Enhancing LLMs' Understanding of Proteins via Multimodal Structure and Sequence Representations

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Abstract

Current Large Language Models (LLMs) for understanding proteins primarily treats amino acid sequences as a text modality. Meanwhile, Protein Language Models (PLMs), such as ESM-2, have learned massive sequential evolutionary knowledge from the universe of natural protein sequences. Furthermore, structure-based encoders like ProteinMPNN learn the structural information of proteins through Graph Neural Networks. However, whether the incorporation of protein encoders can enhance the protein understanding of LLMs has not been explored. To bridge this gap, we propose PROTEINMPNN-EVOLLAMA, a multimodal framework that connects a structure-based encoder, a sequence-based protein encoder and an LLM for protein understanding. PROTEINMPNN-EVOLLAMA consists of a ProteinMPNN structure encoder, an ESM-2 protein sequence encoder, a multimodal projector to align protein and text representations and a Llama-3 text decoder. To train PROTEINMPNN-EVOLLAMA, we fine-tune it on protein-oriented instructions and protein property prediction datasets verbalized via natural language instruction templates. Our experiments show that PROTEINMPNN-EVOLLAMA's protein understanding capabilities have been significantly enhanced, outperforming other fine-tuned LLMs in zero-shot settings and surpassing the state-of-the-art baseline with supervised fine-tuning. On protein property prediction datasets, our approach achieves promising results that are competitive with state-of-the-art task-specific baselines. We will release our code in a future version.

1 Introduction

The rapid advancements in Natural Language Processing (NLP) have led to the development of Large Language Models (LLMs) that are capable of understanding and generating human language. These models such as GPT-3.5 (OpenAI, 2022), GPT-4 (Achiam et al., 2023) and Llama (Touvron et al., 2023a,b; Dubey et al., 2024) have demonstrated remarkable proficiency across a wide range of tasks. Recently, the field of Bioinformatics has seen the emergence of Transformer-based (Vaswani et al., 2017) Protein Language Models (PLMs) like ProtBert (Elnaggar et al., 2021) and ESM (Rives et al., 2021; Lin et al., 2022). These sequence-based encoders are pre-trained on a large number of amino acid sequences to capture the functional information embedded within proteins. Moreover, structure-based encoders like ProteinMPNN (Dauparas et al., 2022) and GearNet (Zhang et al., 2022b) utilize Graph Neural Networks to learn the structural information of proteins.

Despite the success of protein encoders and LLMs in their respective domains, there still remains a significant gap in integrating the knowledge from protein encoders into LLMs to enhance understanding of proteins. Current LLMs treat amino acid sequences as a text modality (Pei et al., 2023; Fang et al., 2023), potentially failing to leverage the rich structural and sequential information of proteins that protein encoders are designed to capture. Moreover, protein encoders face challenges in multi-task learning, making them unable to follow human instructions. Besides, the gap between protein encoders and LLMs leads to significant challenges in aligning different modalities, even between the primary and tertiary structures of proteins (Zhang et al., 2023).

To address the aforementioned challenges, we introduce PROTEINMPNN-EVOLLAMA, a multimodal framework designed to integrate the capabilities of protein encoders with an LLM. PROTEINMPNN-EVOLLAMA combines the ESM-2 (Lin et al., 2022) protein sequence encoder, which captures sequential evolutionary knowledge from amino acid sequences, the ProteinMPNN (Dauparas et al., 2022) structure encoder that learns geometric features from 3D protein structures, a

multimodal projector that aligns protein and text representations, and a Llama-3 (Dubey et al., 2024) text decoder for generating natural language outputs.

We propose a two-stage training approach, and the experimental results demonstrate that PROTEINMPNN-EVOLLAMA with zero-shot outperforms the baselines fine-tuned on the Mol-Instructions (Fang et al., 2023) dataset and surpasses the current state-of-the-art model with supervised fine-tuning. Additionally, on protein property prediction tasks based on the PEER benchmark (Xu et al., 2022), PROTEINMPNN-EVOLLAMA shows promising results that are competitive with task-specific baselines.

The contributions of our approach are listed as follows:

- **Leverage multimodal representations of protein structures and sequences.** We employ ProteinMPNN and ESM-2 as structure-based and sequence-based protein encoders to explicitly extract both structure and sequence representations of proteins. The representations will be embedded through projection layers to align with the embeddings from natural language prompts.

- **Muti-task learning and instruction following capability.** We implement a two-stage training process for our approach. After projection tuning, PROTEINMPNN-EVOLLAMA can follow various human instructions and solve downstream tasks in zero-shot settings. During the supervised fine-tuning stage, experiments demonstrate that tasks in the PEER benchmark (Xu et al., 2022) have few interrelations and do not negatively affect each other when multi-task fine-tuning is employed.

- **Plug-and-play architecture and efficient fine-tuning approach.** Different protein encoders and LLMs can be used in our plug-and-play architecture. Extensive experiments demonstrate that the projection tuning stage can be optional, and the parameters of the LLM can be frozen during supervised fine-tuning, significantly reducing trainable parameters. Additionally, we introduce a simple yet effective fusion method to align structure and sequence representations, reducing language embedding tokens during both training and inference.

2 Protein Instruction-Following Data

In this section, we introduce the construction of protein instruction-following data. It consists of two sets, projection tuning and supervised fine-tuning, which are used at different training stages, described in Sec. 3. An example of the projection tuning data and supervised fine-tuning data is illustrated in Fig. 1. Formally, for each example, we define $\mathbf{X}_p, \mathbf{X}_q, \mathbf{X}_a$ as the protein (fused protein representations, consisting of the 3D structure $\mathbf{X}_{\text{struct}}$ and the amino acid sequence $\mathbf{X}_{\text{seq}}$), the protein-related natural language question, and the corresponding answer, respectively.

Figure 1: An example of the projection tuning data and supervised fine-tuning data. Note that the special token <protein> denotes the fused protein representations of structural and sequential features.

Projection Tuning Data It consists of protein-text pairs originated from the Swiss-Prot (Consortium, 2023) database. Due to limited computational resources, we directly utilize the 3D structures predicted by AlphaFold-2 (Jumper et al., 2021) from Swiss-Prot. The database contains 571K manually-annotated records, each containing information including protein name, subcellular location, function and families. For $\mathbf{X}_q$, we construct 10 templates that ask the model to briefly describe the input protein $\mathbf{X}_p$ from various aspects. For $\mathbf{X}_a$, information is extracted from the filtered Swiss-Prot annotation and constructed using a pre-defined

template to ensure the consistency and clarity of protein descriptions. The question and answer templates are listed in Fig. 4.

Supervised Fine-tuning Data To align the model to follow a variety of instructions, we present and curate diverse instruction-following data about the provided proteins, by verbalizing protein-related tasks. It consists of 10 tasks including Mol-Instructions (Fang et al., 2023) and PEER benchmark (Xu et al., 2022). We use ESMFold (Lin et al., 2022) to accelerate protein structure prediction for sequences in these two datasets.

