

ROBERT WOOD JOHNSON MEDICAL SCHOOL

University of Medicine & Dentistry of New Jersey

Next Generation Computational Chemistry Tools to Predict Toxicity of CWAs William (Bill) Welsh welshwj@umdnj.edu

Prospective Funding by DTRA/JSTO-CBD

etc TC environmental bioinformatics and Computational Toxicology Center

A State-wide, Regional and National Resource

< www.ebCTC.org >

Funded with support from the U.S. EPA

Jan 2007

Consortium Members



ROBERT WOOD JOHNSON Medical School

University of Medicine & Dentistry of New Jersey





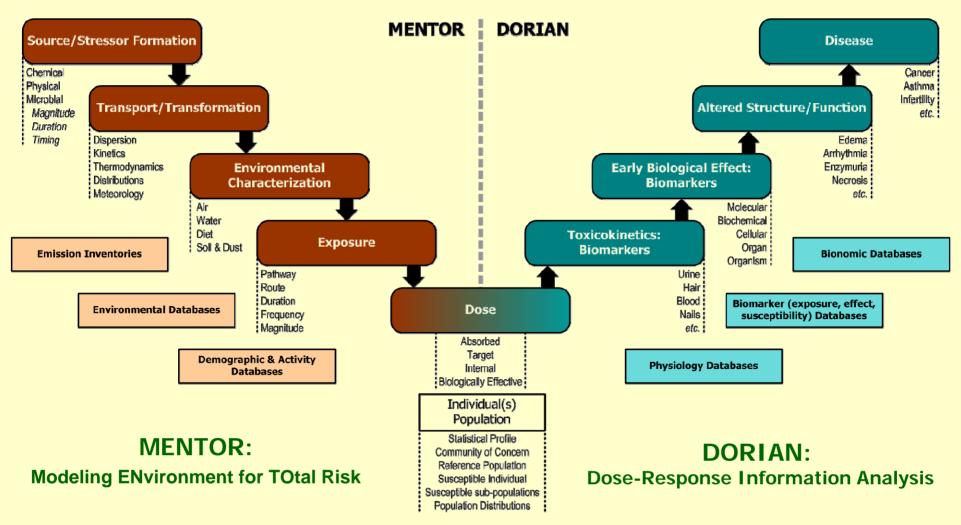


Major Research Thrusts

- MENTOR-DORIAN Computational Toxicology System that spans the Source->Dose->Outcome continuum
- The Environmental Bioinformatics Knowledge Base (ebKB: www.ebCTC.org)
- ArrayTrack: toxicological bioinformatics platform to process genomics, proteomics and metabonomics data
- Hepatocyte Metabolic Model for Xenobiotics
- ChemTox, a suite of chem-informatics tools for toxicant identification & characterization

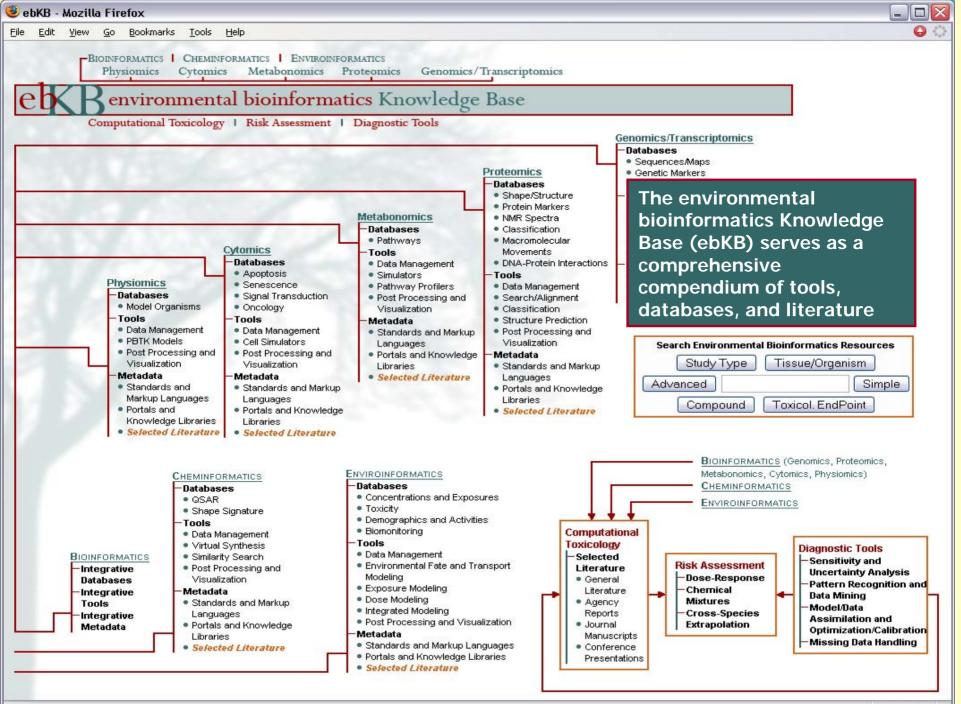
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MENTOR & DORIAN Address the Source-to-Outcome Continuum



