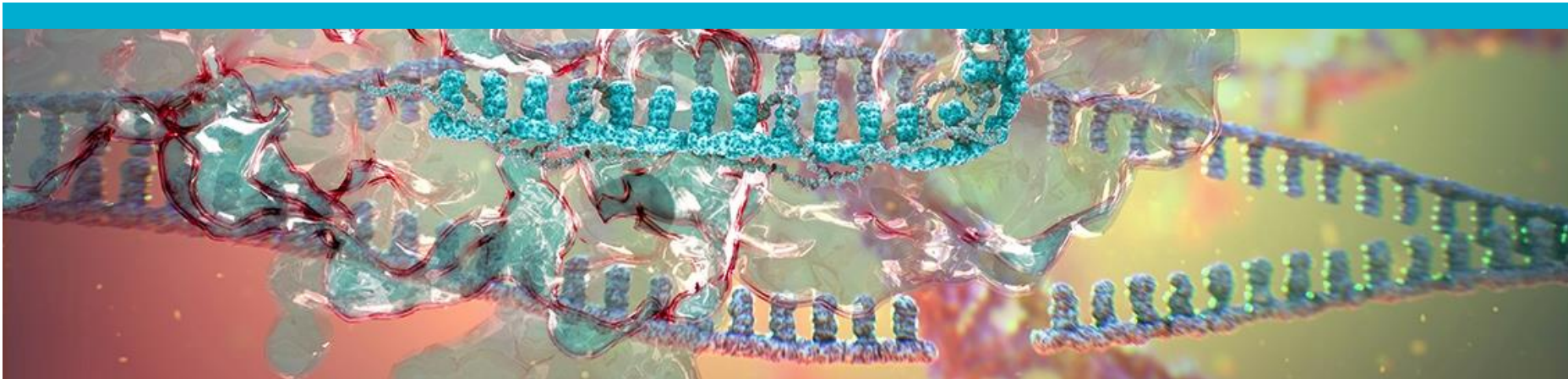


Artificial Intelligence in Drug Design Progress and Bottlenecks

Ola Engkvist, Hit Discovery, Discovery Sciences, R&D AstraZeneca Gothenburg, Sweden

