SPATIAL ECOLOGY

Introduction to Machine Learning & SVM

Antonio Fonseca

Agenda

1) Logistics
- Structure of the classes
- Our roadmap

2) Intro to machine learning
- Defining learning
- Supervised vs Unsupervised learning
- The framework of learning algorithms

3) Example of Supervised learning
- Support Vector Machine (SVM)
- Optimization of SVM
- Extension of SVM to regression (SVR)

Structure of the classes

- Recap of the previous class (aka, warm up) - 15 min
- Address questions from the previous class/assignment - 15 min
- New content - 30 min
- Coffee break - 10 min
- More content / Quiz - 30 min
- Hands-on tutorial - 30 min
- Questions - 20 min

Our roadmap

Class 1: Intro to machine learning (ML) and SVM (Oct 30th)

- Types of learning
- Hyperplanes and boundaries
- Support Vector Machine

Class 2: Optimizers and the Perceptron (pt. 1) (Nov 4thth)

- Regression with and without ML
- Minimizing loss functions
- Optimizers
- Perceptron

Our roadmap

Class 3: Perceptron (pt. 2) and Neural Networks (pt. 1) (Nov 6th)

- Perceptron as a regressor
- Activation functions
- When Perceptrons will fail you
- Neural Networks

Class 4: Neural Networks (pt. 2) (Nov 11th)

- How to train your network
- Hyperparameter search
- Using Weights and Biases to inspect your models

Our roadmap

Class 5: Convolutional Neural Networks (Nov 13th)

- Neural networks for spatial data
- Kernels, padding, pooling
- Study case with satellite images

Class 6: BYOP (Bring Your Own Paper) (Nov 18th)

- Pick a paper related to your field that is using machine learning
- Challenge me!

What is machine learning?

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https://tinyurl.com/geocomp2025

What is machine learning?

Machine learning is the process of identifying patterns in data.

Two kinds of machine learning

Supervised learning

- Have a bunch of labelled data,
  want to label new data

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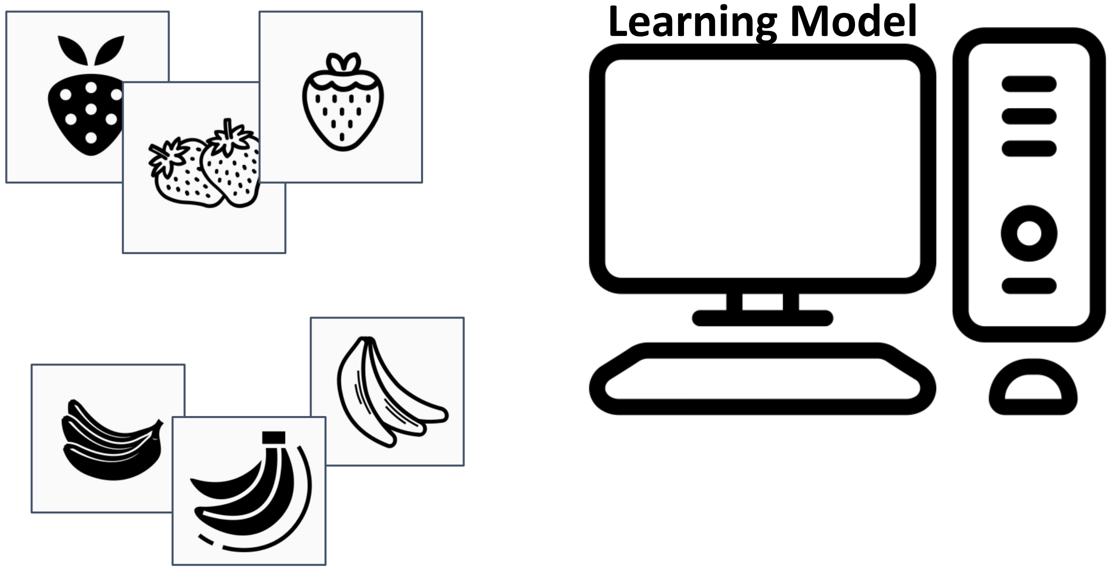
Supervised Learning Model



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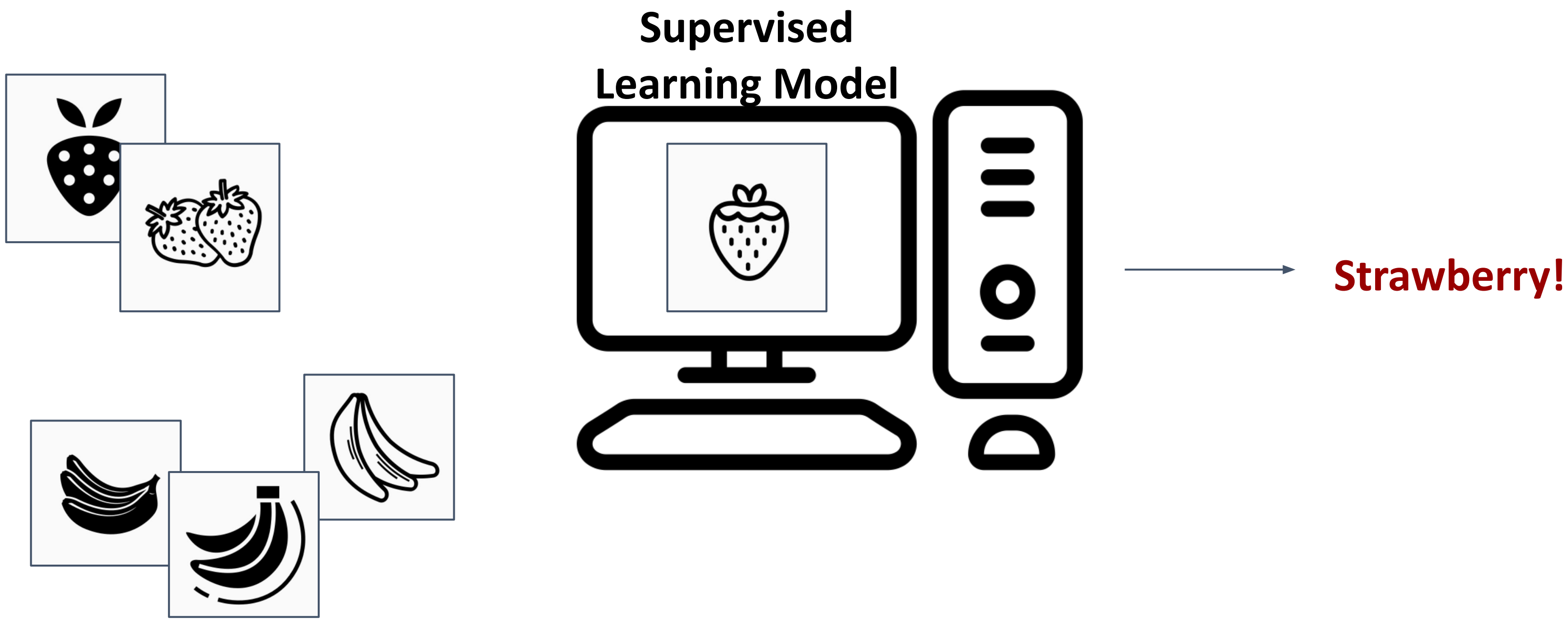

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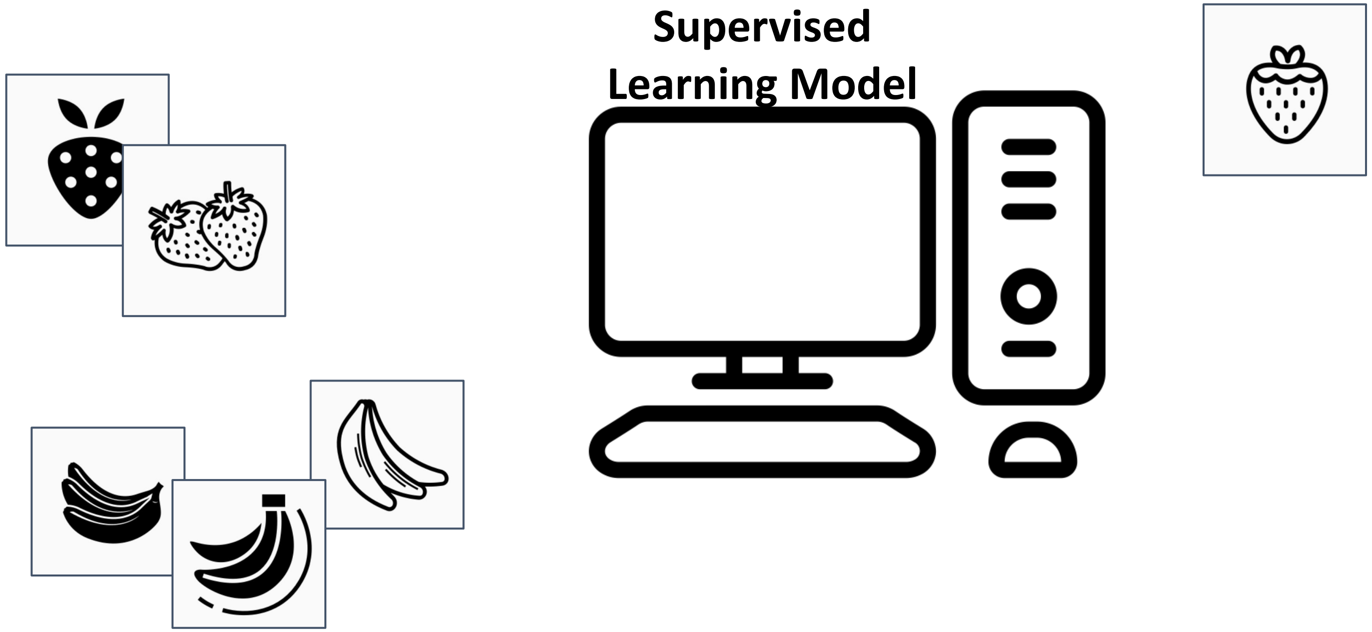

