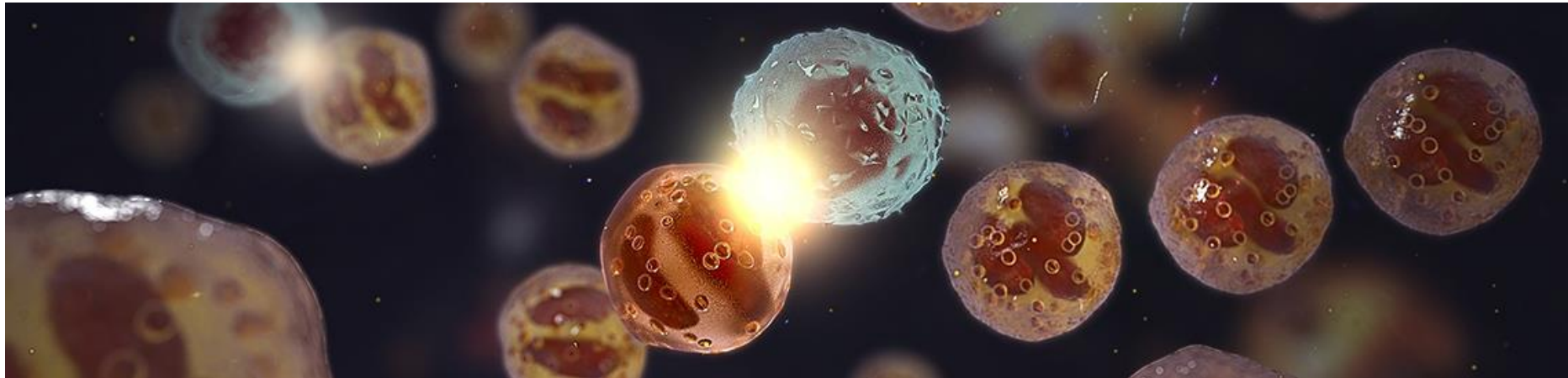


Cheminformatics in Drug Discovery, an Industrial Perspective

Hongming Chen, Thierry Kogej, Ola Engkvist

Hit Discovery, Discovery Sciences, AstraZeneca R&D Gothenburg



Drug Discovery Today

An industry perspective of Today's Challenge



We need to become better, faster & cheaper

Source: PhRMA profile 2016



Cheminformatics @ AstraZeneca

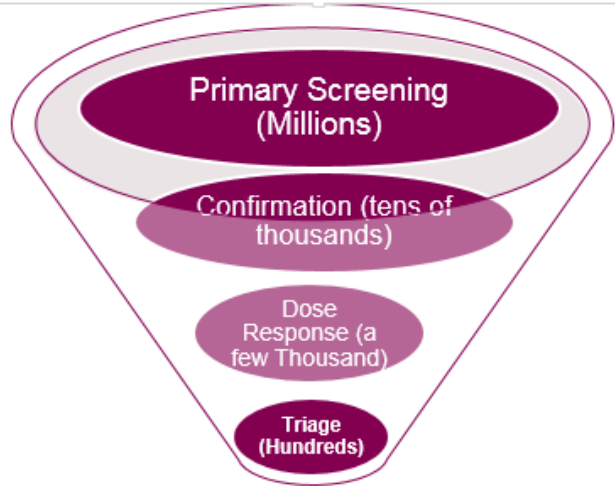
- HTS work-up
- Library design
- Virtual screening
- Machine learning & AI



High Throughput Screening

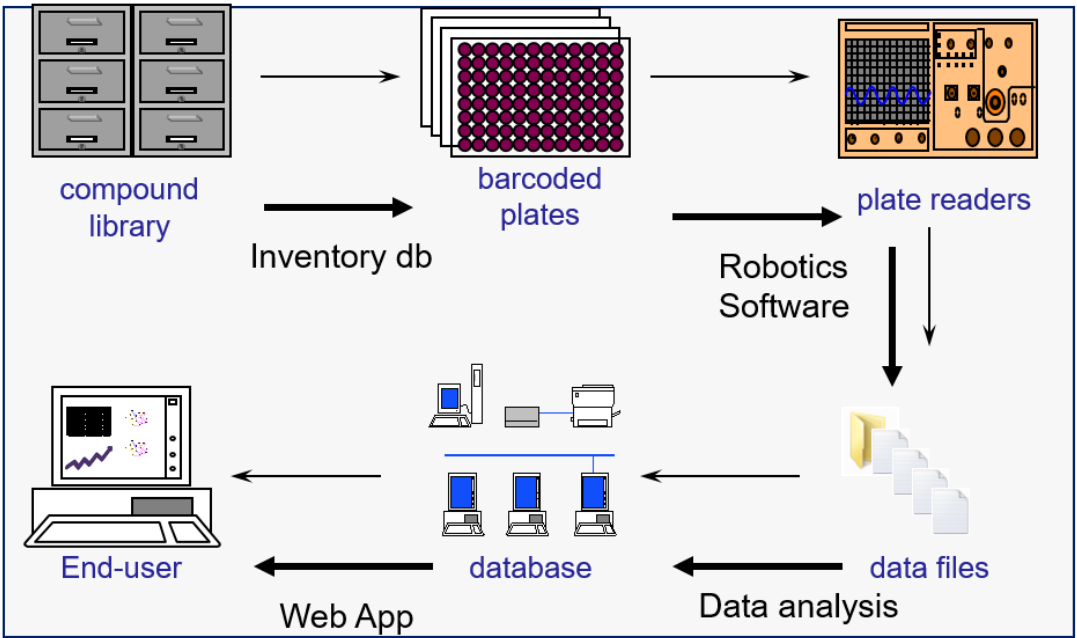
From Millions to just a few

Low cost/compound



~0-4 Chemical Series

High cost/compound



Slide modified from Mark Wigglesworth, AZ, with permission

HTS Analysis: Clustering analysis

Early days

- Heavily dependent on computational chemistry resources
- Linux, scripts, static workflows, data in flat files
- Cutting, pasting and reformatting between applications
- Difficult to revisit or take over an analysis from a colleague
- Time-consuming

iHAT: An Spotfire add-in for HTS Analysis



- Leverage the powerful visualization function of Spotfire
- Annotation of compounds with in-house experimental and predicted data
- Data integration from multiple sources
- Clustering of compounds
- Visualization and manipulation of cluster tree
- NN search

iHAT: Clustering and Reclustering

iHAT v1.9.39

Clustering Search Edit View Retrieve Help

Idle.

