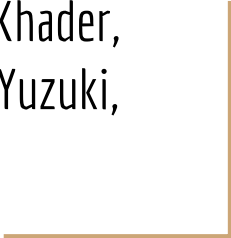






# COVID Death Rates and Diet

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Can we accurately  
predict COVID-19  
death rates using  
country diet data?



# Project Context and Motivation



Is diet partly responsible for differences in COVID-19 death rates between and within countries?

[Jean Bousquet](#),<sup>1,2,3,4</sup> [Josep M. Anto](#),<sup>5,6,7,8</sup> [Guido Iaccarino](#),<sup>9</sup> [Wienczyslaw Czarlewski](#),<sup>10,11</sup> [Tari Haahtela](#),<sup>12</sup> [Aram Anto](#),<sup>10</sup> [Cezmi A. Akdis](#),<sup>13</sup> [Hubert Blain](#),<sup>14,15</sup> [G. Walter Canonica](#),<sup>16</sup> [Victoria Cardona](#),<sup>17</sup> [Alvaro A. Cruz](#),<sup>18</sup> [Maddalena Illario](#),<sup>19,20</sup> [Juan Carlos Ivancevich](#),<sup>21,22</sup> [Marek Jutel](#),<sup>23</sup> [Ludger Klimek](#),<sup>24</sup> [Piotr Kuna](#),<sup>25</sup> [Daniel Laune](#),<sup>26</sup> [Désirée Larenas-Linnemann](#),<sup>27</sup> [Joaquim Mullol](#),<sup>28</sup> [Nikos G. Papadopoulos](#),<sup>29,30</sup> [Oliver Pfaar](#),<sup>31</sup> [Boleslaw Samolinski](#),<sup>32</sup> [Arunas Valiulis](#),<sup>33</sup> [Arzu Yorgancioglu](#),<sup>34</sup> [Torsten Zuberbier](#),<sup>1,2,3,4</sup> and The ARIA group

Relation of Dietary Factors with Infection and Mortality Rates of COVID-19 Across the World

[Deldar Morad Abdulah](#)<sup>1</sup> and [A. B. Hassan](#)<sup>2</sup>



Dataset



# Data Information

- ❑ **Data:** Kaggle COVID-19 Healthy Diet Dataset
- ❑ **4 Data Sets:**
  - ❑ Fat\_Supply\_Quantity\_Data
  - ❑ Food\_Supply\_Quantity\_Data (one by kcal, one by kilograms)
  - ❑ Protein\_Supply\_Quantity\_Data
- ❑ **Rows:** 170 (1 for each country in the data)
- ❑ **Columns** (for each dataset d = [Fat, Food, Protein]):
  - ❑ Percentage of d intake from alcoholic beverages
  - ❑ Percentage of d intake from animal products
  - ❑ Percentage of d intake from animal fats
  - ❑ Percentage of d intake from aquatic products
  - ❑ Percentage of d intake from cereals - excluding beer
  - ❑ Percentage of d intake from eggs
  - ❑ Percentage of d intake from fish, seafood
  - ❑ Percentage of d intake from fruits - excluding wine
  - ❑ Percentage of d intake from meat
  - ❑ Obesity, Death rate, Recovered, Confirmed, Active