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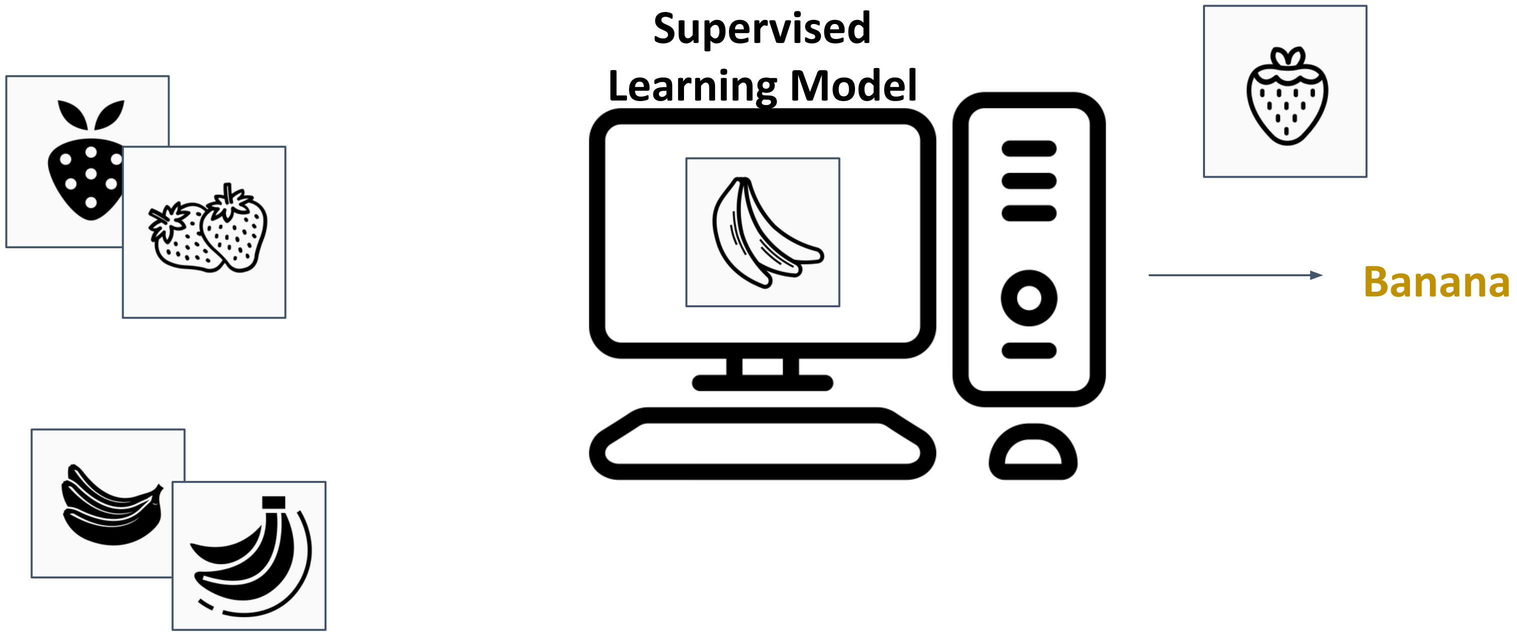

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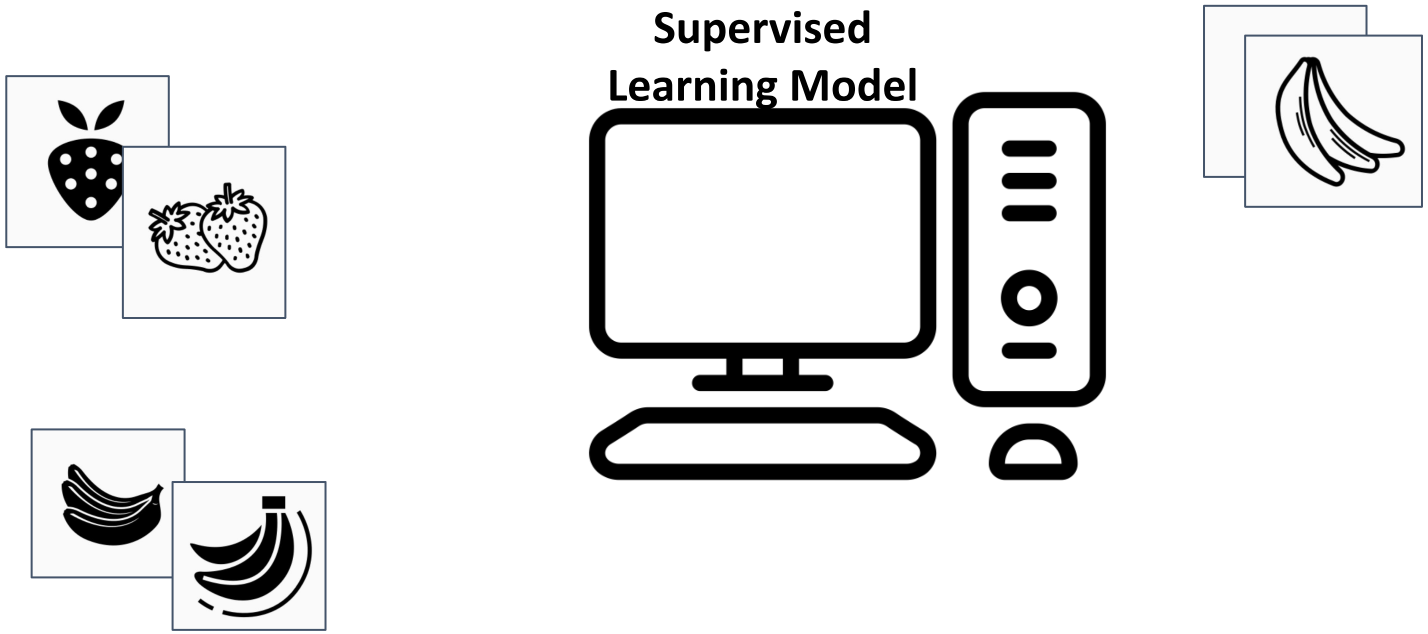

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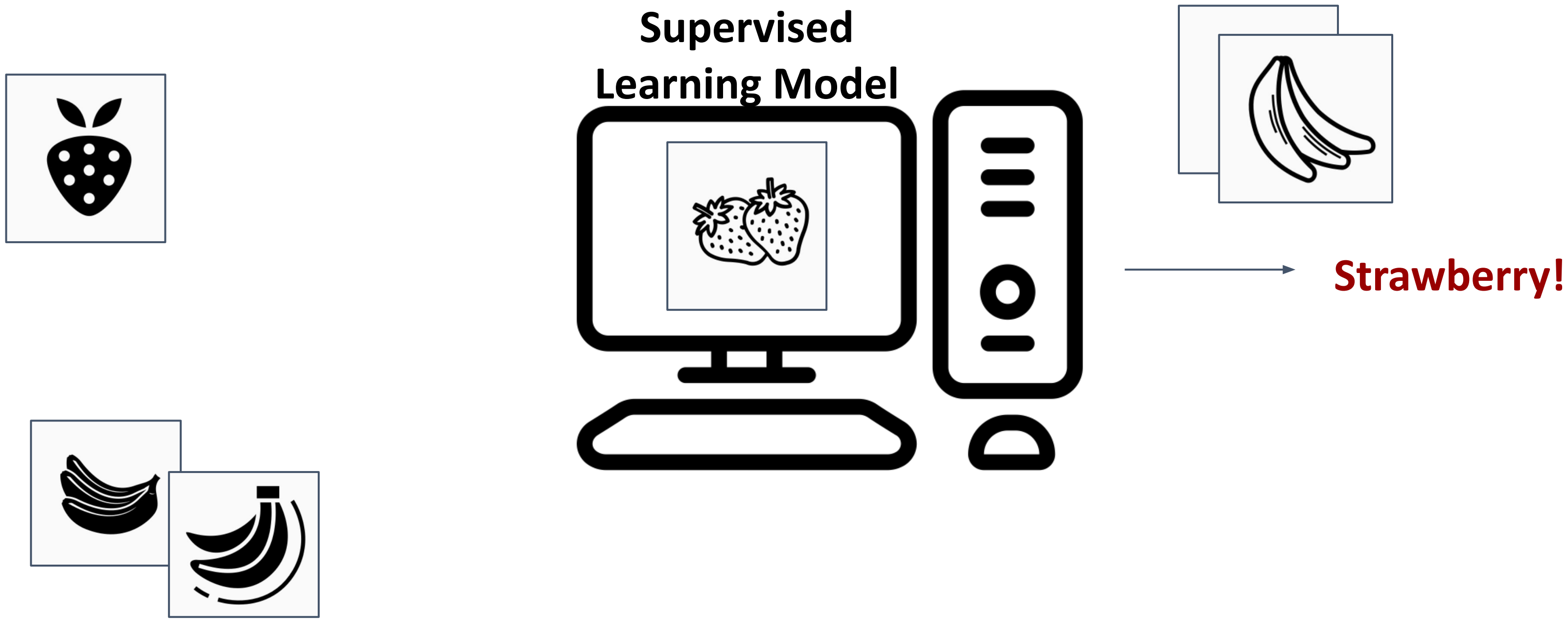

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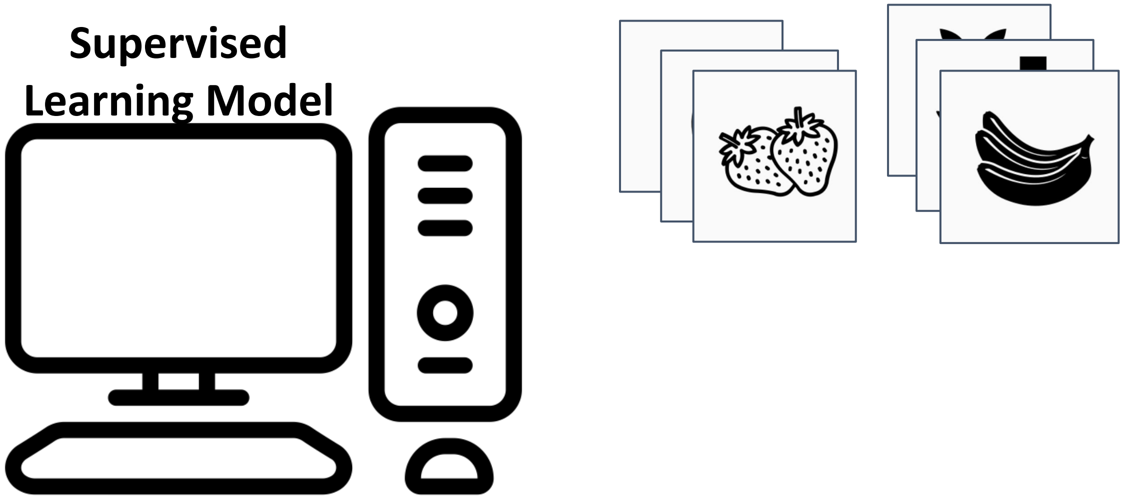

