Regressió generalitzada II

Mètodes empírics 2

03/06/2024

Avui

- Cas d'estudis
- Generalització lineal Binomial/Bernoulli
- Temes avançats
- (Xarxes neuronals & ChatGPT)

Zipf's Law of Abbreviation

Kanwal et al. (2017): Zipf's Law of Abbreviation and the Principle of Least Effort: Language users optimise a miniature lexicon for efficient communication. *Cognition*.

Vols saber quins factors (no) afecten l'ús de la paraula curta a l'experiment de Kanwal et al.; aquestes són les dades:

https://tinyurl.com/2s3p9s2z

1. Descriu les dades

2. Descriu com penses que les variables es podrien relacionar

3. Quins valors poden tenir les variables del teu interès?

Dades

```
##   pairnum          IP trial display   label
## 1       1 67.85.42.18     1       0     zop
## 2       1 67.85.42.18     2       3 zopudon
## 3       1 67.85.42.18     3       0     zop
## 4       1 67.85.42.18     4       0 zopekil
## 5       1 67.85.42.18     5       2 zopudon
## 6       1 67.85.42.18     6       1 zopekil
```

Variables independents (predictors)

- `trial`: 1, 2, …, 31, 32
- `display`: 0, 1, 2, 3

```
df$freq  <- ifelse(df$display %in% c(0,1),  'freq', 'infreq')
```

- `freq`: infreq o freq

Variable dependent (resultat)

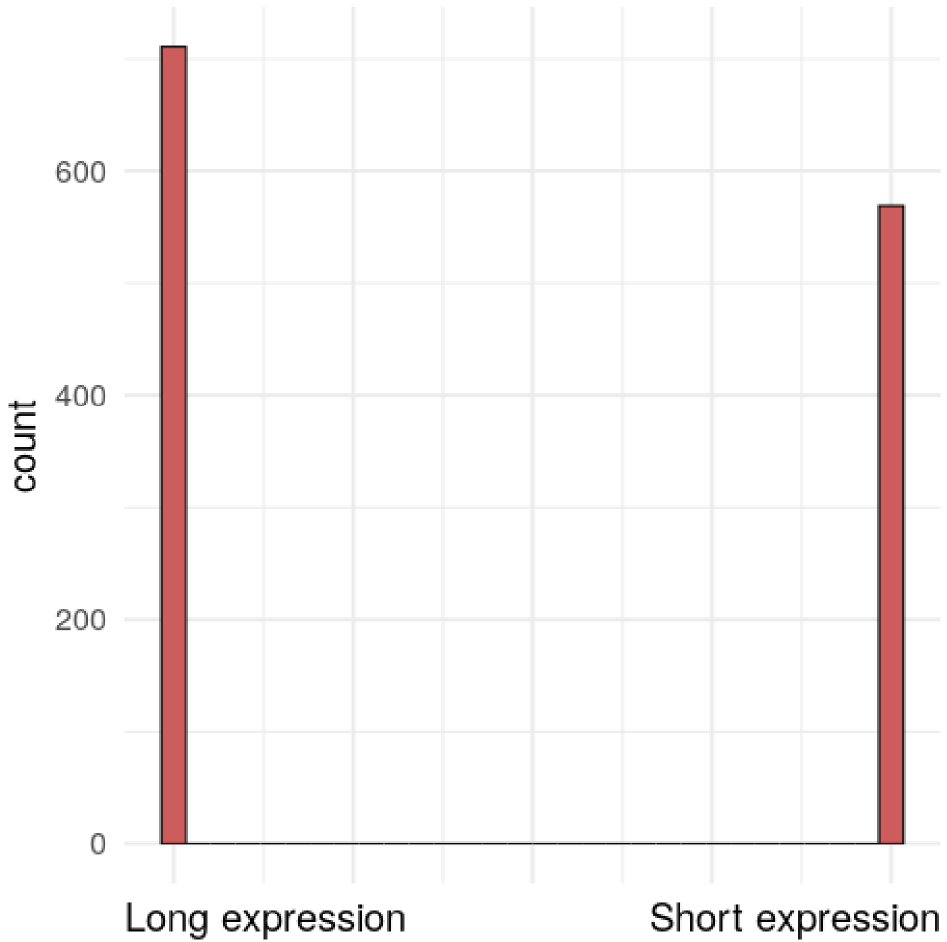
```
df$label[1:10]
```

```
##  [1] zop     zopudon zop     zopekil zopudon zopekil zop     zop     zop
## Levels: zop zopekil zopudon
```

```
df$short <- ifelse(df$label == 'zop', 1, 0)
df$short[1:10]
```

```
##  [1] 1 0 1 0 0 0 1 1 1 1
```

Variable dependent (resultat)



