



# EVOLUTION OF INHIBITION MODELS FOR FLUORINATED *CINCHONA* ALKALOIDS BY MACHINE LEARNING

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## Background and Objective

- **Alzheimer's disease (AD)** ⇒ one of the most common forms of dementia – chronic syndrome of the CNS
  - *Multifactorial disease* → *difficulties with treatment*
  - *The most successful approach to date: improving cholinergic transmission using **cholinesterase inhibitors***
- **Cholinesterases (ChEs):** acetylcholinesterase (AChE) and butyrylcholinesterase (BChE) → hydrolysis of acetylcholine (ACh)
- Normal conditions: ACh is dominantly decomposed by **AChE**; the physiological role of **BChE** is still unclear
- Progressed AD: level of **AChE** in brain = 55-67% of normal values – level of **BChE** = 120% of normal values
  - **Specific BChE or dual inhibitors** (BChE and AChE) might be a potential therapeutic strategy to be utilized in the treatment of AD
- **Derivatives of *Cinchona* alkaloids** ⇒ proved to be potent BChE inhibitors with high selectivity toward BChE

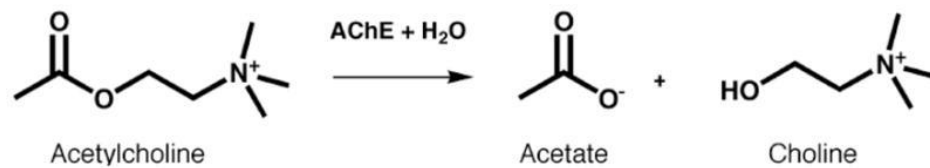
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# Cholinesterases

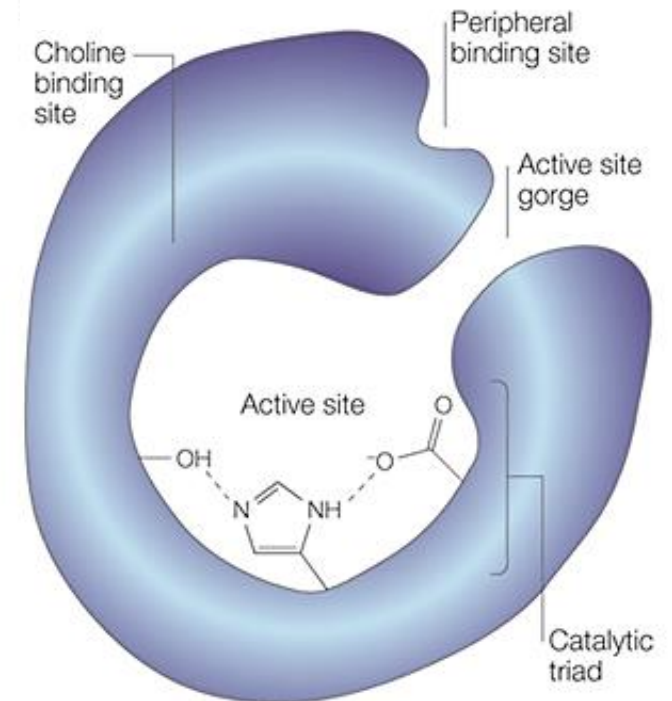
## ■ Enzyme-catalyzed reaction:



## ■ Structure:

- *AChE and BChE share **65%** amino acid sequence homology*
- *Catalytic triad: Ser, His, Glu*