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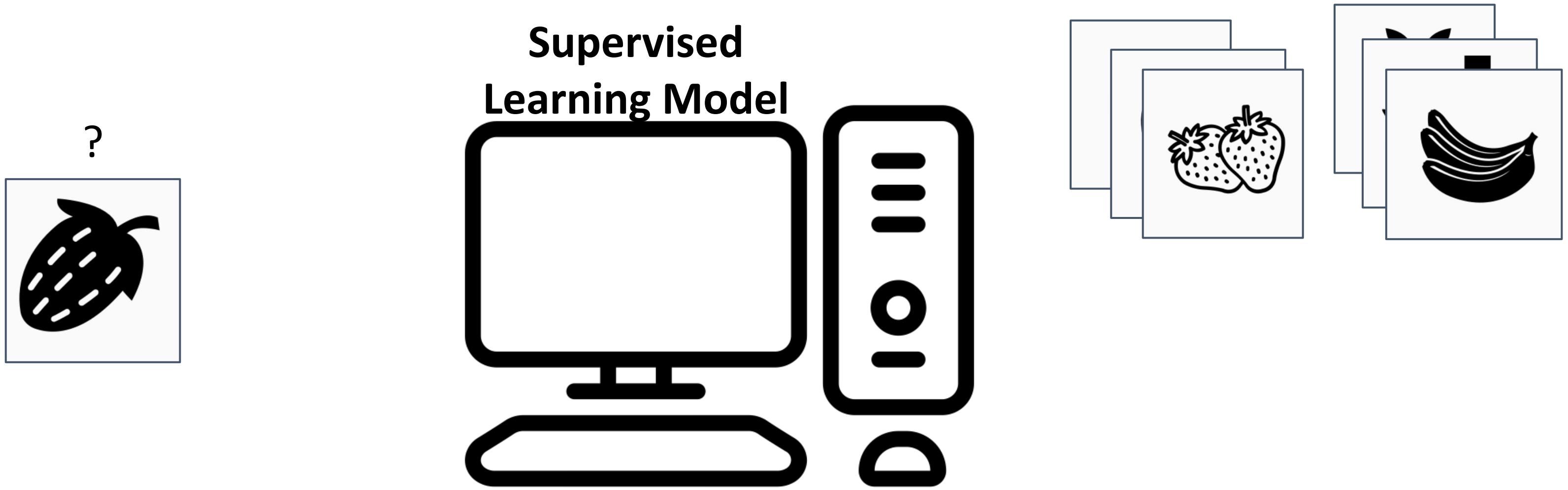

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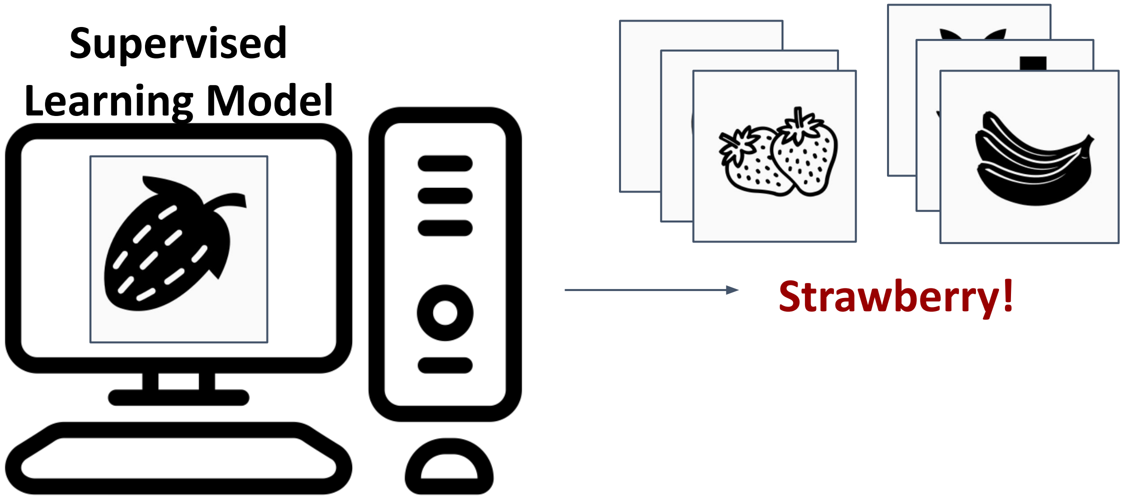

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Supervised learning

- Have a bunch of labelled data, want to label new data

Unsupervised learning

- Have a bunch of unlabeled data, want to organize it

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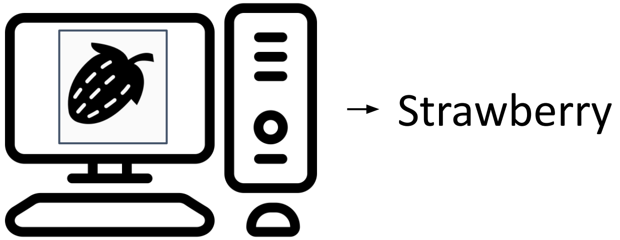
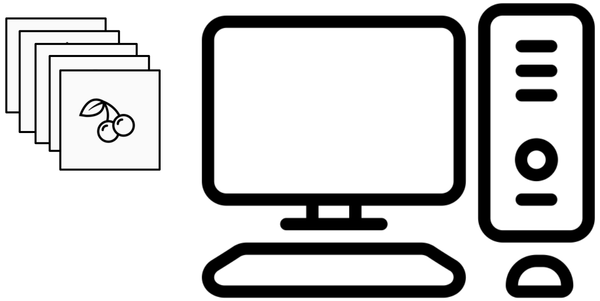


Unsupervised Learning Model



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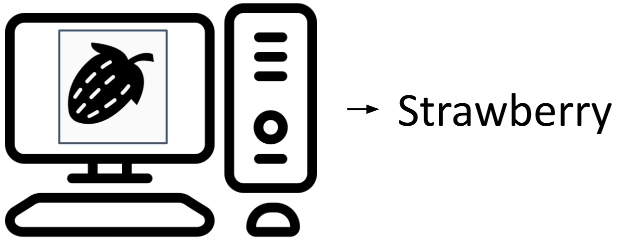
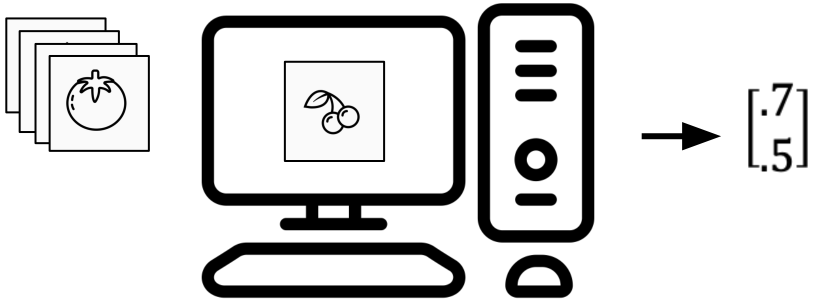


Unsupervised Learning Model



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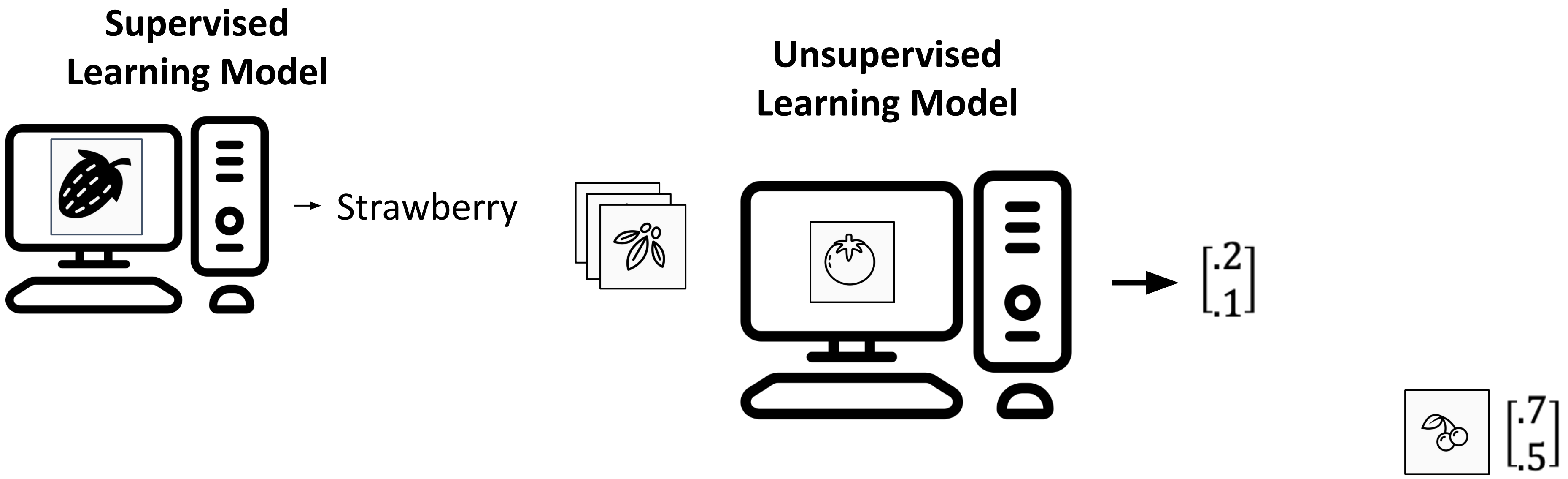

