Supplemental Information for "LYRUS: A Machine Learning Model for Predicting the Pathogenicity of Missense Variants"

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| Datasets | Datasets Pathogenic Variants (P) Benign Variants (B) Total Ratio (P:B) | | | | | | | | | | | |
|--|--|------------------------|---------|---------|--|--|--|--|--|--|--|--|
| ClinVar 11920 10719 22639 1.11 | | | | | | | | | | | | |
| VariBench_selected | 3466 | 4757 | 8223 | 0.73 | | | | | | | | |
| VariBench_limited | 2886 | 2009 | 4895 | 1.44 | | | | | | | | |
| Source | | | | | | | | | | | | |
| ClinVar: https://ftp.ncbi.nlm.nih.gov/pub/clinvar | | | | | | | | | | | | |
| VariBench_selected: http://structure.bmc.lu.se/VariBench/GrimmDatasets.php | | | | | | | | | | | | |
| VariBench_lin | nited: http://structure.bmc | c.lu.se/VariBench/Grim | mDatase | ets.php | | | | | | | | |

Table S1. SAV counts for the ClinVar and VariBench datasets.



Figure S1. Number of SAVs from ClinVar. Among all of the SAVs available in ClinVar, roughly 1.4% of SAVs meet the selection criteria. Among the selected SAVs, 10719 SAVs (47%) are benign and 11920 SAVs (53%) are pathogenic.

| | - |
|----------------------------------|---|
| Feature Name | Link |
| Variation Number | https://github.com/jiaying2508/variation_number |
| ΔE Epistatic Score | https://github.com/debbiemarkslab/EVmutation |
| FIS | http://fathmm.biocompute.org.uk |
| $\Delta PSIC$ | http://genetics.bwh.harvard.edu/pph2/ |
| Wild-type PSIC | http://genetics.bwh.harvard.edu/pph2/ |
| $\Delta\Delta G_{ m fold}$ | http://foldxsuite.crg.eu |
| SASA | https://freesasa.github.io |
| Mutant SSF | https://pbwww.che.sbg.ac.at/?page_id=416 |
| Active Site Value | https://github.com/rdk/p2rank |
| Mutant Reference Energy | http://www.pyrosetta.org |
| $\Delta \text{Reference Energy}$ | http://www.pyrosetta.org |
| MSD | http://prody.csb.pitt.edu |
| Mechanical Stiffness | http://prody.csb.pitt.edu |
| Effectiveness | http://prody.csb.pitt.edu |
| Sensitivity | http://prody.csb.pitt.edu |

Table S2. Links to the software used to compute each feature.



Figure S2. Pipeline for Calculating Variation Number. Variation number counts the number of occurrences of a position as a character attribute in all tree clades, where a character attribute may be defined as a state that exists in some elements of a clade, but not in the alternate clade under the same parent node. For a given amino acid sequence, the orthologous sequences are obtained using the NCBI Orthologs Database. Multiple sequence alignment files are built using Clustal Omega. Phylogenetic trees are generated using PAUP software with the maximum parsimony method. Variation number, calculated using breadth first search, is the number of occurrences of a position as a character attribute in a given tree. For each amino acid sequence, variation numbers at all of the human positions are normalized using min-max normalization. A smaller variation number suggests more conservation. The software is available at https://github.com/jiaying2508/variation_number

