data science @ The New York Times



chris.wiggins@gmail.com

UX: 1851 vs. 1996



#### The New York Times Introduces a Web Site

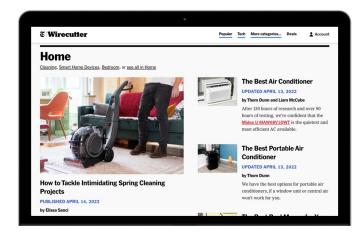
By PETER H. LEWIS Published: January 22, 1996

The New York Times begins publishing daily on the World Wide Web today, offering readers around the world immediate access to most of the daily newspaper's contents.

The New York Times on the Web, as the electronic publication is known, contains most of the news and feature articles from the current day's printed newspaper, classified advertising, reporting that does not appear in the newspaper, and interactive features including the newspaper's crossword puzzle.

1851 1996



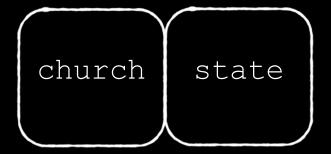








news: organizational chart



## **Data Science @ The Times**

We develop and deploy machine learning solutions for business and newsroom problems (using first party data)

Algorithmic Recommendations



Advertising

Media Innovations Team (MIT) Algorithmic Targeting (ALTA)

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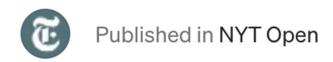
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Rohit Supekar

Aug 10 · 8 min read · • Listen









# How The New York Times Uses Machine Learning To Make Its Paywall Smarter

## history: 2011



## prognosis: doom

## THE NEW YORK TIMES PAYWALL IS DESTINED FOR FAILURE

The New York Times online subscription service was a long time in the making. Originally expected to roll out in January, the plans for the so-called paywall weren't announced until last Thursday. Unfortunately, the long-awaited service is destined for failure.



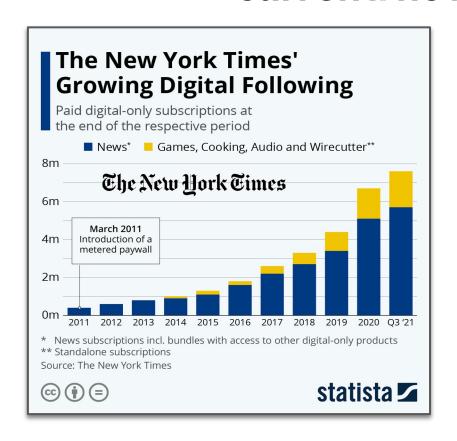


Home About Greg Sat

5 Reasons Why The New York Times Paywall Will Fail (And Why It's Really Dumb)

2011 MARCH 23

#### current: not doom





News publisher increases dividend, sets new target of 15 million total subscribers by end of 2027

#### **NiemanLab**

The New York Times hits 10 million subscribers by using nonnews products as an on-ramp

LINK: NYTCO-ASSETS.NYTIMES.COM / | POSTED BY: SARAH SCIRE | NOVEMBER 8, 2023

## Predictive vs Prescriptive Machine Learning

#### **Predictive ML**

What will happen without an intervention?

(past NYT activity)

Number of pageviews next month

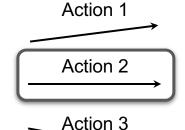
The ground truth is known.

#### **Prescriptive ML**

What is the best action to maximize an outcome?



(past NYT activity)



Whether the user subscribed

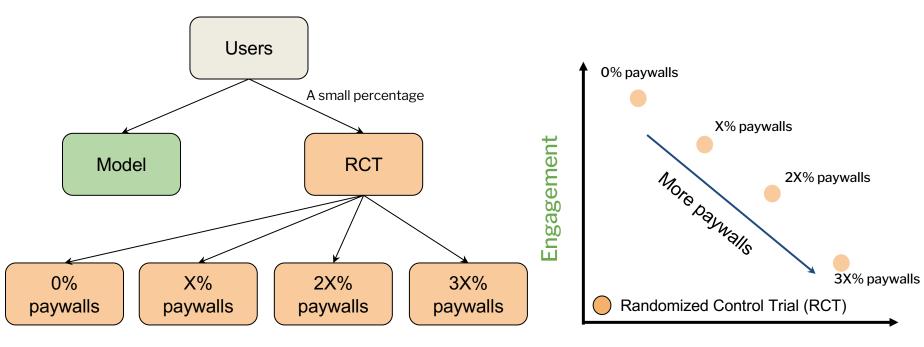
We typically don't know what would have happened if actions 1 and 3 were taken. So the ground truth is unknown and RCTs are important!

