KAIST Korea Advanced Institute of Science and Technology

LAB 2: PSMent

Pyramid stereo matching network, 2018 CVPR, Spatial pyramid pooling module implementation

한국과학기술원

시각지능연구실

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prerequisite

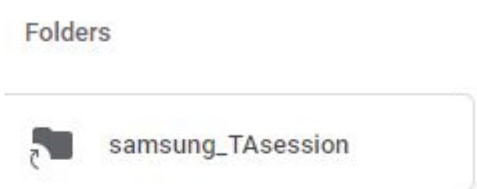
Linking with google drive for colab

1. Google 계정을 로그인 하세요

2. 다음 링크 클릭
https://drive.google.com/drive/folders/1ZB4kTn8fXbsshdX1u-Nzz6Xm5-4cb0rq?usp=sharing

3. 우측 상단의 Samsung_TAsession -> Add shortcut to drive -> My drive

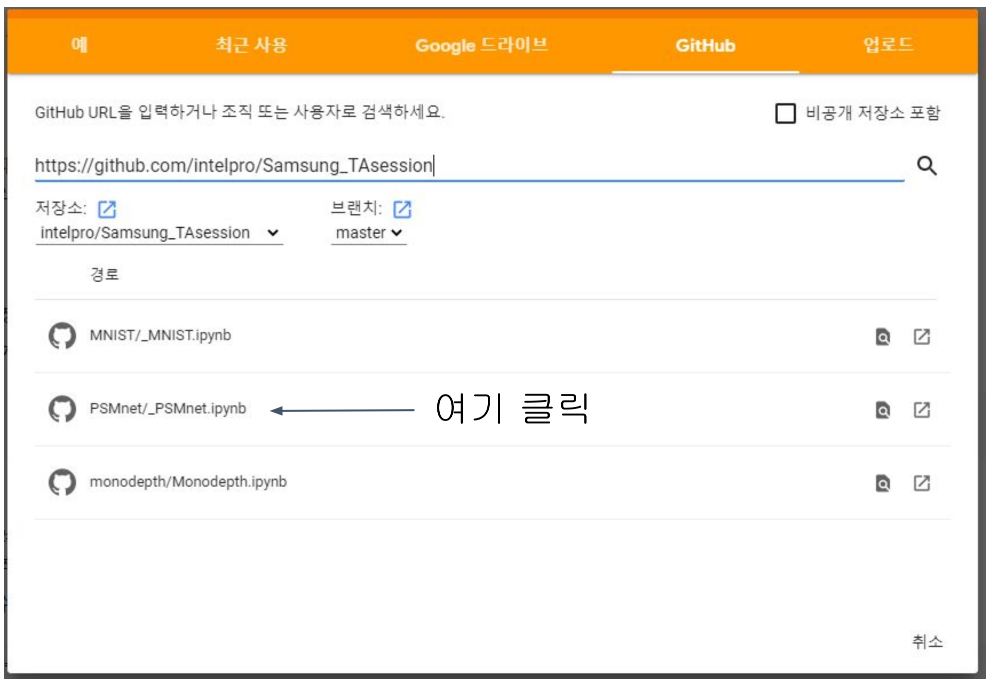
4. My Drive에서 공유된 폴더 확인



Github repository를 Colab 환경에서 열기

1. Colab으로 들어가기
https://colab.research.google.com/notebooks/intro.ipynb

2. 파일 -> 노트 열기 -> Github 탭 클릭 -> 아래 링크 복사 붙여넣기 -> _PSMnet.ipynb 열기
https://github.com/intelpro/Samsung_TAsession



