

Tutorial on Interpreting and Explaining Deep Models in Computer Vision



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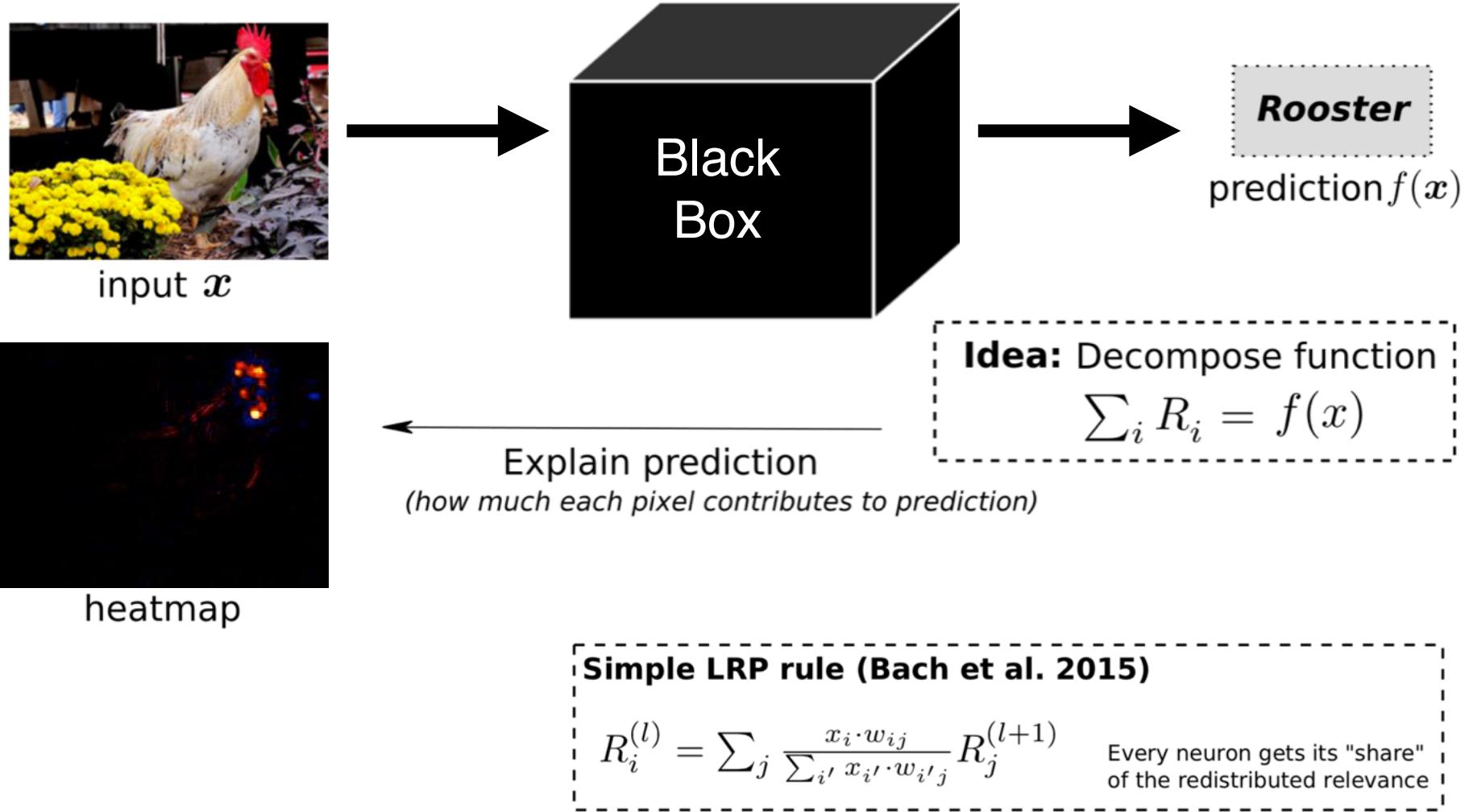


Klaus-Robert Müller
(TU Berlin)

08:30 - 09:15	Introduction KRM
09:15 - 10:00	Techniques for Interpretability GM
10:00 - 10:30	Coffee Break ALL
10:30 - 11:15	Applications of Interpretability WS
11:15 - 12:00	Further Applications and Wrap-Up KRM



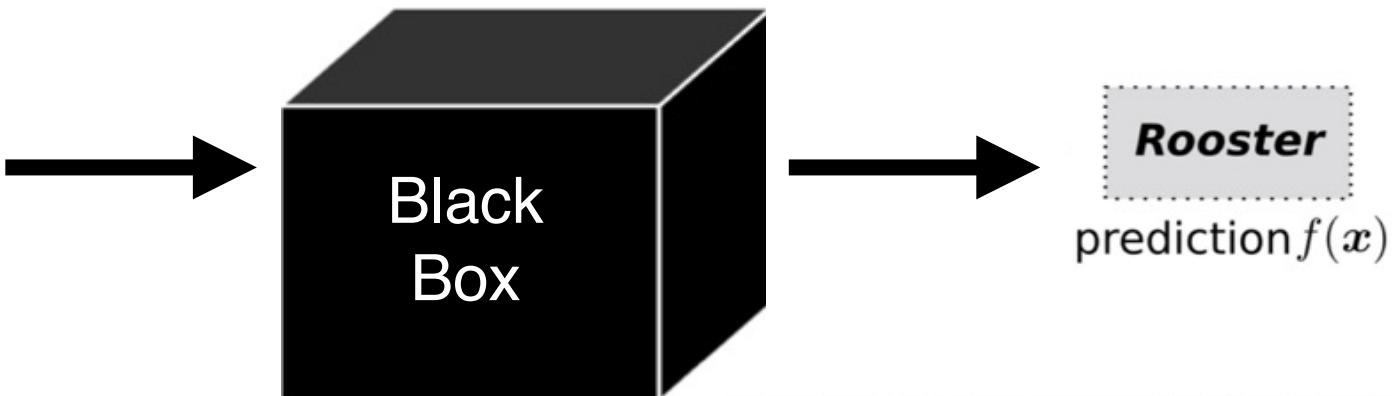
Opening the Black Box with LRP



Opening the Black Box with LRP



input x



heatmap

Theoretical Interpretation
(Deep) Taylor decomposition

Excitation Backprop (Zhang et al., 2016) is special case of LRP ($\alpha=1$). .

Idea: Decompose function
$$\sum_i R_i = f(x)$$

Explain prediction
(*how much each pixel contributes to prediction*)

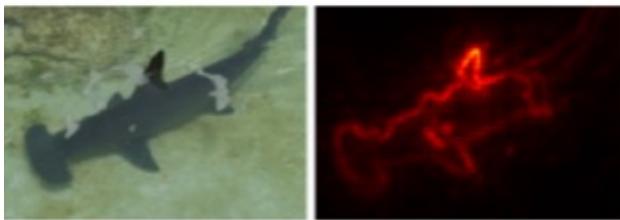
alpha-beta LRP rule (Bach et al. 2015)

$$R_i^{(l)} = \sum_j (\alpha \cdot \frac{(x_i \cdot w_{ij})^+}{\sum_{i'} (x_{i'} \cdot w_{i'j})^+} + \beta \cdot \frac{(x_i \cdot w_{ij})^-}{\sum_{i'} (x_{i'} \cdot w_{i'j})^-}) R_j^{(l+1)}$$

where $\alpha + \beta = 1$

LRP applied to different Data

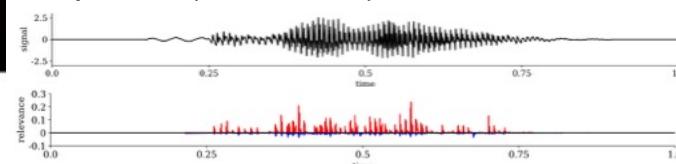
General Images (Bach' 15, Lapuschkin'16)



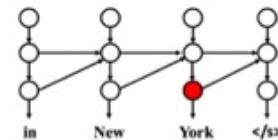
Text Analysis (Arras'16 &17)

do n't waste your money
neither funny nor susper

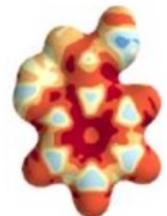
Speech (Becker'18)



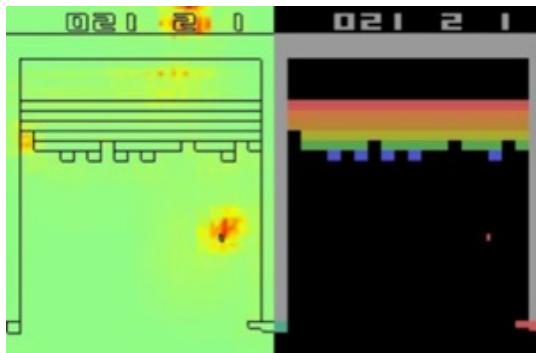
Translation (Ding'17)



Molecules (Schütt'17)

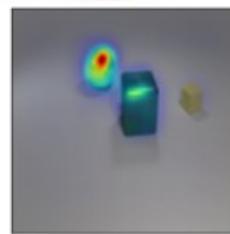


Games (Lapuschkin'18, in prep.)



VQA (Arras'18)

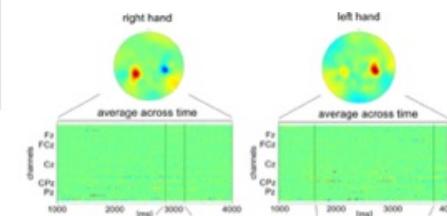
there is a metallic cube ; are
there any large cyan metallic
objects behind it ?



Video (Anders'18)



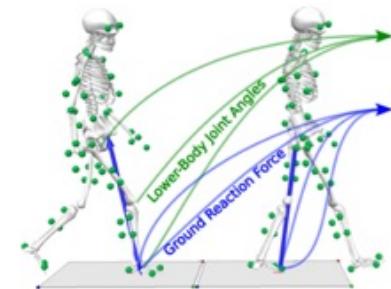
EEG (Sturm'16)



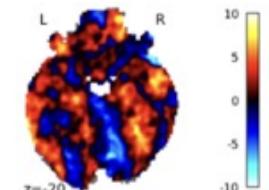
Morphing (Seibold'18)



Gait Patterns (Horst'18, in prep.)



fMRI (Thomas'18)

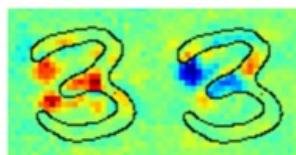


Faces (Arbabzadeh'16, Lapuschkin'17)

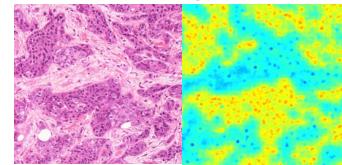


Digits (Bach' 15)

Image Class '3' Class '9'

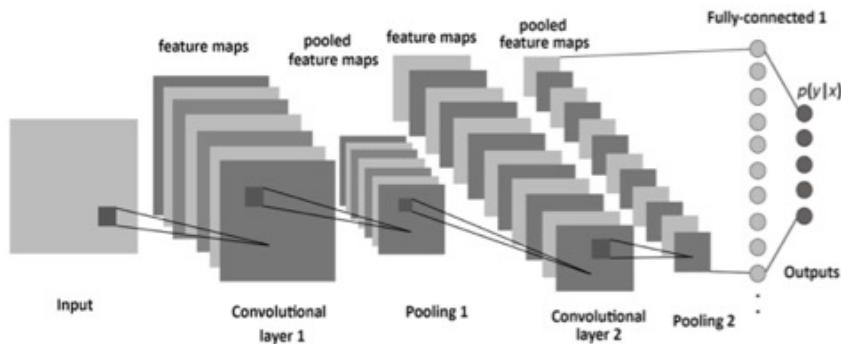


Histopathology (Binder'18)

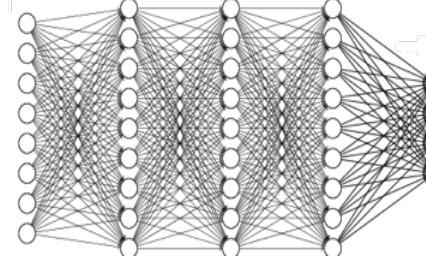


LRP applied to different Models

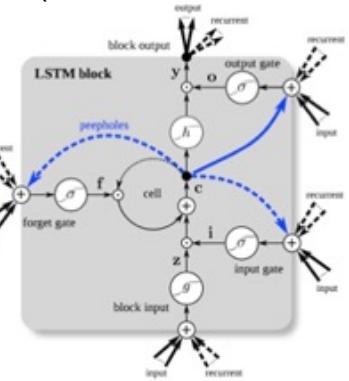
Convolutional NNs (Bach'15, Arras'17 ...)



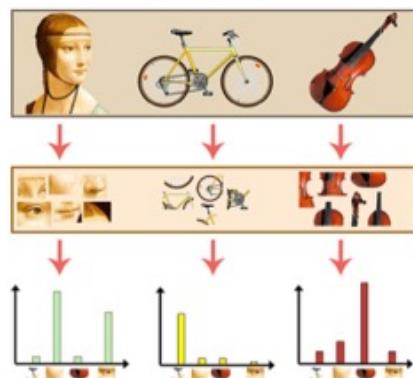
Local Renormalization Layers (Binder'16)



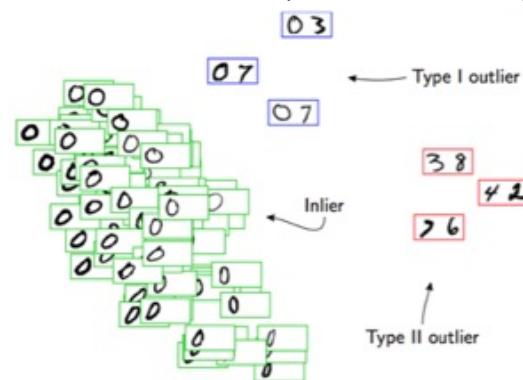
LSTM (Arras'17, Thomas'18)



Bag-of-words / Fisher Vector models
(Bach'15, Arras'16, Lapuschkin'17, Binder'18)

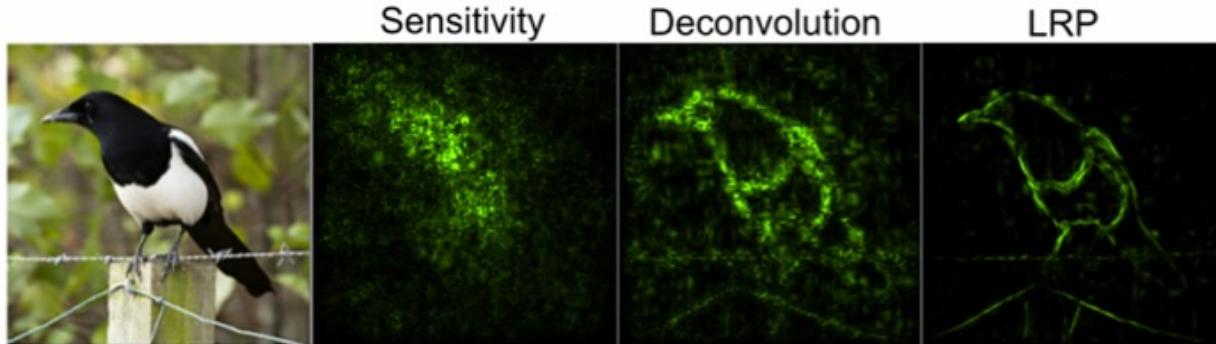


One-class SVM (Kauffmann'18)



Now What ?

Compare Explanation Methods



Can we objectively measure which heatmap is best ?

Idea: Compare selectivity (Bach'15, Samek'17):

“If input features are deemed relevant, removing them should reduce evidence at the output of the network.”

Algorithm (“Pixel Flipping”)

Sort pixels / patches by relevance

Iterate

destroy pixel / patch

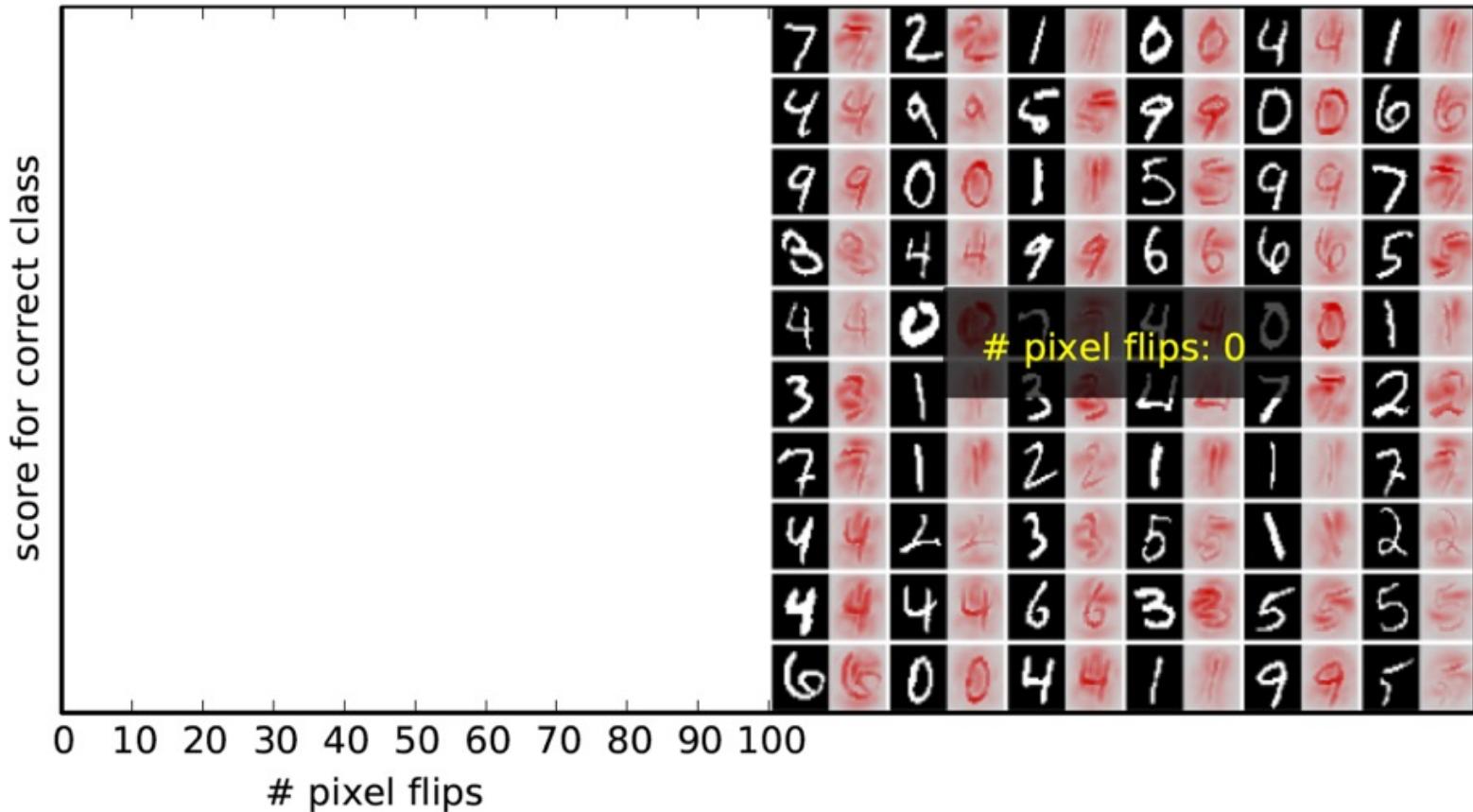
evaluate $f(x)$

Measure decrease of $f(x)$

Important: Remove information in a non-specific manner (e.g. sample from uniform distribution)