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|------------------|--------------------|--|---|
| VEP | Category | Features | Data source, method source, or online website |
| PolyPhen-2 | Supervised | Sequence conservation, sequence features, residue-level structural features | http://genetics.bwh.harvard.edu/pph2/ |
| PROVEAN | Unsupervised | Sequence conservation | http://provean.jcvi.org/seq_submit.php |
| SIFT | Empirical | Sequence conservation | http://provean.jcvi.org/seg_submit.php |
| Rhapsody | Supervised | Sequence features, structural features, | http://rhapsody.csb.pitt.edu/ |
| | | Elastic network model related features | |
| EVmutation | Unsupervised | sequence co-variation | http://rhapsody.csb.pitt.edu/ /evmutation/downloads.html |
| MutationAssessor | Unsupervised | Sequence conservation, conservation between subfamilies | http://mutationassessor.org/r3/ |
| SuSPect | Supervised | Network centrality, uniprot annotations, | http://www.sbg.bio.ic.ac.uk/suspect/ |
| | | sequence conservation, SASA | |
| FATHMM | Supervised | HMM alignments, per-domain mutation consequences | http://fathmm.biocompute.org.uk/inherited.html |
| MVP | Metapredictor | Eigen, VEST3, MutationTaster, PolyPhen-2, | https://github.com/ShenLab/missense |
| | | SIFT, PROVEAN, FATHMM, Mutation Assessor L.PT | |
| PrimateAI | Supervised | Sequence features.structural features | https://github.com/Illumina/PrimateAI |
| UNEECON | Supervised | sequence conservation scores, protein structural features, | https://github.com/yifei-lab/UNEECON |
| | | functional genomic features | |
| M-CAP | Metapredictor | SIFT, PolyPhen-2, CADD, MetaLR, Mutation Taster, | http://bejerano.stanford.edu/mcap/ |
| | | MutationAssessor, FATHMM, LRT, | |
| | | evolutionary conservation metrics, substitution matrices | |
| REVEL | MetaPredictor | MutPred, PROVEAN, SIFT, PolyPhen-2,LRT, | https://sites.google.com/site/revelgenomics/ |
| | | MutationTaster, MutationAssessor, FATHMM | |
| | | VEST3, GERP ++, SiPhy, PhyloP | |
| Envision | Supervised | DMS measurements | https://envision.gs.washington.edu |
| | | | /shiny/envision_new/ |

Summary of the other VEPs assessed in this study and a description of predictive features Incorporated in their methods. Table S3.

Table S4. VEP cutoffs between benign and pathogenic variants. 'Used by' means that the cutoff was used in the source. 'Author recommendation' means that the cutoff was recommended by the author. The cutoffs for MVP and UNEECON were calculated by using the threshold that minimizes the difference between the true positive rate and 1 - false the positive rate in the VariBench_selected dataset.

| VEP | Cutoff | Reason |
|------------------|--------|-----------------------|
| PolyPhen-2 | 0.453 | Used by Polyphen2 |
| PROVEAN | -2.5 | Used by PROVEAN |
| SIFT | 0.05 | Used by PROVEAN |
| Rhapsody | 0.5 | Used by Rhapsody |
| EVmutation | -4.75 | Used by Rhapsody |
| MutationAssessor | 1.94 | Author recommendation |
| SuSPect | 50 | Author recommendation |
| FATHMM | -1.5 | Author recommendation |
| MVP | 0.83 | Calculated |
| PrimateAI | 0.6 | Author recommendation |
| M-CAP | 0.95 | Author recommendation |
| REVEL | 0.5 | Author recommendation |
| UNEECON | 0.16 | Calculated |



Figure S3. Model Accuracy Using Different Numbers of Orthologs. Different models were trained using SAVs with at least 0, 50, 100, 150, 200, 250, or 300 orthologous sequences. Each model was assessed using the ClinVar dataset and the accuracy was estimated using 10-fold cross-validation. The accuracy of each model is similar.



Figure S4. PCA. Plot of the cumulative variance vs. the number of principal components from a PCA analysis of our 15 features. This cumulative variance plot illustrates that 13 components are needed to describe 90% of the variance in the data.



(a) Pearson Correlation Coefficient Heatmap





Figure S5. Feature Correlation Heatmap. (a) Pearson's r calculated between all possible pairwise combinations of the 15 features. Out of the 105 possible pairs of feature combinations, only three pairs had a correlation coefficient (absolute value) greater than 0.4, suggesting that almost all (97%) possible pairwise feature combinations did not exhibit a significant linear relationship. (b) Kendall's Tau calculated between all possible pairwise combinations of the 15 features. Out of the 105 possible pairs of feature combinations, only seven pairs had a coefficient (absolute value) greater than 0.35, suggesting that 93% of all possible pairwise feature combinations did not exhibit a strong monotonic relationship.



Figure S6. Feature Importance Scores from LYRUS. Feature importance scores were calculated using the built-in function "feature_importances_" from the xgboost package in Python. Given the stochastic nature of the xgboost model, feature importance scores vary for each run, and the average of 1000 repeats were taken as the feature importance scores shown here. The sequence-based features had higher weights than structural and dynamics-based features. $\Delta PSIC$ had the highest importance score, followed by the wild-type PSIC, FIS, and variation number. The remaining 11 features had similar importance scores.



