

Correlating borrowing events across concepts to derive a data-driven source of evidence for loanword etymologies

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Table of Contents

Motivation

Data

Method

Results





Motivation







- Historical linguistics often relies on heuristics based on the shared experience of experts
- To integrate this into theoretical frameworks that can be used in conjunction with computational methods:
 How can we formalize and statistically validate such reasoning patterns in historical linguistics?



Motivation: Automated loanword detection

- Usually based on exceptions from sound laws
- What if we don't know the sound laws already / if there aren't any useful exceptions?

LAT menta DEU mints



Motivation: Automated loanword detection

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LAT menta DEU mints

- If some language has already been established as a donor language for some words, it becomes more likely as a candidate donor for other words
- Assumption that words from the same semantic field get borrowed together
- Historical/cultural knowledge

Can we model these in a *data-driven* way?





Table of Contents

Motivation

Data

Method

Results





Data: WOLD

World loanword database (Haspelmath and Tadmor, 2009)

- 41 (recipient) languages
 (26 families)
- 1,500 concepts
 (24 semantic fields)
- Loanword status:
 - 1. clearly borrowed
 - ... 5. no evidence of borrowing

Borrowability

- 1. Religion/belief
- 2. Clothing/grooming
- 3. The house
- 4. The law

. . .

- 21. Kinship
- 22. The body
- 23. Spatial relations
- 24. Sense perception

(Tadmor, 2009, p. 64)



Data: CLICS²

Cross-linguistic colexifications (List et al., 2018)

- 1,200 languages
- 2,500 concepts
- Network: two concepts share an edge if 3+ unrelated languages use the same lexical unit for both concepts

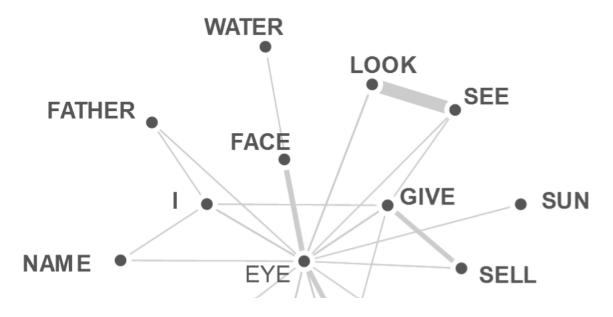






Table of Contents

Motivation

Data

Method

Results





Method

 14,000 clearly/probably borrowed loanwords that do not have inherited synonyms and were borrowed at least 3x

TO BORROW Sakha < Arabic Hausa ...

Thai < Sanskrit Malagasy < Malay ...



Method: Implication strength

Given concepts X and Y, does X being a loanword imply that Y was borrowed by and from the same languages?

$$impl_strength(X,Y) = \frac{\text{\# of donor-target pairs that borrowed X and Y}}{\text{\# of donor-target pairs that borrowed X}}$$



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 $impl_strength(X,Y) = \frac{\text{\# of donor-target pairs that borrowed X and Y}}{\text{\# of donor-target pairs that borrowed X}}$

- THE EAST: borrowed 7x (aqc < ava, kap < ava, rif < ara, rmc < ces, sjd < gmq, swa < ara, vie < cmn)
- THE CAUSE: borrowed 15x (aqc < ava, eng < fra, gwd < amh, hau < ara, ind < ara, kap < ava, knc < ara, qvi < spa, rif < ara, ron < fra, sah < xgn, sjd < rus, swa < ara, tha < san, vie < cmn)

implication_strength(THE EAST, THE CAUSE) $= 5/7 \approx 71\%$ implication_strength(THE CAUSE, THE EAST) $= 5/15 \approx 33\%$





Method: NPMI

Co-occurrence

- What if the concepts were borrowed at very different rates?
- Normalized pointwise mutual information (+1 complete co-occurrence ... 0 independence ... -1 no co-occurrence)

$$\mathsf{NPMI}(x,y) = \frac{\mathsf{In}\frac{p(x,y)}{p(x)p(y)}}{-\mathsf{In}p(x,y)}$$

$$p({\sf THE\ EAST}, {\sf THE\ CAUSE}) = 5/41$$
 $p({\sf THE\ EAST}) = 7/41$ $p({\sf THE\ CAUSE}) = 15/41$ NPMI(THE EAST, THE CAUSE) $pprox 0.32$





Method: Intra-pair similarity

How semantically similar are the concept pairs?

Inverse correlation with CLICS node distance

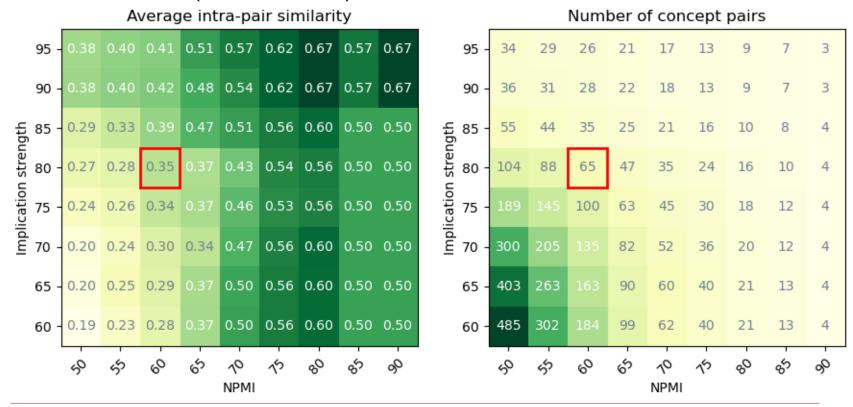
Distance (in edges)	Similarity
1 (colexified)	1
2	0.5
3	0.33
4+	0



