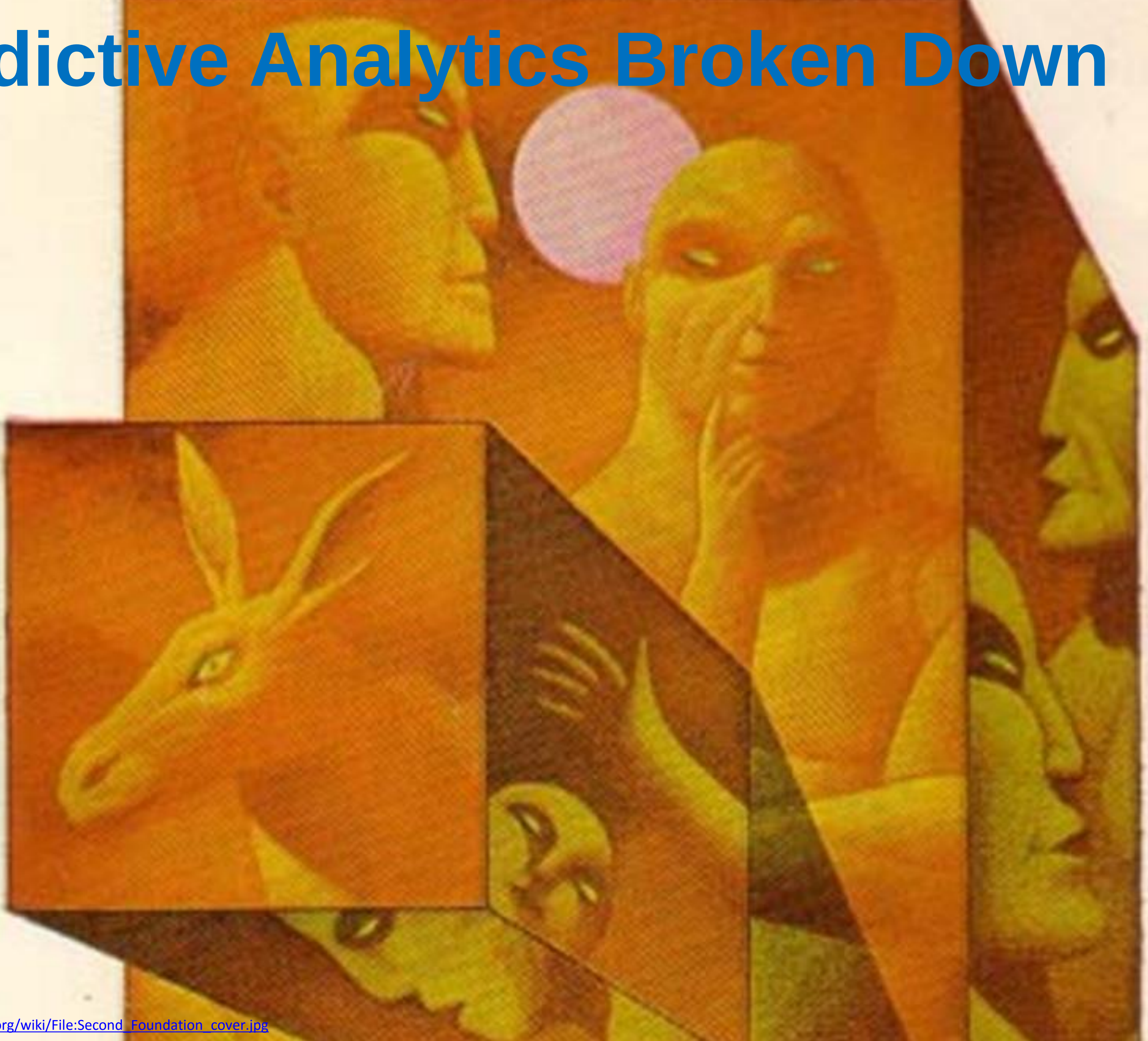
Predictive Analytics Broken Down



https://en.wikipedia.org/wiki/File:Second_Foundation_cover.jpg

Who is this guy?

CEO / Co-Founder Conductrics

www.conductrics.com

matt@conductrics.com

Past: Database Marketing

Education: Artificial Intelligence & Economics

twitter:@mgershoff, @conductrics
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What is Conductrics?

