Segmentation of Indian Traffic

In [ ]:
```
import math
import tensorflow as tf
#tf.compat.v1.enable_eager_execution()

from PIL import Image, ImageDraw
from PIL import ImagePath
import pandas as pd
import os
from os import path
from tqdm import tqdm
import json
import cv2
import numpy as np
import matplotlib.pyplot as plt
import urllib
```

```
1. All your data will be in the folder "data"

2. Inside the data you will be having two folders

|--- data
|-----| ---- images
|-----| ------|----- Scene 1
|-----| ------|--------| ----- Frame 1 (image 1)
|-----| ------|--------| ----- Frame 2 (image 2)
|-----| ------|--------| ----- ...
|-----| ------|----- Scene 2
|-----| ------|--------| ----- Frame 1 (image 1)
|-----| ------|--------| ----- Frame 2 (image 2)
|-----| ------|--------| ----- ...
|-----| ------|----- .....
|-----| ---- masks
|-----| ------|----- Scene 1
|-----| ------|--------| ----- json 1 (labeled objects in image 1)
|-----| ------|--------| ----- json 2 (labeled objects in image 1)
|-----| ------|--------| ----- ...
|-----| ------|----- Scene 2
|-----| ------|--------| ----- json 1 (labeled objects in image 1)
|-----| ------|--------| ----- json 2 (labeled objects in image 1)
|-----| ------|--------| ----- ...
|-----| ------|----- .....
```

Task 1: Preprocessing

In [ ]:

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

In [ ]:

```
!unzip /content/drive/MyDrive/data.zip
```

```
  inflating: data/images/377/frame36144_leftImg8bit.jpg
  inflating: data/images/377/frame36253_leftImg8bit.jpg
  inflating: data/images/377/frame36335_leftImg8bit.jpg
  inflating: data/images/377/frame36553_leftImg8bit.jpg
  inflating: data/images/377/frame36662_leftImg8bit.jpg
  inflating: data/images/377/frame36826_leftImg8bit.jpg
  inflating: data/images/377/frame36935_leftImg8bit.jpg
  inflating: data/images/377/frame37071_leftImg8bit.jpg
  inflating: data/images/377/frame3729_leftImg8bit.jpg
  inflating: data/images/377/frame37317_leftImg8bit.jpg
  inflating: data/images/377/frame37508_leftImg8bit.jpg
  inflating: data/images/377/frame37699_leftImg8bit.jpg
  inflating: data/images/377/frame37917_leftImg8bit.jpg
  inflating: data/images/377/frame38162_leftImg8bit.jpg
  inflating: data/images/377/frame38408_leftImg8bit.jpg
  inflating: data/images/377/frame3849_leftImg8bit.jpg
  inflating: data/images/377/frame38680_leftImg8bit.jpg
  inflating: data/images/377/frame38844_leftImg8bit.jpg
  inflating: data/images/377/frame39199_leftImg8bit.jpg
```

1. Get all the file name and corresponding json files

In [ ]:

```
import re
def return_file_names_df(root_dir):
    # write the code that will create a dataframe with two columns ['images'
    # the column 'image' will have path to images
    # the column 'json' will have path to json files
    image_path=[]
    json_path=[]

    def sort_path(path):
      x=list(map(int,re.findall(r"\d+",path)))
      return x[0]


    for i in os.listdir(root_dir):
      if i=='images':

        screens = sorted(list(map(int,os.listdir(os.path.join(root_dir,i))))

        for j in screens:

          paths=sorted(os.listdir(os.path.join(root_dir,i,str(j))),key=sort_

          for k in paths:
            image_path.append(os.path.join(root_dir,i,str(j),str(k)))


      else:

        screens = sorted(list(map(int,os.listdir(os.path.join(root_dir,i))))

        for j in screens:

          paths=sorted(os.listdir(os.path.join(root_dir,i,str(j))),key=sort_

          for k in paths:
            json_path.append(os.path.join(root_dir,i,str(j),str(k)))




    data_df=pd.DataFrame(np.hstack((np.array([image_path]).reshape(-1,1),np.


    return data_df
```

In [ ]:

```
data_df = return_file_names_df("data")
data_df.head()
```

Out[5]:

	images	json
0	data/images/201/frame0029_leftImg8bit.jpg	data/mask/201/frame0029_gtFine_polygons.json
1	data/images/201/frame0299_leftImg8bit.jpg	data/mask/201/frame0299_gtFine_polygons.json
2	data/images/201/frame0779_leftImg8bit.jpg	data/mask/201/frame0779_gtFine_polygons.json
3	data/images/201/frame1019_leftImg8bit.jpg	data/mask/201/frame1019_gtFine_polygons.json
4	data/images/201/frame1469_leftImg8bit.jpg	data/mask/201/frame1469_gtFine_polygons.json

> If you observe the dataframe, we can consider each row as single data point, where first feature is image and the second feature is corresponding json file

In [ ]:

```
def grader_1(data_df):
    for i in data_df.values:
        if not (path.isfile(i[0]) and path.isfile(i[1]) and i[0][12:i[0].fin
            return False
    return True
```

In [ ]:

```

grader_1(data_df)
```

Out[7]: True

In [ ]:

```
data_df.shape
```

Out[8]: (4008, 2)

2. Structure of sample Json file

```
"imgHeight": 1080,
"imgWidth": 1920,
"objects": [
    {
        "date": "25-Jun-2019 23:13:12",
        "deleted": 0,
        "draw": true,
        "id": 0,
        "label": "sky",
        "polygon": [
            [
                0.0,
                556.1538461538462
            ],
            [
                810.0,
                565.3846153846154
            ],
            [
                1374.2307692307693,
                596.5384615384615
            ],
            [
                1919.0,
                639.2307692307692
            ],
            [
                1919.0,
                0.0
            ],
            [
                0.0,
                0.0
            ]
        ],
        "user": "cvit",
        "verified": 0
    },
```

- Each File will have 3 attributes
  - imgHeight: which tells the height of the image
  - imgWidth: which tells the width of the image
  - objects: it is a list of objects, each object will have multiple attributes,
    - label: the type of the object
    - polygon: a list of two element lists, representing the coordinates of the polygon

Compute the unique labels

Let's see how many unique objects are there in the json file. to see how to get the object from the json file please check [this blog (https://www.geeksforgeeks.org/read-json-file-using-python/)](https://www.geeksforgeeks.org/read-json-file-using-python/)

In [ ]:

```
print(data_df['json'][0])
f = open(data_df['json'][0])

data=json.load(f)

for i in data['objects']:
  print(i)
f.close()
```

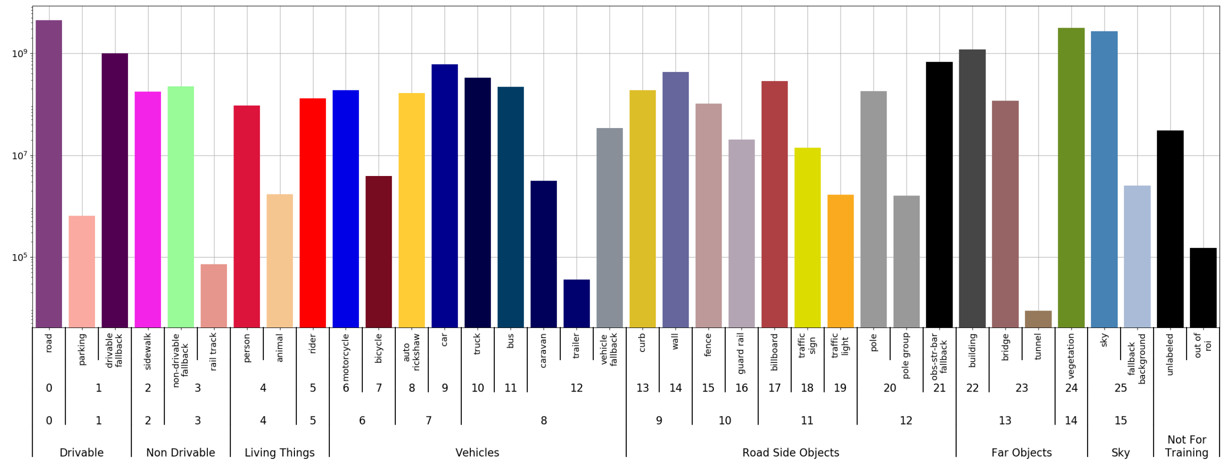

```
{'date': '14-Jun-2019 17:20:55', 'deleted': 0, 'draw': True, 'id': 4, 'labe
l': 'drivable fallback', 'polygon': [[1374.7624309392265, 554.9171270718232],
[1919.0, 640.8397790055249], [1919.0, 735.0], [1620.5966850828731, 679.027624
3093923], [1548.4615384615383, 660.0], [1402.2099447513813, 632.486187845303
9], [1369.9889502762433, 624.132596685083], [1333.8461538461538, 616.15384615
38462], [1308.4615384615383, 608.0769230769231], [1292.3076923076922, 600.0],
[1292.3076923076922, 588.4615384615385], [1296.0, 584.7513812154697], [1309.1
270718232045, 571.6243093922652]], 'user': 'cvit', 'verified': 0}
{'date': '14-Jun-2019 17:33:35', 'deleted': 0, 'draw': True, 'id': 5, 'labe

l': 'motorcycle', 'polygon': [[486.8950276243094, 600.2651933701658], [489.28
17679558011, 605.0386740331492], [488.0883977900553, 608.6187845303867], [48
8.0883977900553, 614.585635359116], [494.05524861878456, 620.5524861878454],
[496.44198895027625, 627.7127071823205], [489.2817679558011, 631.292817679558
1], [480.92817679558016, 625.3259668508288], [480.92817679558016, 619.3591160
220994], [457.060773480663, 614.585635359116], [445.12707182320446, 613.39226
51933702], [445.12707182320446, 605.0386740331492], [471.38121546961327, 611.
0055248618785], [470.18784530386745, 605.0386740331492], [471.38121546961327,
603.8453038674033], [463.0276243093923, 605.0386740331492], [461.834254143646
43, 603.8453038674033], [470.18784530386745, 601.4585635359116], [454.6740331
```


In [ ]:

```
def return_unique_labels(data_df):
    # for each file in the column json
    #       read and store all the objects present in that file
    # compute the unique objects and retrun them
    # if open any json file using any editor you will get better sense of it
    unique_labels=set()
    for i in data_df['json']:

      f=open(i)
      data=json.load(f)

      for j in data['objects']:

        unique_labels.add(j['label'])

    return unique_labels
```

In [ ]:

```
unique_labels=return_unique_labels(data_df)
```



In [ ]:
```python
label_clr = {'road':10, 'parking':20, 'drivable fallback':20,'sidewalk':30,'
                        'person':50, 'animal':50, 'rider':60, 'motorcycle':7
                        'car':80, 'truck':90, 'bus':90, 'vehicle fallback':9
                        'curb':100, 'wall':100, 'fence':110,'guard rail':110
                        'traffic light':120, 'pole':130, 'polegroup':130, 'o
                        'bridge':140,'tunnel':140, 'vegetation':150, 'sky':1
                        'out of roi':0, 'ego vehicle':170, 'ground':180,'rec
                   'train':200}
```

