Modelling Causal Mortality and the Impact of Cause-Elimination

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Why should we look at mortality by cause of death?

Figure: Log-mortality over ages, Switzerland, females

(a) 1950

(b) 2005
Why should we look at mortality by cause of death?

(a) Cancer

(b) Circulatory system

Figure: Log-mortality over ages, Switzerland, females, 1955
Why should we look at mortality by cause of death?

Figure: Percentage of deaths by cause, ages 65 and over, Switzerland, females

(a) Cancer

(b) Circulatory system
Why are causes of death not so often analyzed?

Many problems arise:

- Differences in interpretation of international rules, in coding practices and in training of physicians;
- Cause of death reporting less reliable at older ages where most of the deaths occurs (inaccuracy of reported age at death, sampling error);
- Different causes may impact different age-groups;
- Multiple causes;
- Misclassifications of deaths by cause;
- ...  
  - Causes of death = competing risks → a dependance exist.

[Booth and Tickle(2008)] and [Richards(2009)]
Aim

What? Get a better understanding of mortality by causes of death
→ especially the dependance
→ improve the forecasting performance
Data

Countries:
- USA (1950 - 2007)
- Japan (1950 - 2009)
- France (1952-2008)
- E & W (1950 - 2009)
- Italy (1951 - 2003)
- Australia (1950 - 2004)
- Sweden (1951 - 2010)
- Switzerland (1951 - 2007)
- Singapore (1955 - 2009)
- Norway (1951 - 2009)

Causes of death:
- Diseases of the circulatory system
- Cancer
- Diseases of the respiratory system
- External causes (mainly: accidents)
- Infectious & parasitic diseases
Multinomial logit models

- Typically used for a response with several unordered categories
Multinomial logit models

\[
\log \left( \frac{q_1(x, t)}{p(x, t)} \right) = a_x^{(1)} + b_x^{(1)} \cdot t + c_x^{(1)} \cdot t^2
\]

\[
\log \left( \frac{q_2(x, t)}{p(x, t)} \right) = a_x^{(2)} + b_x^{(2)} \cdot t + c_x^{(2)} \cdot t^2
\]

\[
\log \left( \frac{q_6(x, t)}{p(x, t)} \right) = a_x^{(6)} + b_x^{(6)} \cdot t + c_x^{(6)} \cdot t^2
\]

The logit probabilities depend on a set of factors: the age and a period effect that interacts with age.

→ each age has its own period effect.
Do we have a good fit?

Figure: Data versus model at age 0, females, Australia
Do we have a good fit?

Figure: Data versus model at age-group 50-54, females, Australia
Do we have a good fit?

**Figure:** Data versus model in 1980, females, Australia
Do we have a good fit?

**Figure:** Life expectancy at age 0, females, Australia
What happens if a cure for cancer is found?

**Figure:** Life expectancy at age 0, females, Australia
What happens if a cure for cancer is found?

**Figure:** Life expectancy at age 65, females, Australia
What happens if a cure for cancer is found?

**Figure:** Life expectancy at age 65, females, Australia
Next step

Can we use these models for forecasting?
Cause-of-death mortality forecasts

Figure: Life expectancy at age 0, females, France
Cause-of-death mortality forecasts - continue

Figure: Life expectancy at age 65, females, France
Concluding remarks

- Multinomial logit model is an interesting and easy to understand framework
  - very useful for cause-elimination analysis
  - allows for a straightforward implementation of information with respect to known links between the various causes
  - need to be careful for forecasting purposes

- Models incorporating this information need to be further developed
Bibliography

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*Introduction to Stochastic Process in Biostatistics*.

S J Richards.
Selected issues in modelling mortality by cause and in small populations.
Thank you for your attention!