

RDKit in the Modern Biotech

RDKit User Group Meeting 2018 Ben Tehan & Rob Smith

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Why RDKit?

- Initially Heptares had a multitude of languages, webservers and toolkits
 - **-** 2009 **-** 2013

Languages

Fortran, C, C++, Perl, Java,
 Javascript, Python, Matlab, R,
 etc...

Webservers

Ruby on Rails, PHP, Javascript, etc...

Toolkits

 Indigo, CDK, OEChem, other flavours also available etc...

What we needed going forward

- general purpose language which you can find almost anywhere.
- web applications,
- desktop apps,
- network servers,
- machine learning,
- easily distributable

Why RDKit?

- Heptares Computational Chemistry adopted Python & RDKit as standard
 - 2013 now
- Languages
 - Python
- Webservers
 - Django
- Toolkits
 - Open Source and active
 - RDKit



- What we needed going forward
 - general purpose language which you can find almost anywhere.
 - web applications,
 - desktop apps,
 - network servers,
 - machine learning,
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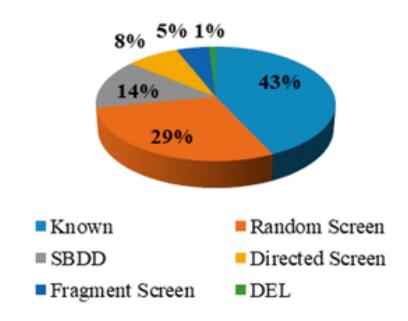




Drug Discovery Process - lite

- Program initiated (not target selection etc...)
- Cpds identified
 - patent
 - literature
- Leads examined
- Hit expansion
- Hit Analyses

Lead generation strategies:





Drug Discovery Process - lite

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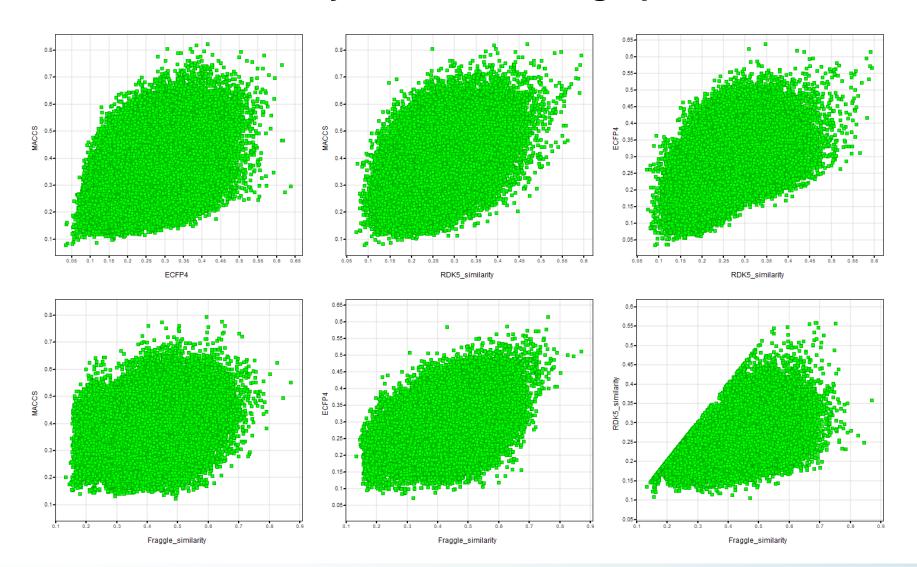
- Explore phase
- Patent Analyses
 - Frequency of R-Group analyses
 - FOG analyses
 - Tyrchan et al. JCIM, 2012, 52
 (6), pp 1480–1489,
 - DOI: 10.1021/ci3001293
- Similarity
 - Structural (fingerprint)
 - Pharmacophoric
 - Shape-based

Similarity – Structural Fingerprints

```
do topogical for comparison (path)
    mfp = Chem.RDKFingerprint(mol, maxPath=5, fpSize=1024, nBitsPerHash=2)
    PATH5 sim = DataStructs.FingerprintSimilarity(originalfp,mfp)
do morgan for comparison (circular)
    mfp2 = rdMolDescriptors.GetMorganFingerprint(mol,2)
    ECFP4 sim=DataStructs.DiceSimilarity(mfp1,mfp2)
do maccs also (functional group count)
    maccsfp2 = MACCSkeys.GenMACCSKeys(mol)
    MACCS sim= DataStructs.FingerprintSimilarity(maccsfp1, maccsfp2)
    molHAC = Chem.MolFromSmiles(smi).GetNumAtoms()
do Fraggle now
    res = DataStructs.BulkTverskySimilarity(mfp,queries,0,1,False)
    # set some values specified in command line
    current highest tver=float(tversim)
    current highest frag=float(fragsim)
    fraggle highest=None
    for i in range(0,len(queries)):
        if((float(res[i]) >= float(tversim)) and (float(molHAC) >= float(queryHAC-3)) and (float(molHAC) <= float(queryHAC+4))):</pre>
            # check greater than tyersky similarity cutoff and query matches are of similar size to initial molecule
            # screen passes tyersky criteria
            rdkit sim, fraggle sim=FraggleSim.compute fraggle similarity for subs(mol,original mol,query smi,out fragments[i])
            if(float(fraggle sim) >= float(current highest frag)):
                fraggle highest=float(fraggle sim)
                current highest frag=fraggle highest
    if((fraggle highest is not None) and (fraggle highest >= float(fraggle sim))):
        # got to end of gueries and passed tversky criteria
        None
    else:
        current highest frag='Null'
```