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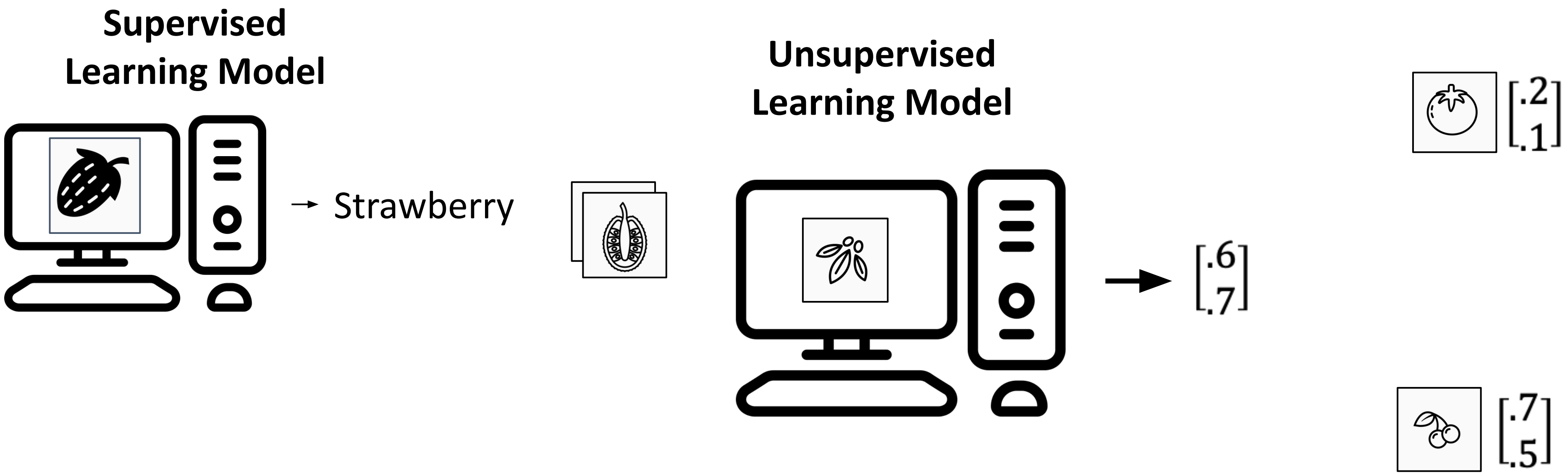

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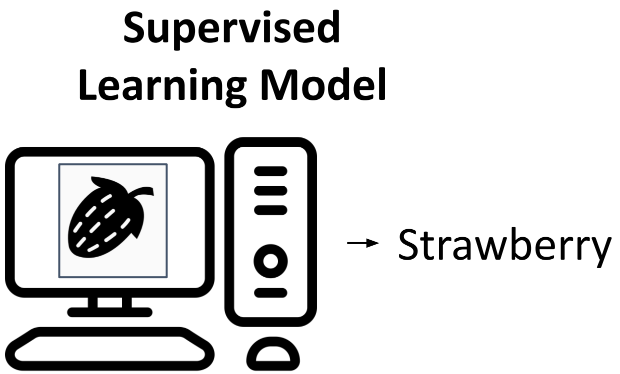
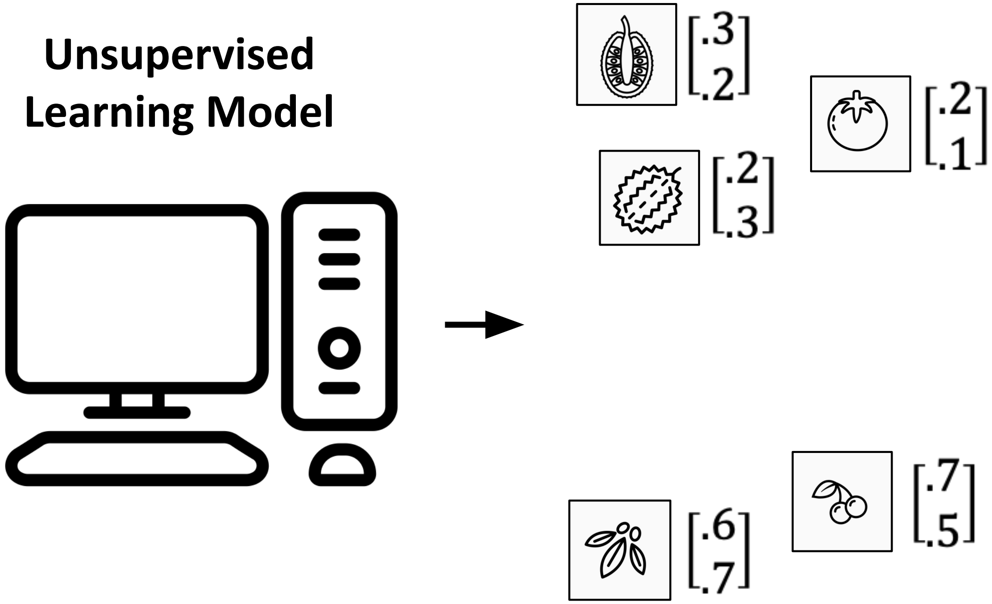




Two kinds of machine learning

Supervised learning

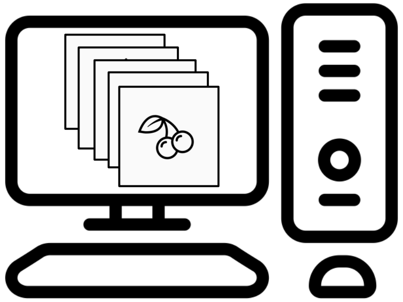
- Have a bunch of labelled data, want to label new data
- Learn a function $f(X) \rightarrow Y$ where all values of Y are known for some samples of X

Unsupervised learning

- Have a bunch of unlabeled data, want to organize it
- Learn an embedding
  $f(X) \rightarrow Y, X \in \mathbb{R}^n, Y \in \mathbb{R}^m, n \gg m$
- Lower dimensional, easier to interpret (e.g. as clusters)

Supervised Learning Model

Unsupervised Learning Model



Learning algorithms

“A computer program is said to learn from experience **E** with respect to some class of tasks **T** and performance measure **P** , if its performance at tasks in **T** , as measured by **P** , improves with experience **E**.”

Tasks (T)
Transcription
Machine Translation
Classification
Anomaly detection
Synthesis and sampling
⋮
Regression

Performance (P)

Accuracy rate

Adjusted R^2
RMSE/MSE/MAE

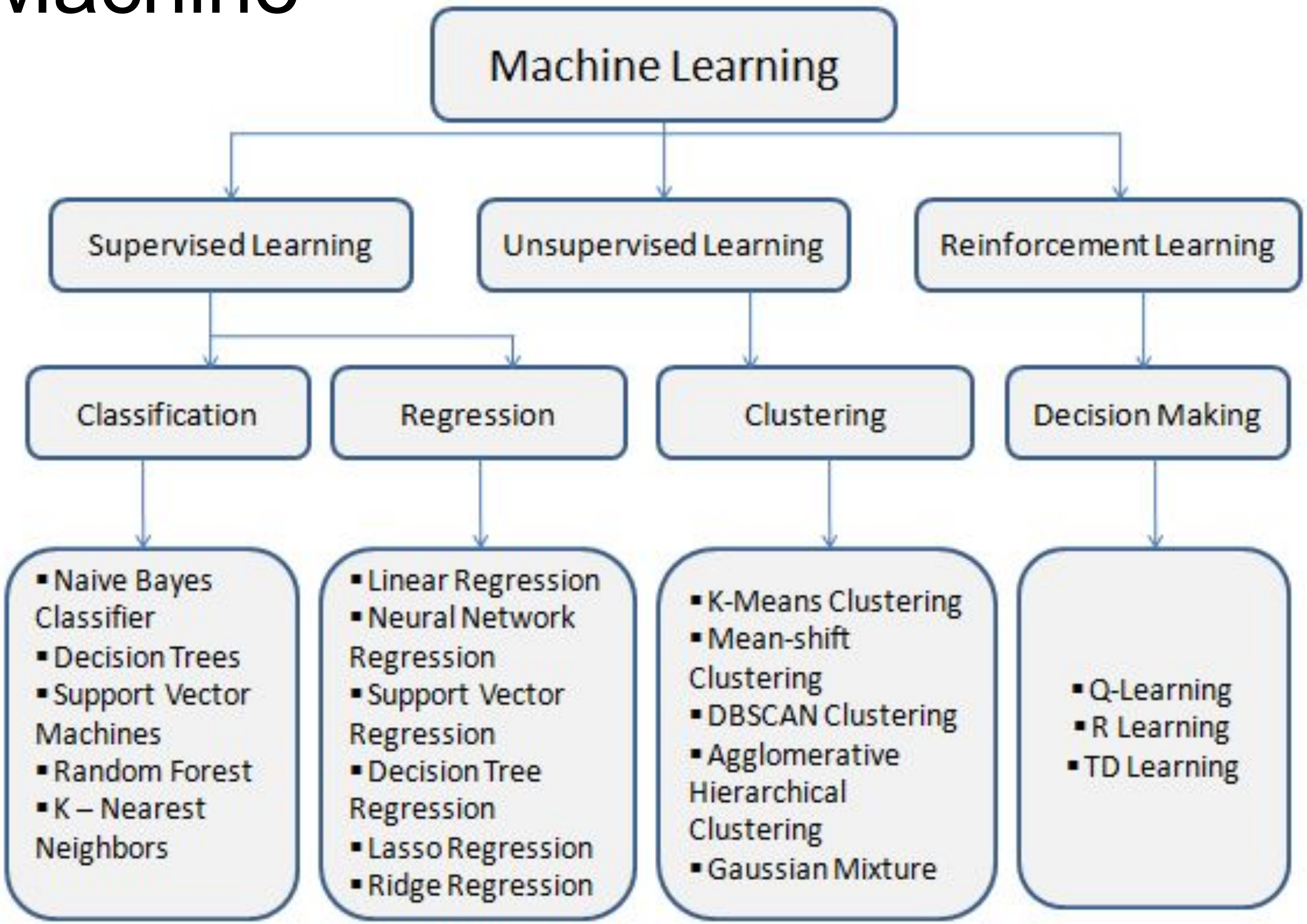
Experience (E)

Supervised Learning

Unsupervised Learning

Reinforcement Learning

Types of Machine Learning



Putting these frameworks in perspective

- **"Pure" Reinforcement Learning** (cherry)
  - The machine predicts a scalar reward given once in a while.
  - **A few bits for some samples**
- **Supervised Learning** (icing)
  - The machine predicts a category or a few numbers for each input
  - Predicting human-supplied data
  - **10→10,000 bits per sample**
- **Unsupervised/Predictive Learning** (cake)
  - The machine predicts any part of its input for any observed part.
  - Predicts future frames in videos
  - **Millions of bits per sample**

- (Yes, I know, this picture is slightly offensive to RL folks. But I'll make it up)

Original LeCun cake analogy slide presented at NIPS 2016

Time for a little quiz!

