

A Minimum Distance Estimator in an Imprecise Probability Model

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Computational Aspects and Applications

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- ▶ Diploma Thesis in Robust Asymptotic Statistics (Helmut Rieder, University of Bayreuth)
- ▶ Ph.D. Thesis: “Data-Based Decisions under Complex Uncertainty” (Thomas Augustin, LMU Munich)
- ▶ Now: University of Bayreuth
Working group: Andreas Christmann (Machine Learning) and Helmut Rieder (Robust Statistics)
- ▶ Research Interests:
 - ▶ Mathematical Foundations of Imprecise Probabilities
 - ▶ (Statistical) Decision Theory under Imprecise Probabilities
 - ▶ Robust Statistics
 - ▶ Nonparametric Statistics

Estimation: Classical Statistics and Generalizations

Data x_1, \dots, x_n are modeled by random variables

$$X_1, \dots, X_n \sim P_0 \quad \text{i.i.d.}$$

P_0 the true distribution (precise probability measure)

▶ classical statistics

- ▶ $(P_\theta)_{\theta \in \Theta}$: a parametric model (precise distributions)
- ▶ $\exists \theta_0 \in \Theta$ such that $P_0 = P_{\theta_0}$

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Goal: Estimate θ_0

An Imprecise Probability Model – Some More Assumptions

An Imprecise Probability Model – Some More Assumptions

... may be found on the poster!

Minimum Distance Estimator

- ▶ Simple **idea**:
 - ▶ Construct empirical measure \mathbb{P}_n from the data
 - ▶ Chose that credal set \mathcal{M}_θ which lies next to \mathbb{P}_n

Minimum Distance Estimator

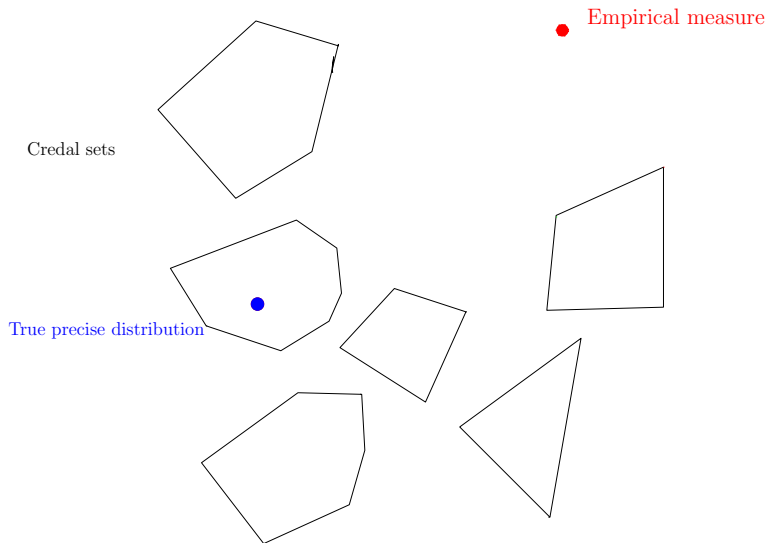
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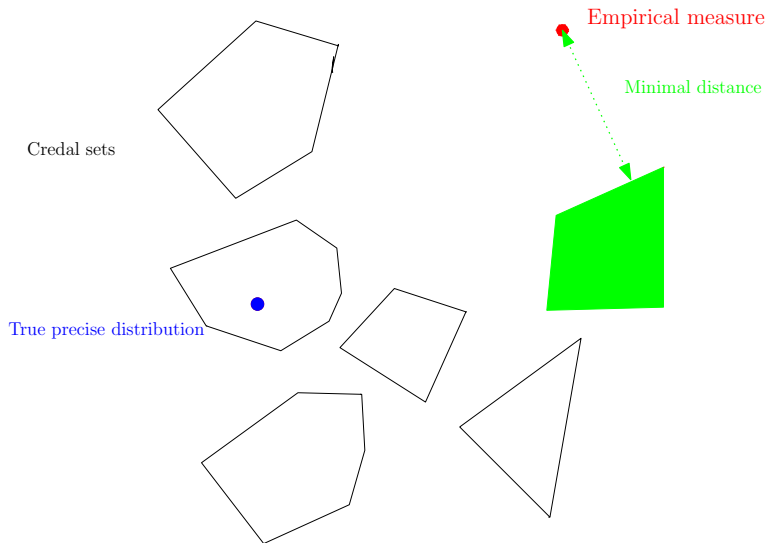
- ▶ **Definition**:

