



Multivariate Fuzzy-Random and Stochastic Arctangent, Algebraic, Gudermannian and Generalized Symmetric Activation Functions Induced Neural Network Approximations

George A. Anastassiou^(✉)

Department of Mathematical Sciences, University of Memphis,
Memphis, TN 38152, USA
ganastss@memphis.edu

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.

Keywords: Fuzzy-Random analysis · Fuzzy-Random neural networks and operators · Fuzzy-Random modulus of continuity · Fuzzy-Random functions · Stochastic processes · Jackson type fuzzy and probabilistic inequalities

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

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

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

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 1 (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 3 (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 2 (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 3 (see [30], p. 655). Fuzzy-random functions that coincide with probability one for each $t \in T$ will be considered equivalent.

Remark 4 (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 4 (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 5 [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 1 [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 2 [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 6 (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 5, just replace D by $|\cdot|$, etc. We denote it as $f \in C_{\mathbb{R}}^{U_q}(W)$.

Similar properties as in Propositions 1, 2 are valid for $\Omega_1(f, \delta)_{L^q}$.

Also we have

Proposition 3 [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 7. 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 1 (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 4 [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 5. 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

$$\psi_1(0) = \frac{1}{\pi} \arctan \frac{\pi}{2} \cong 0.319. \quad (10)$$

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

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

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 $\psi_1(0) \cong 0.319$.

We need

Theorem 2 ([19], p. 286). *We have that*

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

Theorem 3 ([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 4 ([19], p. 288). *Let $0 < \alpha < 1$, and $n \in \mathbb{N}$ with $n^{1-\alpha} > 2$. It holds*

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

Denote by $\lfloor \cdot \rfloor$ the integral part of the number and by $\lceil \cdot \rceil$ the ceiling of the number.

We need

Theorem 5 ([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*

$$\frac{1}{\sum_{k=\lceil na \rceil}^{\lfloor nb \rfloor} \psi_1(nx - k)} < \frac{1}{\psi_1(1)} \cong \mathbf{4.9737} =: \alpha_1, \forall x \in [a, b]. \quad (17)$$

Note 1 ([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 2, 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) $Z_1(x) > 0, \forall x \in \mathbb{R}^N$,
- (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 $k := (k_1, \dots, k_n) \in \mathbb{Z}^N, \forall x \in \mathbb{R}^N$,

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

$$\sum_{k=-\infty}^{\infty} Z_1(nx - k) < \frac{2}{\pi^2(n^{1-\beta} - 2)} = c_1(\beta, n), \quad (24)$$

$$\left\{ \left\| \frac{k}{n} - x \right\|_{\infty} > \frac{1}{n^{\beta}} \right.$$

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

(vi) By Theorem 5 we get that

$$0 < \frac{1}{\sum_{k=\lceil na \rceil}^{\lfloor nb \rfloor} Z_1(nx - k)} < \frac{1}{(\psi_1(1))^N} \cong (4.9737)^N =: \gamma_1(N), \quad (25)$$

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

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

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

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

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

We need

Theorem 6 [20]. *We have that*

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

Theorem 7 [20]. *It holds*

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

Theorem 8 [20]. *Let $0 < \alpha < 1$, and $n \in \mathbb{N}$ with $n^{1-\alpha} > 2$. It holds*

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

We need

Theorem 9 [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 2. 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

$$\sum_{k=-\infty}^{\infty} Z_2(nx - k) < \frac{1}{4m(n^{1-\beta} - 2)^{2m}} = c_2(\beta, n), \quad (44)$$

$$\left\{ \begin{array}{l} k = -\infty \\ \left\| \frac{k}{n} - x \right\|_{\infty} > \frac{1}{n^{\beta}} \end{array} \right.$$

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

(vi) By Theorem 9 we get that

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

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

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

$$f(x) := \frac{2}{\pi} \sigma(x) = \frac{2}{\pi} \int_0^x \frac{dt}{\cosh t} = \frac{4}{\pi} \int_0^x \frac{1}{e^t + e^{-t}} dt, \quad x \in \mathbb{R}. \quad (48)$$

