



## 3rd Internal CINE-CMSC Workshop

# Data Mining Tools Applied to Quantum Chemistry Data

Speaker:

Johnatan Mucelini

Supervisor:

Prof. Dr. Juarez L. F. Da Silva

QC Collaborators:

Paulo de Carvalho Dias Mendes,

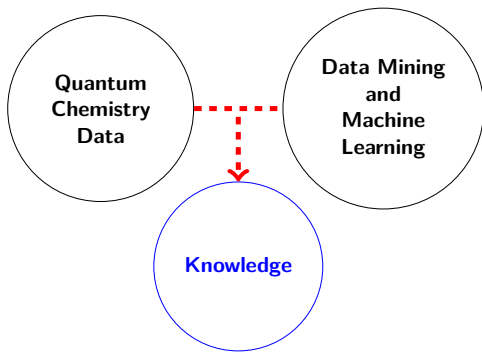
Priscilla Felício-Sousa,

Karla F. Andriani.

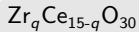
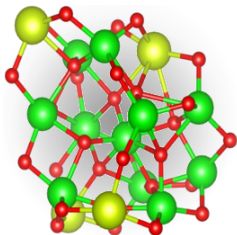
DM/ML Collaborators:

Marcos G. Quiles,

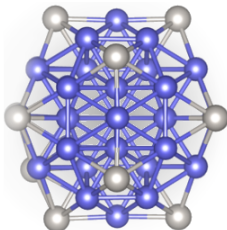
Ronaldo C. Prati.



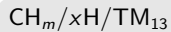
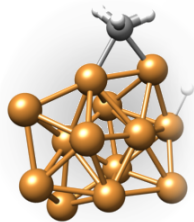
# Introduction - Materials



- Employed in TWC and candidate for others process.
- Explore material in nanoparticles structures.



- Pt-based Catalysts are wildly employed.
- Explore this alloys structural preferences.



- $\text{CH}_4$  dehydrogenation candidates.
- Reaction intermediates study.

## Motivation:

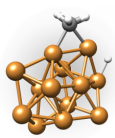
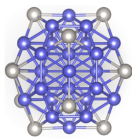
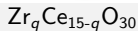
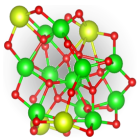
- Develop the chem/comp overlap;
- Develop material science area.

## Objectives:

- Find new patterns;
- Initial Studies;
- Tools Development.

# Data Mining - Challenge

Calculations Sets:



$n$  1600

330

700

$vars$   $q$  (16)

$l$  (2)

$(m, x)$  (9)

TM (9)

TM (4)

Initial Data:

Molecular info (structured data):

- Energy [-42.0 eV];
- HOMO [-4.123 eV];

Atomic info (attribute-vector):

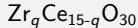
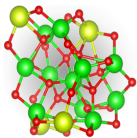
- Exposed to vacuum [True, False, ...];
- Atomic Charges [0.7, -0.8, ...].

DM/ML Input:

attribute-value table	feature0	feature1	...
sample0	data00	data01	...
sample1	data10	data11	...
...	...	...	...

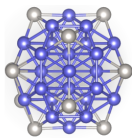
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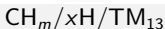
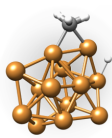
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Quandarium (python):

- Find Calc.
- Extract Info.
- Geometrical Analysis:
- $ECN/d_{av}$
- Find surf. atoms
- Connections Analysis

It operate recursively!