CompBioMed Meeting

March 16 2020

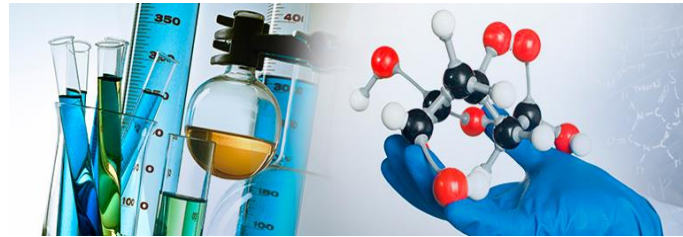


Drug Design

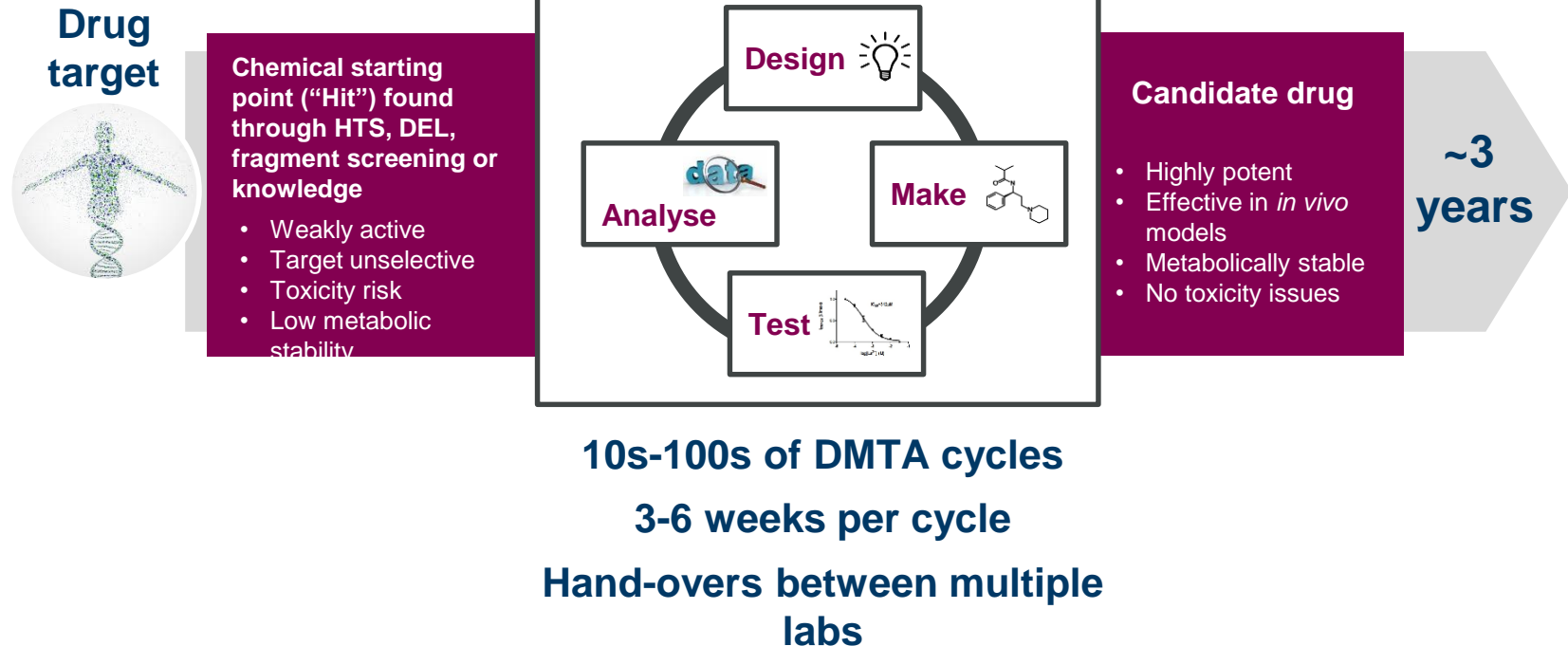
What to make next?



How to make it?

