Explanation techniques for neural networks

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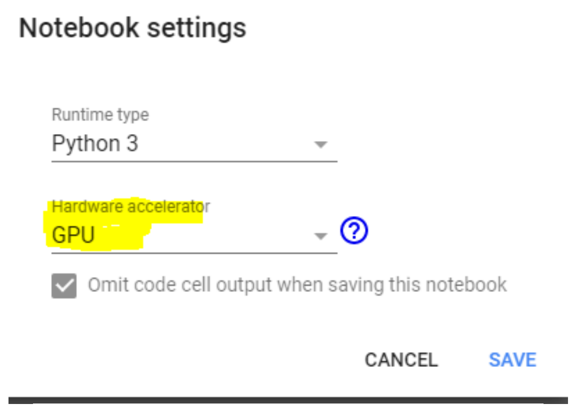
Colab notebook

- Colab notebook:
  - **bit.ly/2PdScxx**
  - File -> Save a Copy in Drive
  - Edit -> Notebook settings -> GPU



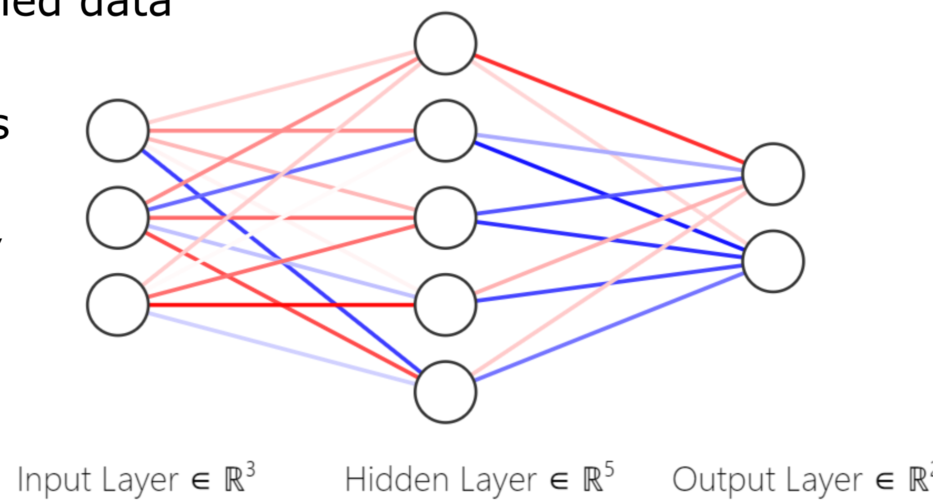
  - Tools -> Preferences -> Misc ->

Intro

- Assumptions
  - Complicated non-linear task
  - Can **not** be solved by an intuitively explainable model
- Complete understanding is not possible
  - Single decision explanations
  - Region-based explanations
- Approaches
  - Backpropagation
  - Local approximation with simple model

Neural Networks

- Complex function composed of smaller functions
- Trained by large amounts of labelled data
- Training:
  - Differentiate loss over weights
  - Update weights
- Differentiation done automatically



$$\mathcal{L}_{(}\theta, X, y) = f_\theta(X) * \log(y) + (1 - f_\theta(X)) * \log(1 - y)$$

$$\Delta\theta = \lambda * \frac{\delta\mathcal{L}_{(}\theta, X, y)}{\theta}$$

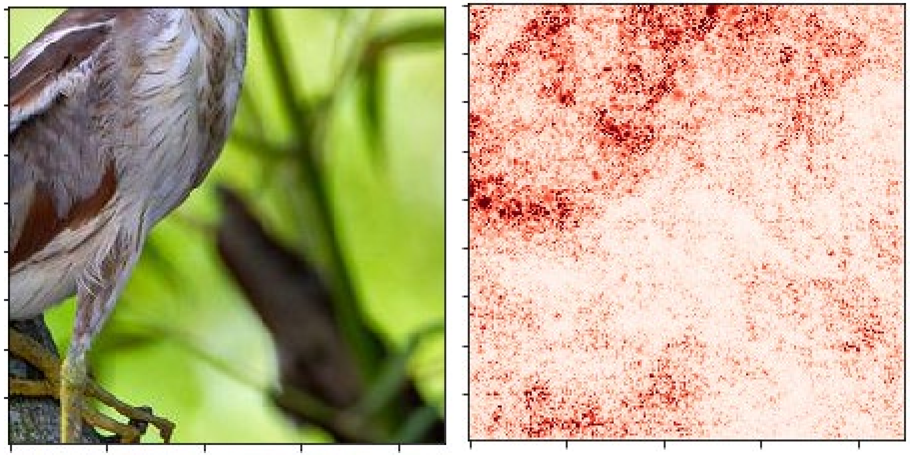
Saliency [1]

