

Multivariate Fuzzy-Random and stochastic arctangent, algebraic, Gudermannian and generalized symmetric activation functions induced Neural Network Approximations

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Abstract

In this article we study the degree of approximation of multivariate pointwise and uniform convergences in the q -mean to the Fuzzy-Random unit operator of multivariate Fuzzy-Random Quasi-Interpolation arctangent, algebraic, Gudermannian and generalized symmetric activation functions based neural network operators. These multivariate Fuzzy-Random operators arise in a natural way among multivariate Fuzzy-Random neural networks. The rates are given through multivariate Probabilistic-Jackson type inequalities involving the multivariate Fuzzy-Random modulus of continuity of the engaged multivariate Fuzzy-Random function. The plain stochastic extreme analog of this theory is also met in detail for the stochastic analogs of the operators: the stochastic full quasi-interpolation operators, the stochastic Kantorovich type operators and the stochastic quadrature type operators.

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1 Fuzzy-Random Functions and Stochastic processes

Background

See also [18], Ch. 22, pp. 497-501.

We start with

Definition 1 (see [35]) Let $\mu : \mathbb{R} \rightarrow [0, 1]$ with the following properties:

(i) is normal, i.e., $\exists x_0 \in \mathbb{R} : \mu(x_0) = 1$.
(ii) $\mu(\lambda x + (1 - \lambda)y) \geq \min\{\mu(x), \mu(y)\}$, $\forall x, y \in \mathbb{R}, \forall \lambda \in [0, 1]$ (μ is called a convex fuzzy subset).

(iii) μ is upper semicontinuous on \mathbb{R} , i.e., $\forall x_0 \in \mathbb{R}$ and $\forall \varepsilon > 0$, \exists neighborhood $V(x_0) : \mu(x) \leq \mu(x_0) + \varepsilon$, $\forall x \in V(x_0)$.

(iv) the set $\text{supp}(\mu) := \{x \in \mathbb{R} : \mu(x) > 0\}$ is compact in \mathbb{R} .

We call μ a fuzzy real number. Denote the set of all μ with $\mathbb{R}_{\mathcal{F}}$.

E.g., $\chi_{\{x_0\}} \in \mathbb{R}_{\mathcal{F}}$, for any $x_0 \in \mathbb{R}$, where $\chi_{\{x_0\}}$ is the characteristic function at x_0 .

For $0 < r \leq 1$ and $\mu \in \mathbb{R}_{\mathcal{F}}$ define $[\mu]^r := \{x \in \mathbb{R} : \mu(x) \geq r\}$ and $[\mu]^0 := \{x \in \mathbb{R} : \mu(x) > 0\}$.

Then it is well known that for each $r \in [0, 1]$, $[\mu]^r$ is a closed and bounded interval of \mathbb{R} . For $u, v \in \mathbb{R}_{\mathcal{F}}$ and $\lambda \in \mathbb{R}$, we define uniquely the sum $u \oplus v$ and the product $\lambda \odot u$ by

$$[u \oplus v]^r = [u]^r + [v]^r, \quad [\lambda \odot u]^r = \lambda [u]^r, \quad \forall r \in [0, 1],$$

where $[u]^r + [v]^r$ means the usual addition of two intervals (as subsets of \mathbb{R}) and $\lambda [u]^r$ means the usual product between a scalar and a subset of \mathbb{R} (see, e.g., [35]). Notice $1 \odot u = u$ and it holds $u \oplus v = v \oplus u$, $\lambda \odot u = u \odot \lambda$. If $0 \leq r_1 \leq r_2 \leq 1$ then $[u]^{r_2} \subseteq [u]^{r_1}$. Actually $[u]^r = [u_-^{(r)}, u_+^{(r)}]$, where $u_-^{(r)} < u_+^{(r)}$, $u_-^{(r)}, u_+^{(r)} \in \mathbb{R}$, $\forall r \in [0, 1]$.

Define

$$D : \mathbb{R}_{\mathcal{F}} \times \mathbb{R}_{\mathcal{F}} \rightarrow \mathbb{R}_+ \cup \{0\}$$

by

$$D(u, v) := \sup_{r \in [0, 1]} \max \left\{ \left| u_-^{(r)} - v_-^{(r)} \right|, \left| u_+^{(r)} - v_+^{(r)} \right| \right\},$$

where $[v]^r = [v_-^{(r)}, v_+^{(r)}]$; $u, v \in \mathbb{R}_{\mathcal{F}}$. We have that D is a metric on $\mathbb{R}_{\mathcal{F}}$. Then $(\mathbb{R}_{\mathcal{F}}, D)$ is a complete metric space, see [35], with the properties

$$\begin{aligned} D(u \oplus w, v \oplus w) &= D(u, v), \quad \forall u, v, w \in \mathbb{R}_{\mathcal{F}}, \\ D(k \odot u, k \odot v) &= |k| D(u, v), \quad \forall u, v \in \mathbb{R}_{\mathcal{F}}, \forall k \in \mathbb{R}, \\ D(u \oplus v, w \oplus e) &\leq D(u, w) + D(v, e), \quad \forall u, v, w, e \in \mathbb{R}_{\mathcal{F}}. \end{aligned} \tag{1}$$

Let (M, d) metric space and $f, g : M \rightarrow \mathbb{R}_{\mathcal{F}}$ be fuzzy real number valued functions. The distance between f, g is defined by

$$D^*(f, g) := \sup_{x \in M} D(f(x), g(x)).$$

On $\mathbb{R}_{\mathcal{F}}$ we define a partial order by " \leq ": $u, v \in \mathbb{R}_{\mathcal{F}}$, $u \leq v$ iff $u_-^{(r)} \leq v_-^{(r)}$ and $u_+^{(r)} \leq v_+^{(r)}$, $\forall r \in [0, 1]$.

\sum^* denotes the fuzzy summation, $\tilde{0} := \chi_{\{0\}} \in \mathbb{R}_{\mathcal{F}}$ the neutral element with respect to \oplus . For more see also [36], [37].

We need

Definition 2 (see also [30], Definition 13.16, p. 654) Let (X, \mathcal{B}, P) be a probability space. A fuzzy-random variable is a \mathcal{B} -measurable mapping $g : X \rightarrow \mathbb{R}_{\mathcal{F}}$ (i.e., for any open set $U \subseteq \mathbb{R}_{\mathcal{F}}$, in the topology of $\mathbb{R}_{\mathcal{F}}$ generated by the metric D , we have

$$g^{-1}(U) = \{s \in X; g(s) \in U\} \in \mathcal{B}. \quad (2)$$

The set of all fuzzy-random variables is denoted by $\mathcal{L}_{\mathcal{F}}(X, \mathcal{B}, P)$. Let $g_n, g \in \mathcal{L}_{\mathcal{F}}(X, \mathcal{B}, P)$, $n \in \mathbb{N}$ and $0 < q < +\infty$. We say $g_n(s) \xrightarrow[n \rightarrow +\infty]{\text{"q-mean"}} g(s)$ if

$$\lim_{n \rightarrow +\infty} \int_X D(g_n(s), g(s))^q P(ds) = 0. \quad (3)$$

Remark 3 (see [30], p. 654) If $f, g \in \mathcal{L}_{\mathcal{F}}(X, \mathcal{B}, P)$, let us denote $F : X \rightarrow \mathbb{R}_+ \cup \{0\}$ by $F(s) = D(f(s), g(s))$, $s \in X$. Here, F is \mathcal{B} -measurable, because $F = G \circ H$, where $G(u, v) = D(u, v)$ is continuous on $\mathbb{R}_{\mathcal{F}} \times \mathbb{R}_{\mathcal{F}}$, and $H : X \rightarrow \mathbb{R}_{\mathcal{F}} \times \mathbb{R}_{\mathcal{F}}$, $H(s) = (f(s), g(s))$, $s \in X$, is \mathcal{B} -measurable. This shows that the above convergence in q -mean makes sense.

Definition 4 (see [30], p. 654, Definition 13.17) Let (T, \mathcal{T}) be a topological space. A mapping $f : T \rightarrow \mathcal{L}_{\mathcal{F}}(X, \mathcal{B}, P)$ will be called fuzzy-random function (or fuzzy-stochastic process) on T . We denote $f(t)(s) = f(t, s)$, $t \in T$, $s \in X$.

Remark 5 (see [30], p. 655) Any usual fuzzy real function $f : T \rightarrow \mathbb{R}_{\mathcal{F}}$ can be identified with the degenerate fuzzy-random function $f(t, s) = f(t)$, $\forall t \in T$, $s \in X$.

Remark 6 (see [30], p. 655) Fuzzy-random functions that coincide with probability one for each $t \in T$ will be consider equivalent.

Remark 7 (see [30], p. 655) Let $f, g : T \rightarrow \mathcal{L}_{\mathcal{F}}(X, \mathcal{B}, P)$. Then $f \oplus g$ and $k \odot f$ are defined pointwise, i.e.,

$$\begin{aligned} (f \oplus g)(t, s) &= f(t, s) \oplus g(t, s), \\ (k \odot f)(t, s) &= k \odot f(t, s), \quad t \in T, s \in X, k \in \mathbb{R}. \end{aligned}$$

Definition 8 (see also Definition 13.18, pp. 655-656, [30]) For a fuzzy-random function $f : W \subseteq \mathbb{R}^N \rightarrow \mathcal{L}_{\mathcal{F}}(X, \mathcal{B}, P)$, $N \in \mathbb{N}$, we define the (first) fuzzy-random modulus of continuity

$$\Omega_1^{(\mathcal{F})}(f, \delta)_{L^q} = \sup \left\{ \left(\int_X D^q(f(x, s), f(y, s)) P(ds) \right)^{\frac{1}{q}} : x, y \in W, \|x - y\|_{\infty} \leq \delta \right\},$$

$0 < \delta, 1 \leq q < \infty$.

Definition 9 ([16]) Here $1 \leq q < +\infty$. Let $f : W \subseteq \mathbb{R}^N \rightarrow \mathcal{L}_{\mathcal{F}}(X, \mathcal{B}, P)$, $N \in \mathbb{N}$, be a fuzzy random function. We call f a (q -mean) uniformly continuous fuzzy random function over W , iff $\forall \varepsilon > 0 \exists \delta > 0$: whenever $\|x - y\|_{\infty} \leq \delta$, $x, y \in W$, implies that

$$\int_X (D(f(x, s), f(y, s)))^q P(ds) \leq \varepsilon.$$

We denote it as $f \in C_{FR}^{U_q}(W)$.

Proposition 10 ([16]) Let $f \in C_{FR}^{U_q}(W)$, where $W \subseteq \mathbb{R}^N$ is convex. Then $\Omega_1^{(\mathcal{F})}(f, \delta)_{L^q} < \infty$, any $\delta > 0$.

Proposition 11 ([16]) Let $f, g : W \subseteq \mathbb{R}^N \rightarrow \mathcal{L}_{\mathcal{F}}(X, \mathcal{B}, P)$, $N \in \mathbb{N}$, be fuzzy random functions. It holds

- (i) $\Omega_1^{(\mathcal{F})}(f, \delta)_{L^q}$ is nonnegative and nondecreasing in $\delta > 0$.
- (ii) $\lim_{\delta \downarrow 0} \Omega_1^{(\mathcal{F})}(f, \delta)_{L^q} = \Omega_1^{(\mathcal{F})}(f, 0)_{L^q} = 0$, iff $f \in C_{FR}^{U_q}(W)$.

