

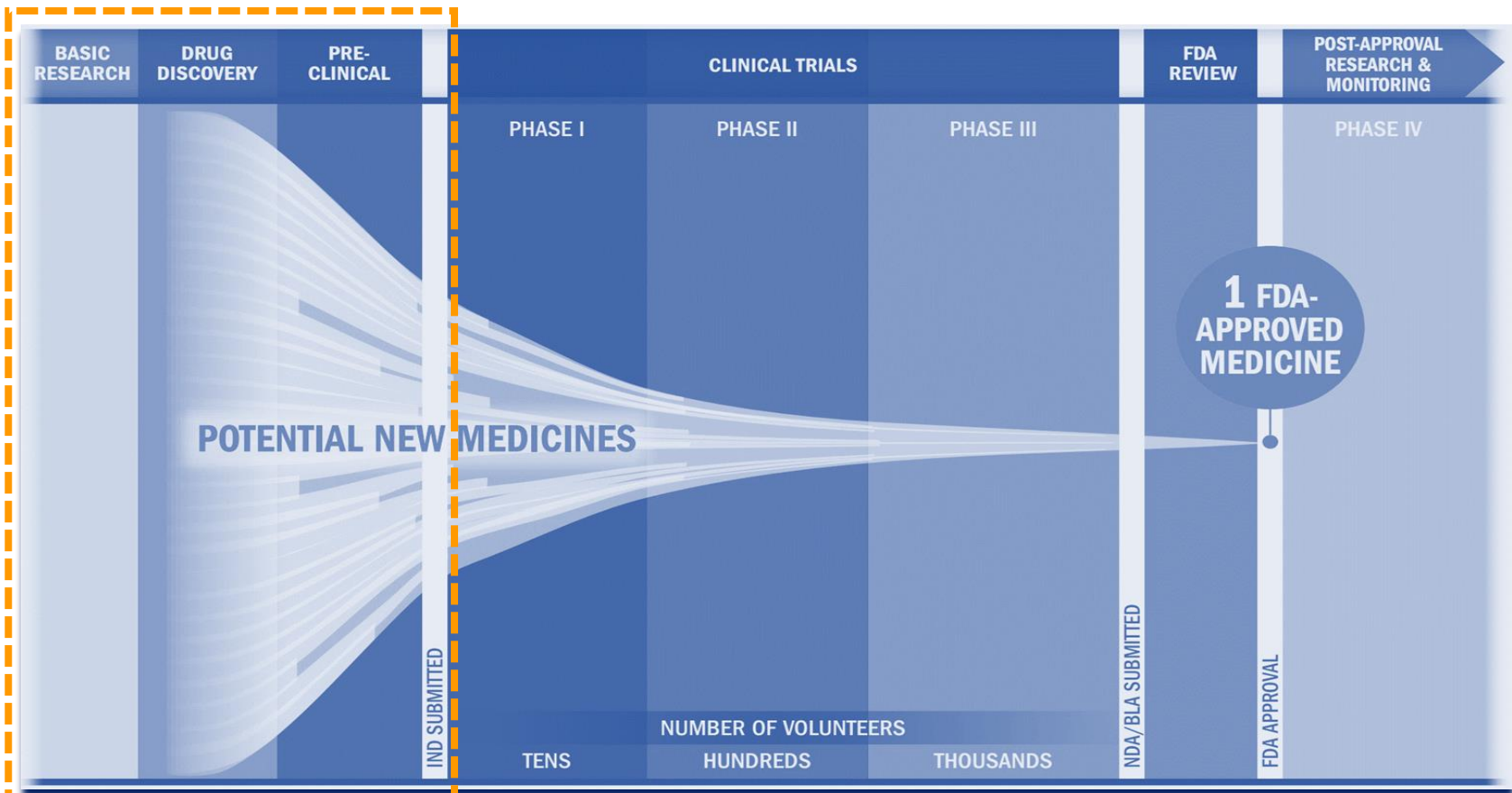


Deep Reinforcement Learning for Pre-Clinical Drug Development

Fellow: Nathan Russell

Advisors: Jian Peng (CS), Marty Burke (Chemistry)

