

Data cleaning and exploratory analysis

A/B TESTING IN PYTHON



Moe Lotfy, PhD

Principal Data Science Manager

Cleaning missing values

- Missing values
 - Drop, ignore, impute

```
# Calculate the mean order value  
checkout.order_value.mean()
```

```
30.0096
```

```
# Replace missing values with zeros and get mean  
checkout['order_value'].fillna(0).mean()
```

```
25.3581
```

Cleaning duplicates

- Duplicates
 - Identical rows should be dropped

```
# Check for duplicate rows due to logging issues
print(len(checkout))
print(len(checkout.drop_duplicates(keep='first')))
```

```
9000
```

```
9000
```

Cleaning duplicates

- Duplicates
 - Duplicate users should be handled with care.

```
# Unique users in group B
print(checkout[checkout['checkout_page'] == 'B']['user_id'].nunique())
# Unique users who purchased at least once
print(checkout[checkout['checkout_page'] == 'B'].groupby('user_id')['purchased'].max().sum())
# Total purchase events in group B
print(checkout[checkout['checkout_page'] == 'B']['purchased'].sum())
```

```
2938
2491.0
2541.0
```

EDA summary stats

- Mean, count, and standard deviation summary

```
checkout.groupby('checkout_page')['order_value'].agg({'mean', 'std', 'count'})
```

	mean	count	std
checkout_page			
A	24.956437	2461	2.418837
B	29.876202	2541	7.277644
C	34.917589	2603	4.869816

EDA plotting

- Bar plots

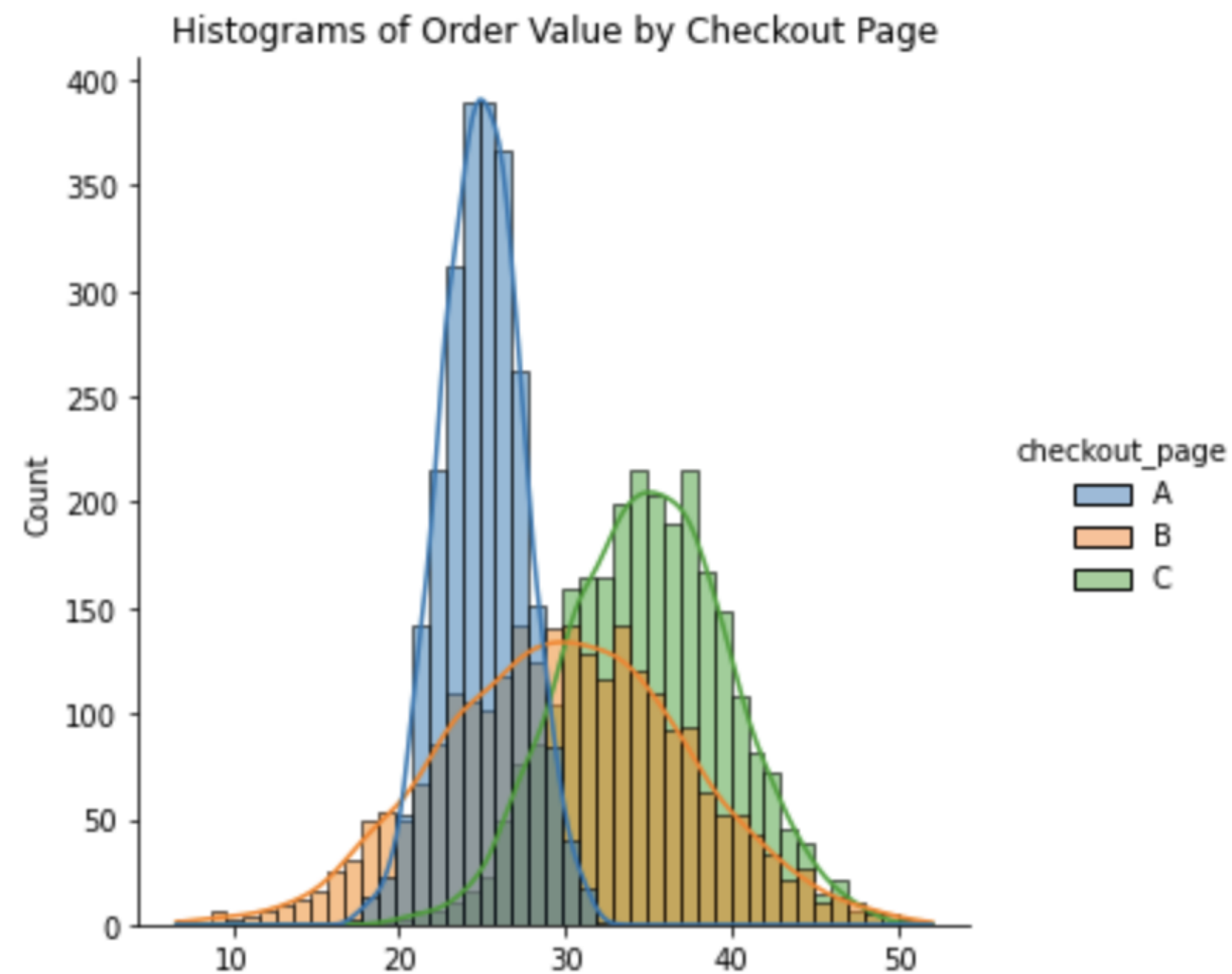
```
sns.barplot(x=checkout['checkout_page'], y=checkout['order_value'], estimator=np.mean)
plt.title('Average Order Value per Checkout Page Variant')
plt.xlabel('Checkout Page Variant')
plt.ylabel('Order Value [$'])
```



