
Bayesian Predictive power: the bathtub phenomenon

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Agenda

- 1 Bayesian Predictive Power
- 2 Excursion: summary measure of a distribution
- 3 Choice of prior for Bayesian Predictive Power
- 4 “Quantify uncertainty” for Bayesian Predictive Power?

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Bayesian Predictive Power

Continuous endpoint, true effect Δ , estimator assumed to follow Normal distribution.

Estimate $\hat{\Delta}_{\text{final}}$ at final analysis of pivotal trial, based on n_{final} observations:

$$\hat{\Delta}_{\text{final}} \sim N(\Delta, \sigma_{\text{final}}^2 = \sigma^2/n_{\text{final}}).$$

Pivotal trial is called a success if $\hat{\Delta}_{\text{final}} \leq \Delta_{\text{suc}}$ (think of log hazard ratio).

Δ_{suc} : can be

- **Minimal detectable difference** (MDD), i.e. effect size such that trial is just significant: Equate standardized test statistic to critical value of z-test:

$$\Delta_{\text{suc}}/\text{SE}(\hat{\Delta}_{\text{final}}) = z_{\alpha_{\text{final}}/2} \Rightarrow \Delta_{\text{suc}} = z_{\alpha_{\text{final}}/2}\text{SE}(\hat{\Delta}_{\text{final}}).$$

- Any **other quantity of interest**, e.g. assumed alternative in sample size planning = target product profile (TPP).

Bayesian Predictive Power

Quantity of interest = **power function**:

$$P(\widehat{\Delta}_{\text{final}} \leq \Delta_{\text{suc}}) = \Phi\left(\frac{\Delta_{\text{suc}} - \Delta}{\sigma_{\text{final}}}\right).$$

Depends on assumed (or true) effect Δ ! What can we do?

- 1 Provide $P(\widehat{\Delta}_{\text{final}} \leq \Delta_{\text{suc}})$ for different assumed values of Δ .
- 2 Assume distribution over Δ with density q and average:

$$\begin{aligned} \text{PoS} &= \mathbb{E}_{\Delta}\left(P_{\Delta}(\widehat{\Delta}_{\text{final}} \leq \Delta_{\text{suc}})\right) \\ &= \int_{-\infty}^{\infty} \Phi\left(\frac{\Delta_{\text{suc}} - \Delta}{\sigma_{\text{final}}}\right) q(\Delta) d\Delta. \end{aligned}$$

Bayesian predictive power initially introduced in Spiegelhalter et al. (1986).

Various names in the literature, we use “Probability of Success” (PoS).

Bayesian Predictive Power

$$\begin{aligned}\text{PoS} &= \mathbb{E}_{\Delta} \left(P_{\Delta}(\widehat{\Delta}_{\text{final}} \leq \Delta_{\text{suc}}) \right) \\ &= \int_{-\infty}^{\infty} \Phi \left(\frac{\Delta_{\text{suc}} - \Delta}{\sigma_{\text{final}}} \right) q(\Delta) d\Delta.\end{aligned}$$

Why “**Bayesian**”?

- At the time, maybe simply because a distribution on a parameter was assumed.
- Start with $q \Rightarrow$ after interim where you **learn** interim estimate (collaborative group framework) update prior $q = q_{\text{prior}}$ with data likelihood to get posterior $q_{\text{posterior}} \Rightarrow$ use this to update PoS.
- Can also update q_{prior} with external data, e.g. other studies, competitor data, etc.

After interim: Power $P_{\Delta}(\widehat{\Delta}_{\text{final}} \leq \Delta_{\text{suc}})$ becomes **conditional power**
 $P_{\Delta}(\widehat{\Delta}_{\text{final}} \leq \Delta_{\text{suc}} | \widehat{\Delta}_{\text{interim}} = \Delta_{\text{interim}})$!

Update after **blinded** interim: [Rufibach et al. \(2015\)](#).

