# How to conduct a classical model study

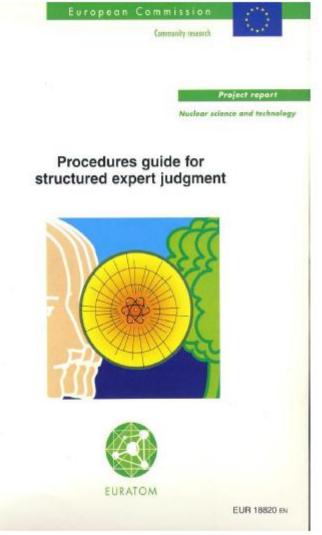
COST TRAINING SCHOOL

WARSAW

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#### Content based on:

- Procedures guide
- Presentations by Roger Cooke
- Personal experience

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Procedures Guide

### The elicitation process

#### **Pre-Elicitation**

- 1. Define case structure.
- 2. Identify variables of interest.
- 3. Identify calibration variables.
- 4. Identify and select experts.
- 5. Write the elicitation protocol.
- 6. Pilot test the protocol.
- 7. Train the experts.

#### Elicitation

8. Conduct elicitation session(s).

#### **Post-Elicitation**

9. Combine expert assessments.

10. Conduct discrepancy and robustness analysis.

- 11. Provide feedback to experts.
- 12. Analyze the processed data.
- 13. Document the results.

### Pre-Elicitation:1. Define case structure.

What values are uncertain?

Is there historical or measurement data?

What hypothetical measurements could be used?

#### Breastfeeding: achieving the new normal



See Comments pages 413 and 416 See Series pages 475 and 491 For more on the **breastfeeding** Series see http://www.thelancet. com/series/breastfeeding

For the Series on maternal and child nutrition see http://www. thelancet.com/series/maternaland-child-nutrition

For more on breastfeeding and the Affordable Care Act see http://www.cdc.gov/ breastfeeding/pdf/BF- Breastmilk makes the world healthier, smarter, and more equal: these are the conclusions of a new *Lancet* Series on breastfeeding. The deaths of 823000 children and 20000 mothers each year could be averted through universal breastfeeding, along with economic savings of US\$300 billion. The Series confirms the benefits of breastfeeding in fewer infections, increased intelligence, probable protection against overweight and diabetes, and cancer prevention for mothers. The Series represents the most in-depth analysis done so far into the health and economic benefits that breastfeeding can produce.

However, although the Series is comprehensive, the message is not new. In 2013, a *Lancet* Series on maternal and child nutrition established that 800 000 child deaths could be prevented through breastfeeding, and called for further support. Despite consolidation of evidence for breastfeeding's benefits in recent years, in particular the economic gains to be reaped, global action has stalled. Why has so little progress been made? Rates of breastfeeding vary wildly; it is one of the few health positive behaviours more componin poor countries.

than rich ones. In low-income countries, most infants are still breastfed at 1 year, compared with less than 20% in many high-income countries and less than 1% in the UK. The reasons why women avoid or stop breastfeeding range from the medical, cultural, and psychological, to physical discomfort and inconvenience. These matters are not trivial, and many mothers without support turn to a bottle of formula. Multiplied across populations and involving multinational commercial interests, this situation has catastrophic consequences on breastfeeding rates and the health of subsequent generations.

There are glimmers of hope. Despite—or perhaps, because of—the execrable provision for paid maternity leave in the USA, the Affordable Care Act provides protected nursing breaks and insurance cover for breast pumps. Such allowances, the Series predicts, could increase breastfeeding by 25%. But, more importantly, genuine and urgent commitment is needed from governments and health authorities to establish a new normal: where every woman can expect to breastfeed, and to receive every

Lancet, The. 2016. "Breastfeeding: Achieving the New Normal." The Lancet 387 (10017): 404. doi:10.1016/S0140-6736(16)00210-5.



Is breast truly best? Estimating the effects of breastfeeding on long-term child health and wellbeing in the United States using sibling comparisons



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#### ARTICLE INFO

Article history: Available online 29 January 2014

Keywords: Breastfeeding Child health Race Socioeconomic status Life course epidemiology Sibling comparisons

#### ABSTRACT

Breastfeeding rates in the U.S. are socially patterned. Previous research has documented startling racial and socioeconomic disparities in infant feeding practices. However, much of the empirical evidence regarding the effects of breastfeeding on long-term child health and wellbeing does not adequately address the high degree of selection into breastfeeding. To address this important shortcoming, we employ sibling comparisons in conjunction with 25 years of panel data from the National Longitudinal Survey of Youth (NLSY) to approximate a natural experiment and more accurately estimate what a particular child's outcome would be if he/she had been differently fed during infancy. Results from standard multiple regression models suggest that children aged 4 to 14 who were breast- as opposed to bottle-fed did significantly better on 10 of the 11 outcomes studied. Once we restrict analyses to siblings and incorporate within-family fixed effects, estimates of the association between breastfeeding and all but one indicator of child health and wellbeing dramatically decrease and fail to maintain statistical significance. Our results suggest that much of the beneficial long-term effects typically attributed to

