

# Phylogenetic Methods for Computer-Aided Language Classification

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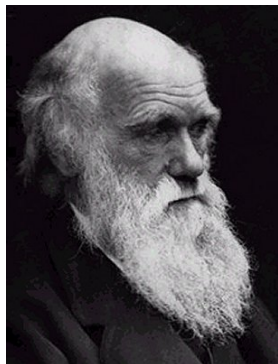


## Sprachwandel und Evolution

*“The formation of different languages and of distinct species, and the proofs that both have been developed through a gradual process, are curiously parallel. [...] We find in distinct languages striking homologies due to community of descent, and analogies due to a similar process of formation. The manner in which certain letters or sounds change when others change is very like correlated growth. [...] The frequent presence of rudiments, both in languages and in species, is still more remarkable. [...]*

*Languages, like organic beings, can be classed in groups under groups; and they can be classed either naturally according to descent, or artificially by other characters. Dominant languages and dialects spread widely, and lead to the gradual extinction of other tongues.”*

(Darwin, The Descent of Man)



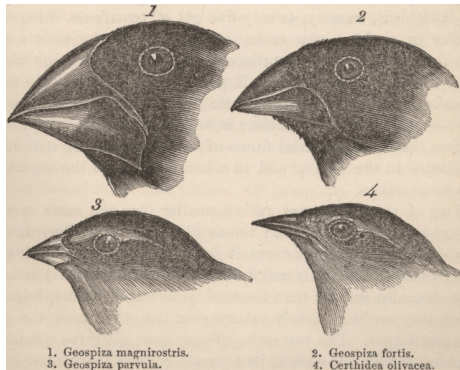
# Language change and evolution

Vater Unser im Himmel, geheiligt  
werde Dein Name

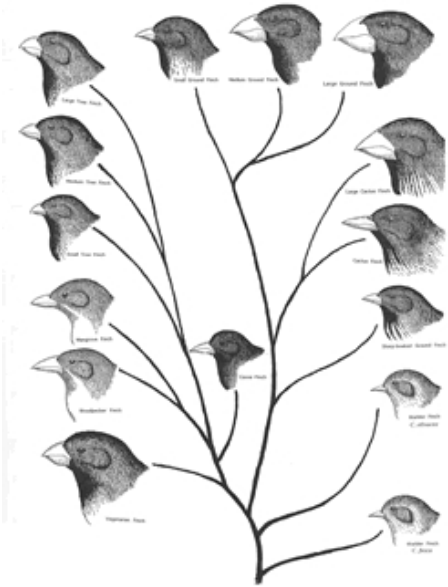
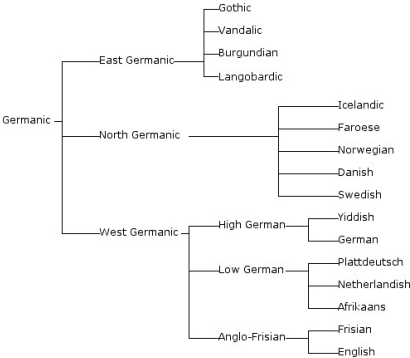
Onze Vader in de Hemel, laat Uw  
Naam geheiligt worden

Our Father in heaven, hallowed be  
your name

Fader Vor, du som er i himlene!  
Helliget vorde dit navn



# Language change and evolution



# Language change and evolution

*Mittelhochdeutsch:*

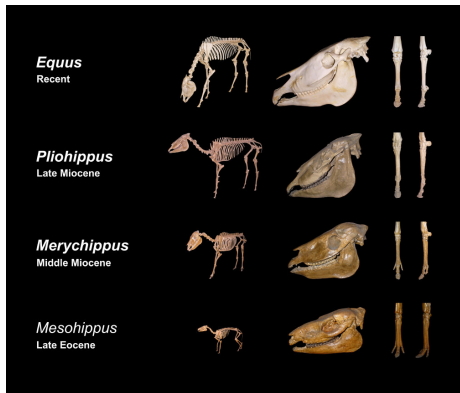
Got vater unser, dâ du bist in dem  
himelrîche gewaltic alles des dir ist,  
geheiligt sô werde dîn nam

*Althochdeutsch:*

Fater unser thû thâr bist in himile, si  
giheilagôt thîn namo

*Gotisch:*

Atta unsar þu in himinam, weihnai  
namo þein



# Convergent evolution

## Taking Flight

To take to the air, three very different vertebrates lightened bones and transformed hands into wings.

