Soc504: Inference

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Princeton

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[1]Much of the material in section 2-7 is edited from Gary King's slides for Gov2000 at Harvard. Section 8 is heavily influenced by Patrick Lam.

Where We've Been and Where We're Going...

- Last Week
  - Intro and Class Overview
- This Week+
  - Theories of inference
  - Likelihood Estimation
  - Simulation
- Next Week+
  - Generalized Linear Models
- Long Run
  - likelihood $\rightarrow$ GLMs $\rightarrow$ advanced methods

Followup

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- Note that today we will be discussing things that border on philosophy. Thus it is particularly important that you ask questions. Often the simplest questions are the most profound!

1. History
2. Likelihood Inference
3. Bayesian Inference
4. Neyman-Pearson
5. Likelihood Example
6. Properties and Tests
7. Simulation
8. Fun With Bayes

Historical Backdrop

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- While an algorithm tells us what to compute and provides a summary of the data, inference answers the question of why we are doing something (i.e. what properties it has).
- For our purposes the central question of inference will be, how do we assess the accuracy of an estimate?

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- We often talk about this as frequentists posing the question: 'what would happen if we reran the same situation over and over again?'
- Why is this hard? Well we need to calculate properties of an estimator obtained from a true distribution F even though F is unknown.

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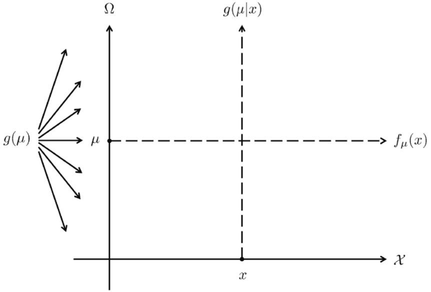

Figure 3.5 Bayesian inference proceeds vertically, given x; frequentist inference proceeds horizontally, given μ.

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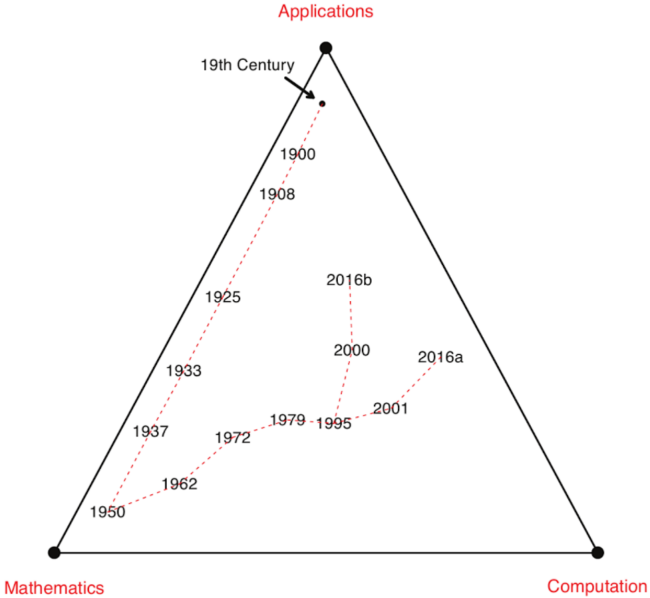
- We will also see that likelihood lends itself nicely to situations where we care a lot about the outcome rather than the coefficients themselves.
- For those interested Stigler's "The epic story of maximum likelihood" is a fantastic account of the history of the idea.

A Perspective on a Historical Arc (Efron and Hastie 2016)



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3. A more reasonable, limited goal. Let $M = \{M^*, \theta\}$, where M^* is assumed & θ is to be estimated:

$$\mathbb{P}(\theta|y, M^*) \equiv \mathbb{P}(\theta|y)$$

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8. The two differ on what is fixed and what is random

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6. $L(\theta|y)$ is a function: for y fixed at the observed values, it gives the "likelihood" of any value of θ.

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11. The likelihood principle: the data only affect inferences through the likelihood function

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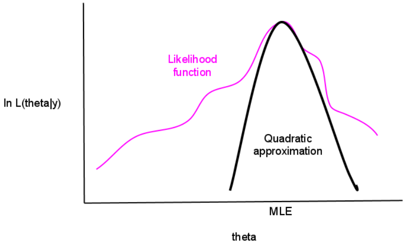

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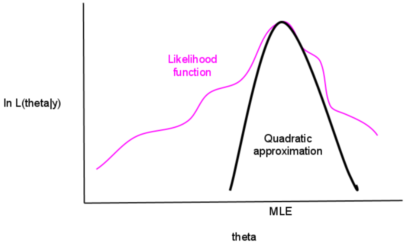

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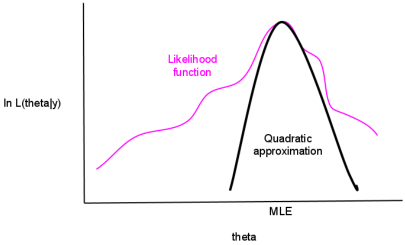

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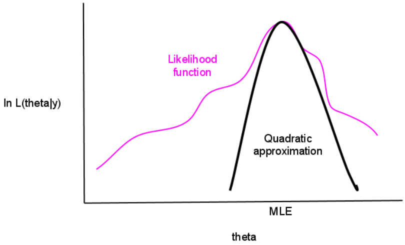

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- Uncertainty of point estimate: curvature at the maximum

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- Notational note: log in math is almost always used as short-hand for the natural log (ln) as opposed to the base-10 log.

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For a fixed set of observations, what does this look like?

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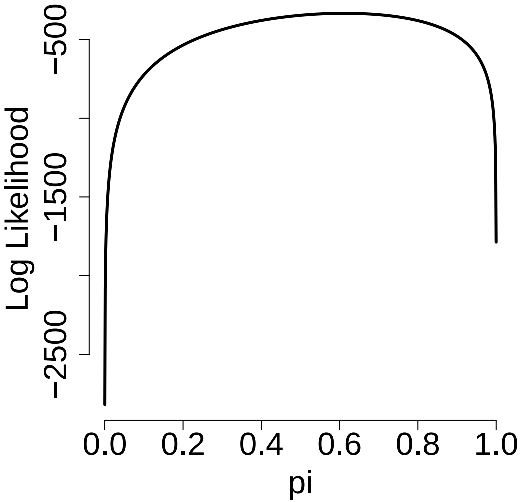

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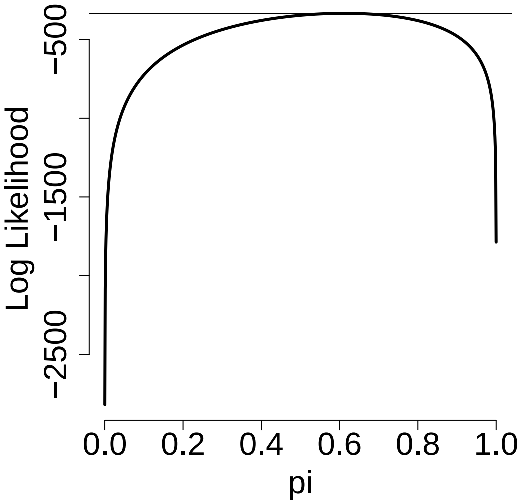

