Introduction to Logistic Regression in R

(with case studies on the phonological organization of mental lexicon)

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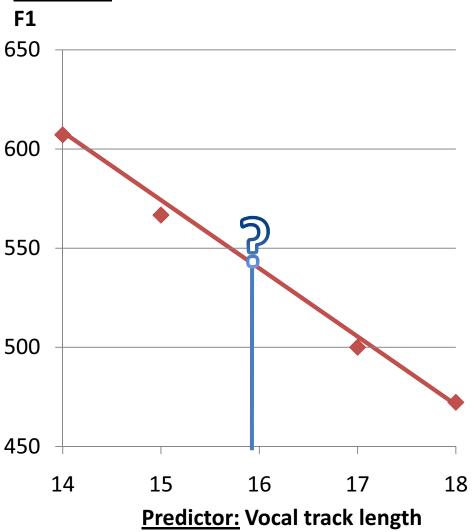
2: Massachusetts Institute of Technology

Intro

- Part I: Geometrical view of things
- Part II: quick intro to GLM and GLMM
- Part III: case study using logistic regression to study similarity avoidance in the mental (phonological) lexicon
- Part V: Discussion but please feel free to ask questions any time

Predicting unobserved data points

Outcome:



- Assume we want to predict F1 from vocal tract length based on a limited sample.
- Fitting a **linear model**: $F1 = intercept + \beta \bullet VocTL$
- NB: what does linear mean here?

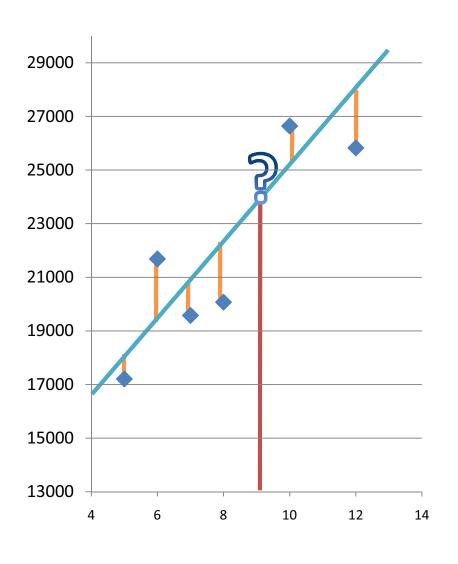
F1 = intercept
+
$$\beta_1 \bullet VocTL$$

+ $\beta_2 \bullet VocTL^2$

Predicting vs. Evaluating Significance

- You can think of regression in at least two ways:
 - Building a predictive model (based on observed data, you want to be able to make best guesses about future observations)
 - Testing whether a predictor affects an outcome (significantly)
- These views are related: in both cases, we need to find the best β

What constitutes the best guess?



- Orange lines = Error in prediction
- This is minimizing the squared deviations from the line (squared error)
- Do you notice something? How does regression differ from correlation?

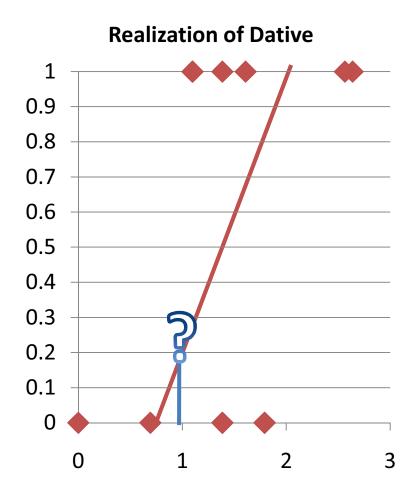
Limitations of Linear Model

- Assumptions:
 - Linearity in coefficients
 - normally distributed outcome (or error around outcome) > non-continuous outcomes are usually *not* normally distributed
- But many/most of the outcomes of interest to linguists are categorical outcomes

Categorical outcomes

- Choices in syntactic/morpho-syntactic variation:
 - Dative alternation, Heavy NP shift, Particle shift
 - that-omission, optional case-marker omission, optional, clitic doubling, argument drop, ellipsis,
 - Auxiliary contraction, phone deletion
- Forced-choice experiments: Grammaticality; yes/no question; multiple choice questions
- Eye-tracking: fixations on one of several referents
- Typological work: absence/presence of grammatical features, words, etc. across languages

Can a linear model do the job?



