



# Hypothesis Testing With Python

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*True Difference or Noise?*

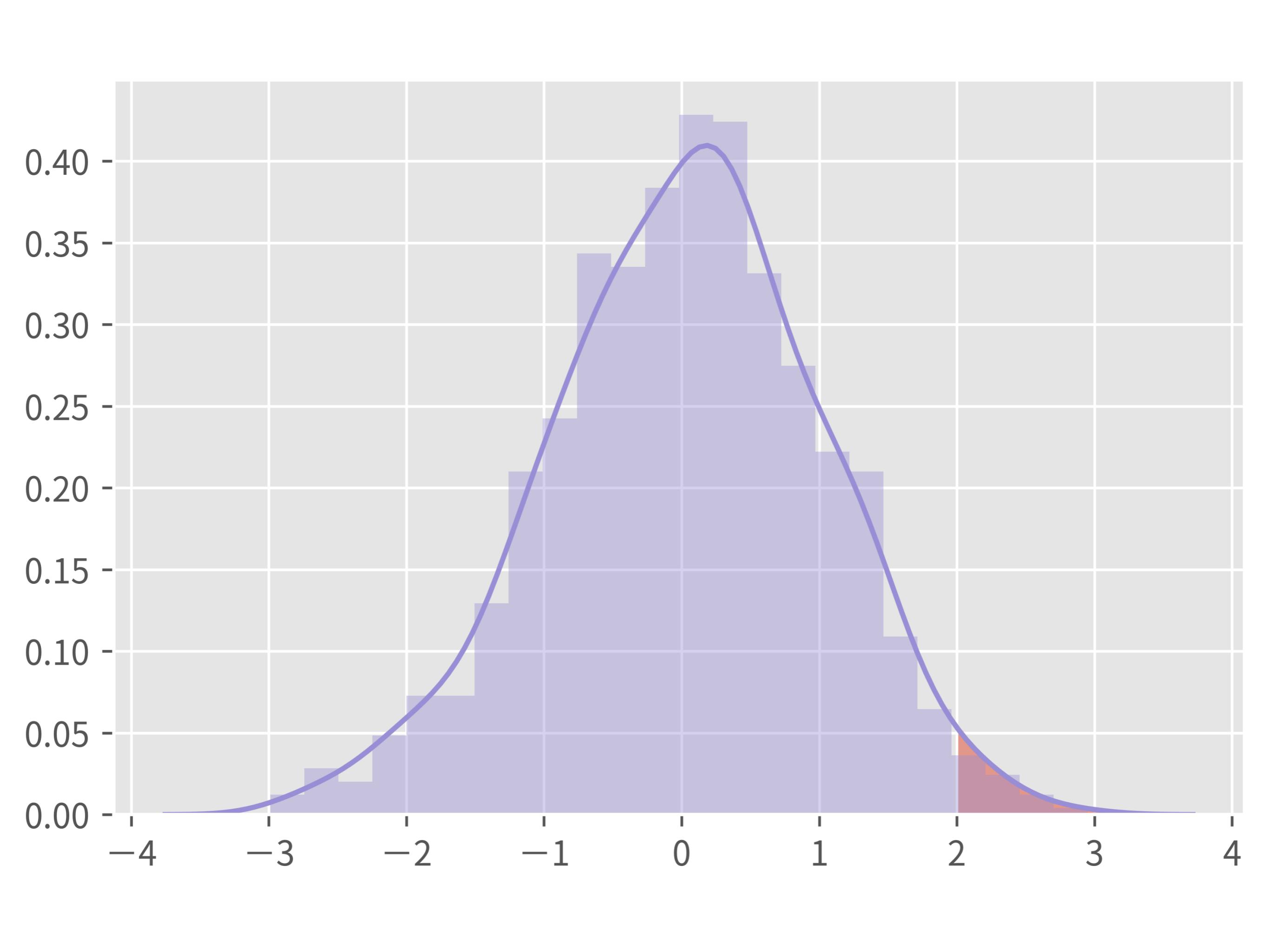
**169.61**

**169.88**

**Which is better?**

# Noise?

**That's a question.**



# Mosky

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- Python Charmer at Pinkoi.
- Has spoken at: PyCons in TW, MY, KR, JP, SG, HK, COSCUPs, and TEDx, etc.
- Countless hours on teaching Python.
- Own the Python packages: ZIPCodeTW, MoSQL, Clime, etc.
- <http://mosky.tw/>

# Outline

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- Tests with simulated datasets
- Tests with actual datasets
- How tests work
- Common tests
- Complete a test

# Tests with datasets

# Go with the notebooks

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- *01\_tests\_with\_simulated\_datasets.ipynb*
- *02\_tests\_with\_actual\_datasets.ipynb*
- The notebooks are available on <https://github.com/moskytw/hypothesis-testing-with-python> .