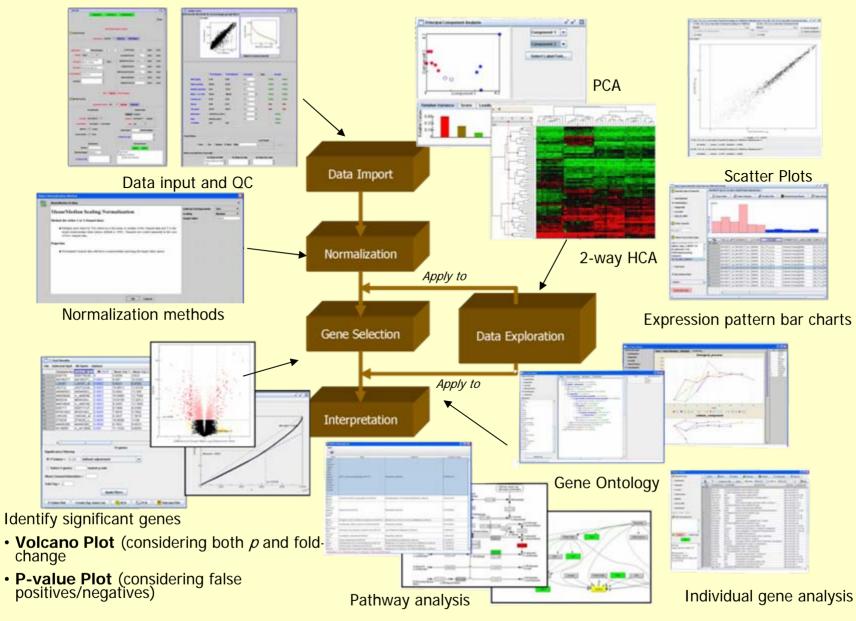
Adapted from chart by R. Calderon, USEPA/NHEERL, 2003

