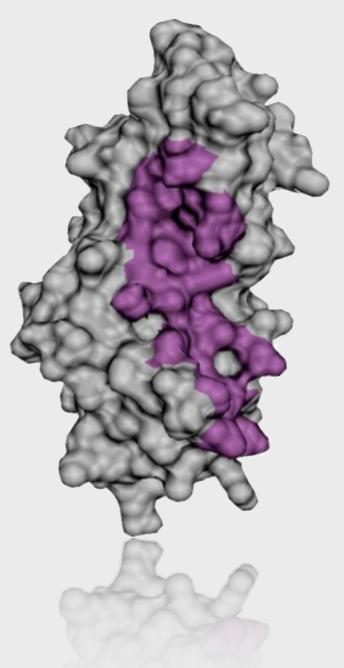
SNP analysis and binding site prediction



Marc A. Marti-Renom

http://sgu.bioinfo.cipf.es

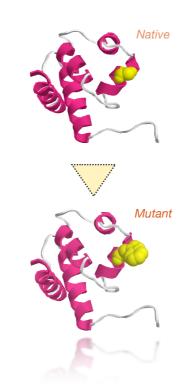
Structural Genomics Unit Bioinformatics Department Prince Felipe Resarch Center (CIPF), Valencia, Spain



Program

SNP analysis from sequence

SNP analysis from structure

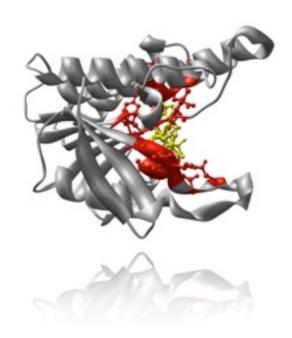




Disease?

Binding site prediction

AutoDock



Objective

TO UNDERSTAND THAT SNPs HAVE
EFFECTS THAT CAN BE PREDICTED
AND TO LEARN HOW-TO USE
AutoDock FOR DOCKING SMALL
MOLECULES IN THE SURFACE OF A
PROTEIN

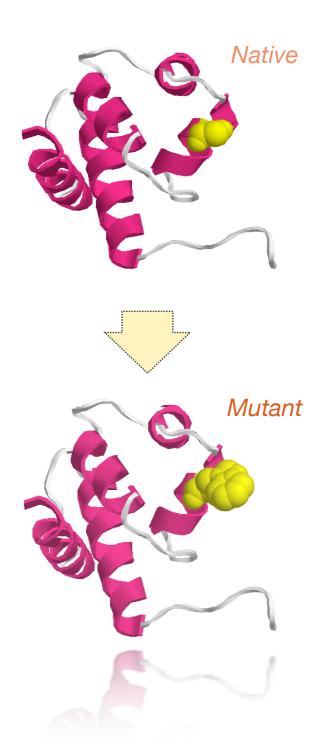
Nomenclature

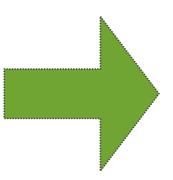
SNP: Single Nucleotide Polymorphism. A single change in the DNA sequence, which may or may not result in a change in the protein sequence.

Ligand: Structure (usually a small molecule) that binds to the binding site.

Receptor: Structure (usually a protein) that contains the active binding site.

Binding site: Set of aminoacids (residues) that physically interact with the lingad (usually within 6 Ångstroms).





Disease?

Gene Sequence << +Protein Sequence << +Protein Structure

Single Nucleotide Polymorphism

Single Nucleotide Polymorphism or SNP

is a DNA sequence variation occurring when a single nucleotide - A, T, C, or G - in the genome differs between members of the species.

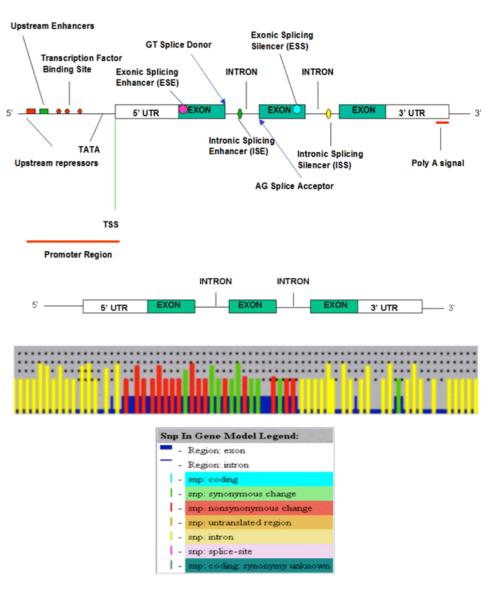
Usually one will want to refer to SNPs when the population frequency is ≥ 1%

SNPs occur at any position and can be classified on the base of their locations.

Coding SNPs can be subdivided into two groups:

Synonymous: when single base substitutions do not cause a change in the resultant amino acid

Non-synonymous: when single base substitutions cause a change in the resultant amino acid.

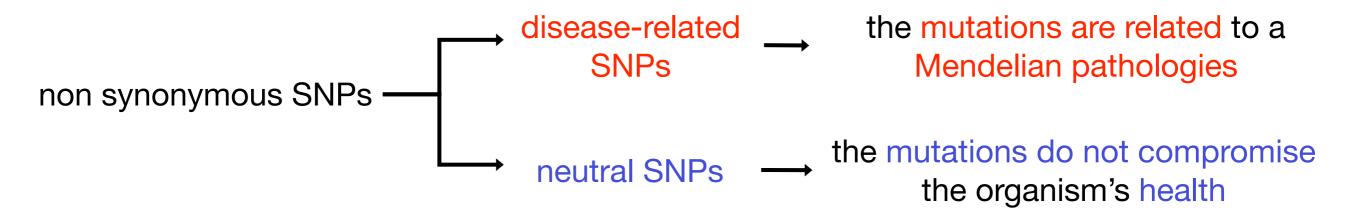


SNPs and disease

Single nucleotide polymorphism are the most common type of genetic variations in human accounting for about 90% of sequence differences (Collins et al., 1998).

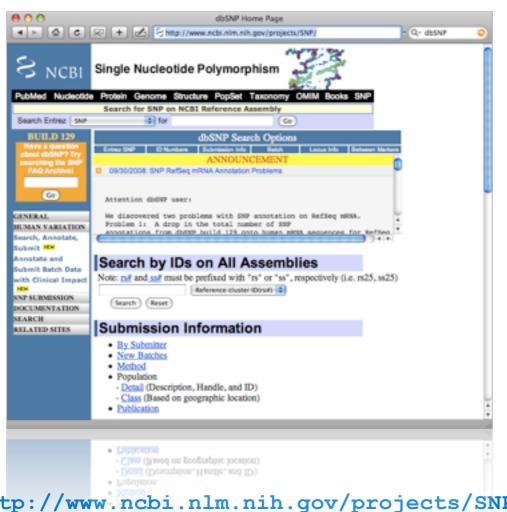
Studying SNPs distribution in different human populations can lead to important considerations about the history of our species (Barbujani and Goldstein, 2004; Edmonds et al., 2004).

SNPs can also be responsible of genetic diseases (Ng and Henikoff, 2002; Bell, 2004).



SNP databases

* * & 6 @ + 🖋) http://www.uniprot.org/



http://www.ncbi.nlm.nih.gov/projects/SNP/



Evolutionary information for SNP analysis of p53 protein.

Arbiza et al. Selective pressures at a codon-level predict deleterious mutations in human disease genes. J Mol Biol (2006) vol. 358 (5) pp. 1390-404



Selective Pressures at a Codon-level Predict Deleterious Mutations in Human Disease Genes

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Deleterious mutations affecting biological function of proteins are constantly being rejected by purifying selection from the gene pool. The non-synonymous/synonymous substitution rate ratio (ω) is a measure of selective pressure on amino acid replacement mutations for protein-coding genes. Different methods have been developed in order to predict nonsynonymous changes affecting gene function. However, none has considered the estimation of selective constraints acting on protein residues. Here, we have used codon-based maximum likelihood models in order to estimate the selective pressures on the individual amino acid residues of a well-known model protein: p53. We demonstrate that the number of residues under strong purifying selection in p53 is much higher than those that are strictly conserved during the evolution of the species. In agreement with theoretical expectations, residues that have been noted to be of structural relevance, or in direct association with DNA, were among those showing the highest signals of purifying selection. Conversely, those changing according to a neutral, or nearly neutral mode of evolution, were observed to be irrelevant for protein function. Finally, using more than 40 human disease genes, we demonstrate that residues evolving under strong selective pressures ($\omega < 0.1$) are significantly associated (p < 0.01) with human disease. We hypothesize that non-synonymous change on amino acids showing ω<0.1 will most likely affect protein function. The application of this evolutionary prediction at a genomic scale will provide an a priori hypothesis of the phenotypic effect of non-synonymous coding single nucleotide polymorphisms (SNPs) in the human genome.

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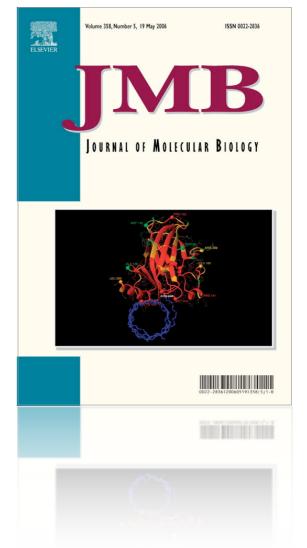
*Corresponding author

Keywords: comparative genomics; deleterious mutations; human diseases; purifying selection; codon-based models

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Keywords: comparative genomics; deleterious mutations; human diseases;



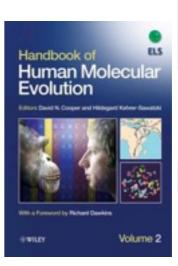
Natural selection & human disease

SNPs can cause alterations of gene function by...

- Alterations at expression level
- **Alternative splicing**
- Alteration (or loss) of gene product function
 - Changes in the stability of the protein
 - **Functionally important residues**
 - Phylogenetic conservation

Natural selection working at codon level

nsSNP's functional prediction JMB 2006; HM 2008, NatGen 2008





doi:10.1016/jmb.2006.02.067

J. Mol. Biol. (2006) 358, 1390-1404



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Selective Pressures at a Codon-level Predict Deleterious Mutations in Human Disease Genes

Leonardo Arbiza¹, Serena Duchi¹, David Montaner², Jordi Burquet² David Pantoja-Uceda³, Antonio Pineda-Lucena³, Joaquín Dopazo² and Hernán Dopazo1*

¹Pharmacogenomics and Comparative Genomics Unit Felipe (CIPF). Autopista del

Deleterious mutations affecting biological function of proteins are constantly being rejected by purifying selection from the gene pool. The Centro de Investigación Principe non-synonymous/synonymous substitution rate ratio (ω) is a measure of selective pressure on amino acid replacement mutations for protein-coding

Selective Constraints and **Human Disease Genes: Evolutionary** and **Bioinformatics** Approaches

Natural selection rejects with variable stren capability to survive and reproduce. Evolut producing disease will be under strong sele codon level will determine if mutation freq METHODS randomly during evolution. This strength fi nonsynonymous single nucleotide polymo humans. By using comparative genomics d approaches we demonstrate that mutation

are significantly associated to disease and r



Conversely, those Online posting date: 15th July 2008 of evolution, were

sing more than 40 ving under strong HUMAN MUTATION 29(I), 198-204, 2008

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Use of Estimated Evolutionary Strength at the Codon Level Improves the Prediction of Disease-Related Protein Mutations in Humans

Emidio Capriotti, ¹ Leonardo Arbiza, ² Rita Casadio, ⁴ Joaquin Dopazo, ³ Hemán Dopazo, ² and Marc A. Marti-Renom ¹

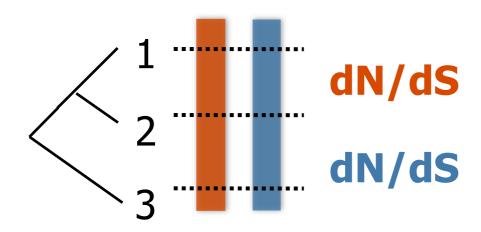
Senctural Genomics Unit, Centro de Insestigación Principe Felipe (CIPF), Valencia, Spain; ⁷Phermocogenomics and Comparative Genomics Unit, Conto de Buestgación Principe Felipe (CDF), Valencia, Spain, ¹Fanctanul Genomics Unit, Bioinformatic Department, Contos de Investigación Principe Felipe (CDF), Valencia, Spain; ¹Laboratory el Biocomparing, CBS/Department el Biology, University el Biologya,

Main Question

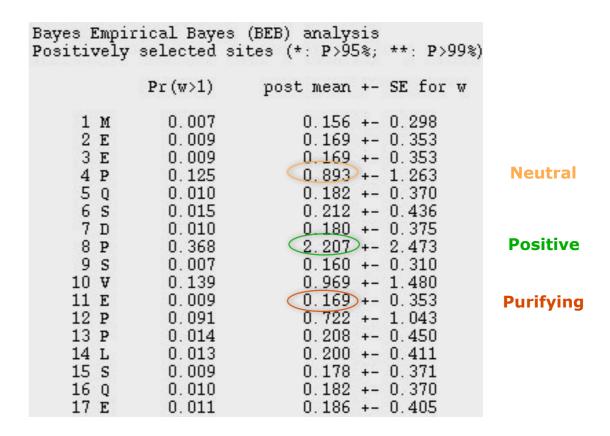
Could an estimator of the selective pressures acting at codon level
 (ω) be used as a predictor of the phenotype effect of SNP's ?

Detecting Positive & Negative Selection

Site-specific models average dN/dS over lineages but differentiate over sites

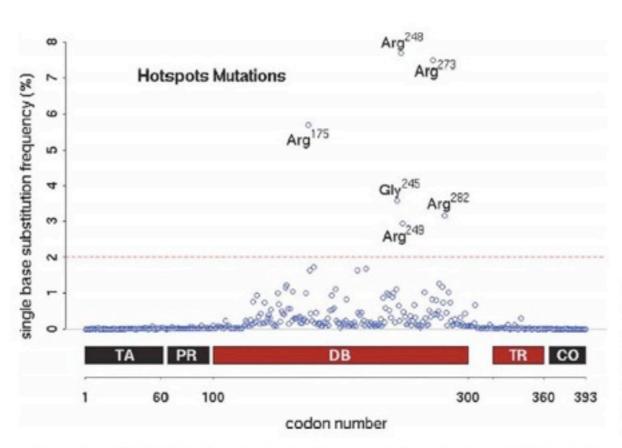


$$\omega = \frac{dN}{dS}$$



p53 evolutionary analysis

Many mutant forms are involved in different types of human cancer



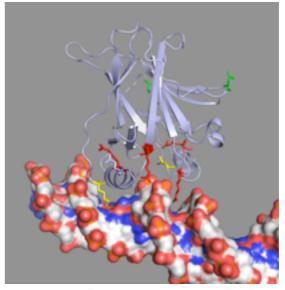


Figure 1. p53 mutations distribution. Mutation frequencies collected in the IARC TP53 R10 database (18,145 non-synonymous mutations) are plotted against the protein domains. The DNAbinding (p53DB) domain contains six residues considered mutational hotspots in cancer.

Table 1. Summary of p53 domains, mutations and ω statistics according to M8 and SLR models

p53 alignment		Mutations			ω statistics				
Domains	Codons	Indelsa	Total	Mps ^b	Model	Min.	Median	Mean	Max.
TA	1-60	38	96	1.6	M8	0.030	0.334	0.379	1.747
					SLR	0.000	0.269	0.369	1.865
PR	61-97	22	151	4.2	M8	0.029	0.314	0.376	1.338
					SLR	0.000	0.307	0.376	1.447
DB	100-300	5	17,389	87.0	M8	0.027	0.039	0.116	1.423
					SLR	0.000	0.029	0.095	2.018
TR	325-355	0	178	5.1	M8	0.028	0.067	0.126	0.456
					SLR	0.000	0.068	0.103	0.379
CO	361-393	11	18	1.6	M8	0.027	0.216	0.255	0.878
					SLR	0.000	0.176	0.226	0.882

Mutations were deduced from the IARC TP53 database.

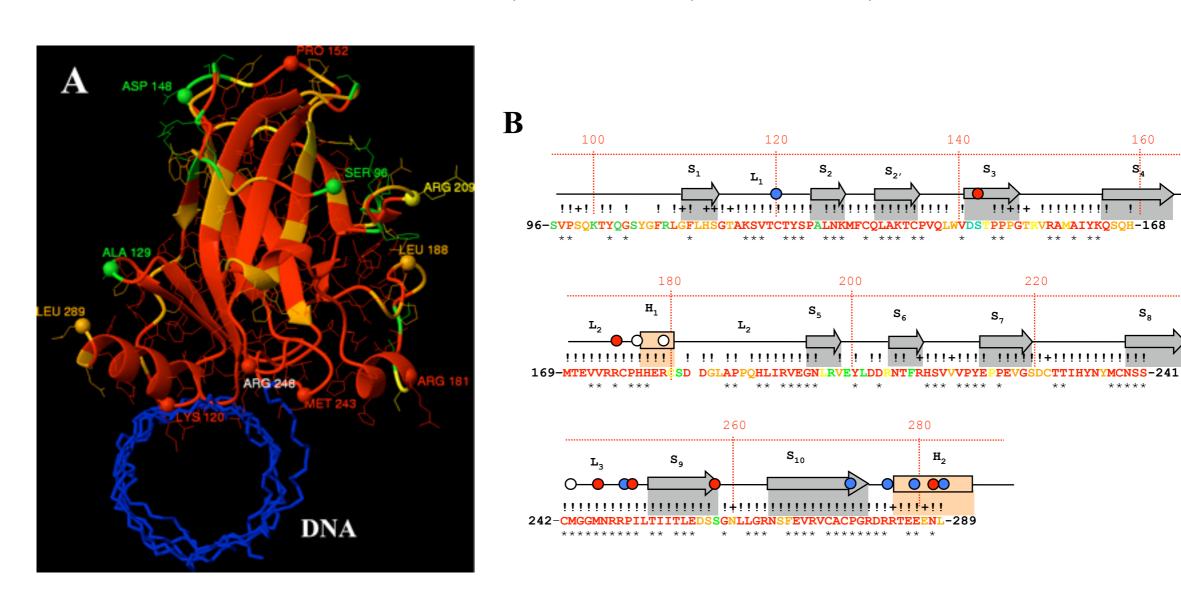
a Insertions/deletions.

b Mean number of mutations per site.

p53 evolutionary analysis

SLR: $\omega \le 0.1$, $0.1 < \omega \le 0.2$, $0.2 < \omega \le 0.3$, $\omega > 0.3$

240



Beyond p53...