Big Picture



1.15 Billion

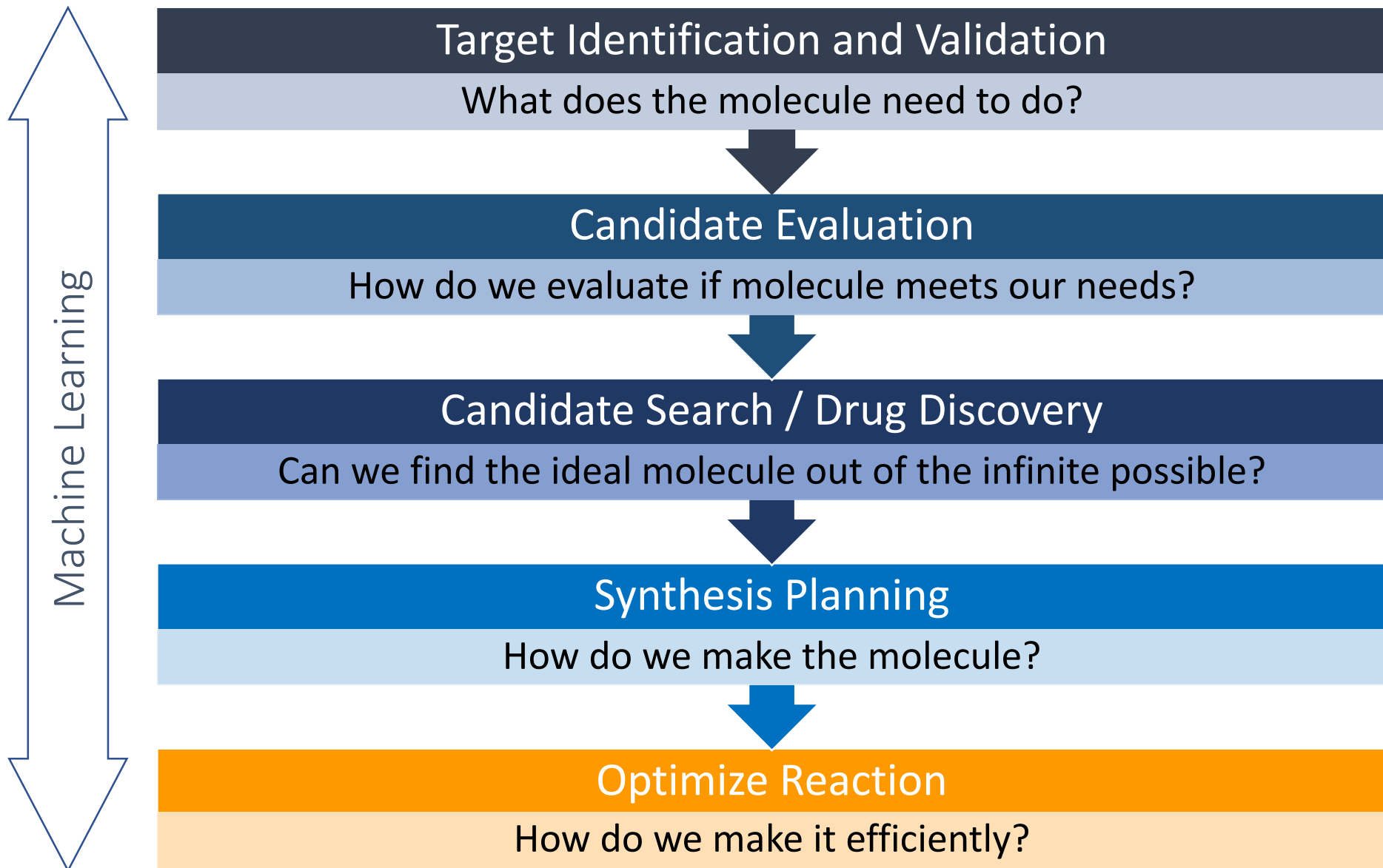
Direct Impact

1.53 Billion

Indirect Impact

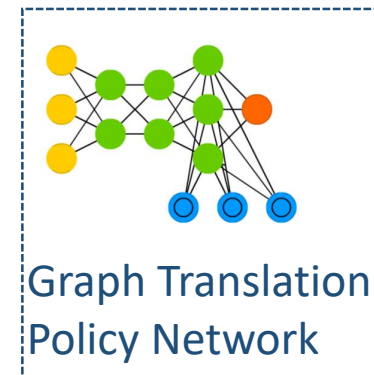
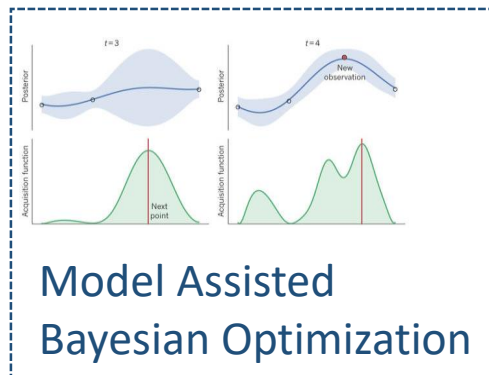
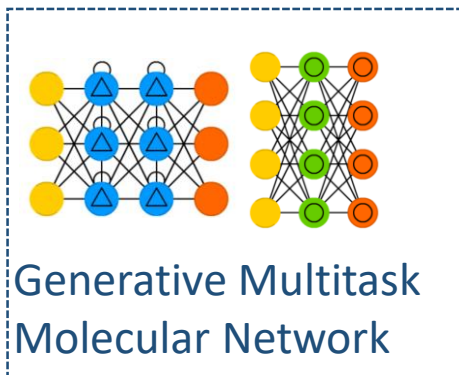
2017 \$
Capitalized Costs
According to
Tufts CSDD 2014

