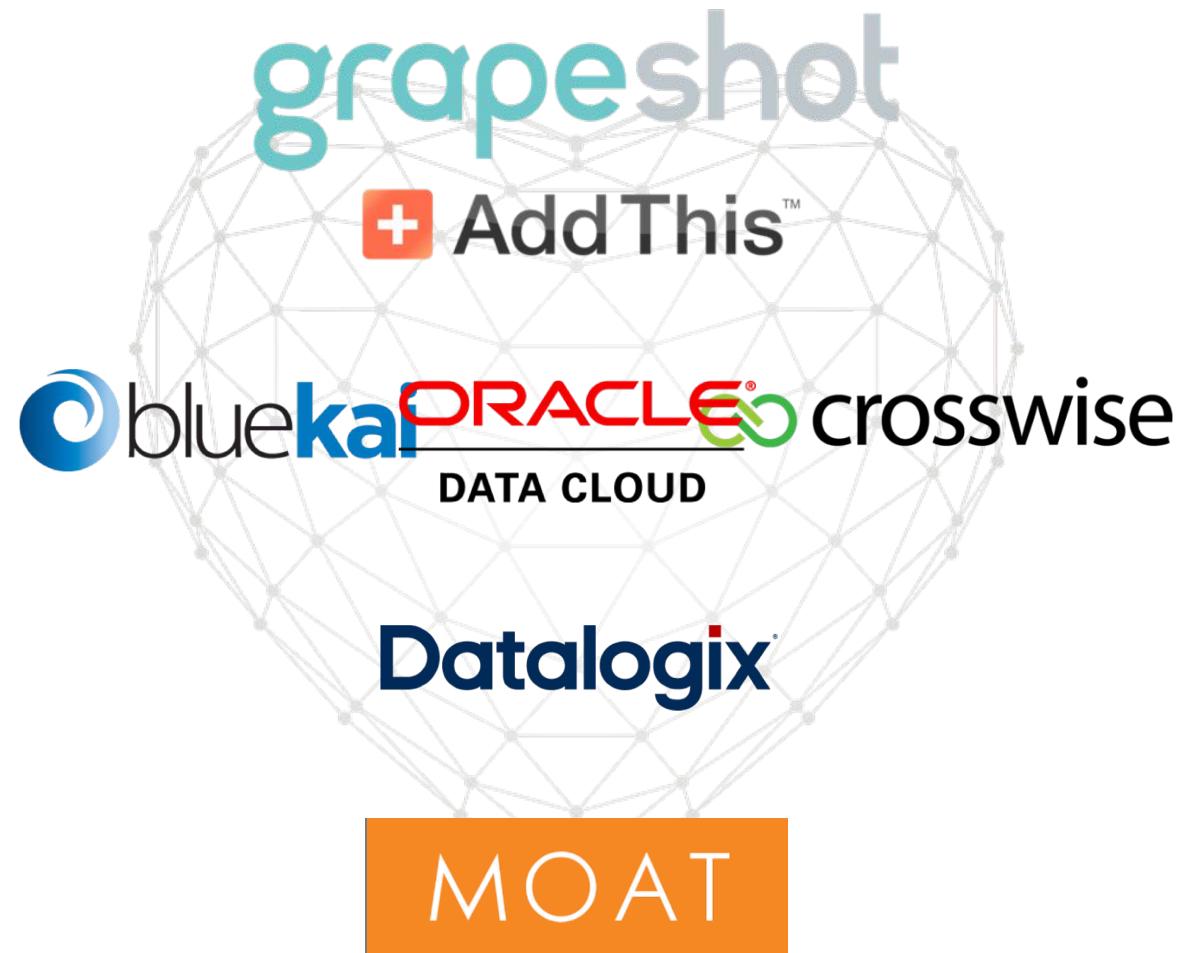


Applied ML in Marketing Tech @ The Oracle Data Cloud

Alex Sadovsky
Senior Director of Data Science





Why so many companies?



Congratulations You Won!!!



It is not a joke
You are the 100,000th visitor of the day!

Claim your winnings?

OK

CANCEL



Message from webpage



Congratulations!

You are Todays Lucky Visitor.

Click OK to continue

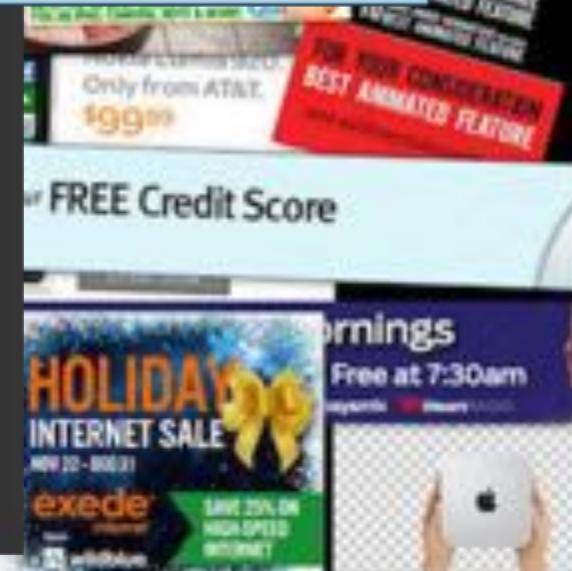
OK

Important message



Slow computer?
Perform a free scan now and
make it run like new!

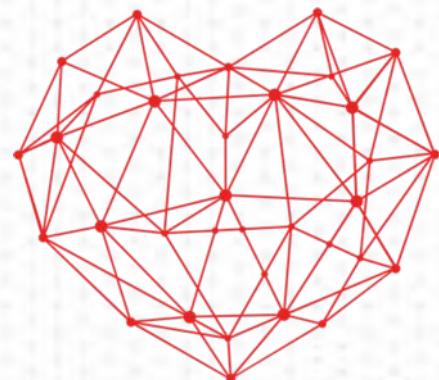
OK





Our mission:

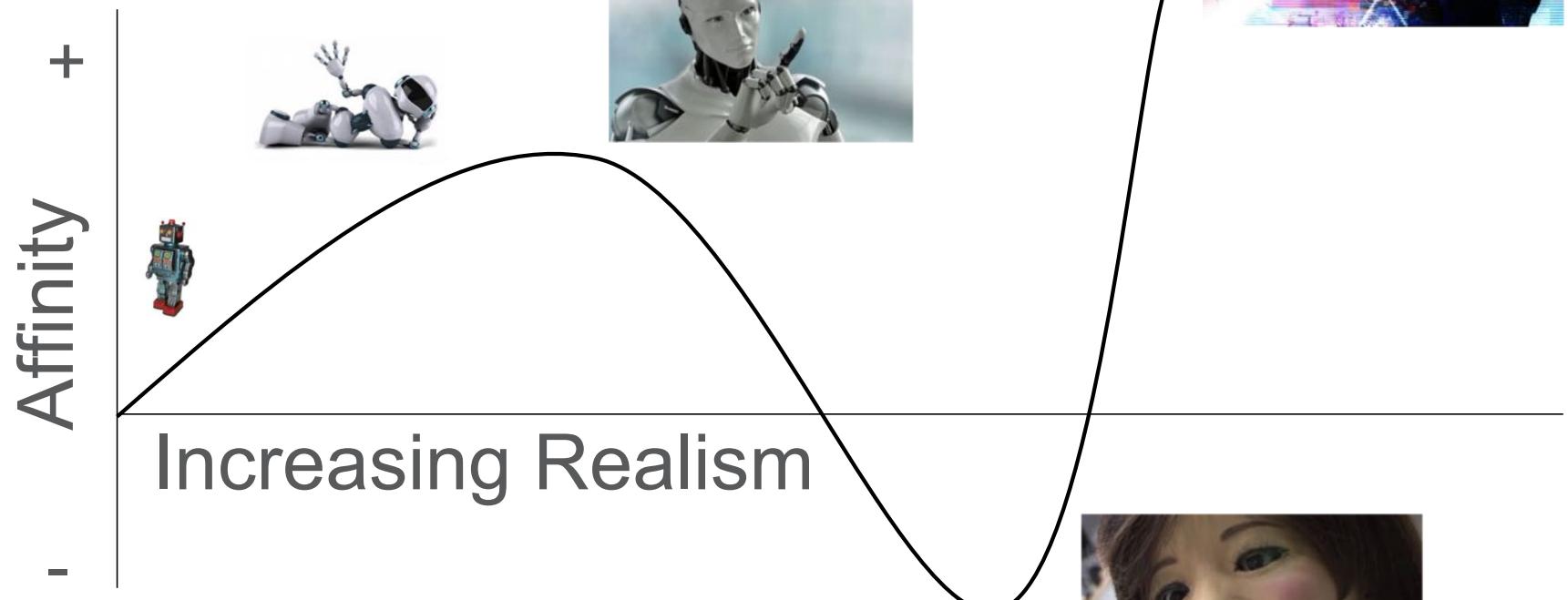
Help advertisers connect with the right customer, personalize every interaction, and measure the effectiveness of each engagement.



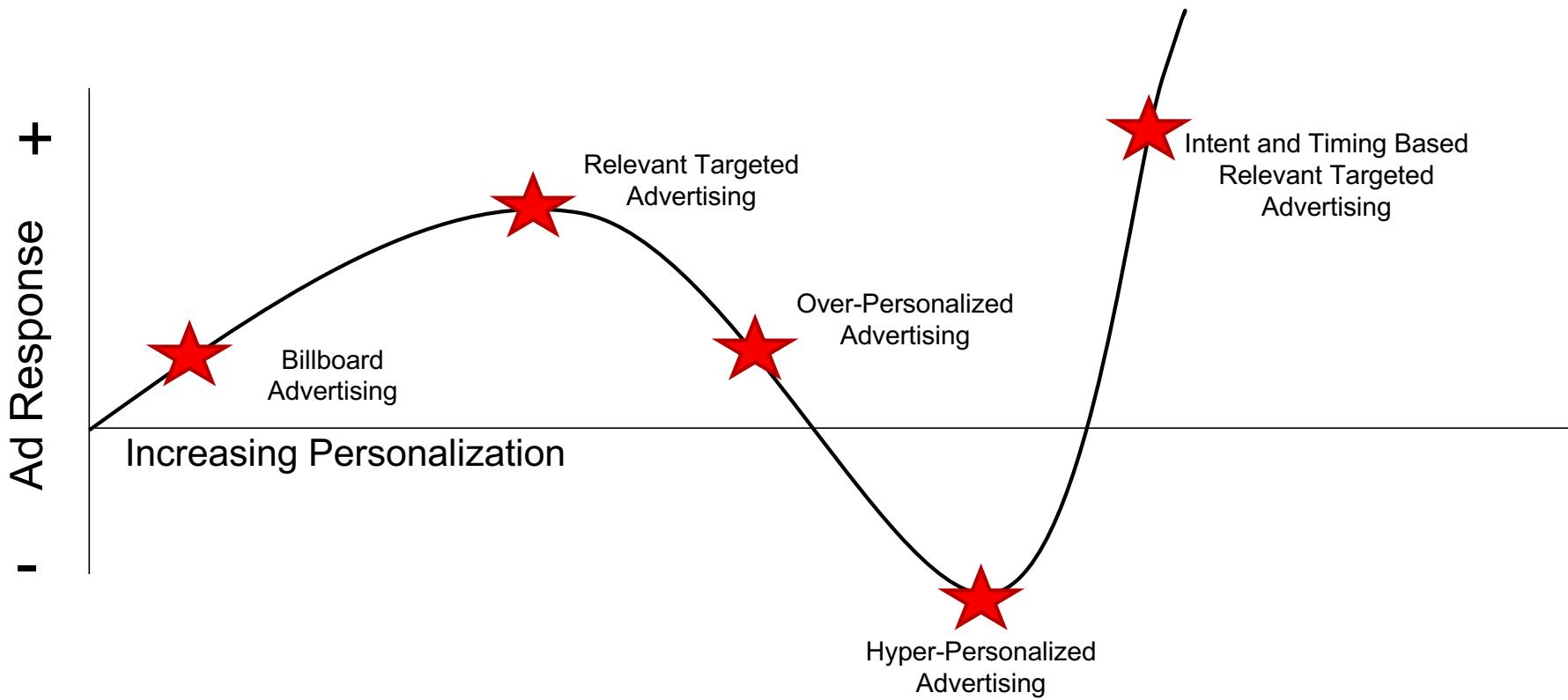
ORACLE®



Uncanny Valley



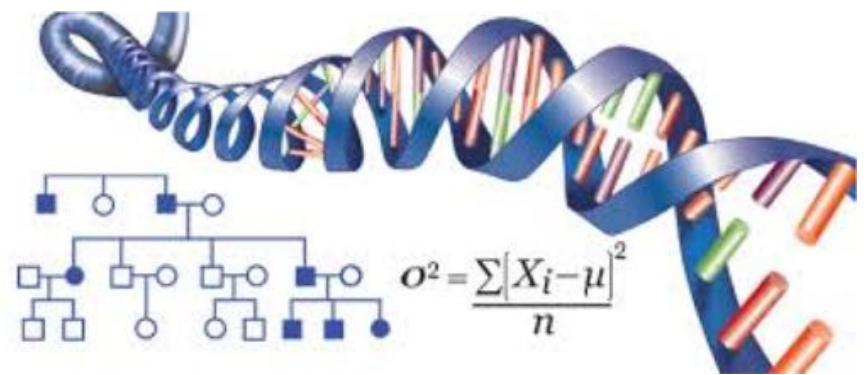
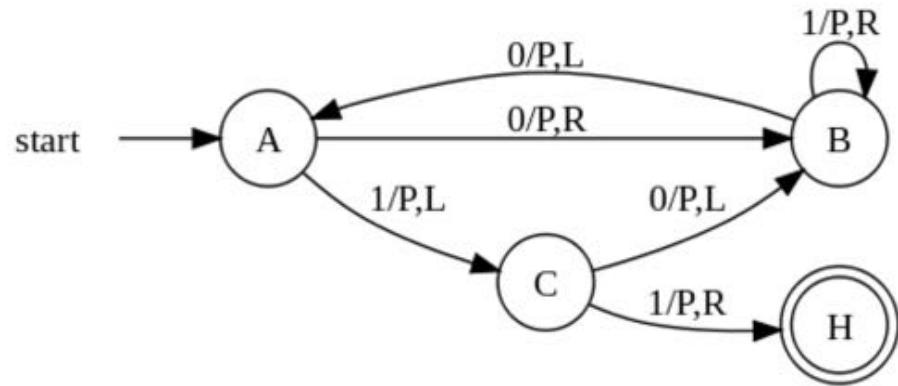
Uncanny Marketing Valley