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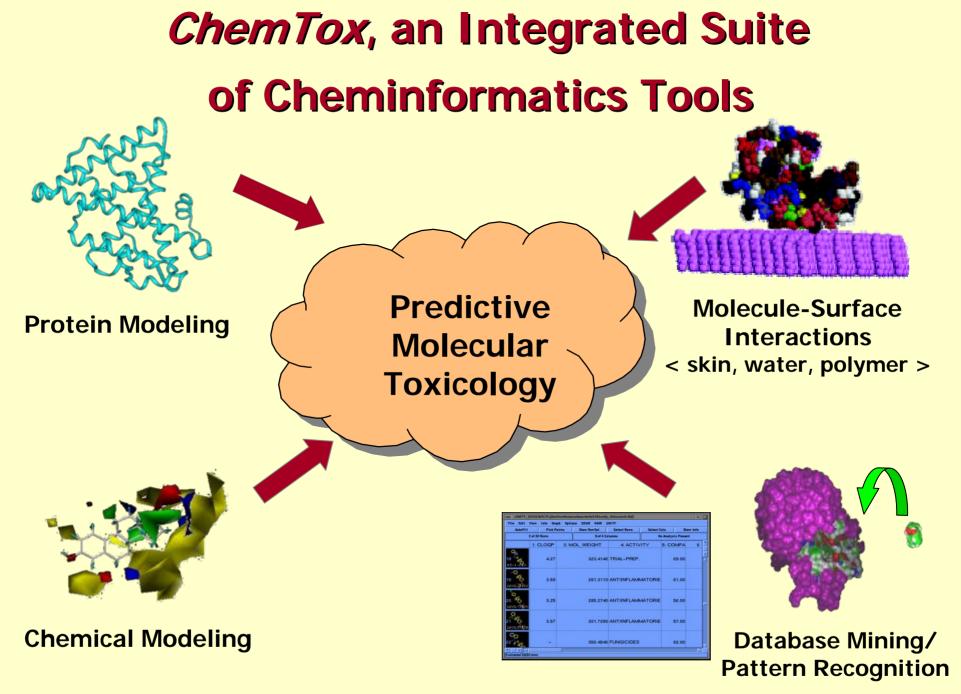
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ArrayTrack Suite of Bioinformatics Tools



