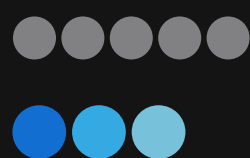
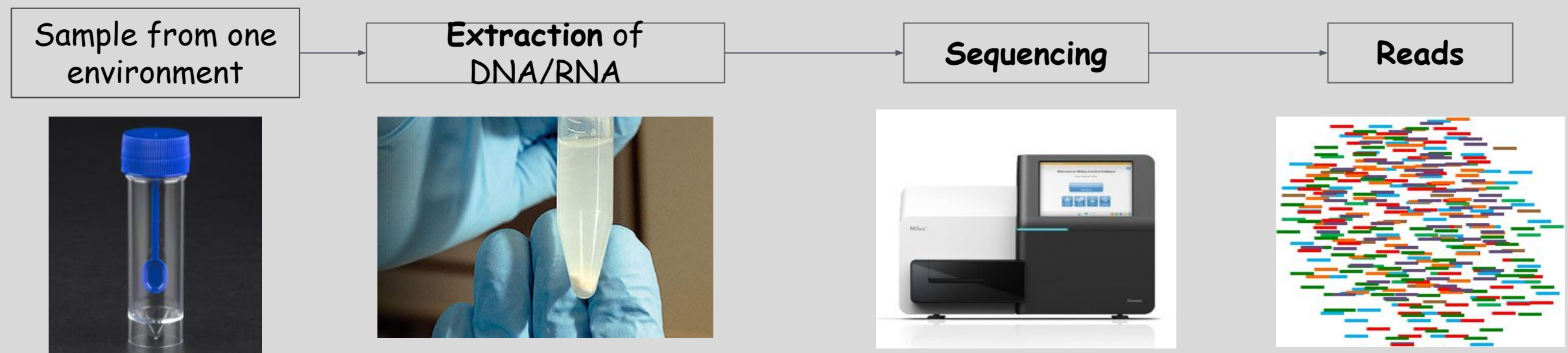




Targeted metagenomics
Amine Ghozlane
June 2016



High-throughput sequencing as a tool for exploring the microbiome



"Metagenomics is like a disaster in a jigsaw shop" Iddo Friedberg

Who is there ?

- **Taxonomical annotation**
- Co-Abundance Gene groups (CAG)
- Binning
- Assembly

What are they able to do ?

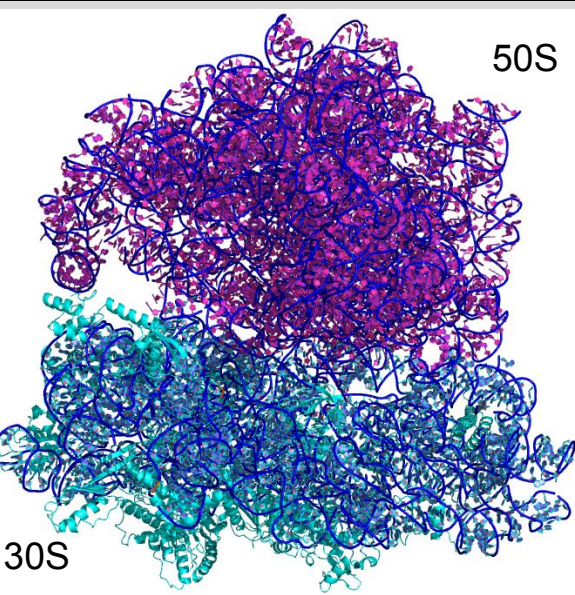
- Gene/protein prediction
- Functional annotation
- Metabolic network reconstruction

What are they doing ?

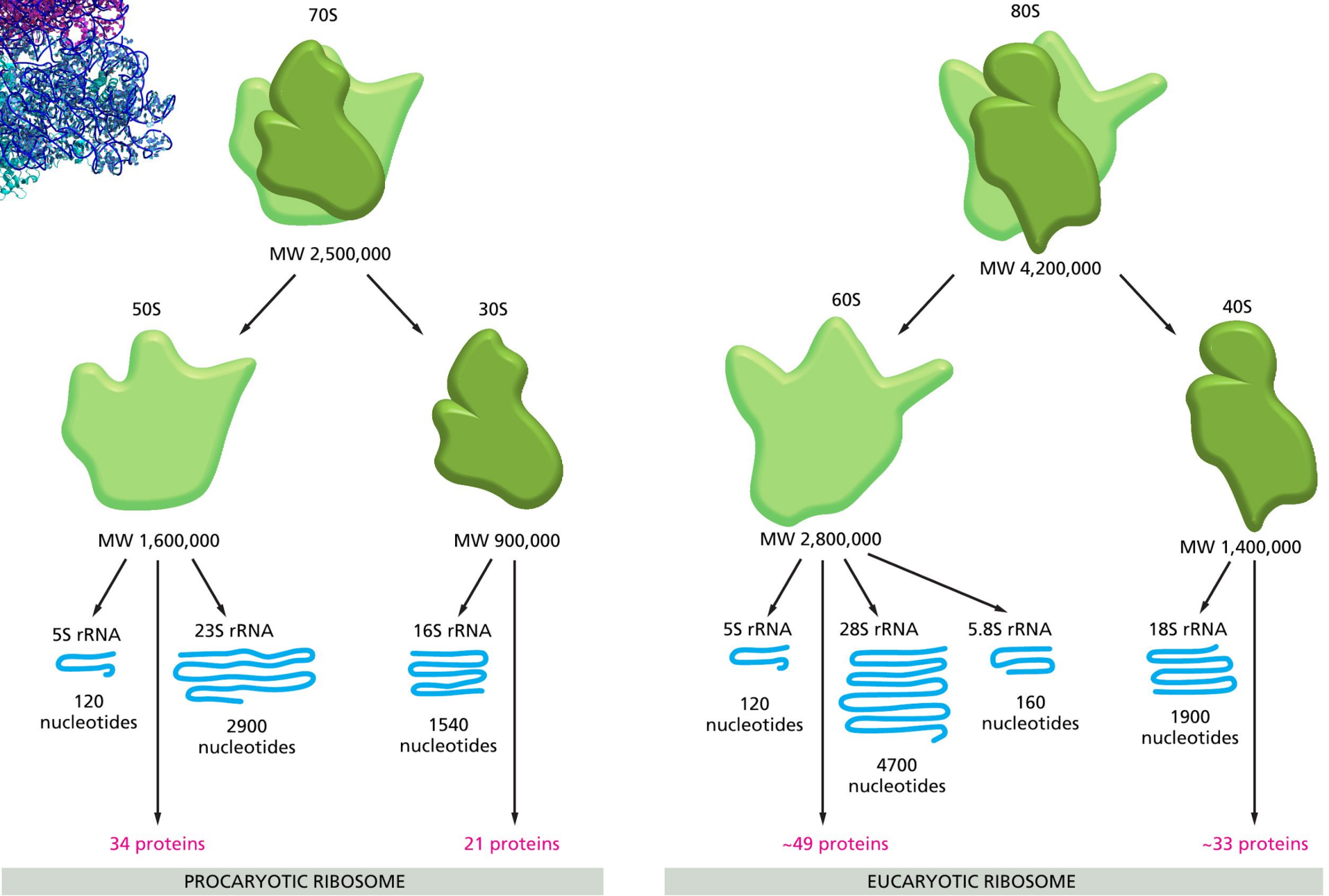
- RNA/Protein quantification

What is the difference between these environments ?

- Comparative metagenomics
- Quantitative metagenomics



Ribosome

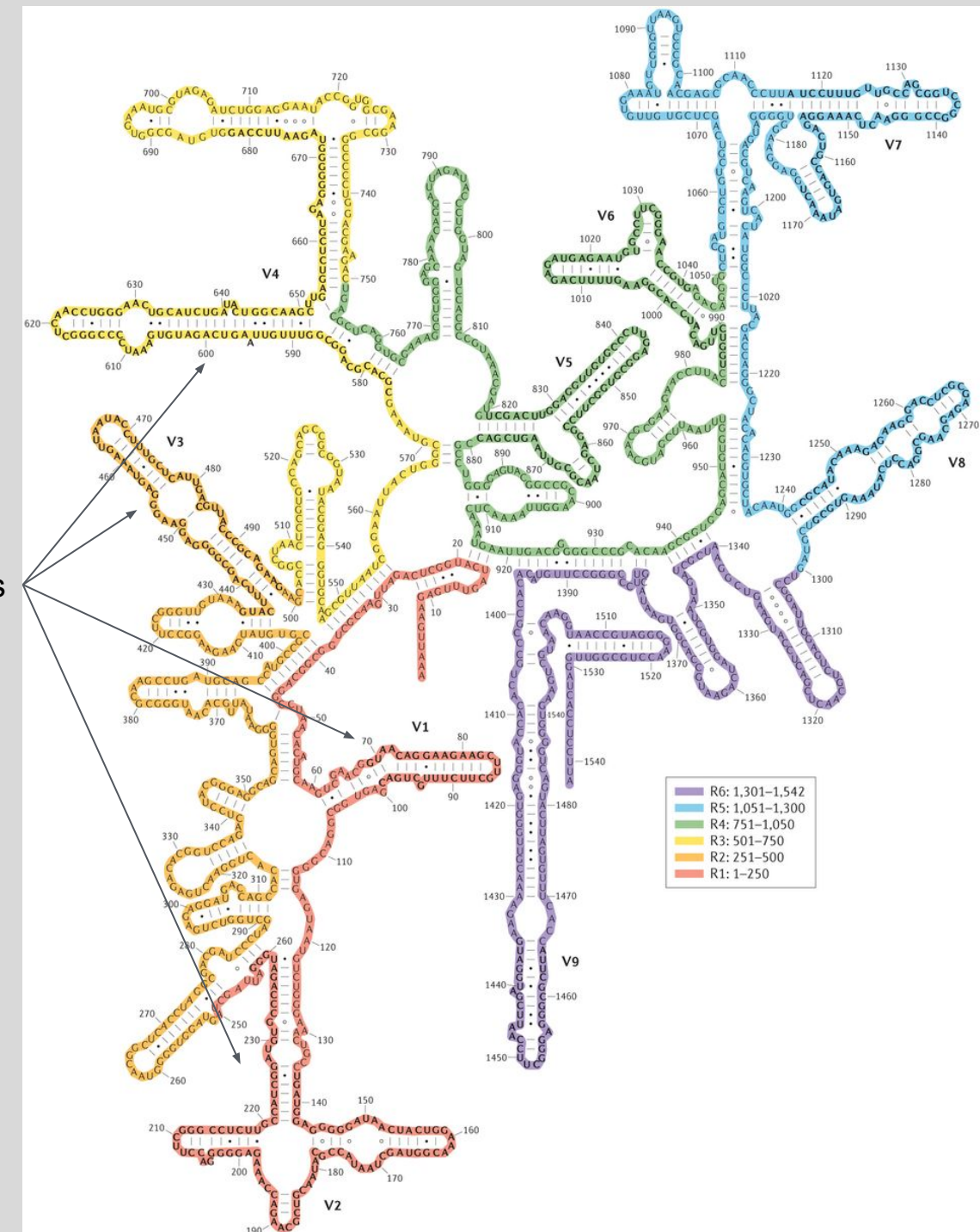


ITS : located between 18S and 5.8S rRNA genes

16S rRNA

- Weakly affected by horizontal gene transfer*
- 9 variable regions surrounded by conserved regions
- Universal primers**, 25 PCR cycle***
- Most well represented gene in Genbank
- Sequencing kits : V1-V3, V3-V4, V3-V5, V5-V6...

Variable regions



Yarza *et al.* 2014 (Nature reviews Microbiology)
Nature Reviews | Microbiology

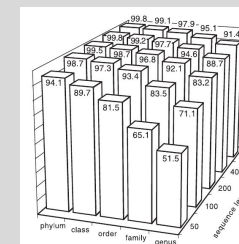
*Daubin *et al.* 2003 (Science) **Weisburg *et al.* 1991 (*J Bacteriol.*) ***
Illumina protocol

*Vetrovsky and Baldrian 2013 (Plos One)

Targeted metagenomics strategies

❖ CLOSED REFERENCE CLUSTERING

- Clustering in a OTU the sequence that are similar to a reference
- Classification



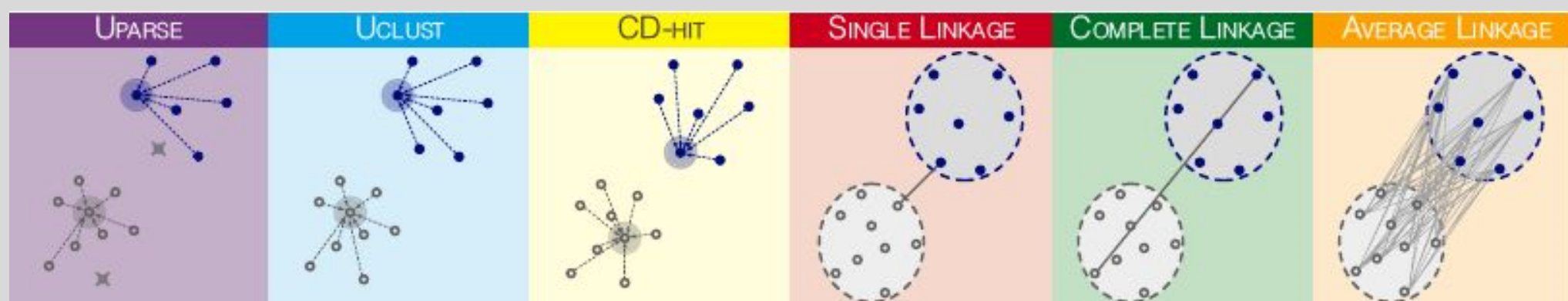
❖ DE NOVO CLUSTERING

- Distance between the sequence is used to cluster sequence into OTUs

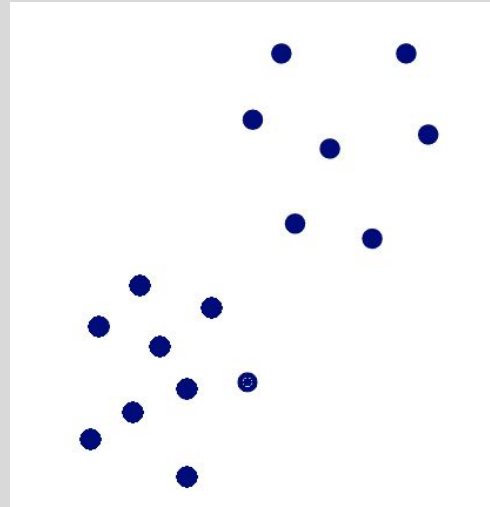
❖ OPEN REFERENCE CLUSTERING

- Closed-reference clustering followed by de novo clustering for sequence that are not similar to the reference