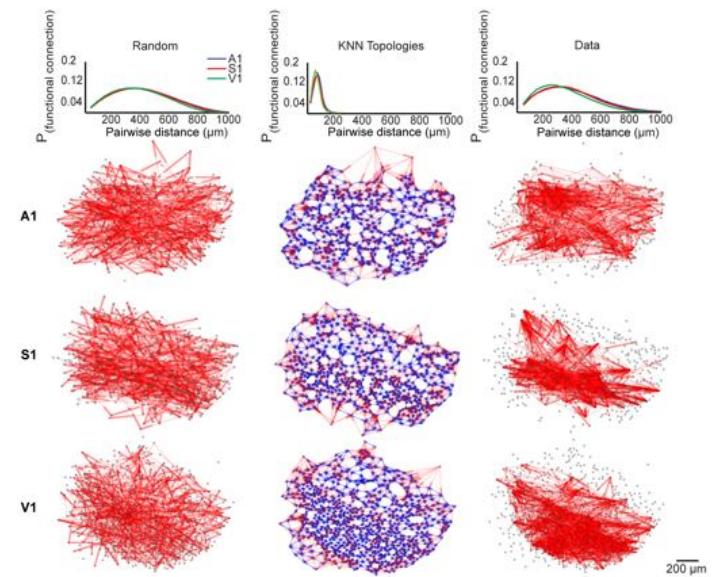
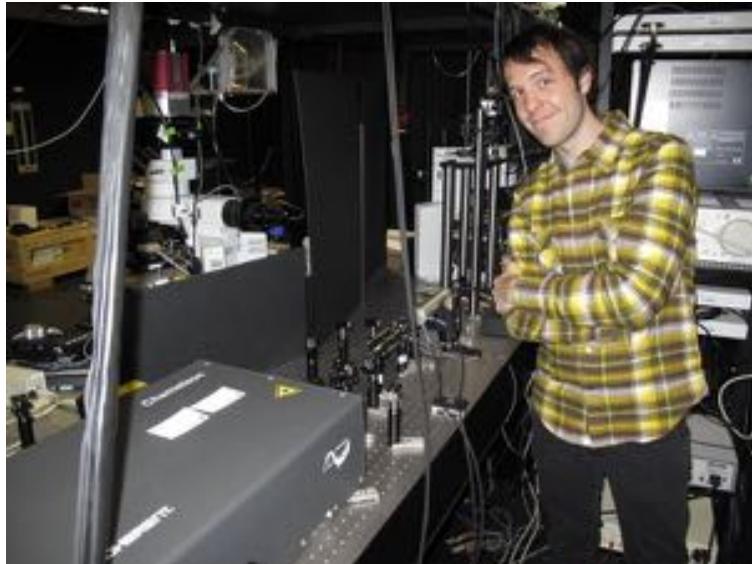
My path to Data Science: Non-formalized training



My path to Data Science: Formal education



My path to Data Science: Formal education



THE UNIVERSITY OF
CHICAGO

What is Data Science?



Big Data Borat

@BigDataBorat

Follow

Data Science is statistics on a Mac.

7:32 AM - 27 Aug 2013

601 RETWEETS 257 FAVORITES



Zvi

@nivertech

Follow

"Data Scientist" is a Data Analyst who lives in California.

7:55 PM - 14 Mar 2012

141 RETWEETS 41 FAVORITES



Josh Wills

@josh_wills

Follow

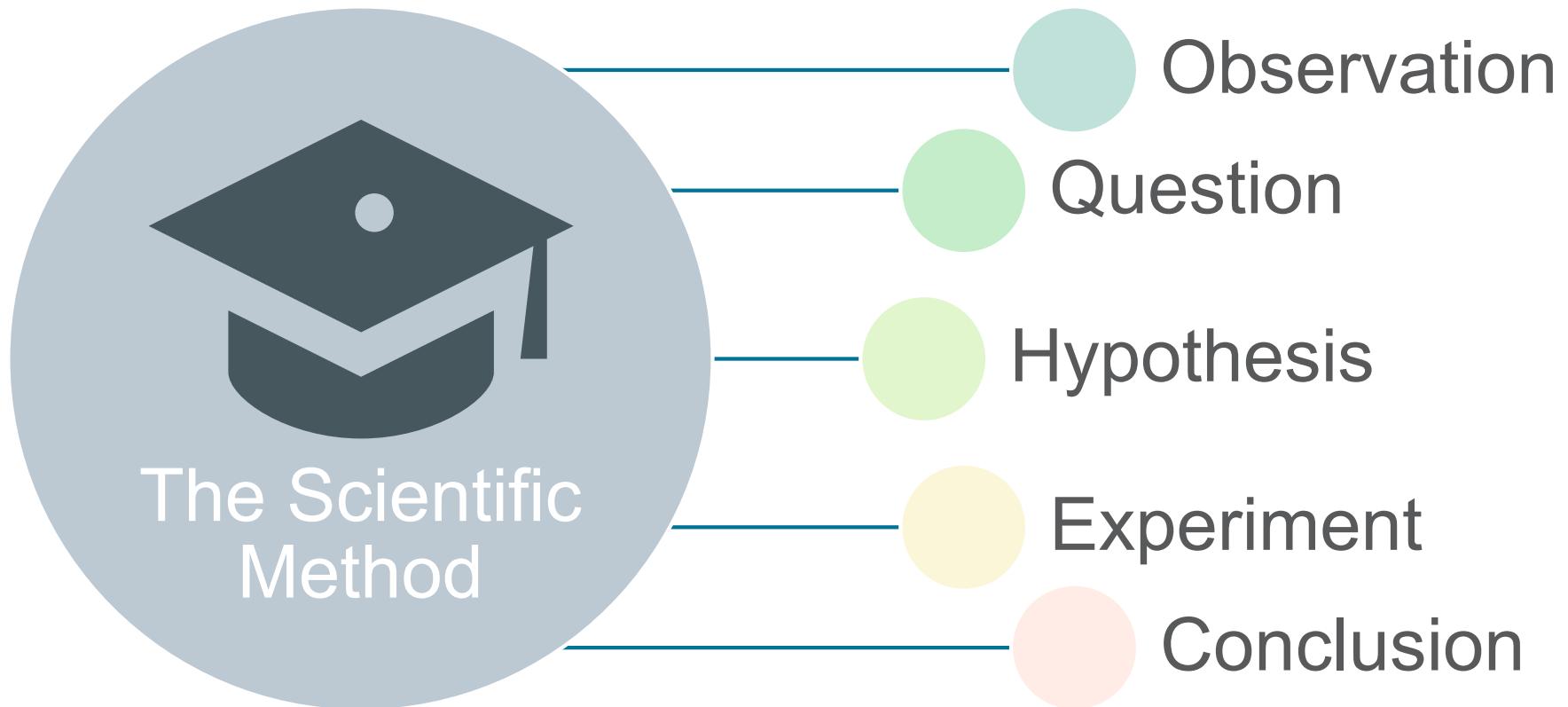
Data Scientist (n.): Person who is better at statistics than any software engineer and better at software engineering than any statistician.

10:55 AM - 3 May 2012

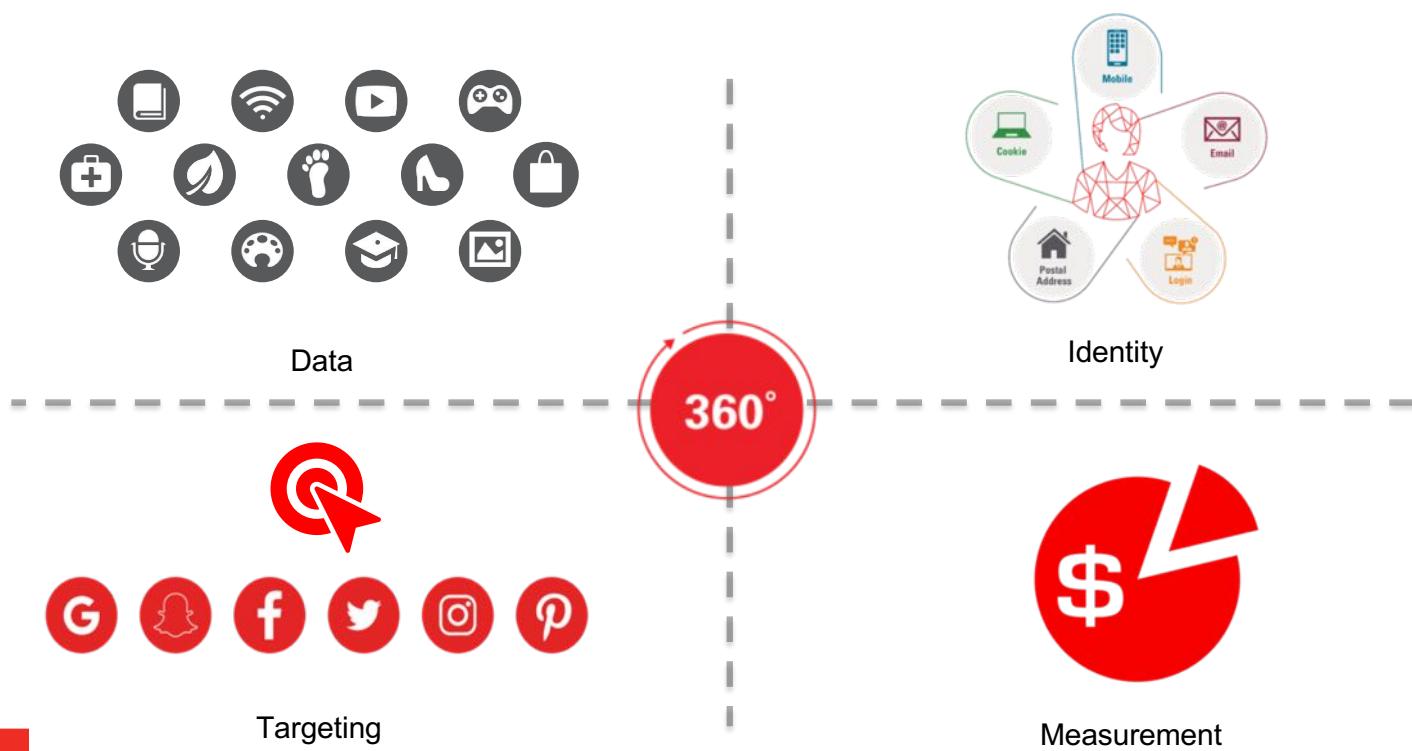
968 RETWEETS 457 FAVORITES



What is Data Science at the Oracle Data Cloud?