Model lineal generalitzat: Bernoulli / Binomial

Sustainability

Model lineal generalitzat: Bernoulli / Binomial

$$y_i \sim \mathrm{Bernoulli}(p_i)$$

$$p_i = f(\beta_0 + \beta_1 x_1 + \ldots \beta_n x_n)$$

$$f(x) = \text{inverse logit}(x)$$

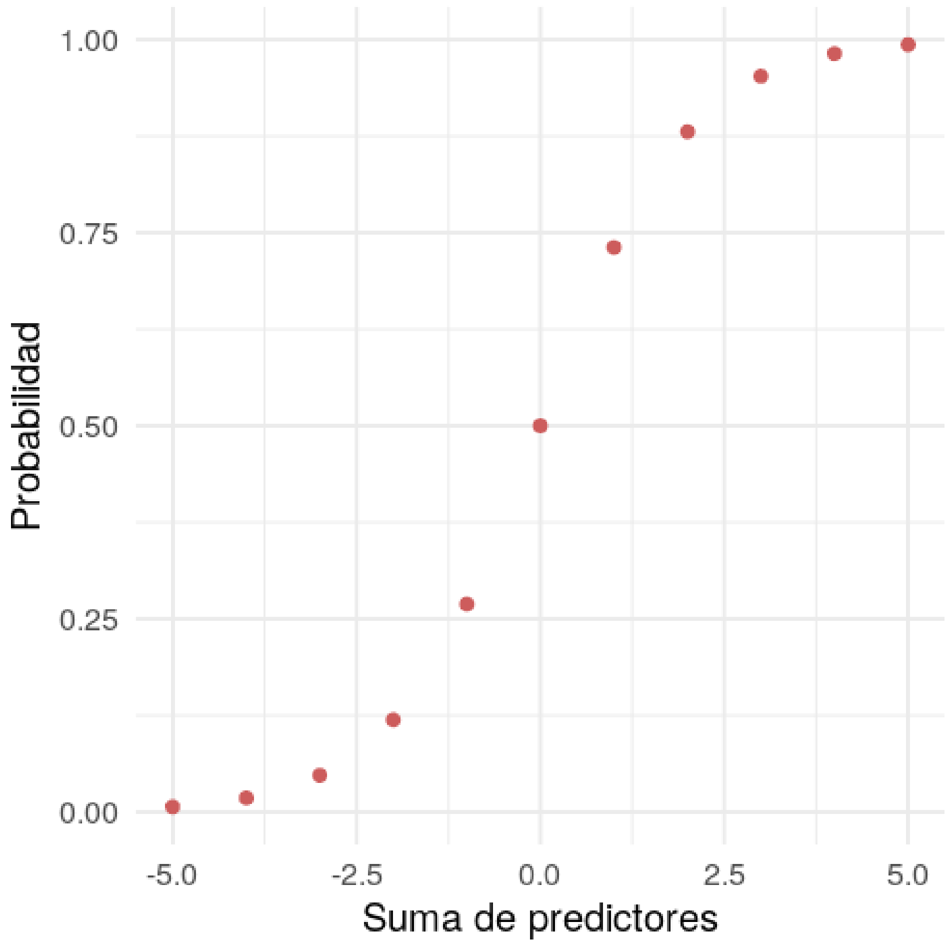
Logit i el seu invers

$$\text{logit}(p) = \log(\frac{p}{1-p})$$

$$\text{inverse logit}(p) = \frac{\exp(p)}{1+\exp(p)}$$

```
inv.logit <- function(x){
  return(exp(x) / (1 + exp(x)) )
}
```

Espai invers logit



Model lineal generalitzat: Bernoulli

$$y_i \sim \mathrm{Bernoulli}(p_i)$$

$$p_i = \mathrm{inv.logit}(\beta_0 + \beta_1 x_1)$$

Model lineal generalitzat: Bernoulli

$$y_i \sim \mathrm{Bernoulli}(p_i)$$

$$\mathrm{logit}(p_i) = \beta_0 + \beta_1 x_1 + \ldots \beta_n x_n$$

Regressió Binomial/Bernoulli (R)

```r
glm(formula = short ~ 1 + freq,
    data    = df,
    family  = binomial(link = 'logit')
    )
```