- Predicting Realization of Dative (NPNP vs. NPPP) from Length of Theme (log).
 - Predicts impossible values (<0, >1)
 - Make unlikely assumptions about distribution of variable

Let's take a step back

- What does a linear model actually predict?
 - The linear predictor (the formula) predicts the mean of the outcome ...
 - ... and then we add some noise

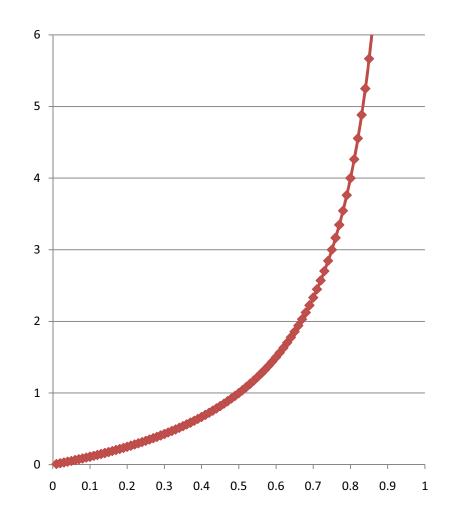
- What do we want to predict for binary outcomes?
 - The probability of outcome A over outcome B

Odds

- Probabilities range between 1 and 0
- We can transform them into a measure ranging from 0 to infinity
- Odds

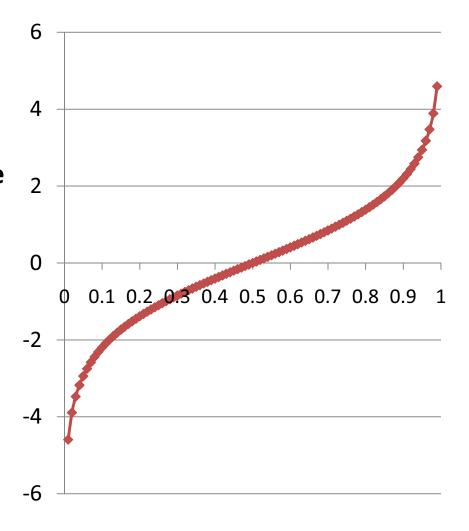
$$o = (p/1-p)$$

- p < .5, 0 < o < 1
- p=.5, o=1
- p>.5, o > 1



Log Odds

- We take the natural logarithm of the odds ratio (a.k.a. logit)
 - A value of 0 at p=.5
 - Probabilities with the same distance above and below
 .5 have the same logits but different signs.



Case Study: The OCP in Javanese

- Prohibitions against or under-attestation of combinations of similar sounds are commonly known as OCP effects
- Javanese is known for co-occurrence restrictions on similar sounds within words (Mester, 1986)
- We'll cover important aspects of logistic regression analysis while constructing a model of the OCP in Javanese

Generative Potential

 A priori we might expect that languages make use of their full generative potential.

 If a language allows words of the general shape CVCVC, every possible permutation of consonants in the C-slots could be a word.

 Nonetheless, the majority of possible permutations of consonants is unattested.

Javanese

30% of all Javanese roots are CVCVC

• Of 9,261 (21³) theoretically possible CVCVC roots 1,913 (20%) are attested (Uhlenbeck, 1978)

 We generated every possible consonant triplet of Javanese and annotated it 1 if attested and 0 if unattested.