- Want to know what parts of the input responsible for the output
- Areas with a high gradient
    - Output changes fast here
        - Probably important

$$\frac{\delta y_c}{\delta X}$$

- Output is fully differentiable
- Basic explainability method
- Super noisy
    - High redundancy
    - Noisy function
- Popular variant:
  Guided Backprop [9]

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

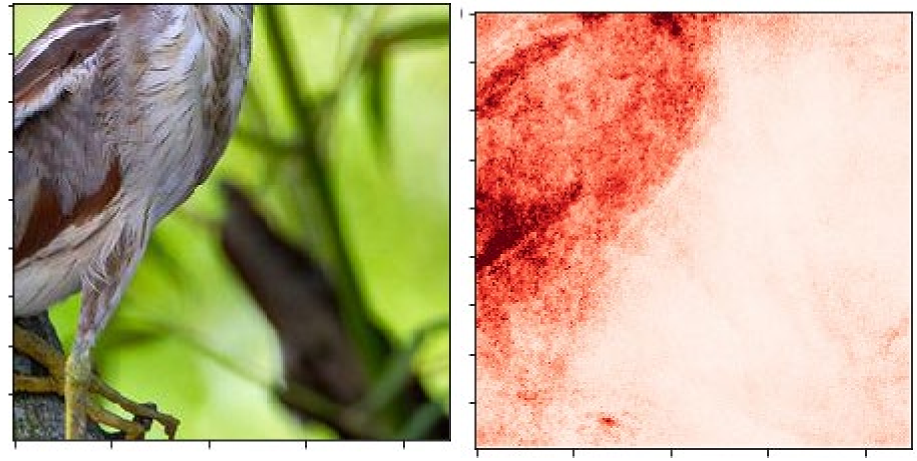


SmoothGrad [15]

- How do we remove noise? With more noise!

$$\sum_N \frac{\delta y_c}{\delta(X + \sigma_n)}$$

- Average over number of input with noise added
- Clears up image
- Applicable to all basic explanation techniques



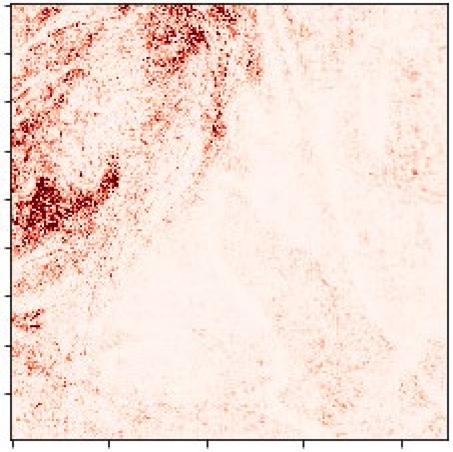
Integrated Gradients [16]

- How do we remove noise? With more (different) noise!

$$\frac{1}{N}\sum_{N}\frac{\delta y_c}{\delta(\mathbf{0}+o_n*(X-\mathbf{0}))}*(X-\mathbf{0}), o_n \sim U(0,1)$$

