# Diabetes Classification with Support Vector Machines

Diabetic



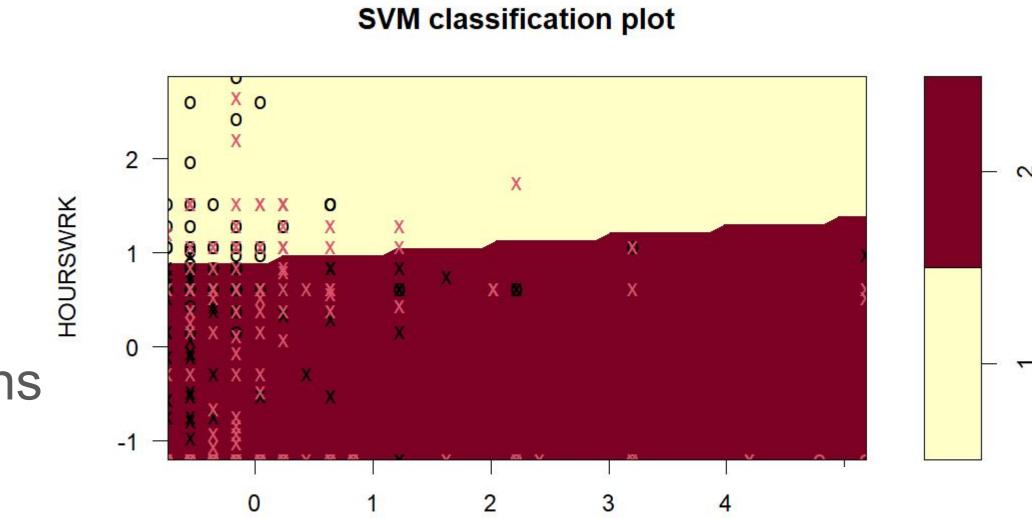
Data Source: IPUMS Health Survey Goal: Classify instances of Diabetes

Nondiabetic

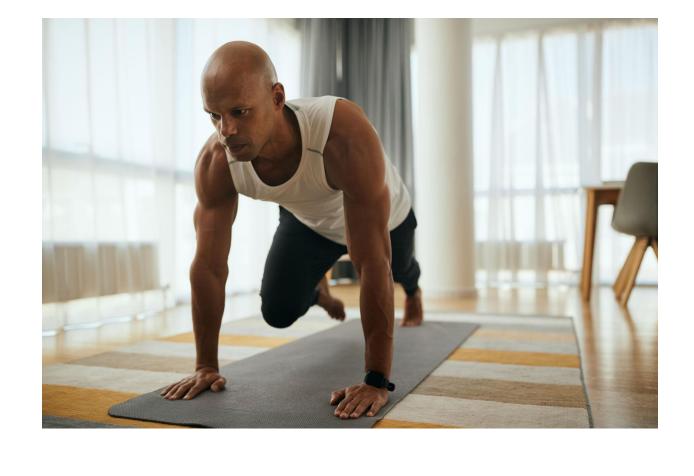
Theoretical Background Support Vector Machine

 Allows classification by drawing a boundary Relevant Equation: the distance between the closest points Parameters

 Cost: How many points can be misclassified Drawbacks: SVM requires no NA data, leading to difficult applications



