teads
Elevated Outcomes

Prediction model improvement in Adtech

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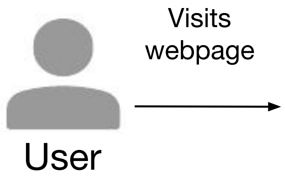
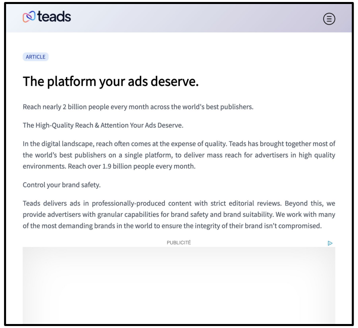
Context

Prediction Model in AdTech

User

Prediction Model in AdTech




The platform your ads deserve.

Reach nearly 2 billion people every month across the world's best publishers.

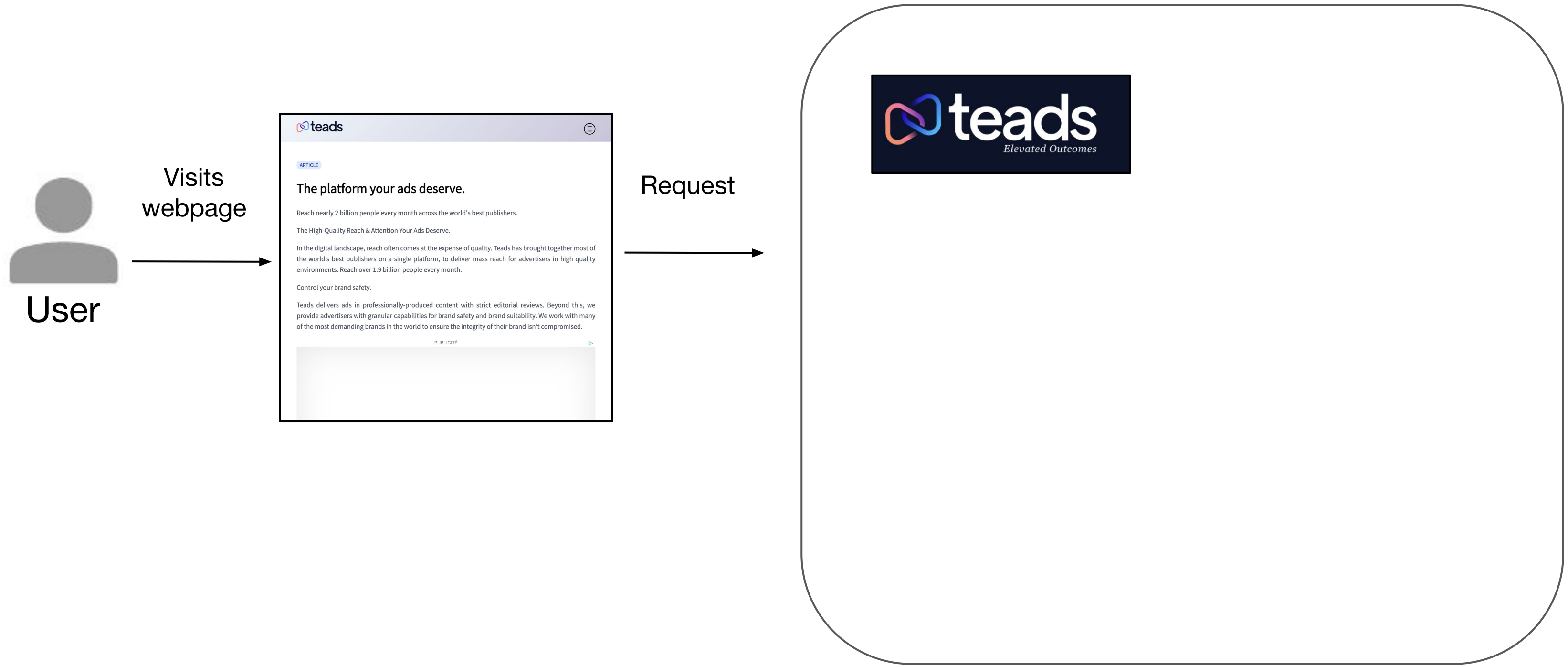
The High-Quality Reach & Attention Your Ads Deserve.

