Model design in R: Class 1

Alexandre Cremers

August 12th, 2019

What are we doing here?

What this course is not:

What are we doing here?

What this course is not:

- An introduction to `R`

What are we doing here?

What this course is not:

- An introduction to R
- A proper introduction to stats

What are we doing here?

What this course is not:

- An introduction to `R`
- A proper introduction to stats

So what is it?

What are we doing here?

What this course is not:

- An introduction to R
- A proper introduction to stats

So what is it?

☞ Identifying some issues with data analysis that are somewhat specific to Semantics & Pragmatics.

What are we doing here?

What this course is not:

- An introduction to R
- A proper introduction to stats

So what is it?

- ☞ Identifying some issues with data analysis that are somewhat specific to Semantics & Pragmatics.
- ☞ Discussing possible solutions and their implementation.

Plan

- Today: introducing the problem and the solution
- Tomorrow: formalize what we'll do today
- Wednesday/Thursday: Applications
  (either my examples or yours!)
- Friday: A few more problems and a few more solutions. . .

Plan

- Today: introducing the problem and the solution
- Tomorrow: formalize what we'll do today
- Wednesday/Thursday: Applications
  (either my examples or yours!)
- Friday: A few more problems and a few more solutions...

We may switch Thursday and Friday if necessary.

Experimental semantics and pragmatics

What's a typical empirical issue in SemPrag?

Experimental semantics and pragmatics

What's a typical empirical issue in SemPrag?

- We want to know what a sentence S means.

Experimental semantics and pragmatics

What's a typical empirical issue in SemPrag?

- We want to know what a sentence S means.
- We usually have at least two candidate meanings, A and B.

Experimental semantics and pragmatics

What's a typical empirical issue in SemPrag?

- We want to know what a sentence S means.
- We usually have at least two candidate meanings, A and B.
- This leaves at least three possible options:

Experimental semantics and pragmatics

What's a typical empirical issue in SemPrag?

- We want to know what a sentence S means.
- We usually have at least two candidate meanings, A and B.
- This leaves at least three possible options:
  - S only means A

Experimental semantics and pragmatics

What's a typical empirical issue in SemPrag?

- We want to know what a sentence S means.
- We usually have at least two candidate meanings, A and B.
- This leaves at least three possible options:
  - S only means A
  - S only means B

Experimental semantics and pragmatics

What's a typical empirical issue in SemPrag?

- We want to know what a sentence S means.
- We usually have at least two candidate meanings, A and B.
- This leaves at least three possible options:
  - S only means A
  - S only means B
  - S is ambiguous between A and B

Experimental semantics and pragmatics

What's a typical empirical issue in SemPrag?

- We want to know what a sentence S means.
- We usually have at least two candidate meanings, A and B.
- This leaves at least three possible options:
  - S only means A
  - S only means B
  - S is ambiguous between A and B
- We might also accept that S is ambiguous and be interested in figuring out in which contexts each reading is available,

Experimental semantics and pragmatics

What's a typical empirical issue in SemPrag?

- We want to know what a sentence S means.
- We usually have at least two candidate meanings, A and B.
- This leaves at least three possible options:
  - S only means A
  - S only means B
  - S is ambiguous between A and B
- We might also accept that S is ambiguous and be interested in figuring out in which contexts each reading is available,

Experimental semantics and pragmatics

What's a typical empirical issue in SemPrag?

- We want to know what a sentence S means.
- We usually have at least two candidate meanings, A and B.
- This leaves at least three possible options:
  - S only means A
  - S only means B
  - S is ambiguous between A and B
- We might also accept that S is ambiguous and be interested in figuring out in which contexts each reading is available, but this amounts to the same question relativized to a context (What does S mean in context C?)

Experimental semantics and pragmatics

Most common method:

Experimental semantics and pragmatics

Most common method: The truth-value judgment task.

Experimental semantics and pragmatics

Most common method: The truth-value judgment task.

- Most often, one reading entails the other ($B \to A$).

Experimental semantics and pragmatics

Most common method: The truth-value judgment task.

- Most often, one reading entails the other $(B \to A)$.
- We can construct a situation in which A is true and B is false.

Experimental semantics and pragmatics

Most common method: The truth-value judgment task.

- Most often, one reading entails the other $(B \rightarrow A)$.
- We can construct a situation in which A is true and B is false.

