

Incorporating Clinical Opinion to Survival Extrapolations: An Applied Example

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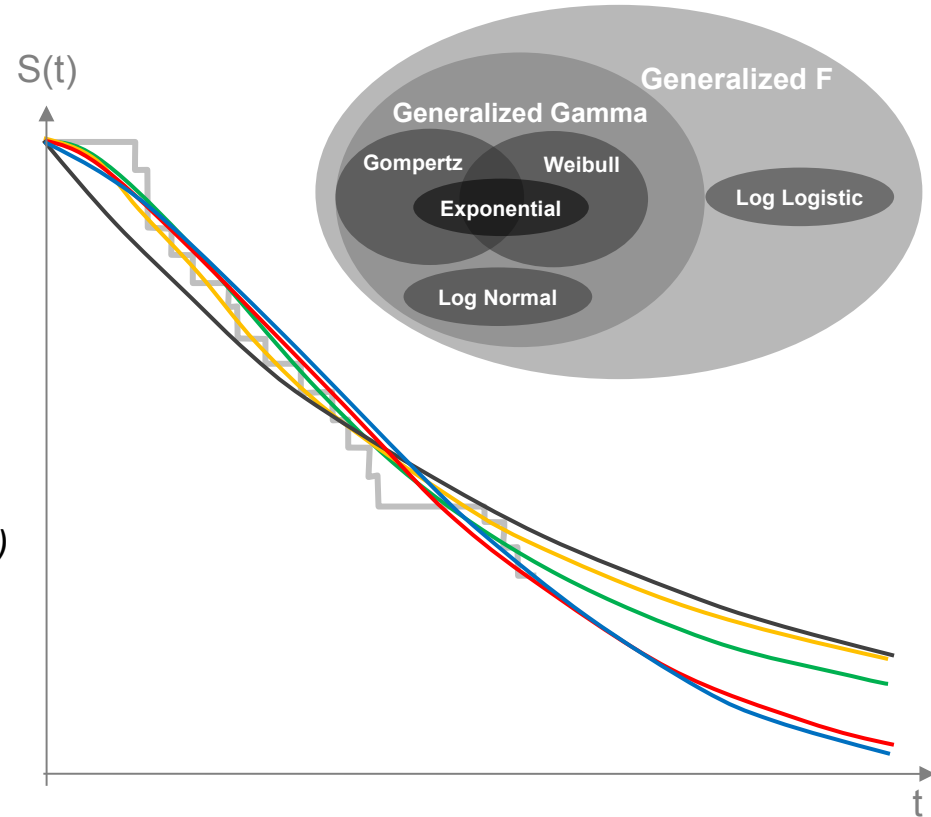
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Background

1. As cited by many authors survival extrapolations are very sensitive to the statistical model used:
 - Exponential ~ Constant Hazard
 - Weibull ~ Monotonically increasing or decreasing Hazards
 - Gompertz ~ Exponentially increasing or decreasing Hazards
 - Log-Normal/Log-Logistic ~ Can initially increase then decrease
2. Give the maturity of the data each model can yield very different extrapolations which may result in different cost effectiveness estimates
3. Extrapolations are based on:
 - Goodness of fit statistics
 - Clinical Opinion
 - External data

Behaviour of some parametric curves

Distr.	Parameters	Hazards
— Exponential	1	—
— Weibull, Gompertz	2	—
— Log Normal	2	—
— Log Logistic	2	—
— Generalized Gamma	3	<i>all above (not LL)</i>
— Generalized F	4	<i>all above</i>
<i>... some more ...</i>		



Extrapolations using Clinical Opinion

1. Acceptance of extrapolations using clinical opinion is generally low:
 - a) Elicited in a very ad-hoc and informal manner (open to bias)
 - b) Implemented in a very subjective manner (i.e. which extrapolation is closest to the experts opinion)
2. Possible Solution - Bayesian Survival Analysis
3. The expert's opinion can be directly incorporated into the trial level analysis!