(a) Area under the ROC Curve (AUC)
(b) Area under the PR Curve (AUPR)
Figure S7. Comparison of ROC and PR Curves of the 13 other VEPs from the ClinVar dataset.
(a) ROC curves.
(b) PR curves.

| Model Name | Accuracy | Sensitivity | Specificity | F-measure | MCC |
|------------------|----------|-------------|-------------|-----------|-------|
| LYRUS | 0.859 | 0.860 | 0.857 | 0.866 | 0.716 |
| PolyPhen-2 | 0.743 | 0.915 | 0.571 | 0.781 | 0.518 |
| PROVEAN | 0.784 | 0.890 | 0.679 | 0.805 | 0.582 |
| SIFT | 0.770 | 0.903 | 0.638 | 0.797 | 0.561 |
| Rhapsody | 0.820 | 0.806 | 0.84 | 0.843 | 0.636 |
| EVMutation | 0.785 | 0.806 | 0.748 | 0.829 | 0.543 |
| MutationAssessor | 0.744 | 0.859 | 0.630 | 0.770 | 0.502 |
| SuSPect | 0.736 | 0.592 | 0.876 | 0.688 | 0.489 |
| FATHMM | 0.724 | 0.755 | 0.694 | 0.729 | 0.449 |
| MVP | 0.691 | 0.985 | 0.363 | 0.77 | 0.453 |
| PrimateAI | 0.767 | 0.795 | 0.74 | 0.774 | 0.536 |
| MCAP | 0.784 | 0.986 | 0.372 | 0.859 | 0.497 |
| REVEL | 0.866 | 0.937 | 0.795 | 0.875 | 0.739 |
| UNEECON | 0.781 | 0.831 | 0.729 | 0.793 | 0.564 |

Table S5. Performance analysis of LYRUS and 13 other VEPs tested on the ClinVar dataset. MCC = Matthews Correlation Coefficient.



Figure S8. LYRUS Statistics Compared to Those of Other VEPs When Tested on the ClinVar Dataset. The accuracy, sensitivity, specificity, F-measure, and MCC for each of the prediction methods were calculated. LYRUS achieved the second highest accuracy, specificity, F-measure, and MCC.

| | | - | | | | - | | | |
|------------------|------|------|------|------|----------|-------------|-------------|-----------|-------|
| Model Name | TP | TN | FP | FN | Accuracy | Sensitivity | Specificity | F-measure | MCC |
| LYRUS | 2581 | 4023 | 734 | 885 | 0.803 | 0.745 | 0.846 | 0.761 | 0.594 |
| PolyPhen-2 | 2432 | 2310 | 2446 | 1034 | 0.577 | 0.702 | 0.486 | 0.583 | 0.188 |
| PROVEAN | 1828 | 2528 | 1615 | 1421 | 0.589 | 0.563 | 0.61 | 0.546 | 0.172 |
| SIFT | 2214 | 2125 | 1983 | 958 | 0.596 | 0.698 | 0.517 | 0.601 | 0.216 |
| EVmutation | 1180 | 614 | 432 | 755 | 0.602 | 0.61 | 0.587 | 0.665 | 0.188 |
| MutationAssessor | 2219 | 2441 | 1624 | 1163 | 0.626 | 0.656 | 0.6 | 0.614 | 0.256 |
| SuSPect | 2714 | 3630 | 589 | 550 | 0.848 | 0.831 | 0.86 | 0.827 | 0.691 |
| FATHMM | 3184 | 3711 | 606 | 251 | 0.889 | 0.927 | 0.86 | 0.881 | 0.782 |
| MVP | 3028 | 3475 | 516 | 421 | 0.874 | 0.878 | 0.871 | 0.866 | 0.747 |
| PrimateAI | 1520 | 3337 | 1241 | 1747 | 0.619 | 0.465 | 0.729 | 0.504 | 0.2 |
| MCAP | 3361 | 1503 | 1364 | 61 | 0.773 | 0.982 | 0.524 | 0.825 | 0.584 |
| REVEL | 2523 | 4043 | 707 | 943 | 0.799 | 0.728 | 0.851 | 0.754 | 0.586 |
| UNEECON | 2227 | 3005 | 1641 | 1239 | 0.645 | 0.643 | 0.647 | 0.607 | 0.287 |

Table S6. Performance analysis of LYRUS and 12 other VEPs using the VariBench_selected dataset.



