ECE228 Project

May 26, 2021

```
[1]: from tensorflow.keras.layers import Conv2D, BatchNormalization, Activation
     import numpy as np
     import cv2
     import os
     def dataset_setup(data_dir='', n_ims=2975, offset_bias=0, img_dim=256):
         Method to import the training data from CityScape and divide into \sqcup
      \hookrightarrow image-label pairs
         Inputs
         data_dir: string
             Location for the data that is being imported
             Number of images contained in the folder chosen
         offset_bias: int
             Optionally, skip some images by starting at a position further than O
         imq_dim: int
             Expected image dimension (assuming square images)
         Outputs
         X: list
             Images
         y: list
             Image labels per pixel
         flist = os.listdir(data_dir)
         img0 = cv2.imread(data_dir+flist[0])
         y_dim,x_dim,_ = np.shape(img0)
         X = np.zeros((n_ims, y_dim, int(x_dim/2), 3))
         y = np.zeros((n_ims, y_dim, int(x_dim/2), 3))
```

```
k = 0
for f in flist[offset_bias:offset_bias+n_ims]:
    X[k] = cv2.imread(data_dir+f)[:,:img_dim]/img_dim
    y[k] = cv2.imread(data_dir+f)[:,img_dim:]/img_dim
    k = k+1

return X, y
```

```
[3]: from tensorflow.keras.layers import MaxPooling2D, Dropout, Conv2DTranspose, □ →Conv2D, concatenate
from tensorflow.keras.layers import Conv2D, BatchNormalization, Activation
from tensorflow.keras.backend import binary_crossentropy, square
from tensorflow.keras.backend import sum as ksum
from tensorflow.keras import Model, Input
import tensorflow as tf

def reconstruction_loss(y_true, y_pred):
    """
    Using binary crossentropy from Keras for reconstruction loss
    """
    return ksum(binary_crossentropy(y_true, y_pred), axis=-1)

def conv2d_block(input_tensor, n_filters=16, filter_size=3, activation='relu', □
→pad='same', batch_norm=True):
    """
    Custom block method to perform consecutive convolutions with optional batch_□
→normalization
```

```
Inputs
    input_tensor: tensor
        Input image tensor data structure defined within Keras
    n_filters: int
        Depth for the convolution layer outputs
    filter_size: int
        Dimensions of the filter convolved with the tensor inputs
    activation: string
        Activation function for the intermediate layers between convolutions
    pad: string
        Determination of if input shape is maintained in convolution
    batch norm: bool
        Flag if batch normalization is used
    Outputs
    __
    x: tensor
        Twice convolved input with optional batch normalization and activation \sqcup
 \rightarrow non-linearities
    11 11 11
    x = Conv2D(filters=n_filters, kernel_size=(filter_size, filter_size),
               kernel_initializer='he_normal', padding=pad)(input_tensor)
    if batch_norm:
        x = BatchNormalization()(x)
    x = Activation(activation)(x)
    x = Conv2D(filters=n_filters, kernel_size=(filter_size, filter_size),
               kernel_initializer='he_normal', padding=pad)(x)
    if batch_norm:
        x = BatchNormalization()(x)
    x = Activation('relu')(x)
    return x
def UNET(input_shape=(256,256,3), conv_block=conv2d_block, n_filters=32,__
→dropout=0.5, padding='same', batch_norm=True):
    {\it UNET architecture as originally outlined in https://arxiv.org/pdf/1505.}
\hookrightarrow 04597.pdf with modifications
    to fit different input dimensions.
    Inputs
    input_shape: tuple(int)
```

```
Tuple in 3D corresponding to the dimensions of the input images
   conv_block: func
       Custom block method to perform consecutive convolutions with optional \sqcup
\hookrightarrow batch normalization
   n_filters: int
       Number of filters corresponding to depth of input for next layer
   dropout: float
       Dropout percentage hyperparameter to tune overfitting
   padding: string
       Descriptor determining if padding maintain size during convolutions
   batch_norm: bool
       Determines if batch normalization is used
   Outputs
   model: Model
       Returns model architecture without compile
   tensor = Input(shape=input_shape)
   print('Contracting Path')
   c1 = conv_block(tensor, n_filters * 1, filter_size=3, activation='relu',_
→pad=padding, batch_norm=batch_norm)
   p1 = MaxPooling2D((2, 2))(c1)
   p1 = Dropout(dropout)(p1)
   c2 = conv_block(p1, n_filters * 2, filter_size=3, activation='relu',_
→pad=padding, batch_norm=batch_norm)
   p2 = MaxPooling2D((2, 2))(c2)
   p2 = Dropout(dropout)(p2)
   c3 = conv_block(p2, n_filters * 4, filter_size=3, activation='relu', __
→pad=padding, batch_norm=batch_norm)
   p3 = MaxPooling2D((2, 2))(c3)
   p3 = Dropout(dropout)(p3)
   c4 = conv_block(p3, n_filters * 8, filter_size=3, activation='relu', __
→pad=padding, batch_norm=batch_norm)
   p4 = MaxPooling2D((2, 2))(c4)
   p4 = Dropout(dropout)(p4)
   c5 = conv_block(p4, n_filters * 16, filter_size=3, activation='relu',_
→pad=padding, batch_norm=batch_norm)
   print('Expanding Path')
```

```
u6 = Conv2DTranspose(n_filters * 8, (3, 3), strides=(2, 2), __
 →padding=padding)(c5)
   u6 = concatenate([u6, c4])
   u6 = Dropout(dropout)(u6)
   c6 = conv_block(u6, n_filters * 8, filter_size=3, activation='relu', u
 →pad=padding, batch norm=batch norm)
   u7 = Conv2DTranspose(n_filters * 4, (3, 3), strides=(2, 2),
 →padding=padding)(c6)
   u7 = concatenate([u7, c3])
   u7 = Dropout(dropout)(u7)
   c7 = conv_block(u7, n_filters * 4, filter_size=3, activation='relu', u
→pad=padding, batch_norm=batch_norm)
   u8 = Conv2DTranspose(n_filters * 2, (3, 3), strides=(2, 2), __
