

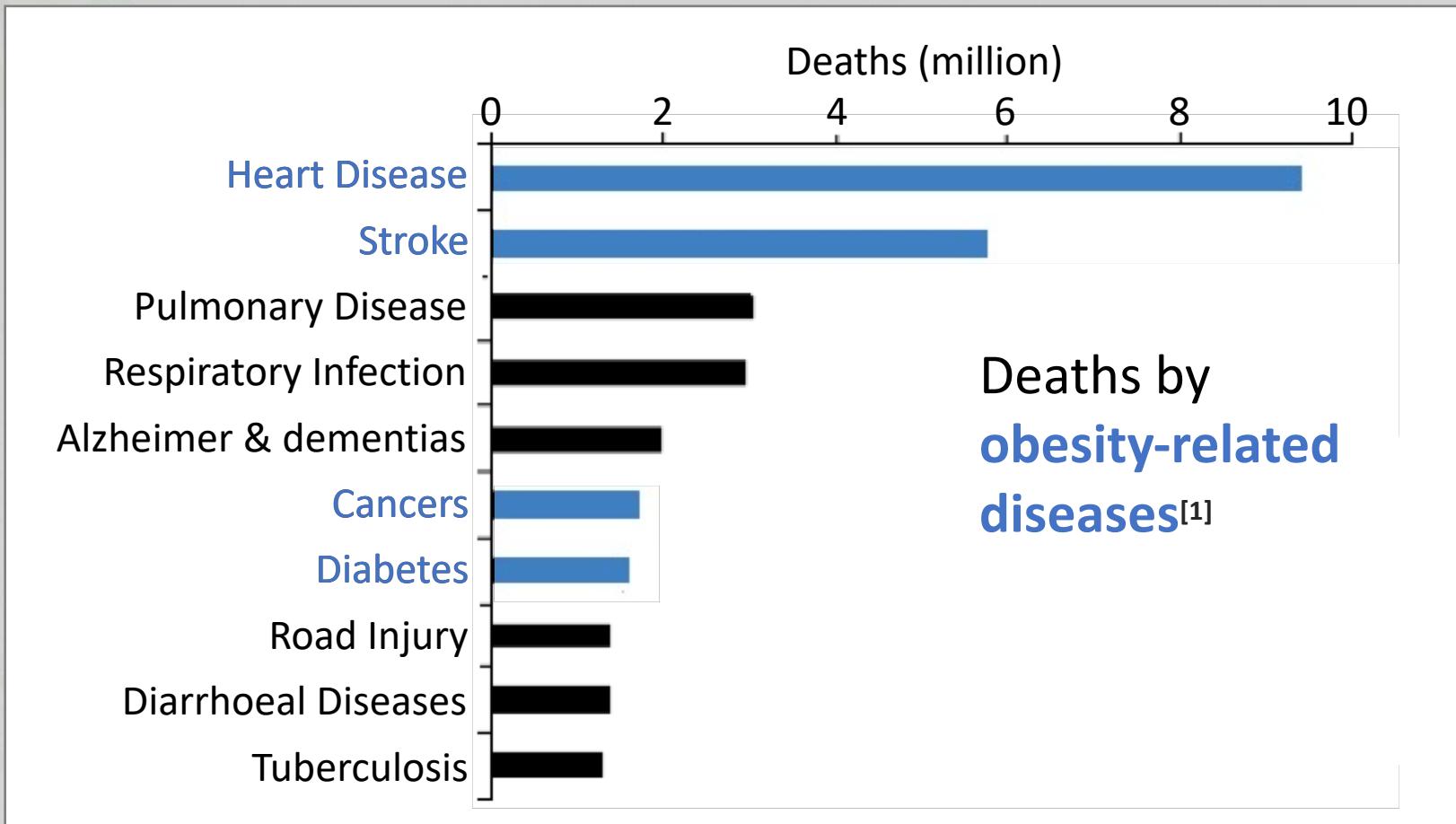
You Are What You Eat:

Obesity Classification Based on Weekly Habits

Project-2 @ **METIS**
Jhonsen Djajamuliadi

Obesity-Related Diseases

Top 10 Causes of Death Worldwide

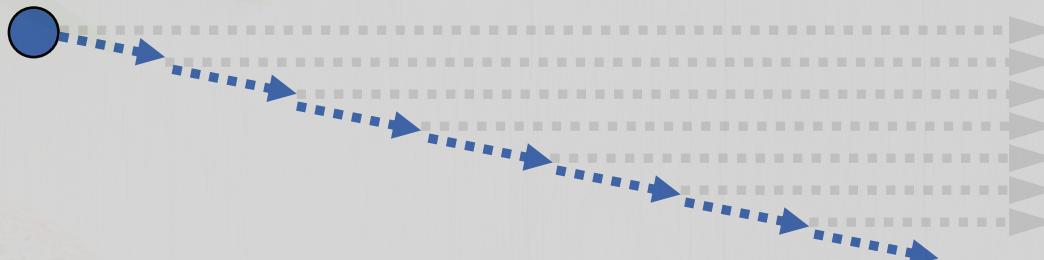


Global Health Estimates 2016, from WHO, 2018

[1] Obesity related diseases <https://www.cdc.gov/obesity/adult/causes.html>

Project Motivation & Theme

Small changes \propto Big impact
today *future*



Obese | Not Obese
Disease *Healthy*

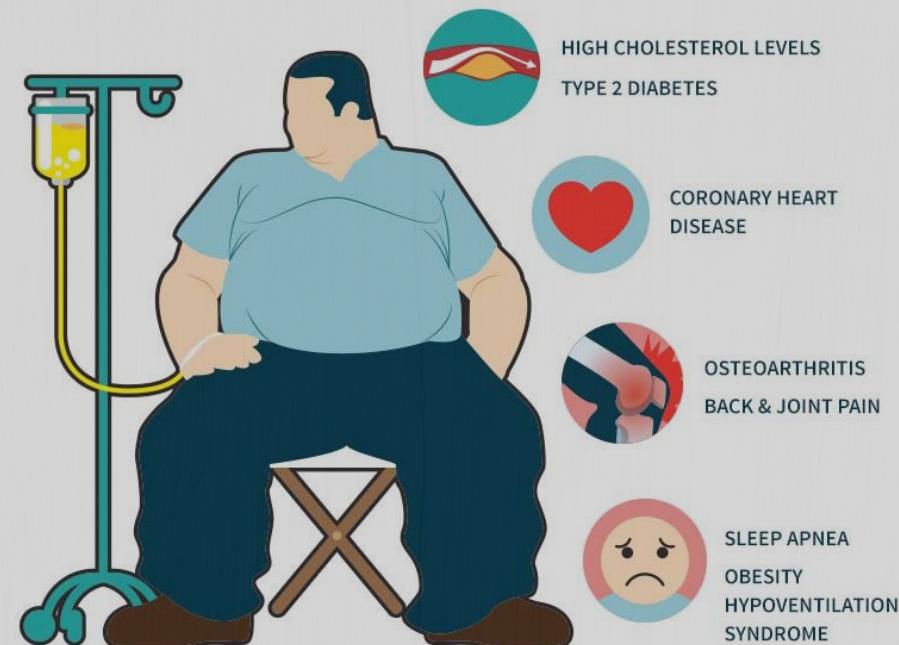
Question:

What small changes can I make, today?

Charles Eugster, 97



<https://www.agebrilliantly.org/charles-eugster-champion-elderly-world-record/>



<https://www.pinterest.com/pin/367606388318247552/>

Data-Driven Investigation

American Time Use Survey (ATUS)
Eating & Health Module Microdata
Files



6 years
(2006-2008, 2014-2016)

