

Explaining embedding results for scoring alignments

by

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List of Abbreviations

ALBERT A Lite BERT [4](#)

BERT Bidirectional Encoder Representations from Transformers [3](#), [4](#)

BLAST Basic Local Alignment Search Tool [6](#)

ENNA Evolutionary Neural Network Algorithm [5](#)

LLM Large Language Models [9](#)

LoRA Low-Rank Adaptation [10](#)

MSA Multiple Sequence Alignments [8](#), [10](#)

NLP Natural Language Processing [1–3](#), [6](#)

PEFT Parameter-Efficient Fine Tuning [10](#)

RoBERTa Robustly Optimized BERT [4](#)

T5 Text-To-Text Transfer Transformer [3](#)

Chapter 1

Introduction

Proteins are one of the four molecules of life. Finding similarities among protein sequences is essential in identifying protein structure and function. This is done by computing alignments between sequences.

The *E*-score method is a method to compute alignments between sequences using contextual embeddings produced by [transformer](#) models [2]. This method uses several different transformer models based off of models in [Natural Language Processing \(NLP\)](#).

This research addresses the results observed for the *E*-score method. Namely, I explain the observed cosine similarity results and explain significant differences and similarities between the models used (Table 2.2), both qualitative and quantitative. Combining the comparison of models with visualization and analysis of embedding vector and cosine similarity distributions, I propose the contributing factors to better *E*-score performance.

Using inference about the proposed factors contributing to *E*-score performance, I describe the procedure and techniques for fine-tuning ProtT5 and other models to produce better embeddings for sequence alignment.

1.1 Thesis outline

Chapter 2 provides a reader with background on important concepts and details discussed later in the thesis. Chapter 3 outlines the materials and methods used in the research conducted on the *E*-score method. Chapter 4 provides the results from analysis performed in the data science investigation. Chapter 5 concludes the study by addressing the research questions outlined in the thesis proposal, and discusses impact and novelty of the results.

Chapter 2

Background

2.1 Natural Language Processing

Natural Language Processing is the branch of artificial intelligence that deals with providing computers with the ability to understand text and spoken words, similar to how human being do [16]. NLP includes tasks such as summarization, sentiment analysis, and spam detection [16].

One significant advancement within NLP was the introduction of transformer models [36]. Before the introduction of Transformers within NLP, neural networks such as word2vec [24] and GloVe [29] generated contextual independent embedding vectors for words. Transformer models such as T5, BERT, ALBERT, RoBERTa, and XLNet outperformed these models with the introduction of contextual embeddings generated through self-attention [36].

The transformer models used in NLP vary significantly. Examples of differences between models includes with architecture, training procedure, and size. These differences contribute to different use cases and performance between models. The models used in the *E*-score method for protein sequence alignment are based on the models introduced below for NLP. Comparison between the GLUE benchmark scores for these models is shown in Table 2.1

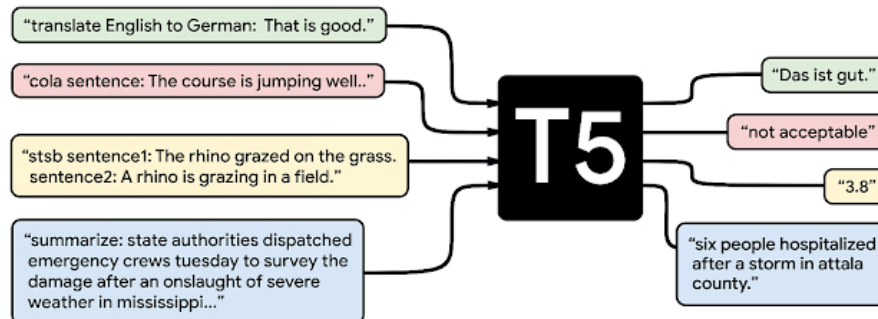


Figure 2.1: Diagram of T5’s text-to-text framework. Each task uses text as the model input, which is trained to generate some target text [31].

