Real-time Optimization of Advertising Content

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IADS Big Data and Analytics Summer School
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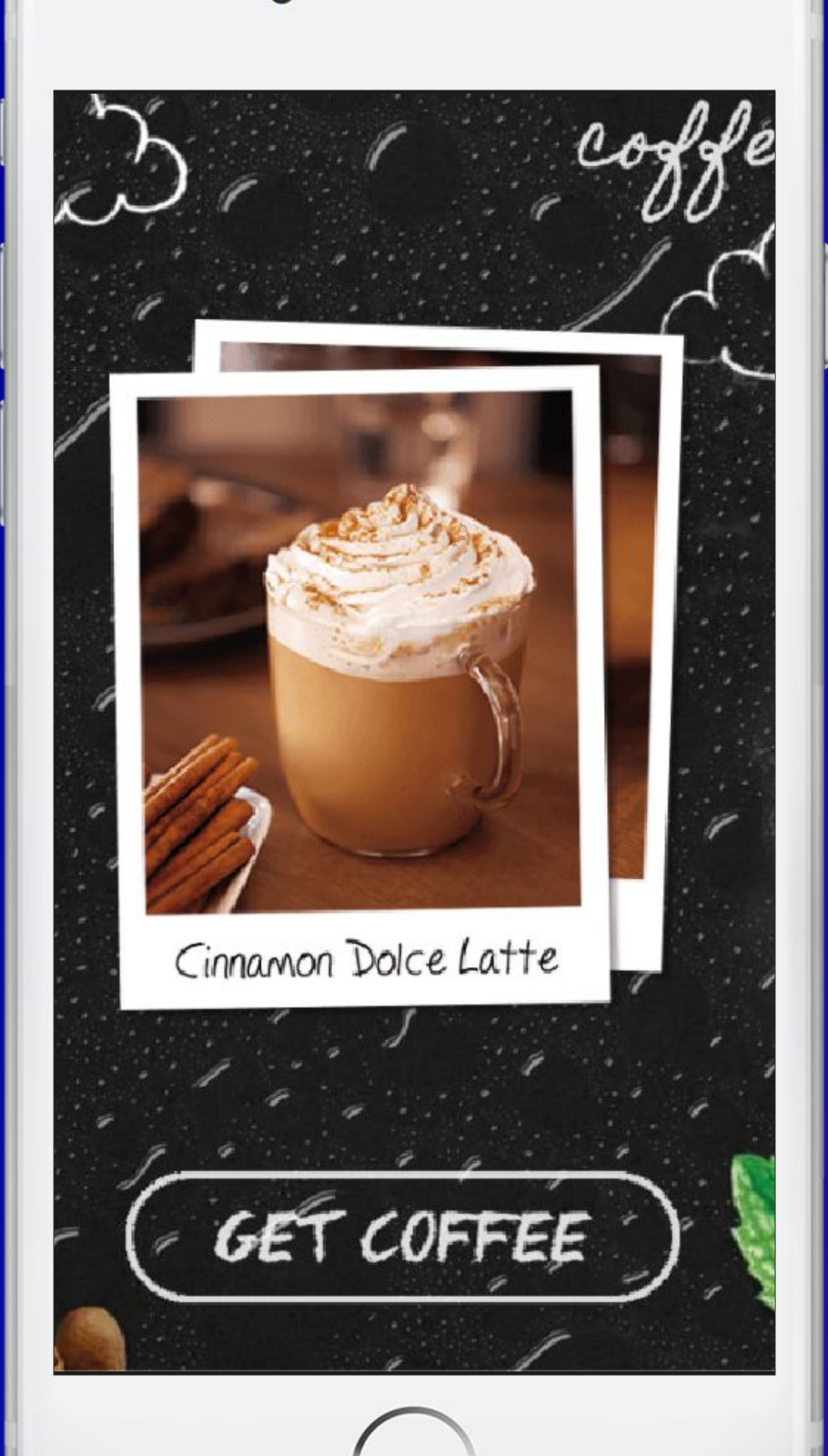
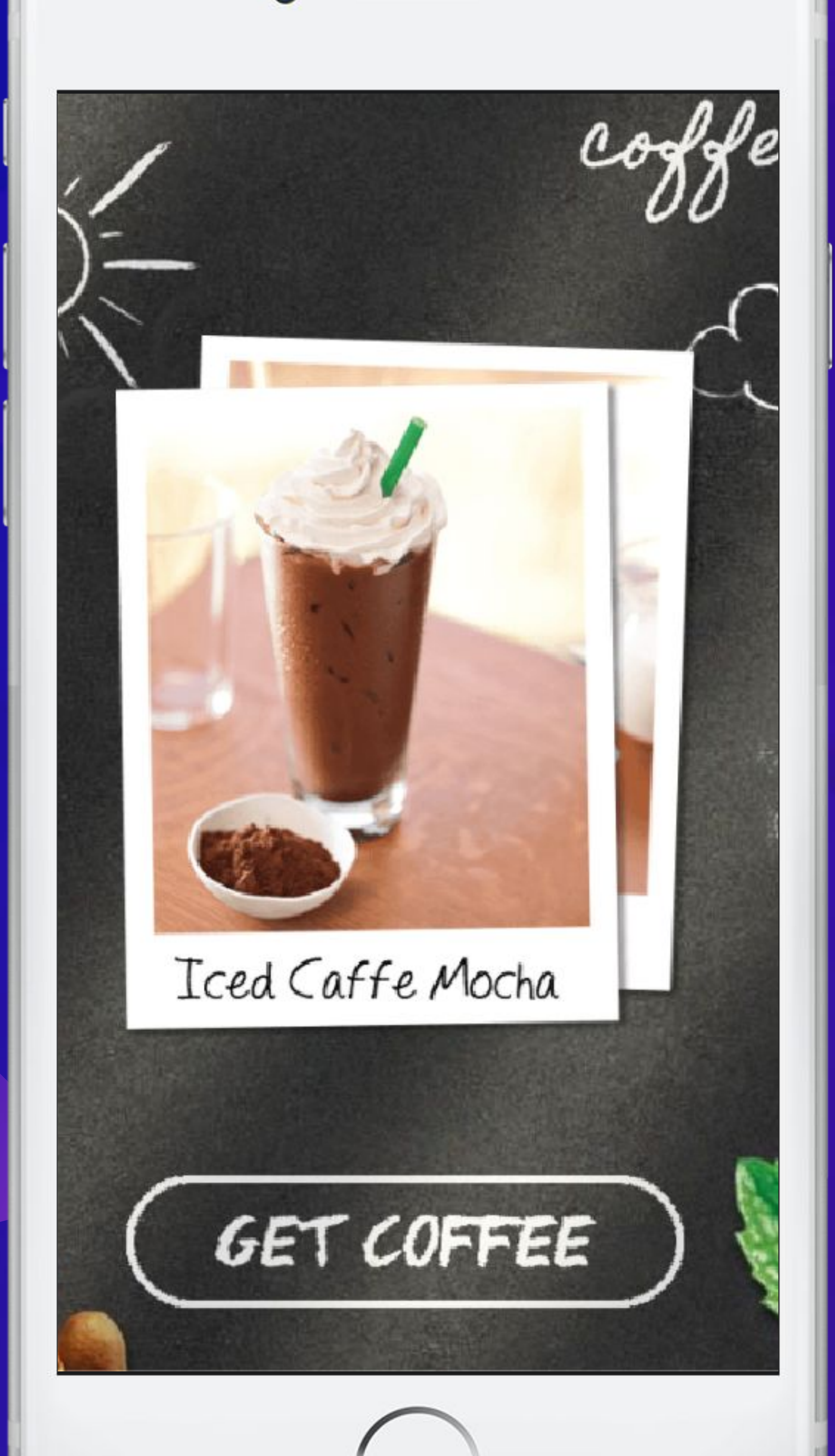