1. **Cloud-based Adaptive Testing and Decision Engine**
2. **API-Based Testing, Targeting and Optimization**
   - *REST API: Compatibility with CMS systems and other platforms*
   - *Native Programming Wrappers (iOS, PHP, jQuery, Node, etc.)*
   - *New JavaScript API for super fast decisions at scale*
3. **“WAX” Framework for point-and-click style customers**
   - *Client-side, tag-based, “skip IT” style implementation*
4. **Browser UI**
   - *Admin Console*
   - *Reporting*

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What does Conductrics do?

1. **Experimentation**
   - *AB and Multivariate Testing*
   - *Adaptive / Bandit Testing*
2. **Personalization**
   - *Targeting with Business Logic*
   - *Targeting via machine learning*

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Promise of Predictive Analytics

The Promises:

- Help make predictions about the future
- Predictions about customer:
  - Preferences
  - Intent

Benefits of Predictive Analytics

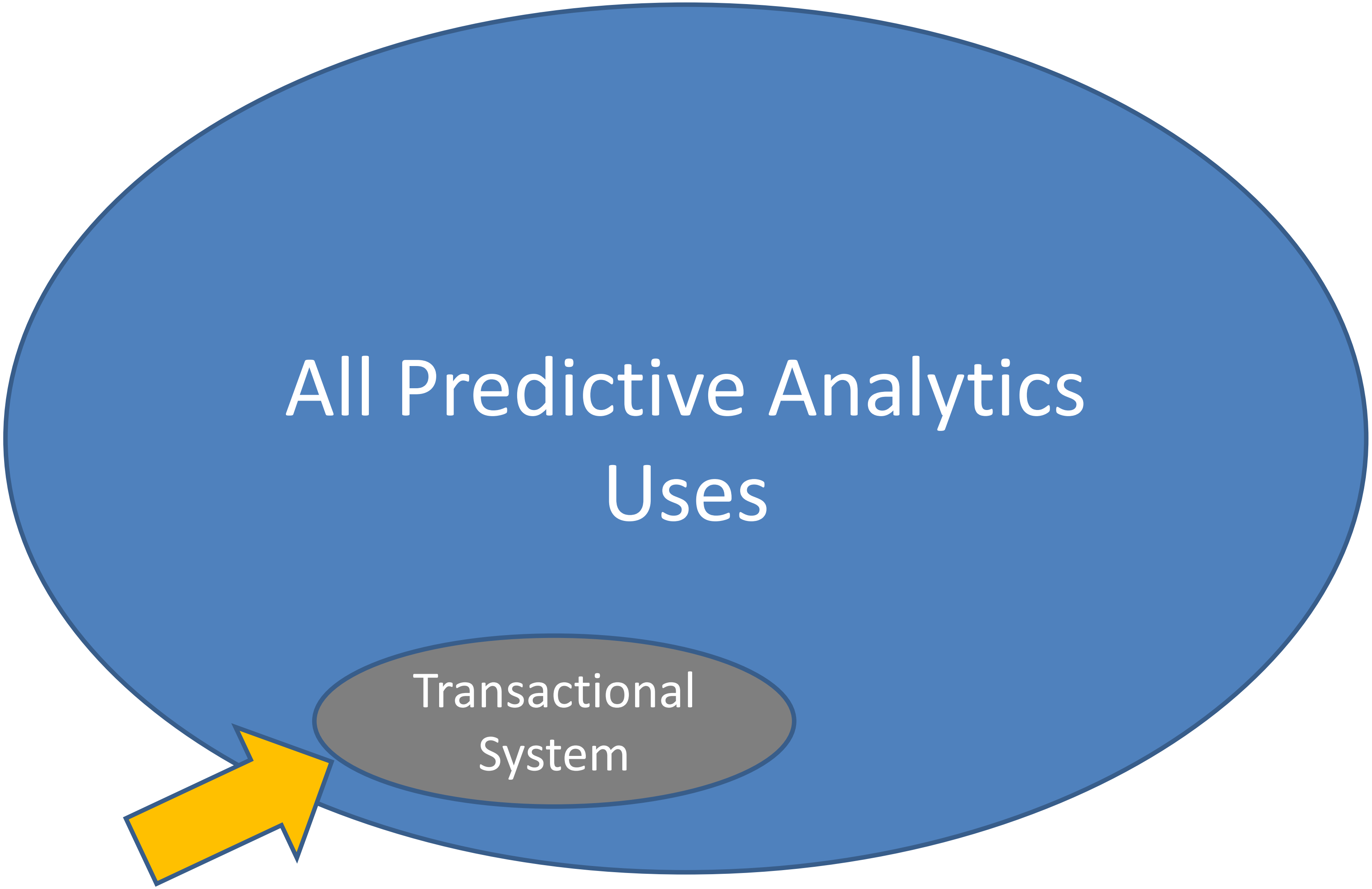
The Benefits:

- Provide customers with right set of experiences
- Eliminate marketing waste

Why care how it works?

- Better consumer of predictive analytics tools
- How to get the most out of it predictive analytics
- Help ensure you understand its limitations

Scope of talk?



Two Requirements for Personalization

1. Data
2. Logic

Data: ‘Sensing’ the World

Types of Data

Observable

- **Return Customer**
- **Weekend/Weekday**
- Mobile/DeskTop
- Browser Type
- User Age
- Geo/Census
- Weather
- Tenure/RFM Score

Intervention

- **Lottery Game**
- Price
- Sales Offers
- Shipping Type
- Layout/UX
- Which Products
- Suggested Quantities

Two Requirements for Personalization

1. Data
2. Logic

Requirements for Personalization

Decision logic links

Observations to **Actions**

How to come up with the Logic?

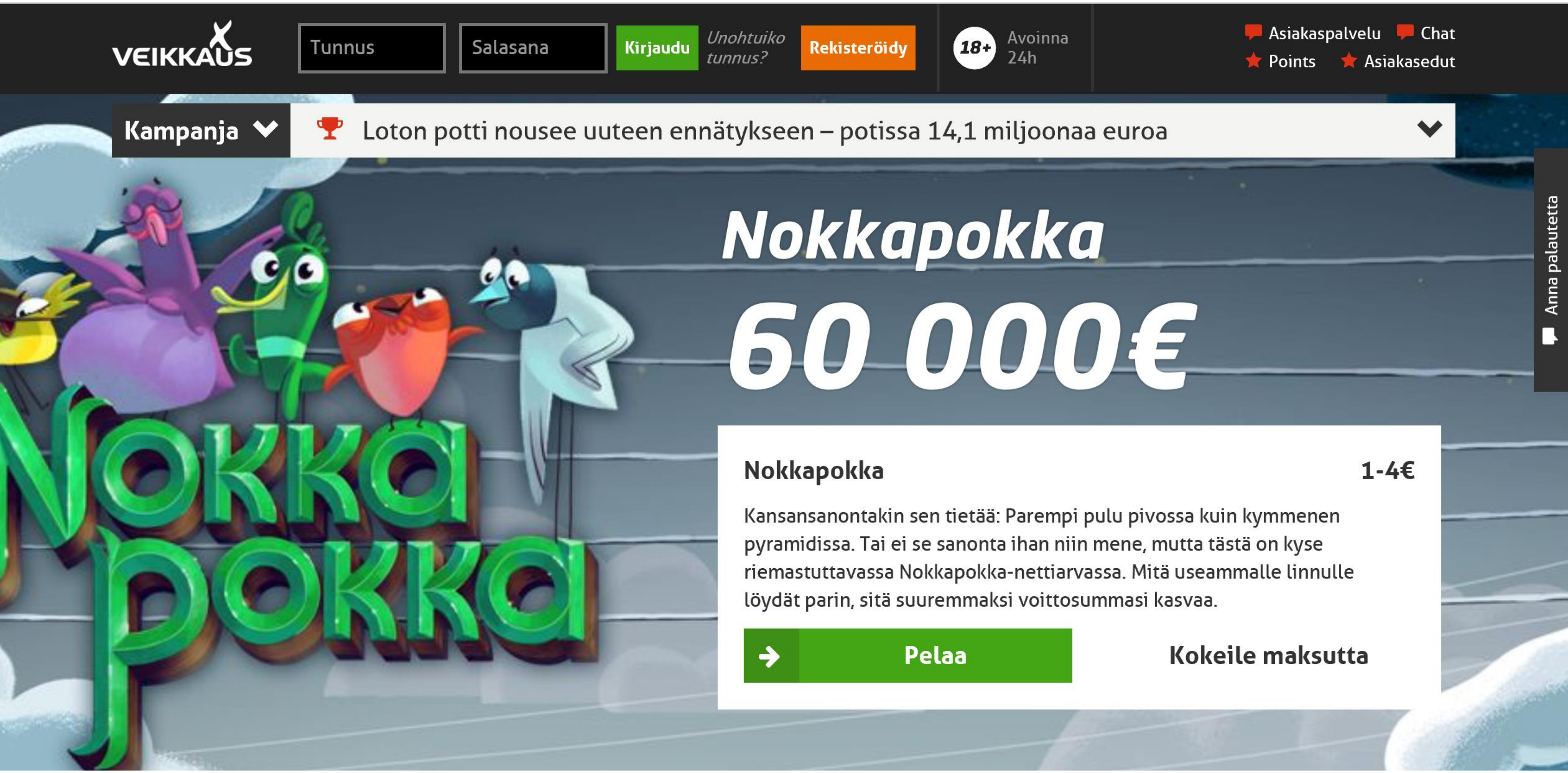
IF [Customer]
THEN
[Experiences?]

