LoRaLay Evaluation Interface

Evaluation guidelines

Document 0806.3537 (1/50)

Statistical Learning of Arbitrary Computable Classifiers

Link to full document

Model A   Model B

Ground-truth abstract

Statistical learning theory chiefly studies restricted hypothesis classes, particularly those with finite Vapnik-Chervonenkis (VC) dimension. The fundamental quantity of interest is the **sample** complexity: the **number** of **samples** required to **learn** to a **specified level** of **accuracy.** Here we consider **learning** over the set of all computable labeling functions. Since the VC-dimension is infinite and a priori (uniform) **bounds** on the **number** of **samples** are impossible, we let the **learning** algorithm decide when it has seen sufficient **samples** to have learned. We first show that **learning** in this setting is indeed possible, and develop a **learning** algorithm. We then show, however, that bounding **sample** complexity independently of the distribution is impossible. Notably, this impossibility is entirely due to the requirement that the **learning** algorithm be computable, and not due to the **statistical** nature of the problem.

You selected the following sentence generated by Model B. Highlight the parts in the sentence that can be found in the ground-truth abstract.

Conventional statistical learning theory attempts to bound the number of samples needed to learn to a specified level of accuracy for each of the above models (e.g. neural networks, support vector machines).

Next sentence

Summary generated by Model B

	Sentence	Precision (%)
☑	Conventional statistical learning theory attempts to bound the number of samples needed to learn to a specified level of accuracy for each of the above models (e.g. neural networks, support vector machines).	40.62
☐	However, if we allow ourselves to change the model, then the VC-dimension of the overall learning algorithm is not finite, and much of statistical learning theory does not directly apply.	16.67
☐	In contrast, we prove that distribution-independent bounds do not exist altogether for computable learning algorithms in our setting.	72.22
☐	Our results imply that computable learning algorithms in the universal setting must "waste samples" in the sense of requiring more samples than is necessary for statistical reasons alone.	0.0

Recall (%)

30.15

Coherence

○ 0 ○ 1 ○ 2 ○ 3 ● 4 ○ 5

Fluency

○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ● 5

☐ I am unable to evaluate this document.

Next