- **Mol-Instructions** is a comprehensive instruction dataset designed for the biomolecular realm. It includes three components: molecule-oriented instructions, protein-oriented instructions and biomolecular text instructions. We adopt protein-oriented instructions in Mol-Instructions (named PMol) for the supervised fine-tuning stage. PMol details will be discussed in Sec. 4.1. For each task in Mol-Instructions, we make simple modifications to the original prompts to ensure that they are suitable for our use cases and maintain coherence. Details are discussed in Appendix B.2 and some modification cases are listed in Fig. 7.

- **PEER** is a comprehensive benchmark for general protein sequence understanding tasks including protein localization prediction, protein structure prediction and protein-protein interaction prediction. PEER benchmark details will be discussed in Sec. 4.2. For each task in PEER benchmark, there are 10 question templates and 1 answer template, some of which are listed in Fig. 6. In response templates for other tasks, categories are represented by natural language. However, for fold classification, we use integers from 0 to 1194 due to the large number of categories.

3 Approach

PROTEINMPNN-EVOLLAMA aims to align protein information from both pre-trained structure-based and sequence-based protein encoders with an advanced large language model (LLM). Both language and protein models are open-sourced. We target to bridge the gap between the protein encoders and LLM using MLP projection layers (Sec. 3.1), with an overview of our model displayed in Fig. 2. To achieve an effective PROTEINMPNN-EVOLLAMA, we propose a two-stage training approach (Sec. 3.2). The initial stage involves pre-training the model on a large collection of aligned protein-text pairs to acquire protein language knowledge. In the second stage, we fine-tune the model with the high-quality protein-text dataset to enhance generation reliability and usability.

3.1 Architecture

In this section, we will introduce the overall PROTEINMPNN-EVOLLAMA in three parts: the protein encoders, the projection layer and the language decoder.

Protein Encoders Given the input amino acid sequence $\mathbf{X}_{\text{seq}}$, we consider the pre-trained protein encoder ESM-2 (Lin et al., 2022), which provides the protein feature $\mathbf{Z}_{\text{seq}} = \texttt{SeqEncoder}(\mathbf{X}_{\text{seq}})$. The 3D structure of the given amino acid sequence is predicted using AlphaFold-2 (Jumper et al., 2021) or ESMFold (Lin et al., 2022). A protein structure encoder, such as ProteinMPNN and GearNet, is used to extract the feature $\mathbf{Z}_{\text{struct}} = \texttt{StructEncoder}(\mathbf{X}_{\text{struct}})$.

Projection Layer To map the outputs of the protein encoders into the same space as the text features from word embedding, we apply an MLP to convert $\mathbf{Z}_{\text{seq}}$ and $\mathbf{Z}_{\text{struct}}$ into language embedding tokens $\mathbf{H}_{\text{seq}}$ and $\mathbf{H}_{\text{struct}}$ separately, which have the same dimensionality of the word embedding space in the language model:

$$\begin{cases} \mathbf{H}_{\text{seq}} = \texttt{MLP}_{\text{seq}}(\mathbf{Z}_{\text{seq}}), \\ \mathbf{Z}_{\text{seq}} = \texttt{SeqEncoder}(\mathbf{X}_{\text{seq}}), \\ \mathbf{H}_{\text{struct}} = \texttt{MLP}_{\text{struct}}(\mathbf{Z}_{\text{struct}}), \\ \mathbf{Z}_{\text{struct}} = \texttt{StructEncoder}(\mathbf{X}_{\text{struct}}) \end{cases}$$

Furthermore, since both structure-based and sequence-based protein encoders extract features based on residue positions, the lengths of their feature representations are dependent solely on the length of the amino acid sequence. Therefore, we fuse the structure and sequence features by employing an element-wise addition of the corresponding residue features. The fused protein representations $\mathbf{H}_p = \mathbf{H}_{\text{seq}} \oplus \mathbf{H}_{\text{struct}}$ reduces the protein embedding tokens by half, significantly decreasing the training and inference latency. Note that our simple projection scheme is lightweight and cost-effective, which allows us to iterate data centric experiments quickly. We leave exploring possibly

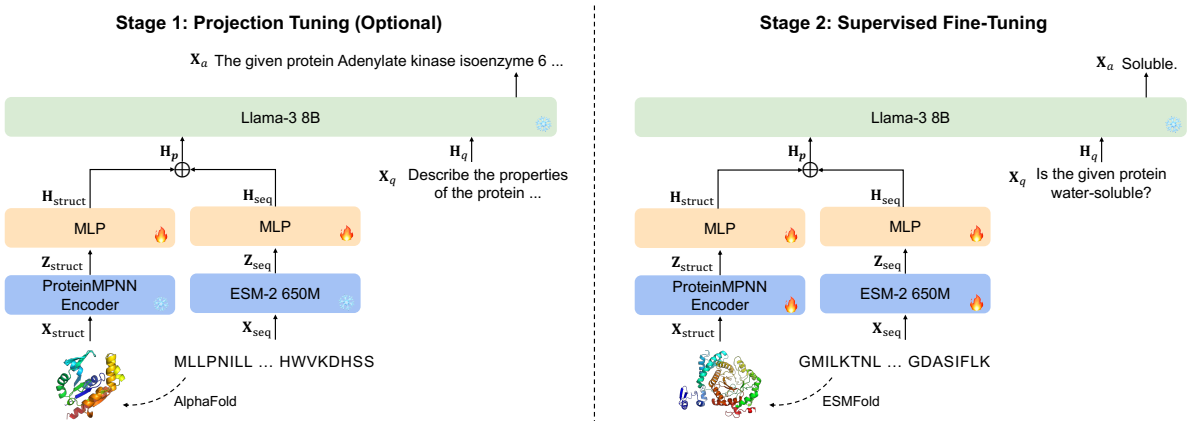

Figure 2: Overall architecture and the training pipeline of the PROTEINMPNN-EVOLLAMA.

more effective and sophisticated architecture designs for PROTEINMPNN-EVOLLAMA as future work.

Language Decoder Given the protein structure $\mathbf{X}_{\text{struct}}$, amino acid sequence $\mathbf{X}_{\text{seq}}$ and the fused projected embeddings $\mathbf{H}_p$, we have conversation data $(\mathbf{X}_q, \mathbf{X}_a)$. We organize them as a sequence and perform instruction-tuning of the LLM on the prediction tokens, using its original auto-regressive training objective. Specifically, we compute the probability of generating target answers $\mathbf{X}_a$ by:

$$p(\mathbf{X}_a|\mathbf{X}_{\text{struct}}, \mathbf{X}_{\text{seq}}, \mathbf{X}_q) = \prod_{i=1}^{|\mathbf{X}_a|} p_\theta(\mathbf{X}_{a,i}|\mathbf{X}_{\text{struct}}, \mathbf{X}_{\text{seq}}, \mathbf{X}_q, \mathbf{X}_{a,<i}) \quad (1)$$

where θ is the trainable parameters. PROTEINMPNN-EVOLLAMA model design is compatible with any off-the-shelf GPT-style pre-trained LLM. PROTEINMPNN-EVOLLAMA adopts Llama-3 8B (Dubey et al., 2024) for further training. A causal mask is applied to all the attention operations, including the attention between protein features $\mathbf{H}_p$.

