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### Practice of Generative AI in lead optimization

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And in Sanofi

CADD: B. Filoche, C. Terrier, C. Grebner, Y. Li, S. Guessreguen, H. Matter, S. Sauer Chemistry: S. Desprets and the medicinal chemists involved in the Molecular Turing Test

"Marc Bianciotto is a Sanofi employee and may hold shares and/or stock options in the company"



### The history of Sanofi



## Integrated Drug Discovery





#### Integrated Drug Discovery France



#### AI for Drug Discovery: the Gold Rush



#### Generate molecules with AI?



#### Generate molecules with AI?

	Lead Gen.	Lead Opt.	) :
Project data	Less	More	4
Predictive models performance	Worse	Better	
Chemical space to explore	Larger	More focused	
Synthesis likelihood	Lower	Higher	
Integration in the legacy workflow	More challenging	Less challenging	)

## Topics of concern in small molecule GenAI for lead optimization



#### e\_challenge\_english Last Checkpoint: 10/17/2022 (unsaved changes)



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#### Translation to practice

### Generative AI for protein kinase X: last effort

#### Objectives:

- Evaluate Med Chemists proposals
- Generate a last round of compounds
  - Close to the pre-candidate (same scaffold, 2 diversification points)
  - Optimized on 8 properties
  - Synthetically readily accessible



#### Protein kinase X: reward function

#### v root:

- ► GLOBAL:
- NNGP\_APDP\_regression-bioch\_pIC50:
- NNGP\_RDKit\_regression-cell\_pIC50:
- NNGP\_RDKit\_regression-FUM\_Brain:
- NNGP\_APDP\_regression-CLint:
- NNGP\_APDP\_regression
- NNGP\_RDKit\_regression
- bioch-pIC50-1:
- b deepchem- cell-pIC50-1:
- > deepchem- FUM\_Brain-percent-1:
- deepchem-logD74\_all-logD-1std:
- deepchem-Solubility-uM\_pH74-1std:
- has\_not\_substructure:

- Composite scoring function
  - Biochemical, cell pIC50s, counter-targets, unbound fraction in Brain, solubility, logD
  - Several models per readout if the models are correct
- AD for generation
- Score thresholds from the Med. Chemists' propositions
  Reward



### Generation outcome

#### Human intelligence + ML score:

- 73 close analogs of known cpds
- 12 « flat cpds » selected
- => 23 synthesized with stereo

#### AI design:

- 857 cpds generated in-criteria
  - 108 selected for Med Chemists
- + 10 « flat » cpds selected for synthesis
- => 17 synthesized with stereo.
- Non-trivial R-groups



A shortlist of 5+3 cpds that fulfill the vast majority of 15 criteria

## Chemical space

Colored by

molecule origin and fate



Legend Assay			
	MedChem, Synthesized		
	MedChem, Best		
	MedChem		
	Known		
	Generated, Synthesized		
	Generated, Selected		
	General d, Rest		
	Comments V		



Colored by

Multi-parametric score















#### Using Chemical Language Models: Practical considerations on execution

#### • Timing

- The lead optimization GenAI window
  - Enough data for good models
  - Still useful to explore (vs exploit)
- "Data Science is teamwork"
  - Even with chemical lead opt data
  - Curate curate curate: Speed and quality



#### Using Chemical Language Models: Practical considerations on integration

- Define clear and shared objectives
- From screen to compound:
  - Quality & synthetisability
  - Or BB availability?
- From screen to data: cycle time
- Acculturate on statistics
- Explicit, transparent, shared design choices
- Generative approaches as part of a strategy
  - Explainable decision making



5 binary models, success rate 0.8

$$0,8^5 = 0.33$$

# Thank you!

