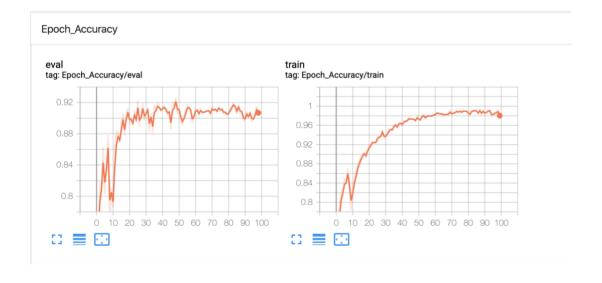
Mathew Varughese

MAV120 CS 1699 HW 4

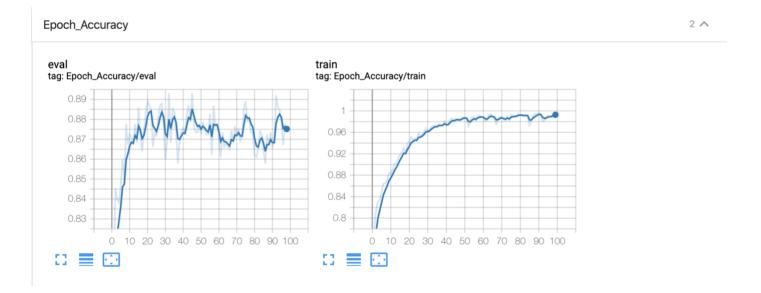
Part I – Implement AlexNet

```
AlexNet(
  (features): Sequential(
    (0): Conv2d(3, 96, kernel size=(11, 11), stride=(4, 4))
    (1): ReLU(inplace=True)
    (2): MaxPool2d(kernel size=3, stride=2, padding=0, dilation=1, ceil mode=False)
    (3): Conv2d(96, 256, kernel size=(5, 5), stride=(1, 1), padding=(2, 2))
    (4): ReLU(inplace=True)
    (5): MaxPool2d(kernel size=3, stride=2, padding=0, dilation=1, ceil mode=False)
    (6): Conv2d(256, 384, kernel size=(3, 3), stride=(1, 1), padding=(1, 1))
    (7): ReLU(inplace=True)
    (8): Conv2d(384, 384, kernel size=(3, 3), stride=(1, 1), padding=(1, 1))
    (9): ReLU(inplace=True)
    (10): Conv2d(384, 256, \text{kernel size}=(3, 3), \text{stride}=(1, 1), padding=(1, 1))
    (11): ReLU(inplace=True)
    (12): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1, ceil_mode=False)
  (flatten): Flatten()
  (classifier): Sequential(
    (0): Dropout(p=0.5, inplace=False)
    (1): Linear(in features=9216, out features=4096, bias=True)
    (2): ReLU(inplace=True)
    (3): Dropout(p=0.5, inplace=False)
    (4): Linear(in features=4096, out features=4096, bias=True)
    (5): ReLU(inplace=True)
    (6): Linear(in features=4096, out features=4, bias=True)
)
```

