

Smoothing 3D protein structure motifs through graph mining and amino-acids similarities

Wajdi Dhifli

Blaise Pascal University Clermont-Ferrand, France

Rabie Saidi

European Bioinformatics Institute Cambridge, United Kingdom

Engelbert Mephu Nguifo

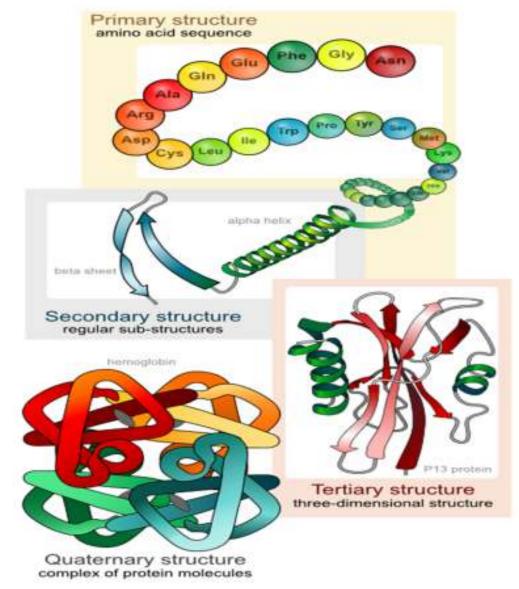
Blaise Pascal University Clermont-Ferrand, France

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Proteins

A combination of amino acids within an alphabet of 20 :

- Calcium
- Arginine
- Glutamine
- Glycine
- ...



- During the evolution, proteins go through changes.
 - **Mutation** : is a substitution that exchanges one amino acid to another



In the literature, there exist substitution matrices expressing scores of substitution between each possible pair of amino acids.

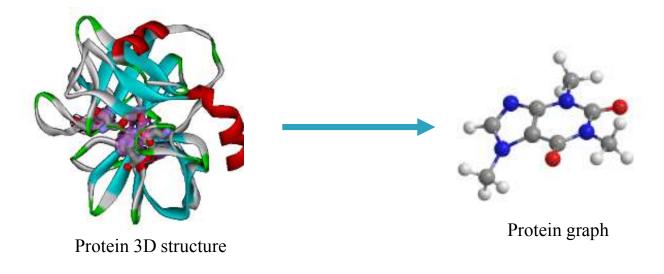


• The primary structure has been extensively studied, unlike the other structures

- However, the tertiary (3D) structure is more interesting:
 - It contains the primary + interactions between amino acids
 - The function of a protein is highly related to its 3D structure



- Graphs are powerful representation framework
- A protein 3D structure can be represented by a graph of amino acids (protein contact map)
 - Amino acids => Nodes (labeled with the amino acid type)
 - Interactions between amino acids => Edges



 \rightarrow Use graph mining techniques to study protein 3D structure

Frequent subgraph mining

- One current trend in graph mining is frequent subgraph discovery
- It consists on finding subgraphs that frequently occur in graph data

 Among the most powerful techniques to study proteins is to look for recurrent substructures then use them for analysis

Protein 3D structures
 Protein graphs
 Use the frequent subgraphs as
 patterns to describe proteins
 Each subgraph represents a 3D-motif

Frequent subgraph discovery approaches

ILP approaches

- WARMR : King R.D., Srinivasan A. and Dehaspe L. (J. of Computer-Aided Molecular Design 2001)
- FARMER : Nijssen, S. and Kok, J. (IJCAI 2001)

• ...

Apriori based approaches

- AGM/AcGM : Inokuchi et al (PKDD 2000)
- FFSM : Huan et al (ICDM 2003)

• ...

