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Constructive Approach of Neural Network Approximation of Trigonometric Activation Function

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Abstract: There are many uses for approximation using neural networks including astronomy, image processing and robots, this is due to its ease of use in approximation.

INTRODUCTION

In recent years, many researchers have studied the issue of approximation using neural networks. There have been many research papers on the possibility of approximation using neural networks which we call density problem. For more you can read[1-7]. All researchers in this research focused on estimating the degree of approximation of neural networks. The more complex issue is complexity problem how to determine the number of neurons necessary for the appropriate approximation. Research has been conducted to study the relationship between the degree of approximation and the counting of neurons in the hidden layer of the neural network. From this study, article[8] which developed a work of[2] and gave a way to find a neural network with a single hidden layer using the step function in the neurons and presented a direct theorem about the error of the best approximation. By[9] studied approximation using neural networks in sigmoidal activation function where he presented a direct theorem for approximation using neural networks whose inputs were real numbers using step functions. There have recently presented important facts about the L_p, p<1 approximation for more read[10-15], they studied the approximation using neural networks of functions in smooth classes and of error rate c/n where the number of neurons in the hidden layer.

In this study, we presented direct estimates of the upper bound for the degree of approximation using feed forward neural networks with one hidden layer and linear output. That is we have studied the complex problem of neural networks approximation which made us present a upper bound approximation method and identified the number of neurons in the hidden layer and that in terms of the first order modulus of smoothness for functions in the L_p spaces, it mean, we present a kind of Jackson's approximation-theorem. The rth symmetric difference of f along direction h is given by Johnen and Scherer[16].

$$\Delta_h^{(r)} f(x) = \sum_{i=0}^{r} \binom{r}{i} (-1)^i f(x+(\frac{r}{2}-i)h)$$

In terms of $\Delta_h^r f(.)$ the r-th modulus of smoothness of f is defined by Johnen and Scherer[16]:

$$\omega_r(f, t)_p = \sup_{0<\|h\|\le t} \|\Delta_h^{(r)} f(.)\|_p$$

The main results: In this section, we introduce our main results begin with:

Theorem 2.1: Let $\varnothing$ is bounded, monotone and odd trigonometric real function. If $f \in L_p[a, b]$ then for any natural number $n \in \mathbb{N}$ there exists one hidden layer neural network satisfies:

$$\|N_n(x) - f(x)\|_p \le c(p)\omega(f, \delta)_p$$

Proof: Define N_n: $[a, b] \to \mathbb{R}$, as:

$$N_n(x) = c_o + \sum_{i=1}^{n} c_i \varnothing(w_i x + \theta_i)$$

where parameters c_i's and w_i's are define as following:

$$c_o = f(a) - \sum_{i=1}^{n} c_i \varnothing(w_i a + \theta_i). \text{ For } 1 \le i \le n, \text{ we get}$$

$$c_i = \frac{1}{2m}(f(x_i) - f(x_{i-1})),\ w_i = \frac{2nd_n}{b-a},\ \theta_i = -\frac{nd_n}{b-a}(x_i + x_{i-1})$$

Define a partion for [a,b] consists of notes of length b-a/n as:

$$a = x_o < x_1 < x_2 <, ..., < x_n = b, \text{ let } m = \sup_{x \in R} \varnothing(x) \text{ and}$$
$$d_n = \varnothing^{-1}\left(m - \frac{m}{2n}\right)$$

According to the choice of c_o we have $N_n(a) = f(a)$. Also, we have $-m \le \varnothing(x) \le m$, for any real number x, we fix m. For any $x \in [a, b]$ there exists $j \in \mathbb{N}$ and $0 < j \le n$, such that $x \in [x_{j-1}, x_j]$ that note that:

$$N_n(x) = c_o + \sum_{i=1}^{n} c_i \varnothing(w_i x + \theta_i)$$

$$N_n(x) = f(a) - \sum_{i=1}^{n} c_i \varnothing(w_i a + \theta_i) + \sum_{i=1}^{n} c_i \varnothing(w_i x + \theta_i)$$

$$= f(a) + \sum_{i=1}^{n} c_i (\varnothing(w_i x + \theta_i) - \varnothing(w_i a + \theta_i))$$

$$= f(a) + \sum_{i=1}^{n} \frac{1}{2m}(f(x_i) - f(x_{i-1})(\varnothing(w_i x + \theta_i) - \varnothing(w_i a + \theta_i))$$

