

Lecture 10:

Convolutional Neural Networks (CNN) – Part II



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Machine Learning Algorithms

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Outline

- Labeling Tools

- Calling a Pretrained CNN



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“labelme”

Description

Labelme is a graphical image annotation tool inspired by <http://labelme.csail.mit.edu>.
It is written in Python and uses Qt for its graphical interface.



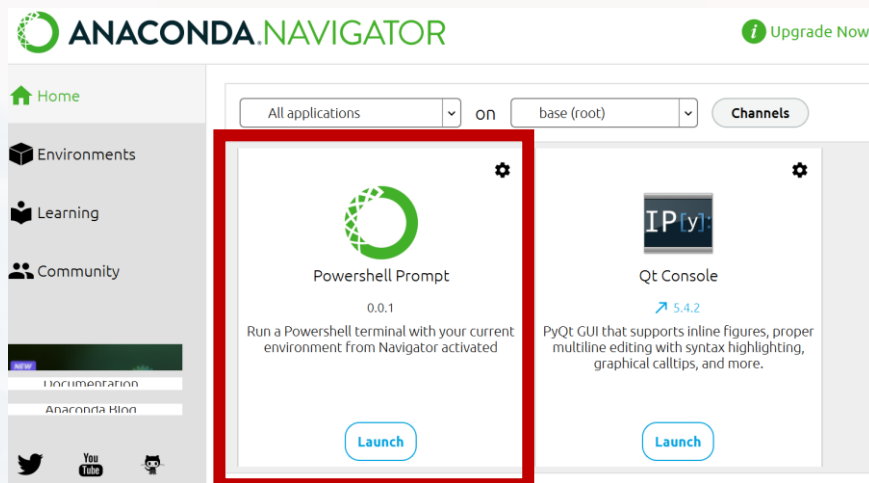
VOC dataset example of instance segmentation.



Other examples (semantic segmentation, bbox detection, and classification).



Various primitives (polygon, rectangle, circle, line, and point).