We mention

Definition 12 (see also [6]) Let $f(t, s)$ be a random function (stochastic process) from $W \times (X, \mathcal{B}, P)$, $W \subseteq \mathbb{R}^N$, into \mathbb{R} , where (X, \mathcal{B}, P) is a probability space. We define the q -mean multivariate first modulus of continuity of f by

$$\Omega_1(f, \delta)_{L^q} := \sup \left\{ \left(\int_X |f(x, s) - f(y, s)|^q P(ds) \right)^{\frac{1}{q}} : x, y \in W, \|x - y\|_{\infty} \leq \delta \right\}, \quad (4)$$

$\delta > 0, 1 \leq q < \infty$.

The concept of f being (q -mean) uniformly continuous random function is defined the same way as in Definition 9, just replace D by $|\cdot|$, etc. We denote it as $f \in C_{\mathbb{R}}^{U_q}(W)$.

Similar properties as in Propositions 10, 11 are valid for $\Omega_1(f, \delta)_{L^q}$.

Also we have

Proposition 13 ([3]) *Let $Y(t, \omega)$ be a real valued stochastic process such that Y is continuous in $t \in [a, b]$. Then Y is jointly measurable in (t, ω) .*

According to [28], p. 94 we have the following

Definition 14 *Let (Y, \mathcal{T}) be a topological space, with its σ -algebra of Borel sets $\mathcal{B} := \mathcal{B}(Y, \mathcal{T})$ generated by \mathcal{T} . If (X, \mathcal{S}) is a measurable space, a function $f : X \rightarrow Y$ is called measurable iff $f^{-1}(B) \in \mathcal{S}$ for all $B \in \mathcal{B}$.*

By Theorem 4.1.6 of [28], p. 89 f as above is measurable iff

$$f^{-1}(C) \in \mathcal{S} \text{ for all } C \in \mathcal{T}.$$

We mention

Theorem 15 (see [28], p. 95) *Let (X, \mathcal{S}) be a measurable space and (Y, d) be a metric space. Let f_n be measurable functions from X into Y such that for all $x \in X$, $f_n(x) \rightarrow f(x)$ in Y . Then f is measurable. I.e., $\lim_{n \rightarrow \infty} f_n = f$ is measurable.*

We need also

Proposition 16 ([16]) *Let f, g be fuzzy random variables from \mathcal{S} into $\mathbb{R}_{\mathcal{F}}$. Then*

- (i) *Let $c \in \mathbb{R}$, then $c \odot f$ is a fuzzy random variable.*
- (ii) *$f \oplus g$ is a fuzzy random variable.*

Proposition 17 *Let $Y(\vec{t}, \omega)$ be a real valued multivariate random function (stochastic process) such that Y is continuous in $\vec{t} \in \prod_{i=1}^N [a_i, b_i]$. Then Y is jointly measurable in (\vec{t}, ω) and $\int_{\prod_{i=1}^N [a_i, b_i]} Y(\vec{t}, \omega) d\vec{t}$ is a real valued random variable.*

Proof. Similar to Proposition 18.14, p. 353 of [7]. ■

2 About neural networks background

2.1 About the arctangent activation function

We consider the

$$\arctan x = \int_0^x \frac{dz}{1+z^2}, \quad x \in \mathbb{R}. \quad (5)$$

We will be using

$$h(x) := \frac{2}{\pi} \arctan\left(\frac{\pi}{2}x\right) = \frac{2}{\pi} \int_0^{\frac{\pi x}{2}} \frac{dz}{1+z^2}, \quad x \in \mathbb{R}, \quad (6)$$

which is a sigmoid type function and it is strictly increasing. We have that

$$h(0) = 0, \quad h(-x) = -h(x), \quad h(+\infty) = 1, \quad h(-\infty) = -1,$$

and

$$h'(x) = \frac{4}{4 + \pi^2 x^2} > 0, \quad \text{all } x \in \mathbb{R}. \quad (7)$$

We consider the activation function

$$\psi_1(x) := \frac{1}{4} (h(x+1) - h(x-1)), \quad x \in \mathbb{R}, \quad (8)$$

and we notice that

$$\psi_1(-x) = \psi_1(x), \quad (9)$$

it is an even function.

Since $x+1 > x-1$, then $h(x+1) > h(x-1)$, and $\psi_1(x) > 0$, all $x \in \mathbb{R}$.

We see that

$$\psi_1(0) = \frac{1}{\pi} \arctan \frac{\pi}{2} \cong 18.31. \quad (10)$$

Let $x > 0$, we have that

$$\begin{aligned} \psi_1'(x) &= \frac{1}{4} (h'(x+1) - h'(x-1)) = \\ &= \frac{-4\pi^2 x}{(4 + \pi^2(x+1)^2)(4 + \pi^2(x-1)^2)} < 0. \end{aligned} \quad (11)$$

That is

$$\psi_1'(x) < 0, \quad \text{for } x > 0. \quad (12)$$

That is ψ_1 is strictly decreasing on $[0, \infty)$ and clearly is strictly increasing on $(-\infty, 0]$, and $\psi_1'(0) = 0$.

Observe that

$$\begin{aligned} \lim_{x \rightarrow +\infty} \psi_1(x) &= \frac{1}{4} (h(+\infty) - h(+\infty)) = 0, \\ \text{and} \\ \lim_{x \rightarrow -\infty} \psi_1(x) &= \frac{1}{4} (h(-\infty) - h(-\infty)) = 0. \end{aligned} \quad (13)$$

That is the x -axis is the horizontal asymptote on ψ_1 .

All in all, ψ_1 is a bell symmetric function with maximum $\psi_1(0) \cong 18.31$.

We need

Theorem 18 ([19], p. 286) *We have that*

$$\sum_{i=-\infty}^{\infty} \psi_1(x-i) = 1, \quad \forall x \in \mathbb{R}. \quad (14)$$

Theorem 19 ([19], p. 287) *It holds*

$$\int_{-\infty}^{\infty} \psi_1(x) dx = 1. \quad (15)$$

So that $\psi_1(x)$ is a density function on \mathbb{R} .

We mention

Theorem 20 ([19], p. 288) *Let $0 < \alpha < 1$, and $n \in \mathbb{N}$ with $n^{1-\alpha} > 2$. It holds*

$$\sum_{\substack{k=-\infty \\ : |nx-k| \geq n^{1-\alpha}}}^{\infty} \psi_1(nx-k) < \frac{2}{\pi^2(n^{1-\alpha}-2)} =: c_1(\alpha, n). \quad (16)$$

Denote by $[\cdot]$ the integral part of the number and by $\lceil \cdot \rceil$ the ceiling of the number.

We need

Theorem 21 ([19], p. 289) *Let $x \in [a, b] \subset \mathbb{R}$ and $n \in \mathbb{N}$ so that $\lceil na \rceil \leq \lfloor nb \rfloor$. It holds*

$$\frac{1}{\sum_{k=\lceil na \rceil}^{\lfloor nb \rfloor} \psi_1(nx-k)} < \frac{1}{\psi_1(1)} \cong \mathbf{0.0868} =: \alpha_1, \quad \forall x \in [a, b]. \quad (17)$$

Note 22 ([19], pp. 290-291)

i) *We have that*

$$\lim_{n \rightarrow \infty} \sum_{k=\lceil na \rceil}^{\lfloor nb \rfloor} \psi_1(nx-k) \neq 1, \quad (18)$$

for at least some $x \in [a, b]$.

ii) *For large enough $n \in \mathbb{N}$ we always obtain $\lceil na \rceil \leq \lfloor nb \rfloor$. Also $a \leq \frac{k}{n} \leq b$, iff $\lceil na \rceil \leq k \leq \lfloor nb \rfloor$.*

In general, by Theorem 18, it holds

$$\sum_{k=\lceil na \rceil}^{\lfloor nb \rfloor} \psi_1(nx-k) \leq 1. \quad (19)$$

We introduce (see [24])

$$Z_1(x_1, \dots, x_N) := Z_1(x) := \prod_{i=1}^N \psi_1(x_i), \quad x = (x_1, \dots, x_N) \in \mathbb{R}^N, \quad N \in \mathbb{N}. \quad (20)$$

Denote by $a = (a_1, \dots, a_N)$ and $b = (b_1, \dots, b_N)$.

It has the properties:

(i) $Z_1(x) > 0, \quad \forall x \in \mathbb{R}^N,$

(ii)

$$\sum_{k=-\infty}^{\infty} Z_1(x-k) := \sum_{k_1=-\infty}^{\infty} \sum_{k_2=-\infty}^{\infty} \dots \sum_{k_N=-\infty}^{\infty} Z_1(x_1-k_1, \dots, x_N-k_N) = 1, \quad (21)$$

where $k := (k_1, \dots, k_n) \in \mathbb{Z}^N, \quad \forall x \in \mathbb{R}^N,$

hence

(iii)

$$\sum_{k=-\infty}^{\infty} Z_1(nx-k) = 1, \quad (22)$$

$\forall x \in \mathbb{R}^N; n \in \mathbb{N},$

and

(iv)

$$\int_{\mathbb{R}^N} Z_1(x) dx = 1, \quad (23)$$

that is Z_1 is a multivariate density function.

(v) It is clear that

$$\sum_{\substack{k=-\infty \\ \left\| \frac{k}{n} - x \right\|_{\infty} > \frac{1}{n^{\beta}}}^{\infty} Z_1(nx-k) < \frac{2}{\pi^2(n^{1-\beta}-2)} = c_1(\beta, n), \quad (24)$$

$0 < \beta < 1, n \in \mathbb{N} : n^{1-\beta} > 2, x \in \mathbb{R}^N.$

(vi) By Theorem 21 we get that

$$0 < \frac{1}{\sum_{k=\lceil na \rceil}^{\lfloor nb \rfloor} Z_1(nx-k)} < \frac{1}{(\psi_1(1))^N} \cong (0.0868)^N =: \gamma_1(N), \quad (25)$$

$\forall x \in \left(\prod_{i=1}^N [a_i, b_i] \right), \quad n \in \mathbb{N}.$

Furthermore it holds

$$\lim_{n \rightarrow \infty} \sum_{k=\lceil na \rceil}^{\lfloor nb \rfloor} Z_1(nx-k) \neq 1, \quad (26)$$

for at least some $x \in \left(\prod_{i=1}^N [a_i, b_i] \right)$.

Above it is $\|x\|_\infty := \max \{|x_1|, \dots, |x_N|\}$, $x \in \mathbb{R}^N$, also set $\infty := (\infty, \dots, \infty)$, $-\infty = (-\infty, \dots, -\infty)$ upon the multivariate context.

2.2 About the algebraic activation function

Here see also [20].

We consider the generator algebraic function

$$\varphi(x) = \frac{x}{\sqrt[2m]{1+x^{2m}}}, \quad m \in \mathbb{N}, x \in \mathbb{R}, \quad (27)$$

which is a sigmoidal type of function and is a strictly increasing function.

