Intro to ML for Input Recognition

CHI Course Computational Interaction 2016

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Advanced Interactive Technologies

ETH
Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich


Oculus
Development Kit


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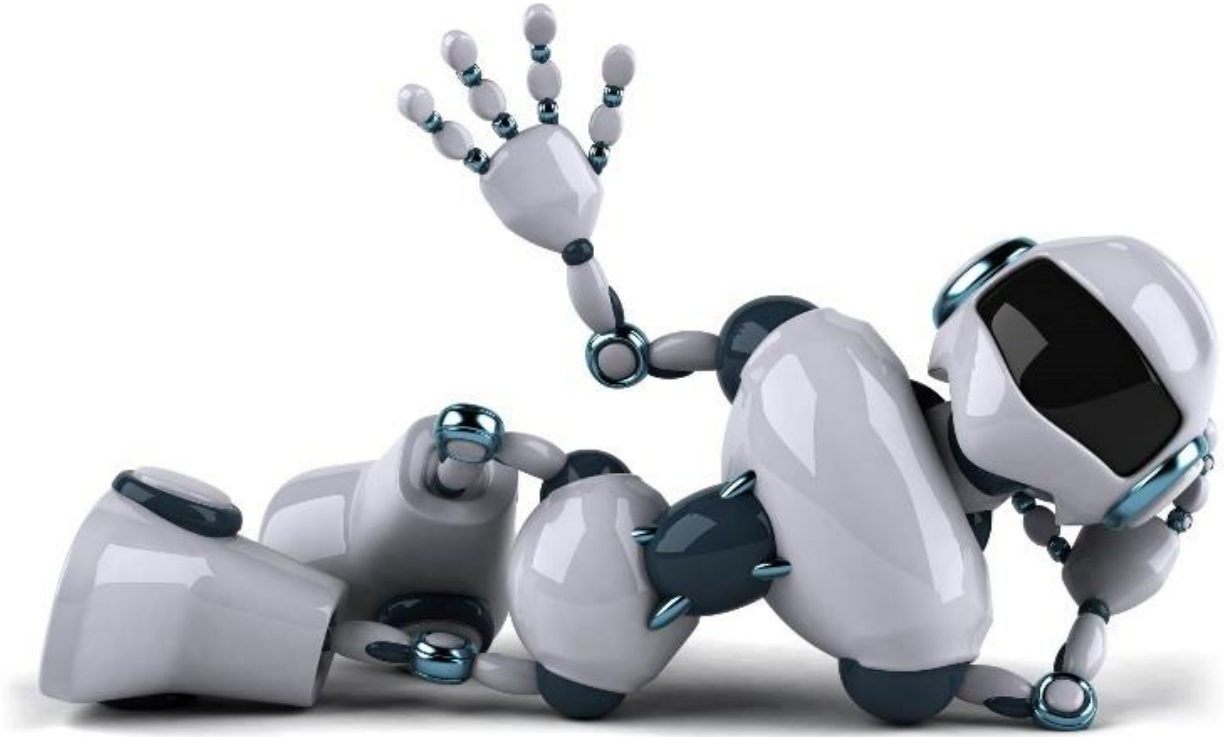
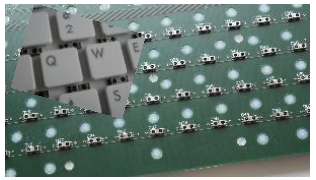


Designing Interactive Systems

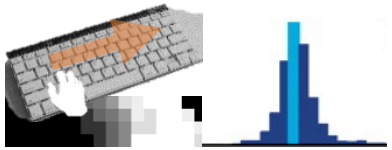
Interaction Task

Sensing Technology

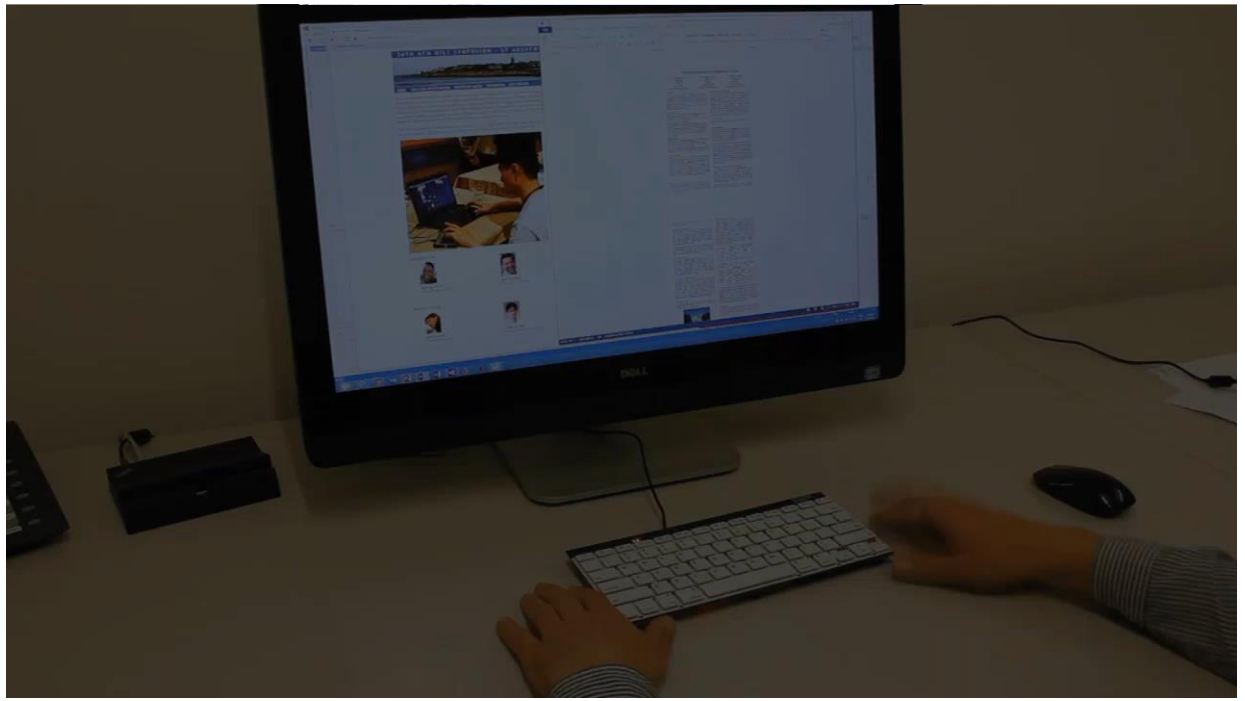
Sensor Placement



Input Recognition



System Output



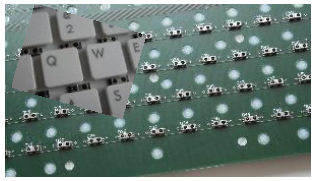
[Motion Sensing Keyboard. ACM CHI'14]

Today's talk – Part I

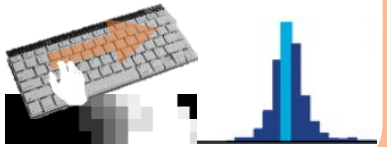
Interaction Task

Sensing Technology

Sensor Configuration



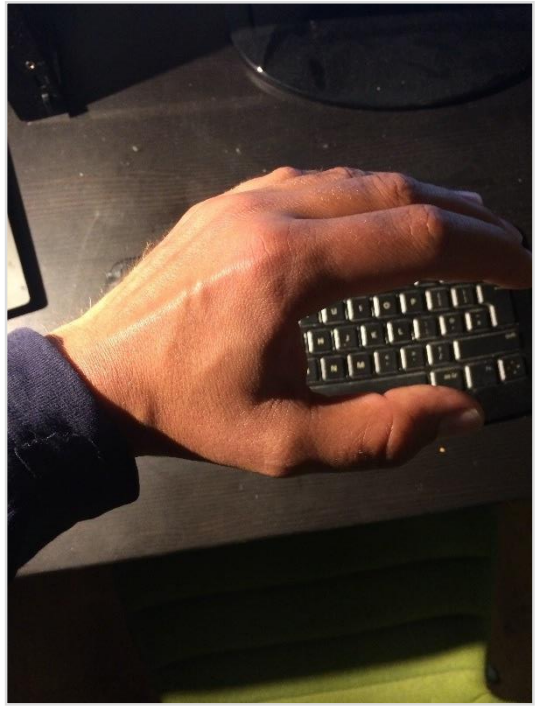
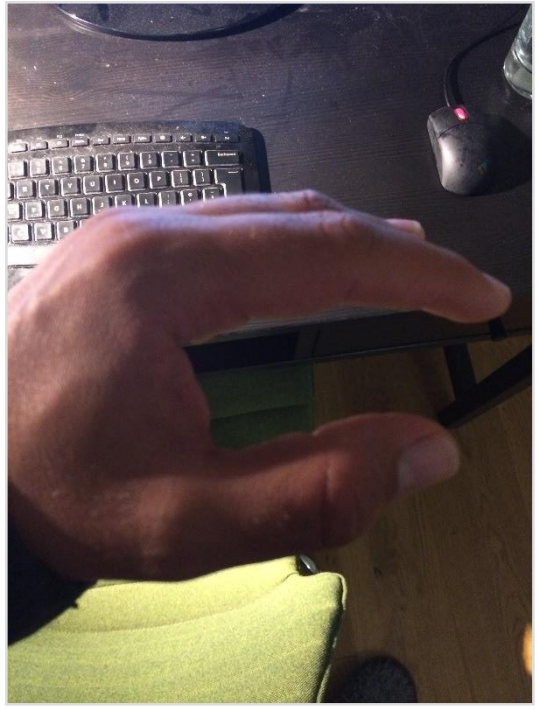
Input Recognition