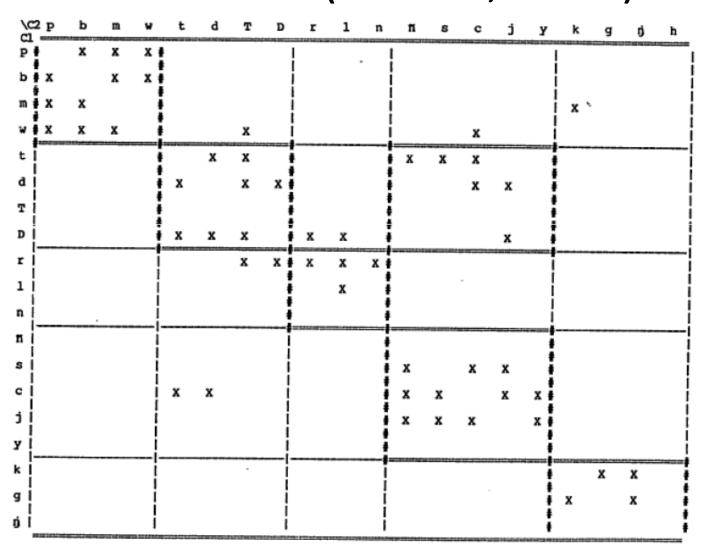
Javanese Corpus Input File

template	attestation	type frequency
tSVIVb	0	0
tSVIVtS	0	0
tSVIVd	0	0
tSVIVg	0	0
tSVIVh	1	5
tSVIVj	0	0
tSVIVk	1	4
tSVIVI	1	1
tSVIVm	1	2

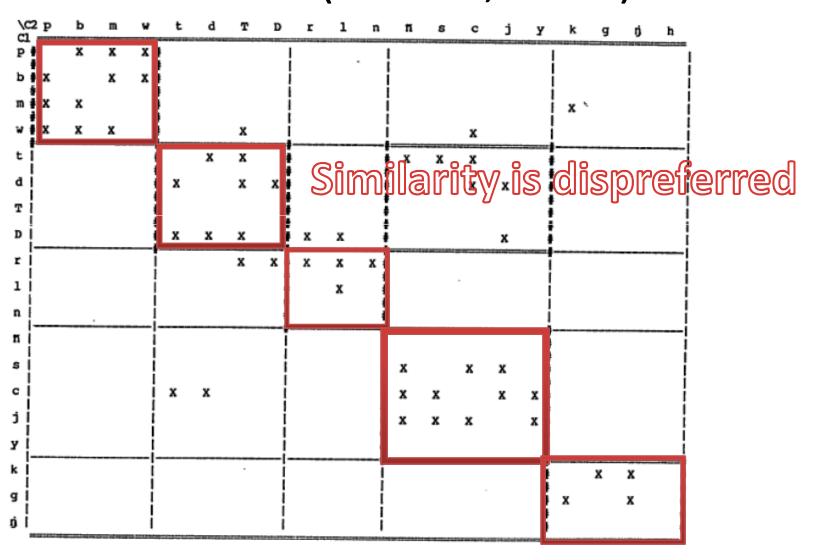
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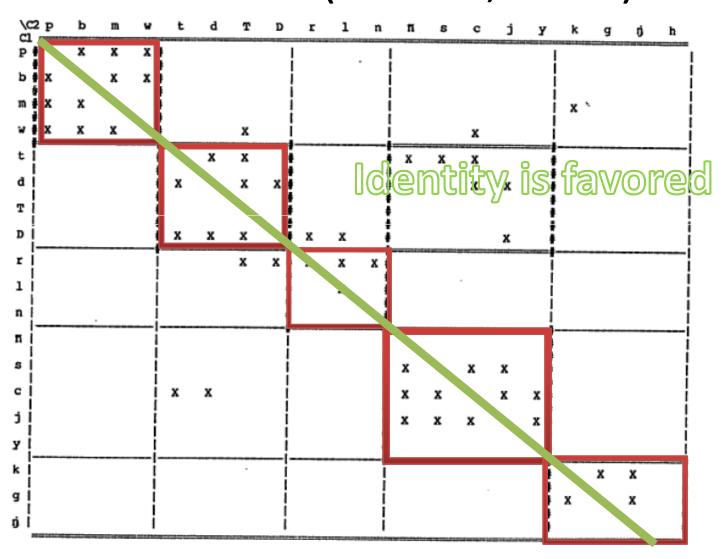
Javanese C₁VC₂ co-occurence restrictions (Mester, 1986)



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What we're doing vs. O/E's

- O/E's have become a standard measure of sound co-occurrence in phonology
- The problem with O/E's is...
 - Inflation of Type I Error
 - Difficult to get E's right if several variables play a role (e.g. identity)
 - Difficult to tease apart the relative contributions of the variables influencing the E's

To ask if the OCP has shaped the lexicon of Javanese...