Colen, Cynthia G., and David M. Ramey. 2014. "Is Breast Truly Best? Estimating the Effects of Breastfeeding on Long-Term Child Health and Wellbeing in the United States Using Sibling Comparisons." *Social Science and Medicine* 109: 55–65. doi:10.1016/j.socscimed.2014.01.027.

### Case study: Introduction

Breastfeeding definitely has high health benefits! In some places...

Breastfeeding more common in high income families! In some places...

However, based on the current evidence, WHO recommends exclusive breastfeeding for 6 months, with partial breastfeeding until 24 months.

### Case study: Introduction

There's a lot of data...from a few places (mostly US and UK).

Current studies struggle with confounding and self-selection bias.

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There's a lot of data...from a few places (mostly US and UK).

Current studies struggle with confounding and self-selection bias.

So we have some data, but it's not *exactly* the data we want. Sounds like a case for expert judgment!

### Case study 1. Define the structure.

The study is focused on the impact (if any) of breastfeeding on cognitive development in three countries: USA, India, and China.

• We will use an IQ-type test as a proxy measurement for cognition.

- We are narrowly focused on this. We don't want to capture:
  - Benefits of breastfeeding instead of using low-quality formula.
  - Benefits from the mother-child interaction of the act of breastfeeding.

### Pre-Elicitation:

- 2. Identify variables of interest.
- You can't use SEJ for everything, so how do you choose?
- Is it uncertain?
- Is there data?
- Does uncertainty on this parameter impact the final endpoint?

Carefully specify these variables: you don't want questions that different experts interpret differently.

There's no rule of thumb for the best number of variables of interest.

### Case study 2. Identify variables of interest.

Questions 12 through 23 concern a hypothetical ideal perfectly randomized experiment with a very large number of subjects from each of three countries. We select India and China because their populations are important from a global health perspective and yet estimates of effects of breastfeeding on cognitive performance from long-term longitudinal studies appear to be sparse for these countries. We include the U.S. because the published literature includes multiple studies of associations between breastfeeding and cognitive performance, using different data.

All infants are randomly assigned to one of four feeding cohorts.

### Case study 2. Identify variables of interest.

		Feeding Patt	terns by Age						
Feeding	Cohorts								
	1 2		3	4					
Breastfeeding, Exclusive	None	3 months	6 months	6 months					
Breastfeeding, Any	None 3 to 9 months		None	6 to 24 months					
Infant Formula, Exclusive	6 months	None	None	None					
Infant Formula, Any	6 to 15 months	3 to 15 months	6 to 15 months	None					
Complementary Foods	From 6 months	From 6 months	From 6 months	From 6 months					

### Case study 2. Identify variables of interest.

All formula is approved by the U.S. Food and Drug Administration and provided by the mother while holding the infant in a position where breastfeeding could have occurred.

All children are tested at age ten with the Wechsler Intelligence Scale for Children, Revised, (WISC) or its foreign equivalent, properly normed. The overall average WISC-R, (IQ) score (within each country and cohorts) is 100, st dev = 15.

You may consider the following data while developing your responses. The reported values are for the most recent data that are publicly available.

# Pre-Elicitation:3. Identify calibration variables.

	predictions	retrodictions	Avoid almanac-type questions or questions that are "google-able".
Domain	+++	++	Rule of thumb: have at
Adjacent field	++	+	least 10 seed questions.

### Case study 3. Identify calibration variables.

In the NLSY79-C the average Peabody Picture Vocabulary Test (PPVT) mean score, among the children with scores, is 90.660. What is the average among first-born children with at least one PPVT score?

In the 2005-06 Demographic Health Survey for India, what is the 50th percentile for duration of breastfeeding (in months), among children who were breastfeed and who were not still breastfeeding at the time of the survey?

In NLSY79-C the average age in weeks when breastfeeding ended is 9.12. What is the average age in weeks when breastfeeding ended among the 1583 only children who were breastfed?

# Pre-Elicitation:4. Identify and select experts.

Identify potential experts through a round robin or snowflake process.

