# Detecting linguistic variation with geographic sampling

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Presentation is available here: tinyurl.com/y7kjsp67

# Outline of the talk

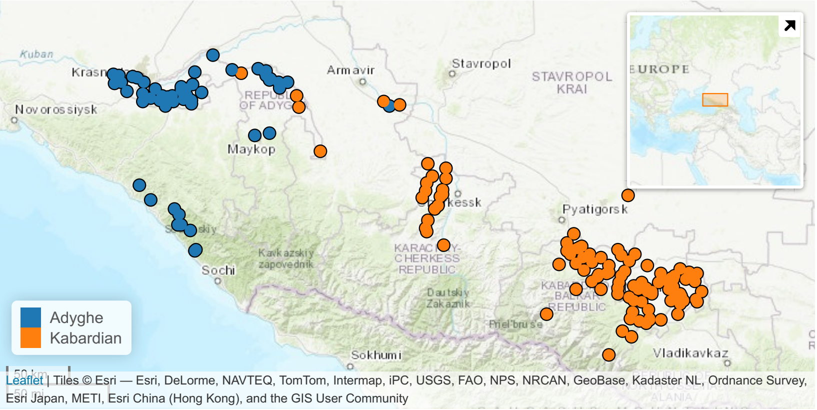
# Introduction

- Geolectal variation is often present in settings where one language is spoken across a vast geographic area [Labov 1963].
- It can be found in phonological, morphosyntactic, and lexical features.
- It could be overlooked by linguists [Dorian 2010].

# Outline of the talk

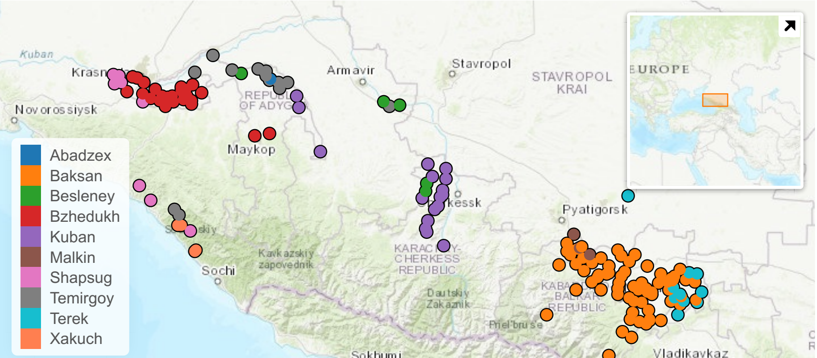
# The problem

- Let us consider a geographical dialect continuum formed by a group of small villages [Chambers and Trudgill 2004: 5–7]
- We are interested in spotting variation of a discrete parameter among the lects spoken on these villages



# The problem

- We will very unlikely be able to conduct fieldwork in each single village. Therefore, we need to choose a *sample* of locations.
- *Research Question*: How to choose the sample of villages to survey?
    1. How many villages is enough for detecting all variation present? (number of categories)
    2. Given an amount of sampled villages, how to decide which ones are representative of our population?



# Outline of the talk

# Our approach

- We want to find the amount of variation present for one feature, and we try different ways of choosing the sampled villages for finding it
- As we assume we do not have any data beyond the geographic location of each village, we use these locations for building our sample
- We generate clusters with different algorithms (k-means, hierarchical clustering) and pick our sampled locations based on them (package stats, [R Core Team 2020]).
- We compare our results against random geographic sampling for multiple categorical data, in two different scenarios:
    - Simulated data
    - Dialects of Circassian languages

