Naming networks and population structure

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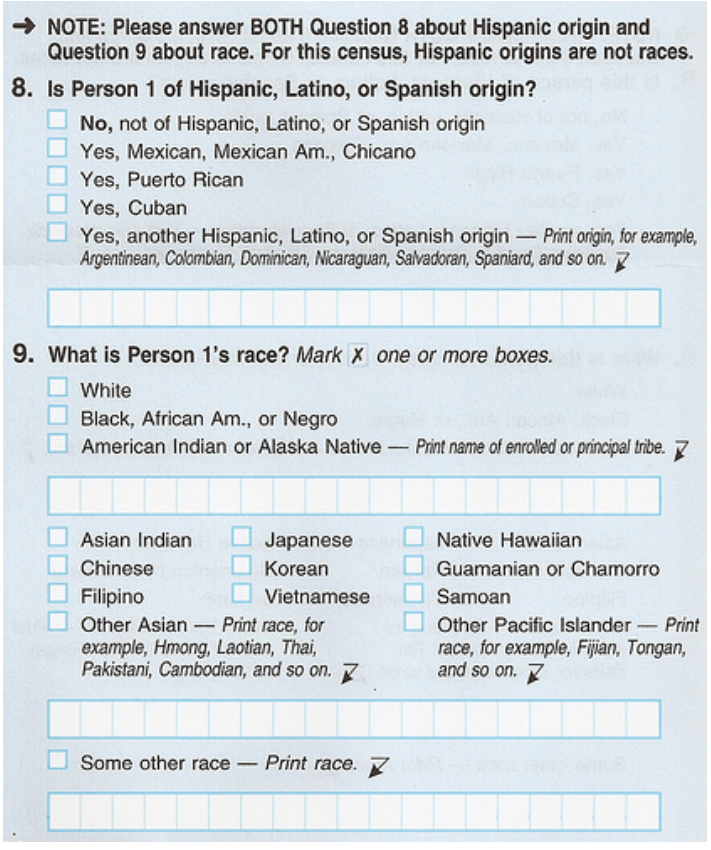
Limits to more conventional 'identity' data

- Ethnicity (or culture or identity) is a tricky and multi-dimensional concept
- Standards for how to collect data don't match
- Conventional instruments don't capture it well
  - Census 'tick boxes'
  - Census 'write-ins'



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8. Is Person 1 of Hispanic, Latino, or Spanish origin?

- ☐ **No,** not of Hispanic, Latino, or Spanish origin
- ☐ Yes, Mexican, Mexican Am., Chicano
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9. What is Person 1's race? *Mark ✗ one or more boxes.*

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- ☐ Black, African Am., or Negro
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- ☐ Other Asian — *Print race, for example, Hmong, Laotian, Thai, Pakistani, Cambodian, and so on.*
- ☐ Native Hawaiian
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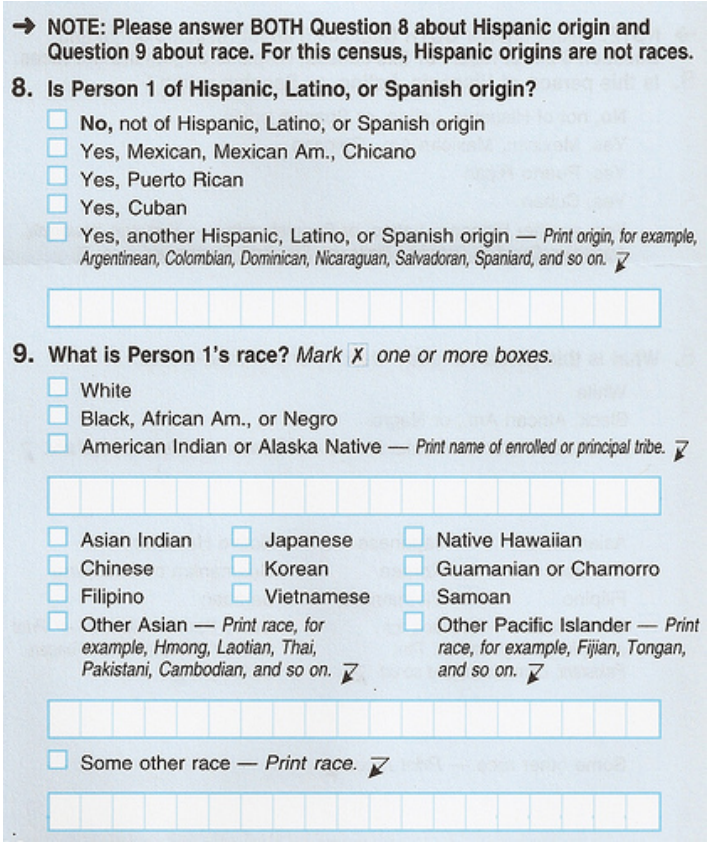

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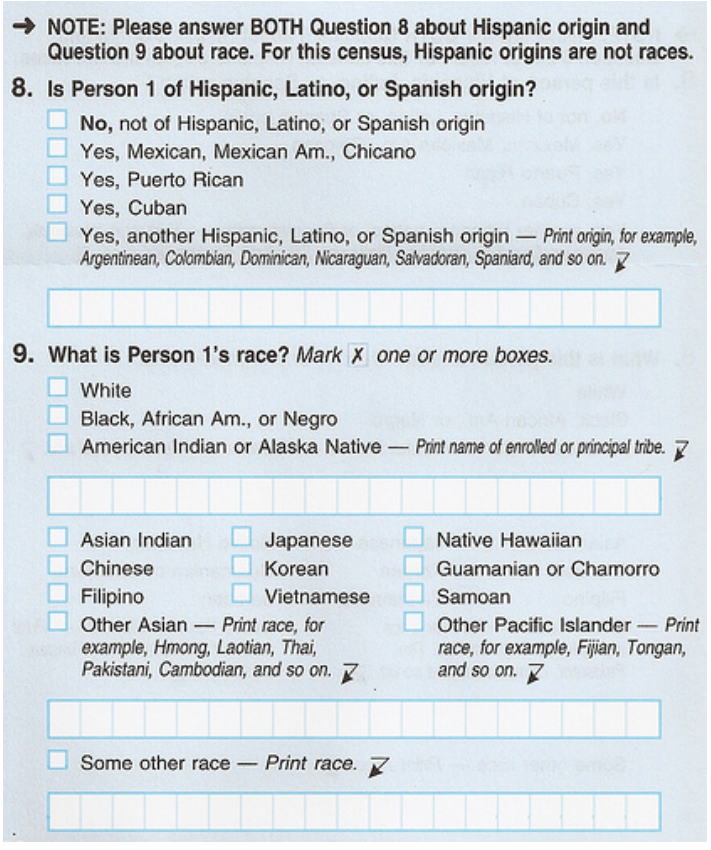

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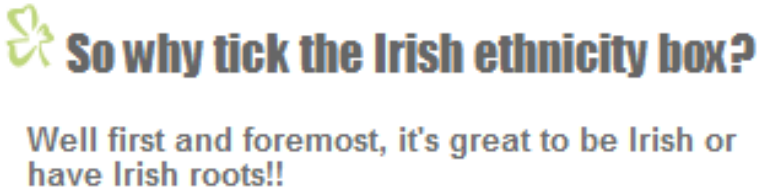

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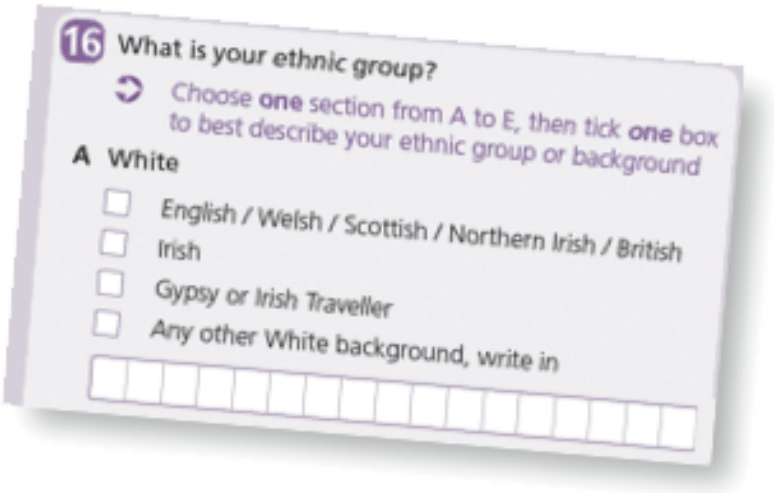

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Email urges 'New Zealander' for Census

By Julie Middleton

A fast-spreading email appeal is urging people to state their ethnicity as "New Zealander" in next Tuesday's Census.

