

the 10th SFCi meetings

IMPROVING SAR ANALYSIS VIA PHARMACOPHORIC FEATURE REDUCTION AND FEATURE TRANSFORMATION

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framework of the Operational Programme ERDF/ESF 2014-2020

General goal

- Structure-activity relationship (SAR) analysis :
 - Cleaning data, searching suitable representation.
 - Clustering ligands by family, finding out activity cliffs.

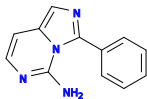
data

- 1485 ligands¹ tested on tyrosine kinase BCR-ABL, often found in patients with chronic myeloid leukemia.
- Each ligand is defined by 112048 pharmacophores (order varying from 3 to 7)
- Two classes : 711 ligands from inactive class and 774 ligands from active class.
- Activity of ligand :
 - $K_i \leq 100nM \implies$ active
 - $K_i \geq 1000nM \implies$ inactive
 - otherwise not considered

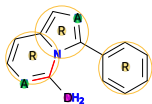
1. GAULTON, Anna, HERSEY, Anne, NOWOTKA, Michal, et al. The ChEMBL database in 2017. Nucleic acids research, 2017, vol. 45, no D1, p. D945-D954.

Pharmacophoric features²

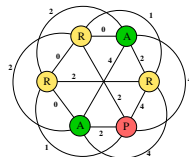
Hydrogen Bond **A**ceptor, Hydrogen Bond **D**onor, aromatic **R**ing, **H**ydrophobic area, **P**ositively ionizable group, **N**egatively ionizable group



Skeletal formula



Feature occurrences



Pharmacophore graph

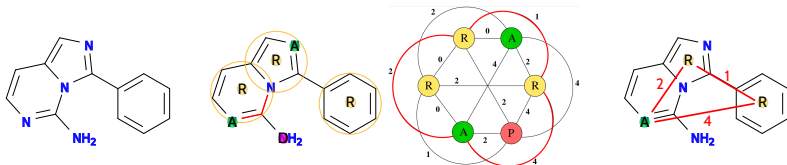
Pharmacophore graph of a molecule

- A vertex : an occurrence of a feature
- An edge : the distance between two features

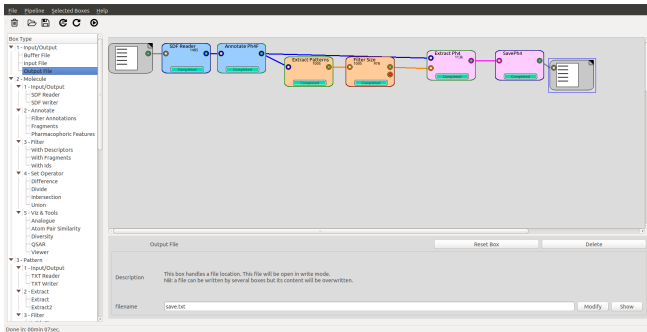
2. OpenBabel, N. M. O'Boyle, M. Banck, C. A. James, C. Morley, T. Vandermeersch, G. R. Hutchison, J. Cheminformatics 2011, 3, 33.

pharmacophore

- fragment of the overall pharmacophore graph of the ligand responsible of its biological activity (active or inactive).
- sufficiently present (e.g., appearing in at least 10 ligands)



Pharmacophoric fingerprint

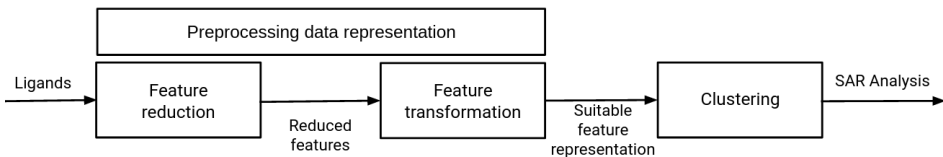


The workflow to extract the pharmacophores by Norns³ tools

| | | | | | |
|--------------|----------|----------|----------|-----|-----------------------|
| Id_Mol | A A A -0 | R A R -1 | A A R -2 | ... | D D H H N N N -112047 |
| CHEMBL250213 | 1 | 0 | 0 | ... | 1 |

3. METIVIER, Jean-Philippe, CUISSART, Bertrand, BUREAU, Ronan, et al. The pharmacophore network : a computational method for exploring structure–activity relationships from a large chemical data set. Journal of medicinal chemistry, 2018, vol. 61, no 8, p. 3551-3564.

