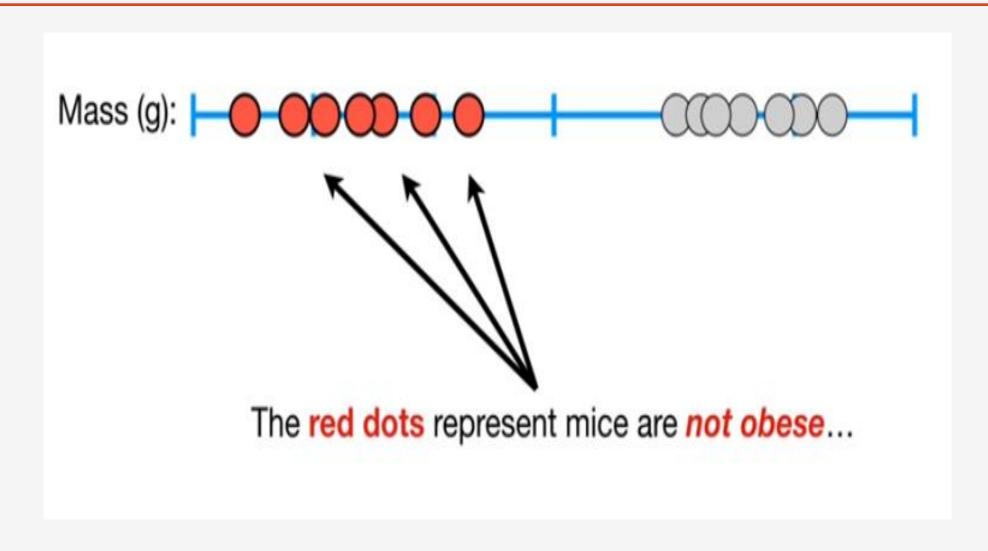
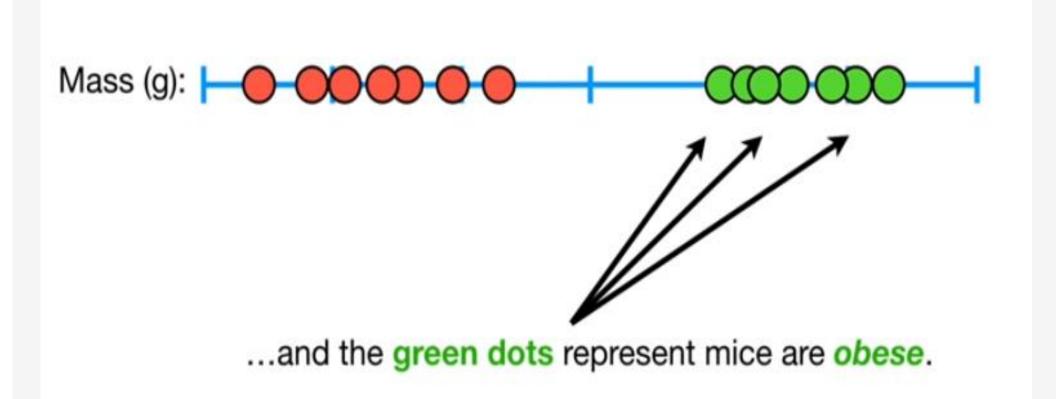
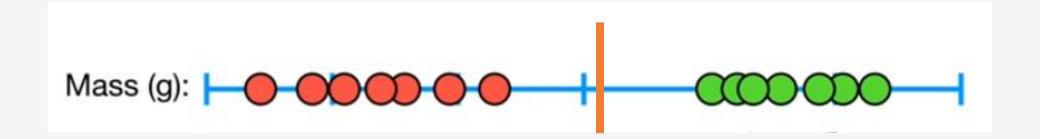
Support Vector Machine