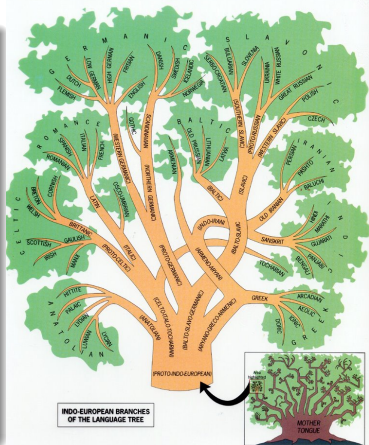


- Old English *docga* > English *dog*
- Proto-Paman *\*gudaga* > Mbabaram *dog* ('dog')

# Language phylogeny

## Comparative method

- 1 identifying *cognates*, i.e. obviously related morphemes in different languages, such as *new/nowy*, *two/dwa*, or *water/voda*
- 2 reconstruction of *common ancestor* and *sound laws* that explain the change from reconstructed to observed forms
- 3 applying this iteratively leads to phylogenetic language trees



# Language phylogeny

## Scope of the method

- reconstructed vocabulary shrinks with growing time depth
- maximal time horizon seems to be about 8,000 years
- grammatical morphemes and categories arguably more stable and less apt to borrowing
- problem here: limited number of features, cross-linguistic variation constrained by language universals, frequently convergent evolution
- comparative method is hard to apply in regions with high linguistic diversity and without written documents (Paleo-America, Papua)
- tree structure might be inappropriate if there is a significant effect of language contact (cf. Australia)



# Computational Methods

- both cognate detection and tree construction lend themselves to algorithmic implementation
- Advantages:
  - easy to scale up
  - comparability of results
  - affords statistical evaluation
- Disadvantages:
  - cognacy judgments require lots of linguistic insight and experience
  - tree construction should be subject to historical (including archeological) and geographical plausibility

# Computational Methods: Data

## Electronic data sources

- **World Atlas of Language Structures** (Haspelmath et al.)
  - categorization of > 2,000 language according to > 140 discrete features relating to phonology, grammar, and vocabulary
- **Automated Similarity Judgment Program** (Wichmann et al.)
  - translation of a 40-item list of basic concepts into > 5,000 languages
  - uniform phonetic transcription
- **Comparative Indoeuropean Database** (Dyen et al.)
  - 200-item list of basic concepts (*Swadesh list*), translated into 95 Indoeuropean languages
  - complete cognacy information based on expert judgments

# Computational Methods: Phylogenetic Algorithms

## Character-based methods

- input: vector of (usually binary) feature values for each data point (= language)
- background assumption: evolution proceeds by randomly changing features values
- **Maximum Parsimony**
  - non-parametric
  - reconstruction of a character vector for each non-leaf node of the reconstructed tree
  - evolutionary changes only along tree branches
  - best tree is the one which requires minimum number of changes
  - NP-hard; heuristic search required

# Computational Methods: Phylogenetic Algorithms

## Character-based methods

- input: vector of (usually binary) feature values for each data point (= language)
- background assumption: evolution proceeds by randomly changing features values
- **Maximum Likelihood**
  - parametric model
  - assumes an explicit stochastic model of the likelihood of an evolutionary change in a given position of a tree
  - algorithm(s) search for tree that maximizes overall likelihood
- **Bayesian Phylogenetic Inference**
  - conceptually similar to Maximum Likelihood
  - incorporates prior knowledge on the probability of tree topologies
- both methods are computationally even more demanding than Maximum Parsimony

# Computational Methods: Phylogenetic Algorithms

## Distance-based methods

- input: matrix of distances between data points
- background assumption: evolution increases distance between species/languages
- no reconstruction of ancestral forms
- **Neighbor Joining**
  - hierarchical clustering
  - bottom-up
  - the two points with the smallest normalized distance are joined into a cluster, the distance of this new point to the other points is computed, and this procedure is repeated until only one cluster is left
  - fast:  $\mathcal{O}(n^3)$  in the number of data points
- NJ consistently outperforms other distance based methods (such as UPGMA) when applied to language phylogeny

# Estimating distances

- basically two approaches to estimating language distances:
  - count the number of shared cognates in a given Swadesh list of of core concepts
  - compute the pairwise phonetic distance between synonymous concepts, and aggregate the results
- latter approach is closely connected to computational dialectometry