Census
- Make your vote count this year, Koreans urged
- One in three working more than 50 hours a week - Census

The email, which came to the Herald from several sources, reads: "Maybe we can get the powers-that-be to sit up and recognise that we are proud of who we are and that we want to be recognised as such, not divided into sub-categories and all treated as foreigners in our own country.

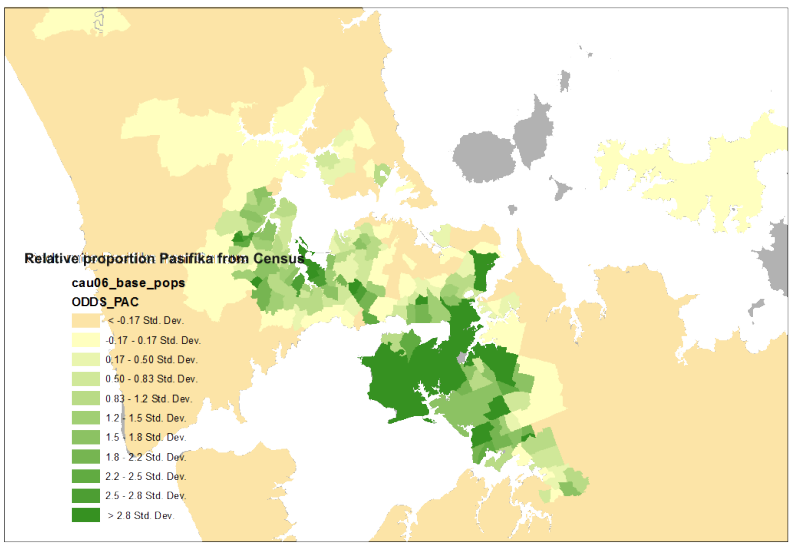
Names as markers of identity

- Minimally invasive
- Readily available
- Carry complex (perhaps limited) information

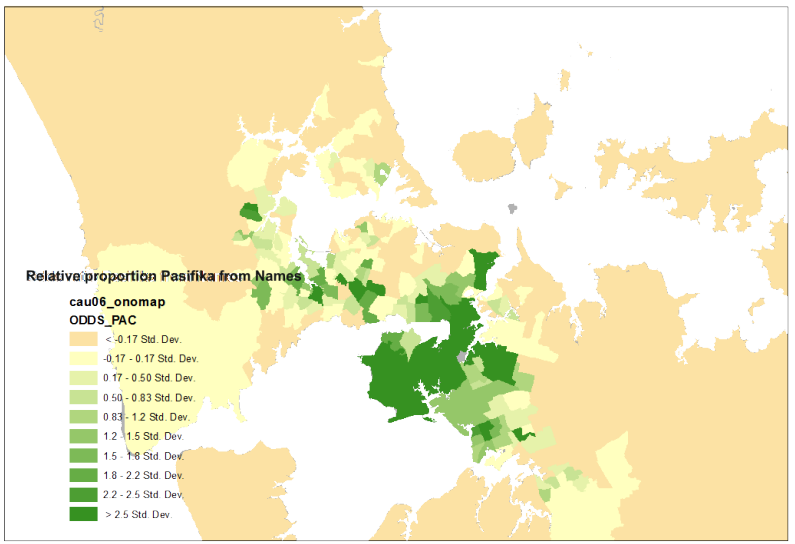
Previous work

- Mateos, P. (2007) A review of name-based ethnicity classification methods and their potential in population studies, *Population Space and Place*, 13(4): 243–63.
- Mateos, P., Webber, R., and Longley, PA. (2007) *The Cultural, Ethnic and Linguistic Classification of Populations and Neighbourhoods using Personal Names*. CASA Working Paper 116, University College London.
- Mateos, P. (2007) *An Ontology of Ethnicity Based upon Personal Names: With Implications for Neighbourhood Profiling*. PhD Thesis, University College London

Example names maps from New Zealand



Pacific people south Auckland (census)



Pacific names

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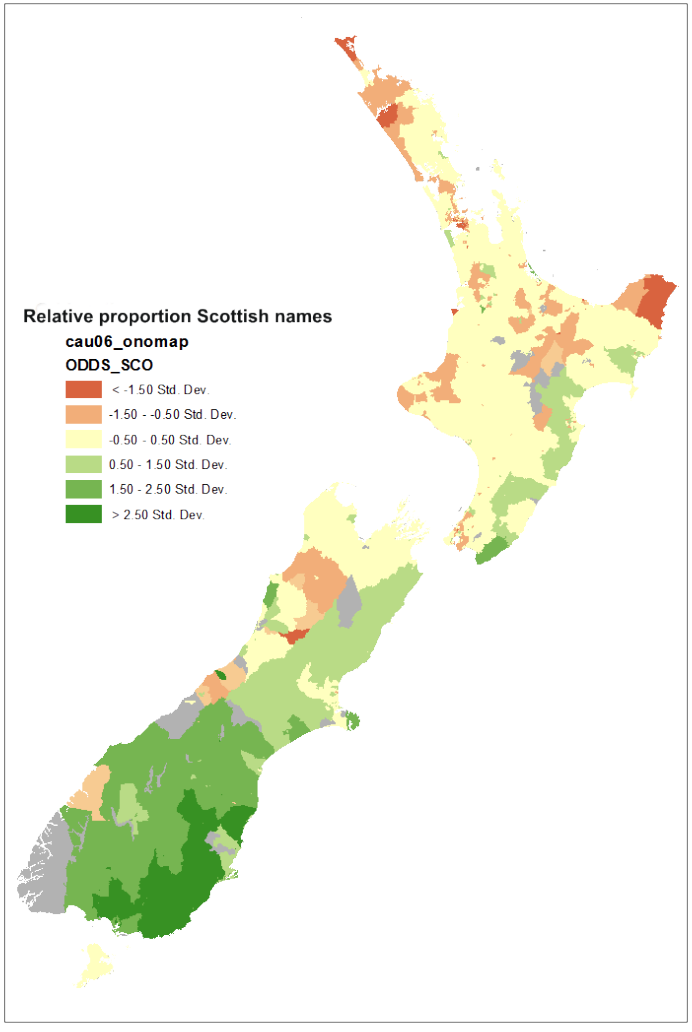

Scottish names countrywide

- No 'Scottish' New Zealand category in the census
- Counts derived from Electoral Roll
- Map reflects the disproportionately Scottish origins of early European migration to the South Island (as well as more recent non-European immigration in the North Island)