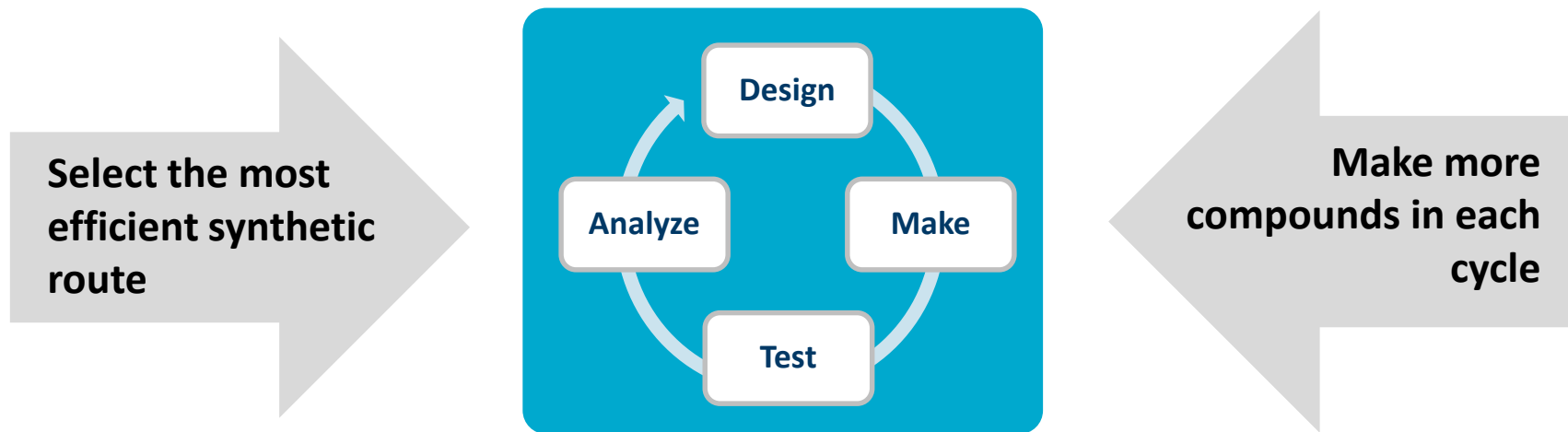


The Design Make Test Analyze cycle in Drug Design



Augmented Drug Discovery

How can we reduce the time to deliver a clinical candidate?



Increase speed

Maximize learning



Key priority areas in ML/AI

Deep learning based de novo
molecular design

Synthesis Prediction

More accurate property predictions

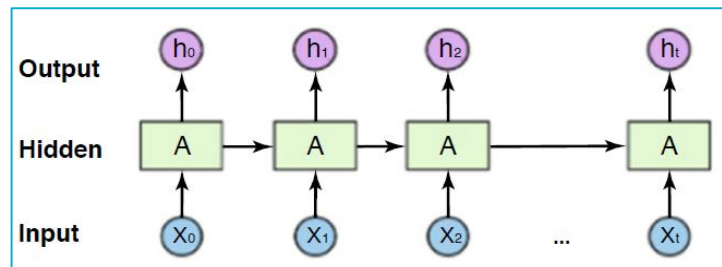
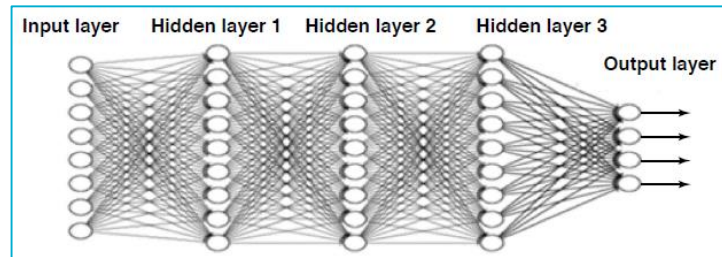
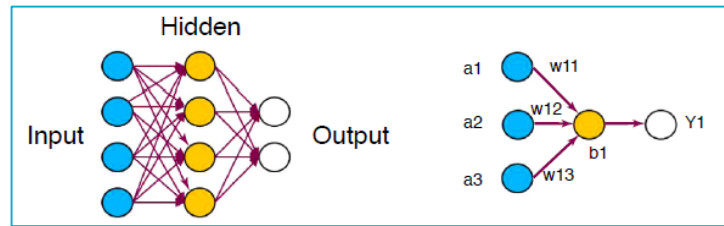
Decision making under uncertainty

+



Neural Networks & Deep Learning

- **Neural Networks known for decades**
 - Inputs, Hidden Layers, Outputs
 - Single layer NNs have been used in QSAR modelling for years
- **Recent Applications use more complex networks such as**
 - Multi-layer Feed-Forward NNs
 - Convolutional NNs
 - biological image processing
 - Auto-encoder NNs
 - Recurrent NNs
 - Trained using Maximum Likelihood Estimation to maximize the likelihood of next character



Why? Generation of Novel Compounds in the 10^{60} Chemical Space!



$10^{10}-10^{12}$



10^{60}

Journalist units:

Known space: 0,00017 ng of Hydrogen atoms

Possible space: The Hydrogen atoms in 90 Suns

Where's the impact?

- Use for de novo Molecular Design
 - Scaffold Hopping
 - Novelty
 - Virtual Screening
 - Library Design



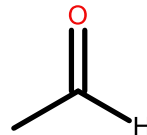
Natural language generation and molecular structure generation

- Can we borrow concepts from natural language processing and apply to SMILES description of molecular structures to generate molecules?

The \longrightarrow grass \longrightarrow is \longrightarrow ?