coffee
Cinnamon Dolce Latte
GET COFFEE


coffee
Iced Caffe Mocha
GET COFFEE

Choosing the best variant

Difficult for marketers to predict which variant will perform better

Depends on specific environment

Might change with time

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Possible solution: automated real-time optimization

Business goal

Develop methodology to achieve as **high performance** as possible and **measure it with confidence** to show it to clients.

Project goals

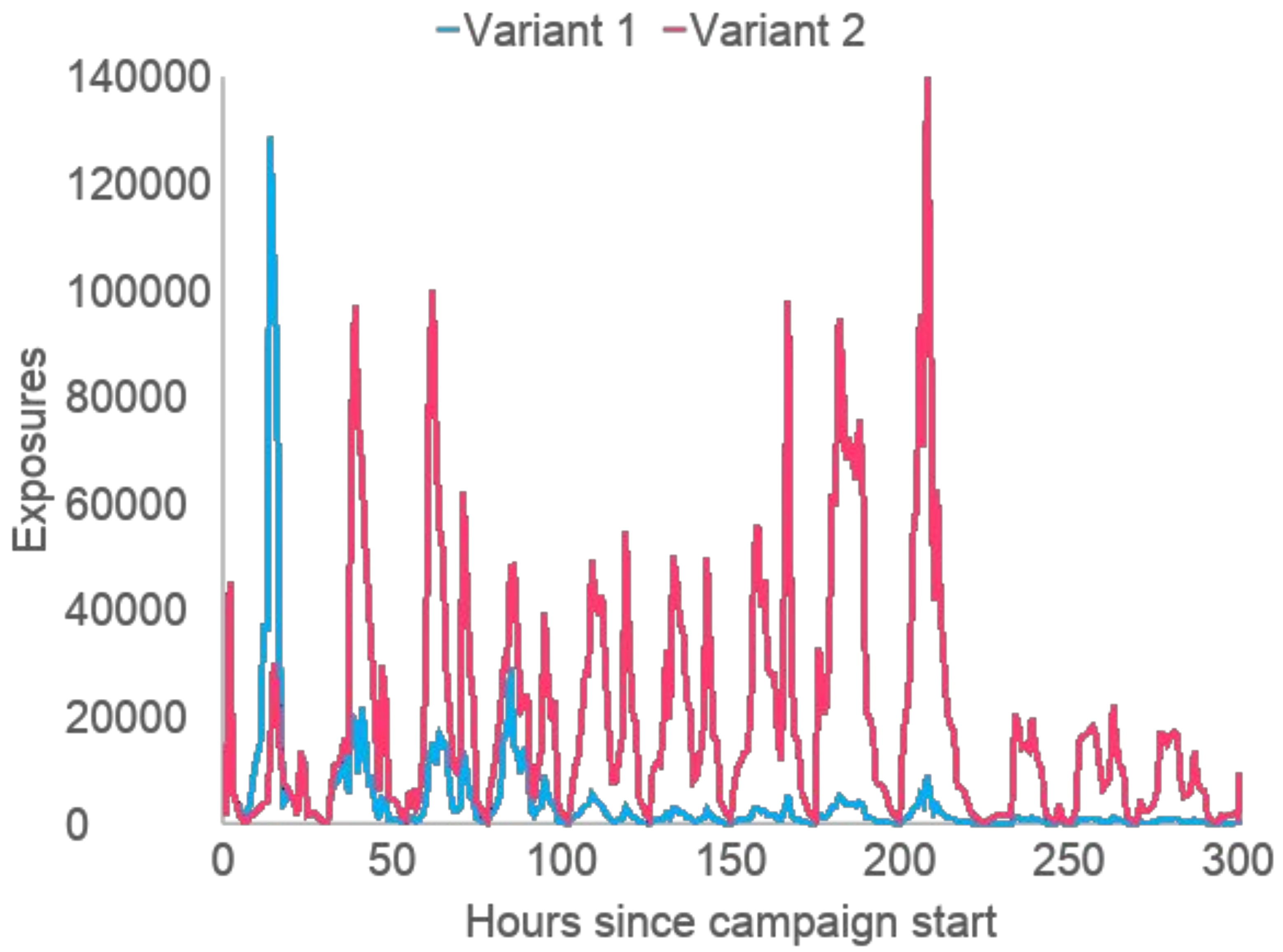
Measure the performance of the DCO system

