Explainable AI : Shapley Values

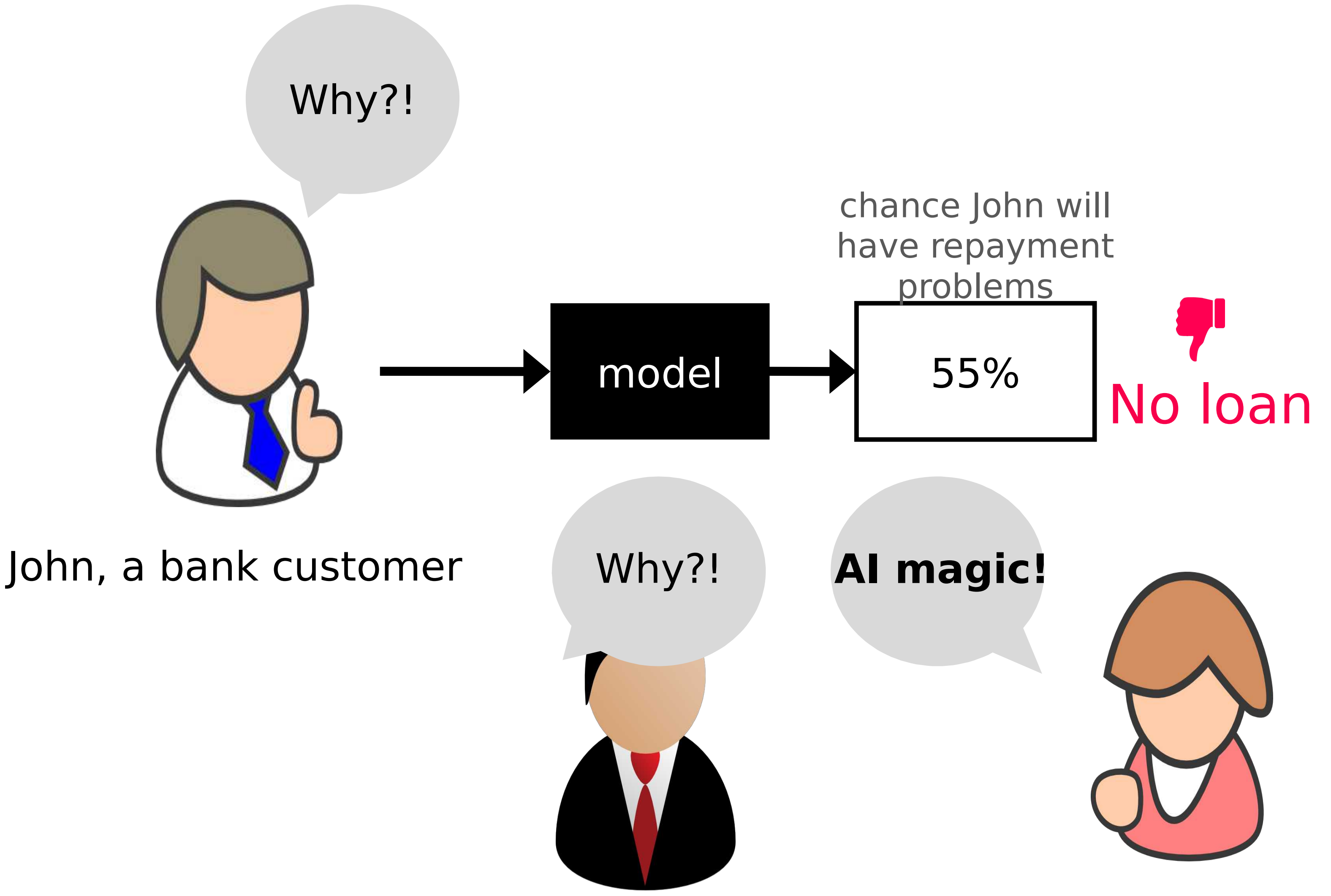
A Unified Approach to Interpreting Model Predictions
Scott Lundberg, Su-In Lee

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

Background on myself

- Graduated from NUS science 2015
- Working in A*STAR Bioinformatics Institute in areas of computational biology (2015-17) and crop analytics (2018 onwards)
- Attempted machine learning in areas of work and greatly helped by Deep Learning Developer's course
- Hobbies : Deep Learning, keeping fit, church

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

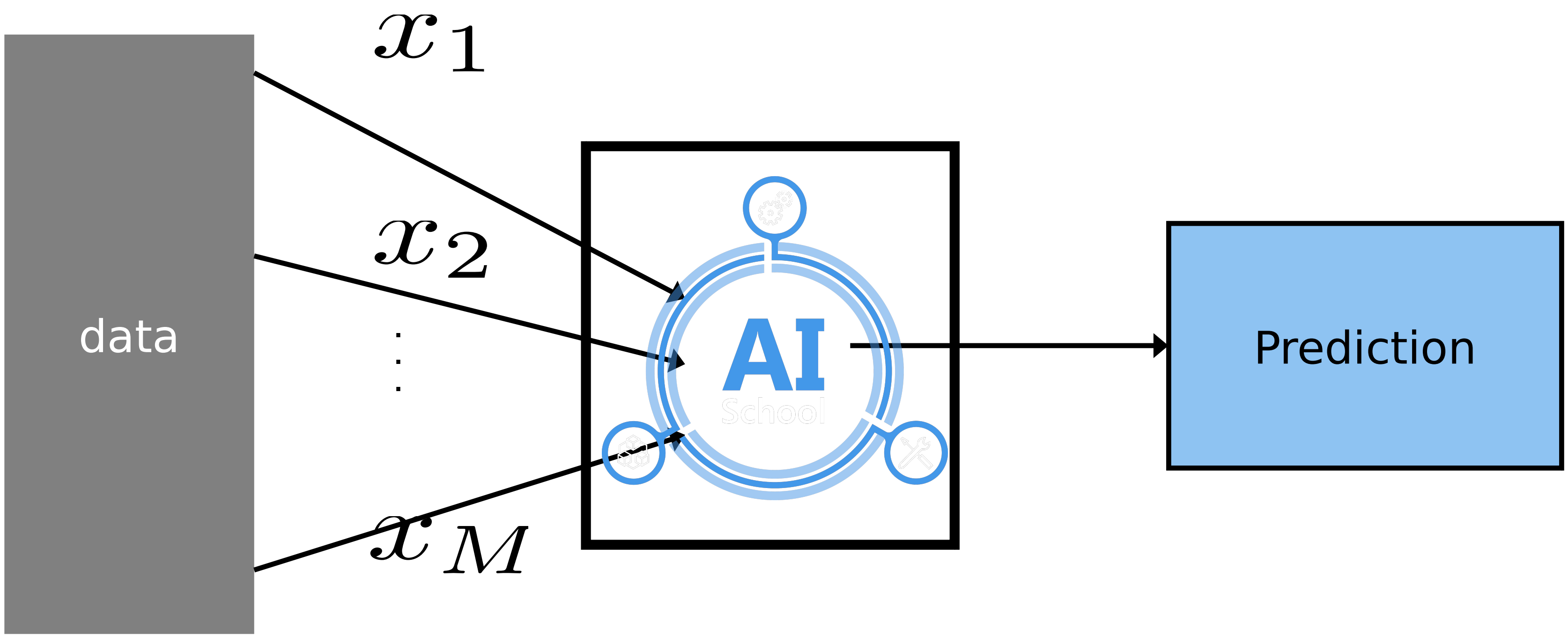
Starting May 25, the European Union will require algorithms to explain their output, making deep learning illegal.

