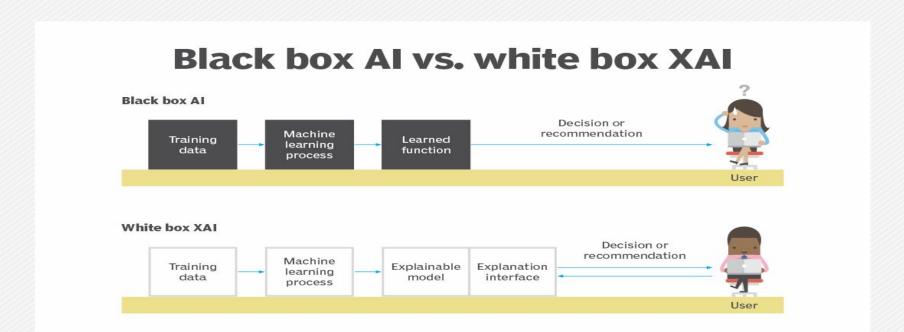
Explainability for Deep Learning Models

Group 5: Manoj Padala Ram Mannuru Sailesh

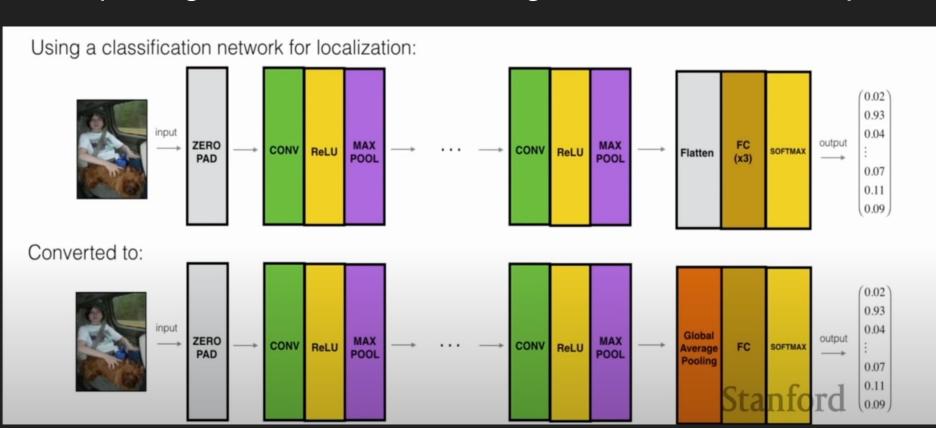
WHAT & WHY??



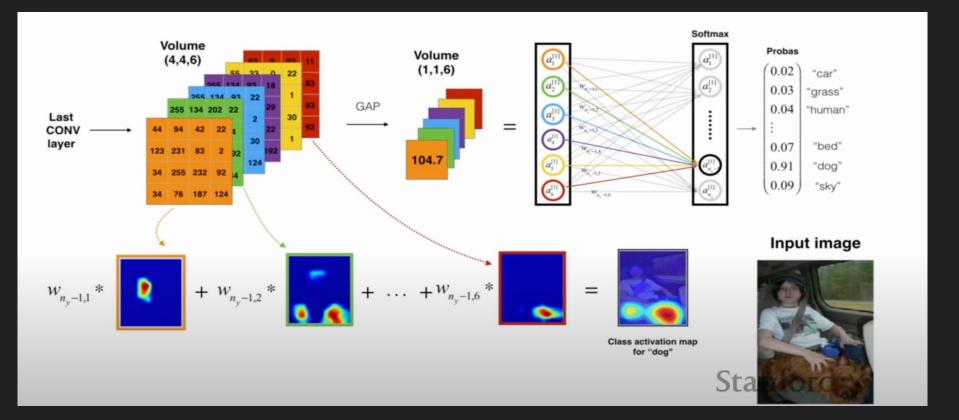
XAI Models

- 1. Class Activation Maps
- 2. Deep Feature Factorization
- 3. LIME and SHAP
- 4. GradCam
- 5. Occlusion Sensitivity

