Computational Overview of Finnish Hydronyms

Antti Leino leino@cs.helsinki.fi Helsinki Institute for Information Technology Research Institute for the Languages of Finland

Abstract

The spatial distribution of a wide range of linguistic phenomena has traditionally been visualised in the form of maps. Distribution maps are very useful when dealing with only a few different phenomena at a atime, but they soon become rather unwieldy as the number of different distributions increases. This is related to what is known in the field of data analysis as the "curse of dimensionality": in general, a lot of traditional methods tend to become unusable when dealing simultaneously with a massive number of different variables.

There are ways to cope with the problems that arise from massive dimensionality. This article shows how some of these methods, most notably principal component analysis, can be applied to onomastic data. Starting with raw data that consists of all hydronyms that appear on Finnish basic maps, the goal is to find a few of the most important trends that lie behind the distributions of individual names. Some of the results are rather predictable in view of present knowledge about Finnish dialects and settlement history; others are less so.

1 Introduction

The National Land Survey of Finland has, for its own purposes of producing maps, a Geographic Names Register. A part of this register is the Place Name Register, which contains all names that appear on the 1:20 000 Basic Map (Leskinen 2002). The study leading to this presentation concentrates on common hydronyms, *common* in this case meaning those names that appear on at least ten or five municipalties. The number of names that fulfill this criterion is shown in table 1.

	Total	In data set	Municipalities
Lakes	25 178	1 492	≥ 10
Parts of lakes	17 469	939	≥ 10
Rivers	14 650	797	≥ 10
Rapids	3 460	84	≥ 5
Other parts of rivers	5 372	67	≥ 5

Table 1: Finnish National Land Survey Place Name Register

The purpose of this study was to distill an overview from this corpus of data. This problem resembles in some respects the field of dialectometry (eg. Goebl 1982; Nerbonne 2003; Nerbonne and Heeringa 2001), although there are differences between an onomastic study — like the present one — and one dealing with dialectal variation. When dialectometric researchers have studied broad, national-scale trends they have often concentrated on developing and using more and more sophisticated methods for computing the distances between dialects, based on the variation of several linguistic features.

The geographical distribution of linguistic features in dialectology — and by extension, dialectometry — is not discrete, but rather the distributions of different variants overlap. Toponyms, on the other hand, are a discrete set: for the purposes of this study it is reasonable to claim that the places and their names are known. This is a rather major difference between traditional dialectometry and the type of onomastic study presented here.

2 Methods

2.1 Principal Component Analysis

One of the well-known problems in the field of data analysis is what is called the "curse of dimensionality". That is, as the number of different variables increases most traditional statistical methods become first cumbersome and rather soon in practice entirely unusable. Often the best way to cope with a data set with a massive number of separate variables is to try to decrease the dimensionality. One of the tools commonly used for this purpose is Principal Component Analysis (eg. Mardia et al. 1979).

In short, the aim of Principal Component Analysis is to take the data and transform it so that one gets components that are not correlated with each other. These components are weighted combinations of the original variables, and they are presented in order of decreasing variance. Thus the first principal component accounts for the largest fraction of the total variance and the entire set of components accounts for all of it.

A geometrical interpretation is that one plots the data in a multidimensional space, where each axis of the coordinate system corresponds with one of the variables. To get the principal components, one turns the coordinate system so that one axis, which corresponds with the first principal component, points in the direction where the variance of the data is greatest; the second axis, while at right angles to the first, is then turned in the direction where the residual variance is the greatest, and so on. This interpretation is also useful in that it makes it intuitively clear that as one sets the direction of the axes, they could equally well be turned exactly around. Thus in principal component analysis the direction of the +/- sign in any of the components is arbitrary.

The ordering of the principal components means that in most cases the first few principal components give a rough overview of the data. Also, it is usually possible to reduce the noise of the data by concentrating on the first components and ignoring the last ones, as the latter contain relatively little real information.