11:59 AM - Jan 29, 2018

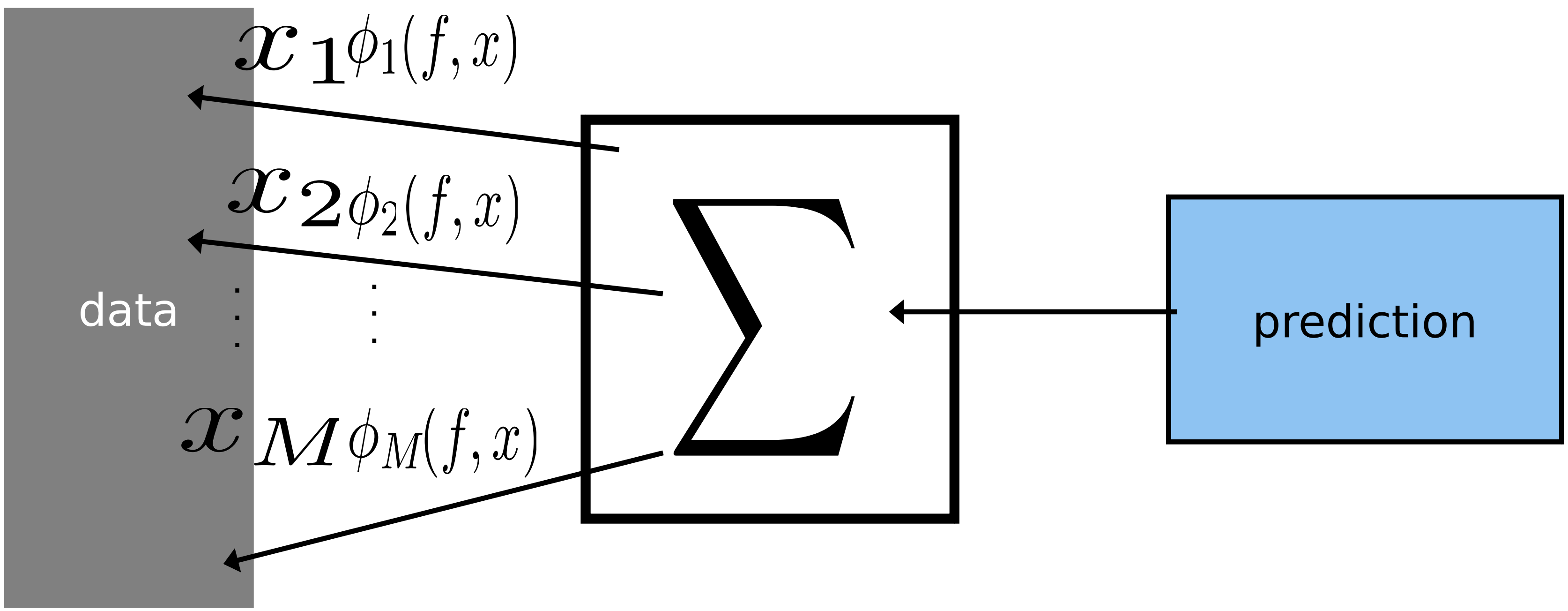
344 249 people are talking about this

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

Complicated AI Model



Explainable model: Additive feature attribution model



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

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

Σ

Shapley reg. values

Lipovetsky et al. 2001

Relevance prop.