3.2 Training

As illustrated in Fig. 2, the training process of the PROTEINMPNN-EVOLLAMA model consists of two stages: projection tuning and supervised fine-tuning, with the first stage being optional.

Stage 1: Projection Tuning We keep both the protein encoders and LLM weights frozen, and maximize the likelihood of Eq. 1 with the parameters of projection MLP only (Fig. 2(a)). In this way, the protein features $\mathbf{H}_p$ can be aligned with the pre-trained LLM word embedding. This stage can be understood as training a compatible protein projector for the frozen LLM.

Stage 2: Supervised Fine-Tuning To efficiently fine-tune PROTEINMPNN-EVOLLAMA and preserve the internal knowledge of the LLM, its parameters are frozen during this stage. Continuing to update the pre-trained weights of the projection layers and protein encoders helps PROTEINMPNN-EVOLLAMA learn more protein knowledge and enhance its instruction following capability.

4 Experiments

We evaluate PROTEINMPNN-EVOLLAMA on downstream tasks including protein understanding tasks based on Mol-Instructions (Fang et al., 2023) (Sec. 4.1) and protein property prediction tasks based on PEER benchmark (Xu et al., 2022) (Sec. 4.2). Additionally, the structure encoder in our approach is replaced with GearNet (Zhang et al., 2022b) to construct GEARNET-EVOLLAMA for the experiments. We evaluate our approach in both zero-shot settings, where only the projection layers are aligned during the projection tuning stage, and in supervised fine-tuning without the projection tuning stage. Details of the experimental setups are discussed in Appendix C.

4.1 Protein Understanding Tasks

Task Descriptions Protein understanding tasks use PMol for fine-tuning and evaluation, which consist of four distinct tasks with datasets constructed based on UniProtKB (Consortium, 2021). Protein function prediction outputs the function of the given protein. Catalytic activity prediction outputs the catalytic activity of the input protein and the chemical reactions it promotes. Domain/motif

prediction outputs the domains or motifs that the given protein may contain. Functional description generation outputs the description of the input protein's function, subcellular localization, and any biological processes it may be a part of.

Baselines We compare our approach with the baselines in Mol-Instructions including LLaMA (Touvron et al., 2023a), Alpaca (Tloen, 2023), Baize (Xu et al., 2023), ChatGLM (Zeng et al., 2022), Galactica (Taylor et al., 2022) and Vicuna. Apart from these LLMs, we use Prot2Text (Abdine et al., 2024) and ProLLaMA (Lv et al., 2024) as our baseline models in zero-shot settings. These models do not accept arbitrary prompts as inputs and Prot2Text is designed to generate protein descriptions, while ProLLaMA predicts protein superfamilies. Therefore, we evaluate protein function prediction for Prot2Text and domain/motif prediction for ProLLaMA. For protein understanding tasks, we follow Mol-Instructions, taking ROUGE-L (Lin, 2004) as the evaluation metric.

Results As shown in Tab. 1, PROTEINMPNN-EVOLLAMA and GEARNET-EVOLLAMA with zero-shot not only handle all protein understanding tasks but also outperform Prot2Text and ProLLaMA. Furthermore, they surpass or approach ChatGLM, Llama-2-7B-Chat and Vicuna fine-tuned on protein-oriented instructions by 1%-8%, demonstrating that during the projection tuning stage, PROTEINMPNN-EVOLLAMA and GEARNET-EVOLLAMA learn protein knowledge and can follow human instructions to generalize their knowledge for various downstream tasks. Additionally, PROTEINMPNN-EVOLLAMA outperforms all baseline models, including Llama-2-7B-Chat fine-tuned on the complete Mol-Instructions dataset (Mol) after supervised fine-tuning, highlighting the effectiveness of our approach. Notably, our approach uses a relatively small amount of data and has significantly fewer trainable parameters than the baseline models using full-parameter fine-tuning. The experimental results highlight the importance of leveraging the multimodal structure and sequence representations during training LLMs.

4.2 Protein Property Prediction Tasks

Task Descriptions Protein property prediction tasks use PEER benchmark for fine-tuning and evaluation, which consist of 6 tasks. Solubility prediction (Khurana et al., 2018), defined as a binary classification task, aims to predict whether a given protein is soluble or not. Subcellular localization prediction (Almagro Armenteros et al., 2017), defined as a ten-class classification task, aims to predict where a given protein locates in the cell. Binary localization prediction, a simplified version of subcellular localization prediction, is defined as a binary classification task that aims to determine whether a given protein is soluble or membrane-bound. Fold classification (Fox et al., 2014; Hou et al., 2018) requires the model to classify the global structural topology of a given protein into one of 1195 classes at the fold level. Yeast PPI prediction (Guo et al., 2008) and human PPI prediction (Peri et al., 2003; Pan et al., 2010) are defined as binary localization tasks, which aim to predict whether two given yeast or human proteins interact or not respectively.

Baselines We compare our approach with the following baselines in PEER benchmark. Feature engineers include Dipeptide Deviation from Expected Mean (DDE) (Saravanan and Gautham, 2015) and Moran correlation (Moran) (Feng and Zhang, 2000). Protein sequence encoders include LSTM (Hochreiter and Schmidhuber, 1997), Transformer (Vaswani et al., 2017), shallow CNN (Shanehsazzadeh et al., 2020) and ResNet (He et al., 2016). Pre-trained PLMs include ProtBert (Elnaggar et al., 2021) and ESM-1b (Rives et al., 2021). For the protein property prediction tasks, we take accuracy (Acc) as the evaluation metric.

Results As displayed in Tab. 2, PROTEINMPNN-EVOLLAMA with zero-shot achieves a comparable performance with both task-specific and single models on several tasks including solubility prediction, binary localization prediction and PPI prediction tasks. GEARNET-EVOLLAMA with zero-shot performs relatively worse than PROTEINMPNN-EVOLLAMA due to its lower capability to follow instructions. Besides, the supervised fine-tuning stage significantly enhances the performance of GEARNET-EVOLLAMA and PROTEINMPNN-EVOLLAMA, allowing our method outperforms or approaches the previous state-of-the-art models on multiple tasks. When jointly fine-tuning models on various tasks through multi-task learning, the performance improves compared to task-specific models, demonstrating no negative impact between tasks. However, more interrelated downstream tasks or data could be introduced in future work to further enhance the model's performance.

