Protein Design and Variant Prediction Using Autoregressive Generative Models Supplementary Information

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Supplementary Figures



Supplementary Fig. 1. Autoregressive models of biological sequences. **a** Instead of finding correlations between columns in a multiple sequence alignment (left), the autoregressive model predicts a residue given all the preceding positions (right). **b** Causal dilated convolutions are used to model the autoregressive likelihood.





Supplementary Fig. 2. Individual scatterplots of the experimental results and the mutation effect prediction using the autoregressive model trained on each individual family of naturally occurring proteins. Experimental measures of fitness are on the y-axis and fitness predictions are on the x-axis. Spearman correlation values and corresponding two-tailed p-values are displayed per plot.



Supplementary Fig. 3. Comparison of model performance across datasets. **a** The Spearman correlation distributions of predictions for each model compared to 40 experimental datasets of deep mutational scans across 33 proteins, totaling 690,257. Two fragment lengths were used to build the HMM models (0.5 and 0.7), and only 0.5 is displayed in Figure 2. Two hidden sizes (24 and 48) were tested for the autoregressive model; 48 was chosen for further study. The box-plot elements are as follows: center line, median; box limits, upper and lower quartiles; whiskers, range of values. Mean and quartile values are displayed for each model in the box-and-whisker plot, whiskers span the entire range. **b** A comparison of model prediction Spearman correlations, including Envision LOPO prediction correlations. BRCA1 RING and UBE4B were validated but not tested by Envision due to poor validation performance. **c** A comparison of model predictions' Spearman correlation with every dataset for which experimental Spearman or Pearson correlations are available for biological or technical replicates. Pearson correlations have been included where a Spearman correlation is unavailable.



Supplementary Fig. 4. Spearman correlations for models trained on alignments of 8 protein families at 4 depths. Spearman correlations shown as-is (left) or normalized to the highest observed correlation for each family (right). Meff/L is the length-normalized number of nonredundant sequences after weighting sequences at 80% identity. Prediction accuracy for aliphatic amidase is nearly identical between a 151,555 sequence set (Meff=36,020; Meff/L=136; ρ =0.542) and a 3,982 sequence set (Meff=123; Meff/L=0.38; ρ =0.536).

Autoregressive:







Supplementary Fig. 5. Fitness prediction of the autoregressive and HMM models vs. experimental thermostability measurements from nanobody thermostability datasets for which there are at least ten data points. Thermostability measurements are in degrees Celsius and the fitness predictions are reported as log probability scores of each nanobody sequence. Spearman correlation values and corresponding two-tailed p-values are displayed per plot.



snoRNA insertions and deletions



Supplementary Fig. 6. Indel mutation scan measurement comparisons for three proteins and one RNA: IGP dehydratase, snoRNA, β -lactamase and P53. Spearman correlation values and corresponding two-tailed p-values are displayed per plot.



Supplementary Fig. 7. Pathogenic single amino acid deletions (as annotated by Clinvar) are predicted to be on the more deleterious spectrum of all possible single amino acid deletion effect predictions in a gene indicated in Alzheimer's (APOE), and two genes indicated in cancer (P53, BRCA1). Other single amino acid deletions that are predicted to be highly deleterious by the autoregressive model may be interesting to test for pathogenicity.





Supplementary Fig. 8. (top) *In silico* mutation scan of all single mutants for the human Tau protein, isoform Tau-4 (P10636-8). (bottom) Distribution of fitness predictions relative to wild-type for all mutations and for known variants annotated as pathogenic or not pathogenic in the Alzforum repository (<u>https://www.alzforum.org/mutations/mapt</u>). The box-plot elements are as follows: center line, median; box limits, upper and lower quartiles; whiskers, 1.5x interquartile range; points, outliers. Fitness predictions distinguish pathogenic and not pathogenic groups (two-tailed independent t=-4.5, p= 3.8×10^{-5} (****, *p* < 0.0001); AUC=0.86).



