DeepLearning_Interpretability_clean

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1 Interpretability of Deep Learning: Estimating importance scores

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Adapted from https://github.com/srinadhu/CS231n/blob/master/assignment3/NetworkVisualization-PyTorch.ipynb

In this lab, we estimate importance scores using backpropagation, creating saliency maps.

In the process, we also learn how to use a pre-trained model, called SqueezeNet (AlexNet-level accuracy with 50x fewer parameters and 0.5MB model size), which can be loaded directly from PyTorch.
https://arxiv.org/abs/1602.07360 https://en.wikipedia.org/wiki/SqueezeNet

We further look at the ImageNet which is one of the most popular and important database consisted of milliions of images across 20000 categories. For Colab, we use only a small portion of the ImageNet https://ieeexplore.ieee.org/document/5206848 https://en.wikipedia.org/wiki/ImageNet

Using these ingredients, we calculate backpropgagtion based importance scores from scratch.

Please be mindful of both original (multi-channel) values and summaried 2D values. Both are used and researched in practice.

[1]:
```
import torch
import torchvision
import torchvision.transforms as T
import random
import numpy as np
import pandas as pd
from scipy.ndimage.filters import gaussian_filter1d
import matplotlib.pyplot as plt
import seaborn as sns

from PIL import Image

from matplotlib import cm
%matplotlib inline
plt.rcParams['figure.figsize'] = (10.0, 8.0) # set default size of plots
plt.rcParams['image.interpolation'] = 'nearest'
```

```python
plt.rcParams['image.cmap'] = 'gray'

SQUEEZENET_MEAN = np.array([0.485, 0.456, 0.406], dtype=np.float32)
SQUEEZENET_STD  = np.array([0.229, 0.224, 0.225], dtype=np.float32)

#only if you are running this from google colab an
from google.colab import drive
drive.mount('/content/gdrive')

#sample ImageNet data from https://github.com/CNN-ADF/Task2020
!wget 'https://raw.githubusercontent.com/CNN-ADF/Task2020/master/resources/
 ↪imagenet_val_25.npz' -q
```

```
---------------------------------------------------------------------------
ModuleNotFoundError                       Traceback (most recent call last)
Cell In[1], line 1
----> 1 import torch
      2 import torchvision
      3 import torchvision.transforms as T

ModuleNotFoundError: No module named 'torch'
```

[ ]:
```python
def preprocess(img, size=224):
    transform = T.Compose([
        T.Resize(size),
        T.ToTensor(),
        T.Normalize(mean=SQUEEZENET_MEAN.tolist(),
                    std=SQUEEZENET_STD.tolist()),
        T.Lambda(lambda x: x[None]),
    ])
    return transform(img)

def rescale(x):
    low, high = x.min(), x.max()
    x_rescaled = (x - low) / (high - low)
    return x_rescaled

def deprocess(img, should_rescale=True):
    transform = T.Compose([
        T.Lambda(lambda x: x[0]),
        T.Normalize(mean=[0, 0, 0], std=(1.0 / SQUEEZENET_STD).tolist()),
        T.Normalize(mean=(-SQUEEZENET_MEAN).tolist(), std=[1, 1, 1]),
        T.Lambda(rescale) if should_rescale else T.Lambda(lambda x: x),
        T.ToPILImage(),
    ])
    return transform(img)
```

```python
def blur_image(X, sigma=1):
    X_np = X.cpu().clone().numpy()
    X_np = gaussian_filter1d(X_np, sigma, axis=2)
    X_np = gaussian_filter1d(X_np, sigma, axis=3)
    X.copy_(torch.Tensor(X_np).type_as(X))
    return X
```

[ ]:
```python
def load_imagenet_val(num=None):
    f = np.load('imagenet_val_25.npz', allow_pickle=True)
    X = f['X']
    y = f['y']
    class_names = f['label_map'].item()
    idx = np.arange(25)
    np.random.shuffle(idx)
    if num is not None:
        idx = idx[:num]
        X   = X[idx]
        y   = y[idx]
    return X, y, class_names

#X, y, class_names = load_imagenet_val(num=5)
```

[ ]:
```python
#Load and use all 25 images from a smaller set, downloaded
f = np.load('imagenet_val_25.npz', allow_pickle=True)
X = f['X']
y = f['y']
class_names = f['label_map'].item()
print(X.shape)
print(y.shape)
```

```
(25, 224, 224, 3)
(25,)
```

