Week 3

Read the remainder of Hurlbert 1984

What type of **pseudoreplication** are we committing if we don't declare Person as Random in Experiment 3?

Sit Stand Sit # people # measures #EU 3) Jill
$$\begin{bmatrix} X \\ X \end{bmatrix}$$
 T1 Bob $\begin{bmatrix} X \\ X \end{bmatrix}$ T2 Amy $\begin{bmatrix} X \\ X \end{bmatrix}$ T2 40 80 80

More Design Tables and writing R models

Comparing experimental designs with Replicates and Subsamples

Standard Errors and Estimated Standard Errors

Fitting models in R

- 1) Write the model
- 2) Pass it to the function to fit the model: Im() or Imer()
- 3) Pass the result to a function to get estimates, SE, CI, etc emmeans(), contrast(), etc

Writing the model

- Response ~ every variable in Treatment + Design with # levels < # responses combined with "+"
- 2) Any variable that is a **EU** gets declared with (1IX)
 + Variable => + (1IVariable)
 call these "random"
- 3) Replicate variables combined with treatments are random
 + (1|Replicate:Treatment)
 - This can be omitted for narrower scope
- 4) If any random variable is included, use Imer(). Otherwise use Im()

For our purposes, the only difference between these functions is the type of model statement they allow

The underlying code is very different

Some arguments of emmeans are different

Sit Stand Sit

1) Jill X Bob X Amy X 80 80

Structure	Variable	Type	#levels	Replicate	EU
Treatment	Posture	Cat	2	None	Person
Design	Person	Cat	80		
Response	Pulse	Num	80		

Write the model: Im(Pulse ~ Posture)

 Response ~ every variable in Treatment + Design with # levels < # responses combined with "+"

- 2) Any variable that is a **EU** gets declared with (1IX)
 + Variable => + (1IVariable)
 call these "random"
- 3) Replicate variables combined with treatments are random+ (1lReplicate:Treatment)This can be omitted for narrower scope
- 4) If any random variable is included, use Imer(). Otherwise use Im()

		Jill		Bob		Amy	# people	# measures	#EU
2)	T1	Sit	T1	Stand	T1	Sit	40	80	80
,	T2	Stand	T2	Sit	T2	Stand	10	00	

Structure	Variable	Туре	#levels	Replicate	EU
Treatment	Posture	Cat	2	Person	Person:Trial
Design	Person	Cat	40		
	Trial	Cat	2		
	Person:Trial	Cat	80		
	Person:Posture	Cat	80		
Response	Pulse	Num	80		

Write the model: Im(Pulse ~ Posture + Person + Trial)

- Response ~ every variable in Treatment + Design with # levels < # responses combined with "+"
- 2) Any variable that is a **EU** gets declared with (1IX)
 + Variable => + (1IVariable)
 call these "random"
- 3) Replicate variables combined with treatments are random+ (1|Replicate:Treatment)This can be omitted for narrower scope
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$$\begin{bmatrix} X \\ X \end{bmatrix}$$
 T1 Bob $\begin{bmatrix} X \\ X \end{bmatrix}$ T2 Amy $\begin{bmatrix} X \\ X \end{bmatrix}$ T2 40 80 80

Structure	Variable	Туре	#levels	Replicate	EU
Treatment	Posture	Cat	2	None	Person
Design	Person	Cat	40		
	Trial	Cat	2		
	Person:Trial	Cat	80		
Response	Pulse	Num	80		

Write the model: Imer(Pulse ~ Posture + (1|Person) + Trial)

- Response ~ every variable in Treatment + Design with # levels < # responses combined with "+"
- 2) Any variable that is a **EU** gets declared with (1IX)
 + Variable => + (1IVariable)
 call these "random"
- 3) Replicate variables combined with treatments are random+ (1|Replicate:Treatment)This can be omitted for narrower scope
- 4) If any random variable is included, use Imer(). Otherwise use Im()

Why don't we use Trial as a Replicate in 2) and 3)?