⇒padding=padding)(c7)
   u8 = concatenate([u8, c2])
   u8 = Dropout(dropout)(u8)
   c8 = conv_block(u8, n_filters * 2, filter_size=3, activation='relu',_
→pad=padding, batch_norm=batch_norm)
   u9 = Conv2DTranspose(n_filters * 1, (3, 3), strides=(2, 2),
→padding=padding)(c8)
   u9 = concatenate([u9, c1])
   u9 = Dropout(dropout)(u9)
   c9 = conv_block(u9, n_filters * 1, filter_size=3, activation='relu',_
 →pad=padding, batch_norm=batch_norm)
   outputs = Conv2D(3, (1, 1), activation='sigmoid')(c9)
   model = Model(inputs=[tensor], outputs=[outputs])
   # Return model architecture
   return model
def UNET_plusplus(input_shape=(256,256,3), conv_block=conv2d_block,_
 UNET++ architecture as originally outlined in https://arxiv.org/pdf/1807.
\hookrightarrow 10165.pdf with modifications
    to fit different input dimensions.
   Inputs
    input_shape: tuple(int)
        Tuple in 3D corresponding to the dimensions of the input images
```

```
conv_block: func
       Custom block method to perform consecutive convolutions with optional \sqcup
\hookrightarrow batch normalization
   n filters: int
       Number of filters corresponding to depth of input for next layer
   dropout: float
       Dropout percentage hyperparameter to tune overfitting
   padding: string
       Descriptor determining if padding maintain size during convolutions
   batch_norm: bool
       Determines if batch normalization is used
   Outputs
   model: Model
       Returns model architecture without compile
   tensor = Input(shape=input_shape)
   print('Backbone')
   c00 = conv_block(tensor, n_filters * 1, filter_size=3, activation='relu',_
→pad=padding, batch_norm=batch_norm)
   p00 = MaxPooling2D((2, 2))(c00)
   p00 = Dropout(dropout)(p00)
   c10 = conv_block(p00, n_filters * 2, filter_size=3, activation='relu',__
→pad=padding, batch_norm=batch_norm)
   p10 = MaxPooling2D((2, 2))(c10)
   p10 = Dropout(dropout)(p10)
   c20 = conv_block(p10, n_filters * 4, filter_size=3, activation='relu', __
→pad=padding, batch_norm=batch_norm)
   p20 = MaxPooling2D((2, 2))(c20)
   p20 = Dropout(dropout)(p20)
   c30 = conv_block(p20, n_filters * 8, filter_size=3, activation='relu', __
→pad=padding, batch_norm=batch_norm)
   p30 = MaxPooling2D((2, 2))(c30)
   p30 = Dropout(dropout)(p30)
   c40 = conv_block(p30, n_filters * 16, filter_size=3, activation='relu',_
→pad=padding, batch_norm=batch_norm)
   print('First Up Path')
```

```
u01 = Conv2DTranspose(n_filters * 1, (3, 3), strides=(2, 2),
→padding=padding)(c10)
   u01 = concatenate([u01, c00])
   u01 = Dropout(dropout)(u01)
   c01 = conv block(u01, n filters * 1, filter size=3, activation='relu', |
→pad=padding, batch_norm=batch_norm)
   print('Second Up Path')
   u11 = Conv2DTranspose(n_filters * 2, (3, 3), strides=(2, 2),
→padding=padding)(c20)
   u11 = concatenate([u11, c10])
   u11 = Dropout(dropout)(u11)
   c11 = conv_block(u11, n_filters * 2, filter_size=3, activation='relu', u
→pad=padding, batch_norm=batch_norm)
   u02 = Conv2DTranspose(n_filters * 1, (3, 3), strides=(2, 2),
→padding=padding)(c11)
   u02 = concatenate([u02, c01, c00])
   u02 = Dropout(dropout)(u02)
   c02 = conv_block(u02, n_filters * 1, filter_size=3, activation='relu', __
→pad=padding, batch_norm=batch_norm)
   print('Third Up Path')
   u21 = Conv2DTranspose(n_filters * 4, (3, 3), strides=(2, 2),
→padding=padding)(c30)
   u21 = concatenate([u21, c20])
   u21 = Dropout(dropout)(u21)
   c21 = conv_block(u21, n_filters * 4, filter_size=3, activation='relu', __
→pad=padding, batch_norm=batch_norm)
   u12 = Conv2DTranspose(n_filters * 2, (3, 3), strides=(2, 2),
→padding=padding)(c21)
   u12 = concatenate([u12, c11, c10])
   u12 = Dropout(dropout)(u12)
   c12 = conv_block(u12, n_filters * 2, filter_size=3, activation='relu', __
→pad=padding, batch_norm=batch_norm)
   u03 = Conv2DTranspose(n_filters * 1, (3, 3), strides=(2, 2),
→padding=padding)(c12)
   u03 = concatenate([u03, c02, c01, c00])
   u03 = Dropout(dropout)(u03)
   c03 = conv_block(u03, n_filters * 1, filter_size=3, activation='relu',_
→pad=padding, batch_norm=batch_norm)
```

```
print('Final Up Path')
   u31 = Conv2DTranspose(n_filters * 8, (3, 3), strides=(2, 2),
→padding=padding)(c40)
   u31 = concatenate([u31, c30])
   u31 = Dropout(dropout)(u31)
   c31 = conv_block(u31, n_filters * 8, filter_size=3, activation='relu',__
→pad=padding, batch_norm=batch_norm)
   u22 = Conv2DTranspose(n_filters * 4, (3, 3), strides=(2, 2),_{\sqcup}
→padding=padding)(c31)
   u22 = concatenate([u22, c21, c20])
   u22 = Dropout(dropout)(u22)
   c22 = conv_block(u22, n_filters * 4, filter_size=3, activation='relu', u
→pad=padding, batch_norm=batch_norm)
   u13 = Conv2DTranspose(n_filters * 2, (3, 3), strides=(2, 2),
→padding=padding)(c22)
   u13 = concatenate([u13, c12, c11, c10])
   u13 = Dropout(dropout)(u13)
   c13 = conv_block(u13, n_filters * 2, filter_size=3, activation='relu', u
→pad=padding, batch_norm=batch_norm)
   u04 = Conv2DTranspose(n_filters * 1, (3, 3), strides=(2, 2),
→padding=padding)(c13)
   u04 = concatenate([u04, c03, c02, c01, c00])
   u04 = Dropout(dropout)(u04)
   c04 = conv_block(u04, n_filters * 1, filter_size=3, activation='relu', __
→pad=padding, batch_norm=batch_norm)
   #Outputs
   outputs = Conv2D(3, (1, 1), activation='sigmoid')(c04)
   model = Model(inputs=[tensor], outputs=[outputs])
   # Return model architecture
   return model
```

```
[4]: # Initialize UNET
model = UNET_plusplus(input_shape=(256,256,3), conv_block=conv2d_block,

→n_filters=8, dropout=0.5, padding='same', batch_norm=True)
print(model.summary())
```

