

Deciphering species-level phylogenetic relationships in the evolutionary complex genus *Rosa* using an amplicon-sequencing approach

Kevin Debray¹, Marie-Christine Le Paslier², Aurélie Bérard², Tatiana Thouroude¹, Gilles Michel¹, Fabrice Foucher¹ and Valéry Malécot¹

¹IRHS, Agrocampus-Ouest, INRA, Université d'Angers, SFR 4207 QuaSaV, Beaucouzé, France

²INRA, US 1279 EPGV, Université Paris-Saclay, Evry, France

PHY-ROSE
2016-2019



Colloque EPGV
October, 3rd 2018

Background – *The Tree and Classification of Life*

Domain: Eukaryota

Kingdom: Plantae

Subkingdom: Tracheobionta

Superdivision: Spermatophyta

Division: Magnoliophyta

Class: Magnoliopsida

Subclass: Rosidae

Order: Rosales

Family: Rosaceae

Subfamily: Rosoideae

Tribe: Roseae

Genus: *Rosa*

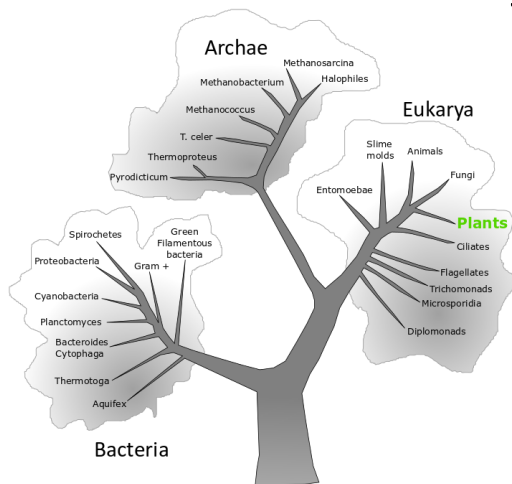
Subgenus: *Rosa*

Section: *Caninae*

Subsection: *Caninae*

Species: *Rosa canina* L.

Levels of interest



Background – *The genus Rosa*



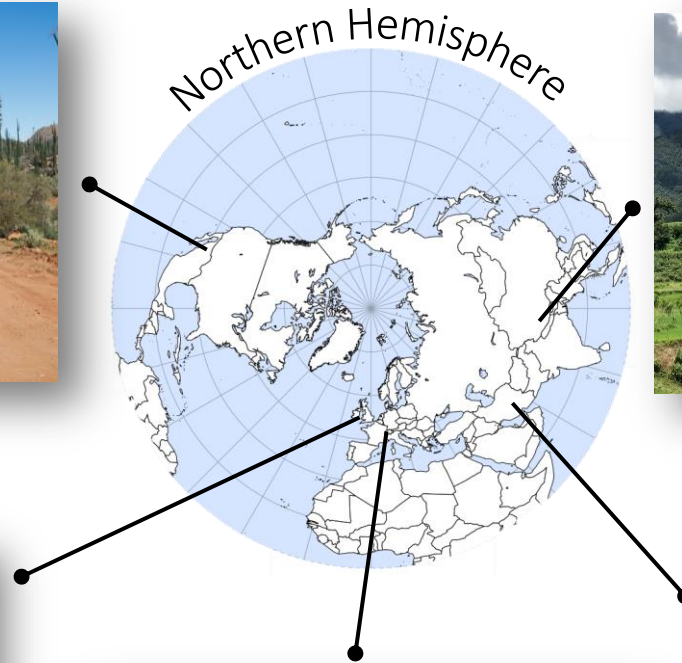
150-200 species



Background – *Wild roses distribution*



Mexican valleys



Himalayas



British coast

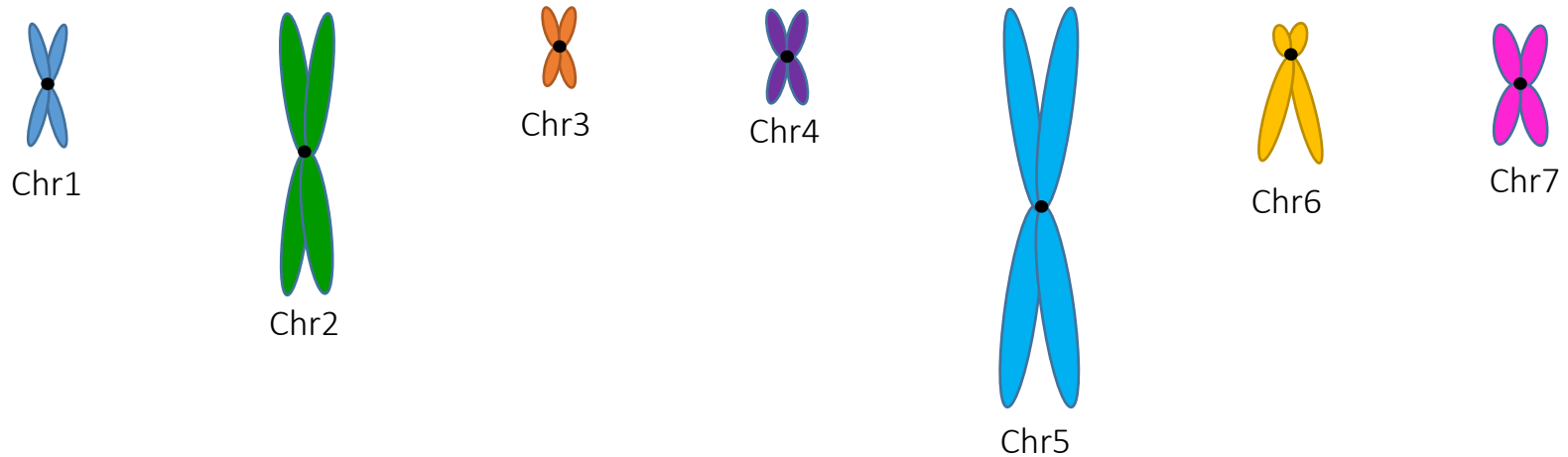


Alpine mountains



Iranian desert

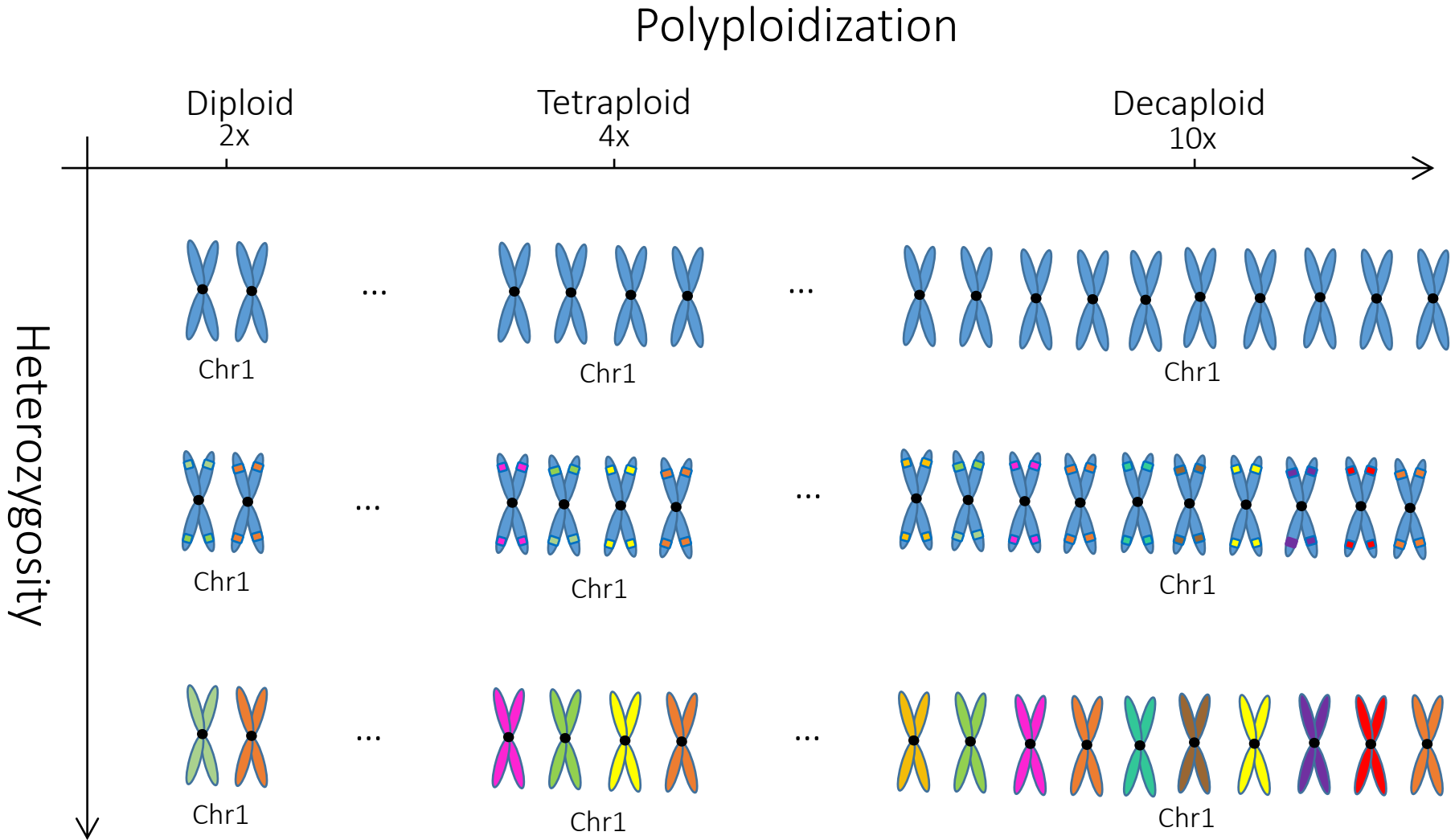
Background – *The Rose genome*



Haploid chromosome number: $n=7$ (*Voanioala gerardii* $n=298$)

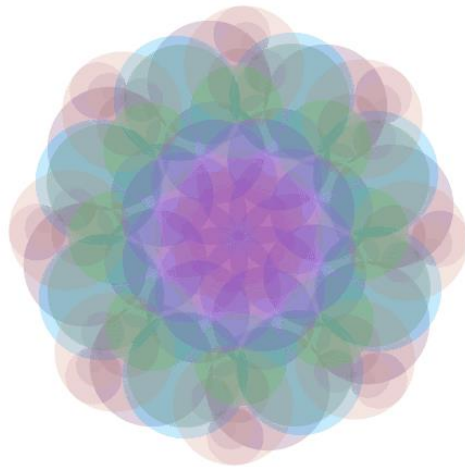
Monoploid genome size: $1Cx = 0,4-0,6 \text{ Gb}$ (*Fritallaria platyptera* $1Cx = 84 \text{ Gb}$)

Background – Adding complexity



Background – *Complex genomes*

Roses genomes are very flexible...
...as modeling clay!



... And this questions the notion of 'species' ...

Background – *Current phylogenetic issues*

Morphological issues



Rosa canina L.



