Supporting Information

NB: All data and analyses reported in this paper are publicly accessible via the Harvard Dataverse at http://dx.doi.org/10.7910/DVN/JZZIYU (Montero-Melis, 2016)

A. Description of target stimuli

Table 1

Full description of target items.

item	Path	MannerCause	MannerObject	Direction	Object	Ground
1	across	pull	roll	left-right	pram	street
2	across	pull	roll	right-left	pram	road
3	across	pull	slide	left-right	rocking horse	street
4	across	pull	slide	right-left	rocking horse	road
5	across	push	roll	left-right	cart wheel	road
6	across	push	roll	right-left	cart wheel	street
7	across	push	slide	left-right	apple basket	road
8	across	push	slide	right-left	apple basket	street
9	down	pull	roll	left-right	wheelbarrow	hill
10	down	pull	roll	right-left	wheelbarrow	snowy hill
11	down	pull	slide	left-right	trunk	hill
12	down	pull	slide	right-left	trunk	snowy hill
13	down	push	roll	left-right	ball	snowy hill
14	down	push	roll	right-left	ball	hill
15	down	push	slide	left-right	suitcase	snowy hill
16	down	push	slide	right-left	suitcase	hill
17	into	pull	roll	left-right	shopping cart	cave
18	into	pull	roll	right-left	shopping cart	barn
19	into	pull	slide	left-right	chair	barn
20	into	pull	slide	right-left	chair	cave
21	into	push	roll	left-right	wheel	cave
22	into	push	roll	right-left	wheel	barn
23	into	push	slide	left-right	table	barn
24	into	push	slide	right-left	table	cave
25	up	pull	roll	left-right	toy car	dune

item	Path	MannerCause	MannerObject	Direction	Object	Ground
26	up	pull	roll	right-left	toy car	roof
27	up	pull	slide	left-right	bag	dune
28	up	pull	slide	right-left	bag	roof
29	up	push	roll	left-right	rubber ring	dune
30	up	push	roll	right-left	rubber ring	roof
31	up	push	slide	left-right	gift	dune
32	up	push	slide	right-left	gift	roof

B. Norming study (participant descriptions of the events)

To test for between-language differences in the likelihood of expressing the three key event components manipulated in the study, we fitted three separate logistic mixed models (Jaeger, 2008), one for each of the dependent variables Path, Manner of cause and Manner of object. Analyses were run in *R* (R Development Core Team, 2013) using the *glmer* function from the lme4 package (Bates, Maechler, Bolker, & Walker, 2014). The model formulae were:

```
PathMention ~ 1 + language + (1 | subject) + (1 | item) +
    (0 + language | item)
MannerCauseMention ~ 1 + language + (1 | subject) +
    (1 + language | item)
MannerObjectMention ~ 1 + language + (1 | subject) +
    (1 + language | item)
```

The models above were the maximal models that converged (Barr, Levy, Scheepers, & Tily, 2013). In the path model, a model analogous to the ones for Manner of cause and Manner of object did not converge, so we removed the by-item random correlation between the intercept and language (see difference in by-item random effects in model formulae above).

Because the analyses involved multiple tests on the same data, one for each semantic component, we Bonferroni-corrected the *p* values by multiplying the original *p* values by 3 (the number of models), to stay at the nominal level of $\alpha = .05$. Table 2 summarizes the results of each model.

Table 2

Informational content of descriptions in norming study (model summaries). Each logit mixed model estimates the log-likelihood that the dependent variable was encoded in Spanish (intercept) and the difference in log-likelihood between languages (Swedish vs. Spanish).

Model	Dependent variable	Predictor	Coef. $\hat{\beta}$	SE($\hat{\beta}$)	*z*	*p*
1	Path	Spanish (intercept)	4.20	0.66	6.39	<.0001
		Swedish vs. Spanish	3.03	1.46	2.08	=.113
2	Manner of cause	Spanish (intercept)	0.32	0.50	0.65	=1
		Swedish vs. Spanish	5.01	1.36	3.67	<.001
3	Manner of object	Spanish (intercept)	−5.06	0.87	−5.79	<.0001
		Swedish vs. Spanish	2.55	0.89	2.88	=.018

Note. For each separate model, the table shows coefficient estimates $\hat{\beta}$ (in log-odds), standard errors SE($\hat{\beta}$), associated Wald's *z* score ($\hat{\beta}$ / SE ($\hat{\beta}$)), and Bonferroni-adjusted significance level *p* for predictors (i.e., original *p* values multiplied by three with upper bound 1).

