

# Face Identification Game

An exploration of the (best) linguistic  
predictors of game success

*By Lotte Verheijen*

# Content

---

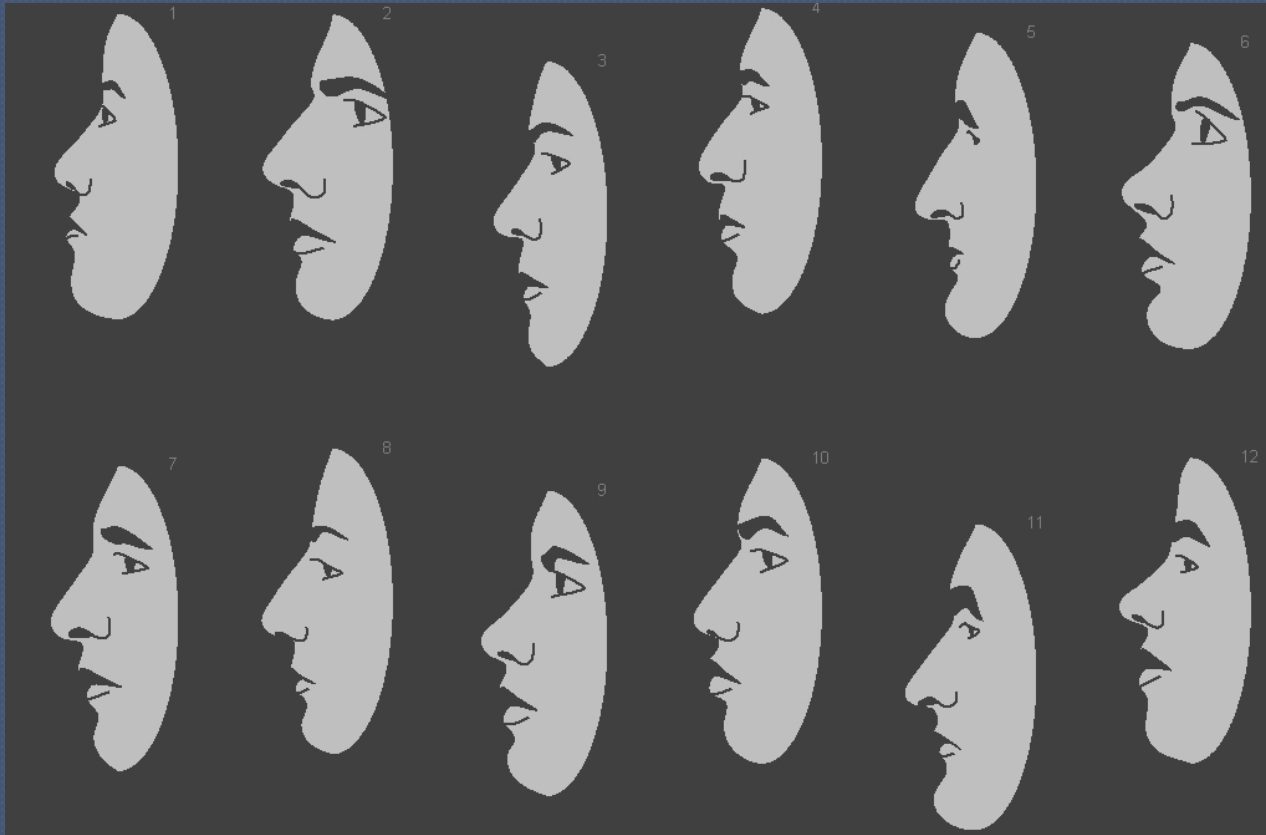
- Introduction
  - Research design
  - Variables/Data
  - Research questions
  - Expectations (based on CMC coordination research)
- Method
  - Multiple logistic regression
    - assumptions
  - Model selection
    - Unclean data
    - Clean data + assumptions
    - Exclude an outlier + assumptions
- Tentative conclusions: best model
- Questions?

# Research Design

---

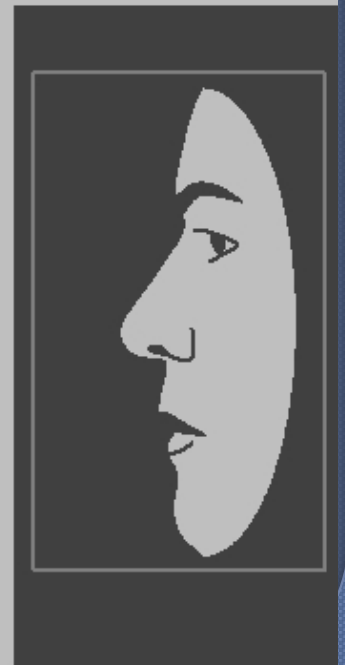
- Face identification: CMC coordination game
- Akin to the tangram task
  - Director: sees 1 face
  - Matcher: sees 12 faces
  - Alternated
  - They have to match (via communicating) the one face to the director is seeing to one out of the 12 the matcher is seeing (Bangerter & Clark, 2003)

