

# The Bayesian Cramér-Rao lower bound in Astrometry

**Studying the impact of prior information  
In the location of an object**

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Given a set of measurements  $I_i$  ( $i=1\dots n$ ) that follow an underlying distribution  $f_\theta$  that depends on parameter  $\theta$ :

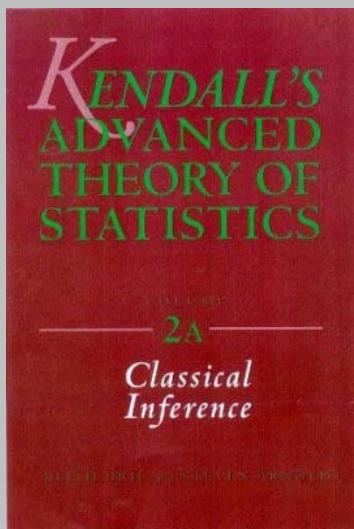
What is the *minimum variance* of the parameter ?

How do we estimate the parameter ?

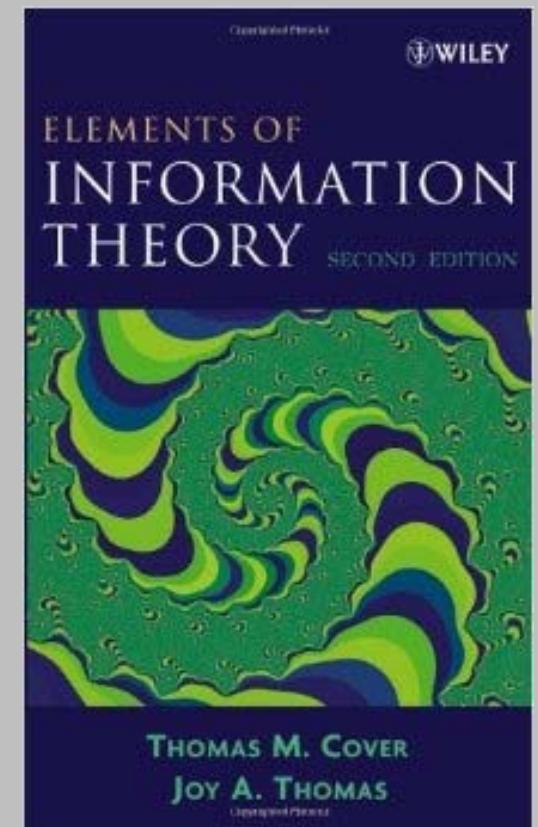
*Optimal parameter estimation* can, in general, be formulated using “decision-making” theory (Cover & Thomas 2006).

Claude Shannon, 1948: “A mathematical theory of communication” (transmission of information over a noisy channel).

This framework can also provide absolute lower bounds to the *uncertainty* of these estimators.



The Cramer-Rao (CR) lower uncertainty bound determines the minimum theoretical variance achievable by *any* unbiased estimator (Stuart, Ord, & Arnold 2004).



# Classical parameter estimation & the Cramér-Rao minimum variance bound

$$\begin{aligned}\hat{\theta}() &\equiv \arg \min_{\hat{\theta}} \text{minVar}(\hat{\theta}(I_1, \dots, I_n)) \\ &= \arg \min_{\hat{\theta}} \mathbb{E}_{I_1, \dots, I_n \sim f_\theta^n} (\hat{\theta}(I_1, \dots, I_n) - \theta)^2\end{aligned}$$



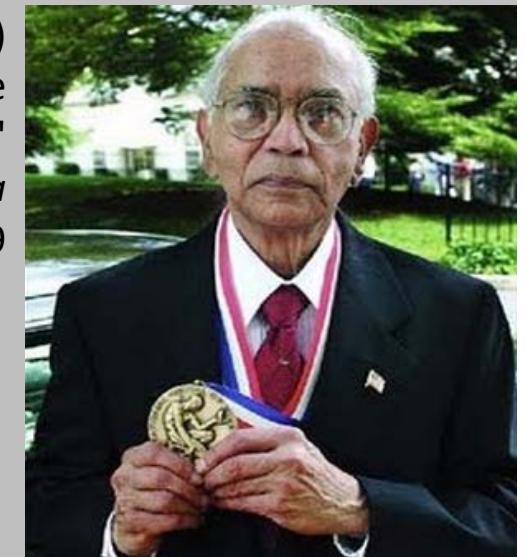
Untractable, as it requires knowledge of the unknown  $\theta$   $\Rightarrow$  performance bounds



