INTRODUCTION TO DEEP LEARNING FOR COMPUTER VISION

DAY 2 – FEATURE-BASED IMAGE CLASSIFICATION

SEBASTIAN HOUBEN

Schedule

Today

- Histogram of Oriented Gradients (HOG)
- Dimensionality Reduction with Principal Component Analysis (PCA)
- Going Deeper into Classification
    - Underfitting / Overfitting
    - Training-Test-Validation
- Support Vector Machine (SVM)
- Multi-Class SVM

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Classification pipeline

Feature Extraction

$$\begin{bmatrix} 2 \\ 5 \\ 1 \\ 8 \end{bmatrix} \longrightarrow \boxed{\text{Classifier}} \longrightarrow \{cat,dog\}$$

Classification pipeline (Multi-class)

Feature Extraction

Histogram-of-Oriented-Gradients

$$\rightarrow \begin{bmatrix} 2 \\ 5 \\ 1 \\ 8 \end{bmatrix} \rightarrow \boxed{\text{Multi-class SVM}} \rightarrow$$

{speed limit 20, speed limit 30, …, derestriction, yield way, …}

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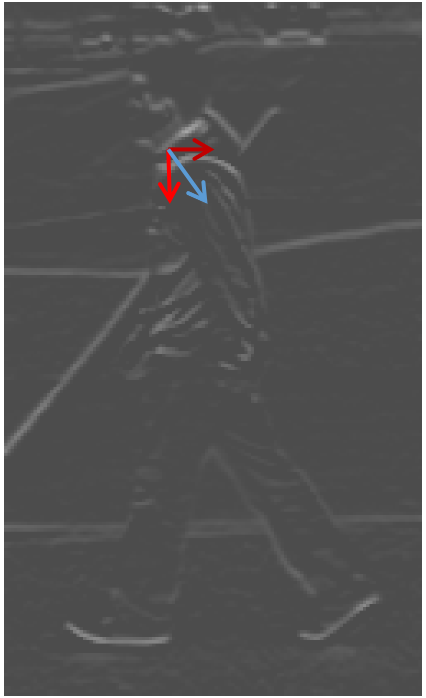

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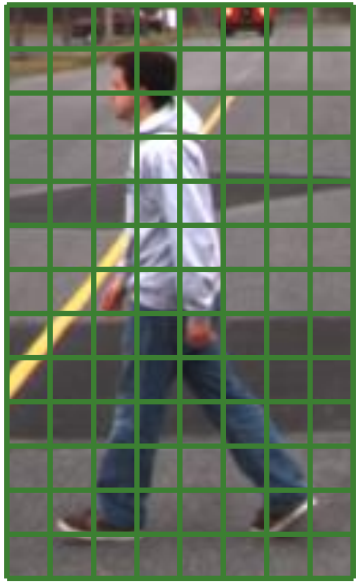

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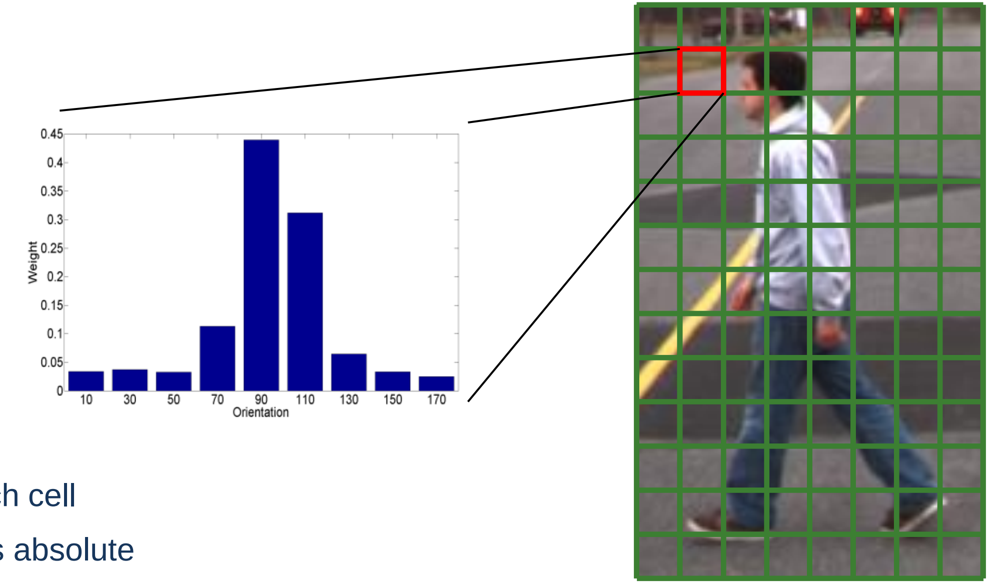

