# Lipschitz Constants for Some Approximation Operators of a Lipschitz Continuous Function 

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## 1. Introduction

For a function $f$, continuous on $[0,1]$, the $n$th ( $n \geqslant 1$ ) Bernstein polynomial of $f$ is the polynomial of degree $\leqslant n$ defined by

$$
B_{n}(f, x):=\sum_{k=0}^{n} f\left(\frac{k}{n}\right)\binom{n}{k} x^{k}(1-x)^{n-k} .
$$

$B_{n}(f)$ is a polynomial, so there exists for every $\mu \in(0,1]$ a constant $A$ such that $B_{n}(f) \in \operatorname{Lip}_{A} \mu$ (where $A$ may depend on $f$ and $\mu$ ). Brown et al. [2] gave an elementary proof that the Lipschitz constant is preserved, i.e.:

Theorem 1. If $f \in \operatorname{Lip}_{A} \mu$, then for all $n \geqslant 1, B_{n}(f) \in \operatorname{Lip}_{A} \mu$.
For a brief history of the problem see [2]. By using some simple results from probability theory, we shall prove that the identical result holds for a general class of univariate and multivariate approximation operators. This class includes the Szász, Bernstein, Gamma, and translation operators, the tensor product operators formed from them, and the Bernstein operators over simplices. The central idea is to exploit the splitting property of the probability distributions involved in these approximation operators.
In this paper a function from a convex subset $I_{k} \subseteq \mathbb{R}^{k}$ into $\mathbb{R}$ is said to be Lipschitz continuous of order $\mu, \mu \in(0,1]$, if there exists a constant $A \geqslant 0$ such that for every pair of points $x, y \in I_{k}$ we have

$$
|f(x)-f(y)| \leqslant A\|x-y\|^{\mu}
$$

$\left(\|\cdot\|\right.$ is the $l_{1}$ norm in $\left.\mathbb{R}^{k}\right)$. We write this as $f \in \operatorname{Lip}_{A} \mu\left(I_{k}\right)$ or simply $f \in \operatorname{Lip}_{A} \mu$, suppressing the $I_{k}$.

We shall use the multivariate Feller operator which generalizes the above-mentioned approximation operators. For the properties of the Feller operator see $[4,6,9]$. Let $f \in C\left(I_{k}\right)$. Suppose that $S_{n, x}, n \geqslant 1$, is a sequence of $k$-dimensional random vectors over $I_{k}$ with $E\left(S_{n, x}\right)=n x$ and with $\operatorname{Cov}\left(S_{n, x}, S_{n, x}\right)=\sigma_{n}^{2}(x)$ a non-singular variance-covariance matrix, where $x$ is a $k$-dimensional vector of parameters. Stancu [9] defined the multivariate version of the Feller operator:

$$
\begin{aligned}
L_{n}(f, x) & :=E\left\{f\left(\frac{S_{n, x}}{n}\right)\right\} \\
& :=\int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} f\left(\frac{t_{1}}{n}, \ldots, \frac{t_{k}}{n}\right) d F_{n, x}\left(t_{1}, \ldots, t_{k}\right),
\end{aligned}
$$

where $F_{n, x}$ is the joint distribution function $(d f)$ of $S_{n, x}$ and $E\left|f\left(S_{n, x} / n\right)\right|<\infty$. In the next section the principal result is proved. A few special cases are outlined in the last section.

## 2. Principal Result

The tool used to prove Theorem 1 is to split a binomial random variable into a multinomial random vector. Consider the experiment of rolling $n$ times a three-sided die that has sides one and two colored blue and side three colored white. Let $S_{n}$ be the number of times blue comes up, $U$ be the number of times side one comes up, and $V$ be the number of times side two comes up. $S_{n}$ has the same probability distribution as $U+V$, i.e., $P\left(S_{n}=k\right)=P(U+V=k), k=0,1, \ldots, n$, which we write as $S_{n} \sim U+V$. This shows that a binomial random variable $S_{n}$ can be split into a trinomial random vector ( $U, V$ ) such that $S_{n} \sim U+V$. If the probability of a blue face coming up on one roll is $x$ and the probability of side one coming up is $y$ (clearly $x \geqslant y$ ) then the expected value of $V, E(V)$, is $n(x-y)$. Also note that $B_{n}(f, x)=E f\left(S_{n} / n\right)=E f((U+V) / n)$ and $B_{n}(f, y)=E f(U / n)$. We formalize this concept of the splitting of a random variable in the following definition:

Definition. The random vector $S_{n, x}$ is said to have the splitting property if for every $x, y \in I_{k}$ there exist random vectors $U, R_{x}$, and $R_{y}$ such that $U, R_{x}$, and $R_{y}$ are defined over the same probability space with

$$
S_{n, x} \sim U+R_{x} \quad \text { and } \quad S_{n, y} \sim U+R_{y}
$$

and $E\left\|R_{x}-R_{y}\right\| \leqslant n\|x-y\|$.

The random vectors $R_{x}$ and $R_{y}$ need not be independent of $U$. For $k=1$ and $x>y$, the splitting property would hold if $S_{n, x} \sim U+R$, and $S_{n, y} \sim U$, where $E|R| \leqslant n(x-y)$ and $U$ and $R$ are defined over the same probability space. The main result of this paper is the following:

Theorem 2. Assume that $S_{n, x}$ has the splitting property. If $f \in \operatorname{Lip}_{A} \mu\left(I_{k}\right)$ then $L_{n}(f) \in \operatorname{Lip}_{A} \mu\left(I_{k}\right)(0<\mu \leqslant 1)$.

Proof. Split $S_{n, x}$ and $S_{n, y}$. Then

$$
\begin{aligned}
\left|L_{n}(f, x)-L_{n}(f, y)\right| & =\left|E f\left(\frac{S_{n, x}}{n}\right)-E f\left(\frac{S_{n, y}}{n}\right)\right| \\
& =\left|E f\left(\frac{U+R_{x}}{n}\right)-E f\left(\frac{U+R_{y}}{n}\right)\right| \\
& \leqslant E\left|f\left(\frac{U+R_{x}}{n}\right)-f\left(\frac{U+R_{y}}{n}\right)\right|
\end{aligned}
$$

The equality holds by the splitting property and the last inequality follows since the underlying probability space is the same. Consequently,

$$
\begin{aligned}
\left|L_{n}(f, x)-L_{n}(f, y)\right| & \leqslant A E\left(\left\|\frac{R_{x}-R_{y}}{n}\right\|^{\mu}\right) \\
& \leqslant A\left(E\left\|\frac{R_{x}-R_{y}}{n}\right\|\right)^{\mu} \\
& \leqslant A\|x-y\|^{\mu} .
\end{aligned}
$$

The first inequality is due to the Lipschitz hypothesis, the second inequality is by Jensen's inequality, and the last inequality follows by the splitting property. This completes the proof.

Remark. The converse of Theorem 2 is trivially true if $L_{n}(f, x) \rightarrow f(x)$ as $n \rightarrow \infty$.

Remark. Since the $l_{p}$ norms have the property

$$
C_{p}\|\cdot\| \leqslant\|\cdot\|_{p} \leqslant\|\cdot\|,
$$

where $C_{p}=k^{1 / p-1}$, it follows that if $f \in \operatorname{Lip}_{A}(\mu, p)$ (i.e., $\operatorname{Lip}_{A} \mu$ with respect to the $l_{p}$ norm, $1<p$ ) and $S_{n, x}$ has the splitting property then $L_{n}(f) \in$ $\operatorname{Lip}_{A^{*}}(\mu, p)$, where $A^{*}=C_{p}^{-\mu} A$.

## 3. Special Cases

## 1. Bernstein Operator

Let

$$
P\left(S_{n, x}=k\right)=\binom{n}{k} x^{k}(1-x)^{n-k} ; \quad k=0,1, \ldots, n
$$

For this distribution $L_{n}(f, x)$ reduces to $B_{n}(f, x)$. Let $(U, V)$ have a trinomial distribution [5] with parameters ( $n, x_{1}, x_{2}-x_{1}$ ), where $0<x_{2}<1$, $0<x_{1}<x_{2}$, i.e.,

$$
P(U=j, V=l)=\frac{n!}{j!l!(n-j-l)!} x_{1}^{j}\left(x_{2}-x_{1}\right)^{l}\left(1-x_{2}\right)^{n-j-l}
$$

