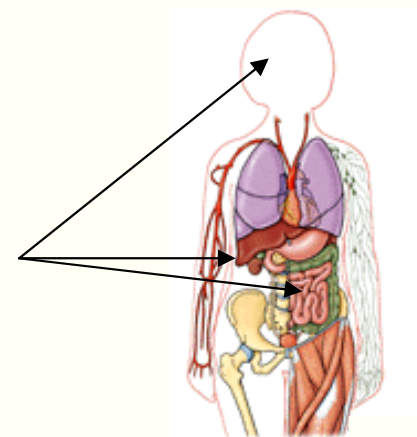
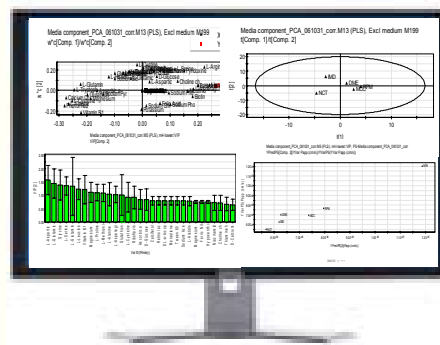
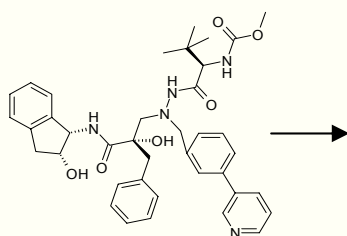




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Computational Tools in Prediction of Drug Absorption and Distribution

Christel Bergström, PhD
Department of Pharmacy, Uppsala University





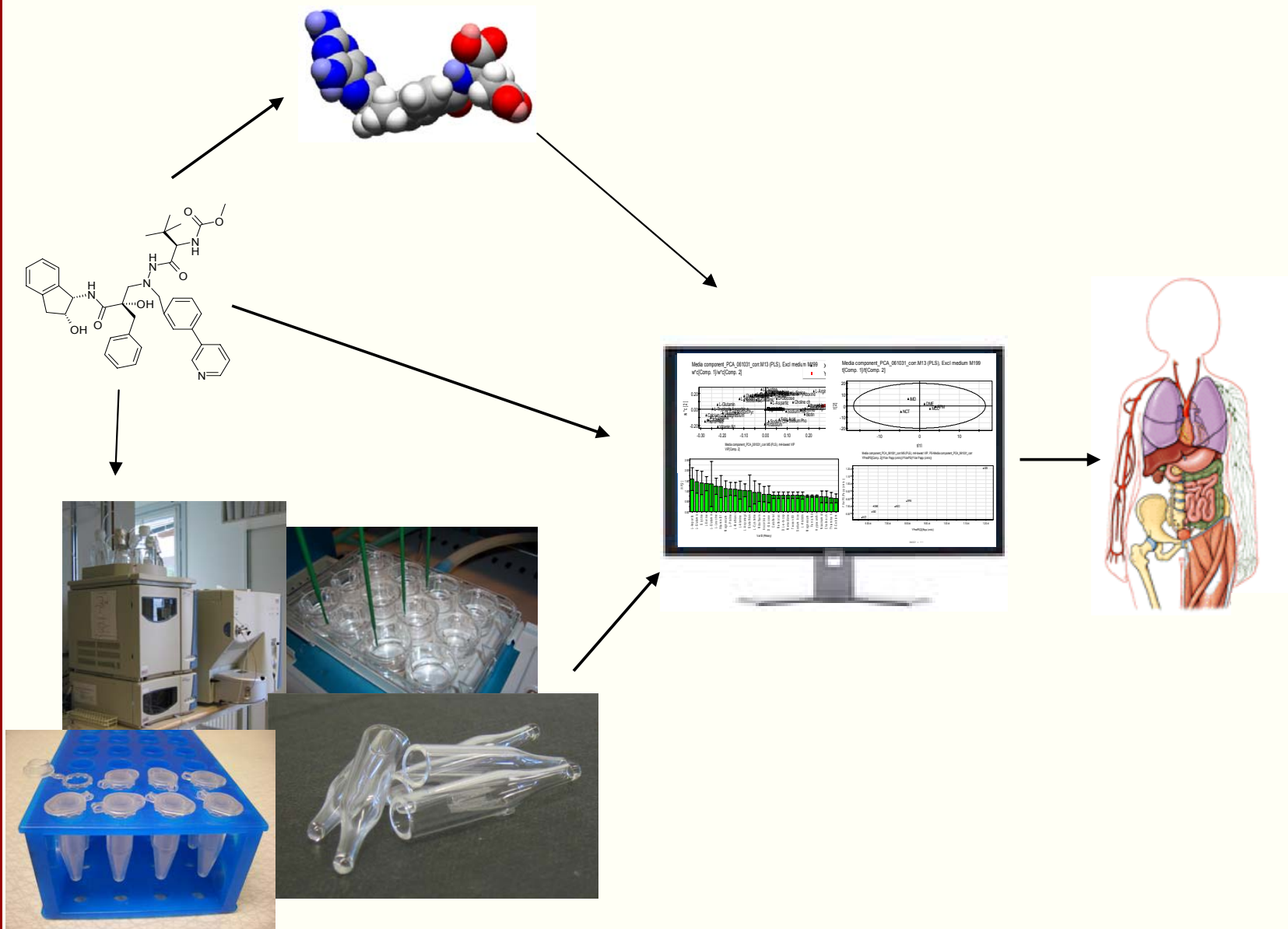
Outline

- Background; ADMET (absorption, distribution, metabolism, elimination/excretion, toxicity) modeling
- Computational tools used
 - Descriptor generation
 - Statistical methods
- Quality of experimental data
- Case studies:
 - Aqueous solubility
 - Membrane permeability
 - Active transport mechanisms
 - Absorption
- Conclusion



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ADMET modeling



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Typical ADMET properties assessed in early process of drug discovery

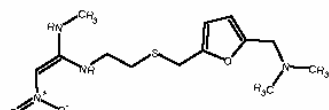
- Dissolution/solubility
 - Passive membrane permeation (permeability)
 - Transport mechanisms
 - CYP metabolism
 - Specific toxicity
- } **BCS**



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Computational tools: Descriptors

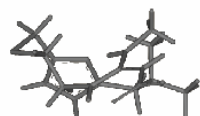
Representation



2-D structure

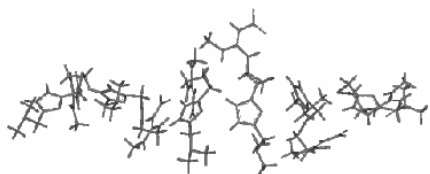
Descriptors

Atom counts, fragment counts, topological indices



3-D structure

Molecular surface properties, molecular volume, drug-probe interactions (GRID/VolSurf), CoMFA, etc