Harald Cramér (1946)  
“A contribution to the theory of statistical estimation”  
*Scandinavian Actuarial Journal* **1**: 85-94

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Calyampudi Radakrishna Rao (1945)  
“Information and accuracy attainable  
in the estimation of statistical parameters”  
*Bulletin of the Calcutta  
Mathematical Society* **37**: 81–89



Let  $\hat{\theta}()$  be an unbiased estimator of  $\theta$ . If we define the function  $L(I_1, \dots, I_n; \theta)$  as the likelihood of the observation given the model parameter  $\theta$ , and we have  $n$  independent random variables  $I_i$  driven by the probability function  $f_\theta$ , then the Cramér-Rao bound states that:

$$Var(\hat{\theta}(I_1, \dots, I_n)) \equiv \mathbb{E}_{I_1, \dots, I_n \sim f_\theta^n} \left( \hat{\theta}(I_1, \dots, I_n) - \theta \right)^2 \geq \frac{1}{\mathcal{I}_\theta(n)}$$

provided that we satisfy the constraint:

$$\mathbb{E}_{I_1, \dots, I_n \sim f_\theta^n} \left( \frac{d}{d\theta} \ln L(I_1, \dots, I_n; \theta) \right) = 0$$

and where:

**“Fisher information about  $\theta$ ”**

$$\mathcal{I}_\theta(n) \equiv \mathbb{E}_{I_1, \dots, I_n \sim f_\theta^n} \left( \left( \frac{d}{d\theta} \ln L(I_1, \dots, I_n; \theta) \right)^2 \right)$$

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## Analysis and Interpretation of the Cramér-Rao Lower-Bound in Astrometry: One-Dimensional Case

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## Analysis of the Cramér-Rao Bound in the Joint Estimation of Astrometry and Photometry

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## Performance Analysis of the Least-Squares Estimator in Astrometry

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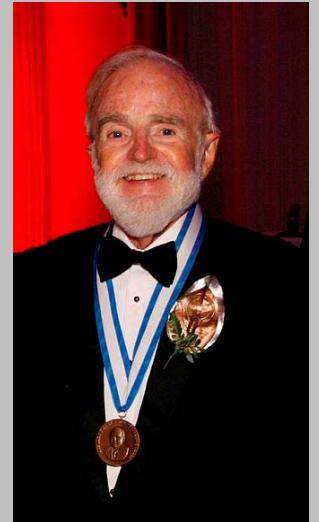
# What's next ?

- Is the classical (parametric) Cramér-Rao lower bound the ultimate precision limit, **really** ? **No (A&A paper)**
- Can we **avoid** some of the losses in precision found on classical estimators ? **Yes (Espinosa & Lobos, in prep)**
- + ambitious: Can we have a **prescription** (rule/recipe) on how to do the “best” estimation of parameters ? **Yes**
- ++ ambitious: Is there an estimator that **approaches** the ultimate limit ? **Yes!**

# The Bayesian CR limit

(Harry L.) van Trees (b.1930) Theorem (1968)

$$\min_{\tau^n: \mathbb{N}^n \rightarrow \mathbb{R}} \mathbb{E}_{(X_c, I^n)} \left\{ (\tau^n(I^n) - X_c)^2 \right\} \geq \left[ \mathbb{E}_{(X_c, I^n)} \left\{ \left( \frac{d \ln \tilde{L}(X_c, I^n)}{dx} \right)^2 \right\} \right]^{-1}$$



But, note that, now,  $X_c$  is a *random variable*, not a *parameter*.

A key new element of the Bayesian approach is the prior information, which can take any mathematical form (a distribution, a bound, or any other constrain).