Suppose $E_i(x) = \varnothing(w_i x + \theta_i)$ then:

$$N_n(x) = f(a) + \sum_{i=1}^{n} \frac{1}{2m}(f(x_i) - f(x_{i-1}))(E_i(x) - E_i(a))$$

$$= f(a) + \sum_{i=1}^{j-1} \frac{1}{2m}(f(x_i) - f(x_{i-1}))(E_i(x) - E_i(a)) + \frac{1}{2m}$$
$$(f(x_j) - f(x_{j-1}))(E_j(x) - E_j(a)) + \sum_{i=j+1}^{n} \frac{1}{2m}$$
$$(f(x_i) - f(x_{i-1})(E_i(x) - E_i(a))$$

For $i>j$, we have $x \le x_j \le x_{i-1}$. So, the properties of $\varnothing$ give $0 < E_i(x) - E_i(a) \le E_i(x_j) - E_i(a) \le E_i(x_{i-1}) - E_i(a) \le E_i(x_{i-1}) - m = \varnothing(w_i x_{i-1} + \theta_i) + m = \varnothing(-d_n) + m = -\varnothing(\varnothing^{-1}(m - m/2n)) = m/2n$. So,

$$\sum_{i=j+1}^{n} \left\|\frac{1}{2m}(f(x_i) - f(x_{i-1})(E_i(x) - E_i(a))\right\|_p \le$$
$$\sum_{i=j+1}^{n} \left\|\frac{1}{2m}(f(x_i) - f(x_{i-1}))\right\|_p (E_i(x) - E_i(a)) \le$$
$$\sum_{i=j+1}^{n} \left\|\frac{1}{2m}(f(x_i) - f(x_{i-1}))\right\|_p \left(\frac{m}{2n}\right)$$

$$\le \frac{1}{2m}\left(\frac{m}{2n}\right) \sum_{i=j+1}^{n} \|(f(x_i) - f(x_{i-1}))\|_p$$

$$\le \frac{1}{4n} \sum_{i=j+1}^{n} \|(f(x_i) - f(x_{i-1}))\|_p$$

$$\le c(p)\omega\left(f, \frac{b-a}{n}\right)_p$$

$$\left\|\frac{1}{2m}(f(x_j) - f(x_{j-1}))(E_j(x) - E_j(a))\right\|_p \le \frac{1}{2m}\|f(x_j) - f$$
$$(x_{j-1})\|_p \left(\frac{m}{2n}\right) \le c(p)\omega\left(f, \frac{b-a}{n}\right)_p$$

And:

$$\sum_{i=1}^{j-1} \frac{1}{2m}(f(x_i) - f(x_{i-1})(E_i(x) - E_i(a)) = \frac{1}{2m}\sum_{i=1}^{j-1}(f(x_i) -$$
$$f(x_{i-1})E_i(x) - E_i(a) - 2m) + (f(x_{j-1}) - f(a))$$

For $1 \leq i < j$, we have $x_i \leq x_{j-1} \leq x$ and so, $2m \geq E_i(x)-E_i(a) > E_i(x_i)-E_i(x_{i-1}) = \varnothing(d_n)-\varnothing(-d_n) = 2m-m/n$ which implies $\|E_i(x)-E_i(a)-2m\|_p \leq m/n$. So:

$$N_n(x)-f(x_{j-1}) = \frac{1}{2m}\sum_{i=1}^{j-1}\big(f(x_i)-f(x_{i-1})\big(E_i(x)-E_i(a)-2m\big)+\frac{1}{2m}\big(f(x_j)-f(x_{j-1})\big)\Big(E_j(x)-E_j(a)+\sum_{i=j+1}^{n}\frac{1}{2m}f(x_i)-\big(f(x_{i-1})\big(E_i(x)-E_i(a)\big)\Big)$$