- Aim for 5-10 experts.
  - 4 can work
  - Returns drop off after 10+ experts

### Too few experts

Bay	yesian Up	oring experts dates: no We Level: 0.0329		-	ation: 1	yes			Microsof Docur
Nr.	Id	Calibr.	Mean relative	Mean relative	Numb	UnNormalized	Normaliz.weigh	Normaliz.weig	
			total	realization	real	weight	without DM	with DM	
1	NE01	7.341E-009	2.1	2.156	10	0	0	0	
2	NE02	0.0003719	0.847	1.002	10	0	0	0	
3	NE03	0.03297	1.282	1.447	10	0.04771	1	0.5	
4	NE04	7.832E-005	1.122	1.735	10	0	0	0	
5	PW	0.03297	1.282	1.447	10	0.04771		0.5	
6	EW	0.3684	0.3958	0.6951	10	0.2561		0.8415	

#### Too many experts



Expert scores: CDC ROI Final Results of scoring experts

۱r.	ld	Calibr.	Mean relative	Mean relative	Numb	UnNormalized	Normaliz.weigh	Normaliz.weig
			total	realization	real	weight	without DM	with DM
1	01	0.7203	2.597	2.305	10	1.66	1	0.5
2	02	1.602E-005	1.904	1.655	10	0	0	0
3	03	1.273E-006	2.344	3.49	10	0	0	0
4	04	5.559E-006	2.961	2.719	10	0	0	0
5	05	0.4988	2.341	1.39	10	0	0	0
6	06	0.01651	1.39	1.355	10	0	0	0
7	07	2.181E-007	2.09	3.345	10	0	0	0
8	08	0.4988	3.825	1.737	10	0	0	0
9	09	0.1321	4.623	1.719	10	0	0	0
10	10	1.273E-006	3.08	3.071	10	0	0	0
11	11	0.02366	4.113	1.82	10	0	0	0
12	12	0.00917	2.797	2.304	10	0	0	0
13	13	0.007147	2.758	2.063	10	0	0	0
14	14	0.0001328	3.815	3.279	10	0	0	0
15	15	0.1249	3.843	2.66	10	0	0	0
16	16	0.0003053	2.79	2.057	10	0	0	0
17	17	0.02919	2.471	1.745	10	0	0	0
18	18	1.428E-006	2.727	3.155	10	0	0	0
19	19	0.4988	2.032	1.91	10	0	0	0
20	20	0.04675	2.208	2.183	10	0	0	0
21	PW	0.7203	2.597	2.305	10	1.66		0.5
22	EW	0.2328	1.117	1.23	10	0.2864		0.0543

- - -

# Pre-Elicitation:4. Identify and select experts.

After identifying experts, tell them:

- Purpose of study
- Format of elicitations
- Payment details
- Use of experts' names
  - Link between name and assessments (or qualitative information) preserved but not published
  - List of experts and affiliations published

# Pre-Elicitation:5. Write the elicitation protocol.

Include:

- The motivation for the study
- The questions (calibration questions can be labelled or not)
- May want to include a briefing book



# Pre-Elicitation:6. Pilot test the protocol.

With a substantive expert (who wasn't involved in writing the protocol), check:

- Are the questions clear?
- Does the structure make sense?
- Is additional information needed to make sure we're capturing what we want to capture?
- Is the timing appropriate?

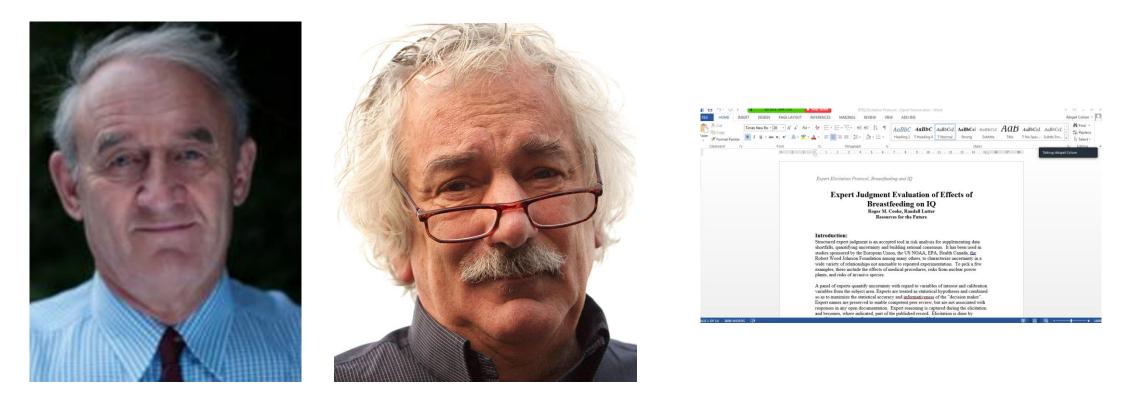
# Pre-Elicitation:7. Train the experts.