Some elephants have trunks

False | True

Bott&Noveck 2004

Experimental semantics and pragmatics

Most common method: The truth-value judgment task.

- Most often, one reading entails the other ($B \to A$).
- We can construct a situation in which A is true and B is false.
- Asking participants whether they think that the sentence is true or false informs us on what their preferred reading is.

Some elephants have trunks

False | True

Bott&Noveck 2004

Predictions in Experimental SemPrag

S potentially ambiguous between readings A (true) and B (false).

Predictions in Experimental SemPrag

S potentially ambiguous between readings A (true) and B (false).

- If A is available, S should be judged true significantly more than an unambiguous false control

Predictions in Experimental SemPrag

S potentially ambiguous between readings A (true) and B (false).

- If A is available, S should be judged true significantly more than an unambiguous false control
- If B is available, S should be judged true significantly more than an unambiguous true control

Predictions in Experimental SemPrag

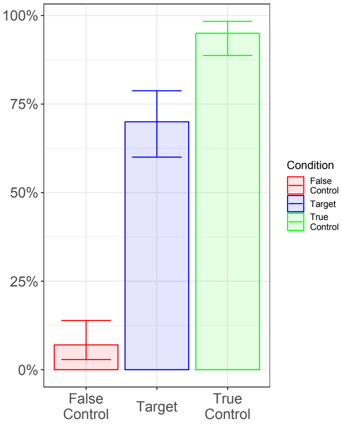
S potentially ambiguous between readings A (true) and B (false).

- If A is available, S should be judged true significantly more than an unambiguous false control
- If B is available, S should be judged true significantly more than an unambiguous true control

☞ We can simply compare our target to true and false controls.

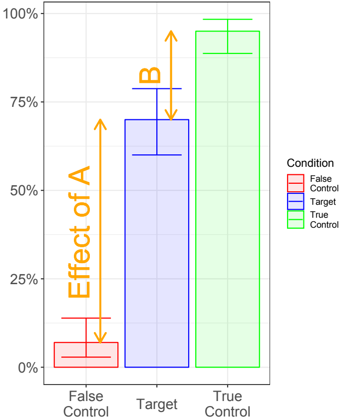
Predictions in Experimental SemPrag

S potentially ambiguous between readings A (true) and B (false).



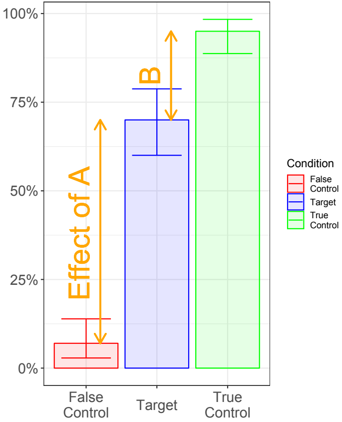
Predictions in Experimental SemPrag

S potentially ambiguous between readings A (true) and B (false).



Predictions in Experimental SemPrag

S potentially ambiguous between readings A (true) and B (false).



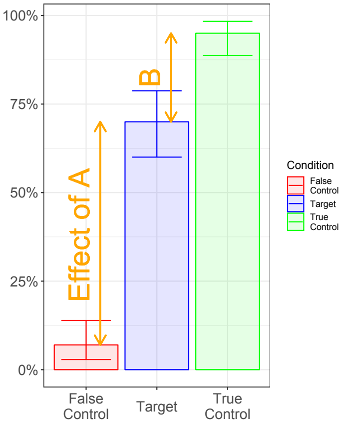
Possible statistical model:

```
Cond <- factor(Cond,levels=
c("target","false","true"))

glm(Response~Cond)
```

Predictions in Experimental SemPrag

S potentially ambiguous between readings A (true) and B (false).



Possible statistical model:

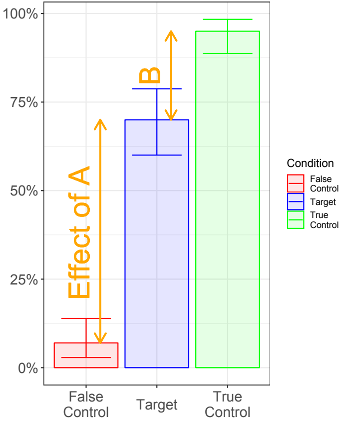
```
Cond <- factor(Cond,levels=
c("target","false","true"))

glm(Response~Cond)
```

-`Cond:false` gives an estimate of A,
`Cond:true` gives an estimate of B.