Data Science at Oracle Data Cloud



Data



Data

To market efficiently, the **Oracle Data Cloud** uses a full view of consumer behavior



Who they **ARE**

Working mom,
Millennial



Where they **GO**

Shops at Big Box stores
Went to South by Southwest



What they **DO**

Searches for baking recipes
Visits hiking blogs

On the internet no one knows you're a dog



Aspirational vs IRL

Car search on the internet



Car ownership in real life



To market efficiently, the **Oracle Data Cloud** uses a full view of consumer behavior



What they **BUY**

Mac and Cheese,
Salty Snacks,
Tablet Computers,
Videogames



Who they **ARE**

Working mom,
Millennial



Where they **GO**

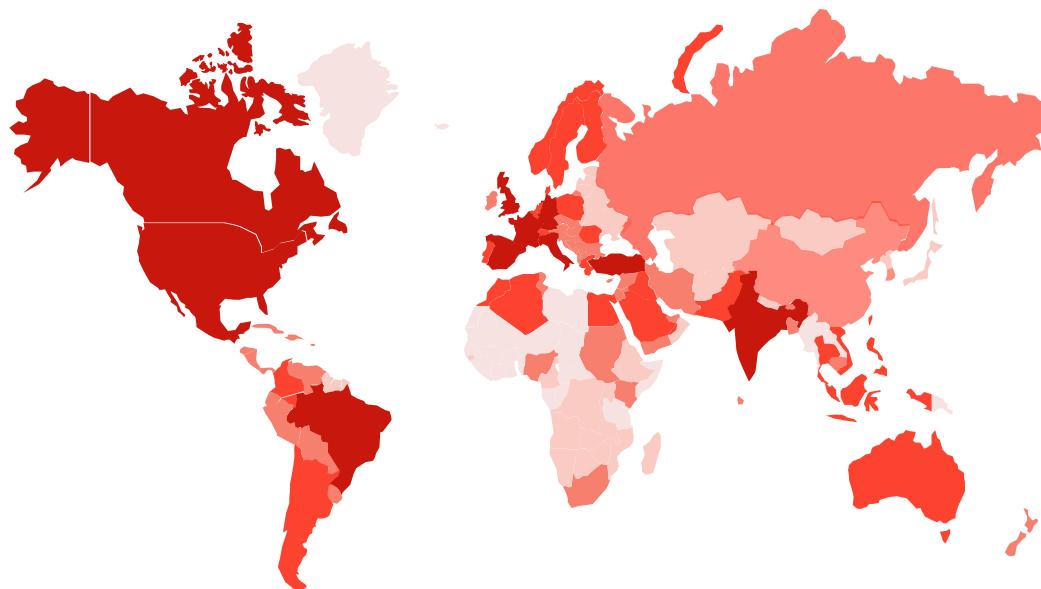
Shops at Big Box stores
Went to South by Southwest



What they **DO**

Searches for baking recipes
Visits hiking blogs

Our data is huge in scale



Lowest Activity Highest Activity

Digital

Over 5 Billion global cookie IDs

Over 1 Billion mobile device IDs

Over 15 Million domains

1.1 Trillion page views

Analog

115M US House Holds

\$3 Trillion in annual observed consumer spending

And exists at an **extremely detailed** level

Married: Yes

Kids: 2

Education level:
College grad

Online sites:

- Kayak travel – Italy
- Travel - High-end hotels
- Cars - cross-over vehicle

Location:
San Diego, CA

Hobby: Photography



Buy high-end women's apparel

Drives a Honda CRV

Avid home cook

Organic product purchaser

Buys children's apparel

Favorite wine is Pinot Noir

Shops at luxury retailers

Datalogix data retail data



Q: What differentiates ODC from others with these data?

A: Our specificity in cataloging every transaction

Transaction Data

Household ID: #12345ab6789
Date: December 2, 2013
Client Name: Hanna Anderson
Client SKU: #HT32966
Amount Paid: \$50.00

Product Data

Client Name: Hanna Andersson
Client SKU: #HT32966
Product Description: Our Nordic-inspired crewneck sweaters are tightly knit from 100% combed cotton yarns. This is quality to hand down; you won't find a single loose thread inside the smoothly finished knit, so there's no catching on fingers. Washable. Certified by Öko-Tex Standard 100. Imported.
Product Categories: Sweater Wool Clothing Children's Clothing

How do we do it?

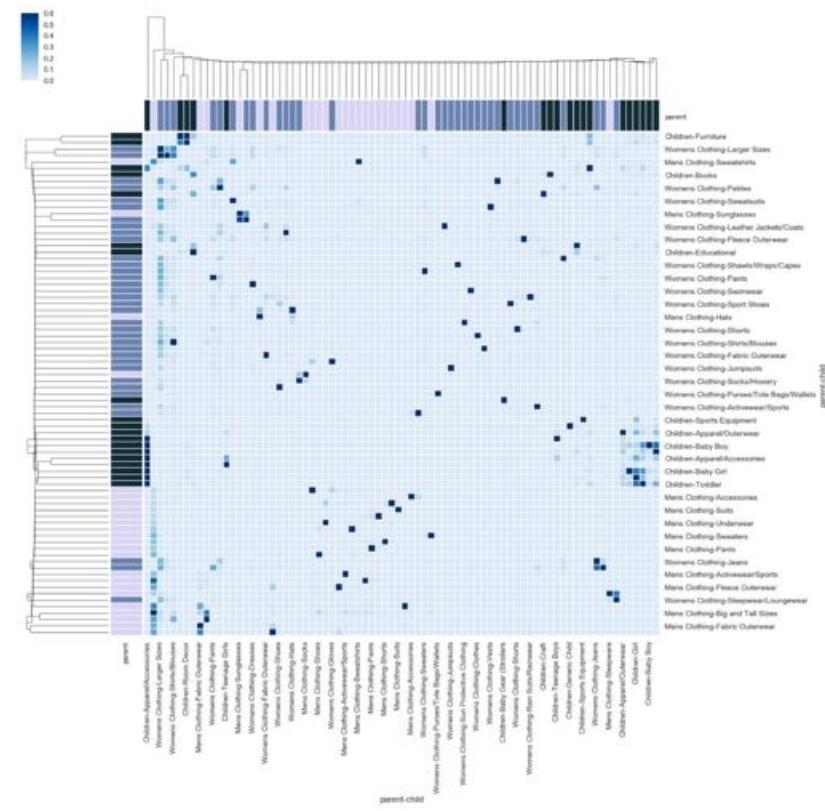
Very Deep Convolutional Networks for Text Classification

Alexis Conneau, Holger Schwenk, Loïc Barrault, Yann Lecun

(Submitted on 6 Jun 2016 (v1), last revised 27 Jan 2017 (this version, v2))

The dominant approach for many NLP tasks are recurrent neural networks, in particular LSTMs, and convolutional neural networks. However, these architectures are rather shallow in comparison to the deep convolutional networks which have pushed the state-of-the-art in computer vision. We present a new architecture (VDCNN) for text processing which operates directly at the character level and uses only small convolutions and pooling operations. We are able to show that the performance of this model increases with depth: using up to 29 convolutional layers, we report improvements over the state-of-the-art on several public text classification tasks. To the best of our knowledge, this is the first time that very deep convolutional nets have been applied to text processing.

Comments: 10 pages, EACL 2017, camera-ready
Subjects: Computation and Language (cs.CL); Machine Learning (cs.LG); Neural and Evolutionary Computing (cs.NE)
Cite as: arXiv:1606.01781 [cs.CL]
(or arXiv:1606.01781v2 [cs.CL] for this version)



AddThis data

...Derived from javascript-based marketing tools on +15M domains

Customizable Audience Targeting Tools

Drive 6x more email subscriptions



Content Recommendations

Increase on-site engagement by personalizing content based on cross-web interests



Tools are all Data-Driven

Leveraging network effects around our scale

Geolocation Data – Accuracy problem or opportunity?

Marketers Must Question Location Data Before They Use It for Attribution

Mobile Data Has A Quality Control Problem

by [Allison Schiff](#) // Monday, March 5th, 2018 – 9:00 am

Until We Fix Location Data Inaccuracy, We Will Never Close the Mobile Spending Gap

by [AdExchanger](#) // Friday, July 28th, 2017 – 1:05 am

GPS isn't the answer when it comes to location-based marketing

With GPS still only accurate to 10 meters and failing to account for height, marketers need to start figuring out novel ways of implementing their location-based marketing strategies. PoweredLocal's Gary Tramer explains.

How an internet mapping glitch turned a random Kansas farm into a digital hell

Report: Only 1% of exchange location data useful for offline attribution

Study also found that average accuracy of exchange-derived locations is 'over 4 New York City blocks.'

Why does accurate location data matter?



Testing location data: 30+ Provider RFP

Each location provider was challenged to send us their “best” list possible for buyers at each of the three chains and we would compare to our data in the follow scenarios:

Better
than random



How likely was the location data to outperform random buyers?

Location based
machine learning



Can location data power a model built to find shopper look-a-likes?

Too much
Information



How well could a location provider describe our own employees’ day to day lives?

Better than random

Question: When is it the busiest time to head to the grocery store?

Answer: Saturday, followed by Sunday, followed by any weekday before a holiday or major sporting event

Question: Who is most likely to make a purchase at a store?

Answer: Someone who has purchased there before

We wanted our random tests to reflect this!

Better than random: Creating random



Location Data			
Thursday	Friday	Saturday	Sunday
*			*



Purchase Data			
Thursday	Friday	Saturday	Sunday
*			*

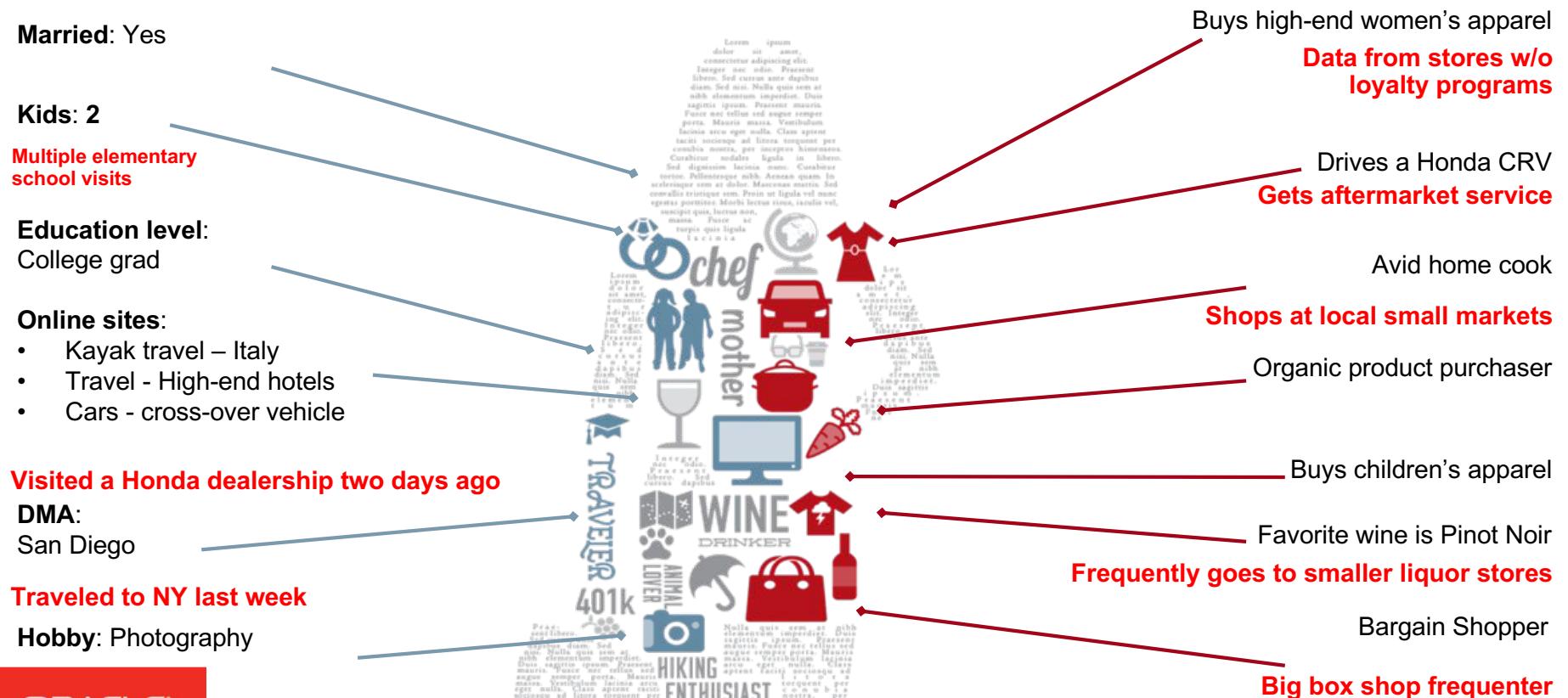
Joe's Location Data

Joe's Location Data			
Thursday	Friday	Saturday	Sunday
*			*

Purchase Data

Purchase Data			
Thursday	Friday	Saturday	Sunday
	*		*

Data driven view of a consumer with location data



Identity



Data

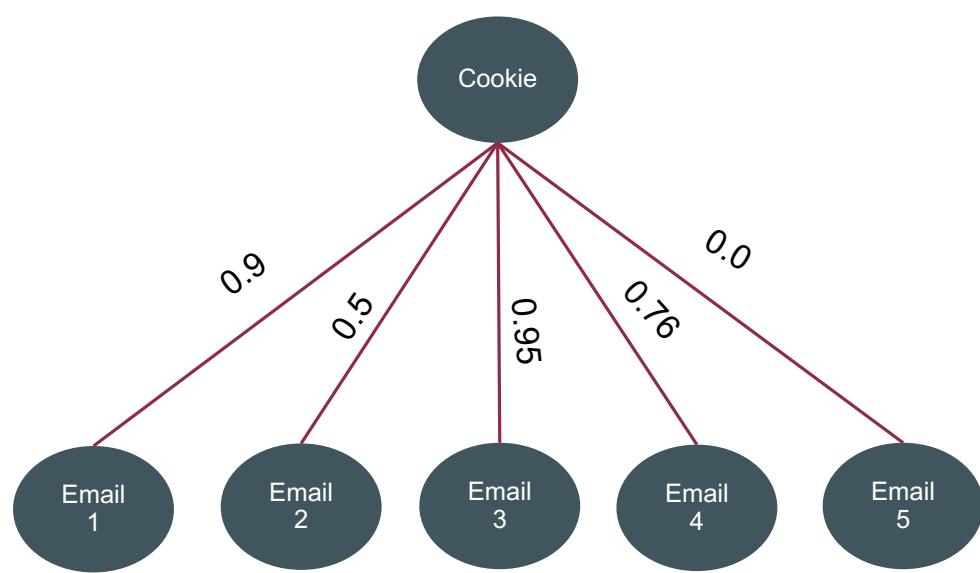


Identity

Where does data come from?



