Stylometry with R

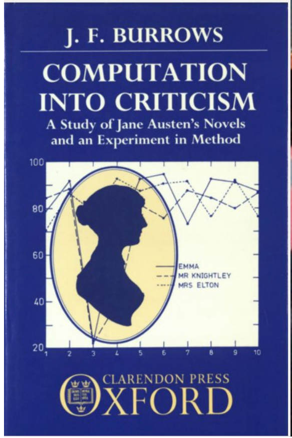
Part 3. Distance and uncertainty

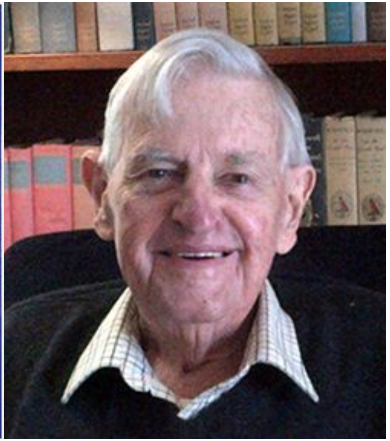
Joanna Byszuk, Artjoms Šeļa and Maciej Eder

1. Quick intro to Burrows' Delta

"Wealth of variables, many of which may be weak discriminators, almost always offer more tenable results than a smaller number of strong ones. [...] At all events, **a distinctive 'stylistic signature' is usually made up of many tiny strokes.**"

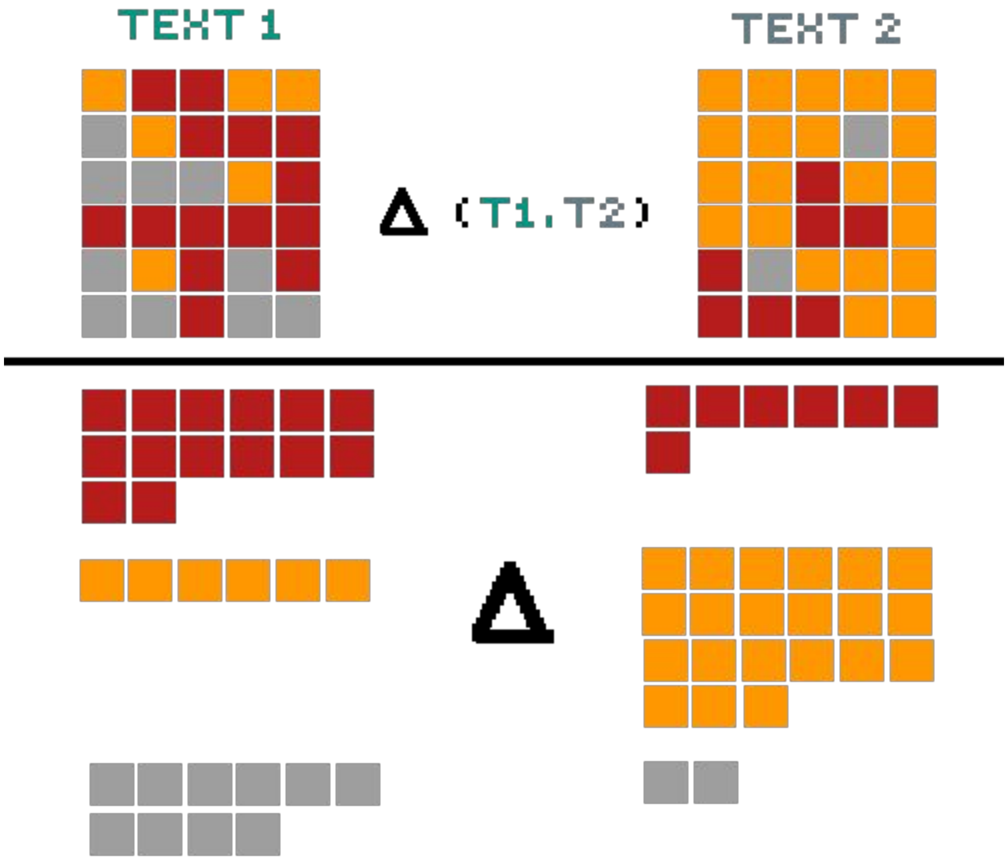
$$\Delta = \sum_{i=1}^{n} \frac{|z(x_i) - z(y_i)|}{n}$$

