

# A weighted random survival forest for constructing controllable models

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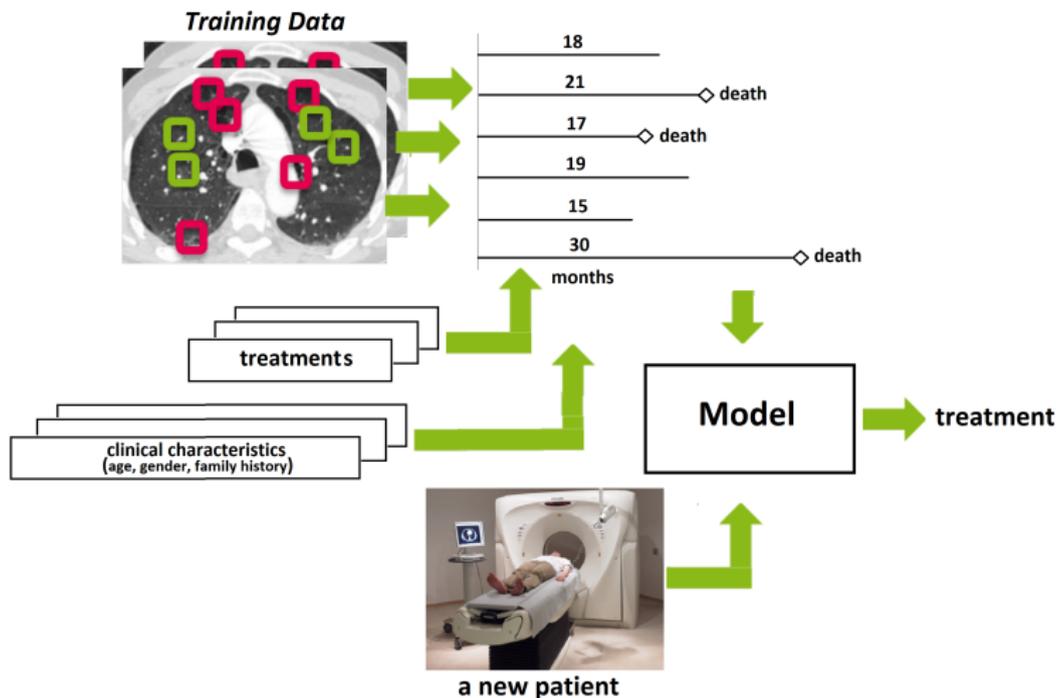


Anna A. Meldo

# Two main stages of the patient diagnostics and treatment

- 1 Cancer detection (computer-aided diagnostic system)
- 2 **Survival analysis and competing risk analysis (medical treatment recommendation system)**

# Survival analysis and competing risk analysis



# Formal problem statement of survival analysis

- A patient  $i$  is represented by a triplet  $(\mathbf{x}_i, \delta_i, T_i)$ ,  
 $\mathbf{x}_i = (x_{i1}, \dots, x_{im})$  are patient characteristics (features);  $T_i$  is time to death
- $\delta_i = 1$ , if death is observed (uncensored observation)
- $\delta_i = 0$ , if death is not observed (censored observation)
- Training set  $D$  consists of  $n$  triplets  $(\mathbf{x}_i, \delta_i, T_i)$ ,  $i = 1, \dots, n$ .
- **The goal** is to estimate the time to the death  $T$  for a new patient with  $\mathbf{x}$  by using  $D$

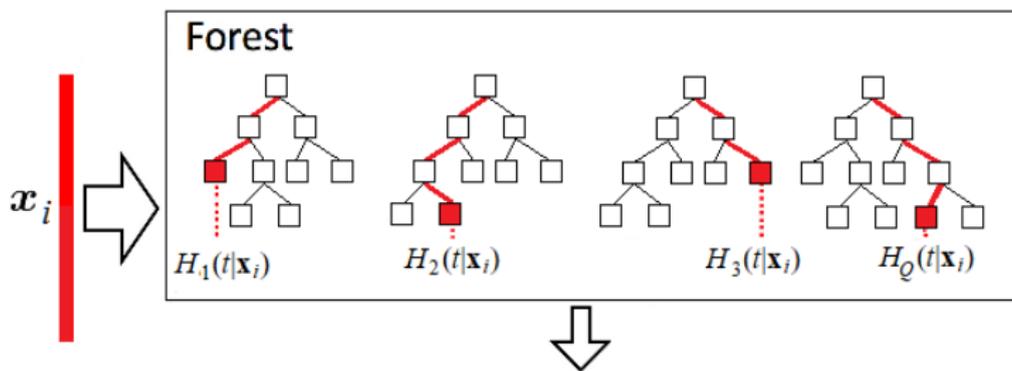
# Difficulties of solving the survival analysis problem

- 1 there are a few training data
- 2 data may be censored
- 3 data may be heterogeneous
- 4 every patient in the training set is under a single treatment (this is a fundamental problem)