2.1.1 T5

[Text-To-Text Transfer Transformer \(T5\)](#) uses a text-to-text approach using the [transformer](#) architecture. That is, T5’s input and output are always text strings [31]. It uses both the encoder and decoder from the transformer architecture, and relies on [transfer learning](#) to fine-tune the model on downstream tasks. An example of T5’s input and output is shown in Figure 2.1.

By training [T5](#) with fill-in-the-blank-style [denoising](#) objectives, where T5 was trained to recover missing words in the input, and using transfer learning on smaller labeled datasets, T5 was able to achieve state-of-the-art [NLP](#) performance [31].

2.1.2 BERT, ALBERT, and RoBERTa

[Bidirectional Encoder Representations from Transformers \(BERT\)](#) achieved state-of-the-art [NLP](#) performance at the time of it being published [7]. ALBERT and RoBERTa are both derivations of BERT, and [T5](#) also drew significant inspiration from BERT, such as the [denoising](#) objective being inspired by BERT’s masked language modeling objective.

[BERT](#) is an encoder-only model that applies bidirectional training using the ”masked language modeling” objective that was created for the model. This contrasts the previous framework where models read the text input sequentially, allowing for a deeper sense of context. Masked Language Modeling works by replacing 15% of the words in an input

Table 2.1: GLUE benchmark scores [38] for the Natural Language Processing models that serve as foundation for the E -score models.

Model	Avg	CoLA	SST-2	MRPC	STS-B	QQP	MNLI	RTE	WNLI
T5	88.7	71.6	97.5	92.8	93.1	75.1	92.1	92.8	94.5
XLNet	87.5	70.2	97.1	92.9	93.0	74.7	90.9	88.5	92.5
ALBERT	87.3	69.1	97.1	93.4	92.5	74.2	91.1	89.2	91.8
RoBERTa	86.4	67.8	96.7	92.3	92.2	74.3	90.5	88.2	89.0

sequence being replaced with a "MASK" token, which the model attempts to predict the original value of based on the context from the other words [7].

A Lite BERT (ALBERT) addresses the limitations of training time and GPU/TPU memory by presenting parameter-reduction techniques for BERT [19].

Robustly Optimized BERT (RoBERTa) addresses the observation that BERT was significantly under-trained. RoBERTa improved upon BERT by training longer, removing the next-sentence pretraining objective from BERT, and training with larger mini-batches and learning rates [21].

2.1.3 XLNet

XLNet is a model that overcomes the pretrain-finetune discrepancy that BERT suffers from because it relies on masking the input during training [41]. XLNet is a decoder-only model (also known as autoregressive) that overcomes BERT's limitations because of its autoregressive formulation.

XLNet outperforms BERT significantly on 20 tasks, such as question answering and sentiment analysis [41].

2.2 Sequence alignment

Sequence similarity is essential in sequence analysis within bioinformatics [27]. Peptide sequence alignment is the most complex case, with a language of 20 common amino acid forming a theoretically countably infinite amount of unique peptide sequences shown in Equation 2.1 by taking the n-ary Cartesian product.

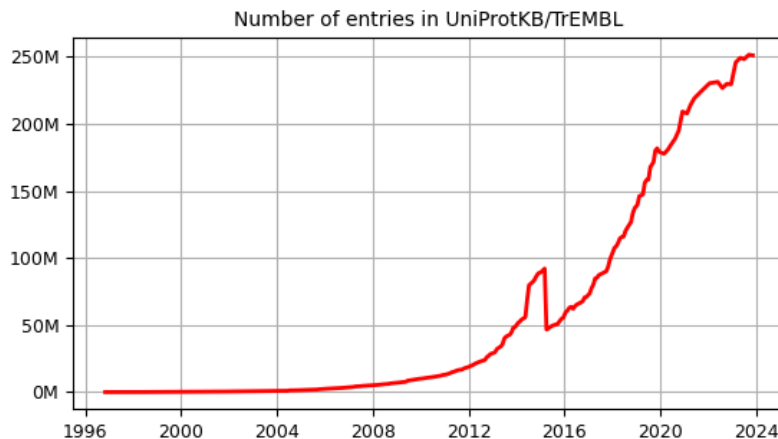


Figure 2.2: UniProtKB protein database release statistics as of May 2023 [4].