# Normalized Levenshtein Distance

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

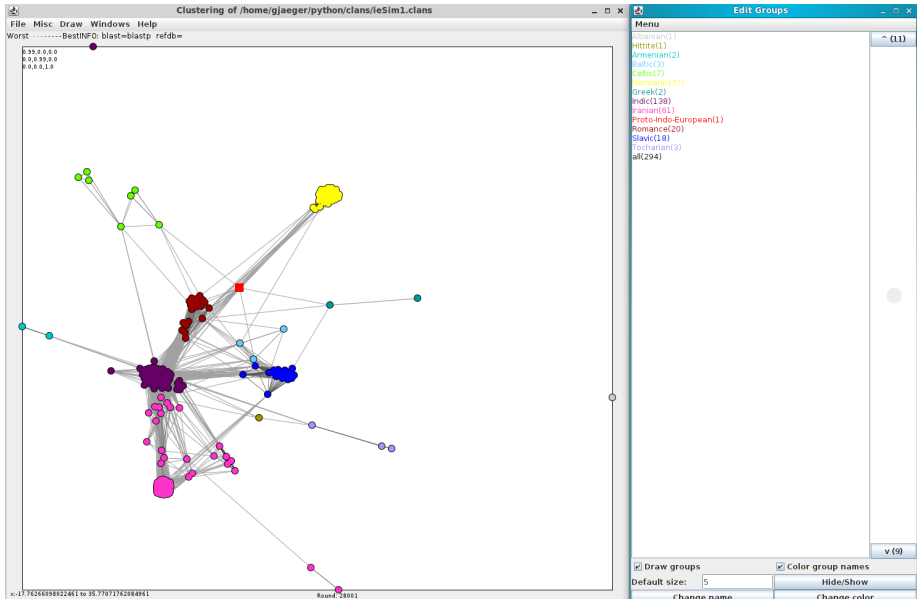
h o r n  
| | | | |  
k o r n u

- edit distance = 2
- transformation into similarity measure to correct for varying word lengths:

$$\text{sim}(x, y) \doteq \frac{2(\max(l(x), l(y)) - d_{Lev}(x, y))}{l(x) + l(y)}$$

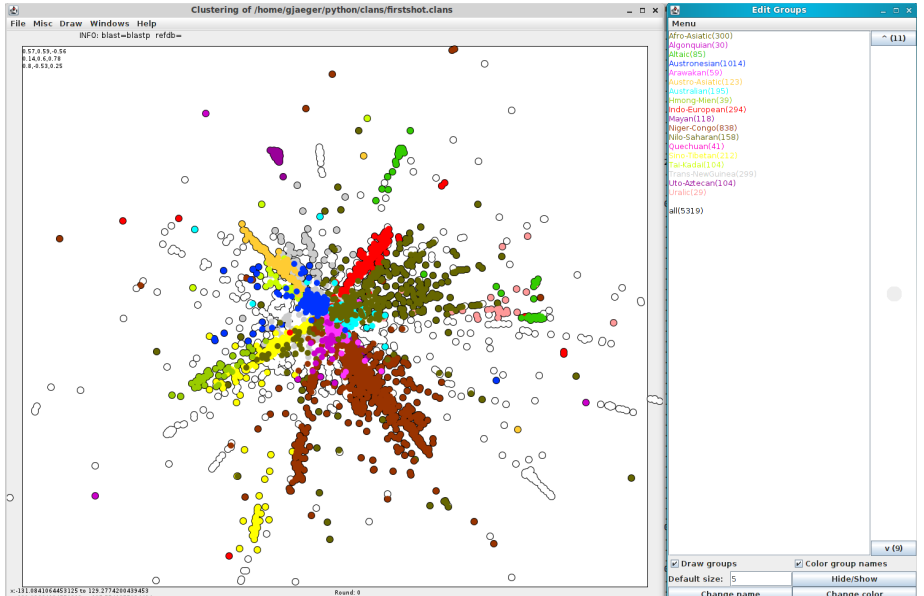
- similarity between  $L_1$  and  $L_2$ : average similarity of translation pairs between  $L_1$  and  $L_2$