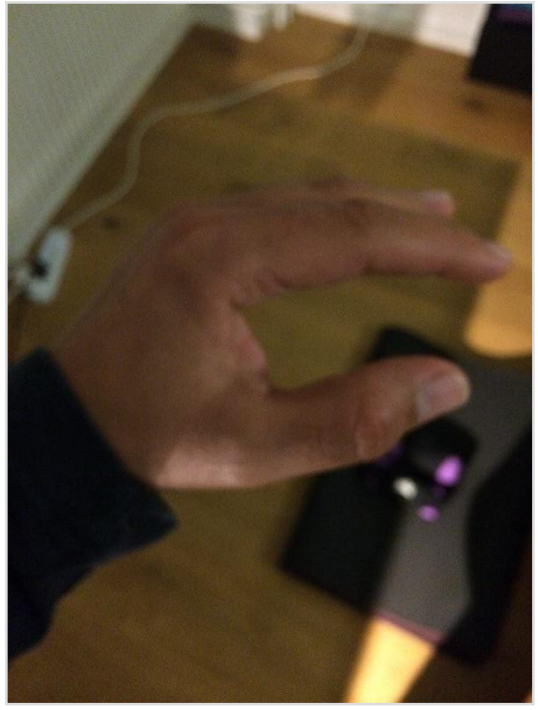
System Output

Today: Machine Learning for Gesture Recognition







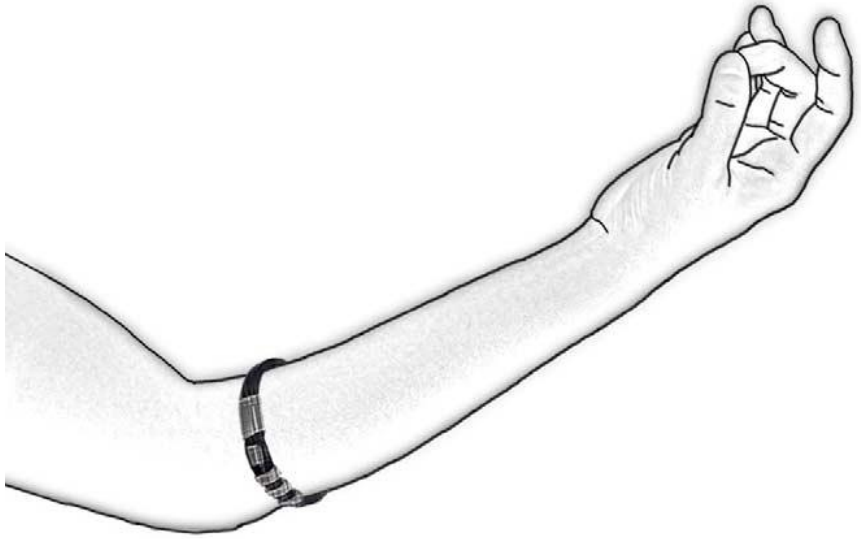
Muscle-Computer Interfaces

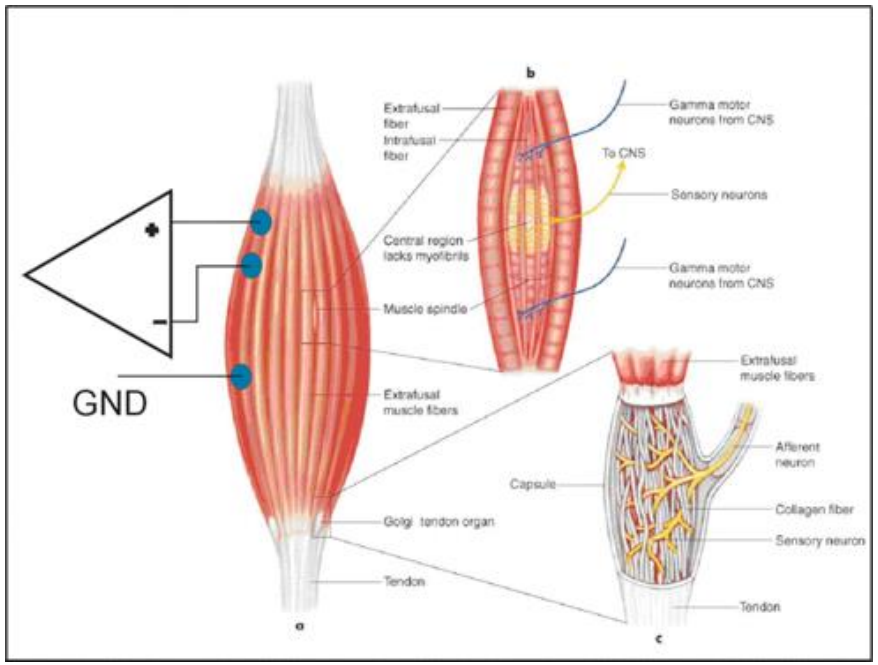
Hands free interaction – even when holding an object

EMG or Electromyography (primarily used in medical therapy)

Action potential generated by muscle when signal arrives from motor neuron

Can be sensed non-invasively by placing electrodes on the skin





[Saponas et al., *Proceedings of ACM UIST '09*]

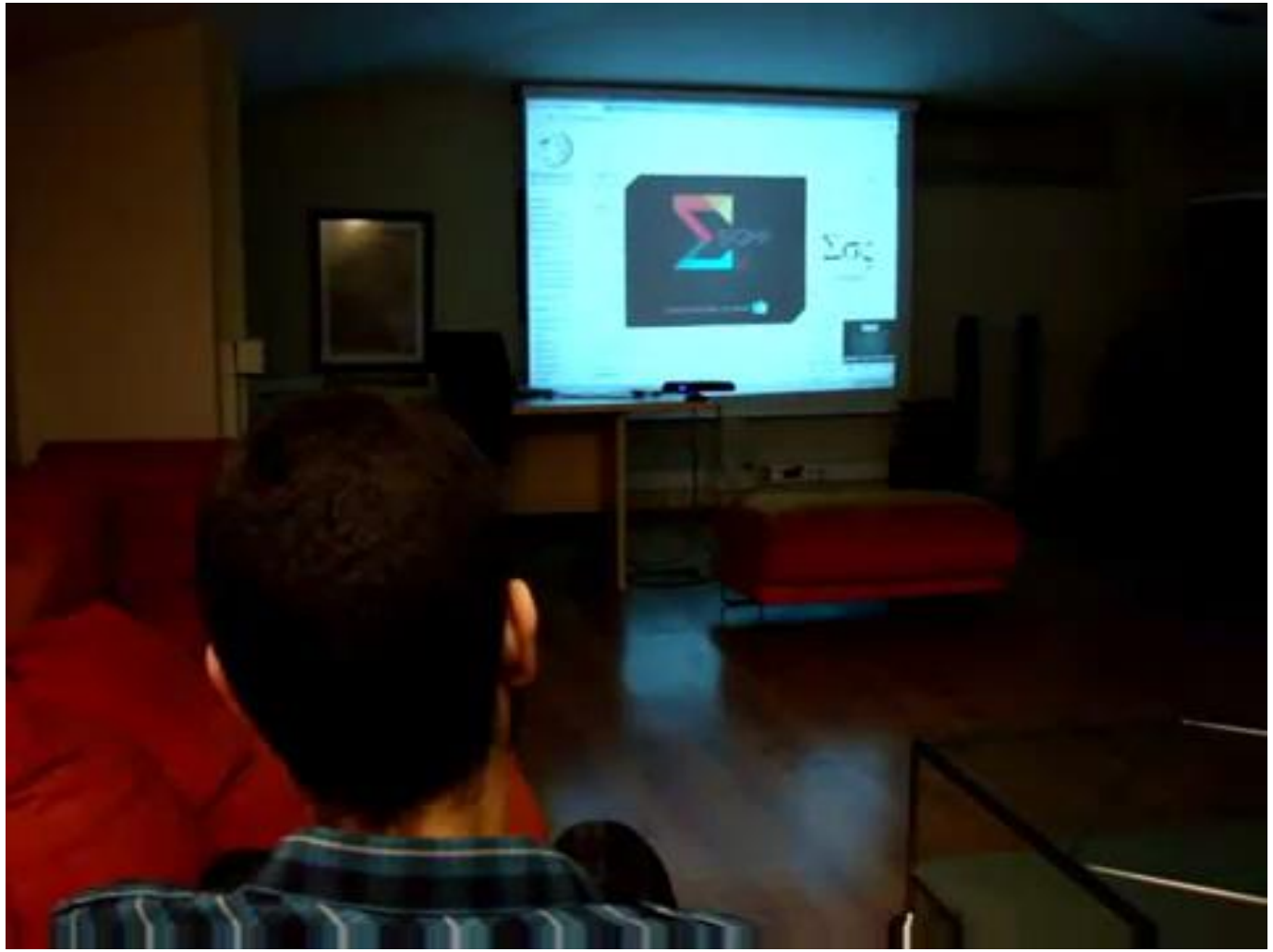
Video

[Saponas et al., *Proceedings of ACM UIST '09*]