How to come up with the Logic?

IF [Customer] THEN [Experiences?]

…in way that Optimizes Performance

Example: Veikkaus



Example: Lottery Games

Show high price games …

Example: Lottery Games

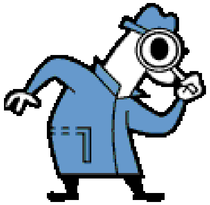
Or show the low price games

Example: Lottery Games

To keep it simple just look at:

- New or Repeat Player
- Weekday or Weekend

How to come up with the Logic?



IF [Repeat and/or Weekend]
THEN [High/Low Price?]

…in order to be most profitable

How its Done

1 Learn how Repeat and Weekend customers predict low price games

How its Done

1 Learn how Repeat and Weekend customers predict low price games

2 Learn how Repeat and Weekend customers predict high price games

How its Done

1 Learn how Repeat and Weekend customers predict low price games

2 Learn how Repeat and Weekend customers predict high price games

3 Then compare for each customer

(Choose the one with the highest value)

Predictive Analytics Methods

- Deep Learning Nets
- Decision Trees
- Gaussian Process (is a Bayesian method)
- Support Vector Machines
- KNN - actually kinda like segmentation
- Naive Bayes (is NOT a Bayesian method)
- Logistic Regression

http://conductrics.com/data-science-resources/
http://conductrics.com/data-science-resources-2

We are going to use Linear Regression

Why Linear Regression?

Benefits:

1. Has nice Statistical Properties
2. Easy(ish) to interpret
3. In practice, often all you need

What is Linear Regression

A model of relationships in this form:

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Prediction = Base + B1*Attribute1 … + Bj*Attributej

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Just Add up all of the customer 'attributes' by the impact (B) of the Feature

What is Linear Regression

We will learn two models, one for each game:

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Game High = $Base_H + W_H * Weekend + R_H * Return$

What is Linear Regression

We will learn two models, one for each game:

Game High = $Base_H + W_H * Weekend + R_H * Return$

Game Low = $Base_L + W_L * Weekend + R_L * Return$

Linear Regression
+
Sequential Learning

Benefits of Sequential Learning

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1. Don’t have to wait to collect the data
2. Constantly updating you can use it real time
3. Scalable–any real production PA is almost certainly going to use the method
4. The computations are simple to understand


We Can Do It!

The Sequential Algorithm in words

1) Observe the data for a single customer
2) Using the current parameter values to make a prediction
3) See how far off your predicted value was from the actual value
4) Use how far off you prediction was to update your parameter values
5) Adjust how much you update by something like O(1/n) – sort of like an average
6) Repeat

The Sequential Algorithm

Adjustment = (Predicted - Actual) * 1/sqrt(n)

The Difference (Error) of the actual value and the predicted result

$\text{Parameter}_{\text{New}} := \text{Parameter}_{\text{old}} - \text{Adjustment}$

Current Value

How it is done: No data yet, high cost game

Hidden			What We Know				
Base	R	W	Return	WkEnd	Sales	Predict	Error
0	0	0					

Observe New Customer on Weekend

Hidden			What We Know				
Base	R	W	Return	WkEnd	Sales	Predict	Error
0	0	0	0	1	1.00		