Figure S9. LYRUS Statistics Compared to Those of Other VEPs When Test on the VariBench_selected Dataset. The accuracy, sensitivity, specificity, F-measure, and MCC for each of the prediction methods were shown.



(a) Area under the ROC Curve (AUC)
(b) Area under the PR Curve (AUPR)
Figure S10. Comparison of ROC and PR Curves of 12 VEPs from the VariBench_limited
Dataset. (a) ROC curves. (b) PR curves.

| Model Name | TP | TN | FP | FN | Accuracy | Sensitivity | Specificity | F-measure | MCC |
|------------------|------|------|------|------|----------|-------------|-------------|-----------|-------|
| LYRUS | 2164 | 1577 | 432 | 722 | 0.764 | 0.75 | 0.785 | 0.789 | 0.527 |
| PolyPhen-2 | 2013 | 835 | 1174 | 873 | 0.582 | 0.698 | 0.416 | 0.663 | 0.117 |
| PROVEAN | 1683 | 1080 | 929 | 1203 | 0.564 | 0.583 | 0.538 | 0.612 | 0.119 |
| SIFT | 2035 | 933 | 1076 | 851 | 0.606 | 0.705 | 0.464 | 0.679 | 0.173 |
| MutationAssessor | 1963 | 1071 | 938 | 923 | 0.62 | 0.68 | 0.533 | 0.678 | 0.214 |
| SuSPect | 2426 | 1653 | 356 | 460 | 0.833 | 0.841 | 0.823 | 0.856 | 0.659 |
| FATHMM | 2702 | 1683 | 326 | 184 | 0.896 | 0.936 | 0.838 | 0.914 | 0.784 |
| MVP | 2506 | 1673 | 336 | 380 | 0.854 | 0.868 | 0.833 | 0.875 | 0.699 |
| PrimateAI | 1261 | 1292 | 717 | 1625 | 0.522 | 0.437 | 0.643 | 0.519 | 0.08 |
| MCAP | 2841 | 1029 | 980 | 45 | 0.791 | 0.984 | 0.512 | 0.847 | 0.59 |
| REVEL | 2079 | 1571 | 438 | 807 | 0.746 | 0.72 | 0.782 | 0.77 | 0.494 |
| UNEECON | 1891 | 1078 | 931 | 995 | 0.607 | 0.655 | 0.537 | 0.663 | 0.191 |

 Table S7. Comparison to Other VEPs using VariBench_limited.



Figure S11. Statistics Compared to Other Software using VariBench_limited. The accuracy, sensitivity, specificity, F-measure, and MCC for each of the prediction methods are shown.



Figure S12. PTEN Prediction Heatmap. The x-axis represents PTEN amino acid positions and the y-axis represents different amino acid substitutions. The color coding of each heatmap cell represents the predicted probability of the SAV being pathogenic. Wild-type amino acids were assigned a probability of 0. LYRUS predicts most PTEN SAVs to be pathogenic.



Figure S13. Cartoon and Surface Representations of the PTEN Protein. (a) The red surface corresponds to PTEN positions 286 to 305. (b) Visualization of the positions of the four false negative variants.

Table S8. PTEN Case Study. A total of 110 SAV classifications are available from ClinVar. True positive (TP), true negative (TN), false positive (FP), false negative (FN), no prediction (NP), accuracy, sensitivity, specificity, F-measure, and MCC are listed.