CLUSTERING ALGORITHMS



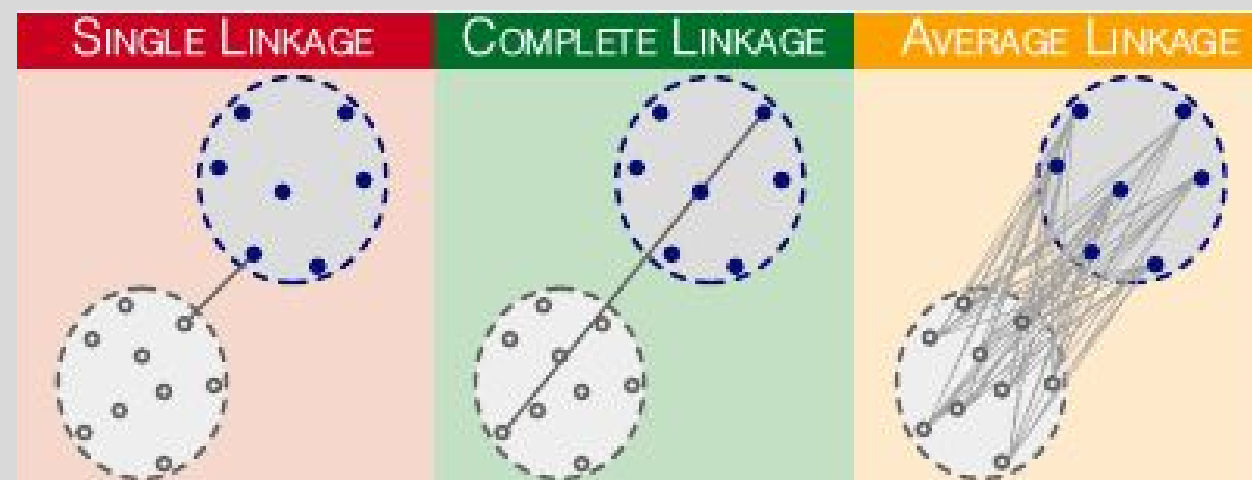
Hierarchical clustering



Algorithm:

- ❖ Initial n groups
- ❖ Each step:
 - Merge of two group considering linkage

Hierarchical clustering



Algorithm:

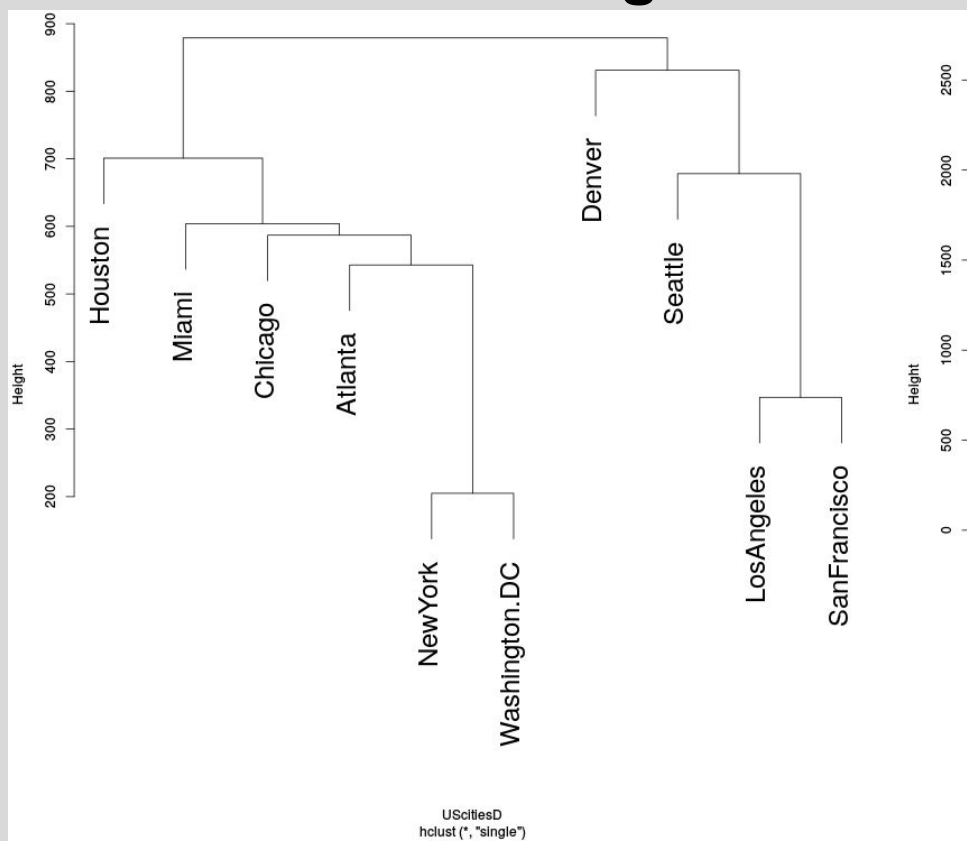
- ❖ Initial n groups
- ❖ Each step:
 - Merge of two group considering linkage

Distances:

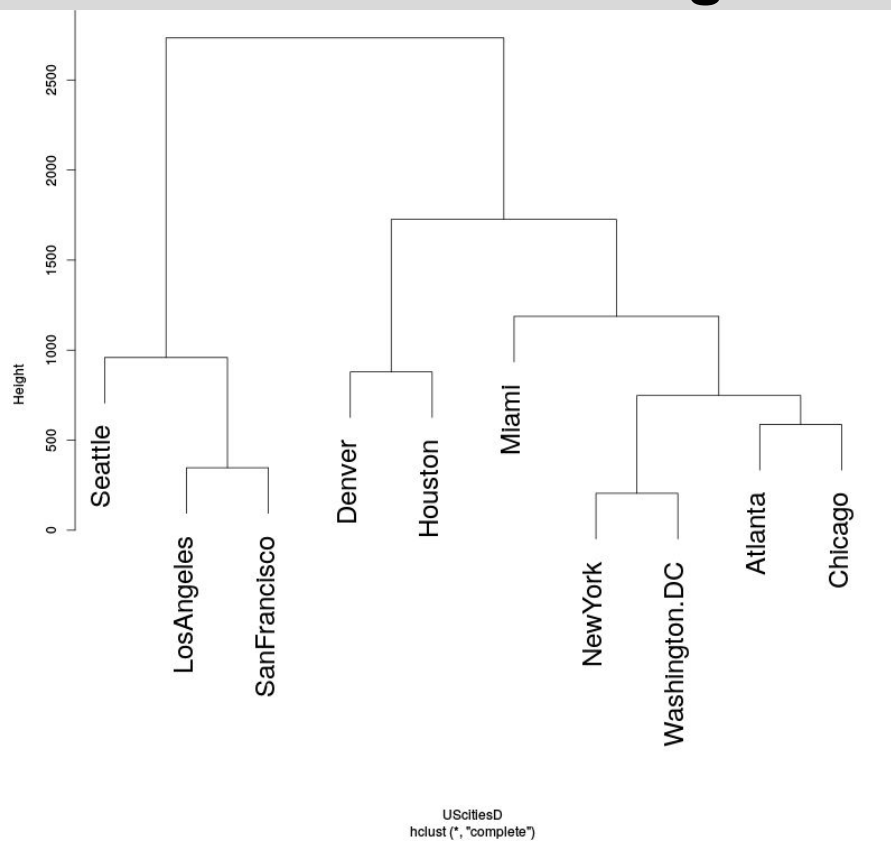
- ❖ **Single linkage**
 - the distance between two clusters is defined as the **shortest** distance between two points in each cluster
- ❖ **Complete linkage**
 - the distance between two clusters is defined as the **longest** distance between two points in each cluster
- ❖ **Average linkage**
 - the distance between two clusters is defined as the **average** distance to every point in the other cluster
- ❖ ...