Pre-Clinical Tasks

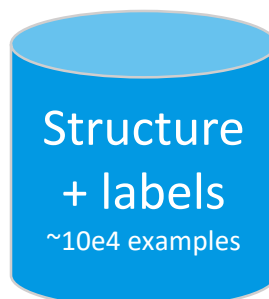
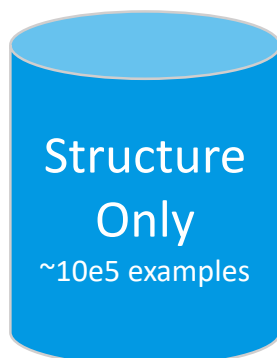
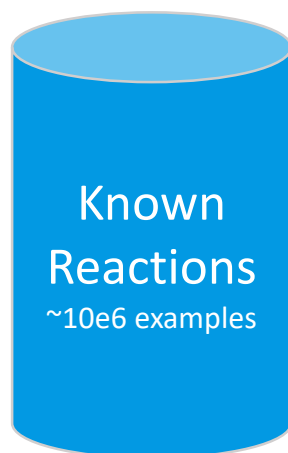


Resources & Contributions

Contributions



Resources

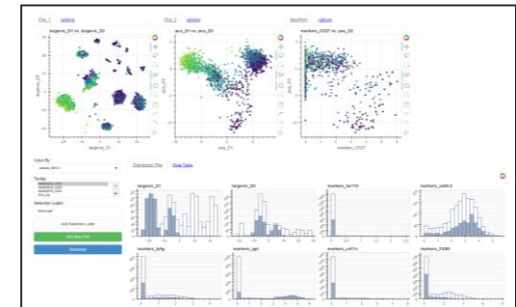
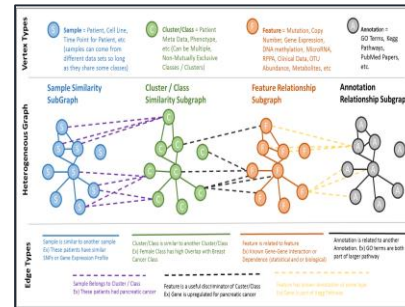


