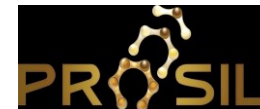


QSAR and computational tools



The Nobel Prizes in Chemistry 1998, 2013

The Nobel Prize in Chemistry 2013 has gone to Michael Levitt, Martin Karplus and Arieh Warshel, who “took the chemical experiments into cyberspace”



The second prize after the Nobel Prize in 1998 to John Pople and Alter Kohn for computational chemistry



Chemistry and cyberspace

All science is computer science (*New York Times*)

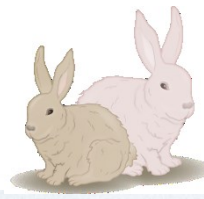
Millions of data to be processed, more and more common

In silico methods like the glue to integrate multiple evidences

Seven Reasons

to use QSAR

1. **Innovation** (also in view of millions of new data - ToxCast)
2. **Time for experiments**
3. **Occurrence of enough laboratories/resources**
4. **Reduction of costs**
5. **Use of animals**
6. **Prioritization needs**
7. **Pro-active approach for greener chemicals**

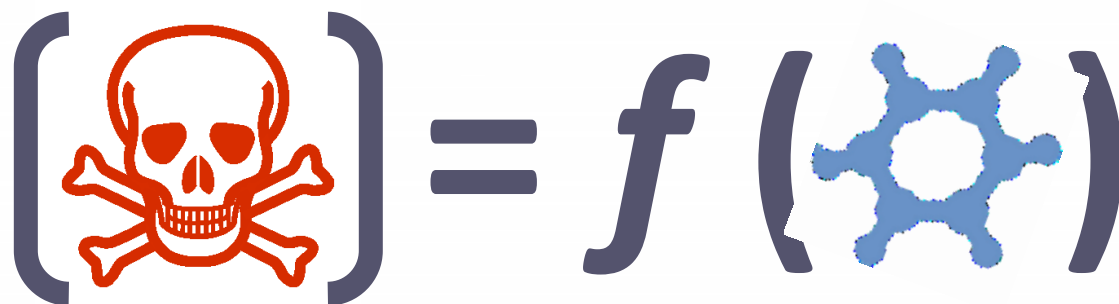




(Q)SAR

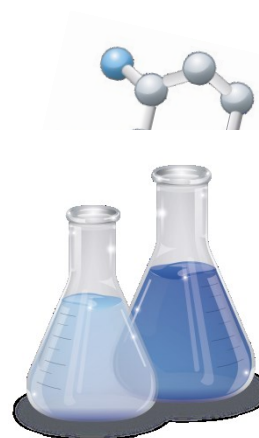
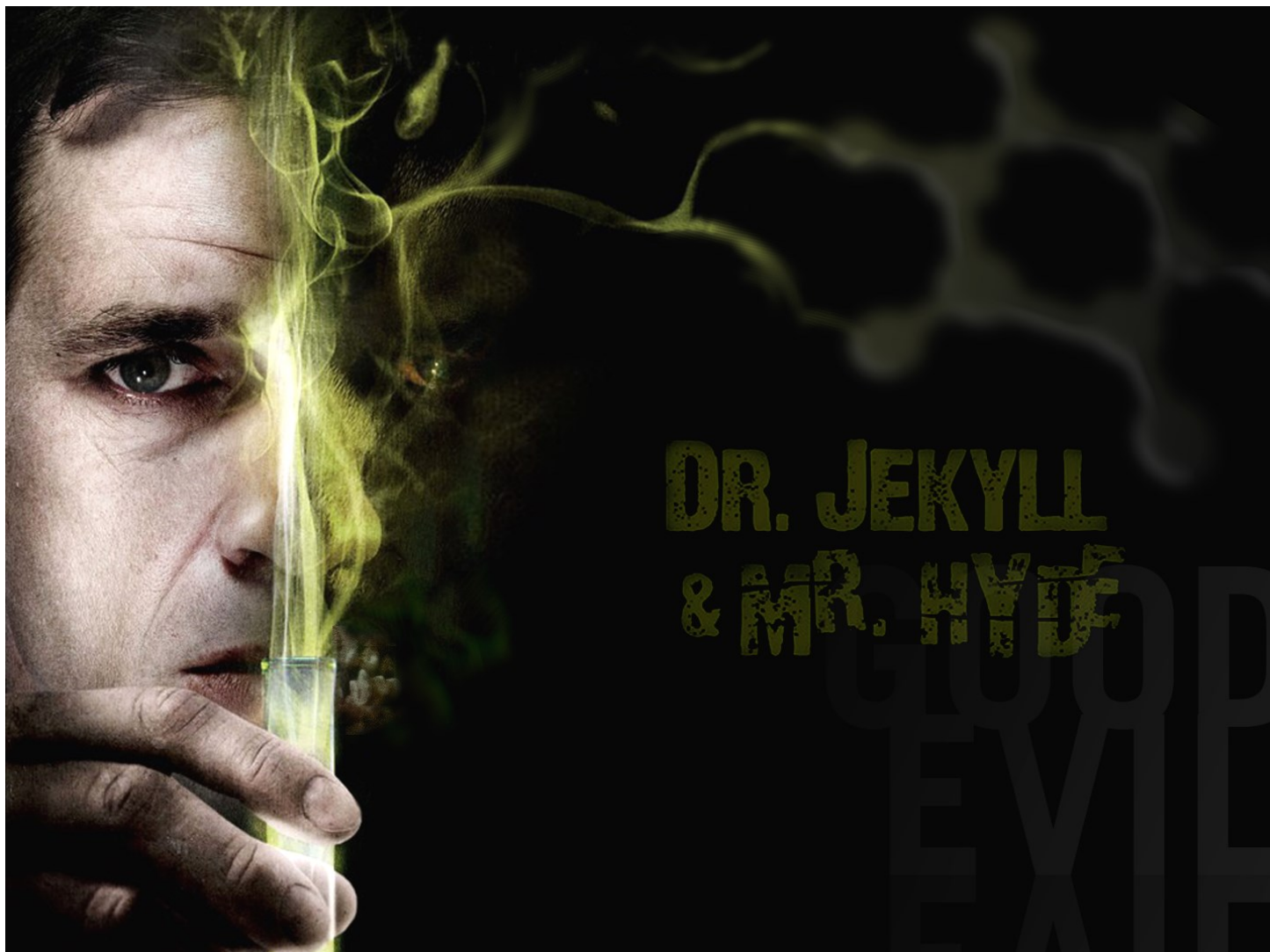
=

(Quantitative) Structure-activity relationship

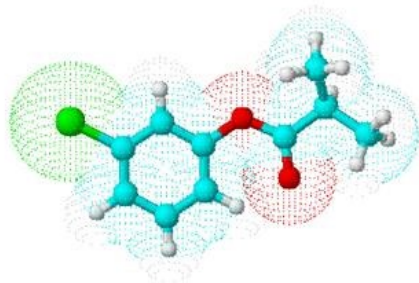


IN SILICO

CHEMICALS: GOOD and EVIL



QSAR flow-chart

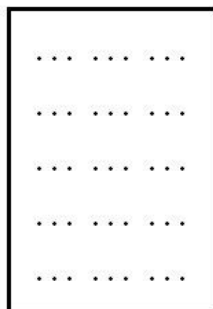


Molecular structure

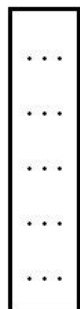


$$y = f(x)$$
$$f(x)?$$

Activity
(e.g.: ER binding affinity)