Here

$$f'(x) = \frac{2}{\pi \cosh x} > 0, \quad \forall x \in \mathbb{R},$$

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

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

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

$$\psi_3(0) = \frac{1}{\pi}gd(1) \cong 0.2757. \tag{52}$$

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

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

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 10 [21]. *It holds that*

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

Theorem 11 [21]. *We have that*

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

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

Theorem 12 [21]. *Let $0 < \alpha < 1$, and $n \in \mathbb{N}$ with $n^{1-\alpha} > 2$. It holds*

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

Theorem 13 [21]. *Let $[a, b] \subset \mathbb{R}$ and $n \in \mathbb{N}$, so that $\lceil na \rceil \leq \lfloor nb \rfloor$. It holds*

$$\frac{1}{\sum_{k=\lceil na \rceil}^{\lfloor nb \rfloor} \psi_3(nx - k)} < \frac{2\pi}{gd(2)} \cong 4.824 =: \alpha_3, \tag{57}$$

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

We make

Remark 5 [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) $Z_3(x) > 0, \quad \forall x \in \mathbb{R}^N,$
 (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 $k := (k_1, \dots, k_n) \in \mathbb{Z}^N, \quad \forall x \in \mathbb{R}^N,$

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

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

$$\left\{ \begin{array}{l} k = -\infty \\ \left\| \frac{k}{n} - x \right\|_{\infty} > \frac{1}{n^{\beta}} \end{array} \right.$$

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

(vi) By Theorem 13 we get that

$$0 < \frac{1}{\sum_{k=\lceil na \rceil}^{\lfloor nb \rfloor} Z_3(nx - k)} < \left(\frac{2\pi}{gd(2)} \right)^N \cong (4.824)^N =: \gamma_3(N), \quad (65)$$

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

Furthermore it holds

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

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

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

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 14 [22]. *It holds*

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

Theorem 15 [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 16 [22]. *Let $0 < \alpha < 1$, and $n \in \mathbb{N}$ with $n^{1-\alpha} > 2$. It holds*

$$\sum_{\substack{j = -\infty \\ : |nx - j| \geq n^{1-\alpha}}}^{\infty} \psi_4(nx - j) < \frac{1}{2\lambda(n^{1-\alpha} - 2)^\lambda} =: c_4(\alpha, n), \quad (78)$$

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

We also need

Theorem 17 [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 6 [22]. (1) We have that

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

(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

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

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

(vi) By Theorem 17 we get that

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

$\forall x \in \left(\prod_{i=1}^N [a_i, b_i]\right), n \in \mathbb{N}, \lambda$ 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 ($j = 1, 2, 3, 4$)

$${}_j C_n(f, x) := {}_j C_n(f, x_1, \dots, x_N) := \sum_{k=-\infty}^{\infty} \left(n^N \int_{\frac{k}{n}}^{\frac{k+1}{n}} f(t) dt \right) Z_j(nx - k) := \quad (91)$$

$$\sum_{k_1=-\infty}^{\infty} \sum_{k_2=-\infty}^{\infty} \dots \sum_{k_N=-\infty}^{\infty} \left(n^N \int_{\frac{k_1}{n}}^{\frac{k_1+1}{n}} \int_{\frac{k_2}{n}}^{\frac{k_2+1}{n}} \dots \int_{\frac{k_N}{n}}^{\frac{k_N+1}{n}} f(t_1, \dots, t_N) dt_1 \dots dt_N \right)$$

$$\cdot \left(\prod_{i=1}^N \psi_j(nx_i - k_i) \right),$$

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

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

$$\sum_{\bar{r}=0}^{\theta} w_{\bar{r}} = \sum_{r_1=0}^{\theta_1} \sum_{r_2=0}^{\theta_2} \dots \sum_{r_N=0}^{\theta_N} w_{r_1, r_2, \dots, r_N} = 1; k \in \mathbb{Z}^N \text{ and}$$

$$\delta_{nk}(f) := \delta_{n, k_1, k_2, \dots, k_N}(f) := \sum_{\bar{r}=0}^{\theta} w_{\bar{r}} f\left(\frac{k}{n} + \frac{\bar{r}}{n\theta}\right) :=$$

$$\sum_{r_1=0}^{\theta_1} \sum_{r_2=0}^{\theta_2} \cdots \sum_{r_N=0}^{\theta_N} w_{r_1, r_2, \dots, r_N} f \left(\frac{k_1}{n} + \frac{r_1}{n\theta_1}, \frac{k_2}{n} + \frac{r_2}{n\theta_2}, \dots, \frac{k_N}{n} + \frac{r_N}{n\theta_N} \right), \quad (92)$$

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

$${}_j D_n(f, x) := {}_j D_n(f, x_1, \dots, x_N) := \sum_{k=-\infty}^{\infty} \delta_{nk}(f) Z_j(nx - k) := \quad (93)$$

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

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

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 18 (see [23–26]). *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 18 to the fuzzy-random level.