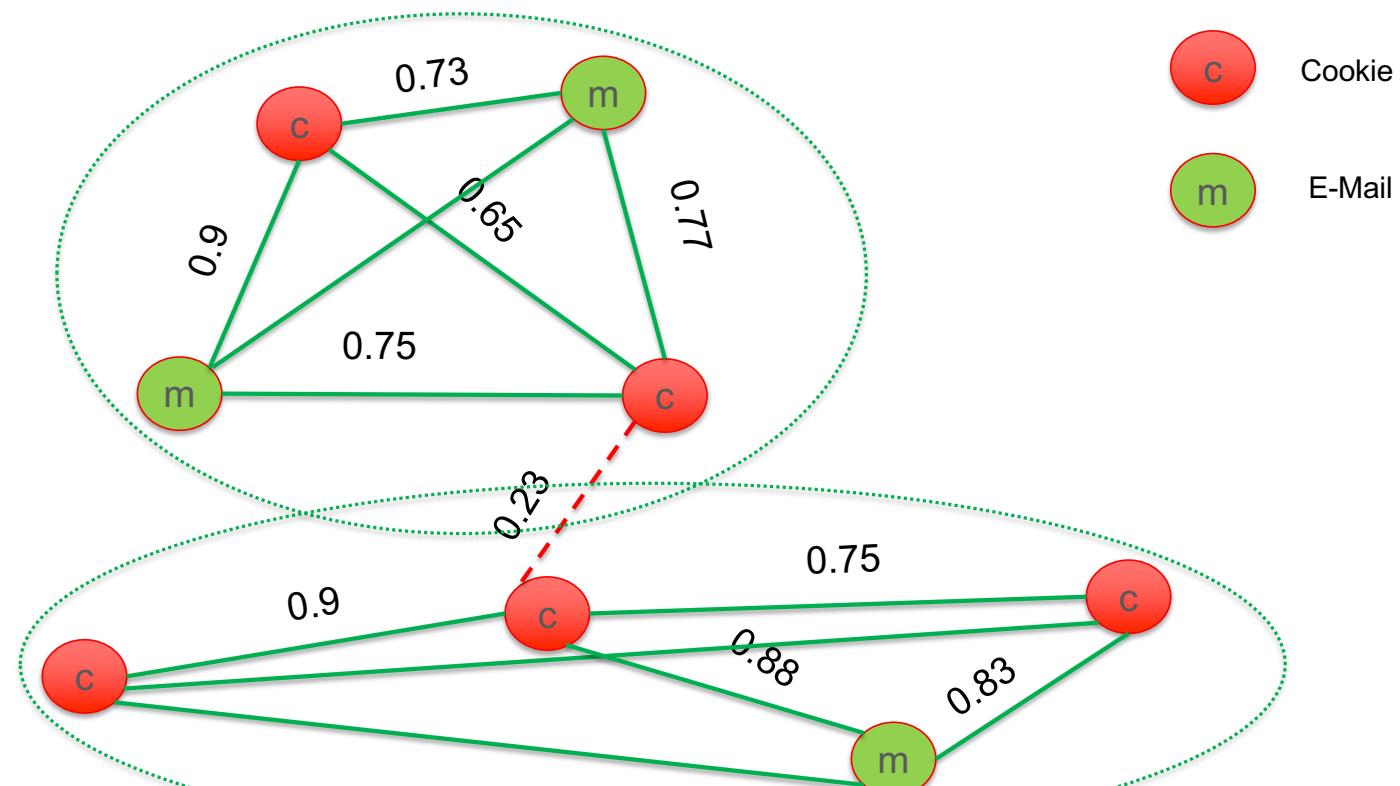
The problem: defining linkage



We use machine learning to generate probabilities for each candidate

- Natural language processing of email address
- Supervised learning on known linkages based upon relevant features

The problem: grouping linkage types



Why does a strong ID Graph matter for marketing?

You reach



instead of



Wasted media spend

Your target
ends up in

Control

instead of

Test

Inaccurate results

You can only
target via



instead of



**Limited cross-channel reach
and disjointed consumer
experience**

Targeting



Data

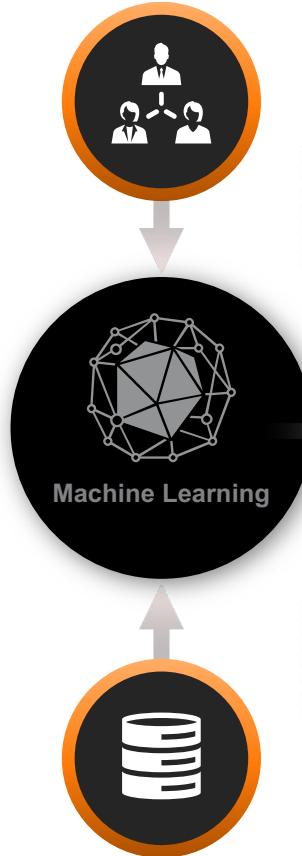


Identity



Targeting

Start with an event or group



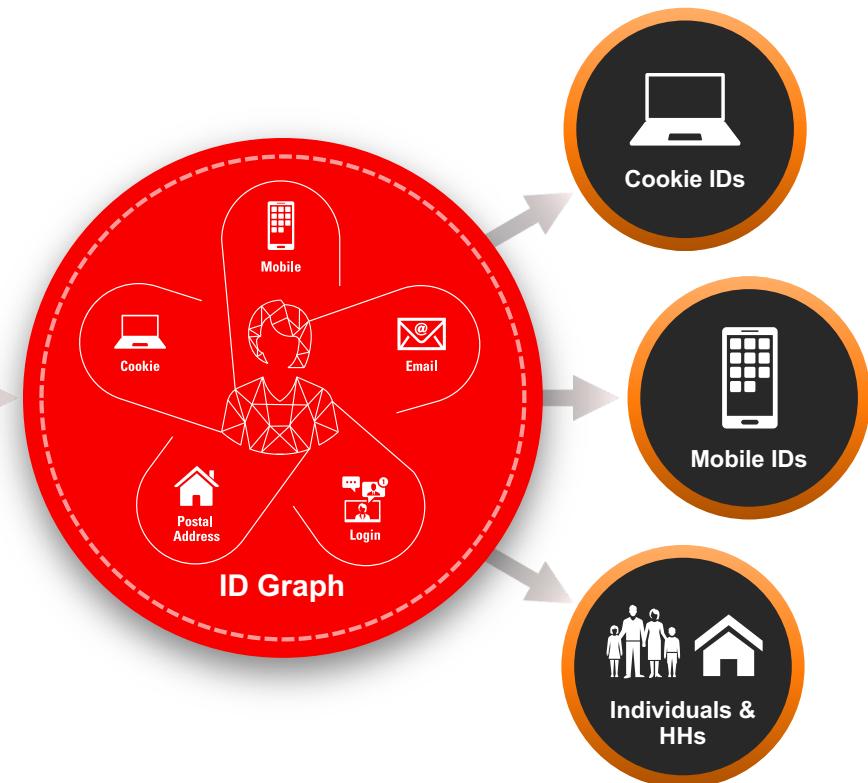
We use **machine learning** to go from data to targeted advertising

Seed = action to predict group you wish to identify
(e.g. purchase, click, url visit, "Soccer Mom" etc.)

Model

Scoring

Data = features used to predict the seed
(e.g. purchases, demos, web behavior, etc.)



We do this on a stable,
self built, machine learning
Platform: M360

Every month we create:

10,000+ models

**Each with terabytes
of data...**

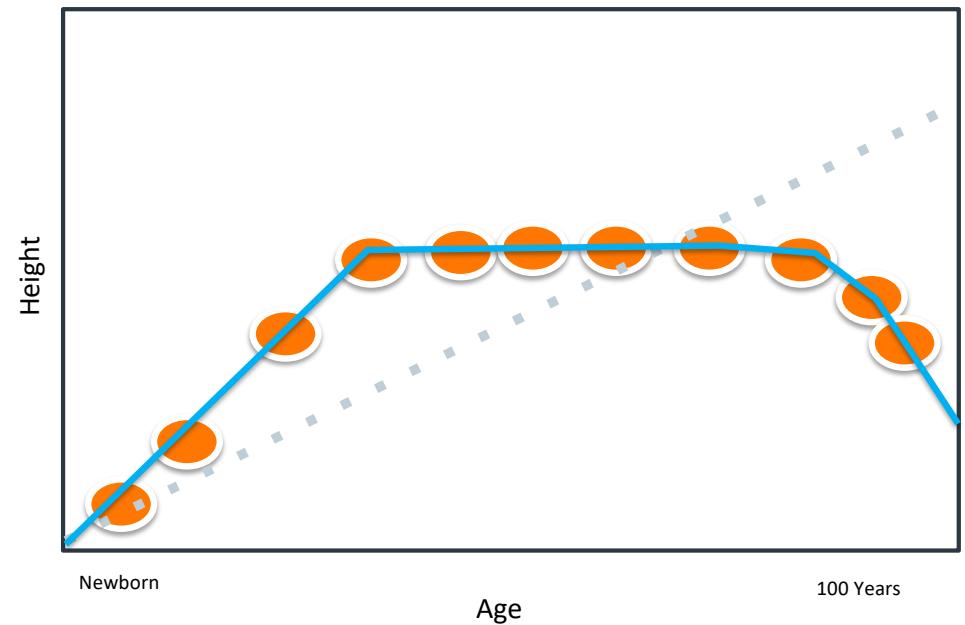
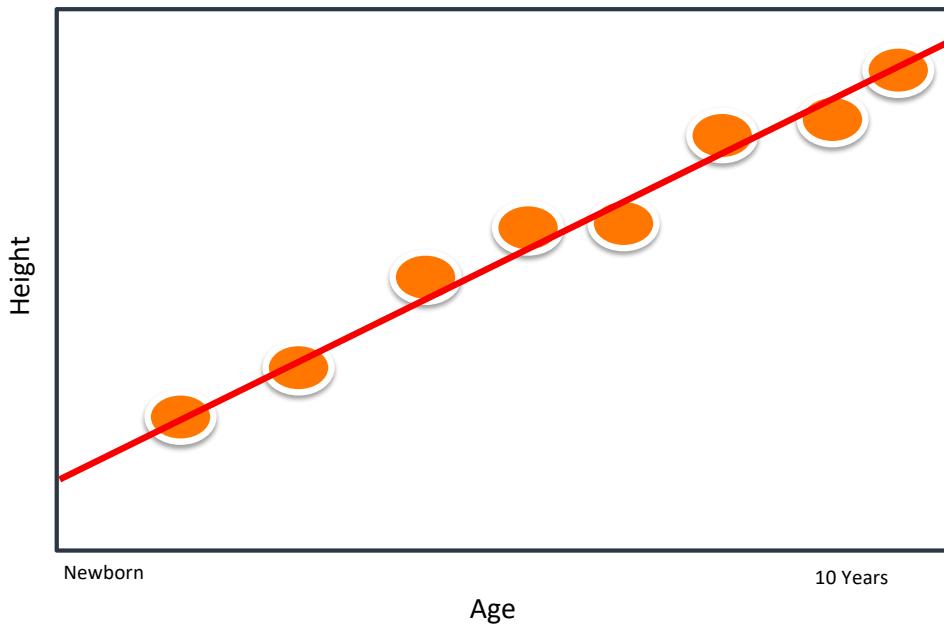
... and best in class machine learning accuracy



The key to doing this successfully is letting the data tell the story

The non-data driven way to model data:

- Manually pick a modeling method for your data
- Apply it



Letting the data tell the story

No Free Lunch Theorem

- For any model, any elevated performance for one type of problems is offset by poor performance for another type