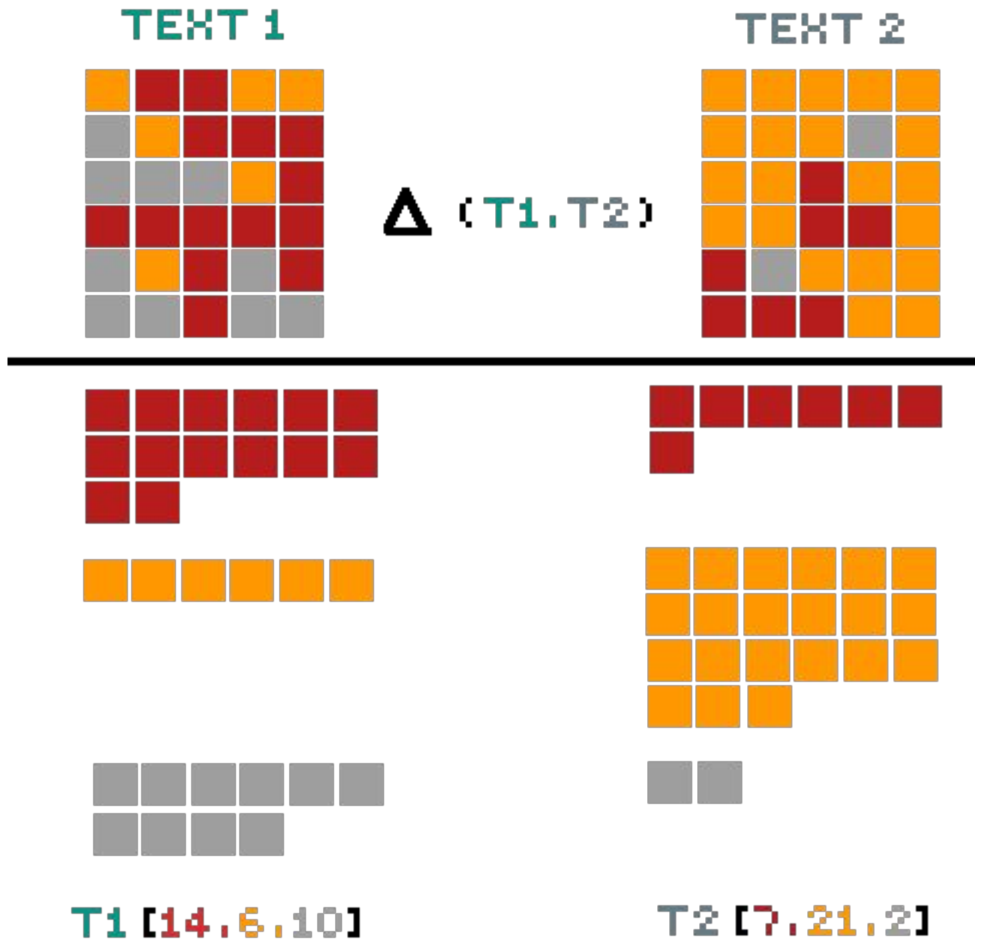




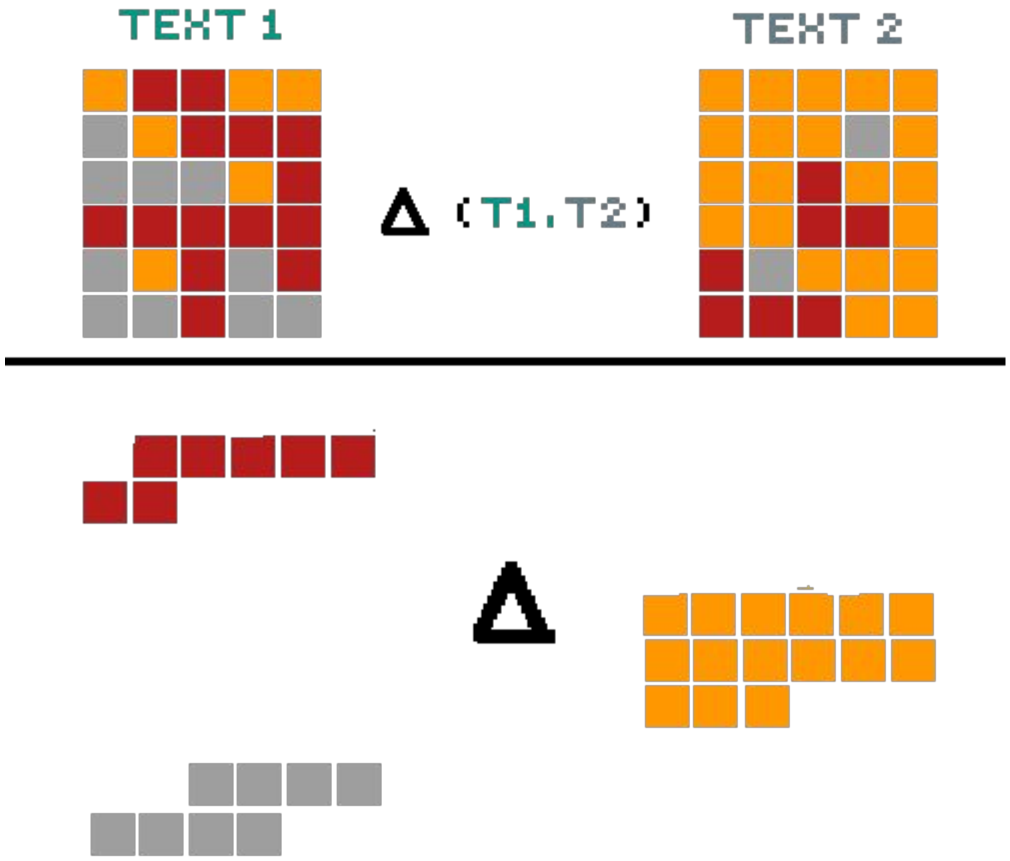
John Burrows (1928-2019)

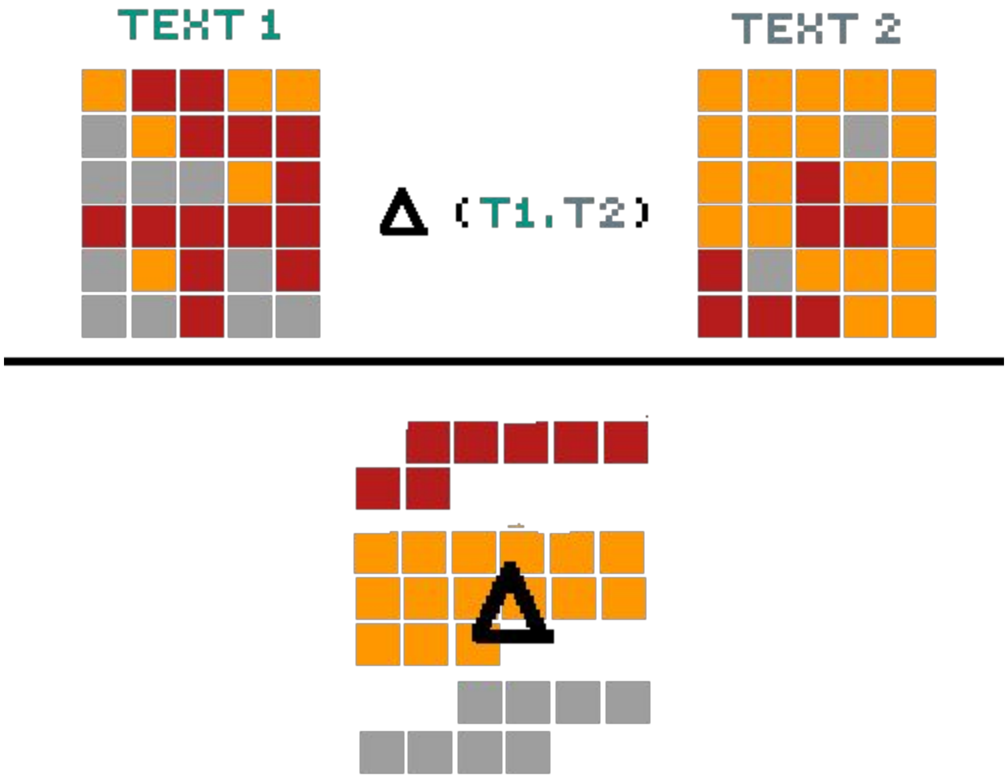

TEXT 1
TEXT 2
Δ (T1,T2)


TEXT 1
TEXT 2
Δ (T1,T2)
Δ

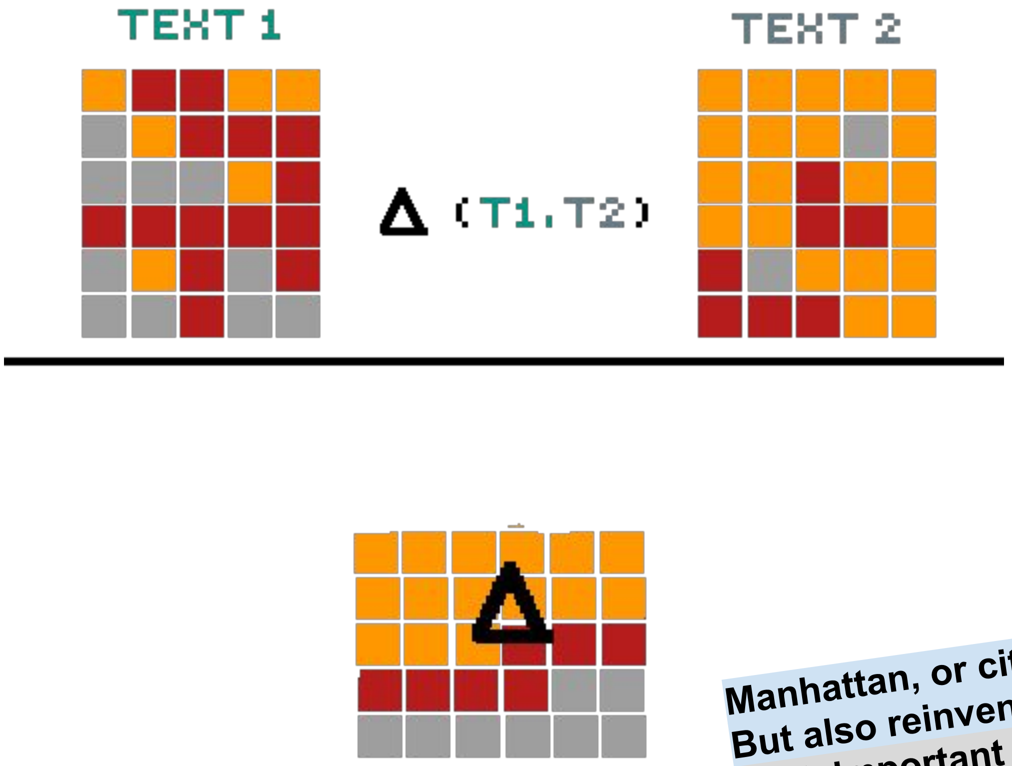


TEXT 1
TEXT 2
Δ (T1,T2)
T1 [14,6,10]
T2 [7,21,2]