Conformational space

Dynamic molecular surface properties and molecular volume



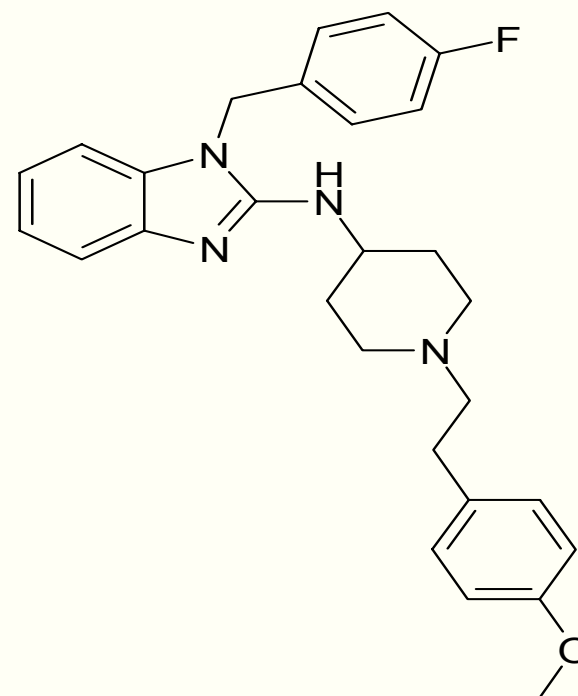
Wave function

Molecular valence properties



Molecular descriptors – 2D

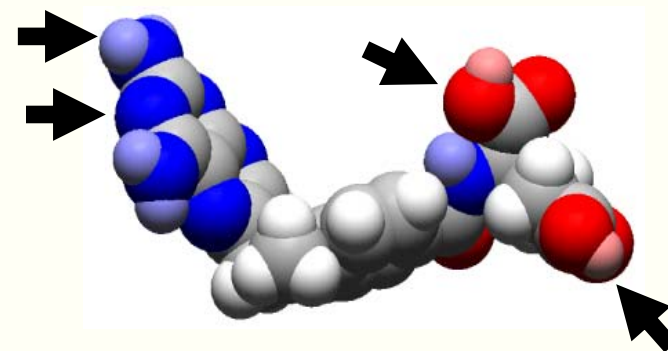
- Size
- Ring structure
- Flexibility
- H-bonds
- Polarity
- Electronic environment
- Charge
- Lipophilicity (ClogP)



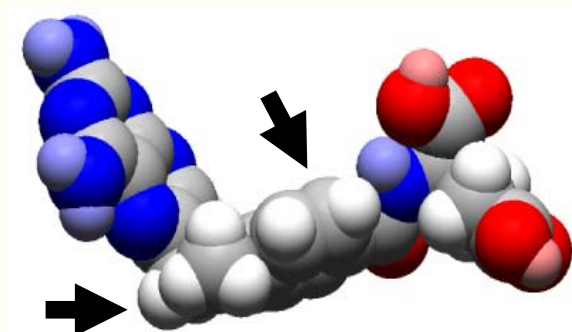


Molecular descriptors – 3D

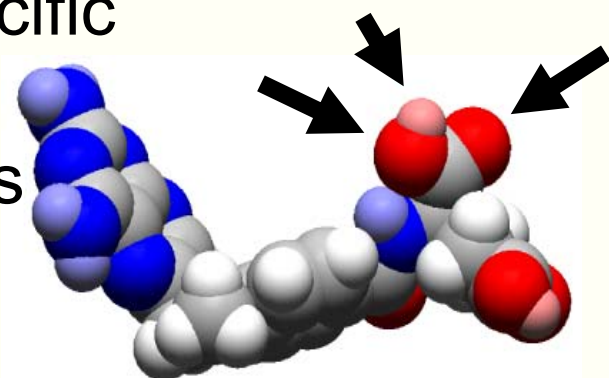
Polar surface area (PSA):
O, N and H bound to these
heteroatoms



Non-polar surface area (NPSA):
Total surface area – PSA
Non-polar atoms (C, halides etc)



Partitioned Total Surface
Area (PTSA): Surface area of a specific
atom/functional group (eg. $-\text{COOH}$)
 $\text{sp}^3\text{-O}$ ($-\text{OH}$) and $\text{sp}^2\text{-O}$ ($=\text{O}$) plus H's





Computational tools: statistics

- Rule-based system/ decision tree
- Correlations: linear/ sigmoidal
- Multivariate problems – linear:
 - Multilinear regression (MLR)
 - Principal component analysis (PCA)
 - Partial least squares projection to latent structures (PLS)
- Multivariate problem – non-linear:
 - Non-linear PLS
 - Neural network (NN)



Multivariate data analysis: PCA & PLS

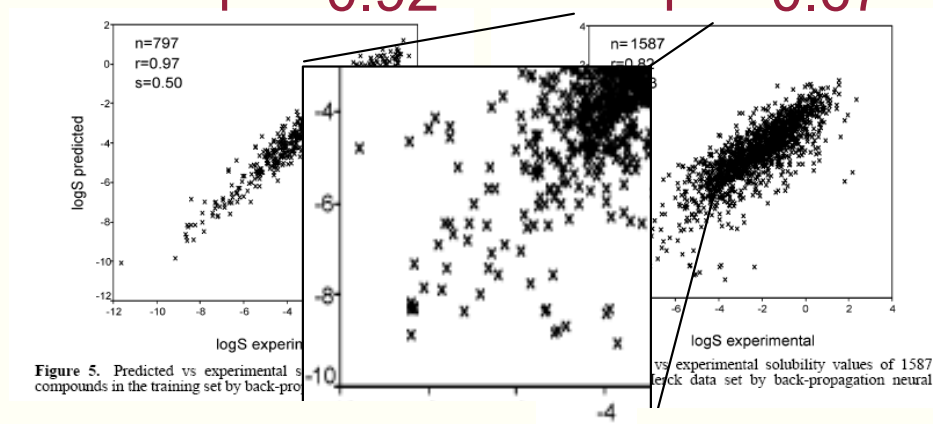
- PCA: Multivariate data analysis of characteristics of the observations:
 - Groups/outliers/trends
 - Correlationa obs./descr. och descr./descr.
- PLS; relates two matrices, X and Y, to each other by linear mathematics
- Instead of all variables that are included in the matrix, super variables with condensed information are extracted and used for prediction.
- PLS-DA (discriminant analysis) uses the supervariables to separate between two groups



Quality of data; typical "literature" data

- Mixed sources and methods; introduces large noise
- Understanding the applicability domain: usage of training set and the transparency of the models

