

Explainable AI : Shapley Values and other stuff

A Unified Approach to Interpreting Model Predictions

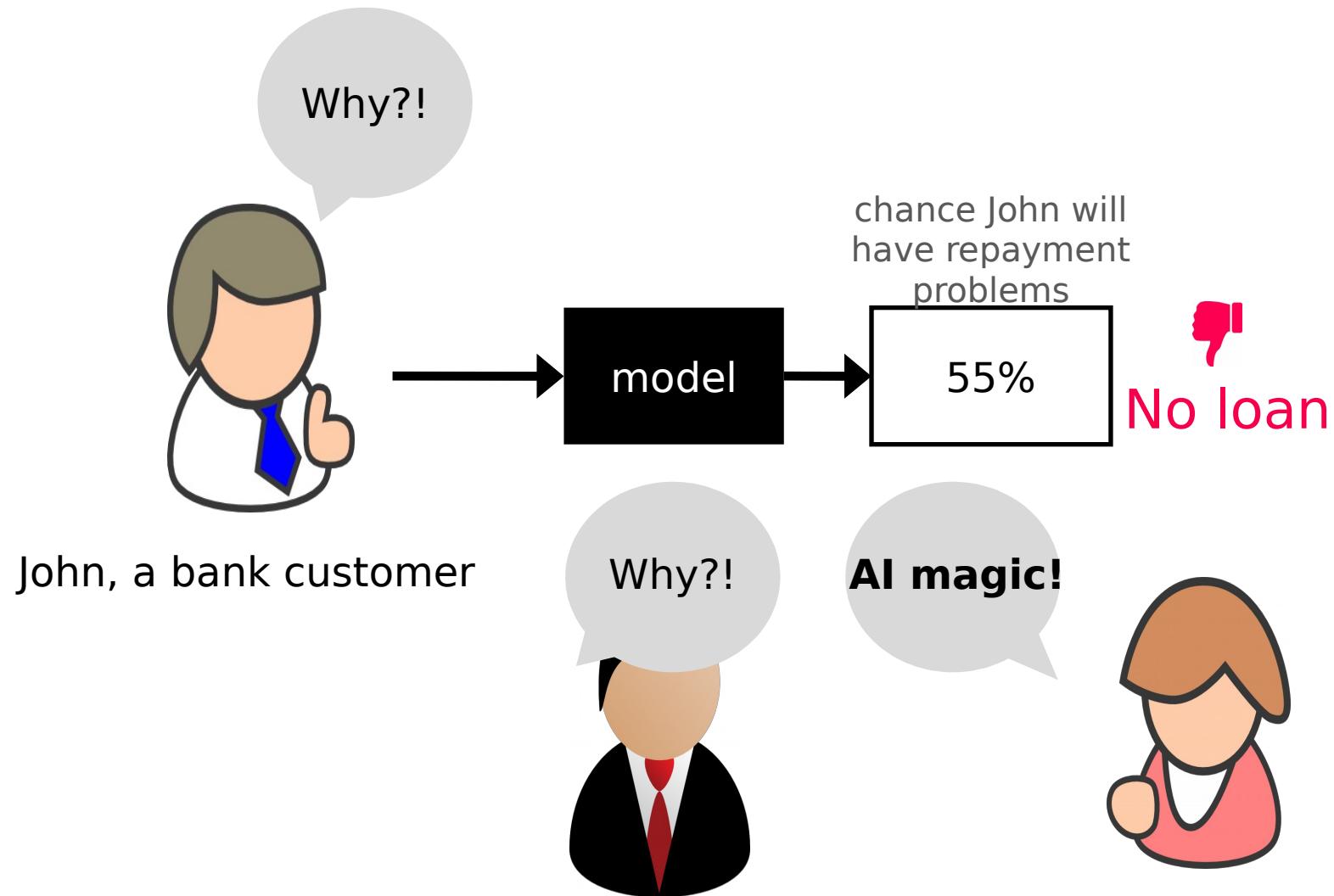
Scott Lundberg, Su-In Lee

https://colab.research.google.com/github/leexxa90/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, now in Crop analytics

Need for Explainable AI



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

A screenshot of a Twitter post from user @pmddomingos. The post features a profile picture of Pedro Domingos, the name "Pedro Domingos" in bold, and the handle "@pmddomingos". To the right of the handle is a blue Twitter bird icon. The tweet itself reads: "Starting May 25, the European Union will require algorithms to explain their output, making deep learning illegal." Below the tweet is the timestamp "11:59 AM - Jan 29, 2018". At the bottom left are engagement metrics: 344 likes (indicated by a heart icon) and 249 people talking about the tweet (indicated by a speech bubble icon). A small info icon is located at the bottom right of the tweet area.

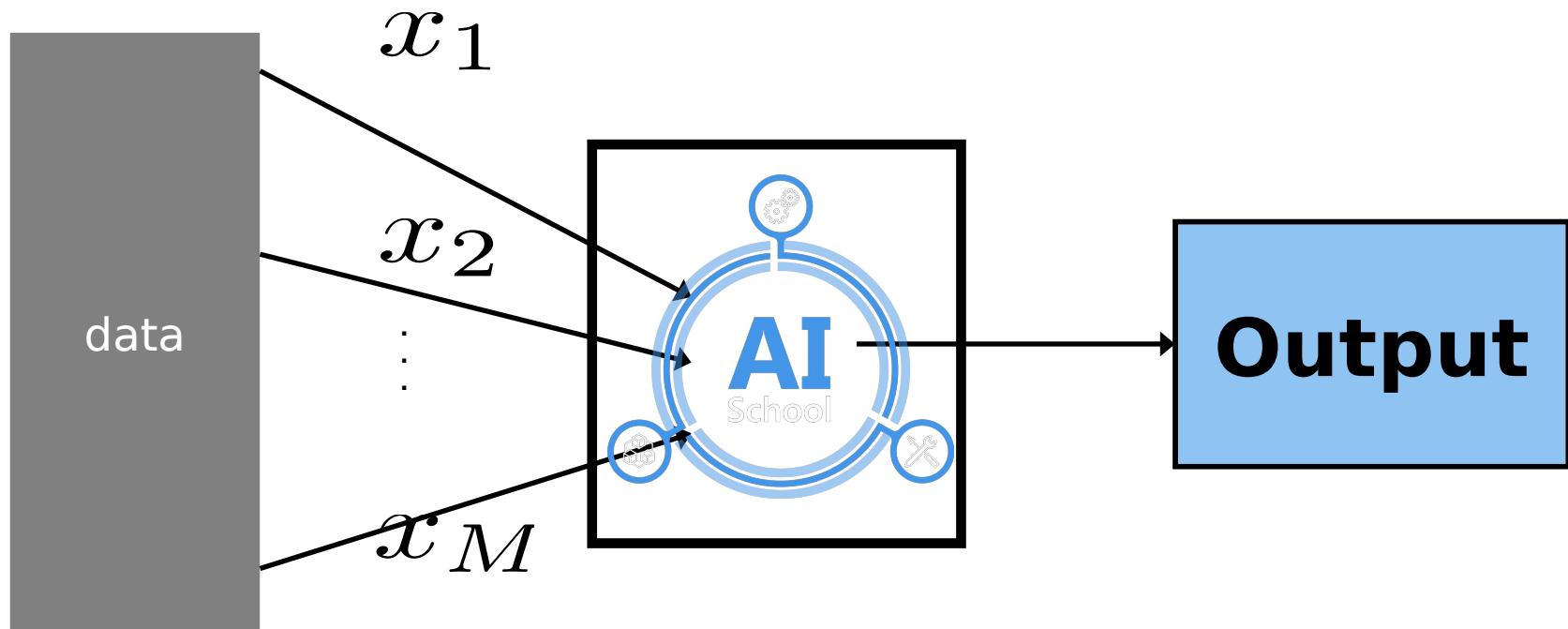
Starting May 25, the European Union will require algorithms to explain their output, making deep learning illegal.

