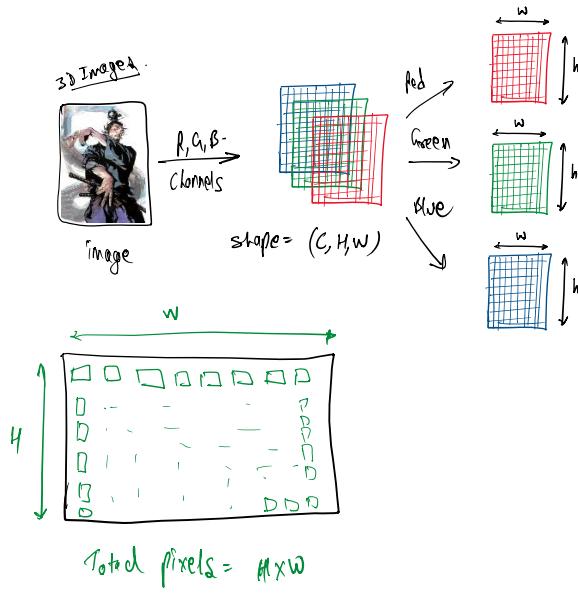


Understanding Images

26 December 2025 04:27 PM

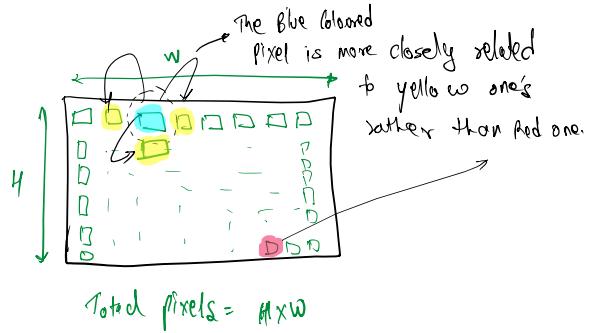
#Images
↳ A discrete sampling from a continuous radiance field

#Physical properties of Images



as locality

↳ nearby pixels matters more than distant ones



b> spatial feature.

↳ feature formed by neighbourhood pixels.

Conclusion :- for decoding the pattern in Images
we need to learn the nearby pixels rather than distant ones.