In particular, compared to task-specific mod-

Models	Data	Trainable/Total #Params.	ROUGE-L(↑)				
			PF	GF	CA	DP	Avg.
ChatGLM	PMol	6B/6B	0.15	0.14	0.13	0.10	0.1300
Llama-2-7B-Chat	PMol	7B/7B	0.15	0.14	0.16	0.12	0.1425
Llama-2-7B-Chat	Mol	7B/7B	0.42	0.44	0.52	0.46	0.4600
Vicuna	PMol	7B/7B	0.07	0.08	0.08	0.06	0.0725
Alpaca	PMol	7B/7B	0.2	0.1	0.23	0.12	0.1625
Baize	PMol	7B/7B	0.2	0.15	0.22	0.13	0.1750
Galactica (*zero-shot*)	-	-	0.12	0.12	0.13	0.09	0.1150
Prot2Text (*zero-shot*)	-	-	0.14	-	-	-	0.1400
ProLLaMA (*zero-shot*)	-	-	-	-	-	0.02	0.0200
GearNet-EvoLlama (*zero-shot*)	-	-	0.16	0.16	0.21	0.15	0.1700
ProteinMPNN-EvoLlama (*zero-shot*)	-	-	0.16	0.14	0.15	0.11	0.1400
GearNet-EvoLlama	PMol, PEER	720M/8.8B (8.2%)	*0.25*	*0.32*	*0.34*	*0.31*	*0.3050*
ProteinMPNN-EvoLlama	PMol, PEER	690M/8.8B (7.9%)	**0.48**	**0.50**	**0.60**	**0.50**	**0.5200**

Table 1: Results of protein understanding tasks (**Best**, Second Best, *Third Best*). PF refers to protein function prediction. GF refers to functional description generation. CA refers to catalytic activity prediction. DP refers to domain/motif prediction. Note that Mol refers to the Mol-Instructions with 3 components: molecule-oriented instructions, protein-oriented instructions (named PMol), and biomolecular text instructions. - indicates the data is not applicable to the task.

els, ProteinMPNN-EvoLlama outperforms or approaches them in several tasks, except for fold classification. A possible explanation for the promising results is that ProteinMPNN-EvoLlama learns the properties of proteins through various tasks by leveraging multimodal structure and sequence representations. Notably, both ProteinMPNN-EvoLlama and Llama-3-8B-Instruct achieve the best performance on binary localization task, demonstrating the significant potential of LLMs to understand proteins. Additionally, BioT5 and BioT5+ are trained to solve four tasks, excluding subcellular localization prediction and fold classification, achieving average accuracy scores of 79.36 and 79.01, respectively, across these tasks. In comparison, ProteinMPNN-EvoLlama has an average score of 75.57, showing comparable performance with these two models. A possible explanation for the relatively higher accuracy of these two models is that they incorporate molecules as a new modality and leverage more molecule-related data, potentially yielding positive effects, while we focus only on protein structures and sequences. A similar result can be observed in Tab. 1, where Llama-2-7B-Chat fine-tuned on the complete Mol-Instructions dataset, including molecule-related data, performs significantly better than when fine-tuned only on protein-oriented instructions. We leave the exploration of incorporating more biomolecular modalities, such as molecules and DNA, for future work.

Additionally, compared to Llama-3-8B-Instruct, used as a text decoder in our approach, ProteinMPNN-EvoLlama improves performance on all tasks by incorporating the multimodal structure and sequence representations of proteins.

4.3 Ablation Study

In this section, we conduct ablation studies to explore the effect of the projection tuning stage, structure and sequence representations, and the fusion method. For fair comparison, the baselines are trained using the same experimental setups discussed in Appendix C with 10K steps. We conduct more evaluations on protein property prediction tasks in Appendix D.

Effect of the projection tuning stage We compare the performance of ProteinMPNN-EvoLlama with and without the projection tuning stage in Tab. 3. ProteinMPNN-EvoLlama, when continued to be fine-tuned after the projection tuning stage, achieves lower performance compared to direct supervised fine-tuning. A possible reason is that we use protein structures predicted by AlphaFold-2 during the projection tuning stage, while structures predicted by ESMFold are used during the supervised fine-tuning stage. The zero-shot ability discussed in Sec. 4.1 and Sec. 4.2 highlights the effectiveness of the projection tuning stage, demonstrating that the model learns to generalize its structural knowledge from structures

Models	Sol	Sub	Bin	Fold	Yst	Hum	Avg.
Task-specific model							
DDE	59.77±1.21	49.17±0.40	77.43±0.42	9.57±0.46	55.83±3.13	62.77±2.30	52.42
Moran	57.73±1.33	31.13±0.47	55.63±0.85	7.10±0.56	53.00±0.50	54.67±4.43	43.21
CNN	64.43±0.25	58.73±1.05	82.67±0.32	10.93±0.35	55.07±0.02	62.60±1.67	55.74
ResNet	67.33±1.46	52.30±3.51	78.99±4.41	8.89±1.45	48.91±1.78	68.61±3.78	54.17
LSTM	*70.18±0.63*	62.98±0.37	88.11±0.14	8.24±1.61	53.62±2.72	63.75±5.12	57.81
Transformer	70.12±0.31	56.02±0.82	75.74±0.74	8.52±0.63	54.12±1.27	59.58±2.09	54.02
ProtBert	68.15±0.92	76.53±0.93	91.32±0.89	16.94±0.42	**63.72±2.80**	77.32±1.10	65.66
ESM-1b	70.23±0.75	**78.13±0.49**	92.40±0.35	**28.17±2.05**	*57.00±6.38*	**78.17±2.91**	**67.35**
Single model							
Llama-3-8B-Instruct	69.13±0.39	51.36±0.06	98.91±0.00	8.77±0.40	56.05±0.53	62.87±0.34	57.85
GearNet-EvoLlama (*zero-shot*)	34.65±0.48	-	50.89±0.88	-	2.52±0.11	3.70±0.10	22.94
ProteinMPNN-EvoLlama (*zero-shot*)	50.76±0.47	8.16±0.27	*92.85±0.21*	0.65±0.06	53.59±0.36	50.21±0.79	42.70
GearNet-EvoLlama	61.13±0.15	42.27±0.23	85.21±0.34	3.11±0.36	50.42±0.57	67.72±1.08	51.64
ProteinMPNN-EvoLlama	**72.37±0.35**	*73.25±0.27*	**99.73±0.05**	*10.96±0.36*	57.45±0.78	*72.71±1.15*	*64.41*

Table 2: Results (in %) of protein property prediction tasks (**Best**, Second Best, *Third Best*). Sol represents solubility prediction. Sub represents subcellular localization prediction. Bin represents binary localization prediction. Fold represents fold classification. Yst represents yeast PPI prediction. Hum represents human PPI prediction. - indicates the data is not applicable to the task.

predicted by AlphaFold-2 to those predicted by ESMFold during inference. However, it's challenging for models to learn the gap between protein structures predicted by AlphaFold-2 and ESMFold when the structure encoder and projection layer are updated simultaneously during the supervised fine-tuning stage.

Models	PF	GF	CA	DP	Avg.
ProteinMPNN-EvoLlama	0.43	0.46	0.55	0.48	**0.4800**
ProteinMPNN-EvoLlama w/ PT	0.28	0.34	0.40	0.34	0.3400

Table 3: Effect of the projection tuning stage. The experiments are conducted on protein understanding tasks. PT refers to the projection tuning stage.