Automated Lab Evaluation

Common Tasks

Tools made to Support those Tasks

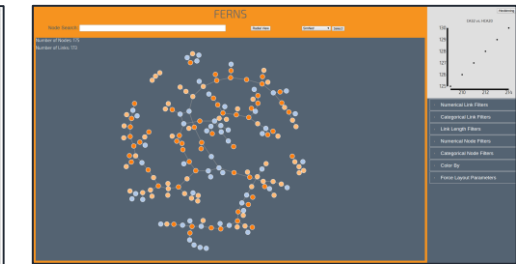
- Gene / Protein Expression Studies
- Biomarker Discovery
- Biochemical and Cellular Pathway Analysis
- Cell Analysis



Heterogeneous Network Embedding Scalable Manifold Embedding and Viz



Interpretable Pattern Discovery



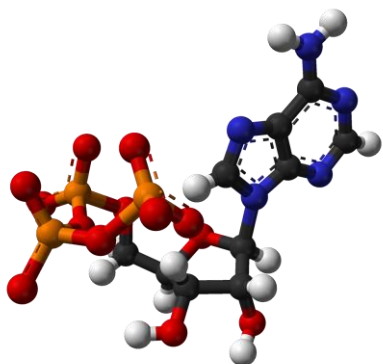
Real Time Filtering and Querying of Biological Networks

$$\begin{aligned}
 &\text{Update } w^{(k)} \text{ based on...} \\
 &\underbrace{\sum_{i=1}^{|N|} \alpha_i \sum_{j=1}^{|N_i|} \sum_{d=1}^D \frac{\delta_{ij}}{\delta_{ij}^2} + s_{ij} \|y_i^{(k)} - y_j^{(k)}\|_2^2}_{\text{Latent Similarity}} + \underbrace{\sum_{i=1}^{|N|} \|(x_i - x_i) \odot b_{i-} - \frac{\delta_i}{\delta_i}\|_2^2}_{\text{Sparse-Bias Reconstruction Loss}} + \underbrace{\lambda \sum_{k=1}^K \|w^{(k)}\|_2^2 + \|w^{(k)}\|_1^2}_{\text{Regularization}} \\
 &\text{Sum over Edge Types} \\
 \\
 &\text{Update } \delta_i \text{ based on...} \\
 &\underbrace{\sum_{d=1}^D \sum_{i=1}^{|N|} \alpha_i \sum_{j=1}^{|N_i|} s_{ij} \|y_i^{(k)} - y_j^{(k)}\|_2^2}_{\text{Latent Similarity}} + \underbrace{\sum_{i=1}^{|N|} \|(x_i - x_i) \odot b_{i-}\|_2^2}_{\text{Sparse-Bias Reconstruction Loss}} \\
 &\text{Sum over Edge Types}
 \end{aligned}$$

Deep Graph Embedding

Insilco Candidate Evaluation

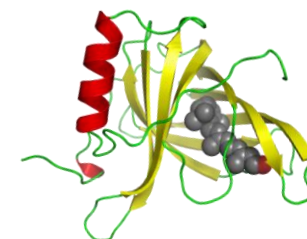
Molecule



Experimentation

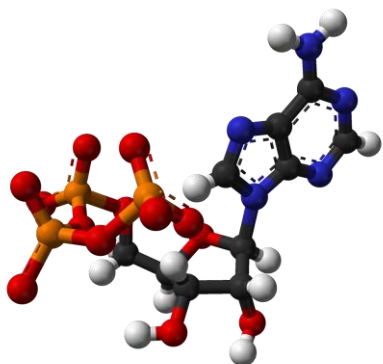


Ground Truth

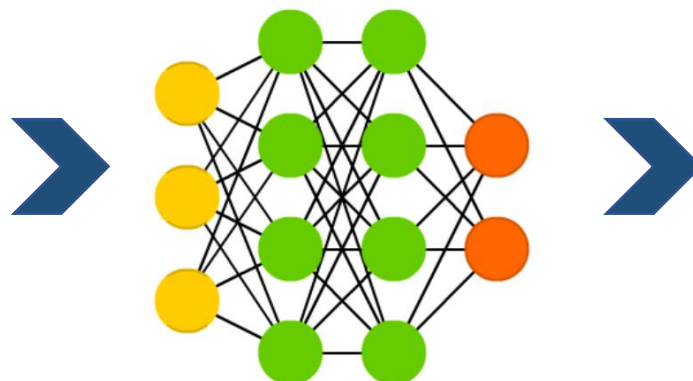


Binds to Protein
(Yes / No)

