Workshop
Single-Case Regression Analyses

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- arrow keys: move through slides
- f: toggle full-screen

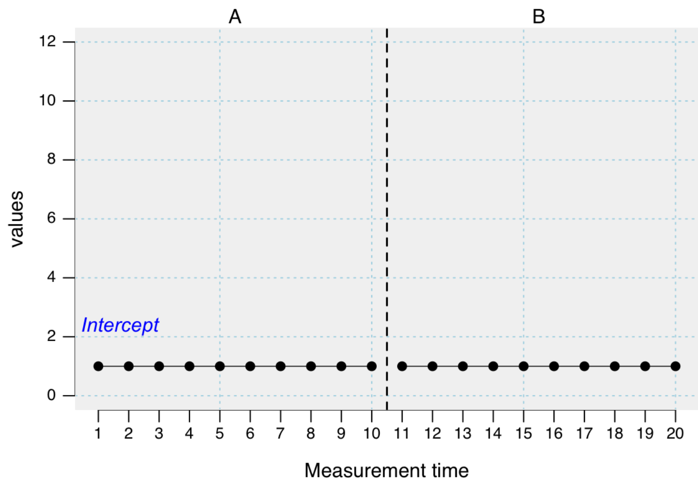
My general perspective on single-case data

Statistics is modeling the world

- Statistical models are "translations" of (scientific) hypotheses and entities.
- The formulation of the correct model is a crucial and insightful process.
- When we have a "good" statistical model we can draw valid conclusions.
- Single-case data are … "just" data.
- We don't need a new statistic for analyzing single-case data.
- We "just" need good models.