Bach et al. 2015

QII

Datta et al. 2016

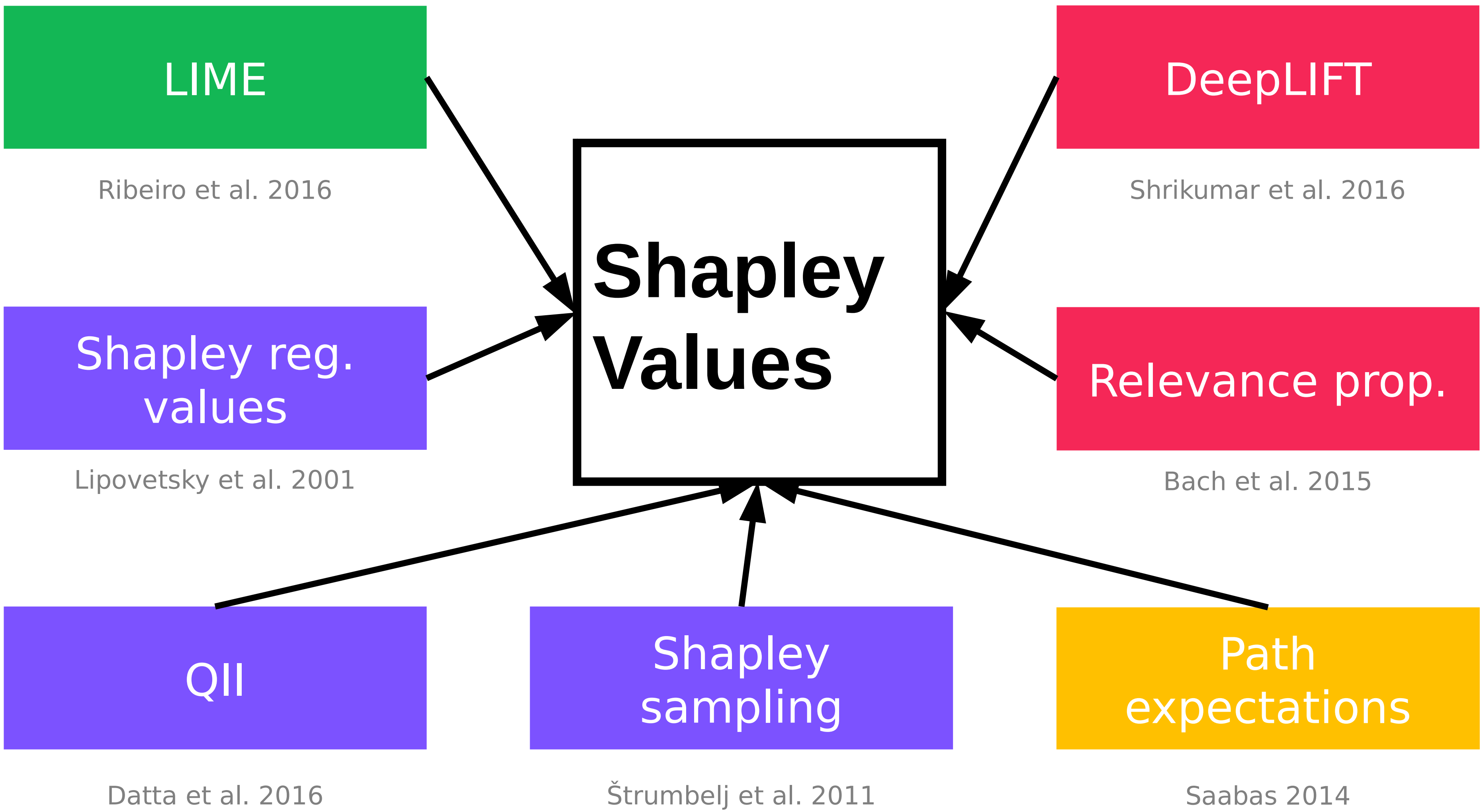
Shapley sampling

Štrumbelj et al. 2011

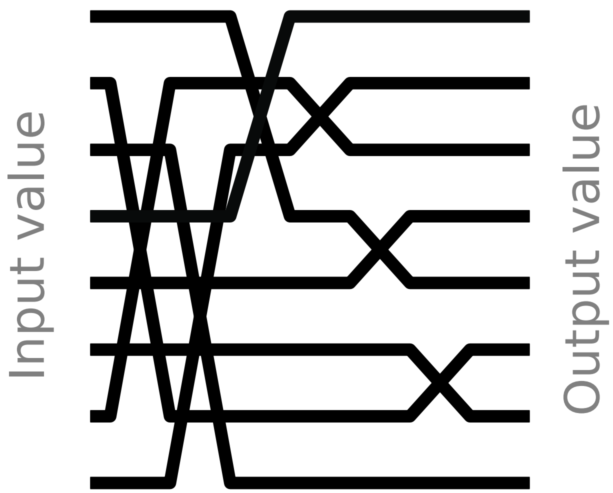
Path expectations

Saabas 2014

Additive feature attribution methods



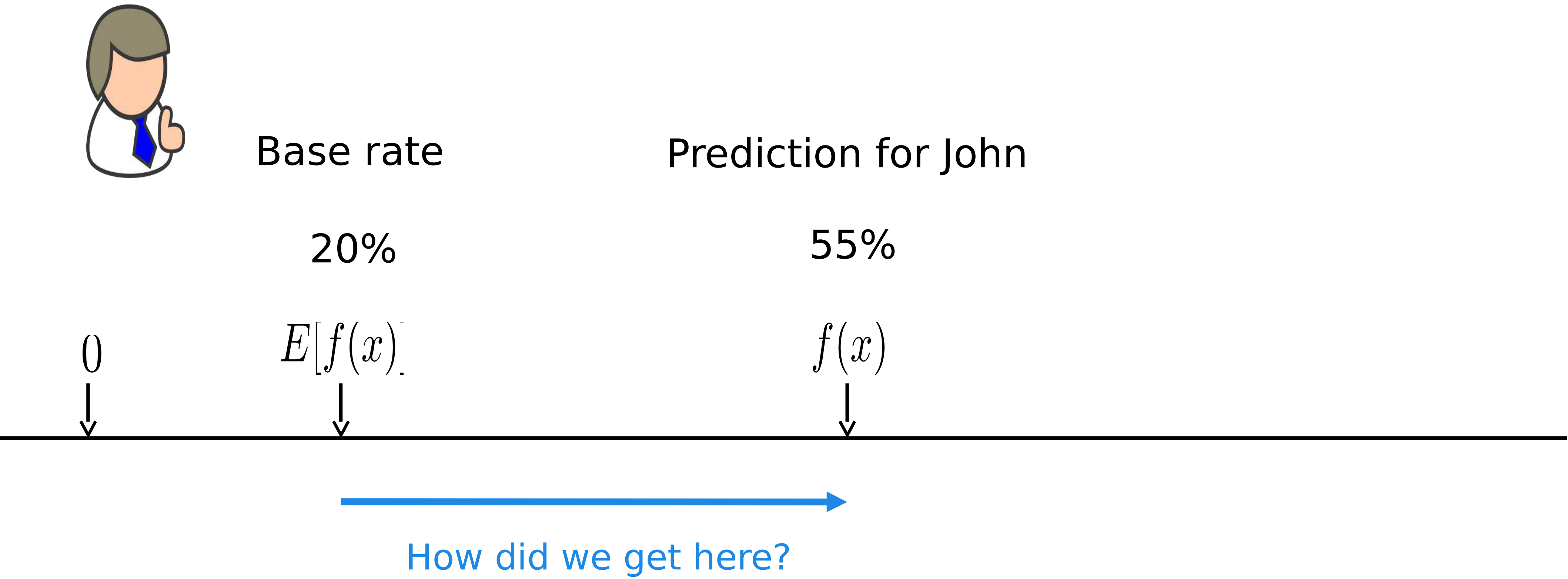
Why additive feature attribution methods may work



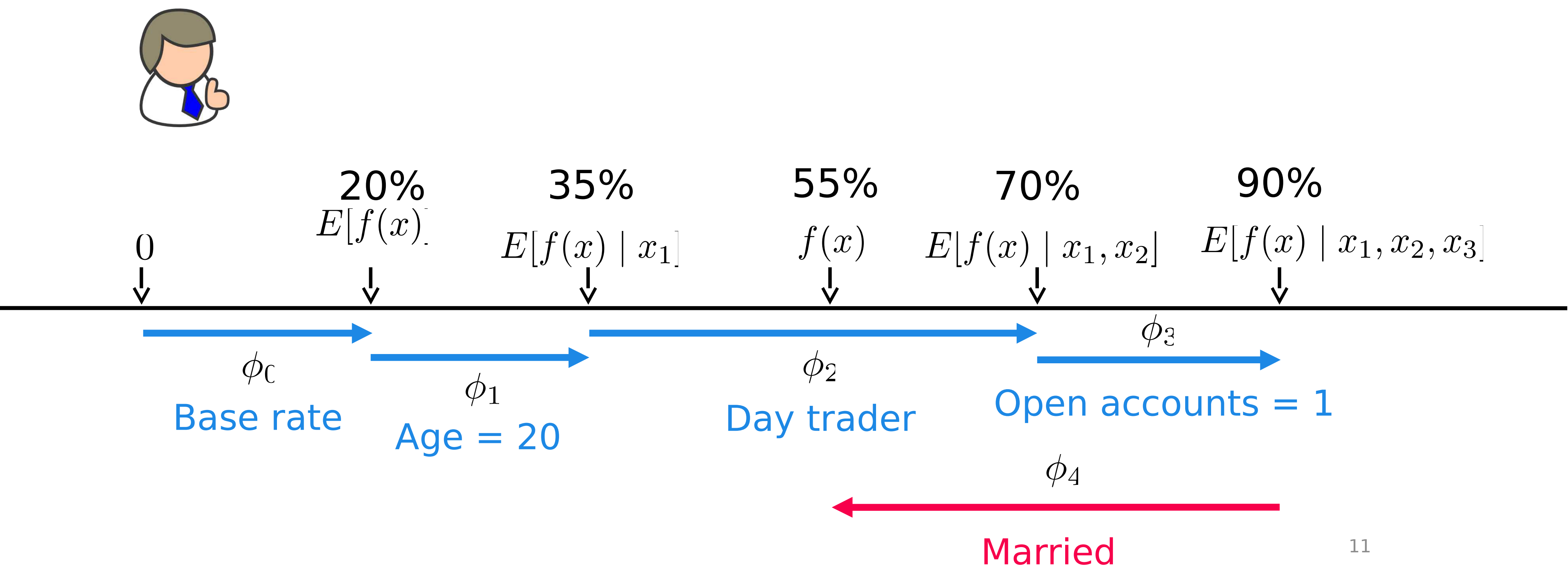
Complex models are inherently complex!