2.2 Cluster Analysis

Cluster analysis (Tryon 1939) is a family of methods for organising data to structures

that are, one hopes, meaningful. A good introduction to the topic is Kaufman and Rousseeuw (1990), but in a nutshell the goal is to divide the data to clusters, so that the difference between items in the same cluster is as small as possible, and the difference between items in different clusters as large as possible. There are several ways to do this, but in general clustering methods can be divided into hierarchical (often called also agglomerative or joining) and partitioning (also called divisive) methods. Both of these have their own strengths and weaknesses.

In hierarchical clustering first individual items are joined to each other, and the groups to each other, so that the result is a tree of cluster associations. In this tree, the different branches are the clusters, and one can choose the appropriate level of detail by deciding which branches are viewed as separate clusters. One of the serious problems with hierarchical clustering, especially with such data as analysed in the current study, is that small-scale variation, while in reality rather unimportant, can have a large effect on the results of the analysis: when one joins two elements at a time it is possible, and in practice common, that a larger group gets split into two branches which in turn get separated.

In partitioning (also called divisive) methods, on the other hand, the data is divided to a specified number of clusters. Here the the typical difficulty is that one has to know — or guess — the number of clusters in advance. Also, since these methods compare an item to the cluster as a whole, instead of simply two items to each other, they often do not allow one to use as wide a range of similarity measures as the hierarchical methods.

Finding the optimal clustering is in most cases what computer scientists call an NP-hard problem: that is, in practice impossible. Approximations are of course possible, but these often give slightly different clusterings each time the analysis is performed. However, Ben-Hur and Guyon (2003) note that the stability of cluster analysis can be increased by using principal component analysis as a first step. In the present study this was done; subsequently, cluster analysis was performed by the K-medoids partitioning method (Kaufman and Rousseeuw 1990, chapter 2).

3 Analysis of the Hydronyms

3.1 Lakes

The lake names were set as a matrix, with the municipalities as variables and the distributions of each name as observations. The goal, thus, was to transform the actual geographic regions to components that explain the distributions of lake names.

The maps in figures 1—3 show the weights of each municipality in the first three components, drawn in shades of gray on a map with main dialectal divisions shown as black lines; next to each map is a table of the 20 names most strongly associated with each end of the spectrum. The first component, which accounts for 13 % of the variation in name distributions, appears to be related to the division of Eastern and Western Finnish dialects. The second component, which with 4% of the total variation is already markedly less significant, is concentrated mainly in the Kainuu region, and the third component is strongest in Tavastland and Lapland.

The first component, in figure 1, can be considered an expected result: the East

—West division is the most fundamental one in Finnish dialects. The second component is rather less expected, and it may have something to do with the fact that the center is in the municipalities where the density of lakes is at its highest. The names most strongly associated with the darker end of the scale in figure 2 are consistent with the lakes being uniformly small; the names associated with the light end of the scale imply a wider variation in lake sizes. On the other hand, this area shows up rather prominently in the river data as well, so there may be other reasons besides the small size of lakes.

The third component seems again linguistically or culturally related. The dark region in the northernmost part of Lapland in figure 3 may be an anomaly caused by the fact that the area was originally Lappish-speaking, and so the Finnish names are either new or translations of old Lappish ones. However, the dark regions slightly more south in Kainuu and the southernmost one in Tavastland are possibly related: for instance, Talvio (2002) lists 11th century coin hoards in both areas but not in the region between.

A two-way clustering based on the first three components, shown on the rightmost map of figure 4, results in a division of Finland into the Eastern region, in light gray, and the Western one, in darker gray. As the number of clusters increases, first the Western cluster splits to, on one hand, Tavastland and the area around the Tornio river in Lapland, shown an intermediate shade, and on the other hand the rest; this division appears consistent with the settlement history of the Tornio river valley (cf. Vahtola 1980). Later on the rest of Lapland, shown in very dark gray, splits off from the Western cluster and the Eastern cluster splits into the old provinces, very light, and the region that was settled in the 17th century, slightly darker.

Figures 5—7 and 8 show similar maps based on the names of parts of lakes, such as bays. The three principal components are roughly similar, but the clustering is geographically somewhat less consistent. One contributing factor is likely that this data set is smaller than that of lake names, so one should not expect quite as thorough results. Another partial explanation is that the names in Lapland — the area where the clustering results are least consistent — are generally much younger than those in the south.