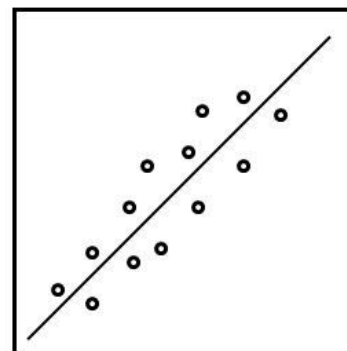
X
Molecular
descriptors



Y
Response
variable



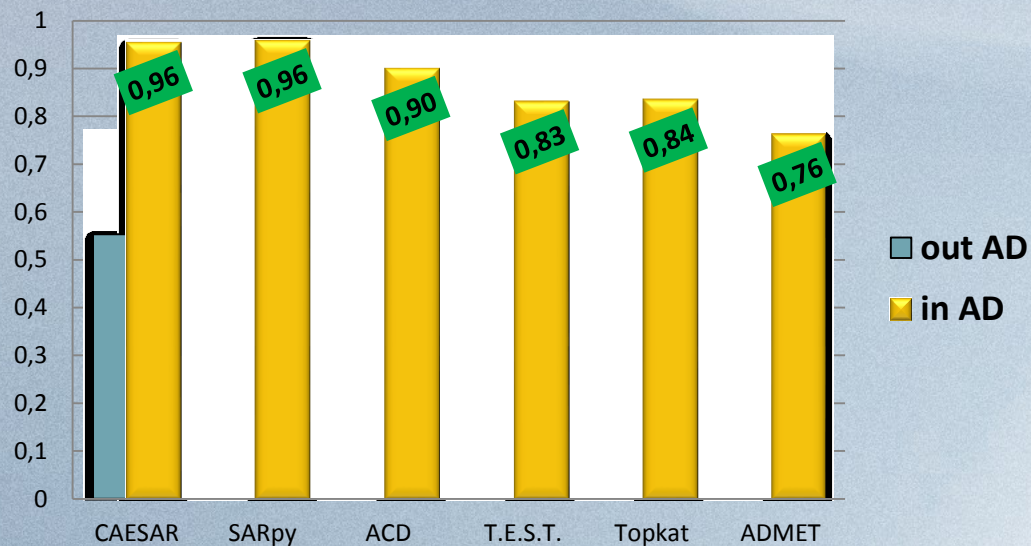
**Statistical
Analysis**



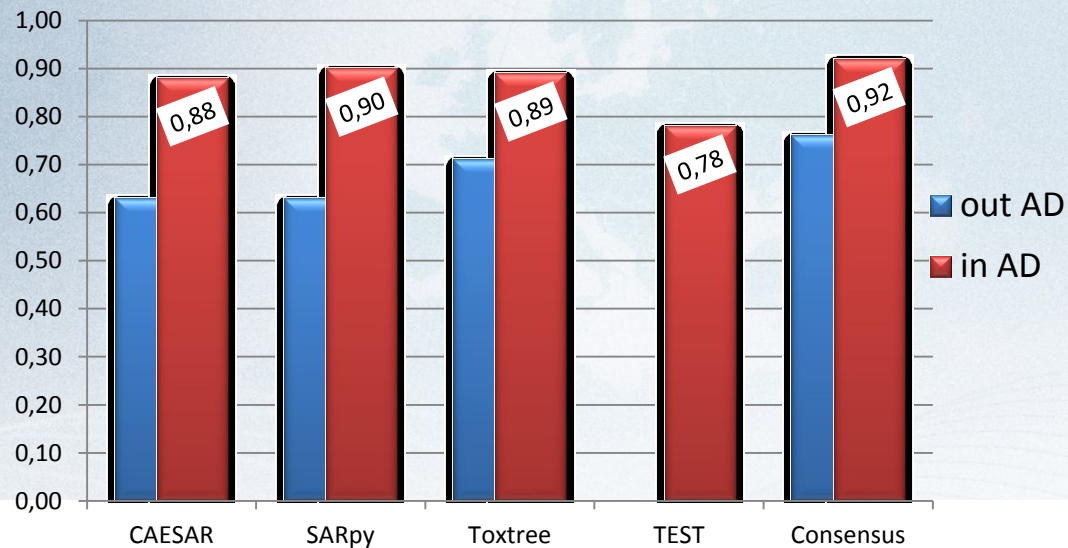
Validation
of QSAR



MUTAGENICITY: Performance of QSAR models



$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP}$$



Issues: Work in progress

- *Max accuracy for carcinogenicity models: 0.75 (Toxtree, in VEGA)*
- *Max accuracy for devtox models: 0.78 (SARpy + P&G, in VEGA), but MCC 0.24 (false negatives)*
- Problem 1: Complexity of the endpoints
- Problem 2: Lack of data



