Part 2

Planning, Running, and Analyzing Controlled Experiments on the Web

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Planning and Analysis of Online Experiments

- What to measure
- How to compare Treatment to Control
- How long to run test
- Start up options
- Good test design
- Data validation and cleansing
- Before your first experiment
- Common errors
- MultiVariable Tests

What to Measure

- Start with objective
  - Of the site (content, ecommerce, marketing, help/support,…)
  - Of the experiment
- What can you measure to tell you if you met your objective?
  - **Content site:** clicks/user, pageviews/user, time on site
  - **Ecommerce:** rev/visitor, units purchased/visitor, cart-adds/visitor
  - **Marketing:** referrals/visitor, time on site
  - **Help/support:** Pct of users engaged, Pct of users who print, email or download content, time on site

What to Measure

- Measures of user behavior
  - Number of events (clicks, pageviews, scrolls, downloads, etc)
  - Time (minutes per session, total time on site, time to load page)
  - Value (revenue, units purchased)

- Experimental units
  - Per user (e.g. clicks per user)
  - Per session (e.g. minutes per session)
  - Per user-day (e.g. pageviews per day)
  - Per experiment (e.g. clicks per pageview)

Overall Evaluation Criterion

- It is very helpful to have a single metric that summarizes whether the Treatment is successful or not – the Overall Evaluation Criterion, or OEC
- Examples:
  - **Content site:** OEC could be clicks/user or time on site
  - **Ecommerce:** rev/user or lifetime value
  - **Help/support site:** Survey responses
- OEC could also capture monetary value of the site, aka ROI (return on investment)

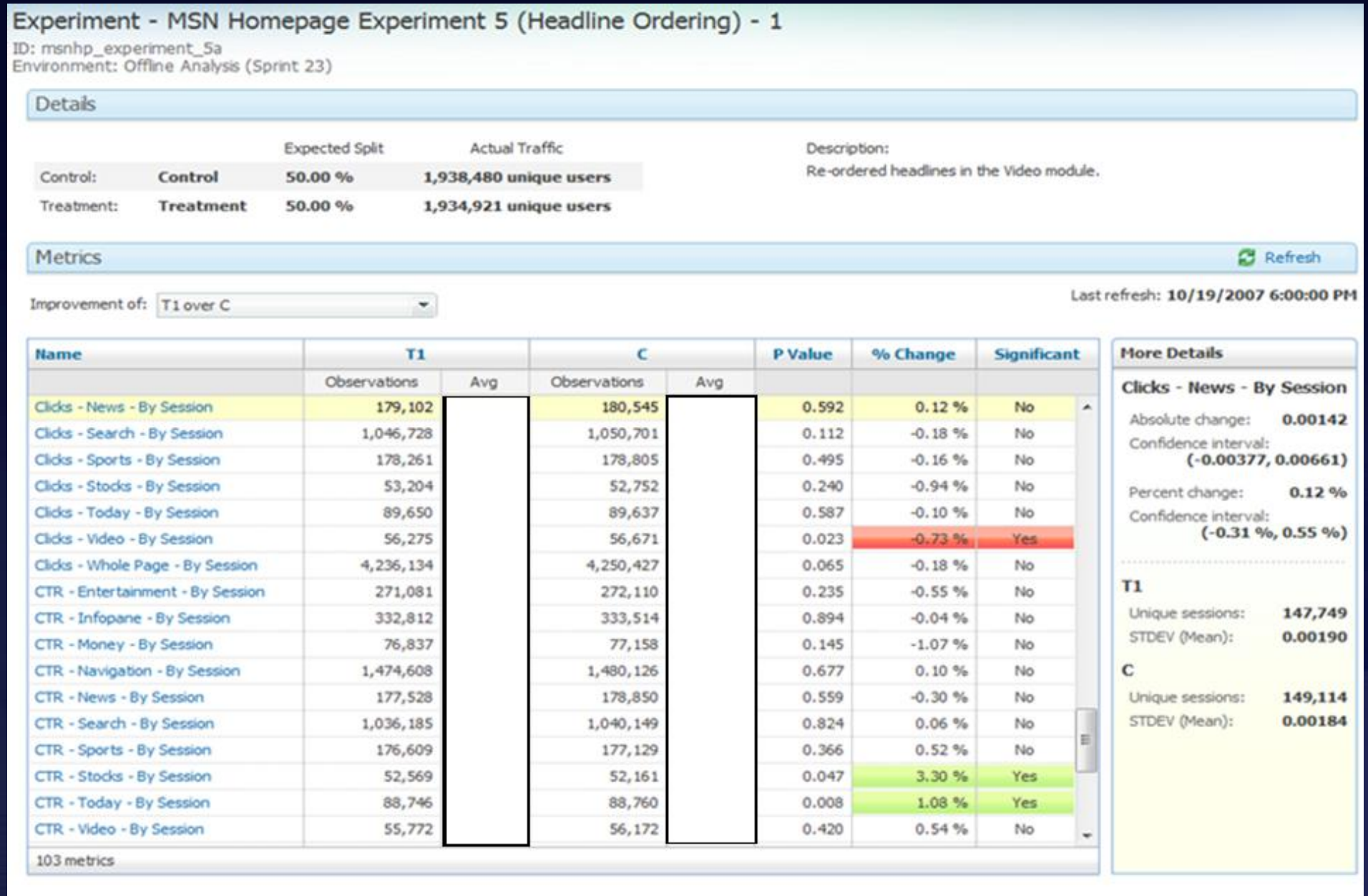
Comparing Treatment to Control

- Single Treatment
  - Two-sample t test works well
    - Large samples sizes => Normal distribution for means
    - Calculate 95% Confidence Interval for difference in two means

$$(\bar{X}_T - \bar{X}_C) \pm 1.96 * s_{\bar{X}_T - \bar{X}_C}$$

      if zero not in the interval conclude Treatment mean different from Control
  - May have many tests, OEC critical
- Multiple Treatments
  - Multiple applications of two-sample t test
  - Analysis of Variance

Sample UI for test results



Experiment - MSN Homepage Experiment 5 (Headline Ordering) - 1

ID: msnhp_experiment_5a
Environment: Offline Analysis (Sprint 23)

Details

		Expected Split	Actual Traffic
Control:	Control	50.00 %	1,938,480 unique users
Treatment:	Treatment	50.00 %	1,934,921 unique users

Description:
Re-ordered headlines in the Video module.