Disease Proteins, Immune, Cancer ~ 250 proteins

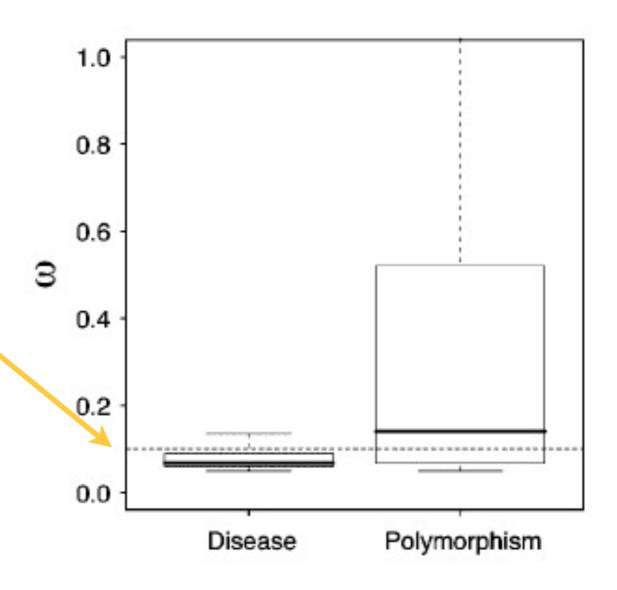
Table 3. Evaluation of alternative $\omega_{\text{cut-off}}$ values and mutational frequencies in disease

	Mamm	als	Vertebrates			
ω _{cut-off}	PAML	SLR	PAML	SLR		
0.03	0.9748	0.0095	0.0504	0.0061		
0.05	0.0114	0.0075	0.0026	0.0008		
0.10	3.0×10^{-05}	0.0076	0.0016	0.0009		
0.12	0.0007	0.0077	0.0010	0.0023		
0.15	0.0025	0.0078	0.0012	0.0018		
0.20	0.0715	0.0074	0.0019	0.0019		
0.25	0.1938	0.0074	0.0044	0.0043		
0.30	0.0188	0.0076	0.0035	0.0065		
0.40	0.0486	0.0101	0.0176	0.0254		
0.50	0.1849	0.0223	0.0534	0.1010		
G ^a	43	43	43	43		
G ^a R ^b	24,375	24,375	17,424	17,435		
M^c	8970	8970	8081	8083		

One-tail K–S tests reject the null hypothesis, which considers that the frequency of mutations are not differentially distributed above and bellow the given $\omega_{\text{cut-off}}$. The alternative hypothesis, which considers that disease-associated mutations are preferentially associated with values below the $\omega_{\text{cut-off}}$ is accepted with the highest confidence using ω_{PAML} estimations on mammal ($\omega_{\text{cut-off}}$ =0.10) and vertebrate ($\omega_{\text{cut-off}}$ =0.12) datasets. The K–S test on SLR estimates reject the null hypothesis for all values of $\omega_{\text{cut-off}}$ evaluated. This is the consequence of the undesirable behaviour of the SLR method, which drops low values of ω to 0 (see the text and Figure 6 for explanation).

- a Number of genes evaluated.
- b Number of residues evaluated.
- Number of mutations evaluated.

SwissProt Database, ~3,000 proteins



Evolution and disease.

Capriotti et al. Use of estimated evolutionary strength at the codon level improves the prediction of disease-related protein mutations in humans. Hum Mutat (2008) vol. 29 (1) pp. 198-204

HUMAN MUTATION 29(1), 198-204, 2008

METHODS

Use of Estimated Evolutionary Strength at the Codon Level Improves the Prediction of Disease-Related Protein Mutations in Humans

Emidio Capriotti, 1 Leonardo Arbiza, 2 Rita Casadio, 4 Joaquín Dopazo, 3 Hernán Dopazo, 2* and Marc A. Marti-Renom1*

Structural Genomics Unit Centro de Investigación Príncite Felite (CIPF) Valencia Strain. 2 Pharmacogenomics and Combarative Genomics. Structural Verionias Orin, Centro de investigación interpretape (CIPF), Valencia, Spain; Finctional Genomics Unit, Bioinformatics Department, Centro de Investigación Principe Felipe (CIPF), Valencia, Spain; *Laboratory of Biocomputing, CIRB/Department of Biology, University of Bologna,

Communicated by David N. Cooper

Predicting the functional impact of protein variation is one of the most challenging problems in bioinformatics. A rapidly growing number of genome-scale studies provide large amounts of experimental data, allowing the application of rigorous statistical approaches for predicting whether a given single point mutation has an impact on human health. Up until now, existing methods have limited their source data to either protein or gene on human health. Up until now, existing methods have limited their source data to either protein or gene information. Novel in this work, we take advantage of both and focus on protein evolutionary information by using estimated selective pressures at the codon level. Here we introduce a new method (SeqProfCod) to predict the likelihood that a given protein variant is associated with human disease or not. Our method relies on a support vector machine (SVM) classifier trained using three sources of information: protein sequence, multiple protein sequence alignments, and the estimation of selective pressure at the codon level. SeqProfCod has been benchmarked with a large dataset of 8,987 single point mutations from 1,434 human proteins from SWISS-PROT. It achieves 82% overall accuracy and a correlation coefficient of 0.59, indicating that the SWISS-PROI. It achieves 82% overall accuracy and a correlation coefficient of 0.59, indicating that the estimation of the selective pressure helps in predicting the functional impact of single-point mutations. Moreover, this study demonstrates the synergic effect of combining two sources of information for predicting the functional effects of protein variants: protein sequence/profile-based information and the evolutionary estimation of the selective pressures at the codon level. The results of large-scale application of SeqProfCod over all annotated point mutations in SWISS-PROT (available for download at http://sgu.bioinfo.cipf.es/ services/Omidios/; last accessed: 24 August 2007), could be used to support clinical studies. Hum Mutat 29(1), 198–204, 2008. © 2007 Wiley-Liss, Inc.

KEY WORDS: SNP; nsSNP; disease; sequence profile; evolutionary strength; bioinformatics

INTRODUCTION

Studies characterizing the relationship between protein variants Studies characterining the relationship between protein variants and human disease have grown rapidly over the past years, in part due to genomic-scale sequencing efforts [Krawcrak et al., 2000; Sherry et al., 2001; Sterson et al., 2003]. For example, it is now known that single nucleotide polymorphisms (SNPs) constitute about the 90% of human protein sequence variability [Collins et al., 1998]. Synonymous and nonsynonymous SNPs (nsSNPs) (n et al., 1998]. Synonymous and nonsynonymous SNPs (nsSNPs)
may occur every ~350 bp in coding regions [Cargill et al., 1999]
and about 50% of nsSNPs may be associated to pathologies of
genetic origin. Therefore, predicting which nsSNPs are responsible
thermational Reintegration Grant; Grant number: FP6-039722. Grant

genetic origin. Ineretore, predicting which insNrs are responsible for human disease is one of the major challenges in bioinformatics.

Recently, different methods have been developed for predicting the effect of single point mutations in humans [Arbita et al., 2006; Chan et al., 2007; Ramensky et al., 2005; Agricut et al., 2006; Chan et al., 2007; Karchin et al., 2007; and Henikoff, 2007; Ramensky et al., 2002; Santibanez Koref et al., 2003; Thomas et al., 2003b; Yue and Moult, 2006]. In spite of the effort, however, interscience.wiley

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BESTARTATIVE RC







Sequence and evolutive - based predictors

Mutation C->W

ACD EF G HIK LMNPQ RS T VWY

Sequence Environment

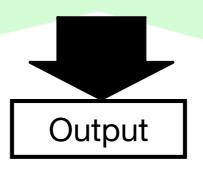
Profile Codon

ACD EF G HI K LMNPQ RS T VWY

MR AS W dS dN



RBF Kernel



O(i) where i = disease or neutral polymorphism

SEQ: Mutation+ Sequence Environment

SEQPROF: Mutation+ Sequence Environment + Profile SEQCOD Mutation+ Sequence Environment + Codon

OMIDIOS: Mutation+ Sequence Environment + Profile + Codon

Profile: MR and AS sequence profile information

Codon: omega, dS,dN: selective pressure at codon level, synonymous and

non-synonymous rate at branch level.

Classification results



	Mutation	Disease	Neutral	Proteins
Single point mutation with reported effect	21,185	12,944	8,241	3,587
Single point mutation with reported effect and profile	8,718	3,852	4,866	2,538

SeqCod and SeqProf methods reach the same level of accuracy of about 79% and when the two different types of evolutive information are used the resulting predictor Omidios overcomes the others showing an overall accuracy of 82%

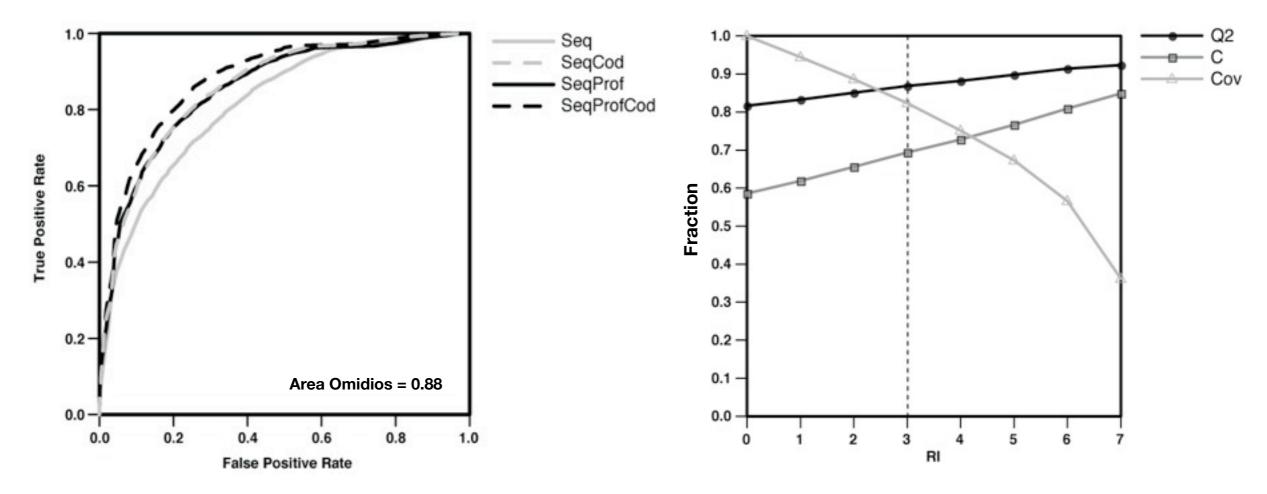
	Q2	P[D]	Q[D]	P[N]	Q[N]	С
Seq	73	86	72	54	74	0.43
SeqCod	79	87	82	64	74	0.53
SeqProf	79	88	81	63	75	0.54
Omidios	82	89	84	68	76	0.59

D = Disease related N = Neutral

Omidios method

Omidios has higher accuracy than the previous two methods increasing the accuracy up to 82% and the correlation coefficient to 0.59.

	Q2	P[D]	Q[D]	P[N]	Q[N]	С
Omidios	82	88	84	68	76	0.59



Q2: Overall Accuracy C: Correlation Coefficient DB: Fraction of database that are predicted with a reliability ≥ the given threshold

Comparison

Omidios results in higher accuracy and correlation than the other available methods covering the 100% of the dataset (see column %PM).

Omidios results in higher accuracy with respect to SIFT and although the quality of Omidios is comparable to PANTHER, when our prediction are selected by RI index the accuracy of our method is higher than PANTHER.

	Q2	P[D]	Q[D]	P[N]	Q[N]	С	РМ
Omidios	82	89	84	68	76	59	100
SIFT	71	84	72	51	69	38	97
PANTHER	74	87	75	53	72	43	83

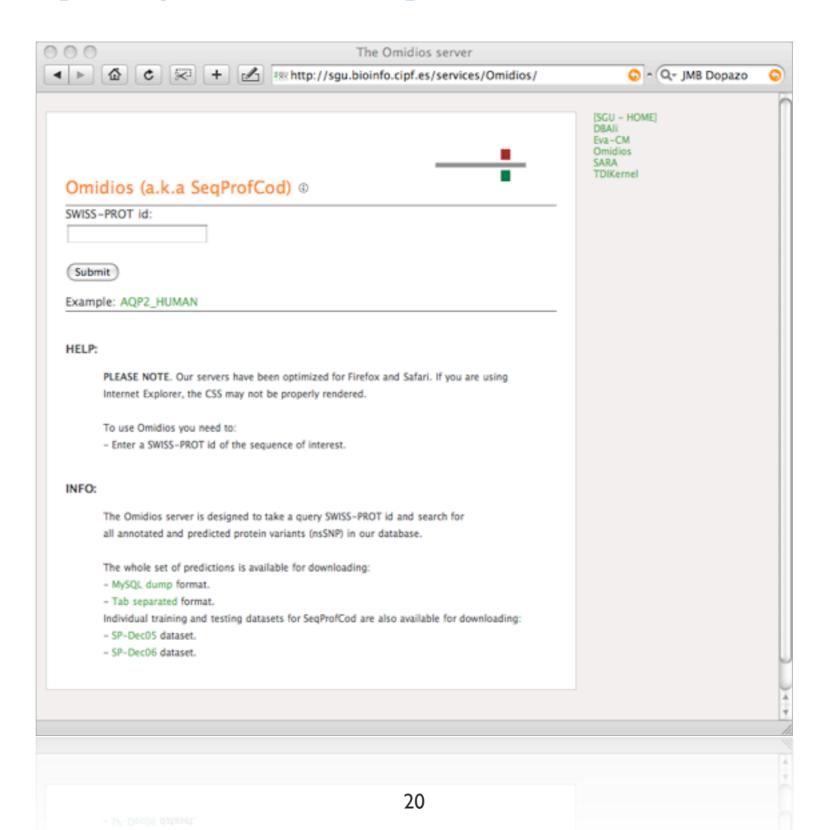
HM-Dic05: 8987 mutations

	Q2	P[D]	Q[D]	P[N]	Q[N]	С	PM
Omidios	74	65	79	83	72	48	100
SIFT	71	63	70	78	72	42	96
PANTHER	77	73	71	79	81	52	77

HM-Dic06: 2008 mutations

Omidios server

http://sgu.bioinfo.cipf.es/services/Omidios



Structural analysis of missense mutations in human BRCA1 BRCT domains

Mirkovic et al. Structure-based assessment of missense mutations in human BRCA1: implications for breast and ovarian cancer predisposition. Cancer Res (2004) vol. 64 (11) pp. 3790-7

Structure-Based Assessment of Missense Mutations in Human BRCA1: Implications for Breast and Ovarian Cancer Predisposition

Nebojsa Mirkovic, Marc A. Marti-Renom, Barbara L. Weber, Andrej Sali, and Alvaro N. A. Monteiro^{4,5}

Laboratory of Molecular Biophysics, Pels Family Center for Biochemistry and Structural Biology, Rockefeller University, New York, New York; Popartments of Biopharmaceutical Sciences and Pharmaceutical Chemistry, and California Institute for Quantitative Biomedical Research, University of California at San Francisco, San Francisco, California: Abarmaon Family Cancer Research Institute, University of Pennsylvania, Philadelphia, Pennsylvania, Strang Cancer Prevention Center, New York, New York; and Department of Cell and Developmental Biology, Weill Medical College of Cornell University, New York, New York, New York

can be screened for the presence of mutations. However, the cancer association of most alleles carrying missense mutations is unknown, thus creating significant problems for genetic counseling. To increase our ability to identify cancer-associated mutations in BRCA1, we set out to use transcriptional activation and binding to RNA polymerase II (18–21) transcriptional activation. Thirty-one of 37 missense mutations of known tion function of BRCA1 leads to tumor development and provides a impact on the transcriptional activation function of BRCA1 are readily rationalized in structural terms. Loss-of-function mutations involve nonconservative changes in the core of the BRCA1 C-terminus (BRCT) fold or are localized in a groove that presumably forms a binding site involved in the transcriptional activation by BRCA1; mutations that do not abolish are on the surface outside of the putative binding site. Next, structurebased rules for predicting functional consequences of a given missense mutation were applied to 57 germ-line BRCA1 variants of unknown cancer association. Such a structure-based approach may be helpful in an integrated effort to identify mutations that predispose individuals to

INTRODUCTION

Many germ-line mutations in the human BRCA1 gene are associated with inherited breast and ovarian cancers (1, 2). This information

BRCT-like domains was obtained by the SALIGN command in MODELLER has allowed clinicians and genetic counselors to identify individuals at high risk for developing cancer. However, the disease association of of the two human BRCA1 BRCT domains (Protein Data Bank code IJNX; relatively low frequency and ethnic specificity limit the usefulness of the population-based statistical approaches to identifying cancer-causing mutations. To address this problem, we use here the threedimensional structure of the human BRCA1 BRCT domains to assess the transcriptional activation functions of BRCA1 mutants. Our study is made possible by the recently determined sequences (3-6) and three-dimensional structures of the BRCA1 homologs (7, 8). In addition, we benefited from prior studies that attempted to rationalize and tion, we benefited from prior studies that attempted to rationalize and predict functional effects of mutations in various proteins (9-12), three-dimensional model for each of the 94 mutants. The crystallographic including those of BRCA1 (13, 14).

BRCA1 is a nuclear protein that activates transcription and facilitates DNA damage repair (15, 16). The tandem BRCT domains at the

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cancerres@aacrjournals.org).

Requests for reprints: Alvaro N. A. Monteiro, H. Lee Moffitt Cancer Center and Research Institute, MRC 3 West, 12902 Magnolia Drive, Tampa, FL 33612. Phone: (813) 745-6321; Fax: (813) 903-6847; E-mail: monteian@moffitt.usf.edu.

COOH-terminus of BRCA1 are involved in several of its functions including modulation of the activity of several transcription factors The BRCAI gene from individuals at risk of breast and ovarian cancers (15), binding to the RNA polymerase II holoenzyme (17), and activating transcription of a reporter gene when fused to a heterologous DNA-binding domain (18, 19), Importantly, cancer-associated mutan between the cancer-associated mutations and those that abolish

These observations suggest that abolishing the transcriptional activa-

The multiple sequence alignment (MSA) of orthologous BRCA1 BRCT domains from seven species, including *Homo sapiens* (GenBank accession number U14680), *Pan troglodytes* (AF207822), *Mus musculus* (U68174), Rattus norvegicus (AF036760), Gallus gallus (AF355273), Canis familiaris (U50709), and Xenopus laevis (AF416868), was obtained by using program ClustalW (22) and contains only one gapped position (Supplementary Fig. 1).

According to PSI-BLAST (23), the latter six sequences are the only sequences in the nonredundant protein sequence database at National Center for Biotechnology Information that have between 30% and 90% sequence identity to the human BRCA1 BRCT domains (residues 1649-1859).

The multiple structure-based alignment of the native structures of the (Supplementary Fig. 2). It included the experimentally determined str XRCC1 protein (1CDZ; Ref. 13). Structure variability was defined by the root-mean-square deviation among the superposed $C\alpha$ positions, as calculated by the COMPARE command of MODELLER. The purpose of these calculations was to gain insight into the variability of surface-exposed residues (left panel in Fig. 2). In conjunction with observed mutation clustering, these data may point to putative functional site(s) on the surface of BRCT repeats.

