Explanation techniques for neural networks

An overview with practical examples

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Different approaches

- We assume
  - Complicated non-linear task
  - Can **not** be solved by an intuitively explainable model
- Complete understanding is not possible
- Three basic approaches shown
  - Backpropagation approach
  - Local approximation
  - Network representation

Based on backpropagation

- Derivative of output in regards to input
- Optimized in most libraries
- Simple implementation
- Many variants
  - SmoothGrad [11]
  - CAM [2]
  - GradCAM [13]
  - LRP [12]
  - ...

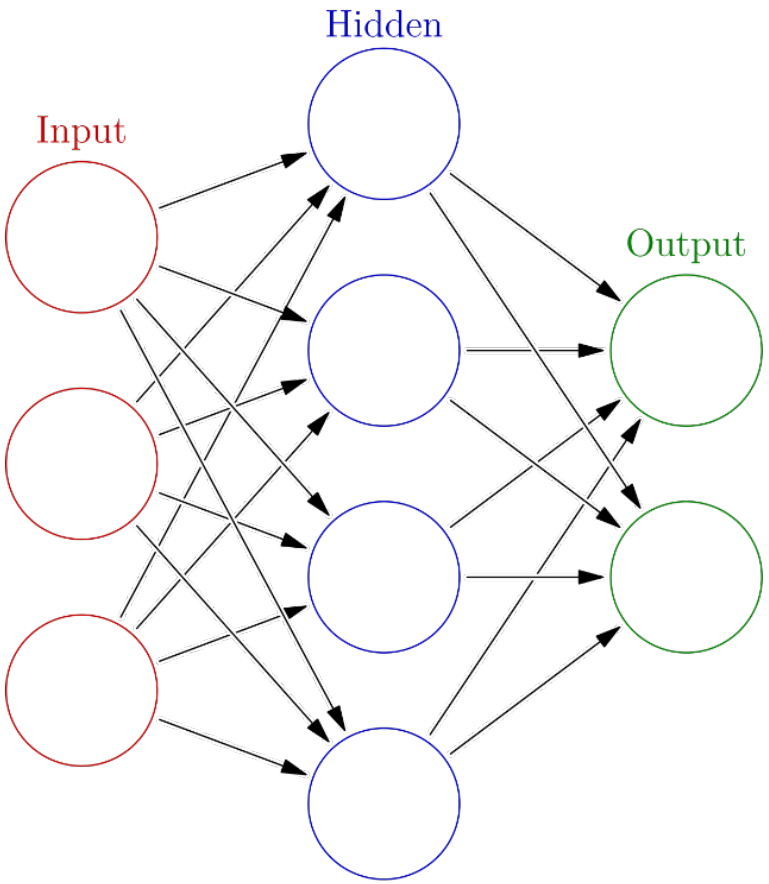


Image from https://en.wikipedia.org/wiki/Artificial_neural_network

Saliency

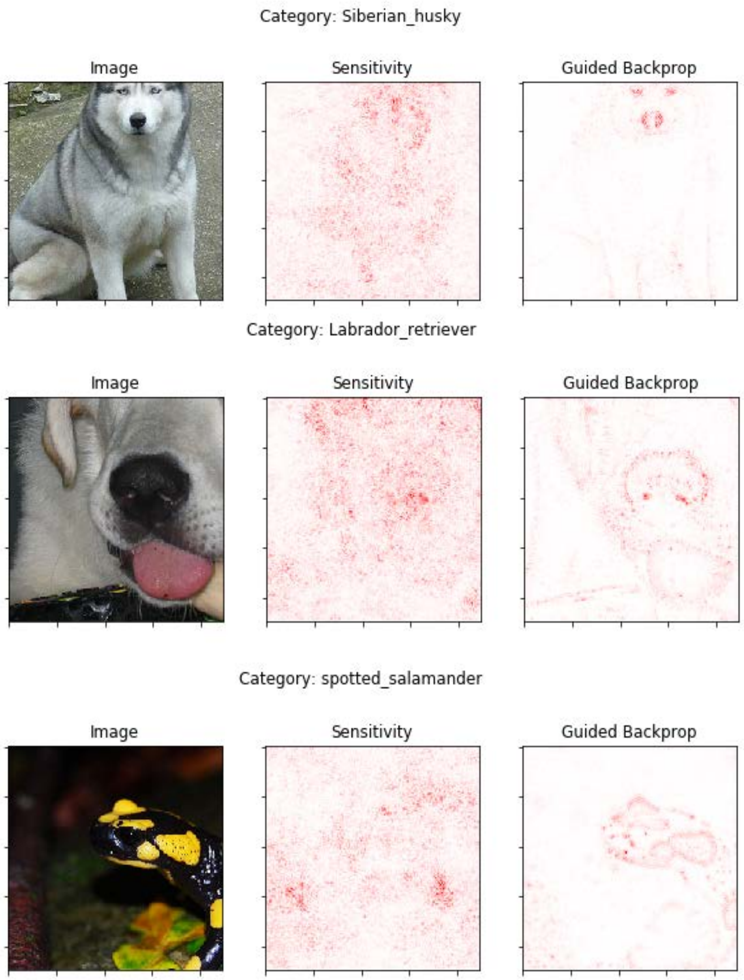
- Basic variant [1]