Metrics — Refresh

Improvement of: T1 over C

Last refresh: 10/19/2007 6:00:00 PM

Name	T1		C		P Value	% Change	Significant
	Observations	Avg	Observations	Avg			
Clicks - News - By Session	179,102		180,545		0.592	0.12 %	No
Clicks - Search - By Session	1,046,728		1,050,701		0.112	-0.18 %	No
Clicks - Sports - By Session	178,261		178,805		0.495	-0.16 %	No
Clicks - Stocks - By Session	53,204		52,752		0.240	-0.94 %	No
Clicks - Today - By Session	89,650		89,637		0.587	-0.10 %	No
Clicks - Video - By Session	56,275		56,671		0.023	-0.73 %	Yes
Clicks - Whole Page - By Session	4,236,134		4,250,427		0.065	-0.18 %	No
CTR - Entertainment - By Session	271,081		272,110		0.235	-0.55 %	No
CTR - Infopane - By Session	332,812		333,514		0.894	-0.04 %	No
CTR - Money - By Session	76,837		77,158		0.145	-1.07 %	No
CTR - Navigation - By Session	1,474,608		1,480,126		0.677	0.10 %	No
CTR - News - By Session	177,528		178,850		0.559	-0.30 %	No
CTR - Search - By Session	1,036,185		1,040,149		0.824	0.06 %	No
CTR - Sports - By Session	176,609		177,129		0.366	0.52 %	No
CTR - Stocks - By Session	52,569		52,161		0.047	3.30 %	Yes
CTR - Today - By Session	88,746		88,760		0.008	1.08 %	Yes
CTR - Video - By Session	55,772		56,172		0.420	0.54 %	No

103 metrics

More Details

Clicks - News - By Session

Absolute change: 0.00142
Confidence interval: (-0.00377, 0.00661)

Percent change: 0.12 %
Confidence interval: (-0.31 %, 0.55 %)

T1
Unique sessions: 147,749
STDEV (Mean): 0.00190

C
Unique sessions: 149,114
STDEV (Mean): 0.00184

Note:

- Averages for both variants
- P-values
- Percent change
- Significance
- Confidence Intervals
- 103 metrics

Comparing Treatment to Control

- P-value is the probability of getting a difference farther from zero than observed under assumption of no difference
- CI for percent effect must use special formulas
- Care must be taken in calculating standard deviations
  - When randomization is by user, any metric that is not per user must take into account non-independence in calculating standard deviation
  - We routinely use bootstrapping to estimate standard deviations

$$n = \frac{16 * r * \sigma^2}{\Delta^2}$$

Power and Sample Size

- The power of a test is the probability of detecting a difference (Δ) of a given size i.e., it is 1-Prob(Type II error)

Power depends on

- The size of effect you want to be able to detect, Δ
- Variability of the metric
- Number of users in each group (T/C)

It is typical to determine the sample size needed to achieve 80% power

Power and Sample Size

- Example: Total number of users needed to achieve 80% power, with equal number of users in Treatment and Control and with standard deviation s is

Ramp up

- Often good practice is to start with small percent in Treatment and increase when you have confidence Treatment is bug-free
- Sample ramp up schedule:
  - 1% in Treatment for 4 hours
  - 5% in Treatment for 4 hours
  - 20% in Treatment for 4 hours
  - 50 % in Treatment for 14 days

Simpson's Paradox

- Beware Simpson's paradox when percent in Treatment changes
- Example: data generated for 7day test with Treatment mean 5% higher than Control mean each day.

  First 5 days Treatment had 20% of visitors/day (100,000 visitors/day)

  Last 2 days Treatment had 50% of visitors (100,000/day)

  (Assume last two days were weekend and averages dropped from about 1.7 to 1.2)

Simpson's Paradox example

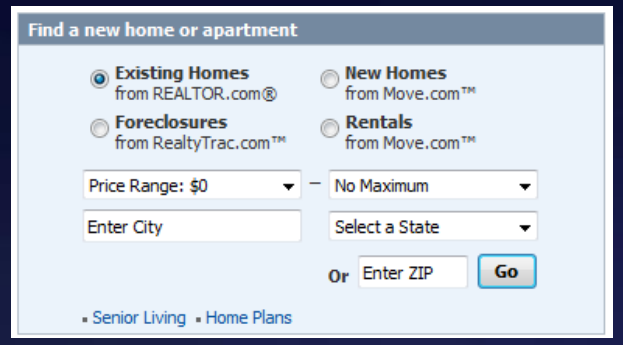
Metric is number of sessions per user per day

Day	T mean	C mean	% in T	users	T users	C users	T total	C total	% effect
M	1.89	1.8	20%	100000	20000	80000	37800	144000	5.00%
T	1.995	1.9	20%	100000	20000	80000	39900	152000	5.00%
W	1.89	1.8	20%	100000	20000	80000	37800	144000	5.00%
Th	1.785	1.7	20%	100000	20000	80000	35700	136000	5.00%
F	1.785	1.7	20%	100000	20000	80000	35700	136000	5.00%
Sa	1.155	1.1	50%	100000	50000	50000	57750	55000	5.00%
Su	1.26	1.2	50%	100000	50000	50000	63000	60000	5.00%
						totals	307650	827000	
						Averages	1.53825	1.654	-7.00%

The Treatment effect each day is +5% but estimated cumulative effect is -7%

MultiTreatment Tests

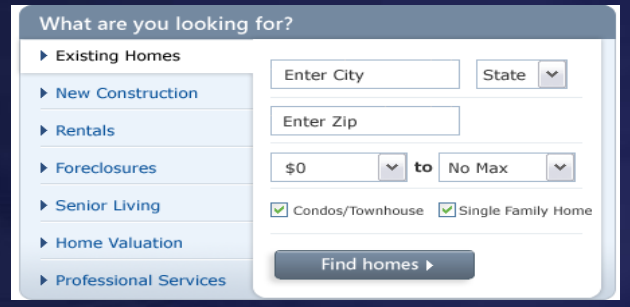
- Example: Real Estate widget design
  - Test five alternatives to the current design
  - OEC: clicks to links weighted by revenue per click



Control

T1

T2



T3

T4

T5

Real Estate Widget

- The widget that performed the best was the simplest

- Revenue increase over control: +9.7%

Note Ronny's example earlier compared the best Treatment to another Treatment, not the Control

BREAK

Design of Experiments

- Triggering
- Blocking
- Measuring non-test factors
- Randomization

Triggering

Only allow users into your experiment if they “trigger” the experiment. i.e. a user’s data should only be used in the analysis of the experiment if they saw one of the variants

Example: MSN UK Hotmail experiment

Which users do you want to track as part of your experiment?

