







<sup>&</sup>lt;sup>1.</sup> Faculty of Mathematics, Informatics, and Mechanics, University of Warsaw, 02-096, Warsaw, Poland <sup>2.</sup> Centre of New Technologies, University of Warsaw ul. Stefana Banacha 2c 02-097 Warsaw, Poland

### Pipeline



Select TrmD based on biological context

#### **Ligand Selection**

Select known ligands for chosen TrmD

#### **Compound Filtering and Similarity Search**

Search for new potential ligands using SMILES similarity

#### **Compound Generation**

Generate novel compounds structurally similar to identified ligands

#### **Molecular Docking**

Perform in silco docking to asses binding affinity

# Target selection

- 1. Selected TrmD structures from the PDB database of bacterial species that are pathogenic to humans and antibiotic resistant:
  - Mycobacterium abscessus (PDB Id: 6QRB) blue
  - Acinetobacter baumannii (PDB ld: 7MYS) pink
  - Pseudomonas aeruginosa (PDB ld: 5WYQ) brown

#### 2. Structural Superimposition

 Validated similarity of TrmD chain A active site across selected species in Chimera.



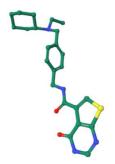
	A. baumannii	M. abscessus	P. aeruginosa
A. baumannii	0.0 Å	0.7 Å	0.3 Å
M. abscessus	0.7 Å	0.0 Å	0.8 Å
P. aeruginosa	0.3 Å	0.8 Å	0.0 Å
Overall RMSD	0.6 Å		

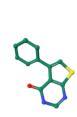
# Ligand selection



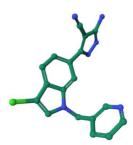
# Ligands crystallised with TrmD in PDB for selected species

• 59 ligands











- Wilkinson, Andrew J., et al. "Evaluating the druggability of TrmD, a potential antibacterial target, through design and microbiological profiling of a series of potent TrmD inhibitors." Bioorganic & Medicinal Chemistry Letters 90 (2023): 129331. 1
  - 7 liganads
- Zhong, Wenhe, et al. "Thienopyrimidinone derivatives that inhibit bacterial tRNA (guanine37-N 1)-methyltransferase (TrmD) by restructuring the active site with a tyrosine-flipping mechanism." Journal of medicinal chemistry 62.17 (2019): 7788-7805.
  - 4 ligands
- Vlasov, S. V., et al. "Synthesis, docking study and antimicrobial activity evaluation of pyridyl amides of thieno [2, 3-d] pyrimidine-4-carboxylic acid." (2023).
  - 5 ligands

# **Ligand Similarity-Based Exploration**

### Filter the PubChem Database (Initial: 2,512,731 compounds):

- Lipinski's Rules: Drug-likeness criteria.
- Charge<sup>4</sup>: Net charge between -2 and +2.
- Polar Surface Area (TPSA)<sup>4</sup>:  $\leq 140 \text{ Å}^2$ .
- **Result**: 1,187,012 compounds.

### **Search for Similar Compounds:**

 Use the LINGO similarity metric₅ to identify compounds similar to known ligand SMILES strings from the filtered dataset.

cid	isosmiles	$_{\rm sim}$	target
11652085	COC(=O)C@HN	0.79	68910199
11701139	C1=CC=C(C=C1)COC(=O)CNN	0.75	68910199
20713065	C1=CC=C(C=C1)COC(=O)CNN=C(N)N	0.73	68910199
84733164	C1=CC=C(C=C1)COC(=O)CCNN	0.72	68910199
101383098	C1=CC=C(C=C1)CO13C[13CH2][15NH2]	0.71	68910199
11701101	C1=CC=C(C=C1)COC(=O)C[15NH2]	0.71	68910199
10725758	[2H]C([2H])(C(=O)OCC1=CC=CC=C1)N	0.71	68910199
10797159	C1=CC=C(C=C1)CO13C[13CH2]N	0.71	68910199
927308	C1=CC(=CC(=C1)NCC2=CC=CS2)C(=O)O	0.71	2819674
409140	C1=CC=C(C=C1)COC(=O)CN	0.71	68910199

# **Compound Generation**

**SMILES** input

**ENCODER** Neural Network

New chemical structures inspired by known ligands and similar compounds are generated using a Variational Autoencoder (VAE)6,7 in a matrix-based format from Keras' API<sup>8</sup>.