R. nitidula Besser



R. caesia Smith

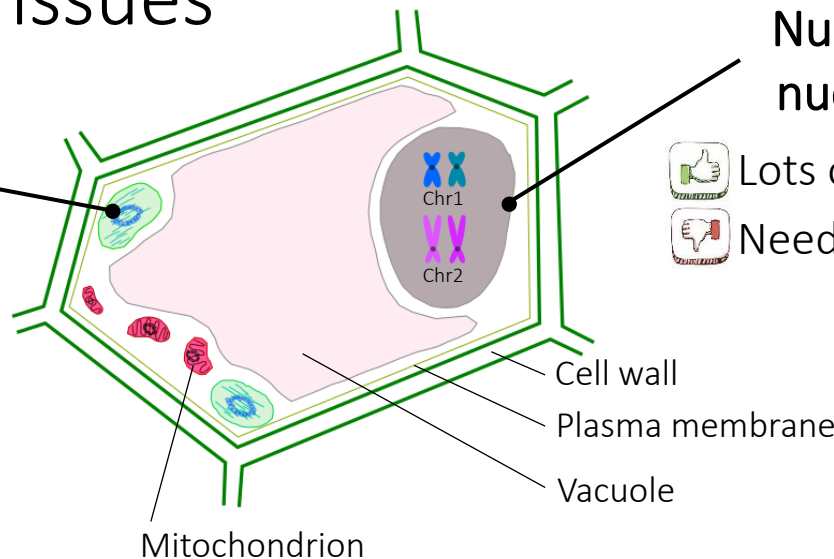


R. corymbifera Borkh.

Plastid sequences issues

Chloroplast with plastid DNA

- Easy to target and analyze
- No individual polymorphism
- Slow rate of evolution
- Putative maternal heredity



Nucleus with nuclear DNA

- Lots of allelic variations
- Need prior knowledge

Background – *Current phylogenetic issues*

Morphological traits and plastid sequences have **significant flaws** to study roses relationships...

...One solution would be to analyze **many nuclear loci** across rose genomes...



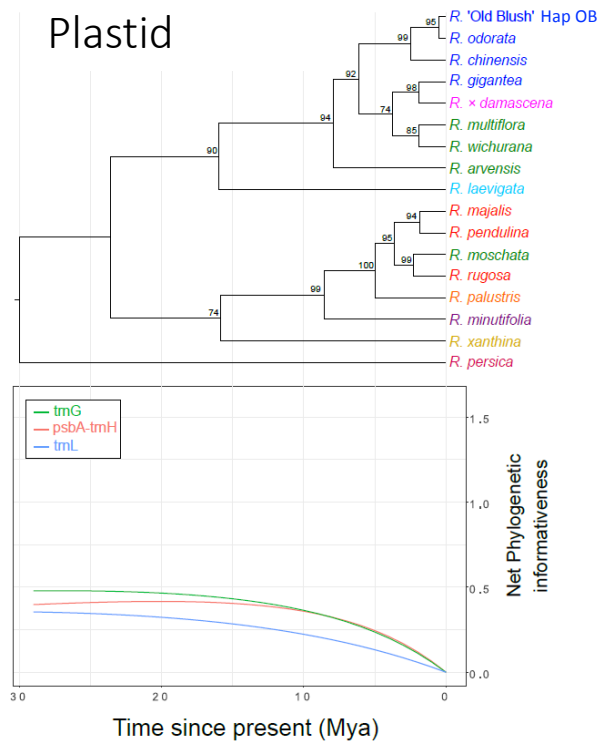
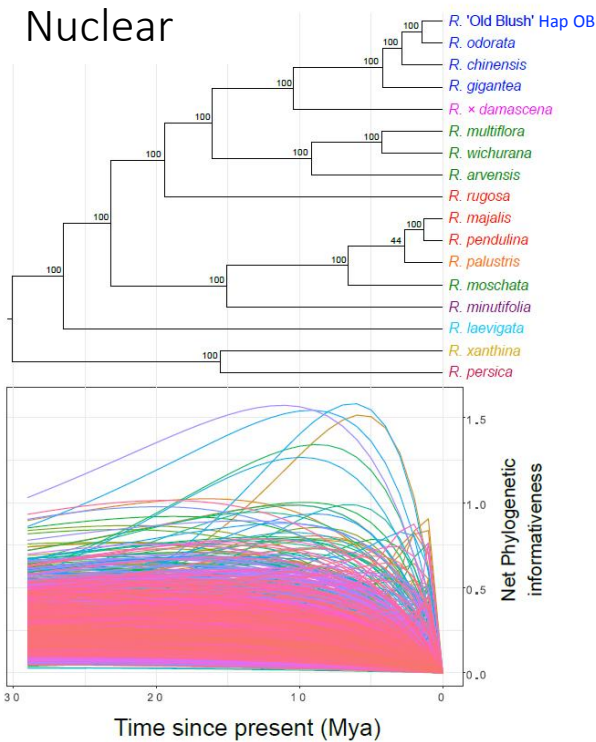
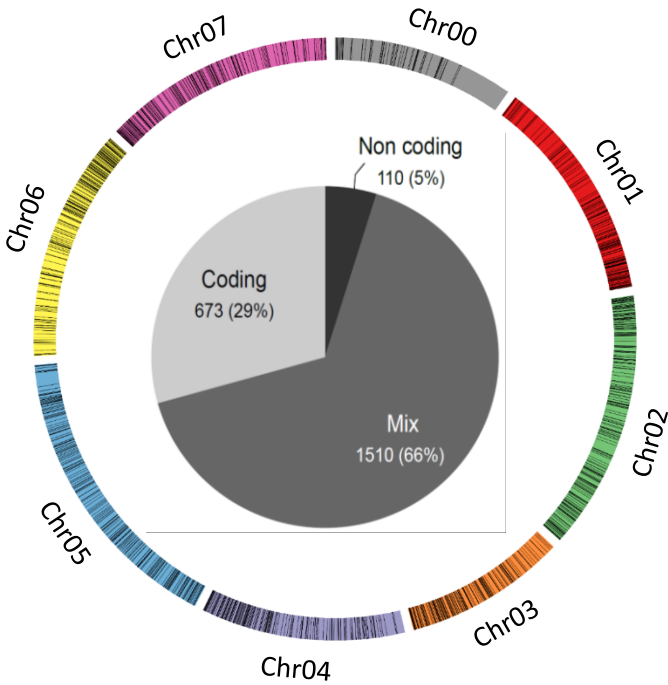
...Welcome to **Phylogenomics!**

Objectives – *Whole thesis objectives*

1. Identifying and assessing of **single-copy nuclear loci** for *Rosa* phylogenomics

2. Building a **phylogenomic network** of *Rosa* species highlighting **polyploidizations and hybridizations** as well as **traits evolution and biogeography**

Methods – “Previously in PHY-ROSE...”



A genome-mining strategy identifies **2,293 variable single-copy nuclear loci** for rose phylogenomics

Methods – “Previously in PHY-ROSE...”



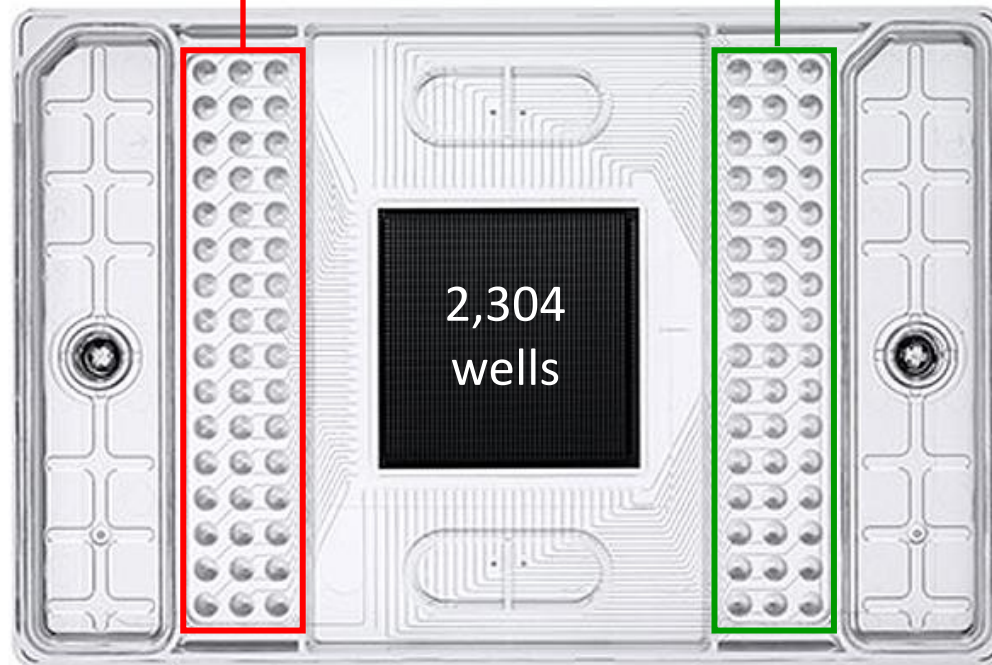
Silica-dried leaves bank of ca. 300 accessions
(131 species)