# P-value & $\alpha$

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P-value &  $\alpha$

Wording

p-value < 0.01

Very significant

p-value < 0.05

Significant

p-value  $\geq 0.05$

*Not significant*

# How tests work

# Seeing is believing

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- $p\text{-value} = 0.0027 (< 0.01)$ 
  - 
- $p\text{-value} = 0.0271 (0.01\text{--}0.05)$ 
  -  ?  ? ? ?
- $p\text{-value} = 0.2718 (\geq 0.05)$ 
  - ? ? ? ? ? ?
- *03\_how\_tests\_work.ipynb*

# Fair coin testing

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- “The coin is fair.”
- Case 1: Toss the coin 100 times, comes up 53 heads.
  - “Hmmm ... somehow fair.”
- Case 2: Toss the coin 100 times, comes up 87 heads.
  - “Not fair! So extreme!”

# Hypothesis testing

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- “The means of two populations are equal.”
- Case 1:  $p\text{-value} \geq 0.05$ .
  - “Hmmm ... somehow equal.”
- Case 2:  $p\text{-value} < 0.05$ .
  - “Not equal! So extreme!”

# Hypothesis testing in a “null” taste

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- $\langle \text{null hypothesis} \rangle$
- Case 1:  $p\text{-value} \geq a$ .
  - Can't reject  $\langle \text{null hypothesis} \rangle$ .
- Case 2:  $p\text{-value} < a$ .
  - Reject  $\langle \text{null hypothesis} \rangle$ .

# Hypothesis testing in an “alternative” taste

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- $\langle \text{alternative hypothesis} \rangle \equiv \text{not } \langle \text{null hypothesis} \rangle$
- Case 1:  $p\text{-value} \geq \alpha$ .
  - Can't accept  $\langle \text{alternative hypothesis} \rangle$ .
- Case 2:  $p\text{-value} < \alpha$ .
  - Accept  $\langle \text{alternative hypothesis} \rangle$ .

# Hypothesis testing in “-+” taste

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- “The case is negative.”
- Case 1:  $p\text{-value} \geq \alpha$ .
  - “Hmmm ... somehow negative.”
- Case 2:  $p\text{-value} < \alpha$ .
  - “Positive! So extreme!”

# Common tests

# The cheat sheet

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- If testing independence:
  - If total size < 1000, or more than 20% of cells have expected frequencies < 5, **Fisher's exact test**.
  - Use **Chi-squared test**.
- If testing difference:
  - If median is better, don't want to trim outliers, variable is ordinal, or any group size < 20:
    - If groups are paired, **Wilcoxon signed-rank test**.
    - If groups are independent, **Mann–Whitney U test**.
  - If groups are paired, **Paired Student's t-test**.
  - If groups are independent, **Welch's t-test**, not Student's.

# More cheat sheets & references

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- More cheat sheets:
  - [http://abacus.bates.edu/~ganderso/biology/resources/stats\\_flow\\_chart\\_v2014.pdf](http://abacus.bates.edu/~ganderso/biology/resources/stats_flow_chart_v2014.pdf)
  - <http://www.biostathandbook.com/testchoice.html>
  - [https://www.sheffield.ac.uk/mash/what\\_test](https://www.sheffield.ac.uk/mash/what_test)
- References:
  - <http://www.biostathandbook.com/fishers.html>
  - [https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5426219/#\\_sec5title](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5426219/#_sec5title)
  - <http://blog.minitab.com/blog/adventures-in-statistics-2/choosing-between-a-nonparametric-test-and-a-parametric-test>
  - [https://www.sheffield.ac.uk/mash/what\\_test](https://www.sheffield.ac.uk/mash/what_test)
  - [https://en.wikipedia.org/wiki/Welch%27s\\_t-test#Advantages\\_and\\_limitations](https://en.wikipedia.org/wiki/Welch%27s_t-test#Advantages_and_limitations)
  - [https://en.wikipedia.org/wiki/Student%27s\\_t-test#Dependent\\_t-test\\_for\\_paired\\_samples](https://en.wikipedia.org/wiki/Student%27s_t-test#Dependent_t-test_for_paired_samples)

# The tests in Python

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- *04\_common\_tests.ipynb*

# Complete a test

# Is p-value enough?

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- sample size?
- alpha?
- beta?
- effect size?
- ? ? ? ? ?