#### **Business trade-offs**

- NYT mission and business goal:
  - Engagement: We seek the truth and help people understand the world
  - Conversion: 15 million subscribers by 2027
- Engagement and Conversion have a inherent trade-off that is controlled by paywall rate.
  - More paywalls give us more subscribers but hurt engagement and reader habituation.
- We use Randomized Control Trials (RCTs) or A/B tests to understand the relationship between the engagement and conversion tradeoff.

The New Hook Times

#### **Learning trade-offs from RCTs**



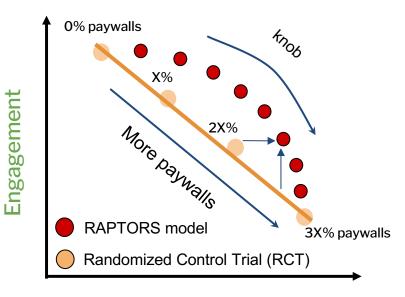
- Users in these variants have a random chance of seeing a paywall
- RCT is constantly active to capture any time-varying effects

**Conversion Rate** 

The New Hook Times

#### **RCT** data power **ML** model training

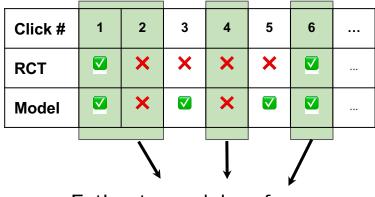
- Use of RCT data:
  - a. the model learns the effect of paywalls applied to access requests on the conversion/engagement tradeoff
  - b. model performance can be measured
- The goal of the model is to
  - improve the trade-off by only paywalling the most worthwhile clicks
  - provide a "knob" to change the level of the trade-off



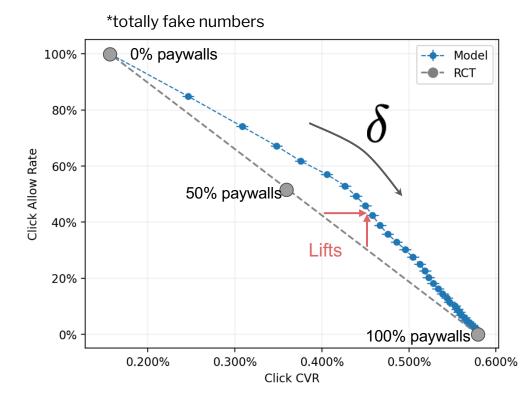
**Conversion Rate** 

### **Backtesting: Offline model evaluation**

How would the model have performed in the past?



Estimate model performance



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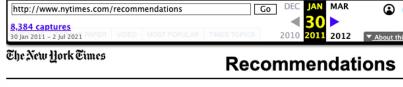


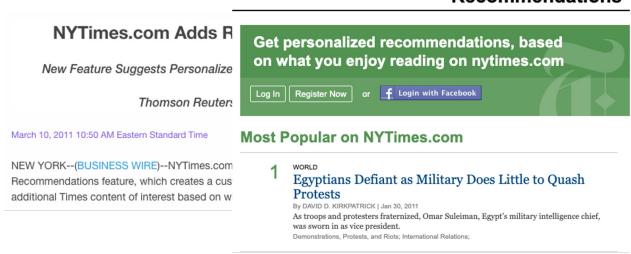
Advertising

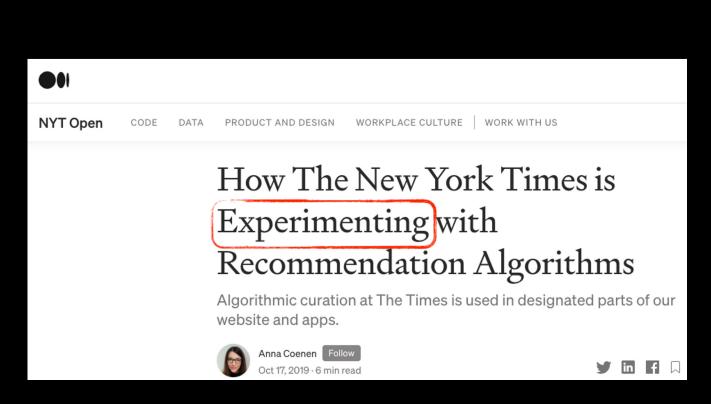
Media Innovations Team (MIT) Algorithmic Targeting (ALTA)

