

# Comparison of treatments via empirical likelihood

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Partly based on joint work with Yichuan Zhao.

# Outline

- Motivating examples
- Background on empirical likelihood (EL)
- EL methods for one-sample problems in survival analysis
- Two-sample problems
- Conclusions

# Motivating examples

## Mayo Clinic trial

Randomized clinical trial for primary biliary cirrhosis of the liver. Treatment and placebo groups to be compared.

Aim: find an EL-based simultaneous confidence band for the *relative survival function*:

$$\theta(t) = S_1(t)/S_2(t)$$

More suitable than the difference  $S_1(t) - S_2(t)$  when the risk of failure is moderate.

# Vaccine efficacy estimation

Halloran, Struchiner and Longini (1997)

VE is defined as 1 minus some measure of relative risk in the vaccinated group compared with the unvaccinated group:

$$VE(t) = 1 - \frac{\alpha_{\text{vaccine}}(t)}{\alpha_{\text{placebo}}(t)}$$

$$VE_c(t) = 1 - \frac{A_{\text{vaccine}}(t)}{A_{\text{placebo}}(t)}$$

Aim: find an EL-based simultaneous confidence band for  $VE_c(t)$

# Background on empirical likelihood

- Thomas and Grunkemeier (1975) for survival function estimation. Owen (1988, 1990, . . . , 2001).
- First developed for finite-dimensional features  $\theta = \theta(F)$  of a cdf (e.g., mean, median, cdf at a single point).

## Nonparametric likelihood

$$L(F) = \prod_{i=1}^n (F(X_i) - F(X_{i-})).$$

## EL ratio

$$\tilde{R}(F) = \frac{L(F)}{L(F_n)} = \prod_{i=1}^n np_i$$

where (part of) the mass on  $X_i$  is  $p_i \geq 0$ ,  $\sum_{i=1}^n p_i \leq 1$ , and  $F_n$  is the empirical cdf.

## EL function

$$R(\theta_0) = \sup\{\tilde{R}(F) : \theta(F) = \theta_0\}$$

Equivalently

$$R(\theta_0) = \frac{\sup\{L(F) : \theta(F) = \theta_0\}}{\sup\{L(F)\}}$$

EL hypothesis tests

Accept  $\theta(F) = \theta_0$  when  $R(\theta_0) \geq r_0$  for some threshold  $r_0$ .

EL confidence regions

$$\{\theta : R(\theta) \geq r_0\}$$

with  $r_0$  chosen via an EL analogue of Wilks's theorem.

## EL for means

$$\mu = E(X) \in \mathbb{R}^d$$

$$R(\mu) = \max \left\{ \prod_{i=1}^n np_i : \sum_{i=1}^n p_i X_i = \mu, p_i \geq 0, \sum_{i=1}^n p_i = 1 \right\}$$

**Theorem** (ELT, Owen 1990)  $X_1, \dots, X_n$  iid with finite mean  $\mu_0$ , finite covariance matrix of rank  $q > 0$ . Then

$$-2 \log R(\mu_0) \xrightarrow{\mathcal{D}} \chi_q^2.$$



## Extensions

- Smooth functions of means:  $\theta = h(\mu)$
- Linear functionals of  $F$ :  $\theta = E(h(X)) = \int h(x) dF(x)$ .
- Implicitly defined parameters:  $E(m(X, \theta)) = 0$  where  $m(X, \theta)$  is the estimating function; e.g., median,  $m(X, \theta) = 1\{X \leq \theta\} - .5$ .

$$R(\theta) = \max \left\{ \prod_{i=1}^n np_i : \sum_{i=1}^n p_i m(X_i, \theta) = 0, p_i \geq 0, \sum_{i=1}^n p_i = 1 \right\}$$

**Theorem** (Owen 1990) Let  $X_1, \dots, X_n$  be iid, and suppose  $m(X, \theta_0)$  has finite covariance matrix of rank  $q > 0$ . If  $E(m(X, \theta_0)) = 0$ , then

$$-2 \log R(\theta_0) \xrightarrow{\mathcal{D}} \chi_q^2.$$

**Proof** Immediate from ELT upon some changes in notation:  $X$  is replaced by  $m(X, \theta)$ , which has mean zero when  $\theta = \theta_0$ .