CONTINUOUS **MOLECULAR** REPRESENTATION

(Latent Space)

#### **Encoding Molecules:**

#### **Connection Matrix:**

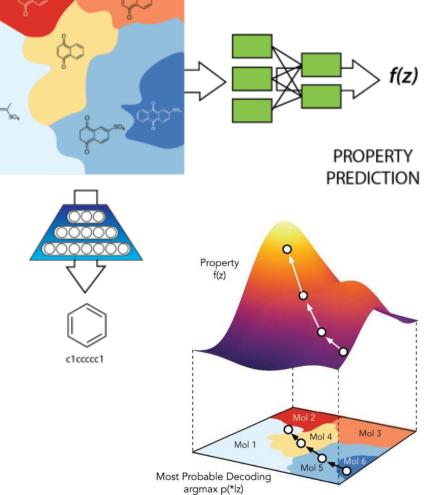
 Triangular matrix where numbers represent bond types (e.g., 1 = single, 2 = double).

#### **Feature Vector:**

 Atom-specific information, such as the index in an atom dictionary.

DECODER Neural Network

SMILES output



6. S. Hafeez et al. Designing of fragment-based inhibitors with improved activity against E. coli AmpC βlactamase compared to conventional antibiotics. Saudi J. Biol. Sci., 31, Elsevier BV, 2024.

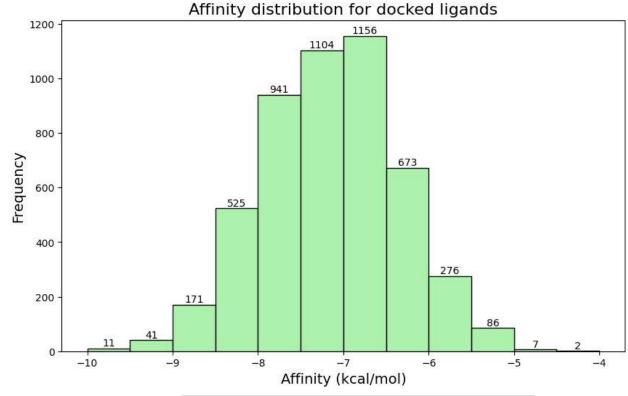
7. R. W. Grosse-Kunstleve et al. The Computational Crystallography Toolbox: crystallographic algorithms in a reusable software framework. J. Appl. Cryst., 35, International Union of Crystallography (IUCr), 200

8. https://keras.io/examples/generative/molecule\_generation/

# Molecular docking

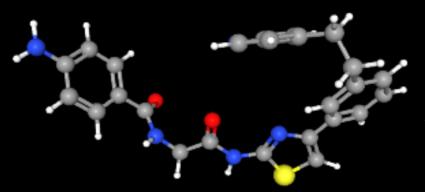
- Preparation: Meeko
  - Ligand from a Smiles String
  - Receptor preparation from PDB
- Software: AutoDock Vina
  - Very fast and robust
  - Open-source





	PubChem ID	Affinity (kcal/mol)
0	155792348	-9.981
1	8171885	-9.885
2	54844255	-9.872
3	8842407	-9.756
4	155792345	-9.641
5	54811489	-9.637
6	54844164	-9.635
7	45861272	-9.592
8	54841777	-9.54
9	56295120	-9.519

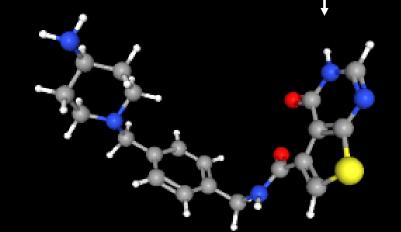
# Top hit



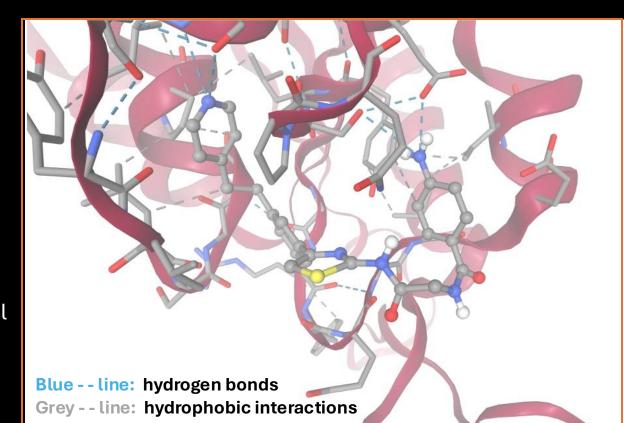
4-amino-N-[2-oxo-2-[[4-[3-(2-pyridin-4-ylethyl)phenyl]-1,3-thiazol-2-yl]amino]ethyl]benzamide