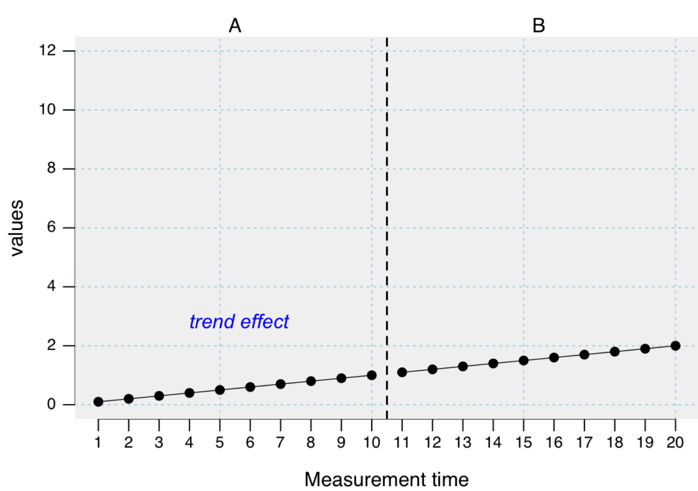
A basic model

Component 1: The intercept



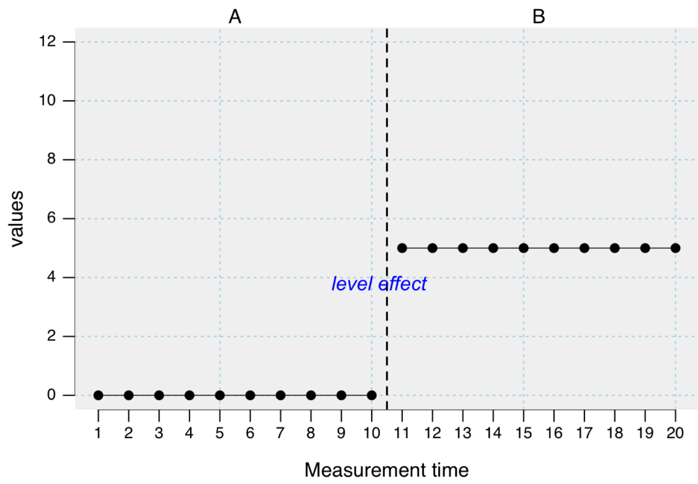
$y_i = \beta_0$

Component 2: Trend effect



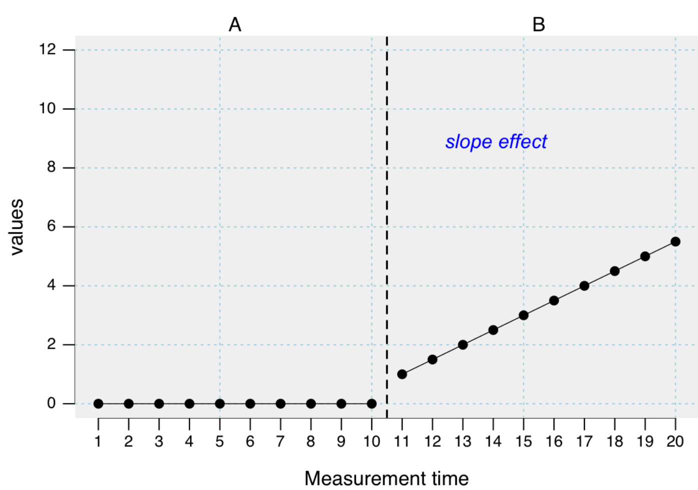
$y_i = \beta_1 MT_i$

Component 3: Level effect



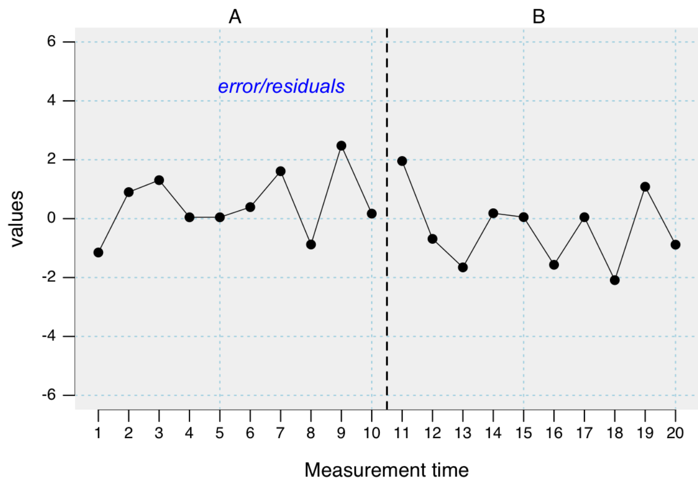
$y_i = \beta_2 Phase_i$

Component 4: Slope effect



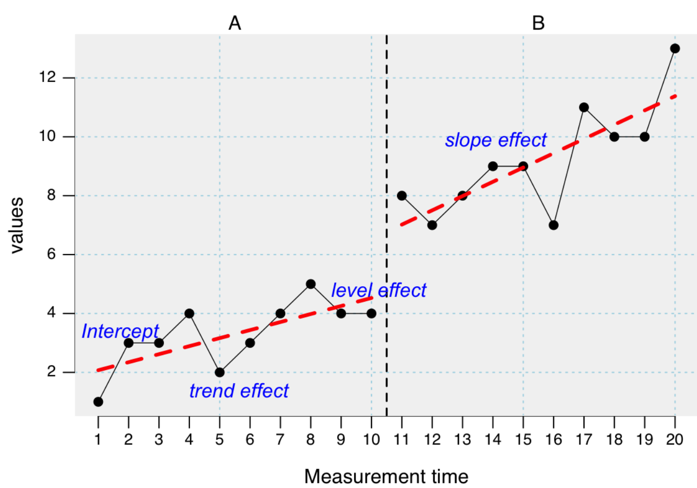
$y_i = \beta_3(MT_i - \sigma) \times Phase_i$
σ := MT at which Phase B starts minus one (Berry & Lewis-Beck)
—— Alternative: σ := MT at which Phase B starts (Huitema & McKean)

Component 5: Error/Residual



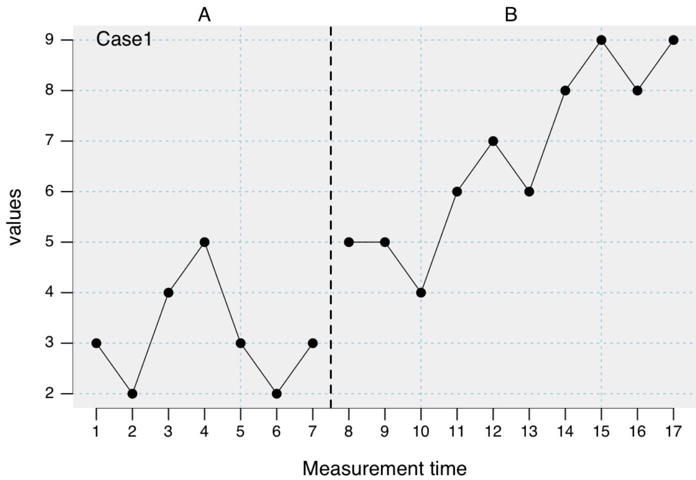
$y_i = \epsilon_i$

The full model



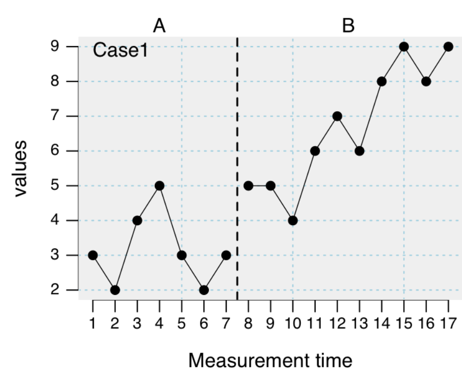
$y_i = \beta_0 + \beta_1 MT_i + \beta_2 Phase_i + \beta_3 (MT_i - \sigma) \times Phase_i + \epsilon_i$

Example: First visualize the data



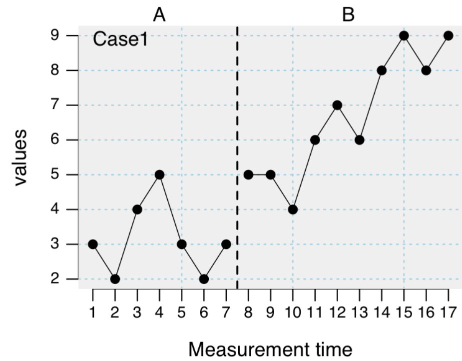
Second: Describe the data

```
Describe Single-Case Data

Design:  A B

        Case1
    n.A     7
    n.B    10
  mis.A     0
  mis.B     0

        Case1
    m.A  3.14
    m.B  6.70
   md.A  3.00
   md.B  6.50
   sd.A  1.07
   sd.B  1.77
  mad.A  1.48
  mad.B  2.22
  min.A  2.00
  min.B  4.00
  max.A  5.00
  max.B  9.00
trend.A -0.04
trend.B  0.53
```