$$\psi(x)$$

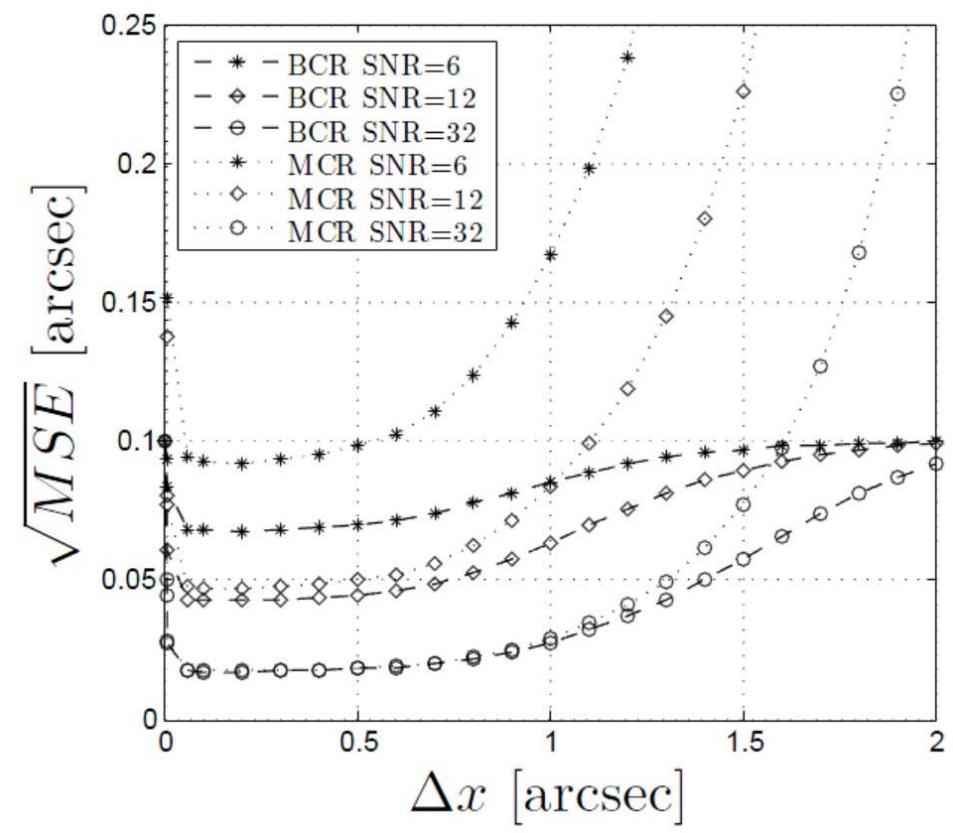
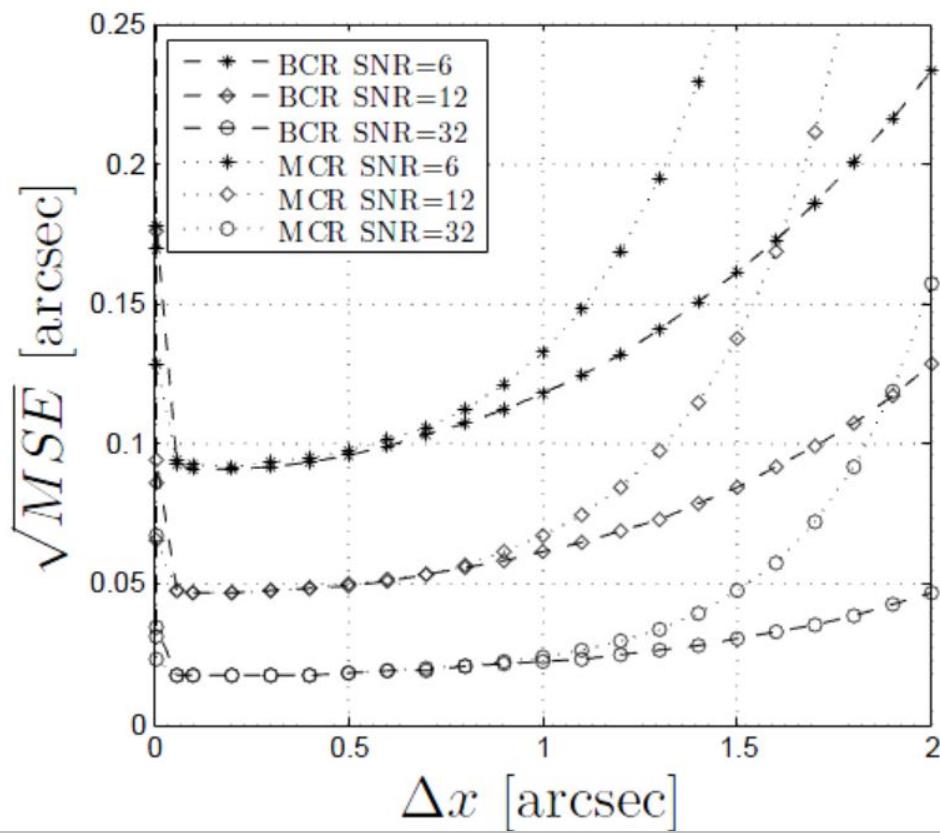
$$\sigma_{BCR}^2 = \frac{1}{\mathbb{E}_{X_c \sim \psi} \{ \mathcal{I}_{X_c}(n) \} + \mathcal{I}(\psi)}$$