The compound analysis revealed that Spanish speakers relied more than Swedish speakers on ground when judging similarity. Is this mirroring a greater tendency by Spanish speakers to include ground information in their descriptions? In fact, speakers of both languages were almost at ceiling with respect to ground mentions: 96% of Spanish and 97% of Swedish descriptions mentioned this component. We fitted a mixed logistic regression model analogous to the ones above. The results showed no language differences in speakers' tendency to mention ground (Language$_{\text{Swedish-vs-Spanish}}$: $\hat{\beta}$ = 2.08, *SE* = 1.31, *z* = 1.31, *p* > .10), see Table 3.

Table 3

Model summary for mentions of ground in norming study. The table shows coefficient estimates $\hat{\beta}$ (in log-odds), standard errors SE($\hat{\beta}$), associated Wald's *z* score (=$\hat{\beta}$ / SE ($\hat{\beta}$)), and significance level *p* for predictors.

Dependent variable	Predictor	Coef. $\hat{\beta}$	SE($\hat{\beta}$)	*z*	*p*
Ground	Spanish (intercept)	5.28	1.12	4.69	<.0001
	Swedish vs. Spanish	2.08	1.31	1.59	.011

Model formula in R: GroundMention ~ 1 + language + (1 | subject) + (1 + language | item)

Finally, we summarize the mean proportion of descriptions that encoded each of the six event dimensions that varied in the stimuli. Table 4 shows by-subject means and standard errors.

Table 4

Proportion of mentions of each event component in norming study by language. Values indicate by-subject means and standard errors.

	Spanish	Swedish
Path (e.g. into)	0.95 (±0.02)	0.99 (±0.01)
Manner of cause (e.g., push)	0.55 (±0.07)	0.78 (±0.02)
Manner of object (e.g., roll)	0.10 (±0.03)	0.29 (±0.03)
Direction (e.g., left)	0.07 (±0.04)	0.02 (±0.02)
Ground (e.g., hill)	0.96 (±0.02)	0.97 (±0.03)
Object (e.g., ball)	1.00 (±0.00)	0.99 (±0.00)

C. Experiments 1–3 (linear mixed effects regression models)

All models were fitted in R (R Development Core Team, 2013) using the *lmer* function from the lme4 library (Bates et al., 2014). The models for Experiments 1-3 all had the same structure:

```
Similarity ~ 1 + (P + MC + MO + Di) ^ 2 * Language + Gr * Language
+ Ob * Language + (1 + (P + MC + MO + Di) ^ 2 + Gr + Ob | Subject)
+ (1 | Item)
```

(P = Path, MC = Manner of Cause, MO = Manner of Object, Di = Direction left/right, Gr = Ground, Ob = Object)

A description of the predictors that went into the models is shown in Table 5. All predictors were centred with a difference of 1, so that the reported coefficients represent the estimated difference in similarity ratings between the two levels of the predictor. Collinearity among predictors in the analyses for Experiments 1–3 was small, $\kappa < 5$ (cf. Baayen, 2008, p. 182). The fixed-effects estimates for each experiment are shown in Table 6 to Table 8. Significance codes were determined using the *confint.merMod* function from the lme4 library (method = “Wald”, nsim = 10000).

Table 5

Input variables in linear mixed models for Experiments 1–3.

Predictors	Type	Levels [a]
Path	Within-subject	Same (e.g., both scenes *into*), different (e.g., one scene *into*, other *up*)
Manner of cause	Within-subject	Same (e.g., both scenes *push*), different (e.g., one scene *push*, other *pull*)
Manner of object	Within-subject	Same (e.g., both scenes *roll*), different (e.g., one scene *roll*, other *slide*)
Direction	Control (within-subject)	Same (e.g., both scenes *left-right*), different (e.g., one scene *left-right*, other *right-left*)
Ground	Control (within-subject)	Same (e.g., both scenes *cave*), different (e.g., one scene *cave*, other *barn*)
Object	Control (within-subject)	Same (e.g., both scenes *tyre*), different (e.g., one scene *tyre*, other *table*)
Language	Between-subject	Swedish, Spanish

[a] All predictors were centred: the first level was positive and the second level was negative.

Table 6

Results Experiment 1: linguistic encoding condition. Output of mixed-effects model used to analyse the similarity arrangement task: Coefficient estimates $\hat{\beta}$, standard errors SE($\hat{\beta}$), associated *t* value, and significance values.