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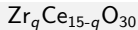
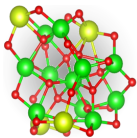
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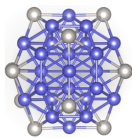
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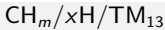
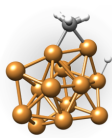
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# Data Mining

## How to get molecular data from atomic data?

Take **molecular data** from **operator** over a **bag** (properties), for all or a **class** of atoms.

$$\text{Molecular\_Data} = \underbrace{\text{OPERATOR}}_{\text{average}} \left[ \underbrace{\text{BAG}}_{\text{ECN}} \left[ \underbrace{\text{CLASS}}_{\text{Pt}} \right] \right]$$

$$1.65 = \text{Av.} \left[ \begin{bmatrix} 1.1 \\ 2.2 \end{bmatrix} \right] = \text{Av.} \left[ \begin{bmatrix} 1.1 \\ 3.3 \\ 2.2 \\ 3.1 \end{bmatrix} \begin{bmatrix} \checkmark \\ \times \\ \checkmark \\ \times \end{bmatrix} \right]$$

**Operator:** Operates over one or more arguments, and return a number (Ex.: sum).

**Classes:** Set of atoms that meet a condition!

- Ex.: O, O exposed to the vacuum, O exposed to the vacuum with  $1 < ECN < 2$ , ....

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Quandarium (python):

Flexible data manipulation:

- bag  $\rightarrow$  class
- class1 + class2  $\rightarrow$  class3
- class + bag  $\rightarrow$  class
- class  $\rightarrow$  bag

It operate recursively!

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- class + bag  $\rightarrow$  class
- class  $\rightarrow$  bag

It operate recursively!

Thus we access many molecular data (attribute-value table).

Lets **analyse** the data!



# Correlation Analysis

## Pearson

$$r = \frac{\text{cov}(x, y)}{\sigma(x)\sigma(y)}$$

- Non-ranked data;
- Sensitive to outliers.

## Spearman

$$r_s = \frac{\text{cov}(r_x, r_y)}{\sigma(r_x)\sigma(r_y)}$$

- Ranked data;
- Robust to outliers.

## Correlation Interpretation:

- $-1 \geq r \geq 1$
- If  $X$  increase,  $Y$  is **expected** to go:

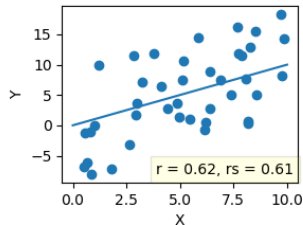
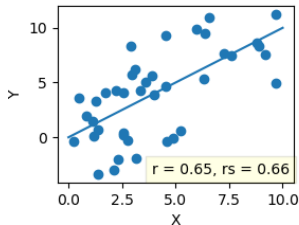
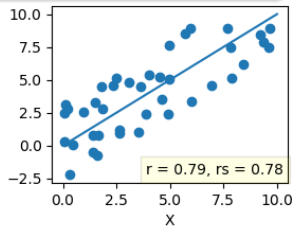
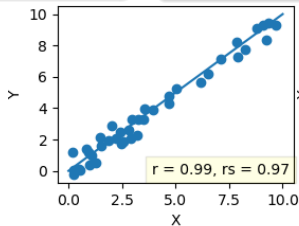
downward

$$r < 0 < r$$

upward

- How much expected?  
"How strong correlated?"

"As large as was  $|r|$ ."



# Correlation Analysis

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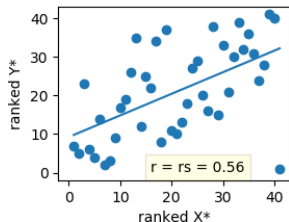
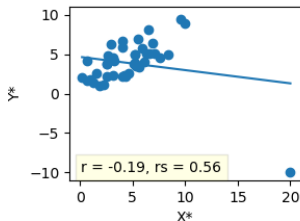
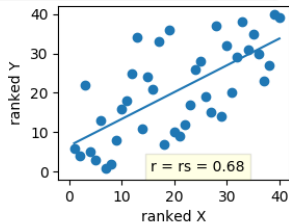
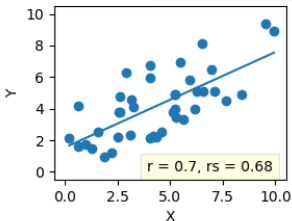
## Spearman

$$r_s = \frac{\text{cov}(r_x, r_y)}{\sigma(r_x)\sigma(r_y)}$$

- Ranked data;
- Robust to outliers.

