How Good are Typological Distances for Determining Genealogical Relationships among Languages?

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Introduction

- **Language family**: There are more than 7000 languages in this world (Lewis 2009), which fall into more than 140 genetic families.
- **Typological relatedness**: Languages can also share structurally common features such as *word order*, *similar phoneme inventory size* and *morphology*. But typological relatedness does not imply genetic relation between languages.
- In computational linguistics, genealogical distances between two language families have been shown to be useful for predicting the difficulty of machine translation (Birch et al. 2008).

Contributions

- Do we really need a clustering algorithm to measure the internal classification accuracy of a language family?
- How well do the typological distances within a family correlate with the lexical distances derived from ASJP lists?
- Given that there are more than dozen vector similarity measures, which vector similarity measure is the best for the above mentioned tasks?

Resources

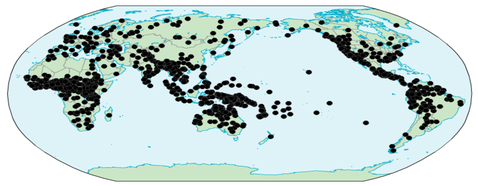
- **WALS**: The WALS database [a] has typological features for 2676 languages of 144 types. We removed entries for all languages with less than 25 attested features and features with less than 10% attestations (Georgi et al. 2010). Each of the WALS features (binary or multi-valued) are also binarized by recording presence or absence of a particular feature value.
- **ASJP**: A database of Swadesh word lists (Swadesh 1952) (short concept meaning list) for more than 58% of the world's languages (Brown et al. 2008).

[a] accessed on 2011-09-22

Previous work

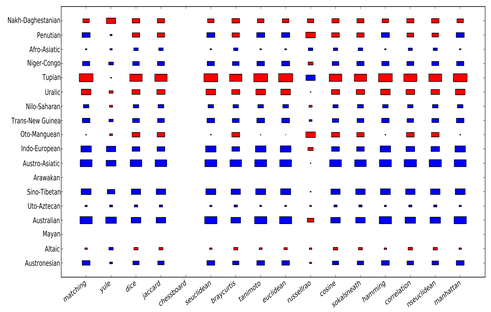
- Daume III (2009) and Georgi et al. (2010) use typological features from WALS to investigate relation between phylogenetic groups and feature stability.
- Georgi et al. (2010) motivate the use of clusters derived from typological distances to project linguistic resources from "resource-rich" to "low-resource" languages.
  - Do not take into account *geographical bias* in the dataset.

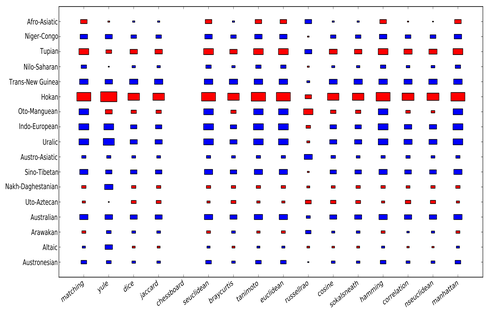
Experiments



- Distances between feature vectors from the WALS typological database are computed using 15 different similarity measures.
- For each similarity measure
  - The typological distance matrix is compared to a 2D WALS classification matrix
  - Pair-wise correlation between the typological distance matrix and the lexical distance matrix used in ASJP classification.
  - ASJP distance between two languages is computed as average pair-wise length-normalized Levenshtein distance (LDND).

Results





- **Internal classification accuracy** using point-biserial correlation shown above.
- Australian, Austro-Asiatic, Indo-European and, Sino-Tibetan language families, except for 'russellrao'.
- The worst performing language family is Tupian. Tupian has 5 genera with one language in each and a single genus comprising the rest of family.
- None of the vector similarity measures seem to perform well for Austronesian and Niger-Congo families.
- Correlation between typological distance matrices and distance matrix obtained using lexicostatistical lists from ASJP.
- Pairwise correlation ρ is high across Australian, Sino-Tibetan, Uralic, Indo-European and Niger-Congo families.
- The Hokan family shows the lowest amount of correlations across all distance measures.

Conclusions and Future Work

- Choosing the right vector similarity measure when calculating typological distances makes a difference in the internal classification accuracy.
- Choice of similarity measure does not influence the correlation between WALS distances and LDND distances within a family.
- Combination of a smaller set of typological features (from the ranking of Wichmann & Holman (2009)) and right similarity measure might achieve higher accuracies.

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