Predictor	Coef. $\hat{\beta}$	SE($\hat{\beta}$)	*t*	
Intercept	0.55	0.01	94.12	***
P	0.18	0.02	8.43	***
MC	0.08	0.02	4.74	***
MO	0.04	0.01	3.88	***
Di	0.04	0.02	2.22	*
Language	0.02	0.01	1.67	
Gr	0.04	0.01	2.47	*
Ob	0.06	0.02	2.60	**
P:MC	0.05	0.02	2.87	**
P:MO	0.01	0.02	0.55	
P:Di	0.03	0.01	1.93	
MC:MO	0.03	0.01	1.98	*
MC:Di	0.00	0.01	0.22	
MO:Di	0.00	0.01	-0.04	
P:Language	-0.02	0.04	-0.58	
MC:Language	0.05	0.03	1.54	
MO:Language	0.04	0.02	2.28	*
Di:Language	-0.05	0.03	-1.56	
Language:Gr	-0.03	0.02	-1.32	
Language:Ob	0.03	0.03	0.96	
P:MC:Language	0.01	0.03	0.49	
P:MO:Language	0.00	0.02	0.11	
P:Di:Language	-0.03	0.02	-1.48	
MC:MO:Language	0.02	0.02	0.92	
MC:Di:Language	-0.01	0.01	-1.36	
MO:Di:Language	0.00	0.01	-0.07	

Note. Significance codes: * $p < .05$, ** $p < .01$, *** $p < .001$
Legend: P = Path, MC = Manner of Cause, MO = Manner of Object, Di = Direction left/right, Gr = Ground, Ob = Object

Table 7

Results Experiment 2: free encoding condition. Output of mixed-effects model used to analyse the similarity arrangement task: Coefficient estimates $\hat{\beta}$, standard errors SE($\hat{\beta}$), associated *t* value, and significance values.

Predictor	Coef. $\hat{\beta}$	SE($\hat{\beta}$)	*t*	
Intercept	0.54	0.00	117.03	***
P	0.11	0.02	6.66	***
MC	0.12	0.02	5.45	***
MO	0.04	0.01	3.11	**
Di	0.14	0.02	5.63	***
Language	0.01	0.01	0.92	
Gr	0.03	0.01	1.92	
Ob	0.04	0.02	1.61	
P:MC	0.05	0.01	3.43	***
P:MO	0.01	0.01	0.76	
P:Di	0.06	0.02	4.00	***
MC:MO	0.03	0.01	2.27	*
MC:Di	0.02	0.01	1.96	
MO:Di	0.00	0.01	0.23	
P:Language	0.03	0.03	0.87	
MC:Language	0.03	0.04	0.70	
MO:Language	0.05	0.02	2.27	*
Di:Language	-0.08	0.05	-1.67	
Language:Gr	-0.05	0.02	-1.89	
Language:Ob	0.03	0.03	1.05	
P:MC:Language	0.01	0.02	0.59	
P:MO:Language	0.02	0.01	1.08	
P:Di:Language	-0.08	0.03	-3.05	**
MC:MO:Language	0.03	0.02	1.61	
MC:Di:Language	-0.01	0.01	-0.50	
MO:Di:Language	0.00	0.01	0.10	

Note. Significance codes: * $p < .05$, ** $p < .01$, *** $p < .001$
Legend: P = Path, MC = Manner of Cause, MO = Manner of Object, Di = Direction left/right, Gr = Ground, Ob = Object

Table 8

Results Experiment 3: verbal interference condition. Output of mixed-effects model used to analyse the similarity arrangement task: Coefficient estimates $\hat{\beta}$, standard errors SE($\hat{\beta}$), associated *t* value, and significance values.