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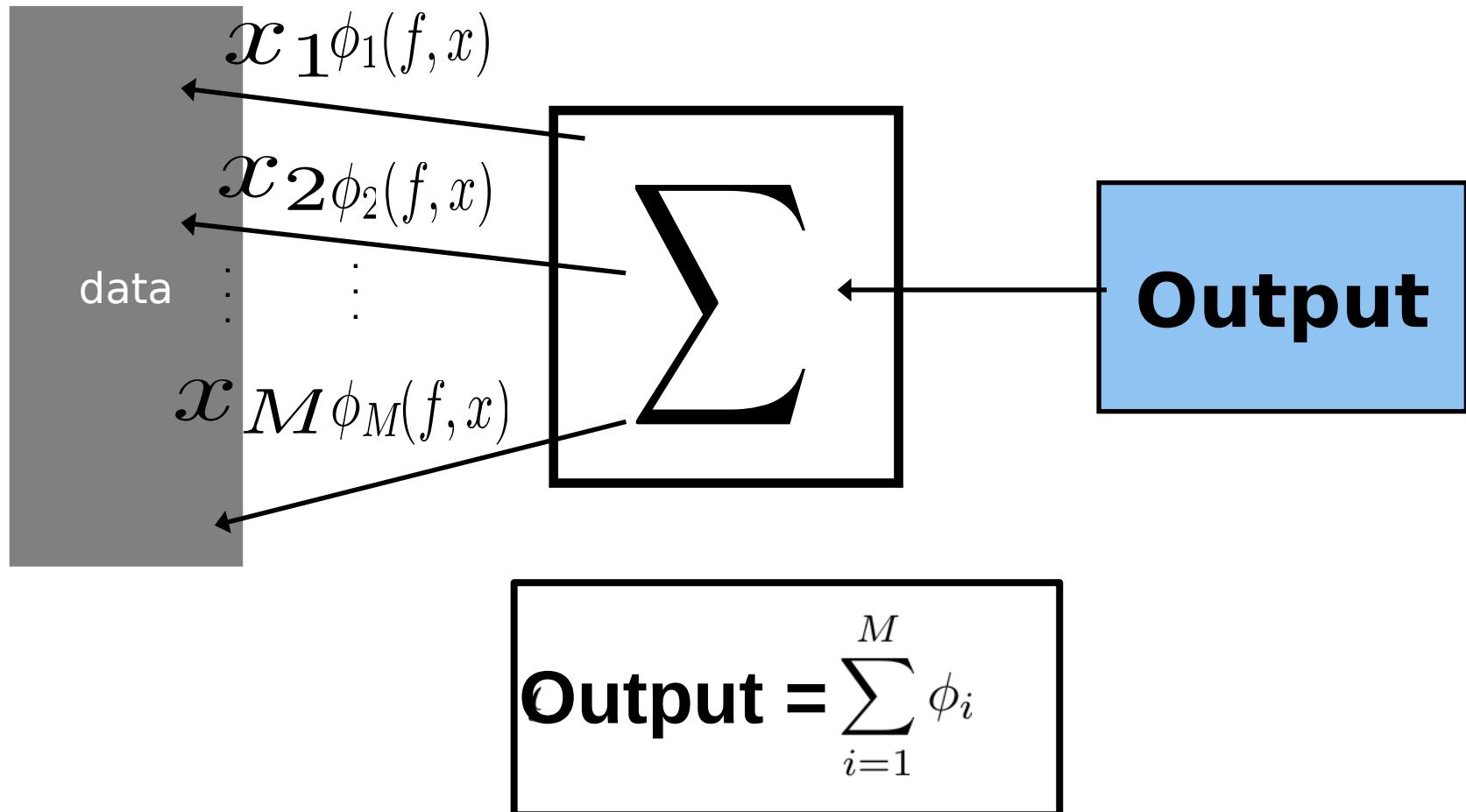
344 249 people are talking about this

Cognitive, Human-Like, Empathetic & Explainable Machine-Learning (CHEEM)

Complicated AI Model



Explainable model: Additive feature attribution model



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

Additive feature attribution methods

LIME

Ribeiro et al. 2016

Shapley reg.
values

Lipovetsky et al. 2001

QII

Datta et al. 2016

$$\sum$$

DeepLIFT

Shrikumar et al. 2016

Relevance prop.

