Multi-state piecewise exponential model of hospital outcomes after injury

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Hospital outcomes after serious injury (or illness)

- Most common outcome variables are hospital mortality and length of stay (LOS); LOS is a strong determinant of hospital cost
- But LOS will be short in the least injured (who go home) and the most injured (who die)
- Furthermore, many injured patients (especially older) go to long-term care (LTC)
- How can we predict LOS accurately and analyze the factors affecting it?

Methods

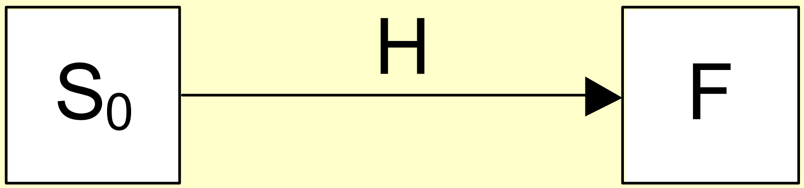
- Nationwide Inpatient Sample, 2002
- 306,303 cases, principal diagnosis injury
- Excluded 15.1% for missing age, sex, E-code, or outcome
- Calculated Injury Severity Score (ISS) and Charlson Comorbidity Score
- "Piecewise" observation periods: 1-2 days, 3-7 days, 8-11 days, 12+ days

Time-to-event models

- Usually anticipate an adverse event, thus “Failure-time analysis”, “Survival analysis”,
- Terminology also includes the potentially confusing terms “hazard” and “risk”
- However, the same mathematics can be used to study time until a generally favorable event, such as leaving the hospital, i.e. LOS

A basic two-state model

- S is the population still hospitalized, starting at S_0
- F is those who have left the hospital
- H is the "hazard", or instantaneous probability, that a patient still in state S will enter state F

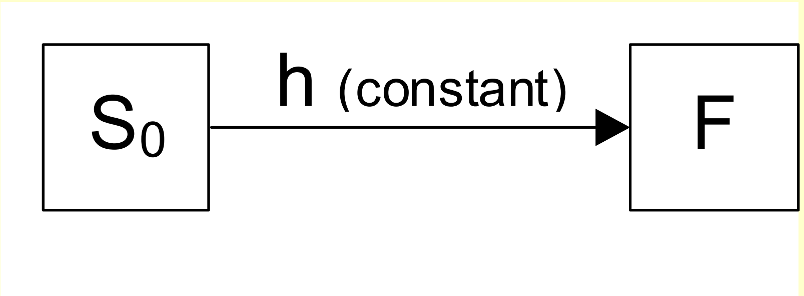


Proportional hazards

- So far, we have made no assumptions about H
- A common (verifiable) assumption is that $H = H_{base} * Z$, where there is an incidence rate ratio or "hazard ratio" $Z = z_1 * z_2 * \ldots z_k$
- This is the famous (Cox) proportional hazards (PH) model

An exponential model

- Parametric models make assumptions about the functional form of H
- One of the simplest assumptions is that H is a constant, say h
- This leads to an exponential model (which can also be a proportional hazards model with $h = h_{base}*Z$)

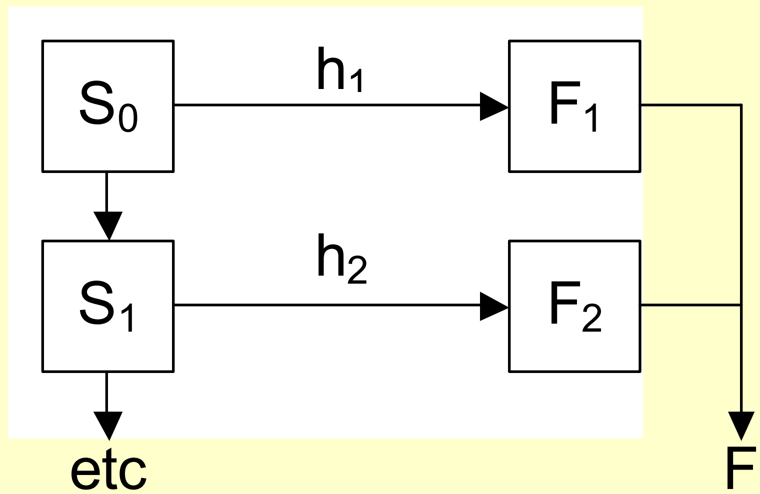


A little calculus

- $dS/dt = h\ S$
- $(1/S)\ dS = h\ dt$
- $\text{Log}\ S = h\ t + C$
- $C=0$ and $h<0$, given that $S_0=1$ and $S_\infty=0$, so we can write $S = e^{-ht}$, or $S(t) = \exp(-ht)$
- If a time-to-event variable is exponential, the number of occurrences in a given time period is Poisson
- $P(X=x) = e^{-h\Delta t}\ (h\Delta t)^x / x!$
- *This means we can fit an exponential model using standard software for Poisson regression*

Piecewise exponential models

- The assumption of a constant hazard is usually unrealistic
- But by considering constant hazards for several shorter time periods, we can develop very flexible PWE models
- $S_i(t) = \exp(-h_i\,(t-t_{i-1}))$