Affinity: -9.98 kcal/mol

Similar to known ligand (71724899 – PubChem) SIM = 0.6



**Affinity**: -9.21 kcal/mol



### **Sources**

- 1. Wilkinson, Andrew J., et al. "Evaluating the druggability of TrmD, a potential antibacterial target, through design and microbiological profiling of a series of potent TrmD inhibitors." Bioorganic & Medicinal Chemistry Letters 90 (2023): 129331.
- 2. Zhong, Wenhe, et al. "Thienopyrimidinone derivatives that inhibit bacterial tRNA (guanine37-N 1)-methyltransferase (TrmD) by restructuring the active site with a tyrosine-flipping mechanism." Journal of medicinal chemistry 62.17 (2019): 7788-7805.
- 3. Vlasov, S. V., et al. "Synthesis, docking study and antimicrobial activity evaluation of pyridyl amides of thieno [2, 3-d] pyrimidine-4-carboxylic acid." (2023).
- 4. Kralj, Sebastjan, Marko Jukič, and Urban Bren. "Molecular filters in medicinal chemistry." Encyclopedia 3.2 (2023): 501-511.
- 5. Öztürk, H., Ozkirimli, E., & Özgür, A. (2016). A comparative study of SMILES-based compound similarity functions for drug-target interaction prediction. *BMC bioinformatics*, 17, 1-11.
- 6. Ralf W. Grosse-Kunstleve, Nicholas K. Sauter, Nigel W. Moriarty, Paul D. Adams. The Computational Crystallography Toolbox: crystallographic algorithms in a reusable software framework. *Journal of Applied Crystallography* **35** International Union of Crystallography (IUCr), 2002.
- 7. Sidrah Hafeez, Rehan Zafar Paracha, Fazal Adnan. Designing of fragment based inhibitors with improved activity against E. coli AmpC β-lactamase compared to the conventional antibiotics. *Saudi Journal of Biological Sciences* **31** Elsevier BV, 2024.
- 8. <a href="https://keras.io/examples/generative/molecule\_generation/">https://keras.io/examples/generative/molecule\_generation/</a>

# The Lingosim Method

• A metric comparing 3-element segments (lingos) within SMILES strings.

### Analysis Process:

- Use canonical SMILES strings.
- Compare difference of counts for every lingo and aggregate into single value.

cid	isosmiles	$\sin$	target
11652085	COC(=O)C@HN	0.79	68910199
11701139	C1=CC=C(C=C1)COC(=O)CNN	0.75	68910199
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### The Generative Model (VAE)

**SMILES** input

ENCODER Neural Network

#### VAE Architecture:

- Encoding molecules into a latent space.
- Decoding from the latent space to create new molecules.

CONTINUOUS MOLECULAR REPRESENTATION (Latent Space)

### Inspiration:

Adapted from image generation techniques.

#### So far results:

• Able to produce simple molecules (up to 7 atoms with single branch).

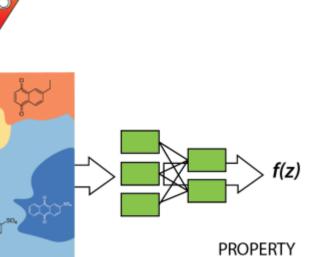
DECODER Neural Network

SMILES output

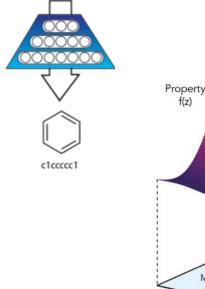
#### • To do:

Gradually incorporate more complex structures.





**PREDICTION** 

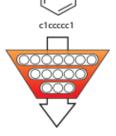


Most Probable Decoding argmax p(\*|z)

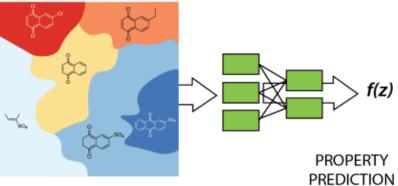
# Problems when training the model

SMILES input

ENCODER Neural Network



 Molecules are long and complex, which prevents the model from efficiently learning (loss extremely high). CONTINUOUS MOLECULAR REPRESENTATION (Latent Space)

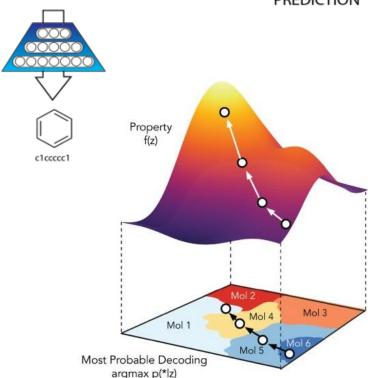


 Data composed mostly of carbon, leading to the model falling into local minimum of generating carbon chains with occasional nitrogen or oxygen atoms in between.

