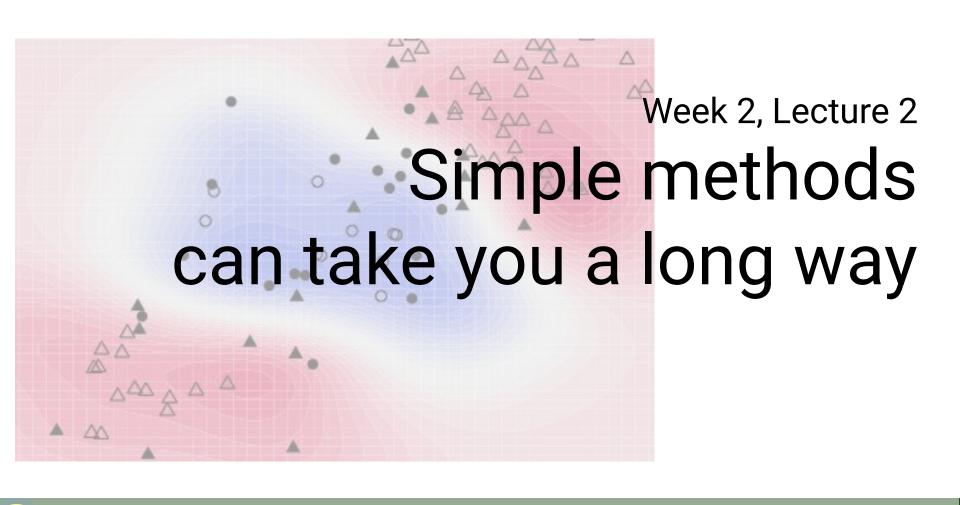
Class core values

- 1. Be **respect**ful to yourself and others
- 2. Be **confident** and believe in yourself
- 3. Always do your **best**
- 4. Be cooperative
- 5. Be **creative**
- 6. Have **fun**
- 7. Be **patient** with yourself while you learn
- 8. Don't be shy to **ask "stupid" questions**
- 9. Be **inclusive** and **accepting**



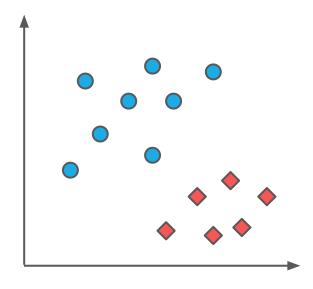


Learning Objectives

- 1. Describe the basic concept of a support vector machines
- 2. Describe the basic concept of a kernel
- 3. Apply computational coding to create and train a SVM
- 4. Evaluate the performance of models
- 5. Critically evaluate literature using RF