EDA plotting

- Histograms

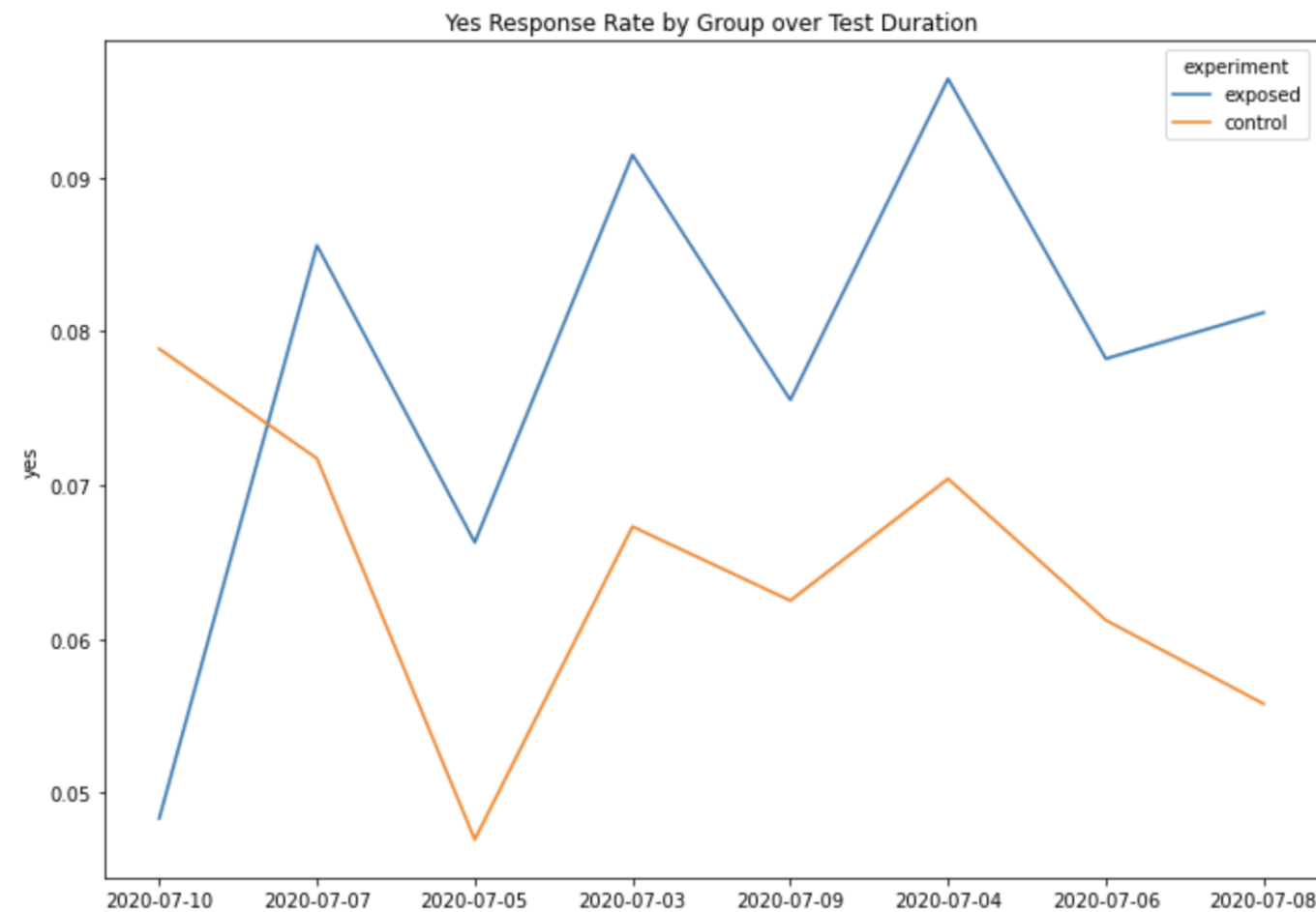
```
sns.displot(data=checkout, x='order_value', hue = 'checkout_page', kde=True)
```