- Work process

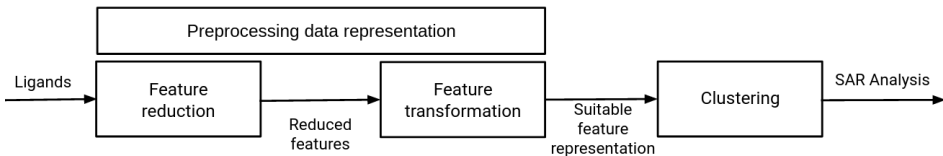


- Experimental environment

Programming language and frameworks

- language : python.
- frameworks : Keras, tensorflow, sklearn.

- Work process

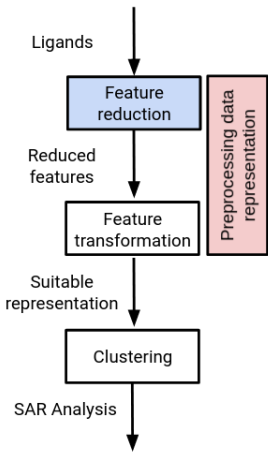


- Experimental environment

| Processors | Cores | RAM | GPU | Disk space |
|--|-------|-------|---------------------------------------|------------|
| 2 Processors Intel Xeon E5-2680 v2 2.80GHz | 40 | 512 G | 2 Tesla K40M 2880 Cores 12G RAM | 9.9 T |

Programming language and frameworks

- language : python.
- frameworks : Keras, tensorflow, sklearn.



Objective : Simplifying data

- Eliminate redundancy.
- Keep relevant information.

Pharmacophoric equivalence class⁴(EC)

- EC : group of pharmacophores that appear in exactly the same ligands.
- Columns (pharmacophores) belonging to the same EC are reduced to one representative column.

| Id | EC1 | | | EC2 | |
|----------|---------|-----------|-------------|---------|-----------|
| | A R D H | A R R D H | A R R R D H | A A R D | A A R R D |
| ligand_1 | 1 | 1 | 1 | 0 | 0 |
| ligand_2 | 0 | 0 | 0 | 0 | 0 |
| ligand_3 | 1 | 1 | 1 | 1 | 1 |

4. FOURNIER-VIGER, Philippe, GUENICHE, Ted, ZIDA, Souleymane, et al. ERMiner : sequential rule mining using equivalence classes. In : International Symposium on Intelligent Data Analysis. Springer, Cham, 2014. p. 108-119.

- Reduction of 86.50%

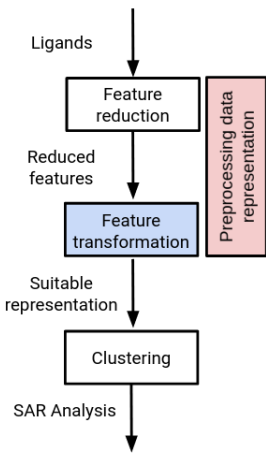
| #ligands | # old features | # new features | Type of data | #classes |
|----------|----------------|----------------|---------------|----------|
| 1485 | 112048 | 15129 | binary (0, 1) | 2 |