$$Theoretical\ Limit = \prod_{k=1}^{\infty} |A| = \prod_{k=1}^{\infty} 20 = 20 \times 20 \times \dots \quad (2.1)$$

While there is theoretically a countably infinite number of [peptide](#) sequences, the observed sequences in living organisms are constrained by biological, genetic, and functional factors. For example, the average eukaryotic protein size is 353 ± 62.5 [residues](#) [26].

Databases such as UniProt [4] and PeptideAtlas [6] are repositories filled with [peptide](#) sequences. UniProt contains over 250 million unique peptide sequences and counting, showcased in Figure 2.2.

Peptide sequences are not completely random because of the constraints imposed on them. Similar to letters or words in a given language within natural language, the frequency of each amino acid observed in nature is not equally distributed [3], which can be observed in Figure 2.3.

Proteins are also not completely random and form different secondary structures as part of the tertiary and quaternary structure of a protein. The most common of these secondary structures are α helices and β pleated sheets [22]. Because of the nature of proteins, algorithms such as an [Evolutionary Neural Network Algorithm \(ENNA\)](#) are able to distinguish natural proteins from randomly generated proteins with an accuracy of over 94% [5].

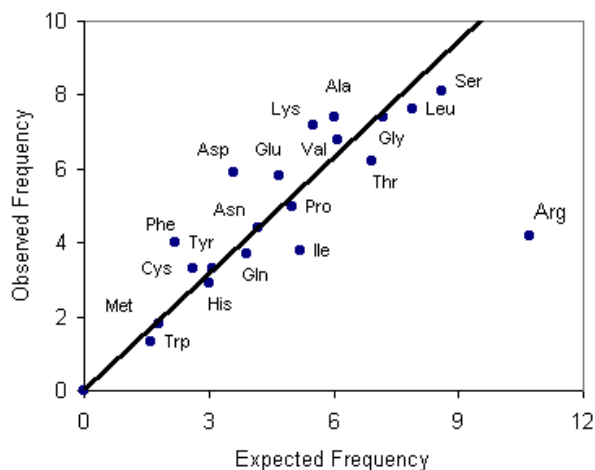


Figure 2.3: Observed frequency versus expected frequency of the 20 amino acids in vertebrates [3]

Finding similarities among protein sequences is essential in identifying protein structure and function. This is done by computing alignments between sequences. The [Basic Local Alignment Search Tool \(BLAST\)](#) program¹ is one of the most widely used tools in science [1]. An essential part of BLAST is the scoring function; the most widely used functions are provided by the BLOSUM matrices [11].

The *E*-score protein alignment scoring method [2] is another one of these scoring functions, and outperforms state-of-the-art methods. The improved performance was supported by comparing ProtT5 [8] *E*-score results with BLOSUM45 [11, 2].

2.3 *E*-score

E-score uses [transformer](#) models to produce contextual embeddings for the [residues](#) in [peptide](#) sequences. Model information is available in Table 2.2. These models are based off of their [NLP](#) equivalents [31, 7, 19, 41, 32].

Contextual embeddings are embeddings produced by the self-attention mechanism in the [transformer](#) architecture [36]. Similar to word embeddings in [NLP](#), they describe the position of a [residue](#) in a high-dimensional vector space. Contextual embeddings have

¹Exceeds 108,000 citations, according to Google Scholar.

Table 2.2: Transformer models available in the E -score method; n = number of residues. ProtT5, ProtBert, ProtAlbert, and ProtXLNet come from ProtTrans [8]. ESM1b and ESM2 come from the Meta Fundamental AI Research Protein Team [32].