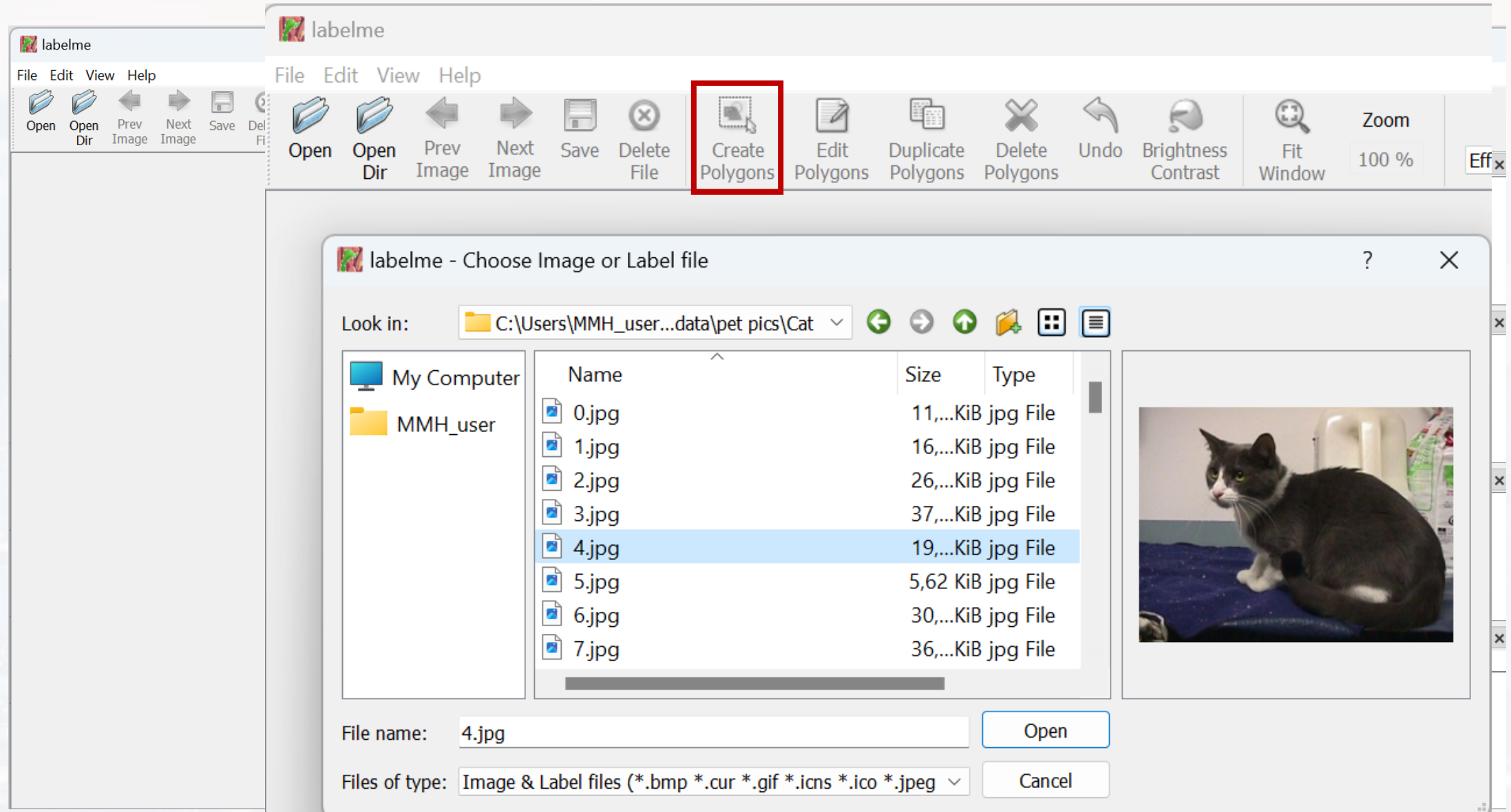


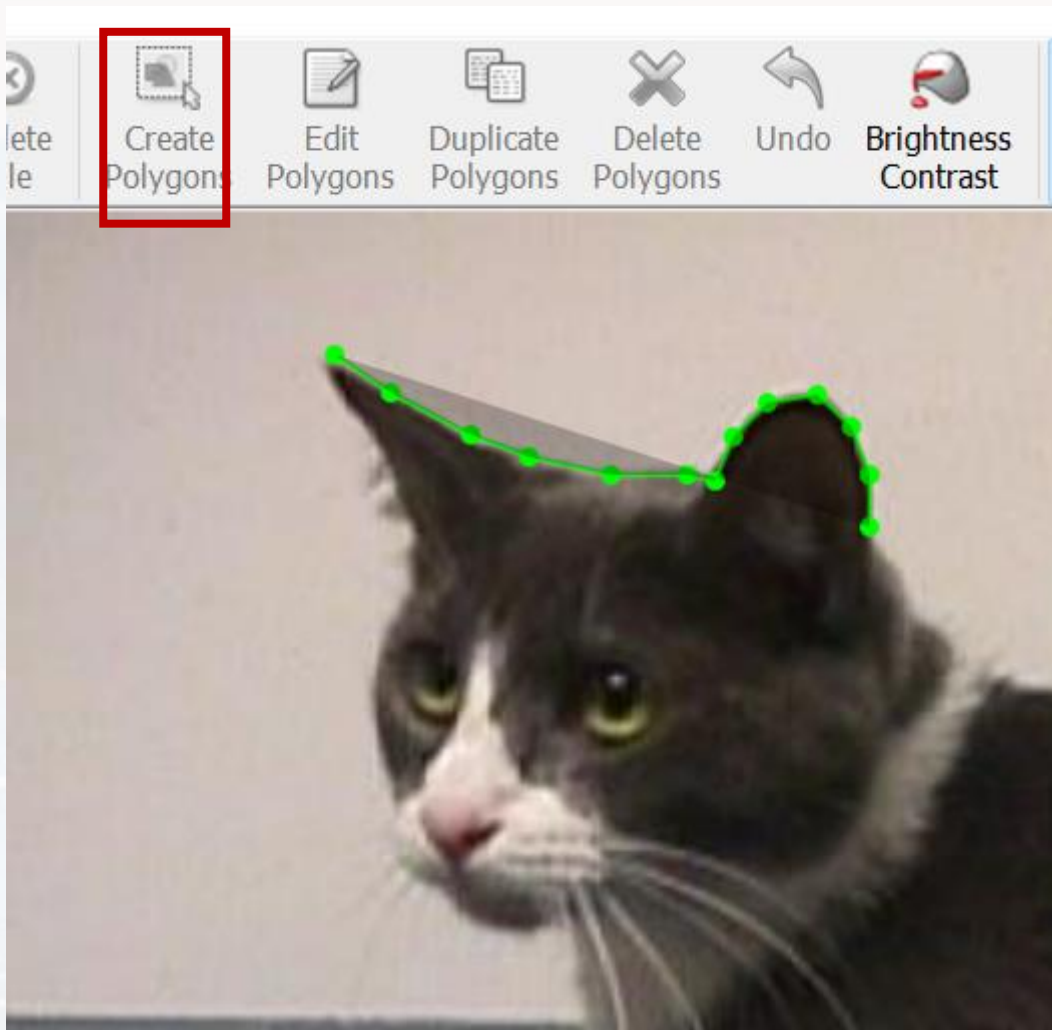
conda install labelme

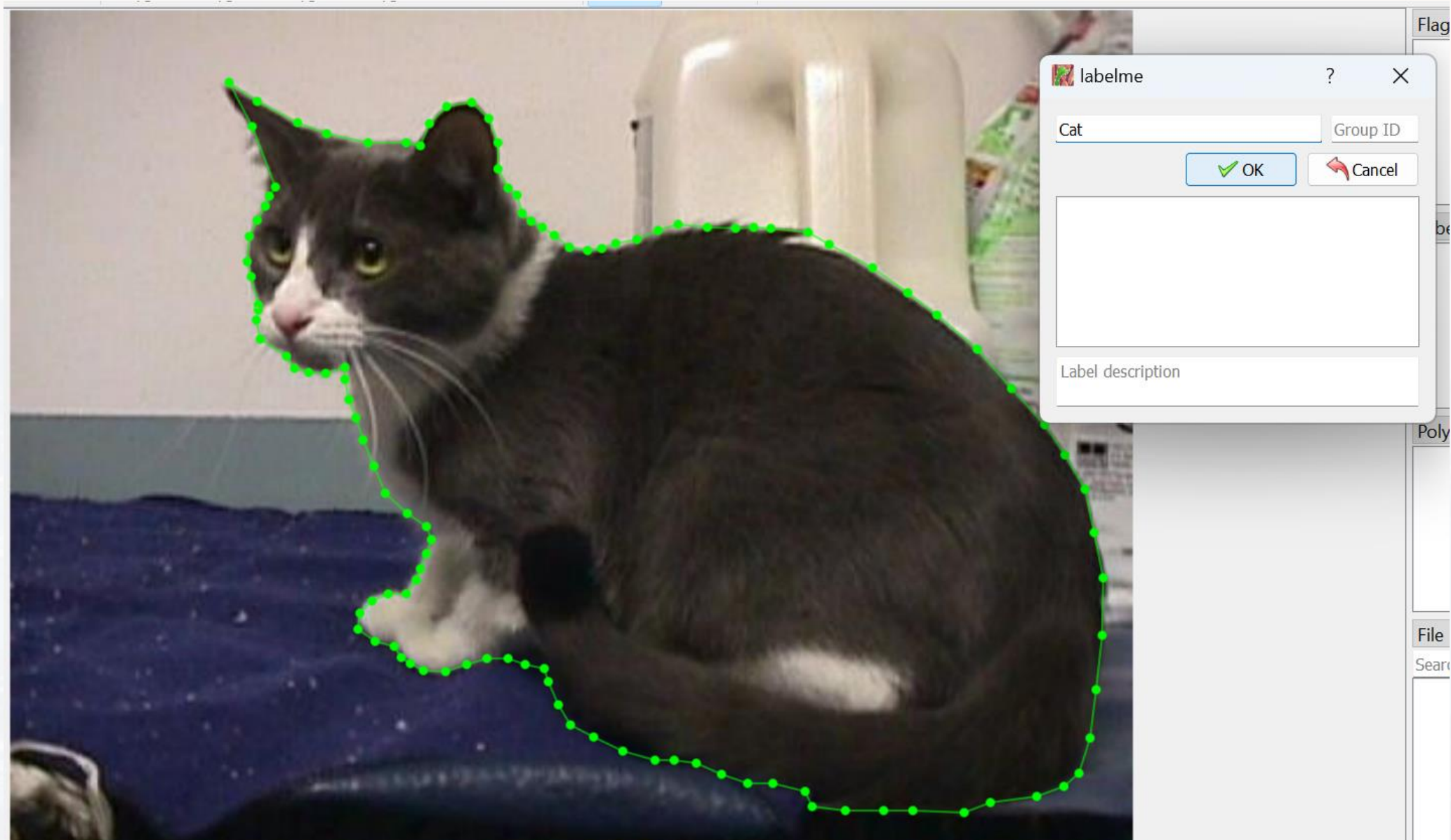
```
C:\WINDOWS\System32\Win... x + v