Training set n = 797 Test set n = 1587
 $r^2 = 0.92$ $r^2 = 0.67$



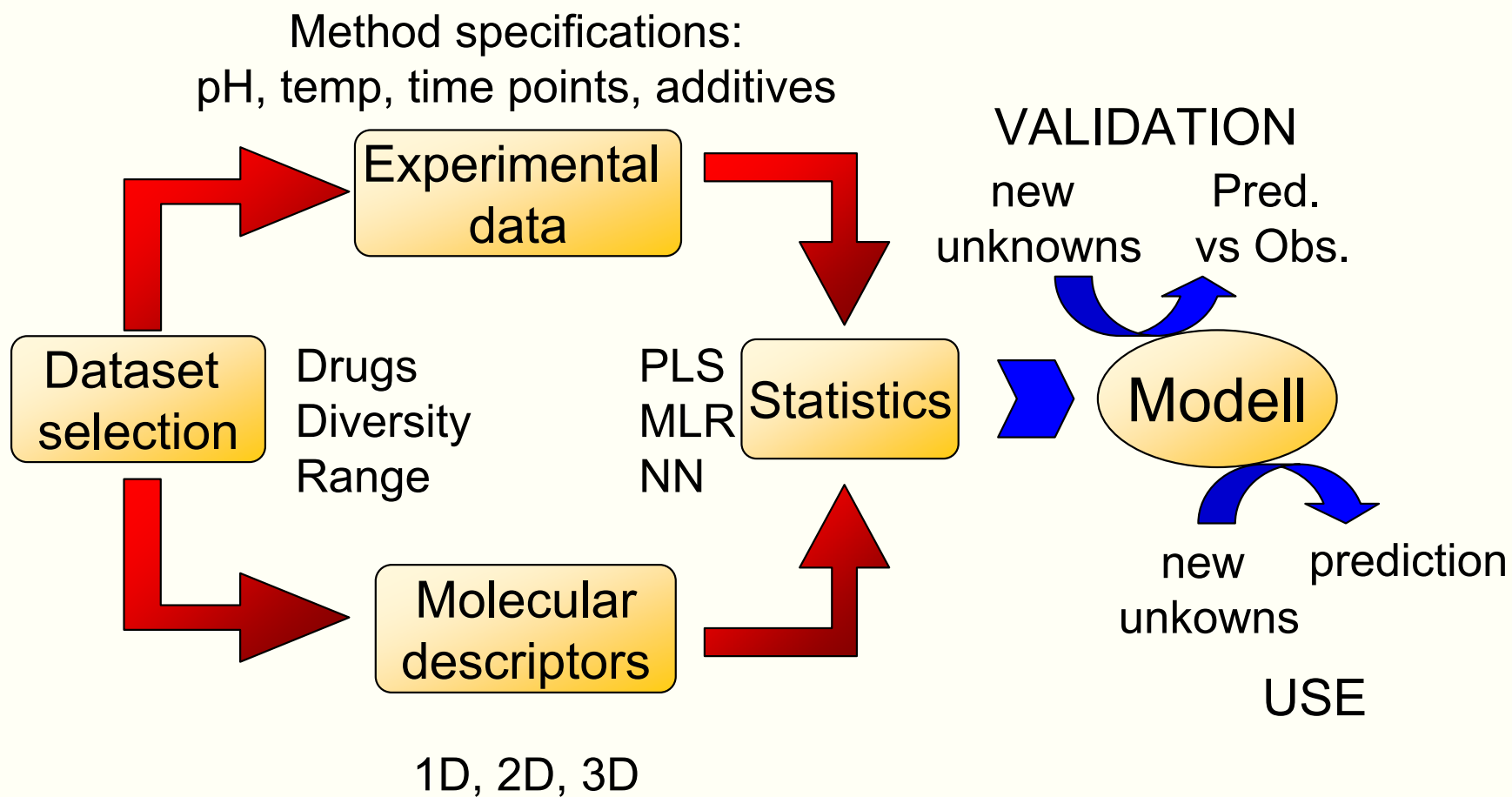
Huuskonen data set

MERCK data set



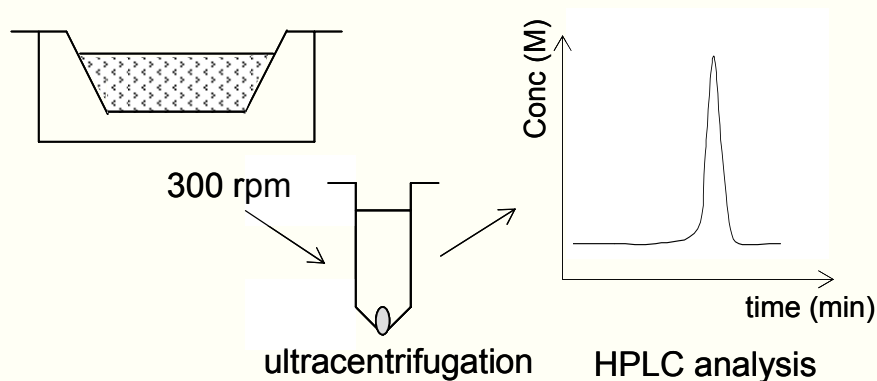
ADMET modeling: the flow

Use training set/test set

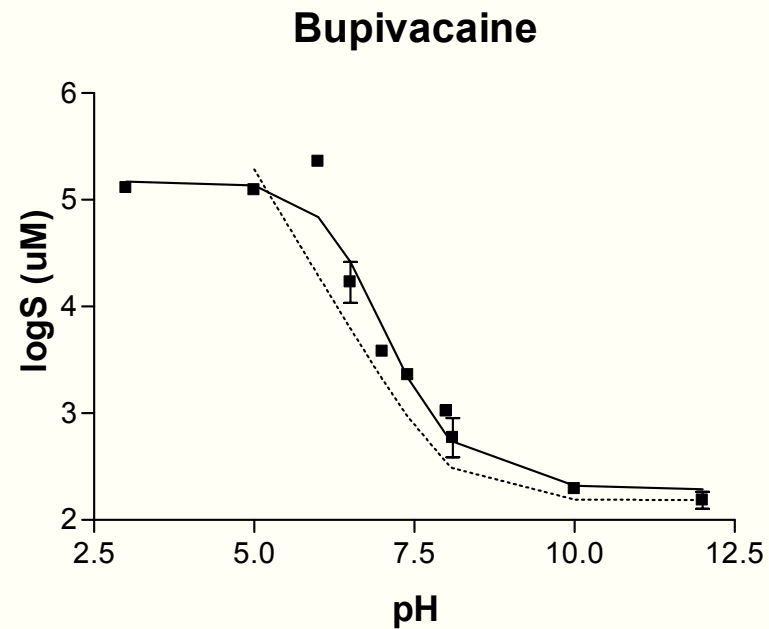
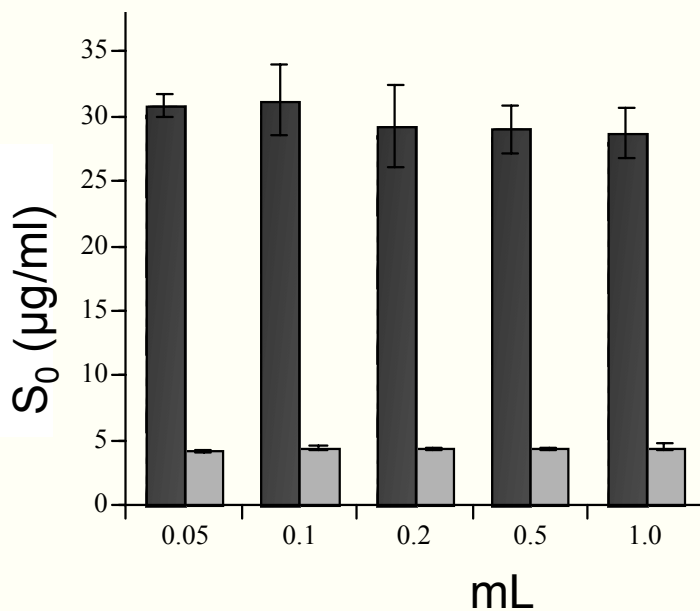