Jill Bob Amy # people # measures #EU
2) T1 Sit T1 Stand T1 Sit 40 80 80

Sit Stand Sit # people # measures #EU
3) Jill
$$\frac{X}{X}$$
 T1 Bob $\frac{X}{X}$ T1 Amy $\frac{X}{X}$ T1 40 80 80

In both cases, we have 2 trials, each with observations of sitting and standing

We could get a "direct" estimate of the standing effect in each trial

Benefit

Control for changes in Pulse / treatment effect between trials

Cost

With only 2 trials, we only have (n-1) = 1 degree of freedom $t_c(\alpha=0.05)=12.7$ (huge confidence intervals)

Why?

Trials are replicates if our goal is to extrapolate to **new trials**Otherwise, we are limited to the **average** of these two trials

Are we concerned about the treatment effect **changing**between our two trials?

Are all treatment effects the same if we do only 1 trial?

$$\hat{\delta}_{B-A} = \frac{1}{n} \sum_{i} \hat{\delta}_{j}$$
 Direct estimate = average of *n* observations

$$\sigma_r(\hat{\delta}) = \sqrt{\begin{array}{c} \text{Variance of population + Variance of measurements} \\ \text{Sample size} \end{array}}$$

$$\hat{\delta}_{B-A} = \hat{\mu}_B - \hat{\mu}_A$$
 Indirect estimate of δ

$$\hat{\mu}_A = \frac{1}{n_A} \sum \hat{\mu}_{Aj}$$
 $\hat{\mu}_B = \frac{1}{n_B} \sum \hat{\mu}_{Bj}$ direct estimates of μ_B and μ_A

$$\sigma_{\!r}(\hat{\mu}_i) = \sqrt{\begin{array}{c} \text{Variance of population + Variance of measurements} \\ \text{Sample size} \end{array}}$$

$$\sigma_r(\hat{\delta}) = \sqrt{\begin{array}{c} \sigma_r^2(\hat{\mu}_B) + \sigma_r^2(\hat{\mu}_A) \\ \end{array}} \qquad \begin{array}{c} \text{Add the two variances} \\ \text{Because errors } \epsilon_B \text{ and } \epsilon_A \\ \text{are independent} \end{array}$$

Use different EU

$$\sigma_r(\hat{\delta}) = \sqrt{\frac{\text{Variance of population + Variance of measurements}}{\text{Sample size}}}$$
 Direct Standard Error

population = TRUE **Standing effects** $\delta_j = \mu_{Bj} - \mu_{Aj}$ measurements = Estimates of effect of each person $\hat{\delta}_j = \hat{\mu}_{Bj} - \hat{\mu}_{Aj}$ sample size = # Replicates

$$\sigma_r(\hat{\delta}) = \sqrt{\frac{\sigma_{\delta}^2 + \sigma_r^2(\hat{\delta}_j)}{40}}$$

people # measures #EU

$$\sigma_r(\hat{\delta}) = \sqrt{\sigma_r^2(\hat{\mu}_B) + \sigma_r^2(\hat{\mu}_A)}$$
 Indirect Standard Error

$$\sigma_r(\hat{\mu}_i) = \sqrt{ egin{array}{c} \mbox{Variance of population + Variance of measurements} \mbox{Sample size} } \mbox{ } \mbox{Direct Standard Error}$$

population = TRUE **Standing pulse** μ_{Aj} sample size = # replicates/level measurements = Estimates of Standing pulse $\hat{\mu}_{Aj} = y_{Aj}$

$$\sigma_r(\hat{\mu}_A) = \sqrt{\frac{\sigma_{\mu_A}^2 + \sigma_r^2(\hat{\mu}_{Aj})}{40}} \qquad \sigma_r(\hat{\delta}) = \sqrt{\frac{\sigma_{\mu_B}^2 + \sigma_r^2(\hat{\mu}_{Bj})}{40} + \frac{\sigma_{\mu_A}^2 + \sigma_r^2(\hat{\mu}_{Aj})}{40}}$$

Design 2

 $\sigma_r(\hat{\delta}) = \sqrt{\frac{\sigma_{\delta}^2 + \sigma_r^2(\hat{\delta}_j)}{40}}$ # people