Predictions in Experimental SemPrag

S potentially ambiguous between readings A (true) and B (false).



Possible statistical model:

```
Cond <- factor(Cond,levels=
c("target","false","true"))
```

glm(Response~Cond)

-Cond:false gives an estimate of A,
Cond:true gives an estimate of B.

☞ We have a direct mapping between Cond and our theoretical parameters.

Interim conclusion

- Very simple experimental design (Target/True/False)

Interim conclusion

- Very simple experimental design (Target/True/False)
- Direct mapping between theoretical parameters (availability of a reading) and experimental factors (differences between conditions / parameters in the statistical model)

Interim conclusion

- Very simple experimental design (Target/True/False)
- Direct mapping between theoretical parameters (availability of a reading) and experimental factors (differences between conditions / parameters in the statistical model)
- Relies on systematic entailment between the two readings of interest.

Breaking systematic entailment

(1) A child rode every camel

(2) Every child rode a camel

Breaking systematic entailment

(1) A child rode every camel

a. Surface Scope: a $>$ every

b. Inverse Scope: every $>$ a

(2) Every child rode a camel

a. Surface Scope: every $>$ a

b. Inverse Scope: a $>$ every

Breaking systematic entailment

(1) A child rode every camel

a. Surface Scope: a > every

b. Inverse Scope: every > a

$SS \rightarrow IS$

(2) Every child rode a camel

a. Surface Scope: every > a

b. Inverse Scope: a > every

$IS \rightarrow SS$

Breaking systematic entailment

(1) A child rode every camel
  a. Surface Scope: a > every
  b. Inverse Scope: every > a

$\Big\}\ SS \rightarrow IS$

(2) Every child rode a camel
  a. Surface Scope: every > a
  b. Inverse Scope: a > every

$\Big\}\ IS \rightarrow SS$

The entailment alternates from $A \rightarrow B$ to $B \rightarrow A$.

Experimental design

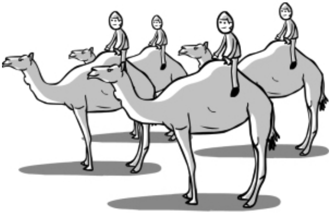
(1) A child rode every camel

(2) Every child rode a camel

Experimental design

(1) A child rode every camel

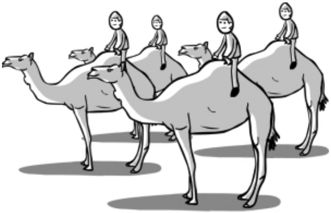
(2) Every child rode a camel



Experimental design

(1) A child rode every camel

(2) Every child rode a camel

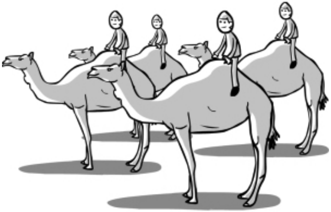


- Impossible to systematically associate an answer to a reading

Experimental design

(1) A child rode every camel

(2) Every child rode a camel

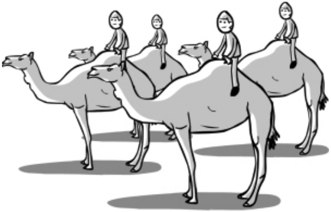


- Impossible to systematically associate an answer to a reading
- We can however test each sentence and associate each answer to an interpretation:

Experimental design

(1) A child rode every camel

(2) Every child rode a camel

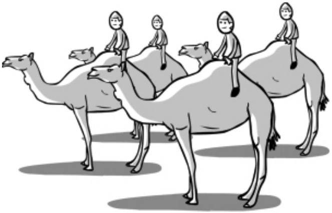


- Impossible to systematically associate an answer to a reading
- We can however test each sentence and associate each answer to an interpretation:
  - T1: true under IS, false under SS

