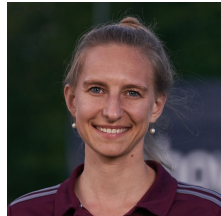


Guided by an Expert Teacher

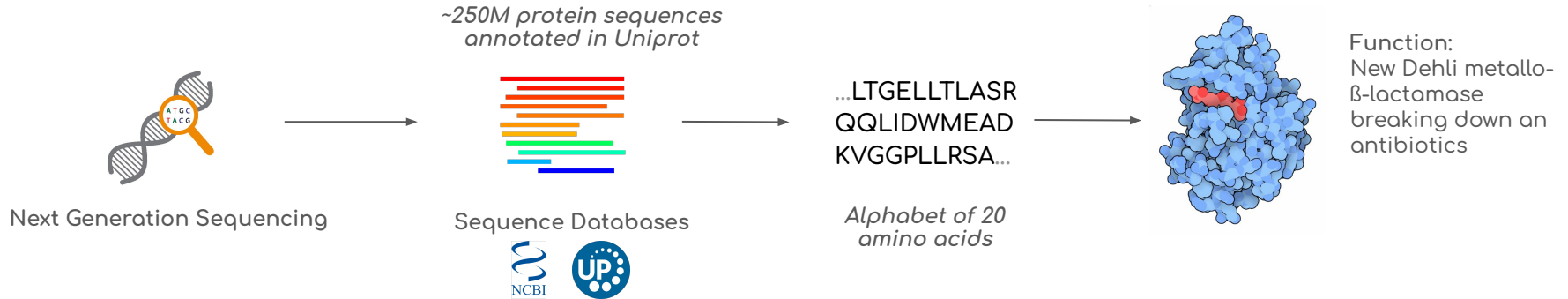
Accurate and blazingly fast variant effect prediction using protein language model embeddings

Julius Schlensook, Céline Marquet, Marina Abakarova, Burkhard Rost & Elodie Laine



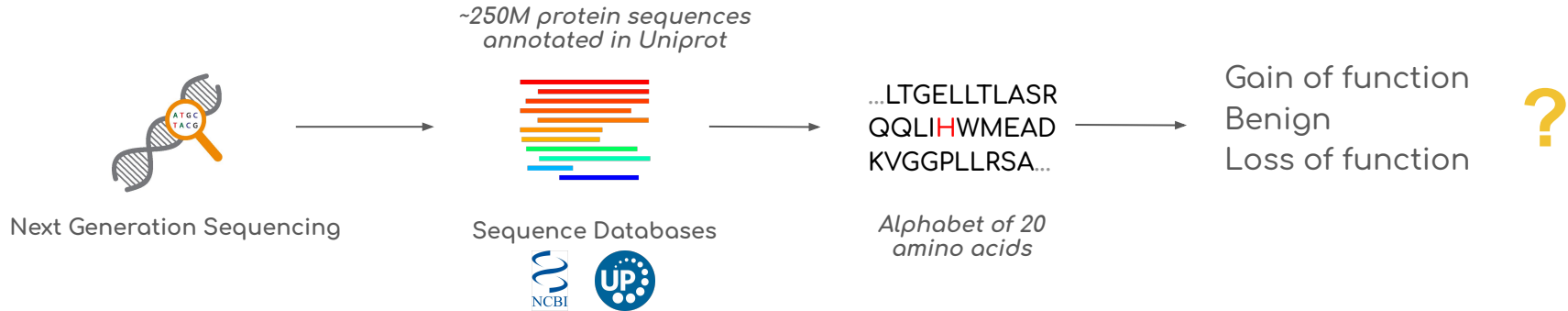
Motivation

Understanding the impact of **single amino acid variants** (SAVs) on protein function



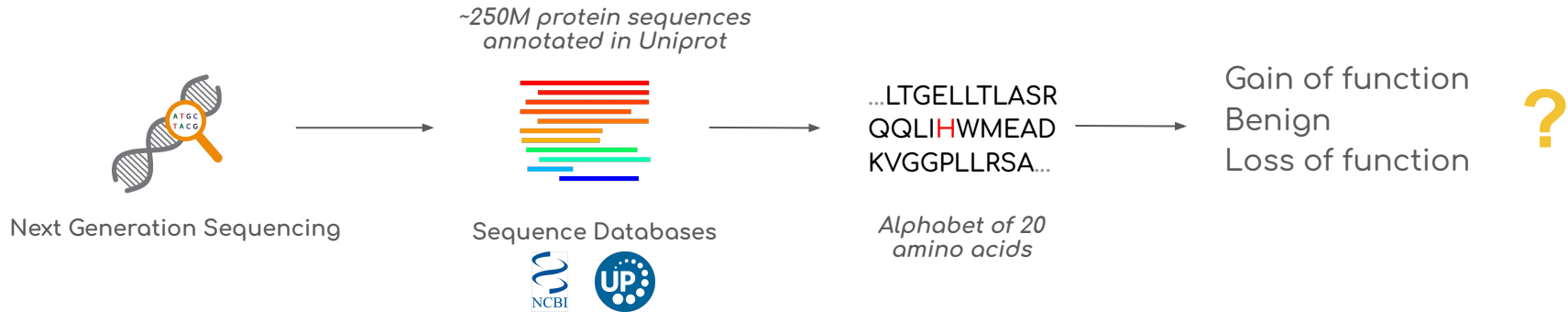
Motivation

Understanding the impact of **single amino acid variants** (SAVs) on protein function



Motivation

Understanding the impact of **single amino acid variants** (SAVs) on protein function



- ❑ Fundamental biology
- ❑ Bioengineering
- ❑ Drug design

Experimental answer

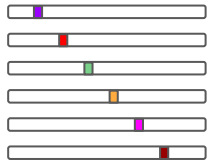
Deep Mutational Scanning (DMS)

Quantification of mutational outcomes on a large scale

Protocol

Library of mutants

All possible
substitutions at all
positions



Phenotype

localization,
growth, enzyme
function, binding...



Experimental answer

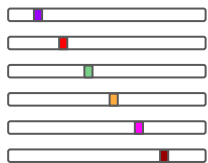
Deep Mutational Scanning (DMS)

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The largest collection of DMS datasets

ProteinGym substitution benchmark

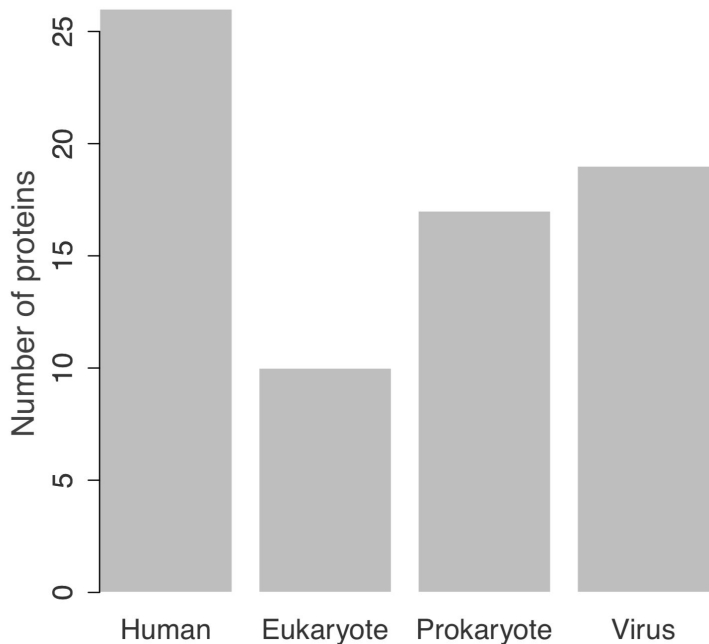
~1.5M SAVs across 72 protein families

<https://www.proteingym.org>



Notin *et al.* 2022

ProteinGym substitution benchmark



A wide variety of proteins...

- between 70 and 3500 residues
- kinases, ion channels, g-protein coupled receptors, polymerases, transcription factors, tumor suppressors...