Methods – *The Amplicon sequencing technique*

Step 1/2: Target PCR amplification of loci

48 DNA samples

48 pairs of primers



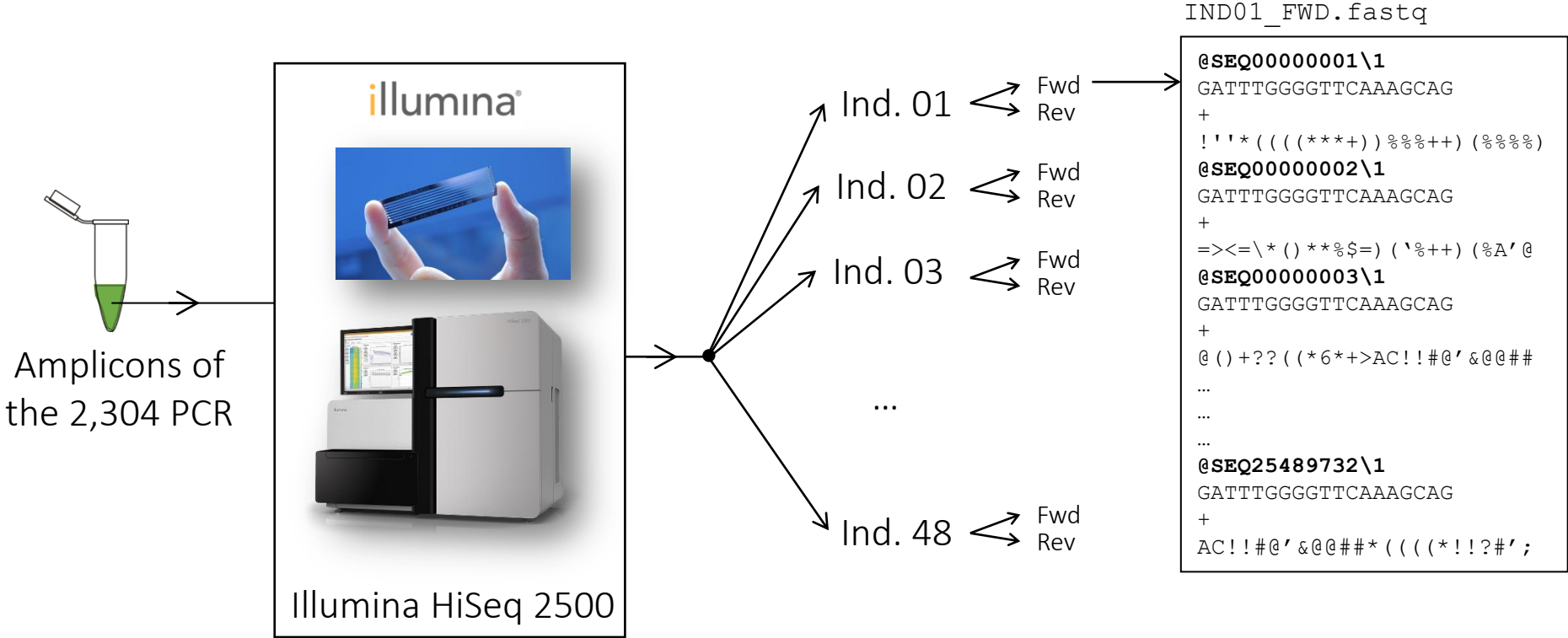
FLUIDIGM®

Access Array 48*48



Methods – *The Amplicon sequencing technique*

Step 2/2: Illumina sequencing 2*300 bp



96 files to demultiplex

Methods – *Post-sequencing workflow*

IND01_FWD.fastq

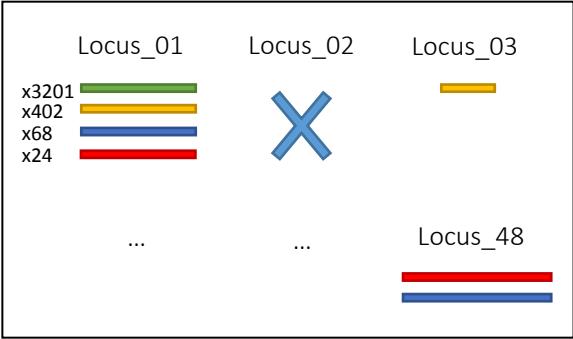
```
@SEQ00000001\1
GATTTGGGGTTCAAAGCAG
+
!''*(((((***+))%%%%)) (%%%%)
@SEQ00000002\1
GATTTGGGGTTCAAAGCAG
+
=><=\* () **%$=) ('%++) (%A'@
@SEQ00000003\1
GATTTGGGGTTCAAAGCAG
+
@ () +?? (( *6*+>AC!!#@' &@@##
...
...
...
@SEQ25489732\1
GATTTGGGGTTCAAAGCAG
+
AC!!#@' &@@##* ((( (*!?!?#';
```

IND01_REV.fastq

```
@SEQ00000001\2
CTGCTTTGAACCCCAAATC
+
DJ!!#@' &@@##* ((( (*!?!?#';
@SEQ00000002\2
CTGCTTTGAACCCCAAATC
+
*+>AC!!#@' &%$=) ('%++) (%
@SEQ00000003\2
CTGCTTTGAACCCCAAATC
+
@ () +?? (( *6*+>AC!!#@' &@@
...
...
...
@SEQ25489732\2
CTGCTTTGAACCCCAAATC
+
DJ!!#@' &@@##* @ () +?? (( *6
```



GOAL



- 1 QUALITY CHECKS
- 2 DEMULTIPLEXING
- 3 TRIMMING
- 4 ASSEMBLY
- 5 CLUSTERING
- 6 HAPLOTYPING



Methods – *Phylogenomics networks*

Method 1: with a priori

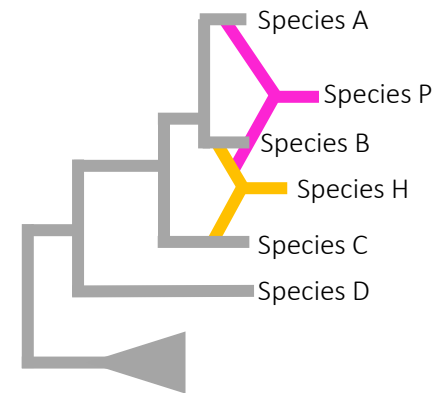
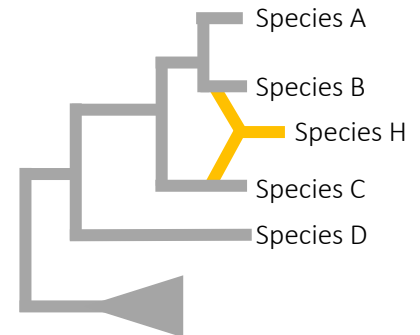
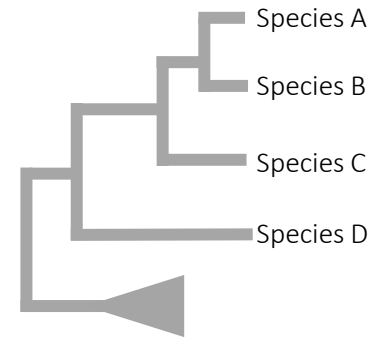
① Diploid non-hybrid tree
= Backbone diploid progenitors tree

② Graft alleles from diploid hybrids
and merge

Diploid-Hybrids detection?

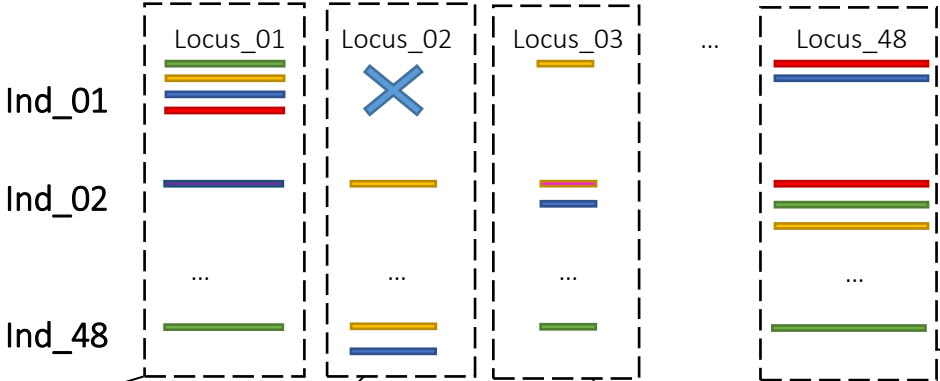
③ Graft alleles from polyploids
and merge

Polyploids detection?



Methods – *Phylogenomics networks*

Method 2: without a priori



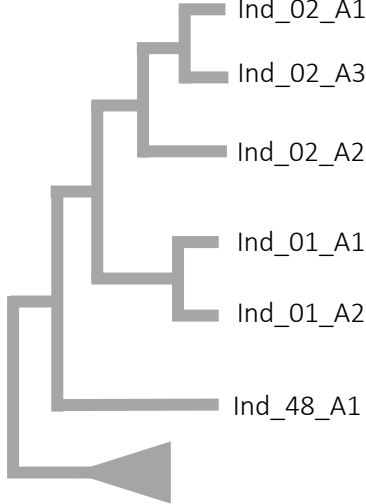
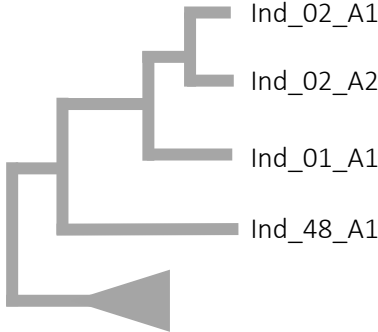
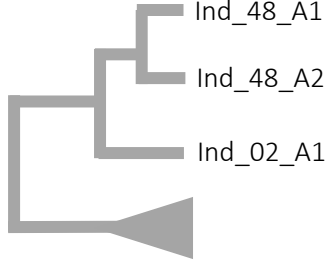
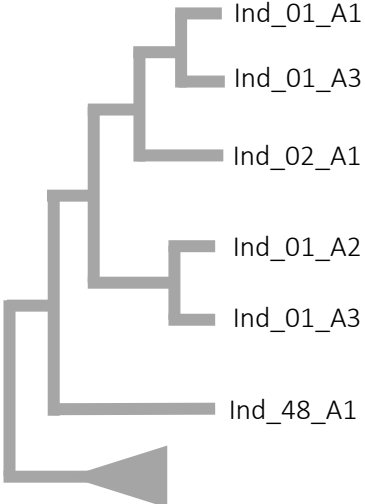
Locus_01

Locus_02

Locus_03

...