# Confusion matrix, where $A = 00_2 = C[0, 0]$

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		predicted - AC	predicted + BD
actual - AB	true - A	true - A	false - B
	false + C	false + C	true + D
actual + CD			

# False positive rate = B / AB = observed $\alpha$

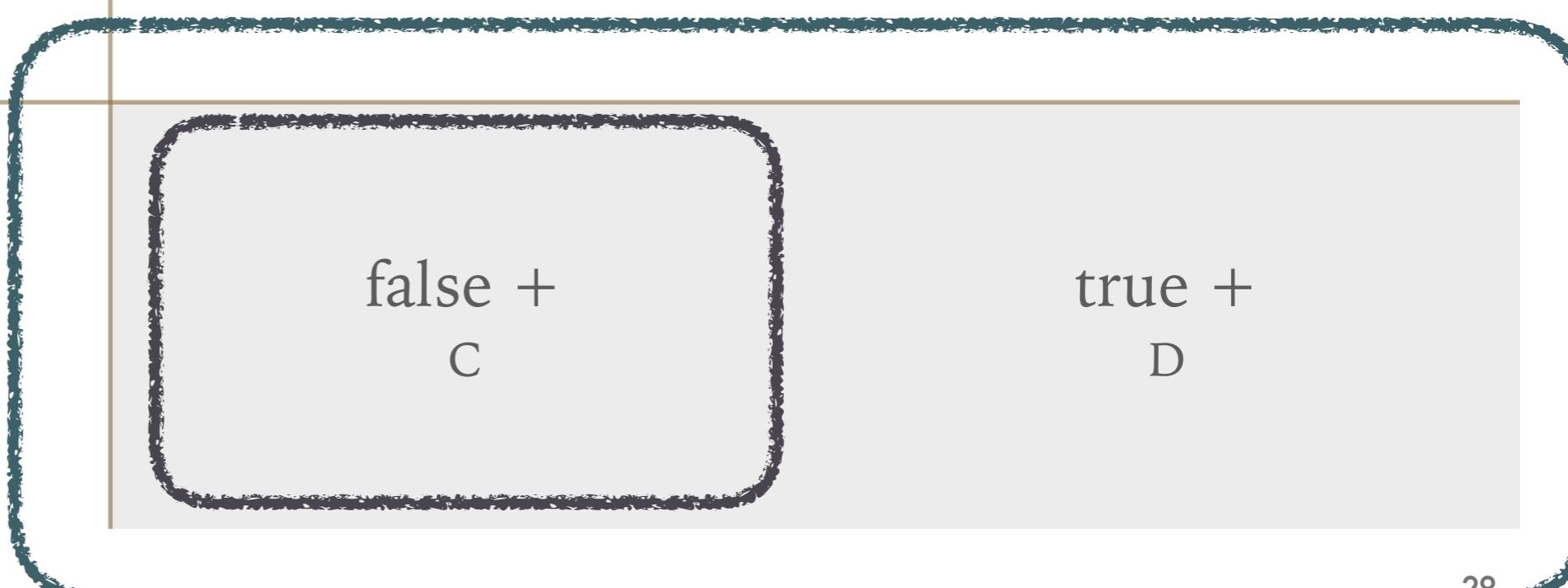
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		predicted - AC	predicted + BD
actual - AB	true -	A	false - B
	false +	C	true + D
actual + CD			

# False negative rate = C / CD = observed $\beta$

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		predicted - AC	predicted + BD
actual - AB	true -	false - B	
	A		
actual + CD	false + C		true + D



The diagram illustrates a 2x2 confusion matrix. The top row is labeled "predicted -" and "predicted +", and the left column is labeled "actual -" and "actual +". The cell "false +" is highlighted with a thick black border.

## When sample size ↑ ; $\alpha$ , $\beta$ , effect size ↓

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- Increase *sample size* to decrease  $\alpha$ ,  $\beta$ , *effect size*.
  - The *effect size* is the distance between groups.
$$\text{➤ } = \frac{\mu_1 - \mu_2}{\sigma}$$
  - <http://www.drcoplan.com/dsm5-the-case-for-double-standards>
    - The figures explain  $\alpha$ ,  $\beta$  perfectly,  
but due to the copyright, only put the link here.
- When  $\alpha$ ,  $\beta$ , *effect size* are defined, get the *sample size*.
- When  $\alpha$ ,  $\beta$ , *sample size* are defined, get the *effect size*.



