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EVOLAEMP
Language Evolution:
The Empirical Turn

Information-Weighted Sequence Alignment

Workshop “Trees and what to do with them”

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Table of Contents

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Cognate Detection

- **cognate sets** in quantitative historical linguistics: sets of etymologically related words (which includes borrowings)
- **cognate detection** task: partitioning a set of words with the same meaning into cognate sets
- can be viewed as a binary classification problem for word pairs: are a from language L_a and b from language L_b cognates?
- most common approach: compute some pairwise form distance measure, use distances as input for clustering algorithm
- benchmark for all recent advances: **LexStat** by List (2012)
- improvements over LexStat in B-Cubed score have been small:
  - ▷ Jäger and Sofroniev (2016): 0.700 → 0.718
  - ▷ Rama et al. (2017): 0.819 → 0.841 (NED: 0.804)
  - ▷ List et al. (2017): 0.883 → 0.894 (NED: 0.814)

Table of Contents

Information Weighting: Idea

- recent advances mainly driven by better clustering methods:
  - ▷ List et al. (2017) show that LexStat distances are the best, but InfoMap clustering beats UPGMA clustering on them
  - ▷ improvement in Rama et al. (2017) is also partially due to InfoMap clustering (in addition to better PMI scores)
- what about the other component? any clustering method would profit from improvements to the form distances
- observation: not all segments in a word are equally important
- simple rules like focusing on the first syllable do not generalize, a specialized model would be needed for every language
- instead: use trigram models to learn from the data which parts are more relevant for comparison!

Information Weighting: Definition

Segment-wise **information content** of *c* in context *abcde*:

$$I_L(c, [ab\_de]) := -\log \left\{ \frac{c_{abc} + c_{bcd} + c_{cde}}{c_{abX} + c_{bXd} + c_{Xde}} \right\}$$

- c_{abc}, c_{abX}, c_{Xbc}, c_{aXc} are trigram and extended bigram counts extracted from all word forms of *L*
- expanded by # at word boundaries (creating a full context)
- the quotient defines a probability distribution $P(c, [ab\_de])$ over possible segments *c* in context $[ab\_de]$
- $I_L(c, [ab\_de])$ is a measure of surprisal or self-information!

Information Weighting: Examples

- example for [t͡ɕ] in Polish *dać* [dat͡ɕ] “to give”:
  I_{pol}(t͡ɕ,[da_##])
  $= (c_{\text{dat͡ɕ}} + c_{\text{at͡ɕ\#}} + c_{\text{t͡ɕ\#\#}})\ /(c_{daX} + c_{daX\#} + c_{X\#\#})$
  $= (13 + 132 + 350)/(30 + 339 + 1124)$
  $= 1.287$
- for comparison: I_{pol}(d,[##_at͡ɕ]) $= 3.306$

Table of Contents

Information-Weighted Sequence Alignment (IWSA)

- idea: modify Needleman-Wunsch algorithm
- multiply achievable score for each operation by a combined information score baed on information models of both languages
- when computing the costs for an alignment, give a discount for alignment of ill-fitting material that has low information content in both languages
- at the same time, avoid aligning high-information material to low-information material (e.g. stems to suffixes)

IWSA: Definition

- aligning two IPA strings $a \in L_a$ of length m and $b \in L_b$ of length n
- combined information content for two aligned segments:

$$I^2_{L_a,L_b}(a_i, b_j) := \sqrt{\frac{I_{L_a}(a_i, [a_{i-2} \ldots a_{i+2}])^2 + I_{L_b}(b_j, [b_{j-2} \ldots b_{j+2}])^2}{2}}$$

- modified dynamic programming procedure for computing $sc(a, b) := M(m, n)$:

$$\begin{aligned}
M(0,0) &:= 0 \\
M(i,0) &:= M(i-1,0) + w(a_i, \epsilon) \cdot I^2_{L_a,L_a}(a_i, a_i) \\
M(0,j) &:= M(0,j-1) + w(\epsilon, b_j) \cdot I^2_{L_b,L_b}(b_j, b_j) \\
M(i,j) &:= min \begin{pmatrix} M(i-1,j-1) + w(a_i, b_j) \cdot I^2_{L_a,L_b}(a_i, b_j), \\ M(i-1,j) + w(a_i, \epsilon) \cdot I^2_{L_a,L_a}(a_i, a_i), \\ M(i,j-1) + w(\epsilon, b_j) \cdot I^2_{L_b,L_b}(b_j, b_j), \end{pmatrix}
\end{aligned}$$

