permute: A Python Package for Randomization Inference

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DEPARTMENT OF STATISTICS

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Outline

1 Introduction

2 Examples
- Gender bias in teaching evaluations
- Inter-rater reliability

3 The role of software development in Statistics

Permutation tests

- Fisher [1935] introduced permutation tests for randomized experiments

Permutation tests

R has several packages for randomization inference.

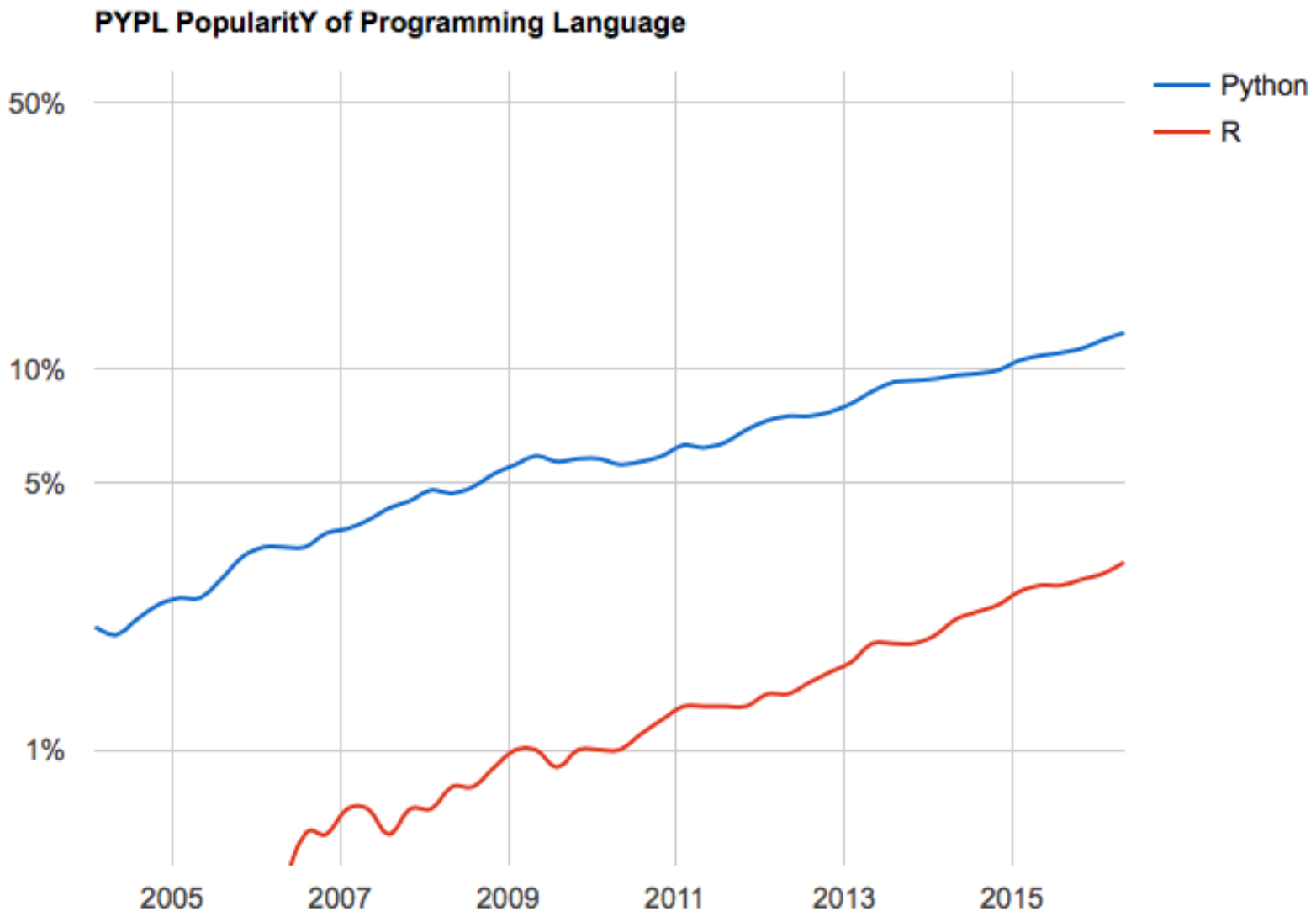
- `ri`
- `RItools`
- `coin`
- `perm`

In Python, statistics packages are limited.