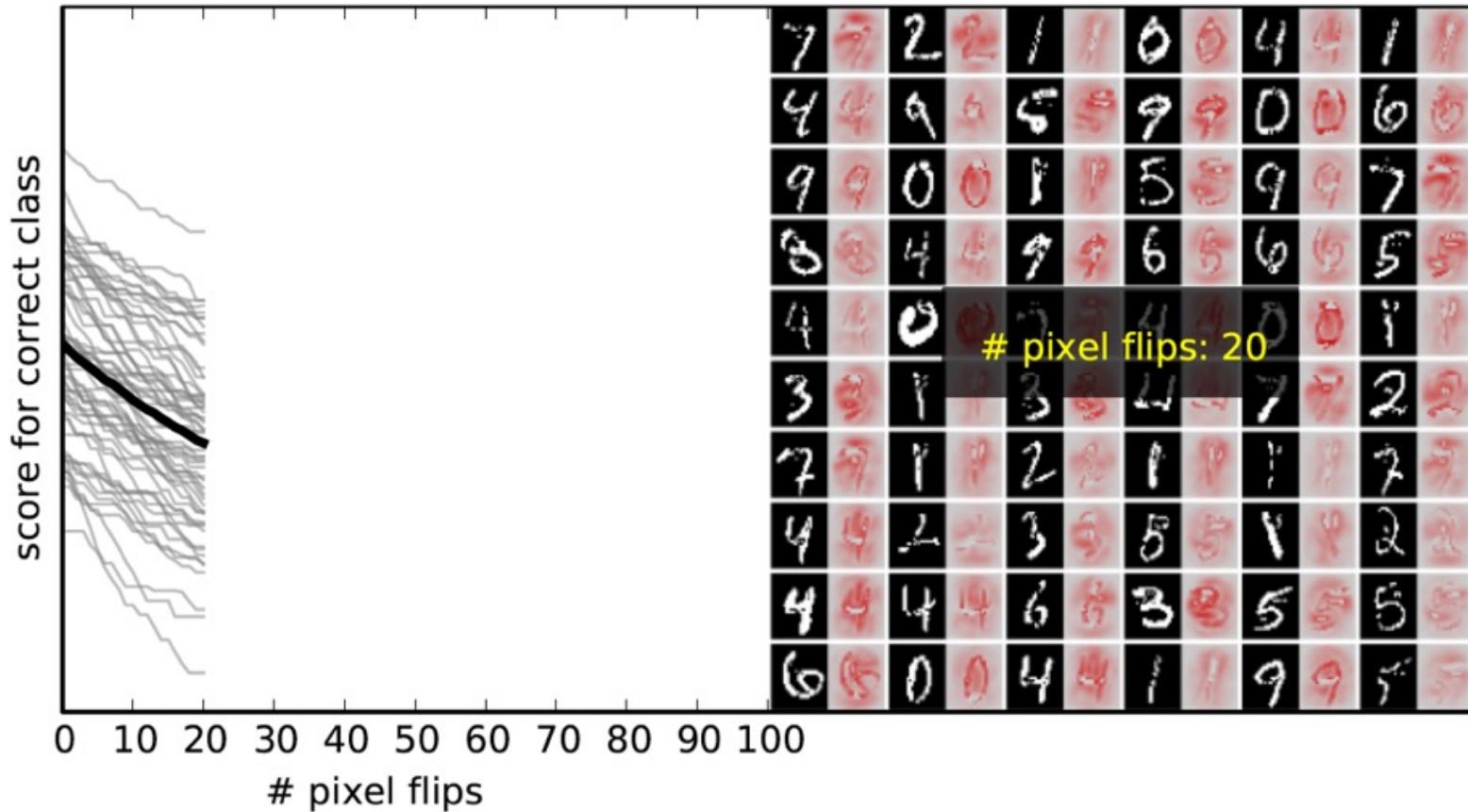
Compare Explanation Methods

LRP



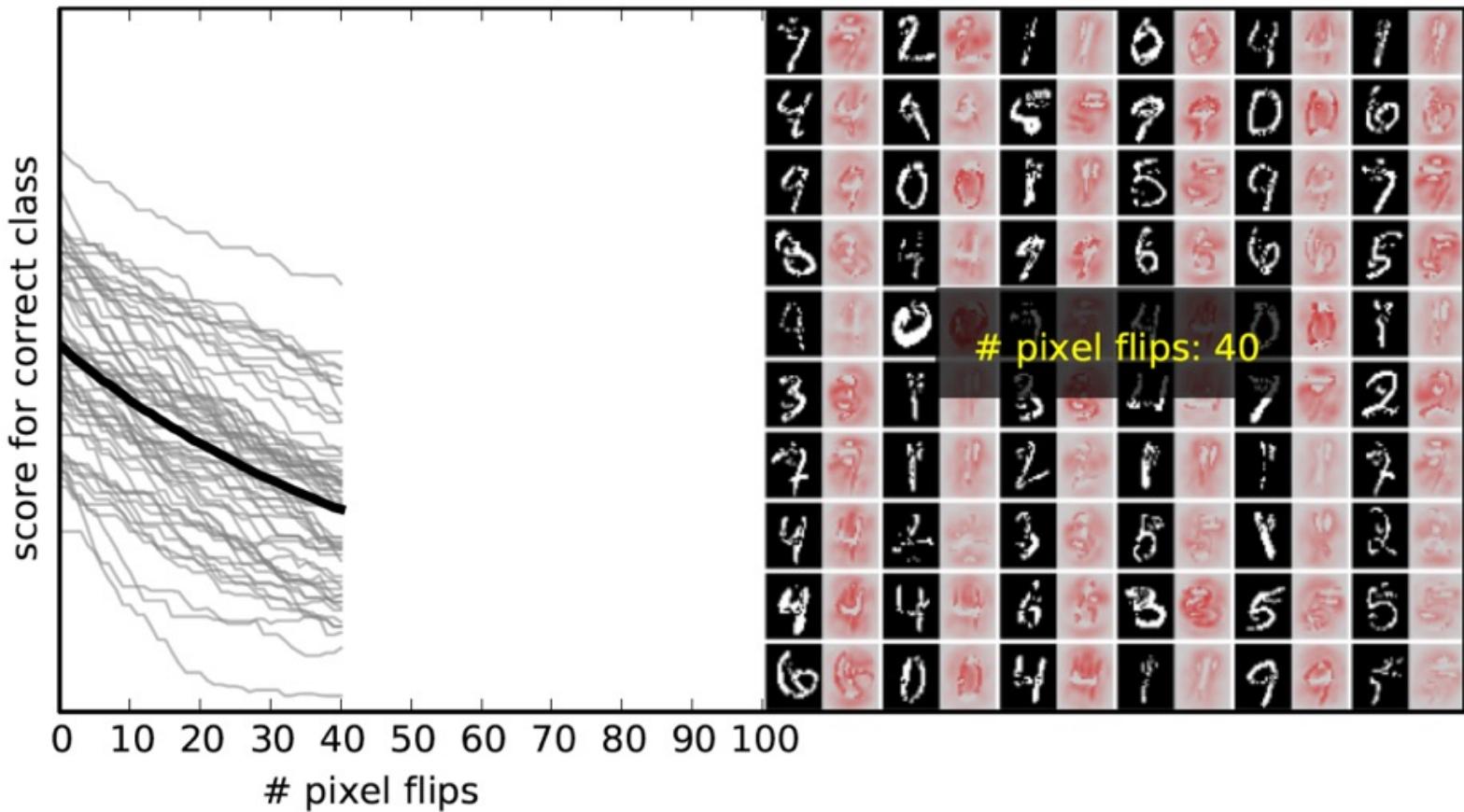
Compare Explanation Methods

LRP



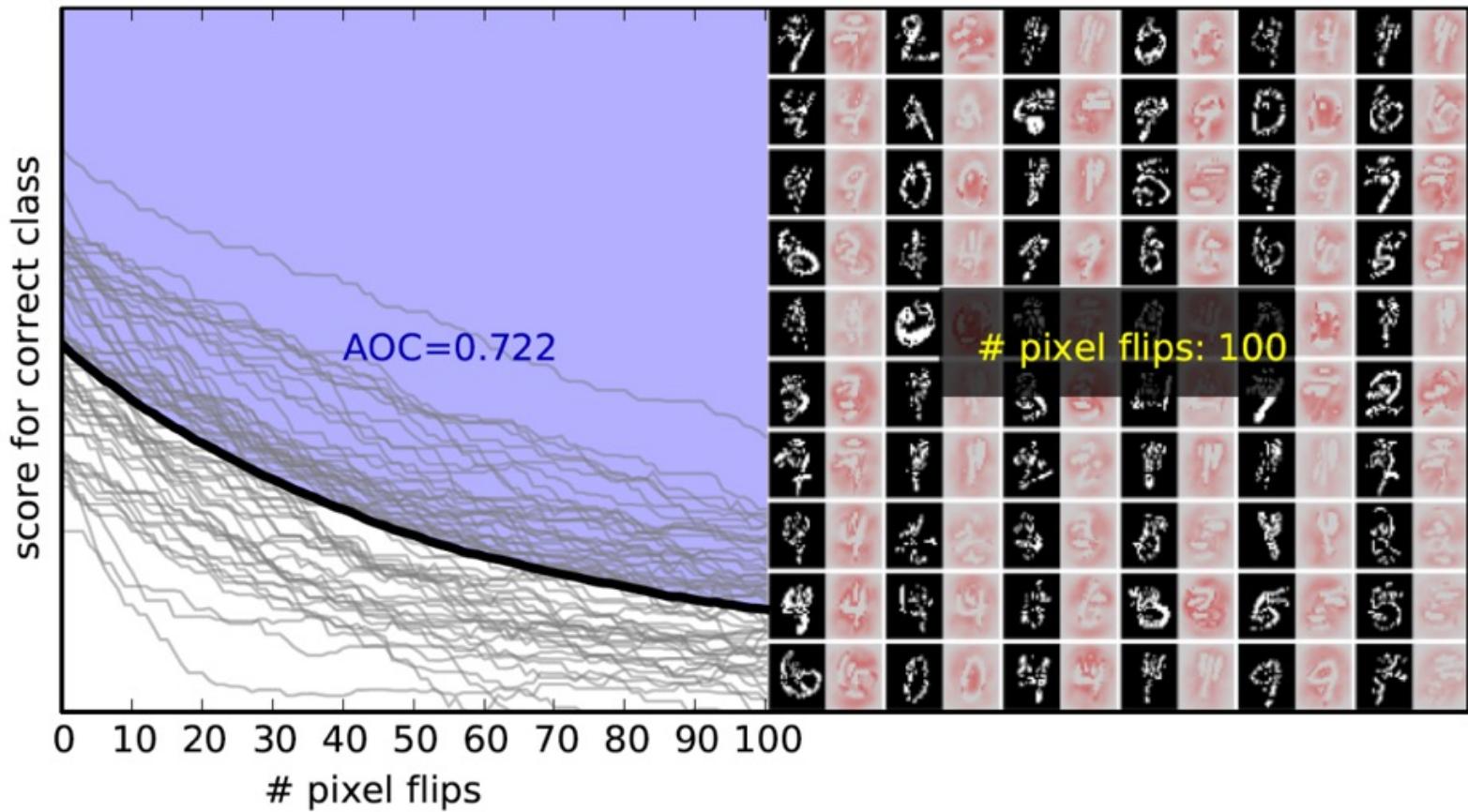
Compare Explanation Methods

LRP



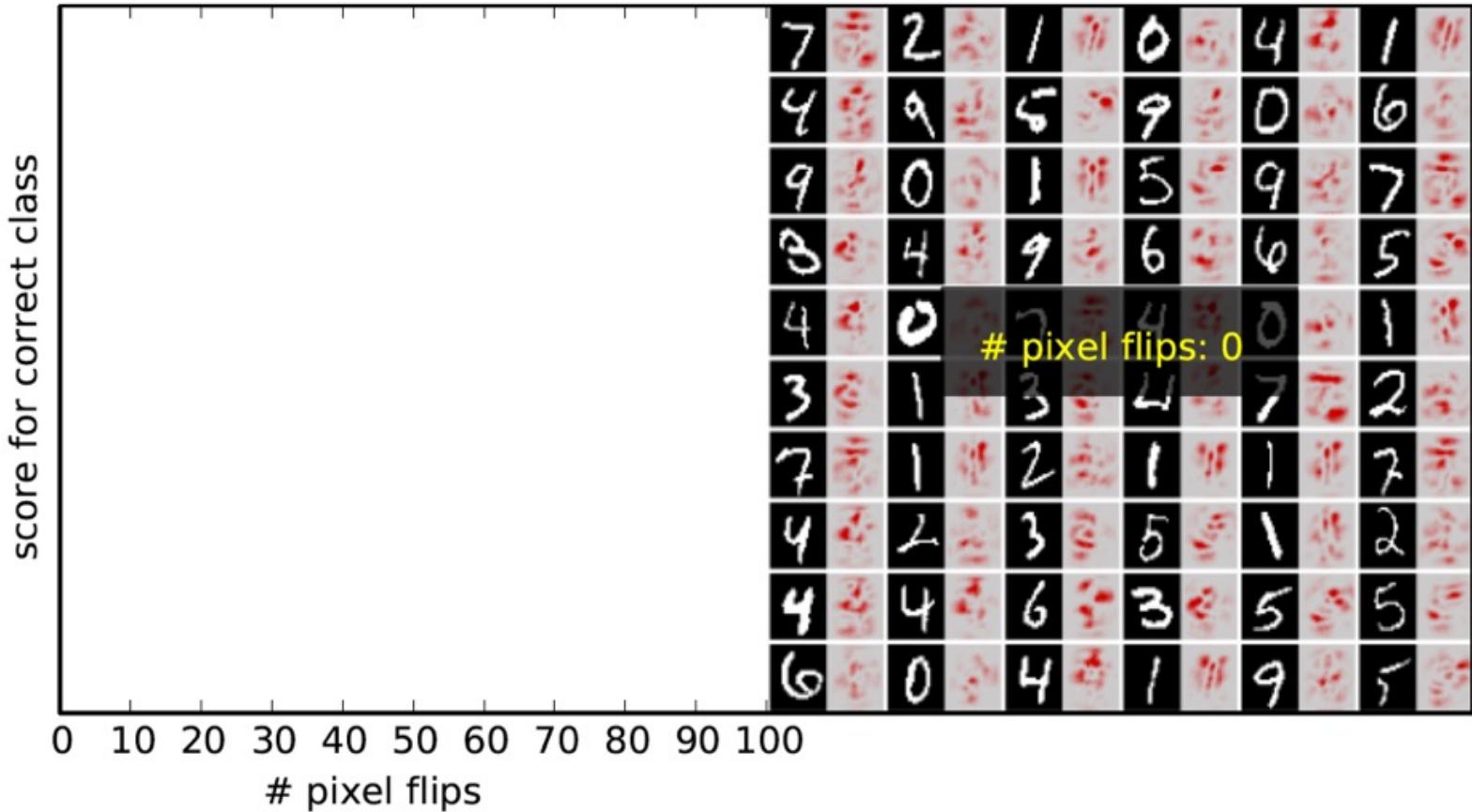
Compare Explanation Methods

LRP



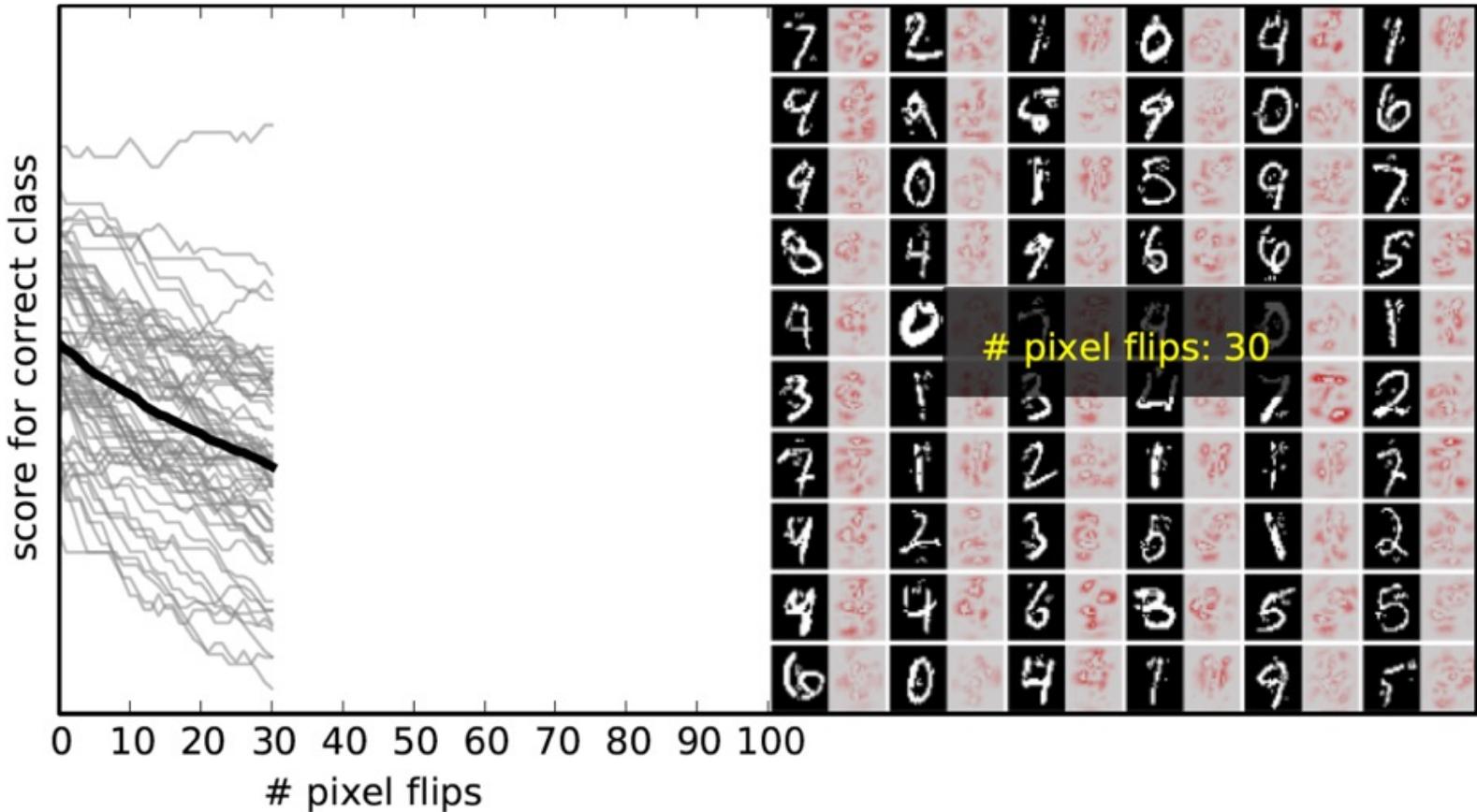
Compare Explanation Methods

Sensitivity



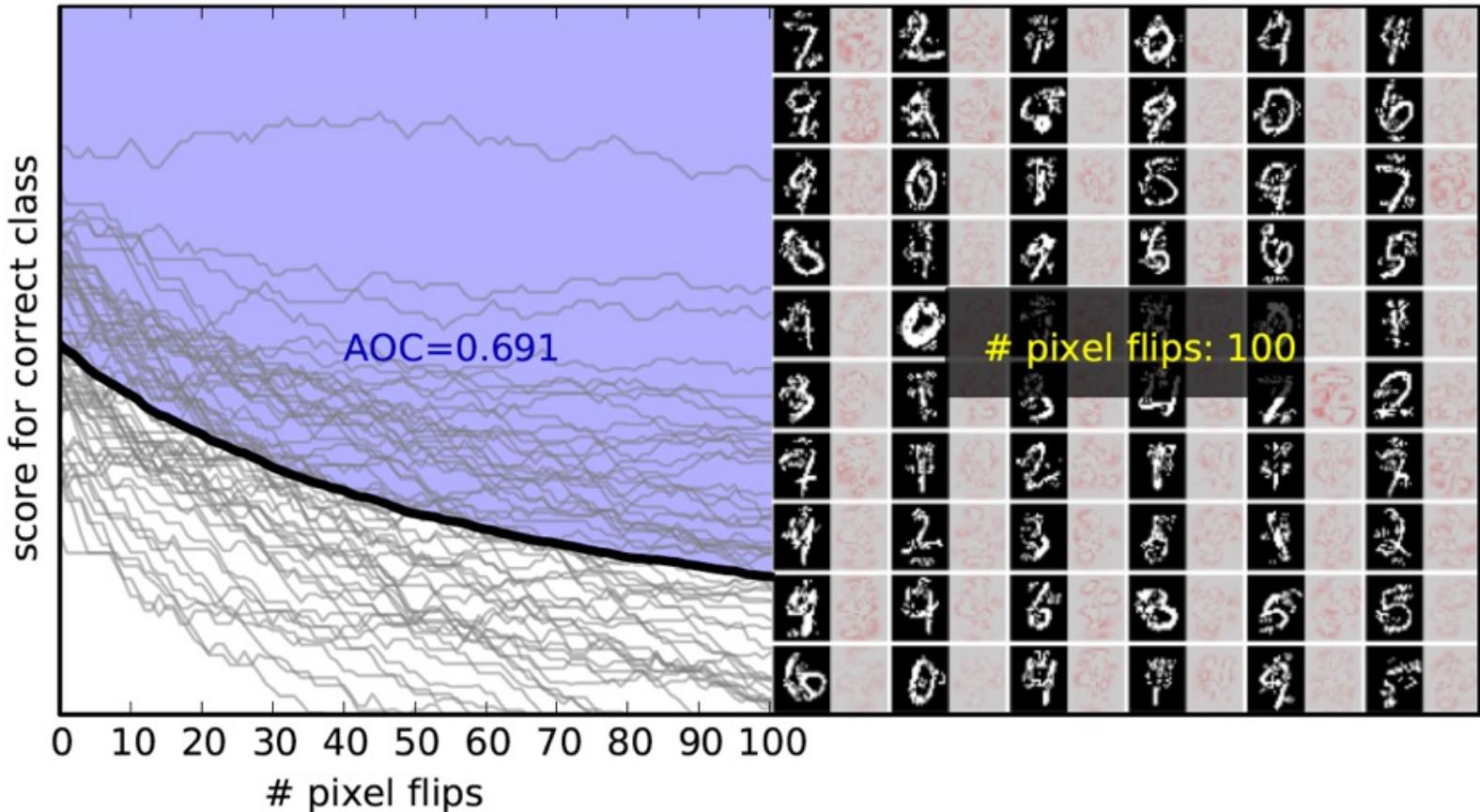
Compare Explanation Methods

Sensitivity



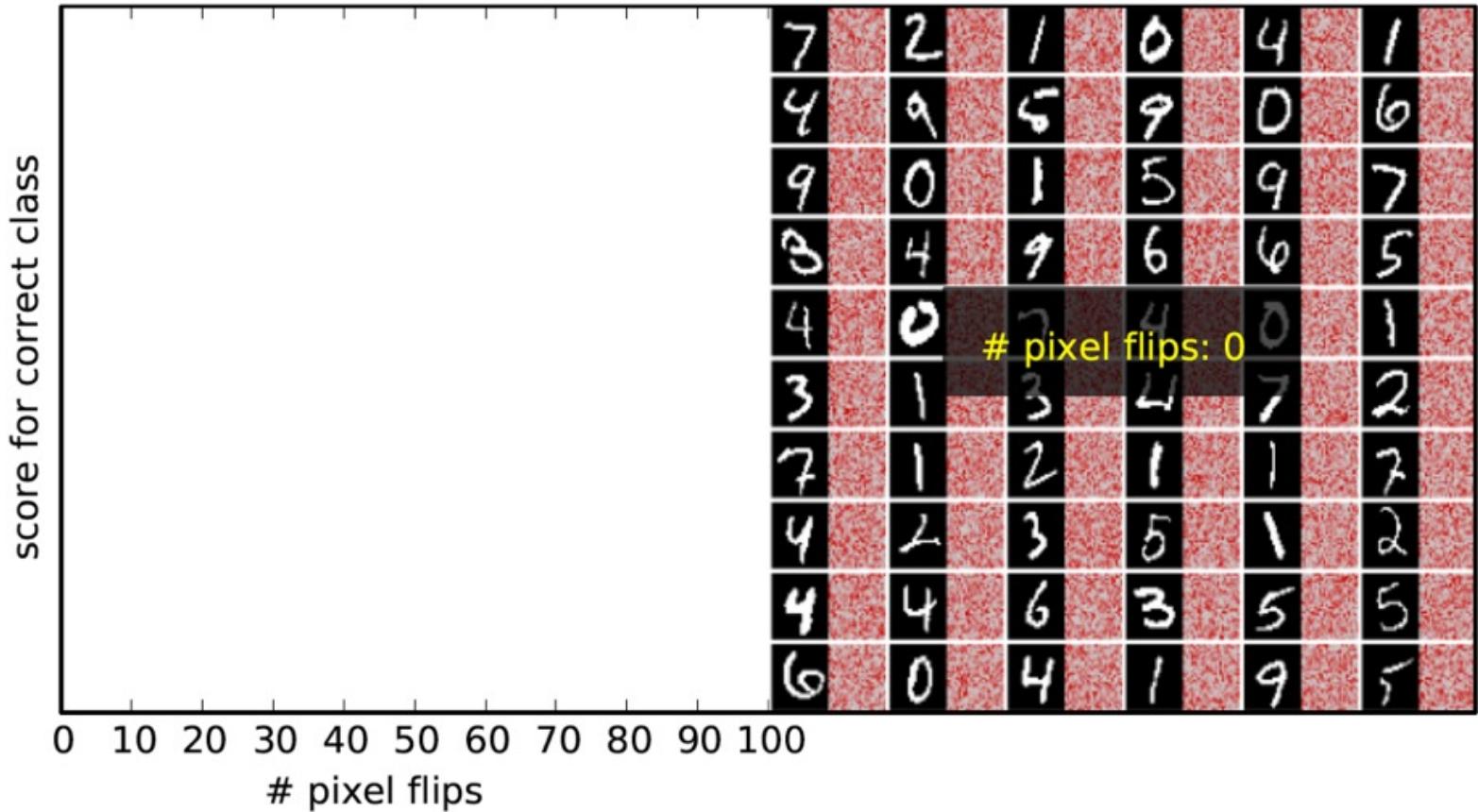
Compare Explanation Methods

Sensitivity



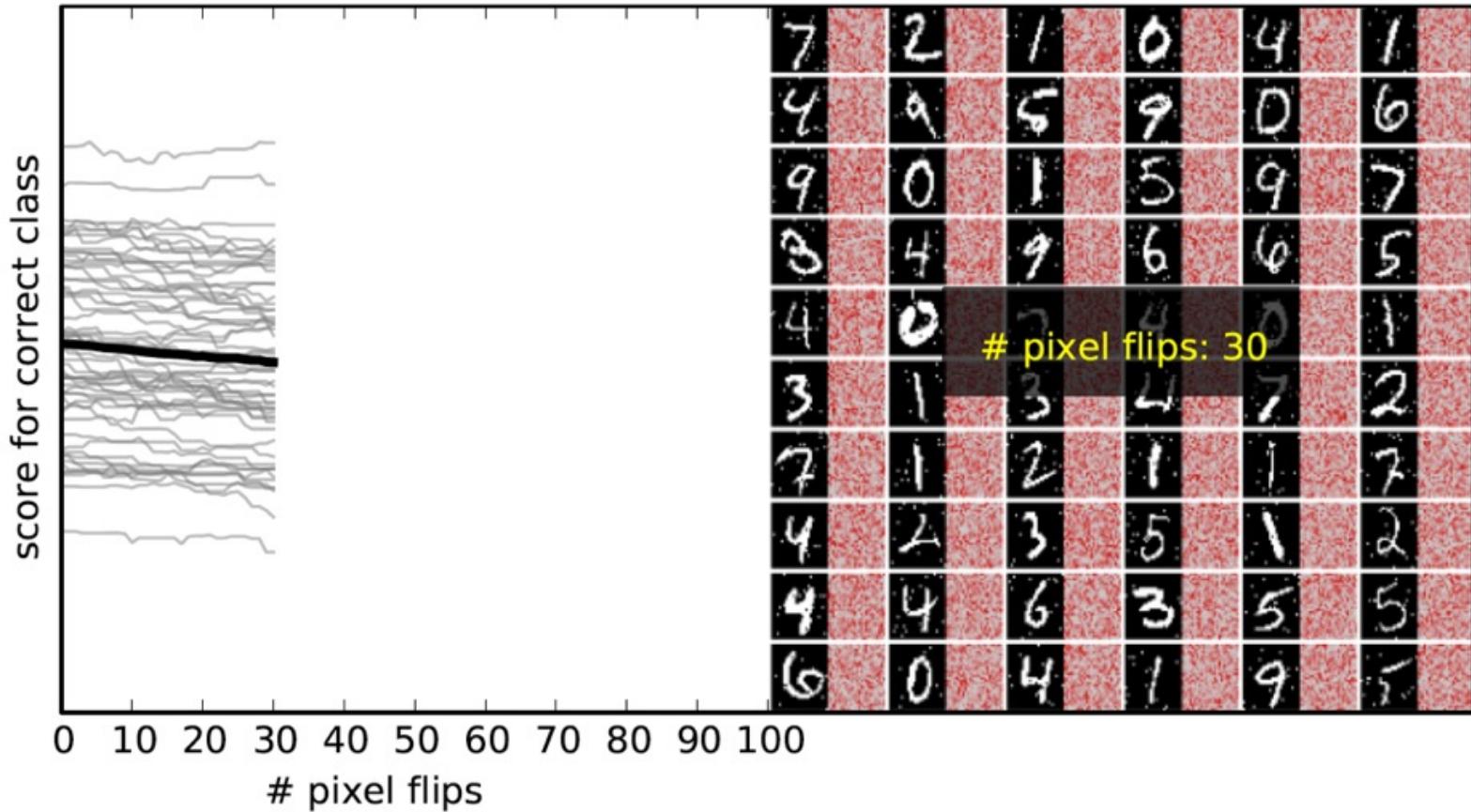
Compare Explanation Methods

Random



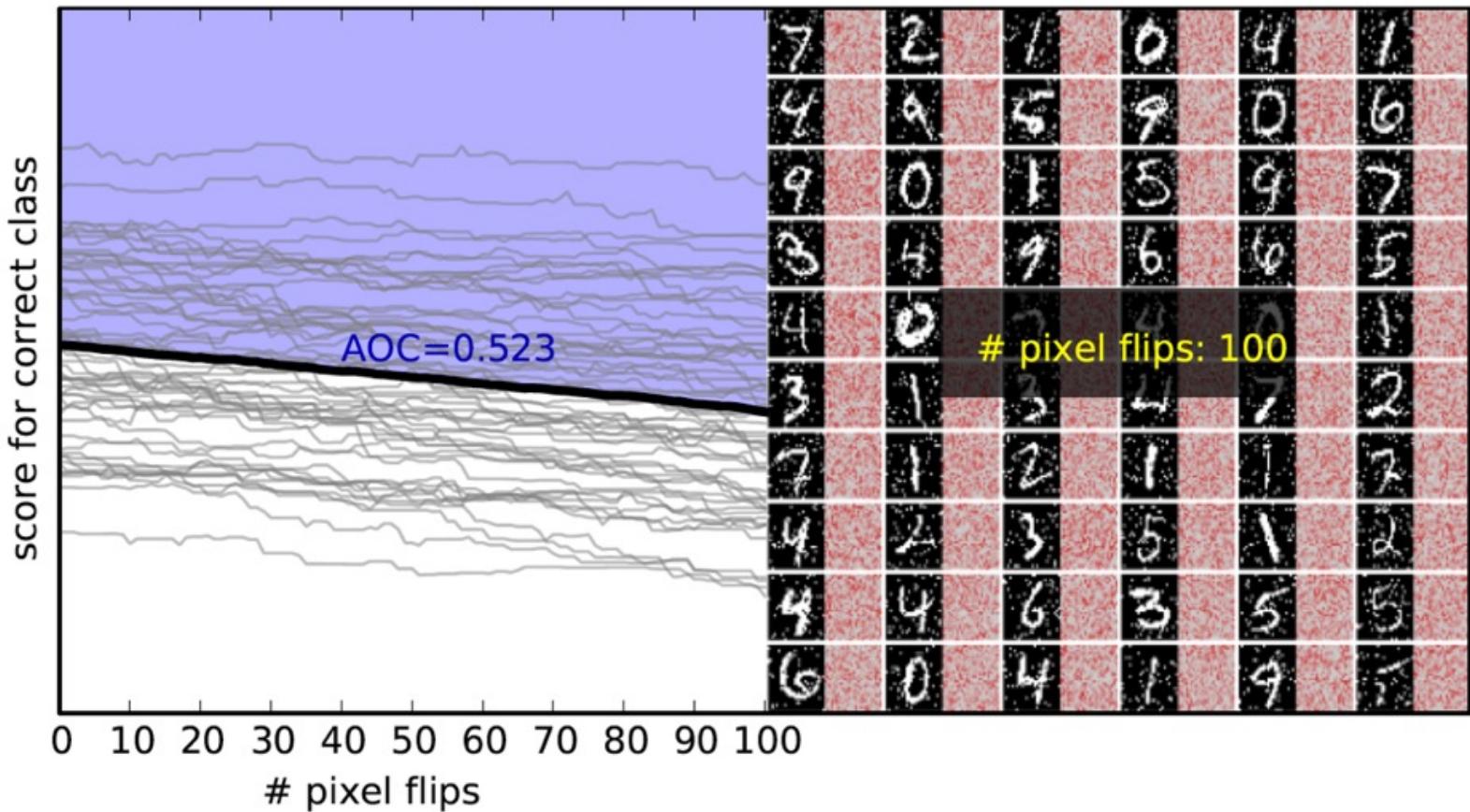