Backbone First Up Path Second Up Path Third Up Path Final Up Path Model: "model"

 Layer (type)	Output	Shape	e =====		Param #	Connected to
input_1 (InputLayer)	[(None	, 256	, 256	, 3)	0	
conv2d (Conv2D)					224	_
batch_normalization (BatchNorma	(None,	256,	256,	8)	32	conv2d[0][0]
activation (Activation) batch_normalization[0][0]	(None,					
conv2d_1 (Conv2D) activation[0][0]	(None,	256,	256,	8)	584	
batch_normalization_1 (BatchNor	(None,	256,	256,	8)	32	conv2d_1[0][0]
activation_1 (Activation) batch_normalization_1[0][0]	(None,	256,	256,	8)	0	
	(None,	128,	128,	8)	0	
dropout (Dropout) max_pooling2d[0][0]	(None,					
conv2d_2 (Conv2D)	(None,	128,	128,	16)	1168	dropout[0][0]
batch_normalization_2 (BatchNor	(None,	128,	128,	16)	64	conv2d_2[0][0]
activation_2 (Activation) batch_normalization_2[0][0]						

conv2d_3 (Conv2D) activation_2[0][0]	(None, 128, 128, 16) 2320	
batch_normalization_3 (BatchNor	(None, 128, 128, 16) 64	conv2d_3[0][0]
activation_3 (Activation) batch_normalization_3[0][0]	(None, 128, 128, 16) 0	
max_pooling2d_1 (MaxPooling2D) activation_3[0][0]	(None, 64, 64, 16) 0	
dropout_1 (Dropout) max_pooling2d_1[0][0]	(None, 64, 64, 16) 0	
conv2d_4 (Conv2D)	(None, 64, 64, 32) 4640	dropout_1[0][0]
batch_normalization_4 (BatchNor	(None, 64, 64, 32) 128	
activation_4 (Activation) batch_normalization_4[0][0]	(None, 64, 64, 32) 0	
conv2d_5 (Conv2D) activation_4[0][0]	(None, 64, 64, 32) 9248	
batch_normalization_5 (BatchNor		conv2d_5[0][0]
activation_5 (Activation) batch_normalization_5[0][0]	(None, 64, 64, 32) 0	
max_pooling2d_2 (MaxPooling2D) activation_5[0][0]		
dropout_2 (Dropout) max_pooling2d_2[0][0]	(None, 32, 32, 32) 0	

conv2d_6 (Conv2D)					18496	dropout_2[0][0]
batch_normalization_6 (BatchNor	(None,	32,	32,	64)		conv2d_6[0][0]
activation_6 (Activation) batch_normalization_6[0][0]	(None,		32,	64)	0	
conv2d_7 (Conv2D) activation_6[0][0]	(None,		32,	64)	36928	
batch_normalization_7 (BatchNor			32,	64)	256	conv2d_7[0][0]
activation_7 (Activation) batch_normalization_7[0][0]	(None,	32,	32,	64)	0	
max_pooling2d_3 (MaxPooling2D) activation_7[0][0]	(None,	16,	16,	64)	0	
dropout_3 (Dropout) max_pooling2d_3[0][0]	(None,	16,	16,	64)	0	
conv2d_8 (Conv2D)	(None,	16,	16,	128)	73856	dropout_3[0][0]
batch_normalization_8 (BatchNor						conv2d_8[0][0]
activation_8 (Activation) batch_normalization_8[0][0]	(None,	16,	16,	128)	0	
conv2d_9 (Conv2D) activation_8[0][0]	(None,	16,	16,	128)	147584	
batch_normalization_9 (BatchNor	(None,	16,	16,	128)	512	conv2d_9[0][0]
activation_9 (Activation)	(None,					

batch_normalization_9[0][0]		
conv2d_transpose_6 (Conv2DTrans activation_9[0][0]	(None, 32, 32, 64)	73792
concatenate_6 (Concatenate) conv2d_transpose_6[0][0] activation_7[0][0]	(None, 32, 32, 128)	
conv2d_transpose_3 (Conv2DTrans activation_7[0][0]	(None, 64, 64, 32)	
dropout_10 (Dropout) concatenate_6[0][0]	(None, 32, 32, 128)	
concatenate_3 (Concatenate) conv2d_transpose_3[0][0] activation_5[0][0]	(None, 64, 64, 64)	
conv2d_transpose_1 (Conv2DTransactivation_5[0][0]		
conv2d_22 (Conv2D) dropout_10[0][0]	(None, 32, 32, 64)	73792
dropout_7 (Dropout) concatenate_3[0][0]	(None, 64, 64, 64)	0
concatenate_1 (Concatenate) conv2d_transpose_1[0][0] activation_3[0][0]	(None, 128, 128, 32)	0
conv2d_transpose (Conv2DTranspo activation_3[0][0]		1160
batch_normalization_22 (BatchNo		