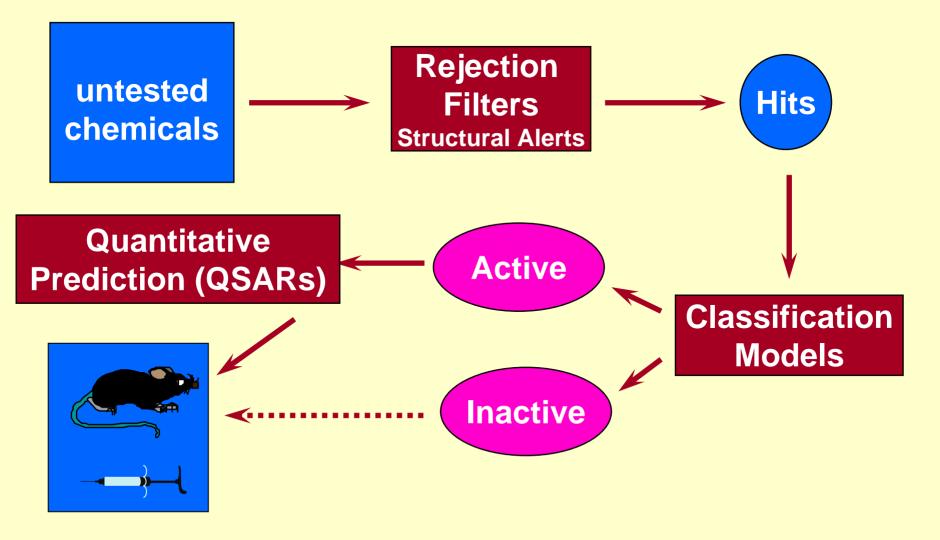
CBIS Conference

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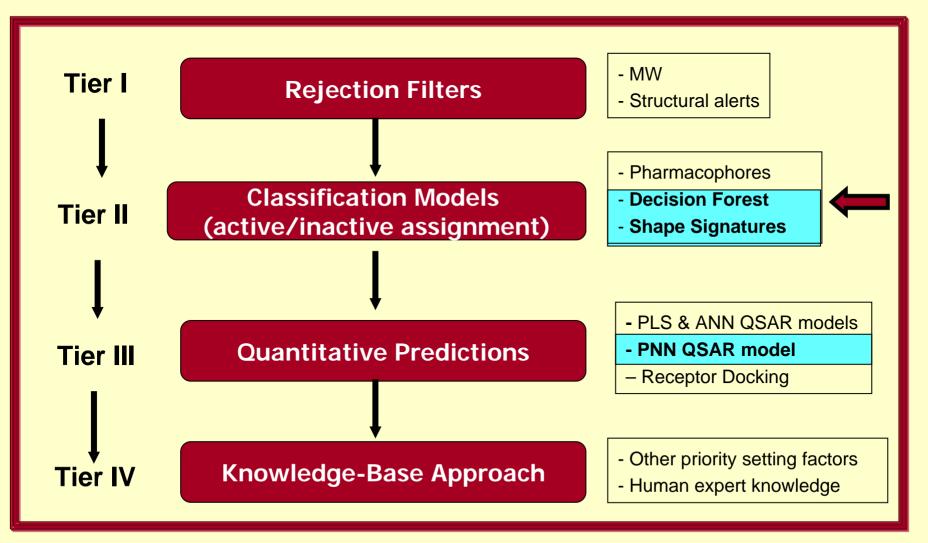
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Computational Screening Paradigm - Priority Setting -



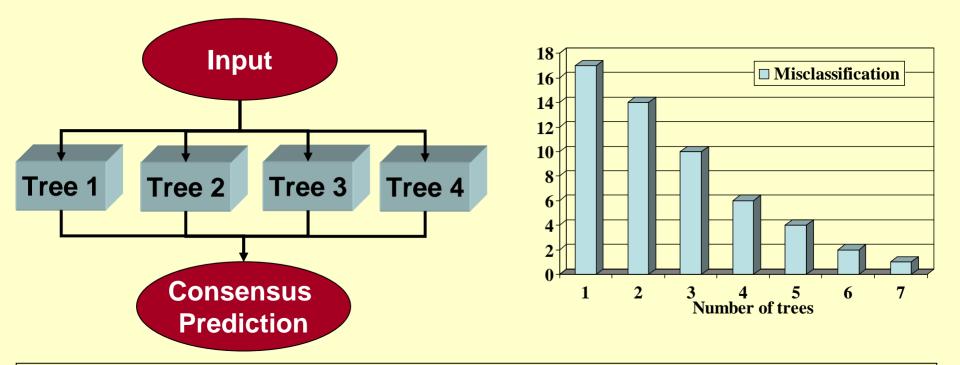
Hierarchical Screening Framework

- addresses the need to minimize *false negatives* and *uncertainties*
- recognizes that no single computational model is adequate



Decision Forest

- Improved classification by combining independent Decision Tree models -



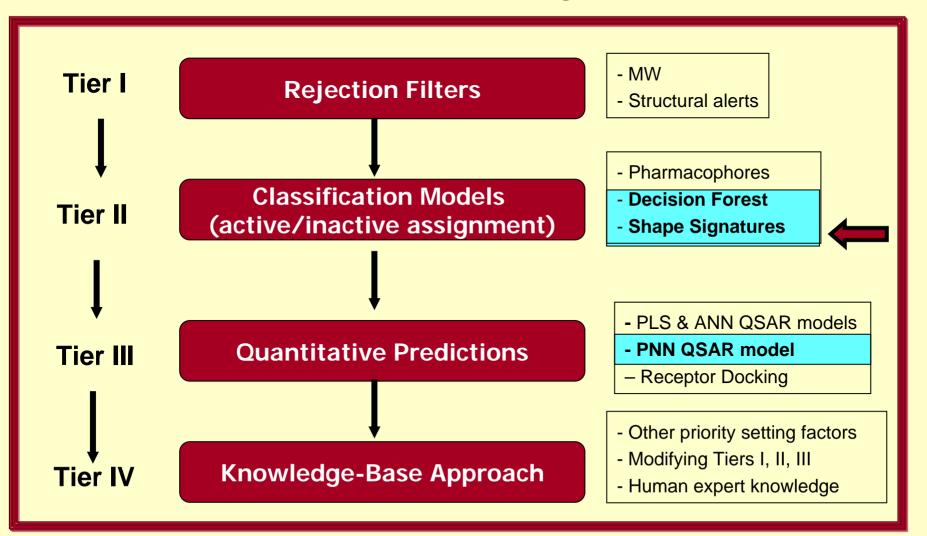
Key Features

- Combining several independent yet predictive trees reduces misclassification
- DF structure permits assessment of prediction confidence
- Each tree consists of simple 'If-Then' branches, hence the DF is extremely fast