But a single prediction involves only a small piece of that complexity.

SHapley Additive exPlanation - (SHAP) values (1)



SHapley Additive exPlanation (SHAP) values (2)



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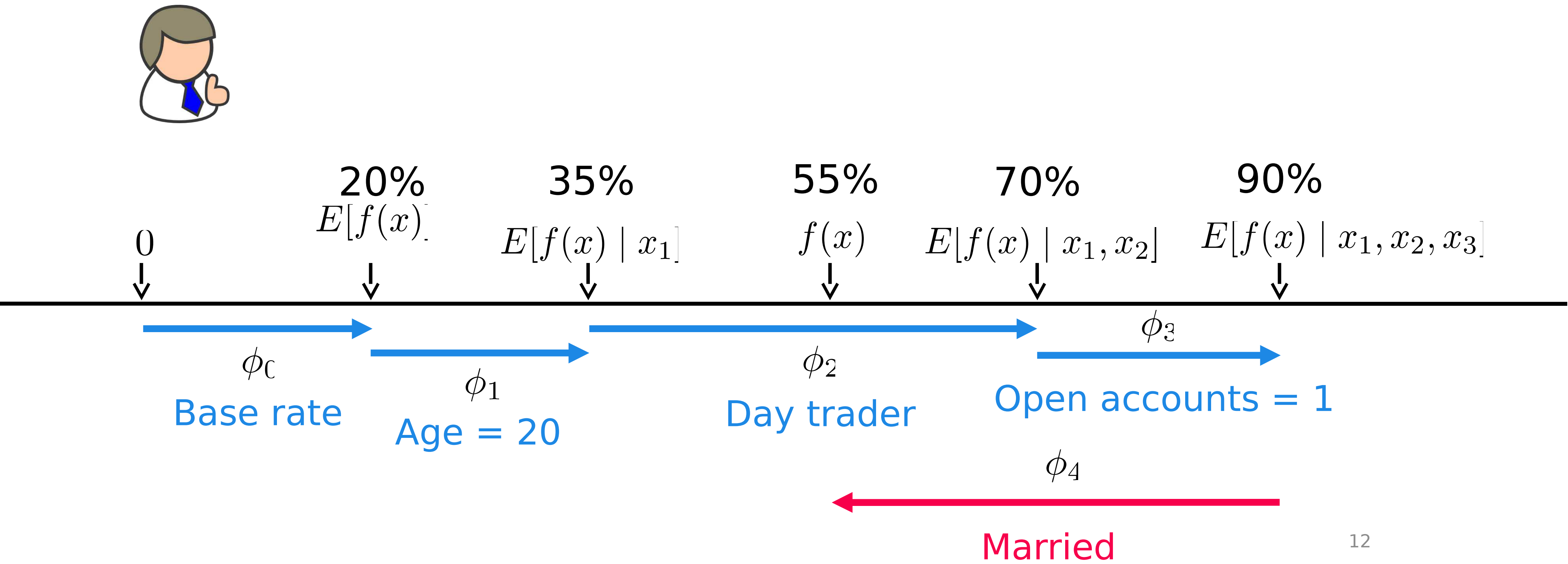


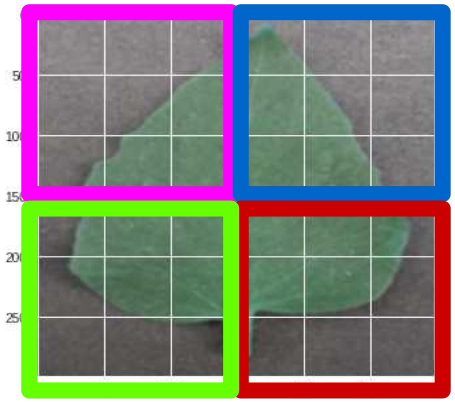
SHapley Additive exPlanation (SHAP) values (3) – Computation

