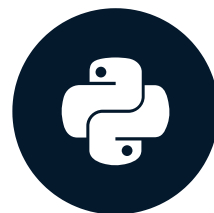


# A/B testing

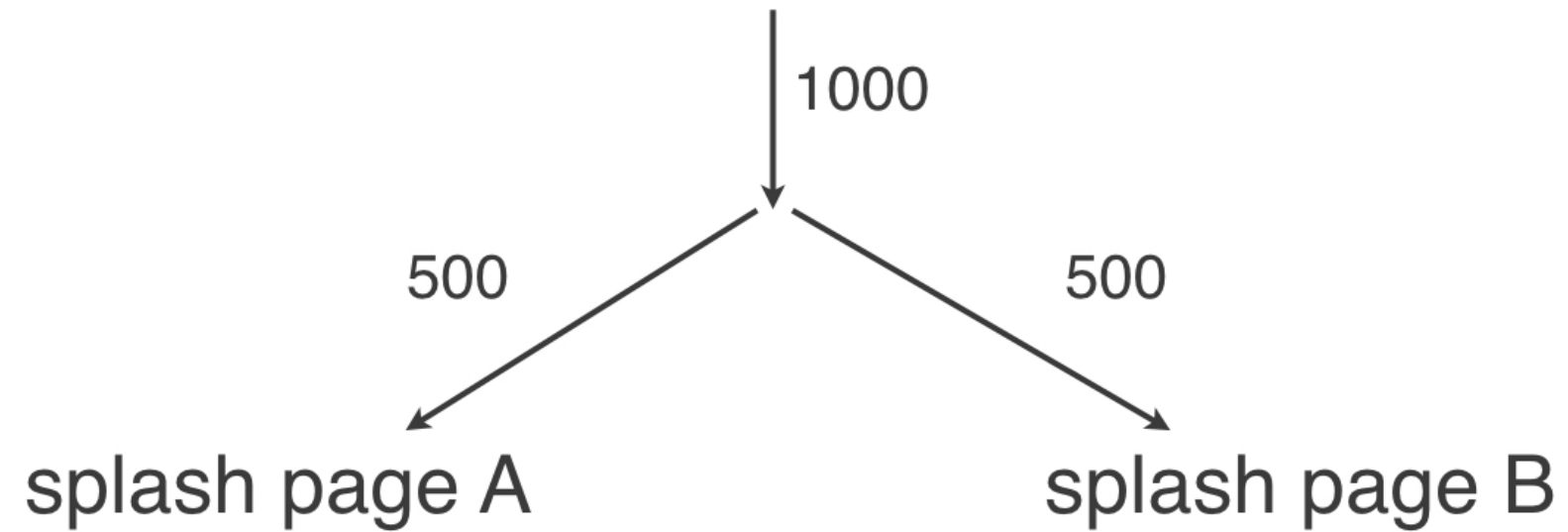
STATISTICAL THINKING IN PYTHON (PART 2)