Experimental design

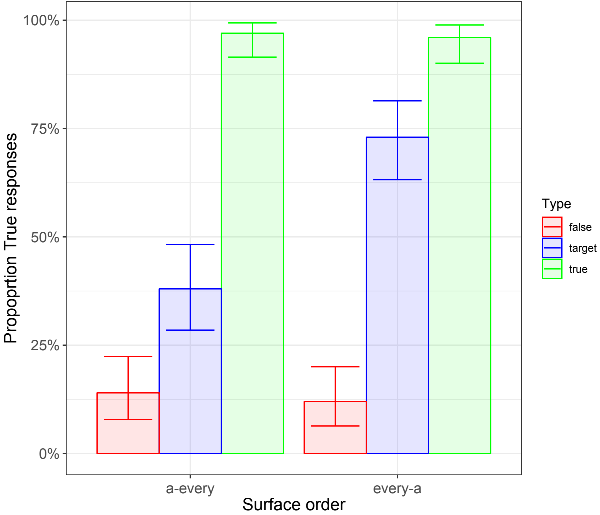
(1) A child rode every camel

(2) Every child rode a camel



- Impossible to systematically associate an answer to a reading
- We can however test each sentence and associate each answer to an interpretation:
    - T1: true under IS, false under SS
    - T2: true under SS, false under IS

Interpreting results



Direct comparison

Type: factor with levels: `c('target','true','false')`
`Order`: sum coded (‘a. . . every’:-0.5, ‘every. . . a’:$+0.5$)
`Answer ~ Type * Order`

Direct comparison

Type: factor with levels: `c('target','true','false')`

`Order`: sum coded (‘a. . . every’:-0.5, ‘every. . . a’:$+0.5$)

`Answer ~ Type * Order`

	β	z-value	p-value
(Intercept)	0.27	1.61	.107
Type:true	3.06	7.21	$< .001^{***}$
Type:false	-2.49	-7.02	$< .001^{***}$
Order	1.60	4.91	$< .001^{***}$
[Type:true]×[Order]	-1.90	-2.25	$.025^{*}$
[Type:false]×[Order]	-1.79	-3.26	$.001^{**}$

What can we conclude from this model?

What can we conclude from this model?

- The "weak" reading '$\forall > \exists$' is more frequent with surface order 'every. . . a' (i.e. when it matches the surface order).

What can we conclude from this model?

- The “weak” reading ‘$\forall > \exists$’ is more frequent with surface order ‘every. . . a’ (i.e. when it matches the surface order).
- This suggests that inverse scope is dispreferred.

What can we conclude from this model?

- The "weak" reading '$\forall > \exists$' is more frequent with surface order 'every…a' (i.e. when it matches the surface order).
- This suggests that inverse scope is dispreferred.
- But is inverse scope equally dispreferred in every configuration?

What can we conclude from this model?

- The "weak" reading '$\forall > \exists$' is more frequent with surface order 'every. . . a' (i.e. when it matches the surface order).
- This suggests that inverse scope is dispreferred.
- But is inverse scope equally dispreferred in every configuration?
- We could recode our dependent variable: instead of rates of True answers, look at rates of "Inverse scope" answers.

What can we conclude from this model?

- The "weak" reading '$\forall > \exists$' is more frequent with surface order 'every. . . a' (i.e. when it matches the surface order).
- This suggests that inverse scope is dispreferred.
- But is inverse scope equally dispreferred in every configuration?
- We could recode our dependent variable: instead of rates of True answers, look at rates of "Inverse scope" answers.

What can we conclude from this model?

- The "weak" reading '$\forall > \exists$' is more frequent with surface order 'every. . . a' (i.e. when it matches the surface order).
- This suggests that inverse scope is dispreferred.
- But is inverse scope equally dispreferred in every configuration?
- We could recode our dependent variable: instead of rates of True answers, look at rates of "Inverse scope" answers. But what does that mean for controls?

What does the `Type` factor really mean?

Let's forget about `Order` for a second and focus on `1+Type`:

What does the Type factor really mean?

Let's forget about `Order` for a second and focus on `1+Type`:

```
> contrasts(Type)
```

What does the Type factor really mean?

Let's forget about `Order` for a second and focus on `1+Type`:

```
> contrasts(Type)
        true  false
 target    0      0
 true      1      0
 false     0      1
```

What does the Type factor really mean?

Let's forget about `Order` for a second and focus on `1+Type`:

	`true`	`false`	`(inter.)`
`target`	0	0	1
`true`	1	0	1
`false`	0	1	1

A bit of algebra...

```
Answer ~ 1+Type
```

	(inter.)	true	false
target	1	0	0
true	1	1	0
false	1	0	1

A bit of algebra...