- `numpy.random`
- `scipy.stats`
- `StatsModels`
- `scikit-learn`

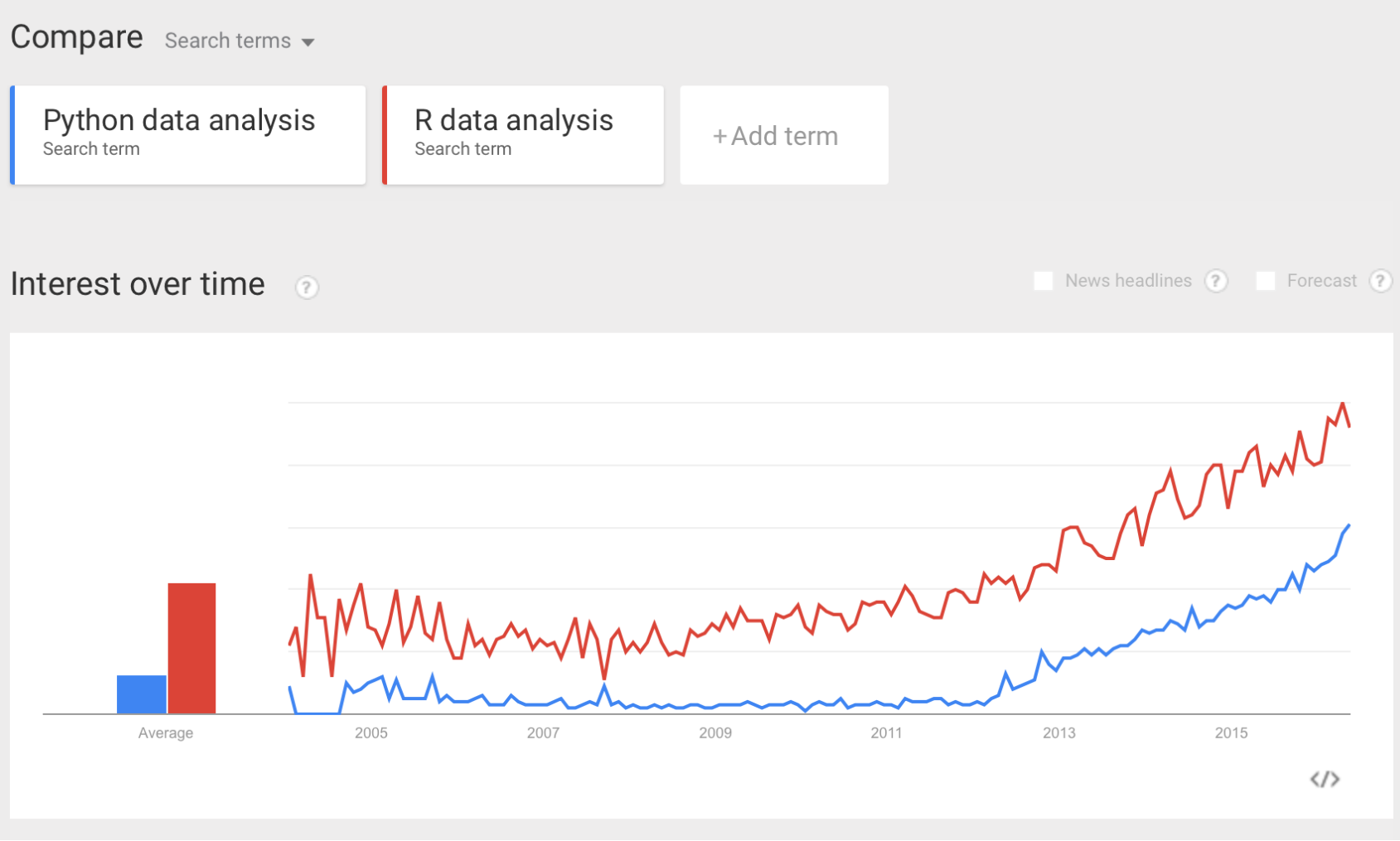
Python is gaining popularity for doing data analysis