We see that $\varphi(-x) = -\varphi(x)$ with $\varphi(0) = 0$. We get that

$$\varphi'(x) = \frac{1}{(1+x^{2m})^{\frac{2m+1}{2m}}} > 0, \quad \forall x \in \mathbb{R}, \quad (28)$$

proving φ as strictly increasing over \mathbb{R} , $\varphi'(x) = \varphi'(-x)$. We easily find that $\lim_{x \rightarrow +\infty} \varphi(x) = 1$, $\varphi(+\infty) = 1$, and $\lim_{x \rightarrow -\infty} \varphi(x) = -1$, $\varphi(-\infty) = -1$.

We consider the activation function

$$\psi_2(x) = \frac{1}{4} [\varphi(x+1) - \varphi(x-1)]. \quad (29)$$

Clearly it is $\psi_2(x) = \psi_2(-x)$, $\forall x \in \mathbb{R}$, so that ψ_2 is an even function and symmetric with respect to the y -axis. Clearly $\psi_2(x) > 0$, $\forall x \in \mathbb{R}$.

Also it is

$$\psi_2(0) = \frac{1}{2^{\frac{2m}{2m+1}}}. \quad (30)$$

By [20], we have that $\psi_2'(x) < 0$ for $x > 0$. That is ψ_2 is strictly decreasing over $(0, +\infty)$.

Clearly, ψ_2 is strictly increasing over $(-\infty, 0)$ and $\psi_2'(0) = 0$.

Furthermore we obtain that

$$\lim_{x \rightarrow +\infty} \psi_2(x) = \frac{1}{4} [\varphi(+\infty) - \varphi(+\infty)] = 0, \quad (31)$$

and

$$\lim_{x \rightarrow -\infty} \psi_2(x) = \frac{1}{4} [\varphi(-\infty) - \varphi(-\infty)] = 0. \quad (32)$$

That is the x -axis is the horizontal asymptote of ψ_2 .

Conclusion, ψ_2 is a bell shape symmetric function with maximum

$$\psi_2(0) = \frac{1}{2^{\frac{2m}{2m+1}}}, \quad m \in \mathbb{N}. \quad (33)$$

We need

Theorem 23 ([20]) *We have that*

$$\sum_{i=-\infty}^{\infty} \psi_2(x-i) = 1, \quad \forall x \in \mathbb{R}. \quad (34)$$

Theorem 24 ([20]) *It holds*

$$\int_{-\infty}^{\infty} \psi_2(x) dx = 1. \quad (35)$$

Theorem 25 ([20]) *Let $0 < \alpha < 1$, and $n \in \mathbb{N}$ with $n^{1-\alpha} > 2$. It holds*

$$\left\{ \begin{array}{l} \sum_{k=-\infty}^{\infty} \psi_2(nx-k) < \frac{1}{4m(n^{1-\alpha}-2)^{2m}} =: c_2(\alpha, n), \quad m \in \mathbb{N}. \\ : |nx-k| \geq n^{1-\alpha} \end{array} \right. \quad (36)$$

We need

Theorem 26 ([20]) *Let $[a, b] \subset \mathbb{R}$ and $n \in \mathbb{N}$ so that $\lceil na \rceil \leq \lfloor nb \rfloor$. It holds*

$$\frac{1}{\sum_{k=\lceil na \rceil}^{\lfloor nb \rfloor} \psi_2(nx-k)} < 2 \left(\sqrt[2m]{1+4^m} \right) =: \alpha_2, \quad (37)$$

$\forall x \in [a, b], m \in \mathbb{N}$.

Note 27 1) *By [20] we have that*

$$\lim_{n \rightarrow \infty} \sum_{k=\lceil na \rceil}^{\lfloor nb \rfloor} \psi_2(nx-k) \neq 1, \quad (38)$$

for at least some $x \in [a, b]$.

2) *Let $[a, b] \subset \mathbb{R}$. For large $n \in \mathbb{N}$ we always have $\lceil na \rceil \leq \lfloor nb \rfloor$. Also $a \leq \frac{k}{n} \leq b$, iff $\lceil na \rceil \leq k \leq \lfloor nb \rfloor$.*

In general it holds that

$$\sum_{k=\lceil na \rceil}^{\lfloor nb \rfloor} \psi_2(nx-k) \leq 1. \quad (39)$$

We introduce (see also [25])

$$Z_2(x_1, \dots, x_N) := Z_2(x) := \prod_{i=1}^N \psi_2(x_i), \quad x = (x_1, \dots, x_N) \in \mathbb{R}^N, \quad N \in \mathbb{N}. \quad (40)$$

It has the properties:

(i) $Z_2(x) > 0, \forall x \in \mathbb{R}^N,$

(ii)

$$\sum_{k=-\infty}^{\infty} Z_2(x-k) := \sum_{k_1=-\infty}^{\infty} \sum_{k_2=-\infty}^{\infty} \dots \sum_{k_N=-\infty}^{\infty} Z_2(x_1-k_1, \dots, x_N-k_N) = 1, \quad (41)$$

where $k := (k_1, \dots, k_n) \in \mathbb{Z}^N, \forall x \in \mathbb{R}^N,$

hence

(iii)

$$\sum_{k=-\infty}^{\infty} Z_2(nx-k) = 1, \quad (42)$$

$\forall x \in \mathbb{R}^N; n \in \mathbb{N},$

and

(iv)

$$\int_{\mathbb{R}^N} Z_2(x) dx = 1, \quad (43)$$

that is Z_2 is a multivariate density function.

(v) It is clear that

$$\sum_{\substack{k=-\infty \\ \left\| \frac{k}{n} - x \right\|_{\infty} > \frac{1}{n^{\beta}}} }^{\infty} Z_2(nx-k) < \frac{1}{4m(n^{1-\beta}-2)^{2m}} = c_2(\beta, n), \quad (44)$$

$0 < \beta < 1, n \in \mathbb{N} : n^{1-\beta} > 2, x \in \mathbb{R}^N, m \in \mathbb{N}.$

(vi) By Theorem 26 we get that

$$0 < \frac{1}{\sum_{k=\lceil na \rceil}^{\lfloor nb \rfloor} Z_2(nx-k)} < \frac{1}{(\psi_2(1))^N} \cong [2(\sqrt[2m]{1+4^m})]^N := \gamma_2(N), \quad (45)$$

$\forall x \in \left(\prod_{i=1}^N [a_i, b_i] \right), n \in \mathbb{N}.$

Furthermore it holds

$$\lim_{n \rightarrow \infty} \sum_{k=\lceil na \rceil}^{\lfloor nb \rfloor} Z_2(nx-k) \neq 1, \quad (46)$$

for at least some $x \in \left(\prod_{i=1}^N [a_i, b_i] \right).$

2.3 About the Gudermannian activation function

See also [21], [34].

Here we consider $gd(x)$ the Gudermannian function [34], which is a sigmoid function, as a generator function:

$$\sigma(x) = 2 \arctan\left(\tanh\left(\frac{x}{2}\right)\right) = \int_0^x \frac{dt}{\cosh t} =: gd(x), \quad x \in \mathbb{R}. \quad (47)$$

Let the normalized generator sigmoid function

$$f(x) := \frac{4}{\pi} \sigma(x) = \frac{4}{\pi} \int_0^x \frac{dt}{\cosh t} = \frac{8}{\pi} \int_0^x \frac{1}{e^t + e^{-t}} dt, \quad x \in \mathbb{R}. \quad (48)$$

Here

$$f'(x) = \frac{4}{\pi \cosh x} > 0, \quad \forall x \in \mathbb{R},$$

hence f is strictly increasing on \mathbb{R} .

Notice that $\tanh(-x) = -\tanh x$ and $\arctan(-x) = -\arctan x$, $x \in \mathbb{R}$.

So, here the neural network activation function will be:

$$\psi_3(x) = \frac{1}{4} [f(x+1) - f(x-1)], \quad x \in \mathbb{R}. \quad (49)$$

By [21], we get that

$$\psi_3(x) = \psi_3(-x), \quad \forall x \in \mathbb{R}, \quad (50)$$

i.e. it is even and symmetric with respect to the y -axis. Here we have $f(+\infty) = 1$, $f(-\infty) = -1$ and $f(0) = 0$. Clearly it is

$$f(-x) = -f(x), \quad \forall x \in \mathbb{R}, \quad (51)$$

an odd function, symmetric with respect to the origin. Since $x+1 > x-1$, and $f(x+1) > f(x-1)$, we obtain $\psi_3(x) > 0$, $\forall x \in \mathbb{R}$.

By [21], we have that

$$\psi_3(0) = \frac{2}{\pi} gd(1) \cong 0.551. \quad (52)$$

By [21] ψ_3 is strictly decreasing on $(0, +\infty)$, and strictly increasing on $(-\infty, 0)$, and $\psi_3'(0) = 0$.

Also we have that

$$\lim_{x \rightarrow +\infty} \psi_3(x) = \lim_{x \rightarrow -\infty} \psi_3(x) = 0, \quad (53)$$

that is the x -axis is the horizontal asymptote for ψ_3 .

Conclusion, ψ_3 is a bell shaped symmetric function with maximum $\psi_3(0) \cong 0.551$.

We need

Theorem 28 ([21]) *It holds that*

$$\sum_{i=-\infty}^{\infty} \psi_3(x-i) = 1, \quad \forall x \in \mathbb{R}. \quad (54)$$

Theorem 29 ([21]) *We have that*

$$\int_{-\infty}^{\infty} \psi_3(x) dx = 1. \quad (55)$$

So $\psi_3(x)$ is a density function.

Theorem 30 ([21]) *Let $0 < \alpha < 1$, and $n \in \mathbb{N}$ with $n^{1-\alpha} > 2$. It holds*

$$\left\{ \begin{array}{l} \sum_{k=-\infty}^{\infty} \psi_3(nx-k) < \frac{4}{\pi e^{(n^{1-\alpha}-2)}} = \frac{4e^2}{\pi e^{n^{1-\alpha}}} =: c_3(\alpha, n). \\ : |nx-k| \geq n^{1-\alpha} \end{array} \right. \quad (56)$$

Theorem 31 ([21]) *Let $[a, b] \subset \mathbb{R}$ and $n \in \mathbb{N}$, so that $\lceil na \rceil \leq \lfloor nb \rfloor$. It holds*

$$\frac{1}{\sum_{k=\lceil na \rceil}^{\lfloor nb \rfloor} \psi_3(nx-k)} < \frac{\pi}{gd(2)} \cong 2.412 =: \alpha_3, \quad (57)$$

$\forall x \in [a, b]$.

We make

Remark 32 ([21])

(i) *We have that*

$$\lim_{n \rightarrow \infty} \sum_{k=\lceil na \rceil}^{\lfloor nb \rfloor} \psi_3(nx-k) \neq 1, \quad (58)$$

for at least some $x \in [a, b]$.

