Placating pugilistic pachyderms

Proper priors prevent poor performance

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Outline

Long ago, and so far away

Through the latter half of the 20th century Bayesian methods became a dominant force in applied and applicable statistics.

- Bayesian statistics provides a coherent way to update probabilities (or "belief statements") in the light of new data
- For a number of classical problems, Bayesian methods are eventually equivalent (with enough data) to the corresponding non-Bayesian/frequentist method
- The basic intuition is that **If you have enough information about a parameter of inference, any sensible statistical method will work**
- The interesting problems occur when there is *not* an over-abundance of information.

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Beast of Burden

A Savage Quotation

You should build your model as big as an elephant

A von Neumann quote

With four parameters I can fit an elephant, and with five I can make him wiggle his trunk.

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Come to the supermarket (in old Peking)

There's a whole smorgasbord of features of modern Bayesian models. Notably:

- An overabundance of random effects
- Multilevel models that borrow strength across different subpopulations to improve estimates
- Correlated random effects, such as spatial or spatiotemporal random effects
- Nonlinear effects of covariates (splines, splines, and more splines)

With all these effects, it is not uncommon to have more parameters than data.

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Busby Berkleey Dreams

We have made things worse

- Estimating the mean of a Gaussian
- MCMC changed everything
- BUGS brought it to the masses
- I work on INLA, which does fast infrerence for latent Gaussian models
- Stan is even worse!

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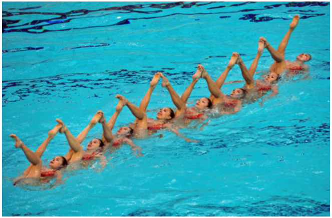

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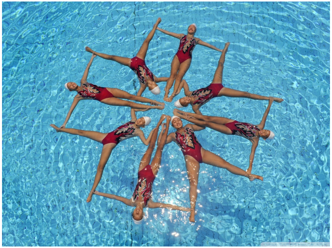

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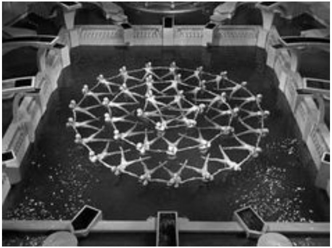

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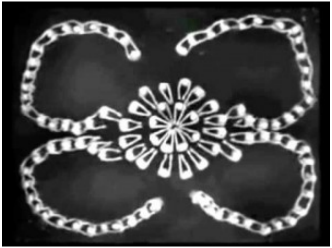


You cain't get a man with a gun

The real question is then **How do you set sensible priors for realistic models?**

- There is no universally applicable way to do this
- There are, however, lots of bad ways to do this
- Some of these bad ways may still work sometimes
- Our focus will be on hierarchical models (specifically Latent Gaussian Models)
- **Nothing** is going to infinity!

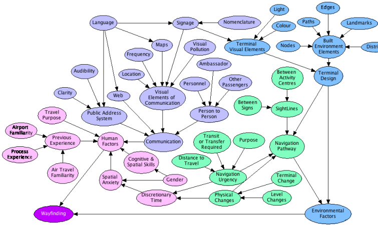
Today I will sketch our approach to this problem: Penalised Complexity (PC) priors.

Outline

Me. **I** am Mariah... the elusive chanteuse

One way to set priors is by **expert elicitation**

- Elicit probabilities for each quantity of interest
- Easiest when nodes are discrete
- A *Bayesian Network* is a useful tool for eliciting and combining information
- Turns elicited *conditional* probabilities in to a joint distribution



But what if there's more than one expert?

I've got 99 problems

Airports of the future project (ARC Linkage project LP0990135)

- From **99 "experts"** (airport users)
- probabilities for **49 binary nodes** were elicited
- All experts are equal
- Questions about how different elements of airport design affect the "wayfinding" experience

Treat the experts as measuring devices

We can consider this as a **measurement error** problem, in which each expert is providing a noisy measurement of the 49 nodes;

Expert elicitation as a measurement error model [Farr, S, Ruggeri, Mengersen, 2014]

Observed probability of node j for expert i:

$$\boldsymbol{p}_{ij} \sim \mathcal{B}(a_{ij}, b_{ij})$$

GLMM for the logit-mean

$$\text{logit}\left(\frac{a_{ij}}{a_{ij} + b_{ij}}\right) = \mu_j + w_i + \epsilon_j$$

Latent level:

- μ_j: Consensus (logit) probability for node j
- w_i: Systemic bias for expert i
- ϵ_j: The measurement bias for node j

Outline

The Ganzfeld Effect

Now it's time to attack the nuisance effects.