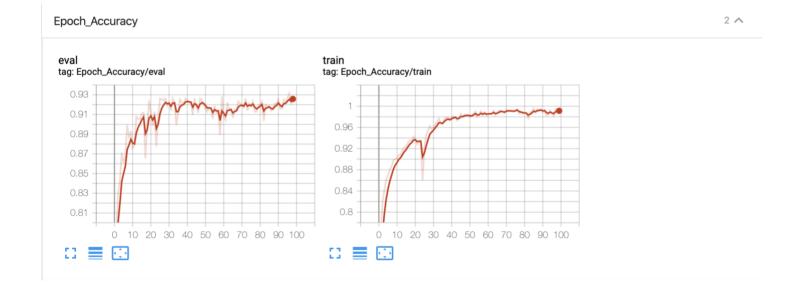


Part II - Enhancing AlexNet

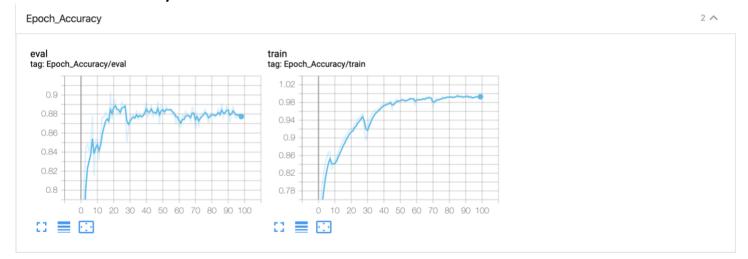
```
AlexNetLargeKernel(
  (features): Sequential(
    (0): Conv2d(3, 96, kernel_size=(21, 21), stride=(8, 8), padding=(1, 1))
    (1): ReLU(inplace=True)
    (2): Conv2d(96, 256, kernel_size=(7, 7), stride=(2, 2), padding=(2, 2))
    (3): ReLU(inplace=True)
    (4): Conv2d(256, 384, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (5): ReLU(inplace=True)
    (6): Conv2d(384, 384, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (7): ReLU(inplace=True)
    (8): Conv2d(384, 256, kernel_size=(3, 3), stride=(2, 2))
    (9): ReLU(inplace=True)
  (flatten): Flatten()
  (classifier): Sequential(
    (0): Dropout(p=0.5, inplace=False)
    (1): Linear(in_features=9216, out_features=4096, bias=True)
    (2): ReLU(inplace=True)
    (3): Dropout(p=0.5, inplace=False)
    (4): Linear(in_features=4096, out_features=4096, bias=True)
    (5): ReLU(inplace=True)
    (6): Linear(in_features=4096, out_features=4, bias=True)
)
```