Zipf's Law of Abbreviation

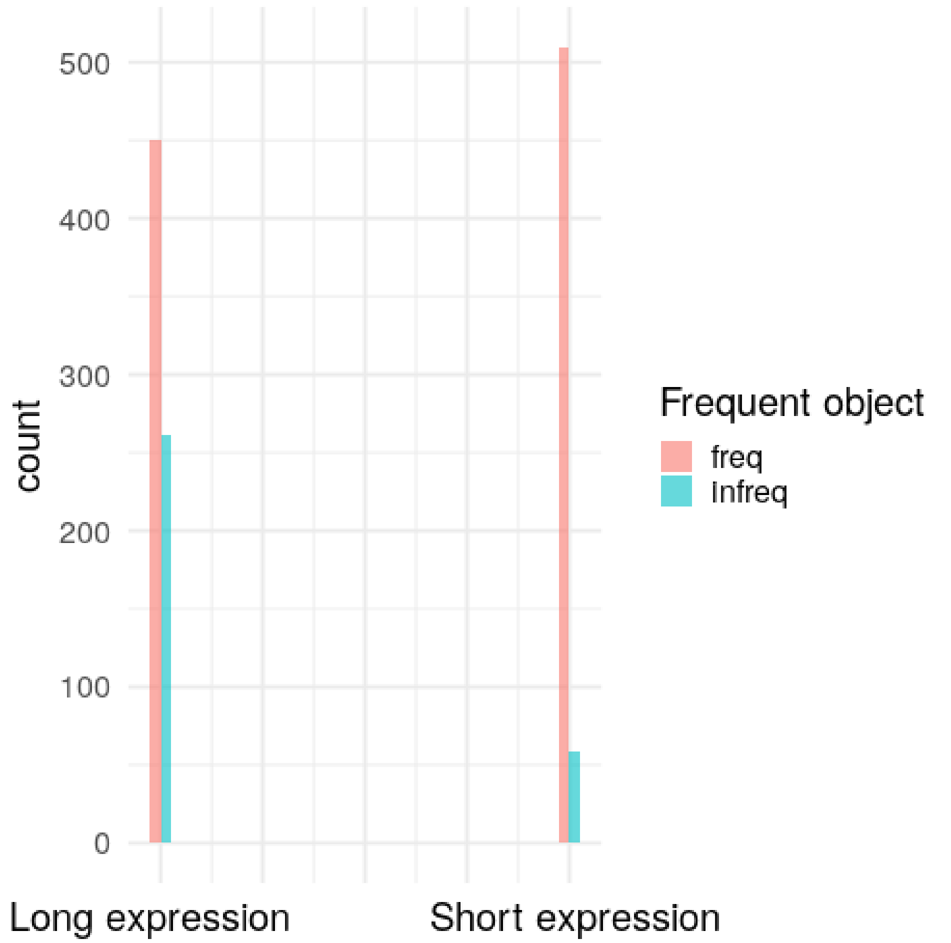
Kanwal et al. (2017): Zipf's Law of Abbreviation and the Principle of Least Effort: Language users optimise a miniature lexicon for efficient communication. *Cognition*.

Dades

```
head(df)
```

```
##   pairnum            IP trial display    label    freq short
## 1       1 67.85.42.18     1       0      zop    freq     1
## 2       1 67.85.42.18     2       3 zopudon infreq     0
## 3       1 67.85.42.18     3       0      zop    freq     1
## 4       1 67.85.42.18     4       0 zopekil    freq     0
## 5       1 67.85.42.18     5       2 zopudon infreq     0
## 6       1 67.85.42.18     6       1 zopekil    freq     0
```

longitud d'expressió ~ freqüència d'objecte



Model 1: Freqüència

```
zipf_freq <- glm(formula = short ~ 1 + freq,
                 data    = df,
                 family  = binomial(link = 'logit')
                 )
coef(zipf_freq)
```

```
## (Intercept)  freqinfreq
##   0.1251631  -1.6121461
```

$$\text{logit}(p_i) \approx 0.13 - (\text{infrec} \times 1.612) \approx -1.482$$

Model 1: Freqüència

$$\text{logit}(p_i) \approx 0.13 - (\text{infrec} \times 1.612) \approx -1.482$$

```
inv.logit(0.13 - 1.612)
```

```
## [1] 0.1851255
```

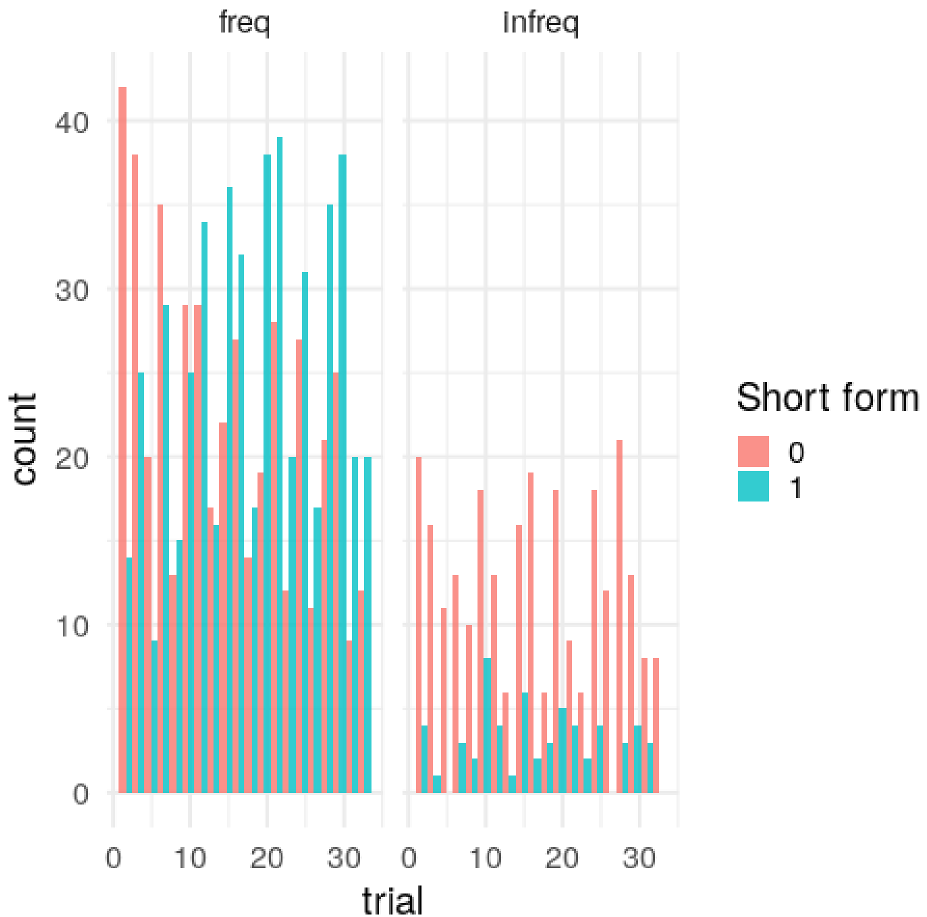
```
inv.logit(0.13)
```

```
## [1] 0.5324543
```