In the digital landscape, reach often comes at the expense of quality. Teads has brought together most of the world's best publishers on a single platform, to deliver mass reach for advertisers in high quality environments. Reach over 1.9 billion people every month.

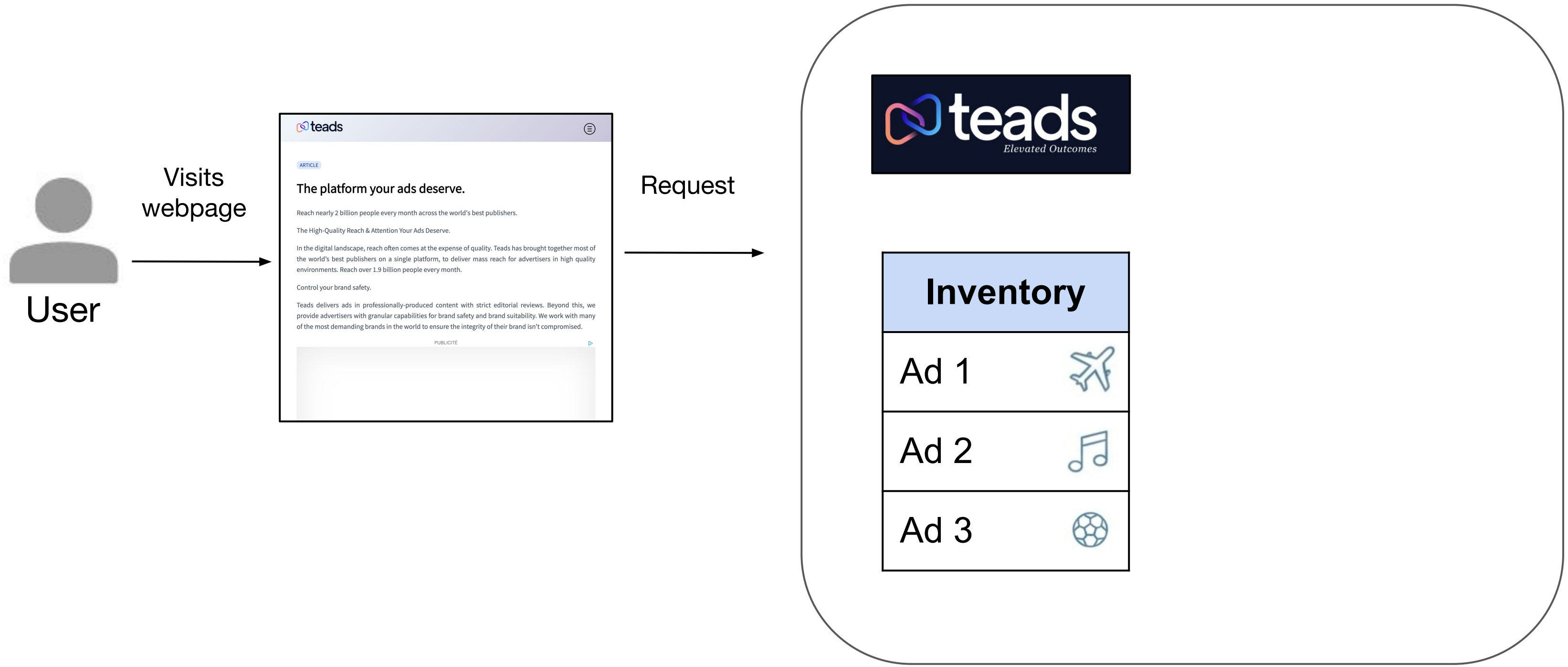
Control your brand safety.

Teads delivers ads in professionally-produced content with strict editorial reviews. Beyond this, we provide advertisers with granular capabilities for brand safety and brand suitability. We work with many of the most demanding brands in the world to ensure the integrity of their brand isn't compromised.