# Research Design



Matcher

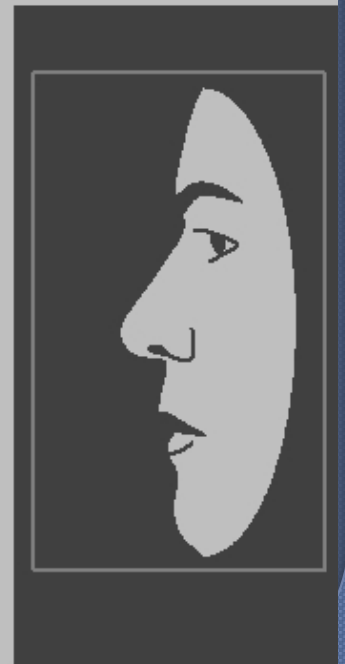
Director



# Research Design



Director



Matcher

# Research Design

mouth, eyes, and brows are all drooped down	, 24ee
brows are very drooped down	, 24ee
looks sad	, 24ee
he has a fat chin right?	, liao
like blockish	, liao
? or is it rounder	, liao
yea, the bottom of his chin is a little bit slanted	, 24ee
doesnt bulge out too much	, 24ee
nose is the thing that stands out	, 24ee
eye brows arent bushy?	, liao
no	, 24ee
kinda thin	, 24ee
mouth and chin are the second thing that stands out the most	, 24ee
his are looking forward?	, liao
then the forehead	, 24ee
yea straight ahead	, 24ee
his forehead to the nose is making sorta like a paperclip s?	, liao
err that was a bad question	, liao
noo....?	, 24ee
i think i know	, liao
Correct. Your score is 10	, tgliaoliao
Correct. Your score is 10	, nkyung24ee
/10((NEWLINE))	
Game success: 1	

# Variables

---

- Quantified conversation analysis
- Outcome: Success of Trial (binomial)
- Predictors:
  - 1. Deletes per trial
  - 2. Typing time per trial
  - 3. Nr. of text turns per trial
  - 4. Total trials attempted
  - 5. Characters typed per trial
  - 6. Nr. of question marks per trial

# Research Questions

---

- What is the best model for predicting game success in the face identification game and which variables are included in this model?
- What is the influence of cleaning up the data on such a model? (regarding AIC levels, assumptions)



# Expectations

- Exploration of (best) predictors... unknown
- Type of predictor
  - 1. Deletes per trial = negative
  - 2. Typing time per trial = negative
  - 3. Nr. of text turns per trial = negative
  - 4. Total trials attempted = positive/negative\*
  - 5. Characters typed per trial = negative
  - 6. Nr. of question marks per trial = negative
- \*cutoff point instead of practice effect

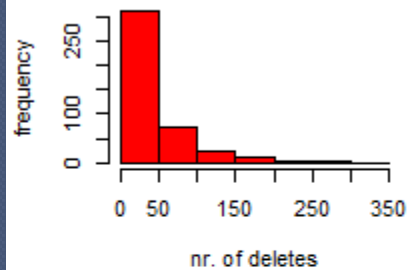
# CMC Coordination

---

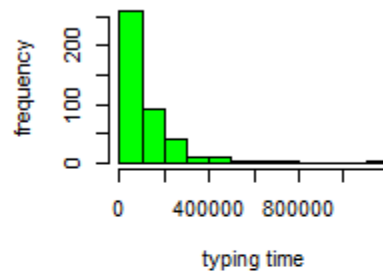
- ◉ Uncertainty or repair hints at decreased coordination (deletes, typing time, question marks, also related to nr. of text turns and characters typed) (Hayashi, Raymond & Sidnell, 2013).
- ◉ High turn rate: lower coherence/coordination level (Smith, Cadiz & Burkhalter, 2000; Herring, 1999)
- ◉ Decreased coordination is assumed to lead to a lower success rate (Garrod & Anderson, 1987)

