CSE 6740 A/ISyE 6740: Computational Data Analysis: Introductory lecture

Nisha Chandramoorthy

August 22, 2023

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- Canvas (see syllabus), gradescope, Piazza, Github

Machine learning and data mining: what are they?

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- Compute: Optimization, representation/models
- Data: distributions, features/compression, statistics

Categorizations of learning

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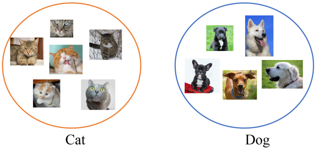
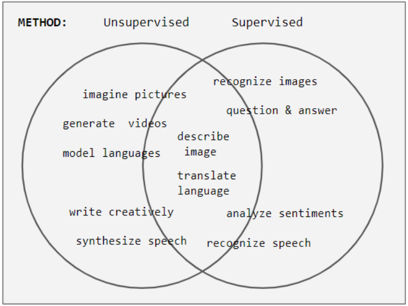
- Mode of learning and testing are different
- You sample peaches across several grocery stores in Atlanta. Now you are given a new peach of unknown origins. Can you tell if it would taste good?

Supervised, unsupervised, in-between, semi-supervised, self-supervised...





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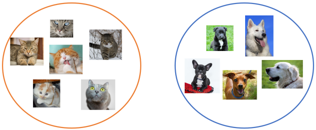
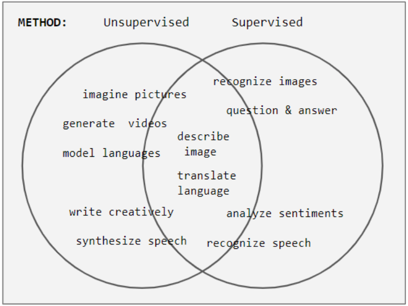


Cat

Dog



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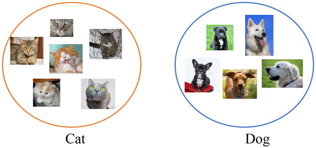

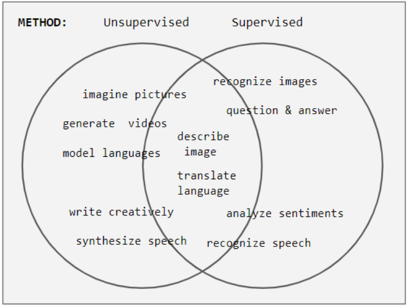

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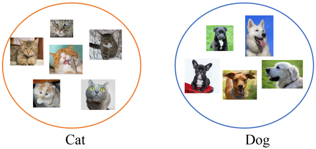

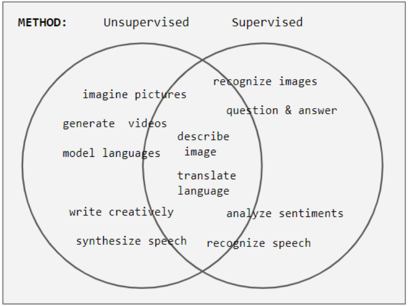

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- New research frontier for theory: understand how and why large ML models work the way they do?

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- Perhaps biggest contribution advance to LLMs: transformers and their training.

(partial) History - trace back from transformers (source:Wikipedia)

- Transformer architecture: 2017, Google Brain [Vaswani et al]
- Deep learning, unsupervised learning 2010s (e.g., GANs 2014)...
- ImageNet: 2009, Fei Fei Li
- Long-short term memory (LSTM) architecture: 1997, [Hochreiter and Schmidhuber]
- Convolutional NNs: (inspired from) 1979 work by [Fukushima]; Recurrent neural networks: 1982 [Hopfield]
- ...
- Automatic Differentiation: 1970 [Linnainmaa]
- ...
- First neural networks: 1950s [Minsky and others]

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- Generalization error or risk:

$$R(h) = E_{z \sim \mathcal{D}} \ell(z, h)$$

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- Next time: Linear models.

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- Now: simple case of finite $\mathcal{H}$.