 Phonotactics and a preference for identity might obscure the result!

We need to control for both identity and occurrence effects

Control 1: Occurrence Restrictions

- Restrictions on the occurrence of certain sounds in certain positions affect the probability of a form's attestation.
 - Javanese tVbVw is unattested. It is possible to attribute the non-attestation to co-occurrence restrictions on labials but there is no word that ends in /w/.
- Occurrence as positional frequency.

Positional Frequency Factors (3)

- One frequency factor per consonant-slot.
 - = number of attested templates in which ith consonant of the template occurs in position i.
- Example (235 attested templates start with /t/)

tVtVk

Frequency. C_1 in C_1 = 235

Control 2: Identity

 Several languages with strong OCP effects allow for total identity between consonants.

(McEachern 1997, Gallagher and Coon 2009)

 Identity might even be preferred crosslinguistically.

(Zuraw, 2002)

Identity Factors (3)

- One factor per pair of C-slots
 - = 1 if C_i and C_i are identical
 - = 0 otherwise

Example

tVtVk

Identity. C_1 in $C_2 = 1$

Outline

Nested and Non-nested Model Comparison

- Are there OCP effects after other factors have been controlled for?
- Does the OCP have to refer to individual features?
- Does the OCP require a notion of locality?
- How does our model compare to other models of the OCP?

• Effect size

– Does the strength of OCP effects differ for different phonological features?

Question 1

Are there OCP effects after other factors have been controlled for?

Feature System

Place

Manner+

Laryngeal

labial

lateral

breathy

alveolar

rhotic

post-alveolar

nasal

palatal

strident

velar

continuant

glottal

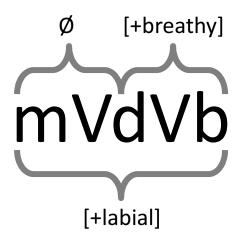
sonorant

retroflex

approximant

OCP Model 1: Sum of Matches

- One variable
 Sum of feature matches between C₁&C₂, C₂&C₃
 and C₁&C₃
- Example

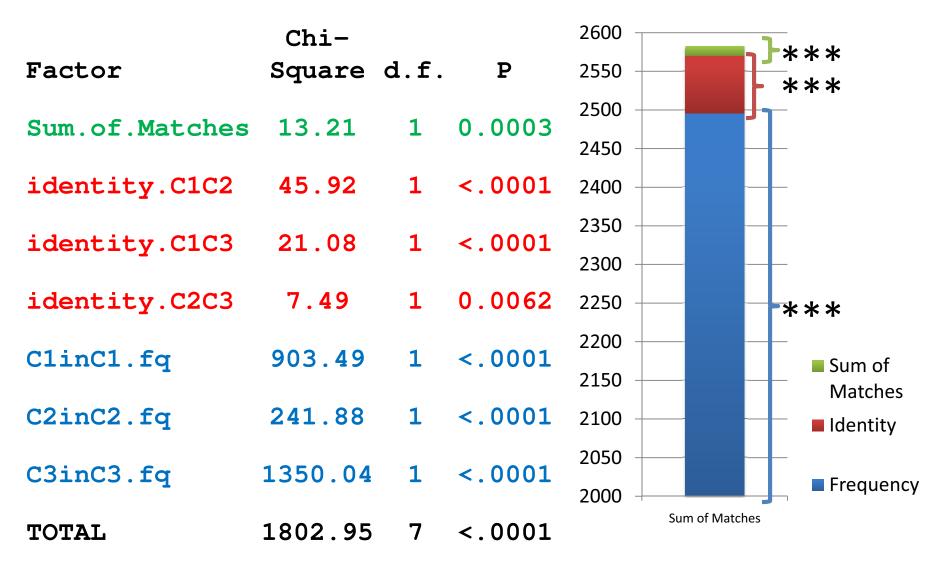


Sum.of.Matches = 2

Fitting the Model

```
lrm(attestation~
OCP sum.of.matches+
ClinCl.fq+C2inC2.fq+
C3inC3.fq+
identity.ClC2+
identity.ClC3+
identity.C2C3
                   , data=jav) ->jav1
```

anova (jav1) gives us...