[ ]:
```python
# show some images
plt.figure(figsize=(12, 6))
for i in range(5):
    plt.subplot(1, 5, i + 1)
    plt.imshow(X[i])
    plt.title(class_names[y[i]])
    plt.axis('off')
plt.gcf().tight_layout()
```

SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and 0.5MB model size https://arxiv.org/abs/1602.07360

Recent research on deep neural networks has focused primarily on improving accuracy. For a given accuracy level, it is typically possible to identify multiple DNN architectures that achieve that accuracy level. With equivalent accuracy, smaller DNN architectures offer at least three advantages: (1) Smaller DNNs require less communication across servers during distributed training. (2) Smaller DNNs require less bandwidth to export a new model from the cloud to an autonomous car. (3) Smaller DNNs are more feasible to deploy on FPGAs and other hardware with limited memory. To provide all of these advantages, we propose a small DNN architecture called SqueezeNet. SqueezeNet achieves AlexNet-level accuracy on ImageNet with 50x fewer parameters. Additionally, with model compression techniques we are able to compress SqueezeNet to less than 0.5MB (510x smaller than AlexNet).

https://github.com/forresti/SqueezeNet

[ ]:
```python
# Iandola et al, "SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and < 0.5MB model size", arXiv 2016
model = torchvision.models.squeezenet1_1(pretrained=True)
#print(model)

for param in model.parameters():
    param.requires_grad = False
```

```
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:208:
UserWarning: The parameter 'pretrained' is deprecated since 0.13 and may be
removed in the future, please use 'weights' instead.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:223:
UserWarning: Arguments other than a weight enum or `None` for 'weights' are
deprecated since 0.13 and may be removed in the future. The current behavior is
equivalent to passing `weights=SqueezeNet1_1_Weights.IMAGENET1K_V1`. You can
also use `weights=SqueezeNet1_1_Weights.DEFAULT` to get the most up-to-date
weights.
  warnings.warn(msg)
```

[ ]:
```python
X_tensor = torch.cat([preprocess(Image.fromarray(x)) for x in X], dim=0)
y_tensor = torch.LongTensor(y)
model.eval()
```

```python
scores = model(X_tensor)
print(scores)
scores_y = scores.gather(1, y_tensor.view(-1, 1)).squeeze()
print(scores_y)
```

```
tensor([[ 9.0406,  1.1808,  3.4227,  …,  4.6864,  8.0145,  5.2129],
        [ 5.9101,  4.6083,  6.9259,  …,  9.7415,  9.6305,  9.3974],
        [ 1.6097,  4.0396,  4.4560,  …,  3.4892, 11.6411, 12.5561],
        …,
        [ 5.5077,  3.8930,  3.3218,  …,  4.5410,  7.9065, 15.4184],
        [ 7.6427,  8.8772,  4.0593,  …,  9.6345,  7.5668, 10.8771],
        [ 8.6750, 13.4218, 11.4606,  …,  6.1399,  5.2605, 10.4970]])
tensor([24.1313, 25.1475, 38.8825, 25.4514, 30.2723, 25.4353, 15.6568, 34.9214,
        22.9094, 13.7762, 18.1419, 10.5448, 23.5066, 46.3714, 39.0091, 27.1299,
        25.8614, 19.7288, 18.6807, 20.9641, 25.2686, 18.7046, 21.7245, 12.6422,
        15.0523])
```

[ ]:
```python
def compute_saliency_maps(X, y, model):
    """
    Compute a class saliency map using the model for images X and labels y.

    Input:
    - X: Input images; Tensor of shape (N, 3, H, W)
    - y: Labels for X; LongTensor of shape (N,)
    - model: A pretrained CNN that will be used to compute the saliency map.

    Returns:
    - saliency: A Tensor of shape (N, H, W) giving the saliency maps for the␣
↪input
    images.
    """
    model.eval()
    X.requires_grad_()

    # 1. Forward pass
    scores = model(X)

    # 2. Get correct class scores
    scores = scores.gather(1, y.view(-1, 1)).squeeze()

    # 3. Backward pass
    scores_size = scores.shape
    ones_tensor = torch.ones(scores_size)
    scores.backward(ones_tensor)

    # 4. retrieve the gradient as saliency map
    saliency = X.grad
```