Quantities

- 1 **Power** $P(\hat{\Delta}_{\text{final}} \leq \Delta_{\text{suc}})$. At trial start, function of assumed effect Δ .
- 2 **Conditional power**: “Updated” power after trial has started, function of Δ .
- 3 **Bayesian predictive power** (BPP): average over (conditional) power with respect to distribution over Δ .
- 4 **Predictive probability**: At interim, what is probability to beat Δ_{suc} at final, given current information (expectation of posterior conditional on every possible future outcome)? Depends on prior parameters. See e.g. [Berry et al. \(2011\)](#) for details.

Different quantities that

- depend on different assumptions,
- have different properties,
- have different interpretations.

Keep them apart!

Time-to-event framework

Approximate distribution of **estimated log(hazard ratio)** $\hat{\theta} := \log \hat{\lambda}$:

$$\hat{\theta} \approx N(\theta, 4/d).$$

- $\theta = \log \lambda$: **true underlying effect**, true log-hazard ratio.
- 1:1 randomized trial: $\text{Var}(\hat{\theta}) = 4/d$.
- d : total number of events in both arms.

In context of pivotal trial:

- Random variable $\hat{\theta}_{\text{final}} \sim N(\theta, \sigma_{\text{final}}^2 = 4/d_{\text{final}})$.
- d_{final} : number of events at final analysis.
- α_{final} : significance level at final analysis. May be adjusted for group-sequential design.

Closed form of PoS if prior is Normal

Lemma (Explicit computation of PoS)

Assuming the prior is Normal with density q_{prior} , mean θ_0 , variance σ_0^2 , and is independent of the random variable $\hat{\theta}_{\text{final}}$. Then

$$\text{PoS} := \int P_{\theta}(\hat{\theta}_{\text{final}} \leq \theta_{\text{suc}}) q_{\text{prior}}(\theta) d\theta = \Phi\left(\frac{\theta_{\text{suc}} - \theta_0}{\sqrt{\sigma_{\text{final}}^2 + \sigma_0^2}}\right).$$

Proof: Use law of total probability and properties of Normal distribution. See [Rufibach et al. \(2015\)](#).

References containing alternative proofs: [Spiegelhalter et al. \(1986\)](#), [O'Hagan et al. \(2005\)](#), [Proschan et al. \(2006\)](#), or [Dmitrienko and Wang \(2006\)](#).

Example

Assumptions:

- Phase 2 result: $\hat{\theta}_{\text{Phase 2}} = \log(0.700)$, based on $d_{\text{prior}} = 50$ events.
- Hazard ratio used as alternative in sample size computation: 0.75.
- Final analysis after $d_{\text{final}} = 380$ events.
- $\alpha_{\text{final}} = 0.050$.
- Minimal detectable difference: $\theta_{\text{suc}} = \log(0.818)$.

PoS at start of Phase 3 trial, assuming we know the Phase 2 result:

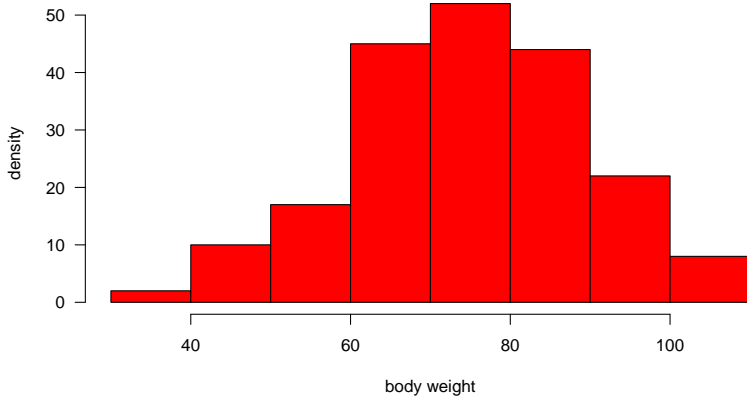
$$\text{PoS} = \int_{-\infty}^{\infty} P_{\theta}(\hat{\theta}_{\text{final}} \leq \theta_{\text{suc}}) \phi_{\mu=\log(0.700), \sigma^2=4/50}(\theta) d\theta = \mathbf{0.697}.$$