`Answer ~ 1+Type`

		(inter.)	true	false
experimental conditions	target	1	0	0
	true	1	1	0
	false	1	0	1

A bit of algebra...

`Answer ~ 1+Type`

$$
\begin{array}{ll|ccc}
 & & \multicolumn{3}{c}{\overbrace{\hspace{6cm}}^{\texttt{model parameters}}} \\
 & & \texttt{(inter.)} & \texttt{true} & \texttt{false} \\
\texttt{experimental} & \texttt{target} & 1 & 0 & 0 \\
\texttt{conditions} & \texttt{true} & 1 & 1 & 0 \\
 & \texttt{false} & 1 & 0 & 1
\end{array}
$$

A bit of algebra. . .

`Answer ~ 1+Type`

$$
\begin{array}{ll|ccc}
 & & \multicolumn{3}{c}{\overbrace{\hspace{8em}}^{\texttt{model parameters}}} \\
 & & \texttt{(inter.)} & \texttt{true} & \texttt{false} \\
\texttt{experimental} & \left\{\begin{array}{l}\texttt{target}\\ \texttt{true}\\ \texttt{false}\end{array}\right. & \begin{array}{c}1\\1\\1\end{array} & \begin{array}{c}0\\1\\0\end{array} & \begin{array}{c}0\\0\\1\end{array} \\
\texttt{conditions} & & \beta_0 & \beta_1 & \beta_2
\end{array}
$$

A bit of algebra...

`Answer ~ 1+Type`

$$
\begin{array}{ll|ccc}
 & & \multicolumn{3}{c}{\overbrace{\hphantom{\texttt{(inter.)} \quad \texttt{true} \quad \texttt{false}}}^{\texttt{model parameters}}} \\
 & & \texttt{(inter.)} & \texttt{true} & \texttt{false} \\
\texttt{experimental} & \left\{ \begin{array}{l} \texttt{target} \\ \texttt{true} \\ \texttt{false} \end{array} \right. & \begin{array}{c} 1 \\ 1 \\ 1 \end{array} & \begin{array}{c} 0 \\ 1 \\ 0 \end{array} & \begin{array}{c} 0 \\ 0 \\ 1 \end{array} \\
\texttt{conditions} & & \beta_0 & \beta_1 & \beta_2
\end{array}
$$

$$y_i = \beta_0 x_{i0} + \beta_1 x_{i1} + \beta_2 x_{i2} + \varepsilon_i$$

A bit of algebra...

`Answer ~ 1+Type`

$$
\begin{array}{ll|ccc}
 & & \multicolumn{3}{c}{\overbrace{\hspace{12em}}^{\texttt{model parameters}}} \\
 & & \texttt{(inter.)} & \texttt{true} & \texttt{false} \\
\texttt{experimental} & \texttt{target} & 1 & 0 & 0 \\
\texttt{conditions} & \texttt{true} & 1 & 1 & 0 \\
 & \texttt{false} & 1 & 0 & 1 \\
 & & \beta_0 & \beta_1 & \beta_2
\end{array}
$$

$$y_i = \beta_0 x_{i0} + \beta_1 x_{i1} + \beta_2 x_{i2} + \varepsilon_i$$

Predicted values for each experimental condition:

target: $\beta_0 \times 1 + \beta_1 \times 0 + \beta_2 \times 0$

A bit of algebra...

`Answer ~ 1+Type`

$$
\begin{array}{ll|ccc}
 & & \multicolumn{3}{c}{\overbrace{\hspace{6cm}}^{\texttt{model parameters}}} \\
 & & \texttt{(inter.)} & \texttt{true} & \texttt{false} \\
\texttt{experimental} & \texttt{target} & 1 & 0 & 0 \\
\texttt{conditions} & \texttt{true} & 1 & 1 & 0 \\
 & \texttt{false} & 1 & 0 & 1 \\
 & & \beta_0 & \beta_1 & \beta_2
\end{array}
$$

$$y_i = \beta_0 x_{i0} + \beta_1 x_{i1} + \beta_2 x_{i2} + \varepsilon_i$$

Predicted values for each experimental condition:
target: β_0 (intercept)

A bit of algebra...