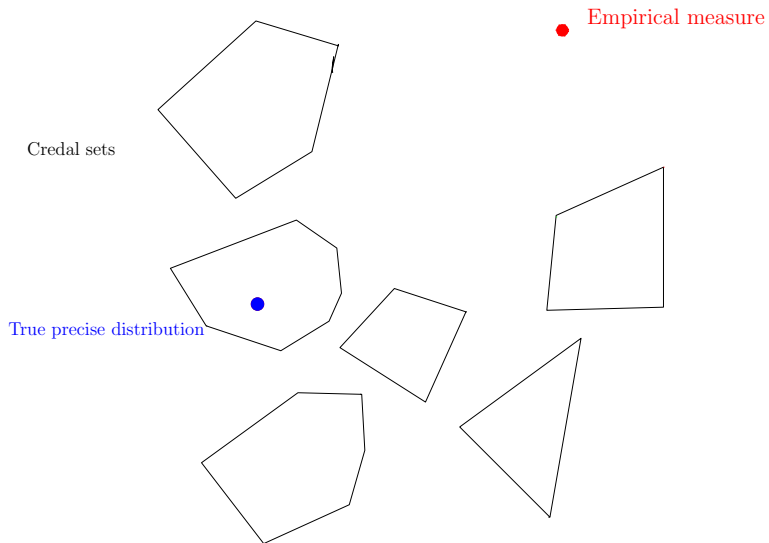
Estimator $\hat{\theta}_n$ minimizes

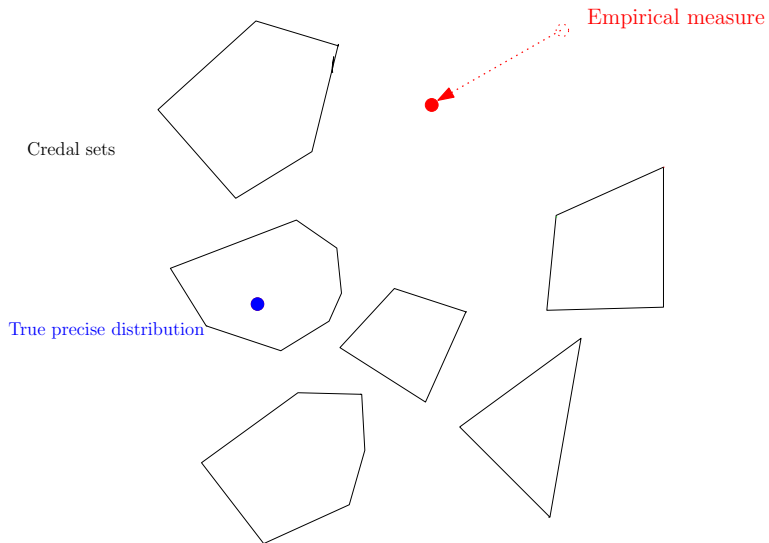
$$\theta \mapsto d(\mathbb{P}_n, \mathcal{M}_\theta) = \inf_{P_\theta \in \mathcal{M}_\theta} d(\mathbb{P}_n, P_\theta)$$