N.B. Saw this topic presented at ISPOR 2018 by Dr. Mario Ouwens

Bayesian Methods

$$p(\theta|data) = \frac{p(data|\theta) \times p(\theta)}{p(data)}$$

- You update your **Prior Belief*** (i.e. **Clinical Opinion**) with **Data** (i.e. **Trial Data**) and obtain a **Posterior Belief**
- The $p(data)$ typically has no analytical solution, therefore, software such as BUGS, JAGS or STAN is required
- You can use Goodness of fit measures to see which model fits **both** your data and clinical opinion best!

*About a parameter

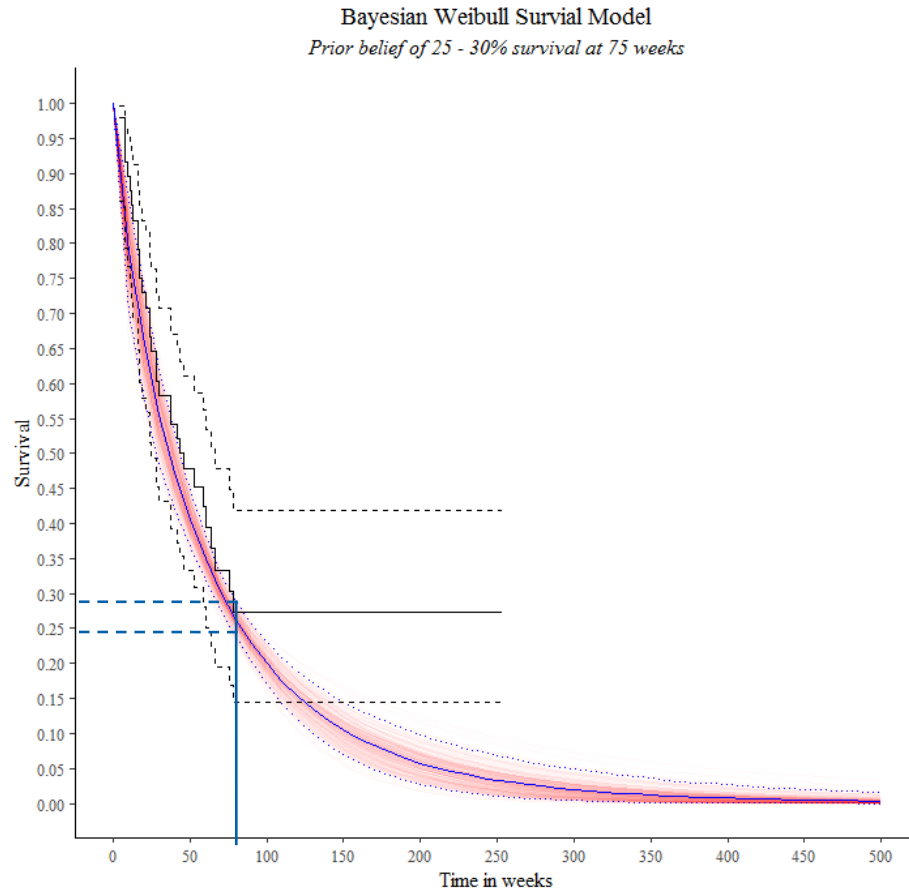
Eliciting the Opinion and Fitting the model

1. Ask an expert to think of the plausible range of survival probabilities at a specific timepoint i.e.:

At 10 years what is the plausible range of survival probabilities for Treatment X?

2. *A plausible range means the upper and lower survival probabilities so the expert is 95% sure that the actual survival probability will be within the range*
3. *Through a hierarchical sampling technique the parameters of the survival distribution are selected to cover this distribution*