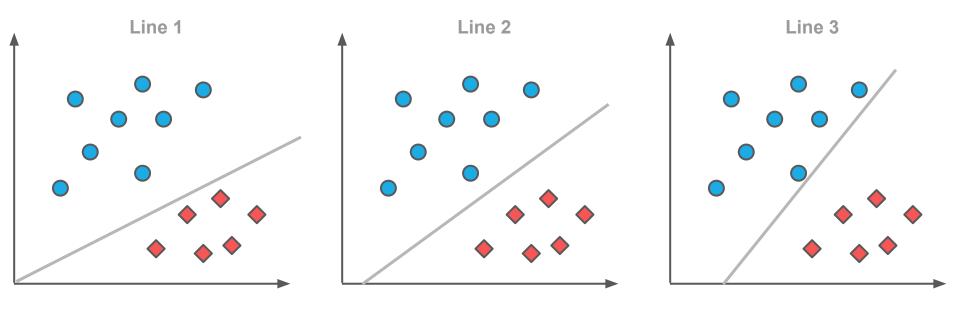


Selecting the best line



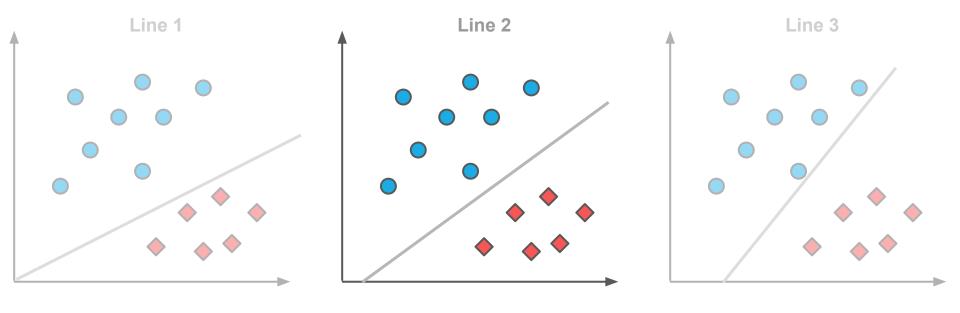


Selecting the best line



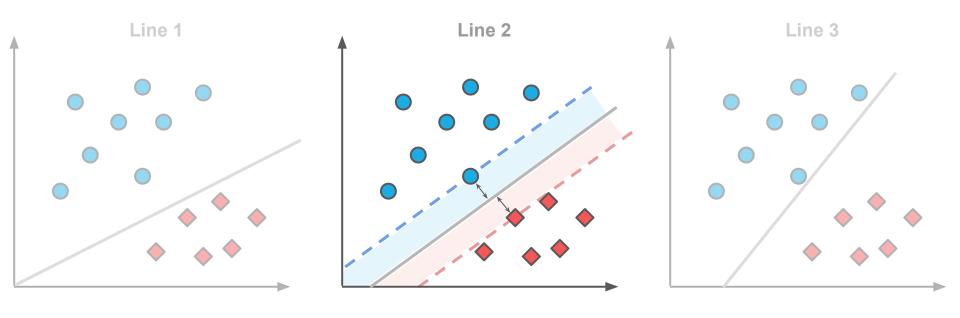


Selecting the best line



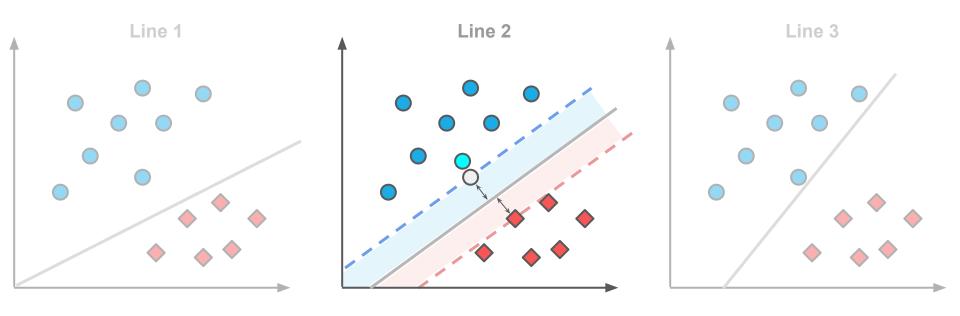


The best separating line is the one that has the largest **margins** from data



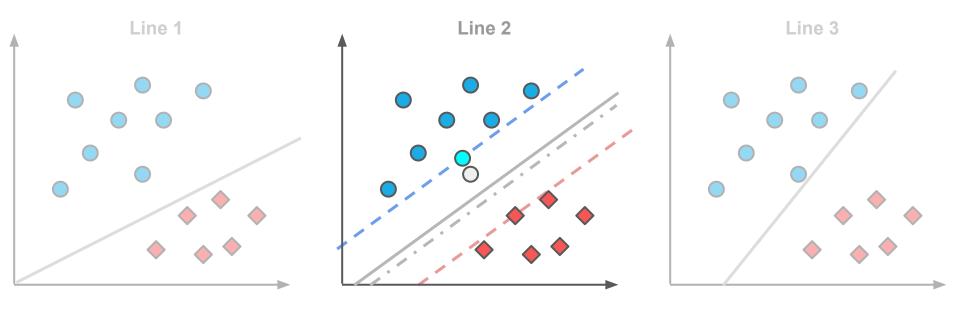


Closest points to the selected lines are called **support vectors**



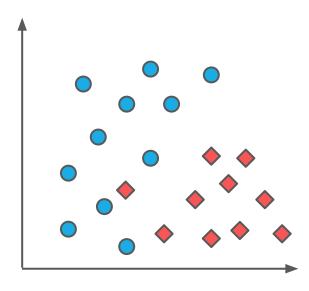


Changing the position of support vectors will change the selection of the best lie

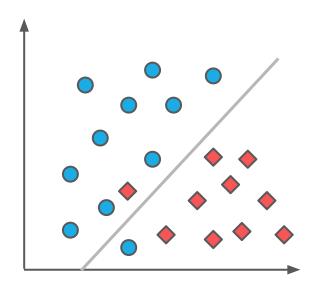




When there is no line that perfectly separates the data ...