(base) PS C:\Users\MMH_user> conda create --name=labelme python=3|
```

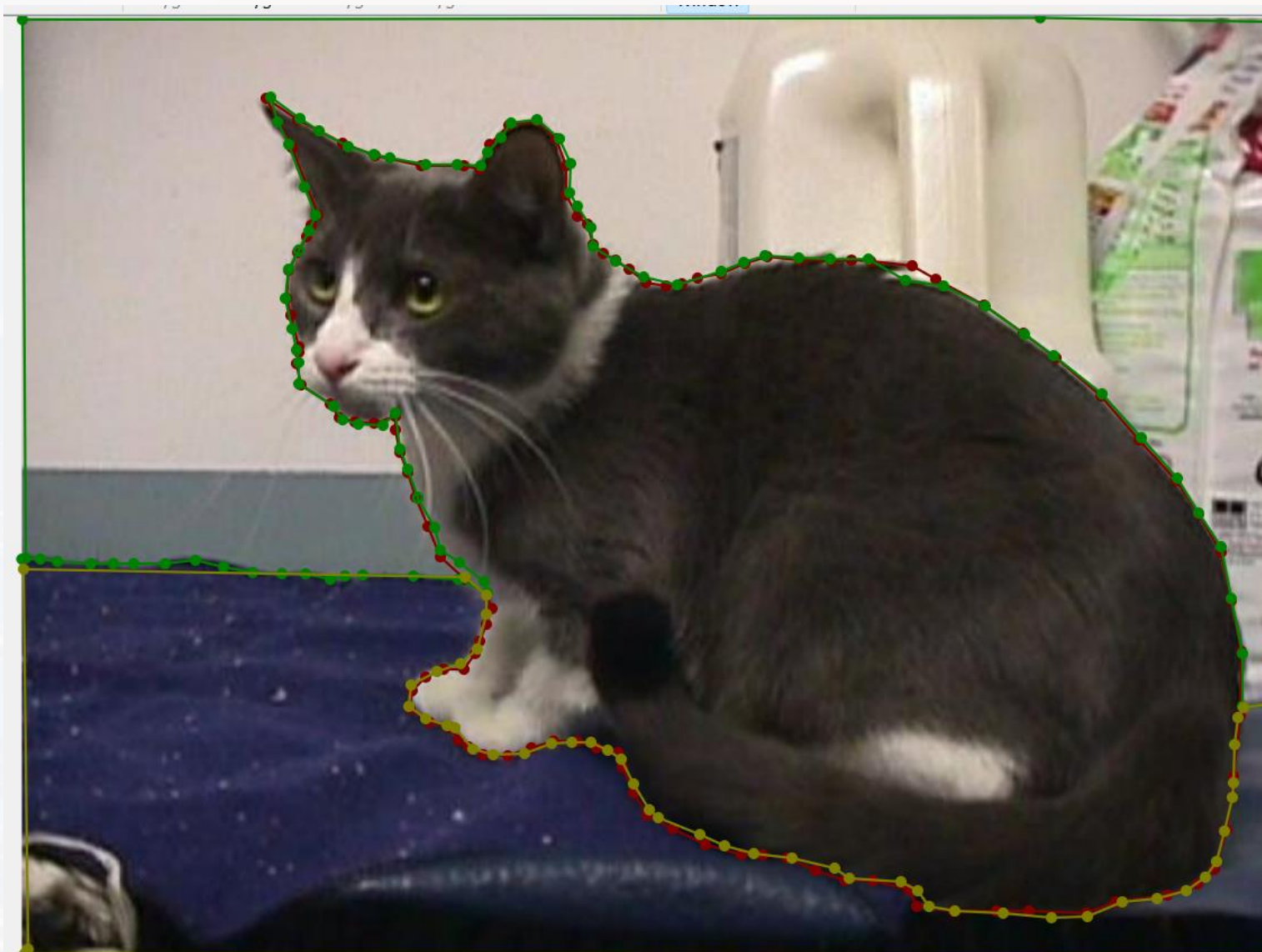
```
(base) PS C:\Users\MMH_user> conda activate labelme|
```


```
(labelme) PS C:\Users\MMH_user> labelme|
```