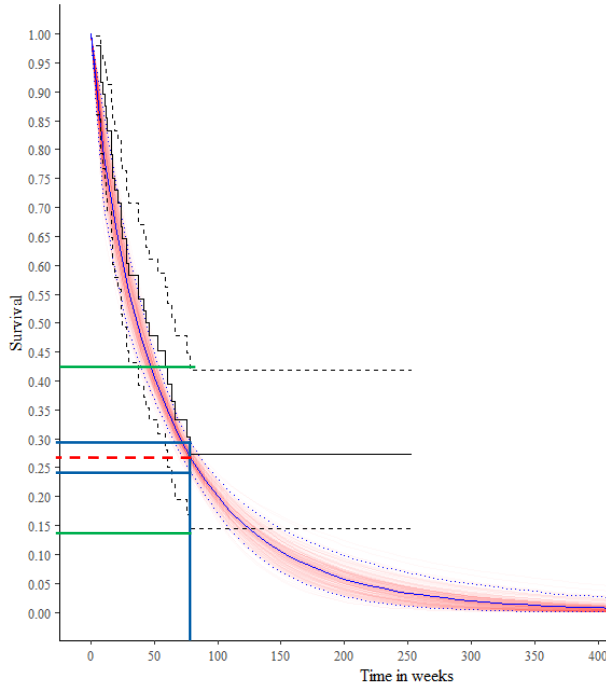
For Illustration: Gastric Cancer Example



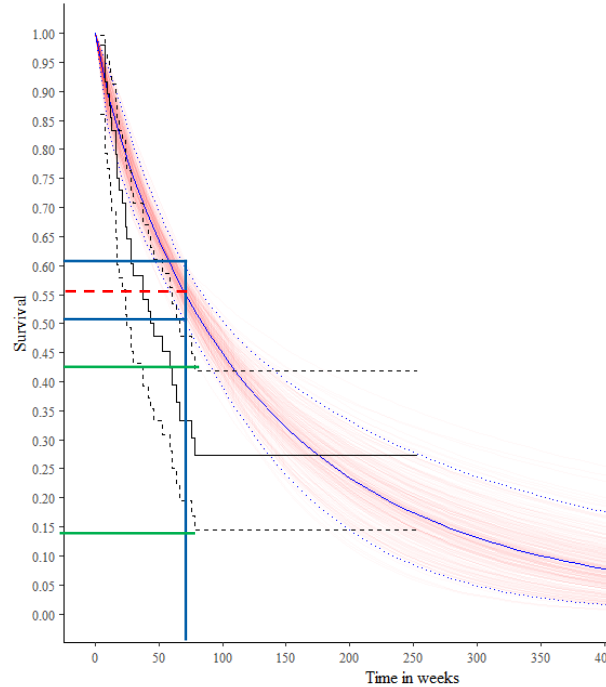
- Dataset available on R, relatively few patients and events (48 and 32)
- For illustration I have constrained the survival at 75 weeks to be between 25-30%
- Exponential, Gompertz, Log-Logistic and Log-Normal all can be fit

For Illustration: Gastric Cancer Example (2)

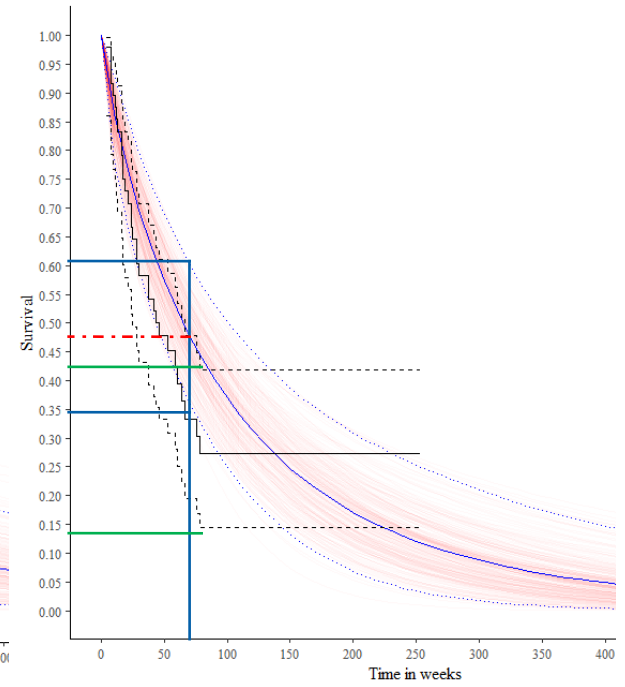
Bayesian Weibull Survival Model
Prior belief of 25 - 30% survival at 75 weeks