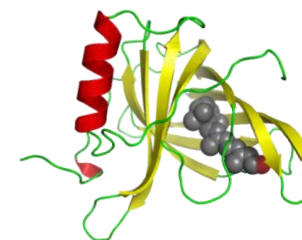
Molecule



Neural Network



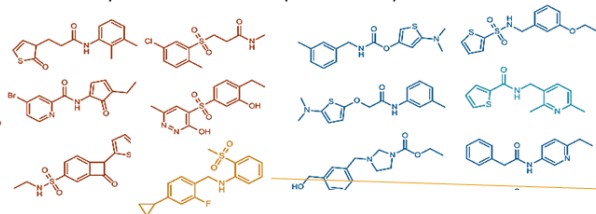
Prediction



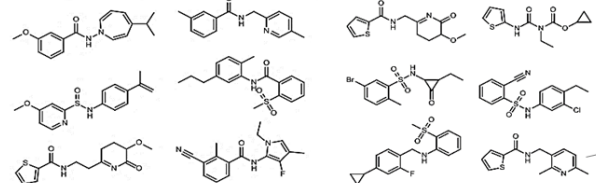
Probability of
Binding (0,1)

Supervised + Unsupervised

A Small Supervised Datasets (10e2-10e4)



B Large Unsupervised Datasets (10e7+)