`Answer ~ 1+Type`

$$
\begin{array}{ll|ccc}
 & & \multicolumn{3}{c}{\overbrace{\hspace{6cm}}^{\texttt{model parameters}}} \\
 & & \texttt{(inter.)} & \texttt{true} & \texttt{false} \\
\texttt{experimental} & \left\{\begin{array}{l}\texttt{target} \\ \texttt{true} \\ \texttt{false}\end{array}\right. & \begin{array}{c}1\\1\\1\end{array} & \begin{array}{c}0\\1\\0\end{array} & \begin{array}{c}0\\0\\1\end{array} \\
\texttt{conditions} & & \beta_0 & \beta_1 & \beta_2
\end{array}
$$

$$y_i = \beta_0 x_{i0} + \beta_1 x_{i1} + \beta_2 x_{i2} + \varepsilon_i$$

Predicted values for each experimental condition:

target: β_0 (intercept)

true: $\beta_0 \times 1 + \beta_1 \times 1 + \beta_2 \times 0$

A bit of algebra...

```
Answer ~ 1+Type
```

$$
\begin{array}{ll|ccc}
 & & \multicolumn{3}{c}{\overbrace{\hspace{6cm}}^{\texttt{model parameters}}} \\
 & & \texttt{(inter.)} & \texttt{true} & \texttt{false} \\
\texttt{experimental conditions} & \left\{ \begin{array}{l} \texttt{target} \\ \texttt{true} \\ \texttt{false} \end{array} \right. & \begin{array}{c} 1 \\ 1 \\ 1 \end{array} & \begin{array}{c} 0 \\ 1 \\ 0 \end{array} & \begin{array}{c} 0 \\ 0 \\ 1 \end{array} \\
 & & \beta_0 & \beta_1 & \beta_2
\end{array}
$$

$$y_i = \beta_0 x_{i0} + \beta_1 x_{i1} + \beta_2 x_{i2} + \varepsilon_i$$

Predicted values for each experimental condition:

target:	β_0	(intercept)
true:	$\beta_0 + \beta_1$	(intercept) + Type:true

A bit of algebra...

`Answer ~ 1+Type`

$$
\begin{array}{llccc}
 & & \multicolumn{3}{c}{\overbrace{\hspace{8cm}}^{\texttt{model parameters}}} \\
 & & \texttt{(inter.)} & \texttt{true} & \texttt{false} \\
\multirow{3}{*}{\begin{array}{c}\texttt{experimental}\\ \texttt{conditions}\end{array}} & \left\{\begin{array}{l}\texttt{target}\\ \texttt{true}\\ \texttt{false}\end{array}\right. & \begin{array}{c}1\\1\\1\end{array} & \begin{array}{c}0\\1\\0\end{array} & \begin{array}{c}0\\0\\1\end{array} \\
 & & \beta_0 & \beta_1 & \beta_2
\end{array}
$$

$$y_i = \beta_0 x_{i0} + \beta_1 x_{i1} + \beta_2 x_{i2} + \varepsilon_i$$

Predicted values for each experimental condition:

target:	β_0	(intercept)
true:	$\beta_0 + \beta_1$	(intercept) + Type:true
false:	$\beta_0 \times 1 + \beta_1 \times 0 + \beta_2 \times 1$	

A bit of algebra...

```
Answer ~ 1+Type
```

$$
\begin{array}{ll|ccc}
 & & \multicolumn{3}{c}{\overbrace{\hspace{6cm}}^{\texttt{model parameters}}} \\
 & & \texttt{(inter.)} & \texttt{true} & \texttt{false} \\
\texttt{experimental conditions} & \texttt{target} & 1 & 0 & 0 \\
 & \texttt{true} & 1 & 1 & 0 \\
 & \texttt{false} & 1 & 0 & 1 \\
 & & \beta_0 & \beta_1 & \beta_2
\end{array}
$$

$$y_i = \beta_0 x_{i0} + \beta_1 x_{i1} + \beta_2 x_{i2} + \varepsilon_i$$

Predicted values for each experimental condition:

target:	β_0	(intercept)
true:	$\beta_0 + \beta_1$	(intercept) + Type:true
false:	$\beta_0 + \beta_2$	(intercept) + Type:false