- Conditional probability distributions given context
- $P(\text{green} \mid \text{is}, \text{grass}, \text{The})$

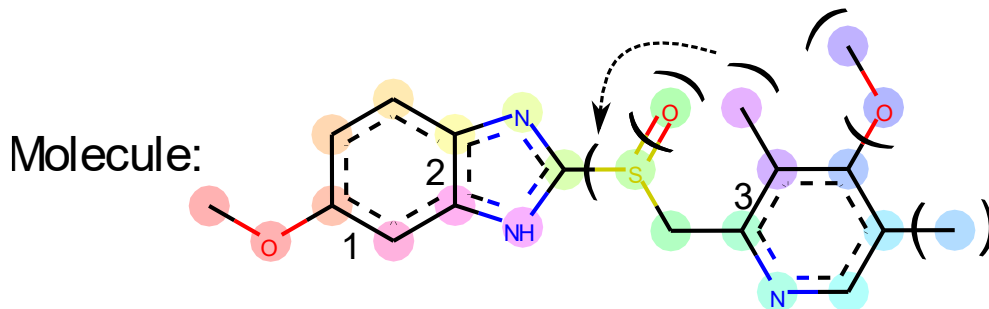
C \longrightarrow C \longrightarrow = \longrightarrow ?



- $P(O \mid =, C, C)$



Simplified Molecular Input Line Entry Specification (SMILES)

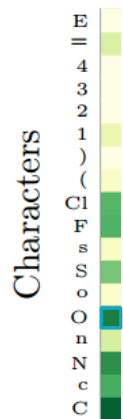


SMILES: COc1ccc2nc(S(=O)Cc3ncc(C)c(OC)c3C)[nH]c2c1

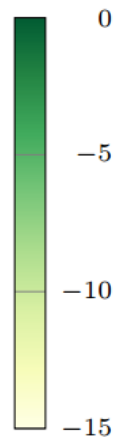
- A sequence format for molecules
- Allows us to use the progresses made with natural language processing in the recent years 😊