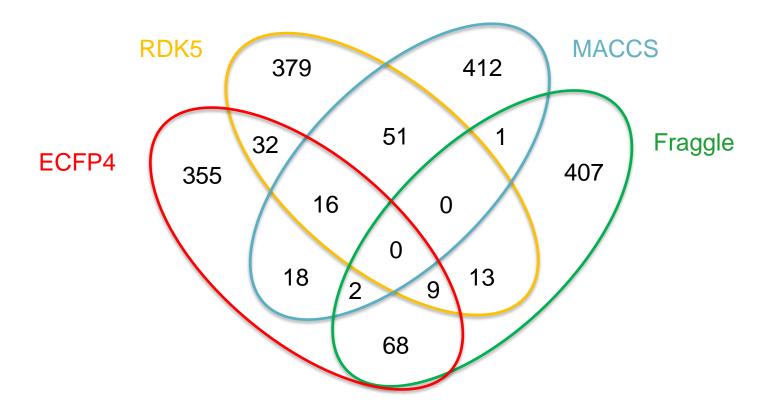


Similarity – Structural Fingerprints





Similarity – Structural Fingerprints



Top 500 from each method



Similarity – All Fingerprints

RESEARCH ARTICLE

Open Access



Comparing structural fingerprints using a literature-based similarity benchmark

Noel M. O'Boyle* and Roger A. Sayle

Abstract

Background: The concept of molecular similarity is one of the central ideas in cheminformatics, despite the fact that it is ill-defined and rather difficult to assess objectively. Here we propose a practical definition of molecular similarity in the context of drug discovery: molecules A and B are similar if a medicinal chemist would be likely to synthesise and test them around the same time as part of the same medicinal chemistry program. The attraction of such a definition is that it matches one of the key uses of similarity measures in early-stage drug discovery. If we make the assumption that molecules in the same compound activity table in a medicinal chemistry paper were considered similar by the authors of the paper, we can create a dataset of similar molecules from the medicinal chemistry literature. Furthermore, molecules with decreasing levels of similarity to a reference can be found by either ordering molecules in an activity table by their activity, or by considering activity tables in different papers which have at least one molecule in common.

Results: Using this procedure with activity data from ChEMBL, we have created two benchmark datasets for structural similarity that can be used to guide the development of improved measures. Compared to similar results from a virtual screen, these benchmarks are an order of magnitude more sensitive to differences between fingerprints both because of their size and because they avoid loss of statistical power due to the use of mean scores or ranks. We measure the performance of 28 different fingerprints on the benchmark sets and compare the results to those from the Riniker and Landrum (J Cheminf 5:26, 2013. doi:10.1186/1758-2946-5-26) ligand-based virtual screening benchmark.

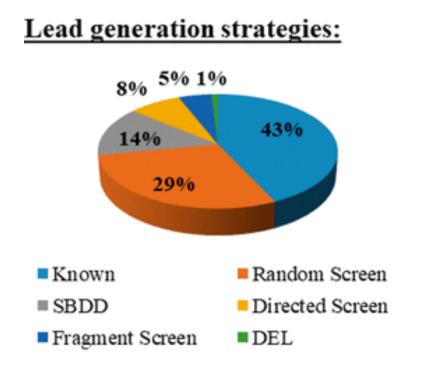
Conclusions: Extended-connectivity fingerprints of diameter 4 and 6 are among the best performing fingerprints when ranking diverse structures by similarity, as is the topological torsion fingerprint. However, when ranking very close analogues, the atom pair fingerprint outperforms the others tested. When ranking diverse structures or carrying out a virtual screen, we find that the performance of the ECFP fingerprints significantly improves if the bit-vector length is increased from 1024 to 16,384.

Keywords: Similarity searching, Molecular fingerprints, Structural similarity, Similarity benchmark



Similarity – Shape-based

 Molecular shape based alignment is useful for VS, scaffold hopping, knowledge based ligand identification -> lead generation



Target classes:

•	Kinases	(30%)
٠	Other enzymes	(23%)
٠	GPCR's	(17%)

100013

Epigenetic (9%)

Disease areas:

٠	Oncology	(30%)
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CNS/Pain (18%)

Infection (14%)

Metabolic (12%)

Where Do Recent Small Molecule Clinical Development Candidates Come From?

J. Med. Chem. ASAP, Dean Brown & Jonas Bostrom



Similarity – Shape-based – Alignment Methods

AlignMol

- The 3D transformation required to align the specified conformation in the probe molecule to a specified conformation in the reference molecule is computed so that the root mean squared distance between a specified set of atoms is minimized.
- This transform is then applied to the specified conformation in the probe molecule

Greg 2014 – ROCs -> subshape investigation https://iwatobipen.wordpress.com/2014/06/15/ try-to-subshape-alignment/

It was hard to me to do it using RDKit. Hmm...

GetO3A

 Get an O3A object with atomMap and weights vectors to overlay the probe molecule onto the reference molecule based on MMFF atom types and charges

GetCrippenO3A

- Get an O3A object with atomMap and weights vectors to overlay the probe molecule onto the reference molecule based on **Crippen logP** atom contributions
- O3A objects then subsequently applied to reference and probe conformer to give O3A rmsd



Similarity – Shape-based – Assessing Alignments

RMSD

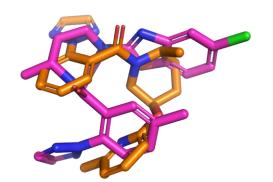
from alignment methods

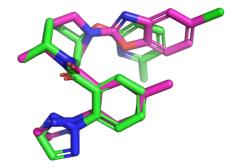
ShapeTanimotoDist

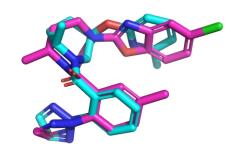
 Compute the shape tanimoto distance between two molecule based on a predefined alignment