Case I: Models of aqueous drug solubility



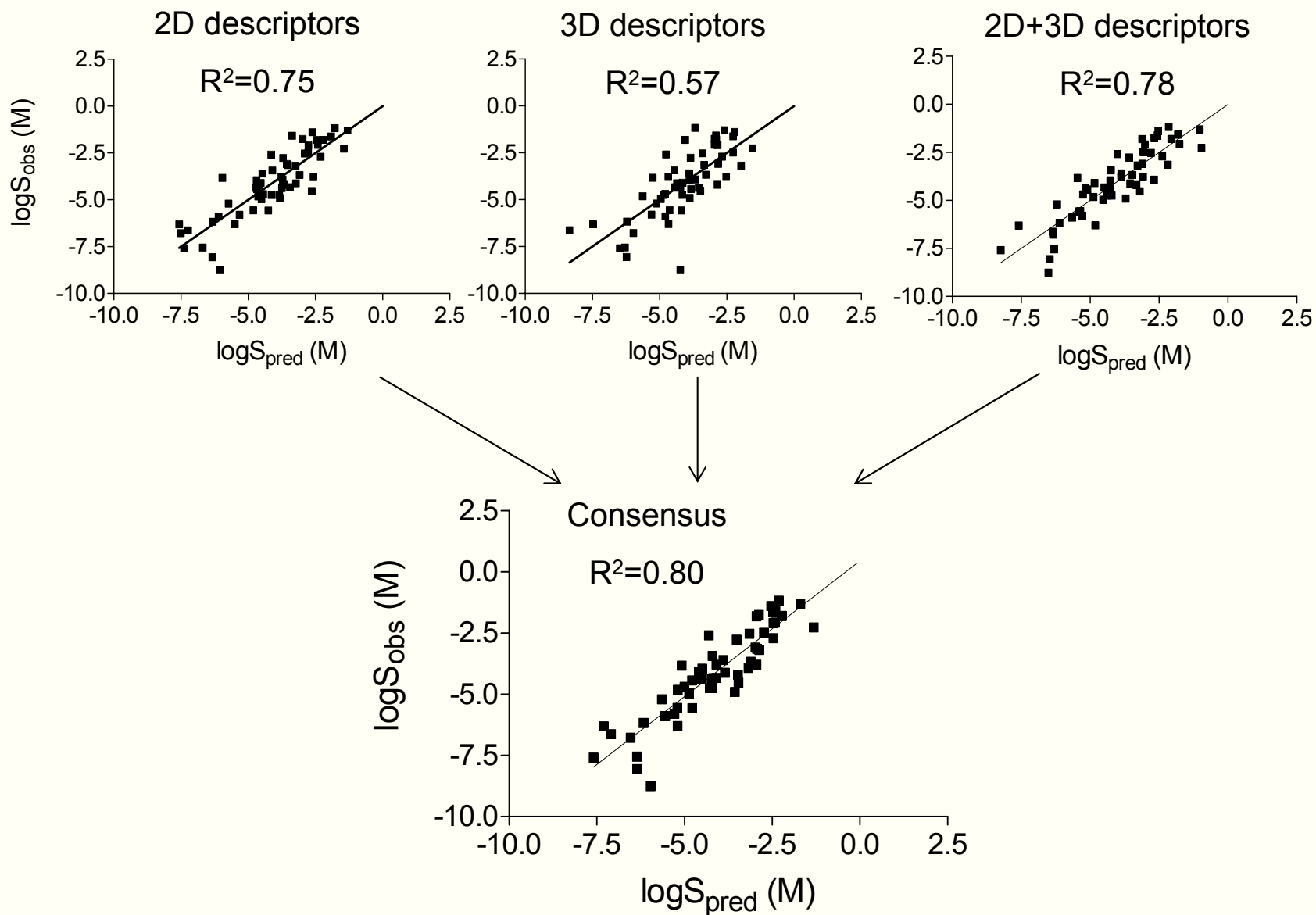
Solubility range determined;
tamoxifen intrinsic 2.9 nM
verapamil pH-dep 2 M





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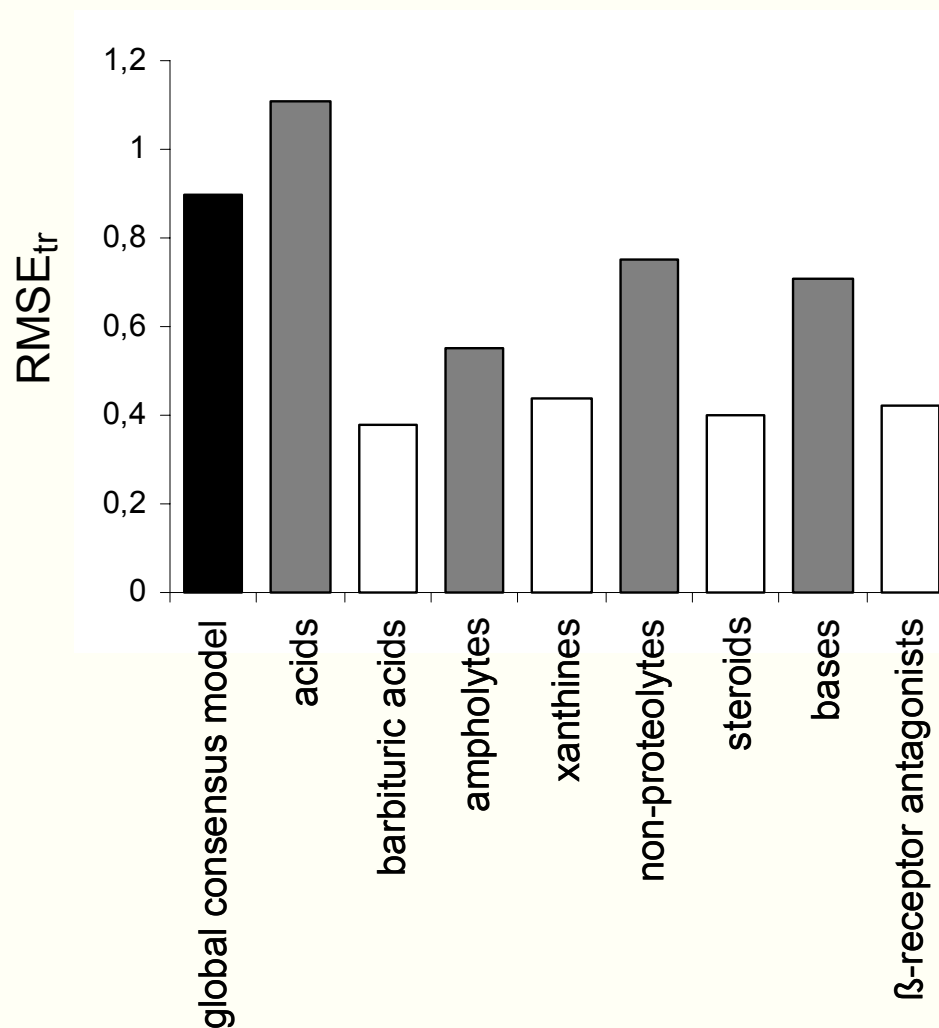
Global Models for Larger Datasets





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Local Models Result in Higher Accuracy