(ii) *Let $[a, b] \subset \mathbb{R}$. For large n we always have $\lceil na \rceil \leq \lfloor nb \rfloor$. Also $a \leq \frac{k}{n} \leq b$, iff $\lceil na \rceil \leq k \leq \lfloor nb \rfloor$.*

In general it holds

$$\sum_{k=\lceil na \rceil}^{\lfloor nb \rfloor} \psi_3(nx-k) \leq 1. \quad (59)$$

We introduce (see also [23])

$$Z_3(x_1, \dots, x_N) := Z_3(x) := \prod_{i=1}^N \psi_3(x_i), \quad x = (x_1, \dots, x_N) \in \mathbb{R}^N, \quad N \in \mathbb{N}. \quad (60)$$

It has the properties:

(i) $Z_3(x) > 0, \forall x \in \mathbb{R}^N,$

(ii)

$$\sum_{k=-\infty}^{\infty} Z_3(x-k) := \sum_{k_1=-\infty}^{\infty} \sum_{k_2=-\infty}^{\infty} \dots \sum_{k_N=-\infty}^{\infty} Z_3(x_1-k_1, \dots, x_N-k_N) = 1, \quad (61)$$

where $k := (k_1, \dots, k_n) \in \mathbb{Z}^N, \forall x \in \mathbb{R}^N,$

hence

(iii)

$$\sum_{k=-\infty}^{\infty} Z_3(nx-k) = 1, \quad (62)$$

$\forall x \in \mathbb{R}^N; n \in \mathbb{N},$

and

(iv)

$$\int_{\mathbb{R}^N} Z_3(x) dx = 1, \quad (63)$$

that is Z_3 is a multivariate density function.

(v) It is also clear that

$$\sum_{\substack{k=-\infty \\ \|\frac{k}{n}-x\|_{\infty} > \frac{1}{n^{\beta}}}}^{\infty} Z_3(nx-k) < \frac{4e^2}{\pi e^{n^{1-\beta}}} = c_3(\beta, n), \quad (64)$$

$0 < \beta < 1, n \in \mathbb{N} : n^{1-\beta} > 2, x \in \mathbb{R}^N, m \in \mathbb{N}.$

(vi) By Theorem 31 we get that

$$0 < \frac{1}{\sum_{k=\lceil na \rceil}^{\lfloor nb \rfloor} Z_3(nx-k)} < \left(\frac{\pi}{gd(2)} \right)^N \cong (2.412)^N =: \gamma_3(N), \quad (65)$$

$\forall x \in \left(\prod_{i=1}^N [a_i, b_i] \right), n \in \mathbb{N}.$

Furthermore it holds

$$\lim_{n \rightarrow \infty} \sum_{k=\lceil na \rceil}^{\lfloor nb \rfloor} Z_3(nx-k) \neq 1, \quad (66)$$

for at least some $x \in \left(\prod_{i=1}^N [a_i, b_i] \right).$

2.4 About the generalized symmetrical activation function

Here we consider the generalized symmetrical sigmoid function ([22], [29])

$$f_1(x) = \frac{x}{(1 + |x|^\mu)^{\frac{1}{\mu}}}, \quad \mu > 0, x \in \mathbb{R}. \quad (67)$$

This has applications in immunology and protection from disease together with probability theory. It is also called a symmetrical protection curve.

The parameter μ is a shape parameter controlling how fast the curve approaches the asymptotes for a given slope at the inflection point. When $\mu = 1$ f_1 is the absolute sigmoid function, and when $\mu = 2$, f_1 is the square root sigmoid function. When $\mu = 1.5$ the function approximates the arctangent function, when $\mu = 2.9$ it approximates the logistic function, and when $\mu = 3.4$ it approximates the error function. Parameter μ is estimated in the likelihood maximization ([29]). For more see [29].

Next we study the particular generator sigmoid function

$$f_2(x) = \frac{x}{\left(1 + |x|^\lambda\right)^{\frac{1}{\lambda}}}, \quad \lambda \text{ is an odd number, } x \in \mathbb{R}. \quad (68)$$

We have that $f_2(0) = 0$, and

$$f_2(-x) = -f_2(x), \quad (69)$$

so f_2 is symmetric with respect to zero.

When $x \geq 0$, we get that ([22])

$$f_2'(x) = \frac{1}{(1 + x^\lambda)^{\frac{\lambda+1}{\lambda}}} > 0, \quad (70)$$

that is f_2 is strictly increasing on $[0, +\infty)$ and f_2 is strictly increasing on $(-\infty, 0]$. Hence f_2 is strictly increasing on \mathbb{R} .

We also have $f_2(+\infty) = f_2(-\infty) = 1$.

Let us consider the activation function ([22]):

$$\begin{aligned} \psi_4(x) &= \frac{1}{4} [f_2(x+1) - f_2(x-1)] = \\ &= \frac{1}{4} \left[\frac{(x+1)}{\left(1 + |x+1|^\lambda\right)^{\frac{1}{\lambda}}} - \frac{(x-1)}{\left(1 + |x-1|^\lambda\right)^{\frac{1}{\lambda}}} \right]. \end{aligned} \quad (71)$$

Clearly it holds ([22])

$$\psi_4(x) = \psi_4(-x), \quad \forall x \in \mathbb{R}. \quad (72)$$

and

$$\psi_4(0) = \frac{1}{2\sqrt[\lambda]{2}}, \quad (73)$$

and $\psi_4(x) > 0, \forall x \in \mathbb{R}$.

Following [22], we have that ψ_4 is strictly decreasing over $[0, +\infty)$, and ψ_4 is strictly increasing on $(-\infty, 0]$, by ψ_4 -symmetry with respect to y -axis, and $\psi_4'(0) = 0$.

Clearly it is

$$\lim_{x \rightarrow +\infty} \psi_4(x) = \lim_{x \rightarrow -\infty} \psi_4(x) = 0, \quad (74)$$

therefore the x -axis is the horizontal asymptote of $\psi_4(x)$.

The value

$$\psi_4(0) = \frac{1}{2\sqrt[\lambda]{2}}, \quad \lambda \text{ is an odd number}, \quad (75)$$

is the maximum of ψ_4 , which is a bell shaped function.

We need

Theorem 33 ([22]) *It holds*

$$\sum_{i=-\infty}^{\infty} \psi_4(x-i) = 1, \quad \forall x \in \mathbb{R}. \quad (76)$$

Theorem 34 ([22]) *We have that*

$$\int_{-\infty}^{\infty} \psi_4(x) dx = 1. \quad (77)$$

So that $\psi_4(x)$ is a density function on \mathbb{R} .

We need

Theorem 35 ([22]) *Let $0 < \alpha < 1$, and $n \in \mathbb{N}$ with $n^{1-\alpha} > 2$. It holds*

$$\left\{ \begin{array}{l} \sum_{j=-\infty}^{\infty} \psi_4(nx-j) < \frac{1}{2\lambda(n^{1-\alpha}-2)^\lambda} =: c_4(\alpha, n), \\ : |nx-j| \geq n^{1-\alpha} \end{array} \right. \quad (78)$$

where $\lambda \in \mathbb{N}$ is an odd number.

We also need

Theorem 36 ([22]) *Let $[a, b] \subset \mathbb{R}$ and $n \in \mathbb{N}$ so that $\lceil na \rceil \leq \lfloor nb \rfloor$. Then*

$$\frac{1}{\sum_{k=\lceil na \rceil}^{\lfloor nb \rfloor} \psi_4(|nx-k|)} < 2\sqrt[\lambda]{1+2^\lambda} =: \alpha_4, \quad (79)$$

where λ is an odd number, $\forall x \in [a, b]$.

We make

Remark 37 ([22]) (1) We have that

$$\lim_{n \rightarrow \infty} \sum_{k=\lceil na \rceil}^{\lfloor nb \rfloor} \psi_4(nx - k) \neq 1, \quad \text{for at least some } x \in [a, b]. \quad (80)$$

(2) Let $[a, b] \subset \mathbb{R}$. For large enough n we always obtain $\lceil na \rceil \leq \lfloor nb \rfloor$. Also $a \leq \frac{k}{n} \leq b$, iff $\lceil na \rceil \leq k \leq \lfloor nb \rfloor$.

In general it holds that

$$\sum_{k=\lceil na \rceil}^{\lfloor nb \rfloor} \psi_4(nx - k) \leq 1. \quad (81)$$

We introduce (see also [26])

$$Z_4(x_1, \dots, x_N) := Z_4(x) := \prod_{i=1}^N \psi_4(x_i), \quad x = (x_1, \dots, x_N) \in \mathbb{R}^N, \quad N \in \mathbb{N}. \quad (82)$$

It has the properties:

(i) $Z_4(x) > 0$, $\forall x \in \mathbb{R}^N$,

(ii)

$$\sum_{k=-\infty}^{\infty} Z_4(x - k) := \sum_{k_1=-\infty}^{\infty} \sum_{k_2=-\infty}^{\infty} \dots \sum_{k_N=-\infty}^{\infty} Z_4(x_1 - k_1, \dots, x_N - k_N) = 1, \quad (83)$$

where $k := (k_1, \dots, k_n) \in \mathbb{Z}^N$, $\forall x \in \mathbb{R}^N$,

hence

(iii)

$$\sum_{k=-\infty}^{\infty} Z_4(nx - k) = 1, \quad (84)$$

$\forall x \in \mathbb{R}^N$; $n \in \mathbb{N}$,

and

(iv)

$$\int_{\mathbb{R}^N} Z_4(x) dx = 1, \quad (85)$$

that is Z_4 is a multivariate density function.

(v) It is clear that

$$\sum_{\substack{k=-\infty \\ \left\| \frac{k}{n} - x \right\|_{\infty} > \frac{1}{n^{\beta}}}^{\infty} Z_4(nx - k) < \frac{1}{2\lambda(n^{1-\beta} - 2)^{\lambda}} = c_4(\beta, n), \quad (86)$$

$0 < \beta < 1$, $n \in \mathbb{N} : n^{1-\beta} > 2$, $x \in \mathbb{R}^N$, λ is odd.

(vi) By Theorem 36 we get that

$$0 < \frac{1}{\sum_{k=\lceil na \rceil}^{\lfloor nb \rfloor} Z_4(nx - k)} < \left(2 \sqrt[{\lambda}]{1 + 2^\lambda}\right)^N =: \gamma_4(N), \quad (87)$$

$\forall x \in \left(\prod_{i=1}^N [a_i, b_i]\right)$, $n \in \mathbb{N}$, λ is odd.

Furthermore it holds

$$\lim_{n \rightarrow \infty} \sum_{k=\lceil na \rceil}^{\lfloor nb \rfloor} Z_4(nx - k) \neq 1, \quad (88)$$

for at least some $x \in \left(\prod_{i=1}^N [a_i, b_i]\right)$.

Set

$$\lceil na \rceil := (\lceil na_1 \rceil, \dots, \lceil na_N \rceil),$$

$$\lfloor nb \rfloor := (\lfloor nb_1 \rfloor, \dots, \lfloor nb_N \rfloor),$$

where $a := (a_1, \dots, a_N)$, $b := (b_1, \dots, b_N)$, $k := (k_1, \dots, k_N)$.

Let $f \in C\left(\prod_{i=1}^N [a_i, b_i]\right)$, and $n \in \mathbb{N}$ such that $\lceil na_i \rceil \leq \lfloor nb_i \rfloor$, $i = 1, \dots, N$.