Bach et al. 2015

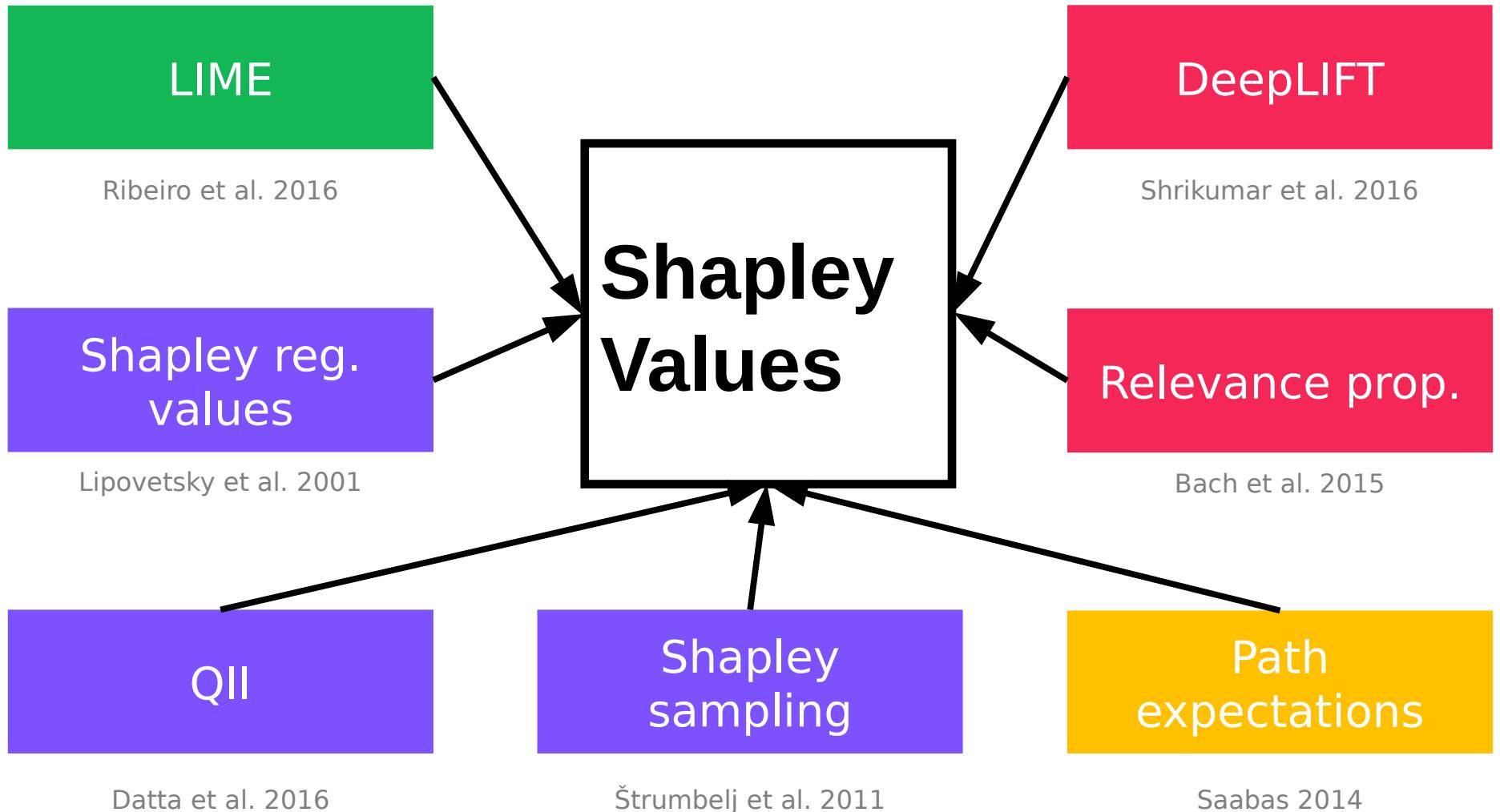
Shapley
sampling

Štrumbelj et al. 2011

Path
expectations

Saabas 2014

Additive feature attribution methods



SHapley Additive exPlanation - (SHAP) values (1)



Base rate

Prediction for John

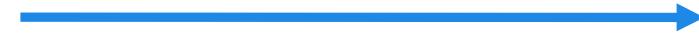
20%

55%

0
↓

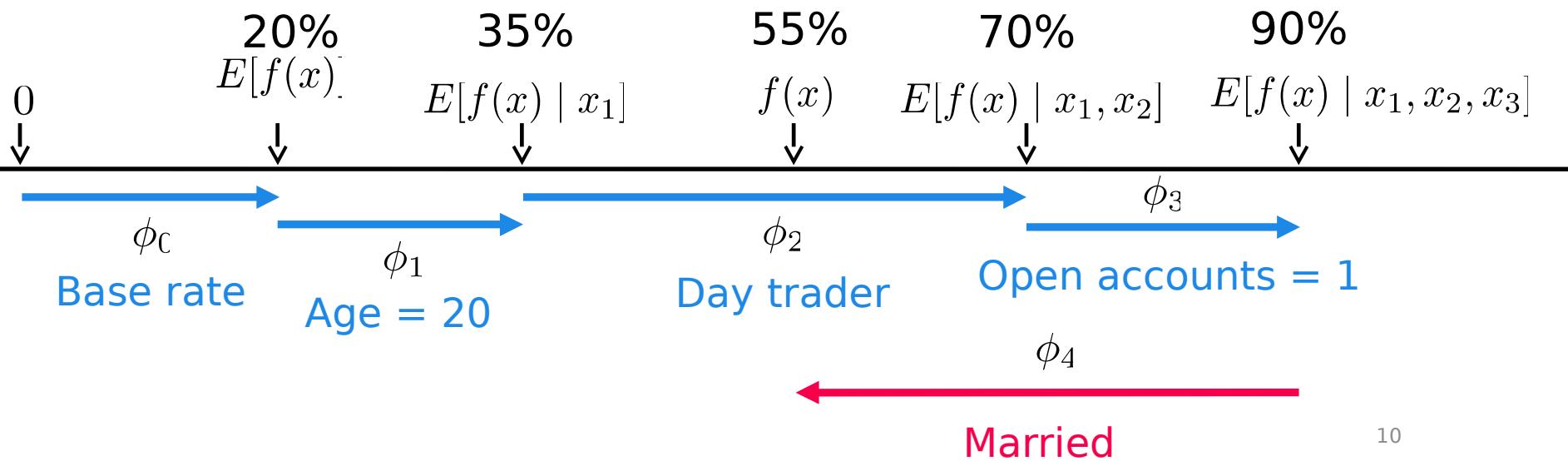
$E[f(x)]$
↓

$f(x)$
↓

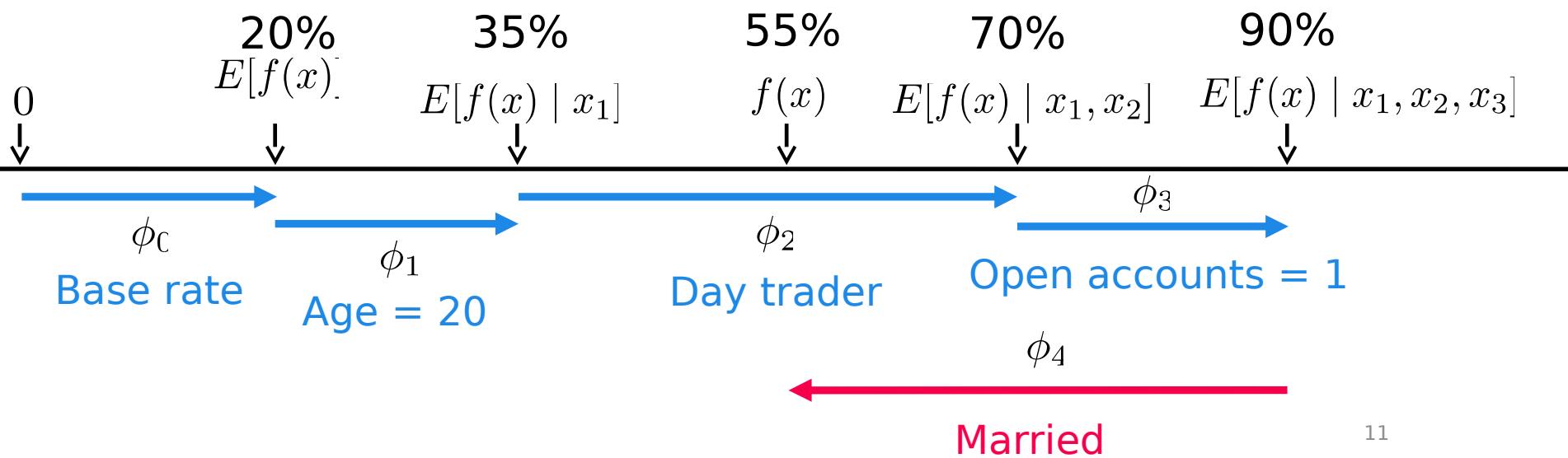


How did we get here?