# Unclean Data: First Look

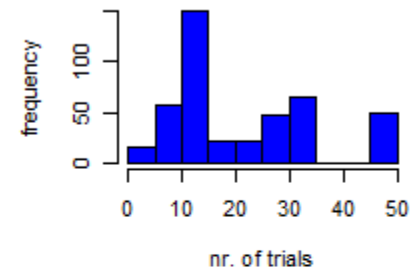
Deletes Per Trial



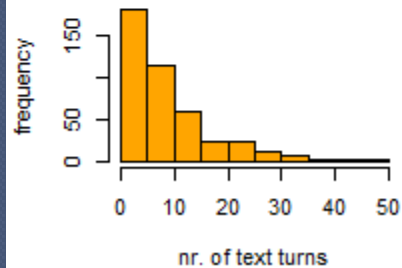
Typing Time Per Trial



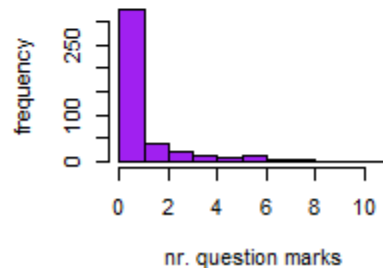
Total Trials Attempted



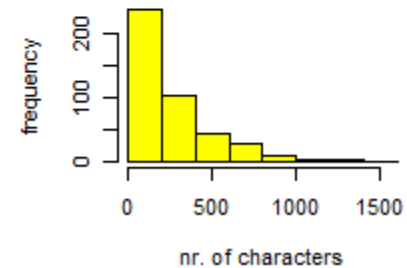
Text Turns Per Trial



Question Marks Per Trial



Characters Typed Per Trial

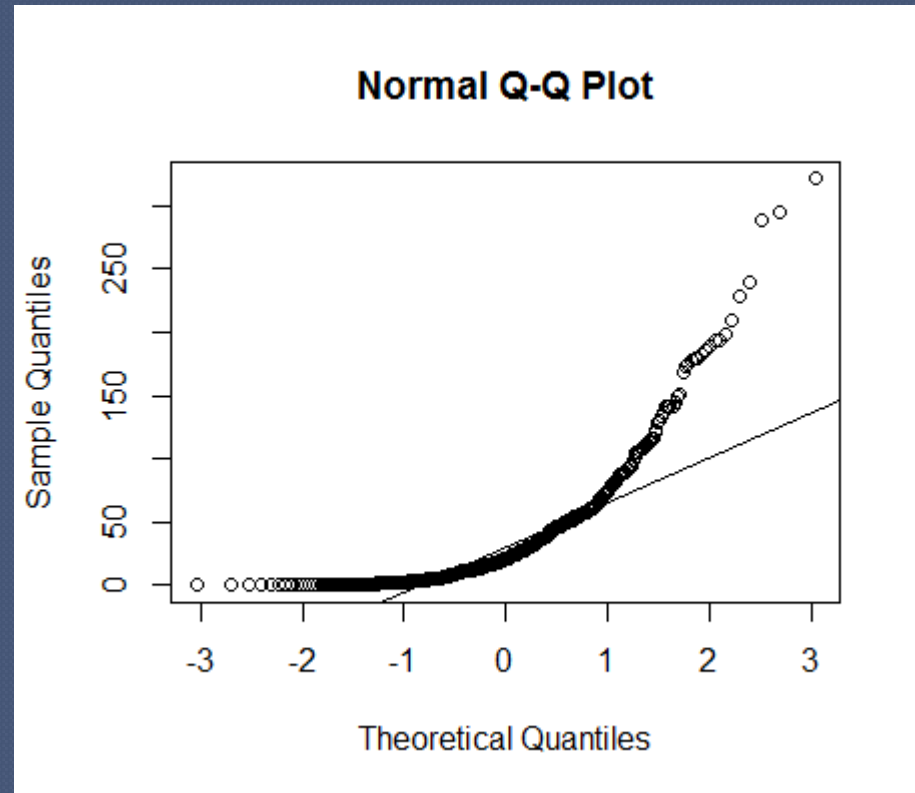


# Unclean Data: First Look

- Non-normal distribution
- QQplots and Shapiro-Wilk tests Confirm this.

See, for example, 'Deletes'

$W = 0.74059$ ,  
 $p\text{-value} < 2.2e-16$



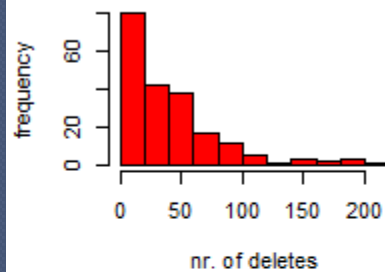
# Clean data

---

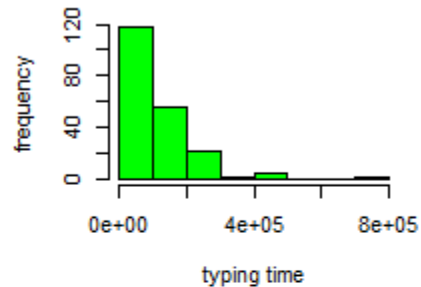
- Completed more than 12 trials
- Only first 12 faces
  - see the actual strategies
  - nice subset for a pilot study