Pattern growth based approaches

- Gspan : Yan and Han (ICDM 2002)
- Gaston : Nijssen and Kok (KDD 2004)

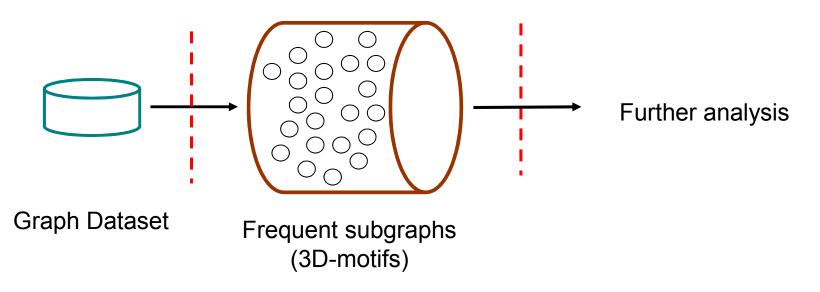
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Closed and maximal

• Closegraph : Yan and Han (KDD 2003)

• Margin : Thomas, L.T., Valluri, S.R. and Karlapalem, K. (ICDM 2006)

Frequent subgraph issues

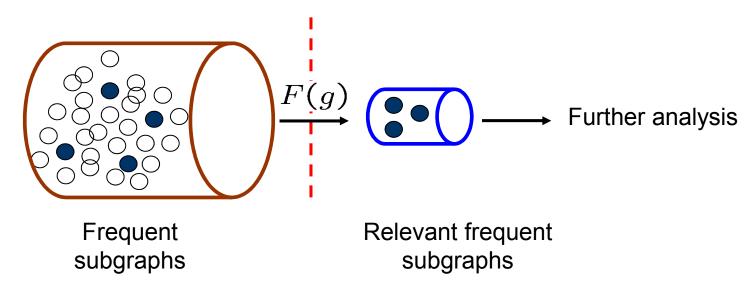


Main issues:

- **×** Exponential Pattern Set : huge number of subgraphs
- **×** Interpretation : role of each subgraphs ?
- ★ No guarantee of the relevance of the discovered subgraphs: redundancy due to structural or semantic similarities

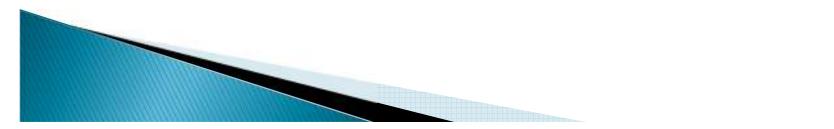
Feature selection

General framework of feature selection



Aims:

- Decreasing the exponential number of discovered frequent subgraphs
- Enhancing (or at least maintaining) the quality of the feature set



Feature selection

Feature selection techniques

Learning task dependent selection

• Find a subset of features that preserves/enhance the output prediction capabilities

Learning task independent selection

• Reduce the features without regard to the learning task

1. Filter approaches (univariate / multivariate)

• Assess the relevance of features based on their properties

2. Wrapper approaches

• Various subsets of features are generated and evaluated by training and testing a specific learning model

3. Embedded approaches

• The selection is made into the model construction by searching in the combined space of feature subsets. Thus, they are specific to a given learning algorithm

Feature selection

Existing feature selection approaches for subgraphs

Random sampling

• MUSK: Geng Li, Murat Semerci, Bulent Yener, and Mohammed J. Zaki (SDM 2009)

• ...

• Top-k and Clustering based approaches

- Extracting redundancy-aware top-k patterns: Dong Xin, Hong Cheng, Xifeng Yan, and Jiawei Han (KDD 2006)
- RING: Shijie Zhang, Jiong Yang, and Shirong Li. (ICDM 2009)
- TGP: Yuhua Li, Quan Lin, Ruixuan Li, and Dongsheng Duan (ADMA 2010)

• ...

Constraints based approaches

- D&D : Yuanyuan Zhu, Jeffrey Xu Yu, Hong Cheng, and Lu Qin (CIKM 2012)
- CORK : Marisa Thoma, Hong Cheng, Arthur Gretton, Jiawei Han, Hans-Peter Kriegel, Alex Smola, Le Song, Philip S. Yu, Xifeng Yan, and Karsten M. Borg-wardt. (SADM 2010)
- MIP : Frédéric Pennerath, and Amedeo Napoli (ECML-PKDD 2009)
- COM : Ning Jin, Calvin Young, and Wei Wang (CIKM 2009)

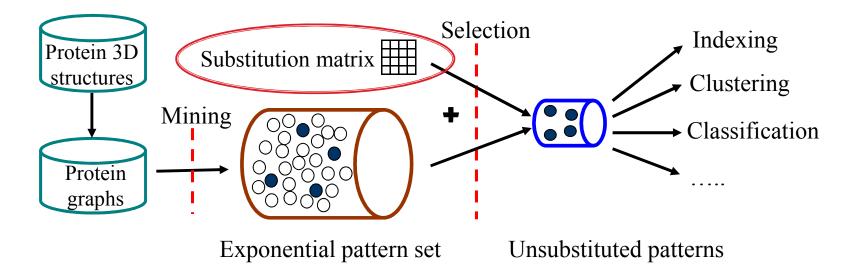
What about the domain knowledge ? Can we use them in the selection ?

