

## SETR paper Resume

→ segmentation has always been done using a FCN leveraging an encoder-decoder architecture. This approach was very successful, until it was clear that the bottleneck of the model was context in very precise segmentation tasks (self-driving, inventory...)

⇒ researchers tried to augment context by increasing receptive field, but receptive field increased linearly with  $\left[ \text{number of conv layers} \times \text{kernel size} \right]$

- increasing number of conv layers  $\Rightarrow$  more depth  $\Rightarrow$  more compute + risk of overfitting

- increasing kernel size  $\Rightarrow$  model can't be able to detect intricate details which is especially important in segmentation tasks, due to pixel-level labeling //

⇒ receptive field remains resolved  
w/ 1d Non

→ SETR comes to solve this receptive  
field problem with Transformer  
architecture which enables context  
to the fullest extent known now

3 main architectures proposed in the paper:

SETR

MLA

multi-level  
feature  
aggregation

SETR

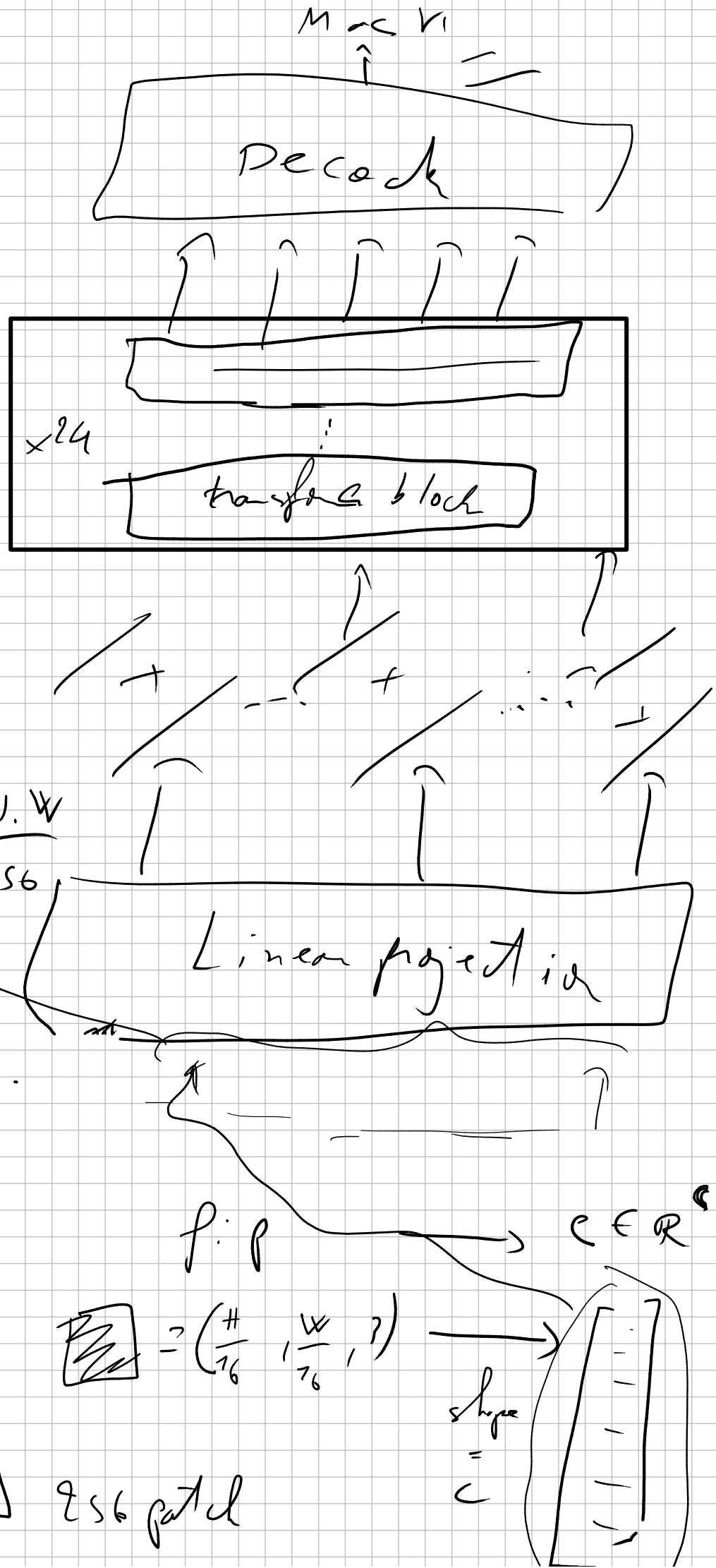
segmentation  
Transformer

SETR

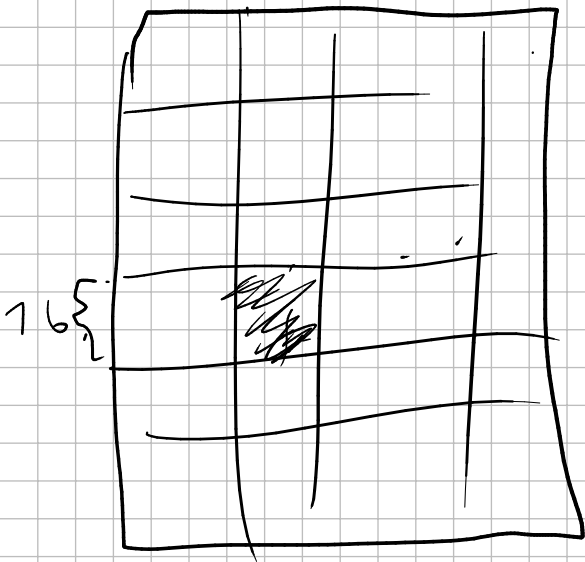
PUP

progressive  
upsampling

SFTR:

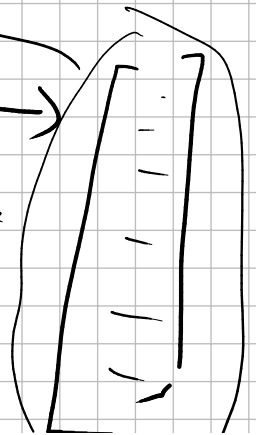


sequence length  $T = L = \frac{H \cdot W}{16 \cdot 16}$



256 patch

shape  
=



decoder design: 16

$$\text{decode input} = \left[ \begin{array}{c} \vdots \\ \vdots \end{array} \right], \left[ \begin{array}{c} \vdots \\ \vdots \end{array} \right], \dots$$