SHapley Additive exPlanation (SHAP) values (2)



SHapley Additive exPlanation (SHAP) values (2)



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

- Train AI model

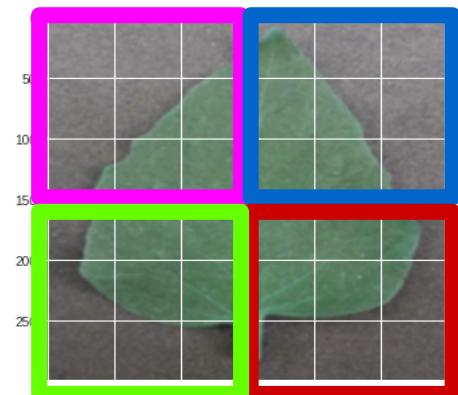
For each picture containing 4 superpixels

{ *Explain model :*

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

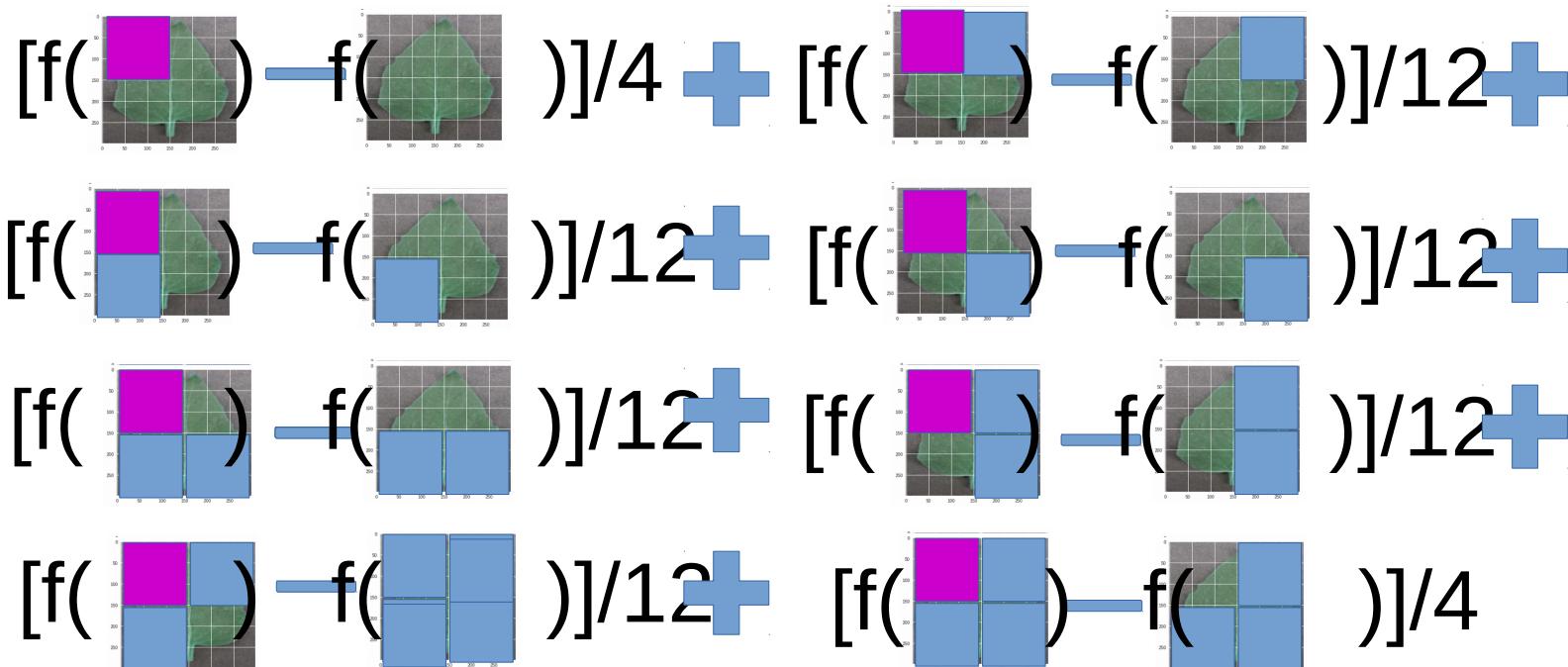
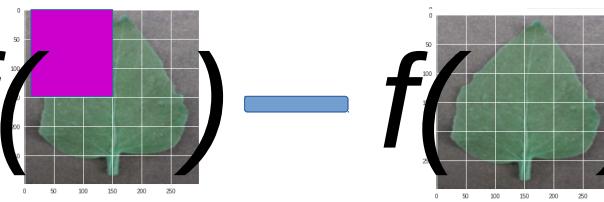
φ_i is the shapley value of the feature