# Clean Data: First look

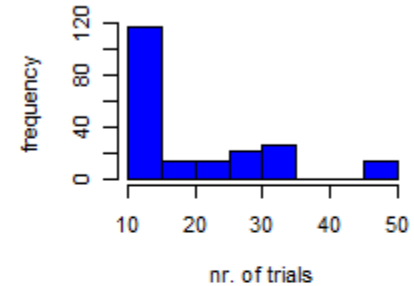
Deletes Per Trial



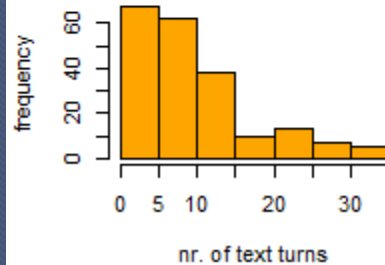
Typing Time Per Trial



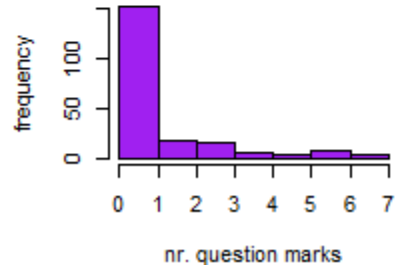
Total Trials Attempted



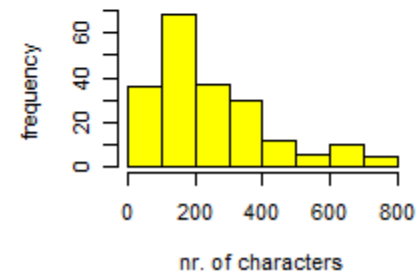
Text Turns Per Trial



Question Marks Per Trial



Characters Typed Per Trial

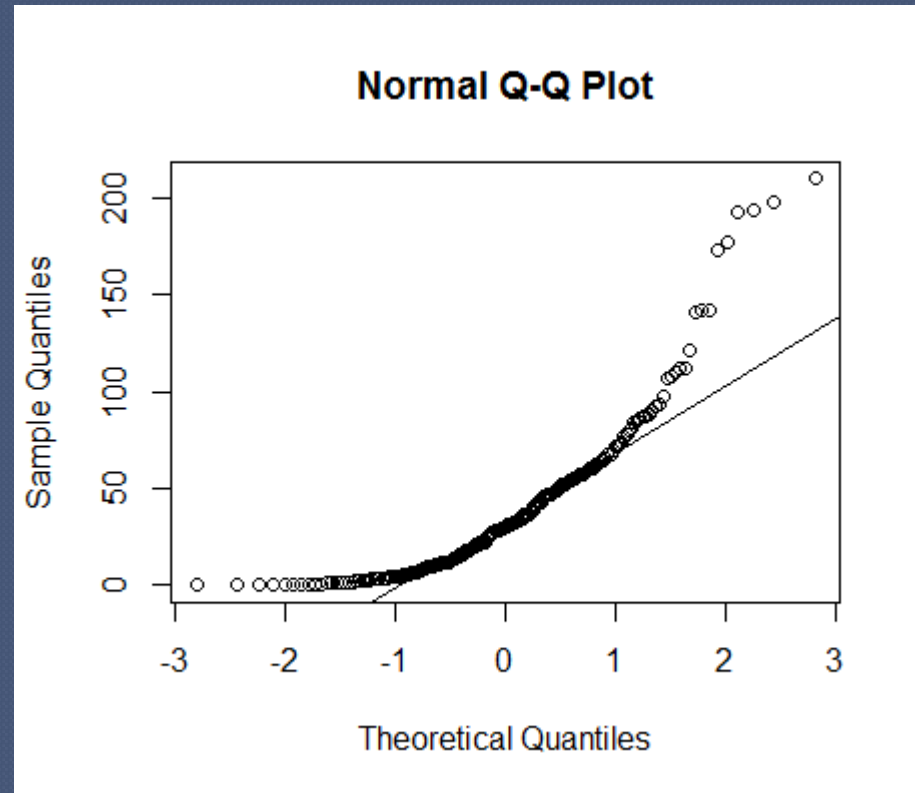


# Clean Data: First Look

- Non-normal distribution
- QQplots and Shapiro-Wilk tests Confirm this.

See, for example, 'Deletes'

$W = 0.82373$ ,  
 $p\text{-value} = 2.239e-14$



# Multiple logistic regression

---

- ◉ Outcome variable: categorical
- ◉ Predictor variables: continuous
  
- ◉ Non-normal distribution
  
- ◉ Binomial



# Multiple Logistic Regression

---

- Best model: no over/underfitting
- AIC instead of R-squared
- Deviances: related to model fit
  - “the null deviance measures the discrepancy between the intercept only model and the data and the [residual] deviance measures the discrepancy between the fitted model and the data. In other words, the smaller the deviance is, the better the model fits the data” (Speelman, 2014, p. 24).
  - the lower the better

# Assumptions

---

- Multicollinearity:
  - predictors should not be too highly correlated. VIF.
- Dispersion:
  - there should be no over/underdispersion.
  - Overdispersion: large difference between residual deviance and df → coefficients will seem more confident than they are. Smaller SE's (Nerbonne).
- Linearity of the logit:
  - “The linearity assumption in logistic regression is (...) that there is a linear relationship between any continuous predictors and the logit of the outcome variable (...) Look at whether the interaction terms between the predictor and its log transformation is significant” (Field, 2012, p. 321). It should not be significant.

# Step(): Model Selection

---

- Full model → best model
- Forward/backward
- Critique: “a joke, not based on a theory (...) unconstrained coefficients” (Gelman, 2014).
- Backward better, according Field (2012, p. 265)
  - suppressor effects: when a predictor is significant only when another is held constant. Forward elimination is more likely to exclude factors involved in suppressor effects and consequently more likely to make a Type II error (saying something is insignificant when it is significant).
- Gives you the model with the lowest AIC . Is it also the best model?

# Unclean Data: Full Model

```
Call:
glm(formula = SuccessOfTrial ~ DeletesPerTrial + TypingTimePerTrial +
  CharactersTypedPerTrial + NumberOfTextTurnsPerTrial +
  TotalTrialsAttemptedByDyad +
  NoOfQuestionMarksPerTrial, family = "binomial", data = fd)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.1658	-1.2026	0.7323	0.7881	1.8802

Coefficients:

	Estimate	Std. Error	z value
(Intercept)	1.294e+00	3.662e-01	3.533
DeletesPerTrial	1.284e-02	4.120e-03	3.115
TypingTimePerTrial	-3.084e-06	1.125e-06	-2.742
CharactersTypedPerTrial	-1.071e-04	1.077e-03	-0.099
NumberOfTextTurnsPerTrial	-3.565e-02	3.162e-02	-1.127
TotalTrialsAttemptedByDyad	-2.700e-03	1.067e-02	-0.253
NoOfQuestionMarksPerTrial	2.477e-02	1.201e-01	0.206

	Pr(> z )
(Intercept)	0.000411 ***
DeletesPerTrial	0.001838 **
TypingTimePerTrial	0.006115 **
CharactersTypedPerTrial	0.920821
NumberOfTextTurnsPerTrial	0.259591
TotalTrialsAttemptedByDyad	0.800234
NoOfQuestionMarksPerTrial	0.836588

---  
Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 494.27 on 424 degrees of freedom  
Residual deviance: 479.33 on 418 degrees of freedom  
AIC: 493.33

Number of Fisher Scoring iterations: 4

# Unclean Data: Best Model