We mention

Theorem 19 (see [23–26]). *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)

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

2)

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

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

We also need

Theorem 20 (see [23–26]). 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)

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

2)

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

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

We also need

Theorem 21 (see [23–26]). 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)

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

2)

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

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

In this article we extend Theorems 19, 20, 21 to the random level.

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

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 Sects. 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 22. 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 $\int_X (D^*(f(\cdot, s), \tilde{\omega}))^q P(ds) < \infty$; $j = 1, 2, 3, 4$. Then

1)

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

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

2)

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

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

$$D \left(f \left(\frac{\vec{k}}{n}, s \right), f(\vec{x}, s) \right) \leq D \left(f \left(\frac{\vec{k}}{n}, s \right), \tilde{\omega} \right) + D(f(\vec{x}, s), \tilde{\omega}) \quad (107)$$

$$\leq 2D^*(f(\cdot, s), \tilde{o}).$$

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

$$D(({}_jA_n^{\mathcal{FR}}(f))(\vec{x}, s), f(\vec{x}, s)) = \quad (110)$$

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

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

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

So that

$$D(({}_jA_n^{\mathcal{FR}}(f))(\vec{x}, s), f(\vec{x}, s)) \leq$$

$$\sum_{\vec{k}=\lceil na \rceil}^{\lfloor nb \rfloor} \left(\frac{Z_j(nx-k)}{\sum_{\vec{k}=\lceil na \rceil}^{\lfloor nb \rfloor} Z_j(nx-k)} \right) D \left(f \left(\frac{\vec{k}}{n}, s \right), f(\vec{x}, s) \right) = \quad (113)$$

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

Hence it holds

$$\left(\int_X D^q \left(({}_j A_n^{\mathcal{FR}}(f))(\vec{x}, s), f(\vec{x}, s) \right) P(ds) \right)^{\frac{1}{q}} \leq \quad (114)$$

$$\begin{aligned} & \sum_{\substack{\vec{k}=\lceil na \rceil \\ \|\frac{\vec{k}}{n}-\vec{x}\|_\infty \leq \frac{1}{n^\beta}}}^{\lfloor nb \rfloor} \left(\frac{Z_j(nx-k)}{\sum_{\vec{k}=\lceil na \rceil}^{\lfloor nb \rfloor} Z_j(nx-k)} \right) \left(\int_X D^q \left(f \left(\frac{\vec{k}}{n}, s \right), f(\vec{x}, s) \right) P(ds) \right)^{\frac{1}{q}} + \\ & \sum_{\substack{\vec{k}=\lceil na \rceil \\ \|\frac{\vec{k}}{n}-\vec{x}\|_\infty > \frac{1}{n^\beta}}}^{\lfloor nb \rfloor} \left(\frac{Z_j(nx-k)}{\sum_{\vec{k}=\lceil na \rceil}^{\lfloor nb \rfloor} Z_j(nx-k)} \right) \left(\int_X D^q \left(f \left(\frac{\vec{k}}{n}, s \right), f(\vec{x}, s) \right) P(ds) \right)^{\frac{1}{q}} \leq \\ & \left(\frac{1}{\sum_{\vec{k}=\lceil na \rceil}^{\lfloor nb \rfloor} Z_j(nx-k)} \right) \cdot \left\{ \Omega_1^{(\mathcal{F})} \left(f, \frac{1}{n^\beta} \right)_{L^q} + \right. \quad (115) \\ & \left. 2 \left(\int_X (D^*(f(\cdot, s), \tilde{o}))^q P(ds) \right)^{\frac{1}{q}} \left(\sum_{\substack{\vec{k}=\lceil na \rceil \\ \|\frac{\vec{k}}{n}-\vec{x}\|_\infty > \frac{1}{n^\beta}}}^{\lfloor nb \rfloor} Z_j(nx-k) \right) \right\} \end{aligned}$$

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

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

We have proved claim.

