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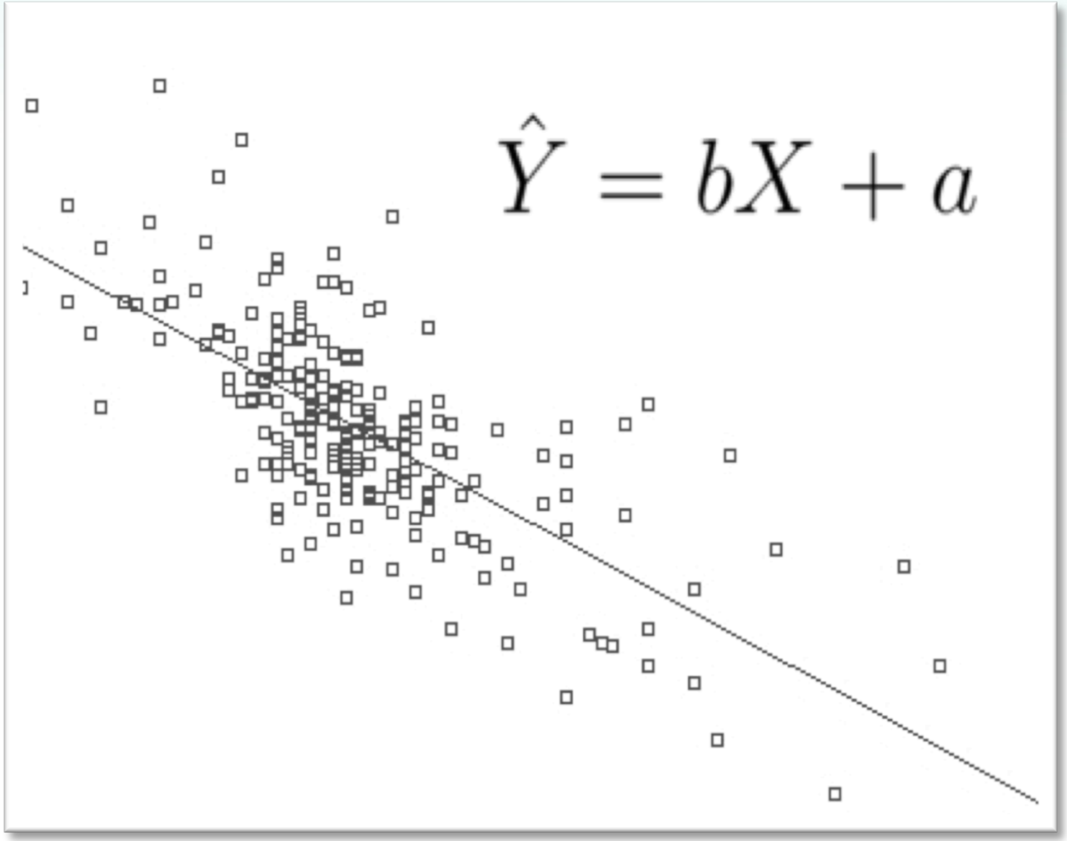
Talk Overview

- Basics of machine learning vs. regression, interpreting MLMs
- LTV and churn modeling
- LTV vs. CaC
- Network models and adjusting/accounting for social
- Attribution & approaches, empirical benchmarks

Regression



Machine learning and predictive models: power vs. understandability

- A->B->C->D 45/50 times. Now A->B->C->?
- Now you have 90% probability. Awesome. But . . .
- So, *do* you need to understand "Why?"

Machine learning models

- Tools: WEKA, SAS, SPSS; Spark MLLib, R
- Varying levels of black boxyness
- Rule-set (Jrip example)
- Decision-tree
- Support Vector Machines