Our Vision

Our Mission

News & Updates

September 21

ANTARES list of predicting software for several REACH endpoints available

September 12

VEGA announced at the EUROTOX conference, Paris 2011

VegaNIC - VEGA Non-Interactive Client - version 1.1.0

Select models

VEGA NIC

Tox Ecotox Environ Phys-Chem

- Mutagenicity (Ames test) model (CAESAR) - v. 2.1.13
- Mutagenicity (Ames test) model (SarPy/IRFMN) - v. 1.0.7
- Mutagenicity (Ames test) model (ISS) - v. 1.0.2
- Mutagenicity (Ames test) model (KNN/Read-Across) - v. 1.0.0
- Carcinogenicity model (CAESAR) - v. 2.1.9
- Carcinogenicity model (ISS) - v. 1.0.2
- Developmental Toxicity model (CAESAR) - v. 2.1.7
- Developmental/Reproductive Toxicity library (PG) - v. 1.0.0
- Relative Binding Affinity model (IRFMN) - v. 1.0.1
- Skin Sensitisation model (CAESAR) - v. 2.1.6

All models

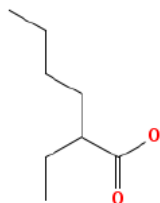
INSERT

SELECT

EXPORT

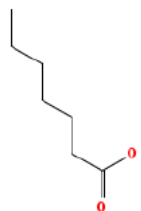
PREDICT

3.1 Applicability Domain: Similar Compounds, with Predicted and



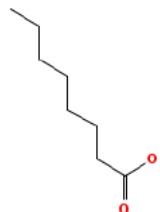
CAS: 149-57-5
Dataset id: 536 (Training s
SMILES: O=C(O)C(CC)C
Similarity: 0.989

Experimental value: NON-
Predicted value: NON-Mu



CAS: 111-14-8
Dataset id: 86 (Training s
SMILES: O=C(O)CCCC
Similarity: 0.946

Experimental value: NON-
Predicted value: NON-Mu



CAS: 124-07-2
Dataset id: 418 (Training
SMILES: O=C(O)CCCCC
Similarity: 0.941

Experimental value: NON-
Predicted value: NON-Mu

3.2 Applicability Domain: Measured Applicability Domain Scores



Global AD Index

AD index = 0.978

Explanation: the predicted compound is into the Applicability Domain of the model.



Similar molecules with known experimental value

Similarity index = 0.956

Explanation: strongly similar compounds with known experimental value in the training set have been found.



Accuracy of prediction for similar molecules

Accuracy index = 1

Explanation: accuracy of prediction for similar molecules found in the training set is good.



Concordance for similar molecules

Concordance index = 1

Explanation: similar molecules found in the training set have experimental values that agree with the predicted value.



Model's descriptors range check

Descriptors range check = True

Explanation: descriptors for this compound have values inside the descriptor range of the compounds of the training set.



