Language change as a random walk in vector space

Gerhard Jäger

Tübingen University, Department of Linguistics

Cluster Colloquium *Machine Learning in Science*

Cluster of Excellence *Machine Learning*, Tübingen, July 23, 2019

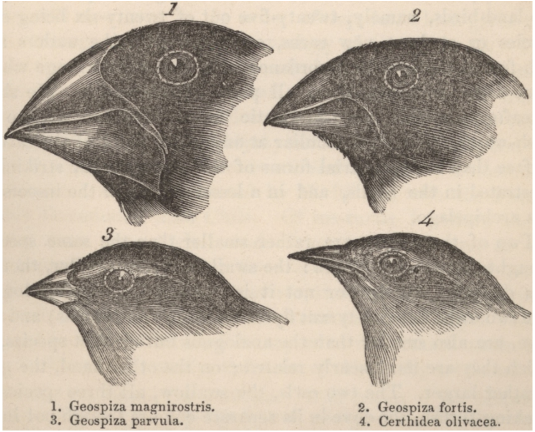
Introduction

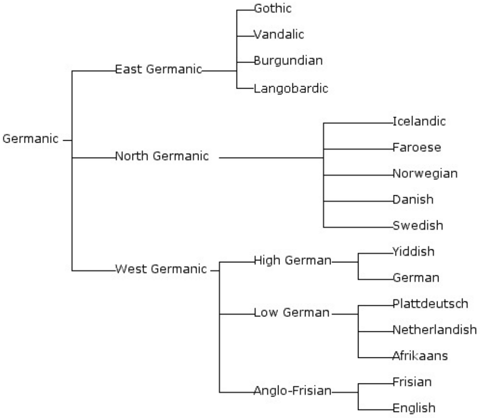
Vater Unser im Himmel, geheiligt werde Dein Name

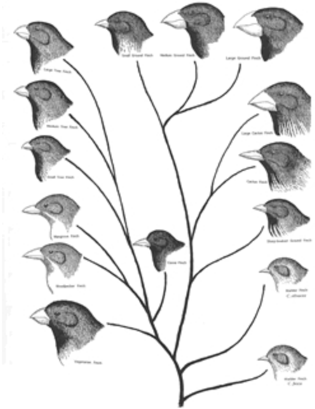
Onze Vader in de Hemel, laat Uw Naam geheiligd worden

Our Father in heaven, hallowed be your name

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



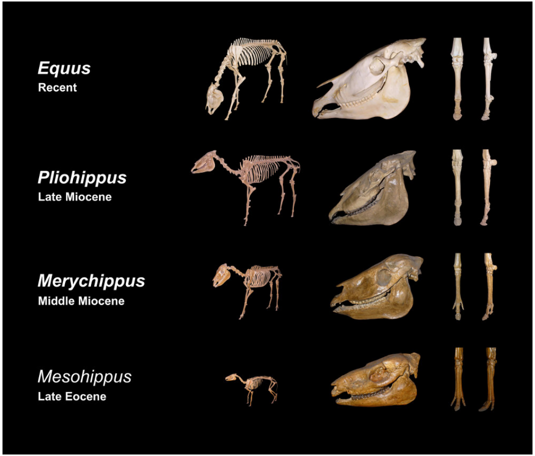

Germanic
East Germanic
Gothic
Vandalic
Burgundian
Langobardic
North Germanic
Icelandic
Faroese
Norwegian
Danish
Swedish
West Germanic
High German
Yiddish
German
Low German
Plattdeutsch
Netherlandish
Afrikaans
Anglo-Frisian
Frisian
English

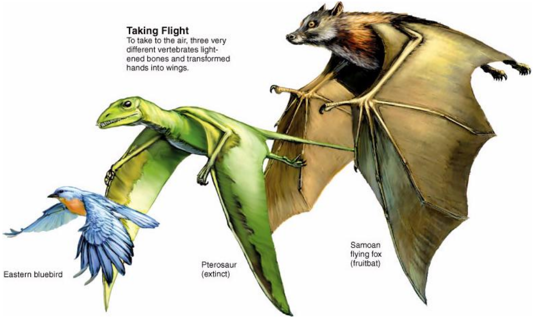


Mittelhochdeutsch:
Got vater unser, dâ du bist in dem himelrîche gewaltic alles des dir ist, geheiliget sô werde dîn nam

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

Gotisch:
Atta unsar þu in himinam, weihnai namo þein

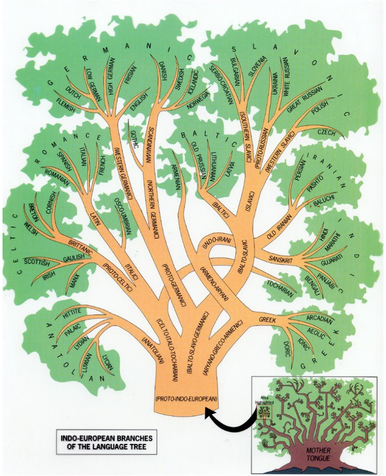




- Old English *docga* > English *dog*
- Proto-Paman **gudaga* > Mbabaram *dog* ('dog')

Comparative method

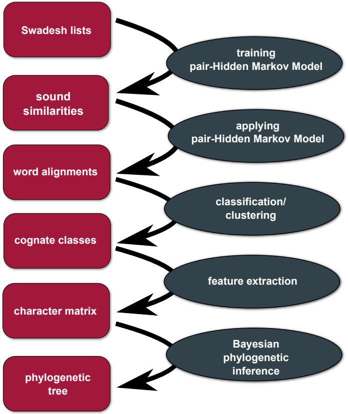
1. identifying *cognates*, i.e. obviously related morphemes in different languages, such as *new/nowy*, *two/dwa*, or *water/voda*
2. reconstruction of *common ancestor* and *sound laws* that explain the change from reconstructed to observed forms
3. applying this iteratively leads to phylogenetic language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



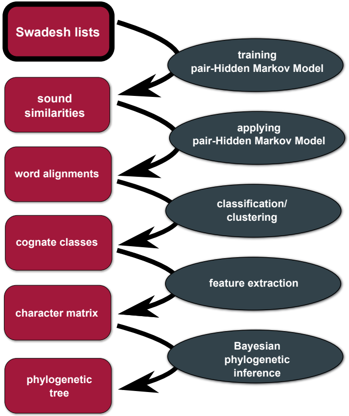
Scope of the method

- 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)

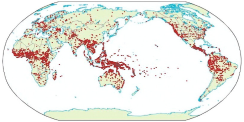
- both cognate detection and tree construction lend themselves to algorithmic implementation
- Advantages:
  - easy to scale up
  - comparability of results
  - affords statistical evaluation
- Disadvantages:
  - cognacy judgments require lots of linguistic insight and experience
  - tree construction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

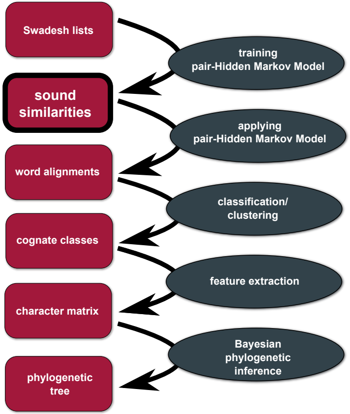

Swadesh lists
training
pair-Hidden Markov Model
sound
similarities
applying
pair-Hidden Markov Model
word alignments
classification/
clustering
cognate classes
feature extraction
character matrix
Bayesian
phylogenetic
inference
phylogenetic
tree

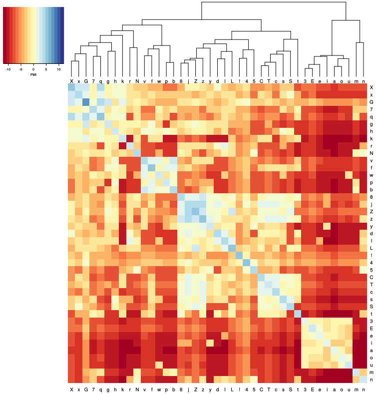
From words to trees

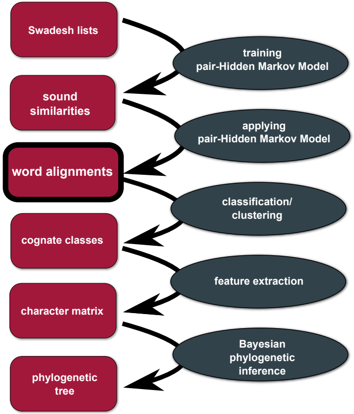


concept	Latin	English
I	ego	Ei
you	tu	yu
we	nos	wi
one	unus	w3n
two	duo	tu
person	persona, homo	pers3n
fish	piskis	fiS
dog	kanis	dag
louse	pedikulus	laus
tree	arbor	tri
leaf	foly∼u*	lif
skin	kutis	skin
blood	saNgw∼is	bl3d
bone	os	bon
horn	kornu	horn
ear	auris	ir
eye	okulus	Ei