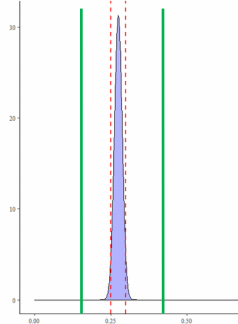
Bayesian Weibull Survival Model
Prior belief of 50 - 60% survival at 75 weeks



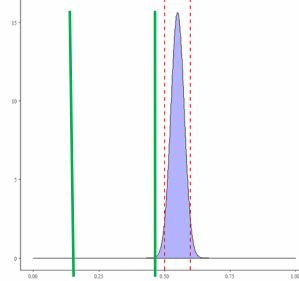
Bayesian Weibull Survival Model
Prior belief of 30 - 90% survival at 75 weeks



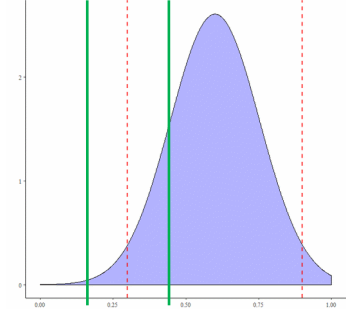
Prior Probability Density with 30-25% Survival estimates



Prior Probability Density with 60-50% Survival estimates



Prior Probability Density with 90-30% Survival estimates



Shiny Tool

The analysis is done in R but it would be potentially easier to elicit opinions if the priors on the survival probabilities could be viewed