TEXT 1
TEXT 2
Δ (T1,T2)
Δ



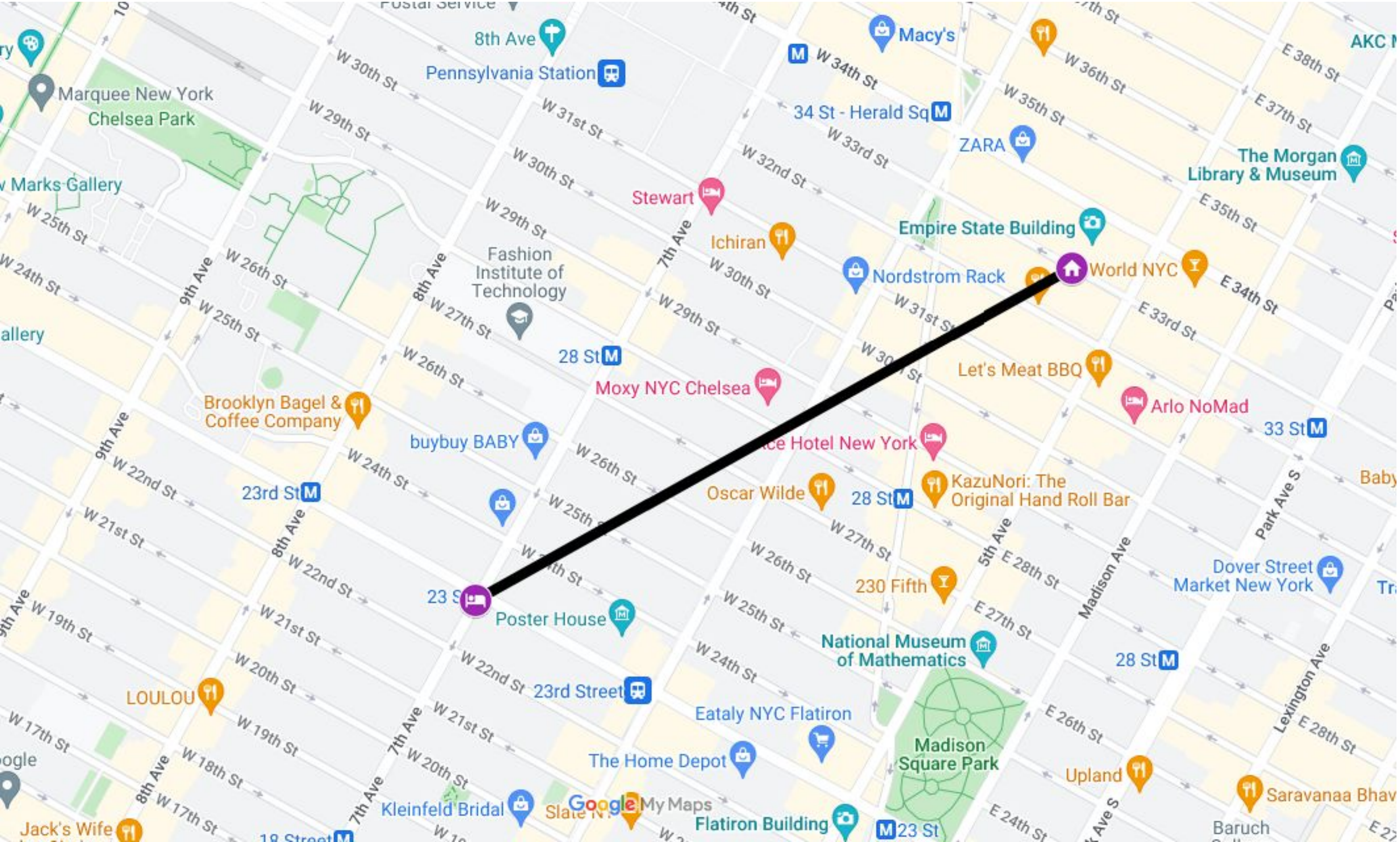
Δ (T1,T2)= [6,15,10]



$\Delta(T1,T2) = 7 + 15 + 8 = 30$

Manhattan, or city-block distance!
But also reinvented by Burrows
(with important adjustment)

Petr Plecháč: https://versologie.cz/talks/2017chicago/



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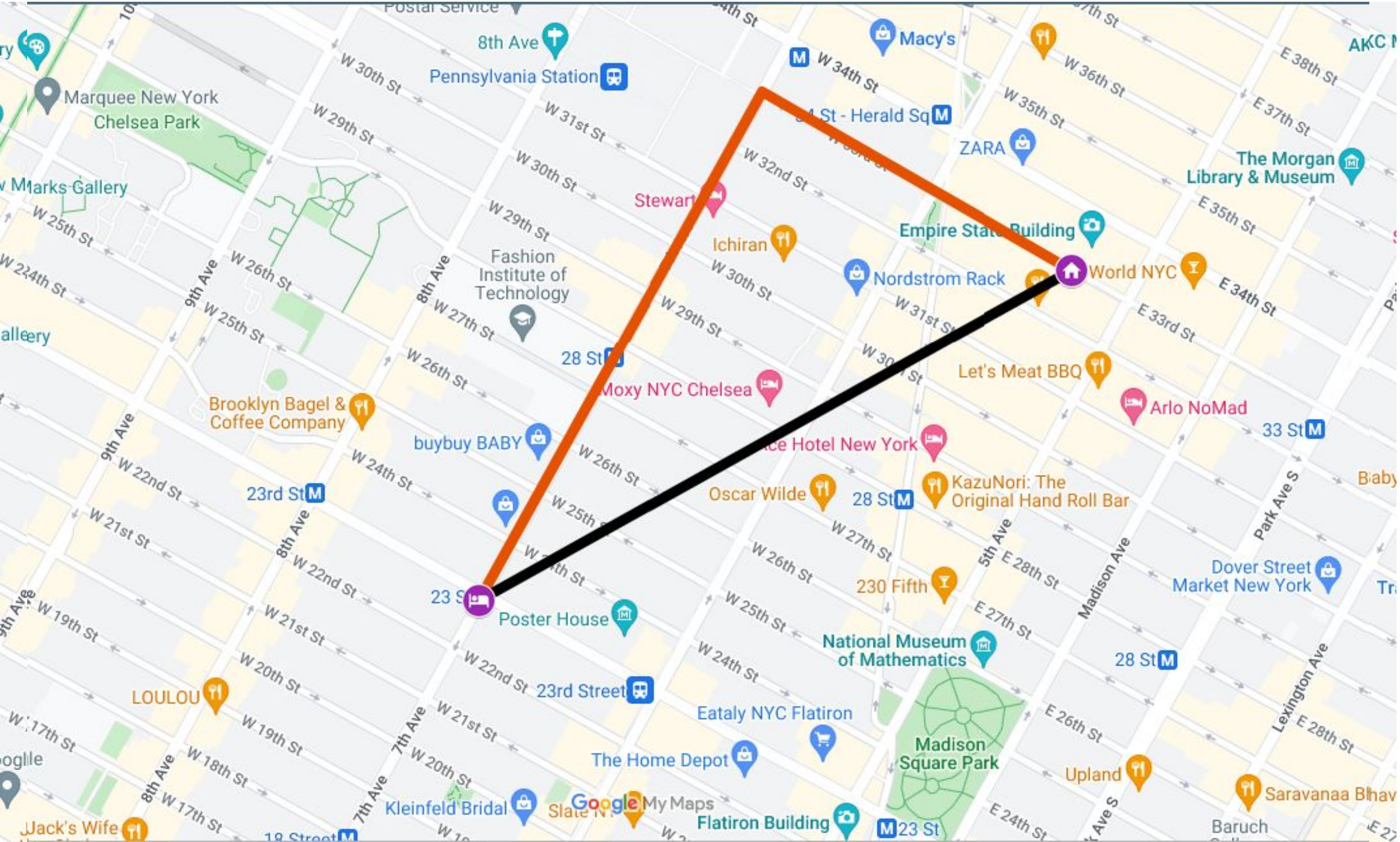