In [ ]:
```python
def grader_2(unique_labels):
    if (not (set(label_clr.keys())-set(unique_labels))) and len(unique_label
        print("True")
    else:
        print("Flase")

grader_2(unique_labels)
```

```
True
```

```
* here we have given a number for each of object types, if you see we ar
e having 21 different set of objects
* Note that we have multiplies each object's number with 10, that is jus
t to make different objects look differently in the segmentation map
* Before you pass it to the models, you might need to devide the image a
rray /10.
```

3. Extracting the polygons from the json files

In [ ]:
```
def get_poly(file):
    # this function will take a file name as argument

    # it will process all the objects in that file and returns

    # label: a list of labels for all the objects label[i] will have the cor
    # len(label) == number of objects in the image

    # vertexlist: it should be list of list of vertices in tuple formate
    # ex: [[(x11,y11), (x12,y12), (x13,y13) .. (x1n,y1n)]
    #     [(x21,y21), (x22,y12), (x23,y23) .. (x2n,y2n)]
    #      .....
    #     [(xm1,ym1), (xm2,ym2), (xm3,ym3) .. (xmn,ymn)]]
    # len(vertexlist) == number of objects in the image

    # * note that label[i] and vertextlist[i] are corresponds to the same ob
    # the other represents the location

    # width of the image
    # height of the image

    f=open(file)
    data=json.load(f)

    h=data['imgHeight']
    w=data['imgWidth']
    vertexlist=[]
    label=[]
    for i in data['objects']:
      if len(i['polygon'])>=2:
        label.append(i['label'])
        list_of_co_ordinates=[]
        for j in i['polygon']:
          if len(j)==2:
            list_of_co_ordinates.append(tuple(j))
          else:
            print(len(j))
        vertexlist.append(list_of_co_ordinates)

    return w, h, label, vertexlist
```

In [ ]:
```
w,h,label,vertex=get_poly('data/mask/201/frame0029_gtFine_polygons.json')
len(label),len(vertex),w,h
```

Out[15]: (227, 227, 1920, 1080)

In [ ]:
```
def grader_3(file):
    w, h, labels, vertexlist = get_poly(file)
    print(len((set(labels)))==18 and len(vertexlist)==227 and w==1920 and h=
          and isinstance(vertexlist,list) and isinstance(vertexlist[0],list)

grader_3('data/mask/201/frame0029_gtFine_polygons.json')
```

True

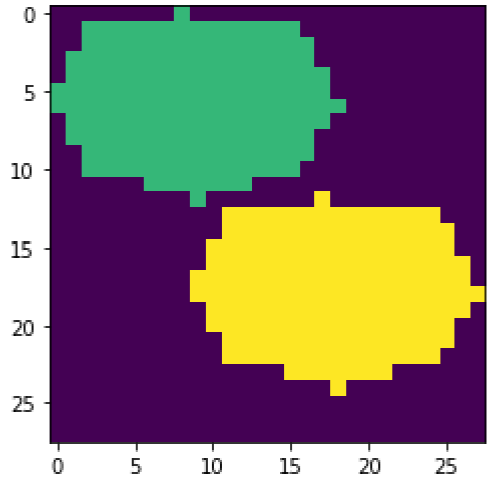
4. Creating Image segmentations by drawing set of polygons

Example

In [ ]:

```
import math
from PIL import Image, ImageDraw
from PIL import ImagePath
side=8
x1 = [ ((math.cos(th) + 1) *9, (math.sin(th) + 1) * 6) for th in [i * (2 * m
x2 = [ ((math.cos(th) + 2) *9, (math.sin(th) + 3) *6) for th in [i * (2 * ma

img = Image.new("RGB", (28,28))
img1 = ImageDraw.Draw(img)
# writing the first polygon
img1.polygon(x1, fill =20)
# writing the second polygon
img1.polygon(x2, fill =30)

img=np.array(img)
# note that the filling of the values happens at the channel 1, so we are co
plt.imshow(img[:,:,0])
print(img.shape)
print(img[:,:,0]//10)
im = Image.fromarray(img[:,:,0])
im.save("test_image.png")
```

```
(28, 28, 3)
[[0 0 0 0 0 0 0 0 2 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 2 2 2 2 2 2 2 2 2 2 2 2 2 2 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 0 0 0 0 0 0 0 0 0 0 0]
 [0 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 0 0 0 0 0 0 0 0 0 0 0]
 [0 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 0 0 0 0 0 0 0 0 0 0]
 [2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 0 0 0 0 0 0 0 0 0 0]
 [2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 0 0 0 0 0 0 0 0 0]
 [0 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 0 0 0 0 0 0 0 0 0 0]
 [0 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 2 2 2 2 2 2 2 2 2 2 2 2 2 2 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 2 2 2 2 2 2 2 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 2 0 0 0 0 0 0 0 3 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 3 3 3 3 3 3 3 3 3 3 3 3 3 3 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 0 0]
 [0 0 0 0 0 0 0 0 0 0 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 0 0]
 [0 0 0 0 0 0 0 0 0 0 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 0]
 [0 0 0 0 0 0 0 0 0 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 0]
 [0 0 0 0 0 0 0 0 0 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3]
 [0 0 0 0 0 0 0 0 0 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 0]
 [0 0 0 0 0 0 0 0 0 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 3 3 3 3 3 3 3 3 3 3 3 3 3 3 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 3 3 3 3 3 3 3 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 3 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]]
```



Mask

In [ ]:

```
from tqdm import tqdm
def compute_masks(data_df):
    # after you have computed the vertexlist plot that polygone in image lik

    # img = Image.new("RGB", (w, h))
    # img1 = ImageDraw.Draw(img)
    # img1.polygon(vertexlist[i], fill = label_clr[label[i]])

    # after drawing all the polygons that we collected from json file,
    # you need to store that image in the folder like this "data/output/scen

    # after saving the image into disk, store the path in a list
    # after storing all the paths, add a column to the data_df['mask'] ex: d
    output_paths=[]
    for i in tqdm(data_df['json']):

      w,h,label,vertexlist=get_poly(i)
      img=Image.new("RGB",(w,h))
      img1=ImageDraw.Draw(img)
      for j in range(len(label)):
        img1.polygon(vertexlist[j],fill=label_clr[label[j]])

      path=re.sub("mask","output",i)
      path=re.sub("json","png",path)

      directory=re.findall("data/output/\d+",path)[0]
      if os.path.isdir(directory):
        img.save(path)

      else:

        os.makedirs(directory)
        img.save(path)

      output_paths.append(path)
    data_df['output']=np.array([output_paths]).reshape(-1,1)
    return data_df
```

In [ ]:
```
final_data_df=compute_masks(data_df)
```

```
100%|██████████| 4008/4008 [06:30<00:00, 10.26it/s]
```

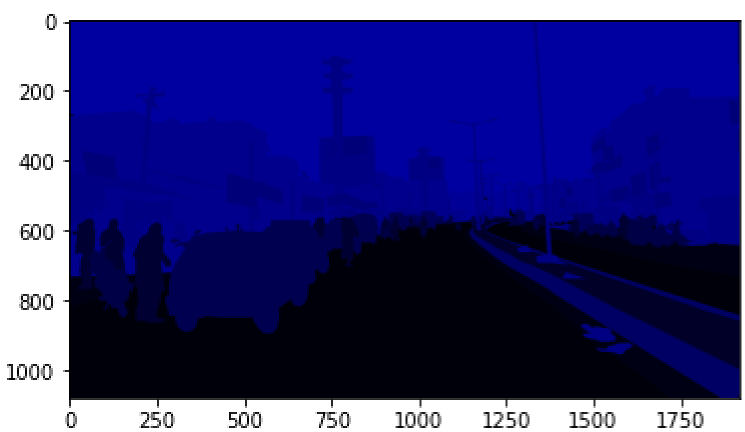
In [ ]:
```
final_data_df.head()
```

Out[20]:

	images	json	
0	data/images/201/frame0029_leftImg8bit.jpg	data/mask/201/frame0029_gtFine_polygons.json	data/output/20
1	data/images/201/frame0299_leftImg8bit.jpg	data/mask/201/frame0299_gtFine_polygons.json	data/output/20
2	data/images/201/frame0779_leftImg8bit.jpg	data/mask/201/frame0779_gtFine_polygons.json	data/output/20
3	data/images/201/frame1019_leftImg8bit.jpg	data/mask/201/frame1019_gtFine_polygons.json	data/output/20
4	data/images/201/frame1469_leftImg8bit.jpg	data/mask/201/frame1469_gtFine_polygons.json	data/output/20

In [ ]:
```
plt.imshow(cv2.imread(final_data_df['output'][0],cv2.IMREAD_UNCHANGED))
```

Out[21]: <matplotlib.image.AxesImage at 0x7fca078081d0>



In [ ]:
```
#daving the final dataframe to a csv file
final_data_df.to_csv('preprocessed_data.csv', index=False)
```

Task 2: Applying Unet to segment the images

Task 2.1: Dice loss

Dice loss = 1 - dice coefficient

where dice coefficient = $\frac{2TP}{2TP+FP+FN}$

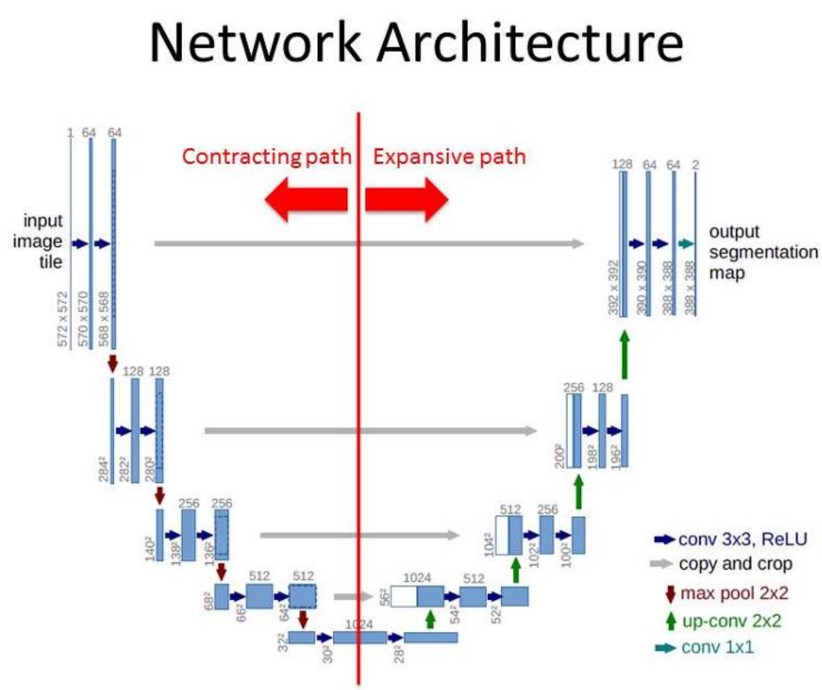
Range of a loss function is $\{0, 1\}$

If model predicts all True Positives correctly then dice coefficient will be 1 and dice loss becomes 0 else dice loss will be in between $\{0, 1\}$

we can use cross-entropy loss as well but it is sensitive to imbalance dataset , In image segmentation we will deal with images which are having imbalanced labels because of this cross-entropy will not give proper measurement of True positives, people often use dice loss or iou loss for image segmentation task which penalizes the false positives and measure the True positive rate efficiently when compares to cross entropy , they are more robust to imbalance data and it can be differentiable where we can easily back-propagate to updates weights

