DEEP LEARNING FOR PATIENT-SPECIFIC KIDNEY GRAFT SURVIVAL ANALYSIS

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INTRODUCTIONS

An accurate model of patient-specific kidney graft survival distributions can help to improve shared-decision making in the treatment and care of patients.
It is mainly a prediction of time of the event on how long a patient will survive. The estimated time will predict the situation of patients based on the disease.

PARTS WE UNDERSTAND

- Data are characterized without any assumptions.
- There are two points “Intake” & “Endpoint” defined as the length of two events.
- The system needs mathematical terms & equations to acquire correct prediction.
- They used deep learning method for survival analysis, based on multi-task learning.

PARTS WE UNDERSTAND

- Survival data analysis has three main characteristics:
  (i) it examines the relationships of survival distributions to features;
  (ii) it models the time it takes for events to occur, and
  (iii) the event we want to predict.

- This study used data from the Scientific Registry of Transplant Recipients (SRTR).

- They split the dataset into training (80%) and test (20%) sets in which the percentage of uncensored patients, and the proportion of events occurring per time-step is preserved.

PARTS WE DO NOT UNDERSTAND

- The system works with huge amount of formulas which are very hard to know.
- In this paper they used Deep learning, survival function, hazard function, multi-task learning which are new to us.

PARTS WE DO NOT UNDERSTAND

- mathematical formulas:

Let T be a continuous random variable representing survival time. The survival function S(t) is the probability of a patient surviving longer than t, i.e.,

S(t) = P(T >= t)

The hazard function denoted by (t) is the instant probability that the event occurs knowing that it did not occur before t. We can define (t) as

$$\lambda(t) = \lim_{dt \to 0} \frac{P(t \leq T < t + dt | T \geq t)}{dt}.$$

The survival function can be expressed as a function of the hazard at all durations up to t

$$S(t) = \exp\Big(- \int_0^t \lambda(x)\, \mathrm{d}x \Big).$$

PARTS WE DO NOT UNDERSTAND

- Linear models: Cox proportional hazards model

Some common approaches attempt to model the hazard function using the proportional hazards assumption. Different modelizations of λ have been considered. Among the most well known, the semi-parametric Cox proportional hazards model [1] defines λ at time t for an individual with features $\mathbf{x_i}$ as

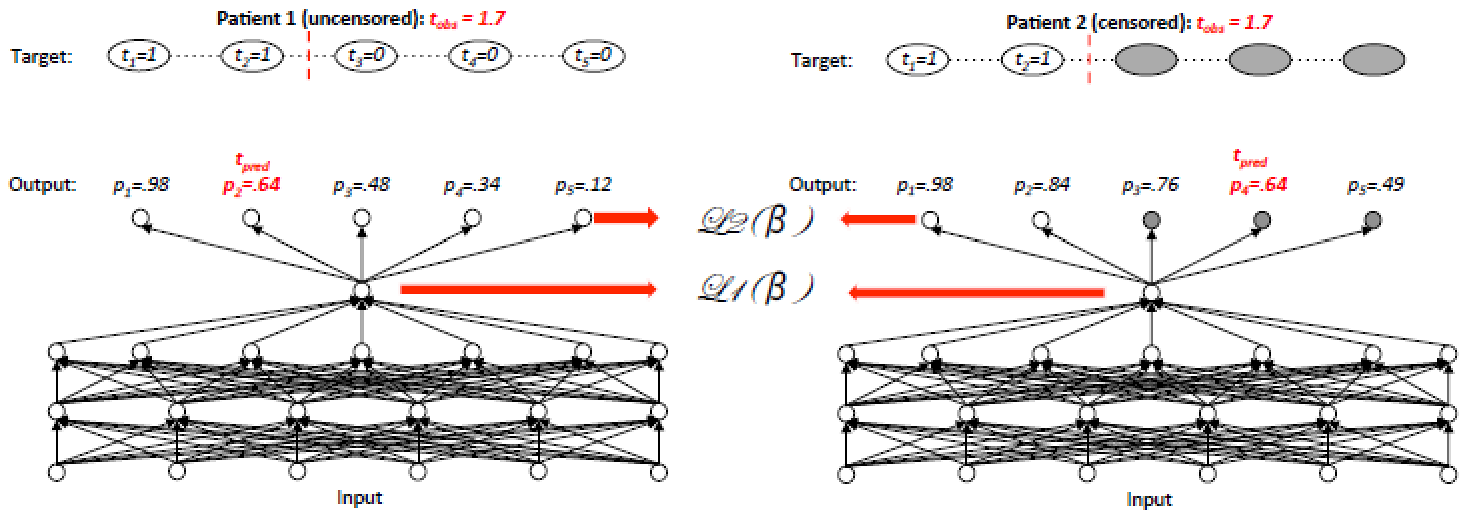
$$\lambda_i(t|\mathbf{x_i}) = \lambda_0(t)\exp(\theta \cdot \mathbf{x_i}).$$

- And Non-linear models

PARTS WE DO NOT UNDERSTAND

- Model:

The proposed model takes as input the different continuous and discrete features characterizing a patient and, in the case of the main dataset of this paper, a donor-recipient couple. The second-to-last layer consists of a single unit with linear activation.

