# Estimating and Visualizing Language Similarities Using Weighted Alignment and Force-Directed Graph Layout 

Gerhard Jäger

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joint work with Armin Buch, David Erschler \& Andrei Lupas

## Force Directed Graph Layout

- method to visualize graphs or similarity matrices in two or three dimensions
- simulation of a physical system:
- data items $\Leftrightarrow$ physical particles
- pairwise attractive force between particles proportional to their similarity
- constant repelling force between any pair of particles
- this is just one of many protocols to determine forces
- initially, all particles are placed at random
- in each time step, each particle is move a small amount along the resulting force vector
- last step is repeated until a stable state is reached
- tends to stabilize in a state where groups of mutually similar items form clusters


## CLANS

- Cluster Analysis of Sequences
- developed by bioinformaticians Tancred Frickey and Andrei Lupas as exploratory tool to explore evolutionary relationships among protein sequences (Frickey and Lupas 2004)
- similarities of proteins is determined via sequence alignment; resulting matrix is visualized using CLANS
- advantages in comparison to tree-based algorithms:
- does not a priori assume a tree like signal (useful when lateral transfer plays a role)
- fast (esp. in comparison to character based algorithms)
- robust (noise in data items does not accumulate)
- general impression so far (Lupas, p.c.):
- tree algorithms are more precise when evolutionary distances are small; CLANS is more sensitive to weak evolutionary signals


## The Automated Similarity Judgment Program

- Project at MPI EVA in Leipzig around Sören Wichmann
- covers more than 5,000 languages
- basic vocabulary of 40 words for each language, in uniform phonetic transcription
- freely available
used concepts: I, you, we, one, two, person, fish, dog, louse, tree, leaf, skin, blood, bone, horn, ear, eye, nose, tooth, tongue, knee, hand, breast, liver, drink, see, hear, die, come, sun, star, water, stone, fire, path, mountain, night, full, new, name


## First shot: Levenshtein Distance

- first step: finde minmal edit distance between all translation pairs of the languages to be compared
- e.g. German $\leftrightarrow$ Latin

- edit distance $=2$
- transformation into similarity measure

$$
\operatorname{sim}(x, y) \doteq \frac{2\left(\max (l(x), l(y))-d_{L e v}(x, y)\right)}{l(x)+l(y)}
$$

- similarity between L1 and L2: average similarity of translation pairs between L1 and L2


## First shot: normalized Levenshtein Distance



## First shot: normalized Levenshtein Distance



## First shot: normalized Levenshtein Distance

- basic problem here: the smaller the sound inventories of the languages compared, the higher is the probability of false positives



## Benchmark: LDND measure

- Wichmann et al.: doubly normalized Levenshtein distance (Levenshtein Distance Normalized and Divided)
- normalization for word length

$$
\begin{equation*}
\operatorname{nld}(x, y) \doteq \frac{d_{L e v}(x, y)}{\max (l(x), l(y))} \tag{1}
\end{equation*}
$$

- normalization for language specific patterns (including sound inventory size):
- normalization factor $1 / \mu$
- $\mu_{L_{1}, L_{2}}$ : mean of $\left\{n l d(x, y) \mid x \in L_{1}, y \in L_{1},\|x\| \neq\|y\|\right\}$

$$
\begin{aligned}
\operatorname{ldnd}\left(x, y, L_{1}, L_{2}\right) & \doteq \frac{n l d(x, y)}{\mu_{L_{1}, L_{2}}} \\
\operatorname{ldnd}\left(L_{1}, L_{1}\right) & \doteq \frac{\sum_{x \in L_{1}, y \in L_{2}}\left\{\operatorname{ldnd}\left(x, y, L_{1}, L_{2}\right):\|x\|=\|y\|\right\}}{\#\{x, y:\|x\|=\|y\|\}}
\end{aligned}
$$

## Benchmark: LDND measure



## Needleman-Wunsch-Algorithmus

- Levenshtein distance is somewhat coarse grained

- simply normalized distance is 0.5 in both cases
- after second normalization, [hant] even appears somewhat closer to [mano] (ldnd $=0.54)$ than to [hEnd] $(l d n d=0.55)$
- correspondences $a \sim E, t \sim d$ are (according to linguistic criteria like place of articulation) much more natural than $h \sim m$ or $t \sim 0$
- German appears equidistant to English and Spanish here, even though the distance to English is clearly smaller