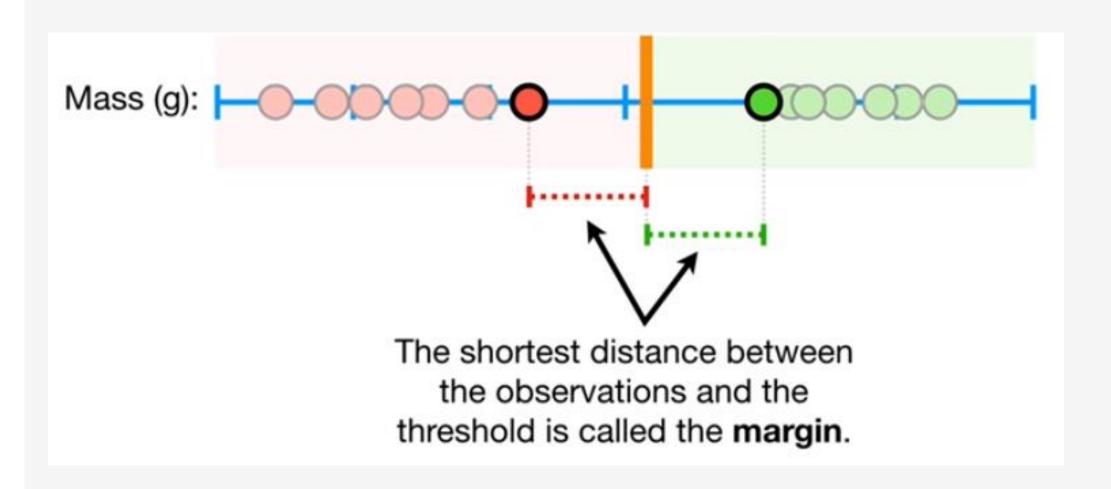
- SVM is a supervised learning model for classification and regression analysis. When it is used for Classification, it is called Support Vector Classifier.
- The algorithm involves finding a hyper-plane in a higher dimensional space which can be used to separate the two different class for binary classification. That is it provides a decision boundary for classifying data points
- The criteria for finding this hyperplane is based on the so-called "widest street approach" that has the largest margin: i.e. largest distance to the nearest training data points of any class
- https://www.youtube.com/watch?v=N1vOgolbjSc
- https://www.youtube.com/watch?v=efR1C6CvhmE

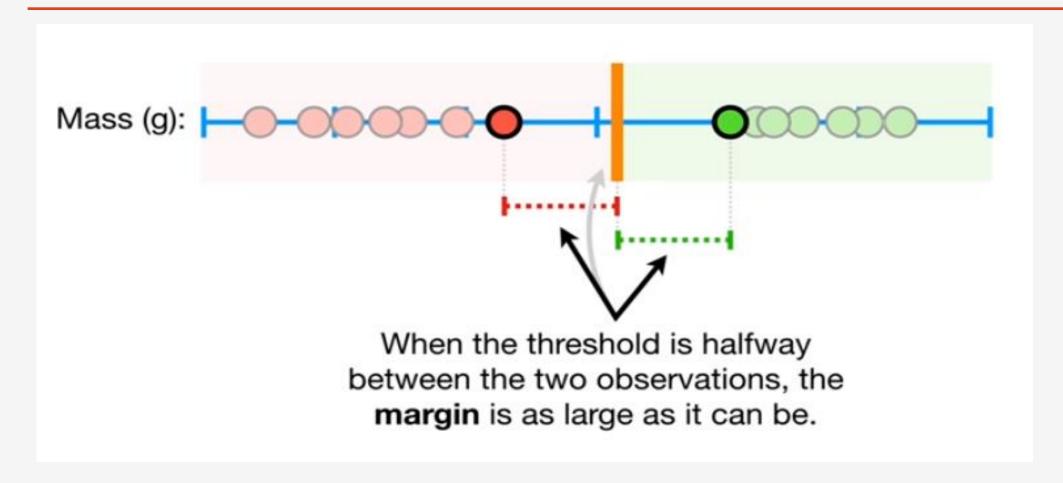




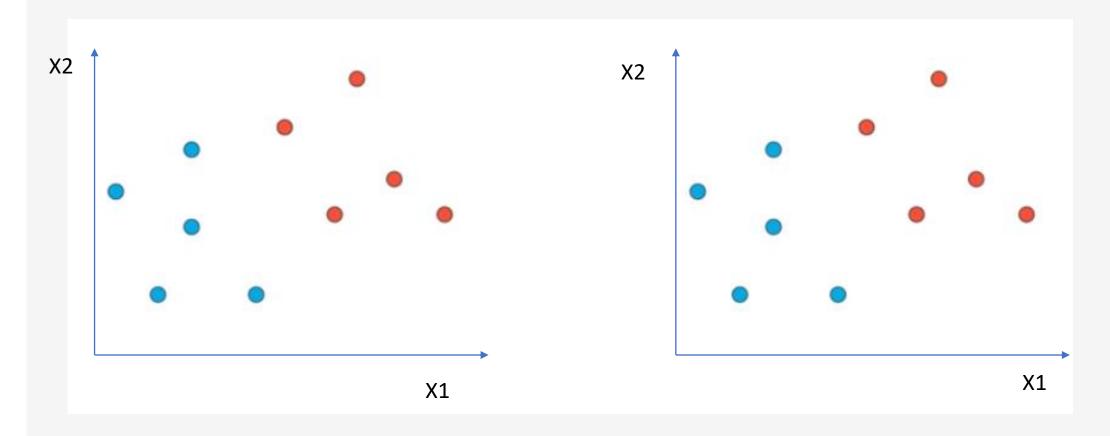
How to choose the threshold to decide whether the Mice is obese



