Machine Learning and Pattern Recognition

A High Level Overview

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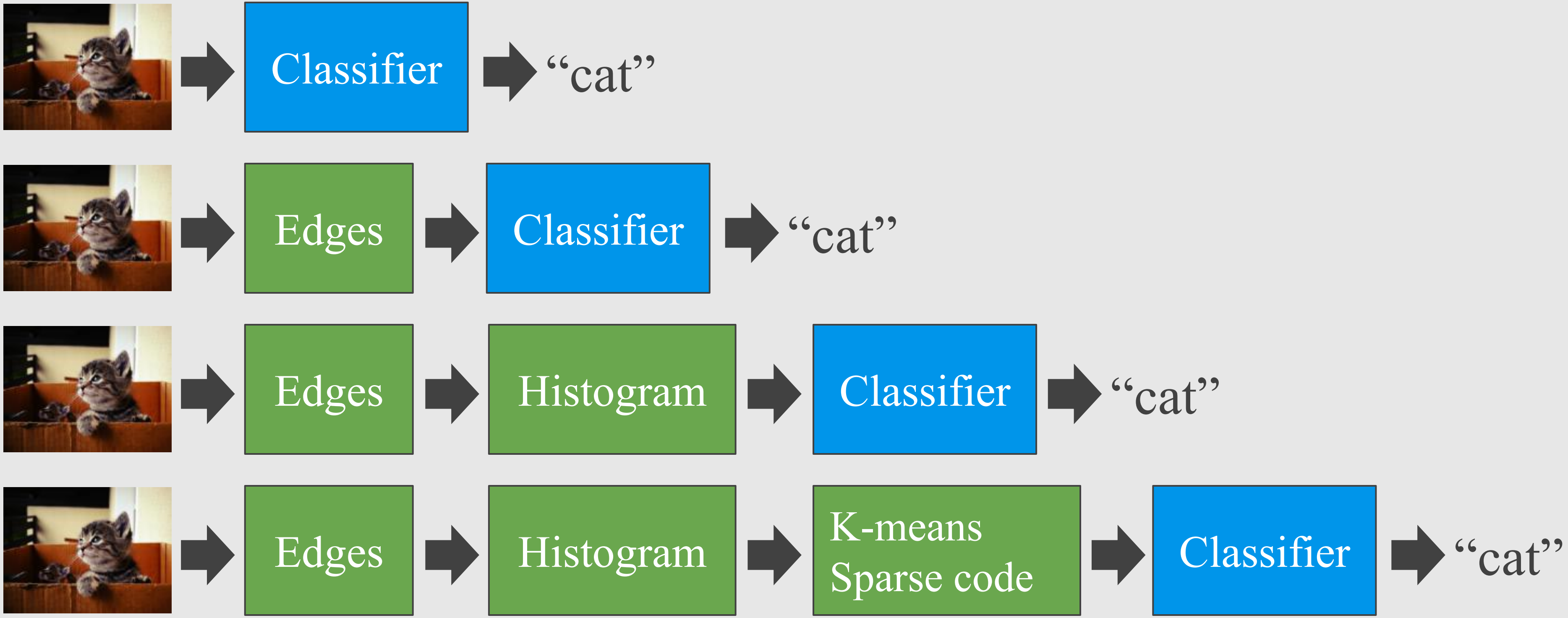
(Main bulk of slides kindly provided by **Prof. Sandra Avila**)

Institute of Computing (IC/Unicamp)

MC886/MO444

SVMs are among the best “off-the-shelf” supervised learning algorithm.

Traditional Recognition



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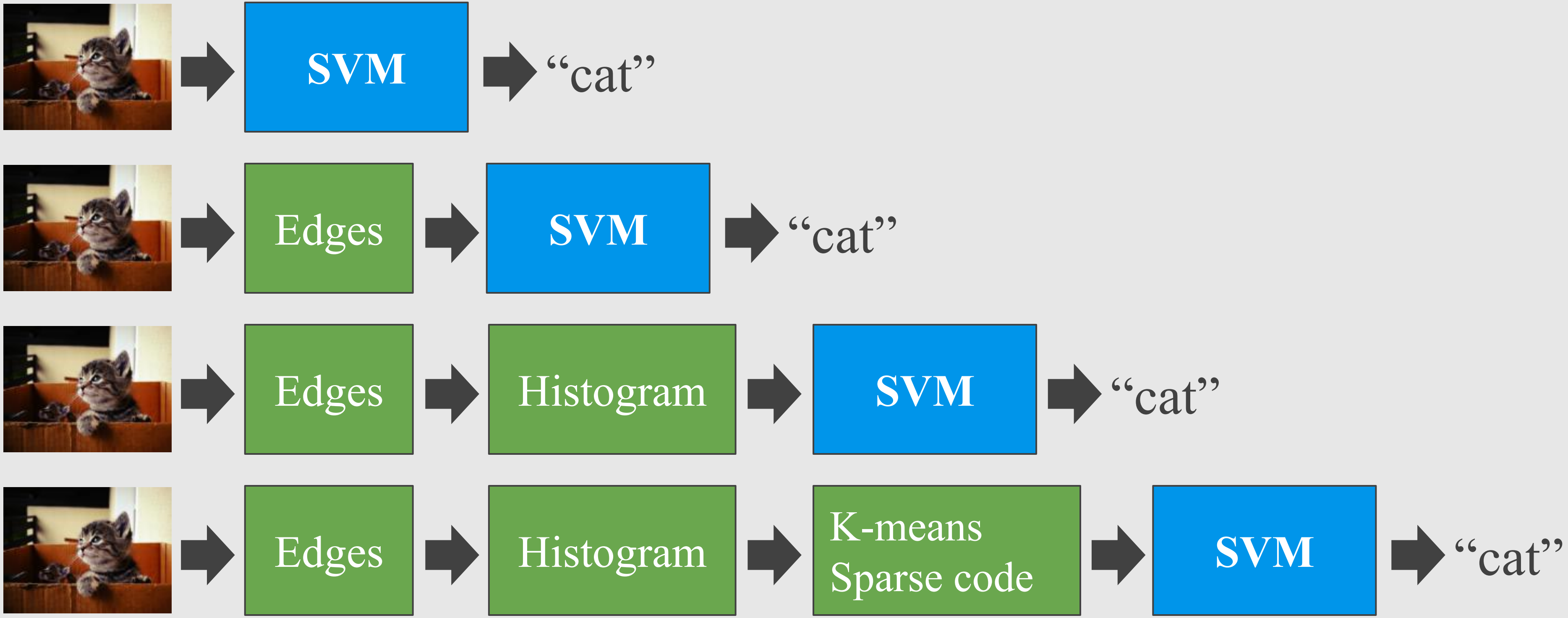
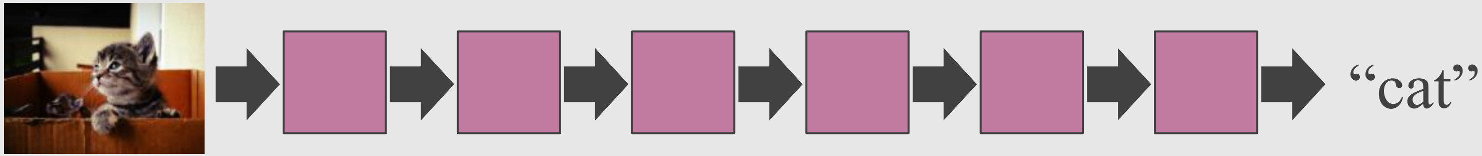