Design 1

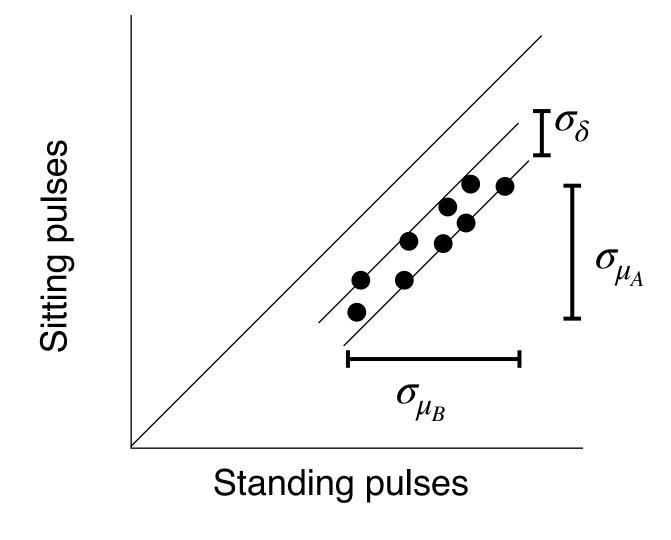
$$\sigma_r(\hat{\delta}) = \sqrt{\begin{array}{c} \sigma_{\mu_B}^2 + \sigma_r^2(\hat{\mu}_{Bj}) \\ 40 \\ / \end{array} + \begin{array}{c} \sigma_{\mu_A}^2 + \sigma_r^2(\hat{\mu}_{Aj}) \\ 40 \\ / \end{array} \\ \text{\# people} \\ \text{Standing} \end{array} \begin{array}{c} \theta_{\mu_A} + \sigma_r^2(\hat{\mu}_{Aj}) \\ \theta_{Aj} + \sigma_r^2(\hat{\mu}_{Aj})$$

Which is bigger: measurement error for $\hat{\delta}_j$ or measurement error for $\hat{\mu}_{Bj}$ or $\hat{\mu}_{Aj}$?

 $\sigma_r^2(\hat{\delta}_j)$ is 2x as big because it's from 2 separate pulse measurements (σ_m^2)

$$\sigma_r^2(\hat{\delta}_j) = 2\sigma_m^2, \, \sigma_r^2(\hat{\mu}_{ij}) = \sigma_m^2$$

Which is bigger: TRUE variance of **effects** or TRUE variance of **sitting(standing) pulses?** $\sigma_{\mu_i}^2$ is generally bigger because μ_{Bj} and μ_{Aj} are **correlated**



$$\delta_j = \mu_{Bj} - \mu_{Aj}$$

When you add two **correlated** variables, the total variance is less than the sum of each variance

Design 2

people

Design 1

$$\sigma_r(\hat{\delta}) = \sqrt{\frac{\sigma_\delta^2 + 2\sigma_m^2}{40}}$$

$$\sigma_r(\hat{\delta}) = \sqrt{\frac{\sigma_{\mu_B}^2 + \sigma_m^2}{40} + \frac{\sigma_{\mu_A}^2 + \sigma_m^2}{40}}$$
people # people Standing Sitting

If the variances of Sitting and Standing are the same

And the sample sizes are the same, we can simplify

$$\sigma_r(\hat{\delta}) = \sqrt{\frac{2\sigma_{\mu_i}^2 + 2\sigma_m^2}{40}}$$

Since $\sigma_{\delta}^2 < 2\sigma_{\mu_i}^2$, Design 2 has a smaller standard error

With same # measurements and #EU, but fewer people

What about Design 3?

Direct or Indirect?

What is the formula for $\sigma_r(\hat{\delta})$?

Is the total population variance less than designs 1 or 2?

Is the measurement error of each estimate less than designs 1 or 2?

What about Design 3?

Sit Stand Sit # people # measures #EU 3) Jill
$$\begin{bmatrix} X \\ X \end{bmatrix}$$
 T1 Bob $\begin{bmatrix} X \\ X \end{bmatrix}$ T2 Amy $\begin{bmatrix} X \\ X \end{bmatrix}$ T2 40 80 40

$$\sigma_r(\hat{\delta}) = \sqrt{\sigma_r^2(\hat{\mu}_B) + \sigma_r^2(\hat{\mu}_A)}$$
 Indirect Standard Error

$$\sigma_r(\hat{\mu}_i) = \sqrt{ egin{array}{c} {
m Variance\ of\ population\ +\ Variance\ of\ measurements} } {
m Sample\ size}$$
 Direct Standard Error

population = TRUE **Standing pulse**
$$\mu_{Aj}$$
 population variance = $\sigma_{\mu_i}^2$ (same as Design 1)

measurements = Estimates of Standing pulse
$$\hat{\mu}_{Aj} = \frac{y_{Aj_1} + y_{Aj_2}}{2}$$