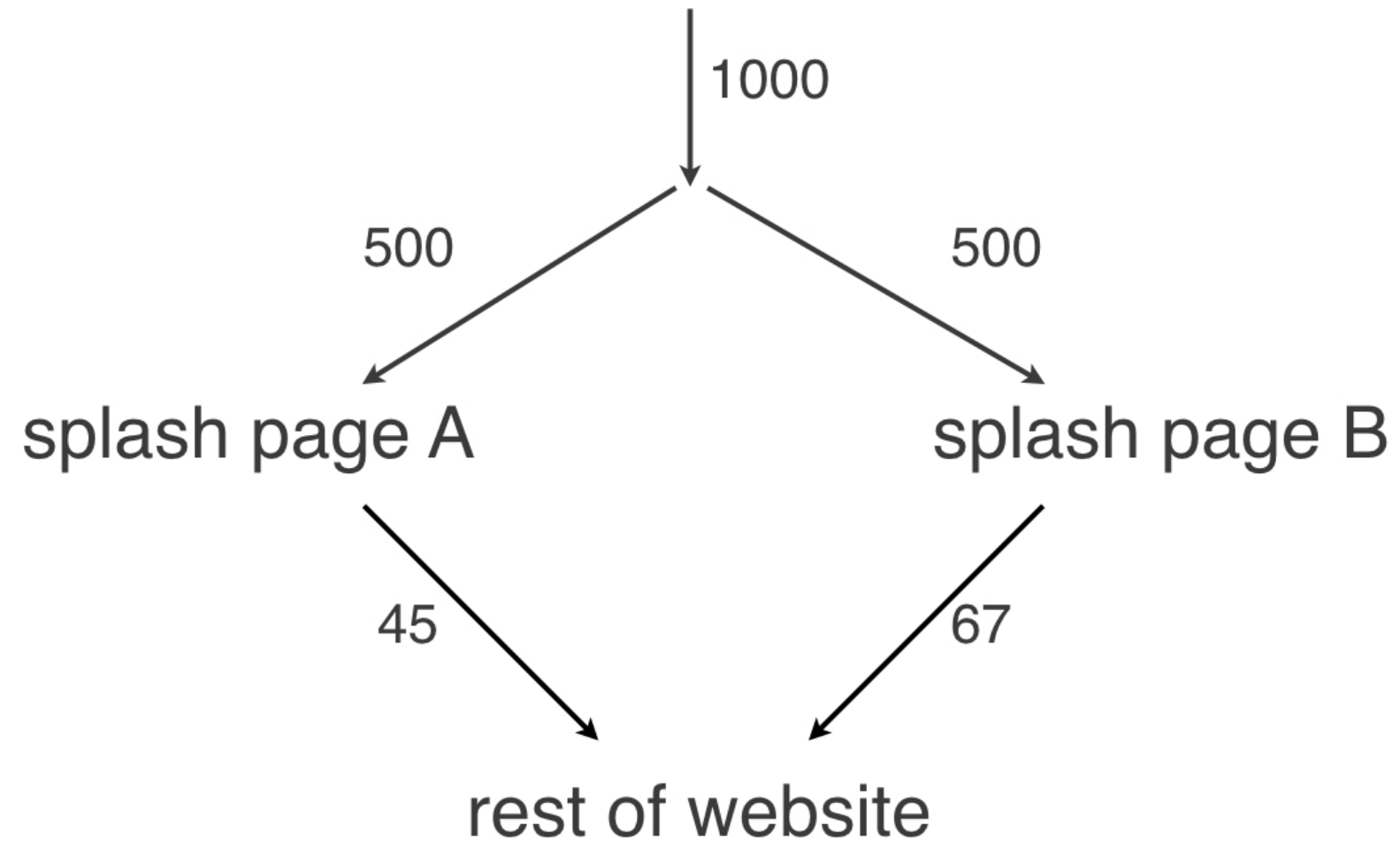
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# Is your redesign effective?



# Is your redesign effective?



# Null hypothesis

- The click-through rate is not affected by the redesign

# Permutation test of clicks through

```
import numpy as np
# clickthrough_A, clickthrough_B: arr. of 1s and 0s
def diff_frac(data_A, data_B):
    frac_A = np.sum(data_A) / len(data_A)
    frac_B = np.sum(data_B) / len(data_B)
    return frac_B - frac_A
diff_frac_obs = diff_frac(clickthrough_A,
                           clickthrough_B)
```

# Permutation test of clicks through

```
perm_replicates = np.empty(10000)
for i in range(10000):
    perm_replicates[i] = permutation_replicate(
        clickthrough_A, clickthrough_B, diff_frac)
p_value = np.sum(perm_replicates >= diff_frac_obs) / 10000
p_value
```

0.016

# A/B test

- Used by organizations to see if a strategy change gives a better result

# Null hypothesis of an A/B test

- The test statistic is impervious to the change



# Let's practice!

STATISTICAL THINKING IN PYTHON (PART 2)