Deep Learning



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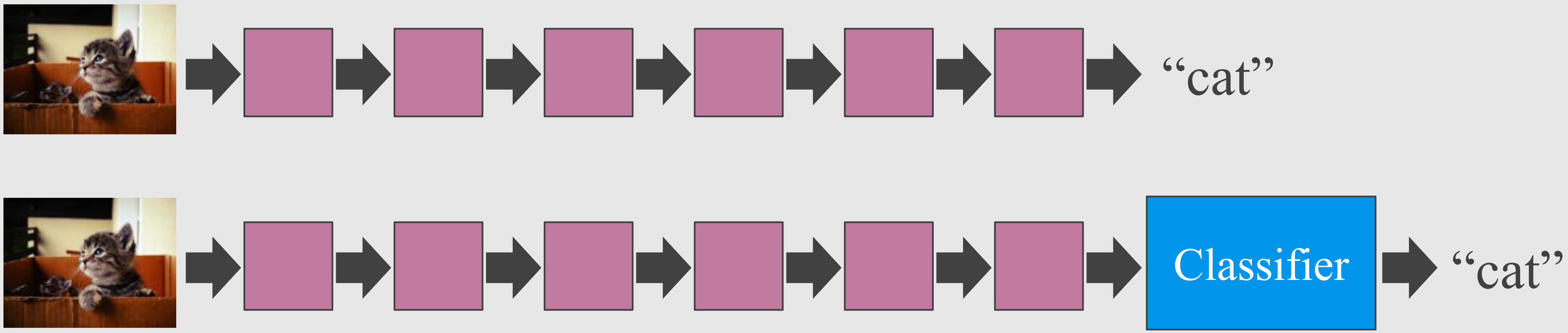

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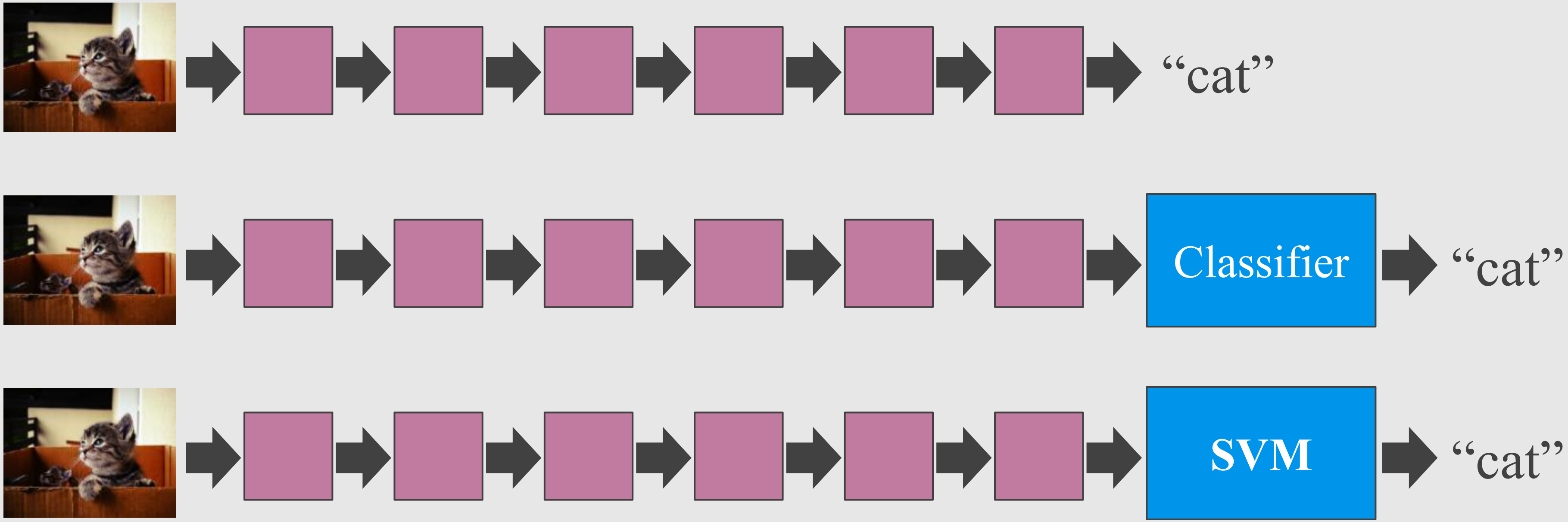
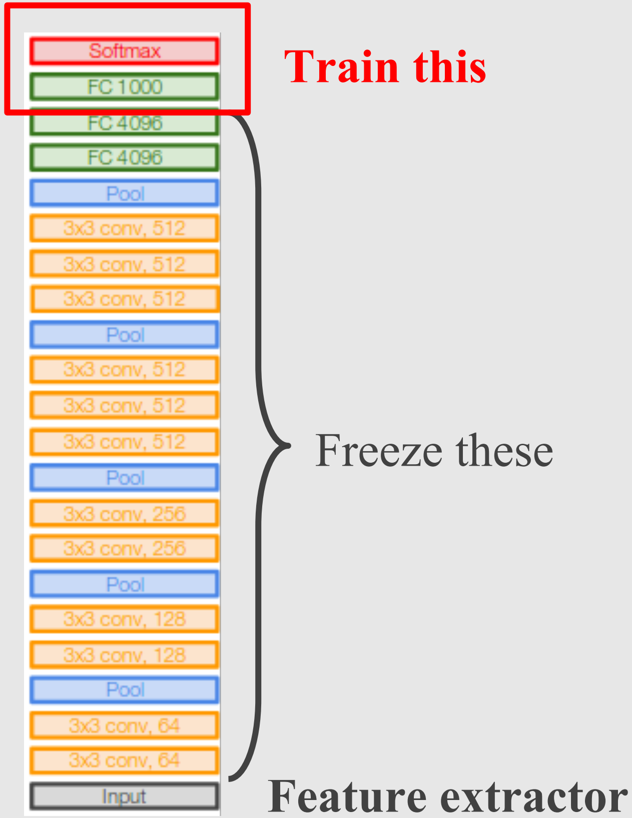