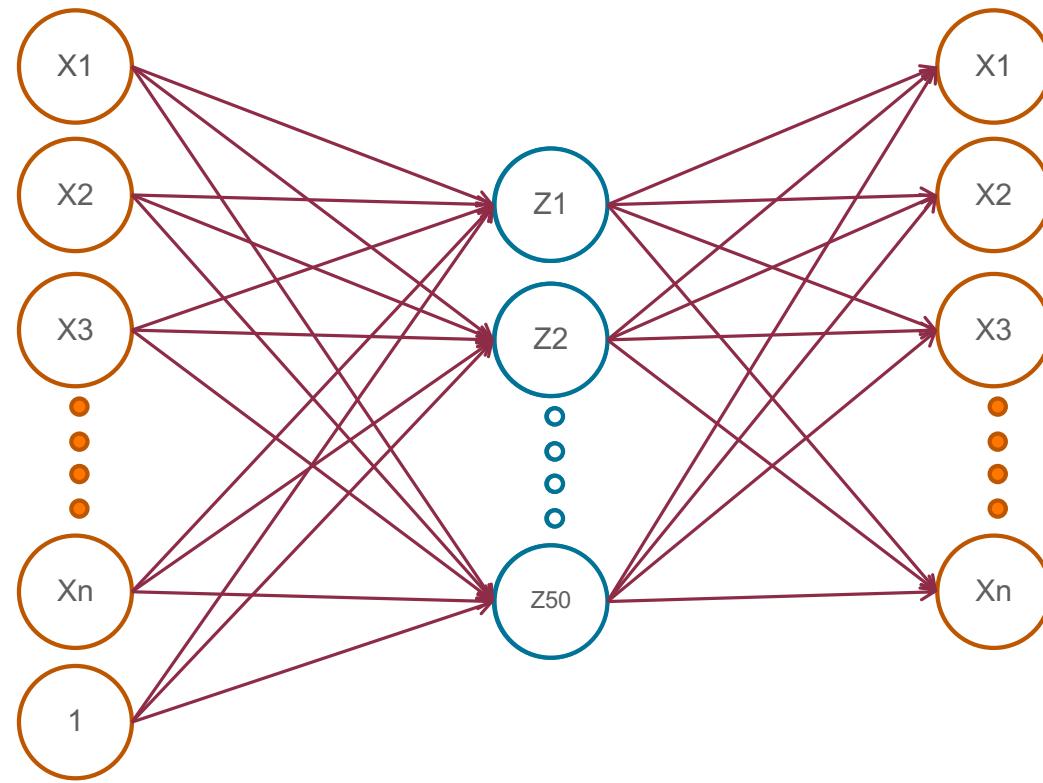
So what can we do?

- Try multiple models with training data and pick the one or combination that works best with machine learning
- We can do it easily in under 50 lines of code!

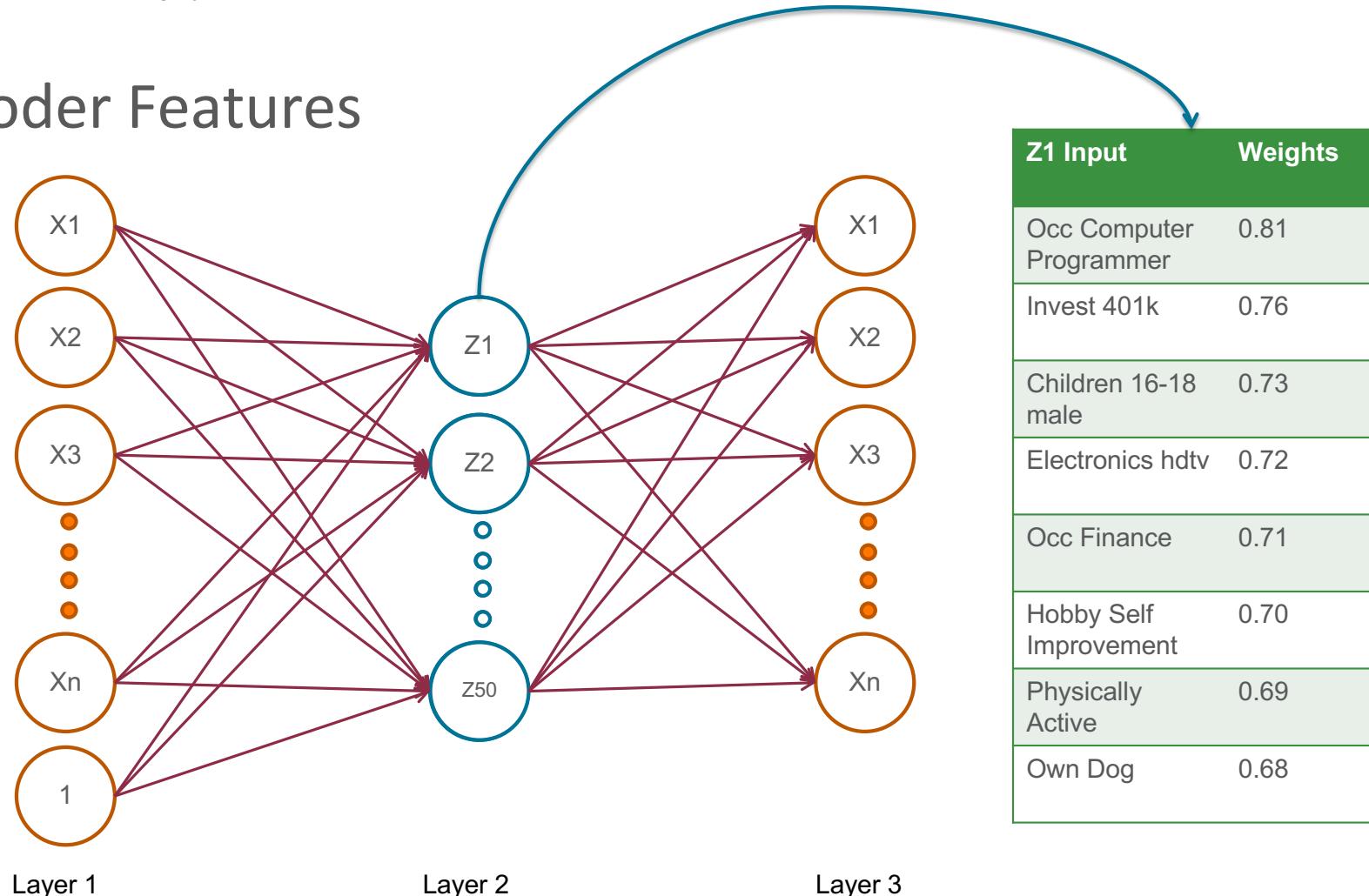


https://github.com/sadovsky/no-free-lunch/blob/master/no_free_lunch.ipynb

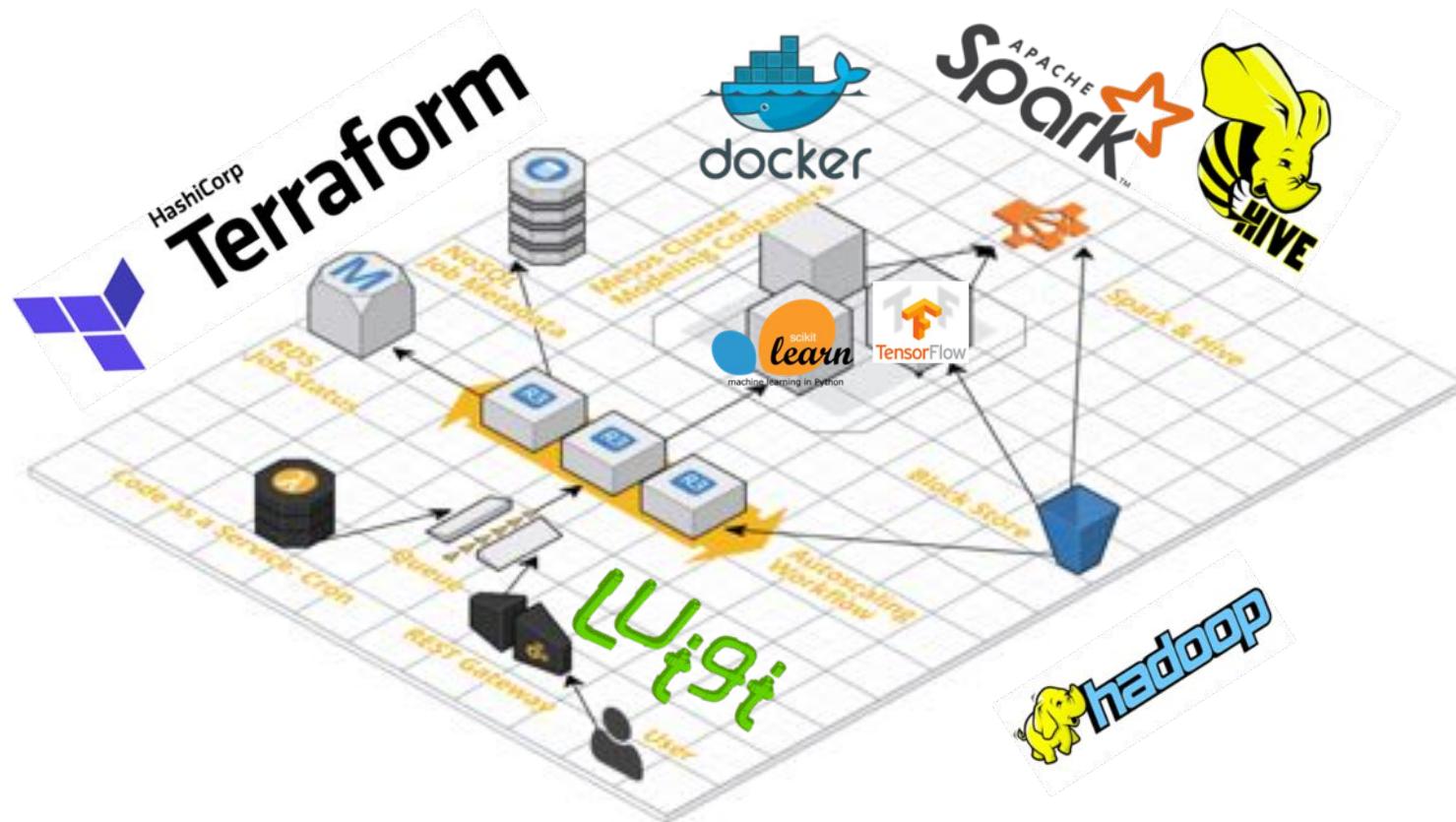
Letting (some of) the data tell the story: Autoencoders



Autoencoder Features



What do you do if you can't reduce dimensionality enough?



Why Spark/Hive/Hadoop?



Running multiple models: Hive solution

- Initial Solution: Data Science at the Command line

Bourne-again shell (BASH)

HIVE

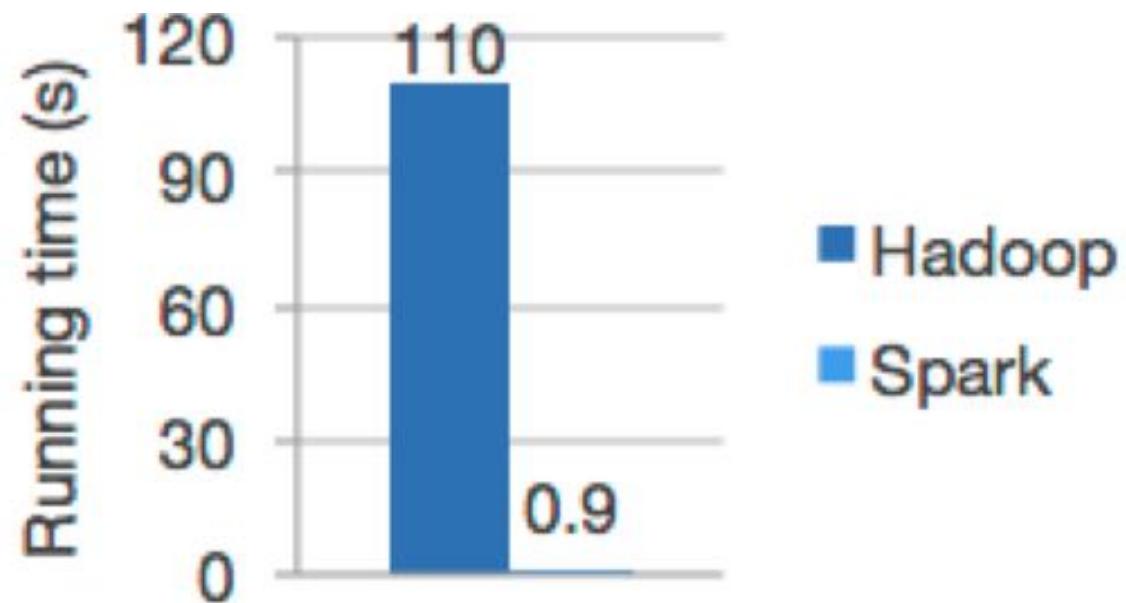


Takes about a week to run. Uses a ton of computer resources.