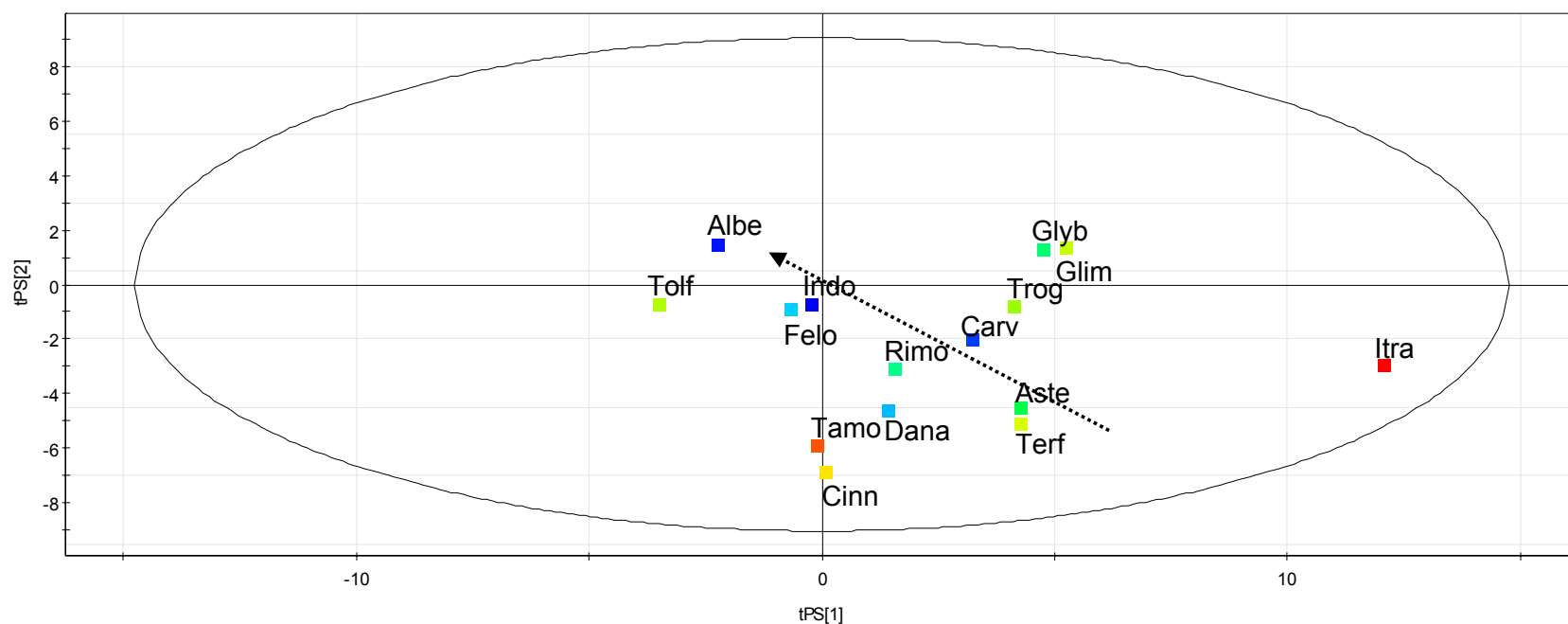


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Bergström et al., JCICS 2004



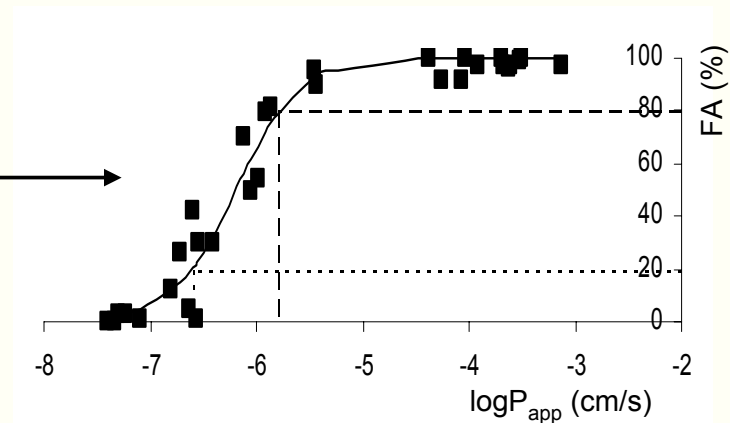
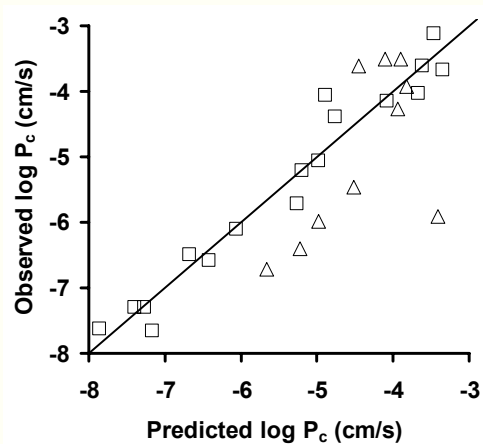
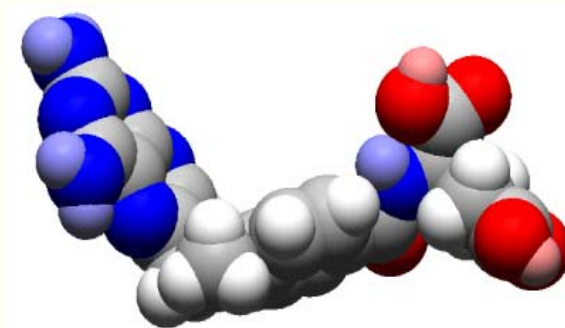
Identifying poorly soluble compounds





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Case II: Models of membrane permeability (passive)

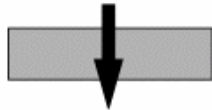
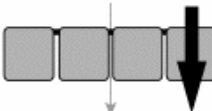
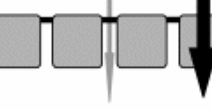


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Bergström et al., JMC 2003

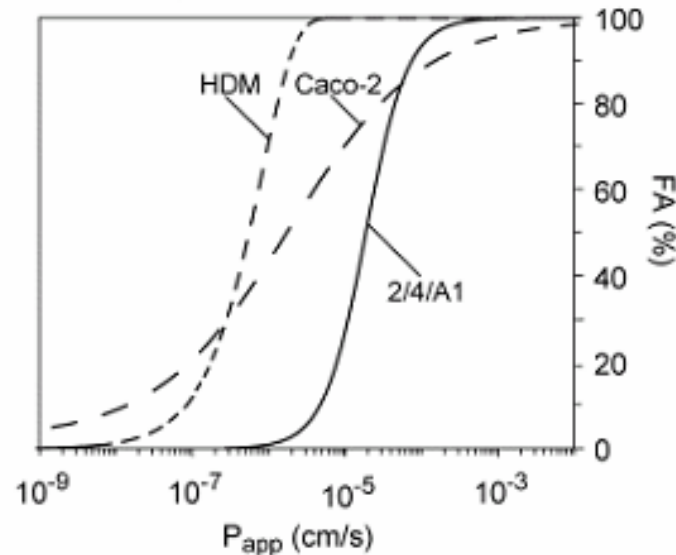


In vitro systems for prediction of fraction absorbed

Membrane model	TEER ^a	Paracellular pathway
HDM 	5000 $\Omega \times \text{cm}^2$	Non-paracellular
Caco-2 	230 $\Omega \times \text{cm}^2$	Tight-paracellular
2/4/A1 	50 $\Omega \times \text{cm}^2$	Leaky-paracellular

