Gradient grammaticality of the indefinite object drop in Italian: behavioral evidence

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Goal of the study

Modeling the gradient grammaticality of the indefinite object drop construction in Italian using five predictors in a Stochastic Optimality Theoretic model

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Indefinite object drop

Some transitive verbs allow for the omission of the dObj[1]

Definite object drop: contextually recoverable meaning

(1) I did not finish $\emptyset_{dObj}$.
$\emptyset$ = the job

Indefinite object drop: meaning recoverable from the semantics of the verb itself

(2) John is eating $\emptyset_{dObj}$.
$\emptyset$ = anything edible

[1] Fillmore 1986; Mittwoch 1982.

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Elements of novelty

- experimental data in support of untested theory
- behavioral experiment on Italian
- Stochastic OT model with 5 predictors
  (Medina 2007 only had three, and focused on English)

Predictors

Semantic and aspectual predictors

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predictor	type
semantic selectivity	continuous
telicity	binary
perfectivity	binary
iterativity	binary
manner specification	binary

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Semantic selectivity

A well-known predictor of object drop[2]

for any given verb,
semantic narrowness of dObjs $\sim$ likelihood of object drop

(3) John ate $\emptyset_{dObj}$.
(4) *John made $\emptyset_{dObj}$.

[2] Glass 2013; Goldberg 2005; Levin 1993; Medina 2007; Resnik 1993, 1996.

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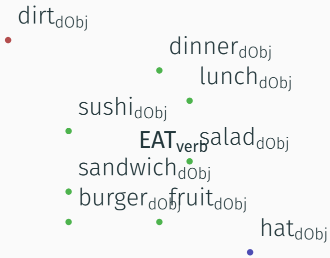
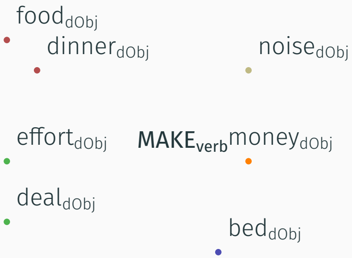
Implementing semantic selectivity



the dObjs of *to eat* are close together in this semantic space



the dObjs of *to make* are very sparse in this semantic space

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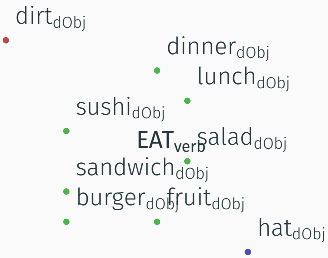

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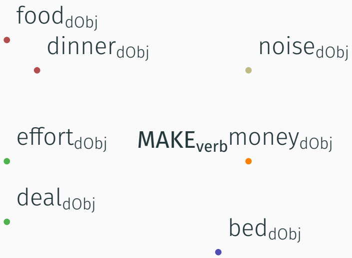

the dObjs of *to make* are very sparse in this semantic space

Intuition: the semantic selectivity of transitive verbs is positively correlated with the semantic density of their dObjs

Semantic selectivity: Behavioral PISA

Implementation: semantic density of a verb as the mean pairwise similarity between a subset of its dObjs, gauged via human judgments

in **Cappelli and Lenci 2020**, we measured it with distributional semantics (pairwise cosine similarity between all the dObjs of verbs)

⟶ Computational PISA, measure of Preference In Selection of Arguments

---

25 Italian native speakers judged the similarity of 6 pairs of dObjs (randomly extracted from itWaC) for 30 verbs on a 7-point Likert scale

The Behavioral PISA score for each verb is the average of the ratings relative to all the dObj pairs of that verb (see 1)

$$PISA_v = \frac{\sum_i r_v}{i} \quad (1)$$

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Telicity

The inherent endpoint of a telic verb has to be realized syntactically as a dObj (as in 5), while the dObj of an atelic verb may be omitted (as in 6)[3].

(5) *John killed $\emptyset_{dObj}$.
(6) John ate $\emptyset_{dObj}$.

[3] Hopper and Thompson 1980; Medina 2007; Olsen and Resnik 1997.

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Perfectivity

imperfective aspect = ongoing event
perfective aspect = event that reached its end

Perfective predicates require overt dObjs (as in 7), while imperfective predicates allow for object drop (as in 8)[4].

(7) ? John painted $\emptyset_{dObj}$.
(8) John was painting $\emptyset_{dObj}$.

[4] Comrie 1976; Medina 2007.