Moving from Hive to Spark

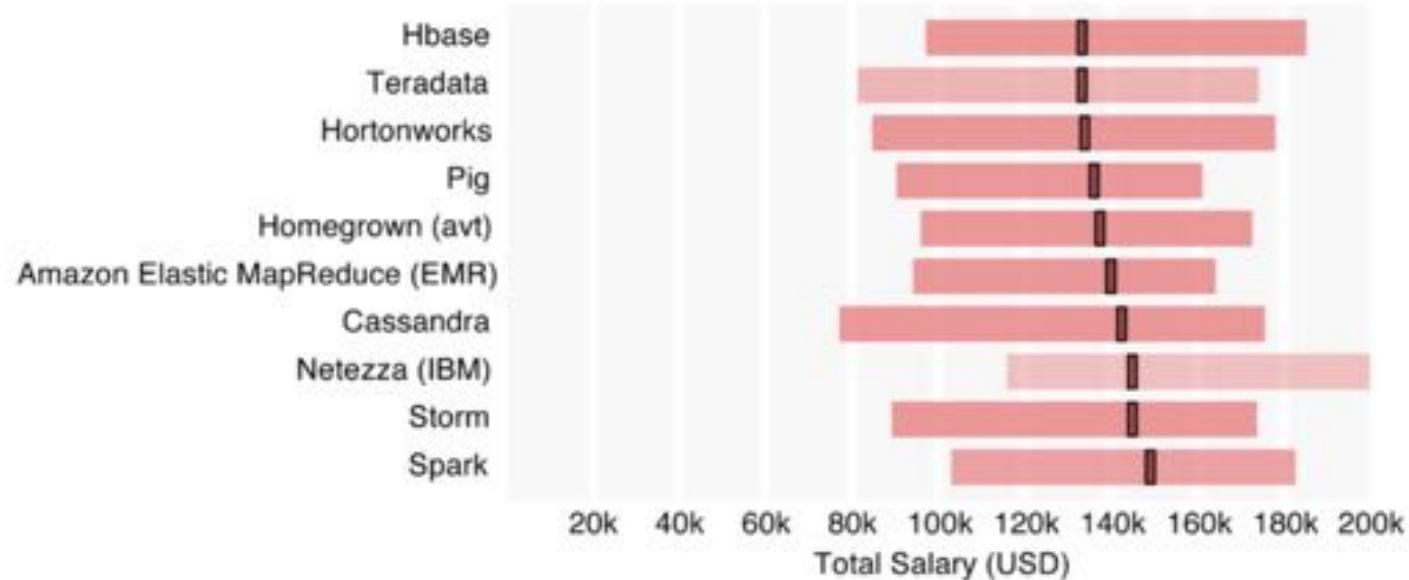


Why Spark?



Why else Spark?

High-salary tools: median salaries of respondents who use a given tool

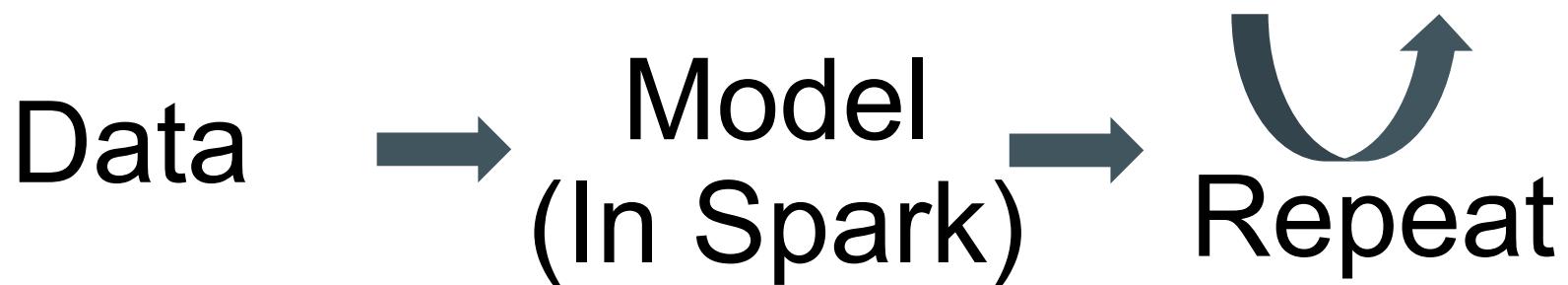


<http://www.oreilly.com/data/free/2014-data-science-salary-survey.csp>

Running multiple models: Spark solution

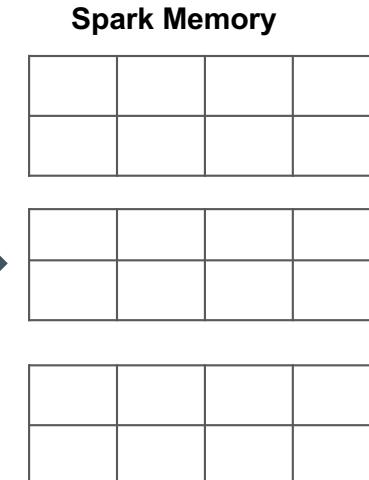
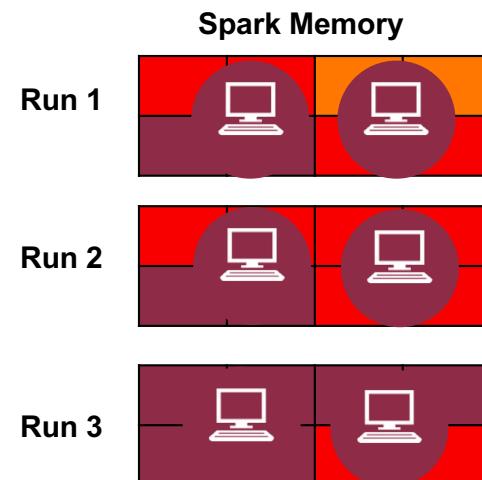
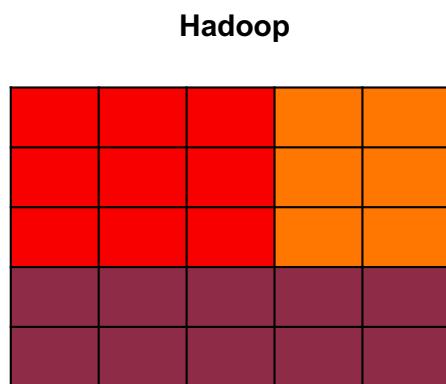
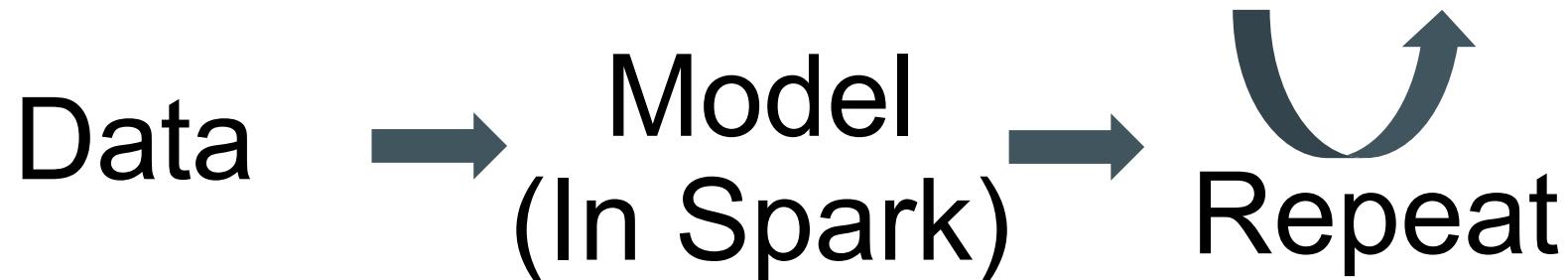
- Novel Solution

All spark



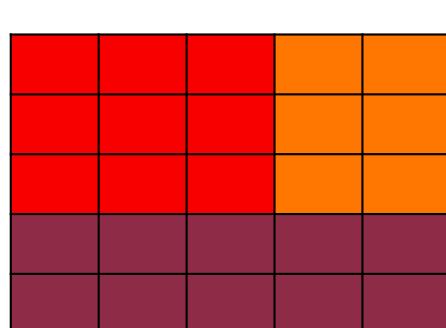
Still takes forever to run.

Running multiple models: Spark solution



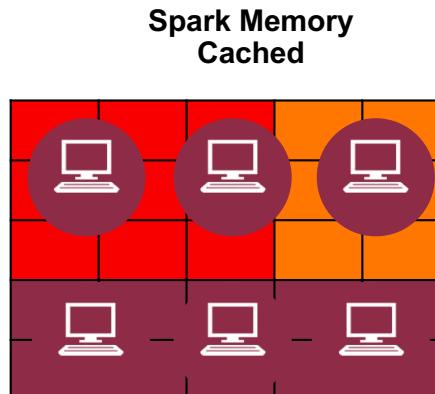
Running multiple models: Spark solution w/caching

Data



Model
(In Spark)

Run 1
Run 2
Run 3



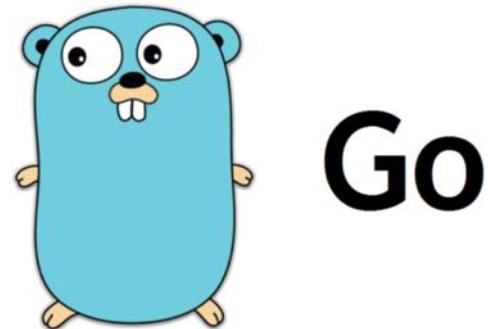
Repeat Modeling

1 Week Process -> 11 Hours

- More computers but way shorter duration
- Faster and Cheaper

Python is great, but not always the answer

FORTRAN

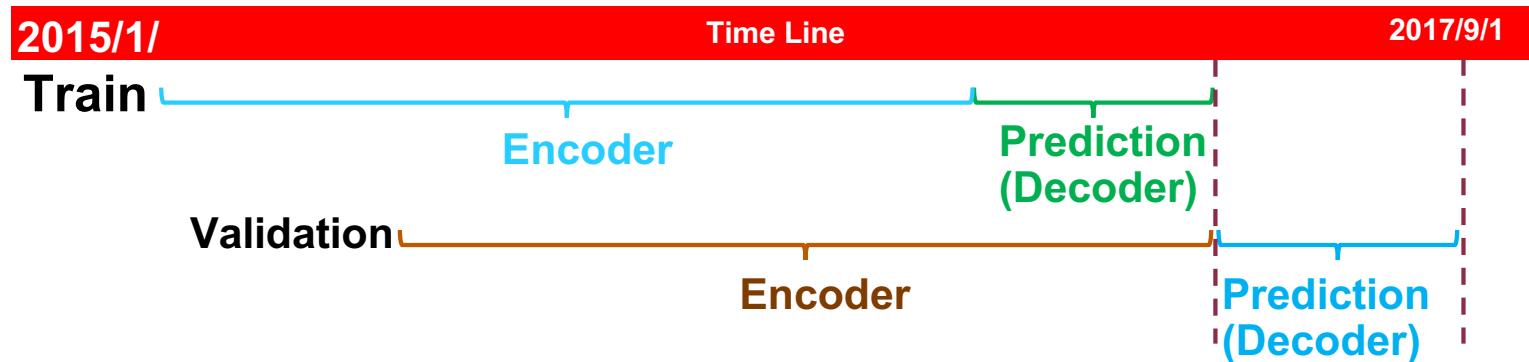


https://github.com/sadovsky/binomial_sim

Targeting beyond buy-alike/look-alike modeling

- Sales cycle / Temporal models
- Contextual targeting

Predictive HH Purchase Forecasting

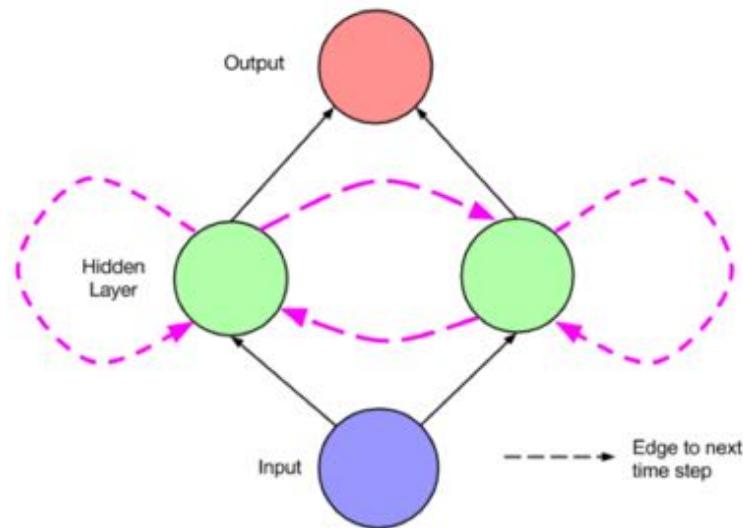


Work inspired by:

Laptev, Nikolay et al. "Time-series Extreme Event Forecasting with Neural Networks at Uber." (2017).

Zhu, Lingxue and Nikolay Laptev. "Deep and Confident Prediction for Time Series at Uber." 2017 IEEE International Conference on Data Mining Workshops (ICDMW)(2017): 103-110.