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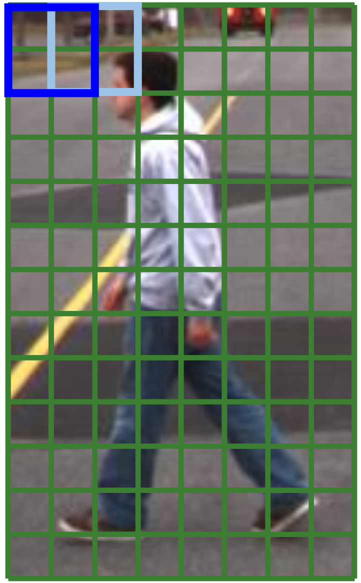

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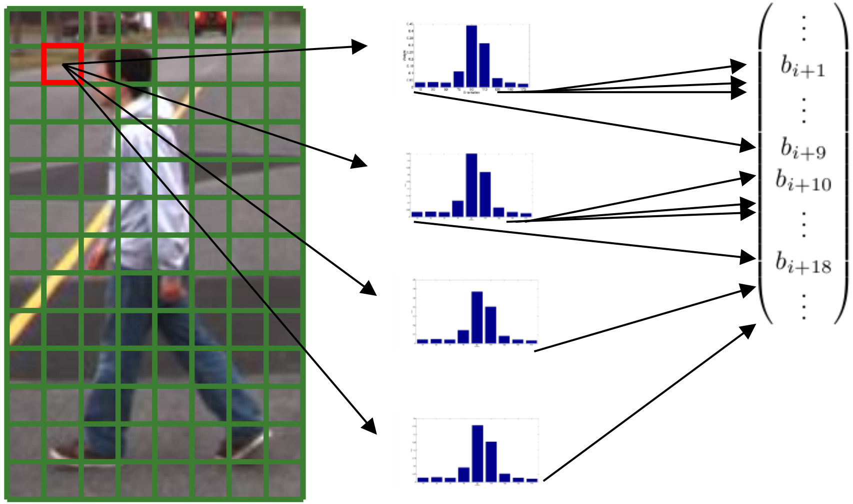
- For all blocks for all cells concatenate the histograms



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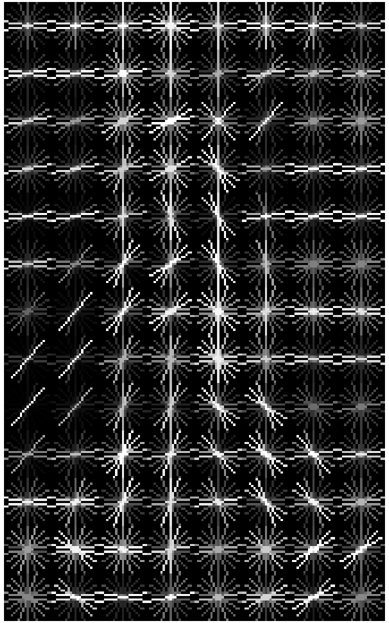
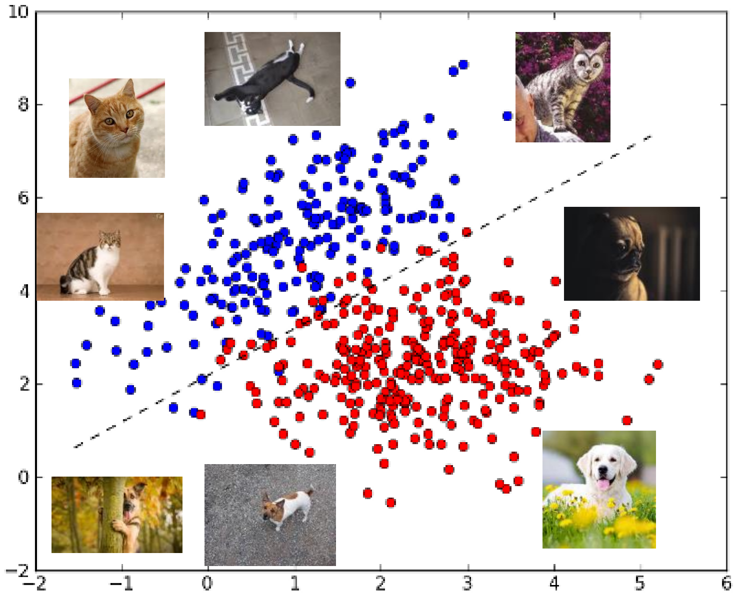