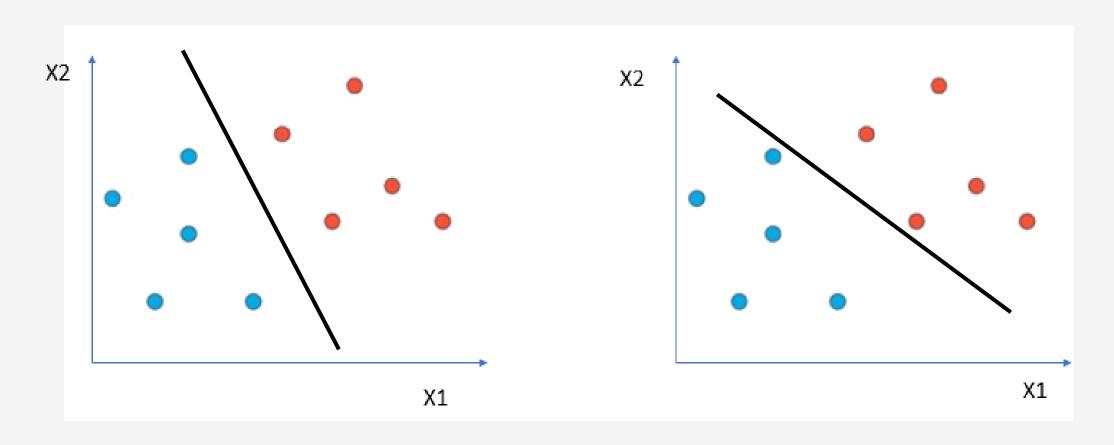




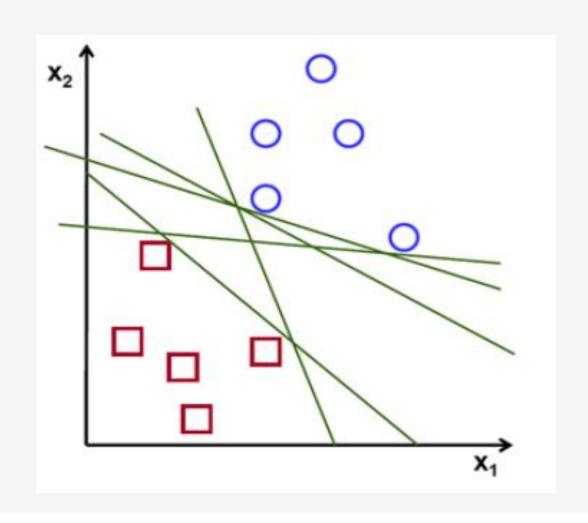
Draw a line that can separate the blue and red dots. The line will serves as the decision boundary.

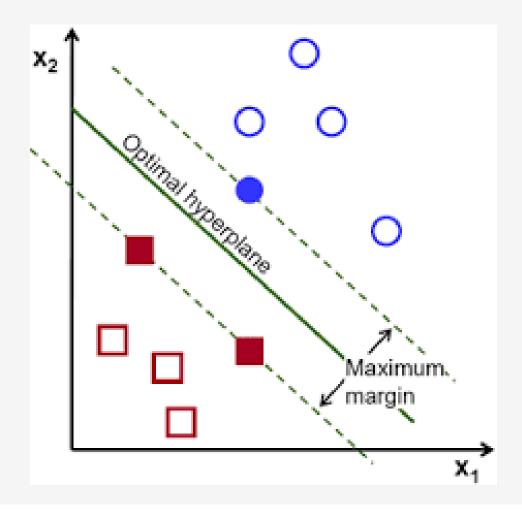


Which line will be a better line?



Which of the green line separate the blue circle from the red square data points?





Support Vector Machine Terminology

So SVM is to try to find the hyperplane that maximize the margin between the plane and its nearest data points which are called the support vectors.

