# Single and Multi-Objective Optimization in Drug Design

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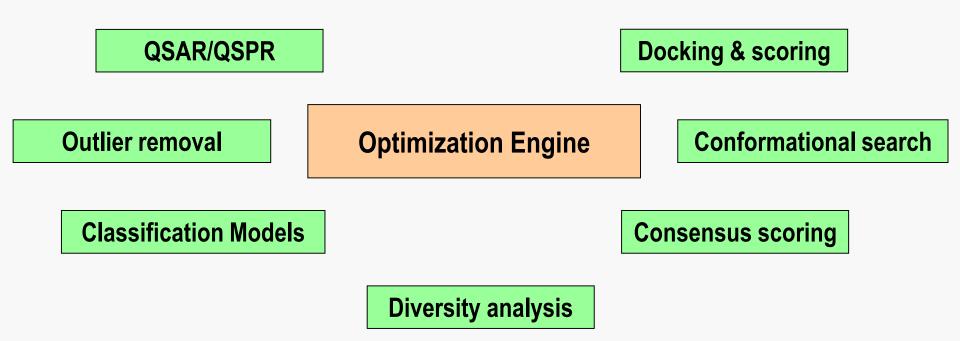
# **Presentation Outline**

- Drug development as an optimization problem
- Single objective optimization (SOOP) and multi objective optimization (MOOP)
- Examples
- Future directions

# **Optimization in Chemoinformatics and Drug Design**

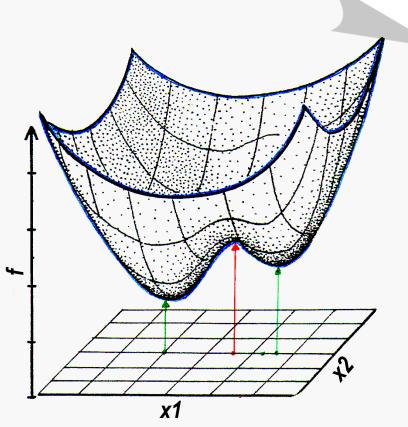
• Many problems in chemoinformatics and drug design could be formulated as (single or multi objectives) optimization problems

## Synthesis design

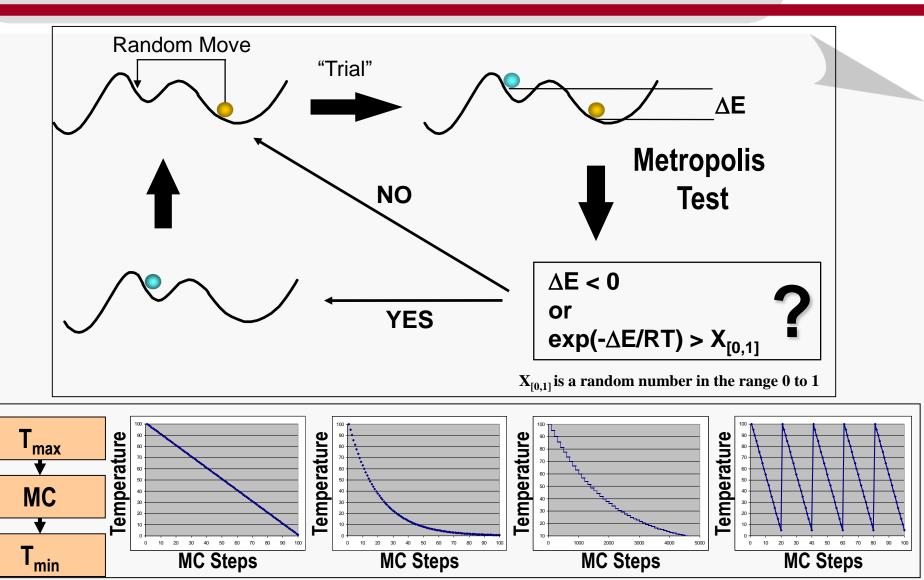


# **Optimization I: Target Function and Variables**

- Define a target function (*f*) and corresponding variables *f* = *f*(*x*<sub>1</sub>, *x*<sub>2</sub>, *x*<sub>3</sub>...*x<sub>n</sub>*)
  - Target function and variables related to the scientific problem
  - Target function and variables define a multi-dimensional surface
- Target function often non-differentiable
- Location of minima is unknown
- Identify minima
  - Global minimum
  - A set of low lying minima



# Optimization II: Monte Carlo/Simulated Annealing (MC/SA) Based Optimization Engine



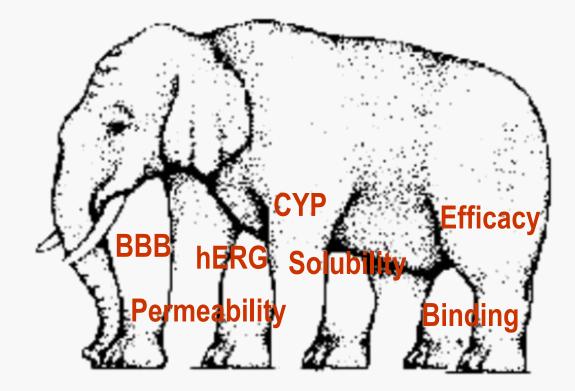
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# **Optimization Problems**