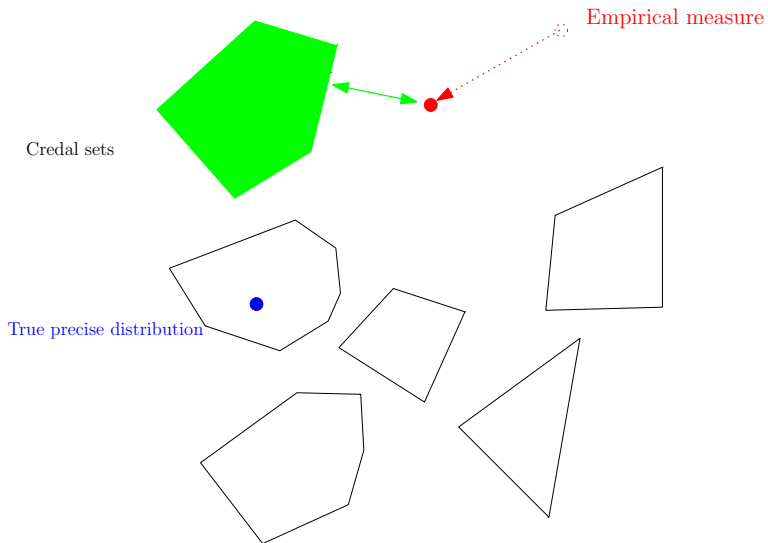
Distance d : total variation

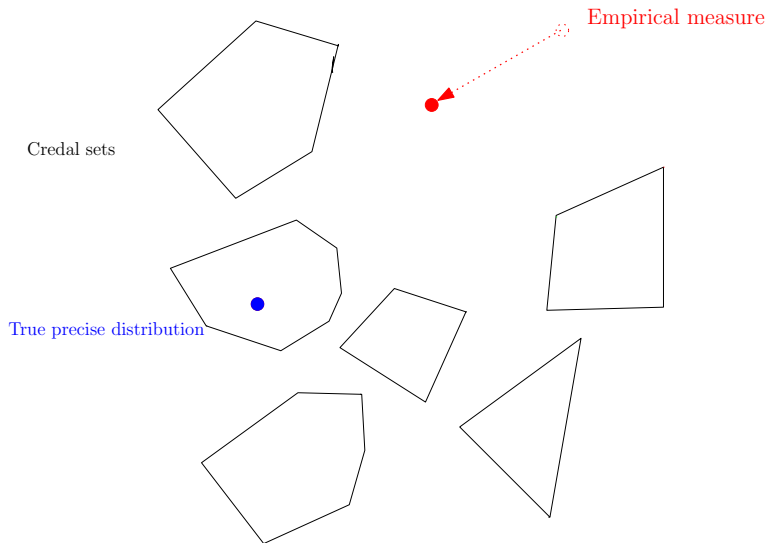


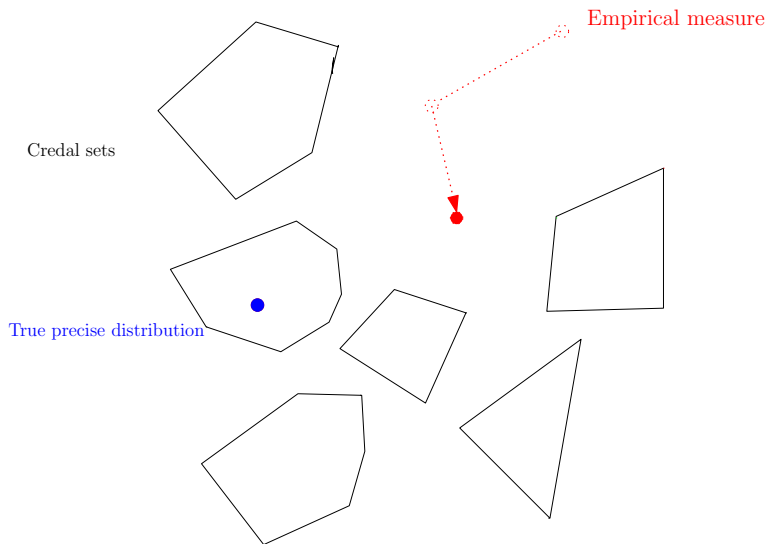


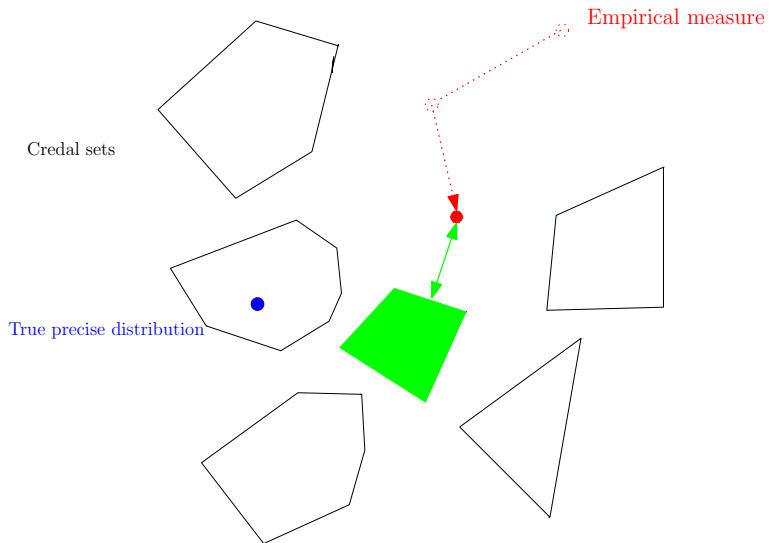


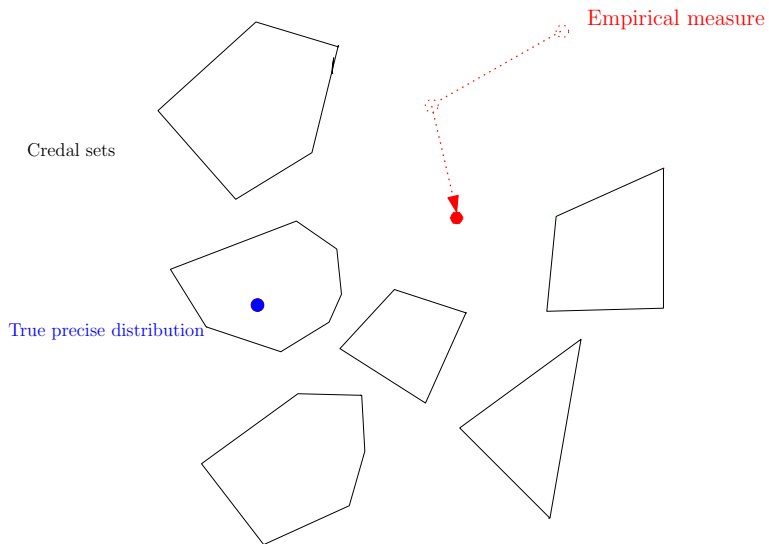


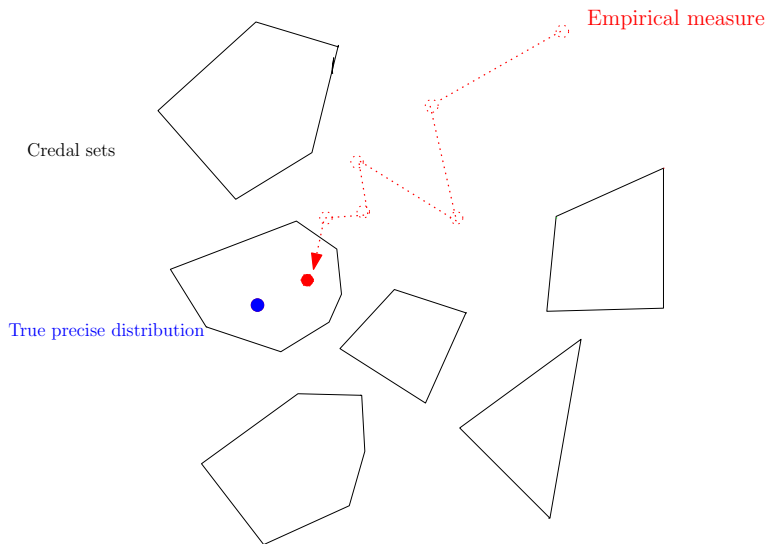


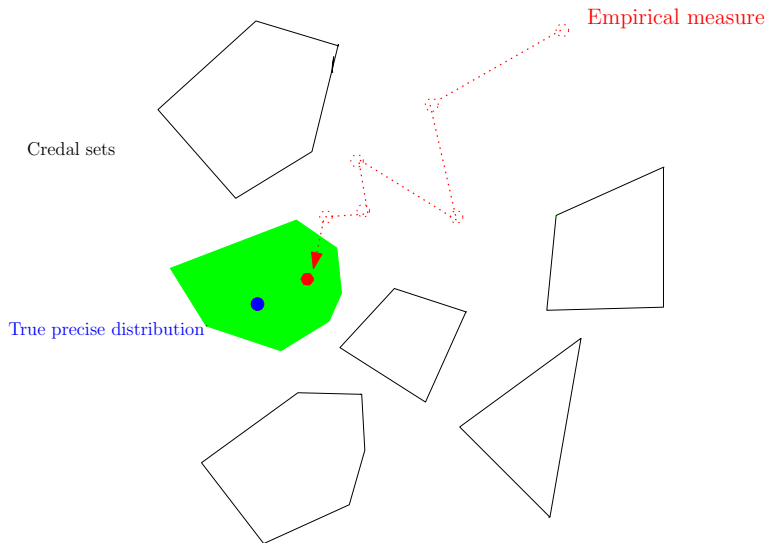












Calculations

- ▶ Replace original sample space $(\mathcal{X}, \mathcal{B})$ by a suitable discrete sample space $(\mathcal{X}, \mathcal{C})$
- ▶ Approximate calculation of $d(\mathbb{P}_n, \mathcal{M}_\theta)$ by linear programming

