Probabilistic Opinion Pooling

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March 2015 University of Cergy-Pontoise drawing on work with Christian List (LSE) and work in progress with Marcus Pivato (Cergy-Pontoise)

The problem of group agency:

teating a group as an agent, whith its own beliefs, desires, intensions, actions, plans, ...

Example: the House of Lords



The aggregative approach:

Group attitudes – beliefs, preferences, goals, ... – are not disconnected from people's attitudes, but a function ('aggregation') of them

My focus today: beliefs / opinions

Problem: how merge people's conflicting opinions into group opinions?

Testing your intuition 1

- Ann and Bob wonder whether it will rain tomorrow (they will go hiking).
- Assumption:
 - Ann thinks it will rain with 90% probability;
 - Bob thinks it will rain with 80% probability.
- How probable is rain overall, i.e., from the group's perspective?

Testing your intuition 2

- New start!
- Assumption:
 - Ann thinks rain is 9 times more likely than no rain;
 - Bob thinks rain is 4 times more likely than no rain;
- How much more likely is rain than no rain overall?

Oh!

- The two scenarios are equivalent: Rain is 9 (4) times more likely than no rain *if and only if* rain is 90% (80%) likely.
- So: If your first answer was 'rain is 85% probable', your second answer should be 'rain is $\frac{85\%}{15\%} \approx 5.666...$ times more likely than no rain'.

Lesson:

if group beliefs are averages of individual beliefs, then it's unclear what exactly to average

Next test question

• After Ann and Bob tell each other their subjective probabilities of rain (90% and 80%), Ann says:

"Look, Bob. We both came up independently with high probabilities of rain. This is double confirmation for rain! The overall probability of rain must be at least 95%."

• Who agrees with Ann?

N.B.: exaggerating rather than averaging

If Ann is right, then the group's overall opinion (probability) should be more extreme than each group member's opinion

 rather than some average or compromise between the group members' opinions.

Is Ann right?

This depends, among other things, on Ann's and Bob's sources of information:

- If both drew on similar information (e.g., both heard the same weather forecast), there is no real 'double-confirmation', and Ann is wrong.
- If both drew on independent information, Ann might be right.

Bottom line:

Opinion pooling is non-trivial !!

Three rival approaches

- What should a group's overall probability of a scenario be?
- Three potential answers:
 - an arithmetic average of people's probabilities ('linear pooling')
 - a geometric average of people's probabilities ('geometric pooling')
 - a product of people's probabilities ('multiplicative pooling')¹

¹The exact definitions of geometric and multiplicative pooling involve slightly more than taking a geometric average or product. Details soon!

Opinion pooling formalized

The individuals

A group of $n \ge 2$ individuals, labelled i = 1, ..., n, who have to assign collective probabilities to some relevant events.

The scenarios ('possible worlds')

- Ω : set of possible *worlds/states/scenarios/*... (Ω is non-empty and finite)
- Examples:

- ...

- $\Omega = \{ rainy, not-rainy \}$
- $\Omega = \{\text{rainy}, \text{ cloudy}, \text{ bright}\}$
- $\Omega = \{$ Hollande wins next presidential election, Sarcozy wins, someone else wins $\}$
- $\Omega = \{0, 1, ..., m\}$, where a ω in Ω represents the number of students coming to my office hours next week

Probability functions

- An individual's beliefs/opinions are captured by his probability function.
- A probability function is a function P which maps each scenario ω in Ω to a probability P(ω) ≥ 0 such that the total probability is Σ_{ω∈Ω} P(ω) = 1.

Aggregation (pooling)

- A combination of opinion functions across the n individuals,
 (P₁,..., P_n), is called a profile.
- A pooling function or aggregation function is a function F which transforms any profile $(P_1, ..., P_n)$ of individual probability functions into a single collective probability function $P = F(P_1, ..., P_n)$, often denoted $P_{P_1,...,P_n}$.

Linear pooling ("arithmetic averaging")

 The pooling function is linear if, for every profile (P₁, ..., P_n), the collective probability of each scenario ω is a weighted arithmetic average

$$P_{P_1,\ldots,P_n}(\omega) = w_1 P_1(\omega) + \cdots + w_m P_n(\omega)$$

of people's probabilities, for some fixed weights $w_1, ..., w_n \ge 0$ of sum 1.

• Extreme case: If $w_i = 1$ for some 'expert' *i* and $w_j = 0$ for all other individuals *j*, then we obtain an 'expert rule' given by $P_{P_1,...,P_n} = P_i$.

Geometric pooling ("geometric averaging")

The pooling function is geometric if, for every profile (P₁,..., P_n), the collective probability of each scenario ω takes the form

$$P_{P_1,\ldots,P_n}(\omega) = c[P_1(\omega)]^{w_1}\cdots [P_n(\omega)]^{w_n}$$

where $w_1, ..., w_n$ are fixed non-negative weights with sum 1 and c is a scaling factor, given by

$$c = rac{1}{\sum_{\omega' \in \Omega} [P_1(\omega')]^{w_1} \cdots [P_n(\omega')]^{w_n}}.$$

- Extreme case: If $w_i = 1$ for some 'expert' *i* and $w_j = 0$ for all other individuals *j*, then we again obtain an 'expert rule' given by $P_{P_1,...,P_n} = P_i$.
- Geometric pooling assumes that ∩_isupp(P_i) ≠ Ø (to ensure c is well-defined).