$$\frac{\partial y_c}{\partial x_{i,j}} = \left(\frac{\partial y_c}{\partial l_{-1}}\right) \dots \left(\frac{\partial l_1}{\partial x_{i,j}}\right)$$

- Variant: Guided Backprop [9]

$$\frac{\partial' y_c}{\partial' x_{i,j}} = \mathrm{ReLU}\left(\frac{\partial y_c}{\partial l_{-1}}\right) \dots \mathrm{ReLU}\left(\frac{\partial l_1}{\partial x_{i,j}}\right)$$

- Easy to implement
- Very noisy



Sensitivity heatmaps obtained with kerasvis library from pretrained VGG16

Gradient-weighted Class Activation Mapping (Grad-CAM)

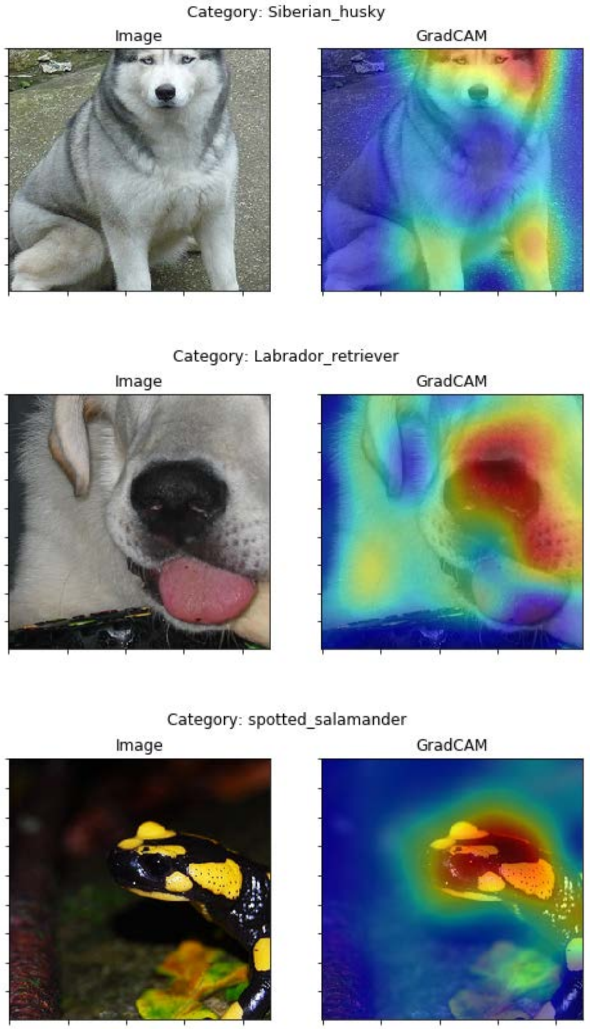
- Combining CAM[2] and gradients
- Requires CNN structure
- Coarse localization due to upfiltering
- CAM [2]:

$$M_c(x,y) = \sum_k w_k^c f_k(x,y)$$

- Grad-CAM [13]:

$$\alpha_k^c = \frac{1}{Z}\sum_i \sum_j \frac{\partial y^c}{\partial A_{ij}^k}$$

$$M_{GradC}^c(x,y) = ReLU\left(\sum_k a_k^c f_k(x,y)\right)$$



GradCAM heatmaps obtained with kerasvis library from pretrained VGG16

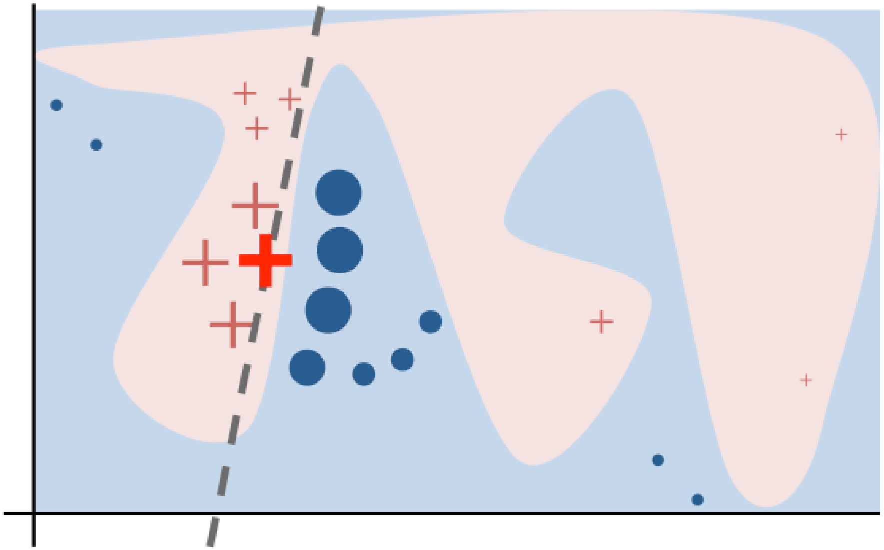
Overview

	Fidelity	Understandability	Sufficiency	Low construction overhead	Efficiency
Backprop	+	-	O	+	+
Local					
High-level					

Desiderate taken from [14]

Local approximation with interpretable model – LIME

- Intuition:
  - Sample around **x**
  - Weigh samples according to distance
  - Train linear classifier
  - Obtain explanation
- Low-dimensional representation necessary
  - For images: segment into super-pixels
  - For text: bag of words



From https://github.com/marcotcr/lime

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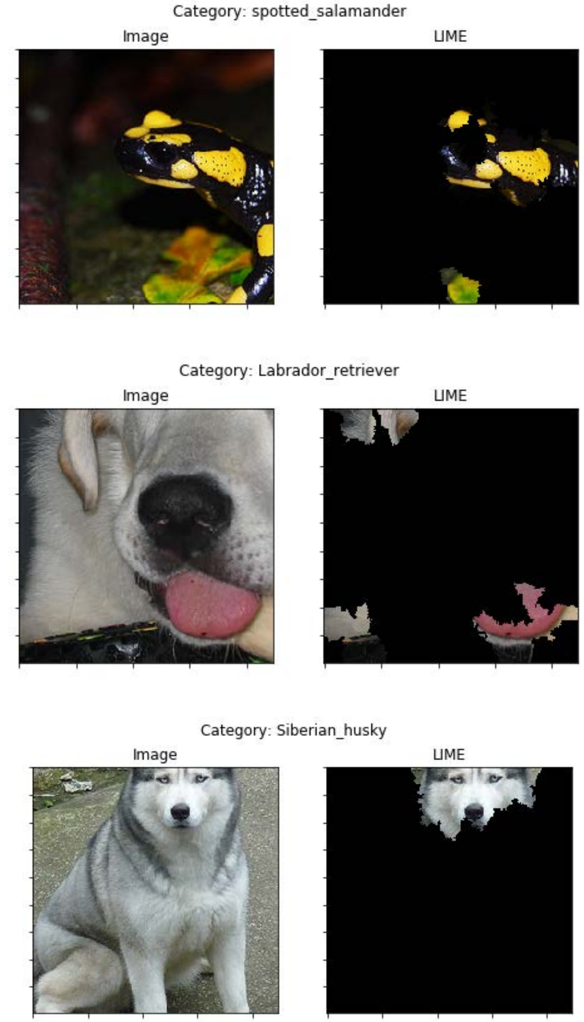