## EL simultaneous band for $F$

Local EL function at  $\theta_0 = F_0(t)$ :

$$\begin{aligned} R(t) &= \frac{\sup\{L(F) : F(t) = F_0(t)\}}{\sup\{L(F)\}} \\ &= \left( \frac{\sqrt{n}(F_n(t) - F_0(t))}{\sqrt{F_0(t)(1 - F_0(t))}} \right)^2 + o_P(1) \end{aligned}$$

As a process in  $t \in [a, b]$ :

$$\begin{aligned} -2 \log R(t) &\xrightarrow{\mathcal{D}} \left( \frac{W^o(F_0(t))}{\sqrt{F_0(t)(1 - F_0(t))}} \right)^2 \\ &\stackrel{\mathcal{D}}{=} \left( \frac{W(\sigma^2(t))}{\sigma(t)} \right)^2, \end{aligned}$$

$W^o$  standard tied-down Wiener process (Brownian bridge)

$W$  standard Wiener process

$$\sigma^2(t) = \frac{F_0(t)}{1 - F_0(t)}.$$

Simultaneous confidence band for  $F$  over an interval  $[a, b]$ :

$$\{(t, F_0(t)) : -2 \log R(t) \leq C_\alpha, t \in [a, b]\}$$

$C_\alpha$  the upper  $\alpha$ -quantile of

$$\sup_{t \in [\hat{\sigma}^2(a), \hat{\sigma}^2(b)]} \frac{W^2(t)}{t}.$$

Equal precision LR band. Narrower in tail than Hollander, McKeague, Yang (1997) band.

# Survival analysis setting

## Right-censored lifetime data

Observe  $n$  iid pairs  $(Z_i, \delta_i)$

$Z_i = \min(X_i, Y_i)$ ,  $\delta_i = I\{X_i \leq Y_i\}$ ,  $X_i$  and  $Y_i$  independent.

$F$  : cdf of  $X_i$

$G$  : cdf of  $Y_i$

$S = 1 - F$  : survival function,  $S(0) = 1$

$A$ : cumulative hazard function

$$A(t) = \int_{(0,t]} \frac{dF(s)}{1 - F(s-)}$$

## Nonparametric likelihood

$$L(S) = L(F) = \prod_{i=1}^n (F(Z_i) - F(Z_i-))^{\delta_i} (1 - F(Z_i))^{1-\delta_i}.$$

To maximize  $L(F)$ , we only need consider  $F$  supported on the uncensored lifetimes.

## EL function

$$R(\theta_0) = \frac{\sup\{L(S) : \theta(S) = \theta_0\}}{\sup\{L(S)\}}$$

EL suddenly becomes difficult because of the censoring!

Unless  $\theta(S)$  has a particularly simple form,  $R(\theta_0)$  may be intractable.

Known tractable forms of  $\theta(S)$  or  $\theta(A)$ :

- $S(t_0)$
- $A(t_0)$
- quantiles
- linear functionals  $\theta(F) = \int h(t) dF(t)$
- linear functionals  $\theta(A) = \int h(t) dA(t)$

Thomas and Grunkemeier (1975), Li (1995), Murphy (1995), Li, Hollander, McKeague and Yang (1996), Murphy and van der Vaart (1997), Pan and Zhou (2002)



## EL for the Cox model regression parameters

$$\alpha(t|z) = \alpha_0(t) \exp(\beta' z)$$

Estimating equation for  $\beta$ :

$$E(U(\beta_0)) = 0$$

where  $U$  is the partial likelihood score function.

Qin and Jing (2001): standard EL for this estimating equation.

Murphy and van der Vaart (1997): a profile EL for  $\beta$  for current status data.

## EL for survival function at a fixed point

$p = S(t_0)$ , with  $t_0$  fixed,  $0 < p < 1$ .

Method of Lagrange multipliers is tractable.

**Theorem** If  $S$  is continuous,  $0 < p = S(t_0) < 1$  and  $G(t_0) < 1$ , then

$$-2 \log R(p) \xrightarrow{\mathcal{D}} \chi_1^2$$

Thomas and Grunkemeier (1975), Li (1995), Murphy (1995)

## EL simultaneous band for $S$

As a process in  $t \in [a, b]$ ,

$$-2 \log R(t) \xrightarrow{\mathcal{D}} \left( \frac{W(\sigma^2(t))}{\sigma(t)} \right)^2,$$

Simultaneous confidence band for  $S$  over an interval  $[a, b]$ :

$$\{(t, S(t)) : -2 \log R(t) \leq C_\alpha, t \in [a, b]\}$$

$C_\alpha$  the upper  $\alpha$ -quantile of

$$\sup_{t \in [\hat{\sigma}^2(a), \hat{\sigma}^2(b)]} \frac{W^2(t)}{t}$$

Equal precision LR band. Narrower in the tail than Hollander, McKeague, Yang (1997) band.