| Model Name | TP | TN | FP | FN | Accuracy | Sensitivity | Specificity | F-measure | MCC |
|------------------|-----|----|----|----|----------|-------------|-------------|-----------|--------|
| LYRUS | 104 | 2 | 0 | 4 | 0.964 | 0.963 | 1.0 | 0.981 | 0.567 |
| PolyPhen-2 | 98 | 2 | 0 | 10 | 0.909 | 0.907 | 1.0 | 0.951 | 0.389 |
| PROVEAN | 103 | 2 | 0 | 5 | 0.955 | 0.954 | 1.0 | 0.976 | 0.522 |
| SIFT | 102 | 2 | 0 | 6 | 0.945 | 0.944 | 1.0 | 0.971 | 0.486 |
| Rhapsody | 88 | 2 | 0 | 20 | 0.818 | 0.815 | 1.0 | 0.898 | 0.272 |
| EVMutation | 105 | 0 | 2 | 3 | 0.955 | 0.972 | 0.0 | 0.977 | -0.023 |
| MutationAssessor | 102 | 2 | 0 | 6 | 0.945 | 0.944 | 1.0 | 0.971 | 0.486 |
| SuSPect | 108 | 1 | 1 | 0 | 0.991 | 1.0 | 0.5 | 0.995 | 0.704 |
| FATHMM | 108 | 0 | 2 | 0 | 0.982 | 1.0 | 0.0 | 0.991 | N/A |
| MVP | 108 | 0 | 2 | 0 | 0.982 | 1.0 | 0.0 | 0.991 | N/A |
| PrimateAI | 108 | 0 | 2 | 0 | 0.982 | 1.0 | 0.0 | 0.991 | N/A |
| M-CAP | 108 | 0 | 2 | 0 | 0.982 | 1.0 | 0.0 | 0.991 | N/A |
| REVEL | 108 | 1 | 1 | 0 | 0.991 | 1.0 | 0.5 | 0.995 | 0.704 |
| UNEECON | 106 | 2 | 0 | 2 | 0.982 | 0.981 | 1.0 | 0.991 | 0.701 |



Figure S14. LYRUS Statistics Compared to Those of Other Software When Tested on PTEN. The accuracy, sensitivity, specificity, F-measure, and MCC are shown.



Figure S15. TP53 Prediction Heatmap. The x-axis represents TP53 amino acid positions and the y-axis represents different amino acid substitutions. The color coding of each heatmap cell represents the predicted probability of the SAV being pathogenic. Wild-type amino acids were assigned a probability of 0.

Table S9. TP53 Case Study. A total of 142 SAV classifications are available from ClinVar. True positive (TP), true negative (TN), false positive (FP), false negative (FN), accuracy, sensitivity, specificity, F-measure, and MCC are listed.

| Model Name | TP | TN | FP | FN | Accuracy | Sensitivity | Specificity | F-measure | MCC |
|------------------|-----|----|----|----|----------|-------------|-------------|-----------|--------|
| LYRUS | 128 | 7 | 6 | 1 | 0.951 | 0.992 | 0.539 | 0.973 | 0.664 |
| PolyPhen-2 | 125 | 13 | 0 | 4 | 0.972 | 0.969 | 1.0 | 0.984 | 0.861 |
| PROVEAN | 122 | 12 | 1 | 7 | 0.944 | 0.946 | 0.923 | 0.968 | 0.736 |
| SIFT | 127 | 12 | 1 | 2 | 0.979 | 0.984 | 0.923 | 0.988 | 0.878 |
| Rhapsody | 129 | 6 | 7 | 0 | 0.951 | 1.0 | 0.462 | 0.974 | 0.662 |
| EVmutation | 107 | 9 | 4 | 22 | 0.817 | 0.829 | 0.692 | 0.892 | 0.364 |
| MutationAssessor | 127 | 12 | 1 | 2 | 0.979 | 0.984 | 0.923 | 0.988 | 0.878 |
| SuSPect | 110 | 1 | 12 | 19 | 0.782 | 0.853 | 0.077 | 0.876 | -0.058 |
| FATHMM | 129 | 0 | 13 | 0 | 0.908 | 1.0 | 0.0 | 0.952 | N/A |
| MVP | 129 | 0 | 13 | 0 | 0.908 | 1.0 | 0.0 | 0.952 | N/A |
| PrimateAI | 111 | 11 | 2 | 18 | 0.859 | 0.86 | 0.846 | 0.917 | 0.505 |
| M-CAP | 129 | 0 | 13 | 0 | 0.908 | 1.0 | 0.0 | 0.952 | N/A |
| REVEL | 129 | 6 | 7 | 0 | 0.951 | 1.0 | 0.462 | 0.974 | 0.662 |
| UNEECON | 95 | 13 | 0 | 34 | 0.761 | 0.736 | 1.0 | 0.848 | 0.451 |



Figure S16. TP53 Statistics Compared to Other Software. The accuracy, sensitivity, specificity, F-measure and MCC are shown.