## ■ Turnover number: $\sim 1.5 \times 10^4 \text{ s}^{-1}$



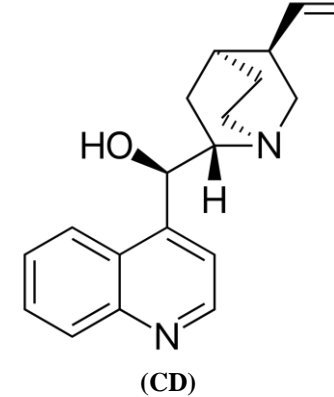
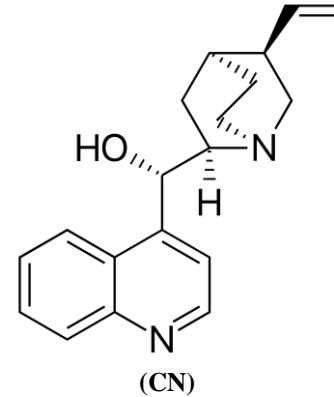
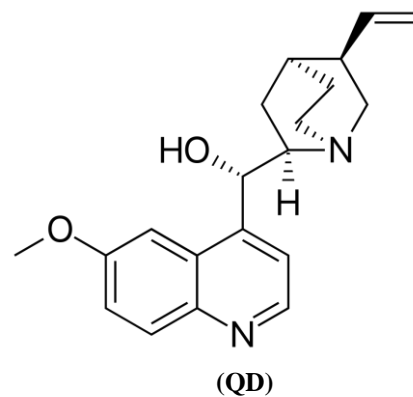
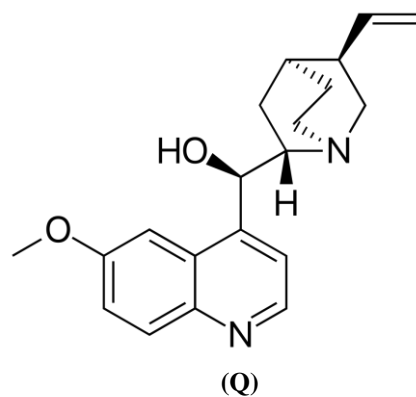
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# Cinchona alkaloids

- **Cinchona alkaloids**  $\Rightarrow$  natural products isolated from the bark of the *Cinchona* tree
- The most researched: quinine (**Q**), quinidine (**QD**), cinchonine (**CN**), and cinchonidine (**CD**)
- Bioactivity

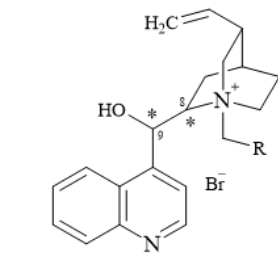


## Methodology

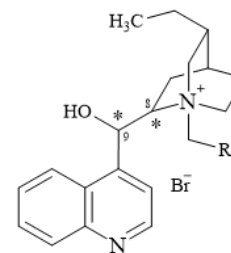
- Creating an activity/PES model using machine learning multivariate linear regression

# Investigated compounds

- A series of **46** *Cinchona* alkaloid derivatives which differ in positions of fluorine atom(s) in the molecule were previously prepared:

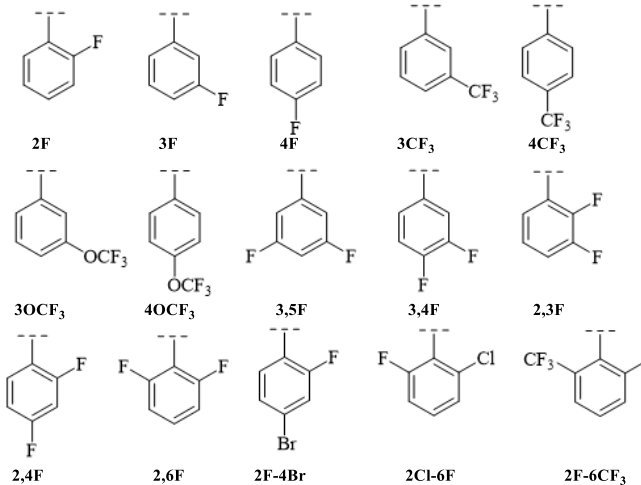


(8*S*, 9*R*)-cinchonidine series (**CD**)  
(8*R*, 9*S*)-cinchonine series (**CN**)



(8*S*, 9*R*)-10,11-dihydrocinchonidine series (**DHCD**)  
(8*R*, 9*S*)-10,11-dihydrocinchonine series (**DHCN**)

R:



## Activity data

- Dissociation constants of the enzyme-inhibitor complex ( $K_i$ )  
⇒ measure of compound's inhibition potency
- **Principal components** of the activity data extracted by 2<sup>nd</sup>-order tensor decomposition using our own program *moonee*