Li and Van Keilegom (2001): adjustment for a covariate effect (continuous one-dimensional covariate).

# Two-sample problem

Comparison of treatment and placebo groups.

## Notation

Index sample by  $j$

Assume  $n_j/n \rightarrow p_j > 0$

Total sample size  $n = n_1 + n_2$

Nonparametric likelihood:  $L(S_1, S_2) = L_1(S_1)L_2(S_2)$ .

- Standard method: logrank test for  $S_1 = S_2$ .
- Wald-type comparison of  $S_1$  and  $S_2$  using some smooth functional  $\varphi(S_1, S_2)$  and the functional delta method typically leads to intractable limiting distributions. Simulation needed.

### Gaussian multiplier simulation technique

Martingale increments  $dM_i(t)$  replaced by  $G_i dN_i(t)$ , where  $G_i \sim N(0, 1)$ . (Lin, Wei and Ying, 1993)

Parzen, Wei and Ying (1997) constructed a Wald-type confidence band for  $S_1(t) - S_2(t)$  using this technique.

## Q-Q plot

$$\{(F_1^{-1}(p), F_2^{-1}(p)) : 0 < p < 1\}$$

Einmahl and McKeague (1999) constructed an EL confidence band for the Q-Q plot:

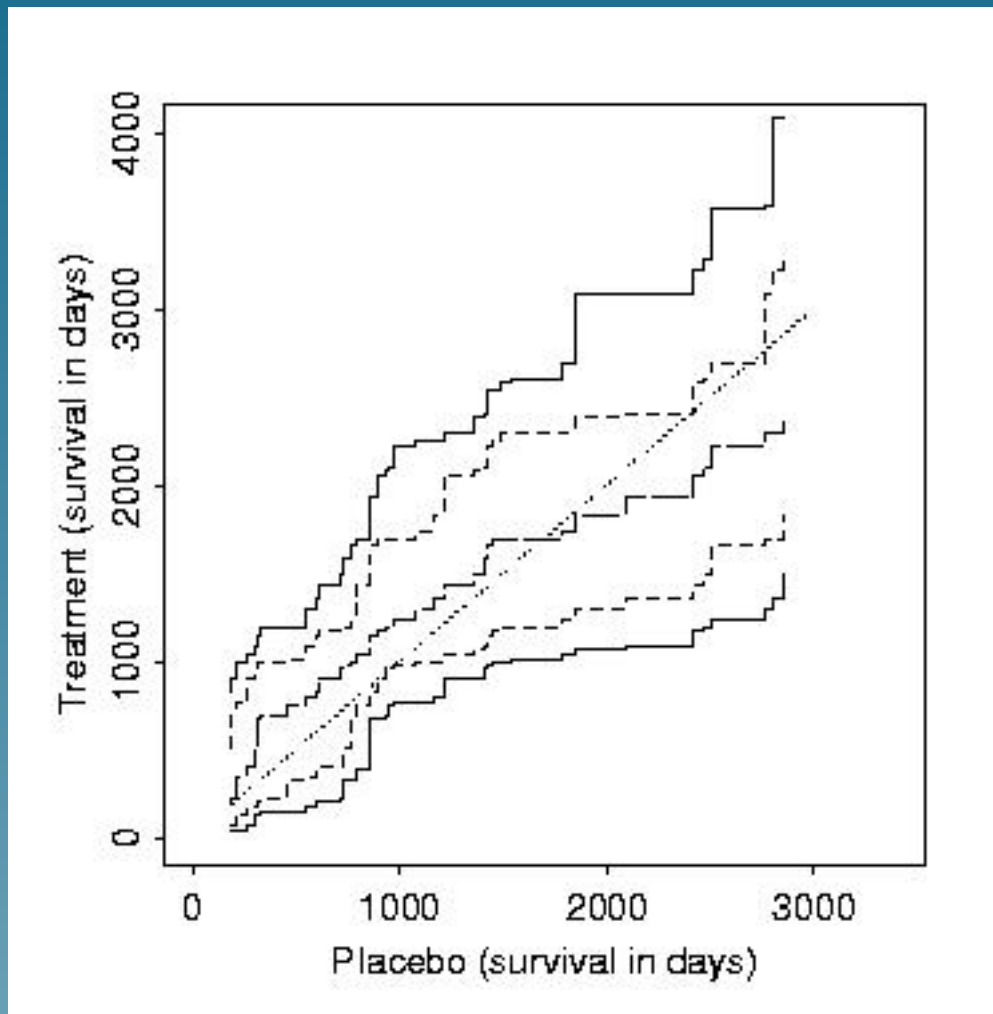
$$\{(t_1, t_2) : -2 \log R(t_1, t_2) \leq C_\alpha, t_1 \in [a, b]\}$$

where  $C_\alpha$  uses

$$\sigma^2(t) = \sigma_1^2(t)/p_1 + \sigma_2^2(t')/p_2$$

and  $t' = F_2^{-1}(F_1(t))$ . Simulation not needed.

