For range of t's and given Δt (D.D.I.)
- D.D.I. Dynamic discrimination index.

Step 3 Continued:

- Logic:

$$\text{Prob}[\pi_i(t+\Delta t|t) < \pi_j(t+\Delta t|t)|\{T_i^* \in (t, t+\Delta t]\} \cap \{T_j^* > t+\Delta t\}]$$

Model

- Time to first rehospitalization:

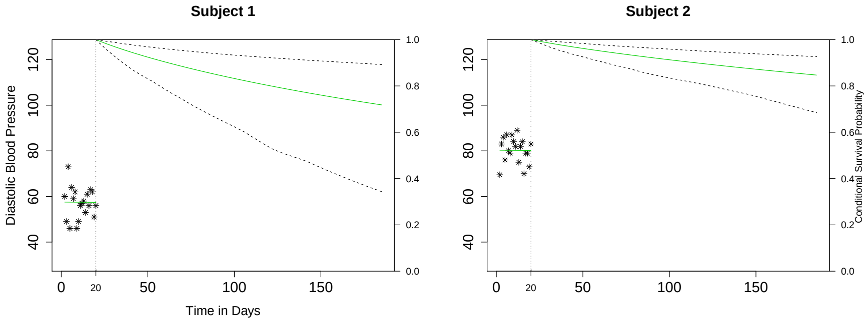
$$h_i(t|\mathcal{M}_i(t), w_i) = \rho\, t^{\rho-1} \exp\{\gamma_0 + \boldsymbol{\gamma}' \boldsymbol{w}_i + \alpha m_i(t)\},$$

- Longitudinal DBP:

$$y_i(t) = m_i(t) + \varepsilon_i(t) = \beta_0 + \beta_1 t + b_{0i} + \varepsilon_i(t),$$

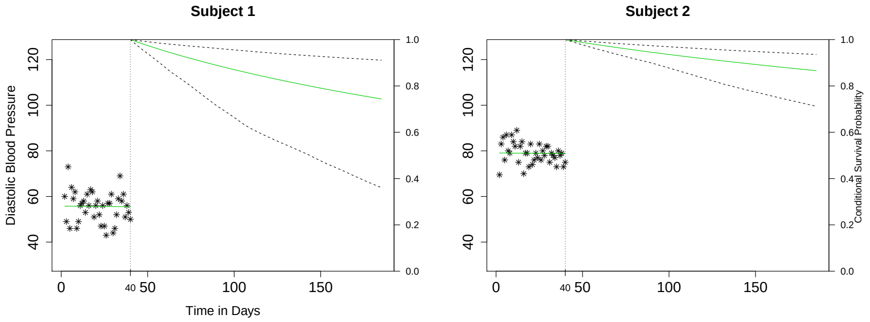
- "Non-informativeness".

Conditional Survival Probabilities, Day 20



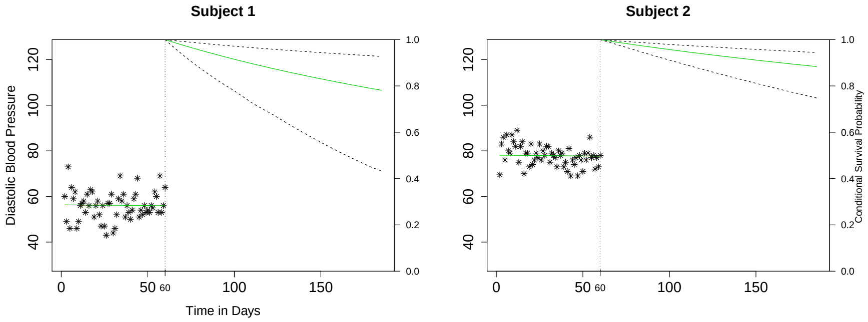
Conditional survival probabilities at each of the remaining time points till study end.