Contribution:

- Some amino acids have similar proprieties
 - Some substitution can be without effect on the function nor the structure of the protein
 - → Same thing can be deduced for subgraphs
- Idea : use substitution matrices to define similarity between the discovered frequent subgraphs
 - Number of features will be reduced ?
 - Any impact on the quality of the pattern set?



General framework of the selection approach



- Incorporate a domain knowledge (the substitution matrix) in the selection
- Keep only one subgraph from every set of substitutable subgraphs
- The selected subgraphs represents the set of **representative unsubstituted patterns**



Preliminaries

1. Ranking function :

$$M_{el} = \frac{M(l, l)}{\sum_{i=1}^{|L|} M(l, l_i)}$$
$$M_{patt}(P) = 1 - \prod_{i=1}^{|V_P|} M_{el}(P[i])$$

2. Similarity function :

$$S_{el}(v,v') = \frac{\mathcal{M}(l,l')}{\mathcal{M}(l,l)}$$

$$S_{patt}(P, P') = \frac{\sum_{i=1}^{|V_P|} S_{el}(P[i], P'[i])}{|V_P|}$$

Main algorithm

Data: Ω , M, τ (set of frequent subgraphs, substitution matrix, substitution threshold) Result: : Ω^* (unsubstituted patterns)

Begin UnSubPatt

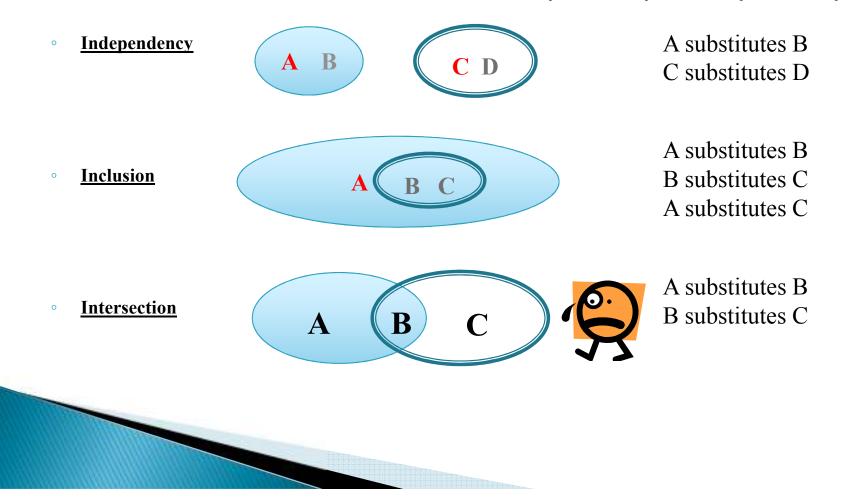
- 1. Divide the set of frequent subgraphs into groups of subgraphs having the same size and order
- 2. For each group of subgraphs
 - 3. Sort the subgraphs by descending order of M_{patt}
 - 4. For each subgraph Sg_i
 - 5. Delete all the other subgraphs Sg_j it substitutes
 - 6. Occurences $(Sg_i) = 0$ ccurences $(Sg_i) \cup 0$ ccurences (Sg_j)

End.



