

# StoreIQ

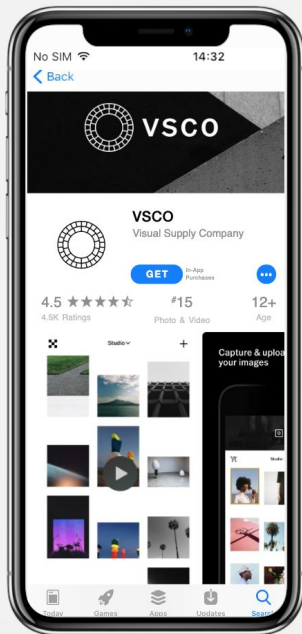
The Multi-Armed Bandit  
for App Store Optimization

# Introduction

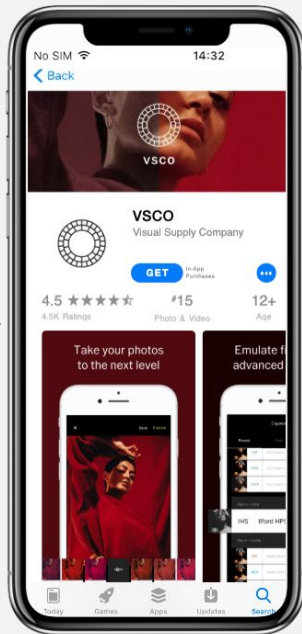
100% of users pass through the App Store essentially making it your new “homepage” and impacting your business success.