ShapeProtrudeDist

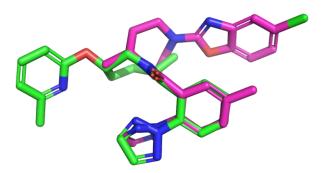
 Compute the shape protrude distance between two molecule based on a predefined alignment







minimise rmsd



Similarity – Shape-based – Assessing Alignments

- RMSD
 - from alignment methods
- ShapeTanimotoDist
 - Compute the shape tanimoto distance between two molecule based on a predefined alignment

minimise rmsd



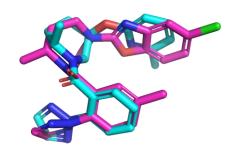
AlignMol



GetO3A



GetCrippenO3A





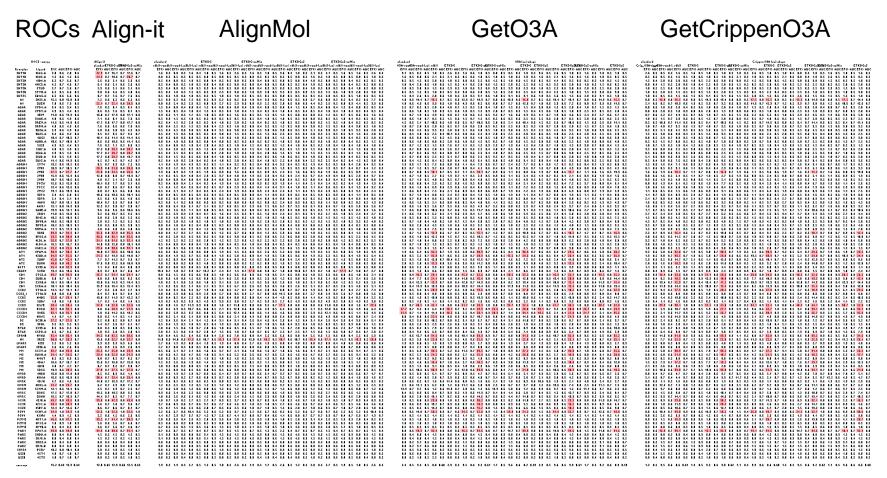
Similarity – Shape-based – Python Script

```
for cid in range(0, eachMol.GetNumConformers()):
        transform O3A=rdMolAlign.GetO3A(eachMol,eachquery,prbCid=cid,refCid=-1)
        rmsd O3A=transform O3A.Align()
        tani O3A=rdShapeHelpers.ShapeTanimotoDist(eachMol,eachquery,confId1=cid,confId2=-1)
        if tani O3A < tani O3A opt:
            tani O3A opt = tani O3A
            bestconf tani O3A = cid
        if rmsd O3A < rmsd O3A opt:
            rmsd O3A opt = rmsd O3A
            rmsd O3A opt tani = tani O3A
           bestconf O3A = cid
   except:
    try:
        rmsd rdkit=rdMolAlign.AlignMol(eachMol,eachquery,prbCid=cid,refCid=-1,atomMap=zip(range(eachMol.GetNumAtoms()),range(eachquery.GetNumAtoms())))
        tani rdkit=rdShapeHelpers.ShapeTanimotoDist(eachMol,eachquery,confId1=cid,confId2=-1)
        if tani rdkit < tani rdkit opt:
            tani rdkit opt = tani rdkit
           bestconf tani rdkit = cid
        if rmsd rdkit < rmsd rdkit opt:</pre>
            rmsd rdkit opt = rmsd rdkit
            rmsd rdkit opt tani = tani rdkit
            bestconf rdit = cid
   except:
        None
```

Use futures to distribute jobs over multiple processors



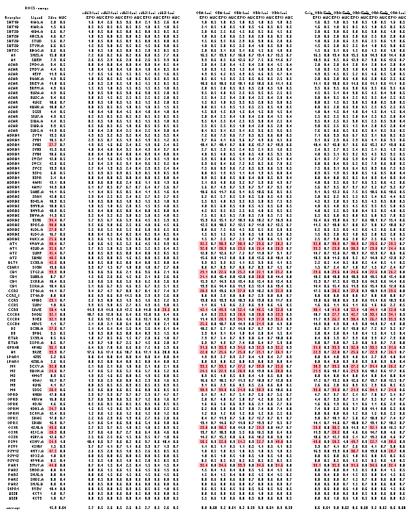
Matrix comparison – GPCR Bench dataset



~200 protein/ligand complexes, grouped by identical ligand at protein -> giving ~100 separate analyses EF1% calculated using RMSD, tanimoto shape of best RMSD conformer & best tanimoto shape conformer alone Result highlighted if EF1% > 20%