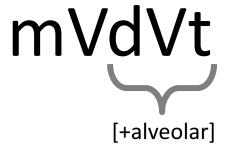
Question 2

Does the OCP have to refer to individual features?

OCP Model 2: Feature Specific OCP

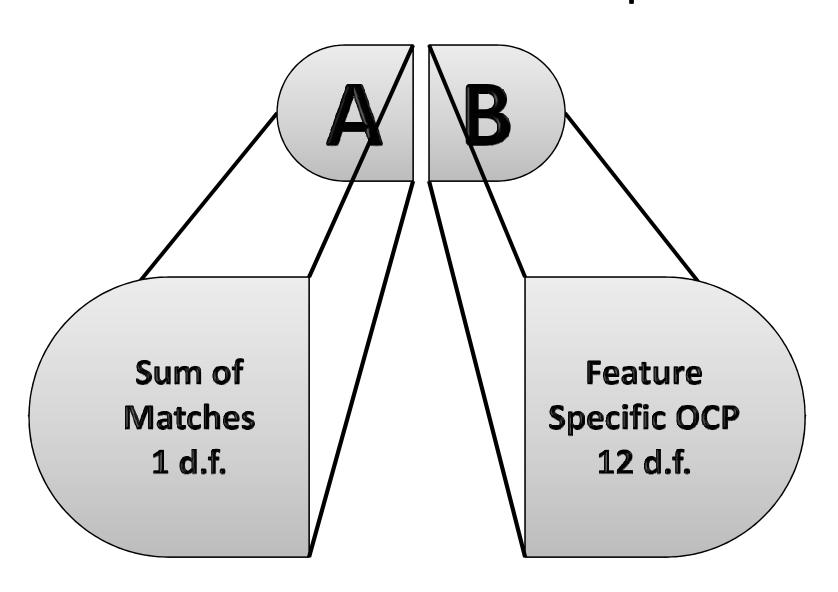
- One variable per feature
 - = 1 if one pair of consonants match for that feature
 - = 2 if all three consonants match for that feature