Transfer Learning



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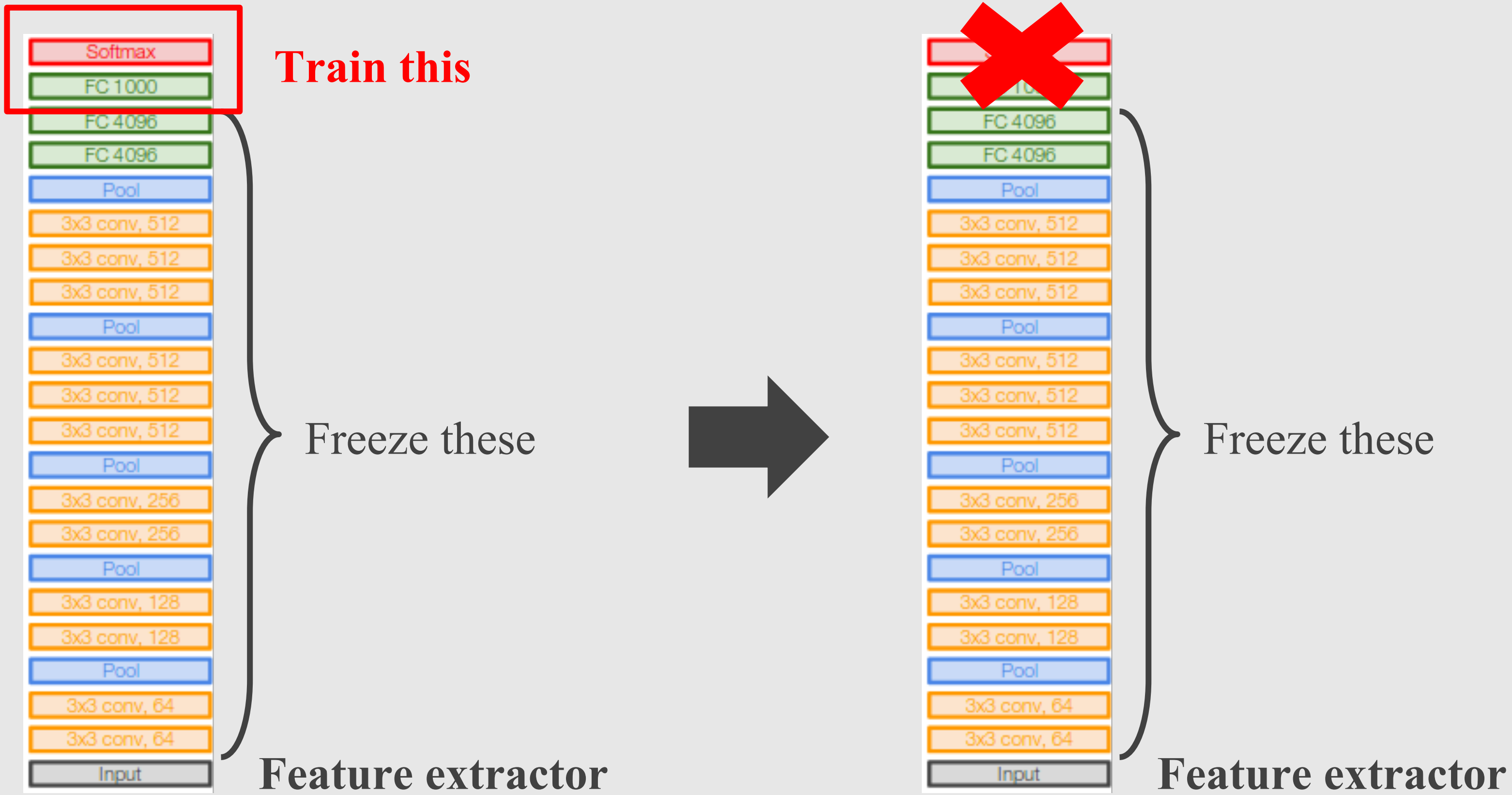