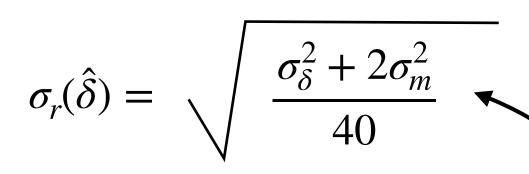
measurement variance is 1/2 that of Design 1:
$$\frac{\sigma_m^2}{2}$$

samples / treatment level is 1/2 that of design 1

Final Standard Error:

$$\sigma_r(\hat{\delta}) = \sqrt{\frac{2\sigma_{\mu_i}^2 + 2/2\sigma_m^2}{20}}$$

Design 2



Smaller population variance

Design 1

$$\sigma_r(\hat{\delta}) = \sqrt{\frac{2\sigma_{\mu_i}^2 + 2\sigma_m^2}{40}}$$

Design 3

 $\sigma_r(\hat{\delta}) = \sqrt{\frac{2\sigma_{\mu_i}^2 + 2/2\sigma_m^2}{20}}$

Smaller measurement error

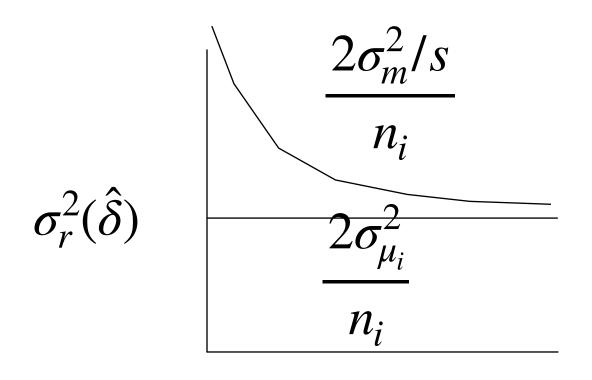
Smaller sample size (#EU / level)

Sit Stand

Jill
$$\begin{bmatrix} X \\ X \end{bmatrix}$$
 T1 Bob $\begin{bmatrix} X \\ X \end{bmatrix}$ T2 Amy T2

Repeated measures of the same sample are subsamples

Not declaring EU causes pseudoreplication



Subsamples (s)

More subsamples = less measurement error / EU

More subsamples = fewer EU

Optimal number of subsamples

Tradeoff between EU and subsamples based on cost

Optimal number of subsamples $\sqrt{\frac{k}{c}}$

$$k = \frac{\sigma_m^2}{\sigma_{\mu_i}^2} \qquad \frac{\hat{\mu}_{ij1} - \hat{\mu}_{ij2}}{2} \qquad \text{half the difference among replicate measures of the same individual}}{\frac{\mu_{i1} - \mu_{i2}}{2}} \qquad \text{half the difference among different individuals}}$$

k c Optimal number of subsamples

.5 1 .7 −−−−− 1

1 1 — 1

 $2 \qquad 1 \qquad \qquad 14 \longrightarrow 1$

4 1 2 ----- 2

.5 1/10 2.2 ----- 2

1 1/10 3.1 — 3

2 1/10 4.5 --- 4

Estimated Standard Errors for each design

Design 2

"Direct"

$$\hat{\delta}_{B-A} = \frac{1}{n} \sum_{i} \hat{\delta}_{j}$$
 Direct estimate = average of *n* observations

TRUE Standard
$$\sigma_r(\hat{\delta}) = \sqrt{\frac{\text{Variance of population + Variance of measurements}}{\text{Sample size}}}$$

Estimated Standard Error:

Sample Variance of $\hat{\delta}_i pprox$ Variance of TRUE values + Variance of erro

$$s_{\hat{\delta}}^2 = \frac{\sum (\hat{\delta}_j - \hat{\delta})^2}{n - 1}$$

SED =
$$\sqrt{\frac{s_{\hat{\delta}}^2}{n}}$$
 This is an estimate of $\sigma_r(\hat{\delta})$

