DEEP LEARNING FOR PATIENT-SPECIFIC KIDNEY GRAFT SURVIVAL ANALYSIS

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INTRODUCTIONS

In previous presentation we didn't understood deep learning, survival function, hazard function, cox proportional hazard model etc. in this presentation we will discuss details about those topics.

Deep Learning

Deep learning is a class of machine learning algorithms that uses multiple layers to progressively extract higher level features from the raw input. For example, in image processing, lower layers may identify edges, while higher layers may identify the concepts relevant to a human such as digits or letters or faces.

In deep learning, each level learns to transform its input data into a slightly more abstract and composite representation. In an image recognition application, the raw input may be a matrix of pixels; the first representational layer may abstract the pixels and encode edges; the second layer may compose and encode arrangements of edges; the third layer may encode a nose and eyes; and the fourth layer may recognize that the image contains a face.

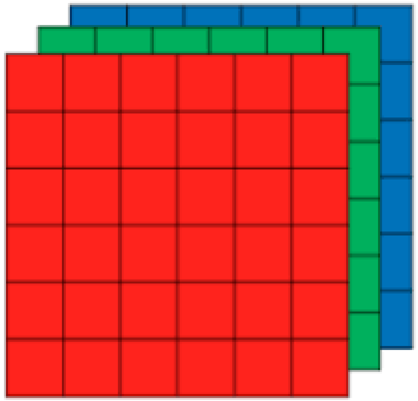


Figure: Matrix of Pixels

Deep Learning

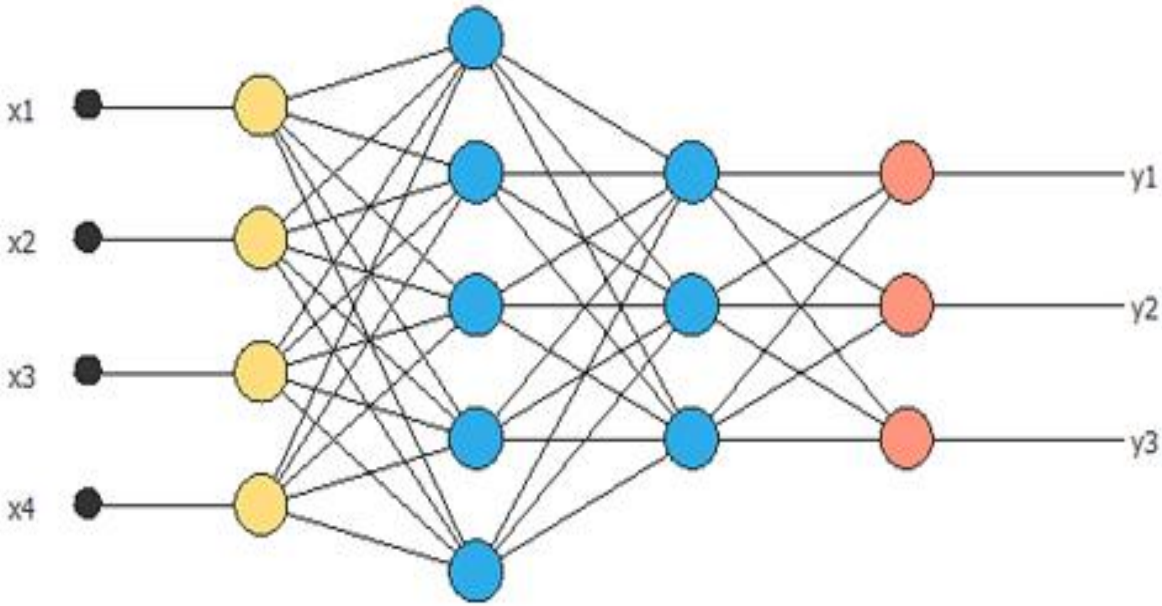
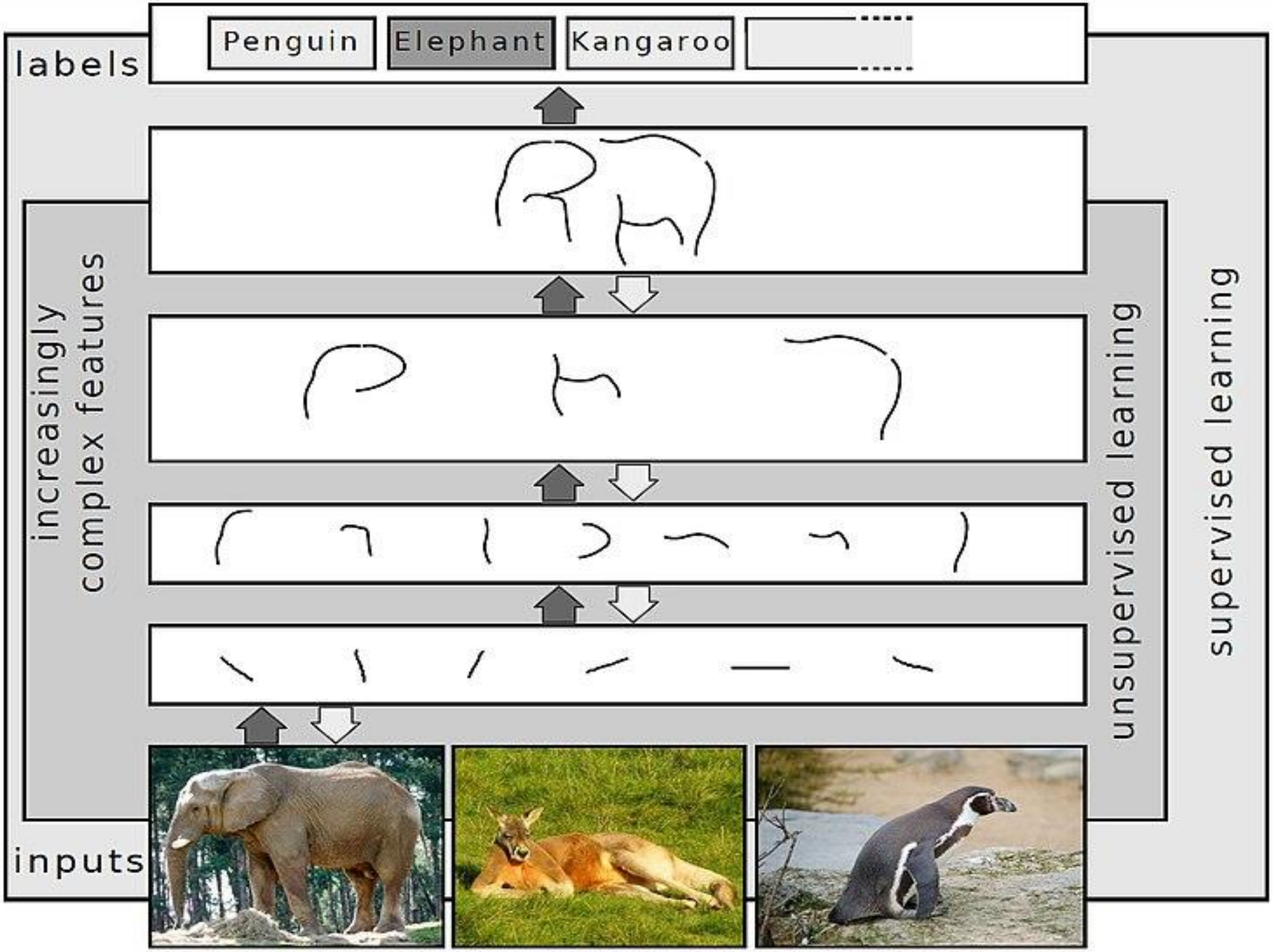