An example of outlier effect:

- $r$  reduced 0.89;
- $r_s$  reduced 0.12;



# Correlation Analysis

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## Spearman

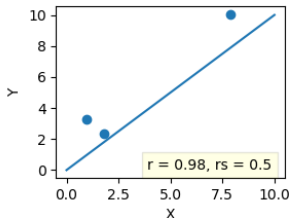
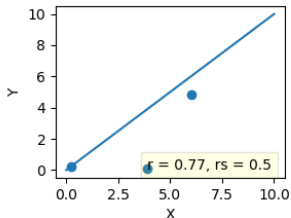
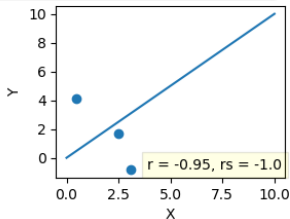
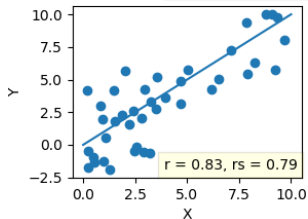
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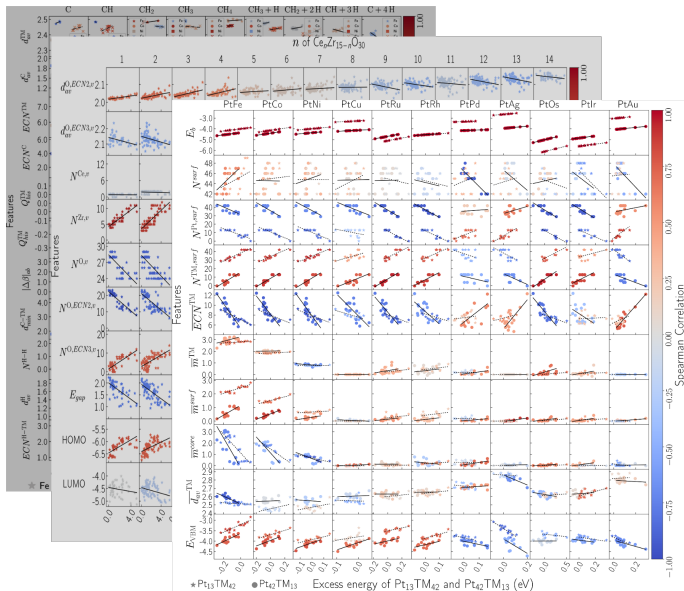
- Should I trust large correlation?

Depend on data **size** and **distribution**.

Good practice:  
Hypothesis test  
(Bootstrap) and pvalue.



# Data Representation



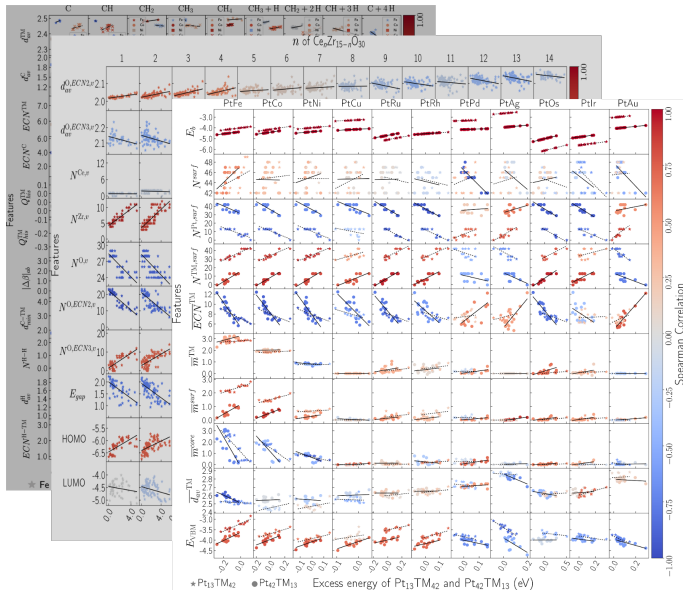
Scatter-plot Matrix:

- Rows: Features;
- Columns: Dataset part.