Clustering CLU2

- Cluster 000001 (38)
- Cluster 000004 (24)
- Cluster 000003 (18)
- Cluster 000005 (15)
- Cluster 000007 (15)
- Cluster 000008 (15)
- Cluster 000002 (14)
- Cluster 000006 (12)
- Cluster 000015 (12)
- Cluster 000009 (11)
- Cluster 000010 (11)
- Cluster 000012 (11)
- Cluster 000013 (11)
- Cluster 000016 (11)
- Cluster 000020 (11)
- Cluster 000021 (11)
- Cluster 000017 (10)
- Cluster 000022 (10)
- Cluster 000023 (10)
- Cluster 000025 (10)
- Cluster 000018 (9)
- Cluster 000024 (9)
- Cluster 000029 (9)
- Cluster 000011 (8)
- Cluster 000026 (8)
- Cluster 000030 (8)
- Cluster 000033 (8)
- Cluster 000014 (7)
- Cluster 000028 (7)
- Cluster 000034 (7)

Current Cluster 000003 Nearest Clusters Molecule 001882 Nearest Molecules

Cluster ID	Similarity	Count
<input checked="" type="checkbox"/> Cluster 000229	0,695	2
<input type="checkbox"/> Cluster 000019	0,546	6
<input type="checkbox"/> Cluster 000012	0,472	11
<input type="checkbox"/> Cluster 000020	0,470	11
<input type="checkbox"/> Cluster 000026	0,453	8
<input type="checkbox"/> Cluster 000088	0,453	5
<input type="checkbox"/> Cluster 000774	0,436	1
<input type="checkbox"/> Cluster 000022	0,430	10
<input type="checkbox"/> Cluster 000138	0,429	4
<input type="checkbox"/> Cluster 000044	0,425	6
<input type="checkbox"/> Cluster 000064	0,424	6
<input type="checkbox"/> Cluster 000155	0,424	3
<input type="checkbox"/> Cluster 000008	0,420	15
<input type="checkbox"/> Cluster 000051	0,416	7
<input type="checkbox"/> Cluster 000015	0,413	12
<input type="checkbox"/> Cluster 000021	0,413	11
<input type="checkbox"/> Cluster 000077	0,407	3
<input type="checkbox"/> Cluster 000018	0,406	9
<input type="checkbox"/> Cluster 000368	0,405	2
<input type="checkbox"/> Cluster 000006	0,405	12
<input type="checkbox"/> Cluster 000103	0,402	5
<input type="checkbox"/> Cluster 000168	0,398	4
<input type="checkbox"/> Cluster 000989	0,397	1

CCID201419835
CCID201419835
0,81
389,47

CCID200001750
CCID200001750
2,50
325,43

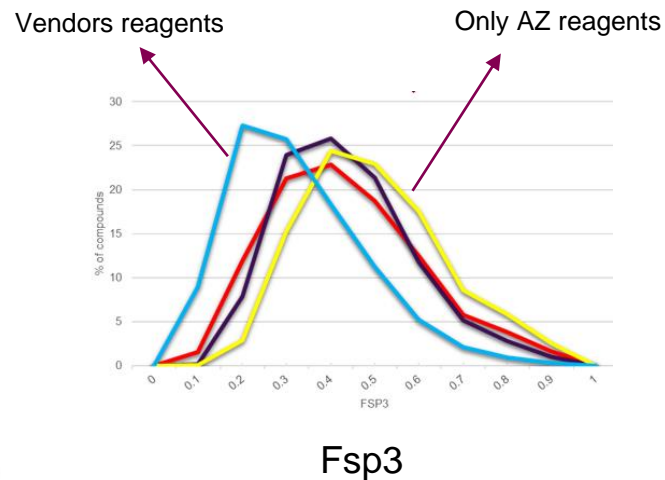
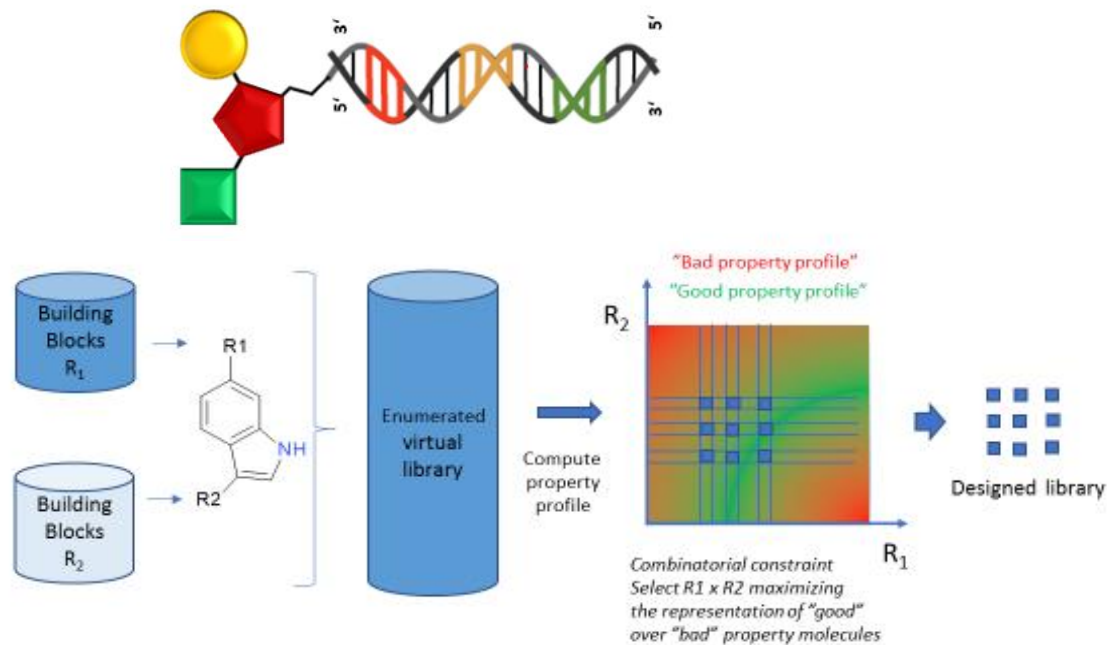
CCID200001230
CCID200001230
2,05
401,44

CCID200001246
CCID200001246
2,66
453,87



Library design @ AstraZeneca

- Diversity library is generally out of fashion
- Focused library fit for specific project need
- DNA encoded libraries become popular, but analysis is challenging, >60M to 8B library sizes
Currently, use classical library design method to reduce to 50M preferred AZ library size