Task 2.2: Training Unet

```
* please check the paper: https://arxiv.org/abs/1505.04597

*
```




```
* As a part of this task we won't writing this whole architecture, rathe
r we will be doing transfer learning

* please check the library https://github.com/qubvel/segmentation_models

* You can install it like this "pip install -U segmentation-models==0.2.
1", even in google colab you can install the    same with "!pip install
 -U segmentation-models==0.2.1"

* Check the reference notebook in which we have solved one end to end ca
se study of image forgery detection using same  unet
```

* The number of channels in the output will depend on the number of classes in your data, since we know that we are having 21 classes, the number of channels in the output will also be 21

* **This is where we want you to explore, how do you featurize your created segmentation map note that the original map will be of (w, h, 1) and the output will be (w, h, 21) how will you calculate the loss**, you can check the examples in segmentation github

* Split the data into 80:20.
* Train the UNET on the given dataset and plot the train and validation loss.

split data

In [ ]:
```
from sklearn.model_selection import train_test_split

X_train,X_test=train_test_split(final_data_df[["images","output"]],test_size
```

In [ ]:
```
X_test,X_val=train_test_split(final_data_df[["images","output"]],test_size=0
```

In [ ]:
```
len(X_train),len(X_test),len(X_val)
```

Out[25]: (3607, 2004, 2004)

In [ ]:
```
X_test.head(2)
```

Out[26]:

	images	output
1801	data/images/302/frame17538_leftImg8bit.jpg	data/output/302/frame17538_gtFine_polygons.png
1628	data/images/288/frame21619_leftImg8bit.jpg	data/output/288/frame21619_gtFine_polygons.png

Dataset building

In [ ]:

```
import imgaug.augmenters as iaa

def normalize(img):
  return (img/255).astype("float")

aug2 = iaa.Fliplr(1)
aug3 = iaa.Flipud(1)
aug4 = iaa.Emboss(alpha=(1), strength=1)
aug5 = iaa.DirectedEdgeDetect(alpha=(0.8), direction=(1.0))
aug6 = iaa.Sharpen(alpha=(1.0), lightness=(1.5))

class Dataset:

  def __init__(self,dataframe,classes,training=True):

    self.Classes={'road':10, 'parking':20, 'drivable fallback':20,'sidewalk'
                       'person':50, 'animal':50, 'rider':60, 'motorcycle':7
                       'car':80, 'truck':90, 'bus':90, 'vehicle fallback':9
                       'curb':100, 'wall':100, 'fence':110,'guard rail':110
                       'traffic light':120, 'pole':130, 'polegroup':130, 'o
                       'bridge':140,'tunnel':140, 'vegetation':150, 'sky':1
                       'out of roi':0, 'ego vehicle':170, 'ground':180,'rec
                  'train':200}
    self.training=training

    self.image_paths=dataframe["images"].reset_index(drop=True)
    self.output_paths=dataframe['output'].reset_index(drop=True)
    self.labels=sorted(list(set(self.Classes[i] for i in classes)))

  def __getitem__(self,i):

    image = cv2.imread(self.image_paths[i], cv2.IMREAD_UNCHANGED)
    image = cv2.resize(image,(512,512),interpolation=cv2.INTER_AREA)
    image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
    image=normalize(image)

    mask  = cv2.imread(self.output_paths[i], cv2.IMREAD_UNCHANGED)
    mask= cv2.resize(mask,(512,512),interpolation=cv2.INTER_AREA)



    if self.training:
      a = np.random.uniform()
      if a<0.2:
        image = aug2.augment_image(image)
        image_mask = aug2.augment_image(mask)
      elif a<0.4:
        image = aug3.augment_image(image)
        image_mask = aug3.augment_image(mask)
      elif a<0.6:
        image = aug4.augment_image(image)
        image_mask = aug4.augment_image(mask)
      elif a<0.8:
        image = aug5.augment_image(image)
        image_mask = aug5.augment_image(mask)
      else:
```

```
        image = aug6.augment_image(image)
        image_mask = aug6.augment_image(mask)

      ohe_mask=[(image_mask[:,:,2]==i) for i in self.labels]
      onehotenocded=np.stack(ohe_mask,axis=-1).astype('float')

      return image, onehotenocded
    else:

      ohe_mask=[(mask[:,:,2]==i) for i in self.labels]
      onehotenocded=np.stack(ohe_mask,axis=-1).astype('float')

      return image , onehotenocded

  def __len__(self):
    return len(self.image_paths)

```

Data generator

In [ ]:

```
class Dataloder(tf.keras.utils.Sequence):
    def __init__(self, dataset, batch_size=1, shuffle=False):
        self.dataset = dataset
        self.batch_size = batch_size
        self.shuffle = shuffle
        self.indexes = np.arange(len(dataset))

    def __getitem__(self, i):

        # collect batch data
        start = i * self.batch_size
        stop = (i + 1) * self.batch_size
        data = []
        for j in range(start, stop):
            data.append(self.dataset[j])

        batch = [np.stack(samples, axis=0) for samples in zip(*data)]

        return tuple(batch)

    def __len__(self):
        return len(self.indexes) // self.batch_size

    def on_epoch_end(self):
        if self.shuffle:
            self.indexes = np.random.permutation(self.indexes)
```

In [ ]:
```
1 pip install segmentation_models
```

```
Collecting segmentation_models
  Downloading segmentation_models-1.0.1-py3-none-any.whl (33 kB)
Collecting efficientnet==1.0.0
  Downloading efficientnet-1.0.0-py3-none-any.whl (17 kB)
Collecting image-classifiers==1.0.0
  Downloading image_classifiers-1.0.0-py3-none-any.whl (19 kB)
Collecting keras-applications<=1.0.8,>=1.0.7
  Downloading Keras_Applications-1.0.8-py3-none-any.whl (50 kB)
     |████████████████████████████████| 50 kB 7.4 MB/s
Requirement already satisfied: scikit-image in /usr/local/lib/python3.7/dist-
packages (from efficientnet==1.0.0->segmentation_models) (0.18.3)
Requirement already satisfied: h5py in /usr/local/lib/python3.7/dist-packages
(from keras-applications<=1.0.8,>=1.0.7->segmentation_models) (3.1.0)
Requirement already satisfied: numpy>=1.9.1 in /usr/local/lib/python3.7/dist-
packages (from keras-applications<=1.0.8,>=1.0.7->segmentation_models) (1.19.
5)
Requirement already satisfied: cached-property in /usr/local/lib/python3.7/di
st-packages (from h5py->keras-applications<=1.0.8,>=1.0.7->segmentation_model
s) (1.5.2)
Requirement already satisfied: networkx>=2.0 in /usr/local/lib/python3.7/dist
-packages (from scikit-image->efficientnet==1.0.0->segmentation_models) (2.6.
3)
Requirement already satisfied: scipy>=1.0.1 in /usr/local/lib/python3.7/dist-
packages (from scikit-image->efficientnet==1.0.0->segmentation_models) (1.4.
1)
Requirement already satisfied: matplotlib!=3.0.0,>=2.0.0 in /usr/local/lib/py
thon3.7/dist-packages (from scikit-image->efficientnet==1.0.0->segmentation_m
odels) (3.2.2)
Requirement already satisfied: pillow!=7.1.0,!=7.1.1,>=4.3.0 in /usr/local/li
b/python3.7/dist-packages (from scikit-image->efficientnet==1.0.0->segmentati
on_models) (7.1.2)
Requirement already satisfied: PyWavelets>=1.1.1 in /usr/local/lib/python3.7/
dist-packages (from scikit-image->efficientnet==1.0.0->segmentation_models)
(1.2.0)
Requirement already satisfied: imageio>=2.3.0 in /usr/local/lib/python3.7/dis
t-packages (from scikit-image->efficientnet==1.0.0->segmentation_models) (2.
4.1)
Requirement already satisfied: tifffile>=2019.7.26 in /usr/local/lib/python3.
7/dist-packages (from scikit-image->efficientnet==1.0.0->segmentation_models)
(2021.11.2)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/dist-
packages (from matplotlib!=3.0.0,>=2.0.0->scikit-image->efficientnet==1.0.0->
segmentation_models) (0.11.0)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /u
sr/local/lib/python3.7/dist-packages (from matplotlib!=3.0.0,>=2.0.0->scikit-
image->efficientnet==1.0.0->segmentation_models) (3.0.6)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.7/
dist-packages (from matplotlib!=3.0.0,>=2.0.0->scikit-image->efficientnet==1.
0.0->segmentation_models) (1.3.2)
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python
3.7/dist-packages (from matplotlib!=3.0.0,>=2.0.0->scikit-image->efficientnet
==1.0.0->segmentation_models) (2.8.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-pack
ages (from python-dateutil>=2.1->matplotlib!=3.0.0,>=2.0.0->scikit-image->eff
```

```
icientnet==1.0.0->segmentation_models) (1.15.0)
Installing collected packages: keras-applications, image-classifiers, efficie
ntnet, segmentation-models
Successfully installed efficientnet-1.0.0 image-classifiers-1.0.0 keras-appli
cations-1.0.8 segmentation-models-1.0.1
```

Model

In [ ]:

```python
import segmentation_models as sm
sm.set_framework('tf.keras')

from segmentation_models import Unet
# prepare model
tf.keras.backend.clear_session()
model1 = Unet(backbone_name='resnet101', encoder_weights='imagenet',decoder_
```

```
Segmentation Models: using `keras` framework.
Downloading data from https://github.com/qubvel/classification_models/releases/
download/0.0.1/resnet101_imagenet_1000_no_top.h5 (https://github.com/qubvel/cla
ssification_models/releases/download/0.0.1/resnet101_imagenet_1000_no_top.h5)
171171840/171164896 [==============================] - 5s 0us/step
171180032/171164896 [==============================] - 5s 0us/step
```

In [ ]:

```python
model1.summary()
```

```
Model: "model_1"
____________________________________________________________________________
_____________________
 Layer (type)                   Output Shape         Param #     Connected to
============================================================================
=====================
 data (InputLayer)              [(None, 512, 512, 3  0           []
                                )]

 bn_data (BatchNormalization)   (None, 512, 512, 3)  9           ['data[0]
[0]']

 zero_padding2d (ZeroPadding2D)  (None, 518, 518, 3)  0          ['bn_data[0]
[0]']

 conv0 (Conv2D)                 (None, 256, 256, 64  9408        ['zero_paddi
ng2d[0][0]']
                                )
```

In [ ]:

In [ ]:
```
CLASSES = unique_labels
train_dataset = Dataset(X_train, classes=CLASSES,training=True)
test_dataset  = Dataset(X_test, classes=CLASSES,training=False)
val_dataset  = Dataset(X_val, classes=CLASSES,training=False)


train_dataloader = Dataloder(train_dataset, batch_size=5, shuffle=True)
test_dataloader = Dataloder(test_dataset, batch_size=4, shuffle=True)
val_dataloader = Dataloder(val_dataset, batch_size=4, shuffle=True)

print(train_dataloader[0][0].shape)
assert train_dataloader[0][0].shape == (5, 512, 512, 3)
assert train_dataloader[0][1].shape == (5, 512, 512, 21)
```

```
(5, 512, 512, 3)
```

In [ ]:
```
import segmentation_models as sm
from segmentation_models.metrics import IOUScore

optim = tf.keras.optimizers.Adam(0.00001)
focal_loss = sm.losses.cce_dice_loss
model1.compile(optimizer=optim, loss=focal_loss,metrics=[IOUScore(threshold=
```

Training

In [ ]:
```
def scheduler(epoch, lr):
 if epoch%2==0:
   return 0.6*lr
 else:
   return lr
lrdecay=tf.keras.callbacks.LearningRateScheduler(scheduler)

callbacks = [
    tf.keras.callbacks.ModelCheckpoint('./best_model_103_.h5', save_weights_
model1.load_weights('./best_model_102_.h5')
history = model1.fit(train_dataloader, steps_per_epoch=len(train_dataloader)
                              validation_data=val_dataloader,callbacks=callb
```

```
Epoch 1/30
721/721 [==============================] - 754s 1s/step - loss: 0.5327 - iou_
score: 0.4085 - val_loss: 0.5547 - val_iou_score: 0.4725
Epoch 2/30
721/721 [==============================] - 750s 1s/step - loss: 0.5314 - iou_
score: 0.4098 - val_loss: 0.5510 - val_iou_score: 0.4735
Epoch 3/30
721/721 [==============================] - 746s 1s/step - loss: 0.5271 - iou_
score: 0.4142 - val_loss: 0.5505 - val_iou_score: 0.4800
Epoch 4/30
721/721 [==============================] - 756s 1s/step - loss: 0.5207 - iou_
score: 0.4206 - val_loss: 0.5495 - val_iou_score: 0.4762
Epoch 5/30
721/721 [==============================] - 755s 1s/step - loss: 0.5243 - iou_
score: 0.4179 - val_loss: 0.5464 - val_iou_score: 0.4784
Epoch 6/30
721/721 [==============================] - 753s 1s/step - loss: 0.5182 - iou_
score: 0.4229 - val_loss: 0.5452 - val_iou_score: 0.4804
Epoch 7/30
721/721 [==============================] - 756s 1s/step - loss: 0.5158 - iou_
score: 0.4253 - val_loss: 0.5444 - val_iou_score: 0.4837
Epoch 8/30
721/721 [==============================] - 756s 1s/step - loss: 0.5112 - iou_
score: 0.4290 - val_loss: 0.5414 - val_iou_score: 0.4903
Epoch 9/30
721/721 [==============================] - 749s 1s/step - loss: 0.5117 - iou_
score: 0.4294 - val_loss: 0.5392 - val_iou_score: 0.4933
Epoch 10/30
721/721 [==============================] - 754s 1s/step - loss: 0.5096 - iou_
score: 0.4315 - val_loss: 0.5372 - val_iou_score: 0.4959
Epoch 11/30
721/721 [==============================] - 743s 1s/step - loss: 0.5039 - iou_
score: 0.4367 - val_loss: 0.5379 - val_iou_score: 0.4952
Epoch 12/30
721/721 [==============================] - 747s 1s/step - loss: 0.5072 - iou_
score: 0.4338 - val_loss: 0.5365 - val_iou_score: 0.4979
Epoch 13/30
721/721 [==============================] - 744s 1s/step - loss: 0.5035 - iou_
score: 0.4371 - val_loss: 0.5324 - val_iou_score: 0.4986
Epoch 14/30
721/721 [==============================] - 730s 1s/step - loss: 0.4988 - iou_
score: 0.4422 - val_loss: 0.5324 - val_iou_score: 0.5023
Epoch 15/30
```

```
721/721 [==============================] - 740s 1s/step - loss: 0.4974 - iou_
score: 0.4424 - val_loss: 0.5315 - val_iou_score: 0.5009
Epoch 16/30
721/721 [==============================] - 745s 1s/step - loss: 0.4947 - iou_
score: 0.4455 - val_loss: 0.5301 - val_iou_score: 0.5063
Epoch 17/30
721/721 [==============================] - 745s 1s/step - loss: 0.4918 - iou_
score: 0.4474 - val_loss: 0.5292 - val_iou_score: 0.5079
Epoch 18/30
721/721 [==============================] - 737s 1s/step - loss: 0.4932 - iou_
score: 0.4462 - val_loss: 0.5270 - val_iou_score: 0.5074
Epoch 19/30
721/721 [==============================] - 740s 1s/step - loss: 0.4876 - iou_
score: 0.4528 - val_loss: 0.5268 - val_iou_score: 0.5119
Epoch 20/30
721/721 [==============================] - 736s 1s/step - loss: 0.4905 - iou_
score: 0.4501 - val_loss: 0.5265 - val_iou_score: 0.5132
Epoch 21/30
721/721 [==============================] - 738s 1s/step - loss: 0.4856 - iou_
score: 0.4540 - val_loss: 0.5244 - val_iou_score: 0.5106
Epoch 22/30
721/721 [==============================] - 724s 1s/step - loss: 0.4831 - iou_
score: 0.4573 - val_loss: 0.5229 - val_iou_score: 0.5162
Epoch 23/30
721/721 [==============================] - 732s 1s/step - loss: 0.4859 - iou_
score: 0.4548 - val_loss: 0.5221 - val_iou_score: 0.5172
Epoch 24/30
721/721 [==============================] - 723s 1s/step - loss: 0.4799 - iou_
score: 0.4590 - val_loss: 0.5243 - val_iou_score: 0.5175
Epoch 25/30
721/721 [==============================] - 726s 1s/step - loss: 0.4780 - iou_
score: 0.4609 - val_loss: 0.5200 - val_iou_score: 0.5200
Epoch 26/30
721/721 [==============================] - 749s 1s/step - loss: 0.4770 - iou_
score: 0.4637 - val_loss: 0.5199 - val_iou_score: 0.5222
Epoch 27/30
721/721 [==============================] - 739s 1s/step - loss: 0.4777 - iou_
score: 0.4638 - val_loss: 0.5193 - val_iou_score: 0.5228
Epoch 28/30
721/721 [==============================] - 735s 1s/step - loss: 0.4721 - iou_
score: 0.4667 - val_loss: 0.5193 - val_iou_score: 0.5198
Epoch 29/30
721/721 [==============================] - 725s 1s/step - loss: 0.4706 - iou_
score: 0.4674 - val_loss: 0.5177 - val_iou_score: 0.5243
Epoch 30/30
721/721 [==============================] - 728s 1s/step - loss: 0.4723 - iou_
score: 0.4685 - val_loss: 0.5182 - val_iou_score: 0.5235
```

Model evaluation

In [ ]:

```
model1.load_weights('./best_model_103_.h5')
```

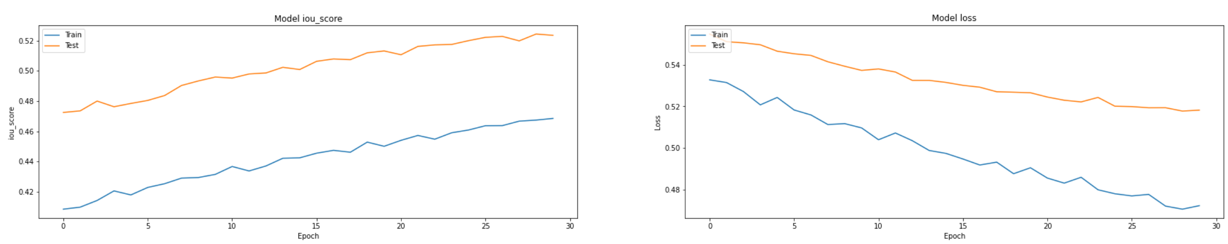
In [ ]:
```
model1.evaluate(test_dataloader)
```

```
501/501 [==============================] - 242s 482ms/step - loss: 0.5083 - iou
_score: 0.5306
```

Out[40]:
```
[0.5083001255989075, 0.530604362487793]
```

Model Performance

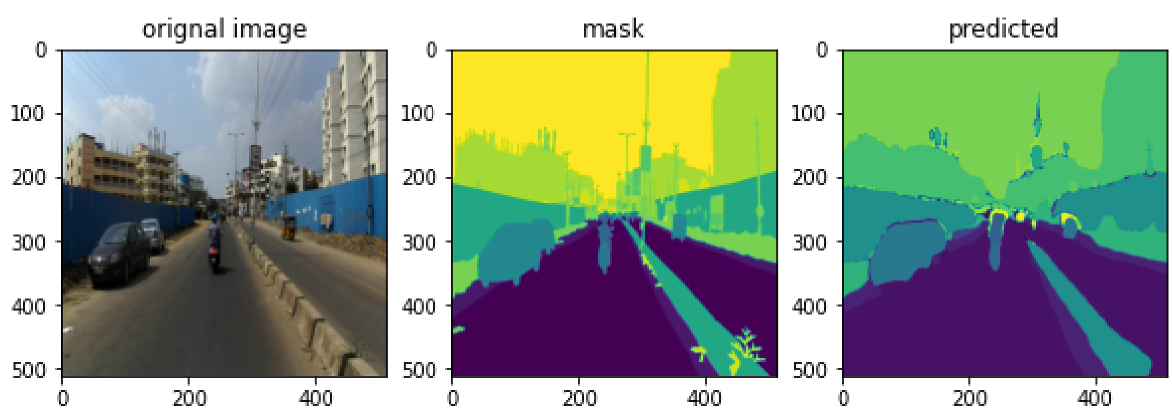
In [ ]:
```
plt.figure(figsize=(30, 5))
plt.subplot(121)
plt.plot(history.history['iou_score'])
plt.plot(history.history['val_iou_score'])
plt.title('Model iou_score')
plt.ylabel('iou_score')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')

# Plot training & validation loss values
plt.subplot(122)
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
plt.show()
```



Predictions

In [ ]:

```
plot_images=X_val[:10].reset_index(drop=True)
x=[0,10,20,30,40,50,60,70,80,90,100,110,120,130,140,150,160,170,18,190,200]

for p, i in enumerate(range(10)):
    #original image
    image = cv2.imread(plot_images['images'][p], cv2.IMREAD_UNCHANGED)
    image = cv2.resize(image, (512,512),interpolation=cv2.INTER_AREA)
    image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
    image=normalize(image)


    #predicted segmentation map
    predicted  =np.where(model1.predict(np.array([image]))>0.5,1,0)

    m=np.zeros((512,512))
    for j , k in enumerate(x):
      b=np.where(predicted[0][:,:,j]==1,k,0)
      m=m+b


    #original segmentation map
    image_mask = cv2.imread(plot_images['output'][p], cv2.IMREAD_UNCHANGED)
    image_mask = cv2.resize(image_mask, (512,512))[:,:,2]



    plt.figure(figsize=(10,6))
    plt.subplot(131)
    plt.imshow(image,)
    plt.title("orignal image")
    plt.subplot(132)
    plt.imshow(image_mask)
    plt.title("mask")
    plt.subplot(133)
    plt.imshow(m)
    plt.title("predicted")
    plt.show()
```