Third: Fit a statistical model

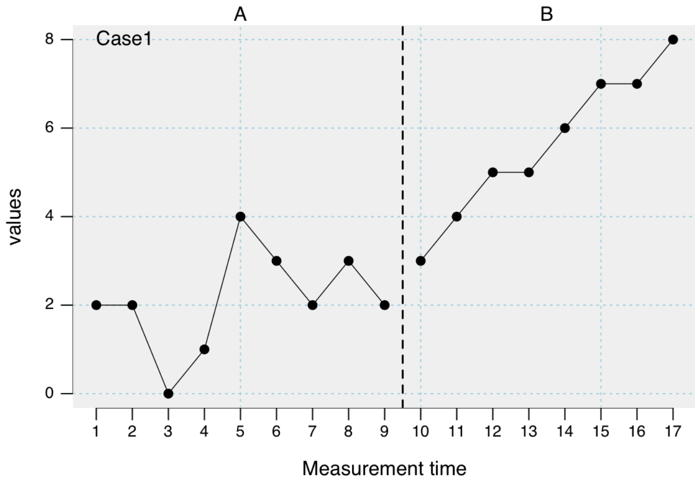
```
Piecewise Regression Analysis

Dummy model:  B&L-B

Fitted a gaussian distribution.
F(3, 13) = 27.14; p = 0.000; R² = 0.862; Adjusted R² = 0.831

                   B   2.5% 97.5%    SE      t     p    ΔR²
Intercept      3.286  1.695 4.876 0.811  4.049 0.001
Trend mt      -0.036 -0.391 0.320 0.181 -0.197 0.847 0.0004
Level phase B  0.764 -1.051 2.580 0.926  0.825 0.424 0.0072
Slope phase B  0.563  0.151 0.975 0.210  2.681 0.019 0.0761

Autocorrelations of the residuals
 lag    cr
   1 -0.04
   2 -0.67
   3  0.09

Formula: values ~ 1 + mt + phaseB + interB
```



Task: Recreate the following example

```
library(scan)
dat <- scdf(c(A = 2,2,0,1,4,3,2,3,2, B = 3,4,5,5,6,7,7,8))
plot(dat)
describeSC(dat)
plm(dat)
```

Task: `plot(dat)`



Task: `describeSC(dat)`

```
Describe Single-Case Data

Design:  A B

        Case1
    n.A     9
    n.B     8
  mis.A     0
  mis.B     0

        Case1
    m.A  2.11
    m.B  5.62
   md.A  2.00
   md.B  5.50
   sd.A  1.17
   sd.B  1.69
  mad.A  1.48
  mad.B  2.22
  min.A  0.00
  min.B  3.00
  max.A  4.00
  max.B  8.00
trend.A  0.15
trend.B  0.68
```

Task: `plm(dat)`

```
Piecewise Regression Analysis

Dummy model:  B&L-B

Fitted a gaussian distribution.
F(3, 13) = 31.39; p = 0.000; R² = 0.879; Adjusted R² = 0.851

                   B   2.5% 97.5%    SE      t     p    ΔR²
Intercept      1.361  0.108 2.615 0.640  2.128 0.053
Trend mt       0.150 -0.073 0.373 0.114  1.320 0.210 0.0163
Level phase B -0.140 -1.852 1.573 0.874 -0.160 0.875 0.0002
Slope phase B  0.529  0.181 0.876 0.177  2.984 0.011 0.0831

Autocorrelations of the residuals
 lag    cr
   1  0.00
   2 -0.58
   3 -0.03

Formula: values ~ 1 + mt + phaseB + interB
```


Which effects do I need?

Whether you need to include a trend, level, or slope effect is a theoretical decision:

- What effects did prior studies reveal?
- How do you expect the process to evolve?
  - Learning processes are often continuously (slope effects)
  - Medication might have an immediate full effect (level effect)
  - Motivation and attention effects of an intervention are also immediate (level effect)
- Do you expect a continuous change independent of the intervention? (trend effect)
  - participants get familiar with the test material
  - patients' symptoms mitigate or increase with time
  - children mature
  - students get additional support outside the classroom

Setting up a restricted model

```
Piecewise Regression Analysis

Dummy model:  B&L-B

Fitted a gaussian distribution.
F(3, 13) = 14.53; p = 0.000; R² = 0.770; Adjusted R² = 0.717

                    B   2.5% 97.5%    SE      t     p    ΔR²
Intercept       1.250 -0.332 2.832 0.807  1.548 0.146
Trend mt        0.150 -0.131 0.431 0.143  1.046 0.315 0.0193
Level phase B   2.364  0.203 4.526 1.103  2.144 0.052 0.0812
Slope phase B  -0.031 -0.469 0.407 0.224 -0.138 0.892 0.0003

Autocorrelations of the residuals
 lag    cr
   1 -0.21
   2 -0.08
   3 -0.45

Formula: values ~ 1 + mt + phaseB + interB
```


Restricting models with scan

The plm function comes with three additional parameters:

`trend`, `level`, and `slope`

All are set to `TRUE` by default. That is, all three effects are included into the model.

By explicitly setting an argument to FALSE (e.g. `level = FALSE`) you drop this effect from the model.

In this example:

$$y_i = \beta_0 + \beta_1 MT_i + \beta_2 Phase_i + \beta_3(MT_i - \sigma) \times Phase_i + \epsilon_i$$

becomes

$$y_i = \beta_0 + \beta_1 MT_i + \beta_3(MT_i - \sigma) \times Phase_i + \epsilon_i$$

Dropping effects

$y_i = \beta_0 + \beta_1 MT_i + \beta_2 Phase_i + \beta_3 (MT_i - \sigma) \times Phase_i + \epsilon_i$

$y_i = \beta_0 + \beta_2 Phase_i + \epsilon_i$ (basically a t-test)

```
plm(dat, trend = FALSE, slope = FALSE)
```

```
Piecewise Regression Analysis

Dummy model:  B&L-B

Fitted a gaussian distribution.
F(1, 15) = 43.24; p = 0.000; R² = 0.742; Adjusted R² = 0.725

                B  2.5% 97.5%    SE     t p    ΔR²
Intercept     2.0 1.284 2.716 0.365 5.477 0
Level phase B 3.5 2.457 4.543 0.532 6.575 0 0.7424

Autocorrelations of the residuals
 lag    cr
   1 -0.01
   2  0.00
   3 -0.37

Formula: values ~ 1 + phaseB
```