↓ Passive transcellular transport ↓ Passive paracellular transport

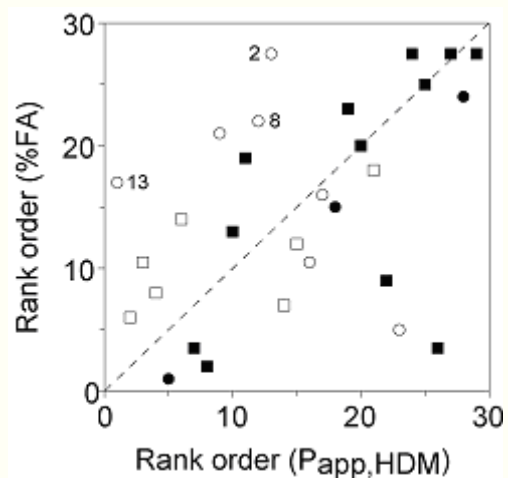
D All experimental models



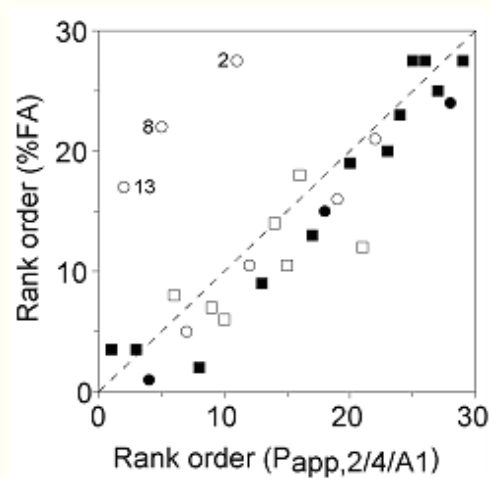


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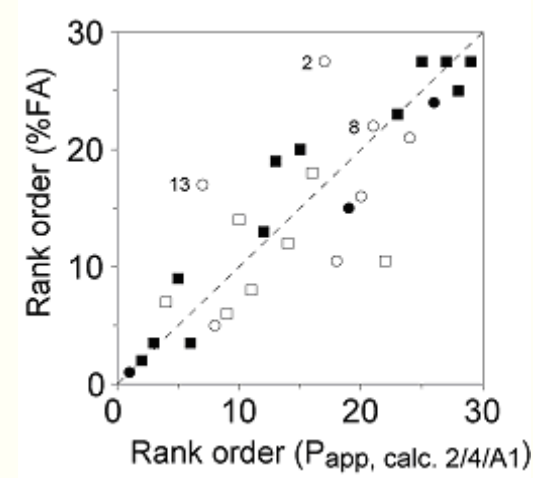
In silico prediction of permeability



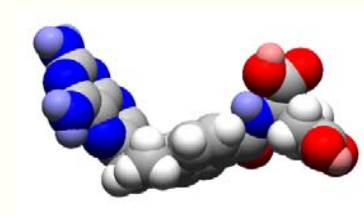
In vitro



In vitro

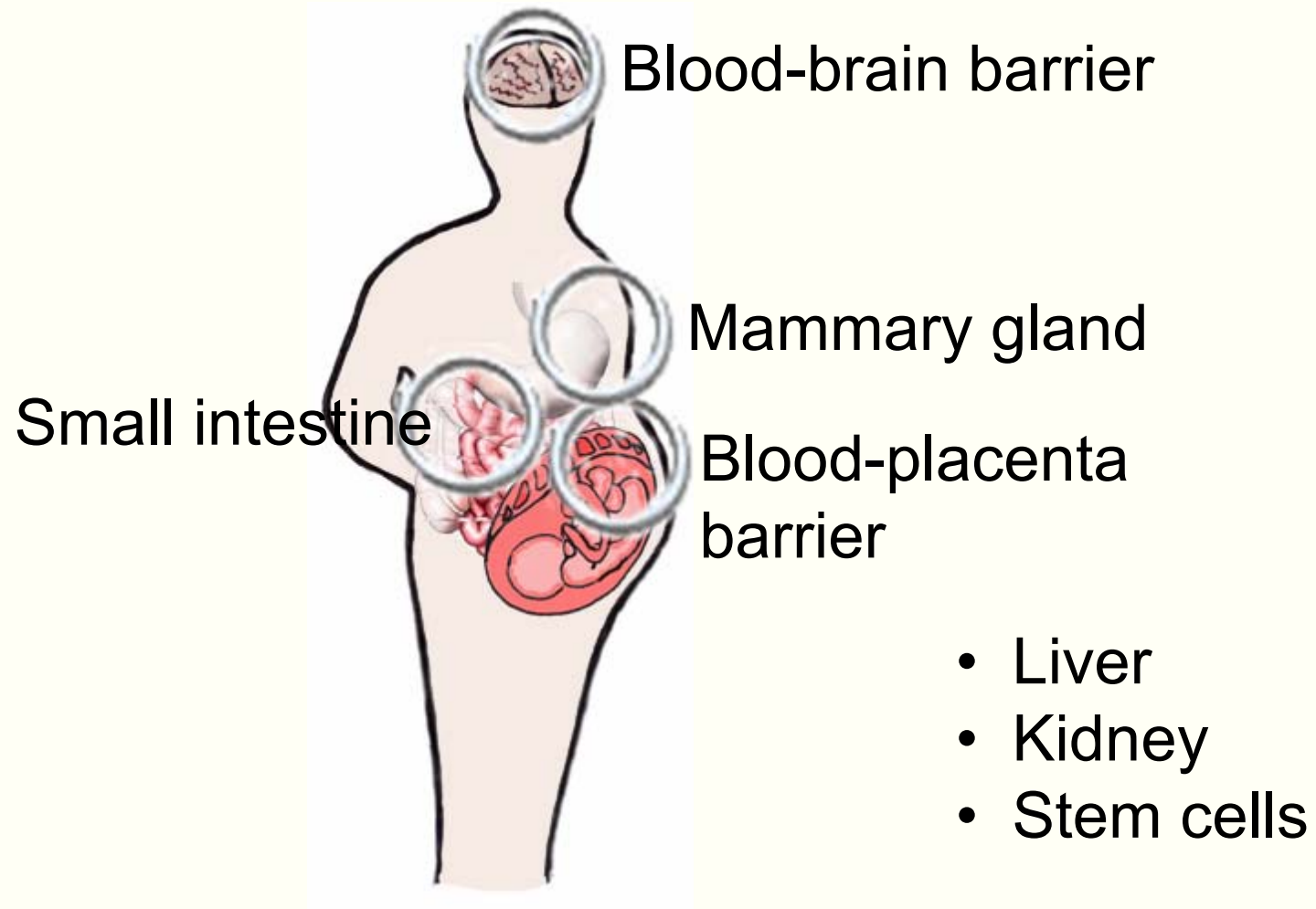


In silico



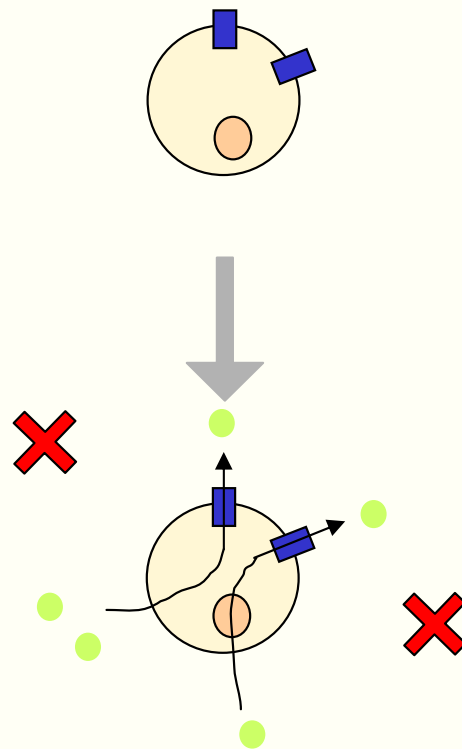


Case III: Active transport . Breast Cancer Resistance Protein (BCRP)