Estimate theoretical potential of DCO optimization in Celtra campaigns

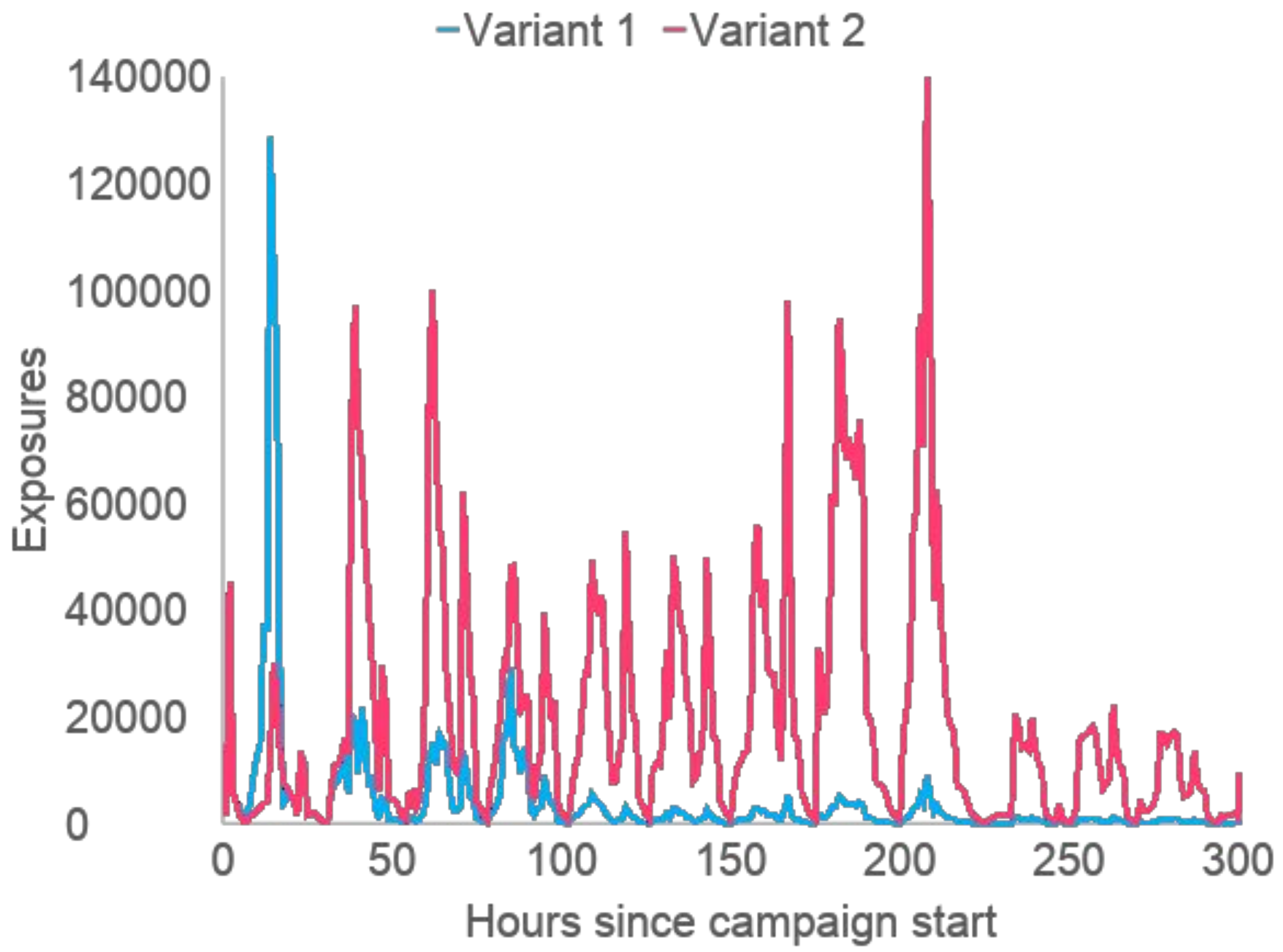
Estimate how much of the theoretical potential can algorithms achieve