Blocking non-test Factors

- Factor is controlled such that it affects both treatment and control equally, hence not affecting the estimate of the effect
- Blocking on a factor is more common than keeping it fixed (keeping it constant throughout the experiment)
- Advantages to blocking
  - Can estimate the effect of the different levels of the factor, e.g. what is the effect on weekends/weekdays
  - Can make inference to a broader population

Examples of Blocking

- Time (time of day, day of week, etc.)
  - Bad test design => run control at 100% M-W
    - then treatment at 100% Th-Sa
  - Always run treatment and control concurrently in online experiments
- Content
  - Ex: If content of a site changes during the experiment it must be the same for both Treatment and Control at all times

Design Principle

The Treatment and Control groups should be as alike as possible except for application of the treatment

- Who is in the experiment
- What is done during the experiment
- etc.

Updates to the site during the test must be applied to all variants in the test

Design Principle

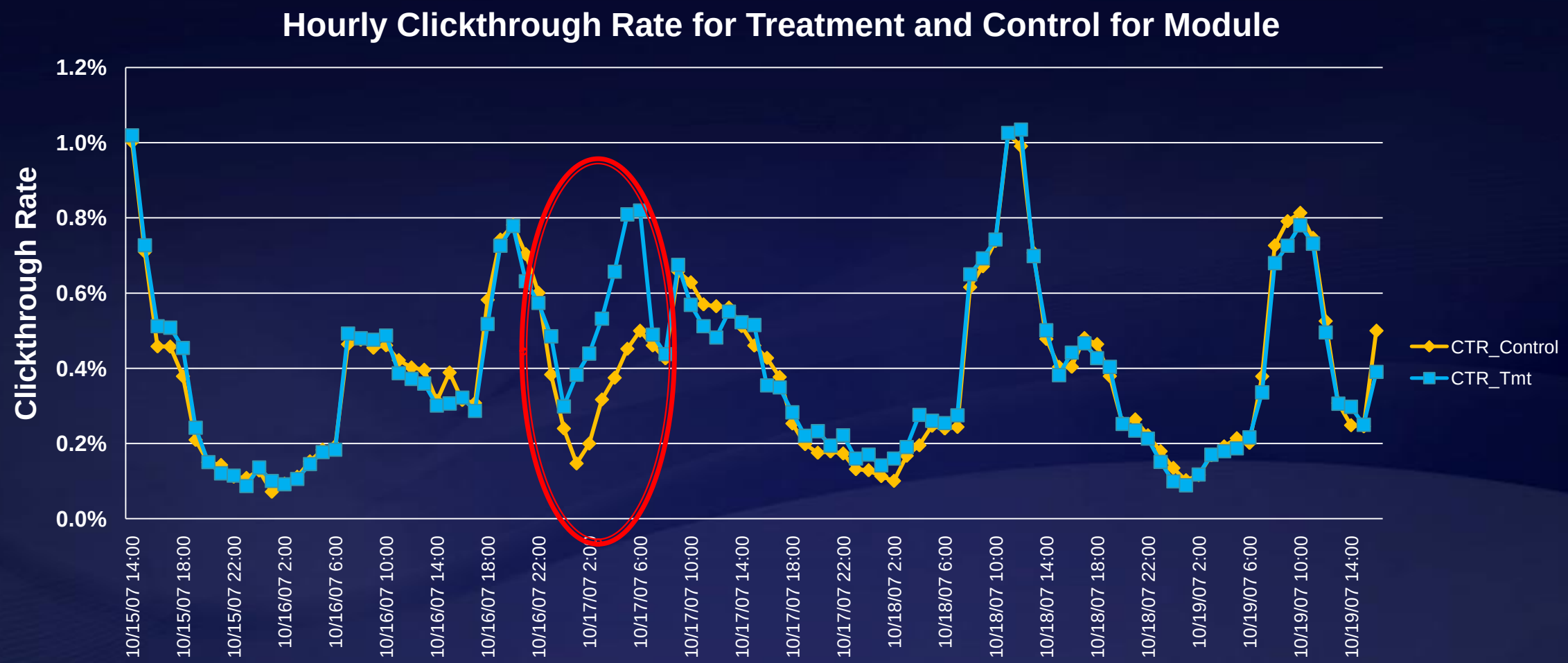
Example: One partner was conducting an A/A test (same as an A/B test but no real change is made) What would you expect?

Results: T very significant (much more than it should be) Why?

Found out another group was using their Treatment group to test something so there really *was* a difference between T and C

Design Principle

- Ex: A site was testing a change to the layout of their page
  - Content to T and C was not the same for a 7 hour period



Measure non-test Factors

Measuring the value of non-test factors allows you to

- Delve into why the treatment had the effect it did (e.g. more PVs are correlated with faster load time which explains almost all the effect of T)
- Determine if subpopulations behave the same (e.g. did the treatment have the same effect for new users as for experienced users?)

Randomize

Why randomize?

So that those factors you can't control (or don't know about) don't bias your results

"Randomization is too important to be left to chance"
Robert Coveyou, ORNL

Randomize

How to randomize? (online tests)

Randomly assign T or C to user (alternately could use user-session, search query, page view or product/SKU)

Usually best by user (store UserID in cookie)

How persistent is the UID?