We need our networks to remember



LSTMs

Input gate learns when to let activation into the **internal state**

Output gate learns when to let value out of the **internal state**

When both gates are closed, the activation is trapped in the memory cell, neither growing nor shrinking, nor affecting the output at intermediate time steps

Constant error carousel enables the gradient to propagate back across many time steps, neither exploding nor vanishing

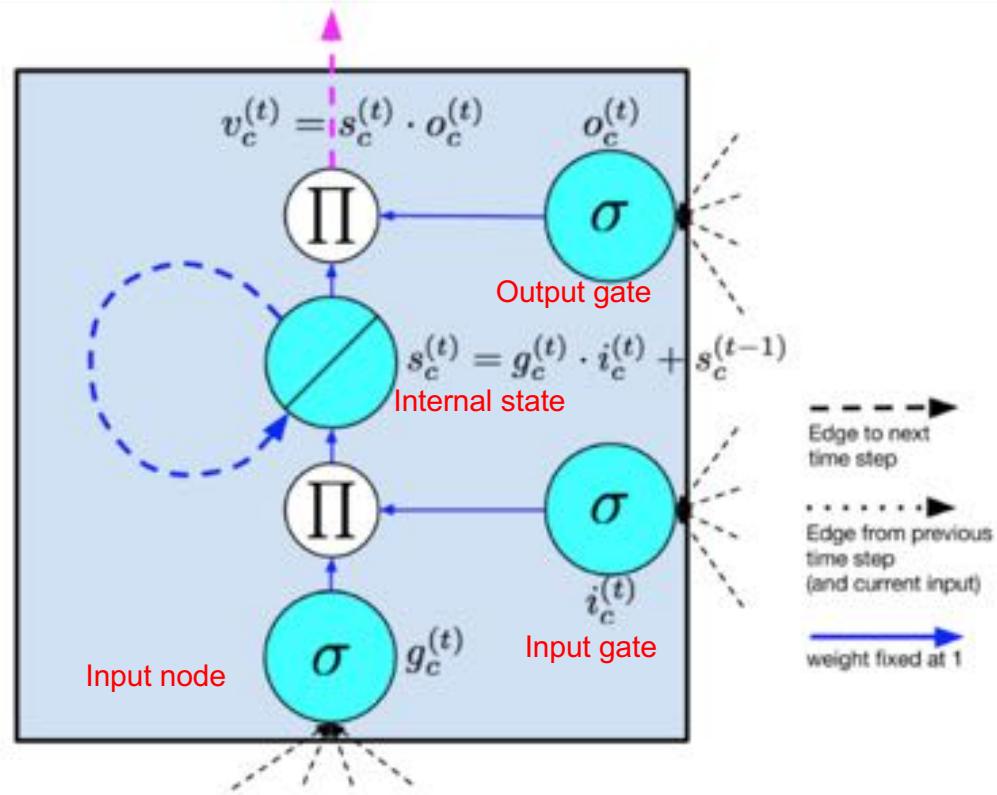
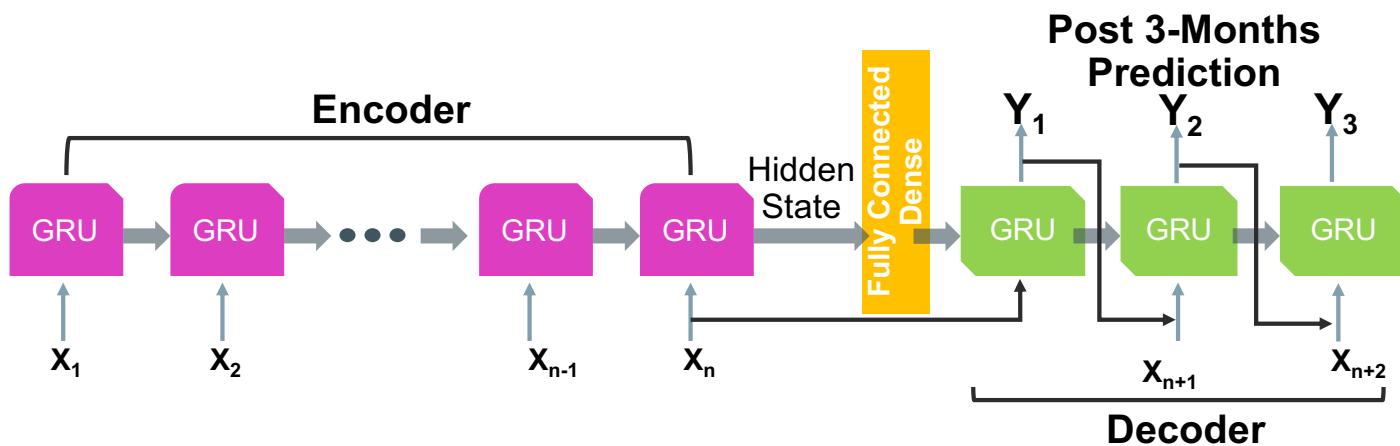


Figure 9: One LSTM memory cell as proposed by Hochreiter and Schmidhuber [1997]. The self-connected node is the internal state s . The diagonal line indicates that it is linear, i.e. the identity link function is applied. The blue dashed line is the recurrent edge, which has fixed unit weight. Nodes marked Π output the product of their inputs. All edges into and from Π nodes also have fixed unit weight.

Predictive HH Purchase Forecasting

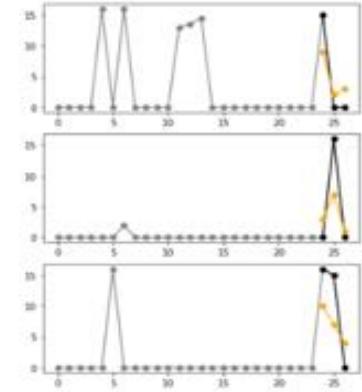


- Teacher-Forcing is used during model training
- X_n is monthly input features
- Y_n is monthly sales prediction
- $n = 24$, two-year worth of monthly sales data was used for encoder

Predictive HH Purchase Forecasting

Lagging Largest-Sale Month Accuracy

For the households that have purchases over prediction period, the predicted largest-sale month within one-month distance to true largest-sale month. The predicted largest-sale month has to predict largest-sale month



- ❖ Households are ranked by three-month predictive accuracy
- ❖ Baseline: ranking buyers by pre-period sales (pre-period monthly sales data)

Accuracy	Baseline
9%	0.28%
0%	1.31%
1%	4.93%

Grapeshot: Contextual brand safety

11-year-old charged with driving drunk

REUTERS 

NEWS ALERTS

Get an alert when there
are new stories about: 

- Orange Beach, Alabama
- Perdido Key, Florida
- Chevrolet Monte Carlo

[Add Selected Alerts](#)

[More Alerts](#)

Fri Jul 6, 3:23 PM ET

MIAMI (Reuters) - An 11-year-old girl was charged with drunken driving after leading police on a chase at speeds of up to 100 mph that ended when she flipped the car in an Alabama beach town.

A video camera in the police car captured the look of surprise on the officer's face when he approached the wrecked car and got a look at the motorist.

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CNN.COM
Explosion rocks besieged
mosque in Pakistani capital

ABC NEWS
'Out of the Blue': Do Aliens
Exist?

THE CHRISTIAN SCIENCE
MONITOR
William Bratton: Lauded chief
of troubled LAPD

The Mobile Press-Register newspaper said the patrolman saw the Chevrolet Monte Carlo speeding and flashed his lights to signal the driver to stop. Instead, the car sped faster, traveling at up to 100 mph (160 kph) before sideswiping another vehicle and flipping over in the Gulf Coast town of Orange Beach, Alabama, on Tuesday night.

The young driver, who lived nearby in Perdido Key, Florida, was treated at a hospital for scrapes and bruises and released to relatives. Police also charged her with speeding, leaving the scene of an accident and reckless endangerment.

The car belonged to a relative and police were still trying to find out where she got the alcohol. There was none in the vehicle but her blood alcohol level was over the limit for adult motorists, police told the newspaper.



[Email Story](#) [IM Story](#) [Printable View](#)

Grapeshot Part Deux



Grapeshot Part Three

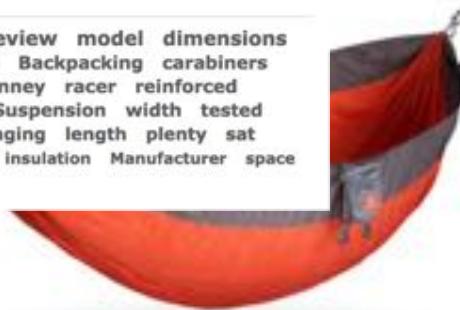
The screenshot shows the Backcountry website's homepage. At the top, there is a navigation bar with categories: Men's, Women's, Footwear, Camp/Hike, Climb, Bike, Snow, Paddle, Fitness, and Travel. On the far right, there are links for 'Sign In' and a search icon. Below the navigation bar, a breadcrumb trail indicates the user is at 'Home / Camping & Hiking / Ultralight / Hammocks'. A prominent banner in the center of the page reads '15% Off Your Entire First Order' followed by 'New Customer Offer' and a 'Shop Now' button. The background of the banner features a scenic view of a forested mountain.

grapeshot KEYWORD ANALYSIS

<https://www.outdoorgearlab.com/reviews/camping-and-hiking/hammock/kammok-roo> ENGLISH

EXTRACTED KEYWORDS ON PAGE

Roo hammock Kammok simple comfortable Review model dimensions pounds Capacity weight camping fun ahhh audible Backpacking carabiners cooler cozy Durable elicit Garrett generous hems Penney racer reinforced slings stitching Straps stylish USD Verdict softness Suspension width tested rated set Analysis beautiful climbing easily grade Hanging length plenty sat triple upgradable weather construction lounging Best Buy insulation Manufacturer space buggy campsite purchase rain stargaze suited the open



Hands-on Gear Review

Where's the Best Price?

Seller	Price
Backcountry	\$79.20 - 21% off
REI	\$99.00
Moosejaw	\$99.00

[Compare prices at 4 sellers >](#)

*You help support OutdoorGearLab's product testing and reviews by purchasing from our retail partners.

Table of Contents

- Performance Comparison
 - Comfort
 - Weight
 - Ease of Set Up
 - Durability and Protection

Measurement



Data



Identity



Targeting



Measurement

Did our targeting *cause* consumers to go out and buy?

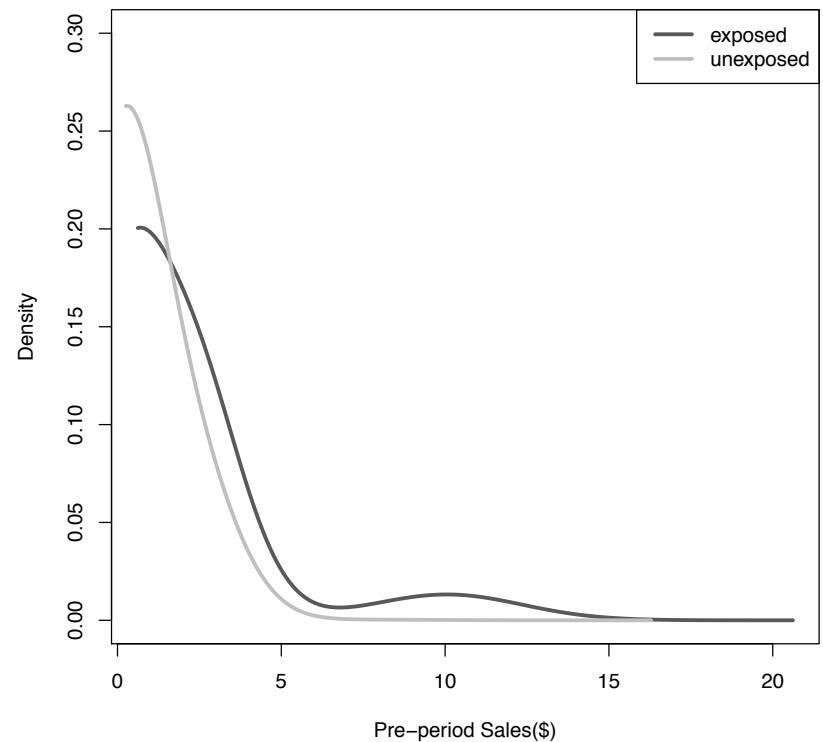
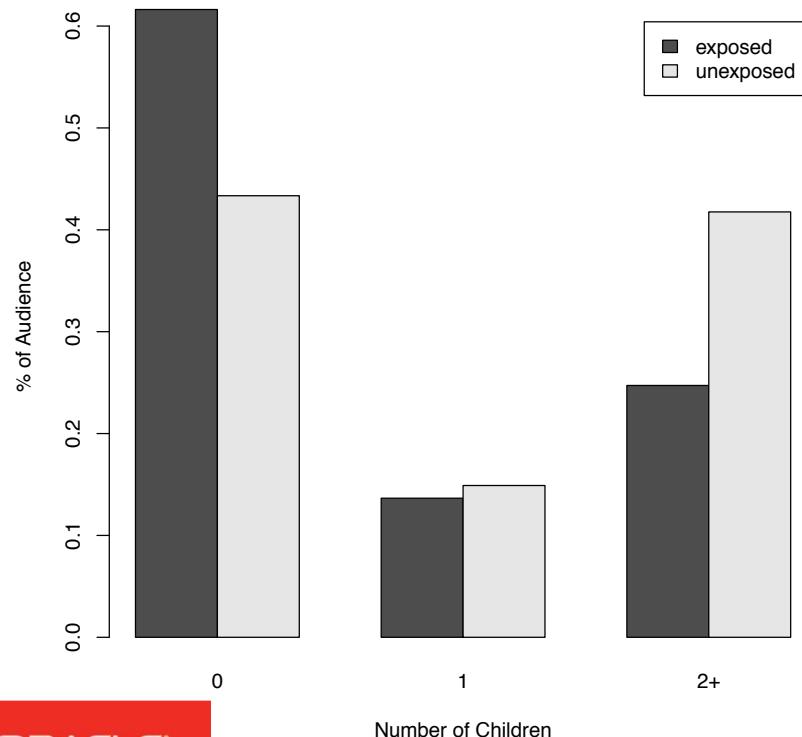


Ideally, we want to do a careful test/control experiment...



