# Non-Standard Behavior of Density Estimators for Functions of Independent Observations

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**Abstract.** Densities of functions of two or more independent random variables can be estimated by local U-statistics. Frees (1994) gives conditions under which they converge *pointwise* at the parametric root-$n$ rate. *Uniform* convergence at this rate was established by Schick and Wefelmeyer (2004) for sums of random variables. Giné and Mason (2007) give conditions under which this rate also holds in $L_p$-norms. We present several natural applications in which the parametric rate fails to hold in $L_p$ or even pointwise.

1. The density estimator of a sum of squares of independent observations typically slows down by a logarithmic factor. For exponents greater than two, the estimator behaves like a classical density estimator.

2. The density estimator of a product of two independent observations typically has the root-$n$ rate pointwise, but not in $L_p$-norms. An application is given to semi-Markov processes and estimation of an inter-arrival density that depends multiplicatively on the jump size.

3. The stationary density of a nonlinear or nonparametric autoregressive time series driven by independent innovations can be estimated by a local U-statistic (now based on dependent observations and involving additional parameters), but the root-$n$ rate can fail if the derivative of the autoregression function vanishes at some point.

**Keywords:** Density estimator, Local U-statistic, Local von Mises statistic, Convergence rate, Autoregressive time series, Semi-Markov process.

## 1 Introduction

It is often of interest to estimate densities of known or unknown functions of independent observations. Consider for example a regression model $Y = r(X) + \varepsilon$ with independent error $\varepsilon$ and covariate $X$. If we have independent

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observations $(X_i, Y_i)$, $i = 1, \dots, n$, then the density of the response $Y$ could be estimated by a kernel estimator based on $Y_1, \dots, Y_n$. However, a much better estimator is obtained if we exploit the independence of $\varepsilon$ and $X$ and write $Y$ as a sum $r(X)+\varepsilon$ of independent random variables. Then the density $p$ of $Y$ can be estimated by a local von Mises statistic

$$\hat{p}(z) = \frac{1}{n^2} \sum_{i,j=1}^{n} K_b(z - \hat{r}(X_i) - \hat{\varepsilon}_j).$$

Here $K_b(z) = K(z/b)/b$ with kernel $K$ and bandwidth $b$, $\hat{r}$ is some estimator of the regression function $r$, and $\hat{\varepsilon}_j = Y_j - \hat{r}_j(X_j)$ are the corresponding residuals. Under appropriate conditions, the estimator $\hat{p}(z)$ converges at the parametric rate $n^{1/2}$; see Støve and Tjøstheim, 2012 [22], Escanciano and Jacho-Chávez, 2012 [1], and, for nonlinear regression and with responses missing at random, Müller, 2012 [5]. It is the purpose of this review to indicate why such rates are possible, and to illustrate when they fail.

The most straightforward version of the problem is the following. Let $X_1, \dots, X_n$ be independent real-valued observations with density $f$. We want to estimate the density $p$ of some transformation $T(X_1, \dots, X_m)$ of $m$ of these observations, with $m$ at least 2. Frees, 1994 [2] proposed as an estimator of $p(z)$ the local U-statistic

$$\hat{p}(z) = \frac{1}{\binom{n}{m}} \sum_{1 \le i_1 < \dots < i_m \le n} K_b(z - T(X_{i_1}, \dots, X_{i_m})).$$

He showed that this estimator can be pointwise $n^{1/2}$-consistent under some assumptions on $f$ and $T$. Saavedra and Cao, 2000 [9] consider the function $T(X_1, X_2) = X_1 + \varphi X_2$. It is even possible to obtain $n^{1/2}$-consistency in various norms, together with functional central limit theorems in the corresponding spaces. Schick and Wefelmeyer, 2004 [11], 2007 [13] prove such results for transformations of the form $T(X_1, \dots, X_m) = T_1(X_1) + \dots + T_m(X_m)$ and $T(X_1, X_2) = X_1 + X_2$ in the sup-norm and in $L_1$-norms. Giné and Mason, 2007 [3] consider general transformations $T(X_1, \dots, X_m)$ and obtain such results in the $L_p$-norms. Their results hold locally uniformly in the bandwidth. More general results applicable here are in Nickl, 2007 [6] and Nickl, 2009 [7].