Degrees of Freedom

(n-1) from denominator of $s_{\hat{s}}^2$

Estimated Standard Errors for each design

Design 1

"Indirect"

$$\hat{\delta}_{B-A} = \hat{\mu}_B - \hat{\mu}_A$$

Indirect estimate of δ

$$\hat{\mu}_A = \frac{1}{n_A} \sum \hat{\mu}_{Aj}$$

direct estimates of μ_B and μ_A

TRUE Standard Error:

$$\sigma_{\it r}(\hat{\mu}_i) = \sqrt{\begin{array}{c} {\rm Variance~of~population} + {\rm Variance~of~measurements} \\ {\rm Sample~size} \end{array}}$$

Estimated Standard Error:

Sample Variance of $\hat{\mu}_{ij} pprox$ Variance of TRUE values + Variance of error

$$s_{\hat{\mu}_i}^2 = \frac{\sum (\hat{\mu}_{ij} - \hat{\mu}_i)^2}{n_i - 1}$$
 Observed variance of estimates around their mean

TRUE Standard Error:

$$\sigma_r(\hat{\delta}) = \sqrt{\sigma_r^2(\hat{\mu}_B) + \sigma_r^2(\hat{\mu}_A)}$$

Estimated Standard Error:

SED =
$$\sqrt{\frac{s_{\hat{\mu}_B}^2}{n_B} + \frac{s_{\hat{\mu}_A}^2}{n_A}}$$

Problem:

Degrees of Freedom

$$(n_B - 1)$$
 from $s_{\hat{\mu}_R}^2$ or $(n_A - 1)$ from $s_{\hat{\mu}_A}^2$?

Can't use 2 degrees of freedom for the t-distribution Best Df is closer to the **smaller** of $(n_B - 1)$ and $(n_A - 1)$ Solution: **Pooled** $s_{\hat{\mu}}^2$

Sample Variance of $\hat{\mu}_{ij} \approx$ Variance of TRUE values + Variance of errors

if Variances of pulses are similar for both treatments

And measurement errors are similar

We can **pool** all deviations together into a **pooled** $s_{\hat{\mu}}^2$

$$s_{\hat{\mu}}^2 = \frac{\sum (\hat{\mu}_{Bj} - \hat{\mu}_B)^2 + \sum (\hat{\mu}_{Aj} - \hat{\mu}_A)^2}{(n_B - 1) + (n_A - 1)} -$$

All deviations² from the sample means

independent deviations per treatment

Estimated Standard Error:

$$\mathbf{SED} = \sqrt{\frac{s_{\hat{\mu}}^2}{n_B} + \frac{s_{\hat{\mu}}^2}{n_A}}$$

If variances are equal, this is a **better** (more accurate) estimate of $\sigma_r(\hat{\delta})$

Here, we have a single df to use for confidence intervals:

Degrees of Freedom

$$(n_B - 1) + (n_A - 1)$$

Key points:

Follow the sample sizes for each treatment level

Each is used 2x

We will always use the **pooled** $s_{\hat{\mu}}^2$ in this class because of limitations of the lm() and lmer() functions

Estimated Standard Errors for each design

Which equation for s^2 and SED?

Which components will tend to be different from Design 1 / 2 ?

* our data will be different, so all estimates will be different *

$$\hat{\delta}_{B-A} = \hat{\mu}_B - \hat{\mu}_A \qquad \qquad s_{\hat{\mu}}^2 = \frac{\sum (\hat{\mu}_{Bj} - \hat{\mu}_B)^2 + \sum (\hat{\mu}_{Aj} - \hat{\mu}_A)^2}{(n_B - 1) + (n_A - 1)}$$

$$\mathbf{SED} = \sqrt{\frac{s_{\hat{\mu}}^2}{n_B} + \frac{s_{\hat{\mu}}^2}{n_A}}$$

 $s_{\hat{u}}^2$ will **tend to be** smaller because of less measurement error

 n_B and n_A will be smaller (or equal) because of costs

If so, SED might be larger and DF would be smaller

Rules for making Design Table

Include all variable necessary to describe the experiment

Treatments: Variables we want to study

Response: One Variable, always numeric

Design

EU of the Treatment variable(s)

any Replicate and Replicate:Treatment

Variable with a unique level for each observation (Response)

