

# Bridges between Frequentist Statistics and Objective Bayesianism

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Multiplicity and Unification in Statistics and Probability  
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# 1 The Statistical View

**Stats** works like this:

1. Conceptualise the problem. Isolate a set  $\mathbb{M}$  of models for consideration.
  - Models are probability functions.
2. Gather evidence  $\mathcal{E}$ .
3. Apply statistical methods to evaluate models in  $\mathbb{M}$  in the light of  $\mathcal{E}$ .
  - Inferences and decisions will be made on the basis of a set  $\mathbb{E} \subseteq \mathbb{M}$  of models that are appropriate given  $\mathcal{E}$ .

**Frequentist stats** works like this:

1. Conceptualise the problem. Isolate a set  $\mathbb{M}$  of models for consideration.
  - $\mathbb{M}$  is a set of candidates for physical probability  $P^*$ .
2. Gather evidence  $\mathcal{E}$ .
3. Apply statistical methods to evaluate models in  $\mathbb{M}$ .
  - Inferences and decisions will be made on the basis of a set  $\mathbb{E} \subseteq \mathbb{M}$  of models that render the evidence sufficiently likely, assuming the evidence is gathered in an appropriate way etc.

**Bayesianism** works like this:

1. Choose appropriate variables,  $\mathbb{M}$ , and a prior function  $P$  over  $\mathbb{M}$ .
2. Gather evidence, ensuring  $\mathcal{E}$  is in the domain of  $P$ .
3. Take a new stance  $P' = P(\cdot|\mathcal{E})$  over  $\mathbb{M}$  (conditionalisation).
  - Typically via Bayes' theorem.
  - $\mathbb{E}$  is the set of models with sufficiently high  $P'$ .

**Subjective:**  $P$  is a matter of personal choice.

**Objective:**  $P$  is maximally equivocal.

It looks like the two approaches are just incompatible ways of doing stats.

But what are the questions that the two approaches are trying to answer?

**Frequentist:** How does evidence impact on the set of candidate physical probability functions?

**Bayesian:** How does evidence impact on rational degree of belief?

- ▶ Not so incompatible after all?

## 2 The Epistemological View

**Key Question.** How strongly should an agent with evidence  $\mathcal{E}$  believe the various propositions expressible in her language  $\mathcal{L}$ ?

- E.g., a finite propositional language  $\mathcal{L} = \{A_1, \dots, A_n\}$ .
- $\mathcal{E}$  is *total evidence*, everything that is taken for granted: data, assumptions, theoretical knowledge ...
  - Not necessarily expressible as propositions of  $\mathcal{L}$ .

**The Bayesian Answer.** An agent's belief function  $P_{\mathcal{E}}$  over  $\mathcal{L}$  should satisfy certain norms:

**Probability:** It should be a probability function.

**Calibration:** It should be compatible with evidence,

- in particular, calibrated with known physical probabilities.

**Equivocation:** It should otherwise equivocate sufficiently between the basic possibilities expressible in  $\mathcal{L}$ .

Strict subjectivism: Probability (+ conditionalisation)

Empirically-based subjectivism: Probability + Calibration (+ conditionalisation)

Objectivism: Probability + Calibration + Equivocation

## Explicating the Norms

**Probability:**  $P_{\mathcal{E}}$  should be a probability function:

**P1:**  $P_{\mathcal{E}}(\omega) \geq 0$  for each  $\omega \in \Omega = \{\pm A_1 \wedge \cdots \wedge \pm A_n\}$ ,

**P2:**  $P_{\mathcal{E}}(\tau) = 1$  for some tautology  $\tau \in S\mathcal{L}$ , and

**P3:**  $P_{\mathcal{E}}(\theta) = \sum_{\omega \models \theta} P_{\mathcal{E}}(\omega)$  for each  $\theta \in S\mathcal{L}$ .

**Calibration:** It should be compatible with evidence,

**C1:**  $P_{\mathcal{E}} \in \mathbb{E} = \langle \mathbb{P}^* \rangle \cap \mathbb{S}$

- $\mathbb{P}^*$  set of candidate physical probability functions.
- $\langle \cdot \rangle$  convex hull.
- $\mathbb{S}$  structural constraints.

**Equivocation:** It should otherwise equivocate sufficiently between the basic possibilities expressible in  $\mathcal{L}$ .

**E1:**  $P_{\mathcal{E}}$  sufficiently close to equivocator  $P_{=}(\omega) = 1/2^n$ .

- $d(P, P_{=}) = \sum_{\omega \in \Omega} P(\omega) \log P(\omega)/P_{=}(\omega)$ .
- proximity to the equivocator = entropy.

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- $\mathbb{P}^*$  set of candidate physical probability functions. ← **Frequentist statistics!**
- $\langle \cdot \rangle$  convex hull.
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- ▶ proximity to the equivocator = entropy.