Compound	$K_i/\mu\text{M}$		SI*	Compound	$K_i/\mu\text{M}$		SI*
	BChE	AChE			BChE	AChE	
CD Bzl	0.075±0.007	15±2		CN Bzl	2.9±0.3	121±12	
CD 2F	0.82 ± 0.03	33 ± 1	40	CN 2F	2.4 ± 0.1	80 ± 2	33
CD 3F	0.075 ± 0.005	40 ± 2	533	CN 3F	6.1 ± 0.3	13 ± 0.4	2.1
CD 4F	1.5 ± 0.1	69 ± 3	46	CN 4F	2.6 ± 0.1	3.9 ± 0.2	1.5
CD 3CF <sub>3</sub>	2.4 ± 0.1	34 ± 1	14	CN 3CF <sub>3</sub>	4.4 ± 0.2	59 ± 2	13
CD 4CF <sub>3</sub>	2.0 ± 0.1	21 ± 1	11	CN 4CF <sub>3</sub>	6.0 ± 0.3	31 ± 1	5.2
CD 3,5F	0.081±0.01	10±1	123	CN 3,5F	6.3 ± 0.2	34 ± 3	5.4
CD 3,4F	1.3 ± 0.1	13 ± 1	10	CN 3,4F	6.1 ± 0.2	14 ± 0.2	2.3
CD 2,3F	0.75 ± 0.03	19 ± 1	25	CN 2,3F	9.6 ± 0.4	46 ± 3	4.8
CD 2,4F	6.1 ± 0.5	6.4 ± 0.3	1.1	CN 2,4F	6.0 ± 0.2	27 ± 1	4.5
CD 2,6F	9.9 ± 0.4	7.7 ± 0.5	0.77	CN 2,6F	5.2 ± 0.2	30 ± 2	5.8
CD 3OCF <sub>3</sub>	7.4 ± 0.4	8.2 ± 1.1	1.1	CN 3OCF <sub>3</sub>	4.7 ± 0.2	41 ± 2	8.7
CD 4OCF <sub>3</sub>	7.6 ± 0.5	7.3 ± 0.5	0.96	CN 4OCF <sub>3</sub>	7.8 ± 0.3	19 ± 2	2.4
CD 2F-6CF <sub>3</sub>	5.7 ± 0.6	35 ± 4	6.1	CN 2F-6CF <sub>3</sub>	7.7 ± 0.4	61 ± 2	7.9
CD 2F-4Br	0.68 ± 0.05	7.2 ± 0.4	10	CN 2F-4Br	5.5 ± 0.3	16 ± 1	2.9
CD 2Cl-6F	5.0 ± 0.3	9.9 ± 0.8	1.9	CN 2Cl-6F	1.2 ± 0.0	17 ± 1	14
DHCD	19±2	206±6	11	DHCN	1.2±0.1	43±2	43
DHCD Bzl	0.4±0.02	4.8±0.4	12	DHCN Bzl	0.9x±0.04	21±1	23
DHCD 3F	0.3±0.02	27±2	84	DHCN 3F	1.2±0.1	20±1	20
DHCD 4F	4.3±0.2	31±1	8	DHCN 4F	1.6±0.1	64±2	40
DHCD 3CF <sub>3</sub>	1.4±0.1	25±1	18	DHCN 3CF <sub>3</sub>	1.2±0.05	41±2	34
DHCD 4CF <sub>3</sub>	3.2±0.2	15±1	5	DHCN 4CF <sub>3</sub>	1.6±0.1	18±1	9
DHCD 3OCF <sub>3</sub>	6.8±0.3	36±1	5	DHCN 3OCF <sub>3</sub>	1.3±0.5	68±1	52
DHCD 4OCF <sub>3</sub>	5.9±0.2	17±1	3	DHCN 4OCF <sub>3</sub>	2.2±0.1	22±1	10

\* SI denotes stereoselective index calculated from  $K_i(\text{AChE})/K_i(\text{BChE})$