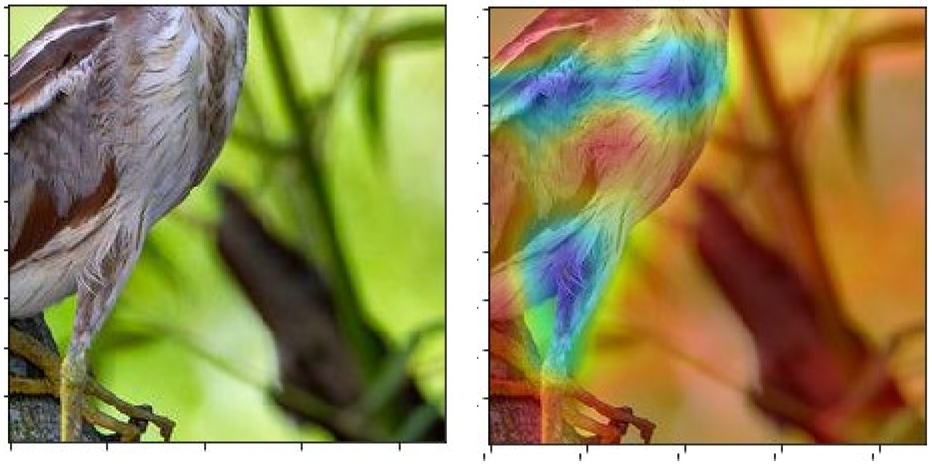
- Average over samples on the pathway between baseline
- Dependent on choice of baseline (all black, average, …)

- Recent extension: use samples as baseline



GradCAM [13]

- Gradient-weighted Class Activation Mapping
- Way less noisy
- No finegrained input
- Procedure:
- Calculate gradient to last convolutional layer
- Average gradient for each channel
- Multiply average gradient with all activations
- Average over all channels
- Upsample

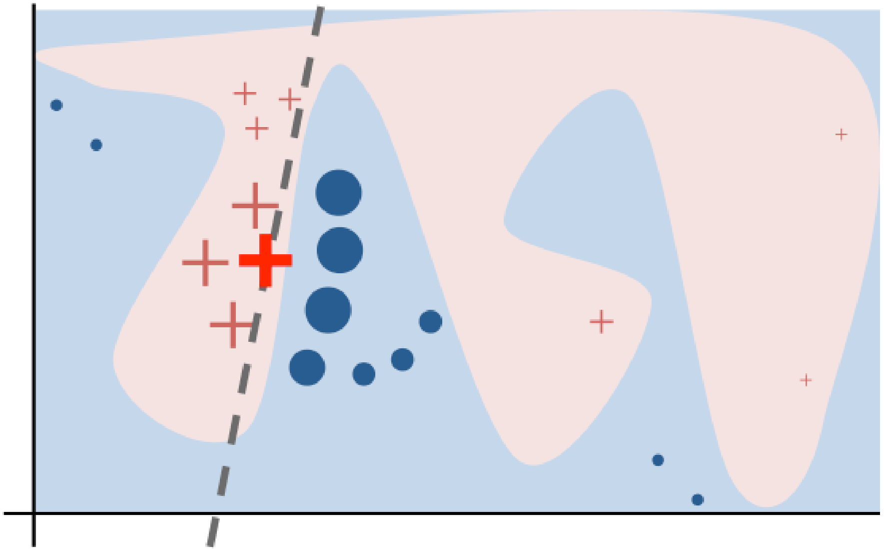


Other methods based on backpropagation

- LRP [12]
- Expected Gradients [17]
- CAM [2]
- GuidedBackprop [9]

Local approximation with interpretable model – LIME [4]

- 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

Local approximation with interpretable model – LIME [4]

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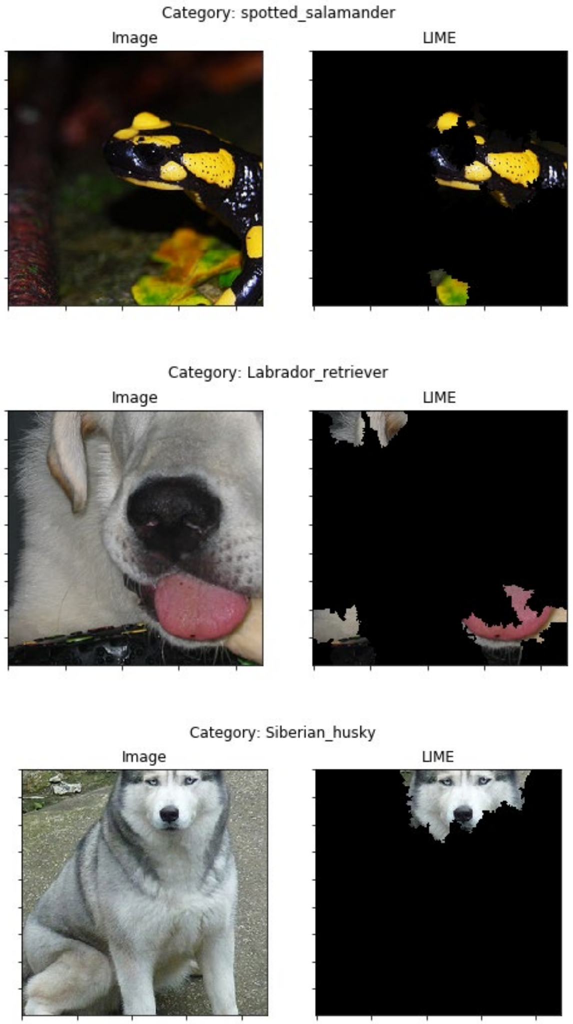


