

# Accessible AI for Small Molecule Discovery Research

Considerations and Value Drivers

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#### Agenda

- Very brief introduction to Optibrium
- Applying AI in drug discovery
  - Al for different organisation types
  - Introduction to Cerella™
- Case studies
  - Practical application to heterogeneous drug discovery project data
  - Large-scale application to global pharma data
  - Combination with generative methods
- Conclusions



### Introduction to Optibrium

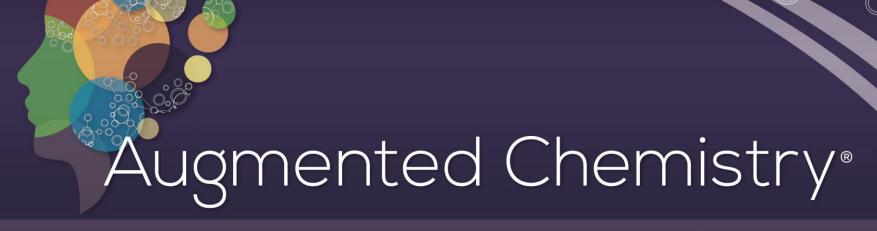
#### www.optibrium.com





- Optibrium creates elegant software solutions for small molecule design, optimisation and data analysis
  - R&D of novel technologies to guide decisions and improve efficiency in drug discovery
- Global customer base from top-ten pharma to small biotech and academia
  - >170 customers worldwide
  - Adoption in other chemistry fields, e.g. animal health, agrochemicals, etc.





... enhance your expertise with AI to make better decisions

Applying AI to Drug Discovery



# Al for Different Types of Drug Discovery Organisation



### Al's potential: Better decisions, faster progress, high-quality candidates

#### Large Pharma

- Extract maximum value from large, global, cross-project data sets
- Frequently dedicate big teams to data science and AI research
  - o Often struggle to get buy-in and adoption by users

#### Biotech

- Resource constraints limit the amount of data that can be generated
- Need a turnkey solution to leverage limited data effectively
  - o Caveat: Need *enough* data not a 'magic bullet'



# Al for Different Types of Drug Discovery Organisation



# Al's potential: Better decisions, faster progress, high-quality candidates

#### Academic groups and consortia

and we want to find them

- Heterogeneous data from multiple collaborations and public data sets
- Data is often highly variable it is difficult to get a consistent picture

#### **Consistent themes**

- Predicting intractable, hard-to-model endpoints, to make best use of valuable resources
  - o For example, PK properties, and expensive, downstream experimental endpoints
- We know we are missing opportunities because of missing, uncertain or inaccurate data



# Al for Different Types of Drug Discovery Organisation



### Al's potential: Better decisions, faster progress, high-quality candidates

#### VC or Investor carrying out Due Diligence

- Investments and acquisitions are \$ multi-million bets made with very little information
- More information about a project provides a better understanding about its chance of success
  - o Is the data consistent?
  - o Will it be possible to improve on the lead compound?
  - o Are there already some hidden gems?
- A rigorous, data-driven analysis can help to quantify the risk



# Challenges of Using Data in Drug Discovery



- It's impossible to measure all of my compounds in all of my assays, how do I make the most of the data I have?
- I know there is variability in my experiments, how do I avoid being led astray by artefacts and errors?

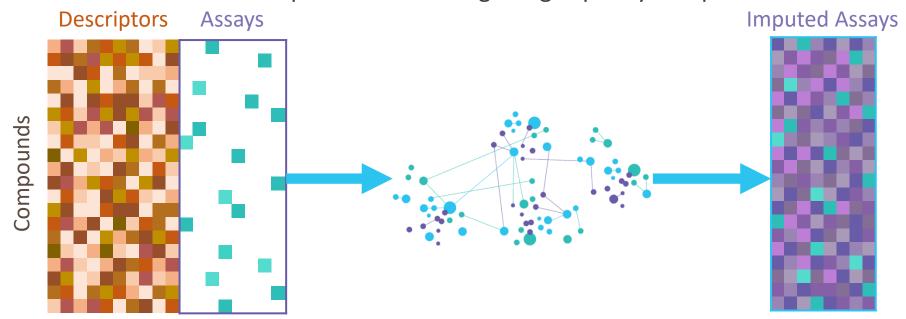


- What are the most valuable experiments to run? What data will give me the most information with which to make decisions?
- How can I use the limited data I have to make better predictions for new compound designs, and choose the best ones for synthesis?