Effect of structure and sequence representations As shown in Tab. 4, ProteinMPNN-EvoLlama incorporating both structure and sequence representations outperforms those utilizing only structure or sequence representations, demonstrating the effectiveness of utilizing both protein representations. Furthermore, GearNet-EvoLlama significantly enhances the model's performance by leveraging the structure and sequence representations. Specifically, ProteinMPNN-EvoLlama with only a sequence-based protein encoder surpasses the one with only a structure-based protein encoder, regardless of the protein structure encoder chosen. A possible explanation is that the features extracted by ESM-2 implicitly contain structural information, indicating that sequence representations are easier for LLMs to learn. Moreover, the parameters of the structure encoder are one to two orders of magnitude fewer than those of the sequence encoder, leading to a more limited extraction of structural features. A case study on effect of structure and sequence representations is conducted in Appendix E.

Models	PF	GF	CA	DP	Avg.
ProteinMPNN-EvoLlama	0.43	0.46	0.55	0.48	**0.4800**
ProteinMPNN-EvoLlama w/o ProteinMPNN	0.39	0.46	0.54	0.48	0.4675
ProteinMPNN-EvoLlama w/o ESM-2	0.35	0.42	0.50	0.41	0.4200
GearNet-EvoLlama	0.30	0.32	0.36	0.30	**0.3200**
GearNet-EvoLlama w/o ESM-2	0.20	0.28	0.31	0.29	0.2700

Table 4: Effect of structure and sequence representations. The experiments are conducted on protein understanding tasks. Note that GearNet-EvoLlama (w/o GearNet) is equivalent to ProteinMPNN-EvoLlama (w/o ProteinMPNN), as both only utilize the sequence representations extracted by the protein sequence encoder.

Effect of the fusion method To evaluate the effect of the fusion method, we directly use the structure and sequence features instead of fusing their representations. As shown in Tab. 5, ProteinMPNN-EvoLlama with fused representations surpass the one without, demonstrating the effectiveness of our fusion method. However, GearNet-EvoLlama without fused representations outperforms the one with them, indicating

that for different protein structure encoders, different fusion methods may be chosen. Furthermore, the fused representations reduce the token cost of the LLM, resulting in approximately 20% lower inference latency.

Models	PF	GF	CA	DP	Avg.	Latency
PROTEINMPNN-EVOLLAMA	0.43	0.46	0.55	0.48	**0.4800**	×**1.0**
PROTEINMPNN-EVOLLAMA w/o fused representations	0.42	0.44	0.55	0.48	0.4725	×1.17
GEARNET-EVOLLAMA	0.30	0.32	0.36	0.30	0.3200	×**0.8**
GEARNET-EVOLLAMA w/o fused representations	0.31	0.34	0.39	0.36	**0.3500**	×1.0

Table 5: Effect of the fusion method. The experiments are conducted on protein understanding tasks.

5 Related Work

Large Multimodal Models OntoProtein (Zhang et al., 2022a) integrate external factual knowledge from gene ontology into PLMs to enhance protein representations. BioT5 (Pei et al., 2023) and BioT5+ (Pei et al., 2024) captures the underlying relations and properties of bio-entities such as molecules and proteins. ProLLaMA (Lv et al., 2024) introduces a training framework to transform a LLM into a multi-task protein LLM, focusing on protein sequence generation and superfamily prediction tasks. These methods utilize text-format protein sequences while PROTEINMPNN-EVOLLAMA focuses on leveraging multimodal representations of proteins. Prot2Text (Abdine et al., 2024) directly fuses the structure and sequence representations as inputs into the multi-head cross-attention module within the Transformer decoder. Compared to Prot2Text, PROTEINMPNN-EVOLLAMA maps the structure and sequence features into language embedding tokens, enabling it to handle PPI prediction tasks, which typically requires two proteins as inputs. Additionally, Prot2Text is designed to generate protein descriptions rather than handle various protein-oriented tasks, whereas PROTEINMPNN-EVOLLAMA can follow human instructions, even in zero-shot settings. ProteinChat (Guo et al., 2023) utilizes a Graph Neural Network encoder block combined with a Transformer encoder block to extract features from protein structures. Instead of introducing complex Transformer blocks, PROTEINMPNN-EVOLLAMA uses MLP as a lightweight and cost-effective approach to align different modalities. ProtChatGPT (Wang et al., 2024) is trained with sequence-text pairs using a Protein-Language Pretraining Transformer initialized with the pre-trained weights of PubMedBERT (Gu et al., 2021) to incorporate external knowledge. In contrast, PROTEINMPNN-EVOLLAMA does not require external protein knowledge and tunes the projection layers from scratch, demonstrating its ability to learn and understand protein structures and sequences independently.

Protein Representations BERT-based PLMs such as ProtBert (Elnaggar et al., 2021), ProteinBERT (Brandes et al., 2022) and ESM (Rives et al., 2021; Lin et al., 2022) learn protein sequence representations through Masked Language Modeling objective. Gligorijević et al. (2021) propose a Graph Convolutional Network to encode protein structures. Zhang et al. (2022b) present a protein graph encoder to learn protein geometric features. Apart from these sequence-based protein encoders, some work employ Graph Neural Networks to learn the geometric features of proteins. Dauparas et al. (2022) introduce a protein sequence design method based on Message Passing Neural Network with 3 encoder and 3 decoder layers. We adopt the encoder layers of ProteinMPNN as a structure-based encoder in our approach. GearNet (Zhang et al., 2022b) performs relational message passing on protein residue graphs for protein representation learning. While these methods effectively learn the protein representations through sequences or structures, they do not utilize natural language with knowledge of protein properties. Therefore, PROTEINMPNN-EVOLLAMA aligns the features extracted by ProteinMPNN and ESM-2 with Llama-3 to enhance LLM's understanding of proteins.

6 Conclusion

In this paper, we propose PROTEINMPNN-EVOLLAMA, a multimodal framework that connects ProteinMPNN, ESM-2 650M and Llama-3 8B for protein understanding through a two-stage training process. The experimental results demonstrate that after the projection tuning stage, PROTEINMPNN-EVOLLAMA in zero-shot settings outperforms the baselines using full-parameter fine-tuning, surpassing the current state-of-the-art model with supervised fine-tuning on the Mol-Instructions dataset. Additionally, our approach achieves promising results that are competitive with state-of-the-art task-specific baselines on the PEER benchmark.

Limitations

PROTEINMPNN-EVOLLAMA incorporates the structure and sequence representations of proteins to enhance LLM's understanding of proteins. Due to the lack of experimentally determined structures for many proteins in our experiments, we use 3D structures predicted by AlphaFold-2 and ESMFold to fully leverage the data. These computationally predicted structures generally have relatively lower accuracy compared to wet lab experiments. Besides, training a single model to predict various protein properties presents challenges, causing PROTEINMPNN-EVOLLAMA to only approach the state-of-the-art performance for some tasks in protein property prediction.

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A Further Related Work

Large Language Models Llama-3 (Dubey et al., 2024) is a family of pre-trained and fine-tuned open-source LLMs with sizes ranging from 8B to 70B parameters. Baize (Xu et al., 2023) is an open source model aligned by introducing self-distillation with feedback. ChatGLM (Zeng et al., 2022) is an open bilingual language model based on General Language Model (GLM) framework (Du et al., 2021), with 6B parameters. Galactica (Taylor et al., 2022) is a large language model that trained on an extensive scientific corpus of papers and knowledge bases, capable of storing, combining and reasoning about scientific knowledge.

