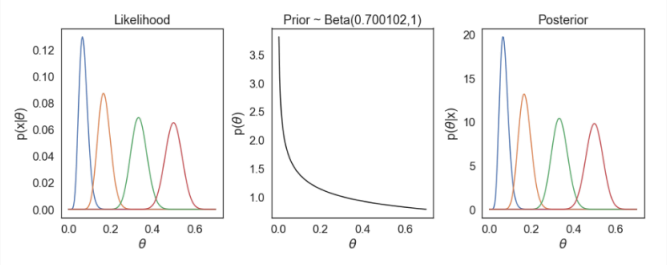
Mathematical Statistics II

STA2212H S LEC9101

Week 8

March 10 2021

Start recording!



More on vaccines

Boyang Zhao's blog post

link

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Vaccine efficacy

The way we measure vaccine efficacy is defined as follows,

$$\text{vaccine efficacy (VE)} = 1 - R$$

The R can be ratio of risks (RR, risk ratio); rates (IRR, incidence rate ratio); or hazards (HR, hazard ratio). Because of the ratios, we see that vaccine efficacy is a relative measure - in how much relative reduction in infection or disease in the vaccinated group compared to the unvaccinated group. A VE of 90% means there are 90% fewer cases in the vaccinated group compared to the placebo group. We will use the subscripts $_v$ and $_p$ to denote vaccinated and placebo groups, respectively; but obviously the discussion is applicable for comparing between any two treatment arms - not necessarily have to be a placebo.

With RR

$$\text{VE} = 1 - \text{RR} = 1 - \frac{c_v/N_v}{c_p/N_p}$$

where N_v and N_p are the total number of participants in the vaccinated and placebo group, respectively.

With IRR

$$\text{VE} = 1 - \text{IRR} = 1 - \frac{c_v/T_v}{c_p/T_p}$$

where T_v and T_p are the time-person years for the vaccinated and placebo group, respectively.

With HR

$$\text{VE} = 1 - \text{HR} = 1 - \frac{\lambda_v}{\lambda_p}$$

where λ_v and λ_p are the hazard rates for the vaccinated and placebo group, respectively. This measures the relative reduction in the hazard of infection. The hazard ratio can be

More on vaccines

Stephen Senn's blog post

link

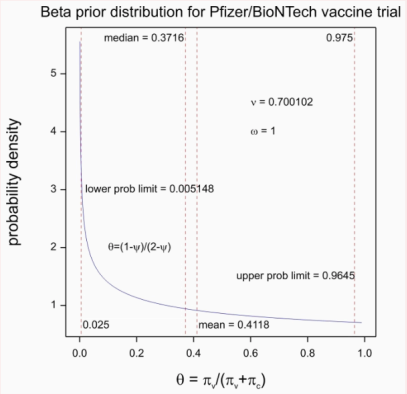
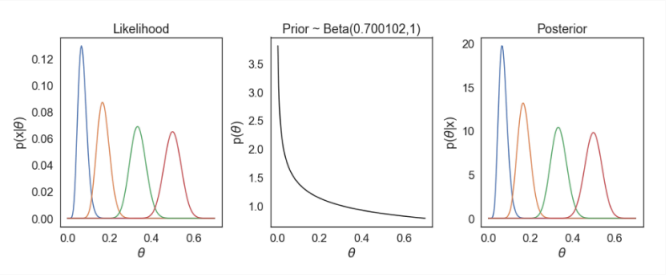


Figure 4 Prior distribution for θ



$\theta = (1 - VE)/(2 - VE)$

POLLING

US election polls: a quick postmortem

How did the 2020 US presidential election polls really do?
Ole J. Forsberg gives his assessment

The American Association for Public Opinion Research (AAPOR) is expected to produce a report early this year that explores the strengths and weaknesses of the polls in the 2020 US election cycle. The polls were criticised in some quarters immediately after the election, when it became clear that Donald Trump had done better than expected and that Joseph R. Biden Jr's margin of victory in the popular vote was not as large as anticipated.[1]

In preparation for this report, I wanted to provide some insight into the polls and some suggestions of my own for moving forward. Specifically, I hope to convince polling houses to use some type of model averaging – or even Bayesian methods – to closing weeks of the campaign.