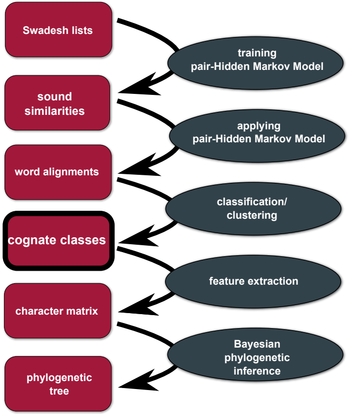


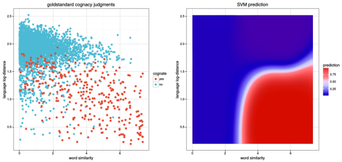

Swadesh lists
training
pair-Hidden Markov Model
sound similarities
applying
pair-Hidden Markov Model
word alignments
classification/
clustering
cognate classes
feature extraction
character matrix
Bayesian
phylogenetic
inference
phylogenetic
tree


-10 -5 0 5 10
PMI
X x G 7 q g h k r N v f w p b 8 j Z z y d l L ! 4 5 C T c s S t 3 E e i a o u m n



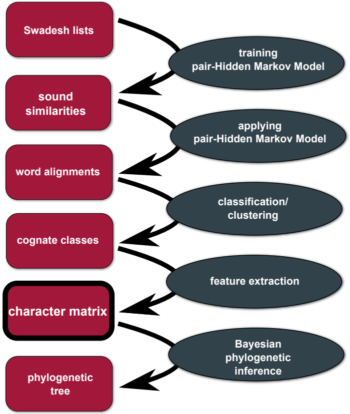
Language	*fish:z*	*tongue:1*	*smoke:1*
Abui-Atangmelang	-af-u		
Abui-Fuimelang	-af-u	tal-i-fi--	
Adang	aab--	tal-E-b---	awai--b-a-n-o-7o-
Blagar-Bakalang	-ab--	--j-e-bur-	--ad--b-a-n-aNka-
Blagar-Bama	aab--	teg-e-bur-	------b-e-n-a-xa-
Blagar-Kulijahi	-ab--	tej-e-bur-	------b-e-n-aNka-
Blagar-Nule	aab--	tej-e-bur-	--ad--b-e-n-aNka-
Blagar-Tuntuli	aab--	tej-e-bur-	a-adgeb-a-n-a-q--
Blagar-Warsalelang	-ab--	tel-e-bur-	a-ad--b-a-n-a-x--
Bunaq			------b-o-t-o-h--
Deing	haf--		------buu-n------
Hamap	7ab--	nar-ø-buN-	------b-a-n-o-7--
Kabola	hab--	tal-e-b---	awal--b-e-n-e-7o-
Kaera-Padangsul	-ab--	talee-b---	a-ad--b-e-naa-x--
Kafoa	-afUi	tal-i-p---	------f-o-n-a----
Kamang	-ap-i	nal---pu--	------p-u-n----a-
Kiraman	-Eb--	nal-i-bar-	--ar--b-a-n-o-kan
Klon	-eb-i	gel-E-b---	--ed-ab-o-n------
Kui	-eb--	tal-i-ber-	--ar--b-o-n-o-k--
Kula	-ap-i	-il-I-p---	------p---n-ekka-
Nedebang	aaf-i	gel-e-fu--	--ar-ab-u-n------
Reta	aab--	nal-e-bul-	a-ad--b-o-n-a----
Sar-Adiabang	haf--	--p-e-fal-	--ar--buu-n------
Sar-Nule	haf--	nal-e-faj-	
Sawila	-ap-i	gal-impuru	------p-u-n-a-ka-
Teiwa-Madar	xaf--	gel-i-vi--	------buu-n------
Wersing	-ap-i	nej-e-bur-	--ad-ap-u-n-a-k--
Wpantar	hap--	nal-e-bu--	------b-unn-a----



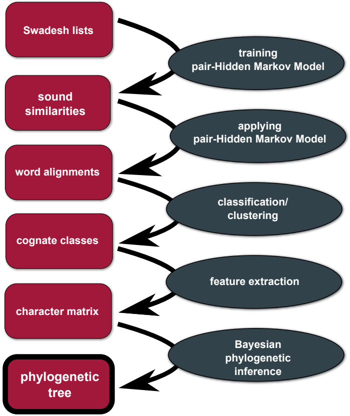


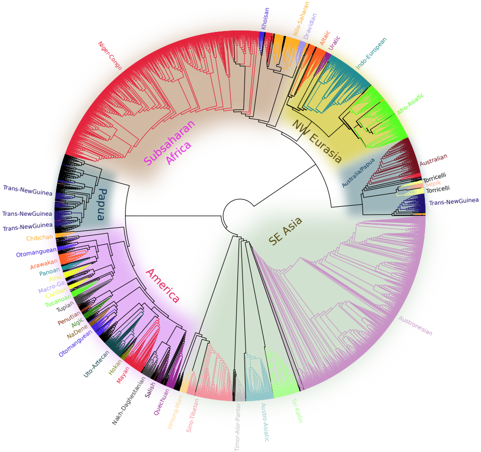
	English	Spanish	Modern Greek	Standard German
I	Ei:A	yo:B	exo:C	iX:D
you	yu:A	ustet:B, tu:C	esi:D	du:E
we	wi:A	nosotros:B	emis:C	vir:A
one	w3n:A	uno:B	enas:C, ena:C	ains:D
two	tu:A	dos:B	8y∼o:C, 8io:D	cvai:E
person	pers3n:A	persona:A	an8∼ropos:B	mEnS:C
fish	fiS:A	peskado:A, pes:A	psari:B	fiS:A
dog	dag:A	pero:B	sTili:C, sTilos:C	hunt:D
come	k3m:A	veni:B	erx∼o:C	kh∼om3n:A
sun	s3n:A	sol:B	ily∼os:C, iLos:C	zon3:A
star	star:A	estreya:A	asteri:A, astro:A	StErn:A
water	wat3r:A	agw∼a:B	nero:C	vas3r:A
stone	ston:A	piedra:B	petra:B	Stain:A
fire	fEir:A	fuego:B	foty∼a:C	foia:D
path	pE8:A	senda:B	8romos:C	pf∼at:A, vek:D
mountain	maunt3n:A	sero:B, monta5a:A	vuno:C, oros:D	bErk:E
full	ful:A	yeno:B	yematos:C, pliris:D	fol:A
new	nu:A	nuevo:A	neos:A, Tenury∼os:B	noi:A
name	nem:A	nombre:A	onoma:A	nam3:A

From words to trees




```
TNG.ENGAN.MAIBI                10000000000000000000000000000000000000000000
TNG.ENGAN.POLE                 00000000000000000000000000000000000010000000
TNG.ENGAN.SAU                  00000000000000000000000000000000000000000000
TNG.ENGAN.YARIBA               10000000000000000000000000000000000000000000
TNG.FASU.FASU                  00000000000000000000000000000000000010000000
TNG.FASU.NAMUMI                00000000000000000000000000000000000000001000
TNG.FINISTERRE-HUON.AWARA      00000000000000000000000000000000000010000000
TNG.FINISTERRE-HUON.BORONG     00000000000000000000000000000000000010000000
TNG.FINISTERRE-HUON.BURUM      00000000000000000000000000000000000010000000
TNG.FINISTERRE-HUON.BURUM_MIND 00000000000000000000000000000000001010000000
TNG.FINISTERRE-HUON.DEDUA      00000000000000000000000000000000000010000000
TNG.FINISTERRE-HUON.HUBE       00000000000000000000000000000000000010000000
TNG.FINISTERRE-HUON.KATE       00000000000000000000000000000000000010000000
TNG.FINISTERRE-HUON.KOMBA      00000000000000000000000000000000000010000000
TNG.FINISTERRE-HUON.KOSORONG   00000000000000000000000000000000000010000000
TNG.FINISTERRE-HUON.MAPE       00000000000000000000000000000000001000000000
TNG.FINISTERRE-HUON.MAPE_2     00000000000000000000000000000000000010000000
TNG.FINISTERRE-HUON.MIGABAC    00000000000000000000000000000000000010000000
TNG.FINISTERRE-HUON.MINDIK     00000000000000000000000000000000000010000000
TNG.FINISTERRE-HUON.MOMOLILI   00000000000000000000000000000000000010000000
TNG.FINISTERRE-HUON.NABAK      00000000000000000000000000000000001000000000
TNG.FINISTERRE-HUON.NANKINA    00000000000000000000000000000000000010000000
TNG.FINISTERRE-HUON.NEK        00000000000000000000000000000000000001000000
TNG.FINISTERRE-HUON.NUKNA      00000000000000000000000000000000000001000000
TNG.FINISTERRE-HUON.ONO        00000000000000000000000000000000000010000000
TNG.FINISTERRE-HUON.SELEPET    00000000000000000000000000000000000010000000
TNG.FINISTERRE-HUON.TIMBE      00000000000000000000000000000000000010000000
TNG.FINISTERRE-HUON.TOBO       00000000000000000000000000000000000010000000
TNG.FINISTERRE-HUON.WANTOAT    00000000000000000000000000000000000110000000
TNG.FINISTERRE-HUON.YOPNO      00000000000000000000000000000000000001000000
TNG.GOILALAN.AFOA              00000000000000000000000000000000000110000000
TNG.GOILALAN.KUNIMAIPA         00000000000000000000000000000000000010000000
TNG.GOILALAN.MAFULU            00000000000000000000000000000000000010000000
```