summary(zipf_freq)

```
##
## Call:
## glm(formula = short ~ 1 + freq, family = binomial(link = "logit"),
##     data = df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.2310  -1.2310  -0.6384   1.1247   1.8389
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.12516    0.06468   1.935    0.053 .
## freqinfreq  -1.61215    0.15800 -10.204   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1758.7  on 1279  degrees of freedom
## Residual deviance: 1633.0  on 1278  degrees of freedom
## AIC: 1637
##
## Number of Fisher Scoring iterations: 4
```

longitud d'expressió ~ torn



Model 2: Torn

```
zipf_trial <- glm(formula = short ~ 1 + trial,
                  data    = df,
                  family  = binomial(link = 'logit')
                   )
coef(zipf_trial)
```

```
## (Intercept)       trial
## -0.73645501  0.03085928
```

Prediccions

```
inv.logit(-0.74 + (1  * 0.039))
```

```
## [1] 0.3315906
```

```
inv.logit(-0.74 + (20 * 0.039))
```

```
## [1] 0.5099987
```

```
inv.logit(-0.74 + (32 * 0.039))
```

```
## [1] 0.6243375
```

summary(zipf_freq)

```
##
## Call:
## glm(formula = short ~ 1 + trial, family = binomial(link = "logit"),
##     data = df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.2857  -1.0889  -0.9189   1.2285   1.4879
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.736455   0.118639  -6.208 5.38e-10 ***
## trial        0.030859   0.006204   4.974 6.54e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1758.7  on 1279  degrees of freedom
## Residual deviance: 1733.5  on 1278  degrees of freedom
## AIC: 1737.5
##
## Number of Fisher Scoring iterations: 4
```

Model 3: Tots dos predictors

```
zipf_trial_freq <- glm(formula = short ~ 1 + trial + freq,
                       data    = df,
                       family  = binomial(link = 'logit')
                        )
coef(zipf_trial_freq)
```

```
## (Intercept)       trial  freqinfreq
## -0.42733747  0.03359338 -1.64081659
```

Model 3: Tots dos predictors

```
##
## Call:
## glm(formula = short ~ 1 + trial + freq, family = binomial(link = "logit"
##     data = df)
##
## Deviance Residuals:
##    Min       1Q   Median       3Q      Max
## -1.462  -1.097  -0.562   1.089   2.077
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.427337   0.125352  -3.409 0.000652 ***
## trial        0.033593   0.006536   5.140 2.75e-07 ***
## freqinfreq  -1.640817   0.159698 -10.275  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1758.7  on 1279  degrees of freedom
## Residual deviance: 1606.0  on 1277  degrees of freedom
## AIC: 1612
##
```

AICs

```
zipf_freq$aic
```

```
## [1] 1636.987
```

```
zipf_trial$aic
```

```
## [1] 1737.473
```

```
zipf_trial_freq$aic
```

```
## [1] 1611.984
```

Temes avançats

Interaccions

```
m4 <- glm(formula = short ~ 1 + trial + freq + trial:freq,
                       data    = df,
                       family  = binomial(link = 'logit')
                        )
coef(m4)
```

```
##      (Intercept)            trial       freqinfreq trial:freqinfreq 
##      -0.53501091       0.04018210      -0.99080221      -0.03782272
```

Models hierarquics

```r
library(lme4)

m5 <- glmer(formula = short ~ 1 + trial + freq +
                             trial:freq +
                             (1 | IP),
                      data    = df,
                      family  = binomial(link = 'logit')
                       )
```

Models hierarquics

```
fixef(m5)
```

```
##      (Intercept)            trial       freqinfreq trial:freqinfreq 
##      -1.19210355       0.07232261      -1.18527634      -0.07347172
```

```
head(ranef(m5)$IP)
```

```
##                 (Intercept)
## 100.10.40.83      1.897175
## 100.2.122.157     1.737037
## 104.174.222.43   -1.743050
## 107.161.163.8    -2.364535
## 115.99.18.32     -1.490564
## 117.213.33.129   -2.768317
```