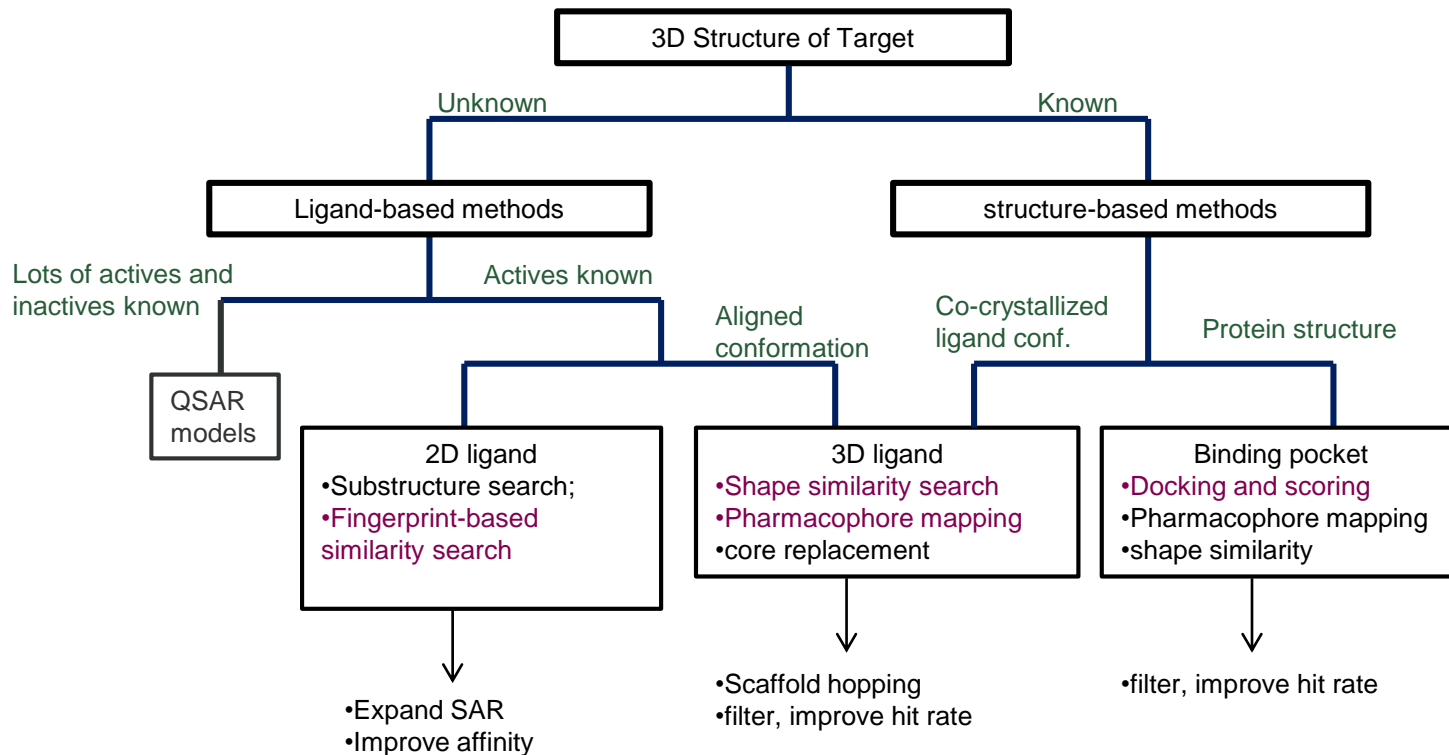


Definition of VS

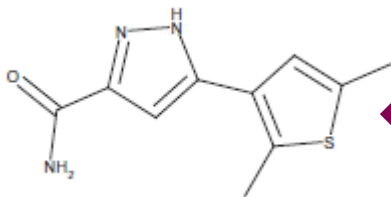
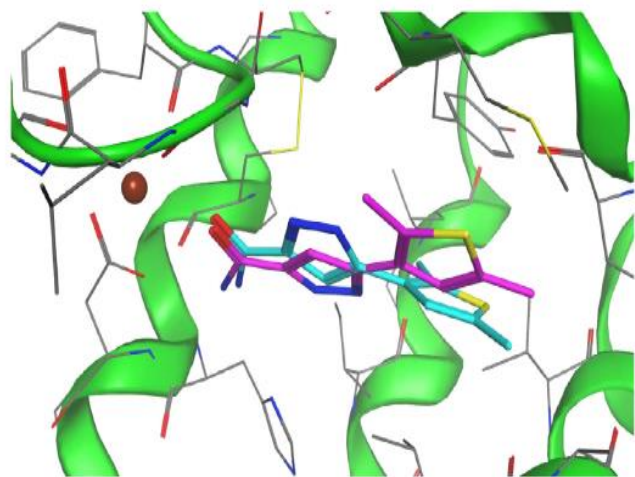
- Virtual screening refers to any in-silico techniques used to search large compound databases (available chemicals or virtual libraries) to select a smaller number for biological testing
- Virtual screening can be used to
 - Select compounds for screening from in-house databases
 - Choose compounds to purchase from external suppliers
 - Select compounds from virtual libraries to be synthesized
- The technique applied depends on the amount of information available about the particular disease target and the desired outcome



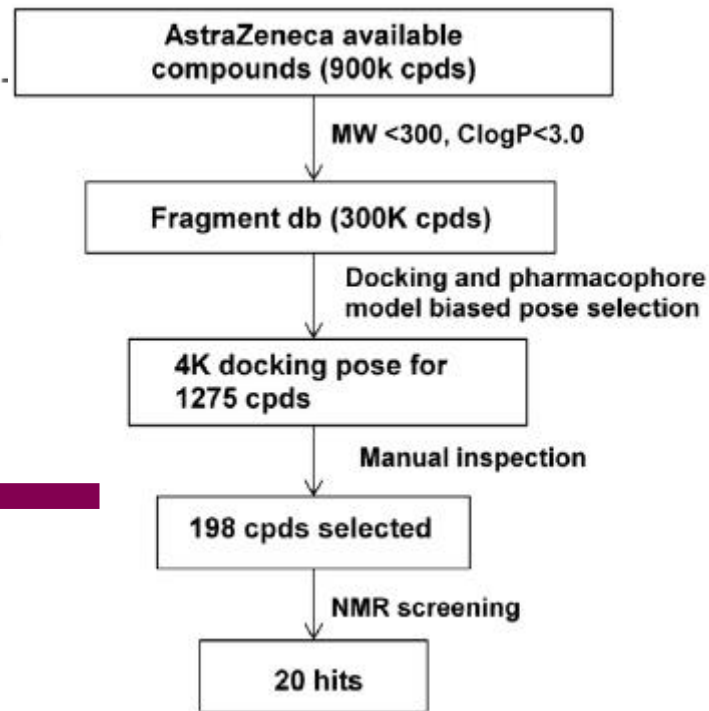
VS methods



VS example



IC₅₀ (NMR) 20uM

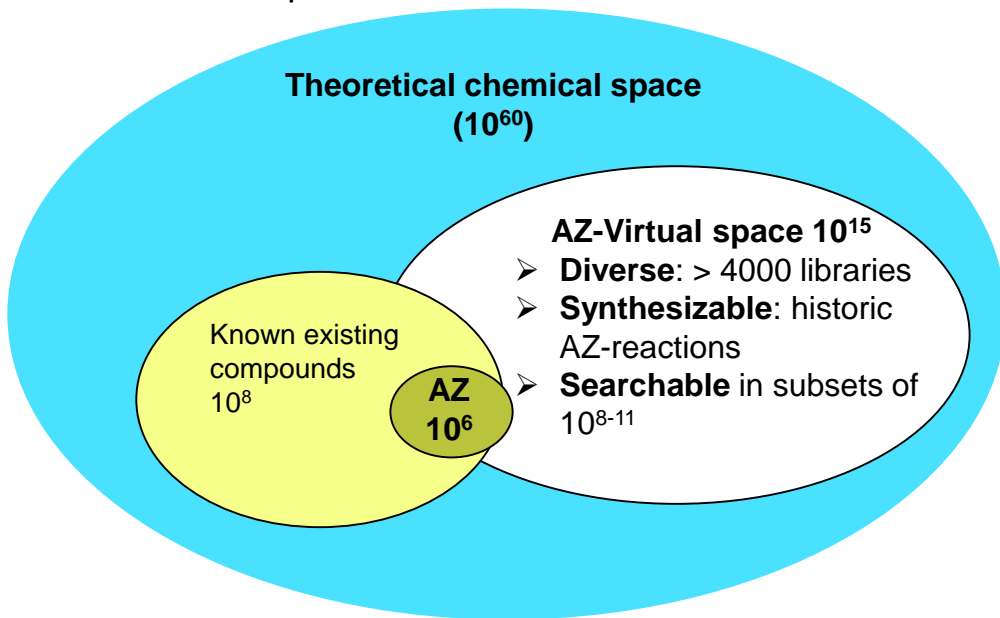


- Identification of sPLA2X inhibitors using ligand and structure based virtual screening