... and phenotypes

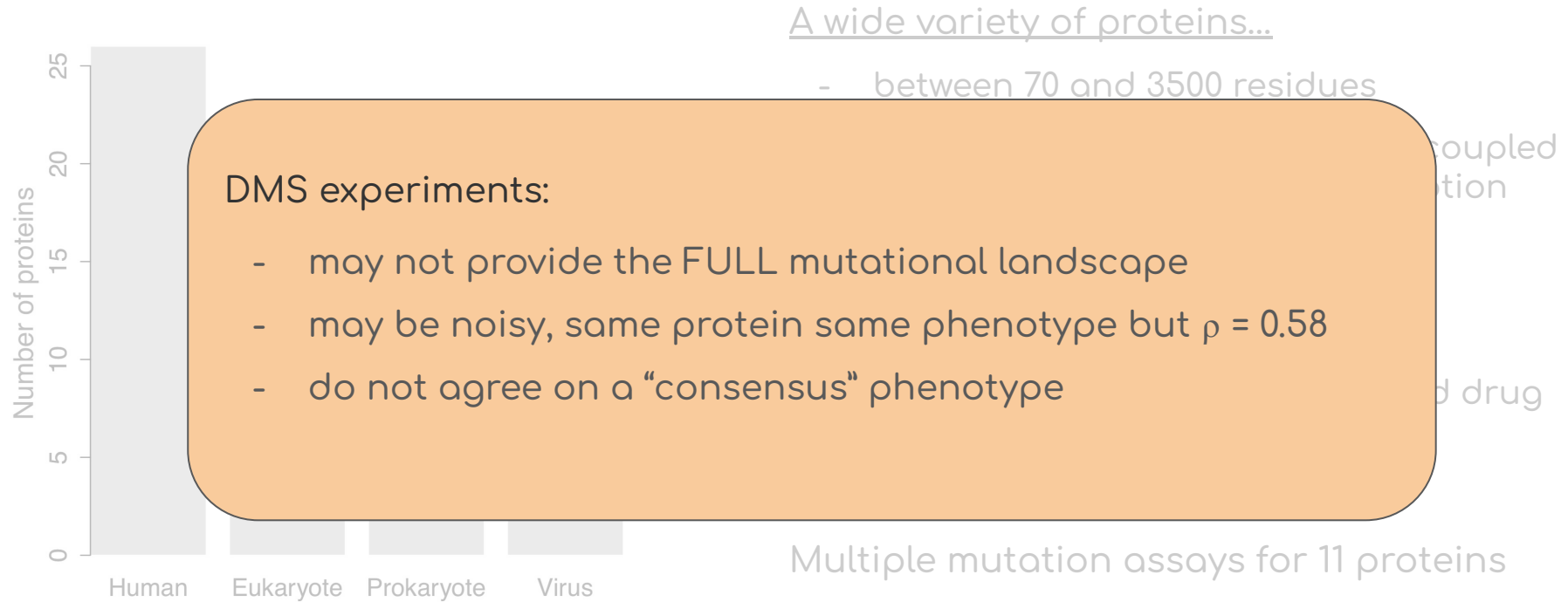
- thermostability, ligand binding, aggregation, viral replication, and drug resistance

Between 1 and 4 DMS assays per protein

Multiple mutation assays for 11 proteins

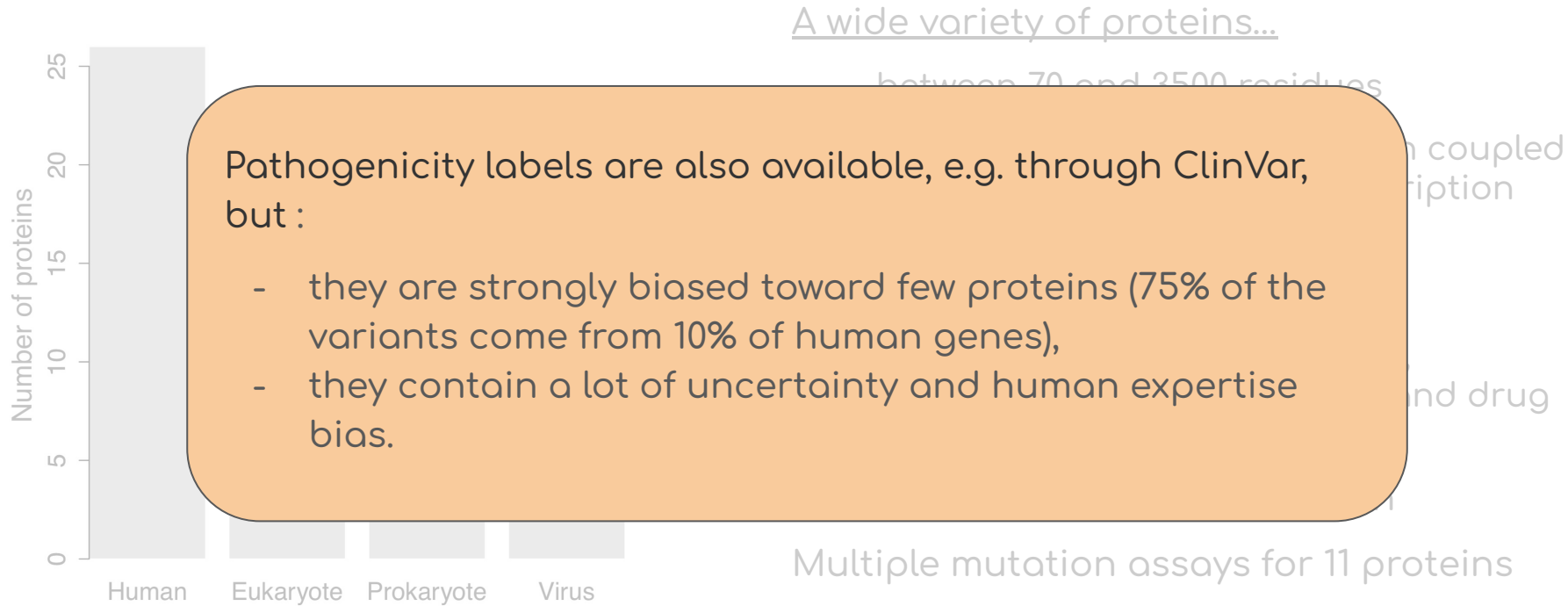
DMS (or MAVE) experiments remain too costly for proteome scanning.

ProteinGym substitution benchmark



DMS (or MAVE) experiments remain too costly for proteome scanning.

ProteinGym substitution benchmark



DMS (or MAVE) experiments remain too costly for proteome scanning.

Computational predictive methods

Supervised

Polyphen-2 (Adzhubei *et al.* 2013)

Envision (Gray *et al.* 2018)

Song *et al.* 2021

VESPA (Marquet *et al.* 2022)

FiTMuSiC (Tsishyn *et al.* 2023)

...

SOTA methods leverage protein
sequence information across species.
A few also exploit population data.

Weakly or Un-supervised

CADD (Kircher *et al.* 2014)

DCA (Figliuzzi *et al.* 2016)

DeepSequence (Riesselman *et al.* 2018)

GEMME (Laine *et al.* 2019)

PrimateAI (Sundaram *et al.* 2019)

EVE (Frazer *et al.* 2021)

ESM (Meier *et al.* 2021)

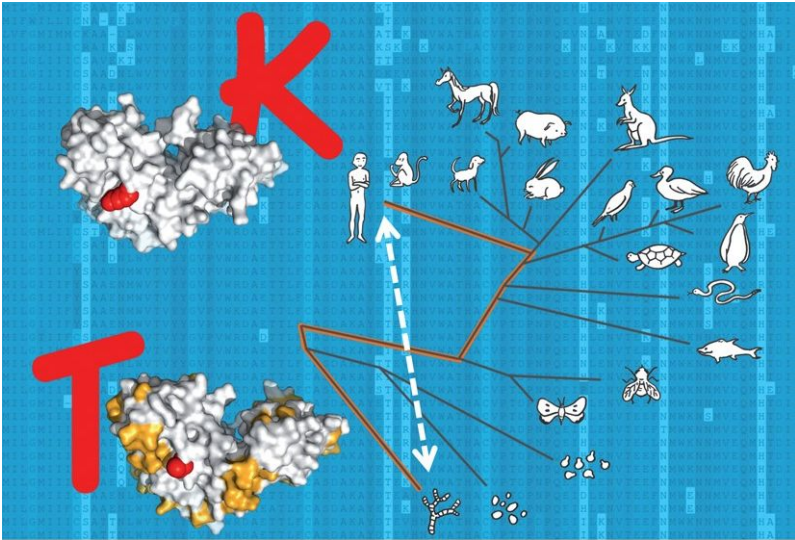
Tranception (Notin *et al.* 2022)

PoET (Truong Jr and Bepler 2023)

AlphaMissense (Cheng *et al.* 2023)

...