Images obtained with LIME library from pretrained VGG16

Overview

	Fidelity	Understandability	Sufficiency	Low construction overhead	Efficiency
Backprop	+	-	O	+	+
Local	O	+	O	+	-
High-level					

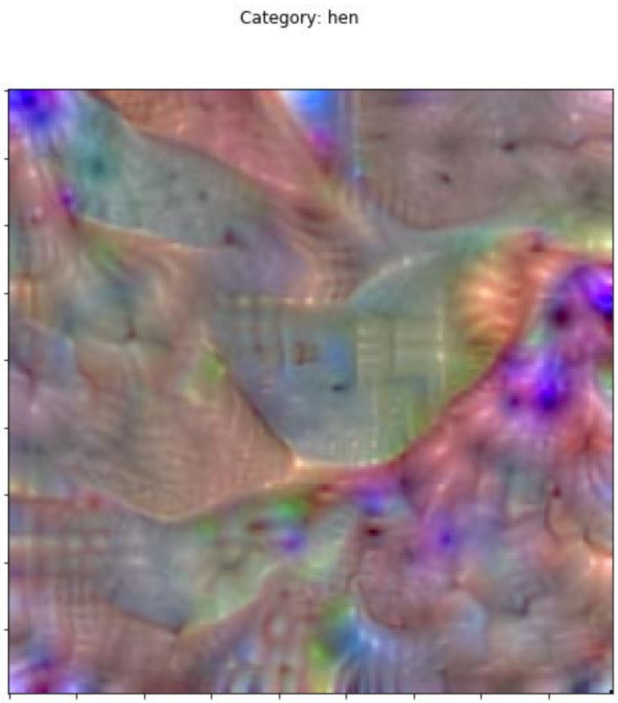
Desiderate taken from [14]

Higher-level

- Network level explanations
- Requires domain knowledge
- Interesting for risk and fairness analysis
- Two approaches presented
  - Analyzing specific network parts
  - Analyzing specific aspects

Probing the network

- “Understanding Neural Networks Through Deep Visualization” [5]
  - Idea: iteratively optimize activation of neurons with backpropagation
  - Regularize to encourage realistism
  - For output or intermediate layers
- Alternatives
  - Bau, David, et al. "Network Dissection: Quantifying Interpretability of Deep Visual Representations." *Computer Vision and Pattern Recognition (CVPR), 2017 IEEE Conference on*. IEEE, 2017.
  - Alain, Guillaume, and Yoshua Bengio. "Understanding intermediate layers using linear classifier probes." (2016).



Obtained with kerasvis
from pretrained VGG16

Testing with Concept Activation Vectors CAV

- Recently proposed by Kim et al [8]
- Requires high domain knowledge
- Idea:
  - assemble dataset {P,N}
  - Train linear classifier on representation of given layer
  - Obtain weights
- Useful for
  - Evaluating given input
  - Identifying a known bias in dataset and model

Kim, Been, et al.
"TCAV: Relative concept importance testing with Linear Concept Activation Vectors." (2018).