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Results and modelling

Circassian data example

Entropy

Conclusions

# Simulated data

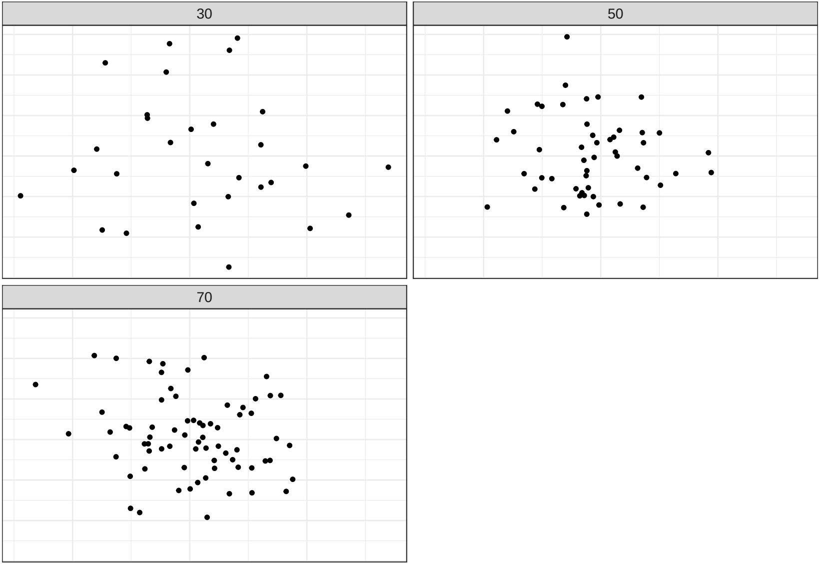
**Data** * total number of locations ($N$): $30, 50, 70$ * number of categories ($n$): $3, 4, 5$ * type of spatial configuration: * uniform: variation is uniformly distributed across space * equadistant: $n$ groups with unique values, partially overlaping * central-periphery: one main group in the center, and the rest around it * count configuration ($c$): how the $n$ categories are distributed across the $N$ locations (e.g., for $N$=30, $n$=3, the count configuration could be $c$=10-10-10, $c$=20-8-2, etc.)

**Sampling** * clustering method: hierarchical clustering, k-means, random sampling * proportion of villages sampled: $p = 0.05, 0.10, \ldots, 0.95$

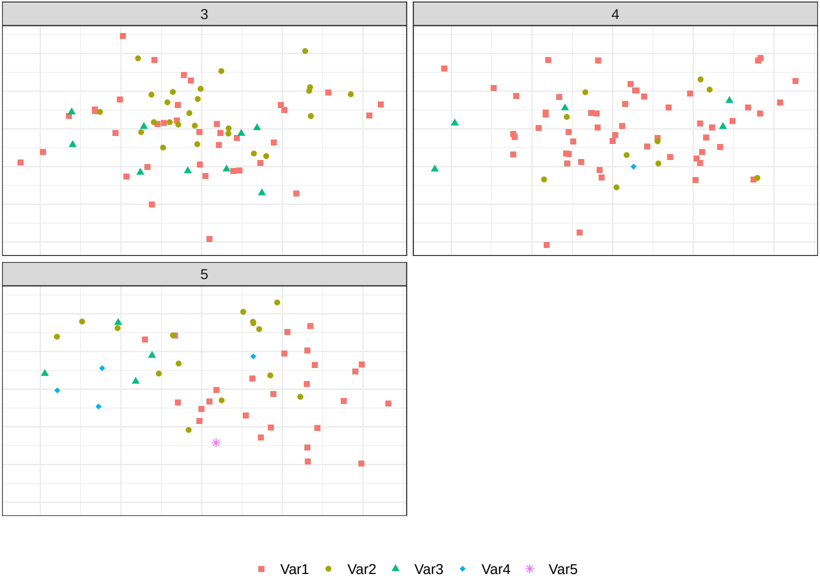
From those values we could derive the number of sampled locations, or number of clusters ($k$):

$$n = p \times N$$

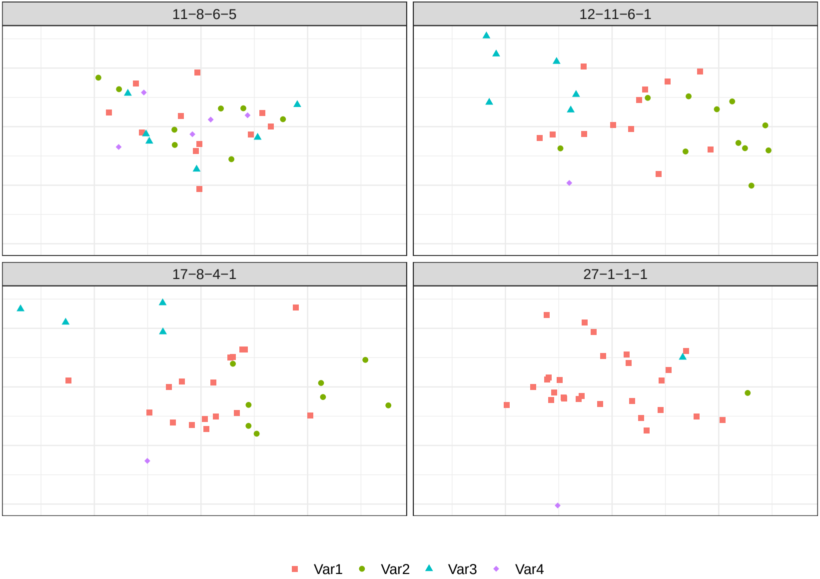
# Example of different number of locations ($N$)