Swadesh lists
training
pair-Hidden Markov Model
sound
similarities
applying
pair-Hidden Markov Model
word alignments
classification/
clustering
cognate classes
feature extraction
character matrix
Bayesian
phylogenetic
inference
phylogenetic
tree


Subsaharan
Africa
NW Eurasia
Papua
SE Asia
America
Niger-Congo
Khoisan
Nilo-Saharan
Dravidian
Altaic
Uralic
Indo-European
Afro-Asiatic
Australian
AustraliaPapua
Torricelli
Sepik
Torricelli
Trans-NewGuinea
Austronesian
Tai-Kadai
Austro-Asiatic
Timor-Alor-Pantar
Sino-Tibetan
Hmong-Mien
Quechuan
Salish
Nakh-Daghestanian
Mayan
Hokan
Uto-Aztecan
Otomanguean
NaDene
Algic
Penutian
Tupian
Tucanoan
Cariban
Macro-Ge
Ainu
Panoan
Arawakan
Otomanguean
Chibchan
Trans-NewGuinea
Trans-NewGuinea
Trans-NewGuinea

From word lists to distances

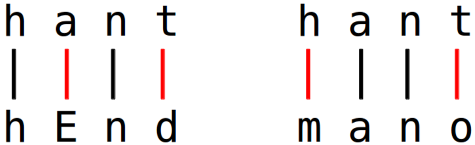
- Project at MPI EVA in Leipzig around Søren Wichmann
- covers more than 6,000 languages and dialects
- basic vocabulary of 40 words for each language, in uniform phonetic transcription
- freely available

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*

concept	Latin	English
I	ego	Ei
you	tu	yu
we	nos	wi
one	unus	w3n
two	duo	tu
person	persona, homo	pers3n
fish	piskis	fiS
dog	kanis	dag
louse	pedikulus	laus
tree	arbor	tri
leaf	foly∼u*	lif
skin	kutis	skin
blood	saNgw∼is	bl3d
bone	os	bon
horn	kornu	horn
ear	auris	ir
eye	okulus	Ei

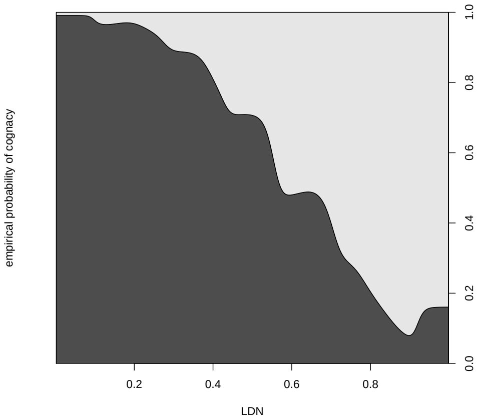
concept	Latin	English
nose	nasus	nos
tooth	dens	tu8
tongue	liNgw∼E	t3N
knee	genu	ni
hand	manus	hEnd
breast	pektus, mama	brest
liver	yekur	liv3r
drink	bibere	drink
see	widere	si
hear	audire	hir
die	mori	dEi
come	wenire	k3m
sun	sol	s3n
star	stela	star
water	akw∼a	wat3r
stone	lapis	ston
fire	iNnis	fEir

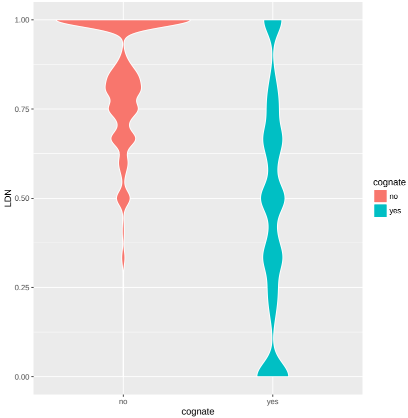
- based on string *alignment*
- baseline: Levenshtein alignment ⇒ count matches and mis-matches



- too crude as it totally ignores sound correspondences

How well does normalized Levenshtein distance predict cognacy?





- binary distinction: match vs. non-match
- frequently genuin sound correspondences in cognates are missed:

c	v	a	i	n	a	**z**	3	-	-	-	**f**	i	S
-	-	**t**	u	n	-	o	**s**	**p**	i	s	k	i	s

- corresponding sounds count as mismatches even if they are aligend correctly

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

- substantial amount of chance similarities

- weighted alignment using **P**ointwise **M**utual **I**nformation (PMI, a.k.a. *log-odds*):

$$s(a,b) = \log \frac{p(a,b)}{q(a)q(b)}$$

  - $p(a,b)$: probability of sound a being etymologically related to sound b in a pair of cognates
  - $q(a)$: relative frequency of sound a
- **Needleman-Wunsch algorithm:** given a matrix of pairwise PMI scores between individual symbols and two strings, it returns the alignment that maximizes the aggregate PMI score
- but first we need to estimate $p(a,b)$ and $q(a), q(b)$ for all soundclasses a and b
- $q(a)$: relative frequency of occurence of segment a in all words in ASJP
- $p(a,b)$: that's a bit more complicated...

Substitution matrix for the ASJP data

1. identify large sample of pairs of closely related languages (using expert information or heuristics based on aggregated Levenshtein distance)

```
An.NORTHERN_PHILIPPINES.CENTRAL_BONTOC
An.MESO-PHILIPPINE.NORTHERN_SORSOGON

WF.WESTERN_FLY.IAMEGA
WF.WESTERN_FLY.GAMAEWE

Pan.PANOAN.KASHIBO_BAJO_AGUAYTIA
Pan.PANOAN.KASHIBO_SAN_ALEJANDRO

AA.EASTERN_CUSHITIC.KAMBAATA_2
AA.EASTERN_CUSHITIC.HADIYYA_2

ST.BAI.QILIQIAO_BAI_2
ST.BAI.YUNLONG_BAI

An.SULAWESI.MANDAR
An.OCEANIC.RAGA

An.SULAWESI.TANETE
An.SAMA-BAJAW.BOEPINANG_BAJAU

An.SOUTHERN_PHILIPPINES.KAGAYANEN
An.NORTHERN_PHILIPPINES.LIMOS_KALINGA

An.MESO-PHILIPPINE.CANIPAAN_PALAWAN
An.NORTHWEST_MALAYO-POLYNESIAN.LAHANAN

NC.BANTOID.LIFONGA
NC.BANTOID.BOMBOMA_2

IE.INDIC.WAD_PAGGA
IE.INDIC.TALAGANG_HINDKO

NC.BANTOID.LINGALA
NC.BANTOID.LIFONGA

An.CENTRAL_MALAYO-POLYNESIAN.BALILEDO
An.CENTRAL_MALAYO-POLYNESIAN.PALUE

AuA.MUNDA.HO
AuA.MUNDA.KORKU
```

2. pick a concept and a pair of related languages at random
   - languages: `Pen.MAIDUAN.MAIDU_KONKAU`, `Pen.MAIDUAN.NE_MAIDU`
   - concept: *one*
3. find corresponding words from the two languages:
   - `nisam`, `niSem`
4. do Levenshtein alignment

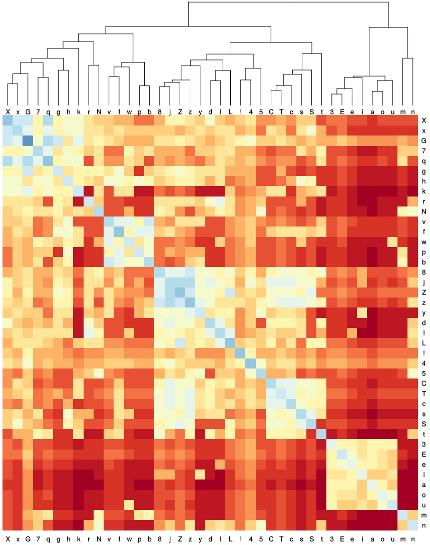
n	i	s	a	m
n	i	S	e	m

5. for each sound pair, count number of correspondences
   - nn: 1; ii: 1; sS; 1; ae: 1; mm: 1

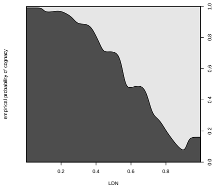
- Dynamic Programming

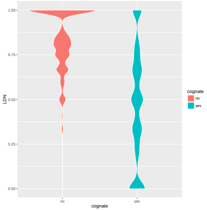
	–	m	E	n	S
–	0	−2.5	−4.1	−5.7	−7.3
m	−2.5	4.13	1.53	0.03	−1.47
e	−4.1	1.53	5.65	3.05	1.55
n	−5.7	0.03	3.05	9.2	6.6
E	−7.3	−1.47	4.75	6.6	7.62
s	−8.9	−2.97	2.15	5.1	8.84