# Test of correlation

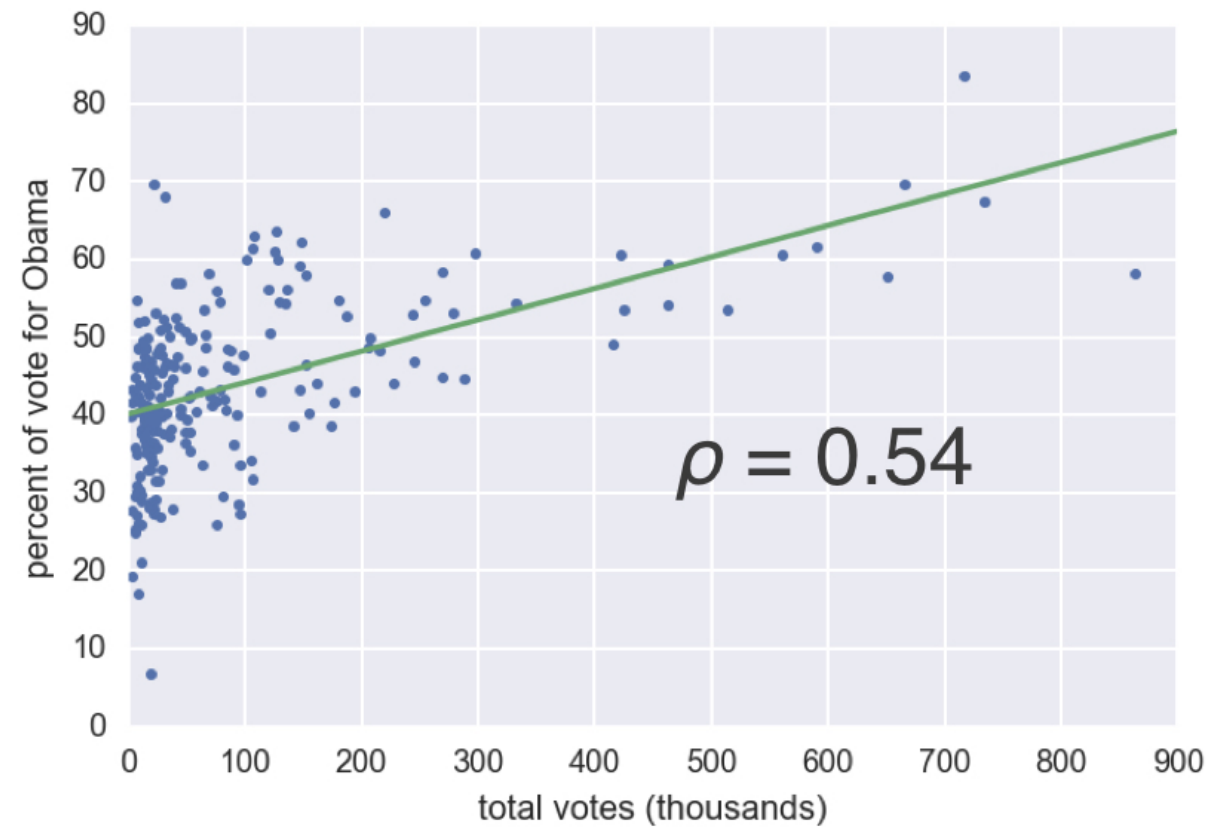
STATISTICAL THINKING IN PYTHON (PART 2)



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# 2008 US swing state election results