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- ▶ Replace original sample space $(\mathcal{X}, \mathcal{B})$ by a suitable discrete sample space $(\mathcal{X}, \mathcal{C})$
- ▶ Approximate calculation of $d(\mathbb{P}_n, \mathcal{M}_\theta)$ by linear programming:

$$\sum_{j \in \mathcal{J}_1} q_j - \gamma_j \longrightarrow \max!$$

$$\sum_{j=1}^r q_j = 1$$

$$\sum_{j=1}^r q_j h_k(c_j) \leq \bar{P}_\theta[f_k] + \varepsilon_\theta^{(k)} \quad \forall k \in \{1, \dots, s\}$$

$$q_j - \gamma_j \leq \frac{n_j}{n} \quad \forall j \in \mathcal{J}_1$$

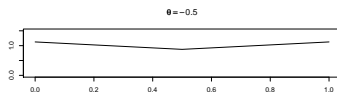
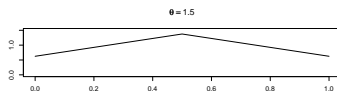
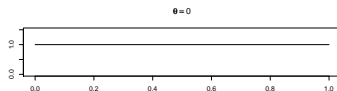
$$(q_1, \dots, q_r) \in \mathbb{R}^r, \quad q_j \geq 0 \quad \forall j \in \{1, \dots, r\},$$

$$(\gamma_j)_{j \in \mathcal{J}_1} \subset \mathbb{R}, \quad \gamma_j \geq 0 \quad \forall j \in \mathcal{J}_1$$

- ▶ Implemented as R-Package `imprProbEst`; see Hable (2008).

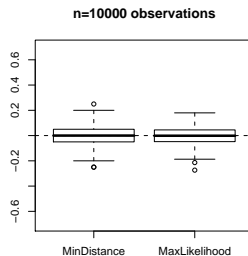
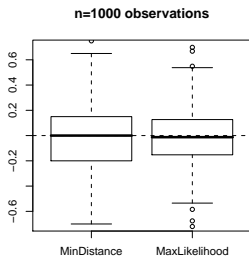
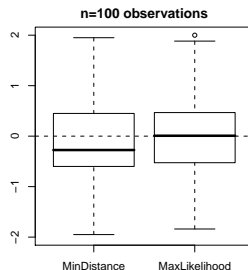
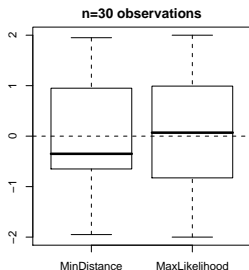
Simulation Study: Model 1