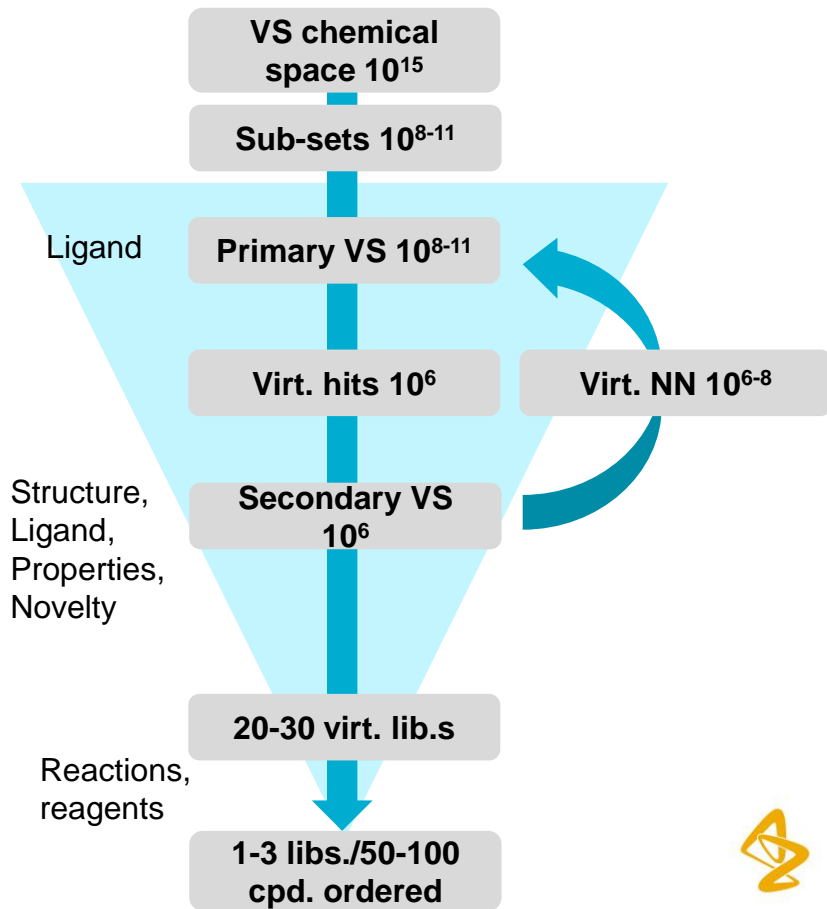
Virtual screening platform @ AZ

Chemical space

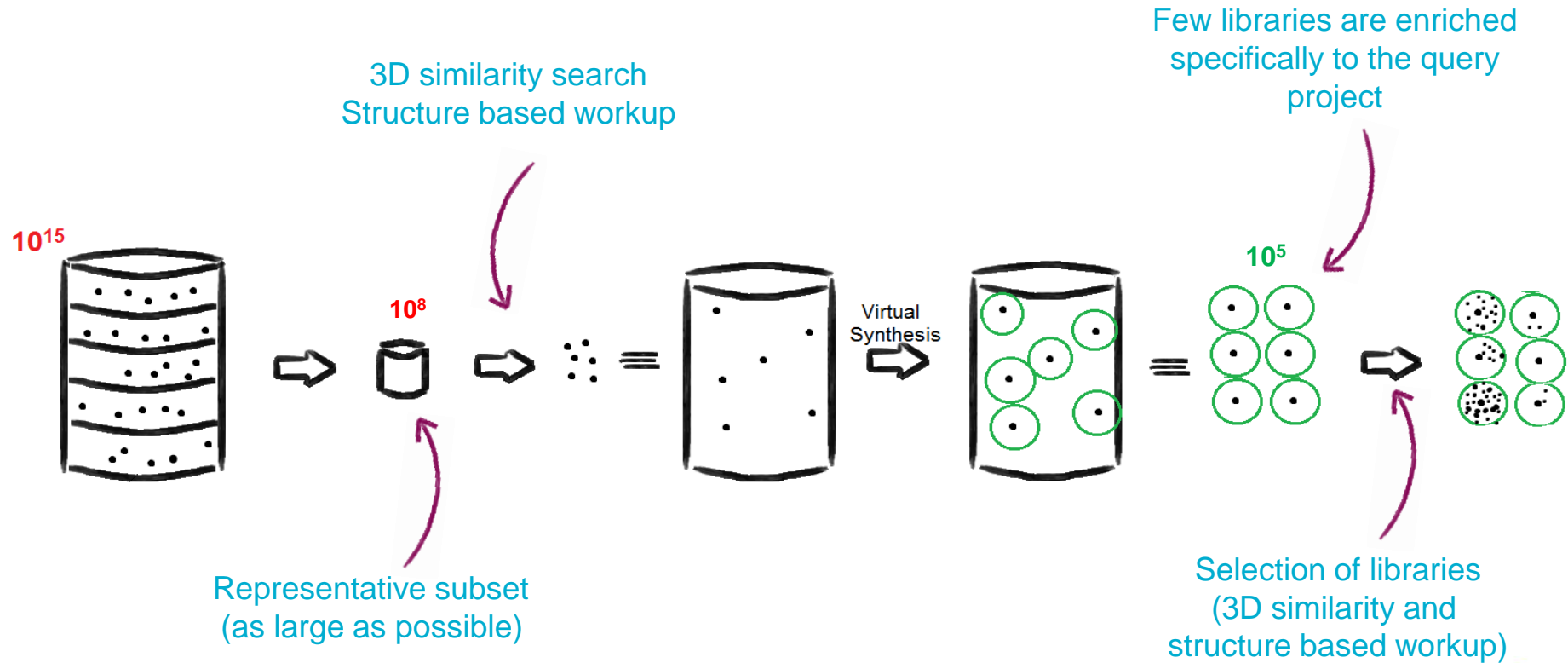


MJ Vainio *J. Chem. Inf. Model.*, 2012, 52 (7), pp 1777–1786.