Visualizing High-dimensional Feature Spaces

- High-dimensional vectors are hard to interpret
- Visualizing in 2d or 3d is preferable
- Dimensionality reduction / embedding
- Several methods:
    - PCA (Principal Component Analysis)
    - t-SNE (t-distributed Stochastic Nearest-Neighbour Embedding)
    - LLE (Locally-Linear Embedding)
    - MDS (Multi-Dimensional Scaling)



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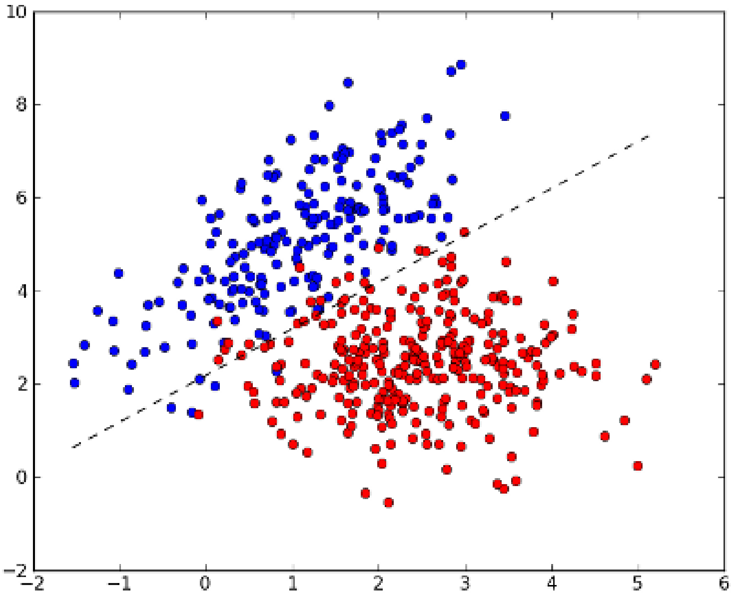

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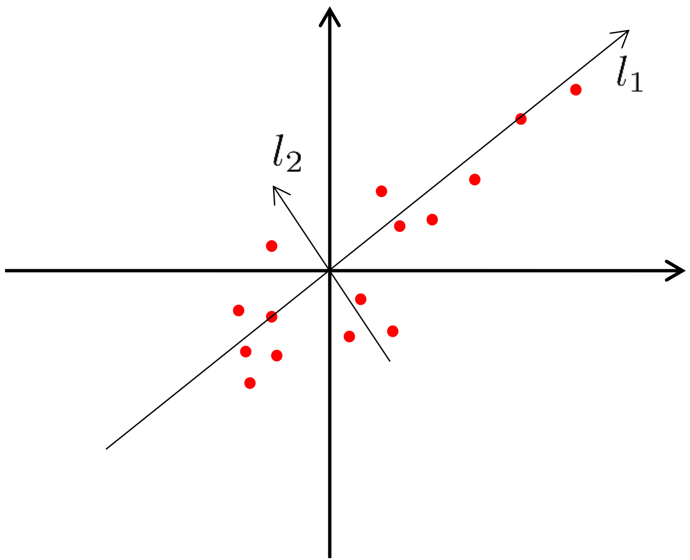
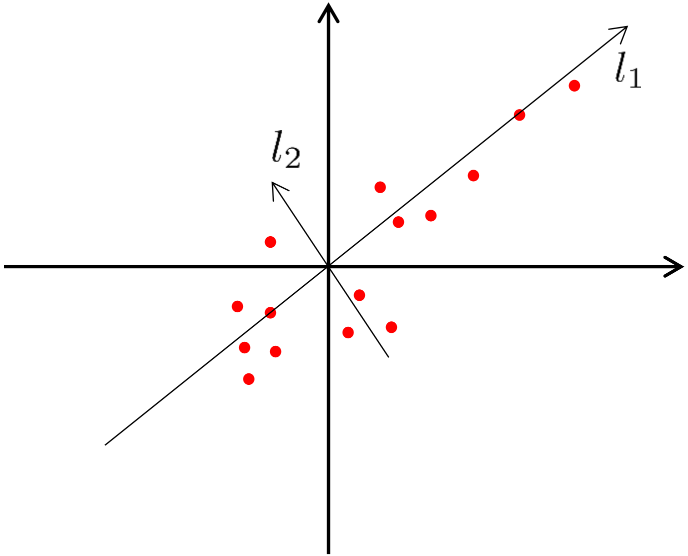


- Find function that maps data points to 2 dimensions: $f : \mathbb{R}^n \to \mathbb{R}^2$
- Make it easy: Linear
- Thus, can be represented by a 2 x n matrix

$$f(x) = Lx = \begin{pmatrix} l_1 \\ l_2 \end{pmatrix} x$$

- But linear means 0 is mapped to 0
  - Subtract mean value from dataset beforehand
- Consists of two rows
- Rows represent the axes of main variance (principal axes)