$j=0,1,2, \ldots, n ; l=0,1, \ldots, n ; j+l \leqslant n$. The joint moment generating function (mgf) of $(U, V)$ is

$$
\phi_{U, V}\left(t_{1}, t_{2}\right)=E\left(e^{t_{1} U+t_{2} V}\right)=\left(1-x_{2}+x_{1} e^{t_{1}}+\left(x_{2}-x_{1}\right) e^{t_{2}}\right)^{n}
$$

Hence, by letting $t_{1}=t_{2}$ we get $S_{n, x_{2}} \sim U+V$. Also note that by letting $t_{2}=0$ we get $U \sim S_{n, x_{1}}$ and similarly $V \sim S_{n, x_{2}-x_{1}}$. Furthermore $E|V|=$ $E(V)=n\left(x_{2}-x_{1}\right)$. Therefore by taking $V=R$, we have that $S_{n, x}$ has the splitting property and Theorem 1 follows from Theorem 2.

## 2. Szász Operator

Let $P\left(S_{n, x}=k\right)=\exp (-n x)(n x)^{k} / k!; k=0,1,2, \ldots$, and $x>0 . L_{n}(f, x)$ reduces to the Szász operator [6]

$$
S_{n}(f, x)=e^{-n x} \sum_{k=0}^{\infty} f\left(\frac{k}{n}\right) \frac{(n x)^{k}}{k!}
$$

Define the joint probability distribution of $(U, V)$ as

$$
P(U=j, V=l)=e^{-n x_{1}} \frac{\left(n x_{1}\right)^{j}}{j!} e^{-n\left(x_{2}-x_{1}\right)} \frac{\left(n\left(x_{2}-x_{1}\right)\right)^{l}}{l!},
$$

$j=0,1,2, \ldots ; l=0,1, \ldots ; 0<x_{1} \leqslant x_{2}$. Again, it is easily verified that

$$
P(U+V=k)=\sum_{0 \leqslant j+l=k} P(U=j, V=l)=P\left(S_{n, x_{2}}=k\right)
$$

for all $k=0,1, \ldots$. Also note that $U, V$ are independent Poisson random variables and $E(V)=n\left(x_{2}-x_{1}\right)$. Taking $U=S_{n, x_{1}}$, and $V=R$, we have by Theorem 2 that if $f \in \operatorname{Lip}_{A} \mu$ then $S_{n}(f) \in \operatorname{Lip}_{A} \mu$.

## 3. Baskakov Operator

Let $S_{n, x}$ have a negative binomial distribution with parameters $(n, x)$, $x>0$, i.e.,

$$
P\left(S_{n, x}=k\right)=(1+x)^{-n}\binom{n+k-1}{k}\left(\frac{x}{1+x}\right)^{k}, \quad k=0,1,2, \ldots .
$$

The Feller operator reduces to the Baskakov operator

$$
B_{n}^{*}(f, x)=\sum_{k=0}^{\infty} f\left(\frac{k}{n}\right) P\left(S_{n, x}=k\right)
$$

Let $(U, V)$ have negative multinomial distribution [5] with parameters ( $n, p_{1}, p_{2}$ ), where $0<p_{1}, p_{2}$; and let $q=p_{1}+p_{2}+1$.

$$
P(U=j, V=l)=\frac{(n+j+l-1)!}{j!l!(n-1)!} q^{-n}\left(\frac{p_{1}}{q}\right)^{j}\left(\frac{p_{2}}{q}\right)^{l}
$$

$j=0,1, \ldots ; l=0,1, \ldots$. The mgf of $(U, V)$ is

$$
\phi_{U, V}\left(t_{1}, t_{2}\right)=\left(q-p_{1} e^{t_{1}}-p_{2} e^{t_{2}}\right)^{-n}
$$

By letting $t_{1}=t_{2}$ we have that $U+V$ has a negative binomial distribution with parameters $\left(n, p_{1}+p_{2}\right)$. By letting $t_{2}=0$ we get that $U \sim S_{n, p_{1}}$, and similarly $V \sim S_{n, p_{2}}$. Therefore, for $0<x_{1}<x_{2}$, by taking $p_{1}=x_{1}$ and $p_{2}=$ $x_{2}-x_{1}$ we have that

$$
S_{n, x_{2}} \sim U+V
$$

Also, $E(V)=n\left(x_{2}-x_{1}\right)$. Hence, by Theorem 2, if $f \in \operatorname{Lip}_{A} \mu$ then $B_{n}^{*}(f) \in$ $\operatorname{Lip}_{A} \mu$.