Hierarchical clustering

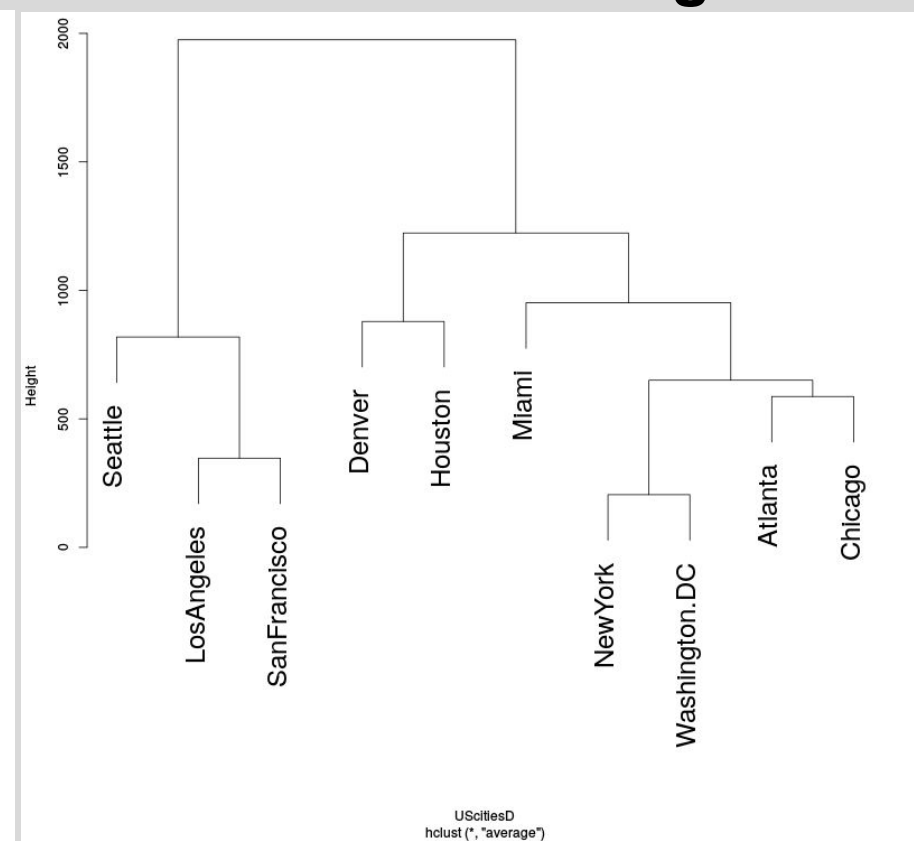
SINGLE linkage



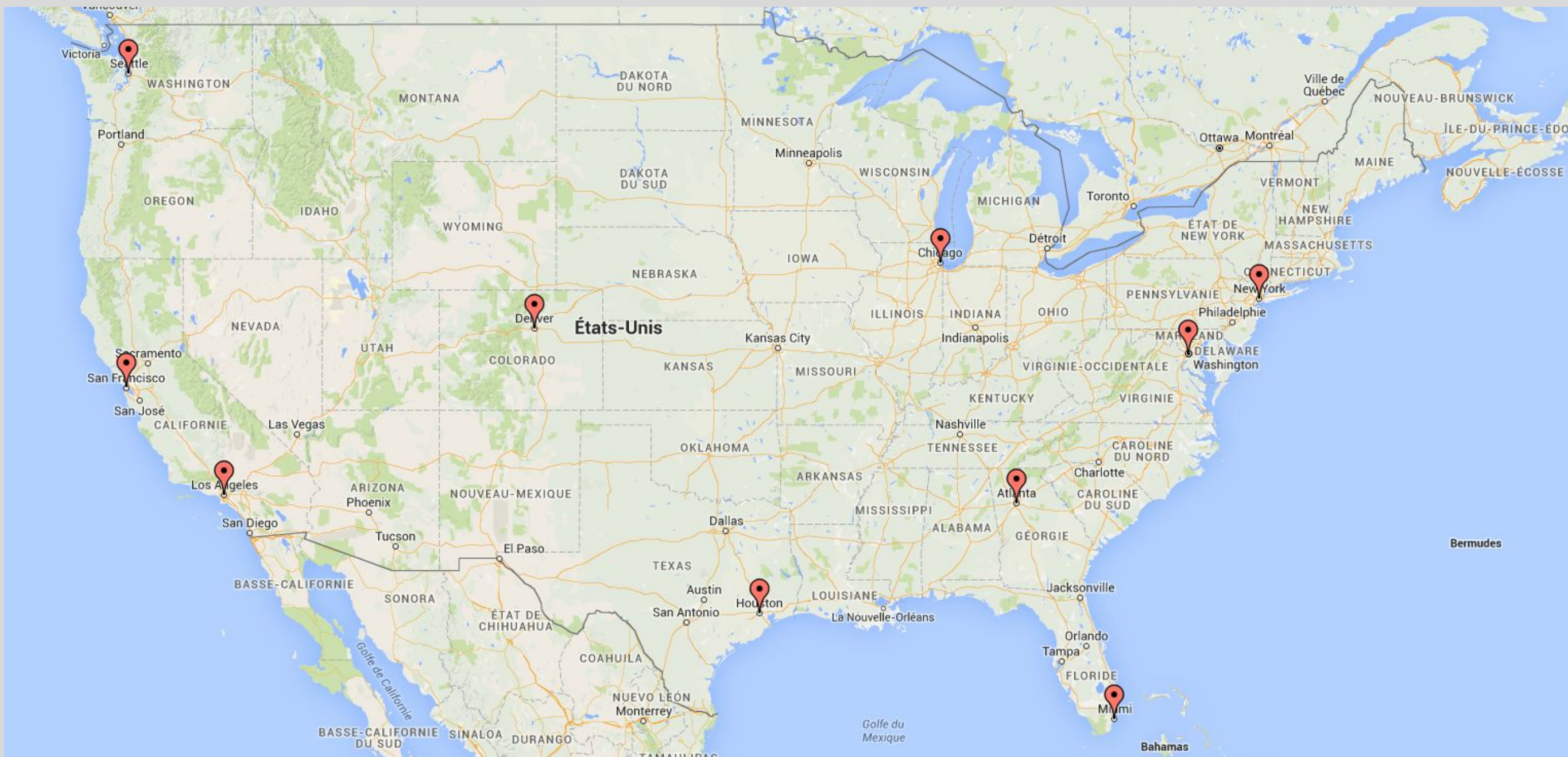
COMPLETE linkage



AVERAGE linkage



Let's play at clustering

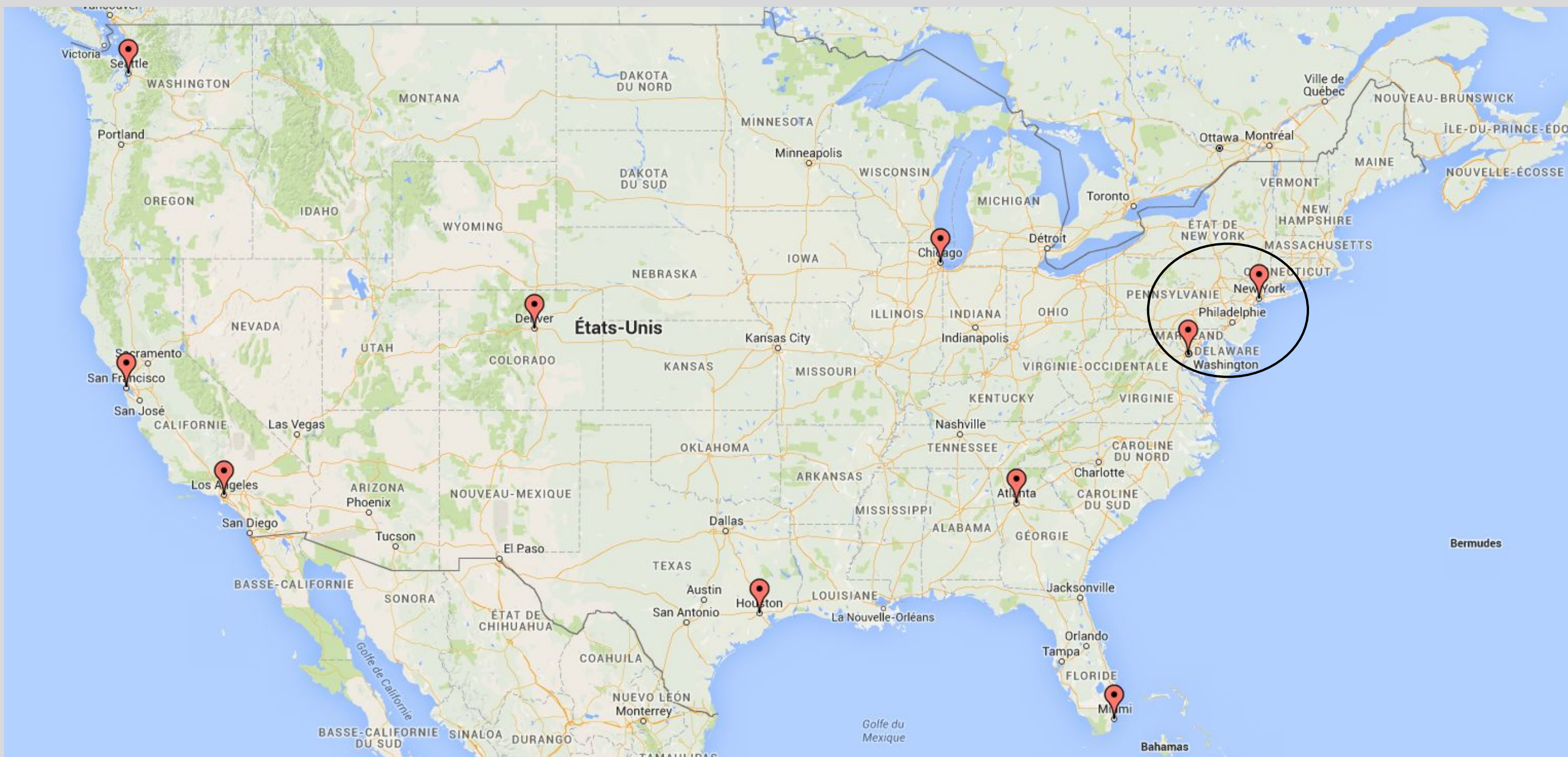


Criteria : “A group is composed of cities with less than 800 km of distance”

Distance

Distance between US cities	Atlanta	Chicago	Denver	Houston	Los Angeles	Miami	New York	San Francisco	Seattle
Atlanta									
Chicago	587								
Denver	1212	920							
Houston	701	940	879						
Los Angeles	1936	1745	831	1374					
Miami	604	1188	1726	968	2339				
New York	748	713	1631	1420	2451	1092			
San Francisco	2139	1858	949	1645	347	2594	2571		
Seattle	2182	1737	1021	1891	959	2734	2408	678	
Washington DC	543	597	1494	1220	2300	923	205	2442	2329

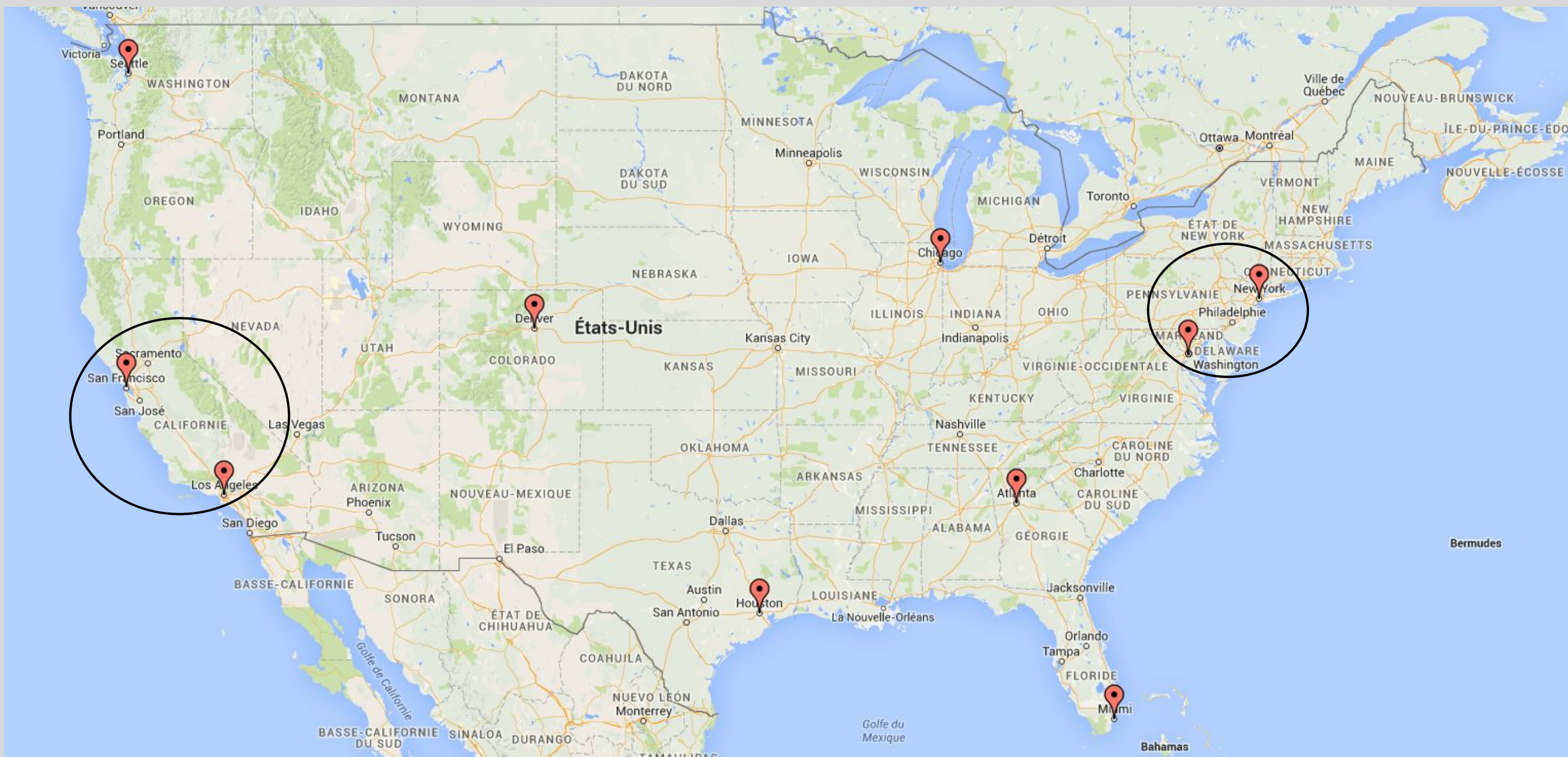
Hierarchical clustering



Distance

Distance between US cities	Atlanta	Chicago	Denver	Houston	Los Angeles	Miami	New York	San Francisco	Seattle
Atlanta									
Chicago	587								
Denver	1212	920							
Houston	701	940	879						
Los Angeles	1936	1745	831	1374					
Miami	604	1188	1726	968	2339				
New York	748	713	1631	1420	2451	1092			
San Francisco	2139	1858	949	1645	347	2594	2571		
Seattle	2182	1737	1021	1891	959	2734	2408	678	
Washington DC	543	597	1494	1220	2300	923	205	2442	2329

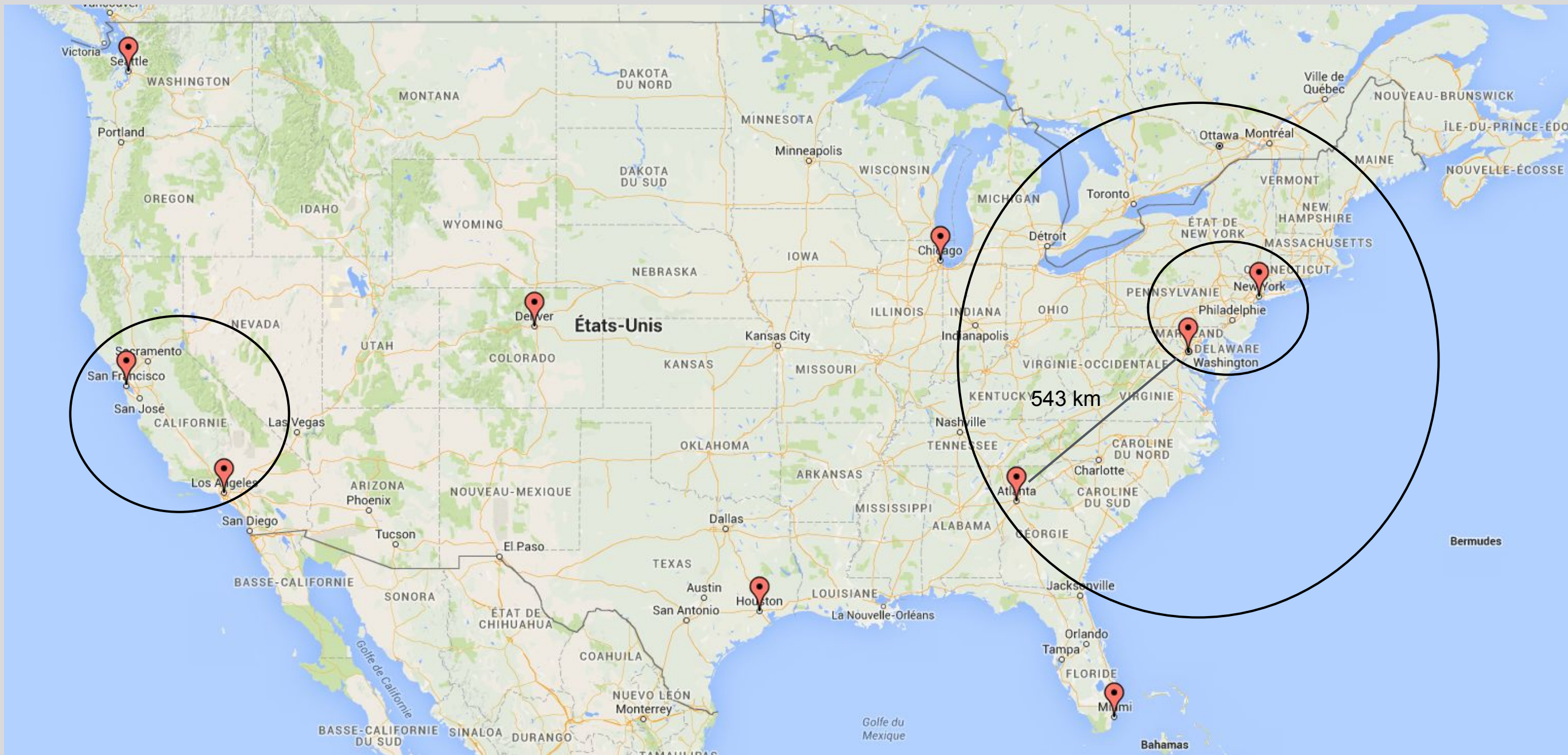
Hierarchical clustering - single linkage



Next in single-linkage ?

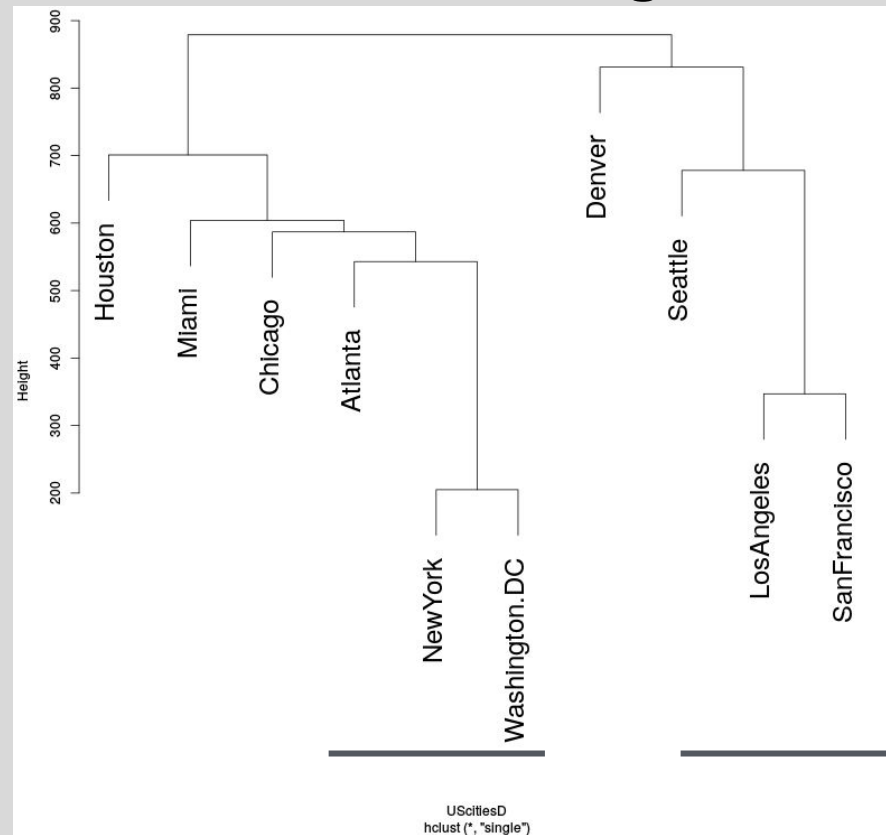
Distance between US cities	Atlanta	Chicago	Denver	Houston	Los Angeles	Miami	New York	San Francisco	Seattle
Atlanta									
Chicago	587								
Denver	1212	920							
Houston	701	940	879						
Los Angeles	1936	1745	831	1374					
Miami	604	1188	1726	968	2339				
New York	748	713	1631	1420	2451	1092			
San Francisco	2139	1858	949	1645	347	2594	2571		
Seattle	2182	1737	1021	1891	959	2734	2408	678	
Washington DC	543	597	1494	1220	2300	923	205	2442	2329