Iterative virtual screening workflow

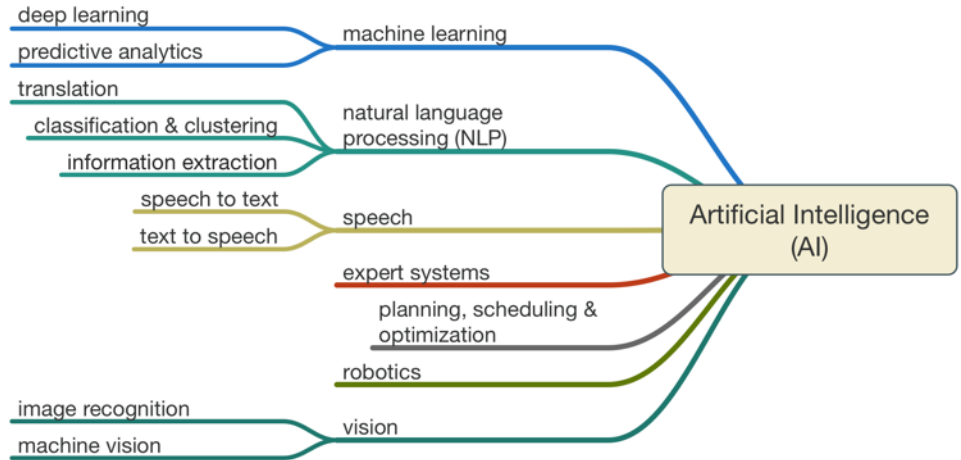
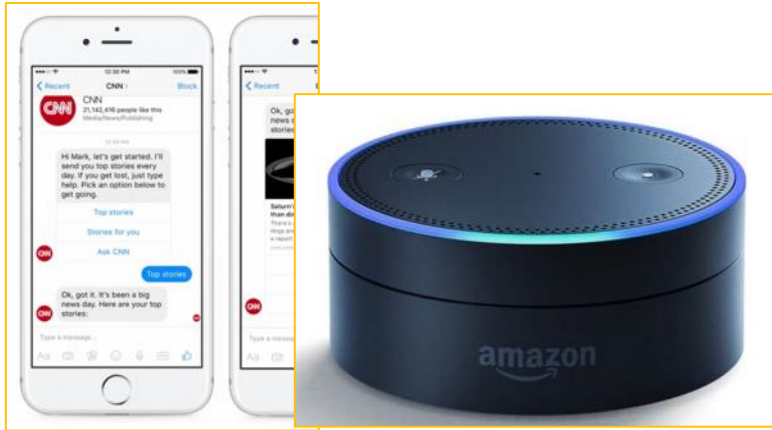


Computational strategy

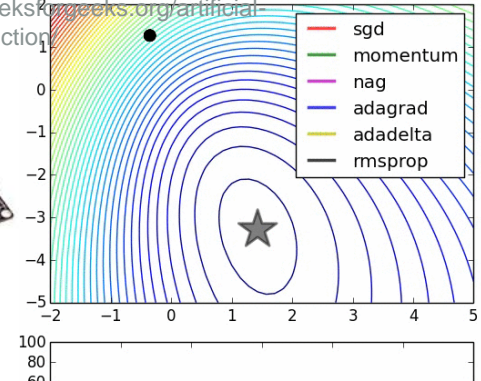


AI & Machine Learning Today

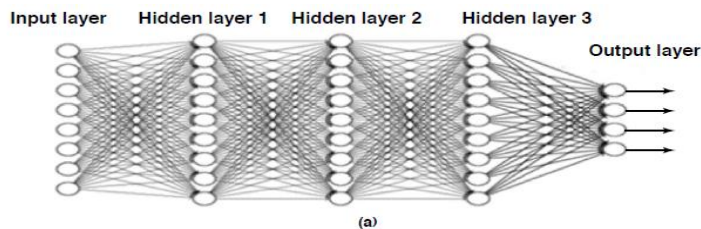
Context, Definition & Advances



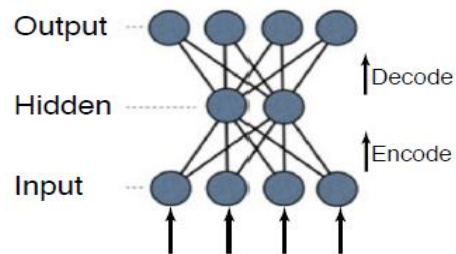
Source: <http://www.geekstogeeks.org/artificial-intelligence-an-introduction/>



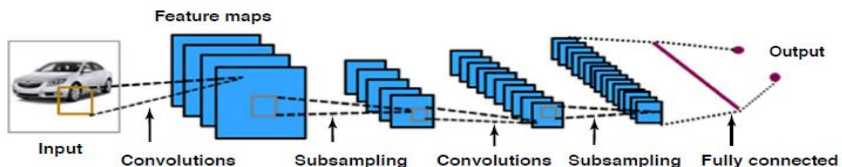
The rise of deep learning in drug discovery



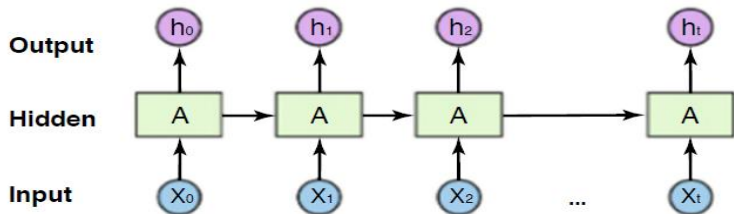
(a)



(d)



(b)



(c)

- Deep learning technologies have been adopted in drug discovery
- Various forms of NN have been applied so far



De novo molecular generation with deep learning has developed very rapidly

molecular
pharmaceutics

druGAN: An Advanced Generative Adversarial Autoencoder Model for de Novo Generation of New Molecules with Desired Molecular Properties in Silico

Artur Kadurin,^{*,†,§,||} Sergey Nikolenko,^{*,§,||} Kuzma Khrabrov,[⊥] Alex Aliper,[†] and Alex Zhavoronkov^{*,†,||,¶}

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Research Article

Automatic Chemical Design Using a Data-Driven Continuous Representation of Molecules

Rafael Gómez-Bombarelli^{1#}, Jennifer N. Wei^{1#}, David Duvenaud^{2#}, José Miguel Hernández-Lobato^{2#}, Benjamin Sánchez-Lengeling¹, Dennis Sheberla¹, Jorge Aguilera-Iparraguirre¹, Timothy D. Hirzeli¹, Ryan P. Adams^{2¶}, and Alán Aspuru-Guzik^{1,†}

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Cite This: ACS Cent. Sci. 2018, 4, 120–131

Generating Focused Molecule Libraries for Drug Discovery with Recurrent Neural Networks

Marwin H. S. Segler,^{*,†} Thierry Kogej,[‡] Christian Tyrchan,[§] and Mark P. Waller^{*,||}

RESEARCH

Molecular De-Novo Design through Deep Reinforcement Learning

Marcus Olivecrona^{*}, Thomas Blaschke[†], Ola Engkvist[†] and Hongming Chen[†]

The rise of deep learning in drug discovery

Hongming Chen¹, Ola Engkvist¹, Yinhai Wang², Marcus Olivecrona¹ and Thomas Blaschke¹