PYPL Popularity of Programming Language Index, Worldwide



Python is gaining popularity for doing data analysis

Google trends on May 22, 2016



Keyword: data analysis

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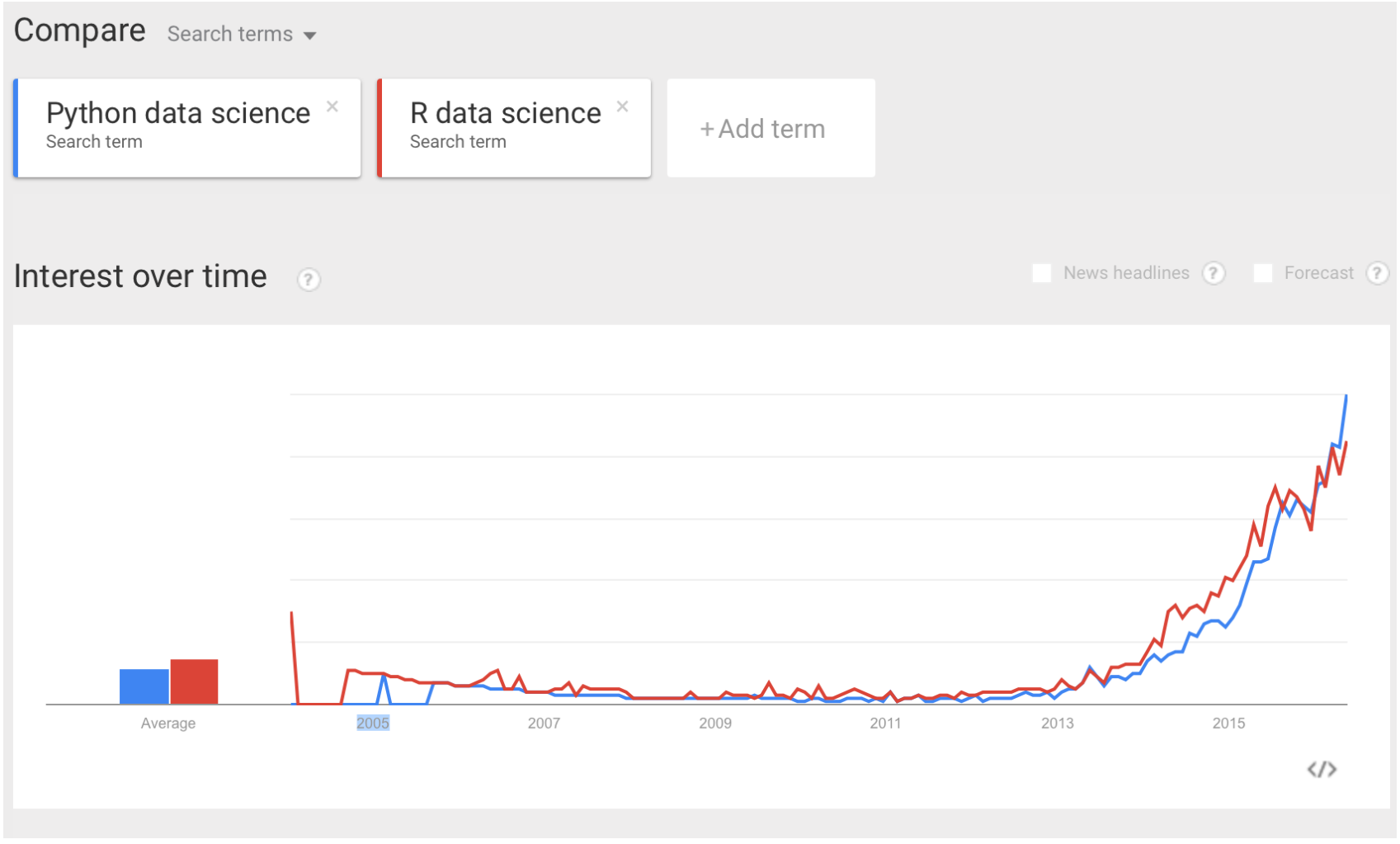

Keyword: data science

Python for teaching Statistics

Data Science 8, Spring 2016 at UC Berkeley

Download `permute`!

Permutation tests and confidence sets

build passing coverage 99%

Permutation tests and confidence sets for a variety of nonparametric testing and estimation problems, for a variety of randomization designs.

- **Website (including documentation):** http://statlab.github.io/permute
- **Mailing list:** http://groups.google.com/group/permute
- **Source:** https://github.com/statlab/permute
- **Bug reports:** https://github.com/statlab/permute/issues

Installation from binaries

```
$ pip install permute
```

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Teaching Evaluations

Student evaluations of teachers (SET) are used to

- Quantify teaching effectiveness
- Compare instructors across courses
- Make hiring, firing, and promotion decisions

Are SET a valid measure of teaching effectiveness?

Teaching evaluations

No!

We reanalyzed data from MacNell et al. [2014].

- Students were randomized to 4 online sections of a course.
- In two sections, the TAs swapped identities.
- Was the TA who identified as female rated lower on average?

Neyman-Rubin model, generalized

Student i is represented by a ticket with 4 numbers, their response to each "treatment."

$$r_{ijk} = \text{ SET given by student } i \text{ to instructor } j \text{ when they appear to have gender } k$$

$$i = 1, \ldots, N; \qquad j = 1, 2; \qquad k \in \{\text{male, female}\}$$

Numbers are fixed; randomization reveals one of the numbers.

Assume non-interference: each student's response depends only on that student's treatment.

If gender doesn't matter,

$$r_{ij\text{male}} = r_{ij\text{female}}.$$

Randomization

TO DO: REDO THIS SLIDE

Under this null, it's as though

1. N_m students are randomly assigned to the male TA, N_f to the female TA
2. N_{mm} of the N_m students and N_{fm} of the N_f students are told that their TA is male

We know what the data would have been for all

$$\binom{N_m}{N_{mm}} \times \binom{N_f}{N_{fm}}$$

equally likely assignments of students to sections.

This determines the conditional null distribution of **any statistic**.

Stratified two-sample test

```
# load packages
import numpy as np
from permute.data import macnell2014
from permute.stratified import stratified_two_sample

# initialize PRNG
rs = np.random.RandomState(seed=1)

# load the data
ratings = macnell2014()

# Ratings vs reported instructor gender (difference in means)
(p, t) = stratified_two_sample(group=ratings.taidgender,
                               response=ratings.overall,
                               condition=ratings.tagender,
                               alternative="two-sided",
                               stat="mean", reps=10**5)
```

Results

TO DO: UPDATE P-VALUES In all categories, the male-identified TA was rated higher.

