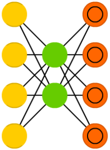


Representation learning

Dan Oneață

Bucharest CV – Reading group #3

Overview

Introduction to representation learning

Uses of representations

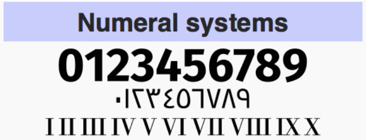
Types of representations learnt by deep learning

Learning good representations

Introduction

- Learning representations: the distinctive feature of deep learning

Introduction



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- Representations for humans:
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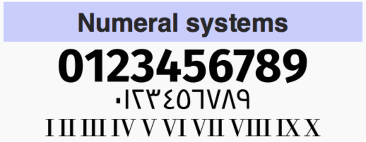

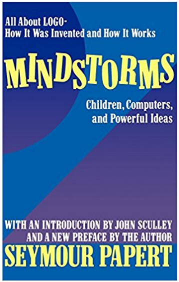

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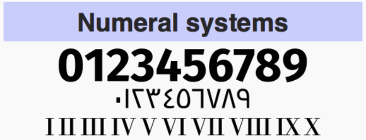

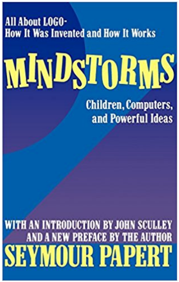

- Learning representations: the distinctive feature of deep learning
- Representations for humans:
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  - Models to assimilate knowledge
  - Ability to learn from very few examples

Examples of representations in neural networks

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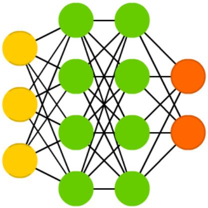

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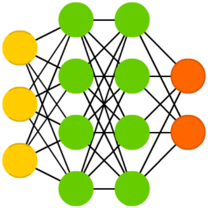

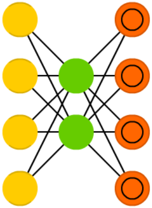

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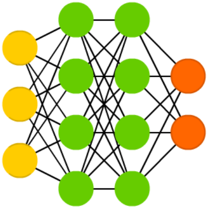
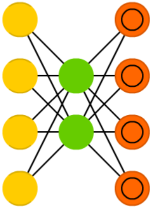
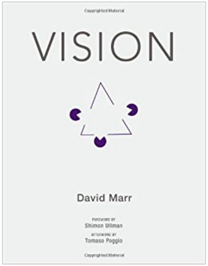




- Supervised learning – implicit representations
- Unsupervised learning – explicit representations
- Representations: high-level, many-to-one mapping of the input

Representation learning: A definition



A representation is a formal system which makes explicit certain entities or types of information, together with a specification of how the system does this.

(Marr, 1982)

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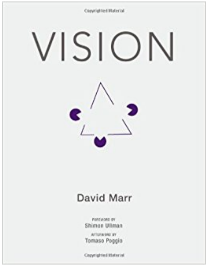

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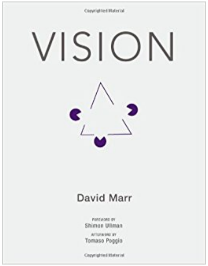

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  - set of symbols with rules of putting them together
- *makes explicit certain types of information*
  - usually a trade-off
  - representations are tied to a given task

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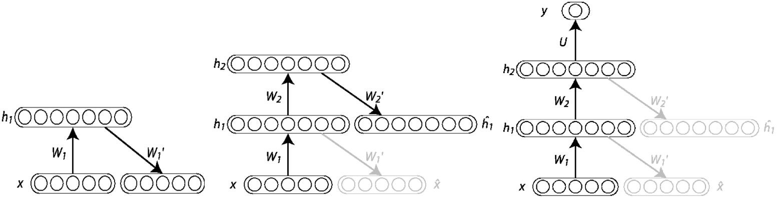
Uses of representations: Unsupervised pre-training



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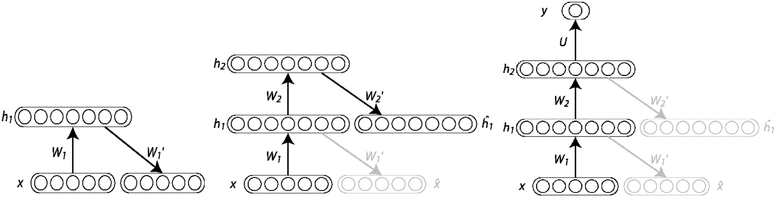
Uses of representations: Unsupervised pre-training



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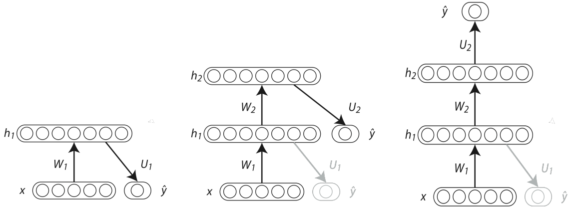

