A Pseudo-Boolean programming approach to compute differences and similarities between two genomes

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Context Notation

The genome consists of genes



FLAGdb - Arabidopsis thaliana

Context Notation

Evolution of a genome

Ancestral genome



Context Notation

Evolution of a genome

An inversion



Context Notation

Evolution of a genome

A duplication



Context Notation

Evolution of a genome

A deletion



Context Notation

Evolution of a genome

A transposition



Context Notation

Phylogenetic tree



Context Notation

Comparison between two genomes



Fugu/Human chromosome 12 [Wang et al., 2006]

Context Notation

Computation of a scenario based on the principle of parsimony



Context Notation

Computation of a scenario based on the principle of parsimony





Context Notation

Computation of a scenario based on the principle of parsimony



Context Notation

Computation of a measure of (dis)similarity

Compute the (dis)similarities between two genomes.

Synteny

Group of genes conserved between two species.



Context Notation

Comparative genomic

Comparative genomic allows to better understand the evolution of species.

- Scenario or computation of measure of (dis)similarity,
- Study of measures of (dis)similarity: number of common intervals, number of adjacencies, number of breakpoints, MAD, SAD...

Context Notation

Compare two genomes

Two genomes without duplication

$$G_1$$
 +0 +1 +2 +3 +4 +5 +6 +7 +8 +9
 G_2 +0 +7 +3 -5 -4 +6 +1 +2 -8 +9

The genome is a signed permutation.

Context Notation

The number of common intervals [Uno et Yagiura, 2000].

A measure of similarity



 \Rightarrow 23 common intervalles between G_1 and G_2 .

Context Notation

Number of adjacencies [Angibaud et al., 2008]

A second measure of similarity

$$G_1$$
 +0 +1 +2 +3 +4 +5 +6 +7 +8 +9
 G_2 +0 +7 +3 -5 -4 +6 +1 +2 -8 +9

 \Rightarrow 2 adjacencies between G_1 and G_2 .

Context Notation

Number of breakpoints [Sankoff et Blanchette, 1997]

A measure of dissimilarity

$$G_1 + 0 + 1 + 2 + 3 + 4 + 5 + 6 + 7 + 8 + 9$$

$$G_2 + 0 + 7 + 3 - 5 - 4 + 6 + 1 + 2 - 8 + 9$$

Dual measure to the measure of number of adjacencies:

$$\operatorname{bkp}(G_1, G_2) + \operatorname{adj}(G_1, G_2) = n - 1$$

 \Rightarrow 7 breakpoints between G_1 and G_2 .

Context Notation

Outline

Comparison between two genomes with duplications

Comparison between two partially ordered genomes

Exact algorithms Experimentation Heuristics

Comparison between two genomes with **duplications**

Exact algorithms Experimentation Heuristics

Duplications of genes on 5 chromosomes of the *Arabidopsis thaliana* 's genome



[Arabidopsis genome initiative, 2000]

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Comparison of two genomes

Two genomes with duplications

We need to find a matching between both genomes.



Exact algorithms Experimentation Heuristics

Matching model: exemplar



Exact algorithms Experimentation Heuristics

Matching model: exemplar



Exact algorithms Experimentation Heuristics

Matching model: exemplar



Exact algorithms Experimentation Heuristics

Matching model: exemplar



Exact algorithms Experimentation Heuristics

Matching model: maximum

The matching is required to saturate as many genes as possible of each gene family [Tang and Moret, 2003].



Exact algorithms Experimentation Heuristics

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Exact algorithms Experimentation Heuristics

Matching model: maximum

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Exact algorithms Experimentation Heuristics

New matching model: intermediate

The matching is required to saturate at least one gene of each gene family.



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Exact algorithms Experimentation Heuristics

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Strategy

Framework study

Studied models: exemplar, intermediate, maximum.

Studied measures: numbers of adjacencies and breakpoints.

The corresponding problems are **NP**-hard [Bryant, 2000].