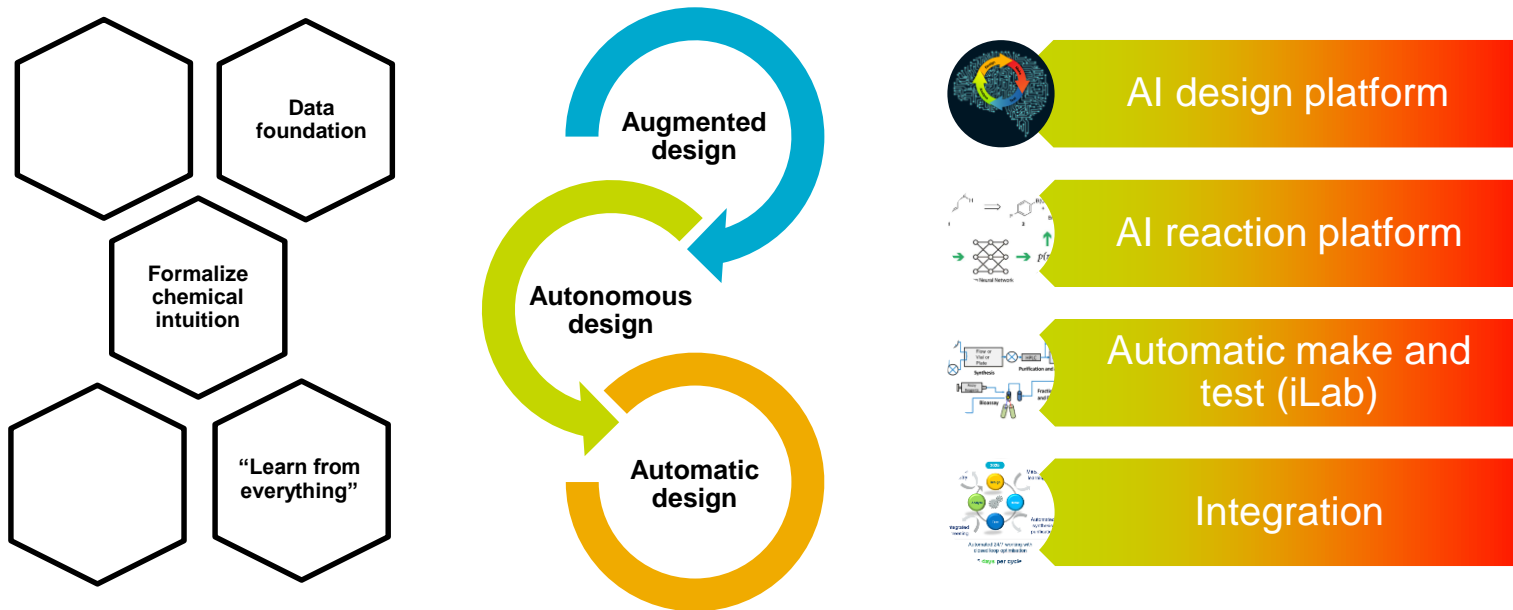
¹Hit Discovery, Discovery Sciences, Innovative Medicines and Early Development Biotech Unit, AstraZeneca R&D Gothenburg, Mölndal 43183, Sweden

²Quantitative Biology, Discovery Sciences, Innovative Medicines and Early Development Biotech Unit, AstraZeneca, Unit 310, Cambridge Science Park, Milton Road, Cambridge CB4 0WG, UK



Deep learning @ AstraZeneca: Vision

- Creating an integrate AI platform to impact drug discovery projects



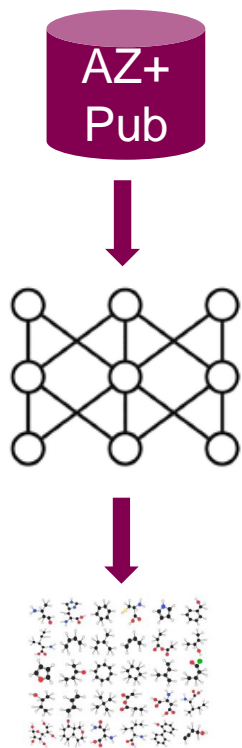
Segler M.H.S. et al. Neural-Symbolic Machine Learning for Retrosynthesis and Reaction Prediction, Chemistry, 2017, 23(25), 5966-5971

Segler M.H.S. et al. Planning chemical syntheses with deep neural networks and symbolic AI, Nature, 2018, 555, 604-610

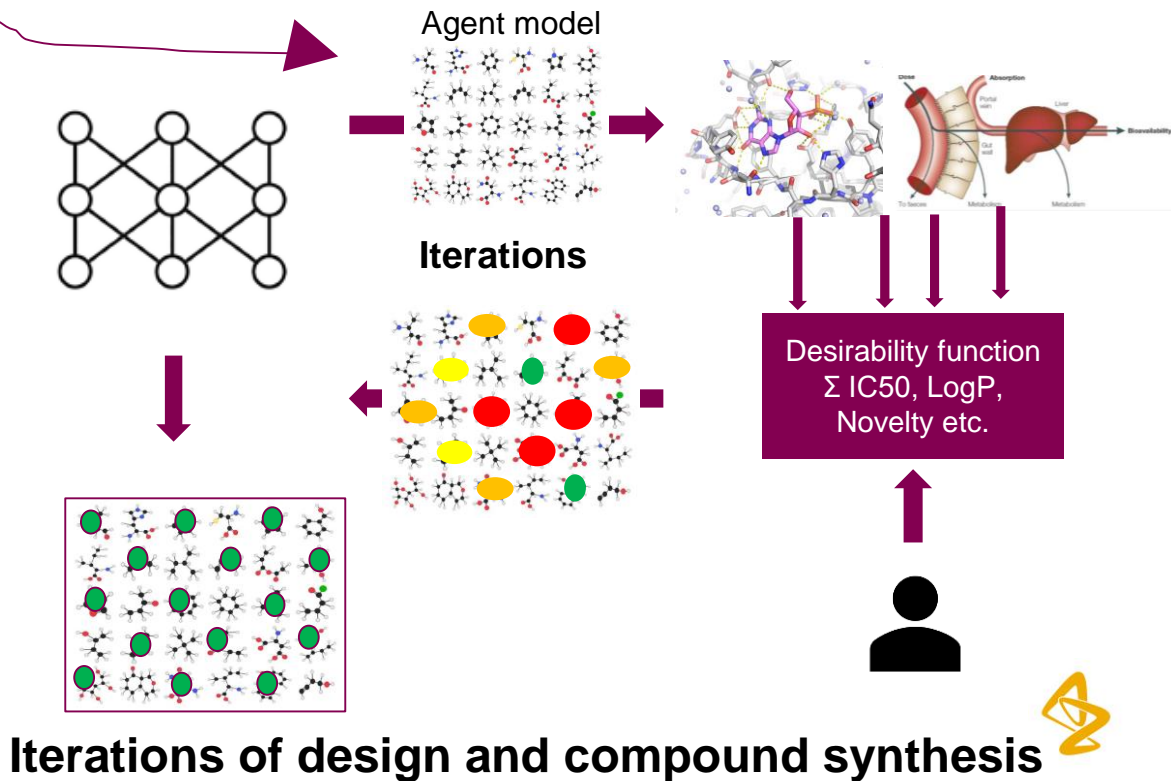


Deep learning @ AZ: De Novo Molecular Augmented Design Platform (REINVENT)