Task 3: Training CANet

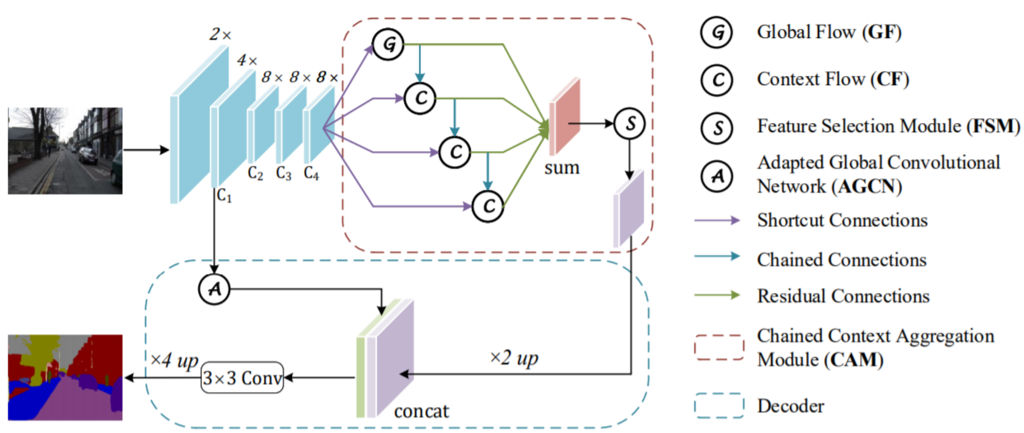
In [ ]:

```
import tensorflow as tf
# tf.compat.v1.enable_eager_execution()
from tensorflow import keras
from tensorflow.keras.layers import *
from tensorflow.keras.preprocessing import image
from tensorflow.keras.models import Model, load_model
from tensorflow.keras.layers import UpSampling2D
from tensorflow.keras.layers import MaxPooling2D, GlobalAveragePooling2D
from tensorflow.keras.layers import concatenate
from tensorflow.keras.layers import Multiply
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint
from tensorflow.keras import backend as K
from tensorflow.keras.layers import Input, Add, Dense, Activation, ZeroPaddi
from tensorflow.keras.models import Model, load_model
from tensorflow.keras.utils import plot_model
from tensorflow.keras.initializers import glorot_uniform
K.set_image_data_format('channels_last')
K.set_learning_phase(1)
```

```
/usr/local/lib/python3.7/dist-packages/keras/backend.py:414: UserWarning: `tf.k
eras.backend.set_learning_phase` is deprecated and will be removed after 2020-1
0-11. To update it, simply pass a True/False value to the `training` argument o
f the `__call__` method of your layer or model.
  warnings.warn('`tf.keras.backend.set_learning_phase` is deprecated and '
```

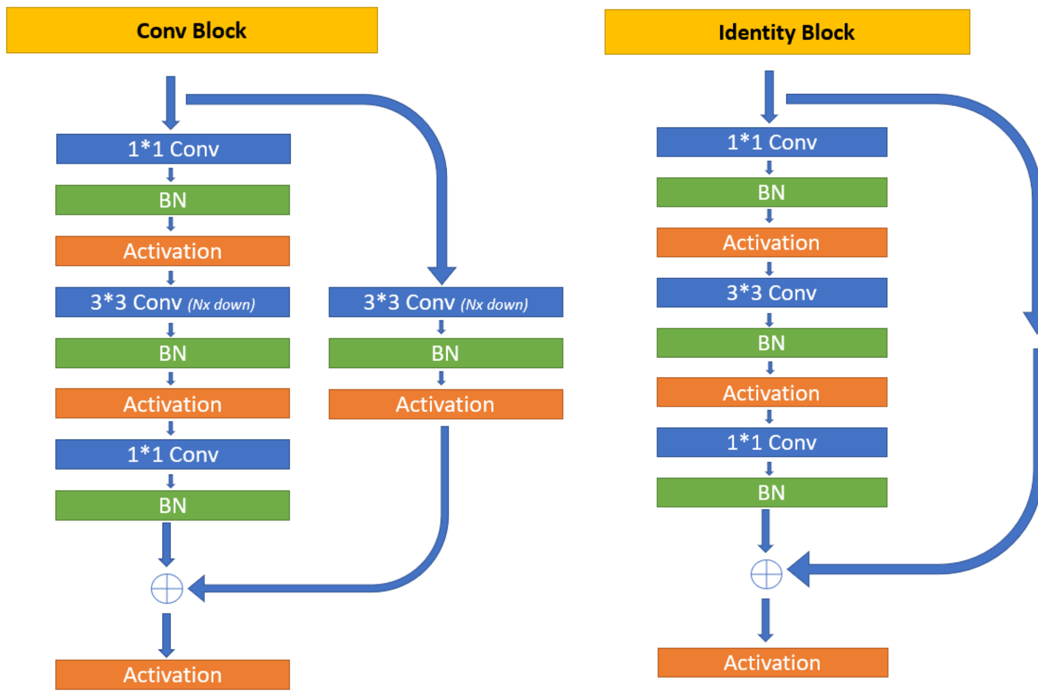
- as a part of this task we will be implementing the architecture based on this paper [https://arxiv.org/pdf/2002.12041.pdf (https://arxiv.org/pdf/2002.12041.pdf)](https://arxiv.org/pdf/2002.12041.pdf)
- We will be using the custom layers concept that we used in seq-seq assignment
- You can devide the whole architecture can be devided into two parts

    1. Encoder
    2. Decoder



- Encoder:
    - The first step of the encoder is to create the channel maps $[C_1, C_2, C_3, C_4]$

- C_1 width and heigths are 4x times less than the original image
- C_2 width and heigths are 8x times less than the original image
- C_3 width and heigths are 8x times less than the original image
- C_4 width and heigths are 8x times less than the original image
- *you can reduce the dimensions by using stride parameter*.
- $[C_1, C_2, C_3, C_4]$ are formed by applying a "conv block" followed by k number of "identity block". i.e the C_k feature map will single "conv block" followed by k number of "identity blocks".



- **The conv block and identity block of C_1**: the number filters in the covolutional layers will be $[4, 4, 8]$ and the number of filters in the parallel conv layer will also be 8.
- **The conv block and identity block of C_2**: the number filters in the covolutional layers will be $[8, 8, 16]$ and the number of filters in the parallel conv layer will also be 16.
- **The conv block and identity block of C_3**: the number filters in the covolutional layers will be $[16, 16, 32]$ and the number of filters in the parallel conv layer will also be 32.
- **The conv block and identity block of C_4**: the number filters in the covolutional layers will be $[32, 32, 64]$ and the number of filters in the parallel conv layer will also be 64.
- Here $\oplus$ represents the elementwise sum

NOTE: these filters are of your choice, you can explore more options also

- Example: if your image is of size $(512, 512, 3)$
  - the output after C_1 will be $128 * 128 * 8$
  - the output after C_2 will be $64 * 64 * 16$
  - the output after C_3 will be $64 * 64 * 32$
  - the output after C_4 will be $64 * 64 * 64$

In [ ]:

```python
tf.keras.backend.clear_session()
class convolutional_block(tf.keras.layers.Layer):

    def __init__(self, kernel=3,  filters=[4,4,8], stride=1, name="convoluti
        super().__init__(name=name)
        self.F1, self.F2, self.F3 = filters
        self.kernel = kernel
        self.stride = stride

        self.conv1=Conv2D(filters=self.F1,kernel_size=1,padding='same',name=
        self.batch_1=BatchNormalization(name=name+"_b1")

        self.conv2=Conv2D(filters=self.F2,kernel_size=self.kernel,strides=se
        self.batch_2=BatchNormalization(name=name+"_b2")

        self.conv3=Conv2D(filters=self.F3,kernel_size=1,padding='same',name=
        self.batch_3=BatchNormalization(name=name+"_b3")


        self.conv_parallel=Conv2D(filters=self.F3,kernel_size=self.kernel,st
        self.batch_parallel=BatchNormalization(name=name+"_b_parallel")


        self.add=Add()
        self.activation=Activation("relu")

    def call(self, X):
        # write the architecutre that was mentioned above
        x=X

        #first conv block
        conv_1=self.conv1(x)
        batch1=self.batch_1(conv_1)
        activation1=self.activation(batch1)

        #second conv block
        conv_2=self.conv2(activation1)
        batch2=self.batch_2(conv_2)
        activation2=self.activation(batch2)

        #third conv block
        conv_3=self.conv3(activation2)
        batch3=self.batch_3(conv_3)

        #skip block
        conv_ii=self.conv_parallel(x)
        batch_ii=self.batch_parallel(conv_ii)
        activation_ii=self.activation(batch_ii)

        X=self.add([batch3,activation_ii])

        return X
```

In [ ]:

```python

tf.keras.backend.clear_session()
X=Input(shape=(512,512,3))

conv1=convolutional_block(stride=8)(X)
model=Model(X,conv1)
model.summary()
```

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 input_1 (InputLayer)        [(None, 512, 512, 3)]     0         
                                                                 
 convolutional_block (convol  (None, 64, 64, 8)        524       
 utional_block)                                                  
                                                                 
=================================================================
Total params: 524
Trainable params: 476
Non-trainable params: 48
_________________________________________________________________
```

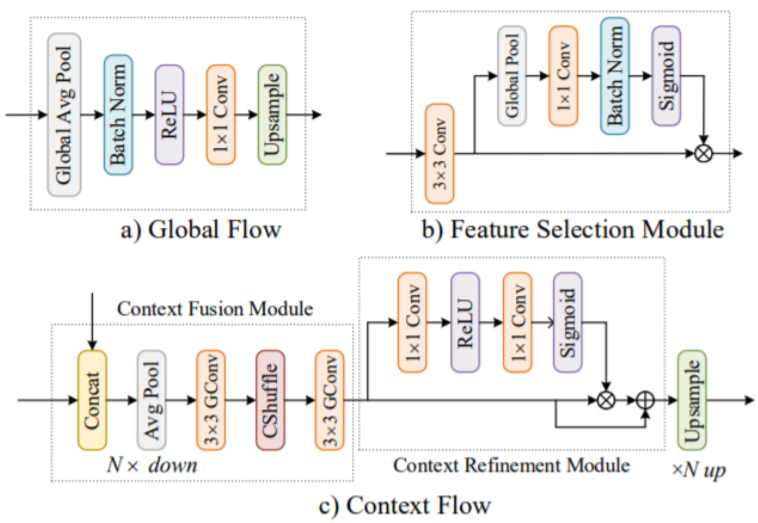
In [ ]:

```
class identity_block(tf.keras.layers.Layer):
    def __init__(self, kernel=3,  filters=[4,4,8], name="identity_block"):
        super().__init__(name=name)
        self.F1, self.F2, self.F3 = filters
        self.kernel = kernel
        self.conv1=Conv2D(filters=self.F1,kernel_size=self.kernel,padding='s
        self.batch_1=BatchNormalization(name=name+"_b1")
        self.conv2=Conv2D(filters=self.F2,kernel_size=self.kernel,padding='s
        self.batch_2=BatchNormalization(name=name+"_b2")
        self.conv3=Conv2D(filters=self.F3,kernel_size=self.kernel,padding='s
        self.batch_3=BatchNormalization(name=name+"_b3")
        self.add=Add()
        self.activation=Activation("relu")

    def call(self, X):
        # write the architecutre that was mentioned above
        X_parallel=X

        #first conv block
        conv_1=self.conv1(X_parallel)
        batch1=self.batch_1(conv_1)
        activation_1=self.activation(batch1)

        #second conv block
        conv_2=self.conv2(activation_1)
        batch2=self.batch_2(conv_2)
        activation_2=self.activation(batch2)

        #third conv block
        conv_3=self.conv3(activation_2)
        batch3=self.batch_3(conv_3)


        x=self.add([batch3,X_parallel])

        return x
```

In [ ]:
```
tf.keras.backend.clear_session()
X=Input(shape=(64, 64, 8))

conv1=identity_block()(X)
model=Model(X,conv1)
model.summary()
```

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 input_1 (InputLayer)        [(None, 64, 64, 8)]       0         
                                                                 
 identity_block (identity_bl  (None, 64, 64, 8)        800       
 ock)                                                            
                                                                 
=================================================================
Total params: 800
Trainable params: 768
Non-trainable params: 32
_________________________________________________________________
```

- The output of the C_4 will be passed to $\text{Chained Context Aggregation Module (CAM)}$



- The CAM module will have two operations names Context flow and Global flow
- **The Global flow**:
  - as shown in the above figure first we willl apply [global avg pooling (https://www.tensorflow.org/api_docs/python/tf/keras/layers/GlobalAveragePooling2D)](https://www.tensorflow.org/api_docs/python/tf/keras/layers/GlobalAveragePooling2D) which results in (#, 1, 1, number_of_filters) then applying [BN (https://www.tensorflow.org/api_docs/python/tf/keras/layers/BatchNormalization?version=nightly)](https://www.tensorflow.org/api_docs/python/tf/keras/layers/BatchNormalization?version=nightly), [RELU (https://www.tensorflow.org/api_docs/python/tf/keras/layers/ReLU)](https://www.tensorflow.org/api_docs/python/tf/keras/layers/ReLU), $1 * 1 \text{ Conv}$ layer sequentially which results a matrix (#, 1, 1, number_of_filters). Finally apply [upsampling (https://www.tensorflow.org/api_docs/python/tf/keras/layers/UpSampling2D)](https://www.tensorflow.org/api_docs/python/tf/keras/layers/UpSampling2D) / [conv2d transpose (https://www.tensorflow.org/api_docs/python/tf/keras/layers/Conv2DTranspose)](https://www.tensorflow.org/api_docs/python/tf/keras/layers/Conv2DTranspose)

to make the output same as the input dimensions (#, input_height, input_width, number_of_filters)
  - If you use [upsampling (https://www.tensorflow.org/api_docs/python/tf/keras/layers/UpSampling2D)](https://www.tensorflow.org/api_docs/python/tf/keras/layers/UpSampling2D) then use bilinear pooling as interpolation technique
- **The Context flow**:
  - as shown in the above figure (c) the context flow will get inputs from two modules `a. C4` `b. From the above flow`
  - We will be [concatinating (https://www.tensorflow.org/api_docs/python/tf/keras/layers/Concatenate)](https://www.tensorflow.org/api_docs/python/tf/keras/layers/Concatenate) the both inputs on the last axis.
  - After the concatination we will be applying [Average pooling (https://www.tensorflow.org/api_docs/python/tf/keras/layers/AveragePooling2D)](https://www.tensorflow.org/api_docs/python/tf/keras/layers/AveragePooling2D) which reduces the size of feature map by $N\times$ times
  - In the paper it was mentioned that to apply a group convolutions, but for the assignment we will be applying the simple conv layers with kernel size $(3*3)$
  - We are skipping the channel shuffling
  - similarly we will be applying a simple conv layers with kernel size $(3*3)$ consider this output is X
  - later we will get the Y=(X $\otimes \sigma((1\times 1)conv(relu((1\times 1)conv(X)))) \oplus X$, here $\oplus$ is elementwise addition and $\otimes$ is elementwise multiplication
  - Finally apply [upsampling (https://www.tensorflow.org/api_docs/python/tf/keras/layers/UpSampling2D)](https://www.tensorflow.org/api_docs/python/tf/keras/layers/UpSampling2D) / [conv2d transpose (https://www.tensorflow.org/api_docs/python/tf/keras/layers/Conv2DTranspose)](https://www.tensorflow.org/api_docs/python/tf/keras/layers/Conv2DTranspose) to make the output same as the input dimensions (#, input_height, input_width, number_of_filters)
  - If you use [upsampling (https://www.tensorflow.org/api_docs/python/tf/keras/layers/UpSampling2D)](https://www.tensorflow.org/api_docs/python/tf/keras/layers/UpSampling2D) then use bilinear pooling as interpolation technique

NOTE: here N times reduction and N time increments makes the input and out shape same, you can explore with the N values, you can choose N = 2 or 4

- Example with N=2:
  - Assume the C4 is of shape (64,64,64) then the shape of GF will be (64,64,32)
  - Assume the C4 is of shape (64,64,64) and the shape of GF is (64,64,32) then the shape of CF1 will be (64,64,32)
  - Assume the C4 is of shape (64,64,64) and the shape of CF1 is (64,64,32) then the shape of CF2 will be (64,64,32)
  - Assume the C4 is of shape (64,64,64) and the shape of CF2 is (64,64,32) then the shape of CF3 will be (64,64,32)

In [ ]:

```
class global_flow(tf.keras.layers.Layer):
    def __init__(self, inputshape,name="global_flow"):
        super().__init__(name=name)

        self.inputshape=inputshape
        self.global_average=GlobalAveragePooling2D()
        self.batch_norm=BatchNormalization()
        self.activation=Activation('relu')
        self.conv2d=Conv2D(32,kernel_size=1,padding='same')
        self.upsample=tf.keras.layers.UpSampling2D(size=(self.inputshape[0],
    def call(self, X):
        # implement the global flow operatiom
        x=self.global_average(X)
        x=self.batch_norm(x)
        x=self.activation(x)

        x=tf.expand_dims(x,1)
        x=tf.expand_dims(x,1)
        x=self.conv2d(x)
        x=self.upsample(x)

        return x
```

In [ ]:

```
tf.keras.backend.clear_session()
X=Input(shape=(64, 64, 8))

conv1=global_flow(inputshape=(64, 64, 8))(X)
model=Model(X,conv1)
model.summary()
```

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 input_1 (InputLayer)        [(None, 64, 64, 8)]       0         
                                                                 
 global_flow (global_flow)   (None, 64, 64, 32)        320       
                                                                 
=================================================================
Total params: 320
Trainable params: 304
Non-trainable params: 16
_________________________________________________________________
```

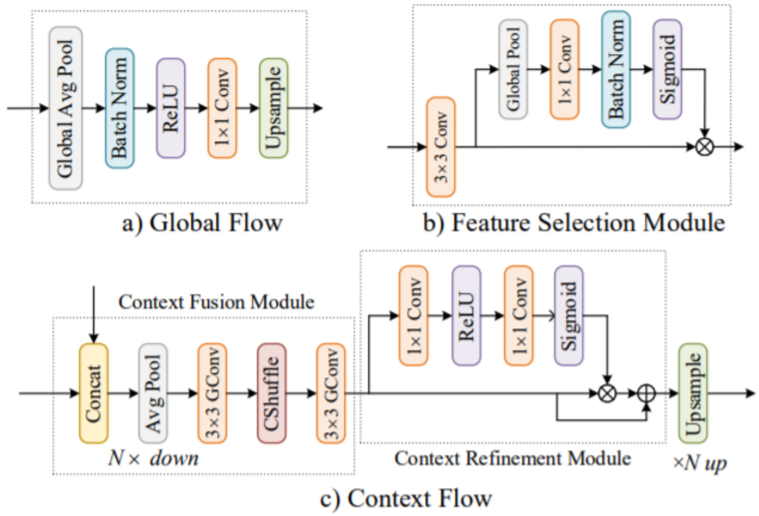
In [ ]:

```
class context_flow(tf.keras.layers.Layer):
    def __init__(self, name="context_flow"):
        super().__init__(name=name)
        self.averagepool=AveragePooling2D(pool_size=(2,2))
        self.batch_norm=BatchNormalization()

        self.activation_relu=Activation('relu')
        self.activation_sigmoid=Activation('sigmoid')

        self.conv2d1=Conv2D(32,kernel_size=3,padding='same')
        self.conv2d2=Conv2D(32,kernel_size=3,padding='same')
        self.conv2d_1=Conv2D(32,kernel_size=1,padding='same')
        self.conv2d_2=Conv2D(32,kernel_size=1,padding='same')

        self.upsample=tf.keras.layers.UpSampling2D(size=(2,2),interpolation=
        self.concatenate=Concatenate()
        self.add=Add()
        self.multiply = Multiply()

    def call(self, X):
        # here X will a list of two elements
        INP, FLOW = X[0], X[1]
        # implement the context flow as mentioned in the above cel]

        concat=self.concatenate([FLOW,INP])
        Avrgpool=self.averagepool(concat)
        conv_1=self.conv2d1(Avrgpool)
        conv_2=self.conv2d2(conv_1)

        #context refinement modle

        conv_3=self.conv2d_1(conv_2)
        activation_1=self.activation_relu(conv_3)
        batch_1=self.batch_norm(activation_1)
        conv2d_4=self.conv2d_2(batch_1)
        activation_2=self.activation_sigmoid(conv2d_4)


        multiplication=self.multiply([conv_2,activation_2])
        add=self.add([multiplication,conv_2])
        x=self.upsample(add)

        return x
```

In [ ]:
```
tf.keras.backend.clear_session()
X=Input(shape=(64, 64, 32))
y=Input(shape=(64, 64, 64))
conv1=context_flow()([X,y])
model=Model([X,y],conv1)
model.summary()
```

```
Model: "model"
________________________________________________________________________________
___________________
 Layer (type)                   Output Shape         Param #     Connected to
================================================================================
===================
 input_1 (InputLayer)           [(None, 64, 64, 32)  0           []
                                ]

 input_2 (InputLayer)           [(None, 64, 64, 64)  0           []
                                ]

 context_flow (context_flow)    (None, 64, 64, 32)   39168       ['input_1[0]
[0]',
                                                                  'input_2[0]
[0]']