# Alchemite<sup>™</sup> Deep Learning Imputation Optibrium's exclusive partnership with Intellegens



- Learns directly from relationships between experimental endpoints as well as SAR
  - Makes better use of sparse and noisy experimental data than conventional QSAR models
- 'Fills in' the gaps in your data and makes predictions for 'virtual' compounds
  - Generates more accurate predictions to target high-quality compounds

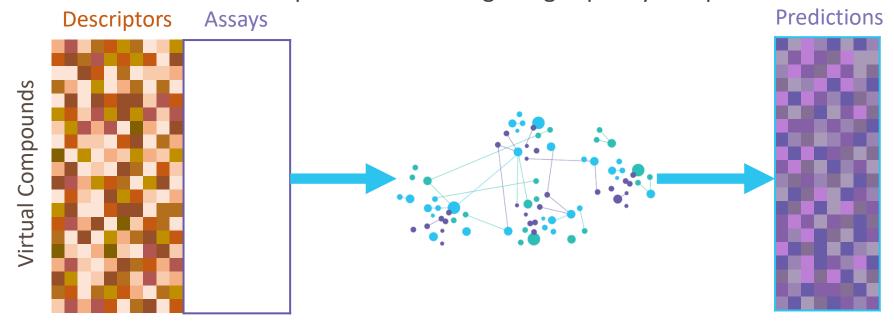


Whitehead et al. J. Chem Inf. Model. (2019) **59**(3) pp. 1197-1204, Irwin et al. J. Chem. Inf Model. (2020) **60**(6), pp. 2848–2857

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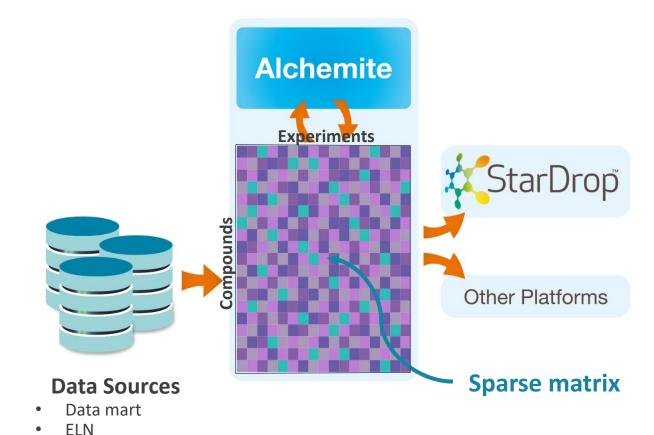
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### Cerella

### Enabling active learning in drug discovery



- Automatically updates and prepares experimental data for model building
  - Connects seamlessly to data repositories
  - Applies cleaning, business rules and transformations to data for best model performance
- Automatically updates Alchemite models as new data become available
  - Always work with results based on the latest information
  - Remove the burden of manually building and updating models
- Manage 'massive matrix' of imputed results for easy access
  - May contain O(10<sup>10</sup>) data points!
- Provide seamless access to results
  - Using StarDrop™ or any platform via a RESTful API



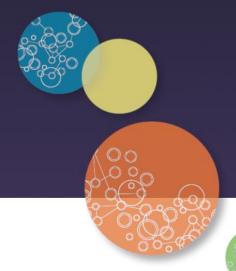
Watch our webinar at http://bit.ly/cerella\_active

# Deep Learning with Cerella Reducing the time and cost of discovery cycles



- Proactively highlight high-quality compounds by more accurately 'filling in' sparse data (imputation)
- Increase confidence in decision making, identify hidden opportunities, flag outliers and false negatives
- Translate Al insights into planning of experiments and focus on the most valuable measurements
- Gain more value from your compound data, accurately predicting complex endpoints, intractable with conventional QSAR modelling
- Add value even for individual project datasets, while scaling to global compound data repositories

#### **Case Studies**





### Alchemite Application In Biotech



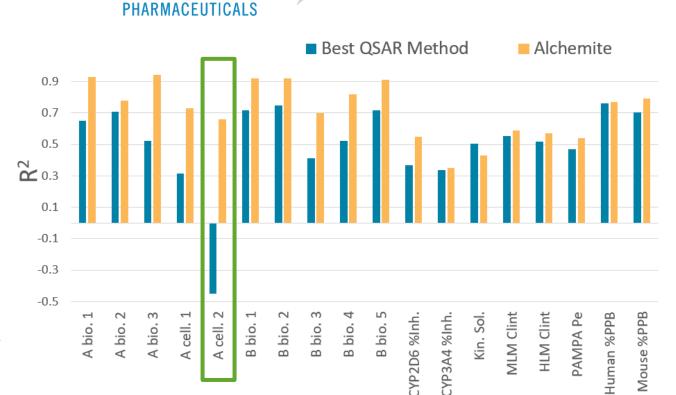
- Application to heterogeneous data across two projects
  - Target and phenotypic activities and ADME endpoints
  - 2453 compounds across 18 endpoints
- Significant improvement in accuracy