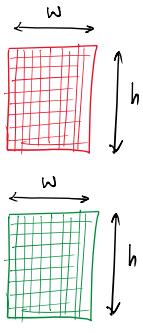
#Learning Patterns in Images

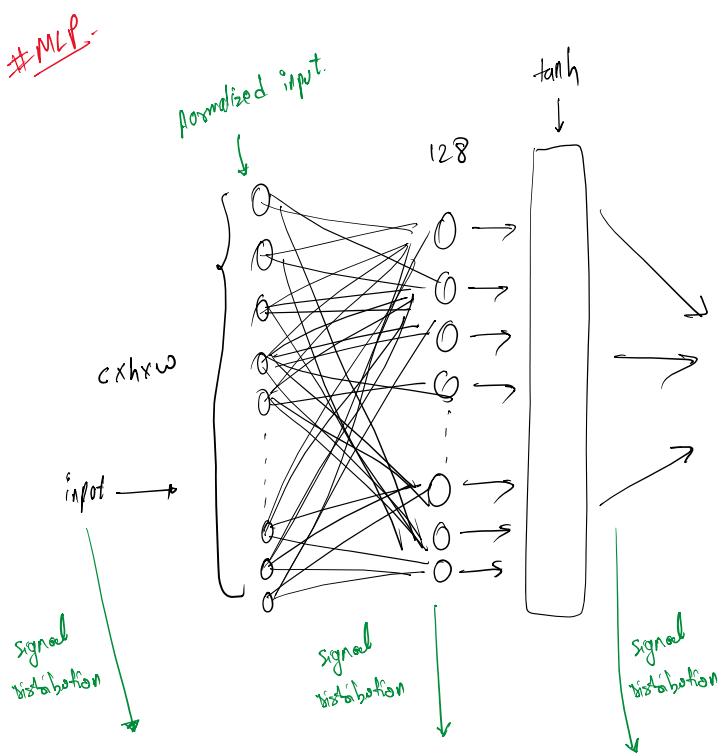
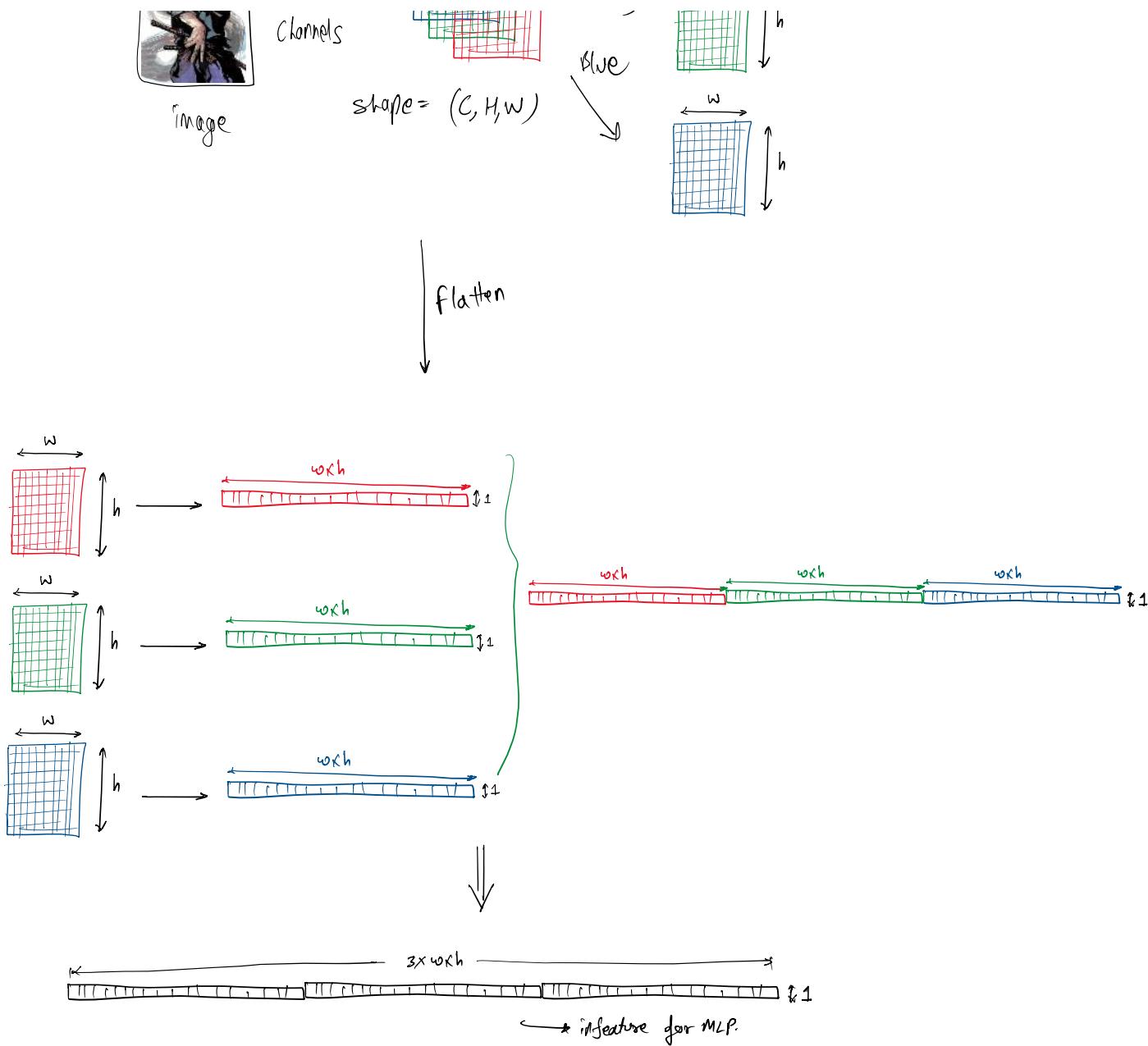
Before learning pattern in Images
let see how data/signal flows in MLP

3D Image



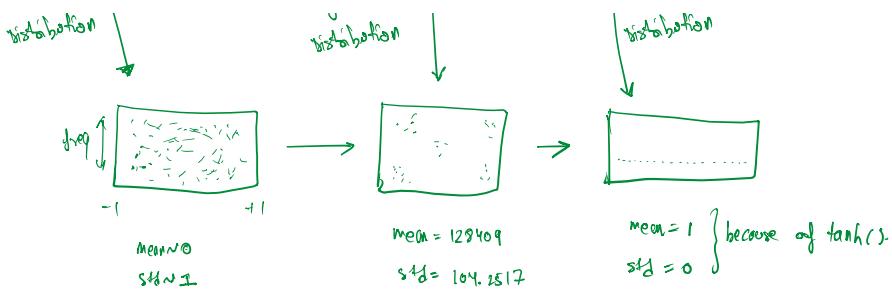
R, G, B -
Channels





#MLP

- Linear Layer :-** $y_i = \sum_{i=0}^n x_i w_i + b_i$
- Layer Norm :-** $x \leftarrow \frac{x - \bar{x}_{\text{mean}}}{\sqrt{\text{var} + \epsilon}}$
- Activation** $f(x) = \tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$