Data from an ideal, precise model with densities such as



- ▶ **Maximum likelihood estimator:** complete information about precise model
- ▶ **Minimum distance estimator:** only imprecise information about precise model

Simulation Study: Model 1



Simulation Study: Model 2

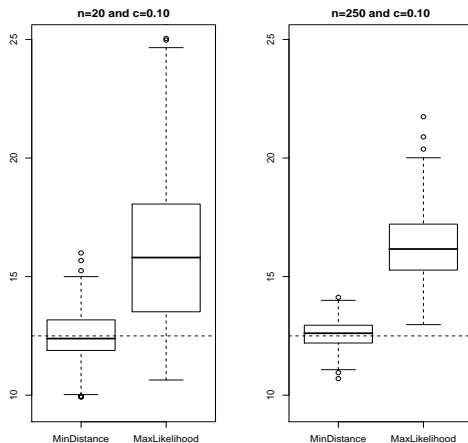
Model: Approximate Poisson Distribution

- ▶ **90%** of the data (in average) from **Poisson** distribution
- ▶ **10%** of the data (in average) from **uniform** distribution

Simulation Study: Model 2

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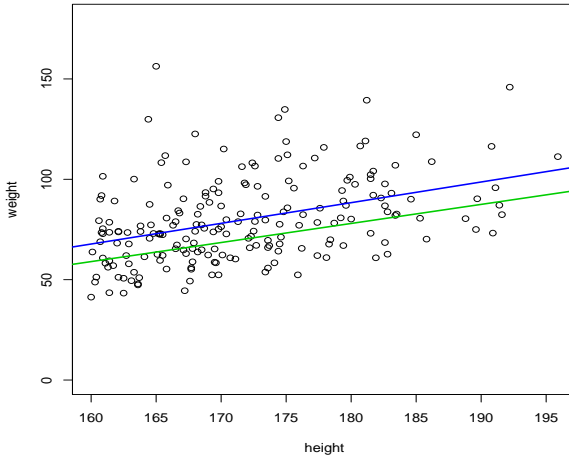


Real Data Set: Linear Regression

NHANES: persons' body weight depending on persons' height

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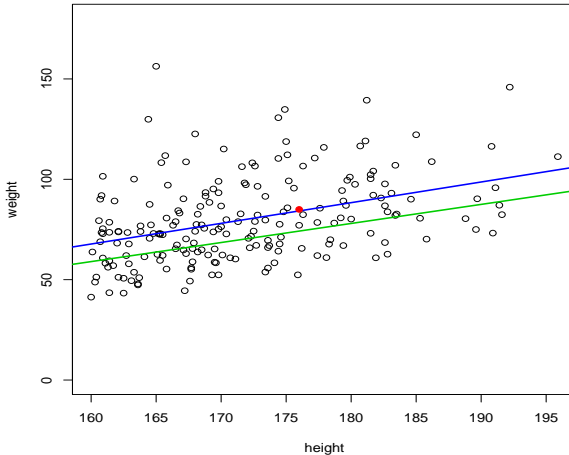


Minimum Distance Estimator

Least Squares Estimator

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Minimum Distance Estimator

Least Squares Estimator

References

- ▶ Hable, R. (2008). *imprProbEst: Minimum distance estimation in an imprecise probability model*. Contributed R-Package on CRAN, Version 1.0, 2008-10-23; maintainer Hable, R.
- ▶ Hable, R. (2009a). Data-based decisions under complex uncertainty. *Ph.D. Thesis*.
<http://edoc.ub.uni-muenchen.de/9874/>
- ▶ Hable, R. (2009b). A minimum distance estimator in an imprecise probability model – computational aspects and applications. *6th International Symposium on Imprecise Probability: Theories and Applications (ISIPTA'09)*.

The handout to this talk is also available on my homepage

<http://www.staff.uni-bayreuth.de/~btms04/index.html>