# False discovery rate

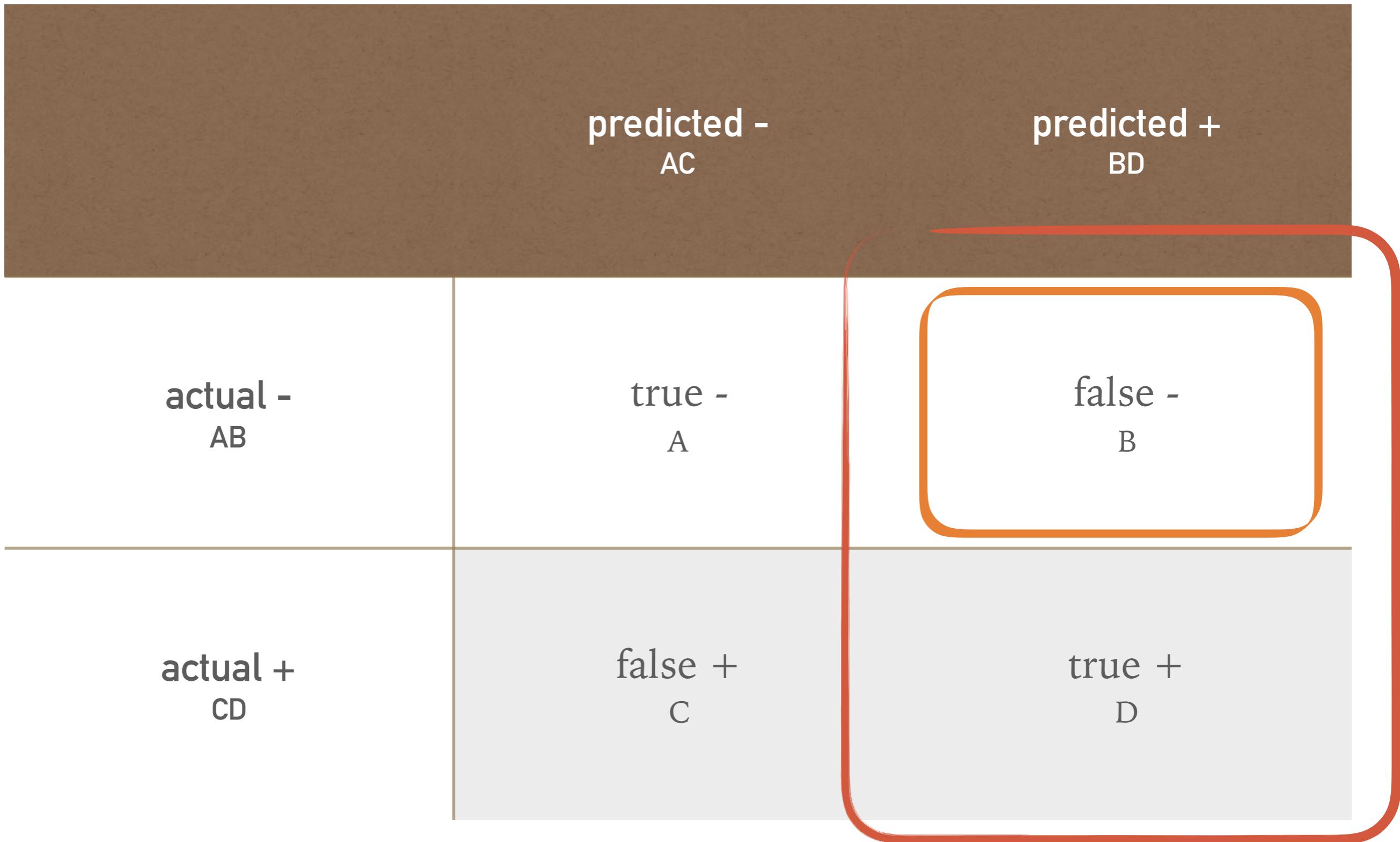
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- Suppose:
  - A drug test has observed  $\alpha = 1\%$  and observed  $\beta = 1\%$
  - $99.5\%$  of people are *not* drug users.
- What is the probability that a person with a positive test is a drug user?

$$\begin{aligned}P(\text{non-user} \mid +) &= \frac{P(+ \mid \text{non-user})P(\text{non-user})}{P(+)} \\&= \frac{P(+ \mid \text{non-user})P(\text{non-user})}{P(+ \mid \text{non-user})P(\text{non-user}) + P(+ \mid \text{user})P(\text{user})} \\&= \frac{0.01 \times 0.995}{0.01 \times 0.995 + 0.99 \times 0.005} \\&\approx 66.8\%\end{aligned}$$