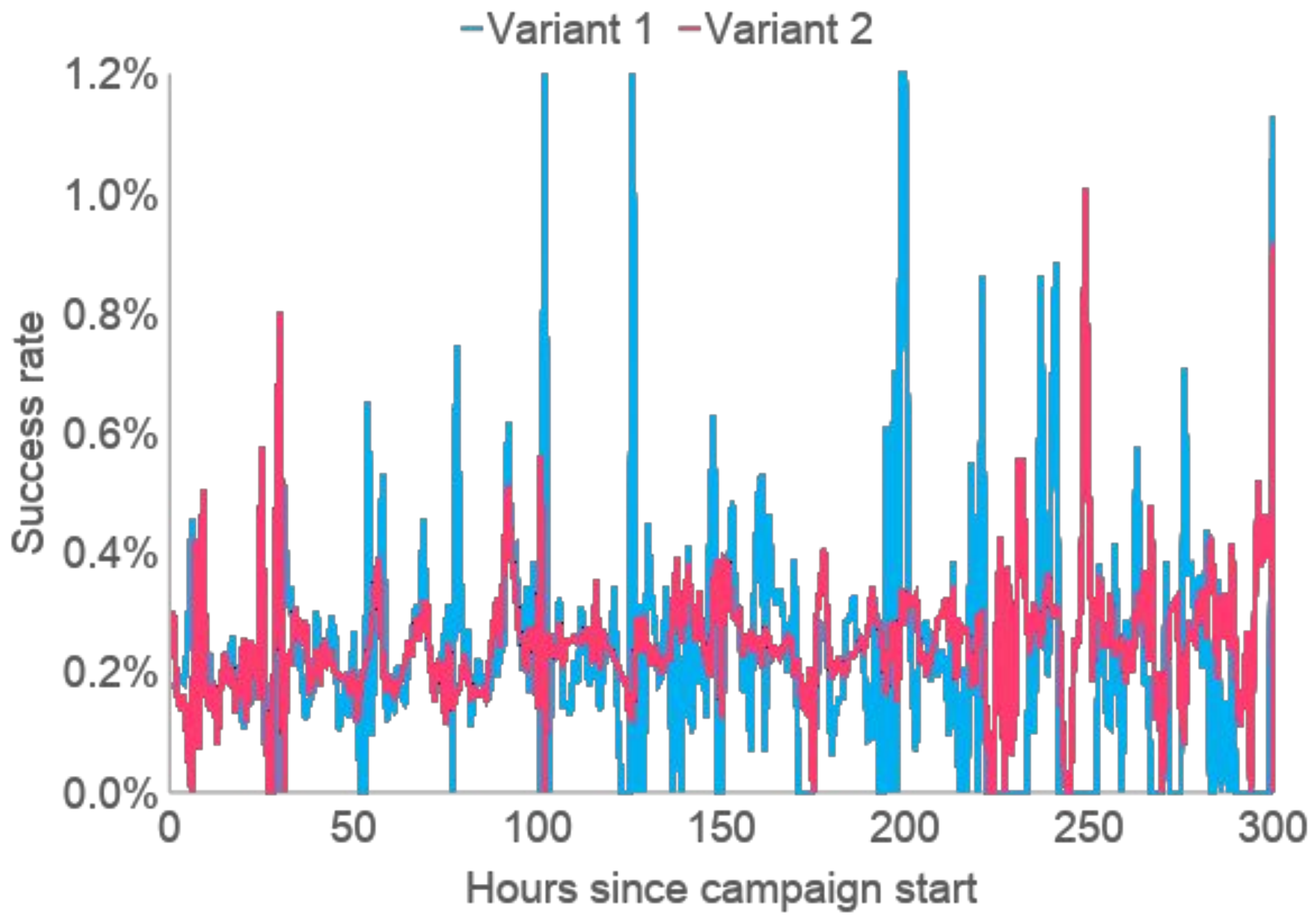
Improve performance of the algorithms = research and develop new ones