Github repository를 Colab 환경에서 열기

3. 런타임 변경
런타임 탭 -> 런타임 유형변경 -> 하드웨어 가속기: GPU

4. 맨 위의 google drive 공유 폴더를 colab 환경에 docking 시키는 코드 실행

google drive의 공유 폴더를 colab docker 환경으로 drive를 mount 시키는 코드

만약, mount 된 드라이브가 /contet/gdrive/My Drive/samsung_TAsession과 다를경우

해당경로를 확인하여 datapath에 붙여넣을것.

```
[ ] %cd /content/
    !git clone https://github.com/intelpro/Samsung_TAsession/
    %cd /contet/Samsung_TAsession/PSMnet/
    !ls
    !mkdir saved_model
    from google.colab import drive
    drive.mount('/content/gdrive/')
    datapath = '/content/gdrive/My Drive/samsung_TAsession/KITTI_2015/training/'
    savemodel = './saved_model'
```

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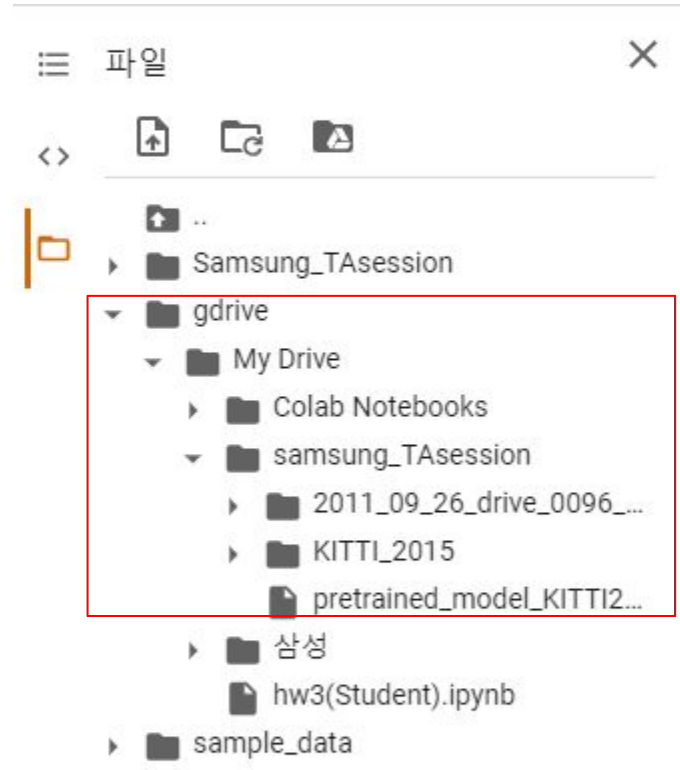
Google drive mount 확인

5. 정상적으로 google drive가 colab환경에서 mount 됨을 확인

```
/content
Cloning into 'Samsung_TAsession'...
remote: Enumerating objects: 167, done.
remote: Counting objects: 100% (167/167), done.
remote: Compressing objects: 100% (131/131), done.
remote: Total 167 (delta 69), reused 107 (delta 29), pack-reused 0
Receiving objects: 100% (167/167), 6.08 MiB | 4.77 MiB/s, done.
Resolving deltas: 100% (69/69), done.
/content/Samsung_TAsession/PSMnet
dataloader  preprocess.py  _PSMnet.ipynb  __pycache__  submodule.py
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_

Enter your authorization code:

Mounted at /content/gdrive/
```