Ideally user always gets same treatment group

Limitations:

- Clearing cookies => can change treatment
- Different browser => may get different treatment
- Can’t allow opt-in or opt-out

Representative Test

Make sure users and conditions are as representative of launch environment as possible

- Time period: not holiday (unless holiday factor), pre-holiday, complete cycle (day, week)
- Users: all users who would see T in the future,

  not robots, not internal testers, outliers(?)
- Not during special events

Robot Detection and Removal

- Remove robots (web crawlers, spiders, etc.) from analysis
  - They can generate many pageviews or clicks in Treatment or Control skewing the results
  - Remove robots with known identifiers (found in the user agent)
  - Develop heuristics to identify robots with many clicks or pageviews in short period of time
  - Other patterns may be used to identify robots as well, such as very regular activity

Data Validation checks

- Carry out checks to make sure data is not affected by some unknown factor
  - Check that percentage of users in each variant is not different from planned (statistical test)
  - Check that number of users in the experiment is approximately what was expected (and doesn’t change too much during experiment)
  - Check that the Treatment effect does not change too much during experiment
  - Check that means for primary metrics do not change unexpectedly

Before Your First Experiment

- Conduct logging audit
  - Compare data collected for experiment to system of record
  - Should have approximately same number of users, clicks, pageviews, orders, etc.
- Conduct A/A test
  - Split users into two groups that get same experience
  - Should have about 5% of tests significant
  - p-values should have U(0,1) distribution
  - No p-values should be extremely small (say <.001)

Common Errors

- Not conducting logging or A/A tests
  - Find caching issues, UID reassignment
- Not keeping all factors constant or blocking
  - Content changes to site
  - Redirect for Treatment but not for Control
- Sample size too small
- Not measuring correct metric for OEC
  - Measure clicks to buy button (instead of revenue)
  - Clicks to download button (instead of completed downloads)

MultiVariable Tests (MVTs)

- Several factors/variables, each of which has two or more levels (C/T1/T2/…)
- *Main effects:* Comparison of Treatments to Control for each variable (i.e. compare means for T and C same as before)
- *Interactions:* Determine if combinations of variables have different effect than adding main effects

Example: MultiVariable Test on MSN HP

Factors/variables

F1: Size of Right col ad
- C = current size
- T1 = 10% larger
- T2 = 10% smaller

F2: MSNBC news stories
- C = Top international
- T = Specific to country ID'd

F3: Sports/Money placement
- C = Sports above Money
- T = Money above Sports

OEC: Clicks per User
Other metrics: PVs, CTR

(This is for illustration purposes only, it does not reflect any previous or planned test on MSN HP)

Multivariable Tests

Advantages:

- Can test many things at once, accelerating innovation
- Can estimate interactions between factors

Disadvantages

- Some combinations of factors may give negative customer experience
- Analysis and interpretation is more difficult
- May take longer to set up test

Designs for Multivariable Tests

On-line experiments can simply run overlapping, concurrent, independently randomized experiments

Example: Test 7 factors each at 2 levels

Set up 7 separate experiments to run at the same time with the same users. Get all 128 combinations in the results.

Advantages:

- Easier to implement
- Can turn off one experiment if negative
- Get all interactions

Analysis for Interactions

Procedure for analyzing an MVT for interactions

1. Since there are potentially a vary large number of interactions among the variables being tested, restrict the ones you will look at to a few you suspect may be present. (If 7 factors, 21 two-factor interactions, 35 three-factor interactions, etc.)
2. Conduct the test to determine if the interaction between two factors is present or not
3. If interaction is not significant, stop!

   If the interaction IS significant, look at the graphical output to interpret.

Analysis for Interactions

Example: Factors from MSN HP illustration

F2: MSNBC news stories
- C = Top international
- T = Specific to country ID'd

F3 Sports/Money placement
- C = same order every day
- T = Sports higher on wkends and Money higher wkdays

Hypothesis tests for interactions similar to main effects (details omitted)

Example: MVT Experiment on MSN HP

Factors/variables

F2: MSNBC news stories
C = Top international
T = Specific to country ID'd

F3: Sports/Money placement
C = Sports above Money
T = Money above Sports

OEC: Clicks per User
Other metrics: PVs, CTR

(This is for illustration purposes only, it does not reflect any previous or planned test on MSN HP)

Graphical Analysis of Interactions

- If hypothesis test for interaction is not significant
  - Assume no interaction present
  - Interaction graph would show lines approximately parallel
- If interaction is statistically significant
  - Plot interaction to interpret

Graphical Analysis of Interactions

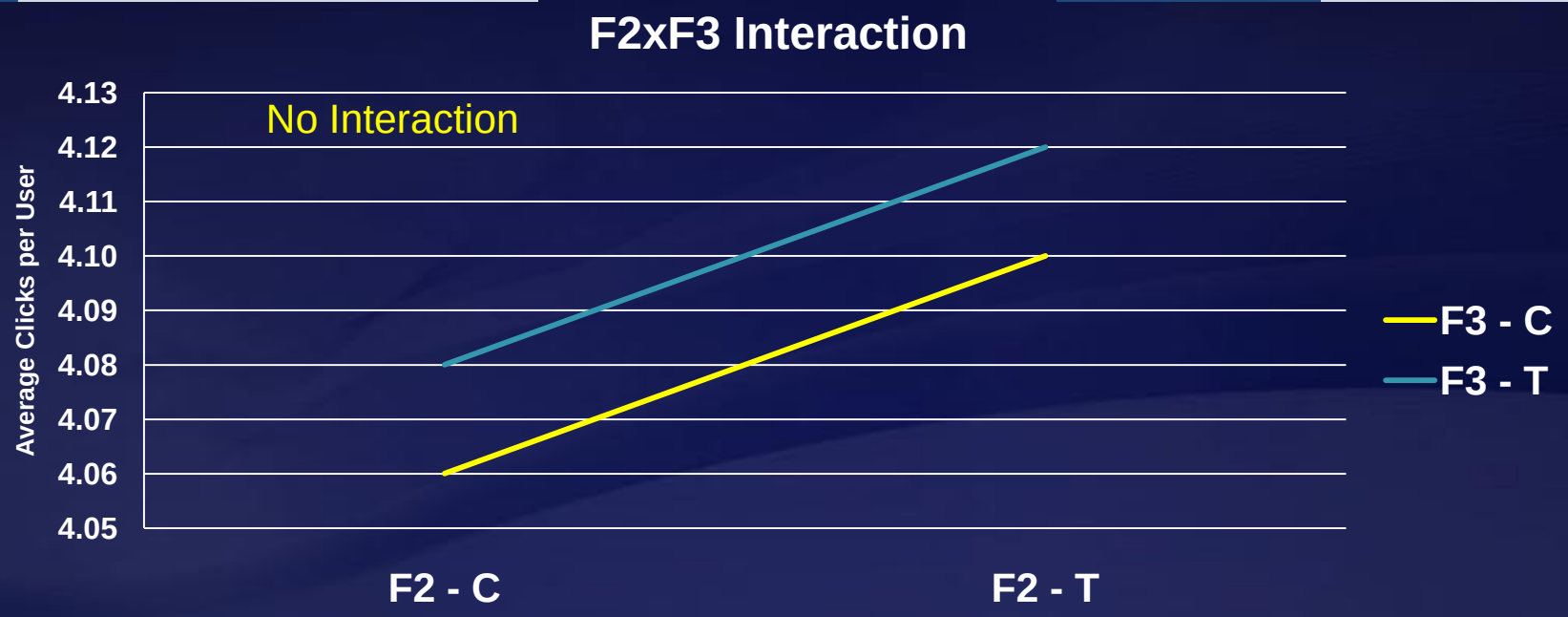
Case 1: No Interaction (parallel lines)