### 3 Frequentist Statistics for Calibration

A new picture of the relation between frequentist statistics and objective Bayesianism:

1. Be explicit about language  $\mathcal{L}$  and evidence  $\mathcal{E}$ .
2.  $\mathbb{M} = \mathbb{P}^*$  = candidate physical probability functions, given  $\mathcal{E}$  (**frequentist statistics**).
3.  $\mathbb{E} = \langle \mathbb{P}^* \rangle \cap \mathbb{S}$  = belief functions compatible with evidence.
4. Choose a belief function  $P_{\mathcal{E}}$  in  $\mathbb{E}$  sufficiently close to the equivocator (**OBE**).
  - ▶ Use  $P_{\mathcal{E}}$  as a basis for action.

Objection:

- The nice thing about maxent is that it is precise enough to implement in a decision support system.
- Frequentist statistics is a hotch-potch of vaguely formulated methods.
- ▶ They are combined at the expense of precision and automation.

Not necessarily ...

- **Evidential Probability** (EP) is Henry Kyburg's implementation of frequentist statistics,
- it can more or less plug into the above scheme.
  - EP can be thought of as determining  $\langle \mathbb{P}^* \rangle$  rather than  $\mathbb{P}^*$ .

## 4 Evidential Probability and OBE

Joint work with Greg Wheeler ([Wheeler and Williamson, 2009](#)).

- Evidence  $\mathcal{E}$  can include statistical statements

$$\%x(\tau(x), \rho(x), [l, u])$$

- the proportion of  $\rho$ -s that satisfy  $\tau$  is between  $l$  and  $u$ :  $\text{freq}_\rho(\tau) \in [l, u]$ .
- $\rho$  is the *reference class*.
- The language  $\mathcal{L}$  of EP is a 1st order language in which such statements can be expressed.
- Apply rules for manipulating reference classes.
- ▶ *Evidential probability*  $\text{Prob}(\theta, \Gamma_\delta) = [l, u]$ .
  - An interval rather than a sharp probability.
  - Interpret this as bounds on  $P^*(\theta)$ , the sharp probability of  $\theta$ .
  - $\langle \mathbb{P}^* \rangle$  is the set of functions satisfying EP-consequences of  $\mathcal{E}$ .
  - (Need some consistency maintenance procedure.)

**Urn Example.** It is known just that

- the proportion of White balls in an Urn is in  $[l, u]$ ,  $\%x(W(x), U(x), [l, u])$ .
- ball  $t$  is drawn from the Urn,  $U(t)$ .
- ▶ Then we can derive  $P^*(W(t)) \in [l, u]$ .
  - If  $l = u = n/N$  then we can derive  $P^*(W(t)) = n/N$ .
  - If there is conflicting statistical evidence then EP applies conflict resolution rules.
  - If there is no statistical evidence we derive  $P^*(W(t)) \in [0, 1]$ .

## Conflict Resolution

**Reference Class Problem:** How can one calculate the probability that an individual satisfies  $\tau$  when it belongs to several reference classes  $\rho_i$  with known statistics?

Suppose we know that

- $[p, q]$  is the smallest interval covering reports of the proportion of  $R$ s that are  $U$ s.
- $[l, u]$  is the smallest interval covering reports of the proportion of  $S$ s that are  $V$ s.
- $U(t_1) \leftrightarrow V(t_2), R(t_1), S(t_2)$ .

Say  $[p, q]$  and  $[l, u]$  *conflict* if neither interval is strictly contained in the other. One can ignore the  $S, V$  evidence if

**Richness:** The intervals conflict and  $R$  measures  $S$  together with other properties.

- $R = (S, T, \dots)$

**Specificity:** The intervals conflict and  $R$  holds of fewer individuals than  $S$ .

**Strength:**  $[l, u]$  contains all intervals that survive Richness and Specificity.

The remaining statistics are the *relevant statistics*.

- ▶ The smallest interval covering these gives the evidential probability.

## Example

- Evidential certainties:
  - Bob smokes a packet of cigarettes a day and is a politician.
  - 1. The proportion of smokers that live to the age of 80 is in  $[.5, .8]$
  - 2. The proportion of obese smokers living to 80 is in  $[.3, .7]$  while the proportion of non-obese smokers living to 80 is in  $[.6, .7]$ .
  - 3. The proportion of those who smoke a packet a day living to 80 is in  $[.4, .75]$ .
  - 4. The proportion of politicians living to 80 is in  $[.6, .7]$ .
- 1 is eliminated in favour of 2 by Richness.
- 2 is eliminated in favour of 3 by Specificity.
- 3 is eliminated in favour of 4 by Strength.
- ▶ We conclude that the probability that Bob will live to 80 is in  $[.6, .7]$ .
  - A claim about physical probability,  $\langle \mathbb{P}^* \rangle$ .
- ▶ Then maxent will give probability .6 to Bob living to 80.
  - A claim about rational degree of belief.