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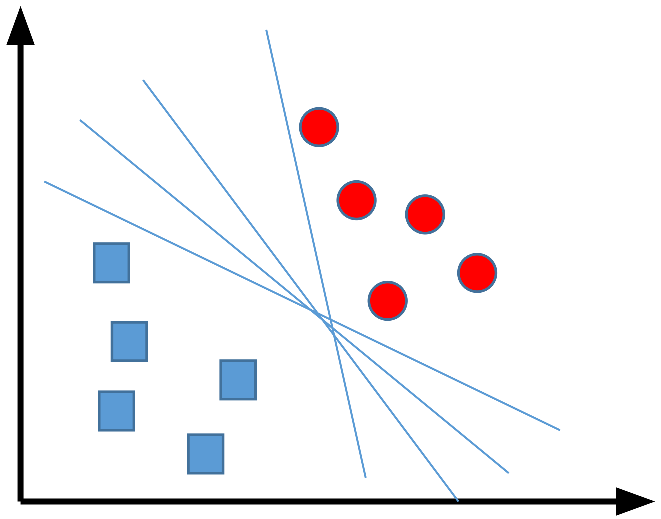
Decision Boundaries

Find a hyperplane in an N-dimensional space that distinctly classifies the data points.



What is the correct decision boundary for this problem?

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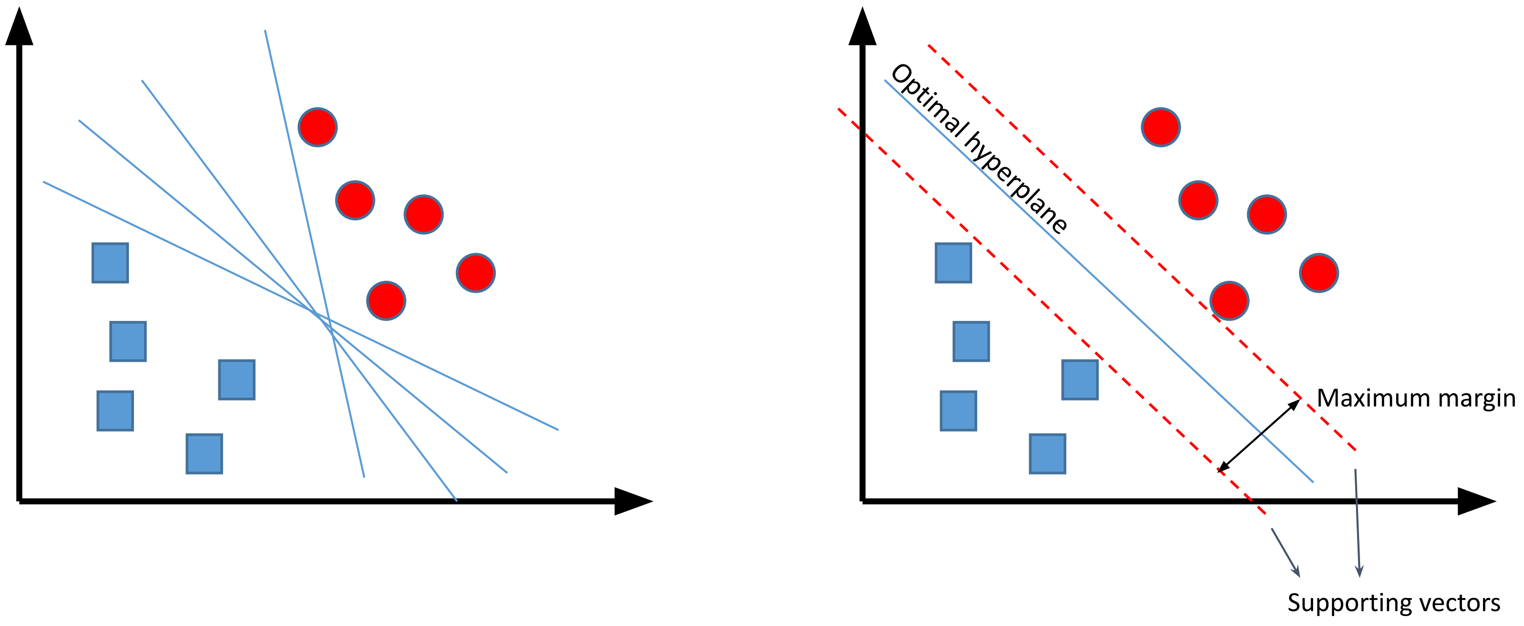
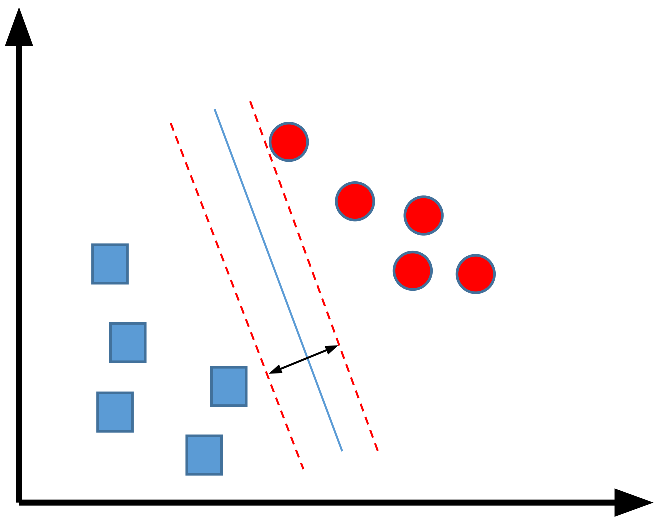
Support Vector Machine

Find the optimal hyperplane in an N-dimensional space that distinctly classifies the data points.

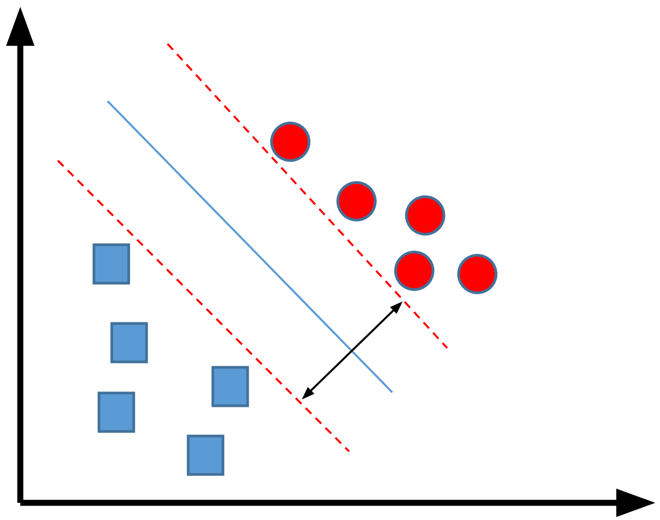


Support Vector Machine

Maximize the margin of the classifier

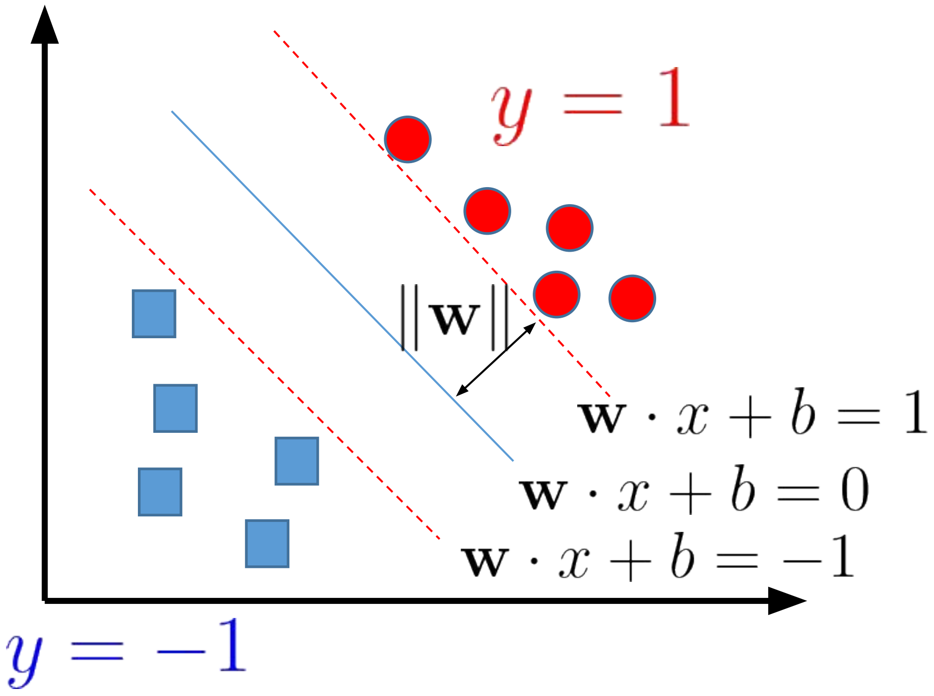


Small margin



Large margin

Support Vector Machine



Hyperplane equation: $f(x) = \mathbf{w} \cdot x + b$

Distance (D) from a point to the hyperplane

$$D = \frac{|\mathbf{w} \cdot x + b|}{\|\mathbf{w}\|}$$

Minimize the weights, increase distance

Classification task

$$\begin{cases} wx_i + b \geq +1 & \text{when } y_i = +1 \\ wx_i + b \leq -1 & \text{when } y_i = -1, \end{cases}$$

SVM Optimization

Hinge loss function

$$c(x, y, f(x)) = \begin{cases} 0, & \text{if } y * f(x) \geq 1 \\ 1 - y * f(x), & \text{else} \end{cases}$$