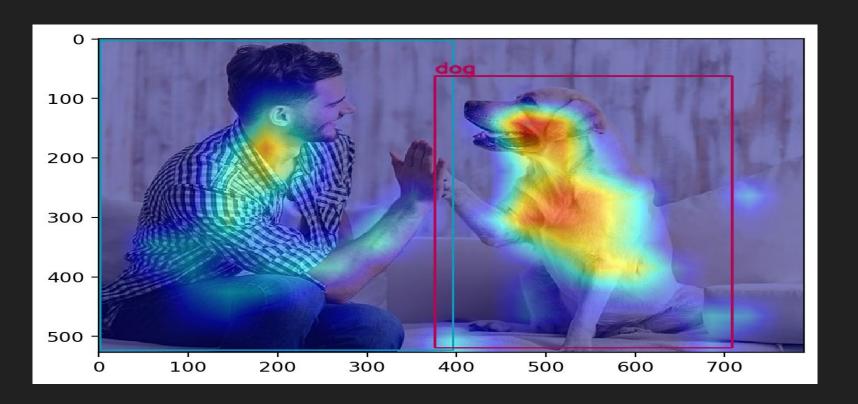
Interpreting Neural networks using Class Activation Maps:



Interpreting Neural networks using Class Activation Maps:



Dashboard:



What do Models See?



Interpreting NNs using Deep feature factorization:

- 1.Model Selection: Pre Trained (CNNS)
- 2. Target Layer Selection : Typically deeper layer where representations are more abstract.
- 3. Computation On Concepts: Analysing activations of neurons.
- 4. Factorization: decomposing a matrix to understand more.

Dashboard:



Uploaded Image

Predicted class using Resnet

Why is that result??



Visualization Result

LIME Image Classifier

LIME - Local Interpretable Model agnostic Explanation

Model agnostic - Pre Trained, Custom or Pre Trained + Custom

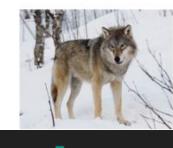
Interpretable Representation

Real Time Usage of LIME - HealthCare Decision Support System, Financial Fraud Detection and in some IOT industries.



How **LIME** predicts?

SEGMENTED IMAGE













Model Prediction

Segmentation of the Image

Generate Preturbations

Model Re-evaluation

Train the Local Model

Explanation Generation

Visualization and Interpretation

AI Explainability Dashboard

LIME for Image Classification Model

Select the Deep Learning framework:	
O PyTorch	
TensorFlow	
Pretrained	
Pre-trained	
Instantiate pre-trained model with corresponding weights. Note: write full library. TensorFlow as tf and tor	ch as torch.
model = tf.keras.applications.MobileNetV2(weights='imagenet')	<u>©</u> 📵
<pre>model = tf.keras.applications.MobileNetV2(weights='imagenet')</pre>	
Enter the image size for your model (Note: For pre-trained models, it must match with image size that was the model)	used to train
224	
Enter your desired image normalization - Mean	
0.5, 0.5, 0.5	
Enter your desired image normalization - Standard Deviation	
0.5, 0.5, 0.5	
Applied pre-processing	
torchvision.transforms.Compose([torchvision.transforms.ToTensor(), torchvision.transforms.Resize((224, 224)), torchvision.transforms.Normalize(mean=[0.5, 0.5, 0.5],	

Upload the image you want to explain



photo-1560275619-4662e36fa65c.jpg 166.4KB



Uploaded Image

Your Predicted Output from the model is as follows:

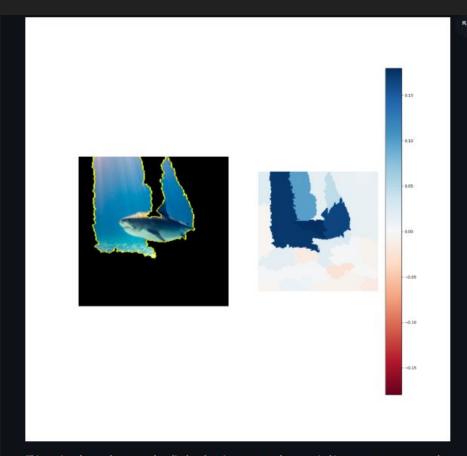
0.0002	0.0002	0.0029	0.8631	0.0201	0.0021	0.0046	0	0.0001	0.0001	0.0001	0.0001	0.0001

Explain Model





Image on the left denotes the super-pixels or region-of-interest based on LIME analysis. Classification is done due to the highlighted super-pixels. Image on the right imposes this region-of-interest on original image giving a more intuitive understanding.



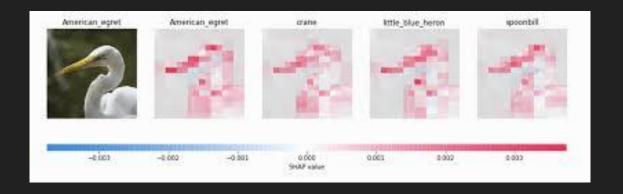
This section shows a heat-map that displays how important each super-pixel is to get some more granular explaianbility. The legend includes what color-coded regions of interest move the decision of the model. Blue indicates the regions that influences the decision of the model in the predicted class and red indicates the regions that influence the decision to other classes.