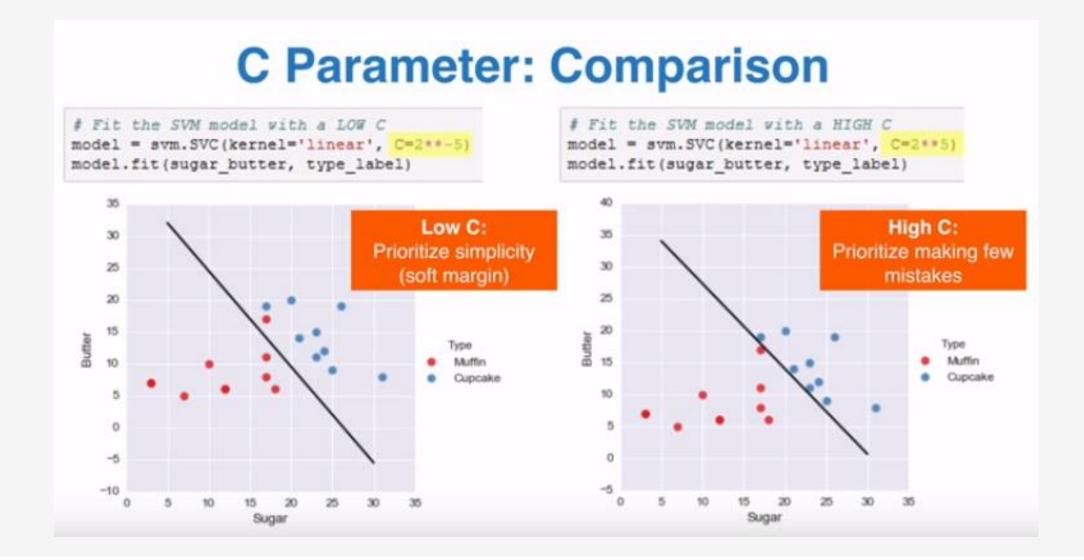
Watch https://www.youtube.com/watch?v=N1vOgolbjSc

- Hyperplane
- Maximum Margin Classifier
- Margin, Soft Margin
- Support Vectors
- C parameters
- Kernel tricks

Learning by doing

Support Vector Machine (continued with C-parameters and Kernel Trick)

- C-Parameter
 - Default value is 1, but can be changed inside the SVM call
 - Low C-Parameter
 - allows mis-classification
 - Soft margin
 - Less complicated model, high bias, low variance, may underfit
 - High C-Parameter value
 - Try to fit as much as possible, allows no mis-classification
 - Hard margin
 - More complicated model, low bias, high variance, may overfit



Support Vector Machine (Kernel Trick)

Default is linear, but can use Polynomial, RBF (Radial Basis Function), or Gaussian

Kernel Trick: Code

```
Original Code
   (linear)
```

```
# Fit basic SVC model (linear kernel)
model = svm.SVC(kernel='linear')
model.fit(sugar butter, type label)
```

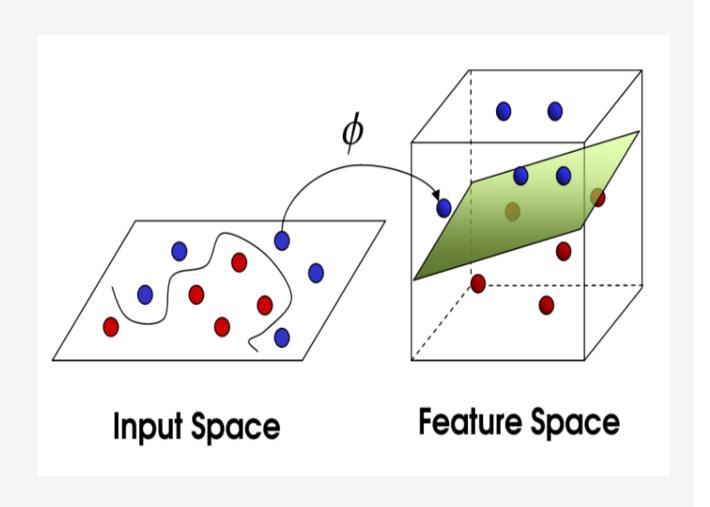
```
Updated Code
   (RBF)
```

```
# Fit the SVC model with radial kernel
model = svm.SVC(kernel='rbf', C=1, gamma=2**-5)
model.fit(sugar butter, type label)
```

Support Vector Machine (Kernel Trick)

Kernel Trick is a trick to transform the dataset from a lower dimension space to a higher dimension so that at higher dimension, the dataset can be separated by a linear hyperplane