Characteristic	**M-F**	**perm** P	**t-test** P
Overall	0.47	0.12	0.128
Caring	0.52	0.10	0.071
Consistent	0.47	0.21	0.045
Enthusiastic	0.57	0.06	0.112
Fair	0.76	0.01	0.188
Feedback	0.47	0.16	0.054
Helpful	0.46	0.17	0.049
Knowledgeable	0.35	0.29	0.038
Praise	0.67	0.01	0.153
Professional	0.61	0.07	0.124
Prompt	0.80	0.01	0.191
Respectful	0.61	0.06	0.124
Responsive	0.22	0.48	0.013

Omnibus Test

Nonparametric combination of tests (NPC): combine individual p-values into a single omnibus test when there are many responses

Test whether **all null** hypotheses are true or **at least one alternative** is true.

Fisher's combining function:

$$X^2 = -2 \sum_{j=1}^{J} \ln(P_j)$$

$X^2 \sim \chi^2_{2J}$ if $\{P_j\}_{j=1}^{J}$ are independent and all nulls are true.

Omnibus Test

Ratings for different categories are **dependent**.

$\Longrightarrow$ Calibrate the distribution of X^2 using the permutation distributions of each individual statistic.

- Calculate the vector of observed values of test statistics (use the **same permutation** of section memberships to compute all statistics)
- Apply the combining function to get a single combined statistic for the permutation.
- Repeat a large number B times to find the permutation distribution of the combined statistic.

Omnibus Test

```
# Initialize placeholders
ind = 0
test_distr = np.zeros( (10**5, len(categories)) )
pvalues = np.zeros( len(categories) )

# Loop over rating categories
for col in categories:
    (p, t, distr) = stratified_two_sample(
                            group=ratings.taidgender,
                            response=ratings[col],
                            condition=ratings.tagender,
                            alternative="two-sided",
                            stat="mean", seed = seed,
                            reps = 10**5, keep_dist = True)
    ind += 1
    test_distr[:,ind] = distr; pvalues[ind] = p

# NPC
omnibus_pvalue = npc(pvalues, test_distr, combine="fisher",
                             alternatives="two-sided")
```

Conclusions

Omnibus test: $P = 0$

- Reject the null hypothesis that there is no difference in ratings for any category
- The male-identified TA was rated significantly higher than the female-identified TA on several dimensions, **even on objective measures** such as how promptly assignments were returned
- SET measure something other than teaching effectiveness

NSGK Data

- Naomi Stark and Gilbert Kliman (NSGK) collected videos of therapy sessions with children on the autism spectrum
- A team of trained raters watched and tagged each 30-second interval of video from a collection of 183 clinically relevant tags
- Is tagging of therapist-patient interactions reliable? (Millman et al. [2016]) Which tags do raters agree on?

Inter-rater reliability test

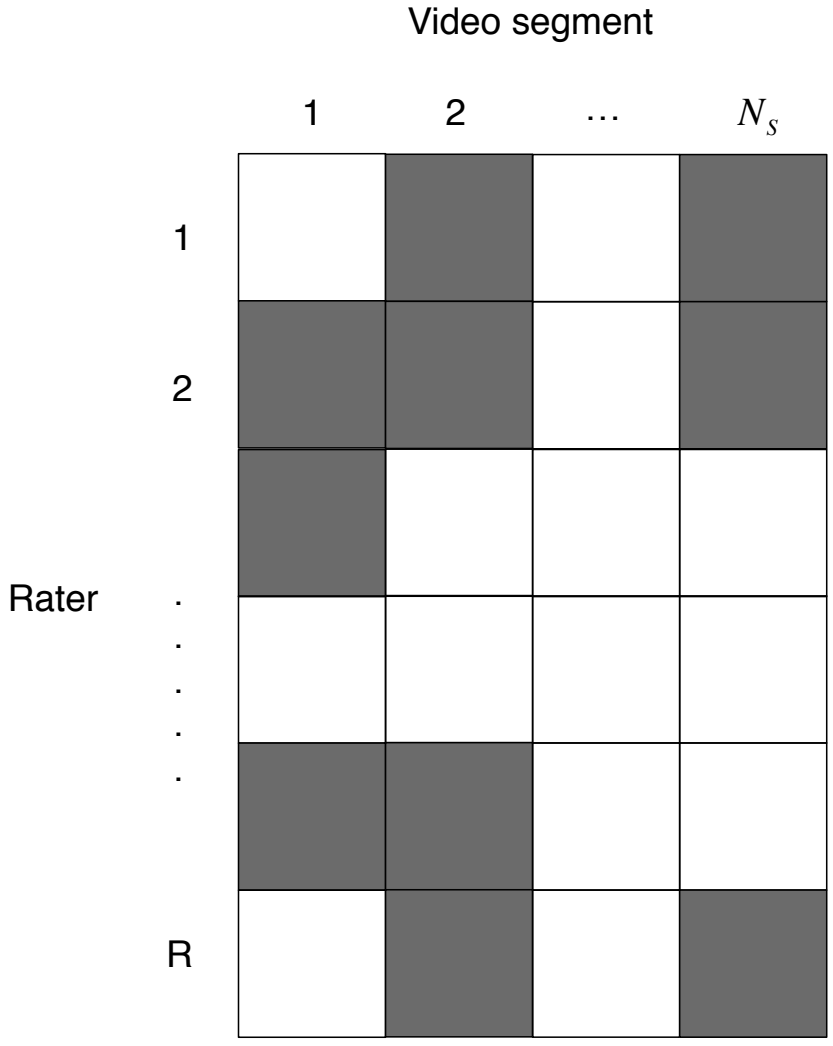
There are four dimensions. Can we simplify?