conv2d_16 (Conv2D)		64, 64, 32)		dropout_7[0][0]
dropout_5 (Dropout) concatenate_1[0][0]	(None,	128, 128, 32)	0	
concatenate (Concatenate) conv2d_transpose[0][0] activation_1[0][0]		256, 256, 16)		
activation_22 (Activation) batch_normalization_22[0][0]		32, 32, 64)		
batch_normalization_16 (BatchNo				
conv2d_12 (Conv2D)		128, 128, 16)		dropout_5[0][0]
dropout_4 (Dropout) concatenate[0][0]		256, 256, 16)		
conv2d_23 (Conv2D) activation_22[0][0]		32, 32, 64)		
activation_16 (Activation) batch_normalization_16[0][0]	(None,	64, 64, 32)	0	
batch_normalization_12 (BatchNo				
 conv2d_10 (Conv2D)	(None,	256, 256, 8)	1160	dropout_4[0][0]
batch_normalization_23 (BatchNo	(None,	32, 32, 64)	256	conv2d_23[0][0]
conv2d_17 (Conv2D) activation_16[0][0]	(None,	64, 64, 32)	9248	
	- -	_ _		3-

activation_12 (Activation) batch_normalization_12[0][0]		128, 128, 16)		
batch_normalization_10 (BatchNo	(None,		32	conv2d_10[0][0]
activation_23 (Activation) batch_normalization_23[0][0]				
batch_normalization_17 (BatchNo				
conv2d_13 (Conv2D) activation_12[0][0]		128, 128, 16)		
activation_10 (Activation) batch_normalization_10[0][0]	(None,	256, 256, 8)	0	
conv2d_transpose_7 (Conv2DTrans activation_23[0][0]			18464	
activation_17 (Activation) batch_normalization_17[0][0]	(None,	64, 64, 32)	0	
batch_normalization_13 (BatchNo	(None,	128, 128, 16)	64	conv2d_13[0][0]
conv2d_11 (Conv2D) activation_10[0][0]		256, 256, 8)		
concatenate_7 (Concatenate) conv2d_transpose_7[0][0] activation_17[0][0] activation_5[0][0]	(None,	64, 64, 96)	0	
conv2d_transpose_4 (Conv2DTrans activation_17[0][0]	(None,	128, 128, 16)	4624	
activation_13 (Activation)		128, 128, 16)		

batch_normalization_13[0][0]				
batch_normalization_11 (BatchNo	(None,	256, 256, 8)	32	conv2d_11[0][0]
dropout_11 (Dropout) concatenate_7[0][0]	(None,	64, 64, 96)	0	
concatenate_4 (Concatenate) conv2d_transpose_4[0][0] activation_13[0][0] activation_3[0][0]	(None,	128, 128, 48)	0	
conv2d_transpose_2 (Conv2DTrans activation_13[0][0]				
activation_11 (Activation) batch_normalization_11[0][0]		256, 256, 8)		
 conv2d_24 (Conv2D) dropout_11[0][0]		64, 64, 32)		
dropout_8 (Dropout) concatenate_4[0][0]		128, 128, 48)		
concatenate_2 (Concatenate) conv2d_transpose_2[0][0] activation_11[0][0] activation_1[0][0]				
batch_normalization_24 (BatchNo	(None,	64, 64, 32)	128	conv2d_24[0][0]
conv2d_18 (Conv2D)	(None,	128, 128, 16)	6928	dropout_8[0][0]
dropout_6 (Dropout) concatenate_2[0][0]	(None,	256, 256, 24)	0	

activation_24 (Activation) batch_normalization_24[0][0]		64, 64, 32)		
batch_normalization_18 (BatchNo	(None,		64	conv2d_18[0][0]
conv2d_14 (Conv2D)	(None,		1736	dropout_6[0][0]
conv2d_25 (Conv2D) activation_24[0][0]		64, 64, 32)		
activation_18 (Activation) batch_normalization_18[0][0]	(None,	128, 128, 16)	0	
batch_normalization_14 (BatchNo	(None,	256, 256, 8)	32	conv2d_14[0][0]
batch_normalization_25 (BatchNo	(None,	64, 64, 32)	128	conv2d_25[0][0]
conv2d_19 (Conv2D) activation_18[0][0]		128, 128, 16)		
activation_14 (Activation) batch_normalization_14[0][0]		256, 256, 8)		
activation_25 (Activation) batch_normalization_25[0][0]			0	
batch_normalization_19 (BatchNo	(None,	128, 128, 16)	64	conv2d_19[0][0]
	(None,	256, 256, 8)	584	
conv2d_transpose_8 (Conv2DTrans activation_25[0][0]	(None,	128, 128, 16)	4624	
activation_19 (Activation)		128, 128, 16)		

batch_normalization_19[0][0]						
batch_normalization_15 (BatchNo						
concatenate_8 (Concatenate) conv2d_transpose_8[0][0] activation_19[0][0] activation_13[0][0] activation_3[0][0]	(None,					
conv2d_transpose_5 (Conv2DTrans activation_19[0][0]	(None,	256,	256,	8)	1160	
activation_15 (Activation) batch_normalization_15[0][0]	(None,	256,	256,	8)	0	
dropout_12 (Dropout) concatenate_8[0][0]	(None,	128,				
concatenate_5 (Concatenate) conv2d_transpose_5[0][0] activation_15[0][0] activation_11[0][0] activation_1[0][0]	(None,	256,				
conv2d_26 (Conv2D) dropout_12[0][0]	(None,					
dropout_9 (Dropout) concatenate_5[0][0]	(None,	256,	256,	32)	0	
batch_normalization_26 (BatchNo						
conv2d_20 (Conv2D)	(None,	256,	256,	8)	2312	dropout_9[0][0]
activation_26 (Activation) batch_normalization_26[0][0]	(None,					

