Explainable AI : Shapley Values and other stuff

A Unified Approach to Interpreting Model Predictions

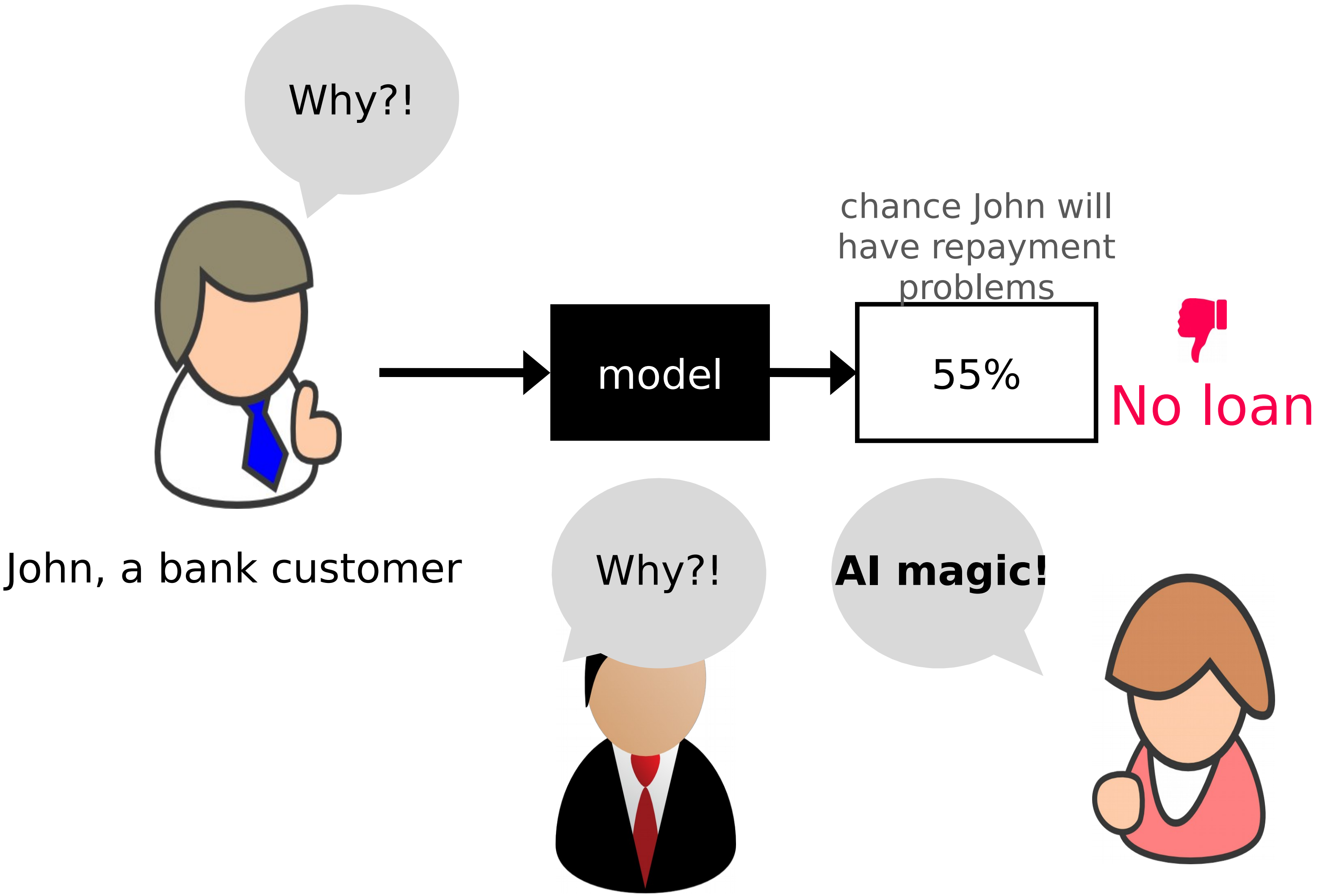
Scott Lundberg, Su-In Lee

https://colab.research.google.com/github/**leexa90**/Explainable_AI_image_classification/blob/master/colabs_script.ipynb

Background on myself

- Graduated from NUS science 2015
- Attended Deep Learning Developer Course 2017
- Working in A*STAR Bioinformatics Institute, using various methods and analysis on crop analytics

Need for Explainable AI



https://github.com/slundberg/shap/blob/master/docs/presentations/NIPS%202017%20Talk.pptx

Need for Explainable AI

Some of the articles of GDPR can interpreted as requiring explanation of the decision made by a machine learning algorithm, when it is applied to a human subject.

UW Prof. Pedro Domingos, a leading AI researcher, started a firestorm with his tweet