Conclusion 6. By Theorem 22 we obtain the pointwise and uniform convergences with rates in the q -mean and D -metric of the operator ${}_jA_n^{\mathcal{FR}}$ to the unit operator for $f \in C_{\mathcal{FR}}^{Uq} \left(\prod_{i=1}^N [a_i, b_i] \right)$, $j = 1, 2, 3, 4$.

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

Let $g \in C_{\mathcal{R}}^{U1}(\mathbb{R}^N)$, $0 < \beta < 1$, $\vec{x} \in \mathbb{R}^N$, $n, N \in \mathbb{N}$, with $\|g\|_{\infty, \mathbb{R}^N, X} < \infty$, (X, \mathcal{B}, P) probability space, $s \in X$.

We define

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

(see also (90)).

We give

Theorem 23. Let $g \in C_{\mathcal{R}}^{U1}(\mathbb{R}^N)$, $0 < \beta < 1$, $\vec{x} \in \mathbb{R}^N$, $n, N \in \mathbb{N}$, with $n^{1-\beta} > 2$, $\|g\|_{\infty, \mathbb{R}^N, X} < \infty$; $j = 1, 2, 3, 4$. Then

1)

$$\int_X \left| ({}_jB_n^{(\mathcal{R})}(g))(\vec{x}, s) - g(\vec{x}, s) \right| P(ds) \leq \left\{ \Omega_1 \left(g, \frac{1}{n^\beta} \right)_{L^1} + 2c_j(\beta, n) \|g\|_{\infty, \mathbb{R}^N, X} \right\} =: \mu_{j1}^{(\mathcal{R})}, \quad (118)$$

2)

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

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

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

$$\left(\sum_{\vec{k}=-\infty}^{\infty} g\left(\frac{\vec{k}}{n}, s\right) - g(\vec{x}, s) \right) Z_j(nx - k).$$

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

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

Furthermore it holds

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

proving the claim.

Conclusion 7. *By Theorem 23 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 24. *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)

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

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

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

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

However it holds

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

Hence

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

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

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

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

Furthermore it holds

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

proving the claim.

Conclusion 8. *By Theorem 24 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

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

where

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

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

We finally give

Theorem 25. *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)

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

2)

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

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

$$\begin{aligned} & \left({}_j D_n^{(\mathcal{R})} (g) \right) (\vec{x}, s) - g(\vec{x}, s) = \\ & \sum_{\vec{k}=-\infty}^{\infty} (\delta_{n \vec{k}} (g)) (s) Z_j (n\vec{x} - \vec{k}) - g(\vec{x}, s) = \\ & \sum_{\vec{k}=-\infty}^{\infty} ((\delta_{n \vec{k}} (g)) (s) - g(\vec{x}, s)) Z_j (n\vec{x} - \vec{k}). \end{aligned} \quad (144)$$

Thus

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

Hence it holds

$$\begin{aligned} & \left| \left({}_j D_n^{(\mathcal{R})} (g) \right) (\vec{x}, s) - g(\vec{x}, s) \right| \leq \\ & \sum_{\vec{k}=-\infty}^{\infty} |(\delta_{n \vec{k}} (g)) (s) - g(\vec{x}, s)| Z_j (n\vec{x} - \vec{k}) = \end{aligned}$$

$$\sum_{\vec{k}=-\infty}^{\infty} |(\delta_{n\vec{k}}(g))(s) - g(\vec{x}, s)| Z_j(n\vec{x} - \vec{k}) + \sum_{\substack{\vec{k}=-\infty \\ \|\frac{\vec{k}}{n} - \vec{x}\|_{\infty} \leq \frac{1}{n^{\beta}}} }^{\infty} |(\delta_{n\vec{k}}(g))(s) - g(\vec{x}, s)| Z_j(n\vec{x} - \vec{k}). \tag{146}$$

Furthermore we derive

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

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

proving the claim.

Conclusion 9. From Theorem 25 we obtain pointwise and uniform convergences with rates in the 1-mean of random operators ${}_j D_n^{(\mathcal{R})}$ to the unit operator for $g \in C_{\mathcal{R}}^{U_1}(\mathbb{R}^N)$, $j = 1, 2, 3, 4$.

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