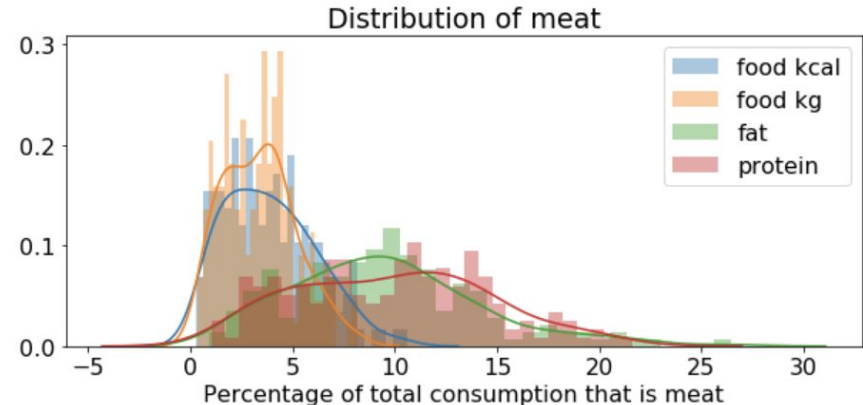
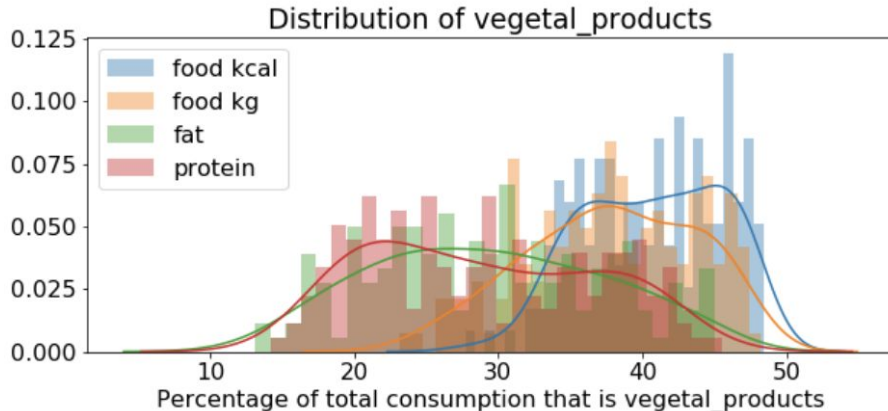
# Our Process

- ❑ Trained independent models to explore possible areas of interest
  - ❑ Fat content
  - ❑ Protein content
  - ❑ Caloric content
  - ❑ Food Quantity
- ❑ Trained and optimized models on combined data sets to predict death rate (continuous)
  - ❑ Linear regression
  - ❑ Neural Network
- ❑ Trained models on combined dataset to predict categorical death rate (high/medium/low)
  - ❑ Logistic Regression
  - ❑ Neural Network (Tensor Flow)