Model	Architecture	Embedding Dim	Pre-Trained Dataset
ProtT5	Encoder-Decoder	$n * 1024$	UniRef50
ESM1b	Encoder	$n * 1280$	UniRef50
ESM2	Encoder	$n * 1280$	UniRef50
ProtBert	Encoder	$n * 1024$	UniRef100
ProtAlbert	Encoder	$n * 4096$	UniRef100
ProtXLNet	Decoder	$n * 1024$	UniRef100

many important applications in biology, including structure prediction [33, 40, 15] and function prediction [17, 9, 18].

The E -score alignment method is another application for these embeddings, outperforming the state-of-the-art methods [2] by completely changing the way alignments are computed.

The embedding vector produced for each protein [residue](#) varies based on the model that was used. For example, the embedding for a protein sequence of 310 residues using ProtT5 will have the dimensions [310, 1024]. The embedding dimensions are outlined in Table 2.2. The dimensionality of the embedding vectors represents the number of features encoded in the embedding, and is a fixed value for a given model.

2.3.1 Calculations

The embeddings produced by a model for a protein P , calculated in Equation 2.2, are used as the input to calculate the cosine similarity.

$$E(P) = GetEmbeddings(Model = ProtT5) \quad (2.2)$$

Calculating the cosine similarity between two vectors $A = (A_i)_{i=1..n}$ and $B = (B_i)_{i=1..n}$ is shown in Equation 2.3.

$$CosSim(A, B) = \cos(\theta) \equiv \frac{A \cdot B}{\|A\| \|B\|} \equiv \frac{\sum_{i=1}^n A_i B_i}{\sqrt{\sum_{i=1}^n A_i^2} \sqrt{\sum_{i=1}^n B_i^2}} \quad (2.3)$$

E -score is calculated by taking the cosine similarity between the embedding vector for two residues (i, j) , shown in Equation 2.4 where P_1 and P_2 are proteins [2].

$$E\text{-score}(i, j) = CosSim(E(P_1)_i, E(P_2)_j) \quad (2.4)$$

In calculating sequence alignment using the E -score method, the cosine similarity results were mostly less than $\frac{\pi}{2}$. It was also determined that ProtT5 performed better than the other models [2].

Below are two examples that demonstrate obtaining the E -score between two protein sequences.

1. Two protein sequences, P_1 and Q_1 , are highly similar and have diverged slightly through evolution. The embedding vectors produced by any of the Transformer models within E -score for these sequences should be highly similar. Calculating the cosine similarity between the embedding vectors produced for P_1 and Q_2 should produce a result that is close to 1. The alignment score produced by the E -score method through dynamic programming should be high.
2. Two protein sequences, P_2 and Q_2 , are very different and have diverged extensively through evolution. The embedding vectors produced for these sequence should be highly dissimilar. Calculating the cosine similarity between the embedding vectors produced for P_2 and Q_2 should produce a result that is close to -1 . The alignment score produced by the E -score method through dynamic programming should be low.

2.3.2 Transformers

The transformer models used in the E -score method described in Table 2.2 vary in performance. ProtT5 outperformed the 5 other models available when computing end-gap-free alignments for six different conserved domain Multiple Sequence Alignments (MSA). ESM2 and ProtBERT outperformed ProtT5 in one conserved domain each. ProtT5 and ESM2

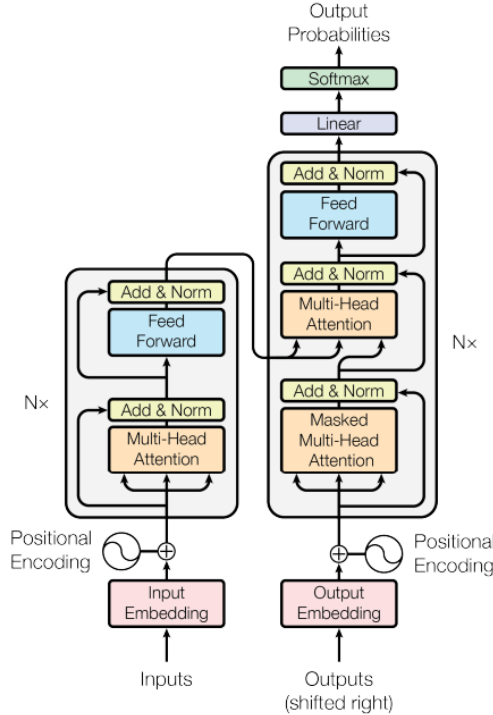


Figure 2.4: Transformer model architecture [36].

were compared and it was evident that ProtT5 outperformed ESM2 with statistically significant results.