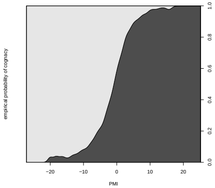
- memorizing in each step which of the three cells to the left and above gave rise to the current entry lets us recover the corresponing optimal alignment

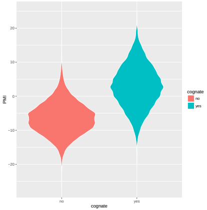

X x G 7 q g h k r N v f w p b 8 j Z z y d l L ! 4 5 C T c s S t 3 E e i a o u m n

expert cognacy judgments used as gold standard







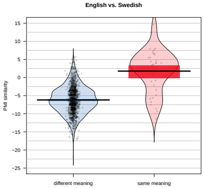


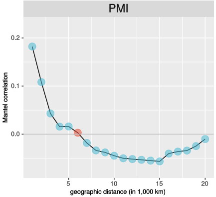
English / Swedish

	Ei	yu	wi	w3n	tu	fiS	...
yog	**−7.77**	0.75	−7.68	−7.90	−8.57	−10.50	
du	−7.62	**0.33**	−5.71	−7.41	2.66	−8.57	
vi	−2.72	−2.83	**4.04**	−1.34	−6.45	0.70	
et	−5.47	−7.87	−5.47	**−6.43**	−1.83	−4.70	
tvo	−7.91	−4.27	−3.64	−4.57	**0.39**	−6.98	
fisk	−7.45	−11.2	−3.07	−9.97	−8.66	**7.58**	
⋮							

- values along diagonal give similarity between candidates for cognacy (possibility of meaning change is disregarded)
- values off diagonal provide sample of similarity distribution between non-cognates

- let s be the PMI-similarity between the English and Swedish word for concept c
- **calibrated string similarity**: $-\log($probability that random word pairs are more similar than $s)$
- **language similarity:** average word similarity for all concepts



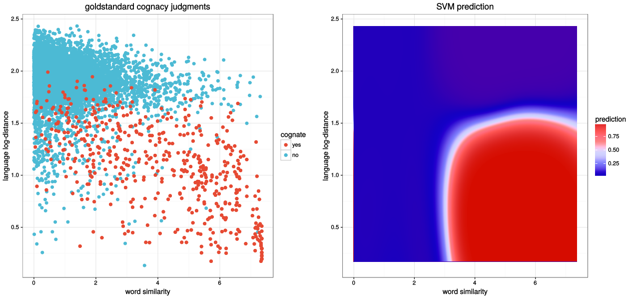


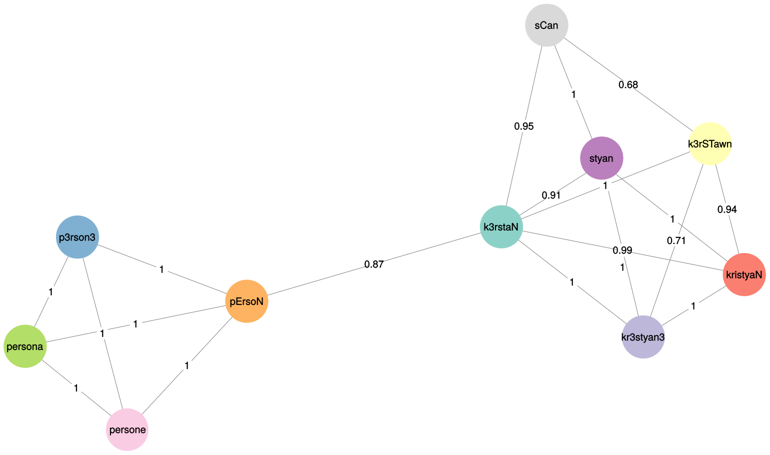
Cognate clustering

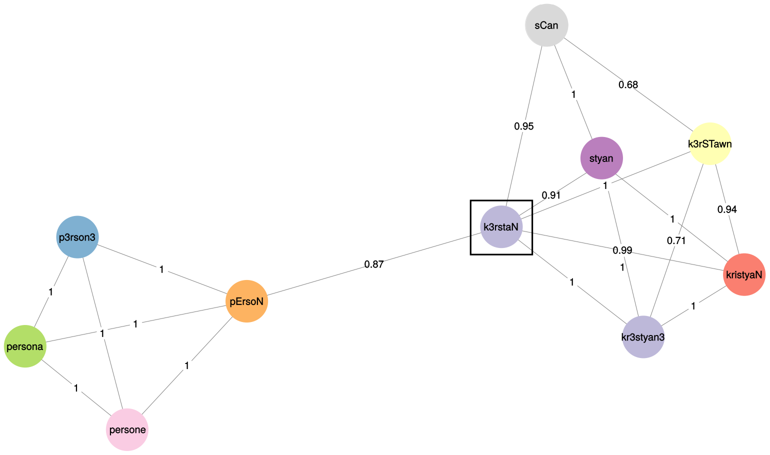
- clustering of ASJP strings into *automatically inferred cognate classes* (Jäger and Sofroniev, 2016; Jäger et al., 2017) (take "cognate" with a grain of salt)
- supervised learning, based on expert cognacy judgments as goldstandard
- sources (only the 40 ASJP concepts were used)

Dataset	Source	Words	Concepts	Languages	Families	Cognate classes
ABVD	Greenhill et al. (2008)	2,306	34	100	Austronesian	409
Afrasian	Militarev (2000)	770	39	21	Afro-Asiatic	351
Chinese	Běijng Dàxué (1964)	422	20	18	Sino-Tibetan	126
Huon	McElhanon (1967)	441	32	14	Trans-New Guinea	183
IELex	Dunn (2012)	2,089	40	52	Indo-European	318
Japanese	Hattori (1973)	387	39	10	Japonic	74
Kadai	Peiros (1998)	399	40	12	Tai-Kadai	102
Kamasau	Sanders and Sanders (1980)	270	36	8	Torricelli	59
Mayan	Brown et al. (2008)	1,113	40	30	Mayan	241
Miao-Yao	Peiros (1998)	206	36	6	Hmong-Mien	69
Mixe-Zoque	Cysouw et al. (2006)	355	39	10	Mixe-Zoque	79
Mon-Khmer	Peiros (1998)	579	40	16	Austroasiatic	232
ObUgrian	Zhivlov (2011)	769	39	21	Uralic	68
total		10,106	40	318	13	2,311

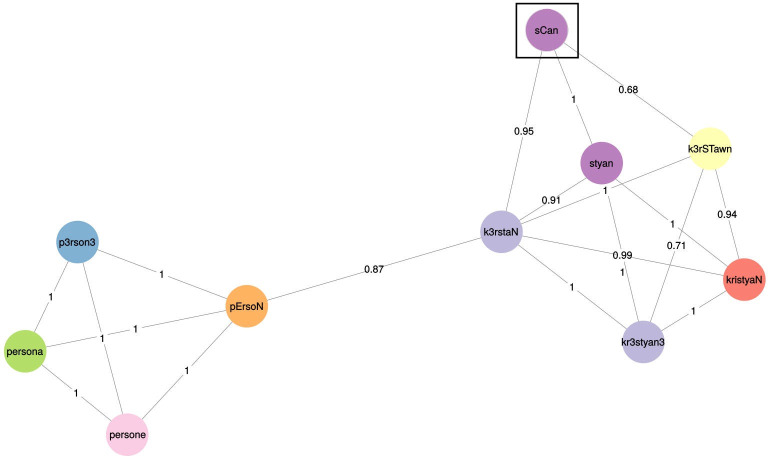
- calibrated word similarity and language similarity were used as predictors to train a *Support Vector Machine* → probability of being cognate for each pair of synonymous ASJP entries
- *Label Propagation* (Raghavan et al., 2007) for clustering
- 0.84 B-cubed F-score with cross-validation on goldstandard data

