Predictions of Intrinsic Aqueous Solubility of Crystalline Drug-like Molecules

NSCCS





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Overview

- Introduction.
- Solution model Our solubility prediction model.
- Results The performance of the solubility predictions.
- Further models Work following on from the initial model.
- Current/future work Where we are currently and where we are going.

Why is solubility prediction important?

 Crucial factor to control bioavailability of drug candidates.

Solution model

Introduction

- Critical component in determining the environmental impact of pesticides.
- Accurate *in silico* predictions of solubility can save time and money.



Why should we care about solubility ?

Results



Solution model

Introduction

It's not funny When your next

- New drug candidates are often more insoluble than their predecessors.
- Formulation of these drugs often involve less pleasant administration methods.

 Certain pesticides can cause extensive damage and potentially enter the water cycle.

Existing Theoretical Approaches

- So far, although theoretical methods have shown promise, they have not matched the accuracy of QSPR. Theoretical methods do have the advantage of being physically tractable.
- Industry also requires high through put methods.
 QSPR models are generally much faster than computational chemistry models.
- There are many theoretical models to make solubility predictions.

Our Methodologies

Results

- We have decomposed the solution (solu) free energy prediction in to two distinct steps.
 - Sublimation (sub)

Solution model

- Hydration (hyd)

Introduction

- We have applied a range of methodologies to each step.
- Methodologies include simulation, QM calculation and machine learning.

Thermodynamic cycle



Crystalline

Sublimation : Predictions by DMACRYS

∆G sub

Solution model

Introduction

- DMACRYS a periodic lattice simulation program.
- Electrostatics, from distributed multipoles.
- Buckingham potential to account for repulsion and dispersion.
- Calculates lattice energy and crystal entropy from phonon modes.
- Gas phase contributions calculated in Gaussian 09.

Solid

Hydration: Solvation models



- Continuum solvent, solvation model based on density (SMD).
- An integral equation theory (IET) of molecular liquids methodology the Reference Interaction Site Model (RISM).

Dilute solution

Hydration: RISM

- Combines features of explicit and implicit solvent models.
- Solvent density is modelled, but no explicit molecular coordinates or dynamics.



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Hydration: RISM





- We use the 3D RISM variation.
- We employ the Kovalenko-Hirata (KH) closure and Gaussian fluctuation free energy functional.
- We also employ the universal correction (UC).

 $\Delta G_{hyd}^{3DRISM-KH/UC} = \Delta G_{hyd}^{3DRISM} + a(\rho V) + b$

The methodology we used will be referred to as 3DRISM-KH/UC.

Solution Free Energy

Results



Solution model

Introduction

 The sum of our predictions of ΔG sub and ΔG hyd produce
 a ΔG solu prediction.

Further models

- These methods were carried out for 25 chemically diverse drug-like molecules.
- Chemical accuracy ~4 kJ/mol or ~ 1 LogS unit.
- Useful predictions are within the standard deviation (SD) of the experimental values.

Current/future work



Sublimation free energy predictions



- Validation of the sublimation free energy prediction.
- B3LYP/6-31G(d,p) multipole.
- FIT repulsion dispersion potential.
- Correlation coefficient (R) 0.87.
- RMSE 5.66kJ/mol.

Hydration Free Energy Predictions



- Validation of the hydration free energy predictions.
- SMD HF/6-31G(d,p).
- Both have strong R values 0.93 RISM, 0.97 SMD.
- RISM has a significantly higher RMSE 4.85kJ/mol RISM, 2.91kJ/mol SMD.

Solution Free Energy Predictions

Results



Solution model

Introduction

• The full 25 molecule set is compared to experiment.

Further models

Current/future work

- Chemical accuracy ~ 1logS unit.
 Experimental SD 1.79 LogS.
- Reasonable correlation
 R 0.85 RISM, R 0.84 SMD.
- RISM method provides best RMSE, RMSE of 1.45LogS RISM, RMSE of 2.03LogS SMD.
- SMD outliers Niflumic Acid and Pteridine.

Palmer, D. S.; McDonagh, J. L.; Mitchell, J. B. O.; van Mourik, T.; Fedorov, M. V., *Journal of Chemical Theory and Computation* **2012**. 16

To sum up

- From these results we concluded it was possible to make predictions of a reasonable accuracy.
- In our methodology a larger portion of error could be attributed to the sublimation free energy prediction.
- Larger datasets were required to fully validate the methodology.

Further models

- We took two approaches to follow up this work:
 - Parameterisation and machine learning approaches to predict ΔG solution.
 - Systematic theoretical improvements in Sublimation free energy predictions. (work currently ongoing).

Introduction

Informatics and machine learning

- We selected a dataset of 100 molecules.
- Calculated descriptors using the chemistry development kit (CDK).
- We followed our previously laid out theoretical methodology for the 100 molecules.
- We combined descriptors and theoretically calculated energies.



Descriptors

- SMILES are input into CDK.
- Structural and some predicted properties are output for use as descriptors.
- These cheminformatics descriptors were used as part of the input for the machine learning methods.



| Descriptor | Value | |
|------------------------|--------|--|
| Molecular Weight | 280 | |
| Molecular Formula | С9Н8О4 | |
| XLogP | 1.24 | |
| Freely rotatable bonds | 3 | |
| H bond acceptor | 4 | |
| | | |
| | | |

Computational Chemistry Calculations

Results

 DMACRYS –B3LYP/ 6-31G(d,p), FIT potential.