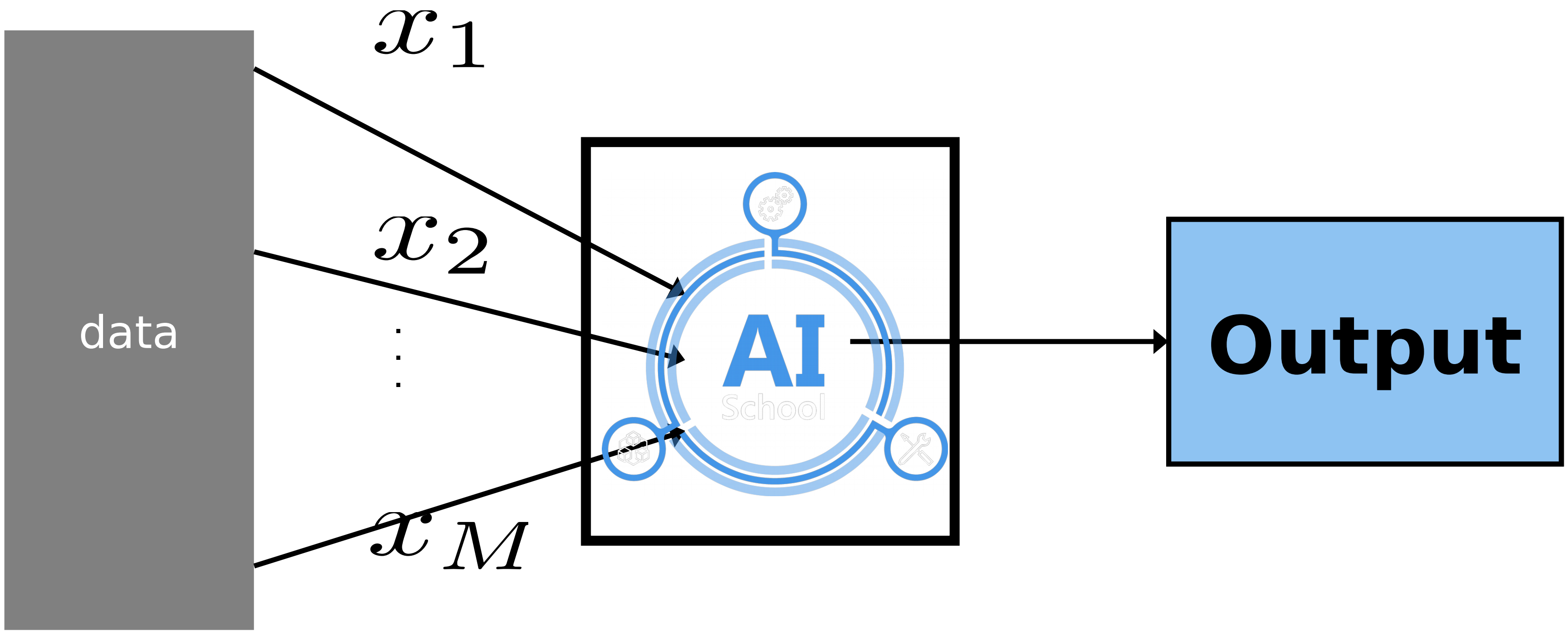
Pedro Domingos
@pmddomingos

Starting May 25, the European Union will require algorithms to explain their output, making deep learning illegal.

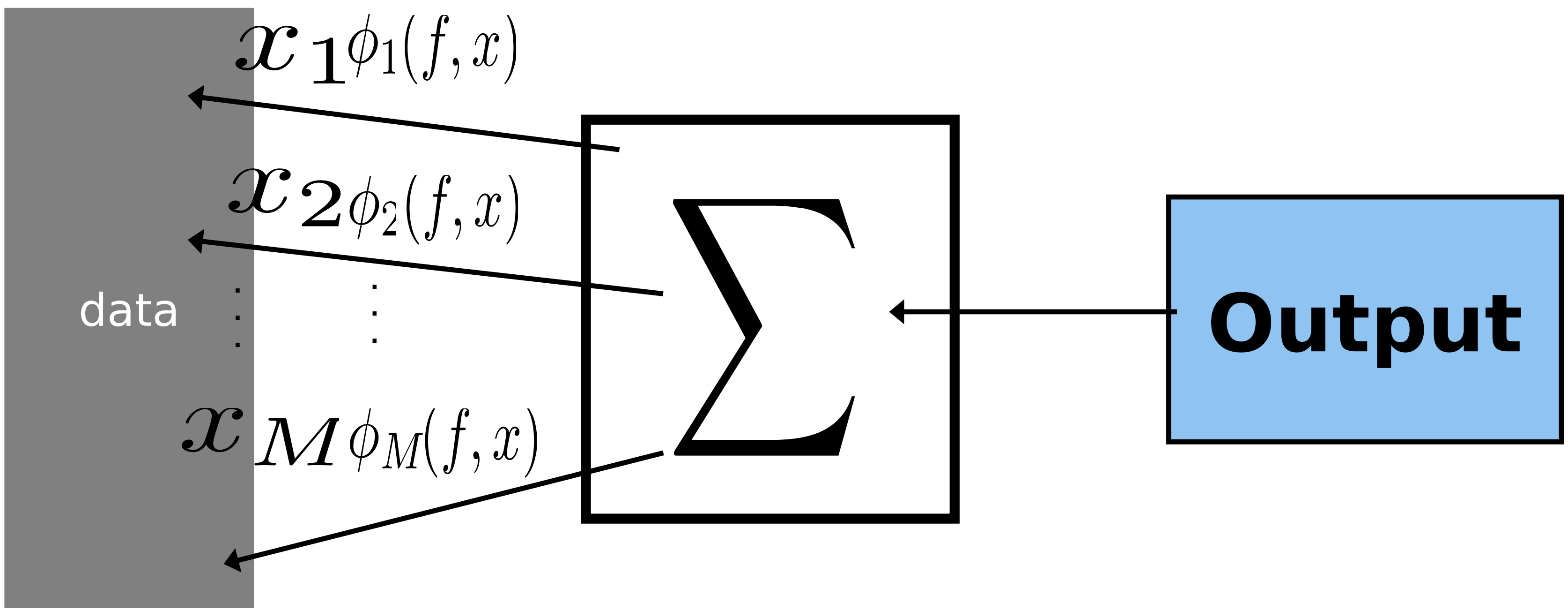
11:59 AM - Jan 29, 2018

344 249 people are talking about this

Complicated AI Model



Explainable model:
Additive feature attribution model



Output = $\sum_{i=1}^{M} \phi_i$

M is the number of simplified input features, and $\phi_i \in \mathbb{R}$.

Additive feature attribution methods

LIME

Ribeiro et al. 2016

DeepLIFT

Shrikumar et al. 2016

$$\boxed{\Sigma}$$

Shapley reg. values

Lipovetsky et al. 2001

Relevance prop.