Multiplicative pooling

The pooling function is multiplicative if, for every profile (P₁,..., P_n), the collective probability of each scenario ω takes the form

$$P_{P_1,\ldots,P_n}(\omega)=cP_1(\omega)\cdots P_n(\omega)$$

where c is a scaling factor, given by

$$c = rac{1}{\sum_{\omega' \in \Omega} P_1(\omega') \cdots P_n(\omega')}.$$

Multiplicative pooling assumes that ∩_isupp(P_i) ≠ Ø (to ensure c is well-defined).

Which of the three pooling methods – linear, geometric, multiplicative – is best?

The axiomatic method can help us give answers!

The "indifference preservation" axiom

- The axiom informally: If each individual finds all scenarios equally likely, then so does the group.
- The axiom formally: If each of $P_1, ..., P_n$ is the uniform probability distribution, so is $P_{P_1,...,P_n}$.
- => Satisfied by linear, geometric and multiplicative pooling

The "consensus preservation" axiom

- The axiom informally: If all individuals agree, i.e., have the same beliefs, then these shared beliefs become thee collective beliefs.
- The axiom formally: If $P_1 = \cdots = P_n = P$, then $P_{P_1,\dots,P_n} = P$.
- => Plausible?
- => Satisfied by linear and geometric pooling, not multiplicative pooling

The axiom of "scenarios-wise pooling"

- The axiom informally: The group's probability of a scenario is determined by people's probabilities of *this* scenario (irrespective of people's probabilities of other scenarios).
 - So the group's probability of "rain" depends only on people's probabilities of rain, not on people's probabilities of "clouds", "sunshine", "hail", "snow", ...
- The axiom formally: The collective probability of a world ω is expressible as a function of people's probabilities of this world, $P_1(\omega), ..., P_n(\omega)$.
- => Plausible?
- => Satisfied by linear pooling only

The axiom of "Bayesianity"

- The axiom informally: If all individuals learn the same event, then group beliefs change by conditionalisation on this event.
- The axiom formally: for any event $E \subseteq \Omega$ (consistent with profile), $P_{P_1^E,...,P_n^E} = P_{P_1,...,P_n}^E$.
- => Satisfied by geometric and multiplicative pooling

The axiom of "external Bayesianity"

- This axiom concerns learning a likelihood function $L: \Omega \to (0, \infty)$, not en event.
- Example: Learning statistical data in Bayesian statistics with multiple statisticians, where Ω is the parameter space.
- For a probability function P and a likelihood function L : Ω → (0,∞), we write P^L for the *posterior probability* function conditional on L, defined as the unique probability function which, as a function of worlds, is proportional to P · L.
- The axiom informally: If all individuals learn a likelihood function, then group beliefs change by conditionalisation on it.
- The axiom formally: for any likelihood fn. L, $P_{P_1^L,...,P_n^L} = (P_{P_1,...,P_n})^L$.
- => Satisfied by geometric pooling only

The axiom of "individual-wise Bayesianity"

- Assume only one individual learns the information.
 => idea: people have access to different sources of information ('informational asymmetry')
- The axiom informally: It someone learns a likelihood function, group beliefs change be conditionalisation on it.
- The axiom formally: For any information L and individual i, $P_{P_1,...,P_i}$ = $(P_{P_1,...,P_n})^L$.
- => Plausible?
- => Satisfied by multiplicative pooling only

Summary

	linear	geometric	multiplicative
indifference preserving?	Х	X	X
consensus preserving?	Х	X	
scenario-wise?	Х		
Bayesian?		X	X
externally Bayesian?		Х	
individual-wise Bayesian?			X

Three theorems

Theorem 1. (Aczél-Wagner 1980, McConway 1981) The linear pooling functions are the only consensus-preserving and scenario-wise pooling functions (assuming Ω contains more than two scenarios).

Theorem 2. (Genest 1984) The geometric pooling functions are unanimity-preserving and externally Bayesian (but there exist other pooling functions with these two properties).

Theorem 3. (Dietrich-List 2014) The multiplicative pooling function is the only indifference-preserving individual-wise Bayesian pooling function.

Our question "which of the three pooling functions is best?" has been reduced to another question: "which axioms are appropriate?"

Which pooling functions and axioms are right?

= Soal-dependence

- Do we pursue an epistemic or procedural goal?
- I.e., should group opinions 'track the truth' or 'track people's opinions'?

Under the epistemic goal, linear pooling looks bad:

- It can't handle information-learning! Neither externally nor individual-wise Bayesian.
- Its central axiomatic property scenario-wise pooling lacks an epistemic justification.

Which pooling function and axioms are right?

=> Context-dependence

Suppose the goal is epistemic: we aim for *true* group beliefs!

How to aggregate depends crucially on the informational setting:

Case 1: **symmetric information:** all individuals base their beliefs on the same information

=> Here, geometric pooling and external Bayesianity are plausible.

Case 2: **asymmetric information:** each individual holds private information => Here, multiplicative pooling and individual-wise Bayesianity are plausible.

Cases between public and private information

Informational axioms

- "If information is learnt, group beliefs change by conditionalisation on it"
- There are $2 \cdot 3 = 6$ variants of this axiom, depending on
 - what is being learnt, i.e., an event or a likelihood function,
 - who learns the information, i.e., everyone (public info), a single individual (private info) or an arbitrary subgroup.

Conjectures

Bottom line: It depends!

Before pooling opinions, one must know

(i) the goal,

(ii) the informational context.

Thanks!