Visualizing High-dimensional Feature Spaces



- Rows represent the axes of main variance (principal axes)
- $$\min_{l_1, ||l_1||^2=1} \sum_i (x_i^T l_1)^2$$
- Row vector maximizing this, is given by eigenvector of
  $$C = \sum_i x_i x_i^T$$
  w.r.t. largest eigenvalue (covariance matrix C)
- Generally: Take the eigenvectors corresponding to the largest eigenvalues of the covariance matrix and project the zero-mean dataset to these vectors

$$\min_{l_1, ||l_1||^2=1} \sum_i (x_i^T l_1)^2$$

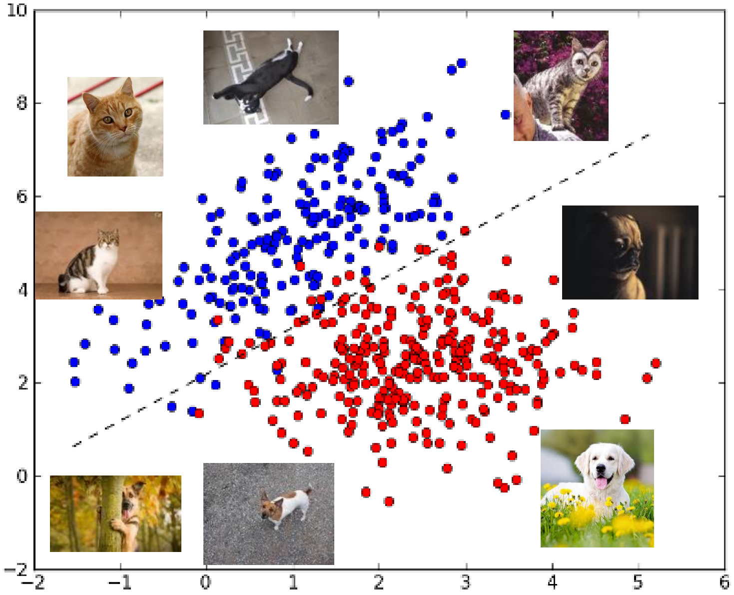
$$= \min_{l_1, ||l_1||^2=1} \sum_i l_1^T x_i x_i^T l_1$$

$$= \min_{l_1} \max_{\lambda \geq 0} \sum_i l_1^T x_i x_i^T l_1 + \lambda(||l_1||^2 - 1)$$

$$\min_{\lambda \geq 0} 2 \sum_i x_i x_i^T l_1 + 2\lambda l_1 = 0$$

$$\min_{\lambda \geq 0} \left(\sum_i x_i x_i^T \right) l_1 = \lambda l_1$$

Image Classification



- Linear classifier finds hyperplane to seperate sets of points
- A more complex classifier might find a better way to seperate the two datasets

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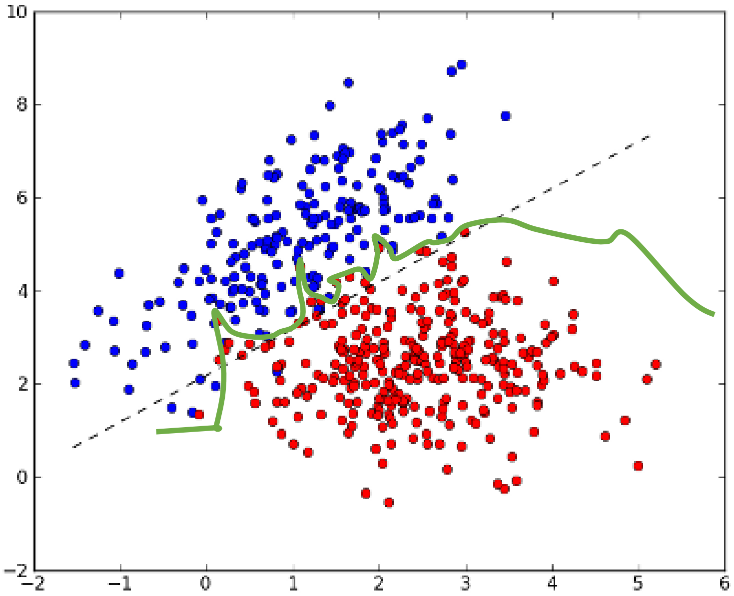

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- A more complex classifier might find a better way to seperate the two datasets
- Many ML methods have hyper-parameters that control the complexity of the function to fit
- But: In general, very complex functions tend to perform <u>worse on unseen data</u>