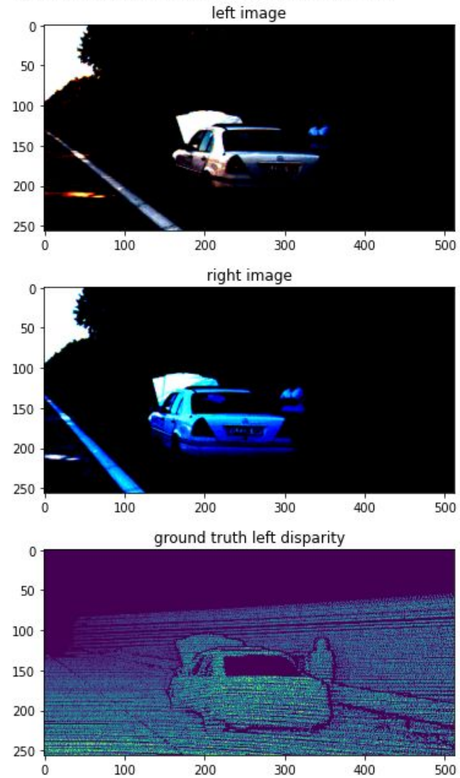


< 결과 이미지 >

Dataloader 정상 동작 확인

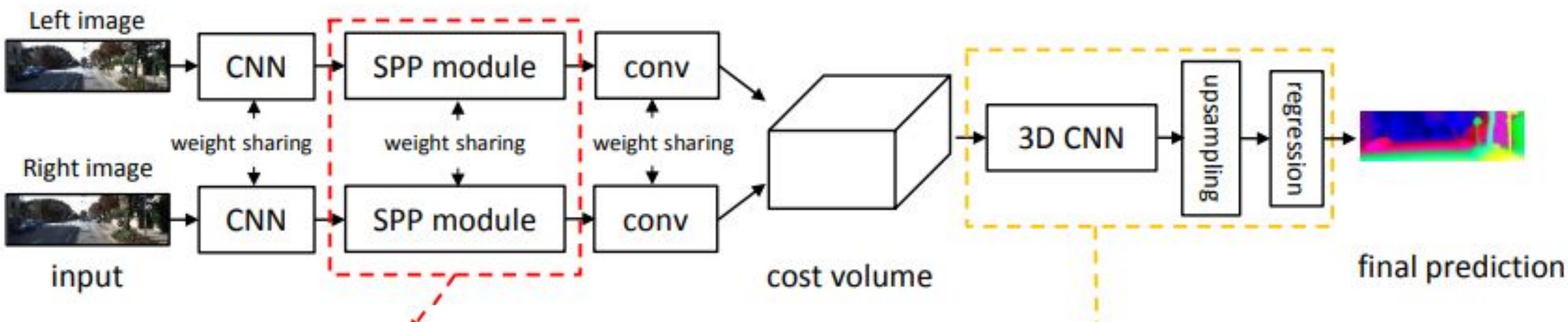
6. import로 모듈 가져오기 -> Get dataset string
-> Define dataloader -> Check KITTI dataset data 순차적으로 실행시킨다.

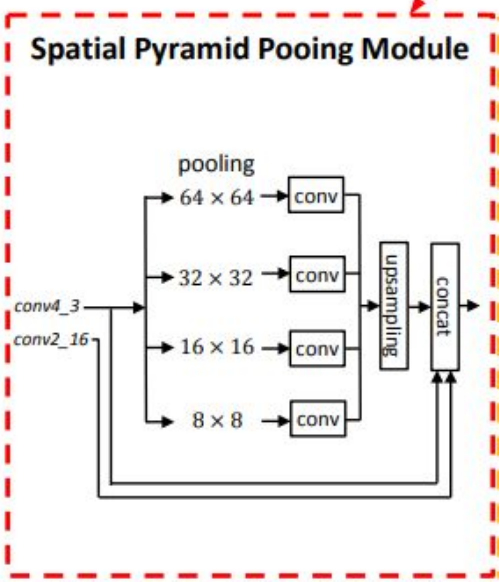
```
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
<matplotlib.image.AxesImage at 0x7fca0bf63320>
```



Assignment

Spatial pyramid pooling module





Note

- Average pooling window size를 64, 32, 16, 8 의 여러 레벨로 pooling을 하면서 CNN의 receptive field를 늘리기 위한 방법
- Stereo matching 뿐만이 아니라 object detection, semantic segmentation, image classification 등 여러 분야에 광범위하게 사용됨.