## Weighted Alignment

- Needleman Wunsch Algorithm
- similar to computation of Levenshtein distance
- edit operations are weighted: algorithm finds optimal alignment, that minimizes total weight
- $a \sim E, d \sim t$ should have lower weight than $t \sim o$
- How to determine these weights?
- bioinformatics: log-odds
- logarithm of the probability of a replacement, divided by probability of chance co-occurrence of molecula pair in question


## Weighted Alignment

- estimation of correspondence probabilities of two sounds in cognates:
- large sample of pairwise related languages
- replacement operation under Levenshtein alignment of translation pairs are counted
- substantive part of word pairs considered are true cognates: replacement operations thus reflect genuine language change processes
- replacement of sounds between non-cognates is randomly distributed and boils down to an additive constant in the logarithmic term


## Weighted Alignment

- log odds:
- $d \sim t: 0.69$
- $a \sim E: 0.07$
- $h \sim m:-0.61$
- $t \sim o:-0.80$



## Weighted Alignment

- total value of optimal alignment is interpreted as similarity between strings
- similarity between languages is computed via $p$-values:

$$
\begin{aligned}
\operatorname{nwpv}\left(x, y, L_{1}, L_{2}\right) & \doteq \frac{\#\left\{\left(x^{\prime}, y^{\prime}\right) \mid \operatorname{nw}\left(x^{\prime}, y^{\prime}\right) \geq \operatorname{nw}(x, y)\right\}}{\# L_{1} \times \# L_{2}} \\
\operatorname{nwpv}\left(L_{1}, L_{2}\right) & \doteq \frac{\sum_{x \in L_{1}, y \in L_{2}}-\log (\operatorname{pv}(x, y))}{\#\{(x, y):\|x\|=\|y\|\}}
\end{aligned}
$$

## Weighted Alignment

- similarities of English to
- Dutch 0.60 / 3.38
- German: 0.68 / 3.16
- Proto-Indoeuropean: 0.86 / 2.33
- Latin: 0.88 / 1.85
- Spanish: 0.93 / 1.59
- Russian: 0.93 / 1.52
- Hungarian: 0.95 / 1.30
- Turkish: 1.03 / 0.83



## Comparison

- two reasonable Gold standards for comparing these two similarity/distance measures:
- expert judgments on cognacy
- expert judgments on language classification


## Comparison: cognacy

- Dyen-Kruskal database: cognacy judgment for 200-item Swadesh lists from 95 Indo-European languages
- experiment:
- extract those items from the Dyen-Kruskal database that occur in ASJP
- define a cognacy estimator based on LDND by finding the optimal cutoff
- do the same for NWPV
- compare
- result
- LDND: optimally achievable Matthews Correlation Coefficient: 0.547
- NWPV: optimally achievable Matthews Correlation Coefficient:
0.574
( +1 means perfect prediction, -1 perfect mis-prediction)


## Comparison: language classification

- Ethnologue: provides taxonomic classification of virtually all living languages
- Robinson-Foulds metric:
- compares two trees over the same set of leafs
- returns number of partitions that one of the two trees makes and the other doesn't
- Neighbor Joining Algorithm: bottom up cluster algorithm to extract an unrooted tree from a distance matrix


## Comparison: language classification

- Experiment:
- compute NJ-tree for all languages in ASJP based on LDND and NWPV distances
- extract sub-tree of Ethnologue tree for the languages in ASJP
- compute Robinson-Foulds metric between Ethnologue tree and each of the two NJ trees
- Outcome:
- LDND: 5,522 (4,550 false positives, 972 false negatives)
- NWPV: 5,476 (4,527 false positives, 949 false negatives)


## Qualitative comparison

- NJ trees for the languages of Eurasia (left: LDND; right: NWPV)



## Qualitative comparison

- CLANS visualization for the languages of Eurasia (LDND left, NWPV right)



## CLANS and dimensionality reduction

- CLANS performs a kind of (non-deterministic) dimensionality reduction
- How does this relate to more established methods?


## CLANS vs. Multi-Dimensional Scaling

- MDS applied to NWPV-matrix of the Eurasian languages



## CLANS vs. Principal Component Analysis

- PCA applied to NWPV-matrix of the Eurasian languages



## CLANS and dimensionality reduction

- language families massively vary in size
- MDS and PCA only provide information about the largest families
- CLANS is sensitive to local patterns


## Conclusion

- weighted alignment improves results of lexico-statistical language classification
- more powerful methods from bioinformatics (such as progressive multiple alignment) are likely to lead to further improvement
- CLANS is a useful exploratory tool

Frickey, T. and A. N. Lupas (2004). Clans: a java application for visualizing protein families based on pairwise similarity. Bioinformatics, 20(18):3702-3704.

