

Title

Author

Date

## 1 Introduction

In the latest few years, machine learning and deep learning have revolutionized the natural language processing field (NLP)[11]. At the same time some fundamental ideas developed in NLP have been successfully applied to another type of language, the biological one: DNA, RNA and amino acid sequences bringing to excellent results even in the complex task of protein structure prediction[10, 13]. One of these fundamental ideas is word embedding [15] because it transforms words into points in space, therefore easy to process. It is well known that sequence similarity do not always correspond to functional similarity [12]. Application of protein language model embeddings to downstream tasks was first demonstrated by Bepler and Berger (2019) [2]

## 2 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 pro-

duced. We want to address the following problems: 1) compare different methods to join together the amino acid-specific contextual representations in order to have a representation for the whole chunk and subsequently join together the representations of the chunks in order to have a representation for the whole protein; 2) find out if these representations reflect known properties of the proteins.

### 2.1 Represent protein sequences as continuous vectors

short description of the main characteristics of each embedder

#### 2.1.1 Prose [3]

The model structure is a multi-layer bidirectional Long Short Term Memory (bi-LSTM). Following the intuition that some aspect of proteins structure and semantic can never be discoverable by statistical sequence models alone, they came up with the idea of multi-task learning with structural supervision. The

learning tasks are: 1) classical masked language modeling task, 2) residue-residue contact prediction, 3) structural similarity prediction. This model outperformed existing approaches in both transmembrane position labeling and phenotypes prediction of sequence variants.

### 2.1.2 Alphafold [10]

This is the only approach that does not rely on a language model but is a combination of a bioinformatics and physical approaches. It relies on large datasets of protein sequences that are similar enough to be aligned with high confidence but contain enough divergence to confidently infer statistical couplings between positions. It consists in two modules, Evoformer module and structure module. The Evoformer builds separate MSA and residue-pairwise embedding spaces. As it is structured, this system is not able to learn patterns across large-scale databases of possibly unrelated proteins [3]. In the experiments we used the “single” representation of the sequence, without the MSA and the templates.

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### 2.1.3 SeqVec [7]

To build their model Heinzinger et al. [7] adapted the standard ELMo configuration [16] to work with protein sequences modifying the number of tokens and the unroll steps. It is composed by 1 CharCNN and 2 LSTM-Layers. Given a protein sequence of arbitrary length it returns 3072 features for each residue derived by concatenating the outputs

of the three layers of ELMo, each describing a token with a vector of length 1024. In order to obtain a smaller representation for each aminoacid we computed the mean of the three layers (as also suggested in the official repository). Given the architecture of the ELMo, these representations are contextual-dependent.

### 2.1.4 Evolutionary scale modeling [14]

The underlying architecture is a BERT [6] style encoder transformer with modifications in the number of layers, number of attention heads, hidden size and feed forward hidden size. A further improvement is the use of Rotary Position Embedding [19] that allows to generalize beyond the context window it is trained on. The main advantages compared to AlphaFold are the removal of the need of multiple sequence alignment and an increasing up to two orders of magnitude of the speed of the prediction pipeline. We used the version with 33 layers and 650B parameters (compare with alphafold)

## 2.2 Combining the (contextual) representations

We tried four methods to join together the aminoacid embeddings in order to produce a fixed size embedding for the chunk: average, maximum, sum and principal component analysis (PCA).

The same operator used to combine the aminoacid embeddings is also used to combine the embeddings of the chunks of the sequence.

Note on the contextual embedding: seqvec: contextual

## 2.3 Comparison with known informations

Given a set of embeddings of sequences we want to analyze their distribution in the embedding space comparing it with both the distance matrix produced during the multiple sequence alignment with Clustal Omega [17] and higher level annotations as Gene Ontology [4, 1], UniProtKB Keywords and NCBI Taxonomy [5].

### 2.3.1 Similarity between distance matrices

In order to compare two distance matrices we performed an agglomerative clustering on both, the resulting tree is then cut at each level obtaining flat partitions of all possible number of clusters. We performed a pairwise comparison of the partitions having the same number of clusters using the adjusted rand score [8]. The mean of these score, starting from two clusters up to  $\#elements - 1$  clusters is called mean adjusted rand score (MARS). We compared different distance metrics as well as different methods to perform the hierarchical clustering.

