Supporting Information

Machine learning classification can reduce false positives in structure-based virtual screening

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Supplemental Figures

Figure S1: Features incorporated into vScreenML. These features derive from six sources: Rosetta energy terms, Rosetta structural quantifiers, RF-Score's rfscore_v1 features, BINANA's analysis of intermolecular contacts, ChemAxon's cxcalc features, OpenEye's SZYBKI conformational entropy term.

Figure S2: Retraining rfscore v1 using D-COID. (A) Overlaid histograms for scores obtained when scoring active complexes (*blue*) and decoy complexes (*red*) from D-COID using the original rfscore v1. Performance measures are presented as the average of 10 experiments, each of which uses different partitions for 10-fold cross-validation. Uncertainty is presented as 95% confidence intervals. **(B)** Overlaid histograms after re-training rfscore_v1. **(C)** Comparison of the original and re-weighted versions of rfscore_v1 applied to the DEKOIS benchmark. **(D)** Comparison of the original and reweighted versions of rfscore_v1 applied to the PPI benchmark. **(E)** Comparison of re-weighted rfscore v1 versus vScreenML on the DEKOIS benchmark. **(F)** Comparison of re-weighted rfscore v1 versus vScreenML on the PPI benchmark. p-values were computed using the two-tailed Wilcoxon Signed-Rank test.

Figure S3: Heatmap showing similarity between the 23 compounds tested as candidate AChE inhibitors. All compounds are included in this heatmap, labels include only odd numbers for clarity. Similarity is measured via 2D fingerprints. As highlighted by this analysis, several subsets of these compounds are similar to one another: AC1/AC23 group together, AC3/AC18 group together, AC4/AC12/AC14 group together, AC7/AC9/AC16 group together, AC10/AC16/AC17/AC20 group together, and AC13/AC15 group together. On the other hand, some of these compounds are completely unrelated to any others in this set (e.g., $AC5$, $AC21$, $AC22$). The similarity shown here is also confirmed by visual inspection of the compounds themselves (**Table S6**).

Results of Job: search db0bb886-036f-46b6-a2c2-cdf653a20a86

Datasets

Figure S4: Positive control for target identification methods. We confirmed that all three methods would successfully identify AChE as the target of a known AChE inhibitor (donepezil, CHEMBL1678). **(A)** Similarity Ensemble Approach (SEA). **(B)** SwissTargetPrediction. **(C)** PharmMapper. We note that AChE was only ranked #112 among the PharmMapper hits because the 3D conformations it built for donepezil were not sufficiently well-matched to the active conformation to produce a better ranking.

Supplemental Tables

Table S1: Effect of hyperparameter tuning on vScreenML. The performance is shown for the optimized and non-optimized vScreenML models (both use XGBoost, with the complete feature set. Performance measures are presented as the average of 100 trained models, each of which derived from 10-fold cross-validation (see *Methods*). Uncertainty is presented as 95% confidence intervals. In all cases, performance measures were calculated for a subset of the data that was held out from the training step.

Table S2: Results of hyperparameter tuning. The parameters resulting from optimization for vScreenML are shown.

Table S3: Performance from alternate learning schemes. Using the complete vScreenML feature set, alternate learning schemes were evaluated. Performance measures are presented as the average of 100 trained models, each of which derived from 10-fold cross-validation (see *Methods*). Uncertainty is presented as 95% confidence intervals. In all cases, performance measures were calculated for a subset of the data that was held out from the training step.

Table S4: Performance with restricted feature sets. Examination of models in which all features from a given origin are added/removed en masse; all models are trained using XGBoost. Performance measures are presented as the average of 100 trained models, each of which derived from 10-fold crossvalidation (see *Methods*). Uncertainty is presented as 95% confidence intervals. In all cases, performance measures were calculated for a subset of the data that was held out from the training step.

Table S5: Similarity of proteins in DEKOIS benchmark to training set. The complete DEKOIS set comprises 81 proteins. Some were present in our D-COID training set as well, and were therefore excluded when we carried out the benchmark experiment. For each of 23 protein targets included in our benchmark, we present the closest protein present in our D-COID training set (on the basis of sequence identity). The EF1% values listed here correspond to those presented in **Figure 3a** (zeros correspond to cases in which none of the active compounds were ranked in the top 1%). The fact that vScreenML does not exhibit superior performance when a closer protein homolog is available suggests that its performance does not rely on identifying a related protein homolog in the training set.

Table S6: Compounds tested as candidate AChE inhibitors. Chemical structures and SMILES strings are presented for each of the 23 compounds selected by vScreenML as a candidate AChE inhibitor.

Table S7: Ranking of first-round compounds selected by vScreenML by other methods. Using each of the scoring functions methods evaluated in this study, we ranked the 20,000 docked models from the first round of AChE screening (corresponding data is not shown for the second round of screening, because at that point already vScreenML had been used to focus the search). Because we did not explicitly test the compounds selected by these other methods, we cannot say whether these other compounds are true AChE inhibitors that were missed by vScreenML. However, because none of these methods assign favorable (low) ranking to the same compounds selected by vScreenML (the compounds presented in this table), we can conclude that the particular compounds selected by vScreenML would not have been selected by these other methods.

Table S8: Similarity of compounds selected by vScreenML to D-COID set. For each compound selected by vScreenML as a candidate AChE inhibitor, we show the closest compound from D-COID (used in training vScreenML). In each case, the PDB and ligand ID are shown, along with the protein to which this ligand was bound in the solved structure. None of these compounds come from complexes with proteins related to AChE, ruling out any concern that vScreenML might have recognized some subtle features of the binding sites from proteins related to AChE.

Table S9: Activity predictions for candidate AChE inhibitors. Predicted activity of the compounds selected by vScreenML, from SEA and SwissTarget. Neither recognizes these compounds as AChE inhibitors, suggesting that indeed these are new scaffolds for this target.

Table S10: Comparison of vScreenML's candidate AChE inhibitors to known AChE inhibitors. For each compound selected by vScreenML as a candidate AChE inhibitor, we present the two closest compounds (as measured by 2D fingerprint similarity) that are annotated in ChEMBL as AChE inhibitors. The lack of similarity implies that these compounds would not have been identified as AChE inhibitors on the basis of 2D fingerprint similarity.

Table S11: Provenance of AChE inhibitors. For each of the 10 AChE inhibitors that provided more than 50% inhibition at a concentration of 50 μ M, we determined at what stage this compound was prioritized for testing. Our strategy included two stages of screening: first we screened only 15 million diverse compounds from the Enamine collection, then we expanded our search by collecting analogs for each of these hits. We note that 7 of these 10 compounds were identified in the first round of screening; after re-refinement in the second round, 3 of these were still highly-ranked whereas 4 had been surpassed by analogs (or received lower scores upon re-refinement). Only 3 of these 10 compounds would have been missed if our screening had been limited to a single round of 15 million compounds.