Measuring Mutual Intelligibility: Phonetic Distance & Conditional Entropy

Kim Heiligenstein Seminar in Methodology and Statistics May 2013

Mutual Intelligibility

- Among speakers of languages with same roots
- Elasticity: Difficulty in establishing distances
- Romance languages: Spanish, Portuguese, French, Italian.
- Subjective tests: intelligibility/proficiency tests
 Hearing tests
- Objective tests: phonetic distances
 - Orthographic distances

Objective Test: Phonetic Distance

- Levenshtein Distance Algorithm
 - Calculates the least expensive cost of transforming one string into another through deletion, insertion or substitution.
 - Symmetric
 - Can be normalized
- Conditional Entropy
 - Measures the difficulty of predicting the outcome of an unknown random variable given a known one.
 - Asymmetric

Data

- Database of word lists from 4 Romance languages
- Cognates: for all 4 languages, words that have same root derivation.

English	French	Italian	Spanish	Portuguese
adjective	adjectif	aggettivo	adjetivo	adjetivo

• Phonetic transcriptions in IPA and X-SAMPA

Transcription	French	Italian	Spanish	Portuguese
IPA	ad3ektif	ad ₃ etivo	aðxetiβo	adʒet∫ivu
X-SAMPA	adZEktif	adZetivo	aDxetiBo	adZetSivu

Levenshtein Distance

- What it can do for us: Compute how different a word is to another based on the pronunciation.
- The experiment:
 - Hypotheses:
 - There is a significant distance from one language to another.
 - Distances are significantly different from pair to pair.
 - Variables:
 - 1 6-leveled independent variable language pair
 - 1 dependent variable: Normalized LD

Levenshtein Distance

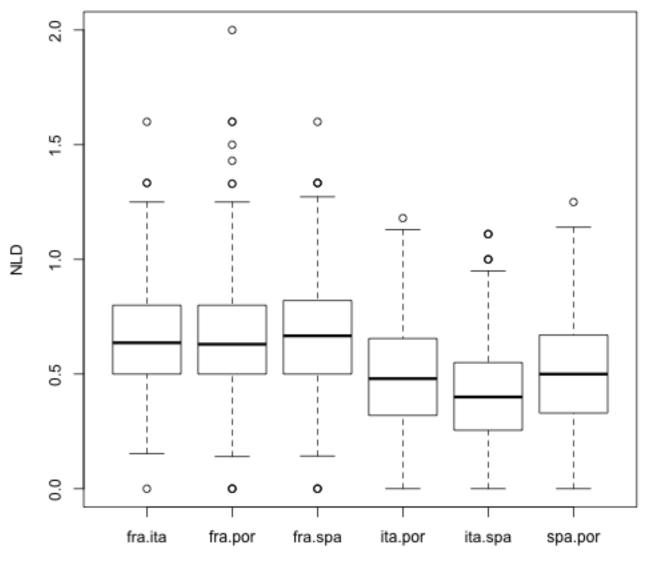
Example: t∫imit∈ro | simtj∈R

	Italian	t	ſ	i	m	i	t		3	r	0
_	French		S	i	m		t	j	3	R	
	Operation	del	sub			del		ins		sub	del
С	Cost ost of operation	1 ns = 6	5 1			1		1		1	1
N	Normalized LD = <u>Non-normalized LD</u>										
Average Length of Both Strings = 0.75											

Descriptives

	Ν	Mean	SD	SE	Min	Max
fra.ita	399	0.65	0.24	0.01	0	1.60
fra.spa	399	0.66	0.25	0.01	0	1.25
fra.por	399	0.66	0.27	0.01	0	2
ita.spa	399	0.42	0.22	0.01	0	1.11
ita.por	399	0.49	0.23	0.01	0	1.18
spa.por	399	0.51	0.23	0.01	0	1.25

NLD Data



Language Pairs

Levene's Test for Equality of Variances

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The Levene's test is not significant (F(5) = 1.56, p = 0.17).
Assumption of homogeneity of variance is met.
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ANOVA

Analysis of Variance Table Response: NLD Df Sum Sq Mean Sq F value Pr(>F) lang.pair 5 22.474 4.4949 77.642 < 2.2e-16 *** Residuals 2388 138.246 0.0579 ---Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1

There is a significant effect of the language pair on the Levenshtein distance (F(5) = 77.64, p < 0.05).