Touch & Activate: Video

[Ono et al., *Proceedings of ACM UIST '13*]

Gesture Recognition



http://www.sigmard.com/portfolio/sigmanil-framework/

Take Home Message

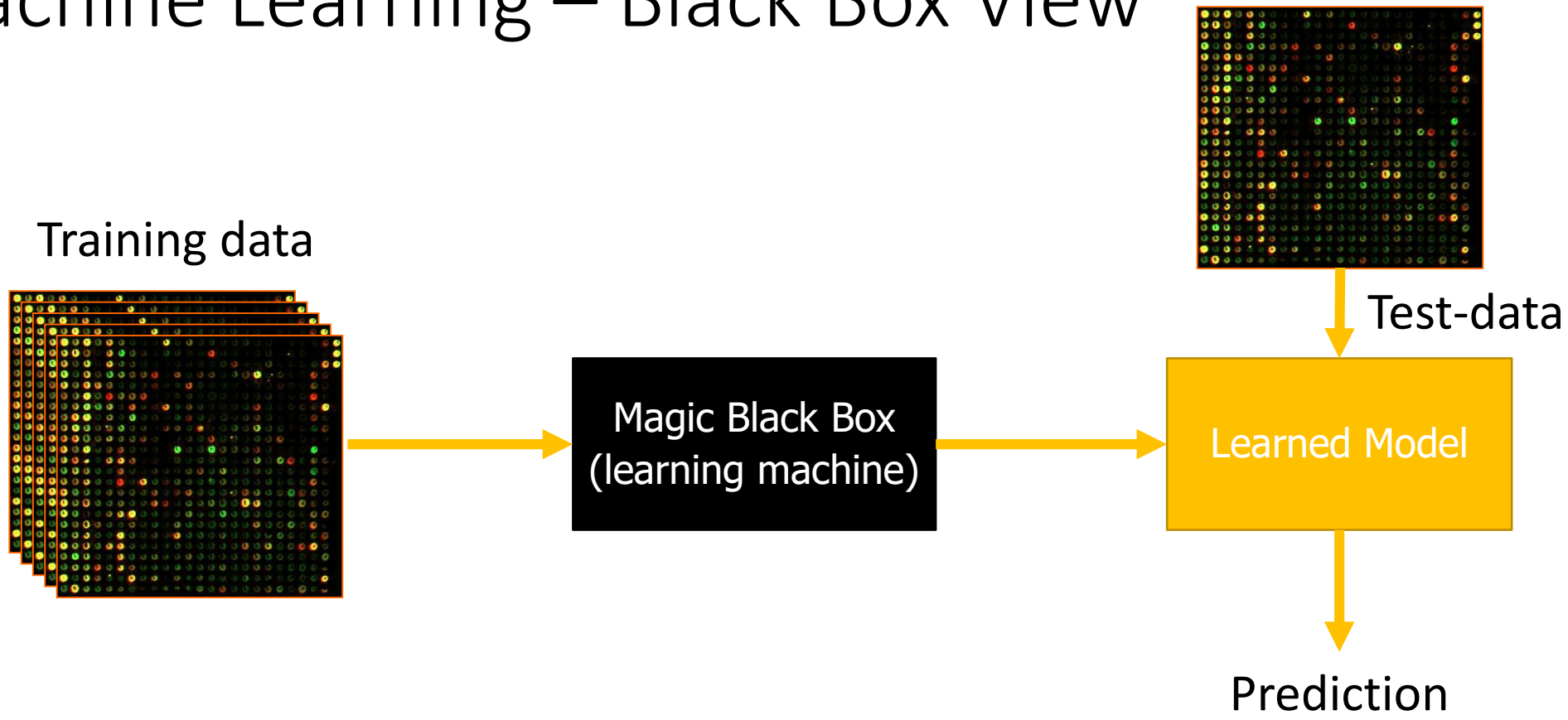
Humans use a variety of channels to interact & communicate

- Human behavior is highly complex
- Human behavior is highly ambiguous
- Too create we intuitive interfaces we want to use:
    - Small, low-effort natural motion
    - Avoid heavy user instrumentation

In consequence,

- Recognizing human input is challenging
- Most heuristic / traditional approaches are not powerful enough to model the variance in (gesture) execution
- Many different sensor modalities, often noisy data

Machine Learning – Black Box View



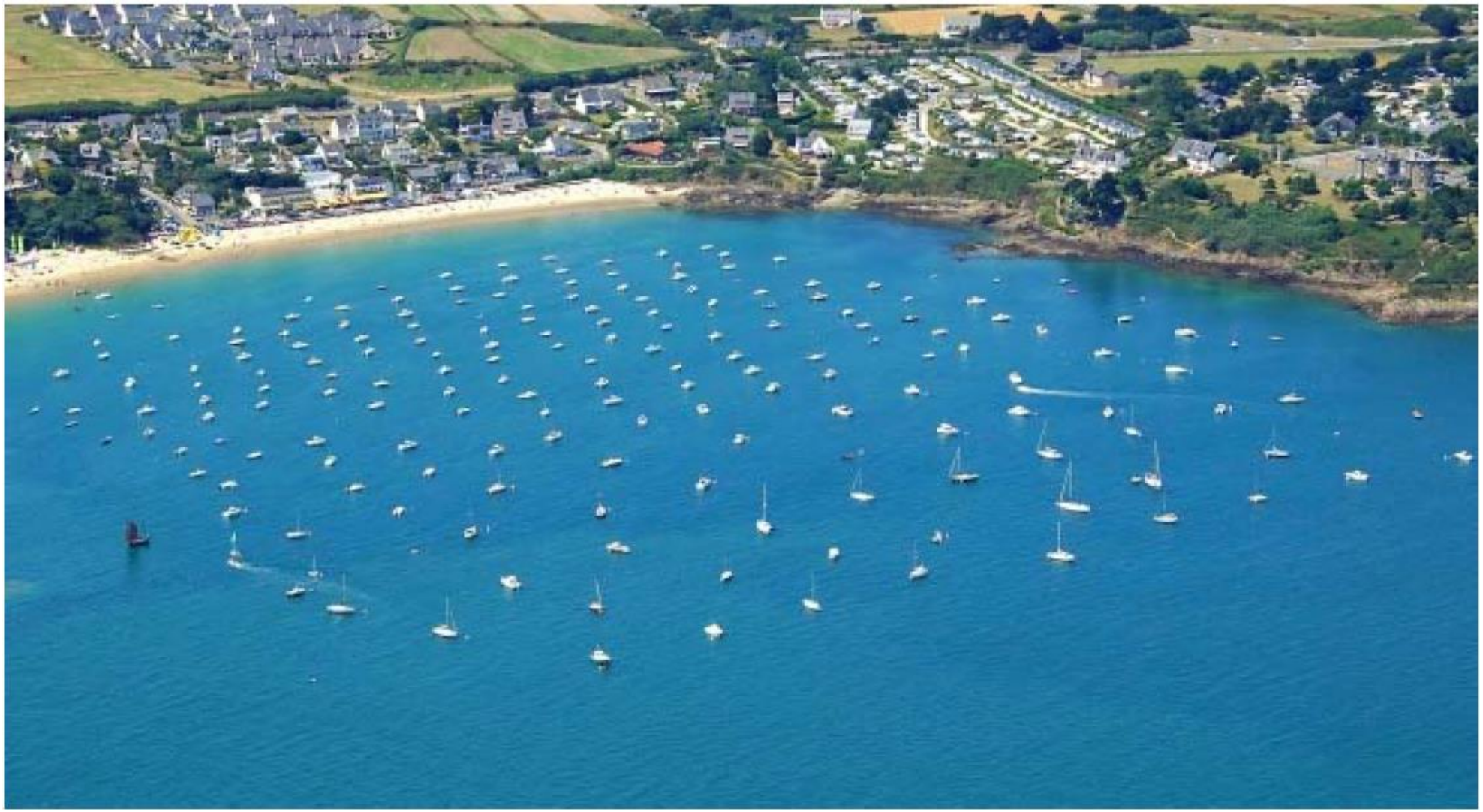
<u>Training data:</u>

-Positive *and* negative examples. Data has to be labelled (ground truth).

