Rule Discovery and Probabilistic Modeling for Onomastic Data

http://www.cs.helsinki.fi/u/leino/jutut/pkdd-03/

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Introduction

- High-dimensional marked point processes
 - Spatial statistics: mostly single processes, at best low dimensionality
 - Data mining: mostly non-spatial data
- Onomastics
 - Study of names, in this case place names
 - Multidisciplinary: linguistics, history, some geography
- Goals
 - Dependences between occurrences of different names
 - * New information on how places are named
 - Homogeneous regions
 - New information on the relationships between settlement history, linguistic regions and naming
- Methods
 - Pretty straightforward application of data mining techniques to a novel data set



Place Name Data

- Finnish National Land Survey Place Name Register [1]
 - 718 000 name instances
 - 58 000 lakes
 - 25 000 different lake names
 - 54 most common lake names: 9 008 lakes
 - 45 name endings: 55 538 lakes

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Pitkäjärvi;1;Suomi;410;Vakavesi;6682578;2541586;6684464;3375471;049;

Espoo - Esbo;011;Helsingin seutukunta;01;Uusimaa - Nyland;1;Uusimaa - Nyland;

1;Etelä-Suomen lääni - Södra Finlands län;204301A;1901D4;1;

Virallinen kieli tai saame;1;Enemmistön kieli;1;Maastotietokanta;10011998;

40011998
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Pitkäjärvi;6684464;3375471;049

järvi;Pitkäjärvi;6684464;3375471;049

Figure 1: Example of raw Place Name Register data, common names data and name endings data



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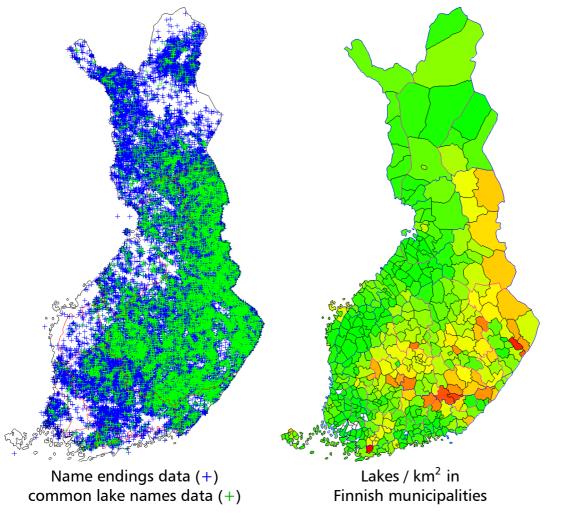


Figure 2: Lake names in the Place Name Register data



Association Rules

- $X \Rightarrow Y$, where $X, Y \subseteq \{A_1, \ldots, A_n\}$
 - Frequency $f(X \cup Y)$
 - Accuracy $\frac{f(X \cup Y)}{f(X)}$
- Spatial association rules
 - Various views on these [2, 3, 4, 5]
 - Here: $X \Rightarrow_r Y$, where r is radius

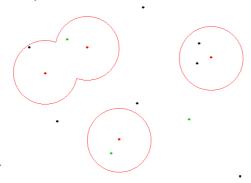


Figure 3: Spatial association rule $A \Rightarrow_r B$ as selection

• If no association (ie. A and B independent of each other), selection in Figure 3 is a random sample



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Results

• Figure 4 shows the distribution of two pairs of names. The distributions look relatively similar.

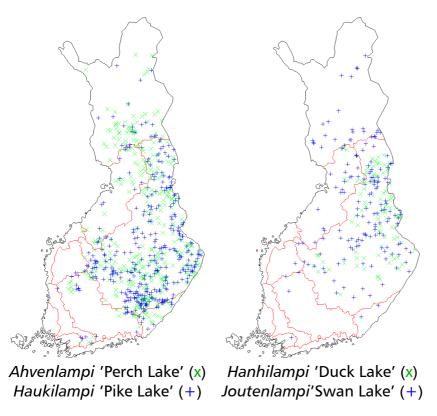


Figure 4: Distribution of two pairs of names



- Figure 5 shows the Poisson-approximated probabilities.
 - Ahvenlampi \Rightarrow_r Haukilampi: a strong association at small radii
 - Hanhilampi \Rightarrow_r Joutenlampi: much weaker and at longer radii