Data Table

	F2 - C	F2 - T
F3 - C	4.06	4.10
F3 - T	4.08	4.12

Main Effects Results

	Pct Effect	p-value
Effect(F2)	0.98%	<.001
Effect(F3)	0.49%	0.032



Graphical Analysis of Interactions

- When interaction is statistically significant

  Two types of interactions:

  - Synergistic – when the presence of both is **more** than the sum of the individual treatments
  - Antagonistic – when the presence of both is **less** than the sum of the individuals

Graphical Analysis of Interactions

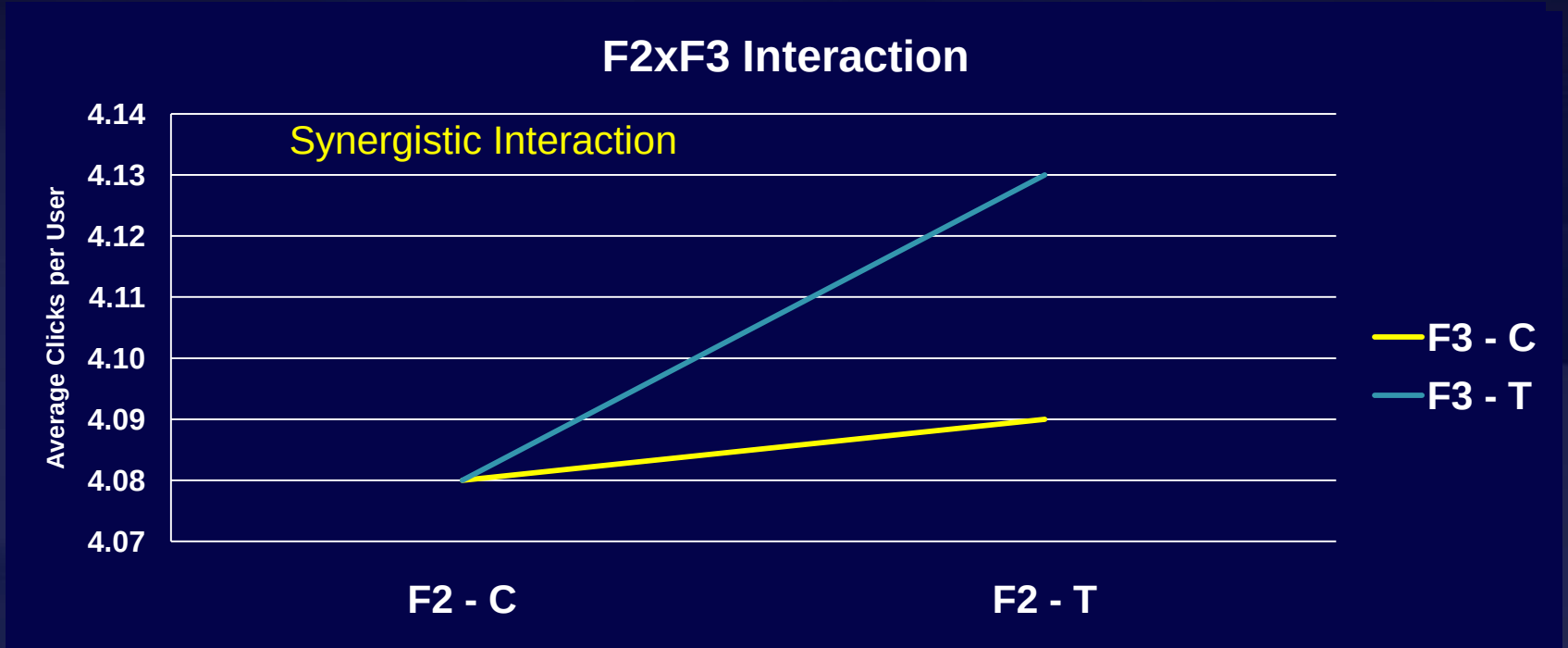
Case 2: Synergistic Interaction

Data Table

	F2 - C	F2 - T
F3 - C	4.08	4.09
F3 - T	4.08	4.13

Main Effects Results

	Pct Effect	p-value
Effect(F2)	0.74%	0.008
Effect(F3)	0.49%	0.032



Graphical Analysis of Interactions

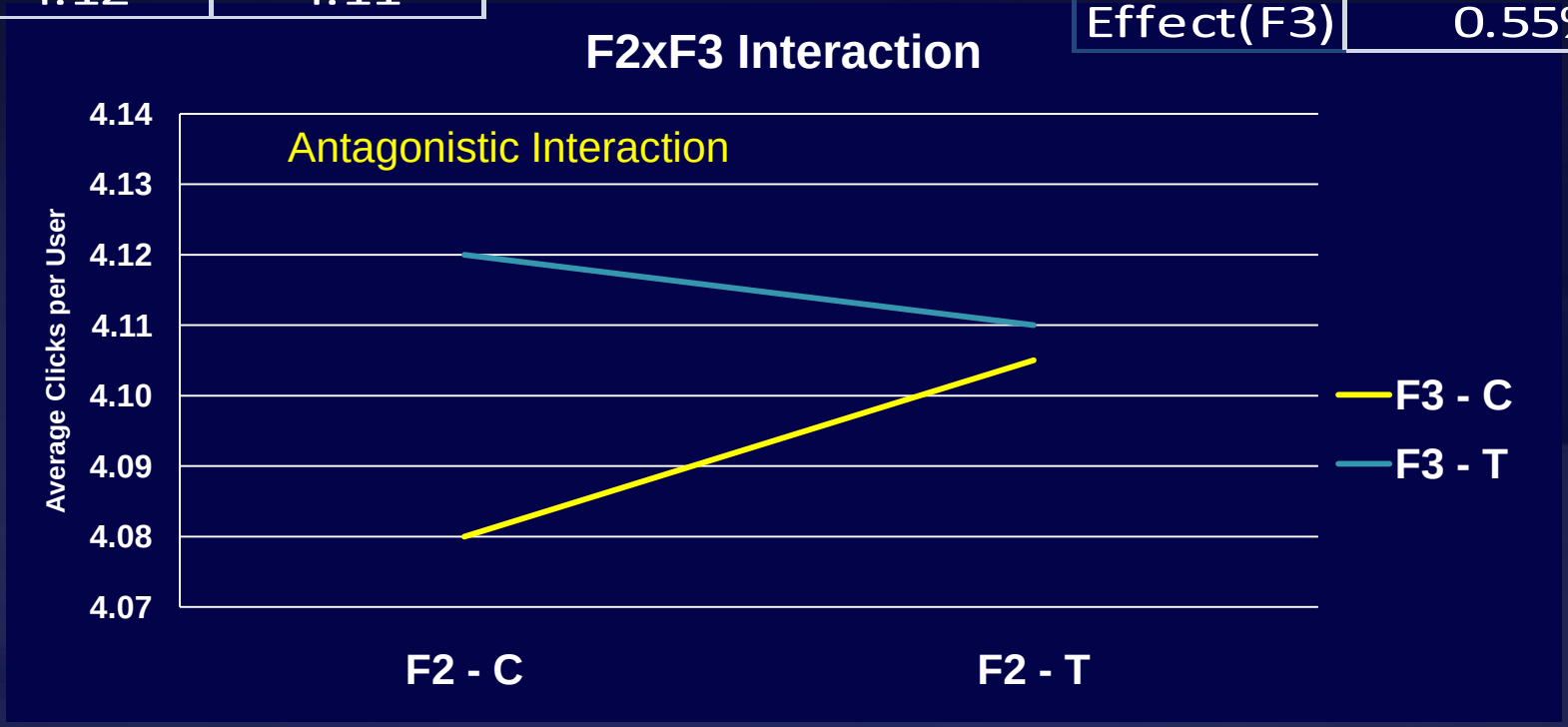
Case 3: Antagonistic Interaction

Data Table

	F2 - C	F2 - T
F3 - C	4.08	4.11
F3 - T	4.12	4.11

Main Effects Results

	Pct Effect	p-value
Effect(F2)	0.18%	0.396
Effect(F3)	0.55%	0.028



Case Study: EVS Experiment

Current Model

- Pre-roll ad played before first content stream
- Don’t disturb users by playing ad when a content stream is playing
- Ad stream played before the content stream when content streams played for more than 180 seconds continuously

Case Study: EVS Experiment (cont.)

Business Questions

- Could removing pro-roll ad stream attract more returning users?
- Could shortening the minimum time between two ad streams attract more returning users?
- Would ad stream gain from returning users offset the loss of not playing pre-roll or playing ad less frequently?

Case Study: EVS Experiment (cont.)

Experiment Design

- Factor 1: Play (Control) or Do Not Play pre-roll
- Factor 2: 5 levels of minimum time between two ad streams
  - 90, 120, 180 (Control), 300, 900 seconds
- Users who received treatments in two week observation window continued to receive treatments and were monitored for the following six weeks for their return rate

Case Study: EVS Experiment (cont.)

Assuming the Overall Evaluation Criterion (OEC) is *Percent of Returning Users*

Vote for result on Factor 1:

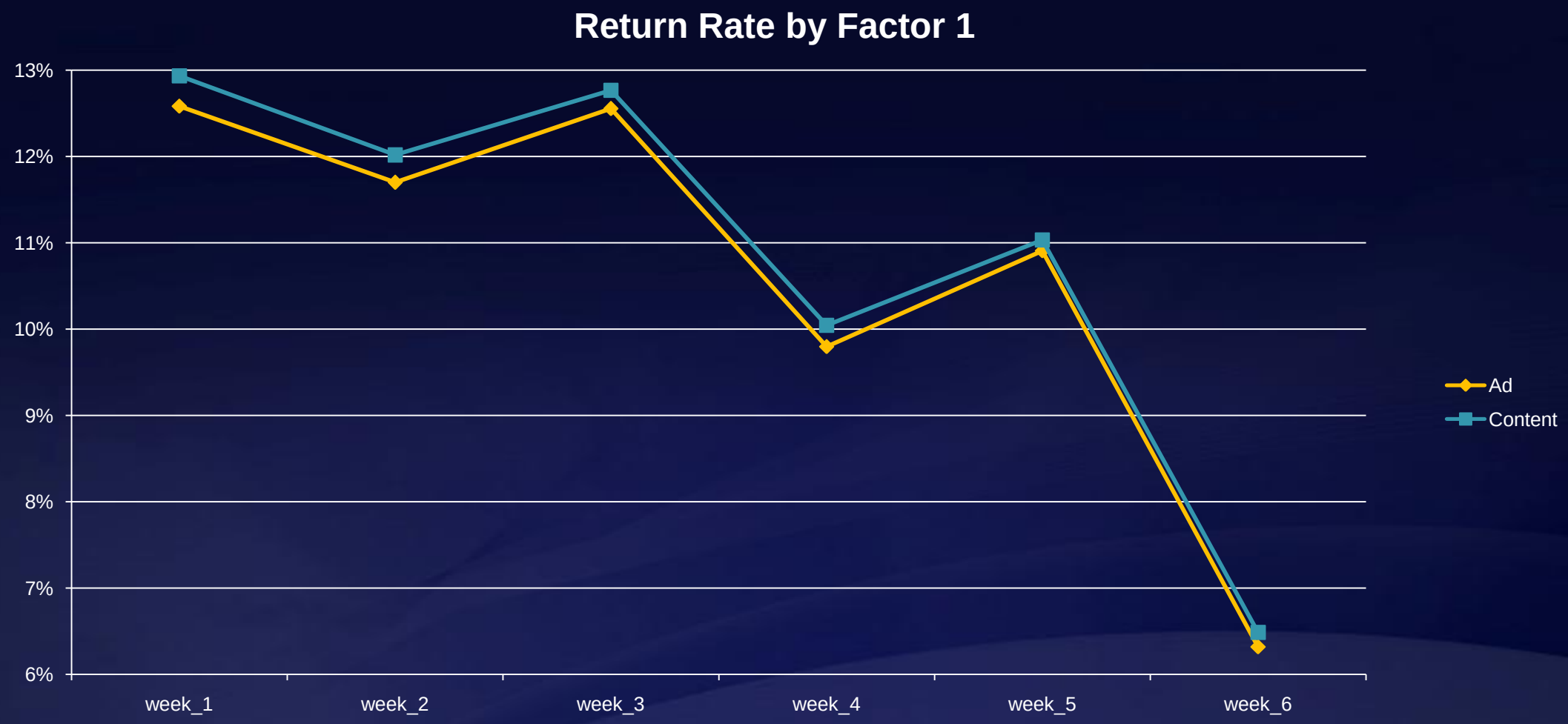
1. Playing pre-roll is statistically significantly better
2. Flat (no statistical difference)
3. Playing pre-roll is statistically significantly worse

Case Study: EVS Experiment (cont.)

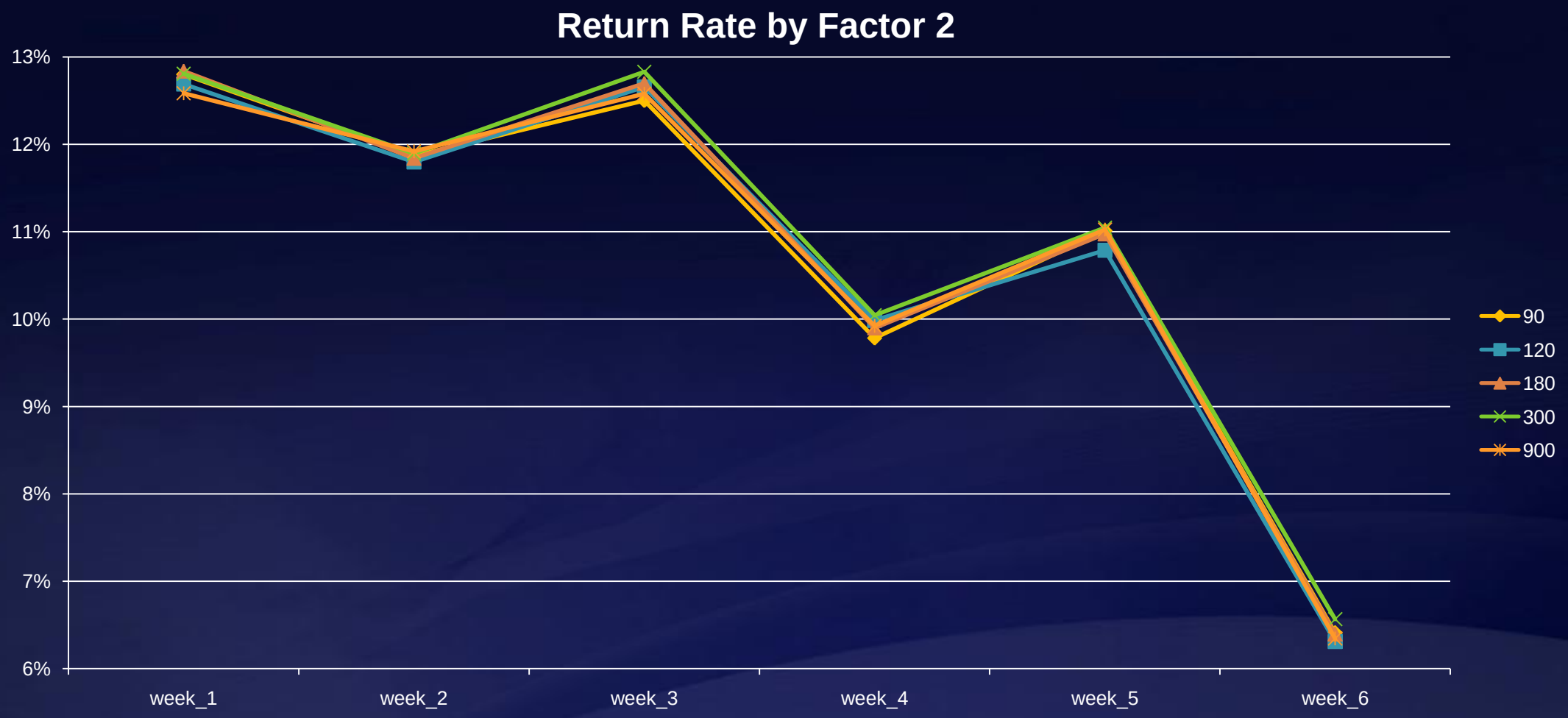
Vote for result on Factor 2: which of the following attract statistically significantly more returning users