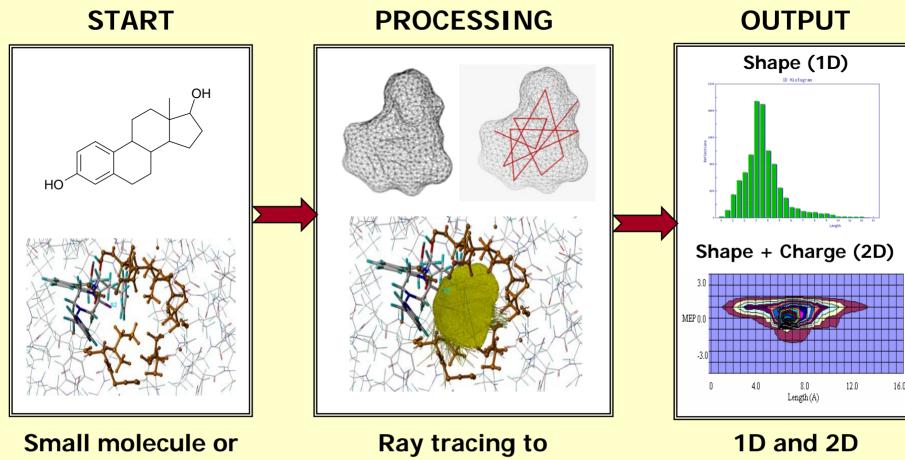
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Schematic of Hierarchical Framework