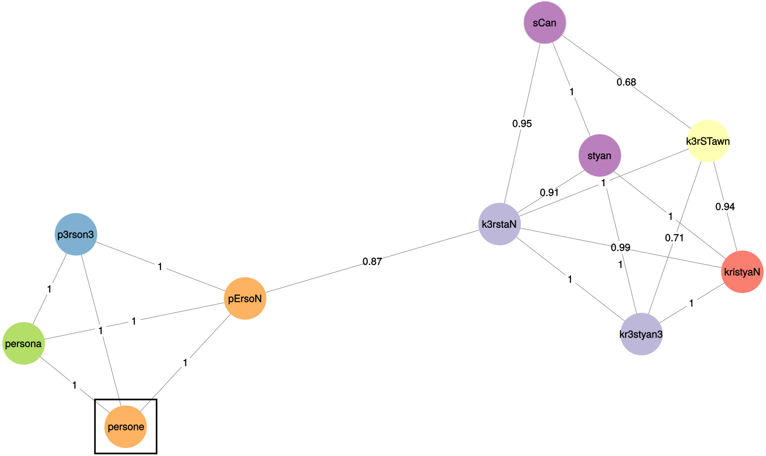


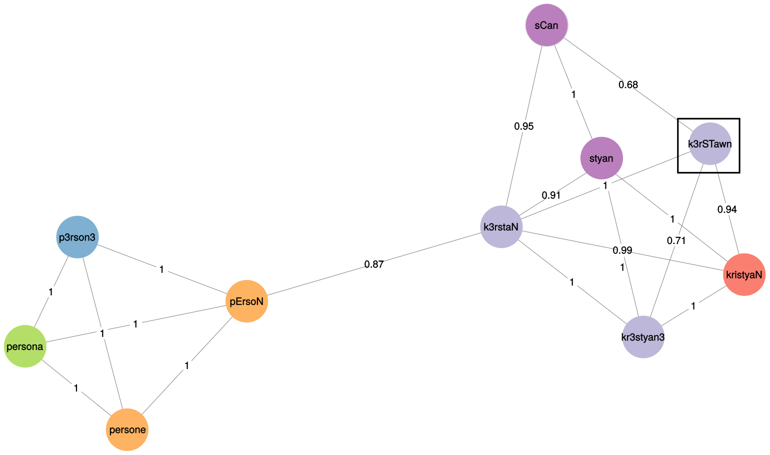

sCan
0.68
1
0.95
k3rSTawn
styan
1
0.91
0.94
1
k3rstaN
p3rson3
0.71
0.99
1
kristyaN
1
0.87
1
1
pErsoN
1
1
1
kr3styan3
persona
1
1
1
persone

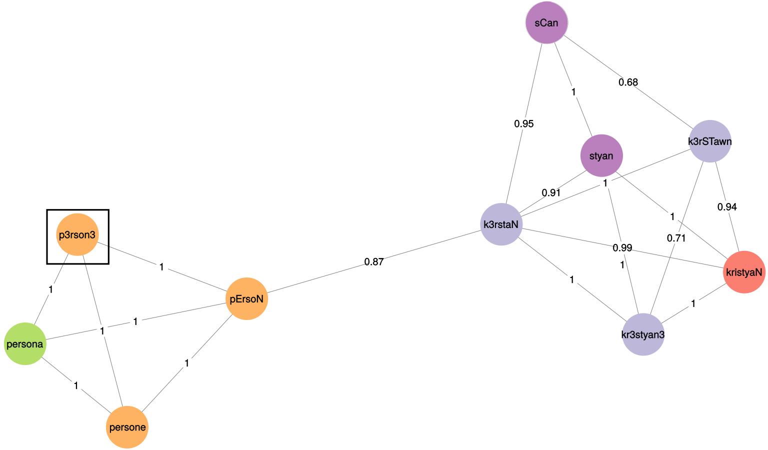

sCan
0.95
1
0.68
styan
k3rSTawn
0.91
1
0.94
k3rstaN
1
0.71
0.99
p3rson3
1
0.87
kristyaN
1
1
pErsoN
1
1
1
kr3styan3
persona
1
1
1
persone

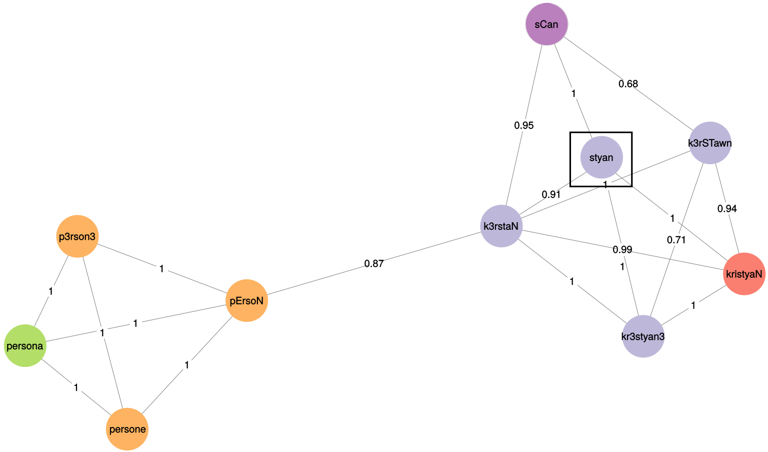
Clustering via Label Propagation



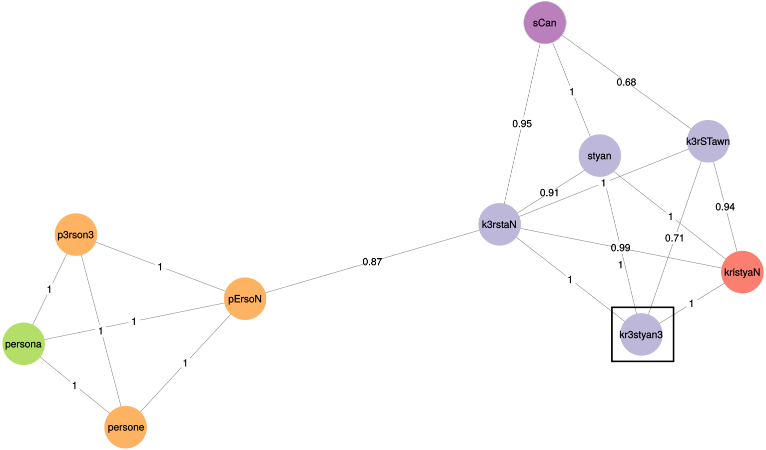

sCan
styan
k3rSTawn
k3rstaN
kristyaN
kr3styan3
p3rson3
pErsoN
persona
persone
0.68
1
0.95
0.91
1
0.94
1
0.71
0.99
1
0.87
1
1
1
1
1
1
1
1

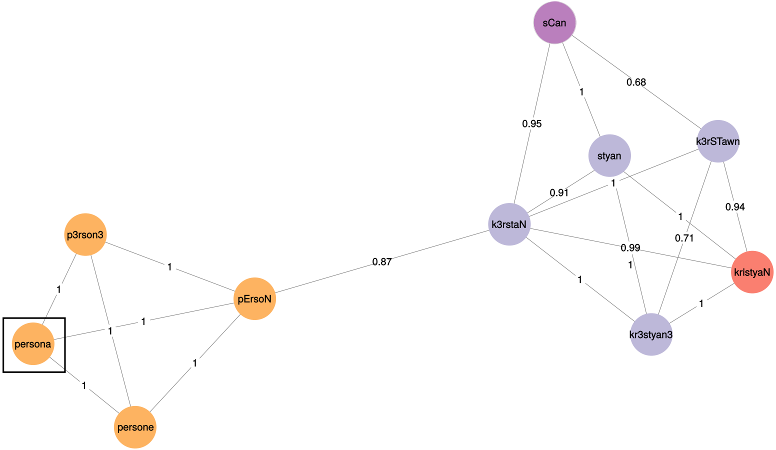

sCan
0.68
1
0.95
k3rSTawn
styan
1
0.91
0.94
1
k3rstaN
0.71
0.99
p3rson3
1
1
0.87
kristyaN
1
1
pErsoN
1
1
1
kr3styan3
persona
1
1
persone

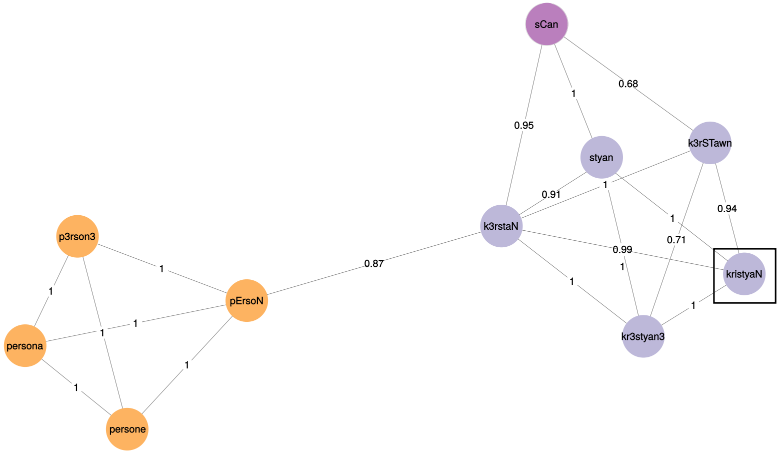

sCan
styan
k3rSTawn
k3rstaN
kristyaN
kr3styan3
p3rson3
pErsoN
persona
persone
0.68
1
0.95
0.91
1
1
0.94
0.71
0.99
1
1
1
0.87
1
1
1
1
1
1
1