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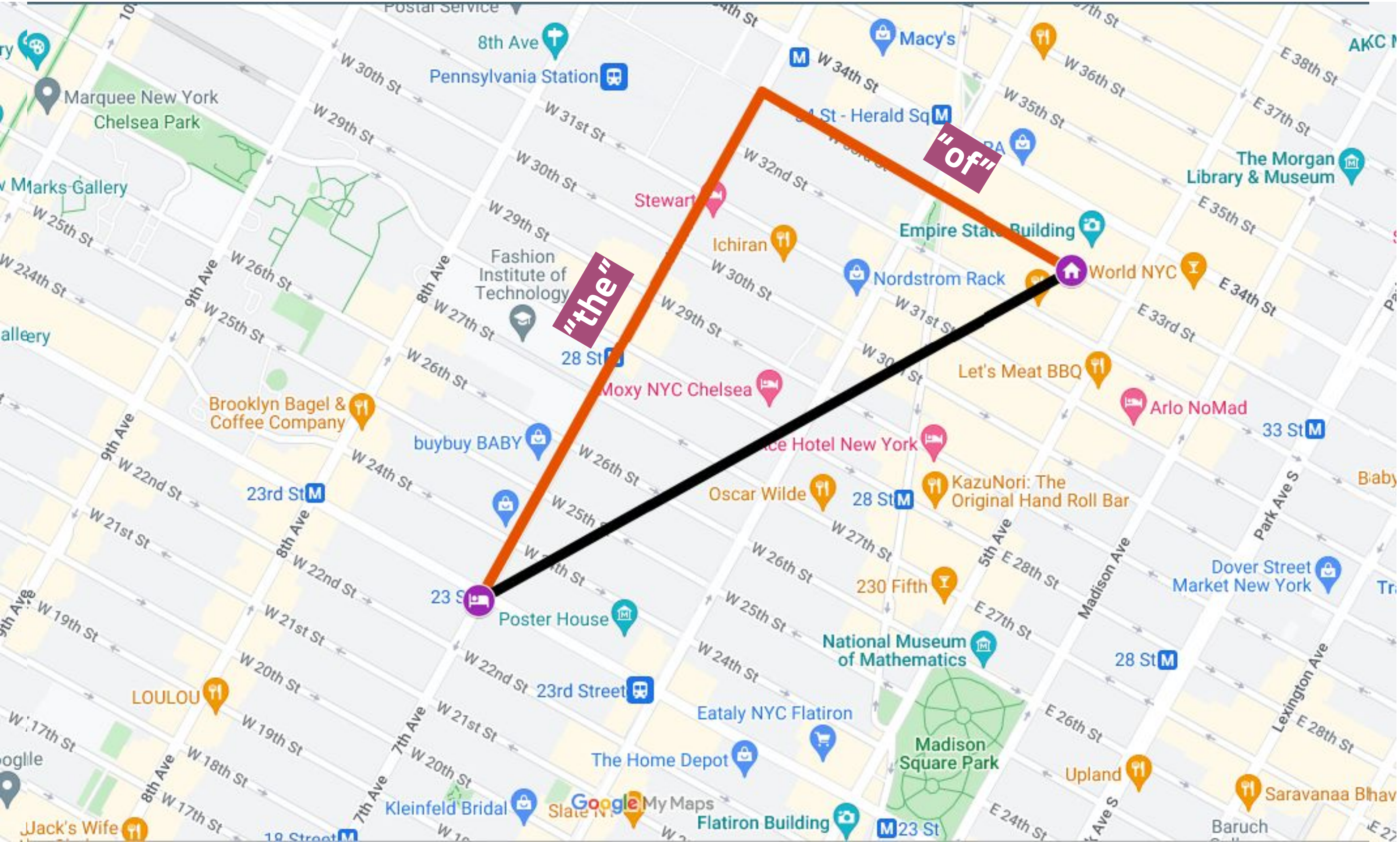

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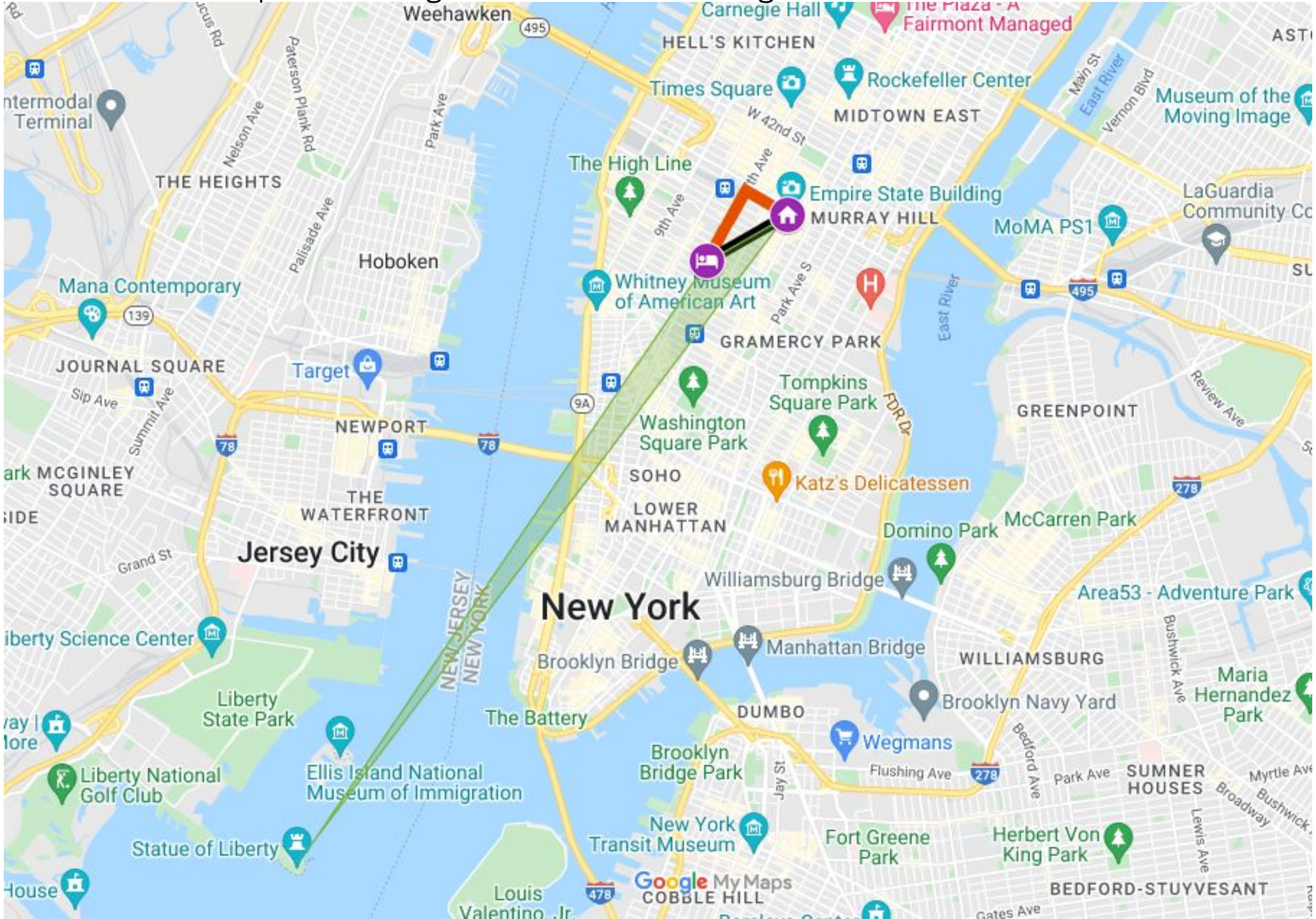

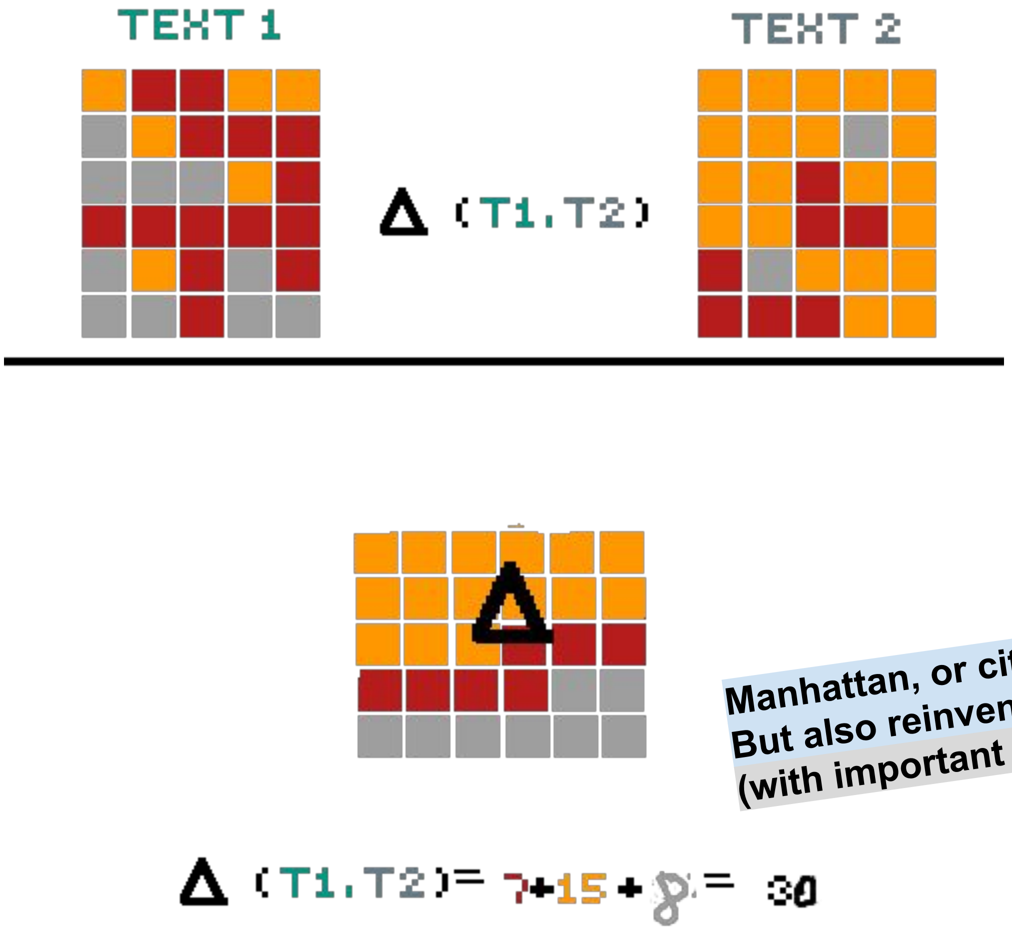

Manhattan, or city-block distance!
But also reinvented by Burrows
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DISTANCE MATRIX