An advertising campaign



An advertising campaign





Evaluating the performance

Measure of performance – *lift*

Successes of optimization algorithm / successes of random algorithm

Measure of potential – lift of an *oracle* optimization algorithm

Challenges and solutions

Address the ***exploration-exploitation dilemma*** > bandit algorithms

Solution: ε-greedy, Thompson sampling, UCB algorithms

Real-time optimization causes ***selection bias*** > compute only from unbiased data

Need a control set for unbiased analysis

Solution: Three-set sampling

Challenges and solutions

Technical limitations: feedback **delayed** and in **batches**

Solutions: prediction + simulated feedback

Non-stationarity

Solution: Detection of abrupt changes in trends

Solution: Forgetting

Solution: Two-memory structure

Challenges and solutions

<u>Obtaining samples is expensive</u>

Low success rates - **noisy data**, few samples

Solution: Estimation of confidence bounds (Fieller's theorem)

How to **compare different** algorithms??

Solution: Creation of artificial campaigns as an approximation of real campaigns

Data and experiments

40 real campaigns (= 40 bandit problems)

- Up to 10 variants
- Up to 10 million exposures
- Up to 6 months of duration

Best-case and worst-case sets of artificial campaigns

Multiple repeats on each campaign for each algorithm

Results: potential in campaigns

How much potential is there?

- 26% – 55% of campaigns have at least 5% potential lift
- 18% – 53% of campaigns have at least 10% potential lift
- 18% – 34% of campaigns have at least 20% potential lift

Results: potential in campaigns

How much potential is there?

- 26% – 55% of campaigns have at least 5% potential lift
- 18% – 53% of campaigns have at least 10% potential lift
- 18% – 34% of campaigns have at least 20% potential lift

Roughly one in four campaigns has meaningful potential

Results: efficiency of optimization

In how many campaigns with significant potential can the algorithms achieve at least 5% lift?

Thompson sampling	in 25% – 39% of campaigns
UCB	in 30% – 44% of campaigns

Results: efficiency of optimization

In how many campaigns with significant potential can the algorithms achieve at least 5% lift?

Thompson sampling	in 25% – 39% of campaigns
UCB	in 30% – 44% of campaigns
Augmented Thompson sampling	in 36% – 55% of campaigns
Augmented UCB	in 34% – 59% of campaigns

Results: efficiency of optimization

In how many campaigns with significant potential can the algorithms achieve at least 5% lift?

Thompson sampling	in 25% – 39% of campaigns
UCB	in 30% – 44% of campaigns
Augmented Thompson sampling	in 36% – 55% of campaigns
Augmented UCB	in 34% – 59% of campaigns

The algorithms can exploit roughly half of the potential

Algorithm	Ratio [%] of artificial campaigns with lift above		
	5 %	10 %	20 %
Original TS	39	27	16
+ periodic forgetting	48	32	23
+ two-memory	51	37	29
+ prediction	55	36	30
+ change-point detection	55	36	30

Summary

Metric for performance of content-optimization algorithms

Metric for potential in advertising campaigns

Methodology for measuring algorithm performance

Evaluation of algorithms

Improvements for algorithms

Future and Conclusion

Algorithmic Performance

Dual-layer UCB

Budget-limited bandits

Optimal ratio of three sampling sets

Signal processing and time-series prediction

Campaign Potential

Correlating campaign features to potential (learning what to do to have potential to exploit - and telling it to those who build variants)

References

Our conference paper: Vodopivec et al., Real-time Content Optimization in Digital Advertisement, 2017

Fieller's theorem: Fieller, Some Problems in Interval Estimation, 1954

Variance and covariance estimation: Moineddin et al., On the Location Quotient Confidence Interval, 2003

Two-set sampling (un-biasing the data): Xu et al., Estimation Bias in Multi-Armed Bandit Algorithms for Search Advertising, 2013

Bandit algorithms: Kuleshov and Precup, Algorithms for multi-armed bandit problems, 2014

Change detection methods: Sebastiao and Gama, A study on change detection methods, 2009

Budget-limited multi-armed bandit algorithms: Tran-Thanh et al., Knapsack based optimal policies for budget-limited multi-armed bandits, 2012