In Memory of Lucien Le Cam (1924 - 2000):

Seven theorems every statistician should know

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References

Appeal

Lucien Le Cam: a few facts

- 77 published papers, 4-6 books.
- 38 PhD students (Stigler, Ferguson, Yang , ...)
- Chair of Statistics Dept., Berkeley, 1961-1965.
- President of the IMS, 1973
- Editor, Proceedings of the 5th and 6th Berkeley Symposia

Further Reading:

- Lucien Le Cam. In *More Mathematical People*, 161-180, D. J. Albers, G. L. Alexanderson, and C. Reid, editors. Harcourt Brace Jovanovich, Boston.
- Lehmann, E. L. (1997). Le Cam at Berkeley. In *Festschrift for Lucien Le Cam*, 297 - 304. D. Pollard, E. Torgersen, G. Yang, editors. Springer-Verlag, New York.
- Le Cam, L. (1998). Recollections on my contacts with Jaroslav Hájek. In *Collected Works of Jaroslav Hájek - With Commentary*, 21 - 28. Compiled by M. Huskova, R. Beran, and V. Dupac. Wiley, New York.

1. Poisson approximation

$X_i \sim \text{Bernoulli}(p_i)$, $i = 1, 2, \ldots$.
$S_n = X_1 + \cdots + X_n$, $n = 1, 2, \ldots$.
$\lambda = \sum_1^n p_i$.
Let $Y \sim \text{Poisson}(\lambda)$: thus

$$P(Y = y) = e^{-\lambda}\frac{\lambda^k}{k!}, \quad k = 0, 1, \ldots$$

Theorem 1. (Le Cam, 1960).

$$\sum_{k=0}^{\infty} |P(S_n = k) - P(Y = k)| \leq \sum_{i=1}^{n} p_i^2 .$$

Theorem 2. (Le Cam, 1960). If $\max_{1 \leq i \leq n} p_i \leq 1/4$, then

$$\sum_{k=0}^{\infty} |P(S_n = k) - P(Y = k)| \leq \frac{8}{\lambda}\sum_{i=1}^{n} p_i^2 .$$

References:

- Le Cam (1960a),
- Le Cam (1960b),
- Serfling (1975),
- Barbour, Holst and Janson (1992).

2. Contiguity and Le Cam's three Lemmas

$(X_1, \ldots, X_n) \sim P_n \quad (= P^n_{\theta_0})$
or
$(X_1, \ldots, X_n) \sim Q_n \quad (= P^n_{\theta_n})$

$Q_n \lhd P_n$ (in words, $\{Q_n\}$ is *contiguous* w.r.t. $\{P_n\}$ if,
$P_n(A_n) \to 0 \quad$ implies $\quad Q_n(A_n) \to 0$.

Le Cam's first lemma. (Le Cam, 1960).

If $L_n \equiv dQ_n/dP_n$ satisfies

$$L_n \to_d L \;\text{ under }\; P_n$$

with $E(L) = 1$, then $\{Q_n\} \lhd \{P_n\}$.

Suppose:
$P_n = P_{n1} \times \cdots \times P_{nn}$ with densities $p_{n1}, \ldots, p_{nn}$;
$Q_n = Q_{n1} \times \cdots \times Q_{nn}$ with densities $q_{n1}, \ldots, q_{nn}$.

Set

$$W_n = 2 \sum_{i=1}^{n} \left\{ \frac{q_{ni}^{1/2}}{p_{ni}^{1/2}}(X_{ni}) - 1 \right\} .$$

Le Cam's second lemma. (Le Cam, 1960).
If $W_n \rightarrow_d N(-\sigma^2/4, \sigma^2)$ and

$$P_n \left(\max_{1 \le i \le n} \left| \frac{q_{ni}}{p_{ni}}(X_{ni}) - 1 \right| > \epsilon \right) \rightarrow 0$$

for every $\epsilon > 0$, then

$$\log \frac{dQ_n}{dP_n}(\underline{X}) \rightarrow_d N(-\sigma^2/2, \sigma^2) \quad \text{under} \quad P_n .$$

Suppose:
T_n is a (real-valued) statistic for each n.