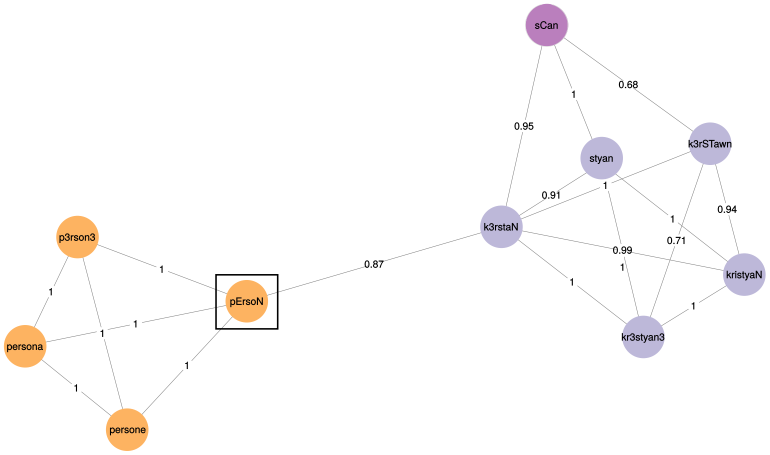

sCan
1
0.68
0.95
k3rSTawn
styan
1
0.91
0.94
1
k3rstaN
0.71
0.99
p3rson3
1
0.87
1
kristyaN
1
1
pErsoN
1
1
1
kr3styan3
persona
1
1
1
persone

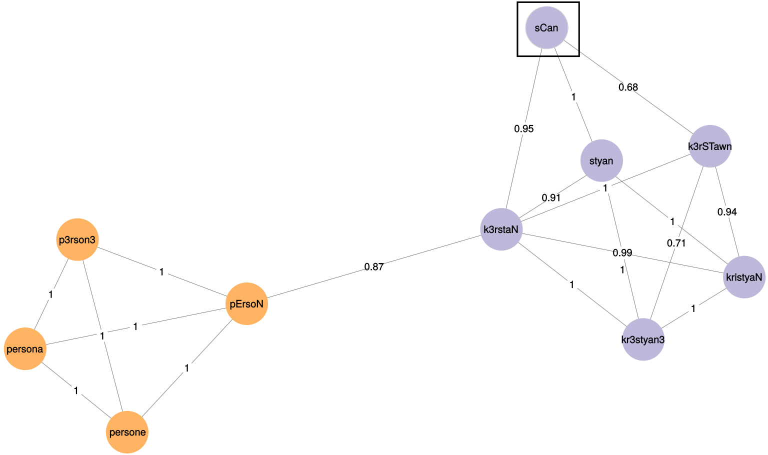
Clustering via Label Propagation




sCan
0.68
1
0.95
k3rSTawn
styan
1
0.91
1
0.94
k3rstaN
0.71
0.99
p3rson3
0.87
1
1
1
kristyaN
1
1
pErsoN
1
1
persona
kr3styan3
1
1
persone


sCan
0.68
1
0.95
k3rSTawn
styan
1
0.91
0.94
1
k3rstaN
0.71
0.99
p3rson3
kristyaN
1
0.87
1
1
1
pErsoN
1
1
1
kr3styan3
persona
1
1
persone

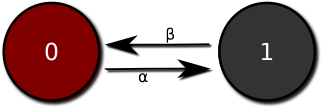

sCan
0.68
1
0.95
k3rSTawn
styan
1
0.91
0.94
k3rstaN
1
0.71
p3rson3
0.99
1
1
kristyaN
0.87
1
1
pErsoN
1
1
1
1
kr3styan3
persona
1
1
persone


sCan
0.68
1
0.95
k3rSTawn
styan
1
0.91
0.94
1
k3rstaN
0.71
p3rson3
0.99
1
1
kristyaN
1
0.87
1
pErsoN
1
1
1
persona
1
kr3styan3
1
1
persone

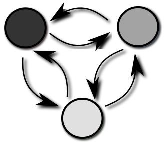
doculect	word	class label
ALBANIAN	vet3	0
ALBANIAN_TOSK	vEt3	0
ARAGONESE	ombre	1
ITALIAN_GROSSETO_TUSCAN	omo	2
ROMANIAN_MEGLENO	wom	2
VLACH	omu	2
ASTURIAN	persona	3
BALEAR_CATALAN	p3rson3	3
CATALAN	p3rson3	3
FRIULIAN	pErsoN	3
ITALIAN	persona	3
SPANISH	persona	3
VALENCIAN	persone	3
CORSICAN	nimu	4
DALMATIAN	om	5
EMILIANO_CARPIGIANO	om	5
ROMANIAN_2	om	5
TURIA_AROMANIAN	om	5
EMILIANO_FERRARESE	styan	6
LIGURIAN_STELLA	kristyaN	6
NEAPOLITAN_CALABRESE	kr3styan3	6
ROMAGNOL_RAVENNATE	sCan	6
ROMANSH_GRISHUN	k3rSTawn	6
ROMANSH_SURMIRAN	k3rstaN	6
GALICIAN	ome	7
GASCON	omi	7
PIEMONTESE_VERCELLESE	omaN	8
ROMANSH_VALLADER	uman	8
ALBANIAN_GHEG	5eri	9
SARDINIAN_CAMPIDANESE	omini	9
SARDINIAN_LOGUDARESE	omine	9

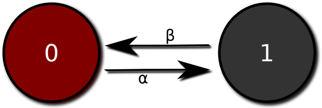
concept	doculect	glot_fam	transcription
eye	DORASQUE	Chibchan	oko
eye	NORTHERN_LOW_SAXON	Indo-European	ok
eye	NORTH_FRISIAN_AMRUM	Indo-European	uk
eye	STELLINGWERFS	Indo-European	ok
eye	ASSAMESE	Indo-European	soku
eye	CHAKMA_UnnamedInSource	Indo-European	sog
eye	DALMATIAN	Indo-European	vaklo
eye	FRIULIAN	Indo-European	voli
eye	ITALIAN	Indo-European	okkyo
eye	ITALIAN_GROSSETO_TUSCAN	Indo-European	okyo
eye	JUDEO_ESPAGNOL	Indo-European	oxo
eye	LATIN	Indo-European	okulus
eye	NEAPOLITAN_CALABRESE	Indo-European	woky3
eye	ROMANIAN_2	Indo-European	oky
eye	ROMANIAN_MEGLENO	Indo-European	wokLu
eye	SARDINIAN	Indo-European	ogu
eye	SARDINIAN_CAMPIDANESE	Indo-European	oxu
eye	SARDINIAN_LOGUDARESE	Indo-European	okru
eye	SICILIAN_UnnamedInSource	Indo-European	okiu
eye	SPANISH	Indo-European	oho
eye	TURIA_AROMANIAN	Indo-European	okLu
eye	VLACH	Indo-European	okklu
eye	BELARUSIAN	Indo-European	voka
eye	BOSNIAN	Indo-European	oko
eye	BULGARIAN	Indo-European	oko
eye	CROATIAN	Indo-European	oko
eye	CZECH	Indo-European	oko
eye	KASHUBIAN	Indo-European	wokwo
eye	LOWER_SORBIAN	Indo-European	voko
eye	LOWER_SORBIAN_2	Indo-European	woko
eye	MACEDONIAN	Indo-European	oko
eye	OLD_CHURCH_SLAVONIC	Indo-European	oko
eye	POLISH	Indo-European	oko
eye	SERBOCROATIAN	Indo-European	oko
eye	SLOVAK	Indo-European	oko
eye	SLOVENIAN	Indo-European	oko
eye	UKRAINIAN	Indo-European	oko
eye	UPPER_SORBIAN	Indo-European	voCko
eye	UPPER_SORBIAN	Indo-European	voko
eye	BAINOUK_GUNYAAMOLO	Atlantic-Congo	g3li
eye	USINO	Nuclear_Trans_New_Guinea	ogo

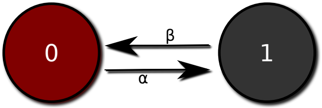
Phylogenetic inference based on continuous time Markov process