EDA plotting

- Time series (line plots)

```
sns.lineplot(data=AdSmart, x='date', y='yes', hue='experiment', ci=False)
```



¹ Adsmart Kaggle dataset: <https://www.kaggle.com/datasets/osuolaleemmanuel/ad-ab-testing>

Let's practice!

A/B TESTING IN PYTHON

Sanity checks: Internal validity

A/B TESTING IN PYTHON



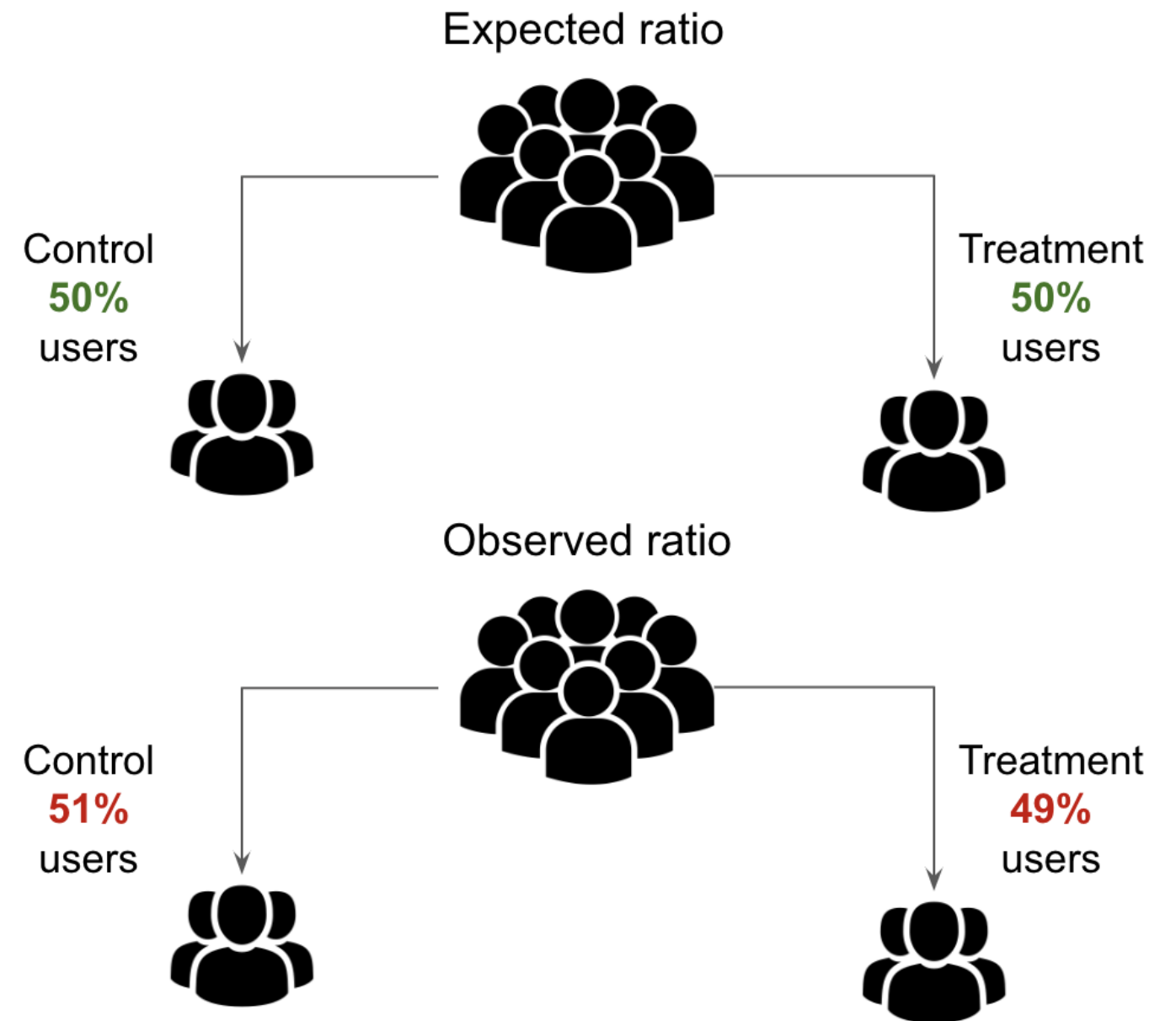
Moe Lotfy, PhD

Principal Data Science Manager

Sample Ratio Mismatch (SRM)

- Sample Ratio Mismatch (SRM)
 - Allocation across variants deviates from design
- Chi-square goodness of fit test

$$\chi^2 = \sum \frac{(\text{Observed} - \text{Expected})^2}{\text{Expected}}$$



SRM python example

```
# Calculate the unique IDs per variant
AdSmart.groupby('experiment')['auction_id'].nunique()
```

```
experiment
control    4071
exposed    4006
```

```
# Assign the unique counts to each variant
control_users=AdSmart[AdSmart['experiment']=='control']['auction_id'].nunique()
exposed_users=AdSmart[AdSmart['experiment']=='exposed']['auction_id'].nunique()
total_users=control_users+exposed_users
# Calculate allocation ratios per variant
control_perc = control_users / total_users
exposed_perc = exposed_users / total_users
print("Percentage of users in the Control group:",100*round(control_perc,5),"%")
print("Percentage of users in the Exposed group:",100*round(exposed_perc,5),"%")
```

```
Percentage of users in the Control group: 50.402 %
Percentage of users in the Exposed group: 49.598 %
```

¹ Adsmart Kaggle dataset: <https://www.kaggle.com/datasets/osuolaleemmanuel/ad-ab-testing>

SRM python example

```
# Create lists of observed and expected counts per variant
observed = [ control_users, exposed_users ]
expected = [ total_users/2, total_users/2 ]
# Import chisquare from scipy library
from scipy.stats import chisquare
# Run chisquare test on observed and expected lists
chi = chisquare(observed, f_exp=expected)
# Print test results and interpretation
print(chi)
if chi[1] < 0.01:
    print("SRM may be present")
else:
    print("SRM likely not present")
```

```
Power_divergenceResult(statistic=0.5230902562832735, pvalue=0.4695264353014863)
SRM likely not present
```

¹ Adsmart Kaggle dataset: <https://www.kaggle.com/datasets/osuolaleemmanuel/ad-ab-testing>

SRM root-causing

Common causes of SRM:¹

- Assignment: incorrect bucketing or faulty randomization functions
- Execution: delayed variants starting time or ramp up rates
- Data logging: logging delays or bot filtering
- Interference: experimenter pausing a variant

¹ Diagnosing Sample Ratio Mismatch in Online Controlled Experiments: A Taxonomy and Rules of Thumb for Practitioners

A/A tests

- A/A test
 - Presents an identical experience to two groups of users
 - Reveals bugs in experimental setup
 - No statistically significant differences between the metrics
 - False positives can still happen at the specified α (5% of the time)
 - Reveals imbalances in distributions across groups (e.g. browsers, devices, etc.)

Distributions balance Python example

- Balanced browsers distribution
- Valid test
- Imbalanced browsers distribution
- Invalid test

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

checkout_page	browser	
A	chrome	0.341333
	safari	0.332000
	firefox	0.326667
B	safari	0.352000
	firefox	0.325000
	chrome	0.323000
C	safari	0.346000
	chrome	0.330000
	firefox	0.324000

```
AdSmart.groupby('experiment')['browser'].value_counts(normalize=True)
```

experiment	browser	
control	Chrome Mobile	0.591992
	Facebook	0.137804
	Samsung Internet	0.120855
	Chrome Mobile WebView	0.071727
	Mobile Safari	0.060427
	Chrome Mobile iOS	0.008352
exposed	Mobile Safari UI/WKWebView	0.007369
	Chrome Mobile	0.535197
	Chrome Mobile WebView	0.298802
	Samsung Internet	0.082876
	Facebook	0.050674
	Mobile Safari	0.022716
	Chrome Mobile iOS	0.004244

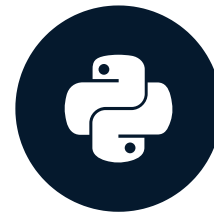
¹ Adsmart Kaggle dataset: <https://www.kaggle.com/datasets/osuolaleemmanuel/ad-ab-testing>

Let's practice!