## Potential energy surfaces (PES)

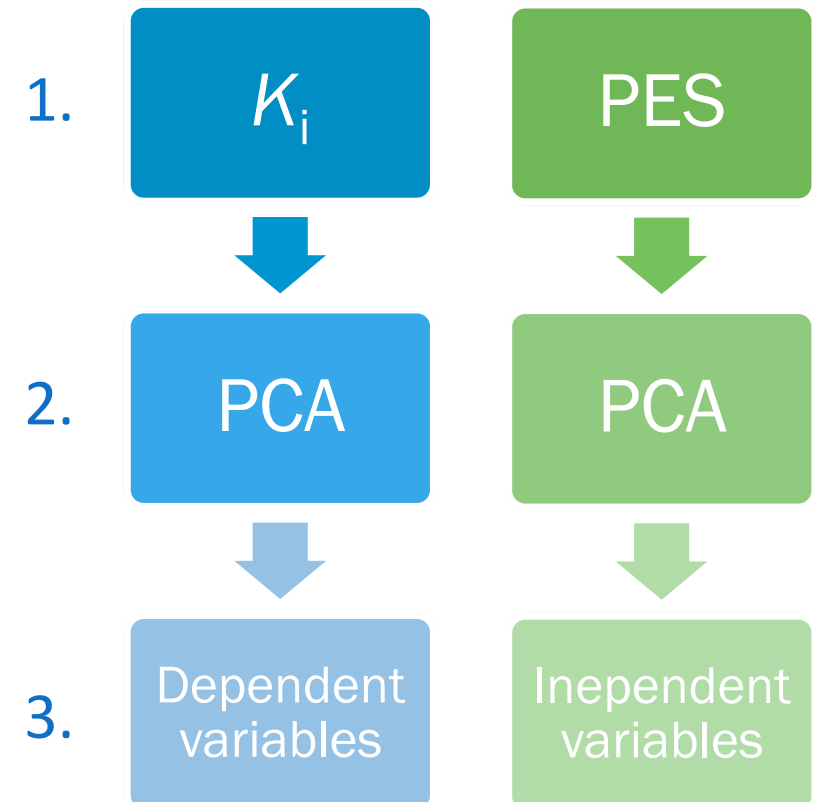
- **Potential energy surfaces (PES)** were sampled by performing *ab initio* molecular dynamics simulations using our own program **qcc**:
  - *On-the-fly calculations of forces in each point of the simulation using the semi-empirical PM7 Hamiltonian implemented in MOPAC2016*
  - *Integration: velocity Verlet algorithm with a 0.5 fs step size*
  - *Initial temperature: 773.15 K; kept constant using a velocity scaling algorithm*
  - *Total length of the simulation: 2.5 ps (total of 5 000 000 steps for each compound)*
- Construction of **strict local maxima plateaus** by counting all strict local maxima points in the probability distribution functions  $\Rightarrow$  criterion for conformational space coverage
- Multidimensional PES were reduced in dimension by principal component analysis

## Generating principal components

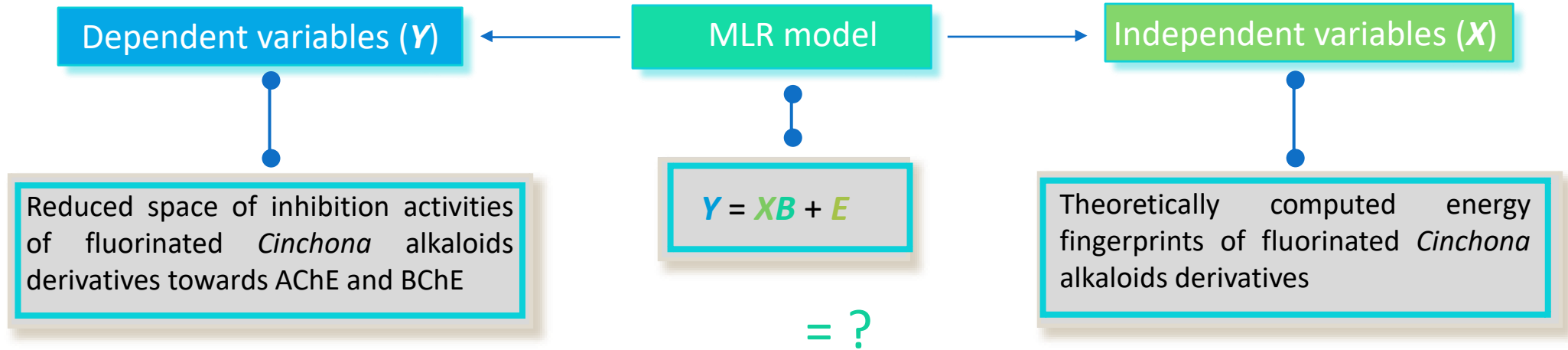
### ■ Principal components analysis (PCA): eigenvalues and