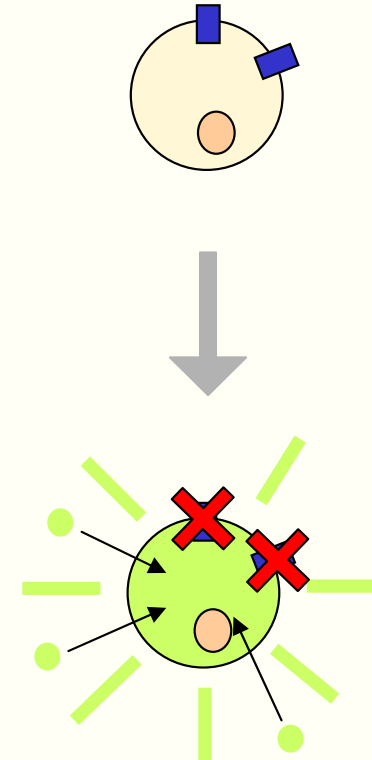




Experimental assay: Efflux inhibition



No inhibitory effect:
mitoxantrone is effluxed
→ low intracellular
fluorescence

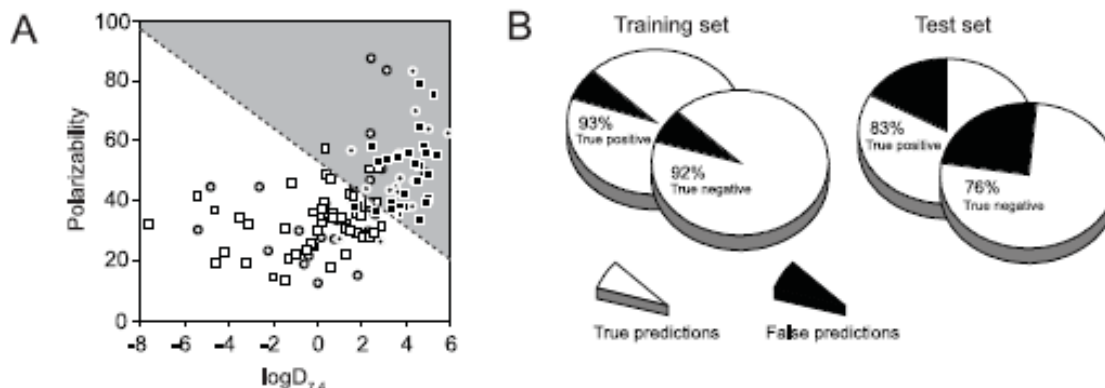


Inhibition:
mitoxantrone is retained in
the cells
→ high intracellular
fluorescence

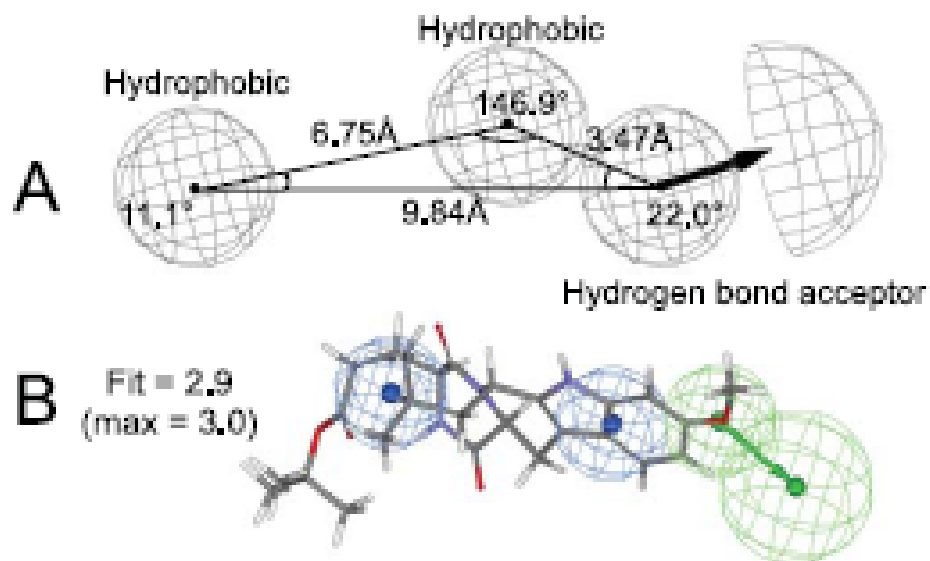


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Computational modeling



PLS-DA



Common features
pharmacophore
modeling

Matsson et al., submitted



Case IV: BCS prediction

- To investigate accuracy of absorption prediction when both solubility and permeability are incorporated.
- Used the WHO list of essential drugs
- 15 compounds used for developing the two models, validated with 21 compounds.



