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An Introduction to Marginal Structural models(MSM)

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We proposed the Marginal Structural Model(MSM) adjusting for the time-dependent covariates in competing risk and consider the stabilized inverse probability of treatment weighting (IPTW) and stabilized inverse probability of censoring weighting (IPCW).

We use the following stabilized form of the IPTW: --------------------(Figure 1)

The denominator of the stabilized IPTW can be derived from a multiple logistic regression model of the probability of exposure at a given time with previous exposure, baseline covariates, and time-dependent covariates. The numerator can be derived from a multiple logistic regression model of the probability of exposure at the given time with previous exposure and baseline covariates. The IPCW is similar to the IPTW, and we use the following stabilized form of the IPCW-------------------(Figure 2)

The stabilized IPTW and IPCW were defined at multiple time points. The final weight at each time point was defined as IPTW*IPCW. We truncate the final weights at less than 0.1% or over 99.9% to increase the confounding bias and reduce the variance due to non-positivity. We proposed a marginal structural model (MSM) to estimate the time-dependent causal effect of the cumulative incidence of an interest event using the relation between the cause-specific hazard and the sub-distribution hazard for competing risks. Application of this method on the Korean National Health Insurance data (NHIS, N = 5,779), showed that the cumulative incidence of cerebral infarction recurrence was decreased by adherence to antiplatelet therapy (PDC ≥ 80%) after adjusting for time-dependent bleeding events, while it was increased by non-adherence to warfarin (PDC < 80%).

Figure : stabilized form of the IPTW or IPCW

Figure 1.

$$w_{i,IPTW}(t_k) = \frac{\prod_{l=0}^{k} p(X_{i,l} = x|\bar{X}_{i,l-1}, V_i)}{\prod_{l=0}^{k} p(X_{i,l} = x|\bar{X}_{i,l-1}, V_i, \bar{Z}_{i,l})}$$

where $p(X_{i,l} = x|\bar{X}_{i,l-1}, V_i, \bar{Z}_{i,l})$ is the probability that the i^{th} patient has observed exposure x given the past exposure $\bar{X}_{i,l-1}$ up to time $l-1$, the baseline covariates V_i, and the histories of the time-dependent covariates $\bar{Z}_{i,l}$ up to time l, and $p(X_{i,l} = x|\bar{X}_{i,l-1}, V_i)$ is the probability that the i^{th} patient has observed exposure x given the past exposure $\bar{X}_{i,l-1}$ up to time $l-1$ and the baseline covariates V_i.

Figure 2.

$$w_{i,IPCW}(t_k) = \frac{\prod_{l=0}^{k} p(C_{i,l}|\bar{C}_{i,l-1}, V_i)}{\prod_{l=0}^{k} p(C_{i,l}|\bar{C}_{i,l-1}, V_i, \bar{Z}_{i,l})}$$

where $\prod_{l=0}^{k} p(C_{i,l}|\bar{C}_{i,l-1}, V_i, \bar{Z}_{i,l})$ is the probability that the i^{th} patient has censoring given the past censoring $\bar{C}_{i,l-1}$ up to time $l-1$, the baseline covariates V_i, and the histories of the time-dependent covariates $\bar{Z}_{i,l}$ up to time l, and $p(C_{i,l}|\bar{C}_{i,l-1}, V_i)$ is the probability that the i^{th} patient has censoring given past censoring up to time $l-1$ and the baseline covariates V_i.