batch_normalization_20 (BatchNo					32	
conv2d_27 (Conv2D) activation_26[0][0]	(None,					
activation_20 (Activation) batch_normalization_20[0][0]	(None,	256,	256,	8)	0	
batch_normalization_27 (BatchNo	(None,	128,	128,	16)	64	conv2d_27[0][0]
conv2d_21 (Conv2D) activation_20[0][0]	(None,					
activation_27 (Activation) batch_normalization_27[0][0]	(None,	128,	128,	16)	0	
batch_normalization_21 (BatchNo	(None,	256,	256,	8)	32	conv2d_21[0][0]
conv2d_transpose_9 (Conv2DTransactivation_27[0][0]	(None,	256,	256,	8)	1160	
activation_21 (Activation) batch_normalization_21[0][0]	(None,	256,	256,	8)	0	
concatenate_9 (Concatenate) conv2d_transpose_9[0][0] activation_21[0][0] activation_15[0][0] activation_11[0][0] activation_1[0][0]	(None,	256,	256,	40)	0	
dropout_13 (Dropout) concatenate_9[0][0]	(None,	256,	256,	40)	0	
conv2d_28 (Conv2D)	(None,	256,	256,	8)	2888	

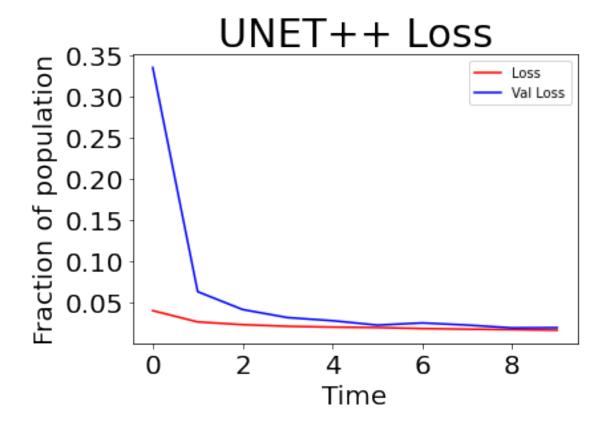
```
dropout_13[0][0]
   ______
   batch_normalization_28 (BatchNo (None, 256, 256, 8) 32 conv2d_28[0][0]
   ______
   activation 28 (Activation) (None, 256, 256, 8) 0
   batch_normalization_28[0][0]
   ______
   conv2d_29 (Conv2D)
                      (None, 256, 256, 8) 584
   activation_28[0][0]
   batch_normalization_29 (BatchNo (None, 256, 256, 8) 32 conv2d_29[0][0]
   activation_29 (Activation) (None, 256, 256, 8) 0
   batch_normalization_29[0][0]
   -----
   conv2d_30 (Conv2D)
                      (None, 256, 256, 3) 27
   activation_29[0][0]
   ______
   Total params: 641,491
   Trainable params: 639,667
   Non-trainable params: 1,824
   None
[5]: # Compile model with specified optimizer and loss
   optimizer = tf.keras.optimizers.Adam(learning_rate=0.01)
   metrics = ['accuracy']
   model.compile(optimizer=optimizer, loss='mse', metrics = metrics)
[6]: datagen1 = tf.keras.preprocessing.image.ImageDataGenerator()
   datagen1.fit(x_train)
   datagen2 = tf.keras.preprocessing.image.ImageDataGenerator(
      rotation range=20,
      width_shift_range=0.2,
      height_shift_range=0.2,
     horizontal_flip=True
   )
```

```
datagen2.fit(x_train)
# Track model history as it trains
h_11 = model.fit(datagen1.flow(x_train, y_train, batch_size=32), \
       steps_per_epoch=len(x_train) // 32, epochs=10, \
          validation_data=datagen1.flow(x_val, y_val, batch_size=32))
h_12 = model.fit(datagen2.flow(x_train, y_train, batch_size=32), \
       steps_per_epoch=len(x_train) // 32, epochs=5, \
          validation_data=datagen2.flow(x_val, y_val, batch_size=32))
# Save the weights
model.save_weights('./checkpoints/UNET++')
WARNING:tensorflow:sample weight modes were coerced from
  to
 ['...']
WARNING:tensorflow:sample_weight modes were coerced from
  to
 ['...']
Train for 83 steps, validate for 10 steps
Epoch 1/10
accuracy: 0.4225 - val_loss: 0.3345 - val_accuracy: 0.3696
Epoch 2/10
accuracy: 0.6078 - val_loss: 0.0629 - val_accuracy: 0.4163
Epoch 3/10
accuracy: 0.6062 - val_loss: 0.0412 - val_accuracy: 0.5231
Epoch 4/10
accuracy: 0.6067 - val_loss: 0.0314 - val_accuracy: 0.5633
Epoch 5/10
accuracy: 0.6185 - val_loss: 0.0276 - val_accuracy: 0.3961
Epoch 6/10
83/83 [============ ] - 25s 300ms/step - loss: 0.0193 -
accuracy: 0.5944 - val_loss: 0.0223 - val_accuracy: 0.4178
Epoch 7/10
83/83 [============ ] - 25s 302ms/step - loss: 0.0181 -
accuracy: 0.5843 - val_loss: 0.0249 - val_accuracy: 0.3544
Epoch 8/10
accuracy: 0.5887 - val_loss: 0.0224 - val_accuracy: 0.4425
```

```
accuracy: 0.5908 - val_loss: 0.0189 - val_accuracy: 0.4738
    Epoch 10/10
    accuracy: 0.6073 - val_loss: 0.0193 - val_accuracy: 0.6206
    WARNING:tensorflow:sample weight modes were coerced from
       to
     ['...']
    WARNING:tensorflow:sample_weight modes were coerced from
       to
     ['...']
    Train for 83 steps, validate for 10 steps
    Epoch 1/5
    83/83 [============= ] - 25s 299ms/step - loss: 0.0237 -
    accuracy: 0.5029 - val_loss: 0.0327 - val_accuracy: 0.3545
    Epoch 2/5
    83/83 [============= ] - 24s 288ms/step - loss: 0.0230 -
    accuracy: 0.5144 - val_loss: 0.0259 - val_accuracy: 0.4163
    Epoch 3/5
    accuracy: 0.5171 - val_loss: 0.0233 - val_accuracy: 0.3898
    Epoch 4/5
    accuracy: 0.5335 - val_loss: 0.0244 - val_accuracy: 0.3869
    Epoch 5/5
    accuracy: 0.5030 - val_loss: 0.0242 - val_accuracy: 0.5918
[11]: # Print results for training MSE and validation MSE
    plt.plot(h_11.history['loss'], 'r', label='Loss')
    plt.plot(h_11.history['val_loss'], 'b', label='Val Loss')
    plt.title('UNET++ Loss', fontsize=30)
    plt.xlabel("Time", fontsize=20)
    plt.xticks(fontsize=20)
    plt.ylabel("Fraction of population", fontsize=20)
    plt.yticks(fontsize=20)
    plt.legend(loc='best')
    plt.show()
    plt.plot(h_12.history['loss'], 'm', label='Loss Augmented')
    plt.plot(h_12.history['val_loss'], 'c', label='Val Loss Augmented')
    plt.title('UNET++ Loss', fontsize=30)
    plt.xlabel("Time", fontsize=20)
    plt.xticks(fontsize=20)
    plt.ylabel("Fraction of population", fontsize=20)
```