Supplementary Fig. 9. Compared to a synthetic library generated by codon randomization (McMahon et al., 2018), the designed library has more similar properties to the natural repertoire, while maintaining nearly the diversity of the synthetic library. **a** Synthetic CDR3s have slightly different distributions of hydrophobicity and isoelectric point from the natural repertoire, and the synthetic library contains CDR3s of 3 lengths rather than a broad length distribution. **b**, **c** The designed library contains nearly as much diversity as the synthetic library as measured by **b**, distances to the nearest neighbors within each library, and **c**, distances to the nearest neighbors in the natural llama single-domain antibody repertoire.



Supplementary Fig. 10. Full distributions of nanobody expression in the original synthetic library and our designed library. The designed library has a larger fraction of cells expressing nanobodies compared to the synthetic library (large difference in replicate 1 and small in replicate 2) and is closer to resembling the positive control. The vertical lines are the local minima between the non-expressing cells (the mode to the left of the line) and the expressing cells (to the right of the line). The distribution of the expressing cells are displayed in the main text in Fig. 4a.



Supplementary Fig. 11. Experimental measurements of polyreactivity in the designed library (green) as compared to the original synthetic library (blue) shows similar, if not slightly lower proportions of poly-reactive nanobodies in the designed library when sorted for binding to a non-specific insect cell membrane reagent. The log experimental fluorescent measurements are shown on the x-axis, in two replicates (left and right).

Design nanobody library



Synthetic nanobody library (McMahon, et al, 2018)



Supplementary Fig. 12. Example of flow cytometer yeast gating. Standard gating was used. Yeast form a single population in an FSC/SSC plot and were gated accordingly. Cells were further gated on an FSC-A/ FSC-H plot to exclude doublets. FL1-A uses AlexaFluor 647 and measures expression of the nanobodies per cell (Fig. 4a,b, Supplementary Fig. 10). FL4-A uses AlexaFluor 488 and is used to measure binding to antigen (HSA: Fig. 4c,d; PSR (poly-reactivity reagent): Supplementary Fig. 11).

Supplementary Tables

			# Mutations		Number			
	Uniprot ID (Nov		(mutant		of	Replicate	Correlation	
Protein name	2015)	Measurement	type)	Coverage	replicates	correlations	notes	Reference
B-alucosidase	(Sequence from dataset)	Enzyme	3000 (single)	1-501	2	0.97	Pearson R, from paper	Romero et al., PNAS 2015
p-graeosidase	uataset)	Tunetion	(single)	1-501	2	0.97	they report	11145,2015
							an	
							estimated	
			3000				error per	Firnberg et al. Mol
β-lactamase	BLAT ECOLX	Growth	(single)	24-286	1	n/a	nt	Biol Evol. 2014
							Pearson	
0.1	DI LE DOOL V	a 1	4997	a (a a a			R^2, from	Stiffler et al., Cell,
β-lactamase	BLAT_ECOLX	Growth	(single)	26-290	2	0.91	paper	2015
							experiment	
							al	
							conditions	
			000				reported, 1	Inoquiar at al
β-lactamase	BLAT ECOLX	MIC	(single)	24-286	1	n/a	each	PNAS 2013
							One	
			4998				replicate	Deng et al., JMB,
β-lactamase	BLAT_ECOLX	Growth	(single)	24-286	1	n/a	provided	2012
PSD95 (PDZ		Pentide	1578				replicate	McLaughlin et al
domain)	DLG4 RAT	binding	(single)	311-393	1	n/a	provided	Nature, 2012
							One	
GAL4 (DNA-		a 1	1196			,	replicate	Kitzman et al., Nat
binding domain)	GAL4_YEAST	Growth	(single)	2-65	1	n/a	Pearson	Methods, 2015
Influenza	(Sequence from	Viral	10717			0.66, 0.59,	R^2, from	Doud & Bloom,
hemagglutinin	paper)	replication	(single)	2-565	3	0.59	paper	Viruses, 2016
							Pearson	
							R^2, from	
							only for 20	
HSP90 (ATPase			4324				amino acid	Mishra et al., Cell
domain)	HSP82_YEAST	Growth	(single)	2-231	2	0.92	positions	Reports, 2016
Kanamycin kinase			4582- 4996				Pearson R	Melnikov et al
APH(3')-II	KKA2 KLEPN	Growth	(single)	1-264	2	0.91	from paper	NAR, 2014
			1957				••	
	(, 1 ¹¹ 1		(single,					
DNA methylase	(stabilized sequence		full), 1778 (single				One	al PLOS Comp
HaeIII	MTH3 HAEAE)	Growth	filtered)	2-330	1	n/a	provided	Bio, 2015
Influenza	/		ĺ				•	
polymerase PA	(Sequence from	Viral	1822	0.716	2	0.07	Pearson R,	Wu et al., PLOS
subunit	paper)	replication	(single)	8-/16	2	0.96	from paper	Genetics, 2015
Poly(A)-binding			(single),				One	
protein (RRM			36522				replicate	Melamed et al.,
domain)	PABP_YEAST	Growth	(double)	126-200	1	n/a	provided	RNA, 2013
		Viral	1632	1994-			replicate	Oietal PLOS
Hepatitis C NS5A	POLG HCVJF	replication	(single)	2097	1	n/a	provided	Pathogens, 2014
							Pearson	
TH: '.'	DI 401 MEACT	C 1	1196	2.76	2	0.02	R^2, from	Roscoe et al, JMB,
Obiquitin	KL401_YEASI	Growth	(single)	2-70	2	0.93	Pearson	2013
			1366				R^2, from	Roscoe et al, JMB,
Ubiquitin	RL401_YEAST	E1 reactivity	(single)	2-76	2	0.96	paper	2014
LIDEAD (II have			000	1072			One	Storito at c1 DNIAS
domain)	UBE4B MOUSE	Ligase activity	(single)	1173	1	n/a	provided	2013