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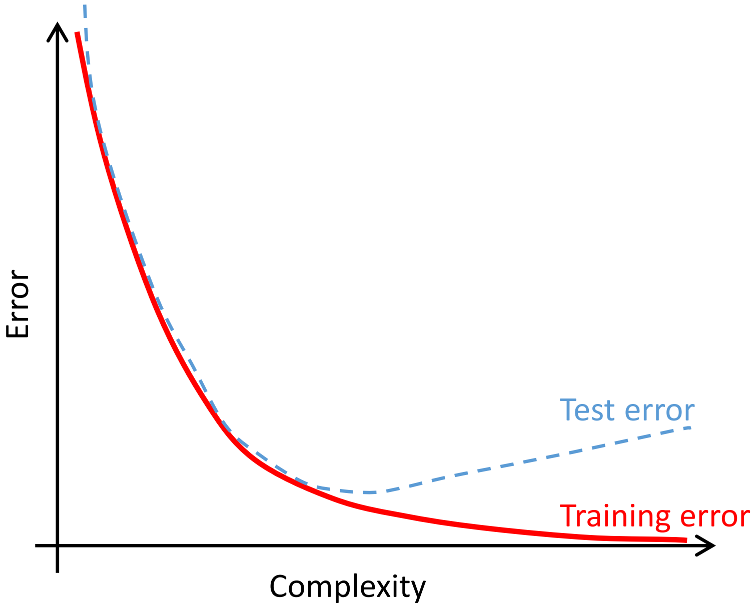

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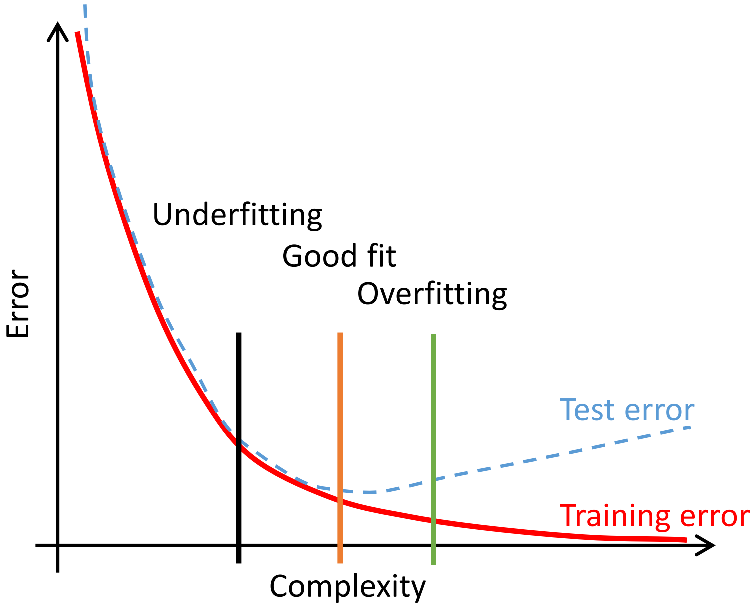