```
Call:
glm(formula = SuccessOfTrial ~ DeletesPerTrial + TypingTimePerTrial,
     family = "binomial", data = fd)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.1340  -1.2202   0.7556   0.7917   1.6524

Coefficients:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)    1.033e+00  1.431e-01  7.219 5.22e-13 ***
DeletesPerTrial  1.024e-02  3.636e-03  2.816  0.00486 **
TypingTimePerTrial -3.369e-06  1.048e-06 -3.213  0.00131 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 494.27  on 424  degrees of freedom
Residual deviance: 482.48  on 422  degrees of freedom
AIC: 488.48

Number of Fisher Scoring iterations: 4
```

- (Best model according to step()) also included text turns'. That model had a lower AIC (487.4), but was not significantly different and in order to avoid overfitting, this model was chosen)

# ANOVA

---

- AIC:

  - 493.33 vs. 488.84

- ANOVA comparison:

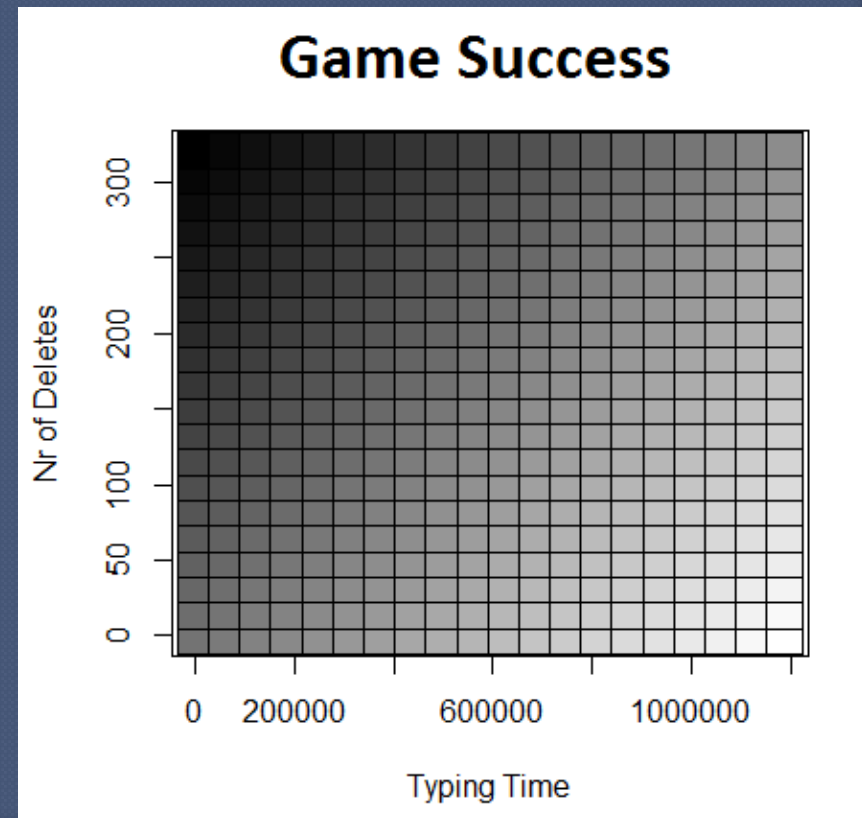
  - $p: 0.5339$

  - no significant difference. However, this model is simpler, and has an AIC of  $>2$  points lower, and is therefore better (no overfitting)



# Predictors

- Best predictors: Deletes & Typing Time
- Typing Time: negative
- Deletes: unexpected positive predictor



# Clean Data: Full Model

```
Call:
glm(formula = SuccessOfTrial ~ DeletesPerTrial + TypingTimePerTrial +
     CharactersTypedPerTrial + NumberOfTextTurnsPerTrial +
     TotalTrialsAttemptedByDyad +
     NoOfQuestionMarksPerTrial, family = "binomial", data = fdc)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.1411	-0.9368	0.5916	0.8111	2.5874

Coefficients:

	Estimate	Std. Error	z value
(Intercept)	2.890e+00	6.349e-01	4.553
DeletesPerTrial	1.374e-02	6.685e-03	2.055
TypingTimePerTrial	-5.610e-06	2.291e-06	-2.449
CharactersTypedPerTrial	2.911e-03	2.296e-03	1.268
NumberOfTextTurnsPerTrial	-1.431e-01	5.693e-02	-2.514
TotalTrialsAttemptedByDyad	-5.699e-02	1.821e-02	-3.130
NoOfQuestionMarksPerTrial	1.098e-01	1.719e-01	0.638

	Pr(> z )
(Intercept)	5.29e-06 ***
DeletesPerTrial	0.03985 *
TypingTimePerTrial	0.01433 *
CharactersTypedPerTrial	0.20486
NumberOfTextTurnsPerTrial	0.01194 *
TotalTrialsAttemptedByDyad	0.00175 **
NoOfQuestionMarksPerTrial	0.52320