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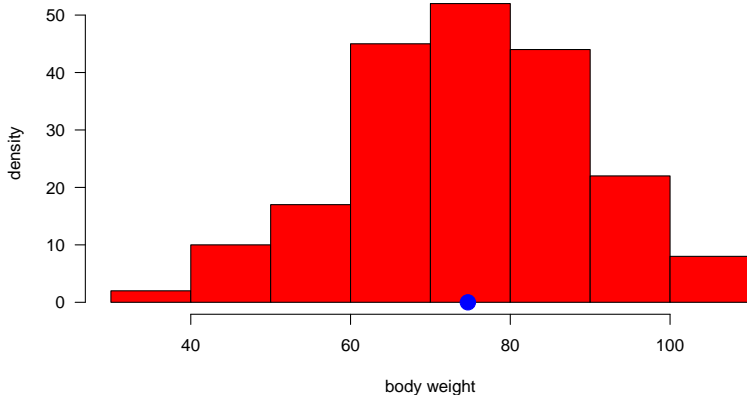
How do you summarize this density in **one number**?

Histogram of body weight (n = 200)



How do you summarize this density in **one number**?

Histogram of body weight (n = 200)

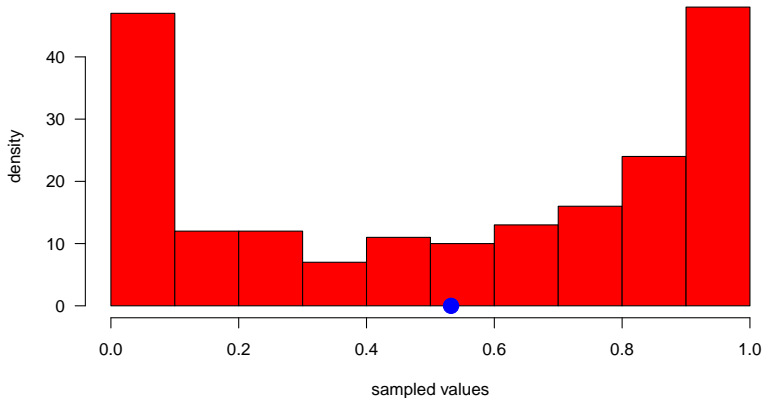


Using the **mean**!

- Value that is most common, i.e. $\text{mean} \approx \text{mode}$.
- Represents center of data.

How do you summarize this density in **one number**?

Histogram of sample from beta distribution (n = 200)



Really using the **mean**? Or rather provide histogram? Or table with frequencies?

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Recall definitions and example

PoS definition:

$$\begin{aligned}\text{PoS} &= \mathbb{E}_{\theta} \left(P_{\theta}(\hat{\theta}_{\text{final}} \leq \theta_{\text{suc}}) \right) \\ &= \int_{-\infty}^{\infty} P_{\theta}(\hat{\theta}_{\text{final}} \leq \theta_{\text{suc}}) q_{\text{prior}}(\theta) d\theta.\end{aligned}$$

Power function:

$$T(\theta) := P_{\theta}(\hat{\theta}_{\text{final}} \leq \theta_{\text{suc}}) = \Phi\left(\frac{\theta_{\text{suc}} - \theta}{\sigma_{\text{final}}}\right).$$

Compute PoS via simulation (law of large numbers!):