 \Rightarrow Result of **no-approximation**.

\Rightarrow Heuristics.

 \Rightarrow **Exact** algorithms.

Exact algorithms Experimentation Heuristics

Comparison between two genomes with **duplication** Exact algorithms

Exact algorithms Experimentation Heuristics

A pseudo-boolean program

Objective	$\max(z); \ z = x_1 + 2x_2 - x_3$		
Constraints	$x_1 - 2x_2 + 3x_3 x_1 + x_2 + x_3 2x_1 + x_2 + x_3$	> = <	1 1 3
Boolean variables	$x_i \in \{0,1\}$		$\forall i=1,2,3.$

Exact algorithms Experimentation Heuristics

Variables

We have 4 types of variables:

a(i, k) denotes a **matching** between two genes; $b_x(i)$ denotes the **saturation** of a gene in genome G_x ; $c_x(i, j)$ denotes two genes **consecutives** in genome G_x ; d(i, j, k, l) denotes an **adjacency**.


Exact algorithms Experimentation Heuristics

Illustration of the variables a(i, k) and $b_x(i)$



Exact algorithms Experimentation Heuristics

Illustration of the variables a(i, k) and $b_x(i)$

We have two genomes:





Exact algorithms Experimentation Heuristics

Illustration of the variables a(i, k) and $b_x(i)$

We have one family of duplicated genes:



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Illustration of the variables a(i, k) and $b_x(i)$

We have a matching between $G_1(i)$ and $G_2(k_j)$:



Exact algorithms Experimentation Heuristics

Illustration of the variables a(i, k) and $b_x(i)$

We have a matching between $G_1(i)$ and $G_2(k_j)$:



Exact algorithms Experimentation Heuristics

Illustration of the variables $c_x(i,j)$ and d(i,j,k,l)

We have an adjacency between $G_0[i]$ and $G_1[j]$:



Exact algorithms Experimentation Heuristics

Comparison between two genomes with **duplication**

Experimentation

Exact algorithms Experimentation Heuristics

Experimentation

Dataset [Lerat et al. 2003]

- 12 γ -proteobacteria complete genomes,
- size: between 565 and 5474 genes,
- 7.6% of duplicated genes.

Solver

 For this work, the solver used is CPLEX http://www.ilog.com/products/cplex.

Exact algorithms Experimentation Heuristics

Results for the comparison between 12 genomes

Quadri Intel(R) Xeon(TM) CPU 3.00 GHz with 16GB of memory.

Results under the maximum model

- All results: 66 pairs of genomes (100%);
- Total time: \simeq 3 minutes.

Results under the exemplar model

- 65 out of 66 (98%) memory problem
- Total time: \simeq 3 minutes.

Results under the intermediate model

- Maximization of number of adjacencies:
 - 63 out of 66 (95%); Total time: \simeq 16 minutes.
- Minimization of number of breakpoints:
 - 59 out of 66 (89%); Total time: $\simeq 1$ hour.

Exact algorithms Experimentation Heuristics

Comparison between the exemplar and maximum models

The choice of model depends on the measure considered

- Between two genomes, under the maximum model there are 8% of adjacencies more than under the exemplar model.
- Between two genomes, under the exemplar model there are 11% of breakpoints less than under the maximum model.

Exact algorithms Experimentation Heuristics

Gain from intermediate model to exemplar and maximum models

During the miminization of the number of breakpoints

Datia	Intermediate		
NduO	Adjacencies	Breakpoints	
Exemplar	2% 0%		
Maximum	-5% 10%		

During the maximization of the number of adjacencies

Patia	Intermediate		
NduU	Adjacencies	Breakpoints	
Exemplar	10%	-3%	
Maximum	1%	8%	

Exact algorithms Experimentation Heuristics

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Exact algorithms Experimentation Heuristics

Comparison between two genomes with **duplications** Heuristics





G1	1	2	3	4	-5	1	6	7	2
G2	6	2	7	-6	5	-4	1	2	3

- **O** Compute *S*: the Longest Common Substring up to a reversal
- 2 Map all the genes of S accordingly
- ③ Remove genes that cannot be matched any longer according to the model
- Iterate the process until saturation



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Heuristics

Introduction Duplications Partial order

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Exact algorithms Experimentation Heuristics

Hybrid: IILCS then exact algorithm

- Partial matching by iteration of IILCS;
- Stopping criterion: size of a LCS less than a parameter k;
- Then, total matching using our exact algorithm.