Explicitly exploiting
natural sequences
evolutionary history



GEMME - an evolutionary-informed predictor

Input

Query-centered multiple sequence alignment (MSA)

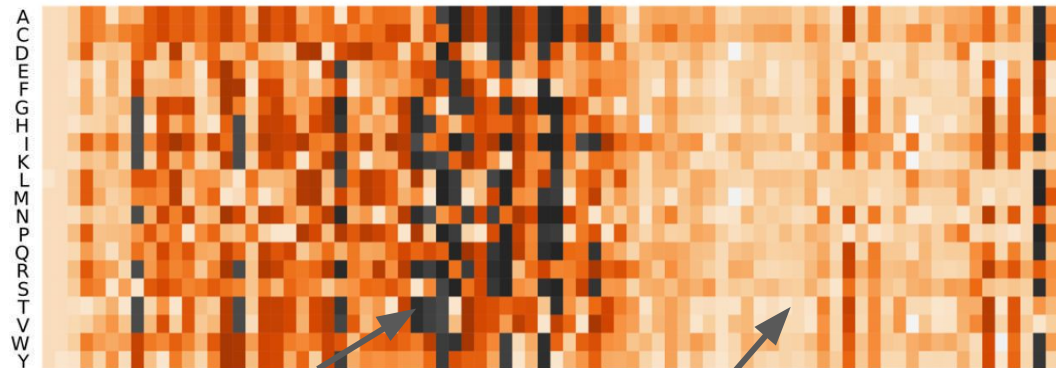


Aligned homologous sequences

GEMME

Output

Complete single-mutational landscape of the query

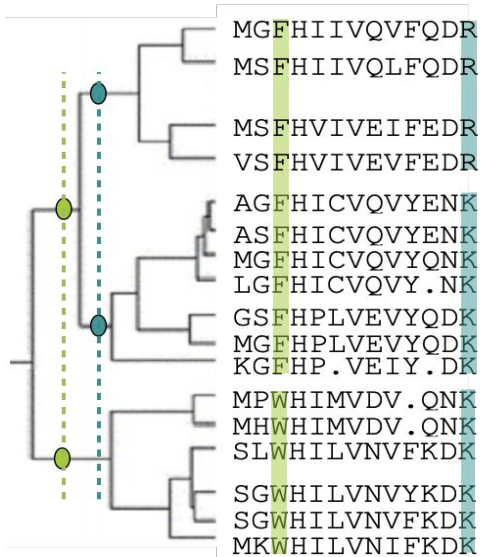


high impact

neutral

GEMME - an evolutionary-informed predictor

- Main hypotheses:
- **conservation** is an indicator of mutational sensitivity
 - **epistasis**: positions interact with each other

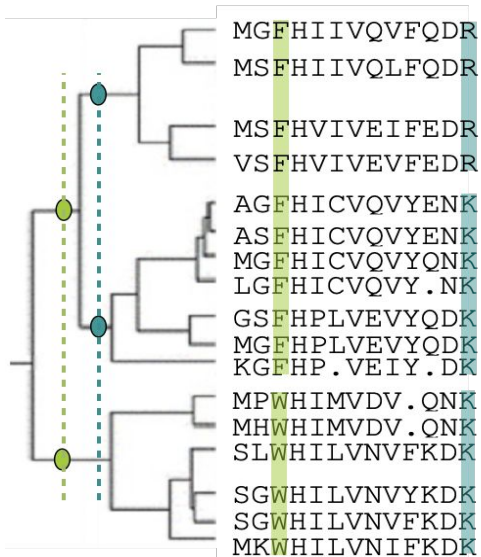


Joint Evolutionary Trees

S. Engelen *et al.* PLOS CB 2009

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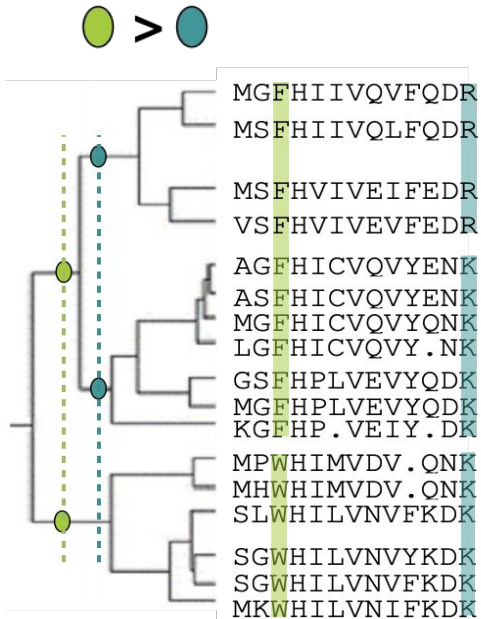
A measure of **conservation** accounting for the global context

Joint Evolutionary Trees

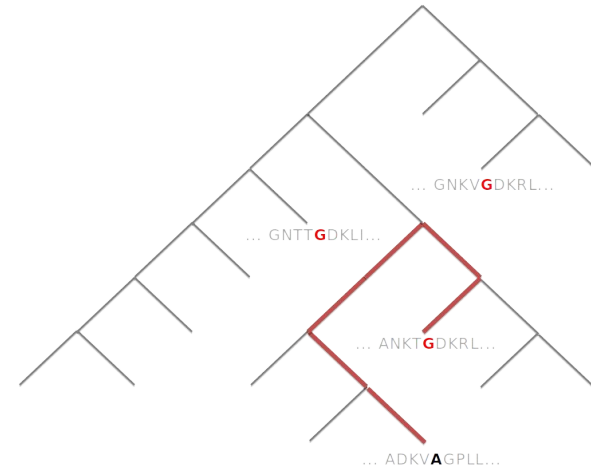
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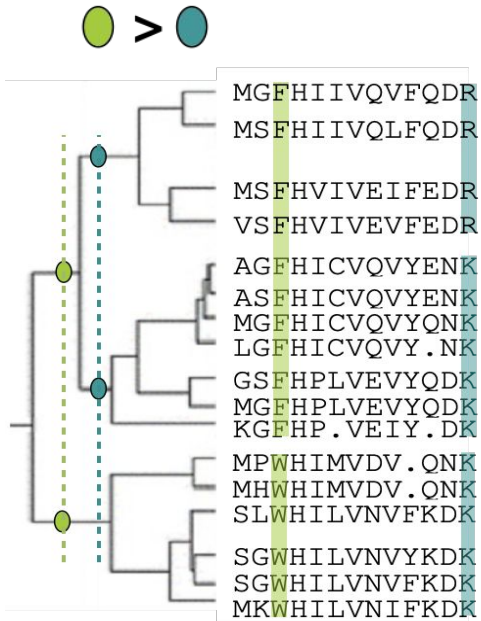
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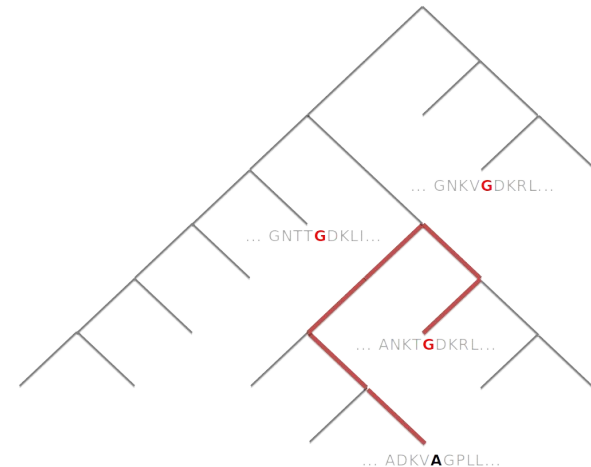
Joint Evolutionary Trees

GEMME - an evolutionary-informed predictor

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A measure of **conservation** accounting for the global context



Evolutionary distance to a natural sequence with the mutation



Joint Evolutionary Trees

GEMME - scaling to entire proteomes

GEMME provides a **clear readout** of the input alignment.

*many-to-many
sequence search*

ColabFold

MMseqs2
Uniref100 + Env.

<25K

ProteinGym-MSA

JackHMMer
Uniref100

<550K

*Profile HMM
search*

ProteinNet

JackHMMer
UniParc + Env.

<1.4M

Pfam

HMMer
UniProtKB

<300K

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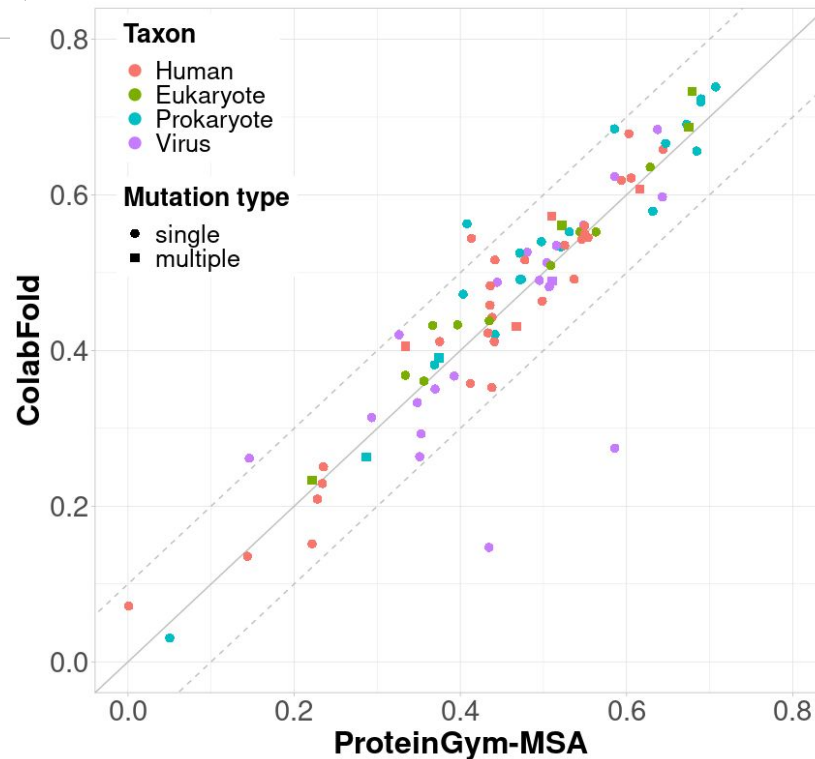
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The same prediction accuracy can be attained with **much cheaper** alignments.