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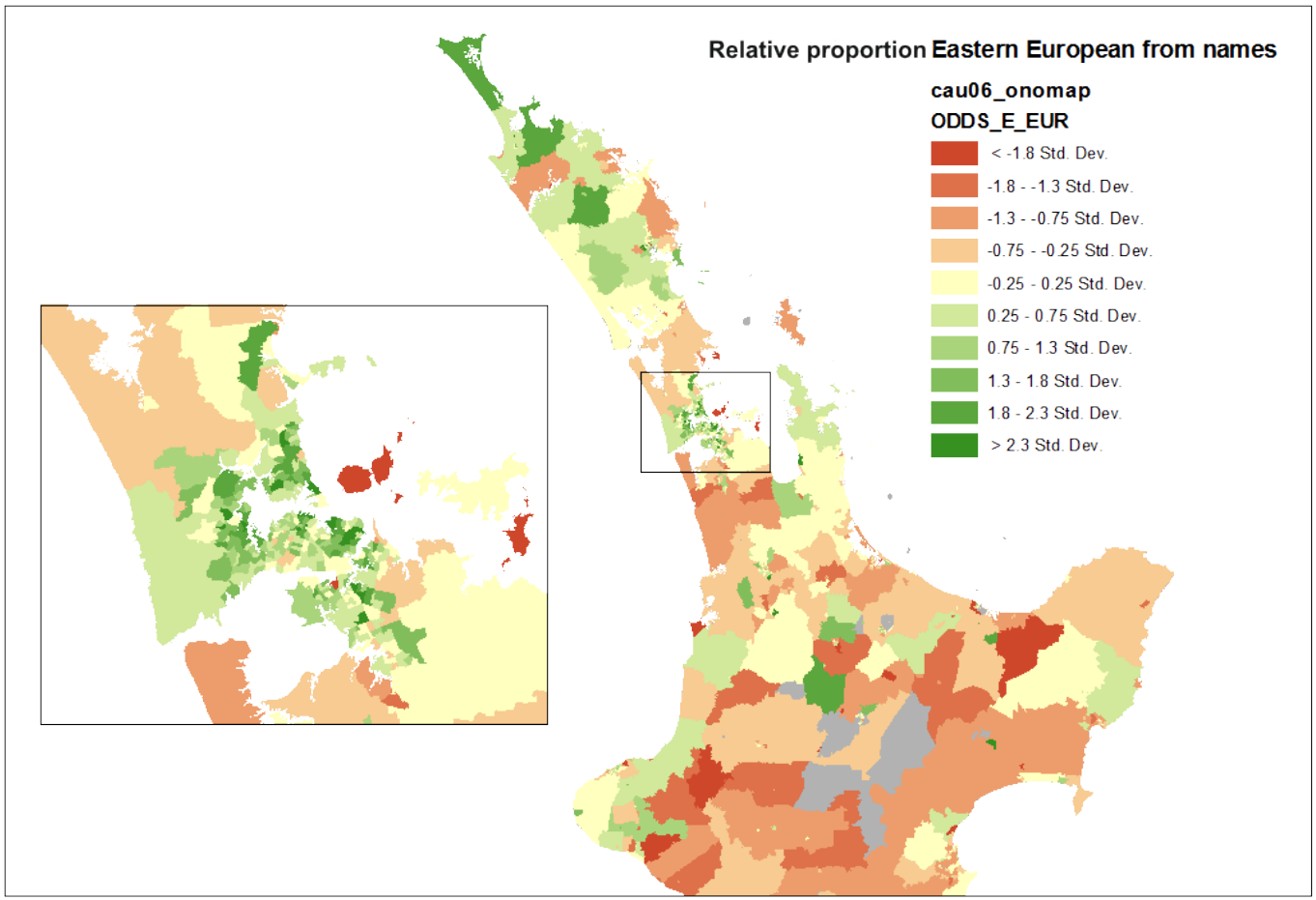
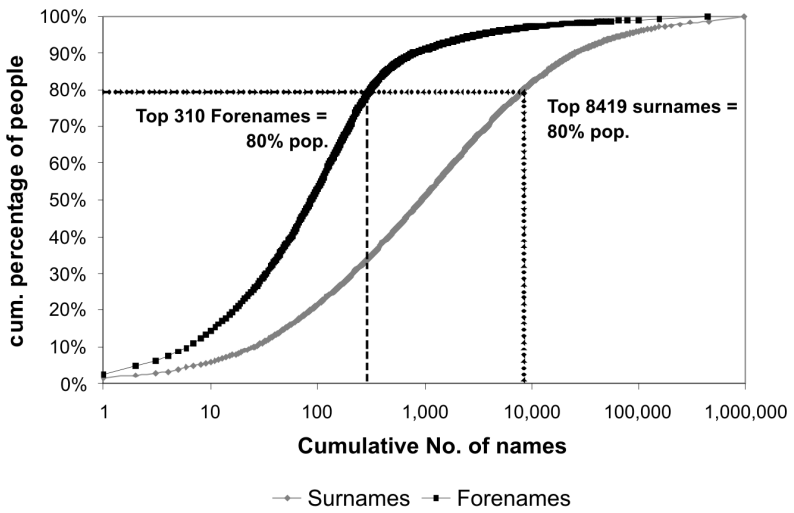


Eastern European names, west Auckland

Difficulties with names as data

- *Very* unevenly distributed



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- Prone to misspellings, with no easy fixes, e.g.,
  - Is MICHEAL a real name?
  - Should ABBAGAIL - ABBEGAIL - ABBIGAIL - ABBYGAIL be 'corrected'?
- Interpretation labour-intensive, dependent on expert knowledge

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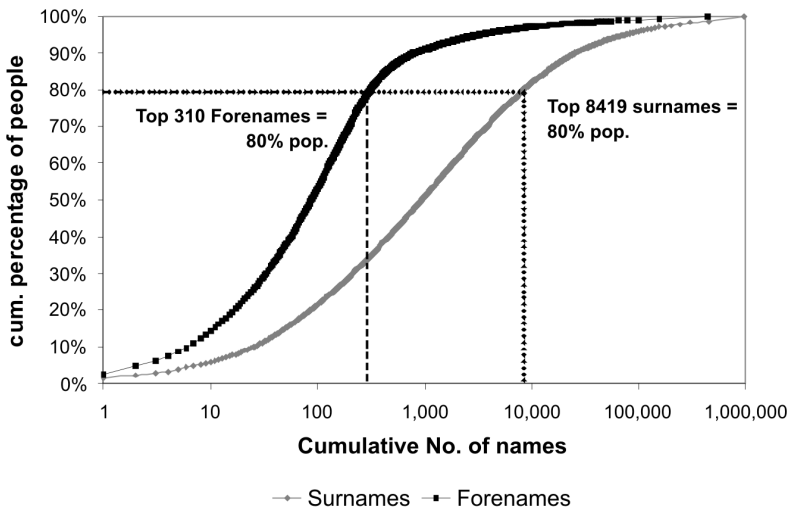

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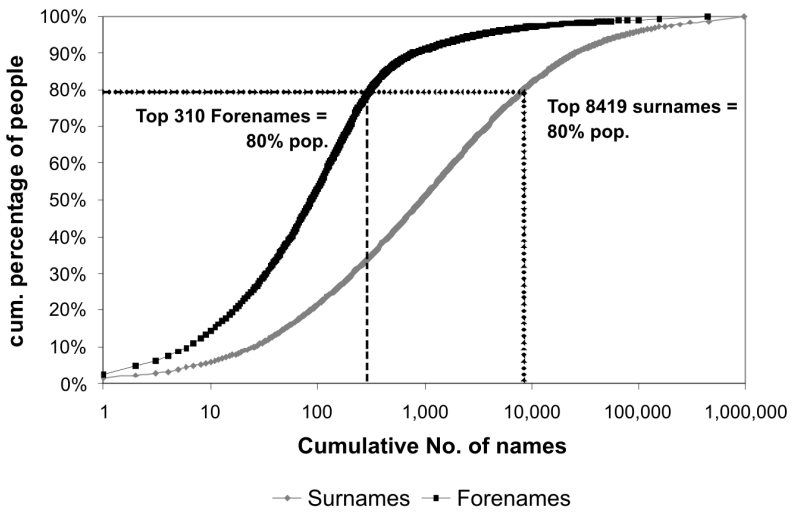