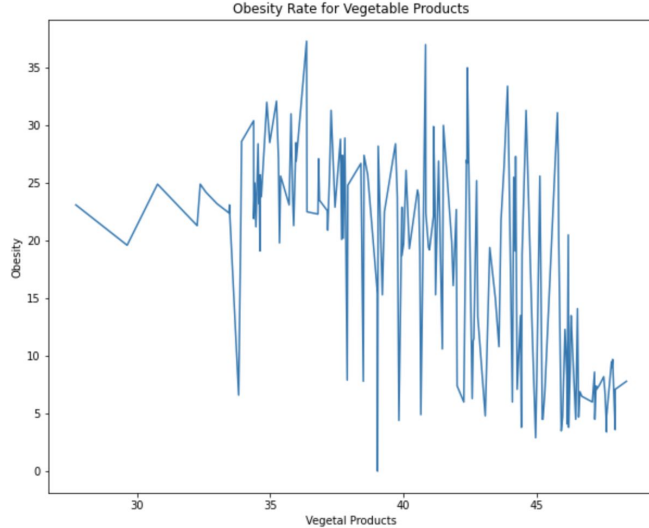
# Understanding the Data

Combined the food kcal, food kg, fat, and protein supply datasets

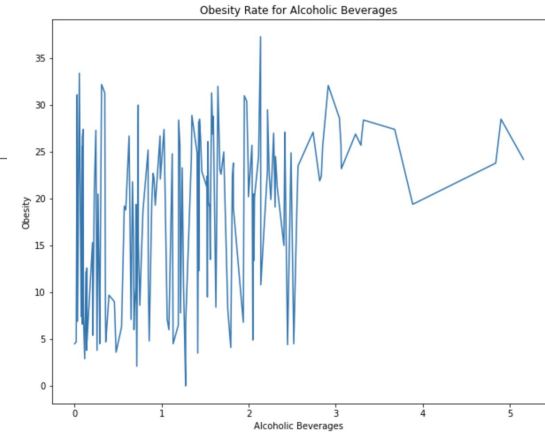
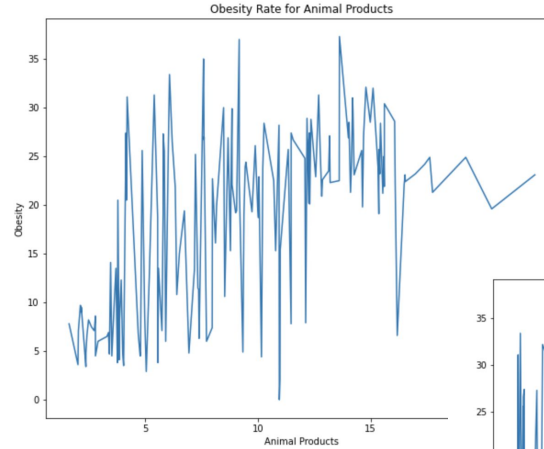
- Vegetable products typically make up between 30-50% of the diet, both by weight and by calories
- Countries are fairly spread out in terms of how much fat/protein they get from vegetal products
- For almost all countries, less than 10% of the total food intake is meat
- Meat provides typically between 0-20% of fat and protein content in the diet



# Obesity and Diet



- Inverse relationship between obesity rates and vegetable product consumption



- Positive relationship between obesity rates and Alcohol and Animal product consumption



