

CS-C3240 – Machine Learning D

Round 3: From features to classification

Stephan Sigg

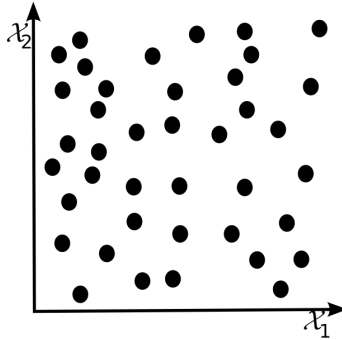
Department of Communications and Networking
Aalto University, School of Electrical Engineering
stephan.sigg@aalto.fi

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Semi-supervised learning

Unlabelled training data often easy to obtain

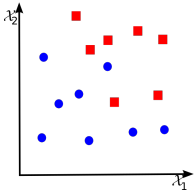
Caveat: labelling the data requires significant manual work



Semi-supervised learning

Increase amount of labelled data:

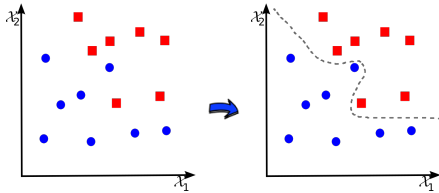
- 1 Start with labelled data



Semi-supervised learning

Increase amount of labelled data:

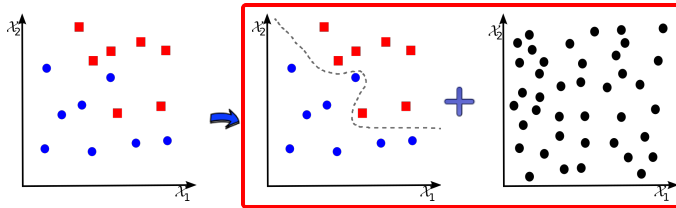
- 1 Start with labelled data
- 2 Train the classifier on the labelled data



Semi-supervised learning

Increase amount of labelled data:

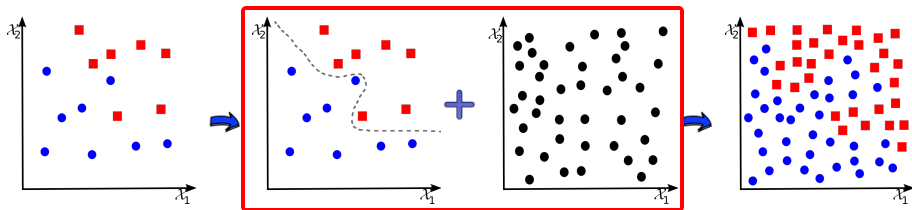
- 1 Start with labelled data
- 2 Train the classifier on the labelled data



Semi-supervised learning

Increase amount of labelled data:

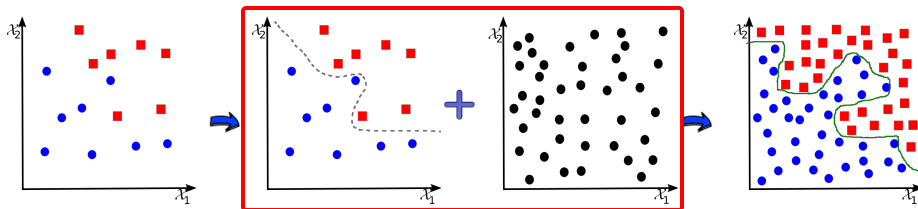
- 1 Start with labelled data
- 2 Train the classifier on the labelled data
- 3 Use the classifier to learn labels for the unlabelled data



Semi-supervised learning

Increase amount of labelled data:

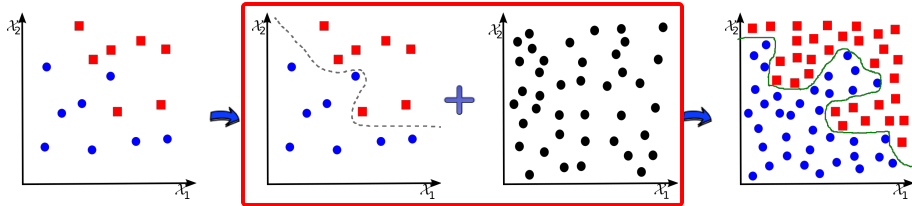
- 1 Start with labelled data
- 2 Train the classifier on the labelled data
- 3 Use the classifier to learn labels for the unlabelled data
- 4 Train a new classifier on this data



Semi-supervised learning

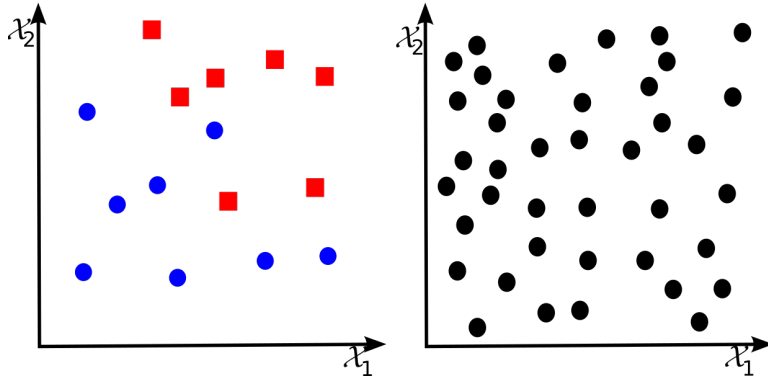
Remarks:

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



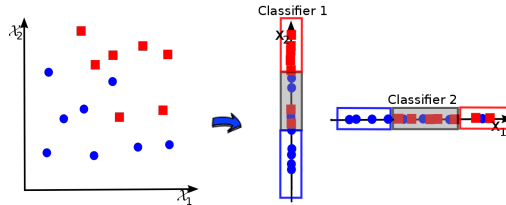
Co-training – Automated labelling

Provided independent feature sub-sets (perspectives), multiple classifiers trained to these sub-sets can iteratively label unlabelled data