================================================================================
===================
Total params: 39,168
Trainable params: 39,104
Non-trainable params: 64
________________________________________________________________________________
___________________
```

- As shown in the above architecture we will be having 4 context flows
- if you have implemented correctly all the shapes of Global Flow, and 3 context flows will have the same dimension
- the output of these 4 modules will be [added (https://www.tensorflow.org/api_docs/python/tf/keras/layers/Add)](https://www.tensorflow.org/api_docs/python/tf/keras/layers/Add) to get the same output matrix



* The output of after the sum, will be sent to the **Feature selection module** FSM

- Example:
  - if the shapes of GF, CF1, CF2, CF3 are (64,64,32), (64,64,32), (64,64,32), (64,64,32), (64,64,32) respectivly then after the sum we will be getting (64,64,32), which will be passed to the next module.

Feature selection module:

- As part of the FSM we will be applying a conv layer (3,3) with the padding="same" so that the output and input will have same shapes
- Let call the output as X
- Pass the X to global pooling which results the matrix (#, 1, 1, number_of_channels)
- Apply $1 * 1$ conv layer, after the pooling
- the output of the $1 * 1$ conv layer will be passed to the Batch normalization layer, followed by Sigmoid activation function.
- we will be having the output matrix of shape (#, 1, 1, number_of_channels) lets call it 'Y'
- **we can interpret this as attention mechanisum, i.e for each channel we will having a weight**
- the dimension of X (#, w, h, k) and output above steps Y is (#, 1, 1, k) i.e we need to multiply each channel of X will be multiplied (https://www.tensorflow.org/api_docs/python/tf/keras/layers/Multiply) with corresponding channel of Y
- After creating the weighted channel map we will be doing upsampling such that it will double the height and width.
- apply upsampling (https://www.tensorflow.org/api_docs/python/tf/keras/layers/UpSampling2D) with bilinear pooling as interpolation technique
- Example:
  - Assume the matrix shape of the input is (64,64,32) then after upsampling it will be (128,128,32)

In [ ]:

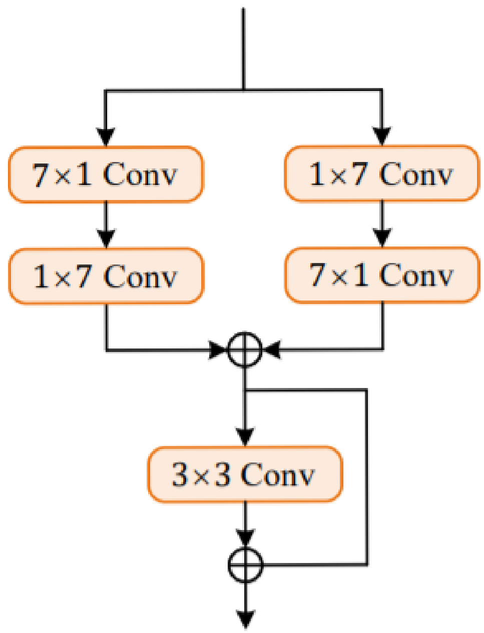
```
class fsm(tf.keras.layers.Layer):
    def __init__(self, name="feature_selection"):
        super().__init__(name=name)
        self.global_pool=GlobalAveragePooling2D()
        self.upsample=tf.keras.layers.UpSampling2D(size=(2,2),interpolation=

        self.conv2d_1=Conv2D(32,kernel_size=1,padding='same')
        self.conv2d_3=Conv2D(32,kernel_size=3,padding='same')

        self.batch_norm=BatchNormalization()
        self.activation_sigmoid=Activation("sigmoid")

    def call(self, X):
        # implement the FSM modules based on image in the above cells

        x_in=self.conv2d_3(X)
        x=self.global_pool(x_in)
        x= tf.expand_dims(x, 1)
        x = tf.expand_dims(x, 1)
        x= self.conv2d_1(x)
        x=self.batch_norm(x)
        x=self.activation_sigmoid(x)

        FSM_Conv_T=tf.math.multiply(x,x_in)
        FSM_Conv_T=self.upsample(FSM_Conv_T)
        return FSM_Conv_T
```

In [ ]:

```
tf.keras.backend.clear_session()
X=Input(shape=(64, 64, 32))

conv1=fsm()(X)
model=Model(X,conv1)
model.summary()
```

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 64, 64, 32)]      0

 feature_selection (fsm)     (None, 128, 128, 32)      10432

=================================================================
Total params: 10,432
Trainable params: 10,368
Non-trainable params: 64
_________________________________________________________________
```

- **Adapted Global Convolutional Network (AGCN)**:



b) AGCN

  - AGCN will get the input from the output of the "conv block" of C_1
  - In all the above layers we will be using the padding="same" and stride=(1,1)
  - so that we can have the input and output matrices of same size
- Example:
  - Assume the matrix shape of the input is (128,128,32) then the output it will be (128,128,32)

In [ ]:

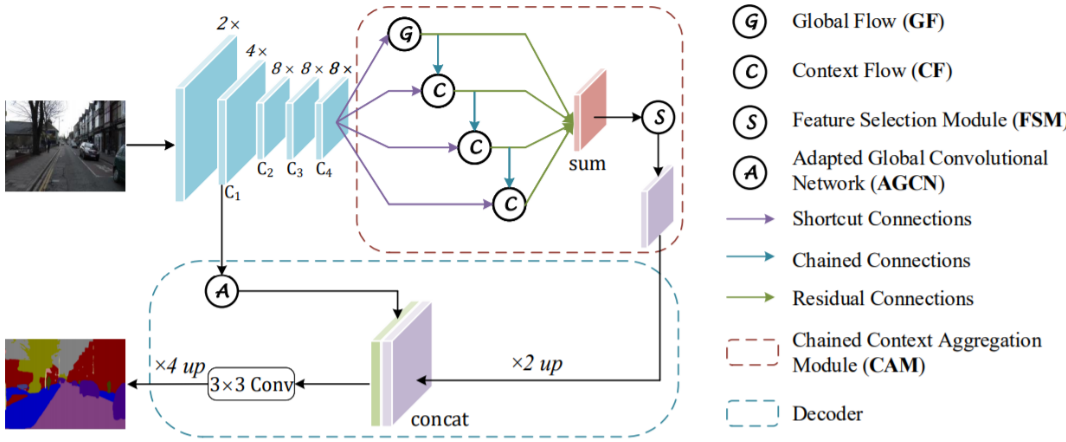
```
class agcn(tf.keras.layers.Layer):
    def __init__(self, name="agcn"):
        super().__init__(name=name)
        self.conv2d_1  = Conv2D(32,kernel_size=(1,7),padding='same')
        self.conv2d_2  = Conv2D(32,kernel_size=(7,1),padding='same')
        self.conv2d_3  = Conv2D(32,kernel_size=(1,7),padding='same')
        self.conv2d_4  = Conv2D(32,kernel_size=(7,1),padding='same')
        self.conv2d_5  = Conv2D(32,kernel_size=(3,3),padding='same')
        self.add = Add()

    def call(self, X):
        # please implement the above mentioned architecture
        x_1=self.conv2d_1(X)
        x_1=self.conv2d_2(x_1)

        x_2=self.conv2d_3(X)
        x_2=self.conv2d_4(x_2)

        x_out=self.add([x_1,x_2])

        x=self.conv2d_5(x_out)

        x=self.add([x,x_out])

        return x
```

In [ ]:

```
tf.keras.backend.clear_session()
X=Input(shape=(128, 128, 8))

conv1=agcn()(X)
model=Model(X,conv1)
model.summary()
```

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 128, 128, 8)]     0

 agcn (agcn)                 (None, 128, 128, 32)      27296

=================================================================
Total params: 27,296
Trainable params: 27,296
Non-trainable params: 0
_________________________________________________________________
```

-



- as shown in the architecture, after we get the AGCN it will get concatinated with the FSM output
- If we observe the shapes both AGCN and FSM will have same height and weight
- we will be concatinating both these outputs over the last axis
- The concatinated output will be passed to a conv layers with filters = number of classes in our data set and the activation function = 'relu'
- we will be using padding="same" which results in the same size feature map
- If you observe the shape of matrix, it will be 4x times less than the original image
- to make it equal to the original output shape, we will do 4x times upsampling of rows and columns
- apply [upsampling (https://www.tensorflow.org/api_docs/python/tf/keras/layers/UpSampling2D)](https://www.tensorflow.org/api_docs/python/tf/keras/layers/UpSampling2D) with bilinear pooling as interpolation technique
- Finally we will be applying sigmoid activation.
- Example:
  - Assume the matrix shape of AGCN is (128,128,32) and FSM is (128,128,32) the concatination will make it (128, 128, 64)
  - Applying conv layer will make it (128,128,21)
  - Finally applying upsampling will make it (512, 512, 21)
  - Applying sigmoid will result in the same matrix (512, 512, 21)

In [ ]:

```
X_input = Input(shape=(128,128,3))

# Stage 1
X = Conv2D(64, (3, 3), name='conv1', padding="same", kernel_initializer=glor
X = BatchNormalization(axis=3, name='bn_conv1')(X)
X = Activation('relu')(X)
X = MaxPooling2D((2, 2), strides=(2, 2))(X)
print(X.shape)
```

```
(None, 64, 64, 64)
```

- If you observe the arcitecture we are creating a feature map with 2x time less width and height
- we have written the first stage of the code above.
- Write the next layers by using the custom layers we have written

Model building

In [ ]:

```
# write the complete architecutre

tf.keras.backend.clear_session()


X_input = Input(shape=(512,512,3))

# Stage 1
X = Conv2D(64, (3, 3), name='conv1', padding="same", kernel_initializer=glor
X = BatchNormalization(axis=3, name='bn_conv1')(X)
X = Activation('relu')(X)
X = MaxPooling2D((2, 2), strides=(2, 2))(X)

#c_1 conv block followed by one identity block

conv_1=convolutional_block(stride=2)(X)
identity_1=identity_block(name='identity_block1')(conv_1)

#c_2 conv block follwed by two identity blocks

conv_2=convolutional_block(name="convolutional_block2",stride=2)(identity_1)
identity_21=identity_block(name='identity_block_21')(conv_2)
identity_22=identity_block(name='identity_block_22')(identity_21)

#c_3 conv block followed by three identity blocks

conv_3=convolutional_block(name="convolutional_block3",stride=1)(identity_22
identity_31=identity_block(name='identity_block_31')(conv_3)
identity_32=identity_block(name='identity_block_32')(identity_31)
identity_33=identity_block(name='identity_block_33')(identity_32)

#c_4 conv block followed by four identity blocks

conv_4=convolutional_block(name="convolutional_block4",stride=1)(identity_33
identity_41=identity_block(name='identity_block_41')(conv_4)
identity_42=identity_block(name='identity_block_42')(identity_41)
identity_43=identity_block(name='identity_block_43')(identity_42)
identity_44=identity_block(name='identity_block_44')(identity_43)

