

Statistics with Spa OWS

Lecture 11-c

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Outline

- Linear models – going big
 - Multiple continuous predictors
 - Interactions between continuous predictors
 - Interactions between categorical predictors
 - ...

Multiple continuous predictors

```
> summary(lm(Y0~Cont1+Cont2,data=a))
```

Call:

```
lm(formula = Y0 ~ Cont1 + Cont2, data = a)
```

Residuals:

| Min | 1Q | Median | 3Q | Max |
|----------|----------|---------|---------|---------|
| -1.22886 | -0.29364 | 0.00364 | 0.32803 | 1.25419 |

Coefficients:

| | Estimate | Std. Error | t value | Pr(> t) | |
|-------------|----------|------------|---------|----------|-----|
| (Intercept) | 1.89714 | 0.28444 | 6.67 | 1.58e-09 | *** |
| Cont1 | -4.05761 | 0.04663 | -87.01 | < 2e-16 | *** |
| Cont2 | 3.79363 | 0.05129 | 73.97 | < 2e-16 | *** |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4757 on 97 degrees of freedom

Multiple R-squared: 0.9922, Adjusted R-squared: 0.992

F-statistic: 6144 on 2 and 97 DF, p-value: < 2.2e-16

Main effects cannot be interpreted in isolation

IF Cont2 is being held constant, then, with increasing Cont1, Y increases

If Cont1 is being held constant, then, with increasing Cont2, Y decreases

-> cannot visualize well

- helpful to account for environmental variables

Interactions between continuous predictors

- Really hard (if not impossible) to properly interpret
- Only do this if you know what it means

Interactions between categorical predictors

- Cat1: male, female
- Cat2: Orange, Green, Purple
- → Possible combinations:
 - Male Orange, Male Green, Male Purple
 - Female Orange, Female Green, Female Purple

Interactions between categorical predictors

```
> summary(lm(Y3~Cat1*Cat2,data=a))
```

Call:

```
lm(formula = Y3 ~ Cat1 * Cat2, data = a)
```

Residuals:

| | Min | 1Q | Median | 3Q | Max |
|--|---------|---------|--------|--------|--------|
| | -1.2190 | -0.2519 | 0.0102 | 0.3457 | 1.2261 |

Coefficients:

| | | Estimate | Std. Error | t value | Pr(> t) |
|----|-------------------|----------|------------|---------|--------------|
| b0 | (Intercept) | -5.7993 | 0.1162 | -49.890 | < 2e-16 *** |
| b1 | Cat1male | 16.4021 | 0.1567 | 104.646 | < 2e-16 *** |
| b2 | Cat2Orange | 14.4821 | 0.1552 | 93.313 | < 2e-16 *** |
| b3 | Cat2Purple | -6.4878 | 0.2096 | -30.960 | < 2e-16 *** |
| b4 | Cat1male:C2Orange | 4.4325 | 0.2266 | 19.559 | < 2e-16 *** |
| b5 | Cat1male:C2Purple | -1.9261 | 0.2690 | -7.161 | 1.76e-10 *** |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4932 on 94 degrees of freedom

Multiple R-squared: 0.9984, Adjusted R-squared: 0.9983

F-statistic: 1.168e+04 on 5 and 94 DF, p-value: < 2.2e-16

Female Green (Reference): b_0

Difference between reference and

Male Green: $b_0 + b_1$

Female Orange: $b_0 + b_2$

Female Purple: $b_0 + b_3$

Male Orange: $b_0 + b_4$

Male Purple: $b_0 + b_5$

Interactions between categorical predictors

- Does not test between all categories
- → Tukey test

```
> m1<-lm(Y3~Cat1*Cat2,data=a)
> an<-aov(m1)
> TK<-TukeyHSD(x=an)
> TK
Tukey multiple comparisons of means
 95% family-wise confidence level
```

```
Fit: aov(formula = m1)
```

```
$Cat1
```

| | diff | lwr | upr | p adj |
|-------------|----------|----------|----------|-------|
| male-female | 13.91706 | 13.72118 | 14.11294 | 0 |

```
$Cat2
```

| | diff | lwr | upr | p adj |
|---------------|------------|------------|------------|-------|
| Orange-Green | 15.845950 | 15.579905 | 16.111995 | 0 |
| Purple-Green | -7.498879 | -7.810613 | -7.187145 | 0 |
| Purple-Orange | -23.344830 | -23.659461 | -23.030198 | 0 |

```
$`Cat1:Cat2`
```

| | diff | lwr | upr | p adj |
|-----------------------------|------------|------------|------------|-------|
| male:Green-female:Green | 16.402149 | 15.946138 | 16.858159 | 0 |
| female:Orange-female:Green | 14.482141 | 14.030614 | 14.933669 | 0 |
| male:Orange-female:Green | 35.316741 | 34.815130 | 35.818352 | 0 |
| female:Purple-female:Green | -6.487805 | -7.097479 | -5.878131 | 0 |
| male:Purple-female:Green | 7.988251 | 7.476961 | 8.499540 | 0 |
| female:Orange-male:Green | -1.920007 | -2.347889 | -1.492126 | 0 |
| male:Orange-male:Green | 18.914592 | 18.434156 | 19.395029 | 0 |
| female:Purple-male:Green | -22.889954 | -23.482328 | -22.297579 | 0 |
| male:Purple-male:Green | -8.413898 | -8.904431 | -7.923365 | 0 |
| male:Orange-female:Orange | 20.834600 | 20.358416 | 21.310783 | 0 |
| female:Purple-female:Orange | -20.969946 | -21.558877 | -20.381016 | 0 |
| male:Purple-female:Orange | -6.493891 | -6.980259 | -6.007522 | 0 |
| female:Purple-male:Orange | -41.804546 | -42.432699 | -41.176393 | 0 |
| male:Purple-male:Orange | -27.328490 | -27.861680 | -26.795301 | 0 |
| male:Purple-female:Purple | 14.476056 | 13.840147 | 15.111964 | 0 |

What to use when

- Depends on your question

Do you want to:

- predict
- explain
- explore
- account for variables
- ...

Take home

- When running models, always be aware what is categorical and what is continuous, because the the interpretation differs
- Know your data structure!
- Do not overfit – less complex models are better