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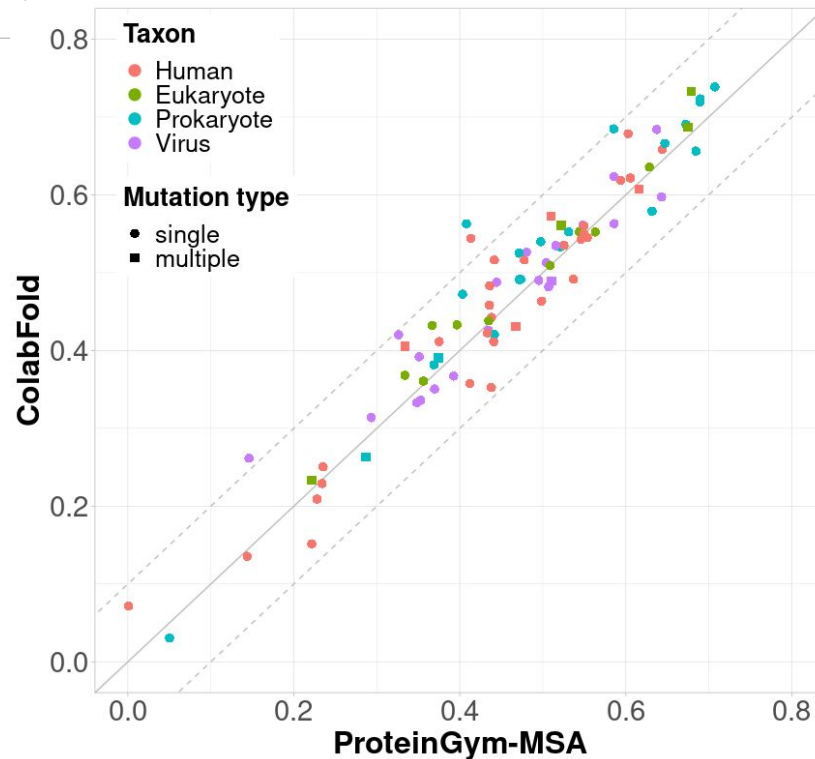
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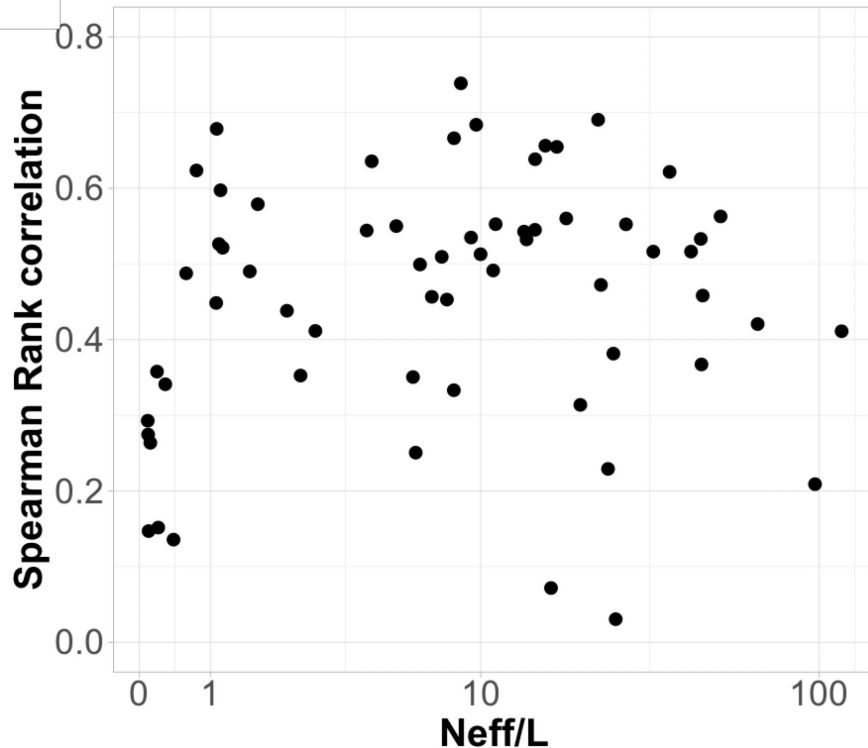
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Pfam

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<300K

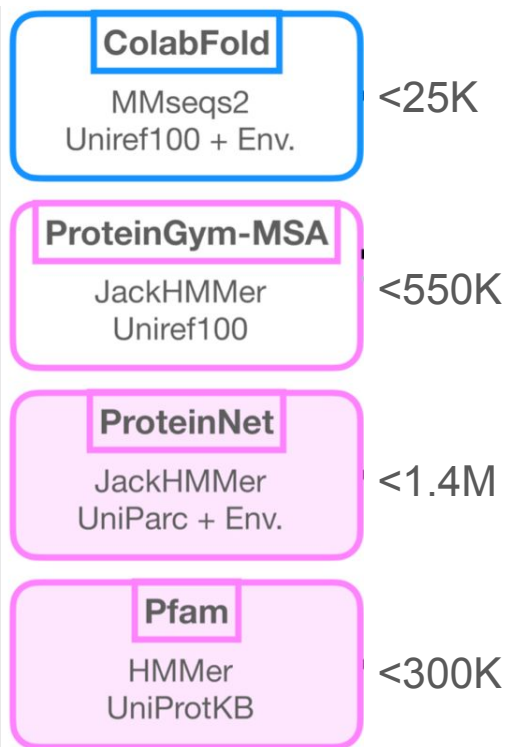
The alignment **depth** is not as good an indicator of prediction accuracy as one might expect.



GEMME - scaling to entire proteomes

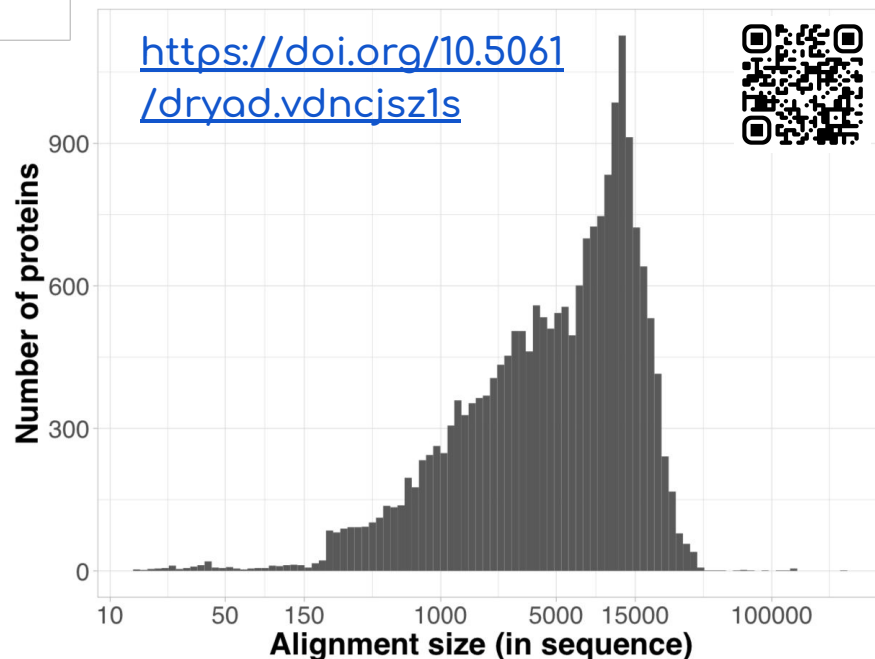
GEMME provides a **clear readout** of the input alignment.

*many-to-many
sequence search*



*Profile HMM
search*

Combining ColabFold & GEMME, it takes only **a few days** to generate the complete single-mutational landscape of the **human proteome**.