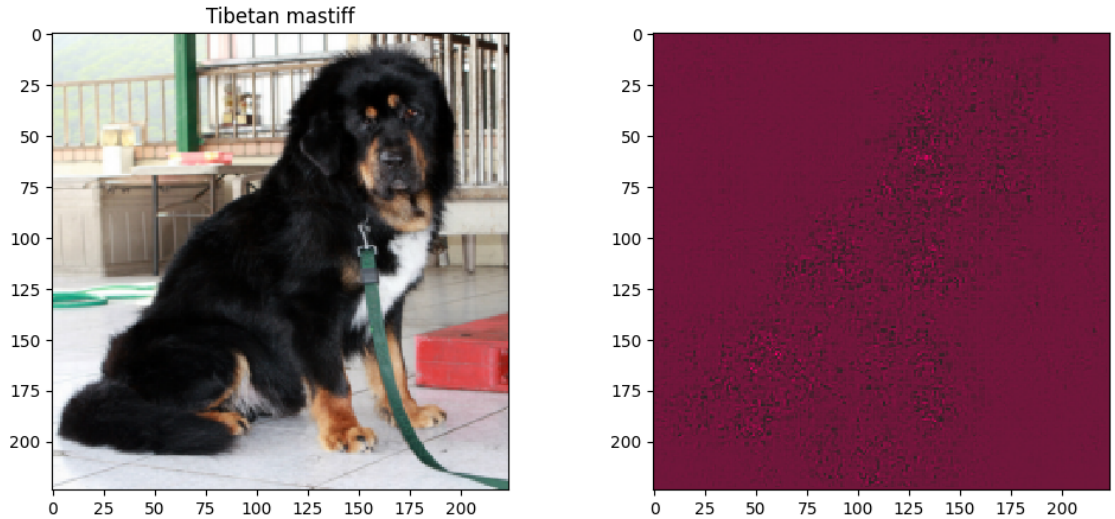
```python
    return saliency

def compute_abs(saliency):
    saliency_abs = saliency.abs()
    return saliency_abs

def compute_max(saliency):
    saliency_max, _= torch.max(saliency, dim=1)
    return saliency_max
```

[ ]:
```python
## calculating gradients for CORRECT labels
# Convert X and y from numpy arrays to Torch Tensors
X_tensor = torch.cat([preprocess(Image.fromarray(x)) for x in X], dim=0)
y_tensor = torch.LongTensor(y)

# Compute saliency maps for images in X
saliency = compute_saliency_maps(X_tensor, y_tensor, model)
saliency_max = compute_max(saliency)
saliency_maxabs = compute_max(compute_abs(saliency)) # what original authors did

# Convert the saliency map from Torch Tensor to numpy array and show images
# and saliency maps together.
#saliency = saliency.numpy()
print(saliency.shape)
```

```
torch.Size([25, 3, 224, 224])
```

[ ]:
```python
hue_neg, hue_pos = 0, 359
cmap = sns.diverging_palette(hue_neg, hue_pos, s=100, center="dark",␣
 ↪as_cmap=True)
```

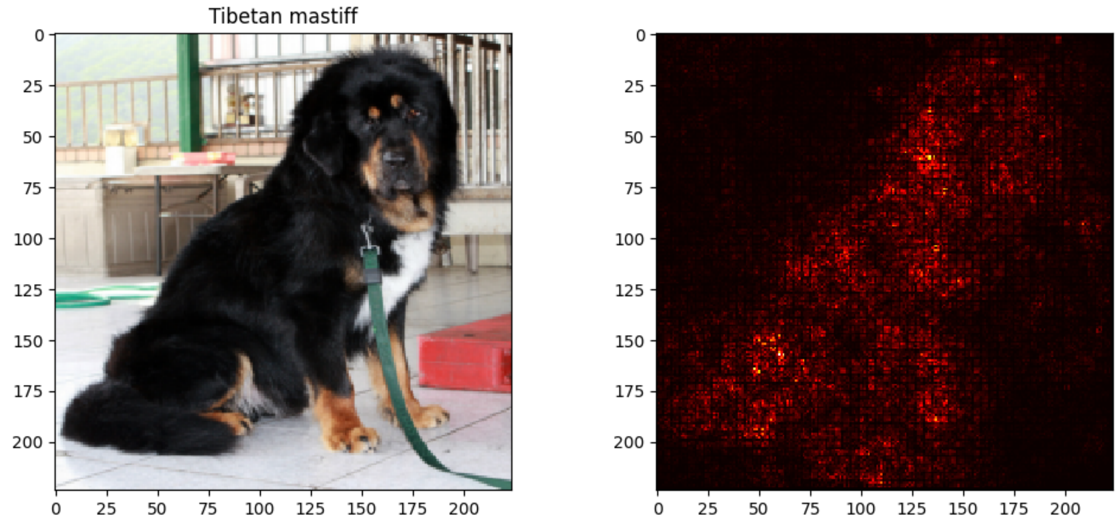
[ ]:
```python
i = 2

plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.imshow(X[i,:,:,:])
plt.title(class_names[y[i]])
plt.subplot(1, 2, 2)
plt.imshow(saliency_max[i,:,:].numpy(), cmap=cmap)
plt.gcf().set_size_inches(12, 5)
```