- Consider each clinical tag individually
- Do a partial hypothesis test for each video, then combine using NPC

NSGK	**IRR**
183 types of activity	T tags
8 videos	S strata
$\sim$40 segments/videos	N_s items/strata
10 raters	R raters

Inter-rater reliability test

Is agreement within columns better than expected by chance?



Inter-rater reliability test

Define

- $\{L_{s,i,r}\}$ = indicator for whether rater r tagged item i in stratum s
- $y_{si} = \sum_{r=1}^{R} L_{s,i,r}$ = number of raters who tagged item i in stratum s

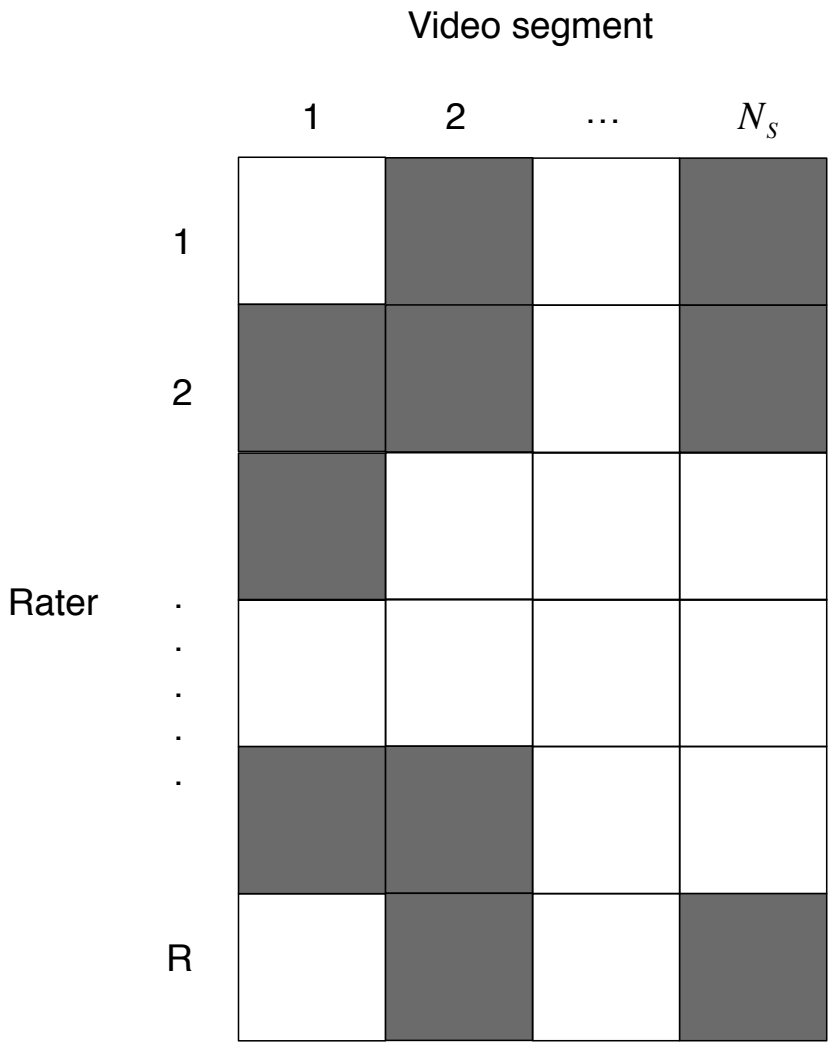
The test statistic within stratum s is

$$\rho_s \equiv \frac{1}{N_s \binom{R}{2}} \sum_{i=1}^{N_s} \sum_{r=1}^{R-1} \sum_{v=r+1}^{R} \mathbf{1}(L_{s,i,r} = L_{s,i,v})$$

$$= \frac{1}{N_s R(R-1)} \sum_{i=1}^{N_s} (y_{si}(y_{si}-1) + (R-y_{si})(R-y_{si}-1)).$$

Inter-rater reliability test

Now we have a measure of concordance. What is the chance model?