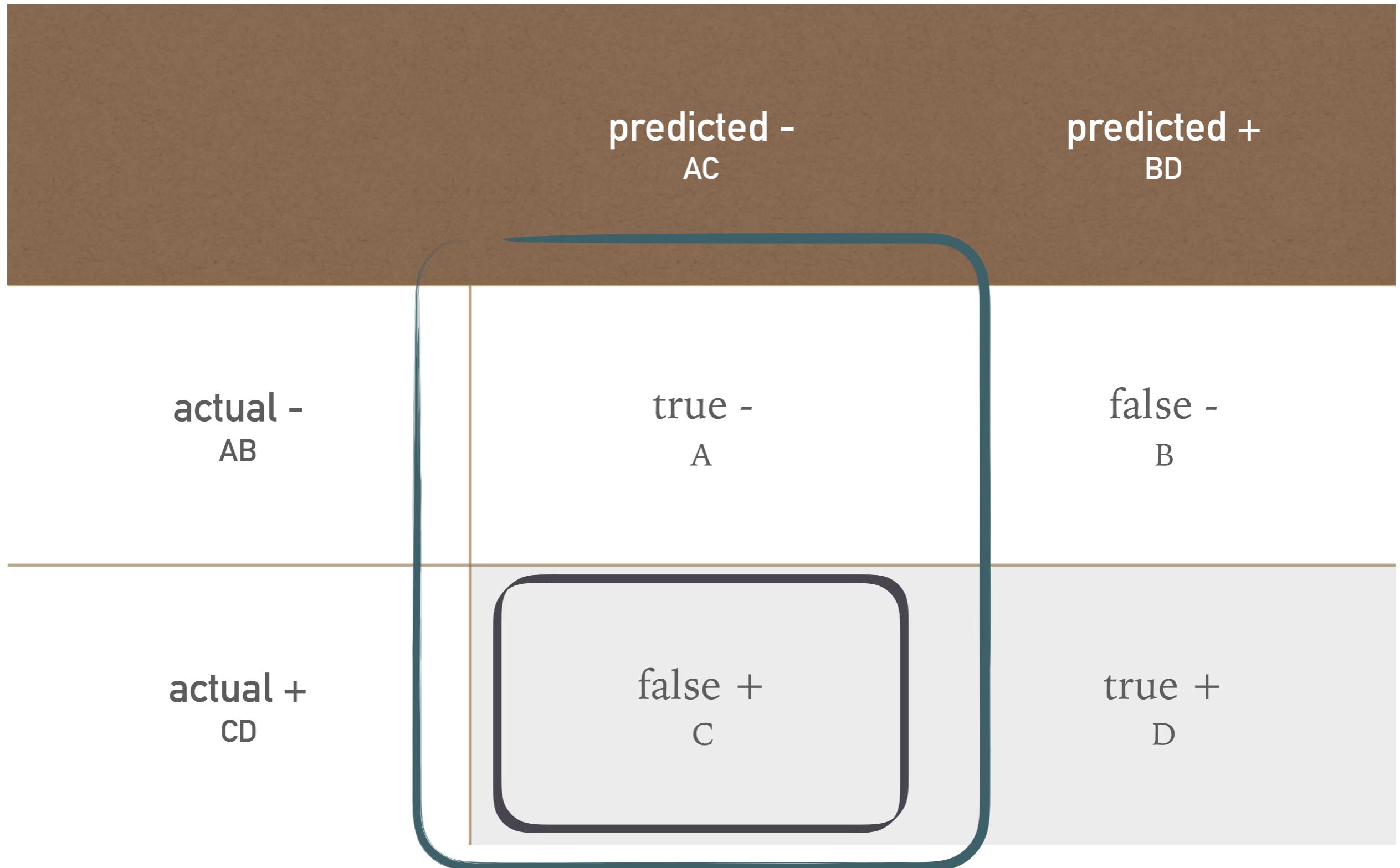
# False discovery rate = B / BD

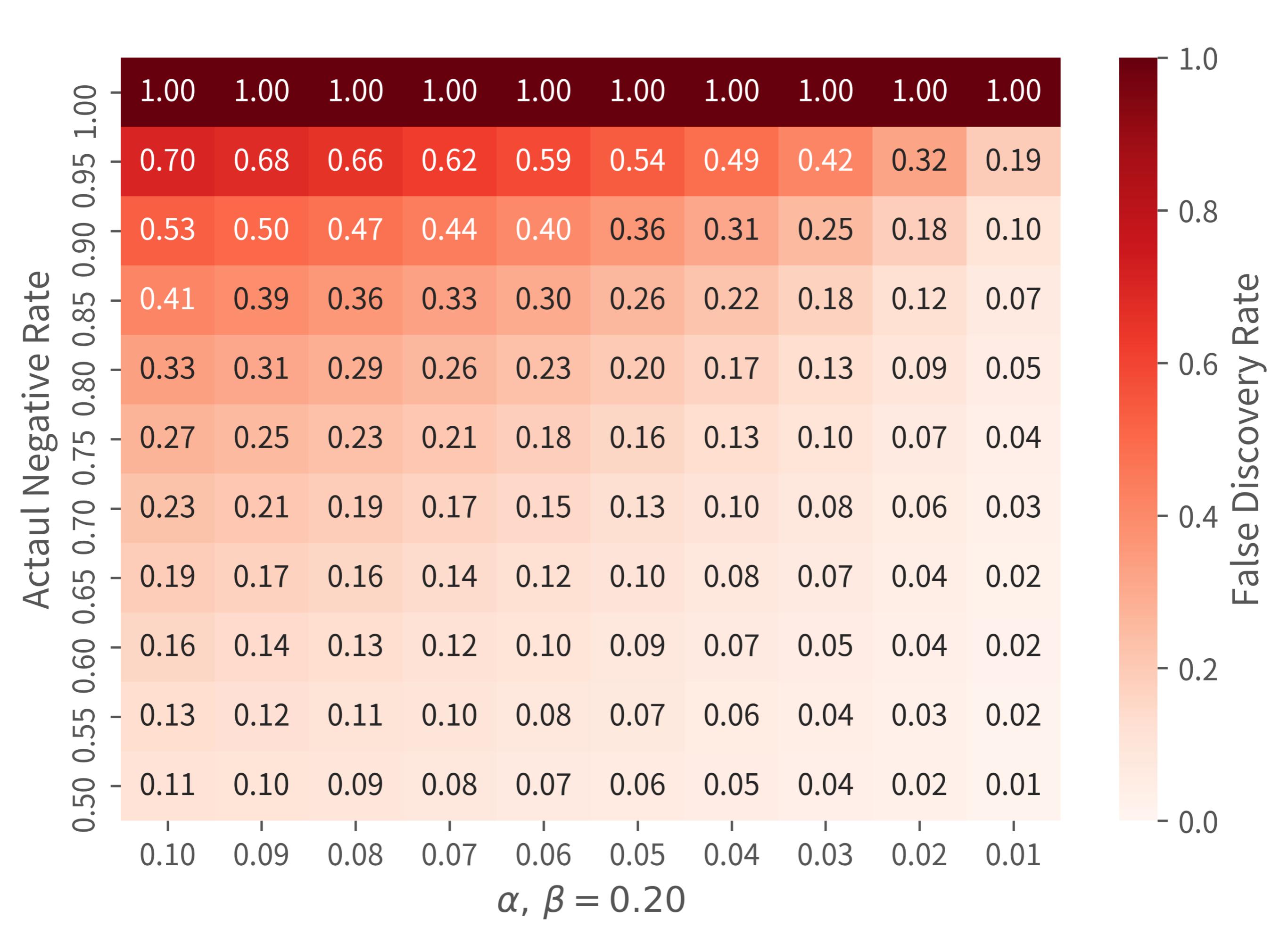