- addresses the need to minimize false negatives and uncertainties -



Shape Signatures Tool



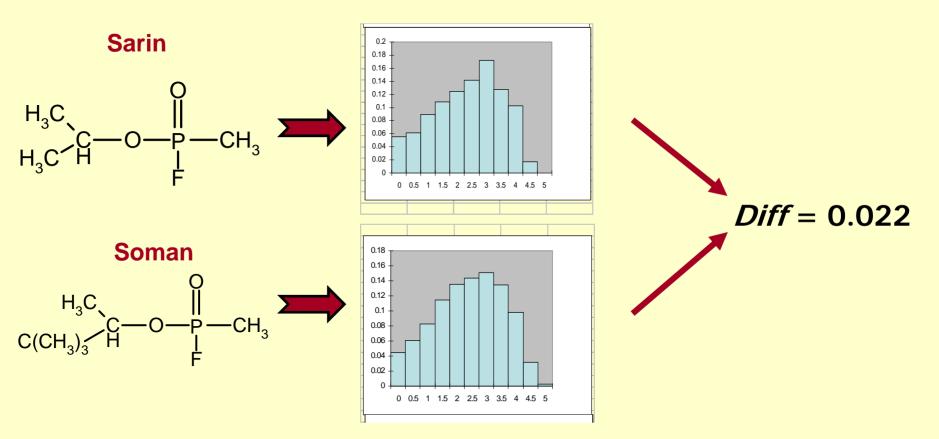
Protein binding pocket

generate the raw data

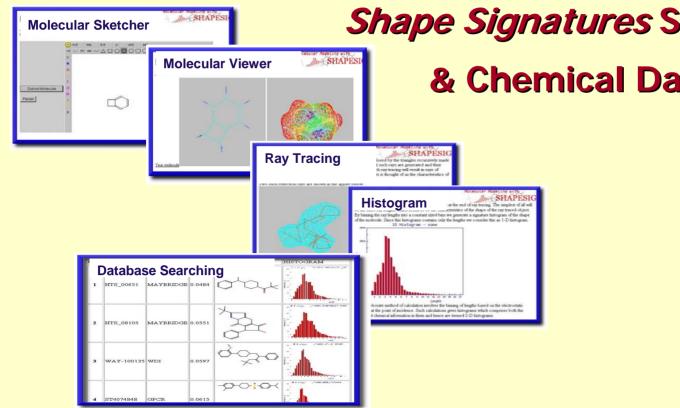
Shape Signatures

Shape Signatures Tool

molecules are compared by subtracting their histograms



Small Diff value means that two molecules have similar shape and polarity



Shape Signatures Software Tool

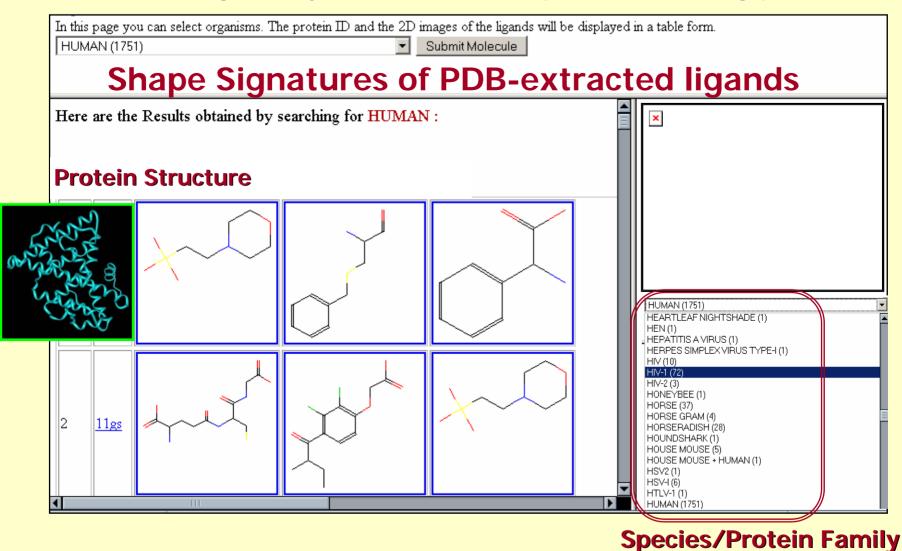
& Chemical Databases

Searchable Shape Signatures Databases

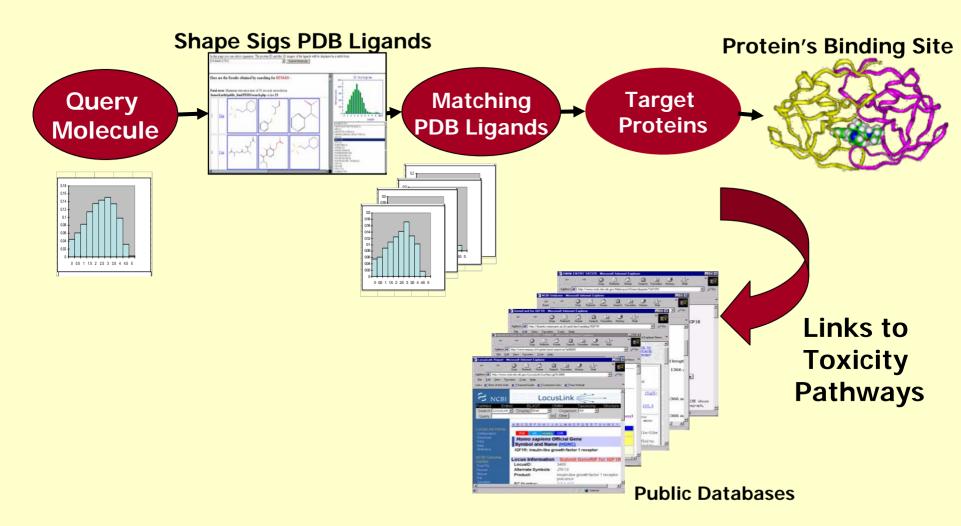
- 3+ million commercially available organic compounds
- 40,000 Natural Products
- Hazardous Chemicals (pesticides, nerve agents, mustards, psychotropic agents, other real or potential CWAs, TICs)
- PDB-extracted ligands