Bach et al. 2015

QII

Datta et al. 2016

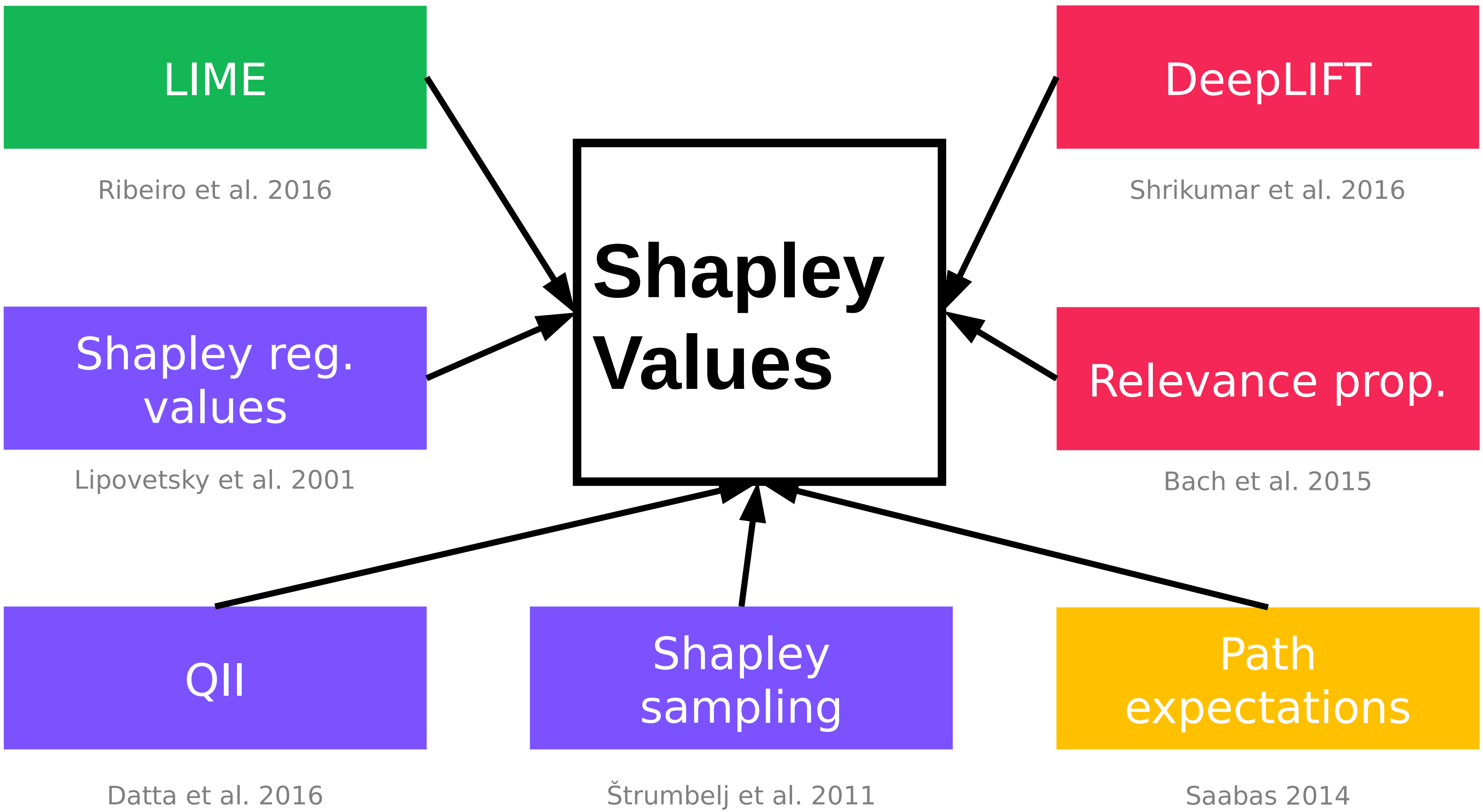
Shapley sampling

Štrumbelj et al. 2011

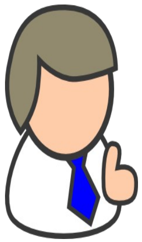
Path expectations

Saabas 2014

Additive feature attribution methods



SHapley Additive exPlanation - (SHAP) values (1)



Base rate

20%

$E[f(x)]$

Prediction for John

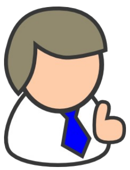
55%

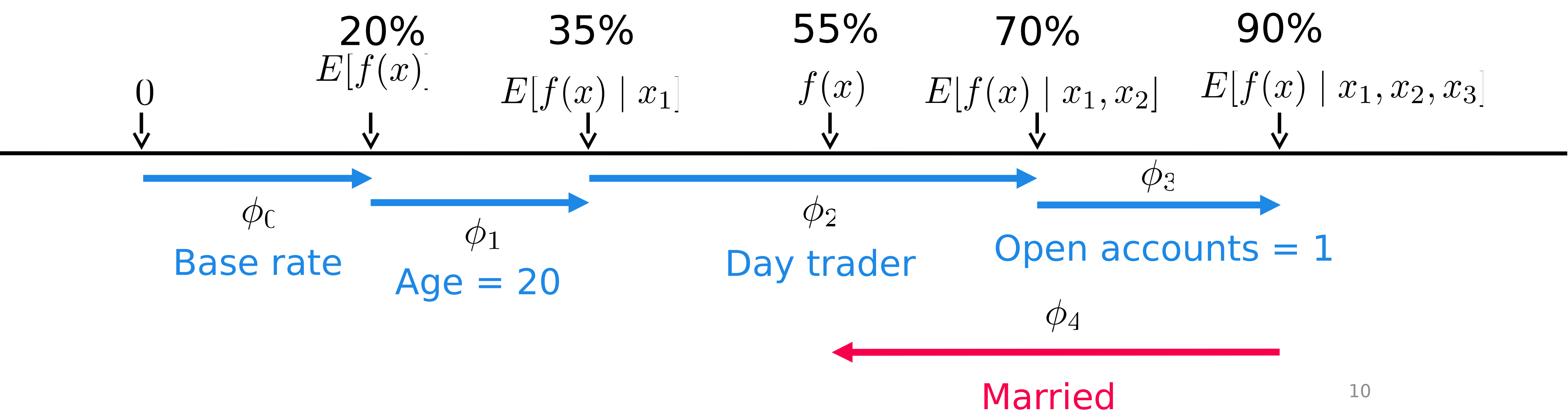
$f(x)$

0

How did we get here?

