Protein Language Models in Directed Evolution

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Background: Protein Development

- Key area in biotechnology
- Traditional methods are laborious and inefficient
 - Experimental directed evolution may require >10 000 screening samples
- ML-integrated protein engineering holds promise in de protein design and guided directed evolution
- Most ML models have lacked robustness

Abstract

Our approach: novel framework + *in vitro* data + validation

- Few-shot protein language modelling
 - Adapt MSA transformer to include *in vitro* fitness measurements
- Extensive model evaluation & variant characterisation *in vitro*
- Improved *in silico* sequence predictions for high-performing variants
 - **62%** improved PET degradation over starting variant
 - **16%** improved PET degradation over current state-of-the-art

In Silico Mutagenesis via Simulated Annealing



- heat-treated activity.

References

- Tournier V et al., Nature 2020;580(7802):216-219. doi:10.1038/s41586-020-2149-4
- Sulaiman S et al., PDB, 4EB0, 2012b. doi:10.2210/pdb4Eb0/pdb
- Rao R et al., bioRxiv 2021.02.12.430858; doi:10.1101/2021.02.12.430858



Mutation locations found in variants fitter than wild-type are shown in red; mutation locations found in variants less fit than wild-type are shown in blue. Highlighted on the crystal structure of LCC obtained from the protein databank, PDB ID: 4EB0



Conclusions

- High success rate: 39% of few-shot variants show improved fitness
- Wide exploration of protein space & scope for further improvement by recombining mutations
- Few-shot learning enables model tailoring to **diverse phenotypes**
- High sample efficiency: 240 in vitro examples used in 2nd round training