---  
Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 240.38 on 201 degrees of freedom  
Residual deviance: 214.70 on 195 degrees of freedom  
AIC: 228.7

Number of Fisher Scoring iterations: 4



# Clean Data: Best Model

```
Call:
glm(formula = SuccessOfTrial ~ DeletesPerTrial + TypingTimePerTrial +
     NumberOfTextTurnsPerTrial + TotalTrialsAttemptedByDyad, family =
     "binomial",
     data = fdc)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.1215	-1.0081	0.6063	0.7954	2.7030

Coefficients:

	Estimate	Std. Error	z value
(Intercept)	2.940e+00	6.114e-01	4.809
DeletesPerTrial	1.591e-02	6.509e-03	2.445
TypingTimePerTrial	-5.044e-06	2.183e-06	-2.311
NumberOfTextTurnsPerTrial	-7.814e-02	3.249e-02	-2.405
TotalTrialsAttemptedByDyad	-5.837e-02	1.793e-02	-3.256

	Pr(> z )	
(Intercept)	1.52e-06 ***	
DeletesPerTrial	0.01450 *	Way more significant than in full model
TypingTimePerTrial	0.02085 *	Less significant than in full model
NumberOfTextTurnsPerTrial	0.01618 *	Less significant than in full model
TotalTrialsAttemptedByDyad	0.00113 **	More significant than in full model

---  
Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 240.38 on 201 degrees of freedom  
Residual deviance: 216.89 on 197 degrees of freedom  
AIC: 226.89

Number of Fisher Scoring iterations: 4

# ANOVA

---

- AIC:
  - 228.7 vs. 226.89
- ANOVA comparison:
  - $p: 0.3358$
  - no significant difference. However, this model is simpler and therefore better (no overfitting)
  - smaller model does differ significantly from other smaller models

# Assumptions

---

- Multicollinearity:
  - could not use VIF, but deletes/typing time/tekst turns are highly correlated ( $r > .5$ ) → assumption violated.
- Dispersion: Binomial response variables rarely lead to over/underdispersion
  - Residual Deviance = 216.89
  - Df = 197
  - No over or underdispersion (also checked this with 'family=quasibinomial')
- Linearity of the logit

# Linearity of the logit

```
Call:
glm(formula = SuccessOfTrial ~ DeletesPerTrial + TypingTimePerTrial +
     NumberOfTextTurnsPerTrial + TotalTrialsAttemptedByDyad +
     deleteslogint + timelogint + turnslogint + trialslogint,
     family = binomial, data = fdc)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.3739	-0.9522	0.5468	0.7957	1.4307

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	4.547e+00	2.525e+00	1.801	0.0717	.
DeletesPerTrial	1.288e-01	5.681e-02	2.268	0.0233	*
TypingTimePerTrial	-1.456e-04	6.779e-05	-2.148	0.0317	*
NumberOfTextTurnsPerTrial	-1.307e-01	2.643e-01	-0.494	0.6211	
TotalTrialsAttemptedByDyad	-1.795e-01	3.650e-01	-0.492	0.6228	
deleteslogint	-2.106e-02	1.052e-02	-2.002	0.0453	*
timelogint	1.057e-05	5.067e-06	2.086	0.0370	*
turnslogint	1.613e-02	7.182e-02	0.225	0.8223	
trialslogint	2.521e-02	8.460e-02	0.298	0.7657	

---  
Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 226.24 on 191 degrees of freedom  
Residual deviance: 199.06 on 183 degrees of freedom  
(10 observations deleted due to missingness)  
AIC: 217.06

Number of Fisher Scoring iterations: 4

# Linearity of the logit

---

- ◉ Deletes & Typing Time interaction terms are in fact significant → problematic
- ◉ Linearity of the logit cannot be assumed