DEPENDS ON TIME, BUDGET, LOCATION OF THE EXPERTS, AND COMPLEXITY OF THE ELICITATION.

- 30 minute, 1:1 training session
- Webinar
- Half day group meeting
- Multi-day workshop

- Discuss case structure
- Explain method and scoring
- Discuss over-confidence

### Elicitation: 8. Conduct elicitation session(s).



Capture qualitative reasoning alongside the quantitative judgments.

# Post-Elicitation:9. Combine expert assessments.

									Set the desired paran	ieters and click on	Calculate/Run
									Weights	Chi2	Inf
									💿 Global 💿 Equal	New	New
	pert score	s: bfiq pring experts							🔘 Item 🛛 🔘 User	🔘 Old	🔘 Old
	ld	Calibr.	Mean relative					Normaliz.weig	Calibration Power	Intrin	sic Range
			total	realization	real	weight	without DM	with DM			
1	1	0.001231	total 1.483	realization 1.34	real 11	weight 0	without DM 0	with DM 0	0.1 <= 1.000 <= 1.0		0.10 <= 100.0
-	1 2	0.001231				-					
2			1.483	1.34	11	0	0	0	0.1 <= 1.000 <= 1.0		
2 3	2	0.08609	1.483 0.7272	1.34 0.7368	11 11	0	0	0	0.1 <= 1.000 <= 1.0 Decision Maker Name		
2 3 4	2 3	0.08609 0.004671	1.483 0.7272 1.15	1.34 0.7368 0.951	11 11 11	0	0 0 0	0 0 0	0.1 <= 1.000 <= 1.0		
2 3 4 5	2 3 4	0.08609 0.004671 0.002048	1.483 0.7272 1.15 0.5076	1.34 0.7368 0.951 0.7861	11 11 11 11	0 0 0 0 0	0 0 0 0	0 0 0 0	0.1 <= 1.000 <= 1.0 Decision Maker Name Calculate	0.01 <=	
2 3 4 5 6	2 3 4 5	0.08609 0.004671 0.002048 0.2306	1.483 0.7272 1.15 0.5076 0.3592	1.34 0.7368 0.951 0.7861 0.4153	11 11 11 11 11	0 0 0 0	0 0 0 0	0 0 0 0 0	0.1 <= 1.000 <= 1.0 Decision Maker Name Calculate	0.01 <=	0.10 <= 100.0

Range Graph (avpertewice) Range Graph (itemwice)

# Post-Elicitation: 10. Conduct discrepancy and robustness analysis.

											Run Parameters	
											Set the desired paramet	ers and click on Calculate/
Exp	ert scores:	bfiq and Relat	ive Inforamtior	n to DM						- • ×	Weights	Chi2 Inf
ay	lts of scori esian Upda nificance L	ates: no We	d Relative Info ights: equal Calibration Po	DM Optimis		no					◯ Global	New     New     Old     Old
r.	ld	Calibr.	Mean relative	Mean relative	Numb	UnNormalized	Normaliz.weigh	Normaliz.weigh	Rel.Inf to DM	Rel.Inf to DM	🔲 DM optimisation 🔲 Ba	yesian Update 🛛 📝 Disc
			total	realization	real	weight	without DM	with DM	total	realiz.		Joolan opaalo
I	1	0.001231	1.483	1.34	11	0.001649	0.1429	0.002393	0.7659	0.8845	Calibration Power	Intrinsic Range
2	2	0.08609	0.7272	0.7368	11	0.06343	0.1429	0.09206	0.4662	0.5146	0.1 <= 1.000 <= 1.0	0.01 <= 0.10 <=
3	3	0.004671	1.15	0.951	11	0.004442	0.1429	0.006447	0.5555	0.5141	Decision Maker Name	
ŧ.	4	0.002048	0.5076	0.7861	11	0.00161	0.1429	0.002337	0.5858	0.6469		
5	5	0.2306	0.3592	0.4153	11	0.09578	0.1429	0.139	0.3603	0.3831		
6	6	0.6924	1.031	0.573	11	0.3968	0.1429	0.5759	0.4843	0.3734	Calculate	
7	7	0.0003015	1.341	1.517	11	0.0004574	0.1429	0.0006638	0.8466	0.9427	RUN Robustness	(items) Robustness (e
	E M	0.4245	0.3621	0.2942	11	0.1249		0.1812	0	0		
3	EVV											

