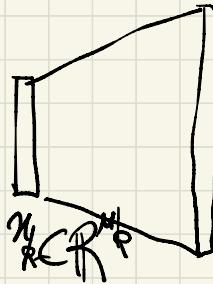
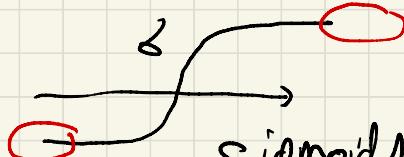


Recap : MLP

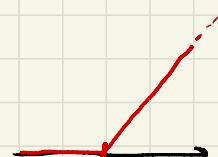


$$x_{k+1} = \sigma(W_k x_k + b_k)$$

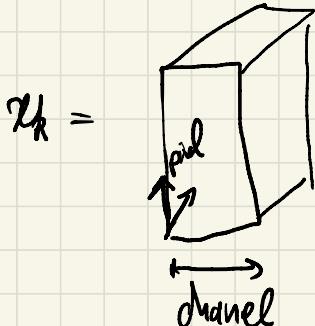


$$\Theta_k = (W_k, b_k)$$

$$\sigma(x) = \begin{cases} \text{Arctan}(x) & \sigma(x) = \text{Relu}(x) \\ \frac{e^x}{1+e^x} \end{cases}$$



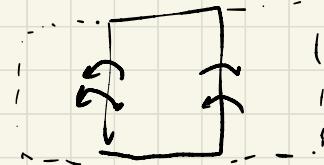
Design choices : "Weight sharing" → convolution
audio / image / video



$$w_k = \left(w_k^{[0, 0, \Delta]} \right)_{\Delta=1}^S$$

"Translation invariant operator \Leftrightarrow convolution"

$$T_T : x[\underline{\dots}, \underline{\dots}] \xrightarrow{\text{pixel channel}} u[-\tau_1, \dots -\tau_2, \dots]$$



Theorem: $W: x \in \mathbb{R}^{n \times n \times s} \rightarrow \mathbb{R}^{n \times n \times t}$

that commutes with transfo

$$W \circ T_T = T_T \circ W$$

$$\begin{matrix} n & \xrightarrow{W} & n \\ \downarrow T_T & & \uparrow T_T \\ \overline{W} & & \end{matrix}$$

so that

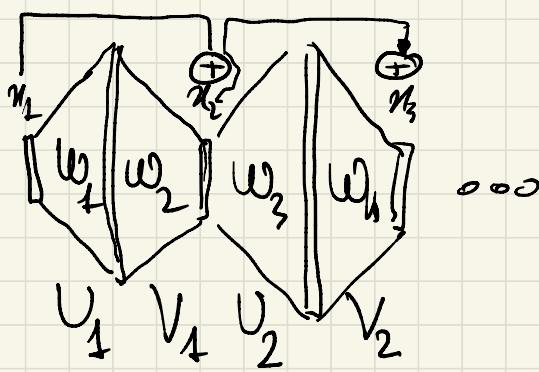
if and only if $\{\psi_{st}\}_{\substack{s=1 \dots s \\ t=1 \dots T}}$

$$Wn = \left(\sum_s \psi_{st} * x[\underline{\dots}, \underline{s}] \right)_t$$

Example: 1.1 conv

2nd design choice: skip connex

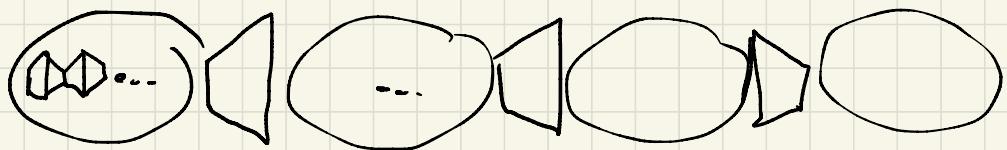
Res-Net



$$U_k = \boxed{\quad} \quad V_k = \boxed{\quad}$$

$$x_{k+1} = x_k + \sigma \left[V_k \circ [U_k x_k] \right]$$

↑
removed / batch norm



Generative net

U-Net → seqt. generative model

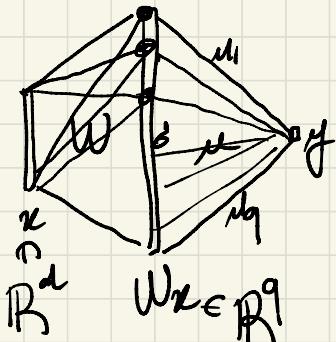
Transformers : convolut + nonlinearity → Attention