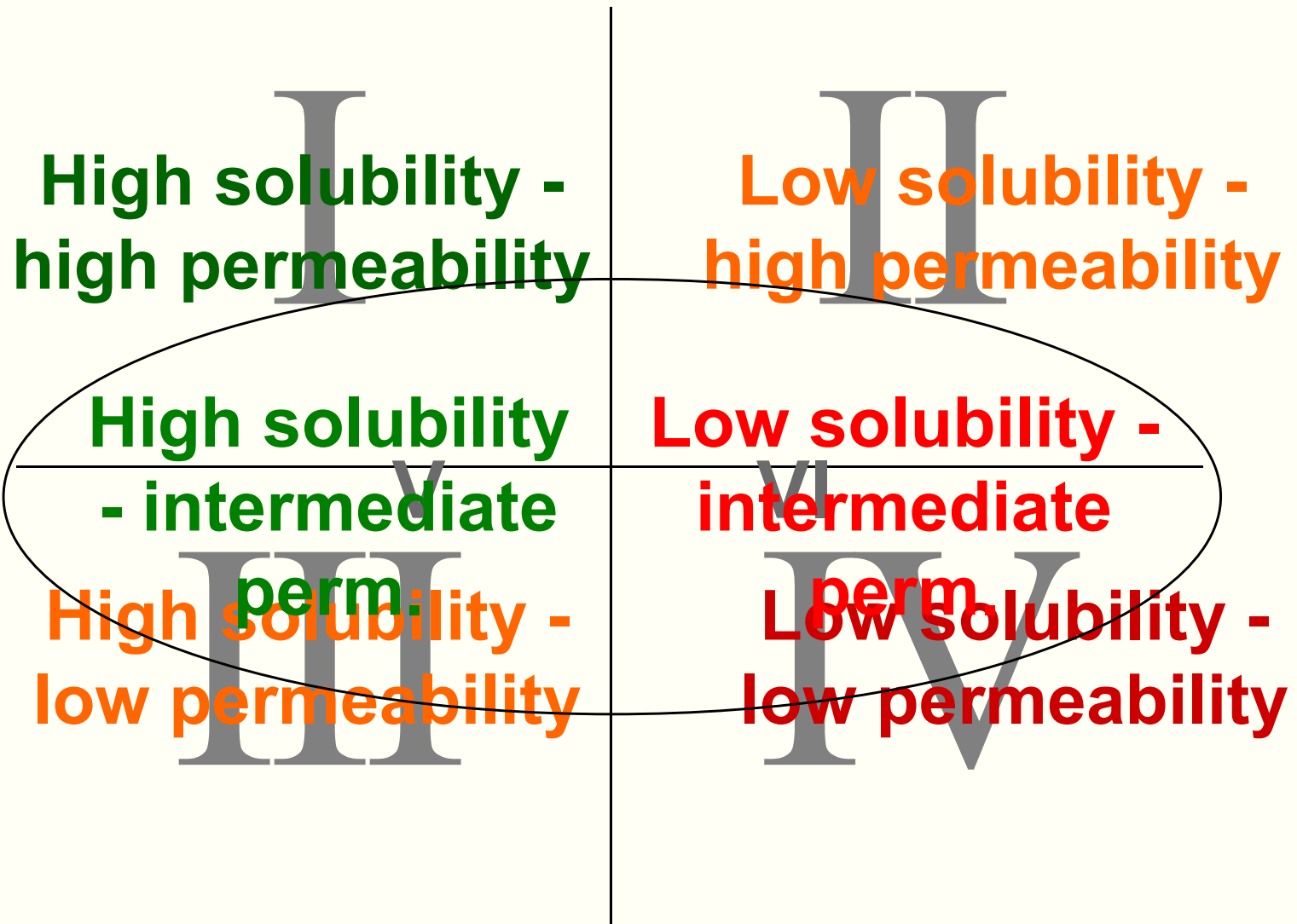
A BCS extended for the drug discovery process

- High solubility: maximum dose given orally is soluble in 250 ml, pH 1-7.5
- High permeability: >80% absorbed
- Low permeability: <20% absorbed
- Intermediate permeability: 20-80%

Summary: six classes instead of "normal" four.

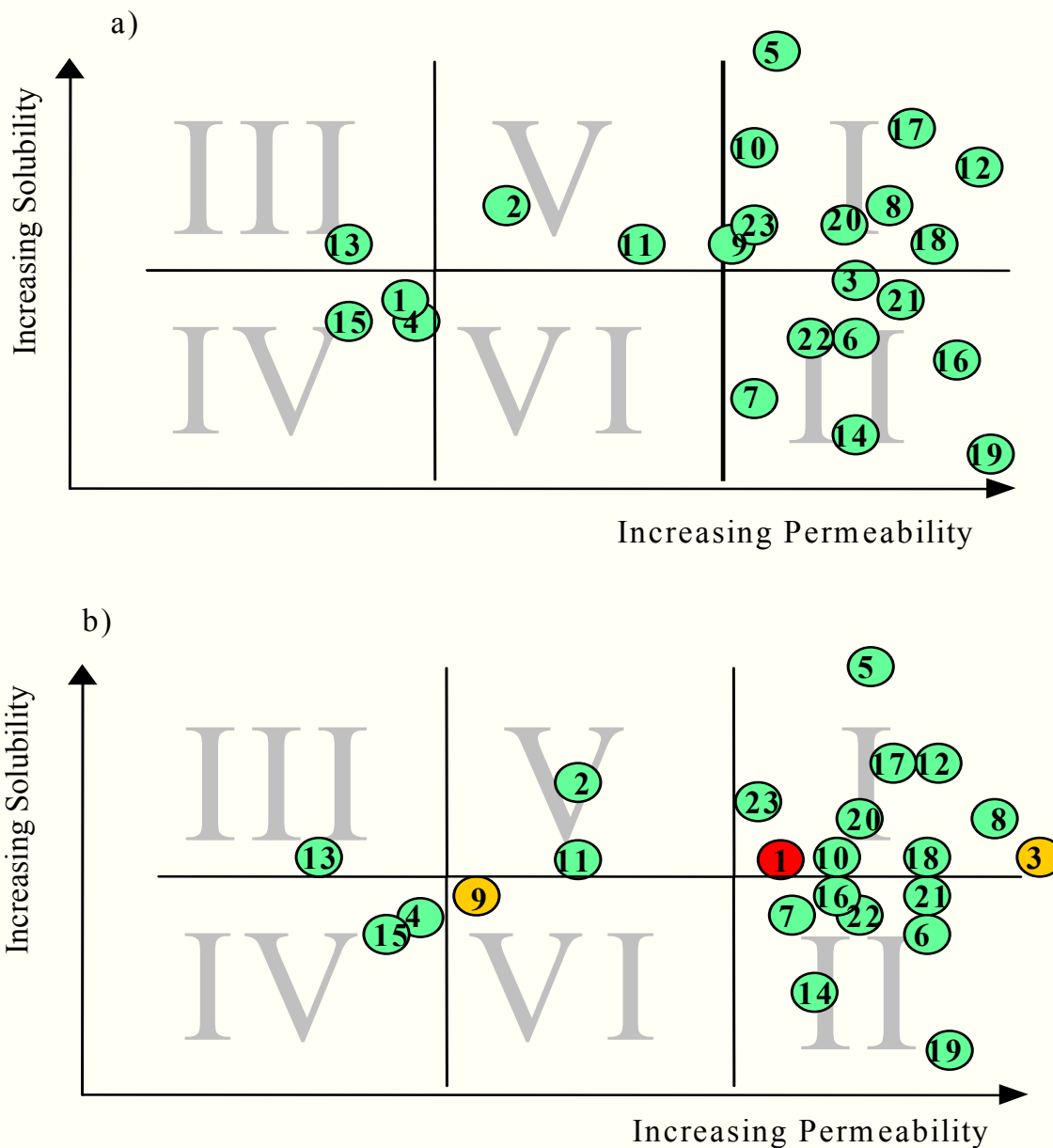


BCS Classes





Theoretical BCS



Bergström *et al.*, *J.Med.Chem.* 2003



Conclusions

- Need to use different computational tools when developing models for underlying mechanisms/ processes involved in drug absorption, distribution and elimination
- Important to base the models on high quality experimental data
- Very important to use a training set which covers the "chemical" space under investigation
- Always make a proper validation of your model



Conclusions

- It is an advantage if the model developer understands the experiments and/or the responses which are to be predicted.
- Several ADMET properties have been modeled and predictive models are available. Now remains
 - to simultaneously model the properties to investigate how mechanisms interact
 - to evaluate the relevance of the combination of in silico+in vitro models for prediction of the in vivo situation.



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