Comparative protein structure modeling by satisfaction of spatial restraints

structure of the human wild-type BRCA1 BRCT domains was used as the template for modeling (8). The four residues missing in the crystallographic structure (1694 and 1817–1819) were modeled *de novo* (27). All of the models are available in the BRCA1 model set deposited in our ModBase database of comparative protein structure models (28).6

For the native structure of the human BRCT tandem repeat and each of the 94 mutant models, a number of sequence and structure features were calcu lated. These features were used in the classification tree in Fig. 3 (values for all 94 mutations are given in Supplementary Tables 1 and 2).

Buriedness. Accessible surface area of an amino acid residue was calcu-University Presidential Postdoctoral Fellow, A. S., is an Irma T. Hrischl Trust Career Scientist; and B. L. W. is an Arbamson Investigated.

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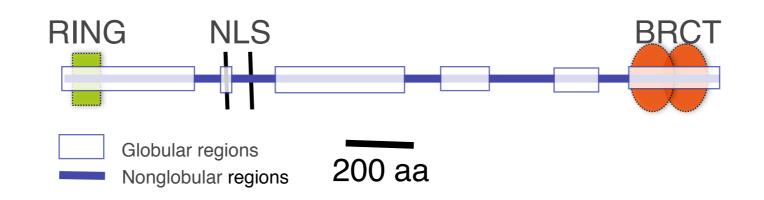
Note: The authors declare that they have no competing financial interests, Supplemental data for this article are available at Cancer Research Online (http:

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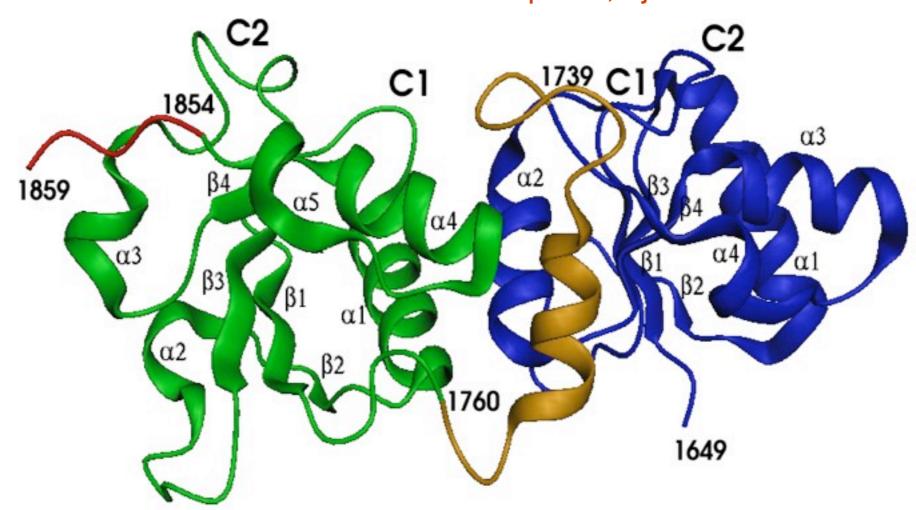
mutation of a more exposed residue is less likely to change the structure and when the competition of the control of the control of the structure and when the control of the control o lated by the program DSSP (29) and normalized by the maximum accessible therefore its function



Human BRCA1 and its two BRCT domains



BRCA1 BRCT repeats, 1jnx



CONFIDENTIAL



BRACAnalysis 14 Comprehensive BRCA1-BRCA2 Gene Sequence Analysis Result

Niecee Singer, MS Strang Cancer Prevention Center

428 E 72nd St New York, NY 10021 SPECIMEN Blood

Specimen Type: Draw Date: Accession Date:

Report Date:

Oct 27, 2000 Nov 17, 2000

PATIENT Name:

Date of Birth: Feb 02, 1953 Patient ID:

Gender: Female 00019998 Accession #: Requisition #: 56694

Physician: Fred Gilbert, MD

Test Result

Gene Analyzed BRCA2 BRCA1

Specific Genetic Variant H2116R None Detected

Interpretation

GENETIC VARIANT OF UNCERTAIN SIGNIFICANCE

The BRCA2 variant H2116R results in the substitution of arginine for histidine at amino acid position 2116 of the BRCA2 protein. Variants of this type may or may not affect BRCA2 protein function. Therefore, the contribution of this variant to the relative risk of breast or ovarian cancer cannot be established solely from this analysis. The observation by Myriad Genetic Laboratories of this particular variant in an individual with a deleterious truncating mulation in BRCA2, however, reduces the likelihood that H2116R is itself deleterious.

Authorized Signature:

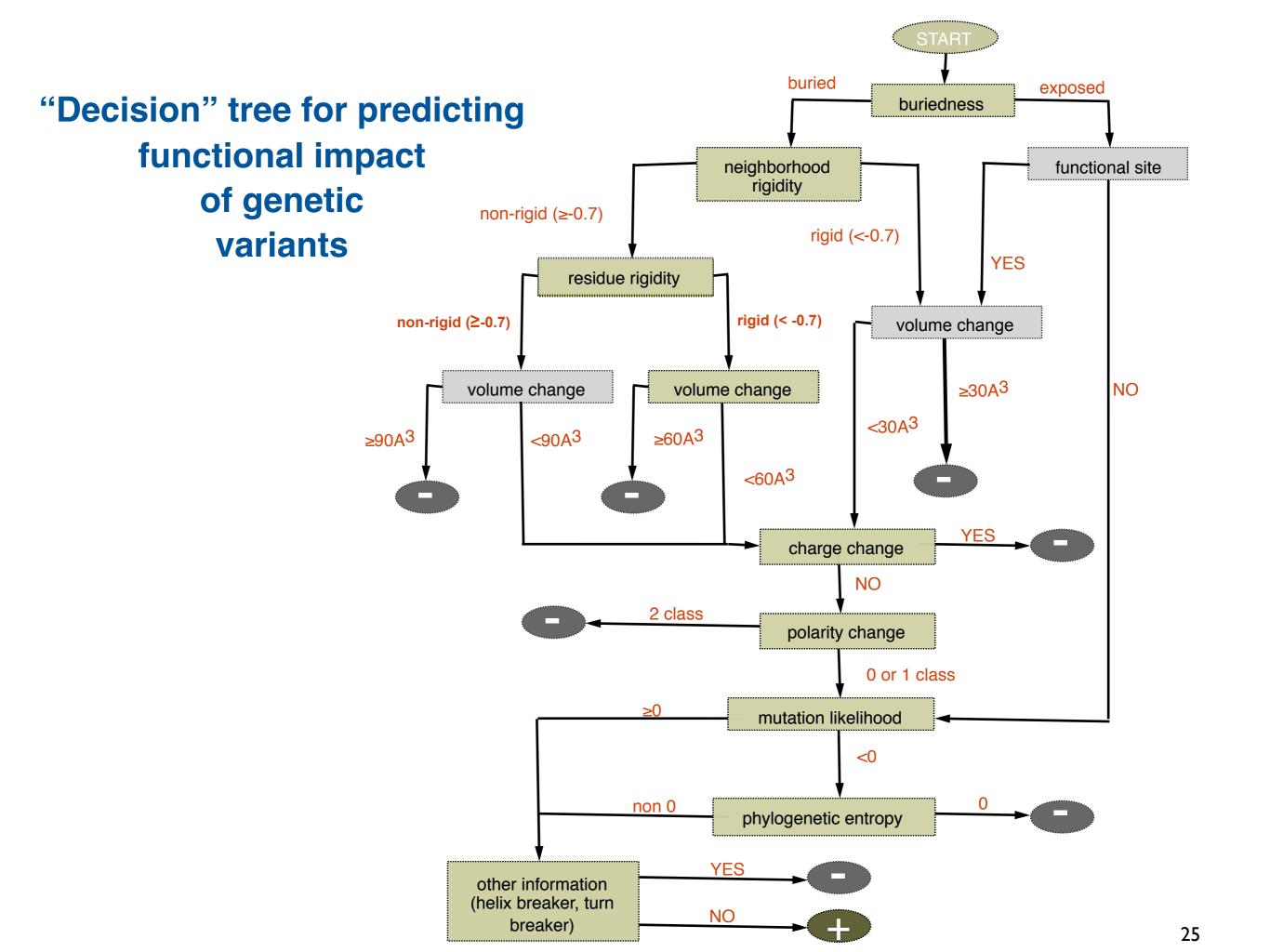
Brian E. Ward, Ph.D. Laboratory Director

Medical Director

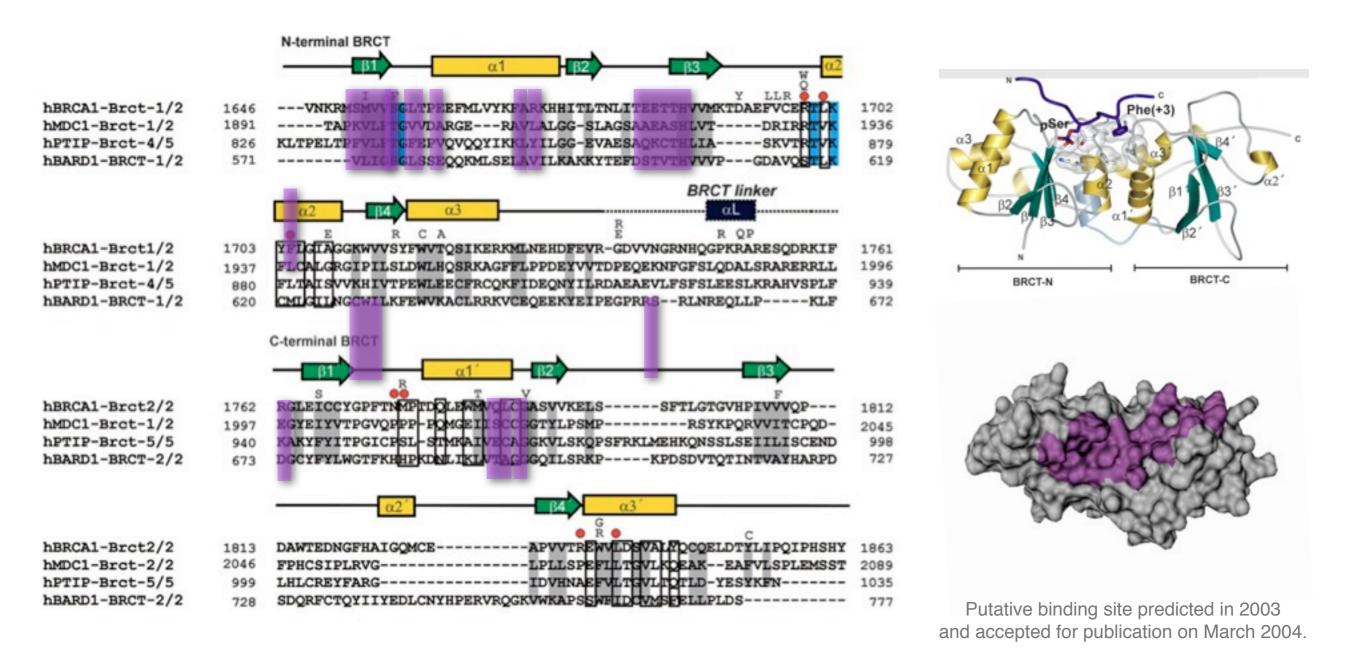
These teraresults should only be used in conjunction with the patient's clinical history and any previous analysis of appropriate family members. It is strongly recommended that these results be communicated to the patient in a setting that includes appropriate counseling. The accompanying Technical Specifications summary describes the analysis, method, performance characteristics, nomencionire, and interpretive outpile of this test. This test may be considered investigational by some states. This test was developed and its performance characteristics determined by Myriad Genetic Laboratories. It has not been reviewed by the U.S. Food and Orug Administration. The FDA has determined that such Gearance or approval is not necessary.

Missense mutations in BRCT domains by function

	cancer associated	not cancer associated		?		
no transcription activation	C1697R R1699W A1708E S1715R P1749R M1775R		E1660G 1 H1686Q 7 R1699Q 3 K1702E 8 Y1703HF R	.1705PS 715NS1 722FF17 4LG173 EG1743 A1752P F1761I	F1761 M1775 M1775 L1780 I18079 V1833 A1843	SE SK S S SE
transcription activation		M1652I A1669S		V1665M D1692N G1706A D1733G M1775V P1806A		
?			M1652T W1718S V1653M T1720A L1664P W1730S T1685A F1734S T1685I E1735K M1689R V1736A D1692Y G1738R D1739E F1695L D1739G V1696L D1739Y G1706E V1741G W1718C H1746N	R1751P R1751Q R1758G L1764P I1766S P1771L T1773S P1776S D1778N D1778G D1778H M1783T	C1787S G1788D G1788V G1803A V1804D V1808A V1809F V1810G Q1811R P1812S N1819S	A1823T V1833M W1837R W1837G S1841N A1843P T1852S P1856T P1859R



Putative binding site on BRCA1



Williams et al. 2004 Nature Structure Biology. June 2004 11:519

Mirkovic et al. 2004 Cancer Research. June 2004 64:3790

Supervised learning approach

Karchin et al. Functional Impact of Missense Variants in BRCA1 Predicted by Supervised Learning. PLoS Comput Biol (2007) vol. 3 (2) pp. e26

Functional Impact of Missense Variants in BRCA1 Predicted by Supervised Learning

Rachel Karchin^{1,2*}, Alvaro N. A. Monteiro³, Sean V. Tavtigian⁴, Marcelo A. Carvalho³, Andrej Sali^{5,6*}

1 Department of Biomedical Engineering, Johns Hopkins University, Baltimore, Maryland, United States of America, 2 Institute of Computational Medical Engineering, Johns Hopkins University, Baltimore, Maryland, United States of America, 2 Institute of Computational Medical Engineering, Johns Hopkins University, Baltimore, Maryland, United States of America, 2 Institute of Computational Medical Engineering, Johns Hopkins University, Baltimore, Maryland, United States of America, 2 Institute of Computational Medical Engineering, Johns Hopkins University, Baltimore, Maryland, United States of America, 2 Institute of Computational Medical Engineering, Johns Hopkins University, Baltimore, Maryland, United States of America, 2 Institute of Computational Medical Engineering, Description of Computational Medical Engineering, Description of Computational Medical Engineering, Description of Computational Engineering (Institute Institute Instit University, Baltimore, Maryland, United States of America, 3 Risk Assessment, Detection, and Intervention Program, H. Lee Moffitt Cancer Center and Research Institute Tampa, Florida, United States of America, 4 International Agency for Research on Cancer, Lyon, France, 5 Department of Pharmaceutical Chemistry, University of California San Francisco, San Francisco, California, United States of America, 6 California Institute for Quantitative Biomedical Research, University of California San Francisco, San Francisco, California, United States of America

Many individuals tested for inherited cancer susceptibility at the BRCA1 gene locus are discovered to have variants of unknown clinical significance (UCVs). Most UCVs cause a single amino acid residue (missense) change in the BRCA1 protein. They can be biochemically assayed, but such evaluations are time-consuming and labor-intensive. Computational methods that classify and suggest explanations for UCV impact on protein function can complement functional tests. Here we describe a supervised learning approach to classification of BRCA1 UCVs. Using a novel combination of 16 predictive features, the algorithms were applied to retrospectively classify the impact of 36 BRCA1 C-terminal (BRCT) domain UCVs biochemically assayed to measure transactivation function and to blindly classify 54 documented UCVs. Majority vote of three supervised learning algorithms is in agreement with the assay for more than 94% of the UCVs. Two UCVs found deleterious by both the assay and the classifiers reveal a previously uncharacterized putative binding site. Clinicians may soon be able to use computational classifiers such as those described here to better inform patients. These classifiers can be adapted to other cancer susceptibility genes and systematically applied to prioritize the growing number of potential causative loci and variants found by large-scale disease association

Citation: Karchin R. Monteiro ANA, Taytigian SV. Carvalho MA. Sali A (2007) Functional impact of missense variants in BRCA1 predicted by supervised learning. PLoS Comput

The BRCA1 gene encodes a large multifunction protein involved in cell-cycle and centrosome control, transcriptional regulation, and in the DNA damage response [1–3]. Inherited mutations in this gene have been associated with an increased lifetime risk of breast and ovarian cancer (6-8 times that of the general population) [4]. There are several thousand known deleterious BRCAI mutations that result in frameshifts and/or premature stop codons, producing a truncated protein product [5]. In contrast, the functional impact of most missense variants that result in a single amino acid residue change in BRCA1 protein is not known. The Breast Cancer Information Core database (http://research.nhgri.nih.gov/bic/), a central repository of BRCA1 and BRCA2 mutations identified in genetic tests, currently contains 487 unique missense BRCA1 variants (April 2006), of which only 17 have sufficient genetic/epidemiological evidence to be classified as deleterious (Clinically Important) and 33 as neutral or of little clinical importance (Not Clinically Important). As genetic testing for inherited disease predispositions becomes more commonplace, predicting the clinical significance of missense variants and other UCVs will be increasingly important for

Because most LICVs in BRCA1 and BRCA2 occur at very low population frequencies (<0.0001) [6], direct epidemiological asures, such as familial cosegregation with disease, are often not sufficiently powerful to identify the variants associated with cancer predisposition. A promising approach is to supplement epidemiological and clinical analysis of UCVs with indirect approaches such as biochemical studies of

protein function and bioinformatics analysis [6-8]. In the future, physicians and genetic counselors may be able to rely on all these sources of information about UCVs when counseling their patients.

Previous bioinformatics analysis of BRCA1 UCVs has depended primarily on measures of evolutionary conservation in multiple sequence alignments of human BRCA1 and related proteins from other organisms [9-11]. Two groups have attempted to include information about BRCA1 protein structure. Williams et al. predicted the impact of $25~\mathrm{missense}$ variants in BRCA1's C-terminal BRCT domains by considering both conservation and location of variant amino acid residues in an X-ray crystal structure [12]. Variants were predicted deleterious if their properties were similar to

Editor: Greq Tucker-Kellogg, Lilly Systems Biology, Singapore

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A previous version of this article appeared as an Early Online Release on December 28, 2006 (doi:10.1371/journal.pcbi.0030026.eor). Copyright: © 2007 Karchin et al. This is an open-access article distributed under the terms of the Creative Commons Attribution License, which permits unrestricted

use, distribution, and reproduction in any medium, provided the original author and source are credited.

sion tree; SIFT, Sorting Intolerant from Tolerant; UCV, variant of unkn

* To whom correspondence should be addressed. E-mail: karchin@karchinlab.org (RK); sali@salilab.org (AS)

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February 2007 | Volume 3 | Issue 2 | e26



Î 8 8 8 4 4 Î Î Î Î Î Î Î Î Î 8 8 8 Î **1** β-sheet **B** buried Correctly or incorrectly classified as deleterious E exposed **bend** H-bonded turn Correctly or incorrectly classified as neutral ☐ loop O Insufficient confidence to classify

a-helix

Predictors are combined in support vector machine supervised learning

$X_1..X_k$ = TRAINING

Grantham distance

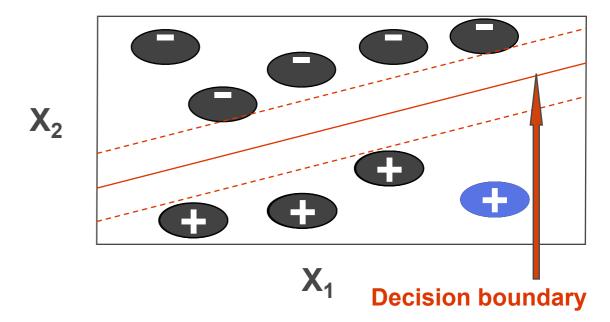
Solvent accessibility

methyl(ene) groups

volume change



0.12 21 7 45 -3.2 3.1 120 30 8 1.5



0.7

0

17

TESTING? PREDICTING...