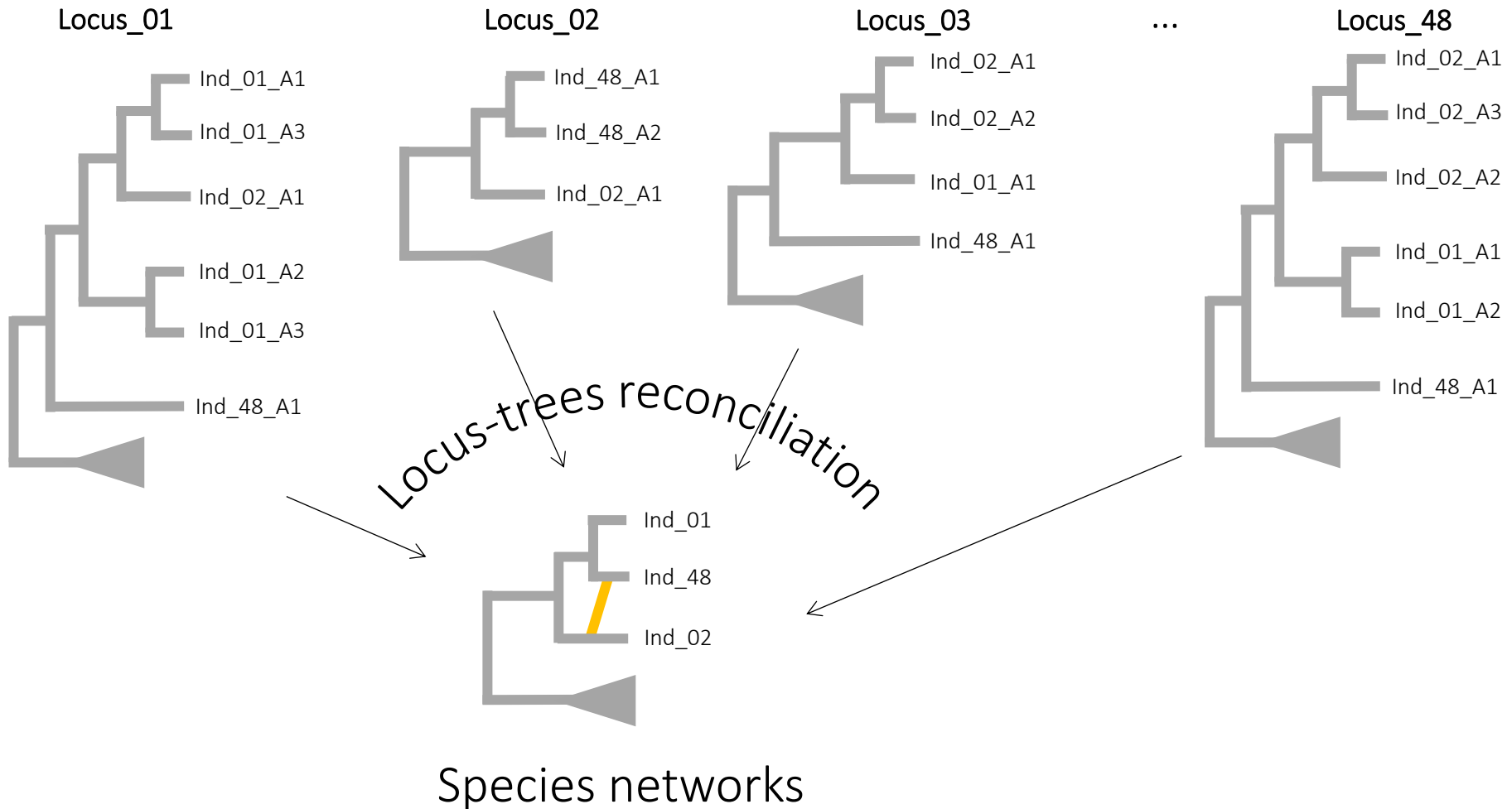
Locus_48



Multilabeled trees

Methods – *Phylogenomics networks*

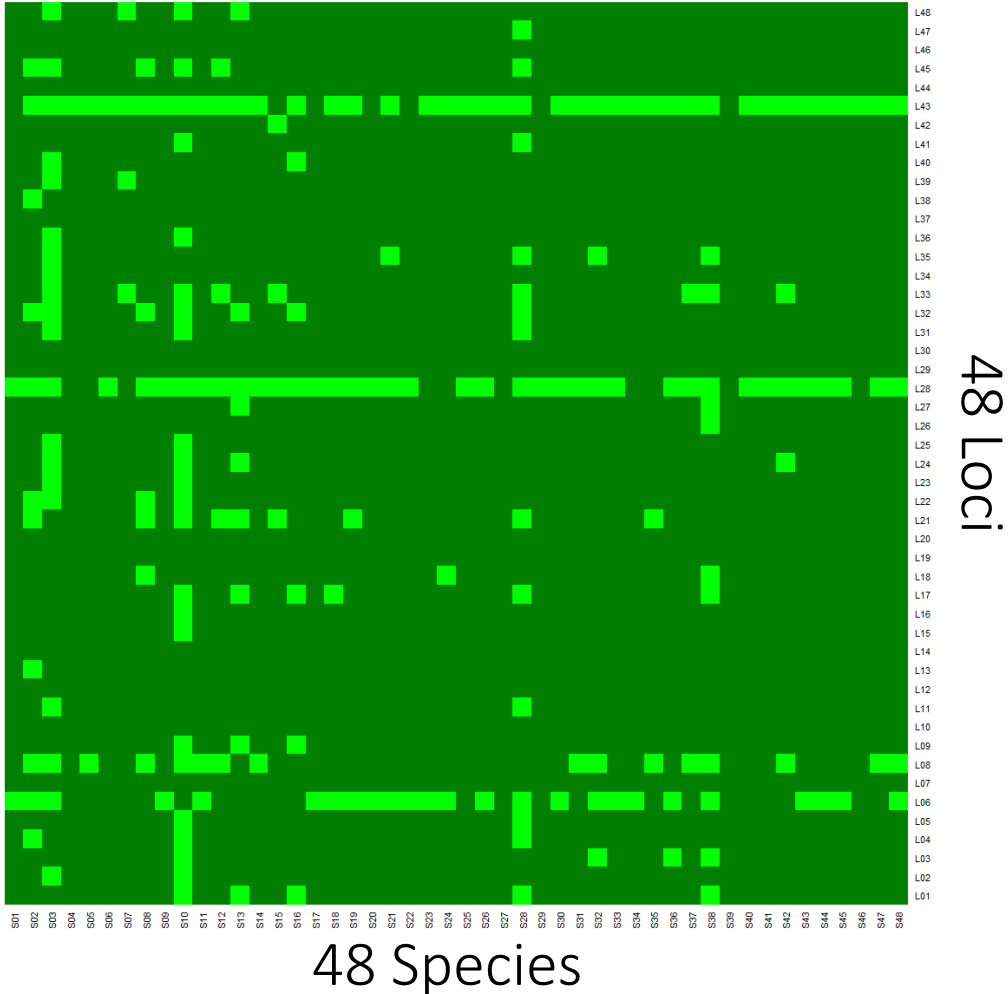
Method 2: without a priori



Results – Amplicon Sequencing

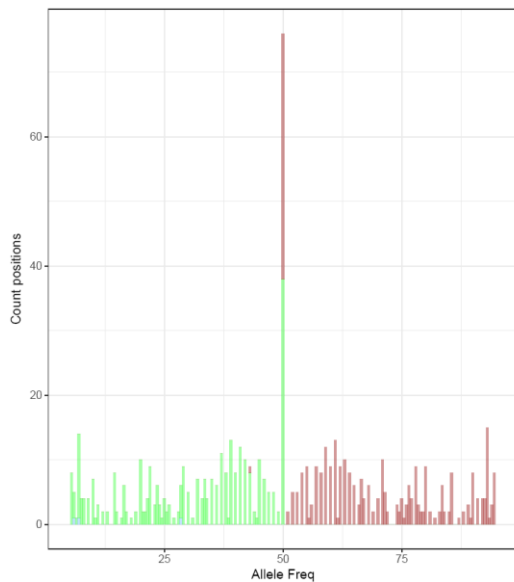
1 pilot run already analyzed: 90% of success

Success
Failure

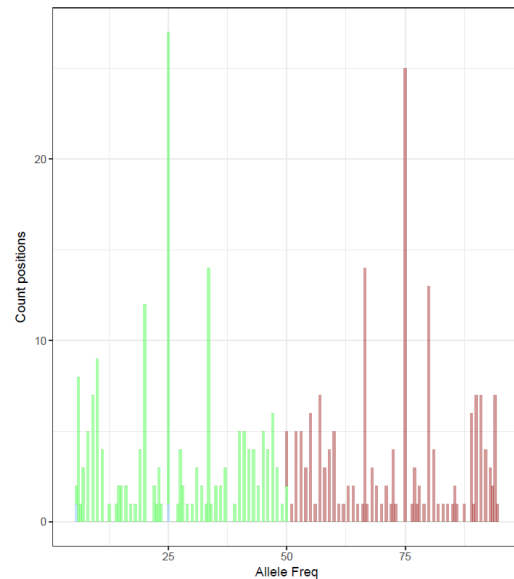


Results – Method 1: with a priori

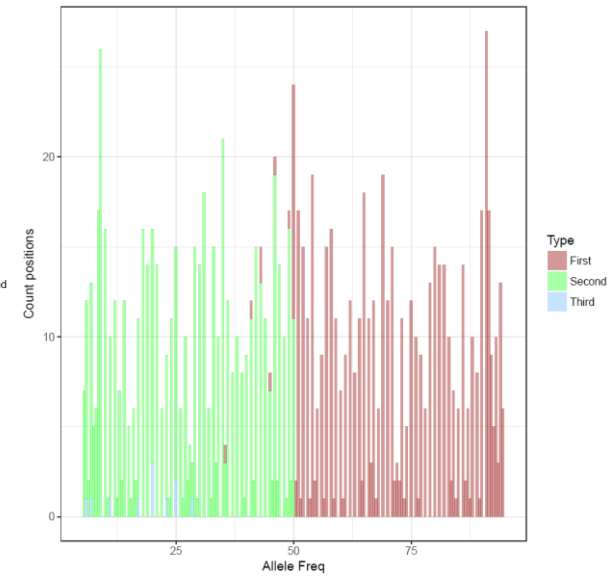
Polyploid detection?



50:50
2x



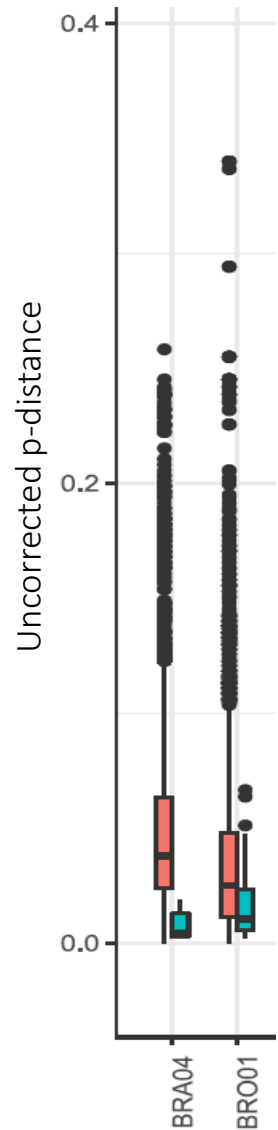
25:75
4x



?
> 2x

Alleles frequencies in combination with literature
give an idea of the **ploidy level**

Results – Method 1: with a priori



Diploid-hybrids detection?

Comparison of **intra/inter**
specific sequence **variations**

*“Intra-individual variations \ll Inter-individual variations
in diploids non-hybrids”*

■ Inter-individual
■ Intra-individual

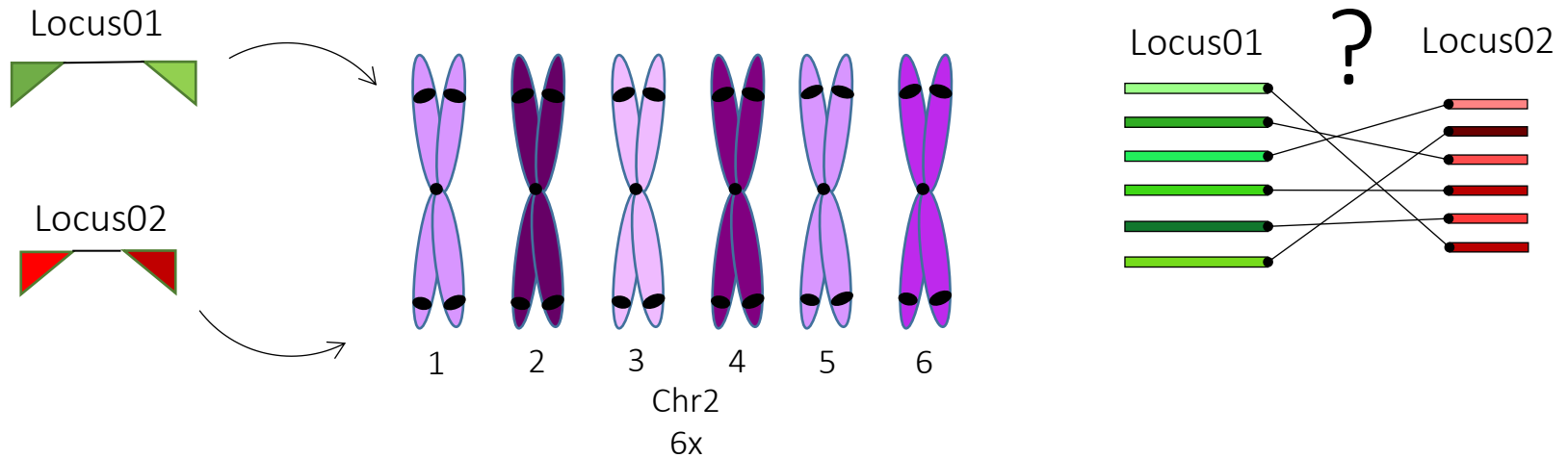
Discussion – Amplicon sequencing

- Prior (genomic) knowledge on the taxa studied

Barstia (Orobanchaceae) Uribe-Convers *et al.* 2016 PLoS ONE 11(2):28pp

Cucurbita (Cucurbitaceae) Kates *et al.* 2017 MPE 111:98-109

- Targeting alleles



-  Allele variation
-  Allele phasing

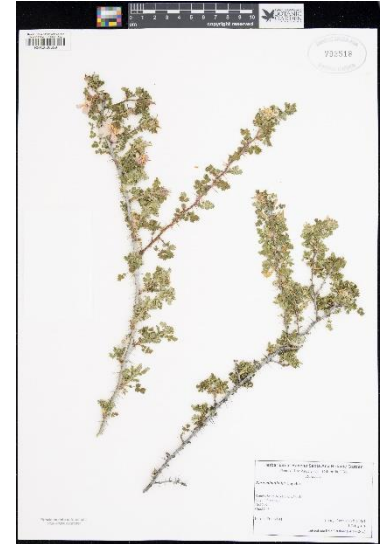
Discussion – *Amplicon sequencing*

- Robustness toward DNA quality

 - Carefree sampling and storage

 - Herbarium samples can be used

 - Some accessions were sampled before 2000



- High-quality sequencing for low price

 - Deep sequencing coverage (up to 11,591 X – mean was **3,308 X**)

 - 0,83€/locus/species** vs. ca. 3 €/locus/species using 1X Sanger sequencing

Perspectives – *On the origin of Rosa persica*

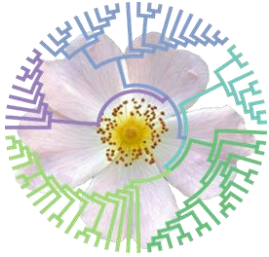


Rosa persica: Living fossil or super evolved rose?