Matrix comparison – GPCR Bench dataset



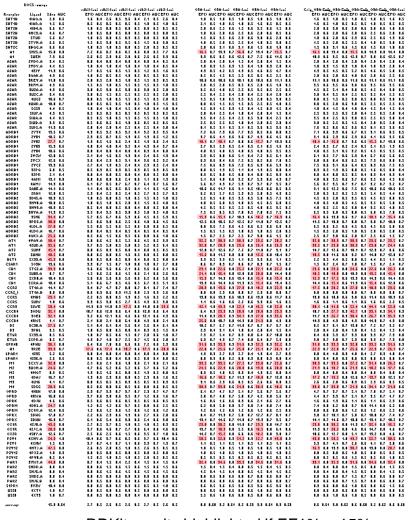
Shape tanimoto ranking

- AlignMol
- GetO3A
- GetCrippenO3A

Result highlighted if EF1% > 20%



Matrix comparison – GPCR Bench dataset



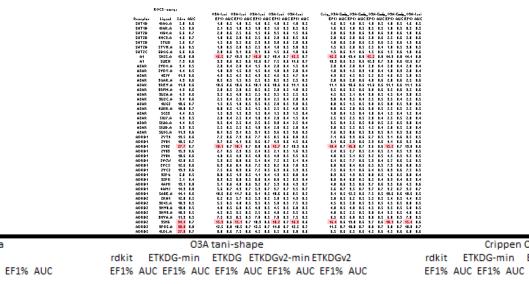
Shape tanimoto ranking

- AlignMol
- GetO3A
- GetCrippenO3A

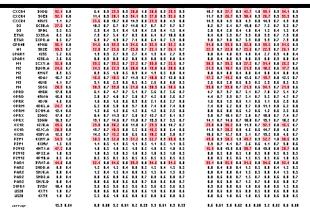




Matrix comparison – Comparison to ROCs

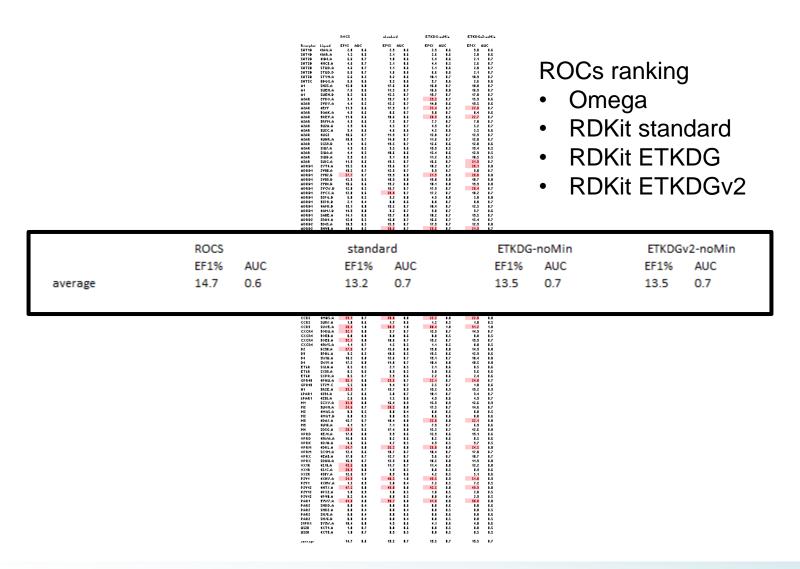


Receptor Ligand EF1% AUC EF1%





Matrix comparison – Comparison of Conformers





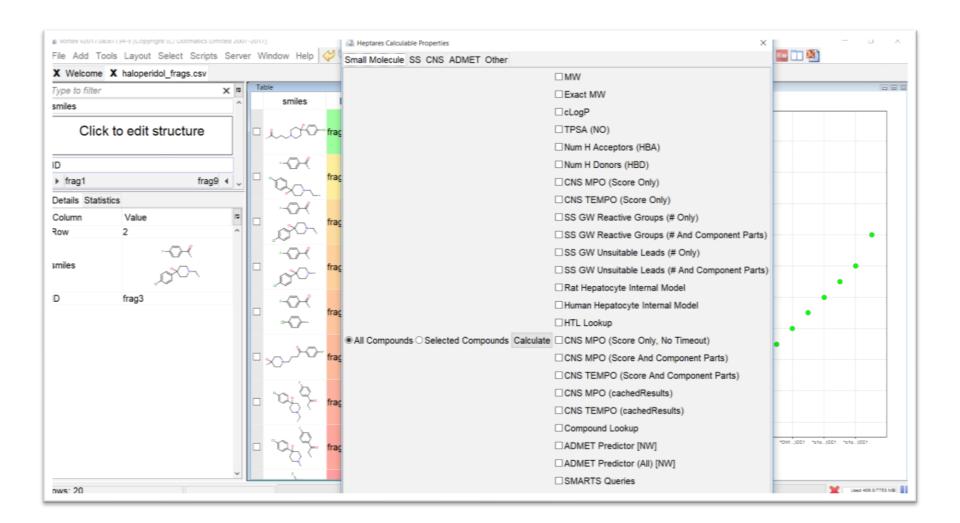
Drug Discovery Process - lite

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- All phases continuous
 - PAINS filters
 - Lead-like suitability
 - MPO
 - TEMPO
 - In-silico models
 - Clearance, Solubility, off target panel, etc...
 - RF, XGboost, Bayesian etc.
 - SA scores



End User Accessibility

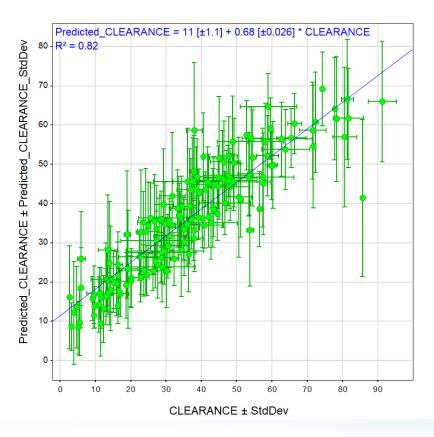




Improving Compound Success Through Models

Rat and Human Clearance Model generation

- data points from Rat HepClint, and data points for Human HepClint
- 10 independently generated random forest models implemented via RDKit and SKLearn

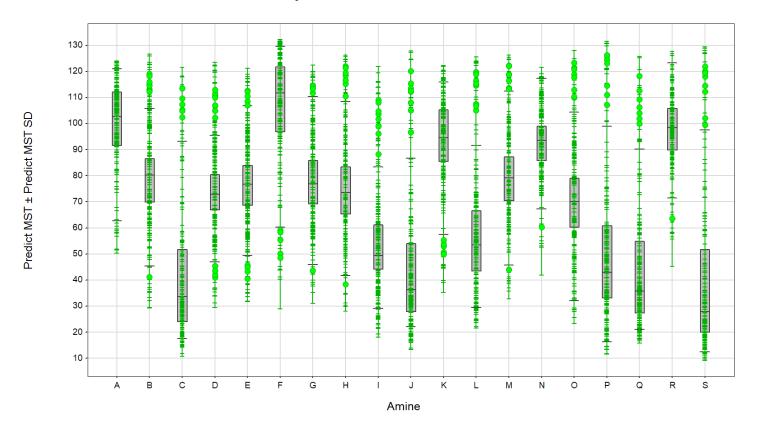


```
□class randomForestModel():
     def __init__(self, modelToLoad=None, fingerPrintType='ECFP6', numberOfModels=10):
         self. model = []
         if (modelToLoad is not None):
             # Load it in...
             # With the options...
                 with gzip.open (modelToLoad, 'rb') as fileHandle:
                     (self.fingerPrintRoutine, self.fingerPrintDistance, self._model) = pickle.1
                print("Error loading model")
             self. model = [RandomForestRegressor() for i in range(0, numberOfModels)]
             if (fingerPrintType == 'ECFP6'):
                 self.fingerPrintRoutine = generateMorganFingerprintsForMols
                 self.fingerPrintDistance = 3
             elif (fingerPrintType == 'ECFP4'):
                 self.fingerPrintRoutine = generateMorganFingerprintsForMols
                 self.fingerPrintDistance = 2
             elif (fingerPrintType == 'ECFP2'):
                 self.fingerPrintRoutine = generateMorganFingerprintsForMols
                 self.fingerPrintDistance = 1
         return None
     def del (self):
         return None
     def saveModel(self, saveFile=None):
             with gzip.open(saveFile, 'wb') as fileHandle:
                pickle.dump((self.fingerPrintRoutine, self.fingerPrintDistance, self. model), 1
            print("Error saving model")
         return None
     def buildModel(self, propertyValuesToPredict=None, compoundList=None):
         # Buidl the FPs for training the model
         xFeatures = self.fingerPrintRoutine(compoundList, self.fingerPrintDistance)
         z = [eachModel.fit(xFeatures, propertyValuesToPredict) for eachModel in self. model]
     def predictMolecules(self, moleculesToPredict=None):
         predictions = []
         meanPredictions = []
         sdPredictions = []
```