Predictor	Coef. $\hat{\beta}$	SE($\hat{\beta}$)	*t*	
Intercept	0.54	0.01	99.36	***
P	0.10	0.02	6.33	***
MC	0.07	0.02	3.46	***
MO	0.02	0.01	2.46	*
Di	0.11	0.02	4.49	***
Language	0.02	0.01	1.52	
Gr	0.02	0.02	1.51	
Ob	0.06	0.03	1.92	
P:MC	0.03	0.02	1.96	*
P:MO	0.00	0.01	0.22	
P:Di	0.08	0.02	4.32	***
MC:MO	0.03	0.01	2.03	*
MC:Di	0.02	0.01	2.01	*
MO:Di	0.00	0.01	-0.21	
P:Language	-0.01	0.03	-0.32	
MC:Language	0.00	0.04	-0.01	
MO:Language	0.00	0.01	0.41	
Di:Language	0.03	0.05	0.70	
Language:Gr	-0.04	0.03	-1.35	
Language:Ob	-0.04	0.04	-0.89	
P:MC:Language	0.05	0.02	2.51	*
P:MO:Language	0.01	0.02	0.66	
P:Di:Language	0.00	0.03	-0.13	
MC:MO:Language	-0.01	0.02	-0.54	
MC:Di:Language	0.02	0.01	1.41	
MO:Di:Language	0.00	0.01	-0.22	

Note. Significance codes: * $p < .05$, ** $p < .01$, *** $p < .001$
Legend: P = Path, MC = Manner of Cause, MO = Manner of Object, Di = Direction left/right, Gr = Ground, Ob = Object

D. Compound analysis

The model for the compound analysis was fitted in *R* (R Development Core Team, 2013) using the *lmer* function from the lme4 library (Bates et al., 2014). The model formula was:

```
Similarity ~ 1 + (P + MC + MO + Di) ^ 2 * Language * Encoding +
    Gr * Language * Encoding + Ob * Language * Encoding +
    (1 + P + MC + MO + Di + Gr + Ob | Subject) + (1 | Item)
```

(P = Path, MC = Manner of Cause, MO = Manner of Object, Di = Direction left/right, Gr = Ground, Ob = Object)

The same predictors as for Experiments 1 to 3 went into this models (Table 5), but we added the factor ENCODING CONDITION, with three levels: linguistic, free and interference (corresponding to Experiments 1–3, respectively). Encoding condition was forward coded, so as to compare the linguistic against the free condition, and the free condition against verbal interference. All other predictors were centred with a difference of 1, so that reported coefficients represent the estimated difference in similarity ratings between the two levels of each predictor (as for Experiments 1–3). The random effects structure differed from the models for Experiments 1–3 in that there were no by-subject random slopes for the *interactions* between Path, MannerCause, MannerObject and Direction (compare model formula above with that on p. 5). This was due to non-convergence of a model that did include those terms. Therefore fixed-effect estimates involving interactions between event components might suffer from inflated *t*-values, leading to unreliable significance estimates for those coefficients. Collinearity among predictors was moderate, $\kappa = 6.6 < 10$ (cf. Baayen, 2008). Fixed-effects estimates for each experiment are shown in Table 9. Significance codes were determined using the *confint.merMod* function from the lme4 library (method = "Wald", nsim = 10000).

Table 9

Results from compound analysis. Output of mixed-effects model used to analyse the similarity arrangement task: Coefficient estimates $\hat{\beta}$, standard errors SE($\hat{\beta}$), *t* value, and significance level .

Predictor	Coef. $\hat{\beta}$	SE($\hat{\beta}$)	*t*	
(Intercept)	0.54	0.00	162.67	***
P	0.13	0.01	11.01	***
MC	0.09	0.01	7.75	***
MO	0.03	0.01	4.71	***
Di	0.10	0.01	7.40	***
Language	0.01	0.01	2.47	*
Encodingling_vs_free	0.01	0.01	1.12	
Encodingfree_vs_interf	0.00	0.01	0.60	
Gr	0.03	0.01	2.77	**
Ob	0.05	0.02	2.44	*
P:MC	0.04	0.01	3.62	***