Solution model

 SMD with HF/6-31G(d,p)

Introduction

- The same level of theory was used in the gas phase as the solution phase.
- SMD selected over RISM as it provided a better correlation in the previous work.



Further models



Current/future work

Machine Learning Models

• Random Forest (RF) – A forest of decision trees.

Results

Introduction

Solution model



IntroductionSolution modelResultsFurther modelsCurrent/future work• Support Vector Machines (SVM) – Classification by
projection into a higher space and separation by a
hyperplane.- Classification by
a
by a



 Partial least squares Regression (PLS) – can be considered as classification by deflation.



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Work flow/Experimental design



Results



Introduction

Experimental LogS

- <u>Results of the purely</u> <u>theoretical prediction</u>.
- Our results are correlative.
- Standard linear regression is a poor fitting model.
- Chemical accuracy ~1logS unit.
- Experimental SD 1.71 LogS units.

Descriptors only





- Results of prediction exclusively using the CDK descriptors.
- All machine learning methods perform better than theory alone.
- Red bars show the SD and mean result.
- Boxes represent 75% of the predictions. Dark blue line shows the median.

| | PLS | RF | SVM | Theory |
|---------------------|--------------|--------------|--------------|--------|
| Mean | | | | |
| RMSE | 1.174(±0.08) | 1.134(±0.03) | 1.132(±0.03) | 2.95 |
| Mean R ² | 0.56(±0.03) | 0.56(±0.03) | 0.56(±0.03) | 0.32 |

PLS

Combined model



RF

SVM

- The model contains HF/6-31G(d,p) energies and descriptors.
- All show improvement over pure theory.
- Result are similar to those of the descriptors alone.
- **Experimental SD 1.71** LogS units.

| | PLS | RF | SVM | Theory |
|------------------------|---------------|--------------|--------------|--------|
| Average | | | | |
| RMSE | 1.110(± 0.04) | 1.107(±0.03) | 1.111(±0.04) | 2.95 |
| Average R ² | 0.594(±0.04) | 0.583(±0.04) | 0.576(±0.04) | 0.32 |

Summary

- The information from theoretical calculations at this level has a minor impact but does improve accuracy and correlation of the results.
- The descriptors already hold much of the information.
- Further exploration of models of this type could allow us to find information not held in the descriptors that is accessible by chemical calculation.

Exploration of sublimation free energy prediction

- The largest source of error in the initial method was the sublimation free energy prediction.
- We have a dataset of 60 molecules.
- We made sublimation free energy predictions using this dataset with our previously outlined method.
- We look to DFT methods to provide improved predictions.

Periodic DFT

- We are using Periodic DFT to make sublimation free energy predictions.
- We are exploring dispersion corrections.
- We will look at the accuracy of prediction of the components of the free energy.



Free Energy of Sublimation

Results

 From our initial methodology.

Introduction

- A poor correlation.
- Significant RMSE.
- Outliers hold significant leverage.

Solution model

 All outliers contain NO₂ groups (in red) which are known to be difficult to represent accurately in force fields.



Experimental Vs Predicted ΔG sub

Introduction Solutio

Summary

- We have explored a purely theoretical methodology for predictions of solvation free energy.
- We have expanded from this to produce a combined computational chemistry cheminformatics methodology.
- We have begun exploration of sublimation free energy, due to the large error it contributed in our original methodology.

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Current Preliminary Results

Enthalpy of Sublimation

- Using DMACRYS B3LYP multipoles FIT potential and Gaussian 09.
- 48 molecules.
- A fair correlation but significant RMSE.



Entropy of Sublimation

- Crystal entropy calculated in DMACRYS, gas phase in Gaussian 09.
- No meaningful correlation.
- Significant RMSE.
- 48 molecules



Additional notes

- Buckingham potential $E_{lk} = Bexp(-Cr_{lk}) - Ar_{lk}^{-6}$
- Universal correction $\Delta G_{hyd}^{3DRISM-UC} = \Delta G_{hyd}^{3DRISM} + a(\rho V) + b$
- LogS



• 1logS unit = 5.71 in terms of ΔG

 $\Delta G_{sol}^{o} = \Delta G_{sub}^{o} + \Delta G_{hyd}^{o} = -RTln(S_{0}v_{m})$ Molar volume of the crystal Vm Intrinsic solubility So

- Thermodynamics
- $\Delta H_{sub} = -U_{latt} + 2RT$
- $\Delta S_{sub} = (S_r + S_t) S_{crys}$
- $\Delta G_{sub} = \Delta H_{sub} T\Delta S_{sub}$

•
$$\Delta G_{hyd} = E_{sol} - E_{gas}$$

•
$$\Delta G_{solu} = \Delta G_{sub} + \Delta G_{hyd}$$

 $\Delta G^{GF} = K_B T \sum_{\alpha=1}^{N \text{ solvent}} \rho_{\alpha} \int_{R^3} \left[c_{\alpha}(r) - \frac{1}{2} c_{\alpha}(r) h_{\alpha}(r) \right] dr$