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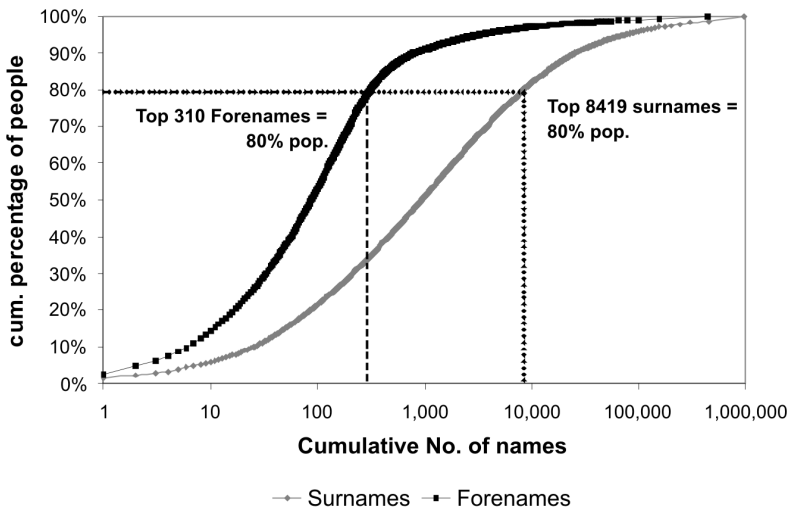

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What about when we meet a name we don't know?

The New Zealand case presented some specific challenges

- A major problem dealing with names unknown from previous experience, esp. Māori, Pacific names
- Limited expert knowledge
- Is there a way to infer 'new' groups from the relationships between names?
- $\Rightarrow$ concept of a network of names

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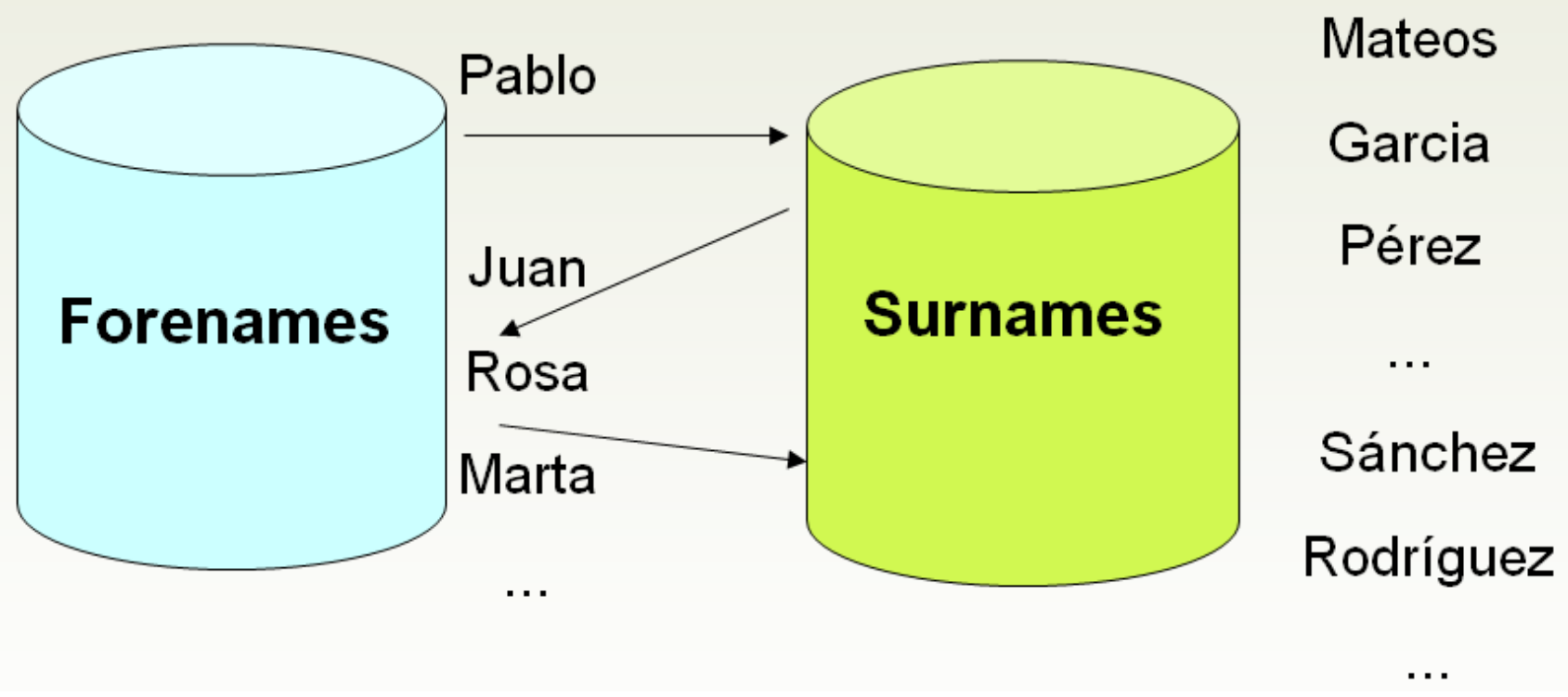