YAP1 (WW domain 1)	YAP1 HUMAN	Peptide binding	363 (single)	170-203	1	n/a	One replicate provided	Araya et al., PNAS, 2012
Aliphatic amidase	AMIE PSEAE	Enzyme function	4507- 4554 (single)	1-341	1	0.889	Pearson R, from paper	Wrenbeck et al., Nat Commun, 2017
TIM Barrell (T. thermophilus)	P84126_THETH	Growth	1520 (single)	44-238	1	n/a	One replicate provided	Chan et al., Nat Commun, 2017
TIM Barrell (S. solfataricus)	TRPC SULSO	Growth	1520 (single)	44-235	2	0.946	Pearson R, from paper, but only for 20 amino acid positions	Chan et al., Nat Commun, 2017
TIM Barrell (T.	TRPC THEMA	Growth	1520 (single)	40-230	1	n/a	One replicate provided	Chan et al., Nat Commun, 2017
Translation initiation factor IF-1	IF1 ECOLI	Growth	1274 (single)	1-72	1	n/a	One replicate provided	Kelsic et al., Cell Systems, 2016
Mitogen-activated			5463	2.2(0	1.6	0.00	Pearson R, calculated from raw	Brenan et al., Cell
Hras	RASH HUMAN	Enzyme function	3040 (single)	2-360	1	n/a	One replicate provided	Bandaru et al., Elife, 2017
Ubiquitin	RL401 YEAST	Growth	1142- 1201 (single)	2-76	2	0.79	Pearson R^2, from paper	Mavor et al., Elife, 2016
BRCA 1 (RING domain)	BRCA1_HUMAN	Growth	492 (single)	1631- 1855	2	0.88	Spearman R, from paper	Findlay et al., Nature 2018
BRCA 1 (BRCT domain)	BRCA1_HUMAN	Growth	1185 (single)	1-101	2	0.88	Spearman R, from paper	Findlay et al., Nature 2018
Thiopurine S- methyltransferase	TPMT_HUMAN	Protein stability	2659 (single)	1-245	8	0.67	Spearman R, from paper	Matreyek et al., Nat Gen, 2019
Phosphatidylinositol 3,4,5-trisphosphate 3-phosphatase and dual-specificity protein phosphatase PTEN	PTEN HUMAN	Protein stability	3014 (single)	2-403	8	0.62	Spearman R, from paper	Matreyek et al., Nat Gen, 2019
Levoglucosan kinase (stabilized)	(Stabilized sequence based on B3VI55 LIPST)	Growth	6327 (single)	1-439	2	n/a	Plot provided, but no correlation metric	Klesmith et al., ACS Synth Bio, 2015
Levoglucosan kinase	B3VI55_LIPST	Growth	6541 (single)	1-439	2	n/a	Plot provided, but no correlation metric	Klesmith et al., ACS Synth Bio, 2015
HIV env protein (BF520)	(Sequence from paper)	Viral replication	12236 (single)	30-691	3	0.59,0.60,0. 64	Pearson R, from paper	Haddox et al. Elife, 2018
(BG505)	(Sequence from paper)	replication	12217 (single) 496137	30-699	3	0.76,0.77,0. 78	from paper	Pokusaeva et al.
Imidazoleglycerol- phosphate dehydratase (His3)	HIS7 YEAST	Growth	(1-28 mutations	1-220	2	0.9	Pearson R^2, from paper	PLOS Genetics, 2019 (bioRxiv 2017)
Calmodulin-1	CALM1_HUMAN	Yeast growth	1730 (single)	2-149	1	n/a	One replicate provided	Weile et al., MSB, 2017