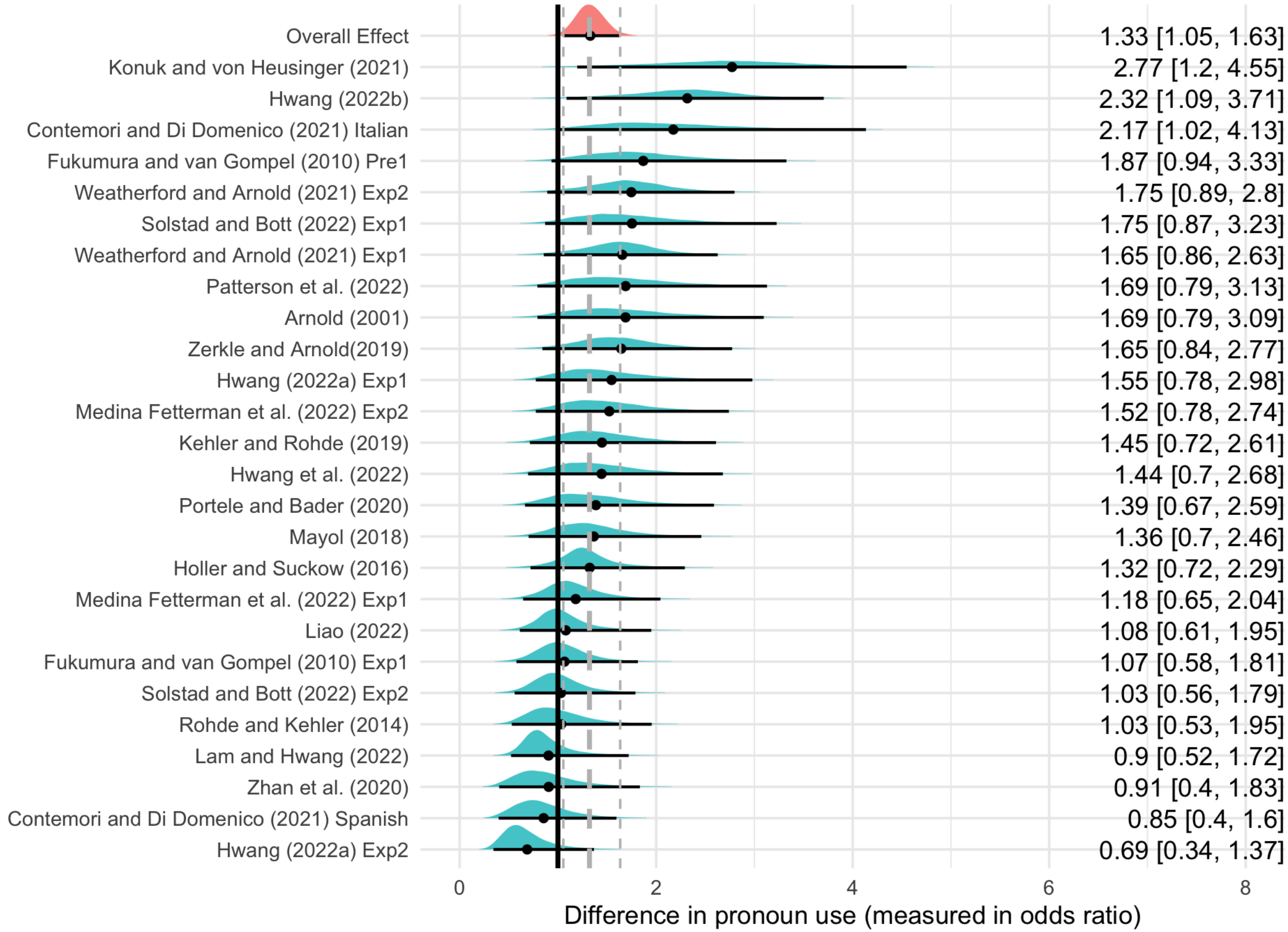
Mes temes

- meta anàlisi
- GAMs
- Xarxes neuronals

Meta anàlisi

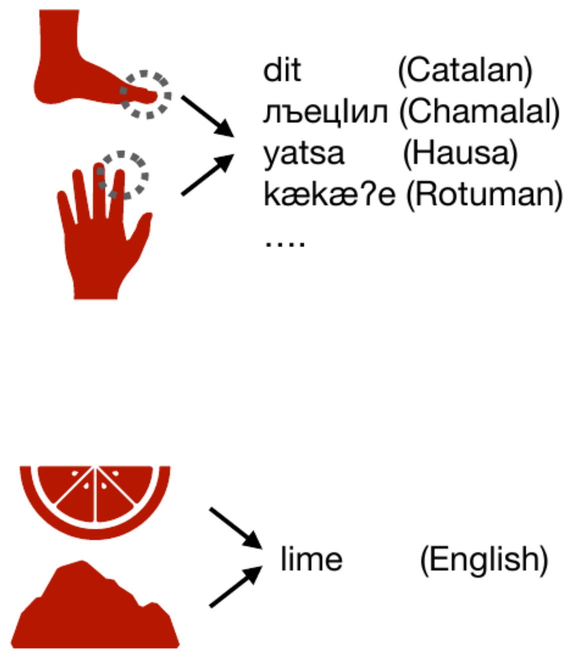
T'interessa saber si l'ús d'un pronom (vs. nom) és més probable per a una entitat més predictible. La literatura té resultats que es contradiuen. Alguns experiments diuen que sí; altres que no. Què fas?