"Theory": Universality / Expressivity

2 layers NN

"Clear" single layer

$q = \# \text{neurons}$



$$y = \left\langle \underbrace{\begin{pmatrix} u_1 \\ u_2 \\ \vdots \\ u_q \end{pmatrix}}_{\in \mathbb{R}^q}, \sigma(Wx) \right\rangle$$

$$W = \begin{pmatrix} w_1 \\ w_2 \\ \vdots \\ w_q \end{pmatrix}$$

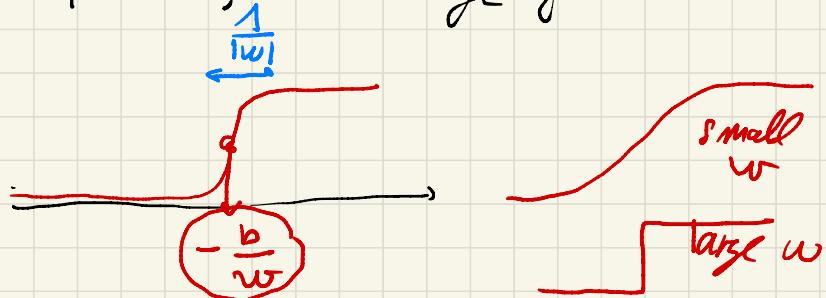
$$y = \sum_k u_k \sigma(\langle x, w_k \rangle + b_k)$$

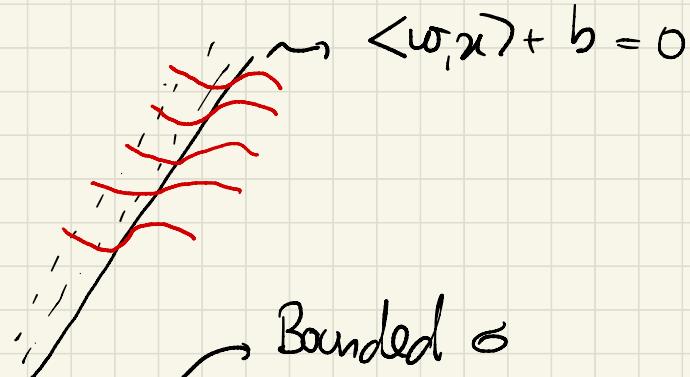
$$\varphi(x) = \sum_k u_k \varphi_{w_k, b_k}(x)$$

$$\varphi_{w, b}(x) = \sigma(\langle x, w \rangle + b)$$

"Ridge funct."

1-D

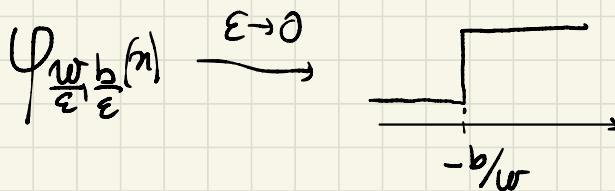




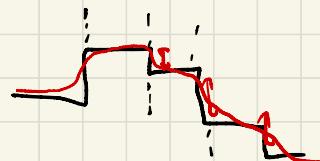
Thm: [Cybernetics] if $f(x)$ continuous, $\epsilon > 0$ precision,
 $R > 0$, $\exists q = \# \text{neurons}$, $\exists \frac{w}{\epsilon}, \frac{b}{\epsilon}$

such that, $\forall \|x\| \leq R$ $|f(x) - \sum_{k=1}^q u_k \varphi_{\frac{w_k}{\epsilon}, \frac{b_k}{\epsilon}}(x)| \leq \epsilon$

$\underbrace{\quad}_{\text{NN. } q \text{ neurons.}}$



$$\sum u_k \varphi_{\frac{w_k}{\epsilon}, \frac{b_k}{\epsilon}}(x)$$



Speed of approx: No free lunch

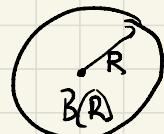
Barron's function: $\hat{f}(\omega) = \int f(x) \cdot e^{-i\langle \omega, x \rangle} dx$

Barron's norm: $\|f\|_B \triangleq \int \|w\| \cdot |\hat{f}(w)| dw$

Sobolev norm: $\|f\|_{W^2}^2 = \int \|w\|^2 \cdot \|\hat{f}(w)\|^2 dw$

$$\begin{aligned}\hat{f}'(\omega) &= i\omega \cdot \hat{f}(\omega) \\ &= \int \|\hat{f}'(w)\|^2 dw \\ &= \int |f'(x)|^2 dx = \|f'\|_{L^2}^2\end{aligned}$$

thm: If $\|f\|_B < +\infty$ then $\forall q > 0, \exists$ a neural net $f_q(x) = \sum_{k \in K} \varphi_{w_k b_k}(x)$, such that



$$\sqrt{\frac{1}{|B(R)|} \int_{B(0)} |f(x) - f_q(x)|^2 dx} \leq \frac{\|f\|_B}{\sqrt{q}} = \epsilon$$

↑
Loss

with pol.