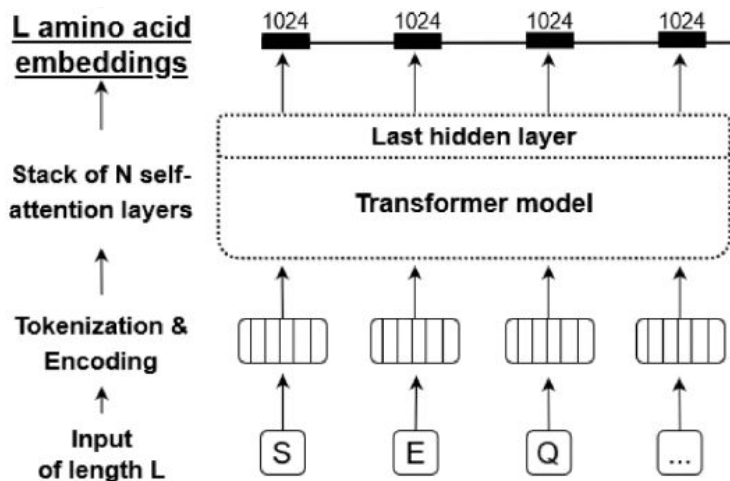


Modeling raw protein sequence data at scale



J. Searle's Chinese Room thought experiment

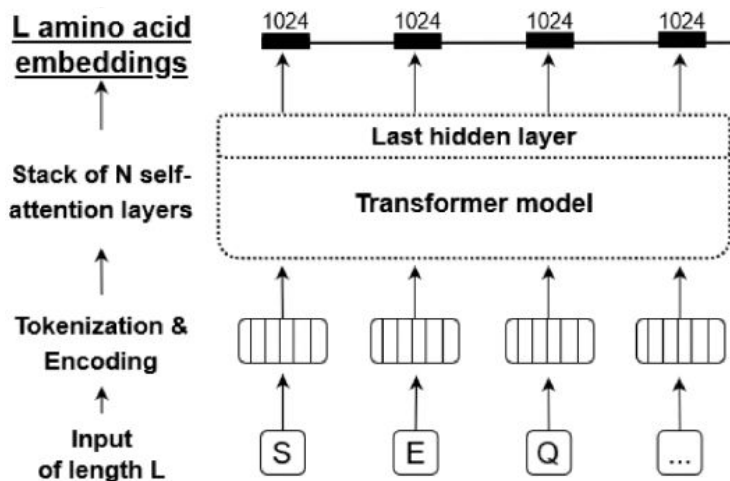
Large language models for proteins



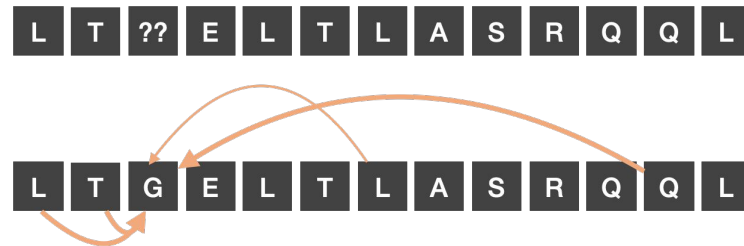
- High capacity **transformers**
- Input: single sequence (length L)
Output: high dimensional **embedding** $d \times L$
- Trained on hundreds of millions of protein sequences to reconstruct **masked** tokens

L T ?? E L T L A S R Q Q L

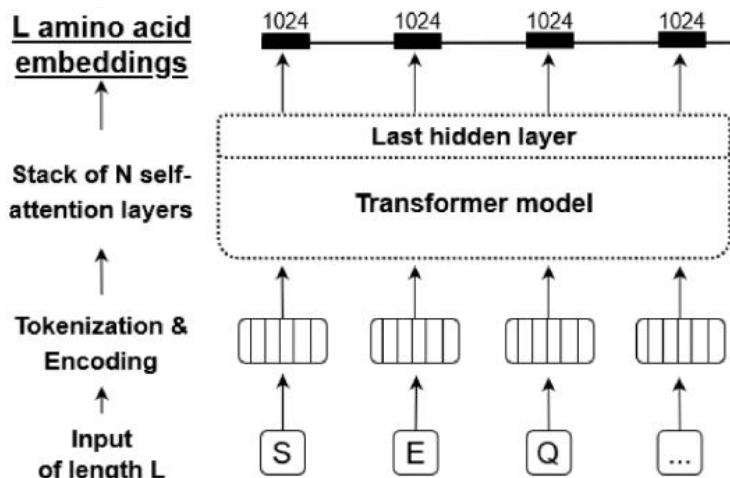
Large language models for proteins



- High capacity **transformers**
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Large language models for proteins



- High capacity **transformers**
- Input: single sequence (length L)
Output: high dimensional **embedding** $d \times L$
- Trained on hundreds of millions of protein sequences to reconstruct **masked** tokens
- They can be used as a **zero-shot** variant effect predictors through their log-odds ratios.

$$\log \frac{P(x^{mut})}{P(x^{wt})}$$

But they do not reach the state of the art.

Large language models for proteins

L amino acid
embeddin
↑
Stack of N
attention la
↑
Tokenizatio
Encodin
↑
Input
of length L

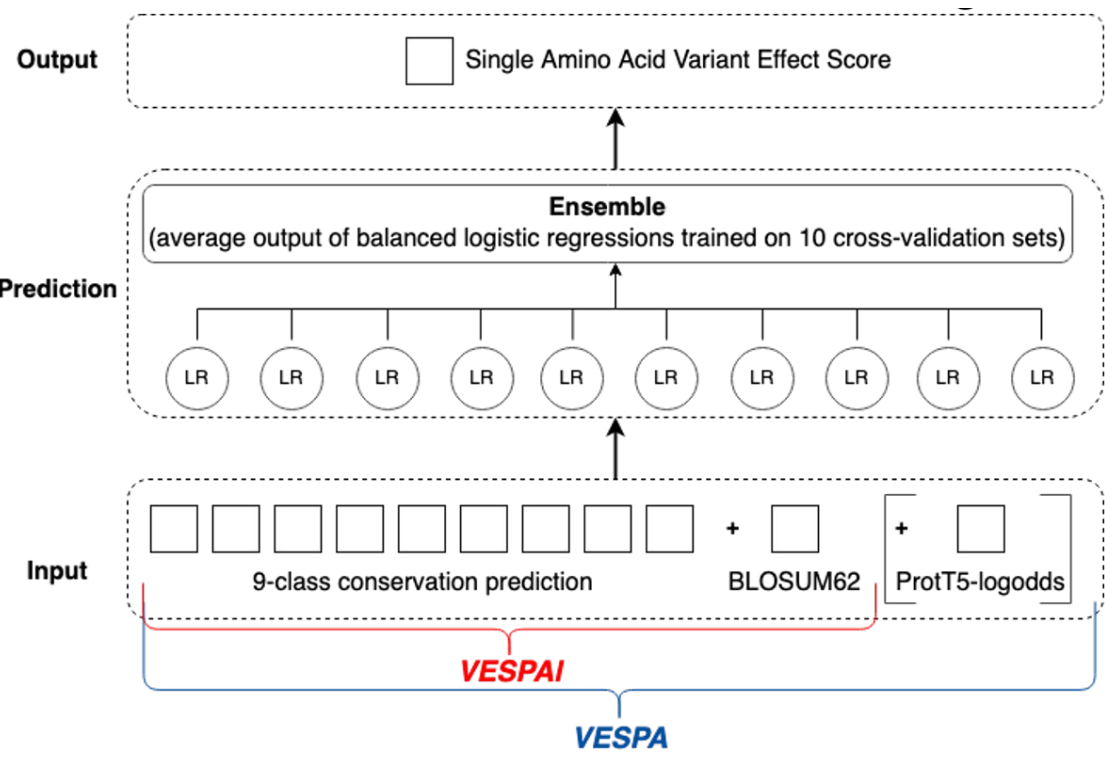
Limitation: they do not explicitly account for the evolutionary relationships between natural sequences.
Ways to overcome it:

- augmenting the input with alignments,
- extracting features from embeddings with supervision (3D structure, conservation, binary variant effect).

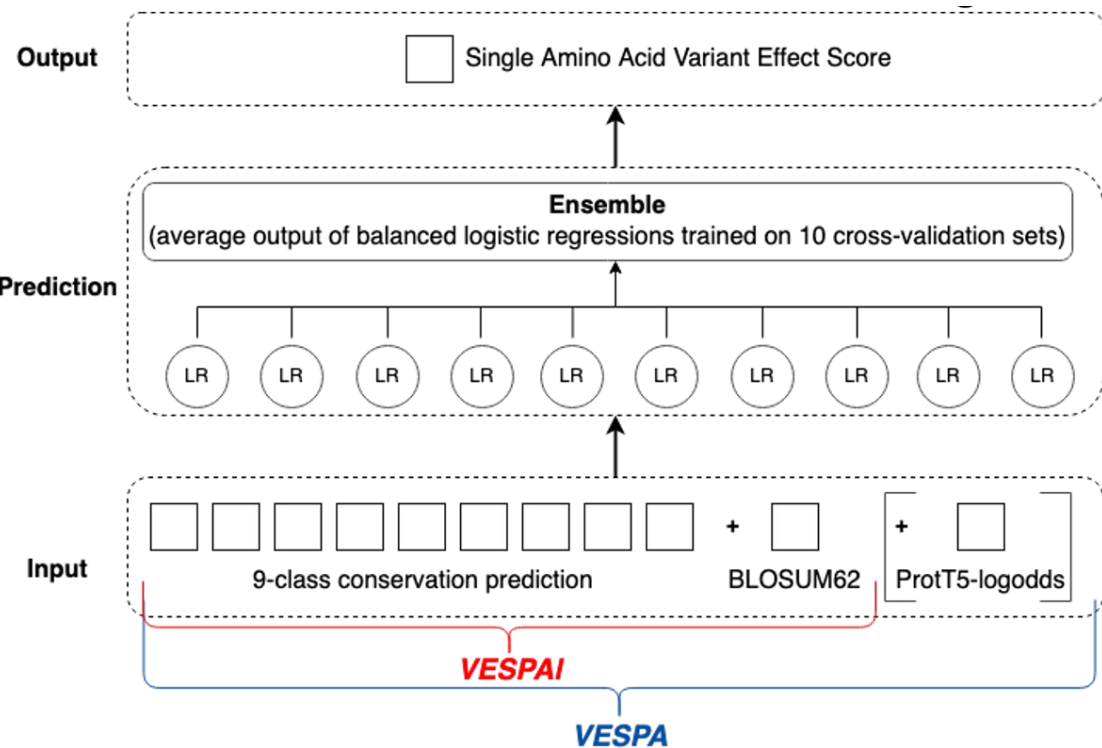
g d x L
protein
kens
t effect
ios.