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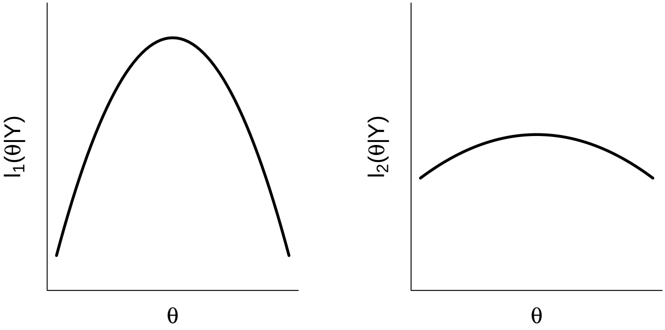

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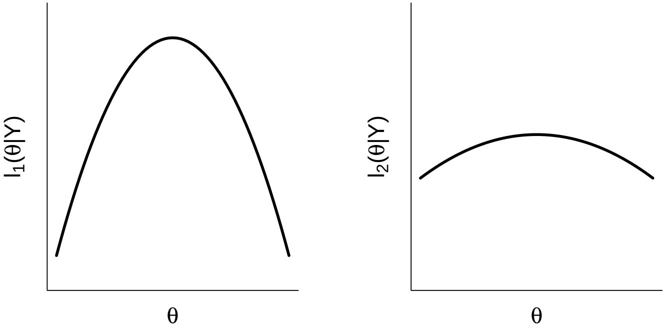

Second derivative captures this curvature

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4. A philosophical assumption that nonsample information should matter (as it always does) and be formalized and included in all inferences.

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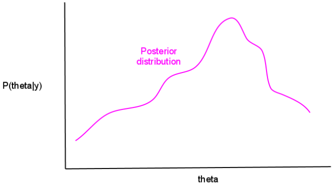
The posterior density, $\mathbb{P}(\theta|y)$



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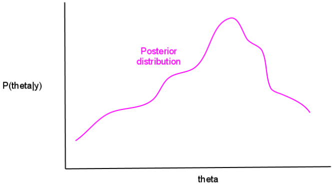

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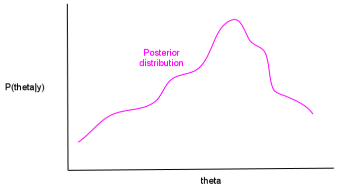

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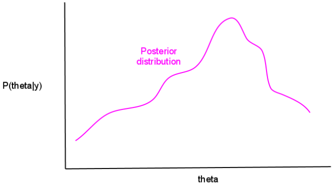

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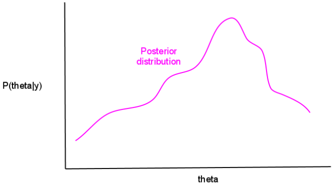

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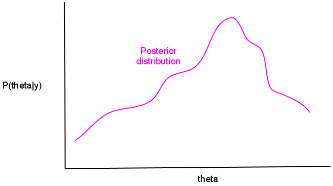

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- If $\mathbb{P}(\theta) = 1$, i.e., is uniform in the relevant region, then $L(\theta|y) = \mathbb{P}(\theta|y)$.

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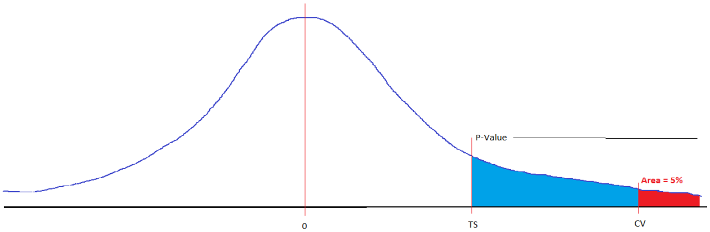

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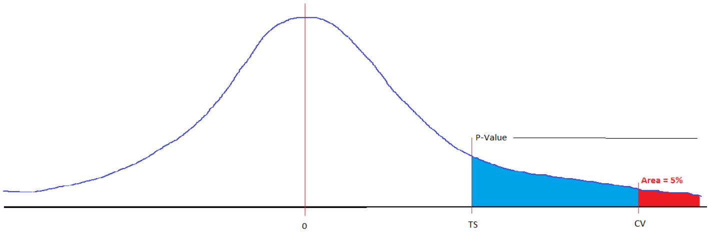

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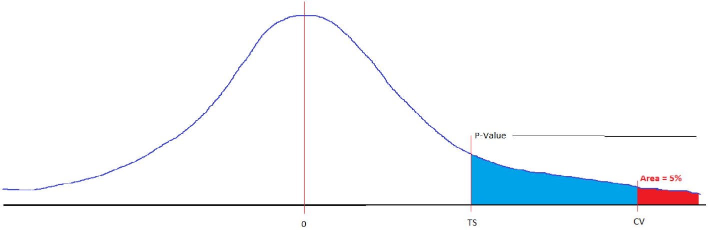

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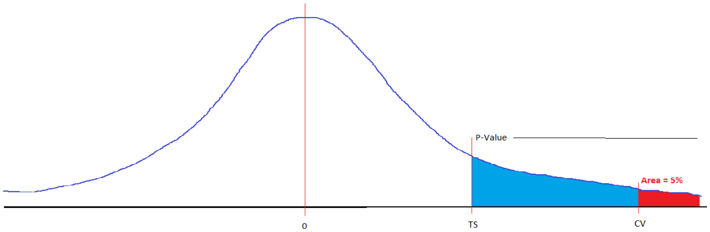

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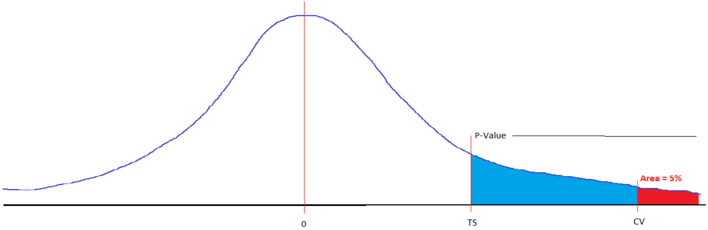

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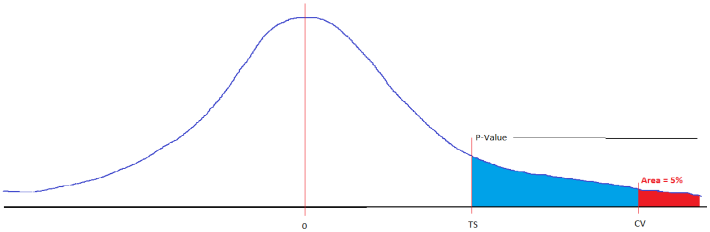