# Normalized Levenshtein Distance



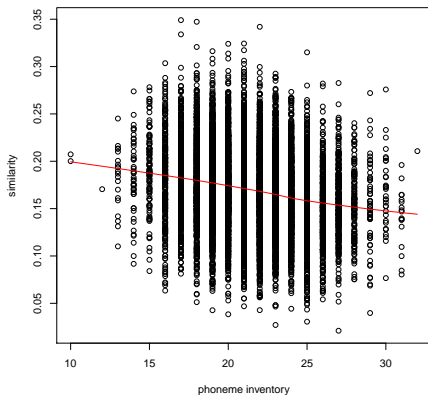


# Normalized Levenshtein Distance



# Normalized Levenshtein Distance

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

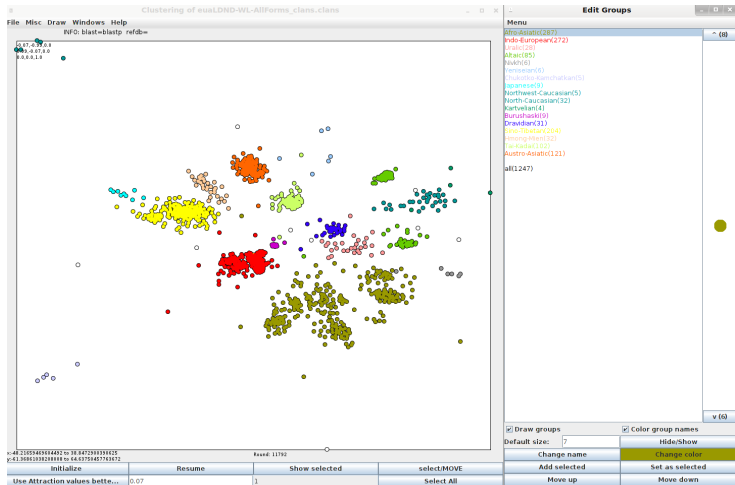


# Levenshtein Distance, Normalized and Divided (LDND)

- Wichmann et al.:
  - 1 correct for word length by dividing by the length of the longer word
  - 2 divide by the average normalized distance between words from  $L_1$  and words from  $L_2$  that are not translation pairs

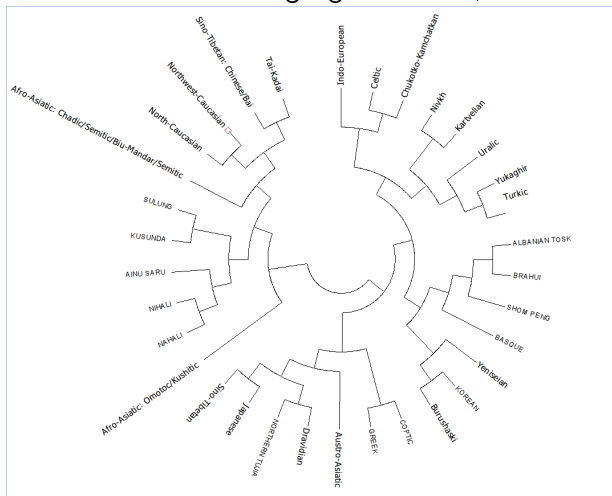
# Levenshtein Distance, Normalized and Divided (LDND)

- Application to all Eurasiatic languages in ASJP:



# Levenshtein Distance, Normalized and Divided (LDND)

- Application to all Eurasiatic languages in ASJP; NJ-tree:



# Weighted Alignment

- Levenshtein distance is very coarse grained

h	a	n	t	h	a	n	t
h	E	n	d	m	a	n	o

- similarity is 0.5 in both cases
- correspondences  $a \sim E$ ,  $t \sim d$  are (according to linguistic criteria like place of articulation) much more natural than  $h \sim m$  or  $t \sim o$
- 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
  - can be done in  $\mathcal{O}(nm)$  (with  $n$  and  $m$  being the lengths of the strings to be aligned) via dynamic programming
  - $a \sim E$ ,  $d \sim t$  should have lower weight than  $t \sim o$
- How to determine these weights?
  - bioinformatics: **pointwise mutual information** (a.k.a. **log-odds**)
  - logarithm of the probability of a replacement, divided by probability of chance co-occurrence of molecular pair in question

# Pointwise Mutual Distance

- pointwise mutual information between event  $x$  and event  $y$ :

$$pmi(x, y) = \log \frac{p(x, y)}{p(x)p(y)}$$

- Prokic (2010):
  - let  $x$  and  $y$  be two segments
  - $p(x, y)$ : probability that  $x$  and  $y$  are aligned to each other in a pair of cognates
  - $p(x), p(y)$ : probability of  $x/y$  to occur individually
- iterative procedure:
  - perform Levenshtein alignment between a given training set of cognate pairs
  - estimate  $pmi(x, y)$  for all segment pairs by using relative frequencies as proxy for probabilities
  - perform Needleman-Wunsch alignment with  $pmi(x, y)$  as weight of  $x \sim y$
  - repeat this procedure until weights do not change anymore



# Weighted Alignment

- dialectometry: cognate pairs are known
- language classification: only limited set of expert-compiled cognate lists are available, and only for small number of language families
- quick and dirty procedure to obtain cognate lists from ASJP data:
  - $p$ -value of translation pair  $(w_1, w_2)$  from languages  $L_1, L_2$ :

$$P(\text{sim}(w_1, w_2) > P(w_1, w_w) | (w'_1, w'_2) \in L_1 \times L_2; \|w_1\| \neq \|w_2\|)$$