## Predictors



VIG10DMIN: vigorous exercise per day



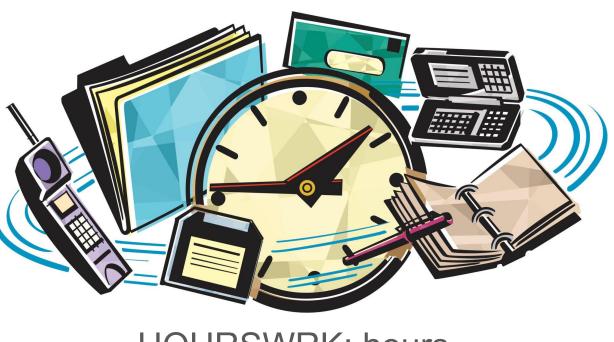
SALADSNO: salads consumed



**EDUC**: education level

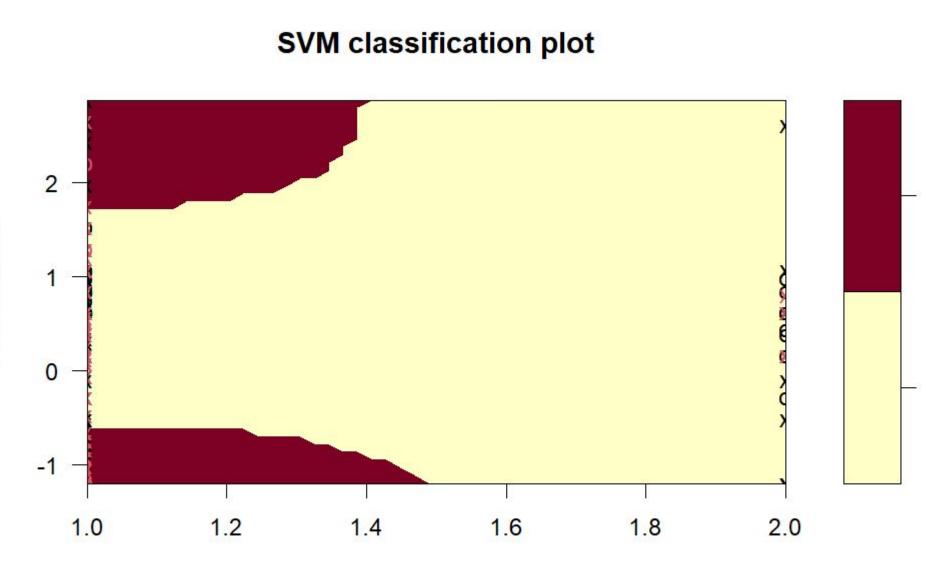


HINOTCOVE: health insurance coverage



**HOURSWRK:** hours worked per week

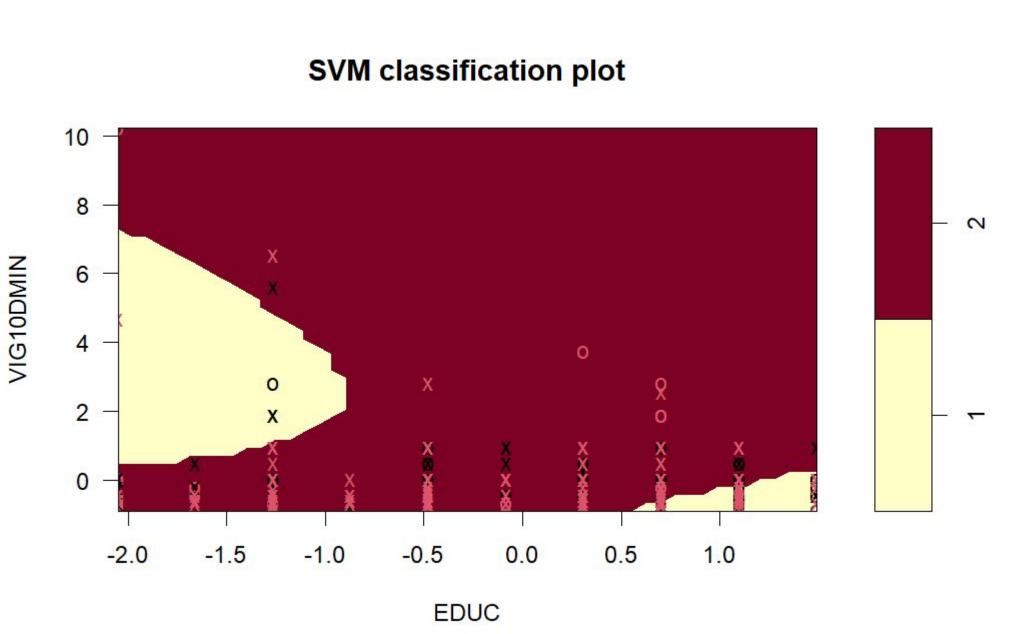
SVM Kernels



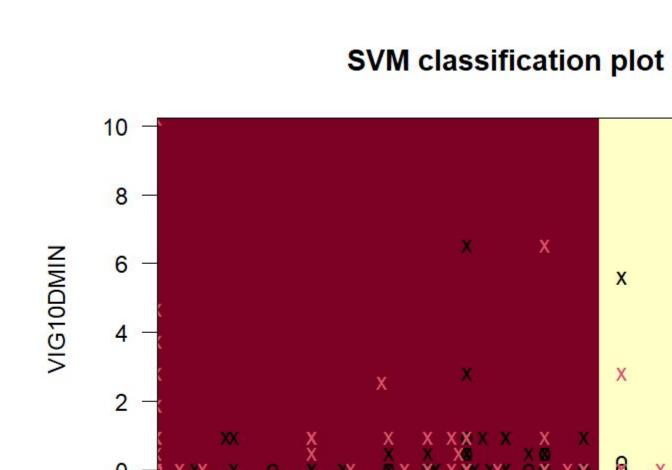
HINOTCOVE

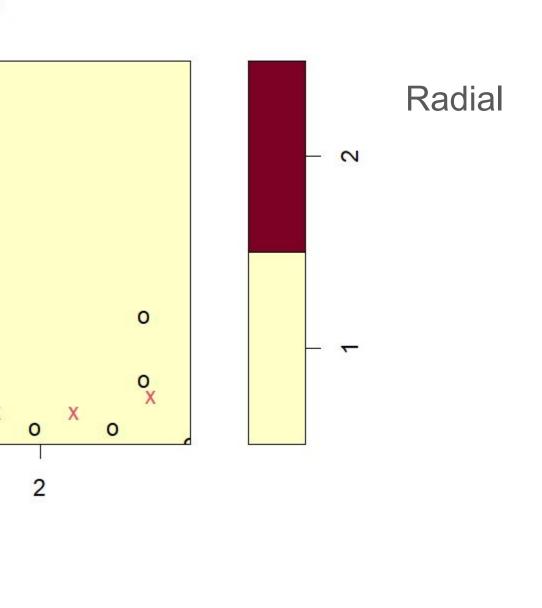
SALADSNO Quadratic

**SVM** classification plot



Cubic





Linear

#### Methodology:

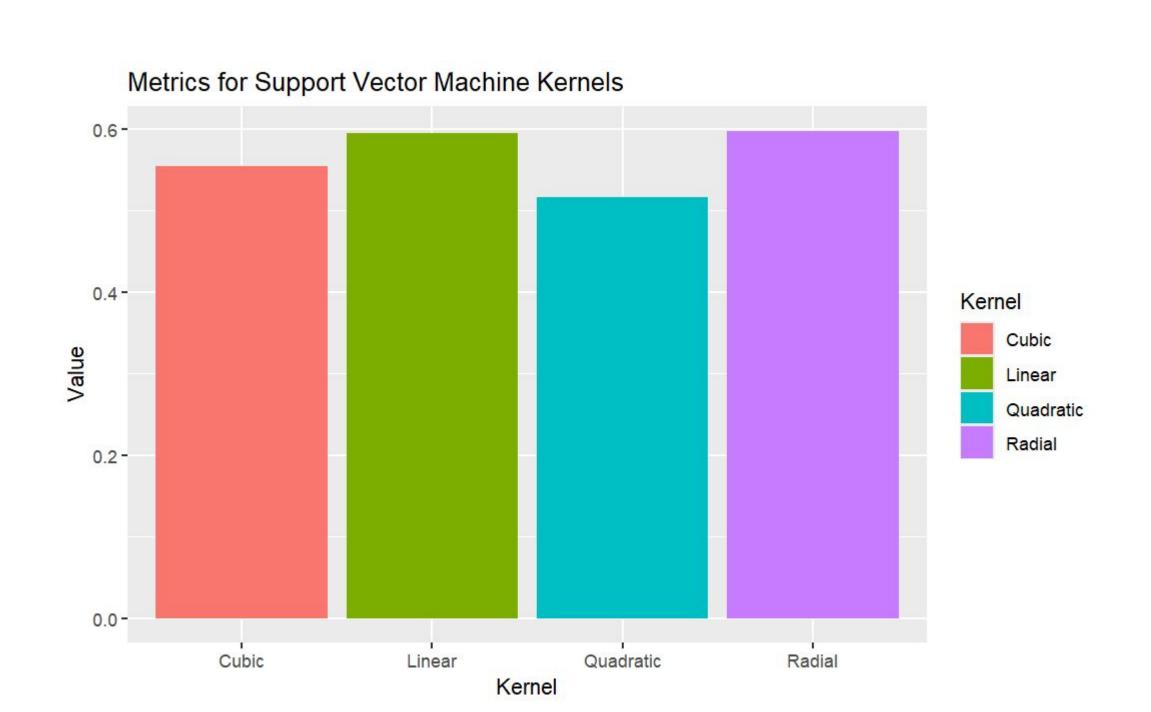
Problem with unbiased data.

HOURSWRK

Solve by decreasing the amount of non-diabetic samples to balance data

#### Results:

- Intuitively healthy habits seems to be associated with higher rates of diabetes classification
- Models including the 5 above predictors did not have very strong predictions



### Conclusion:

High levels of vigorous activity and healthy eating are often a response to diabetes.

Diabetes Status

Low work hours are also associated with diabetes

- Perhaps diabetes prevents long hours of work
- Perhaps less work entails a more sedentary lifestyle (unlikely) Likely explanation: diabetes causes the lifestyles, not the other way around

Lynn A. Blewett, Julia A. Rivera Drew, Miriam L. King, Kari C.W. Williams, Daniel Backman, Annie Chen, and Stephanie Richards. IPUMS Health Surveys: National Health Interview Survey, Version 7.4 [dataset]. Minneapolis, MN: IPUMS, 2024. https://doi.org/10.18128/D070.V7.4. http://www.nhis.ipums.org Drazen Zigic/Getty Images

rez-art/Getty Images Jeffrey Hamilton/Getty Images Dynamic Graphics/Getty Images