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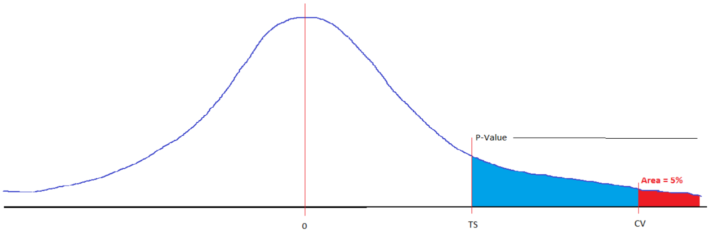

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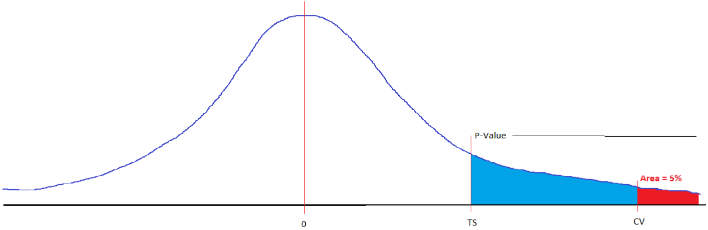

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4. Methods for applied researchers: either useful or irrelevant $\rightarrow$ learn something then validate it.

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- This motivates different views of the core material such as agnostic and robust statistics.

A Simple Likelihood Model: Stylized Normal, no X

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- What can you do with this probability density?

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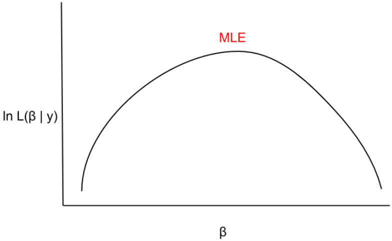
Log-likelihood interpretation



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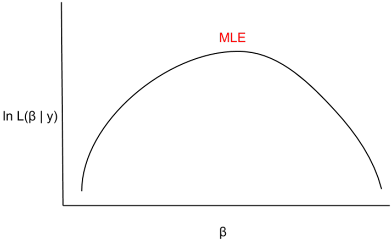

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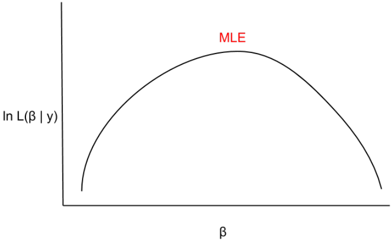

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2. This curve summarizes all information the data gives about β, assuming the model.

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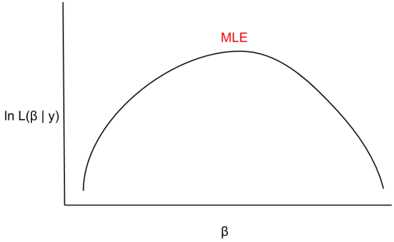

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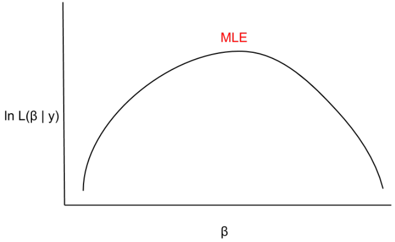

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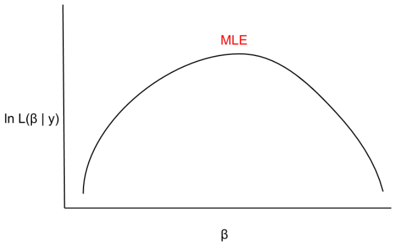

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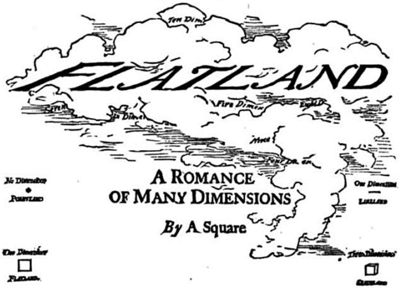
Summarizing k-dimensional space

- The problem of Flatland



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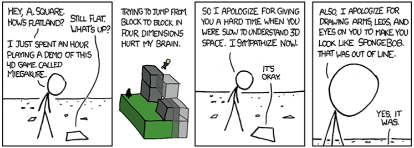

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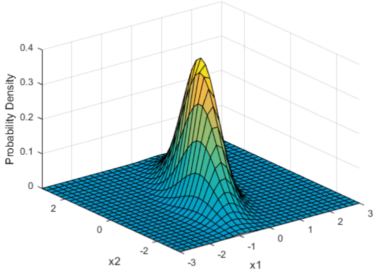

Summarizing k-dimensional space

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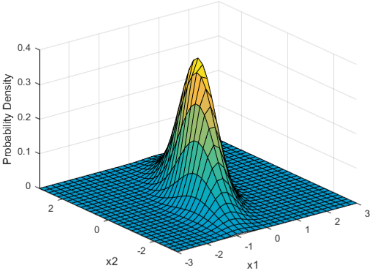
- The curse of dimensionality
- Maximum
- The curvature at the maximum (standard errors, about which more shortly)



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   - Not a sharp divide- some analytic work helps numerical optimization

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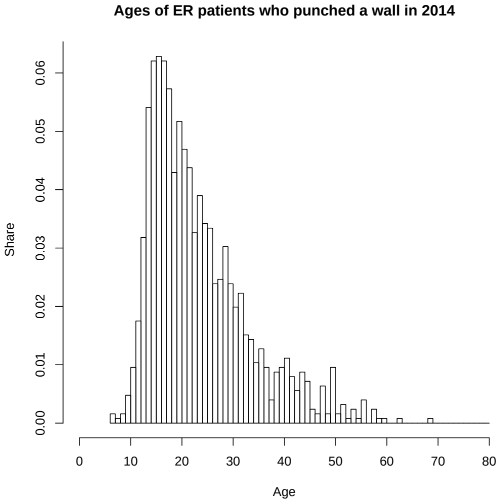
- To do this, we write down a probability model for the data.

Empirical distribution of wall-punching ages



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Example: Age distribution of ER visits due to wall punching

The density of the log-normal distribution is given by

$$f(Y_i|\mu,\sigma^2) = \frac{1}{Y_i\sigma\sqrt{2\pi}}\exp\left(-\frac{(\ln(Y_i)-\mu)^2}{2\sigma^2}\right)$$

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Basically the same as saying $\ln(Y_i)$ is normally distributed!