- Train AI model

For each data point , containing 4 superpixels

{ Explain model =

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

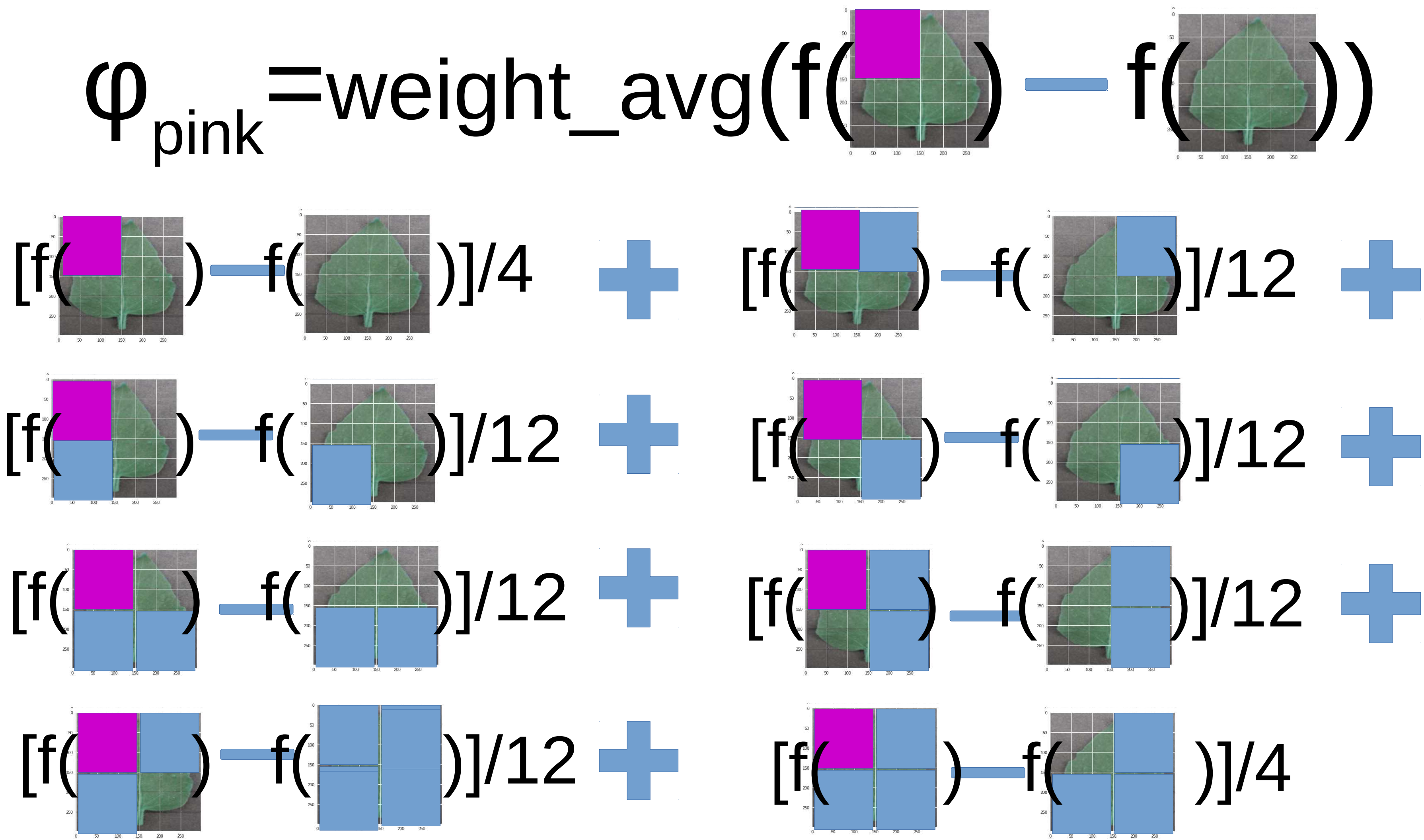


φ_i is the shapley value of X_i

and X_i is a feature

}

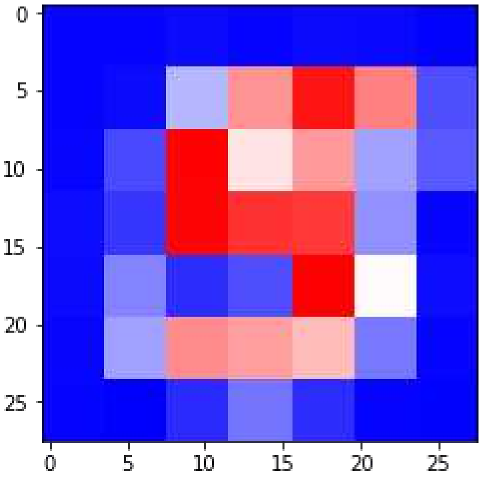
SHapley Additive exPlanation (SHAP) values (4) – computation



Applying to Mnist (1)

- Mnist model with 4 convolutional layers and 2 dense layers.
- Accuracy is 99.6%
- for each test image {
  - Split image to 7*7 = 49 superpixels for shapley value computation
  - Sample 7367 combinations of pixels
    ~ all -1 pixel images, ${}^{49}C_1 = 49$
    ~ all -2 pixel images, ${}^{49}C_2 = 1176$
    ~ 33% of -3 pixel images, ${}^{49}C_3/3 = 6142$
  - Calculate shapley values for each pixel using weighted regression

  }

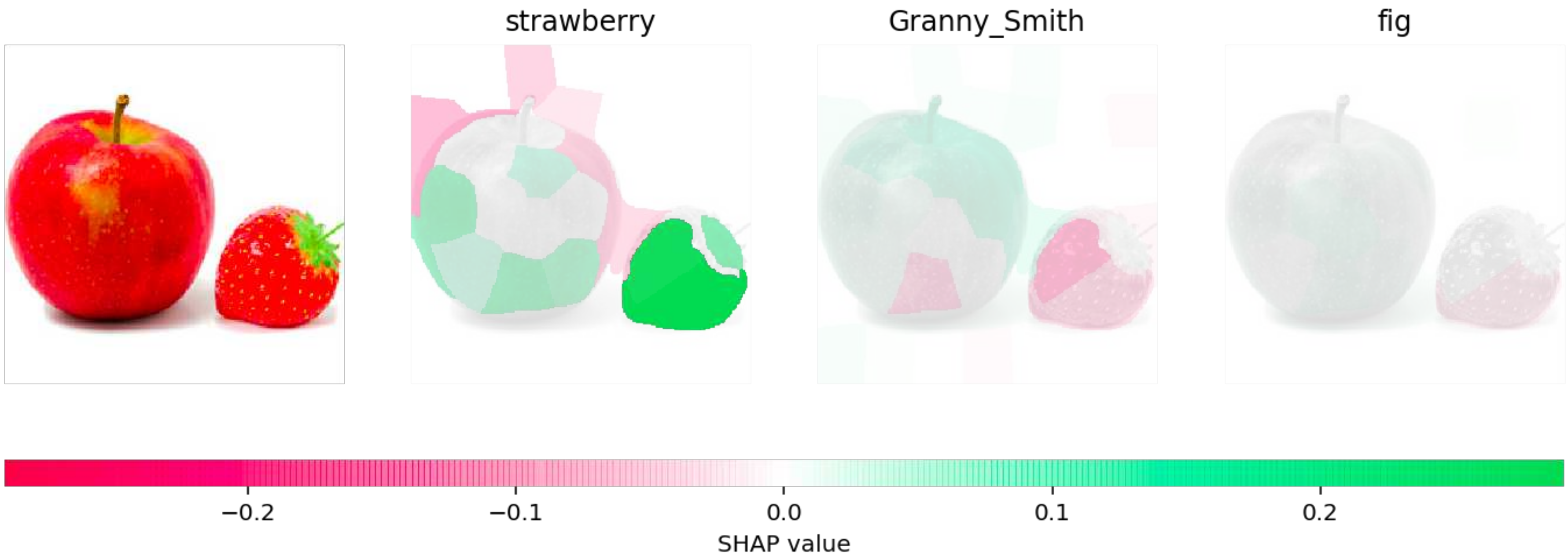


SHapley Additive exPlanation (SHAP) values (5) – solved using weighted linear regression

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

X_i is the feature binary vector of X, 2^m * m matrix
W is shapley kernel weights, m * m diagonal matrix
y is model output for each x, 2^m column vector
Where m refers to number of features