3.2 Rivers

The maps in figures 9—11 showing principal components of river names show also drainage basins as white lines. One can see that the first principal component appears to be correlated on whether the municipality is up- or downriver. The second component is concentrated on the basins of the Oulu and Kemi rivers, or more generally in Northern Finland; the third, like the second component in lake names, is again concentrated in Kainuu.

Figures 12 and 13 show clusterings based on river name components. Figure 12 shows a two-way clustering based on different numbers of components; it is interesting how the one based on only two first components assigns Kainuu to the same cluster as the coastal regions. With a larger set of components one cluster, shown in light gray, would seem to include the northern Bothnia and Kainuu in addition to the traditionally settled regions in the south. As noted above in the discussion about lake names, it is perhaps not altogether impossible to see in this last map a rough reflection of the areas under permanent Finnish influence in late Viking age, although it is not clear that this in fact is the reason for the results.

The three-way clustering, on the two leftmost maps in figure 13, starts to look somewhat more understandable: the old hunting regions appear as a separate cluster in light gray, the old agricultural lands in the south as another in an intermediate shade, and the coastal regions as the third one in dark gray. In the fiveway clustering on the rightmost map, Lapland and the old Savolax separate as the very dark and second-lightest clusters.

All in all, the distributions of river names do not combine into quite as expected structures as was the case in lake names. One possible reason is that river names are more closely related to physical phenomena; another one would be that river names were treated differently from lakes in the old hunting cultures. Yet another one would simply suggest that the problem is in the data: the coordinates for rivers are given as a point in the mouth of the river, which may at least partially account for the first component.

The data sets of names of rapids and other parts of rivers were much smaller, so it is understandable if the analyses are less definite than with the other data. Also, the difference between these two types is not necessarily clear; from the names it is apparent that places that are — or have been — viewed as rapids by the local people are classified as other parts of rivers. On the other hand, there is no obvious reason to suspect that this ambiguity affects the analysis.

All in all, the first components derived from the rapids data, shown in figures 14—16, parallel those from the river names, except for Lapland. This is a reasonably strong argument against the hypothesis that the difference in distribution between lake and river names is caused by the coordinate encoding in the data: the problems inherent in representing a river by a point near its mouth do not apply to rapids.

The principal components in the other parts of rivers, which are shown in figures 17—19, have also some similarity to the river and rapids names. However, there is even more noise apparent in the data than in the rapids names. This is not surprising, considering that this is the smallest data set.

While the principal components show structures that support the analysis on river names, cluster analysis, as shown in Figure 20, resulted in very little interesting information. Essentially the only interesting structure can be seen in the five-way clustering on the names of rapids, where Lapland emerges as a separate cluster shown in very dark gray.

4 Conclusions

For the most part, the methods used in this study would appear to work. Analyses on the larger data sets resulted in clusters that were geographically homogeneous, even though the methods themselves did not use any geographical information before the last step of actually drawing the map. The resulting maps were close to traditional dialectal borders, which also supports the validity of the results; on the other hand, they were also sufficiently different from these that the results are interesting.

The names of lakes, and also parts of lakes, have an overall distribution that closely follows dialectal variation. This is not surprising, and neither is it surprising that names appear somewhat more conservative than the language currently spoken, so that the regions can be interpreted in terms of Finnish settlement history. The results obtained are more or less in line with what has already been known.

River names, however, are different. Are the reasons for this difference rooted in the old hunting culture, or is this because of the distribution of natural features? Some further study would seem to be warranted. Another interesting result is that in all data sets the difference between Kainuu and the rest of the country shows up within the first three principal components. There is no immediately obvious reason for this, so again further study seems indicated.