Probability model

If tags are assigned completely at random, then

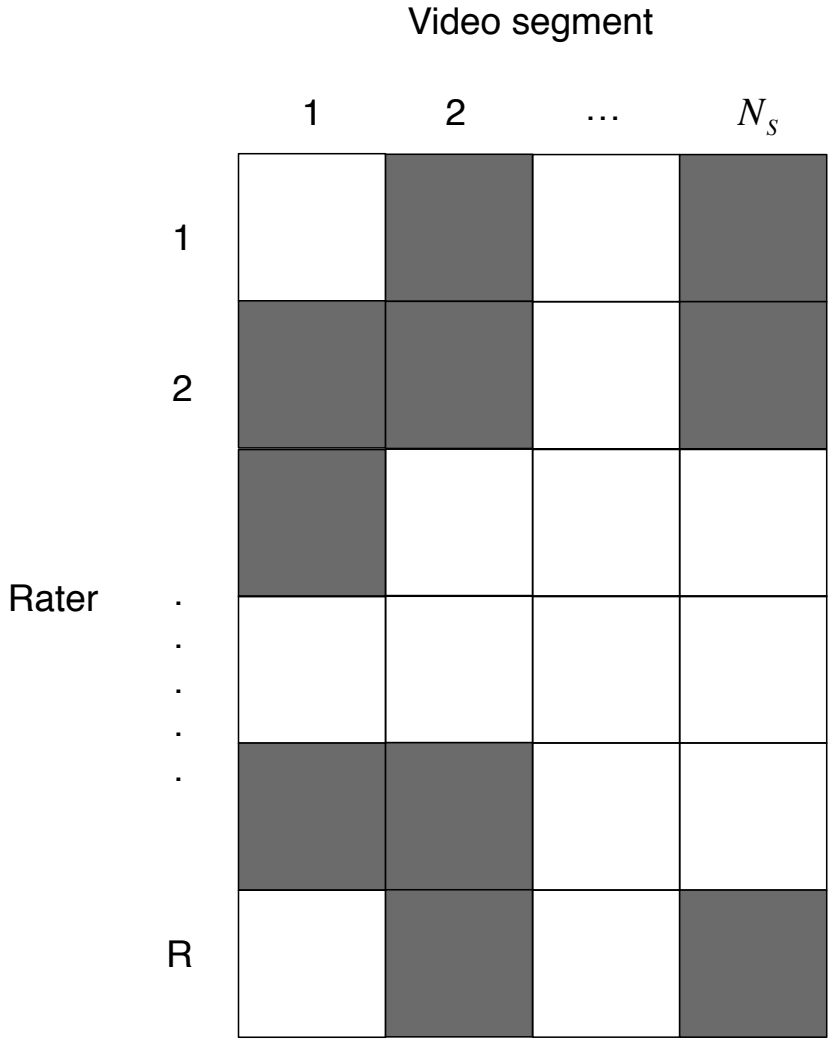
- any of 2^{N_s} assignments of tags are equally likely for each rater.
- raters assign tags independently of each other

Each rater may have different "propensity" to assign a tag
$\implies$ condition on the number of items that a rater tagged.

Permute tags within rows, independently across rows and across strata.

