What is A/B testing?

A/B TESTING IN PYTHON



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Intro to A/B testing

- An A/B test is...
 - an experiment designed to test which version is better
 - based on metric(s): signup rate, average sales per user, etc.
 - using random assignment and analyzing results

To A/B test or not to test?

Good use of A/B testing:

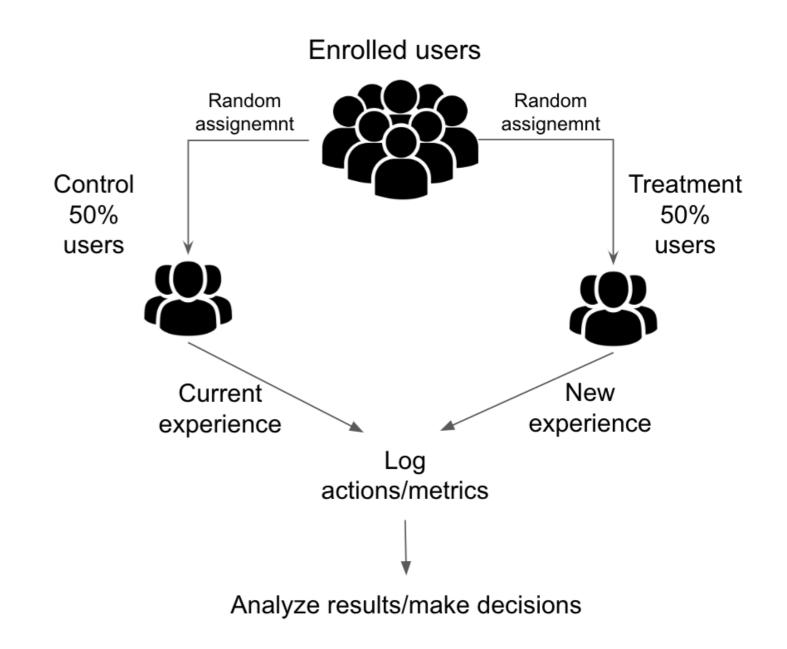
- Optimizing conversion rates
- Releasing new app features
- Evaluating incremental effects of ads
- Assessing the impact of drug trials

Do not A/B test if:

- No sufficient traffic/"small" sample size
- No clear logical hypothesis
- Ethical considerations
- High opportunity cost

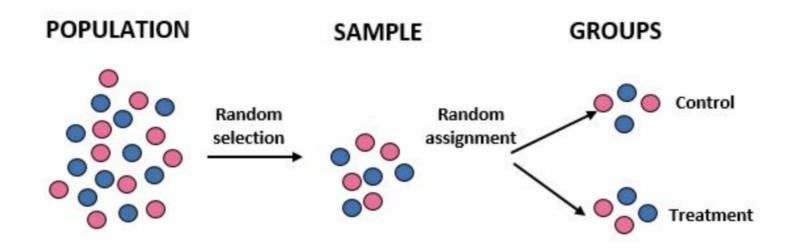
A/B testing fundamental steps

- 1. Specify the goal and designs/experiences
- 2. Randomly sample users for enrollment
- 3. Randomly assign users to:
 - control variant: current state
 - treatment/test variant(s): new design
- 4. Log user actions and compute metrics
- 5. Test for statistically significant differences



Value of randomization

- Generalizability and representativeness
- Minimizing bias between groups
- Establishing causality by isolating treatment effect



¹ https://www.statology.org/random-selection-vs-random-assignment/



Python example of random assignment

checkout.info()

```
RangeIndex: 9000 entries, 0 to 8999
Data columns (total 6 columns):
    Column
                   Non-Null Count
                                   Dtype
    user_id
                   9000 non-null
                                   int64
 0
    checkout_page 9000 non-null
                                  object
    order_value
                   7605 non-null
                                   float64
    purchased
                   9000 non-null
                                   float64
    gender
                   9000 non-null
                                   object
 4
 5
                   9000 non-null
                                   object
    browser
dtypes: float64(2), int64(1), object(3)
memory usage: 422.0+ KB
```