These results are less generally valid than appears at first sight. In Section 2 we restrict attention to $m = 2$ and to transformations of the special form $T(X_1, X_2) = T_1(X_1) + T_2(X_2)$ and explain under which conditions the local U-statistic $\hat{p}(z)$ is asymptotically linear, $n^{1/2}$-consistent, and asymptotically normal. The rate is typically slower when, say, $T_1(y) = T_1(x) + c(y - x)^\nu + o(|y - x|^\nu)$ for $y$ to the left or right of some point $x$, with $\nu \ge 2$. Then the density of $T_1(X)$ has a strong peak. Specifically, we consider $T_1(x) = T_2(x) = x^\nu$ and describe the rates of the local U-statistic. Then we discuss the two-sample case and applications to regression, to time series driven by independent innovations, and to renewal processes with multiplicative waiting times.

## 2 Results and Applications

Let $X_1, \dots, X_n$ be independent copies of a random variable $X$ with density $f$. An estimator for the density $p$ of a transformation of the form $T(X_1, X_2) = T_1(X_1) + T_2(X_2)$ is the local U-statistic

$$\hat{p}(z) = \frac{2}{n(n-1)} \sum_{1 \le i < j \le n} K_b(z - T_1(X_i) - T_2(X_j)),$$

where $K_b(z) = K(z/b)/b$ for a kernel $K$ and a bandwidth $b$. Suppose that $T_1(X)$ and $T_2(X)$ have densities $g_1$ and $g_2$. The estimator $\hat{p}(z)$ has the Hoeffding decomposition

$$\hat{p}(z) = p * K_b(z) + \frac{1}{n} \sum_{i=1}^{n} \big( g_1 * K_b(z - T_2(X_i)) - p * K_b(z) \\ + g_2 * K_b(z - T_1(X_i)) - p * K_b(z) \big) + U(z),$$

where

$$U(z) = \frac{2}{n(n-1)} \sum_{1 \le i < j \le n} \big( K_b(z - T_1(X_i) - T_2(X_i)) - g_1 * K_b(z - T_2(X_i)) \\ - g_2 * K_b(z - T_1(X_i)) + p * K_b(z) \big)$$

is a degenerate local U-statistic. We have

$$n(n-1)E[U^2(z)] \le 2E[K_b^2(z - T_1(X_1) - T_2(X_2))] = 2p * K_b^2(z)$$

and

$$p * K_b^2(z) = \frac{1}{b} \int p(z - bu) K^2(u)\, du \le \frac{\|p\|_\infty}{b} \int K^2(u)\, du.$$

If $p$ is bounded and $\int K^2(u)\, du$ is finite, we obtain $U(z) = O_P(1/(nb^{1/2}))$, which is of order $o_P(n^{-1/2})$ if $nb \to \infty$. The Hoeffding decomposition then says that the centered local U-statistic $\hat{p}(z) - p * K_b(z)$ is approximated by a sum of two centered and smoothed empirical "estimators" of $p(z)$ (that involve the unknown densities $g_1$ and $g_2$). Under mild assumptions one can remove the smoothing; see e.g. Schick and Wefelmeyer, 2004 [11]. If $p$ is Hölder with exponent $\alpha$, then the bias $p * K_b(z) - p(z)$ is of order $o(n^{-1/2})$ if $nb^{2\alpha} \to 0$. This implies that $\hat{p}(z)$ is asymptotically linear,

$$\hat{p}(z) = p(z) + \frac{1}{n} \sum_{i=1}^{n} \big( g_1(z - T_2(X_i)) + g_2(z - T_1(X_i)) - 2p(z) \big) + o_P(n^{-1/2}). \quad (1)$$

If $E[g_1^2(z - T_2(X_2))]$ and $E[g_2^2(z - T_1(X_1))]$ are finite, then $\hat{p}(z)$ is $n^{1/2}$-consistent and asymptotically normal.