Conditional Survival Probabilities, Day 40



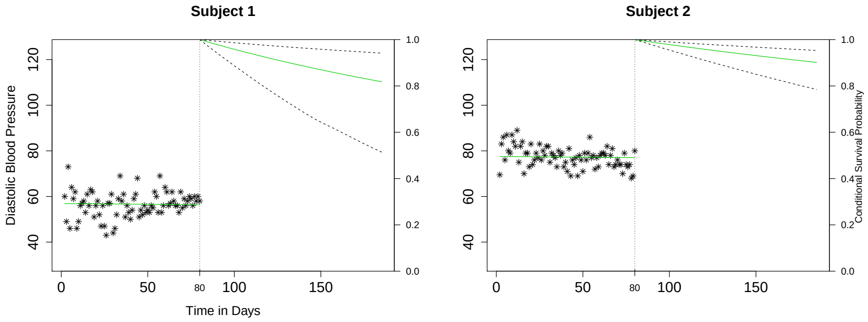
Conditional survival probabilities at each of the remaining time points till study end.

Conditional Survival Probabilities, Day 60



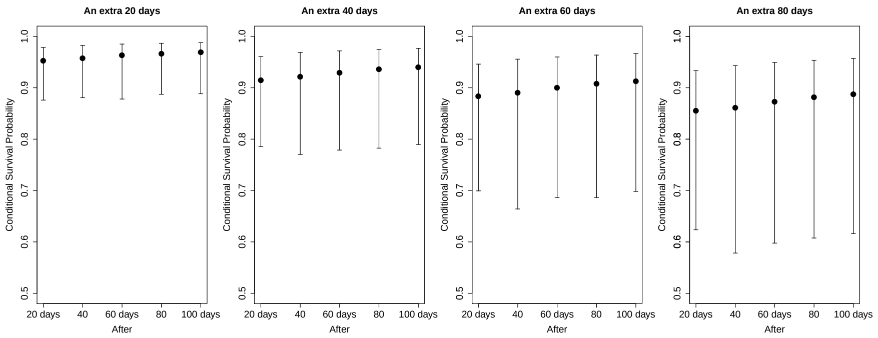
Conditional survival probabilities at each of the remaining time points till study end.

Conditional Survival Probabilitie, Day 80



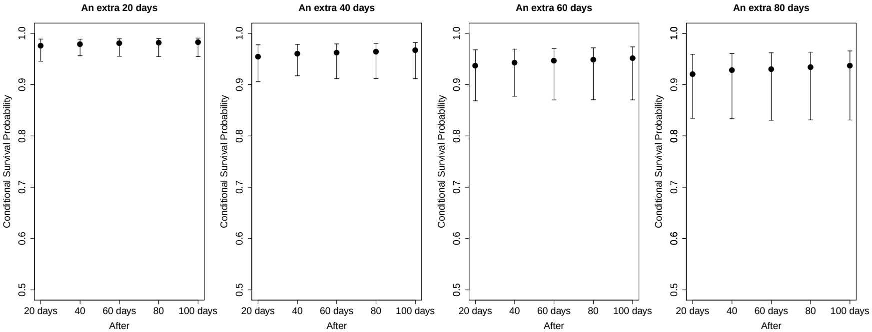
Conditional survival probabilities at each of the remaining time points till study end.

Dynamic Updates of Survival Probabilities



Patient 1: Conditional surv. probs. of an extra 20, 40, 60 and 80 days, with each additional 20 days' measurements.

Dynamic Updates of Survival Probabilities



Patient 2: Conditional surv. probs. of an extra 20, 40, 60 and 80 days, with each additional 20 days' measurements.

Predictive Performance

Δt	t	AUC(t)	DDI
2	14	0.6944	0.4875
	28	0.7429	
	42	0.9552	
	84	0.3770	
	168	0.0862	
4	14	0.6944	0.4949
	28	0.7714	
	42	0.8955	
	84	0.3770	
	168	0.0862	
8			0.5814
16			0.5745

Predictive Performance

Δt	DDI
2	0.6698
4	0.6698
8	0.7433
16	0.6576

- The probabilities and their confidence intervals.
- Additional information to aid intervention decisions.
- Predictive performance quantified.

More Work On:

- All markers simultaneously.
- Recurrent nature of the time-to-hospitalization.
- Consider more parameterizations, e.g. value plus slope.

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Thank you for Your Attention.