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$$\mathcal{L}(\mu, \sigma^2|\mathbf{Y}) \propto \prod_{i=1}^{N} f(Y_i|\mu, \sigma^2)$$

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Plotting the log-likelihood

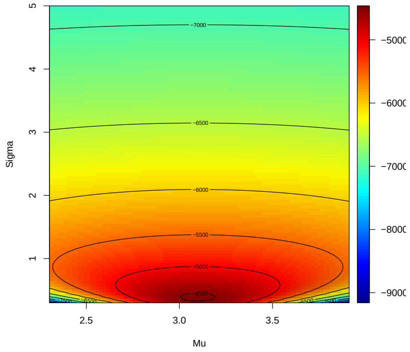
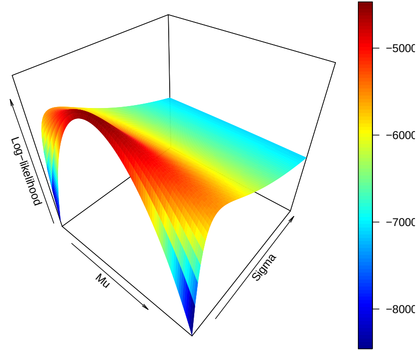


Figure: Contour plot of the log-likelihood for different values of μ and σ

Plotting the likelihood



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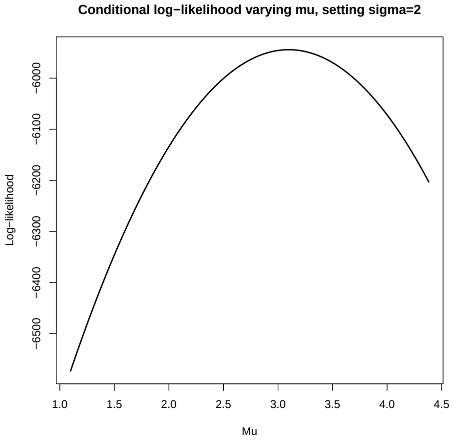

Figure: Plot of the conditional log-likelihood of μ given $\sigma = 2$

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- Let's plot the implied distribution of Y_i for each parameter set over the empirical histogram!

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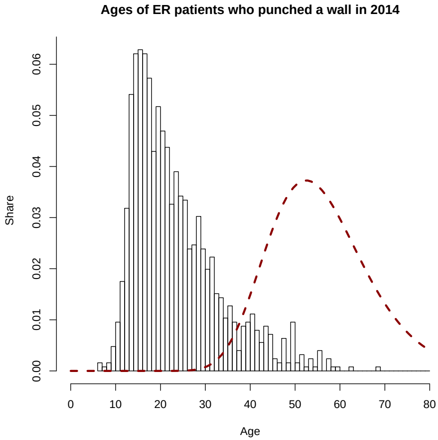

Figure: Empirical distribution of ages vs. log-normal with $\mu = 4$ and $\sigma = .2$

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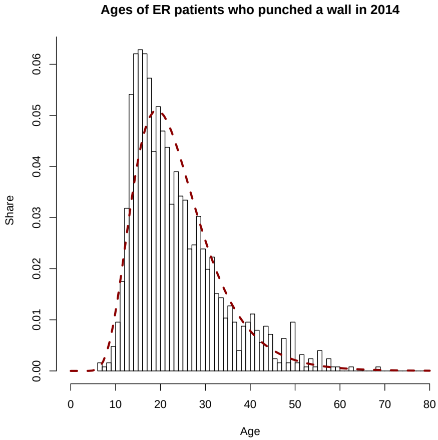

Figure: Empirical distribution of ages vs. log-normal using MLEs of parameters

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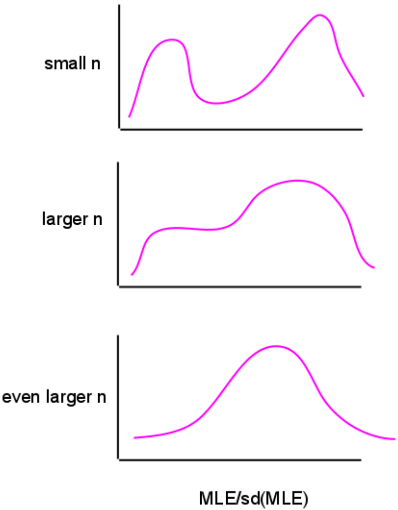
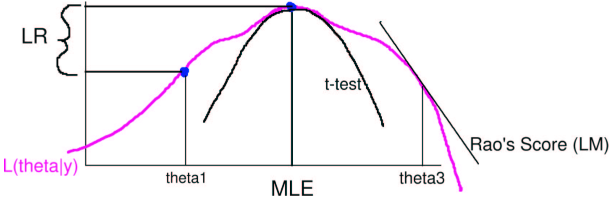
3. Asymptotic efficiency. The MLE contains as much information as can be packed into a point estimator.

Sampling distributions of the MLE: CLT vs LLN



Uncertainty: Likelihood Ratios for nested models



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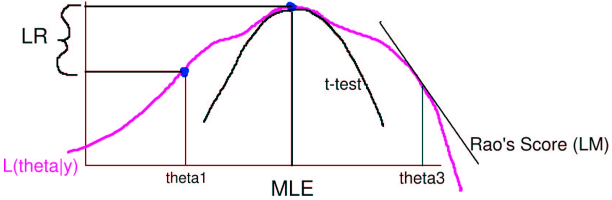

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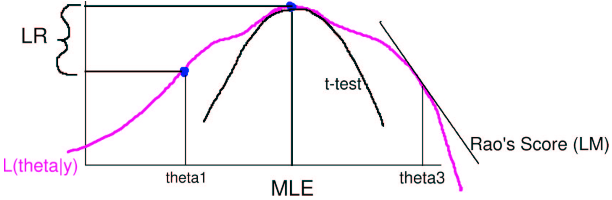

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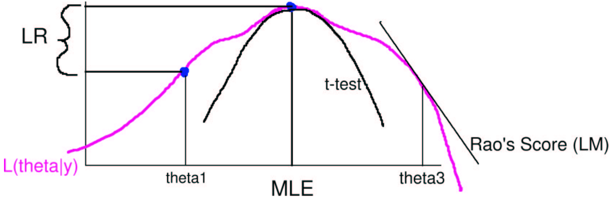

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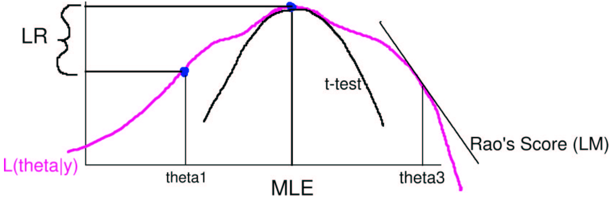

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- $\implies L^* \geq L_R^* \implies \frac{L_R^*}{L^*} \leq 1$
- This is a direct generalization of F-tests that we learned about in regression.