C Typed Tree Encoder

Negative Labeled Example

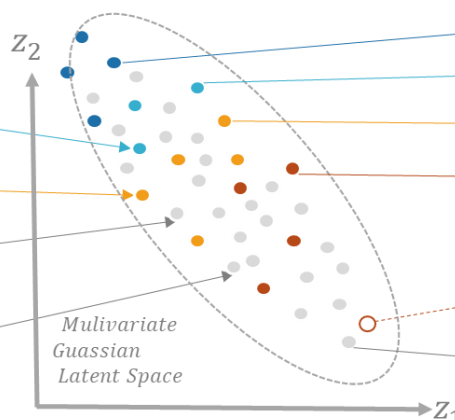
Positive Labeled Example

Un Labeled Example

Un Labeled Example

Variational Autoencoder

D Bayesian Optimization in Generative space



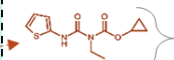
Joint Training

E Multi-Task Network



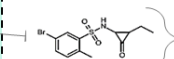
Multi-Task Prediction and Loss

F Typed Tree Decoder



Novel Molecule Suggested by Bayesian Optimization

A3



Unlabeled Molecule and Reconstruction Loss

$$Q(\text{Chemical Structure}) = z$$

$$P(z) = \text{Chemical Structure}$$

Novel Tree Encoder / Decoder Network
+ Regularization of Multiple Roots

Graph Translation Policy Network with External Memory

Machine Translation

English ▷ 中文

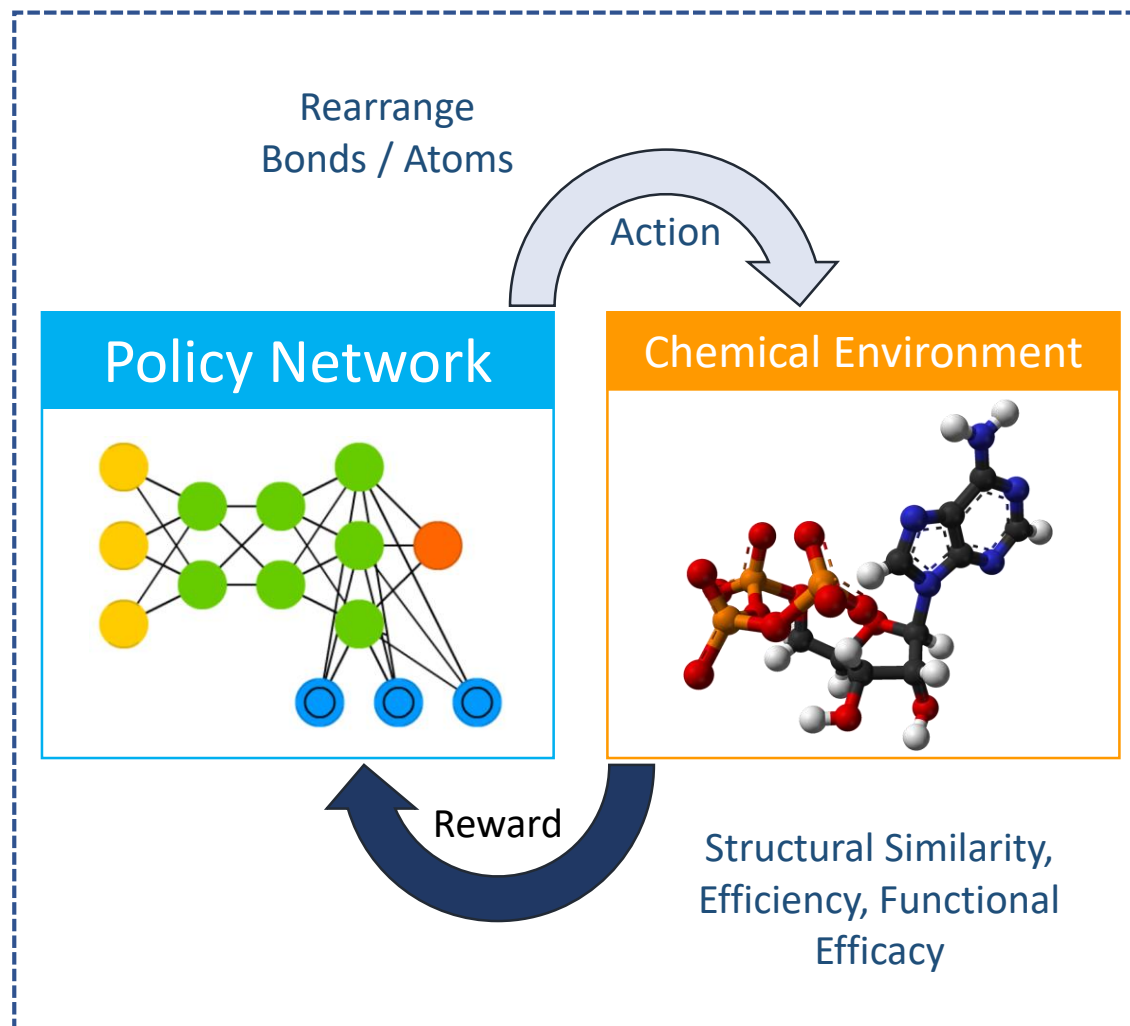
Reactants ▷ Products

Folded ▷ Unfolded

Good ▷ Great Molecule

- ✓ No Compression Bottleneck
- ✓ Arbitrary Input / output
- ✓ Reward Signal better than character level cross entropy