Example



OCP.alveolar = 1

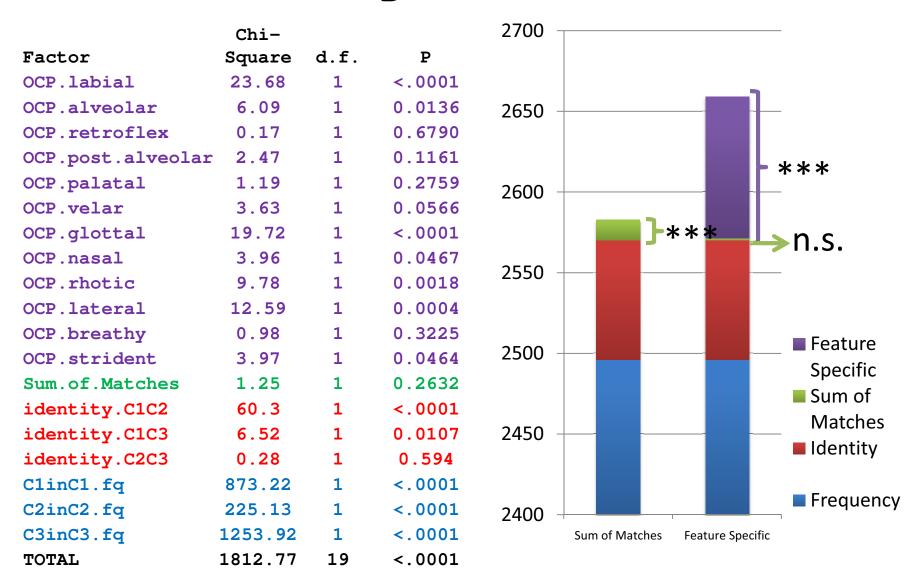
Non-nested Model Comparison



Fitting the Model

```
lrm(attestation~
          OCP.labial+OCP.alveolar+
          OCP.retroflex+
          OCP.post.alveolar+
          OCP.palatal+OCP.velar+
OCP (new)
          OCP.glottal+OCP.nasal+
          OCP.rhotic+OCP.strident+
          OCP.lateral+OCP.breathy+
          Sum.of.Matches+
 OCP (old)
          ClinC1.fq+C2inC2.fq+C3inC3.fq+
Frequency
          identity.C1C2+identity.C1C3+
  Identity
          identity.C2C3
           , data=jav) -> jav2
```

anova (jav2) gives us...



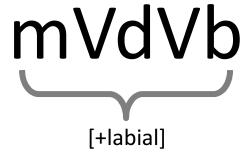
Question 3

Does the OCP require a notion of locality?

OCP Model 3: Non-local OCP

- One additional variable per feature
 - = 1 if C1 and C3 match for that feature

Example

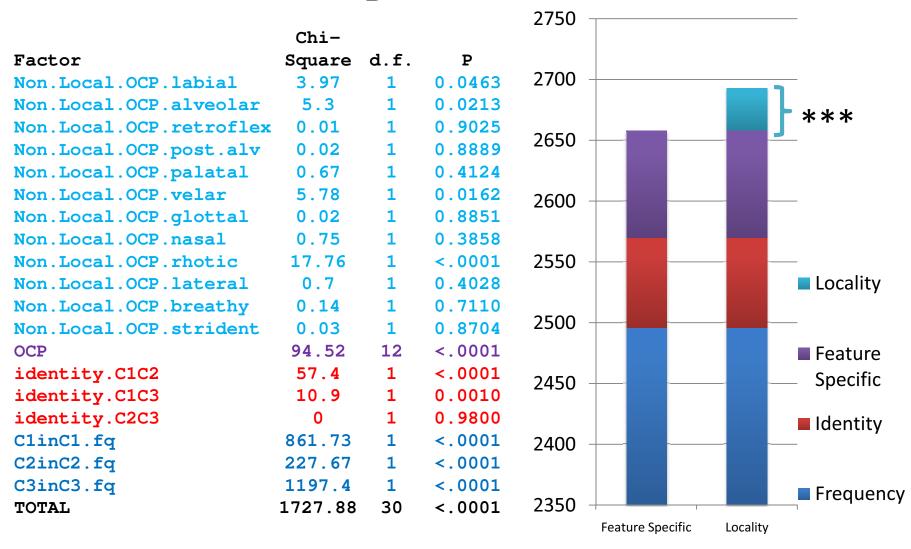


Non.Local.OCP.labial = 1

Fitting the Model

```
lrm(attestation~
              OCP.labial+OCP.alveolar+ OCP.retroflex+
              OCP.post.alveolar+ OCP.palatal+OCP.velar+
              OCP.glottal+OCP.nasal+
OCP.rhotic+OCP.strident+
              OCP.lateral+OCP.breathy+
              OCP.labial+OCP.alveolar+ OCP.retroflex+
              OCP.post.alveolar+ OCP.palatal+OCP.velar+
OCP (new
              OCP.glottal+OCP.nasal+
              OCP.rhotic+OCP.strident+
              OCP.lateral+OCP.breathv+
Frequency
              ClinCl.fq+C2inC2.fq+C3inC3.fq+
              identity.C1C2+identity.C1C3+
  Identit
              identity.C2C3
              , data=jav) ->jav3
```

anova (jav3) gives us...



Conclusion

- The lexicon is shaped by the OCP even after controlling for language-specific phonology in a systematic way.
- We have shown evidence that OCP effects are Feature-Specific and require a notion of Locality