Large Multimodal Models Large multimodal models (LMMs) such as LLaVA (Liu et al., 2024) and InstructBLIP (Dai et al., 2024) have demonstrated their capability to understand visual content. LLaVA introduces an end-to-end LMM that connects a visual encoder and a LLM for visual and language understanding. InstructBLIP proposes a instruction tuning framework towards generalized vision-language models.

Protein Representations DDE (Saravanan and Gautham, 2015), based on the dipeptide frequency within the protein sequence, and Moran (Feng and Zhang, 2000), which defines the distribution of amino acid properties along a protein sequence, are two typical protein sequence feature descriptors. Shallow CNN (Shanehsazzadeh et al., 2020) and ResNet (He et al., 2016) are protein sequence encoders designed to capture the short-range interactions within the protein sequence, while LSTM (Hochreiter and Schmidhuber, 1997) and Transformer (Vaswani et al., 2017) aim to capture the long-range interactions. The output layers of these protein sequence encoders aggregate the representations of different residues into a protein-level representation.

B Dataset Construction Details

B.1 Projection Tuning Data

As illustrated in Fig. 3, projection tuning data consists of sequence-description pairs originated from the Swiss-Prot (Consortium, 2023) database. The database contains 571K manually-annotated records, each containing information including protein name, subcellular location, function and families. To prevent from data leakage, we filter the Swiss-Prot annotation to 369K as our projection tuning data based on the downstream tasks.

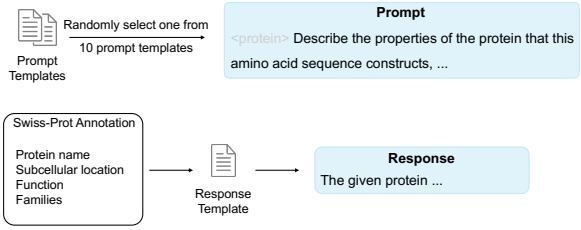


Figure 3: Overview of the projection tuning data construction.

For prompts, we construct 10 templates that ask the model to briefly describe the input protein from various aspects. For responses, information is extracted from the filtered Swiss-Prot annotation and constructed using a pre-defined template to ensure the consistency and clarity of protein descriptions. The prompt and response templates are listed in Fig. 4.

B.2 Supervised Fine-Tuning Data

As shown in Fig. 5, fine-tuning dataset consists of 10 tasks including PEER benchmark (Xu et al., 2022) and Mol-Instructions (Fang et al., 2023). For

Prompt Template

`<protein>` Elaborate on the characteristics of the protein specified by this amino acid sequence, detailing its biological role, cellular compartmentalization, and its classification within protein families.

`<protein>` Provide a comprehensive analysis of the protein encoded by the given amino acid sequence, focusing on its physiological function, location within the cell, and the protein family it is associated with.

`<protein>` Examine the protein determined by the provided amino acid sequence, including an in-depth look at its function, where it resides within the cell, and the broader family of proteins it is a member of.

`<protein>` Offer a detailed account of the protein described by this sequence of amino acids addressing its functional significance, subcellular niche, and its familial lineage within the protein taxonomy.

`<protein>` Describe the properties of the protein that this amino acid sequence constructs, including its operational role in the cell, its intracellular positioning, and the protein family to which it pertains.

`<protein>` Furnish a detailed exposition of the protein that correlates with the specified amino acid sequence, highlighting its role within cellular processes, its subcellular habitat, and the family of proteins it integrates with.

`<protein>` Detail the profile of the protein corresponding to the listed amino acid sequence, encompassing its function within the organism, its cellular localization, and the protein family it is derived from.

`<protein>` Discuss the protein that this amino acid sequence forms, including an analysis of its functional role, subcellular distribution, and its affiliation with particular protein families.

`<protein>` Present a thorough description of the protein represented by the amino acid sequence given, considering its function in biological systems, its localization within the cell, and the family of proteins it belongs to.

`<protein>` Illustrate the features of the protein specified by this sequence of amino acids, with emphasis on its functional activity, place within the cell structure, and its classification among protein families.

Response Template

{% if `function` is not none and `similarity` is not none %}
The given protein `{{ protein_name }}` suggests its potential function as `{{ function }}` It `{{ similarity }}`
{% elif `function` is none and `similarity` is not none %}
The given protein `{{ protein_name }}` `{{ similarity }}`
{% else %}
The given protein `{{ protein_name }}` suggests its potential function as `{{ function }}`
{% endif %}

Figure 4: The prompt and response template of the projection tuning data. In the response template, `similarity` refers to the families of the protein in Swiss-Prot.

each task in PEER benchmark, there are 10 prompt templates and 1 response template, some of which are listed in Fig. 6. Except for fold classification, the categories in the response templates for other tasks are represented by natural language. For fold classification, we use integers ranging from 0 to 1194 to represent its categories due to the excessive number of categories.

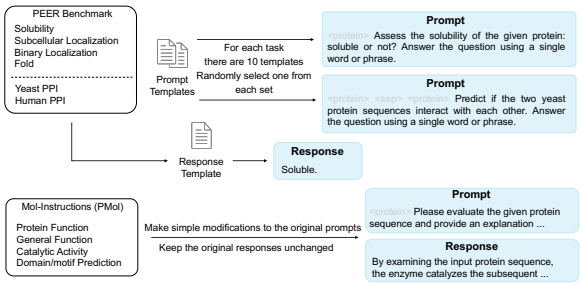


Figure 5: Overview of the supervised fine-tuning data construction.

For each task in Mol-Instructions, we make simple modifications to the original prompts to ensure that they are suitable for our use cases and maintain coherence. First, we remove the appended text-format FASTA sequences. Additionally, we modify some expressions in the original prompts. Some modification cases are listed in Fig. 7.

C Experimental Setups

For protein understanding tasks, we follow Mol-Instructions to split the dataset into an 8:1:1 ratio for training/validation/test, where the training and validation sets are used for the supervised fine-tuning stage, and the test set is used for assessing model performance. For protein property prediction tasks, we follow the PEER benchmark to split the dataset for each task. The details of dataset splits are listed in Tab. 6. The results are averaged over three runs with different random seeds. Specifically, we follow the PEER benchmark to report the mean and standard deviation of three runs' results.

We conduct both the projection tuning stage and supervised fine-tuning stage on 80GB H800 GPUs. The experiments to evaluate the inference latency, reported in Tab. 10, are conducted on 24GB RTX 3090 GPUs. The hyperparameters are listed in

Prompt Template	Response Template
<protein> Is the given protein water-soluble? Answer the question using a single word or phrase. ... (omit the other 9 prompt templates) ...	Not soluble./Soluble.
<protein> Identify the subcellular localization of the specified protein. Answer the question using a single word or phrase. ... (omit the other 9 prompt templates) ...	Cell membrane./Cytoplasm./ Endoplasmic reticulum./ ... (omit the other 7 responses) ...
<protein> Is the given protein membrane-bound or soluble? Answer the question using a single word or phrase. ... (omit the other 9 prompt templates) ...	Membrane-bound./Soluble.
<protein> Analyze the global fold topology of the specified protein. Answer the question using an integer between 0 and 1194 as the classification label. ... (omit the other 9 prompt templates) ...	0./1./.../1194.
<protein> <sep> <protein> Analyze the potential interaction between the two protein human sequences. Answer the question using a single word or phrase. ... (omit the other 9 prompt templates) ...	No./Yes.
<protein> <sep> <protein> Analyze the potential interaction between the two protein yeast sequences. Answer the question using a single word or phrase. ... (omit the other 9 prompt templates) ...	No./Yes.