The first source of error, faulty weighting, is extremely important for polling houses to take seriously. While the number of US polling houses taking education level into consideration increased in 2020, the education characteristics of the voting population remain uncertain.

"Shy voters" – the second source of error – may be more myth than reality (53eig.ht/30NEb6R). But whether shy or not, there are some voters who either choose not to respond to polls, or who choose not to answer honestly when surveyed. Pollsters need to address this, either by asking additional questions to model respondent preference for those who choose not to say how they will vote, or by finding new ways to encourage the public to

interpretation, not of polling. The mistake happens in how we interpret a poll result such as "48% Biden, 44% Trump". Do we focus on the two-party vote and claim that Biden is ahead, or do we acknowledge that there is a sizeable portion of voters – 8% – who may only decide how to vote once in the polling booth? Clearly, the latter interpretation is more appropriate, but it makes for a less straightforward story, so these undecided voters tend to be overlooked in media reports.

Missing data

The majority of polls in the 2020 election cycle contained just three response options for those asked about their intended vote: "Biden", "Trump", and "undecided". The implied fourth

mentioned earlier constitute a huge amount of missing data about voting intention. Ignoring these missing data leads to false precision in the polls' assessment of the state of the election.

While some undecided voters ultimately will not vote, many will eventually decide between the two candidates. This increases the uncertainty in polling estimates beyond what is reported in terms of confidence intervals and margins of error. As a result, when those late-deciding voters finally vote, polls may look very wrong.

To illustrate this point, compare the polls in the final two weeks of the 2020 election to the final election result (Table 1). In this sample of 174 polls, the actual Biden vote was within the polls' margins of error 85% of the time, while the actual Trump vote was within the polls' margins of error only 43% of the time. For the 57% of confidence intervals that missed Trump's actual vote, they were always too low, never too high – meaning that the polls consistently underestimated Trump's final vote. The 15% of confidence intervals

Table 1: Results from comparing candidate support levels in polls from the last two weeks of the US presidential election with the actual outcome of the election (vote share). Polls are a mix of state-level and national polls from a variety of polling houses, using a variety of methods.

		Confidence interval hits		Average miss (standard error)	
Source	***n***	**Biden**	**Trump**	**Biden**	**Trump**
All polls	174	85% (79% to 90%)	43% (35% to 50%)	−0.09	+2.41
Online only	23	96% (78% to 99%)	30% (13% to 53%)	−0.79	+2.21
Online + telephone	26	92% (75% to 99%)	54% (33% to 73%)	−0.78	+2.24
Telephone only	125	82% (74% to 88%)	42% (34% to 52%)	−0.18	+2.48
University	60	92% (82% to 97%)	27% (16% to 40%)	−0.10	+2.99
Non-university	114	82% (73% to 88%)	51% (41% to 60%)	−0.09	+2.10
Partisan	52	79% (65% to 89%)	75% (61% to 86%)	+0.62	+1.33
Non-partisan	122	88% (81% to 93%)	29% (21% to 38%)	−0.40	+2.87

"Personally, I favour the Bayesian solution because it provides a solid statistical structure for estimation and communication of results." link

Latest issue of Applied Statistics (JRSS C)

Journal of the Royal Statistical Society: Series C (Applied Statistics)
Volume 70, Issue 2

Pages: 249-506

March 2021

ISSUE INFORMATION

Free Access

Issue Information

Pages: 249-250 | First Published: 08 March 2021

ORIGINAL ARTICLES

Finite mixtures of semiparametric Bayesian survival kernel Application to breast cancer gene pathway subgroup analy

Lin Zhang, Inyoung Kim
Pages: 251-269 | First Published: 01 December 2020

Quantile-frequency analysis and spectral measures for diag with nonlinear dynamics

Ta-Hsin Li
Pages: 270-290 | First Published: 22 November 2020

Open Access

Future proofing a building design using history matching inspired level-set techniques

Evan Baker, Peter Challenor, Matt Eames
Pages: 335-350 | First Published: 19 December 2020

