

# On the choice of weights for logarithmic pooling of probability distributions.

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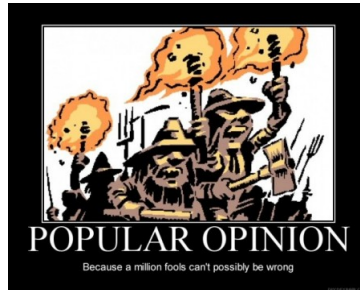
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## Logarithmic pooling – Motivation

- Obtain important insights on consensus belief formation and group decision making (Genest and Zidek, 1986);



- Applications in a range of fields, from infectious disease modelling (Coelho and Codeço, 2009) and wildlife conservation (Poole and Raftery, 2000) to engineering (Savchuk and Martz, 1994);
- BUT how to give each expert/information source a weight without being (totally) arbitrary?



## Logarithmic pooling – Definition & Notation

Let  $\mathbf{F}_\theta = \{f_0(\theta), f_1(\theta), \dots, f_K(\theta)\}$  be the set of prior distributions representing the opinions of  $K + 1$  experts and let  $\alpha = \{\alpha_0, \alpha_1, \dots, \alpha_K\}$  be the vector of weights, such that  $\alpha_i > 0 \forall i$  and  $\sum_{i=0}^K \alpha_i = 1$ . Then the log-pooled prior is

$$\pi(\theta) = t(\alpha) \prod_{i=0}^K f_i(\theta)^{\alpha_i} \quad (1)$$

with  $t(\alpha) = \int_{\Theta} \prod_{i=0}^K f_i(\theta)^{\alpha_i} d\theta$ .

- Enjoys rather desirable properties, such as *external Bayesianity* (Genest and Zidek, 1986);
- Poole and Raftery (2000) prove that  $t(\alpha)$  is always finite for the case  $K = 1$  (2 experts/priors), which we extend for any finite  $K$ . See Theorem 1 in <http://arxiv.org/pdf/1502.04206v1.pdf> for a simple proof.



## Maximise the entropy of $\pi(\theta)$

- If there is no information about the reliabilities of the experts one might want to assign  $\alpha$  so as to maximise entropy of the resulting distribution:

$$H_{\pi}(\theta) = - \int_{\Theta} \pi(\theta) \ln \pi(\theta) d\theta$$
$$H_{\pi}(\theta; \alpha) = \sum_{i=0}^K \alpha_i E_{\pi}[-\ln f_i(\theta)] - \ln t(\alpha)$$

- Formally, we want to find  $\hat{\alpha}$  such that

$$\hat{\alpha} := \arg \max H_{\pi}(\theta; \alpha)$$

- Caveats: (i) is not guaranteed to yield an unique solution; (ii) is rather prone to yield “trivial” solutions.



## Minimise KL divergence between the $f_i$ 's and $\pi(\theta)$

- What if we want to minimise conflict between the consensus and each individual opinion?
- Let  $d_i = \text{KL}(f_i || \pi)$  and let  $L(\alpha)$  be a loss function such that

$$L(\alpha) = \sum_{i=0}^K d_i \quad (2)$$

$$= -K \ln t(\alpha) + \sum_{i=0}^K \sum_{j \neq i}^K \alpha_j \text{KL}(f_i || f_j) \quad (3)$$

$$\hat{\alpha} := \arg \min L(\alpha) \quad (4)$$

- Contrary to the above, the loss function is convex, thus there is a unique solution (Rufo et al., 2012).



## Place a prior on the weights

- An appealing alternative is to place a (hyper) prior on the weights ( $\alpha$ );
- Two options:
  - (a) Dirichlet prior:

$$\pi(\alpha) = \frac{1}{\mathcal{B}(\mathbf{x})} \prod_{i=0}^K \alpha_i^{x_i-1}$$

- (b) logistic-normal:

$$\alpha_i = \frac{e^{m_i}}{\sum_{i=0}^K e^{m_i}}, \quad m_i \sim N(\mu_i, \sigma_i^2)$$

- Advantage: accomodates uncertainty in natural way, and is very flexible;
- Caveat(s): may yield inconsistent results and hardly ever allows for analytical solutions.



## Application: binomial probabilities

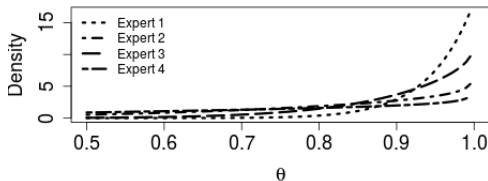
- $Y \sim \text{Bernoulli}(\theta)$  and

$$f_i(\theta; a_i, b_i) = \frac{\Gamma(a_i + b_i)}{\Gamma(a_i)\Gamma(b_i)} \theta^{a_i-1} (1 - \theta)^{b_i-1}$$

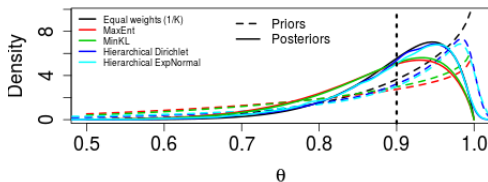
- Allows for simple expressions for the entropy and KL divergence [ $\pi(\theta; \alpha)$  is also Beta], and efficient sampling from the hyperpriors;
- Savchuk and Martz (1994) consider an example in which four experts are required supply prior information about the survival probability of a certain unit for which there have been  $y = 9$  successes out of  $n = 10$  trials;
- We propose to evaluate performance using integrated (marginal) likelihoods, a.k.a., prior evidence.