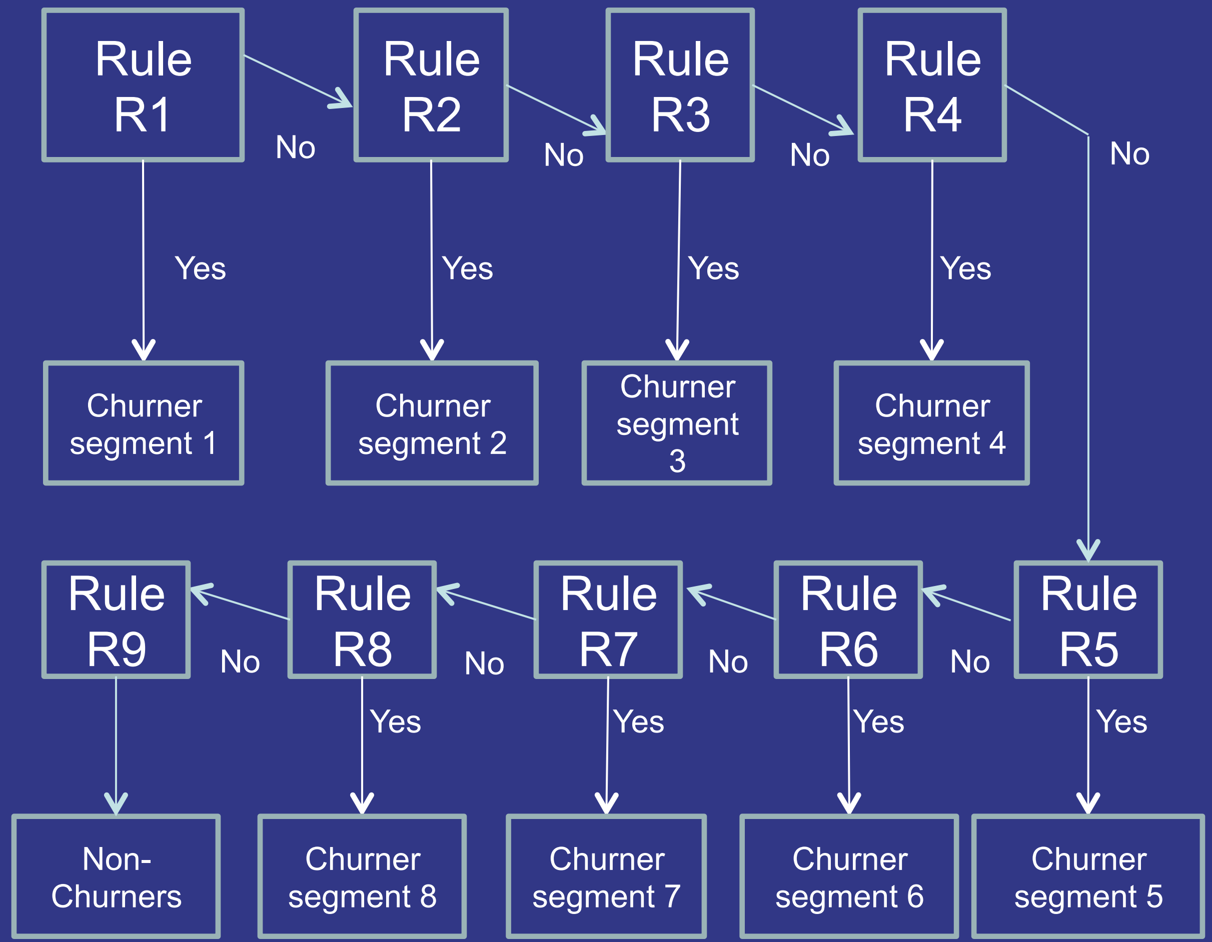
Choosing the feature space

- Huh?
- Hello, “domain expert”
- Feature selection
- Why bother with the domain experts?

Rule set (JRIP, FOIL, others)

- How do you read these?
- Mutually exclusive rules
- Coverage numbers: how many cases does it apply to? How many cases does it get right? (XX/ XX)
- Interpretation of the meaning, somewhat like regression in that you look at coefficients, but mostly like interaction effects rather than betas.
- Then, sometimes, actionability: requires a medium to high level of abstraction so they can be interpreted and acted upon. You need a person who gets the math *and* the context.
- Rule examples from a rejected JRIP model that was only about 67% accuracy:
  - (account_age <= 21) => ischurner=1 (23.16% / 70.63%)
  - (SOCIAL_VALUE <= 0) and (account_age >= 28) and (account_age <= 31) => ischurner=1 (0.86% / 64.84%)
  - (account_age <= 123) and (SOCIAL_VALUE <= 0.000653) and (account_age <= 93) and (account_age >= 68) and (NUM_XXX <= 0) => ischurner=1 (4.64% / 51.83%)