eigenvectors of the covariance matrix  $C_X = \frac{1}{n}XX^T$

1. Data ( $K_i$  or PES of CD, CN, DHCD and DHCN, and 46 of their derivatives – total of 50 compounds) were:
  - exported to the ASCII format,
  - *arranged* in the matrix  $X$  with numbers written in a free format,
  - *mean-centered*
2. PCA on the covariance matrix was carried out using our own multivariate analysis code *moonee* based on the NIPALS algorithm
3. The most important principal components were used as dependent or independent variables in multivariate linear regression



# Multivariate linear regression (MLR) model



$$\begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1p} \\ y_{21} & y_{22} & \cdots & y_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ y_{n1} & y_{n2} & \cdots & y_{np} \end{bmatrix} = \begin{bmatrix} 1 & x_{11} & x_{12} & \cdots & x_{1m} \\ 1 & x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \cdot \begin{bmatrix} b_{01} & b_{02} & \cdots & b_{0p} \\ b_{11} & b_{12} & \cdots & b_{1p} \\ b_{21} & b_{22} & \cdots & b_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ b_{m1} & b_{m2} & \cdots & b_{mp} \end{bmatrix} + \begin{bmatrix} e_{11} & e_{12} & \cdots & e_{1p} \\ e_{21} & e_{22} & \cdots & e_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ e_{n1} & e_{n2} & \cdots & e_{np} \end{bmatrix}$$

- $n$  – number of samples
- $m$  – number of independent variables
- $p$  – number of dependent variables

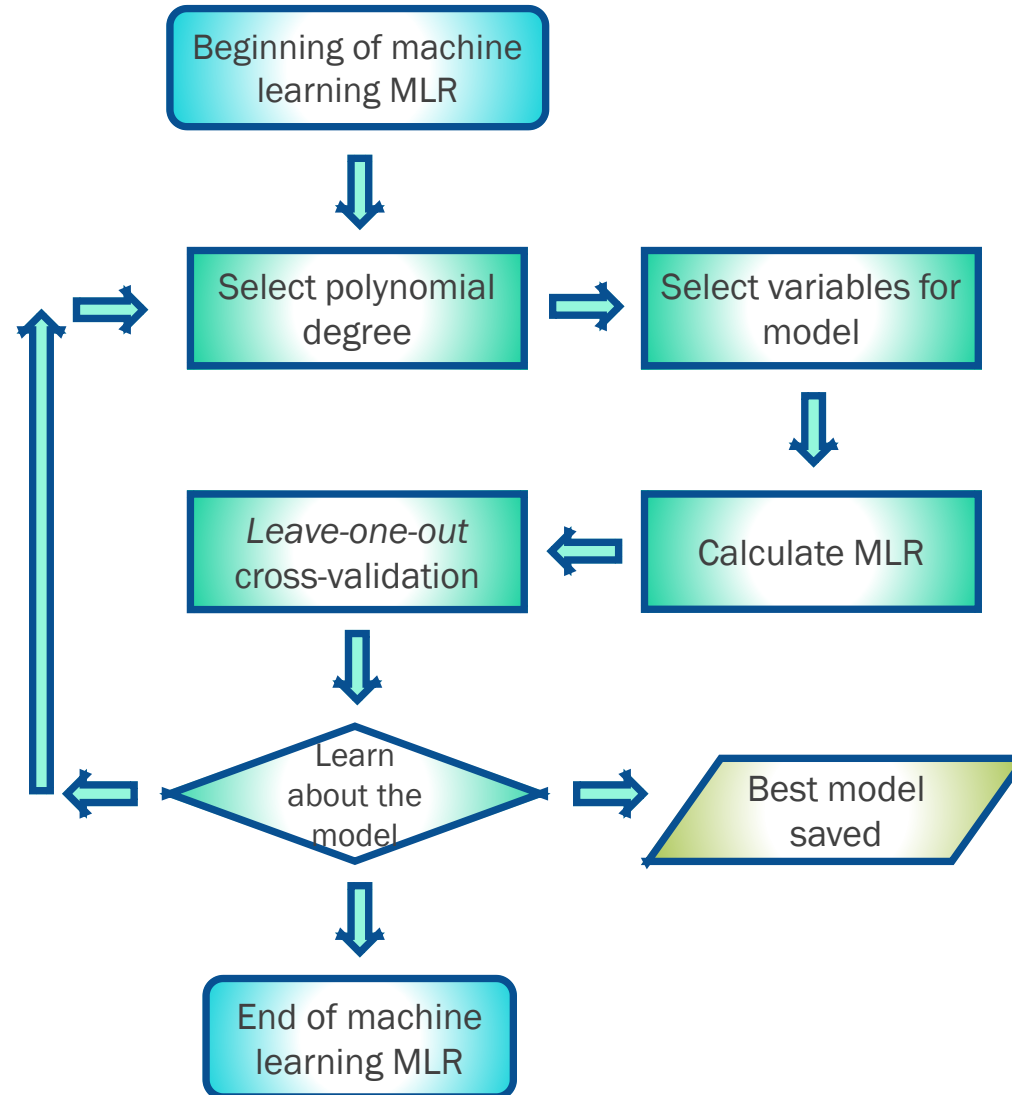
## Machine learning multivariate linear regression (ML-MLR)