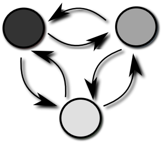
Markov process



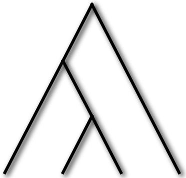




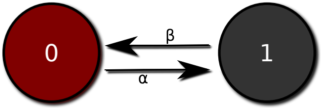
Markov process

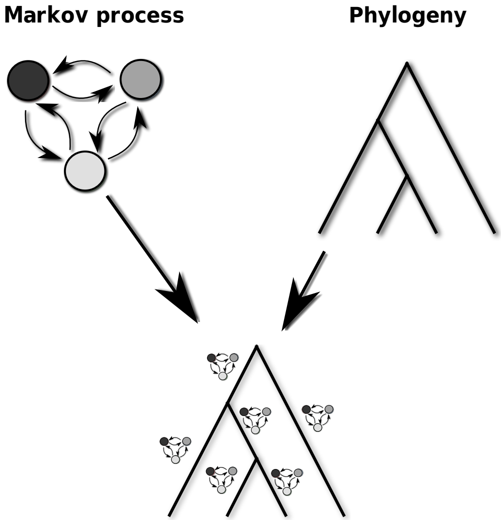


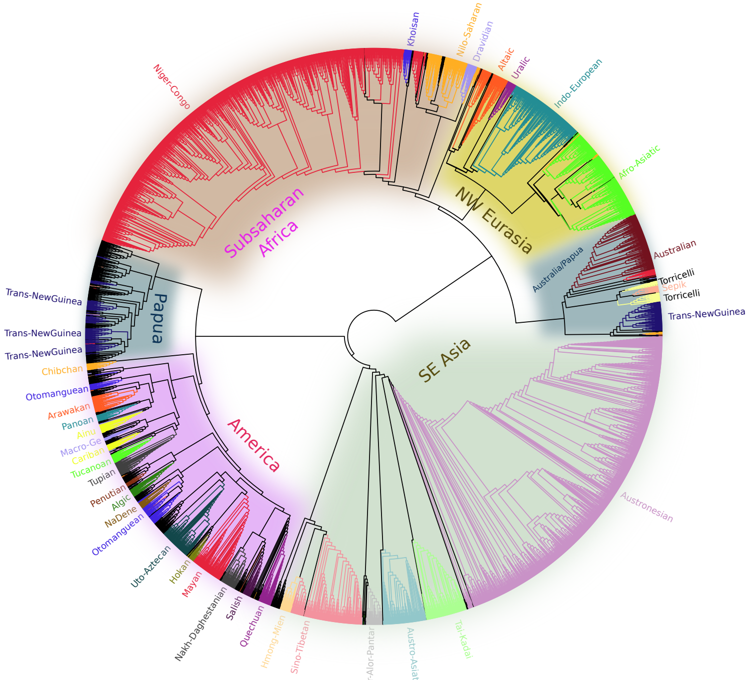
Phylogeny



Phylogenetic inference based on continuous time Markov process






Niger-Congo
Khoisan
Nilo-Saharan
Dravidian
Altaic
Uralic
Indo-European
Afro-Asiatic
Subsaharan Africa
NW Eurasia
Australia/Papua
Australian
Torricelli
Sepik
Torricelli
Trans-NewGuinea
Papua
Trans-NewGuinea
Trans-NewGuinea
Trans-NewGuinea
SE Asia
Austronesian
Tai-Kadai
Sino-Tibetan
Hmong-Mien
Quechuan
Salish
Nakh-Daghestanian
Mayan
Hokan
Uto-Aztecan
Otomanguean
NaDene
Algic
Penutian
Tupian
Tucanoan
Cariban
Macro-Ge
Ainu
Panoan
Arawakan
Otomanguean
Chibchan
America

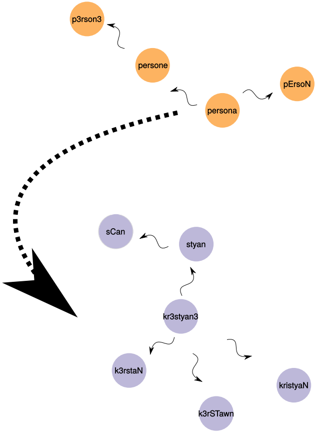
Embedding words into vector space

disadvantes

- fine phonetic details lost after clustering ⇒ these details are actually important for reconstructing language change
- *ascertainment bias*: unobserved states cannot be reconstructed

alternative approach (programmatic)

- map words into *feature space of fixed dimensionality*
- sound change ⇒ small step
- lexical substitution ⇒ (mostly) large jump
- enables reconstruction of unobserved states via interpolation



one-hot encoding of sound classes

sound class
X
G
7
q
s
t
k
C
T
a
E
3

X	G	7	q	s	t	k	C	T	a	E	3
1	0	0	0	0	0	0	0	0	0	0	0
0	1	0	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0	0	0
0	0	0	1	0	0	0	0	0	0	0	0
0	0	0	0	1	0	0	0	0	0	0	0
0	0	0	0	0	1	0	0	0	0	0	0
0	0	0	0	0	0	1	0	0	0	0	0
0	0	0	0	0	0	0	1	0	0	0	0
0	0	0	0	0	0	0	0	1	0	0	0
0	0	0	0	0	0	0	0	0	1	0	0
0	0	0	0	0	0	0	0	0	0	1	0
0	0	0	0	0	0	0	0	0	0	0	1

sound class
X
G
7
q
s
t
k
C
T
a
E
3

➔

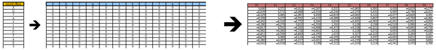
X	G	7	q	s	t	k	C	T	a	E	3
1	0	0	0	0	0	0	0	0	0	0	0
0	1	0	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0	0	0
0	0	0	1	0	0	0	0	0	0	0	0
0	0	0	0	1	0	0	0	0	0	0	0
0	0	0	0	0	1	0	0	0	0	0	0
0	0	0	0	0	0	1	0	0	0	0	0
0	0	0	0	0	0	0	1	0	0	0	0
0	0	0	0	0	0	0	0	1	0	0	0
0	0	0	0	0	0	0	0	0	1	0	0
0	0	0	0	0	0	0	0	0	0	1	0
0	0	0	0	0	0	0	0	0	0	0	1

dense embedding of sound classes

X	G	7	q	s	t	k	C	T	a	E	3
1	0	0	0	0	0	0	0	0	0	0	0
0	1	0	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0	0	0
0	0	0	1	0	0	0	0	0	0	0	0
0	0	0	0	1	0	0	0	0	0	0	0
0	0	0	0	0	1	0	0	0	0	0	0
0	0	0	0	0	0	1	0	0	0	0	0
0	0	0	0	0	0	0	1	0	0	0	0
0	0	0	0	0	0	0	0	1	0	0	0
0	0	0	0	0	0	0	0	0	1	0	0
0	0	0	0	0	0	0	0	0	0	1	0
0	0	0	0	0	0	0	0	0	0	0	1

➔

F0	F1	F2	F3	F4	F5	F6	F7	F8	F9
0.040	0.371	−0.912	−0.267	0.537	−0.063	0.991	0.430	−0.819	−0.279
−0.039	0.572	−0.466	−0.919	−0.240	−0.370	0.431	0.905	−0.796	−0.423
−0.329	0.485	−1.067	0.450	−0.619	−0.002	0.121	−0.477	−0.826	0.301
−0.358	0.270	−0.552	−0.233	−0.066	−0.048	0.807	0.651	−0.794	−0.481
−0.942	−0.316	−0.752	0.044	0.634	−0.491	−0.063	−0.441	−0.691	−0.816
−0.390	−0.279	0.622	−0.550	1.391	0.128	0.156	−0.519	0.990	−0.323
−0.617	0.552	−0.202	−0.698	−0.473	−0.318	−0.221	0.640	−0.892	−0.716
−0.962	−0.384	−0.728	−0.601	1.232	0.126	0.072	0.053	0.108	−0.046
−0.811	−0.556	−0.840	−0.295	1.015	0.327	−0.323	−0.031	0.264	0.187
−0.070	0.360	−0.133	−0.156	−0.345	−0.476	0.297	−0.043	0.872	0.207
−0.360	−0.367	−0.217	−0.041	−0.359	−0.155	−0.370	−0.071	0.836	0.694
−0.042	−0.018	−0.112	0.336	−0.222	−0.203	0.214	−0.341	0.470	0.766

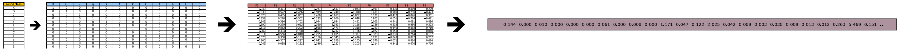


LSTM string embedding

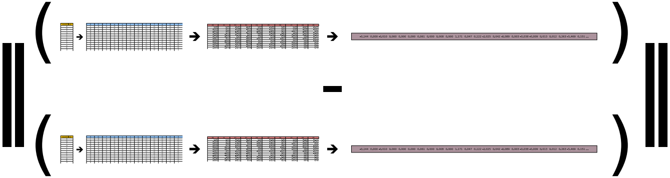
sound class
p
e
r
s
o
n
a

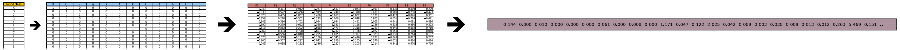
F0	F1	F2	F3	F4	F5	F6	F7	F8	F9
0.196	−1.239	1.177	−1.640	0.340	0.673	−0.303	−0.093	−1.291	−0.304
−0.352	−0.279	−0.211	0.013	−0.216	−0.068	−0.547	0.141	0.718	0.699
−0.859	0.438	0.939	1.145	−0.255	1.230	0.229	0.220	−0.421	−0.161
−0.942	−0.316	−0.752	0.044	0.634	−0.491	−0.063	−0.441	−0.691	−0.816
0.265	0.211	−0.012	0.188	−0.240	−0.368	0.400	−1.081	−0.039	0.301
1.087	0.984	−0.081	0.271	0.013	0.629	−0.226	0.195	0.281	−0.567
−0.070	0.360	−0.133	−0.156	−0.345	−0.476	0.297	−0.043	0.872	0.207

-0.144 0.000 -0.010 0.000 0.000 0.000 0.061 0.000 0.008 0.000 1.171 0.047 0.122 -2.025 0.042 -0.089 0.003 -0.038 -0.009 0.013 0.012 0.263 -5.469 0.151 ...