Task

Take the previous data example …

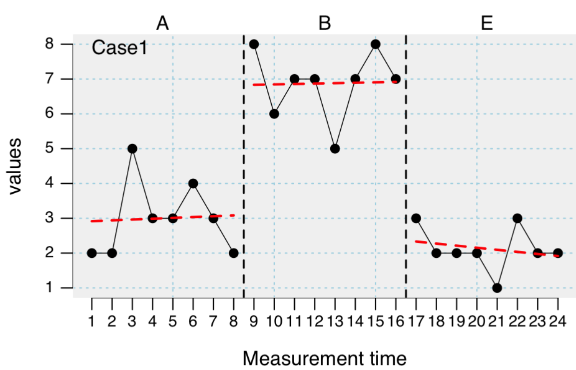
```
dat <- scdf(c(A = 2,2,0,1,4,3,2,3,2, B = 3,4,5,5,6,7,7,8))
```

and recalculate a plm model without a level effect.

```
plm(dat, level = FALSE)
```

```
Piecewise Regression Analysis

Dummy model:  B&L-B

Fitted a gaussian distribution.
F(2, 14) = 50.60; p = 0.000; R² = 0.878; Adjusted R² = 0.861

                  B   2.5% 97.5%    SE     t     p    ΔR²
Intercept     1.393  0.242 2.543 0.587 2.373 0.033
Trend mt      0.141 -0.043 0.324 0.094 1.501 0.155 0.0196
Slope phase B 0.523  0.195 0.851 0.167 3.125 0.007 0.0848

Autocorrelations of the residuals
 lag    cr
   1  0.01
   2 -0.58
   3 -0.02

Formula: values ~ 1 + mt + interB
```


Multiple phase change models



What is your hypothesis here?

1. An increase in phase B compared to A and a decrease in phase E compared to B or
2. An increase in phase B compared to A and an increase in phase E compared to A

it depends …

Contrasts

Contrasts are model settings that define which levels of a categorical variable are compared in a model.

In single-case models the phase variable is such a categorical variable.

The level-effect and the slope-effect in a model depend on the setting of the contrasts.

Here we will learn about two contrast settings:

1. Compare all phases to the first phase.
2. Compare all phases to the preceding phase.

Dummy variables

- Categorical predictor variables are recoded in regression analyses.
- Each category level becomes a “dummy” variable comprising a series of 0s and 1s
  - ! more complex values are possible but not discussed here
  - ! when an intercept is included, a reference category is not included, these aspects are also not discussed here

Two contrast models (it gets a bit complicated)

Contrast with A Phase

(phase)	mt	values	level_B	level_C	slope_B	slope_C
A	1	3	0	0	0	0
A	2	6	0	0	0	0
A	3	4	0	0	0	0
A	4	7	0	0	0	0
B	5	5	1	0	1	0
B	6	3	1	0	2	0
B	7	4	1	0	3	0
B	8	6	1	0	4	0
C	9	7	0	1	0	1
C	10	5	0	1	0	2
C	11	6	0	1	0	3
C	12	4	0	1	0	4

Constrast with preceding phase

(phase)	mt	values	level_B	level_C	slope_B	slope_C
A	1	3	0	0	0	0
A	2	6	0	0	0	0
A	3	4	0	0	0	0
A	4	7	0	0	0	0
B	5	5	1	0	1	0
B	6	3	1	0	2	0
B	7	4	1	0	3	0
B	8	6	1	0	4	0
C	9	7	1	1	5	1
C	10	5	1	1	6	2
C	11	6	1	1	7	3
C	12	4	1	1	8	4

Two contrasts models in `scan`

The `plm` function has an argument `model` (default `model = "B&L-B"`)

`model = "B&L-B"` will set contrasts for each phase against phase A.

`model = "JW"` will set contrasts for each phase against its preceding phase.

Example:

```
plm(case, model = "JW")
```

An example

Comparing phase effects to phase A

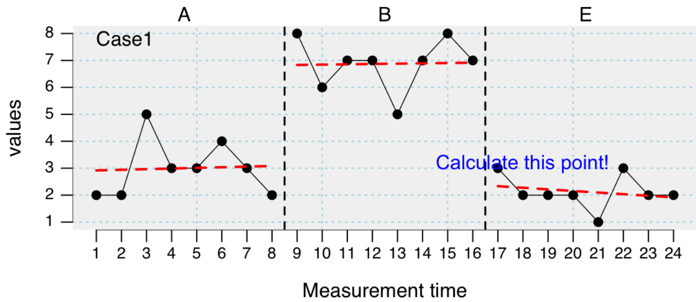
```
Piecewise Regression Analysis

Dummy model:  B&L-B

Fitted a gaussian distribution.
F(5, 18) = 20.99; p = 0.000; R² = 0.854; Adjusted R² = 0.813

                    B   2.5% 97.5%    SE      t     p    ΔR²
Intercept       2.893  1.384 4.402 0.770  3.758 0.001
Trend mt        0.024 -0.275 0.323 0.152  0.156 0.878 0.0002
Level phase B  3.738  1.779 5.698 1.000  3.739 0.002 0.1137
Level phase E -0.881 -4.696 2.934 1.946 -0.453 0.656 0.0017
Slope phase B -0.012 -0.434 0.411 0.216 -0.055 0.957 0.0000
Slope phase E -0.083 -0.506 0.339 0.216 -0.387 0.704 0.0012

Autocorrelations of the residuals
 lag    cr
   1 -0.26
   2 -0.20
   3  0.25

Formula: values ~ 1 + mt + phaseB + phaseE + interB + interE
```


An example

Comparing phase effects of each phase to the to previous phase

```
Piecewise Regression Analysis

Dummy model:  JW

Fitted a gaussian distribution.
F(5, 18) = 20.99; p = 0.000; R² = 0.854; Adjusted R² = 0.813

                    B   2.5%  97.5%    SE      t     p    ΔR²
Intercept       2.893  1.384  4.402 0.770  3.758 0.001
Trend mt        0.024 -0.275  0.323 0.152  0.156 0.878 0.0002
Level phase B  3.738  1.779  5.698 1.000  3.739 0.002 0.1137
Level phase E -4.524 -6.483 -2.564 1.000 -4.525 0.000 0.1666
Slope phase B -0.012 -0.434  0.411 0.216 -0.055 0.957 0.0000
Slope phase E -0.071 -0.494  0.351 0.216 -0.331 0.744 0.0009

Autocorrelations of the residuals
 lag    cr
   1 -0.26
   2 -0.20
   3  0.25

Formula: values ~ 1 + mt + phaseB + phaseE + interB + interE
```

Both models are depictions of the same data!