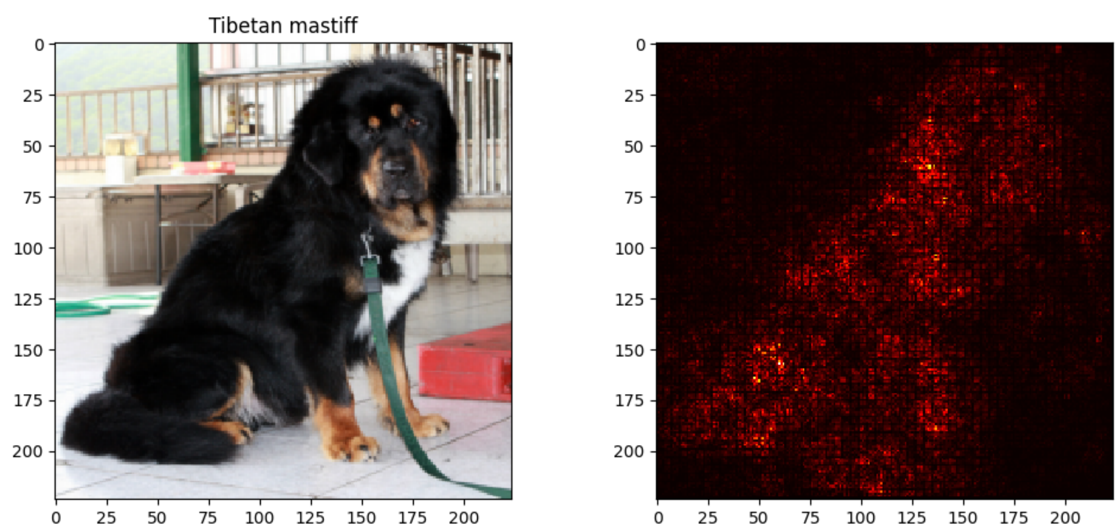
[ ]:
```
saliency_max[i,:,:].numpy()
```

[ ]:
```
array([[-5.6959433e-04,  1.3885004e-03,  2.3240333e-03, …,
         -8.9034060e-05,  4.9511982e-05,  0.0000000e+00],
       [ 2.9082103e-03,  6.1952830e-03,  7.6641212e-03, …,
         4.2653101e-04,  2.0675986e-06,  0.0000000e+00],
       [ 9.0336129e-03,  7.4838907e-03,  6.1066970e-03, …,
         1.1076747e-04,  3.6587339e-04,  0.0000000e+00],
       …,
       [-2.7070096e-04,  2.3340620e-03, -1.3610231e-03, …,
         9.5762481e-04,  9.9336915e-04,  0.0000000e+00],
       [ 4.3300042e-04,  7.3457870e-04,  3.6031934e-03, …,
         7.6837727e-04,  6.5263757e-04,  0.0000000e+00],
       [ 0.0000000e+00,  0.0000000e+00,  0.0000000e+00, …,
         0.0000000e+00,  0.0000000e+00,  0.0000000e+00]], dtype=float32)
```