Cell:

- Scatter-plot;
- Y axis: Feature;
- X axis: Energy;
- Correlation: Colors;
- Linear Model.

# Data Representation



## Scatter-plot Matrix:

- Rows: Features;
- Columns: Dataset part.

## Cell:

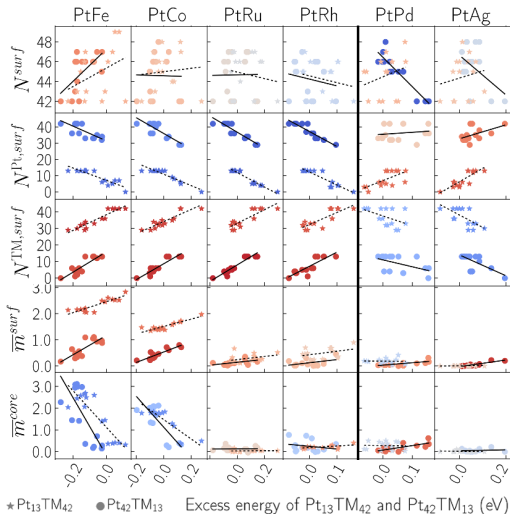
- Scatter-plot;
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## Quandarium:

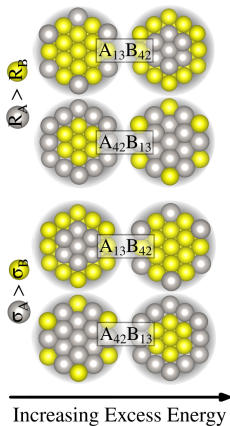
- Scatterplot
- bag histograms

# Results

## Pt<sub>13</sub>TM<sub>42</sub> and Pt<sub>42</sub>TM<sub>13</sub>



- High correlation! Few samples.
- TM vs Pt sites preference ( $N, ECN$ );
- Influence in other properties ( $m, d_{av}$ );



$R$ : Radius =  $d_{av}^{bulk}/2$

$\sigma$ : Surface Energy

$x$ : Electronegativity

$R(\text{\AA})$			
Fe	Co	Ni	Cu
1.26	1.24	1.24	1.28
Ru	Rh	Pd	Ag
1.34	1.35	1.39	1.47
Os	Ir	<b>Pt</b>	Au
1.36	1.37	<b>1.40</b>	1.47

$\sigma$ (eV/atom)			
Fe	Co	Ni	Cu
0.88	0.71	0.65	0.47
Ru	Rh	Pd	Ag
1.05	0.81	0.56	0.33
Os	Ir	<b>Pt</b>	Au
1.21	0.90	<b>0.64</b>	0.32

# Conclusion

## Quantum Chemistry Data Mining with Correlations:

### Analysis Benefits:

- Easy access to useful **chemistry information**;
- **Quantitative trends** analysis;
- Very **little explored**.

### Analysis Limitation:

- Small **dataset size**;
- Many **variables** in the study.

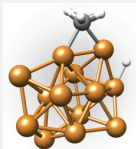
### Analysis Applicability:

- Can be applied to **any material**;
- Require small **programming skills**;
- Require some **statistical concepts**.

# Perspectives 2019 - 2020

Complete the data mining works in progress!

## Molecules over TM

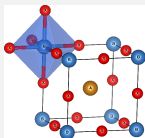


- $CH_n/H_m/TM_{13}$  Dataset (previously presented).

## Article: Nanocluster DM Analysis

- **DM and correlation analysis;**
- For **chemists;**
- 5 QC datasets (3+2);
- Release **Quandarium**.

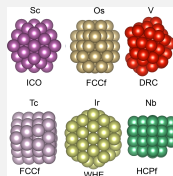
## Perovskites



- Solid State Feature Extraction.

TM Nanoclusters and Alloys Energy Regression:

## TM nanoclusters and alloys:



- Employ several previous QTNano studies ( $TM_{13}$ ,  $TM_{55}$ );
- Methodological normalisation;
- Algorithms: MLP, random-forest, kernel regression...



# Acknowledgements



Thanks for your Attention!