Meta anàlisi

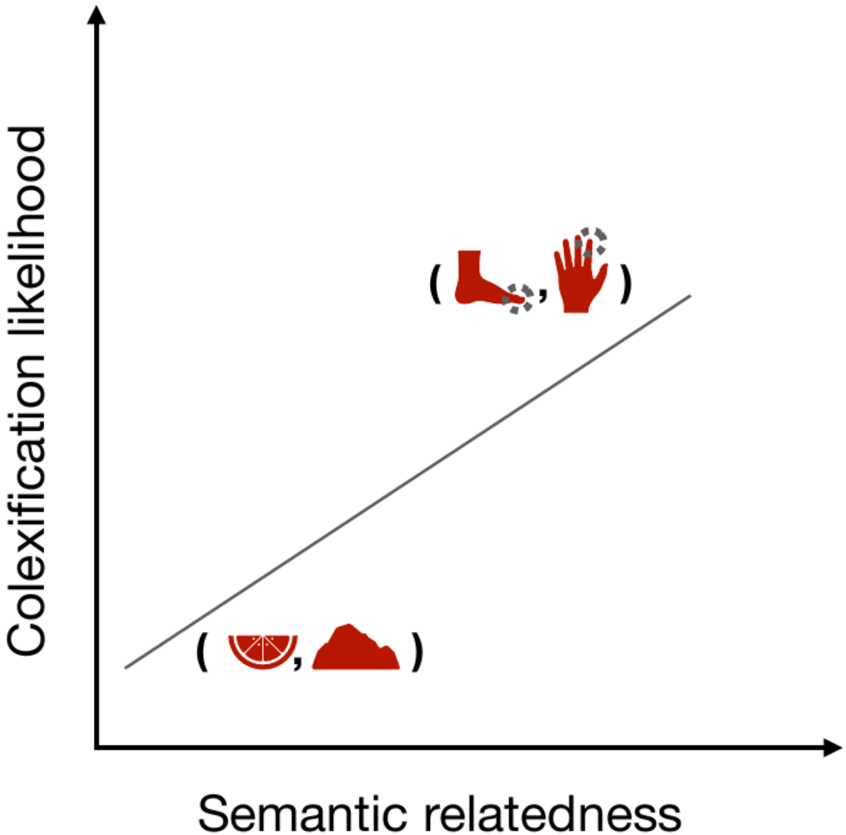


GAMs

How do pressures shape colexification?