Rule-based logic

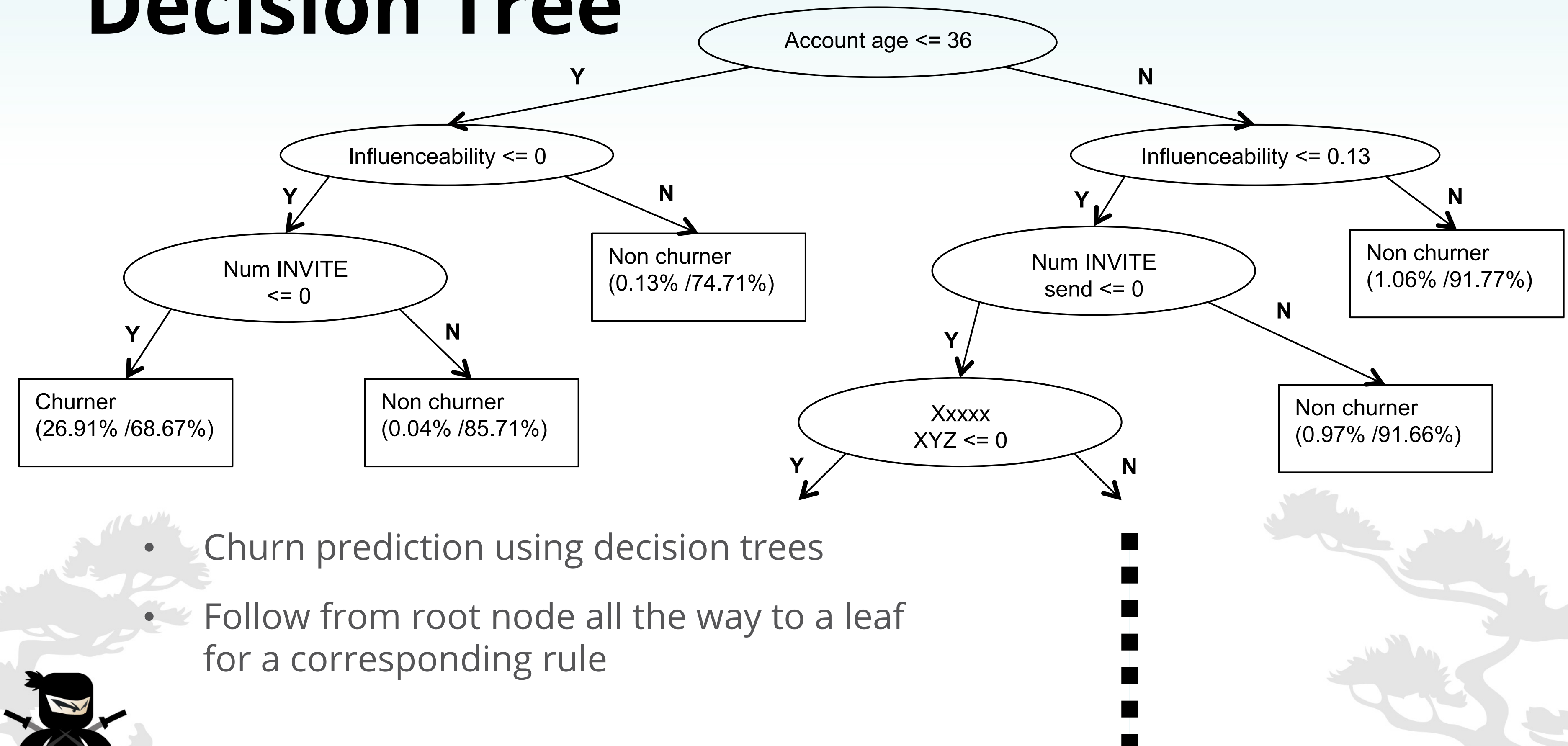


Decision Trees

```
account_age  <= 36
|   INFLUENCEABILITY  <= 0
|   |   NUM_INVITE  <= 0: 1 (34763.0/10892.0)
|   |   NUM_INVITE  > 0: 0 (56.0/8.0)
|   INFLUENCEABILITY  > 0: 0 (170.0/43.0)
account_age  > 36
|   INFLUENCEABILITY  <= 0.13
|   |   NUM_INVITE  <= 0
|   |   |   NUM_xxxxx   <= 0
|   |   |   |   account_age  <= 94
|   |   |   |   |   NUM_GIVE_CURRENCY  <= 0
|   |   |   |   |   |   account_age  <= 88: 0 (10511.0/4826.0)
|   |   |   |   |   |   account_age  > 88: 1 (2584.0/1222.0)
|   |   |   |   |   NUM_GIVE_CURRENCY  > 0: 0 (112.0/26.0)
|   |   |   |   account_age  > 94: 0 (78164.0/25158.0)
|   |   |   NUM_xxxxx   > 0: 1 (38.0/8.0)
|   |   NUM_INVITE  > 0: 0 (1259.0/105.0)
|   INFLUENCEABILITY  > 0.13: 0 (1373.0/113.0)
```

- Churn prediction using decision trees
- Follow from root node all the way to a leaf for a corresponding rule

Decision Tree



- Churn prediction using decision trees
- Follow from root node all the way to a leaf for a corresponding rule

Support Vector Machines

```
+    -2.1931 * (normalized)  account_age
+    -3.7646 * (normalized)  number_transactions
+    -0.1759 * (normalized)  days_inactive_spending
+    -2.0108 * (normalized)  different_transactions
+    -1.234  * (normalized)  NUM_give_currency
+    -1.909  * (normalized)  NUM_Recruited
+    -1.909  * (normalized)  NUM_invite_to_play
+    -5.2997 * (normalized)  NUM_joint_viewing
+    -6.0633 * (normalized)  NUM_played_with
+     1.6118 * (normalized)  NUM_XXXXXX
+     1.0722 * (normalized)  ASOCIAL_VALUE
+    -1.8388 * (normalized)  SOCIAL_VALUE
+    -2.5029 * (normalized)  INFLUENCEABILITY
+     2.5578
```

- Attribute weights from a support vector machine model

Looking for patterns

- Are you trying to simply get the best model?
- Are you trying to answer “why?”
- These were three models of the same population. What were the patterns?

Conclusion: people are compelling

Conclusion: people are compelling

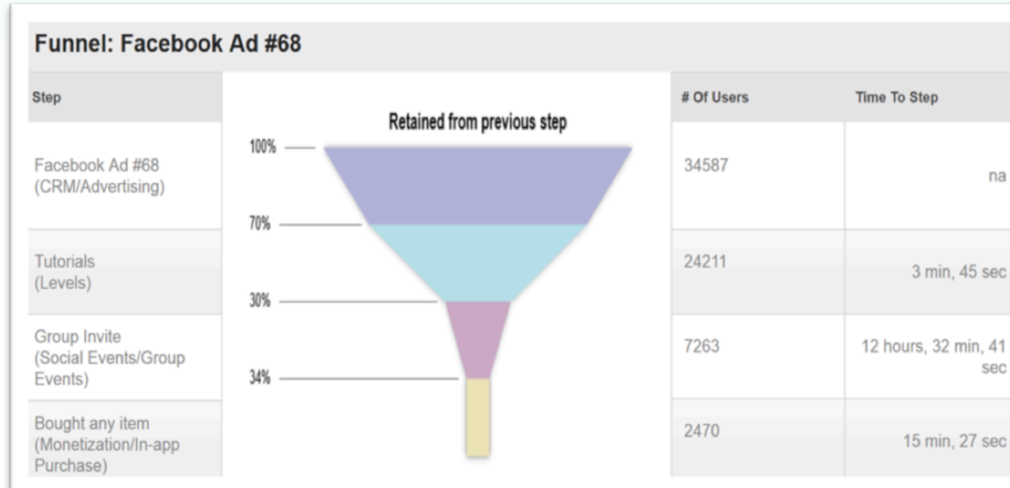
The black box factor

The black box factor

- “Deep learning” neural networks
- Used heavily by FB and Google, e.g. voice recognition and image understanding (self-driving cars recognizing the environment)
- Zero actionability possible, but most accurate by far
- There is no output, no model—just a bunch of relationships like the brain’s neuron pathways

LTV modeling

- Two components: LT and V
- LT models: TTL/Churn.
- Cox/Hazard model
- Note the inverse nature of retention and churn approaches



- Value models
- Social interactions impacting models
- Historical or predictive use by your team?

LTV vs. CaC

- What do these acronyms mean, and why is this the most important equation in gaming?
- Cost of Customer Acquisition. Also CPI cost per install.
- How do you measure return on investment (ROI)?
- Revenue/ARPU/ARPPU must be tied back to acquisition source—reinforcing importance of good attribution data. Use of revenue to set RTB pricing
- Complication from the CFO in currency-based games: Revenue recognized at purchase or exercise?
- Can you trust the numbers? Not exactly, no.