Patent Analysis – 'Fixing' Sparse Data

O Do we see trends for stability in the amines?



Amines A, F, K, N, R look interesting



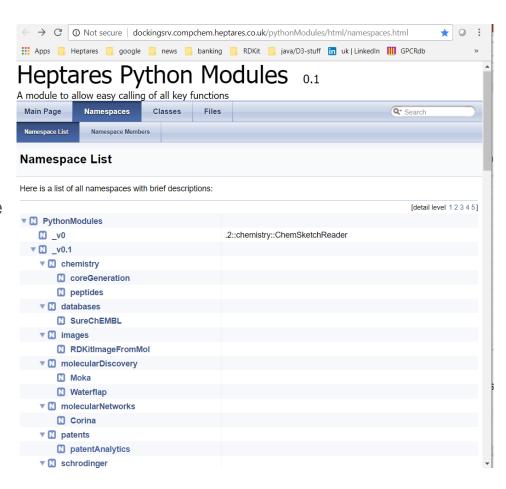
Accessibility

All scripts centralised

- Curated
- Modified
- Deposited

doxygen

- a tool for writing software reference documentation.
- Doxygen is free software, released under the terms of the GNU General Public License version 2 (GPLv2).





Drug Discovery Process - lite

- Program initiated (not target selection etc...)
- Cpds identified
 - patent
 - literature
- Leads examined
- Hit expansion
- Hit Analyses

- Exploit phase
 - Matched Pair Analyses
 - Bioisosteric Replacements
 - MMPdb
 - SIB, MedChemica
 - MedChemIdeas
 - Compound Enumeration



- MMP contribution
 - Hussain, J., & Rea, C. (2010).
 "Computationally efficient algorithm to identify matched molecular pairs (MMPs) in large data sets." JCIM, 50(3), 339-348.
 - doi:10.1021/ci900450m
 - Wagener, M., & Lommerse, J. P.
 (2006). "The quest for bioisosteric replacements." JCIM, 46(2), 677-685.

- o mmpa github forked to
- o mmpdb github
- MedChemIdeas
- MedChemica
- Swiss Institute of Biotechnology
 - Reaxys integration

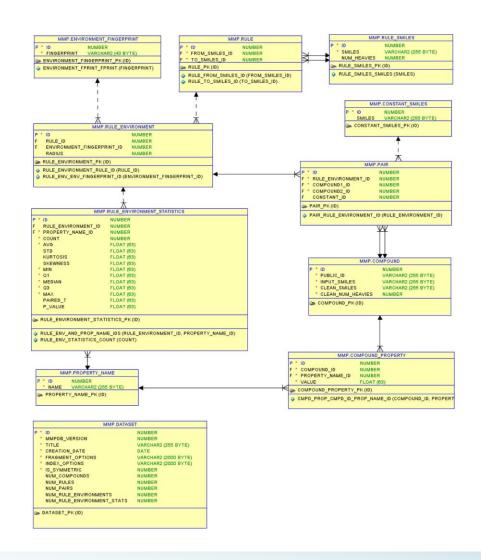


mmpdb – github contribution

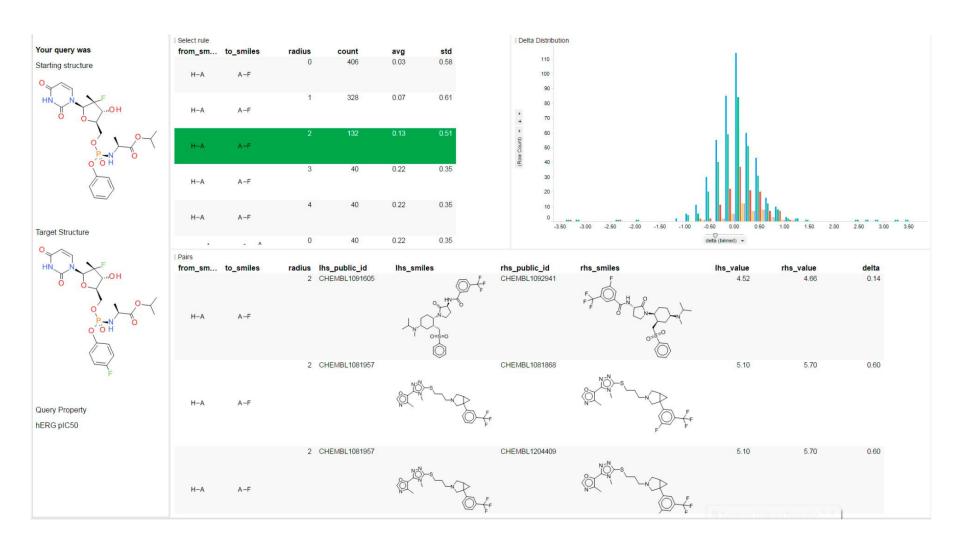
A. Dalke, J. Hert, C. Kramer.
mmpdb: An Open-Source Matched
Molecular Pair Platform for Large
Multiproperty Data Sets. JCIM,
2018, 58 (5), pp 902–910.,
doi:10.1021/acs.jcim.8b00173