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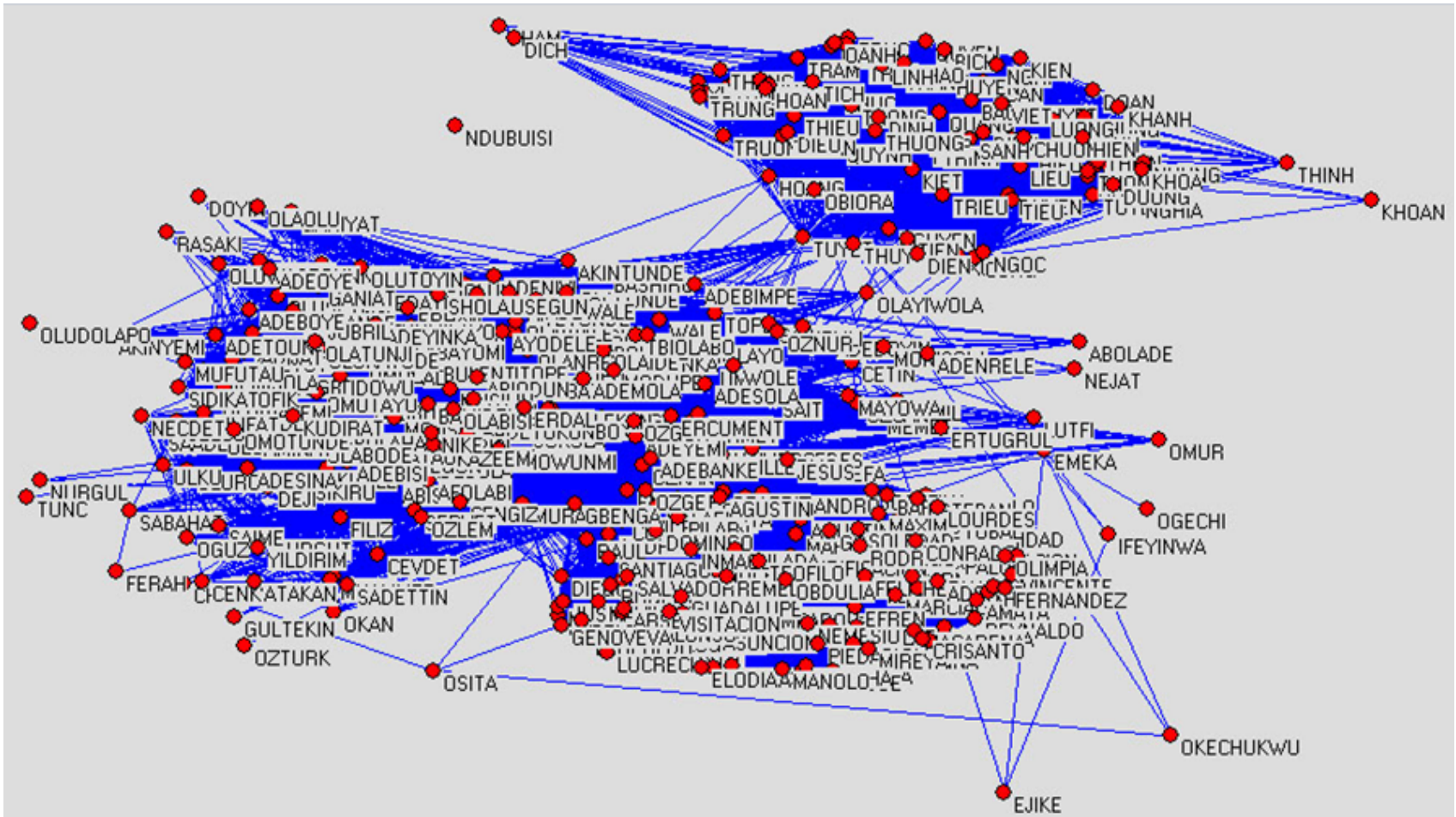
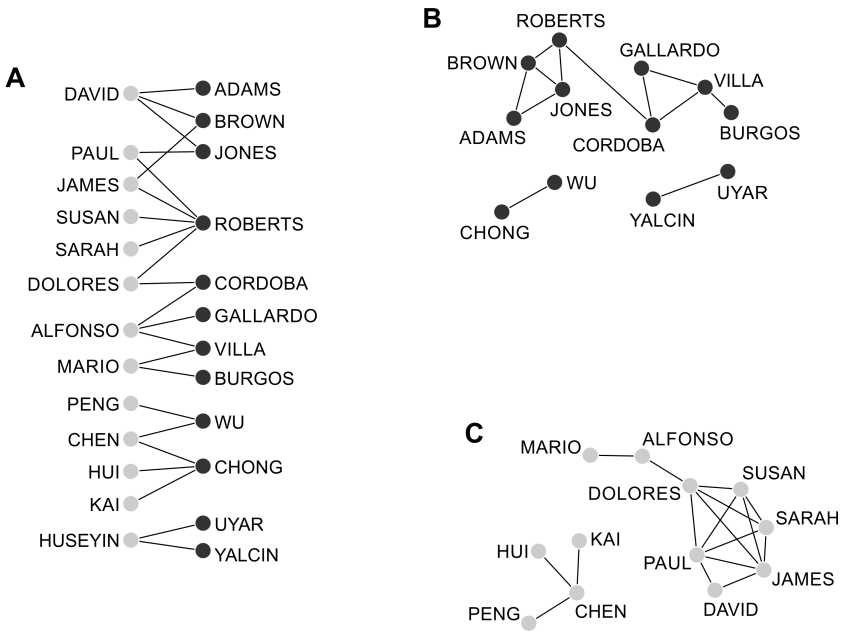


From two-mode to one-mode networks

We can replace all that database querying back and forth with some simple matrix arithmetic



Graph adjacency matrix maths

Form a forename-surname coincidence matrix, $\mathbf{A} = [w_{fs}]$, where w_{fs} is the weight of association between forename f and surname s

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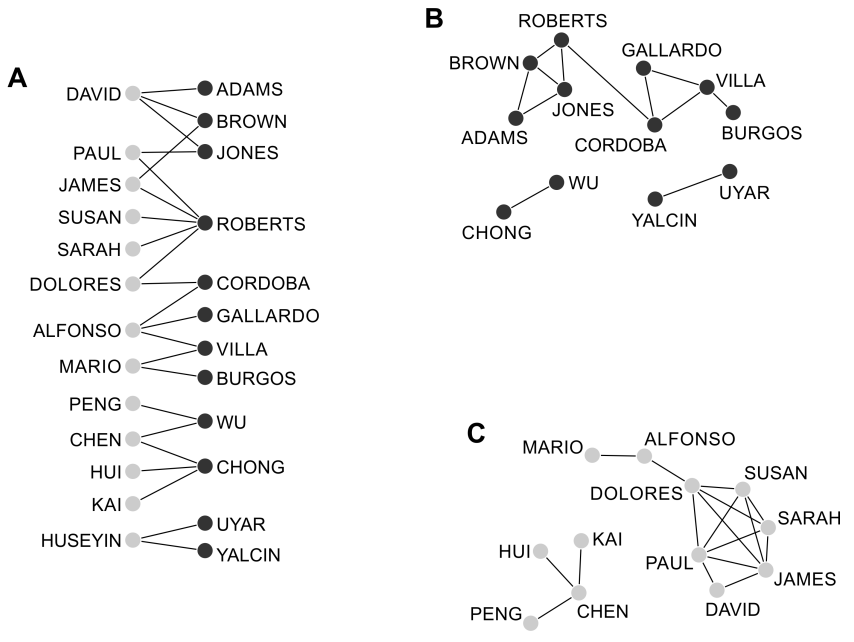

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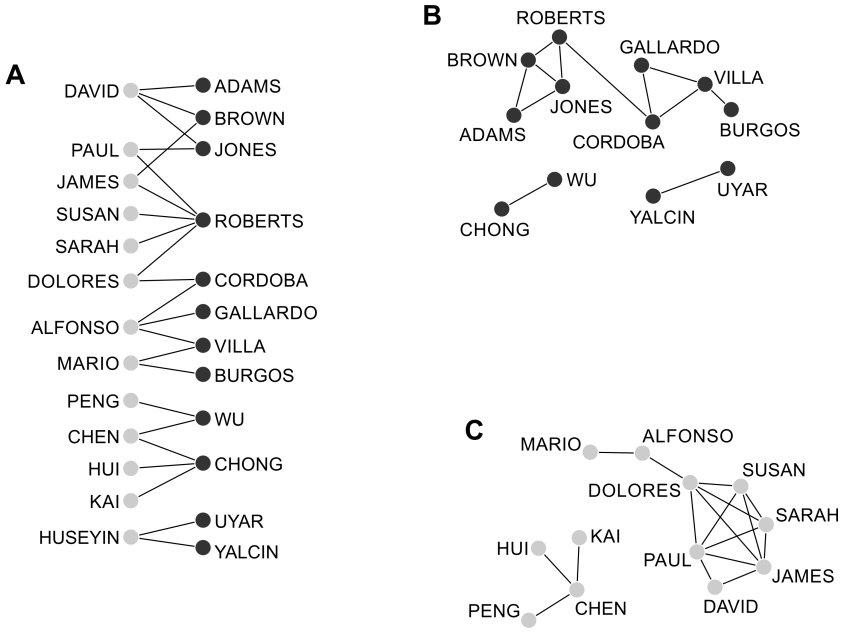

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Salience matters more than frequency

A key issue is how to determine the w_{fs} weights

- Common names form the majority of forename↔surname links
- But interesting forename-links are those that are common with respect to a surname relative to overall prevalence
- After some experimentation, we arrived at

$$w_{fs} \propto \frac{n_{fs}}{\sqrt{n_f \left(n_f - 1\right)}}$$

where n_{fs} is the number of times a particular forename-surname combination occurs, and n_f is the total number of occurrences (across all surnames) of that forename

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Tools of the trade

Recent developments in free software and tools for handling large networks have enormously benefitted this research:

- Python libraries scientific computing, `numpy` and `scipy`
- Python libraries for network analysis, `igraph` particularly network 'community detection'
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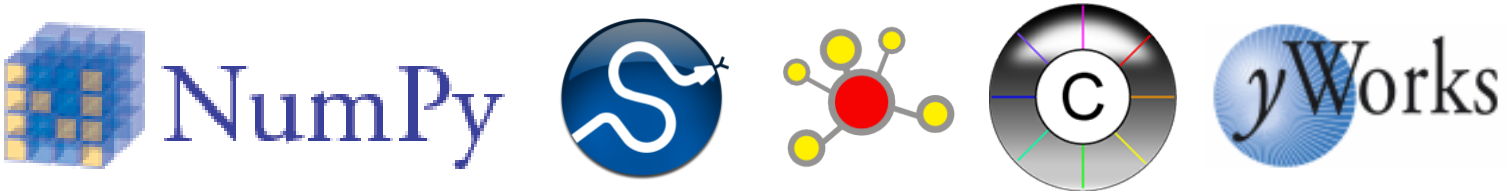