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Andrew C. Titman, Martin J. Wolfsegger, Thomas F. Jaki
Pages: 351-371 | First Published: 07 January 2021

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Ilenia Lovato, Alessia Pini, Aymeric Stamm, Maxime Taquet, Simone Vantini
Pages: 372-397 | First Published: 22 January 2021

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Bayesian semi-parametric G-computation for causal inference in a cohort study with MNAR dropout and death

Maria Josefsson, Michael J. Daniels

STATISTICS

An Official Journal of the
Institute of Mathematical Statistics

Articles

Vol. 13, No. 3—September 2019

of

APPLIED STATISTICS

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Articles—*Continued from front cover*

Recap

Are you recording?

- approximate posterior normality
- choosing a prior: subjective, conjugate, flat, convenience
- matching priors; Jeffreys' prior
- multiple parameters, marginal posterior
- Bayesian and frequentist philosophy

AoS §11.1

- empirical and epistemic probability

RE: Meeting suggestions and new committee members

Today

Start Recording

1. Friday: Jeffreys-Lindley paradox (HW 6 (c)); DF re χ^2;
2. Bayesian inference overview
3. ~~Two~~ One weird example~~s~~ AoS 11.9, ~~11.10~~
4. empirical Bayes
5. hierarchical Bayes

- Mar 15 5.15 – 6.15 pm EDT
  Data Science Speaker Series
  Jesse Cresswell
  Machine Learning Scientist, Layer 6 AI at TD
  "Evaluating Model Performance on Highly Imbalanced Datasets"

Overview

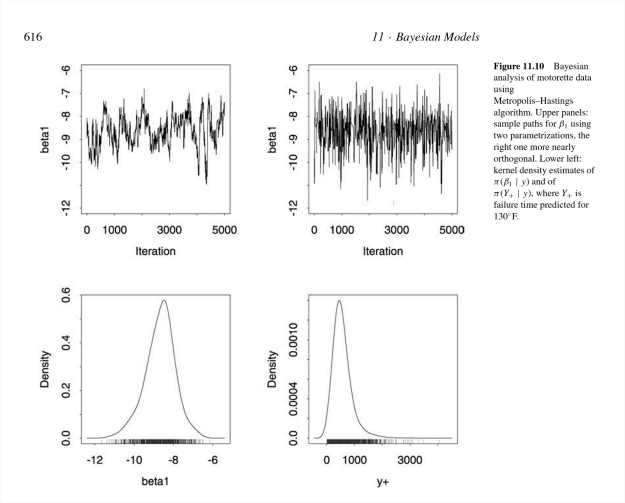
- all information about θ contained in posterior density $\pi(\theta \mid x^n) = f(x^n \mid \theta)\pi(\theta)/f_{X^n}(x^n)$
- inference about $\psi(\theta)$ based on marginal posterior
- for comparing two (or more) points θ in $\pi(\theta \mid x^n)$, don't need marginal distribution of X^n
- for choosing between models, do need marginal distribution of X^n, as in HW 6 (c)
- Bayesian predictions of future values: posterior predictive

$$\pi(x_{new} \mid x^n) = \int f(x_{new} \mid x^n, \theta)\pi(\theta \mid x^n)d\theta,$$

- probability statements refer to uncertainty of knowledge
- choosing priors can be difficult, and can have large impact in high-dimensional settings
- most applications of Bayesian inference involve sampling from the posterior density
- or approximating the posterior density normal, Laplace

Bayesian computation

- excellent overview of Bayesian computational methods in SM 11.3
- Laplace approximation of integrals
- importance sampling
- Markov chain Monte Carlo sampling
  - Gibbs sampling
  - Metropolis-Hastings algorithm



Example 11.9 AoS

$(X_1, R_1, Y_1), \ldots, (X_n, R_n, Y_n)$ i.i.d.; parameter $\theta = (\theta_1, \ldots, \theta_B)$, B very large

Example 11.9 AoS

Example 11.9 AoS

Bayesian hierarchical models

SM 11.4, Eg. 11.25

Bayesian hierarchical models

SM 11.4. Eg. 11.25

Fig 11.11

Empirical Bayes

SM 11.4. Eg. 11.28