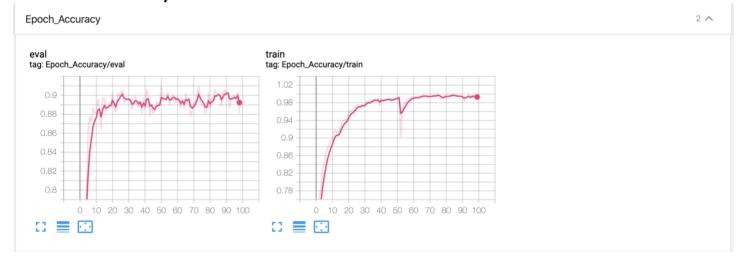
```
AlexNetTinv(
  (features): Sequential(
    (0): Conv2d(3, 48, kernel size=(11, 11), stride=(4, 4))
    (1): ReLU(inplace=True)
    (2): MaxPool2d(kernel size=3, stride=2, padding=0, dilation=1, ceil mode=False)
    (3): Conv2d(48, 128, kernel size=(5, 5), stride=(1, 1), padding=(2, 2))
    (4): ReLU(inplace=True)
    (5): MaxPool2d(kernel size=3, stride=2, padding=0, dilation=1, ceil_mode=False)
    (6): Conv2d(128, 192, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (7): ReLU(inplace=True)
    (8): Conv2d(192, 192, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (9): ReLU(inplace=True)
    (10): Conv2d(192, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (11): ReLU(inplace=True)
    (12): MaxPool2d(kernel size=3, stride=2, padding=0, dilation=1, ceil mode=False)
  (flatten): Flatten()
  (classifier): Sequential(
    (0): Dropout(p=0.5, inplace=False)
    (1): Linear(in features=4608, out features=2048, bias=True)
    (2): ReLU(inplace=True)
    (3): Dropout(p=0.5, inplace=False)
    (4): Linear(in features=2048, out features=1024, bias=True)
    (5): ReLU(inplace=True)
    (6): Linear(in features=1024, out features=4, bias=True)
)
```



```
AlexNetAvgPooling(
  (features): Sequential(
    (0): Conv2d(3, 96, kernel size=(11, 11), stride=(4, 4))
    (1): ReLU(inplace=True)
    (2): AvgPool2d(kernel size=3, stride=2, padding=0)
    (3): Conv2d(96, 256, kernel size=(5, 5), stride=(1, 1), padding=(2, 2))
    (4): ReLU(inplace=True)
    (5): AvgPool2d(kernel size=3, stride=2, padding=0)
    (6): Conv2d(256, 384, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (7): ReLU(inplace=True)
    (8): Conv2d(384, 384, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (9): ReLU(inplace=True)
    (10): Conv2d(384, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (11): ReLU(inplace=True)
    (12): AvgPool2d(kernel size=3, stride=2, padding=0)
  (flatten): Flatten()
  (classifier): Sequential(
    (0): Dropout(p=0.5, inplace=False)
    (1): Linear(in_features=9216, out_features=4096, bias=True)
    (2): ReLU(inplace=True)
    (3): Dropout(p=0.5, inplace=False)
    (4): Linear(in features=4096, out features=4096, bias=True)
    (5): ReLU(inplace=True)
    (6): Linear(in_features=4096, out_features=4, bias=True)
)
```



```
AlexNetDilation(
  (features): Sequential(
    (0): Conv2d(3, 96, kernel size=(11, 11), stride=(4, 4), padding=(5, 5), dilation=(2, 2))
    (1): ReLU(inplace=True)
    (2): MaxPool2d(kernel size=3, stride=2, padding=0, dilation=1, ceil mode=False)
    (3): Conv2d(96, 256, kernel size=(5, 5), stride=(1, 1), padding=(4, 4), dilation=(2, 2))
    (4): ReLU(inplace=True)
    (5): MaxPool2d(kernel size=3, stride=2, padding=0, dilation=1, ceil mode=False)
    (6): Conv2d(256, 384, kernel_size=(3, 3), stride=(1, 1), padding=(2, 2), dilation=(2, 2))
    (7): ReLU(inplace=True)
    (8): Conv2d(384, 384, kernel_size=(3, 3), stride=(1, 1), padding=(2, 2), dilation=(2, 2))
    (9): ReLU(inplace=True)
    (10): Conv2d(384, 256, kernel_size=(3, 3), stride=(1, 1), padding=(2, 2), dilation=(2, 2))
    (11): ReLU(inplace=True)
    (12): MaxPool2d(kernel size=3, stride=2, padding=0, dilation=1, ceil mode=False)
  (flatten): Flatten()
  (classifier): Sequential(
    (0): Dropout(p=0.5, inplace=False)
    (1): Linear(in_features=9216, out_features=4096, bias=True)
    (2): ReLU(inplace=True)
    (3): Dropout(p=0.5, inplace=False)
    (4): Linear(in_features=4096, out_features=4096, bias=True)
    (5): ReLU(inplace=True)
    (6): Linear(in features=4096, out features=4, bias=True)
)
```

