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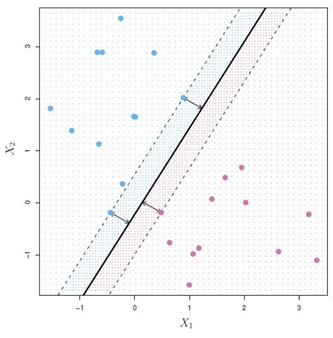
# Diabetes Classification with Support Vector Machines



Problem: chronic diseases impact large proportions of the population, but there are many different lifestyles that may impact prevalence of diseases, like diabetes.

Data Source: IPUMS Health Survey extracts demographic and lifestyle data
Goal: Classify instances of Diabetes based on 5 predictors

Theoretical Background: Support Vector Machines
- Allows classification by drawing a hyperplane (a boundary)
  - In 2-D, a line; in 3-D, a plane
  - Question: aren't there infinitely many boundaries possibles? Yes, so use maximal margin
- Relevant metric: the distance between the closest points (the maximal margin)
  - Determines boundary
  - SVM attempts to draw a boundary that would maximize the distance of the two closest points
    - The closest points serve as our *support vectors*

Kernel: Our boundary does not have to be linear. We can alter the kernel, or closeness function
Parameters
- Cost: How many points can be misclassified
  - Lost cost may lead to overfitting, but a high cost
- Gamma: Describes the influence of training examples

Advantages: intuitive understanding and presentability, many flexible kernels
Drawbacks: SVM requires no NA data, leading to difficult applications

## Predictors

1.HINOTCOVE: health insurance coverage

2. EDUC: education level

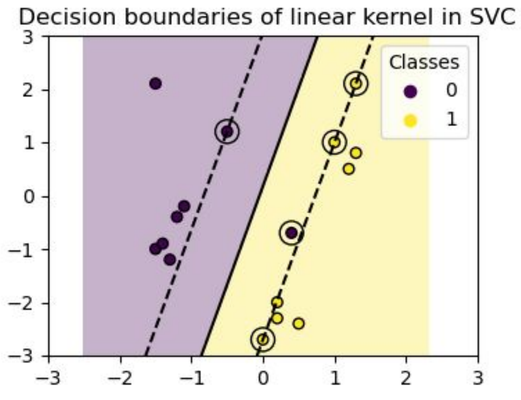
3. VIG10DMIN: vigorous exercise per day

4.HOURSWRK: hours worked per week

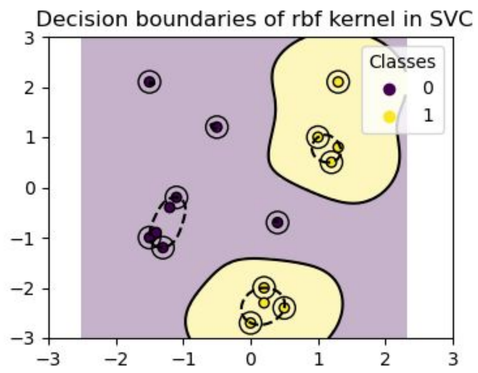
5.SALADSNO: salads consumed

**SVM Kernels**

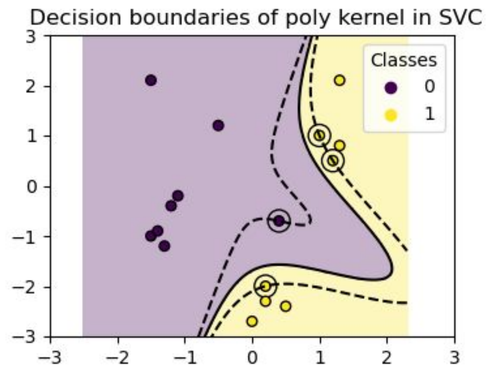
Linear: Creates a straight hyperplane




Radial: Creates a circular and rounded hyperplane, creating grouped boundaries
- Very localized behavior

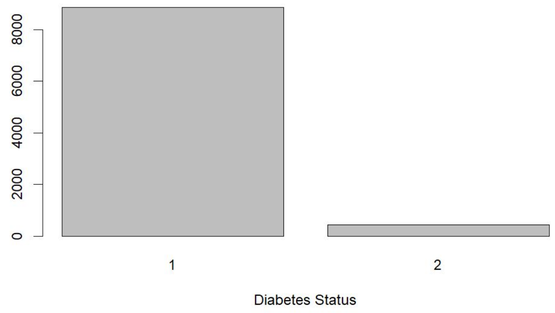



Polynomial: Creates a complex and curved hyperplane that is flexible
- Relevant parameter: degree




Methodology:
- Problem with unbalanced data.
  - Solve by decreasing the amount of non-diabetic samples to balance data
- Resolving difficult NA data
  - Many survey participants refused to answer many questions
  - We set those results to NA and had to remove them from the dataset, as SVM requires all data points to have a value