#### 2011: "Recommended for you"

- Limited to one location
- Simple algos







critical difference: observation vs. intervention

#### NYT Open

How we design and build digital products at The New York Times

Follow



#### A contextual recommendation approach

One recommendation approach we have taken uses a class of al called <u>contextual multi-armed bandits</u>. Contextual bandits lear how people engage with particular articles. They then recomme that they predict will garner higher engagement from readers.' *contextual* part means that these bandits can use additional inforget a better estimate of how engaging an article might be to a pareader. For example, they can take into account a reader's geog region (like country or state) or reading history to decide if a pararticle would be relevant to that reader.

- "bandit": Bush, Robert R., and Frederick Mosteller. "Stochastic models for learning." (1955).

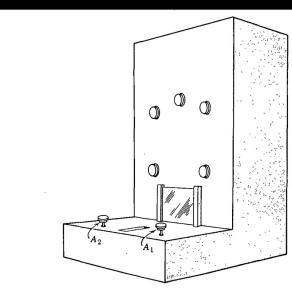
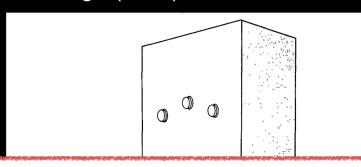


Fig. 13.2. Sketch of the two-armed bandit used by Goodnow, Robillard, and the authors. When the machine is in operation, the three upper lights are on and a soft buzz may be heard. The subject pushes button  $A_1$  or button  $A_2$ , and this turns on the light directly above the button pushed. Poker chips are dropped into the region behind the glass.

<sup>\*</sup> The optimum decision rule (the "best strategy") for playing the two-armed bandit for *n* trials seems not to be known.

- Bush, Robert R., and Frederick Mosteller. "Stochastic models for learning." (1955).



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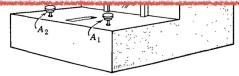
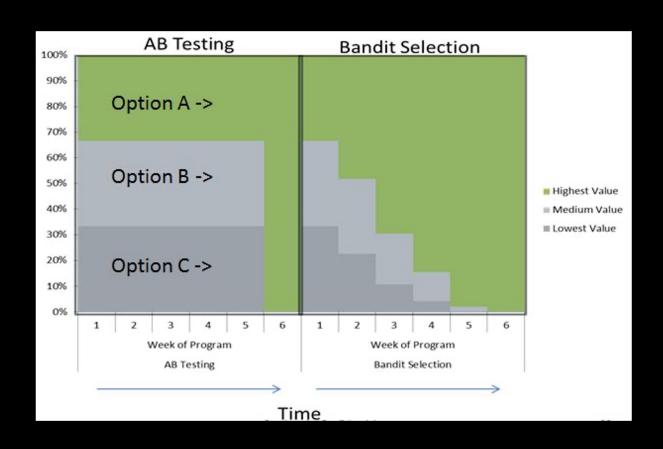


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Bandits and Adaptive Optimization, Matt Gershoff (Conductrics) 2012

## How The New York Times Incorporates Editorial Judgement in Algorithms to Curate Home Screen Content

A look into how editorially-driven algorithms assist content curation on The New York Times home page.





By Zhen Yang

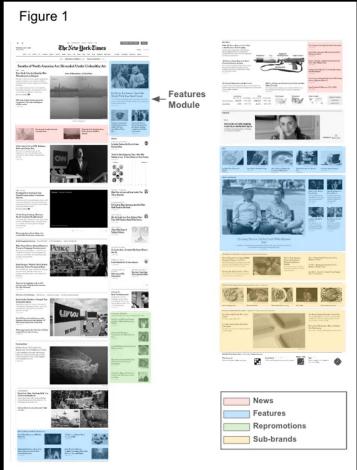


Figure 1. New York Times home page: algorithmically programmed modules are highlighted in different colors.