Feature Selection

37 Questions and Answers

BMI

"User-Friendly" Features

- Actionable, on a weekly basis
- Doable immediately
- No privacy concerns

Time_Eat
Time_Snack
Exercise_Freq
Fastfood_Freq
General_Health

Features of Importance

Obese
Not
Obese

30

Target

Data-Driven Investigation

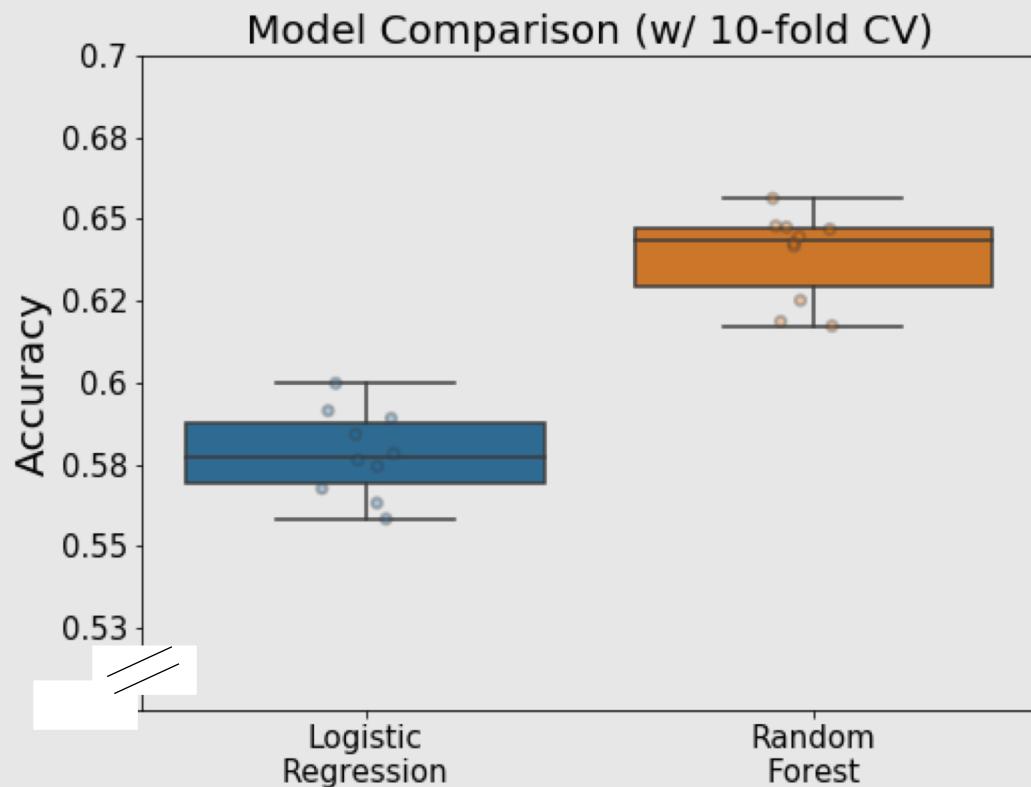
American Time Use Survey (ATUS)
Eating & Health Module Microdata
Files