Any other variable to describe the experiment

Check variable relationships: nested, aliased and crossed

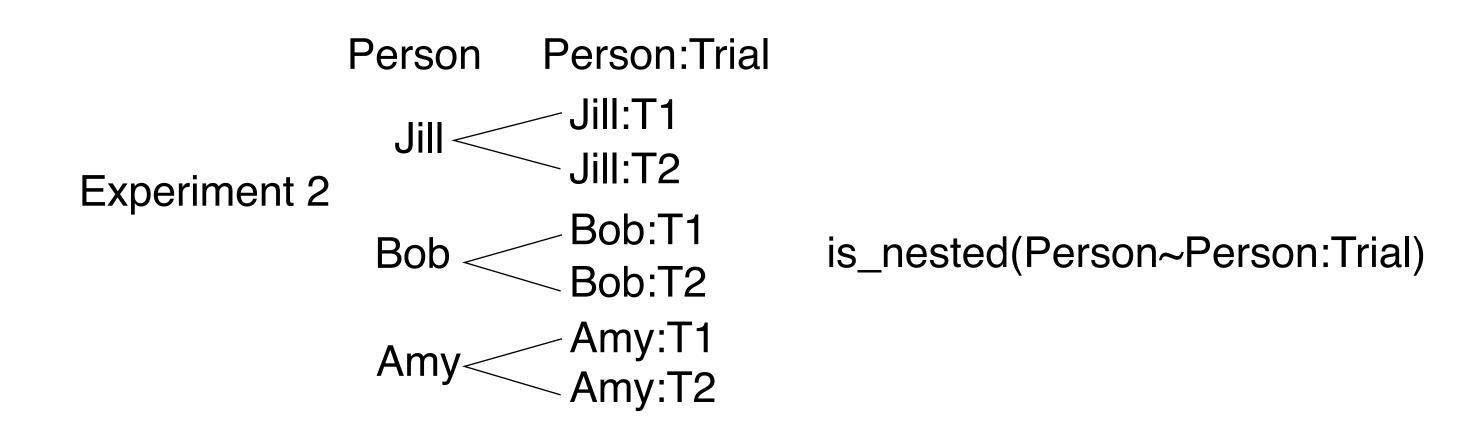
EU Variable must be **nested** in the Treatment variable

If two variables are **aliased**, keep only 1 of them

If two variables are **crossed**, keep only both

Relationships among variables

nested many:one Keep both, if 1 first is random, so is second



aliased one:one Keep one, particularly EU

Person:Trial Person:Posture

Jill:T1 ——Jill:Sit

Jill:T2 ——Jill:Stand

Experiment 2 Bob:T1——Bob:Stand is_aliased(A~B)

Bob:T2——Bob:Sit

Amy:T1——Amy:Sit

Amy:T2——Amy:Stand

crossed many:many Keep both

Posture Trial
is_crossed(A~B)
Experiment 2
Experiment 3
Stand T2

Rules for making Design Table

Include all variable necessary to describe the experiment

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EU of the Treatment variable(s)

any Replicate and Replicate:Treatment

Variable with a unique level for each observation (Response)

Any other variable to describe the experiment

Check variable relationships: nested, aliased and crossed

EU Variable must be **nested** in the Treatment variable Label as EU:Treatment

If two variables are aliased, keep only 1 of them

If one is an EU, keep that one!

If two variables are **crossed**, keep both

Treatments are crossed with their Replication variable

Sit Stand Sit # people # measures #EU 3) Jill
$$\begin{bmatrix} X & T1 \\ X & T2 \end{bmatrix}$$
 Bob $\begin{bmatrix} X & T1 \\ X & T2 \end{bmatrix}$ Amy $\begin{bmatrix} X & T1 \\ X & T2 \end{bmatrix}$ 40 80 40

Person	Posture	Pulse	Trial	Person:Trial
Jill	Sit	60	T1	Jill:T1
Jill	Sit	64	T2	Jill:T2
Bob	Stand	72	T1	Bob:T1
Bob	Stand	68	T2	Bob:T2
Amy	Sit	106	T1	Amy:T1
Amy	Sit	112	T2	Amy:T2
• •				

Structure	Variable	Туре	#levels	Replicate	EU
Treatment	Posture	Cat	2	None	Person
Design	Person	Cat	40		
	Trial	Cat	2		
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