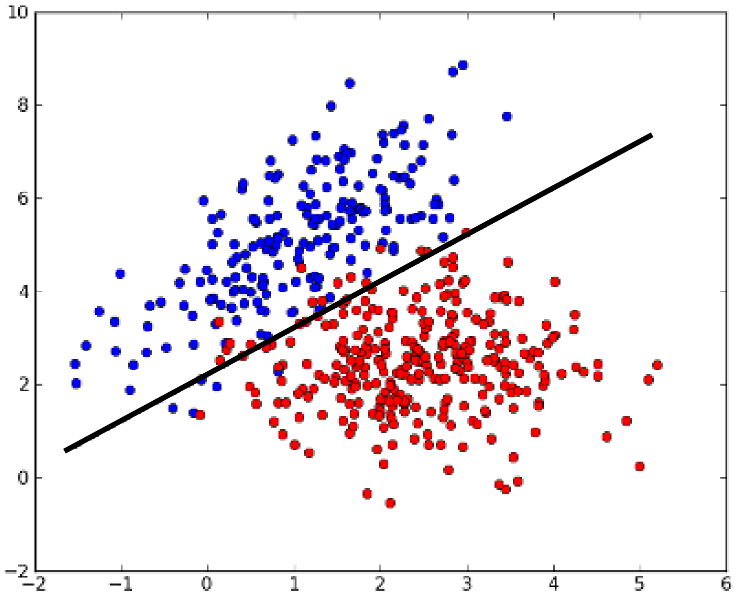

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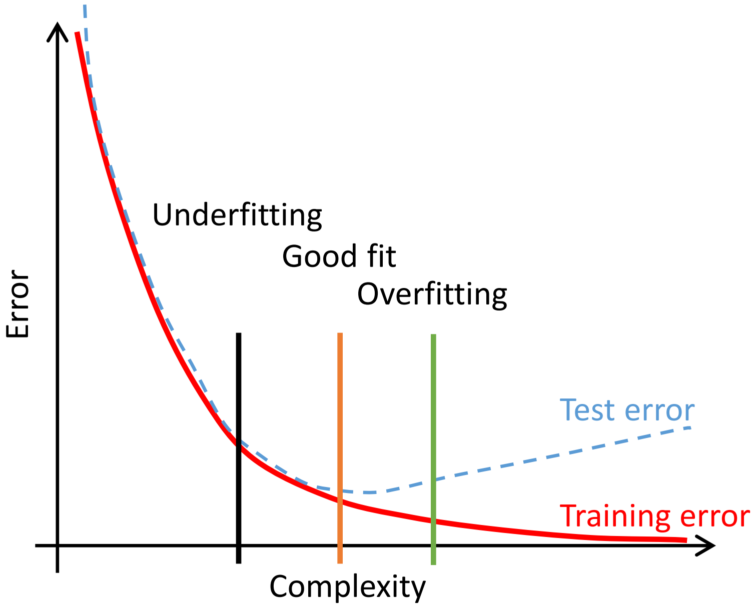

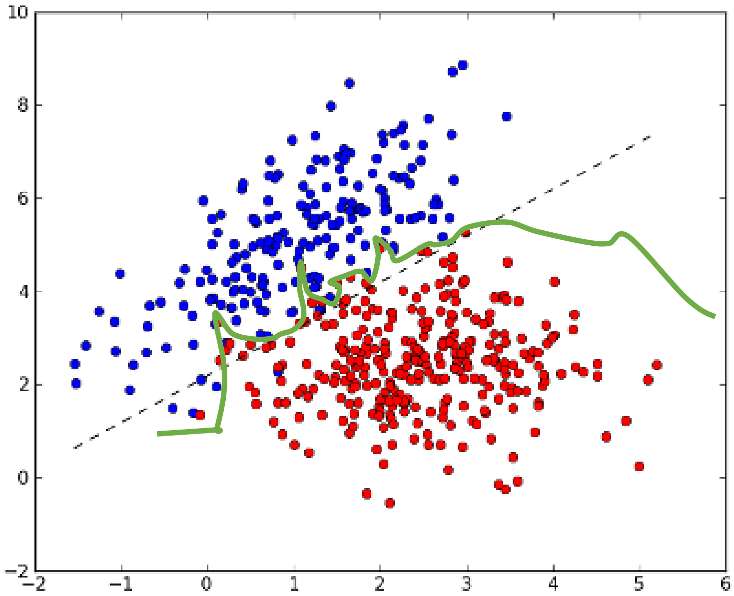

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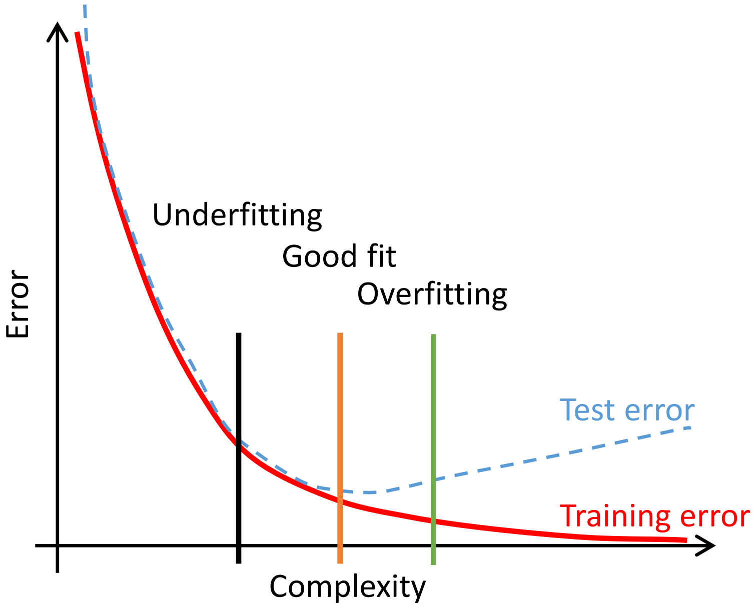