We define the multivariate averaged positive linear quasi-interpolation neural network operators ($x := (x_1, \dots, x_N) \in \left(\prod_{i=1}^N [a_i, b_i]\right)$); $j = 1, 2, 3, 4$:

$${}_j A_n(f, x_1, \dots, x_N) := {}_j A_n(f, x) := \frac{\sum_{k=\lceil na \rceil}^{\lfloor nb \rfloor} f\left(\frac{k}{n}\right) Z_j(nx - k)}{\sum_{k=\lceil na \rceil}^{\lfloor nb \rfloor} Z_j(nx - k)} = \quad (89)$$

$$\frac{\sum_{k_1=\lceil na_1 \rceil}^{\lfloor nb_1 \rfloor} \sum_{k_2=\lceil na_2 \rceil}^{\lfloor nb_2 \rfloor} \dots \sum_{k_N=\lceil na_N \rceil}^{\lfloor nb_N \rfloor} f\left(\frac{k_1}{n}, \dots, \frac{k_N}{n}\right) \left(\prod_{i=1}^N \psi_j(nx_i - k_i)\right)}{\prod_{i=1}^N \left(\sum_{k_i=\lceil na_i \rceil}^{\lfloor nb_i \rfloor} \psi_j(nx_i - k_i)\right)}.$$

For large enough $n \in \mathbb{N}$ we always obtain $\lceil na_i \rceil \leq \lfloor nb_i \rfloor$, $i = 1, \dots, N$. Also $a_i \leq \frac{k_i}{n} \leq b_i$, iff $\lceil na_i \rceil \leq k_i \leq \lfloor nb_i \rfloor$, $i = 1, \dots, N$.

When $f \in C_B(\mathbb{R}^N)$ we define ($j = 1, 2, 3, 4$)

$${}_j B_n(f, x) := {}_j B_n(f, x_1, \dots, x_N) := \sum_{k=-\infty}^{\infty} f\left(\frac{k}{n}\right) Z_j(nx - k) := \quad (90)$$

$$\sum_{k_1=-\infty}^{\infty} \sum_{k_2=-\infty}^{\infty} \dots \sum_{k_N=-\infty}^{\infty} f\left(\frac{k_1}{n}, \frac{k_2}{n}, \dots, \frac{k_N}{n}\right) \left(\prod_{i=1}^N \psi_j(nx_i - k_i)\right),$$

$n \in \mathbb{N}$, $\forall x \in \mathbb{R}^N$, $N \in \mathbb{N}$, the multivariate full quasi-interpolation neural network operators.

Also for $f \in C_B(\mathbb{R}^N)$ we define the multivariate Kantorovich type neural network operators ($j = 1, 2, 3, 4$)

$$\begin{aligned} {}_j C_n(f, x) := {}_j C_n(f, x_1, \dots, x_N) &:= \sum_{k=-\infty}^{\infty} \left(n^N \int_{\frac{k}{n}}^{\frac{k+1}{n}} f(t) dt \right) Z_j(nx - k) := \\ & \sum_{k_1=-\infty}^{\infty} \sum_{k_2=-\infty}^{\infty} \dots \sum_{k_N=-\infty}^{\infty} \left(n^N \int_{\frac{k_1}{n}}^{\frac{k_1+1}{n}} \int_{\frac{k_2}{n}}^{\frac{k_2+1}{n}} \dots \int_{\frac{k_N}{n}}^{\frac{k_N+1}{n}} f(t_1, \dots, t_N) dt_1 \dots dt_N \right) \\ & \cdot \left(\prod_{i=1}^N \psi_j(nx_i - k_i) \right), \end{aligned} \quad (91)$$

$n \in \mathbb{N}, \forall x \in \mathbb{R}^N$.

Again for $f \in C_B(\mathbb{R}^N)$, $N \in \mathbb{N}$, we define the multivariate neural network operators of quadrature type ${}_j D_n(f, x)$, $n \in \mathbb{N}$, as follows. Let $\theta = (\theta_1, \dots, \theta_N) \in \mathbb{N}^N$, $\bar{r} = (r_1, \dots, r_N) \in \mathbb{Z}_+^N$, $w_{\bar{r}} = w_{r_1, r_2, \dots, r_N} \geq 0$, such that $\sum_{\bar{r}=0}^{\theta} w_{\bar{r}} = \sum_{r_1=0}^{\theta_1} \sum_{r_2=0}^{\theta_2} \dots \sum_{r_N=0}^{\theta_N} w_{r_1, r_2, \dots, r_N} = 1$; $k \in \mathbb{Z}^N$ and

$$\begin{aligned} \delta_{nk}(f) &:= \delta_{n, k_1, k_2, \dots, k_N}(f) := \sum_{\bar{r}=0}^{\theta} w_{\bar{r}} f\left(\frac{k}{n} + \frac{\bar{r}}{n\theta}\right) := \\ & \sum_{r_1=0}^{\theta_1} \sum_{r_2=0}^{\theta_2} \dots \sum_{r_N=0}^{\theta_N} w_{r_1, r_2, \dots, r_N} f\left(\frac{k_1}{n} + \frac{r_1}{n\theta_1}, \frac{k_2}{n} + \frac{r_2}{n\theta_2}, \dots, \frac{k_N}{n} + \frac{r_N}{n\theta_N}\right), \end{aligned} \quad (92)$$

where $\frac{\bar{r}}{\theta} := \left(\frac{r_1}{\theta_1}, \frac{r_2}{\theta_2}, \dots, \frac{r_N}{\theta_N}\right)$; $j = 1, 2, 3, 4$.

We put

$$\begin{aligned} {}_j D_n(f, x) &:= {}_j D_n(f, x_1, \dots, x_N) := \sum_{k=-\infty}^{\infty} \delta_{nk}(f) Z_j(nx - k) := \\ & \sum_{k_1=-\infty}^{\infty} \sum_{k_2=-\infty}^{\infty} \dots \sum_{k_N=-\infty}^{\infty} \delta_{n, k_1, k_2, \dots, k_N}(f) \left(\prod_{i=1}^N \psi_j(nx_i - k_i) \right), \end{aligned} \quad (93)$$

$\forall x \in \mathbb{R}^N$.

For the next we need, for $f \in C\left(\prod_{i=1}^N [a_i, b_i]\right)$ the first multivariate modulus of continuity

$$\omega_1(f, h) := \sup_{\substack{x, y \in \prod_{i=1}^N [a_i, b_i] \\ \|x - y\|_{\infty} \leq h}} |f(x) - f(y)|, \quad h > 0. \quad (94)$$

It holds that

$$\lim_{h \rightarrow 0} \omega_1(f, h) = 0. \quad (95)$$

Similarly it is defined for $f \in C_B(\mathbb{R}^N)$ (continuous and bounded functions on \mathbb{R}^N) the $\omega_1(f, h)$, and it has the property (95), given that $f \in C_U(\mathbb{R}^N)$ (uniformly continuous functions on \mathbb{R}^N).

We mention

Theorem 38 (see [23], [24], [25], [26]) Let $f \in C\left(\prod_{i=1}^N [a_i, b_i]\right)$, $0 < \beta < 1$, $x \in \left(\prod_{i=1}^N [a_i, b_i]\right)$, $N, n \in \mathbb{N}$ with $n^{1-\beta} > 2$; $j = 1, 2, 3, 4$. Then

1)

$$|{}_j A_n(f, x) - f(x)| \leq \gamma_j(N) \left[\omega_1\left(f, \frac{1}{n^\beta}\right) + 2c_j(\beta, n) \|f\|_\infty \right] =: \lambda_{j1}, \quad (96)$$

and

2)

$$\|{}_j A_n(f) - f\|_\infty \leq \lambda_{j1}. \quad (97)$$

We notice that $\lim_{n \rightarrow \infty} {}_j A_n(f) = f$, pointwise and uniformly.

In this article we extend Theorem 38 to the fuzzy-random level.

We mention

Theorem 39 (see [23], [24], [25], [26]) Let $f \in C_B(\mathbb{R}^N)$, $0 < \beta < 1$, $x \in \mathbb{R}^N$, $N, n \in \mathbb{N}$ with $n^{1-\beta} > 2$; $j = 1, 2, 3, 4$. Then

1)

$$|{}_j B_n(f, x) - f(x)| \leq \omega_1\left(f, \frac{1}{n^\beta}\right) + 2c_j(\beta, n) \|f\|_\infty =: \lambda_{j2}, \quad (98)$$

2)

$$\|{}_j B_n(f) - f\|_\infty \leq \lambda_{j2}. \quad (99)$$

Given that $f \in (C_U(\mathbb{R}^N) \cap C_B(\mathbb{R}^N))$, we obtain $\lim_{n \rightarrow \infty} {}_j B_n(f) = f$, uniformly.

We also need

Theorem 40 (see [23], [24], [25], [26]) Let $f \in C_B(\mathbb{R}^N)$, $0 < \beta < 1$, $x \in \mathbb{R}^N$, $N, n \in \mathbb{N}$ with $n^{1-\beta} > 2$; $j = 1, 2, 3, 4$. Then

1)

$$|{}_j C_n(f, x) - f(x)| \leq \omega_1\left(f, \frac{1}{n} + \frac{1}{n^\beta}\right) + 2c_j(\beta, n) \|f\|_\infty =: \lambda_{j3}, \quad (100)$$

2)

$$\|{}_j C_n(f) - f\|_\infty \leq \lambda_{j3}. \quad (101)$$

Given that $f \in (C_U(\mathbb{R}^N) \cap C_B(\mathbb{R}^N))$, we obtain $\lim_{n \rightarrow \infty} {}_j C_n(f) = f$, uniformly.

We also need

Theorem 41 (see [23], [24], [25], [26]) Let $f \in C_B(\mathbb{R}^N)$, $0 < \beta < 1$, $x \in \mathbb{R}^N$, $N, n \in \mathbb{N}$ with $n^{1-\beta} > 2$; $j = 1, 2, 3, 4$. Then

1)

$$|{}_j D_n(f, x) - f(x)| \leq \omega_1\left(f, \frac{1}{n} + \frac{1}{n^\beta}\right) + 2c_j(\beta, n) \|f\|_\infty = \lambda_{j3}, \quad (102)$$

2)

$$\|{}_j D_n(f) - f\|_\infty \leq \lambda_{j3}. \quad (103)$$

Given that $f \in (C_U(\mathbb{R}^N) \cap C_B(\mathbb{R}^N))$, we obtain $\lim_{n \rightarrow \infty} {}_j D_n(f) = f$, uniformly.

In this article we extend Theorems 39, 40, 41 to the random level.

We are also motivated by [1] - [16] and continuing [17]. For general knowledge on neural networks we recommend [31], [32], [33].

3 Main Results

I) q -mean Approximation by Fuzzy-Random arctangent, algebraic, Gudermannian and generalized symmetric activation functions based Quasi-Interpolation Neural Network Operators

All terms and assumptions here as in Sections 1, 2.

Let $f \in C_{\mathcal{FR}}^{U_q}\left(\prod_{i=1}^N [a_i, b_i]\right)$, $1 \leq q < +\infty$, $n, N \in \mathbb{N}$, $0 < \beta < 1$, $\vec{x} \in \left(\prod_{i=1}^N [a_i, b_i]\right)$, (X, \mathcal{B}, P) probability space, $s \in X$; $j = 1, 2, 3, 4$.