Alternative

$$
\begin{array}{ll|ccc}
 & & \multicolumn{3}{c}{\overbrace{\hspace{8em}}^{\texttt{model parameters}}} \\
 & & \texttt{target} & \texttt{true} & \texttt{false} \\
\texttt{experimental} & \texttt{target} & 1 & 0 & 0 \\
\texttt{conditions} & \texttt{true} & 0 & 1 & 0 \\
 & \texttt{false} & 0 & 0 & 1 \\
 & & \beta'_0 & \beta'_1 & \beta'_2
\end{array}
$$

$$y_i = \beta'_0 x_{i0} + \beta'_1 x_{i1} + \beta'_2 x_{i2} + \varepsilon_i$$

Predicted values for each experimental condition:

target: β'_0
true: β'_1
false: β'_2

Alternative

$$
\text{experimental conditions}
\left\{
\begin{array}{l}
\texttt{target} \\
\texttt{true} \\
\texttt{false}
\end{array}
\right.
\overbrace{
\begin{array}{ccc}
\texttt{target} & \texttt{true} & \texttt{false} \\
1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1 \\
\beta'_0 & \beta'_1 & \beta'_2
\end{array}
}^{\texttt{model parameters}}
$$

$$y_i = \beta'_0 x_{i0} + \beta'_1 x_{i1} + \beta'_2 x_{i2} + \varepsilon_i$$

Predicted values for each experimental condition:

target:	β'_0	Type:target
true:	β'_1	Type:true
false:	β'_2	Type:false

Alternative

$$\begin{array}{ll|ccc} & & \multicolumn{3}{c}{\overbrace{\hspace{8em}}^{\texttt{model parameters}}} \\ & & \texttt{target} & \texttt{true} & \texttt{false} \\ \texttt{experimental} & \texttt{target} & 1 & 0 & 0 \\ \texttt{conditions} & \texttt{true} & 0 & 1 & 0 \\ & \texttt{false} & 0 & 0 & 1 \\ & & \beta'_0 & \beta'_1 & \beta'_2 \end{array}$$

$$y_i = \beta'_0 x_{i0} + \beta'_1 x_{i1} + \beta'_2 x_{i2} + \varepsilon_i$$

Predicted values for each experimental condition:

target:	$\beta'_0 = \beta_0$	Type:target
true:	$\beta'_1 = \beta_0 + \beta_1$	Type:true
false:	$\beta'_2 = \beta_0 + \beta_2$	Type:false

Alternative

```
Answer ~ 0+Type
```

$$
\begin{array}{ll|ccc}
 & & \multicolumn{3}{c}{\overbrace{\texttt{target} \quad \texttt{true} \quad \texttt{false}}^{\texttt{model parameters}}} \\
\texttt{experimental} & \texttt{target} & 1 & 0 & 0 \\
\texttt{conditions} & \texttt{true} & 0 & 1 & 0 \\
 & \texttt{false} & 0 & 0 & 1 \\
 & & \beta'_0 & \beta'_1 & \beta'_2
\end{array}
$$

$$y_i = \beta'_0 x_{i0} + \beta'_1 x_{i1} + \beta'_2 x_{i2} + \varepsilon_i$$

Predicted values for each experimental condition:

target:	$\beta'_0 = \beta_0$	Type:target
true:	$\beta'_1 = \beta_0 + \beta_1$	Type:true
false:	$\beta'_2 = \beta_0 + \beta_2$	Type:false

Goal for the week

Learn how to choose parameters for our statistical models that correspond to actual parameters in our theories.

Back to scope ambiguities

What we're interested in:

Back to scope ambiguities

What we're interested in: Rate of inverse scope readings

Back to scope ambiguities

What we're interested in: Rate of inverse scope readings

- The diagnosis for inverse scope differs in each condition.

Back to scope ambiguities

What we're interested in: Rate of inverse scope readings

- The diagnosis for inverse scope differs in each condition.

☞ Our IS parameter will depend on both `Type` and `Order`.

Back to scope ambiguities

What we're interested in: Rate of inverse scope readings

- The diagnosis for inverse scope differs in each condition.
- ☞ Our IS parameter will depend on both `Type` and `Order`.
- We need two more parameters to capture all 3 levels of `Type`.