*Remark 1.* (Convolution of density estimators.) The density $p$ has the convolution representation

$$p(z) = \int g_2(z-y)g_1(y)\,dy.$$

Therefore, it can also be estimated by a convolution of density estimators

$$\hat{p}_{conv}(z) = \int \hat{g}_2(z-y)\hat{g}_1(y)\,dy$$

with kernel estimator for $g_1(y)$ based on $T_1(X_1),\dots,T_1(X_n)$,

$$\hat{g}_1(y) = \frac{1}{n}\sum_{i=1}^{n} K_b(y - T_1(X_i)),$$

and, correspondingly,

$$\hat{g}_2(y) = \frac{1}{n}\sum_{i=1}^{n} K_b(y - T_2(X_i)).$$

The estimator $\hat{p}_{conv}$ is asymptotically equivalent to $\hat{p}$. □

*Remark 2.* (Transform density estimator or transform observations.) Suppose that $T_1$, say, is strictly increasing and differentiable. Then the density of $T_1(X)$ at $y$ is

$$g_1(y) = \frac{f(T_1^{-1}(y))}{T_1'(T_1^{-1}(y))}.$$

We obtain an alternative estimator $\tilde{g}_1(y)$ of $g_1(y)$ by plugging in a kernel estimator for $f$,

$$\hat{f}(x) = \frac{1}{n}\sum_{i=1}^{n} K_b(x - X_i).$$

We expect that it depends on $T_1$ whether $\hat{g}_1(y)$ is better than

$$\tilde{g}_1(y) = \frac{\hat{f}(T_1^{-1}(y))}{T_1'(T_1^{-1}(y))}.$$

In the convolution representation $p(z) = \int g_2(z-y)g_1(y)\,dy$ we can use $\hat{g}_1$ or $\tilde{g}_1$. If $T_2$ is also strictly increasing and differentiable, we can combine $\hat{g}_1$ or $\tilde{g}_1$ with $\hat{g}_2$ or $\tilde{g}_2$. □

We now discuss cases in which $\hat{p}(z)$ is not $n^{1/2}$-consistent.

*Remark 3.* (Piecewise constant transformations.) The distribution of $T_1(X)$ does not always have a density. Suppose that $T_1$ is piecewise constant,

$$T_1(X) = \sum_{s=1}^{t} c_s \mathbf{1}[X \in I_s],$$

with $c_s \in \mathbb{R}$, and $I_s$, $s = 1, \dots, t$, a partition of $\mathbb{R}$. If $T_2(X)$ has a density $g_2$, then $T_1(X_1) + T_2(X_2)$ has a density $p$ that is a finite mixture of shifts of $g_2$,

$$p(z) = \sum_{s=1}^{m} a_s g_2(z - c_s)$$

with weights $a_s = P(X \in I_s)$. If each interval $I_s$ contains at least one observation, the constants $c_s$ can be observed, and $p(z)$ can be estimated by

$$\hat{p}(z) = \sum_{s=1}^{t} \hat{a}_s \hat{g}_2(z - c_s),$$

where $\hat{a}_s = (1/n) \sum_{i=1}^{n} \mathbf{1}[X_i = c_s]$. The rate of $\hat{p}(z)$ equals the pointwise rate of $\hat{g}_2$. □