Consequently,

$$\|N_n(x)-f(x_{j-1})\|_p \leq c(p)\sum_{i=1}^{j-1}\frac{1}{2m}\big\|\big(f(x_i)-f(x_{i-1})(E_i(x)-E_i(a)-2m)+\frac{1}{2m}\big(f(x_j)-(x_{j-1})\big)\big(E_j(x)-E_j(a)\big)+\sum_{i=j+1}^{n}\frac{1}{2m}\big(f(x_i)-f(x_{i-1})\big(E_i(x)-E_i(a)\big)\big\|_p \leq \frac{c(p)}{2m}\omega\left(f, \frac{b-a}{n}\right)\sum_{i=1}^{j-1}\big\|\big(E_i(x)-E_i(a)-2m\big)\big\|_p+\frac{1}{2m}\big\|f(x_j)-f(x_{j-1})\big)\big(E_j(x)-E_j(a)\big\|_p+\left\|\sum_{i=j+1}^{n}\frac{1}{2m}\big(f(x_i)-f(x_{i-1})\big(E_i(x)-E_i(a)\big)\right\|_p \leq c(p)\omega\left(f, \frac{b-a}{n}\right)_p$$

Using the direct theorem:

$$\|f(x)-f(x_{j-1})\|_p \leq \omega\left(f, \frac{b-a}{n}\right)_p$$

We have:

$$\|N_n(x)-f(x)\|_p \leq \|N_n(x)-f(x_{j-1})\|_p+\|f(x)-f(x_{j-1})\|_p \leq c(p)\omega\left(f, \frac{b-a}{n}\right)_p$$

Theorem 2.2: Let $\varnothing$ is bounded, monotone and odd trigonometric real function. $f \in Lip(\alpha)$, $\alpha \in (0, 1)$ if and only if there is one hidden layer neural network N_n, satisfying:

$$\|N_n(x)-f(x)\|_p \leq c(p)(\delta)^{\alpha}$$

where, $\delta = \frac{b-a}{n}$.

Proof: Define $N_n:[a, b] \to \mathbb{R}$, as:

$$N_n(x) = c_0+\sum_{i=1}^{n}c_i\varnothing(w_i x+\theta_i)$$

where parameters c_i's and w_i's are define as following:

$$c_o = f(a)-\sum_{i=1}^{n}c_i\varnothing(w_i x+\theta_i)$$

For $1 \leq i \leq n$, we get:

$$c_i = \frac{1}{2m}\big(f(x_i)-f(x_{i-1})\big),\ w_i = \frac{2nd_n}{b-a},\ \theta_i = -\frac{nd_n}{b-a}(x_i+x_{i-1})$$

Let $m = \sup_{x\in\mathbb{R}}\varnothing(x)$ and $d_n = \varnothing^{-1}(m-m/2n)$.

Since, $f \in Lip(\alpha)_k$ then $\omega(f, \delta)_p = O(\delta)^{\alpha}$ $\|N_n(x)-f(x)\|_p = o(\delta^{\alpha})$

Let $f \in L^p_{2\pi}$, $0<p<1$, then $\|N_n(x)-f(x)\|_p \leq c(p)(\delta)^{\alpha}$.

We must prove that $f_i \in Lip(\alpha)_k$. Now, $\|EN_\lambda[f_i]-f_i\|_p \leq c(p)(\delta^{\alpha})$ and by using Theorem 2.1:

$$\|N_n(x)-f(x)\|_p \leq c(p)\omega(f, \delta)$$

Then:

$$c(p)\omega(f, \delta)_p \leq c(p)(\delta^{\alpha})$$

$$\omega(f, \delta)_p \leq 0(\delta^{\alpha})$$

Therefore, the definition of Lipschitian function is conclude we get.

Examples 3: In this section let us demonstrate our theorems.