- u_i is the observer bias
- Standard random effect $w_i \sim N(0, \tau^{-1})$
- We need to put a prior on τ

Key point: We don't want this here!

I'm just a girl who cain't say no

So how do we set a prior on a precision?

- Lots of "expert guidance" from the literature
- Some of it is saying how to set priors on the precision
- Some of it is setting priors on the precision for a specific problem
- Conjugate priors, reference priors, weakly informative priors, ...
- When will it end?

We only want this effect to be in the model if it is required to fit the data.

We don't want a prior that the data has to drag towards "no effect"!

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Basic instinct

A base model

- We have a model component with distribution $\pi(\boldsymbol{x} \mid \xi)$
- ξ is a **flexibility parameter**,
- $\xi = 0$ is indexes the **base model**
- The base model is the **simplest model**

Idea: Build a prior that has a mode at the base model. The posterior only concentrates on $\xi > 0$ if the data requires the more complex model.

Some examples

Case	Parameter	ξ	Base
Student-t	ν (dof)	$\xi = 1/\nu$	$\xi = 0$ (Gaussian)
IID	τ (precision)	$\xi = 1/\tau$	$\xi = 0$ (no random effect)
IGMRFs	τ (precision)	$\xi = 1/\tau$	$\xi = 0$ (const, linear, plane)
AR(1)	ρ (correlation)	$\xi = \rho$	$\xi = 0$ (no dep. in time)
		$\xi = \rho$	$\xi = 1$ (no changes in time)
FGN	H (Hurst param.)	$\xi = H$	$\xi = 0.5$ (White noise)
Correlation matrix	$\boldsymbol{R}$	$\boldsymbol{\xi} = \boldsymbol{R}$	$\boldsymbol{\xi} = \boldsymbol{I}$ (no correlation)

The pleasure principle

To build a prior that knows about the base model, I'm going to introduce the idea of **Penalised Complexity (PC) Priors**

- PC priors are our attempt to put together a set of principles that lead to a unique prior
- You can interrogate / criticise / modify the principles individually

Principle I: Occam's razor

Prefer simplicity over complexity

Consider the more complex model

$$\pi(x|\xi), \qquad \xi \geq 0$$

with base model $\pi(x|\xi = 0)$.

- The prior for $\xi \geq 0$ should penalise the complexity introduced by ξ
- The prior should be decaying with increasing measure by the complexity (the mode should be at the base model)

A prior will cause **overfitting/force complexity** if, loosely speaking,

$$\pi_\xi(\xi = 0) = 0$$

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Principle II: Measure of complexity

Use Kullback-Leibler discrepancy to measure the increased complexity introduced by $\xi > 0$,

$$\mathrm{KLD}(f \| g) = \int f(x) \log\left(\frac{f(x)}{g(x)}\right) dx$$

for flexible model f and base model g.

Gives a measure of the information lost when the base model is used to approximate the more flexible models

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Principle III: Constant rate penalisation

Define

$$d(\xi) = \sqrt{2\ \mathrm{KLD}(\xi)}$$

as the (uni-directional) "distance" from flexible-model to the base model. Need the square-root to get the scale right.

Constant rate penalisation:

$$\pi(d) = \lambda \exp\left(-\lambda d\right), \qquad \lambda > 0$$

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Invariance: OK

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Principle IV: User-defined scaling

The rate λ is determined from knowledge of the *scale* or some interpretable property or impact, $Q(\xi)$ of ξ:

$$\Pr(Q(\xi) > U) = \alpha$$

- Problem dependent: must be!!!
- Can make the prior more informative or weakly informative this way

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The precision of a Gaussian

PC prior for the precision τ when $\tau = \infty$ defines the base model

- "random effects"/iid-model
- The smoothing parameter in spline models
- etc...

Result Let $\pi_\tau(\tau)$ be a prior for $\tau > 0$ where $E(\tau) < \infty$, then $\pi_d(0) = 0$ and the prior overfits.

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The precision case (II)

The resulting prior is a type-2 Gumbel

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Link with the tradition

Other (good) priors for the precision are

- A half-Gaussian on the standard deviation. (lighter tail than the PC prior)
- A half-Cauchy on the standard deviation. (heavier tail)
- A half-Student-t with more than 2 d.o.f. (heavier tail, similar risk properties)

The important thing here is that they all have a maximum at the base model. The tail behaviour is more "controversial"

Outline

Knowing me, knowing you

The final component of our model is nodal measurement error ϵ_j

- Big question: Is the measurement error independent across nodes?
- Maybe not?
- Nearby nodes measure "similar" things, so we would expect correlation
- We propose a BYM model

$$\epsilon_j = v_j + u_j$$

where $v_j \overset{\text{iid}}{\sim} N(0, \tau_v^{-1})$ and $\boldsymbol{u} \sim N(0, \tau_u^{-1}\boldsymbol{Q}^{+})$ is a Besag model.