A/B TESTING IN PYTHON

Sanity checks: external validity

A/B TESTING IN PYTHON



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Principal Data Science Manager

Simpson's paradox

Simpson's Paradox: a statistical phenomenon where certain trends between variables emerge, disappear or reverse when the population is divided into segments.

```
print(simp_imbalanced.groupby('Variant').mean())
```

Variant	Conversion
A	0.80
B	0.64

```
print(simp_imbalanced.groupby(['Variant', 'Device']).mean())
```

Variant	Device	Conversion
A	Phone	0.875
	Tablet	0.500
B	Phone	0.900
	Tablet	0.575

Simpson's paradox

```
simp_imbalanced.groupby(['Variant', 'Device'])\
    ['Device'].count()
```

Variant	Device	
A	Phone	40
	Tablet	10
B	Phone	10
	Tablet	40

Device	A	B
Phone	35/40	9/10
Tablet	5/10	23/40
Total	40/50	32/50
Device	A	B
Phone	0.875	0.9
Tablet	0.5	0.575
Total	0.8	0.64

Simpson's paradox

```
simp_balanced.groupby(['Variant', 'Device'])\n                ['Device'].count()
```

Variant	Device	
A	Phone	40
	Tablet	10
B	Phone	40
	Tablet	10

```
print(simp_balanced.groupby('Variant').mean())
```

Variant	Conversion
A	0.70
B	0.52

```
print(simp_balanced.groupby(['Variant', 'Device']).mean())
```

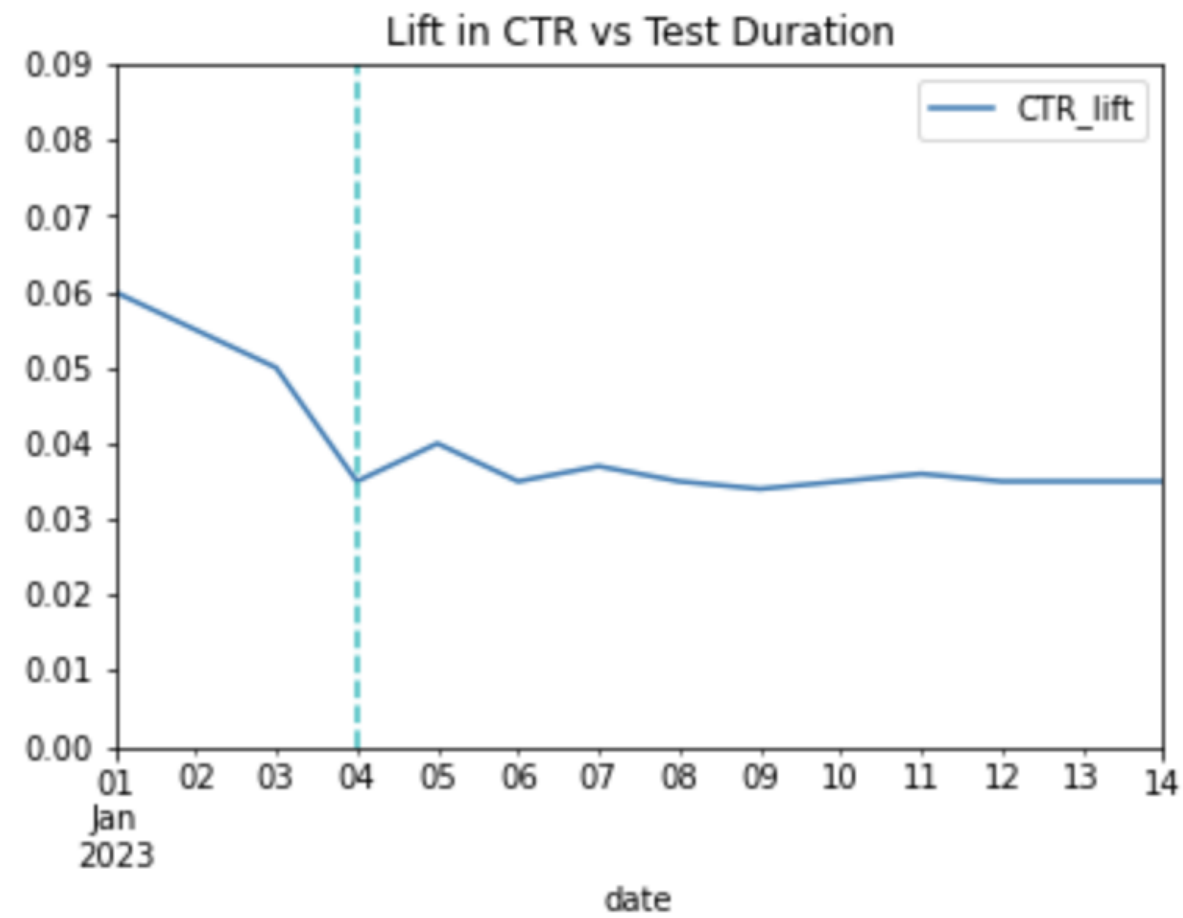
Variant	Device	Conversion
A	Phone	0.750
	Tablet	0.500
B	Phone	0.575
	Tablet	0.300