Features

Feature Category	Feature Description
Structural	Solvent Accessiblity of wild-type amino acid residue (Å ²)
	Solvent Accessibility of wild-type residue normalized by maximum exposed Sol-
	vent Accessibility of that residue type in a GLY-X-GLY tripeptide, using values gi-
	ven by Rose et al. [80]
	Solvent Accessibility of variant residue
	Normalized Solvent Accessibility of variant residue
	Number of methyl(ene) groups within 6 Å of the variant sidechain [81]
	Number of unsatisfied spatial restraints in the MODELLER objective function after
	in silico mutation and simulated annealing refinement of the variant ^a
	Φ and Ψ backbone dihedral angles at the mutated position
	Whether the mutation results in buried charge
Physiochemical differences between wild-type and variant amino acid residues	Change in formal charge
	Change in volume (Å ³) [82]
	Change in polarity [83]
	Grantham difference [37]
Evolutionary conservation of amino acid residues in protein orthologs	Relative entropy estimated by amino acids in the variant's alignment column [84]
	Positional hidden Markov model conservation score based on the probabilities of
	the wild-type, variant, and most probable amino acid residue in the variant's
	alignment column ^b [24]

^aViolated restraints suggest that the mutated sidechain introduced steric clashes or unusual geometries into the protein model. Examples of violated restraints include extreme values of the Lennard-Jones 6–12 potential [85], bond angle potential, bond length potential, sidechain dihedral angle restraints, and nonbonded restraints. Two thresholds are used to identify violated restraints yielding two features.

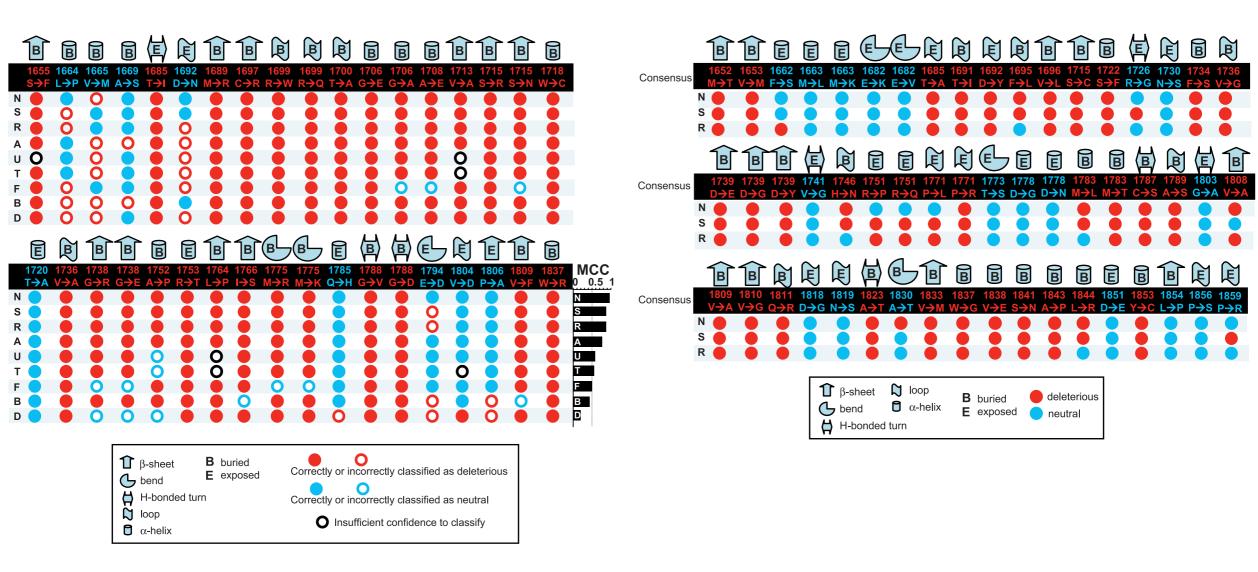
doi:10.1371/journal.pcbi.0030026.t002

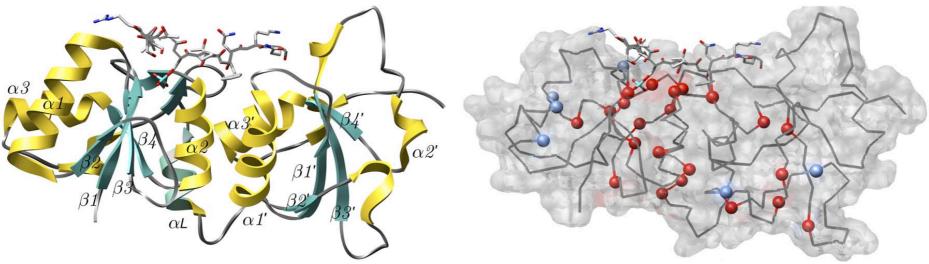
^bThe probabilities are estimated by a hidden Markov model built with SAM-T2K and the w0.5 script [23].

 $[\]mathsf{PHC} = \log(|p(\mathsf{Wild-type}) - p(\mathsf{Variant})|) + \log(p(\mathsf{Wild-type})) + \log(P(\mathsf{Most\ Probable})) - \log\ (p(\mathsf{Variant}))$

The features were computed for 618 TP53 missense variants, 36 BRCA1 BRCT missense variants biochemically characterized in our companion paper [14], and 54 BRCA1 BRCT UCVs found in BIC.

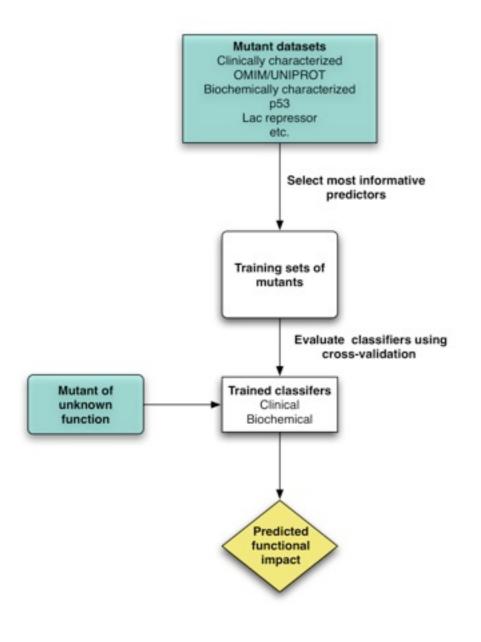
Results

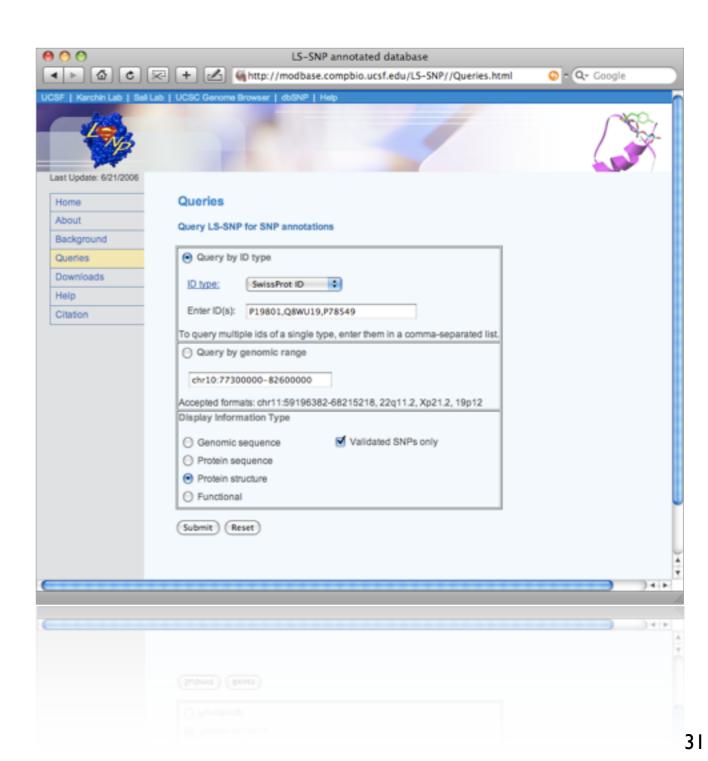




LS-SNP Large Scale SNP analysis

http://salilab.org/LS-SNP/





Protein function from structure

ab-initio *localization of binding sites*

Rossi. Localization of binding sites in protein structures by optimization of a composite scoring function. Protein Science (2006) vol. 15 (10) pp. 2366-2380

Downloaded from www.proteinscience.org on September 18, 2006

Localization of binding sites in protein structures by optimization of a composite scoring function

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(RECEIVED March 28, 2006; Final Revision July 10, 2006; Accepted July 11, 2006)

Abstract

The rise in the number of functionally uncharacterized protein structures is increasing the demand for structure-based methods for functional annotation. Here, we describe a method for predicting the location of a binding site of a given type on a target protein structure. The method begins by constructing a scoring function, followed by a Monte Carlo optimization, to find a good scoring patch on the protein surface. The scoring function is a weighted linear combination of the z-scores of various properties of protein structure and sequence, including amino acid residue conservation, compactness, protrusion, convexity, rigidity, hydrophobicity, and charge density; the weights are calculated from a set of previously identified instances of the binding-site type on known protein structures. The scoring function can easily incorporate different types of information useful in localization, thus increasing the applicability and accuracy of the approach. To test the method, 1008 known protein structures were split into 20 different groups according to the type of the bound ligand. For nonsugar ligands, such as various nucleotides, binding sites were correctly identified in 55%–73% of the cases. The method is completely automated (http://salilab.org/patcher) and can be applied on a large scale in a structural genomics

Keywords: protein function annotation; small ligand binding-site localization

et al. 1999; Brenner 2000, 2001; Sali 2001; Vitkup et al. 2001; Chance et al. 2002; Goldsmith-Fischman and PDB files. 36,606 entries in the Protein Data Bank (PDB) (Kouranov deposited by structural genomics consortia, 985 (70%)

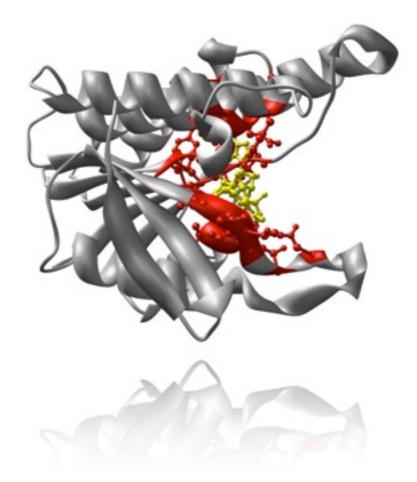
Reprint requests to: Andrea Rossi or Andrei Sali, Departments of Biopharmaceutical Sciences and Pharmaceutical Chemistry, California Institute for Quantitative Biomedical Research, University of California. San Francisco Byers Hall, Office 503B, 1700 4th Street, San Francisco, CA 94143-2552, USA; e-mail: andrea@salilab.org or sali@salilab.org; fax:

Many protein targets of structural biologists are no longer of which had an unknown function according to the chosen because of their function, but rather by their HEADER record of their PDB files. In contrast, only 174 location in the protein sequence-structure space (Burley (0.5%) of the 35,199 protein structures solved outside of structural genomics had no functional annotations in their

Honig 2003). Therefore, the number of functionally uncharacterized protein structures is growing. Of the transfer of thousands of uncharacterized protein structures that will become available over the next few years and millions of comparative models based et al. 2006) as of February 23, 2006, 1407 structures were on the known structures, automated structure-based functional annotation is required (Wallace et al. 1996, 1997; Kleywegt 1999; Thornton et al. 2000; Babbitt 2003; Laskowski et al. 2003). In particular, we need to be able to identify the locations and types of binding sites on a given structure, because the binding sites define the molecular function of a protein.

> The most principled computational approach to pre dicting the molecular function is to dock a large library of potential ligands against the surface of the protein. In

Protein Science (2006), 15:1-15. Published by Cold Spring Harbor Laboratory Press. Copyright © 2006 The Protein Society

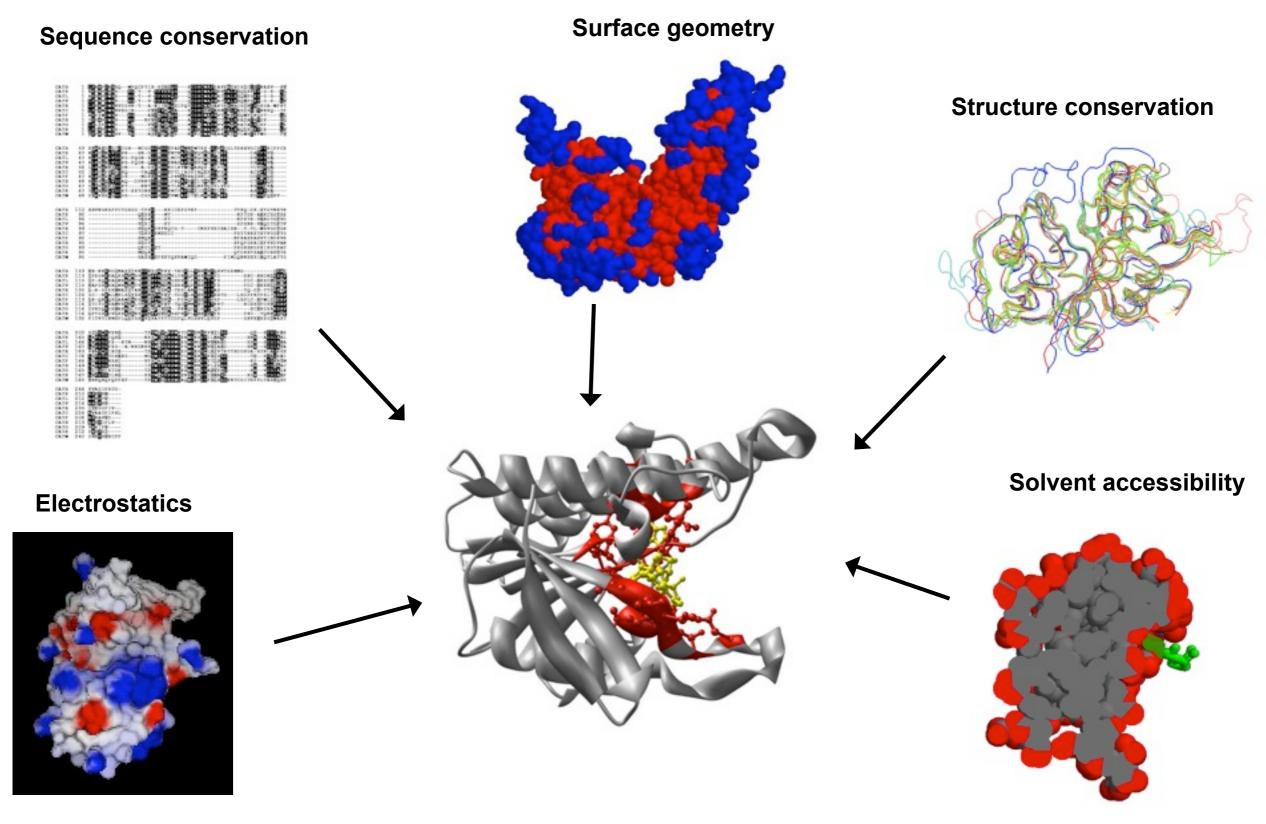


For 20% protein structures function is *unknown*

	Structural Genomics*	Traditional methods
Annotaated**	654	28,342
Not Annotaated	506 (43.6%)	6,815 (19,4%)
Total deposited	1,160	35,157

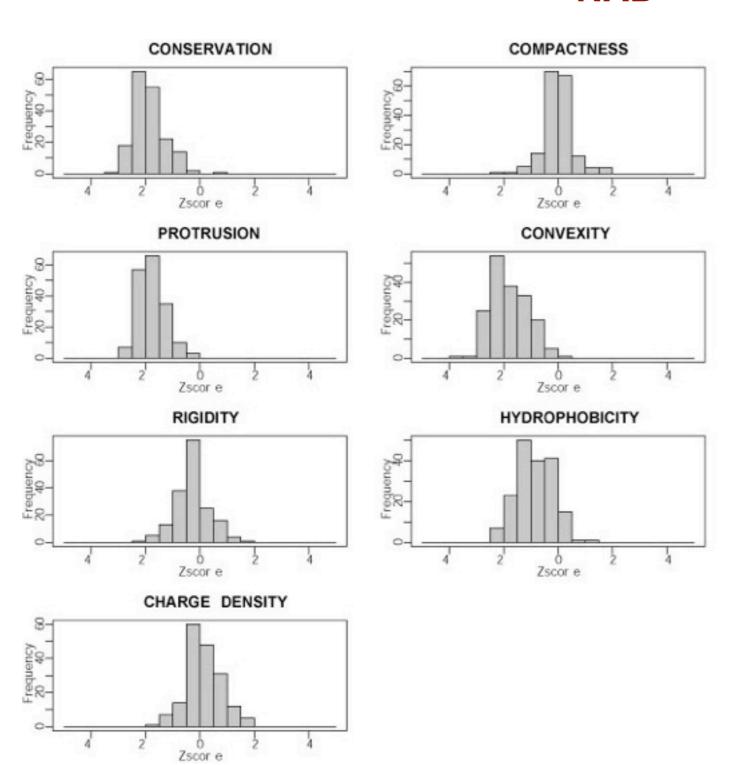
* annotated as STRUCTURAL GENOMICS in the header of the PDB file **annotated with either CATH, SCOP, Pfam or GO terms in the MSD database 36,317 protein structures, as of August 8th, 2006