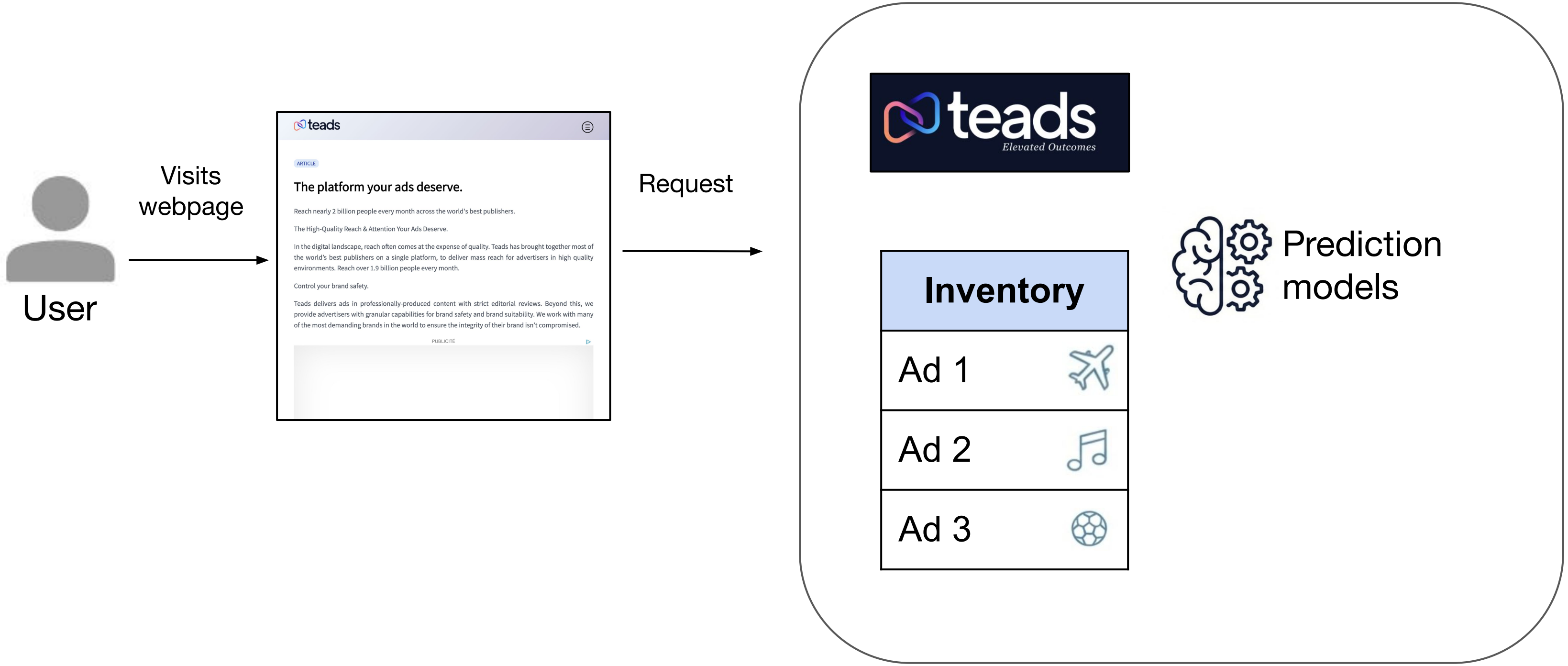
Prediction Model in AdTech



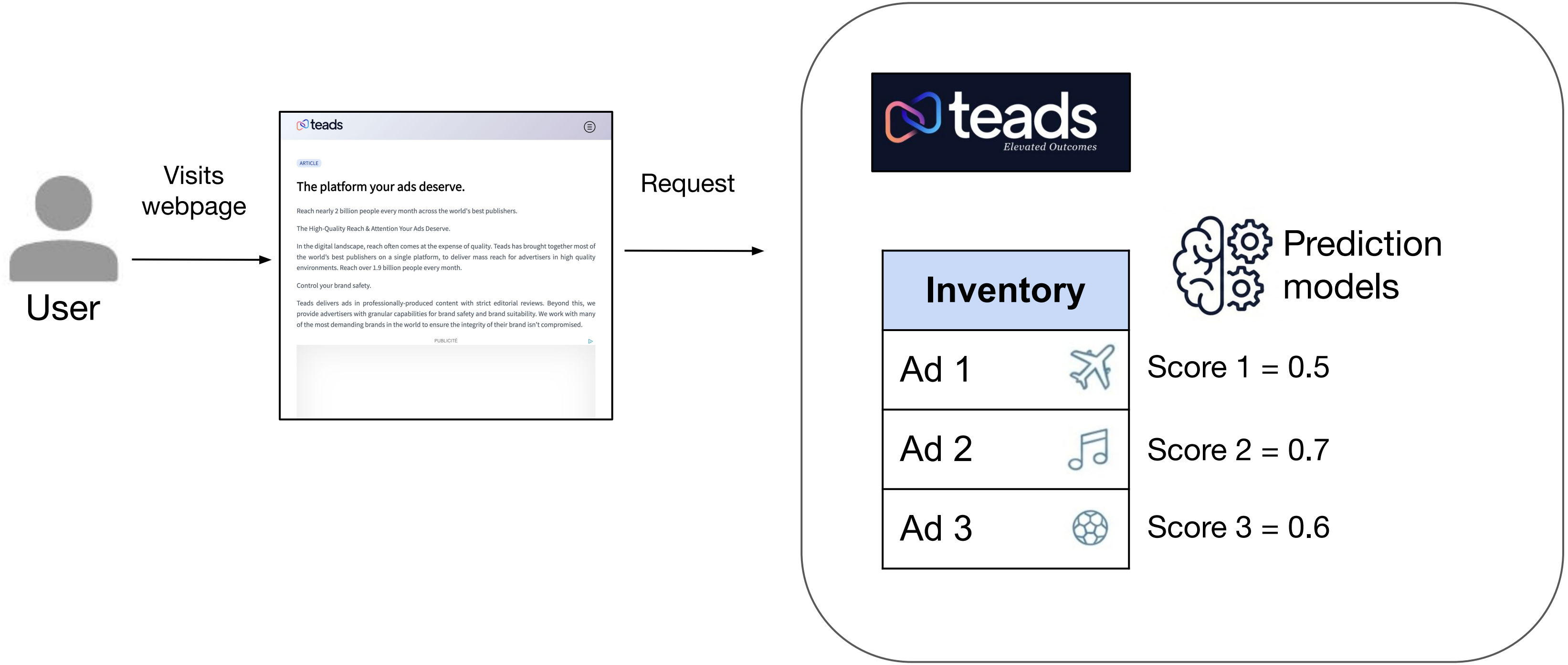
Prediction Model in AdTech



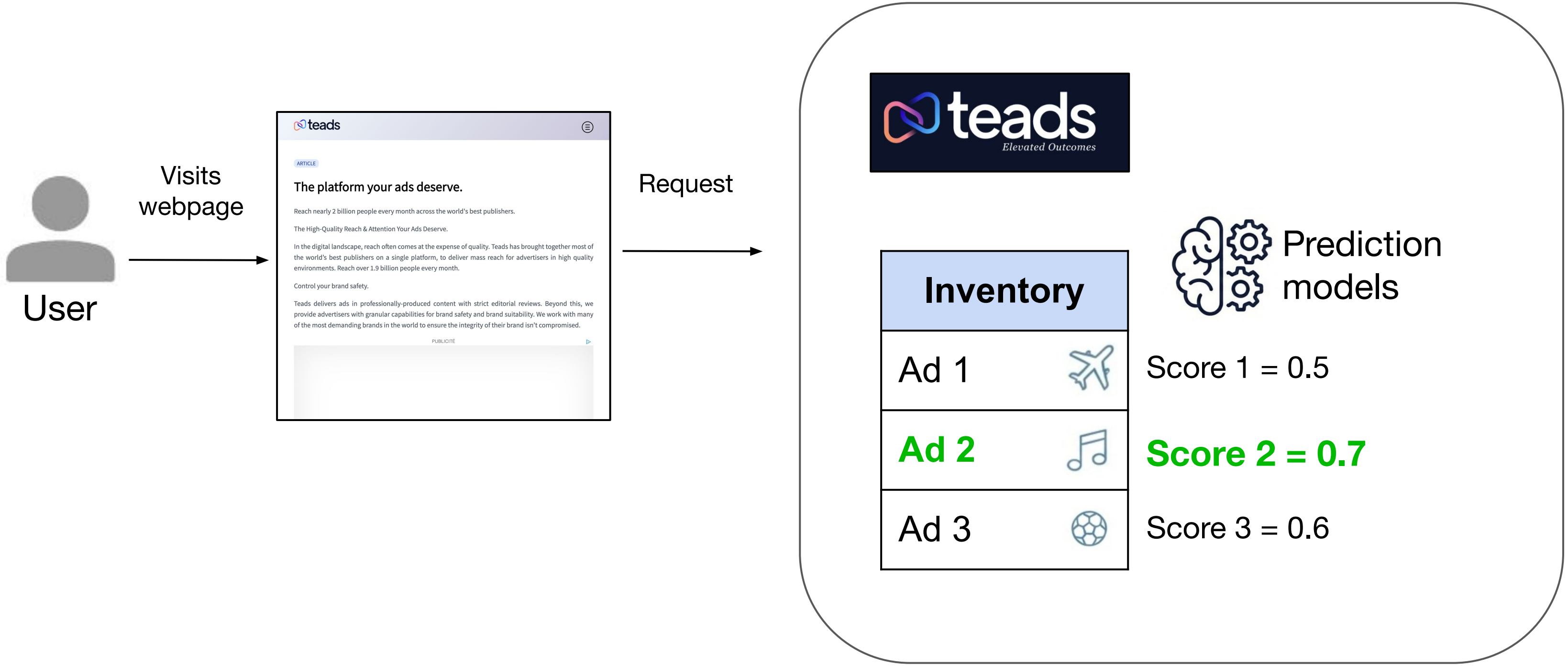
Prediction Model in AdTech



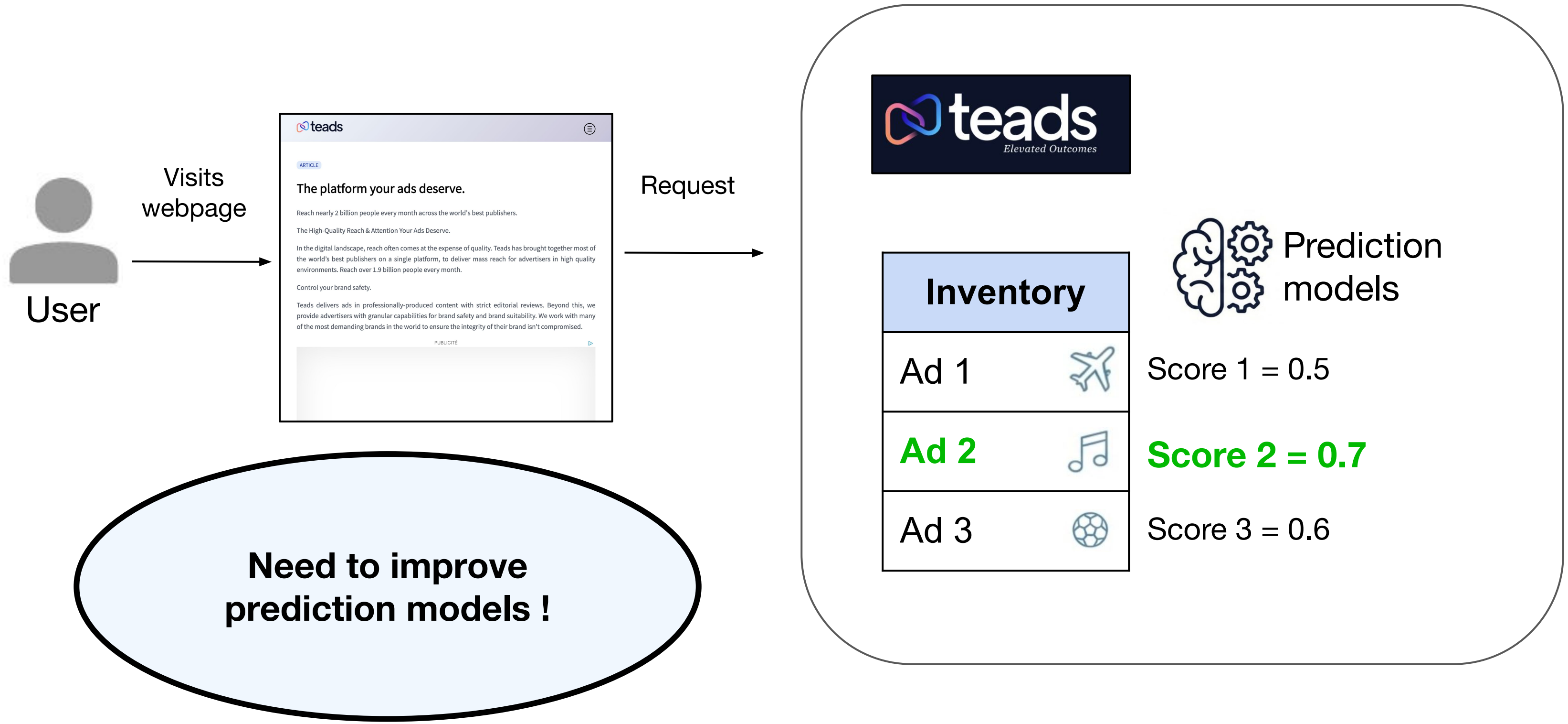
Prediction Model in AdTech



Prediction Model in AdTech



Prediction Model in AdTech

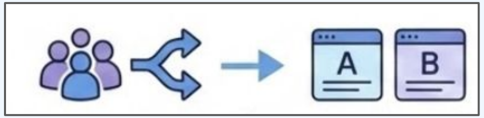


How to evaluate a model? A/B test