}



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

$$\varphi_{pink} = \text{weight_avg}(f(\cdot) - f(\cdot))$$



Legend
Blue solid
squared are
mean-filled
super-pixels

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

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

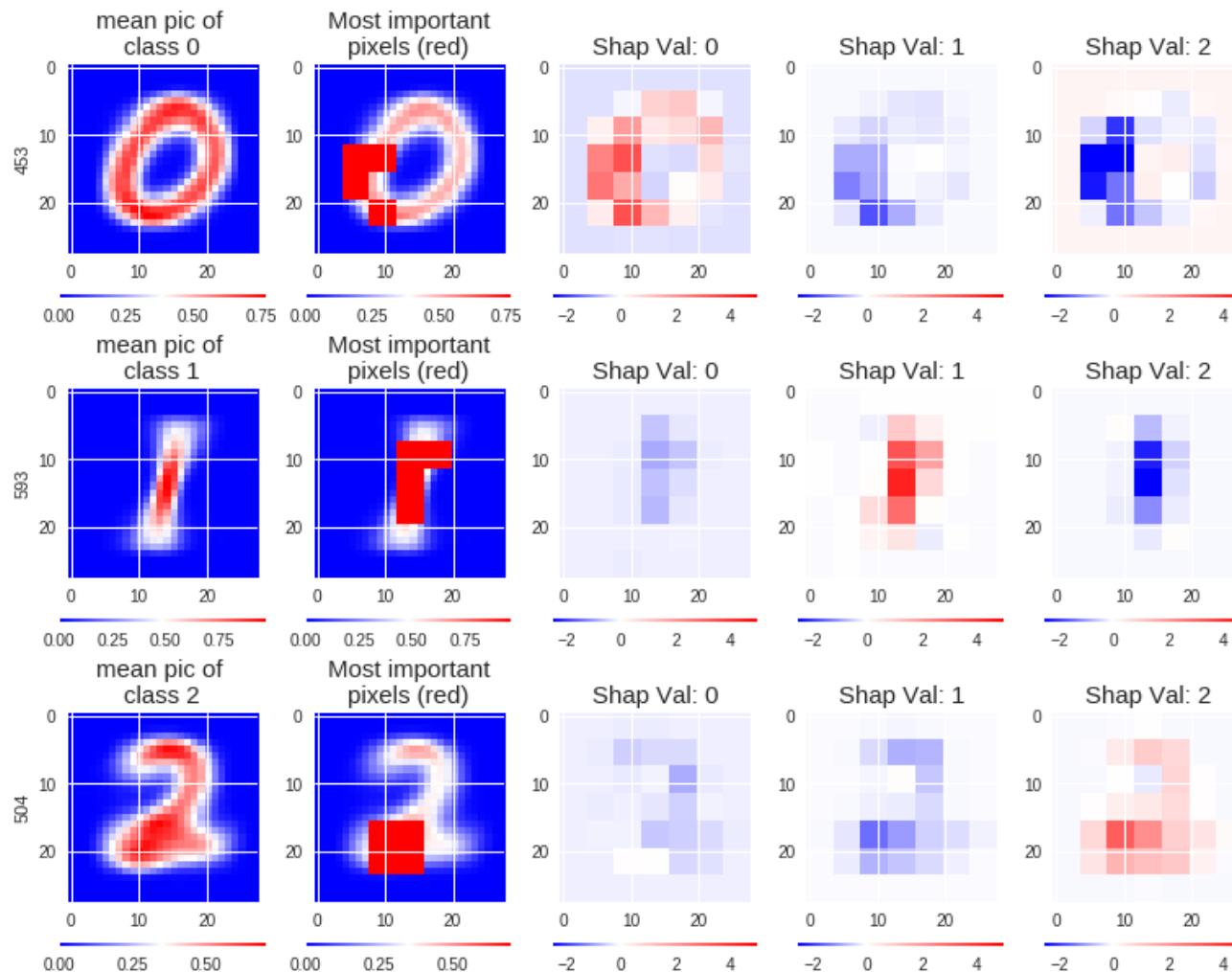
Refer to proof in paper for details, A Unified Approach to Interpreting Model Predictions

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 $7 \times 7 = 49$ superpixels for shapley value computation
 - Sample 7367 combinations of pixels
 - ~ all 1 mean-filled pixel images, ${}^{49}C_1 = 49$
 - ~ all 2 mean-filled pixel images, ${}^{49}C_2 = 1176$
 - ~ 33% of 3 mean-filled pixel images, ${}^{49}C_3 / 3 = 6142$
 - Calculate shapley values for each pixel using weighted regression, with g
- }

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

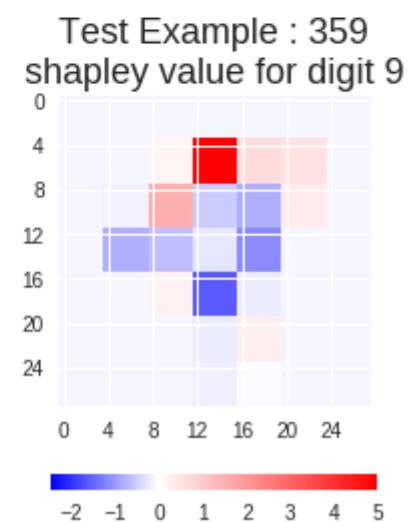
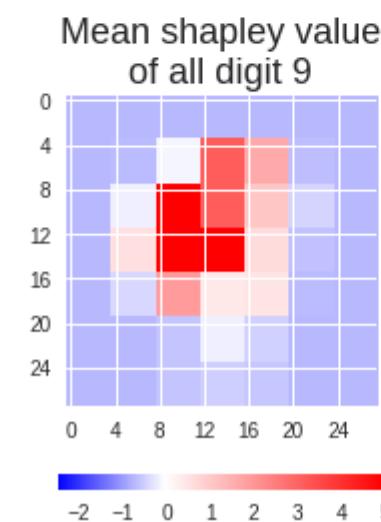
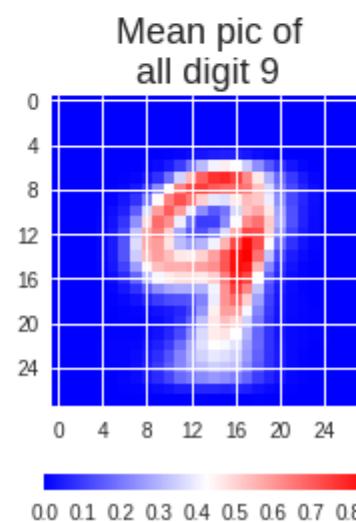
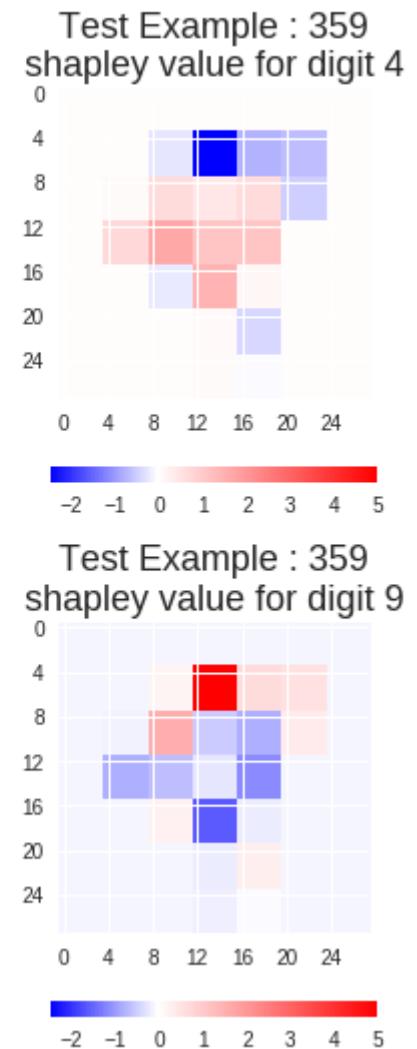
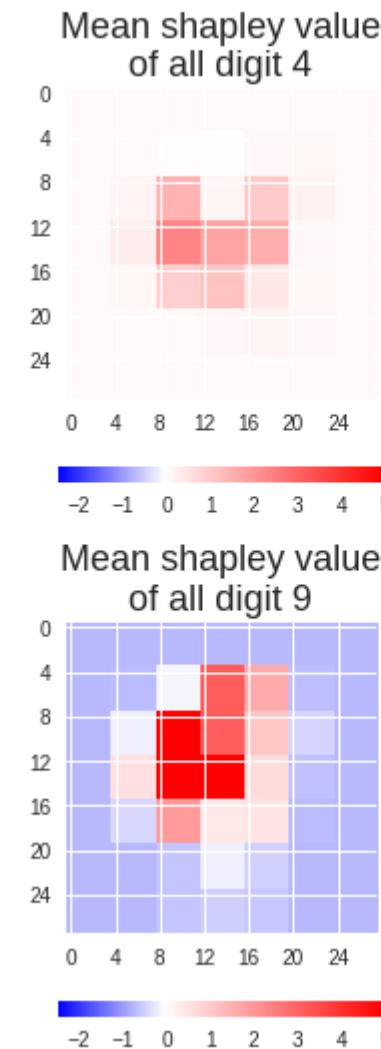
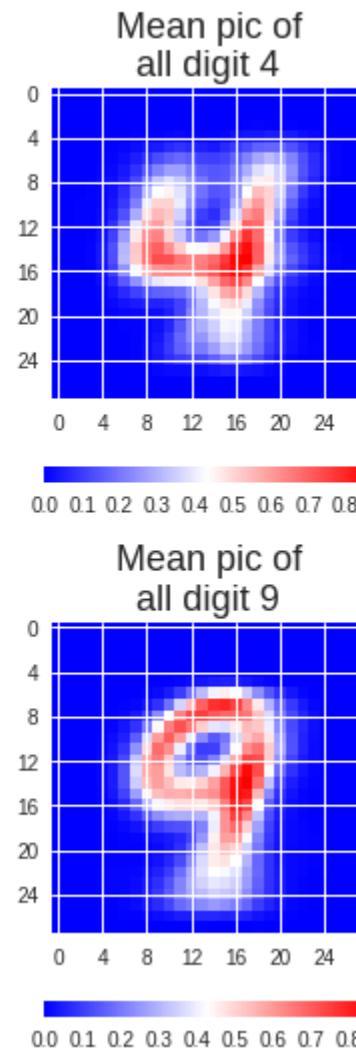
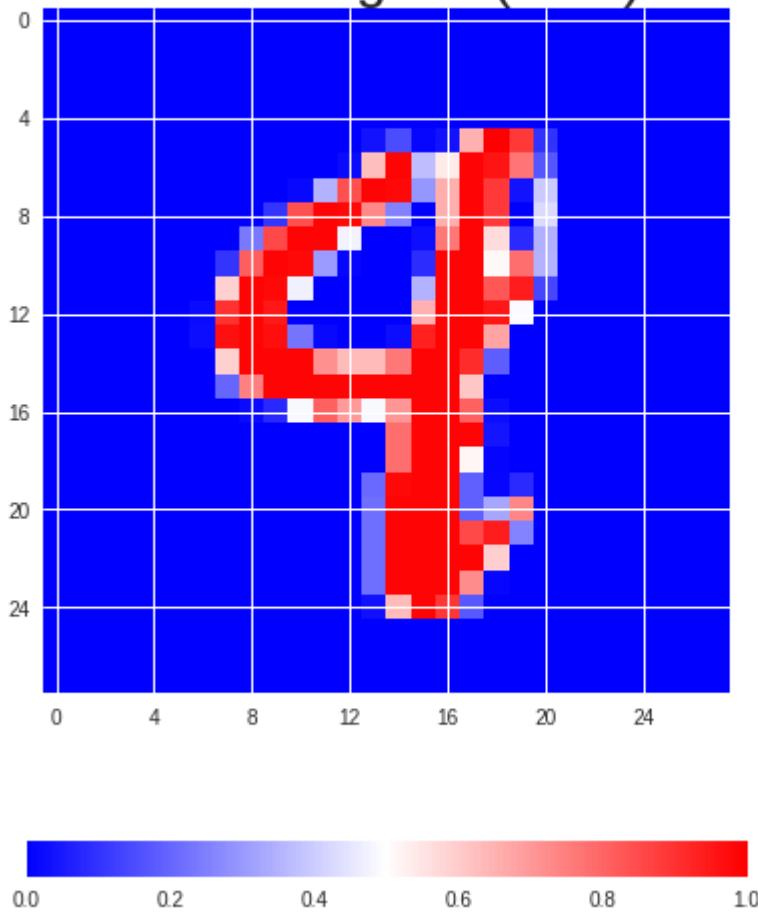
Applying to Mnist (2) – Global analysis