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Iterativity

Iterativity and other types of pluractionality favor the omission of dObjs[5], as shown in (9) vs (10).

(9) # The Joker killed $\emptyset_{dObj}$.
(10) The Joker killed again $\emptyset_{dObj}$.

[5] Glass 2013, 2020; Ruda 2017.

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Manner specification

If a transitive verb allows for object drop, as in (11), then its synonyms with a manner component block it[6], as in (12).

(11) John ate $\emptyset_{dObj}$.
(12) *John devoured/nibbled/chewed $\emptyset_{dObj}$.

[6] Ruda 2017.

Modeling object drop

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Optimality Theory

In standard Optimality Theory[7] the grammaticality of a linguistic structure is defined in terms of well-formedness with respect to a set of conflicting, re-rankable, universal constraints.

fixed constraint ranking: CON. 1 ≫ CON. 2 ≫ CON. 3

	$piovere_V$[present]	FULL-INT	SUBJECT
	a. EXPL piove	*!	
☞	b. piove		*

	$rain_V$[present]	SUBJECT	FULL-INT
☞	a. EXPL rains		*
	b. rains	*!	

binary grammaticality judgments

only one optimal candidate (several equally ungrammatical ones)

[7] Grimshaw and Samek-Lodovici 1998; Legendre 2001, 2019; Smolensky, Legendre, and Miyata 1993.

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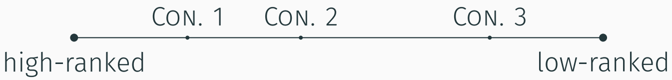
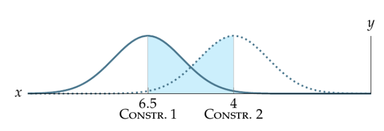
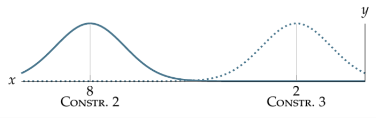
Stochastic Optimality Theory

Stochastic OT constraints are on a continuous, numerical scale (making it possible to model gradient grammaticality)



constraint ranking ranges are defined as (normal) probability distributions, and distribution overlap determines the probability of two constraint re-ranking with respect to one another





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Stochastic Optimality Theory: constraints

***INT ARG (*INTERNAL ARGUMENT STRUCTURE)** markedness constraint
The output must NOT contain an overt dObj

FAITH ARG (FAITHFULNESS TO ARGUMENT STRUCTURE) faithfulness con.
All arguments in the input must be present in the output.

TELIC END (TELIC ENDPOINT) faithfulness con.
Telic predicates must be bounded by a dObj in the output.

PERF CODA (PERFECTIVE CODA) faithfulness con.
Perfective predicates must be identified by a dObj in the output.

NON-ITERATIVE ARGUMENT (NON-ITER ARG) NOT IN MEDINA 2007 faithfulness con.
Non-iterative predicates must occur with a dObj in the output

MANNER-SPECIFIED ARGUMENT (MAN-SPEC ARG) NOT IN MEDINA 2007 faith. con.
Manner-specified predicates must occur with a dObj in the output

what about semantic selectivity?

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Stochastic Optimality Theory: semantic selectivity

Semantic selectivity is continuous $\longrightarrow$ bad candidate for constraint-hood (which requires a binary outcome of evaluation)

In Medina 2007's variant of StOT, constraints are re-ranked wrt semantic selectivity (she models it with Resnik 1993's SPS)

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Stochastic Optimality Theory: Medina 2007

1. grammaticality ratings ⟶ % of implicit dObj output...

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Stochastic Optimality Theory: Medina 2007

1. grammaticality ratings ⟶ % of implicit dObj output...
2. ... used to estimate the relative ranking of *INT ARG...
(implicit dObj output whenever *INT ARG is ranked above all the relevant constraints for a given input)

e.g. $p(\text{implicit})_{\text{Telic Imperfective}} = p(*I \gg F, T, P) + p(P \gg *I \gg F, T) =$
$= p(*I \gg F) \cdot p(*I \gg T) \cdot p(*I \gg P) + p(*I \gg F) \cdot p(*I \gg T) \cdot [1 - p(*I \gg P)]$

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1. grammaticality ratings $\longrightarrow$ % of implicit dObj output...