	T1	T2	T3
T1	0		
T2	0.3	0	
T3	0.7	0.9	0

DISTANCE MATRIX

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T1	0		
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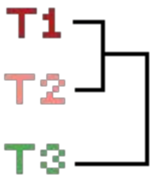
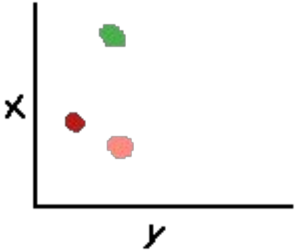
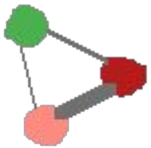


HIERARCHICAL CLUSTERING

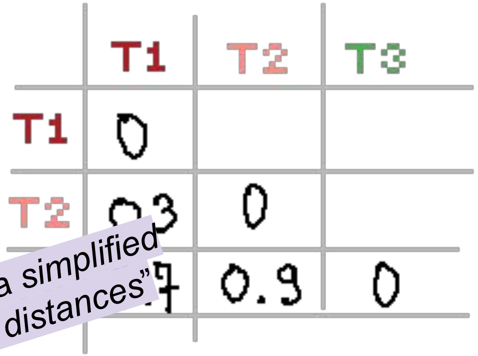
MULTIDIMENSIONAL SCALING



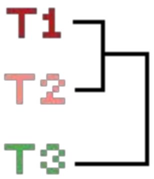


GRAPH

DISTANCE MATRIX



"A tree can be viewed as a simplified description of a matrix of distances" (Cavalli-Sforza et al.)



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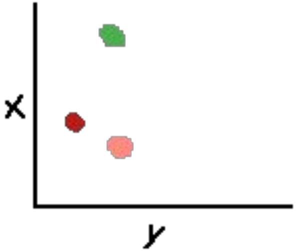
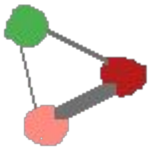
MULTIDIMENSIONAL SCALING





GRAPH

2. Sampling & bootstrapping

Sample: 

p = 0.66

2. Sampling & bootstrapping

Sample:  p = 0.66

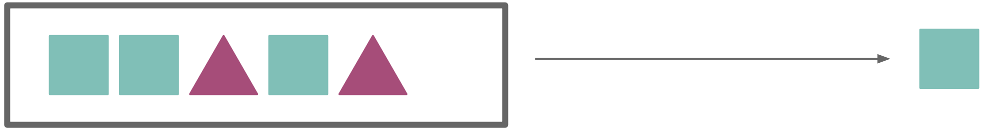
Resample 1:  0.5

Sidenote

Sampling without replacement:

Sidenote

Sampling without replacement:



Sidenote

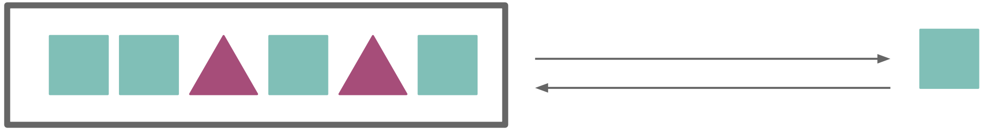
Sampling without replacement:

Sidenote

Sampling without replacement:

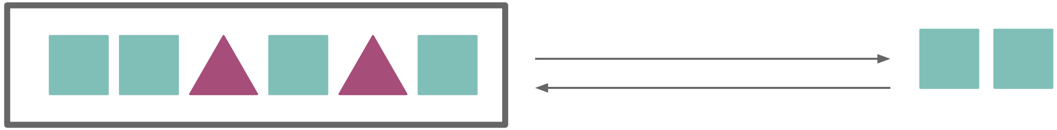
Sidenote

Sampling *with* replacement:



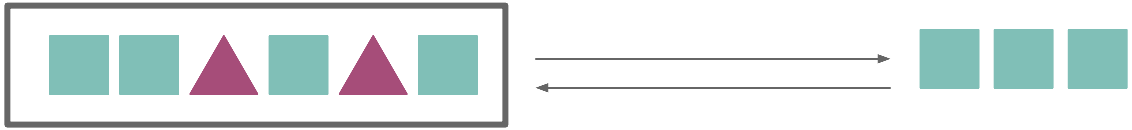
Sidenote

Sampling *with* replacement:



Sidenote

Sampling *with* replacement:



2. Sampling & bootstrapping

Sample:  p = 0.66

Resample 1:  0.5

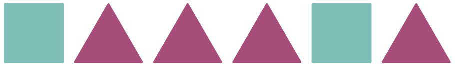
Resample 2:  0.66

2. Sampling & bootstrapping

Sample:  p = 0.66

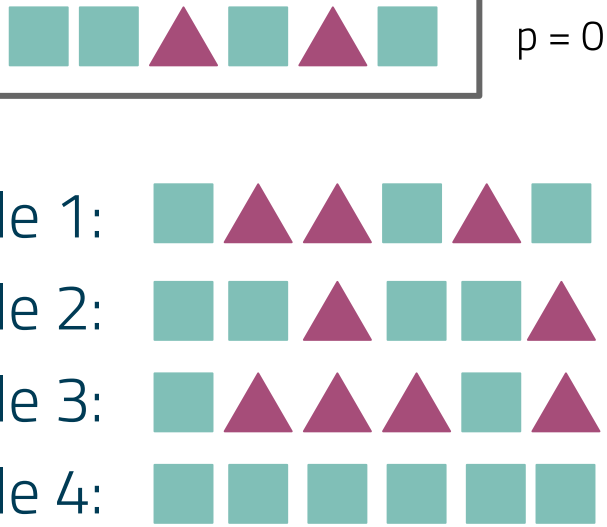
Resample 1:  0.5

Resample 2:  0.66

Resample 3:  0.33

2. Sampling & bootstrapping

Sample:



p = 0.66

Resample 1: 0.5

Resample 2: 0.66

Resample 3: 0.33

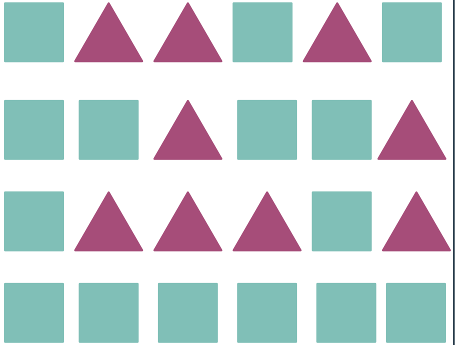
Resample 4: 1

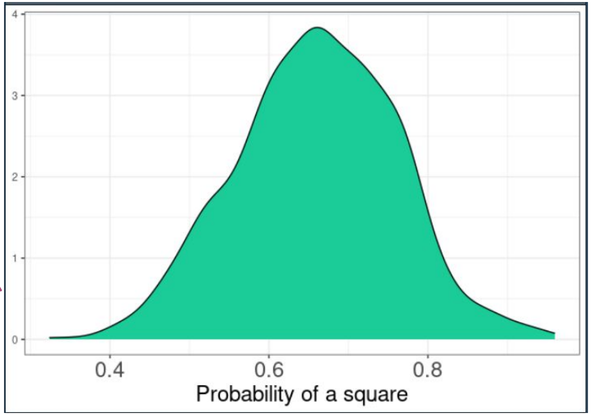
2. Sampling & bootstrapping

Sample: 

p = 0.66

Resample 1:
Resample 2:
Resample 3:
Resample 4:

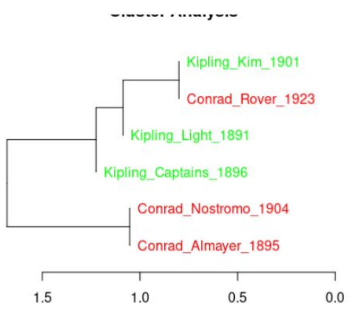




3. Estimating uncertainty in text similarity

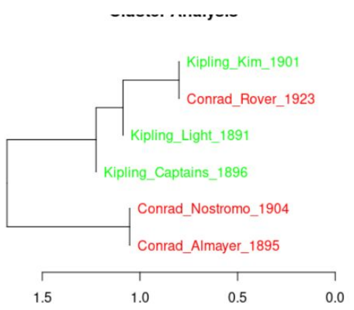
- (Bootstrap) consensus trees (Eder 2013)
- (Bootstrap) consensus networks (Eder 2017)
- General Impostors (Kestemont et al. 2016)

4. Consensus trees

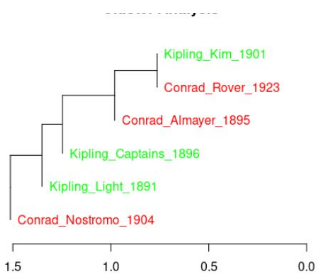


Feature set 1

4. Consensus trees

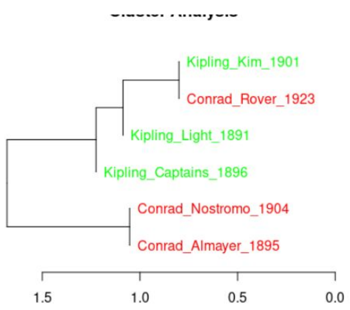


Feature set 1

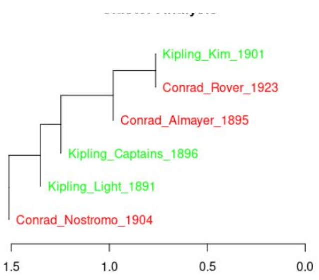


Feature set 2

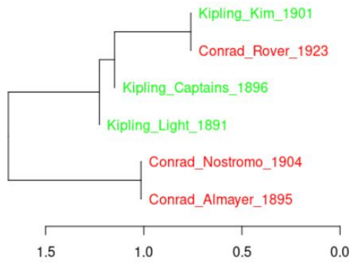
4. Consensus trees



Feature set 1

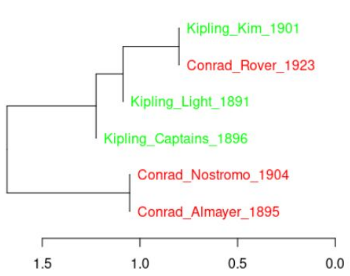


Feature set 2



Feature set 3

4. Consensus trees



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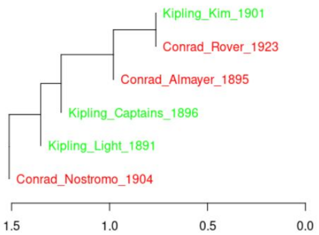
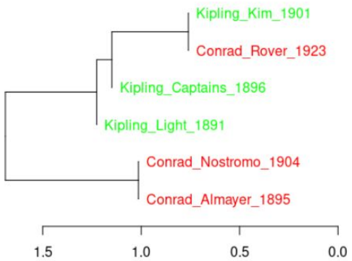
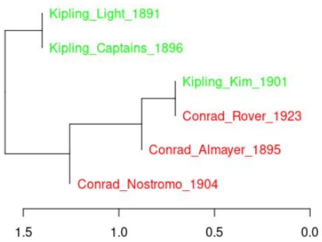


Feature set 2

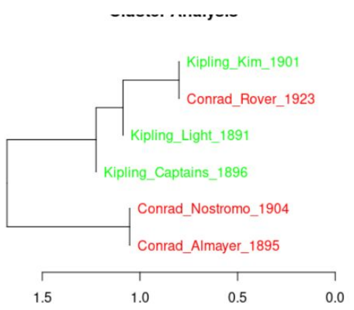


Feature set 3

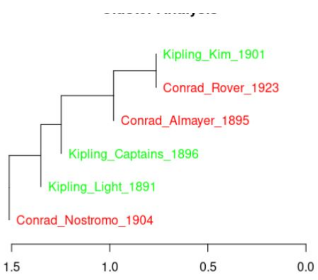


Feature set 4

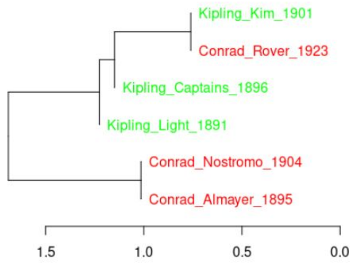
4. Majority rule (>50% of branches)



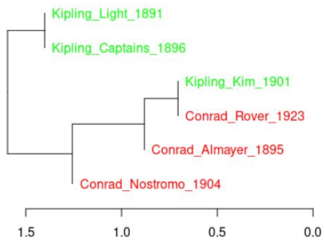
Feature set 1



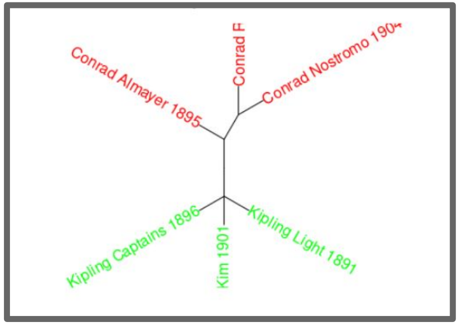
Feature set 2



Feature set 3



Feature set 4



5. Consensus trees

Using stylo() out of the box you can “bootstrap”:

- MFW length
- Culling strength
- Text themselves (take samples from texts)

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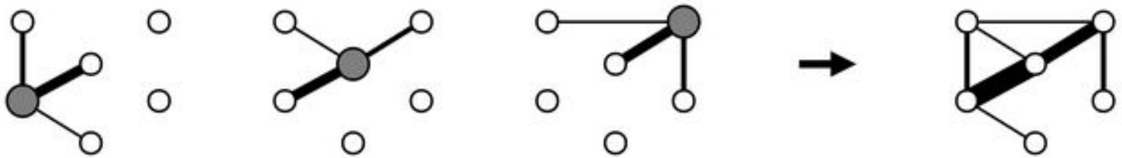
….