Loss function for the SVM

$$min_w \lambda \parallel w \parallel^2 + \sum_{i=1}^{n} (1 - y_i \langle x_i, w \rangle)_+$$

Updating the weights:

No misclassification

$$w = w - \alpha \cdot (2\lambda w)$$

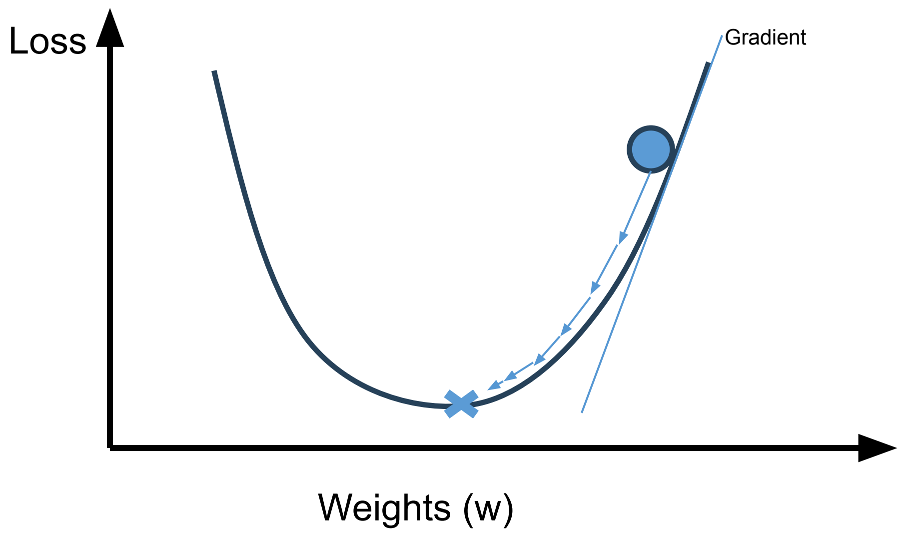
Misclassification

$$w = w + \alpha \cdot (y_i \cdot x_i - 2\lambda w)$$

Gradients

$$\frac{\delta}{\delta w_k} \lambda \parallel w \parallel^2 \quad = 2\lambda w_k$$

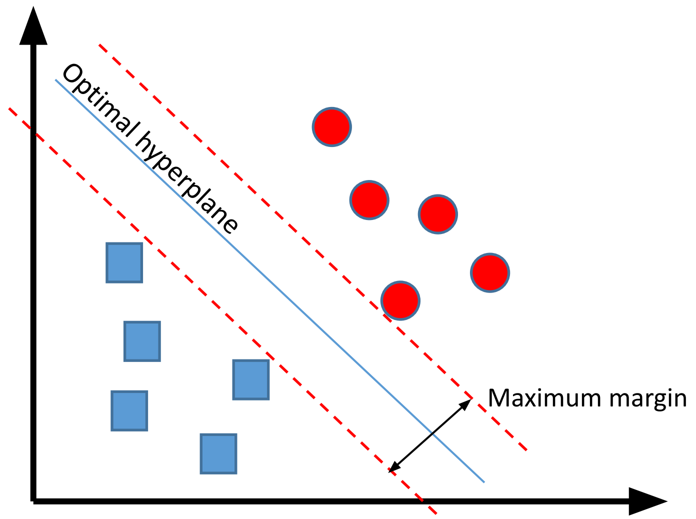
$$\frac{\delta}{\delta w_k} \big(1 - y_i \langle x_i, w \rangle\big)_+ \quad = \begin{cases} 0, & \text{if } y_i \langle x_i, w \rangle \geq 1 \\ -y_i x_{ik}, & \text{else} \end{cases}$$



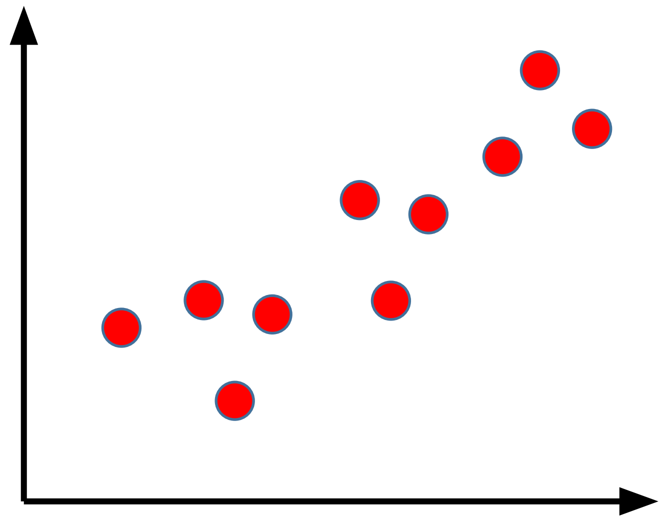
Support Vector Machine for Regression

How do I turn the SVM into a SVR?

SVM



SVR(?)



SVR Optimization

Loss

$$L(y, f(x, \mathbf{w})) = \begin{cases} 0, & |y - f(x, \mathbf{w})| \leq \epsilon \\ |y - f(x, \mathbf{w})| & \text{o.w.} \end{cases},$$

Constraints

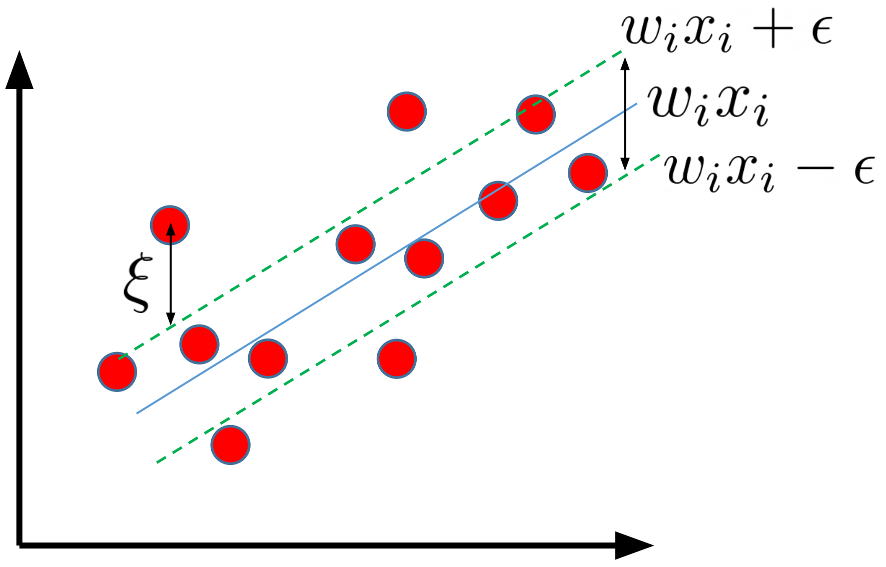
$$|y_i - w_i x_i| \leq \epsilon + |\xi_i|$$

Deviation from the margin (slack)