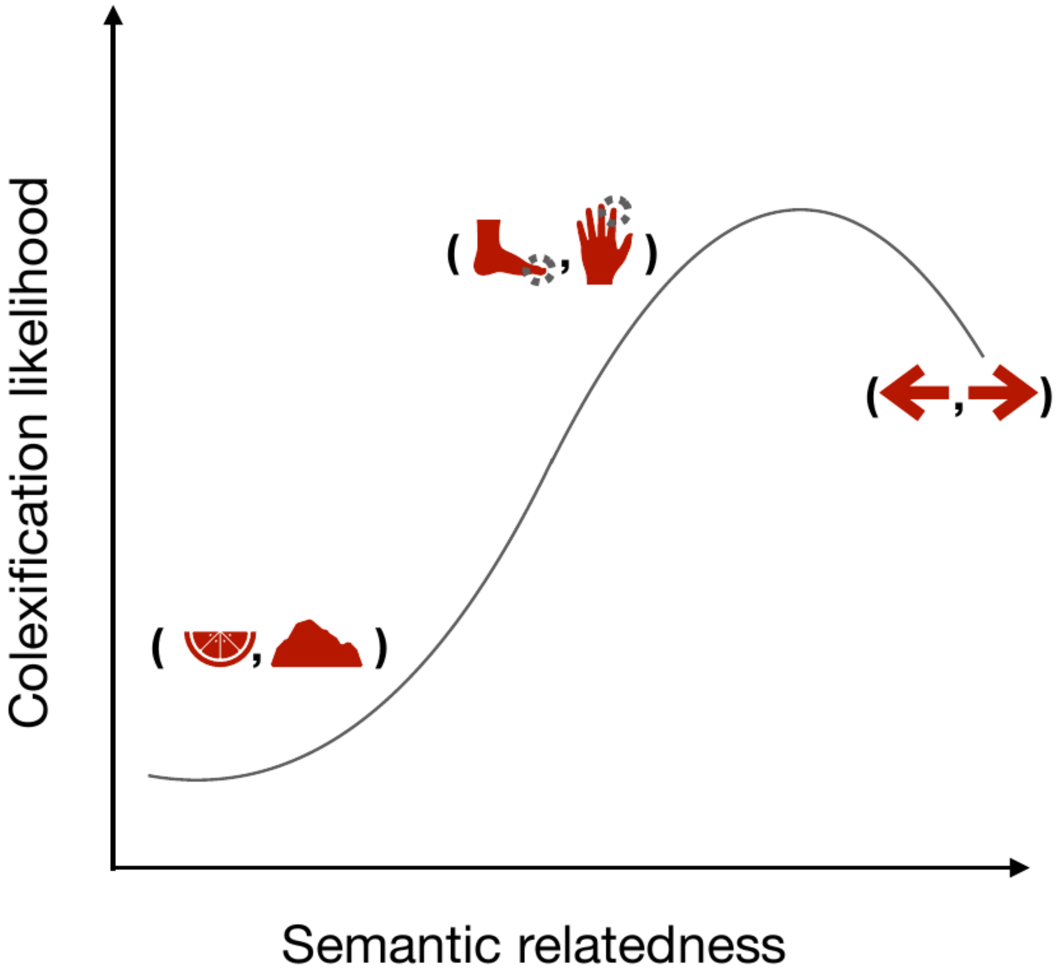


GAMs

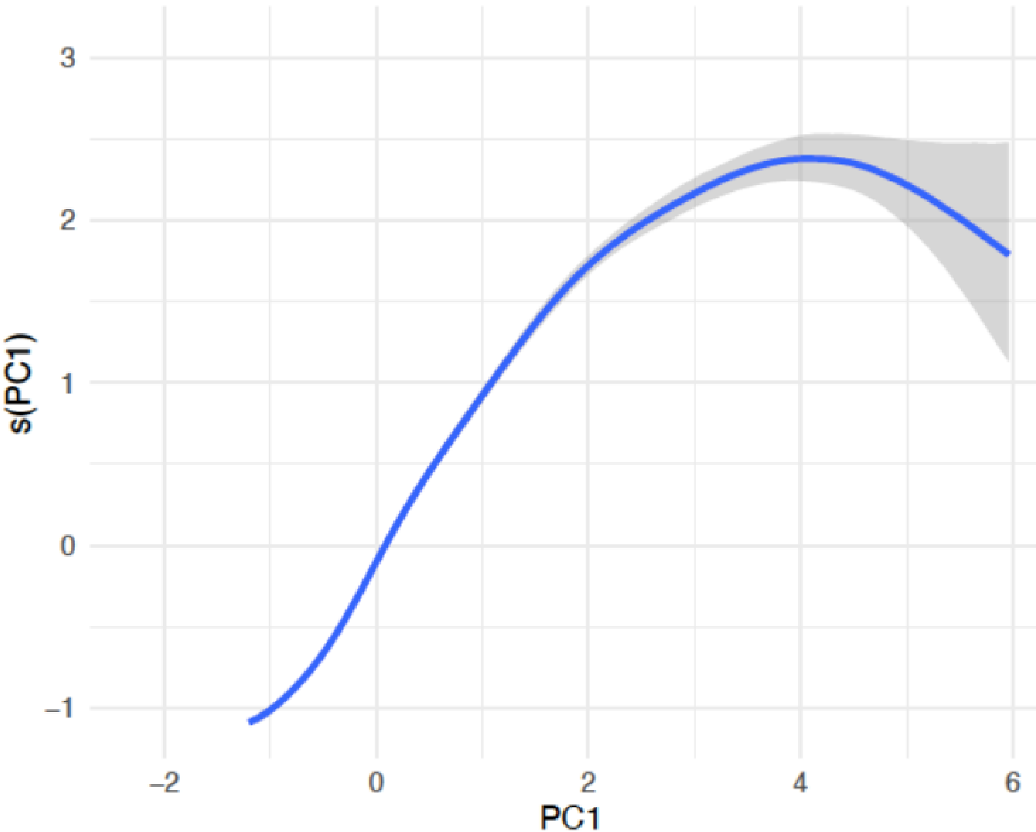


Xu et al. (2020): *Conceptual Relations Predict Colexification across Languages.* Cognition