Flags 

Label List 

Cat ●
background ●
foreground ●

Polygon Labels 

☒ Cat ●
☒ background ●
☒ foreground ●

File List 

Search Filename



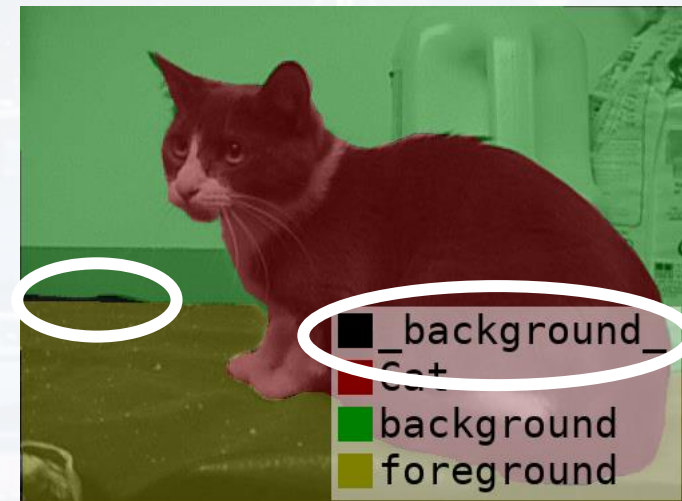
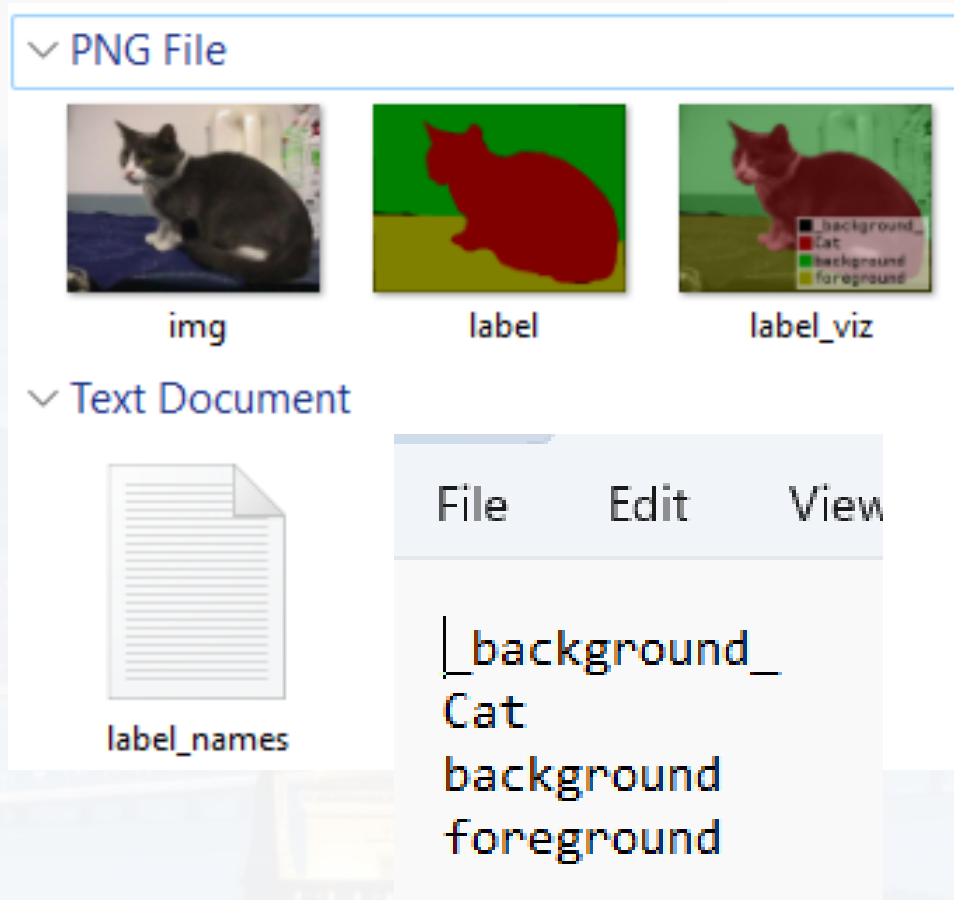
image is saved as .json