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

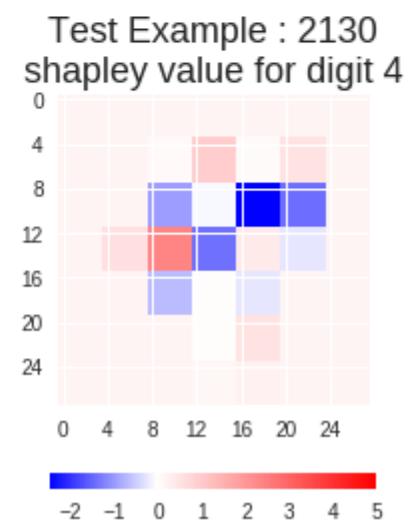
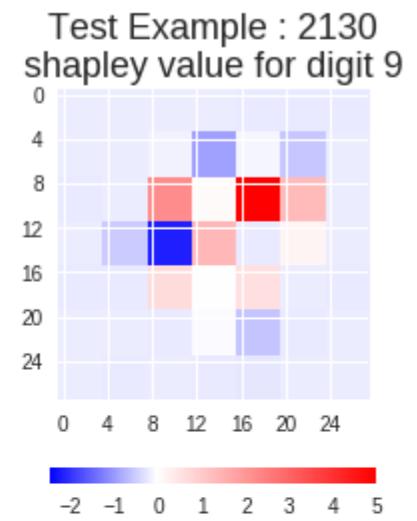
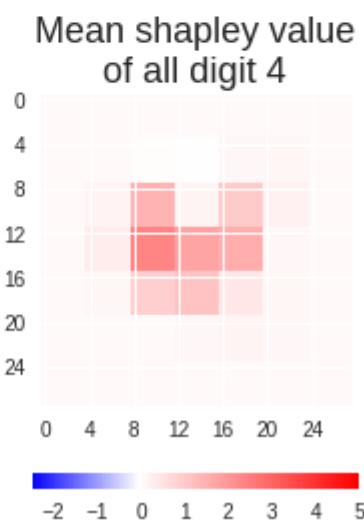
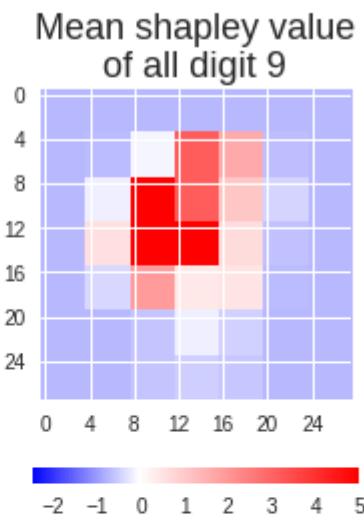
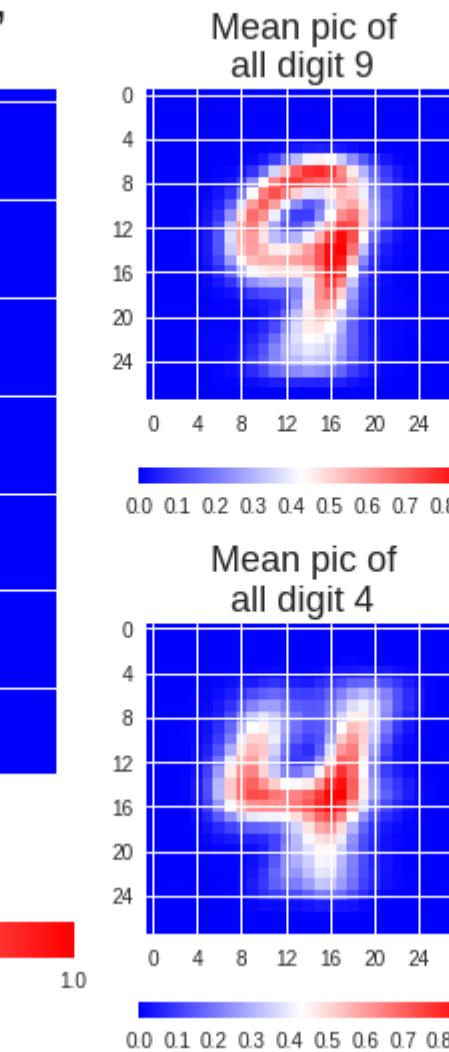
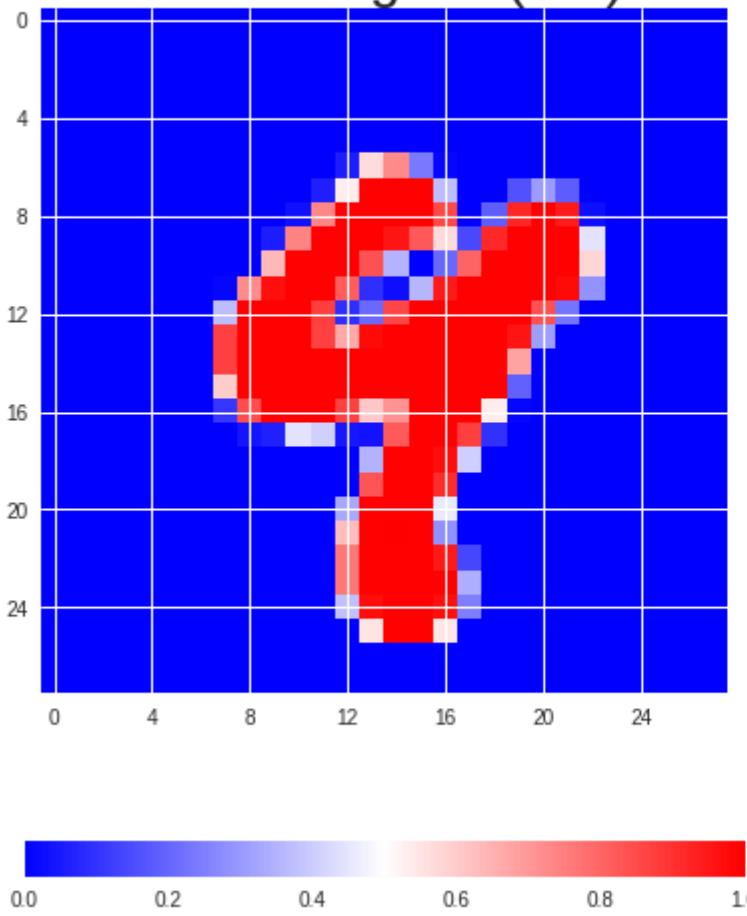
Test Example: 359