Predictor	Coef. $\hat{\beta}$	SE($\hat{\beta}$)	t	
P:MO	0.01	0.01	0.60	
P:Di	0.06	0.01	5.72	***
MC:MO	0.03	0.01	3.19	**
MC:Di	0.01	0.01	1.69	
MO:Di	0.00	0.01	-0.01	
P:Language	0.00	0.02	-0.10	
MC:Language	0.03	0.02	1.20	
MO:Language	0.03	0.01	3.02	**
Di:Language	-0.03	0.02	-1.32	
P:Encodingling_vs_free	0.07	0.02	2.97	**
P:Encodingfree_vs_interf	0.01	0.02	0.58	
MC:Encodingling_vs_free	-0.04	0.03	-1.69	
MC:Encodingfree_vs_interf	0.05	0.03	1.92	
MO:Encodingling_vs_free	0.00	0.01	0.07	
MO:Encodingfree_vs_interf	0.02	0.01	1.48	
Di:Encodingling_vs_free	-0.10	0.03	-3.42	***
Di:Encodingfree_vs_interf	0.03	0.03	0.88	
Language:Encodingling_vs_free	0.01	0.01	0.79	
Language:Encodingfree_vs_interf	-0.01	0.01	-0.55	
Language:Gr	-0.04	0.01	-2.71	**
Encodingling_vs_free:Gr	0.01	0.02	0.44	
Encodingfree_vs_interf:Gr	0.01	0.02	0.34	
Language:Ob	0.01	0.02	0.26	
Encodingling_vs_free:Ob	0.03	0.03	1.03	
Encodingfree_vs_interf:Ob	-0.02	0.03	-0.64	
P:MC:Language	0.02	0.01	2.80	**
P:MO:Language	0.01	0.01	1.10	
P:Di:Language	-0.04	0.01	-5.13	***
MC:MO:Language	0.01	0.01	1.74	.
MC:Di:Language	0.00	0.01	-0.15	
MO:Di:Language	0.00	0.01	-0.13	
P:MC:Encodingling_vs_free	0.00	0.01	0.18	
P:MC:Encodingfree_vs_interf	0.02	0.01	1.92	
P:MO:Encodingling_vs_free	0.00	0.01	-0.16	
P:MO:Encodingfree_vs_interf	0.01	0.01	0.66	

Predictor	Coef. $\hat{\beta}$	SE($\hat{\beta}$)	t	
P:Di:Encodingling_vs_free	-0.04	0.01	-4.50	***
P:Di:Encodingfree_vs_interf	-0.01	0.01	-1.53	
MC:MO:Encodingling_vs_free	0.00	0.01	-0.05	
MC:MO:Encodingfree_vs_interf	0.00	0.01	-0.35	
MC:Di:Encodingling_vs_free	-0.02	0.01	-2.49	*
MC:Di:Encodingfree_vs_interf	0.00	0.01	-0.07	
MO:Di:Encodingling_vs_free	0.00	0.01	-0.37	
MO:Di:Encodingfree_vs_interf	0.00	0.01	0.57	
P:Language:Encodingling_vs_free	-0.05	0.05	-1.09	
P:Language:Encodingfree_vs_interf	0.04	0.05	0.74	
MC:Language:Encodingling_vs_free	0.02	0.05	0.33	
MC:Language:Encodingfree_vs_interf	0.03	0.05	0.58	
MO:Language:Encodingling_vs_free	-0.01	0.03	-0.50	
MO:Language:Encodingfree_vs_interf	0.05	0.03	1.80	
Di:Language:Encodingling_vs_free	0.03	0.06	0.47	
Di:Language:Encodingfree_vs_interf	-0.11	0.06	-1.88	
Language:Encodingling_vs_free:Gr	0.01	0.03	0.44	
Language:Encodingfree_vs_interf:Gr	-0.01	0.03	-0.32	
Language:Encodingling_vs_free:Ob	0.00	0.05	-0.04	
Language:Encodingfree_vs_interf:Ob	0.07	0.05	1.25	
P:MC:Language:Encodingling_vs_free	0.00	0.02	0.11	
P:MC:Language:Encodingfree_vs_interf	-0.04	0.02	-1.82	
P:MO:Language:Encodingling_vs_free	-0.01	0.02	-0.64	
P:MO:Language:Encodingfree_vs_interf	0.00	0.02	0.18	
P:Di:Language:Encodingling_vs_free	0.05	0.02	2.89	**
P:Di:Language:Encodingfree_vs_interf	-0.07	0.02	-4.17	***
MC:MO:Language:Encodingling_vs_free	-0.01	0.01	-0.65	
MC:MO:Language:Encodingfree_vs_interf	0.04	0.02	2.63	**
MC:Di:Language:Encodingling_vs_free	-0.01	0.01	-0.62	
MC:Di:Language:Encodingfree_vs_interf	-0.02	0.01	-1.65	
MO:Di:Language:Encodingling_vs_free	0.00	0.01	-0.13	
MO:Di:Language:Encodingfree_vs_interf	0.00	0.01	0.24	

Note. Significance codes: * $p < .05$, ** $p < .01$, *** $p < .001$
Legend: P = Path, MC = Manner of Cause, MO = Manner of Object, Di = Direction left/right, Gr = Ground, Ob = Object

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