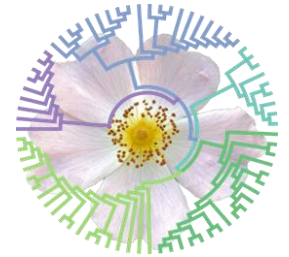


Dr Zahra Karimian
Research Center for Plant Sciences
Ferdowsi University of Mashhad - Iran

Acknowledgments



Thanks for your attention!



Curators and collectors



Sequencing

EPGV
ÉTUDE DU POLYMORPHISME
DES GENOMES VÉGÉTAUX

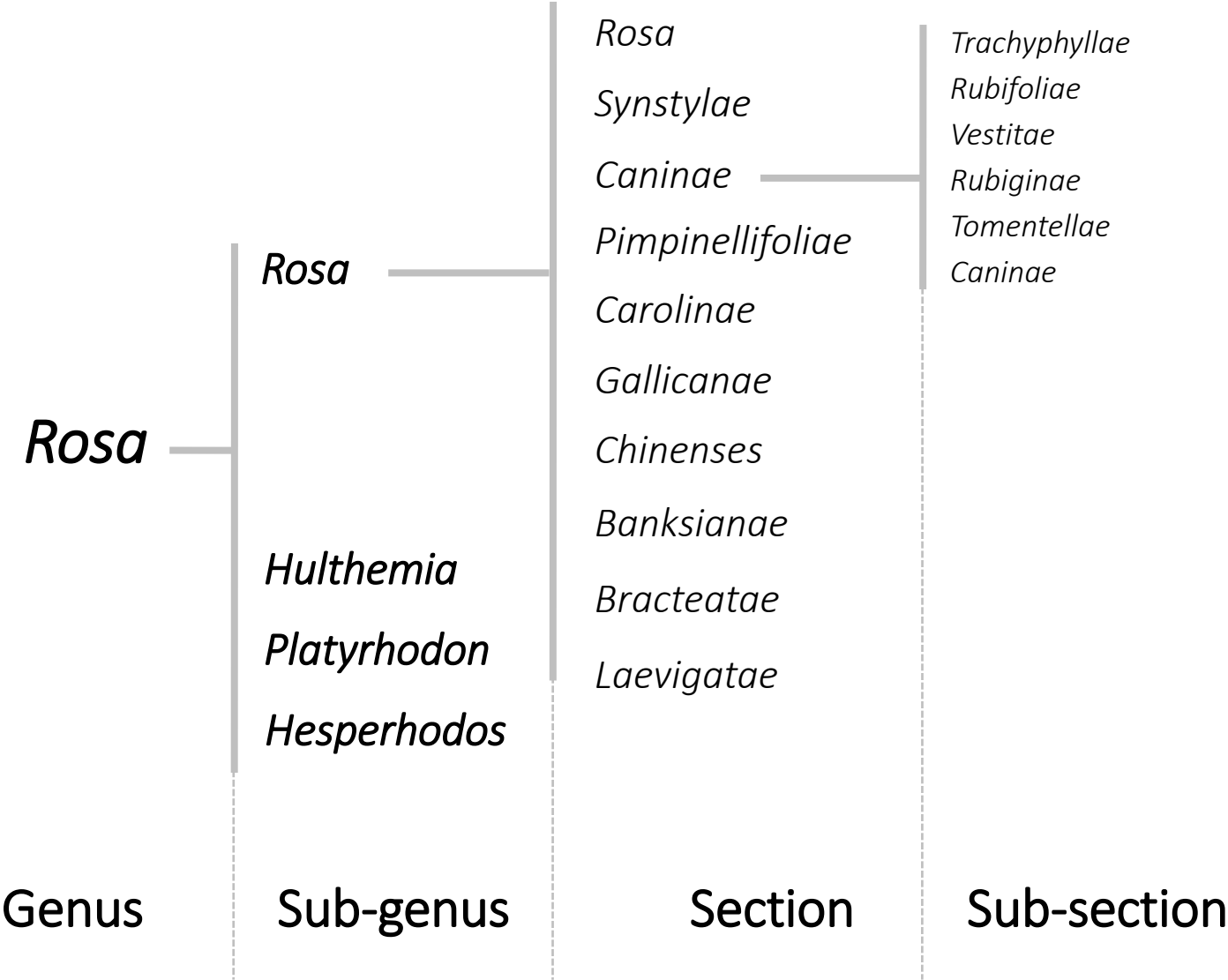
Bioinformatics

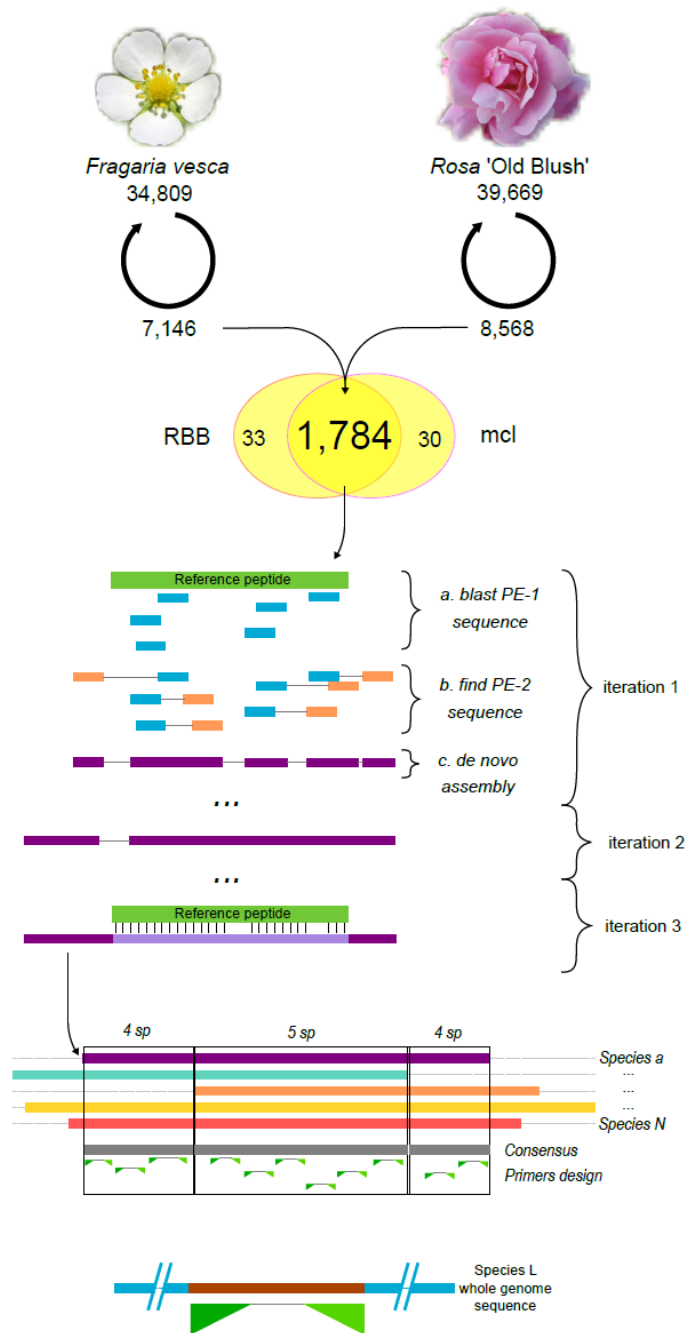


Funding



Background – *The genus Rosa*





STEP 1:

Find Single Copy Genes (SCGs) in both species

STEP 2:

Find shared Single Copy Orthologs (SCOs)

STEP 3:

Target assembly of the 1784 SCOs in **unassembled** genomes

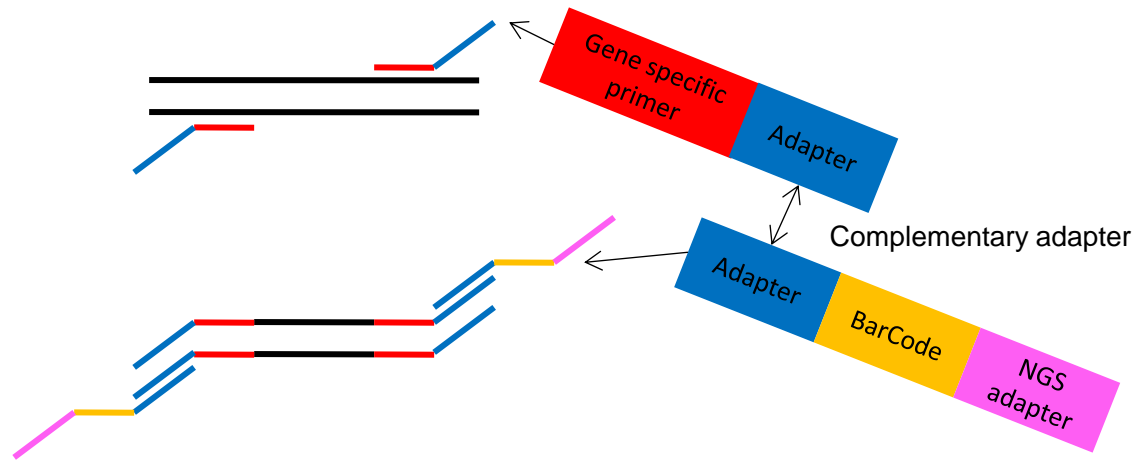
STEP 4:

Align contigs, find blocs with ≥ 4 species (including *R. 'Old Blush'* and *R. persica*) and design primers on consensus sequences

STEP 5:

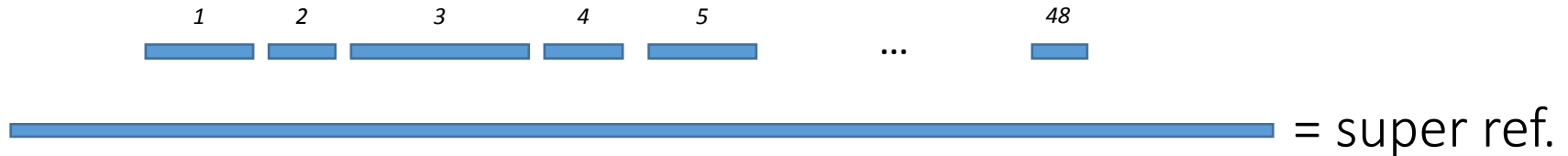
Check primers specificity on *R. 'Old Blush'* genome and find theoretical amplicons on **assembled** genomes