Another Example : VGG16



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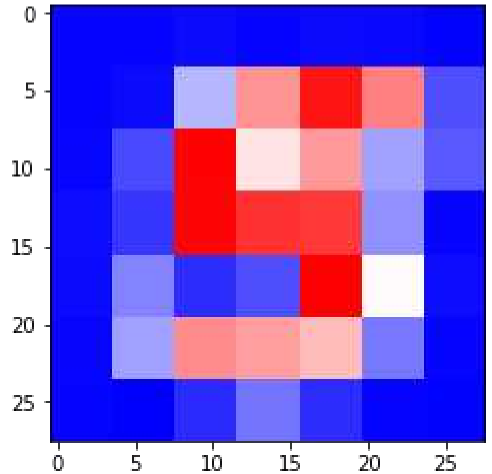
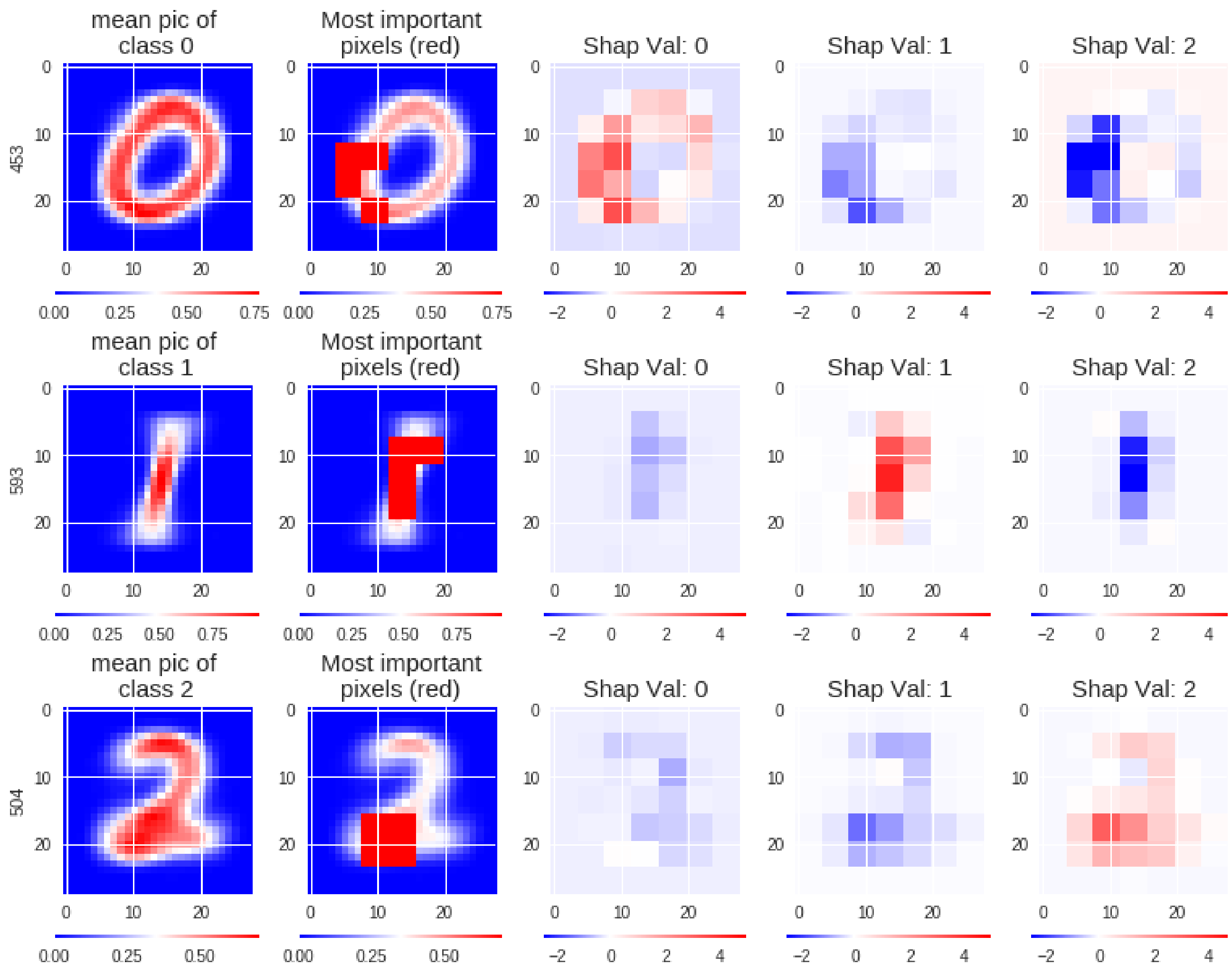
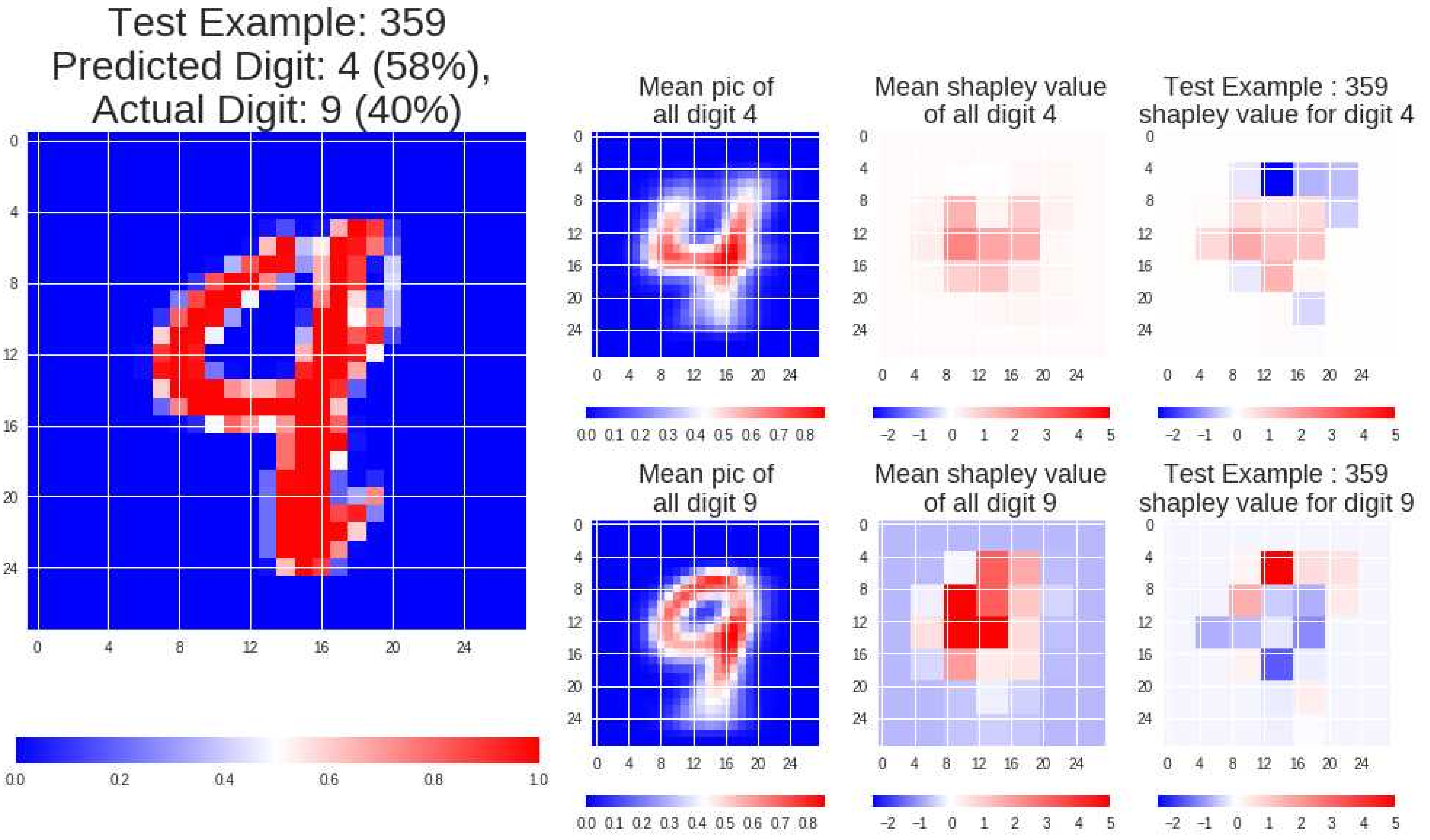