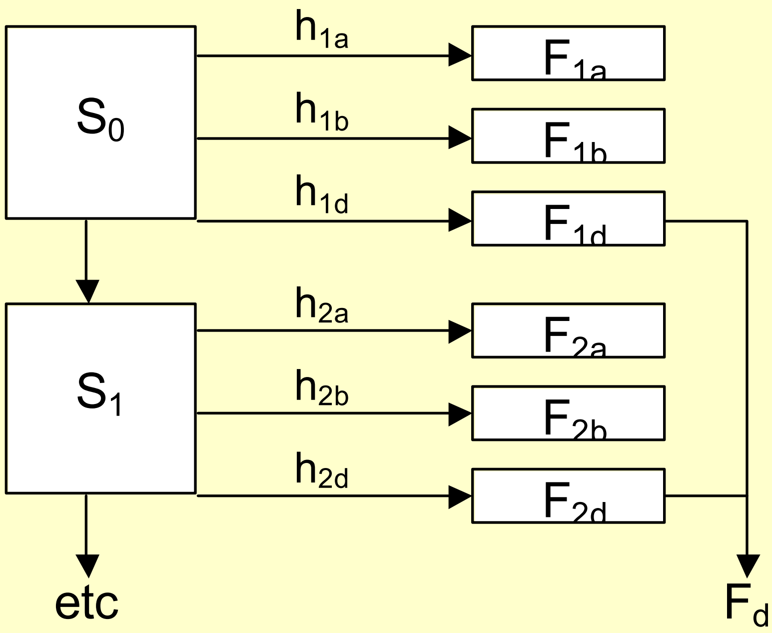


Competing risks

- If there are different terminal events, you have competing outcomes or “risks”
- For LOS, you can exclude deaths or LTC transfers, you can “censor” them, or you can lump outcomes together, but all these approaches have problems
- A better model would analyze outcomes separately as well as in combination

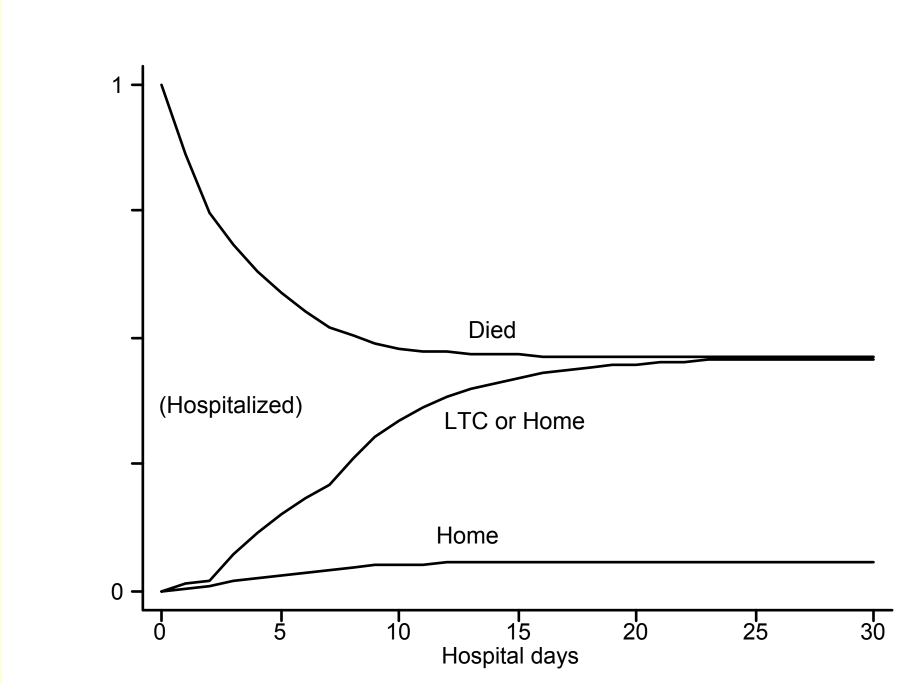
A multi-state piecewise exponential model for hospital outcomes after serious injury

- Separate PWE models for (a) discharge home, (b) discharge to LTC, and (d) death
- PH (Poisson) covariates for each transition and time period
- Calculate LOS and cumulative mortality



Computation and depiction

- The functional form and parameters of all outcomes are specified in the model
- With a little more math, we can calculate LOS and other summary statistics
- Outcomes may also be graphed



Results by injury mechanism

	Knife	Gun	MVC	Other
LOS (days)	3.2	6.4	5.3	4.7
Predicted	**3.4**	**6.6**	**5.5**	**4.9**
LTC	.07	.08	.13	.42
Predicted	**.08**	**.09**	**.15**	**.43**
Died	.007	.087	.026	.022
Predicted	**.007**	**.078**	**.026**	**.023**

Results by injury severity

	ISS<9	ISS 9-15	ISS 16-24	ISS 25-75
LOS (days)	3.4	6.0	8.7	12.7
Predicted	**3.5**	**6.2**	**8.8**	**13.0**
LTC	.18	.55	.31	.29
Predicted	**.20**	**.52**	**.33**	**.30**
Died	.005	.024	.068	.358
Predicted	**.006**	**.025**	**.070**	**.337**

Covariate effects (increased rate)

	Home	LTC	Died
Days 1-2	Younger, male, Low ISS, Charlson=0 Not gun, not MVC	Older, female Low ISS, Charlson>0 Knife, not MVC	Older, male High ISS, Charlson>1 Knife, gun, MVC
Days 3-7	Younger, male Low ISS, Charlson=0 Knife, not gun	Older, female Low ISS, Charlson<2 Not knife, gun, or MVC	Older, male High ISS, Charlson>0 Not knife
Days 8-11	Younger Low ISS, Charlson=0 Knife	Older, female ISS<15 Not knife, gun, or MVC	Older, male High ISS, Charlson>1 Knife, not MVC
Days 12-	Younger, female Low ISS, Charlson<2 Knife or gun	Older, female ISS<15, Charlson=0 Not knife, gun, or MVC	Older, male High ISS, Charlson>0 Not MVC

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