The likelihood approach to statistical decision problems

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- **statistical model**: $(\Omega, \mathcal{F}, P_\theta)$ with $\theta \in \Theta$ (where Θ is a nonempty set) and random variables $X : \Omega \to \mathcal{X}$ and $X_n : \Omega \to \mathcal{X}_n$

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- these methods do not fit well in the setting of statistical decision theory: here they are unified (and generalized) in likelihood decision theory

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- prior information can be described by a prior likelihood function: if X_1 and X_2 are independent, then $\lambda_{(x_1, x_2)} \propto \lambda_{x_1} \lambda_{x_2}$; that is, when $X_2 = x_2$ is observed, the prior λ_{x_1} is updated to the posterior $\lambda_{(x_1, x_2)}$

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- strong similarity with the Bayesian approach (both satisfy the likelihood principle): a fundamental advantage of the likelihood approach is the possibility of not using prior information (since $\lambda_{x_1} \equiv 1$ describes complete ignorance)

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- **likelihood decision function**: $\delta : \mathcal{X} \to \mathcal{D}$ such that $\delta(x)$ minimizes $V(W(\cdot, d), \lambda_x)$

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- likelihood decision criteria have also important **pre-data** properties:
  - equivariance: for invariant decision problems, the likelihood decision functions are equivariant
  - (strong) consistency: under some regularity conditions, the likelihood decision functions $\delta_n : \mathcal{X}_1 \times \cdots \times \mathcal{X}_n \to \mathcal{D}$ satisfy

$$\lim_{n \to \infty} W(\theta, \delta_n(X_1, \ldots, X_n)) = \inf_{d \in \mathcal{D}} W(\theta, d) \quad P_\theta\text{-a.s.}$$

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  - the **likelihood ratio test** with critical value c'/c is the likelihood decision function resulting from the MPL criterion

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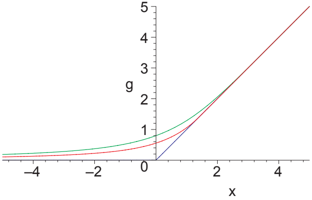

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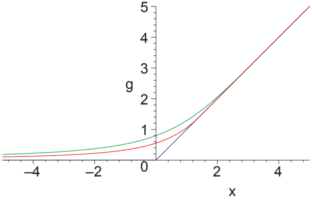

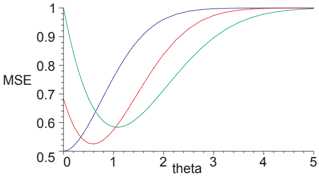

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  - is consistent and asymptotically efficient

conclusion

- this work:
  - fills a gap in the likelihood approach to statistics
  - introduces an alternative to classical and Bayesian decision making
  - offers a new perspective on the likelihood methods
- **likelihood decision making**:
  - is post-data and equivariant
  - is consistent and asymptotically efficient
  - does not need prior information

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