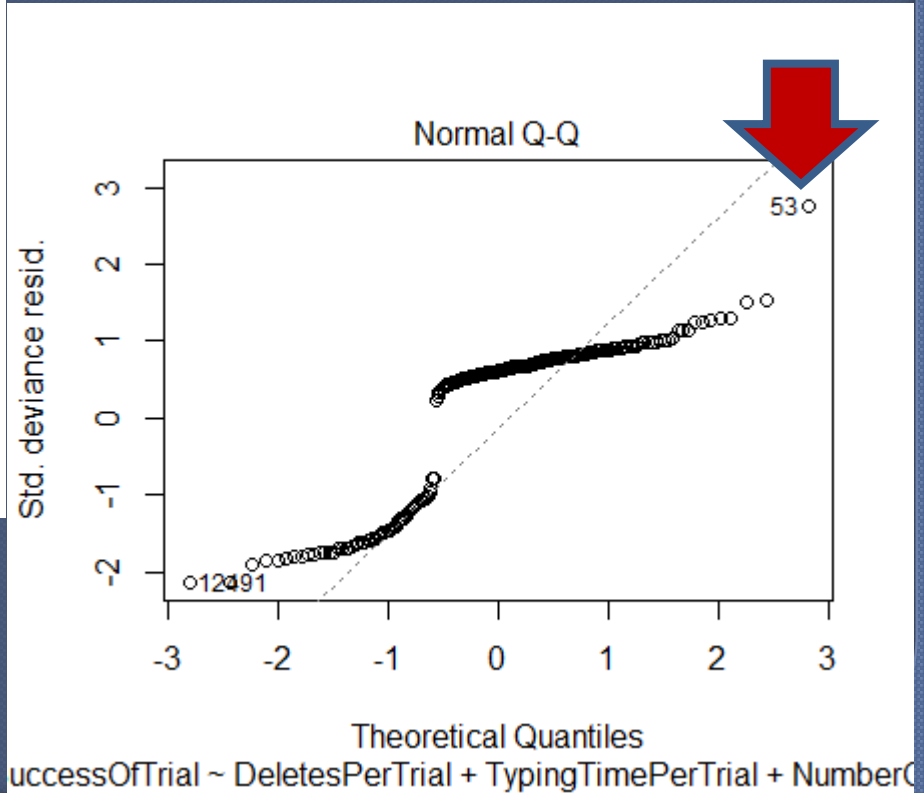
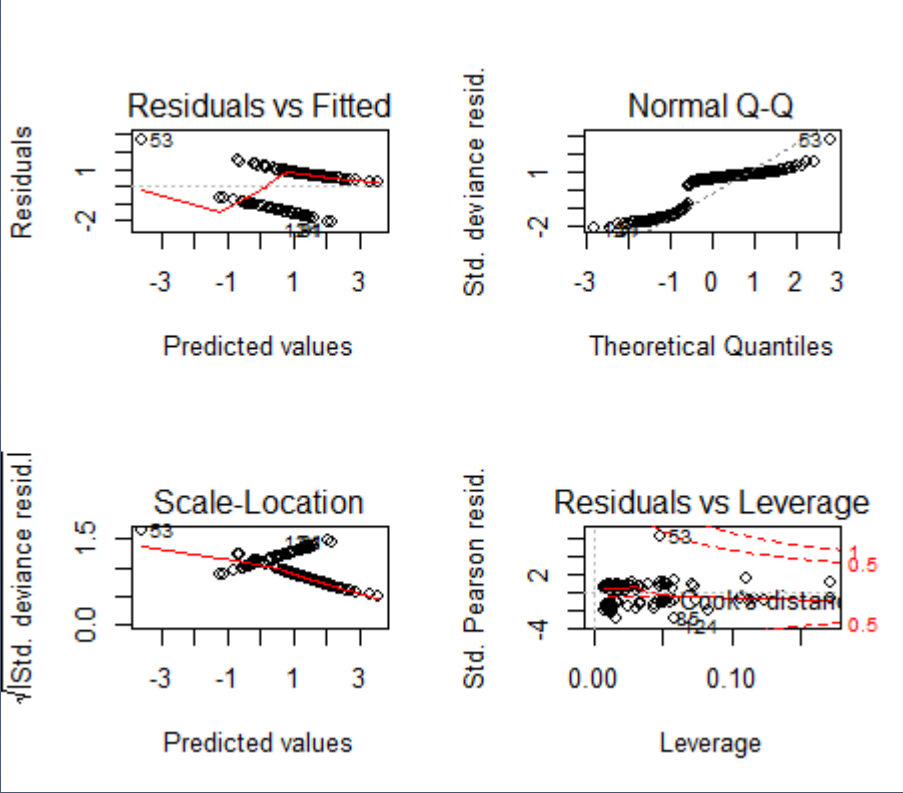
# Model Fit

---

- AIC: 226.89
- Deviances:
  - Null: 240.38
  - Residual: 216.89
- Goodness of fit:
  - 1 - pchisq(23.49, 4)
  - (difference in deviance, difference in df)
  - p = 0.0001010535, better than chance (p < .05)

# Residuals

- Regression models for binomial response variables are not meant to have normally distributed residuals



successOfTrial ~ DeletesPerTrial + TypingTimePerTrial + NumberC



# Outlier Excluded: Best Model

```
> summary(fdc1.out <- glm(SuccessOfTrial ~ DeletesPerTrial +  
TypingTimePerTrial + NumberOfTextTurnsPerTrial +  
TotalTrialsAttemptedByDyad, family = "binomial", data = fdc, subset=-53))
```

Call:

```
glm(formula = SuccessOfTrial ~ DeletesPerTrial + TypingTimePerTrial +  
  NumberOfTextTurnsPerTrial + TotalTrialsAttemptedByDyad, family =  
  "binomial",  
  data = fdc, subset = -53)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.2507	-0.7901	0.5630	0.7925	1.6650

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	3.334e+00	6.429e-01	5.186	2.15e-07	***
DeletesPerTrial	2.237e-02	7.157e-03	3.126	0.001772	**
TypingTimePerTrial	-8.266e-06	2.656e-06	-3.113	0.001852	**
NumberOfTextTurnsPerTrial	-9.263e-02	3.456e-02	-2.681	0.007350	**
TotalTrialsAttemptedByDyad	-6.526e-02	1.847e-02	-3.534	0.000409	***

---  
Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 239.71 on 200 degrees of freedom  
Residual deviance: 207.49 on 196 degrees of freedom  
AIC: 217.49 **LOWEST DEVIANCE AND AIC**

Number of Fisher Scoring iterations: 4



# Assumptions

---

- Multicollinearity:
  - could not use VIF, but deletes/typing time/tekst turns are highly correlated ( $r > .5$ )  
→ assumption violated.
- Dispersion
  - Residual Deviance = 207.49
  - Df = 196
  - No over or underdispersion
- Linearity of the Logit

# Linearity of the Logit