- Example of pharmacophoric equivalence classes

| EC | number_of_ph | concept_score |
|--------------------|--------------|---------------|
| A A R D H N -62790 | 5316 | 12 |
| A A A R R H H -853 | 3889 | 13 |
| A A A R D D H -874 | 3552 | 10 |
| A A A D H H -52830 | 3515 | 10 |
| A A A R R H -48532 | 1527 | 12 |
| A R R H -13429 | 1443 | 11 |
| A A R D -8476 | 1153 | 20 |
| A R R H P P -71742 | 1094 | 12 |
| A R R R D H -67146 | 1047 | 12 |
| A A A A R P -45904 | 1000 | 10 |

```
> outputs > {} Dictionary_classe_equivalence_ph4_bis.json >
  " |A|A|A| -131"
  ],
  " |A|A|A| -132": [
    " |A|A|A| -132"
  ],
  " |A|A|A| -133": [
    " |A|A|A| -133"
  ],
  " |A|A|A| -134": [
    " |A|A|A| -134",
    " |A|A|D| -567",
    " |A|A|D| -751",
    " |A|A|N| -1178",
    " |A|A|N| -1180",
    " |A|A|N| -1181"
  ]
```

- 11577 EC contain one pharmacophore, 3552 EC contain more than one

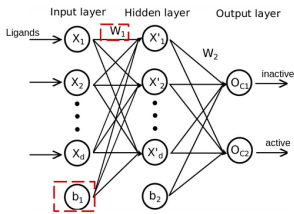


Objective

- Separate active ligands from inactive ones
- Find the suitable linear transformation

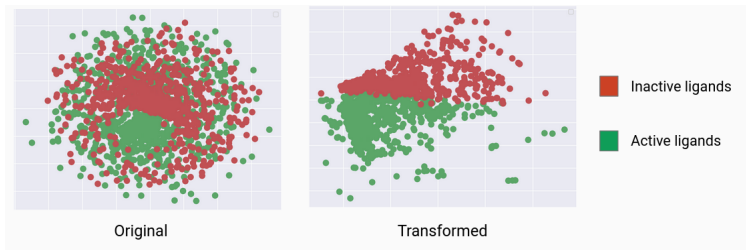
Supervised transformation

- Transform the features of ligands according to their biological activity.
- Use a neural network⁵ (NN) which minimizes the optimization function "categorical_crossentropy".



$$x'_{ij} = x_{ij} \times w_{jj} + b_j$$

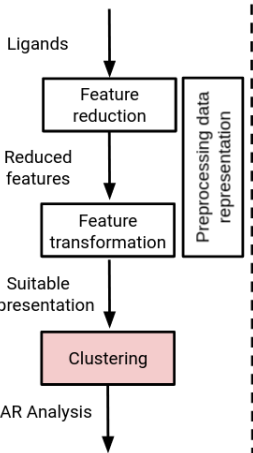
5. BEBIS, George et GEORGIOPOULOS, Michael. Feed-forward neural networks. IEEE Potentials, 1994, vol. 13, no 4, p. 27-31.



Visualization of 2D projection

The 15129 features are projected by the Multidimensional Scaling⁶(MDS) method.

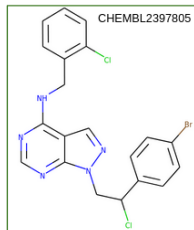
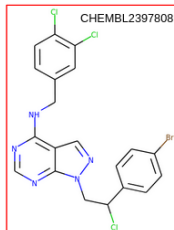
6. COX, Michael AA et COX, Trevor F. Multidimensional scaling. In : Handbook of data visualization. Springer, Berlin, Heidelberg, 2008. p. 315-347.



Objective : group together similar structures

Find out significant ligands

- homogeneous : families of biological activities .
- not homogeneous : potential presence of activity cliffs.