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The structured effect

The structured difference in u between neighbouring regions is $N(0, \tau_u^{-1})$.

$$\pi(\boldsymbol{u}) \propto \tau_u^{(n-1)/2} \exp\left(-\frac{\tau_u}{2} \sum_{i \sim j} (u_i - u_j)^2\right). \tag{1}$$

"$i \sim j$" denotes the set of all *unordered* pairs of neighbours.

- This is the Besag model.
- It is rank deficient.
- How do we put a prior on τ_u?
- Big thing: It will depend on the graph!

Building a better BYM

Base model $= 0 \rightarrow$ iid $\rightarrow$ dependence $=$ more flexible model

Rewrite the model as

$$\eta = \frac{1}{\sqrt{\tau}}\left(\sqrt{1-\gamma}v^* + \sqrt{\gamma}u^*\right)$$

where $\cdot^*$ is a unit-variance standardised model.

- Marginal precisions τ.
- γ gives it interpretation: independence ($\gamma = 0$), maximal dependence ($\gamma = 1$)]
- PC prior on γ (base model $\gamma = 0$) depends on the graph!
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Get behind me, Esther Williams!

What does the PC prior on γ look like?

- The covariance matrix is $\boldsymbol{\Sigma}(\gamma) = \gamma \boldsymbol{I} + (1-\gamma)\boldsymbol{R}^{-1}$
- The squared distance is then

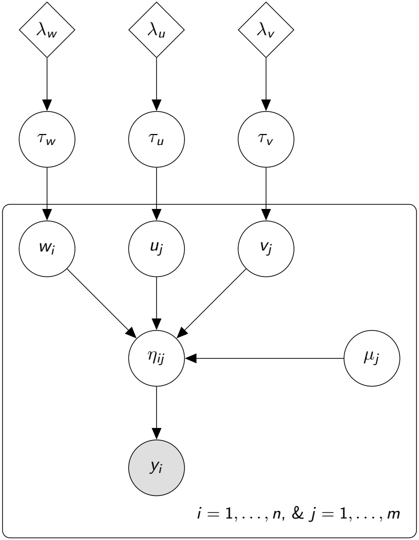
$$d(\gamma)^2 = n\gamma\left(\frac{1}{n}\operatorname{tr}(\boldsymbol{R}^{-1}) - 1\right) - \log\left|(1-\gamma)\boldsymbol{I} + \gamma\boldsymbol{R}^{-1}\right|$$

- For sparse $\boldsymbol{R}$, the trace is easy to compute, and the evaluation costs one sparse Cholesky decomposition
- The PC prior is then

$$\pi(\gamma) = \frac{\lambda\exp(-\lambda d(\gamma))}{1-\exp(-\lambda d(1))}\left|\frac{\partial d(\gamma)}{\partial\gamma}\right|.$$

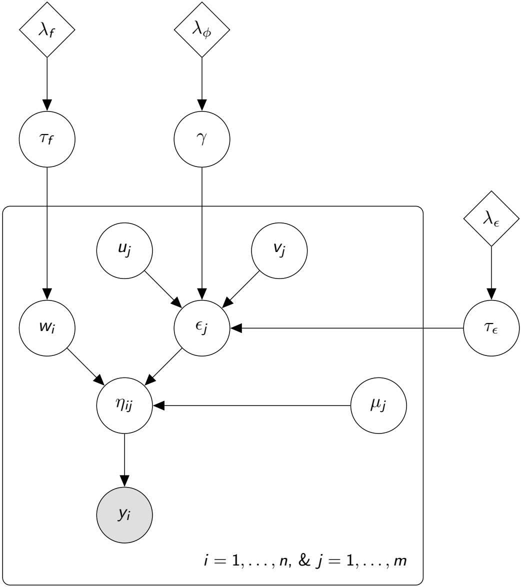
- (NB: $d(1)$ is finite, and so we use a truncated exponential!)

The BYM



Where is the variation coming from?

