H21 A Bayesian Approach to Multifactorial Age-at-Death Estimation

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The goal of this presentation is to inform attendees about a new Bayesian approach to multifactorial age-at-death estimation.

This presentation will impact the forensic science community by presenting a new method for combing several indicators of skeletal age- at-death to arrive at a single age estimate.

Most forensic anthropologists rely on multiple skeletal indicators of age-at-death but lack a statistically sound method for combining individual indicators. Attempts at multifactorial aging (e.g., Brooks, 1955; Lovejoy et al., 1985) have had generally disappointing results because they typically rely on either non-statistical or linear statistical methods, creating problems with validity and applicability.

Recently, paleodemographers have been at the forefront of multifactorial age-at-death estimation. Boldsen and colleagues (2002) developed a computer program (ADBOU) that collects data on multiple skeletal indicators scored as discrete ordinal phases and uses Bayesian inference to calculate the posterior probability density and estimate age- at-death. Unfortunately, tests of the ADBOU program found it only moderately effective (Bethard, 2005; Uhl, 2008), in part because the trait scoring departs from the methods (e.g., Suchey-Brooks) that so many osteologists are accustomed to. Without extensive practice, intra- and inter-observer error can be problematic. Further, the ADBOU program comes with a small choice of prior age-at-death distributions "hard- wired" into the program. Bayesian analyses rely on these prior probabilities, together with the osteological data, to estimate ages at death for individual cases. The current research makes use of a more diverse, and possibly more appropriate, reference sample and familiar skeletal scoring techniques to estimate age-at-death from multiple indicators when combined with an appropriate prior age-at-death distribution.

The present data set consists of age indicator scores for pubic symphysis (6 phases; Brooks and Suchey, 1990), auricular surface (8 phases; Lovejoy et al., 1985), and sternal rib end (8 phases; İşcan et al., 1984, 1985) for 623 individuals from four collections: the Hamann-Todd Collection, the William M. Bass Collection, the R.J. Terry Collection, and the Pretoria Bone Collection.

Results: One initial issue to address is whether the original scoring follows a particular transition model. First, a Lagrange multiplier test indicated that the original six-phase pubic symphysis scoring and the eight-phase rib end scoring fit well in a cumulative log probit model. The auricular surface scoring did not fit well, so the first four phases in the Lovejoy et al. system were collapsed into a single phase. After making this collapse, the scoring did fit well in a cumulative log probit model.

Following initial testing, 100 individuals were randomly sampled structured on age-at-death using a Gompertz model of mortality estimated from the ages at death for Suchey's LA County male forensic data. This Gompertz model was also used as the informative prior in estimating ages for the 100 individuals. After forming this "hold out" sample, transition models were fit using the remaining 523 individuals, and the 95% highest posterior density region was found for each of the 240 morphological patterns (6 pubic symphyseal phases times 5 auricular surface phases times 8 rib phases) combined with the informative prior. The left and right boundaries were stored in a "lookup table" and then compared to the actual ages for the hold out sample. Ninety-five of the 100 individuals had ages that fell within the 95% highest posterior density regions, indicating proper coverage. The widths of the 95% highest posterior density regions were sometimes quite considerable, reaching a maximum of 50 years for anyone in the final phase for all three indicators. The right side for this region is entirely determined by the prior age-at-death distribution.

Conclusions: All analyses were done in "R," which is an open source package that can be downloaded for free. As such, the lookup tables, while they are easy to use can also be adjusted to meet individual researcher's needs. For example, the density regions can be changed (to, for example 50% highest posterior density regions) and the Gompertz model parameters for the prior age-at-death distribution can also be changed.

Age-at-Death Estimation, Bayesian Inference, Multifactorial Age Estimation

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