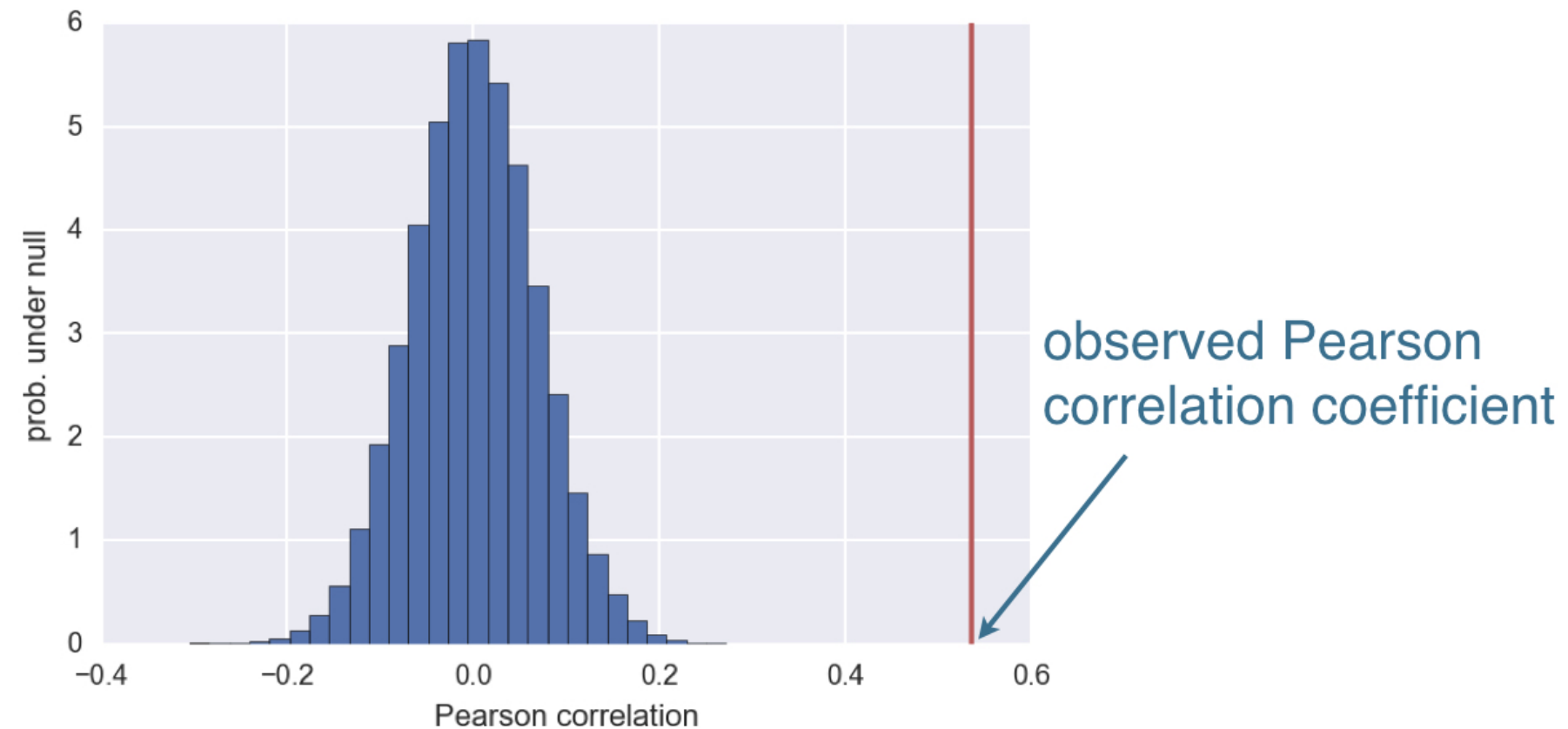


<sup>1</sup> Data retrieved from Data.gov (<https://www.data.gov/>)