Epoch 9/10

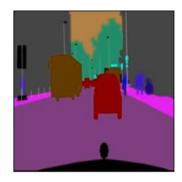
```
plt.yticks(fontsize=20)
plt.legend(loc='best')
plt.show()
```




```
[8]: #show the result
     pp = model.predict(x_test[:5,:,:,:], batch_size=1)
     ni = 5
     for k in range(ni):
         plt.figure(figsize=(10,30))
         plt.subplot(ni,3,1+k*3)
         plt.imshow(x_test[k])
         figure = plt.gca()
         x_axis = figure.axes.get_xaxis()
         x_axis.set_visible(False)
         y_axis = figure.axes.get_yaxis()
         y_axis.set_visible(False)
         plt.subplot(ni,3,2+k*3)
         plt.imshow(y_test[k])
         figure = plt.gca()
         x_axis = figure.axes.get_xaxis()
         x_axis.set_visible(False)
         y_axis = figure.axes.get_yaxis()
         y_axis.set_visible(False)
         plt.subplot(ni,3,3+k*3)
         plt.imshow(pp[k])
```

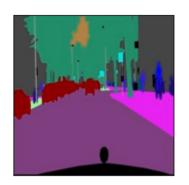
figure = plt.gca()
x_axis = figure.axes.get_xaxis()
x_axis.set_visible(False)
y_axis = figure.axes.get_yaxis()
y_axis.set_visible(False)













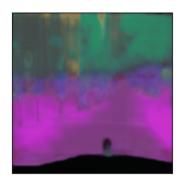




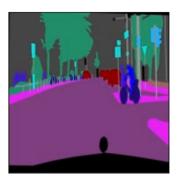














```
[9]: intersection = np.logical_and(y_test[1,:,:,:], pp)
union = np.logical_or(y_test[1,:,:,:], pp)
iou_score = np.sum(intersection) / np.sum(union)
print(iou_score)
```

0.9607899983723959

```
[10]: diff = y_test[1] - pp[1]
m_norm = np.sum(abs(diff))
print(m_norm)
print(m_norm/(256*256))
```

11151.228615228087 0.17015424522747935

```
[4]: # Initialize UNET

model2 = UNET(input_shape=(256,256,3), conv_block=conv2d_block, n_filters=8,

dropout=0.5, padding='same', batch_norm=True)

print(model2.summary())
```

Contracting Path Expanding Path

Model: "model"						
Layer (type)	_	-	e =====			Connected to
input_1 (InputLayer)	[(None	, 256	, 256	, 3)		
conv2d (Conv2D)	(None,	256,	256,	8)	224	input_1[0][0]
batch_normalization (BatchNorma	(None,	256,	256,		32	
activation (Activation) batch_normalization[0][0]	(None,	256,	256,			
conv2d_1 (Conv2D) activation[0][0]	(None,					
batch_normalization_1 (BatchNor						
activation_1 (Activation) batch_normalization_1[0][0]	(None,				0	
max_pooling2d (MaxPooling2D) activation_1[0][0]	(None,					
dropout (Dropout) max_pooling2d[0][0]	(None,					
conv2d_2 (Conv2D)	(None,	128,	128,	16)	1168	dropout[0][0]
batch_normalization_2 (BatchNor	(None,	128,	128,	16)	64	conv2d_2[0][0]
activation_2 (Activation) batch_normalization_2[0][0]						

conv2d_3 (Conv2D) activation_2[0][0]	(None,	128, 128, 16) 2320	
batch_normalization_3 (BatchNor	(None,	128, 128, 16) 64	conv2d_3[0][0]
activation_3 (Activation) batch_normalization_3[0][0]	(None,	128, 128, 16) 0	
max_pooling2d_1 (MaxPooling2D) activation_3[0][0]				
dropout_1 (Dropout) max_pooling2d_1[0][0]	(None,	64, 64, 16)	0	
conv2d_4 (Conv2D)				dropout_1[0][0]
batch_normalization_4 (BatchNor	(None,	64, 64, 32)	128	conv2d_4[0][0]
activation_4 (Activation) batch_normalization_4[0][0]		64, 64, 32)		
conv2d_5 (Conv2D) activation_4[0][0]	(None,	64, 64, 32)	9248	
batch_normalization_5 (BatchNor				_
activation_5 (Activation) batch_normalization_5[0][0]		64, 64, 32)		
max_pooling2d_2 (MaxPooling2D) activation_5[0][0]	(None,	32, 32, 32)	0	
dropout_2 (Dropout) max_pooling2d_2[0][0]	(None,	32, 32, 32)	0	