# Available survival models (pros and cons)

- The Kaplan-Meier model (requires a homogeneous dataset)
- The Cox proportional hazards model (covariates and time to death are linearly dependent)
- Modifications of the Cox model (Lasso, ridge, elastic net)
- A simple neural network as a basis for a non-linear proportional hazards model
- The SVM approach to survival analysis
- **Survival trees and the survival random forests**
- Deep neural networks (large amount of data)

# Random survival forests (RSF)



$$H_f(t|\mathbf{x}_i) = \frac{1}{Q} \sum_{q=1}^Q H_q(t|\mathbf{x}_i)$$

$$S_q(t|\mathbf{x}_i) = \exp(-H_q(t|\mathbf{x}_i))$$

# Cumulative hazard function (CHF)

- Let  $\{t_{j,k}\}$  be the  $N(k)$  distinct death times in terminal node  $k$  of the  $q$ -th tree such that  $t_{1,k} < t_{2,k} < \dots < t_{N(k),k}$
- Let  $Z_{j,k}$  and  $Y_{j,k}$  equal the number of deaths and patients at risk at time  $t_{j,k}$ .
- The CHF estimate for node  $k$  is defined as (the Nelson–Aalen estimator):

$$H_k(t) = \sum_{t_{j,k} \leq t} Z_{j,k} / Y_{j,k}$$

# Measure of the model quality

- Harrell's C-index or the concordance measure: agreement between the predicted and the observed survival.
- Two subjects chosen at random, the one that fails first has a worst predicted outcome.
- Estimates how good the model is at ranking survival times
- C-index is calculated as

$$C = \frac{1}{M} \sum_{i:\delta_i=1} \sum_{j:t_i < t_j} \mathbf{1} [S(t_i^* | \mathbf{x}_i) > S(t_j^* | \mathbf{x}_j)] .$$

- $M$  is the number of all admissible pairs

# Pros and cons of random survival forests

## 1 Pros: They

- belong to ensemble models with all their advantages
- have a small number parameters
- outperform other models by a small amount of training data
- simple from the training and testing implementations
- allow solving the feature selection problem

## 2 Cons: They

- cannot compete with the deep neural networks when a dataset is large
- some complex non-linear dependencies of features cannot be modelled

$$H_f(t, \mathbf{w} | \mathbf{x}_i) = \sum_{q=1}^Q H_q(t | \mathbf{x}_i)$$

⇓

$$H_f(t, \mathbf{w} | \mathbf{x}_i) = \sum_{q=1}^Q w_q H_q(t | \mathbf{x}_i), \quad \mathbf{w} \in \Delta_Q$$

- How to find optimal weights  $\mathbf{w}$
- What is the optimality of weights?

# Maximization of the C-index

- Optimization problem:

$$\max_{\mathbf{w} \in \Delta_Q} C(\mathbf{w}) = \max_{\mathbf{w} \in \Delta_Q} \sum_{(i,j) \in J} \mathbf{1} \left[ \sum_{q=1}^Q w_q (H_q(t_j^* | \mathbf{x}_j) - H_q(t_i^* | \mathbf{x}_i)) > 0 \right]$$

- The indicator functions  $\mathbf{1}[\cdot]$  are replaced with the hinge loss function  $l(x) = \max(0, x)$ :

$$\max \left( 0, \sum_{q=1}^Q w_q (H_q(t_i^* | \mathbf{x}_i) - H_q(t_j^* | \mathbf{x}_j)) \right)$$

- and the regularization term is added  $R(\mathbf{w}) = \|\mathbf{w}\|^2$

# Maximization of the C-index (finally)

- The quadratic optimization problem:

$$\min_{\mathbf{w}, \zeta_{ij}} \left\{ \sum_{(i,j) \in J} \zeta_{ij} + \lambda \|\mathbf{w}\|^2 \right\}$$

subject to  $\mathbf{w} \in \Delta_Q$  and

$$\zeta_{ij} \geq \sum_{q=1}^Q w_q (H_q(t_i^* | \mathbf{x}_i) - H_q(t_j^* | \mathbf{x}_j)), \quad \zeta_{ij} \geq 0, \quad \{i, j\} \in J$$

- $\zeta_{ij}$  are the slack variables

## R package “randomForestSRC”

- 1 The Primary Biliary Cirrhosis Dataset (418 patients, 17 features): **RSF** 83.61, **WRSF** 83.72
- 2 Veteran’s Administration Lung Cancer Trial Dataset (137 patients, 7 features): **RSF** 70.05, **WRSF** 70.25
- 3 The Wisconsin Prognostic Breast Cancer Dataset (198 patients, 30 features): **RSF** 76.46, **WRSF** 76.89

# Conclusion

- 1 The proposed WRSF is a way to enhance the survival analysis accuracy as well as to make a more flexible objectives
- 2 The next improvement of the WRSF is to develop a controllable Deep Survival Forest (Zhou and Feng 2017, a multi-level cascade of random forests, ensemble of ensembles)
- 3 It can be carried out by introducing training weights of survival decision trees or by combining every random forest with a neural network of a special type.

# Questions

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