But they do not reach the state of the art.

Variant Effect Score Prediction without Alignments



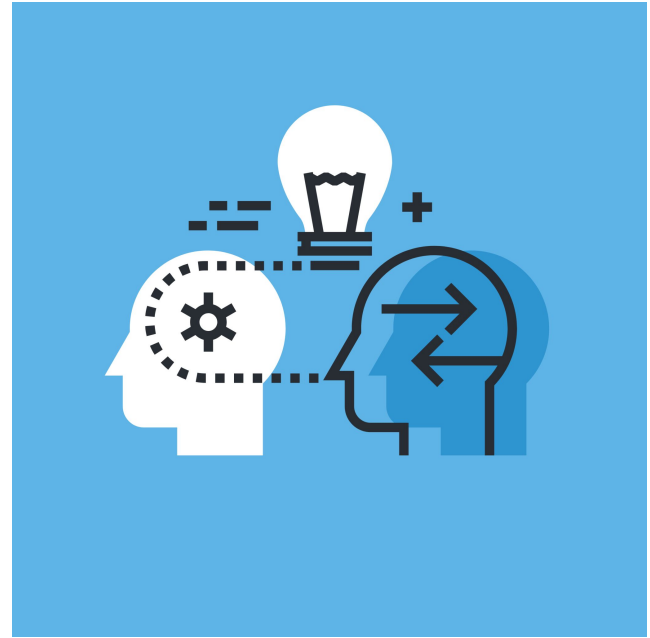
Variation Effect Score Prediction without Alignments



ProteinGym leaderboard

Rank	Model name	Model type	Avg. Spearman
1	TranceptEVE L	Hybrid model	0.472
2	GEMME	Alignment-based model	0.459
3	EVE (ensemble)	Alignment-based model	0.449
4	Tranception L	Hybrid model	0.446
5	VESPA	Protein language model	0.444
6	EVE (single)	Alignment-based model	0.443
7	MSA Transformer (ensemble)	Hybrid model	0.432
8	Tranception M	Hybrid model	0.430
9	DeepSequence (ensemble)	Alignment-based model	0.421
10	MSA Transformer (single)	Hybrid model	0.421
11	Tranception S	Hybrid model	0.419
12	EVmutation	Alignment-based model	0.413
13	Progen2 (ensemble)	Protein language model	0.413
14	VESPAI	Protein language model	0.408
15	DeepSequence (single)	Alignment-based model	0.404

Mapping learnt
representations to
mutational landscape
with an expert teacher



VespaG



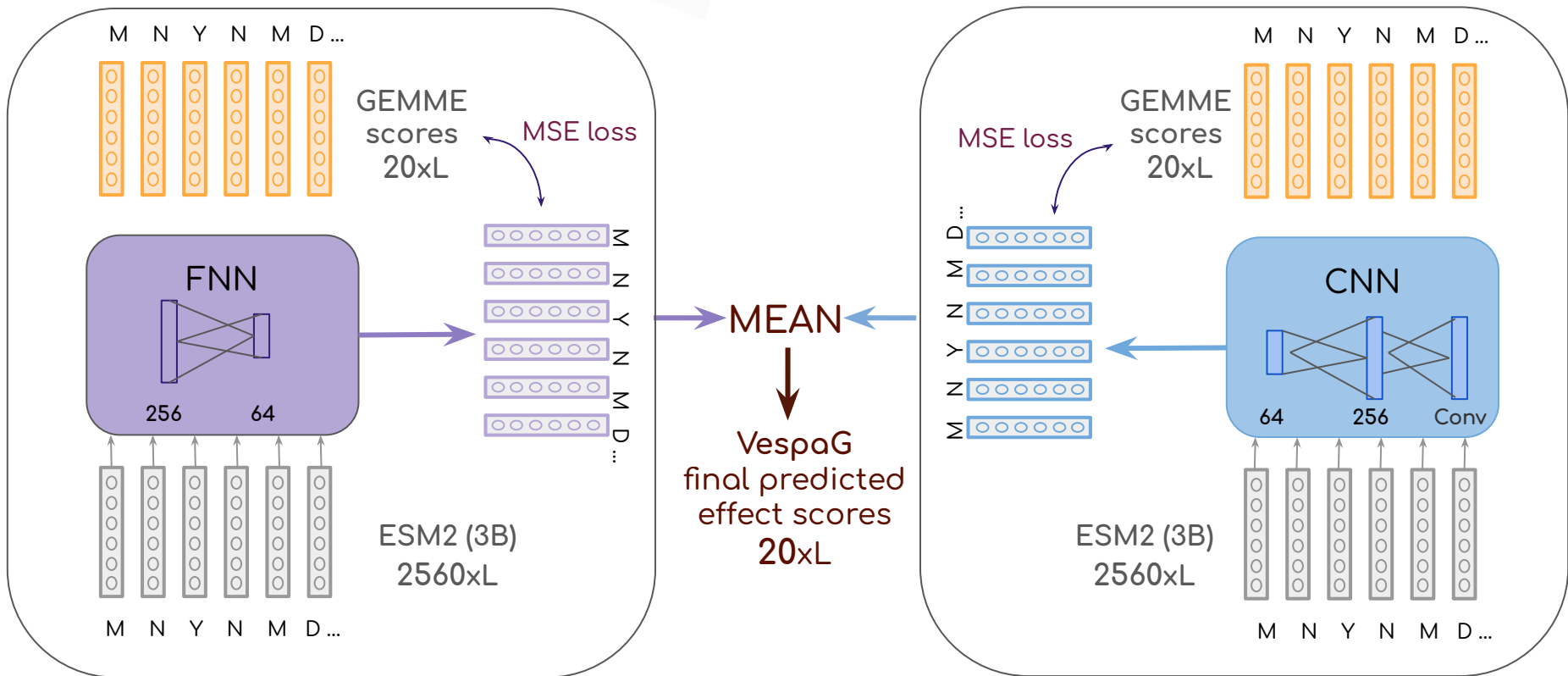
Main idea:

Directly mapping protein language model (pLM) embeddings to mutational landscapes, using an evolutionary-informed model (GEMME) as a **teacher**.

