# Performing Fast and Accurate virtual High-Throughput Screening

Chloé-Agathe Azencott, S. Joshua Swamidass, and Pierre Baldi

# Virtual High-Throughput Screening

Virtual

High-Throughput Screening (vHTS) is the costeffective, in silico complement of experimental High-Throughput Screening (HTS). A vHTS algorithm uses data from HTS experiments to predict the activity of new sets of compounds in silico.

vHTS is most appropriately described as a ranking task, where the goal is to rank compounds such that active ones are close to the top of the

prediction-sorted list as possible. Moreover, being able to assess the performance and evaluate how many hits are retrieved in a fraction of the predictionsorted list is a major asset for a vHTS algorithm.

### Influence Relevance Voter (IRV)

The k-Nearest Neighbors algorithm can be applied to chemical data, but does not perform optimally. The IRV uses a neural network architecture to learn how to **best combine** information from the nearest structural neighbors contained in the training set.

We compute nearest neighbors of chemicals using a standard MinMax similarity on structural fingerprints.



Benchmarked Performance

IJCNN07 Challenge HIV data: train on 4,229 compounds (149 actives), test on 38,449 compounds (1,354 actives).

McMaster 2005 DHFR data: train on 49,995 compounds (66 actives), test on 50,000 compounds (94 actives).

	BER	AUC
IJCNN07	0.283	0.771
SVM	0.269	0.764
IRV	0.271	0.762
LIN/ data (UCNINO7 Challenge)		

.02	0.14
.01	0.04
.03	0.14
	.01 .03



# Early Recognition

To measure vHTS performance, we need to quantify the ability of a method to rank active compounds early at the top of the prediction-sorted test data.

## **CROC Curves**

To better assess the results of vHTS experiments, we propose to replace traditional ROC curves with CROC curves, where an exponential transform of parameter  $\alpha$  has been applied to emphasize the importance of the early portion of the curve.



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8	0.2	0.4	0.6	0.8
	0.2	0.4	0.0	0.0

	$\alpha = 7$	α=80
SVM	0.644	0.310
kNN	0.638	0.365
IRV	0.656	0.400

kN IR

Area under CROC on the HIV data Area under CROC on the DHFR data

	$\alpha = 7$	α=80
Μ	0.290	0.138
N	0.267	0.115
7	0.398	0.154

Institute for Genomics and Bioinformatics Bren School of Information and Computer Sciences

## Statistical Significance

We use the permutation test described by Zhao et al. [A STATISTICAL FRAMEWORK TO EVALUATE VIRTUAL SCREENING. BMC bioinformatics, 2009] to assess the significance of the observed difference in performance between two methods. We pool the ranks of the actives from both methods and repeatedly partition them at random into equally sized sets of ranks. The p-value is computed as the percentage of sampled differences in performance that are greater than the observed difference.

	SVM vs. IRV	kNN vs. IRV
ROC	0.094	0.094
pROC	0.016	0.025
CROC, $\alpha = 7$	0.001	0.055
CROC, α=80	0.002	0.010

We proposed a new vHTS algorithm, the IRV, with the following advantages: (1) the algorithm is suitable for early recognition and achieves state-of-the-art performance; (2) the training time is very short; (3) the risk of overfitting is minimal, due to the small number of free parameters.

Moreover, we proposed a new visualization method, the CROC curve, to better assess the results of vHTS experiments. Our data suggests that the area under the CROC curve has a **better** statistical power than other commonly used early recognition metrics.

### Further Information

S. Joshua Swamidass, Chloé-Agathe Azencott, Ting-Wan Lin, Hugo Gramajo, Sheryl Tsai, and Pierre Baldi. THE INFLUENCE RELEVANCE VOTER: AN ACCURATE AND INTERPRETABLE VIRTUAL HIGH THROUGHPUT SCREENING Метнор, J. Chem. Inf. Model., March 2009. DOI: 10.1021/сi8004379.

S. Joshua Swamidass, Chloé-Agathe Azencott, Kenneth Daily, and Pierre Baldi. A CROC THAT ROC: MEASURING, VISUALIZING, AND OPTIMIZING EARLY RETRIEVAL. Unpublished draft.

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Statistical significance of the difference in performance on the HIV data

### Conclusion