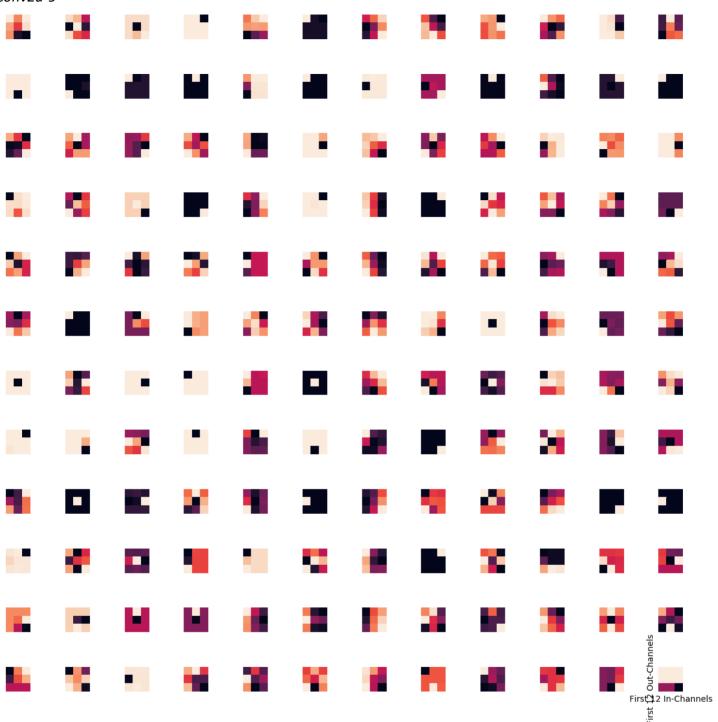


Part III - Visualizing Learned Filters

AlexNet - Domain

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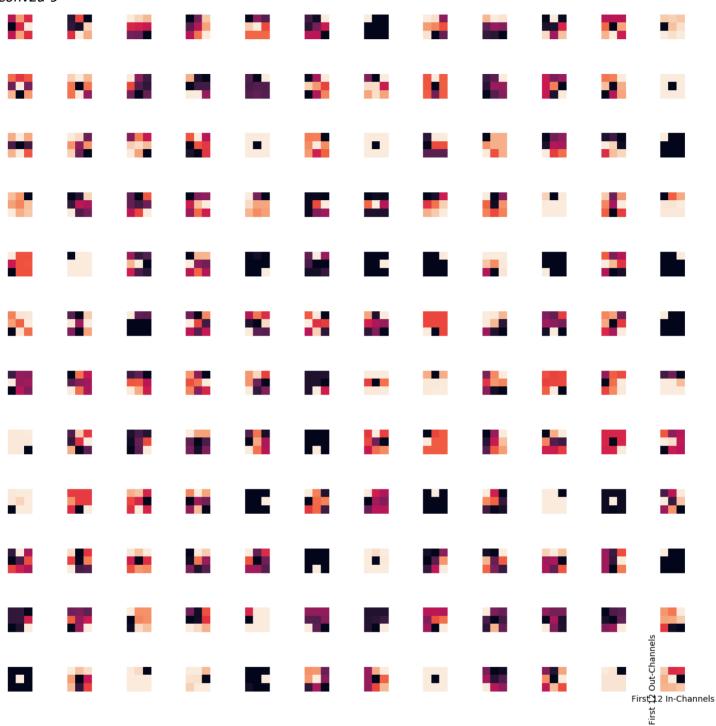




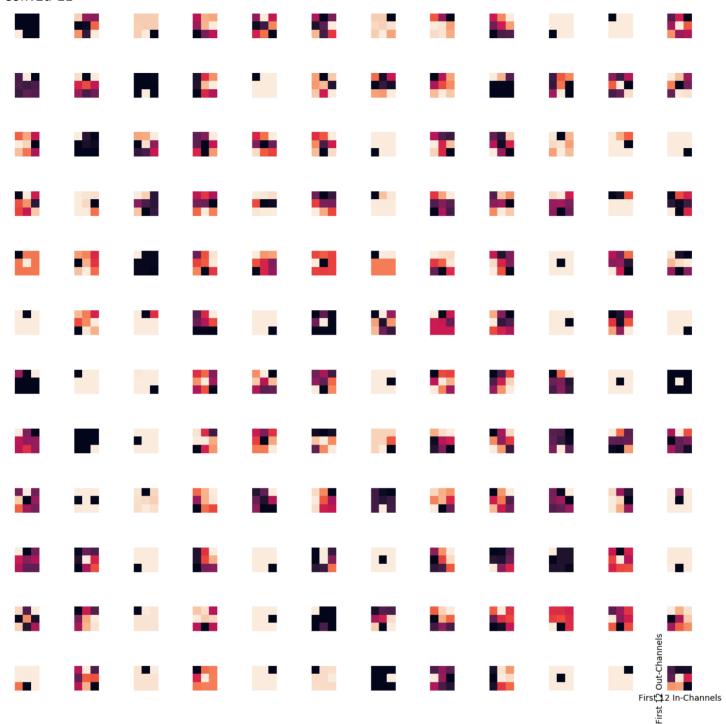
AlexNet - Class







Conv2d-11



Findings

Domain classification is determining if an image is art, cartoon, photo, or a sketch. It seems that in both the domain and the category label type classification, there were kernels learned that seemed to be pretty standard edge detection and point detection kernels. The Conv2d-11 layer for both category and domain look similar. The domain kernel looks like it is finding some sort of bumps. It is really hard to tell. The category kernel looks like it is finding perhaps textures and different shapes. Maybe this is because it is finding different patterns in different categories.