Even if $T_1$ and $T_2$ are not constant on any interval, $\hat{p}(z)$ can fail to be $n^{1/2}$-consistent. In the following we describe a situation in which $T_1(X)$ and $T_2(X)$ have densities, but $g_1(z - T_2(X))$ does not necessarily have finite variance. For notational simplicity, assume that $f$ is supported on $(0, \infty)$, and set $T_1(x) = T_2(x) = x^\nu$ for some $\nu > 0$. Then $g_1 = g_2 = g$ with

$$g(y) = \frac{1}{\nu} y^{1/\nu - 1} f(y^{1/\nu}),$$

and the stochastic expansion (1) of $\hat{p}(z)$ specializes to

$$\hat{p}(z) = p(z) + \frac{2}{n} \sum_{i=1}^{n} g(z - X_i^\nu) + o_P(n^{-1/2}). \tag{2}$$

Here and in the following, $z$ denotes a fixed positive number. In the theorems below, we take the kernel $K$ to be continuously differentiable with support $[-1, 1]$. We also assume that $f$ is bounded. First let $\nu < 2$. Then $g$ is square-integrable, and $g(z - X^\nu)$ has finite variance. Our first theorem is a consequence of Theorem 2 in Schick and Wefelmeyer, 2009 [17].

**Theorem 1.** *Let $\nu < 2$. Suppose the density $f$ is of bounded variation and $f(0+)$ is positive. Let $b \sim (\log n)^{1/2}/n$. Then $\hat{p}(z)$ has the stochastic expansion (2), and*

$$n^{1/2}\big(\hat{p}(z) - p(z)\big) \Rightarrow N\big(0, 4\,\mathrm{Var}(g(z - X^\nu))\big).$$

Schick and Wefelmeyer, 2009 [17] consider, more generally, one-sided kernels, and also mention how to combine these to get results for the two-sided kernels used here.

For $\nu = 2$, square-integrability of $g$ fails just barely, resulting in a rate for $\hat{p}(z)$ that is only slightly worse than $n^{-1/2}$. More precisely, Schick and Wefelmeyer, 2009 [16] prove the following result.

**Theorem 2.** *Let $\nu = 2$. Suppose $f$ is of bounded variation, and $f(0+)$ and $g(z-)$ are positive. Let $b \sim (\log n)^{1/2}/n$. Then*

$$\Big(\frac{n}{\log n}\Big)^{1/2}\big(\hat p(z) - p(z)\big) \Rightarrow N(0, f^2(0+)g(z-)).$$

Schick and Wefelmeyer, 2012 [21] show that the rate of Theorem 2 is optimal, and that the estimator $\hat p(z)$ is asymptotically efficient. To establish this, they prove a nonparametric version of local asymptotic normality at the appropriate nonstandard rate.

For $\nu > 2$, Schick and Wefelmeyer, 2009 [16] prove the following result.

**Theorem 3.** *Let $\nu > 2$. Suppose $f$ is of bounded variation, and $f(0+)$ and $g(z-)$ are positive. Let $b \sim 1/n$. Then*

$$\hat p(z) - p(z) = O_P(n^{-1/\nu}).$$

This result is similar to the usual results for kernel density estimators. We get slightly faster rates for our local U-statistic $\hat p(z)$ than are possible for kernel density estimators based on observations from the density $p$. Faster rates are possible under additional smoothness assumptions on $p$ at $z$.

Even in the case $\nu \ge 2$, the estimator $\hat p(z)$ can be $n^{1/2}$-consistent if $g(z-) = 0$ since this works against the peak of $g$ at 0 in the representation $p(z) = g * g(z)$. For details we refer to Schick and Wefelmeyer, 2009 [16] and 2009 [17].

We will now briefly discuss possible applications of the above results.