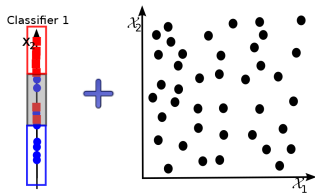
Co-training – Automated labelling

- 1 Train several classifiers wrt different feature-subsets



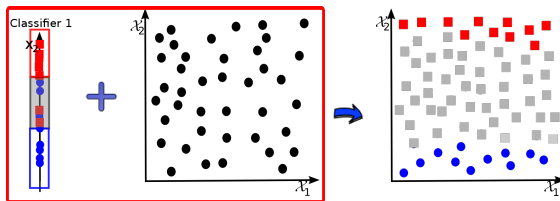
Co-training – Automated labelling

- 1 Train several classifiers wrt different feature-subsets
- 2 Apply one of these to the unlabeled data



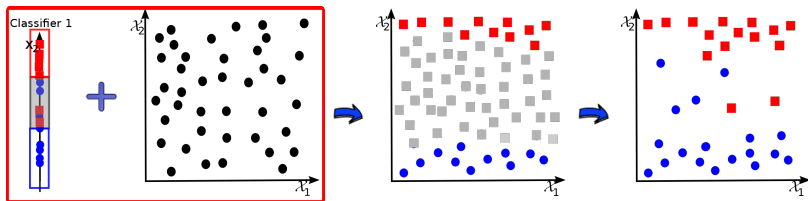
Co-training – Automated labelling

- 1 Train several classifiers wrt different feature-subsets
- 2 Apply one of these to the unlabelled data
- 3 Label those samples with highest probability



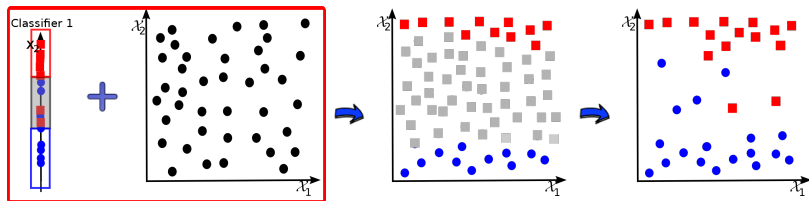
Co-training – Automated labelling

- 1 Train several classifiers wrt different feature-subsets
- 2 Apply one of these to the unlabelled data
- 3 Label those samples with highest probability
- 4 Combine with the original labelled data



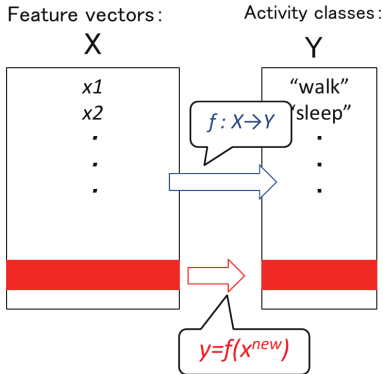
Co-training – Automated labelling

- 1 Train several classifiers wrt different feature-subsets
- 2 Apply one of these to the unlabelled data
- 3 Label those samples with highest probability
- 4 Combine with the original labelled data
- 5 Iterate over over all classifiers until convergence reached



Zero-shot learning

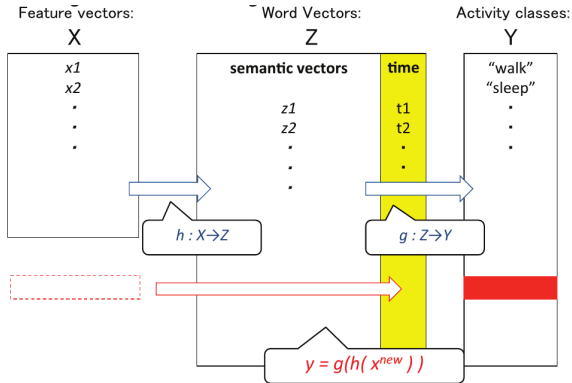
Exploit world-knowledge in order to recognize unknown classes¹



¹ Picture: Matsuki, Inoue. "Recognizing unknown activities using semantic word vectors and twitter timestamps." 2016 ACM Ubicomp Adjunct.

Zero-shot learning

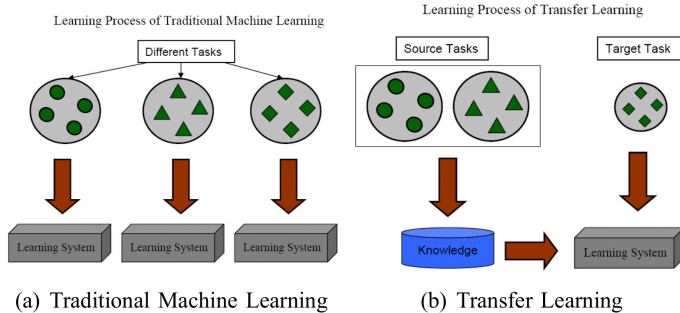
Exploit world-knowledge in order to recognize unknown classes¹



¹ Picture: Matsuki, Inoue. "Recognizing unknown activities using semantic word vectors and twitter timestamps." 2016 ACM Ubicomp Adjunct.

Transfer learning

Apply a classifier to classes slightly differing from those trained²



² Picture from: Pan, Yang. "A survey on transfer learning." IEEE Transactions on knowledge and data engineering 22.10 (2010): 1345-1359.

Questions?

Stephan Sigg

`stephan.sigg@aalto.fi`

Si Zuo

`si.zuo@aalto.fi`

Literature

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