SHapley Additive exPlanation (SHAP) values (2)





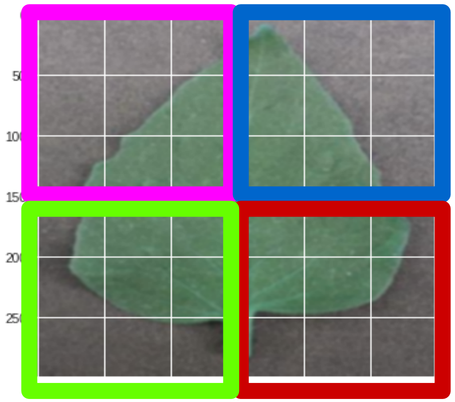
SHapley Additive exPlanation (SHAP) values (3) – Computation

- Train AI model

For each picture containing 4 superpixels

{ *Explain model :*

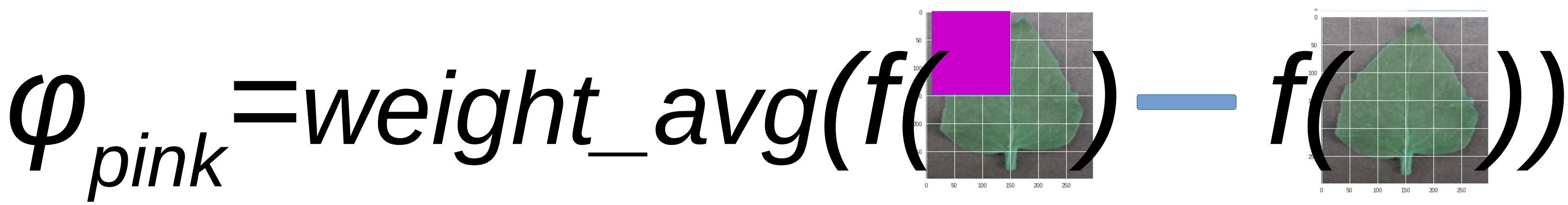
Output $= \varphi_{pink} + \varphi_{blue} + \varphi_{green} + \varphi_{red}$

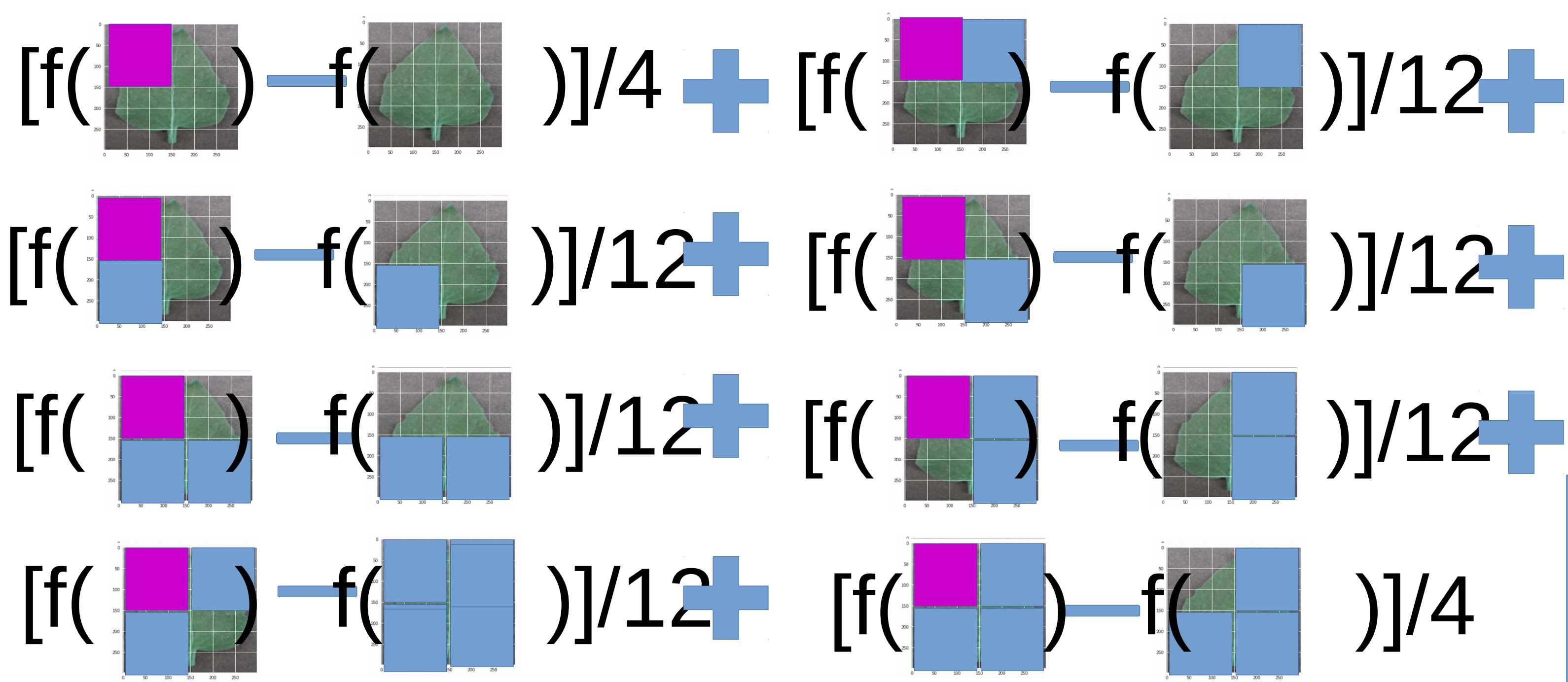


φ_i is the shapley value of the feature

}

SHapley Additive exPlanation (SHAP) values (4) – computation





Legend
Blue solid squared are mean-filled super-pixels

SHapley Additive exPlanation (SHAP) values (5) – solved using weighted linear regression

$$\phi = (X^T W X)^{-1} X^T W y$$

Refer to proof in paper for details, A Unified Approach to Interpreting Model Predictions

