"The DSFP goes to Philadelphia"

Introduction to Machine Learning & Dimensionality Reduction

The learning problem:

Supervised: learn a function h that best approximates the true function f: X --> Y for data sampled from some joint distribution D(X, Y)

Unsupervised: estimate a probability distribution P(X) from data.

Dimensionality Reduction – feature selection and visualization

Unsupervised Learning and the Perceptron (Adam Miller)

Unsupervised learning casts a long shadow touching on many different fields

Clustering can be useful for identifying structure within large multidimensional data sets but there is no definitive way to prove that clusters are correct

Perceptrons are the basic building block for neural networks

Connecting many perceptrons/neurons can provide highly complex non-linear models, which is the basic building block for all deep neural nets

Supervised Learning, Tree, and Ensemble Methods (Viviana Acquaviva)

In supervised learning, there is a risk of overfitting and a risk of information about the test set leaking into the training set via the choice of hyperparameters. Cross-validation is a technique for mitigating this problem without throwing away data.

Boosting is a technique for repeatedly training learners on residuals from previous steps in the training.

Bagging is a technique for combining multiple learners to improve classification.

CNNs and GNNs (John Wu)

In supervised learning, neural network models are trained by (1) inputting data, (2) seeing what the model predicts, (3) comparing the predictions against the known labels, (4) computing the how the model should be adjusted in order to make a better prediction, (5) updating the model parameters, and (6) repeating the whole process.

Convolutional neural networks are best-suited for data that lives on a regular grid, i.e., an image. They learn shape features at multiple size scales and levels of complexity; the early layers learn small, basic features, while the final layers learn large complicated features.

Graph neural networks are best-suited for representing things that interact with other things, especially if those things can be arbitrarily ordered.

Reinforcement Learning (Ari Sravan)

Using bandits as a simple example of needing to make good decisions despite incomplete information, we can show that more intuitive models can perform very badly.

We discussed two approaches, optimism under uncertainty and Bayesian regret, that can perform effective exploration and accumulate sublinear regret.

We noted that in general, the state of the world can evolve as we interact with it (making our data not iid) and the consequences of our decisions may be apparent with a delay. In such situations, the full machinery of reinforcement learning can be deployed and we briefly introduced one example of such planning in the search of gravitational wave counterparts.

See you Next Year at DSFP
Session 20
Safe and Comfortable Travels Home