	Model1: Contrast to phase A	Model2: Contrast to previous phase
Intercept	2.89	2.89
Trend	0.02	0.02
Level B	3.74	3.74
Level E	-0.88	-4.52
Slope B	-0.01	-0.01
Slope E	-0.08	-0.07

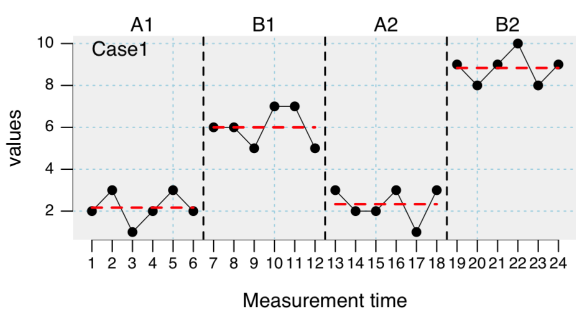
$$2.89 + (16 * 0.02) - 0.88 \approx 2.34$$

$$2.89 + (8 * 0.02) + 3.74 + (8 * (0.02 - 0.01)) - 4.52 \approx 2.34$$

Task

Create the following example dataset

```
case <- scdf( c(A1 = 2,3,1,2,3,2, B1 = 6,6,5,7,7,5, A2 = 3,2,2,3,1,3, B2 = 9,8,9,10,8,9))
plot(case, lines = list("mean", col = "red", lwd = 2))
```



Drop the slope effect from the model and contrast each phase to the previous one.

Task solution

```
plm(case, model = "JW", slope = FALSE)
```

```
Piecewise Regression Analysis

Dummy model:  JW

Fitted a gaussian distribution.
F(4, 19) = 67.35; p = 0.000; R² = 0.934; Adjusted R² = 0.920

                    B   2.5%  97.5%    SE      t p    ΔR²
Intercept       2.167  1.219  3.114 0.483  4.481 0
Trend mt        0.000 -0.194  0.194 0.099  0.000 1 0.0000
Level phase B1  3.833  2.341  5.326 0.762  5.034 0 0.0879
Level phase A2 -3.667 -5.159 -2.174 0.762 -4.815 0 0.0804
Level phase B2  6.500  5.007  7.993 0.762  8.535 0 0.2526

Autocorrelations of the residuals
 lag    cr
   1 -0.47
   2 -0.24
   3  0.44

Formula: values ~ 1 + mt + phaseB1 + phaseA2 + phaseB2
```


Extending the regression model

Adding additonal variables

mt	phase	mood	sleep
1	A	2	4
2	A	3	6
3	A	2	5
4	A	3	7
5	A	1	3
6	A	2	5
7	B	7	7
8	B	6	7
9	B	5	6
10	B	4	4
11	B	5	6
12	B	6	5
13	B	5	7
14	B	8	8

$$mood_i = \beta_0 + \beta_1 mt_i + \beta_2 phase_i + \beta_3 (mt_i - 6) \times phase_i + \beta_4 sleep + \epsilon_i$$


```
Piecewise Regression Analysis

Dummy model:  B&L-B

Fitted a gaussian distribution.
F(3, 10) = 10.80; p = 0.002; R² = 0.764; Adjusted R² = 0.693

                     B   2.5% 97.5%    SE      t     p    ΔR²
Intercept        2.667  0.526 4.807 1.092  2.442 0.035
Trend mt        -0.143 -0.692 0.407 0.280 -0.509 0.622 0.0061
Level phase B    3.619  1.174 6.064 1.248  2.901 0.016 0.1984
Slope phase B    0.214 -0.440 0.868 0.334  0.642 0.535 0.0097

Autocorrelations of the residuals
 lag    cr
   1 -0.05
   2 -0.05
   3 -0.24

Formula: mood ~ 1 + mt + phaseB + interB
```

Task

We can update a regression model with the `update` argument of the `plm` function.

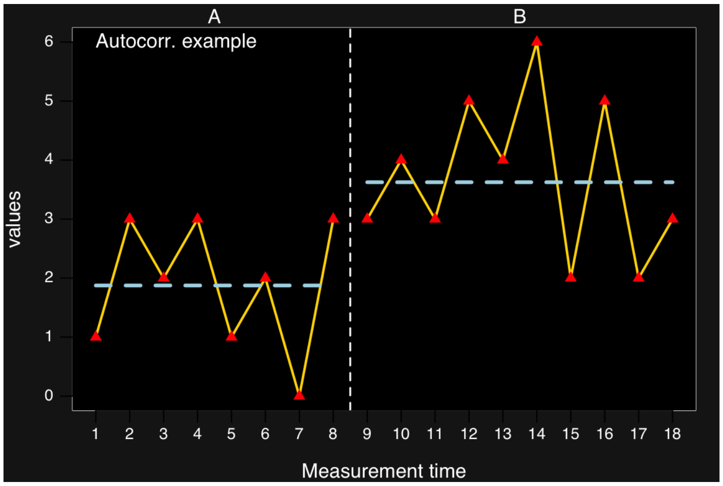
Pleaae execute the following code:

```
case <- scdf(
  mood = c(A = 2,3,2,3,1,2, B = 7,6,5,4,5,6,5,8),
  sleep = c(4,6,5,7,3,5, 7,7,6,4,6,5,7,8),
  dvar = "mood"
)

plm(case, update = .~. + sleep)
```



```
Piecewise Regression Analysis

Dummy model:  B&L-B

Fitted a gaussian distribution.
F(4, 9) = 21.09; p = 0.000; R² = 0.904; Adjusted R² = 0.861

                   B   2.5% 97.5%    SE      t     p    ΔR²
Intercept     -0.553 -2.820 1.714 1.157 -0.478 0.644
Trend mt      -0.107 -0.478 0.263 0.189 -0.568 0.584 0.0035
Level phase B  2.956  1.269 4.642 0.861  3.434 0.007 0.1263
Slope phase B  0.135 -0.308 0.578 0.226  0.596 0.566 0.0038
sleep          0.619  0.283 0.955 0.172  3.608 0.006 0.1394

Autocorrelations of the residuals
 lag    cr
   1 -0.49
   2  0.26
   3 -0.26

Formula: mood ~ mt + phaseB + interB + sleep
```