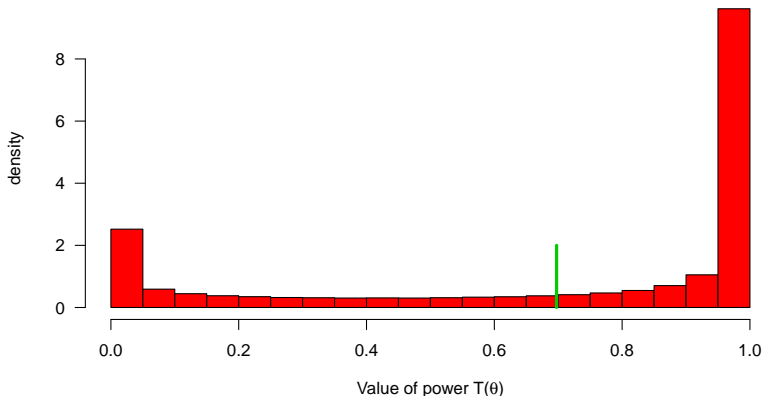
- Draw a sample $(\hat{\theta}_1, \dots, \hat{\theta}_M)$ from prior.
- Compute $(T(\hat{\theta}_1), \dots, T(\hat{\theta}_M))$.
- PoS = average over these values.

Recall example:

- Phase 2 result: $\hat{\theta}_{\text{Phase 2}} = \log(\mathbf{0.700})$, based on 50 events.
- Phase 3 final analysis: Minimal detectable difference $\theta_{\text{suc}} = \log(\mathbf{0.818})$ based on $d_{\text{final}} = 380$ events.

Simulate PoS in example

Histogram of values of $T(\theta)$ for θ sampled from Normal prior
sample size: 1'000'000



- 1 Is mean really appropriate number to **summarize** this histogram?
- 2 Can we compute this density?

Density of power $T(\Theta)$

Assume prior r.v. Θ with PDF q , CDF Q , and define $Y := T(\Theta)$ with PDF g , CDF G .

Use **transformation theorem** and **rule about derivative of an inverse** to get:

$$\begin{aligned}G(y) &= 1 - Q(\theta_{\text{suc}} - \sigma_{\text{final}}z), \\g(y) &= q(\theta_{\text{suc}} - \sigma_{\text{final}}z) \frac{\sigma_{\text{final}}}{\phi(z)}\end{aligned}$$

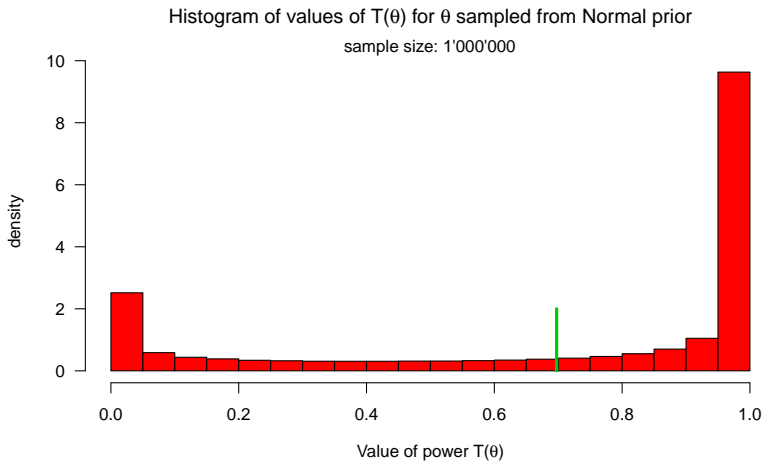
where $z := \Phi^{-1}(y)$ and ϕ the standard Normal density function.

If we assume $\Theta \sim N(\theta_0, \sigma_0^2)$:

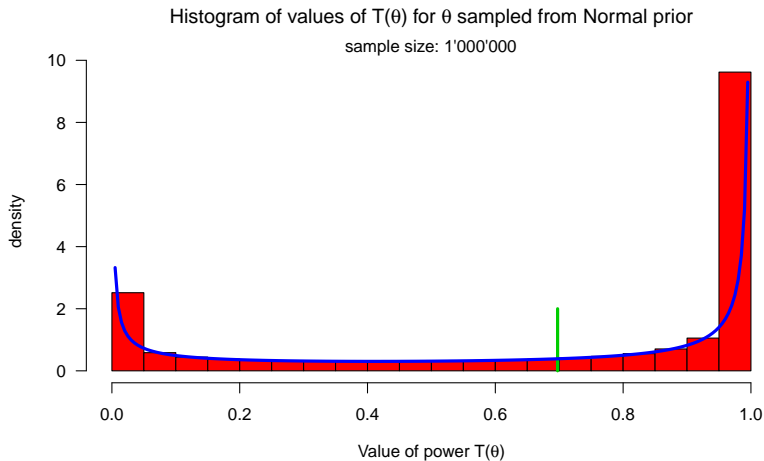
$$\begin{aligned}G(y) &= 1 - \Phi(\beta - \alpha z), \\g(y) &= \alpha \phi(\beta - \alpha z) [\phi(z)]^{-1}\end{aligned}$$