$\in \mathbb{R}^L$

$L \text{ data}$   
 $H.W = \text{data}$   
 $\frac{1}{256}$

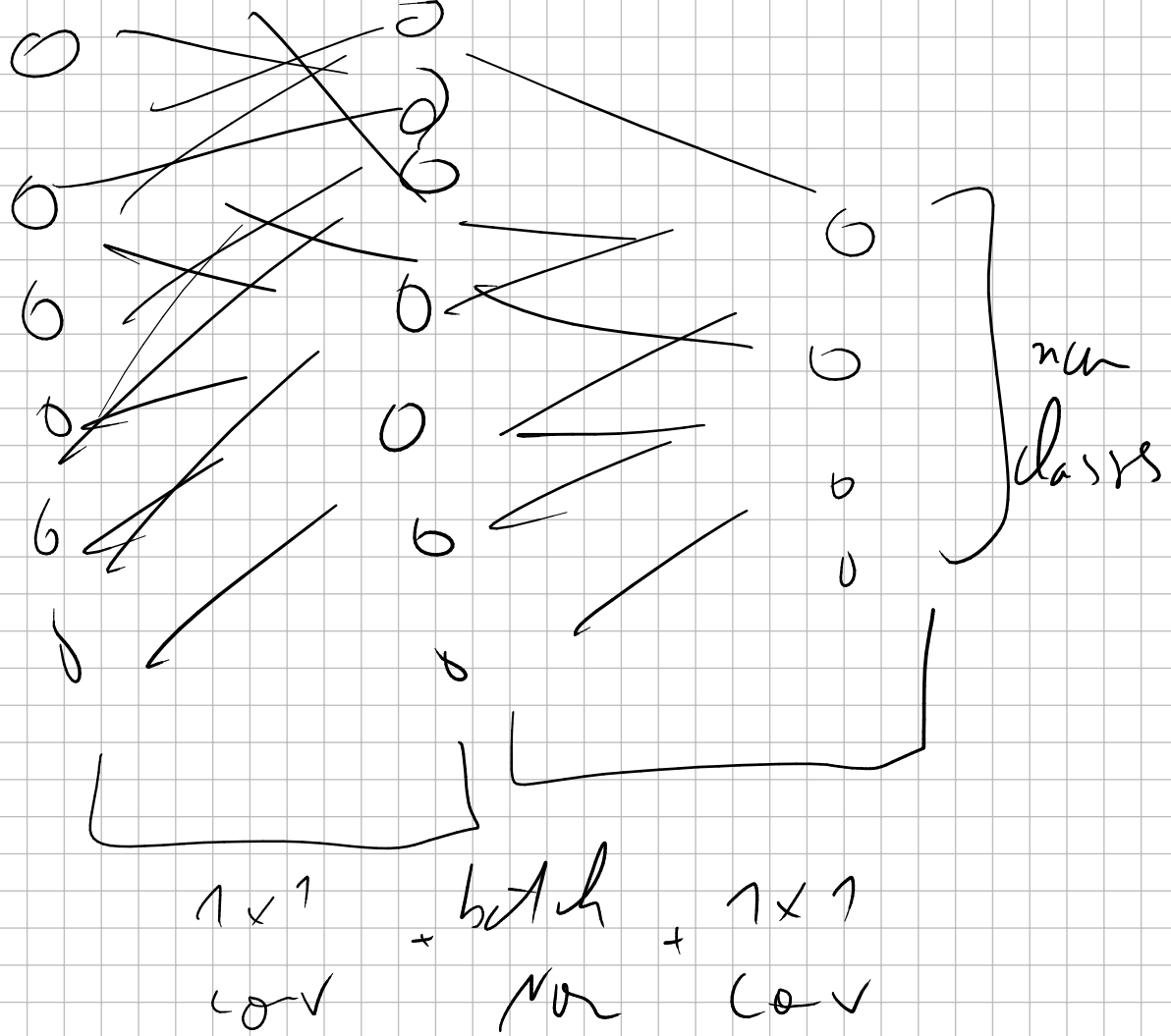
$$\text{decoder output} = \left[ \begin{array}{c} \otimes, \otimes, \dots \end{array} \right]$$