Compare Explanation Methods

Random



Compare Explanation Methods

Random



Compare Explanation Methods

LRP: **0.722**

Sensitivity: 0.691

Random: 0.523

LRP produces quantitatively better heatmaps than sensitivity analysis and random.

What about more complex datasets ?

SUN397



397 scene categories
(108,754 images in total)

ILSVRC2012



1000 categories
(1.2 million training images)

MIT Places



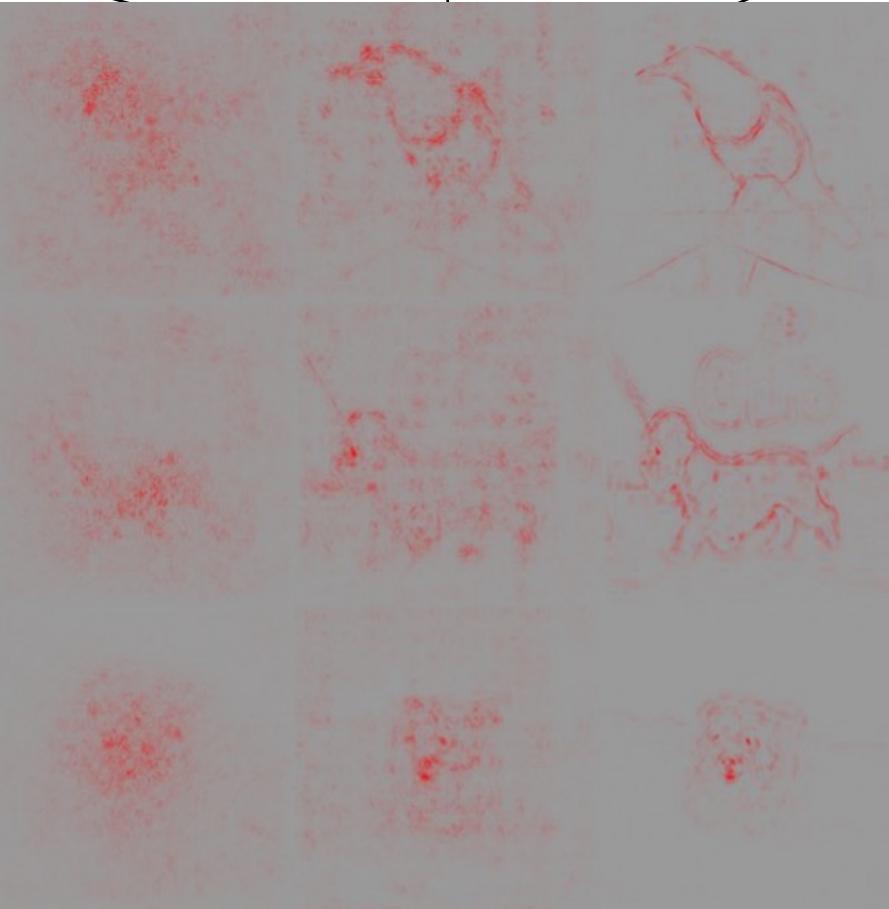
205 scene categories
(2.5 millions of images)

Compare Explanation Methods

Sensitivity Analysis
(Simonyan et al. 2014)



Deconvolution Method
(Zeiler & Fergus 2014)



LRP Algorithm
(Bach et al. 2015)

(Samek et al. 2017)