# Introduction

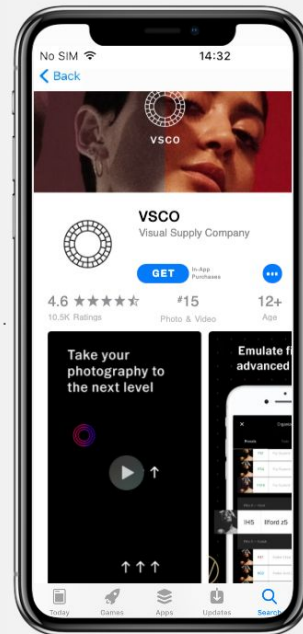
A



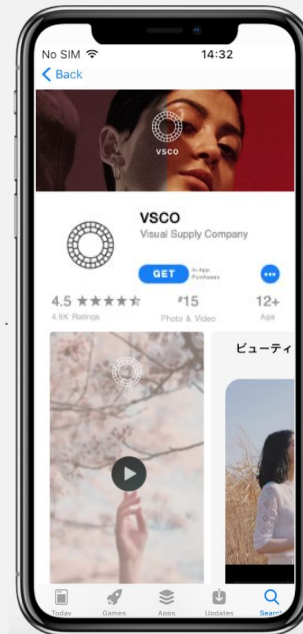
B



C



D



# Goal

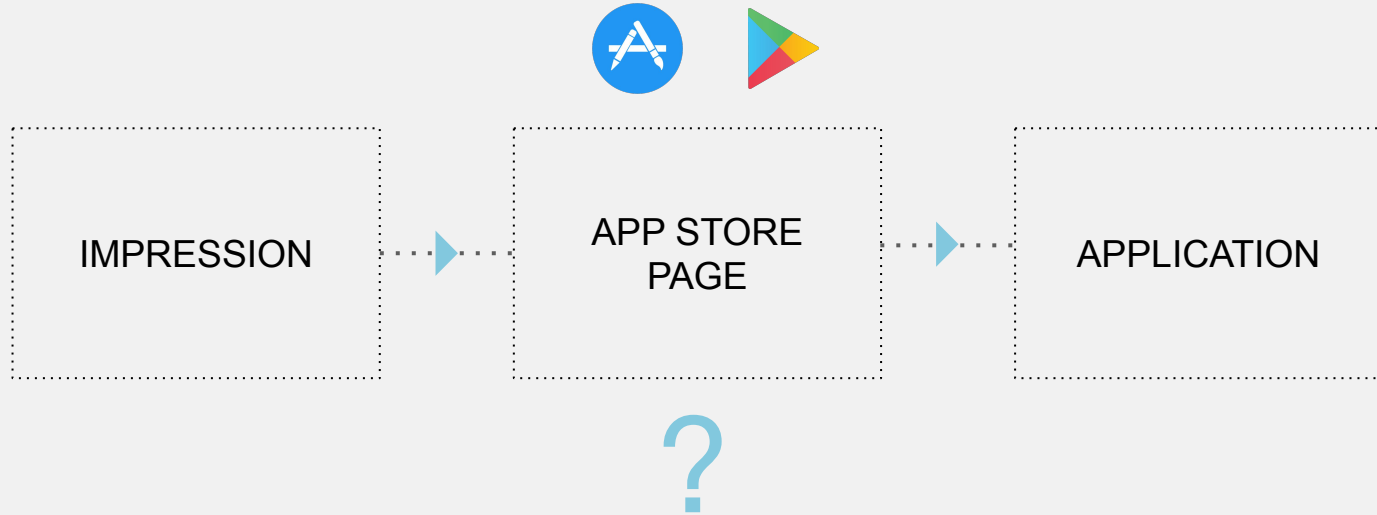
Conversion Rate



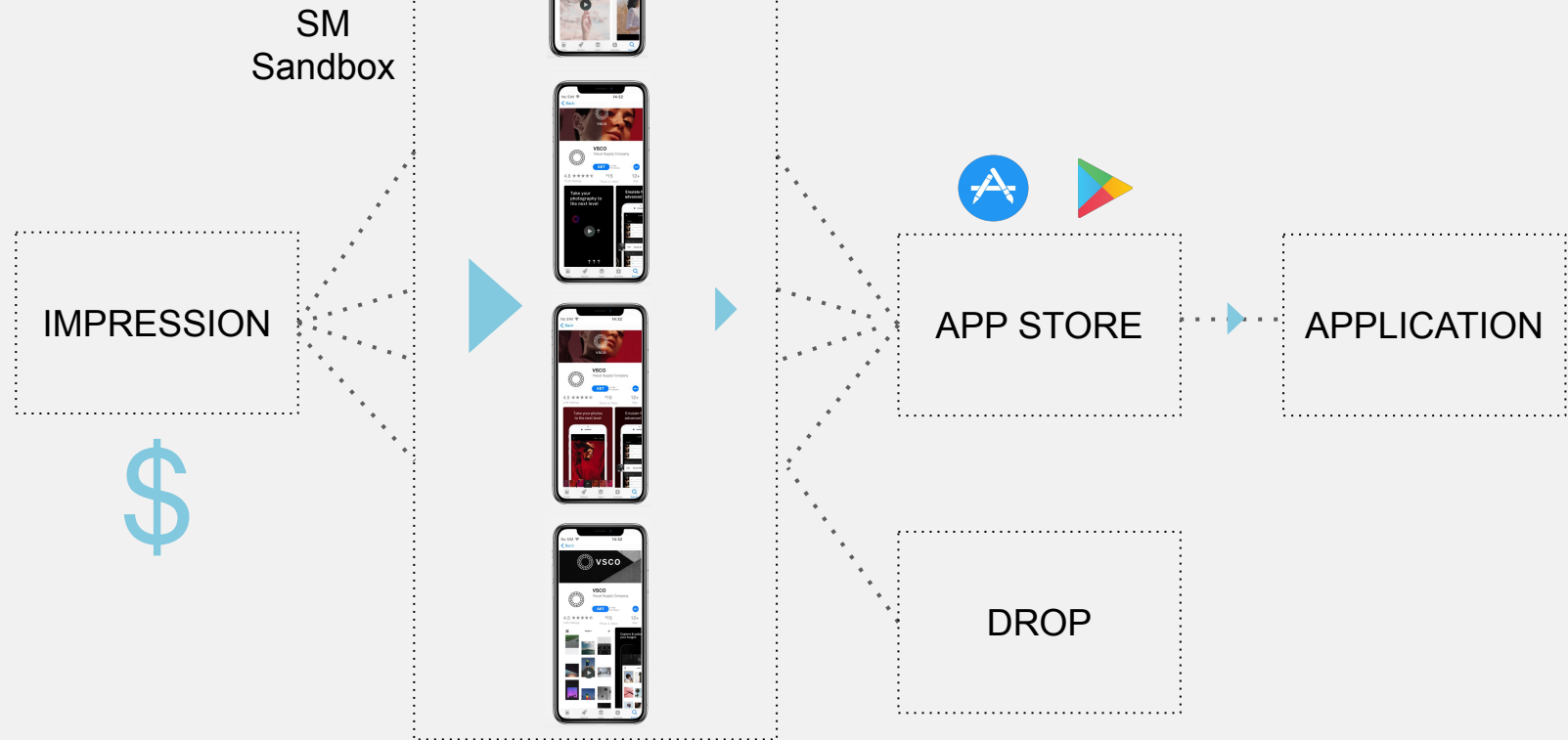
Cost Per Install



# App Installation Flow

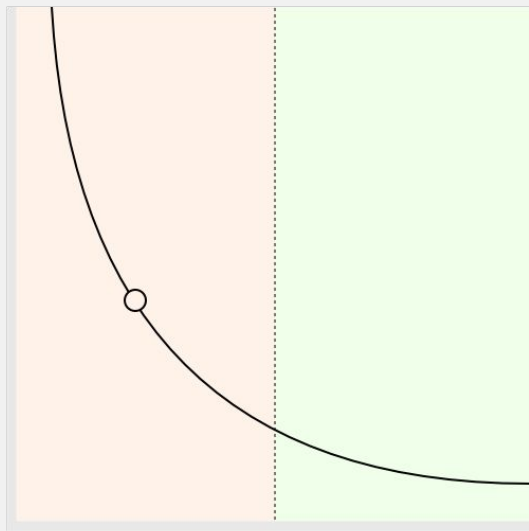


# StoreMaven



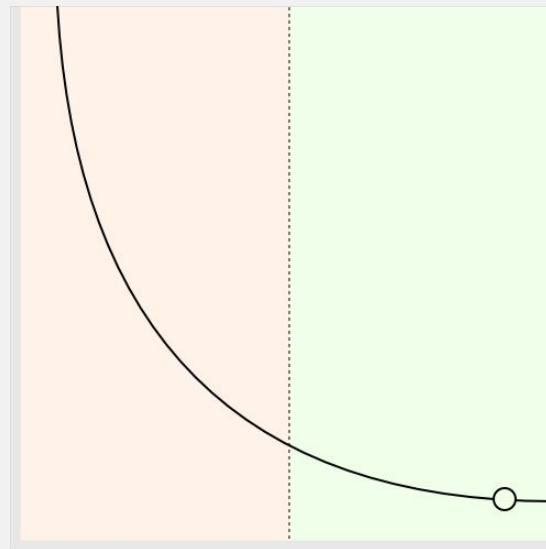
# StoreMaven

Cost Per Insight



Market Size

Cost Per Insight



Market Size

# The Challenge

Minimize the cost per insight  
without compromising accuracy



# Today's Talk

- |   |   |
|---|---|
| 1 | Why not Proportion Testing ?                        |
| 2 | Multi-Armed Bandit – consideration & rejection      |
| 3 | Cracking our business challenge with <b>StoreIQ</b> |
| 4 | Q & A   |
|   |   |