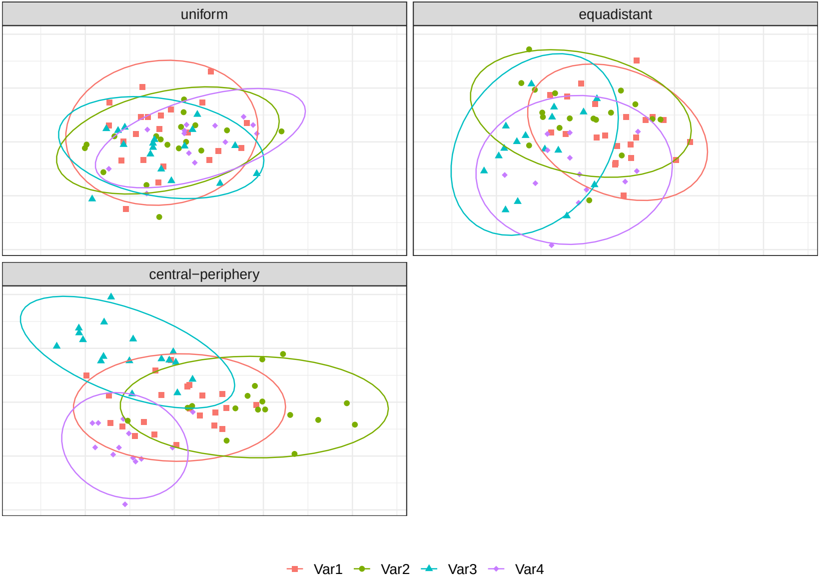
# Example of different number of categories



# Example of different count configurations



# Example of different types of spatial configurations



# Outline of the talk

**Plots of fitting with different parameters (raw proportions, no modelling)**

# Modelling the variation

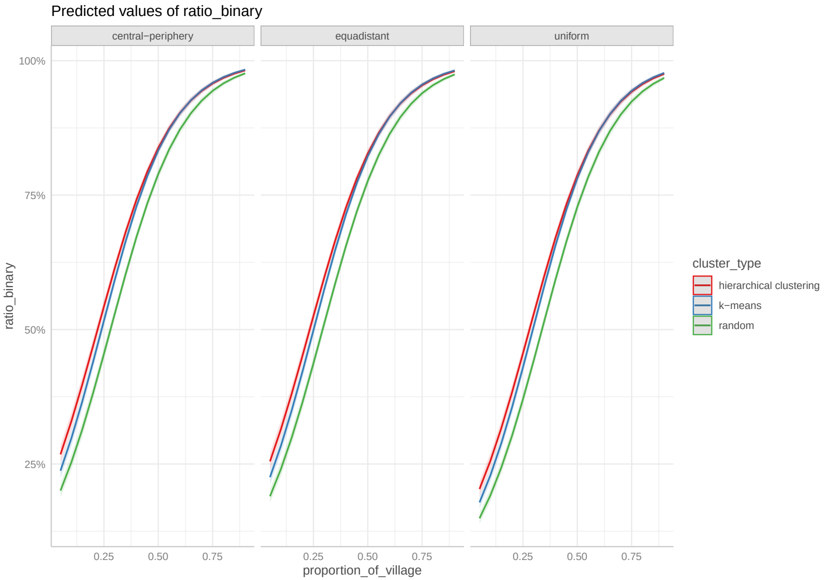
- From the previous slides, we can see that our sampling methods outperform random sampling
- We want to account quantitatively how this improvement depends on different parameters present
- We run a logistic regression with outcomes
  - All varaition discovered / Not all variation discovered
- and parameters:
  - Proportion of villages sampled $p$ (numeric: $0.05. \dots, 0.95$)
  - Type of clustering (hirarchical, K-means, random)
  - **Amount of categories $n$ (numeric: 3,4,5)**
  - Type of geographic distribution (central-periphery, equidistant, uniform)
  - **Amount of total villages $N$ (numeric: 30, 50, 70)**
  - **Entropy $H$ (numeric)**

outcome ~ logistic[
(spatial_configuration+cluster_type)*proportion_villages ]