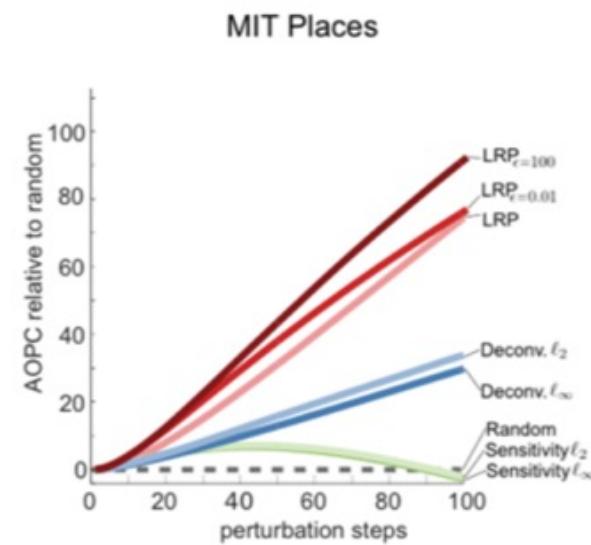
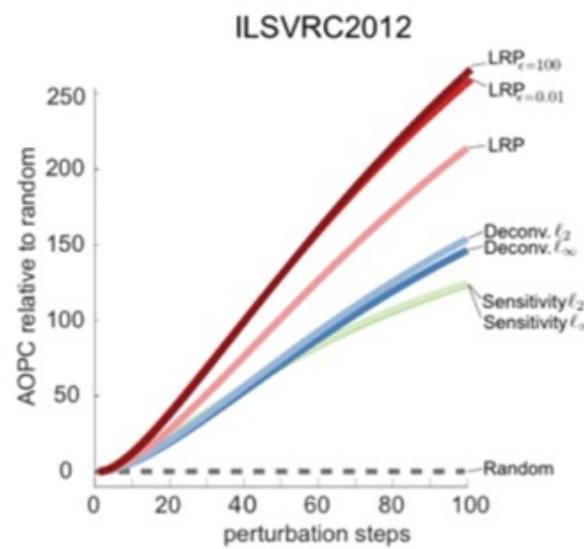
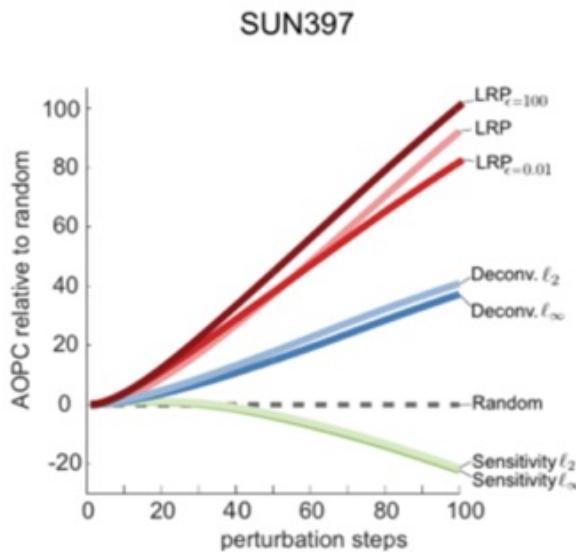
Compare Explanation Methods

Red: LRP method

Blue: Deconvolution method (Zeiler & Fergus, 2014)

Green: Sensitivity method (Simonyan et al., 2014)

- ImageNet: Caffe reference model
- Places & SUN: Classifier from MIT
- AOPC averages over 5040 images
- perturb 9×9 nonoverlapping regions
- 100 steps (15.7% of the image)
- uniform sampling in pixel space



(Samek et al. 2017)

LRP produces better heatmaps

- Sensitivity heatmaps are noisy (gradient shuttering)
- Deconvolution and sensitivity analysis solve a different problem

Compare Explanation Methods

Same idea can be applied for other domains (e.g. text document classification)

“Pixel flipping”
= “Word deleting”

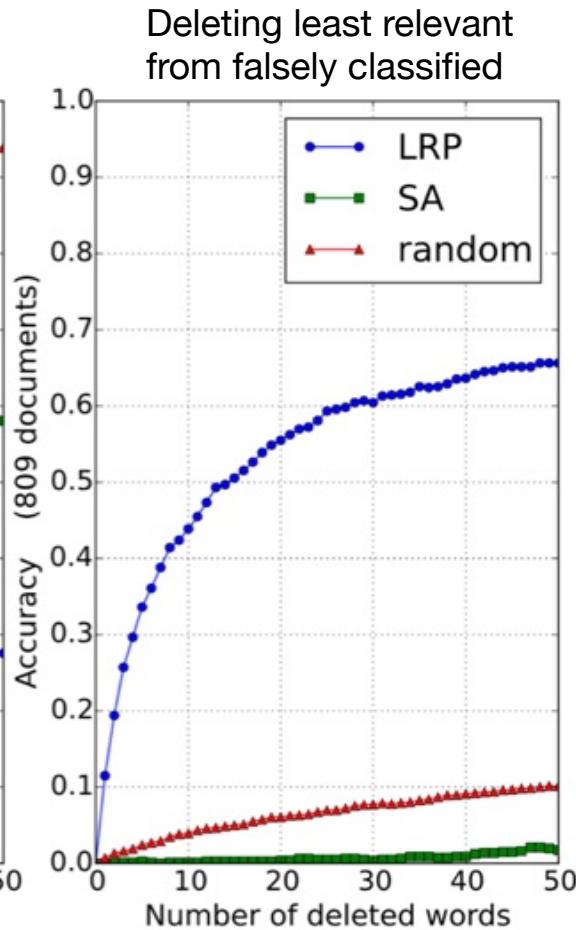
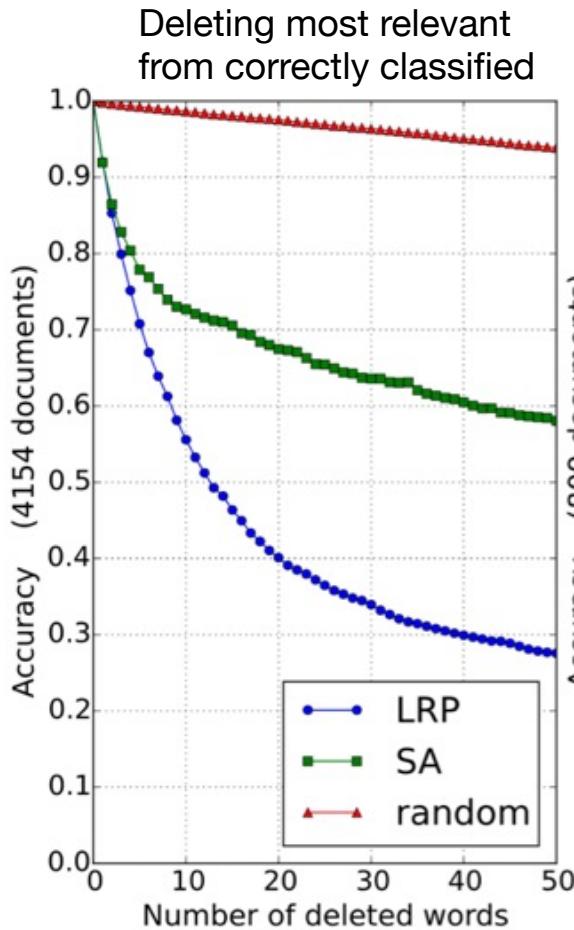
Text classified as “sci.med” → LRP identifies most relevant words.

Yes, weightlessness does feel like falling. It may feel strange at first, but the body does adjust. The feeling is not too different from that of sky diving.

- sci.med (4.1) >And what is the motion sickness
>that some astronauts occasionally experience?
- It is the body's reaction to a strange environment. It appears to be induced partly to physical discomfort and part to mental distress. Some people are more prone to it than others, like some people are more prone to get sick on a roller coaster ride than others. The mental part is usually induced by a lack of clear indication of which way is up or down, ie: the Shuttle is normally oriented with its cargo bay pointed towards Earth, so the Earth (or ground) is "above" the head of the astronauts. About 50% of the astronauts experience some form of motion sickness, and NASA has done numerous tests in space to try to see how to keep the number of occurrences down.

(Arras et al. 2017)

Compare Explanation Methods



- word2vec / CNN model
- Conv → ReLU → 1-Max-Pool → FC
- trained on 20Newsgroup Dataset
- accuracy: 80.19%

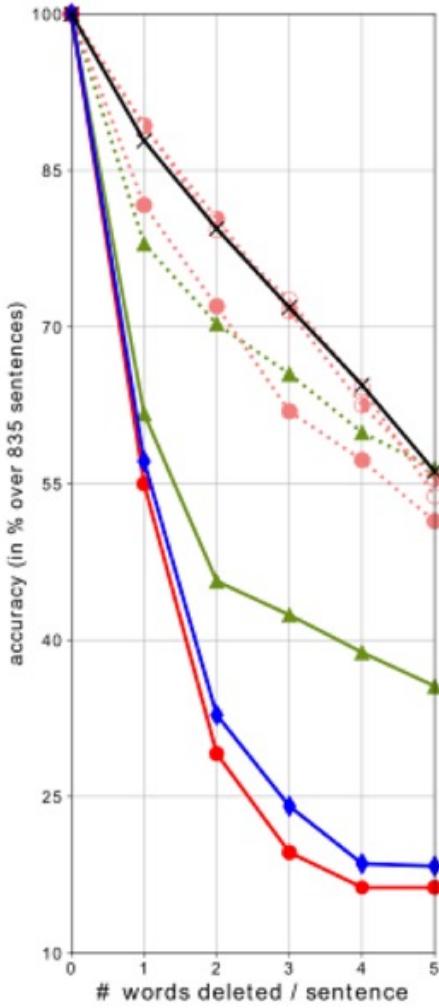
LRP better than SA

LRP distinguishes
between positive and
negative evidence

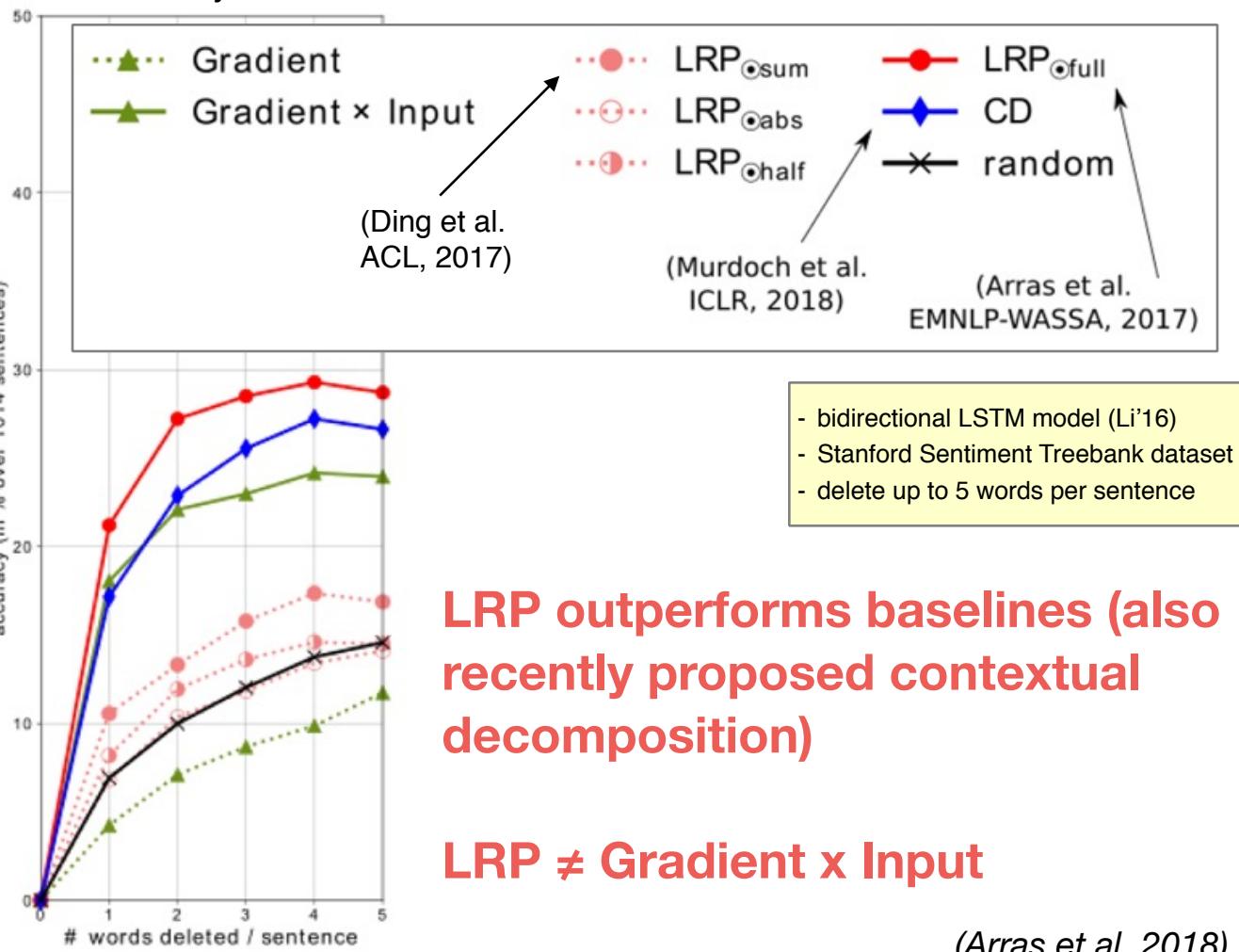
(Arras et al. 2016)

Compare Explanation Methods

Deleting most relevant
from correctly classified



Deleting least relevant
from falsely classified

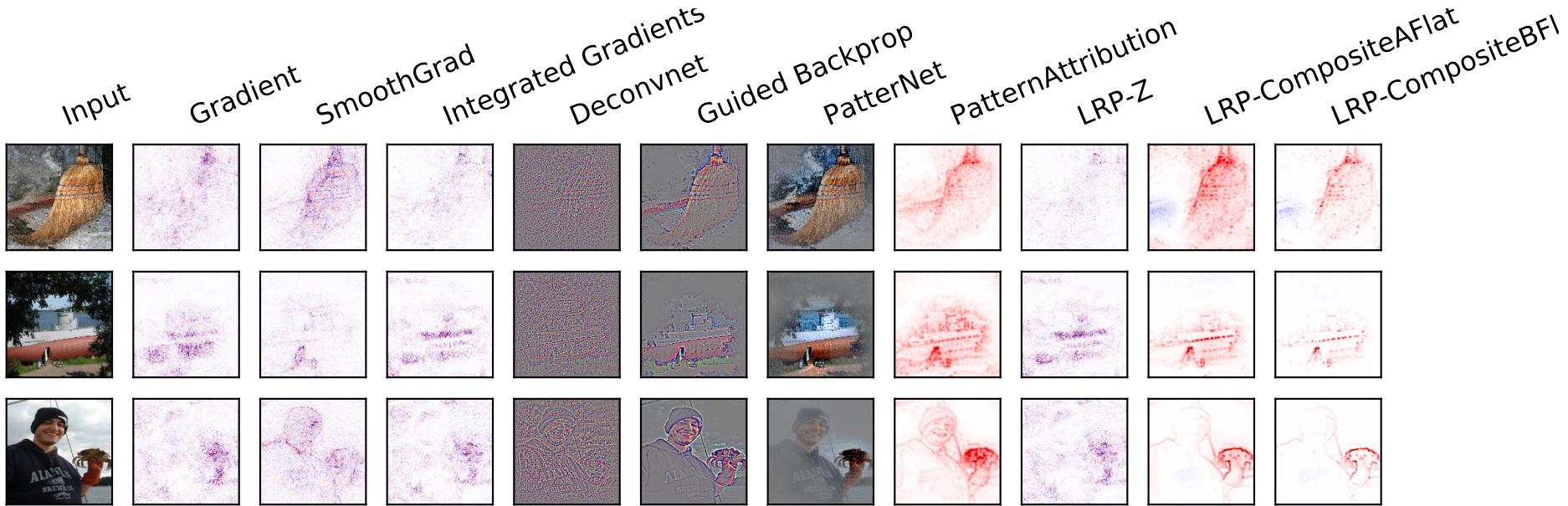


LRP outperforms baselines (also recently proposed contextual decomposition)

LRP \neq Gradient x Input

(Arras et al. 2018)

Compare Explanation Methods



Highly efficient (e.g., 0.01 sec per VGG16 explanation) !

New Keras Toolbox available for explanation methods:
<https://github.com/albermax/innvestigate>

Application of LRP

Compare models

Application: Compare Classifiers

Yes, weightlessness does feel like falling. It may feel strange at first, but the body does adjust. The feeling is not too different from that of sky diving.

word2vec/CNN:

Performance: 80.19%

Strategy to solve the problem:
identify semantically meaningful words related to the topic.

(4.1) >And what is the motion sickness
>that some astronauts occasionally experience?
sci.med It is the body's reaction to a strange environment. It appears to be induced partly to physical discomfort and part to mental distress. Some people are more prone to it than others, like some people are more prone to get sick on a roller coaster ride than others. The mental part is usually induced by a lack of clear indication of which way is up or down, ie: the Shuttle is normally oriented with its cargo bay pointed towards Earth, so the Earth (or ground) is "above" the head of the astronauts. About 50% of the astronauts experience some form of motion sickness, and NASA has done numerous tests in space to try to see how to keep the number of occurrences down.

Yes, weightlessness does feel like falling. It may feel strange at first, but the body does adjust. The feeling is not too different from that of sky diving.

BoW/SVM:

Performance: 80.10%

Strategy to solve the problem:
identify statistical patterns,
i.e., use word statistics

(-0.6) >And what is the motion sickness
>that some astronauts occasionally experience?
sci.med It is the body's reaction to a strange environment. It appears to be induced partly to physical discomfort and part to mental distress. Some people are more prone to it than others, like some people are more prone to get sick on a roller coaster ride than others. The mental part is usually induced by a lack of clear indication of which way is up or down, ie: the Shuttle is normally oriented with its cargo bay pointed towards Earth, so the Earth (or ground) is "above" the head of the astronauts. About 50% of the astronauts experience some form of motion sickness, and NASA has done numerous tests in space to try to see how to keep the number of occurrences down.

(Arras et al. 2016 & 2017)

Application: Compare Classifiers

word2vec / CNN model

sci.med

symptoms (7.3), treatments (6.6), medication (6.4), osteopathy (6.3), ulcers (6.2), sciatica (6.0), hypertension (6.0), herb (5.6), doctor (5.4), physician (5.1), Therapy (5.1), antibiotics (5.1), Asthma (5.0), renal (5.0), medicines (4.9), caffeine (4.9), infection (4.9), gastrointestinal (4.8), therapy (4.8), homeopathic (4.7), medicine (4.7), allergic (4.7), dosages (4.7), esophagitis (4.7), inflammation (4.6), arrhythmias (4.6), cancer (4.6), disease (4.6), migraine (4.6), patients (4.5).