Exact algorithms Experimentation Heuristics

ر ب	Heuristic	IILCS_M	HYB_M(2)	HYB_M(3)
ar sec	Average	99.05%	99.83%	99.94%
ca xi	Worst case	97.43%	99.38%	99.47%
Ma. 66	Best case	100%	100%	100%
	Exact result	16,67%	45,45%	75,76%

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ca a	Worst case	97.89%	99.73%	99.73%
Ex(Best case	100%	100%	100%
	Exact result	20%	83,08%	95,38%

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Exact algorithms Experimentation Heuristics

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Exact algorithms Experimentation Heuristics

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Introduction Notations Exact algorithms Experimental results

Comparison between two partially ordered genomes

Introduction Notations Exact algorithms Experimental results

A partially ordered genome

One chromosome of Sorghum:



[Klein, 2004]

Introduction Notations Exact algorithms Experimental results

A partially ordered genome

A part of partially ordered Sorgum Genome:



[Klein, 2004]

Introduction Notations Exact algorithms Experimental results

A partially ordered genome

Two studies of a same part of Sorghum genome:



[Paterson, 2003]

[Klein, 2004]

Introduction Notations Exact algorithms Experimental results

Comparison between two partially ordered genomes Notations
A partial order



A partially ordered genome represented by a **DAG**.

A partial order



The gene +4 precedes the gene +12, both genes are **comparables**.

A partial order



The genes +1 and +2 are **incomparables**.

A partial order



The width of **P** is the size of the maximal set of incomparable genes: 4.

ntroduction Duplications	Introduction Notations
Partial order	Exact algorithms
Conclusion	Experimental results

A linear extension



T :

 $+0 \ +1 \ +2 \ +3 \ +4 \ +5 \ +6 \ -7 \ -8 \ +9 \ +10 \ +11 \ +12 \ +18 \ +17 \ +16 \ +15 \ +14 \ +13$

Introduction	Introduction
Duplications	Notations
Partial order	Exact algorithms
Conclusion	Experimental results

- Studied measures: number of common intervals, number of adjacencies.
- NP-hard problems [Blin et al. 2007, Fu and Jiang 2006].
- We want, in the future, to evaluate some heuristics.
- We express our problems as pseudo-boolean programs.

\Rightarrow **Exact** algorithms.

Introduction Notations Exact algorithms Experimental results

Comparison between two partially ordered genomes Exact algorithms

Introduction Notations Exact algorithms Experimental results

Three studied problems:

The number of common intervals

• MCIL-1PO: Confront one partially ordered genome P₁ and a reference totally ordered genome *Id* and maximize the number of common intervals.

The number of adjacencies

- MAL-1PO: Confront one partially ordered genome P₁ and a reference totally ordered genome *Id* and maximize the number of adjacencies.
- MAL-2PO: Confront two partially ordered genomes P₁ and P₂ and maximize the number of adjacencies.

ntroduction	
Duplications	
Partial order	Exact algorithms
Conclusion	Experimental resul

We have 1 common variable 's type:

 $a_{g,i}^{\times}$ denotes the gene g at the position $i \ (i \in \{1, n\})$ in the linear extension $T_{X} \ (x \in \{1, 2\})$.