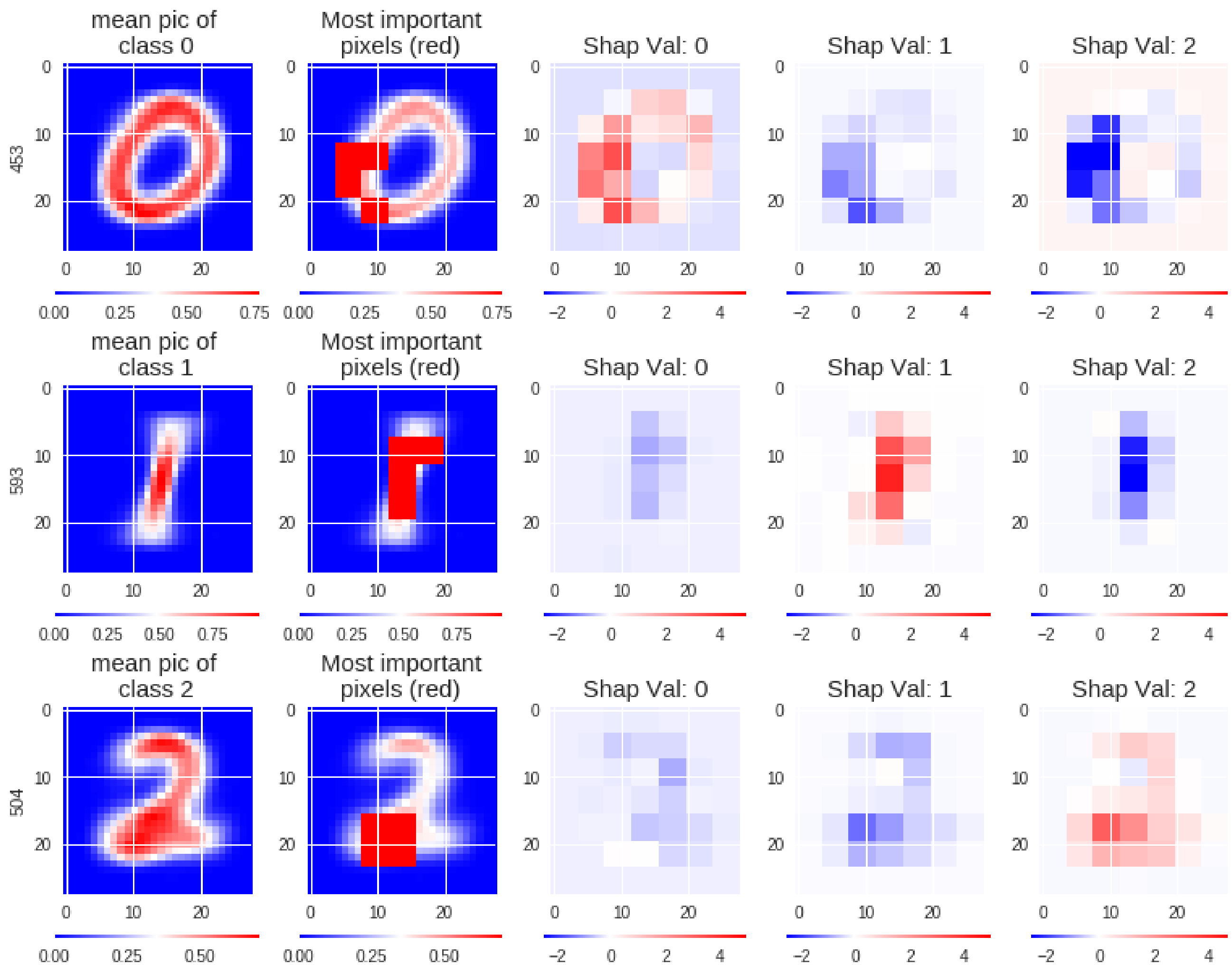
Applying to Mnist (1)

- Mnist model with 4 convolutional layers and 2 dense layers, with test accuracy 99.4%
- for each test image {
  - Split image to 7*7 = 49 superpixels for shapley value computation
  - Sample 7367 combinations of pixels
    ~ all images with 1 mean-filled pixel, $^{49}C_1$ = 49
    ~ all 2 mean with 2-filled pixels, $^{49}C_2$ = 1176
    ~ 33% of images with 3 mean-filled pixel, $^{49}C_3$ /3 = 6142
  - Calculate shapley values for each pixel using weighted regression, with g