- **Multivariate linear regression** was performed using the following expression for matrices of coefficients  $\mathbf{B}$  calculated by singular value decomposition:

$$\mathbf{B} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{Y}$$

- An **extensive machine learning procedure** was applied for generating multivariate linear regression models with linear combination of original variables as well as their higher-order polynomial terms
- Models were thoroughly validated by the ***leave-one-out cross-validation*** technique (LOO-CV)

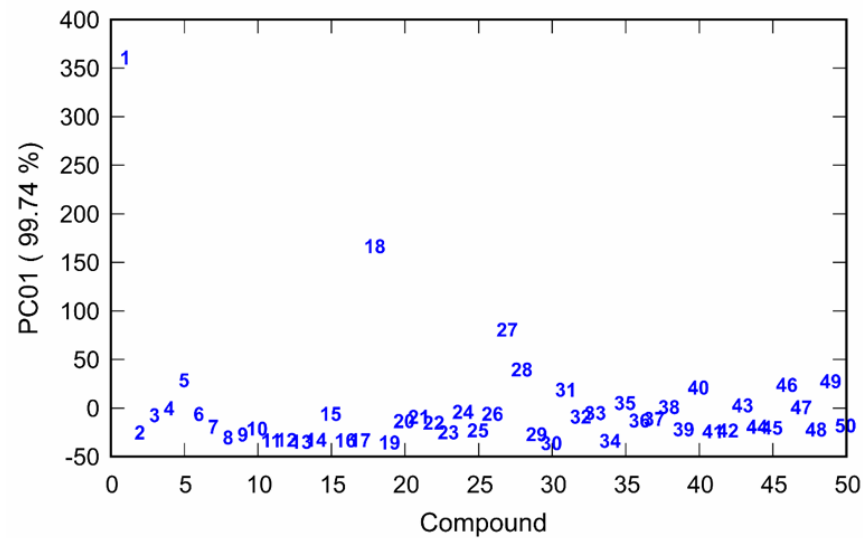
# Machine learning (ML)



# Results

## Classification model based on activities

- PCA on the mean-centered covariance matrix of *Cinchona* alkaloids derivatives inhibition of AChE and BChE showed that the **first** principal component explained more than **99.74%** of the total variance among the data
  - The 1<sup>st</sup> component is the most important in describing the inhibition activity of the compounds
- Possibility of **visualization**