Definition

A/B testing is a randomized experiment on production that compares two models to see which performs better on a key metric

Randomly split users
Each population sees only 1 model version



Measure outcomes
& Analyse difference between A & B

✅ Pros

Ground truth on user impact
Measures real behavior in production

Business alignment
Uses the exact metrics you care about

❌ Cons

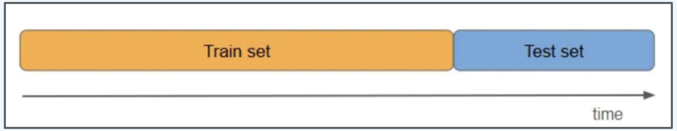
Slow and expensive
Needs enough traffic/time

Prior to AB/test: Offline search

Definition

Offline search is experimenting and tuning a prediction model using past data before trying anything in production

Split train / test



Compute offline metric
& Analyse difference

✅ Pros

Fast iteration
Evaluate many ideas/model versions quickly

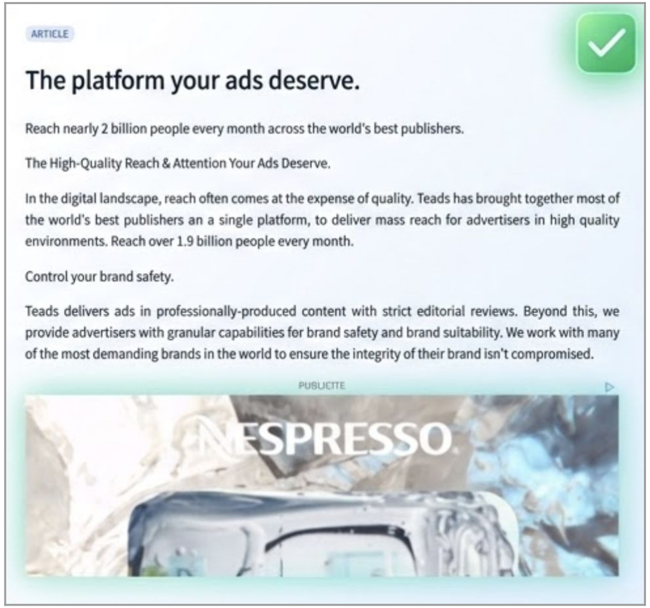
Safety