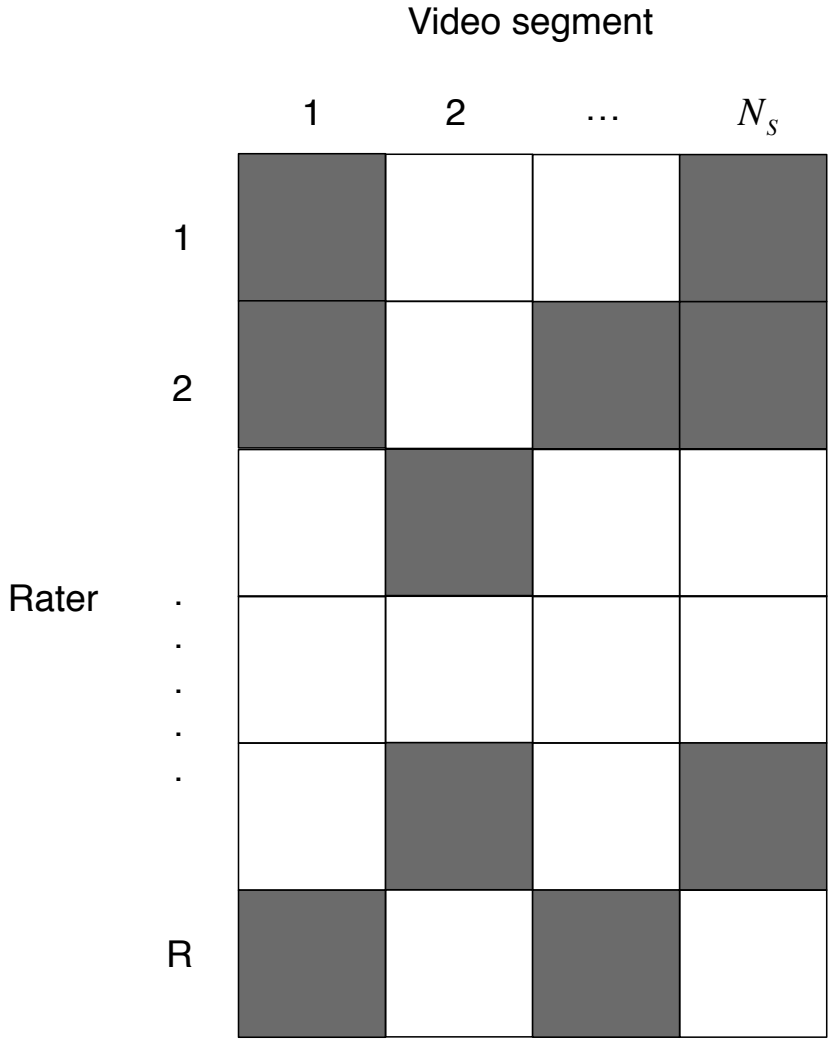
Inter-rater reliability test

Observed tags for stratum s



Inter-rater reliability test

Equally likely tags for stratum s, under the null



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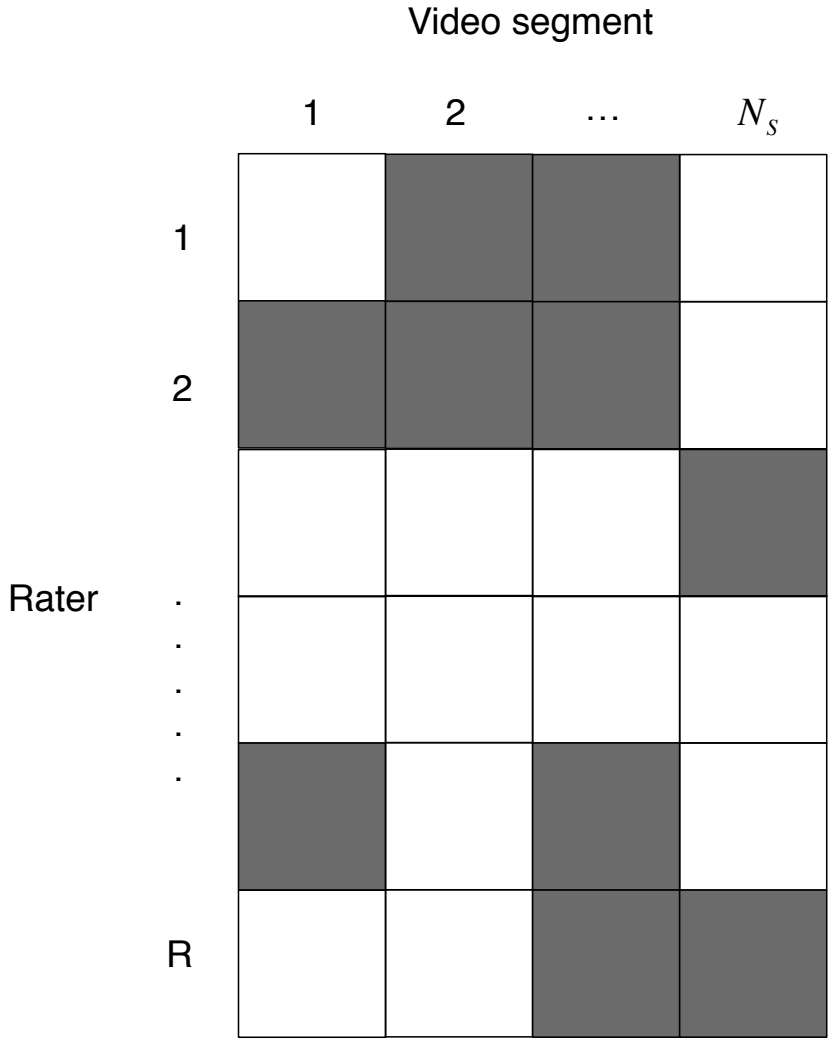