Figure 6: The prompt and response template of PEER benchmark in the supervised fine-tuning data.

Original prompt used in Mol-Instructions:

Given the protein sequence **below**, please analyze and describe the catalytic activity of the corresponding enzyme, specifically the chemical reaction it catalyzes**:**

Modified prompt in our fine-tuning dataset:

<protein> Given the protein sequence **above**, please analyze and describe the catalytic activity of the corresponding enzyme, specifically the chemical reaction it catalyzes**.**

Original prompt used in Mol-Instructions:

Given the **following** protein sequence, can you perform an analysis and identify any potential motifs or domains**? Here is the sequence:**

Modified prompt in our fine-tuning dataset:

<protein> Given the protein sequence, can you perform an analysis and identify any potential motifs or domains?

Figure 7: Examples of modifications to the original prompts in Mol-Instructions. Red expressions are highlighted for modifications.

Tab. 7.

D More Evaluations

We conduct more evaluations on protein property prediction tasks for each ablation study introduced in Sec. 4.3.

As shown in Tab.8, PROTEINMPNN-EVOLLAMA with supervised fine-tuning fails to maintain performance after the projection tuning stage, while PROTEINMPNN-EVOLLAMA in zero-shot settings remains competitive with the baselines fine-tuned on PMol (see Tab.1). This indicates that bridging the gap between protein structures predicted by AlphaFold-2 and ESMFold during the supervised fine-tuning stage is more challenging than inference.

As shown in Tab. 9, PROTEINMPNN-EVOLLAMA and GEARNET-EVOLLAMA enhances the performance on protein understanding tasks by incorporating both structure and sequence representations, specifically on protein function prediction and catalytic activity prediction.

As shown in Tab. 10, PROTEINMPNN-EVOLLAMA with fused representations outperforms the one without, particularly on subcellular localization prediction task, while GEARNET-EVOLLAMA achieves better performance when the structure and sequence representations are not fused. This demonstrates that the fusion method is more effective when ProteinMPNN is used as the structure encoder.

Tasks	Sub-tasks	Data Source	#Training	#Validation	#Test
Protein Understanding Tasks	Solubility	PEER Benchmark	62,478	6,942	1,999
	Subcellular Localization		8,420	2,811	2,773
	Binary Localization		5,184	1,749	1,749
	Fold Classification		12,312	736	718
	Yeast PPI		9,890	190	788
	Human PPI		71,338	630	474
Protein Property Prediction Tasks	Protein Function	Mol-Instructions (PMol)	110,689		3,494
	Catalytic Activity		51,573		1,601
	Domain/Motif		43,700		1,400
	Functional Description		83,939		2,633

Table 6: Details of dataset splits for supervised fine-tuning data.

Stages	lr	Scheduler	Optimizer	#Batch Size	#Epochs/#Steps
Projection Tuning	2×10^{-4}	cosine	AdamW	64	2 epochs
Supervised Fine-tuning	2×10^{-5}	cosine	AdamW	32	25,000 steps

Table 7: Hyperparameters for the projection tuning stage and supervised fine-tuning stage.

Models	Sol	Sub	Bin	Fold	Yst	Hum	Avg.
PROTEINMPNN-EVOLLAMA	71.19±2.27	68.05±0.65	99.10±0.05	6.18±0.29	53.81±1.55	75.95±1.30	**62.38**
PROTEINMPNN-EVOLLAMA w/ PT	62.28±0.25	50.73±0.11	92.37±0.35	2.14±0.92	50.30±0.22	65.54±0.99	53.89

Table 8: More evaluations on the effect of the projection tuning stage. The experiments are conducted on protein property prediction tasks.

Models	Sol	Sub	Bin	Fold	Yst	Hum	Avg.
PROTEINMPNN-EVOLLAMA	71.19±2.27	68.05±0.65	99.10±0.05	6.18±0.29	53.81±1.55	75.95±1.30	**62.38**
PROTEINMPNN-EVOLLAMA w/o ProteinMPNN	70.91±0.10	68.63±0.21	99.73±0.03	7.94±0.11	54.48±0.60	65.12±2.76	61.14
PROTEINMPNN-EVOLLAMA w/o ESM-2	63.06±0.24	40.56±0.56	99.41±0.03	6.78±0.36	53.34±0.61	52.74±0.60	52.65
GEARNET-EVOLLAMA	67.20±0.40	37.96±0.33	91.96±0.06	3.67±0.29	52.16±0.63	60.41±0.10	**52.23**
GEARNET-EVOLLAMA w/o ESM-2	57.63±0.07	12.15±0.18	91.96±0.10	3.90±0.20	49.58±0.74	48.59±0.44	43.97

Table 9: More evaluations on the effect of structure and sequence representations. The experiments are conducted on protein property prediction tasks.

Models	Sol	Sub	Bin	Fold	Yst	Hum	Avg.
PROTEINMPNN-EVOLLAMA	71.19±2.27	68.05±0.65	99.10±0.05	6.18±0.29	53.81±1.55	75.95±1.30	**62.38**
PROTEINMPNN-EVOLLAMA w/o fused representations	69.53±0.87	59.29±2.35	99.16±0.50	10.91±0.37	56.26±1.09	74.40±0.70	61.59
GEARNET-EVOLLAMA	67.20±0.40	37.96±0.33	91.96±0.06	3.67±0.29	52.16±0.63	60.41±0.10	52.23
GEARNET-EVOLLAMA w/o fused representations	64.33±0.00	47.66±0.87	91.90±0.27	6.59±0.23	56.56±1.72	70.04±0.86	**56.18**

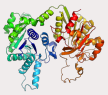
Table 10: More evaluations on the effect of the fusion method. The experiments are conducted on protein property prediction tasks.

E Case Study

As shown in Fig. 8, we compare the outputs of PROTEINMPNN-EVOLLAMA, GEARNET-EVOLLAMA and Mol-Instructions on domain/motif prediction task. Only PROTEINMPNN-EVOLLAMA correctly predicts all possible domains or motifs of the given protein, regardless of whether structure or sequence representations are incorporated. Compared to PROTEINMPNN-EVOLLAMA, Mol-Instructions fails to predict all the domains or motifs while GEARNET-EVOLLAMA generates incorrect ones, indicating that the structure representations extracted by GearNet fail to capture domain- or motif-related information.