No user exposure

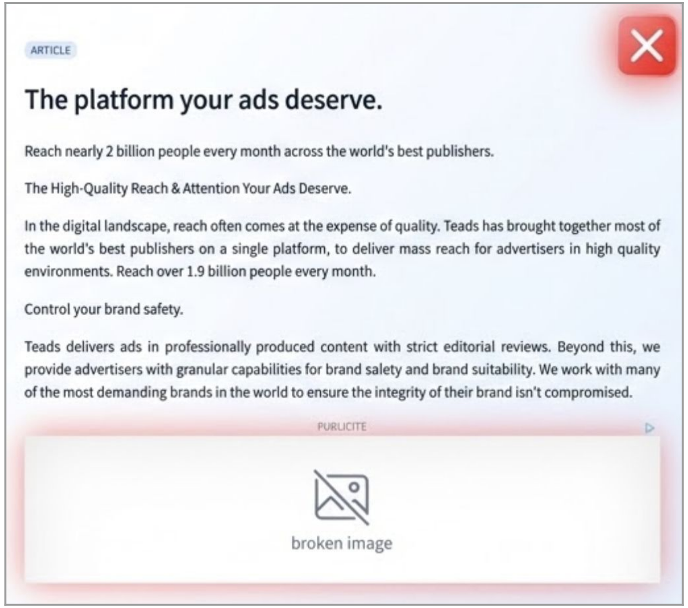
❌ Cons

Offline–online gap
Gains in offline metrics don’t always translate to online outcomes

Use case

Use Case: Broken Ad Detector





Use Case: Broken Ad Detector

Filtering with threshold

For each Ad, we'll compute it's probability to be broken and filter out the ones above a given threshold t

Proba_Broken(Ad) > t

How to choose the threshold t ?