Average R<sup>2</sup>

Best QSAR 0.50

Alchemite<sup>™</sup> 0.72

- Example of value delivered:
  - Few false negatives among confidentlypredicted inactives – could have saved
    \$600,000 in unnecessary synthesis



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Irwin *et al.* J. Chem. Inf Model. (2020) **60**(6), pp. 2848–2857 Watch our webinar: http://bit.ly/practical\_deeplearning

### Alchemite Application in Big Pharma

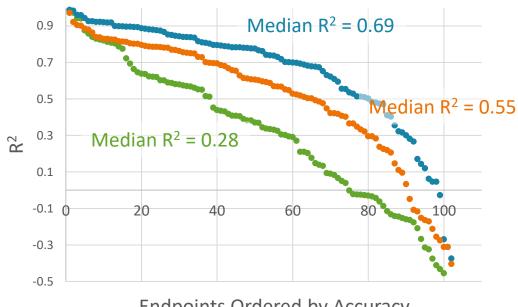
Augmented Chemistry

- Application to large data set
  - **678,994** compounds
  - 1,116 experimental endpoints
  - 2% complete
- Covering a **full range** of drug discovery assays, incl
- Example of value delivered:
  - "...an extension of what medicinal chemists... do in be possible for a person."



#### **ONCOLOGY**

#### Prospective Prediction of Project Target Activities



**Endpoints Ordered by Accuracy** 

Random Forest
Alchemite Imputation
Alchemite Virtual

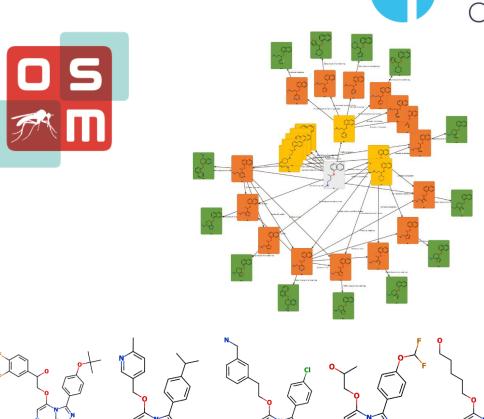
Irwin et al. App. Al Lett. (2021) DOI: 10.1002/ail2.31 Watch our webinar: http://bit.ly/largescale\_imputation

# Collaboration with Open Source Malaria (OSM) Combination with generative methods

Augmented Chemistry

- Application to sparse antimalarial activity data
  - Targeting novel MoA PfATP4
  - Alchemite generated one of the top-ranked models in the OSM competition
- New compound ideas were generated using the Nova<sup>™</sup> module in StarDrop<sup>™</sup>
  - Prioritised with Alchemite model
  - Good activity profile and properties
- A confidently predicted compound was synthesised and tested by OSM
  - Only confirmed active of those proposed by four organisations
- Example of value delivered:
  - "[The Optibrium compound] is something that I am... sure none of the humans involved in the SAR over the years would have bothered making..."

Irwin *et al.* Int. Pharm. Ind. (2020) **12**(2) pp. 28-31 Watch our webinar http://bit.ly/ai\_antimalarials



**Exscientia** 

11 μM

**Molomics** 

>25 µM

**Molomics** 

14 µM

Optibrium/

**Intellegens** 

0.65 μΜ

**Davy Guan** 

>25 µM

#### **Conclusions**



- Organisations of different types and sizes have the same goals
  - Make better use of valuable resources
  - Avoid missed opportunities
  - Make go/no-go decisions with confidence and quickly identify the next drug candidate
- They are looking at the same problems through different lenses
  - Too much data vs too little
  - Sparse, noisy, heterogeneous data
  - Budgetary/resource constraints
- Al approaches, like Cerella™, provide insights by using all the available data.
  - Enables confident decision-making by highlighting interesting data and patterns
  - Significantly reduces the time and cost of discovery cycles

#### Acknowledgements

- Partners at Intellegens Limited
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- Session organisers Marti Head and Kate Hardy

For more information visit: optibrium.com/cerella