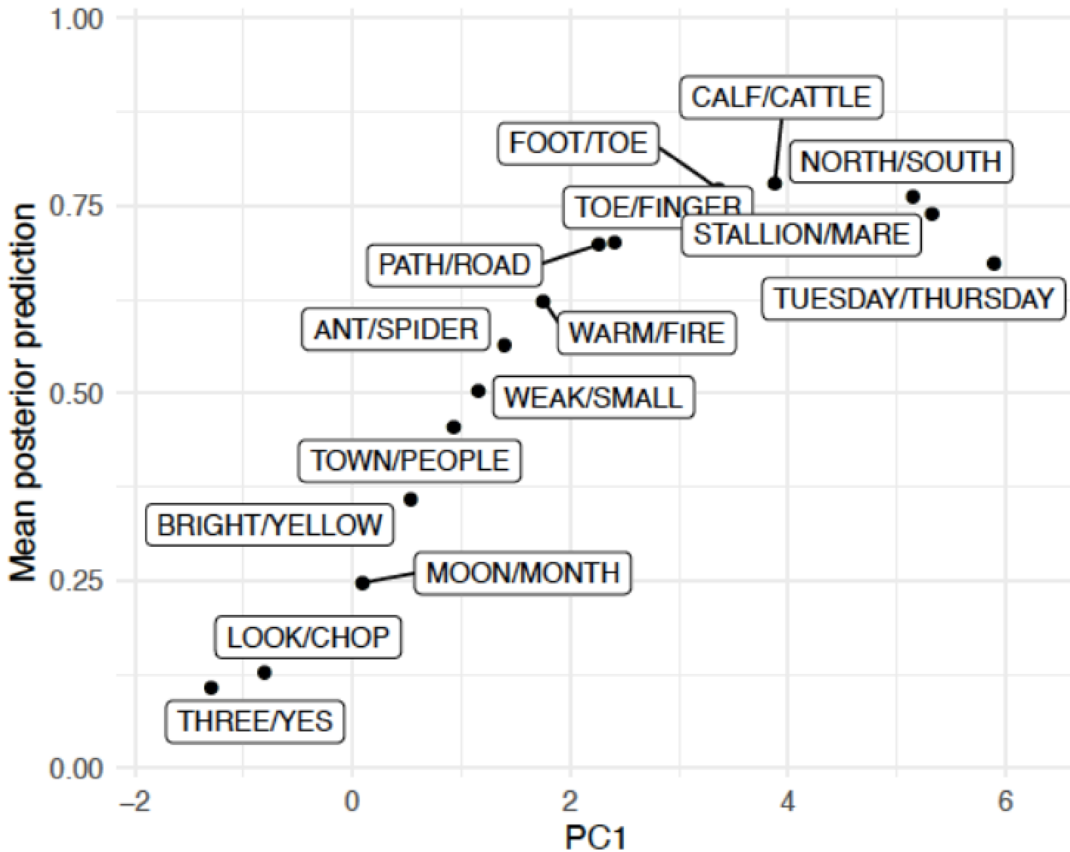
GAMs



GAMs

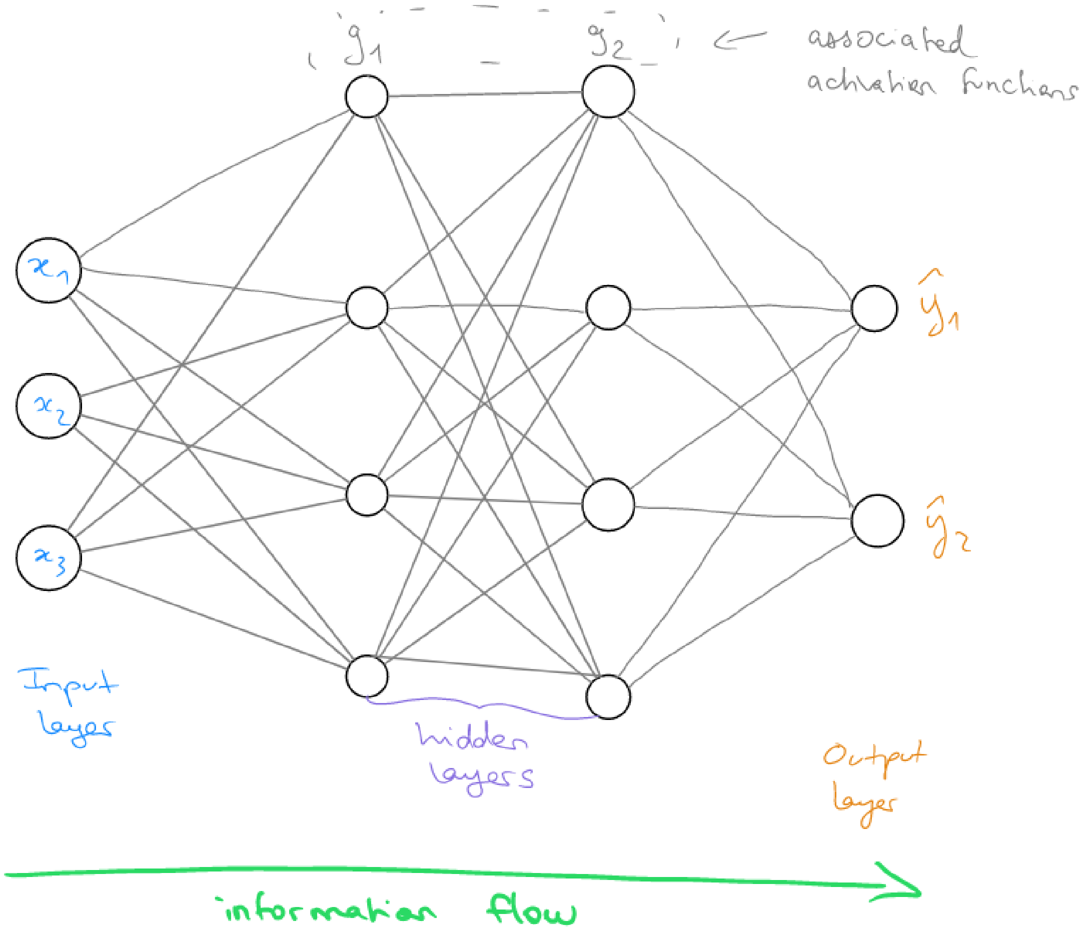


GAMs



CALF/CATTLE
FOOT/TOE
NORTH/SOUTH
TOE/FINGER
STALLION/MARE
PATH/ROAD
TUESDAY/THURSDAY
ANT/SPIDER
WARM/FIRE
WEAK/SMALL
TOWN/PEOPLE
BRIGHT/YELLOW
MOON/MONTH
LOOK/CHOP
THREE/YES
Mean posterior prediction
1.00
0.75
0.50
0.25
0.00
−2
0
2
4
6
PC1

Xarxes neuronals



Final remarks