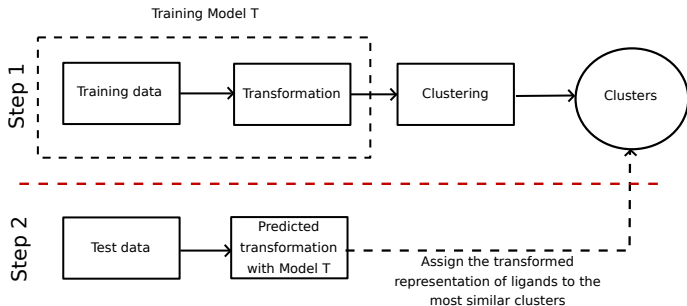


Objective

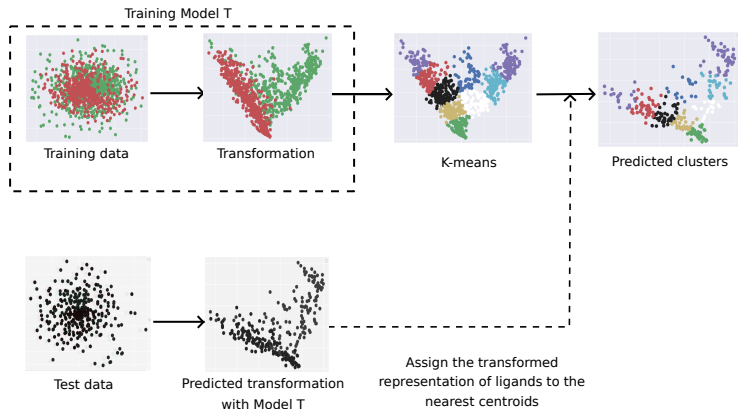
- Predict the cluster (family) of a new unlabeled ligand.

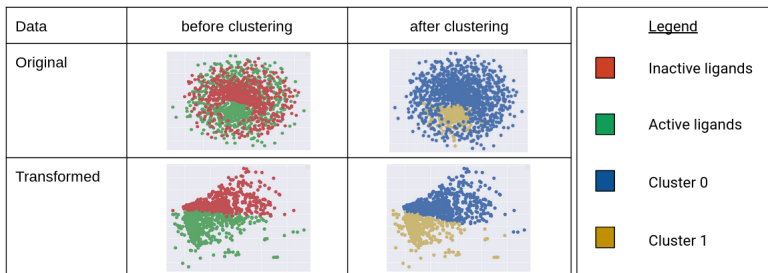
Principle

- Apply one of the clustering methods on the training set after its transformation
- Assign to each cluster built in step (1) the data that corresponds to it (the most similar)



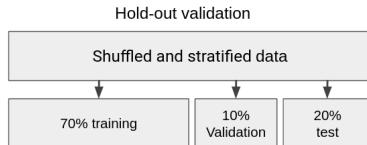
Example : Predictive K -means





| | Original | | Transformed | |
|----------------|--------------|--------------|--------------|--------------|
| | Cluster 0 | Cluster 1 | Cluster 0 | Cluster 1 |
| Inactive (711) | 711 (100%) | 0 (0%) | 710 (99.86%) | 1 (0.14%) |
| Active (774) | 450 (58.14%) | 324 (41.86%) | 197 (25.45%) | 577 (74.55%) |

Evaluation



Evaluation by normalized mutual information⁷ (NMI)

- quality measure which compares the resulting clusters or classes with the ground truth.
- The results vary between 0 (no mutual information) and 1 (perfect correlation)

Evaluation by Silhouette⁸

- measure calculated using the mean intra-cluster distance and the mean distance to the nearest cluster.
- The best value is 1 and the worst is -1. Values close to 0 indicate that the clusters overlap. Negative values usually indicate that a sample was assigned to the wrong cluster.

7. ESTEVEZ, Pablo A., TESMER, Michel, PEREZ, Claudio A., et al. Normalized mutual information feature selection. IEEE Transactions on neural networks, 2009, vol. 20, no 2, p. 189-201.

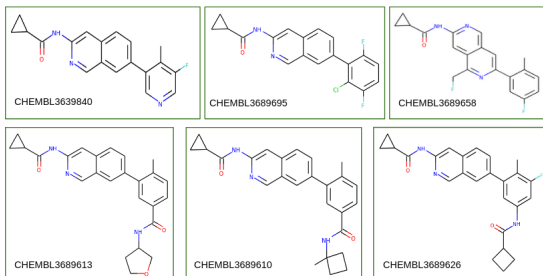
8. ROUSSEUW, Peter J. Silhouettes : a graphical aid to the interpretation and validation of cluster analysis. Journal of computational and applied mathematics, 1987, vol. 20, p. 53-65.