Atom Centered Fragments similarity check

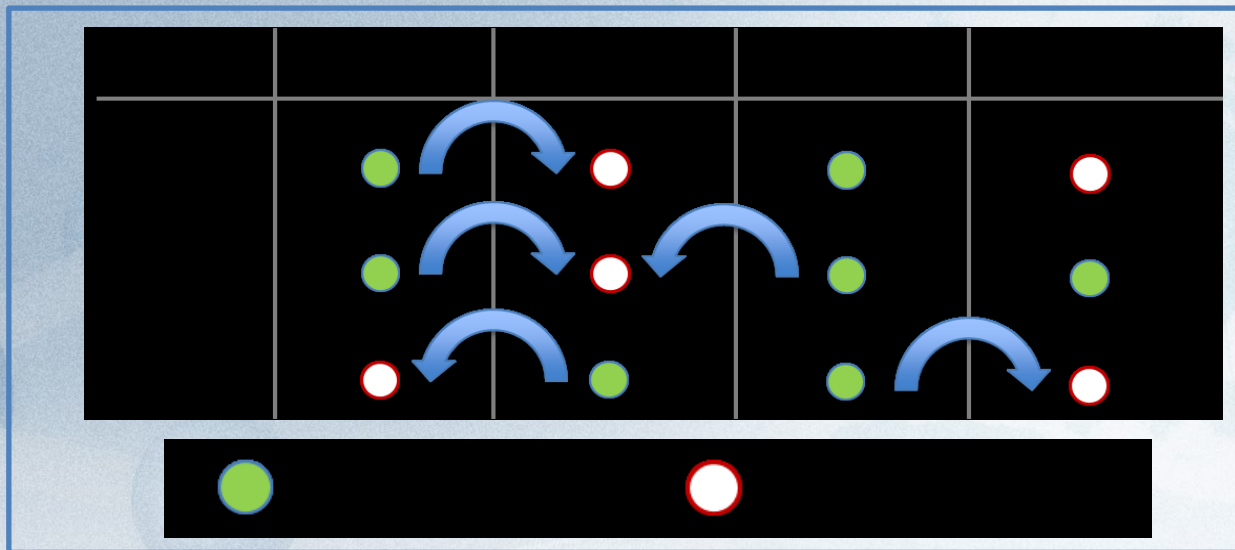
ACF index = 1

Explanation: all atom centered fragment of the compound have been found in the compounds of the training set.

Read-across

Read-across: a correlation or relationship between two separate things

From a chemical point of view: Read-across is a method for data-gap filling where information from one or more chemicals is used to predict the same endpoint for a target chemical





toxRead

- is a software to assist user in making reproducible read across evaluations.
- shows the similar chemicals, structural alerts and relevant features in common between chemicals.

Libraries



Chemicals with associated experimental values

Libraries of chemicals with associated experimental values were checked and originated from the LIFE projects ANTARES, CALEIDOS and PROSIL.



Structural alerts and algorithms of relevant features

Structural alerts derive and relevant features libraries originated from the used within VEGA, ToxTree, and other lists developed within the LIFE projects CALEIDOS and PROSIL, also in collaboration with CRS4

Sources

The list of chemical libraries have been checked and originated from:



Downloads



Developers



POLITECNICO DI MILANO





Details of rule MN...

Details of rule MNM249

Name: MNM249
 Description: IRFMN alert n. 249 for NON-Mutagenicity, define...
 Experimental accuracy: 1
 Fisher test p-value: 0.00183

List of molecules where the rule applies (max: 100)