Figure: Neural Network

Deep Learning



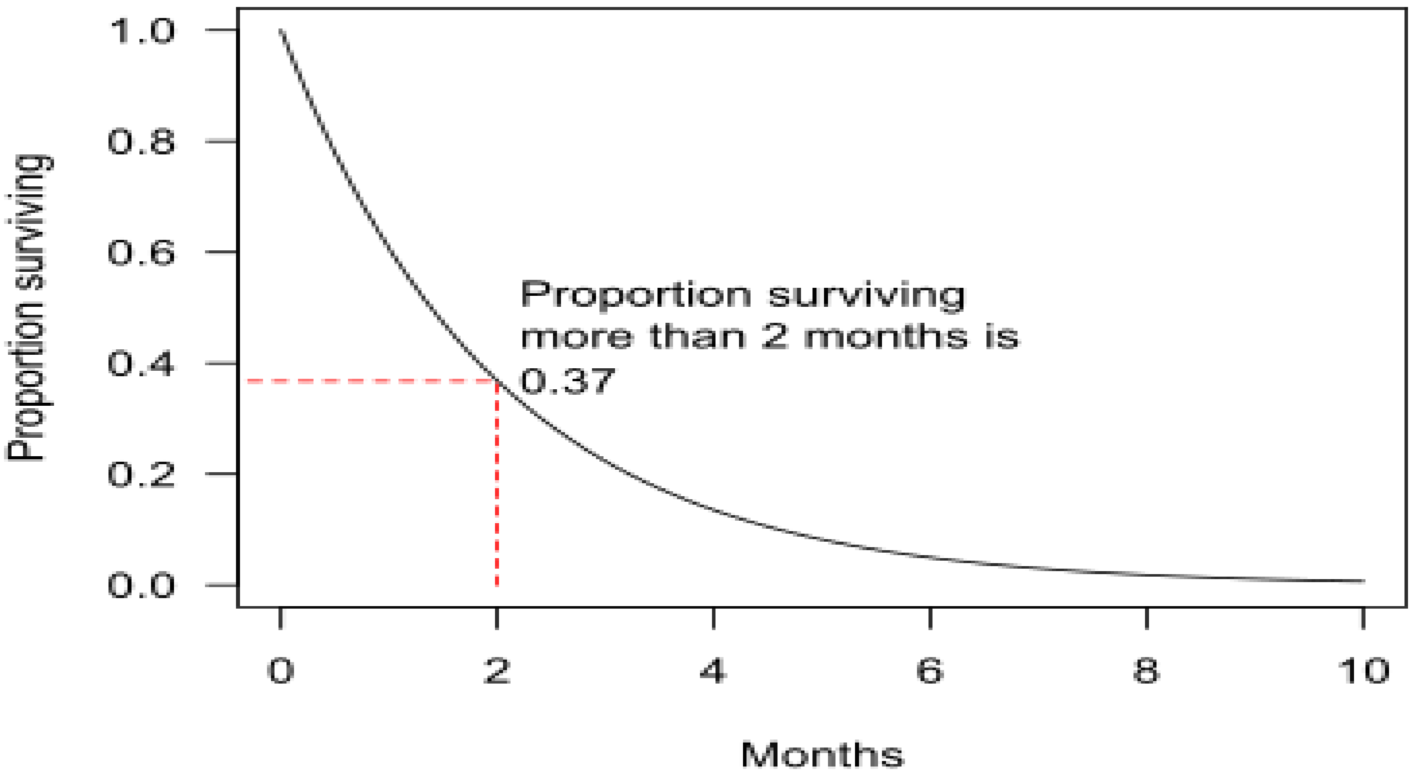
Survival Function

The **survival function** is a function that gives the probability that a patient, device, or other object of interest will survive beyond any specified time.
Let *T* be a continuous random variable with cumulative distribution function *F*(*t*) on the interval [0,∞). Its *survival function* or *reliability function* is:

$$S(t) = P(\{T > t\}) = \int_t^{\infty} f(u)\,du = 1 - F(t).$$

Survival Function

The graph show examples of hypothetical survival functions. The x-axis is time. The y-axis is the proportion of subjects surviving. The graphs show the probability that a subject will survive beyond time t



the probability of surviving longer than t = 2 months is 0.37. That is, 37% of subjects survive more than 2 months.

Hazard Function

The **hazard function** (also called the *force of mortality*, *instantaneous failure rate*, *instantaneous death rate*, or *age-specific failure rate*) is a way to model data distribution in survival analysis. The most common use of the function is to **model a participant's chance of death as a function of their age**.

The hazard function is a conditional failure rate, in that it is **conditional a person has actually survived until time *t***. In other words, the function at year 10 only applies to those who were actually alive in year 10; it doesn't count those who died in previous periods.