Nice Kernel visualization
https://www.youtube.com/watch?v=3liCbRZPrZA



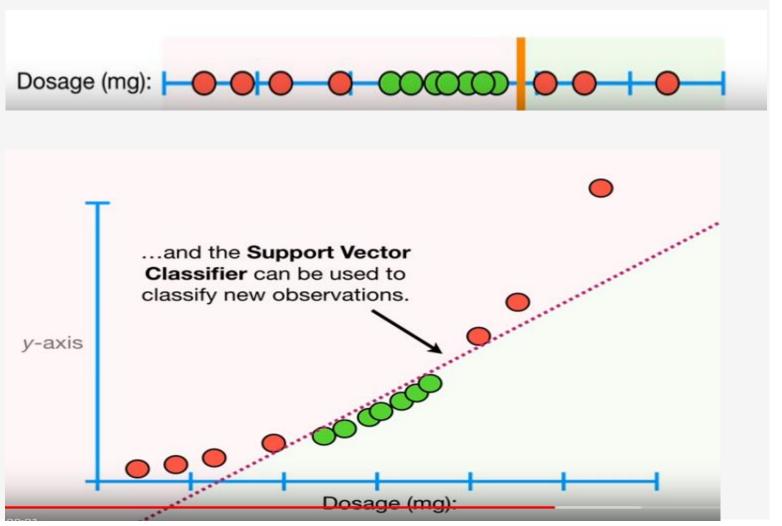
Support Vector Machine (Kernel Trick)

Another example: https://www.youtube.com/watch?v=efR1C6CvhmE starting from 12:10

In 1-dimension, one cannot Separate the high and low dosage for cured patients

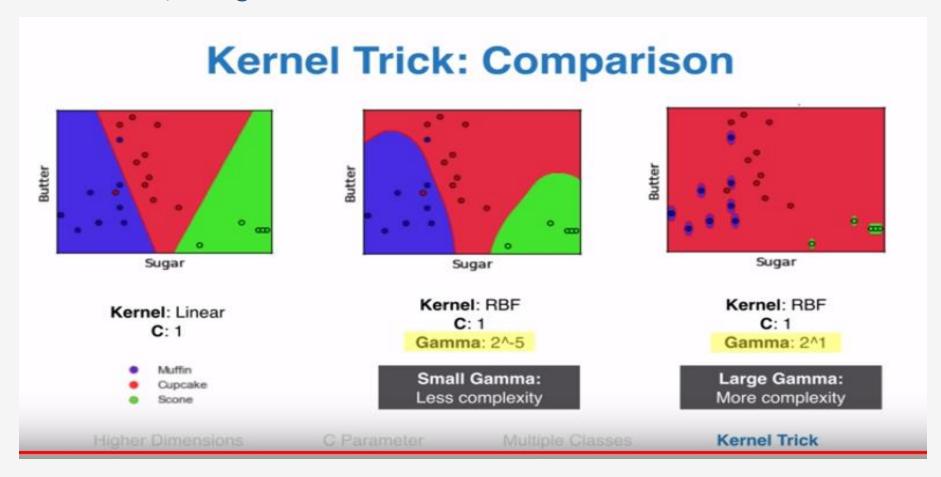
However, if we add another feature, Dosage squares

Then in 2-dimension space, the Data points can be separated by a line



Support Vector Machine (continued)

Need an additional Gamma parameter when using RBF Kernel Large gamma: overfit, Low gamma: underfit



Support Vector Machine (continued)

- So how to use the right Kernel, the right C-parameter and Gamma-parameter
- Use Grid search, i.e. think of C and Gamma parameters as two dimension in a grid, run different combination of C and Gamma until you find a good combination so your result (precision and recall) is good enough.
 - We call this fine-tuning your model.
 - However, how do you know this fine-tuning of C and Gamma is good for other datasets
 - => Cross validation comes to the rescue!
- This is time consuming and difficult. So this is one of the drawbacks in using SVM

Support Vector Machine (summary)

Advantages:

- Works well even when the number of features is much larger than the number of instances. Example in spam filter where a large number of words are the potential signifiers of a message being spam
- Allows a non-linear decision boundary curve. SVM transforms the variables to create new dimensions such that the representation of the classifier is a linear function at higher dimensions

Disadvantages

- No probability associated with each prediction
- Training the SVMs can be time-consuming when data is large and there are lots of noise, hard to compute the soft margin

Some useful references

- https://towardsdatascience.com/support-vector-machine-introduction-to-machine-learning-algorithms-934a444fca47
- Muffin and Cupcakes
- https://www.youtube.com/watch?v=N1vOgolbjSc
- StatQuest
- https://www.youtube.com/watch?v=efR1C6CvhmE
- Bias and Variance:
- https://www.youtube.com/watch?v=EuBBz3bI-aA&feature=youtu.be
- Nice Kernel visualization
- https://www.youtube.com/watch?v=3liCbRZPrZA