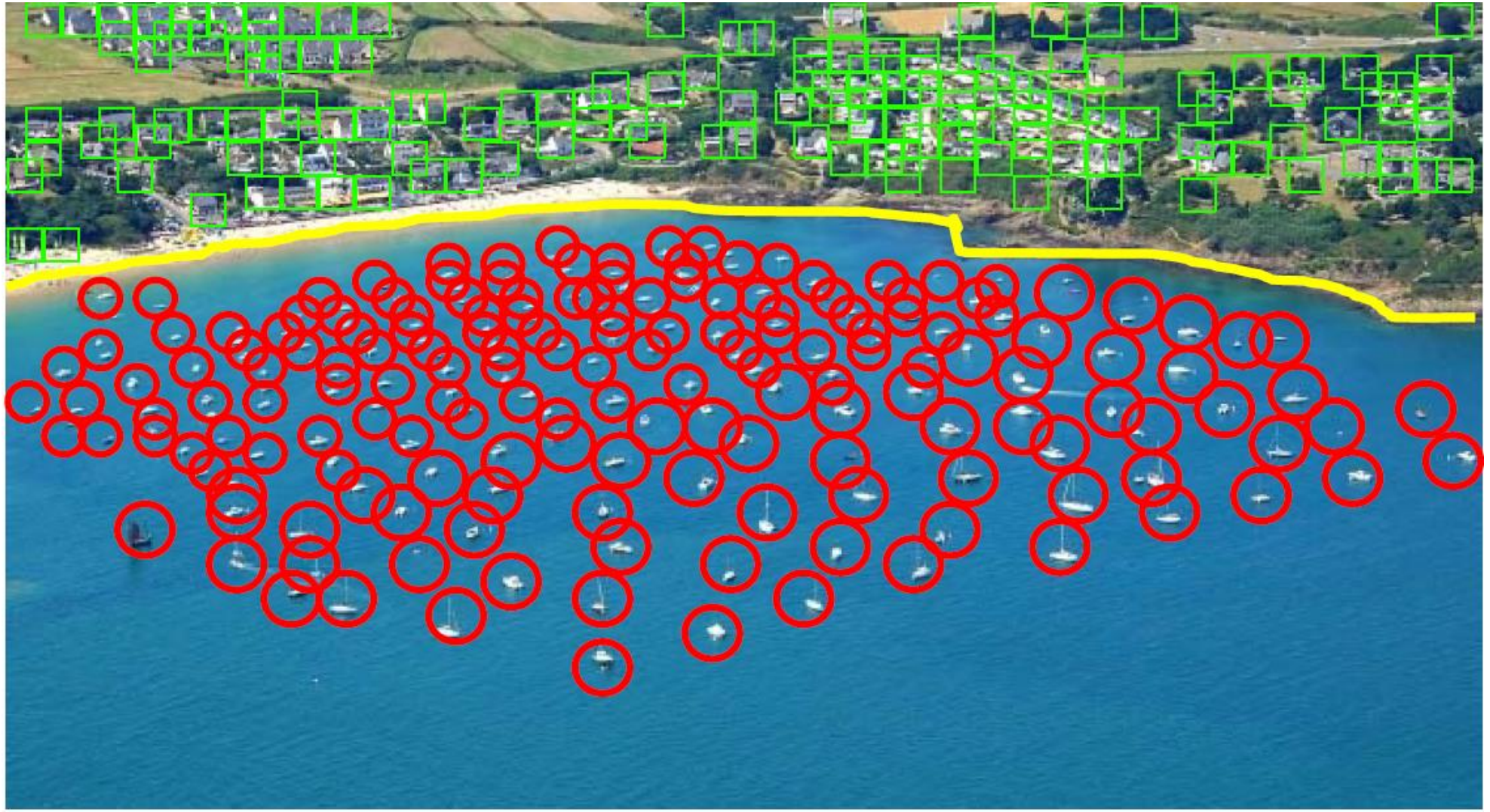
<u>Model:</u>

- The model can distinguish between classes or estimate real valued outcome.