Chemical → Target Protein → Mechanisms

Protein Data Bank (PDB): World Repository of ~35,000 Protein-Ligand Crystal Structures (http://www.rcsb.org/pdb/)

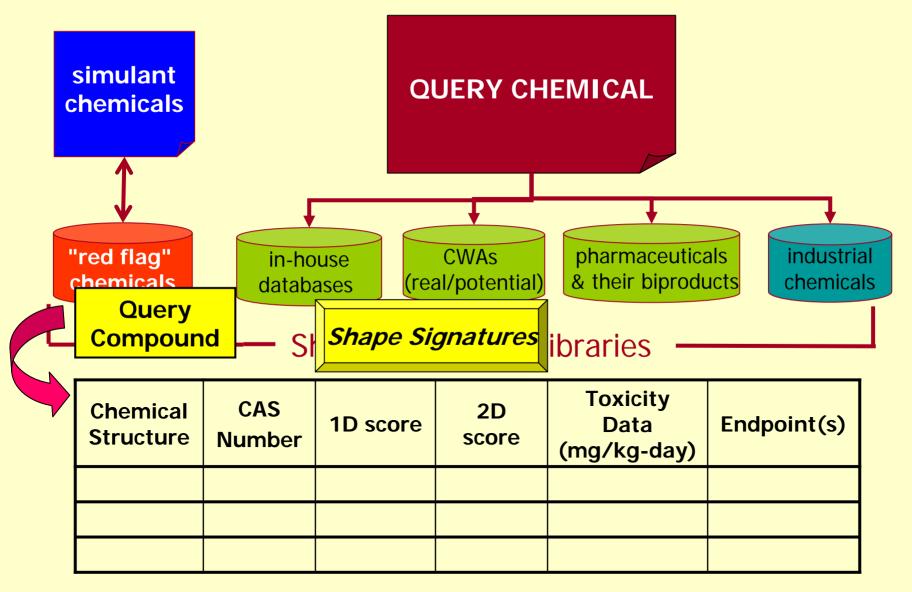






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Identifying Problem Chemicals