- Single objective
  - \* A global minimum exists (although it may be difficult to locate it)
- Multi objective
  - ✤ To single solution
  - A set of equally good (non-dominated) solutions exist that representing various compromises among the objectives

# Lead Optimization: The Art of Balance

- Successful drug candidates necessarily represent a compromise between numerous, sometimes competing objectives
- Drug design is a multi-objective optimization problem

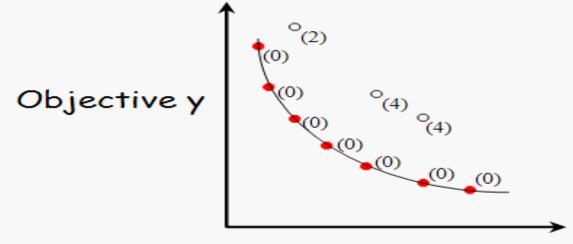


# Strategies for Solving MOOP

Transferring MOOP into SOOP

 $f(n)=w_1$  (Objective<sub>1</sub>)+  $w_2$  (Objective<sub>2</sub>)+...+  $w_n$  (Objective<sub>n</sub>)

Pareto Optimization



#### Objective x

 A set of equally good (non-dominated) solutions, that representing various compromises among the objectives

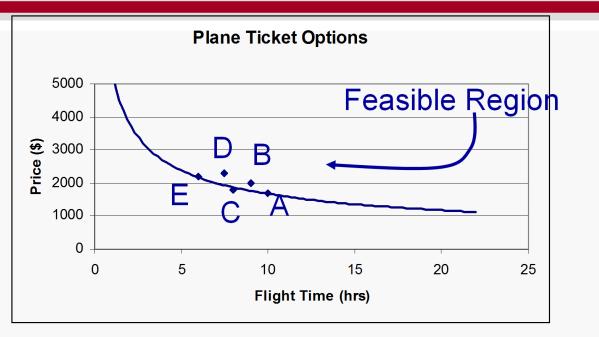
# Pareto Optimization: Example

 Suppose you need to fly on a long trip: Should you choose the cheapest ticket (more connections) or shortest flying time (more expensive)?

Ticket	Time of travel (hr.)	Cost (\$)
А	10	1700
В	9	2000
С	8	1800
D	7.5	2300
Е	6	2200

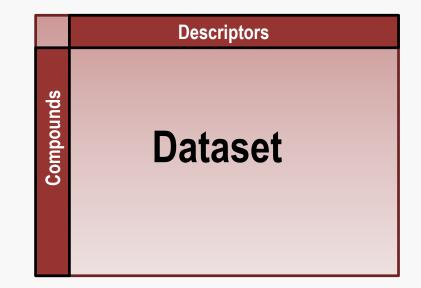
- If we compare tickets A & B, we can't say that either is superior without knowing the relative importance of Travel Time vs. Price
- However, comparing tickets B & C shows that C is better than B in both objectives, so we can say that C "dominates" B
- So, as long as C is a feasible option, there is no reason we would choose B
- If we finish the comparisons, we also see that D is dominated by E
- The rest of the options (A, C, & E) have a trade-off associated with Time vs. Price, so none is clearly superior to the others.
- We call this the "non-dominated" set of solutions become none of the solutions are dominated

# Pareto Optimization: Example



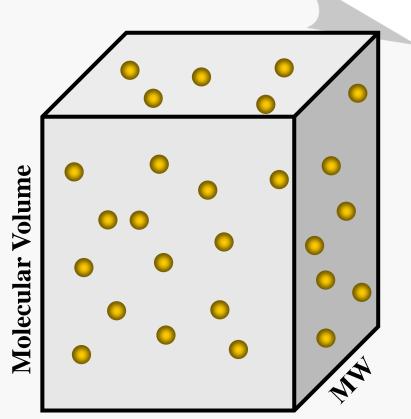
- Solutions that lie along the line are non-dominated solutions while those that lie inside the line are dominated because there is always another solution on the line that has at least one objective that is better
- The line is called the Pareto front and solutions on it are called Pareto-optimal
- All Pareto-optimal solutions are non-dominated
- Thus, it is important in MOO to find the solutions as close as possible to the Pareto front & as far along it as possible

## Dataset



# The Concept of a Property Space

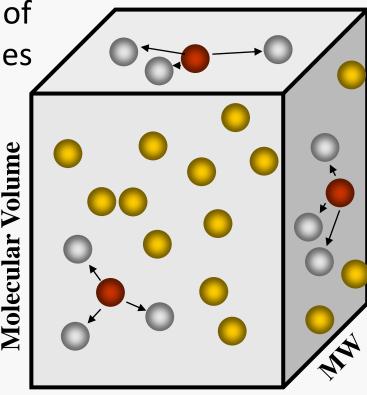
- Each axes describes a molecular property (descriptor).
- Each molecule is represented by a point
- Euclidean distance is calculated in terms of the normalized descriptors
- The distance between any two points represents the degree of similarity between the corresponding molecules in terms of the selected descriptors.