Feature Selection

Model Selection

Interpretability vs. Predictive Power



- Misclassifying a diseased-patient is costly

Data-Driven Investigation

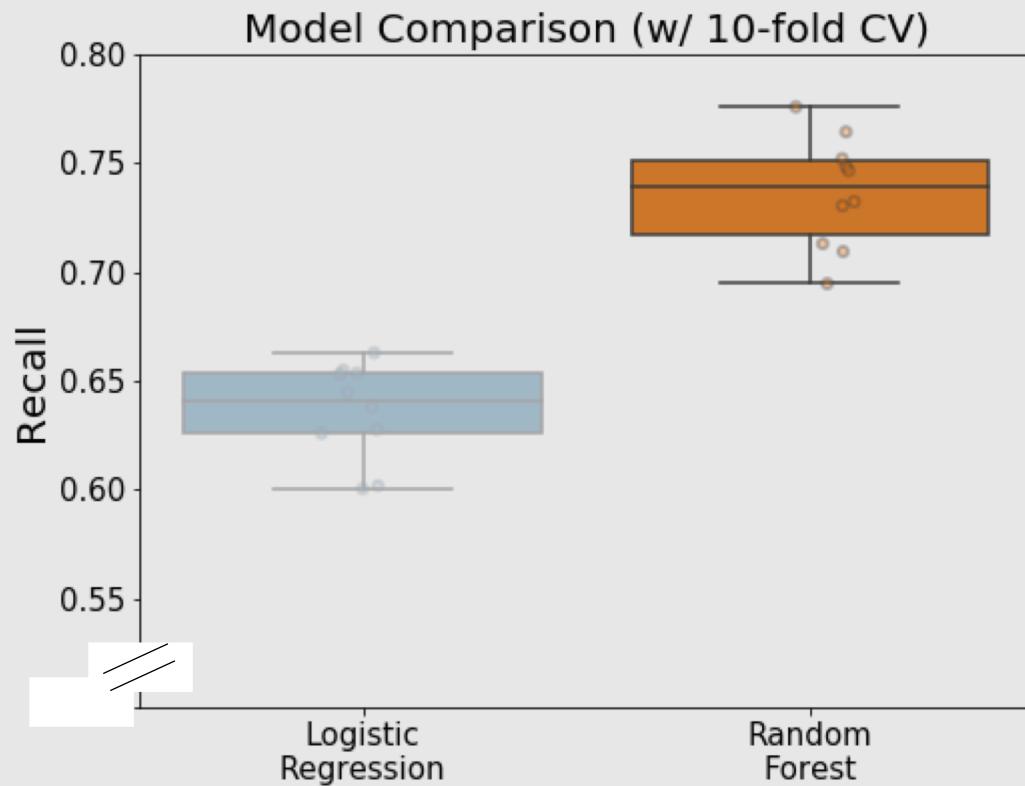
American Time Use Survey (ATUS)
Eating & Health Module Microdata
Files



Feature Selection

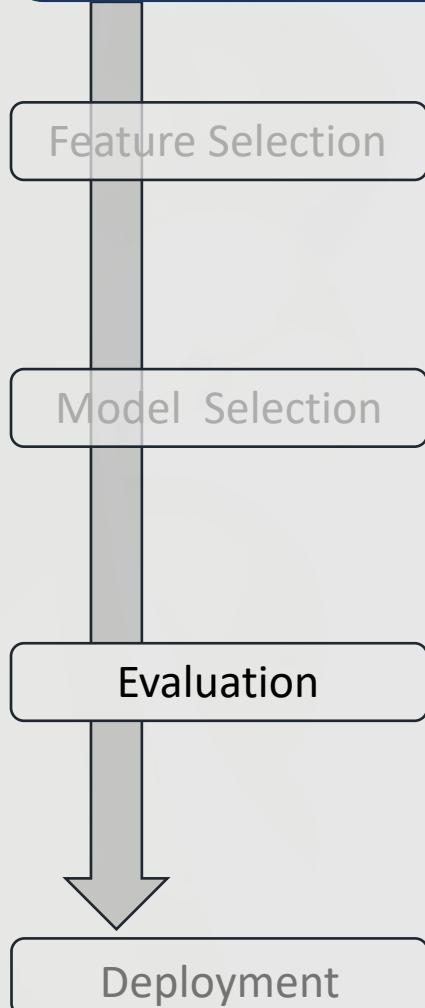
Model Selection

Interpretability vs. Predictive Power



Data-Driven Investigation

American Time Use Survey (ATUS)
Eating & Health Module Microdata
Files



Interpretability & Predictive Power

L ocal
I nterpretable
M odel-agnostic
E xplanations

Case# 1902



TRUTH : Obese

Variation of Features

- $\uparrow \text{exerciseFreq}$ ($0 \rightarrow 1$ a day)
 - $P(\text{Obese}) = 0.51$
- $\downarrow \text{genHealth}$ (Good \rightarrow Poor)
 - $P(\text{Obese}) = 0.62$
- $\downarrow \text{genHealth}, \uparrow \text{exerciseFreq}$
 - $P(\text{Obese}) = 0.57$

LIME references:

- <https://github.com/marcotcr/lime>
- <https://arxiv.org/abs/1602.04938>
- <https://www.oreilly.com/learning/introduction-to-local-interpretable-model-agnostic-explanations-lime>

Summary & Future Work

Project Challenges:

- Survey data (unreliable)
- BMI for obesity?