Shape Signatures - Key Features -

Fast

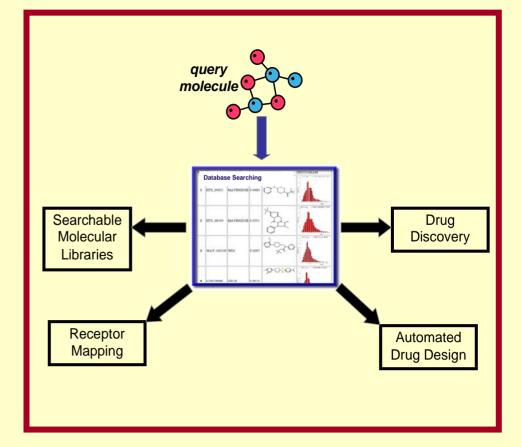
screens large databases in secs

Extensible

works with any kind or number of molecular species

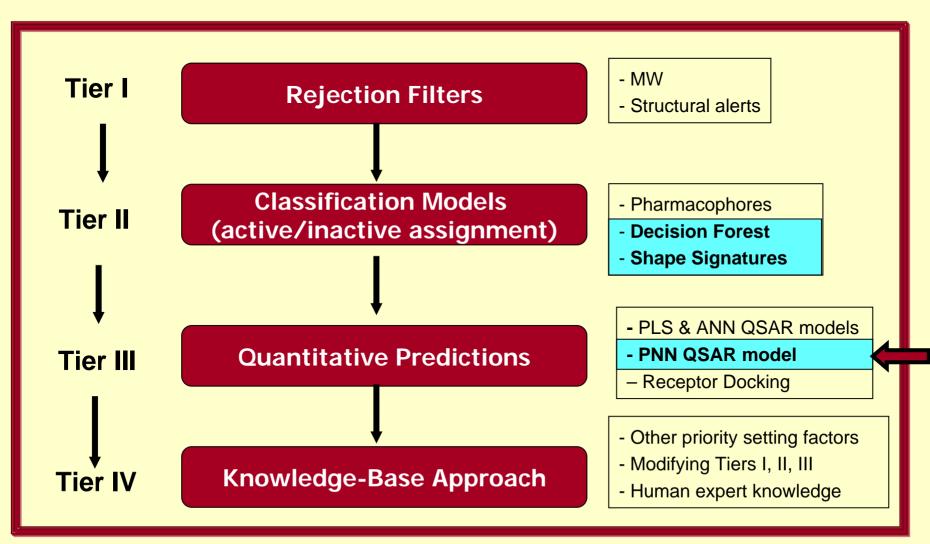
Portable works on any platform

Versatile broad utility, multiple databases



Schematic of Hierarchical Framework

- addresses the need to minimize *false negatives* and *uncertainties* -



Building QSAR Models

target property ∞ (molecular descriptors) $Y = f(X_i)$

Types of Molecular Descriptors

Туре	Example
Constitutional	Molecular composition (M _w , # of atoms/bonds, # of H-bond donors/acceptors)
Topological	2-D structural formula (Kier-Hall indices, extent of branching)
Geometrical	3-D structure of molecule (molecular volume, solvent accessible surface area, polar and non-polar surface area)
Electrostatic	Charge distribution (atomic partial charges, electronegativities)
Quantum Mechanical	Electronic structure (HOMO-LUMO energies, band gap, dipole moment)

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Comparison of Regression Methods

Desirable Features of Methods and Models

- predictions should be fast
- produces linear or non-linear models (i.e., relationship between obs toxicities and calc'd molecular features may be non-linear)
- models should be physically meaningful, interpretable, and assume parametric form

Method	Speed	Linear Models?	Nonlinear Models?	Regression Equation?	Easy to Interpret?
PLS/MVR	**	Yes	No	Yes	Yes
ANN	*	Yes	Yes	No	Yes
PNN	* *	Yes	Yes	Yes	Yes

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Polynomial Neural Network (PNN)

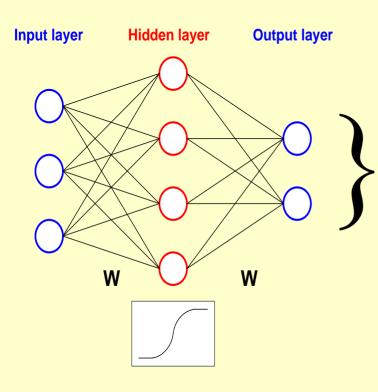
combines best features of linear multivariate models (parametric form) and ANN models (nonlinearity) -

Polynomial Neural Network

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- Produces linear or non-linear QSAR models in parametric form
- User control of model complexity
- Insensitive to irrelevant variables and outliers
- Yields predictive models, even for <u>sparse</u> or noisy data sets
- Trains rapidly, thus amenable to large data sets
- Automatically selects best models
- Customizable to fit user's needs

Polynomial Neural Network (PNN)



1) PNN generates parametric solutions of any desired order 'n":

Act. =
$$w_1(SA) + w_2(V) + w_3(\mu) + ...$$

Act. =
$$W_1(SA) + W_2(V)^2 + W_3(\mu)^3 + ...$$

Act. =
$$w_1(SA)^2 + w_2(V) + w_3(\mu)^2 + ...$$

Act. =
$$w_1(SA)^0 + w_2(V) + w_3(\mu)^2 + ...$$

Act. =
$$w_1(SA) + w_2(V)^2 + w_3(\mu)^2 + ...$$

2) PNN selects best solutions:

Act. =
$$w_1(SA) + w_2(V)^2 + w_3(\mu)^3 + ...$$

Act. =
$$w_1(SA) + w_2(V)^2 + w_3(\mu)^2 + ...$$

Thank You!

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