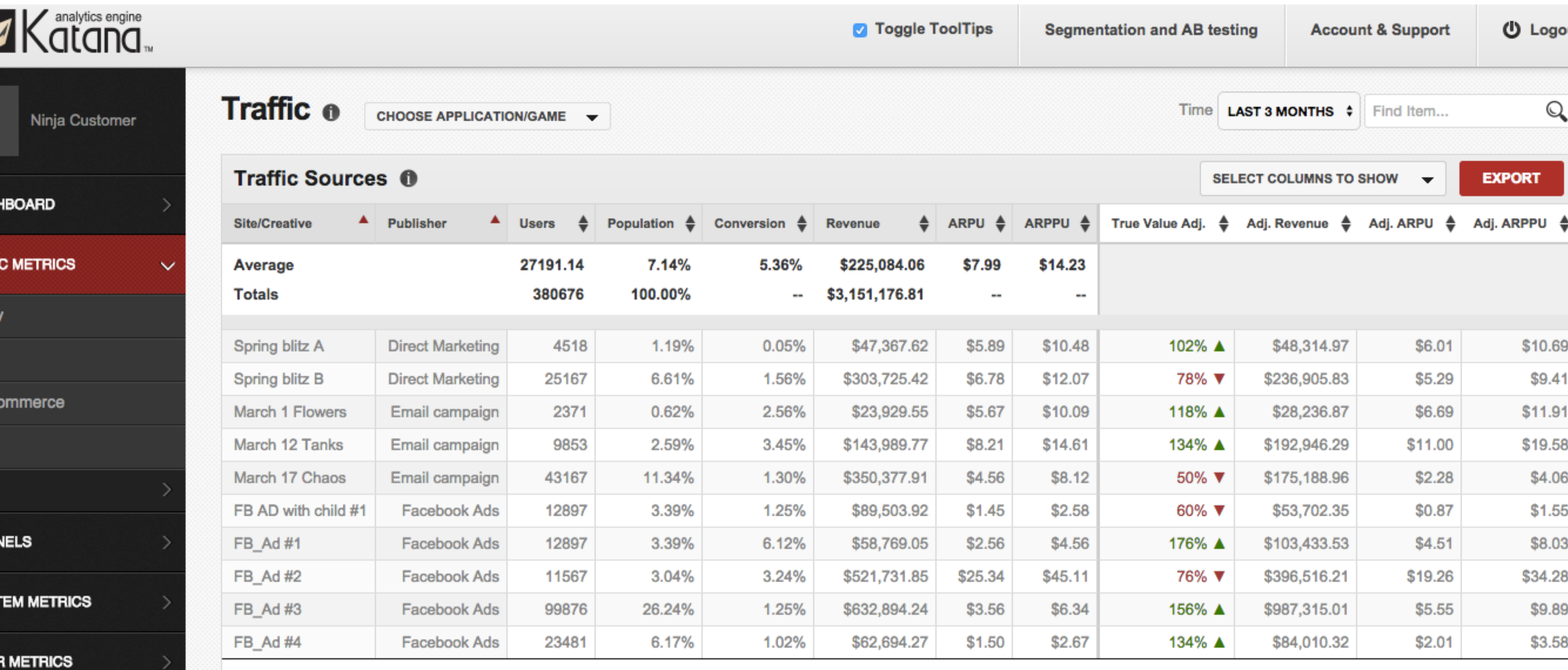
Attribution: Early days

- Overview: Programmatic vs. brand sourcing, RTB systems, ad sources and publishers, examples
- What is attribution? Big picture, big deal, it's fixing advertising.
- Tracking sources. Appsflyer, AdX (going away), Adjust, Kochava, TUNE (Formerly HasOffers). Example:

{"timestamp":"2015-02-17T23:59:59.000Z","data":
{"account_id":"38897195XXX","traffic_source_type":"Blind Ferret
Media","type":"59","traffic_source":"PC_1_1_blif_250_ios_both_CPI_worldwide"}}

- By 2017: Advertisers will spend $174bn online, despite imperfect practices (Magna Global)
- 54% of businesses use some form of attribution, yet 58% think perfect attribution is impossible (Adobe)
- 38% of those who use it, do so manually (ouch)
- Multi-touch data: not on everyone's radar, but should be