References

- Ben-Hur, A. and Guyon, I. (2003). Detecting stable clusters using principal component analysis. In M. Brownstein and A. Kohodursky, editors, *Methods in Molecular Biology*, pages 159–182. Humana press.
- Goebl, H. (1982). Dialektometrie: Prinzipien und Methoden des Einsatzes der numerischen Taxonomie im Bereich der Dialektgeographie. Wien: Österreichischen Akademie derWissenschaften.
- Kaufman, L. and Rousseeuw, P. J. (1990). Finding Groups in Data: An Introduction to Cluster Analysis. Wiley-Interscience.
- Leskinen, T. (2002). The geographic names register of the National Land Survey of Finland. In *Eighth United Nations Conference on the Standardization of Geographical Names*.
- Mardia, K. V., Kent, J. T., and Bibby, J. M. (1979). *Multivariate Analysis*. Academic Press.
- Nerbonne, J. (2003). Linguistic variation and computation. In Proceedings of the 10th Meeting of the European Chapter of the Association for Computational Linguistics, pages 3–10.
- Nerbonne, J. and Heeringa, W. (2001). Computational comparison and classification of dialects. *Dialectologia et Geolinguistica*, 9, 69–83.
- Talvio, T. (2002). *Coins and Coin Finds in Finland AD 800–1200*. Number 12 in ISKOS. Finnish Antiquarian Society.
- Tryon, R. C. (1939). Cluster Analysis. Edwards Brothers.
- Vahtola, J. (1980). Tornionjoki- ja Kemijokilaakson asutuksen synty: nimistötieteellinen ja historiallinen tutkimus. Number 3 in Studia historica septentrionalia. Pohjois-Suomen historiallinen yhdistys.



Light Dark Mustalampi Ahvenlampi Haukilampi Paskolampi Sammakkolampi Tervalampi Särkilampi Likolampi Heinälampi 10 Pahalampi Koiralampi 11 12 Pitkälampi Kangaslampi 13 14 Kortelampi Vehkalampi 16 Umpilampi Saarilampi 17 18 Syvälampi 19 Lehmilampi 20 Myllylampi

Kakarilammi Väärälammi Hanhilammi Hirvilammi Vehkalammi Pitkälammi Takalammi Härjänsilmä Korpilammi Tervalammi Koukkulammi Haaralammi Valkealammi Rapalammi Hautalammi Laihalammi Rimminlammi Kiimalammi Keskinenjärvi Kivilammi

Geographical distribution

Top 20 names



Figure 1: Lakes / Principal Component 1: 13 % of total variation

1

2

3

4

5

6

7

8

9

15

Geographical distribution

Top 20 names

Figure 2: Lakes / Principal Component 2: 4 % of total variation



Light Dark Likolampi Vähäjärvi Hepolampi Särkijärvi Valkealampi Saarijärvi Riihilampi Haukijärvi Aluslampi Ahvenjärvi Mustikkalampi Syväjärvi Valkeinen Salmijärvi Vehkalampi Kalliojärvi Valkeislampi Kivijärvi 10 Väärälampi Pitkäjärvi Louhilampi Mustajärvi 11 12 Sikolampi Kaakkurilampi 13 Pieni Särkilampi Kaitajärvi 14 Iso Valkeinen Pirttijärvi 15 Pohjalampi Latvajärvi 16 Kaatiolampi Alajärvi 17 Lehmilampi Paskolammi 18 Orilampi Valkeajärvi 19 Pieni Heinälampi Kotajärvi 20 Tetrilampi Kortejärvi

Geographical distribution

Top 20 names



1

2

3

4

5

6

7

8

9



2 clusters based on 3 PC's

3 clusters based on 4 PC's

5 clusters based on 6 PC's

Figure 4: Lakes / Clusters



Light Dark Mustalahti Isoperä Santaviiki Pitkälahti Joutavalahti Likolahti Hakalanlahti Savilahti Keinolahti Levälahti Salmenperä Syvälahti Kylmälahti Pohislahti Saunalahti Hietaperä Myllylahti Loukaslahti 10 Letonlahti Jokilahti 11 Soukanpohja Hietalahti 12 Luusua Kortelahti 13 Mustaperä Kotalahti 14 Kaakkurilahti Kivilahti 15 Maijanlahti Riihilahti 16 Ojalanlahti Talvilahti 17 Ruonanlahti Suolahti 18 Vaarinlahti Tervalahti 19 Korvensalmi Laajalahti Haukilahti 20 Lepistönlahti