We define the following multivariate fuzzy random arctangent, algebraic, Gudermannian and generalized symmetric activation functions based quasi-interpolation linear neural network operators

$$({}_j A_n^{\mathcal{FR}}(f))(\vec{x}, s) := \sum_{\vec{k}=\lceil na \rceil}^{\lfloor nb \rfloor^*} f\left(\frac{\vec{k}}{n}, s\right) \odot \frac{Z_j(n\vec{x} - \vec{k})}{\sum_{\vec{k}=\lceil na \rceil}^{\lfloor nb \rfloor} Z_j(n\vec{x} - \vec{k})}, \quad (104)$$

(see also (89)).

We present

Theorem 42 Let $f \in C_{\mathcal{FR}}^{U_q}\left(\prod_{i=1}^N [a_i, b_i]\right)$, $0 < \beta < 1$, $\vec{x} \in \left(\prod_{i=1}^N [a_i, b_i]\right)$, $n, N \in \mathbb{N}$, with $n^{1-\beta} > 2$, $1 \leq q < +\infty$. Assume that $\int_X (D^*(f(\cdot, s), \vec{\partial}))^q P(ds) < \infty$; $j = 1, 2, 3, 4$. Then

1)

$$\left(\int_X D^q \left(({}_j A_n^{\mathcal{FR}}(f))(\vec{x}, s), f(\vec{x}, s) \right) P(ds) \right)^{\frac{1}{q}} \leq \quad (105)$$

$$\gamma_j(N) \left\{ \Omega_1 \left(f, \frac{1}{n^\beta} \right)_{L^q} + 2c_j(\beta, n) \left(\int_X (D^*(f(\cdot, s), \tilde{o}))^q P(ds) \right)^{\frac{1}{q}} \right\} =: \lambda_{j1}^{(\mathcal{FR})},$$

2)

$$\left\| \left(\int_X D^q \left(({}_j A_n^{\mathcal{FR}}(f))(\vec{x}, s), f(\vec{x}, s) \right) P(ds) \right)^{\frac{1}{q}} \right\|_{\infty, \left(\prod_{i=1}^N [a_i, b_i] \right)} \leq \lambda_{j1}^{(\mathcal{FR})}, \quad (106)$$

where $\gamma_j(N)$ as in (25), (45), (65), (87) and $c_j(\beta, n)$ as in (24), (44), (64), (86).

Proof. We notice that

$$\begin{aligned} D \left(f \left(\frac{\vec{k}}{n}, s \right), f(\vec{x}, s) \right) &\leq D \left(f \left(\frac{\vec{k}}{n}, s \right), \tilde{o} \right) + D(f(\vec{x}, s), \tilde{o}) \\ &\leq 2D^*(f(\cdot, s), \tilde{o}). \end{aligned} \quad (107)$$

Hence

$$D^q \left(f \left(\frac{\vec{k}}{n}, s \right), f(\vec{x}, s) \right) \leq 2^q D^{*q}(f(\cdot, s), \tilde{o}), \quad (108)$$

and

$$\left(\int_X D^q \left(f \left(\frac{\vec{k}}{n}, s \right), f(\vec{x}, s) \right) P(ds) \right)^{\frac{1}{q}} \leq 2 \left(\int_X (D^*(f(\cdot, s), \tilde{o}))^q P(ds) \right)^{\frac{1}{q}}. \quad (109)$$

We observe that

$$D \left(({}_j A_n^{\mathcal{FR}}(f))(\vec{x}, s), f(\vec{x}, s) \right) = \quad (110)$$

$$\begin{aligned} &D \left(\sum_{\vec{k}=\lceil na \rceil}^{\lfloor nb \rfloor^*} f \left(\frac{\vec{k}}{n}, s \right) \odot \frac{Z_j(nx-k)}{\sum_{\vec{k}=\lceil na \rceil}^{\lfloor nb \rfloor} Z_j(nx-k)}, f(\vec{x}, s) \odot 1 \right) = \\ &D \left(\sum_{\vec{k}=\lceil na \rceil}^{\lfloor nb \rfloor^*} f \left(\frac{\vec{k}}{n}, s \right) \odot \frac{Z_j(nx-k)}{\sum_{\vec{k}=\lceil na \rceil}^{\lfloor nb \rfloor} Z_j(nx-k)}, f(\vec{x}, s) \odot \frac{\sum_{\vec{k}=\lceil na \rceil}^{\lfloor nb \rfloor} Z_j(nx-k)}{\sum_{\vec{k}=\lceil na \rceil}^{\lfloor nb \rfloor} Z_j(nx-k)} \right) = \end{aligned} \quad (111)$$

$$\begin{aligned}
& D \left(\sum_{\vec{k}=\lceil na \rceil}^{\lfloor nb \rfloor^*} f \left(\frac{\vec{k}}{n}, s \right) \odot \frac{Z_j(nx-k)}{\sum_{\vec{k}=\lceil na \rceil}^{\lfloor nb \rfloor} Z_j(nx-k)}, \sum_{\vec{k}=\lceil na \rceil}^{\lfloor nb \rfloor^*} f(\vec{x}, s) \odot \frac{Z_j(nx-k)}{\sum_{\vec{k}=\lceil na \rceil}^{\lfloor nb \rfloor} Z_j(nx-k)} \right) \\
& \leq \sum_{\vec{k}=\lceil na \rceil}^{\lfloor nb \rfloor} \left(\frac{Z_j(nx-k)}{\sum_{\vec{k}=\lceil na \rceil}^{\lfloor nb \rfloor} Z_j(nx-k)} \right) D \left(f \left(\frac{\vec{k}}{n}, s \right), f(\vec{x}, s) \right). \quad (112)
\end{aligned}$$

So that

$$\begin{aligned}
& D \left(({}_j A_n^{\mathcal{FR}}(f))(\vec{x}, s), f(\vec{x}, s) \right) \leq \\
& \sum_{\vec{k}=\lceil na \rceil}^{\lfloor nb \rfloor} \left(\frac{Z_j(nx-k)}{\sum_{\vec{k}=\lceil na \rceil}^{\lfloor nb \rfloor} Z_j(nx-k)} \right) D \left(f \left(\frac{\vec{k}}{n}, s \right), f(\vec{x}, s) \right) = \quad (113) \\
& \sum_{\vec{k}=\lceil na \rceil}^{\lfloor nb \rfloor} \left(\frac{Z_j(nx-k)}{\sum_{\vec{k}=\lceil na \rceil}^{\lfloor nb \rfloor} Z_j(nx-k)} \right) D \left(f \left(\frac{\vec{k}}{n}, s \right), f(\vec{x}, s) \right) + \\
& \left\| \frac{\vec{k}}{n} - \vec{x} \right\|_{\infty} \leq \frac{1}{n^\beta} \\
& \sum_{\vec{k}=\lceil na \rceil}^{\lfloor nb \rfloor} \left(\frac{Z_j(nx-k)}{\sum_{\vec{k}=\lceil na \rceil}^{\lfloor nb \rfloor} Z_j(nx-k)} \right) D \left(f \left(\frac{\vec{k}}{n}, s \right), f(\vec{x}, s) \right). \\
& \left\| \frac{\vec{k}}{n} - \vec{x} \right\|_{\infty} > \frac{1}{n^\beta}
\end{aligned}$$

Hence it holds

$$\begin{aligned}
& \left(\int_X D^q \left(({}_j A_n^{\mathcal{FR}}(f))(\vec{x}, s), f(\vec{x}, s) \right) P(ds) \right)^{\frac{1}{q}} \leq \quad (114) \\
& \sum_{\vec{k}=\lceil na \rceil}^{\lfloor nb \rfloor} \left(\frac{Z_j(nx-k)}{\sum_{\vec{k}=\lceil na \rceil}^{\lfloor nb \rfloor} Z_j(nx-k)} \right) \left(\int_X D^q \left(f \left(\frac{\vec{k}}{n}, s \right), f(\vec{x}, s) \right) P(ds) \right)^{\frac{1}{q}} + \\
& \left\| \frac{\vec{k}}{n} - \vec{x} \right\|_{\infty} \leq \frac{1}{n^\beta} \\
& \sum_{\vec{k}=\lceil na \rceil}^{\lfloor nb \rfloor} \left(\frac{Z_j(nx-k)}{\sum_{\vec{k}=\lceil na \rceil}^{\lfloor nb \rfloor} Z_j(nx-k)} \right) \left(\int_X D^q \left(f \left(\frac{\vec{k}}{n}, s \right), f(\vec{x}, s) \right) P(ds) \right)^{\frac{1}{q}} \leq \\
& \left\| \frac{\vec{k}}{n} - \vec{x} \right\|_{\infty} > \frac{1}{n^\beta}
\end{aligned}$$

$$\left(\frac{1}{\sum_{\vec{k}=\lceil na \rceil}^{\lfloor nb \rfloor} Z_j(nx-k)} \right) \cdot \left\{ \Omega_1^{(\mathcal{F})} \left(f, \frac{1}{n^\beta} \right)_{L^q} + \right. \quad (115)$$

$$\left. 2 \left(\int_X (D^*(f(\cdot, s), \tilde{\partial}))^q P(ds) \right)^{\frac{1}{q}} \left(\sum_{\vec{k}=\lceil na \rceil}^{\lfloor nb \rfloor} Z_j(nx-k) \right) \right\}$$

(by (24), (25); (44), (45); (64), (65); (86), (87))

$$\leq \gamma_j(N) \left\{ \Omega_1^{(\mathcal{F})} \left(f, \frac{1}{n^\beta} \right)_{L^q} + 2c_j(\beta, n) \left(\int_X (D^*(f(\cdot, s), \tilde{\partial}))^q P(ds) \right)^{\frac{1}{q}} \right\}. \quad (116)$$

We have proved claim. ■

Conclusion 43 *By Theorem 42 we obtain the pointwise and uniform convergences with rates in the q -mean and D -metric of the operator ${}_j A_n^{\mathcal{F}\mathcal{R}}$ to the unit operator for $f \in C_{\mathcal{F}\mathcal{R}}^{U_q} \left(\prod_{i=1}^N [a_i, b_i] \right)$, $j = 1, 2, 3, 4$.*

II) 1-mean Approximation by Stochastic arctangent, algebraic, Gudermannian and generalized symmetric activation functions based full Quasi-Interpolation Neural Network Operators

Let $g \in C_{\mathcal{R}}^{U_1}(\mathbb{R}^N)$, $0 < \beta < 1$, $\vec{x} \in \mathbb{R}^N$, $n, N \in \mathbb{N}$, with $\|g\|_{\infty, \mathbb{R}^N, X} < \infty$, (X, \mathcal{B}, P) probability space, $s \in X$.

We define

$${}_j B_n^{(\mathcal{R})}(g)(\vec{x}, s) := \sum_{\vec{k}=-\infty}^{\infty} g\left(\frac{\vec{k}}{n}, s\right) Z_j(n\vec{x} - \vec{k}), \quad j = 1, 2, 3, 4, \quad (117)$$

(see also (90)).