Autocorrelated residuals
(much ado about nothing?)



Autocorrelated residuals

The `autocorr()` function takes a `lag` argument and provides auto-correlations of the dependent variable for each phase and across all phases.

```
autocorr(case, lag = 3)
```

```
Autocorrelations

               case phase lag_1 lag_2 lag_3
 Autocorr. example     A -0.47  0.33 -0.57
 Autocorr. example     B -0.46  0.50 -0.43
 Autocorr. example   all  0.08  0.61 -0.10
```

Autocorrelated residuals

The `plm()` gives information on the autocorrealtion of the residuals up to lag 3

```
Piecewise Regression Analysis

Dummy model:  B&L-B

Fitted a gaussian distribution.
F(3, 14) = 2.89; p = 0.073; R² = 0.383; Adjusted R² = 0.250

                    B   2.5% 97.5%    SE      t     p    ΔR²
Intercept       2.036  0.013 4.058 1.032  1.973 0.069
Trend mt       -0.036 -0.436 0.365 0.204 -0.175 0.864 0.0013
Level phase B  2.317 -0.123 4.756 1.245  1.861 0.084 0.1527
Slope phase B -0.031 -0.523 0.461 0.251 -0.123 0.904 0.0007

Autocorrelations of the residuals
 lag    cr
   1 -0.56
   2  0.53
   3 -0.57

Formula: values ~ 1 + mt + phaseB + interB
```


Controlling autoregression

The `AR` argument of the `plm()` function allows for modeling autocorrelated residuals up to a provided lag.

```
plm(case)
```

	B	se	t	p
Intercept	2.036	1.032	1.973	0.069
Trend	-0.036	0.204	-0.175	0.864
Level B	2.317	1.245	1.861	0.084
Slope B	-0.031	0.251	-0.123	0.904

```
plm(case, AR = 3)
```

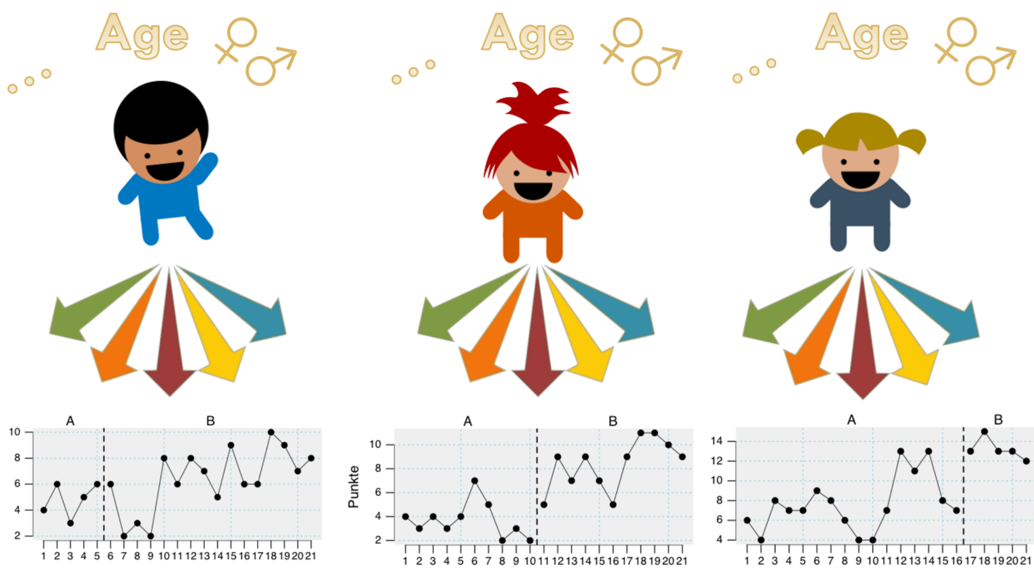
	B	se	t	p
Intercept	2.447	0.598	4.091	0.001
Trend	-0.138	0.122	-1.138	0.274
Level B	3.044	0.753	4.045	0.001
Slope B	0.027	0.136	0.200	0.844

Multilevel models

Why multilevel analyzes of single-cases?