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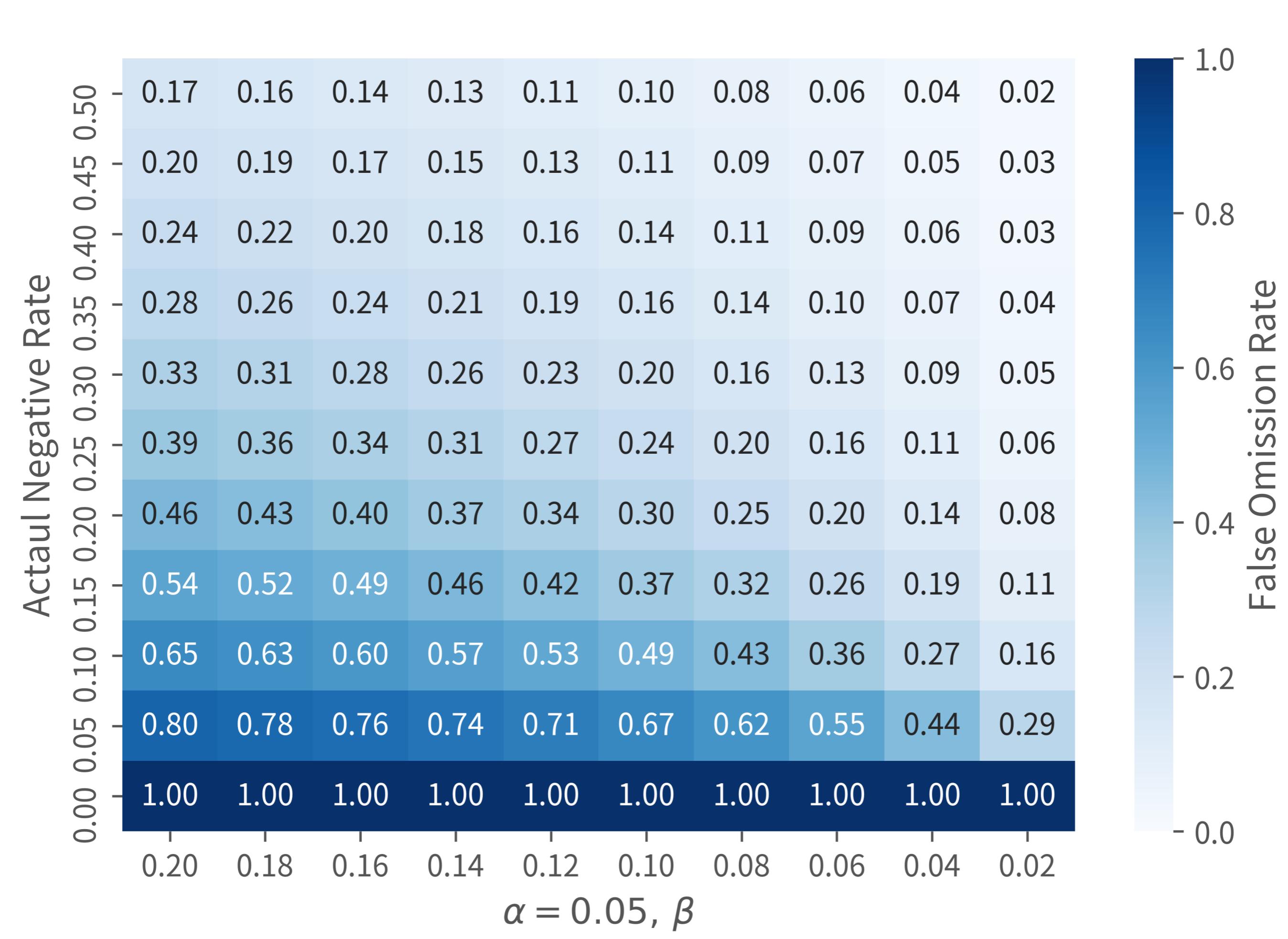