Example 3.1; Cao *et al*.[15]: Let $f(x) = \sin x$, $x \in [0, \pi]$. Choose $\varnothing(x) = 2/\pi \tan^{-1}x$, $x \in \mathbb{R}$. It is clear $f \in Lip_1(1)$ and also we have $f(a) = f(0) = f(b) = 0$. Using the properties of the $\tan^{-1}x$, if $m = 1$, $\varnothing^{-1}(x) = \tan(\pi/2)\,x$ and $d_n = \tan(\pi/2(1-1/2n))$. So,

$$c_i = \frac{1}{2m}\big(f(x_i)-f(x_{i-1})\big)$$

$$c_i = \frac{1}{2}\left(\sin\frac{i\pi}{n}-\sin\frac{(i-1)\pi}{n}\right)$$

$$\theta_i = -\frac{nd_n}{b-a}\left(2a+(2i-1)\frac{b-a}{n}\right)$$

$$= \frac{-n\tan\left(\frac{\pi}{2}\left(1-\frac{1}{2n}\right)\right)}{\pi}(0+2i-1)\frac{\pi}{n}$$

$$= -\tan\left(\frac{\pi}{2}\left(1-\frac{1}{2n}\right)\right)(2i-1)$$

$$w_i = \frac{2nd_n}{b-a} = \frac{2n}{\pi}\tan\left(\frac{\pi}{2}\left(1-\frac{2}{2n}\right)\right)$$

$$c_o = f(a)-\sum_{i=1}^{n} c_i \varnothing(w_i a+\theta_i)$$

$$= 0-\sum_{i=1}^{n}\frac{1}{2}\left(\sin\frac{i\pi}{n}-\sin\frac{(i-1)\pi}{n}\right)\frac{2}{\pi}\arctan\left((1-2i)\tan\left(\frac{\pi}{2}\left(1-\frac{1}{2n}\right)\right)\right).$$

So, we can define the following neural network having one hidden layer and n neural:

$$N_n(x) = c_o+\sum_{i=1}^{n} c_i \varnothing(w_i x+\theta_i),\ x\in[0,\ \pi]$$

From Theorem 2.2, we get:

$$\|N_n(x)-\sin\ x\|_p \le c(p)\left(\frac{\pi}{n}\right)^{\alpha}$$

Example 3.2: If our target function is f(x) = cos x, $x\in[0, \pi]$ we choose the sigmoidal activation function $\varnothing(x) = 2/\pi \tan^{-1}x$, $x\in\mathbb{R}$. And f(a) = cos (0)= f(b) = cos(π) = 1, m = $\sup\varnothing^{-1}(x) = \tan(\pi/2)x$:

$$d_n = \tan\left(\frac{\pi}{2}\right)x\left(1-\frac{1}{2n}\right)$$

$$c_i = \frac{1}{2m}\left(f(x_i)-f(x_{i-1})\right)$$

$$= \frac{1}{2m}\left(\cos\frac{i\pi}{n}-\cos\frac{(i-1)\pi}{n}\right)$$

$$\theta_i = -\frac{nd_n}{b-a}\left(2a+(2i-1)\left(\frac{b-a}{n}\right)\right)$$

$$= \frac{-n\tan\left(\frac{\pi}{2}\right)\left(1-\frac{1}{2n}\right)}{\pi}\left(1+(2i-1)\frac{\pi}{n}\right.$$

$$= -\tan\left(\frac{\pi}{2}\left(1-\frac{1}{2n}\right)\right)(2i)$$

$$w_i = \frac{2nd_n}{b-a} = \frac{2n}{\pi}\tan\left(\frac{\pi}{2}\left(1-\frac{2}{2n}\right)\right)$$

$$c_0 = f(a)-\sum_{i=1}^{n} c_i \varnothing(w_i a+\theta_i)$$

$$= 1-\sum_{i=1}^{n}\frac{1}{2}\left(\cos\frac{i\pi}{n}-\cos\frac{(i-1)\pi}{n}\right)*\frac{2}{\pi}\arctan\left((1-2i)\tan\left(\frac{\pi}{2}\left(1-\frac{1}{2n}\right)\right)\right)$$

So, we can define the neural network approximate as:

$$N_n(x) = c_o+\sum_{i=1}^{n} c_i \varnothing(w_i x+\theta_i),\ x\in[0,\ \pi].$$

From Theorem 2.2. we get:

$$\|N_n(x)-\cos x\|_p \le c(p)(\frac{\pi}{n})a$$

CONCLUSION

The main aim of this study is to introduce a saturation problem for the approximation of function in $L_p, p<1$ quasi normed spaces using neural network with trigonometric activation function, in a constructive approach.

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