*Remark 4.* (Several samples.) The above results carry over to $m$-sample cases. We restrict attention to $m = 2$. Suppose $X_1, \dots, X_n$ and $Z_1, \dots, Z_n$ are real-valued and independent with densities $f_1$ and $f_2$, respectively. An estimator for the density $p$ of a transformation $T_1(X_1) + T_2(Z_1)$ is the local von Mises statistic

$$\hat p_*(z) = \frac{1}{n^2}\sum_{i,j=1}^{n} K_b(z - T_1(X_i) - T_2(Z_j)).$$

Let $g_1$ and $g_2$ denote the densities of $T_1(X_1)$ and $T_2(Z_1)$. As in the one-sample case (1) we obtain a stochastic expansion

$$\hat p_*(z) = p(z) + \frac{1}{n}\sum_{i=1}^{n}\big(g_1(z - T_2(Z_i)) + g_2(z - T_1(X_i)) - 2p(z)\big) + o_P(n^{-1/2}).$$

Appropriate versions of Theorems 1–3 continue to hold. □

*Remark 5.* (Regression.) Two-sample results can be applied to regression models $Y = r(X) + \varepsilon$ with $\varepsilon$ independent of $X$. If we have independent observations $(X_i, Y_i)$, $i = 1, \dots, n$, then the density $p$ of $Y$ can be estimated by the local von Mises statistic

$$\breve{p}(z) = \frac{1}{n^2} \sum_{i,j=1}^{n} K_b(z - \hat{r}(X_i) - \hat{\varepsilon}_j)$$

based on some estimator $\hat{r}$ of the regression function $r$, and on residuals $\hat{\varepsilon}_j = Y_j - \hat{r}(X_j)$. Note that the "pseudo-observations" $\hat{r}(X_i)$ and $\hat{\varepsilon}_j$ are only approximately independent, so we are close to the two-sample case with $Z = \varepsilon$, $T_1(X) = r(X)$, and $T_2(\varepsilon) = \varepsilon$. As seen above, we can expect a rate $n^{-1/2}$ for $\breve{p}(z)$ if $r$ has a derivative that is bounded away from 0. Under this assumption, we have shown $n^{1/2}$-consistency in the sup-norm and the $L_1$-norm, see Schick and Wefelmeyer, 2012 [19] and [20]. Surprisingly, $\breve{p}(z)$ is no longer efficient. Schick and Wefelmeyer, 2012 [19] have constructed an additive correction term to $\breve{p}(z)$ that makes the estimator efficient. Müller, 2012 [5] obtains uniform $n^{1/2}$-rates for parametric regression when responses are missing at random. She uses a weighted local U-statistic that exploits that the errors are centered. In this way she obtains asymptotic efficiency. She also needs that the derivative of the regression function is bounded away from zero.

Monotonicity of the regression function is a strong requirement that is rarely met. Suppose $r$ is only piecewise monotone and continuously differentiable, and there are points $x$ with

$$r(y) = c(y - x)^{\nu} + o(|y - x|^{\nu})$$

for $y$ to the left or right of $x$. Then the convergence rate of $\hat{p}(z)$ will be determined by the largest such $\nu$, similarly as in Theorem 3. Since the regression function is estimated, the rate of convergence may be even slower. □

*Remark 6.* (Time series.) Results for regression carry over to time series driven by independent innovations. Consider a first-order moving average process $X_i = \varepsilon_i + \varphi\varepsilon_{i-1}$, with independent innovations $\varepsilon_i$ that have mean 0, finite variance, and density $f$. If $\varphi \neq 0$, the stationary density $p$ can be estimated by a local von Mises statistic

$$\hat{p}(z) = \frac{1}{n^2} \sum_{i,j=1}^{n} K_b(z - \hat{\varepsilon}_i - \hat{\varphi}\hat{\varepsilon}_j)$$

with $\hat{\varphi}$ an estimator of $\varphi$. Saavedra and Cao, 1999 [8] obtain $n^{1/2}$-consistency; see also Schick and Wefelmeyer, 2004 [10]. Functional results for higher-order moving average processes and general linear processes are obtained in Schick and Wefelmeyer, 2004 [12], 2007 [14], 2008 [15] and 2009 [18]. Nonlinear and nonparametric time series can also be treated. □

