

Social Science Inquiry II

Week 8: Inference for multivariate regression, part II

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Loading packages for this class

```
> set.seed(60637)
> # For plotting:
> library(ggplot2)
> # library(devtools)
> # devtools::install_github("wilkelab/ungeviz")
> library(ungeviz)
> library(ggbridges)
```

► Housekeeping

P-hacking

P-values

Suppose $\hat{\theta}$ is the general form for an estimate produced by our estimator, and $\hat{\theta}^*$ is the value we have actually observed.

P-values

- ▶ A two-tailed p-value under the null hypothesis is

$$p = P_0[|\hat{\theta}| \geq |\hat{\theta}^*|]$$

i.e., the probability *under the null distribution* that we would see an estimate of $\hat{\theta}$ as or more extreme as what we saw from the data.

- ▶ Suppose we have some data, $(Y, X_1, X_2, \dots, X_K)$.
- ▶ Suppose the null distribution represents the truth.
- ▶ If we test one hypothesis, what is the probability that we will find something that is statistically significant at $p \leq 0.05$?
- ▶ If we test two unrelated hypotheses, what is the probability that we will find something that is statistically significant at $p \leq 0.05$?

- ▶ A: event we reject hypothesis 1 at $p \leq 0.05$
- ▶ B: event we reject hypothesis 2 at $p \leq 0.05$
- ▶ $A \perp\!\!\!\perp B$: the two events are independent
- ▶ $P[A] = 0.05$
- ▶ $P[B] = 0.05$
- ▶ $P[A \cup B]$? The probability we see event A OR B?

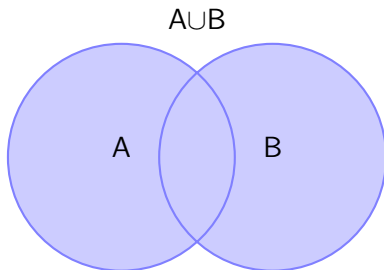
$$P[A \cup B] = P[A] + P[A^C] \times P[B|A^C]$$

A and B are independent, so $P[B|A^C] = P[B]$

$$P[A \cup B] = P[A] + P[A^C] \times P[B]$$

$$P[A \cup B] = 0.05 + 0.95 \times 0.05$$

$$P[A \cup B] = 0.0975$$



If the null is true . . .

- ▶ and we conduct three independent tests, the probability that *at least one of them* will be statistically significant at $p \leq 0.05$ is
 $1 - 0.95^3 = 0.1426$
- ▶ and we conduct four independent tests, the probability that *at least one of them* will be statistically significant at $p \leq 0.05$ is
 $1 - 0.95^4 = 0.1855$
- ▶ and we conduct ten independent tests, the probability that *at least one of them* will be statistically significant at $p \leq 0.05$ is
 $1 - 0.95^{10} = 0.4013$

This becomes a real problem when researchers run many tests in their papers!

	Fail to reject null hypothesis ($p > 0.05$)	Reject null hypothesis ($p \leq 0.05$)
Null hypothesis true	True negative	Type I error, false positive
Null hypothesis false	Type II error, false negative	True positive

- ▶ **Type I error:** (false positive) we see an effect, where one doesn't really exist
- ▶ **Type II error:** (false negative) we didn't see an effect, but one really does exist

Multiple testing scenarios

- ▶ Comparisons across multiple treatments; A to B, B to C, A to C...
- ▶ Multiple outcomes
- ▶ Heterogeneous treatment effects (where is the cut point)
- ▶ Multiple regression specifications (specification search)

These tests aren't all fully independent, but the more tests we do, the more likely we are to uncover a false positive.

Ways to account for multiple testing

- ▶ Pre-specification of analyses
- ▶ Separating data in training and testing sets (more on this with machine learning)
- ▶ *p-value adjustment*

p-value adjustment

	Fail to reject null hypothesis ($p > 0.05$)	Reject null hypothesis ($p \leq 0.05$)
Null hypothesis true	True negative	Type I error, false positive
Null hypothesis false	Type II error, false negative	True positive

- ▶ Family-Wise Error Rate (FWER): the probability of falsely rejecting even one *true* null hypothesis; $P[\text{Type I error} > 0]$
- ▶ False Discovery Rate (FDR): expected proportion of false discoveries among all discoveries; $E[\# \text{ False discoveries} / \# \text{ All discoveries}]$

p-value adjustment

► Correcting FWER

- Bonferroni correction: for m hypotheses, for significance level α , implement α/m
- four independent tests, the probability that *at least one of them* will be statistically significant at $p \leq \alpha$ is $1 - (1 - \alpha)^4$
- For $\alpha = 0.05$, $1 - 0.95^4 = 0.1855$
- With Bonferroni correction: $1 - (1 - \alpha/4)^4 = 0.0491$
- Ten independent tests: $1 - (1 - \alpha/10)^{10} = 0.0489$

p-value adjustment

What if tests are not independent? Bonferroni is too aggressive.