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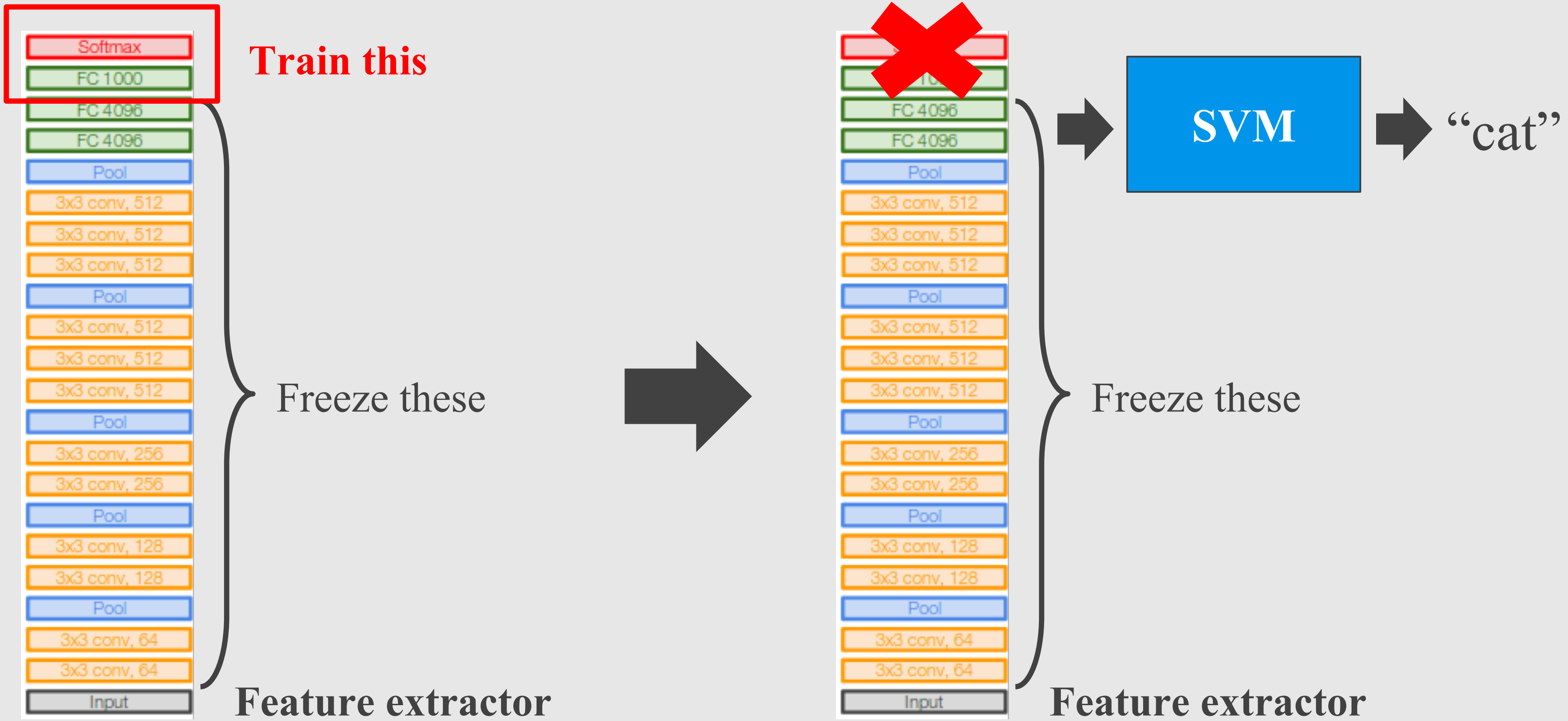
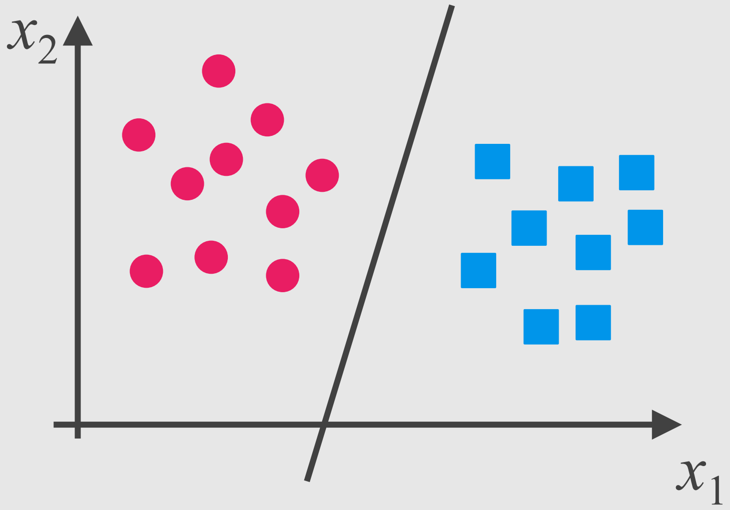


What is Support Vector Machine?

Support Vector Machine

[Vapnik and Chervonenkis, 1964; Vapnik, 1982; Vapnik, 1995]