## Mayo Clinic trial Q-Q plot



## Relative survival

$$\theta(t) = S_1(t)/S_2(t)$$

McKeague and Zhao (2002) construct an EL simultaneous band:

$$\{(t, \theta(t)): -2 \log R(t) \leq C_\alpha, t \in [a, b]\}$$

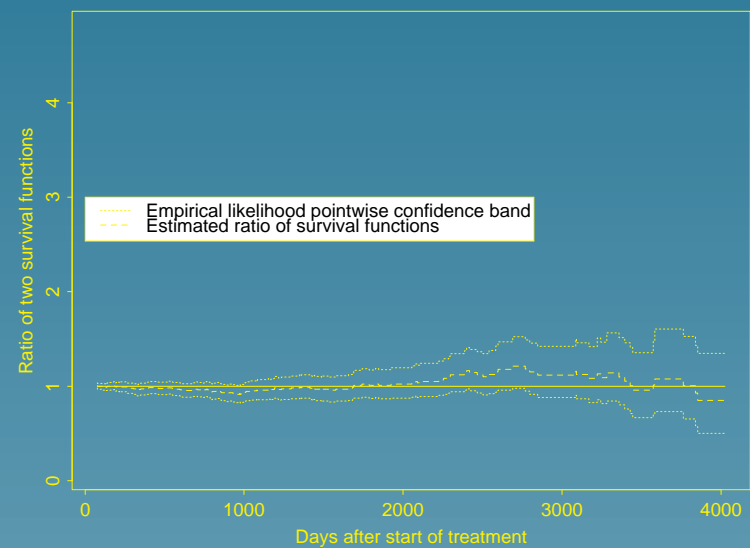
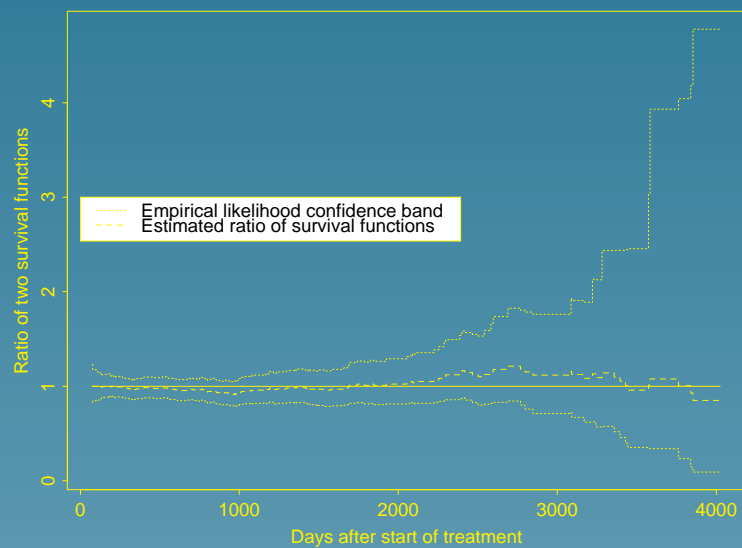
where  $C_\alpha$  uses

$$\sigma^2(t) = \sigma_1^2(t)/p_1 + \sigma_2^2(t)/p_2.$$

Simulation not needed.



# Mayo clinic trail: placebo/treatment relative survival



- Simultaneous band for differences in cumulative hazards:

$$A_1(t) - A_2(t) = -\log(S_1(t)/S_2(t))$$

EL works without simulation, McKeague and Zhao (2002).

- Simultaneous band for vaccine efficacy:

$$VE_c(t) = 1 - \frac{A_{\text{vaccine}}(t)}{A_{\text{placebo}}(t)}$$

EL works, McKeague and Zhao (2002). Gaussian multiplier simulation needed. Reason EL works:

$$A_1(t)/A_2(t) = \log S_1(t) / \log S_2(t)$$

and the product-limit form of the survival function.

- Ratios of cdfs:  $F_1(t)/F_2(t)$ , EL intractable?

# Conclusions

- EL techniques are tractable in the two-sample setting for simultaneous inference concerning *ratios* of survival functions and cumulative hazards.
- EL shows great promise for further development in more complex clinical trial settings.