Assignment

Spatial pyramid pooling module - Feature extraction 정의하기

Name	Layer setting	Output dimension
input		$H \times W \times 3$
CNN		
conv0_1	$3 \times 3, 32$	$\frac{1}{2}H \times \frac{1}{2}W \times 32$
conv0_2	$3 \times 3, 32$	$\frac{1}{2}H \times \frac{1}{2}W \times 32$
conv0_3	$3 \times 3, 32$	$\frac{1}{2}H \times \frac{1}{2}W \times 32$
conv1_x	$\begin{bmatrix} 3 \times 3, 32 \\ 3 \times 3, 32 \end{bmatrix} \times 3$	$\frac{1}{2}H \times \frac{1}{2}W \times 32$
conv2_x	$\begin{bmatrix} 3 \times 3, 64 \\ 3 \times 3, 64 \end{bmatrix} \times 16$	$\frac{1}{4}H \times \frac{1}{4}W \times 64$
conv3_x	$\begin{bmatrix} 3 \times 3, 128 \\ 3 \times 3, 128 \end{bmatrix} \times 3$, dila = 2	$\frac{1}{4}H \times \frac{1}{4}W \times 128$
conv4_x	$\begin{bmatrix} 3 \times 3, 128 \\ 3 \times 3, 128 \end{bmatrix} \times 3$, dila= 4	$\frac{1}{4}H \times \frac{1}{4}W \times 128$
SPP module		
branch_1	64×64 avg. pool $3 \times 3, 32$ bilinear interpolation	$\frac{1}{4}H \times \frac{1}{4}W \times 32$
branch_2	32×32 avg. pool $3 \times 3, 32$ bilinear interpolation	$\frac{1}{4}H \times \frac{1}{4}W \times 32$
branch_3	16×16 avg. pool $3 \times 3, 32$ bilinear interpolation	$\frac{1}{4}H \times \frac{1}{4}W \times 32$
branch_4	8×8 avg. pool $3 \times 3, 32$ bilinear interpolation	$\frac{1}{4}H \times \frac{1}{4}W \times 32$
concat[conv2_16, conv4_3, branch_1, branch_2, branch_3, branch_4]		$\frac{1}{4}H \times \frac{1}{4}W \times 320$
fusion	$3 \times 3, 128$ $1 \times 1, 32$	$\frac{1}{4}H \times \frac{1}{4}W \times 32$

```python
## Your implementation Here
self.branch1 = nn.Sequential(nn.AvgPool2d((None, None), stride=(None,None)),
                             convbn(None, None, 1, 1, 0, 1),
                             nn.ReLU(inplace=True))

self.branch2 = nn.Sequential(nn.AvgPool2d((None, None), stride=(None,None)),
                             convbn(None, None, 1, 1, 0, 1),
                             nn.ReLU(inplace=True))

self.branch3 = nn.Sequential(nn.AvgPool2d((None, None), stride=(None,None)),
                             convbn(None, None, 1, 1, 0, 1),
                             nn.ReLU(inplace=True))

self.branch4 = nn.Sequential(nn.AvgPool2d((None, None), stride=(None,None)),
                             convbn(None, None, 1, 1, 0, 1),
                             nn.ReLU(inplace=True))
## Your implementation end
```

Assignment

- None으로 되어 있는 부분을 채워 넣을 것
- Pooling level은 64, 32, 16, 8
- pooling window size에 맞게 stride도 잘 채워 넣어야 함.
- conv4_x에서 뽑은 feature map이 각 branch를 지나고나면 채널이 128에서 32채널로 바뀜에 유의
- covbn의 정의를 알고싶으면 def convbn(...) 이라고 된 부분을 참고

Assignment

만약 Spatial pooling module을 제대로 구현하였다면..

Training with KITTI dataset 실행시..