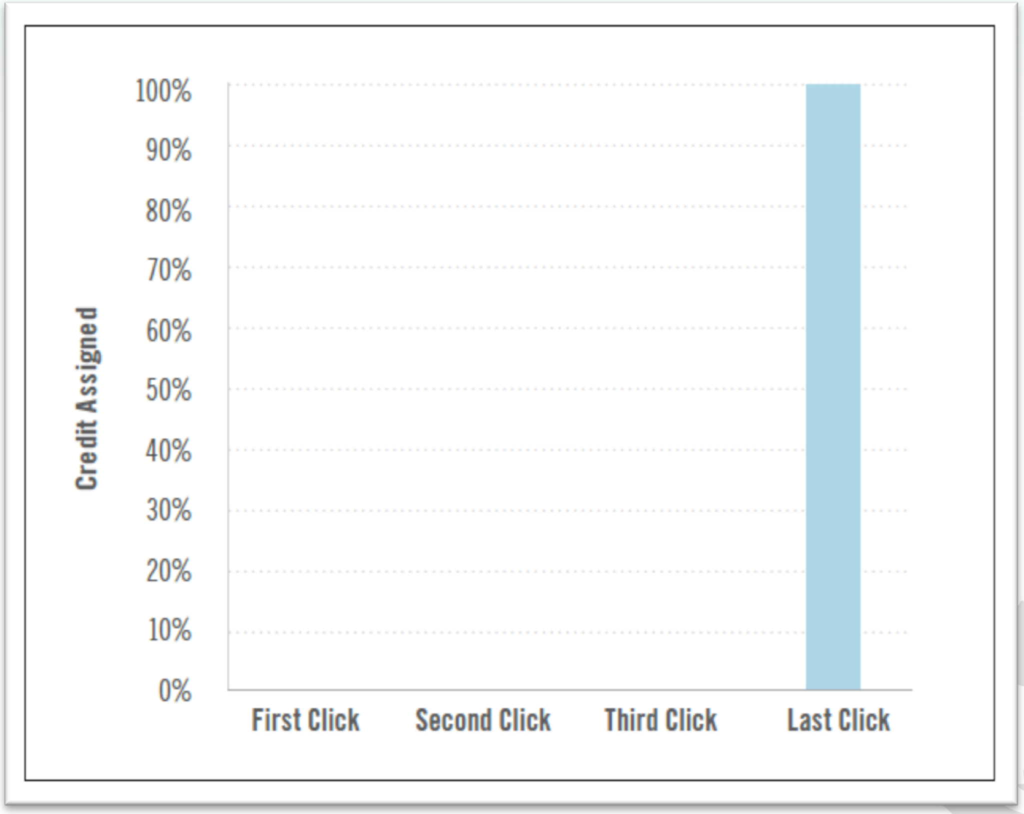
Attribution: Early days



Decent: Last click

20% of advertisers rely on this (TagMan). Why? Simplest.

(Graphs, Marin Software)

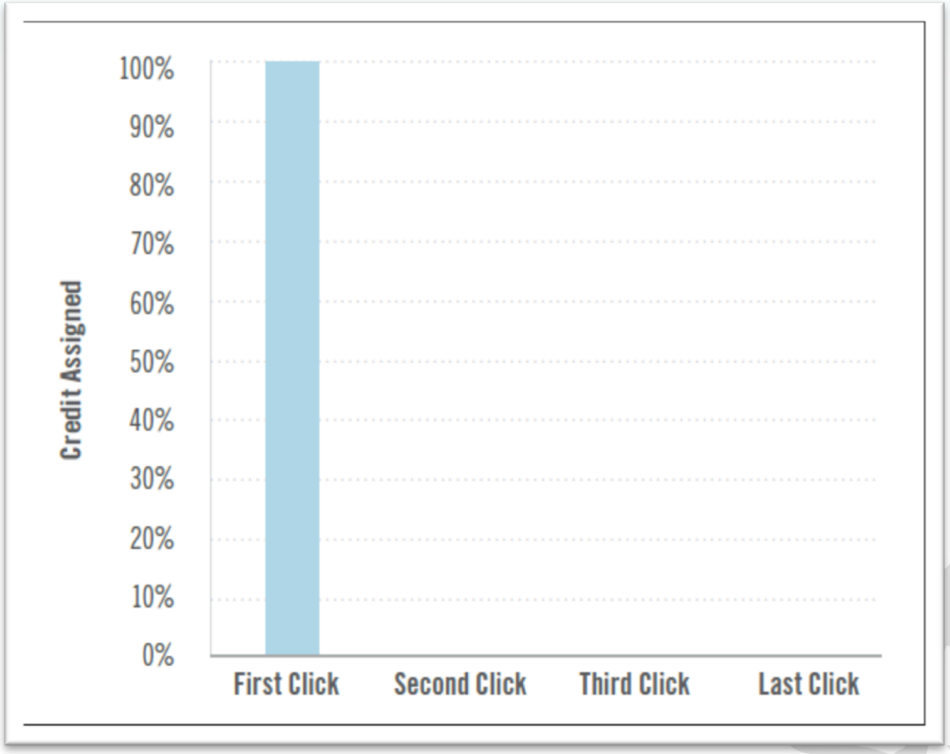


Decent: First click

41% of agencies and 24% of brand managers use it.

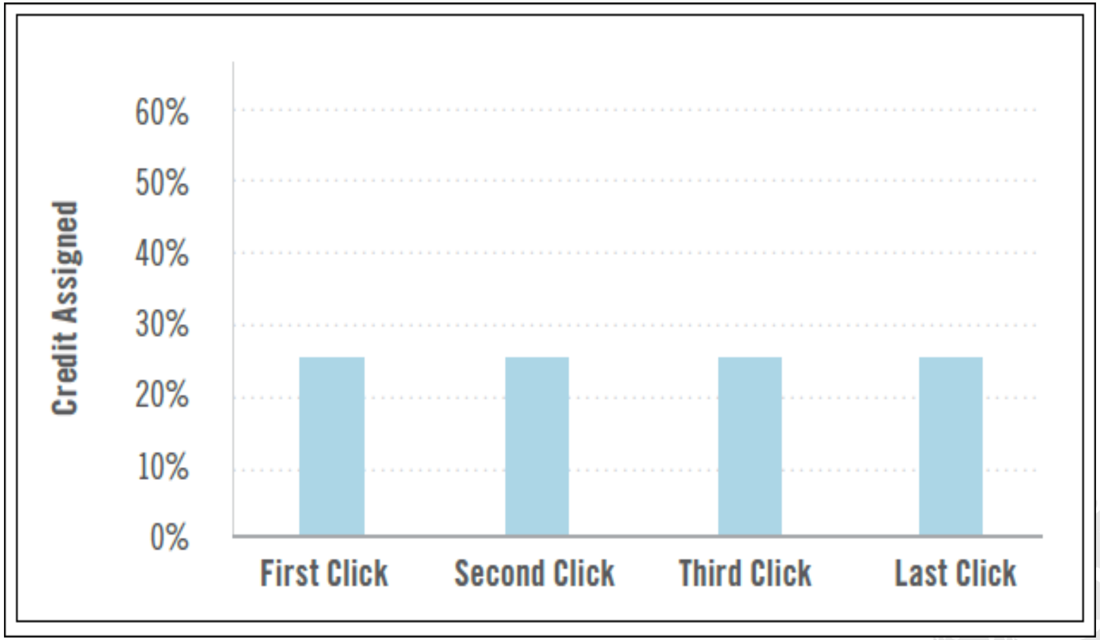
Why?

Awareness generator theory.