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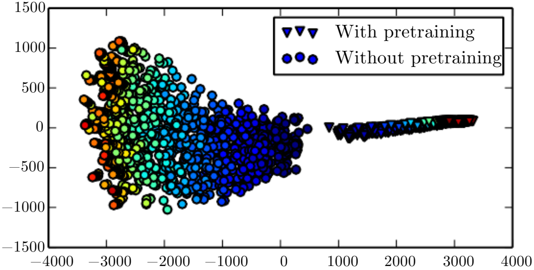
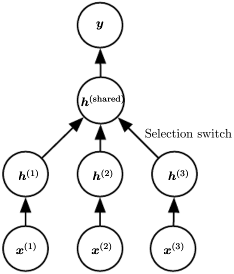


- Pre-training reduces the variance of the estimation process

More uses of representations



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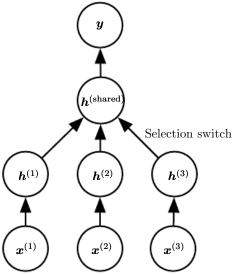

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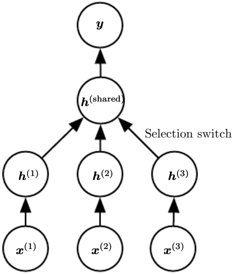

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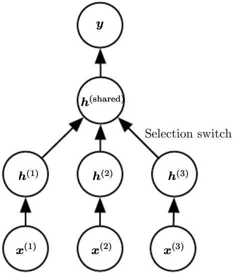

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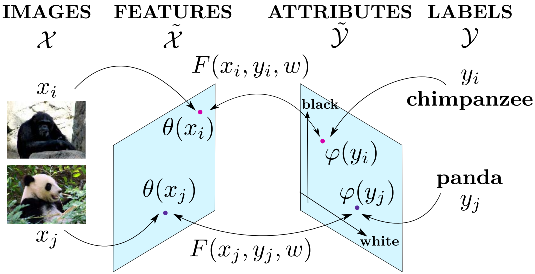

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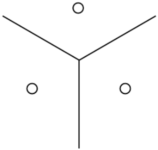

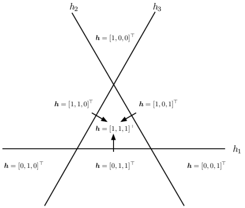

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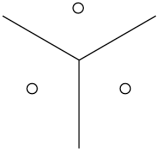

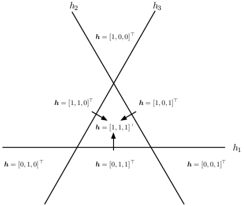

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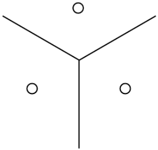

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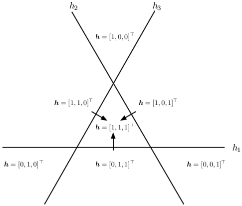

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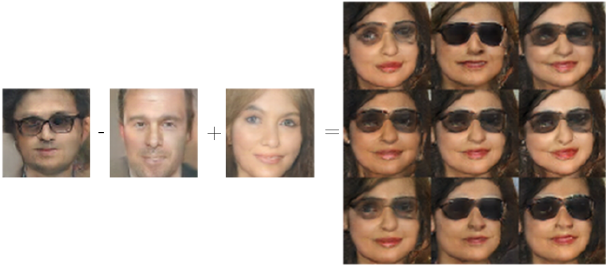

- Directions in representations space capture factors of variations
- Allows generalization to new configurations of features

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- Intuitively hierarchal representations allow reuse

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  - Shared factors across tasks
  - Sparsity: not all features are relevant to describing the input

Further resources

- Y. Bengio's talks and tutorials
  http://www.iro.umontreal.ca/~bengioy/talks/deep-learning-gss2012.html
- Y. Bengio. Learning Deep Architectures for AI (Bengio, 2009)
- Y. Bengio. Representation learning: A review and new perspectives (Bengio et al., 2013)
- Representation Learning workshop (27/03 – 31/03, 2017)
  https://simons.berkeley.edu/workshops/schedule/3750

References

Bengio, Y. (2009). Learning deep architectures for AI. *Foundations and Trends in Machine Learning*, 2(1):1–127.

Bengio, Y., Courville, A., and Vincent, P. (2013). Representation learning: A review and new perspectives. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 35(8):1798–1828.

Goodfellow, I., Bengio, Y., and Courville, A. (2016). *Deep Learning*. MIT Press. `http://www.deeplearningbook.org`.

Marr, D. (1982). *Vision: A Computational Investigation into the Human Representation and Processing of Visual Information*. Henry Holt and Co., Inc., New York, NY, USA.