Le Cam's third lemma. (Le Cam, 1960).
Suppose that

$$\begin{pmatrix} T_n \\ \log \frac{dQ_n}{dP_n} \end{pmatrix} \to_d N_2\left(\begin{pmatrix} 0 \\ -\sigma^2/2 \end{pmatrix}, \begin{pmatrix} \tau^2 & c \\ c & \sigma^2 \end{pmatrix} \right)$$

under $\{P_n\}$. Then

$$\begin{pmatrix} T_n \\ \log \frac{dQ_n}{dP_n} \end{pmatrix} \to_d N_2\left(\begin{pmatrix} c \\ +\sigma^2/2 \end{pmatrix}, \begin{pmatrix} \tau^2 & c \\ c & \sigma^2 \end{pmatrix} \right)$$

under $\{Q_n\}$.

Corollary: asymptotic power of test based on T_n under the alternative(s) Q_n.

References:

- Le Cam (1960c),
- Hajek and Sidak (1967),
- Hall and Loynes (1977),
- Pollard (1997).

3. Hellinger distance of product laws - Independence

$$\begin{aligned} H^2(P,Q) &= \frac{1}{2}\int(\sqrt{p}-\sqrt{q})^2 d\mu \\ &= 1 - \int \sqrt{pq}\, d\mu \\ &= \text{squared Hellinger distance from } P \text{ to } Q \\ &= 1-\rho(P,Q) \end{aligned}$$

where $p = dP/d\mu$, $q = dQ/d\mu$, $\mu = P+Q$ always works. $\rho(P,Q) =$ the affinity between P and Q.

$$(X_{n,1},\ldots,X_{n,n}) \sim P_n, \quad X_{n,i} \sim P_{ni} \text{ indep.}$$

or

$$(X_{n,1},\ldots,X_{n,n}) \sim Q_n \quad X_{n,i} \sim Q_{ni} \text{ indep.}$$

Theorem. (Le Cam, 1970)

$$\begin{aligned} H^2(P_n, Q_n) &= 1 - \rho(P_n, Q_n) = 1 - \prod_{i=1}^{n} \rho(P_{ni}, Q_{ni}) \\ &= 1 - \prod_{i=1}^{n} \left\{ 1 - H^2(P_{ni}, Q_{ni}) \right\} \end{aligned}$$

Corollary. If $P_n = P_{\theta_0}^n$, $Q_n = P_{\theta_0 + c/\sqrt{n}}^n$, and

$$nH^2(P_{\theta_0 + c/\sqrt{n}}, P_{\theta_0}) \to c^T I(\theta_0) c\,,$$

then

$$\begin{aligned} H^2(P_n, Q_n) &= 1 - (1 - H^2(P_{\theta_0}, P_{\theta_0 + c/\sqrt{n}}))^n \\ &\to 1 - \exp(-c^T I(\theta_0) c)\,. \end{aligned}$$

References:

- Kakutani (1948),
- Le Cam (1969),
- Le Cam (1970),
- Le Cam and Yang (1990).

4. Quadratic mean differentiability (QDM) and asymptotic normality of the MLE

The model $\{P_\theta : \ \theta \in \Theta \subset R^k\}$ is **differentiable in quadratic mean** at θ_0 if there exist a vector-valued function $\dot{l}_{\theta_0}$ such that the densities $p_\theta = dP_\theta/d\mu$ satisfy

$$\int \left\{ \sqrt{p_\theta} - \sqrt{p_{\theta_0}} - \frac{1}{2}(\theta - \theta_0)^T \dot{l}_{\theta_0} \sqrt{p_{\theta_0}} \right\}^2 d\mu = o(|\theta - \theta_0|^2) \, .$$

Note that

$$\frac{\partial}{\partial\theta}\sqrt{p_\theta} = \frac{1}{2\sqrt{p_\theta}}\frac{\partial}{\partial\theta}p_\theta = \frac{1}{2}\left(\frac{\partial}{\partial\theta}\log p_\theta\right)\sqrt{p_\theta}\,,$$

so the function $\dot{l}_{\theta_0}$ is really the score function of the model, and

$$I(\theta_0) = P_{\theta_0}(\dot{l}_{\theta_0}\dot{l}_{\theta_0}^T)$$

is the Fisher information matrix. However QDM does *not* require existence of $(\partial/\partial\theta)\log p_\theta(x)$ for every x.