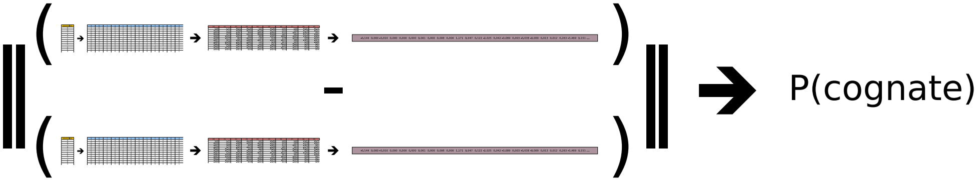


Euclidean distance

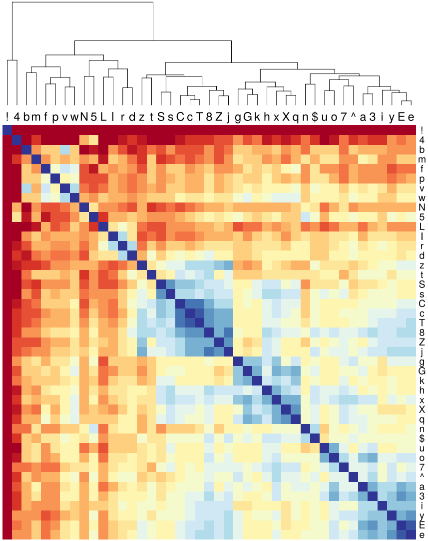




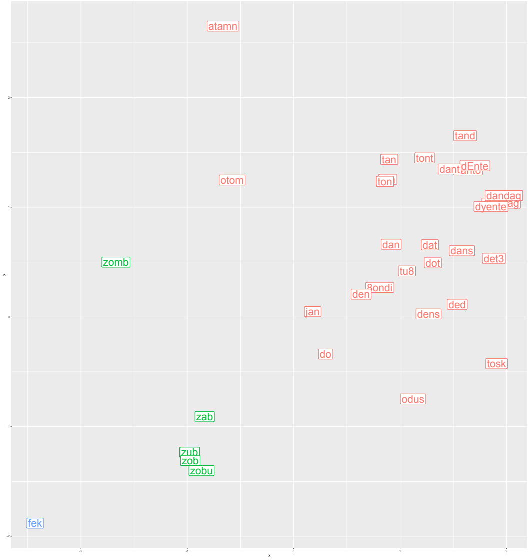
cognacy prediction

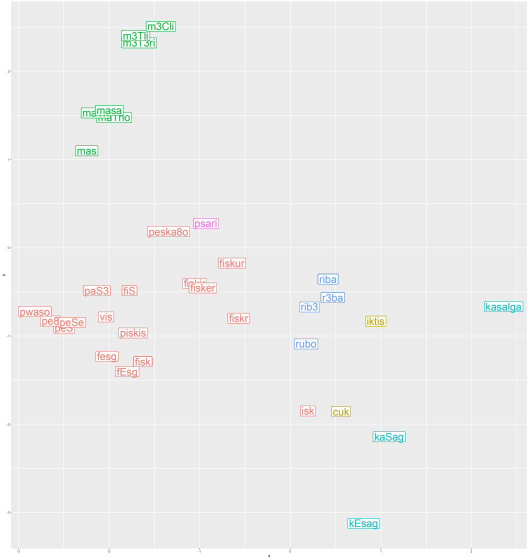


- sound embedding: 10 dimensions
- LSTM:
  - hidden layer with 50 dimensions
  - output layer with 50 dimensions
- training
  - first iteration:
    - 4 mill word pairs (50% cognate, 50% non-cognate)
    - cognacy decision derived from string alignment
  - second/third iteration:
    - negative training data: non-synonyms
    - positive training data: from previous iteration, with $p > 0.5$


! 4 b m f p v w N 5 L l r d z t S s C c T 8 Z j g G k h x X q n $ u o 7 ^ a 3 i y E e

Pilot study: word embeddings

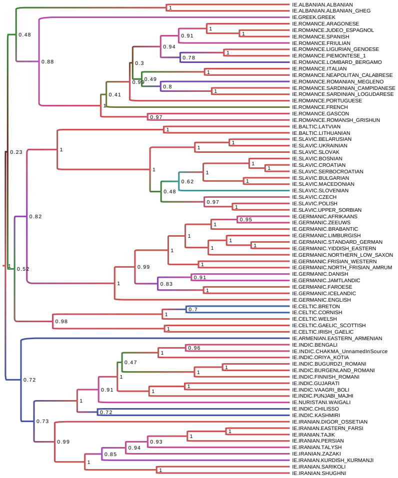




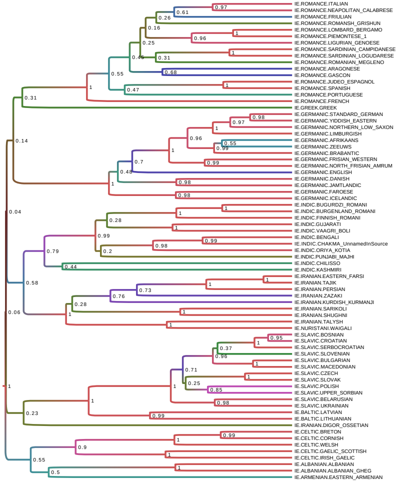
B-cubed	**SVM-based** (supervised)	**embedding-based** (unsupervised)
precision	0.877	0.715
recall	0.770	0.669
F-score	0.820	0.691

(data from `ielex.mpi.nl`)

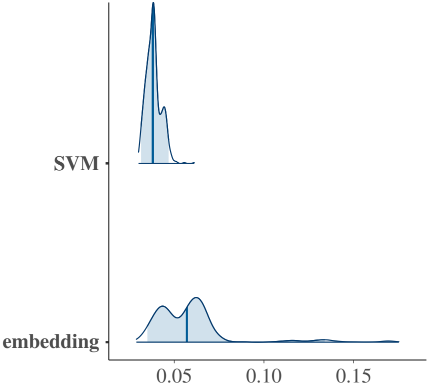
SVM clustering



LSTM embedding



generalized quartet distance to expert tree



Summary

- automatic reconstruction of language change via Bayesian inference
- machine learning indispensable to pre-process data
- deep networks are promising tool to develop unified representation format

References

Cecil H. Brown, Eric W. Holman, Søren Wichmann, and Viveka Velupillai. Automated classification of the world's languages: A description of the method and preliminary results. *STUF — Language Typology and Universals*, 4:285–308, 2008.

Běijng Dàxué. *Hànyǔ fngyán cíhuì* [Chinese dialect vocabularies]. Wénzì Gǎigé, 1964.

Michael Cysouw, Søren Wichmann, and David Kamholz. A critique of the separation base method for genealogical subgrouping. *Journal of Quantitative Linguistics*, 13(2-3):225–264, 2006.

Michael Dunn. Indo-European lexical cognacy database (IELex). URL: `http://ielex.mpi.nl/`, 2012.

Simon J. Greenhill, Robert Blust, and Russell D. Gray. The Austronesian Basic Vocabulary Database: From bioinformatics to lexomics. *Evolutionary Bioinformatics*, 4:271–283, 2008.

Shirō Hattori. Japanese dialects. In Henry M. Hoenigswald and Robert H. Langacre, editors, *Diachronic, areal and typological linguistics*, pages 368–400. Mouton, The Hague and Paris, 1973.

Gerhard Jäger and Pavel Sofroniev. Automatic cognate classification with a Support Vector Machine. In Stefanie Dipper, Friedrich Neubarth, and Heike Zinsmeister, editors, *Proceedings of the 13th Conference on Natural Language Processing*, volume 16 of *Bochumer Linguistische Arbeitsberichte*, pages 128–134. Ruhr Universität Bochum, 2016.

Gerhard Jäger, Johann-Mattis List, and Pavel Sofroniev. Using support vector machines and state-of-the-art algorithms for phonetic alignment to identify cognates in multi-lingual wordlists. In *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics*. ACL, 2017.

Kenneth A. McElhanon. Preliminary observations on Huon Peninsula languages. *Oceanic Linguistics*, 6(1):1–45, 1967. ISSN 00298115, 15279421. URL `http://www.jstor.org/stable/3622923`.

A IU Militarev. *Towards the chronology of Afrasian (Afroasiatic) and its daughter families*. McDonald Institute for Archaelogical Research, Cambridge, 2000.

Ilia Peiros. Comparative linguistics in Southeast Asia. *Pacific Linguistics*, 142, 1998.

Usha Nandini Raghavan, Réka Albert, and Soundar Kumara. Near linear time algorithm to detect community structures in large-scale networks. *Physical Review E*, 76(3):036106, 2007.

Joy Sanders and Arden G Sanders. Dialect survey of the Kamasau language. *Pacific Linguistics. Series A. Occasional Papers*, 56:137, 1980.

Søren Wichmann, Eric W. Holman, and Cecil H. Brown. The ASJP database (version 17). http://asjp.clld.org/, 2016.

Mikhail Zhivlov. Annotated Swadesh wordlists for the Ob-Ugrian group. In George S. Starostin, editor, *The Global Lexicostatistical Database*. RGGU, Moscow, 2011. URL: `http://starling.rinet.ru`.