# Proportion Testing – Why not ?

**High cost per experiment:** collecting large number of samples to achieve statistical validity in classical A/B test

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**Multiple Hypotheses problem:** test that  $H_0: P_i = P_j, i \neq j$  when there are more than 2 variations, significance is 'harder' to reach

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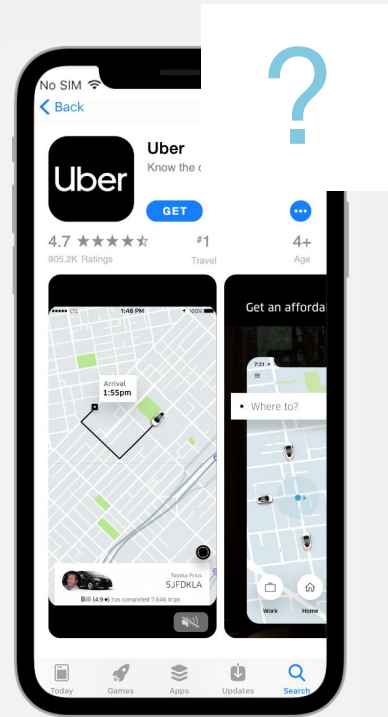
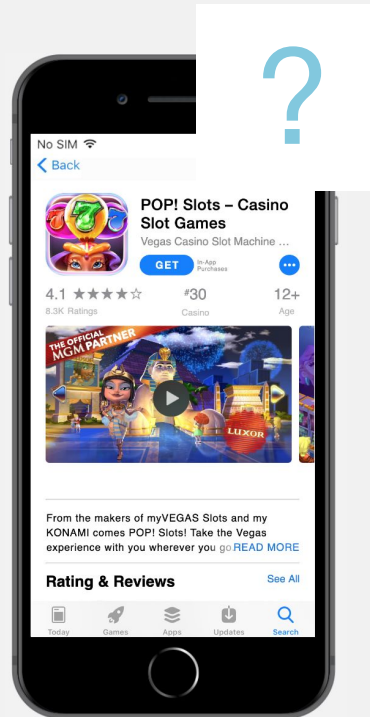
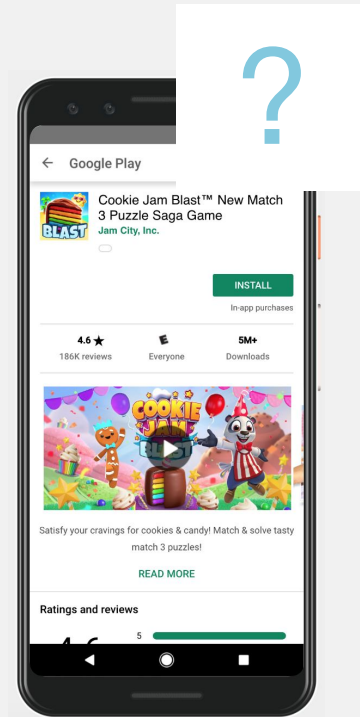
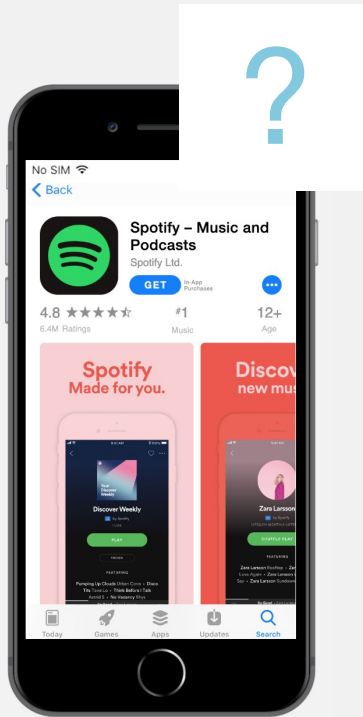
**Accuracy issue:** assumes all observations are IID (Independent Identical Distribution)

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**Robust experimental design** is barely achievable pre-test though crucial for valid frequentist setting in the dynamic ASO ecosystem

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# How?