Idea of separating data with **a large "gap."**



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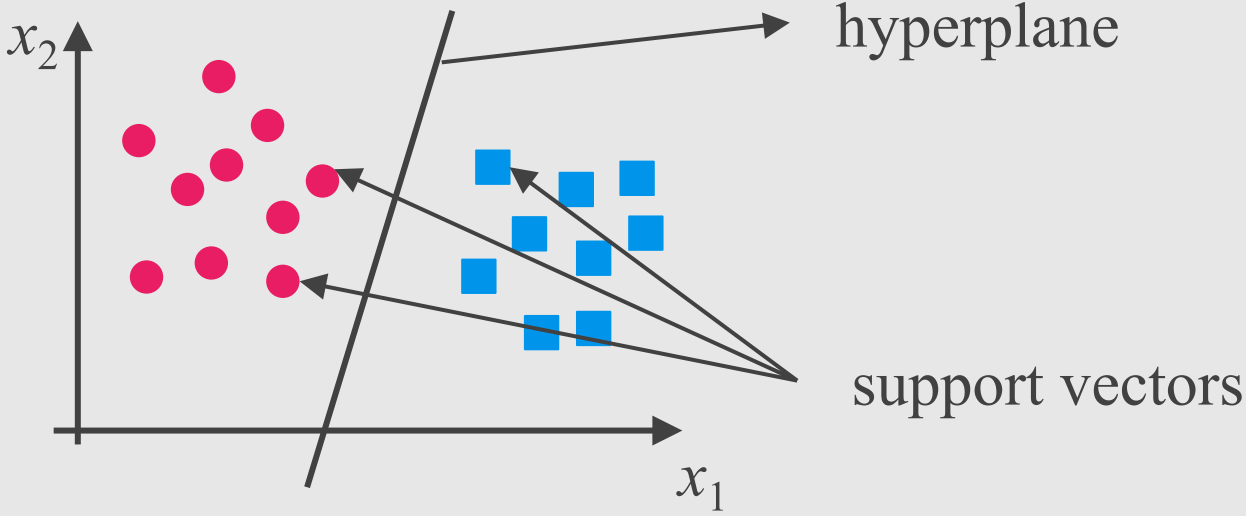
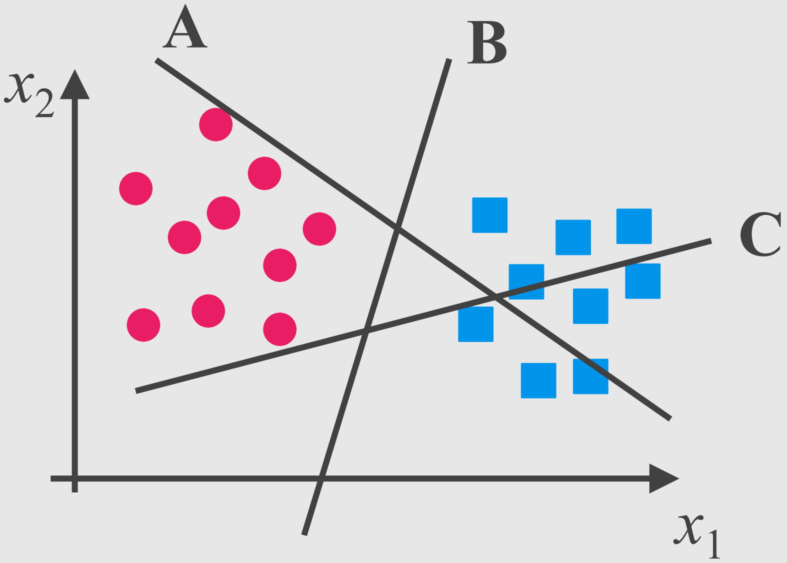


How does SVM work?

How can we identify the right hyperplane?

Scenario 1



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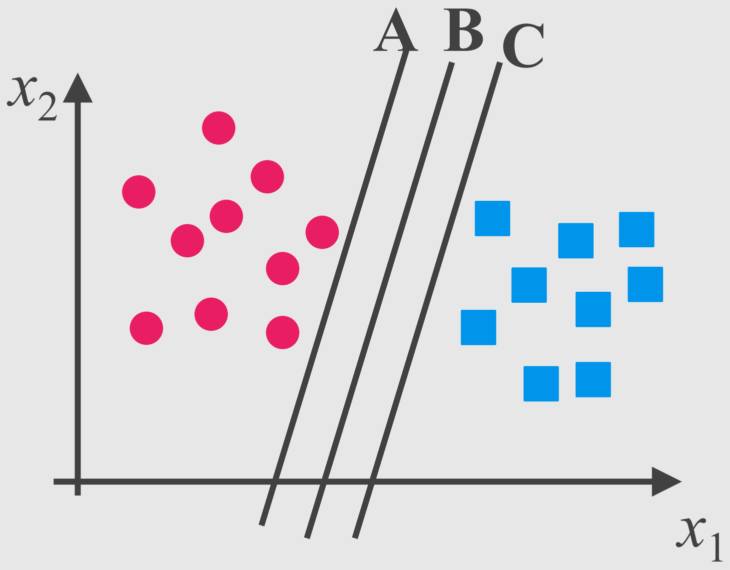
Scenario 2



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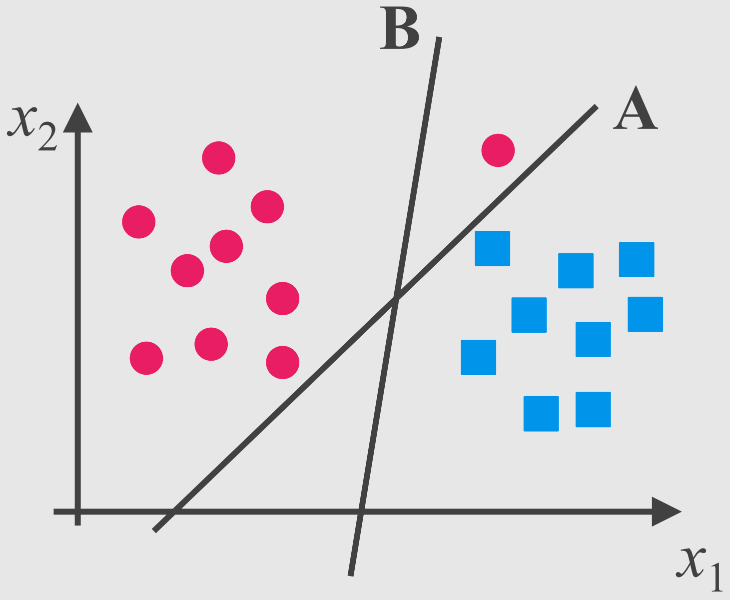
Scenario 3



