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On the usefulness of imprecise Bayesianism in chemical kinetics

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Application to a simple case

- Chemical kinetics: study of the speed of chemical reactions and the factors bearing on it [1].
- Application to a wide range of fields: combustion, catalysis, atmospheric chemistry, water pollution...
- The ultimate goal is to derive predictive models.
- Both frequentist and Bayesian approaches are used to describe and propagate the parameter uncertainty [2,3].
- Unfortunately, they're applied mostly uncritically without being aware of fundamental issues.
- Most preoccupying of all is the researchers' massive reliance on a single (mostly uniform) prior to describe ignorance [4,5].

Basics

Reaction
$$v_A A + v_B B \Rightarrow v_C C + v_D D$$
 $r = \frac{1}{v_A} \frac{d[A]}{dt} = \frac{1}{v_B} \frac{d[B]}{dt} = \frac{1}{v_C} \frac{d[C]}{dt} = \frac{1}{v_{[D]}} \frac{d[D]}{dt} = k[A]^{v_A} [B]^{v_B} = AT^n \exp(\frac{-E_A}{RT}) [A]^{v_A} [B]^{v_B}$

• If there are N_c elementary reactions, ODE:



Two reaction models, one experimental profile

• M_1 : An isomerisation towards product P_1 • M_2 : A recombination towards product P_2 $R \rightarrow P_1$ $R + R \rightarrow P_2$ $\frac{d[R]}{dt} = -k_1[R]$ $\frac{d[R]}{dt} = -2k_2[R]^2$ Frequentism 1400 M₁ (best fit) M₂ (best fit) $F_{\varepsilon} = \{k \mid |m_i(k) - e_i| \le \varepsilon \sigma_i\}, \ i \in [|1;n|]$ Experiment + * + 1200 M1: $F_{\epsilon} = \{ \mathcal{O} \}$ 1000 $M_2: F_{\epsilon} = [8.51E+05; 1.22E+06] mol. cm^{-3}. s^{-1}$ [R] (mol/m³) 800 600 400 0e+00 2e+02 4e+02 6e+02 8e+02 1e+03 1e+03 t (μs) **Precise Bayesianism** $P(k_1|M_1) = 0.00050$ $P(k_2|M_2) = 1/(5^9 - 5^4) = 2^{-10} \rightarrow B = 0.312$ • Uniform prior \rightarrow

The problem of the priors

- The major problem of <u>precise</u> Bayesianism is the choice of the prior.
- In chemical kinetics, almost all practitioners use one single uniform prior.
- But this involves mistaking ignorance for knowledge.





• A prior uniform with respect to *k* can be highly non -uniform with respect to log10(k) or k^c.

• We should reject model M₂ in favour of model M₁ in spite of the poor agreement!

• Lindley's paradox: mixture of knowledge (likelihood) with ignorance (prior) [7].

Imprecise Bayesianism

Variable	Ο	В
k	4.00E-07	3.12E-01
x = 1/k	2.50E+04	1.67E+04
l = log 10(k)	6.00E-01	3.29E+02
y = 1/log 10(k)	2.75E+01	3.74E+03
$z = k^{0.25}$	2.19E-02	7.08E+01
$w = k^2$	1.60E-13	1.98E-04

Dependency of *O* and *B* on the prior

→ conclusion strongly dependent on the prior!



• Bayesianism brings lots of exciting possibilities into chemical kinetics.

- However, the reliance on one single prior undermines the reliability of the results.

• Main difference between frequentism and precise Bayesianism: Ockham's razor.

• <u>Ockham's razor</u>: "All other things being equal, simpler models are more likely to be true than more complex ones".

 $B = \frac{L(E|M_2)}{L(E|M_1)} = \frac{\int_{k_2} L(E, k_2, M_2) f_{2,0}(k_2|M_2) dk_2}{\int_{k_1} L(E, k_1, M_1) f_{1,0}(k_1|M_2) dk_1}$ Bayes' factor Uniform prior \rightarrow $B = \frac{L_{max}(E|k_2)}{L_{max}(E|k_1)} \frac{V p_{M2}}{V p_{M1}} \frac{V_{M1}}{V_{M2}} = F Q_p O$ $F = \frac{L_{max}(E|k_2)}{L_{max}(E|k_1)}$: maximum likelihood ratio. $O = \frac{V p_{M2}}{V p_{M1}}$: Ockham's factor.

• The larger $V_{_{M1}}$ is in comparison to $V_{_{M2}}$, the likelier $M_{_2}$ becomes.

• This, however, assumes that a uniform prior is a legitimate expression of ignorance.

• *O* is strongly dependent on the parametrisation [6].

• Yet, the large majority of chemical kineticists use precisely such a single uniform prior!

• There is an urgent need for robust Bayesian analyses embedded in an imprecise framework.



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