# Results

| term | estimate | std.error | statistic | p.value |
|---|---|---|---|---|
| (Intercept) | -2.04 | 0.05 | -42.96 | 0.00 |
| typeequadistant | 0.30 | 0.05 | 5.74 | 0.00 |
| typecentral-periphery | 0.36 | 0.05 | 7.04 | 0.00 |
| cluster_typek-means | 0.21 | 0.05 | 4.04 | 0.00 |
| cluster_typehierarchical clustering | 0.38 | 0.05 | 7.51 | 0.00 |
| proportion_of_village | 6.06 | 0.11 | 54.26 | 0.00 |
| typeequadistant:proportion_of_village | -0.07 | 0.13 | -0.55 | 0.59 |
| typecentral-periphery:proportion_of_village | -0.05 | 0.13 | -0.40 | 0.69 |
| cluster_typek-means:proportion_of_village | 0.16 | 0.13 | 1.26 | 0.21 |
| cluster_typehierarchical clustering:proportion_of_village | -0.12 | 0.12 | -0.97 | 0.33 |

# Results



Predicted values of ratio_binary
central−periphery
equadistant
uniform
100%
75%
50%
25%
ratio_binary
0.25
0.50
0.75
proportion_of_village
cluster_type
hierarchical clustering
k−means
random

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# Information entropy

In order to measure how the count configuration $c$ affects our sampling method, we used the information entropy, introduced in [Shannon 1948]:

$$H(X) = -\sum_{i=1}^{n} P(x_i) \times \log_2 P(x_i)$$

# Information entropy

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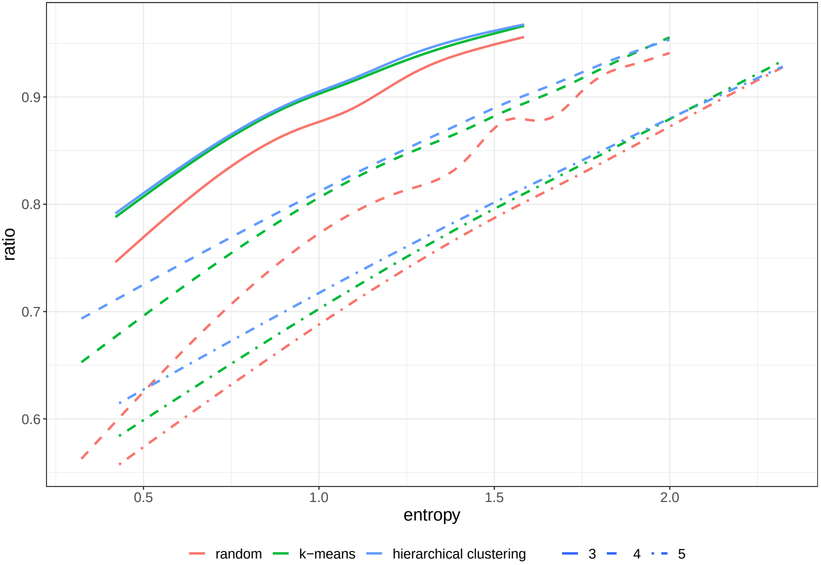
$$H(X) = -\sum_{i=1}^{n} P(x_i) \times \log_2 P(x_i)$$

The range of the information entropy is $H(X) \in [0, +\infty]$:

| data | entropy |
|---|---:|
| A-A-A-A-A | 0.00 |
| A-A-A-A-B | 0.72 |
| A-A-A-B-B | 0.97 |
| A-A-B-B-B | 0.97 |
| A-A-B-B-C | 1.52 |
| A-B-C-A-B | 1.52 |
| A-B-C-D-E | 2.32 |

# Information entropy: simulated data



# Information entropy: simulated data

- We can see that our sampling method performs considerably better than random for lower values of entropy, as expected.

# Outline of the talk

# Conclusions

# References


Chambers, J. K. and Trudgill, P. (2004). *Dialectology, 2nd edition*. Cambridge University Press.

Dorian, N. C. (2010). *Investigating variation: The effects of social organization and social setting*. Oxford University Press.

Labov, W. (1963). The social motivation of a sound change. *Word*, 19(3):273–309.

R Core Team (2020). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria.

Shannon, C. E. (1948). A mathematical theory of communication. *Bell system technical journal*, 27(3):379–423.