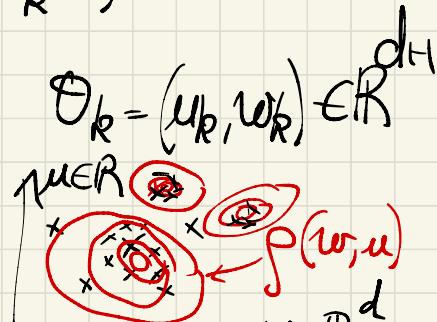
$$\frac{\|f\|_{\text{Lip}}}{q^{\frac{1}{2d}}} = \epsilon \quad \leftarrow \begin{matrix} \text{curse} \\ \text{of} \\ \text{the dim.} \end{matrix}$$

- ⊕ No curse of dim, explicit
- ⊖ 2 layers.
- ⊖ Existence, how to find f_q

Proof: mean field analysis

$$f_q(x) = \frac{1}{q} \sum_{k=1}^q u_k \sigma(\langle x, w_k \rangle)$$

$$\downarrow q \rightarrow +\infty$$



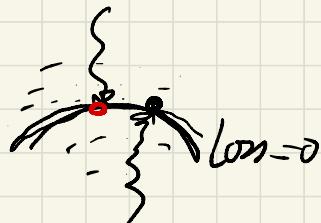
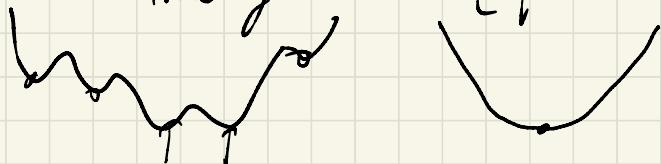
$$f_q(x) = \int u \sigma(\langle x, w \rangle) dp(w, u)$$

Difficult: $\|f\|_B < +\infty \Leftrightarrow \exists f, f = f^q$

Q^o: optimiz^o: chigat / Back.

if $q \rightarrow \infty$, GP on the loss

Q^o: How many neurons ($q=3$)

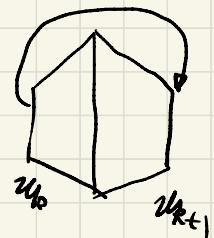


Q^o: Generaliz^o \rightarrow Implicit bias.

Deep & Wide ResNet

$$u_{k+1} \stackrel{\oplus}{=} u_k + \frac{1}{k} V_k \cdot \sigma(U_k u_k) \in \mathbb{R}^q.$$

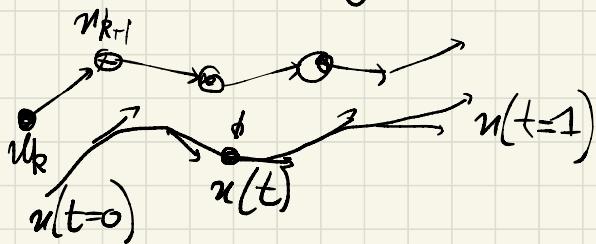
$k = 1 \dots (\textcircled{k})$
Depth



$\begin{cases} k = \text{depth} \\ q = \text{width} \end{cases} \rightarrow \infty$ mean field

$$\textcircled{*} \quad \frac{u_{k+1} - u_k}{1/k} = \nabla_{\theta_k}(u_k) \quad \Theta_k = (U_k, V_k)$$

$$V_\theta(u) = \cup_{\sigma} (V_\sigma)$$



" $k \rightarrow +\infty$ "

$$x(t) = \underbrace{\nabla}_{\Theta(t)}(x(t))$$

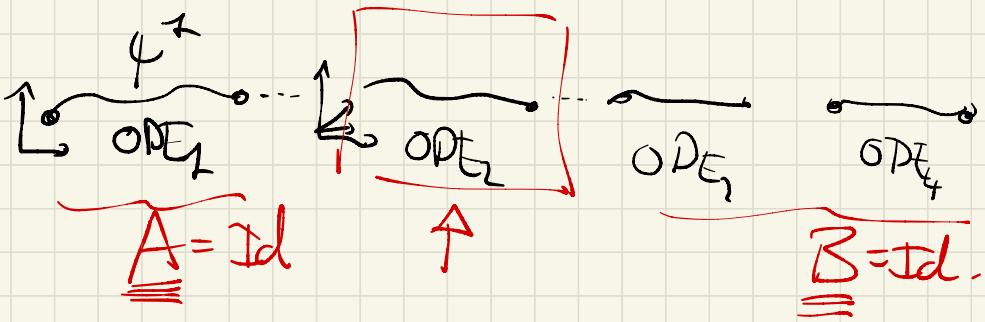
out: $x(1)$

$$u(t=0) = x_0$$

inf. depth limit: $\psi_\theta: x(0) \rightarrow x(1)$
 $\nwarrow ??$ learning ??