Novelty effect

- **Novelty effect**
 - A short-lived improvement in metrics caused by users' curiosity about a new feature.
- **Change aversion**
 - The opposite of novelty effect.
 - Users avoiding trying a new feature due to familiarity with the old one.

Novelty effect visual inspection

```
# Plot Lift in CTR vs test days
novelty.plot('date', 'CTR_lift')
plt.ylim([0, 0.09])
plt.title('Lift in CTR vs Test Duration')
plt.show()
```



Correcting for novelty effects

- Increasing the test duration
 - Start including data after treatment effect stabilizes.
- Examine new and returning user cohorts
 - New users are by default less likely to experience novelty effects.
 - Old users compare consider their old experiences.

Let's practice!

A/B TESTING IN PYTHON

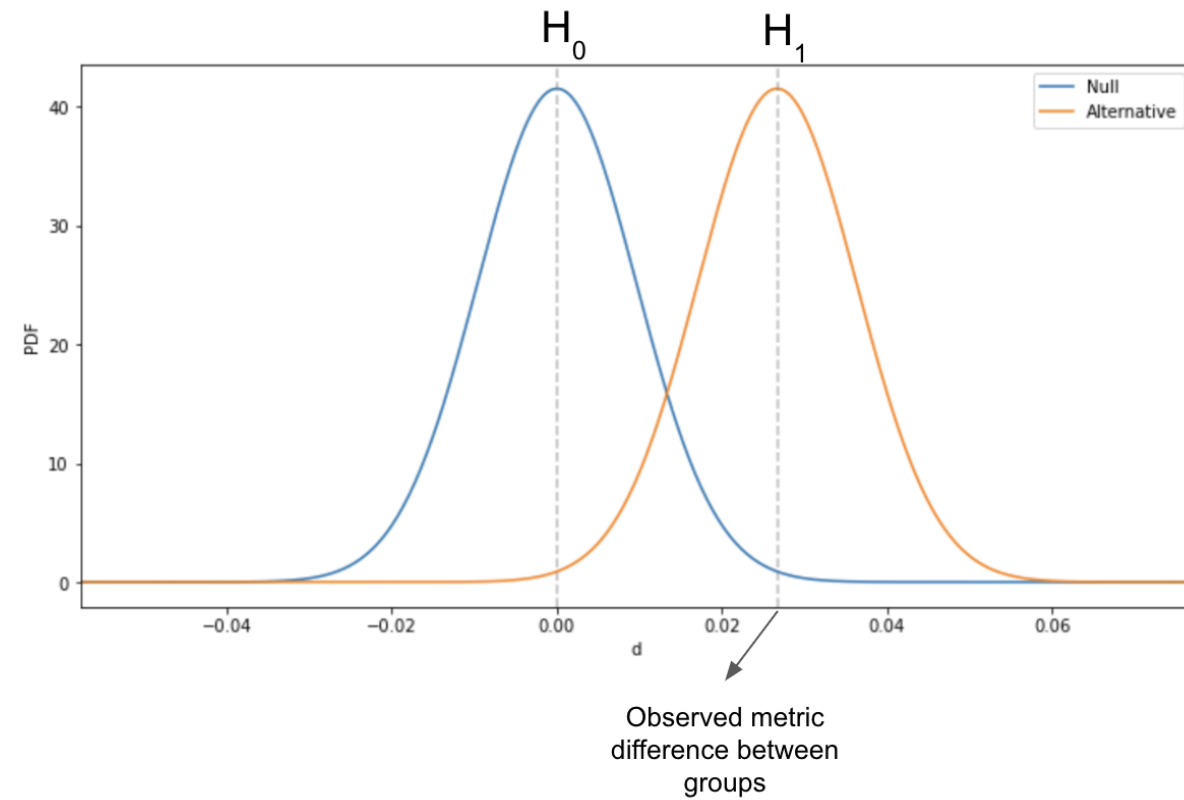
Analyzing difference in proportions A/B tests