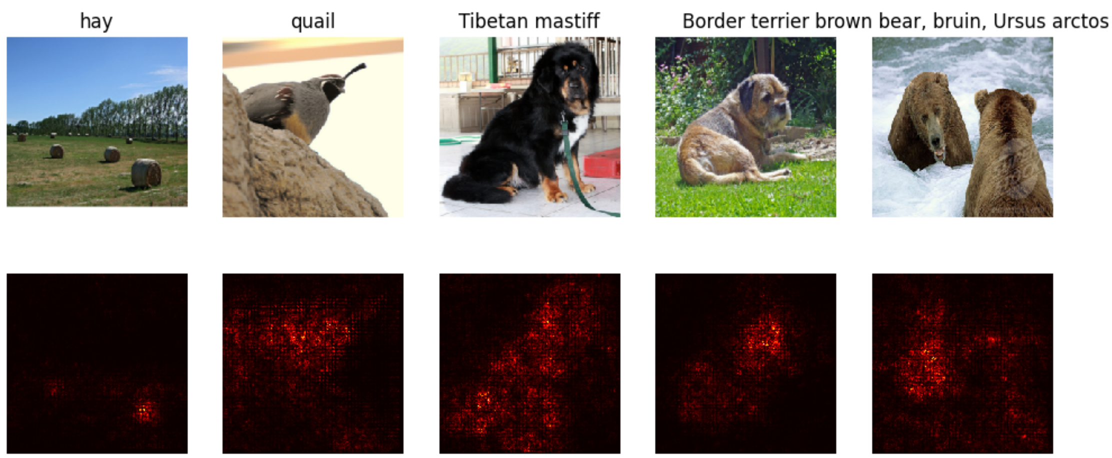
[ ]:
```
i = 2

plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.imshow(X[i,:,:,:])
plt.title(class_names[y[i]])
plt.subplot(1, 2, 2)
plt.imshow(saliency_maxabs[i,:,:].numpy(), cmap=plt.cm.hot)
plt.gcf().set_size_inches(12, 5)
```




```
[ ]: zi = 2

plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.imshow(X[i,:,:,:])
plt.title(class_names[y[i]])
plt.subplot(1, 2, 2)
plt.imshow(saliency_maxabs[i,:,:].numpy(), cmap=plt.cm.hot)
plt.gcf().set_size_inches(12, 5)
```