- Reporting aggregated effects of multi-baseline designs (increasing external validity)
- Controlling for differences between individuals at the start of the investigations (random intercept / ICCs)
- Quantifying individual differences in response to a treatment (random slopes)
- Investigating and modeling variables that explain individual response differences (cross-level Interactions)

Hierarchical piecewise linear model



Hierarchical piecewise linear model

The `hplm()` function is an extension of the `plm()` function taking many of its parameters and allowing to analyze multiple cases at once:

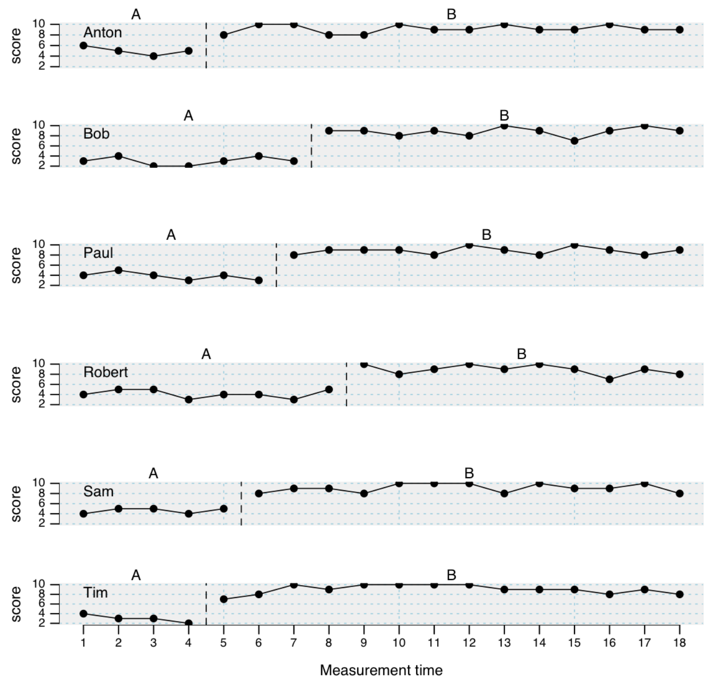
- `trend`, `level`, and `slope` arguments
- `update.fixed` for extending the regression model (fixed part)
- `model` for defining the contrasts

with some additional arguments for multilevel models.

Type `?hplm` to open a help page.

Example: overall effects

Example dataset `GruenkeWilbert2014`



Task

Replicate the following code to get an overview of the `GruenkeWilbert2014` dataset

```
summary(GruenkeWilbert2014)
describeSC(GruenkeWilbert2014)
```

```
summary(GruenkeWilbert2014)
```

```
#A single-case data frame with 6 cases

       Measurements Design
Anton            18    A B
Bob              18    A B
Paul             18    A B
Robert           18    A B
Sam              18    A B
Tim              18    A B

Variable names:
mt <measurement-time variable>
score <dependent variable>
phase <phase variable>


Note:  Data from an intervention study on text comprehension. Gruenke, M., Wilbert, J., & Stegemann-Calder, K. (2013
Author of data:  Matthias Gruenke and Juergen Wilbert
```



```
describeSC(GruenkeWilbert2014)
```

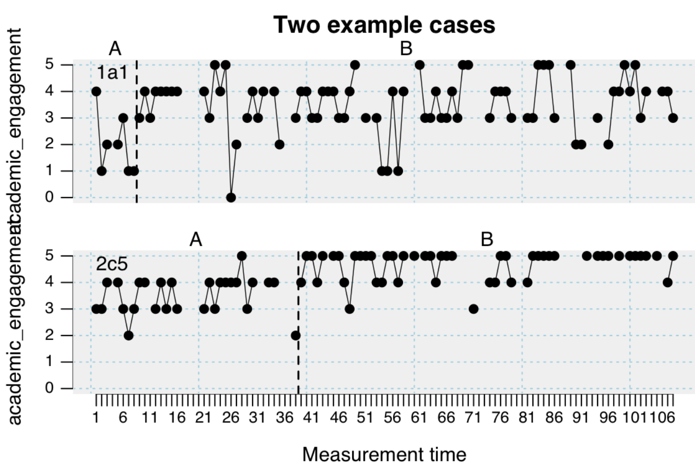
```
Describe Single-Case Data

Design:  A B

        Anton Bob Paul Robert Sam Tim
    n.A     4   7    6      8   5   4
    n.B    14  11   12     10  13  14
  mis.A     0   0    0      0   0   0
  mis.B     0   0    0      0   0   0

        Anton   Bob  Paul Robert   Sam   Tim
    m.A  5.00  3.00  3.83   4.12  4.60  3.00
    m.B  9.14  8.82  8.83   8.90  9.08  9.00
   md.A  5.00  3.00  4.00   4.00  5.00  3.00
   md.B  9.00  9.00  9.00   9.00  9.00  9.00
   sd.A  0.82  0.82  0.75   0.83  0.55  0.82
   sd.B  0.77  0.87  0.72   0.99  0.86  0.96
  mad.A  0.74  1.48  0.74   1.48  0.00  0.74
  mad.B  1.48  0.00  0.74   1.48  1.48  1.48
  min.A  4.00  2.00  3.00   3.00  4.00  2.00
  min.B  8.00  7.00  8.00   7.00  8.00  7.00
  max.A  6.00  4.00  5.00   5.00  5.00  4.00
  max.B 10.00 10.00 10.00  10.00 10.00 10.00
trend.A -0.40  0.04 -0.26  -0.06  0.10 -0.60
trend.B  0.03  0.04  0.02  -0.14  0.03  0.00

Note. The following variables were used in this analysis:
      'score' as dependent variable, 'phase' as phase ,and 'mt' as measurement time.
```

```
Hierarchical Piecewise Linear Regression

Estimation method ML
Slope estimation method: B&L-B
6 Cases

ICC = 0.001; L = 0.0; p = 0.953

Fixed effects (score ~ 1 + mt + phaseB + interB)

                    B    SE df      t     p
Intercept       4.169 0.260 99 16.042 0.000
Trend mt       -0.081 0.059 99 -1.373 0.173
Level phase B   5.208 0.300 99 17.343 0.000
Slope phase B   0.087 0.062 99  1.393 0.167

Random effects (~1 | case)

          EstimateSD
Intercept      0.149
Residual       0.866
```


Example: Different responses between subjects

Example dataset `Leidig2018`

35 cases with up to 108 measurements (AB-Design, effect of a “good behavior game” on academic engagement and disruptive behavior)