# Multi-Armed Bandit

Exploitation vs Exploration dilemma

Bandits try to balance the trade-off to maximize total rewards

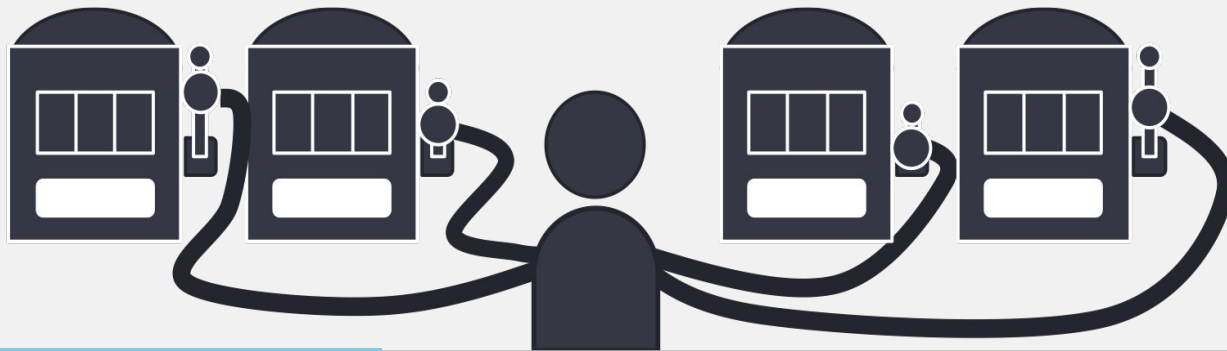
$$R_T = \sum_{t=1}^T (P^* - P A_{(t)})$$

\$2/5 = \$0.40

\$1/3 = \$0.33

\$3/5 = \$0.60

\$2/4 = \$0.50



# Multi-Armed Bandit – Why Not?

Experiments are conducted in our ‘sandbox’ testing environment, no real-time optimizations are done (our regret is defined differently)

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Doesn't necessarily reduce the cost of testing. Usually it is not a testing model it is an optimization method

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Many ways to determine a definitive winner and conclude the experiment

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# StoreIQ



## Backed by

4 years of Mobile App Stores user engagement events

More than 3 billion data points

Hundreds of millions of unique mobile users examined

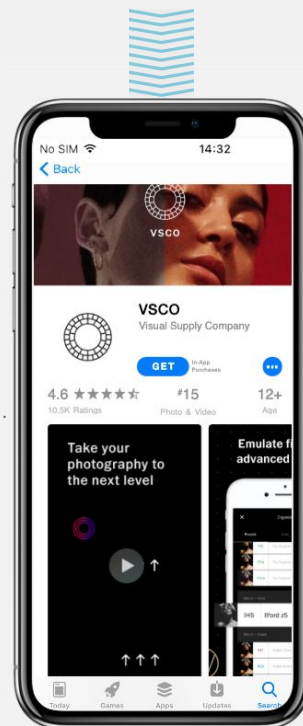
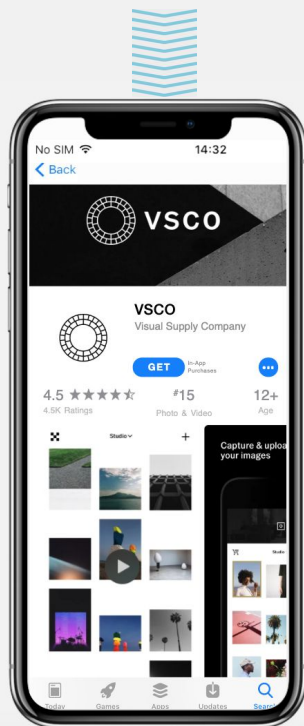
20+ GEOs around the world

## Bayesian approach

We use prior knowledge when calculating statistics

Bayes provides starting point from which we update our knowledge





Each experiment starts with a warm-up period in which the algorithm gathers initial information on the competing variations

Defining **warm-up thresholds**:

**T**; days of traffic (to control for the time of day)

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**O**; minimum observations per variation (users who started a session within the page)

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**C**; minimum conversions per variation (user who clicked through / installed)

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**Prior** knowledge is comprised of:

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Learning the daily volatility of the traffic per variation

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Learning weights per traffic sources & app categories

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Learning 'high quality' user behaviour using app's experiments history

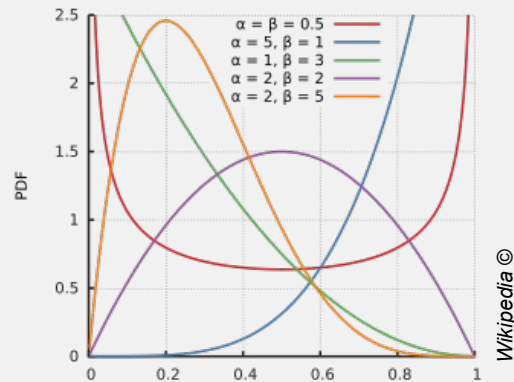
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# StoreIQ

StoreIQ uses beta distribution to model its belief regarding competing variant conversion rates

The beta distribution is a suitable model for the random behavior of percentages and proportions.