The generative process



Sampled SMILES

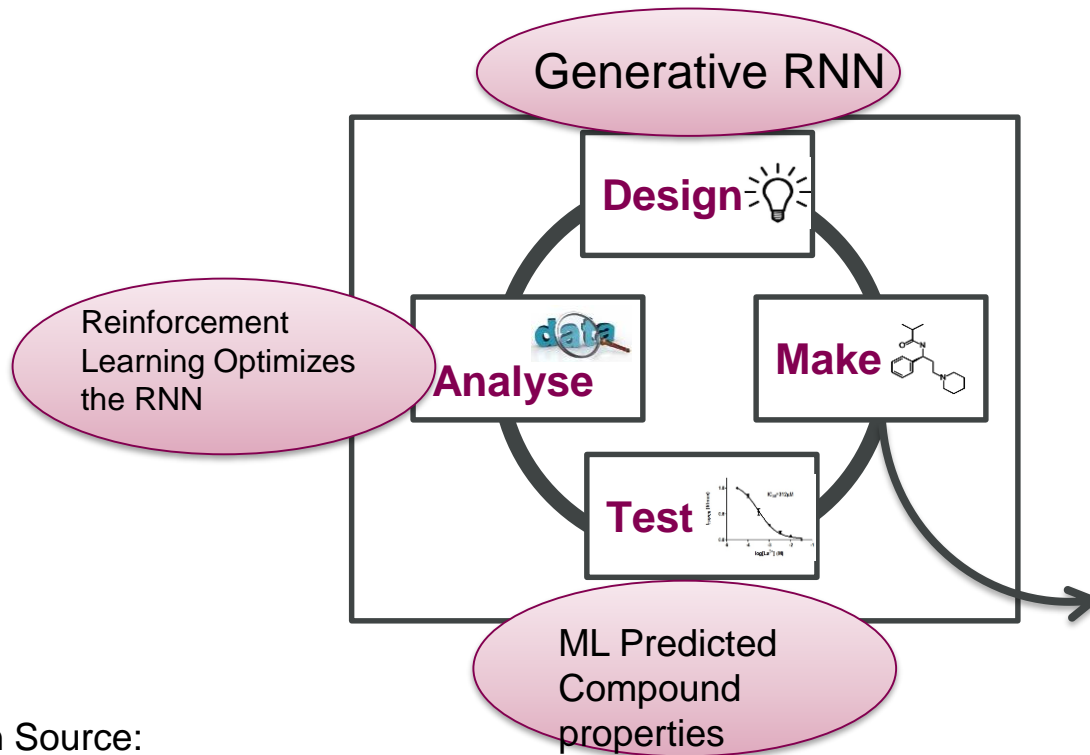


Log P

Structure



Reinforcement Learning: An *In Silico* mini-DMTA cycle



The Value:
Molecules for DMTA cycle

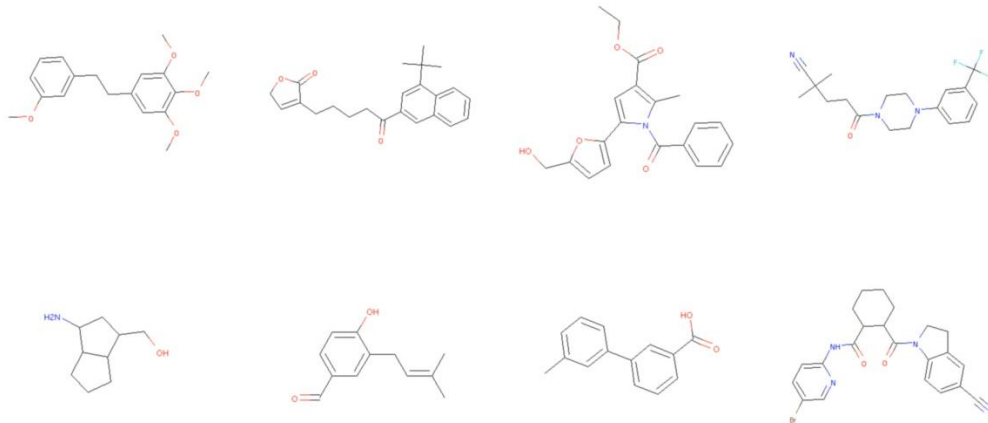
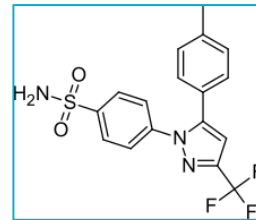
Produces novel scaffolds and improved compound suggestions for drug discovery projects