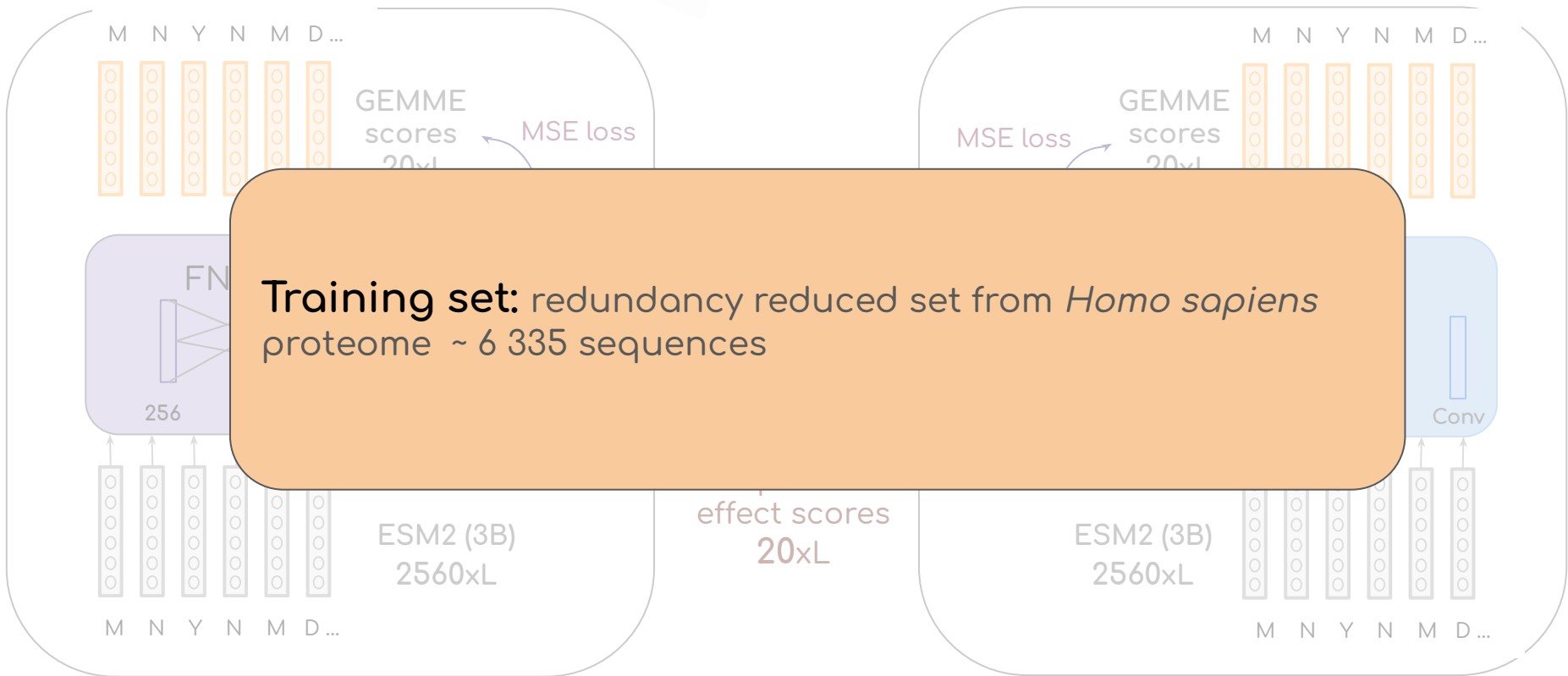
Advantages:

- Avoids the costly computation of log-odd ratios for all substitutions
- Largely increases the body of annotations
- Improves annotations' consistency

Architecture

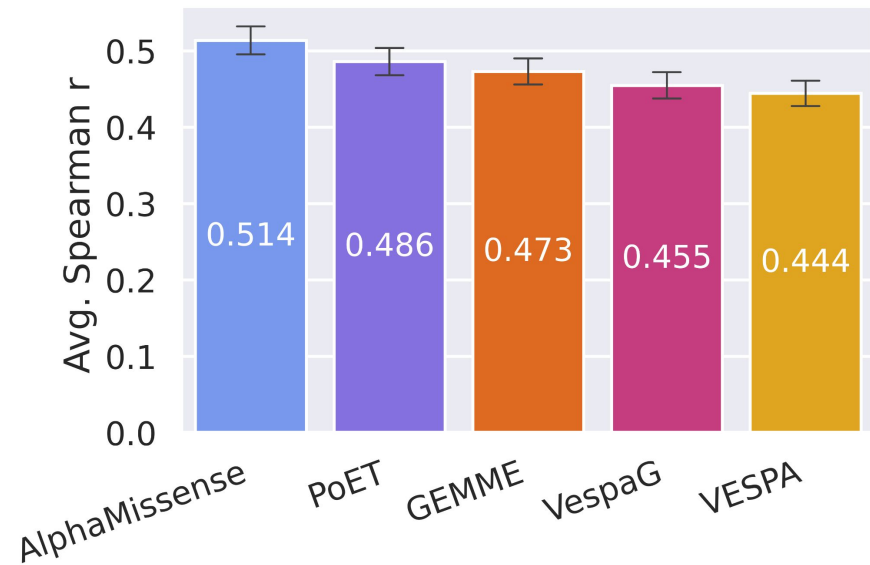


Architecture



Predictive performances

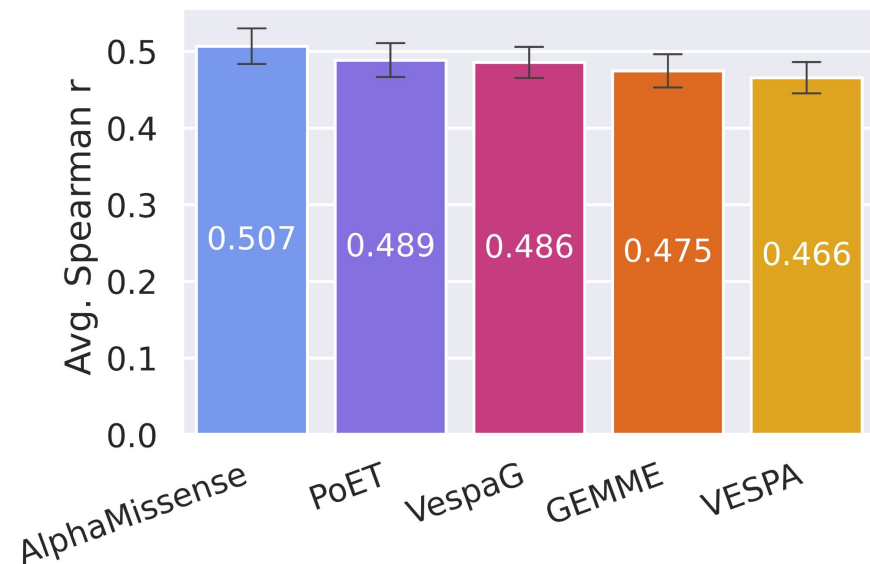
ProteinGym set (1.5M missense mutations)



VespaG achieves results similar to state-of-the-art methods.

Predictive performances

ProteinGym non-viral set (~1.4M missense mutations)

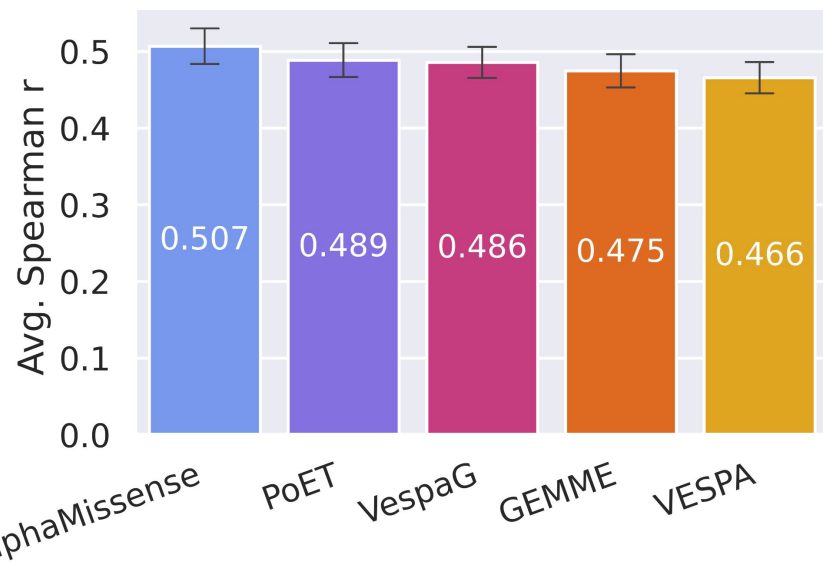


Performance increases when we disregard **viral** proteins.

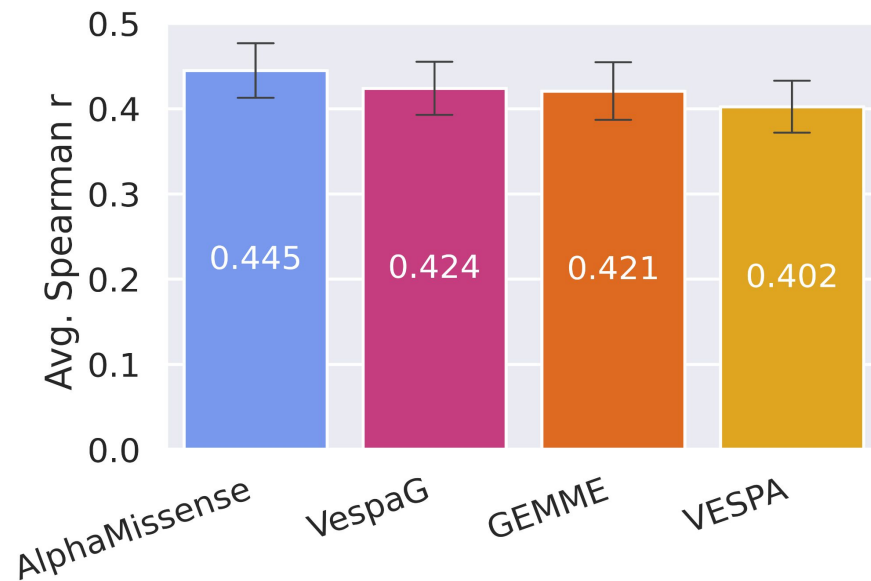
In line with previous observations that pLMs do not behave well with viral sequences.

