

Please use this report template, and upload it in the **PDF format**. Reports in other forms/formats will result in **ZERO point**. Reports written in either Chinese or English is acceptable. The length of your report should **NOT** exceed **6** pages (**excluding bonus**).

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1. (5%) Print the network architecture of your VGG16-FCN32s model.

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 512, 512, 3)	0
block1_conv1 (Conv2D)	(None, 512, 512, 64)	1792
block1_conv2 (Conv2D)	(None, 512, 512, 64)	36928
block1_pool (MaxPooling2D)	(None, 256, 256, 64)	0
block2_conv1 (Conv2D)	(None, 256, 256, 128)	73856
block2_conv2 (Conv2D)	(None, 256, 256, 128)	147584
block2_pool (MaxPooling2D)	(None, 128, 128, 128)	0
block3_conv1 (Conv2D)	(None, 128, 128, 256)	295168
block3_conv2 (Conv2D)	(None, 128, 128, 256)	590080
block3_conv3 (Conv2D)	(None, 128, 128, 256)	590080
block3_pool (MaxPooling2D)	(None, 64, 64, 256)	0
block4_conv1 (Conv2D)	(None, 64, 64, 512)	1180160
block4_conv2 (Conv2D)	(None, 64, 64, 512)	2359808
block4_conv3 (Conv2D)	(None, 64, 64, 512)	2359808
block4_pool (MaxPooling2D)	(None, 32, 32, 512)	0
block5_conv1 (Conv2D)	(None, 32, 32, 512)	2359808
block5_conv2 (Conv2D)	(None, 32, 32, 512)	2359808
block5_conv3 (Conv2D)	(None, 32, 32, 512)	2359808
block5_pool (MaxPooling2D)	(None, 16, 16, 512)	0
fc1 (Conv2D)	(None, 16, 16, 4096)	8392704
fc2 (Conv2D)	(None, 16, 16, 4096)	16781312
conv2d_1 (Conv2D)	(None, 16, 16, 7)	28679
conv2d_transpose_1 (Conv2DTr	(None, 512, 512, 7)	200704
Total params: 40,118,087		
Trainable params: 40,118,087		
Non-trainable params: 0		

2. (10%) Show the predicted segmentation mask of validation/0008\_sat.jpg, validation/0097\_sat.jpg, validation/0107\_sat.jpg during the early, middle, and the final stage during the training stage. (For example, results of 1st, 10th, 20th epoch)



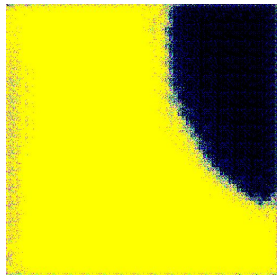
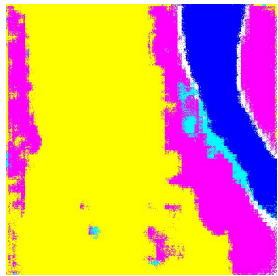

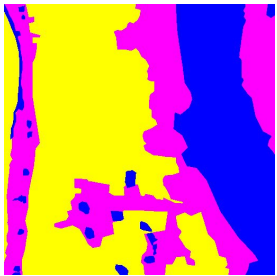
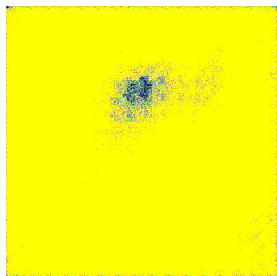
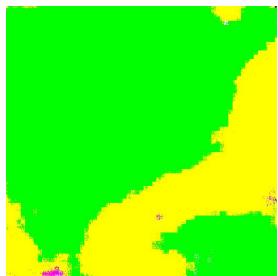

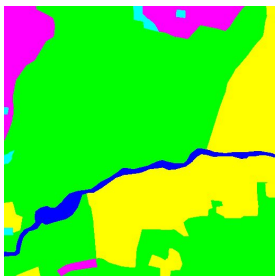
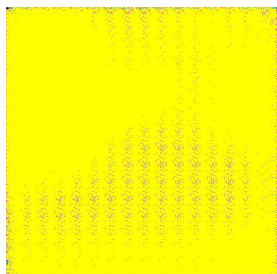

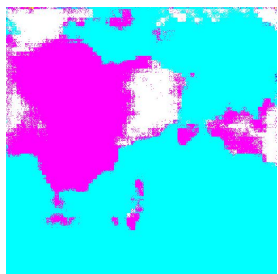
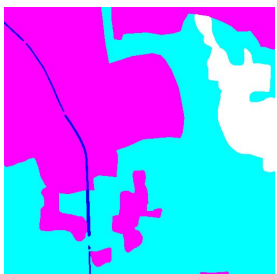
epoch 1	epoch 10	epoch 20	ground truth

3. (15%) Implement an improved model which performs better than your baseline model. Print the network architecture of this model.