Python example of random assignment

```
checkout['gender'].value_counts(normalize=True)
```

```
F 0.507556
M 0.492444
Name: gender, dtype: float64
```

```
sample_df = checkout.sample(n=3000)
sample_df['gender'].value_counts(normalize=True)
```

```
M 0.506333
F 0.493667
Name: gender, dtype: float64
```

Python example of random assignment

```
checkout.groupby('checkout_page')['gender'].value_counts(normalize=True)
```

Let's practice!

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Why run experiments?

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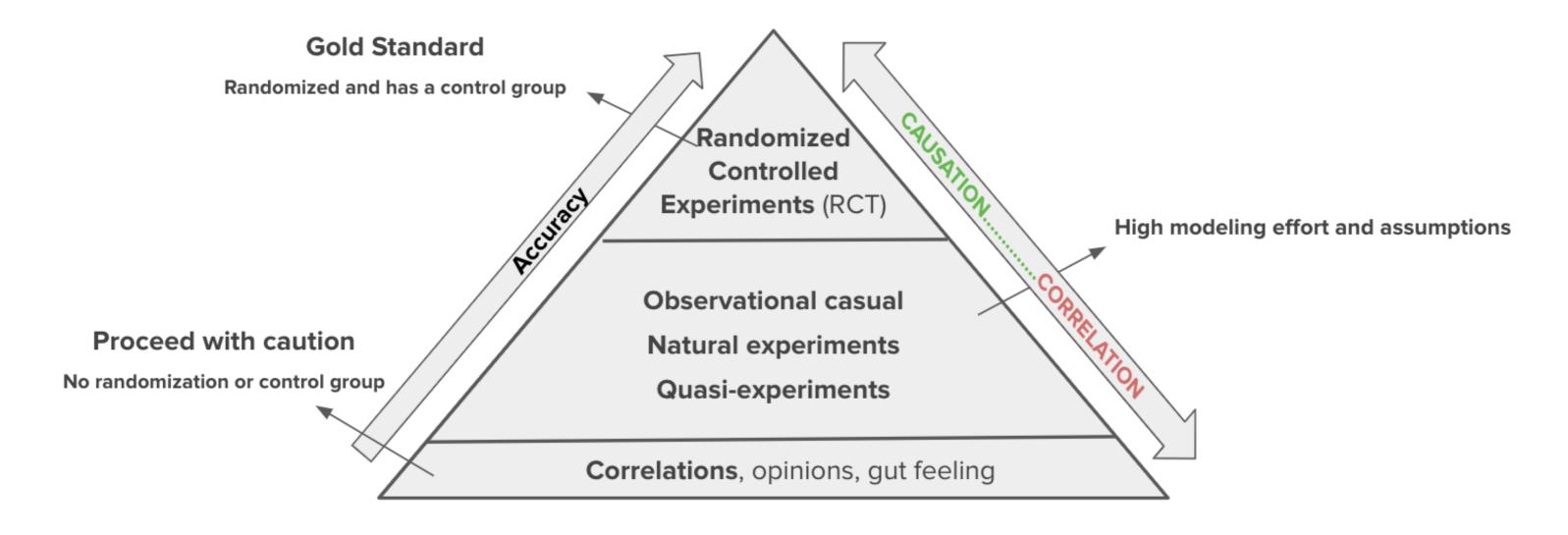
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The value of A/B testing

- Reduce uncertainty around the impact of new designs and features
- Decision-making --> scientific, evidence-based not intuition
- Generous value for the investment: simple changes lead to major wins
- Continuous optimization at the mature stage of the business
- Correlation does not imply causation