Hierarchical clustering - single linkage



Hierarchical clustering

SINGLE linkage

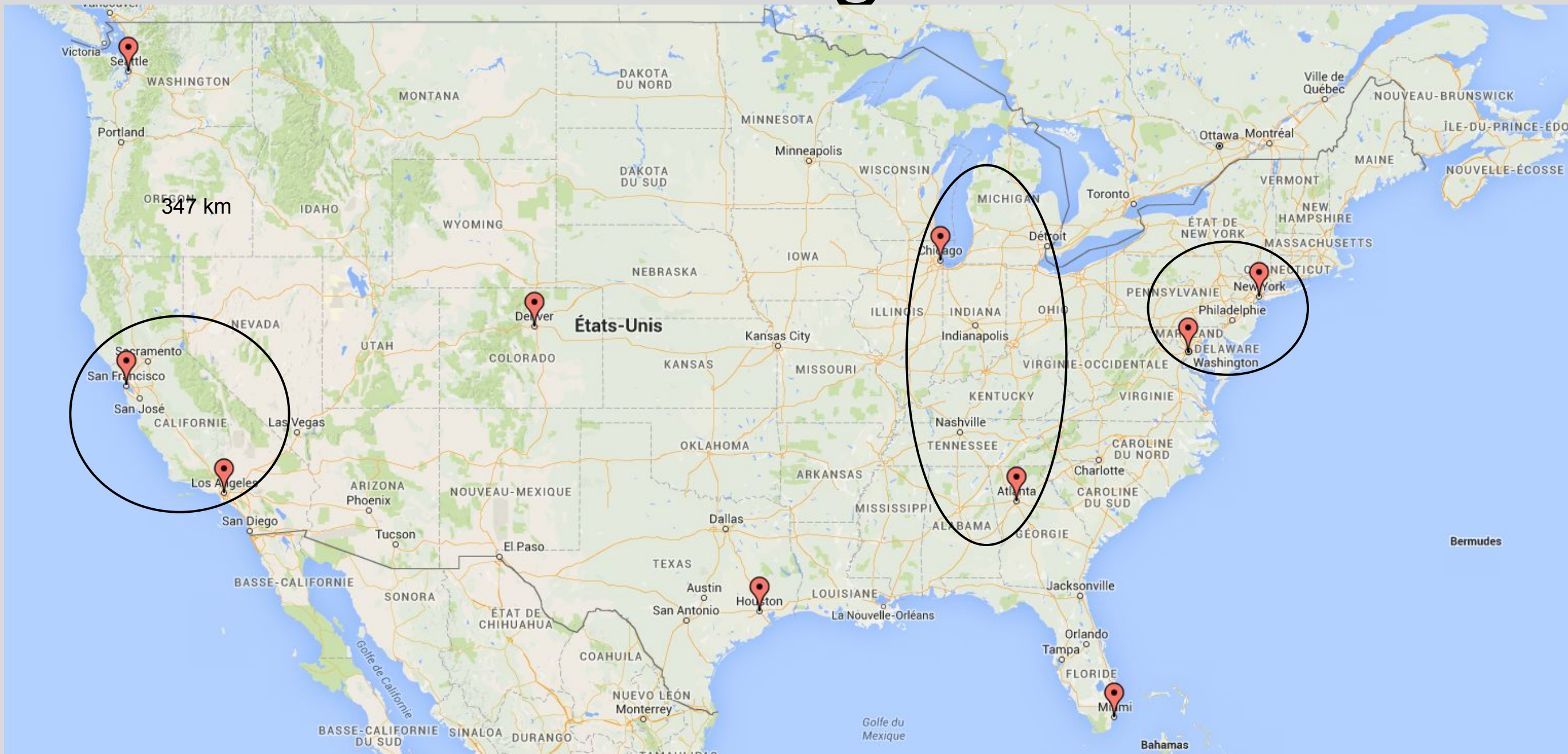


Now in average-linkage

Distance between US cities	Atlanta	Chicago	Denver	Houston	Los Angeles	Miami	New York	San Francisco	Seattle
Atlanta									
Chicago	587								
Denver	1212	920							
Houston	701	940	879						
Los Angeles	1936	1745	831	1374					
Miami	604	1188	1726	968	2339				
New York	748	713	1631	1420	2451	1092			
San Francisco	2139	1858	949	1645	347	2594	2571		
Seattle	2182	1737	1021	1891	959	2734	2408	678	
Washington DC	543	597	1494	1220	2300	923	205	2442	2329

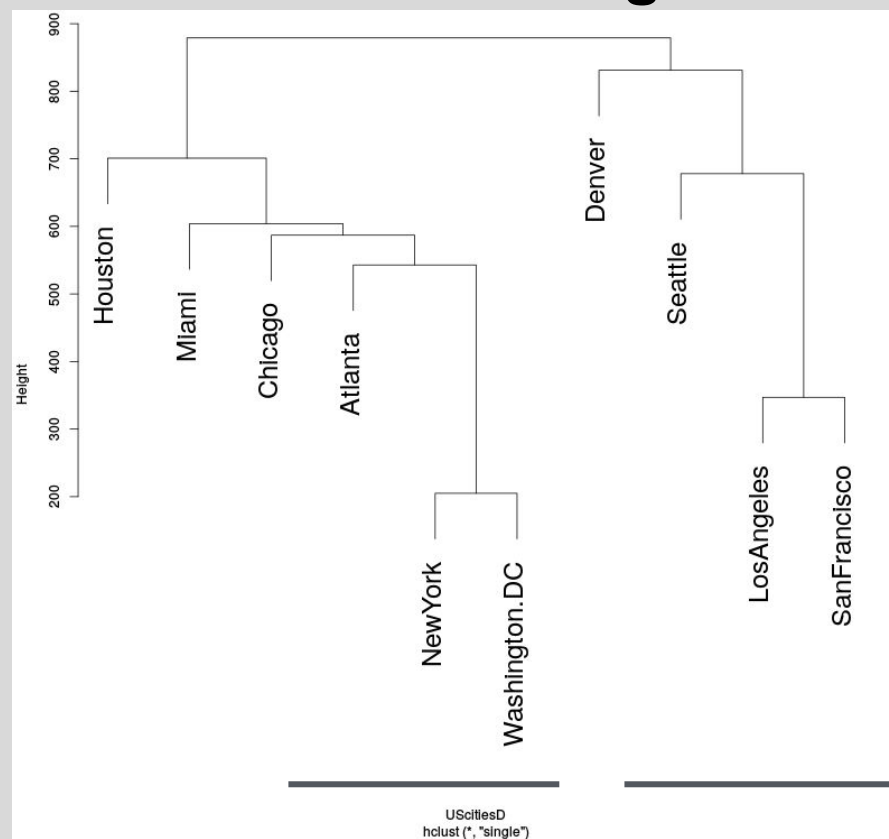
Atlanta - (Washington - New York) = (543 + 748) / 2 = 645.2

Hierarchical clustering - average linkage

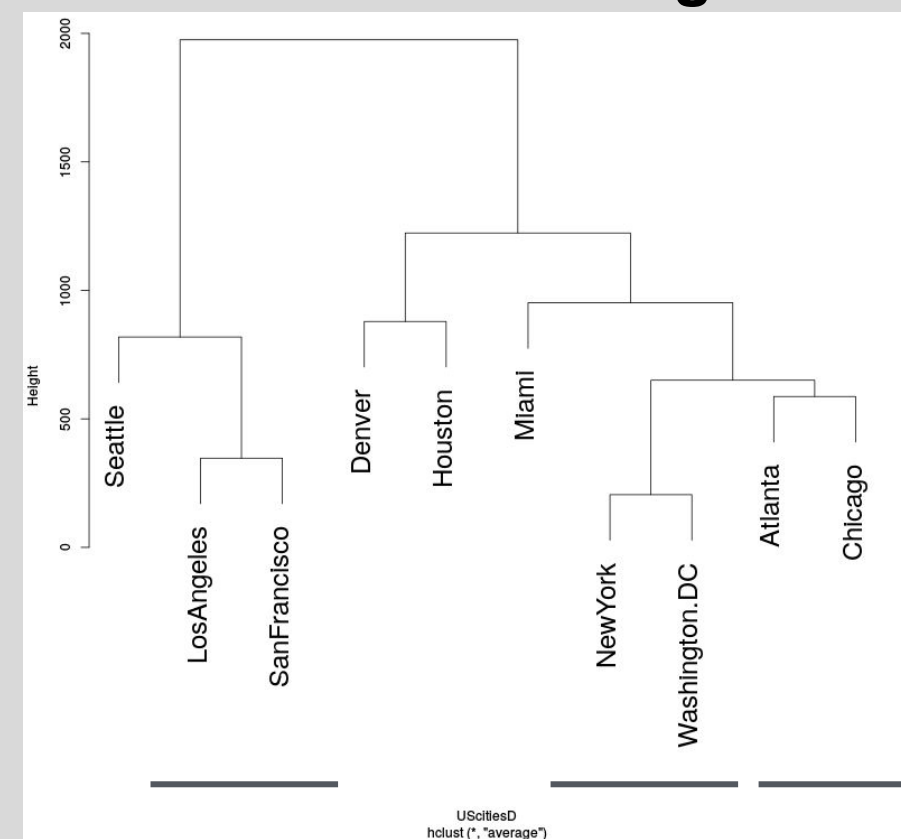


Hierarchical clustering

SINGLE linkage



AVERAGE linkage



Hierarchical clustering

Outcome:

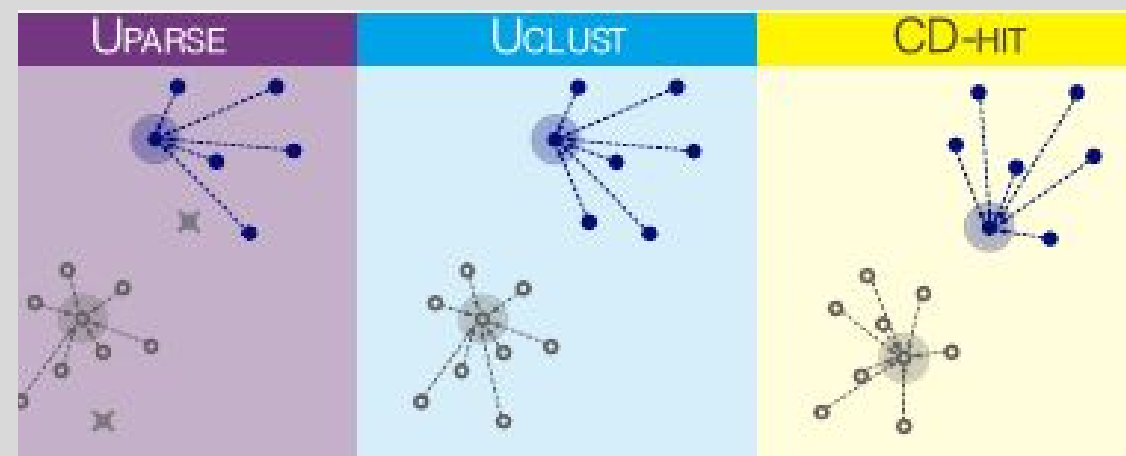
- ❖ Hierarchical clustering depends on the linkage policy
- ❖ All distances need to be known
- ❖ Hierarchical clustering is expensive, in general agglomerative strategies cost $O(n^3)$...

Example :

n=200 sequences

Cost agglomerative = 8e+06 operations

Greedy clustering



Algorithm:

- ❖ Initial n groups ordered in particular way
- ❖ Each step:
 - Pick a group and compare to the reference
 - If close to the reference:
 - Add in reference cluster
 - Otherwise:
 - Add it as a reference
- ❖ Ordering:
 - Length-based Greedy Clustering (CD-HIT, Uclust)
 - Abundance-based Greedy Clustering (AGC) : “Most-Abundant-centroid”

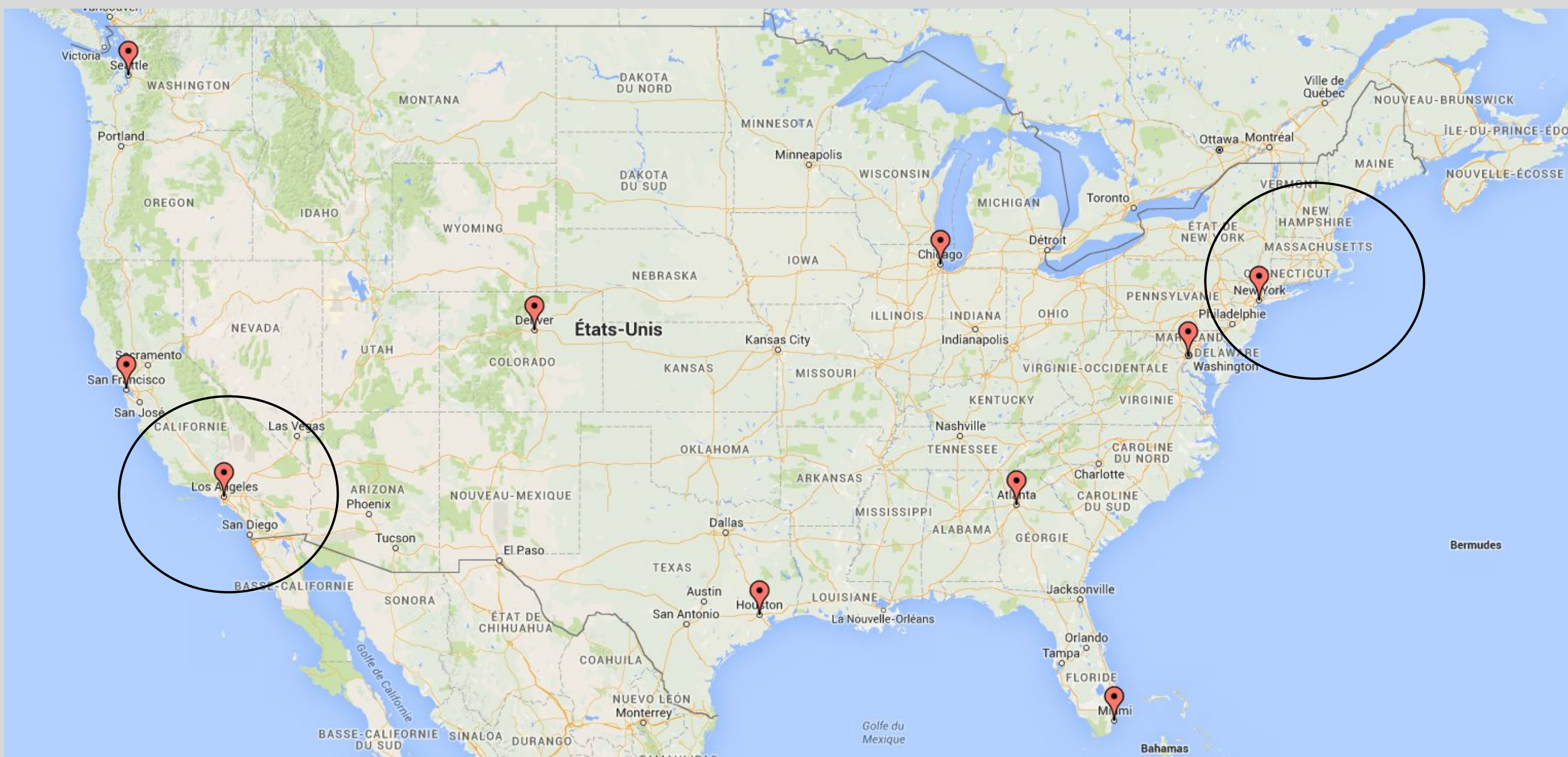
Abundance-based Greedy Clustering methods