Observe New Customer on Weekend

Hidden			What We Know				
Base	R	W	Return	WkEnd	Sales	Predict	Error
0	0	0	0	1	1.00		

$$\text{Prediction} = \text{Base}_H + W_H * \text{Weekend} + R_H * \text{Return}$$

Plug in values

Hidden			What We Know				
Base	**R**	**W**	**Return**	**WkEnd**	**Sales**	**Predict**	**Error**
0	**0**	**0**	**0**	**1**	**1.00**	**0**	**-1.00**

$$0 = 0 + 0*0 + 0*1$$

Update Base and Weekend Impact Score

Hidden			What We Know				
Base	R	W	Return	WkEnd	Sales	Predict	Error
0	0	0	0	1	1.00	0	-1.00

Updated		
Base	R	W
1	0	1

Observe New Customer Weekday

Hidden			What We Know				
Base	R	W	Return	WkEnd	Sales	Predict	Error
1	0	1	0	0	2.00		

Prediction= $Base_H + W_H{*}Weekend + R_H{*}Return$

Plug in values

Hidden			What We Know				
Base	**R**	**W**	**Return**	**WkEnd**	**Sales**	**Predict**	**Error**
1	**0**	**1**	**0**	**0**	**2.00**	**1.00**	**-1.00**

$$1 = 1 + 0*0 + 1*0$$

Update Just the Base Impact Score

Hidden			What We Know				
Base	R	W	Return	WkEnd	Sales	Predict	Error
1	0	1	0	0	2.00	1	-1.00

Updated		
Base	R	W
1.5	0	1

Observe Return Customer on Weekday

Hidden			What We Know				
Base	R	W	Return	WkEnd	Sales	Predict	Error
1.5	0	1	1	0	3.00		

Prediction= $Base_H + W_H * Weekend + R_H * Return$

Plug in values

Hidden			What We Know				
Base	**R**	**W**	**Return**	**WkEnd**	**Sales**	**Predict**	**Error**
1.5	**0**	**1**	**1**	**0**	**3.00**	**1.50**	**-1.50**

$$3 = 1.5 + 0*1 + 1*0$$

Update the Base and Return Impact Score

Hidden			What We Know				
Base	R	W	Return	WkEnd	Sales	Predict	Error
1.5	0	1	1	0	3.00	1.50	-1.50