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	(None, 512, 512, 3)	0	
block1_conv1 (Conv2D)	(None, 512, 512, 64)	1792	input_1[0][0]
block1_conv2 (Conv2D)	(None, 512, 512, 64)	36928	block1_conv1[0][0]
block1_pool (MaxPooling2D)	(None, 256, 256, 64)	0	block1_conv2[0][0]
block2_conv1 (Conv2D)	(None, 256, 256, 128)	73856	block1_pool[0][0]
block2_conv2 (Conv2D)	(None, 256, 256, 128)	147584	block2_conv1[0][0]
block2_pool (MaxPooling2D)	(None, 128, 128, 128)	0	block2_conv2[0][0]
block3_conv1 (Conv2D)	(None, 128, 128, 256)	295168	block2_pool[0][0]
block3_conv2 (Conv2D)	(None, 128, 128, 256)	590080	block3_conv1[0][0]
block3_conv3 (Conv2D)	(None, 128, 128, 256)	590080	block3_conv2[0][0]
block3_pool (MaxPooling2D)	(None, 64, 64, 256)	0	block3_conv3[0][0]
block4_conv1 (Conv2D)	(None, 64, 64, 512)	1180160	block3_pool[0][0]
block4_conv2 (Conv2D)	(None, 64, 64, 512)	2359808	block4_conv1[0][0]
block4_conv3 (Conv2D)	(None, 64, 64, 512)	2359808	block4_conv2[0][0]
block4_pool (MaxPooling2D)	(None, 32, 32, 512)	0	block4_conv3[0][0]
block5_conv1 (Conv2D)	(None, 32, 32, 512)	2359808	block4_pool[0][0]
block5_conv2 (Conv2D)	(None, 32, 32, 512)	2359808	block5_conv1[0][0]
block5_conv3 (Conv2D)	(None, 32, 32, 512)	2359808	block5_conv2[0][0]
block5_pool (MaxPooling2D)	(None, 16, 16, 512)	0	block5_conv3[0][0]
fc1 (Conv2D)	(None, 16, 16, 4096)	102764544	block5_pool[0][0]
fc2 (Conv2D)	(None, 16, 16, 4096)	16781312	fc1[0][0]
conv2d_1 (Conv2D)	(None, 16, 16, 7)	28679	fc2[0][0]
conv2d_transpose_1 (Conv2DTrans	(None, 32, 32, 7)	784	conv2d_1[0][0]
16sforward (Conv2D)	(None, 32, 32, 7)	3591	block4_pool[0][0]
add_1 (Add)	(None, 32, 32, 7)	0	conv2d_transpose_1[0][0] 16sforward[0][0]
conv2d_transpose_2 (Conv2DTrans	(None, 64, 64, 7)	784	add_1[0][0]
8sforward (Conv2D)	(None, 64, 64, 7)	1799	block3_pool[0][0]
add_2 (Add)	(None, 64, 64, 7)	0	conv2d_transpose_2[0][0] 8sforward[0][0]
conv2d_transpose_3 (Conv2DTrans	(None, 512, 512, 7)	12544	add_2[0][0]
Total params: 134,308,725			
Trainable params: 134,308,725			
Non-trainable params: 0			



4. (10%) Show the predicted segmentation mask of validation/0008\_sat.jpg, validation/0097\_sat.jpg, validation/0107\_sat.jpg during the early, middle, and the final stage during the training process of this improved model.

epoch 1	epoch 10	epoch 20	ground truth
			
			
			

5. (15%) Report mIoU score of both models on the validation set. Discuss the reason why the improved model performs better than the baseline one. You may conduct some experiments and show some evidences to support your discussion.

model	32s	8s
class 0	0.74281	0.73002
class 1	0.87113	0.87970
class 2	0.19848	0.27704
class 3	0.79061	0.79446
class 4	0.70357	0.74200
class 5	0.65533	0.66272
mIoU	0.660320	0.680990

將前面還沒因為pooling壓小而解析度下降的資料接到後面來可以幫助segmentation在細節的地方切得更好，由上面的圖片中可看出8s比起32s的圖片找到更多零碎小面積的色塊。這是我覺得兩者表現差異的原因。

6. (5%) [bonus] Calculate the result of  $d/dw G(w)$ :

### objective function:

$$G(\mathbf{w}) = - \sum_n [t^{(n)} \log x(\mathbf{z}^{(n)}; \mathbf{w}) + (1 - t^{(n)}) \log (1 - x(\mathbf{z}^{(n)}; \mathbf{w}))] \geq 0$$

$\mathbf{w}^* = \arg \min_{\mathbf{w}} G(\mathbf{w})$  choose the weights that minimise the network's surprise about the training data

$$\frac{d}{d\mathbf{w}} G(\mathbf{w}) = \sum_n \frac{dG(\mathbf{w})}{dx^{(n)}} \frac{dx^{(n)}}{d\mathbf{w}} = - \sum_n (t^{(n)} - x^{(n)}) \mathbf{z}^{(n)} = \text{prediction error} \times \text{feature}$$

$\mathbf{w} \leftarrow \mathbf{w} - \eta \frac{d}{d\mathbf{w}} G(\mathbf{w})$  iteratively step down the objective (gradient points up hill) 39

Handwritten derivation of the gradient of the logistic loss function:

$$x_i = \frac{1}{1 + e^{-s_i}} \quad s_i = \sum_{j=1} z_j w_{ji}$$

$$\frac{\partial G}{\partial w_{ji}} = \frac{\partial G}{\partial x_i} \frac{\partial x_i}{\partial s_i} \frac{\partial s_i}{\partial w_{ji}}$$

$$\frac{\partial G}{\partial x_i} = -\frac{t_i}{x_i} + \frac{1-t_i}{1-x_i} = \frac{x_i - t_i}{x_i(1-x_i)}$$

$$\frac{\partial x_i}{\partial s_i} = x_i(1-x_i) \quad \frac{\partial s_i}{\partial w_{ji}} = z_j$$

$$\frac{\partial G}{\partial w_{ji}} = (x_i - t_i) z_j \Rightarrow \frac{dG}{d\mathbf{w}} = - \sum_n (t^{(n)} - x^{(n)}) \mathbf{z}^{(n)}$$