Predicted Digit: 4 (58%),
Actual Digit: 9 (40%)



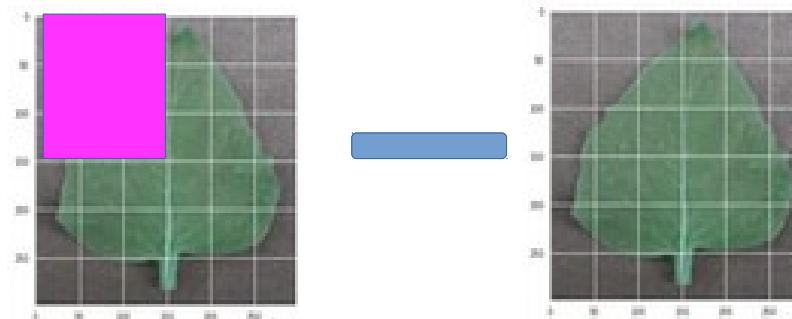
Applying to Mnist (3) – Individual analysis (b)

Test Example: 2130
Predicted Digit: 9 (93%),
Actual Digit: 4 (6%)

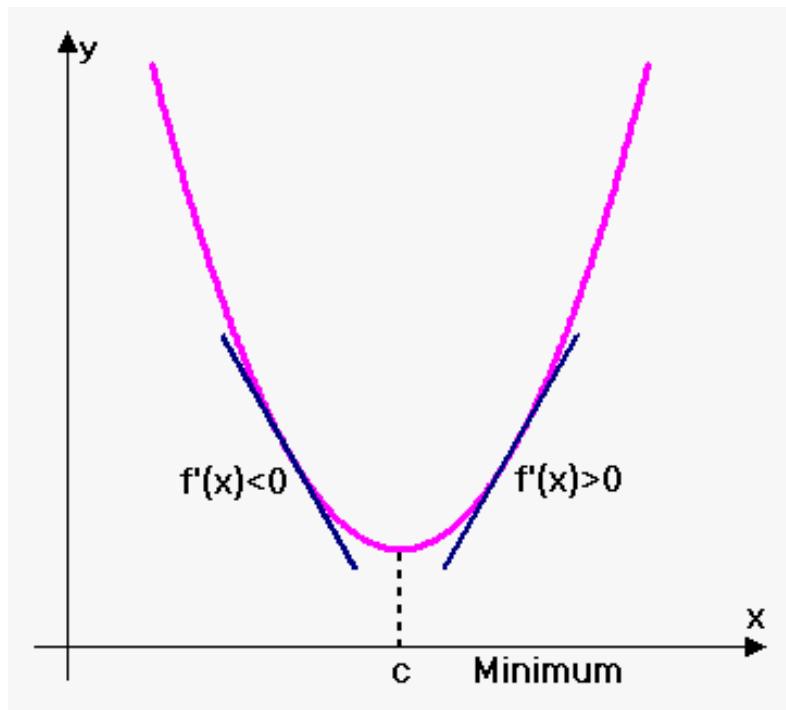


Drawbacks

- 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 ?