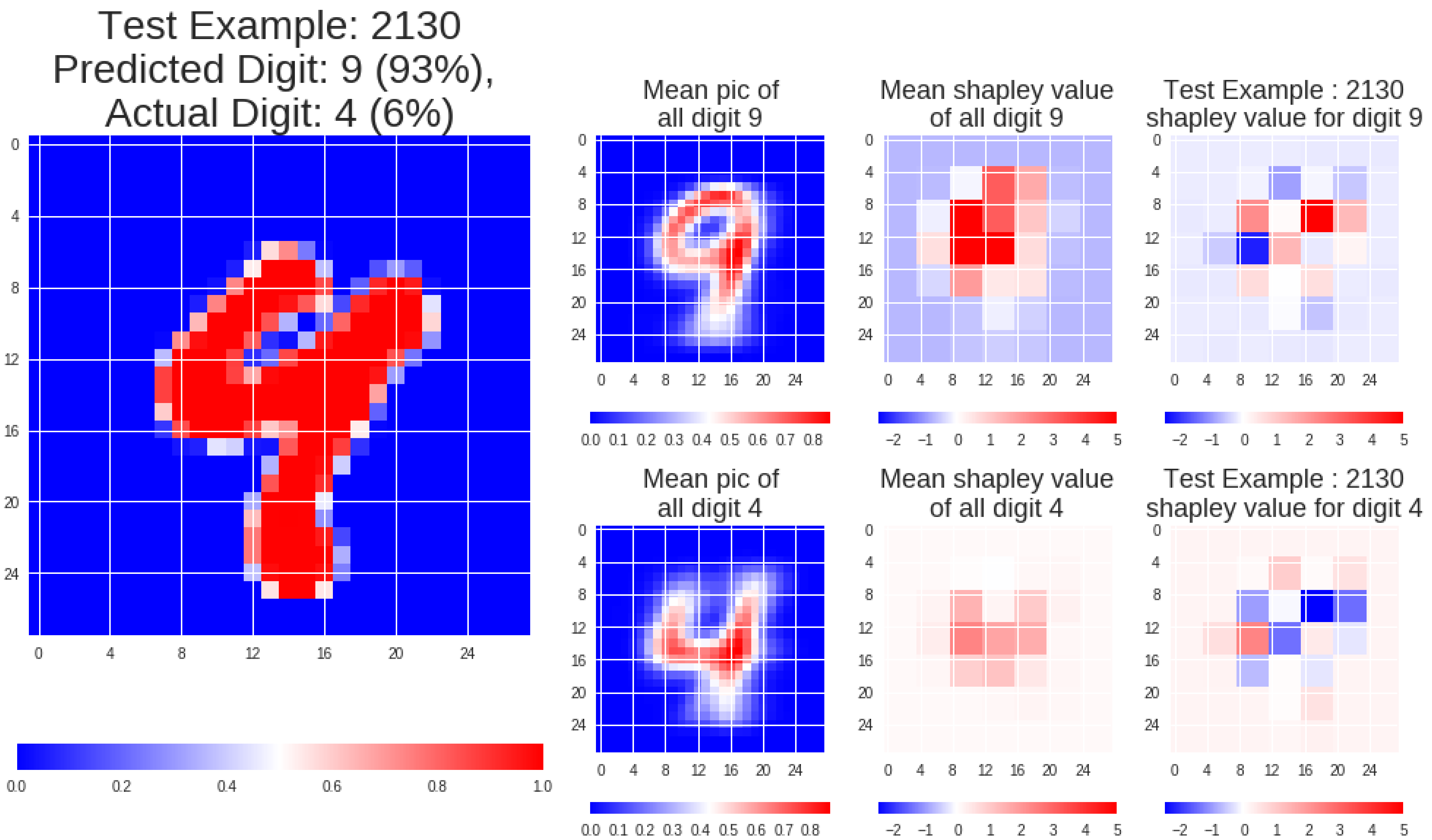
Applying to Mnist (2) – Global analysis



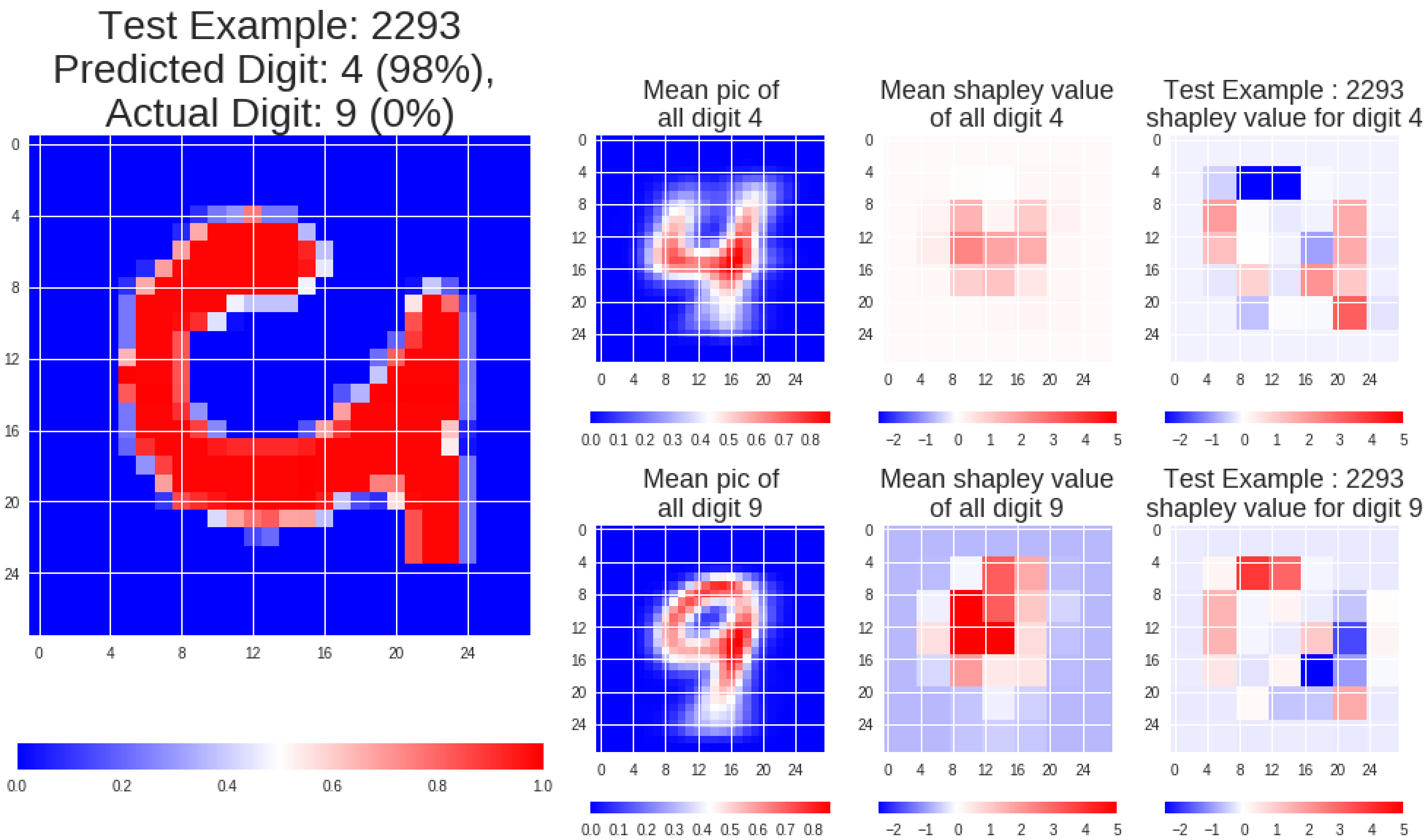
Applying to Mnist (3) – Individual analysis (a)