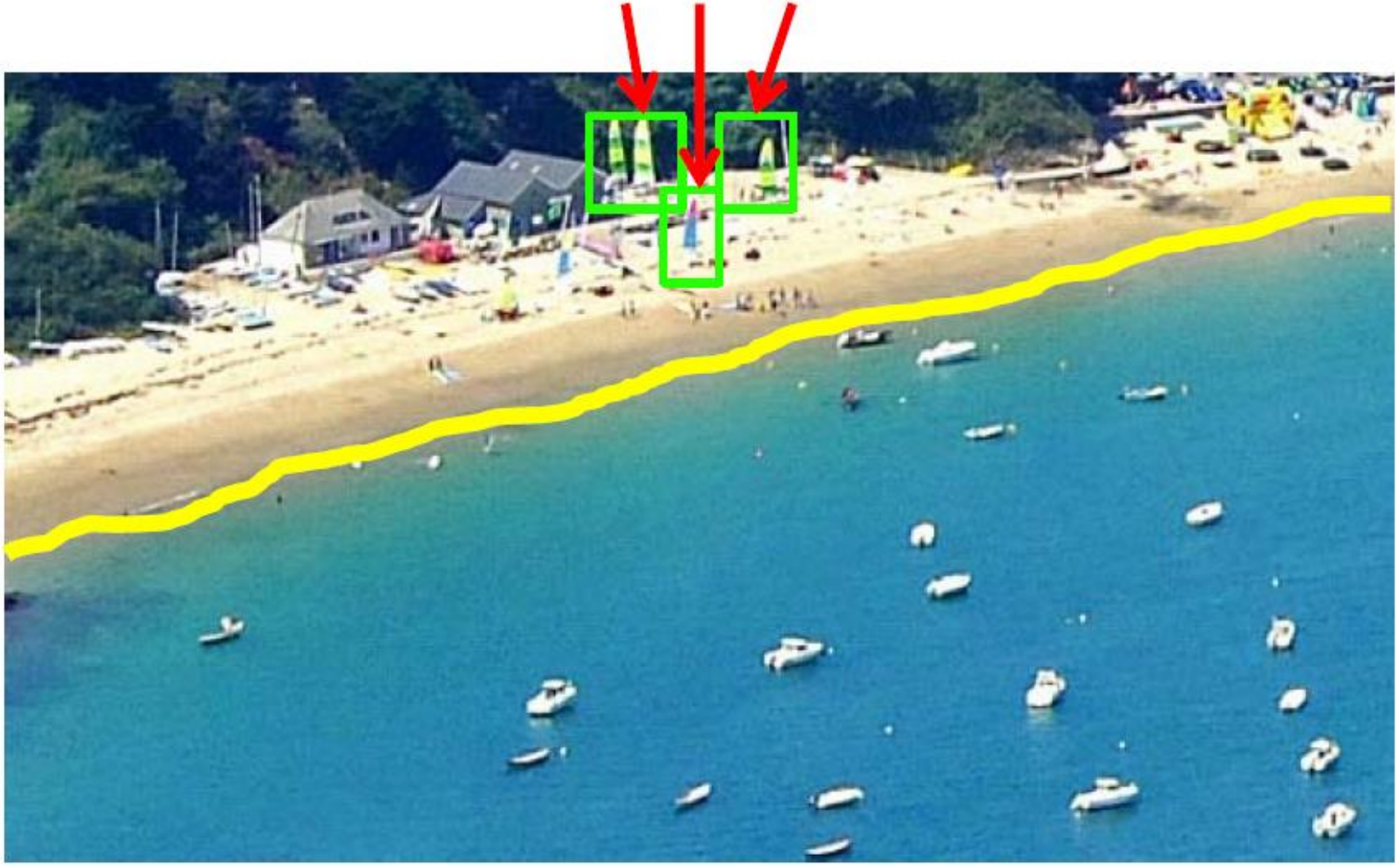
Classification: Basic Principles



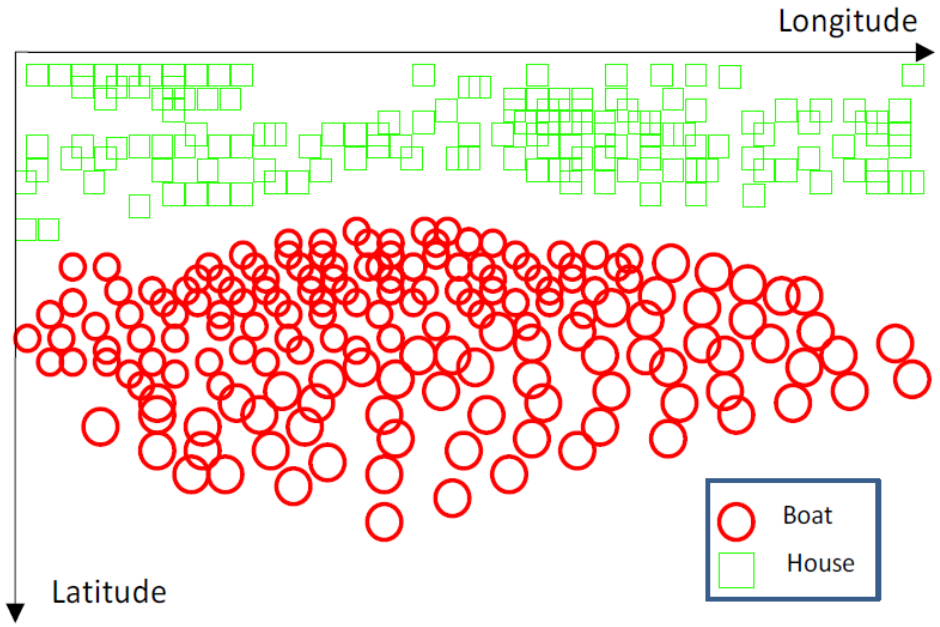
Classification: Decision Surface

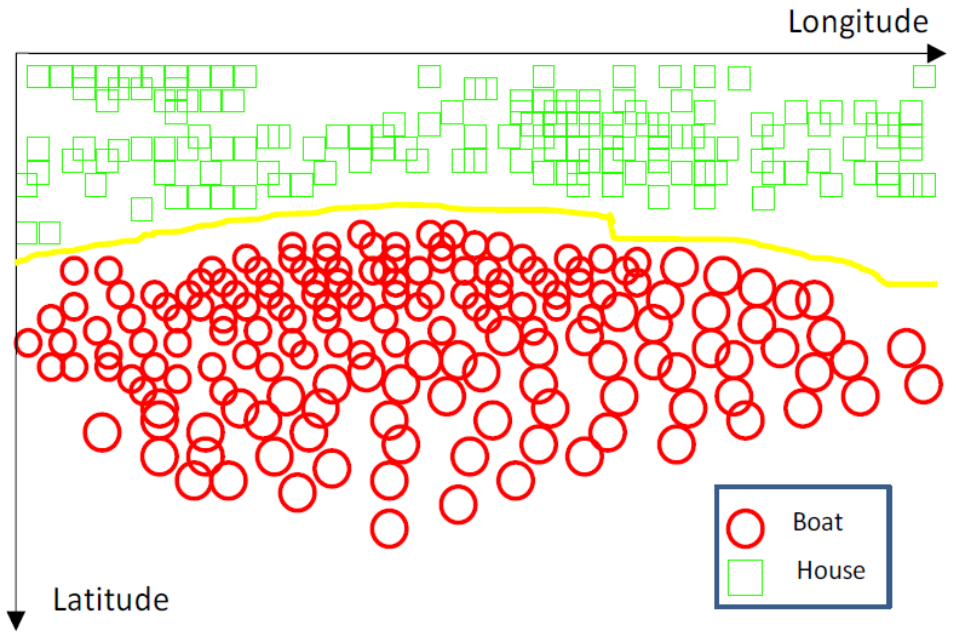


Classification: Classification Errors

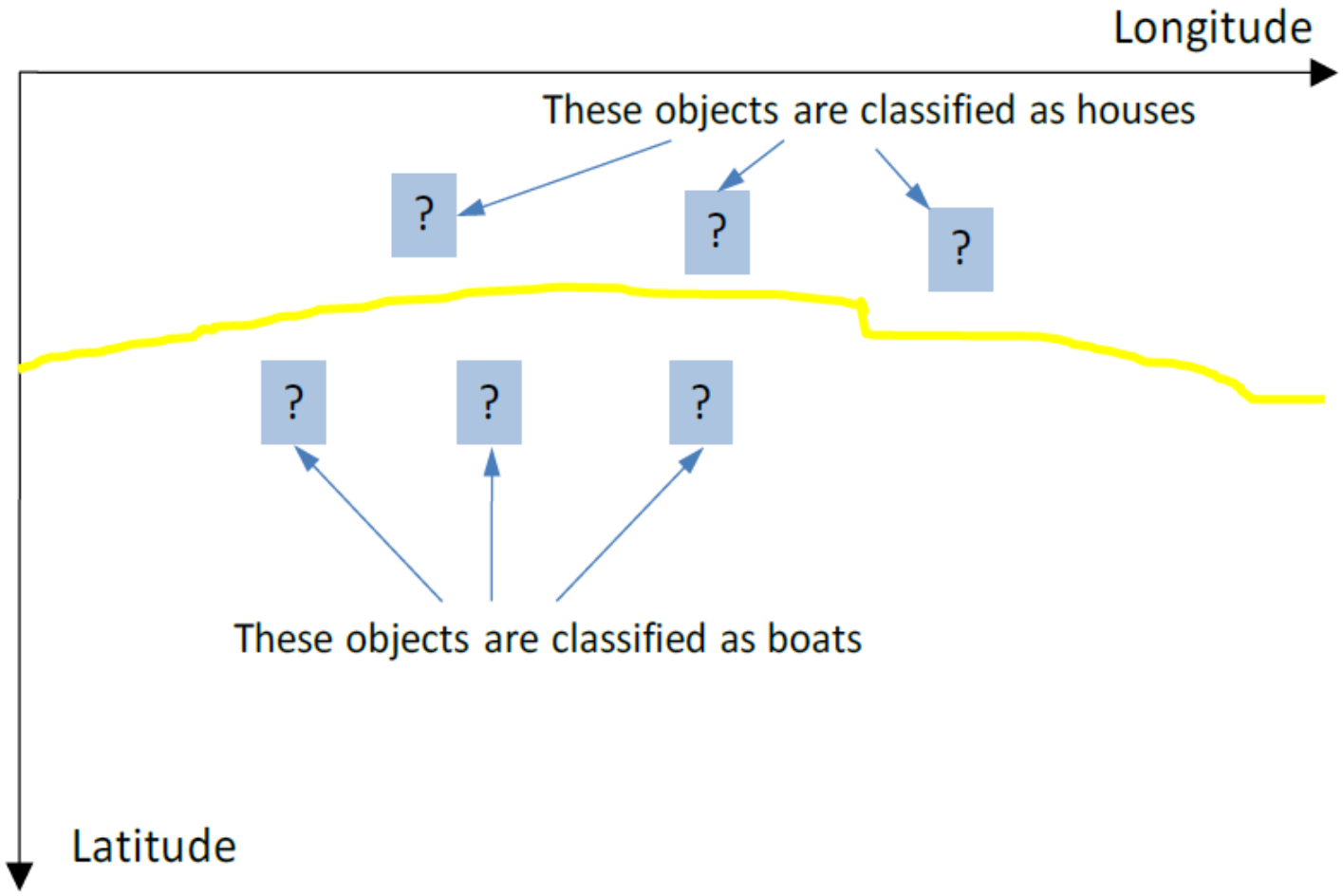


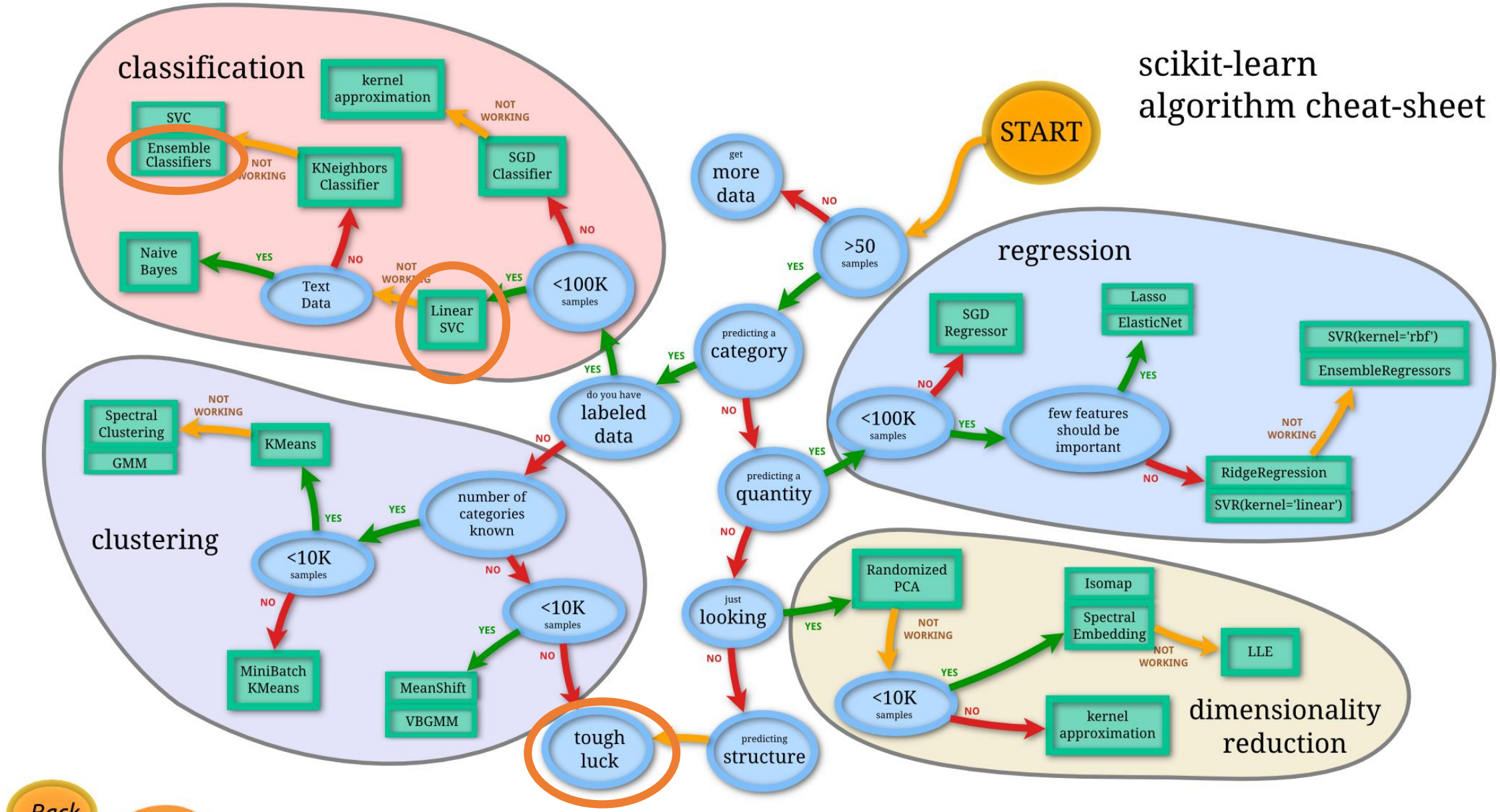
Classification Algorithms – Training time