A/B TESTING IN PYTHON



Moe Lotfy, PhD
Principal Data Science Manager

Framework for difference in proportions



$$d = p_B - p_A$$

$$H_0 : d = p_B - p_A = 0$$

$$H_1 : d = p_B - p_A \neq 0$$

- If $p\text{-value} < \alpha$
 - Reject Null hypothesis
- If $p\text{-value} > \alpha$
 - Fail to reject Null hypothesis
- Confidence intervals
 - 95% CI is the range that captures the true difference 95% of the time
 - Like fishing with a net instead of a spear
 - Centered around the observed difference between the treatment and the control

Two sample proportions z-test

```
from statsmodels.stats.proportion import proportions_ztest, proportion_confint
# Calculate the number of users in groups A and B
n_A = checkout[checkout['checkout_page'] == 'A']['user_id'].nunique()
n_B = checkout[checkout['checkout_page'] == 'B']['user_id'].nunique()
print('Group A users:', n_A)
print('Group B users:', n_B)
```

```
Group A users: 2940
Group B users: 2938
```

```
# Compute unique purchasers in each group
purchased_A = checkout[checkout['checkout_page'] == 'A'].groupby('user_id')['purchased'].max().sum()
purchased_B = checkout[checkout['checkout_page'] == 'B'].groupby('user_id')['purchased'].max().sum()
# Assign groups lists
purchasers_abtest = [purchased_A, purchased_B]
n_abtest = [n_A, n_B]
```

Two sample proportions z-test

```
# Calculate p-value and confidence intervals
z_stat, pvalue = proportions_ztest(purchasers_abtest, nobs=n_abtest)
(A_lo95, B_lo95), (A_up95, B_up95) = proportion_confint(purchasers_abtest, nobs=n_abtest, alpha=0.05)
# Print the p-value and confidence intervals
print(f'p-value: {pvalue:.4f}')
print(f'Group A 95% CI : [{A_lo95:.4f}, {A_up95:.4f}]')
print(f'Group B 95% CI : [{B_lo95:.4f}, {B_up95:.4f}]')
```

```
p-value: 0.0058
Group A 95% CI : [0.8072, 0.8349]
Group B 95% CI : [0.8349, 0.8608]
```

Confidence intervals for proportions

```
# Set random seed for repeatability
np.random.seed(34)
# Calculate the average purchase rate for group A
pop_mean = checkout[checkout['checkout_page'] == 'B']['purchased'].mean()
print(pop_mean)
```

```
0.847
```

Confidence intervals for proportions

```
# Calculate 20 90% confidence intervals for 20 random samples of size 100 each
for i in range(20):
    confidence_interval = proportion_confint(
        count = checkout[checkout['checkout_page'] == 'B'].sample(100)['purchased'].sum(),
        nobs = 100,
        alpha = (1 - 0.90))
    print(confidence_interval)
```

```
(0.7912669777384846, 0.9087330222615153)
(0.8385342148455946, 0.9414657851544054)
(0.8265485838585659, 0.9334514161414341)
(0.7568067872454262, 0.8831932127545737)
(0.8506543911914558, 0.9493456088085442)*
(0.8385342148455946, 0.9414657851544054)
(0.7230037568938057, 0.8569962431061944)
(0.8146830076144598, 0.9253169923855402)
(0.8029257122801267, 0.9170742877198733)
(0.8146830076144598, 0.9253169923855402)
(0.8506543911914558, 0.9493456088085442)*
(0.7454722433688197, 0.8745277566311804)
...
```

Let's practice!

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