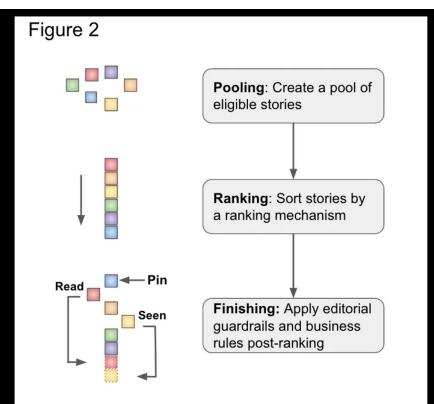


Figure 2. The process of algorithmic programming includes three steps: pooling, ranking, and finishing. Pinning an important story at the top and removing a story that has already been read or seen are examples of applying editorial guardrails and business rules at the finishing step to override the algorithmic output.

#### Figure 4

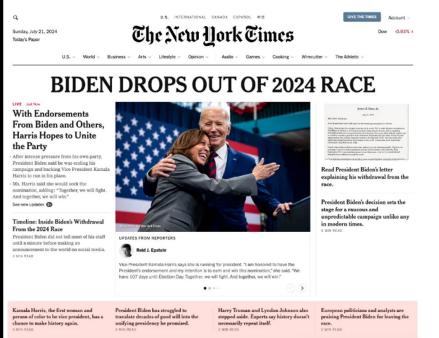
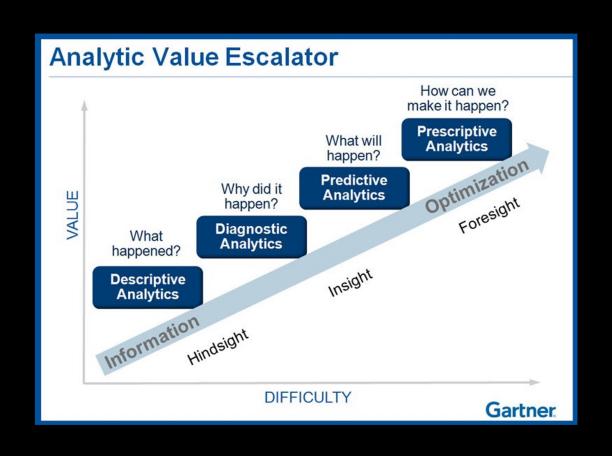


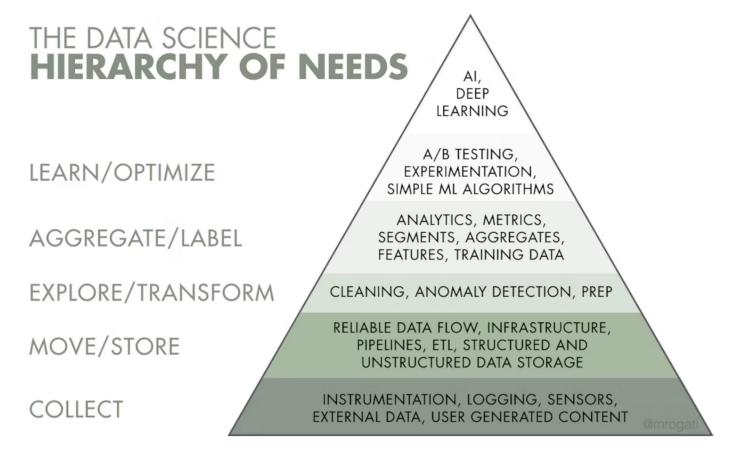


Figure 4. Self-service algorithmic modules were used high on the home page (the pink highlighted areas) during major news events: when President Biden dropped out of the 2024 race (left panel) and during the 2024 Paris Olympics (right panel).

lessons learned

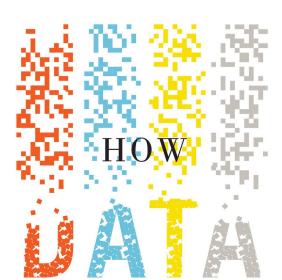






Monica Rogati June 12th, 2017 https://hackernoon.com/the-ai-hierarchy-of-needs-18f111fcc007





#### HAPPENED

A History from the Age of Reason to the Age of Algorithms

 $\begin{array}{c} {\rm CHRIS\ WIGGINS} \\ and\ {\rm MATTHEW\ L.\ JONES} \end{array}$ 

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FOUNDATIONS, CHALLENGES, OPPORTUNITIES

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