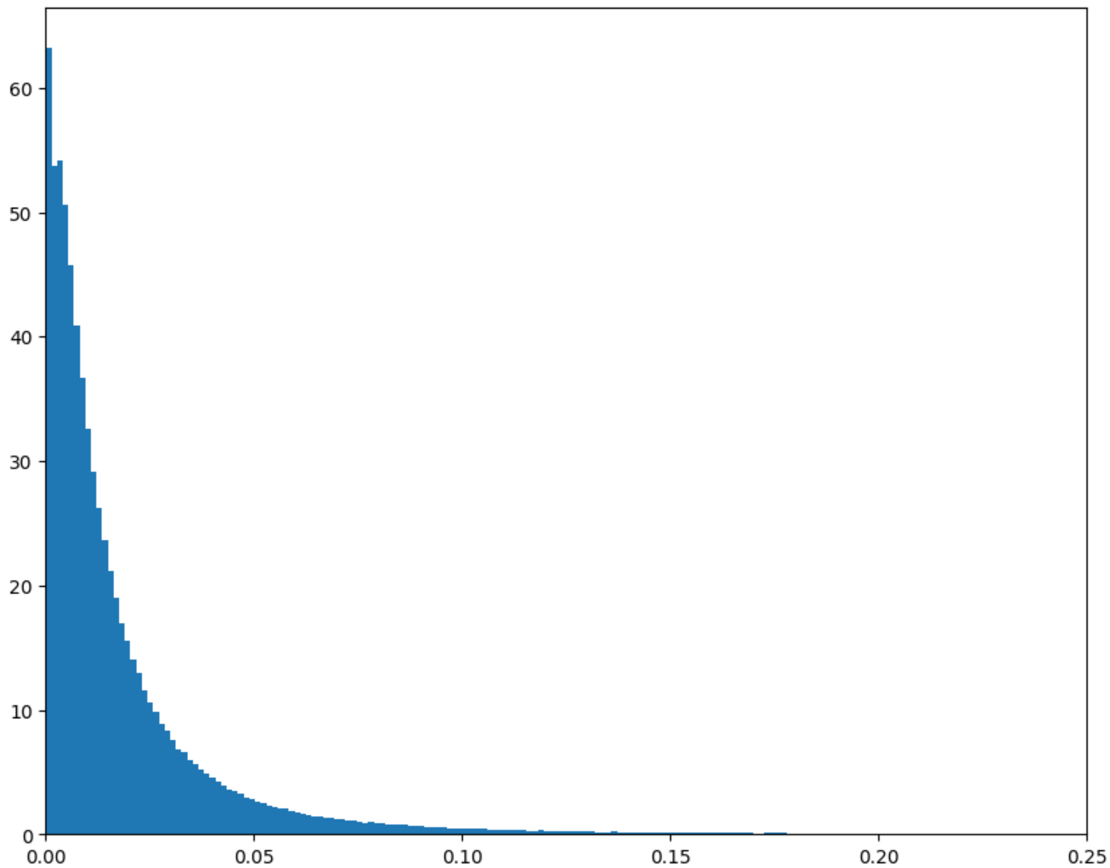


[ ]:
```
N = 5
for i in range(N):
    plt.subplot(2, N, i + 1)
    plt.imshow(X[i])
    plt.axis('off')
    plt.title(class_names[y[i]])
    plt.subplot(2, N, N + i + 1)
    plt.imshow(saliency_maxabs[i].numpy(), cmap=plt.cm.hot)
    plt.axis('off')
    plt.gcf().set_size_inches(12, 5)
plt.show()
```



[ ]:
```
# look at the historgram of the saliency maps
plt.hist(saliency_maxabs.numpy().flatten(), density=True, bins=1000)
plt.xlim([0,0.25])
```

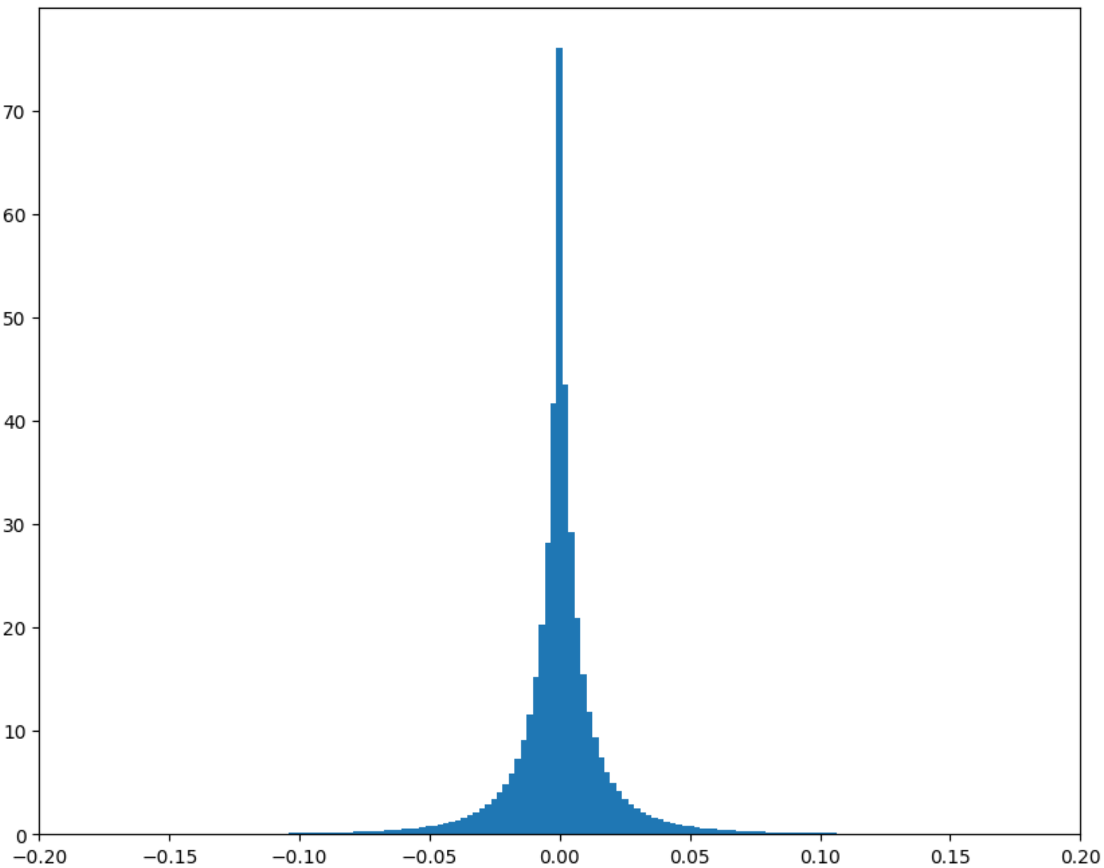
[ ]: (0.0, 0.25)