Updated		
Base	R	W
1.75	0.75	1

Online Regression

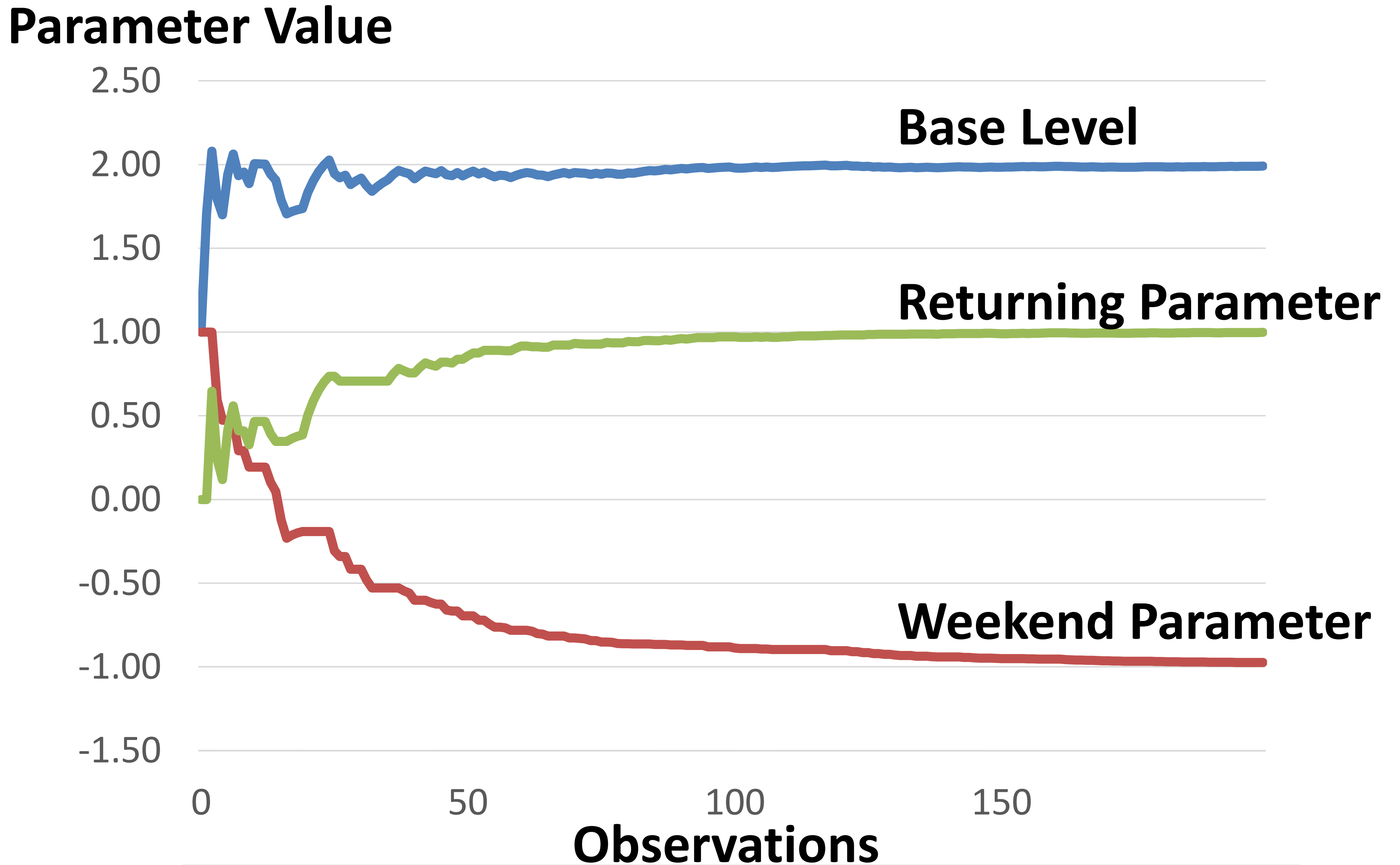
After 200 Iterations

Base	R	W
2.0	**1.0**	**-1.0**

High Price Model Results

Sales = 2.0 + 1.0*Return -1.0*Weekend

Online Results: 200 Iterations



Back to Our Task

Model: High Price Game

High = 2.0 + 1.0*Return -1.0*Weekend

Back to Our Task

Model Low Price Game

Low = 1.0 + 1.0*Return + 0.5*Weekend

Tabular Targeting Logic

Returning	Weekend	High Price	Low Price	Selection
N	N	2.0	1.0	High
Y	N	3.0	2.0	High
N	Y	1.0	1.5	Low
Y	Y	2.0	2.5	Low

Targeting Logic as Rule

IF [Weekend]
THEN [Low]
Else [High]

Targeting Logic as Rule

Expressing the logic as a set of succinct rules is generally a hard problem

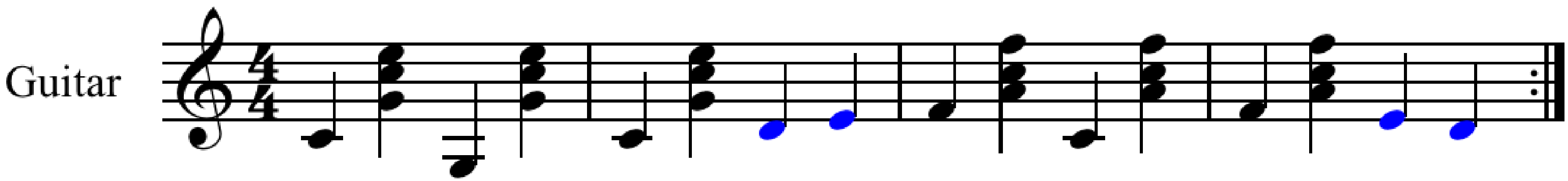
IF [Weekend]
THEN [Low]
Else [High]

How to evaluate our targeting logic?

How do we measure our Targeting?

A/B TEST!!!