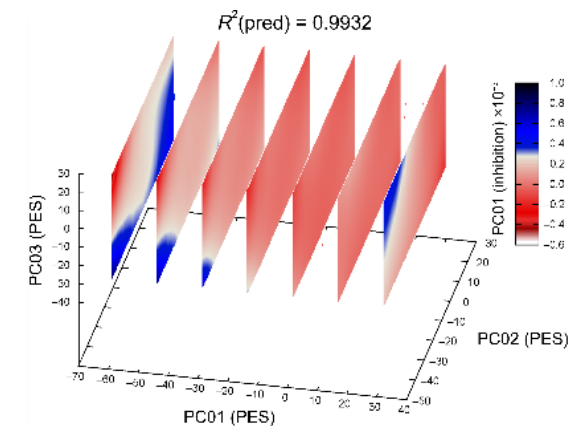
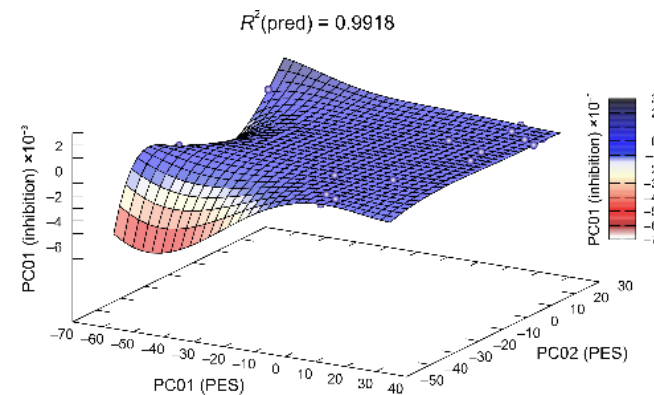
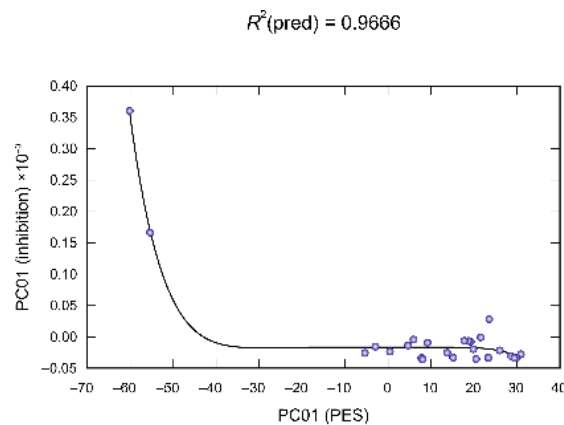
## Activity/PES models

- Models were created using the the **first three** principal components of the reduced PES data and the **1<sup>st</sup>** principal component for inhibition of AChE and BChE
- All possible regression models were generated, and the ***B***-matrices of coefficients were determined
- **Machine learning** was used to determine the best possible regression model
- **3D models** were inspected up to the fourth order, and the total number of investigated models in each case was 17 179 869 184