#global flow

global_flow_1=global_flow((identity_44.shape[1],identity_44.shape[2]))(ident

#context flow 1

context_flow_1=context_flow(name='context_flow1')([global_flow_1,identity_44

#context flow 2

context_flow_2=context_flow(name='context_flow2')([context_flow_1,identity_4

#context flow 3

context_flow_3=context_flow(name='context_flow3')([context_flow_2,identity_4

#context flow 4
```

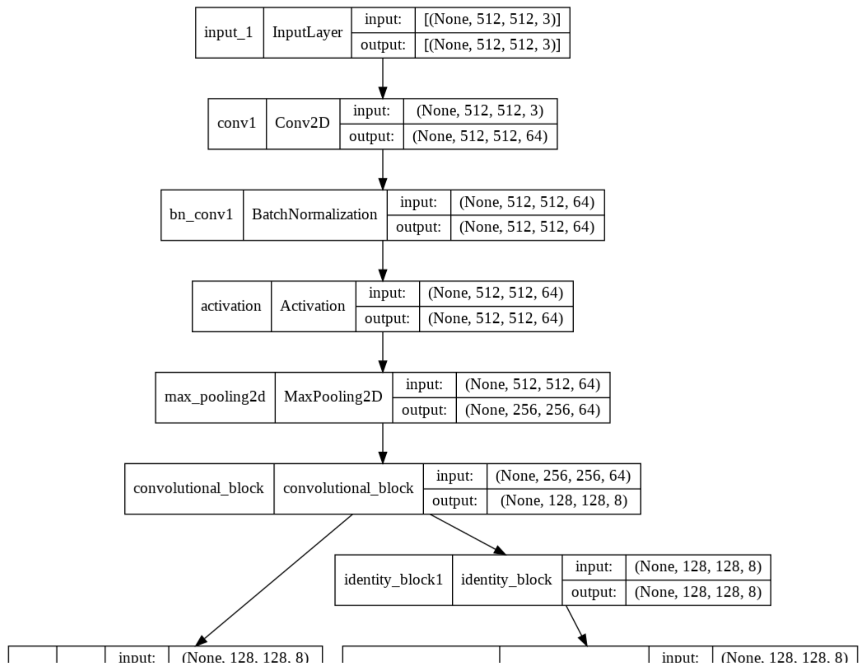
```
context_flow_4=context_flow(name='context_flow4')([context_flow_3,identity_4
# sum
add=Add()([global_flow_1,context_flow_1,context_flow_2,context_flow_3,contex
# feature selection module (FSM)
fsm_1=fsm()(add)
# Adopted Global Convolution Network (AGCN)
agcn_1=agcn()(conv_1)
#concatenate AGCN and FSM
concatenate_agcn_fsm=Concatenate()([agcn_1,fsm_1])
channels_21=Conv2D(filters=21,kernel_size=3,padding='same',activation='relu'
#upsample
upsample=UpSampling2D(size=(4,4),interpolation='bilinear')(channels_21)
output=Activation("softmax")(upsample)
model = Model(inputs = X_input, outputs = output)
model.summary()
```

```
Model: "model"
__________________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #     Connected to
==================================================================================================
 input_1 (InputLayer)           [(None, 512, 512, 3  0           []
                                )]

 conv1 (Conv2D)                 (None, 512, 512, 64  1792        ['input_1[0][0]']
                                )

 bn_conv1 (BatchNormalization)  (None, 512, 512, 64  256         ['conv1[0][0]']
                                )

 activation (Activation)        (None, 512, 512, 64  0           ['bn_conv1[0][0]']
```

In [ ]:

```
tf.keras.utils.plot_model(
    model, to_file='model4.png', show_shapes=True, show_layer_names=True,
    rankdir='TB')
```

Out[46]:



loss function

In [ ]:

```
import segmentation_models as sm
from segmentation_models.metrics import IOUScore
sm.set_framework('tf.keras')

optim = tf.keras.optimizers.Adam(0.001)
focal_loss = sm.losses.cce_dice_loss
model.compile(optimizer=optim, loss=focal_loss,metrics=[IOUScore(threshold=0
```

Training

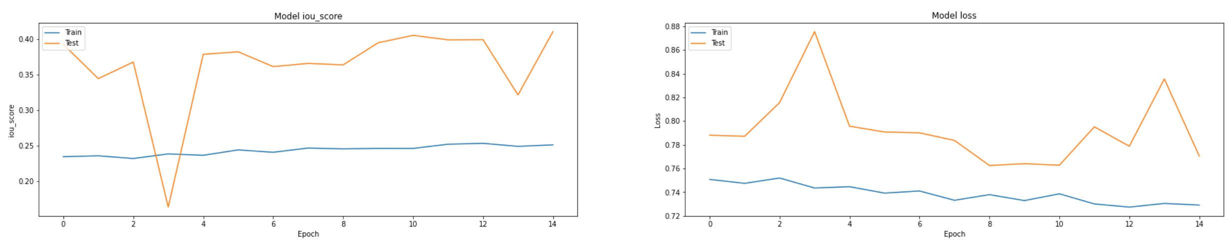
In [ ]:
```
callbacks = [
    tf.keras.callbacks.ModelCheckpoint('./best_model3.h5', save_weights_only
history = model.fit(train_dataloader, steps_per_epoch=len(train_dataloader),
                                   validation_data=val_dataloader,callbacks=callb
```

```
Epoch 1/15
721/721 [==============================] - 584s 810ms/step - loss: 0.7507 - iou
_score: 0.2345 - val_loss: 0.7880 - val_iou_score: 0.3927
Epoch 2/15
721/721 [==============================] - 582s 808ms/step - loss: 0.7474 - iou
_score: 0.2357 - val_loss: 0.7871 - val_iou_score: 0.3445
Epoch 3/15
721/721 [==============================] - 582s 808ms/step - loss: 0.7519 - iou
_score: 0.2319 - val_loss: 0.8155 - val_iou_score: 0.3678
Epoch 4/15
721/721 [==============================] - 579s 803ms/step - loss: 0.7435 - iou
_score: 0.2384 - val_loss: 0.8755 - val_iou_score: 0.1635
Epoch 5/15
721/721 [==============================] - 581s 807ms/step - loss: 0.7446 - iou
_score: 0.2365 - val_loss: 0.7956 - val_iou_score: 0.3787
Epoch 6/15
721/721 [==============================] - 582s 807ms/step - loss: 0.7392 - iou
_score: 0.2440 - val_loss: 0.7908 - val_iou_score: 0.3822
Epoch 7/15
721/721 [==============================] - 584s 810ms/step - loss: 0.7410 - iou
_score: 0.2407 - val_loss: 0.7900 - val_iou_score: 0.3614
Epoch 8/15
721/721 [==============================] - 584s 810ms/step - loss: 0.7331 - iou
_score: 0.2467 - val_loss: 0.7836 - val_iou_score: 0.3659
Epoch 9/15
721/721 [==============================] - 582s 807ms/step - loss: 0.7379 - iou
_score: 0.2455 - val_loss: 0.7625 - val_iou_score: 0.3638
Epoch 10/15
721/721 [==============================] - 582s 808ms/step - loss: 0.7329 - iou
_score: 0.2462 - val_loss: 0.7640 - val_iou_score: 0.3949
Epoch 11/15
721/721 [==============================] - 580s 804ms/step - loss: 0.7386 - iou
_score: 0.2461 - val_loss: 0.7627 - val_iou_score: 0.4054
Epoch 12/15
721/721 [==============================] - 579s 804ms/step - loss: 0.7300 - iou
_score: 0.2520 - val_loss: 0.7951 - val_iou_score: 0.3991
Epoch 13/15
721/721 [==============================] - 581s 806ms/step - loss: 0.7274 - iou
_score: 0.2533 - val_loss: 0.7787 - val_iou_score: 0.3994
Epoch 14/15
721/721 [==============================] - 582s 808ms/step - loss: 0.7304 - iou
_score: 0.2490 - val_loss: 0.8355 - val_iou_score: 0.3215
Epoch 15/15
721/721 [==============================] - 582s 808ms/step - loss: 0.7291 - iou
_score: 0.2511 - val_loss: 0.7704 - val_iou_score: 0.4107
```

Model Performance

In [ ]:

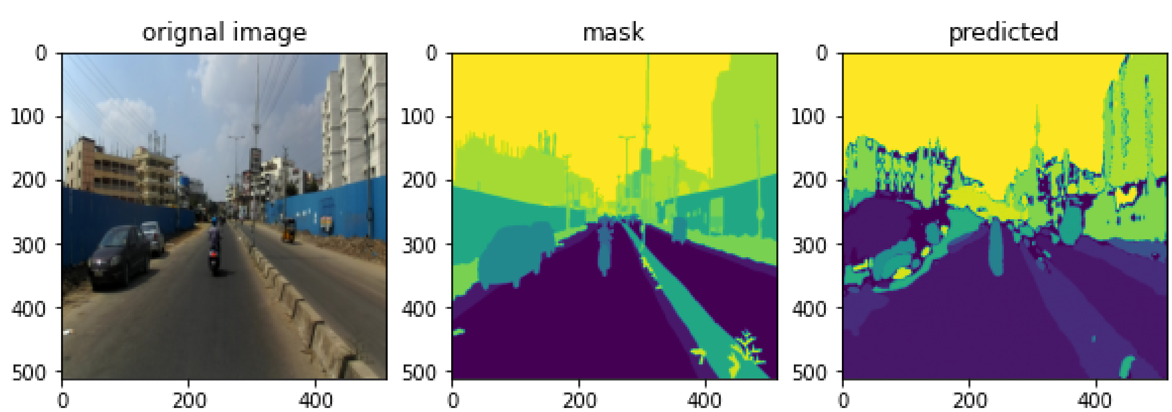
```
plt.figure(figsize=(30, 5))
plt.subplot(121)
plt.plot(history.history['iou_score'])
plt.plot(history.history['val_iou_score'])
plt.title('Model iou_score')
plt.ylabel('iou_score')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')

# Plot training & validation loss values
plt.subplot(122)
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
plt.show()
```



Predictions

In [ ]:

```
plot_images=X_val[:10].reset_index(drop=True)
x=[0,10,20,30,40,50,60,70,80,90,100,110,120,130,140,150,160,170,18,190,200]

for p, i in enumerate(range(10)):
    #original image
    image = cv2.imread(plot_images['images'][p], cv2.IMREAD_UNCHANGED)
    image = cv2.resize(image, (512,512),interpolation=cv2.INTER_AREA)
    image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
    image=normalize(image)


    #predicted segmentation map
    predicted  =np.where(model.predict(np.array([image]))>0.5,1,0)

    m=np.zeros((512,512))
    for j , k in enumerate(x):
      b=np.where(predicted[0][:,:,j]==1,k,0)
      m=m+b


    #original segmentation map
    image_mask = cv2.imread(plot_images['output'][p], cv2.IMREAD_UNCHANGED)
    image_mask = cv2.resize(image_mask, (512,512))[:,:,2]



    plt.figure(figsize=(10,6))
    plt.subplot(131)
    plt.imshow(image,)
    plt.title("orignal image")
    plt.subplot(132)
    plt.imshow(image_mask)
    plt.title("mask")
    plt.subplot(133)
    plt.imshow(m)
    plt.title("predicted")
    plt.show()
```



Usefull tips:

- use "interpolation=cv2.INTER_NEAREST" when you are resizing the image, so that it won't mess with the number of classes
- keep the images in the square shape like $256 * 256$ or $512 * 512$
- Carefull when you are converting the (W, H) output image into (W, H, Classes)
- you can use the tensorboard logss to see how is yours model's training happening
- use callbacks

In [ ]:

```

```