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e.g. $\text{p(implicit)}_{\text{Telic Imperfective}} = \text{p}(^*\text{I} \gg F, T, P) + p(P \gg *I \gg F, T) =$
$= \text{p}(^*\text{I} \gg F) \cdot p(*I \gg T) \cdot p(*I \gg P) + p(*I \gg F) \cdot p(*I \gg T) \cdot [1 - p(*I \gg P)]$

3. ... used to estimate the % of *INT ARG being ranked above each of the other constraints... i.e. $\text{p}(^*\text{I} \gg F), p(*I \gg T), p(*I \gg P)$

Stochastic Optimality Theory: Medina 2007

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$= \text{p}(^*\text{I} \gg F) \cdot p(*I \gg T) \cdot p(*I \gg P) + p(*I \gg F) \cdot p(*I \gg T) \cdot [1 - p(*I \gg P)]$

3. ... used to estimate the % of *INT ARG being ranked above each of the other constraints... i.e. $\text{p}(^*\text{I} \gg F), p(*I \gg T), p(*I \gg P)$
4. ... used to estimate the % of an implicit dObj output for each aspectual type of input (e.g. Telic Perfective, Telic Imperfective...)

Behavioral experiment

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Experimental design

within-subject fully crossed 2x2x2 design
(each participant sees all the stimuli in random order)

overt dObj	perfectivity	iterativity
+	+	+
+	+	–
+	–	+
+	–	–
–	+	+
–	+	–
–	–	+
–	–	–

30 transitive verbs (+ 10 intransitive fillers) participate in each of the 8 experimental conditions

(telicity, PISA and mannspec are inherent properties of each verb ⟶ not in the experimental design itself)

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Stimuli

(1)	Gianni aveva mangiato un panino di nuovo.	[dObj+, perf+, iter+]
(2)	Gianni aveva mangiato un panino.	[dObj+, perf+, iter-]
(3)	Gianni stava mangiando un panino di nuovo.	[dObj+, perf-, iter+]
(4)	Gianni stava mangiando un panino.	[dObj+, perf-, iter-]
(5)	Gianni aveva mangiato di nuovo.	[dObj-, perf+, iter+]
(6)	Gianni aveva mangiato.	[dObj-, perf+, iter-]
(7)	Gianni stava mangiando di nuovo.	[dObj-, perf-, iter+]
(8)	Gianni stava mangiando.	[dObj-, perf-, iter-]

the [dObj-] sentences with transitive verbs are the target stimuli

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Experimental setting

coded in PsychoPy, uploaded on Pavlovia, run on Prolific

gradient, statistically reliable judgments:
7-point Likert scale (then normalized between 0 and 1)
30 participants (graduate native speakers of Italian)

320 randomized stimuli, one by one
training session
control stimuli (non-target sentences)

Results

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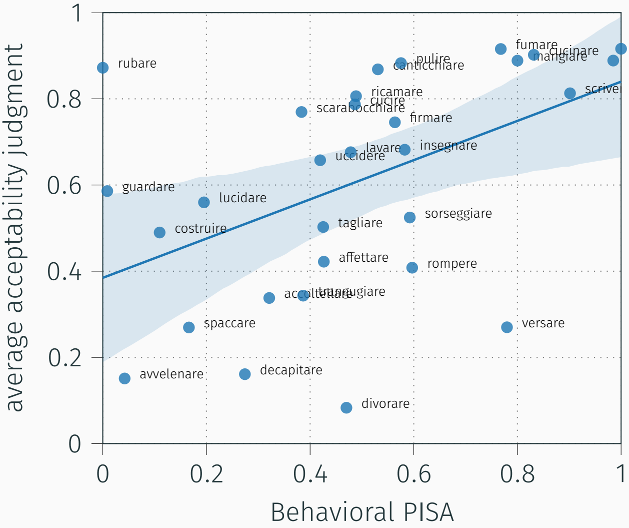
Effect of PISA



