998-62-63 **Miguel A Arcones*** (arcones@math.binghamton.edu), , Binghamton, NY 13902. *The large deviation principle for M–estimators.* Preliminary report.

We discuss the large deviation principle for M–estimators (and maximum likelihood estimators in particular). Under certain smooth conditions mle's satisfy the large deviation principle with speed n and rate function $I_\theta(t) := -\inf_{\lambda\in\Re^d} \ln E_\theta[\exp(\lambda'\nabla_t \ln f(X,t))]$, where $\{f(x,t) : t \in \Theta\}$ is a family of pdf's, $\Theta \subset \Re^d$ and ∇ denotes the gradient. We have that $I_\theta(t) \le K(f(\cdot,t), f(\cdot,\theta)$, where $K(f(\cdot,t), f(\cdot,\theta)$ is the Kullback–Leibler information between $f(\cdot,t)$ and $f(\cdot,\theta)$. We determine the class of parametric for which $I_\theta(t) = K(f(\cdot,t), f(\cdot,\theta)$. For these parametric families the mle is exponentially efficient. If T_n is a consistent estimator of θ, for each $\theta\in\Theta$, then, for each $\theta\in\Theta$,

$$\liminf_{n\to\infty} n^{-1}\ln\left(P_\theta\{|T_n-\theta|>\epsilon\}\right) \ge -\inf\{K(f(\cdot,\theta_1), f(\cdot,\theta)) : \theta_1 \text{ satisfying } |\theta_1-\theta|>\epsilon\}.$$

Whenever, the $I_\theta(t) = K(f(\cdot,t), f(\cdot,\theta)$, the mle minimizes the limit above over all possible estimators. (Received January 17, 2004)