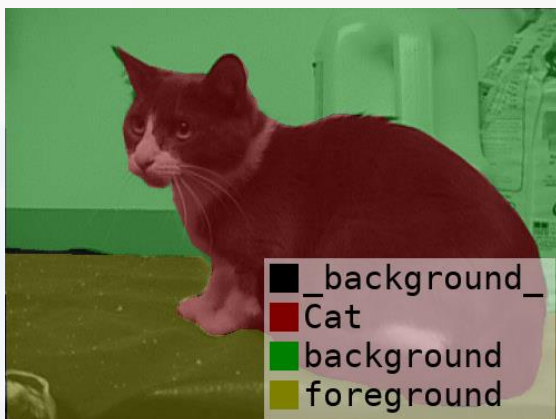


run within the labelme prompt:

```
labelme_export_json .\Cat4label.json -o Cat4label.json
```

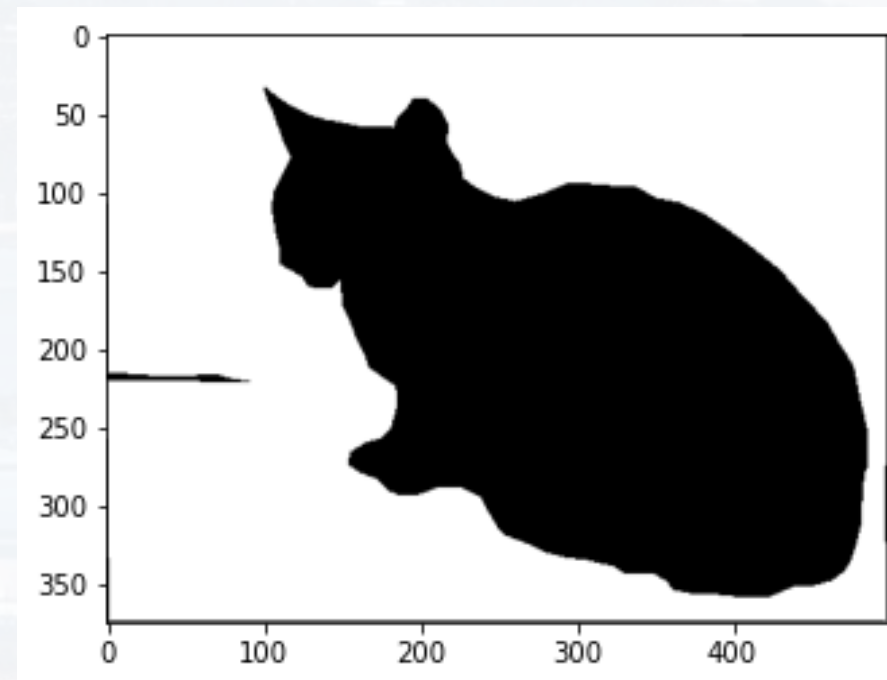
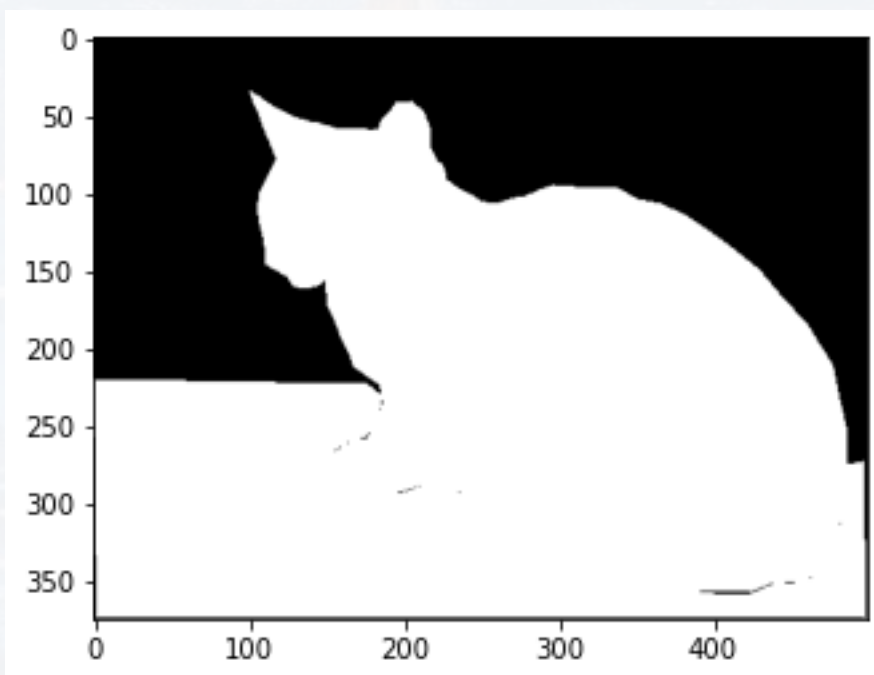