Through the results from the comparison between models, it was evident that the encoder-decoder model ProtT5 outperformed both the encoder-only models (ESM1b, ESM2, ProtBERT, ProtALBERT) and the decoder-only model (XLNet).

The ProtTrans models have significantly different pre-training configurations [8], some of which are highlighted in Table 2.3. These configurations have a heavy impact on the performance of a model for scoring alignment and for model performance as a whole. For example, ProtT5 has 3 billion parameters compared to ProtALBERT having 224 million; as models grow their performance generally increases, which is supported by the Chinchilla paper’s findings for training compute-optimal [Large Language Models \(LLM\)](#) [12].

2.4 Fine-tuning

Fine-tuning [LLMs](#) is a powerful technique to leverage pre-trained models and adapt them to perform better at a specific task or tasks. The purpose of fine-tuning is to avoid the

Table 2.3: Pre-training configuration for the ProtTrans protein language models [8].

Hyperparameter	ProtT5	ProtBERT	ProtXLNet	ProtALBERT
Dataset	UniRef50	UniRef100	UniRef100	UniRef100
# of Layers	24	30	30	12
Hidden Layer Size	1024	1024	1024	4096
Optimizer	AdaFactor	Lamb	Adam	Lamb
# of Parameters	3B	420M	409M	224M
Learning Rate	0.01	0.002	0.00001	0.002

need to pre-train a model from scratch for a task; instead relying on powerful pre-trained models and modifying them to better suit the task.

There are two common approaches to fine-tuning: supervised learning and reinforcement learning. Supervised learning involves providing the model with a labeled dataset, and the model will learn to map the input to the output by minimizing its loss function [25]. Reinforcement learning involves providing a reward signal to the model when it generates a desired output, and the model learns to generate the desired output for a task by maximizing the reward signal [34].

In the case of E -score, fine-tuning refers to taking a pre-existing model from Table 2.2 and training it on a dataset specific to E -score. For supervised learning, this dataset would be comprised peptide sequences and their representative MSAs. Fine-tuning would involve the model minimizing its loss function for this dataset, and the end goal would be a fine-tuned model that outperforms the base model at scoring alignment.

There are multiple optimizations that can be made throughout the fine-tuning process to reduce the memory load and improve the efficiency of the process. **Parameter-Efficient Fine Tuning (PEFT)** is a memory optimization that either selects a subset of the LLMs initial parameters to fine-tune; or freezes the layers of the LLM and introduces a small number of new, trainable layers that the fine-tuned model will use [20]. Another PEFT technique is **Low-Rank Adaptation (LoRA)**, which freezes the pre-trained weights and injects a trainable rank decomposition matrix into each layer of the architecture with much smaller dimensions than the base model [13].

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Glossary

amino acid molecules that combine to form proteins, containing both an amino and a carboxyl group [4](#)

denoising the process of the auto-encoder in a Transformer learning to capture the most important features of the data distribution, ignoring the noise [3](#)

peptide a compound consisting of two or more amino acids linked in a chain, the carboxyl group of each acid being joined to the amino group of the next plural [4–6](#)

residue a single unit that makes up a polymer, such as an amino acid in a polypeptide chain plural [5–8](#)

transfer learning a technique in machine learning in which knowledge learned from a task is re-used to boost performance on a related task. a model already developed for 1 task is re-used in another task. [3](#)

transformer a type of neural network architecture used to solve the problem of transduction or transformation of input sequences into output sequences in deep learning applications using self-attention [1–3, 6, 8](#)