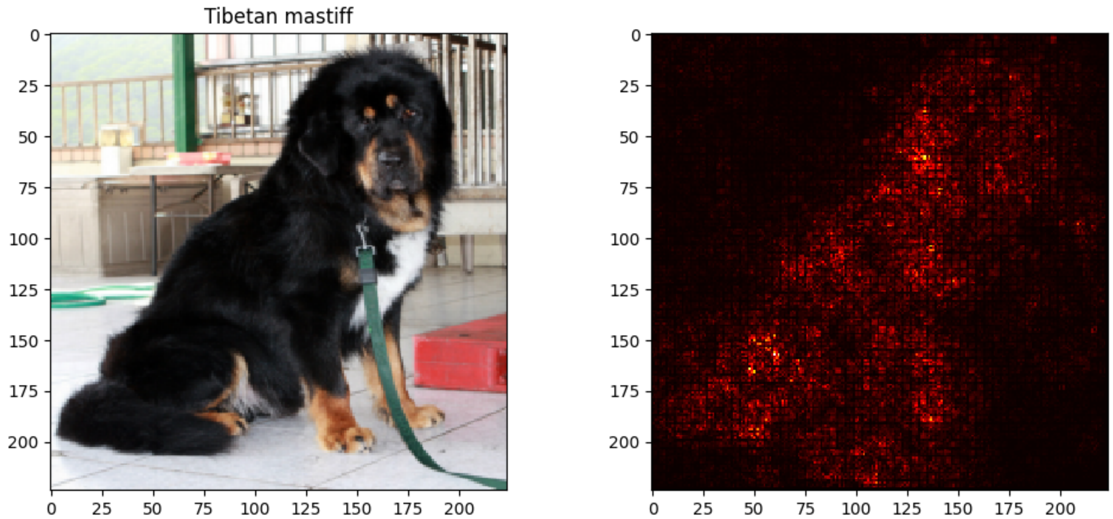
[ ]:

```
# look at the historgram of the saliency maps
plt.hist(saliency.numpy().flatten(), density=True, bins=1000)
plt.xlim([-.2,0.2])
```

[ ]: (-0.2, 0.2)



[ ]:
```
i = 2

plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.imshow(X[i,:,:,:])
plt.title(class_names[y[i]])
plt.subplot(1, 2, 2)
plt.imshow(saliency_maxabs[i,:,:].numpy(), cmap=plt.cm.hot)
plt.gcf().set_size_inches(12, 5)
```



2 Homework

Create a SmoothGrad. The basic steps are written below. See the paper: Smilkov et al. (2017) "SmoothGrad: removing noise by adding noise"

1. Add a slight (i.i.d. Gaussian) noise to the original image, creating multiple versions
2. Calculate importance scores (e.g., vanilla gradients) of those multiple 'noisy' images
3. Calculate average importance scores

You can make a function or write a for-loop. Visualize N=5 samples, with vanilla saliency maps and SmoothGrad maps

[ ]:
```
from skimage.util import random_noise

def add_gaussian_noise(image, stddev):
  return torch.tensor(random_noise(image, mode='gaussian', mean=0, var=stddev**2, clip=True))
```

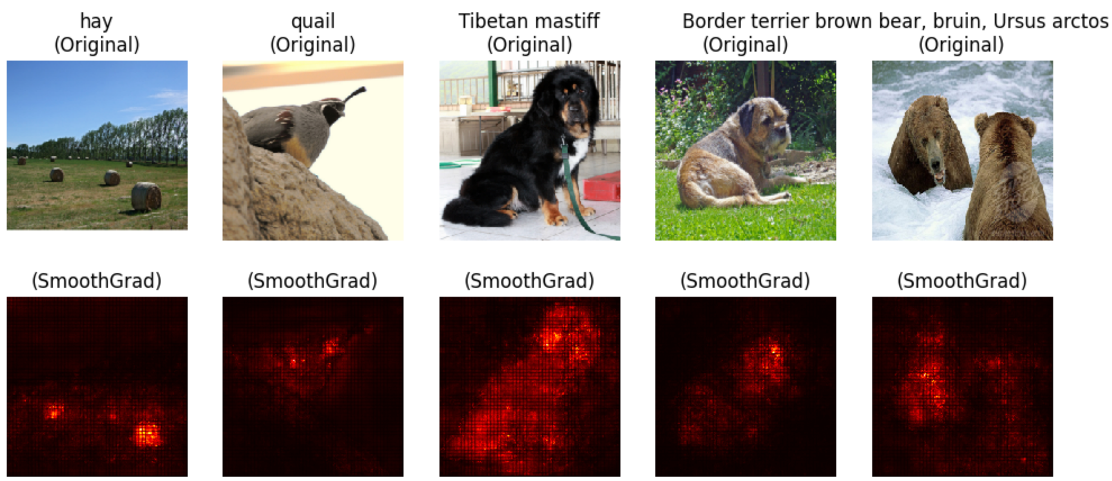
[ ]:
```
sample = X[:5]
labels = y[:5]
X_tensor = torch.cat([preprocess(Image.fromarray(x)) for x in sample], dim=0)
y_tensor = torch.LongTensor(labels)

names = [class_names[i] for i in labels]
```