Predictive performances

ProteinGym non-viral set (~1.4M missense mutations)

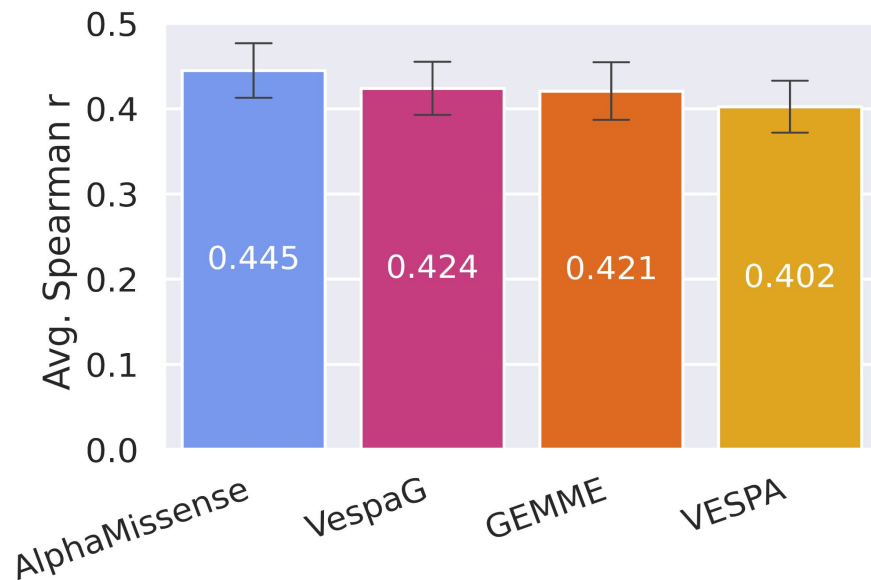
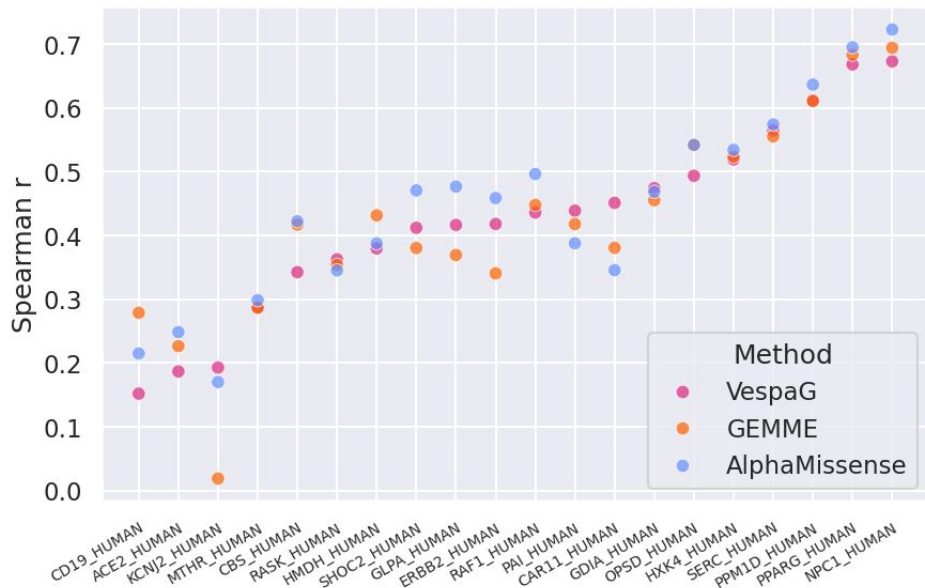


MoveHum23 23 DMS exp for 20 Human proteins (~266k SAVs) from Cheng et al. 2023







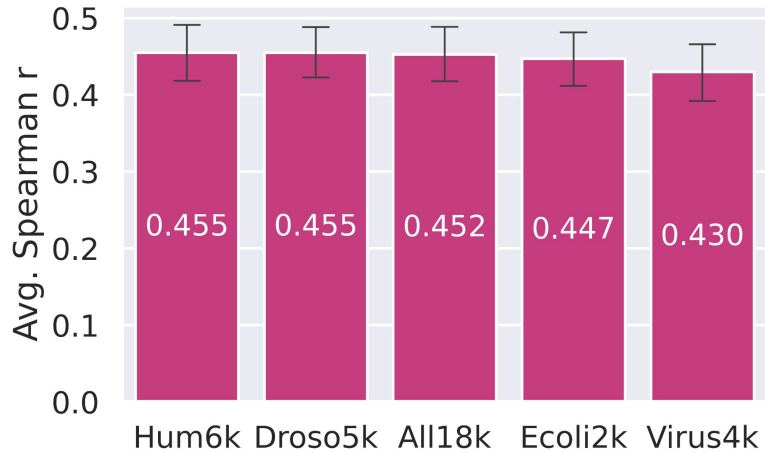
Predictive performances

MoveHum23 23 DMS exp for 20 Human proteins (~266k SAVs) from Cheng et al. 2023







Influence of the training set

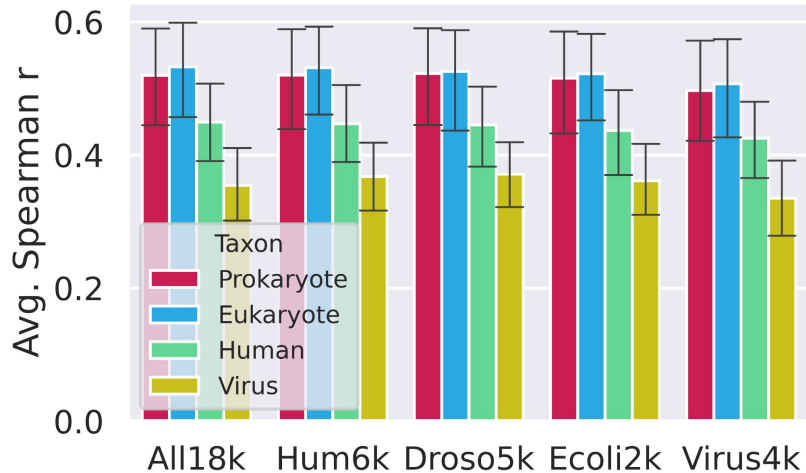
Dataset	Hum6k 	Droso5k 	Ecoli2k 	Virus4k 	All18k
Organism	<i>H.sapiens</i>	<i>D.melanogaster</i>	<i>E.coli</i>	All viral in SwissProt ¹	All
#(proteins)	6 294	5 650	2 108	4 027	18 079



- The performance **saturate** after a few thousands training proteins.
- Training on a **high-quality** proteome from a model species suffices.

Influence of the training set

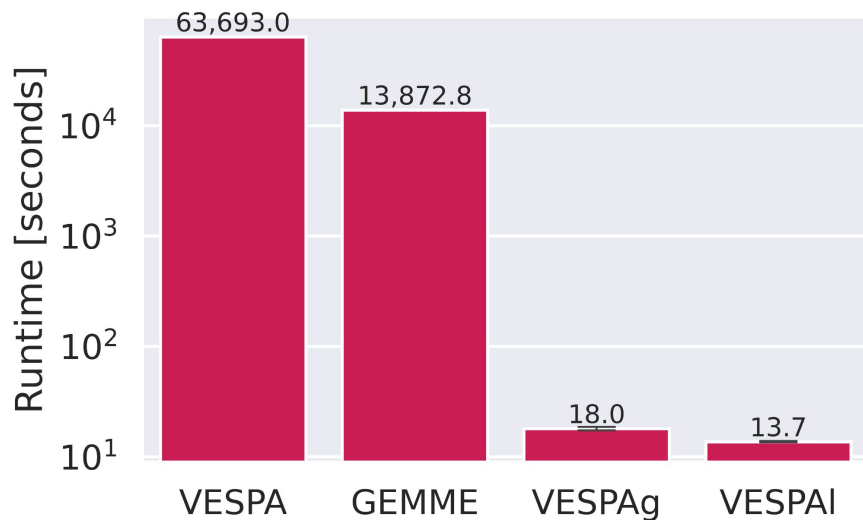
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#(proteins)	6 294	5 650	2 108	4 027	18 079



Training on viral sequences does not help for predicting viral variant effects.

Runtime

runtime on ProtonGym benchmark
(87 proteins)



VespaG provides **blazingly fast** state-of-the-art variant effect predictions from single-sequence-derived pLM embeddings.

Measured @ 64G RAM & 32 CPU cores (+46G VRAM for VESPA), excluding embedding/MSA generation

Conclusions and perspectives

VespaG can...

- directly map pLM embeddings to mutational landscapes
- transfer knowledge across organisms
- produce accurate predictions of variant effects
- scan entire proteomes within an hour

VespaG does not...

- deal well with viral sequences

=> needs further investigation to understand the relationship between predictive performance and the availability of homologous sequences.



Thank you!



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