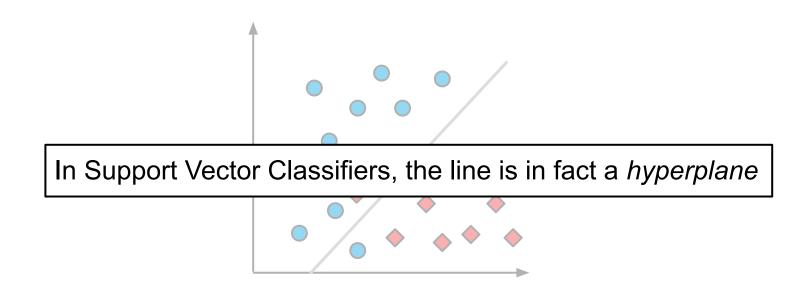


When there is no line that perfectly separates the data, we choose one that *almost* separates them



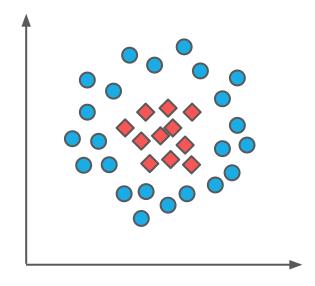


When there is no line that perfectly separates the data, we choose one that *almost* separates them



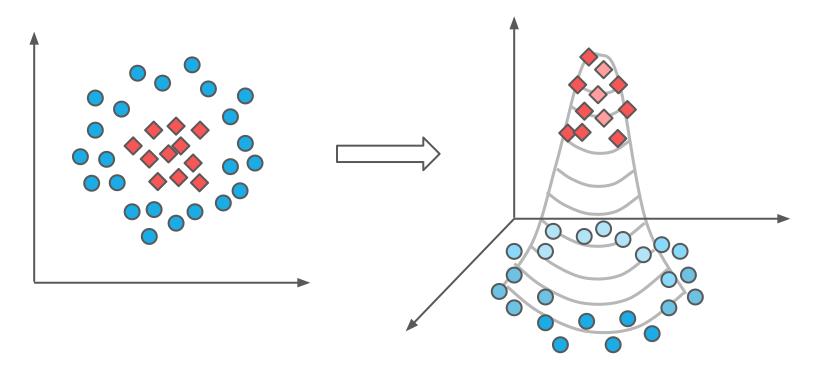


What if there is no linear correlation?