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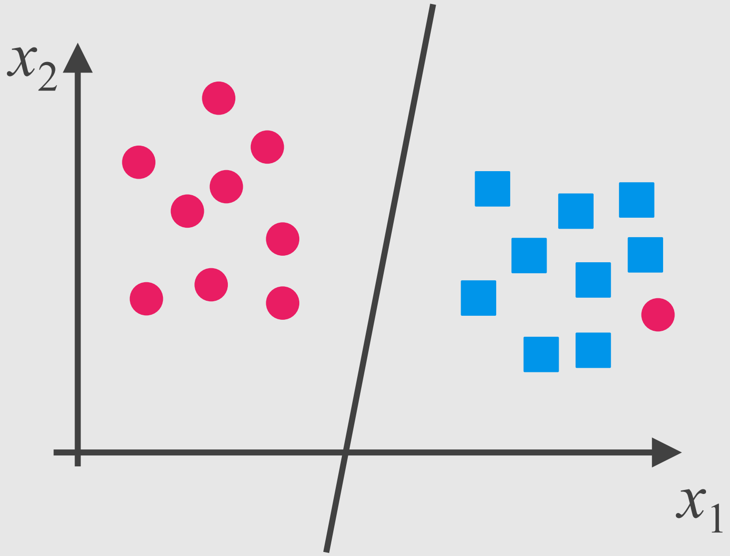
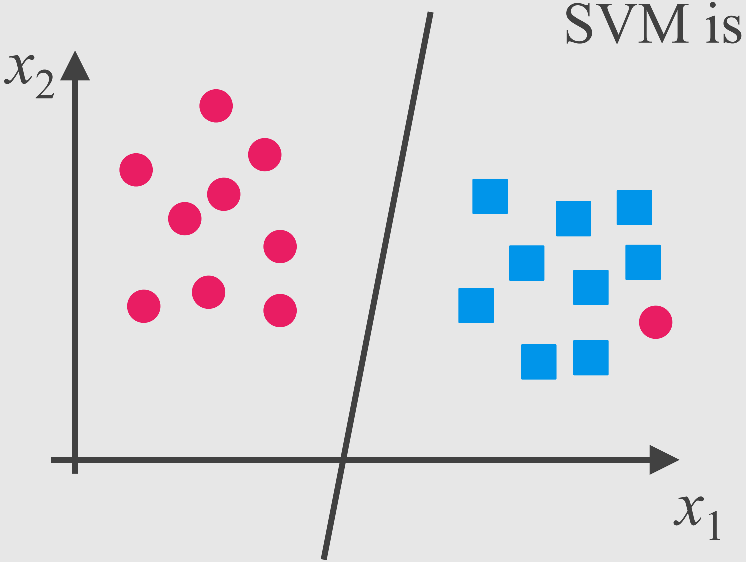
Scenario 4



How can we identify the right hyperplane?

Scenario 4

SVM is robust to outliers



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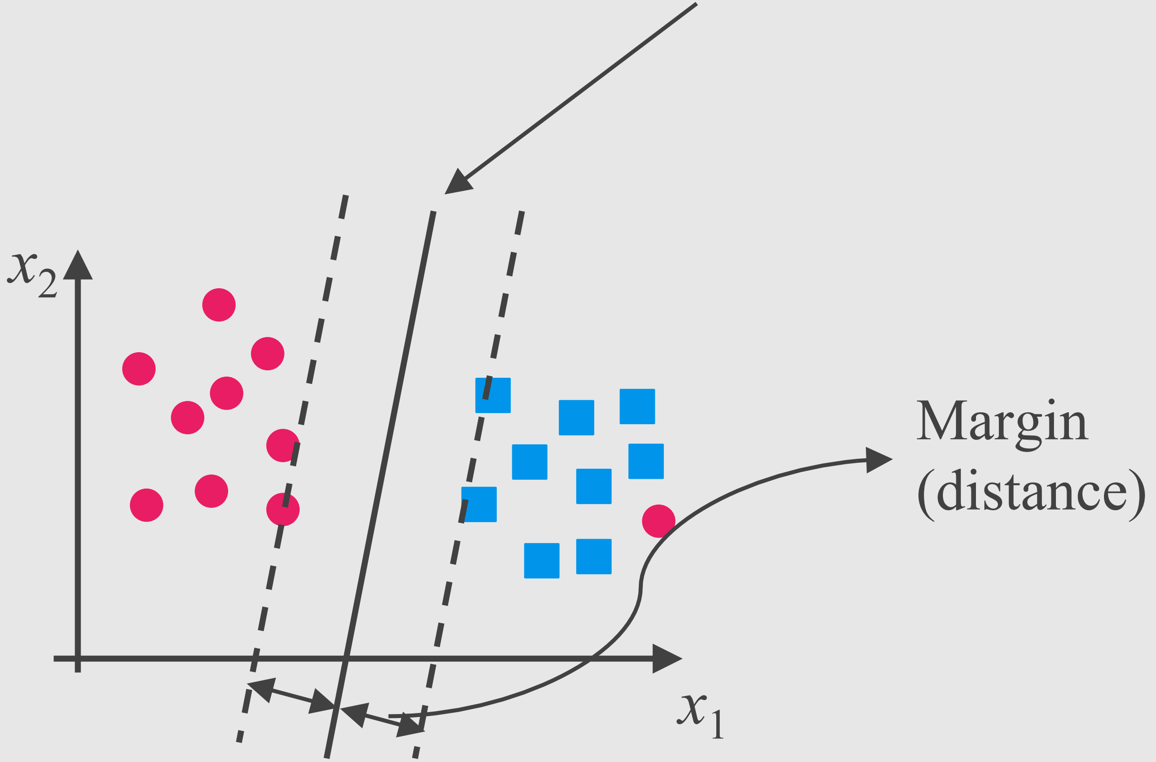
Scenario 4



SVM: Notation

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- Class labels: $y \in \{-1,1\}$ (instead of $\{0,1\}$)
- Parameters: w, b (instead of vector θ)
- Classifier: $h_{w,b}(x) = g(w^T x + b)$
  - $g(z) = 1$ if $z \geq 0$, and $g(z) = -1$ otherwise

SVM: The Optimal Hyperplane

Given a training example $(x^{(i)}, y^{(i)})$, we define the margin of (w, b) with respect to the training example:

$$y^{(i)}(w^T x + b) \geq 1, i = \{1, ..., m\}.$$

SVM: The Optimal Hyperplane

Let $P(x^{(1)}, y^{(1)})$ be a point and l be a line defined by $ax + by + c = 0$. The distance d from P to l is defined by:

$$d(a,b,P) = \frac{|ax^{(1)} + by^{(1)} + c|}{\sqrt{a^2 + b^2}}$$

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$$\Downarrow$$

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$$\downarrow$$

$$\min_{w,b} \ \tfrac{1}{2}||w||^2$$

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http://cs229.stanford.edu/notes/cs229-notes3.pdf