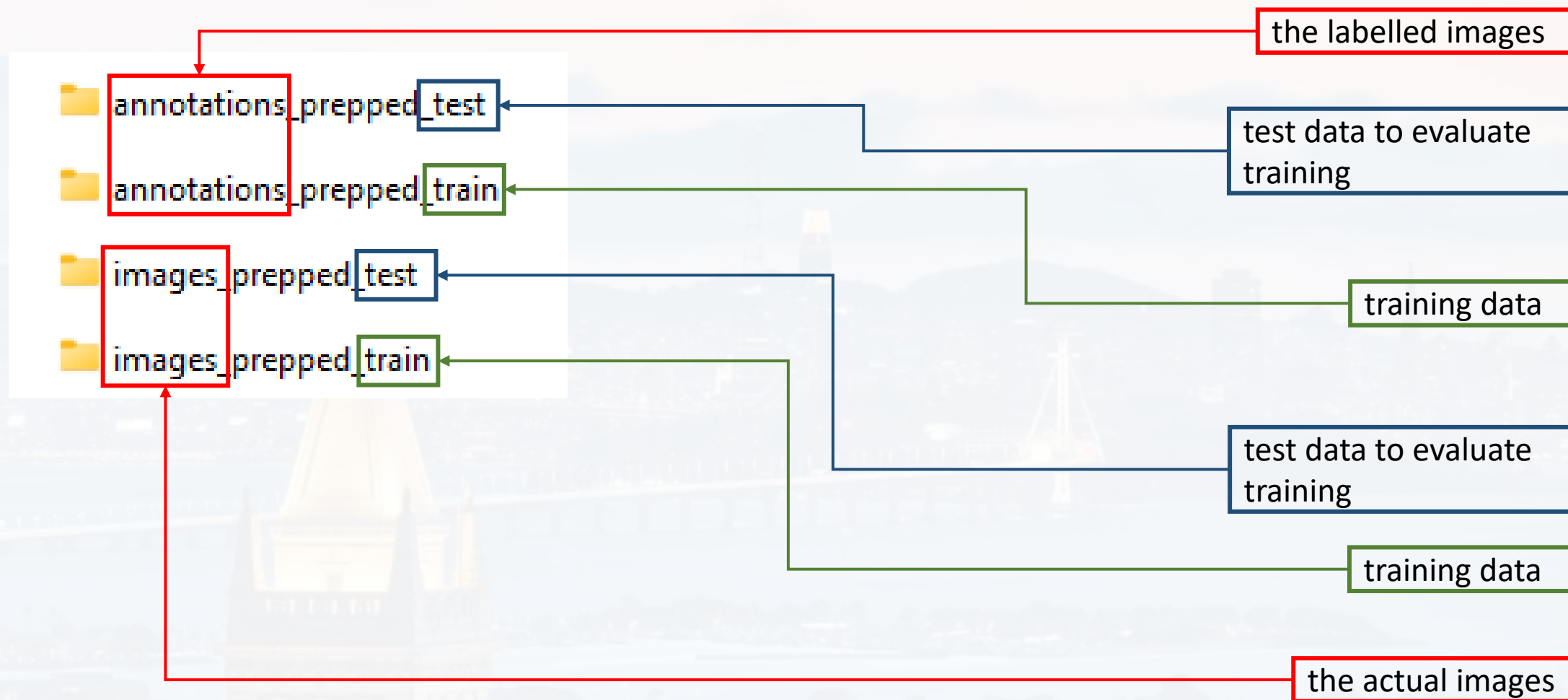




```
I = plt.imread('Cat/Cat4Label_json/label.png')
```

```
I.shape  
(375, 500, 4)
```



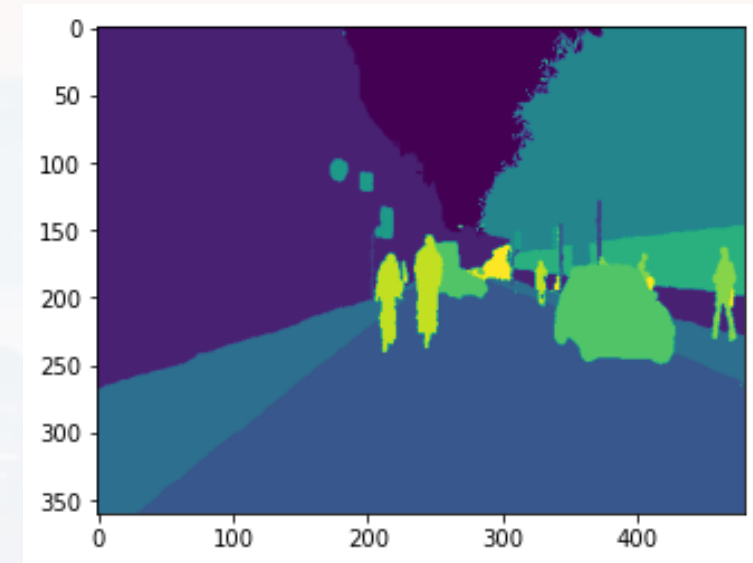




nice dataset



images_prepped_test



annotations_prepped_test

```
I = plt.imread('segmentation/pics/annotations_prepped_test/0016E5_07959.png')
```

```
I.shape  
(360, 480)
```




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demonstrating realistic segmentation with reasonable results will take a few hours

→ check out my code on [GitHub](#)



```
from keras_segmentation.models.unet import *
```