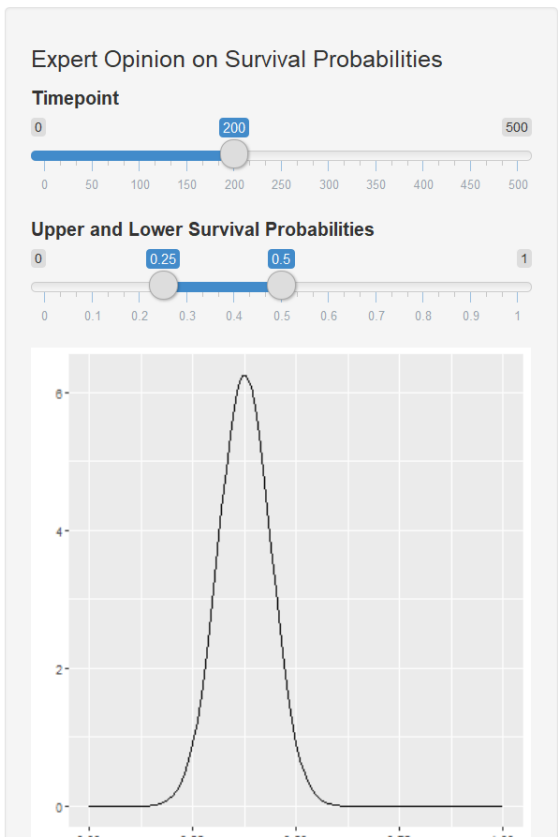
Potential Solution =



Shiny App

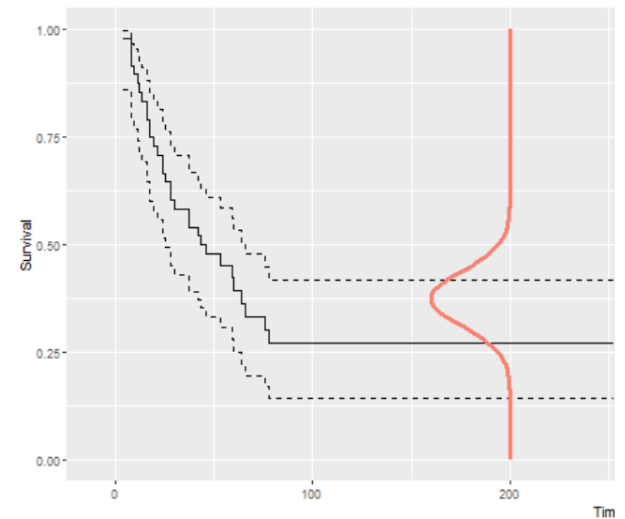
Inputs

Survival Modelling using Expert Opinion



Outputs

Kaplan Meier Survival Plot



Choose a survival model

Weibull

Run Analysis

Output of the Bayesian Analysis

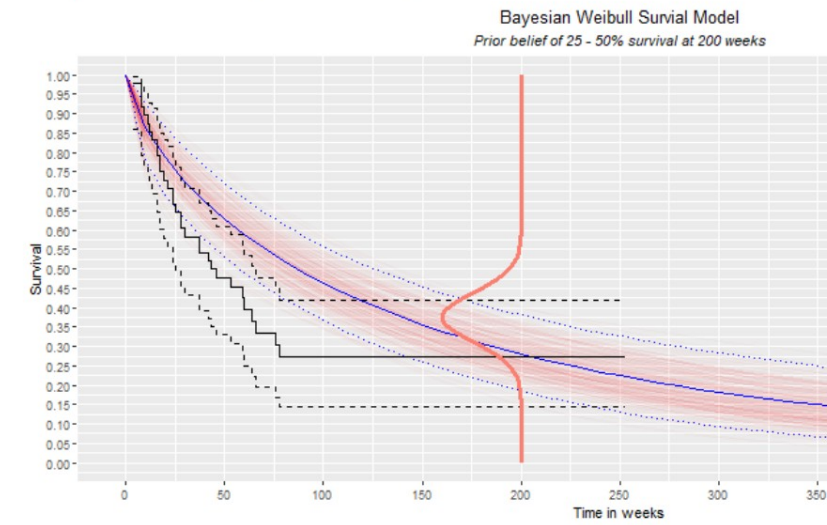


Functionality

We can select the required timepoint & expert's 95% credible interval and see the output update in real time

We can then select the survival model and run the analysis

Output of the Bayesian Analysis



Summary

Advantages:

- ✓ Robust approach to incorporating clinical expert opinion and protects against model misspecification
- ✓ Demands more formal expert elicitation

Disadvantages:

- ❖ Expert elicitation is still the weakest form of evidence; sensitive to overly optimistic/conservative opinions!
- ❖ Approach is limited to one timepoint and cannot incorporate belief about the type of model which is most plausible or external evidence (possibly overcome by Bayesian Model Averaging)
- ❖ Does not (yet) account for more complex 3 parameter models

Backup- Mario Ouwens Presentation

How does it work? Bayesian estimation

Construction of a priori distribution for exponential distribution:

Clinician: "At 10 years, placebo survival percentage is between 10 and 15%"



$\exp(-\lambda t)$

Statistician: $\exp(-\lambda t)$

"I can do my magic with the exponential"

$S = \exp(-\lambda t)$

10% = $\exp(-10 \lambda_{\text{upper bound}})$

15% = $\exp(-10 \lambda_{\text{lower bound}})$

$\lambda_{\text{lower bound}} = 0.19, \lambda_{\text{upper bound}} = 0.23$

27 To be very specific: Our analyses used lognormal λ with log of bounds of confidence intervals



How does it work? Bayesian estimation; Challenge: What to do with multiple parameters

But what to do with distributions with more than 1 parameter?

exp???

Distribution	Functional form	Rewritten for S=10% at t = 10
Exponential	$S = \text{Exp}(-\lambda t)$	$\lambda = -\ln(10\%) / 10$
Weibull	$S = \text{Exp}(-\lambda t^\varphi)$	$\lambda = -\ln(10\%) / 10^\varphi$
Lognormal	$S = 1 - \Phi\left(\frac{\log(t) - \mu}{\sigma}\right)$	$\mu = \log(10) - \sigma \Phi^{-1}(1 - 10\%)$
Loglogistic	$S = \frac{1}{1 + \exp\left(\frac{t}{\beta}\right)^\varphi}$	$\beta = 10 - (\log((1-10\%)/10\%))^{1/\varphi}$
Gompertz	$\exp(-\varphi (\exp(\beta t) - 1))$	$\varphi = -\log(10\%) / (\exp(10\beta) - 1)$



How does it work? Bayesian estimation; Challenge: What to do with multiple parameters



Solution: Sample φ first and compute $\lambda_{\text{upper bound}}$ and $\lambda_{\text{lower bound}}$ using S and φ

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Thank you