We give

Theorem 44 *Let $g \in C_{\mathcal{R}}^{U_1}(\mathbb{R}^N)$, $0 < \beta < 1$, $\vec{x} \in \mathbb{R}^N$, $n, N \in \mathbb{N}$, with $n^{1-\beta} > 2$, $\|g\|_{\infty, \mathbb{R}^N, X} < \infty$; $j = 1, 2, 3, 4$. Then*

1)

$$\int_X \left| ({}_j B_n^{(\mathcal{R})}(g))(\vec{x}, s) - g(\vec{x}, s) \right| P(ds) \leq \quad (118)$$

$$\left\{ \Omega_1 \left(g, \frac{1}{n^\beta} \right)_{L^1} + 2c_j(\beta, n) \|g\|_{\infty, \mathbb{R}^N, X} \right\} =: \mu_{j1}^{(\mathcal{R})},$$

2)

$$\left\| \int_X \left| \left({}_j B_n^{(\mathcal{R})} (g) \right) (\vec{x}, s) - g(\vec{x}, s) \right| P(ds) \right\|_{\infty, \mathbb{R}^N} \leq \mu_{j1}^{(\mathcal{R})}. \quad (119)$$

Proof. Since $\|g\|_{\infty, \mathbb{R}^N, X} < \infty$, then

$$\left| g\left(\frac{\vec{k}}{n}, s\right) - g(\vec{x}, s) \right| \leq 2 \|g\|_{\infty, \mathbb{R}^N, X} < \infty. \quad (120)$$

Hence

$$\int_X \left| g\left(\frac{\vec{k}}{n}, s\right) - g(\vec{x}, s) \right| P(ds) \leq 2 \|g\|_{\infty, \mathbb{R}^N, X} < \infty. \quad (121)$$

We observe that

$$\begin{aligned} & \left({}_j B_n^{(\mathcal{R})} (g) \right) (\vec{x}, s) - g(\vec{x}, s) = \\ & \sum_{\vec{k}=-\infty}^{\infty} g\left(\frac{\vec{k}}{n}, s\right) Z_j(nx - k) - g(\vec{x}, s) \sum_{\vec{k}=-\infty}^{\infty} Z_j(nx - k) = \\ & \left(\sum_{\vec{k}=-\infty}^{\infty} g\left(\frac{\vec{k}}{n}, s\right) - g(\vec{x}, s) \right) Z_j(nx - k). \end{aligned} \quad (122)$$

However it holds

$$\sum_{\vec{k}=-\infty}^{\infty} \left| g\left(\frac{\vec{k}}{n}, s\right) - g(\vec{x}, s) \right| Z_j(nx - k) \leq 2 \|g\|_{\infty, \mathbb{R}^N, X} < \infty. \quad (123)$$

Hence

$$\begin{aligned} & \left| \left({}_j B_n^{(\mathcal{R})} (g) \right) (\vec{x}, s) - g(\vec{x}, s) \right| \leq \\ & \sum_{\vec{k}=-\infty}^{\infty} \left| g\left(\frac{\vec{k}}{n}, s\right) - g(\vec{x}, s) \right| Z_j(nx - k) = \\ & \sum_{\substack{\vec{k}=-\infty \\ \|\frac{\vec{k}}{n} - \vec{x}\|_{\infty} \leq \frac{1}{n^\beta}}}^{\infty} \left| g\left(\frac{\vec{k}}{n}, s\right) - g(\vec{x}, s) \right| Z_j(nx - k) + \\ & \sum_{\substack{\vec{k}=-\infty \\ \|\frac{\vec{k}}{n} - \vec{x}\|_{\infty} > \frac{1}{n^\beta}}}^{\infty} \left| g\left(\frac{\vec{k}}{n}, s\right) - g(\vec{x}, s) \right| Z_j(nx - k). \end{aligned} \quad (124)$$

Furthermore it holds

$$\left(\int_X \left| \left({}_j B_n^{(\mathcal{R})} (g) \right) (\vec{x}, s) - g(\vec{x}, s) \right| P(ds) \right) \leq$$

$$\begin{aligned}
& \sum_{\substack{\vec{k}=-\infty \\ \|\frac{\vec{k}}{n}-\vec{x}\|_\infty \leq \frac{1}{n^\beta}}}^{\infty} \left(\int_X \left| g\left(\frac{\vec{k}}{n}, s\right) - g(\vec{x}, s) \right| P(ds) \right) Z_j(nx - k) + \quad (125) \\
& \sum_{\substack{\vec{k}=-\infty \\ \|\frac{\vec{k}}{n}-\vec{x}\|_\infty > \frac{1}{n^\beta}}}^{\infty} \left(\int_X \left| g\left(\frac{\vec{k}}{n}, s\right) - g(\vec{x}, s) \right| P(ds) \right) Z_j(nx - k) \leq \\
& \Omega_1\left(g, \frac{1}{n^\beta}\right)_{L^1} + 2\|g\|_{\infty, \mathbb{R}^N, X} \sum_{\substack{\vec{k}=-\infty \\ \|\frac{\vec{k}}{n}-\vec{x}\|_\infty > \frac{1}{n^\beta}}}^{\infty} Z_j(nx - k) \leq \\
& \Omega_1\left(g, \frac{1}{n^\beta}\right)_{L^1} + 2c_j(\beta, n)\|g\|_{\infty, \mathbb{R}^N, X},
\end{aligned}$$

proving the claim. ■

Conclusion 45 *By Theorem 44 we obtain pointwise and uniform convergences with rates in the 1-mean of random operators ${}_j B_n^{(\mathcal{R})}$ to the unit operator for $g \in C_{\mathcal{R}}^{U_1}(\mathbb{R}^N)$, $j = 1, 2, 3, 4$.*

III) 1-mean Approximation by Stochastic arctangent, algebraic, Gudermannian and generalized symmetric activation functions based multivariate Kantorovich type neural network operator

Let $g \in C_{\mathcal{R}}^{U_1}(\mathbb{R}^N)$, $0 < \beta < 1$, $\vec{x} \in \mathbb{R}^N$, $n, N \in \mathbb{N}$, with $\|g\|_{\infty, \mathbb{R}^N, X} < \infty$, (X, \mathcal{B}, P) probability space, $s \in X$.

We define ($j = 1, 2, 3, 4$):

$${}_j C_n^{(\mathcal{R})}(g)(\vec{x}, s) := \sum_{\vec{k}=-\infty}^{\infty} \left(n^N \int_{\frac{\vec{k}}{n}}^{\frac{\vec{k}+1}{n}} g(\vec{t}, s) d\vec{t} \right) Z_j(n\vec{x} - \vec{k}), \quad (126)$$

(see also (91)).

We present

Theorem 46 *Let $g \in C_{\mathcal{R}}^{U_1}(\mathbb{R}^N)$, $0 < \beta < 1$, $\vec{x} \in \mathbb{R}^N$, $n, N \in \mathbb{N}$, with $n^{1-\beta} > 2$; $j = 1, 2, 3, 4$, $\|g\|_{\infty, \mathbb{R}^N, X} < \infty$. Then*

1)

$$\begin{aligned}
& \int_X \left| ({}_j C_n^{(\mathcal{R})}(g))(\vec{x}, s) - g(\vec{x}, s) \right| P(ds) \leq \\
& \left[\Omega_1\left(g, \frac{1}{n} + \frac{1}{n^\beta}\right)_{L^1} + 2c_j(\beta, n)\|g\|_{\infty, \mathbb{R}^N, X} \right] =: \gamma_{j1}^{(\mathcal{R})}, \quad (127)
\end{aligned}$$

2)

$$\left\| \int_X \left| ({}_j C_n^{(\mathcal{R})}(g))(\vec{x}, s) - g(\vec{x}, s) \right| P(ds) \right\|_{\infty, \mathbb{R}^N} \leq \gamma_{j1}^{(\mathcal{R})}. \quad (128)$$

Proof. Since $\|g\|_{\infty, \mathbb{R}^N, X} < \infty$, then

$$\begin{aligned} \left| n^N \int_{\frac{\vec{k}}{n}}^{\frac{\vec{k}+1}{n}} g(\vec{t}, s) d\vec{t} - g(\vec{x}, s) \right| &= \left| n^N \int_{\frac{\vec{k}}{n}}^{\frac{\vec{k}+1}{n}} (g(\vec{t}, s) - g(\vec{x}, s)) d\vec{t} \right| \leq \\ &n^N \int_{\frac{\vec{k}}{n}}^{\frac{\vec{k}+1}{n}} |g(\vec{t}, s) - g(\vec{x}, s)| d\vec{t} \leq 2 \|g\|_{\infty, \mathbb{R}^N, X} < \infty. \end{aligned} \quad (129)$$

Hence

$$\int_X \left| n^N \int_{\frac{\vec{k}}{n}}^{\frac{\vec{k}+1}{n}} g(\vec{t}, s) d\vec{t} - g(\vec{x}, s) \right| P(ds) \leq 2 \|g\|_{\infty, \mathbb{R}^N, X} < \infty. \quad (130)$$

We observe that

$$\begin{aligned} &\left({}_j C_n^{(\mathcal{R})}(g) \right) (\vec{x}, s) - g(\vec{x}, s) = \\ &\sum_{\vec{k}=-\infty}^{\infty} \left(n^N \int_{\frac{\vec{k}}{n}}^{\frac{\vec{k}+1}{n}} g(\vec{t}, s) d\vec{t} \right) Z_j(n\vec{x} - \vec{k}) - g(\vec{x}, s) = \\ &\sum_{\vec{k}=-\infty}^{\infty} \left(n^N \int_{\frac{\vec{k}}{n}}^{\frac{\vec{k}+1}{n}} g(\vec{t}, s) d\vec{t} \right) Z_j(n\vec{x} - \vec{k}) - g(\vec{x}, s) \sum_{\vec{k}=-\infty}^{\infty} Z_j(n\vec{x} - \vec{k}) = \\ &\sum_{\vec{k}=-\infty}^{\infty} \left[\left(n^N \int_{\frac{\vec{k}}{n}}^{\frac{\vec{k}+1}{n}} g(\vec{t}, s) d\vec{t} \right) - g(\vec{x}, s) \right] Z_j(n\vec{x} - \vec{k}) = \\ &\sum_{\vec{k}=-\infty}^{\infty} \left[n^N \int_{\frac{\vec{k}}{n}}^{\frac{\vec{k}+1}{n}} (g(\vec{t}, s) - g(\vec{x}, s)) d\vec{t} \right] Z_j(n\vec{x} - \vec{k}). \end{aligned} \quad (131)$$

However it holds

$$\sum_{\vec{k}=-\infty}^{\infty} \left[n^N \int_{\frac{\vec{k}}{n}}^{\frac{\vec{k}+1}{n}} |g(\vec{t}, s) - g(\vec{x}, s)| d\vec{t} \right] Z_j(n\vec{x} - \vec{k}) \leq 2 \|g\|_{\infty, \mathbb{R}^N, X} < \infty. \quad (132)$$