Geographical distribution

Top 20 names

Figure 5: Parts of Lakes / Principal Component 1: 15% of total variation

1

2

3

4

5

6

7

8

9



Geographical distribution

Top 20 names

Figure 6: Parts of Lakes / Principal Component 2: 3 % of total variation



Light Pohjoislahti Tulilahti Itälahti Laajalahti Hiekkalahti Etelälahti Laajanlahti Hiekkakaarre Ruokolahti 10 Sammakkolahti Jokilahti 11 12 Luodelahti 13 Levälahti 14 Viitalahti 15 Tulisalmi 16 Kangaslahti 17 Kylmäkaarre 18 Jynkänlahti 19 Kannaslahti 20 Murtolahti

Dark Leveälahti Kotalahti Syvälahti Myllylahti Isolahti Savilahti Mustalahti Pikkulahti Isoselkä Kirkkolahti Takalahti Kylmälahti Isosalmi Hietalahti Haapalahti Hangaslahti Niittulahti Kutulahti Santalahti Likalahti

Geographical distribution

Top 20 names

Figure 7: Parts of Lakes / Principal Component 3: 2 % of total variation

1

2

3

4

5

6

7

8

9



2 clusters based on 4 PC's

3 clusters based on 4 PC's

5 clusters based on 6 PC's





Dark Light Myllypuro Myllyoja Kylmäpuro Pahaoja Kivipuro Mustaoja Mustapuro Särkioja Tervapuro Kivioja Vehkapuro Hanhioja Haarapuro Välioja Kortepuro Karhuoja Välipuro Saukko.oja 10 Kalliopuro Peuraoja Koirapuro 11 Korteoja 12 Heinäpuro Ruosteoja Ruunapuro 13 Palo.oja 14 Hepopuro Sammaloja Välijoki 15 Pikkuoja 16 Pajupuro Rytioja Myllyjoki Hirvioja 17 18 Karhupuro Hirvasoja 19 Haukipuro Säynäjäoja 20 Palopuro Lammasoja

Geographical distribution

Top 20 names

Figure 9: Rivers / Principal Component 1: 10% of total variation

1

2

3

4

5

6

7

8

9



Geographical distribution

Top 20 names

Figure 10: Rivers / Principal Component 2: 5% of total variation



Light Myllyoja Myllypuro Myllyjoki Kylmäoja Vehkaoja Rajapuro Välijoki Korvenoja Kolunoja 10 Haapajoki Sahinjoki 12 Heinäjoki Kivioja 13 Tervapuro 15 Kolisevanoja Alhonoja Syväoja 17 18 Rajajoki Vehkapuro 20 Kukkopuro

Dark Saarijoki Rytioja Syrjäpuro Ahvenoja Latvajoki Kotipuro Säynäjäjoki Mätäspuro Korteoja Syrjäoja Säynäjäoja Heteoja Saukko.oja Konttipuro Lehto.oja Käärmepuro Kotijoki Raatepuro Ahvenpuro Salmijoki