City	Population
New York	8550405
Los Angeles	3958125
Chicago	2722389
Houston	2099451
San Francisco	852469
Washington DC	646449
Seattle	634535
Denver	634265
Atlanta	443775
Miami	430332



New York - Los Angeles = 2451 km > 800 km

Abundance-based Greedy Clustering methods



Abundance-based Clustering methods

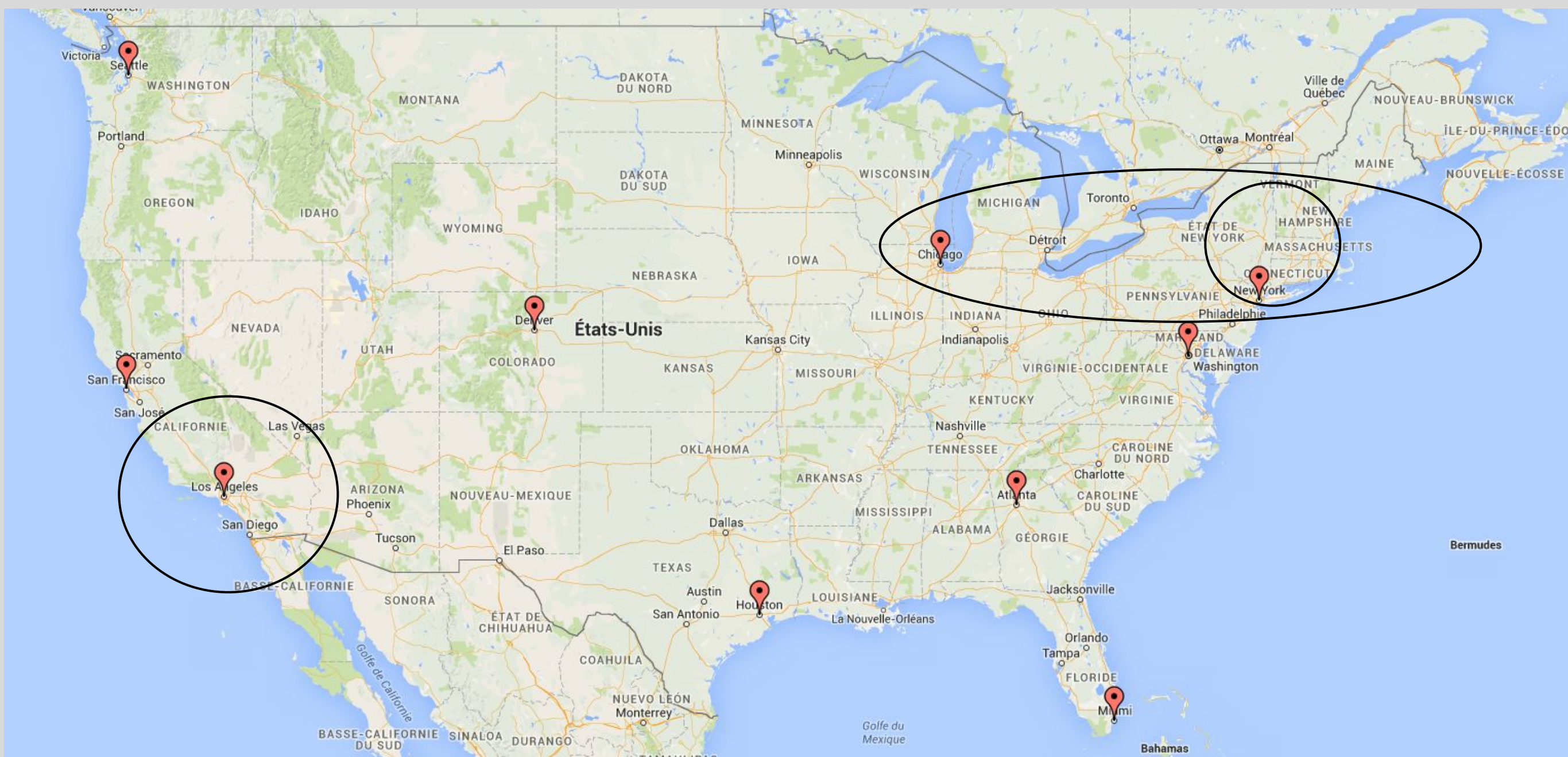
City	Population
New York	8550405
Los Angeles	3958125
Chicago	2722389
Houston	2099451
San Francisco	852469
Washington DC	646449
Seattle	634535
Denver	634265
Atlanta	443775
Miami	430332



New york - Los Angeles = 2451 km > 700 km

New york - Chicago = 713 km

Abundance-based Greedy Clustering methods



Abundance greedy clustering

Outcome:

- ❖ AGC depend on the sorting strategy (length, abundance...)
- ❖ The distance to the reference is guarantee...
- ❖ ...not the distance between sequences in the OTU
- ❖ AGC cost is in the worst case $O(n^2)$...

Example :

n=200 sequences

Cost = 40000 operations <<< 8e+06 operations in hierarchical clustering

What is the best approach ?

Not a simple question, how to evaluate the different approach ?

❖ **Number of OTU ?**

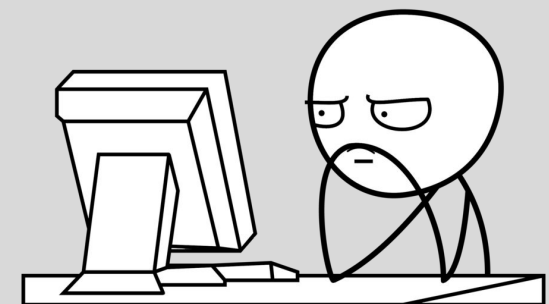
❖ **Stability of OTU ?**

❖ **Quality of OTU ?**

❖ **Diversity ?**

❖ **Computational time ?**

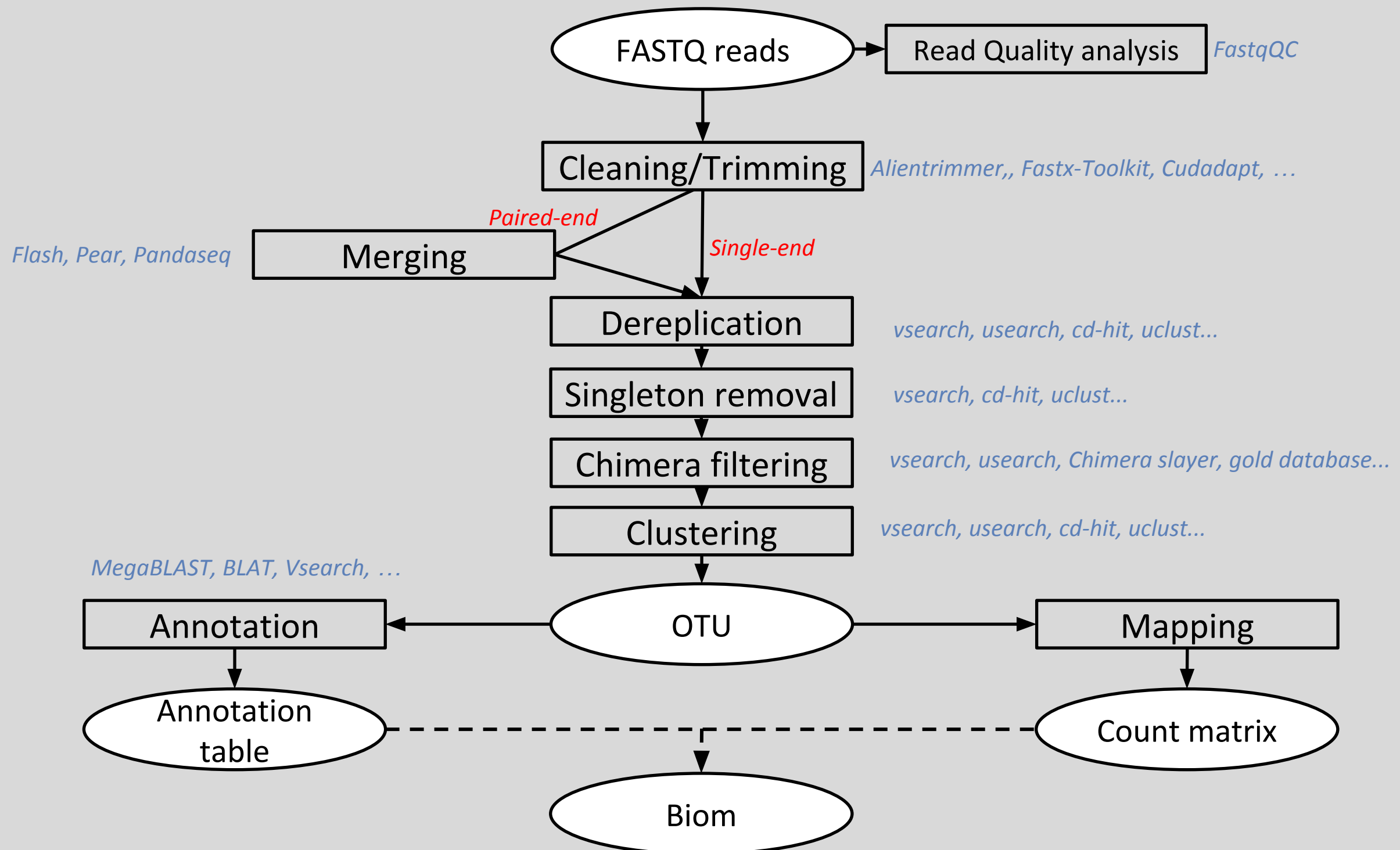
***Sequence quality filtering (trimming, filtering) has huge impact too.**



Answer is maybe all [Westcott, Schloss, 2016 PeerJ; Rideout 2014; Schmidt et al. 2015]

Vsearch seems to stand out in de novo approach

AGC-Targeted metagenomics pipeline



TP

Terminal (in your home folder):

```
$ cd masque/tp/
```

```
$/cahier_handOnmetagenomics.sh
```

Mock communities

	Even Mixture		Staggered Mixture	
	16S copies	gDNA mass	16S copies	gDNA mass
Organism and Repository Number				
<i>Acinetobacter baumannii</i> ATCC 17978	100000	1.60E-10	10000	1.60E-11
<i>Actinomyces odontolyticus</i> ATCC 17982	100000	7.82E-11	1000	7.82E-13
<i>Bacillus cereus</i> ATCC 10987	100000	3.73E-11	100000	3.73E-11
<i>Bacteroides vulgatus</i> ATCC 8482	100000	1.52E-10	1000	1.52E-12
<i>Candida albicans</i> ATCC MY-2876	1120 ^c	3.27E-11	1000 ^c	2.92E-11
<i>Clostridium beijerinckii</i> ATCC 51743	100000	3.81E-11	100000	3.81E-11
<i>Deinococcus radiodurans</i> DSM 20539	100000	1.76E-09	1000	1.76E-11
<i>Enterococcus faecalis</i> ATCC 47077	100000	2.22E-11	1000	2.22E-13
<i>Escherichia coli</i> ATCC 700926	100000	2.71E-11	1000000	2.71E-10
<i>Helicobacter pylori</i> ATCC 700392	100000	4.50E-11	10000	4.50E-12
<i>Lactobacillus gasseri</i> DSM 20243	100000	1.53E-11	10000	1.53E-12
<i>Listeria monocytogenes</i> ATCC BAA-679	100000	3.98E-11	10000	3.98E-12
<i>Methanobrevibacter smithii</i> ATCC 35061	100000	9.50E-11	1000000	9.50E-10
<i>Neisseria meningitidis</i> ATCC BAA-335	100000	6.87E-11	10000	6.87E-12
<i>Propionibacterium acnes</i> DSM16379	100000	1.39E-10	10000	1.39E-11
<i>Pseudomonas aeruginosa</i> ATCC 47085	100000	1.80E-10	100000	1.80E-10
<i>Rhodobacter sphaeroides</i> ATCC 17023	100000	1.30E-10	1000000	1.30E-09
<i>Staphylococcus aureus</i> ATCC BAA-1718	100000	6.97E-11	100000	6.97E-11
<i>Staphylococcus epidermidis</i> ATCC 12228	100000	1.31E-10	1000000	1.31E-09
<i>Streptococcus agalactiae</i> ATCC BAA-611	100000	1.83E-11	100000	1.83E-11
<i>Streptococcus mutans</i> ATCC 700610	100000	4.70E-11	1000000	4.70E-10
<i>Streptococcus pneumoniae</i> ATCC BAA-334	100000	8.11E-11	1000	8.11E-13

*The NIH HMP Working Group, 2009 (Genome Research)