Completed:

- Model with predictive power
- Interpretability

Room for Improvement:

- Test set accuracy **~0.63**
- Test set recall **~0.69**

Future Work:

1. Retrain model with **more data**
2. Adding relevant **features**
3. Other dataset (non-survey)

Obesity Prediction Web App

<https://obesity-predictor.herokuapp.com/>

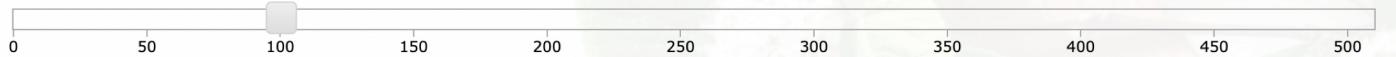
Your Chances of Becoming Obese

97.0%

Q1: How would you generally rate your overall health (1 = Excellent to 5 = Poor)? 3



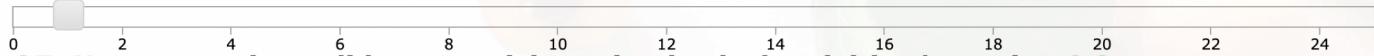
Q2: How many minutes in a day do you spend eating your main meals? 100



Q3: How many minutes in a day did you spend snacking? 0



Q4: How many times did you order takeout or have food delivered this week? 0



Q5: How many times did you participate in physical activities/exercises? 0



+



+



→



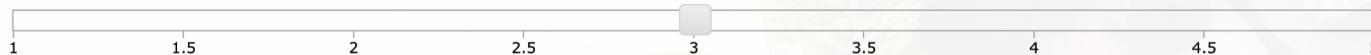
Obesity Prediction Web App

<https://obesity-predictor.herokuapp.com/>

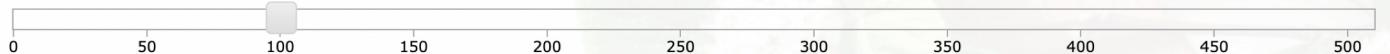
Your Chances of Becoming Obese

97.0%

Q1: How would you generally rate your overall health (1 = Excellent to 5 = Poor)? 3



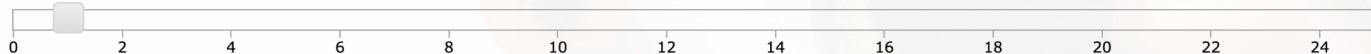
Q2: How many minutes in a day do you spend eating your main meals? 100



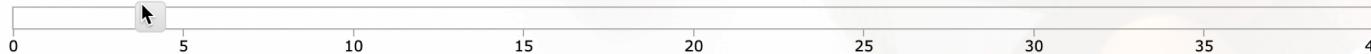
Q3: How many minutes in a day did you spend snacking? 0



Q4: How many times did you order takeout or have food delivered this week? 0



Q5: How many times did you participate in physical activities/exercises? 0



Question:

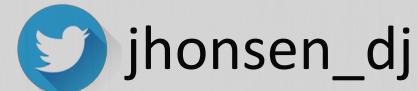
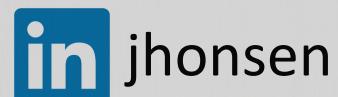
- *What small changes can I make, today?*

Hints:

- *Make adjustments to our weekly habits*

Thank You

Data Scientist | Chemist



Project Description and Goal

*Data Science
for Social Good*



Public Health
Agency



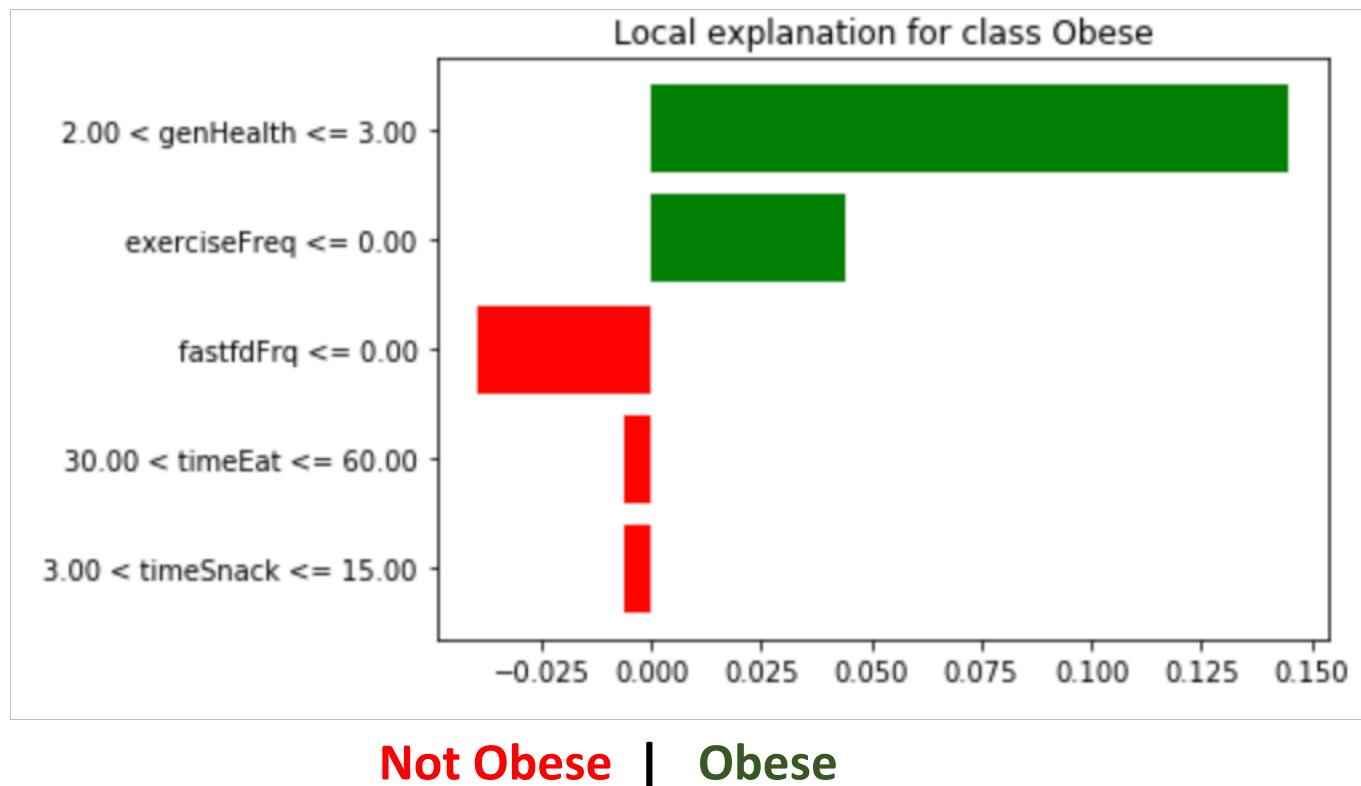
Deployment



Bringing Interpretability to “Black-Box”

Appendix to slide #7

- The impact of each variable on P(Obese)



Bringing Interpretability to “Black-Box”

Appendix to slide #7

- Quick blurb about **LIME**



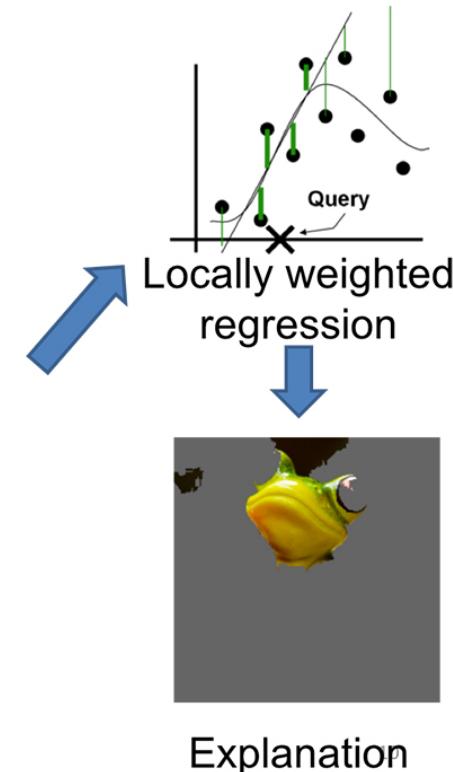
Original Image
 $P(\text{tree frog}) = 0.54$