⚠️ Model is not 100% right

Compromise between

- filtering as much as possible broken Ads from inventory
- prevent filtering too much not broken Ads

⇒ Find the right balance

Metric

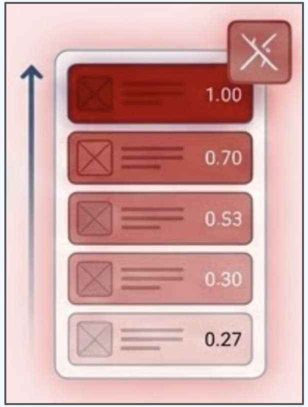
Use-case aligned metrics

We need to use the offline metric reflecting the best the online expectations

Online Metric

↓ broken ad ratio

Offline metric



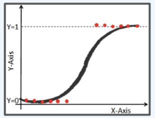
Correctly order ad inventory depending on their probability to be broken

⇒ AUC

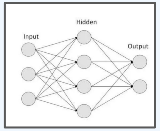
Offline search

Choice of Model

Baseline model



More complex

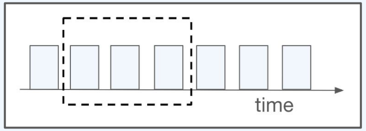


Choice of features

- User
- Ad
- Article content

Data set size

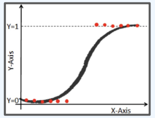
- 1 hour
- 1 day
- 1 week

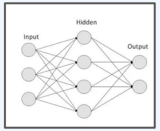


Offline search

Choice of Model

Baseline model **More complex**





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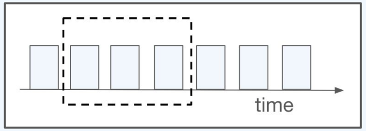


Feature selection

Features

Raw signals

- Country
- Device
- Hour of the day

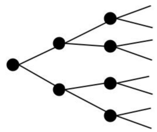
Engineered

- Aggregates (counts/rates)

FS Strategy (100 features)

❌**Test all combinations**

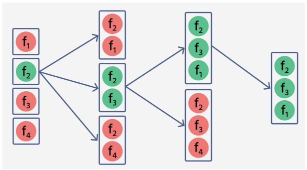
2 ^100 = 1 267 650 600 228 229 401 496 703 205 376



✅ **Forward FS**

Adding feature 1 by 1

5050 (maximum)