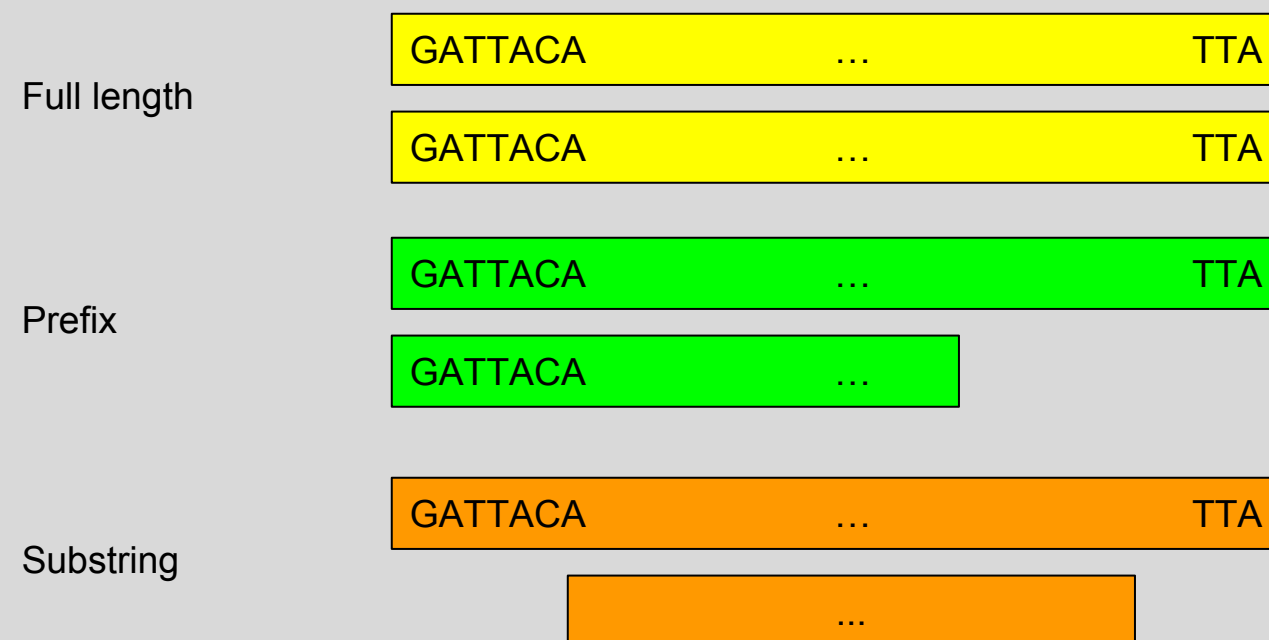
Trimming

READ	Sequence	GATTACA	...	TTA
	Quality	3031	...	161514
READ trimmed	Sequence	GATTACA	...	T
	Quality	3031	...	16

```
vsearch --fastq_filter sample --fastqout sample_filt --fastq_truncqual 16 --fastq_truncflen 250
```

I do not recommend Vsearch trimming, tp only !

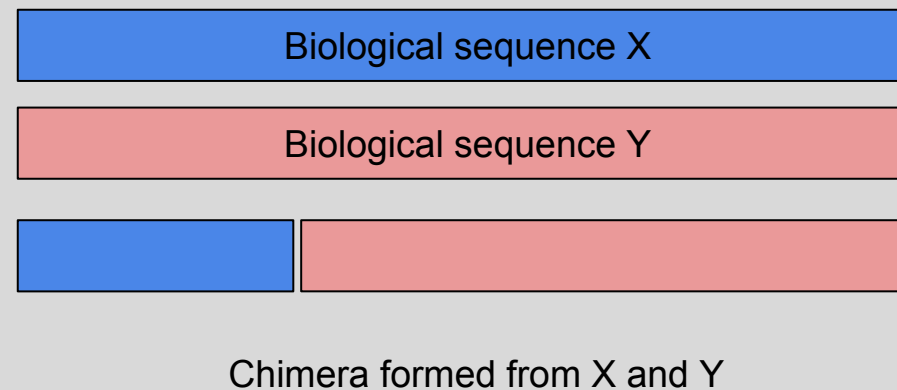
Dereplication and Singleton removal



`vsearch --derep_fulllength sample -output sample_drep -sizeout` ← *Abundance

`vsearch -sortbysize sample_drep -output sample_nosing -minsize 2` ← We could be more stringent

Chimera filtering



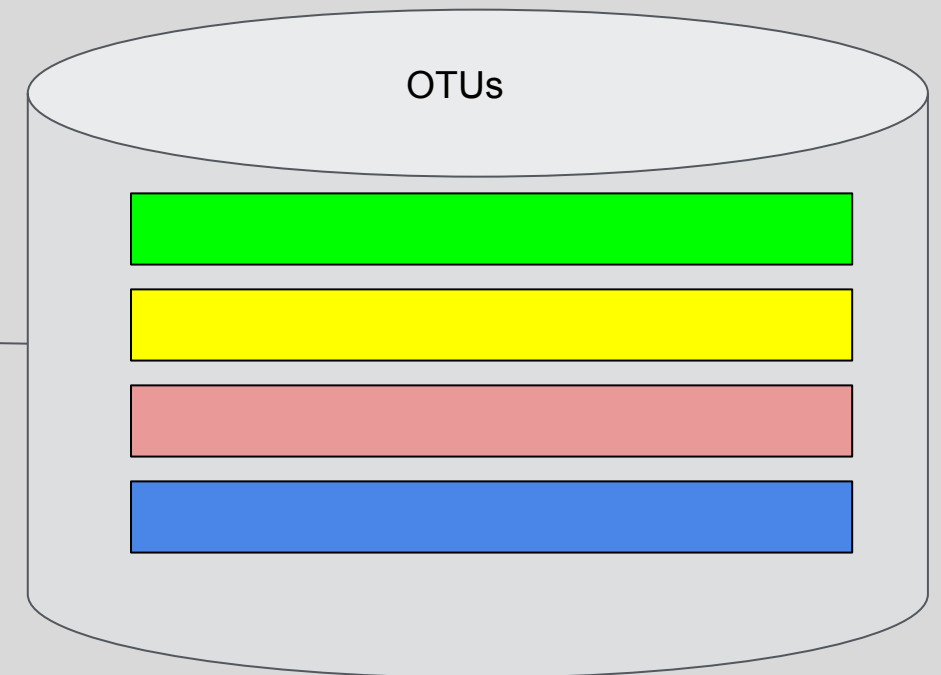
```
vsearch --uchime_denovo sample_nosing --chimeras sample_chim --nonchimeras sample_nochim
```


Clustering

A. Model - Sequence <3%, Assign to OTU

Model

Sequence



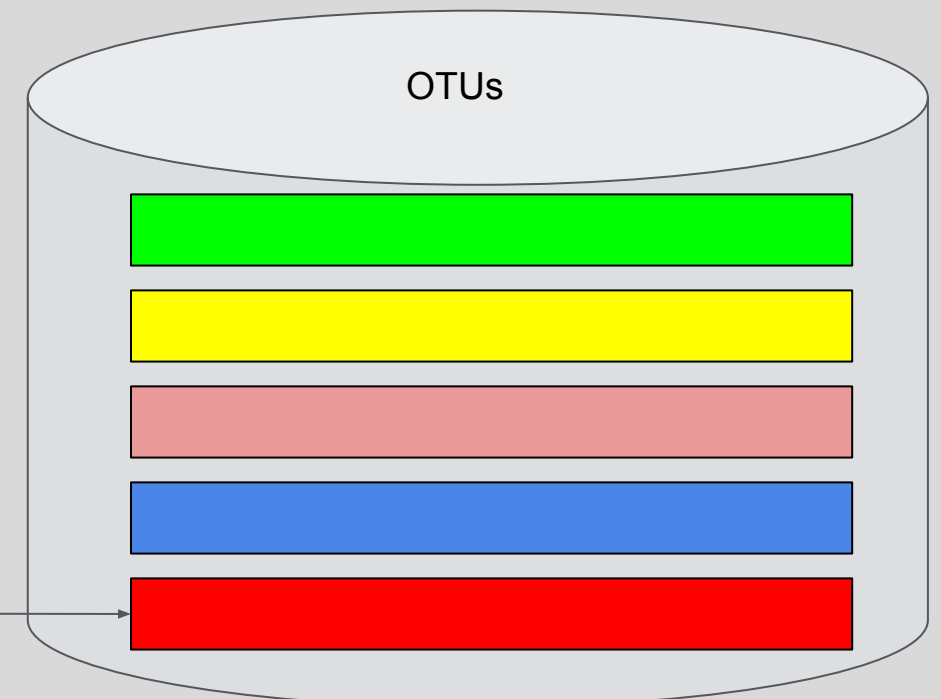
B. Model - Sequence ≥3%, new OTU

No match

Sequence

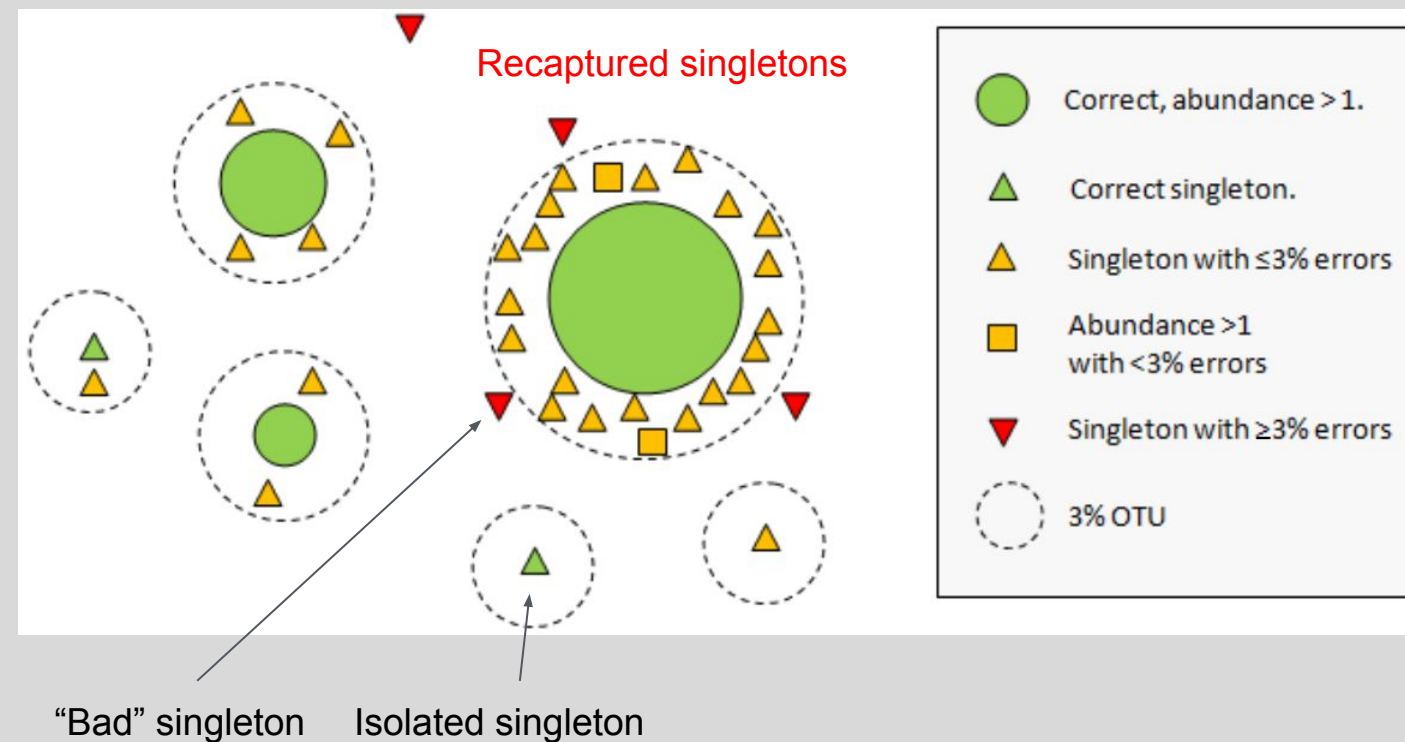


Add to database



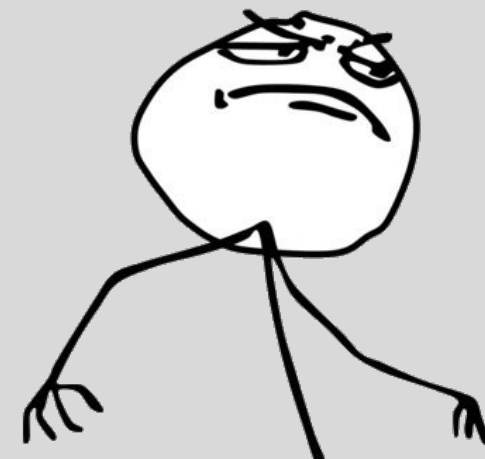
`vsearch --cluster_size sample_nochim --id 0.97 --centroids OTU --sizein --relabel OTU_`

Mapping



```
vsearch -usearch_global sample -db OTU --id 0.97 -uc map
```

```
uc2otutab.py map > otu_table
```



Taxonomical annotation

SILVA [Pruesse, et al. 2007]:

- 597,607 sequences (last update 04/2016)
- Small (16S/18S, SSU) and large subunit (23S/28S, LSU)
- Bacteria, Archaea and Eukarya
- Non redundant (Uclust 99% id)
- Based on EMBL-bank



Greengenes [DeSantis et al. 2006]:

- 1,262,986 sequences (last update 05/2013)
- Small subunit (16S/18S, SSU)
- Bacteria and Archaea
- Non redundant (Uclust 99% id)
- Based on Genbank



Ribosomal Database Project [Maidak et al. 1994]:

- 3,224,600 + 108,901 sequences (last update 05/2015)
- Small subunit (16S/18S, SSU) and Fungal 28S
- Bacteria, Archaea and Fungi



Taxonomical annotation

```
vsearch --usearch_global OTU --db database --id 0.9 --blast6out annotation --alnout alignment  
get_taxonomy.py -i annotation -u OTU -d database -o annotation_table -ob annotation_biom
```



BIOM format

Motivation:

- Encapsulation of the whole project (count table, annotation, metadata...)
- Efficient storage
- Compatibility between softwares