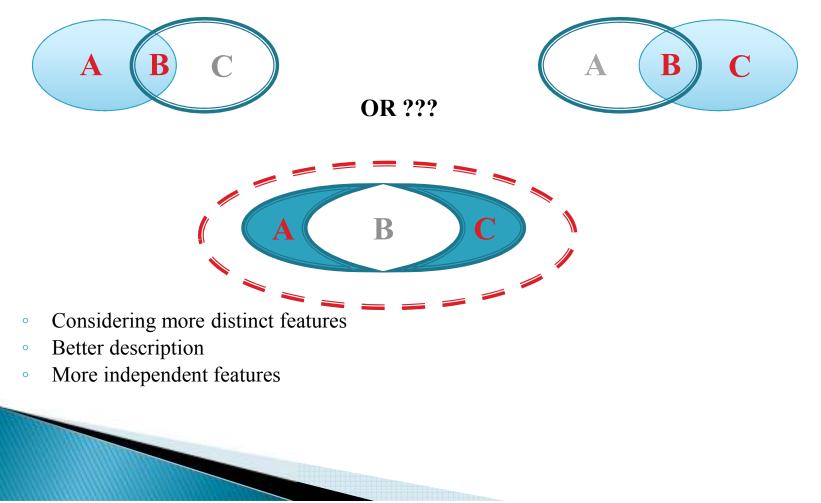
Substitution cases:

A, B, C and D: four structurally isomorphic subgraphs $|M_{patt}(A) > M_{patt}(B) > M_{patt}(C) > M_{patt}(D)$:



Intersection

Solution ?



Experimental data

Dataset	SCOP ID	Family name	Pos	Neg	#Proteins	Avg # nodes	Avg # edges
DS1	52592	G proteins	33	33	66	246	971
DS2	48942	C1 set domains	38	38	76	238	928
DS3	56437	C-type lectin domains	38	38	76	185	719
DS4	88854	Protein kinases, catalytic subunit	41	41	82	275	1077

SCOP ID: identifier of protein family in SCOP, **Pos**: positive proteins sampled from a selected protein family, **Neg**: negative proteins randomly sampled from the Protein Data Bank, **# Proteins**: the number of protein structures in the whole dataset, **Avg# nodes**: average number of nodes, **Avg# edges**: average number of edges.

Evaluation methodology

Reduction

• Selection Rate = Number of selected subgraphs *100 / Number of frequent subgraphs

Interestingness

• Average Classification Accuracy : 5 runs * 5 CV



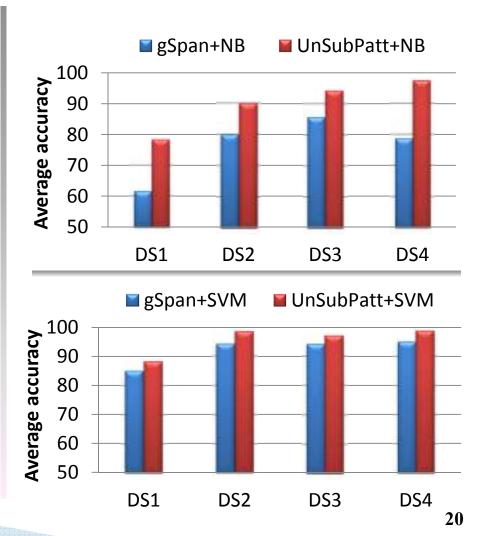
Results

- The frequent subgraphs Ω are extracted using gSpan with a frequency >=30%
- Substitution matrix: Blusom62
- Substitution threshold: 30%

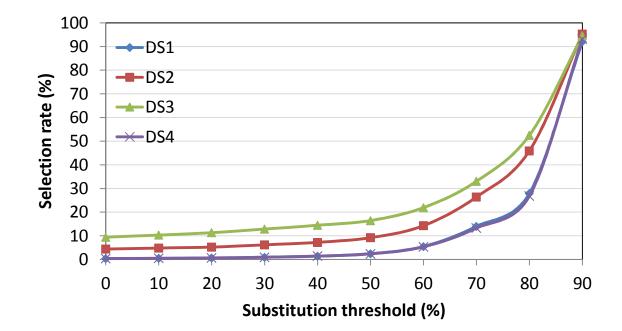
 $|\Omega|$: Number of frequent subgraphs, $|\Omega^{*}|$: unsubstituted patterns, and the selection rate.