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Ahvenlampi => Haukilampi:
+ At 1 km found 20; p(n<20) = 1.0000 (corrected 1.00)
+ At 2 km found 40; p(n<40) = 1.0000 (corrected 1.00)
+ At 3 km found 51; p(n<51) = 1.0000 (corrected 0.99)
+ At 4 km found 75; p(n<75) = 1.0000 (corrected 1.00)
+ At 5 km found 92; p(n<92) = 1.0000 (corrected 0.97)
+ At 6 km found 116; p(n<116) = 1.0000 (corrected 0.98)
+ At 7 km found 137; p(n<137) = 1.0000 (corrected 0.95)
+ At 8 km found 170; p(n<170) = 1.0000 (corrected 1.00)
+ At 9 km found 181; p(n<181) = 1.0000 (corrected 0.96)
+ At 10 km found 204; p(n<204) = 1.0000 (corrected 0.98)
Hanhilampi => Joutenlampi:
  At 1 km found 0; p(n<0) = 0.0000 (corrected 0.00)
  At 2 km found 3; p(n<3) = 0.9259 (corrected 0.00)
  At 3 km found 3; p(n<3) = 0.6418 (corrected 0.00)
  At 4 km found 5; p(n<5) = 0.6983 (corrected 0.00)
  At 5 km found 9; p(n<9) = 0.8927 (corrected 0.00)
  At 6 km found 18; p(n<18) = 0.9990 (corrected 0.00)
  At 7 km found 21; p(n<21) = 0.9985 (corrected 0.00)
+ At 8 km found 31; p(n<31) = 1.0000 (corrected 0.98)
  At 9 km found 33; p(n<33) = 1.0000 (corrected 0.91)
 At 10 km found 37; p(n<37) = 1.0000 (corrected 0.91)
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Figure 5: Associations in two pairs of names



- Various interesting questions on the characteristics of contrastive / variational names
- Other interesting pairs of names as well
 - Lehmilampi 'Cow Lake' \Rightarrow_r Likolampi 'Retting Lake': association results from cultural connection
 - Likolampi 'Retting Lake' \Rightarrow_r Pitkälampi 'Long Lake': association but no obvious reason



Repulsion

- A special case of association rules, $A \Rightarrow_r A$
- Not obvious that a sample like in Figure 3 could be considered random. However, the sum of samples in Figure 6 can.

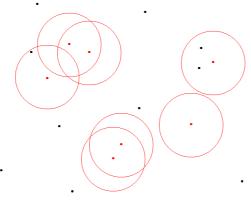


Figure 6: Spatial association rule $A \Rightarrow_r A$ as a series of selections



- Repulsion appears to be rare; this is surprising.
- There are even cases like *Umpilampi* 'Closed Lake' where there is significant attraction (cf. Figure 7). Evidently each of these names is actively used by a very small group of people, likely just a single farm.

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Umpilampi => Umpilampi:
   At 1 km found 9; p(n<9) = 0.9999 (corrected 0.66)
+ At 2 km found 32; p(n<32) = 1.0000 (corrected 1.00)
+ At 3 km found 66; p(n<66) = 1.0000 (corrected 1.00)
+ At 4 km found 82; p(n<82) = 1.0000 (corrected 1.00)
+ At 5 km found 103; p(n<103) = 1.0000 (corrected 1.00)
+ At 6 km found 126; p(n<126) = 1.0000 (corrected 1.00)
+ At 7 km found 136; p(n<136) = 1.0000 (corrected 1.00)
+ At 8 km found 154; p(n<154) = 1.0000 (corrected 1.00)
+ At 9 km found 164; p(n<164) = 1.0000 (corrected 1.00)
+ At 10 km found 171; p(n<171) = 1.0000 (corrected 1.00)</pre>
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Figure 7: Conspicuous absence of repulsion between instances of Umpilampi