Methods – *The 4-primer amplification*

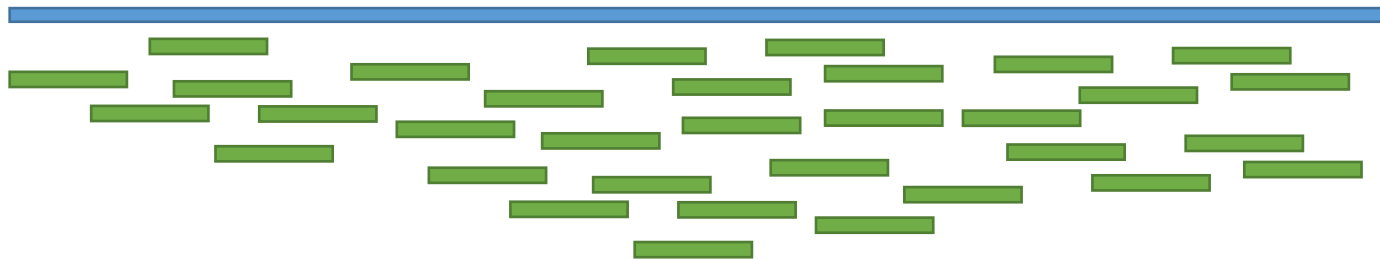


Methods – *Allelic frequencies and ploidy*

- 1 Concatenation of nuclear loci in the ref. hap OB



- 2 Mapping all reads of 1 individual



3 Count Allelic variations

A T G G C C T A G G T T A G C A

= super ref.

A T G G A C T A G G T T A G C A
 A T G G A C T A G G T T A G C A
 A T G G A C T A G G T T A G C A
 C T G G A C T A G G T T A G C A
 C T G G A G T A G G T T A G C A
 C T G G A G T A G G T T A G C A
 C T G G A G T A A A G T A
 C T G G A G T A A A G T A
 C T G G A G T C G G T A A G T G
 C T G G A G T C G G T A A G T G
 C T G G A G T C G G T A A G T G

= mapped reads

★ ★ ★ ★ ★ ★
 1:3 Na 1:2 1:3 1:1 1:1 1:3

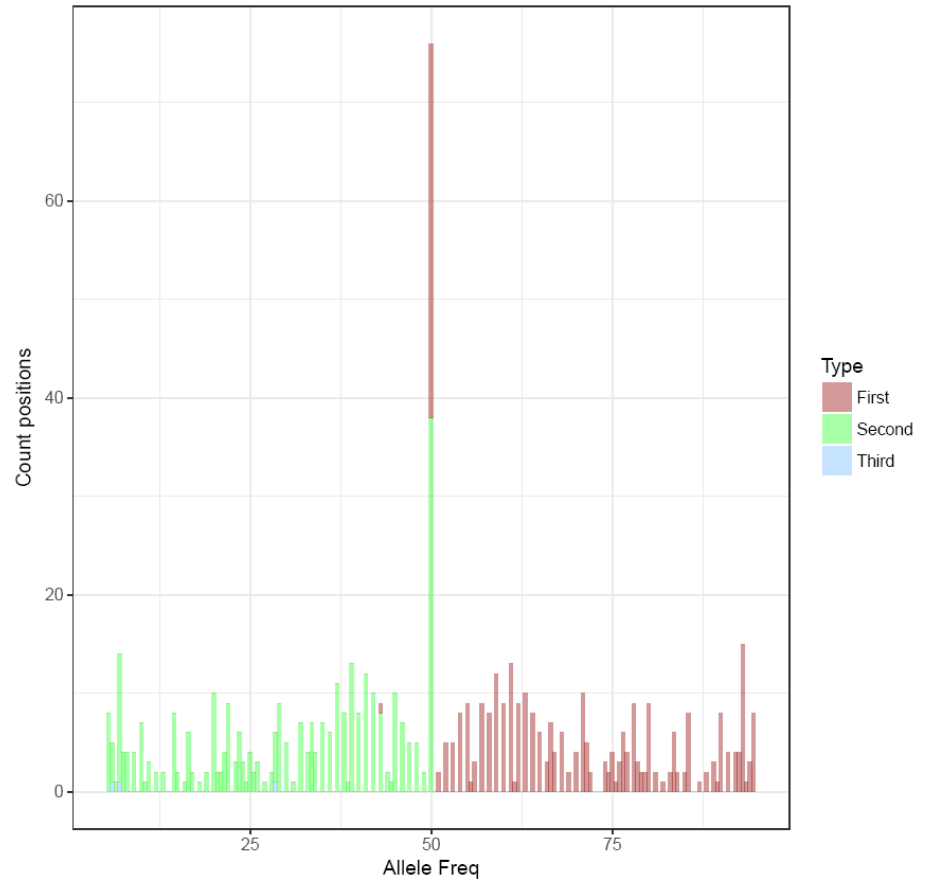
freq	Count A1
0	0
...	...
0,25	15
...	...
0,5	30
...	...
0,75	45
...	...
1	60

freq	Count A2
1	60
...	...
0,75	45
...	...
0,5	30
...	...
0,25	15
...	...
0	0

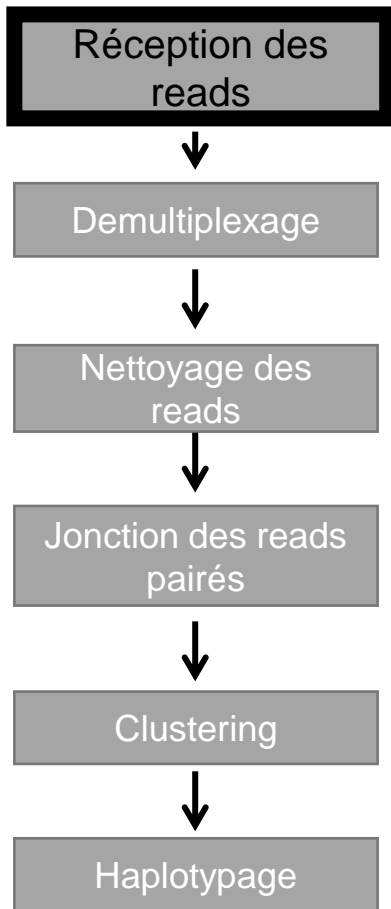
3 Count Allelic variations

freq	Count A1
0	0
...	...
0,25	15
...	...
0,5	30
...	...
0,75	45
...	...
1	60

freq	Count A2
1	60
...	...
0,75	45
...	...
0,5	30
...	...
0,25	15
...	...
0	0

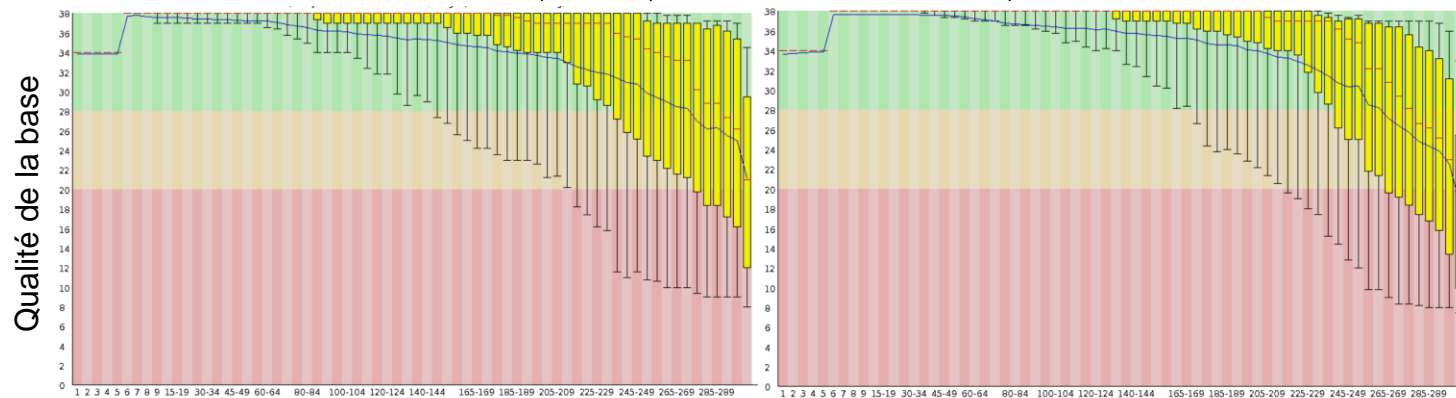


Methods – *Recovering alleles from reads*



Séquençage Illumina paired-end
2 x 300bp

Total : 18,876,898 reads ~ 2,7Go



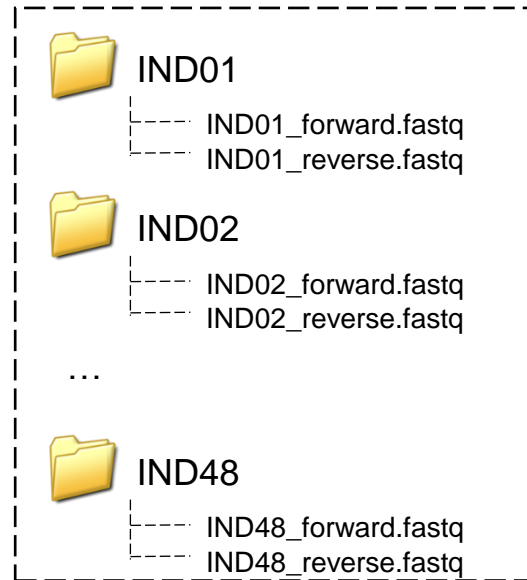
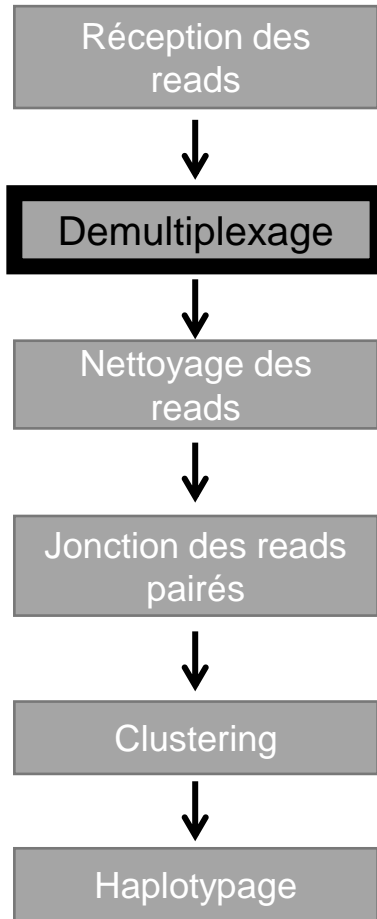
Position dans les reads

Forward

Position dans les reads

Reverse

Methods – *Recovering alleles from reads*



```
Primers.txt  
  
PAIR01_F ACGTGTGACAGT  
PAIR01_R GGACTTTGACTG  
  
PAIR02_F GTGTGCAGGTGG  
PAIR02_R GCCGACGAGACA  
  
...  
  
PAIR48_F CTGTCCCTGATT  
PAIR48_R ATAGCACACACG
```