$$\mathcal{I}(\psi) = \mathbb{E}_{X_c \sim \psi} \left\{ \left( \frac{d \ln \psi(X_c)}{dx} \right)^2 \right\}$$

By comparison, the classical (parametric) CR:

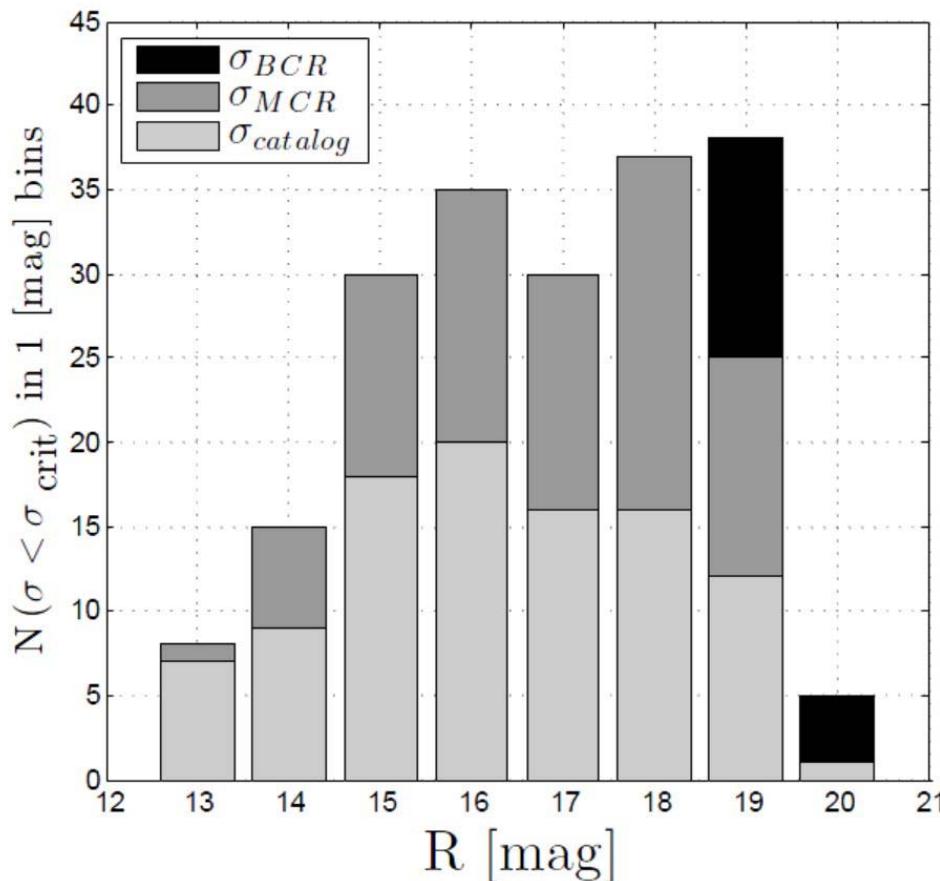
$$\sigma_{MCR}^2 = \mathbb{E}_{X_c \sim \psi} \left\{ \frac{1}{\mathcal{I}_{X_c}(n)} \right\}$$

  $\sigma_{BCR}^2 \leq \sigma_{MCR}^2$  always...