... but we can't actually do this!

Problem: Exposed vs un-exposed is biased



Solution: Forensic Control

A **forensic control** weights the unexposed households to be equivalent to the exposed households

1. Stratification

Create smaller groups (strata) of households with similar characteristics (based on spend and variables related to exposure)

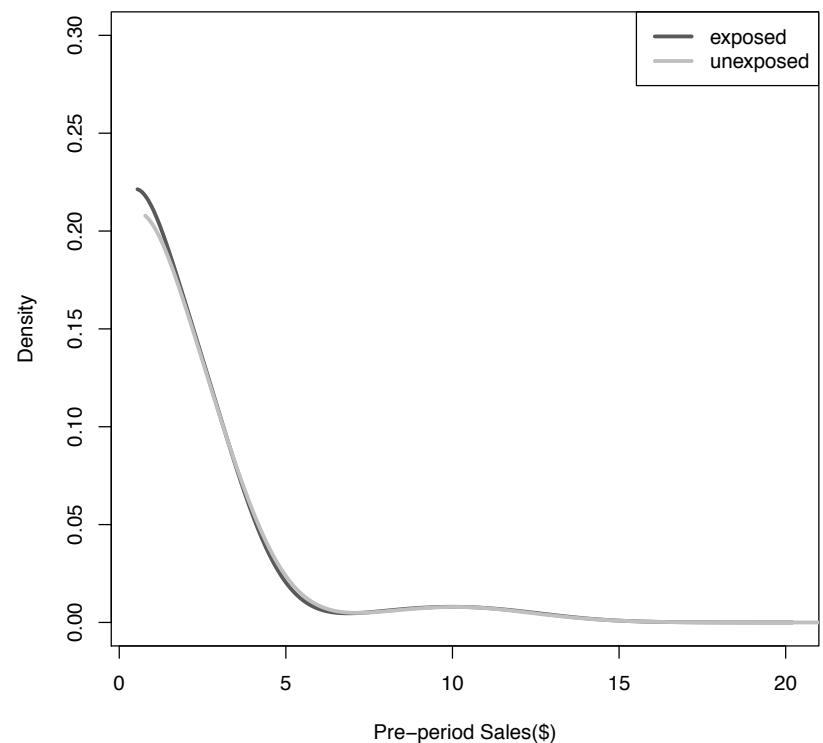
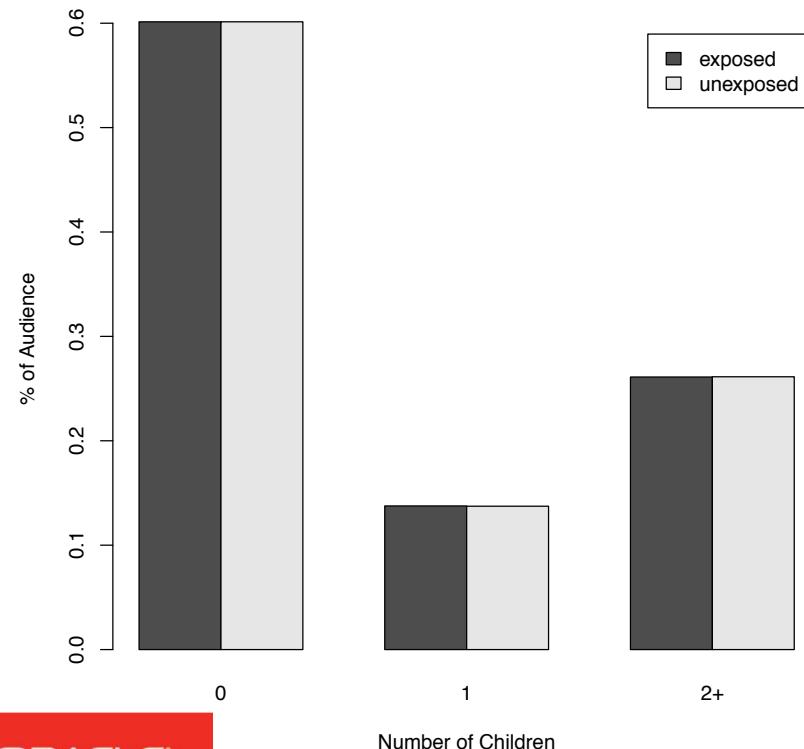
2. Propensity Model

Understand what characteristics define the exposed group

3. Weighting via entropy balancing

For every strata level, use entropy balancing to ensure equal sample size and equal mean, variance, skew for pre-period spend, and likelihood of exposure.

Exposed vs. control (after weighting)

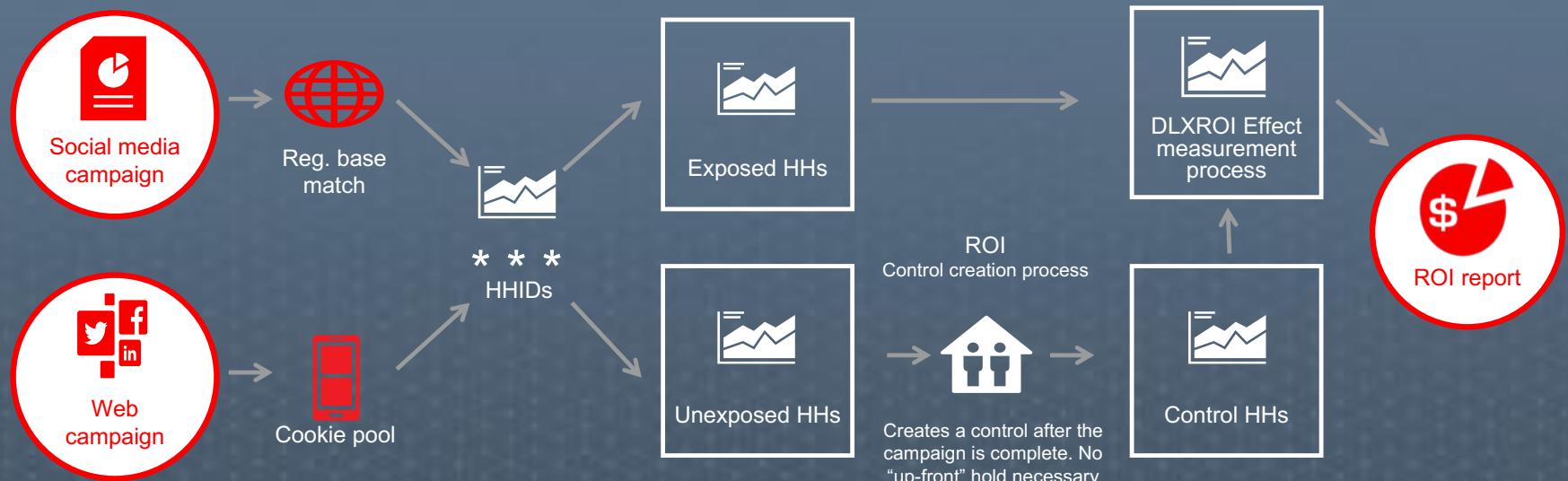


Lift estimation

1. Using only **control** households, we model and estimate post-period sales, given **ALL** available pre-period data.
2. Using this model, compute predicted post-period sales for **BOTH** the control households and the exposed households.
3. Use **the residuals** (observed sales – predicted sales) from step 2 to calculate differences between exposed and control households.
4. The observed **difference in the residuals** between control and exposed is the campaign lift!

A/B testing, without needing an upfront holdout!

Measurement



Yes! Ads (can) have a causal effect on consumers!

Lift in \$ per 1,000 households for a specific grocery brand



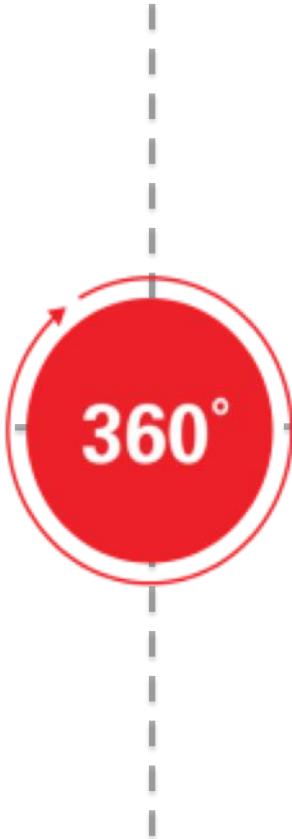
Marketing can't quite brainwash, but it can make an impact

- The value lies in the scale of advertising audiences
- If 33 Million individuals see an ad, and every 1000 ads generate \$2.29 of additional sales...

\$75,570 of immediate, proven, incremental sales



Collecting Data



Creating Individuals

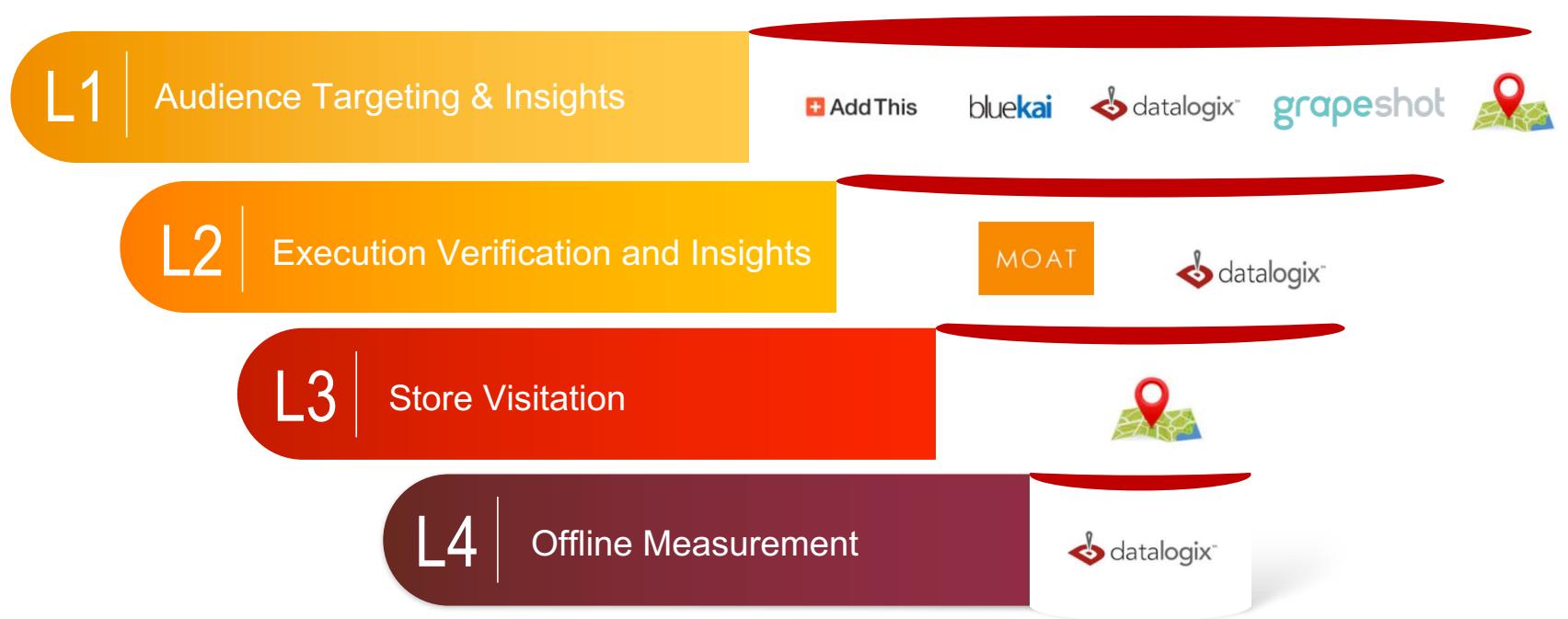


Targeting Campaigns



Measuring Causal Success

A Better Serviced Marketing Funnel



Questions?

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