Building a better BYM

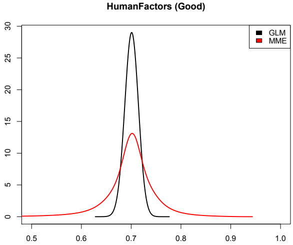


Outline

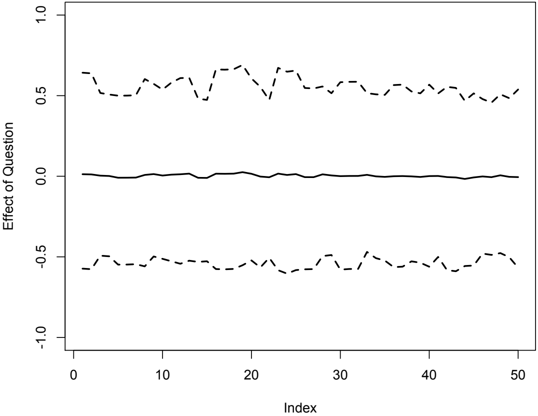
As long as you follow

So what was the outcome with the airports?

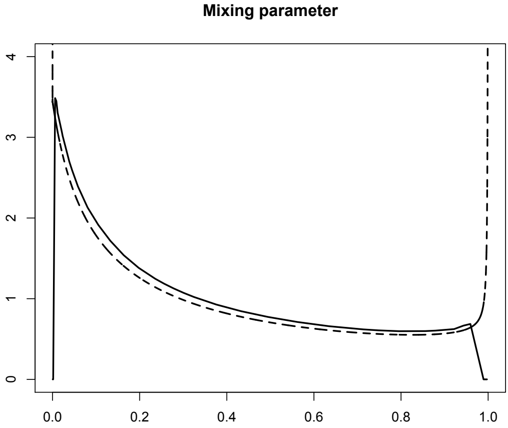
- The observer random effect was small with small credible regions
- The posterior estimates of the consensus probabilities have a larger IQR than those produced with a plain GLM
- But is this real?



Did anything happen?



Was the graphical structure useful?



Miss Otis Regrets

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- The aim of the PC prior project is to make priors that can find nothing when nothing is there
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Outline

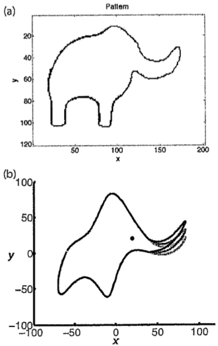
If love were all

This example shows just a corner of the power of PC priors

- Splines
- Skew-Gaussian distributions
- Correlation matrices
- AR(p)
- Over-dispersion in Negative Binomials
- Hurst Parameters for fractional Brownian motion
- Degrees of freedom in a Student-t
- Parameters in Gaussian random fields (partially identifiable!)
- Non-stationary GRFs
- Correlated random effects
- Variances in multilevel models
- $+++$

Placating pugilistic pachyderms

- Under everything, this was a talk about setting prior distributions
- This is hard.
- Bayesian models should not be used / interpreted unless you can interpret all levels of your model (including your prior)
- This doesn't fix the general problem of Bad Bayesian Analysis
- But it helps: we need to match the ambition and complexity of the applied modellers
- Otherwise, instead of giving them enough rope to hang themselves, we are cutting out the middle man



Mayer, Khairy, and Howard, Am. J. Phys. 78, 648 (2010)

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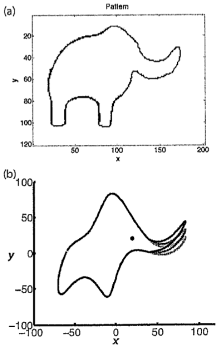

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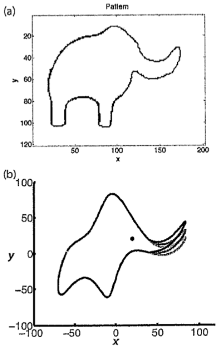

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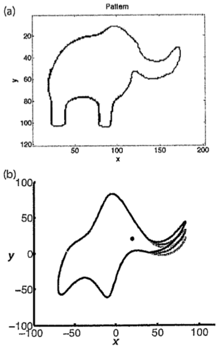

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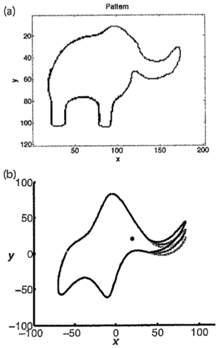

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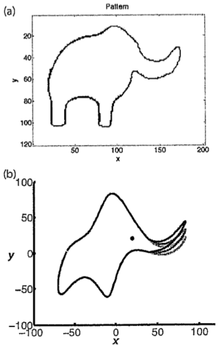

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