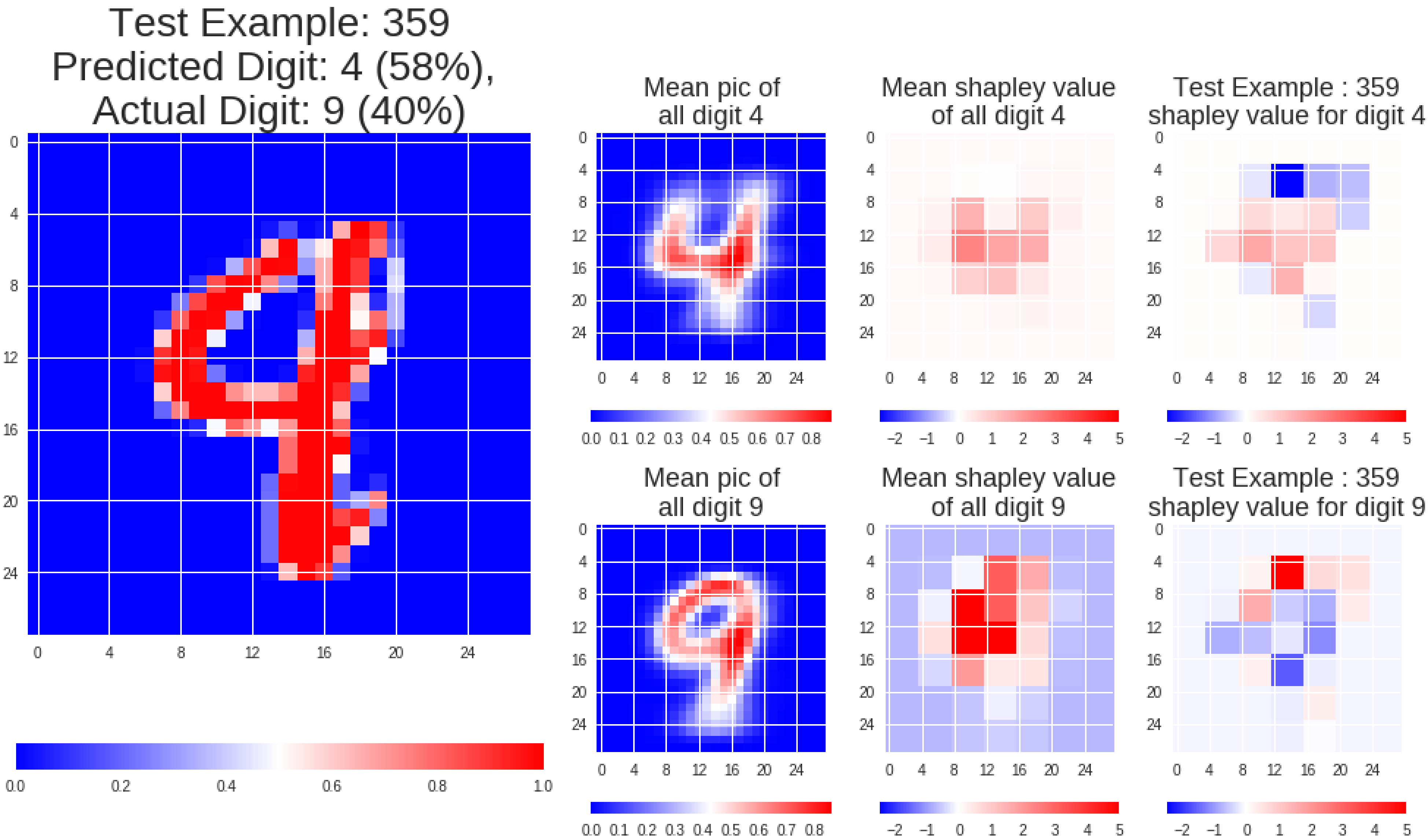
  }

Output = $\sum_{i=1}^{M} \phi_i$

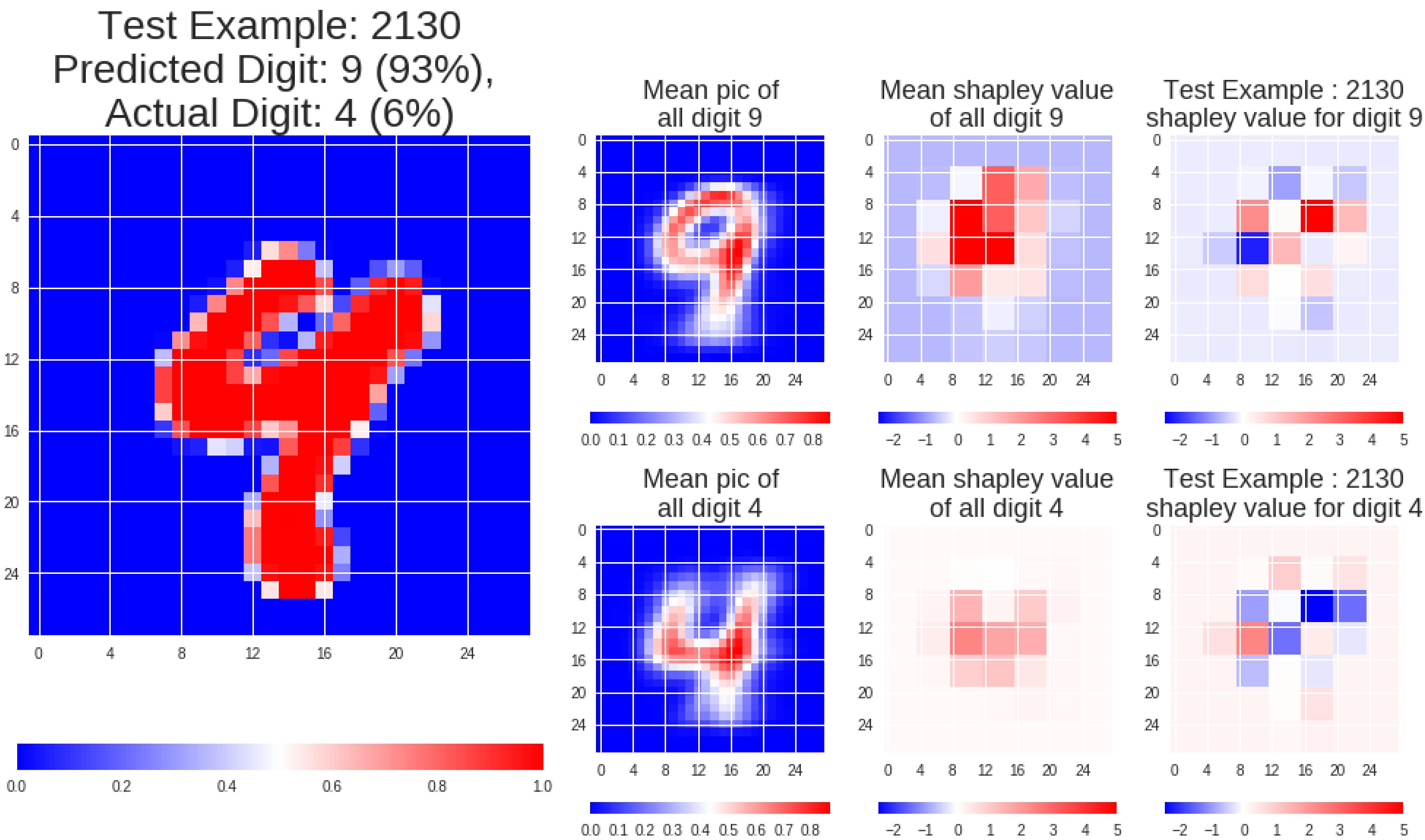
Applying to Mnist (2) – Global analysis



Applying to Mnist (3) – Individual analysis (a)

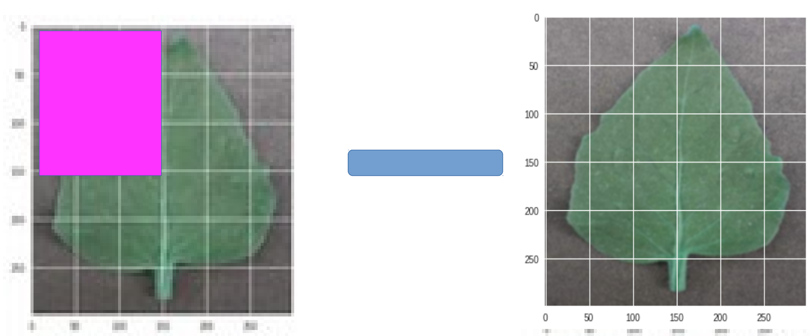


Applying to Mnist (3) – Individual analysis (b)