Choice of the number of clusters K

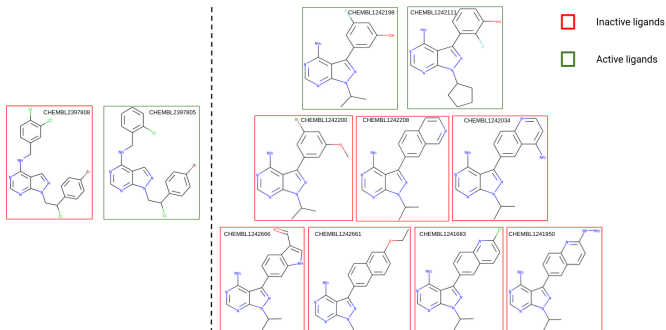
| | Data | NMI | Silhouette | misclassified ligands |
|-----|-------------|-------|------------|-----------------------|
| K=2 | Original | 0.287 | 0.056 | 89 |
| | Transformed | 0.449 | 0.395 | 46 |
| K=3 | Original | 0.229 | 0.073 | 89 |
| | Transformed | 0.371 | 0.354 | 53 |
| K=4 | Original | 0.288 | 0.081 | 80 |
| | Transformed | 0.341 | 0.401 | 57 |
| K=5 | Original | 0.245 | 0.092 | 79 |
| | Transformed | 0.359 | 0.378 | 51 |
| K=6 | Original | 0.246 | 0.099 | 75 |
| | Transformed | 0.291 | 0.356 | 58 |

| | Data | NMI | Silhouette | misclassified ligands |
|------|-------------|-------|------------|-----------------------|
| K=7 | Original | 0.240 | 0.090 | 78 |
| | Transformed | 0.299 | 0.354 | 53 |
| K=8 | Original | 0.230 | -0.109 | 72 |
| | Transformed | 0.326 | 0.387 | 36 |
| K=9 | Original | 0.222 | 0.109 | 74 |
| | Transformed | 0.334 | 0.398 | 39 |
| K=10 | Original | 0.223 | 0.119 | 69 |
| | Transformed | 0.307 | 0.374 | 43 |

| test data | Original | Transformed |
|----------------|-----------------------|------------------------|
| Inactive (142) | 0 111 1 1 1 1 5 22 0 | 21 6 0 64 0 30 0 13 8 |
| Active (155) | 60 52 4 4 1 11 1 17 5 | 14 41 48 7 10 8 6 18 3 |



| test data | Original | Transformed |
|----------------|-----------------------|-------------------------------|
| Inactive (142) | 0 111 1 1 1 1 5 22 0 | 21 6 0 64 0 30 0 13 8 |
| Active (155) | 60 52 4 4 1 11 1 17 5 | 14 41 48 7 10 8 6 18 3 |



A cluster with two activity cliffs⁹

9. STUMPFE, Dagmar, HU, Huabin, et BAJORATH, Jürgen. Evolving concept of activity cliffs. ACS omega, 2019, vol. 4, no 11, p. 14360-14368.

Conclusion

Allowing to an expert an easy SAR analysis by :

- 1 preprocessing step : data cleaning.
- 2 clustering step : significant ligands, activity cliffs.

Perspectives

- Significant pharmacophores : analyse pharmacophores by “feature importance” study.
- Unsupervised transformation : transform unlabeled data.
- Interactivity : introduce the expert in the process.

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



















²Centre d'Etudes et de Recherche sur le Médicament de Normandie, Normandie Univ, UNICAEN,
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Our work is part of the European project "SCHISM", funded by the European Union within the
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appendix

Predictive clustering cross validation

| | Original | | | | | Transformed | | | | |
|-------------------|---|---|---|---|---|---|---|--|---|---|
| before clustering |  |  |  |  |  |  |  |  |  |  |
| K-means results |  |  |  |  |  |  |  |  |  |  |
| NMI | 0.277 | 0.260 | 0.264 | 0.287 | 0.236 | 0.353 | 0.346 | 0.376 | 0.297 | 0.327 |
| silhouette | 0.185 | 0.126 | 0.121 | 0.210 | 0.189 | 0.466 | 0.438 | 0.453 | 0.496 | 0.466 |