Margin of error

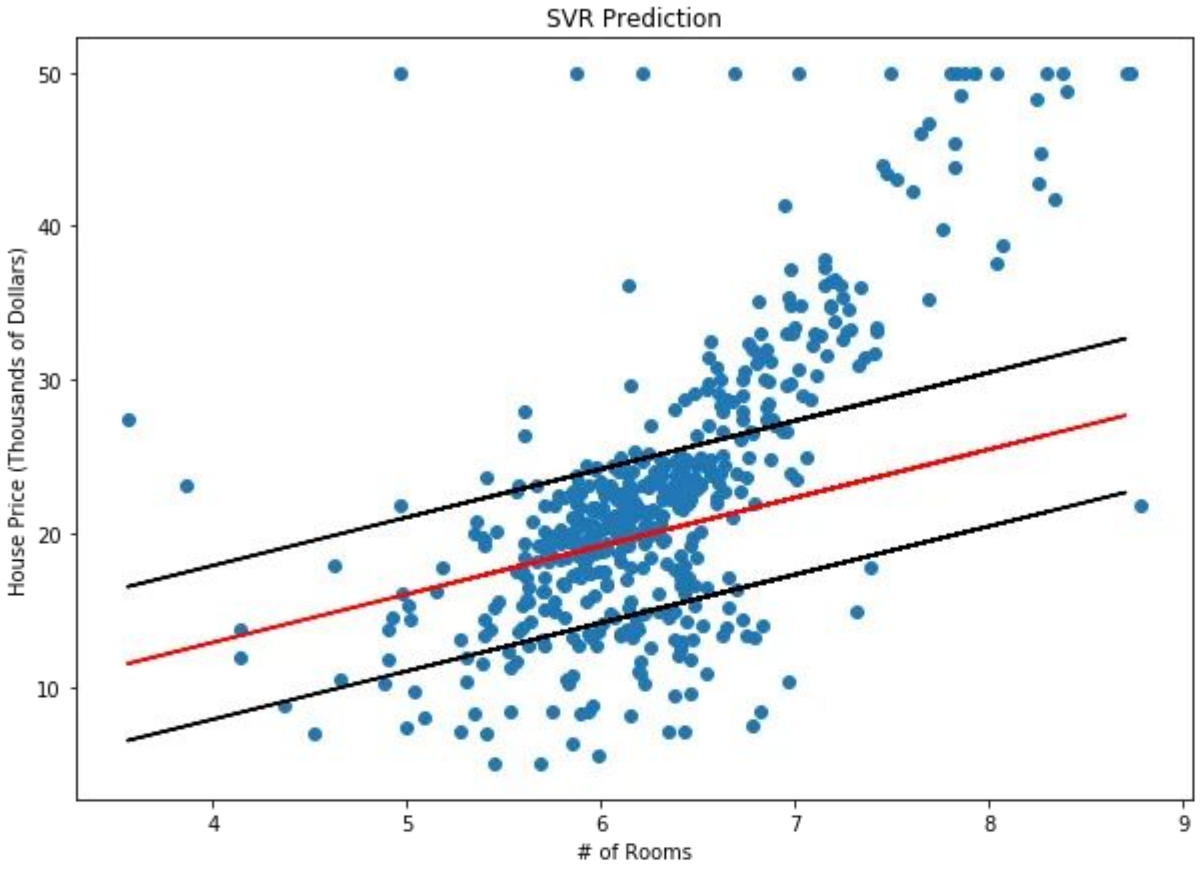
Loss function for the SVR

$$\min \frac{1}{2} \|w\|^2 + C \sum_{i=1}^{n} |\xi_i|$$



Example: House price in Boston

SVR, ϵ=5, C=0

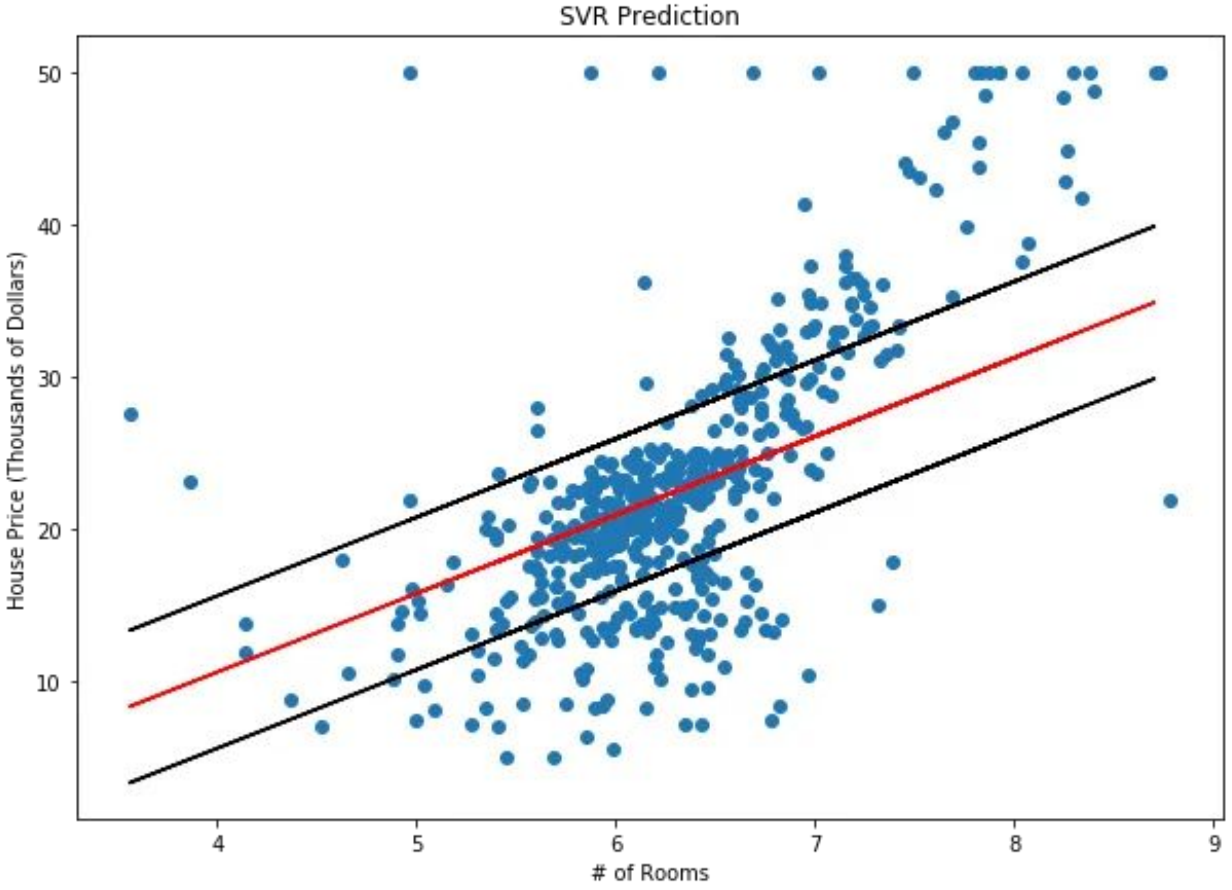


Conclusions:

- Some of the points still fall outside the margins.
- Consider the possibility of errors that are larger than ϵ.
- Add some slack (ie, C)
- Notice that in sklearn, the strength of the regularization is the inverse of C

Example: House price in Boston

SVR, ϵ=5, C=1.0

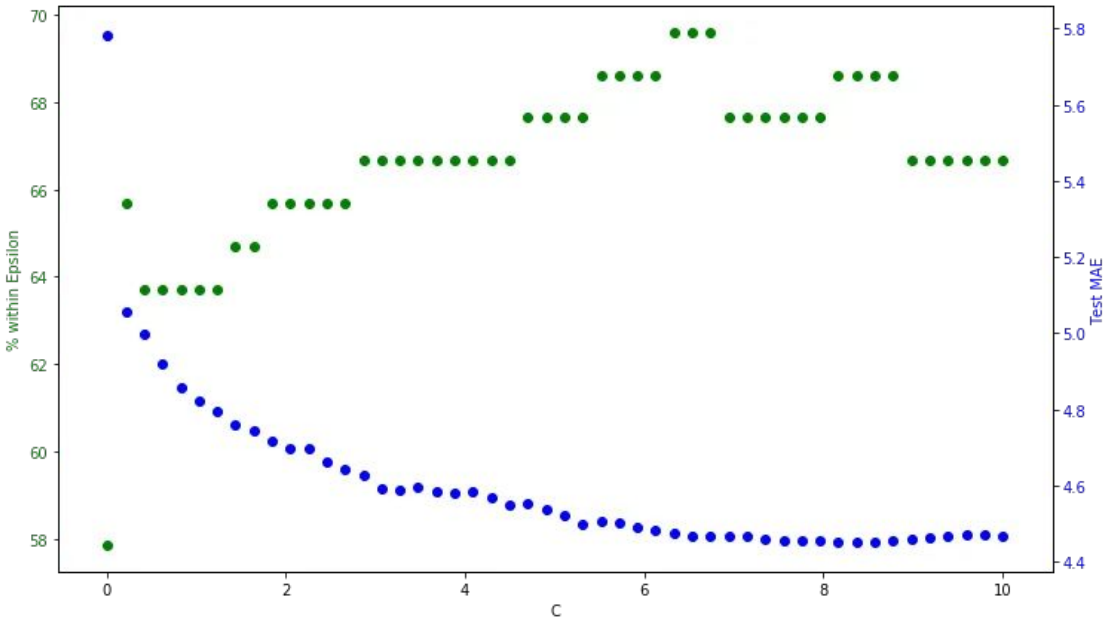


Conclusions:

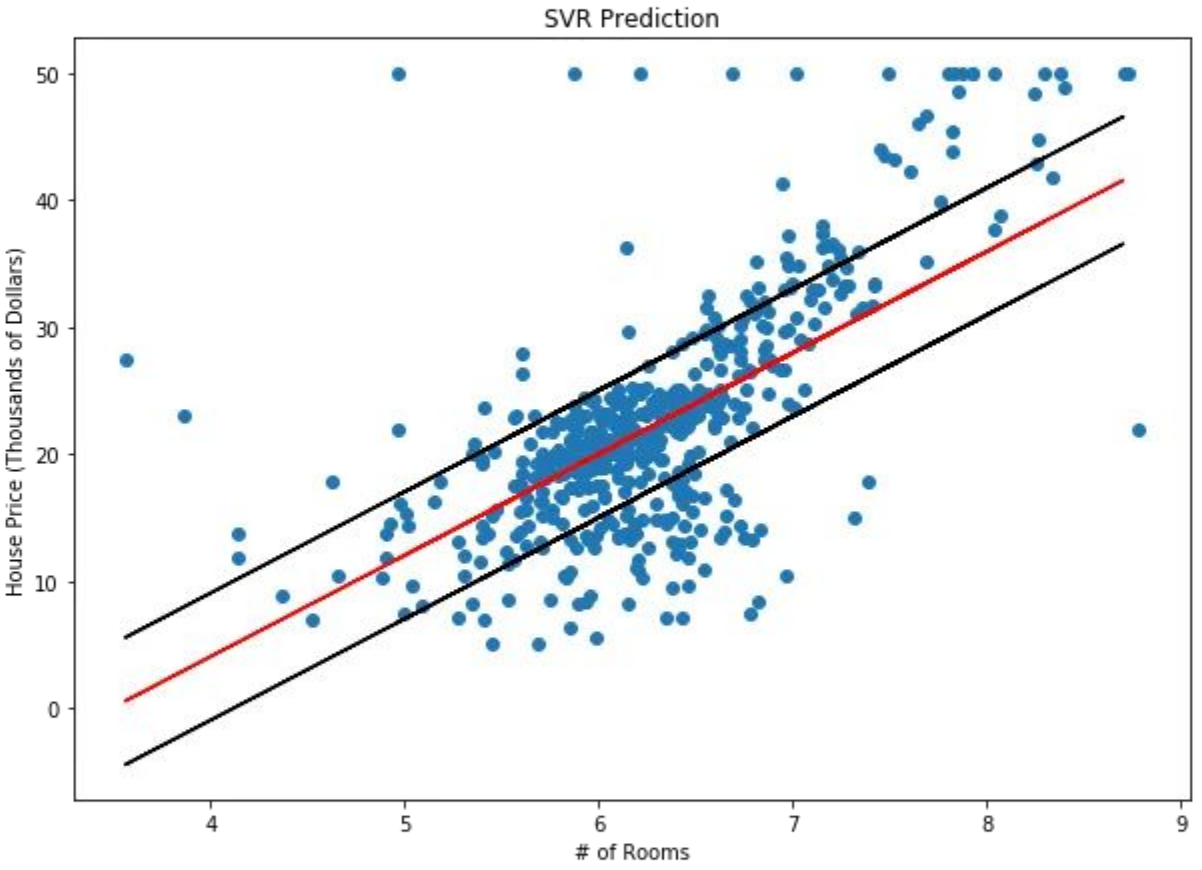
- As C increases, our tolerance for points outside of ϵ also increases.
- As C approaches 0, the tolerance approaches 0 and the equation collapses into the simplified (although sometimes infeasible) one.

Example: House price in Boston

- We can use grid search over *C* to find the ideal amount of slack (more points within margin).
- Since our original objective of this model was to maximize the prediction within our margin of error ($5,000), we want to find the value of *C* that maximizes *% within Epsilon*. Thus, *C*=6.13.