Generation of novel chemical space



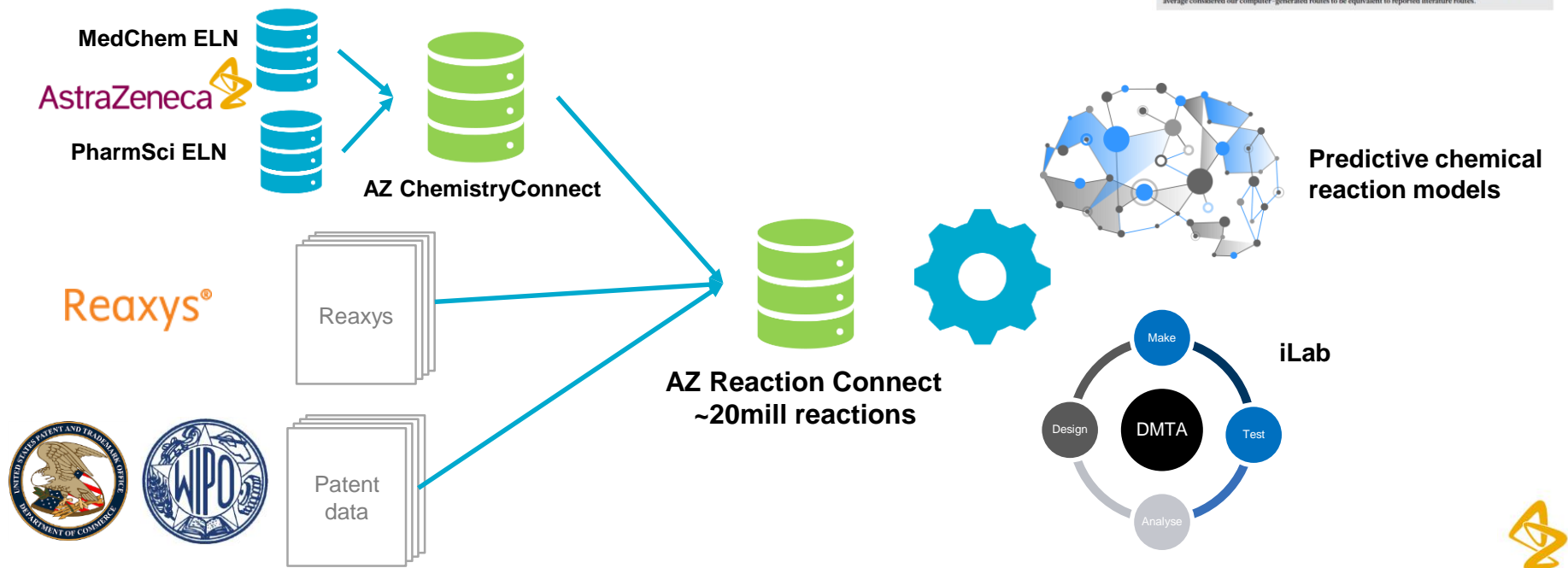
Reinforcement learning to generate project relevant compounds



Prior model

Deep learning at AstraZeneca: Reaction informatics

- First steps, building:
 - World-class Reaction Knowledge Base
 - On our work (past collaboration with M. Segler)



ARTICLE

doi:10.1038/nature21978

Planning chemical syntheses with deep neural networks and symbolic AI

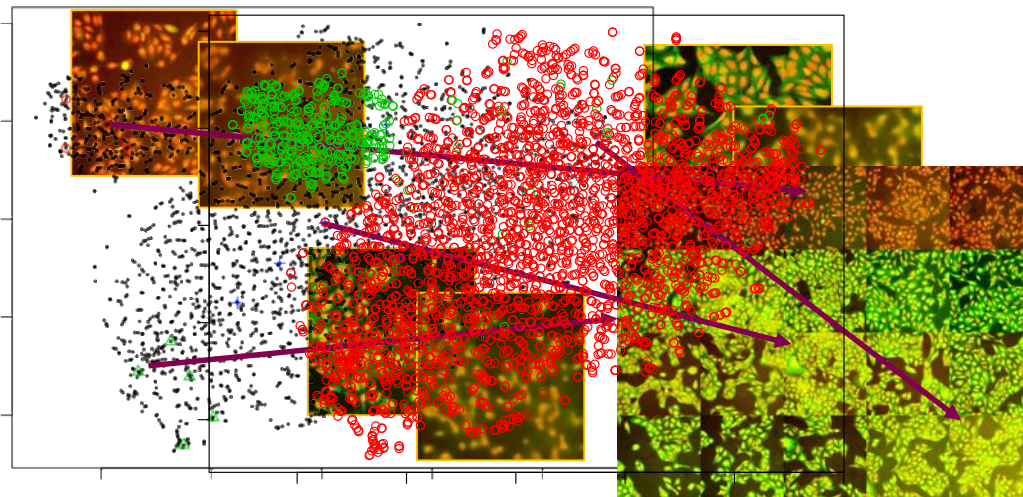
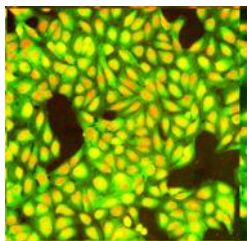
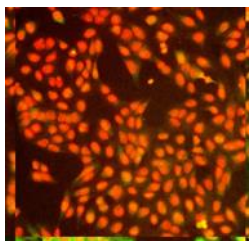
Marwin H. S. Segler^{1,2}, Mike Preuss^{1,2} & Mark P. Waller¹

To plan the syntheses of small organic molecules, chemists use retrosynthesis, a problem-solving technique in which target molecules are recursively transformed into increasingly simpler precursors. Computer-aided retrosynthesis would be a valuable tool but at present it is slow and provides results of unsatisfactory quality. Here we use Monte Carlo tree search and symbolic artificial intelligence (AI) to discover retrosynthetic routes. We combined Monte Carlo tree search with an expansion policy network that guides the search, and a filter network to pre-select the most promising retrosynthetic steps. These deep neural networks were trained on essentially all reactions ever published in organic chemistry. Our system solves for almost twice as many molecules, thirty times faster than the traditional computer-aided search method, which is based on extracted rules and hand-designed heuristics. In a double-blind AB test, chemists on average considered our computer-generated routes to be equivalent to reported literature routes.



Becoming FASTER with AI

Through unsupervised learning for hit identification



Deep CNN
autoencoder



Manifold
Learning
(t-SNE)

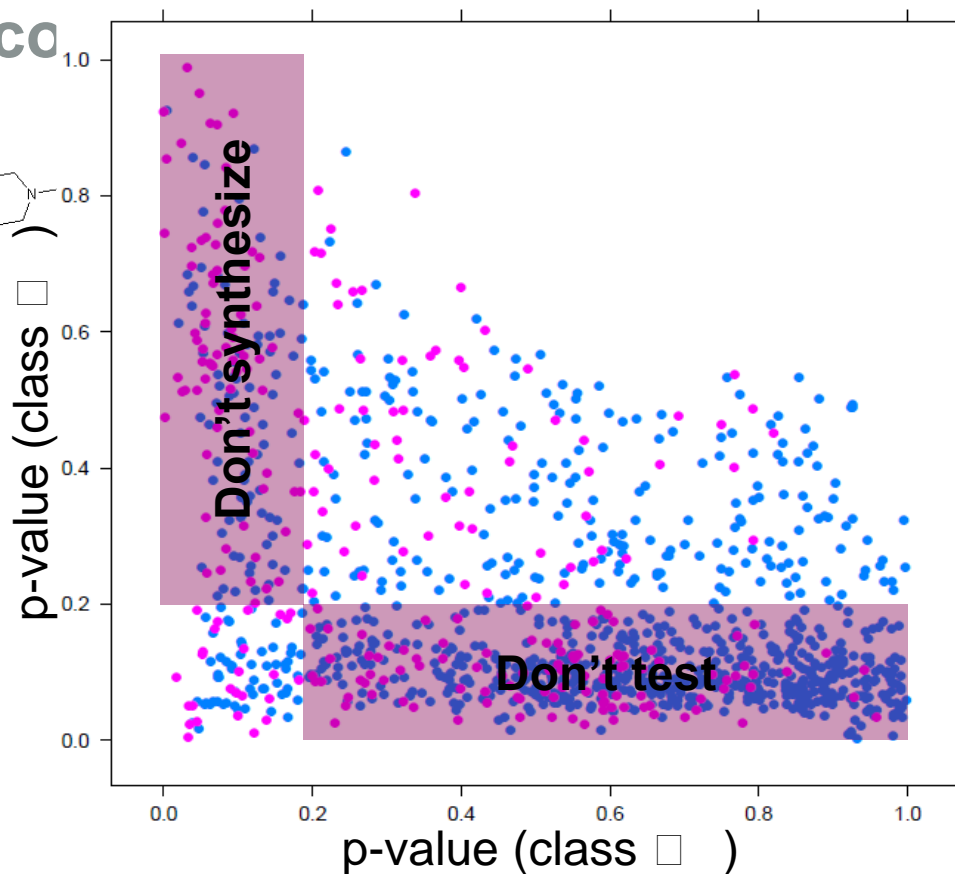
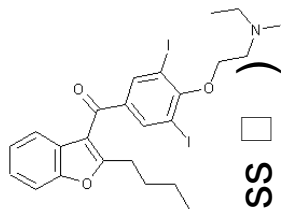