Pearson ρ = 0.481, p = 0.007

Effect of each binary predictor

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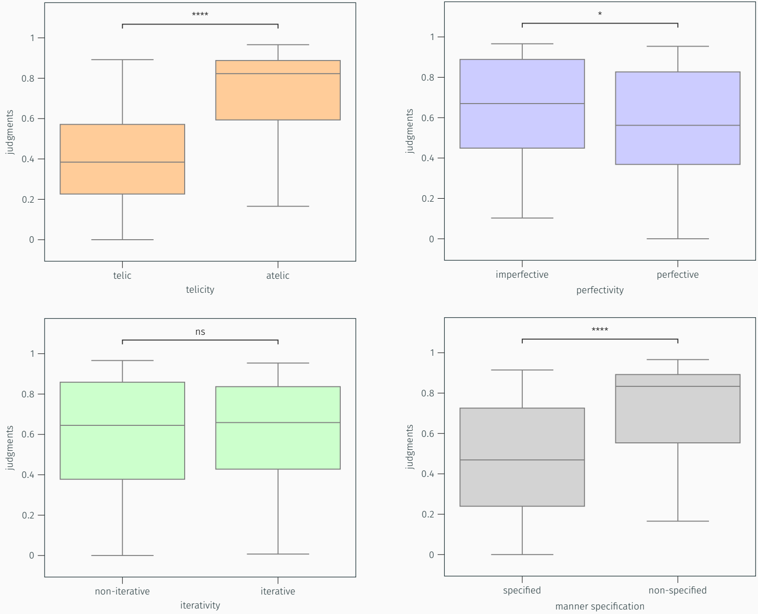

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Joint effect of predictors

taken individually, no predictor is decisive

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Joint effect of predictors

taken individually, no predictor is decisive

What does a linear mixed-effects model show?

- the model converges
- significant (negative) effect of telicity and perfectivity
- non-significant effect of PISA, iterativity and manner specification

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Joint effect of predictors

taken individually, no predictor is decisive

What does a linear mixed-effects model show?

- the model converges
- significant (negative) effect of telicity and perfectivity
- non-significant effect of PISA, iterativity and manner specification

a (Stochastic OT) model of object drop is feasible!

MODEL OUTPUT: p (*INT ARG » other constraints)

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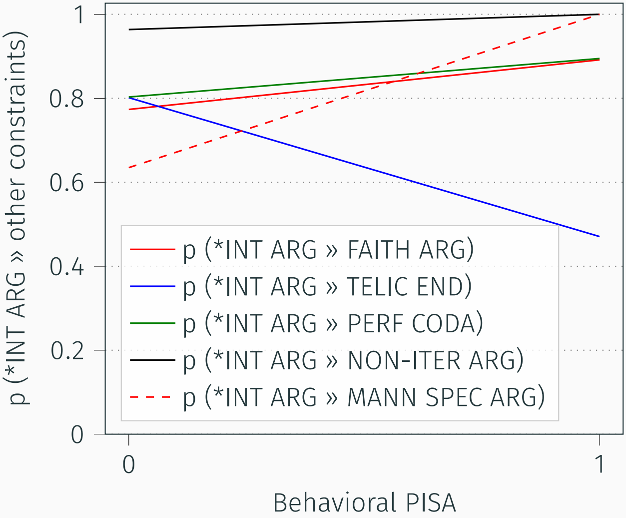

MODEL OUTPUT: probability of implicit object output

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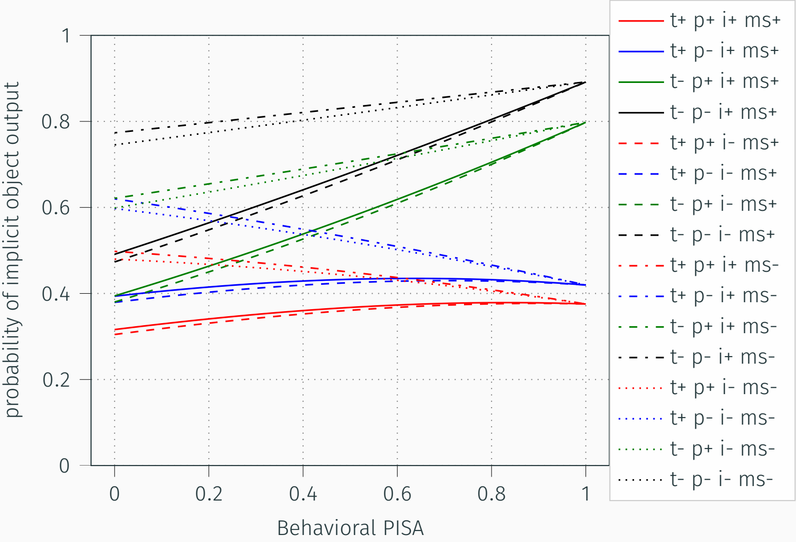

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- gradient grammaticality of object drop
- StOT model with 5 significant predictors
- quantification of predictors' strength

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- comparison with other languages (working on English!)
- what about Instruments?
- modeling corpus frequencies instead of human judgments

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Thank you!