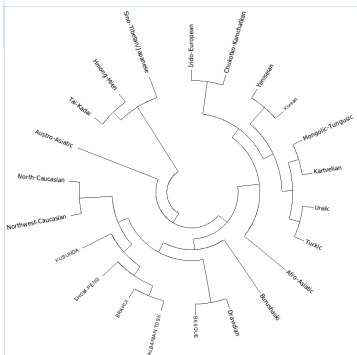
- intuitively: probability that the level of similarity between  $w_1$  and  $w_2$  is as high as it is if the two are not cognates
- two words are considered cognates if
  - $L_1$  and  $L_2$  have a normalized LDND-distance of  $\leq 0.2$ , and
  - $p$ -value of  $(w_1, w_2)$  is  $< 0.01$
- further pairs are added by forming the transitive closure of the cognacy relation

# Weighted Alignment

- calibrated similarity between languages:
  - compute weighted alignment score for all translation pairs
  - compute weighted alignment score for all non-translation pairs
  - determine  $p$ -value for each translation pair (= relative frequency of non-translation pairs with higher weighted alignment score)
  - similarity between  $L_1$  and  $L_2$  is average logarithm of  $p$ -values of all translation pairs

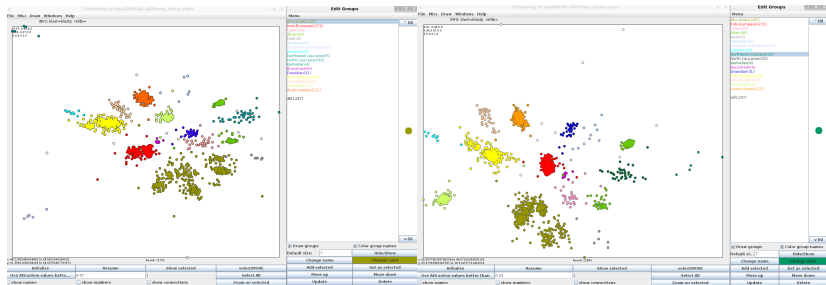
# Qualitative comparison

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



# Qualitative comparison

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



# Benchmarking

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

# Benchmarking: cognacy

- 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)

# Benchmarking: language classification

- expert classifications of languages of the world:
  - WALS: two taxonomic levels for each language (family, genus)
  - Ethnologue: detailed classification
  - Hammerström (2010): equally detailed but more conservative classification
- measure for the quality of a NJ tree: number of internal nodes in the expert tree that have a counterpart in the NJ tree (i.e. a node that dominates the same set of leaves)

# Benchmarking: language classification

Results for LDND vs. *NWPV* (weighted alignment + *p*-value estimation)

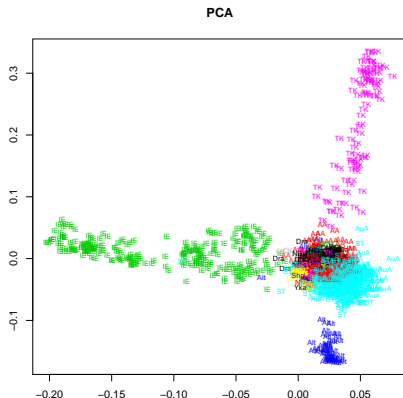
	Africa	Eurasia	Australia/Oceania	America
WALS	0.517(30/58) <i>0.500(29/58)</i>	0.630(46/73) <i>0.644(47/73)</i>	0.573(82/143) <i>0.524(75/143)</i>	0.743(81/109) <i>0.752(82/109)</i>
Ethnologue	0.477(234/490) <i>0.473(232/490)</i>	0.455(148/325) <i>0.489(159/325)</i>	0.510(311/610) <i>0.515(314/610)</i>	0.603(178/295) <i>0.603(178/295)</i>
Hammerström	0.508(248/488) <i>0.5(244/488)</i>	0.467(162/347) <i>0.493(171/347)</i>	0.519(318/613) <i>0.524(321/613)</i>	0.669(195/292) <i>0.682(199/292)</i>





# Visualization: Principal Component Analysis

- PCA applied to NWPV-matrix of the Eurasian languages



# Visualization: CLANS

## 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

# Prospects

- Multiple Sequence Alignment
- Pair Hidden Markov Models for sequence alignment and reconstruction of ancestral forms
- resampling methods (bootstrapping, jackknifing)
- simulations
- correlation with geographic and/or genetic and phenotypic anthropological distance measures