where $\alpha = \sigma_{\text{final}}/\sigma_0 > 0$ and $\beta = (\theta_{\text{suc}} - \theta_0)/\sigma_0$.

Simulate PoS in example

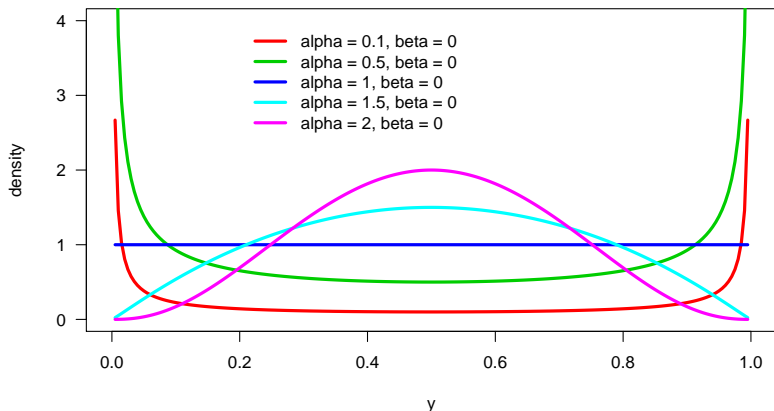


Simulate PoS in example



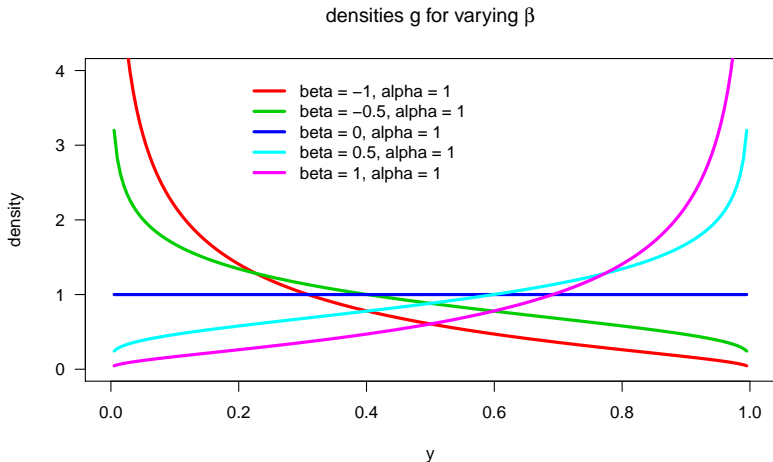
Density g as a function of α , for $\beta = 0$

densities $g(y)$ for varying α



- When summarizing g with PoS \Rightarrow unimodal density most sensible
- $\alpha = 1$: transition between “bathtub-shaped” (even convex?) and unimodal (obviously not concave).
- Make qualitative features precise!

Density g as a function of β , for $\alpha = 1$



- Make qualitative features precise!

Qualitative features of g

Theorem (Qualitative features of g)

We have the following statements:

1 If $\alpha = 1$, then g is

$$\begin{cases} \text{strictly decreasing for} & \beta < 0, \\ \text{constant for} & \beta = 0, \\ \text{strictly increasing for} & \beta > 0. \end{cases}$$

on $[0, 1]$. Minima and maxima of g are accordingly either at 0 or 1.