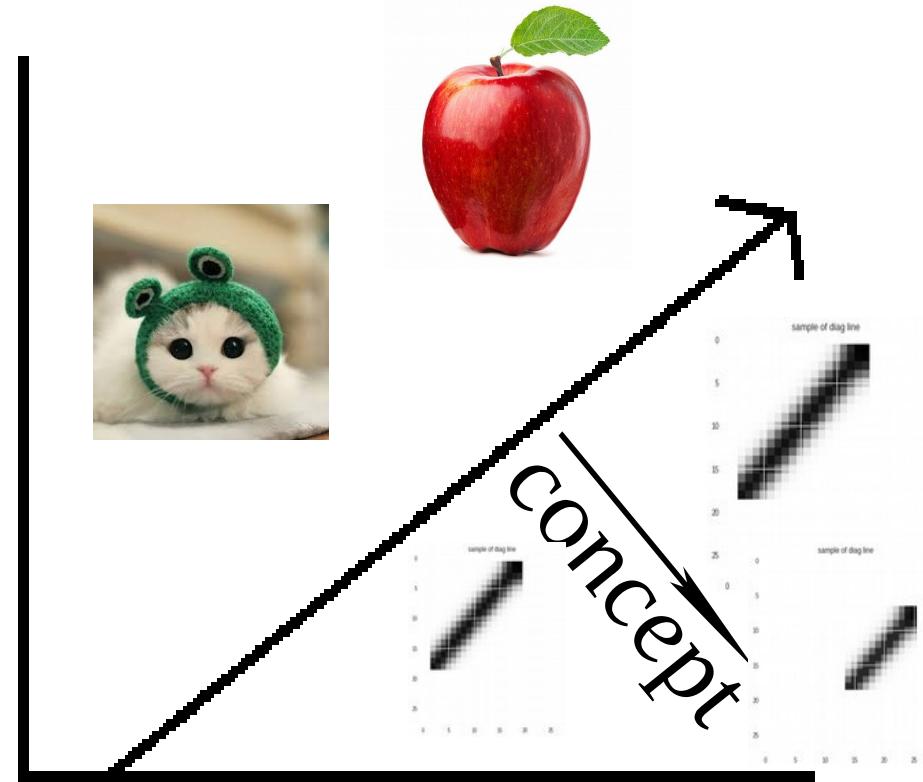
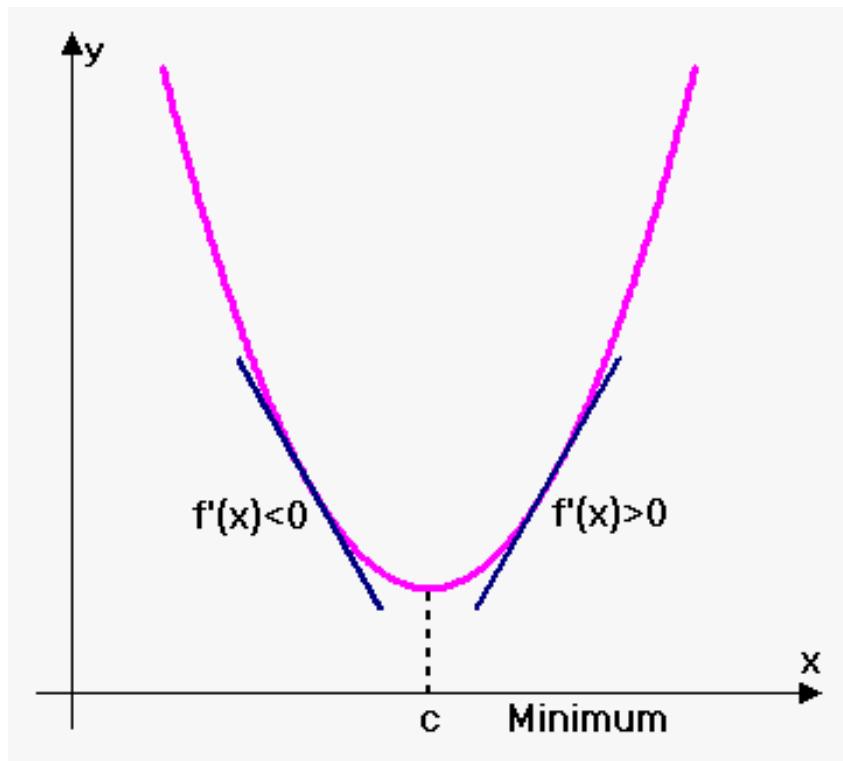
Gradient based methods



$$\frac{\partial J}{\partial X}.$$

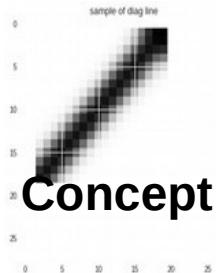
Gradient based methods

$$\text{directional derivative} = \frac{\partial \text{output}_i}{\partial X} \cdot \overrightarrow{\text{concept}}$$



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

Concept activation of mnist model hidden CNN layer



$$\text{directional derivative} = \frac{\partial \text{output}_i}{\partial X} \cdot \overrightarrow{\text{concept}}$$

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

Draw backs of local methods

- Global explanation != local explanation
- Example : Young blacks have higher death rates, while old blacks have lower death rates

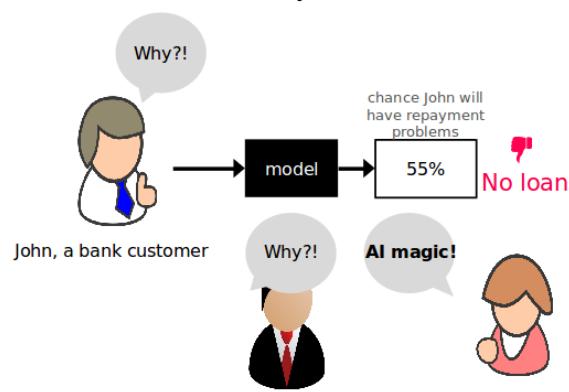
Explainable AI on insurance premium :

- *Because you are black, your price is higher, all things equal relative to your demographic (young, male)*
- *Because you are black, your price is lower, all things equal relative to your demographic (elderly, male)*
- Leads to distrust of the system

Summary

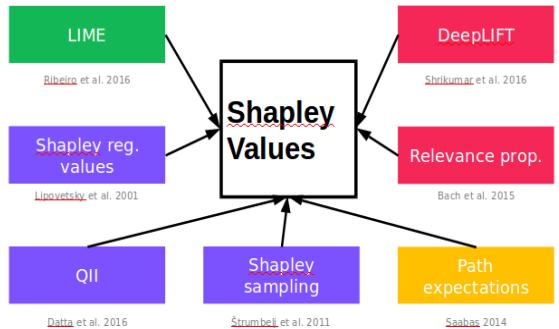
1.

Need for Explainable AI



2.

Additive feature attribution methods

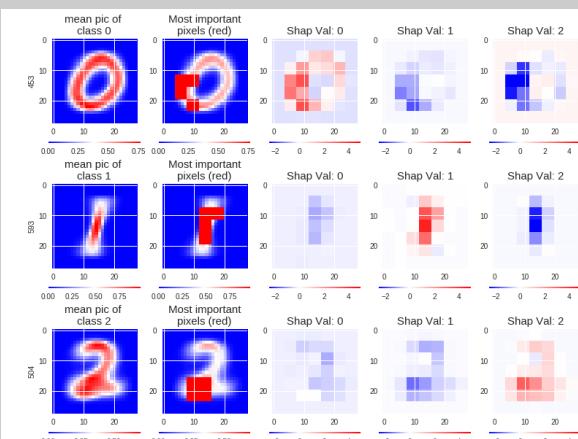


3. Intuition

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

$$\varphi_{pink} = weight_avg(f(\text{pink}) - f(\text{green}))$$

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