## 4 Gamma Operator

For $x>0$, the Gamma operator is defined as

$$
G_{n}(f, x)=\frac{x^{-n}}{(n-1)!} \int_{0}^{\infty} f\left(\frac{y}{n}\right) y^{n-1} e^{-y / x} d y
$$

Let $S_{n, x}$ have the probability density function

$$
g_{S_{n, x}}(y)= \begin{cases}\frac{x^{-n}}{(n-1)!} y^{n-1} e^{-y / x} & \text { if } y>0 \\ 0 & \text { if } y \leqslant 0\end{cases}
$$

Then $L_{n}(f, x)$ reduces to $G_{n}(f, x)$. It is easy to check that $x S_{n, 1} \sim S_{n, x}$.

Therefore, if $0<x_{1}<x_{2}$ then

$$
\begin{aligned}
S_{n, x_{2}} & \sim x_{2} S_{n, 1} \\
& \sim x_{1} S_{n, 1}+\left(x_{2}-x_{1}\right) S_{n, 1} \\
& \sim S_{n, x_{1}}+R .
\end{aligned}
$$

Note that $S_{n, x_{1}}$ and $R$ are dependent random variables and $R \sim S_{n, x_{2}-x_{1}}$. Also, $E(R)=n\left(x_{2}-x_{1}\right)$, which implies, by Theorem 2, that $G_{n}(f) \in \operatorname{Lip}_{A} \mu$ if $f \in \operatorname{Lip}_{A} \mu$.

## 5. Translation Operators

To consider positive translation operators (also known as convolution operators [10]), let $H_{n}(t-x)$ be the kernel for the translation operator

$$
\begin{aligned}
T_{n}(f, x) & =\int_{-\infty}^{\infty} f(t) d_{t} H_{n}(t-x) \\
& =\int_{-\infty}^{\infty} f(u+x) d H_{n}(u)
\end{aligned}
$$

Let $Z_{n}$ be a random variable having df $H_{n}(z)$ and define $S_{n, x}:=n\left(x+Z_{n}\right)$. For this case $L_{n}(f, x)$ reduces to the translation operator $T_{n}(f, x)$. For $x_{2}>x_{1}$

$$
S_{n, x_{2}} \sim n\left(x_{1}+Z_{n}\right)+n\left(x_{2}-x_{1}\right) \sim S_{n, x_{1}}+R
$$

where $R$ is a degenerate random variable taking the value $n\left(x_{2}-x_{1}\right)$ with probability one. Hence, by Theorem 2 , if $f \in \operatorname{Lip}_{A} \mu$ then $T_{n}(f) \in \operatorname{Lip}_{A} \mu$. In the following some of the typical translation operators are provided.
(i) Fejér Operator [3, p. 34]:

$$
F_{n}(f, x)=\frac{1}{n} \int_{-1 / 2}^{1 / 2} f(u+x)\left[\frac{\sin n \pi u}{\sin \pi u}\right]^{2} d u
$$

(ii) Korovkin [1, 7]:

Let $\phi$ be a non-negative, even, and continuous function on $[-r, r]$, decreasing on $[0, r]$ and such that $\phi(0)=1$, and $0 \leqslant \phi(t)<1$ for $0<t \leqslant r$. For a continuous $f$ on $I=[a, b]$ with $b-a \leqslant r$,

$$
K_{n}(f, x)=\rho_{n} \int_{a}^{b} f(t) \phi^{n}(t-x) d t, \quad n=1,2, \ldots
$$

where

$$
1=2 \rho_{n} \int_{0}^{r} \phi^{n}(t) d t
$$

Since $K_{n}(f, x)$ is a special case of $T_{n}(f, x)$, if $f \in \operatorname{Lip}_{A} \mu$ then $K_{n}(f) \in \operatorname{Lip}_{A} \mu$. Several classical smoothing operators [8] such as the Weierstrass and Picard operators are special cases of $K_{n}(f, x)$.