Less real world DMTA cycles
=> Saved time

Open Source:
<https://github.com/MarcusOlivecrona/REINVENT>

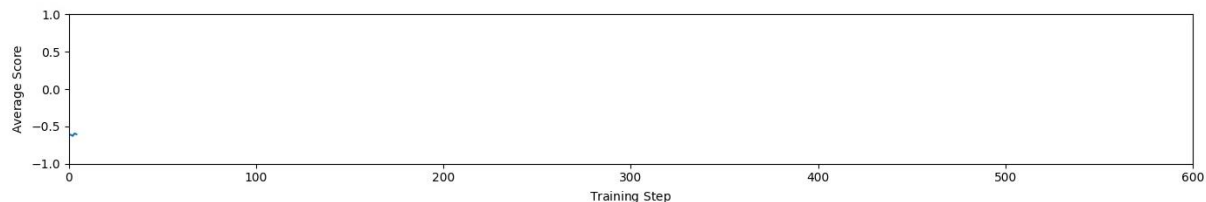


AI live: Create Structures Similar to Celecoxib

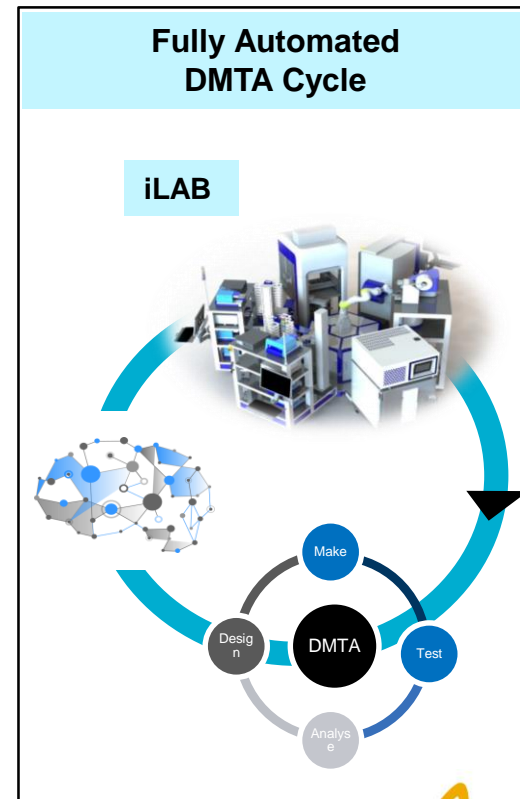
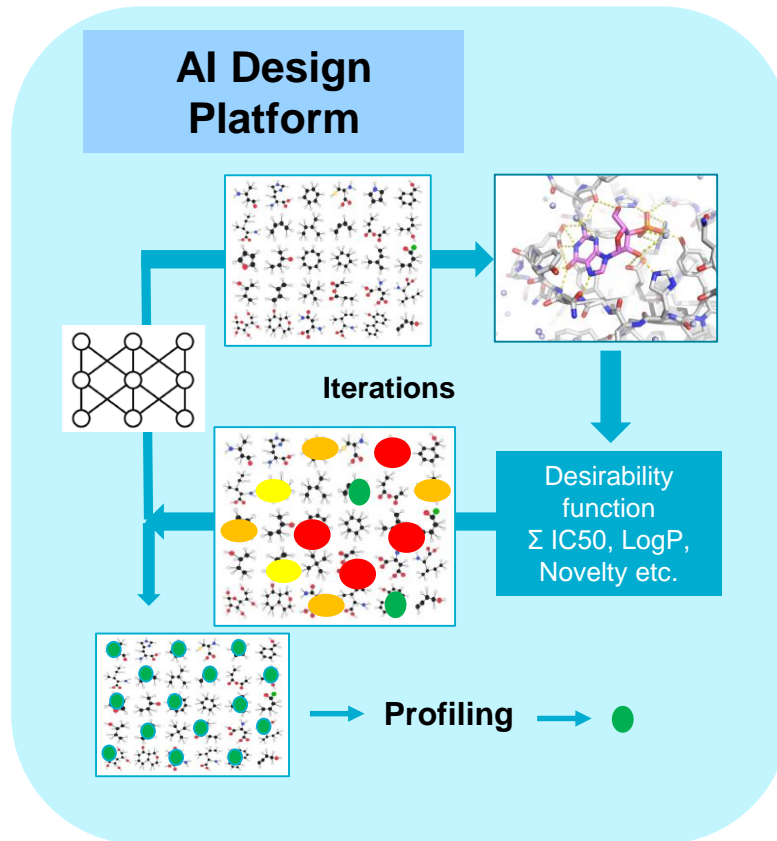
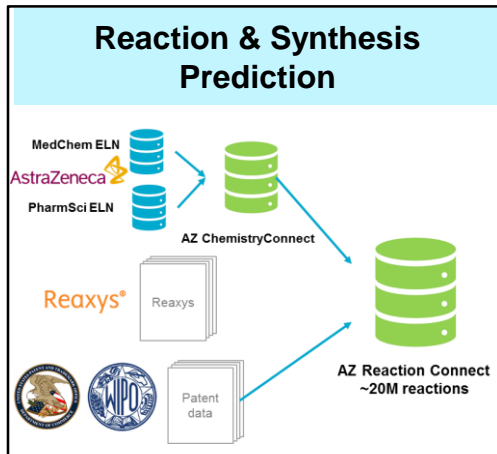
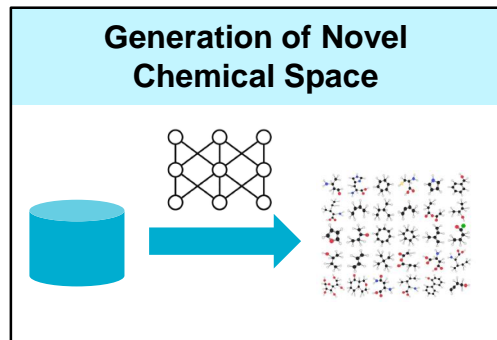