# Post-Elicitation: 10. Conduct discrepancy and robustness analysis.

							🕵 Run Parameters 💿 😐
							Set the desired parameters and click on Calculate/Run
Rol	bustness analysis / it	ems				- • •	Weights Chi2 Inf
Bay	stness analysis on /esian Updates: no nificance Level: 0.6	Weights: globa	•	tion: yes			Image: Original oristra oristra original original original original original origina
Nr.	ld	Rel.info/bgr.	Rel.info/bgr.	Calibr.	Rel.info/or.DM	Rel.info/or.DM	🔽 DM optimisation 🔲 Bayesian Updates 📃 Discrepan
	of excl. item	total	realization		total	realization	
1	PPVT1st	0.7131	0.433	0.9027	0.3723	0.139	Calibration Power Intrinsic Range
2	PPVT1stNoBF	1.025	0.513	0.8444	0	0	0.1 <= 1.000 <= 1.0 0.01 <= 0.10 <= 100.0
3	PIATMathCorr	1.067	0.6049	0.5202	0	0	Decision Maker Name
4	PIATReadCorr	1.071	0.6146	0.5202	0	0	
5	MissingPPVT	1.053	0.5748	0.8444	0	0	
6	AgeBFEnd	0.7025	0.445	0.8226	0.39	0.1701	Calculate
7	MomEd1Kid	0.3652	0.4341	0.44	1.348	1.089	RUN Robustness (items) Robustness (experts)
8	India50	1.064	0.5979	0.5202	0	0	
9	India75	1.059	0.5871	0.8444	0	0	Display
10	WJScores	1.058	0.5851	0.5845	0	0	
11	PSIDInc	1.06	0.5903	0.8444	0	0	Solution Expert Scores Bilinear Loss Robustness
	None	1.031	0.573	0.6924			Range Graph (expertswise) Range Graph (itemwise)

# Post-Elicitation: 10. Conduct discrepancy and robustness analysis.

Ro	bustness fo	or Experts: bfiq				
Bay		alysis on Exper ates:no We .evel: 0.6924			sation: yes 1	
Nr.	ld	Rel.info/bgr.	Rel.info/bgr.	Calibr.	Rel.info/or.DM	Rel.info/or.DM
	excl.exp	total	realization		total	realization
1	1	1.031	0.573	0.6924	0	0
2	2	1.005	0.518	0.6924	0	0
3	3	1.031	0.573	0.6924	0	0
4	4	0.8583	0.5574	0.6924	0	0
5	5	0.9608	0.481	0.6924	0	0
6	6	0.2651	0.1997	0.773	0.9918	0.6094
7	7	1.025	0.5628	0.6924	0	0
8	None	1.031	0.573	0.6924	0	0

💀 Run Parameters										
Set the desired paramete	ers and click on C	Calculate/Run								
Weights ◉ Global ◯ Equal ◯ Item ◯ User	Chi2 New Old	Inf ● New ● Old								
Calibration Power	Calibration Power         Intrinsic Range           0.1 <=									
Calculate RUN Robustness										
Display Solution Expert Scores Range Graph (expertswise	Bilinear Loss	Robustness aph (itemwise)								

### Post-Elicitation:

### 11. Provide feedback to experts.

Have the experts review:

- What you captured of their reasoning
- The combined decision maker assessments
- Their scores (not needed, but experts often ask)

#### Post-Elicitation: 12. Analyze the processed data.

### Post-Elicitation: 13. Document the results.

Koch, Benjamin J., Catherine M. Febria, Roger M. Cooke, Jacob D. Hosen, Matthew E. Baker, Abigail R. Colson, Solange Filoso, et al. 2015. "Suburban Watershed Nitrogen Retention: Estimating the Effectiveness of Stormwater Management Structures." *Elementa: Science of the Anthropocene* 3 (July): 000063. doi:10.12952/journal.elementa.000063.

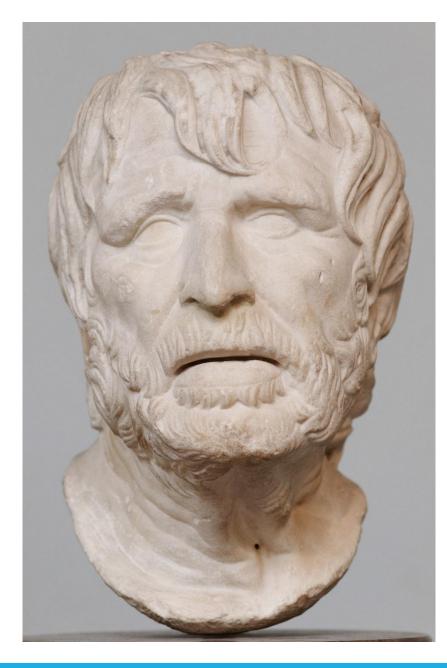
Wittmann, Marion E., Roger M. Cooke, John D. Rothlisberger, and David M. Lodge. 2014. "Using Structured Expert Judgment to Assess Invasive Species Prevention: Asian Carp and the Mississippi—Great Lakes Hydrologic Connection." *Environmental Science & Technology* 48 (4): 2150–56. doi:10.1021/es4043098.