Code

```
from permute.data import nsgk
from permute.irr import simulate_ts_dist, simulate_npc_dist

# load data, set video sizes
x = nsgk()
time_stamps = np.array([36, 32, 35, 37, 31, 35, 40, 32])

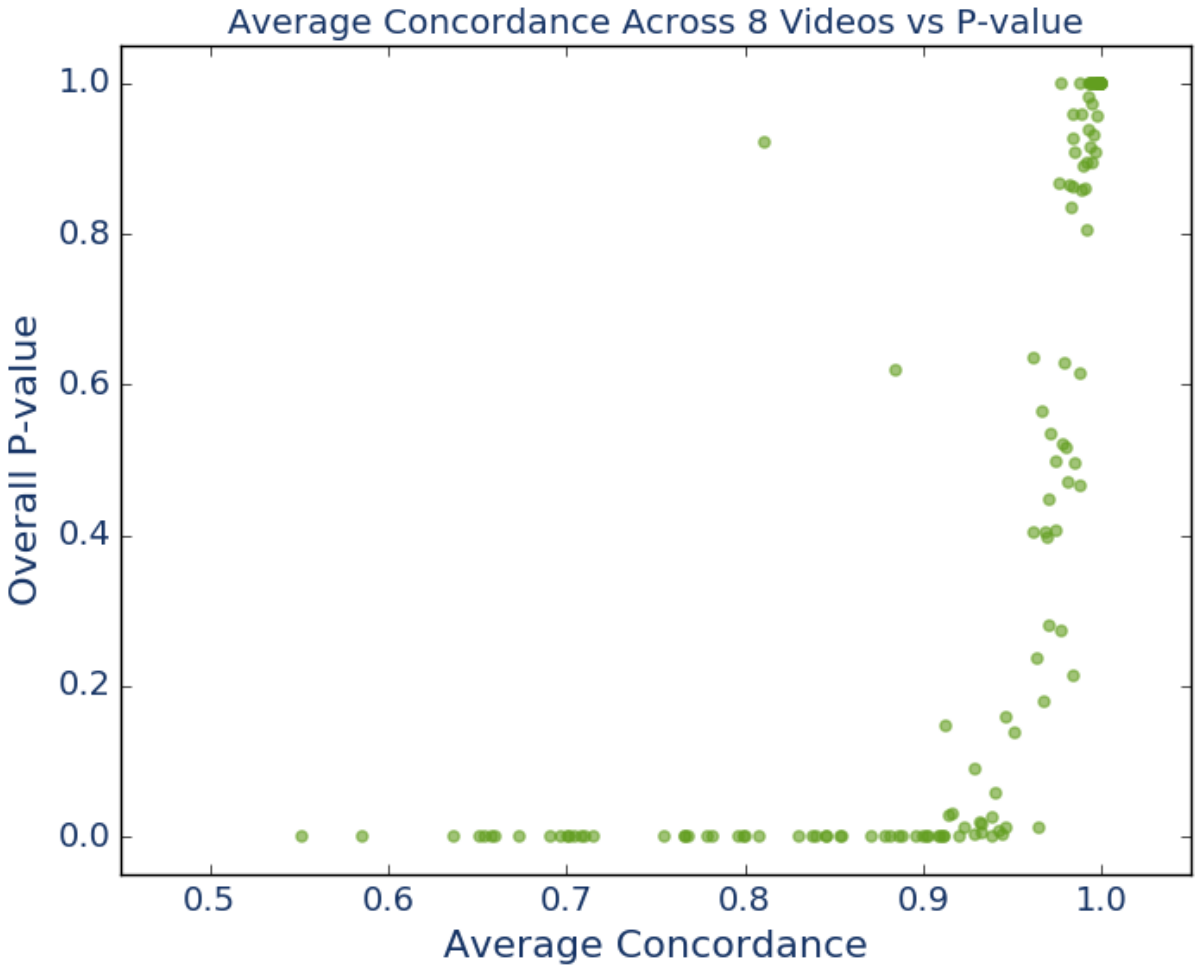
# Empty lists to store distrs and statistics for each video
d = []; tst = [] ; vid_temp = []

# Run analysis for a single category i
for j in range(len(x[i])):  # loop over videos
        res = simulate_ts_dist(x[i][j], keep_dist=True)
        d.append(res["dist"])
        tst.append(res["obs_ts"])
        vid_temp.append(res["pvalue"])

# Combine permutation distributions for each video
perm_distr = np.asarray(d).transpose()
simulate_npc_dist(perm_distr, size=time_stamps,
                        obs_ts=tst, keep_dist=False)
```

Results

- 60 tags had $P < 0.05$
- Many "significant" tags might not be useful – small effect size



Conclusions?

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Reproducibility

Why should Statisticians worry about writing software?

- Ethics
- Impact

Ethics

Monkey Cage

Does social science have a replication crisis?

RESEARCH ARTICLE

Estimating the reproducibility of psychological science

Open Science Collaboration*,†

Cancer Research Is Broken

There's a replication crisis in biomedicine—and no one even knows how deep it runs.

By Daniel Engber

SundayReview

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Gray Matter

By JAY VAN BAVEL MAY 27, 2016

NATURE | EDITORIAL

Reality check on reproducibility

POLICY & ETHICS

Is There a Reproducibility Crisis in Science?

PLOS | MEDICINE

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ESSAY

Why Most Published Research Findings Are False

John P. A. Ioannidis

Published: August 30, 2005 • http://dx.doi.org/10.1371/journal.pmed.0020124

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By John Bohannon | Mar. 3, 2016 , 2:00 PM

NATURE | NEWS

Over half of psychology studies fail reproducibility test

Largest replication study to date casts doubt on many published positive results.

Monya Baker

27 August 2015

Ethics

Much of the reproducibility crisis can be traced back to bad statistics.

- Publication bias: positive findings are more likely to get published
- P-hacking and the garden of forking paths (Gelman and Loken [2013])
- Inappropriate statistical tests (Randomization inference may help here)

It is our responsibility to make it easy for researchers to do the right statistics.

Impact

Let us own data science (Yu [2014]).

If we want to

- facilitate reproducible scientific research,
- enable people to use the methods we develop (correctly!), and
- influence the way people do statistics more broadly,

then **we** have to build the tools.

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- **Bug reports:** https://github.com/statlab/permute/issues

Installation from binaries

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```

https://github.com/statlab/permute

Collaborators

Jarrod Millman
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Philip B. Stark
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Stefan van der Walt
stefanv

References

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Bin Yu. Let us own data science. Institute of Mathematical Statistics (IMS) Presidental Address, ASC-IMS Joint Conference, Sydney, July 2014. URL `https://www.stat.berkeley.edu/~binyu/ps/papers2014/IMS-pres-address14-yu.pdf`.