Representation



Scoring

NAD



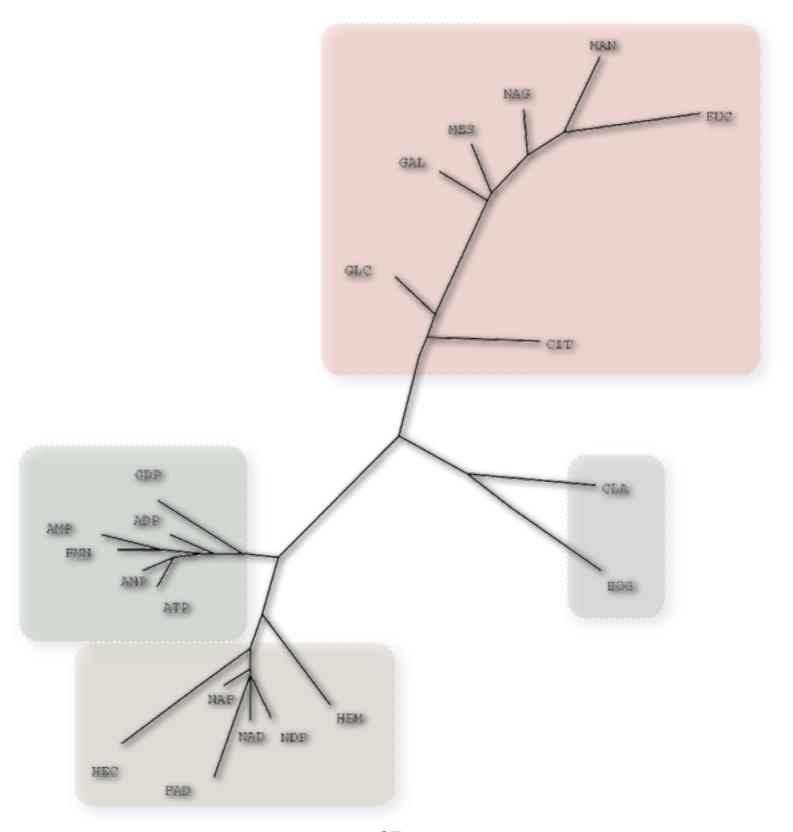
$$\longrightarrow w_k = \frac{1}{M} \sum_{\alpha=1}^M \tilde{f}_k^{(\alpha)}$$

M = number of proteins in training set

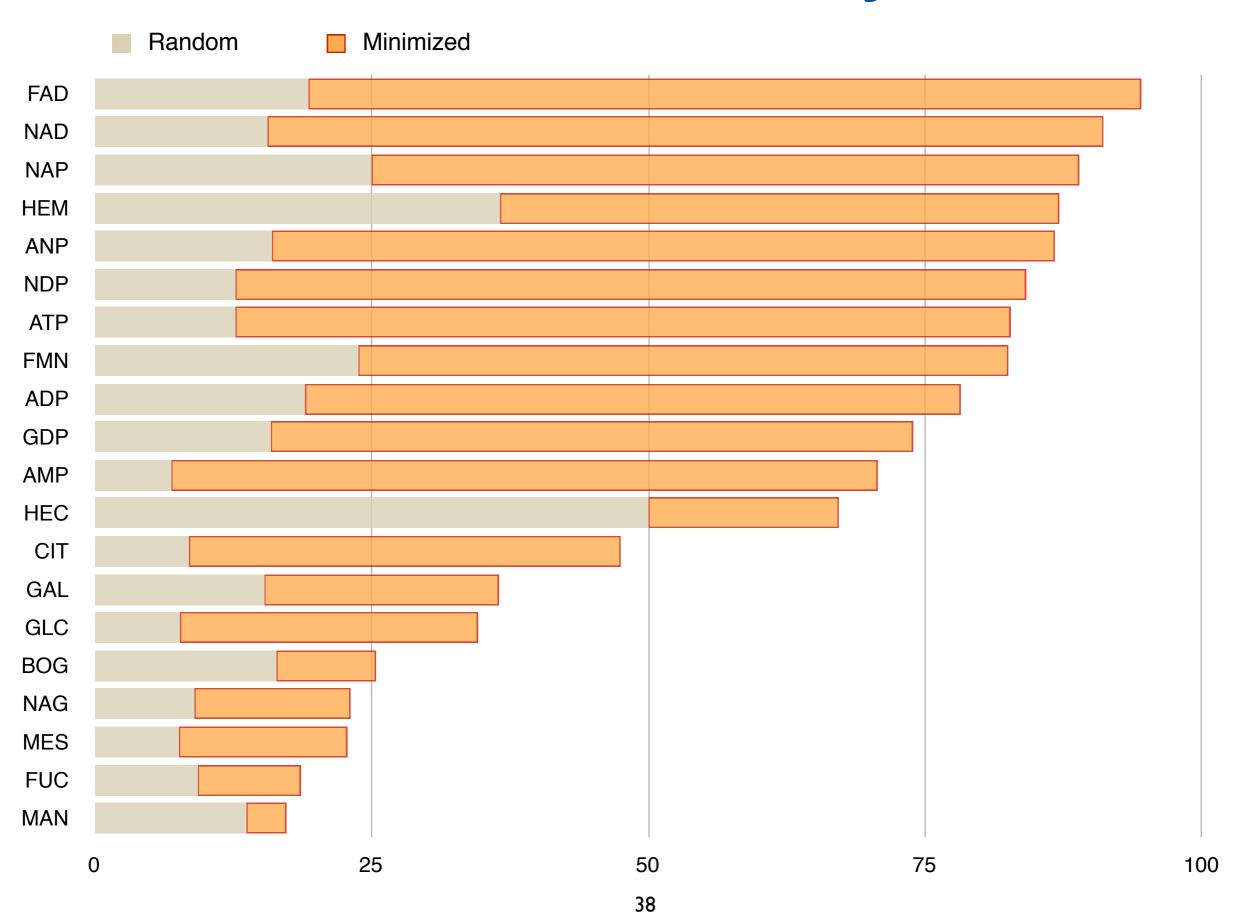
Ligand fingerprints

	Compactness	Conservation	Charge density	B-factor	Protrusion coefficient	Convexity score	Hydrophobicity
ADP	-1.266	-2.009	0.447	-0.414	-1.521	-1.388	-0.118
AMP	-1.62	-1.962	0.341	-0.381	-1.909	-1.944	-0.518
ANP	-1.007	-2.227	0.176	-0.392	-1.706	-1.595	-0.14
ATP	-1.122	-2.156	0.228	-0.274	-1.845	-1.768	0.038
BOG	-2.067	-0.012	0.552	-0.465	-0.356	-0.49	-0.781
CIT	-2.948	-1.58	0.563	-0.527	-0.922	-0.838	-0.113
FAD	0.505	-2.108	0.366	-0.702	-1.735	-1.725	-0.75
FMN	-1.132	-1.98	0.382	-0.387	-1.803	-1.886	-0.695
FUC	-3.43	0.016	-0.295	-0.123	0.002	0.132	0.459
GAL	-3.186	-0.538	-0.234	-0.068	-0.906	-0.987	0.298
GDP	-1.061	-1.471	0.409	-0.81	-1.472	-1.423	0.182
GLC	-2.813	-1.247	-0.207	-0.399	-1.247	-1.337	-0.089
HEC	-0.172	-0.912	0.286	-0.325	-1.153	-1.27	-1.282
HEM	-0.651	-1.571	0.683	-0.51	-1.797	-1.937	-1.47
MAN	-3.72	0.131	0.105	-0.52	-0.605	-0.509	0.405
MES	-3.049	-0.24	-0.338	-0.479	-0.714	-0.926	0.296
NAD	-0.005	-1.852	0.156	-0.232	-1.775	-1.804	-0.858
NAG	-3.419	-0.46	-0.126	-0.154	-0.341	-0.523	-0.078
NAP	-0.009	-1.898	0.612	-0.321	-1.587	-1.656	-0.336
NDP	0.217	-1.741	0.535	-0.312	-1.463	-1.562	-0.498

Ligand fingerprints



Prediction accuracy



Protein function from structure

Comparative annotation. AnnoLite and AnnoLyze.

Marti-Renom et al. The AnnoLite and AnnoLyze programs for comparative annotation of protein structures. BMC Bioinformatics (2007) vol. 8 (Suppl 4) pp. S4

BMC Bioinformatics



Proceedings

The AnnoLite and AnnoLyze programs for comparative annotation of protein structures

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from The Second Automated Function Prediction Meeting La Jolla, CA, USA. 30 August – I September 2006

BMC Bioinformatics 2007, 8(Suppl 4):S4 doi:10.1186/1471-2105-8-S4-S4

This article is available from: http://www.biomedcentral.com/1471-2105/8/S4/S4

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Abstract

Background: Advances in structural biology, including structural genomics, have resulted in a rapid increase in the number of experimentally determined protein structures. However, about half of the structures deposited by the structural genomics consortia have little or no information about their biological function. Therefore, there is a need for tools for automatically and comprehensively annotating the function of protein structures. We aim to provide such tools by applying comparative protein structure annotation that relies on detectable relationships between protein structures to transfer functional annotations. Here we introduce two programs, AnnoLite and AnnoLyze, which use the structural alignments deposited in the DBAli database

Description: Annol ite predicts the SCOP CATH FC InterPro PfamA and GO terms with an average sensitivity of ~90% and average precision of ~80%. AnnoLyze predicts ligand binding site and domain interaction patches with an average sensitivity of ~70% and average precision of ~30%, correctly localizing binding sites for small molecules in ~95% of its predictions

Conclusion: The AnnoLite and AnnoLyze programs for comparative annotation of protein structures can reliably and automatically annotate new protein structures. The programs are fully accessible via the Internet as part of the DBAli suite of tools at http://salilab.org/DBAlii/.

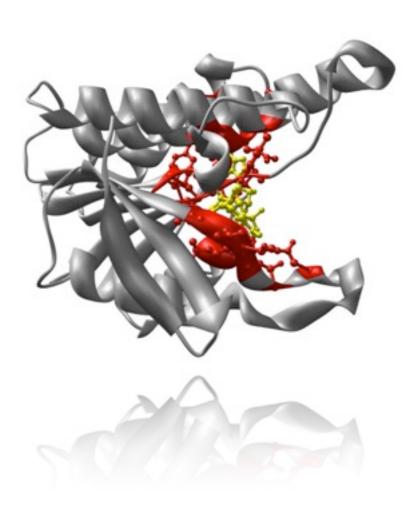
Genomic efforts are providing us with complete genetic blueprints for hundreds of organisms, including humans. genomes. This task is generally facilitated by protein 3D

We are now faced with assigning, understanding, and modifying the functions of proteins encoded by these

(page number not for citation purposes)

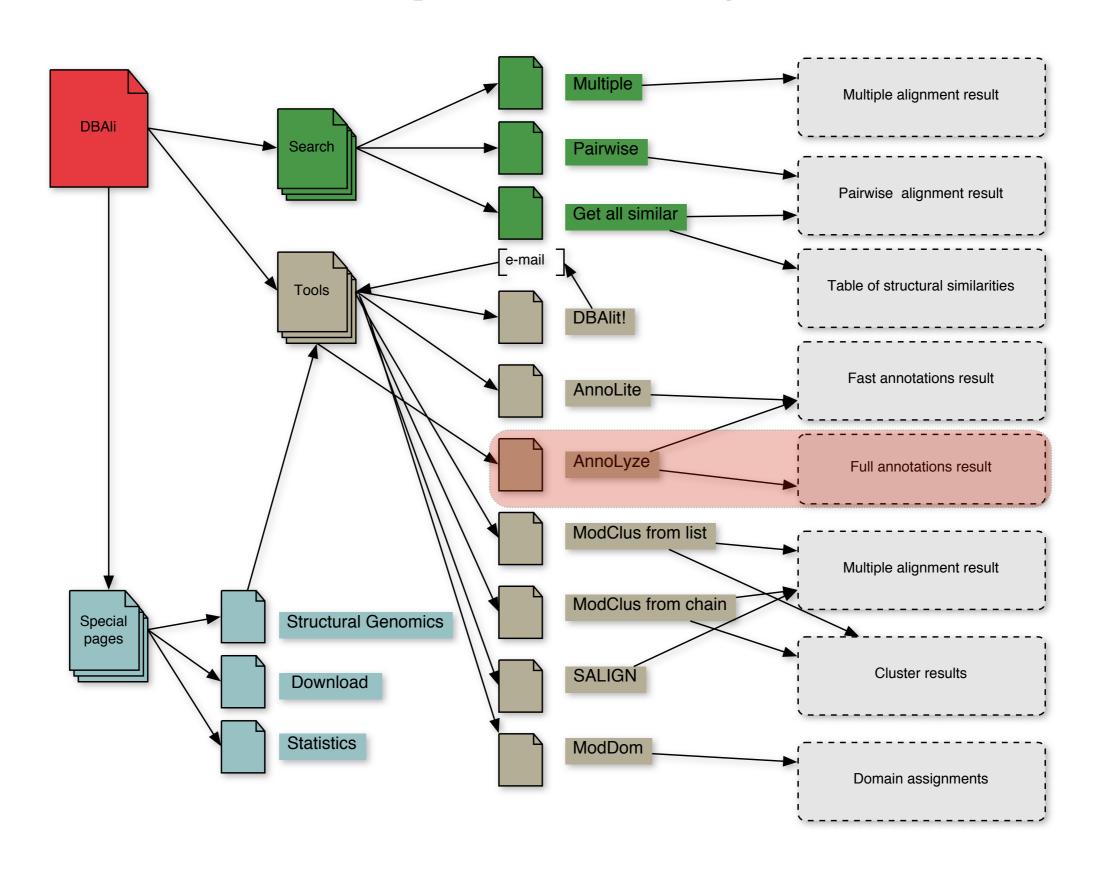
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DBAliv2.0 database

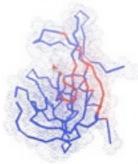
http://www.dbali.org



AnnoLyze

d.113.1.1	23.68	0.948	19 20 50 51 52 53 54 55 56 57 58 77 78 79 80 81 82 83 84 85 93 95 97 99 134 135 138 142 145	
Panner	Av. binding site seq. id.	Av. residue conservation		Residues in predicted binding site (size proportional to the local conservation)
ACY nherited pa	15. rtners:1	87	0.163	23 29 31 37 44 45 81 83 85 94 96 98 103 121 135
80G	20.	00	0.111	19 20 21 48 49 51 96 98 136
	20.			23 29 31 37 44 48 49 83 85 94 96 103 121
MO2				48 49 52 62 63 66 67 113 116





Benchmark

	Number of chains
Initial set*	78,167
LigBase**	30,126
Non-redundant set***	4,948 (8,846 ligands)

*all PDB chains larger than 30 aminoacids in length (8th of August, 2006)

**annotated with at least one ligand in the LigBase database

***not two chains can be structurally aligned within 3A, superimposing more than 75% of their Cα atoms, result in a sequence alignment with more than 30% identity, and have a length difference inferior to 50aa

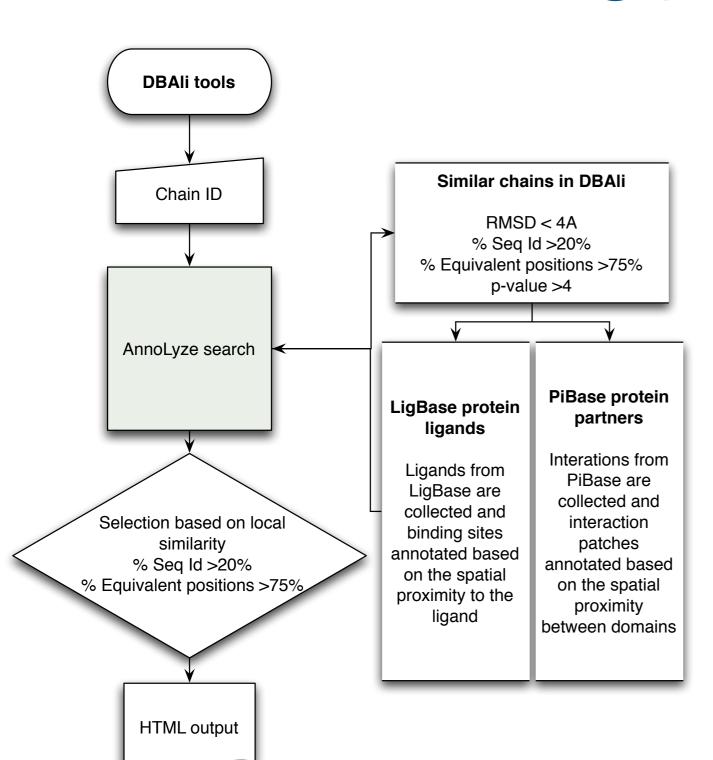
	Number of chains
Initial set*	78,167
πBase**	30,425
Non-redundant set***	4,613 (11,641 partnerships)

*all PDB chains larger than 30 aminoacids in length (8th of August, 2006)

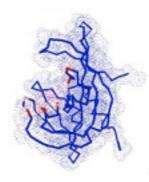
**annotated with at least one partner in the πBase database

***not two chains can be structurally aligned within 3A, superimposing more than 75% of their Cα atoms, result in a sequence alignment with more than 30% identity, and have a length difference inferior to 50aa

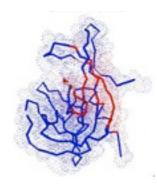
Method



herited ligands: 4					
Ligand	Av. binding site seq. id.	Av. residue conservation	Residues in predicted binding site (size proportional to the local conservation)		
MO2	59.03	0.185	48 49 52 62 63 66 67 113 116		
CRY	20.00	0.111	23 29 31 37 44 48 49 83 85 94 96 103 121		
8OG	20.00	0.111	19 20 21 48 49 51 96 98 136		
ACY	15.87	0.163	23 29 31 37 44 45 81 83 85 94 96 98 103 121 135		



ng Av. residue	Residues in predicted binding site
d.	(size proportional to the local conservation)
8 0.948	19 20 50 51 52 53 54 55 56 57 58 77 78 79 80 81 82 83 84 85 93 95 97 99 134 135 138 142

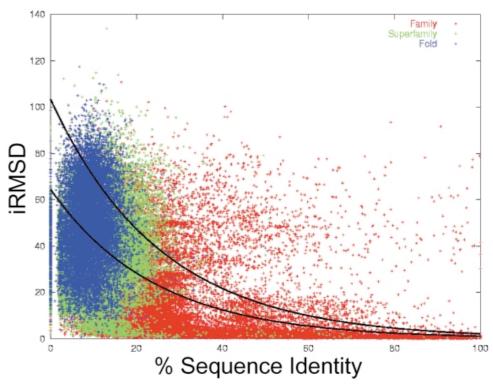


Scoring function

Ligands

100 80 **ATP** Sequence Identity (%) **ADP AMP** 60 GDP **GTP** 40 20 0 20 60 80 100 40 Structure Identity (%)

Partners



Aloy et al. (2003) J.Mol.Biol. 332(5):989-98.