### Expert Priors



### Pooled Priors and Posteriors







## very Preliminary results II

**Table :** Weights obtained using the three methods for the proportion estimation problem.

<sup>1</sup> – Kullback-Leibler <sup>2</sup> – Posterior mean for  $\alpha$ .

Method	$\alpha_0$	$\alpha_1$	$\alpha_2$	$\alpha_3$
Maximum entropy	0.00	1.00	0.00	0.00
Minimum KL <sup>1</sup> divergence	0.04	0.96	0.00	0.00
Hierarchical prior <sup>2</sup>	0.26	0.24	0.26	0.23

**Table :** Integrated likelihoods for the priors of each expert as well as the combined priors.

<sup>1</sup> Calculated using the posterior mean of  $\alpha$

Expert priors		Pooled priors	
Expert 0	0.237	Equal weights	0.254
Expert 1	0.211	Maximum entropy	0.211
Expert 2	0.256	Minimum KL	0.223
Expert 3	0.163	Hierarchical <sup>1</sup>	0.255



- Our results are not yet decisive regarding which method is better;
- The Dirichlet approach seems the most natural from a Bayesian perspective, but prior sensitivity is currently unknown;



## Induce-then-pool or pool-then-induce?

- Let  $\theta \in \Theta \subseteq \mathbb{R}^p$  and  $y \in \mathcal{Y} \subseteq \mathbb{R}^p$  and define the model (transformation) as  $M : \Theta \rightarrow \mathcal{Y}$ .
- Finally recall  $\mathbf{F}_\theta$  is a set of  $K$  distributions on  $\theta$ .
- We may want to gain insight into  $y$ , even though we only have expert opinions on  $\theta$ . If we apply  $M(\cdot)$  to each component of  $\mathbf{F}_\theta$ , we get an **induced** distribution.
- Theorem: if  $M(\cdot)$  is invertible, the order in which one pools or induces (transforms) the distributions does not matter.
- This is not always the case, though, as we shall see.



## Dynamic model example

- Susceptible-Infectious-Removed (SIR) epidemic model:

$$\frac{dS}{dt} = -\beta SI$$

$$\frac{dI}{dt} = \beta SI - \gamma I$$

$$\frac{dR}{dt} = \gamma I$$

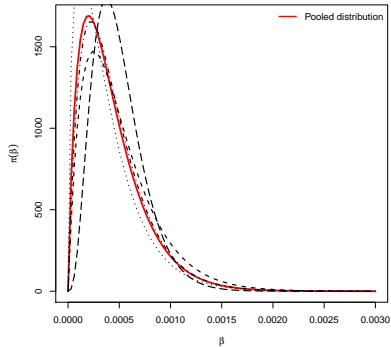
where  $S(t) + I(t) + R(t) = N \forall t$ ,  $\beta$  is the transmission (infection) rate and  $\gamma$  is the recovery rate.

Suppose we have Gamma distributions on the parameters and  $p(\beta, \gamma) = p(\beta)p(\gamma)$ . Interest lies in the distribution of  $\mathcal{R}_0 = \frac{\beta N}{\gamma}$ .



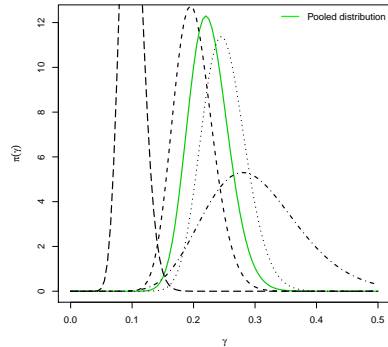
# Dynamic model example – Priors

Pooled distribution for the transmission rate



(a)

Pooled distribution for the recovery/removal rate



(b)



## Pool-then-induce

- Pool:

$$\pi(\beta) = \textit{Gamma}(\theta_1^*, k_1^*)$$

$$\pi(\gamma) = \textit{Gamma}(\theta_2^*, k_2^*)$$

where  $\theta^* = \sum_{i=0}^K \alpha_i a_i$ . Then

- Induce:

$$\pi_1(\mathcal{R}_0) \propto \mathcal{R}_0^{k_1-1} (\theta_2^* \mathcal{R}_0 + N\theta_1^*)^{-(k_1^*+k_2^*)}$$

- Nice!



## Induce-then-pool

- Induce (transform) each distribution (Gamma ratio):

$$\pi_i(\mathcal{R}_0) \propto \mathcal{R}_0^{k_1-1} (\theta_2 \mathcal{R}_0 + N\theta_1)^{-(k_1+k_2)}$$

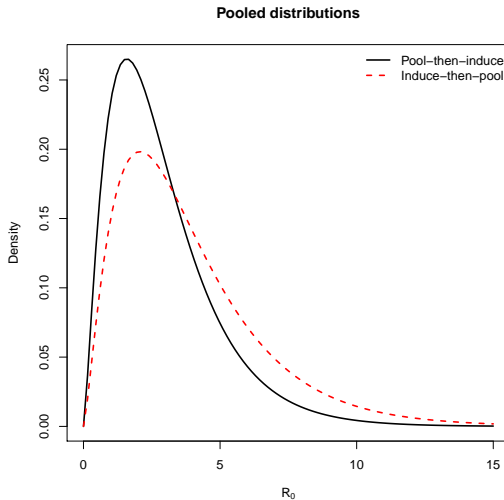
then

- Pool:

$$\pi_2(\mathcal{R}_0) \propto \prod_{i=0}^K \pi_i(\mathcal{R}_0)^{\alpha_i}$$

- Ugly!

## Dynamic model example (cont.)







## Thank you!

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- All the necessary code and data are publicly available at [https://github.com/maxbiostat/opinion\\_pooling](https://github.com/maxbiostat/opinion_pooling)



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