[ ]:
```
def compute_smooth_grad(XX, yy, model, sigma=0.1, n_samples=50):
    """
    Compute a class saliency map using the SmoothGrad method for images X and labels y.
```

```
    Input:
    - X: Input images; Tensor of shape (N, 3, H, W)
    - y: Labels for X; LongTensor of shape (N,)
    - model: A pretrained CNN that will be used to compute the saliency map.
    - sigma: Standard deviation of the Gaussian noise.
    - n_samples: Number of noisy samples to average over.

    Returns:
    - smooth_grad: A Tensor of shape (N, H, W) giving the smooth saliency maps␣
↪for the input
    images.
    """
    model.eval()


    for i in range(n_samples):
        # 1. Add Gaussian noise to the image
        noise = torch.randn(XX.shape).type_as(XX) * sigma
        XX_noisy = XX + noise
        XX_noisy.requires_grad_()
        XX_noisy.retain_grad()
        # 2. Calculate saliency maps for noisy images
        saliency = compute_saliency_maps(XX_noisy, yy, model)
        saliency_maxabs = compute_max(compute_abs(saliency))

        # 3. Accumulate saliency maps
        if i==0:
          smooth_grad = saliency_maxabs
        else:
          smooth_grad += saliency_maxabs

    # 4. Average saliency maps
    smooth_grad /= n_samples
    return smooth_grad
```

[ ]:
```
# Compute SmoothGrad saliency maps for images in X
smooth_grad = compute_smooth_grad(X_tensor, y_tensor, model)

# Visualize
N = 5
for i in range(N):
    # Original Image
    plt.subplot(3, N, i + 1)
    plt.imshow(X[i])
    plt.axis('off')
    plt.title(f"{class_names[y[i]]}\n(Original)")
```

```
    # Vanilla Saliency Map
    plt.subplot(3, N, N + i + 1)
    plt.imshow(saliency_maxabs[i].numpy(), cmap=plt.cm.hot)
    plt.axis('off')
    plt.title("(Vanilla Grad)")

    # SmoothGrad Saliency Map
    plt.subplot(3, N, 2*N + i + 1)
    plt.imshow(smooth_grad[i].numpy(), cmap=plt.cm.hot)
    plt.axis('off')
    plt.title("(SmoothGrad)")

plt.gcf().set_size_inches(12, 8)  # Adjust figure size for 3 rows
plt.show()
```



[ ]:
```
# Compute SmoothGrad saliency maps for images in X with different sigma values
sigmas = [0.1, 0.2, 0.5]  # Experiment with different sigma values
smooth_grads = []
for sigma in sigmas:
    smooth_grads.append(compute_smooth_grad(X_tensor, y_tensor, model,␣
  ↪sigma=sigma))
```

[ ]:
```
# Visualize
N = 5
for i in range(N):
    # Original Image
    plt.subplot(5, N, i + 1)  # 4 rows for original + 3 sigmas
    plt.imshow(X[i])
    plt.axis('off')
```

```python
    plt.title(f"{class_names[y[i]]}\n(Original)")

    # Vanilla Saliency Map
    plt.subplot(5, N, N + i + 1)
    plt.imshow(saliency_maxabs[i].numpy(), cmap=plt.cm.hot)
    plt.axis('off')
    plt.title("(Vanilla Grad)")

    # SmoothGrad Saliency Maps with different sigmas
    for j, sigma in enumerate(sigmas):
        plt.subplot(5, N, (2+j)*N + i + 1)  # Adjust row for each sigma
        plt.imshow(smooth_grads[j][i].numpy(), cmap=plt.cm.hot)
        plt.axis('off')
        plt.title(f"(SmoothGrad, \u03C3={sigma})")  # Unicode for sigma

plt.gcf().set_size_inches(12, 10)  # Adjust figure size for 4 rows
plt.show()
```