3 constraints:

C.a
$$\forall \ 0 \leq g \leq n, \sum_{0 \leq i \leq n} a_{g,i}^x = 1$$

C.b
$$\forall \ 0 \leq i \leq n, \sum_{0 \leq \mathsf{g} \leq n} a^{\mathsf{x}}_{\mathsf{g},i} = 1$$

 $\texttt{C.c} \hspace{0.2cm} \forall \hspace{0.1cm} 0 \leq \texttt{g}_1 \leq \textit{n}, \hspace{0.1cm} 0 \leq \texttt{g}_2 \leq \textit{n}, \hspace{0.1cm} \texttt{g}_1 \prec_{\scriptscriptstyle X} \texttt{g}_2, \hspace{0.1cm} 0 < j \leq \textit{i} \leq \textit{n}, \hspace{0.1cm} a^x_{\texttt{g}_1,\textit{i}} + a^x_{\texttt{g}_2,\textit{j}} \leq 1$

ntroduction	
Duplications	
Partial order	Exact algorithms
Conclusion	Experimental result

We have 4 specific variable's types:

 $b_{g,i,t}$ denotes the gene g at a position between $T_1[i]$ and $T_1[i+t]$;

 $c_{g,i,t}$ denotes the common interval compose of the genes $\{g, g+1, \ldots, g+t\}$ at positions $\{i, i+1, \ldots, i+t\}$ in T_1 ;

 $d_{g,i}$ denotes an adjacency between g and g+1 with g at the position $\mathcal{T}_1[i]$;

 e_{g_1,i,j,g_2} denotes an adjacency between g_1 and g_2 with g_1 at positions $T_1[i]$ and $T_2[j]$.

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artial order	Exact algorithms
Conclusion	Experimental result

Illustration of the variables $a_{g,i}^{\times}$



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artial order	Exact algorithms
Conclusion	Experimental res

Illustration of the variables $b_{g,i,t}$ and $c_{g,i,t}$



Comparison between two partially ordered genomes

Experimentation

ntroduction	
Duplications	
Partial order	Exact algorithms
Conclusion	Experimental results

Experimentation

Simulated dataset [Blin et al. 2006]:

- The *size n* ∈ {30, 40, 50, 60, 70, 80, 90};
- The order rate $p \in \{0.7, 0.9\}$;
- The gene distribution $q \in \{0.4, 0.6, 0.8\};$
- 19 unsigned genomes for each triplet (n, p, q).

Solver

• For this work, the solver used is MiniSat+ [Een et Sorensson, 2006].

ntroduction	
Duplications	
artial order	Exact algorithms
Conclusion	Experimental results

Results for the three programs

 $q \in \{0.4, 0.6, 0.8\}$ Quadri Intel(R) Xeon(TM) CPU 3.00 GHz with 16GB of memory.

$\mathsf{MCIL}\text{-}1\mathsf{PO} \Rightarrow \mathtt{CI}\text{-}1\mathtt{PO}$

- 494 results out of 570 (87%), $n \in \{30, \dots, 90\}$, for p = 0.9, $n \in \{30, \dots, 50\}$, for p = 0.7
- 2 hours in average (6% case > 1 hour).

$MAL-1PO \Rightarrow Adjacency-1PO$

- 778 results out of 798 (97%), $n \in \{30, \ldots, 90\}, p \in \{0.7, 0.9\}$
- in average **2 hours** (9% case > 1 hour).

$MAL-2PO \Rightarrow Adjacency-2PO$

- 1852 results out of 2052 (90%), $n \in \{30, 40, 50\}, p = 0.9$
- 1 hour in average (8% case > 1 hour).

ntroduction	
Duplications	
Partial order	Exact algorithms
Conclusion	Experimental results

Influence on time, Adjacency-1PO



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Duplications	
Partial order	
Conclusion	Ex

Introduction Notations Exact algorithms Experimental results

Influence on the measure, Adjacency-10P



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Conclusion	Experimental r

sults

Comparison between two measures

CI-1PO

90% of results give the maximum number of adjacencies.

Adjacency-1PO

16% of results give the maximum number of common intervals.