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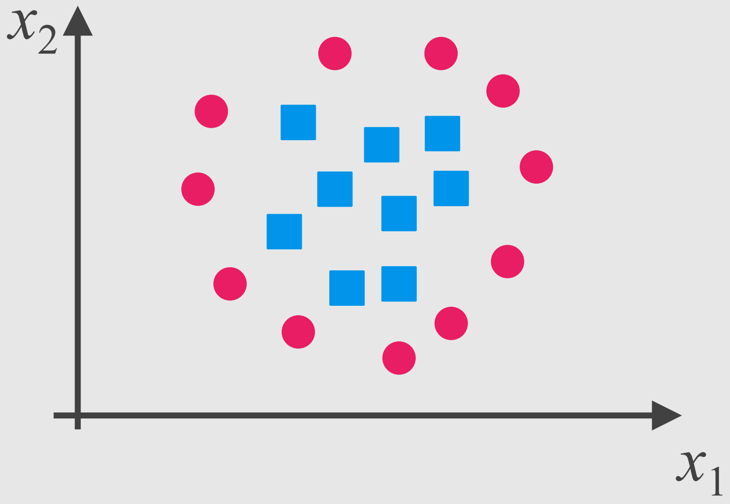
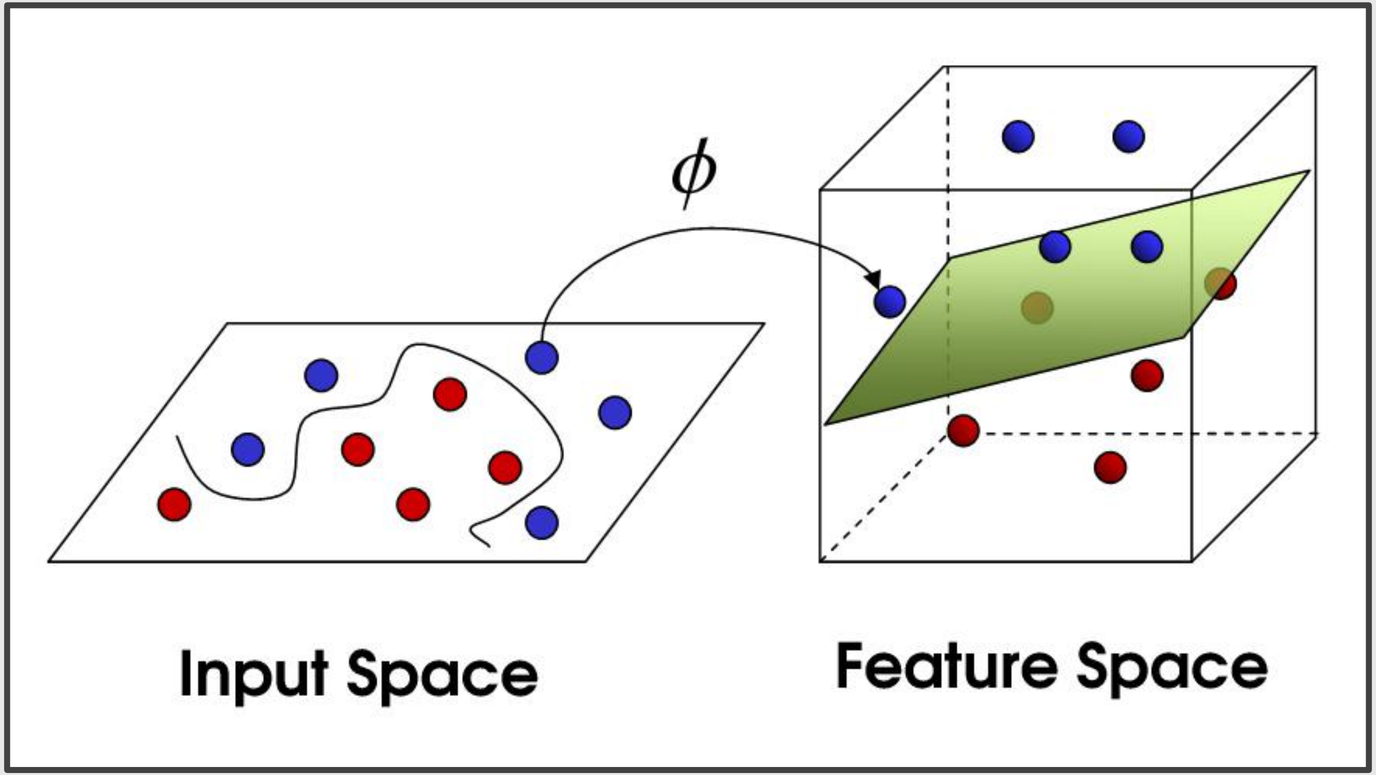
How can we identify the right hyperplane?