Methods – Recovering alleles from reads



Methods – Recovering alleles from reads

```
Primers.txt  
  
PAIR01_F ACGTGTGACAGT  
PAIR01_R GGACTTTGACTG  
  
PAIR02_F GTGTGCAGGTGG  
PAIR02_R GCCGACGAGACA  
  
...  
  
PAIR48_F CTGTCCCTGATT  
PAIR48_R ATAGCACACACG
```

PAIR01_F ACGTGTGACAGT

PAIR01_F ACGTGTGACAGT

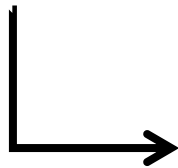
PAIR01_F ACGTGTGACAGT

IND01_forward.fastq

```
@SIM:1:FCX:1:15:7258:9987 1:N:0\1  
GATTTGGGGTTCAAAGCA...TCT  
| '! '* ((( (***) )%%%++) (...#!K  
  
@SIM:1:FCX:1:15:6329:1045 1:N:0\1  
TCGCACTCAACGCCCTGCA...TAG  
| <> ; ## => <9=AAAAAAAAAAA9# : <#  
  
. . .  
  
@SIM:1:FCX:1:15:0254:2202 1:N:0\1  
GTCCATAGCACGTGCATCCC...AAT  
| <> ; ## => <9=AAAAAAAAAAA9# : <#
```

Methods – Recovering alleles from reads

PAIR01_F GATTTGGGGTTC AAAGCA...GAATC
ACGTGTGACAGT



Calcul de la **distance de Levenshtein (LD)**
entre les 2 chaînes de caractères
(ie. nombre minimal de caractères qu'il faut supprimer,
insérer ou remplacer pour passer d'une chaîne à l'autre)

Si $LD \leq 4$:

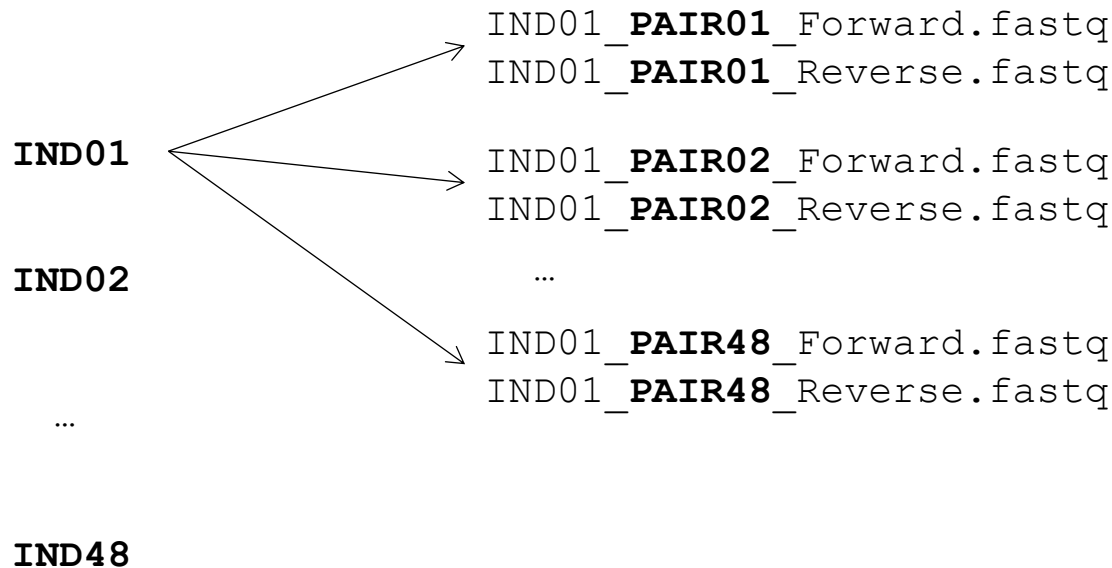
Le read est associé à la PAIR01 en partie forward

Sinon:

Le read est abandonné (*et sa paire reverse aussi...*)

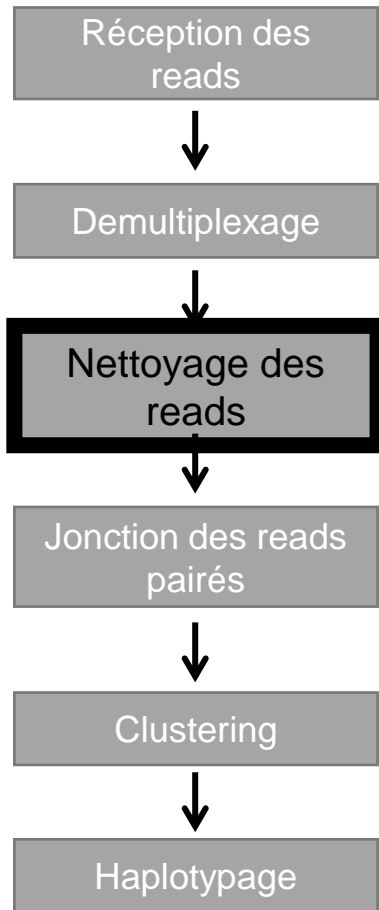
Methods – *Recovering alleles from reads*

Au final j'obtiens une arborescence de fichiers de reads :



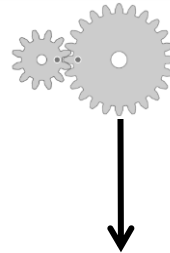
48 individus x 48 paires x 2 sens = 4 608 fichiers

Methods – Recovering alleles from reads



ENTRÉE

IND01_PAIR01_Forward.fastq
IND01_PAIR01_Reverse.fastq



- Retirer les morceaux d'adaptateurs Illumina
- Retirer les fenêtres de 4bp dont la moyenne de qualité est < 20 (99% de confiance dans l'identification des bases)
- Retirer les reads nettoyés < 30 bp

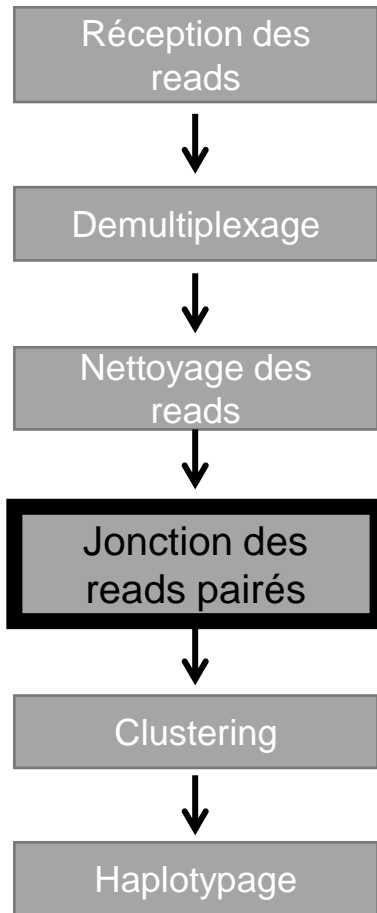
SORTIE

IND01_PAIR01_1P.fastq IND01_PAIR01_1U.fastq
IND01_PAIR01_2P.fastq IND01_PAIR01_2U.fastq

Trimmomatic: A flexible read trimming tool for Illumina NGS data

Bolger *et al.* 2014, *Bioinformatics* 30(15):2114-2120

Methods – Recovering alleles from reads



```
IND01_PAIR01_1P.fastq
@read25486\1
CACCACATATGCTGTCTCTGGCAC
+
<>;##=><9=AAAAAAAAAAA9#:<
@read12579\1
...
```

CACCACATATGCTGTCTCTGGCAC

```
IND01_PAIR01_2P.fastq
@read25486\2
GGTTTAGAGGAATCAGATTCAAGT
+
;??#A=>C9!<<>() / , *-9#;;A
@read12579\2
...
```

GGTTTAGAGGAATCAGATTCAAGT

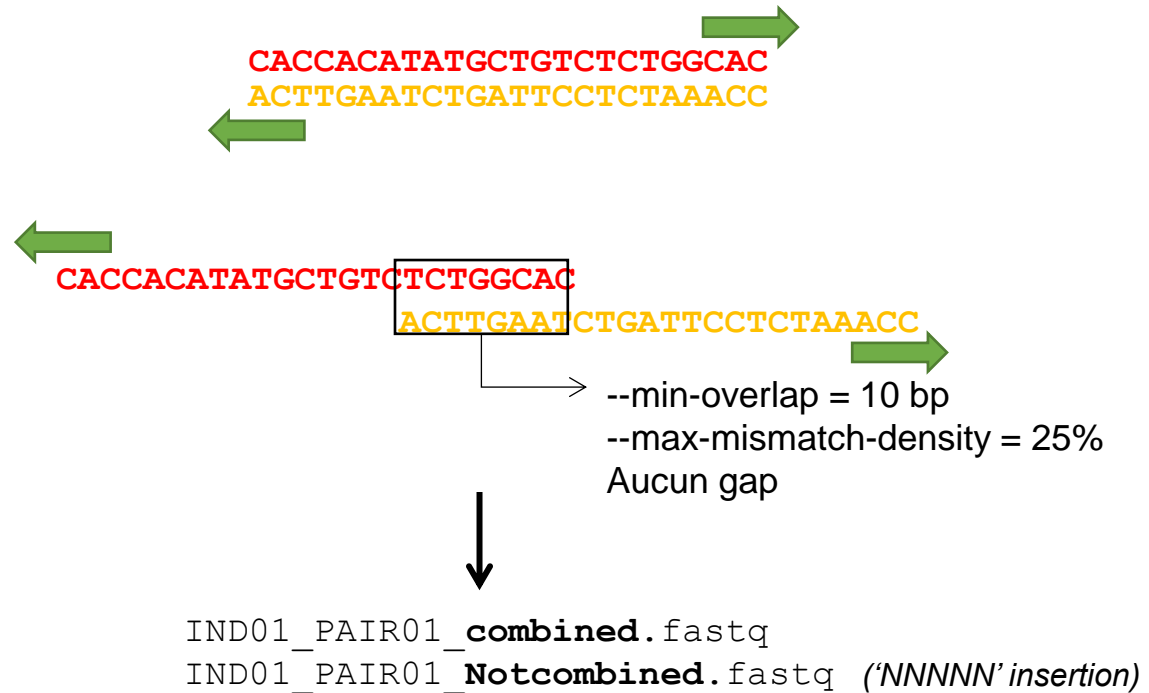
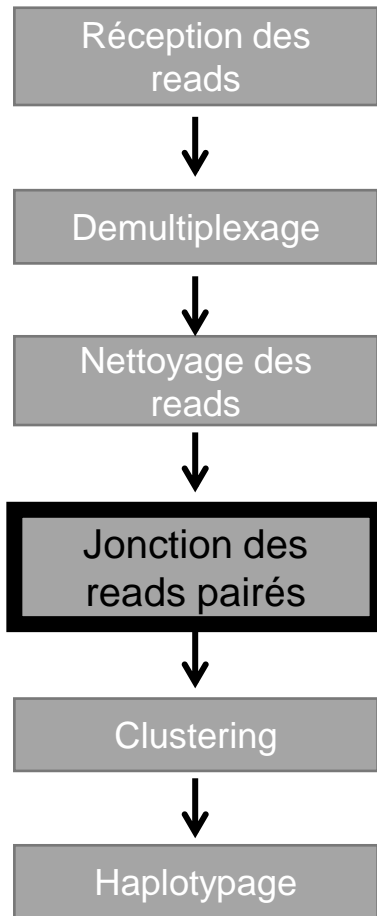
↓ *Reverse complement*