But the possibilities are limitless

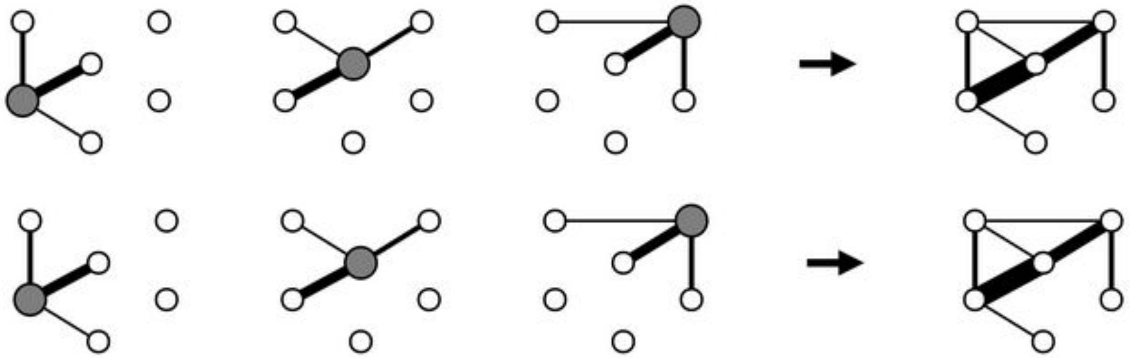
5. Consensus trees

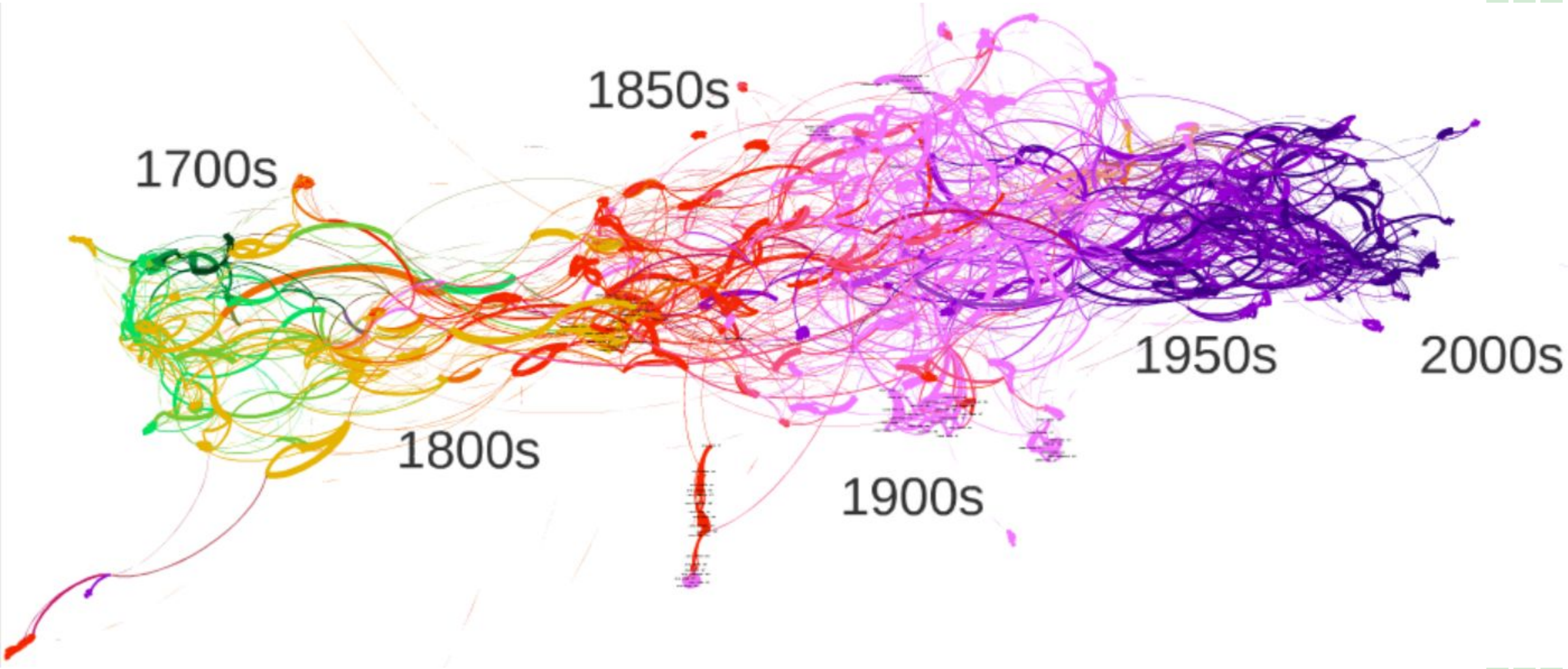
1. Look at the neighbours!



5. Consensus trees

1. Look at the neighbours!
2. Then look at the neighbours many times!




1700s
1800s
1850s
1900s
1950s
2000s

- Try using stylo.network() (alpha version!)
- Or brave the depths of Gephi
- Or work with networks from R!
  - Best tutorial I know:
  - **https://kateto.net/network-visualization**

6. General imposters

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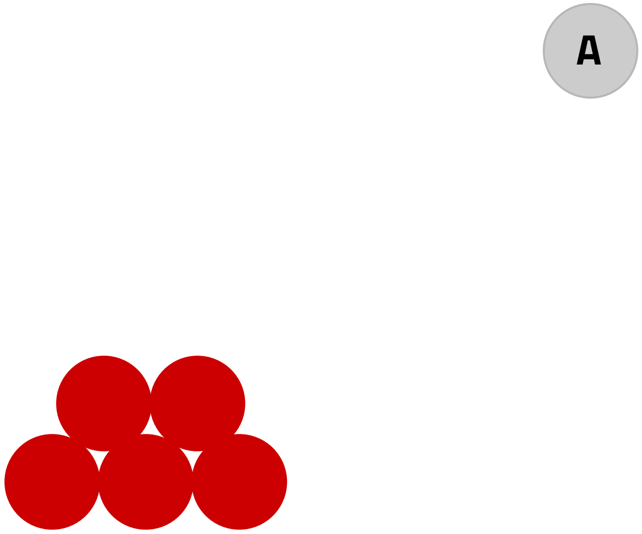
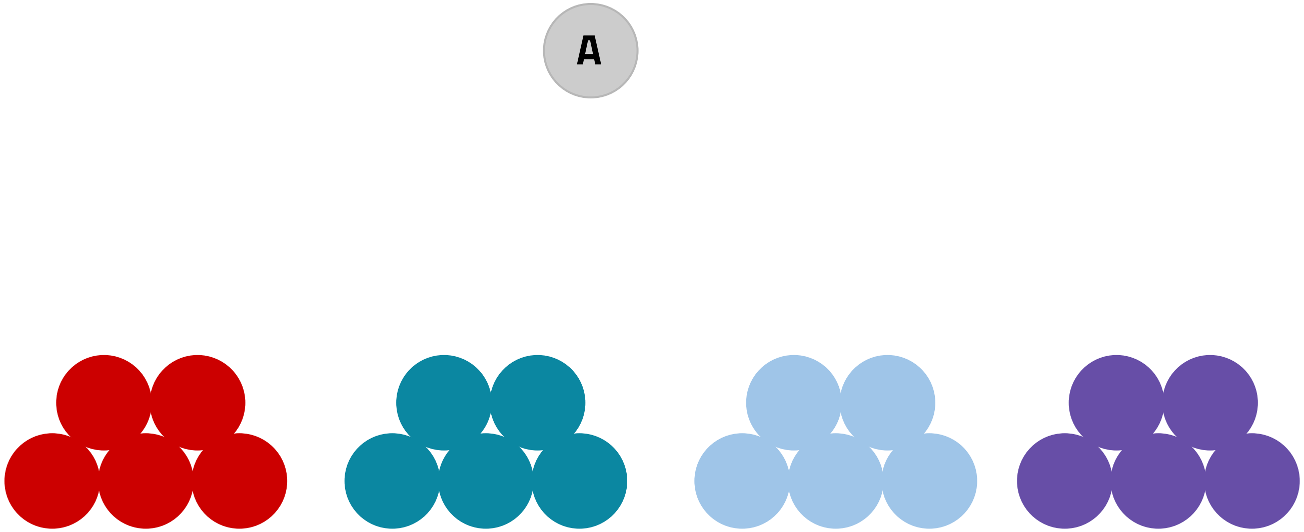


6. General imposters



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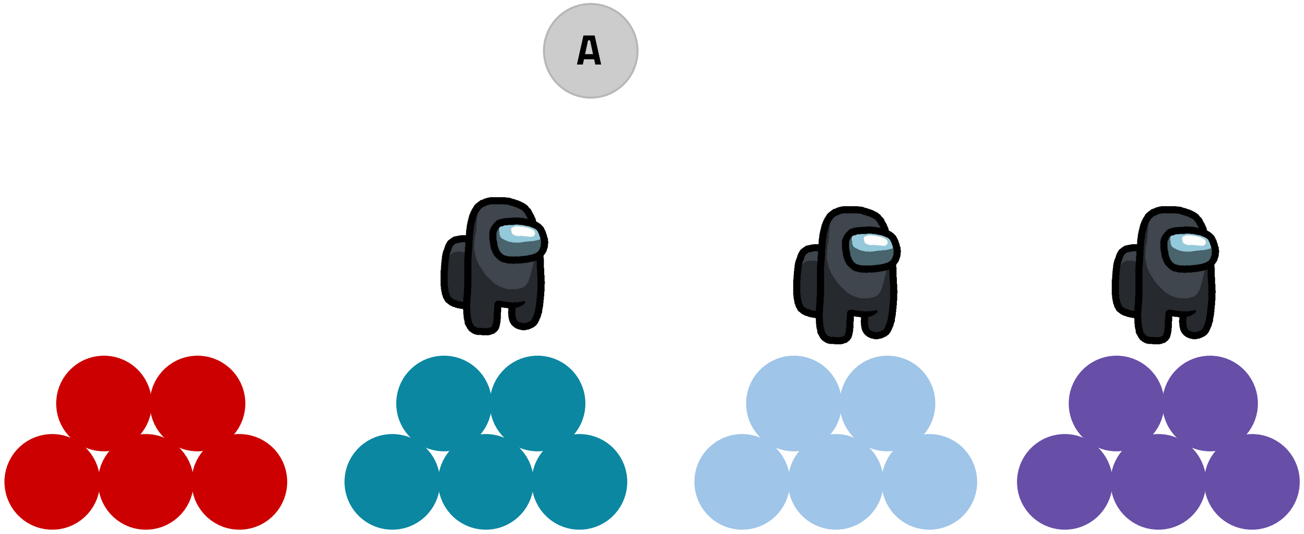