Method: Thresholds

Thresholds (determined a posteriori)

• High implication strength (\geq 0.8) that still shows meaningful connections (NPMI \geq 0.6)





Method: Bootstrapping

1,000 bootstrap samples of language sets (with replacement; one-sided 95 % confidence interval)

- 'Noisy' observations that describe only a small number of instances tend to vary more and tend to get filtered out
- Higher implication and correlation scores

	implication strength	
	before	after bootstrapping
THE PARENTS -> TO PEEL	0.5	0.42
THE ARM -> THE LIP	8.0	0.8





Table of Contents

Motivation

Data

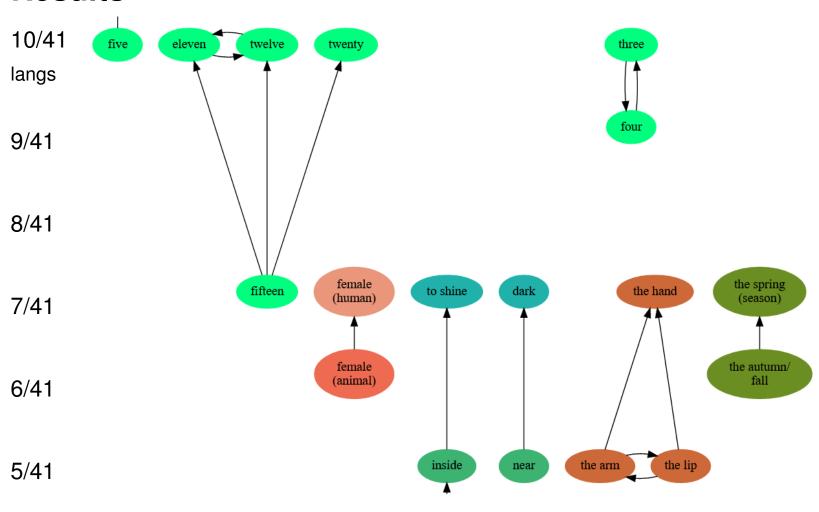
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Results



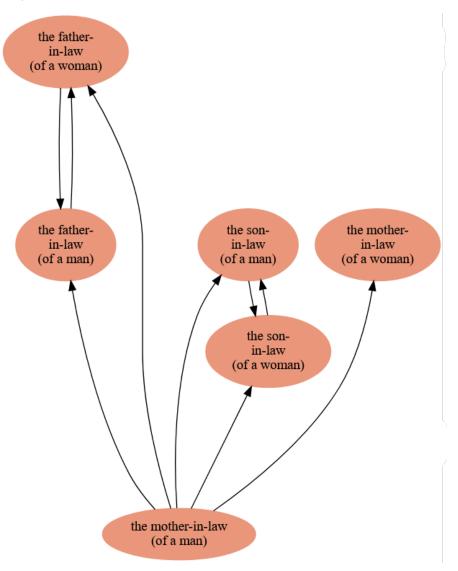




Results

65 concept pairs

- 45 of these are within-domain correlations
- Common semantic fields:
 - ⊳ KINSHIP (!)
 - ▷ QUANTITY (!)
 - > THE BODY
 - ▷ SPATIAL RELATIONS
- ...specifically the rarelyborrowed fields!
- Clusters ('package deals')







Results

Only 20 cross-domain pairs

• 2 largely due to colexification

```
female(2) (ANIMALS) > female(1) (KINSHIP)
the knife(1) (FOOD/DRINK) > the knife(2) (BASIC ACTIONS/TECHNOLOGY)
```

• Some are somewhat plausible, but most appear to be random

```
to kneel (MOTION) > the defeat (WARFARE/HUNTING) > the kidney (THE BODY) ...

to make (BASIC ACTIONS/TECHNOLOGY) > inside (SPATIAL RELATIONS) > to sneeze (THE BODY)
```



To be investigated...

- In some cases, the concept pairs are colexified concepts—how often is that?
- More languages, language families
- How much is there to the cross-domain relations?



Future plans

Incorporate correlation information into model for etymological inference to combine measures of:

- Adherence to soundlaws
- Language contact
- Borrowing frequency by concept, in general and given other borrowed concepts





Conclusion

- Even with a limited sample of languages, we can extract some meaningful borrowing patterns.
- Kinship terms and numerals are not borrowed very often, but when they are, there exist some 'package deals.'

https://github.com/verenablaschke/borrowing-correlations



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References

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Appendix: Bootstrapping

- Sample the set of languages 1,000 times with replacement
- Calculate implication strength and NPMI for each sample
- The scores are the lower bounds of the corresponding (one-sided, right-open, 95%) confidence intervals:

$$\overline{a} - \frac{1.64485s}{\sqrt{1000}}$$

where

- \overline{a} is the arithmetic mean of the given score in all 1,000 samples
- s is the standard deviation of the mean





Appendix: Etymological inference

$$sem_corr(c, L_D, L_R) = \frac{\sum_{c' \in C} P_borr(c', L_D, L_R) \cdot sem_sim(c, c')}{|C|}$$

$$lang_corr(c, L_D, L_R) = \frac{\sum_{c' \in C} P_borr(c', L_D, L_R)}{|C|}$$

$$event_corr(c, L_D, L_R) = \frac{\sum_{c' \in C} P_borr(c', L_D, L_R) \cdot borr_impl(c', c)}{|C|}$$

$$P_borr(c, L_D, L_R) = f(soundlaws(c, L_R), borr_freq(c), sem_corr(c, L_D, L_R), lang_corr(c, L_D, L_R), event_corr(c, L_D, L_R))$$