POST HOC

```
> pairwise.t.test(nld2way$NLD,nld2way$lang1, p.adj="none")
    Pairwise comparisons using t tests with pooled SD
data: nld2way$NLD and nld2way$lang1
    ita
            por
por 1.4e-11 -
spa 9.8e-13 0.3
P value adjustment method: none
> pairwise.t.test(nld2way$NLD,nld2way$lang2, p.adj="none")
    Pairwise comparisons using t tests with pooled SD
data: nld2way$NLD and nld2way$lang2
    fra
            ita
ita < 2e-16 -
spa < 2e-16 0.00022
```

P value adjustment method: none

Levenshtein Distance: Conclusions

- There distances from one language to another are significant.
- The distances are significantly different from one language pair to another.
 - Especially for the Italian-Spanish pair.

Do shorter distances correspond to low entropies ? Conversely, do longer distances predict high entropies ?

Conditional Entropy

 What it can do for us: Quantify the uncertainty of being able to interpret a word in a foreign language.

$$H(X|Y) = -\sum_{x\in X, y\in Y} p(x,y)\log_2 p(x|y)$$

 Ability to map phoneme in foreign language (heard conditioning variable) to phoneme in native language (conditioned variable to be identified)

Conditional Entropy

- The experiment:
 - Hypotheses:
 - The conditional entropy of one language given another is significant.
 - The conditional entropies differ significantly from one language to another, and in one direction from another.
 - Variables:
 - Independent variable: foreign (heard language) and native (language to map to)
 - dependent variable: CE

		Spanis	sh	French		
• Ex	ample: –					
		θero)			
ſ		_I θjelq	}	ZERO		
S	Θ	е	٢	Ο sjεl		
F	Z	е	R	0		
Entropy	((IS 9)10.g₂(1 189)	((IS 9)10.02(11 159)	((IS9)l00g ₂ (f s1))) ((IS 9)10.g₂(11 S2))		
S	Θ	j	е	I	Ο	
F	S	j	ε	I	_	
Entropy	((IS 9)10.g_((I IS))	((IS))I00g ₂ (IIS))	((1s,9)10.02(11 s2)) ((s9)log ₂ (fls))	((IS9)100.g ₂ (11 S2)	
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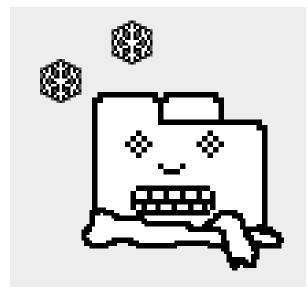
= .66

		Spanis	sh	French			
 Example: ⁻ 							
		θero)				
		_ι θjelq	ן א י	ZERO	l		
F	Z	e	R	Ο sjεl			
S	Θ	e	٢	0			
Entropy	((f;9)log ₂ (\$ f))	((f;9)log ₂ (\$ f))	((ff;9)l0@ ₂ (\$¦f))) ((f;9)I@ ₂ (\$¦f))			
F	S	j	3	I	_		
S	Θ	j	е	I	Ο		
Entropy	((f;9)log ₂ (\$ f))	((f;9)log ₂ (\$ f))	((f;9)log ₂ (\$;f))) ((f;9)log ₂ (\$;f))	((f;9)log ₂ (\$;f))		
• H(Entropy $((f;9)\log_2(s f))$ $((f;9)\log_2(s f))$ $((f;9)\log_2(s f))$ $((f;9)\log_2(s f))$ $((f;9)\log_2(s f))$ • $H(S F) = -(0+0+0+0+0+0+0+0)$						
= 0							

Certainty in correct mapping is 100%

Based on this example...

- Spanish to French conditional entropy is higher than French to Spanish conditional entropy.
- H(F|S) > H(S|F)
- Easier for native speakers of Spanish to understand French than vice versa.



Up Next...

- Finalize the CE data
- Analyze the CE data
- Compare LD to CE for correlation
- Adapt LD algorithm to set different weights depending on pairs
- Compare to subjective data and results