Wittmann, Marion E., Roger M. Cooke, John D. Rothlisberger, Edward S. Rutherford, Hongyan Zhang, Doran M. Mason, and David M. Lodge. 2015. "Use of Structured Expert Judgment to Forecast Invasions by Bighead and Silver Carp in Lake Erie." *Conservation Biology* 29 (1): 187–97. doi:10.1111/cobi.12369.

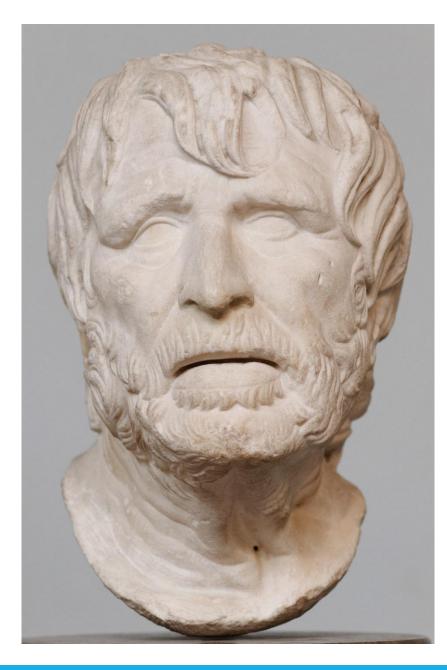


### Frequently Heard Comments & Questions

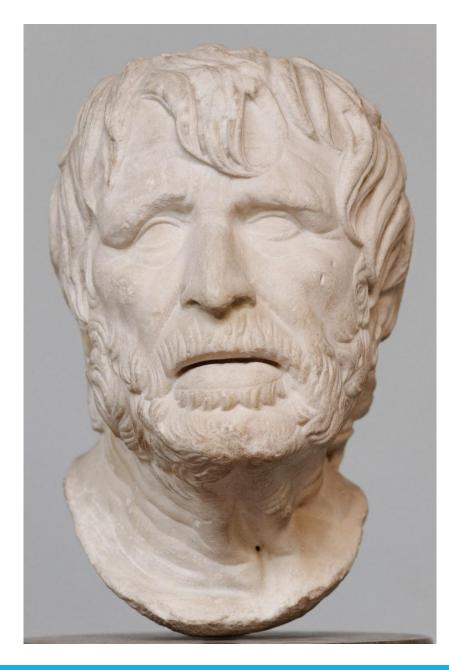
FROM EXPERTS AND PROBLEM OWNERS



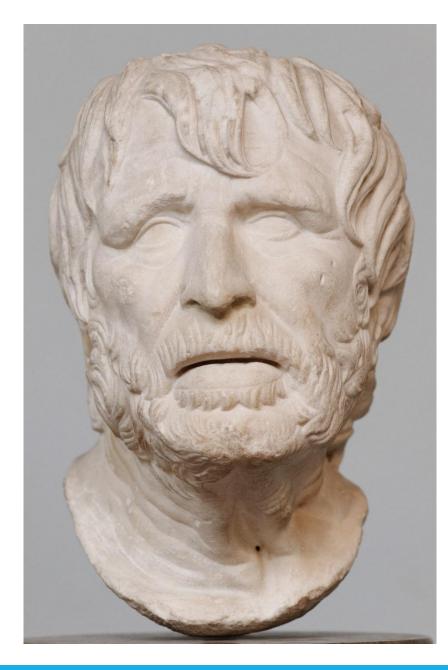
### I don't know that!?!?



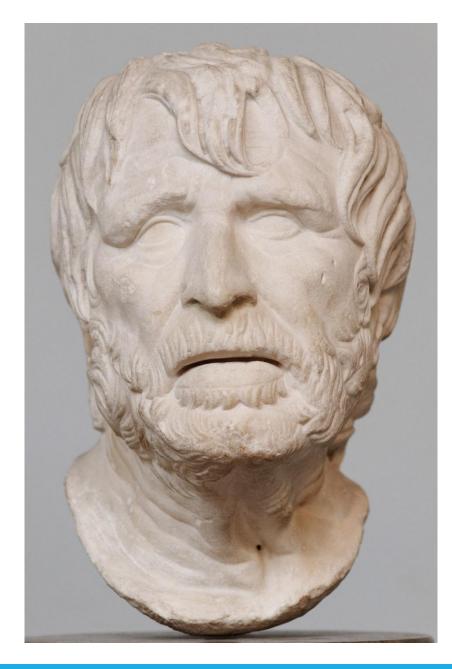
I need more information to assess this.