# Death Rate vs Obesity Rate



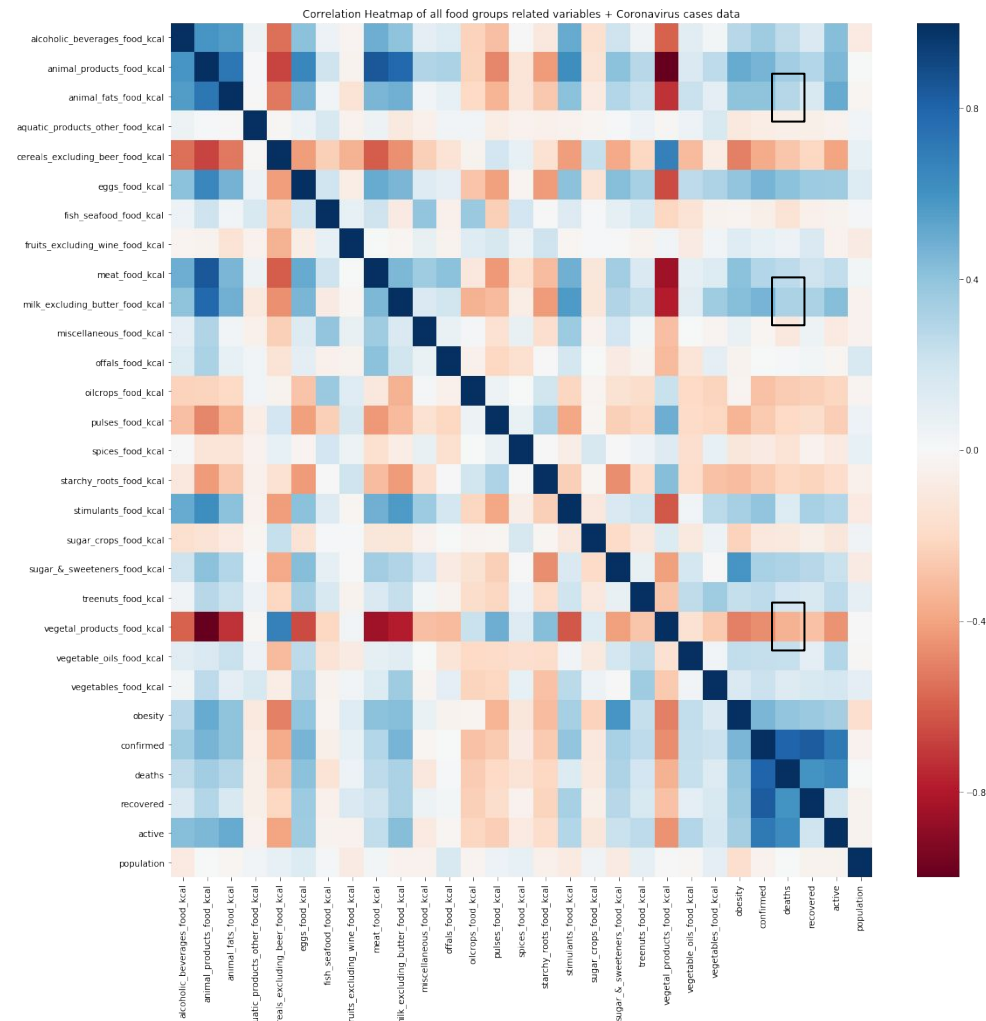
Death Rate



Obesity

# Correlation Heat Map

- Key Takeaways
  - positive association with deaths and animal products, milk (excluding butter)
  - negative association with deaths and vegetable products





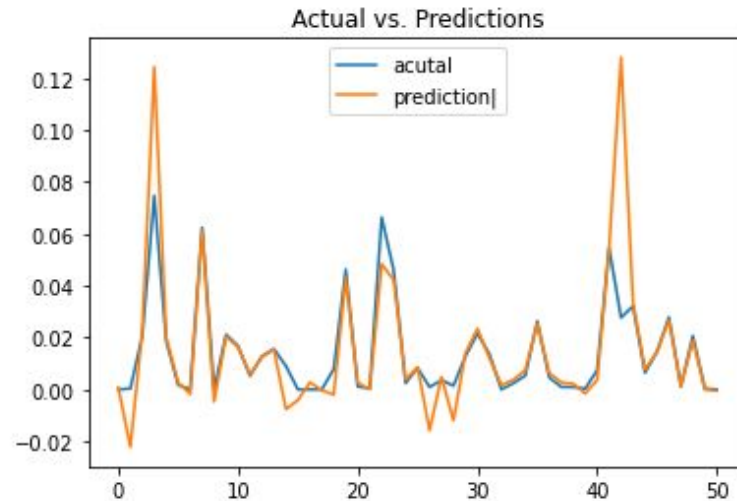
# Approaches



# Linear Regression

`sklearn.linear_model.LinearRegression`

- MSE = 0.000281
- $R^2 = 0.196$



# Linear Regression, contd.

*on complete protein dataset:*

(1) Lasso Regression

- MSE: 0.000327
- $R^2$ : 0.0433

(2) Ridge Regression

- MSE: 0.000294
- $R^2$ : 0.14

*on selected protein dataset:*

(1) Lasso Regression

- MSE: 0.000353
- $R^2$ : 0.166

(2) Ridge Regression

- MSE: 0.000273
- $R^2$ : 0.166

# Neural Network trained on combined dataset

MLPRegressor - Activation: ReLU, Solver: LBFGS

- 2 models - 5 (left) versus 7 (right) hidden layers
- Tradeoff with accuracy on countries with higher death rates versus overall RMSE
- Widely varying  $R^2$  values between models and test/train data