Process

- mmpdb fragment
- mmpdb index
- mmpdb transform
- mmpdb predict







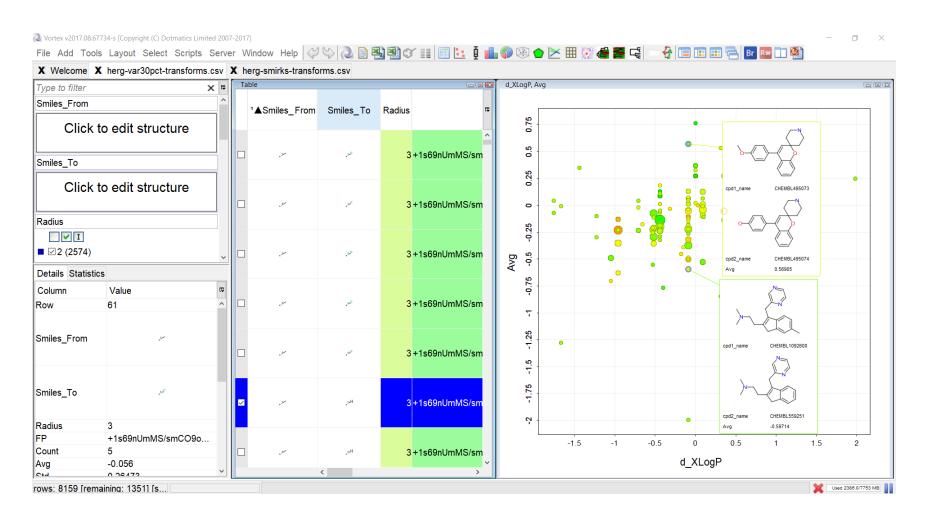


- All transformations all at once
 - with all examples etc...

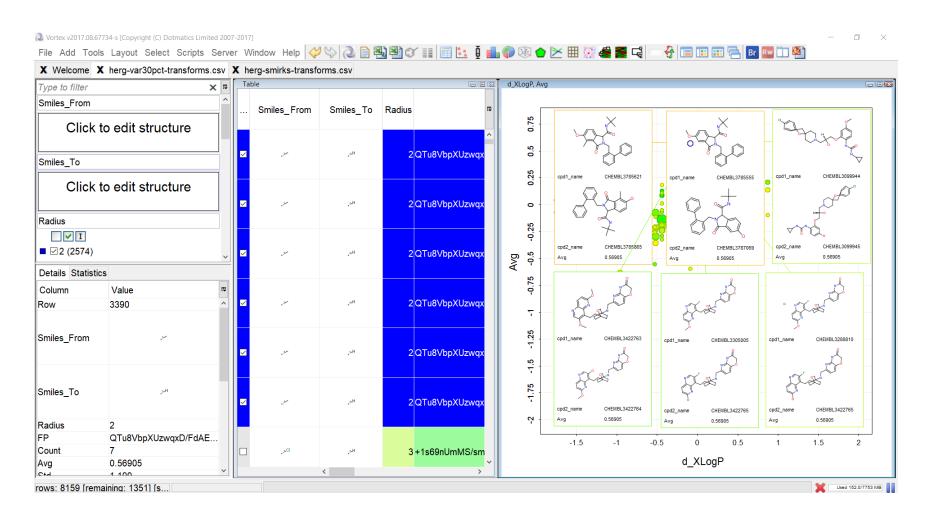
```
import sqlite3
connection = sqlite3.connect('chembl-herg-var30pct.mmpdb')
cursor = connection.cursor()
z = cursor.execute("""select
(select t4.smiles from rule smiles t4 where t4.id = t3.from smiles id) as from smiles,
(select t4.smiles from rule smiles t4 where t4.id = t3.to smiles id) as to smiles,
t2.radius, t6.fingerprint, t1.count, t1.avg, t1.std, t5.name,
(select t8.input smiles from compound t8 where t8.id = t7.compound1 id) as cpd1 smiles,
(select t8.public id from compound t8 where t8.id = t7.compound1 id) as cpd1 name,
(select t8.input smiles from compound t8 where t8.id = t7.compound2 id) as cpd2 smiles,
(select t8.public id from compound t8 where t8.id = t7.compound2 id) as cpd2 name
from rule environment statistics t1, rule environment t2, rule t3,
                                      ame t5, pair t7
                                     and t1.rule environment id = t2.id and t2.rule id = t3.id
                                    to.id and t5.id = t1.property name id and t2.id = t7.rule environment id
order by t5.name desc
q=z.fetchall()
```

count – number of matched pair occurrences radius – fingerprint radius (context)