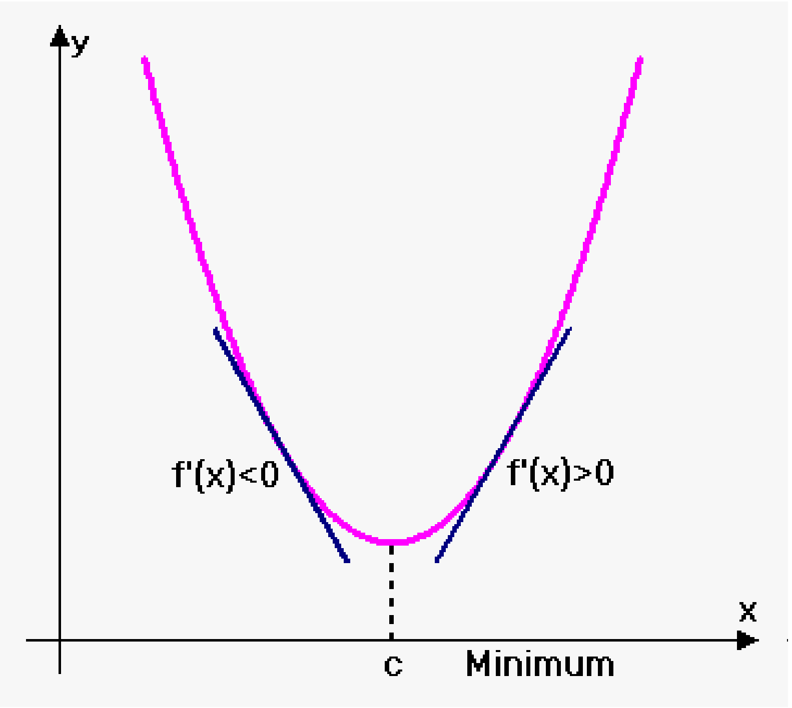
Drawbacks

- Computationally intensive, requires to compute 2^m examples for m features
  ~ I only sampled 10^3 out of 10^{14} combinations
- How do you appropriately remove a feature ?



Global explanation != local explanation

Gradient based methods

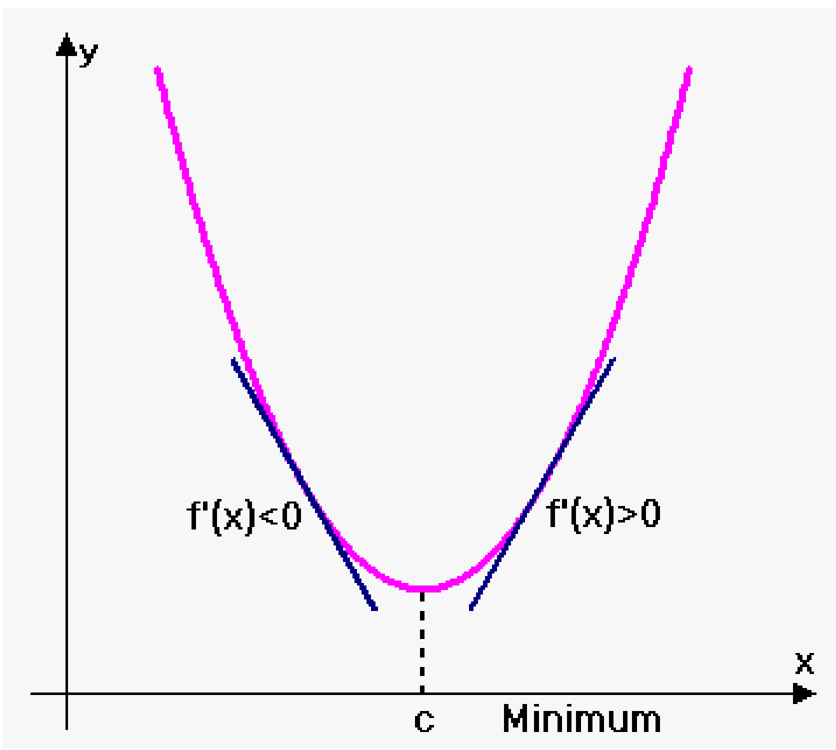


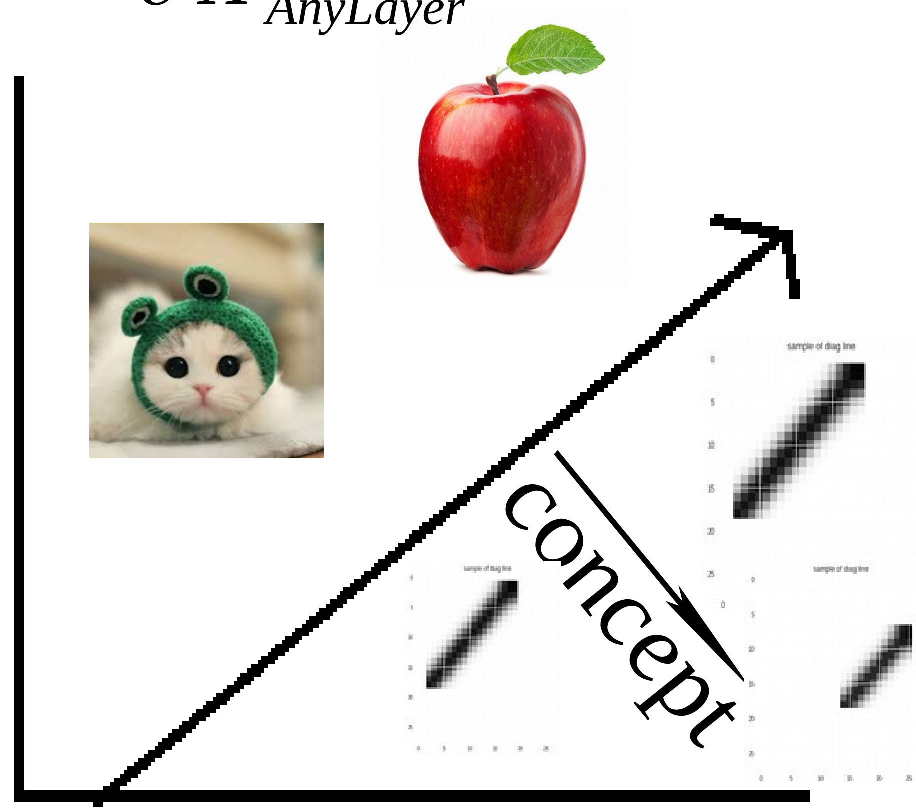
$$\frac{\partial\, output_i}{\partial\, inputs}$$

