

Title

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## **1 Introduction**

## **2 Related Work**

## **3 Methods**

In this section we describe the pipeline used to analyze the embeddings. As shown in Table 1, the input length is different between the models as well as the output produced. We want to address the following problems: 1) compare different methods to join together the aminoacid-specific contextual representations in order to have a representation for the whole chunk; 2) compare different methods to join together the representations of the chunks in order to have a representation for the whole protein; 3) find out if these representations reflect known properties of the proteins.

### **3.1 Single aminoacid contextual representation**

Name	input length (chunk)	embedding dimension
embedding reproduction (rep)[5]	64	64 per chunk
dnabert [2]	512	768 per chunk
prose [1]	512	100 per amino acid
alphafold [3]	1024	384 per ammino acid
evolutionary scale modeling (esm2) [4]	1024	1280 per ammino acid

Table 1: Embedders used in the experiments.

## 4 Results

## References

- [1] Tristan Bepler and Bonnie Berger. Learning the protein language: Evolution, structure, and function. *Cell systems*, 12(6):654–669, 2021.
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- [5] Kevin K Yang, Zachary Wu, Claire N Bedbrook, and Frances H Arnold. Learned protein embeddings for machine learning. *Bioinformatics*, 34(15):2642–2648, 2018.