$\in \mathbb{R}^{\frac{H}{16} \times \frac{W}{16} \times C}$

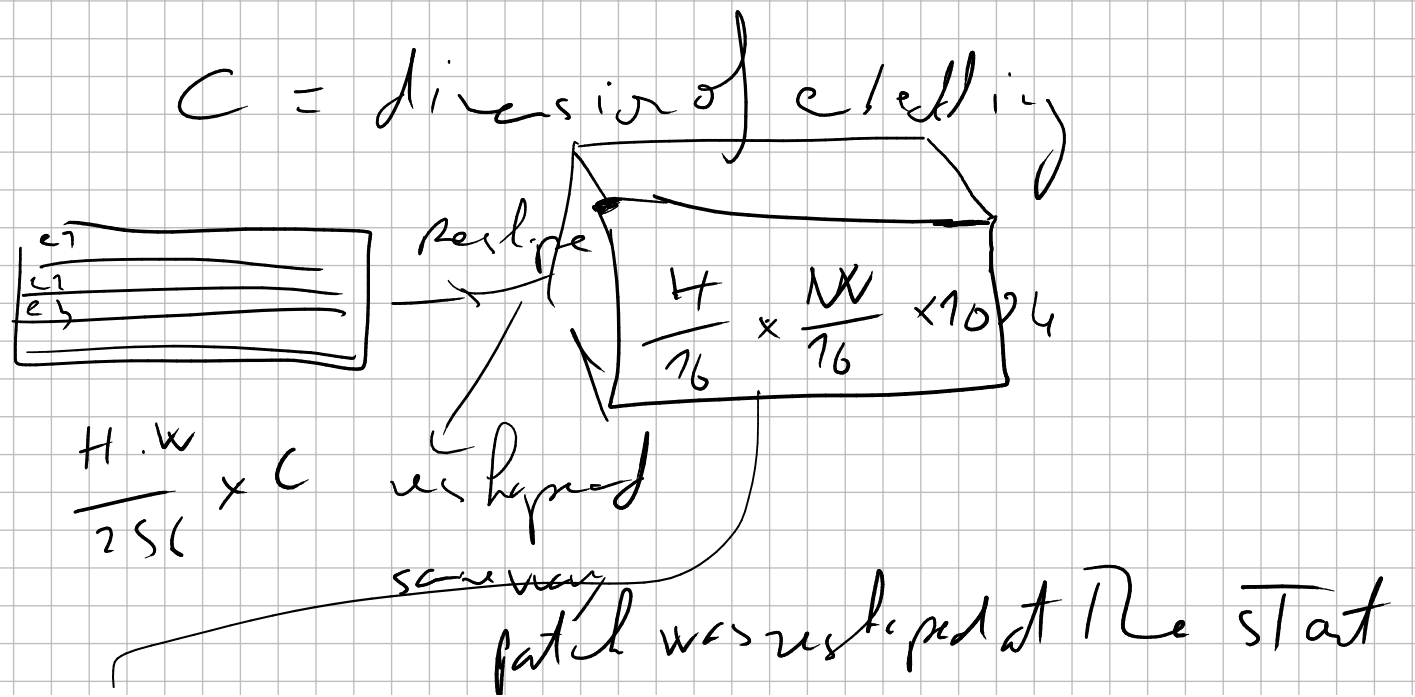
(1) Naive upsampling:

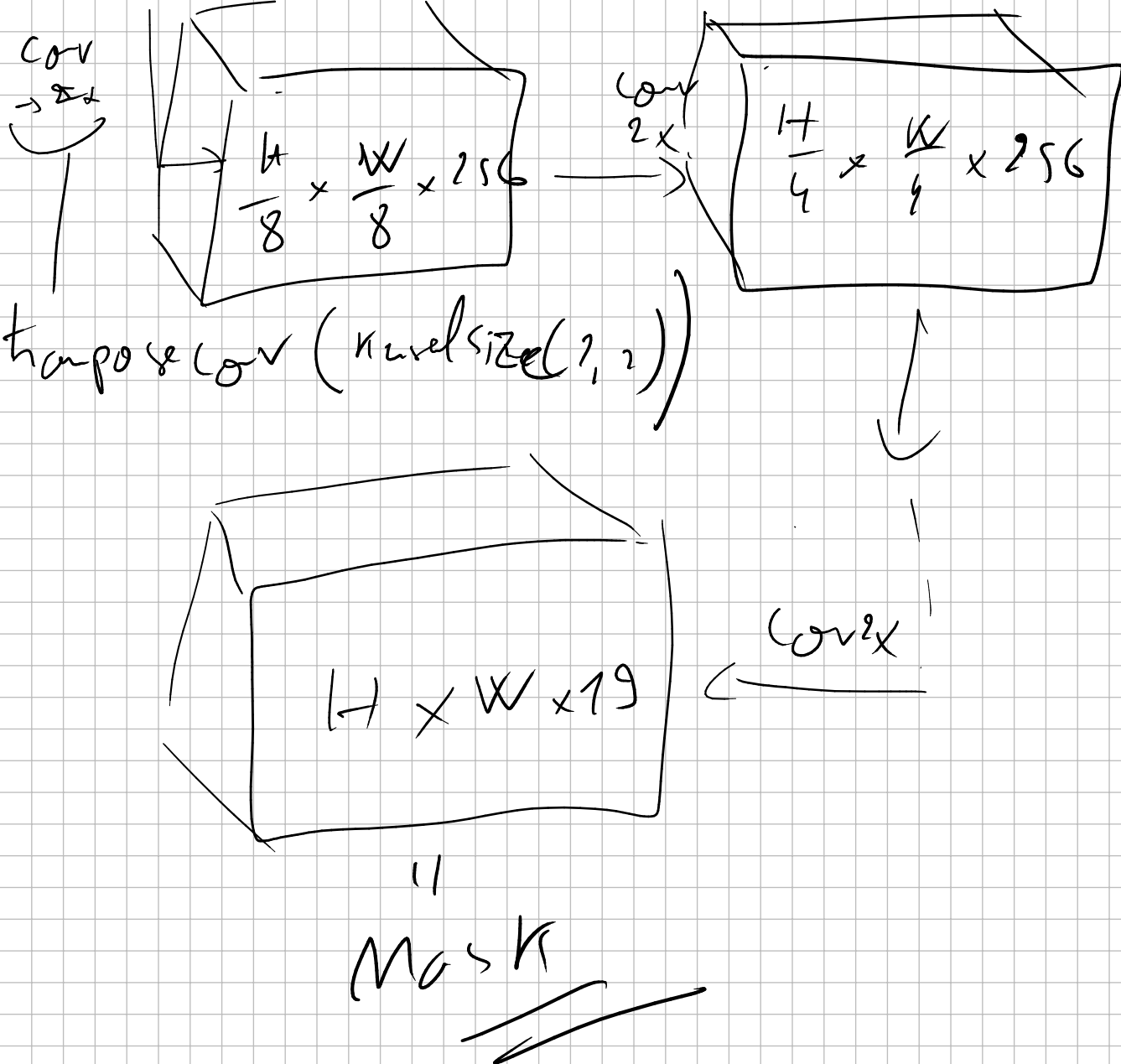
$$x \in \mathbb{R}^C \begin{Bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{Bmatrix} \Rightarrow \left[ \begin{array}{c} \boxed{\phantom{00000}} \end{array} \right] \times 2$$

1x1 + batch norm  
 conv  
 19 [inverted] places  
 1, 1, 1



(2) PUP: as  
 $\frac{H \cdot W}{256} = \text{number of cells} \rightarrow \text{input to decode}$





$\rightarrow$  we do this since one-step upscaling introduced in naive decoder might introduce noise as it might underfit

The scaling process

(1) SETR-PUP have more power than SETR-naive because of this deeper decoder

(3) MLA:

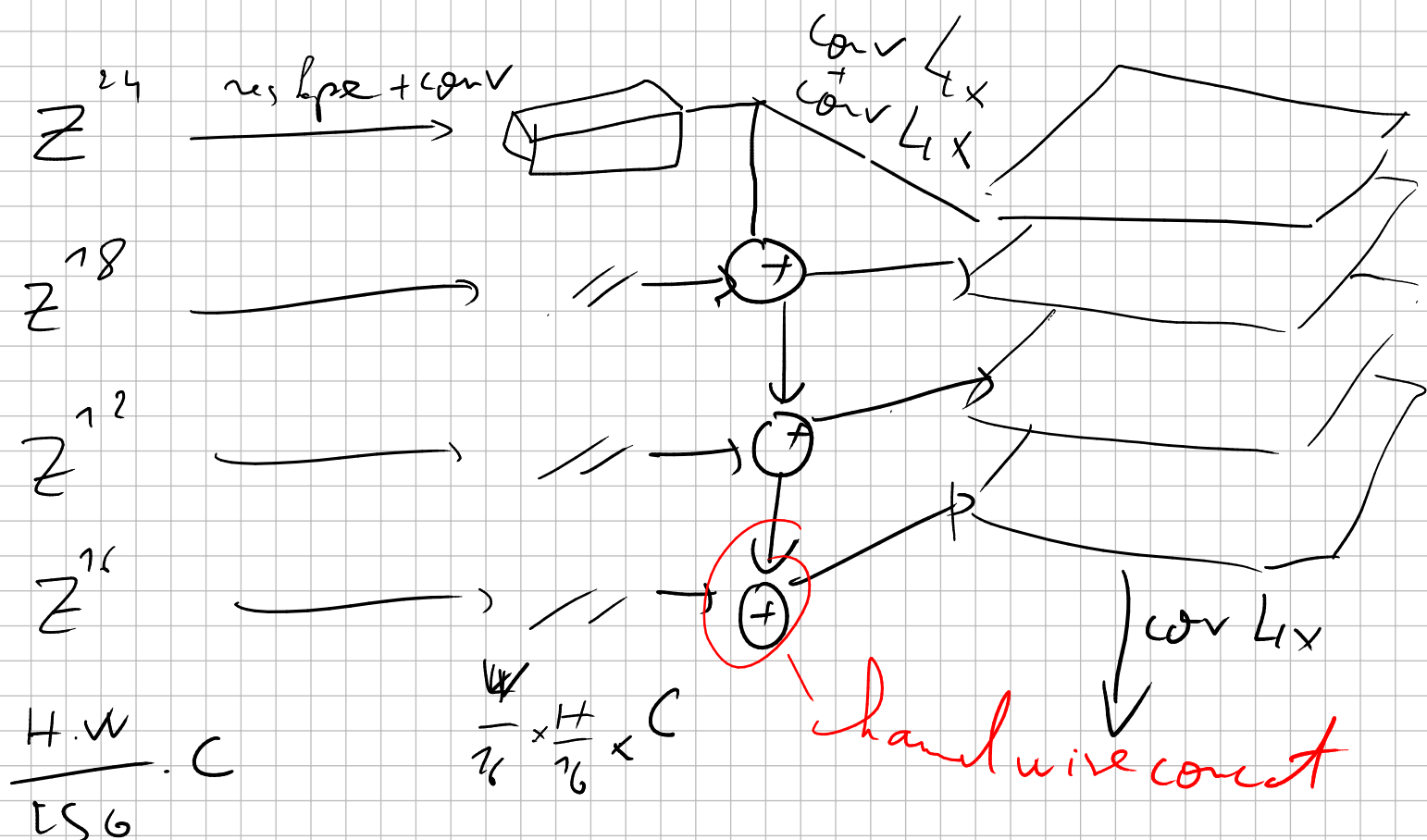
→ This decoder is even larger (Params++)

further proving scale MATTERS, as This

decoder outperformed (2) & (1)

→ Multi-level feature aggregation:

$Z^m$  = output of  $m^{\text{th}}$  Transformer block  
in The encode:  $(\frac{H \cdot W}{256}, C)$



⇒ we fuse all feature from the transformer layers

$\Rightarrow$  SETR-MLA

①  $\rho_{\text{res}}_{\text{MLA}} > \rho_{\text{res}}_{\text{PUP}} > \rho_{\text{res}}_{\text{Naive}}$

$\leftarrow$  scale

② in the paper VIT & DET

weights were used + embeddings

to make up for data-shortage

$\Rightarrow$  VIT: image understanding  
(log-size context)

fine-tuned for segmentation

Task using 3 different  
decoders



$\Rightarrow$  achieves  $\left\{ \begin{array}{l} \cdot \text{SOTA on } \underline{\text{Pascal}} \\ \cdot \text{competitive results on } \underline{\text{cityscapes}} \\ \cdot \text{1}^{\text{st}} \text{ on } \underline{\text{ADE 20K}} \end{array} \right.$