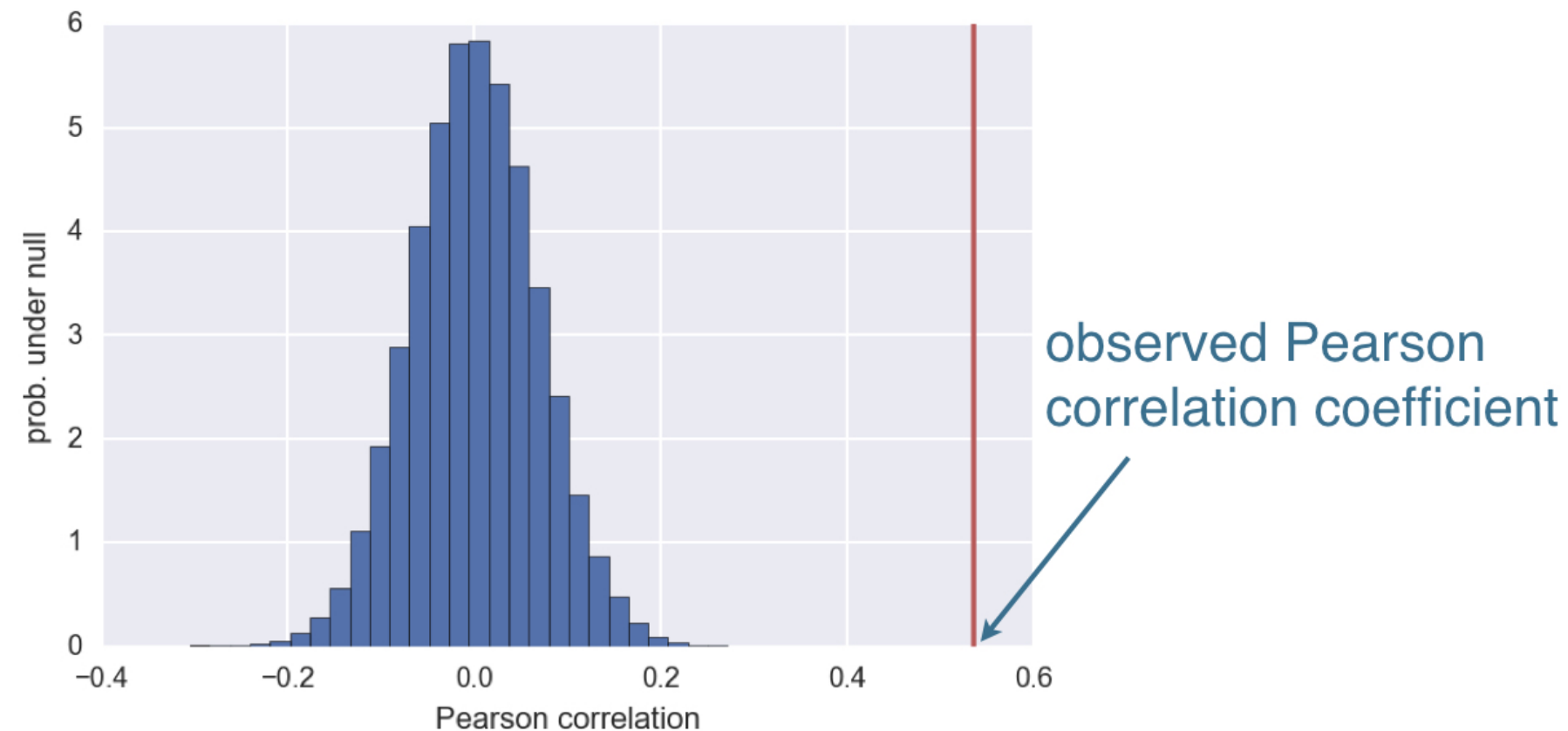
# Hypothesis test of correlation

- Posit null hypothesis: the two variables are completely uncorrelated
- Simulate data assuming null hypothesis is true
- Use Pearson correlation,  $\rho$ , as test statistic
- Compute p-value as fraction of replicates that have  $\rho$  at least as large as observed.

# More populous counties voted for Obama



# More populous counties voted for Obama



p-value is very very small

# Let's practice!

STATISTICAL THINKING IN PYTHON (PART 2)