(a) (b) **Figure S17. Carton Representation of the TP53 Protein.** (a) Visualization of the positions of the six false positive variants. (b) Visualization of the positions of the one false negative variant.

| | s Reference | Matreyek et al. 2018 | Mighell <i>et al.</i> 2018 | Mighell <i>et al.</i> 2018 | Giacomelli <i>et al.</i> 2018 | Giacomelli <i>et al.</i> 2018 | Giacomelli et al. 2018 |
|--|--------------------|--------------------------------------|--|--|---|---|---|
| ctions | Total SAVs | 4112 | 7264 | 6564 | 7467 | 7467 | 7467 |
| in this study for calculating correlation with the VEP predi | Mutagenesis Method | Fluorescence of a GFP fusion protein | Disruption of an artificial genetic circuit in yeast | Disruption of an artificial genetic circuit in yeast | Competitive growth assay in the presence of P53 agonists $_{\parallel}$ | Competitive growth assay in the presence of $P53$ agonists $_{\parallel}$ | Competitive growth as say in the presence of P53 agonists $_{\parallel}$ |
| ry of the DMS datasets used | Functional Assay | Site-directed mutagenesis | Site-directed mutagenesis | Site-directed mutagenesis | Site-directed mutagenesis | Site-directed mutagenesis | Site-directed mutagenesis |
| Cable S10. Summar | Dataset | pten(a) | pten(b) | pten(highqual_b) | p53(wt_nutlin) | $p53(null_nutlin)$ | p53(null_etoposide) |

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Figure S18. Correlation between LYRUS and DMS Measurements. Spearman's correlation calculated (absolute value) between LYRUS and six DMS datasets.



Figure S19. Coverage of Possible Mutations by Three PTEN DMS Data sets and 15 VEPs. The percentages of all PTEN amino acid substitutions covered by three PTEN DMS Datasets are colored in gray; the percentages of all PTEN amino acid substitutions covered by each VEP is colored in corresponding colors. (a) coverage of pten(a) and 15 VEPs (b) coverage of pten(b) and 15 VEPs (c) coverage of pten(highqual_b) and 15 VEPs



Figure S20. Coverage of Possible Mutations by Three TP53 DMS Data sets and 15 VEPs. The percentages of all TP53 amino acid substitutions covered by three TP53 DMS Datasets are colored in gray; the percentages of all TP53 amino acid substitutions covered by each VEP is colored in corresponding colors. (a) coverage of p53(wt_nutlin) and 15 VEPs (b) coverage of p53(null_nutlin) and 15 VEPs (c) coverage of p53(null_etoposide) and 15 VEPs



Prediction Scores. Values on both axes range from 0 to 1. Dashed black lines give linear least-squared regressions. Distributions of experimental Figure S22. Linear Regression Between Normalized pten(b) Experimental Scores and Normalized Variant Effect Predictors' and predicted scores were also plotted within the same subfigure.

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Predictors' Prediction Scores. Values on both axes range from 0 to 1. Dashed black lines give linear least-squared regressions. Distributions of experimental and predicted scores were also plotted within the same subfigure. Figure S23. Linear Regression Between Normalized pten(highqual_b) Experimental Scores and Normalized Variant Effect



Predictors' Prediction Scores. Values on both axes range from 0 to 1. Dashed black lines give linear least-squared regressions. Distributions of Figure S24. Linear Regression Between Normalized p53(wt_nutlin) Experimental Scores and Normalized Variant Effect experimental and predicted scores were also plotted within the same subfigure.





Predictors' Prediction Scores. Values on both axes range from 0 to 1. Dashed black lines give linear least-squared regressions. Distributions of Figure S25. Linear Regression Between Normalized p53(null-nutlin) Experimental Scores and Normalized Variant Effect experimental and predicted scores were also plotted within the same subfigure.



Predictors' Prediction Scores. Values on both axes range from 0 to 1. Dashed black lines give linear least-squared regressions. Distributions of Figure S26. Linear Regression Between Normalized p53(null_etoposide) Experimental Scores and Normalized Variant Effect <u></u> (u) experimental and predicted scores were also plotted within the same subfigure. (E) Ξ (k)







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