The gradient shows sensitivity of outputs to inputs

Gradient based methods : concept directional derivative

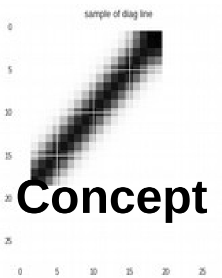
$$directional\,derivative = \frac{\partial\, output_i}{\partial\, X_{AnyLayer}} \cdot \overrightarrow{concept}$$





Interpretability Beyond Feature Attribution: Quantitative Testing with Concept Activation Vectors (TCAV), 2017

Concept activation of mnist model hidden CNN layer : Toy Example



Concept

$$directional\,derivative = \frac{\partial\, output_i}{\partial\, X_{AnyLayer}} \cdot \overrightarrow{concept}$$

Digit	0	1	2	3	4	5	6	7	8	9
Directional derivative	--	++	--	--	--	--	--	+	---	--

The concept directional derivative measures sensitivity of model predictions with respect to concepts at any model layer

Concept activation of mnist model hidden CNN layer : Remove model bias

$$directional\,derivative = \frac{\partial\, output_{apron}}{\partial\, X_{AnyLayer}} \cdot \overrightarrow{woman}$$

The ‘apron’ predictions was positively correlated with respect to the ‘woman’ concept directional derivative

Interpretability Beyond Feature Attribution: Quantitative Testing with Concept Activation Vectors (TCAV), 2017

Concept activation of mnist model hidden CNN layer : Inquire about model learning

- Train image classifier with captioned images (right)
- Concept directional derivative shows sensitivity of logit output to
  i). Image or
  ii). Captions

cab image with caption

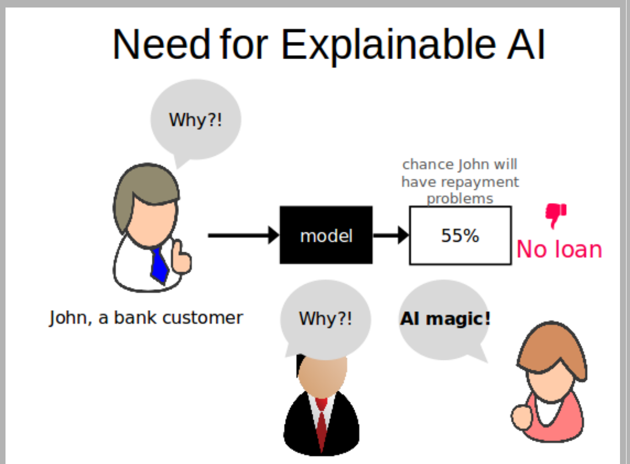
Interpretability Beyond Feature Attribution: Quantitative Testing with Concept Activation Vectors (TCAV), 2017

Draw backs of local methods

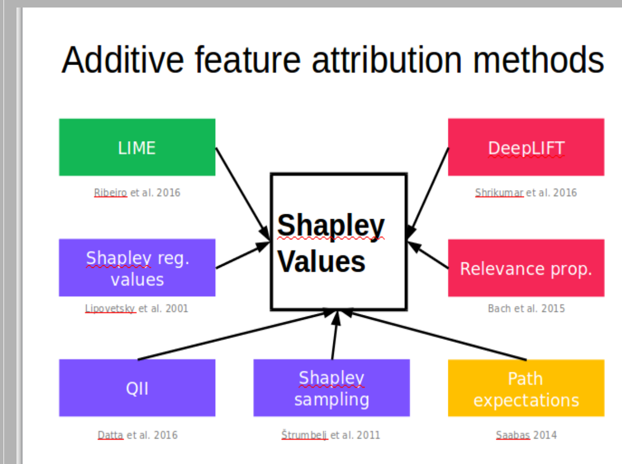
- Indirect – post-processing of model to yields insights

Summary

1.

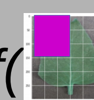
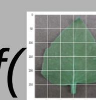


2.

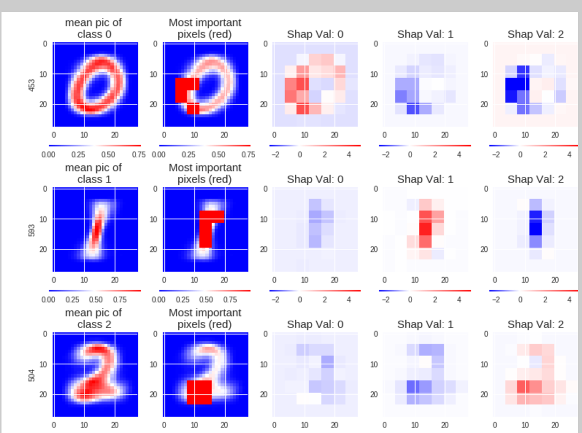


3. Intuition

$$g(z') = \sum_{i=1}^{M} \phi_i$$

φ_{pink} = weight_avg(f() − f())

4. Analysis mnist



5. Drawbacks

6. Gradient based methods

$$\frac{\partial J}{\partial X} \cdot \overrightarrow{concept}$$

References

- Scotts slides https://github.com/slundberg/shap/blob/master/docs/presentations/NIPS%202017%20Talk.pptx
- A Unified Approach to Interpreting Model Predictions(2017), Scott Lundberg, Su-In Lee
- Analysis of regression in game theory approach (2001),Stan Lipovetsky, Michael Conklin
- Interpretability Beyond Feature Attribution: Quantitative Testing with Concept Activation Vectors (TCAV), 2017