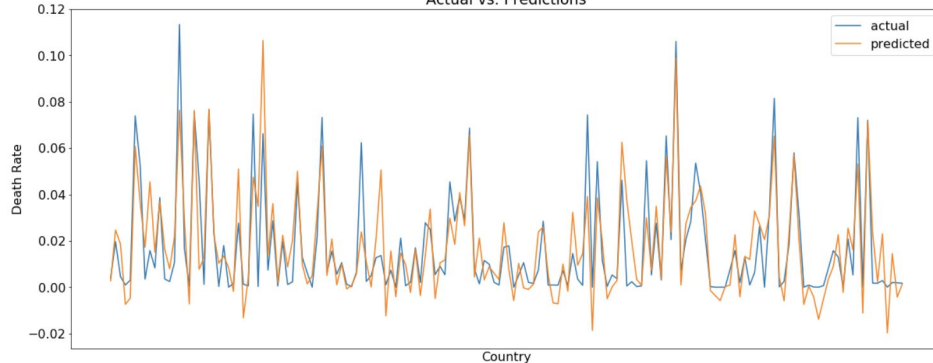
## 5 Hidden Layers

Coefficient of Determination, Train: 0.857

Coefficient of Determination, Test: 0.204

RMSE: 0.020

Actual vs. Predictions



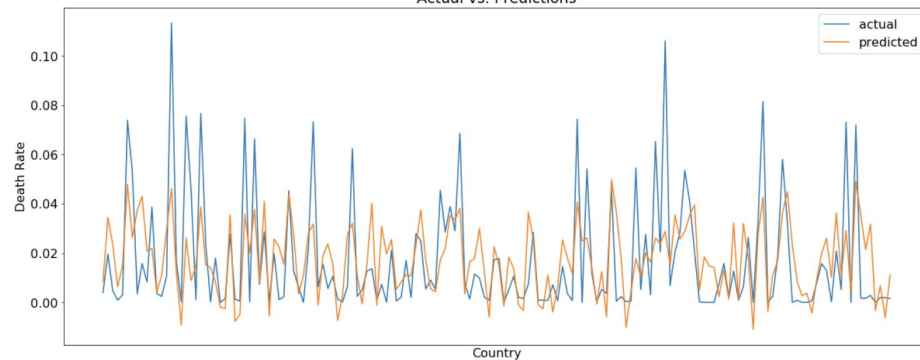
## 7 Hidden Layers

Coefficient of Determination, Train: 0.407

Coefficient of Determination, Test: 0.349

RMSE: 0.018

Actual vs. Predictions



# Binary/Ternary Classification

## Binary

- ❑ Logistic Regression
  - ❑ Accuracy: 75%
  - ❑ AUC: 0.74
- ❑ Keras Tensor Flow NN Model with 2 64 node relu layers and sigmoid output layer
  - ❑ Accuracy: 82%
  - ❑ AUC: 0.9444
- ❑ Most relevant features:

Features	Coef
obesity	2.217811e-14
animal_products_protein	6.418858e-15
animal_products_fat	5.184291e-15
milk_excluding_butter_protein	4.720170e-15
animal_products_food_kcal	4.692738e-15
sugar_&_sweeteners_food_kcal	4.654641e-15
milk_excluding_butter_food_kg	4.086446e-15
animal_products_food_kg	4.065999e-15

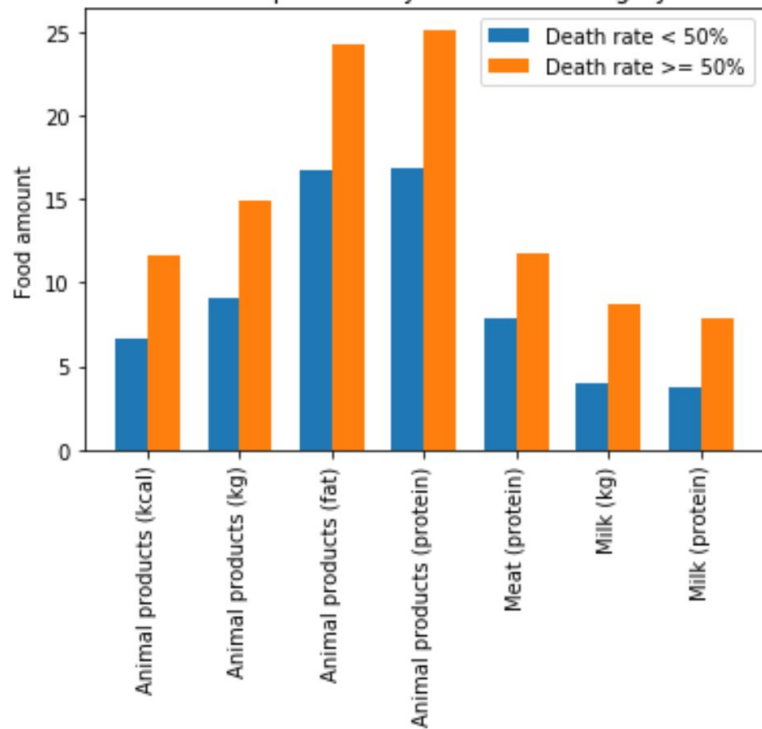
## Ternary

- ❑ Logistic Regression
  - ❑ Accuracy: 39%
- ❑ Keras Tensor Flow NN Model with 2 64 node relu layers and sigmoid output layer
  - ❑ Accuracy: 47%
- ❑ Most relevant features:

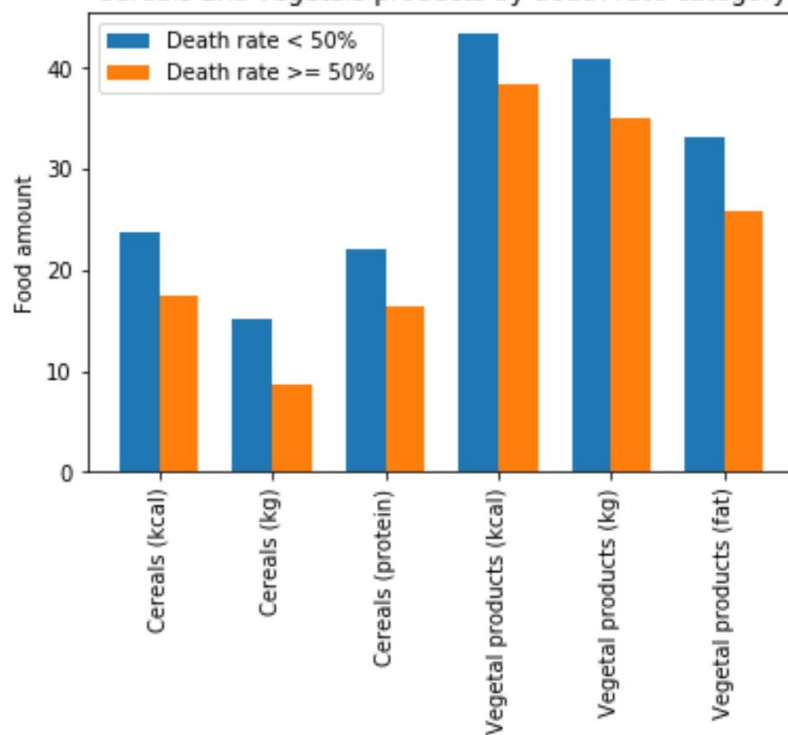
Features	Coef
population	3.194849e-09
vegetal_products_food_kg	3.055966e-14
vegetal_products_food_kcal	2.916529e-14
vegetal_products_protein	2.883876e-14
vegetal_products_fat	2.821662e-14
reals_excluding_beer_food_kcal	1.553541e-14
starchy_roots_food_kg	1.546364e-14
cereals_excluding_beer_protein	1.413555e-14
vegetable_oils_fat	1.229698e-14
cereals_excluding_beer_food_kg	1.222656e-14
starchy_roots_food_kcal	9.637387e-15

# Binary Classifier Exploration

Animal products by death rate category



Cereals and vegetals products by death rate category







# Results and Conclusions



# Summary of Findings

Predicting continuous death rate:

- Low  $R^2$  values indicate poor predictors
- Low RMSE value due to smaller data values (proportions between 0-1)
- High overfitting due to discrepancy in loss between train and test

Predicting categorical (high/low/medium) death rate:

- Higher accuracy, but not as informative
- Binary classification much stronger than ternary
- Key features that distinguish different levels of death rate that is consistent with correlation map
  - Features to distinguish different death rates
    - Vegetable Products
    - Milk
    - Animal Products

# Can we accurately predict COVID-19 death rates using country diet data?

- Predicting exact death rates from this dataset is not possible
- No definitive relationship between diet and death from COVID-19, but there exists an association
- Possible to distinguish high/low death rate for a country with a specific diet

# How could we have done better?

- Larger data set
- More granular data→ death rate and diet by individual would have been more predictive
- There are ultimately larger factors at play that influence death rate (government policy, poverty, healthcare systems, comorbidities, etc.)

# Real World Applications

- These models can be used to anticipate high death rates in countries known to have certain diets
- Changes in diet can't change people's overall health or COVID death rates in the short-term, but other measures can (social distancing, lockdown, contact tracing, etc.)
- In the long term, changes in diet could be used to reduced death rates



Thank you!  
Q&A