Conclusion Future works

Conclusion

Conclusion Future works

Conclusion

Genomes with duplicated genes

- A **pseudo-boolean program** to compute two distances (the number of adjacencies and number of breakpoints) between two genomes with duplication under three models (*exemplar*, *maximum* and *intermediate* matching).
- Rules of reduction to speed-up the programs.
- Two **heuristics** for each model: simple, fast and efficient on the dataset we studied.

Conclusion Future works

Conclusion

Partially ordered genomes

- Dealing with partially ordered genomes.
- Exact algorithms for 3 problems (MICL-1PO, MAL-1PO and MAL-2PO).
- Rules of reduction to speed-up the programs.
- Influence of parameters.

Conclusion Future works

Future works

General

- Test other datasets,
- Improve the running time of the programs,
- Study other (dis)similarity measures: MAD, SAD.

Genomes with duplicated genes

- **Double objective**: minimize the number of breakpoints and maximize the number of adjacencies at the same time.
- See in **details** the differences and similitudes between each model and measure.
- Direct analysis project: No homology assignement.
- Supermarket project: Comparison of two ways.

Conclusion Future works

Future works

Partially ordered genomes

- Define and evaluate heuristics,
- Generalize the programs (CI-2PO, genomes with duplications).
- Compare a set of contigs and a reference genome.

Conclusion Future works

Collaborators

Université Paris-Est (LIGM) Stéphane Vialette Guillaume Fertin Irena Rusu Sébastien Angibaud

Conclusion Future works

Conclusion Future works

Rules to speed-up the resolution

- **Pre-processing**: suppression of genes present in only one genome, specific suppressions under the exemplar model.
- Rule of reduction: matching between no-duplicate genes.
- Pre-matching: between two no-duplicated genes.



Conclusion Future works

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Conclusion Future works

Heuristic IILCS_IA



Each family of genes have at least one gene matched \Rightarrow The heuristic IILCS_IA stop.

Conclusion Future works

Heuristic IILCS_IA



We can again increase the number of adjacencies until the size of LCS if superior than 1.

Conclusion Future works

Parameters of partial order [Blin et al., 2007]



- The gene distribution q: define the disorder;
- The order rate p: probability to have " \rightarrow ".

Conclusion Future works

The heuristics can be bad



Conclusion Future works

Measures MAD and SAD

G_1 +0 +1 +2 +3 +4 +5 +6 +7 +8 +9 G_2 +0 +7 +3 -5 -4 +6 +1 +2 -8 +9
Conclusion Future works

Measures MAD and SAD



Conclusion Future works

State of the art

Previous results [Chen et al., 2006]

Under the exemplar model, there do not exist an approximation allows to minimize the number of breakpoints between two genomes even if every gene is present at most three times in each genome.

Conclusion Future works

Result for the exemplar model

Lemma

Under the exemplar model, define if there exist a matching without breakpoint is a **NP**-complet problem, even if every gene is present at most twice on one genome.

Demonstration.

Reduction from the VERTEX COVER problem. \Box

Conclusion Future works

Result for the exemplar model

Lemma

Under the exemplar model, define if there exist a matching without breakpoint is a **NP**-complet problem, even if every gene is present at most twice on one genome.

Theorem

Under the exemplar model, minimize the number of breakpoints is not approximable even if every gene is present at most twice on one genome.

Conclusion Future works

Results under the intermediate and maximum models

Lemma

Under exemplar and intermediate models, the problems to define if there exist a matching without breakpoint are equivalent problems.

Conclusion Future works

Results under the intermediate and maximum models

Lemma

Under exemplar and intermediate models, the problems to define if there exist a matching without breakpoint are equivalent problems.

Theorem

Minimize the number of breakpoints, under the intermediate model, is a non approximable problem even if every gene is present at more twice on one genome.

 \Rightarrow No equivalence under the **maximum** model. \Rightarrow Currently: equivalent result for 2 genomes where every gene is present **at more twice on each genome** [Sikora, 2009].