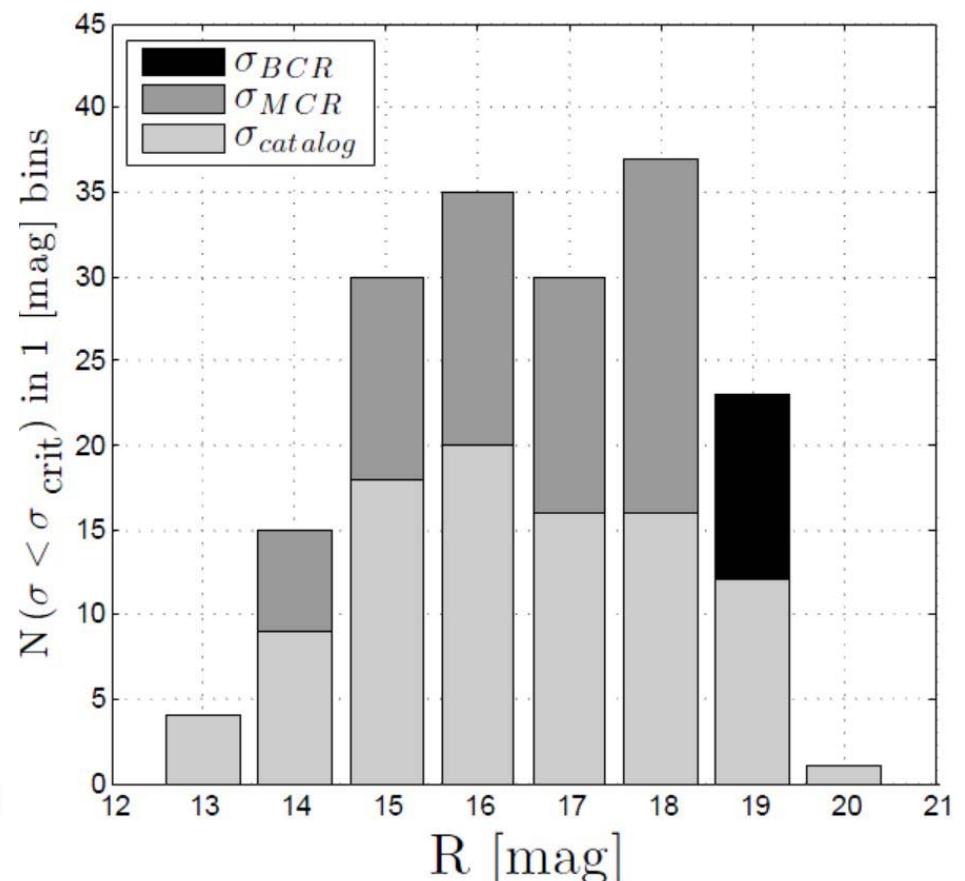


## Example: USNO-B vs new observations @ 1 m telescope

Seeing: 1.2 arcsec



Seeing: 2.0 arcsec

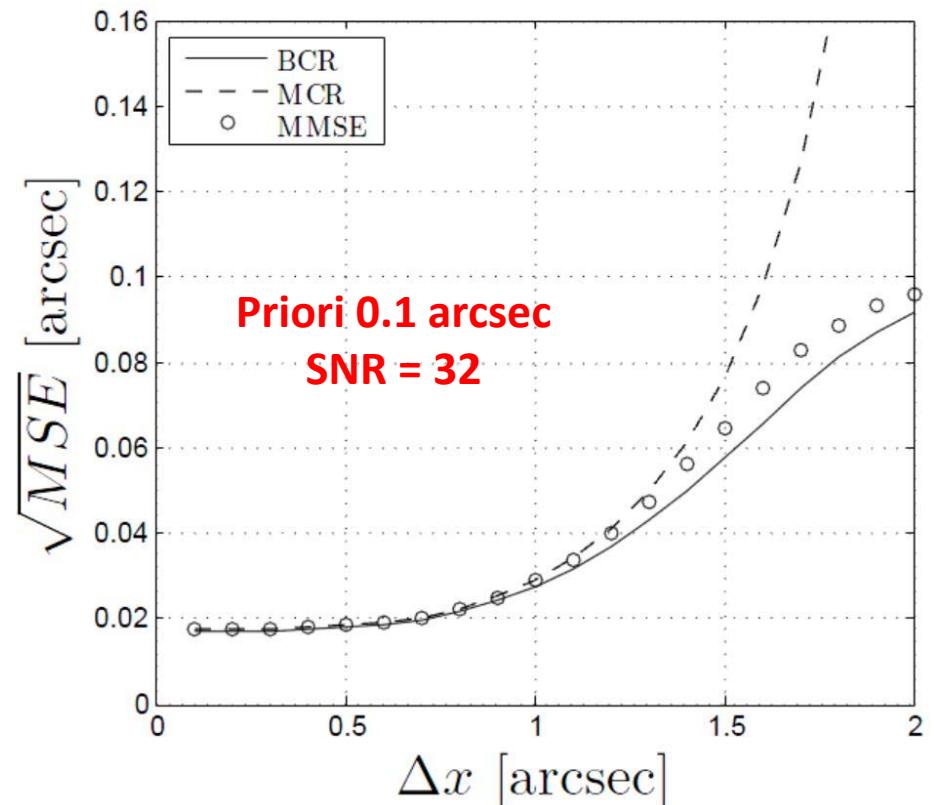
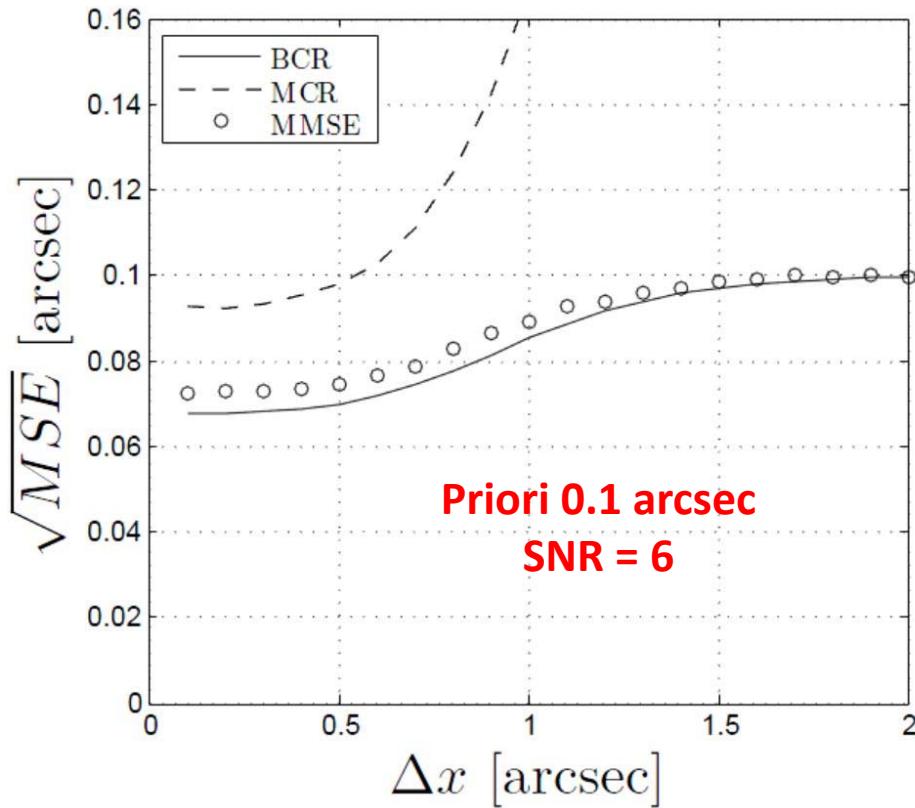


## Can the gains promised by the van Trees theorem be realized in practice ?

- The Minimum MSE estimator in the Bayesian context is the posterior mean for  $X_c$  (or conditional expectation, CE)
- **HUGE** advantage over parametric setting (classical CR does not provide the estimator)
- $\nexists$  theoretical guarantee that it reaches the BCR...

$$\tau_{Bayes}^n(i^n) \equiv \mathbb{E}_{X_c|I^n=i^n} \{X_c\} = \frac{\int_{x \in \mathbb{R}} x \cdot \psi(x) p_x(i^n) dx}{\int_{x \in \mathbb{R}} \psi(x) p_x(i^n) dx}$$

Numerical simulations  $\Rightarrow$  CE (MMSE) follows the BCR tightly  
for a number of reasonable observing conditions !



The Bayesian gains can be realized  
using practical estimators ! 😊

## Caveats & future work

- Study the BCR in photometry - uncertainty on the prior depends on the prior,
- Implement algorithms for astrometry and photometry (eventually, jointly + 2D). CE, MAP.  
Computationally very intensive, explore smart/efficient integrations  
**See poster by Sebastian Espinosa**
- Study the impact of miss-modelling of the prior in the BCR bound and on the eventual biases on the CE estimator  
See papers by Michalik & Lindegren on ADS: Bayesian approach to analysis of Gaia data with low SNR - or poor observational histories.
- Broader collaboration, **see poster by Ruben Clavería** on visual binary star orbits using particle filters & imputations.

To be reported on next ADeLA !   
thanks for listening 

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