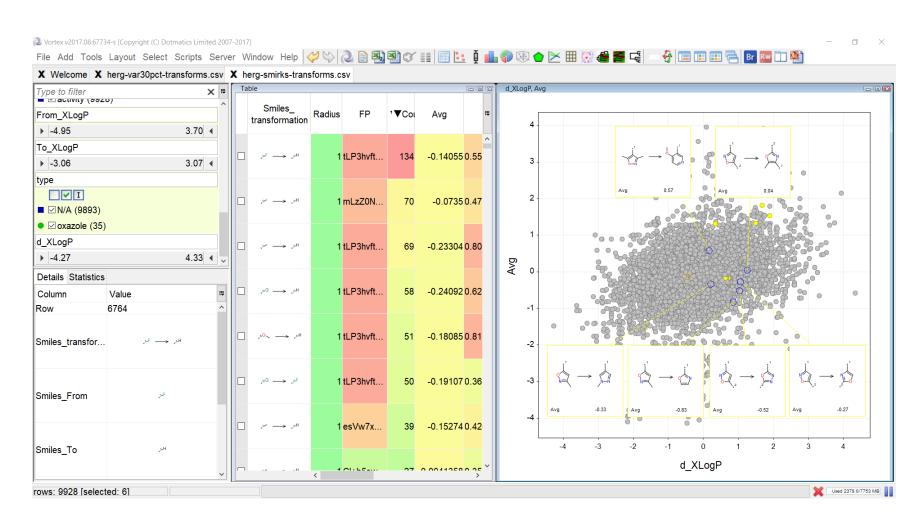












36 oxazole transformations



Bioisosteres

- see blogspot Feb2018
- encode own transformations

```
'[*:1]C(=0)OH',
'[*:1]C1OC(=0)C=C(OH)O1',
'[*:1]S(=0)(=0)[NH]C',
'[*:1]S(=0)(=0)OH',
'[*:1]C(=0)[NH]C#N',
'[*:1]c1nnn[nH]1',
'[*:1]c1nn[nH]n1',
'[*:1]c1nc([OH])c1',
'[*:1]c1onc([OH])c1',
'[*:1]c1snc([OH])c1',
'[*:1]C1=CC(=0)[NH]C1(=0)',
'[*:1]C1=NC(=0)[NH]C1(=0)',
'[*:1]C1SC(=0)[NH]C1(=0)',
'[*:1]C1SC(=0)[NH]C1(=0)',
```

- generate via automated means
 - mmpdb, etc...

```
# Isostere replacement
 # Greg Landrum Feb 2018 - blogspot
 # http://rdkit.blogspot.com/2018/
 from rdkit import Chem
 from rdkit.Chem import AllChem, Draw
□isostere smis = ('[*:1]S(=0)(=0)NC[*:2]',
                 '[*:1]C(C(F)(F)(F))NC[*:2]',
                 '[*:1]N1N=NC([*:2])=N1',
                 '[*:1]C1=NOC([*:2])=N1')
 isosteres = [Chem.MolFromSmiles(x) for x in isostere smis]
def buildIsostereReaction(start,replacement):
     gps = Chem.AdjustOuervParameters()
     gps.adjustDegree = False
     gps.adjustHeavvDegree = False
     gps.adjustRingCount = False
     qps.aromatizeIfPossible = False
     gps.makeAtomsGeneric = False
     gps.makeBondsGeneric = False
     gps.makeDummiesOueries = True
     start = Chem.AdjustQueryProperties(start,qps)
     replacement = Chem.AdjustQueryProperties(replacement,qps)
     product = AllChem.ChemicalReaction()
     product.AddReactantTemplate(start)
     product.AddProductTemplate(replacement)
     product.Initialize()
    return product
 amide = Chem.MolFromSmiles('[*:1]C(=0)NC[*:2]')
 isostereReactions =[buildIsostereReaction(amide,x) for x in isosteres]
 isostereReactions[2]
def doIsostereReplacement(mol,rxn):
     ps = rxn.RunReactants((mol.))
     res = [x[0] for x in ps]
∃def doIsostereReplacements(mol,rxns):
     res = []
     for i,rxn in enumerate(rxns):
         seenSoFar=set()
         ims = doIsostereReplacement(mol,rxn)
         p0 = rxn.GetProductTemplate(0)
         # save where the match is
         for im in ims:
             smi = Chem.MolToSmiles(im,True)
             if smi not in seenSoFar:
                 im.coreMatches = im.GetSubstructMatch(p0)
                 res.append(im)
                 seenSoFar.add(smi)
 mol =Chem.MolFromSmiles('c1cc(F)ccc1C2(O)CCN(CC2)CCC(=O)Nc3ccccc3')
 subs = doIsostereReplacements (mol, isostereReactions)
     print(Chem.MolToSmiles(sub,isomericSmiles=True))
```









$$R1 = [*:1]c1ccc(CI)cc1$$

$$R2 = [*:2]O$$

$$R1 = [*:1]O$$

$$R2 = [*:2]c1ccc(CI)cc1$$

$$R1 = [*:1][H]$$

$$R2 = [*:2]CCN$$



R1 = [*:1]O





Drug Discovery Process - lite

- Program initiated (not target selection etc...)
- Cpds identified
 - patent
 - literature
- Leads examined
- Hit expansion
- Hit Analyses

- Exploit phase
 - Matched Series Analyses
 - Free Wilson methods
 - additivity
 - Graph analyses
 - assessing DOA, etc...
 - Compound Docking
 - MCS ligand selection
 - Protein/ligand interactions
 - Preparing collaborative sessions

Matched Series Analysis

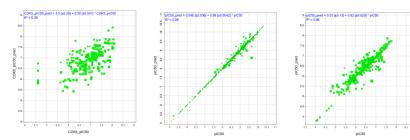
- GSK, AZ, Pfizer etc...
- Pat Walters
 - https://github.com/PatWalters/Free-Wilson (subgraph match)
- Heptares
 - In-house implementation (2013)
 - RDKit, PandasTools, math
 - First principles(ReplaceCore)
 - Rewritten (2015)with numpy

- Error calculation
 - Analysis of each transformation

Ta	Table									
	¹ ▲ Rgroup	² ▲SMILES_ from	³▲SMILES_to	cpd_from	cpd_to	value	ave_value	stdev	⁴ ▼occurances	φ
	Rgroup1		.13	AZ20637832	AZ20637831	-1.2262	0.5594	0.72641	13	^
	Rgroup1	, L)	, NS	AZ20636864	AZ20636931	-0.58518	0.7082	0.53275	12	
	Rgroup1			AZ20637845	AZ20637843	-0	0.82577	0.37911	11	
	Rgroup1			AZ20637286	AZ20638064	1.4941	0.90835	0.28825	10	v

Predictive ability

 Comparative results to Hongming et al. JCIM, 2013, 53, 1324–1336



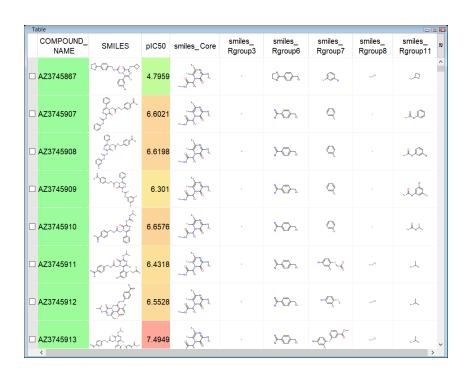
Spencer M. Free and James W. Wilson, A mathematical contribution to structure-activity studies, J. Med. Chem 7.4 (1964): 395-399.