Dataset	$ \Omega $	$ \Omega^* $	Selection rate (%)	
DS1	799 094	7291	0.91	
DS2	258371	15898	6.15	
DS3	114792	14713	12.82	
DS4	1073393	9958	0.93	

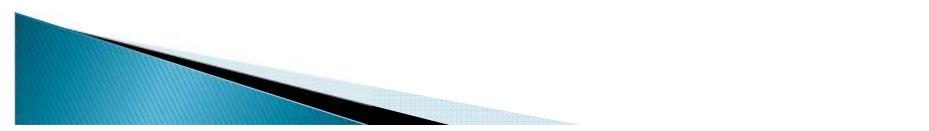
Classification accuracy by NB and SVM using frequent subgraphs (gSpan) and unsubstituted patterns (UnSubPatt).



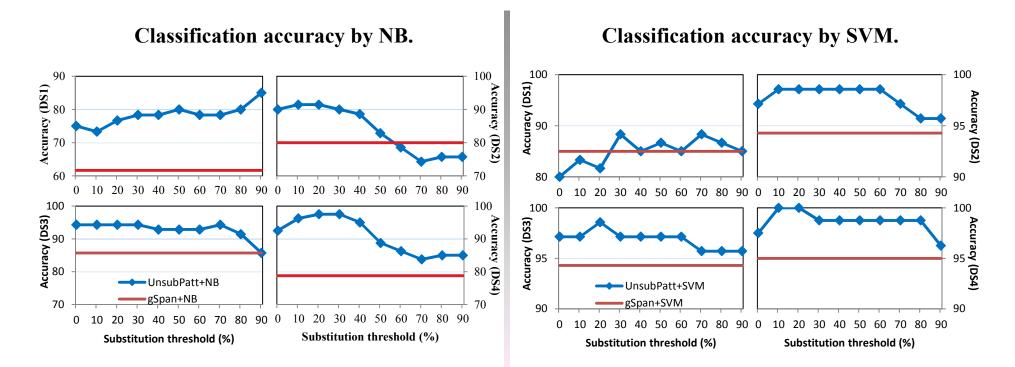
Impact of variation of the substitution threshold on the selection rate

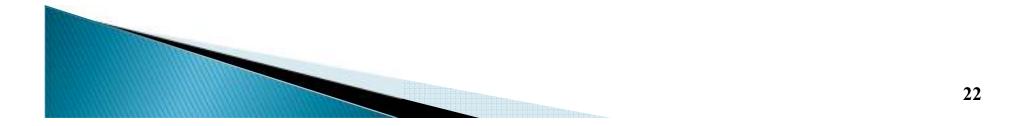


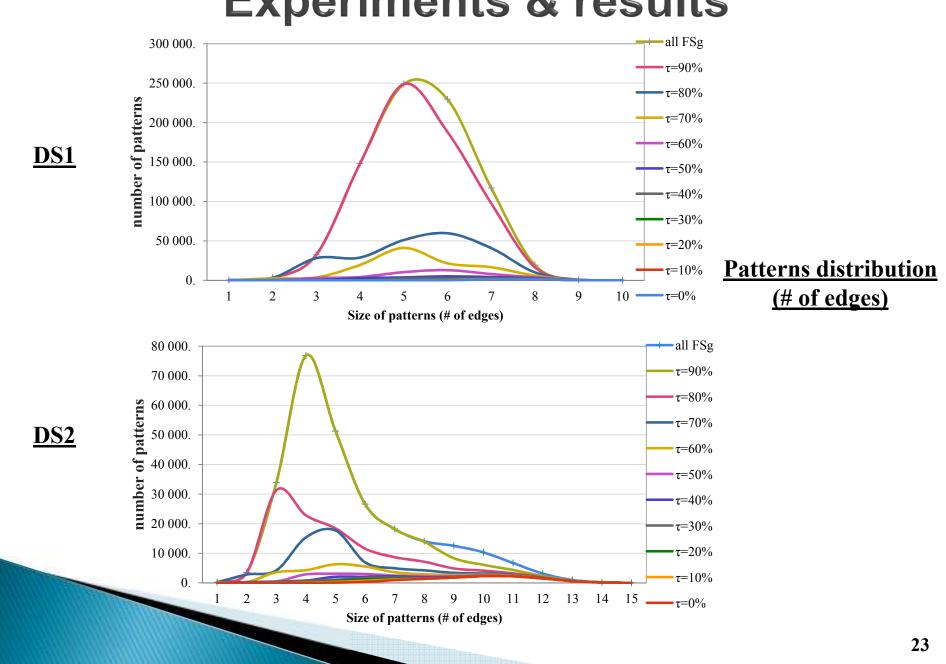
Rate of unsubstituted patterns (Ω^*) from the initial set of frequent subgraphs (Ω) depending on the substitution threshold.