Thiamin pyrophosphokinase 1	TPK1 HUMAN	Yeast growth	2608 (single)	2-243	1	n/a	One replicate provided	Weile et al., MSB, 2017
	-						One	
Small ubiquitin-			1329				replicate	Weile et al., MSB,
related modifier 1	SUMO1_HUMAN	Yeast growth	(single)	2-101	1	n/a	provided	2017
SUMO-conjugating			2281				Pearson R,	Weile et al., MSB,
enzyme UBC9	UBC9_HUMAN	Yeast growth	(single)	2-158	2	0.78	from paper	2017

Supplementary Table 1. Deep mutational scans included in the paper and information regarding the experimental data, including sequence information, number of mutations, and experimental replicate measurements.

		Original #	Original				Sequence		Original	Spearman
Protein name	Uniprot ID	sequences	Meff	Bitscore	# sequences	Meff	coverage	Meff/L	spearman	correlation
	KKA2_KLEPN	29705	9380	0.3	56823	17439	240	72.66	0.554	0.551
Kanamycin kinase				0.5	4314	1034	250	4.14		0.501
APH(3')-II				1	1636	318	255	1.25		0.344
				1.5	119	14	255	0.05		0.144
	BLAT_ECOLX	14691	3667	0.3	40391	10013	253	39.58	0.741	0.738
B lastamasa				0.5	27648	6691	257	26.04		0.760
p-lactallase				1	14614	2346	257	9.13		0.720
				1.5	1539	22	262	0.08		0.290
	HSP82_YEAST	23260	2586	0.3	45433	5672	222	25.55	0.473	0.410
HSP90 (ATPase				0.5	43521	4517	223	20.26		0.483
domain)				1	32922	3176	225	14.12		0.476
				1.5	4719	137	226	0.61		0.255
	BRCA1_HUMAN	39129	6304	0.3	251665	37215	60	620.25	0.571	0.539
BRCA 1 (RING				0.5	78851	9508	76	125.11		0.559
domain)				1	1125	44	109	0.40		0.451
				1.5	845	5	110	0.05		0.380
	BRCA1_HUMAN	8331	1883	0.3	13773	2829	205	13.80	0.545	0.553
BRCA 1 (BRCT				0.5	3272	635	215	2.95		0.508
domain)				1	1099	63	223	0.28		0.421
				1.5	808	17	225	0.08		0.441
	PTEN_HUMAN	8487	994	0.3	15397	1475	323	4.57	0.536	0.527
DTEN phosphotose				0.5	13168	1100	325	3.38		0.518
r i En phosphatase				1	1314	146	392	0.37		0.413
				1.5	709	6	403	0.01		0.245
	AMIE_PSEAE	76187	19554	0.3	151555	36020	264	136.44	0.578	0.542
Aliphatic amidase				0.5	3982	123	324	0.38		0.536
				1	2145	44	340	0.13		0.479
				1.5	2087	27	340	0.08		0.480
	GAL4_YEAST	22980	7026	0.3	156727	42406	47	902.26	0.622	0.548
GAL4 (DNA-				0.5	98386	25868	49	527.92		0.597
binding domain)				1	354	91	67	1.36		0.415
				1.5	101	40	74	0.54		0.325

Supplementary Table 2. Spearman correlations of predictions with experiments using training sequence sets derived from alignments at four different bitscores. Meff is the number of nonredundant sequences after weighting sequences at 80% identity. Sequence coverage is the length of the focus sequence covered by the alignment, including non-focus columns that would have been excluded by alignment-based models.