BoW/SVM model

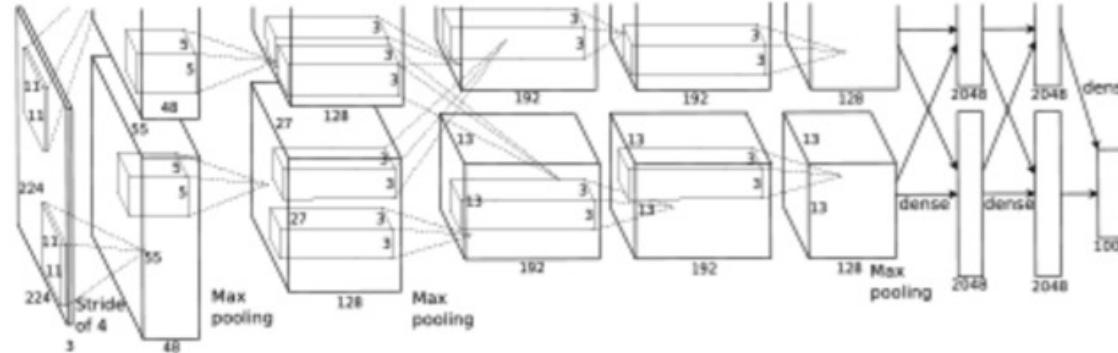
sci.med

cancer (1.4), photography (1.0), doctor (1.0), **msg** (0.9), disease (0.9), medical (0.8), sleep (0.8), radiologist (0.7), eye (0.7), treatment (0.7), prozac (0.7), vitamin (0.7), epilepsy (0.7), health (0.6), yeast (0.6), skin (0.6), pain (0.5), liver (0.5), physician (0.5), **she** (0.5), needles (0.5), **dn** (0.5), circumcision (0.5), syndrome (0.5), migraine (0.5), antibiotic (0.5), **water** (0.5), blood (0.5), fat (0.4), weight (0.4).

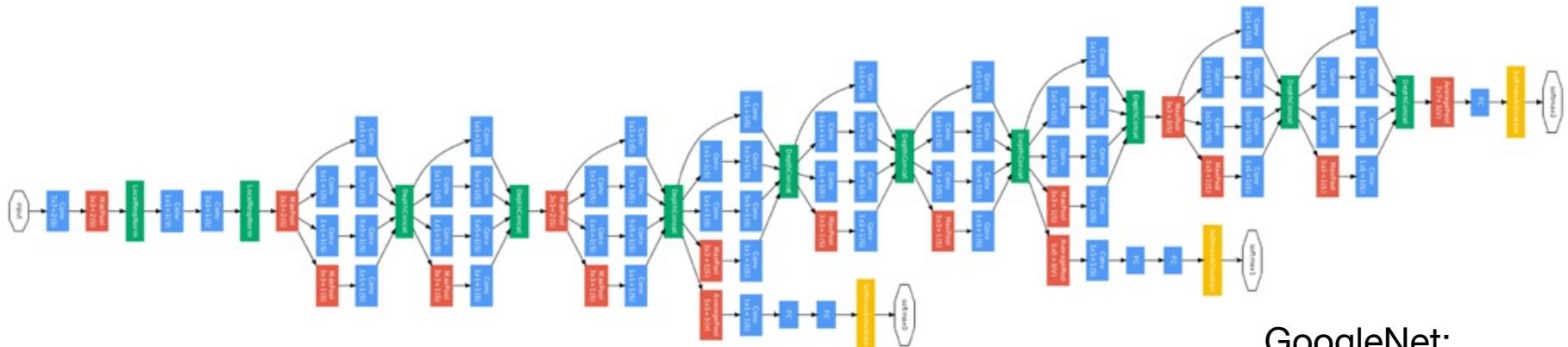
Words with maximum relevance

(Arras et al. 2016 & 2017)

Application: Compare Classifiers

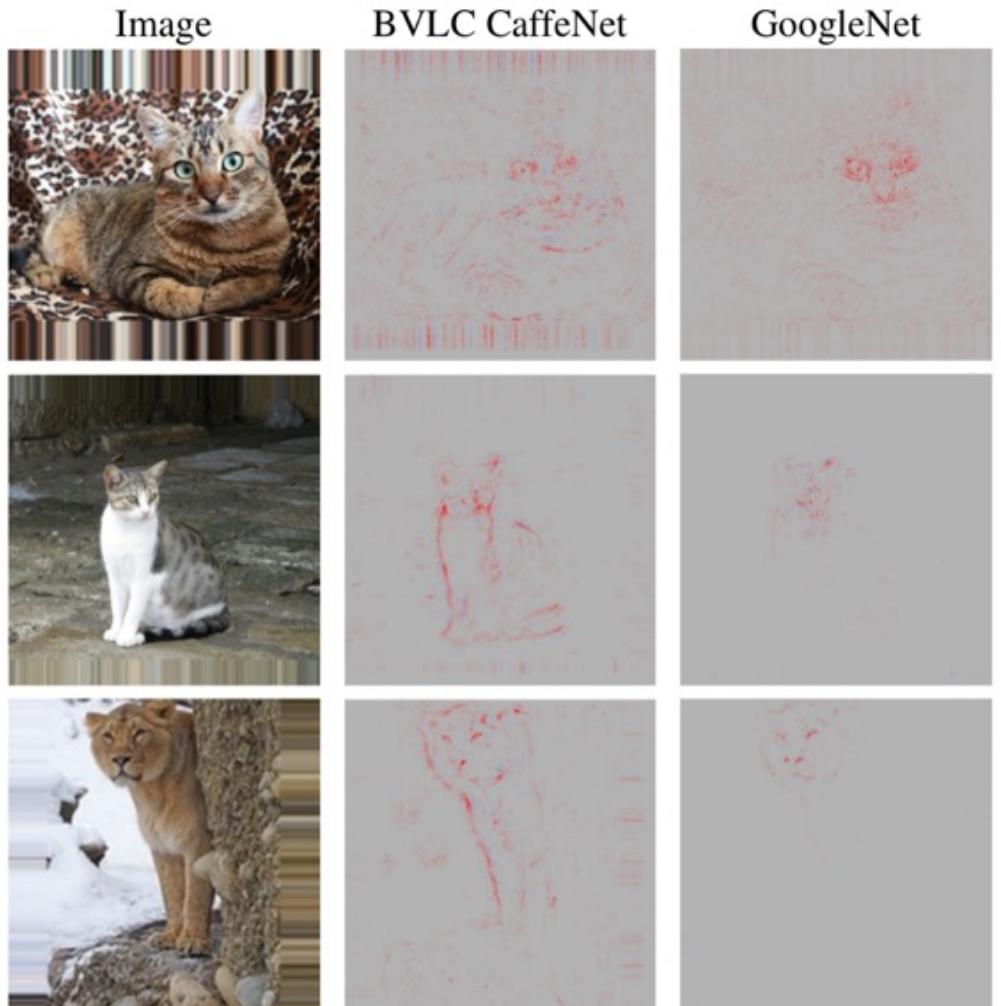


BVLC:
- 8 Layers
- ILSRCV: 16.4%



GoogleNet:
- 22 Layers
- ILSRCV: 6.7%
- Inception layers

Application: Compare Classifiers

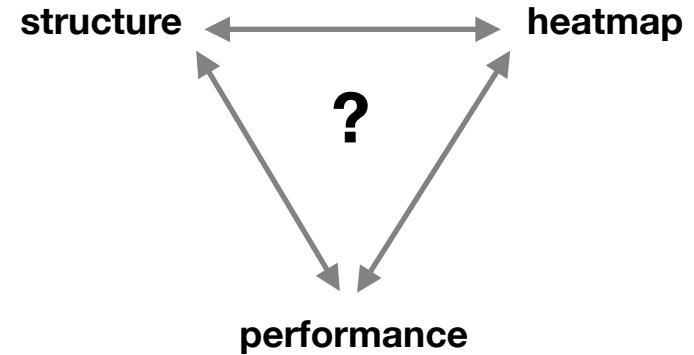


GoogleNet focuses on faces of animal.
—> suppresses background noise

BVLC CaffeNet heatmaps are much more noisy.

Is it related to the architecture ?

Is it related to the performance ?



(Binder et al. 2016)

Application of LRP

Quantify Context Use

Application: Measure Context Use



how important
is context ?

classifier



how important
is context ?

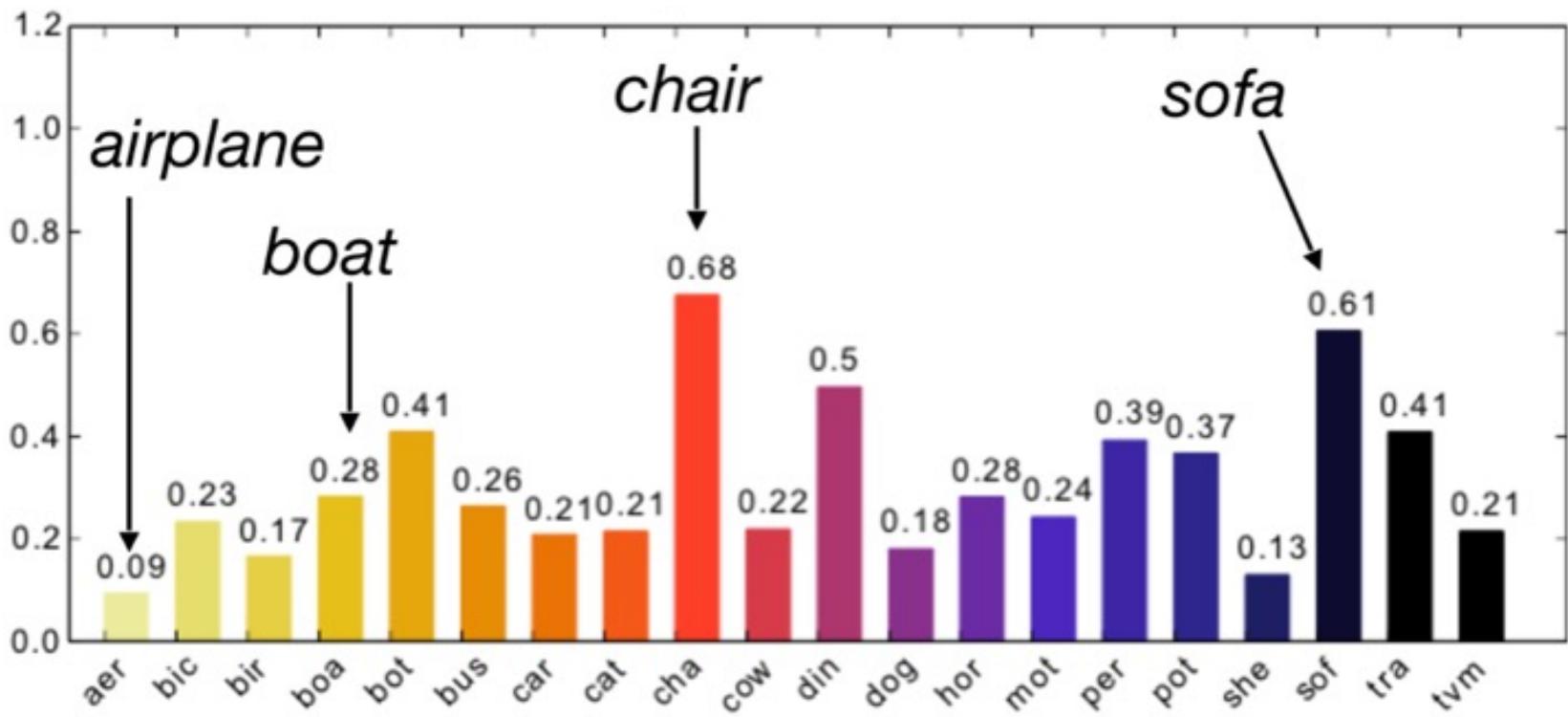
**LRP decomposition allows
meaningful pooling over bbox !**

$$\sum_i R_i = f(x)$$

$$\text{importance of context} = \frac{\text{relevance outside bbox}}{\text{relevance inside bbox}}$$

Application: Measure Context Use

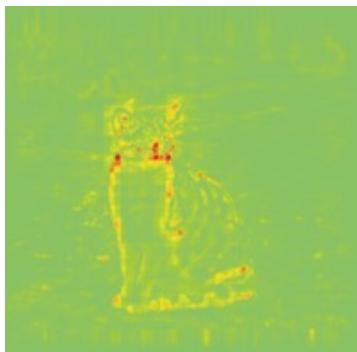
- BVLC reference model + fine tuning
- PASCAL VOC 2007



(Lapuschkin et al., 2016)

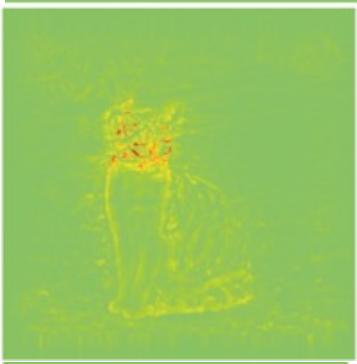
Application: Measure Context Use

BVLC CaffeNet

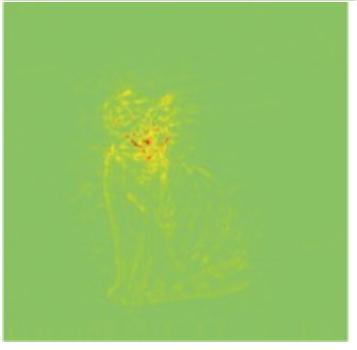


- Different models (BVLC CaffeNet, GoogleNet, VGG CNN S)
- ILSVCR 2012

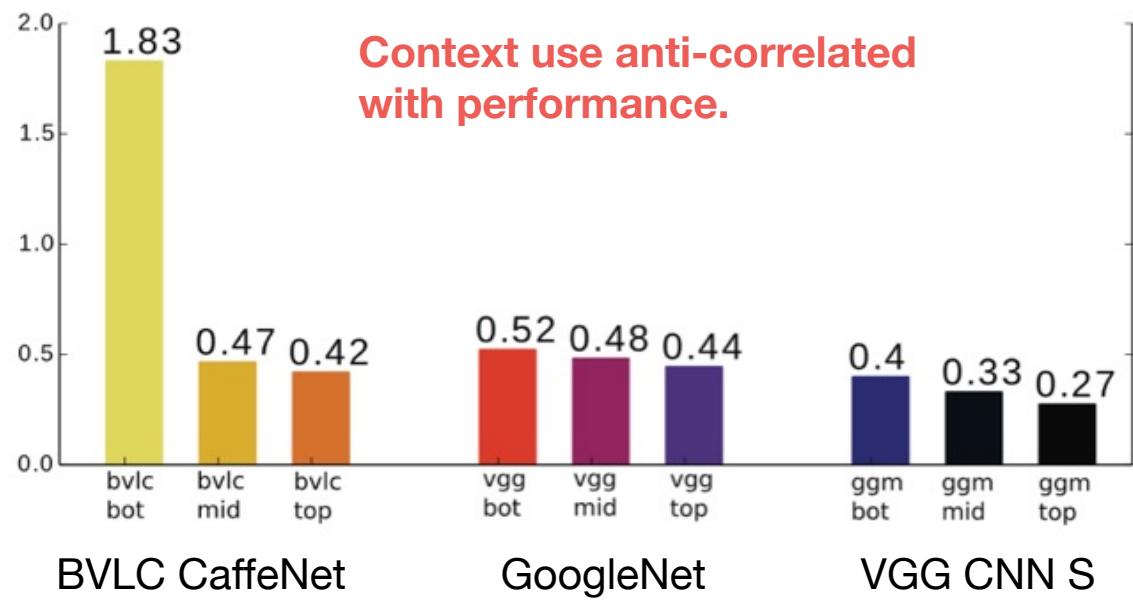
GoogleNet



VGG CNN S



Context use



Context use anti-correlated
with performance.

(Lapuschkin et al. 2016)

Application of LRP
Compare Configuration,
Detect Biases & Improve Models

Application: Face analysis

- Compare AdienceNet, CaffeNet, GoogleNet, VGG-16
- state-of-the-art performance in age and gender classification
- Adience dataset, 26,580 images

Age classification

	A	C	G	V
[i]	51.4 <small>87.0</small>	52.1 <small>87.9</small>	54.3 <small>89.1</small>	—
[r]	51.9 <small>87.4</small>	52.3 <small>88.9</small>	53.3 <small>89.9</small>	—
[m]	53.6 <small>88.4</small>	54.3 <small>89.7</small>	56.2 <small>90.7</small>	—
[i,n]	—	51.6 <small>87.4</small>	56.2 <small>90.9</small>	53.6 <small>88.2</small>
[r,n]	—	52.1 <small>87.0</small>	57.4 <small>91.9</small>	—
[m,n]	—	52.8 <small>88.3</small>	58.5 <small>92.6</small>	56.5 <small>90.0</small>
[i,w]	—	—	—	59.7 <small>94.2</small>
[r,w]	—	—	—	—
[m,w]	—	—	—	62.8 <small>95.8</small>

Gender classification

	A	C	G	V
[i]	88.1	87.4	87.9	—
[r]	88.3	87.8	88.9	—
[m]	89.0	88.8	89.7	—
[i,n]	—	89.9	91.0	92.0
[r,n]	—	90.6	91.6	—
[m,n]	—	90.6	91.7	92.6
[i,w]	—	—	—	90.5
[r,w]	—	—	—	—
[m,w]	—	—	—	92.2

A = AdienceNet

C = CaffeNet

G = GoogleNet

V = VGG-16

[i] = in-place face alignment

[r] = rotation based alignment

[m] = mixing aligned images for training

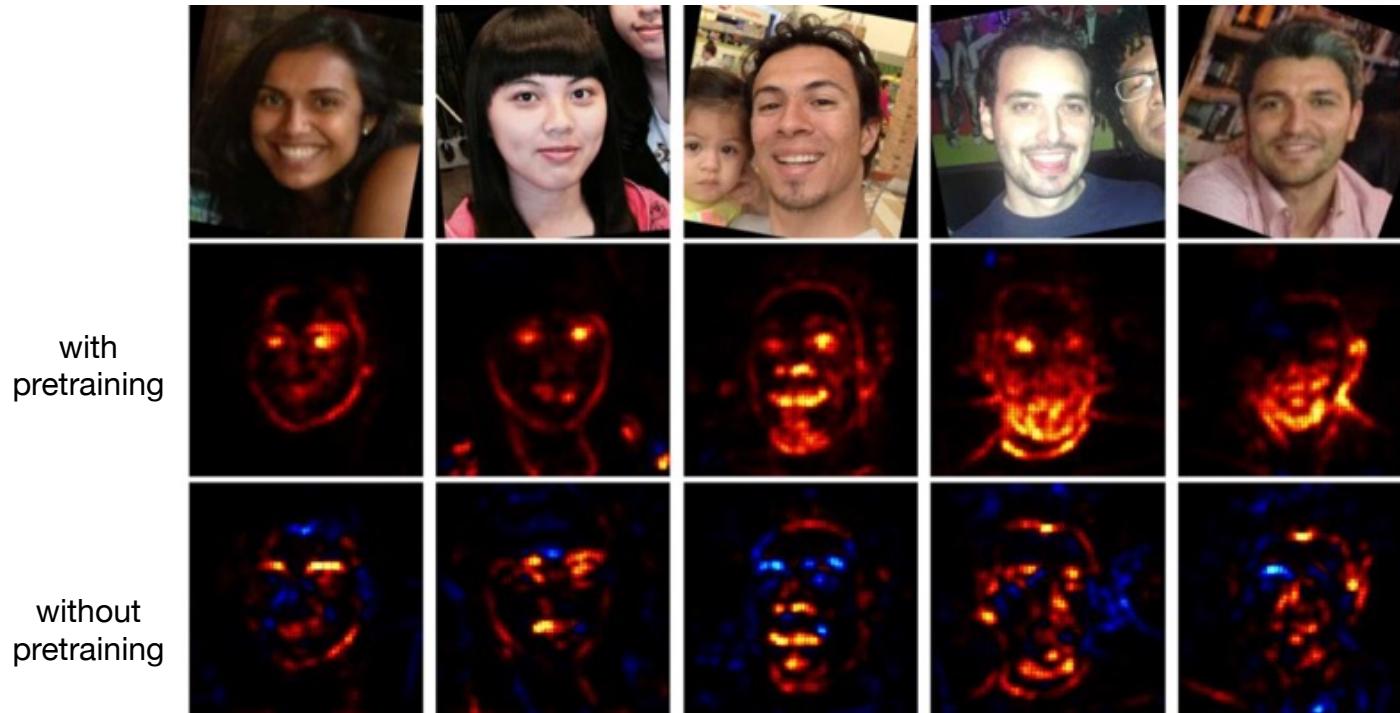
[n] = initialization on Imagenet

[w] = initialization on IMDB-WIKI

(Lapuschkin et al., 2017)

Application: Face analysis

Gender classification



Strategy to solve the problem: Focus on chin / beard, eyes & hair,
but without pretraining the model overfits

(Lapuschkin et al., 2017)

Application: Face analysis

Age classification



Predictions

25-32 years old

Strategy to solve the problem:
Focus on the laughing ...