Datasets

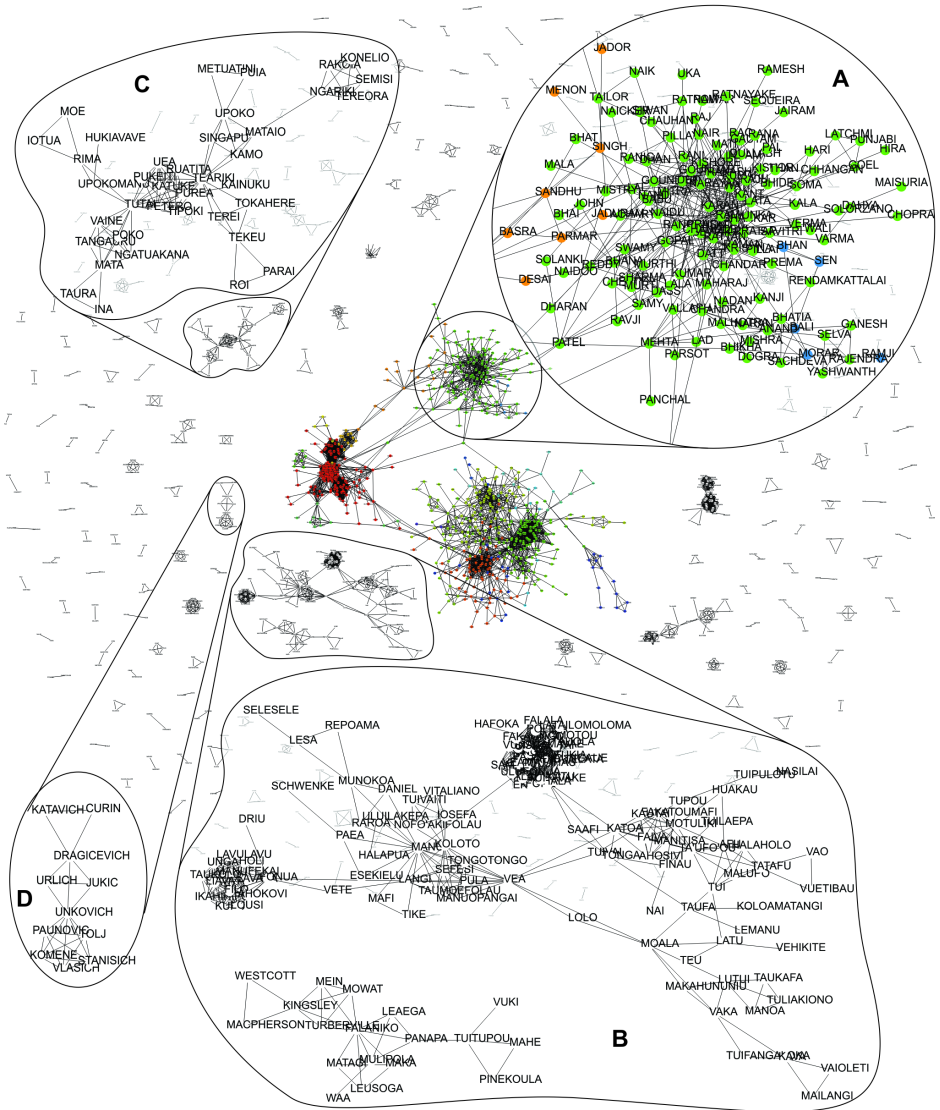
Auckland, New Zealand

- 912,858 registered voters from 2008 Electoral Roll
- 79,855 unique surnames
- 88,760 unique forenames
- 711,807 unique f-s pairs
- Small yet ethnically, culturally diverse
- Many names somewhat unique to New Zealand
- A good testbed for methods

'Diagnostic' synthetic dataset

- 30,479 surnames tagged as one of 40 cultural, ethnic and linguistic (CEL) groups
- tagged names used to retrieve a subset of names from a 300 million person database
- 118.3 million persons from 17 countries
- 4.6 million unique surnames
- 1.8 million unique forenames
- 46.3 million unique f-s pairs

The Auckland names network



A filtered version of the Auckland network:

- A - Subcontinent names in 3 or 4 clusters
- B - Samoan / Tongan / Pacific names
- C - Māori names
- D - Eastern European names

Encouraging that previously untagged names are grouped separately from those already tagged. Note that colours are clusters determined by a community detection

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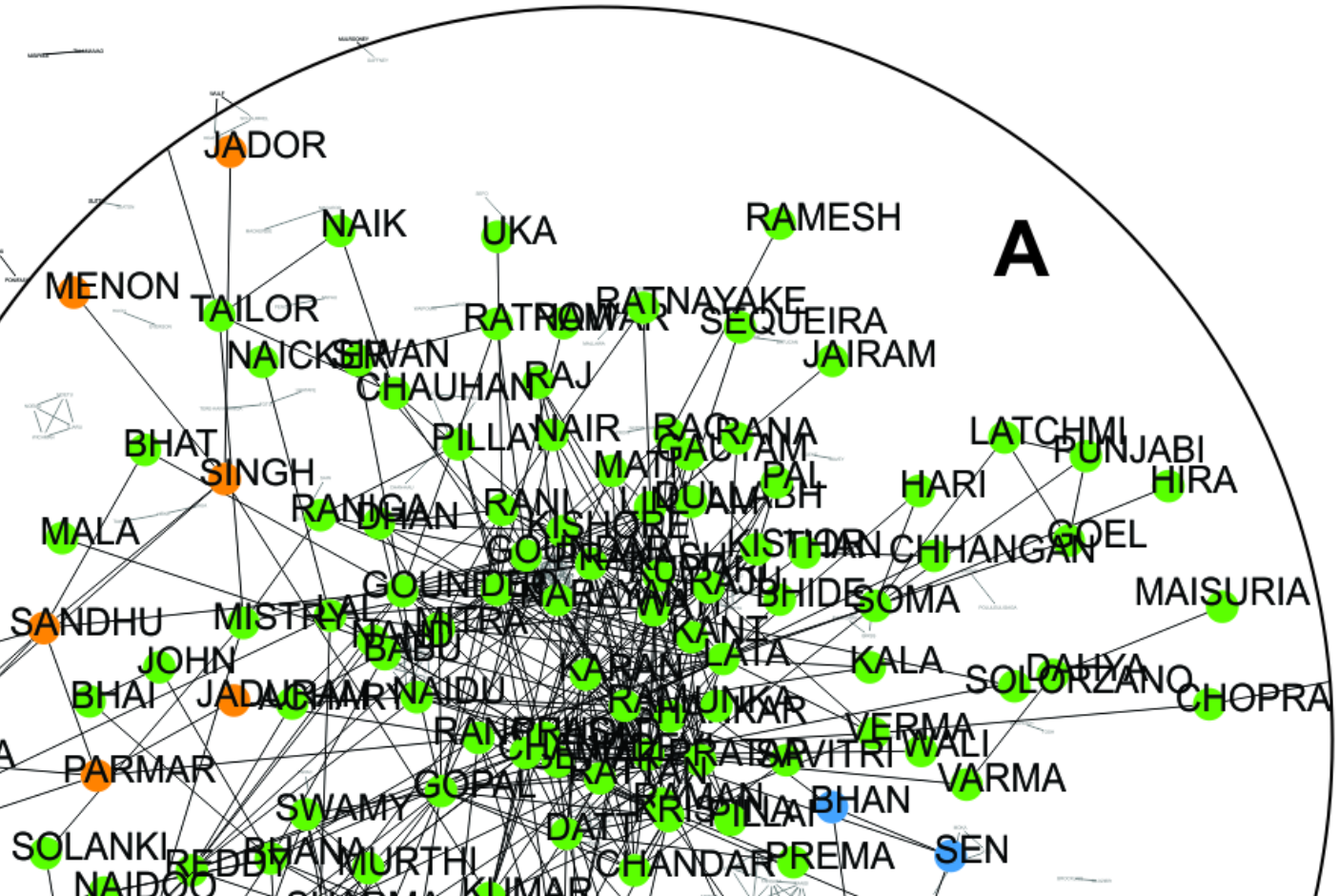