2 If $\alpha \neq 1$ then g

$$\begin{cases} \text{has a minimum at } y_m \text{ if} & \alpha < 1, \\ \text{has a maximum at } y_m \text{ if} & \alpha > 1, \end{cases}$$

for $y_m = \Phi(\alpha\beta/(\alpha^2 - 1))$. Furthermore, g

$$\begin{cases} \text{is decreasing for } y < y_m \text{ and increasing for } y > y_m \text{ if} & \alpha < 1, \\ \text{is increasing for } y < y_m \text{ and decreasing for } y > y_m \text{ if} & \alpha > 1. \end{cases}$$

Proof: Compute g', g'' , discuss these.

Why? And what does it mean?

Simplest case: $\alpha = \beta = 0 \Rightarrow d_{\text{prior}} = d_{\text{final}}, \theta_0 = \theta_{\text{suc}} \Rightarrow g$ uniform.

Prior and distribution of pivotal effect size have same variance \Rightarrow power becomes uniform, either you beat θ_{suc} or not, with equal probability.

Why P(extreme PoS values) so high if $\alpha < 1$? $d_0 < d_{\text{final}} \Rightarrow$ high variance of prior \Rightarrow high probability to have extreme HRs \Rightarrow power for these is either almost 0 or 1.

g unimodal if $\alpha > 1 \Rightarrow \sigma_{\text{final}} > \sigma_0 \Rightarrow d_{\text{final}} < d_0$. **Unrealistic** in clinical development!

How should we choose prior to get unimodal PoS distribution?

Alternative prior 1: simply choose a large variance

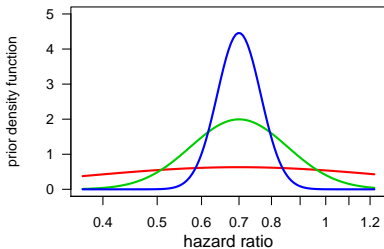
Is Normal prior with large variance “uninformative” - **no!**

If $\sigma_0 > \sigma_{\text{final}} \Rightarrow \alpha < 1 \Rightarrow g$ is bathtub-shaped.

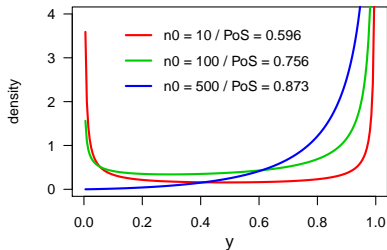
If $\sigma_0 \rightarrow \infty \Rightarrow \text{PoS} \rightarrow 0.5$: improper uniform prior \Rightarrow basically symmetric around θ_{SUC}
 \Rightarrow get same distribution of power values left and right of θ_{SUC} \Rightarrow average of them is 0.5.

Alternative prior 2: truncated Normal prior density

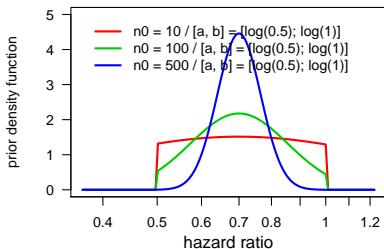
Normal prior density functions



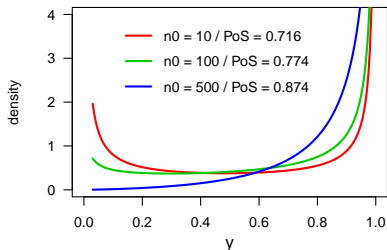
densities g for varying n0



Truncated Normal prior density functions



densities g for varying n0



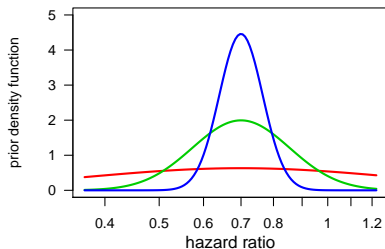
Alternative prior 2: truncated Normal prior density

Observations:

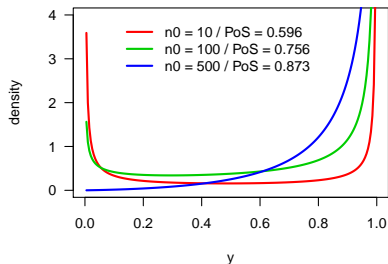
- Prior effect $< \theta_{\text{suc}} \Rightarrow$ the more weight to prior, the higher PoS.
- Truncation only useful if σ_0 not too small \Rightarrow corresponds to low $n_0 \Rightarrow$ still get bathtub-shaped g .
- Prior symmetric but g not (unless $\theta_0 = \theta_{\text{suc}}$). Prior lives on log-scale!

Alternative prior 3: Uniform prior density

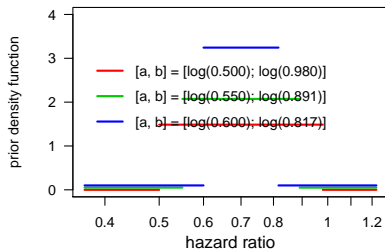
Normal prior density functions



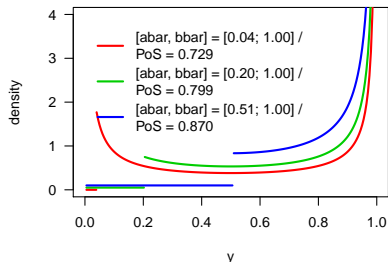
densities g for varying n_0



Uniform prior density functions



densities g for Uniform prior



Alternative prior 3: Uniform prior density

Uniform prior:

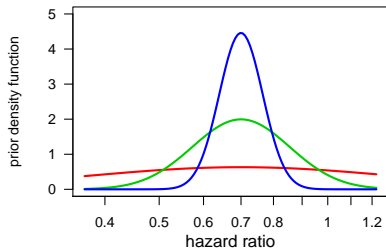
- Uniform priors centered at $\widehat{\theta}_{\text{Phase 2}} = \log(0.700)$.
- When updating with external knowledge or at interim: No matter what we observe \Rightarrow posterior will only have mass in $[a, b]$.

Observations:

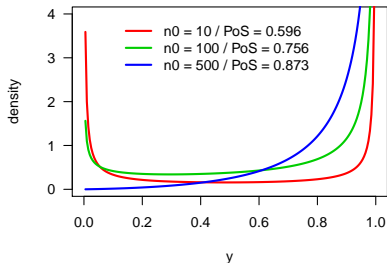
- g has **restricted support**.
- Restriction larger the more weight on Phase 2 (i.e. the larger σ_0^2).

Alternative prior 4: Uniform with Normal tails

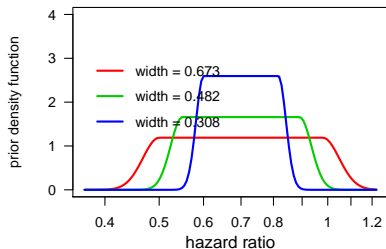
Normal prior density functions



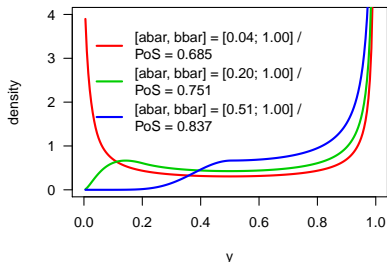
densities g for varying n_0



pessimistic prior density functions



densities g for pessimistic prior



Alternative prior 4: Uniform with Normal tails

Proposed in [Rufibach et al. \(2015\)](#) as “pessimistic prior”.

Still have many low (only if prior is uncertain) and high power values.

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What is “uncertainty” for Bayesian Predictive Power?

What is BPP **not**?

- Not a population parameter to be estimated in a frequentist sense.
- Not a parameter with a prior distribution in a Bayesian framework

What is BPP?

- Average of a transformed effect size (the power function) with respect to a prior on that effect size.

What should “uncertainty” mean in this context? Rather **sensitivity** to assumptions!