Sensitivity .vs. Precision

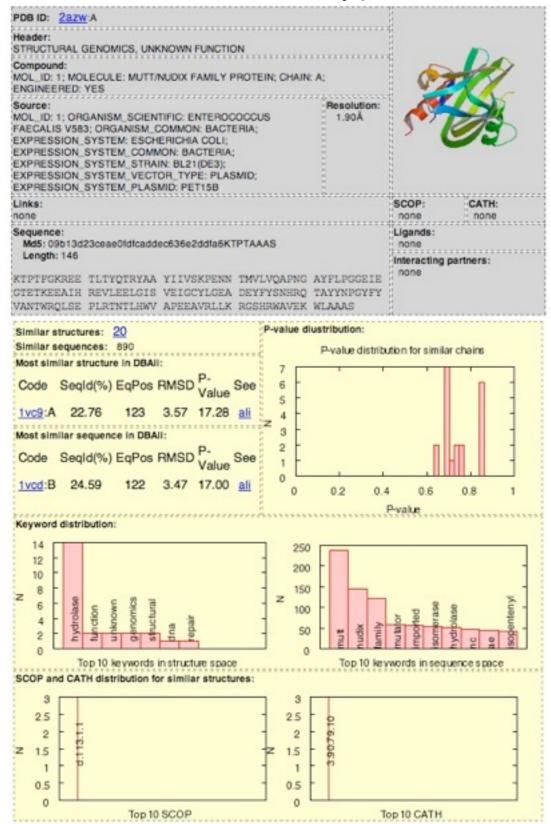
	Optimal cut-off	Sensitivity (%) Recall or TPR	Precision (%)
Ligands	30%	71.9	13.7
Partners	40%	72.9	55.7

Sensitivity =
$$\frac{TP}{TP + FN}$$
 Precision = $\frac{TP}{TP + FP}$

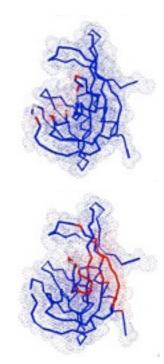
Example (2azwA)

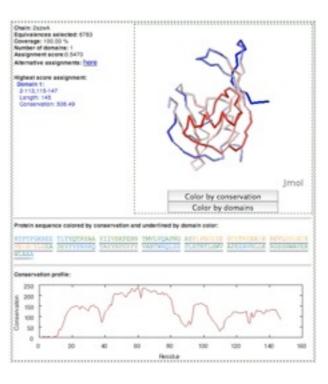
Structural Genomics Unknown Function

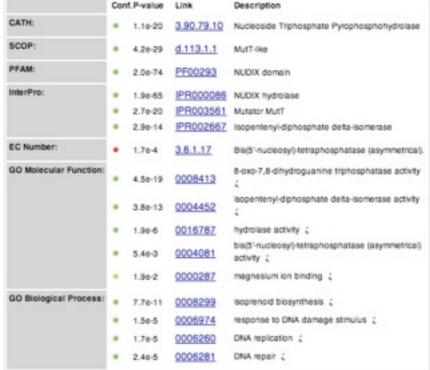
Molecule: MutT/nudix family protein



d.113.1.1	23.68	0.948		19 20 50 51 52 53 54 55 56 57 58 77 78 79 80 81 82 83 84 85 93 95 97 99 134 135 138 142 145	
Partner	Av. binding site seq. id.	Av. residi	200	Residues in predicted binding site (size proportional to the local conservation)	
nherited pa	******		0.163	23 29 31 37 44 45 01 03 05 94 90 90 103 121 135	
8OG ACY	20.00		0.111	19 20 21 48 49 51 96 98 136 23 29 31 37 44 45 81 83 85 94 96 98 103 121 135	
CRY	20.00		0.111	23 29 31 37 44 48 49 83 85 94 96 103 121	
MO2	59.	03	0.185	48 49 52 62 63 66 67 113 116	
Ligand			Av. residue conservation	Residues in predicted binding site (size proportional to the local conservation)	

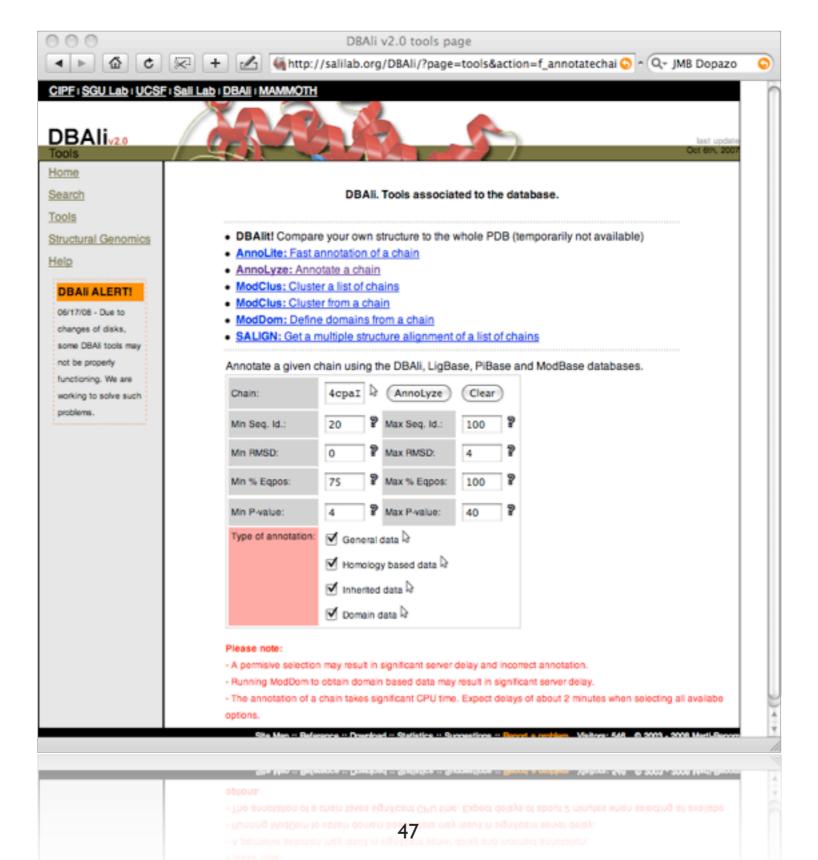






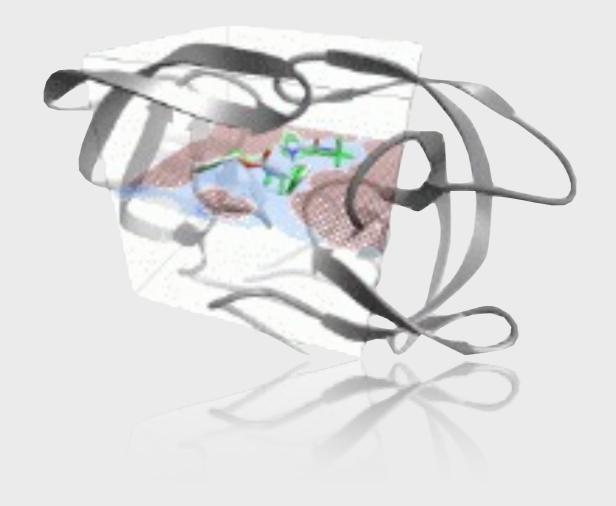
AnnoLyze

http://www.dbali.org





Docking of small molecules. Vina.



Marc A. Marti-Renom

http://bioinfo.cipf.es/sgu/

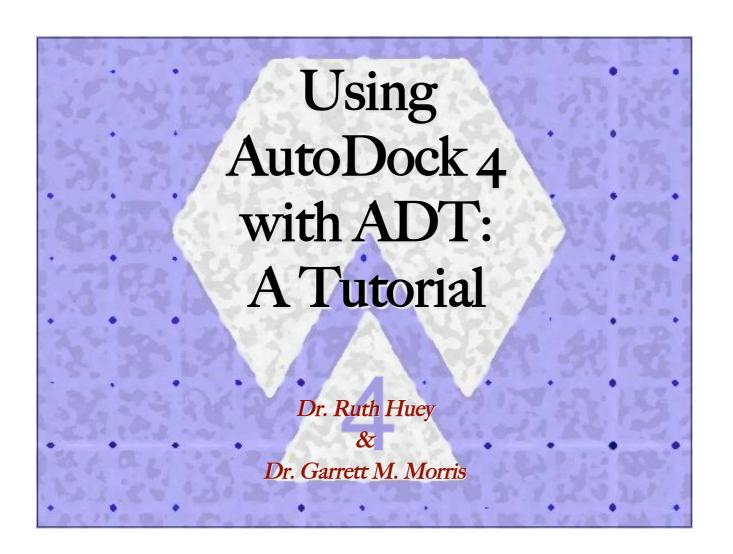
Structural Genomics Unit Bioinformatics Department Prince Felipe Resarch Center (CIPF), Valencia, Spain





DISCLAIMER!

Credit should go to Dr. Oleg Trott, Dr. Ruth Huey and Dr. Garret M. Morris



http://autodock.scripps.edu

http://vina.scripps.edu

Software News and Update

AutoDock Vina: Improving the Speed and Accuracy of
Docking with a New Scoring Function, Efficient
Optimization, and Multithreading

OLIG TRUIT AUTISM L. 1950x

Department of Melocular thiology. The Serope Research Institute. La Jolic, California

Level Man 2009. Accepted 2 April 2009
DOR 100.00002-20138

Abstract: AutoDock Vina. sees program for molecular decking and vistnal sevening, is proceed, AutoDock Vina
schiera, as apparentantly, annual can figure the process of t

O. Trott, A. J. Olson, Journal of Computational Chemistry (2009)

What is Docking?

Summary

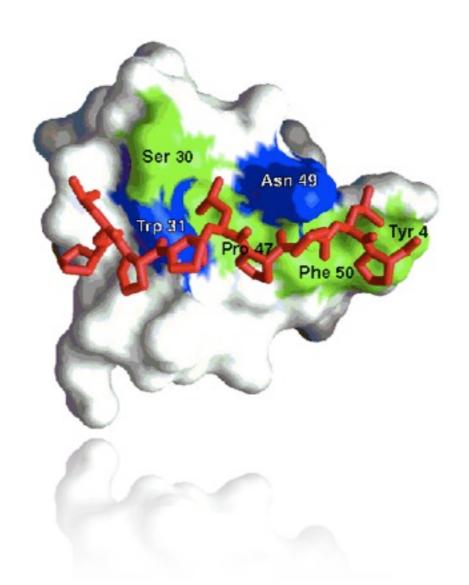
- INTRO
- DOCKING
- SEARCH METHODS
- EXAMPLE

Vina 1.0 with ADT

What is docking?

Predicting the best ways two molecules interact.

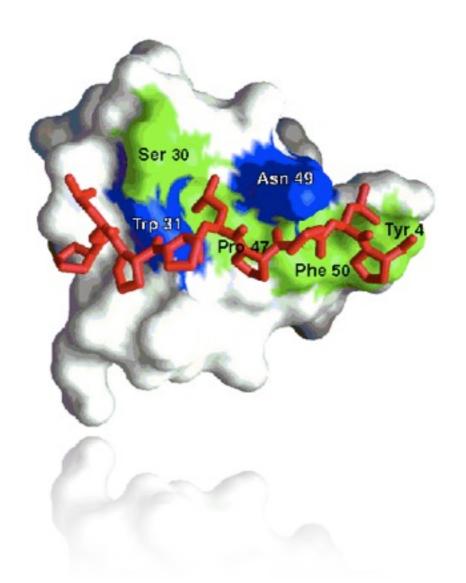
- Obtain the 3D structures of the two molecules
- Locate the best binding site (Remember AnnoLyze?)
- Determine the best binding mode.



What is docking?

Predicting the **best** ways two molecules interact.

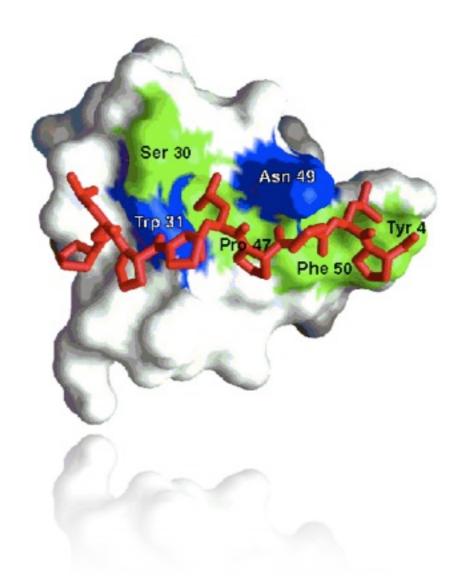
- We need to quantify or rank solutions
- We need a good scoring function for such ranking



What is docking?

Predicting the best ways two molecules interact.

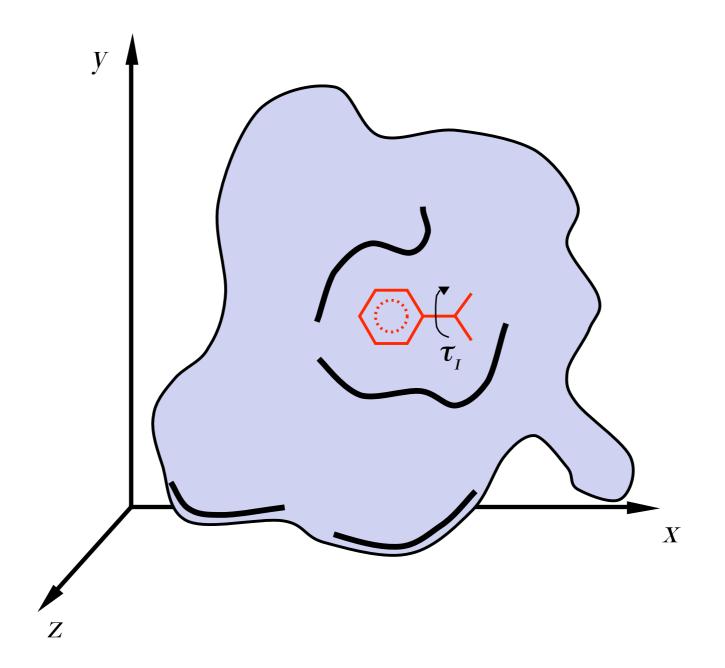
- ♦ X-ray and NMR structures are just ONE of the possible solutions
- ♦ There is a need for a search solution



BIOINFORMATICS

REPRESENTATION SCORING SAMPLING

REPRESENTATION

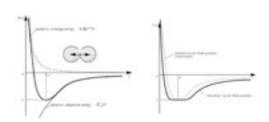


SCORING

AutoDock Vina

$$\Delta G_{binding} = \Delta G_{vdW} + \Delta G_{elec} + \Delta G_{hbond} + \Delta G_{desolv} + \Delta G_{tors}$$

• ΔG_{vdW} 12-6 Lennard-Jones potential



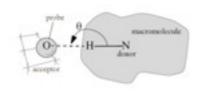
• ΔG_{elec}

Coulombic with Solmajer-dielectric

$$\varepsilon(r) = A + \frac{B}{1 + ke^{-\lambda Br}}$$

• ΔG_{hbond}

12-10 Potential with Goodford Directionality



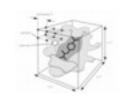
• ΔG_{desolv}

Stouten Pairwise Atomic Solvation Parameters

• ΔG_{tors}

Number of rotatable bonds





SAMPLINGAutoDock Vina

Global search algorithms

- Simulated annealing (Goodsell et al. 1990)
- Distributed SA (Morris et al. 1996)
- Genetic Algorithm (Morris et al. 1998)

Local search algorithms

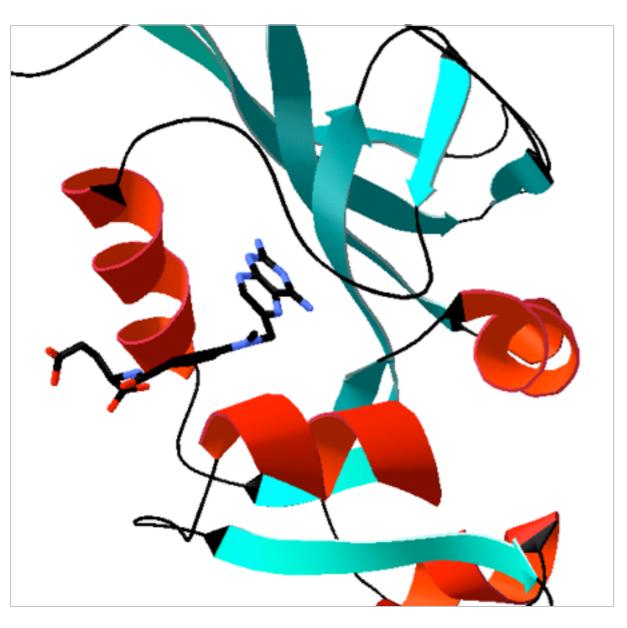
◆Solis & Wets (Morris et al. 1998)

Hybrid global-local search

◆Lamarckian GA (Morris et al. 1998)

PROBLEM!

Very CPU time consuming...



 $N = T^{360/i}$

N: number of conformations

T: number of rotable bonds

1: incremental degrees

Metotrexato

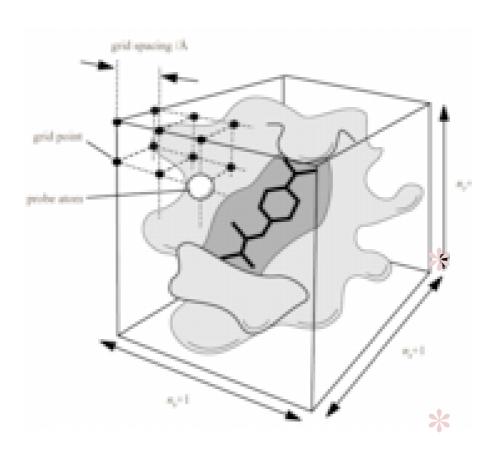
10 rotable bonds

30° increments (discrete)

10¹² plausible conformations!

Dihidrofolate reductase with a metotrexate (4dfr.pdb)

SOLUTIONUse of grid maps!



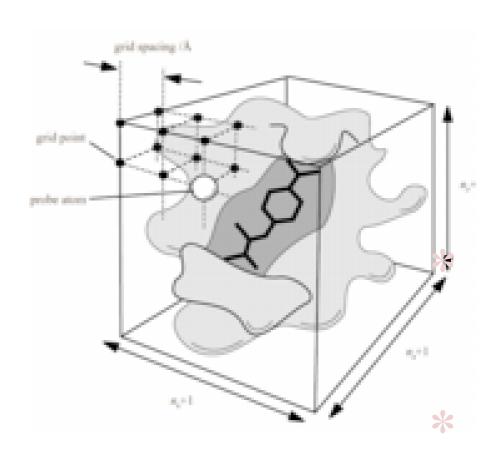
- Saves lots of time (compared to classical MM/MD)
- Need to map each atom to a grid point
- Limits the search space!

