

## University of Cologne | University Hospital Cologne | Institute of Virology | Laboratory for Viral Resistance Research

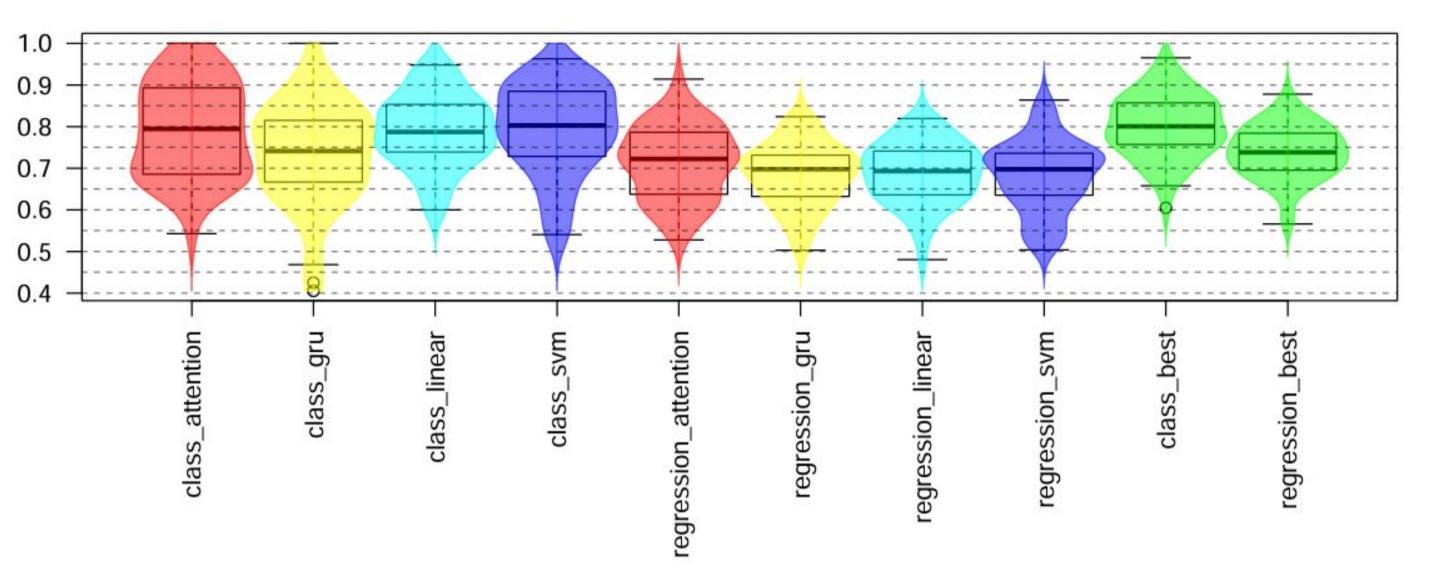
# Geno2pheno-bNAbs: Interpretable and accurate prediction of HIV bNAb resistance

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#### Background

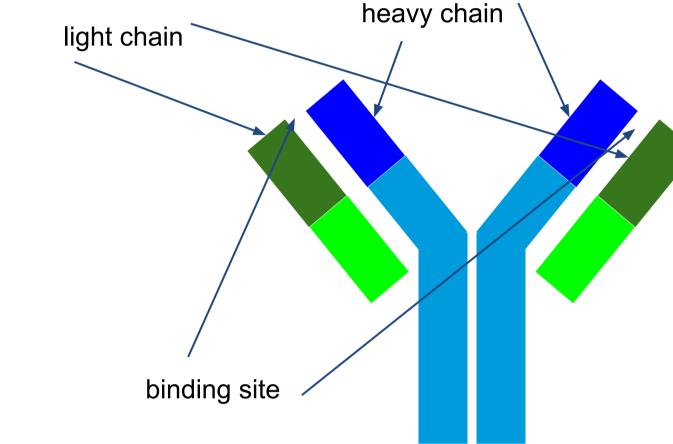
HIV ist still a serious issue with many deaths, especially in countries with poor access to therapeutic options. Antiretroviral therapy (ART) is a useful option for people living with HIV (PLWH) and effective against many viral strains. However, most ARTs are still a relatively large inconvenience for PLWH. The most common ARTs involve combinations of drugs targeting viral or cellular proteins. Most of these drugs have to be taken every day. An alternative to



test accuracy

ARTs with protein inhibitors are broadly neutralizing antibodies (bNAbs, Figure 1). These have been shown to yield long-term viral suppression and have to be administered only once every several weeks or even months. However, bNAbs share the problem of viral resistance with protein inhibitors.