ACTTGAATCTGATTCCTCTAAACC

CACCACATATGCTGTCTCTGGCAC

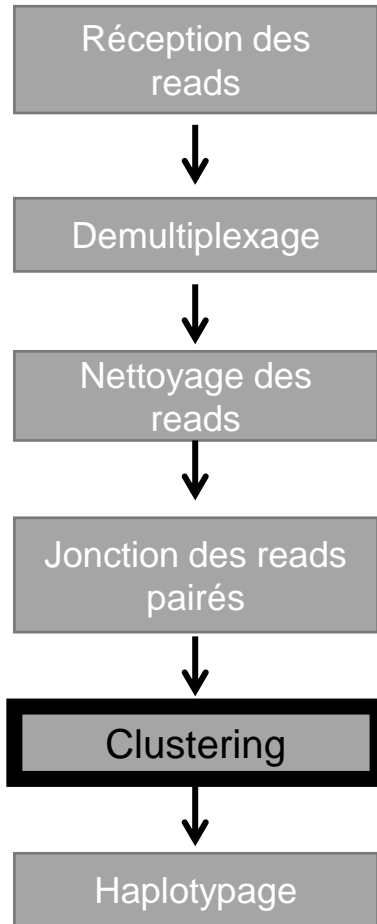
ACTTGAATCTGATTCCTCTAAACC

Methods – Recovering alleles from reads

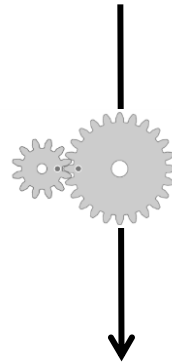


FLASH (Fast Length Adjustment of SHort reads)
Magoc and Salzberg 2011, *Bioinformatics* 27(21):2957-2963

Methods – Recovering alleles from reads



```
IND01_PAIR01_ combined.fastq  
IND01_PAIR01_ Notcombined.fastq
```



Processus itératif (3 répétitions) :

- Détection des chimères de PCR par alignement
- Regroupement des reads similaires avec un seuil croissant d'identité au cours des itérations

Pour chaque locus, pour chaque taxon :

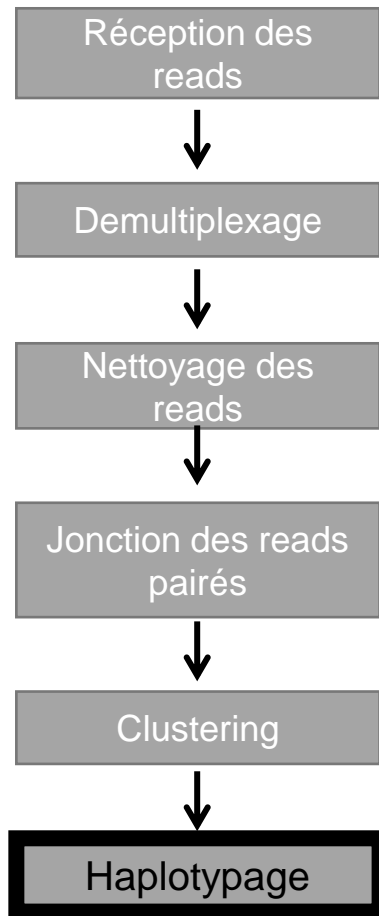
Cluster 1 : 925 séquences
Cluster 2 : 854 séquences
Cluster 3 : 75 séquences
Cluster N : 2 séquences

```
IND01_PAIR01_ PURC_clusters.fastq
```

Pipeline for Untangling Reticulate Complexes (PURC)

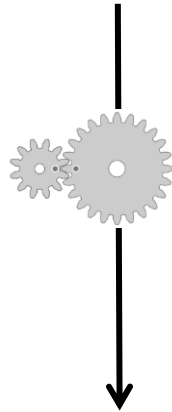
Rothfels et al. 2016, *New Phytologist* 213(1):413-429

Methods – *Recovering alleles from reads*



IND01_PAIR01_PURC_clusters.fastq

*Contient tous les haplotypes possibles.
Leur nombre est surestimé en raison
des insertions de NNNN.*

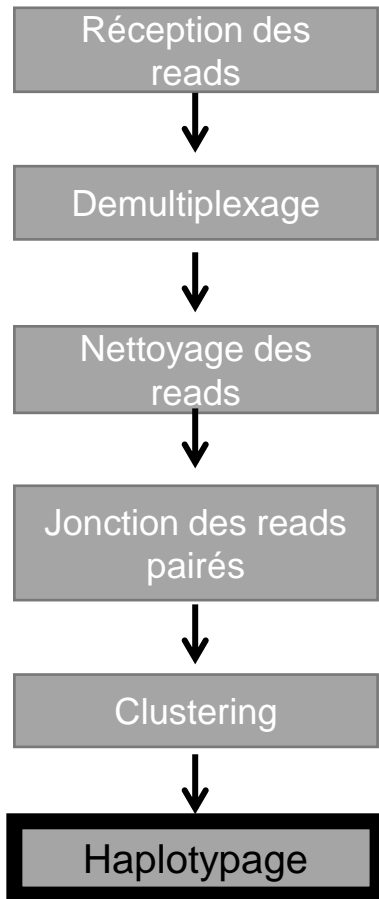


- Regrouper les cluster qui sont identiques (en ignorant les gaps)
- Dédire des haplotypes dans un contexte où la ploidie n'est pas connue

IND01_PAIR01_PURC_clusters_reduced.fastq

Fluidigm2PURC
Blischak et al. 2018, *BioRxiv*

Methods – Recovering alleles from reads



Exemple : L'étape de Clustering identifie 6 clusters chez un individu 4x

On utilise comme variable la taille des clusters et comme paramètre le taux d'erreur de séquençage au locus.

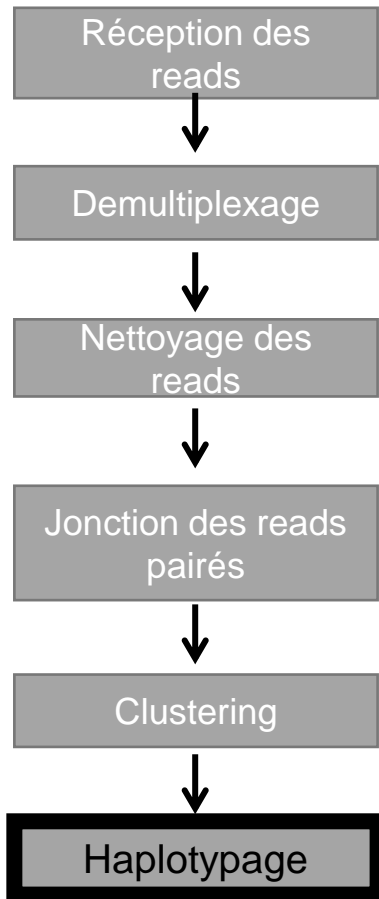


On modélise différents cas de figure :

- Model1 : 0 0 0 0 0 0
- Model2 : 1 0 0 0 0 0
- Model3 : 1 1 0 0 0 0
- Model4 : 1 1 1 0 0 0
- Model5 : 1 1 1 1 0 0
- Model6 : 1 1 1 1 1 0
- Model7 : 1 1 1 1 1 1

Pour chaque modèle, on calcule son **maximum de vraisemblance** et on regarde si le gain obtenu est intéressant

Methods – Recovering alleles from reads



Maximum de vraisemblance pour un modèle à H clusters :

$$l_H = \sum_{i=0}^H C_i \times \log(1 - \epsilon) + \sum_{j>H} C_j \times \log(\epsilon)$$

Nb de clusters envisagés → H

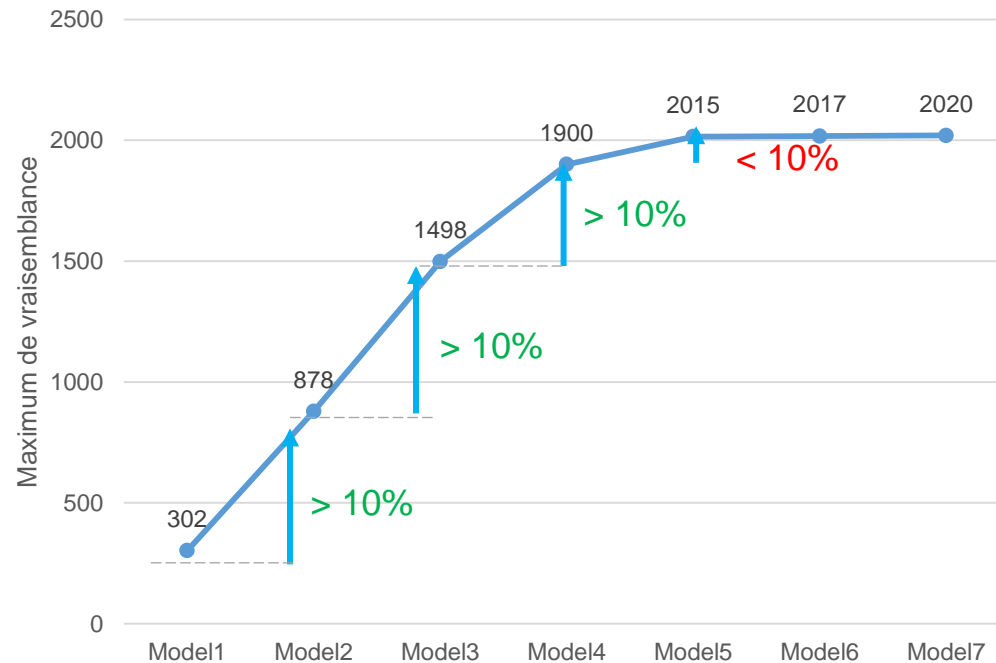
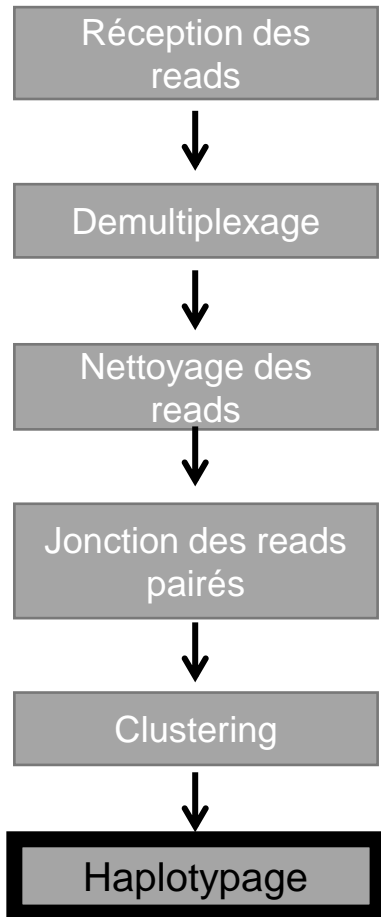
Taille du cluster i | *variable*

Niveau moyen d'erreur de tous les reads à ce locus | paramètre

Les clusters de 0 à H sont de vrais clusters

Les clusters suivants (>H) sont des erreurs

Methods – Recovering alleles from reads



On retient le Model4
(à 3 vrais clusters)