Hierarchy of evidence

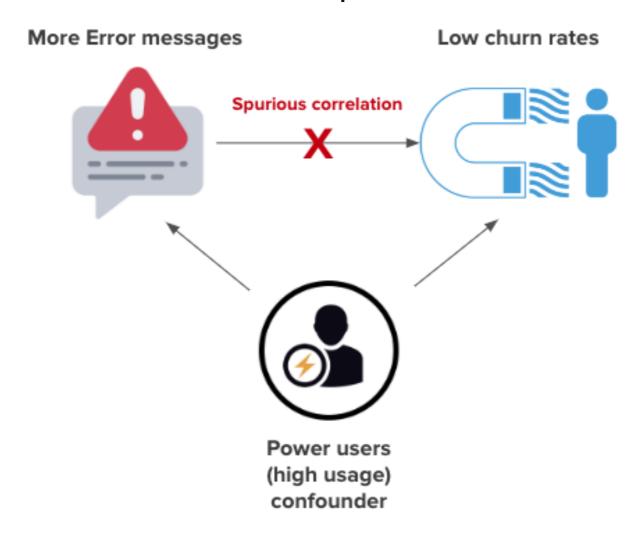


¹ https://jamanetwork.com/journals/jama/article-abstract/392650



Do error messages reduce churn?

Microsoft Office 365 spurious correlation example:¹



Spurious correlation: a strong correlation that appears to be causal but is not.

¹ Kohavi, Ron, Tang, Diane, Xu, Ya. Trustworthy Online Controlled Experiments. Cambridge University Press.



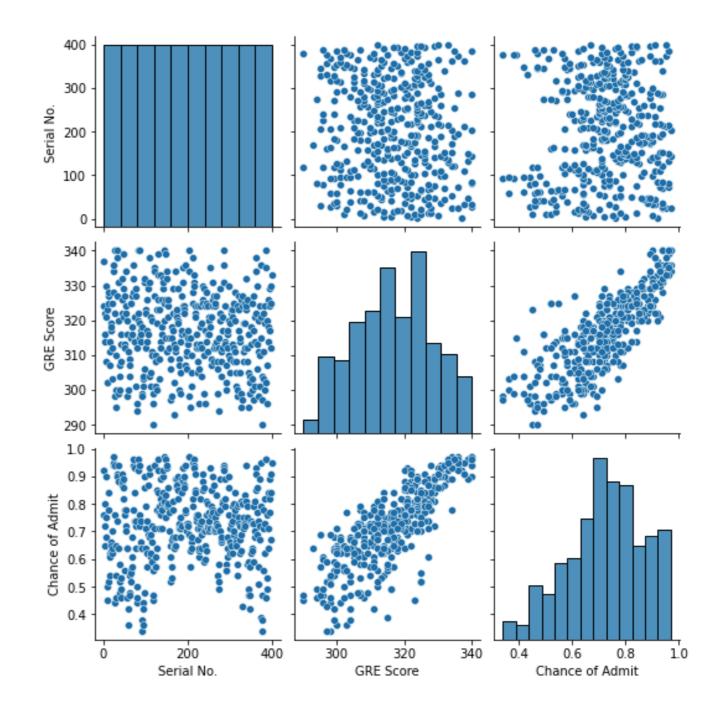
Pearson's correlation coefficient

- A score that measures the strength of a linear relationship between two variables.
- r>0: positive correlation
- r = 0: neutral correlation
- r<0: negative correlation
- Pearson's correlation coefficient (r) formula:

$$r = rac{\sum \left(x_i - ar{x}
ight)\left(y_i - ar{y}
ight)}{\sqrt{\sum \left(x_i - ar{x}
ight)^2 \sum \left(y_i - ar{y}
ight)^2}}$$