Deep CNN
classifier



Becoming CHEAPER with ML/AI

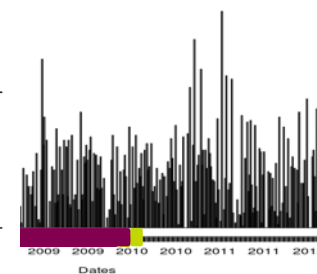
By only co



needed

Apply ML model
(an TCP on SVM)

lements for Classification Data (AZClass)



Becoming FASTER and CHEAPER with AI

AI augmented *de novo* molecule design

Olivecrona et al. *J Cheminform* (2017) 9:48
DOI 10.1186/s13321-017-0235-x

Journal of Cheminformatics

RESEARCH ARTICLE

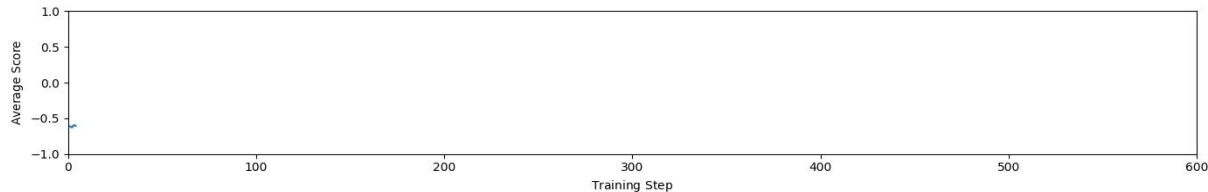
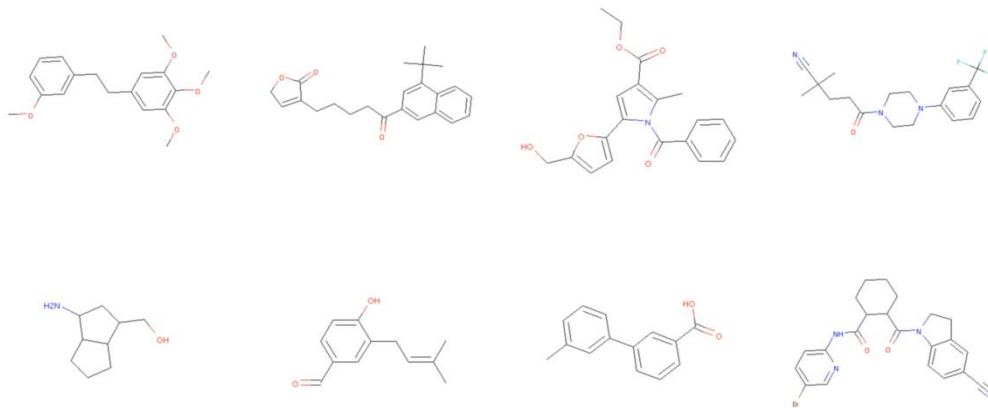
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Molecular de-novo design through deep reinforcement learning

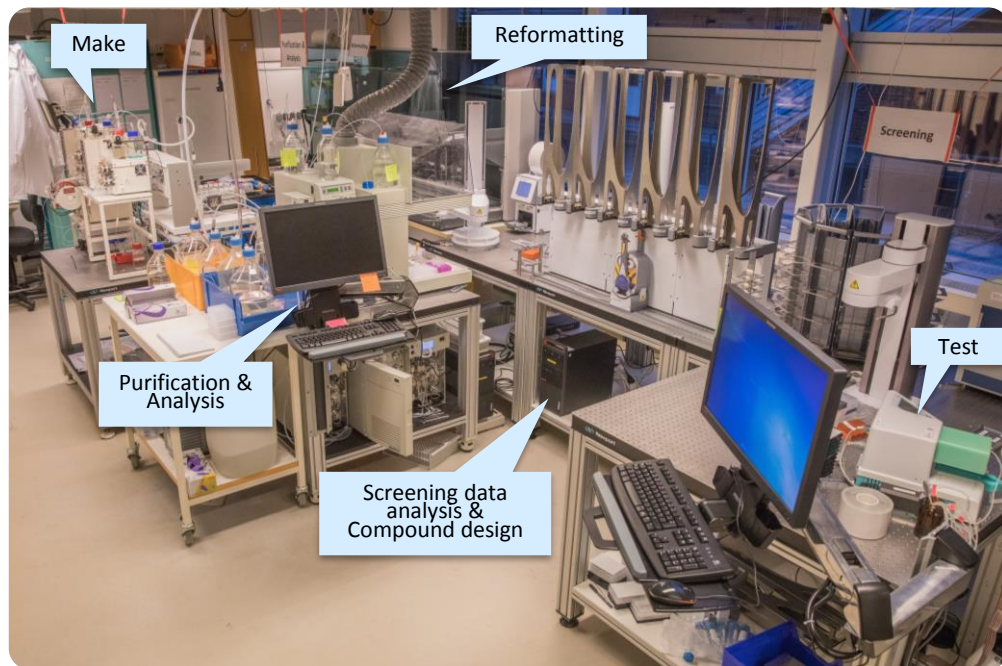
Marcus Olivecrona, Thomas Blaschke, Ola Engkvist and Hongming Chen

RNN + Reinforcement learning



AZ's first DMTA automation platform

- First prototype built during 2017
- All DMTA steps fully integrated
- Suited for 100s of uninterrupted DMTA cycles. ML/AI module is integrated.
- Cycle times of ca. 2h
- Successfully applied in ongoing research project



Conclusions

- Cheminformatics is widely applied in Pharmaceutical industry
- Cheminformatics includes various aspects across different disciplines
- Adoption of machine learning and AI technologies will help Cheminformatics to better fit current and future research needs



Acknowledgement

- Marcus Olivercrona
- Thomas Blaschke
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