Classification Algorithms – Test time





Back

[http://scikit-learn.org/stable/tutorial/machine_learning_map/index.html]

Support Vector Machine (SVM)

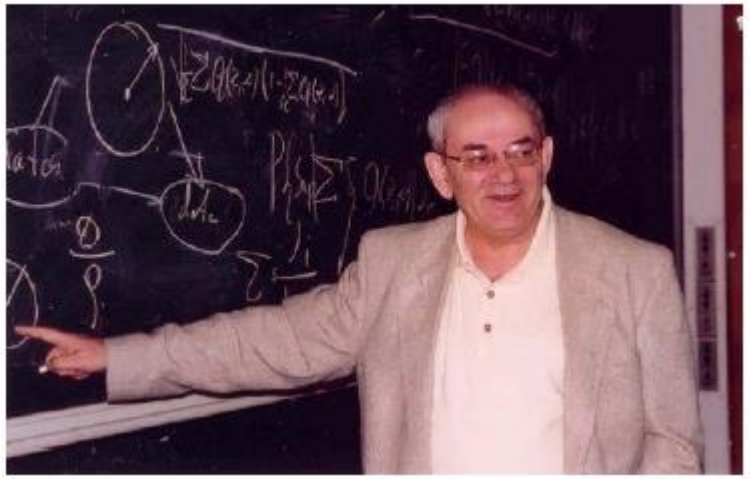
Derived from statistical learning theory by Vapnik, et al. in 1992

Simple SVM achieved accuracy comparable to neural-network with hand-designed features in a handwriting recognition task

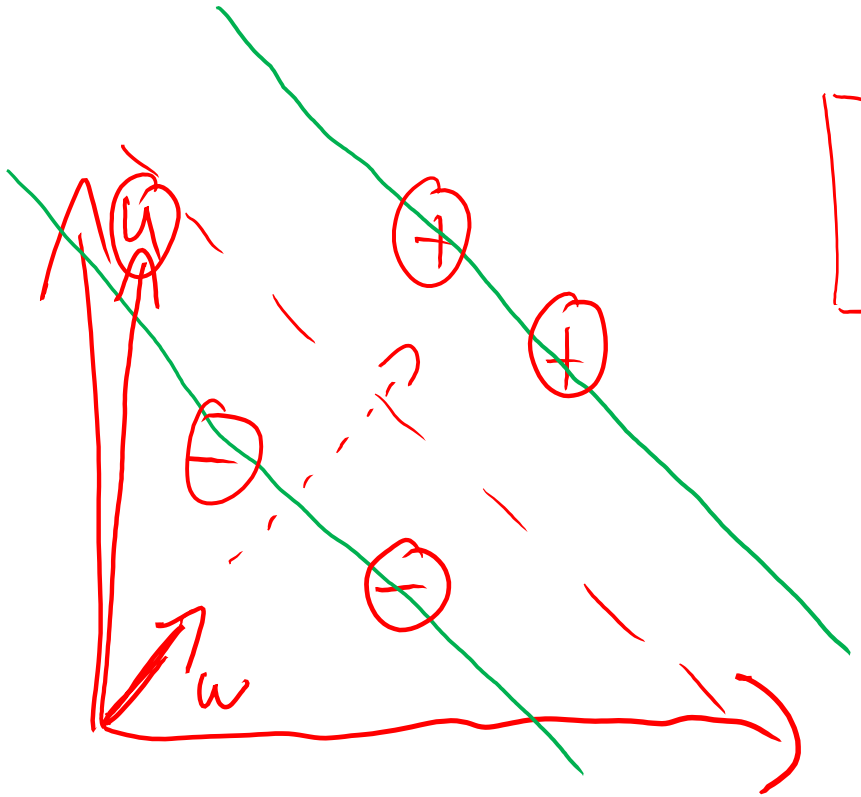
SVM widely used in object detection & recognition, content-based image retrieval, text recognition, biometrics, speech recognition, etc.

Also used for regression (will not cover today)

Vladimir Vapnik



SVM Derivation (Intuition with some slight of hand)



$\bar{w} \cdot \bar{u} \geq c$

$b = -c$

$\bar{w} \cdot \bar{u} + b \geq 0$ then (+)

what are $\bar{w}$ & b

are the unknows

SVM Derivation (Intuition with some slight of hand)

$\bar{\omega} \cdot \bar{x}_+ + b \geq 1$

$\bar{\omega} \cdot \bar{x}_- + b \leq -1$

for convenience we introduce y s.t. $+1$ for $\oplus$, -1 for $\ominus$

$y_i(\bar{\omega} \cdot \bar{x}_i + b) \geq 1$ for SV

$\Rightarrow y_i(\bar{\omega} \cdot \bar{x}_i + b) \geq 1 \Rightarrow$

$y_i(\bar{\omega} \cdot \bar{x}_i + b) = 1$

$y_i(\bar{\omega} \cdot \bar{x}_i +) - 1 = 0$

SVM Derivation (Intuition with some slight of hand)

we need to constrain $\bar{w}$ & b

positive sample

$\bar{w} \cdot \bar{x}_+ + b \geq 1$

$\bar{w} \cdot x_- + b \leq -1$

↑ negative sample

$y_i(\bar{w} \cdot \bar{x}_i + b) \geq 1$

$y_i(\bar{w} \cdot \bar{x}_i + b) \geq 1$

$y_i(\bar{w} \cdot x_i + b) - 1 \geq 0$

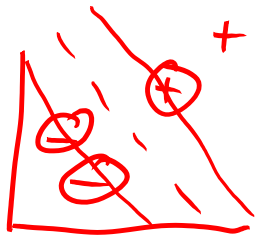
(2)

$y_i(\bar{w} \cdot x_i + b) - 1 = 0$

FOR x_i ON THE GUTTER

y_i such that y_i + 1 for + samples

- 1 for - samples



SVM Derivation (Intuition with some slight of hand)

$y_i(\bar{w} \cdot \bar{x}_i + b) - 1 = 0$ *

width $= (x_+ - x_-) \cdot \frac{w}{\|w\|} = \frac{2}{\|w\|}$ * The primal problem

$1 + b + 1 - b = 2$

x_+: $g_i(\bar{\omega} \cdot \bar{x}_+ + b) - 1 = 0$

$\bar{\omega} \cdot x_+ = 1 - b$

$\max \frac{2}{\|w\|} = \max \frac{1}{\|w\|} = \min \|w\| \sim \min \frac{1}{2}\|w\|^2$

SVM Derivation (Intuition with some slight of hand)

$$y_i(\bar{w} \cdot \bar{x_i} + b) - 1 = 0$$

$$\min \frac{1}{2}\|w\|$$

$$L = \frac{1}{2}\|\bar{\omega}\|^2 - \sum \alpha_i \left[y_i(\bar{\omega} \cdot \bar{x}_i + b) - 1 \right]$$

linear sum of samples $\bar{x}_i$

$$\frac{\partial L}{\partial \omega} = \bar{\omega} - \sum \alpha_i y_i \bar{x}_i = 0 \Rightarrow \boxed{\bar{\omega} = \sum_i \alpha_i y_i \bar{x}_i}$$

$$\frac{\partial L}{\partial b} = -\sum \alpha_i y_i = 0 \Rightarrow \boxed{\sum \alpha_i y_i = 0}$$

$$L = \frac{1}{2}\left(\sum \alpha_i y_i \bar{x}_i\right)\left(\sum \alpha_j y_j \bar{x}_j\right) - \left(\sum \alpha_i y_i \bar{x}_i\right)\left(\sum \alpha_j y_j \bar{x}_j\right) - \underbrace{\sum \alpha_i y_i}_{=0} b + \sum \alpha_i$$

$$= \sum \alpha_i - \frac{1}{2}\sum_i \sum_j \alpha_i \alpha_j y_i y_j \bar{x}_i \cdot \bar{x}_j$$

SVM Derivation (Intuition with some slight of hand)

$$L = \sum \alpha_i - \frac{1}{2} \sum_i \sum_j \alpha_i \alpha_j y_i y_j \boxed{\bar{x}_i \cdot \bar{x}_j}$$

$\alpha_i \alpha_j$: output

$y_i y_j$: coeffs from training data

$\bar{x}_i \cdot \bar{x}_j$: optimization only depends on dot product of sample vecs

DECISION RULE:

$$\sum \alpha_i y_i \boxed{\bar{x}_i \cdot \bar{u}} + b \geq 0 \quad \text{THEN } +$$

decision also only depends on dot product

The Optimization Problem Solution

The solution has the form:

$$\mathbf{w} = \Sigma \alpha_i y_i \mathbf{x_i} \qquad b = y_k - \mathbf{w}^T \mathbf{x_k} \text{ for any } \mathbf{x_k} \text{ such that } \alpha_k \neq 0$$

Each non-zero α_i indicates that corresponding $\mathbf{x_i}$ is a support vector.