- **Key Message**

- RNN generates structures similar to Celecoxib
- Rapid sampling!
- Average score describes how many learning steps are required to reach similar compounds



Artificial Intelligence Guided Drug Design Platform



Lessons learned from project

- Novel scaffolds were identified in a crowded chemical space
- Compound series could be efficiently optimised
- ADME and especially binding affinity predictions are limiting factors
- Too many ideas might make prioritization for synthesis challenging
- Chemistry resources might be frontloaded to assess the generated ideas
- Currently used in 12-15 LG/LO projects at all sites
- Continuously build of REINVENT platform



MACHINE LEARNING LEDGER ORCHESTRATION FOR DRUG DISCOVERY

JUNE 2019 – MAY 2022

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SUBSTR
FOUNDATION

This project has received funding from the Innovative Medicines Initiative 2 Joint Undertaking under grant agreement N° 831472. This Joint Undertaking receives support from the European Union's Horizon 2020 research and innovation programme and EFPIA

imi innovative
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initiative



efpia

What are the challenges for AI driven drug design?

- Scaling AI and chemistry automation for drug design to a whole drug discovery project portfolio including projects with low data volume
- Binding affinity and solubility predictions are major bottlenecks
- “Cambrian revolution” of new AI methods makes it difficult to assess progress
- Educational, cultural & logistical challenges besides scientific
- The bar is set high to transform drug design

Molecular AI Team

Thierry Kogej
Hongming Chen (2001-2019)
Isabella Feierberg
Atanas Patronov
Esben Jannik Bjerrum
Preeti Iyer
Christian Margreitter
Lewis Mervin
Kostas Papadopoulos
Samuel Genheden
Christos Kannas
Alexey Voronov
Jiangming Sun (Postdoc 2015-2017)
Noe Sturm (Postdoc 2017-2018)
Philipp Buerger (Postdoc 2017-2019)
Jiazhen He (Postdoc 2019-2022)
Rocio Mercado (Postdoc 2018-2021)
Tomas Bastys (postdoc 2019-2022)
Thomas Blaschke (PhD student 2017-2018)
Josep Arus Pous (PhD student 2018-2019)
Michael Withnall (PhD student 2018-2019)
Oliver Laufkötter (PhD student 2018-2019)
Laurent David (PhD student 2018-2019)
Amol Thakkar (PhD student 2019-2020)
Ave Kuusk (PhD student 2016-2019)
Marcus Olivecrona (AZ Graduate Program 2017)
Alexander Aivazidis (AZ Graduate Program 2018)
Dhanushka Weerakoon (AZ Graduate Program 2018-2019)
Panagiotis-Christos Kotsias (AZ AI Graduate Program 2018-2020)
Dean Sumner (AZ AI Graduate Program 2019-2020)
Edvard Lindelöf (Master Thesis Student 2018-2019)
Simon Johansson (PhD Student 2019-2024)
Oleksii Prykhodko (Master Thesis Student 2019)
Viktor Norrsjö (Master Thesis Student 2019-2020)

Acknowledgements

Discovery Sciences

Garry Pairaudeau
Clive Green
Lars Carlsson
Nidhal Selmi
Michael Kossenjans
Anna Tomberg