Solutions that are accurate, interpretable and easy to use are necessary to tackle the problem of predicting viral resistance to bNAbs. We developed a web-service g2p-bNAbs that allows users to upload one or more viral genotypes and our service uses trained models to predict resistance to many common bNAbs. The predictions consist of classification (sensitive or resistant) and the IC50 score.



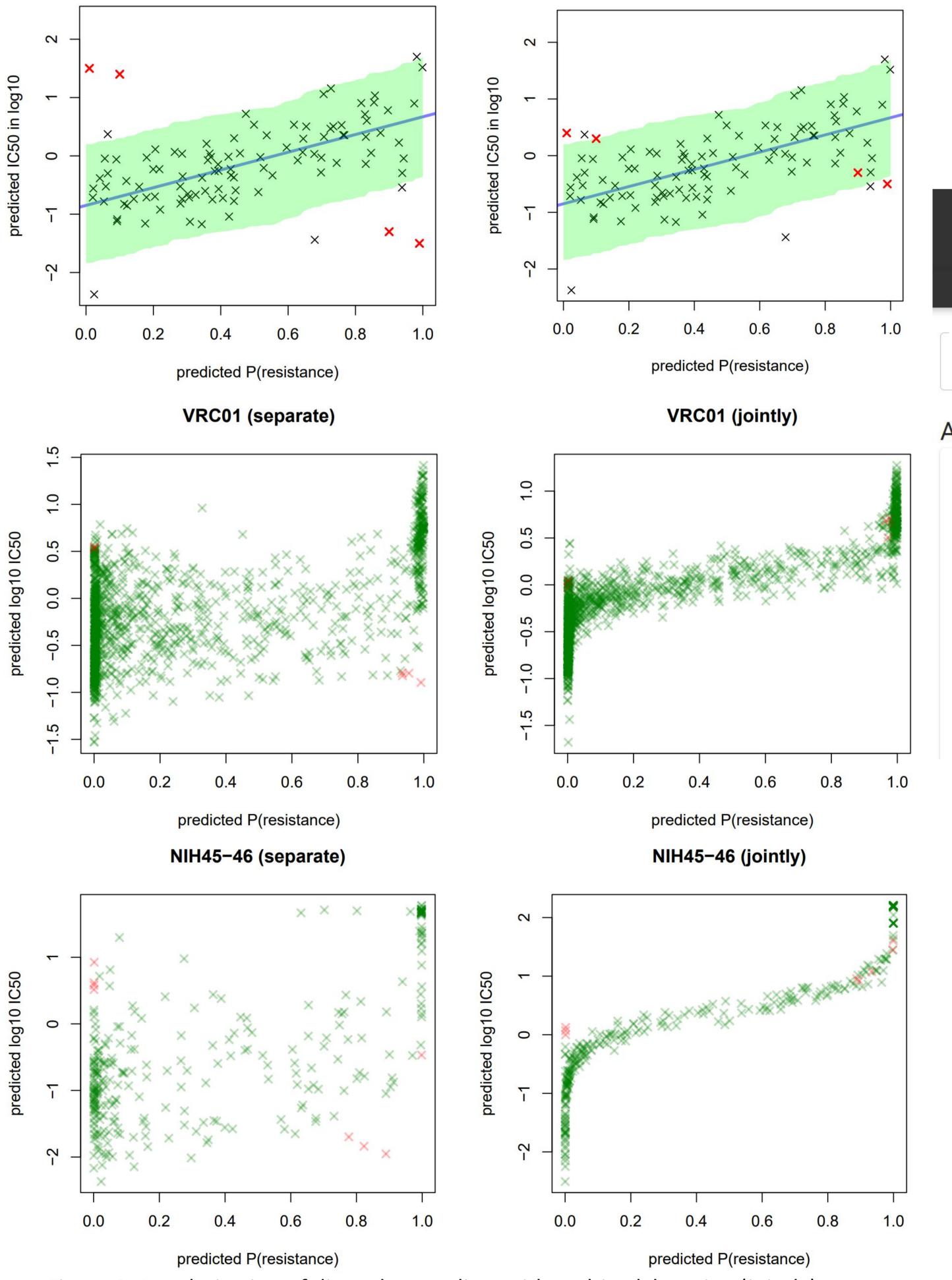


Figure 3: Accuracy of classification (area under the receiver operating characteristic) and regression (Harrell's concordance index<sup>b</sup>) of the different models over 50 bNAbs.