```
Call:
glm(formula = SuccessOfTrial ~ DeletesPerTrial + TypingTimePerTrial +
  NumberOfTextTurnsPerTrial + TotalTrialsAttemptedByDyad +
  deleteslogint + timelogint + turnslogint + trialslogint,
  family = binomial, data = fdc, subset = -53)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.1636	-0.7918	0.5525	0.7932	1.7194

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )
(Intercept)	3.687e+00	2.589e+00	1.424	0.154
DeletesPerTrial	8.853e-02	6.184e-02	1.432	0.152
TypingTimePerTrial	-9.621e-06	9.506e-05	-0.101	0.919
NumberOfTextTurnsPerTrial	-1.788e-01	2.756e-01	-0.648	0.517
TotalTrialsAttemptedByDyad	-1.691e-01	3.701e-01	-0.457	0.648
deleteslogint	-1.308e-02	1.163e-02	-1.125	0.261
timelogint	9.655e-08	7.223e-06	0.013	0.989
turnslogint	2.372e-02	7.465e-02	0.318	0.751
trialslogint	2.475e-02	8.576e-02	0.289	0.773

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 225.60 on 190 degrees of freedom  
Residual deviance: 194.09 on 182 degrees of freedom  
(10 observations deleted due to missingness)  
AIC: 212.09

Number of Fisher Scoring iterations: 4

# Linearity of the logit

---

- None of the interaction terms are significant
- Linearity of the logit can be assumed

# Model Fit

---

- AIC = 217.49
- Deviances
  - Null: 239.71
  - Residual: 207.49
- Goodness of fit:
  - $1 - \text{pchisq}(32.22, 4) = 1.724908e-06$
  - $p < .05$
  - It can be assumed that the model performs better than chance

# Report: Best Model

fdc1.out	B (SE)	95% CI for odds ratio		
		Lower	Odds Ratio	Upper
<b>Included</b>				
Constant	3.334e+00 (6.429e-01)	8.3322635	28.0542325	104.8929683
Deletes	2.237e-02 (7.157e-03)	1.0091658	1.0226228	1.0380148
Typing Time	-8.266e-06 (2.656e-06)	0.9999859	0.9999917	0.9999965
Text Turns	-9.263e-02 (3.456e-02)	0.8487203	0.9115323	0.9729605
Trials Attempted	-6.526e-02 (1.847e-02)	0.9024395	0.9368262	0.9707146

**Odds ratio:** “indicator of the change in odds resulting from a unit change in the predictor” (Field, 2012, p. 319)

# Lack of graphs

---

- “Graphs aren't very useful for showing the results of multiple logistic regression; instead, people usually just show a table of the independent variables, with their *P* values and perhaps the regression coefficients”. (McDonald, 2009)
- Visualisation of a 5-dimensional model (4 predictors, 1 outcome) is often too complicated

# Tentative conclusions

---

- 1. Best Model/predictors:
  - Best AIC: 217.49
  - Includes: Deletes, typing time, nr. of text turns and total trials attempted
- 2. Cleaning up the data:
  - Cleaning the data leads to slightly different and significantly better models than having unclean data
  - Excluding a very influential outlier leads to a significantly lower AIC, lower deviances, and linearity of the logit
- 3. Deletes is a positive predictor in all models: unexpected
- Best predictors:
  - in and of itself, total trials attempted is the best predictor

# Questions?

---

- ◉ Should I exclude more outliers?
- ◉ Exclude total trials attempted?  
Interpretation of this variable is dodgy...
- ◉ Shall I add graphs of the multiple logistic regression model?



# References

- Bangerter, A., & Clark, H. H. (2003). Navigating joint projects with dialogue. *Cognitive Science*, 27(2), 195-225
- Coltekin, C. (2014). Retrieved from <http://coltekin.net/cagri/R/R-exercises.html>
- Field, A. (2012). *Discovering statistics using R*. Sage. Chicago.
- Garrod, S., & Anderson, A. (1987). Saying what you mean in dialogue: A study in conceptual and semantic co-ordination. *Cognition*, 27(2), 181-218.
- Gelman, A. (2014). "Why we hate stepwise regression". Retrieved from <http://andrewgelman.com/2014/06/02/hate-stepwise-regression/>
- Hayashi, M., Raymond, G., & Sidnell, J. (2013). Conversational repair and human understanding: an introduction. In Hayashi, M., Raymond, G., & Sidnell, J. (Eds.) *Conversational repair and human understanding* (Vol. 30) (pp. 1-40). Cambridge, UK: Cambridge University Press. <http://dx.doi.org/10.1017/CBO9780511757464.001>
- Herring, S. (1999). Interactional coherence in CMC. *Journal of Computer-Mediated Communication*, 4(4), 0-0.
- McDonald, J. H. (2009). *Handbook of biological statistics* (Vol. 2, pp. 173-181). Baltimore, MD: Sparky House Publishing. Chicago
- Smith, M., Cadiz, J. J., & Burkhalter, B. (2000, December). Conversation trees and threaded chats. In *Proceedings of the 2000 ACM conference on Computer supported cooperative work* (pp.97-105). ACM.
- Speelman, D. (2014). Logistic regression. *Corpus Methods for Semantics: Quantitative studies in polysemy and synonymy*, 43, 487. ISO 690