Type	Names
VGG	'vgg16' 'vgg19'
ResNet	'resnet18' 'resnet34' 'resnet50' 'resnet101' 'resnet152'
SE-ResNet	'seresnet18' 'seresnet34' 'seresnet50' 'seresnet101' 'seresnet152'
ResNeXt	'resnext50' 'resnext101'
SE-ResNeXt	'seresnext50' 'seresnext101'
SENet154	'senet154'
DenseNet	'densenet121' 'densenet169' 'densenet201'
Inception	'inceptionv3' 'inceptionresnetv2'
MobileNet	'mobilenet' 'mobilenetv2'
EfficientNet	'efficientnetb0' 'efficientnetb1' 'efficientnetb2' 'efficientnetb3' 'efficientnetb4' 'efficientnetb5' 'efficientnetb6' 'efficientnetb7'

```
model = vgg_unet(n_classes = n_classes,\n                 input_height = 416, input_width = 608)
```

```
model.train(\n    train_images      = my_path + r"images_prepped_train/",\n    train_annotations = my_path + r"annotations_prepped_train/",\n    checkpoints_path  = my_path + r"checkpoints/",\n    do_augment        = True,\n    gen_use_multiprocessing = True,\n    auto_resume_checkpoint = True,\n    epochs = 5)
```

calling the specific network

saves current weights

Keras provides an augmentation routine



```
model = vgg_unet(n_classes = n_classes,\n                 input_height = 416, input_width = 608)
```

```
model.train(\n    train_images      = my_path + r"images_prepped_train/",\n    train_annotations = my_path + r"annotations_prepped_train/",\n    checkpoints_path  = my_path + r"checkpoints/",\n    do_augment        = True,\n    gen_use_multiprocessing = True,\n    auto_resume_checkpoint = True,\n    epochs            = 5)
```

Keras provides an
augmentation routine

Note: I always run my **own augmentation** routine,
see e.g. `AugmentMyImages.py`

run:

```
S = SegmentMyImages()
```

```
S.Training()
```



```
S = SegmentMyImages()
```

```
S.Training()
```

```
Dataset verified!
```

```
Epoch 1/5
```

```
512/512 [=====] - ETA: 0s - loss: 4.1406 - accuracy: 0.0353      saved ../data/segmentation  
pics/checkpoints//.0
```

```
512/512 [=====] - 3888s 8s/step - loss: 4.1406 - accuracy: 0.0353
```

```
Epoch 2/5
```

```
512/512 [=====] - ETA: 0s - loss: 3.7805 - accuracy: 0.1636      saved ../data/segmentation  
pics/checkpoints//.1
```

```
512/512 [=====] - 4133s 8s/step - loss: 3.7805 - accuracy: 0.1636
```

```
Epoch 3/5
```

```
512/512 [=====] - ETA: 0s - loss: 3.4534 - accuracy: 0.3338      saved ../data/segmentation  
pics/checkpoints//.2
```

```
512/512 [=====] - 4072s 8s/step - loss: 3.4534 - accuracy: 0.3338
```

```
Epoch 4/5
```

```
512/512 [=====] - ETA: 0s - loss: 3.1926 - accuracy: 0.3980      saved ../data/segmentation  
pics/checkpoints//.3
```

```
512/512 [=====] - 3363s 7s/step - loss: 3.1926 - accuracy: 0.3980
```

```
Epoch 5/5
```

```
512/512 [=====] - ETA: 0s - loss: 3.0071 - accuracy: 0.4318      saved ../data/segmentation  
pics/checkpoints//.4
```

```
512/512 [=====] - 3616s 7s/step - loss: 3.0071 - accuracy: 0.4318
```



```
MyModel = S.TrainedModel
```

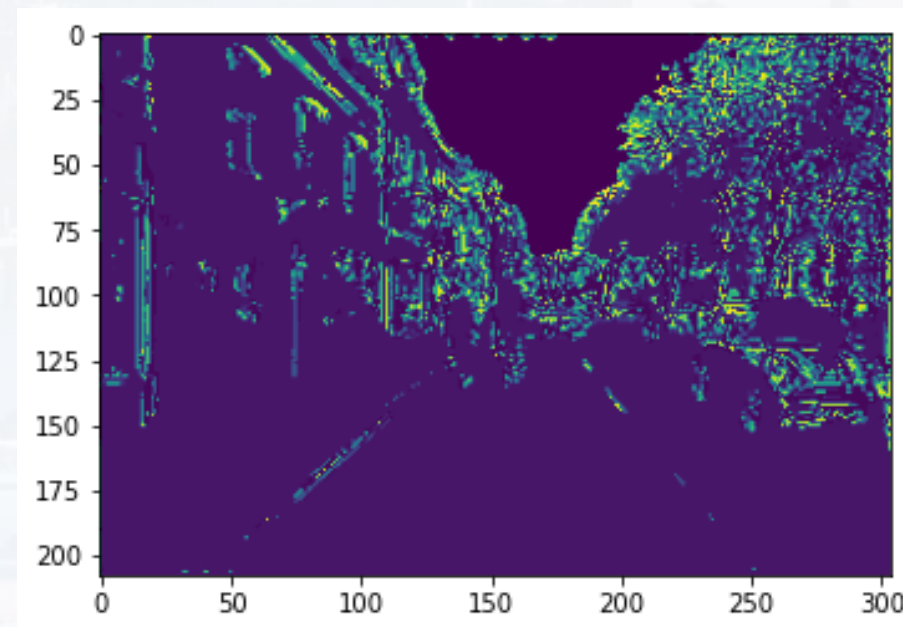
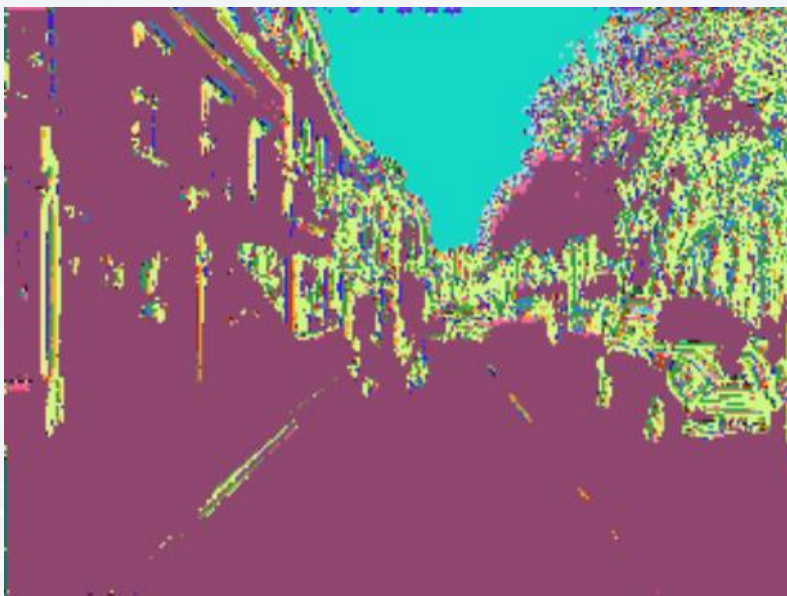
```
MyModel.summary()
```