ϵ=5, *C*=6.13



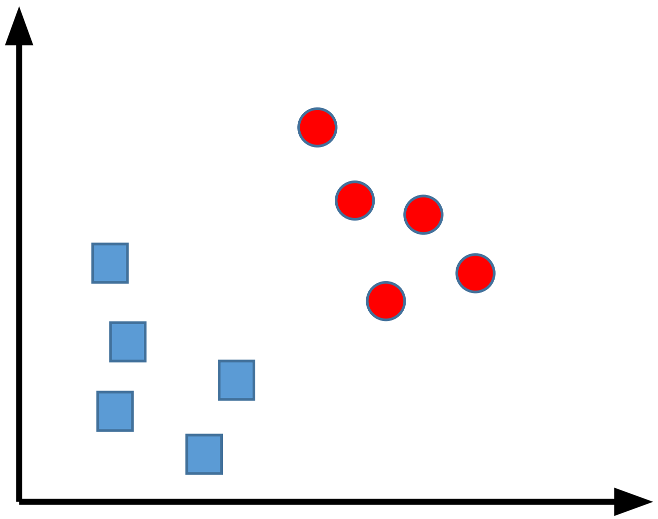
Support Vector Machine for Regression

- The best fit line is the hyperplane that has the maximum number of points.
- Limitations
  - The fit time complexity of SVR is more than quadratic with the number of samples
  - SVR scales poorly with number of samples (e.g., >10k samples). For large datasets, **Linear SVR**
  - Underperforms in cases where the number of features for each data point exceeds the number of training data samples
  - Underperforms when the data set has more noise, i.e. target classes are overlapping.

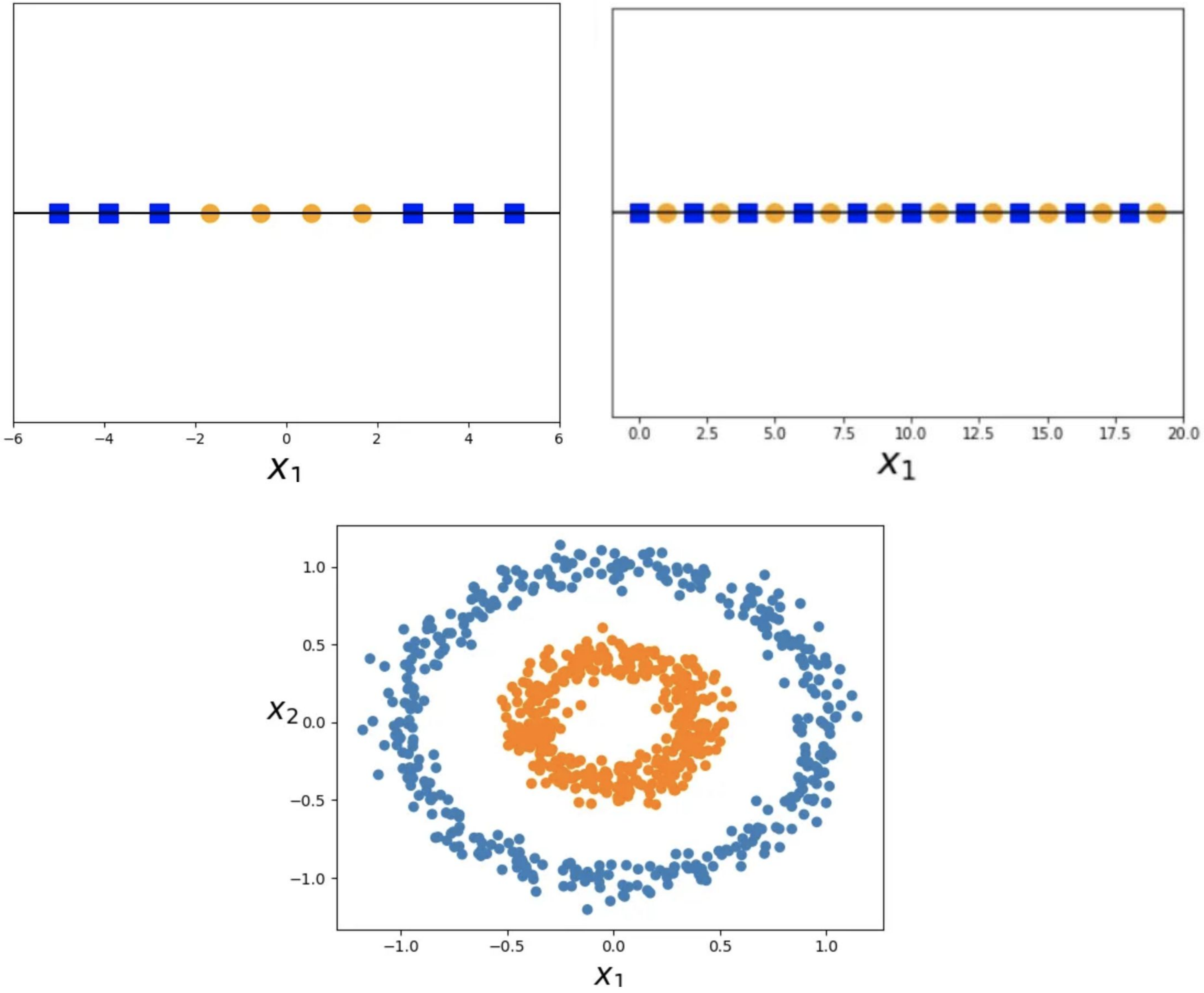
What if…

Non-linear spaces

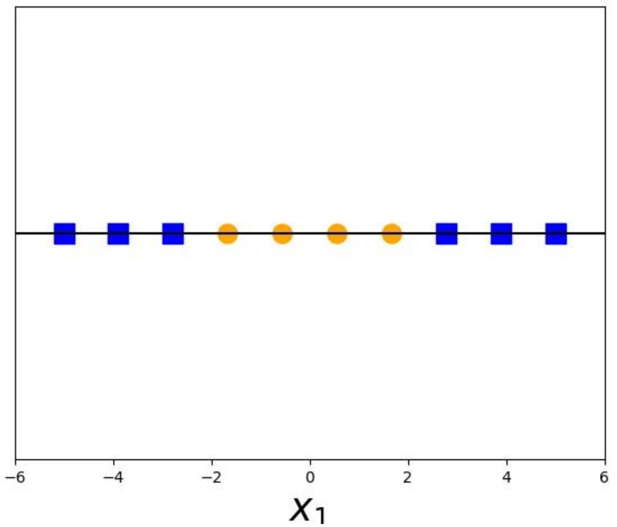
Linearly separable

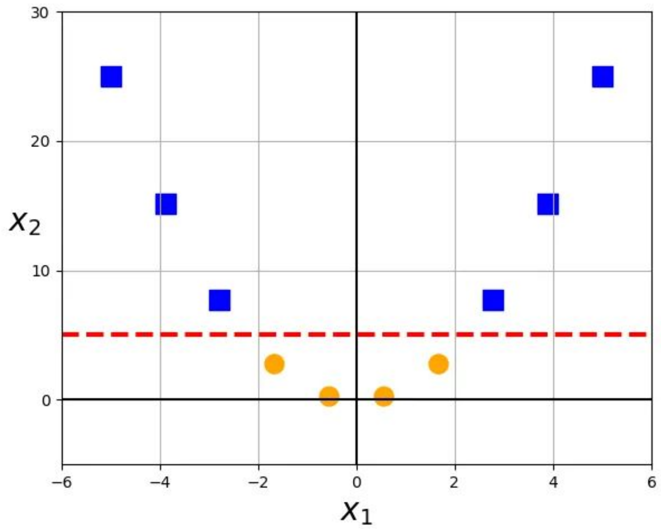


Not linearly separable



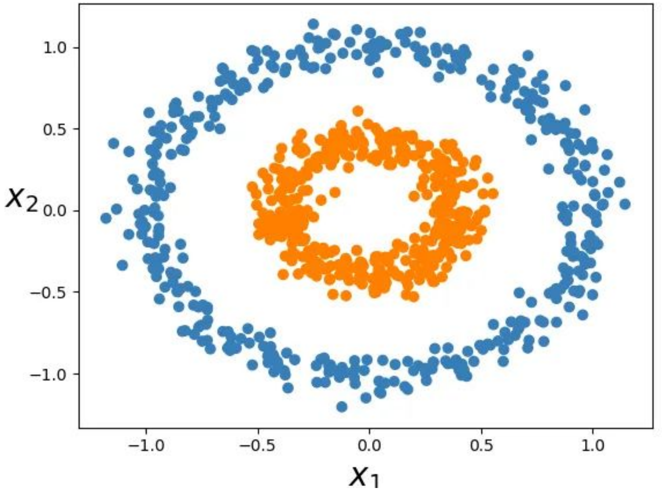
Kernel tricks

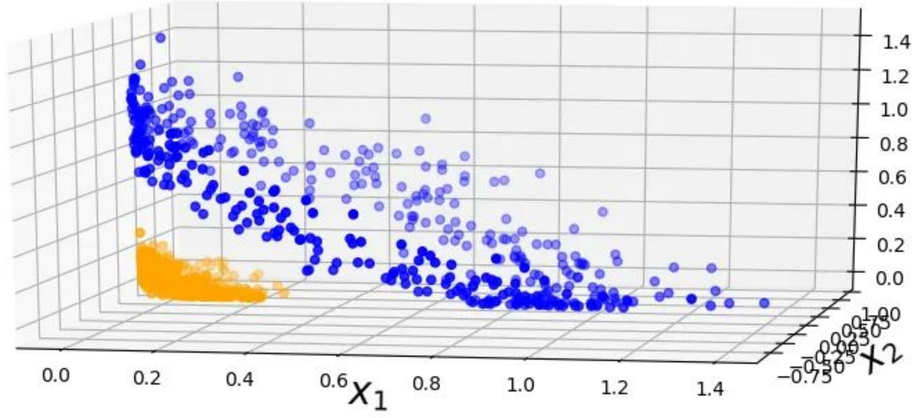




“Give me enough dimensions and I will classify the whole world”.

Zucker, Steve





Additional reading material

- Support Vector Regression (link)
- Review of Linear Algebra terms (link)
- More extensive review (link)
  - Linear Algebra (chapter 2) and Vector Calculus (chapter 5)

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