conv2d_6 (Conv2D)	(None,	32,	32,	64)	18496	dropout_2[0][0]
batch_normalization_6 (BatchNor						_
activation_6 (Activation) batch_normalization_6[0][0]	(None,				0	
conv2d_7 (Conv2D) activation_6[0][0]	(None,					
batch_normalization_7 (BatchNor						
activation_7 (Activation) batch_normalization_7[0][0]	(None,				0	
max_pooling2d_3 (MaxPooling2D) activation_7[0][0]	(None,	16,	16,	64)	0	
dropout_3 (Dropout) max_pooling2d_3[0][0]	(None,	16,	16,	64)	0	
conv2d_8 (Conv2D)				128)		dropout_3[0][0]
batch_normalization_8 (BatchNor				128)	512	conv2d_8[0][0]
activation_8 (Activation) batch_normalization_8[0][0]	(None,					
conv2d_9 (Conv2D) activation_8[0][0]	(None,	16,	16,	128)	147584	
batch_normalization_9 (BatchNor	(None,	16,	16,	128)	512	conv2d_9[0][0]
activation_9 (Activation) batch_normalization_9[0][0]	(None,					

conv2d_transpose (Conv2DTranspo activation_9[0][0]	(None,	32,	32,	64)	73792	
concatenate (Concatenate) conv2d_transpose[0][0] activation_7[0][0]	(None,					
dropout_4 (Dropout) concatenate[0][0]	(None,					
conv2d_10 (Conv2D)					73792	dropout_4[0][0]
batch_normalization_10 (BatchNo						conv2d_10[0][0]
activation_10 (Activation) batch_normalization_10[0][0]	(None,				0	
conv2d_11 (Conv2D) activation_10[0][0]	(None,	32,	32,	64)	36928	
batch_normalization_11 (BatchNo					256	conv2d_11[0][0]
activation_11 (Activation) batch_normalization_11[0][0]	(None,	32,	32,	64)	0	
conv2d_transpose_1 (Conv2DTrans activation_11[0][0]					18464	
concatenate_1 (Concatenate) conv2d_transpose_1[0][0] activation_5[0][0]	(None,				0	
dropout_5 (Dropout) concatenate_1[0][0]	(None,	64,	64,	64)	0	

conv2d_12 (Conv2D)	(None, 64, 64, 32)		
batch_normalization_12 (BatchNo			conv2d_12[0][0]
activation_12 (Activation) batch_normalization_12[0][0]		0	
 conv2d_13 (Conv2D) activation_12[0][0]	(None, 64, 64, 32)	9248	
batch_normalization_13 (BatchNo			
activation_13 (Activation) batch_normalization_13[0][0]	(None, 64, 64, 32)	0	
conv2d_transpose_2 (Conv2DTrans activation_13[0][0]		4624	
concatenate_2 (Concatenate) conv2d_transpose_2[0][0] activation_3[0][0]	(None, 128, 128, 32)	0	
dropout_6 (Dropout) concatenate_2[0][0]	(None, 128, 128, 32)	0	
conv2d_14 (Conv2D)	(None, 128, 128, 16)		-
batch_normalization_14 (BatchNo			
activation_14 (Activation) batch_normalization_14[0][0]			
conv2d_15 (Conv2D) activation_14[0][0]	(None, 128, 128, 16)	2320	

batch_normalization_15 (BatchNo						
activation_15 (Activation) batch_normalization_15[0][0]	(None,	128,	128,	16)	0	
conv2d_transpose_3 (Conv2DTrans activation_15[0][0]						
concatenate_3 (Concatenate) conv2d_transpose_3[0][0] activation_1[0][0]	(None,					
dropout_7 (Dropout) concatenate_3[0][0]	(None,					
conv2d_16 (Conv2D)	(None,	256,	256,	8)	1160	dropout_7[0][0]
batch_normalization_16 (BatchNo						
activation_16 (Activation) batch_normalization_16[0][0]	(None,					
conv2d_17 (Conv2D) activation_16[0][0]	(None,	256,	256,	8)	584	
batch_normalization_17 (BatchNo						
activation_17 (Activation) batch_normalization_17[0][0]	(None,	256,	256,	8)	0	
conv2d_18 (Conv2D) activation_17[0][0]	(None,	256,	256,	3)	27	=========
=======================================						