Assumes: Normal distribution and Linearity

Correlations visual inspection



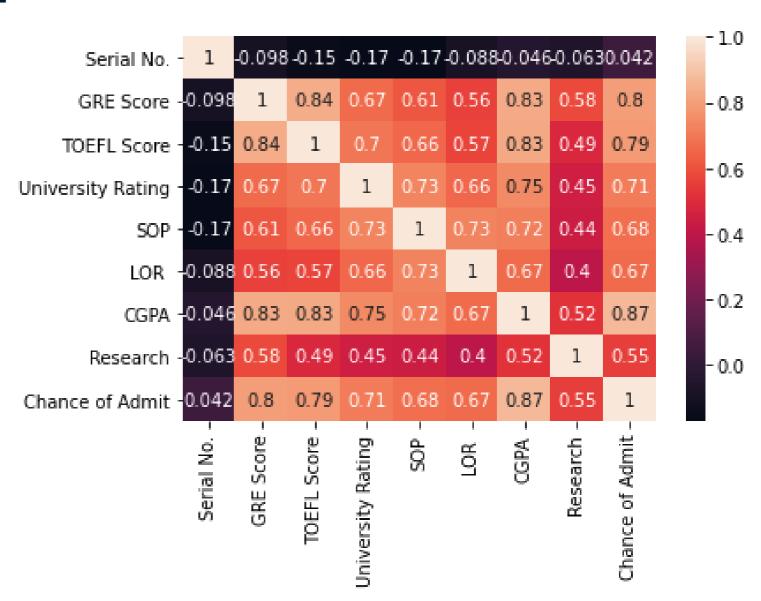
Pearson correlation heatmap

```
# Import visualization library seaborn
import seaborn as sns

# Print Pearson correlation coefficient
print(admissions['GRE Score']\
    .corr(admissions['Chance of Admit']))
```

0.8026104595903503

```
# Plot correlations heatmap
sns.heatmap(admissions.corr(),annot=True)
```



Let's practice!

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Metrics design and estimation

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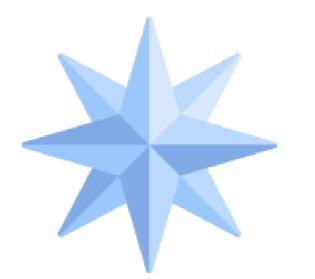


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Types of metrics

- Primary (goal/north-star):
 - Best describes the success of the business or mission
- Granular metrics:
 - Best explain users' behavior
 - More sensitive and actionable
 - Signup rate:
 - = (clicks/visitors) X (signups/clicks)
- Instrumentation/guardrail metrics:
 - Outside the scope of this course



- Signup rate
- Daily active users
- Average sales per user
- Average listening time per user



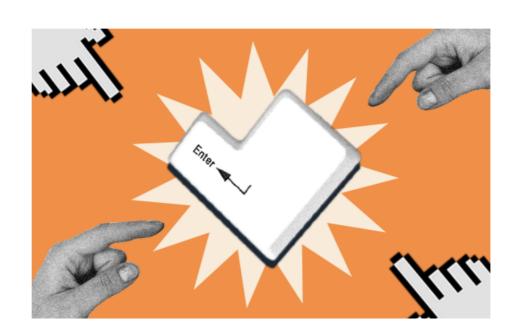
Types of metrics

Quantitative categorization

- Means/percentiles: average sales, median time on page
- Proportions:
 - Signup rate: signups/total visitors
 - Page abandonment rate: page abandoners/total visitors
- Ratios:
 - Click-through-rate(CTR): clicks/page visits or clicks/ad impressions
 - Revenue per session
- Metrics can be combined to form a more comprehensive success/failure criteria

Metrics requirements

- Stable/robust against the unimportant differences
- Sensitive to the important changes
- Measurable within logging limitations
- Non-gameable
 - Bright colors
 - Time on page



Python metrics estimation

```
checkout.groupby('gender')['purchased'].mean()
gender
    0.908056
    0.780009
Name: purchased, dtype: float64
checkout[(checkout['browser']=='chrome')|(checkout['browser']=='safari')]\
    .groupby('gender')['order_value'].mean()
gender
    29.814161
```



30.383431

Name: order_value, dtype: float64

Python metrics estimation

```
checkout.groupby('browser')[['order_value', 'purchased']].mean()
```



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