60+ years old

pretraining on

ImageNet

laughing speaks against 60+
(i.e., model learned that old
people do not laugh)

pretraining on
IMDB-WIKI

(Lapuschkin et al., 2017)

Application: Face analysis



- 1,900 images of different individuals
- pretrained VGG19 model
- different ways to train the models

Different training methods

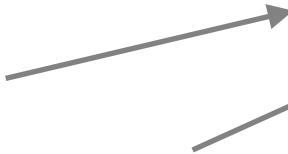
	naive	one morphed	complex morphs	multiclass
true positive	95%	90%	93%	92%
true negative	98%	95%	95%	99%
EER	3.1%	7.2%	6.1%	2.8%

50% genuine images,
50% complete morphs

50% genuine images,
10% complete morphs and
4 × 10% one region morphed

50% genuine images,
10% complete morphs,
partial morphs with 10%
one, two, three and four
region morphed

partial morphs with zero,
one, two, three or four
morphed regions,
for two class classification
last layer reinitialized



(Seibold et al., 2018)

Application: Face analysis

Semantic attack on the model

Table 4. Robustness against partial morphs.

	left eye	right eye	nose	mouth	average
naive	25%	21%	14%	13%	20%
one morphed	81%	89%	79%	71%	80%
complex morphs	78%	74%	73%	54%	70%
multiclass	86%	93%	90%	79%	87%

Black box adversarial attack on the model

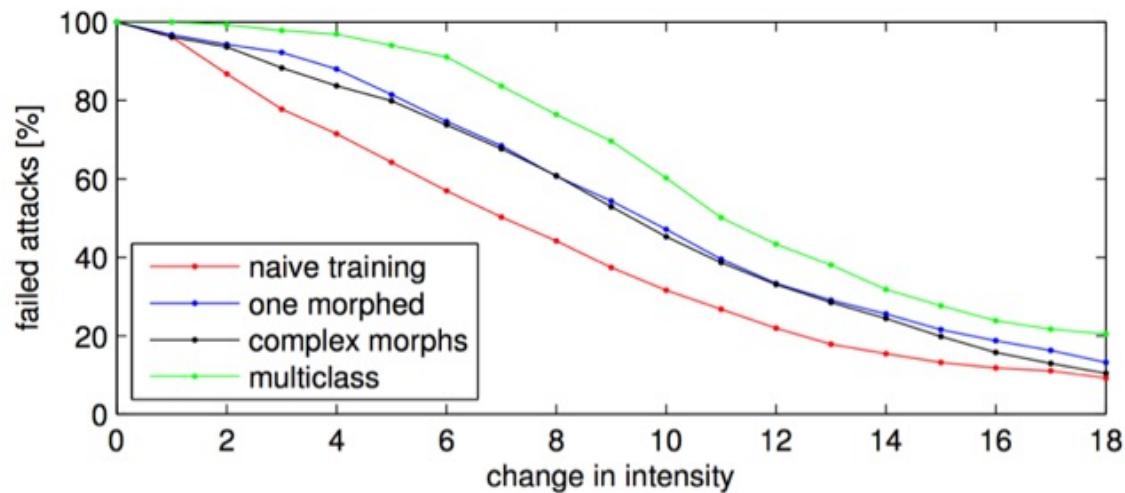


Fig. 5. Robustness against fast gradient sign attacks.

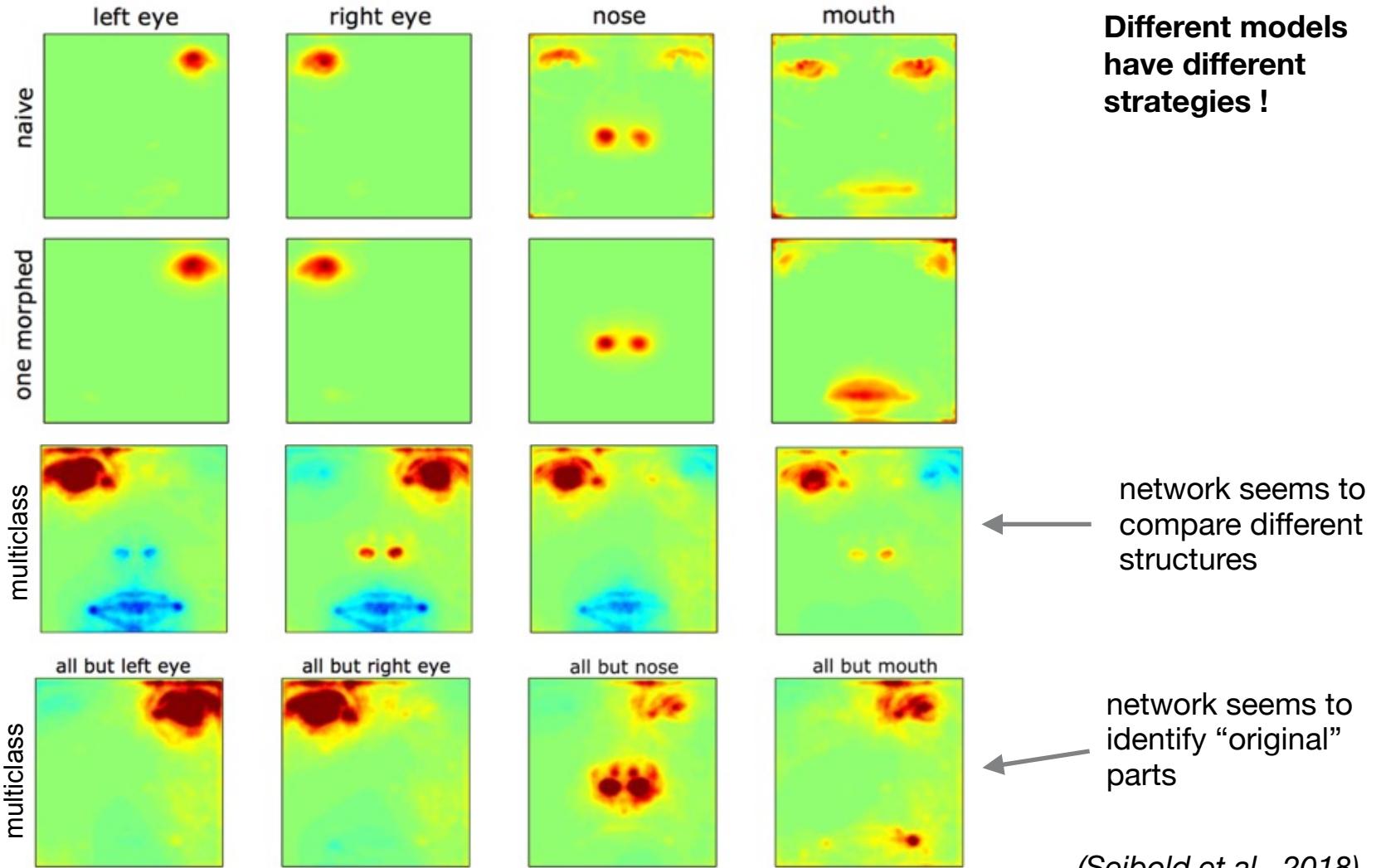
Application: Face analysis

morphed region	relative amount of relevance per region							
	naive				one morphed			
	left eye	right eye	nose	mouth	left eye	right eye	nose	mouth
left eye	0.84	0.00	0.02	0.14	0.96	0.00	0.01	0.04
right eye	0.00	0.91	0.05	0.05	0.00	0.92	0.01	0.07
nose	0.21	0.28	0.47	0.04	0.00	0.01	0.97	0.02
mouth	0.34	0.27	0.04	0.35	0.17	0.12	0.04	0.68

	complex morphs				multiclass			
	left eye	right eye	nose	mouth	left eye	right eye	nose	mouth
	0.98	0.00	0.00	0.02	0.00	0.98	0.00	0.01
left eye	0.98	0.00	0.00	0.02	0.00	0.98	0.00	0.01
right eye	0.00	0.92	0.00	0.08	0.98	0.00	0.02	0.00
nose	0.02	0.03	0.92	0.02	0.01	0.10	0.19	0.70
mouth	0.06	0.00	0.41	0.53	0.11	0.18	0.58	0.13

(Seibold et al., 2018)

Application: Face analysis



Application of LRP

Learn new Representations

Application: Learn new Representations

... some astronauts occasionally ...

$$\begin{pmatrix} v_1 \\ v_2 \\ \vdots \\ v_d \end{pmatrix} = R_a \begin{pmatrix} a_1 \\ a_2 \\ \vdots \\ a_d \end{pmatrix} + R_b \begin{pmatrix} b_1 \\ b_2 \\ \vdots \\ b_d \end{pmatrix} + R_c \begin{pmatrix} c_1 \\ c_2 \\ \vdots \\ c_d \end{pmatrix}$$

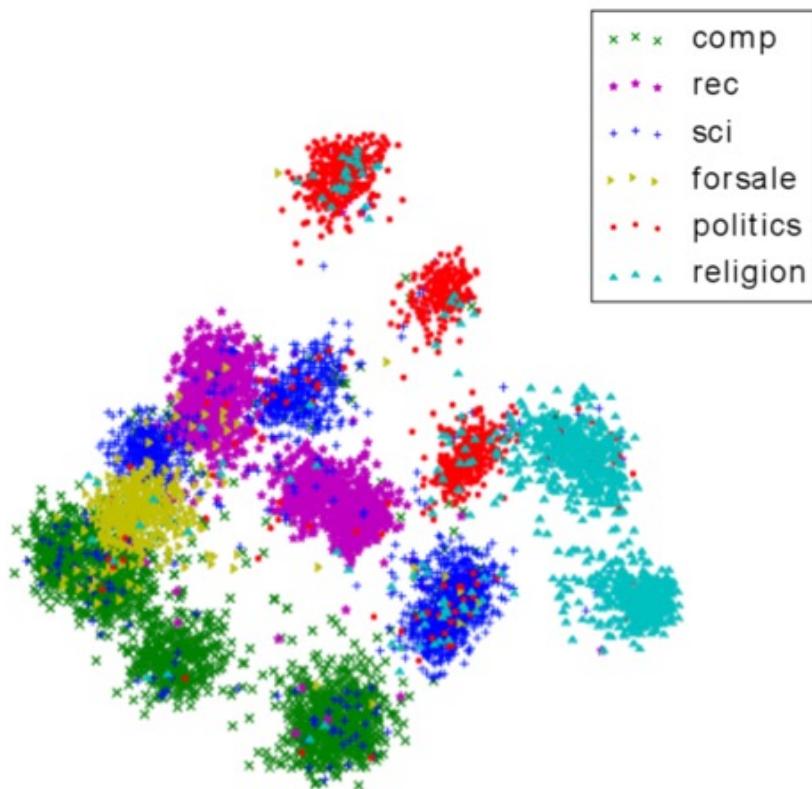
document vector

relevance word2vec relevance word2vec relevance word2vec

(Arras et al. 2016 & 2017)

Application: Learn new Representations

2D PCA projection of document vectors



uniform



TFIDF



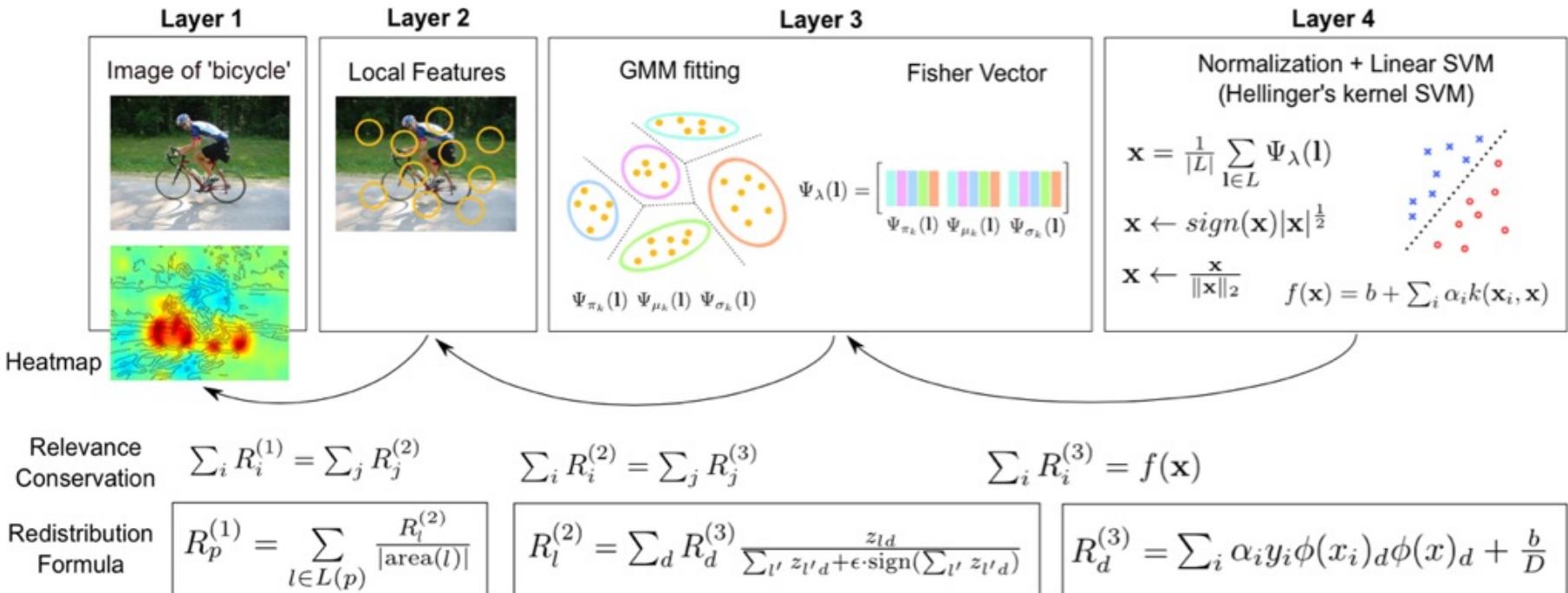
Document vector computation is unsupervised (given we have a classifier).

(Arras et al. 2016 & 2017)

Application of LRP
Understand Model &
Obtain new Insights

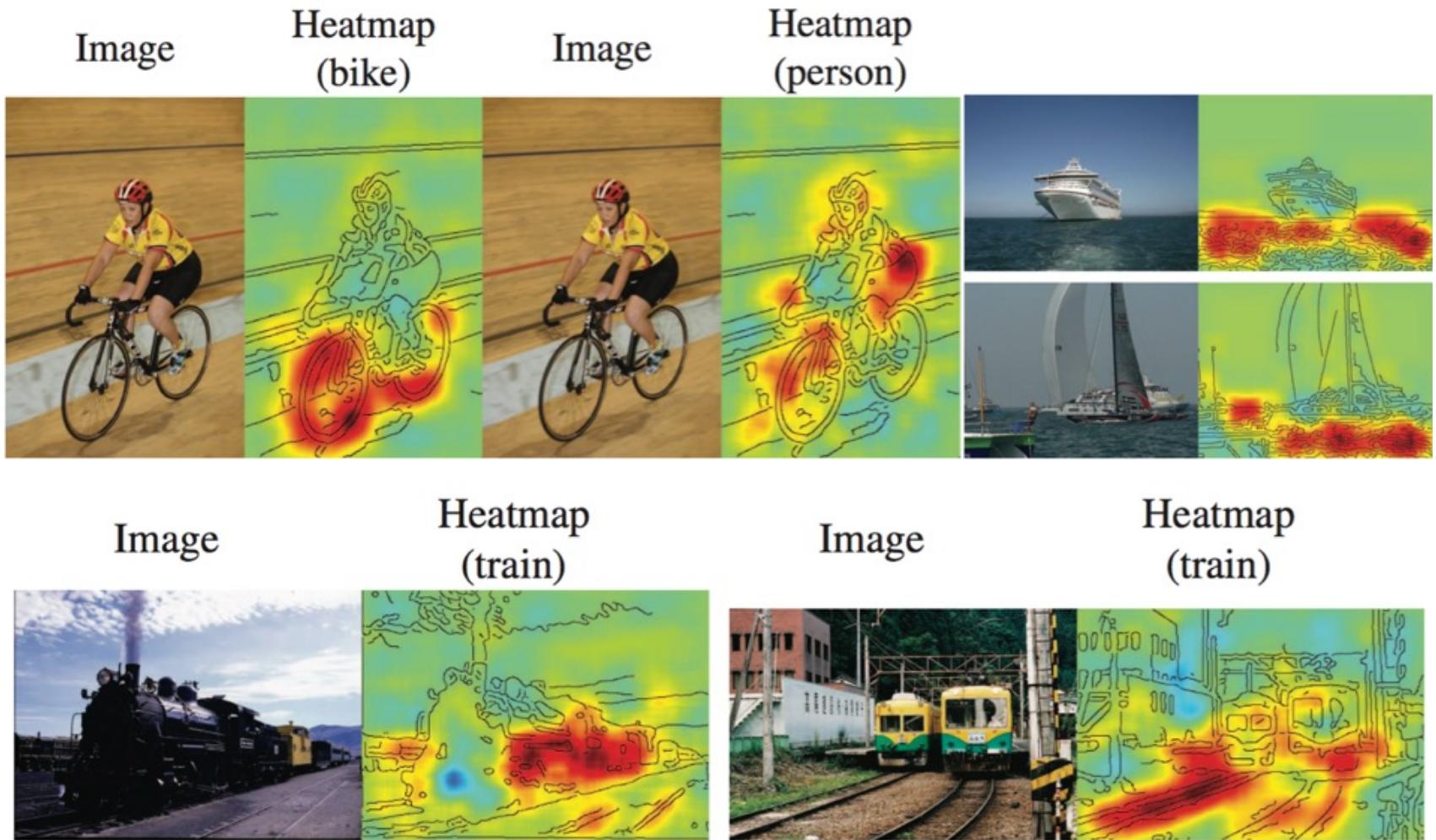
Application: Understand the model

- Fisher Vector / SVM classifier
- PASCAL VOC 2007



(Lapuschkin et al. 2016)