Then the classifying function will have the form:

$$f(\mathbf{x}) = \Sigma \alpha_i y_i \mathbf{x_i}^T \mathbf{x} + b$$

Optimization is provably convex (for linearly separable sets)

Notice that it relies only on the *dot product* between the test point **x** and the support vectors $\mathbf{x_i}$

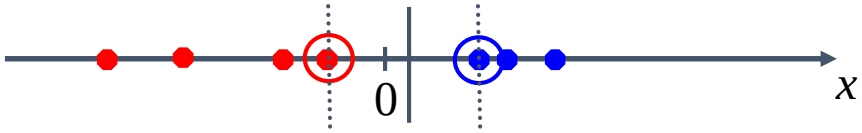
Also keep in mind that solving the optimization problem involved computing the inner products $\mathbf{x_i}^T \mathbf{x_j}$ between all pairs of training points.

Now Some Practical Issues (iPython Notebook)

Non-linear SVMs

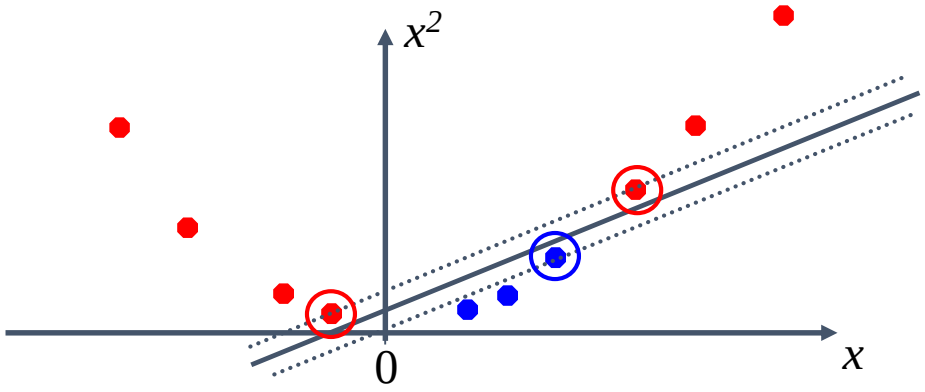
Non-linear SVMs

Datasets that are linearly separable (with some noise) work out great:



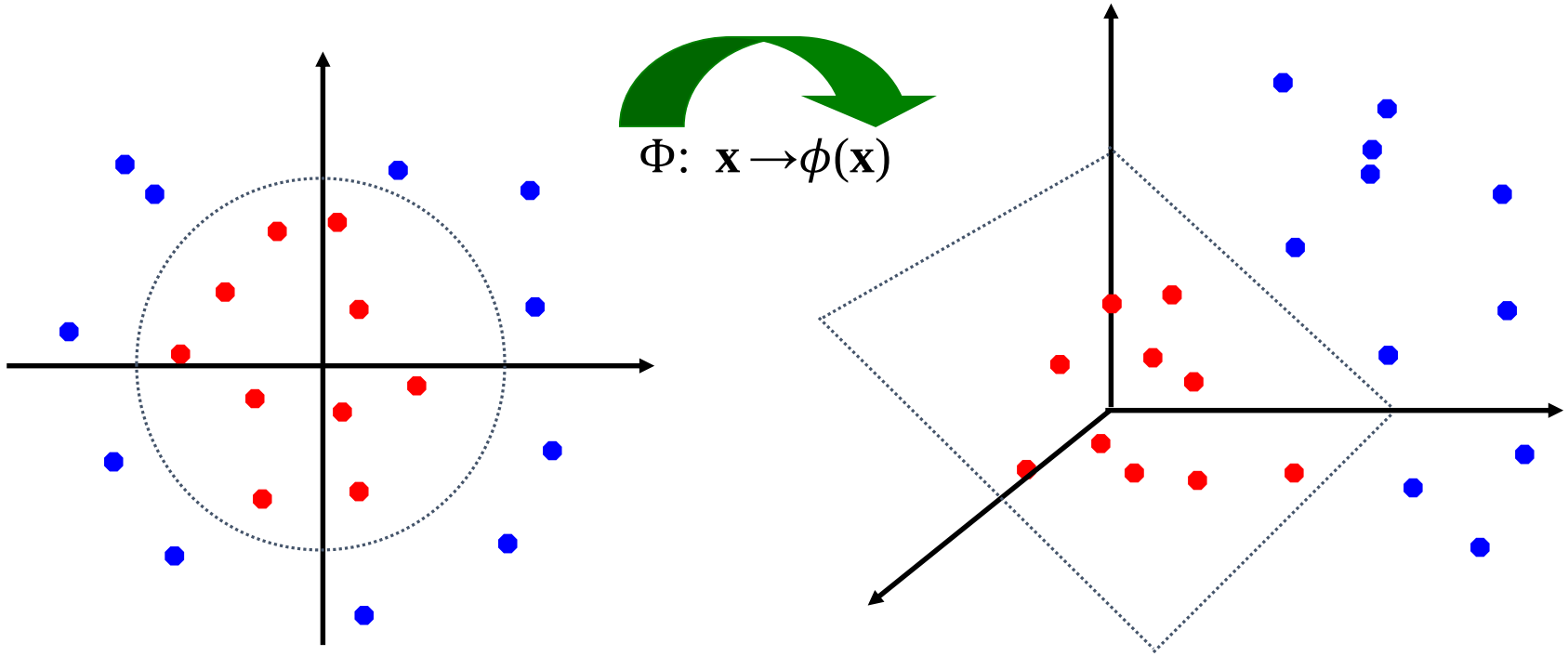
But what are we going to do if the dataset is just too hard?

How about … mapping data to a higher-dimensional space:



Non-linear SVMs: Feature spaces

General idea: the original feature space can always be mapped to some higher-dimensional feature space where the training set is linearly separable:



Non-linear SVMs: The Kernel Trick

With this mapping, our discriminant function is now:

$$y(x) = w^T \phi(x) + b = \sum_{i \in SV} \alpha_i \phi(x_i)^T \phi(x) + b$$

No need to know mapping function ϕ explicitly, because we only use the dot product of feature vectors in both training and test.

A *kernel function* is defined as a function that corresponds to a inner product of two feature vectors in some expanded feature space:

$$K(\mathbf{x}_i, \mathbf{x}_j) \equiv \phi(\mathbf{x}_i)^T \phi(\mathbf{x}_j)$$

Non-linear SVMs: The Kernel Trick

Commonly used kernel functions:

- Linear kernel: $K(\boldsymbol{x_i}, \boldsymbol{x_j}) = \boldsymbol{x_i}^T \boldsymbol{x_j}$
- Polynomial kernel: $K(\boldsymbol{x_i}, \boldsymbol{x_j}) = (1 + \boldsymbol{x_i}^T \boldsymbol{x_j})^p$
- Gaussian (Radial-Basis Function Kernel (RBF)) kernel:

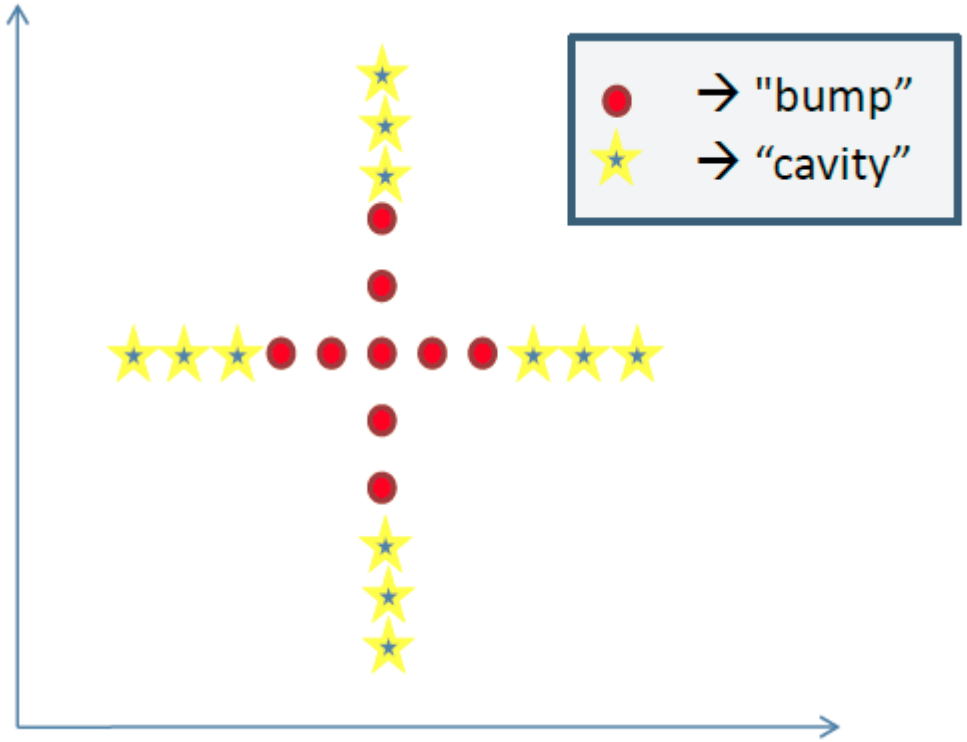
$$K(\boldsymbol{x_i}, \boldsymbol{x_j}) = \exp(-\frac{\|x_i - x_j\|^2}{2\sigma^2})$$

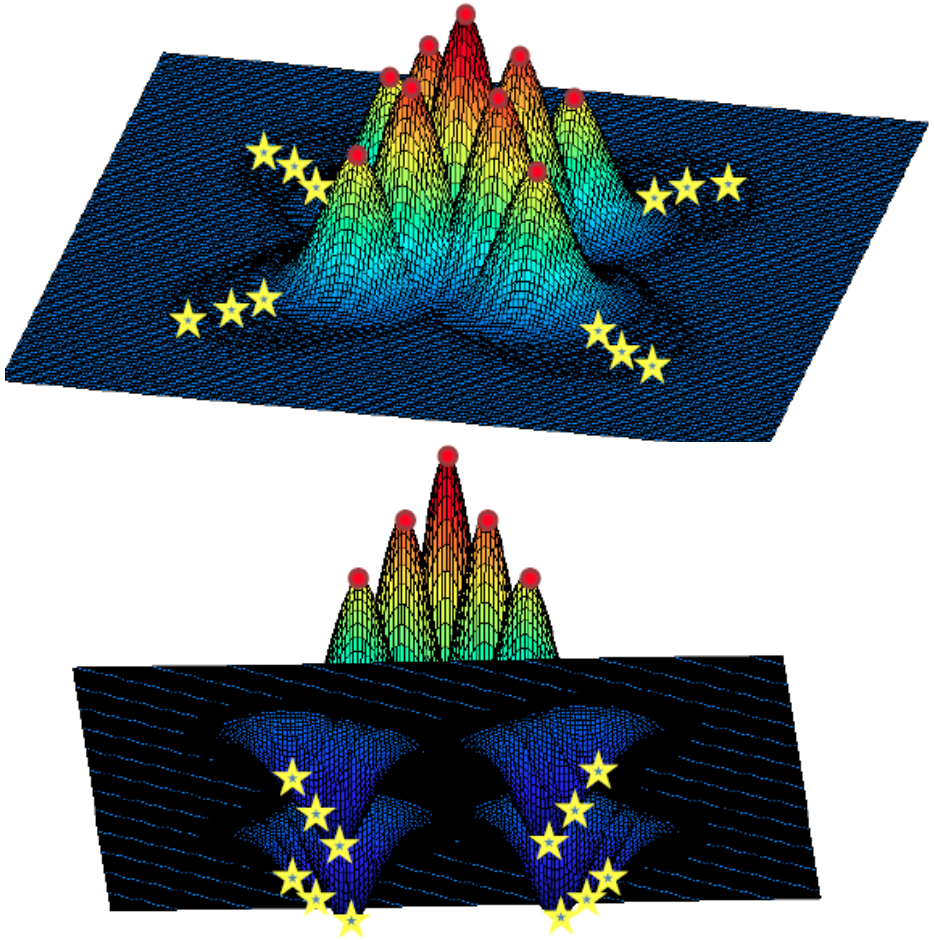
- Sigmoid: $K(x_i, x_j) = \tanh(\beta_0 x_i^T + \beta_1)$

In general, functions that satisfy *Mercer's condition* can be kernel functions.

Example: Gaussian Kernel

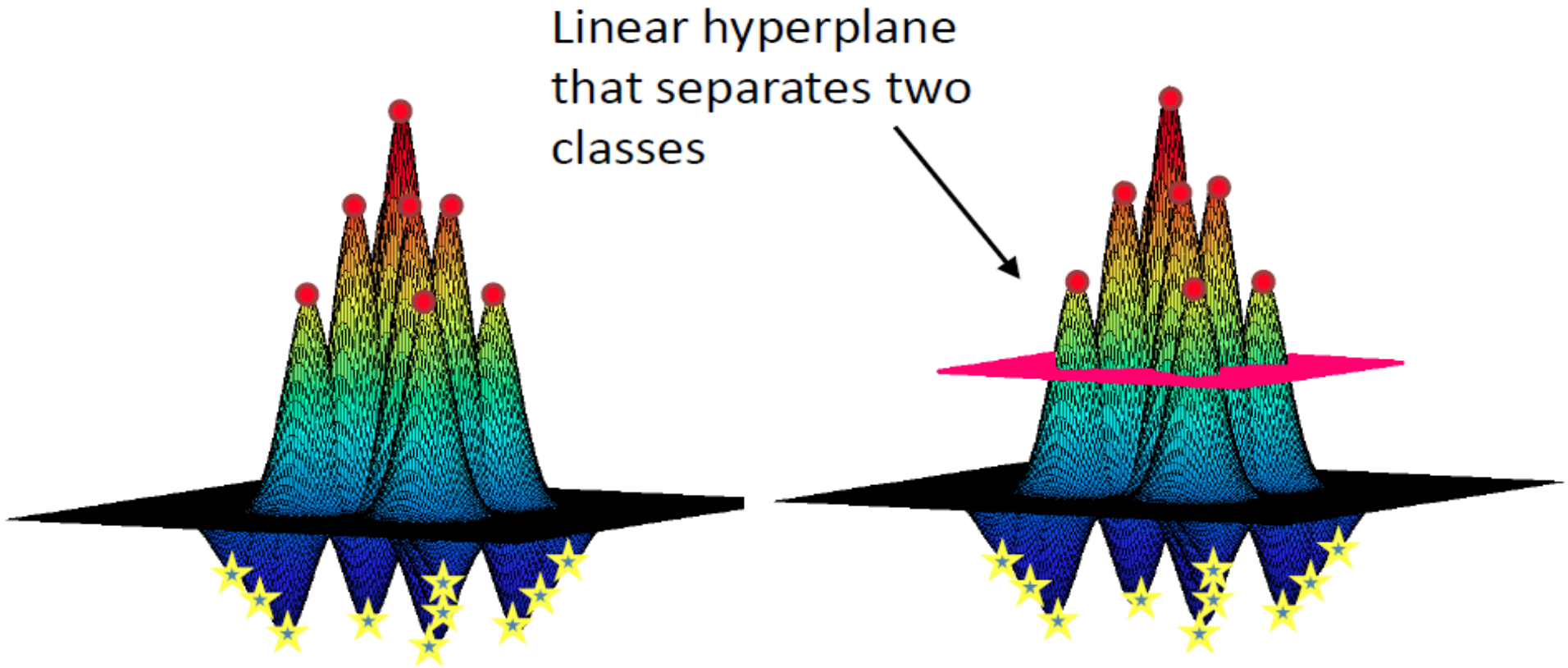
Geometrically, this is a “bump” or “cavity” centered at the training data point x:





Example: Gaussian Kernel - Classification

Geometrically, this is a “bump” or “cavity” centered at the training data point x:



SVMs in HCI

Many software packages exist, implementing linear SVMs, kernel SVMs and more

- LibSVM (http://www.csie.ntu.edu.tw/~cjlin/libsvm/)
- Matlab SVM toolbox (http://www.isis.ecs.soton.ac.uk/resources/svminfo/)
- Weka Data Mining toolbox (http://www.cs.waikato.ac.nz/ml/weka/index.html)

- More resources:
  - http://www.kernel-machines.org

SVMs probably *the most frequently* used ML technique in HCI

Reading Suggestions

V. Vapnik, Statistical Learning Theory. Wiley-Interscience; 1998

Christopher M. Bishop, Pattern Recognition and Machine Learning (Information Science and Statistics), Springer-Verlag New York, Inc., Secaucus, NJ, 2006

C.J.C. Burges. A tutorial on support vector machines for pattern recognition. Data Mining and Knowledge Discovery, 2(2):955-974, 1998.

http://www.kernel-machines.org