Aalto University
School of Electrical Engineering

CS-C3240 – Machine Learning D

Round 3: From features to classification

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Overview

Shortage of labelled data

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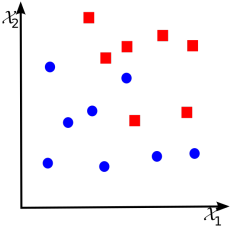
Given a set $\mathcal{Z}$ of data points $\overrightarrow{z}_1, \ldots, \overrightarrow{z}_n$, features $\mathcal{X}_1, \ldots, \mathcal{X}_m$ and labels $y_1, \ldots, y_o$, assume partially labelled sets $\overrightarrow{z}_i = \langle \overrightarrow{x}^{(i)}, y^{(i)} \rangle, i \in \{1, \ldots, l\}$ and $\overrightarrow{z}_j = \langle \overrightarrow{x}^{(j)} \rangle, j \in \{l+1, \ldots, n\}$ as well as $\overrightarrow{x}^{(k)} = x_1^{(k)}, \ldots, x_m^{(k)}, k \in \{1, \ldots, n\}$

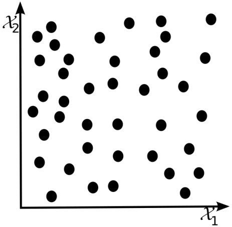
Labelled

$$\overrightarrow{x}^{(1)} \rightarrow y^{(1)}$$
$$\overrightarrow{x}^{(2)} \rightarrow y^{(2)}$$
$$\vdots$$
$$\overrightarrow{x}^{(l)} \rightarrow y^{(l)}$$



Unlabelled

$$\overrightarrow{x}^{(l+1)} \rightarrow ?$$
$$\overrightarrow{x}^{(l+2)} \rightarrow ?$$
$$\vdots$$
$$\overrightarrow{x}^{(n)} \rightarrow$$



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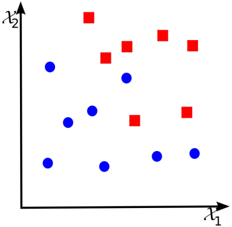

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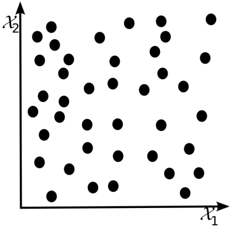

Problem:

- Unlabelled training data is often easy to obtain
- **However:** labelling the data requires significant manual work

Shortage of labelled data

Automated labeling through semi-supervised learning

Increase amount of labelled data via semi-supervised learning

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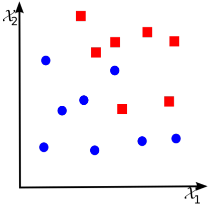

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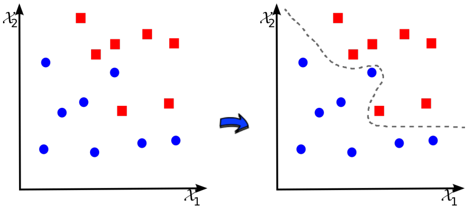
Increase amount of labelled data via semi-supervised learning

1. Start with labelled data $\vec{z}_i = \langle \vec{x}^{(i)}, y^{(i)} \rangle, i \in \{1, \ldots, l\}$
2. Train the classifier on the labelled data $\hat{h}\left(\hat{\vec{w}}, \cdot\right) = \min_{i=1,..l} \mathcal{L}\left(h(\vec{w}, \vec{x}^{(i)}), y^{(i)}\right)$



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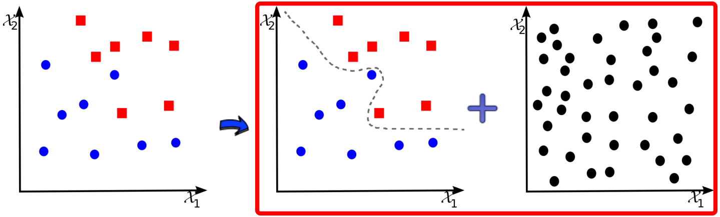

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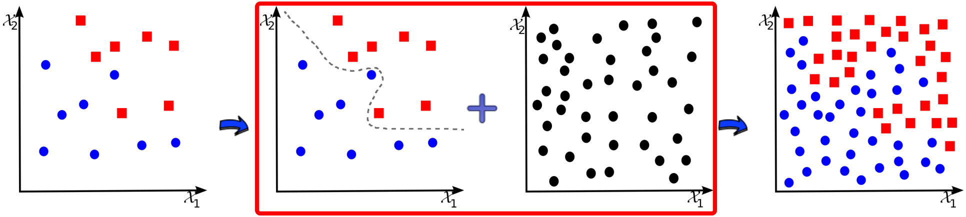