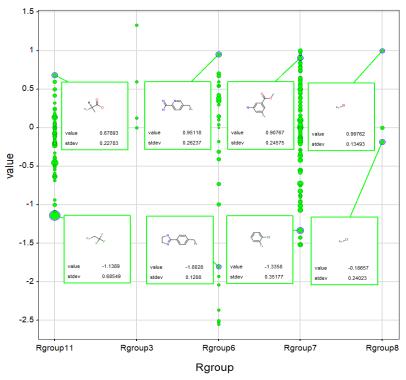


Matched Series Analysis

R group decomposition

R group relative ranking







Further Processing

Compound Docking

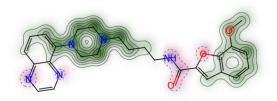
- MCS ligand selection
- Protein/ligand interactions

Preparing collaborative sessions

- Handling molecules
- Checking duplication
- Chemdraw -> 3D

Database collections

 RDKit cartridge enables substructure & similarity searching of prepared/collated collections



```
def ChemDraw To RDKit(fileName='barry-ideas.cdxml'):
    allRDKitMols = []
    allTextItems = []
    if (os.path.splitext(fileName)[1].upper() == '.CDXML'):
        XMLTree = ElementTree.parse(fileName)
        XMLRoot = XMLTree.getroot()
        for eachInitialTag in XMLRoot:
            if (eachInitialTag.tag.upper() == 'PAGE'):
                 # It's a page tag...
                for eachTag in eachInitialTag:
                     if (eachTag.tag == 'fragment'):
                         currentMol = Chem.RWMol()
                         # Need a conformer to be able to set atom co-ordinates
                         currentConformer = currentMol.GetConformer(currentMol.AddC
                         idAtomIdxLookup = {}
                         idBondIdxLookup = {}
                         for eachFragmentPortion in eachTag:
                             if (eachFragmentPortion.tag == 'b'):
                                 # A bond
                                 bondAttributes = eachFragmentPortion.attrib
                                 # Add the bond in
                                 idBondIdxLookup[int(bondAttributes['id'])] = curre
                                 if (bondAttributes.has key('Order')):
                                     if (bondAttributes['Order'] == '2'):
                                         currentMol.GetBondWithIdx(idBondIdxLookup[
                                     elif (bondAttributes['Order'] == '3'):
                                         currentMol.GetBondWithIdx(idBondIdxLookup[
                                         print(bondAttributes)
                                     currentMol.GetBondWithIdx(idBondIdxLookup[int(
                                 if (bondAttributes.has key('Display')):
                                     # There's potential wedging on this bond...
                                     if (bondAttributes['Display'] == 'WedgedHashBe
                                         # Can we be canny, and just adjust the atom
                                         currentPos = currentConformer.GetAtomPosit
                                         currentPos.z = currentPos.z - 0.5
                                         currentConformer.SetAtomPosition(idAtomIdx
                                         currentPos = currentConformer.GetAtomPosit
                                         currentPos.z = currentPos.z + 0.5
```



Further Processing

Compound Docking

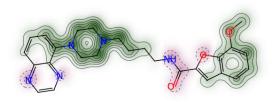
- MCS ligand selection
- Protein/ligand interactions

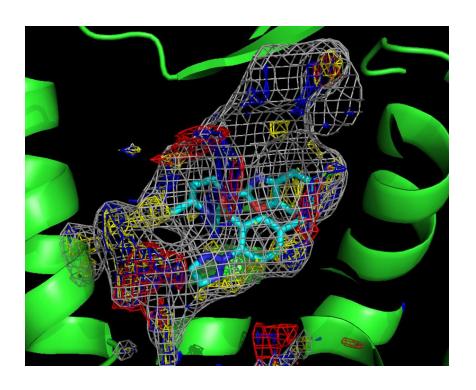
Preparing collaborative sessions

- Handling molecules
- Checking duplication
- Chemdraw -> 3D

Database collections

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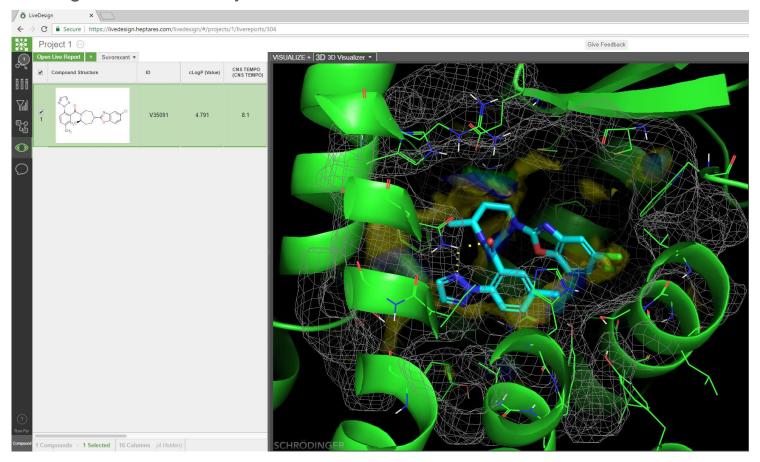






Structure Based Drug (Live)Design

- LiveDesign (Schrodinger)
 - RDKit being used extensively





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Thank you for listening Questions?