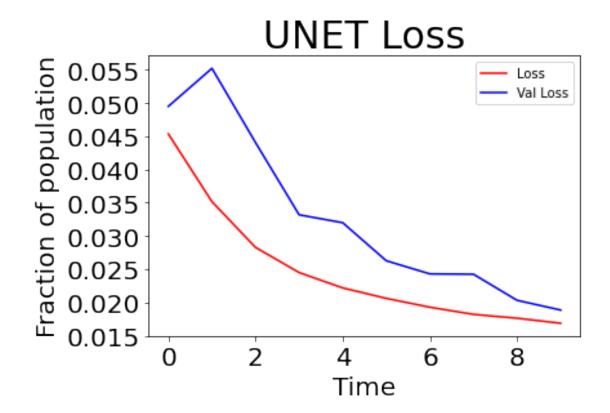
Total params: 543,179 Trainable params: 541,707

```
Non-trainable params: 1,472
    None
[5]: # Compile model with specified optimizer and loss
    optimizer2 = tf.keras.optimizers.Adam(learning_rate=0.01)
    metrics2 = ['accuracy']
    model2.compile(optimizer=optimizer2, loss='mse', metrics = metrics2)
[6]: datagen3 = tf.keras.preprocessing.image.ImageDataGenerator()
    datagen3.fit(x_train)
    datagen4 = tf.keras.preprocessing.image.ImageDataGenerator(
          rotation range=20,
          width shift range=0.2,
          height_shift_range=0.2,
        horizontal_flip=True
    datagen4.fit(x_train)
    # Track model history as it trains
    h_21 = model2.fit(datagen3.flow(x_train, y_train, batch_size=32), \
             steps_per_epoch=len(x_train) // 32, epochs=10, \
                  validation_data=datagen3.flow(x_val, y_val, batch_size=32))
    h_22 = model2.fit(datagen4.flow(x_train, y_train, batch_size=32), \
             steps_per_epoch=len(x_train) // 32, epochs=5, \
                  validation_data=datagen4.flow(x_val, y_val, batch_size=32))
    # Save the weights
    model2.save_weights('./checkpoints/UNET')
    WARNING:tensorflow:sample_weight modes were coerced from
      to
      ['...']
    WARNING:tensorflow:sample_weight modes were coerced from
       to
      ['...']
    Train for 83 steps, validate for 10 steps
    Epoch 1/10
    83/83 [============ ] - 23s 280ms/step - loss: 0.0453 -
    accuracy: 0.4655 - val_loss: 0.0495 - val_accuracy: 0.4701
    Epoch 2/10
```

```
accuracy: 0.3889 - val_loss: 0.0552 - val_accuracy: 0.2923
Epoch 3/10
accuracy: 0.5394 - val_loss: 0.0441 - val_accuracy: 0.3601
Epoch 4/10
accuracy: 0.5435 - val_loss: 0.0332 - val_accuracy: 0.6604
Epoch 5/10
83/83 [============= ] - 12s 146ms/step - loss: 0.0222 -
accuracy: 0.5278 - val_loss: 0.0320 - val_accuracy: 0.5822
Epoch 6/10
83/83 [============= ] - 12s 141ms/step - loss: 0.0206 -
accuracy: 0.5165 - val_loss: 0.0263 - val_accuracy: 0.4682
Epoch 7/10
accuracy: 0.5423 - val_loss: 0.0243 - val_accuracy: 0.4365
Epoch 8/10
83/83 [============ ] - 11s 129ms/step - loss: 0.0182 -
accuracy: 0.5578 - val_loss: 0.0242 - val_accuracy: 0.3964
Epoch 9/10
accuracy: 0.5650 - val_loss: 0.0203 - val_accuracy: 0.4563
Epoch 10/10
83/83 [============ ] - 11s 132ms/step - loss: 0.0169 -
accuracy: 0.5712 - val_loss: 0.0188 - val_accuracy: 0.4536
WARNING:tensorflow:sample_weight modes were coerced from
  to
 ['...']
WARNING:tensorflow:sample_weight modes were coerced from
  to
 ['...']
Train for 83 steps, validate for 10 steps
accuracy: 0.5083 - val loss: 0.0286 - val accuracy: 0.3957
Epoch 2/5
accuracy: 0.5094 - val_loss: 0.0260 - val_accuracy: 0.4152
Epoch 3/5
83/83 [============ ] - 13s 155ms/step - loss: 0.0231 -
accuracy: 0.5348 - val_loss: 0.0256 - val_accuracy: 0.3987
Epoch 4/5
83/83 [============ ] - 12s 147ms/step - loss: 0.0232 -
accuracy: 0.5203 - val_loss: 0.0259 - val_accuracy: 0.3868
Epoch 5/5
```

accuracy: 0.5362 - val_loss: 0.0244 - val_accuracy: 0.3913

```
[7]: # Print results for training MSE and validation MSE
     plt.plot(h_21.history['loss'], 'r', label='Loss')
     plt.plot(h_21.history['val_loss'], 'b', label='Val Loss')
     plt.title('UNET Loss', fontsize=30)
     plt.xlabel("Time", fontsize=20)
     plt.xticks(fontsize=20)
     plt.ylabel("Fraction of population", fontsize=20)
     plt.yticks(fontsize=20)
     plt.legend(loc='best')
     plt.show()
     plt.plot(h_22.history['loss'], 'm', label='Loss Augmented')
     plt.plot(h_22.history['val_loss'], 'c', label='Val Loss Augmented')
     plt.title('UNET Loss', fontsize=30)
     plt.xlabel("Time", fontsize=20)
     plt.xticks(fontsize=20)
     plt.ylabel("Fraction of population", fontsize=20)
     plt.yticks(fontsize=20)
     plt.legend(loc='best')
     plt.show()
```

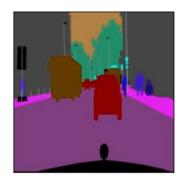


UNET Loss Loss Augmented Val Loss Augmented Val Loss Augmented Val Loss Augmented 0.025 0.025 0.024 0.023 0.0 0.5 1.0 1.5 2.0 2.5 3.0 3.5 4.0 Time

```
[8]: #show the result
     pp2 = model2.predict(x_test[:5,:,:], batch_size=1)
     ni = 5
     for k in range(ni):
         plt.figure(figsize=(10,30))
         plt.subplot(ni,3,1+k*3)
         plt.imshow(x_test[k])
         figure = plt.gca()
         x_axis = figure.axes.get_xaxis()
         x_axis.set_visible(False)
         y_axis = figure.axes.get_yaxis()
         y_axis.set_visible(False)
         plt.subplot(ni,3,2+k*3)
         plt.imshow(y_test[k])
         figure = plt.gca()
         x_axis = figure.axes.get_xaxis()
         x_axis.set_visible(False)
         y_axis = figure.axes.get_yaxis()
         y_axis.set_visible(False)
         plt.subplot(ni,3,3+k*3)
         plt.imshow(pp2[k])
```

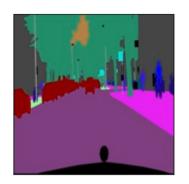
figure = plt.gca()
x_axis = figure.axes.get_xaxis()
x_axis.set_visible(False)
y_axis = figure.axes.get_yaxis()
y_axis.set_visible(False)













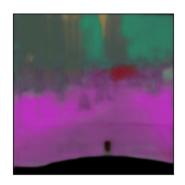




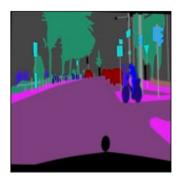














```
[9]: intersection = np.logical_and(y_test[1,:,:,:], pp2)
union = np.logical_or(y_test[1,:,:,:], pp2)
iou_score = np.sum(intersection) / np.sum(union)
print(iou_score)
```

0.9607899983723959

```
[10]: diff2 = y_test[1] - pp2[1]
m_norm2 = np.sum(abs(diff2))
print(m_norm2)
print(m_norm2/(256*256))
```

13774.887988135903 0.21018811017053074