Theorem.
Le Cam (1970) + van der Vaart (1998).
Suppose that $\{P_\theta : \theta \in \Theta \subset R^k\}$ is differentiable in quadratic mean at an interior point θ_0 of Θ. Furthermore, suppose that there exists a measurable function $\dot{l}$ with $P_{\theta_0}(\dot{l}^2) < \infty$ such that, for every θ_1 and θ_2 in a neighborhood of θ_0,

$$|\log p_{\theta_1}(x) - \log p_{\theta_2}(x)| \le \dot{l}(x)|\theta_1 - \theta_2|\,.$$

If $I(\theta_0)$ is non-singular and the MLE $\widehat{\theta}_n$ is consistent, then

$$\sqrt{n}(\widehat{\theta}_n - \theta_0) = I(\theta_0)^{-1}\frac{1}{\sqrt{n}}\sum_{i=1}^{n}\dot{l}_{\theta_0}(X_i) + o_{P_{\theta_0}}(1)$$

and hence

$$\sqrt{n}(\widehat{\theta}_n - \theta_0) \to_d N_k\left(0, I^{-1}(\theta_0)\right)\,.$$

Theorem. (Le Cam, 1970).
Suppose that $\{P_\theta : \theta \in \Theta \subset R^1\}$ is differentiable in quadratic mean at an interior point θ_0 of Θ. Furthermore, suppose that for θ in a neighborhood of θ_0

$$\limsup_{\delta \to 0} \frac{1}{|\delta|} H(P_\theta, P_{\theta+\delta}) \equiv \sigma(\theta) < \infty \,,$$

$\sigma(\theta_0) > 0$, and

$$\lim_{\delta \searrow 0} \delta^{-1} \int_{\theta_0-\delta}^{\theta_0+\delta} |\sigma(\theta) - \sigma(\theta_0)| d\theta = 0 \,.$$

Then with probability tending to 1 the MLE $\widehat{\theta}_n$ of θ exists and satisfies

$$\sqrt{n}(\widehat{\theta}_n - \theta_0) \to_d N_k(0, V(\theta_0))$$

where

$$V(\theta_0) = (I(\theta_0)/4)/(\sigma^2(\theta_0) + I(\theta_0)/4)^2 \le I^{-1}(\theta_0) \,.$$

References:

- Le Cam (1970);
- van der Vaart and Wellner (1996), page 306;
- van der Vaart (1998), page 65.

5. Local asymptotic minimax and convolution theorems

Local asymptotic normality or LAN:
$\underline{X} \sim P_{n,\theta}$, $\theta \in \Theta \subset R^k$.
The family $\{P_{n,\theta}\}$ is LAN at θ_0 if there exist matrices r_n, $I(\theta_0)$, and random vectors $S_n(\theta_0)$ with $S_n(\theta_0) \to_d N(0, I(\theta_0))$ such that for every $h_n \to h$

$$\log \frac{dP_{n,\theta_0 + h_n/r_n}}{dP_{n,\theta_0}} = h^T S_n(\theta_0) - \frac{1}{2} h^T I(\theta_0) h + o_p(1)$$

Theorem. (Minimax theorem;
Hájek (1970), (1972);
Le Cam (1972), (1979)).
Suppose that $q : \Theta \mapsto R$ is differentiable with derivative $\dot{q}(\theta_0)$ at θ_0. For any estimators $\{T_n\}$ of $q(\theta)$ and any bowl-shaped loss function l

$$\begin{aligned} \liminf_{n\to\infty} \sup\{ E_\theta \left(l(r_n(T_n - q(\theta))) \right) : r_n|\theta - \theta_0| \le M\} \\ \ge El(Z_0)\,, \end{aligned}$$

where

$$Z_0 \sim N\left(0, \dot{q}^T(\theta_0) I(\theta_0)^{-1} \dot{q}(\theta_0)\right)\,.$$

Locally regular estimators:
$\{T_n\}$ is locally regular at θ_0 if: for every h, with $\theta_n = \theta_0 + h/r_n$,

$$r_n\left(T_n - q(\theta_n)\right) \to_d E_0$$

under P_{n,θ_n} where the distribution of E_0 does not depend on h.