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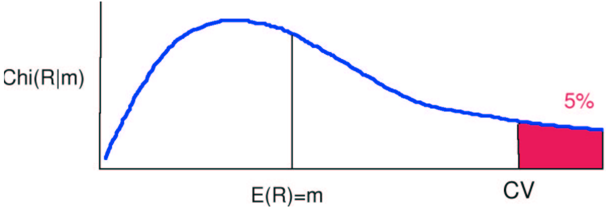

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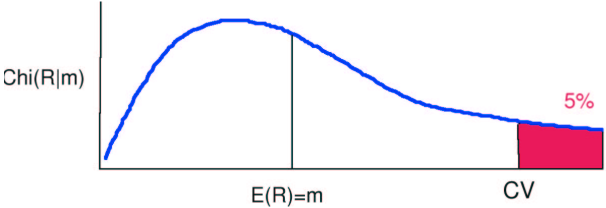

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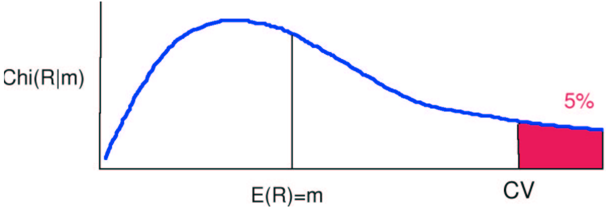

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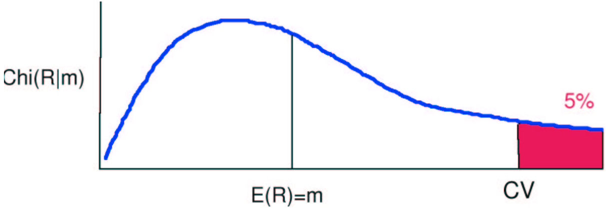

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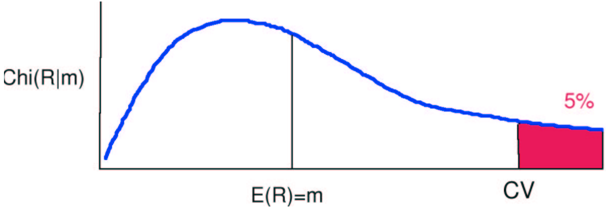

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- Thus, it might be nice to have a summary of uncertainty for every parameter separately $\rightsquigarrow$ standard errors

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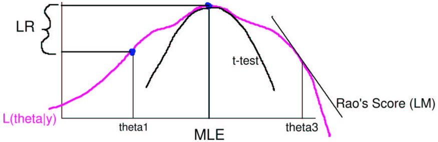

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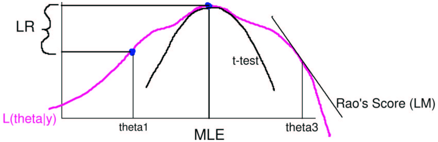

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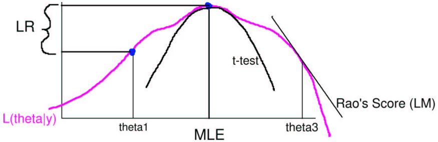

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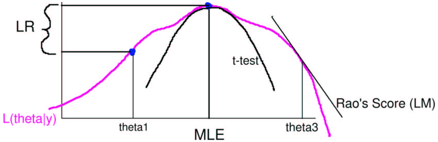

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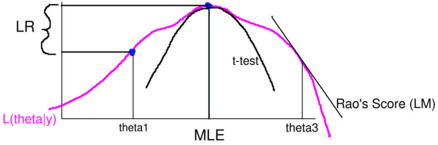

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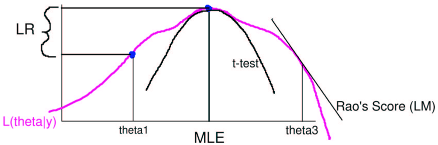

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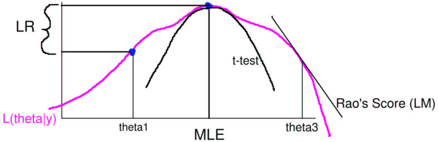

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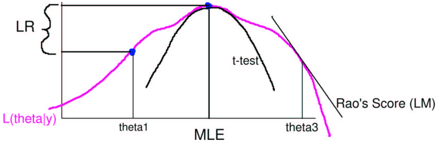

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- In certain settings we can still prove the point estimate is consistent and derive consistent estimators of the sampling variance (heteroskedasticity and serial correlation in normal model, clustering in logit and probit models, overdispersion in GLMs)

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X_{it}	a list of covariates (economic conditions, polls, home state, etc)
$X_{i,2016}$	the same covariates as X_{it} but measured in 2016

ML Example: k Parameters, including an Ancillary Parameter, with Simulation to Interpret.

Forecasting Presidential Elections.

The Data

i	U.S. state, for $i = 1, \ldots, 50$
t	election year, for $t = 1948, 1952, \ldots, 2012$
y_{it}	Democratic fraction of the two-party vote
X_{it}	a list of covariates (economic conditions, polls, home state, etc)
$X_{i,2016}$	the same covariates as X_{it} but measured in 2016
E_i	The number of electoral college votes for each state in 2016

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$$\begin{aligned} L(\mu_{it}, \sigma | y_{it}) &\propto N(y_{it} | \mu_{it}, \sigma^2) \\ &= (2\pi\sigma^2)^{-1/2} e^{\frac{-(y_{it}-\mu_{it})^2}{2\sigma^2}} \end{aligned}$$

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- Compute and save $\hat{V}(\hat{\theta})$, which is $k + 2 \times k + 2$

R Code for the Log-Likelihood

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- Mathematical Form:

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- An R function:

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X <- as.matrix(cbind(1, X))
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- Calling it:

```
ll.normal(c(2,1,2,1,33,4,3.2),x,y)
ll.normal(c(2,1,2,1,33,4,3.7),x,y)
ll.normal(c(2,1,2,1,33,4,3.5),x,y)
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- Repeat Steps 1–3 $M = 1,000$ times, and plot a histogram of the results.

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4. Add fundamental uncertainty: draw $\tilde{y}_{i,2016} \sim N(\tilde{\mu}_{i,2016}, \tilde{\sigma}^2)$

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(calculated before the election by Gelman and King)

(actual results: 69%)

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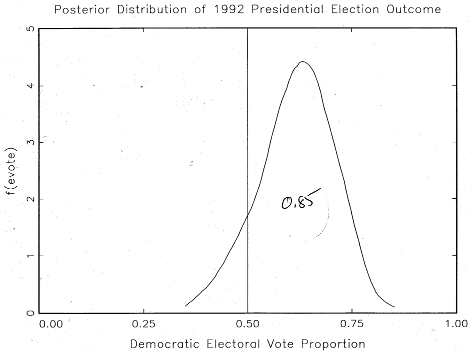

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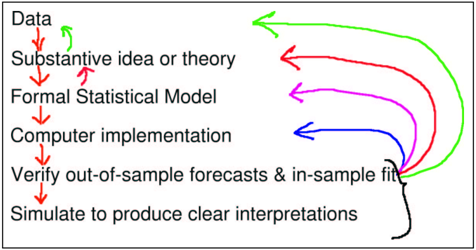
\end{aligned}$$

- For what applications would this model be informative?

An Outline of the Research Process



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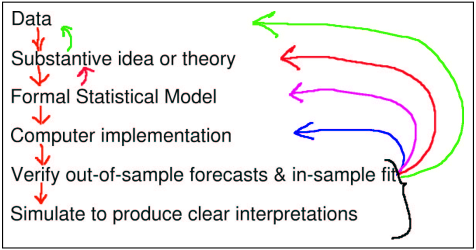

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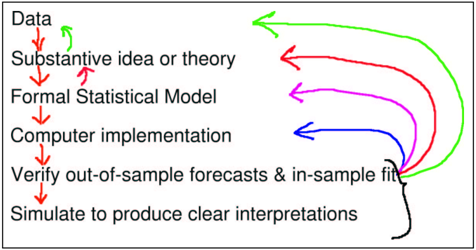

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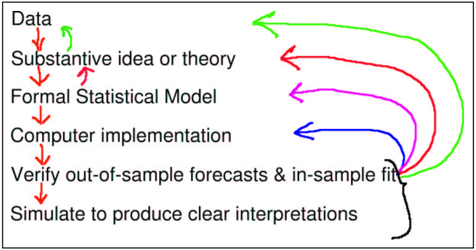

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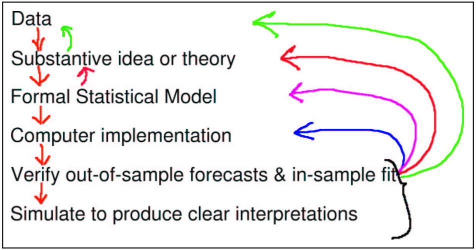

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4. Don't miss any parts.

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- We will talk about this more in the last couple of weeks.

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e.g. when rolling a die, the probability of a 3 *or* 5 is just $\frac{1}{6} + \frac{1}{6}$

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   - "objective", dominant paradigm in statistics, and cheerleaders incl Fischer.

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    - example: our prior over a coin's outcomes (Bernoulli process) might be $p = \frac{1}{2}$ or $p = \frac{1}{3}$ or $p = 1$ ('degenerate')— we can then conduct our trials (the tosses themselves). Alternatively, we might have a prior on the value of some $\hat{\beta}$ in a regression.