If prior knowledge is based on 500 instead of 50 events \Rightarrow should be reflected in BBP.

Sensitivity interval for BPP

Use quantiles of g to compute **sensitivity interval** corresponding to a level of γ (typically chosen to be 0.95):

$$[G^{-1}((1 - \gamma)/2), G^{-1}((1 + \gamma)/2)].$$

Generic example: increase number of events from 50 to 500 \Rightarrow BBP increases from 0.697 to 0.873.

Why does BBP increase? We assumed that $\theta_0 < \theta_{\text{suc}}$.

Sensitivity intervals: [0.000, 1.000] and [0.424, 0.999].

Interpretation: 95% of power values lie in interval when θ drawn from prior p .

Intervals **not of much practical use**, do not restrict interval of plausible BBP values that are compatible with the prior.

Reason: if prior does not carry a lot of information on the underlying true effect \Rightarrow bathtub-shaped $g \Rightarrow$ wide confidence interval.

Discussion

Observations:

- Density of power values often **bathtub-shaped**.
- **Does it make sense** to summarize this distribution in one number which we call BBP?
- Prior with large variance is **not** uninformative!

General questions/comments on bathtub phenomenon:

- How to quantify our prior belief about hazard ratio when we observe $\hat{\theta}_{\text{Phase 2}} = \log(0.700)$ based on 50 events in Phase 2?
- Are we clear what properties PoS should have, as a function of all its input parameters? [Dmitrienko and Wang \(2006\)](#): choice of prior depends on
 - trial's objective,
 - development phase,
 - indication / patient population.

Sensible/possible to come up with a **“one-size-fits-all”** concept?

- Include plot of g in discussion with teams!

Thank you for your attention.



References

- ▶ Berry, S. M., Carlin, B. P., Lee, J. J. and Müller, P. (2011). *Bayesian adaptive methods for clinical trials*, vol. 38 of *Chapman & Hall/CRC Biostatistics Series*. CRC Press, Boca Raton, FL. With a foreword by David J. Spiegelhalter.
- ▶ Dmitrienko, A. and Wang, M.-D. (2006). Bayesian predictive approach to interim monitoring in clinical trials. *Statistics in Medicine* **25** 2178–2195.
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- ▶ Proschan, M., Lan, K. and Wittes, J. (2006). *Statistical Monitoring of Clinical Trials: A Unified Approach*. Springer, New York.
- ▶ Rufibach, K., Jordan, P. and Abt, M. (2015). Sequentially Updating the Likelihood of Success of a Phase 3 Pivotal Time-To-Event Trial based on Interim Analyses or External Information. *Journal of Biopharmaceutical Statistics*, to appear.
- ▶ Spiegelhalter, D., Reedman, L. and Blackburn, P. (1986). Monitoring clinical trials - conditional power or predictive power. *Control Clin Trials* **7** 8–17.

Backup slides.

Why P(extreme PoS values) so high?

Recall g :

$$g(y) = q(\theta_{\text{suc}} - \sigma_{\text{final}}z) \frac{\sigma_{\text{final}}}{\phi(z)}$$

for $z = \Phi^{-1}(y)$.

Why P(extreme PoS values) so high?

Recall g :

$$g(y) = q(\theta_{\text{suc}} - \sigma_{\text{final}}z) \frac{\sigma_{\text{final}}}{\phi(z)}$$

for $z = \Phi^{-1}(y)$.

Increase at both ends:

- $\phi(z)$ in denominator becomes small for $y \rightarrow 0, 1$.
- $\phi(z)$ in denominator derivative of Normal power function \Rightarrow can only be **“nullified”** by choice of prior, but not removed.
- If σ_0 large \Rightarrow high probability for very small / large hazard ratios \Rightarrow power at these hazard ratios virtually 0 or 1.

Doing now what patients need next

R version and packages used to generate these slides:

R version: R version 3.1.1 (2014-07-10)

Base packages: stats / graphics / grDevices / utils / datasets / methods / base

Other packages: mvtnorm / reporttools / xtable / DDCP

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