BIOM format version 1.0

```
{
  "id": null,
  "format": "Biological Observation Matrix 0.9.1-dev",
  "format_url": "http://biom-format.org/documentation/format_versions/biom-1.0.html",
  "type": "OTU table",
  "generated_by": "QIIME revision 1.4.0-dev",
  "date": "2011-12-19T19:00:00",
  "rows": [
    {
      "id": "GG_OTU_1",
      "metadata": {
        "taxonomy": [
          "k__Bacteria",
          "p__Proteobacteria",
          "c__Gammaproteobacteria",
          "o__Enterobacteriales",
          "f__Enterobacteriaceae",
          "g__Escherichia",
          "s__"
        ]
      }
    },
    {
      "id": "GG_OTU_2",
      "metadata": {
        "taxonomy": [
          "k__Bacteria",
          "p__Cyanobacteria",
          "c__Nostocophycideae",
          "o__Nostocales",
          "f__Nostocaceae",
          "g__Dolichospermum",
          "s__"
        ]
      }
    },
    {
      "id": "GG_OTU_3",
      "metadata": {
        "taxonomy": [
          "k__Archaea",
          "p__Euryarchaeota",
          "c__Methanomicrobia",
          "o__Methanosarcinales",
          "f__Methanosarcinaceae",
          "g__Methanosarcina",
          "s__"
        ]
      }
    },
    {
      "id": "GG_OTU_4",
      "metadata": {
        "taxonomy": [
          "k__Bacteria",
          "p__Firmicutes",
          "c__Clostridia",
          "o__Halanaerobiales",
          "f__Halanaerobiaceae",
          "g__Halanaerobium",
          "s__Halanaerobiumsacchar"
        ]
      }
    },
    {
      "id": "GG_OTU_5",
      "metadata": {
        "taxonomy": [
          "k__Bacteria",
          "p__Proteobacteria",
          "c__Gammaproteobacteria",
          "o__Enterobacteriales",
          "f__Enterobacteriaceae",
          "g__Escherichia",
          "s__"
        ]
      }
    }
  ],
  "columns": [
    {
      "id": "Sample1",
      "metadata": {
        "BarcodeSequence": "CGCTTATCGAGA",
        "LinkerPrimerSequence": "CATGCTGCCTCCCGTAGGAGT",
        "BODY_SITE": "gut",
        "Description": "human gut"
      }
    },
    {
      "id": "Sample2",
      "metadata": {
        "BarcodeSequence": "CATACCAGTAGC",
        "LinkerPrimerSequence": "CATGCTGCCTCCCGTAGGAGT",
        "BODY_SITE": "gut",
        "Description": "human gut"
      }
    },
    {
      "id": "Sample3",
      "metadata": {
        "BarcodeSequence": "CTCTCTACCTGT",
        "LinkerPrimerSequence": "CATGCTGCCTCCCGTAGGAGT",
        "BODY_SITE": "gut",
        "Description": "human gut"
      }
    },
    {
      "id": "Sample4",
      "metadata": {
        "BarcodeSequence": "CTCTCGGCCTGT",
        "LinkerPrimerSequence": "CATGCTGCCTCCCGTAGGAGT",
        "BODY_SITE": "skin",
        "Description": "human skin"
      }
    },
    {
      "id": "Sample5",
      "metadata": {
        "BarcodeSequence": "CTCTCTACCAAT",
        "LinkerPrimerSequence": "CATGCTGCCTCCCGTAGGAGT",
        "BODY_SITE": "skin",
        "Description": "human skin"
      }
    },
    {
      "id": "Sample6",
      "metadata": {
        "BarcodeSequence": "CTAACTACCAAT",
        "LinkerPrimerSequence": "CATGCTGCCTCCCGTAGGAGT",
        "BODY_SITE": "skin",
        "Description": "human skin"
      }
    }
  ],
  "matrix_type": "dense",
  "matrix_element_type": "int",
  "shape": [5, 6],
  "data": [
    [0, 0, 1, 0, 0, 0],
    [5, 1, 0, 2, 3, 1],
    [0, 0, 1, 4, 2, 0],
    [2, 1, 1, 0, 0, 1],
    [0, 1, 1, 0, 0, 0]
  ]
}
```

Annotation

Metadata

Count

BIOM format

Motivation:

- Efficient storage
- Encapsulation of the whole project (count table, annotation, metadata...)
- Compatibility between softwares

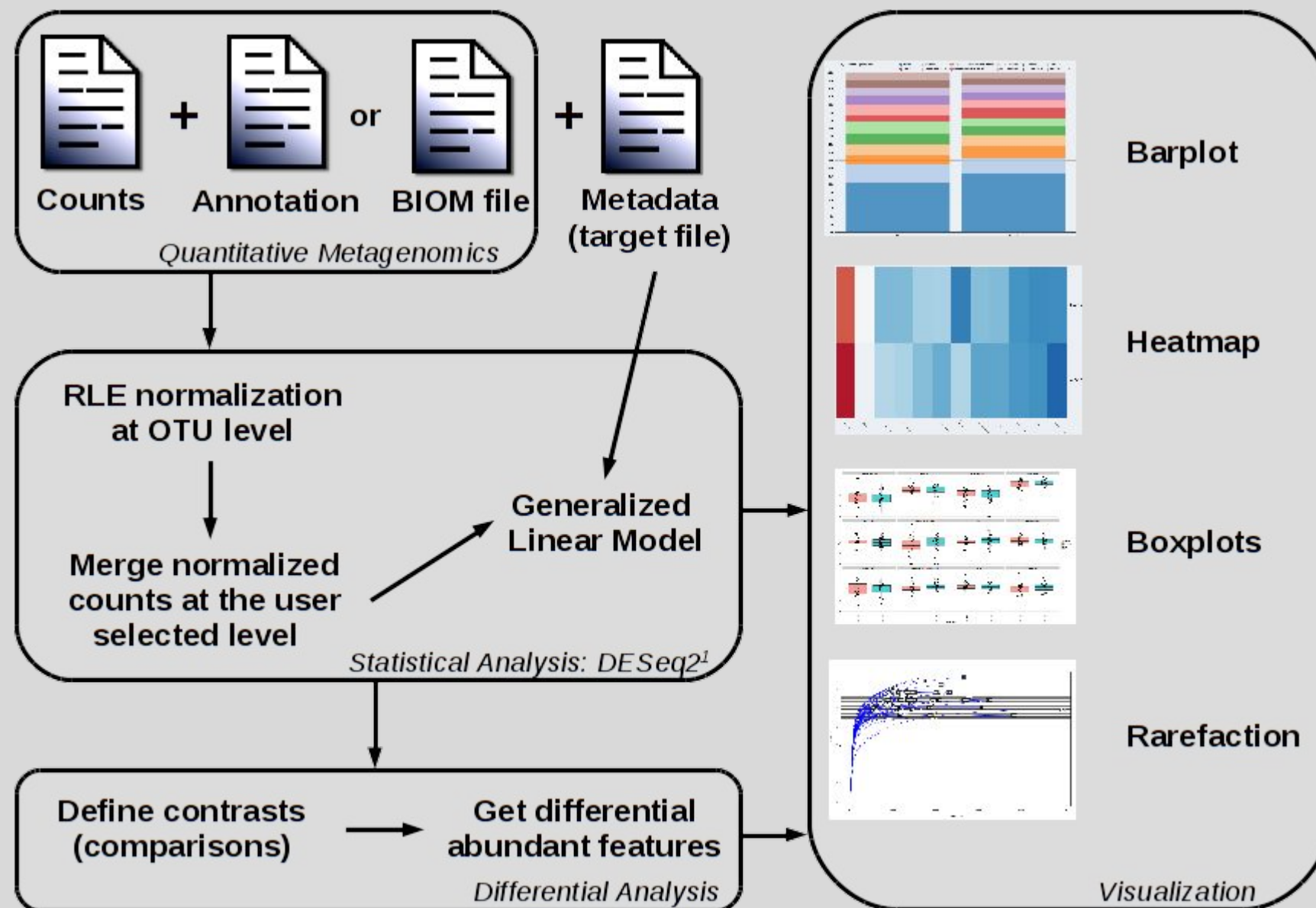
Cons:

- Not human readable
- 3 different versions of BIOM format (1.0, 2.0, 2.1)
- Not strict enough in the version 1.0
- BIOM library does not provide good support of every version

```
biom convert -i otu_table -o biom --table-type="OTU table" --to-json
```

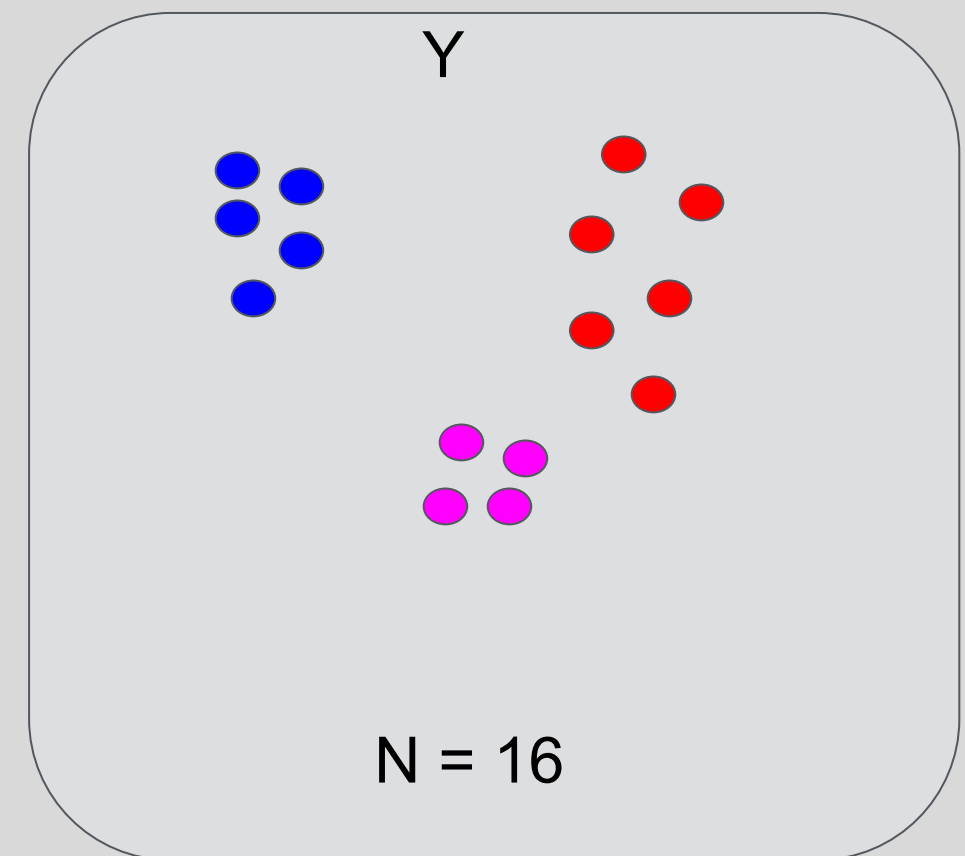
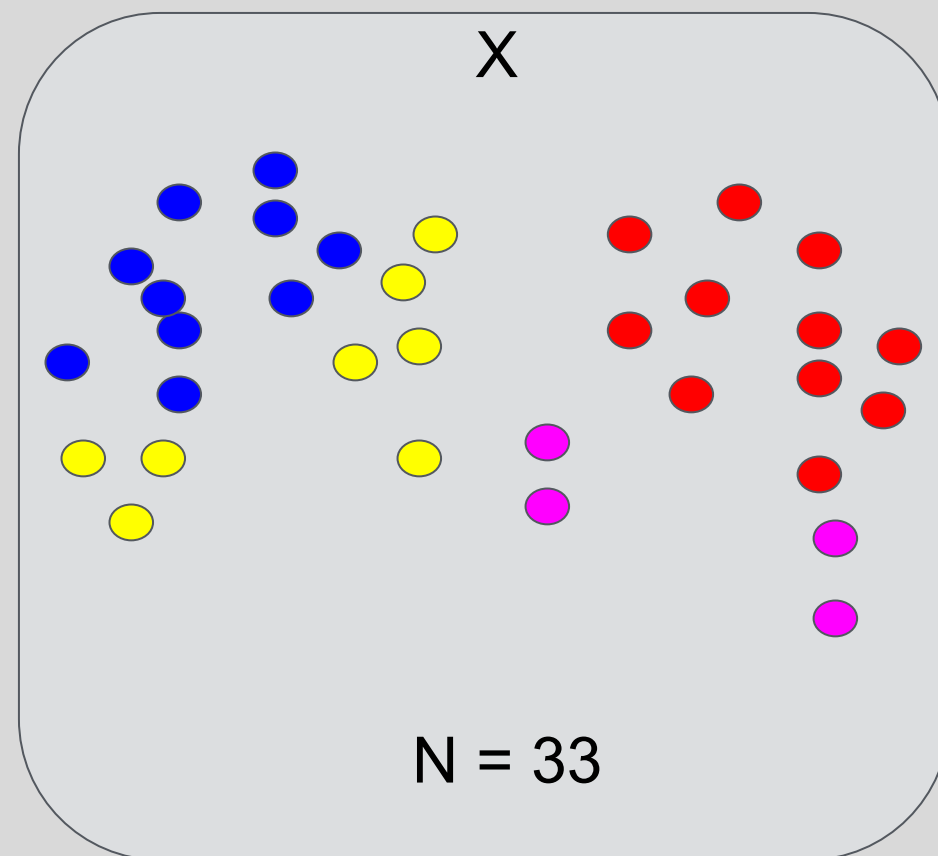
```
biom add-metadata -i biom -o annotated_biom --observation-metadata-fp annotation_table_biom --observation-header id,taxonomy --sc-separated taxonomy
```

Differential analysis : SHAMAN



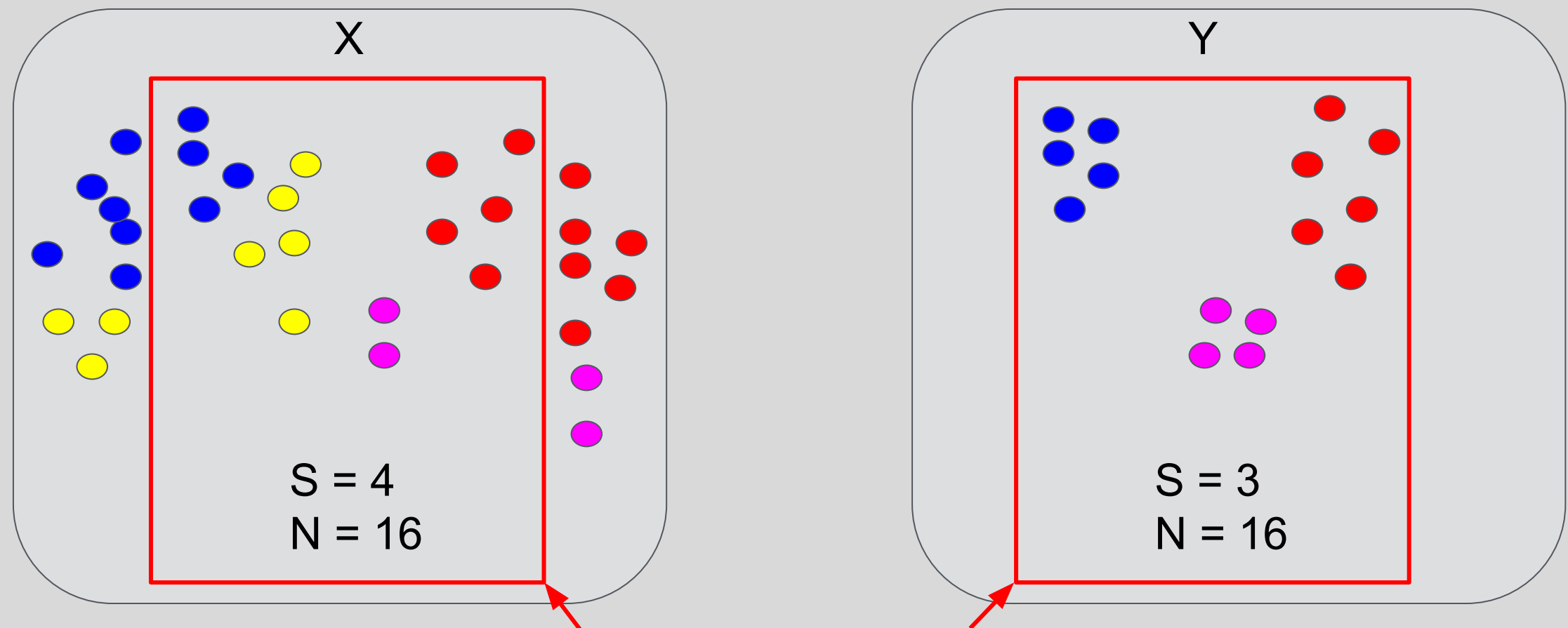
¹Love MI, Huber W, Anders S. Moderated estimation of fold change and dispersion for RNA-seq data with DESeq2. Genome Biol.