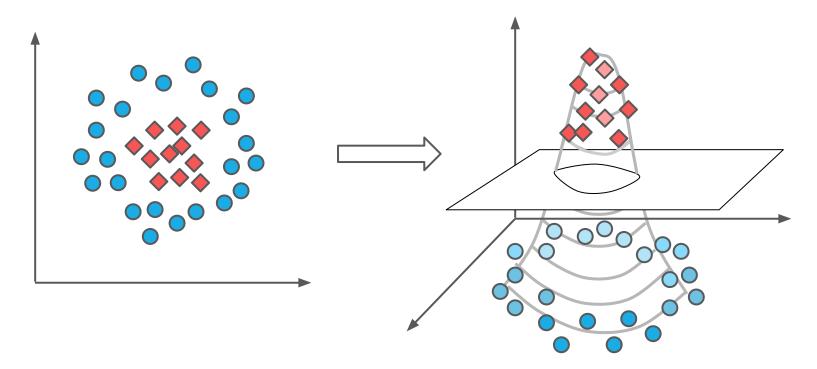


Transforming data into another space can help in finding the desired hyperplane



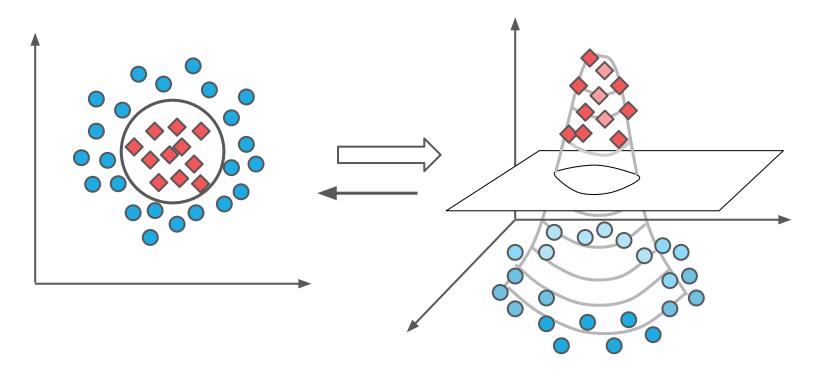


Transforming data into another space can help in finding the desired hyperplane



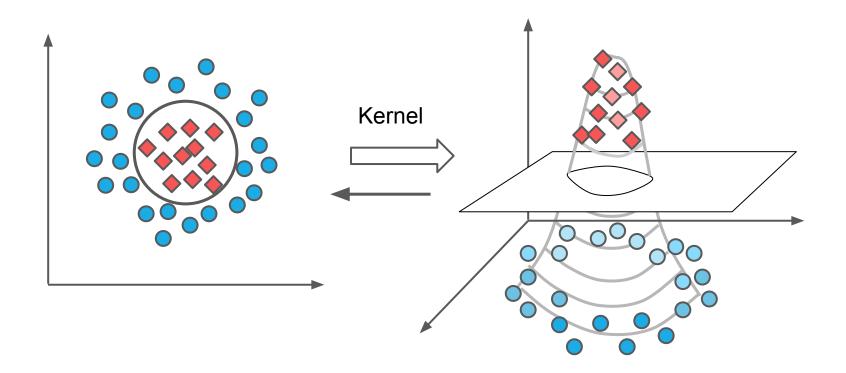


Transforming data into another space can help in finding the desired hyperplane

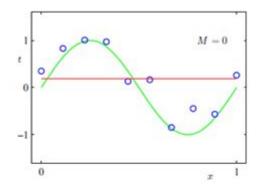


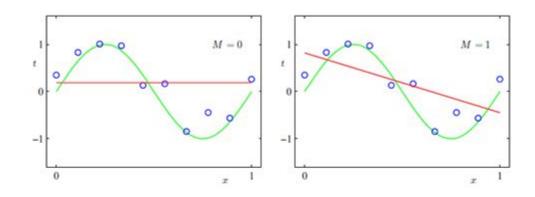


The transformers are called **kernels**

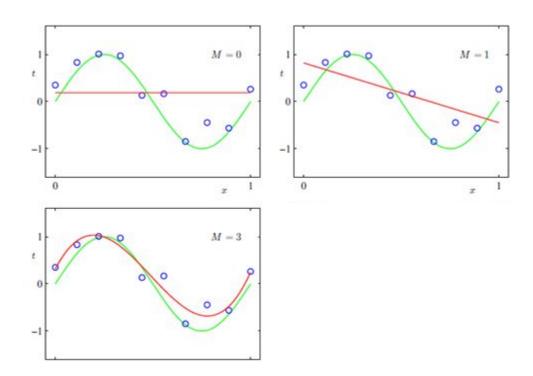




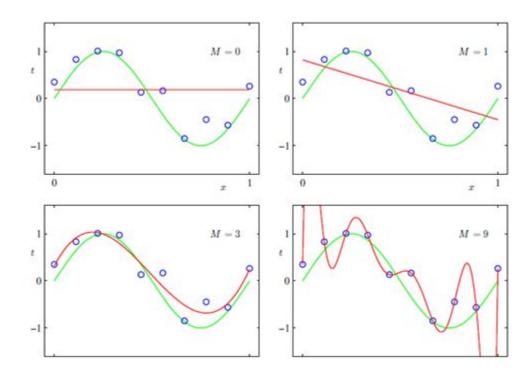








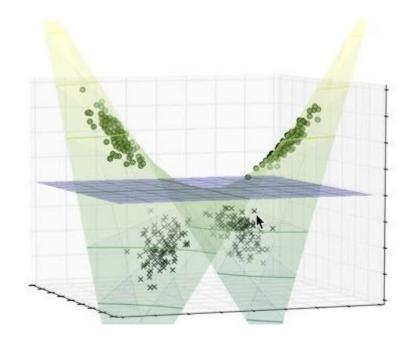






In-class activity

Applying SVM





Notes on SVM

Pros:

- 1. Effective in high dimension
- 2. Works when dimensions (features) are bigger than samples
- 3. Memory efficient
- 4. Versatile



Notes on SVM

Pros:

- 1. Effective in high dimension
- 2. Works when dimensions (features) are bigger than samples
- 3. Memory efficient
- 4. Versatile

Cons:

- 1. Over-fitting can be a problem when # features >> # samples
- 2. Do not directly provide probability estimates
- 3. Not scalable if you have lots of data (> 10000)



Next lecture: A gentle introduction to a "neuron"