### Does this answer look ok?



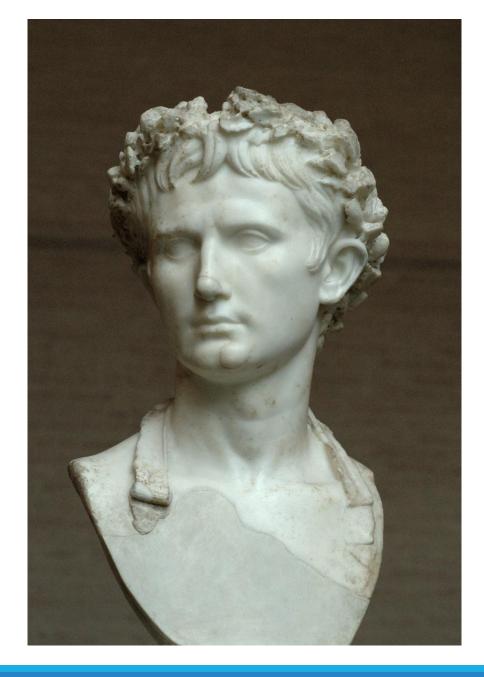
### I can't do this.

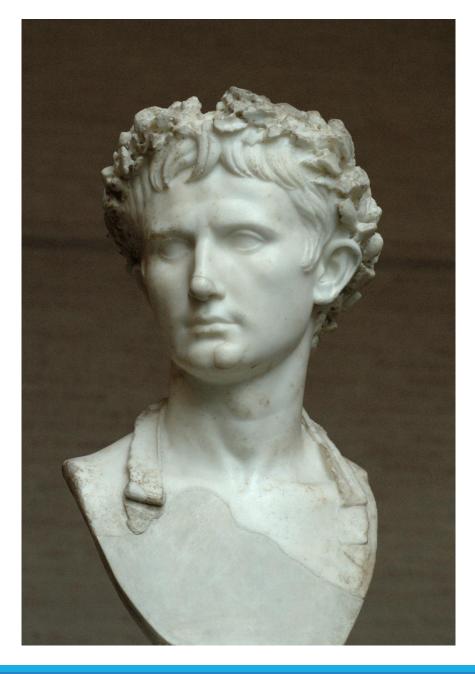


### I can't do this.\*

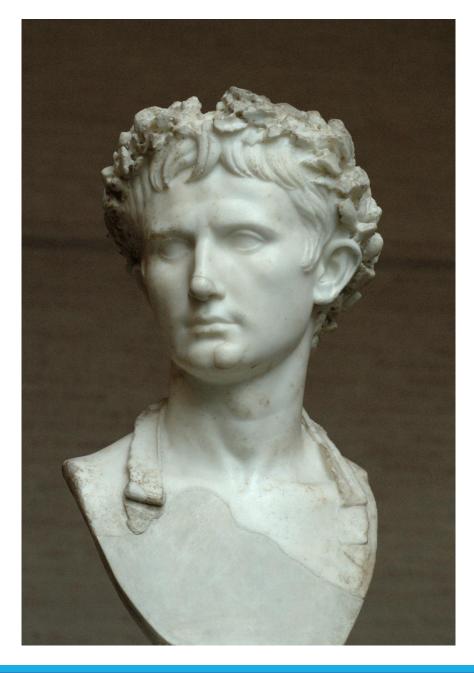
\*Not frequently heard.

### So you test them like school children?!

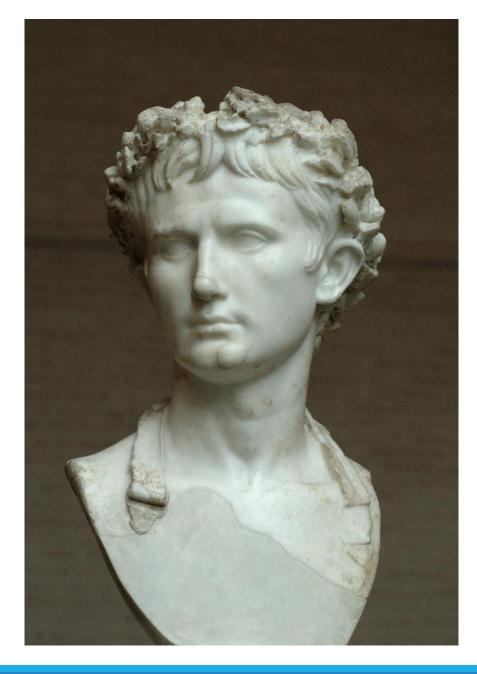




So you test them to see who's *really* an expert?