$$(x_i)_{i=1}^N \longrightarrow (y_i)_{i=1}^N$$

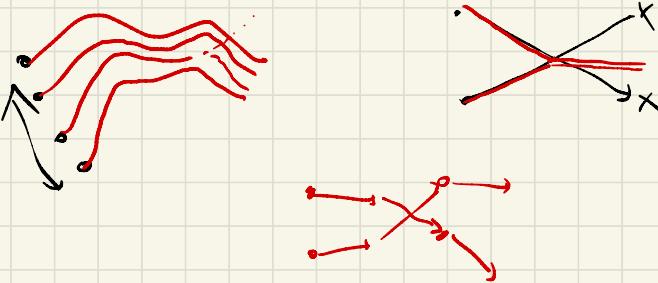
Learn: $\min_{\{\theta(t)\}_{t=0}^1} E(\theta) = \frac{1}{N} \sum_{i=1}^N \ell(\psi_\theta(u_i), y_i)$



Thm: Barani Neunps 2022

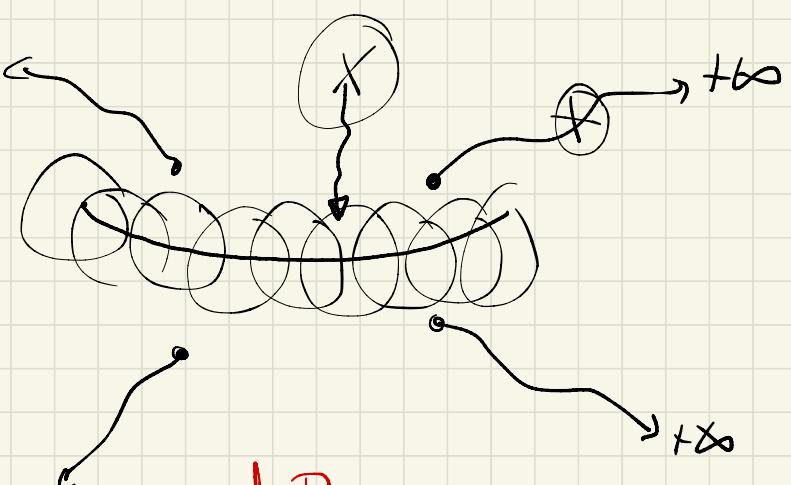
$$C(\theta) \|\nabla E(\theta)\|^2 \stackrel{(2)}{\leq} E(\theta) - E(\theta^*) \stackrel{(1)}{\leq} C(\|\theta\|) \cdot \|\nabla E(\theta)\|^2$$

↑
P-L
Polak - Šejnajevitch .



(1) \Rightarrow No loc. min. but $w \rightarrow +\infty$

(2) \Rightarrow if θ "close" to θ^* $w \cancel{\rightarrow} +\infty$



$$A \in \mathbb{R}^{d \times D}$$

D large enough

$$\overset{\circ}{x}_{k+1} = V_{\theta_k}(x_k)$$

$$x_k = (x_k^1, x_k^2, \dots, x_k^S)$$

↑ # of components

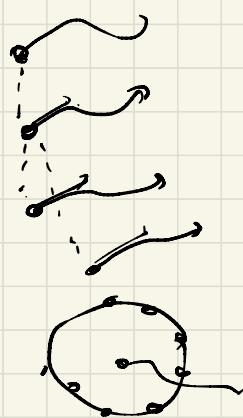
x_k^1 x_k^2 \dots
 \circ \circ \dots

$$x_{k+1} = x_k + \frac{1}{K} A_{\theta_k}(x_k)$$

$$\overset{\circ}{X}(t) = A_{\theta(t)}(x(t))$$

$$\dot{x}_i^{(t)} = V_{\theta(t)}(x_i^{(t)}, X(t))$$

$$x_i \rightarrow \frac{x_i - m_i}{\| \cdot \|}$$



$$v(\hat{x}^1; \hat{x}^2) = \sum_j A_{ij} \cdot (v_{x_j})$$

↙
 (K, Q, V)
 ↓
 $\sum_j A_{ij}$ Hand
 \approx_0

$$A_{ij} = e^{\langle K_i, Q_j \rangle}$$