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



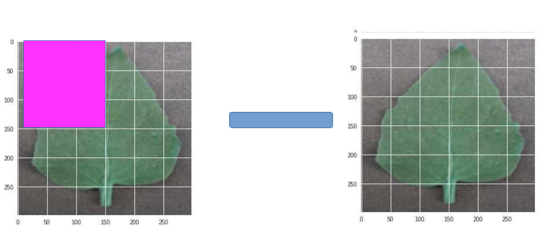
Applying to Mnist (3) – Individual analysis (c)



Drawbacks

$$\varphi_{pink} = \langle f(pink \cup features_{some}) - f(features_{some}) \rangle_{shapley\ values}$$

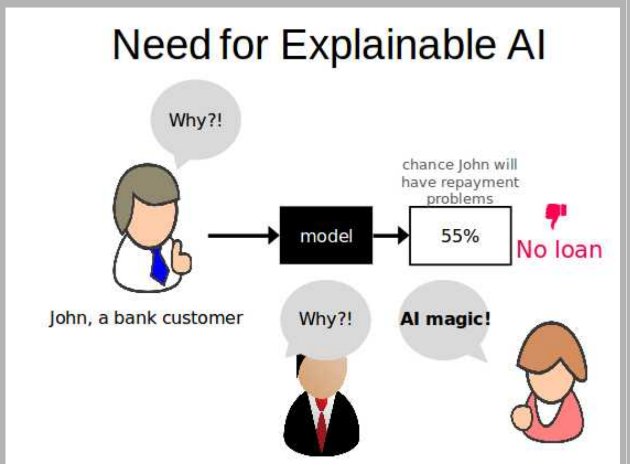
- Computationally intensive, requires to compute 2^m examples for m features followed by inverse of m*m matrix.
  ~ I only sampled 10^3 out of 10^{14} combinations
- How do you appropriately remove a feature ?



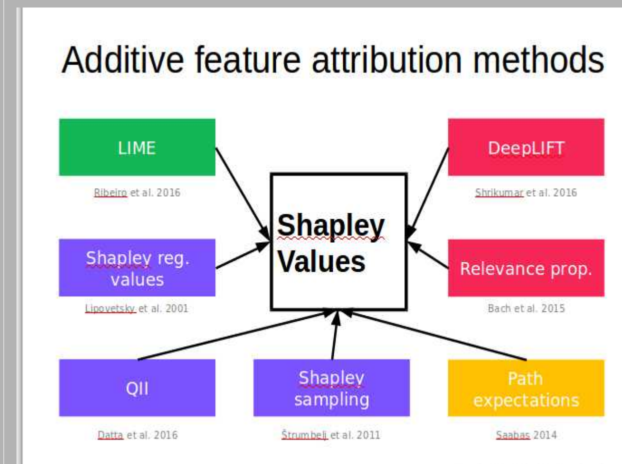
- Method does not explain inner workings, rather it is a model upon a model to explain the final output.

Summary

1.



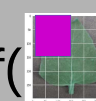
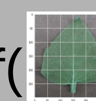
2.



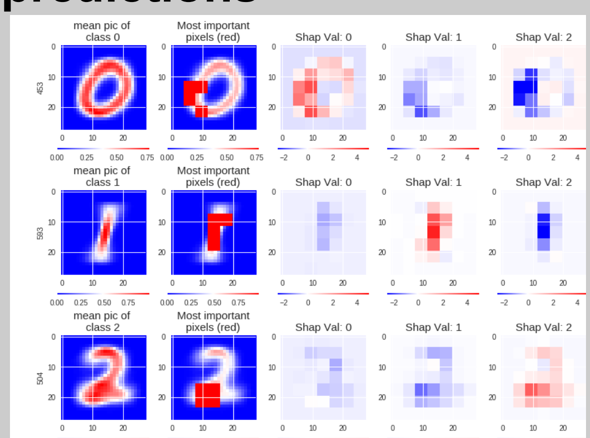
3. Intuition

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

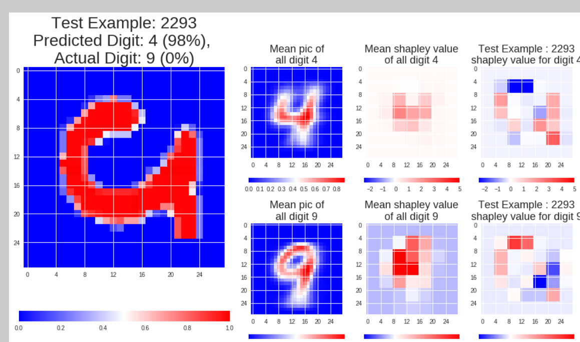
φ$_{pink}$ =

weight_avg(f() − f())

4. Analysis of global predictions

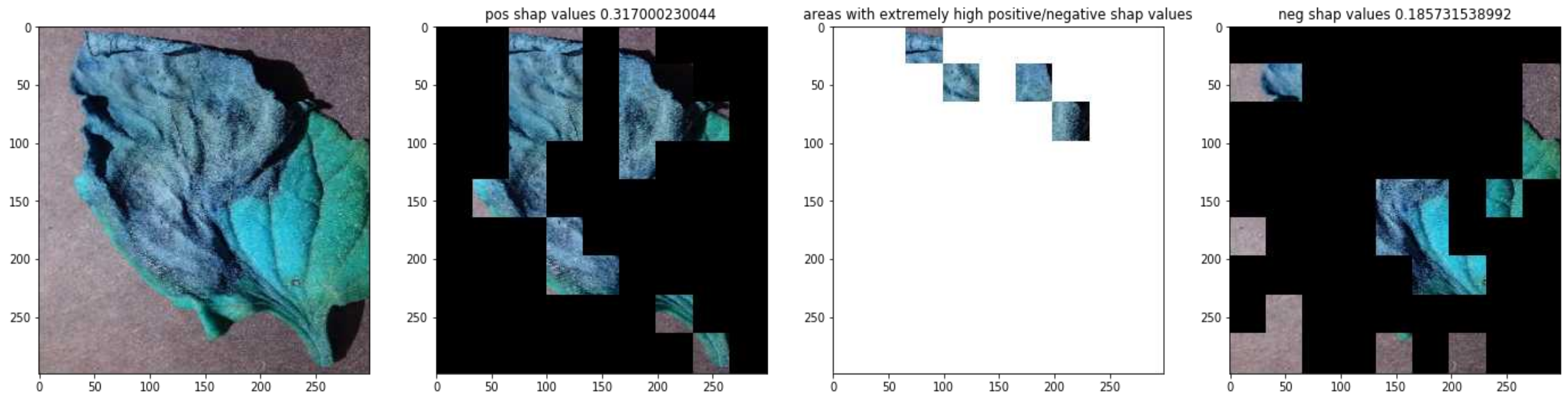


5. Analysis of each prediction



6. Drawbacks

Another application : Transfer-learned Inception3 model



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