The beta distribution is the conjugate prior probability distribution for the Bernoulli distribution



*IF  $CVR \sim \text{Beta}(\alpha, \beta)$   
THEN  $CVR \in [0, 1]$*

*Round 1 :*

$$x \sim \text{Bernoulli}(\theta) \quad \text{IID} \\ x \in \{0, 1\}$$

$X$  – vector of  $x$

$$f_{\theta} = ? \\ \theta = ?$$

In round 1, our prior is a derivation of the Beta distribution and is not dependent on the posterior  $a, b$

$$f_{\theta|X} \propto L(X|\theta) \cdot \text{prior} = \theta^{\sum x} \cdot (1 - \theta)^{N - \sum x} \cdot \text{prior} \\ \sim \\ \text{Beta}(\sum x + 1, N - \sum x + 1)$$

*Round 2:*

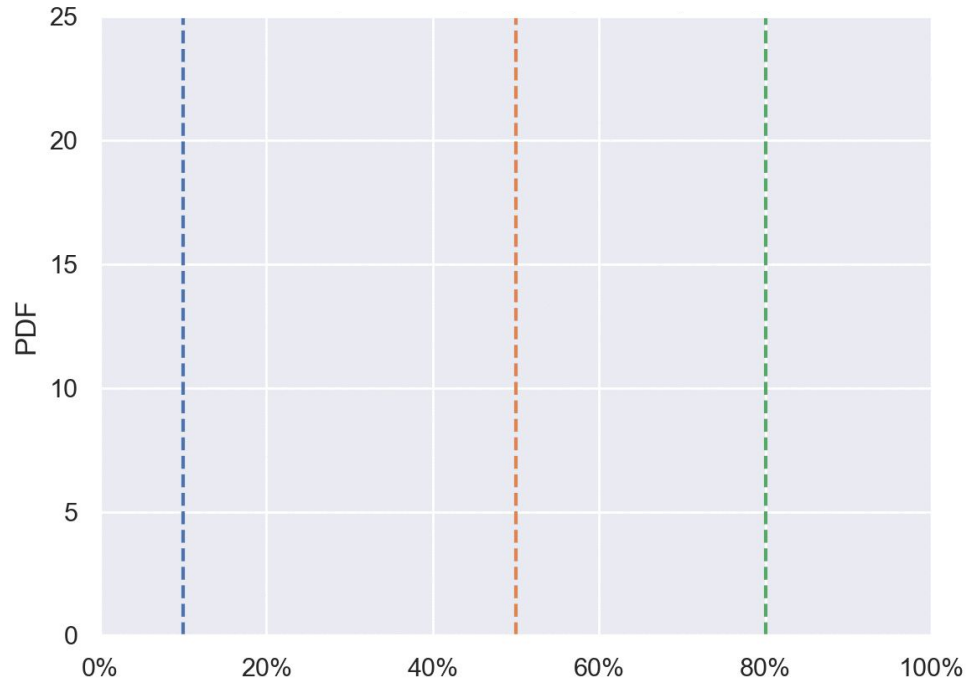
$$y \sim \text{Bernoulli}(\theta) \quad \text{IID} \\ y \in \{0, 1\}$$