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There is a fixed, true value of θ, and we maximize the likelihood to estimate θ and make assumptions to generate uncertainty about our estimate of θ.

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- The prior is usually a probability distribution that integrates to 1 (proper prior).

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NB: *Bayesian is too hard. Why use it?*
B: Bayesian methods allow us to easily estimate models that are too hard to estimate (cannot computationally find the MLE) or unidentified (no unique MLE exists) with non-Bayesian methods. Bayesian methods also allow us to incorporate prior/qualitative information into the model.

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There is a Bayesian way to do any non-Bayesian parametric model.

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Bayesian priors are just adding pseudo observations to the data.

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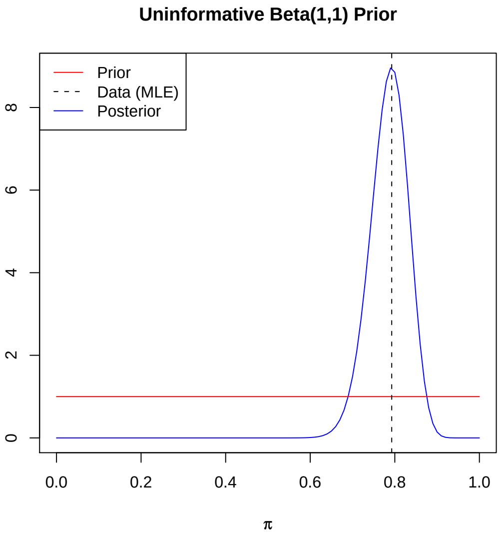
Big Point: Bayesian inference necessitates the estimation of distributions rather than parameters



Uninformative Beta(1,1) Prior
Prior
Data (MLE)
Posterior
0
2
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8
0.0
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0.4
0.6
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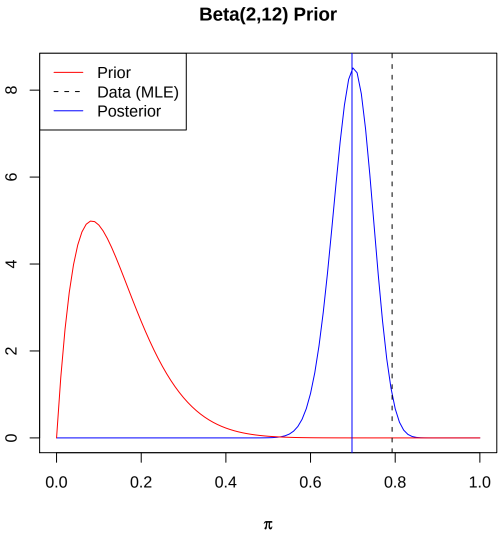
π


Beta(2,12) Prior
Prior
Data (MLE)
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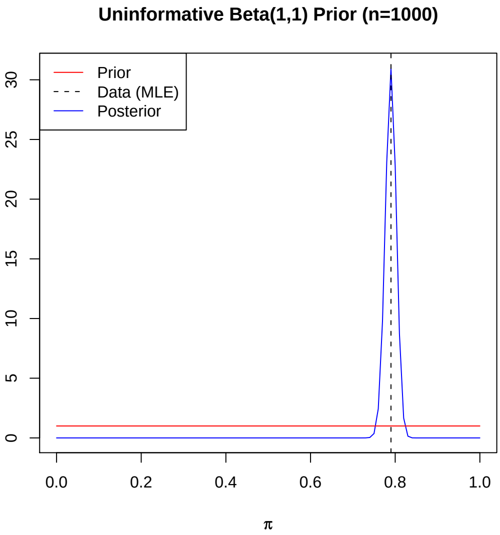
π


Uninformative Beta(1,1) Prior (n=1000)
Prior
Data (MLE)
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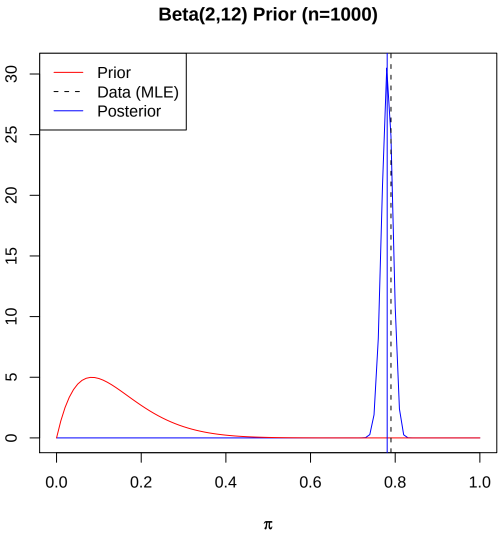
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Conjugate models are great because we can find the exact posterior, but...