Application: Understand the model



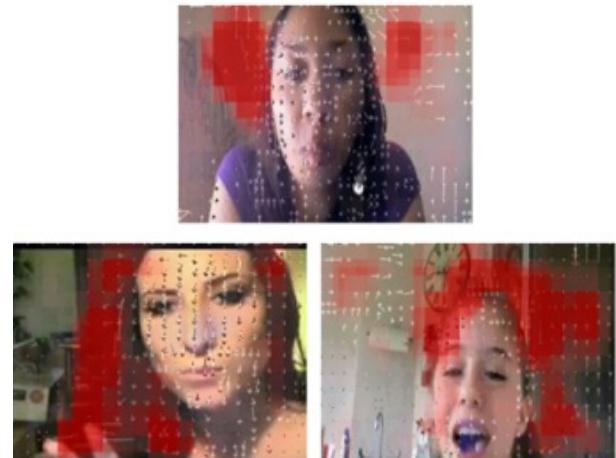
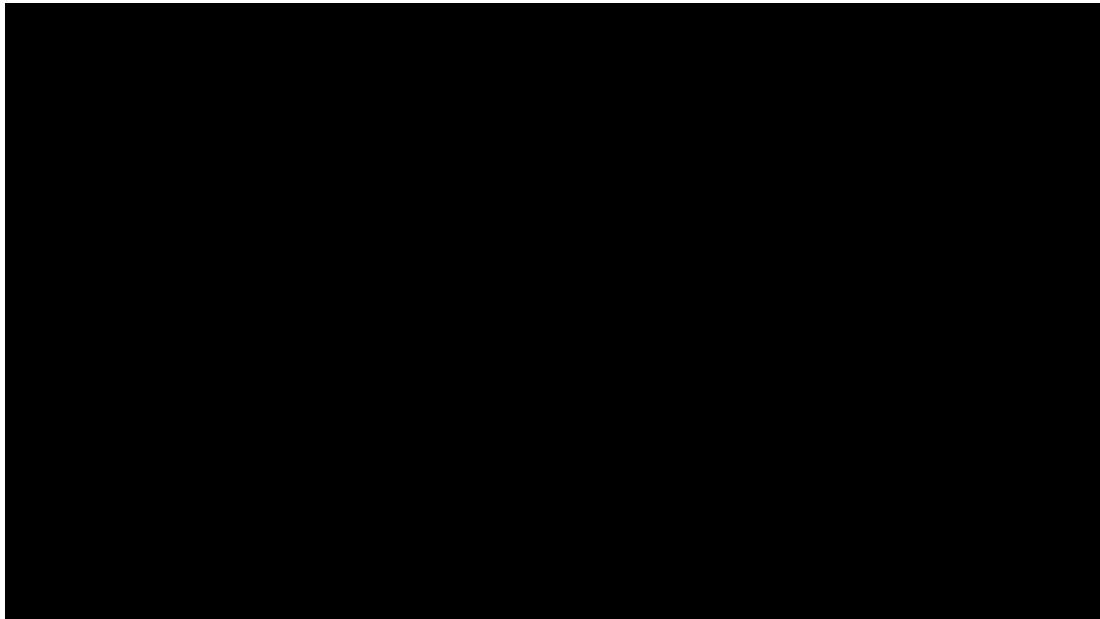
(Lapuschkin et al. 2016)

Application: Understand the model



Motion vectors can be extracted
from the compressed video
-> allows very efficient analysis

- Fisher Vector / SVM classifier
- Model of Kantorov & Laptev, (CVPR'14)
- Histogram Of Flow, Motion Boundary Histogram
- HMDB51 dataset



(Srinivasan et al. 2017)

Application: Understand the model



movie review:
++, -

- bidirectional LSTM model (Li'16)
- Stanford Sentiment Treebank dataset

How to handle multiplicative interactions ?

$$z_j = z_g \cdot z_s$$

$$R_g = 0 \quad R_s = R_j$$

gate neuron indirectly affect relevance distribution in forward pass

Negative sentiment

... too slow , too boring , and occasionally annoying .

it 's neither as romantic nor as thrilling as it should be .

neither funny nor suspenseful nor particularly well-drawn .

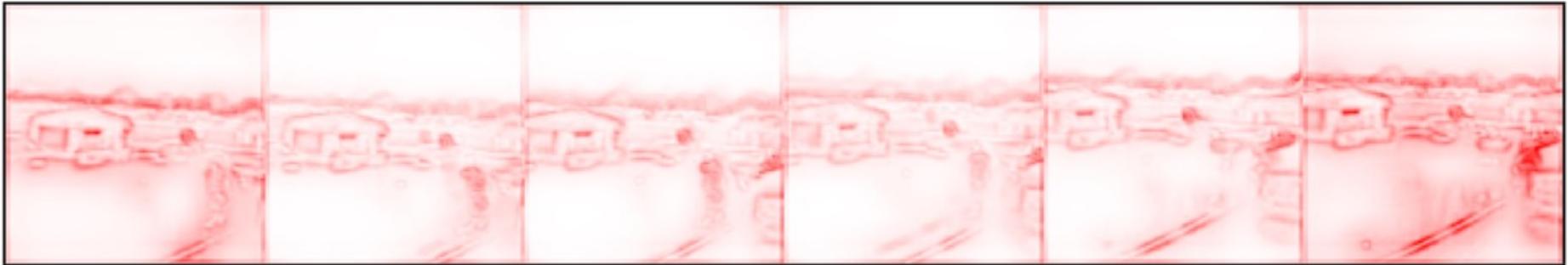
Model understands negation !

(Arras et al., 2017 & 2018)

Application: Understand the model

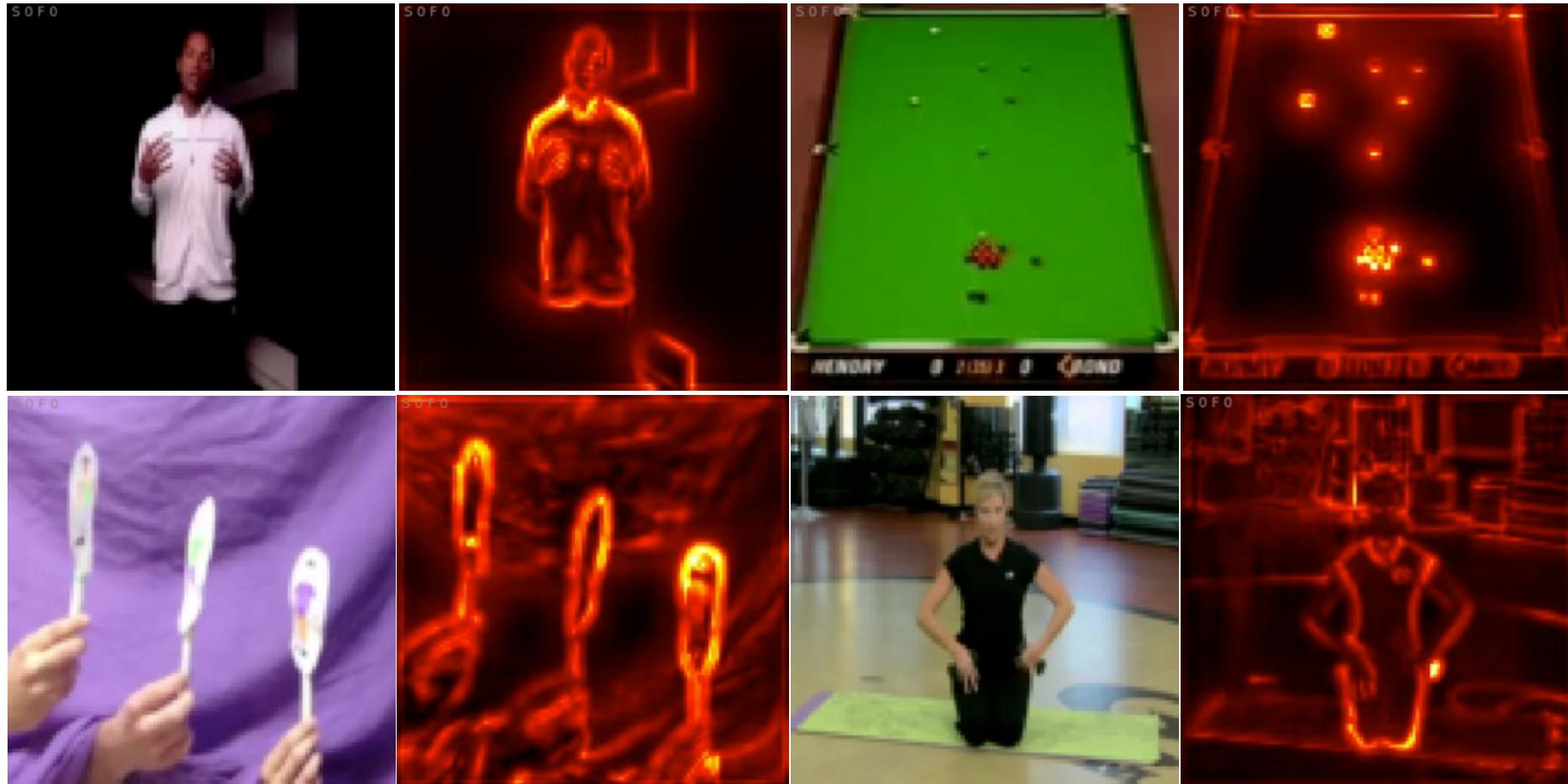
- 3-dimensional CNN (C3D)
- trained on Sports-1M
- explain predictions for 1000 videos from the test set

frame 1 frame 4 frame 7 frame 10 frame 13 frame 16



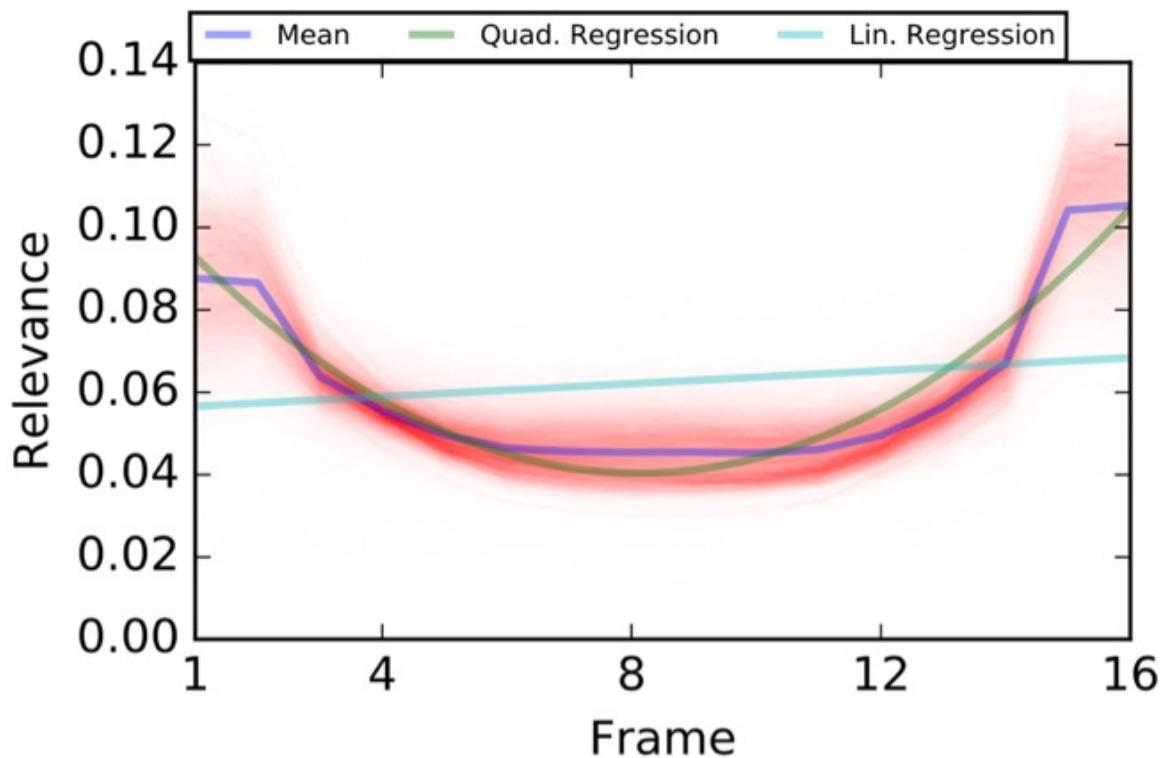
(Anders et al., 2018)

Application: Understand the model



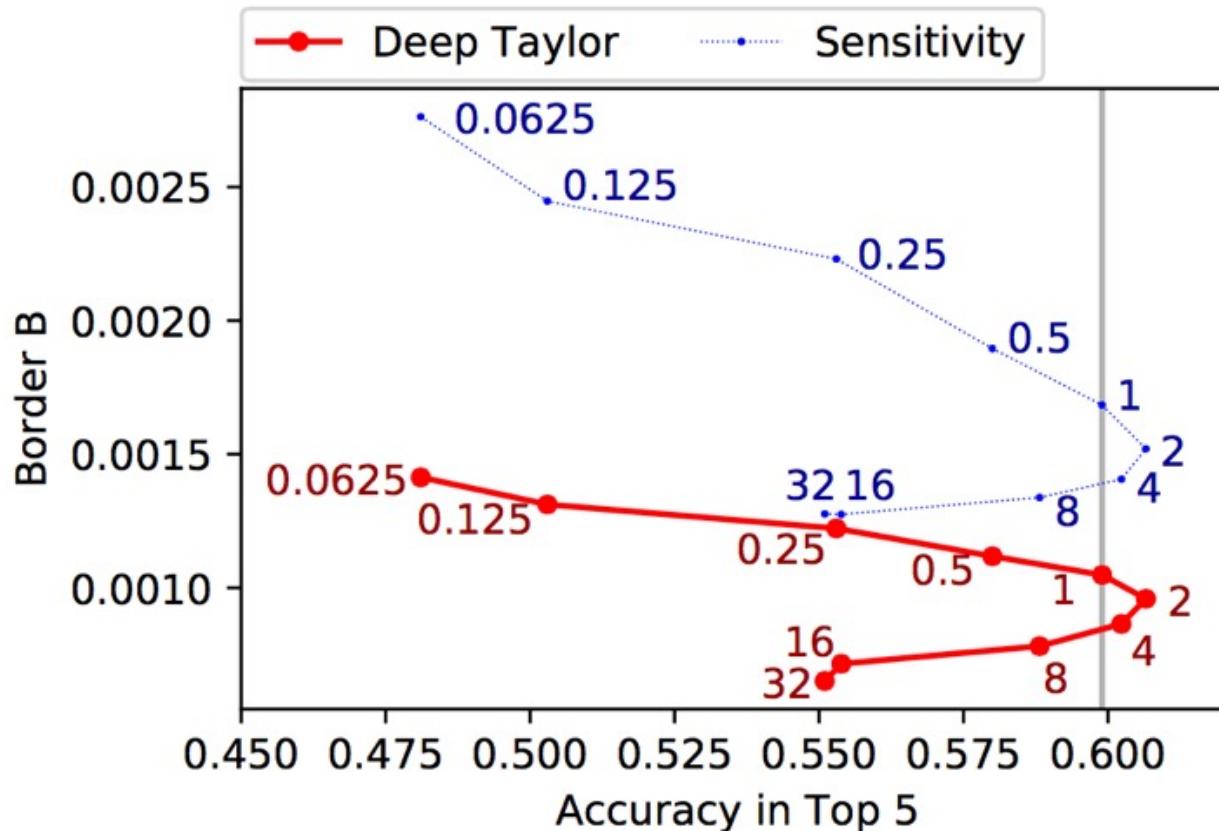
(Anders et al., 2018)

Application: Understand the model



Observation: Explanations focus on the bordering of the video, as if it wants to watch more of it.

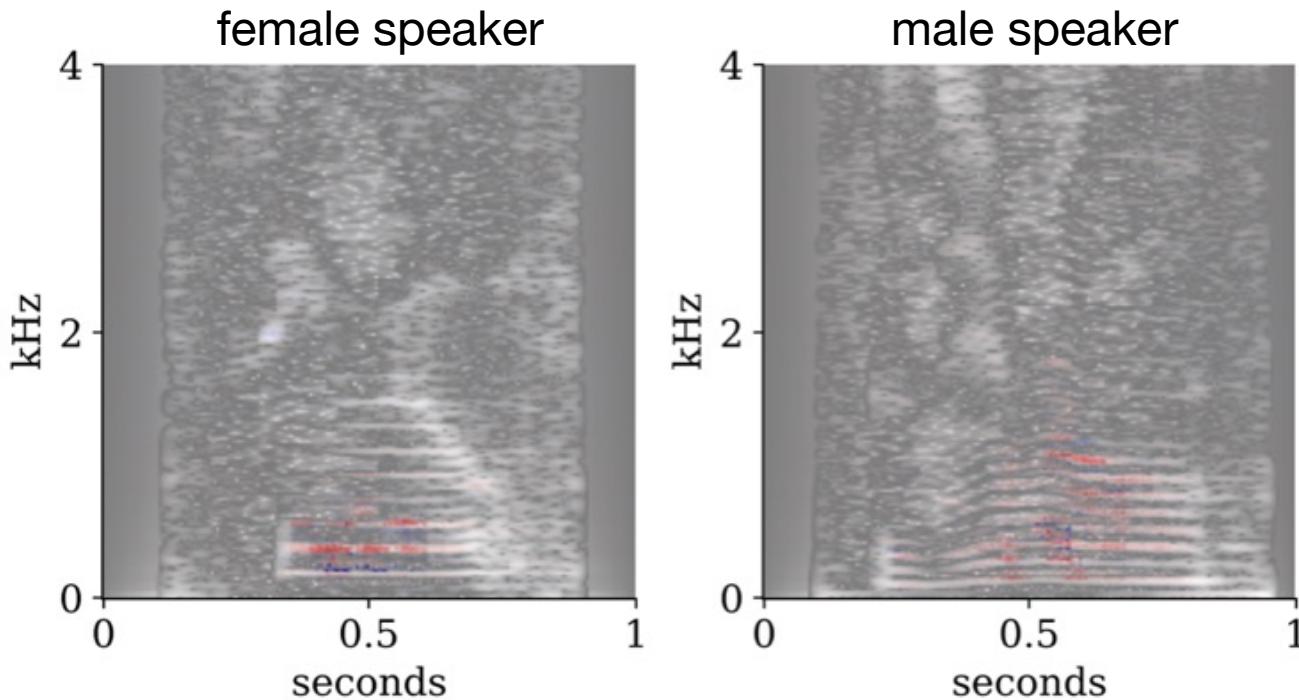
Application: Understand the model



Idea: Play video in fast forward (without retraining) and then the classification accuracy improves.