Academic engagement

```
Hierarchical Piecewise Linear Regression

Estimation method ML
Slope estimation method: B&L-B
35 Cases

ICC = 0.344; L = 875.4; p = 0.000

Fixed effects (academic_engagement ~ 1 + mt + phaseB + interB)

                    B    SE   df      t     p
Intercept       3.042 0.125 2376 24.281 0.000
Trend mt       -0.004 0.004 2376 -0.966 0.334
Level phase B   0.730 0.067 2376 10.823 0.000
Slope phase B   0.008 0.004 2376  2.095 0.036

Random effects (~1 | case)

          EstimateSD
Intercept      0.680
Residual       0.784
```


Disruptive behavior

```
Hierarchical Piecewise Linear Regression

Estimation method ML
Slope estimation method: B&L-B
35 Cases

ICC = 0.311; L = 759.2; p = 0.000

Fixed effects (disruptive_behavior ~ 1 + mt + phaseB + interB)

                    B    SE   df       t p
Intercept       1.267 0.098 2349  12.927 0
Trend mt        0.024 0.003 2349   7.689 0
Level phase B -1.327 0.056 2349 -23.606 0
Slope phase B -0.025 0.003 2349  -7.802 0

Random effects (~1 | case)

          EstimateSD
Intercept      0.525
Residual       0.655
```

Task

Take the `Leidig2018` dataset and calculate an `hplm` model.

Choose `disruptive_behavior` as the dependent variable (`dvar = "disruptive_behavior"`)

Add random slopes to the regression model (`random.slopes = TRUE`) and likelihood ratio tests (`lr.test = TRUE`)


```
Hierarchical Piecewise Linear Regression

Estimation method ML
Slope estimation method: B&L-B
35 Cases

ICC = 0.311; L = 759.2; p = 0.000

Fixed effects (disruptive_behavior ~ 1 + mt + phaseB + interB)

                    B    SE   df      t     p
Intercept       1.493 0.128 2349 11.631 0.000
Trend mt        0.014 0.004 2349  3.189 0.001
Level phase B -1.286 0.147 2349 -8.764 0.000
Slope phase B -0.013 0.004 2349 -3.175 0.002

Random effects (~1 + mt + phaseB + interB | case)

              EstimateSD      L df     p
Intercept          0.710 210.92  4 0.000
Trend mt           0.015  12.90  4 0.012
Level phase B      0.810 138.84  4 0.000
Slope phase B      0.015  10.43  4 0.034
Residual           0.592     NA NA    NA
```

Cross-level predictors

- We found a significant variance in the slope and the level effects between subjects
- Can we explain these differences by means of attributes of the indivudals?
- The `Leidig2018` dataset has an accompanying dataset with information on each subject `Leidig2018_l2`:

```
class, case, gender, migration, first_language_german, SDQ_TOTAL, SDQ_EXTERNALIZING, SDQ_INTERNALIZING, ITRF_TOTAL,
```

class	case	gender	migration	first_language_german	SDQ_TOTAL	SDQ_EXTERNALIZING	SDQ_INTERNALIZING	ITRF_TOTAL	ITRF_ACADEMIC	ITR
1a	1a1	0	0	1	10	9	1	11	7	
1a	1a2	0	0	1	11	11	0	21	10	
1a	1a3	1	0	1	6	6	0	18	1	
1a	1a4	0	1	1	8	5	3	14	7	
1a	1a5	0	1	1	8	7	1	13	4	
2a	2a1	0	1	0	9	8	1	9	2	
2a	2a2	0	1	0	7	4	3	16	16	
2a	2a3	0	1	0	16	13	3	23	14	

Adding an L2 dataset to the `hplm()` function

- An l2 dataset contains information on each case of the single-case dataframe (scdf).
- An l2 dataset must have a variable named `case` with the casenames/id.
- All cases in the scdf must have a casename/id.
- The `data.l2` argument is set accoding to the name of the l2 dataset.
  - `hplm(Leidig2018, data.l2 = Leidig2018_l2)`
- The `update.fixed` argument must be set to include the l2 variables of interest.
  - `hplm(Leidig2018, data.l2 = Leidig2018_l2, update.fixed = .~. + SDQ_EXTERNALIZING * phaseB)`

Task

What effect does externalizing behavior have on the intervention strength on disruptive behavior?

Code and execute the following model.

Note: the `scale` function is needed to center the predictor variable (necessary in multilevel models)

```
hplm(
  Leidig2018,
  data.l2 = Leidig2018_l2,
  update.fixed = .~. + scale(SDQ_EXTERNALIZING) * phaseB + scale(SDQ_EXTERNALIZING) * interB,
  dvar = "disruptive_behavior"
)
```


Task

```
Hierarchical Piecewise Linear Regression

Estimation method ML
Slope estimation method: B&L-B
35 Cases

ICC = 0.311; L = 759.2; p = 0.000

Fixed effects (disruptive_behavior ~ mt + phaseB + interB + scale(SDQ_EXTERNALIZING) +     phaseB:scale(SDQ_EXTERNAI

                                          B    SE   df       t     p
Intercept                             1.319 0.095 2347  13.951 0.000
Trend mt                              0.020 0.003 2347   6.375 0.000
Level phase B                        -1.306 0.056 2347 -23.457 0.000
Slope phase B                        -0.020 0.003 2347  -6.396 0.000
scale(SDQ_EXTERNALIZING)              0.307 0.090   33   3.397 0.002
Level phase B:scale(SDQ_EXTERNALIZING) -0.202 0.043 2347  -4.702 0.000
Slope phase B:scale(SDQ_EXTERNALIZING) -0.001 0.001 2347  -2.522 0.012

Random effects (~1 | case)

          EstimateSD
Intercept      0.501
Residual       0.647
```

What comes next?

Future developments of `scan`

- Multivariate regression models (basic approach already included)
- Multilevel-multivariate models …