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$$p(\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\theta}, \boldsymbol{\sigma}, \boldsymbol{\pi}, \boldsymbol{\tau} | \boldsymbol{Y}) \quad \propto \quad \prod_{k=1}^{K} \prod_{s=1}^{S} \frac{\exp(-\frac{\alpha_{ks}}{1/4})}{1/4} \times \frac{\Gamma(\sum_{w=1}^{W} \lambda_w)}{\prod_{w=1}^{W} \Gamma(\lambda_w)} \prod_{w=1}^{W} \theta_{k,w}^{\lambda_w - 1} \times$$

$$\prod_{i=1}^{n} \prod_{t=2005}^{2007} \prod_{s=1}^{S} \left[\beta_s \frac{\Gamma(\sum_{k=1}^{K} \alpha_{ks})}{\prod_{k=1}^{K} \Gamma(\alpha_{ks})} \prod_{k=1}^{K} \pi_{itk}^{\alpha_{ks} - 1} \prod_{j=1}^{D_{it}} \prod_{k=1}^{K} \left[\pi_{itk} \prod_{w=1}^{W} \theta_{kw}^{y_{ijtw}} \right]^{\tau_{ijtk}} \right]^{\sigma_{its}}$$

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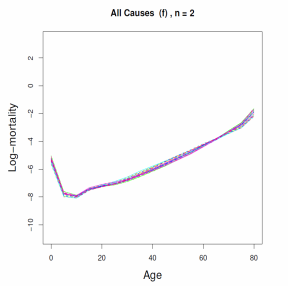

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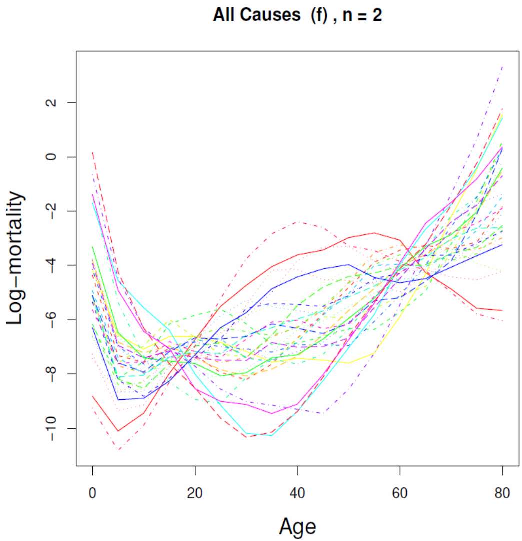

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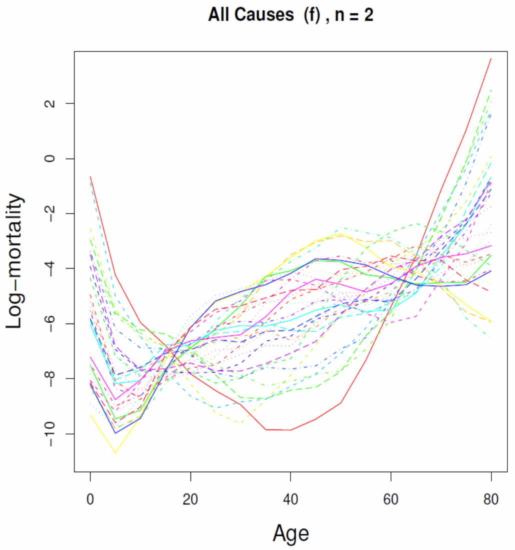

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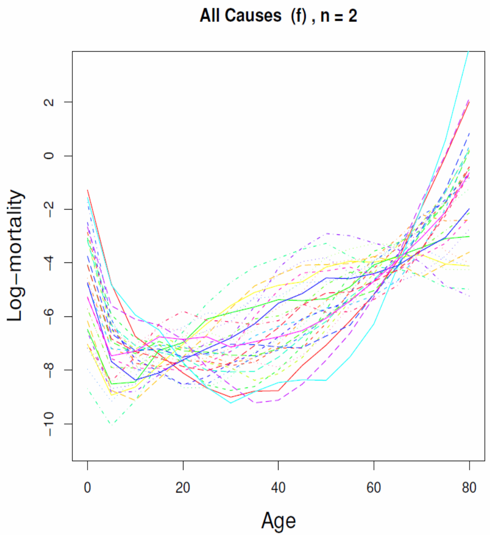

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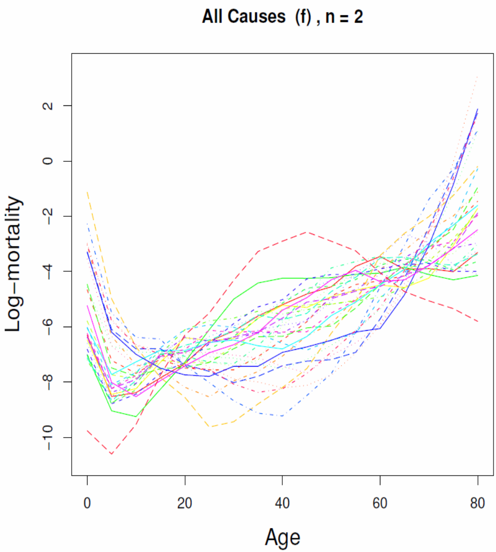

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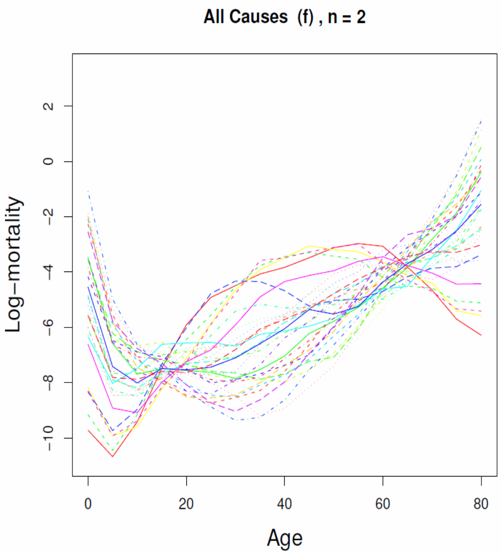

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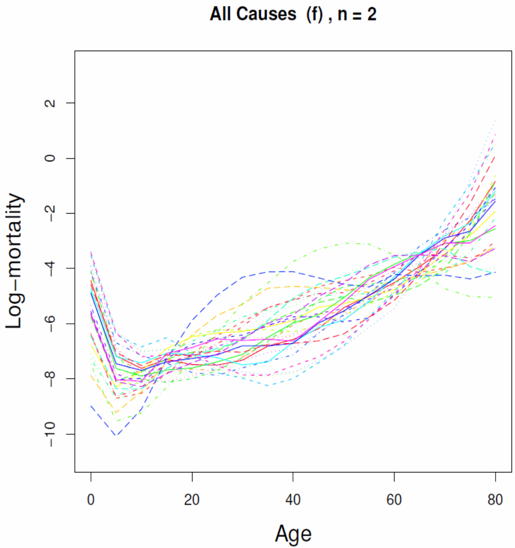

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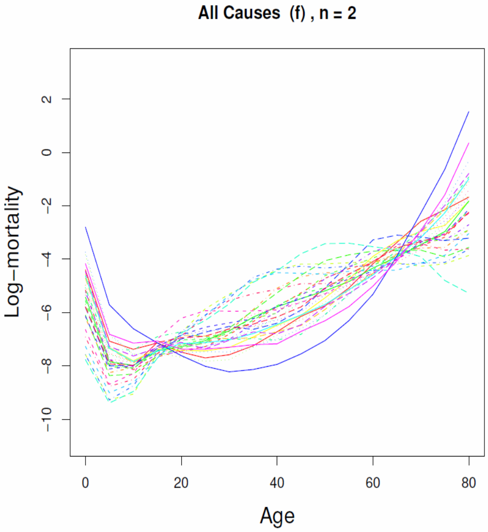

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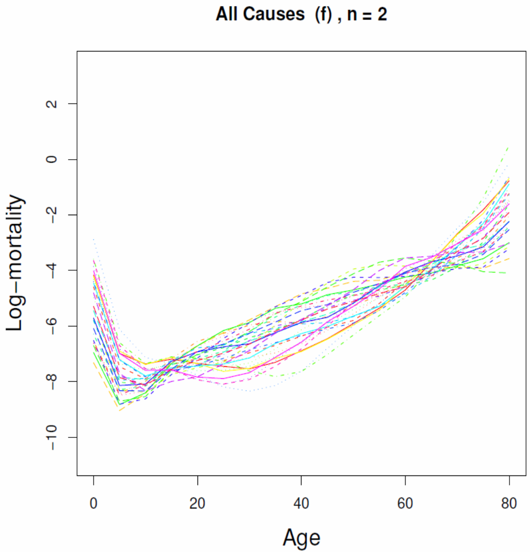

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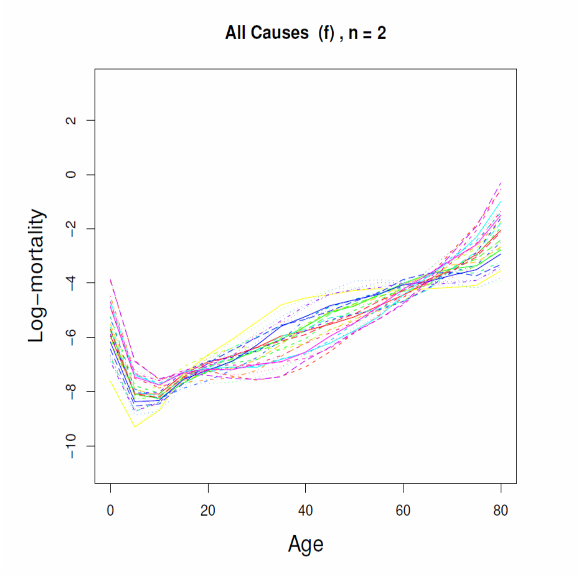

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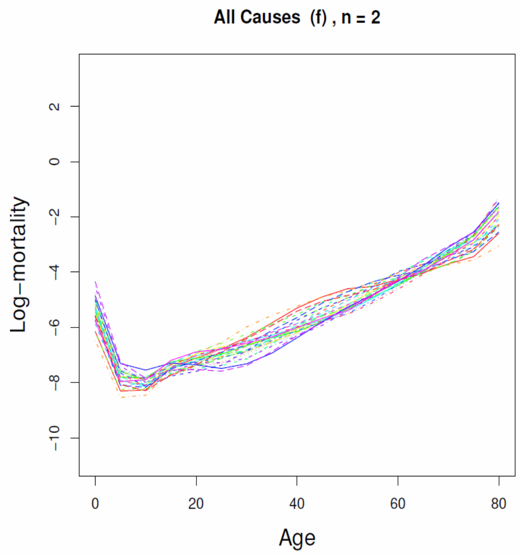

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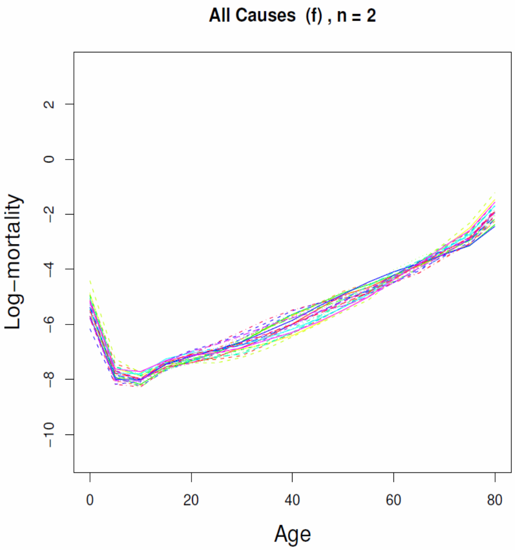

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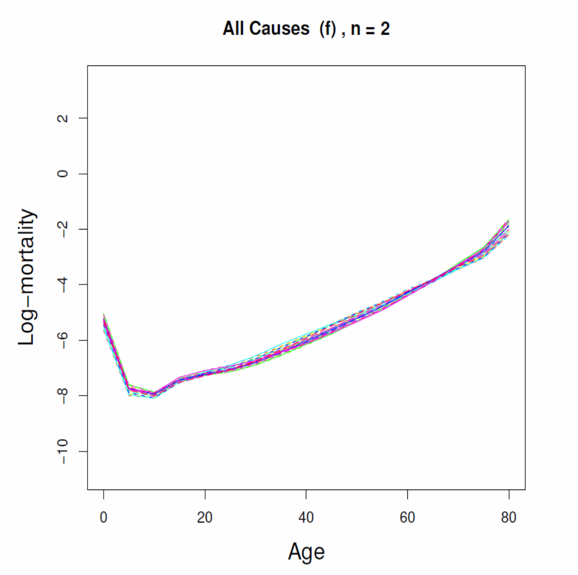

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All solved using Bayesian Hierarchical Models! (See *Demographic Forecasting* and the *YourCast* package.