Interpretable
Components



Perturbed Instances	$P(\text{tree frog})$
A photograph of the frog with several red spots added to its body.	0.85
A photograph of the frog with several yellow dots added to its body.	0.00001
A photograph of the frog with red spots removed from its body.	0.52



LIME references:

- <https://github.com/marcotcr/lime>
- <https://arxiv.org/abs/1602.04938>
- <https://www.oreilly.com/learning/introduction-to-local-interpretable-model-agnostic-explanations-lime>

Bringing Interpretability to “Black-Box”

Appendix to slide #7

- Quick blurb about **LIME**

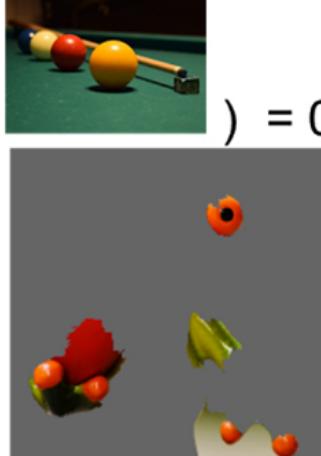
Local segments of
tree-frog picture



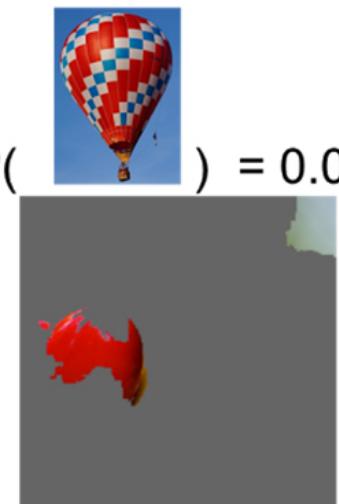
$$P(\text{frog}) = 0.54$$



$$P(\text{billiard balls}) = 0.07$$



$$P(\text{hot air balloon}) = 0.05$$



Strange Feature-Target Pair

Appendix to slide #8

row number: 1742

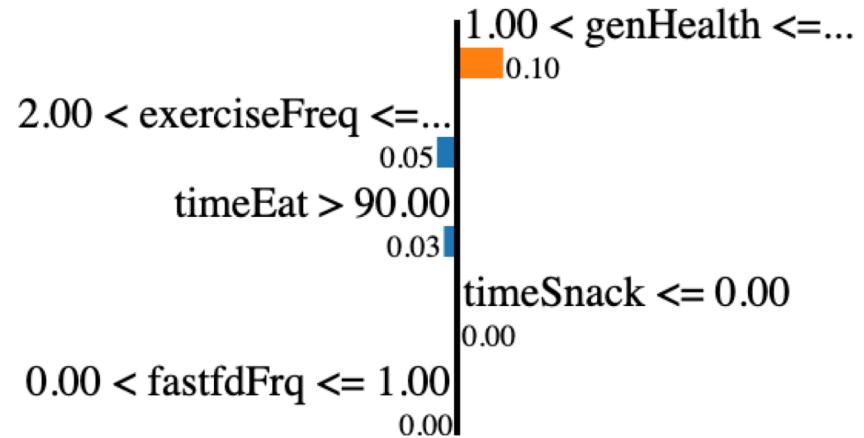
predicted: 1, truth: 1. Therefore, the classifier is CORRECT