$X$  – vector of  $y$

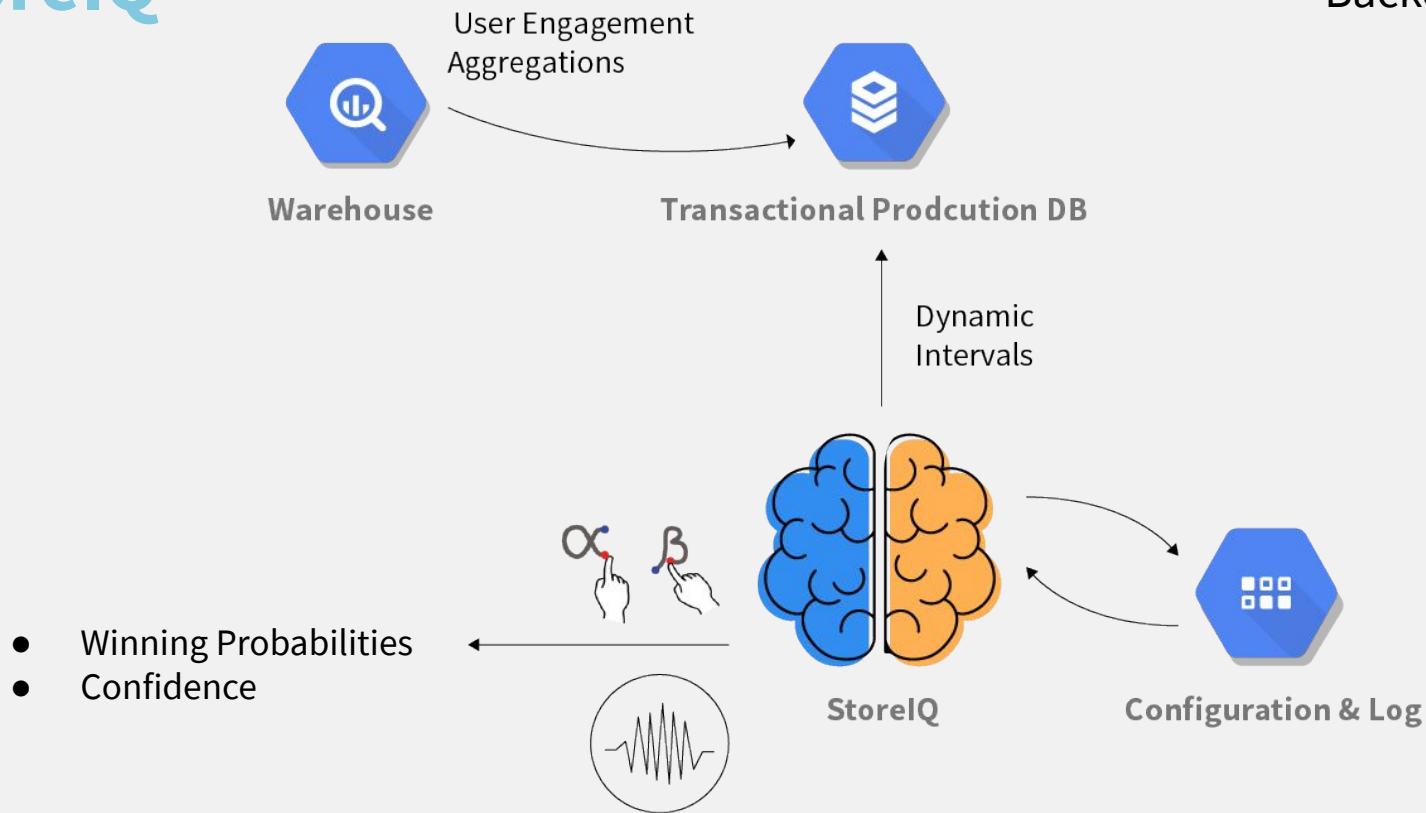
$$f_{\theta} = ? \\ \theta = ?$$

$$f_{\theta|X} \propto L(X|\theta) \cdot \text{prior} = \theta^{\sum x + \sum y} \cdot (1 - \theta)^{M+N - \sum x - \sum y} \cdot \text{prior} \\ \sim \\ \text{Beta}(\sum x + \sum y + 1, M + N - \sum x + \sum y - + 1)$$

# StoreIQ

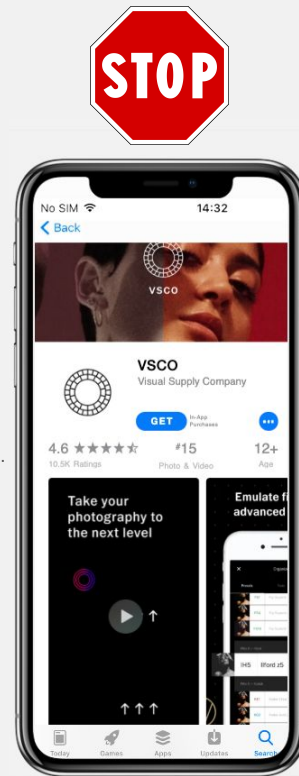
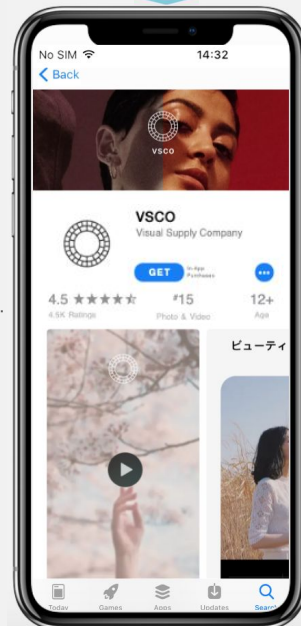
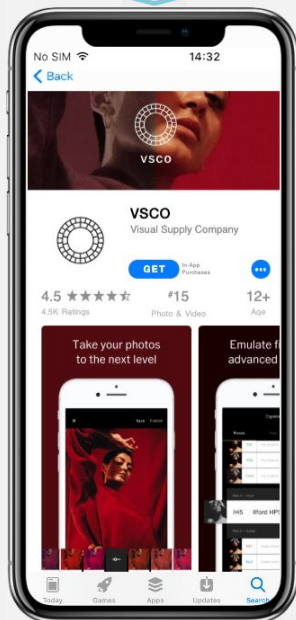
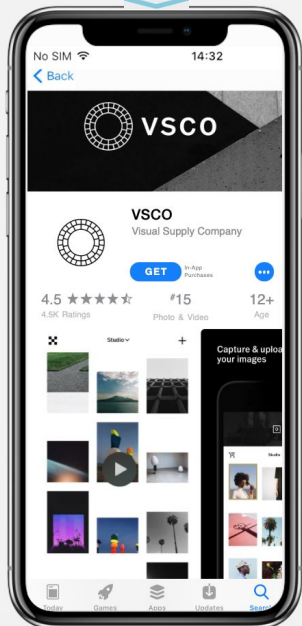


Spotx.tv ©



Iteration	Variation 1	Variation 2	Variation 3	Variation 4
1	0.251654	0.201544	0.4481	0.1043
2	0.355897	0.353784	0.156574	0.13
3	0.484654	0.5464651	0.564546	0.234
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
N	0.3684615	0.2654684	0.68474	0.1593
<b>Winning Probabilities</b>	0.122	0.0005	0.8745 (Leader!)	0.003