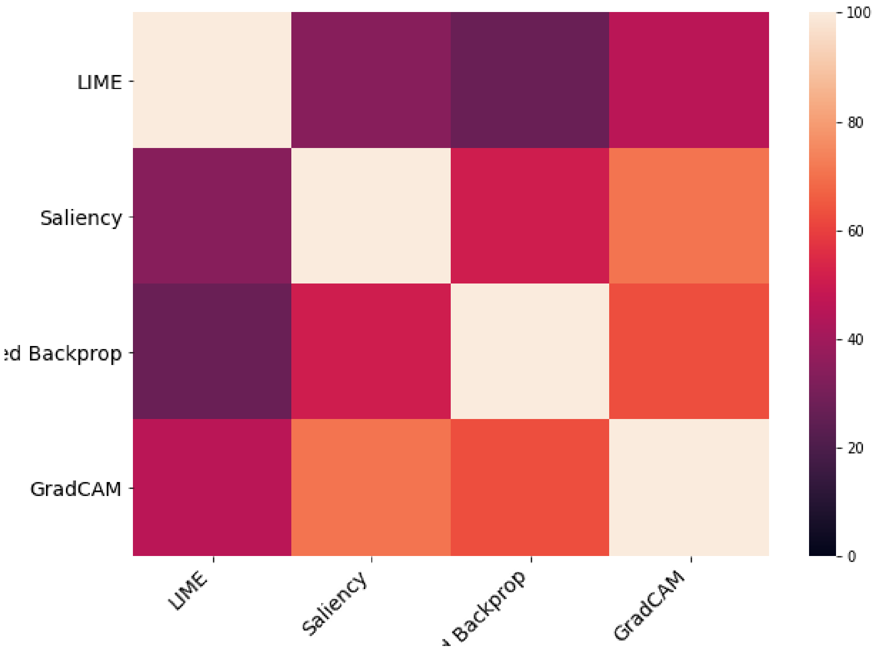
Overview

	Fidelity	Understandability	Sufficiency	Low construction overhead	Efficiency
Backprop	+	-	O	+	+
Local	O	+	O	+	-
High-level	+	+	-	-	O

Desiderate taken from [14]

How much disagreement is there?

- Expectation: explanations are correlated across similar networks
- Compute agreement between heatmaps
  - Between methods
  - Between networks
- LIME is highly changeable compared to other methods



Agreement between explanation methods for VGG16

Pretrained VGG16 and VGG19 from keras,

How much disagreement is there?

- Expectation: explanations are correlated across similar networks
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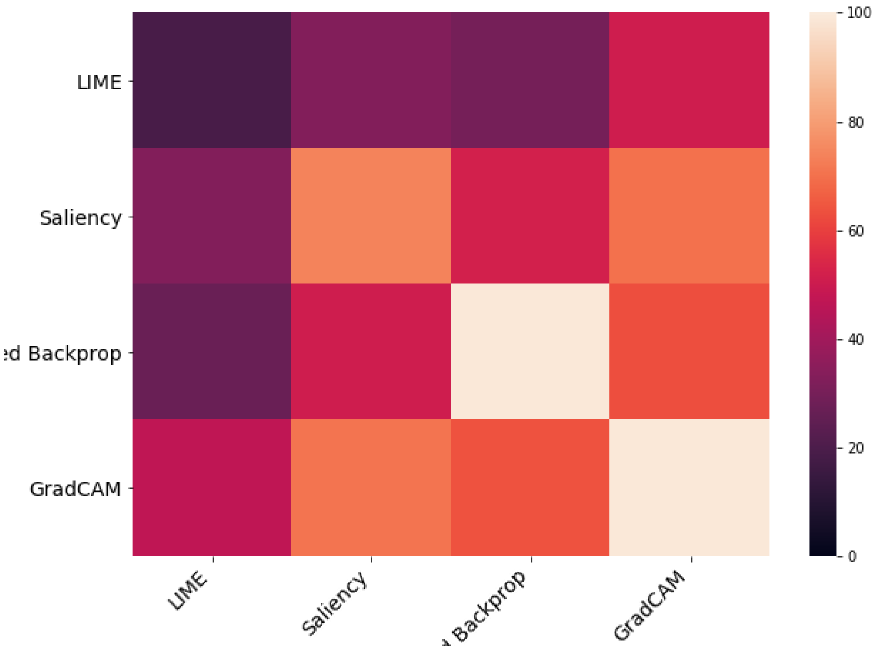

Agreement between explanation methods between VGG16 and VGG19

Pretrained VGG16 and VGG19 from keras,

Take-away

- We have to make a trade-off when obtaining explanations from NNs
- Different approaches have different pros and contras
- Task in question needs to be considered

	Fidelity	Understandability	Sufficiency	Low construction overhead	Efficiency
Backprop	+	-	o	+	+
Local	o	+	o	+	-
High-level	+	+	-	-	o

References

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