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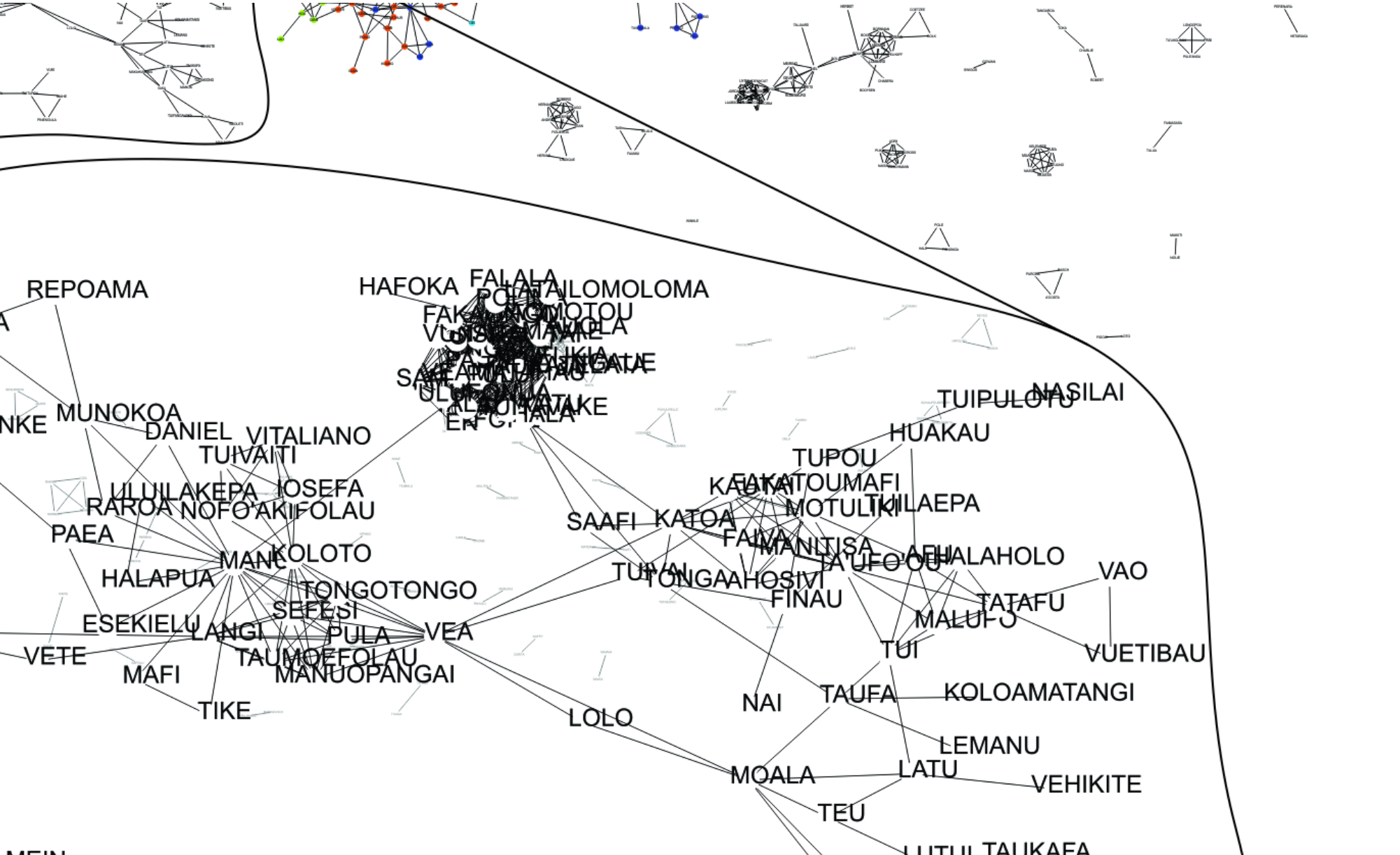

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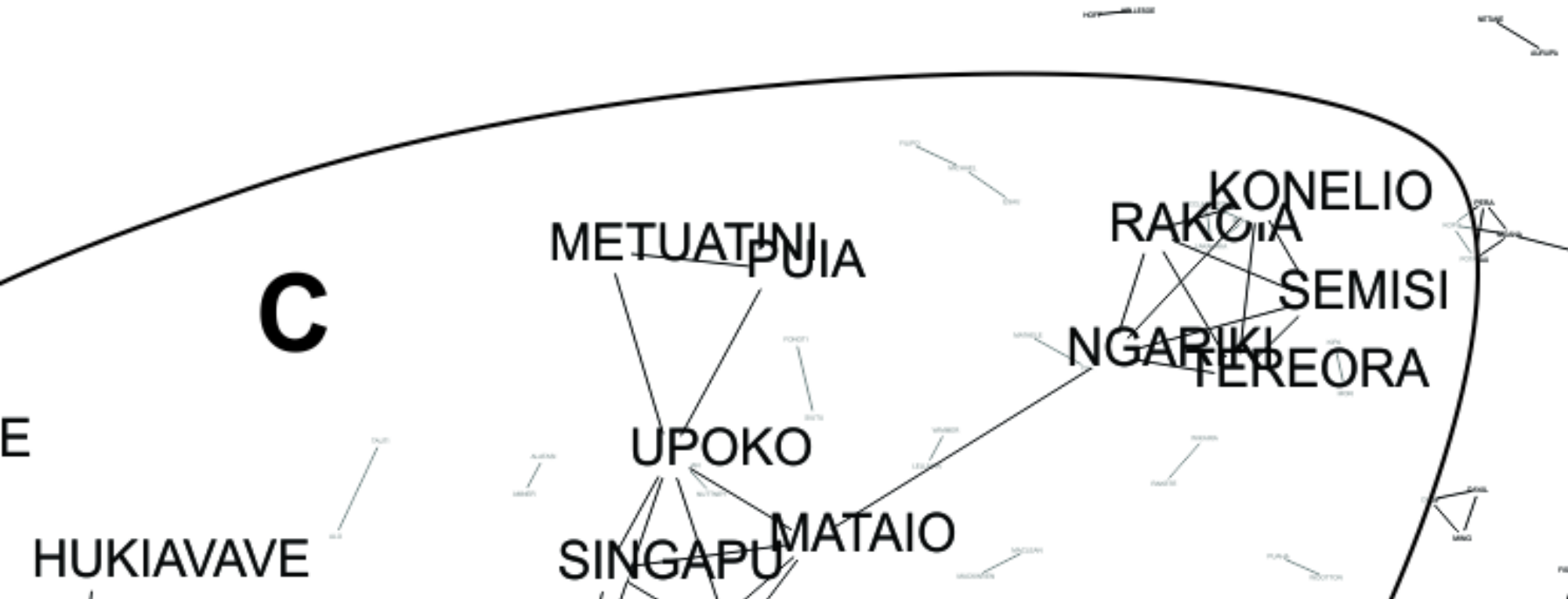