 → returns the structure of the CNN

applying the trained CNN to an image:

```
out = S.ApplyTrainedNetwork()
```

```
plt.imshow(out)
```





recovering model from checkpoints:

```
MyModel = S.TrainedModel  
out      = S.ApplyTrainedNetwork()
```

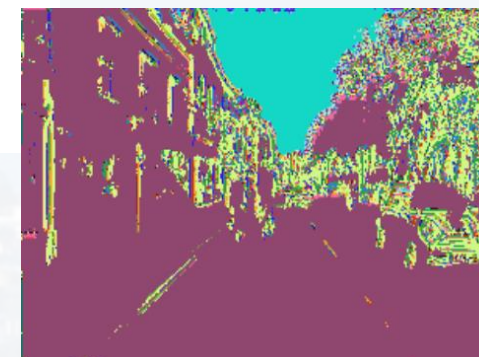
applying the trained CNN to an image:

```
S.RecoverFromCheckpoint()
```

```
#loading untrained CNN  
model = self.model  
  
if not image_name:  
    image_name = '0016E5_07965.png'  
    ....  
#calling input from checkpoints  
latest = tf.train.latest_checkpoint(self.checkpoint_path)  
model.load_weights(latest)
```

untrained
model (just
CNN itself)

transfer the saved weights to untrained
network → now it starts from latest
training state

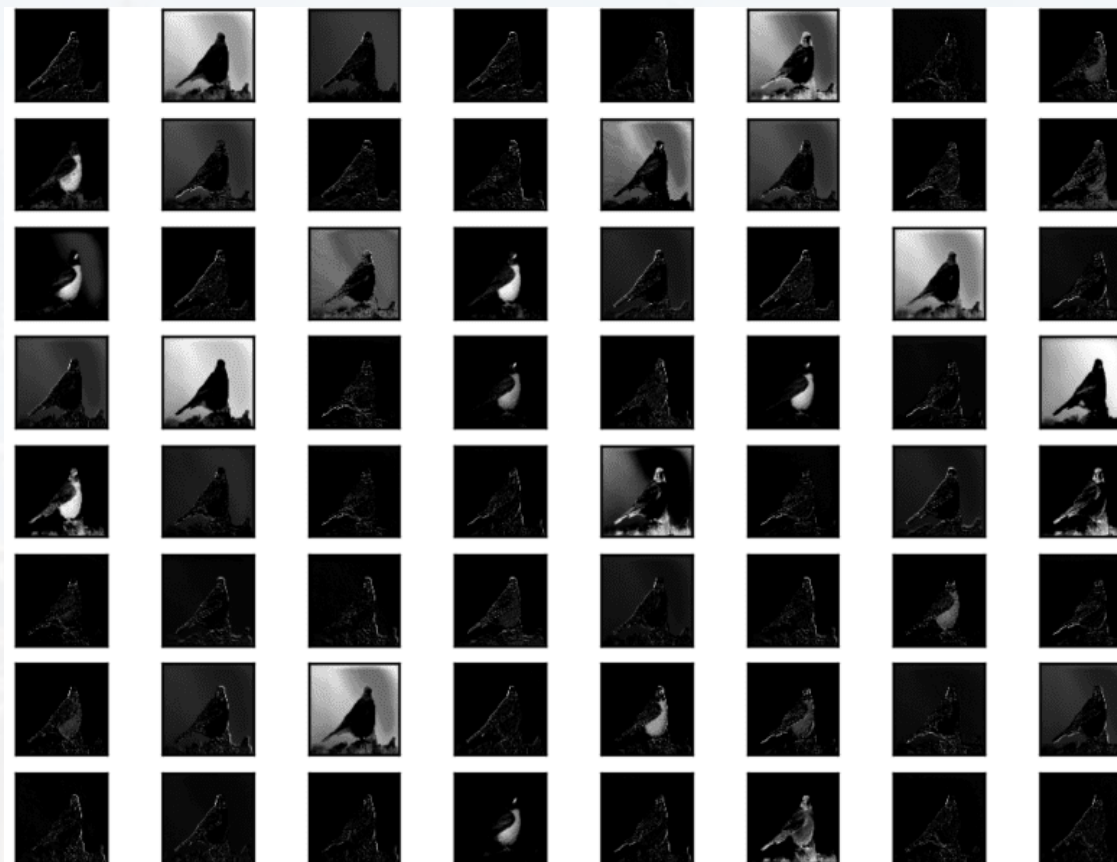




visualizing weights:

→ see `model.layers`

nice example



Thank you very much for your attention!