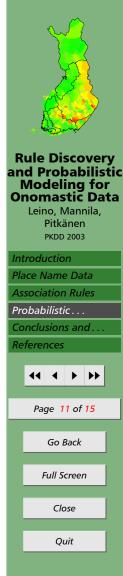


Probabilistic Modeling

- View the data as a matrix, with municipalities as rows and names (or name endings) as columns; each cell has the frequency of these names in the municipality.
- Apply the EM clustering algorithm [6, 7, 8]:
 - Assign random component weights
 - E-step: For each data point, compute the probability that the data resulted from the model
 - M-step: Compute the component weights according to the results of the E-step
 - Iterate the E and M steps as necessary

Observations

- Clusters spatially well connected.
- As the number of clusters increases, new divisions appear but the old boundaries mostly stay in place.
- Clusters correspond with previous onomastic and historical information.
- The old Western Finnish habitation shows fairly well
- Also the boundary between the Eastern and Western dialect groups;
 names reflect an older demographic state than current dialects



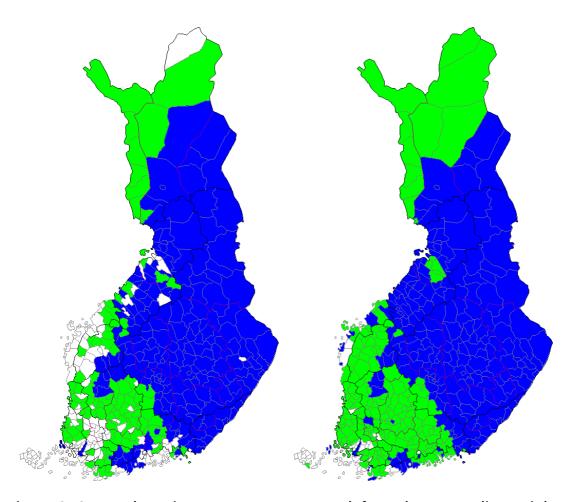


Figure 8: 2-way clustering on common names (left) and name endings (right)



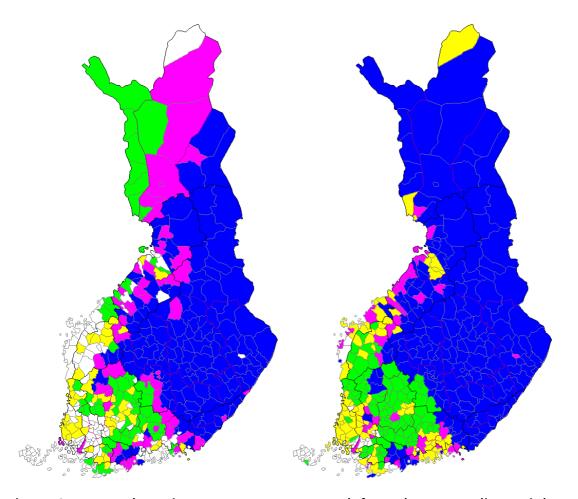


Figure 9: 4-way clustering on common names (left) and name endings (right)



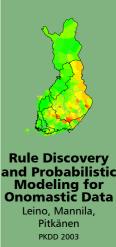
Conclusions and Further Research

- Basic KDD methods can be applied to spatial point data
- Impact on onomastics
 - Certain types of contrastive names are more widespread than previously thought; theories about naming processes have to be re-evaluated
 - Repulsion appears far less noticeable than expected. This, too, has to be explained somehow.
 - Clustering seems a possible starting point for composing an onomastic overview. This can be combined with other data, such as that on dialectal variation.
- Association involving more than two names: $\{A_1, \dots A_i\} \Rightarrow_r B$
 - How to extend known algorithms to spatial data, ie. data with no clear observations?
 - − $\Gamma \Rightarrow_r B$, where $\Gamma \equiv$ 'There are names of type α nearby'
 - Combination of simple association rules and clustering: 'Names $\{A_1, \ldots, A_i\}$ are often found near each other'



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