#### Methods

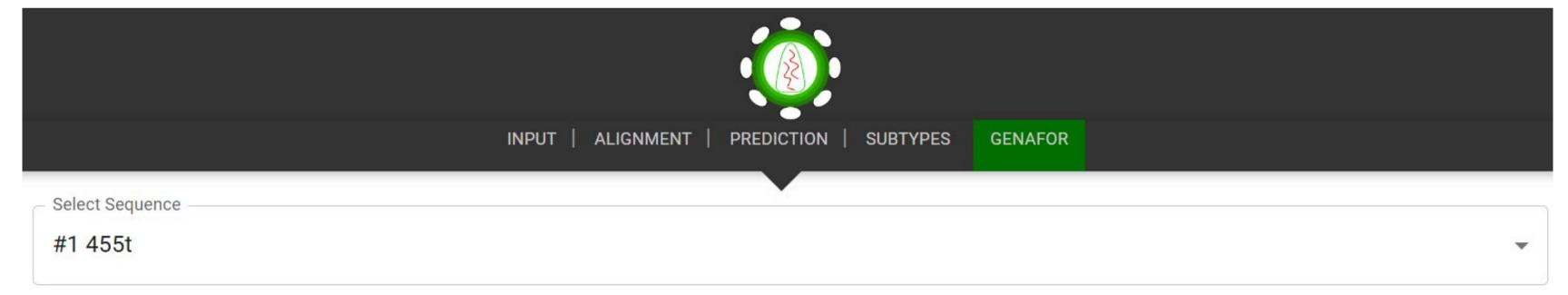
We used logistic and linear regression as our models for each task. We used multi-task learning to train both models simultaneously. I.e., during training we aim to decrease the sum of the cross-entropy (misclassification), the mean-squared-error (IC50 prediction error) and the negative covariance of class probability and IC50 prediction. The negative covariance penalizes models, which predict a high probability of resistance and a low IC50, and vice versa, for the same sample (Figure 2). In addition this can be viewed as a regularization to prevent overfitting to the training data. The training and test data was downloaded from the CATNAP database<sup>a</sup>.

#### Results

We compared the models of g2p-bNAbs to other state-of-the-art methods like support-vector machines (svm), multihead-attention (attention) and recurrent neural networks with grus (gru), and found them to be competitive in regards to accuracy and have the benefit of being easily interpretable in regards to features, i.e., positions on the

Figure 1: Schematic of an antibody with heavy chain, light chain and binding site highlighted.

### envelope (Figure 3).



#### Antibody predictions

NAbs 🛈	decision value	Z-Score	resistance 🛈	probability 🕕	Scored Positions 🕕	IC50 🕕	IC50 Scored Positions
10-1074	-9.0614	-1.16		0 (86%)	325G 810G 722S 142D 166S 816S 190V 675L 330R 804N 699I 402F 553G 315N 282E	0.33 (74%)	325G 816S 190V 315N 826 376S 142D 346N 330R 698 348T 406W 18T 839V 465G
2F5	-3.6156	-0.39	•	0.03 (92%)	477G 300H 106V 766L 183L 832T 17G 145I 786R 674S 68A 184F 507A 442A 461T	0.44 (81%)	671K 460L 563R 477G 699I 300H 756T 145I 633T 182A 148E 766L 106V 591R 68A
2G12	5.8586	0.74	À	1 (82%)	297I 182A 84L 341A 113S 353T 293N 6T 339R 477G 507A 300H 612T 8M 781L	31.5 (70%)	462R 751S 163R 376S 592Y 725T 182A 148E 831G 189I 136K 741E 23L 281E 300H

Figure 4: Screenshot of the g2p-bNAbs web-service showing 3 out of 50 alphabetically ordered bNabs. Besides bNAbs resistance prediction, the analysis includes alignment to the envelope region of HIV-1 and subtype prediction.

Figure 2: Regularization of discordant outliers with multitask learning (jointly).

#### Conclusion

We developed a web-service for antibody resistance (g2p-bNAbs, Figure 4), which is free to use and can be extended to other viruses, like Sars-Cov2, in the future.



#### References

a. Yoon H, Macke J, West AP Jr, Foley B, Bjorkman PJ, Korber B, Yusim K. CATNAP: a tool to compile, analyze and tally neutralizing antibody panels. Nucleic Acids Res. 2015 Jul 1;43(W1):W213-9. doi: 10.1093/nar/gkv404. Epub 2015 Jun 4. PMID: 26044712; PMCID: PMC4489231.
b. Harrell FE, Califf RM, Pryor DB, Lee KL, Rosati RA. Evaluating the Yield of Medical Tests. JAMA. 1982;247(18):2543–2546. doi:10.1001/jama.1982.03320430047030