## Second-Order EP

Where do the intervals come from?

- Marginals:  $freq_{\rho}(\tau) = u$  implies  $freq_{\rho}(\sigma \wedge \tau) \in [0, u]$ .
- Higher order probability: e.g., probability at least .95 that  $freq_{\rho}(\tau) \in [l, u]$ .
  - ▶ Kyburg: if  $.95 > 1 - \delta$ , a given threshold, then infer  $freq_{\rho}(\tau) \in [l, u]$ .
  - ▶ **Wheeler and Williamson (2009)**: second-order EP,  $freq_{\rho}(\tau) \in [l, u]^{[.95, 1]}$ .

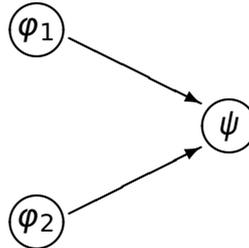
Won't calculations in 2oEP be impractical?

- Not necessarily: can use credal nets.
- Assumptions:
  - Items of evidence are by default independent.
  - 2o probability is by default uniformly distributed over the given interval.

## Constructing a Credal Net

The structure of  $1^o$  EP calculations determine the structure of the credal net:

- Evidence  $\mathcal{E}$ :  $freq_R(F) \in [.2, .4]^{[.9, 1]}, Rt^{\{1\}}$
- What is the probability that  $P^*(Ft) \in [.2, .4]$ ?



The  $X_i$  and  $1^o$  EP inferences determine the conditional probability constraints:

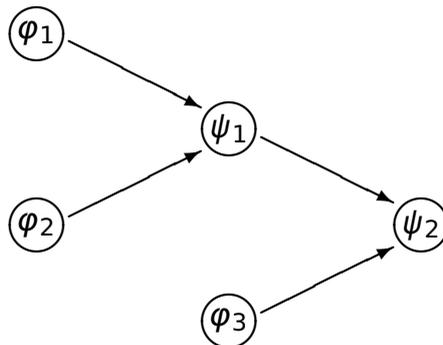
$$P(\varphi_1) \in [.9, 1], P(\varphi_2) = 1$$

$$P(\psi|\varphi_1 \wedge \varphi_2) = 1, P(\psi|\neg\varphi_1 \wedge \varphi_2) = .2 = P(\psi|\varphi_1 \wedge \neg\varphi_2) = P(\psi|\neg\varphi_1 \wedge \neg\varphi_2)$$

We can then chain inferences (won't work in 1° EP):

$$\text{freq}_R(F) \in [.2, .4]^{[.9, 1]}, Rt^{\{1\}} \approx P(Ft) \in [.2, .4]^{Y_1}$$

$$\text{freq}_R(F) \in [.2, .4]^{[.9, 1]}, Rt^{\{1\}}, \text{freq}_F(G) \in [.6, .7]^{[.9, 1]} \approx P(Gt) \in [0, .25]^?$$



$$P(\varphi_1) \in [.9, 1], P(\varphi_2) = 1, P(\varphi_3) \in [0.9, 1]$$

$$P(\psi_1|\varphi_1 \wedge \varphi_2) = 1, P(\psi_1|\neg\varphi_1 \wedge \varphi_2) = .2 = P(\psi_1|\varphi_1 \wedge \neg\varphi_2) = P(\psi_1|\neg\varphi_1 \wedge \neg\varphi_2)$$

$$P(\psi_2|\psi_1 \wedge \varphi_3) = \frac{|[.2 \times .6 + .8 \times .1, .4 \times .7 + .6 \times .1] \cap [0, .25]|}{|[.2 \times .6 + .8 \times .1, .4 \times .7 + .6 \times .1]|} = .31,$$

$$P(\psi_2|\neg\psi_1 \wedge \varphi_3) = .27, P(\psi_2|\psi_1 \wedge \neg\varphi_3) = P(\psi_2|\neg\psi_1 \wedge \neg\varphi_3) = .25$$

## Conclusion

- From the epistemological point of view, frequentist statistics and objective Bayesianism are not just compatible, they are components of the same rational epistemology.
- ▶ We should move away from the standard statistical picture.
  - (We should anyway since the objective Bayesian need not conditionalise.)
- Introducing frequentist statistics need not be at the expense of precision and tractability:
  - Evidential probability and objective Bayesianism can be fruitfully combined;
  - Credal nets can be applied to both formalisms and their unification, making for tractable reasoning.

## Related Work

- <http://www.kent.ac.uk/secl/philosophy/jw>

## References

Wheeler, G. and Williamson, J. (2009). Evidential probability and objective Bayesian epistemology. In Bandyopadhyay, P. S. and Forster, M., editors, *Handbook of the Philosophy of Statistics*. Elsevier.