Decent: Linear

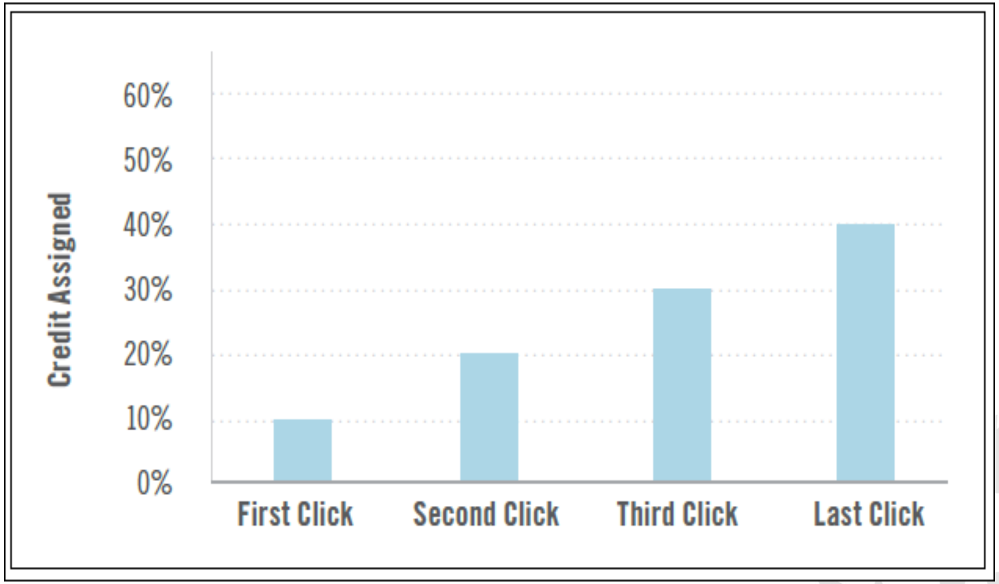
Throwing stuff at the wall here . . .



Better: Time Decay

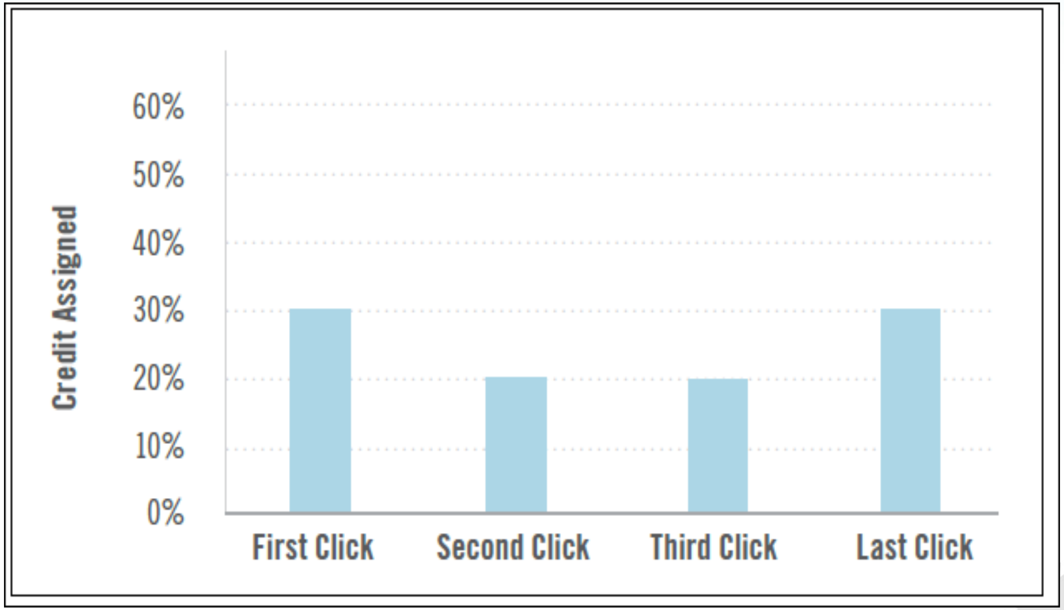
Starting to build in some theory about process and cognition.

May overvalue last click.



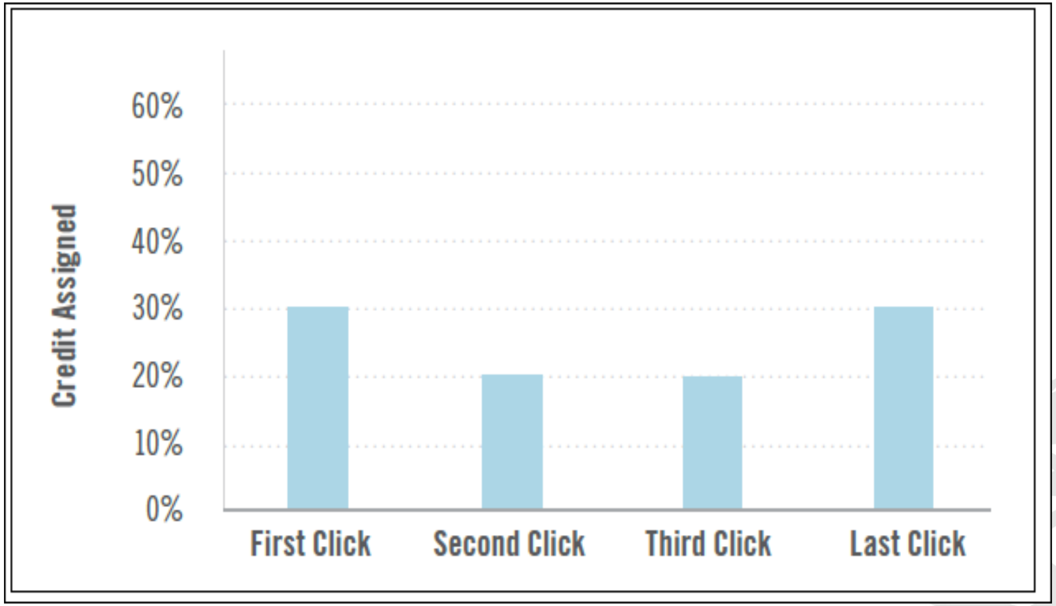
Better: Position-based

Doesn't over- or under-value first or last, but the values are ultimately arbitrary.



