

Constraint choice and model selection in the generalized maximum entropy principle (MEP)

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Introduction: A wide class of entropies can be used in the MEP

- ▶ Jos Uffink [1], generalizing the Shore and Johnson's axioms, proved that the functionals which are suitable to be used in the Maximum Entropy Principle (MEP) belong to a one-parameter family, which the Shannon entropy is a member of.

- ▶ Such functionals are monotonically increasing functions f of

$$U_q(P) = \left(\sum_G p^q(G) \right)^{1/(1-q)}$$

- ▶ For $q \rightarrow 1$, $U_q(P) \rightarrow$ Shannon entropy
- ▶ P. Jizba and J. Korbel discussed [2] that this generalized approach is suitable to study systems which do not respect standard hypothesis such as ergodicity, short-range interactions or exponential growth of the sample space: the resulting probability distributions take into account correlations that may not have been observed.

- ▶ Rényi entropy

$$S_R(P; q) = \log U_q(P)$$

- ▶ Constraint choice: mean vs normalized q-mean

$$\langle C \rangle_q = \frac{\sum_G C(G) p^q(G)}{\sum_G p^q(G)}$$

Methods: Maximum entropy and maximum likelihood

- ▶ Constrained maximization of entropy through Lagrange multiplier technique.
- ▶ Parameter estimation through **Maximum likelihood** estimator: maximize the joint probability of the data in order to fix the parameters.
- ▶ Compare results for both constraint choices.

Mathematical formulation: Mean vs q-mean constraints

- ▶ Constrained maximization

$$\max_P \left[S_R(P; q) - \alpha' \left(\sum_G p(G) - 1 \right) - \theta' \left(\langle C \rangle - C^* \right) \right]$$

$$\max_P \left[S_R(P; q) - \alpha \left(\sum_G p(G) - 1 \right) - \theta \left(\langle C \rangle_q - C^* \right) \right]$$

- ▶ Solutions

$$p(G) = \frac{1}{Z'} (1 - (q-1) \hat{\theta}' C(G))^{1/(q-1)}$$

$$p(G) = \frac{1}{Z} (1 - (1-q) \hat{\theta} C(G))^{1/(1-q)}$$

- ▶ Maximum likelihood

$$\sum_G C(G) p^{2-q}(G | \hat{\theta}'_{ML}) = \sum_G C(G) p^{1-q}(G | \hat{\theta}'_{ML}) \text{freq}(G)$$

$$\sum_G C(G) p^q(G | \hat{\theta}_{ML}) = \sum_G f(G) p^{q-1}(G | \hat{\theta}_{ML}) \text{freq}(G)$$

Discussion: Generalized mean is a better constraint in the MEP

- ▶ The solutions of the MEP show a power-law behavior: the mean could diverge, so it could be a bad constraint choice.
- ▶ If q is such that the distribution is normalizable, then all its q -moments converge.
- ▶ The q -mean allows us to characterize the power law for every possible value of the exponent.
- ▶ The q -mean, unlike the standard one, makes the Maximum entropy and Maximum likelihood consistent each other.
- ▶ Model selection, i.e. choice of the preferred parameters (q , θ) given the data, can be performed through the maximum likelihood approach.

Numerical simulations: Explanation

- ▶ Data sampled from $p(G)$ in the simple case where $C(G) \in [0, +\infty)$ and $g(C) = 1$, for different values of q and θ ($q = 1$ being the exponential distribution)

$$P(C) = (2 - q)\theta(1 - (1 - q)\theta C)^{\frac{1}{1-q}}$$

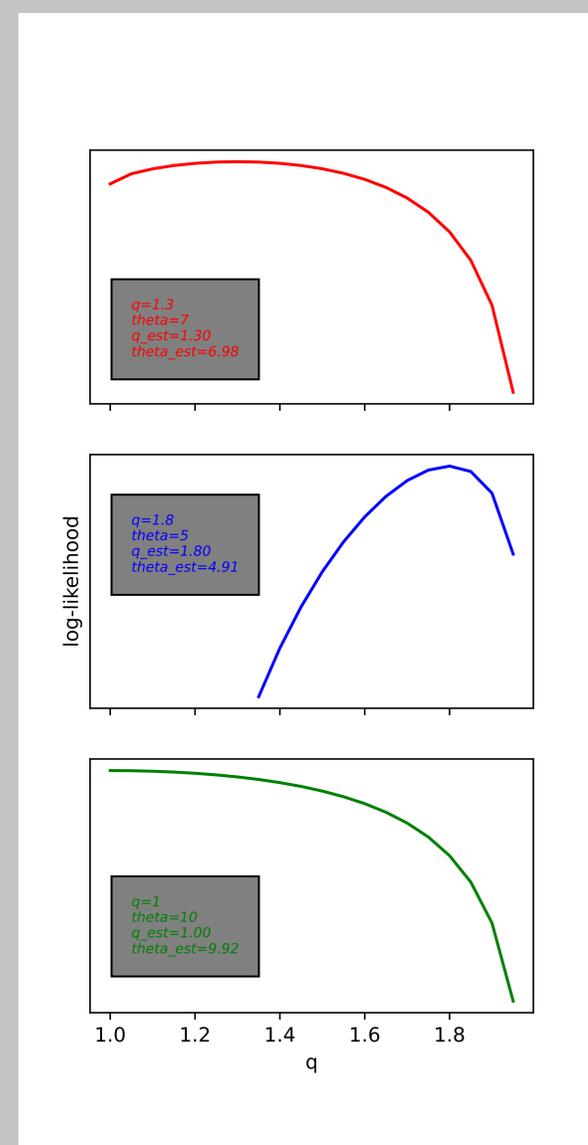
- ▶ Parameters estimated through maximum likelihood model selection

Numerical results: Parameter estimation

- ▶ Number of points sampled $N = 10^5$...
- ▶ ...for each of three PDFs (r , b , g) with different parameters

Probability density	q	θ	q_{est}	θ_{est}
(r), 1st moment converge	1.3	7	1.30	6.98
(b), 1st moment diverge	1.8	5	1.80	4.91
(g), exponential PDF	1	10	1.00	9.92

Numerical results: Log-likelihood vs q plot



Log-likelihood vs q plot. The log-likelihood, for each q , is evaluated in the point $(q, \theta) = (q, \hat{\theta}_{ML}(q))$

References

- [1] Jos Uffink.
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- [2] Petr Jizba and Jan Korbel.
Maximum entropy principle in statistical inference: Case for non-shannonian entropies.
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