



Bayesian modelling of dependence between experts

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Plan of Talk

- Bayesian Structured Expert Judgement Problem to be solved
- Existing Bayesian Models
- Proposed New Bayesian approach for highlighting dependence between experts.
- Issues and potential resolutions
- Next Steps

Bayesian Approaches

- ► 1960s → 1980s. Conceptual, exploring ideas and principles.
 - Not intended for real use
- 1990s-2000s. Some attempts to use in practice, but need to make heroic assumptions about correlations and calibration
- 2010s onwards. Use of hierarchical models and MCMC to learn from seed variable data

Bayesian Approaches – Problems to Solve

- Sensitivity to complex priors
- Extensible to a broader range of cases
- More formal approach to inter-expert correlation

Bayesian Approaches – Underlying Structure



Aggregation

Calibration

- Clemen and Lichtendahl (2002)
- Bayesian Hierarchical modelling approach
 - recalibrates experts' forecasts based on their historical performance using multiplicative factors
 - Identifies correlation between experts



Aggregation

- Albert et al (2012)
- This model clusters groups of experts into homogeneity groups and then utilising a Supra Bayesian Parameter Updating approach assess the variation both between and within these homogeneity classes.



Bayesian Approaches – Underlying Structure



Grouping of Experts

- Hartley and French (circa 2017)
- Clusters experts into homogeneity groups using a Dirichlet Process mixture model to analyse calibration data sets.



Linking the models





Linking the Calibration and the Aggregation Model

Linking the Homogeneity Groups to the Aggregation and Calibration Models





Reparametrising the Calibration Model



Reparametrising the Calibration Model

	0.05	0.5	0.95	Actual
Item1	102.5	242	335	292
Item2	117.5	244	344	24
Item3	132.5	245	346	150
Item4	147.5	250	347.5	97
Item5	162.5	252.5	347.5	823
Item6	180	257.5	347.5	223
Item7	197.5	280	347.5	27
Item8	222.5	300	347.5	287
Item9	238	318	352.5	356
Item_10	260	337	380	508
Item_11	279	357.5	408	187
Item_12	298	375	437.5	12
Item_13	318	396	460	556
Item_14	337.5	415	485	20
Item_15	357.5	435	509	585
Item_16	375	458	534	609
Item_17	392.5	477.5	560	552
Item_18	410.5	500	586	178
Item_19	430	520	617.5	87
Item_20	447.5	540	649	88
Item_21	462.5	558	680	578
Item_22	477.5	578	710	191
Item_23	501	597.5	741	84
Item_24	522	617.5	770	33
Item 25	540	638	800	546



Figure 2: Posterior distribution for Expert 3's β .

	Original Forecast for 0.5	New Model Adjusted Median	Clemens and Lichtendahl Adjusted Median	Actual Result
Item1	242	207	99	292
Item2	244	209	100	24
Item3	245	209	100	150
Item4	250	214	103	97
Item5	252.5	216	104	823
Item6	257.5	220	106	223
Item7	280	239	115	27
Item8	300	257	123	287
Item9	318	272	130	356
Item_10	337	288	138	508
Item_11	357.5	306	147	187
Item_12	375	321	154	12
Item_13	396	339	162	556

sd 2.068

0.1114

1.574

mean miscal[3,1,1] 5.342 miscal[3,1,2] 0.8828 miscal[3,1,3] 5.302

Higher than Actual Result

Approach to assessing the suitability of the model

Expert Judgement studies from the Delft Database
Take a hold out sample from the seed variables
Utilising remaining seed variables use both Cooke's model and the Bayesian Approach to forecast the missing data

Iterate through the seed variables to vary the hold out sample to build up a set of forecasts.

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> Run all of the forecasts through Cooke's model

Results

Dams Space Debris Ground Water Transport Montserrat

	Range graph of input data	
xpert	no.: 1 Expert name: Bayesian	1
1(0)	[]	
Real	·······*	
2(U)	[]	
eal	***************************************	1
3(U)	[]	
leal	***************************************	
4(0)	[]	
Real	#	
5(0)	[]	
leal	#	
600	[]	
Real	••••	
7(0)	[]	
leal	******	
8(U)	[]	
Real		
9(U)	[]	
Real	#	
10(U)	[]	
eal	*	
11(0)	[]	
eal	····	

4		
xpert Iteнs 1(U)	no.: 2 Expert name: Cookes []	
Real	*****	
2(0)	[]	
Real		::#
3(U)	[*]	
leal		
400	[**	1
leal	*	
5(0)	*]	
leal	.:#	
6(U)	1	
Real	****	
7(0)	[***]
leal	**************************************	
8(U)	[*****]
leal	••••••••••••••••••••••••••••••••••••••	
9(0)	[*****]
ear	6. ()	
10(0)]
ea1	#	
11(0)	[****]
leal	***************************************	

Issues and Next Steps

Varying/Logarithmic scaling issues
Calibration impact to variables with variables existing within a predefined range.

Number of seed variables available

Issues and Next Steps

Varying/Logarithmic scaling issues

- Consider using the approach outlined in Wiper & French '95 and pass the variables through the DM;s prior

Calibration impact to variables with variables existing within a predefined mean.

- Consider post modelling truncation of variables.

Number of seed variables available

-Perform some sensitivity analysis utilising a case study and removing seed variables.

≻Potential Risk of Bias from the ROAT approach

-Perform cross-validation on permutations of greater than 1 removed variables

Apply the model to the set of more recent studies in the Delft Database

Thank you