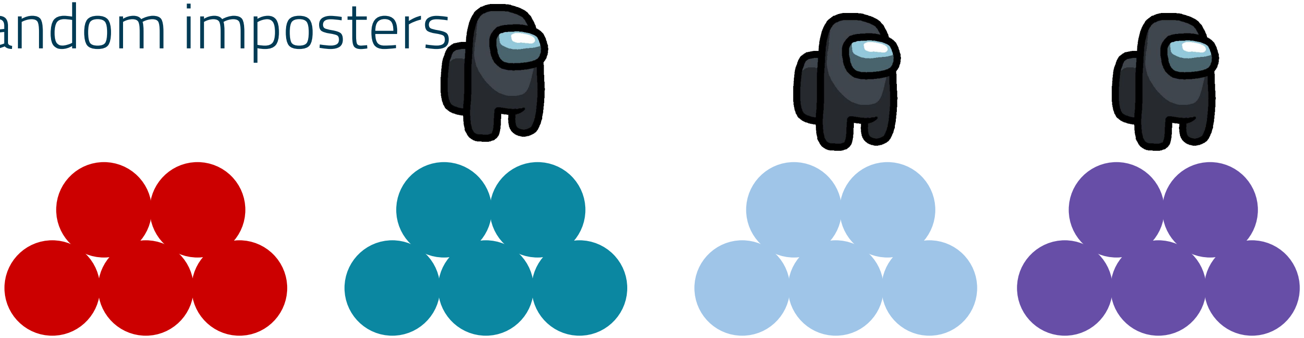
6. General imposters

Random samples

A

Random features

Random imposters



6. General imposters

Random samples

Random features

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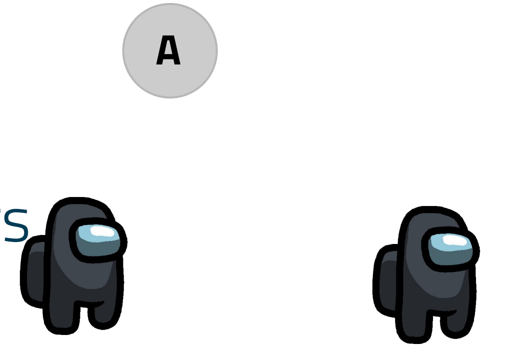

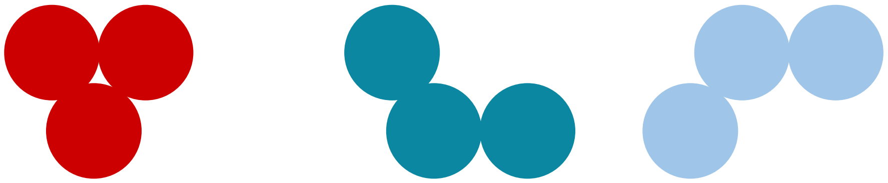

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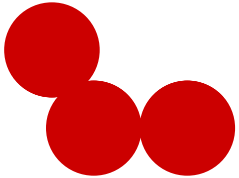

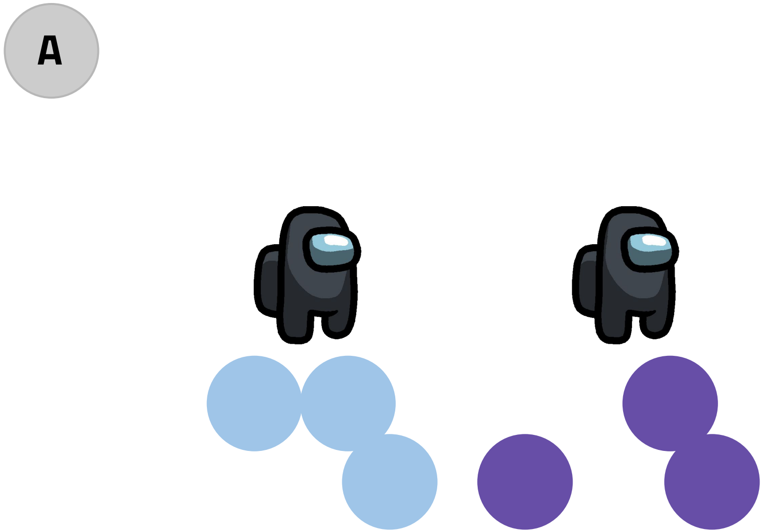

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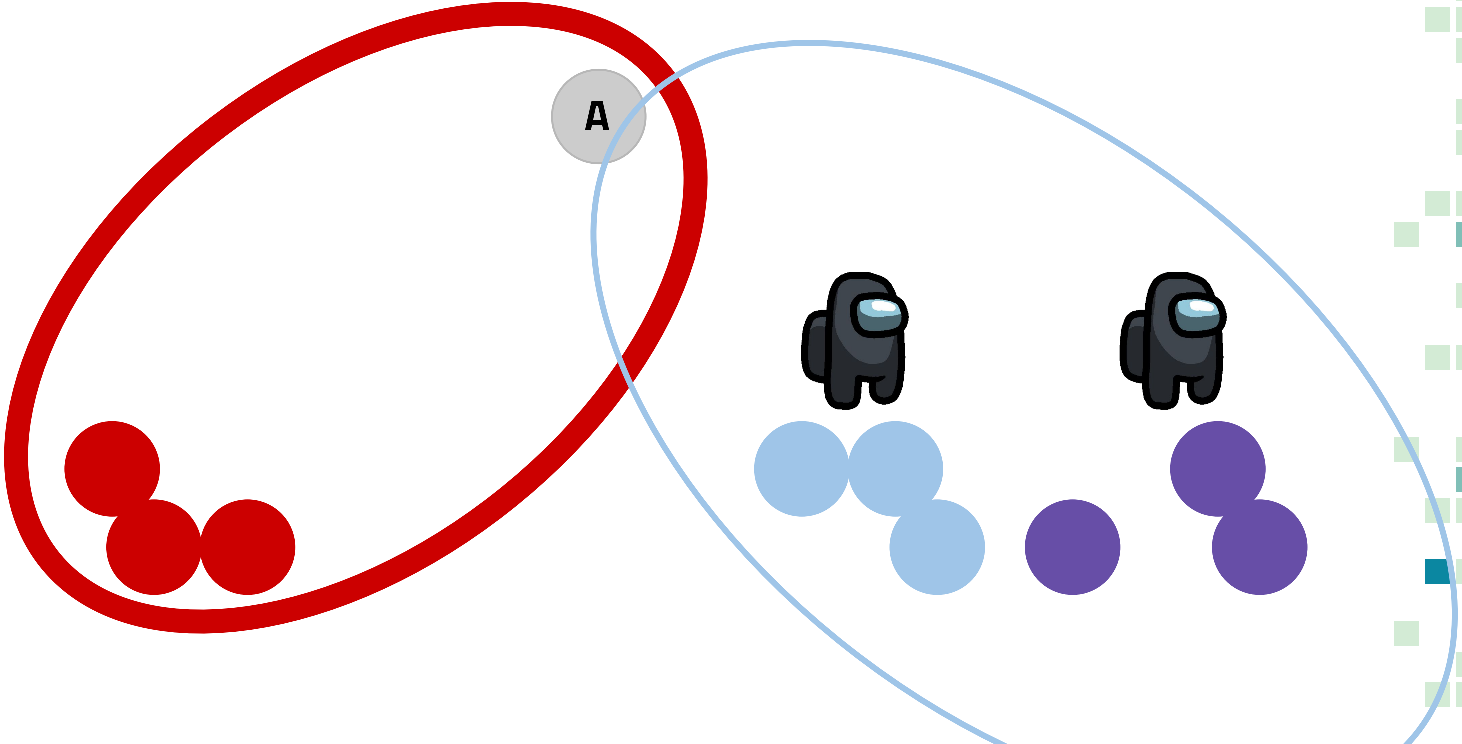

7. Cross-validation: estimating the distribution of prepredictions