# False omission rate = C / AC

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# Common “rates” in confusion matrix

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- false positive rate =  $B / AB$  = observed  $\alpha$
- false negative rate =  $C / CD$  = observed  $\beta$
- false discovery rate =  $B / BD$
- false omission rate =  $C / AC$
- actual negative rate =  $AB / N$
- sensitivity =  $D / CD$  = observed power
- **specificity** =  $A / AB$  = observed confidence level
- precision = positive predictive value =  $1 - FDR$
- recall = sensitivity

# Most formal steps

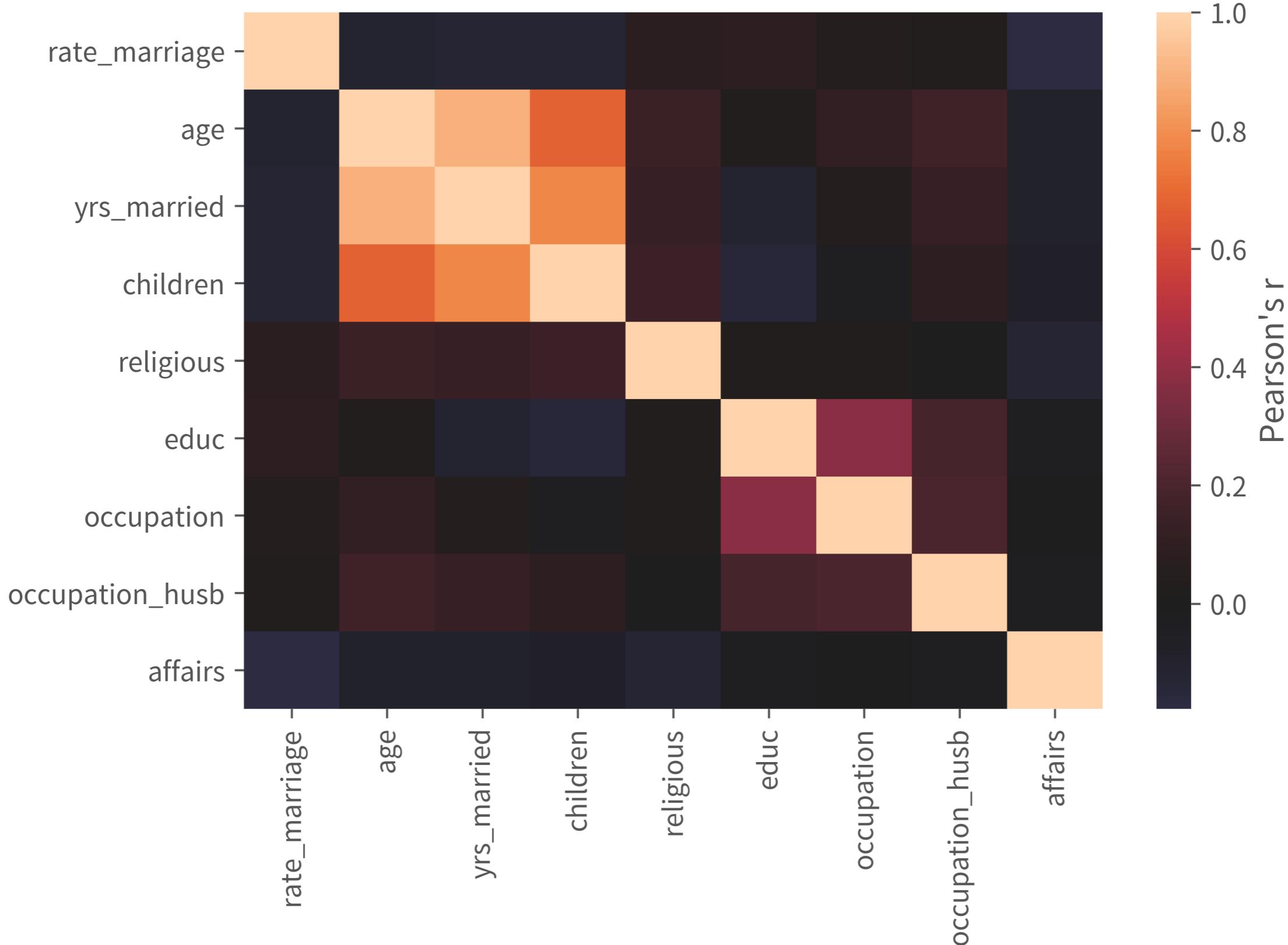
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- State the hypothesis → what *test*.
- Estimate the *actual negative rate*.
- The *actual negative rate* → what  $\alpha, \beta$  is required.
- The  $\alpha, \beta, \text{effect size}$  → what *sample size* is required.
- Still collect a sample as large as possible.
- Understand the sample.
  - Missing data, outliers, Q–Q plot, transform, etc.
- Test and report fully.
- *05\_complete\_a\_test.ipynb*

# Other statistical tools

# Correlation analysis

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# Regression analysis

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```
In [7]: fair_df = sm.datasets.fair.load_pandas().data  
ols_res = smf.ols('children ~ yrs_married', fair_df).fit()  
ols_res.summary()
```

Out[7]: OLS Regression Results

Dep. Variable:	children	R-squared:	0.597			
Model:	OLS	Adj. R-squared:	0.597			
Method:	Least Squares	F-statistic:	9437.			
Date:	Fri, 06 Jul 2018	Prob (F-statistic):	0.00			
Time:	00:40:17	Log-Likelihood:	-8430.3			
No. Observations:	6366	AIC:	1.686e+04			
Df Residuals:	6364	BIC:	1.688e+04			
Df Model:	1					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
Intercept	0.0259	0.018	1.429	0.153	-0.010	0.062
yrs_married	0.1522	0.002	97.142	0.000	0.149	0.155
Omnibus:	449.258	Durbin-Watson:	1.972			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	709.624			
Skew:	0.559	Prob(JB):	8.07e-155			
Kurtosis:	4.193	Cond. No.	18.5			

# Keep learning

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- Statistics
  - Seeing Theory
  - Biological Statistics
  - scipy.stats + StatsModels
  - Research Methods
- Machine Learning
  - Scikit-learn Tutorials
  - Standford CS229
  - Hsuan-Tien Lin

# Recap

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- *p-value* – the “tail” probability given “actual -”.
- *confidence interval* – the values the middle probability maps to.
- *actual negative rate*  $> 0.5 \uparrow \alpha \downarrow$
- *actual negative rate*  $< 0.5 \downarrow \beta \downarrow$
- $\alpha, \beta, \text{effect size} \downarrow \text{sample size} \uparrow$
- Simulation and visualization do help.
- Bonus: *a1\_figures.ipynb* .
- Let's identify noise efficiently!