As shown in Fig. 9, we compare the outputs of these models on catalytic activity prediction task. Both PROTEINMPNN-EVOLLAMA, with fused structure and sequence representations, and Mol-Instructions generate the accurate and complete chemical reaction. Furthermore, models with only structure or sequence representations fail to produce the correct chemical reaction, demonstrating the significance of fused representations.

Domain/motif Prediction

Input $\mathbf{X}_{\text{struct}}$: 

Input $\mathbf{X}_{\text{seq}}$:
MANTKYIFITGGVVSSLGKGIAAASIGALLESRGLSVSLIKVDPYINVDPGTMSPFQHGEVFVTEDGTETDLDLGHYERFVRFKASK
KNNFTAGKVYETVIRNERKGNYLGGTVQVIPHITNEIKKRIKKGGQNKDIAIVEVGGTVGDIESQPFVEALRQMALELPNSSWAFVH
LTLVPFINASGELKTKPTQHSVKELRSLGISPDVLVCRSEQELPKDEKNKIALFCSVPAKSVISMHDVDTVYSIPILLNKQKVDDTILK
KLNLKIKKPNLNDWKRVVKAKLLPEKEVNVSFVGKYTELKDSYKSINEALEHAGIQNKAKVNINFVEAEQITSQNVRKVLKKSDAILV
PGGFGERGIEGMILACKYARENNVPYLGICLGMQIAIIEYARNVLKLKSANSTEFDSSTKFPVIGLITEWSDISGKKEKRTKNSDLGG
TMRLGGQVCKLKKKSNSYKMYKKSEIIERHRHRYEVNPNYKDKMIEQGLDVVGTSIDGKLVEMIELPSHKWFLACQFHPEFTSNP
RDGHPIFNSYIKSTITK

Instruction: Given this protein sequence, can you identify any common protein motifs or domains that it may contain?

Output (Ground Truth): Our predictive analysis of the given protein sequence reveals possible domains or motifs. These include: Glutamine amidotransferase, CTP synthase N-terminal domains.

Output (Mol-Instructions): Based on computational analysis, the provided sequence potentially contains the following protein domains or motifs: Glutamine amidotransferase type-1 domains.

Output (ProteinMPNN-EvoLlama): The computational analysis of the sequence suggests the presence of the following protein domains or motifs: Glutamine amidotransferase, CTP synthase N-terminal domains.

Output (ProteinMPNN-EvoLlama, w/o ProteinMPNN): Upon evaluating your submitted sequence, our predictive algorithms suggest the presence of: Glutamine amidotransferase, CTP synthase N-terminal domains.

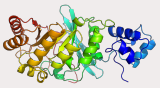
Output (ProteinMPNN-EvoLlama, w/o ESM-2): After analyzing the given sequence, the following protein domains or motifs are predicted: Glutamine amidotransferase, CTP synthase N-terminal domains.

Output (GearNet-EvoLlama): The sequence you provided suggests the presence of a protein with a significant chance of containing a helicase, Rosy domain, SDH C-terminal domain, 'Y' domain, 'Z' domain type of protein.

Output (GearNet-EvoLlama, w/o ESM-2): Our bioinformatics algorithm indicates that the protein with sequence has potentially significant domains or motifs. These include: Helical transmembrane domains (e.g., 4-alpha-helical, 7-transmembrane G-protein coupled receptors).

Figure 8: Case study of performance on protein understanding tasks (Domain/motif prediction).

Catalytic Activity Prediction

Input $\mathbf{X}_{\text{struct}}$: 

Input $\mathbf{X}_{\text{seq}}$:
MDKVAVAGFLPEELCASLSLSPSFRGNQIFQWIGKGVDSFDAMTNLSAELRASLAEKAILRSTRVSDVLKADDGTVKLQIQTEDDL
AVETVLLTDKAARKTACVSCQAGCAMGCAFCKTGTLGLARNLSAAEIVEQFLYLEKHAGALDNIVFMGMGEPLLNLDALRKAIAVL
TDKRGRNLSSRRITVSTVGIVSGIYDLANNGPDVRLAVSLTTADETLRRELMPASLTNPLSDLRQAISYYIEKTGKRVTLEAVLLSGK
NTSEKNADSLIAFAKGLDVHVNLIPWNPVEGLSFVTPDPEETAQFVSRLEKGGLNVTLRMHRGKSISGACGQLGKTNPYA
Instruction: Please evaluate the following protein sequence and provide an explanation of the enzyme's catalytic activity, including the chemical reaction it facilitates:

Output (Ground Truth): Based on the provided protein sequence, the enzyme appears to facilitate the chemical reaction: adenosine(37) in tRNA + 2 reduced [2Fe-2S]-[ferredoxin] + 2 S-adenosyl-L-methionine = 2-methyladenosine(37) in tRNA + 5'-deoxyadenosine + L-methionine + 2 oxidized [2Fe-2S]-[ferredoxin] + S-adenosyl-L-homocysteine.

Output (Mol-Instructions): An analysis of the protein sequence reveals that the enzyme's catalytic function corresponds to the chemical reaction: adenosine(37) in tRNA + 2 reduced [2Fe-2S]-[ferredoxin] + 2 S-adenosyl-L-methionine = 2-methyladenosine(37) in tRNA + 5'-deoxyadenosine + L-methionine + 2 oxidized [2Fe-2S]-[ferredoxin] + S-adenosyl-L-homocysteine.

Output (ProteinMPNN-EvoLlama): By examining the input protein sequence, the enzyme catalyzes the subsequent chemical reaction: adenosine(37) in tRNA + 2 reduced [2Fe-2S]-[ferredoxin] + 2 S-adenosyl-L-methionine = 2-methyladenosine (37) in tRNA + 5'-deoxyadenosine + L-methionine + 2 oxidized [2Fe-2S]-[ferredoxin] + S-adenosyl-L-homocysteine.

Output (ProteinMPNN-EvoLlama, w/o ProteinMPNN): By examining the input protein sequence, the enzyme catalyzes the hydrolytic removal of adenine (A) from tRNAs, resulting in 7,8-dihydro-8-oxo-A and 5,6-methyl-5,6-dihydro formyl-C.

Output (ProteinMPNN-EvoLlama, w/o ESM-2): Based on the provided protein sequence, the enzyme appears to facilitate the chemical reaction: adenosine 5'-phosphosulfamidase + adenosine 5'-phosphosulfate = (R)-(+)- \u00a0 (S)-methylmethionine + adenosine 5'-phosphate + sulfuric acid.

Output (GearNet-EvoLlama): A chemical reaction and its participating enzymes have been identified: S-adenosyl-L-methionine tRNA (cytidine(34) 2'-O-)-methyltransferase [acetyl-CoA pathway].

Output (GearNet-EvoLlama, w/o ESM-2): The enzyme catalyzes the chemical reaction: 2 2-oxo-4-methyl-1,7-diazabicyclo[3.3.0]octane + 2 H(+) + 2 H(2)O = 2 2-oxo-4-methyl-1,7-diazabicyclo[3.3.0]octan-7-ol + 2 H(+) + N(2),N(5)-dimethyl-1,5-diaminopentane.

Figure 9: Case study of performance on protein understanding tasks (Catalytic activity prediction).