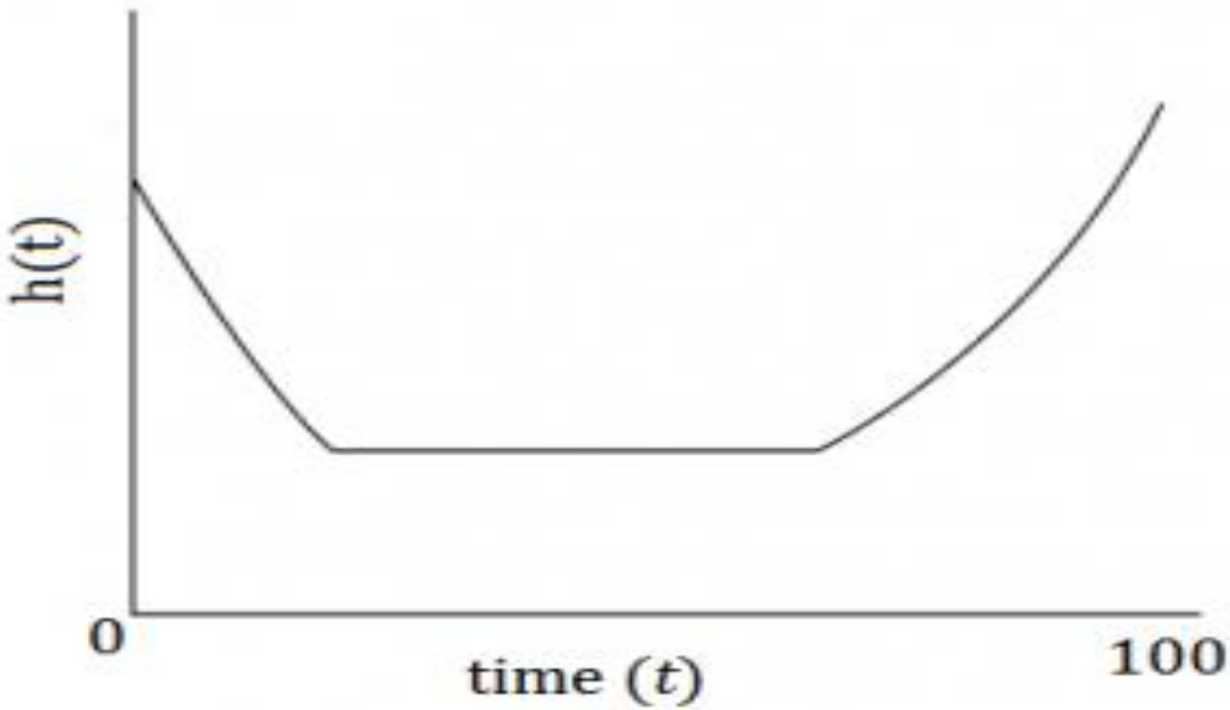
The hazard function formula is:

$$h_Y(y) = \frac{f_Y(y)}{S_Y(y)}$$

Where:

- $f_Y(y)$ = the probability density function of survival time Y,
- S_Y = the Survivor function (the probability of surviving beyond a certain point in time)

Hazard Function



The hazard function h(t) showing the chances of death for a human at any particular age.

Cox Proportional hazards model

The purpose of the model is to evaluate simultaneously the effect of several factors on survival. In other words, it allows us to examine how specified factors influence the rate of a particular event happening (e.g., infection, death) at a particular point in time. This rate is commonly referred as the hazard rate.

Predictor variables (or factors) are usually termed *covariates* in the survival-analysis literature.

The Cox model is expressed by the *hazard function* denoted by h(t). Briefly, the hazard function can be interpreted as the risk of dying at time t. It can be estimated as follow:

$$h(t) = h_0(t) \times exp(b_1x_1 + b_2x_2 + \ldots + b_px_p)$$

where,

- *t* represents the survival time
- $h(t)$ is the hazard function determined by a set of p covariates $(x_1, x_2, \ldots, x_p)$
- the coefficients $(b_1, b_2, \ldots, b_p)$ measure the impact (i.e., the effect size) of covariates.
- the term h_0 is called the baseline hazard. It corresponds to the value of the hazard if all the x_i are equal to zero (the quantity exp(0) equals 1). The 't' in h(t) reminds us that the hazard may vary over time.

Cox Proportional hazards model

The Cox model can be written as a multiple linear regression of the logarithm of the hazard on the variables x_i, with the baseline hazard being an 'intercept' term that varies with time.

The quantities $exp(b_i)$ are called hazard ratios (HR). A value of b_i greater than zero, or equivalently a hazard ratio greater than one, indicates that as the value of the i^{th} covariate increases, the event hazard increases and thus the length of survival decreases.

Put another way, a hazard ratio above 1 indicates a covariate that is positively associated with the event probability, and thus negatively associated with the length of survival.

In summary,

- HR = 1: No effect
- HR < 1: Reduction in the hazard
- HR > 1: Increase in Hazard

Cox Proportional hazards model

Consider two patients k and k′ that differ in their x-values. The corresponding hazard function can be simply written as follow

- Hazard function for the patient k:

$$h_k(t) = h_0(t)e^{\sum_{i=1}^{n} \beta x}$$

- Hazard function for the patient k′:

$$h_{k'}(t) = h_0(t)e^{\sum_{i=1}^{n} \beta x'}$$

- The hazard ratio for these two patients [$\frac{h_k(t)}{h_{k'}(t)} = \frac{h_0(t)e^{\sum_{i=1}^{n} \beta x}}{h_0(t)e^{\sum_{i=1}^{n} \beta x'}} = \frac{e^{\sum_{i=1}^{n} \beta x}}{e^{\sum_{i=1}^{n} \beta x'}}$] is independent of time t.

if an individual has a risk of death at some initial time point that is twice as high as that of another individual, then at all later times the risk of death remains twice as high.