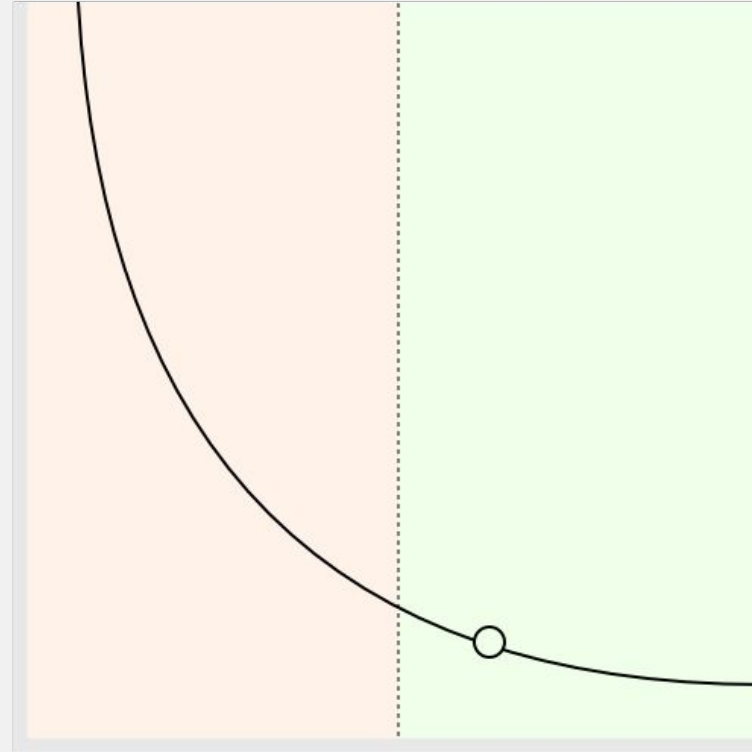
# StoreIQ





# StoreIQ

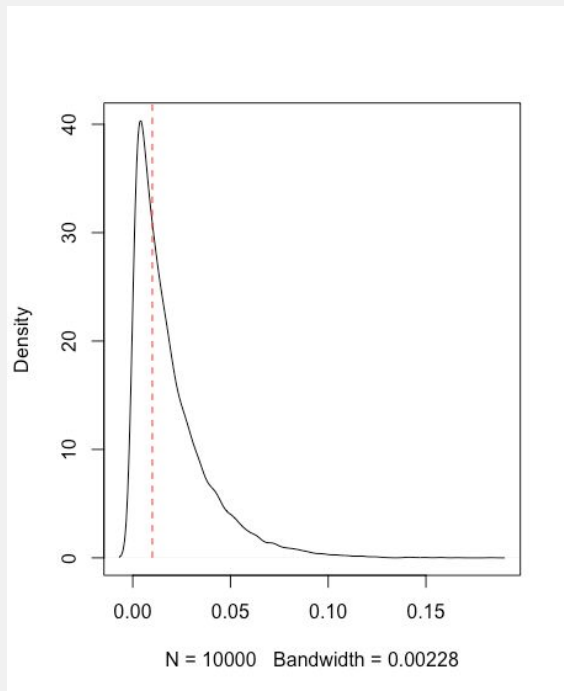
Cost Per Insight



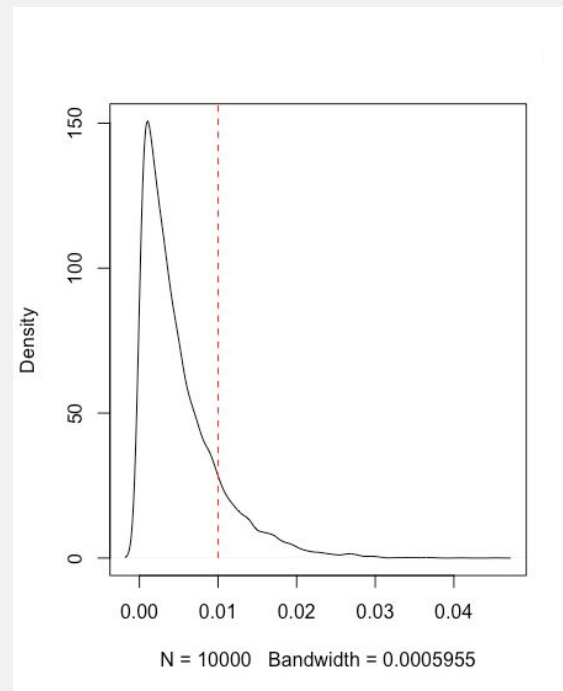
Market Size

Iteration	Variation 1	Variation 2	Variation 3 - Current Leader	Lift function of iteration - Winner from Leader	Lift below threshold
1	0.251654	0.201544	0.5481	0	1
2	0.355897	0.354884	0.33566	0.06029	0
3	0.484654	0.5464651	0.564546	0	1
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
N	0.4684615	0.2654684	0.68474	0	1
<b>Confidence</b>	-	-	-	-	<b>0.95</b>