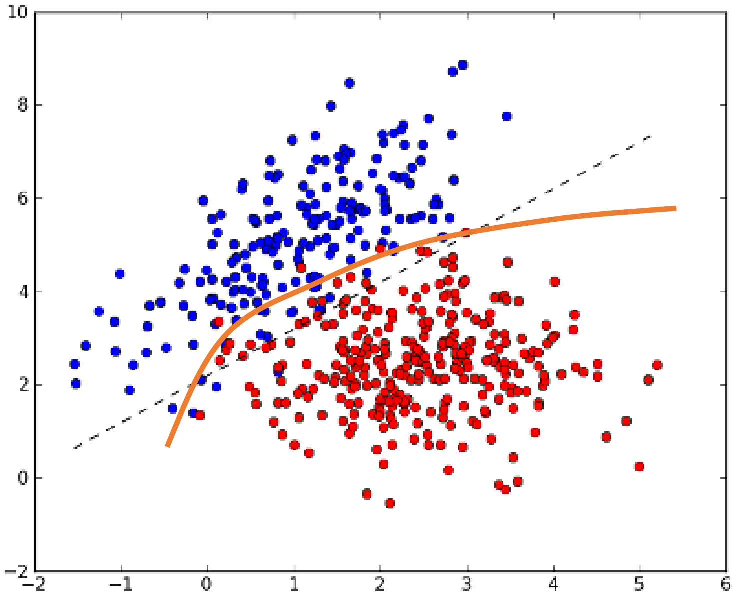

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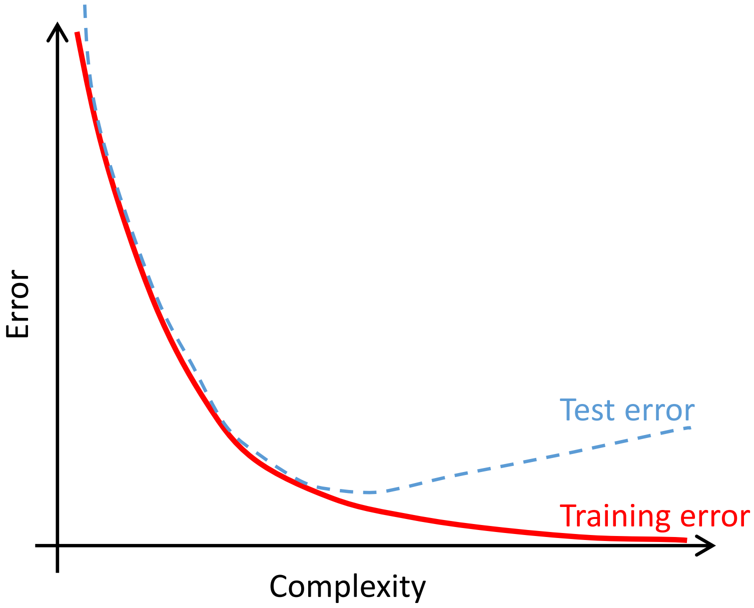
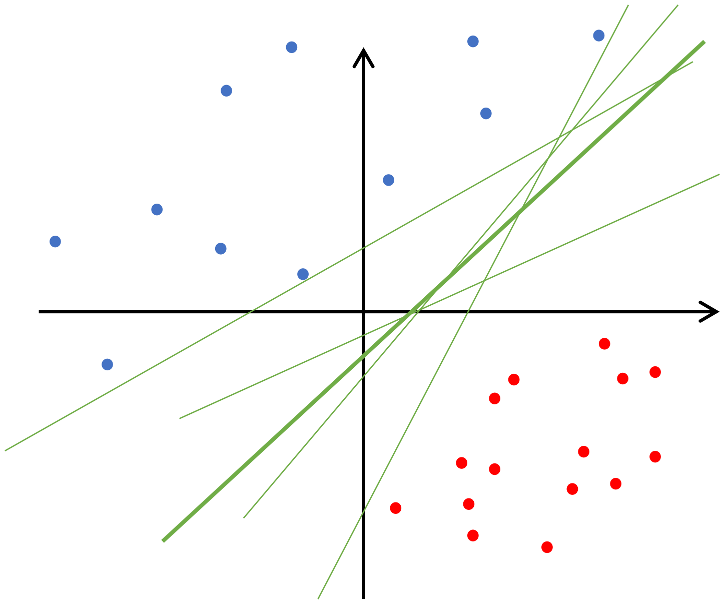


- Linear classifier finds hyperplane to seperate sets of points
- A more complex classifier might find a better way to seperate the two datasets
- Many ML methods have hyper-parameters that control the complexity of the function to fit
- But: In general, very complex functions tend to perform worse on unseen data
- Need to estimate the training error: split dataset into training-validation-test