DECODER Neural Network

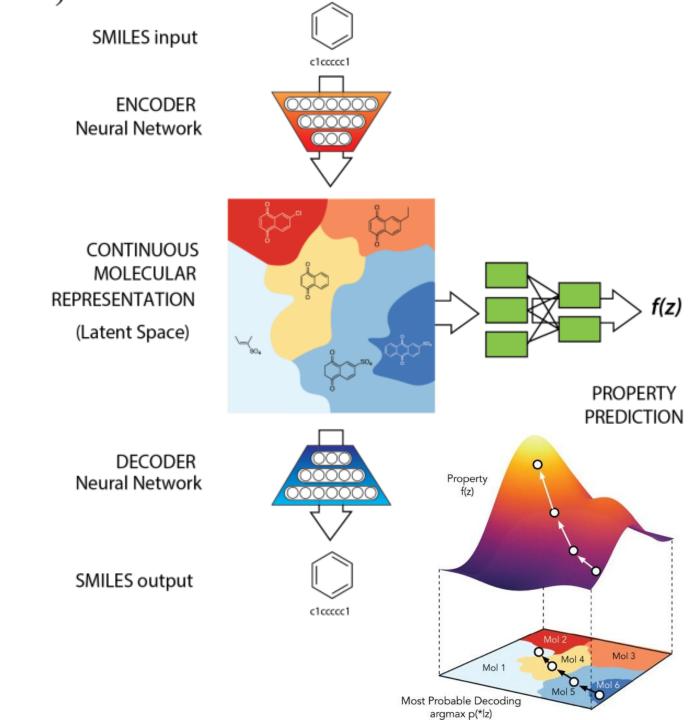
**SMILES** output

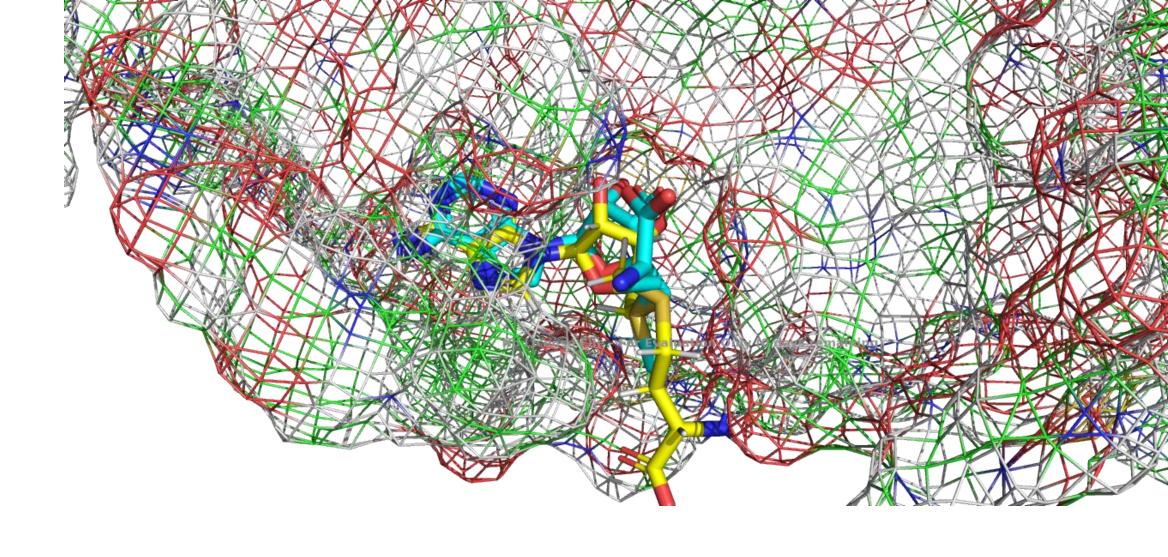
• Large size of input vectors when training on longer molecules (281kb for 70 atoms in molecule).



### Possible solutions

- Pre-train on small molecules starting with simple chains, then tune for target molecules.
- Improve input size by encoding common substructures into tokens.





Example of crystallographic ligand and a docked molecule chosen by smiles similarity

### To do

- Switch rigid docking to some limited flexibility as allowed by Vina
- Increase the numer of docked molecules, so far we're in 5 thousand
- Docking of de novo generated compounds
- Results verification on human Trmt5