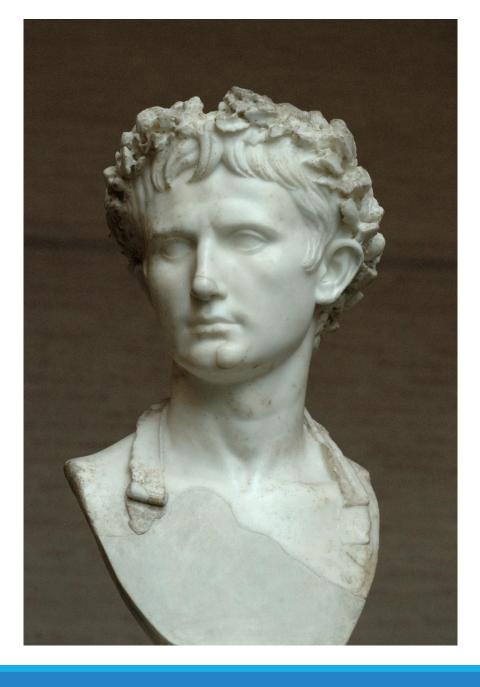


Why am I paying for this expert and then giving her zero weight?



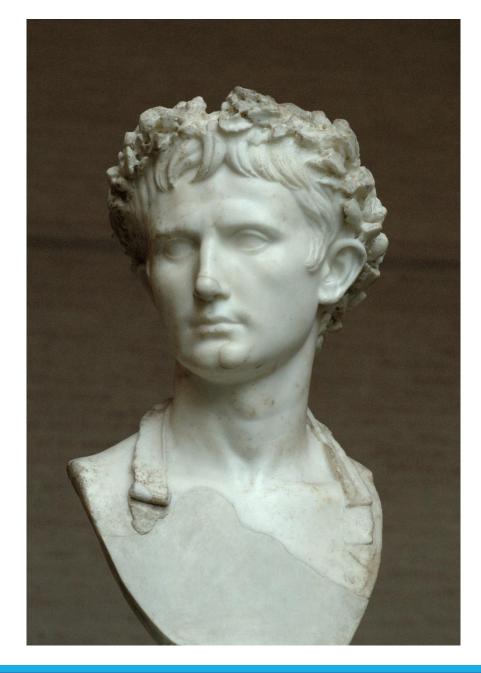
Why am I paying for so many experts and only giving weight to one?!?!

That assessment is crazy! Who said that?



That assessment is crazy! Who said that?\*

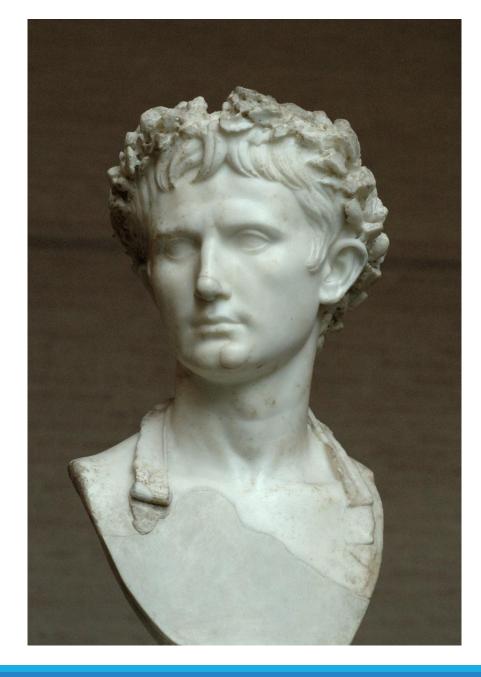
\*Not frequently heard.

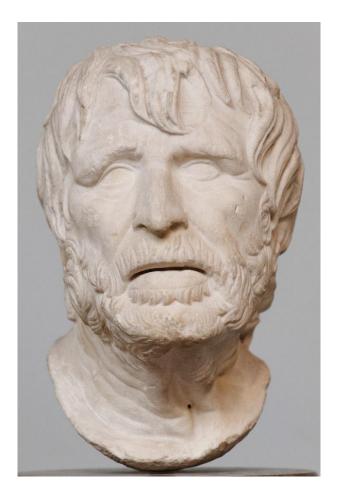




Ok...but I just want to use equal weights after all. Ok...but I just want to use equal weights after all.\*

\*Not frequently heard.





### Questions?