1. 90 seconds
2. 120 seconds
3. 180 seconds
4. 300 seconds
5. 900 seconds
6. Flat (no difference)

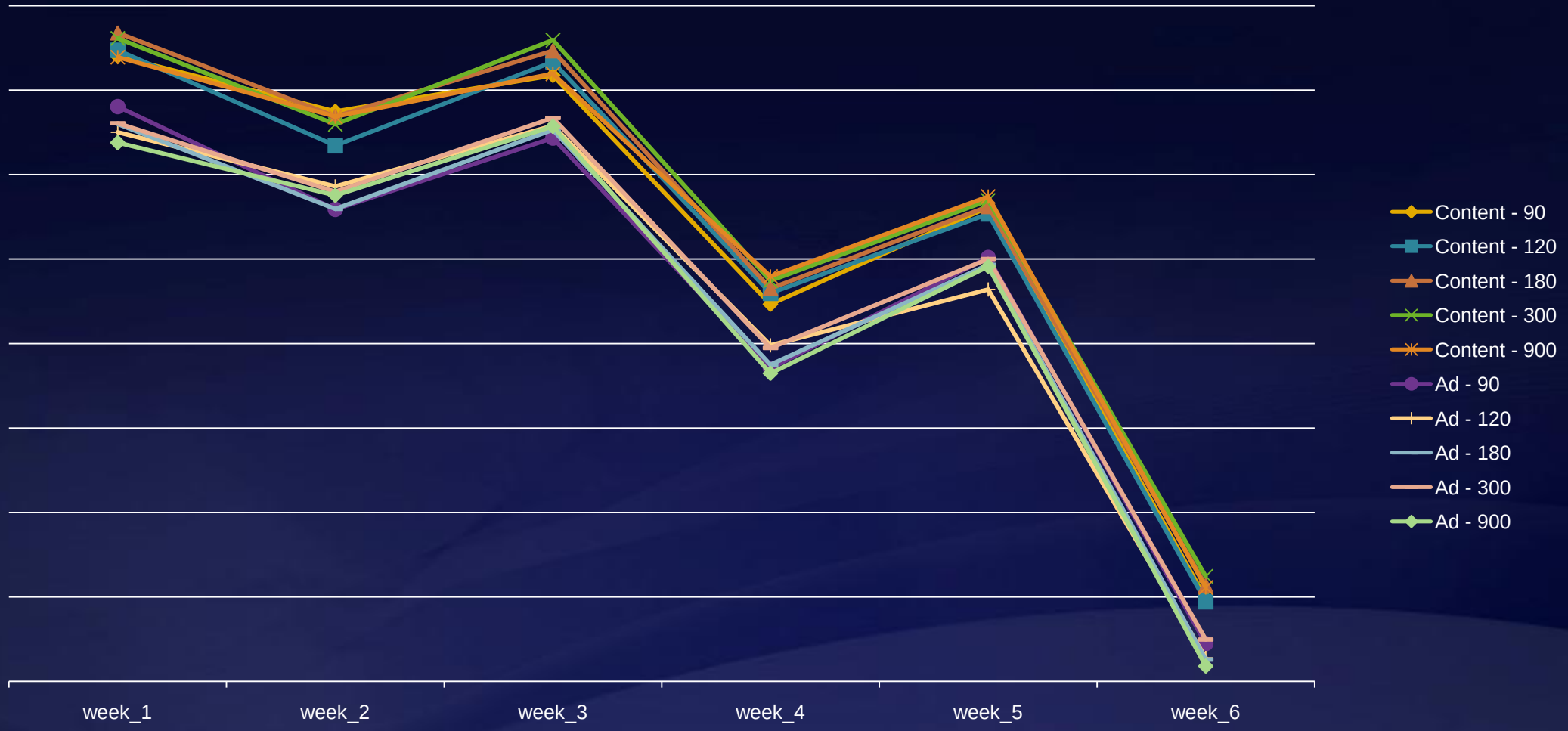
EVS Experiment: Effect on Factor 1



EVS Experiment: Effect on Factor 2



EVS Experiment: Interaction between Factors 1 and 2



Appendix: Challenges and Advanced Statistical Concepts

- Variance calculations for metrics
- Non-parametric alternatives to t-test, ANOVA
- Robot detection
- Automatic detection of interesting population segments
- Experimentation with exploration/exploitation schemes
- Predicting when a metric will be significant

Variance calculations for metrics

- Metrics that are not “per user” currently use bootstrap to estimate variance
  - Can we get a formula to take into account correlation of experimental units?
  - Example: Clickthrough rate (CTR) per experiment

True variance is much larger than that from Binomial distribution

Non-parametric alternatives to t-test, ANOVA

- Permutation or Mann-Whitney tests are natural
- Pros
  - Can get a p-value
  - May have better power for some metrics
  - Works better for small sample sizes
- Cons
  - Understandability by business managers
  - Can be computationally intensive
  - Confidence intervals for effect not straight-forward

Robot filtering

- What is “best” way to develop heuristics to detect robots?
- What is “best” way to assess how well heuristics are doing?
- How to adjust robot detection parameters based on site in the test?

  For example
  - Sites with low traffic may need more aggressive robot filtering
  - Sites that expect active users (e.g. many clicks per hour) need less aggressive robot filtering
  - Sites that have more robot traffic may need more aggressive robot filtering

Automatic detection of interesting population segments

- A population segment is interesting if their response to the Treatment is different from the overall response
- Segments can be defined by a number of variables
  - Browser or operating system
  - Referrer (e.g. from search engine, etc.)
  - Signed-in status
  - Loyalty
  - Demographics
  - Location – country, state, size of city (use IP lookup)
  - Bandwidth

Experimentation with exploration/exploitation schemes

- Want to automatically display best content based on exploration/exploitation strategy
- Is this strategy better than editor-placed content?
- What are the optimal parameter values?
  - Percent in exploration group?
  - How long to test content in exploration group?
  - What level of significance is needed?

Predicting when a metric will be significant

- After experiment has run for some period of time and have estimates of effect and standard deviation can we give a helpful estimate of how long experiment needs to run in order to get a significant result for a particular metric?
  - Statistical philosophical issues
  - Technical issues