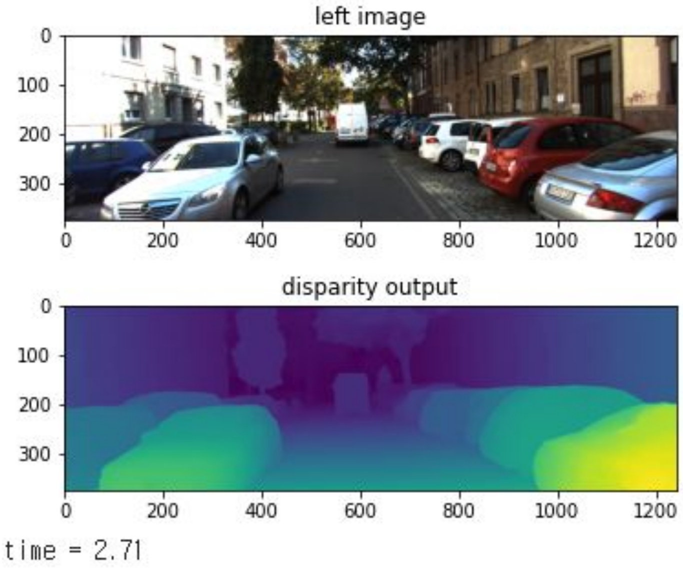
```
••• This is 0-th epoch
    /usr/local/lib/python3.6/dist-packages/torch/nn/functional.py:2796:
      warnings.warn("nn.functional.upsample is deprecated. Use nn.functi
    /usr/local/lib/python3.6/dist-packages/torch/nn/functional.py:2973:
      "See the documentation of nn.Upsample for details.".format(mode))
    /usr/local/lib/python3.6/dist-packages/torch/nn/functional.py:2973:
      "See the documentation of nn.Upsample for details.".format(mode))
    /usr/local/lib/python3.6/dist-packages/torch/nn/_reduction.py:43: Us
      warnings.warn(warning.format(ret))
    Iter 0 training loss = 76.164 , time = 2.01
    Iter 3 training loss = 9.776 , time = 1.76
    Iter 6 training loss = 7.997 , time = 1.77
    Iter 9 training loss = 13.371 , time = 1.78
    Iter 12 training loss = 11.346 , time = 1.77
    Iter 15 training loss = 10.733 , time = 1.75
    Iter 18 training loss = 7.748 , time = 1.75
    Iter 21 training loss = 7.496 , time = 1.74
    Iter 24 training loss = 6.336 , time = 1.73
    Iter 27 training loss = 6.175 , time = 1.74
    Iter 30 training loss = 7.019 , time = 1.74
    Iter 33 training loss = 5.445 , time = 1.74
    Iter 36 training loss = 7.691 , time = 1.74
    Iter 39 training loss = 3.301 , time = 1.73
    Iter 42 training loss = 9.453 , time = 1.72
    Iter 45 training loss = 6.158 , time = 1.72
    Iter 48 training loss = 5.845 , time = 1.74
    Iter 51 training loss = 6.859 , time = 1.74
```

정상적으로 loss가
줄어듬을 확인 할 수 있음.

Assignment

만약 Spatial pooling module을 제대로 구현하였다면..

Test with KITTI test sample 실행시..



정상적으로 disparity output이 나옴을 확인할 수 있음

For your information

nn.AvgPool2d

https://pytorch.org/docs/master/generated/torch.nn.AvgPool2d.html

AVGPOOL2D

CLASS `torch.nn.AvgPool2d(kernel_size: Union[T, Tuple[T, T]], stride: Optional[Union[T, Tuple[T, T]]] = None, padding: Union[T, Tuple[T, T]] = 0, ceil_mode: bool = False, count_include_pad: bool = True, divisor_override: bool = None)` [SOURCE]

Parameters

- **kernel_size** – the size of the window
- **stride** – the stride of the window. Default value is `kernel_size`
- **padding** – implicit zero padding to be added on both sides
- **ceil_mode** – when True, will use *ceil* instead of *floor* to compute the output shape
- **count_include_pad** – when True, will include the zero-padding in the averaging calculation
- **divisor_override** – if specified, it will be used as divisor, otherwise `kernel_size` will be used