Deep Reinforcement Learning



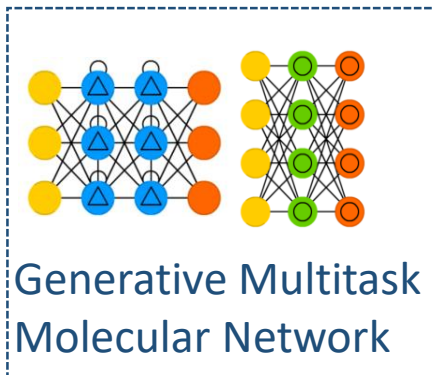
Candidate Search: 3 ways to discover

Pre
2016

Multi-Stage Virtual
Screening

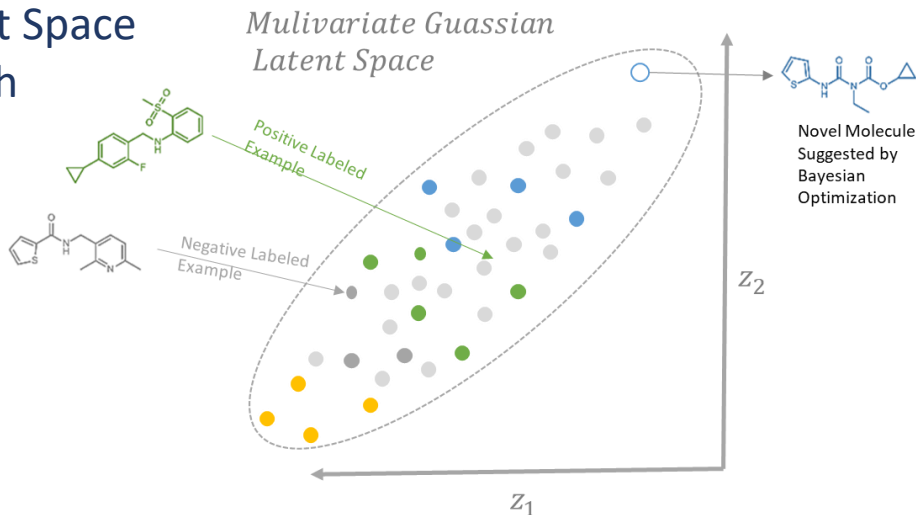


←
Improves

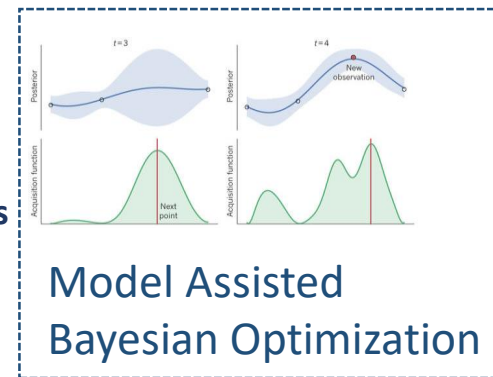


2016

Latent Space
Search

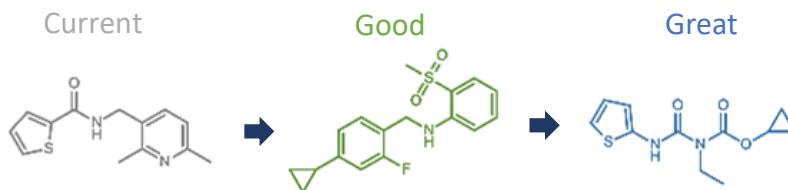


←
Improves

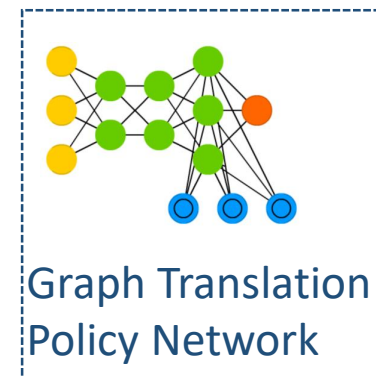


NEW

Search as Recursive
Translation



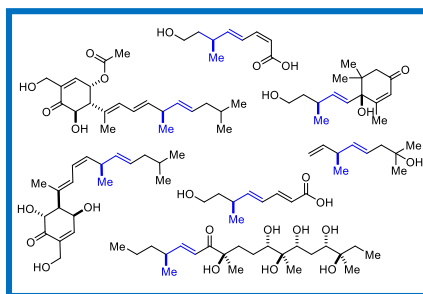
←
Enables for
the 1st Time



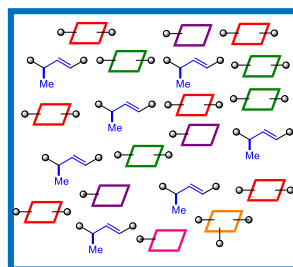
Synthesis Planning

Automation Friendly Natural Product Synthesis Library*

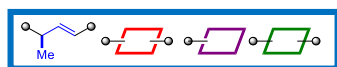
- New Heuristic and Combinatorial Optimization
- New Subgraph Isomorphism Clustering algorithms



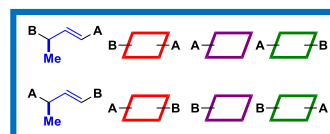
Linear natural products



FRAGMENTS from all allowed retrosyntheses



Smallest set of redundant FRAGMENTS that cover most natural product chemical space