Scenario 5



Kernel Trick



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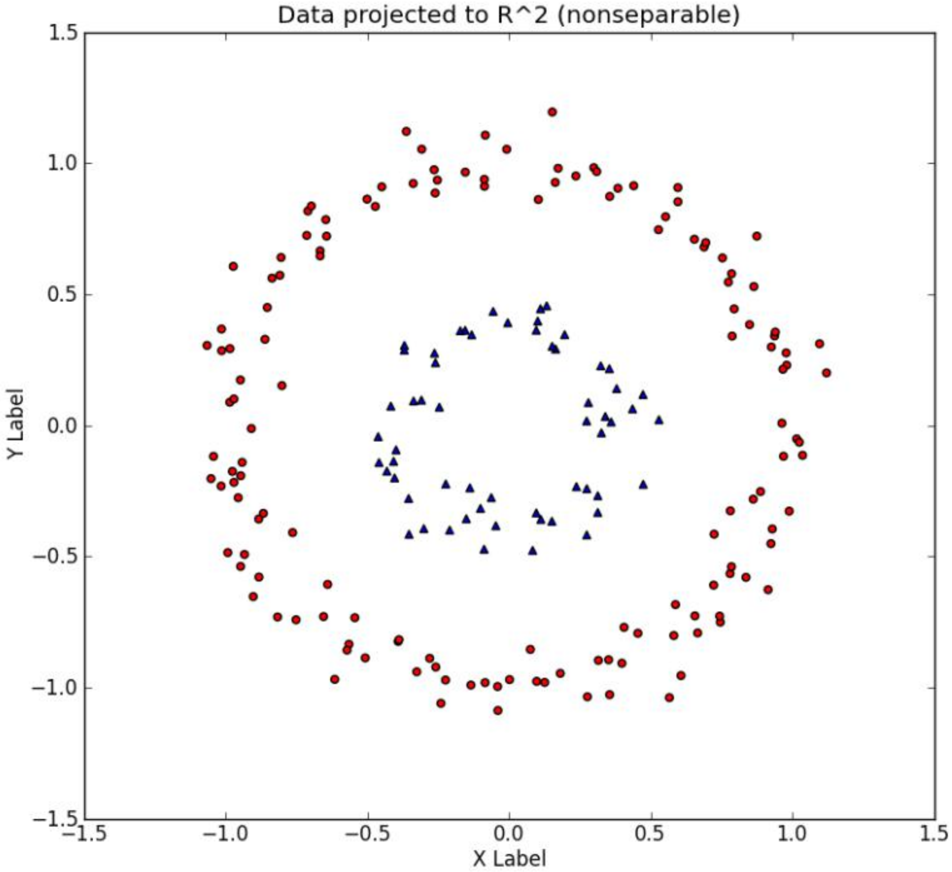
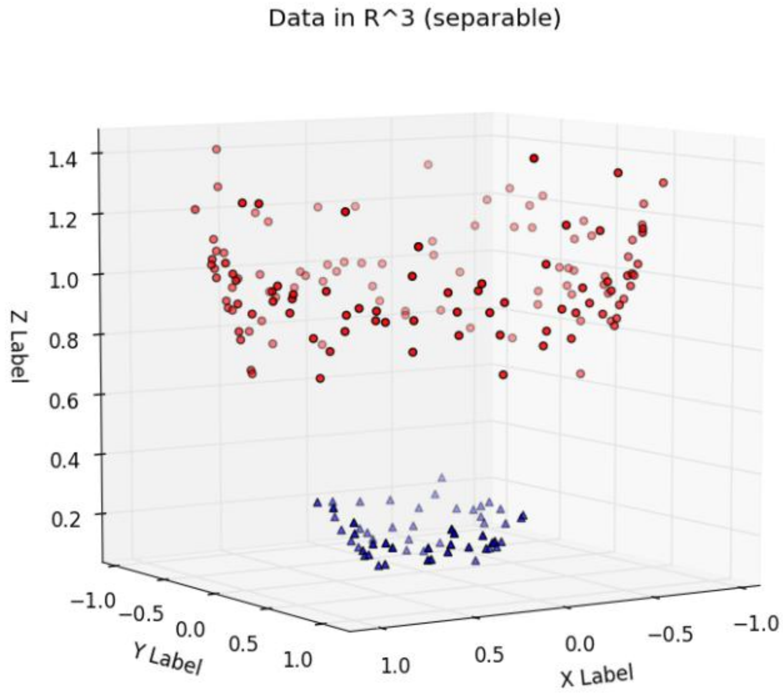
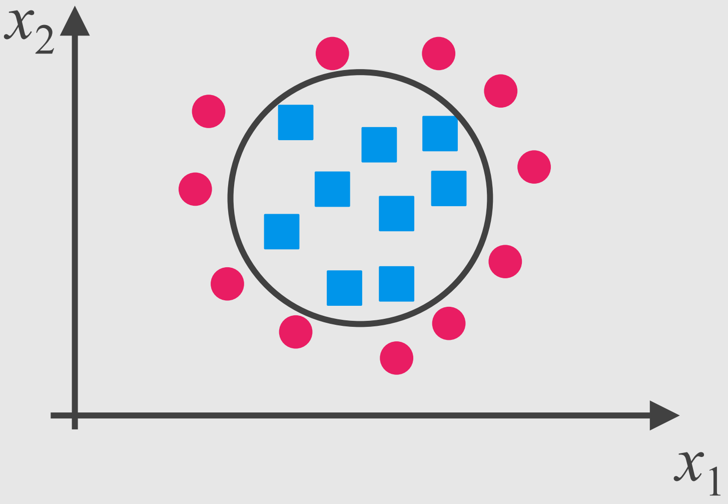
- Gaussian kernel: $K(x_i, x_j) = \exp(-\|x_i - x_j\|^2/(2\sigma^2))$
- Polynomial kernel: $K(x_i, x_j) = (x_i \cdot x_j + 1)^{\mathrm{d}}$, d degree
- Chi-square kernel, histogram intersection kernel, string kernel, ...


Data projected to R^2 (nonseparable)
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
X Label
Y Label


Data in R^3 (separable)
1.4
1.2
1.0
0.8
0.6
0.4
0.2
Z Label
−1.0
−0.5
0.0
0.5
1.0
Y Label
1.0
0.5
0.0
−0.5
−1.0
X Label

How can we identify the right hyperplane?

Scenario 5



SVM & scikit-learn

SVM is also available in scikit-learn library and follow the same structure : import library, object creation, fitting model and prediction.

SVM & scikit-learn

```
#Import Library
from sklearn import svm
#Assumed you have, X (predictor) and Y (target) for training data set and x_test(predictor)
of test_dataset
# Create SVM classification object
model = svm.svc(kernel='linear', c=1, gamma=1)
# there is various option associated with it, like changing kernel, gamma and C value. Will
discuss more # about it in next section.Train the model using the training sets and check s
core
model.fit(X, y)
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object creation

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fitting model

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prediction

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The parameters can be tuned using grid-search.

References

Machine Learning Books

- Hands-On Machine Learning with Scikit-Learn and TensorFlow, Chap. 5
- Pattern Recognition and Machine Learning, Chap. 6 & 7

Machine Learning Courses

- https://www.coursera.org/learn/machine-learning, Week 7
- http://cs229.stanford.edu/syllabus.html, http://cs229.stanford.edu/notes/cs229-notes3.pdf