Best: Data-driven & modeled

Rather than using a theory or intuition, we rely solely on observed patterns.



Data-driven attribution models

- Let Z = installation, and A,B,C,D, … be other events. _ event means the sequence ended.

1. ABCDZ_
2. ABCZ_
3. BCDZ_
4. BCZ_
5. ABC_
6. ACDB_
7. BC_

Data-driven attribution models

- Let Z = installation, and A,B,C,D, … be other events. _ event means the sequence ended.

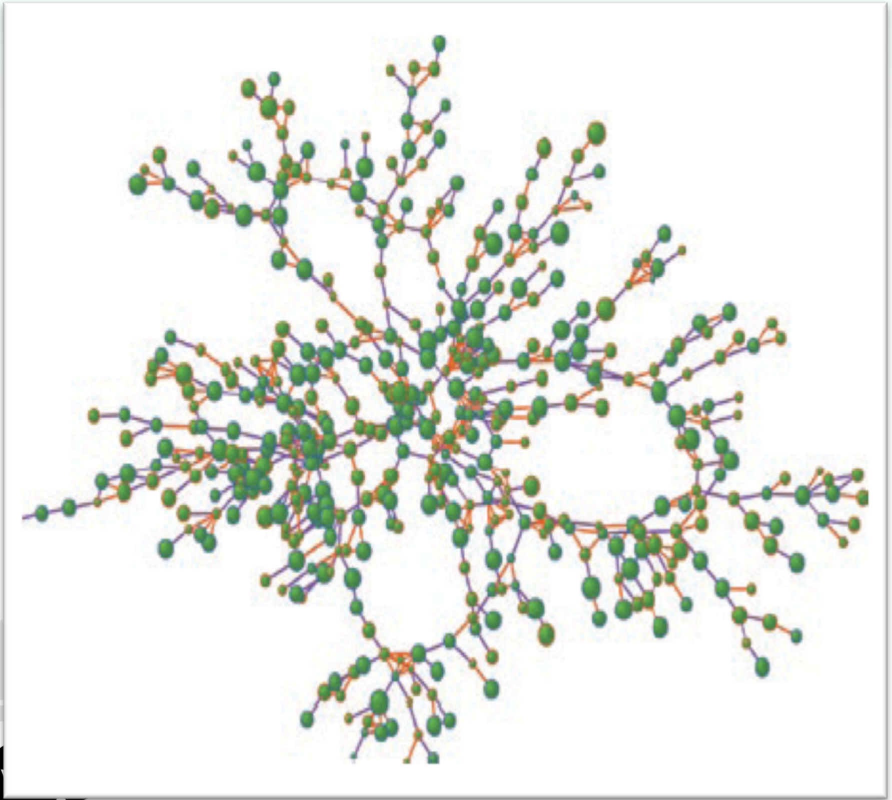
1. ABCDZ_
2. **ABCZ_**
3. BCDZ_
4. **BCZ_**
5. ABC_
6. ACDB_
7. BC_

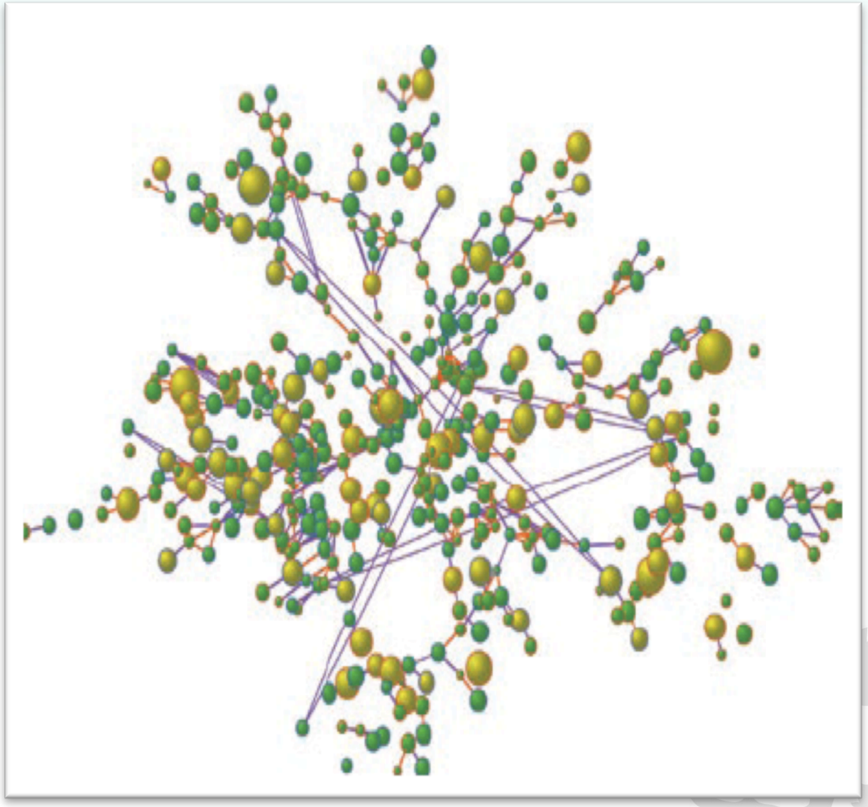
- Path 2 vs. Path 4: Isolates "A"
  - Example: Sequence 2 leads to a 20% install rate
  - Example: Sequence 4 leads to a 15% install rate
- Conclusion: Ad A has an incremental effect of 5%, when sequenced. (May be different solo, but we can have a sequence for that as well).