Back to scope ambiguities

What we're interested in: Rate of inverse scope readings

- The diagnosis for inverse scope differs in each condition.
- ☞ Our IS parameter will depend on both `Type` and `Order`.
- We need two more parameters to capture all 3 levels of `Type`.
- We'll leave `Order` as it is for now.

	a-every			every-a		
	β_{IS}	β_1	β_2	β_{IS}	β_1	β_2
target						
true						
false						

Your turn!

	a-every			every-a		
	β_{IS}	β_1	β_2	β_{IS}	β_1	β_2
target	$+1$			-1		
true						
false						

	a-every			every-a		
	$\beta_{\textsf{IS}}$	β_1	β_2	$\beta_{\textsf{IS}}$	β_1	β_2
target	$+1$			-1		
true	0			0		
false	0			0		

	a-every			every-a		
	β_{IS}	β_1	β_2	β_{IS}	β_1	β_2
target	$+1$			-1		
true	0	1		0	1	
false	0	0		0	0	

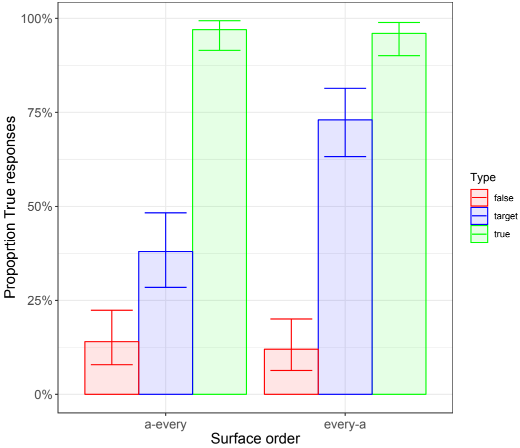
	a-every			every-a		
	β_{IS}	β_1	β_2	β_{IS}	β_1	β_2
target	$+1$			-1		
true	0	1	0	0	1	0
false	0	0	1	0	0	1

	a-every			every-a		
	β_{IS}	β_1	β_2	β_{IS}	β_1	β_2
target	$+1$	0	1	-1		
true	0	1	0	0	1	0
false	0	0	1	0	0	1

	a-every			every-a		
	β_{IS}	β_1	β_2	β_{IS}	β_1	β_2
target	$+1$	0	1	-1	1	0
true	0	1	0	0	1	0
false	0	0	1	0	0	1

	a-every			every-a		
	β_{IS}	β_T	β_F	β_{IS}	β_T	β_F
target	$+1$	0	1	-1	1	0
true	0	1	0	0	1	0
false	0	0	1	0	0	1

Visualizing model parameters



β_F $\beta_F + \beta_{IS}$ β_T β_F $\beta_T - \beta_{IS}$ β_T

Reanalysing the data

We define our new factors in R:

Reanalysing the data

We define our new factors in R:

```
IS <- case_when(
        Order=="a-every"&Type=="target" ~ 1,
        Order=="every-a"&Type=="target" ~ -1,
        T ~ 0
      )
True <- case_when(
          Type=="true" ~ 1,
          Order=="every-a"&Type=="target" ~ 1,
          T ~ 0
        )
False <- case_when(
           Type=="false" ~ 1,
           Order=="a-every"&Type=="target" ~ 1,
           T ~ 0
         )
```

Reanalysing the data

Model:

```
Answer~(0+True+False+Inverse)+(0+True+False+Inverse):Order
```

Reanalysing the data

Model:

```
Answer~(0+True+False+Inverse)+(0+True+False+Inverse):Order
```

Results:

```
Fixed effects:
            Estimate Std. Error z value Pr(>|z|)
True          3.3575     0.3905   8.598  < 2e-16 ***
False        -2.1487     0.2917  -7.367 1.74e-13 ***
IS            1.8409     0.3415   5.390 7.03e-08 ***
True:Order   -0.2984     0.7780  -0.384    0.701
False:Order  -0.1894     0.4360  -0.434    0.664
IS:Order      0.7148     0.6794   1.052    0.293
---
```

Conclusion

- By re-parametrizing the statistical model we were able to get interpretable results.

Conclusion

- By re-parametrizing the statistical model we were able to get interpretable results.
- In this example, this was necessary to show that the rate of inverse scope readings doesn't depend on surface order.

Conclusion

- By re-parametrizing the statistical model we were able to get interpretable results.
- In this example, this was necessary to show that the rate of inverse scope readings doesn't depend on surface order.
- Tomorrow: introduce a bit of formalism, before moving to concrete examples on Wednesday.

Questions?