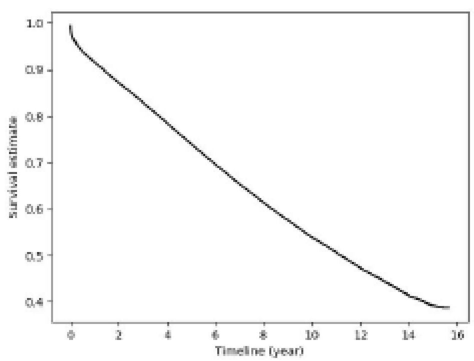


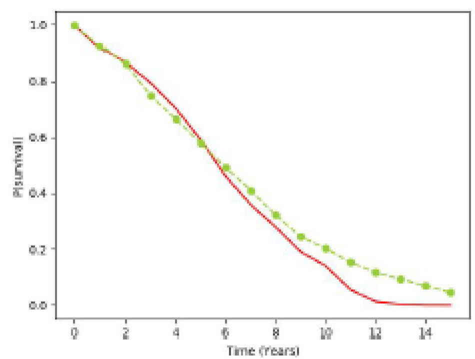
PARTS WE DO NOT UNDERSTAND

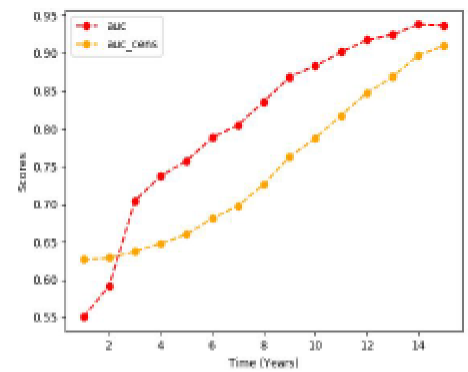
- Hyper-parameters and training
- The concordance statistic or **C-index**

Table 1: C-index obtained for the different models tested.

Datasets	Cox Efron's	MLP Efron's	MLP rank	MLP Efron's + rank
SRTR	0. 6504	0.6535	0.6302	**0.6550**







PARTS WE DO NOT UNDERSTAND

- Variable importance (VIMP)

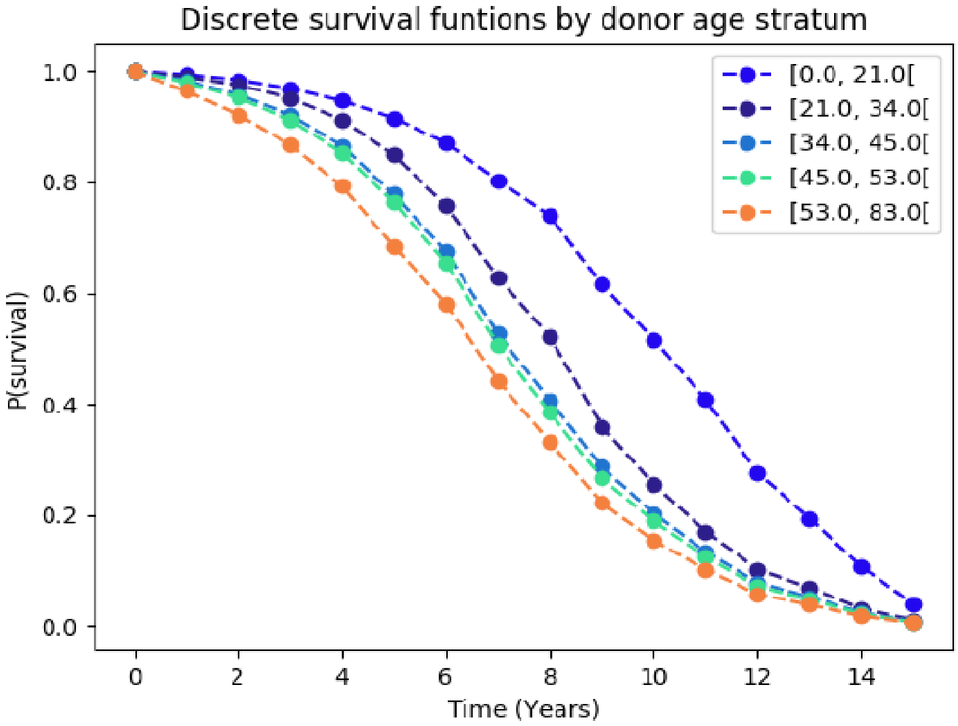


Figure 3: Mean survival rate for different slice of donor age.