AutoGrid Vina

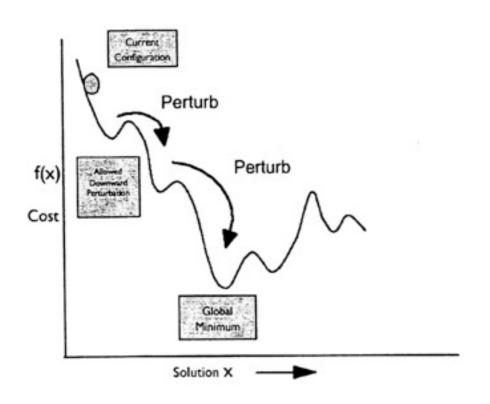
Use of grid maps!

- Center of grid *
 - center of ligand
 - center of receptor
 - a selected atom or coordinate
- ♦ Box dimension *
- Grid resolution (spacing)
 - default 0.375 Angstroms
- Number of grid points (dimension)
 - use ONLY even numbers
- MAKE SURE ALL LIGAND IS INSIDE GRID AND CAN MOVE!

With VINA much simplified (*)



Simulated Annealing



Ligand starts at initial state (random or userdefined)

The temperature of the system is reduced with time and the moves of the atoms are accepted depending on its energy compared to previous energy (with a probability proportional to the temperature!)

Repeat until reaching final solution.

Genetic Algorithm

Use of a Genetic Algorithm as a sampling method

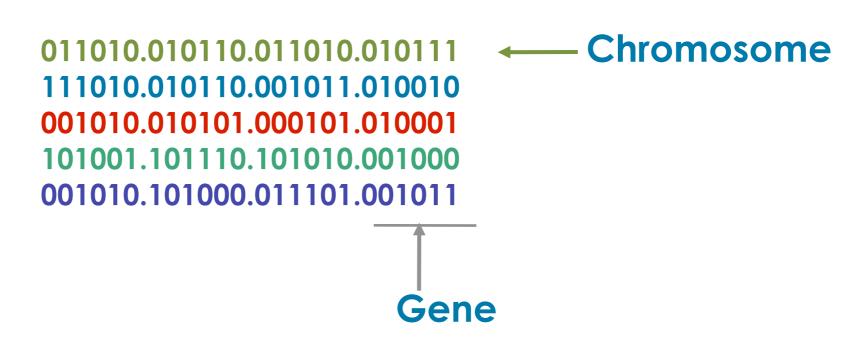
- Each conformation is described as a set of rotational angles.
- 64 possible angles are allowed to each of the bond in the ligand.
- Each plausible dihedral angle is codified in a set of binary bits (26=64)
- Each conformation is codified by a so called chromosome with 4×6 bits (0 or 1)

$$H_2N$$
 H_2N
 H_3
 H_4
 $H_$

$$\Phi_1 = 1 \times 2^5 + 1 \times 2^4 + 1 \times 2^3 + 0 \times 2^2 + 1 \times 2^1 + 0 \times 2^0 = 58^\circ$$

Genetic Algorithm

Population (ie, set of chromosomes or configurations)



Genetic Algorithm

Genetic operators...

$$H_2N$$
 OH

$$H$$
 O
 H_2N
 O
 O
 O
 O
 O
 O
 O

011010.010110.011010.010111

Single mutation

011010.011110.011110.010111

Genetic Algorithm

Genetic operators...

$$H_{O} \longrightarrow O$$
 $H_{2}N$
OH

$$H^{O}$$
 $H_{2}N$
 O
 $H_{2}N$
 O

$$H_{O} \longrightarrow OH$$
 $H_{2}N$
 O

$$H^{O}$$
 $H_{2}N$
 OH

001010.010101.000101.010001
011010.010110.011010.010111

Recombination

001010.010101.011010.010111 011010.010110. 000101.010001

Genetic Algorithm

Genetic operators...

011010.010110.011010.010111
111010.010110.001011.010010
001010.010101.000101.010001
101001.101110.101010.001000
001010.101000.011101.001011

Migration

111110.010010.0111110.010101
101010.110110.011011.011010
001010.010101.000101.01001
101101.101010.101011.001100
011010.100000.011001.101011

Default parameters in AutoDock Vina

Simulated annealing

- Initial temperature
 - \diamond rt0 = 61600 K
- ◆ Temperature reduction factor
 - \diamond rtrf = 0.95 K/cycle
- Termination criteria
 - accepted moves (accs = 25,000)
 - rejected moves (rejs = 25,000)
 - annealing cycles (cycles = 50)

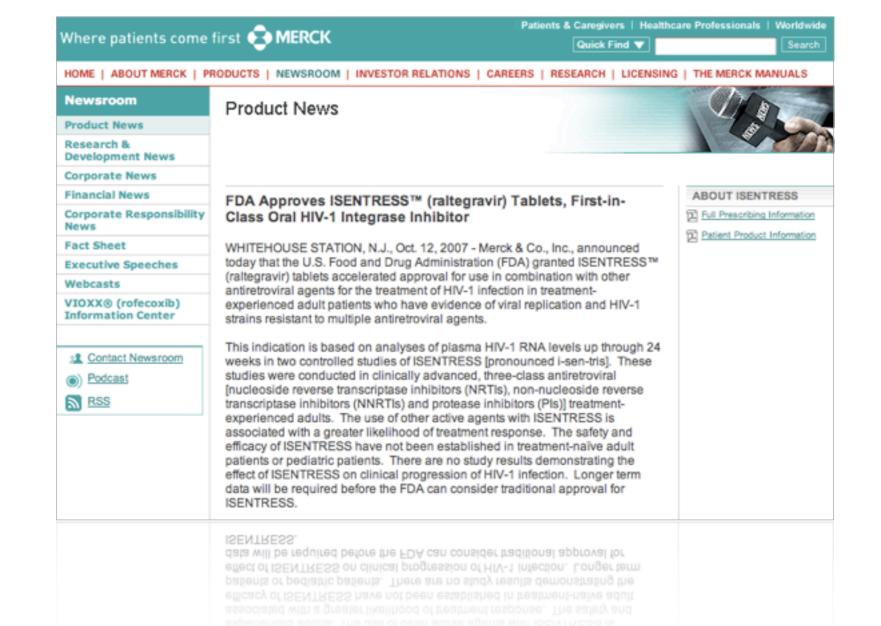
Genetic algorithm

- Population size
 - ga_pop_size = 300
- Crossover rate
 - ga_crossover_rate = 0.8
- Mutation rate
 - ga mutation rate = 0.02
- Solis and Wets local search (LGA only)
 - \diamond sw_max_its = 300
- Termination criteria
 - ga_num_evals = 25,000 (short)
 - ga_num_evals = 250,000 (medium)
 - ga_num_evals = 2,500,000 (large)
 - ga_num_generations = 27,000

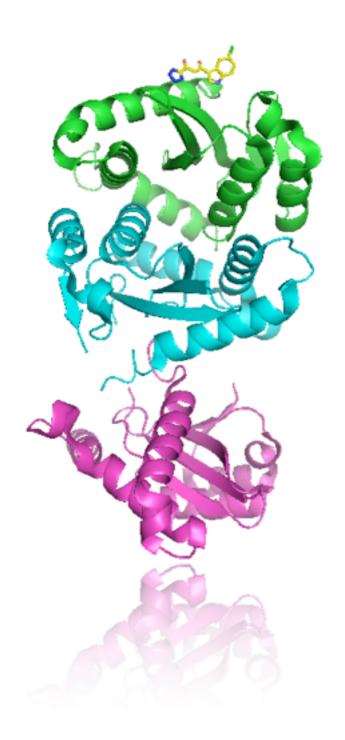
AutoDock Example

Discovery of a novel binding trench in HIV Integrase

Schames, J.R., R.H. Henchman, J.S. Siegel, C.A. Sotriffer, H. Ni, and J.A. McCammon, Discovery of a novel binding trench in HIV integrase. J Med Chem, 2004. 47(8): 1879-81

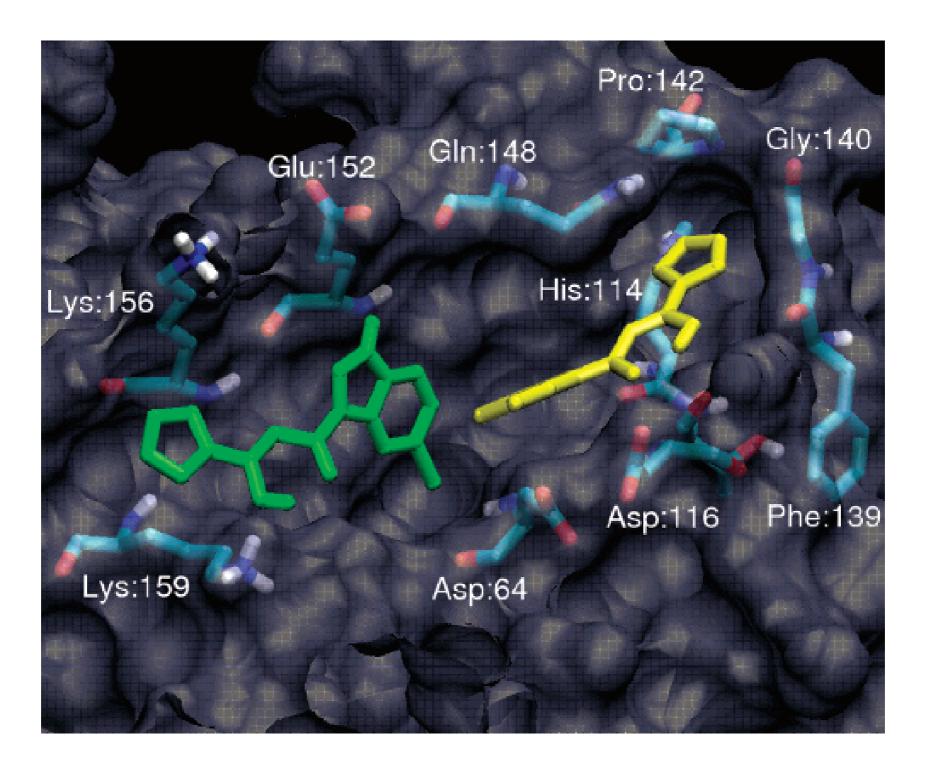


ISENTRESS example

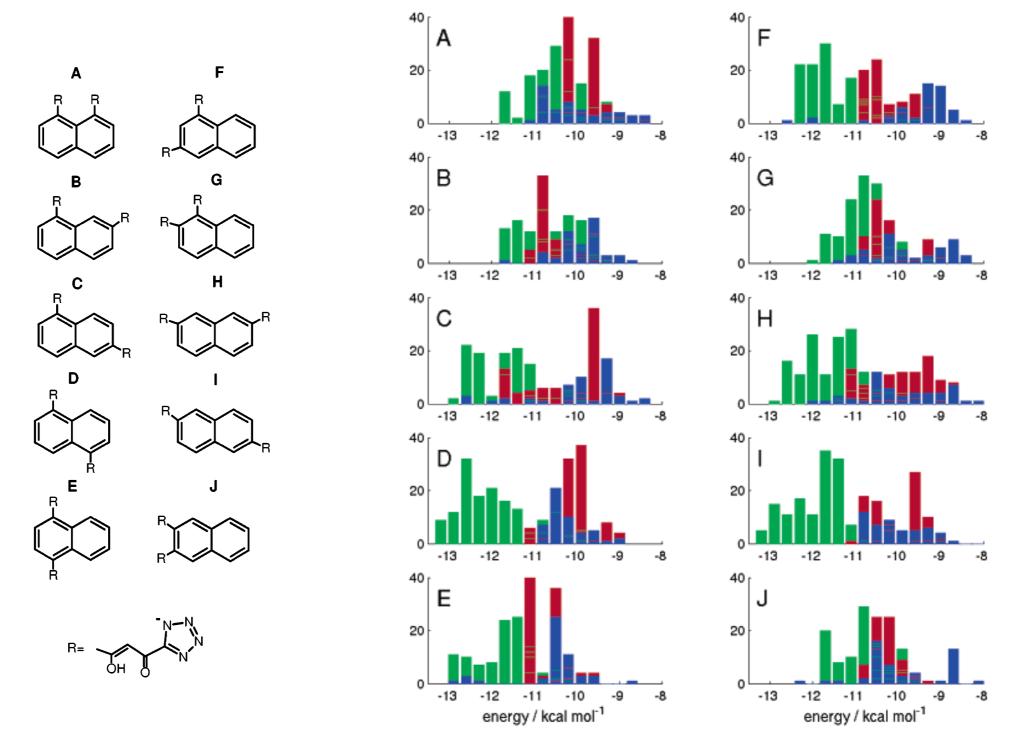


- One structure known with 5CITEP
 - Not clear (low resolution)
 - Binding near to DNA interacting site
 - Loop near the binding
- Docking + Molecular Dynamics
 - AMBER snapshots
 - AutoDock flexible torsion thetetrazolering and indole ring.

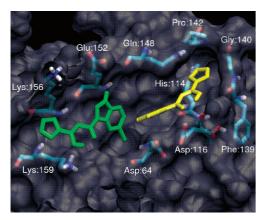
ISENTRESS example

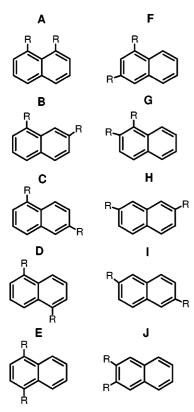


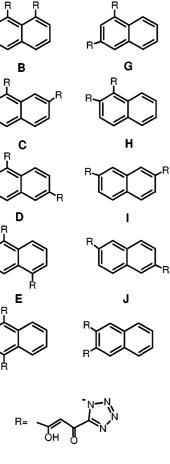
ISENTRESS example

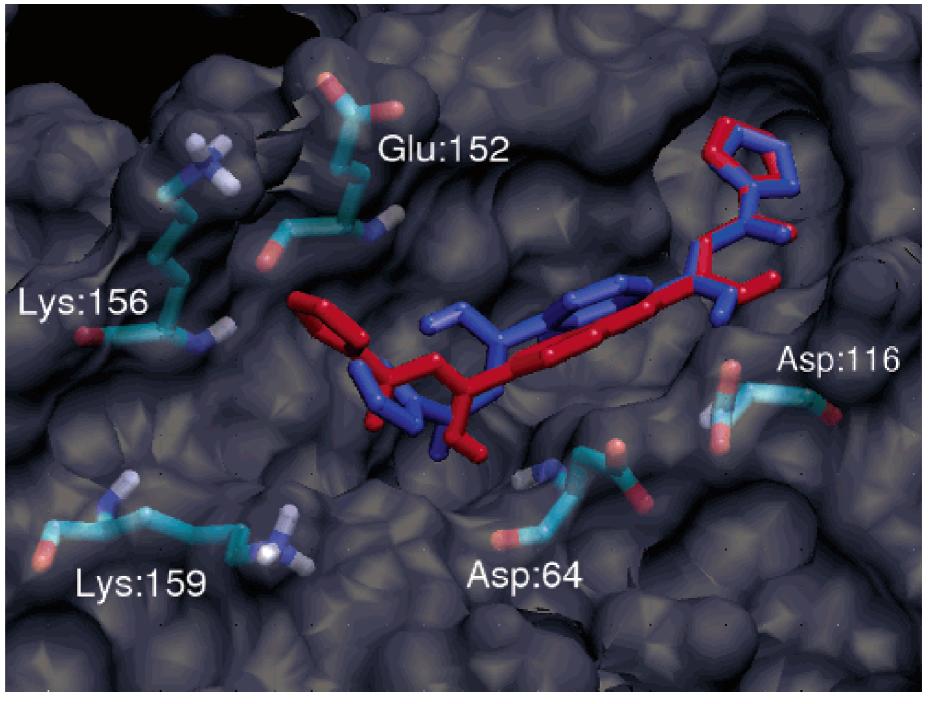


ISENTRESS example









ISENTRESS example

Where patients come first 😝 MERCK



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Product News



FDA Approves ISENTRESS™ (raltegravir) Tablets, First-in-Class Oral HIV-1 Integrase Inhibitor

WHITEHOUSE STATION, N.J., Oct. 12, 2007 - Merck & Co., Inc., announced today that the U.S. Food and Drug Administration (FDA) granted ISENTRESS™ (raltegravir) tablets accelerated approval for use in combination with other antiretroviral agents for the treatment of HIV-1 infection in treatmentexperienced adult patients who have evidence of viral replication and HIV-1 strains resistant to multiple antiretroviral agents.

This indication is based on analyses of plasma HIV-1 RNA levels up through 24 weeks in two controlled studies of ISENTRESS [pronounced i-sen-tris]. These studies were conducted in clinically advanced, three-class antiretroviral [nucleoside reverse transcriptase inhibitors (NRTIs), non-nucleoside reverse transcriptase inhibitors (NNRTIs) and protease inhibitors (PIs)] treatmentexperienced adults. The use of other active agents with ISENTRESS is associated with a greater likelihood of treatment response. The safety and efficacy of ISENTRESS have not been established in treatment-naïve adult patients or pediatric patients. There are no study results demonstrating the effect of ISENTRESS on clinical progression of HIV-1 infection. Longer term data will be required before the FDA can consider traditional approval for ISENTRESS.

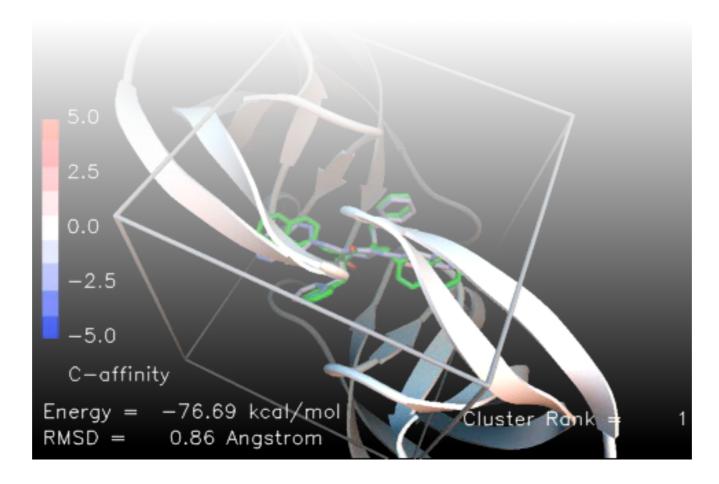
ABOUT ISENTRESS

Full Prescribing Information

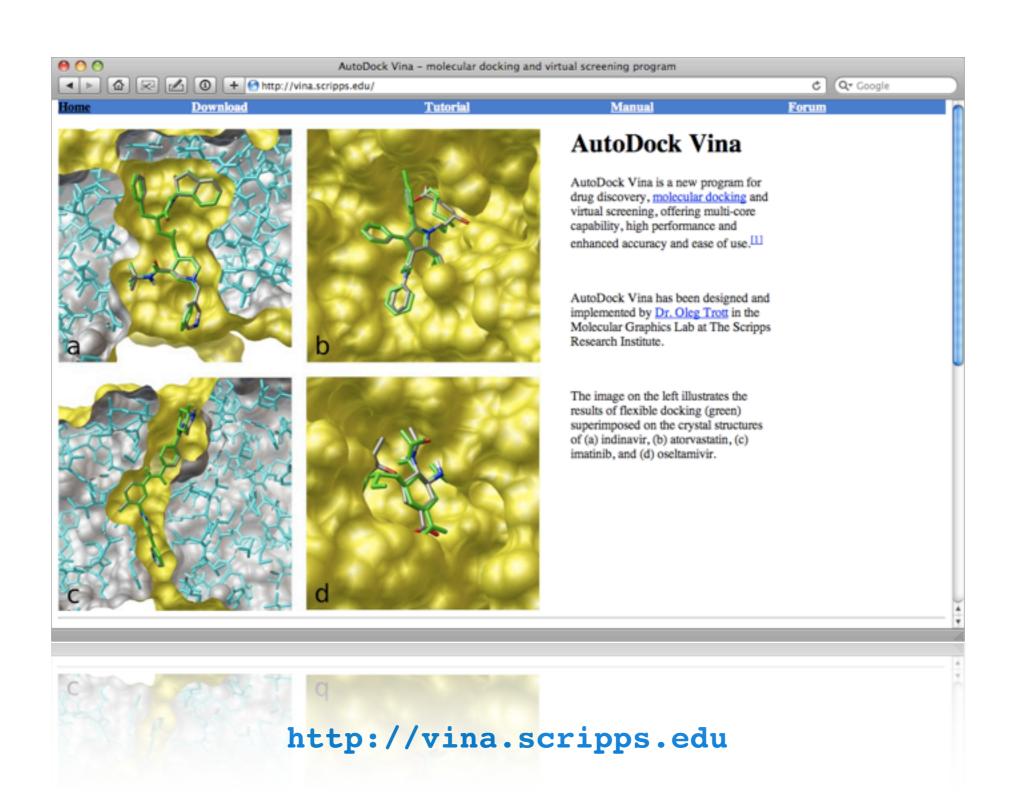
Patient Product Information

ISENTRESS.