### 2.3.2 Enrichment analysis

The alignment distance matrix provide an evolutionary related distance between sequences [18], we also wanted to analyze the properties of the embeddings at an higher

level. The Gene Ontology (GO) describes our knowledge of the sequence with respect to: molecular function, cellular component and biological process; there are also more specific controlled vocabulary as the UniProt Keywords and hierarchical classifications specific for sequences as the NCBI Taxonomy.

Whatever they are the sets of words to describe the sequences in our datasets, we want to build a distance between sequences among them. Given  $A$  and  $B$  the sets of annotations of two sequences we computed the distance in two possible ways:

$$d1 = \frac{2 * |A \cap B|}{|A| + |B|}$$

$$d2 = \max\left\{\frac{|A \cap B|}{|A|}, \frac{|A \cap B|}{|B|}\right\}$$

Both of them vary between 0 and 1, however  $d1$  goes to 1 only when the two sets are equals while  $d2$  goes to 1 also when one set is a subset of the other. After calculating one of these distance between all possible pair in the dataset we end up with a similarity matrix, that can be easily transformed in a distance matrix that is possible to compare with the distance matrix derived from the distance between the embeddings using the MARS as described in subsection 2.3.1.

Name	input length (chunk)	embedding dimension
embedding reproduction (rep)[20]	64	64 per chunk
seqvec [7]	1024	1024 per amminoacid
dnabert [9]	512	768 per chunk
prose [3]	512	100 per amino acid
alphafold [10]	1024	384 per ammino acid
evolutionary scale modeling (esm2) [14]	1024	1280 per ammino acid

Table 1: Embedders used in the experiments, their maximum input length and the dimension of the embedding produced.

Name	description	number of sequences	type	avg length
hemoglobin	hemoglobin for various organisms	761	amminoacids	142
mouse	mouse proteome	974	amminoacids	516
bacterium	bacterium proteome	259	amminoacids	427
covid19	covid19 complete genome	77	nucleotides	29831
meningitis	meningitis complete genome	68	nucleotides	2240049

Table 2: Datasets used in the experiments.

## 3 Results

### 3.1 Phylogenetic

### 3.2 Enrichment

### 3.3 Projections?

### 3.4 Classification?

### 3.5 Pointwise representation similarity?

combiner	dimensional PCA	dnabert	seqvec	prose	alphafold	esm
pca	all	0.076914	0.628944	0.438451	0.592638	0.655989
	default	0.085592	0.462319	0.378802	0.440502	0.556404
average	all	0.150060	0.631618	0.436927	0.584828	0.654195
	default	0.142402	0.468093	0.373694	0.428669	0.562981
sum	all	0.142098	0.632848	0.433519	0.584272	0.651882
	default	0.140880	0.445979	0.365946	0.394104	0.530063
max	all	0.129600	0.648831	0.590373	0.458190	0.754162
	default	0.133080	0.491197	0.460012	0.479472	0.628606

Table 3: Emoglobin Phylogenetic results.

combiner	dimensional PCA	dnabert	seqvec	prose	alphafold	esm
pca	all	0.029854	0.293372	0.263442	0.125250	0.278784
	default	0.036239	0.291775	0.278305	0.090662	0.379791
average	all	0.008628	0.326197	0.306975	0.133504	0.272709
	default	0.019080	0.325723	0.318528	0.204344	0.423269
sum	all	0.037913	0.326197	0.306975	0.133504	0.272709
	default	0.051761	0.254459	0.309792	0.059609	0.205906
max	all	0.039009	0.396257	0.379740	0.053480	0.393414
	default	0.020057	0.090137	0.432732	0.139505	0.187751

Table 4: Mouse Phylogenetic results.

combiner	dimensional PCA	dnabert	seqvec	prose	alphafold	esm
pca	all	-0.005314	0.064490	0.066430	-0.003228	0.063098
	default	-0.004117	0.145555	0.075659	0.067033	0.109153
average	all	-0.005307	0.085411	0.070529	-0.000876	0.054788
	default	-0.003264	0.138811	0.092746	0.067431	0.106074
sum	all	-0.005312	0.085411	0.070529	-0.000876	0.054788
	default	0.006822	0.075365	0.084606	0.006121	0.034575
max	all	-0.005648	0.078479	0.107831	-0.006607	0.080722
	default	-0.003445	0.009905	0.122704	0.027285	0.031228

Table 5: bacterium Phylogenetic results.

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