Need a Baseline



Random Selection as Control

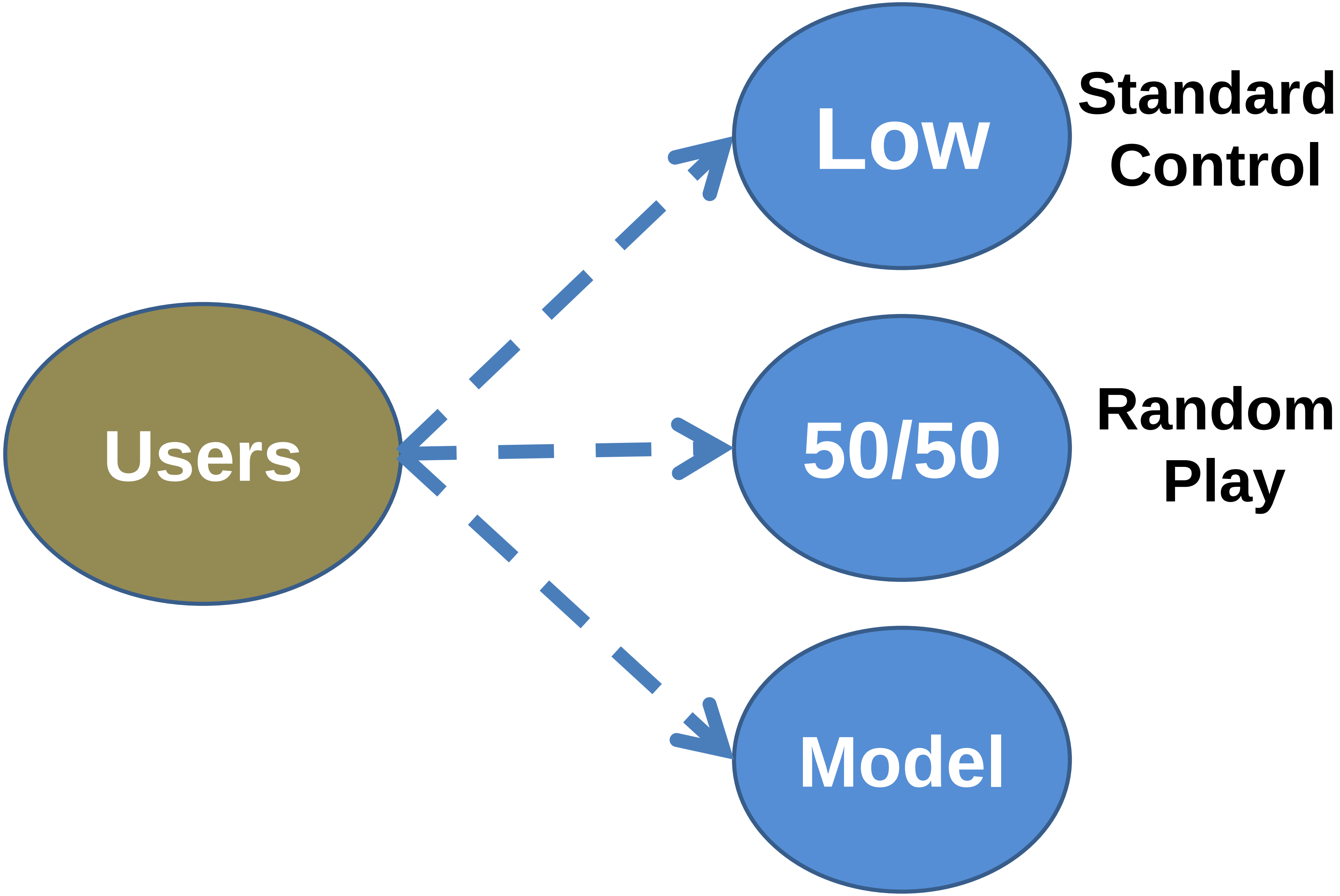
Good:

1. A baseline we can always use

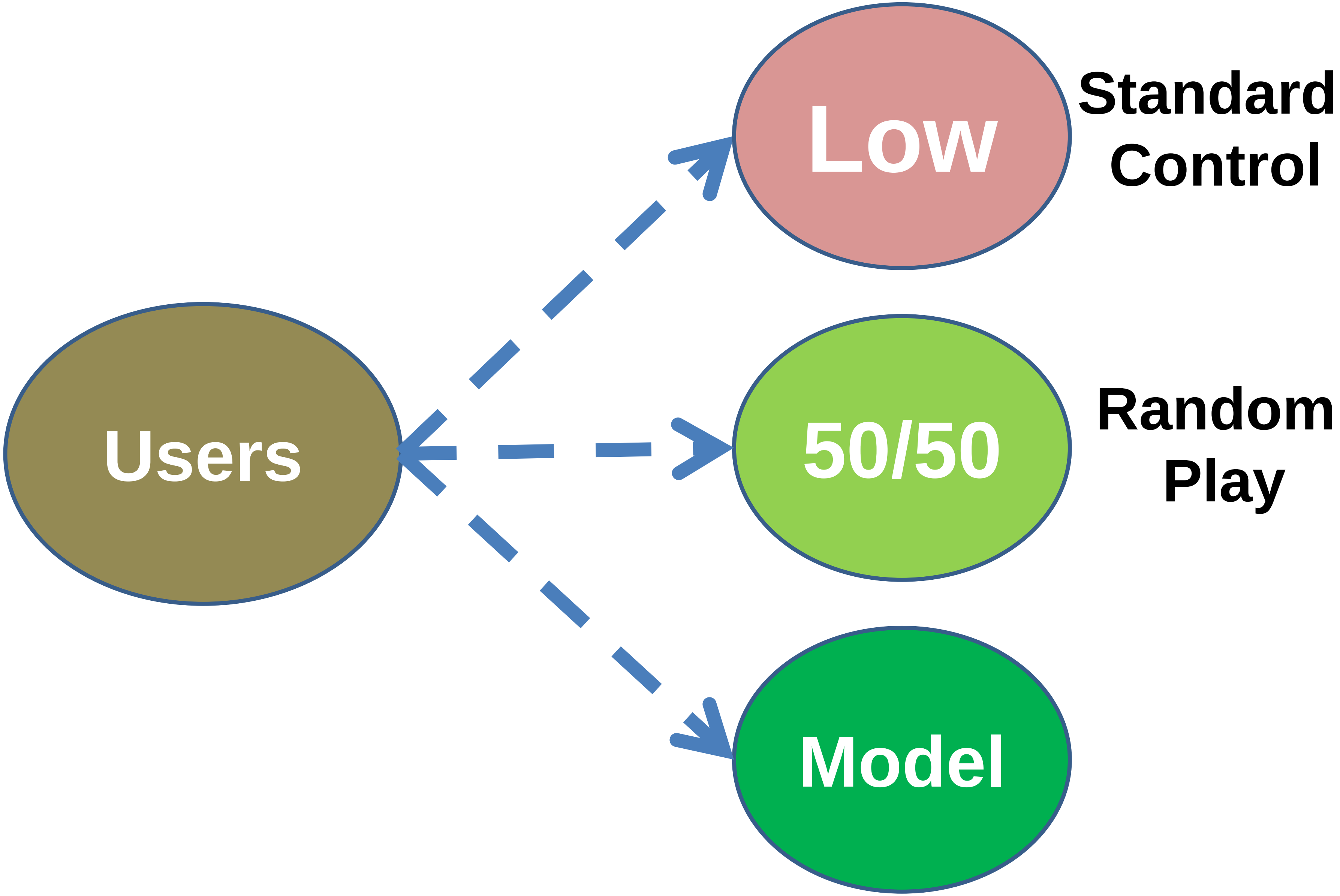
2. Selecting randomly is often good policy when we don’t have any additional information

Bad: Often hard to beat (which is Good)

Model Evaluation: AB Style



Compare the Results of Each



Results: Model ROI/Lift

$$\text{Lift} = \frac{\left[\text{Target} - \text{Random}\right]}{\text{Random}}$$

Beware the Faustian Bargain!

Description	Michał Elwiro Andriolli
Date	1895
Source	http://www.pinakoteka.zascianek.pl/Andriolli/Index.htm

Targeting = Complexity

Customer data needs to be ‘accurate’ AND available at decision time

We need to create AND manage experiences and content

Need to create AND mange our decision logic

Difficult to know what state system is in. Before just one state, now many.

Targeting and the ROI of Complexity

$$\frac{\boldsymbol{Value(Complex\ System) - Value(Simple)}}{\boldsymbol{Value(Simple)}}$$

What about Segmentation?

Segmentation Doesn't Scale

Just 20 Customer Features

1 Million
Combinations

power(2,10) assuming all non mutually exclusive

Image Source: http://en.wikipedia.org/wiki/File:Carl_Sagan_-_1980.jpg;

Wake up. We are Done!

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