Load molecules

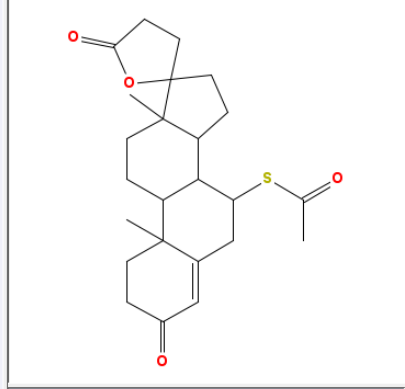
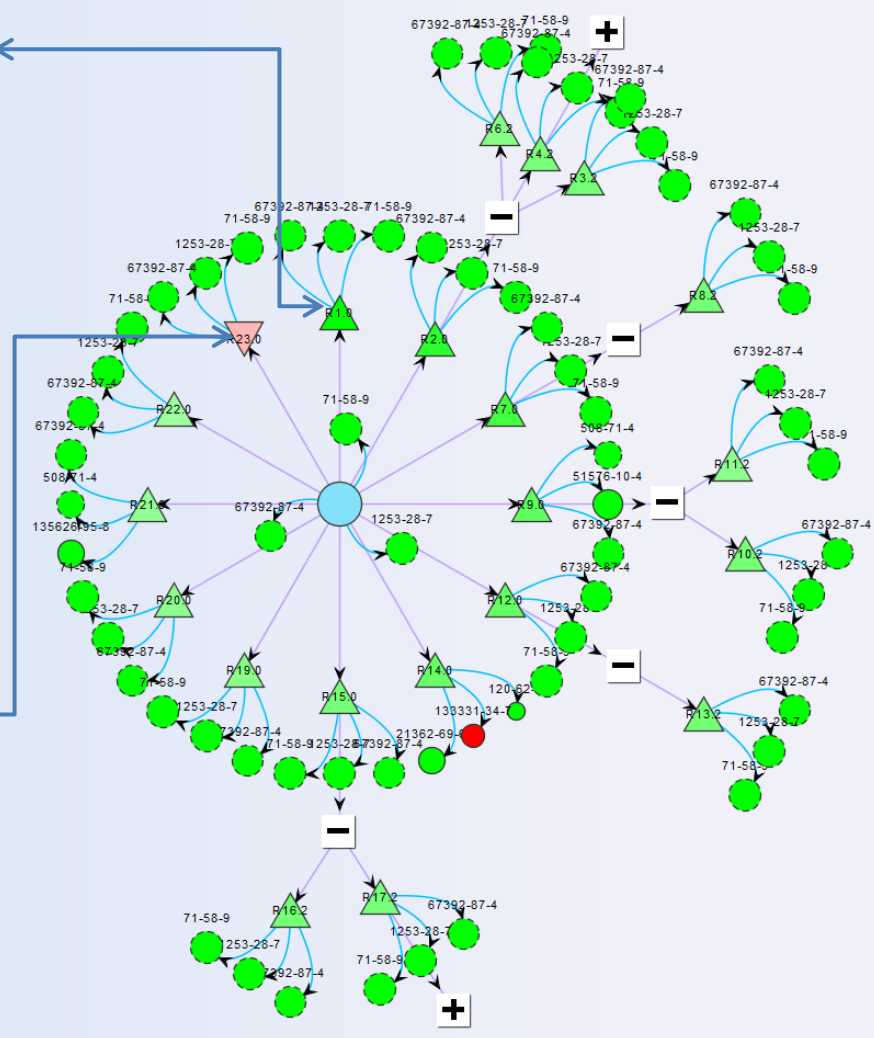
Details of rule SA10

Details of rule SA10

Name: SA10
 Description: Alpha,beta unsaturated carbonyls (Benigni/Bosschi...
 Experimental accuracy: 0.49
 Fisher test p-value: 0.01488

List of molecules where the rule applies (max 100)

Load molecules



Molecular Weight: 414.98
 LogP (experimental): 2.52

Label	Rule Set
R10.2	Sarpy alert n. 163 for NON-Mutagenicity, define...
R23.0	Alpha,beta unsaturated carbonyls (Benigni/Boss...
R6.2	Sarpy alert n. 188 for NON-Mutagenicity, define...
R11.2	Sarpy alert n. 177 for NON-Mutagenicity, define...
R17.2	Sarpy alert n. 169 for NON-Mutagenicity, define...
R12.0	Sarpy alert n. 157 for NON-Mutagenicity, define...
R1.0	IRFMN alert n. 249 for NON-Mutagenicity, defin...
R20.0	Sarpy alert n. 164 for NON-Mutagenicity, define...
R3.2	Sarpy alert n. 163 for NON-Mutagenicity, define...
R18.4	Sarpy alert n. 182 for NON-Mutagenicity, define...
R14.0	Sarpy alert n. 153 for NON-Mutagenicity, define...
R4.2	Sarpy alert n. 169 for NON-Mutagenicity, define...
R13.2	Sarpy alert n. 163 for NON-Mutagenicity, define...
R7.0	Sarpy alert n. 113 for NON-Mutagenicity, define...
R8.2	Sarpy alert n. 163 for NON-Mutagenicity, define...
R22.0	IRFMN alert n. 11 for NON-Mutagenicity, define...
R2.0	Sarpy alert n. 123 for NON-Mutagenicity, define...
R9.0	Sarpy alert n. 143 for NON-Mutagenicity, define...
R21.0	IRFMN alert n. 160 for NON-Mutagenicity, defin...



CONCLUSIONS

- *Computational models as support to human experts*
- *Navigation within data and reasoning*
- *No conflict between “computer” and man*
- *Multiple in silico approaches*
- *Integrating multiple approaches (weight of evidence)*
- *Comparison with the experimental uncertainty/vairability*