$$P[AB] = P[A] + P[A^C] \times P[B|A^C]$$

If A and B are positively correlated $P[B|A^C] \leq P[B]$

► Correcting FWER

- Holm correction: for m hypotheses, for significance level α :
 - Order the m conventionally calculated p-values from smallest to largest
 - Find the *smallest* p-value indexed as k such that $p_k > \frac{\alpha}{m+1-k}$
 - Reject all p-values greater than or equal to p_k , accept all p-values less p_k

p-value adjustment

- ▶ Correcting FDR
 - ▶ Benjamini-Hochberg correction: for m hypotheses, for significance level α :
 - ▶ Order the m conventionally calculated p-values from smallest to largest
 - ▶ Find the *largest* p-value indexed as k such that $p_k \leq \frac{k}{m}\alpha$
 - ▶ Reject all p-values greater than p_k , accept all p-values less than or equal to p_k

p-value adjustment

- ▶ In either case, for more complex settings, try simulation.

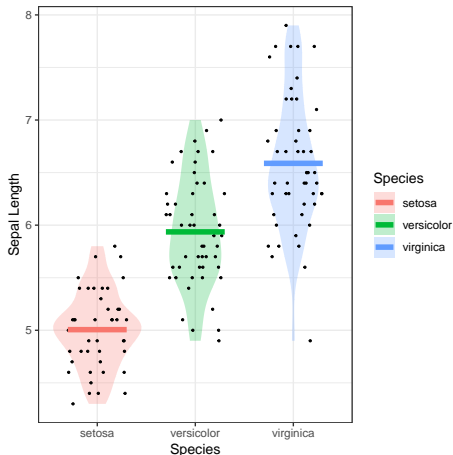
Multiple testing

- ▶ When can you consider tests as unrelated?
- ▶ Exploratory vs. confirmatory hypotheses?

Some alternatives to confidence intervals (via ungeomviz)

Show the underlying data.

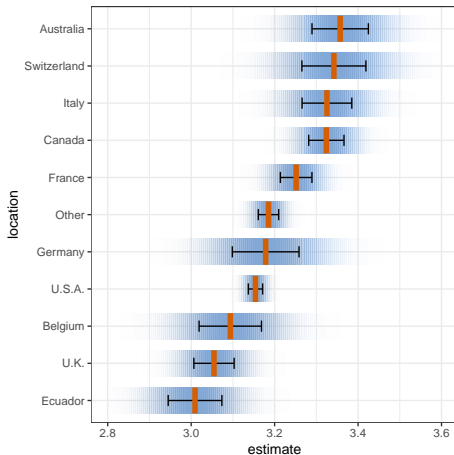
```
> ggplot(iris, aes(Species, Sepal.Length, fill = Species)) +  
+   geom_violin(alpha = 0.25, color = NA) +  
+   geom_point(position = position_jitter(width = 0.3, height = 0), size = 0.5) +  
+   geom_hline(aes(colour = Species), stat = "summary", width = 0.6, size = 1.5, fun = 'mean')
```



Some alternatives to confidence intervals (via ungeviz)

Shaded confidence strips.

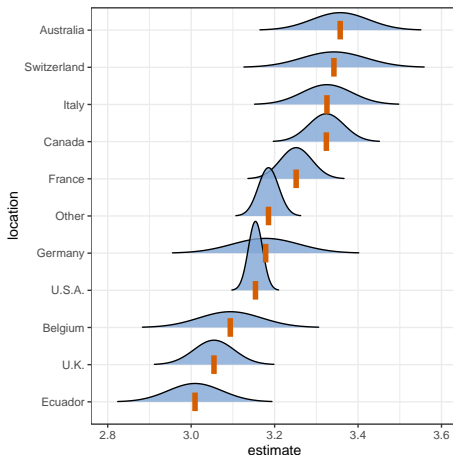
```
> ggplot(cacao_means, aes(x = estimate, y = location)) +  
+   stat_confidence_density(aes(moe = std.error), confidence = 0.68, fill = "#81A7D6", height = 0.7) +  
+   geom_errorbarh(aes(xmin = estimate - std.error, xmax = estimate + std.error), height = 0.3) +  
+   geom_vline(aes(x = estimate), size = 1.5, height = 0.7, color = "#D55E00")
```



Some alternatives to confidence intervals (via ungeviz)

Confidence densities.

```
> ggplot(cacao_means, aes(x = estimate, y = location)) +  
+   stat_confidence_density(  
+     aes(moe = std.error, height = stat(density)), geom = "ridgeline",  
+     confidence = 0.68, fill = "#81A7D6", alpha = 0.8, scale = 0.08, min_height = 0.1) +  
+   geom_vline(aes(x = estimate), size = 1.5, height = 0.5, color = "#D55E00")
```



References I

Clause Wilke: <https://wilkelab.org/ungeviz/index.html>