SHAP Image Classifier

SHAP -**SH**apley **A**dditive ex**P**lanation

Shapley Value

Real Time Usage of LIME - Credit Scoring, E-commerce Product



How does SHAP work?

Feed an Image

Pixel-Level Feature analysis

Create Perturbations and Recalculate Prediction

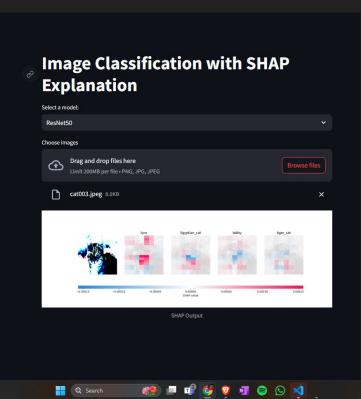
Calculate SHAP Values

Aggregate SHAP Values and Analyze

Color Coding



SHAP integrated with Streamlit





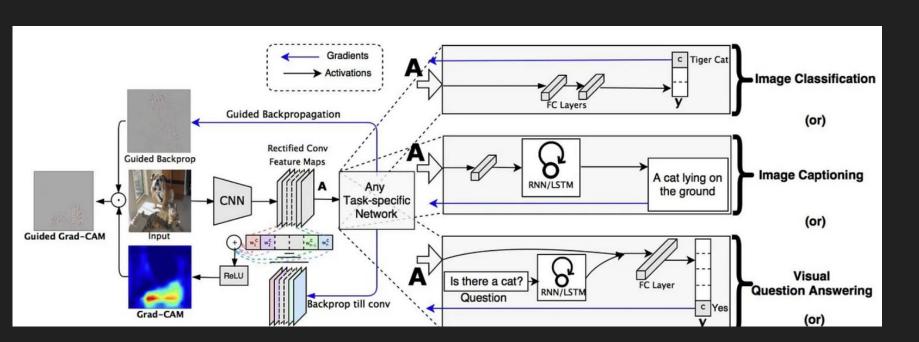
XAI for Convolution

DEEP LEARNING EXPLAINABILITY

- GRADCAM
- OCCLUSION SENSITIVITY

GRADCAM

- Forward Pass
- Gradient Calculation
- Global Average Pooling (GAP)
- Weighted Combination
- ReLU and Upsampling
- Visualization



GRADCAM

1. Forward Pass: Feed Input to last layer of CNN to obtain feature maps

Ak= Activation functions

- 2. Gradient Calculation: $rac{\partial Y_c}{\partial A^k}$
- 3. Global Average Pooling (GAP):

Compute the importance of each feature map by taking the global average of the gradients.

$$lpha_k = rac{1}{Z} \sum_i \sum_j rac{\partial Y_c}{\partial A_{ij}^k}$$

4. Weighted Combination:

Weight the feature maps by their important scores

$$L_{ ext{Grad-CAM}}^c = ext{ReLU}\left(\sum_k lpha_k A^k
ight)$$

OCCLUSION SENSITIVITY

- Model Interpretability
- Detection of Important features
- Localization
- Model Improvement
- Debubbing
- Comparing models

- Input Window
- Occlusion Window
- Sliding Window
- Move Window (Stride)
- Comparing models

OCCLUSION SENSITIVITY

- **1**. Input Image: I_{ij}
- 2. Model Prediction: Output which represents class probabilities f(I)
- 3. Occlusion Window: size (p,q)
- 4. Occlusion value: Replaces the value with pixels of input image
- 5. Occlusion Process: Input, slide occlusion window with stride, Replace pixels and compute model prediction
- 6. Occlusion sensitivity map
- 7. Normalization and Visualization.

GRADCAM

Gradient-weighted Class Activation Mapping

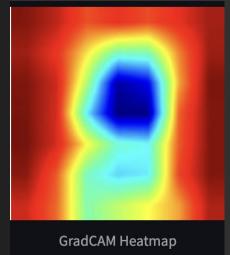
Input Image:



Predicted Class: tabby

Probability: 0.65993613

Model Used: ResNet50





Occlusion Sensitivity

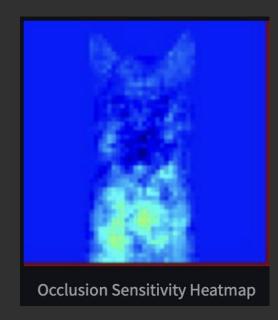
Model Used: ResNet50

Input Image:



Predicted Class: tabby

Probability: 0.65993613



Occlusion Sensitivity