## 6. Bernstein Operator over a Simplex

Let $S_{n, x}=\left(S_{n, x_{1}}, \ldots, S_{n, x_{k}}\right)$ have a multinomial distribution with parameters $\left(n, x_{1}, \ldots, x_{k}, 1-x_{1}-\cdots-x_{k}\right)$, where $x=\left(x_{1}, \ldots, x_{k}\right) \in \Delta_{k}=$ the standard simplex. That is, $\Delta_{k}=\left\{\left(x_{1}, \ldots, x_{k}\right): 0 \leqslant x_{i} \leqslant 1 ; i=1,2, \ldots, k\right.$; and $\left.x_{1}+\cdots+x_{k} \leqslant 1\right\}$. For a continuous $f$ defined over $\Delta_{k}$, the Bernstein operator is defined as

$$
B_{n, k}(f, x)=\sum_{j} f(j / n) P\left(S_{n, x}=j\right)
$$

where $j=\left(j_{1}, \ldots, j_{k}\right) ; j_{i} \geqslant 0 ; i=1,2, \ldots, k ; j_{1}+\cdots+j_{k} \leqslant n$ and

$$
\begin{aligned}
P\left(S_{n, x}=j\right)= & \frac{n!}{j_{1}!j_{2}!\cdots j_{k}!\left(n-j_{1}-\cdots-j_{k}\right)!} \\
& \times\left(1-x_{1}-x_{2}-\cdots-x_{k}\right)^{n-j_{1}-\cdots-j_{k}} \prod_{i=1}^{k} x_{i}^{j_{i}}
\end{aligned}
$$

is the multinomial distribution [5] with parameters ( $n, x_{1}, \ldots, x_{k}$, $1-\sum_{i=1}^{k} x_{i}$ ). Let $f \in \operatorname{Lip}_{A} \mu$. For $x \neq y$ define a $2 k$-dimensional random vector ( $U, V$ ) having multinomial distribution [5] with parameters

$$
\left(n, x_{1}^{*}, \ldots, x_{k}^{*},\left|x_{1}-y_{1}\right|, \ldots,\left|x_{k}-y_{k}\right|, 1-\sum_{i=1}^{k} x_{i}^{*}-\sum_{i=1}^{k}\left|x_{i}-y_{i}\right|\right)
$$

where $U$ is a $k$-dimensional multinomial with parameters $\left(n, x^{*}\right.$, $\left.1-\sum_{i=1}^{k} x_{i}^{*}\right)$ and $V$ is a $k$-dimensional multinomial with parameters $\left(n,\left|x_{1}-y_{1}\right|, \ldots,\left|x_{k}-y_{k}\right|, \quad 1-\sum_{i=1}^{k}\left|x_{i}-y_{i}\right|\right)$ and $x^{*}=\left(\min \left(x_{1}, y_{1}\right), \ldots\right.$, $\min \left(x_{k}, y_{k}\right)$ ). Let $c_{i}=1$ if $x_{i}>y_{i}$ and $c_{i}=0$ otherwise, $i=1,2, \ldots, k$. Define $R_{x}=\left(V_{1} c_{1}, \ldots, V_{k} c_{k}\right)$ and $R_{y}=\left(V_{1}\left(1-c_{1}\right), \ldots, V_{k}\left(1-c_{k}\right)\right)$. Note that

$$
S_{n, x} \sim U+R_{x} \quad \text { and } \quad S_{n, y} \sim U+R_{y}
$$

where $U \sim S_{n, x^{*}}$. Also since $2 c_{i}-1=1$ or $\quad-1, \quad\left\|R_{x}-R_{y}\right\|=$ $V_{1}+V_{2}+\cdots+V_{k}$. Therefore, $\left\|R_{x}-R_{y}\right\|$ has a binomial distribution with
parameters ( $n,\|x-y\|$ ). Hence, $S_{n, x}$ has the splitting property and therefore by Theorem 2 if $f \in \operatorname{Lip}_{A} \mu$ then $B_{n, k}(f) \in \operatorname{Lip}_{A} \mu$.