Prediction probabilities



Not Obese

Obese



Feature Value

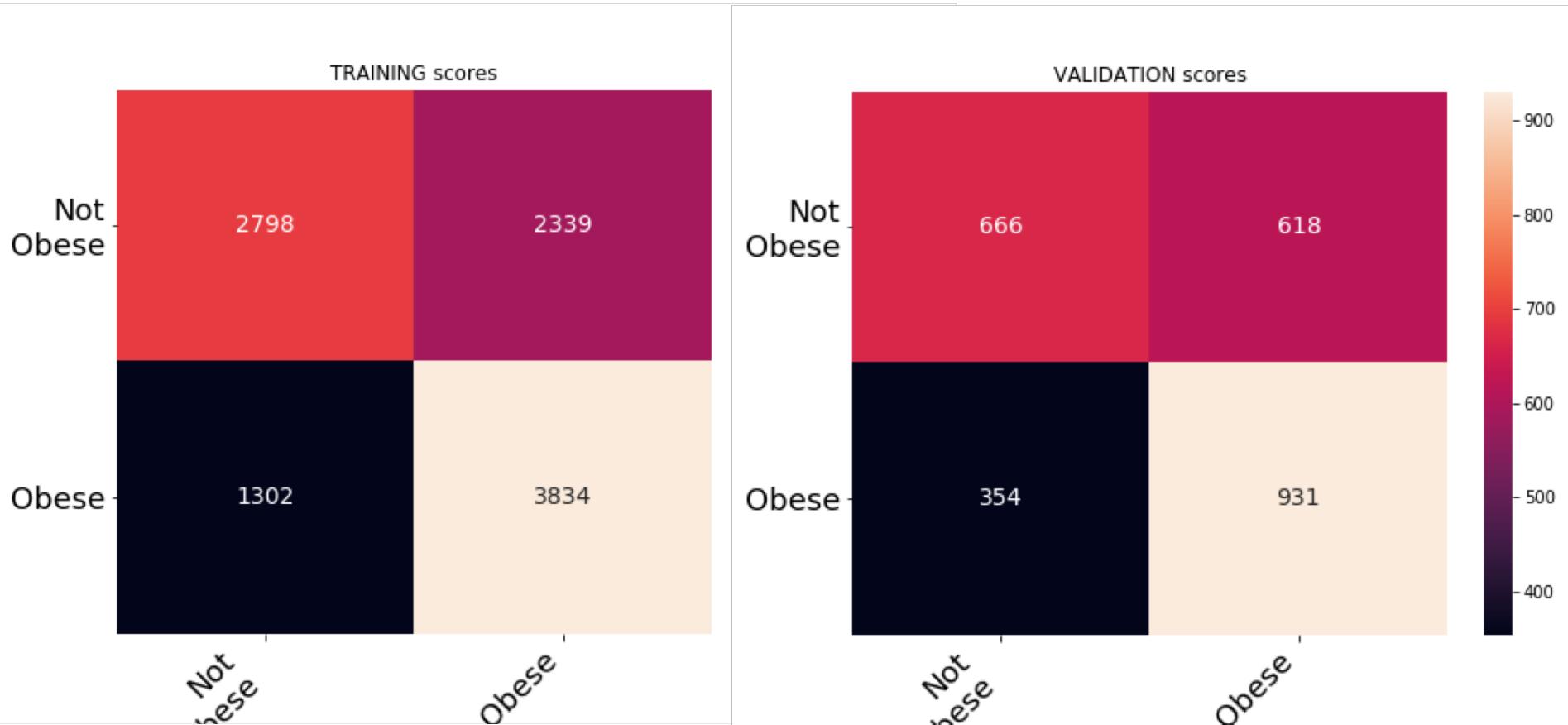
genHealth	2.00	(Very Good)
exerciseFreq	3.00	
timeEat	120.00	(2 hrs)
timeSnack	0.00	
fastfdFrq	1.00	

- Isn't this person generally healthy?

Confusion Matrix for Train-Val Set

Appendix to slide #6

- Performance of models based on Training Set



ROC Curve of Training-Val Set

Appendix to slide #6

- Performance of models based on Training Set
- **Random Forest** model