Hence

$$\begin{aligned} &\left| \left({}_j C_n^{(\mathcal{R})}(g) \right) (\vec{x}, s) - g(\vec{x}, s) \right| \leq \\ &\sum_{\vec{k}=-\infty}^{\infty} \left[n^N \int_{\frac{\vec{k}}{n}}^{\frac{\vec{k}+1}{n}} |g(\vec{t}, s) - g(\vec{x}, s)| d\vec{t} \right] Z_j(n\vec{x} - \vec{k}) = \end{aligned} \quad (133)$$

$$\begin{aligned}
& \sum_{\substack{\vec{k}=-\infty \\ \|\frac{\vec{k}}{n}-\vec{x}\|_\infty \leq \frac{1}{n^\beta}}}^{\infty} \left[n^N \int_{\frac{\vec{k}}{n}}^{\frac{\vec{k}+1}{n}} |g(\vec{t}, s) - g(\vec{x}, s)| d\vec{t} \right] Z_j(n\vec{x} - \vec{k}) + \quad (134) \\
& \sum_{\substack{\vec{k}=-\infty \\ \|\frac{\vec{k}}{n}-\vec{x}\|_\infty > \frac{1}{n^\beta}}}^{\infty} \left[n^N \int_{\frac{\vec{k}}{n}}^{\frac{\vec{k}+1}{n}} |g(\vec{t}, s) - g(\vec{x}, s)| d\vec{t} \right] Z_j(n\vec{x} - \vec{k}) = \\
& \sum_{\substack{\vec{k}=-\infty \\ \|\frac{\vec{k}}{n}-\vec{x}\|_\infty \leq \frac{1}{n^\beta}}}^{\infty} \left[n^N \int_0^{\frac{1}{n}} \left| g\left(\vec{t} + \frac{\vec{k}}{n}, s\right) - g(\vec{x}, s) \right| d\vec{t} \right] Z_j(n\vec{x} - \vec{k}) + \\
& \sum_{\substack{\vec{k}=-\infty \\ \|\frac{\vec{k}}{n}-\vec{x}\|_\infty > \frac{1}{n^\beta}}}^{\infty} \left[n^N \int_0^{\frac{1}{n}} \left| g\left(\vec{t} + \frac{\vec{k}}{n}, s\right) - g(\vec{x}, s) \right| d\vec{t} \right] Z_j(n\vec{x} - \vec{k}). \quad (135)
\end{aligned}$$

Furthermore it holds

$$\begin{aligned}
& \left(\int_X \left| ({}_j C_n^{(\mathcal{R})}(g))(\vec{x}, s) - g(\vec{x}, s) \right| P(ds) \right) \stackrel{\leq}{\text{(by Fubini's theorem)}} \\
& \sum_{\substack{\vec{k}=-\infty \\ \|\frac{\vec{k}}{n}-\vec{x}\|_\infty \leq \frac{1}{n^\beta}}}^{\infty} \left[n^N \int_0^{\frac{1}{n}} \left(\int_X \left| g\left(\vec{t} + \frac{\vec{k}}{n}, s\right) - g(\vec{x}, s) \right| P(ds) \right) d\vec{t} \right] Z_j(n\vec{x} - \vec{k}) + \\
& \sum_{\substack{\vec{k}=-\infty \\ \|\frac{\vec{k}}{n}-\vec{x}\|_\infty > \frac{1}{n^\beta}}}^{\infty} \left[n^N \int_0^{\frac{1}{n}} \left(\int_X \left| g\left(\vec{t} + \frac{\vec{k}}{n}, s\right) - g(\vec{x}, s) \right| P(ds) \right) d\vec{t} \right] Z_j(n\vec{x} - \vec{k}) \leq \\
& \Omega_1 \left(g, \frac{1}{n} + \frac{1}{n^\beta} \right)_{L^1} + 2 \|g\|_{\infty, \mathbb{R}^N, X} \sum_{\substack{\vec{k}=-\infty \\ \|\frac{\vec{k}}{n}-\vec{x}\|_\infty > \frac{1}{n^\beta}}}^{\infty} Z_j(n\vec{x} - \vec{k}) \leq \\
& \Omega_1 \left(g, \frac{1}{n} + \frac{1}{n^\beta} \right)_{L^1} + 2c_j(\beta, n) \|g\|_{\infty, \mathbb{R}^N, X}, \quad (137)
\end{aligned}$$

proving the claim. ■

Conclusion 47 *By Theorem 46 we obtain pointwise and uniform convergences with rates in the 1-mean of random operators ${}_j C_n^{(\mathcal{R})}$ to the unit operator for $g \in C_{\mathcal{R}}^{U_1}(\mathbb{R}^N)$, $j = 1, 2, 3, 4$.*

IV) 1-mean Approximation by Stochastic arctangent, algebraic, Gudermannian and generalized symmetric activation functions based multivariate quadrature type neural network operator

Let $g \in C_{\mathcal{R}}^{U_1}(\mathbb{R}^N)$, $0 < \beta < 1$, $\vec{x} \in \mathbb{R}^N$, $n, N \in \mathbb{N}$, with $\|g\|_{\infty, \mathbb{R}^N, X} < \infty$, (X, \mathcal{B}, P) probability space, $s \in X$, $j = 1, 2, 3, 4$.

We define

$${}_j D_n^{(\mathcal{R})}(g)(\vec{x}, s) := \sum_{\vec{k}=-\infty}^{\infty} (\delta_{n\vec{k}}(g))(s) Z_j(n\vec{x} - \vec{k}), \quad (138)$$

where

$$(\delta_{n\vec{k}}(g))(s) := \sum_{\vec{r}=0}^{\vec{\theta}} w_{\vec{r}} g\left(\frac{\vec{k}}{n} + \frac{\vec{r}}{n\theta}, s\right), \quad (139)$$

(see also (92), (93)).

We finally give

Theorem 48 Let $g \in C_{\mathcal{R}}^{U_1}(\mathbb{R}^N)$, $0 < \beta < 1$, $\vec{x} \in \mathbb{R}^N$, $n, N \in \mathbb{N}$, with $n^{1-\beta} > 2$; $j = 1, 2, 3, 4$, $\|g\|_{\infty, \mathbb{R}^N, X} < \infty$. Then

1)

$$\int_X \left| ({}_j D_n^{(\mathcal{R})}(g))(\vec{x}, s) - g(\vec{x}, s) \right| P(ds) \leq \left\{ \Omega_1 \left(g, \frac{1}{n} + \frac{1}{n^\beta} \right)_{L^1} + 2c_j(\beta, n) \|g\|_{\infty, \mathbb{R}^N, X} \right\} =: \gamma_{j1}^{(\mathcal{R})}, \quad (140)$$

2)

$$\left\| \int_X \left| ({}_j D_n^{(\mathcal{R})}(g))(\vec{x}, s) - g(\vec{x}, s) \right| P(ds) \right\|_{\infty, \mathbb{R}^N} \leq \gamma_{j1}^{(\mathcal{R})}. \quad (141)$$

Proof. Notice that

$$\begin{aligned} & |(\delta_{n\vec{k}}(g))(s) - g(\vec{x}, s)| = \\ & \left| \sum_{\vec{r}=0}^{\vec{\theta}} w_{\vec{r}} \left(g\left(\frac{\vec{k}}{n} + \frac{\vec{r}}{n\theta}, s\right) - g(\vec{x}, s) \right) \right| \leq \\ & \sum_{\vec{r}=0}^{\vec{\theta}} w_{\vec{r}} \left| g\left(\frac{\vec{k}}{n} + \frac{\vec{r}}{n\theta}, s\right) - g(\vec{x}, s) \right| \leq 2 \|g\|_{\infty, \mathbb{R}^N, X} < \infty. \end{aligned} \quad (142)$$

Hence

$$\int_X |(\delta_{n\vec{k}}(g))(s) - g(\vec{x}, s)| P(ds) \leq 2 \|g\|_{\infty, \mathbb{R}^N, X} < \infty. \quad (143)$$

We observe that

$$({}_j D_n^{(\mathcal{R})}(g))(\vec{x}, s) - g(\vec{x}, s) =$$

$$\begin{aligned}
& \sum_{\vec{k}=-\infty}^{\infty} (\delta_{n\vec{k}}(g))(s) Z_j(n\vec{x} - \vec{k}) - g(\vec{x}, s) = \\
& \sum_{\vec{k}=-\infty}^{\infty} ((\delta_{n\vec{k}}(g))(s) - g(\vec{x}, s)) Z_j(n\vec{x} - \vec{k}). \tag{144}
\end{aligned}$$

Thus

$$\begin{aligned}
& \left| {}_j D_n^{(\mathcal{R})}(g)(\vec{x}, s) - g(\vec{x}, s) \right| \leq \\
& \sum_{\vec{k}=-\infty}^{\infty} |(\delta_{n\vec{k}}(g))(s) - g(\vec{x}, s)| Z_j(n\vec{x} - \vec{k}) \leq 2 \|g\|_{\infty, \mathbb{R}^N, X} < \infty. \tag{145}
\end{aligned}$$

Hence it holds

$$\begin{aligned}
& \left| ({}_j D_n^{(\mathcal{R})}(g))(\vec{x}, s) - g(\vec{x}, s) \right| \leq \\
& \sum_{\vec{k}=-\infty}^{\infty} |(\delta_{n\vec{k}}(g))(s) - g(\vec{x}, s)| Z_j(n\vec{x} - \vec{k}) = \\
& \sum_{\vec{k}=-\infty}^{\infty} |(\delta_{n\vec{k}}(g))(s) - g(\vec{x}, s)| Z_j(n\vec{x} - \vec{k}) + \\
& \left\| \frac{\vec{k}}{n} - \vec{x} \right\|_{\infty} \leq \frac{1}{n^\beta} \\
& \sum_{\vec{k}=-\infty}^{\infty} |(\delta_{n\vec{k}}(g))(s) - g(\vec{x}, s)| Z_j(n\vec{x} - \vec{k}). \tag{146} \\
& \left\| \frac{\vec{k}}{n} - \vec{x} \right\|_{\infty} > \frac{1}{n^\beta}
\end{aligned}$$

Furthermore we derive

$$\begin{aligned}
& \left(\int_X |({}_j D_n^{(\mathcal{R})}(g))(\vec{x}, s) - g(\vec{x}, s)| P(ds) \right) \leq \\
& \sum_{\substack{\vec{k}=-\infty \\ \left\| \frac{\vec{k}}{n} - \vec{x} \right\|_{\infty} \leq \frac{1}{n^\beta}}}^{\infty} \sum_{\vec{r}=0}^{\vec{\theta}} w_{\vec{r}} \left(\int_X \left| g\left(\frac{\vec{k}}{n} + \frac{\vec{r}}{n\vec{\theta}}, s\right) - g(\vec{x}, s) \right| P(ds) \right) Z_j(n\vec{x} - \vec{k}) \tag{147}
\end{aligned}$$

$$\begin{aligned}
& + \left(\sum_{\substack{\vec{k}=-\infty \\ \left\| \frac{\vec{k}}{n} - \vec{x} \right\|_{\infty} > \frac{1}{n^\beta}}}^{\infty} Z_j(n\vec{x} - \vec{k}) \right) 2 \|g\|_{\infty, \mathbb{R}^N, X} \leq \\
& \Omega_1 \left(g, \frac{1}{n} + \frac{1}{n^\beta} \right)_{L^1} + 2c_j(\beta, n) \|g\|_{\infty, \mathbb{R}^N, X}, \tag{148}
\end{aligned}$$

proving the claim. ■

Conclusion 49 *From Theorem 48 we obtain pointwise and uniform convergences with rates in the 1-mean of random operators ${}_jD_n^{(\mathcal{R})}$ to the unit operator for $g \in C_{\mathcal{R}}^{U_1}(\mathbb{R}^N)$, $j = 1, 2, 3, 4$.*

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