DSM AI Team

Ernst Ahlberg
Suzanne Winiwarter
Ioana Oprisiu
Graham Smith
Ruben Buendia (Postdoc)

PharmSci

Per-Ola Norrby
Kjell Johner
David Buttar

AI Projects

Werngard Czechtizky
Ina Terstiege
Christian Tyrchan
Anders Johansson
Jonas Boström
Kun Song
Alex Hird
Neil Grimster
Richard Ward
Jeff Johannes
Graeme Robb
Eva Nittinger
Anna Tomberg
Kathryn Giblin

Academic Collaborators

Marwin Segler (Munster)
Juergen Bajorath (Bonn)
Jean-Louis Reymond (Bern)
Andreas Bender (Cambridge)
Sepp Hochreiter (Linz)
Gunther Klambauer (Linz)
Sami Kaski (Helsinki)



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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

Commentary

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Future
**Medicinal
Chemistry**

The convergence of artificial intelligence and chemistry for improved drug discovery

Clive P Green^{*,1}, Ola Engkvist² & Garry Pairaudeau³

Application of Generative Autoencoder in *De Novo* Molecular Design

Thomas Blaschke,^{*,[a, b]} Marcus Olivecrona,^[a] Ola Engkvist,^[a] Jürgen Bajorath,^[b] and Hongming Chen^{*,[a]}

Computational prediction of chemical reactions: current status and outlook

Ola Engkvist¹, Per-Ola Norrby², Nidhal Selmi¹,
Yu-hong Lam³, Zhengwei Peng³, Edward C. Sherer³,
Willi Amberg⁴, Thomas Erhard⁴ and Lynette A. Smyth⁴

Ola Engkvist was
awarded his PhD in
computational chemistry
by the University of Lund in
1997, and continued with
postdoctoral research at

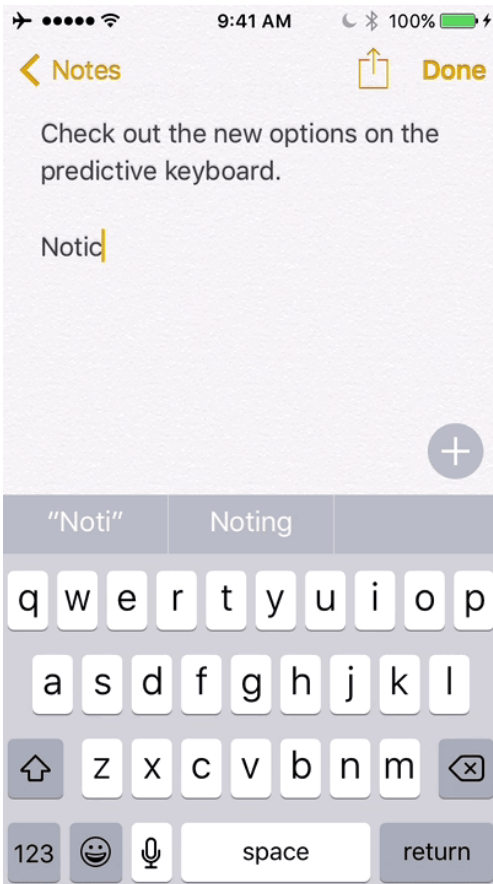


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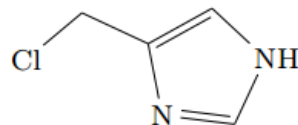
Recurrent Neural Network & Natural language generation



Tokenization of SMILES

- Tokenize combinations of characters like “Cl” or “[nH]”
- Represent the characters as one-hot vectors

Graph:



SMILES:

ClCc1c[nH]cn1

One-hot
encoding:

	Cl	C	c	1	c	nH	c	n	1
C	0	1	0	0	0	0	0	0	0
c	0	0	1	0	1	0	1	0	0
n	0	0	0	0	0	0	0	1	0
1	0	0	0	1	0	0	0	0	1
nH	0	0	0	0	0	1	0	0	0
Cl	1	0	0	0	0	0	0	0	0