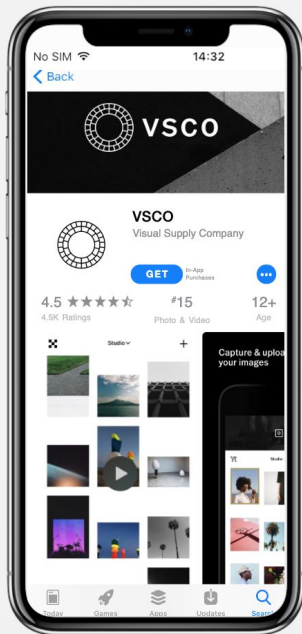
Low confidence



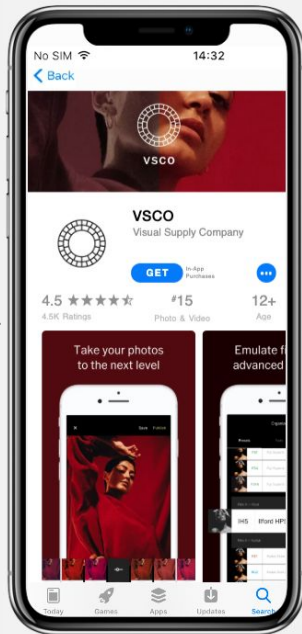
High confidence



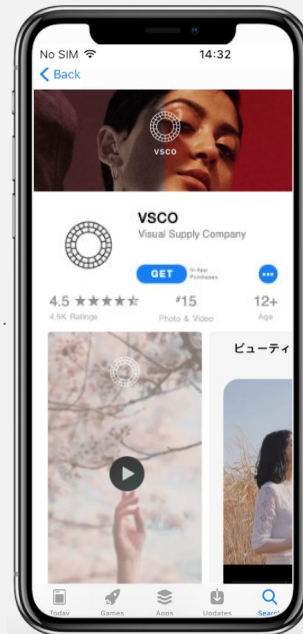
A



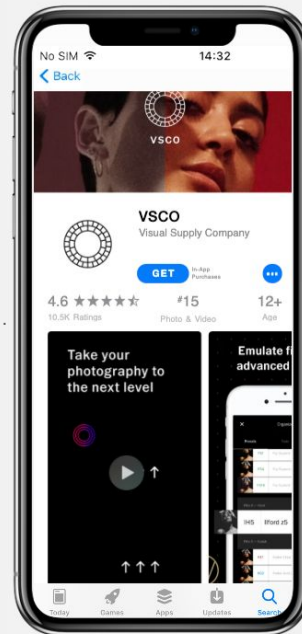
B



C - Winner!



D



# StoreIQ Booster – Bagging Trees (RF)

Train Dataset = user behavior from **app's** experiment history + user activity from a live experiments interval 0 to t-1

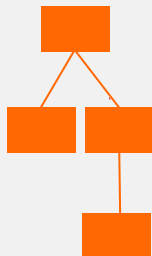
Subset  
A



Subset  
B



Subset  
C



>

C1 = Compute the correlation between **predicted** and **empirical** CVR per variation

C2 = Compute the correlation between the per store CVR of the explorers and non-explorers

C3 = Compute the accuracy of the current model on Test Dataset (users from interval t in a live experiment)

Boost = baseline + (# of boosts given so far \*  $\epsilon$ )

✓

Result = a model that predicts for a given user whether he will **Install** or **not**

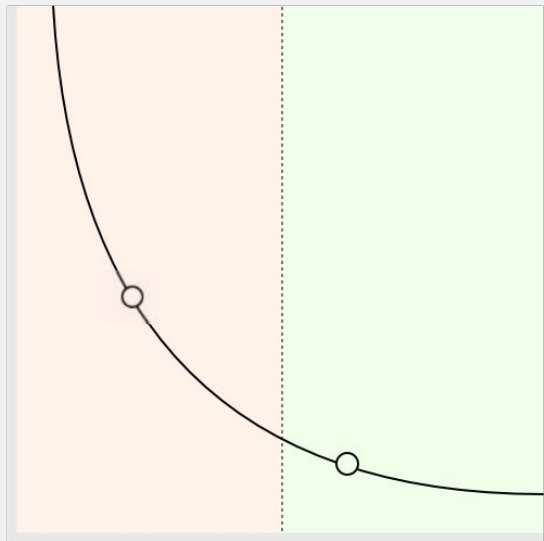
If ( $C3 \geq \text{accuracyThreshold}$  and  $C1 * C2 \geq \text{correlationThreshold}$ ):

observationsToAdd\_i = round( $w_i * C3 * C2 * C1 * \text{boost} * N$ )

conversionsToAdd\_i = round( $\text{cvr}_i * \text{observationsToAdd}_i$ )

# StoreIQ – Boosting

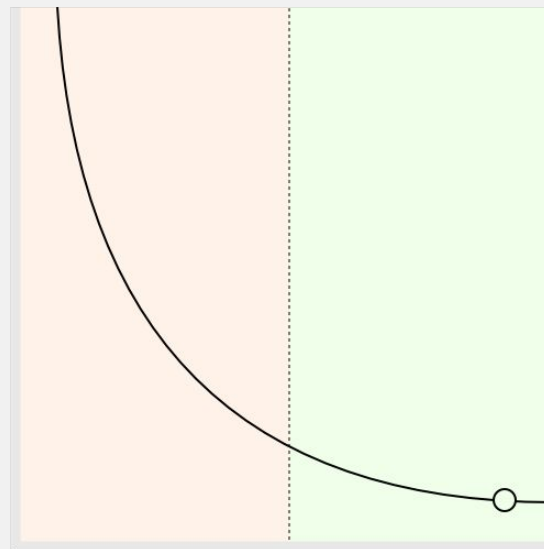
Cost Per Insight



Market Size



Cost Per Insight



Market Size

Q & A

**Thank You!**

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