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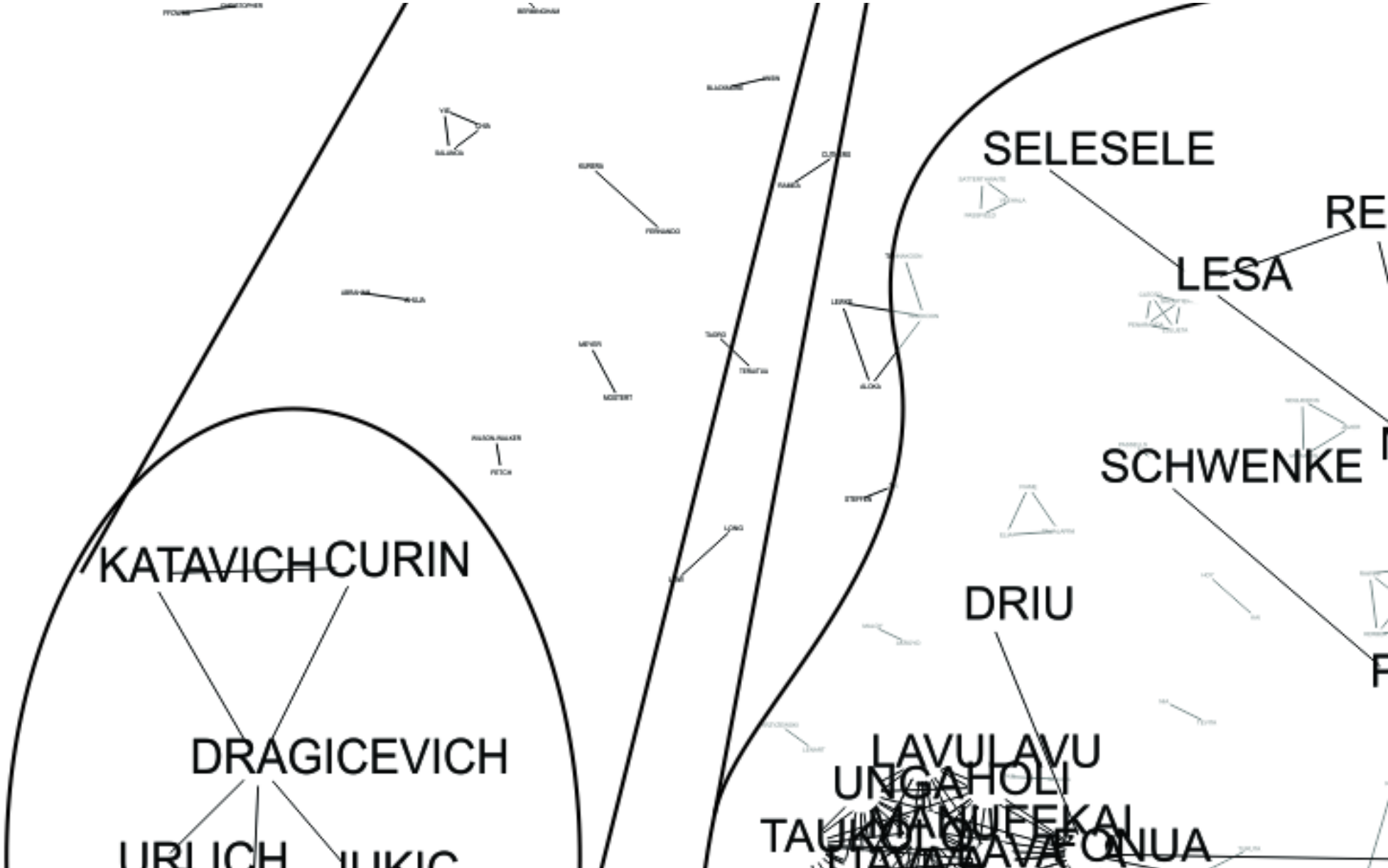
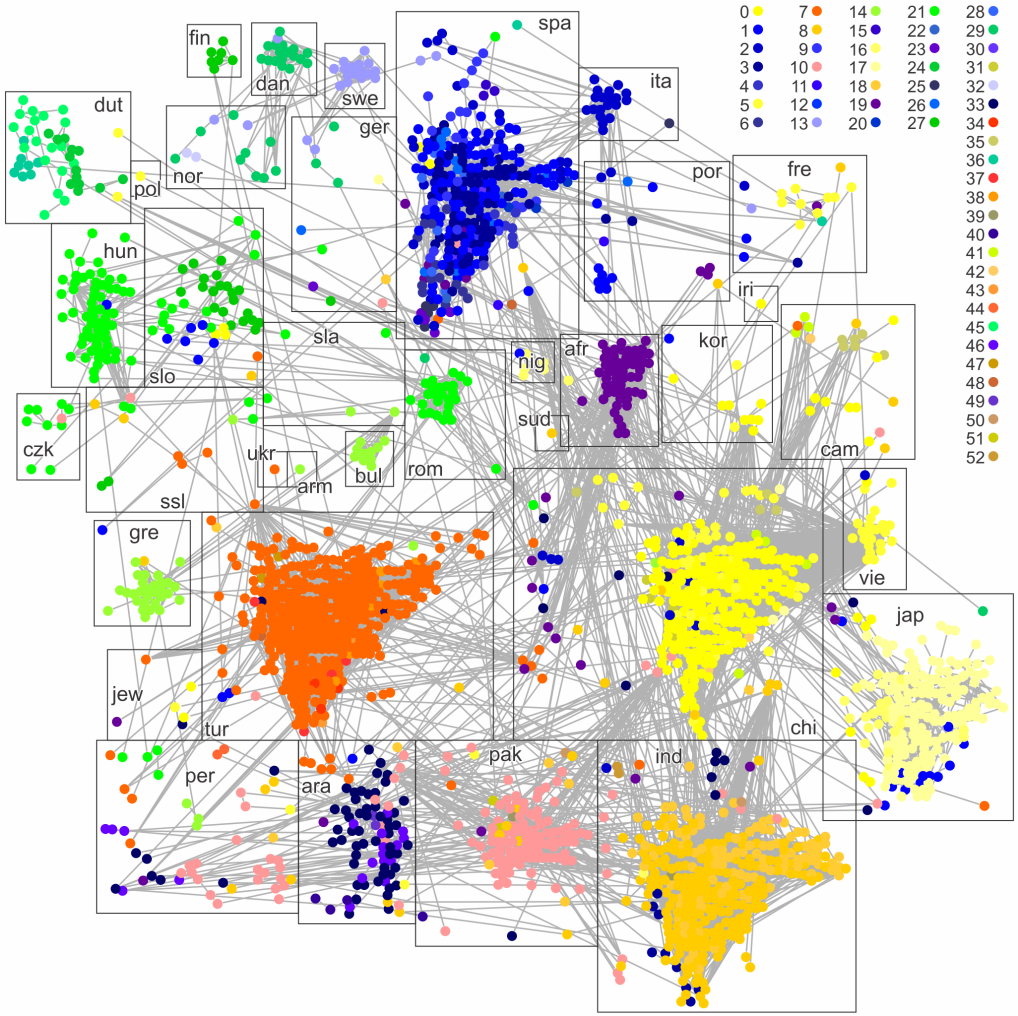


‘Diagnostic names’ network



- Colours reflect assignment to different ‘communities’ by the community detection algorithm
- Assigned groupings are expert-determined CEL associations

Further work

Much remains to be done. . .

- Investigate methods for automatically cleaning up the names themselves (not particularly hopeful)
- Develop an automated way to determine best combinations of parameters for networks that partition cleanly
- Examine the degree to which (if at all) apparent structure in some groups reflects real intra-group divisions and relationships
- Consider possibilities offered by co-clustering methods
- Explore how 'label propagation' methods from graph theory might enable automated inference of CEL associations for unknown names

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Conclusions

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- Perhaps enable a more nuanced view of CEL affiliation than pre-defined 'tick-box' affiliations
- How naming networks have changed (or not) over time may prove a particularly interesting direction to look

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