		Number of
Reference	Dataset description	datapoints
Zabetakis, et al., PLoS One, 2013	Different regions stitched together	12
	Various point mutations introduced in	
Shriver-Lake, et al., Toxicon, 2017	different frameworks	23
Turner, et al., Biotechnol Rep,	Variety of mutation types (15 without	
2015	disulfide linkage)	19
Kunz, et al., Biochim Biophys,	Potentially stabilizing variants	
2017	designed based on sequence analysis	17

Supplementary Table 3. Description of thermostability datasets for llama nanobody sequences used to validate the model's predictive capacity for nanobodies.

Protein			Replicate	Correlation	
name	Uniprot ID	# Mutations	correlations	notes	Reference
PTEN	PTEN HUMAN	340 (deletions)	0.58		Mighell et al., Am. J. Hum. Genet., 2018
HIS3	HIS7_YEAST	5711 (deletions), 391 (insertions)	n/a	197 isolated strains show r = 0.82 for fitness as measured by competition vs growth rate	Pokusaeva et al., PLOS Genetics, 2019
snoRNA	CL00100 (RFAM)	3896 (insertions), 22772 (deletions), 33144 (missense)	0.87	many different measurements with different correlations, but the two with the same conditions: small, 30, glu has a correlation of 0.87	Puchta et al., Science, 2016
		357 (deletions), 5858			Kotler et al., Mol Cell, 2018
P53	P53_HUMAN	(missense)	n/a	n/a	
BLAT	BLAT ECOLX	262 (deletions), 4422 (insertions)	n/a	n/a	Gonzalez et al., J Mol Biol. 2019

Supplementary Table 4. Indel mutation scans that were used for validating the model's predictive power for sequences of different lengths. Experimental scans are included in the paper and their summary statistics.

Step	Number of sequences (millions)
Generate sequences	33.0
Filter for reference final beta strand	23.6
Remove duplicate sequences	21.7
Remove duplicates of training set	6.25
Remove glycosylation motifs	6.11
Remove asparagine deamination motifs	6.04
Remove sulfur-containing amino acids	3.69

Supplementary Table 5. Number of unique nanobody sequences remaining after each step of filtering of the designed nanobody library.

Oligonucleotide name	Sequence
	GCTGCCCAGCCGGCGATGGCCCAGGTCCAACTTCAAGAAT
	CAGGCGGGGGCCTGGTACAGGCAGGCGGTTCTCTCGGCT
	GTCGTGTGCGGCAAGCGGATTTACATTCAGTAGCTACGCT
	ATGGGCTGGTACCGTCAGGCACCGGGGAAAGAACGGGAA
	TTTGTTGCTGCAATCTCTTGGAGCGGTGGGAGCACATATT
	ATGCAGATTCCGTTAAAGGCAGATTCACGATCAGTCGCGA
	TAACGCAAAAAATACAGTGTACTTACAAATGAACTCTTTG
	AAACCCGAAGACACCGCAGTCTATTACTGCGCGGCCGCTA
	CTGGGGACAAGGCACCCAGGTGACTGTATCATCCCACCAC
FragmentGENE NbCM	CACCACCACTGA
	GGTGTTCAATTGGACAAGAGAGAAGCTGACGCAGAAGTC
NILCM audoE2.0	CAACTTGTCGAATCAGGCGGGGGGCCTGGTACAG
NOCIVI pydsr2.0	
NbCM_pydsR	AUTCACCIOOUT
	CAACCCTCACTAAAGGGCGTTCGCCATGAGATTCCCATCT
	ATCTTCA
NotI_removal_1F	
Pyds_NbCM_cloning_ R	CACCTGGGTGCCTTGTCCCCAGTA

Supplementary Table 6. Oligonucleotides used for synthesis and construction for the nanobody library.