Theorem. (Convolution theorem;
Hájek (1970), (1972);
Le Cam (1972), (1979)).
If $\{T_n\}$ is a sequence of regular estimators of $q(\theta)$ with limiting distribution given by $\mathcal{L}(E_0)$, and $\{P_{n,\theta}\}$ satisfies LAN at θ_0, then

$$E_0 =_d Z_0 + W_0$$

where W_0 is independent of

$$Z_0 \sim N\left(0, \dot{q}^T(\theta_0) I(\theta_0)^{-1} \dot{q}(\theta_0)\right) .$$

References:

- Le Cam (1972),
- Le Cam (1979),
- Hajék (1970), Inagaki (1970)
- Hajék (1972) .

6. Preservation of LAN

Suppose that $\mathcal{Q} = \{Q_\theta : \theta \in \Theta\}$ is differentiable in quadratic mean at θ_0 with derivative $\dot{l}_0(\cdot, \mathcal{Q})$ and Fisher information matrix

$$I(\theta_0, \mathcal{Q}) = Q_{\theta_0}(\dot{l}_0(\cdot, \mathcal{Q})\dot{l}_0(\cdot, \mathcal{Q})^T) .$$

Suppose that $X \sim Q_\theta \in \mathcal{Q}$ and $Y \equiv T(X) \sim P_\theta$ for a (measurable) function T.
Let $\mathcal{P} \equiv \{P_\theta : \theta \in \Theta\}$.

Theorem. (Le Cam and Yang, 1988).
If $\mathcal{Q}$ is differentiable in QM at θ_0, then $\mathcal{P}$ is differentiable in quadratic mean at θ_0 with score function

$$\dot{l}(Y, \mathcal{P}) = E\{\dot{l}_{\theta_0}(X; \mathcal{Q})|Y\}$$

and

$$I(\theta_0; \mathcal{P}) \le I(\theta_0; \mathcal{Q}) .$$

References:

- Le Cam and Yang (1988),
- Ibragimov and Has'minskii (1979), page 70,
- Bickel, Klaassen, Ritov and Wellner (1993), page 461.

7. Dimensionality and Estimation: Rates of convergence

$\theta : \mathcal{P} \to \Theta$, (Θ, d) a metric space
$\widehat{\theta}$ an estimator of $\theta(P)$.

Theorem. (Le Cam, 1973). Suppose there are subsets $\Theta_1, \Theta_2 \subset \Theta$ that are $2\delta-$ separated. Suppose that $\mathcal{P}_1$, $\mathcal{P}_2$ are subsets of $\mathcal{P}$ with $\theta(P) \in \Theta_i$ for $P \in \mathcal{P}_i$, $i = 1, 2$. Then

$$\sup_{P \in \mathcal{P}} E_P d(\widehat{\theta}, \theta(P)) \geq \delta \cdot \sup_{P_i \in co(\mathcal{P}_i)} \|P_1 \wedge P_2\|$$

where

$$\|P_1 \wedge P_2\| = \int p_1 \wedge p_2 \, d\mu$$

for any common dominating measure μ of P_1, P_2, and $co(\mathcal{P}_i)$ = the convex hull of $\mathcal{P}_i$. Here

$$\begin{aligned} d_{TV}(P, Q) &= \frac{1}{2} \int |p - q| d\mu \\ &= 1 - \|P \wedge Q\|, \end{aligned}$$

so $\|P \wedge Q\|$ is the "affinity" for total variation distance.

Let $D(\epsilon, \Theta)$ be the $\epsilon-$ packing number of Θ for the metric d; i.e. the maximal number of $\epsilon-$ separated points in Θ.

Corollary. Suppose that $X_1, \ldots, X_n$ are i.i.d. P_θ, $\theta \in \Theta$. Suppose that ϵ_n satisfies

$$D(\epsilon_n) = 4n\epsilon_n^2 + 2\log 2\,.$$

Then

$$\min_{\widehat{\theta}} \max_{\theta \in \Theta} E_\theta d^2(\widehat{\theta}, \theta) \geq (A^2/8)\epsilon_n^2\,.$$

References:

- Le Cam (1973),
- Yu (1997),
- Birgé (1983), (1986)
- Yang and Barron (1999).

8. Approximation of Experiments

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Another talk!

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References:

- Le Cam (1972),
- Le Cam (1986),
- van der Vaart (1998, Chapter 9, pp. 125 - 137,
- van der Vaart (200?).

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