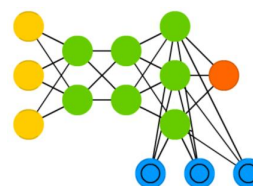
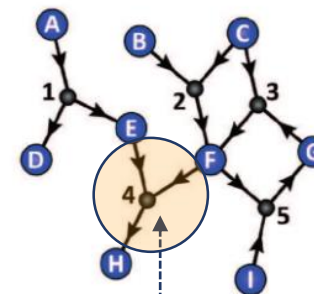


Double the FRAGMENTS to arrive at blocks

Generalized Synthetic Planning

Reactions

- 1) $A \rightarrow D + E$
- 2) $B + C \rightarrow F$
- 3) $C + G \rightarrow F$
- 4) $E + F \rightarrow H$
- 5) $F + I \rightarrow G$



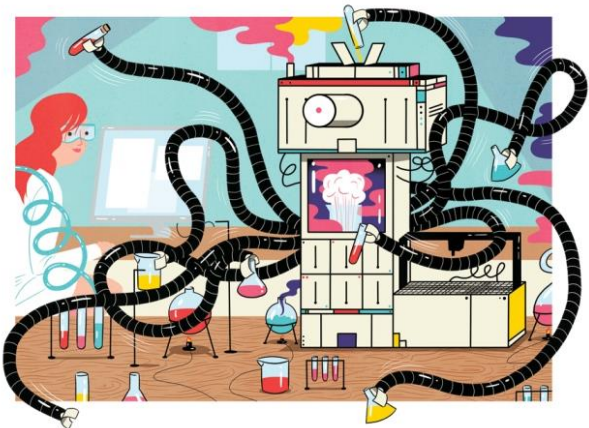
Graph Translation Policy Network

- MCTS based Retrosynthetic Planning can only use existing reactions
- New molecules will require new reactions and the GTPN can be used as a conditional generative model to propose new reactions given end points

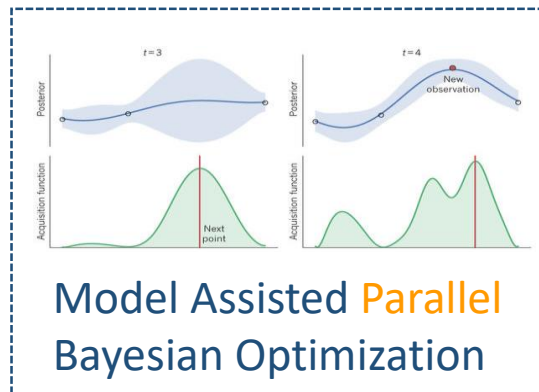
* Martin Burke, Andrea Palazzo, & Claire Simons are leading this endeavor

Optimize Synthesis

Lab Automation



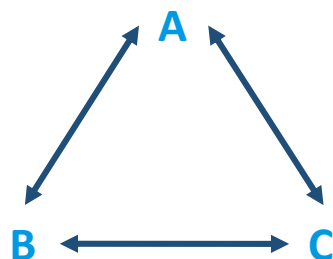
Sequential Decision Making Agent



- I. Pretrained model jointly optimizes over and learns latent distribution
- II. Parallel Bayesian framework enables batch style lab automation
- III. Learns within & between experiment(s)

High Dimensional Sparse Binary Representation

Metric Space Properties

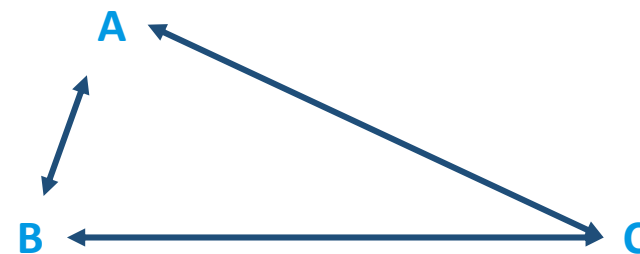


Scaling

N = # of Molecules
 D = Latent Dimensionality

N^2 Scaling

Low Dimensional Dense Real Representation



$N \times D$ Scaling