Network models

- Who cares?
- Origin: Improvements in F-scores in IARPA project
- Cross-sectional (centrality, e.g.) vs. dynamic, causal, over-time

Social Network Analysis



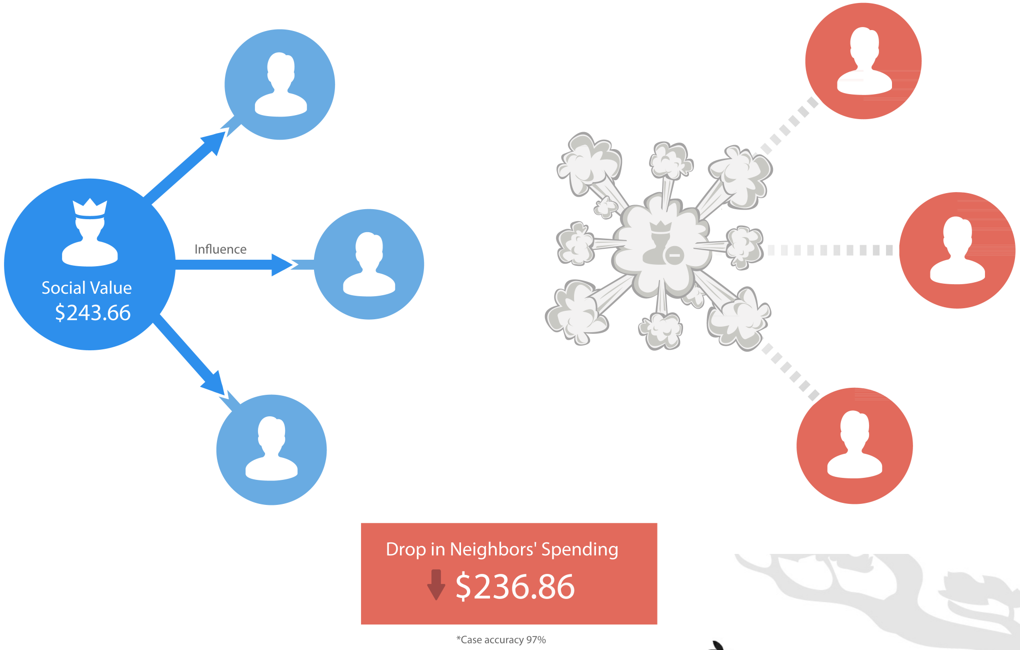


Do Network Forces Matter?

- Ye gods, more than we thought, yes.
- Major benefits: improved models, uncovering new dynamics, associations with product/mechanics.
- Benchmark: 10-70% of play is purely network-driven
- Benchmark: 6-60% of spending is purely network-driven.

General report statistics

- Data size: 365m accounts, 2013-present
- Accuracy rate: 85%



Mobile Single Player Games
Average is 6%

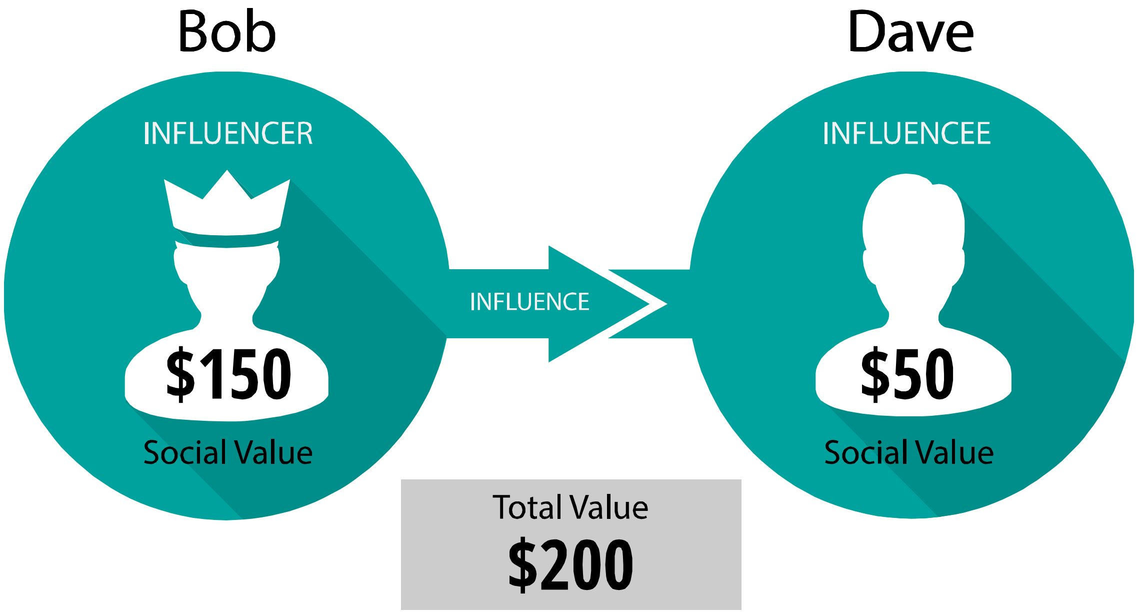
Mobile Social Games
Average is 28%

PC Hardcore Multiplayer
Average is 30%

MMOs
Average is 60%

Adjustments by Geo, Channel, Ad

- Minimum 5,000 accounts



Most influential players, global

Laos: +2,558%

Palestine: +2,331%

Cambodia: +945%

Sudan: +840%

Iran: +672%

Algeria: +2,558%

Ukraine: +2,331%

Belarus: +945%

Pakistan: +840%

Syria: +672%

Least influential players, global

Kenya: -57%

Iceland: -34%

Norway: -26%

Switzerland: -25%

Angola: -25%

Australia: -24%

USA: -24%

Japan: -23%

U.K.: -23%

South Africa: -22%

The most social users, by acquisition source

1. +193%
2. +110%
3. +104%
4. +62%
5. +38.7%

Other notables:

Organic, +14%

Lowest: -27%

What about creative?

- We did not report on creative, and they matter even more:

Creative A vs. B, same channel

High: +900% (second was +310%)

Low: -70%

Variance: 131%

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