*Remark 7.* (Renewal processes.) Here is a two-sample case where $T(X,Z)$ is a product rather than a sum of functions $T_1(X)$ and $T_2(Z)$. Let $(X_i, T_i)$, $i = 0,\dots,n$ be observations of a Markov renewal process with real state space. Assume that the embedded Markov chain is stationary. We make the structural assumption that the waiting times depend multiplicatively on some power of the distance between the previous and the present state of the embedded Markov chain,

$$T_i - T_{i-1} = |X_i - X_{i-1}|^\nu W_i,$$

where $\nu > 0$ and the $W_i$ are independent with density $g$ and independent of the embedded Markov chain. Note that $W_i$ is observable as a function of the observations $(X_{i-1}, T_{i-1})$ and $(X_i, T_i)$. We can estimate the waiting time density $p$ of $T_i - T_{i-1}$ by the local von Mises statistic

$$\hat{p}(z) = \frac{1}{n^2} \sum_{i,j=1}^{n} K_b(z - |X_i - X_{i-1}|^\nu W_j).$$

Greenwood et al., 2011 [4] give conditions under which $\hat{p}(z)$ has rate $n^{-1/2}$ and is asymptotically linear and asymptotically normal. □

*Remark 8.* (Generalizations.) The results discussed in the theorems for the case $m = 2$ have generalizations for $m > 2$. Let us just look at the case $m = 3$. Recall that $n^{1/2}$-consistency typically failed to hold for local U-statistics of the density of $X_1^\nu + X_2^\nu$ when $\nu \ge 2$. The reason was that the density of $X^\nu$ is not square-integrable for $\nu \ge 2$. For $m = 3$ the local U-statistic for the density $p_3 = g * g * g$ of $X_1^\nu + X_2^\nu + X_3^\nu$ is of the form

$$\hat{p}_3(z) = \binom{n}{3}^{-1} \sum_{1 \le i < j < k \le n} K_b(z - X_i^\nu - X_j^\nu - X_k^\nu).$$

The Hoeffding decomposition now yields

$$\hat{p}_3(z) = p_3 * K_b(z) + \frac{3}{n} \sum_{i=1}^{n} g * g * K_b(z - X_i^\nu) + O_p(1/(nb^{1/2})).$$

Assume now that the density $f$ is Lipschitz on $(0,\infty)$. Then $p_3$ is Lipschitz at $z$. Hence $p_3 * K_b(z) = p_3(z) + O(b)$. For $n^{1/2}$-consistency we therefore need that $g * g(z - X^\nu)$ has a finite variance. Using the substitution $y = zs$, we obtain

$$g * g(z) = \int_0^z g(z-y) g(y)\, dy = z^{2/\nu - 1} q(z)$$

with

$$q(z) = \int_0^1 ((1-s)s)^{1/\nu - 1} f((z(1-s))^{1/\nu}) f((zs)^{1/\nu})\, ds$$

If $f(0+)$ is positive, then we have $q(0+) = f^2(0+)\int_0^1((1-s)s)^{1/\nu-1}\,ds$ and see that the square-integrability is typically violated if $2/\nu - 1 \geq -1/2$, i.e., $\nu \geq 4$. Thus for $m = 3$ we expect results similar to the above theorems, but now with critical power $\nu = 4$ rather than $\nu = 2$.

Note that the density of $X_1^2+X_2^2+X_3^2$ can be estimated $n^{1/2}$-consistently, although the density of $X_1^2 + X_2^2$ can be estimated only at the slower rate $(n/\log n)^{1/2}$. The reason is that for $m = 3$ the leading term in the Hoeffding decomposition is an average involving $g * g$, while for $m = 2$ it involves $g$ which is less smooth than $g * g$.

The critical power $\nu$ increases linearly with $m$. More precisely, we have $\nu = 2m - 2$. □

**Conclusion.** The paper gives an overview of several of our recent results on non-standard rates of convergence of local U-statistics for estimating the density of transformations of several independent random variables. We also discuss applications and extensions of these results.

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