IWSA: Examples

Opacity represents $I^2_{L_a,L_b}(a_i, b_j)$, color represents $w(a_i, b_j)$:

German	f	ɛ	ɐ	z	ɪ	ŋ	k	ə	n	"to sink"
English	-	-	-	s	ɪ	ŋ	k	-	-	

Arabic	θ	a	l	-	d͡ʒ	"snow"
Hebrew	ʃ	ɛ	l	ɛ	g	

Information-Weighted Distance

For words *a* of length *m* and *b* of length *n*:

$$d(a, b) := 1 - \frac{2 \cdot \frac{sc(a,b)}{\max\{n,m\}}}{\frac{sc(a,a)}{m} + \frac{sc(b,b)}{n}}$$

- unusual normalization by length necessary
  due to very high self-similarity for pairwise similarity scores
- values concentrate in interval [0.6, 1.4],
  no centralisation or normalisation done in this study
- threshold for candidate cognate pairs: $d(a, b) < 1.2$

Table of Contents

Changes to PMI Score Inference

- staying within the PMI framework, building on resampling in the style of Kessler (2001) and List (2012):

$$w_{glo}(x, y) := \log \frac{p(x, y)}{\hat{p}(x, y)}$$

- in the information-weighted case, the $p(x, y)$ and $\hat{p}(x, y)$ are based on **weighted counts** as well:

$$c(x, y) := \sum_{L_1, L_2 \in \mathcal{L}} \sum_{\substack{(a,b) \in lex(L_a, L_b), \\ sc(a,b) < 1.2}} \sum_{\substack{1 \leq i \leq \max\{m,n\}, \\ al(a,b).a_i = x, \\ al(a,b).b_i = y}} I^2_{L_a, L_b}(a_i, b_i)$$

Local scores for sound correspondences

- global PMI scores based on 1.3M cognate candidate pairs from NorthEuraLex 0.9, and an equal number of random word pairs
- local PMI scores (inferred from the data for a single language pair) to represent some of the sound correspondences:

$$w_{L_1,L_2}(x,y) := \frac{w_{glo}(x,y) + \log \frac{p_{L_1,L_2}(x,y)}{\hat{p}_{L_1,L_2}(x,y)}}{2}$$

- $p_{L_1,L_2}(x,y)$ and $\hat{p}_{L_1,L_2}(x,y)$ are estimated like in the global case, five alternations of re-estimation and re-filtering of candidates

Table of Contents

Test Data: intersection of NorthEuraLex and IELex

The testset was generated from an intersection of NorthEuraLex with IELex cognacy judgments (from the webpage):

- 36 Indo-European languages
- 185 concepts
- 100156 binary cognacy judgments
- available as an appendix to my dissertation

