

Protein Structure Prediction with Deep Neural Networks

Master's Thesis in Bioinformatics

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Abstract

Proteins are one of the most important macromolecules in living organisms due to their ability to perform a broad range of biological functions. These biological functions are strongly dependent on their three-dimensional structure. Unfortunately, the experimental methods for determining the 3D structure proteins are resource-intensive, therefore other methods are needed. From a computational perspective, protein folding is a difficult problem, which has remained unresolved for decades. In 2018, DeepMind’s team AlphaFold showed great potential for predicting inter-residue distances with deep neural networks. These were then used as constraints for structure optimization which resulted in very accurate protein structures. In this thesis, we develop a pipeline capable of constructing a 3D structure from a raw protein sequence, strongly inspired by the AlphaFold one. Furthermore, we test multiple architectures inspired by AlphaFold and compare them to each other and teams from the CASP13.

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