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Risk bounds for deep learning

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Stellingen

Behorende bij het proefschrift

Risk bounds for deep learning

1. Even for simple classification models, interpolation gives rise to infinite Kullback-Leibler risk. (Lemma 2.2.1., Chapter 2)
2. The effective smoothness for compositional models provides a lower bound on the overall smoothness, but the two do not necessarily coincide. (Chapter 3)
3. The extra noise in the Forward Gradient update rule compared to standard gradient descent makes the convergence rate for the squared risk of Forward Gradient in the linear model a factor $d\log(d)$ worse than the convergence rate of standard gradient descent in the same settings. (Chapter 4)
4. The truncated Kullback-Leibler divergence with truncation level $B \geq 2$ can be lower bounded by twice the squared Hellinger distance and upper bounded by $2\exp(B/2) \times$ squared Hellinger distance. (Lemma 2.3.4., Chapter 2)
5. Lack of independence makes statistical theory considerably more complicated.
6. The chosen risk criterion might determine the difficulty of the statistical analysis.
7. Controlling the sparsity of the parameters is at least theoretically a good idea to regulate the entropy/variability of deep neural networks.
8. The abundance of graphical models in density modelling implies that assuming a compositional structure of the density is natural.
9. Just as with statistics, improper use by humans is the most dangerous factor in Artificial Intelligence.
10. Having to wait longer increases the satisfaction gained from skating on natural ice.

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