Evaluation: Overview

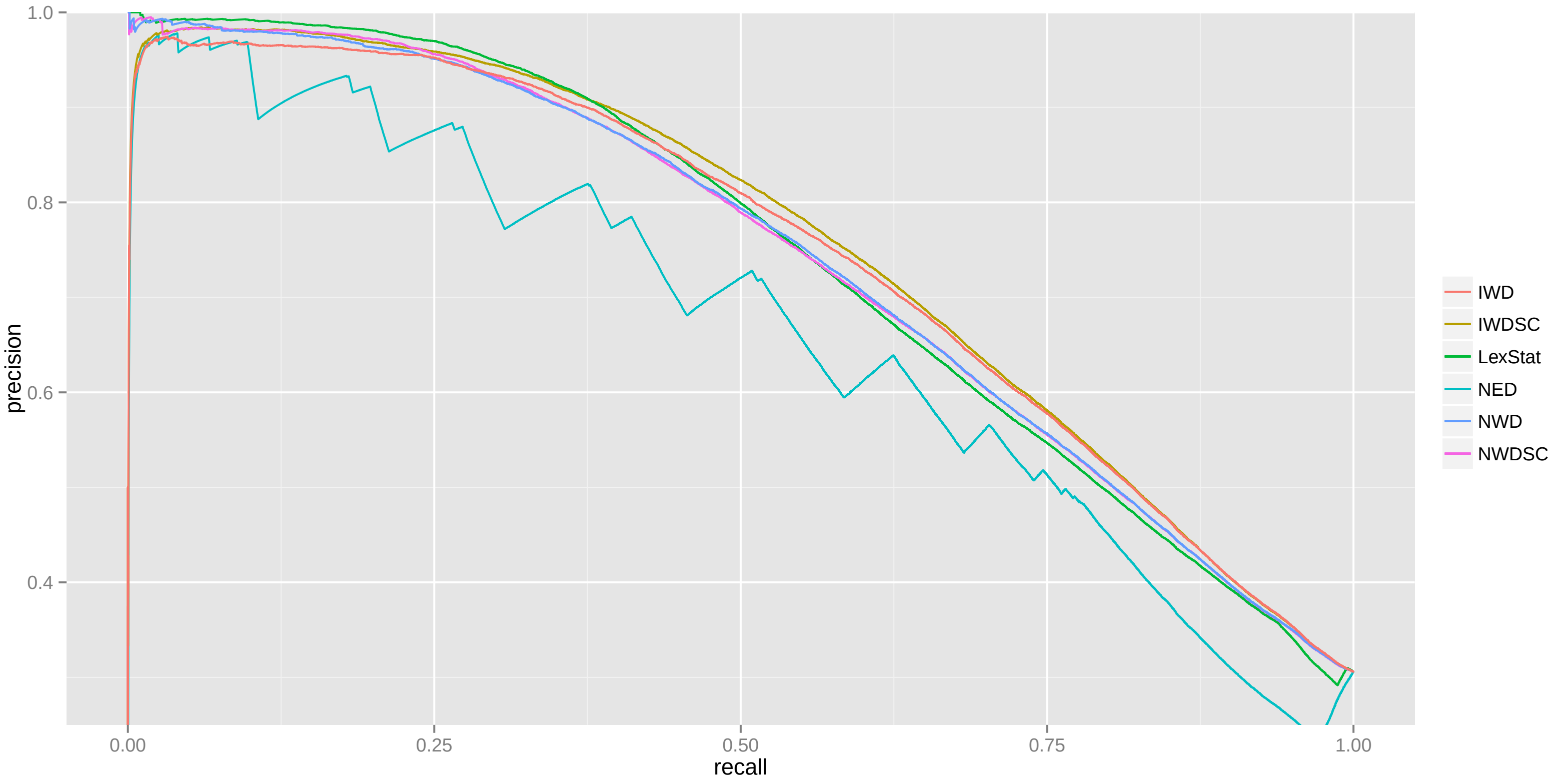
Methods being compared:

- **NED**: Normalized Edit Distance
- **LexStat**: LexStat Distance
- **NWD**: Needleman-Wunsch Distance
- **NWDSC**: NWD with Sound Correspondences
- **IWD**: Information-Weighted Distance
- **IWDSC**: IWD with Sound Correspondences

Evaluation measure: **average precision**

- precision averaged over all recall values
- equivalent to area under precision-recall graph
- threshold-independent criterion
- independent of clustering algorithm

Results: Precision-Recall Graphs



Results: Average Precision

Method	NED	LexStat	NWD	NWDSC	IWD	IWDSC
Avg. Prec.	0.604	0.728	0.741	0.747	0.764	**0.771**
Max. F-score	0.599	0.630	0.652	0.654	0.673	**0.679**
Precision	0.639	0.653	0.666	0.660	0.696	**0.706**
Recall	0.564	0.609	0.639	0.648	0.652	**0.654**

- NWD improves on LexStat by 1.3%, even without SC (advantage for full IPA model on many forms per language?)
- improvements through information weighting and sound correspondences are orthogonal:
  - ▷ information weighting leads to an increase of 2.3%
  - ▷ sound correspondences provide an additional 0.7%

Open Questions

- does information weighting work on smaller wordlists?
- does the advantage disappear on pre-stemmed data?
- how much difference does it make in clustering quality?
- performance of methods on cross-family datasets?
  (where similarity is less predictive of cognacy)

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