Images obtained with LIME library from pretrained VGG16

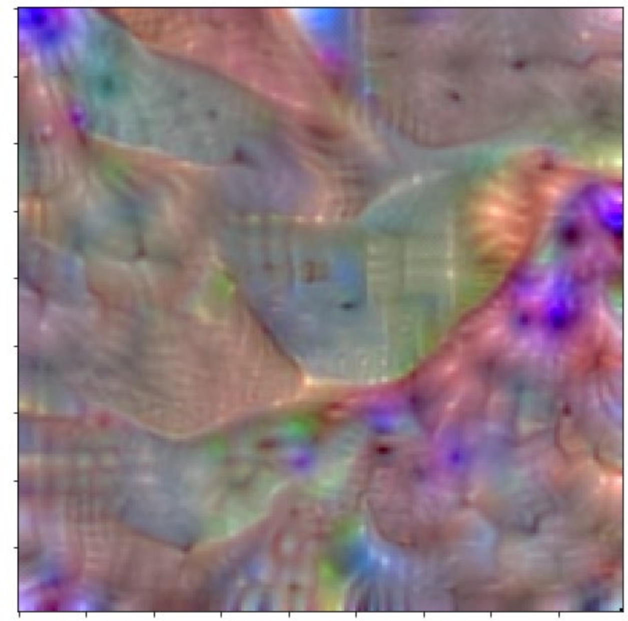
Higher-level

- 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 realisism
  - 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).

Category: hen



Obtained with kerasvis
from pretrained VGG16

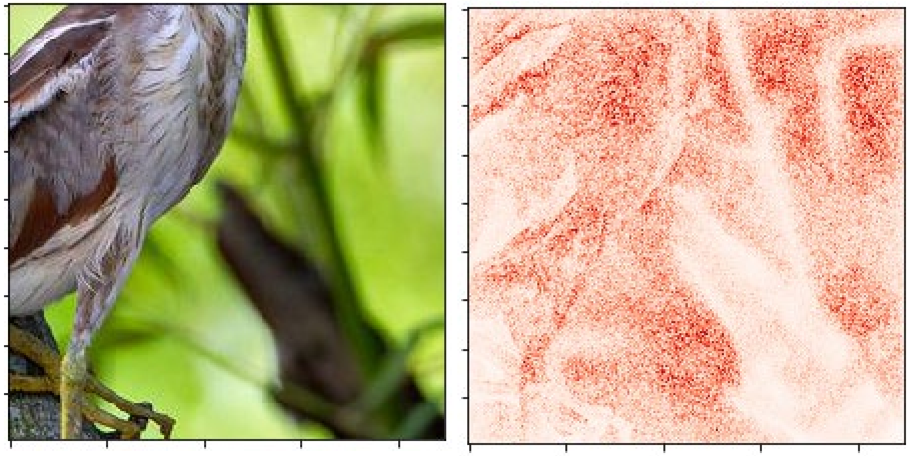
Testing with Concept Activation Vectors CAV

- 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).

What should I use?

- How do we evaluate interpretation methods?
  - Humans are really bad evaluators
- Theoretical properties
- Sanity checks
- Human evaluation
  - Fooled by clearness
- Remove input consecutively – check output degradation



Integrated Gradients on random weights

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

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