Diversity



- ❖ N: Total count of **individual**
- ❖ **Rarefaction**: a type of normalisation : Rarefy to the same number of **individual**

Diversity



RAREFACTION = "DOWNSIZING"

- ❖ N: Total count of **individual**
- ❖ **Rarefaction**: a type of normalisation : Rarefy to the same number of **individual**
- ❖ S = number of species = richness = number of object > 0

Alpha diversity

CONDITION 1

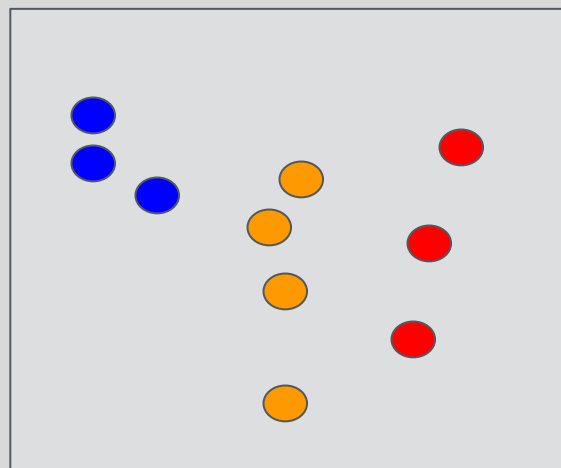
CONDITION 2

A

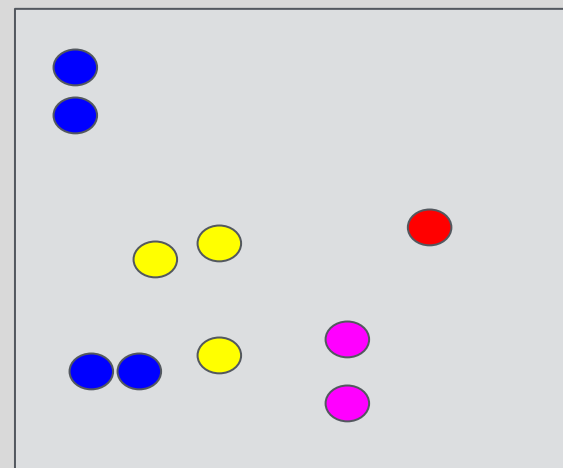
B

C

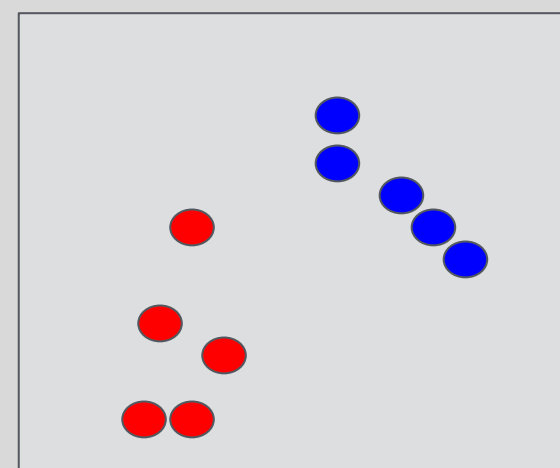
D



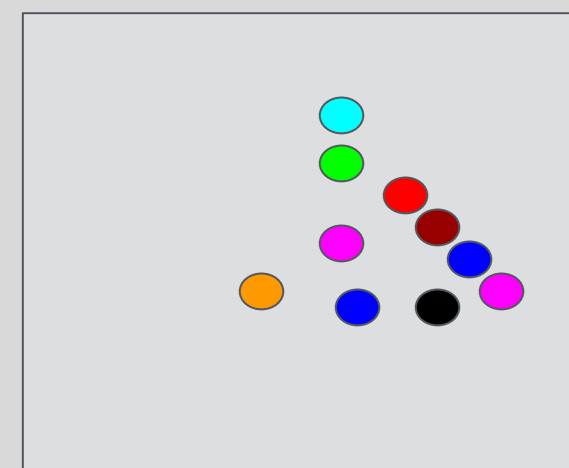
$S = 3$
 $N = 10$



$S = 4$
 $N = 10$



$S = 2$
 $N = 10$



$S = 8$
 $N = 10$

❖ S = number of species = richness = number of object > 0

❖ Alpha diversity:

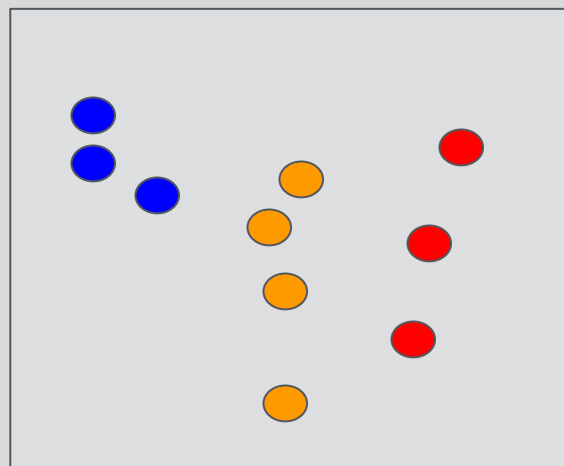
➤ Condition 1 : $\alpha_1 = \text{mean}(S_A, S_B) = 3.5$

➤ Condition 2 : $\alpha_2 = \text{mean}(S_C, S_D) = 5$

Gamma diversity

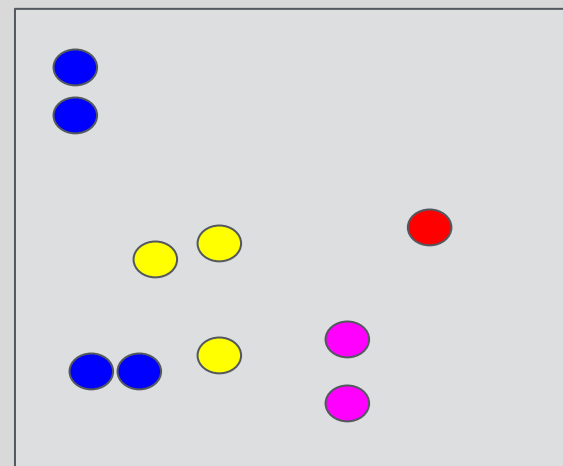
CONDITION 1

A



$S = 3$
 $N = 10$

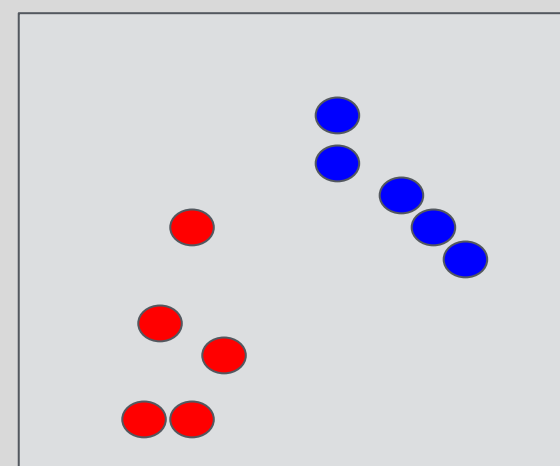
B



$S = 4$
 $N = 10$

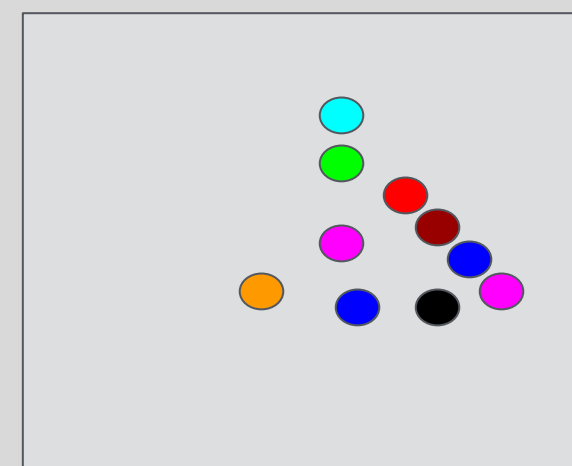
CONDITION 2

C



$S = 2$
 $N = 10$

D



$S = 8$
 $N = 10$

❖ S = number of species = richness = number of object > 0

❖ Gamma diversity:

➤ Condition 1 : $\gamma_1 = S_1 = 5$

➤ Condition 2 : $\gamma_2 = S_2 = 8$

Beta diversity

CONDITION 1

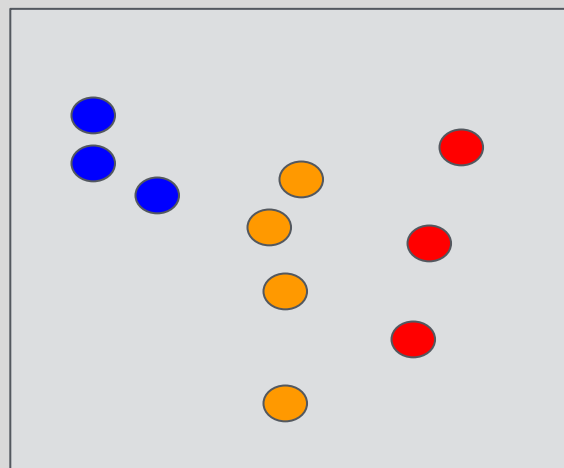
CONDITION 2

A

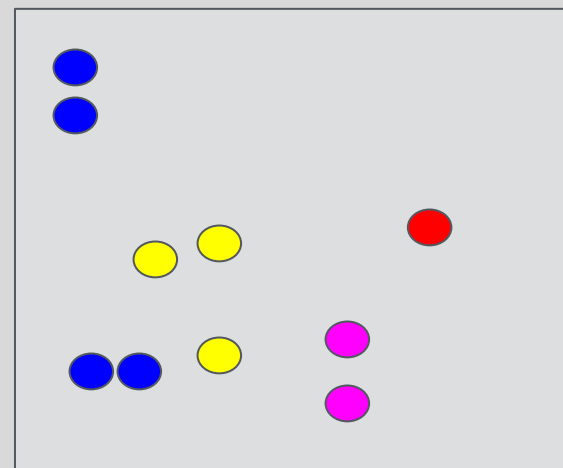
B

C

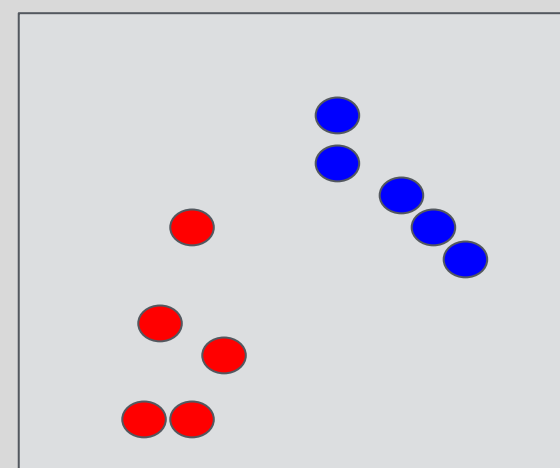
D



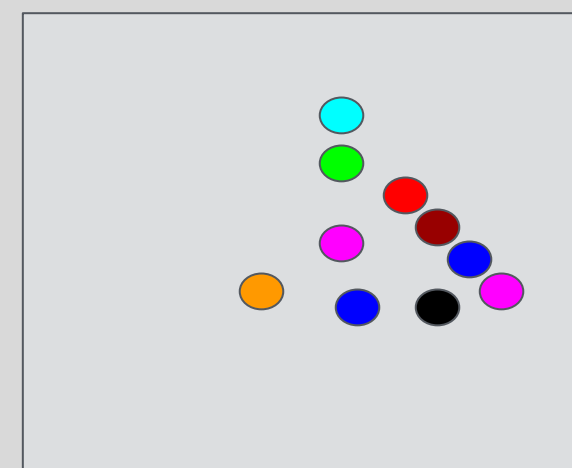
$S = 3$
 $N = 10$



$S = 4$
 $N = 10$



$S = 2$
 $N = 10$



$S = 8$
 $N = 10$

❖ S = number of species = richness = number of object > 0

❖ Beta diversity:

➤ Condition 1 : $\beta_1 = \frac{\gamma_1}{\alpha_1} - 1 = 0.43$

➤ Condition 2 : $\beta_2 = 0.6$

Other diversity measures

$$H = - \sum_{i=1}^S p_i \log_b p_i \quad \text{Shannon-Weaver}$$
$$D_1 = 1 - \sum_{i=1}^S p_i^2 \quad \text{Simpson}$$
$$D_2 = \frac{1}{\sum_{i=1}^S p_i^2} \quad \text{inverse Simpson,}$$

P_i proportion of species i and S number of species

16S rRNA limits

Motivation:

- Copy number varies in the genomes (from 1 to 15)*
- 16S sequence variants in the same specie and even genome** -> impact diversity



16S rRNA limits

Motivation:

- Copy number varies in the genomes (from 1 to 15)*
- 16S sequence variants in the same specie and even genome** -> impact diversity

Solutions:

- rrnDB: ribosomal RNA operon copy number database***
- Good clustering and differential analysis
- Whole Genome Sequencing

16S analysis at Pasteur

Available:

- MASQUE pipeline on bic and on tars
 - module use /pasteur/projets/Matrix/modules
 - module add masque/0.1 -> bic
 - module add masque/0.2 -> tars
- SHAMAN
- Galaxy : FROGS