Feature selection

Iteration 1

f1

f2

…

f100

Feature selection

Iteration 1

f1	AUC = 0.5
f2	AUC = 0.7
…	
f100	AUC = 0.6

Feature selection

Iteration 1

f1 AUC = 0.5

f2 **AUC = 0.7** select f2 →

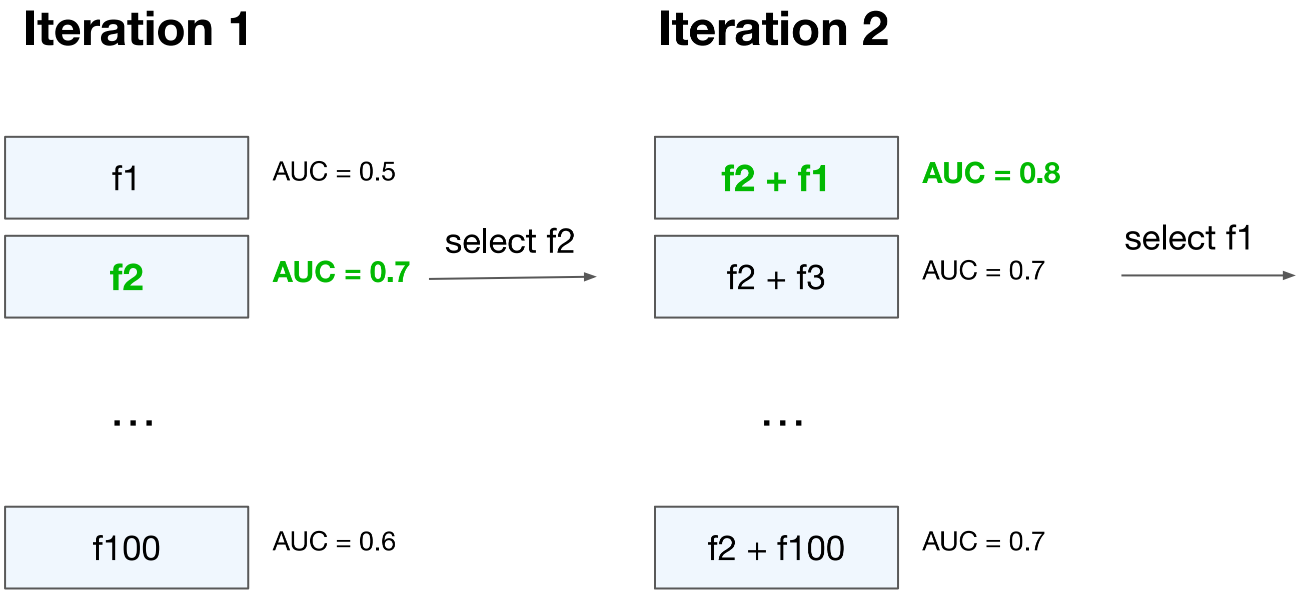
…

f100 AUC = 0.6

Feature selection

Iteration 1			Iteration 2
f1	AUC = 0.5		f2 + f1
f2	**AUC = 0.7**	select f2 →	f2 + f3
…			…
f100	AUC = 0.6		f2 + f100

Feature selection



Feature selection

Iteration 1

f1 AUC = 0.5

f2 **AUC = 0.7**

...

f100 AUC = 0.6

select f2

Iteration 2

f2 + f1 **AUC = 0.8**

f2 + f3 AUC = 0.7

...

f2 + f100 AUC = 0.7

select f1

Keep iterating until the AUC is not improved anymore

Feature selection

Iteration 1

f1 AUC = 0.5

f2 **AUC = 0.7**

...

f100 AUC = 0.6

select f2

Iteration 2

f2 + f1 **AUC = 0.8**

f2 + f3 AUC = 0.7

...

f2 + f100 AUC = 0.7

select f1

Keep iterating until the AUC is not improved anymore

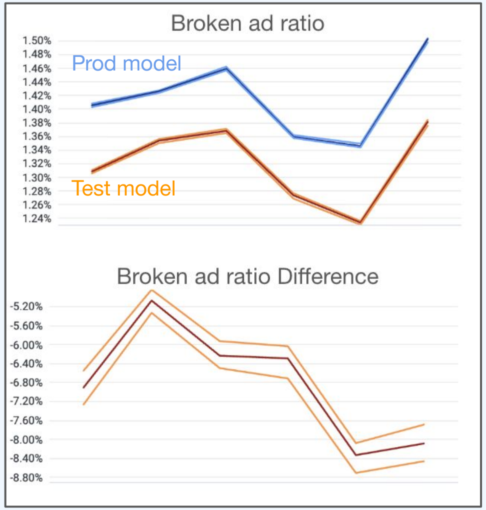
Offline candidate selected

Offline ⇒ Online

Increment offline

↑+ 3% AUC significant

A/B test

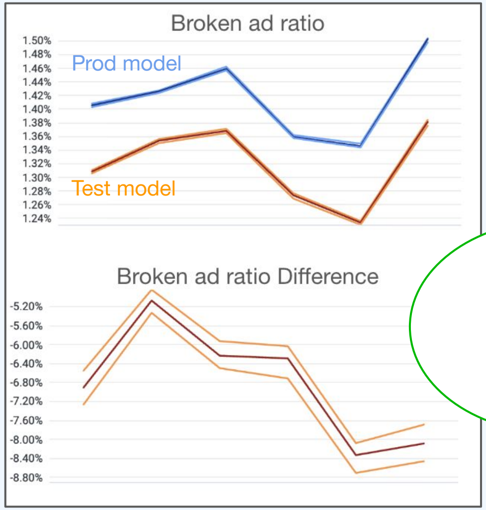


Offline ⇒ Online

Increment offline

↑+ 3% AUC significant

A/B test



-7% broken ads

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Thank you