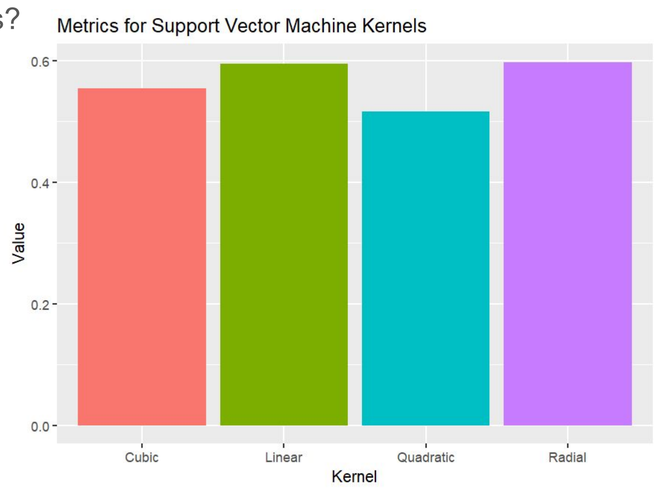
Results:
- Intuitively healthy habits seems to be associated with higher rates of diabetes classification
  - Question: why do high activity and high salad eating individuals have diabetes?
- Models including the 5 above predictors did not have very strong predictions
  - Radial SVMs perform the best, followed by linear

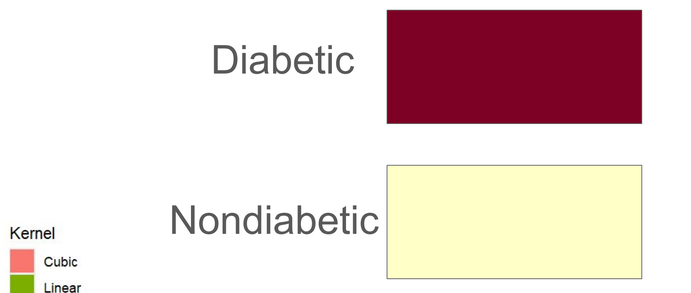


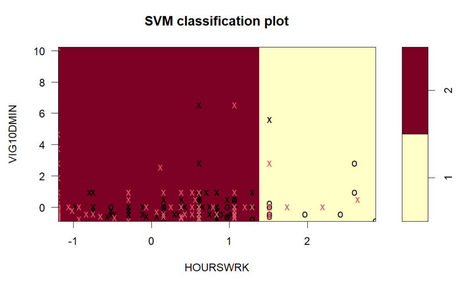

**Issues with Shrinking Imbalanced Data:**
- Unstable initial conditions with testing data
- Less quality in models
- High variance in data and model predictions

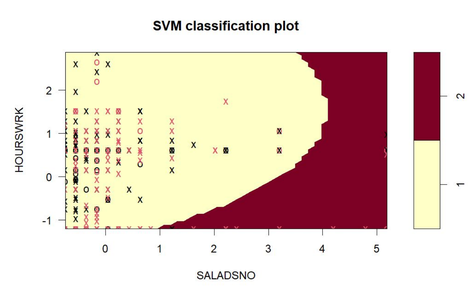
Other options and methods:
Re-sample and bootstrap to create another dataset
Collect more data from other sources
Use less variables to avoid deleting NA rows

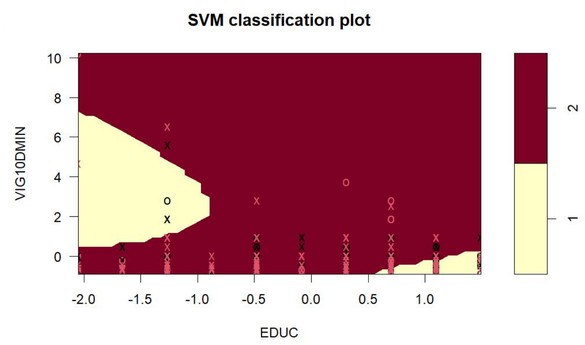
| Kernel | Linear | Radial | Polynomial (Quadratic) | Polynomial (Cubic) |
|---|---|---|---|---|
| Accuracy | 59.57% | 59.78% | 53.33% | 57.63% |




Discussion:
Model Performance: all models did about equally as well with the exception of the quadratic polynomial kernel.
Best model: Radial kernel
- This implies the data has a grouped structure, where ranges of values may have diabetes, but not exactly a strictly linear relationship where the increase of one status implies the increase of another.
- This might explain why some linear kernels and quadratic kernels gave conflicting results

Conclusion and Key takeaways:
High levels of vigorous activity and healthy eating are often a response to diabetes, though not a cause of diabetes
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
- We will need more information such as time since diagnosis to determine any lifestyle changes or causes

Future study should try to attain more data to avoid tricky initial conditions.

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