## 7. Tensor Product Operators

For the tensor product operators formed by the Bernstein, Szász, Baskakov, Gamma, and Weierstrass operators the same result holds. For this more general setup, we need to modify $L_{n}(f, x)$ to incorporate the tensor product operators with different $n_{i}, i=1,2, \ldots, k$. Let $S_{n_{i} x_{i}}, i=$ $1,2, \ldots, k$, be mutually independent univariate random variables defined over $I \subseteq \mathbb{R}$ having the univariate splitting property. Define $S_{n, x}=$ $\left(S_{n_{1}, x_{1}}, \ldots, S_{n_{k}, x_{k}}\right)$, where $x=\left(x_{1}, \ldots, x_{k}\right)$ and $n=\left(n_{1}, \ldots, n_{k}\right)$. The tensor product operator for $f \in C\left(I_{k}\right), I_{k}=I \times I \times \cdots \times I$, is defined as

$$
L_{n}(f, x)=E f\left(\frac{S_{n_{1}, x_{1}}}{n_{1}}, \frac{S_{n_{2}, x_{2}}}{n_{2}}, \ldots, \frac{S_{n_{k}, x_{k}}}{n_{k}}\right) .
$$

If $S_{n_{i}, x_{i}}$ has df $F_{n_{i}, x_{i}}\left(t_{i}\right), i=1,2, \ldots, k$, then by the mutual independence of the random variables the joint df of $S_{n, x}$ is

$$
F_{n, x}(t)=\prod_{i=1}^{k} F_{n_{b} x_{i}}\left(t_{i}\right),
$$

where $t=\left(t_{1}, \ldots, t_{k}\right)$. Let $x, y \in I_{k}$ be fixed vectors. By the univariate splitting property there exist random variables $U_{i}, R_{x_{i}}^{i}$, and $R_{y_{i}}^{i}$ defined over the same probability space such that $S_{n_{i} x_{i}} \sim U_{i}+R_{x_{i}}^{i}, S_{n_{i} y_{i}} \sim U_{i}+R_{y_{i}}^{i}$, and $E\left|R_{x_{i}}^{i}-R_{y_{i}}^{i}\right| \leqslant n_{i}\left|x_{i}-y_{i}\right|, \quad i=1,2, \ldots, k . \quad$ Let $\quad U=\left(U_{1}, \ldots, U_{k}\right), \quad R_{x}=$ $\left(R_{x_{1}}^{1}, \ldots, R_{x_{k}}^{k}\right)$, and $R_{y}=\left(R_{y 1}^{1}, \ldots, R_{y_{k}}^{k}\right)$. Define the joint df of $\left(U, R_{x}, R_{y}\right)$ to be the product measure of the measures of ( $U_{i}, R_{x_{i}}^{i}, R_{y_{i}}^{i}$ ) $, i=1,2, \ldots, k$, so that the random vectors ( $U_{i}, R_{x_{i}}^{i}, R_{y_{i}}^{i}$ ), $i=1,2, \ldots, k$, are mutually independent. By the univariate splitting property and independence,

$$
S_{n, x} \sim U+R_{x} \quad \text { and } \quad S_{n, y} \sim U+R_{y} .
$$

Also, by the univariate splitting property, $E\left|R_{x_{i}}^{i}-R_{y_{i}}^{i}\right| \leqslant n_{i}\left|x_{i}-y_{i}\right|$. We have that

$$
\begin{aligned}
\left|L_{n}(f, x)-L_{n}(f, y)\right| & \leqslant A E\left(\sum_{i=1}^{k} \frac{\left|R_{x_{i}}^{i}-R_{y_{i}}^{i}\right|}{n_{i}}\right)^{\mu} \\
& \leqslant A\left(\sum_{i=1}^{k} E \frac{\left|R_{x_{i}}^{i}-R_{y_{i}}^{i}\right|}{n_{i}}\right)^{\mu} \\
& \leqslant A\|x-y\|^{\mu} .
\end{aligned}
$$

Hence, the tensor product operators are $\operatorname{Lip}_{A} \mu$ for $f \in \operatorname{Lip}_{A} \mu$ whenever the univariate operators have the splitting property.

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