Support Vector Machines

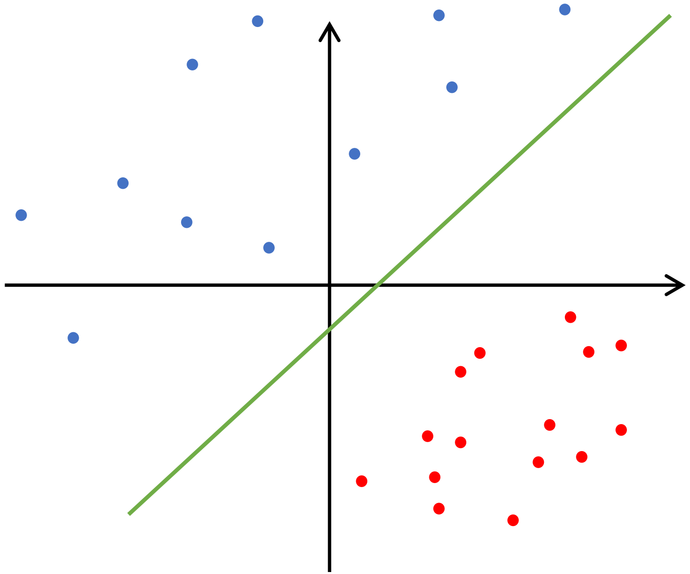


Support Vector Machines

- Labelled Data: $(x_i, y_i), x_i \in \mathbb{R}^n, y_i \in \{-1, 1\}$
- Solve:

$$\min_{w,b} \; w^T w$$

$$\text{s.t. } \; y_i \cdot \left(w^T x_i + b\right) \geq 1$$



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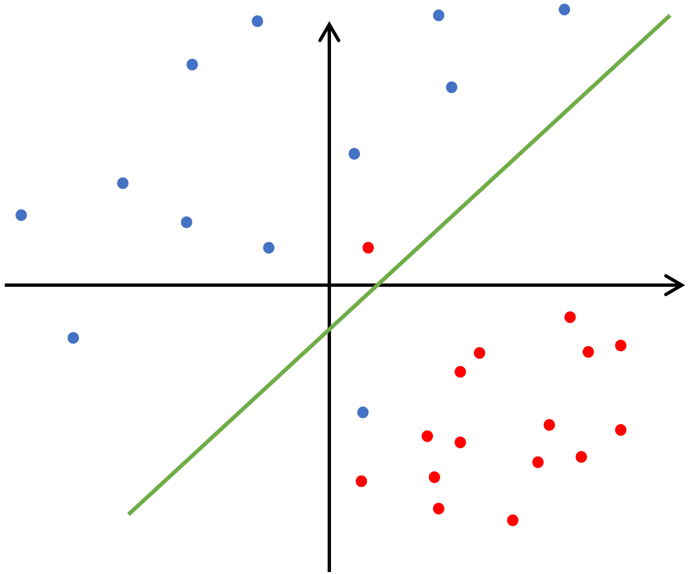
- Solve:

$$\min_{w,b} \; w^T w + C \sum_i \xi_i$$

$$\text{s.t.} \;\; y_i \cdot \left(w^T x_i + b\right) \geq 1 - \xi_i$$

$$\xi_i \geq 0$$



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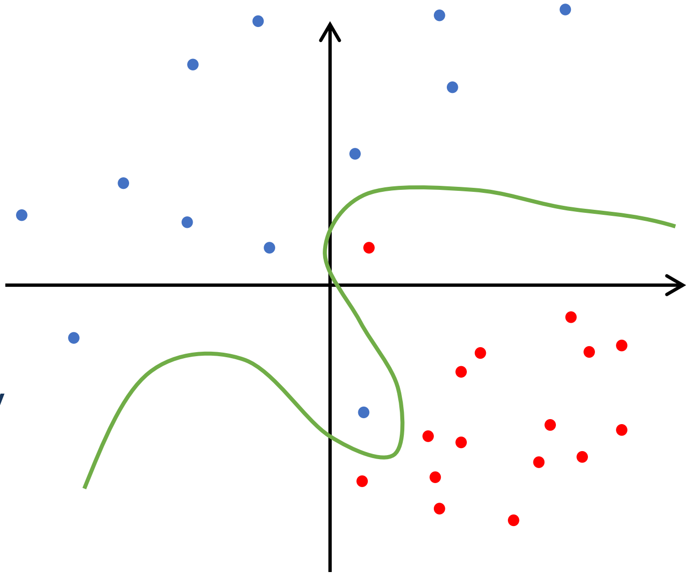
$$\text{s.t.} \; y_i \cdot \left(w^T \phi_\gamma(x_i) + b\right) \geq 1 - \xi_i$$

$$\xi_i \geq 0$$

- C, γ are a hyper-parameter that control complexity
- Multiclass: One-vs-All
  - most confident classifier wins
  - Confidence ist given by distance to border
- Multiclass: One-vs-One



QUESTIONS?

EXERCISES.