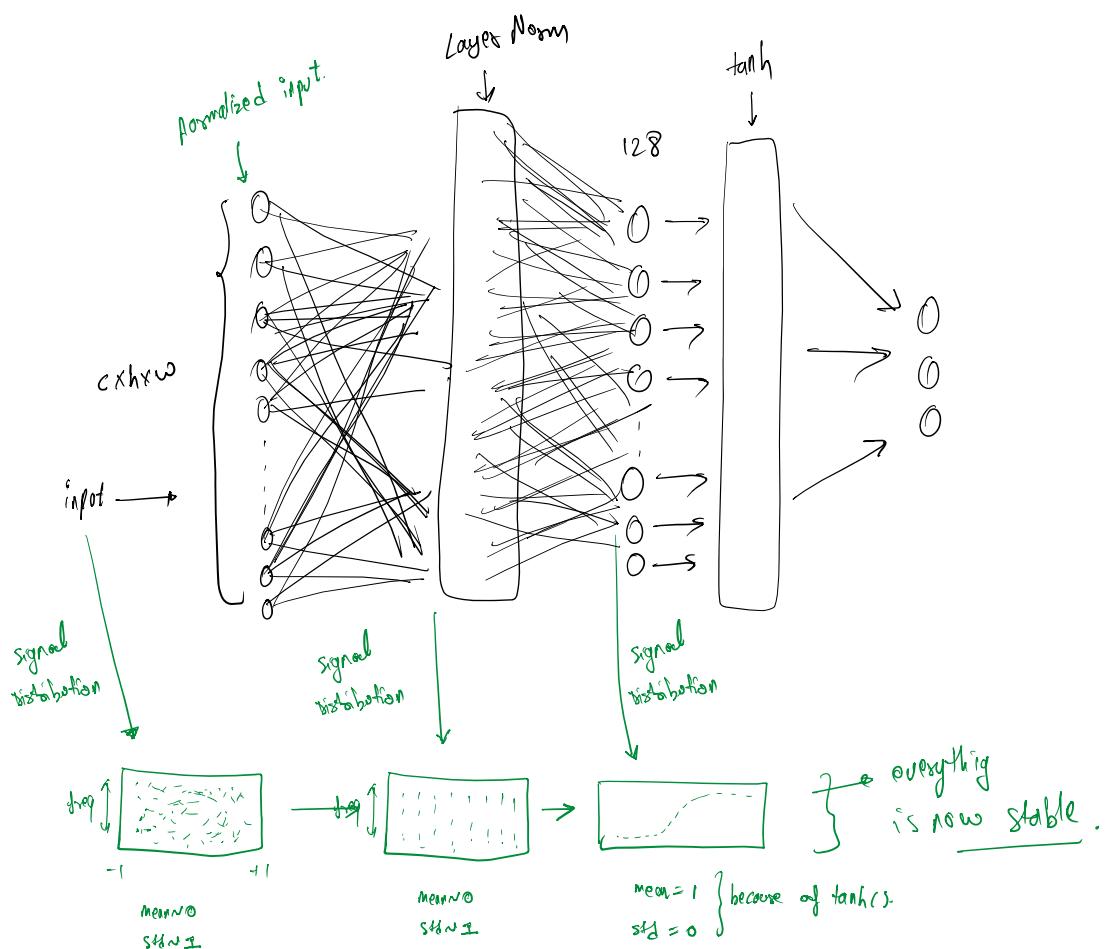
Problem :-

→ Data/Signal's distribution is always changing
and this is bad for Model.

Solution:-

- Layer Norm
- Xavier Initialization { weight Initialization methods }
- He Initialization

After Layer Norm and proper weight Initialization.



Implementation with MLP in Vision Modelling.

Problem with MLP in Vision Modelling

MLP Assumes :-

Every input dimension is independent from each other, and equally related to every other dimension.

example -

$$\mathbf{x} = [x_1, x_2, x_3, \dots, x_n]$$

for MLP
→ x_1 and x_3 are not dependent
→ all x_i are just a number and co-ordinate in a vector space.

but for images.

$$\mathbf{x} = [p_1, p_2, p_3, \dots, p_n]$$



Pixel-1 is closely related than Pixel-2

Images assumed

→ pixels are related (nearby)

→ MLP doesn't care about this.

All relationships must be learned

via data distribution and transformation in MLP.

Conclusion :-

→ MLP ignores Geometry
→ Images are Geometry

Mismatch → we can't use

MLP for understanding patterns in Images.