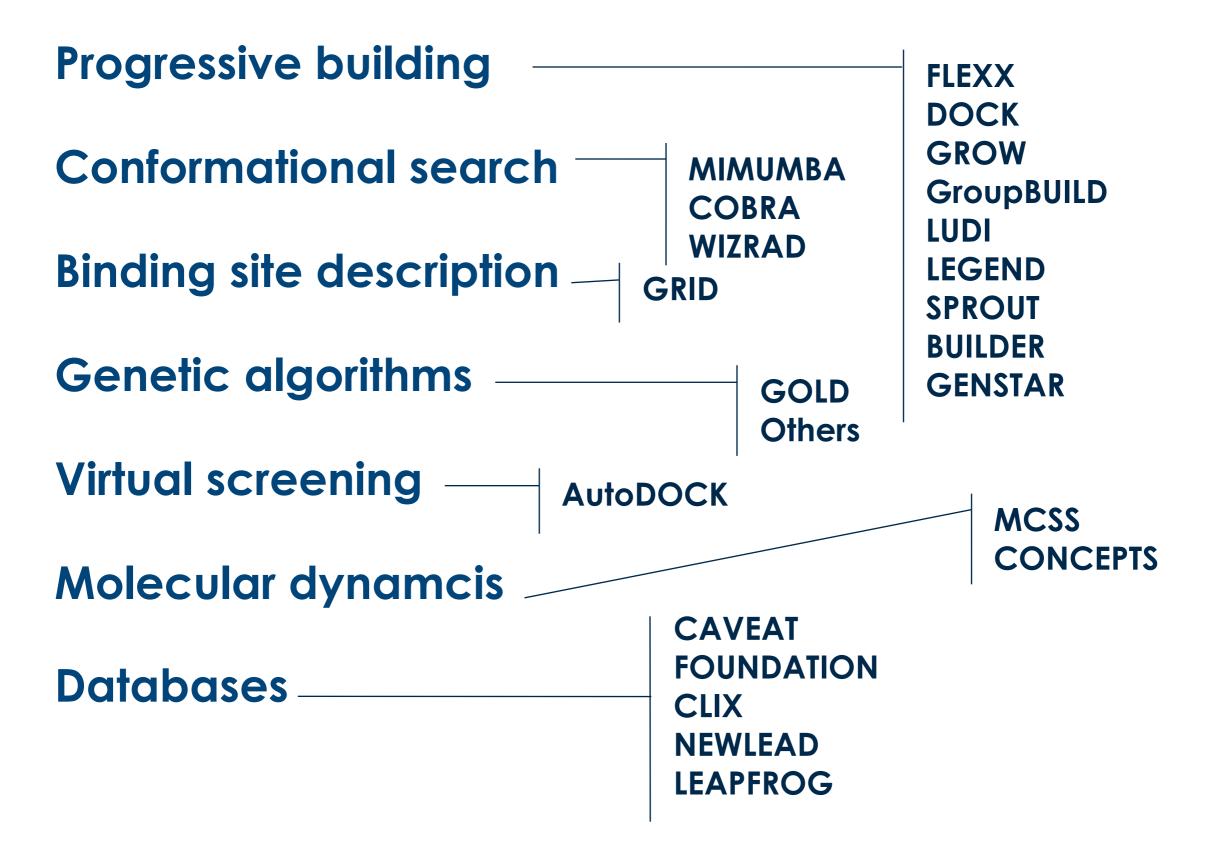
data will be required before the FDA can consider traditional approval for effect of ISENTRESS on clinical progression of HIV-1 infection. Longer term



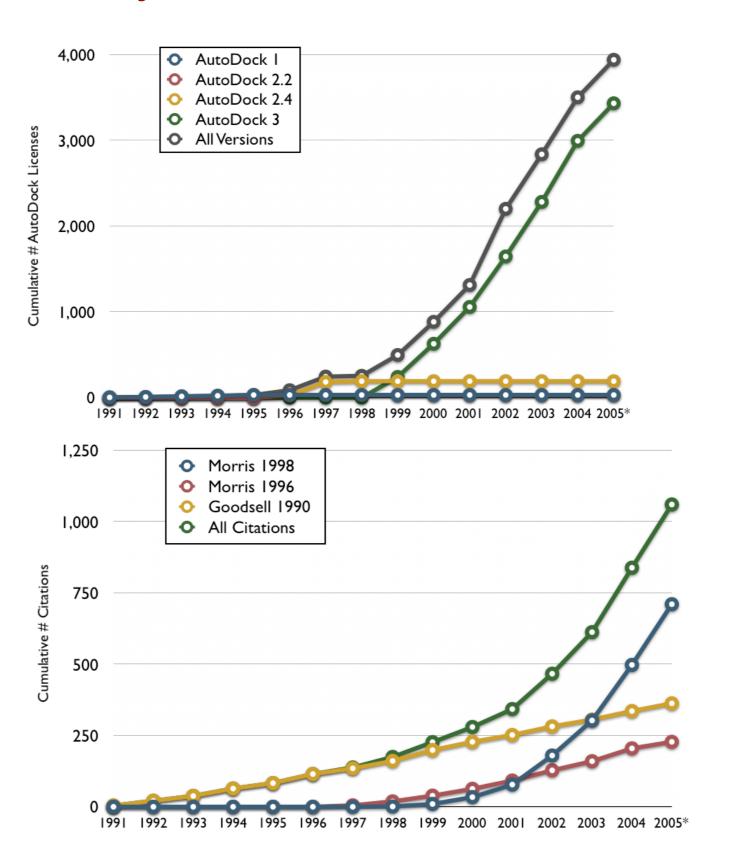
Where to get help...



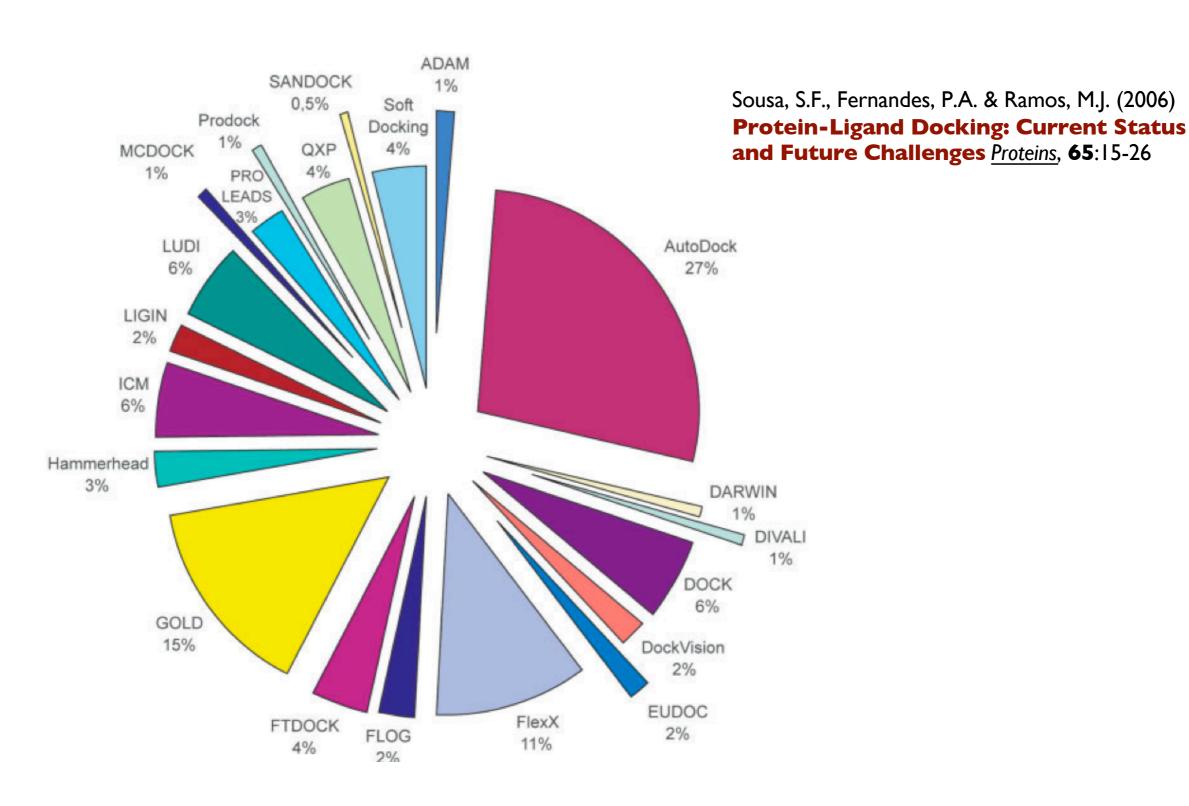
Alternatives



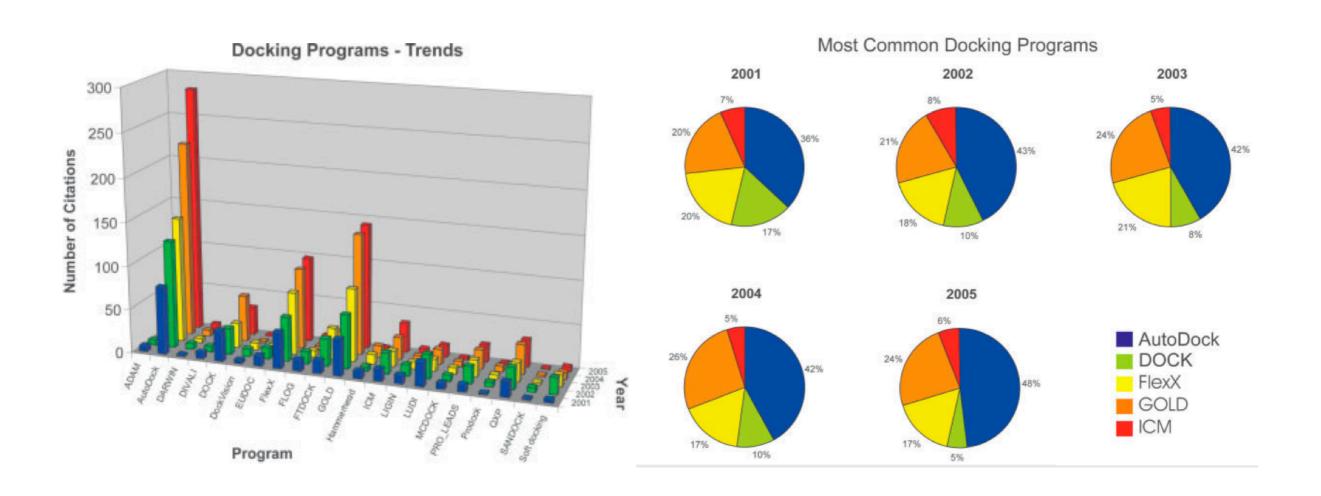
Why AutoDock over others



Why AutoDock over others



AutoDock 4.0 Why AutoDock over others



Sousa, S.F., Fernandes, P.A. & Ramos, M.J. (2006) **Protein-Ligand Docking: Current Status and Future Challenges** *Proteins*, **65**:15-26

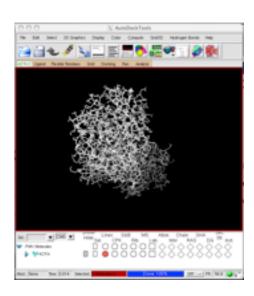
Vina 1.0 Vina and ADT

Vina

AutoDock Tools

- ◆ 1990 (AutoDock)
- ♦ Number crunching (CPU expensive)
- Command-line!
- ♦ C & C++ compiled

- ♦ 2000
- Visualizing set-up
- Graphical user interphase
- Python interpreter



AutoDock / Vina

Practical considerations

- * What problem does AutoDock solve?
 - * Flexible ligands (4.0 flexible protein).
- * What range of problems is feasible?
 - * Depends on the search method:
 - * LGA > GA >> SA >> LS
 - * SA: can output trajectories, D < about 8 torsions.
 - * LGA: D < about 8-32 torsions.
- * When is AutoDock not suitable?
 - * No 3D-structures are available;
 - Modelled structure of poor quality;
 - * Too many (32 torsions, 2048 atoms, 22 atom types);
 - * Target protein too flexible.

Using AutoDock step-by-step

- * Set up ligand PDBQT—using ADT's "Ligand" menu
- * OPTIONAL: Set up flexible receptor PDBQT—using ADT's "Flexible Residues" menu
- * Set up macromolecule & grid maps—using ADT's "Grid" menu
- * Pre-compute AutoGrid maps for all atom types in your set of ligands—using "autogrid4"
- * Perform dockings of ligand to target—using "autodock4", and in parallel if possible.
- * Visualize AutoDock results—using ADT's "Analyze" menu
- * Cluster dockings—using "analysis" DPF command in "autodock4" or ADT's "Analyze" menu for parallel docking results.

Things to know before using AutoDock

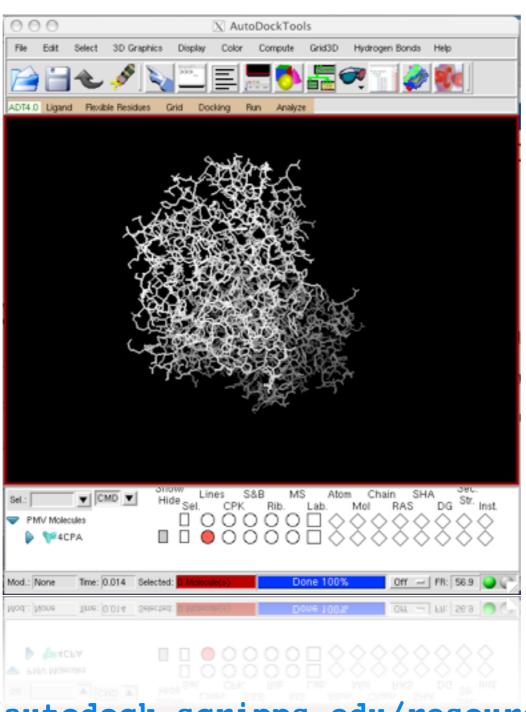
Ligand:

- * Add all hydrogens, compute Gasteiger charges, and merge non-polar H; also assign AutoDock 4 atom types
- * Ensure total charge corresponds to tautomeric state
- Choose torsion tree root & rotatable bonds

Macromolecule:

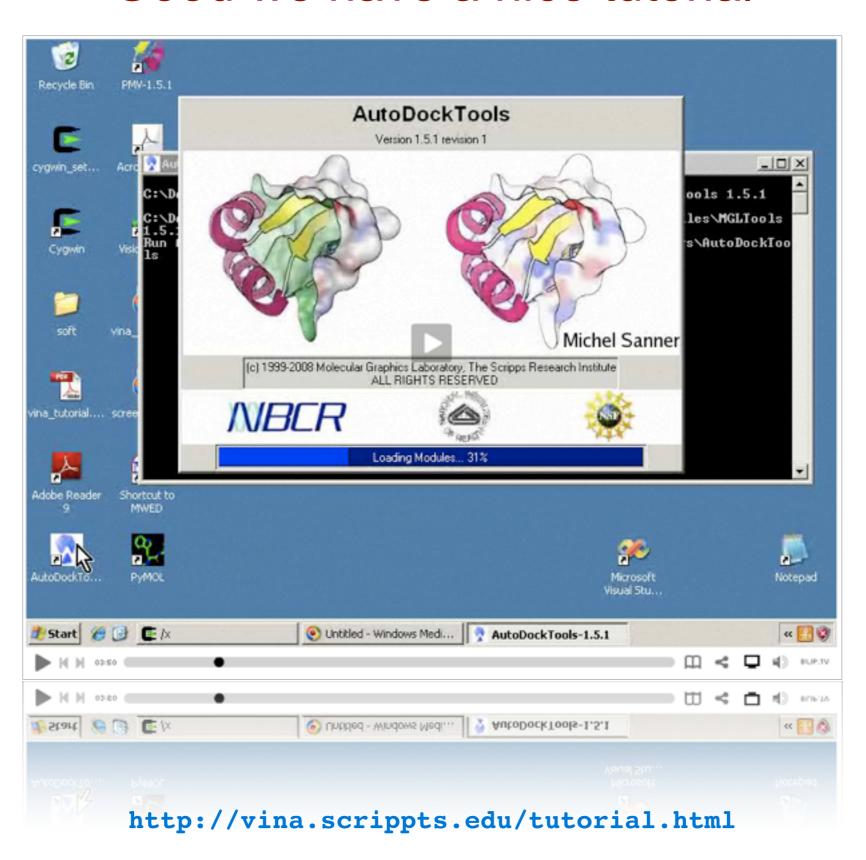
- * Add all hydrogens, compute Gasteiger charges, and merge non-polar H; also assign AutoDock 4 atom types
- * Assign Stouten atomic solvation parameters
- * Optionally, create a flexible residues PDBQT in addition to the rigid PDBQT file
- * Compute AutoGrid maps

Good that we have AutoDock Tools (ATD)



http://autodock.scripps.edu/resources/adt

Good we have a nice tutorial



Acknowledgements

This presentation was based on "Using AutoDock 4 with ADT. A tutorial" by Dr. Ruth Huey and Dr. Garret M. Morris