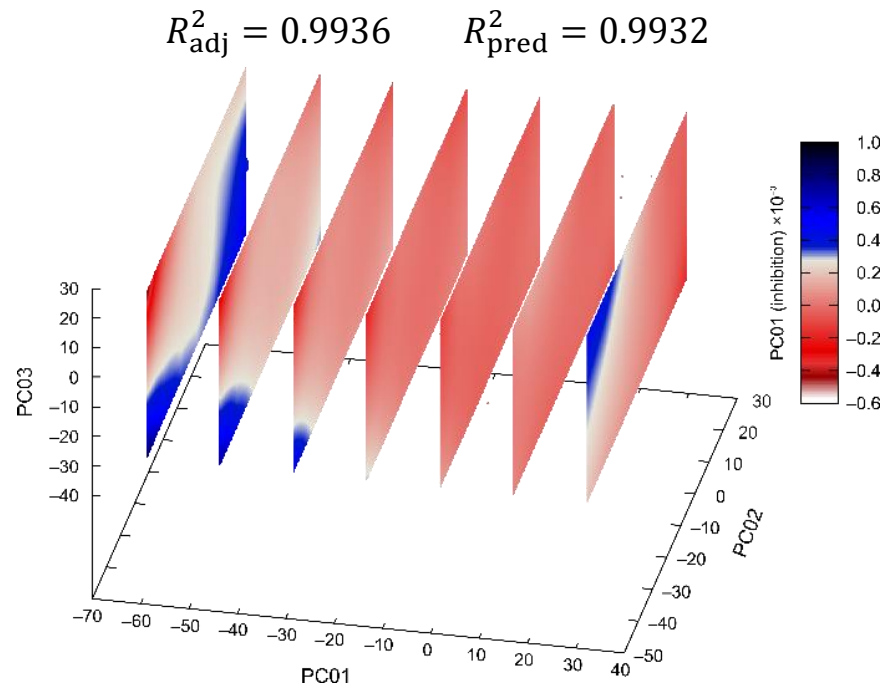
# Evolution of regression models

- Optimal activity/PES models were selected based on the adjusted and predicted  $R^2$  values, LOO-CV mean squared error, as well as the number of variables in the models
- Progression of the best inhibition models for fluorinated *Cinchona* alkaloids derivatives depending on domain dimensionality:



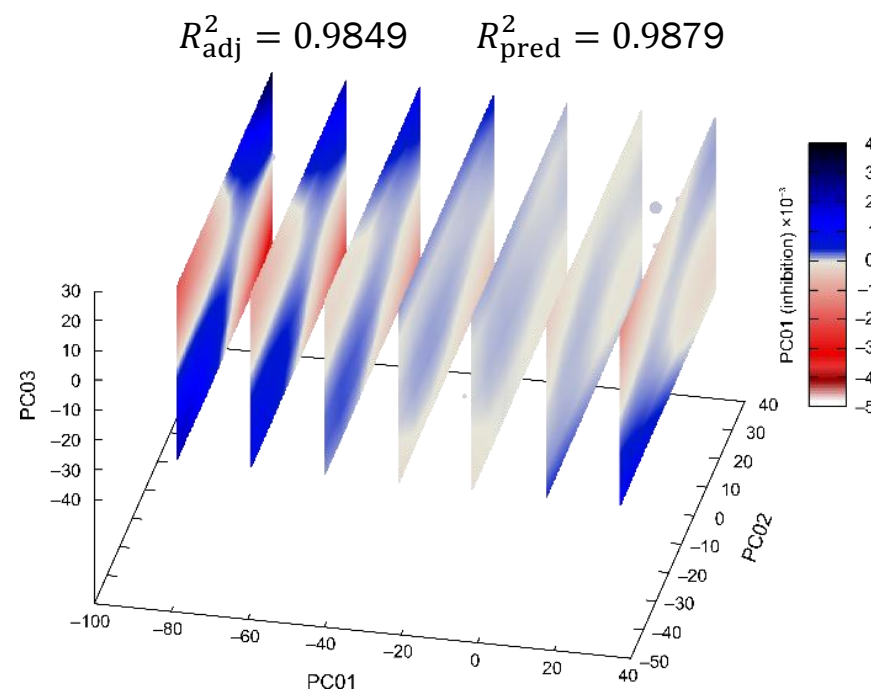
## The best regression model

- The 1<sup>st</sup> principal component for flourinated **CD**-derivatives inhibition of AChE and BChE was regressed on compounds' theoretically computed energy fingerprints, and the best calculated 3D regression model was determined by machine learning:



## The best regression model

- The 1<sup>st</sup> principal component for flourinated **CN**-derivatives inhibition of AChE and BChE was regressed on compounds' theoretically computed energy fingerprints, and the best calculated 3D regression model was determined by machine learning:



## Conclusion

- Activity and PES data were reduced in dimension by a 2<sup>nd</sup> order tensor decomposition tool, PCA.
- The best multivariate linear regression models describing the relationship between activity and PES were determined by machine learning.
- The best activity/PES models can be (and were) used for prediction of inhibition activities for new compounds based only on their theoretically computed PES.
- *N*-quaternary derivatives of *Cinchona* alkaloids proved to be an excellent scaffold for further research towards finding selective cholinesterase inhibitors.

Thank you!