slides, data & Python code
at **giuliacappelli.com**

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Stochastic Optimality Theory: Medina 2007

LOGIC ⇓	
f(SPS) = probability of *INT ARG dominating each constraint	**knowing the relative % of each constraint orderings, estimate the % of *INT ARG dominating each constraint**
these outputs determine the relative % of each of all the possible constraint orderings	**relative % of each of the possible constraint orderings can be estimated via the relative % of impl object output**
these relative % determine the relative % (and thus grammaticality) of the impl object output for a given input	**grammaticality judgments = relative % of impl object output for a given input**
	PROCEDURE ⇑

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StOT model: procedure step 1

the grammaticality of the indefinite object drop is quantified via an acceptability judgment survey

these ratings are equated to the probability of an implicit object output for a given input

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StOT model: procedure step 2

the probability of the possible constraint orderings can be estimated via the % of an implicit object output

In Medina 2007,

$$p(\text{implicit})_{\text{Telic Perfective}} = p(*I \gg F, T, P)$$

$$p(\text{implicit})_{\text{Telic Imperfective}} = p(*I \gg F, T, P) + p(P \gg *I \gg F, T)$$

$$p(\text{implicit})_{\text{Atelic Perfective}} = p(*I \gg F, T, P) + p(T \gg *I \gg F, P)$$

$$p(\text{implicit})_{\text{Atelic Imperfective}} = p(*I \gg F, T, P) + p(T \gg *I \gg F, P) + $$
$$+ p(P \gg *I \gg F, T) + p(T, P \gg *I \gg F)$$

e.g. $p(\text{implicit})_{\text{Telic Perfective}}$ = judgments for telic perfective stimuli

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StOT model: procedure step 2

... which means that the probabilities are computed as follows, considering the relative ranking of *Int Arg with respect to the other three constraints as independent computations

$$p(\text{implicit})_{\text{Telic Perfective}} = p(*I \gg F) \cdot p(*I \gg T) \cdot p(*I \gg P) \quad (2)$$

$$p(\text{implicit})_{\text{Telic Imperfective}} = p(*I \gg F) \cdot p(*I \gg T) \cdot p(*I \gg P) + \\ + p(*I \gg F) \cdot p(*I \gg T) \cdot [1 - p(*I \gg P)] \quad (3)$$

$$p(\text{implicit})_{\text{Atelic Perfective}} = p(*I \gg F) \cdot p(*I \gg T) \cdot p(*I \gg P) + \\ + p(*I \gg F) \cdot [1 - p(*I \gg T)] \cdot p(*I \gg P) \quad (4)$$

$$p(\text{implicit})_{\text{Atelic Imperfective}} = p(*I \gg F) \cdot p(*I \gg T) \cdot p(*I \gg P) + \\ + p(*I \gg F) \cdot [1 - p(*I \gg T)] \cdot p(*I \gg P) + \\ + p(*I \gg F) \cdot p(*I \gg T) \cdot [1 - p(*I \gg P)] + \\ + p(*I \gg F) \cdot [1 - p(*I \gg T)] \cdot [1 - p(*I \gg P)] \quad (5)$$

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StOT model: procedure step 3

$$p(\text{*INT ARG} \gg \text{FAITH ARG}) = \frac{\delta_1 - \gamma_1}{SPS_{max} - SPS_{min}} \cdot (SPS_i - SPS_{min}) + \gamma_1 \quad (6)$$

$$p(\text{*INT ARG} \gg \text{TELIC END}) = \frac{\delta_2 - \gamma_2}{SPS_{max} - SPS_{min}} \cdot (SPS_i - SPS_{min}) + \gamma_2 \quad (7)$$

$$p(\text{*INT ARG} \gg \text{PERF CODA}) = \frac{\delta_3 - \gamma_3}{SPS_{max} - SPS_{min}} \cdot (SPS_i - SPS_{min}) + \gamma_3 \quad (8)$$

These functions take positive values in a range of possible values depending on the verbs' semantic selectivity.

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StOT model: computation

The unknown parameters (gammas and deltas) can be estimated by optimizing an overall function[8] so that:

- the sum-squared error between the predictions of the model and the actual grammaticality judgments are minimized
- gammas and deltas fall between 0 and 1

Thanks to these constraints, the model outputs predicted grammaticality values in the 0-1 probability range.

[8] Medina 2007 used Excel Solver, I used the *curve_fit()* method inside the *optimize* function of the Python library SciPy