Application: Understand the model

- AlexNet model
- trained on spectrograms
- spoken digits dataset (AudioMNIST)



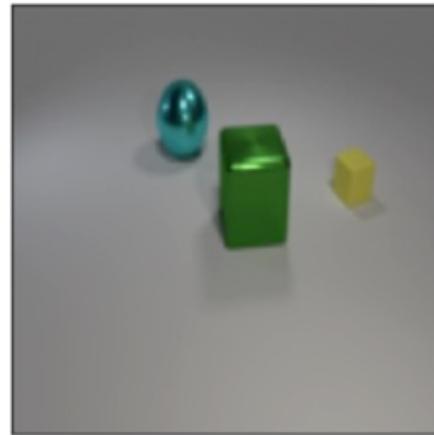
model classifies gender based on the fundamental frequency and its immediate harmonics (see also Traunmüller & Eriksson 1995)

(Becker et al., 2018)

Application: Understand the model

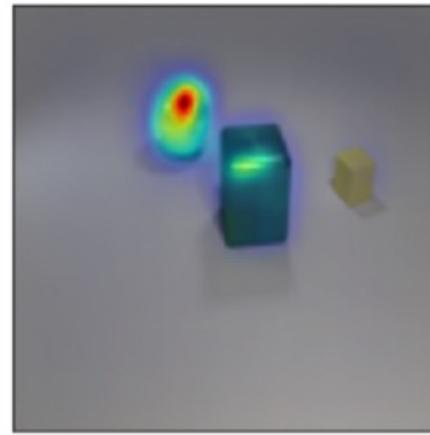
Question

there is a metallic cube ; are
there any large cyan metallic
objects behind it ?



LRP

there is a metallic cube ; are
there any large cyan metallic
objects behind it ?

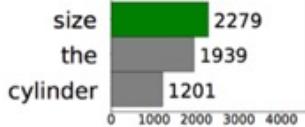


- reimplement model of (Santoro et al., 2017)
- test accuracy of 91,0%
- CLEVR dataset

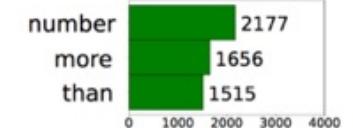
Question Type

LRP

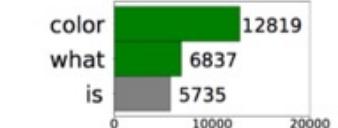
equal_size



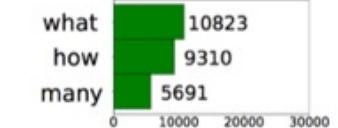
greater_than



query_color



count

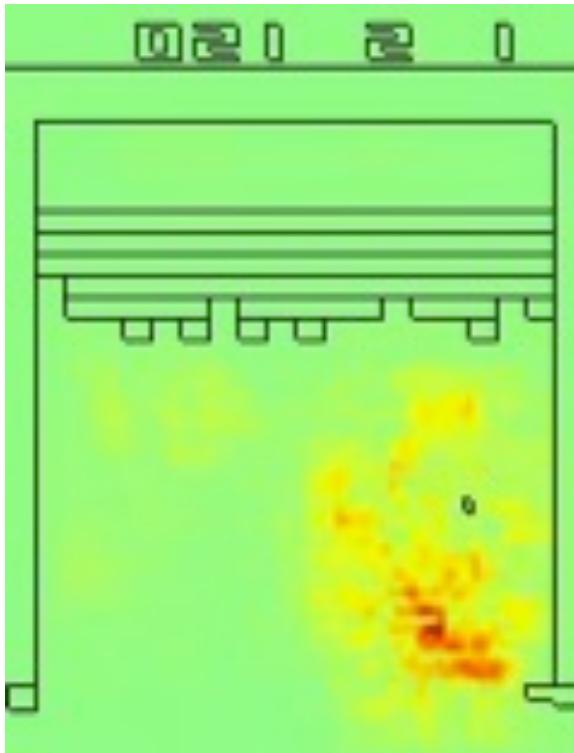


model understands the question and correctly identifies
the object of interest

(Arras et al., 2018)

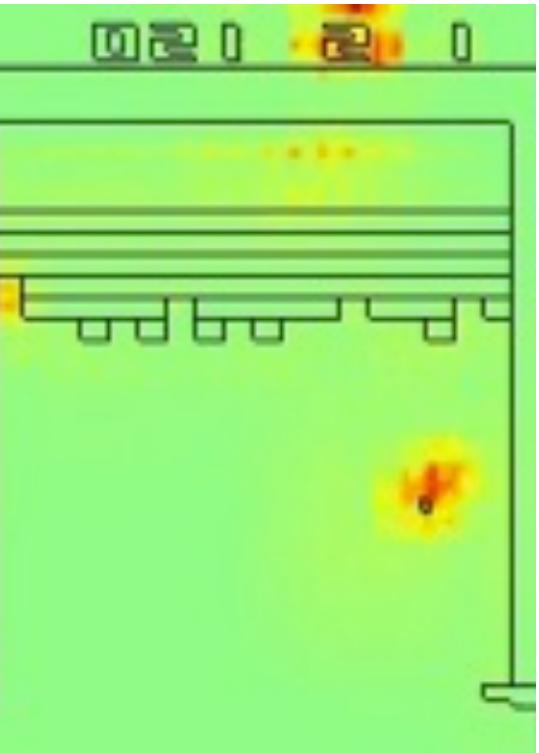
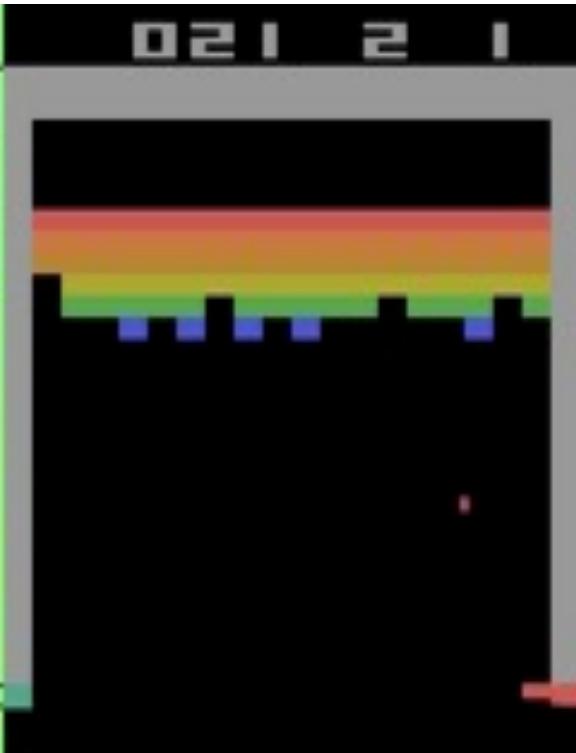
Application: Understand the model

Sensitivity Analysis



*does not focus on where
the ball is, but on where
the ball could be in the
next frame*

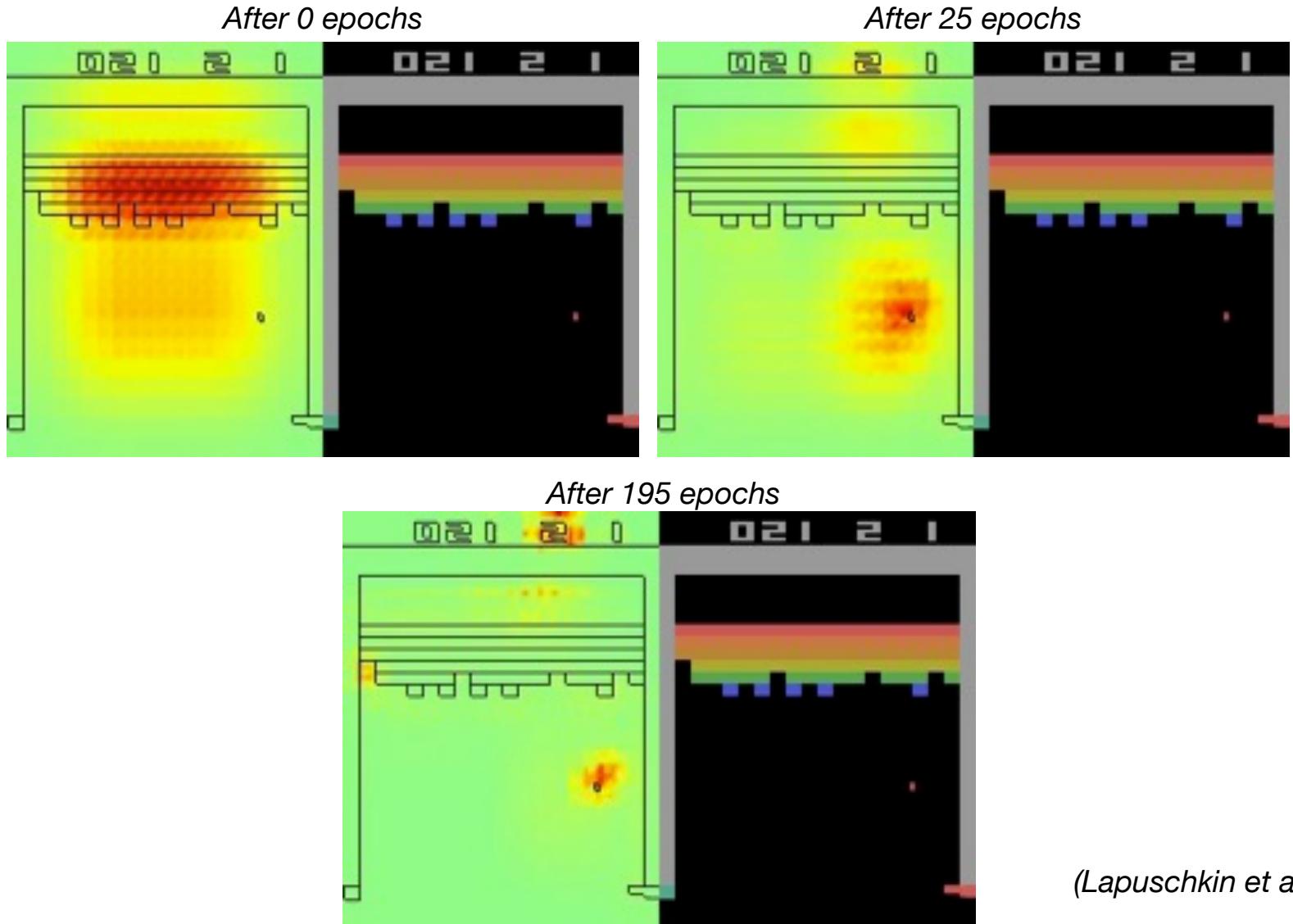
LRP



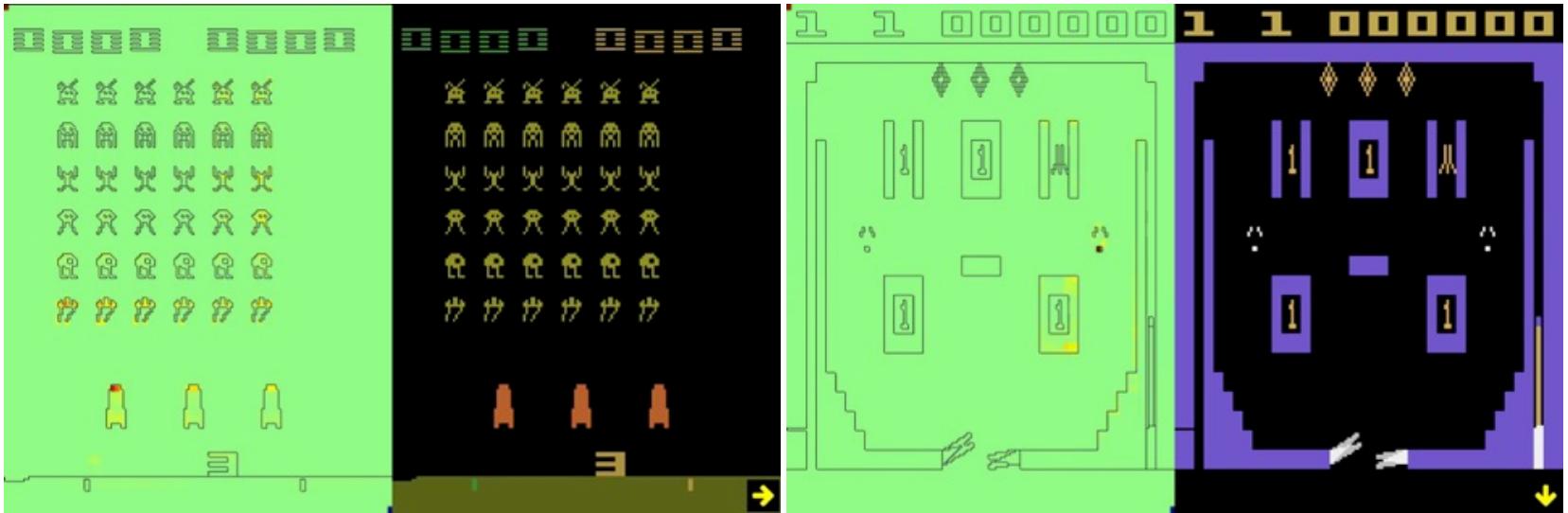
*LRP shows that that
model tracks the ball*

(Lapuschkin et al., in prep.)

Application: Understand the model



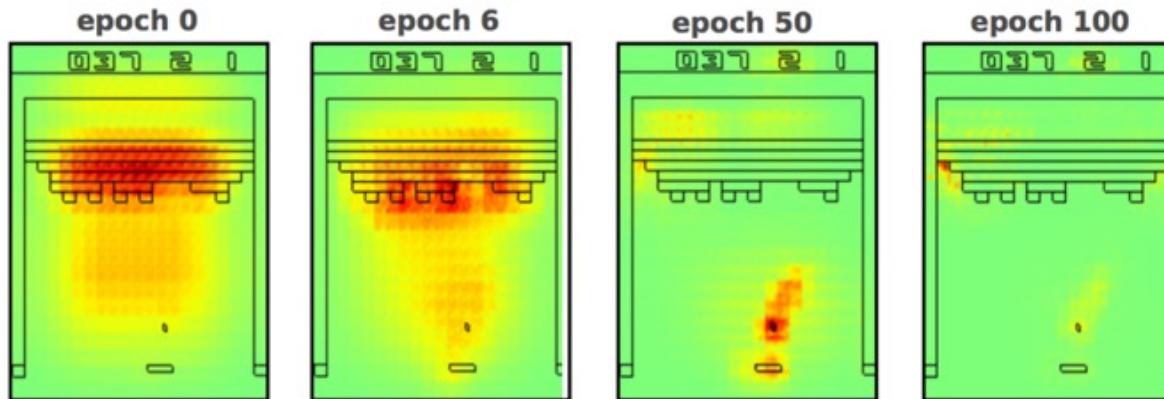
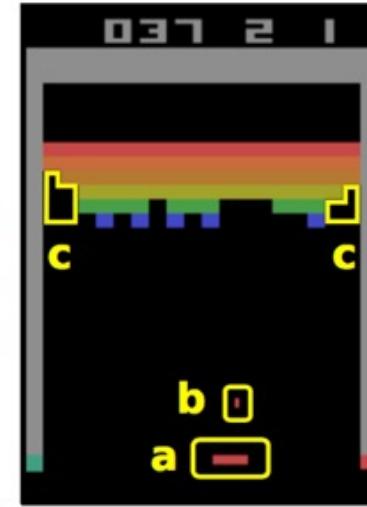
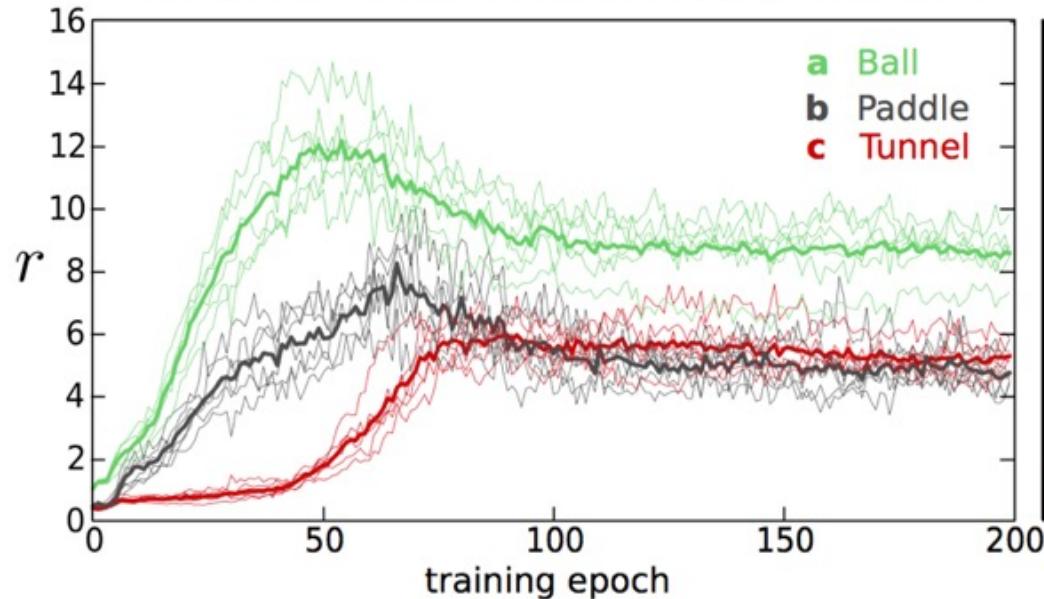
Application: Understand the model



(Lapuschkin et al., in prep.)

Application: Understand the model

Relevance Distribution during Training



model learns
1. track the ball
2. focus on paddle
3. focus on the tunnel

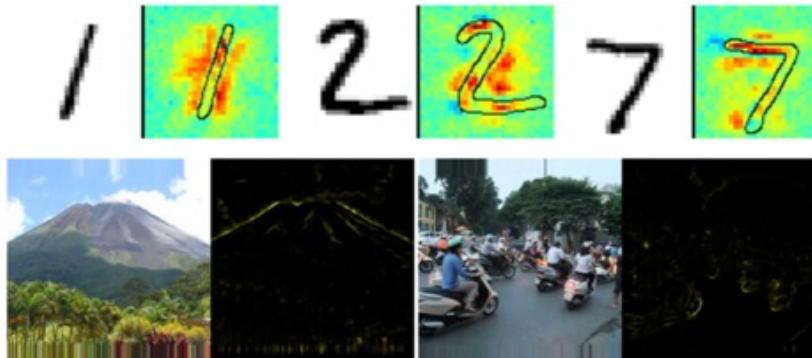
(Lapuschkin et al., in prep.)

More information

Visit:

<http://www.heatmapping.org>

- ▶ Tutorials
- ▶ Software
- ▶ Online Demos



Tutorial Paper

Montavon et al., “Methods for interpreting and understanding deep neural networks”,
Digital Signal Processing, 73:1-5, 2018

Keras Explanation Toolbox

<https://github.com/albermax/innvestigate>

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