Geographical distribution

Top 20 names



1

2

3

4

5

6

7

8

9

11

14

16

19



2 clusters based on 3 PC's

2 clusters based on 4 PC's

2 clusters based on 7 PC's

Figure 12: Rivers / 2 Clusters



3 clusters based on 4 PC's 3 clusters based on 7 PC's 5 clusters based on 7 PC's

Figure 13: Rivers / 3–5 Clusters

		Light	Dark
	1	Kissakoski	Myllykoski
	2	Vuorikoski	Pitkäkoski
	3	Härkäkoski	Saarikoski
	4	Louhenkoski	Kalliokoski
	5	Sahinkoski	Vääräkoski
	6	Leppäkoski	Niskakoski
- internet	7	Heinäkoski	Suukoski
	8	Louhikoski	Alakoski
~~~~ <u>`````````````````````````````````</u>	9	Kuuskoski	Korpikoski
يا     کر چې	10	Lapinkoski	Koivukoski
	11	Katajakoski	Jyrkkäkoski
and the second second	12	Vääräkkä	Kattilakoski
So ling	13	Kellokoski	Haarakoski
	14	Sahankoski	Siikakoski
S and	15	Ruuhikoski	Palokoski
	16	Kärppäkoski	Petäjäkoski
the same of	17	Ruukinkoski	Taivalkoski
	18	Kivikoski	Tuomikoski
De alle and the state	19	Porraskoski	Tammikoski
and the second sec	20	Keskikoski	Siltakoski

Geographical distribution

Top 20 names

Figure 14: Rapids / Principal Component 1: 16 % of total variation

![](_page_13_Picture_0.jpeg)

Light Dark Pitkäkoski Myllykoski Saarikoski Kissakoski Niskakoski Sahankoski Taivalkoski Tervakoski Alakoski Härkäkoski Suukoski Lapinkoski Jyrkkäkoski Tamppikoski Vääräkoski Kuuskoski Korpikoski Sahinkoski Kurjenkoski Lammaskoski Patokoski Hirvikoski 12 Kalliokoski Haapakoski Tammikoski 13 Keskikoski Haarakoski Ahokoski 15 Yläkoski Vuorikoski 16 Koivukoski Vääräkkä 17 Peurakoski Porraskoski 18 Kattilakoski Välikoski 19 Kotakoski Ruukinkoski 20 Vääränkoski Leppäkoski

**Geographical distribution** 

#### **Top 20 names**

## Figure 15: Rapids / Principal Component 2: 6 % of total variation

1

2

3

4

5

6

7

8

9

10

11

14

![](_page_13_Picture_5.jpeg)

## Geographical distribution

#### **Top 20 names**

#### Figure 16: Rapids / Principal Component 3: 5% of total variation

![](_page_14_Picture_0.jpeg)

Light Myllykoski Pitkäkoski Saarikoski Vääräkoski Kalliokoski Korpikoski Pitkäsuvanto Alakoski Louhikoski 10 Pahkakoski 11 Kattilakoski 12 Niskakoski 13 Jyrkkäkoski 14 Hanhikoski 15 Honkakoski 16 Leppikoski Pikkukoski 17 18 Pirttikoski 19 Hautakoski 20 Rosvohotu

Dark Peurasuvanto Kutuniva Saarisuvanto Sahi Syväsalmi Joenpolvi Polvikoski Pajukoski Mukkakoski Lampare Alasuvanto Jokilampi Myllysuvanto Haarakoski Hietakoski Mustalahti Korkeakoski Kuivakoski Savilahti Haapakoski

**Geographical distribution** 

#### **Top 20 names**

### Figure 17: Other Parts of Rivers / Principal Component 1: 13% of total variation

1

2

3

4

5

6

7

8

9

![](_page_14_Picture_6.jpeg)

Geographical distribution

**Top 20 names** 

Figure 18: Other Parts of Rivers / Principal Component 2: 7% of total variation

![](_page_15_Picture_0.jpeg)

Light Pitkäsuvanto Pitkäkoski Kattilakoski Myllykoski Suvanto Mustalahti Myllysuvanto Niva Rosvohotu 10 Patokoski Lohikoski 11 12 Saarisuvanto 13 Pyörre 14 Lampare 15 Siltakoski 16 Kuivakoski 17 Niskakoski 18 Alasuvanto 19 Mukkakoski 20 Mustakoski

Dark Kalliokoski Vääräkoski Palokoski Alakoski Karhukoski Koivukoski Korpikoski Pahkakoski Pikkukoski Haapakoski Leppikoski Koirakoski Aittokoski Hautakoski Jyrkkäkoski Suukoski Koskelankoski Savilahti Saarikoski Honkakoski

**Geographical distribution** 

#### **Top 20 names**

### Figure 19: Other Parts of Rivers / Principal Component 3: 6% of total variation

1

2

3

4

5

6

7

8

9

![](_page_15_Picture_6.jpeg)

**Rapids:** 2 clusters based on 7 PC's

**5** clusters based on 7 PC's

**3** clusters based on 3 PC's

Figure 20: Parts of Rivers / Clusters