**# of H-bond donors** 

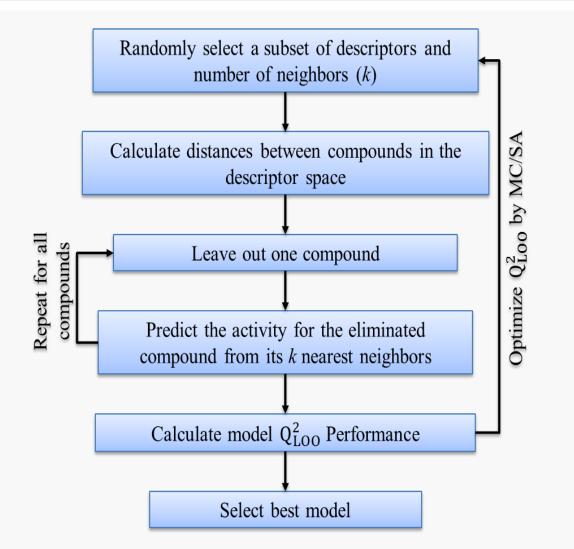
# QSAR Modeling as a SOOP: *k* Nearest Neighbors (*k*NN)

- <u>The idea</u>: Similar compounds have similar activities.
- <u>The method</u>: kNN predicts the activity of a compound from the averaged activities of its k nearest neighbors
- <u>The challenge</u>: Identify the relevant descriptors space
- Advantages: Non-linear



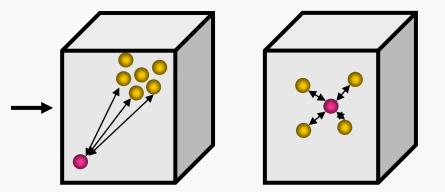
**# of H-bond donors** 

# QSAR Modeling as a SOOP: *k* Nearest Neighbors (*k*NN)



# k Nearest Neighbors (kNN) optimization based outlier removal

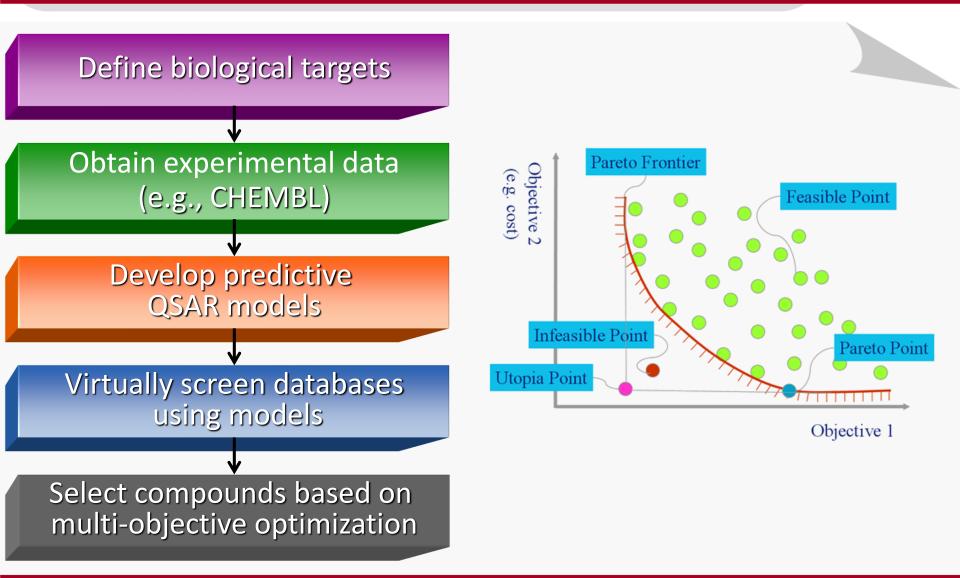
- Remove outliers for a better description of the bulk
- Based on the similar properties principle, predictions over a long distance are less accurate than predictions over a short distance
- Remove the compound which provides the largest increase in  $Q_{LOO}^2$  upon its removal from the data set.
- SOOP => maximizes  $Q_{LOO}^2$
- MOOP => to minimize the number of compounds to be removed and maximizes kNN-derived Q<sup>2</sup><sub>LOO</sub>.



## *stopping criteia* $Q_{LOO}^2 \ge 0.85$

DataBase	Ν	SOOP	МООР	%
LogBBB	152	19	13	32%
F7	355	22	20	9%
DHFR	673	87	75	14%
		AVERAGE		<u>18%</u>

# **QSAR** Modeling as a MOOP



# **Future Directions**

- Introducing MOOP as the method of choice for the optimization of multi-target ligands
- Building a database of QSAR models relevant to the COST action
- Virtual screening using multiple QSAR models (MOOP)

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