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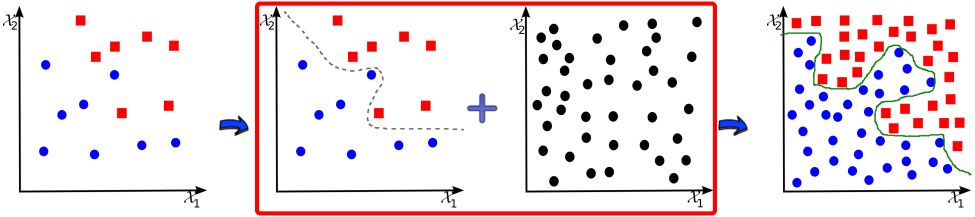
4. Train new classifier $\hat{h}'$ on $\langle \vec{x}^{(1)}, y^{(1)} \rangle, \ldots, \langle \vec{x}^{(l+1)}, \hat{y}^{(l+1)} \rangle$



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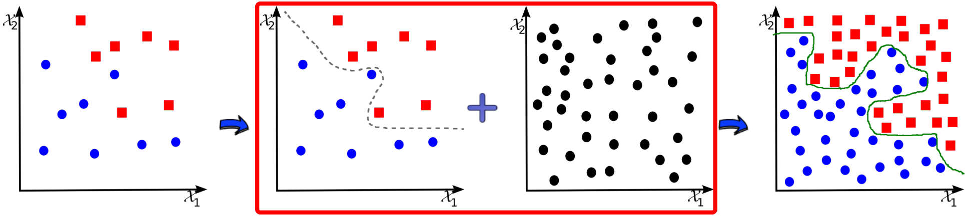
Automated labeling through semi-supervised learning

Remark:

- No guaranteed success → Empirical validation required
- Introducing weights to samples can reduce dependency on learned labels



Shortage of labelled data – Automatic labelling

Co-training

Provided independent feature sub-sets (perspectives) $\{\mathcal{X}\}_s$ with $\bigcup_s \{\mathcal{X}\}_s = \mathcal{X}_1, \ldots, \mathcal{X}_m$ and $\bigcap_s \{\mathcal{X}\}_s = \emptyset$, multiple classification models $h_s(\overrightarrow{w}_s, \overrightarrow{x})$ are trained to these sub-sets using the labelled data $\overrightarrow{z}_i = \langle \overrightarrow{x}^{(i)}, y^{(i)} \rangle, i \in \{1, \ldots, l\}$ to iteratively label unlabelled data $\overrightarrow{z}_j = \langle \overrightarrow{x}^{(j)} \rangle, j \in \{l+1, \ldots, n\}$

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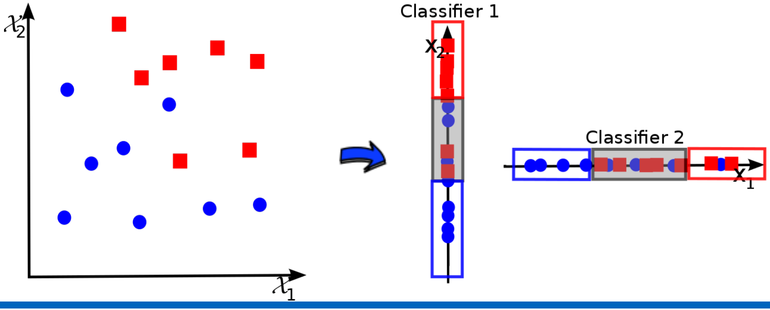
1. Train classifier h_s for each $\{\mathcal{X}\}_s$

$$\hat{h}_s(\overrightarrow{\hat{w}_s}, \cdot) = \min_{i \in \{\mathcal{X}_s\}} \mathcal{L}\left(h(\overrightarrow{w}, \overrightarrow{x}^{(i)}), y^{(i)}\right)$$



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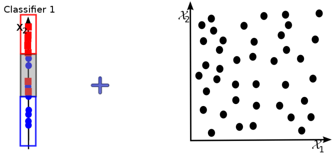

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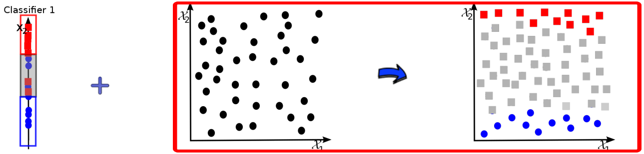
3. Add $\langle \vec{x}, \hat{y}^{(j)} \rangle$ with highest confidence to $\vec{z}_i = \langle \vec{x}^{(i)}, y^{(i)} \rangle, i \in \{1, \dots, l\}$



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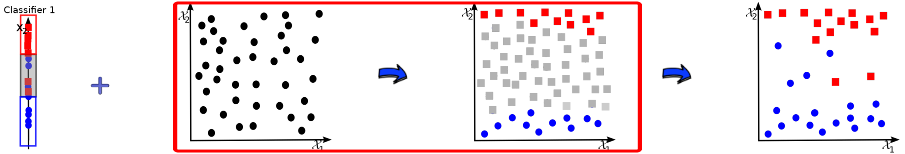
4. Iterate over over all classifiers h_s until convergence reached



Questions?

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Literature

- C.M. Bishop: Pattern recognition and machine learning, Springer, 2007.
- R.O. Duda, P.E. Hart, D.G. Stork: Pattern Classification, Wiley, 2001.