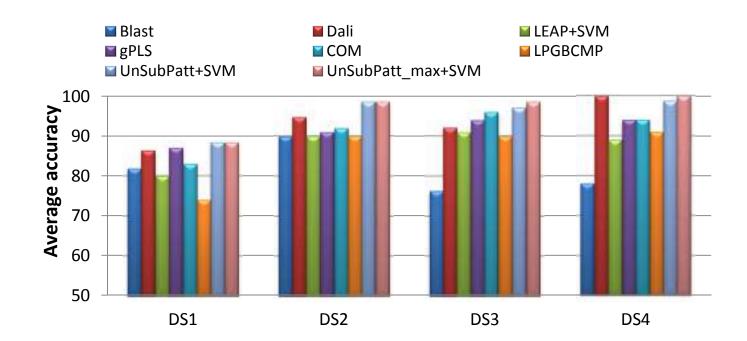
Impact of variation of the substitution threshold on the classification accuracy





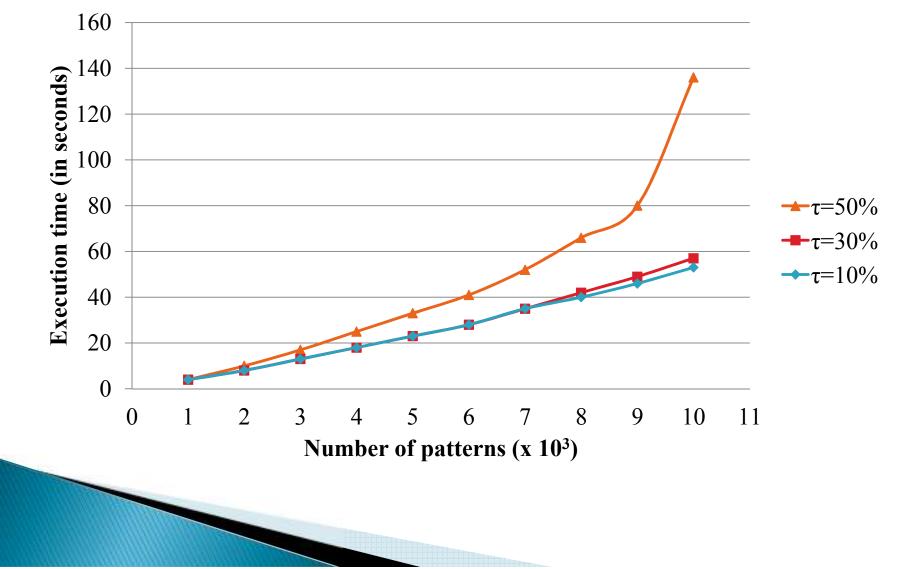


Comparison with other pattern selection methods





Runtime analysis



Parallelization of « UnSubPatt »

Data: Ω , M, τ (set of frequent subgraphs, substitution matrix, substitution threshold) Result: : Ω^* (unsubstituted patterns)

Begin UnSubPatt

End

- 1. Divide the set of frequent subgraphs into groups of subgraphs having the same size and order
- 2. For each group of subgraphs
 - 3. Sort the subgraphs by descending order of M_{patt}
 - 4. For each subgraph Sg_i
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Compute the substitution of each group in Parallel processes

Conclusion

- Considering the substitution between amino acids:
 - Enhance the selection results in terms of reduction and quality
 - Allows detecting similarities between patterns that current selection approaches do not detect
- The proposed approach :
 - Is scalable and can be easily parallelized
 - Can be used on protein 3D structures as well as sequences (seen as line graphs)
 - Is not a learning-task driven approach => can be used in different mining tasks

Prospects

- Embed the selection approach within the extraction process
- Consider also the insertions and deletions over subgraphs with different sizes



Thanks

