

Monetizing Data Assets

Through Data Refinement and Analytics



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WILLOW
DATA STRATEGY
making sense of data

What we will cover



DATA LANDSCAPE



INSIGHTS VIA ANALYTICS



ART OF TARGETING



**"ANALYTICS-READY"
ENVIRONMENT**



**PROPER PERSONALIZATION
USING PERSONAS**



**POST CAMPAIGN ANALYTICS
& ATTRIBUTION**



Data Landscape

Solution-Oriented Data and Analytics Strategy

The Age of Ubiquitous Data & AI

In the world where every channel is turning into an “addressable” medium...

- Data is everywhere, like in the Matrix
- Every breath you take, every move you make...



→ Are you harnessing the power of data?
Or are you just creating mounds of data?

Advanced analytics is within our reach,
as machines are getting continuously smarter

Database Marketing Landscape



- No guessing game – You MUST know your target
- Vast amount of data collected in the name of Big Data → But, are they being used properly?
- Analytics play a huge role in prospecting & CRM
- Short paced marketing cycle getting shorter
- Huge difference between advanced marketers and those who are falling behind

→ It is about the commitment, not technology

Winners are the ones who know how to wield the power of all available data faster.

Where the Data Movement is Going

- Every channel is, or will be interactive
- Every interaction will be data-based, and in real-time
- Marketers must stay relevant to cut through the noise
- Machine Learning & AI will lead to automation on all fronts
- Huge difference between advanced users and those who are falling behind



It's all about staying relevant through “Personalization”, through every channel, with every customer, at all times.

It is NOT about Channels or Technologies

“The Future of Online is Offline” – Stephen H. Yu, 2002

- There is no such thing as an “online person”
 - It is almost offensive to the consumer
 - Channel-centric view confuses buyers
 - New channels and technologies in the future
- This data and analytics business should be about “People”
 - No one is one-dimensional – Adopt “Buyer-centric” point of view
 - Never be channel-, product-, division- or brand-centric
 - But most marketers are
 - Buyer-centric data structure leading to proper “Personalization”
 - Never about the technology, but about the people who are looking at screens (or even thin air)
 - **And they are in control, not the marketers!**



What 1:1 Marketing is about

- **Marketers must know:**

- Whom to contact, and
- What to offer, if they decided to contact someone
 - » And through what channel and when

- **Analytics help marketers with:**

- Targeting
- Personalization

**Everyone is being
bombarded with
marketing messages
through multiple
channels everyday**



It is about the Data Users, too

For Decision Makers

- Take the data seriously, not just your gut feelings
- Define the goals first, then control the flow of data and technologies
- Don't blindly trust machine-based solutions
- Be logical, as there is no toolset that can read minds (yet)
- Set specific goals for small successes

For Data Scientists

- Don't be a "Data Plumber", but a businessman
 - Don't be technology oriented, but solution oriented
 - Don't do things just because you can
 - Don't be part of arrays of machines, only to be replaced by them
- Be the one that wields machines with clear objectives

What is a Data Scientist?

MODERN DATA SCIENTIST

Data Scientist, the sexiest job of 21st century requires a mixture of multidisciplinary skills ranging from an intersection of mathematics, statistics, computer science, communication and business. Finding a data scientist is hard. Finding people who understand who a data scientist is, is equally hard. So here is a little cheat sheet on who the modern data scientist really is.

MATH & STATISTICS

- ☆ Machine learning
- ☆ Statistical modeling
- ☆ Experiment design
- ☆ Bayesian inference
- ☆ Supervised learning: decision trees, random forests, logistic regression
- ☆ Unsupervised learning: clustering, dimensionality reduction
- ☆ Optimization: gradient descent and variants

PROGRAMMING & DATABASE

- ☆ Computer science fundamentals
- ☆ Scripting language e.g. Python
- ☆ Statistical computing package e.g. R
- ☆ Databases SQL and NoSQL
- ☆ Relational algebra
- ☆ Parallel databases and parallel query processing
- ☆ MapReduce concepts
- ☆ Hadoop and Hive/Pig
- ☆ Custom reducers
- ☆ Experience with xaaS like AWS

DOMAIN KNOWLEDGE & SOFT SKILLS

- ☆ Passionate about the business
- ☆ Curious about data
- ☆ Influence without authority
- ☆ Hacker mindset
- ☆ Problem solver
- ☆ Strategic, proactive, creative, innovative and collaborative

COMMUNICATION & VISUALIZATION

- ☆ Able to engage with senior management
- ☆ Story telling skills
- ☆ Translate data-driven insights into decisions and actions
- ☆ Visual art design
- ☆ R packages like ggplot or lattice
- ☆ Knowledge of any of visualization tools e.g. Flare, D3.js, Tableau

But,
who would have
all these skills
at a master level
in one body?

Being an Outstanding Data Scientist

A Data Scientist is a combination of:

- Business Analyst – w/ deep understanding in business challenges and industry landscape
- Master Data Manipulator – w/ functional coding skills
- Statistical Analyst – w/ knowledge in statistical modeling and Machine Learning



Elements of a Good Data Scientist:

1. Technical Skills
2. Positive Attitude
3. Communication Skills
4. Business Acumen

What a Business Analyst does:

- Identify business challenges and issues
- Provide solutions to meet business goals
- Develop analytics projects to produce tangible deliverables
- Identify and examine data sources and procure necessary data
- Consolidate data from disparate sources
- Create technical specs for data refinement and analytical steps
- Define targets using logical expressions
- Act as a project manager to push sub-tasks forward
- Develop reports and data visualization
- Create “stories” based on learnings and share them with business community
- Present “executive summary” and next steps to decision makers

Insights via Analytics

Solution-Oriented Data and Analytics Strategy

Build the Data Roadmap

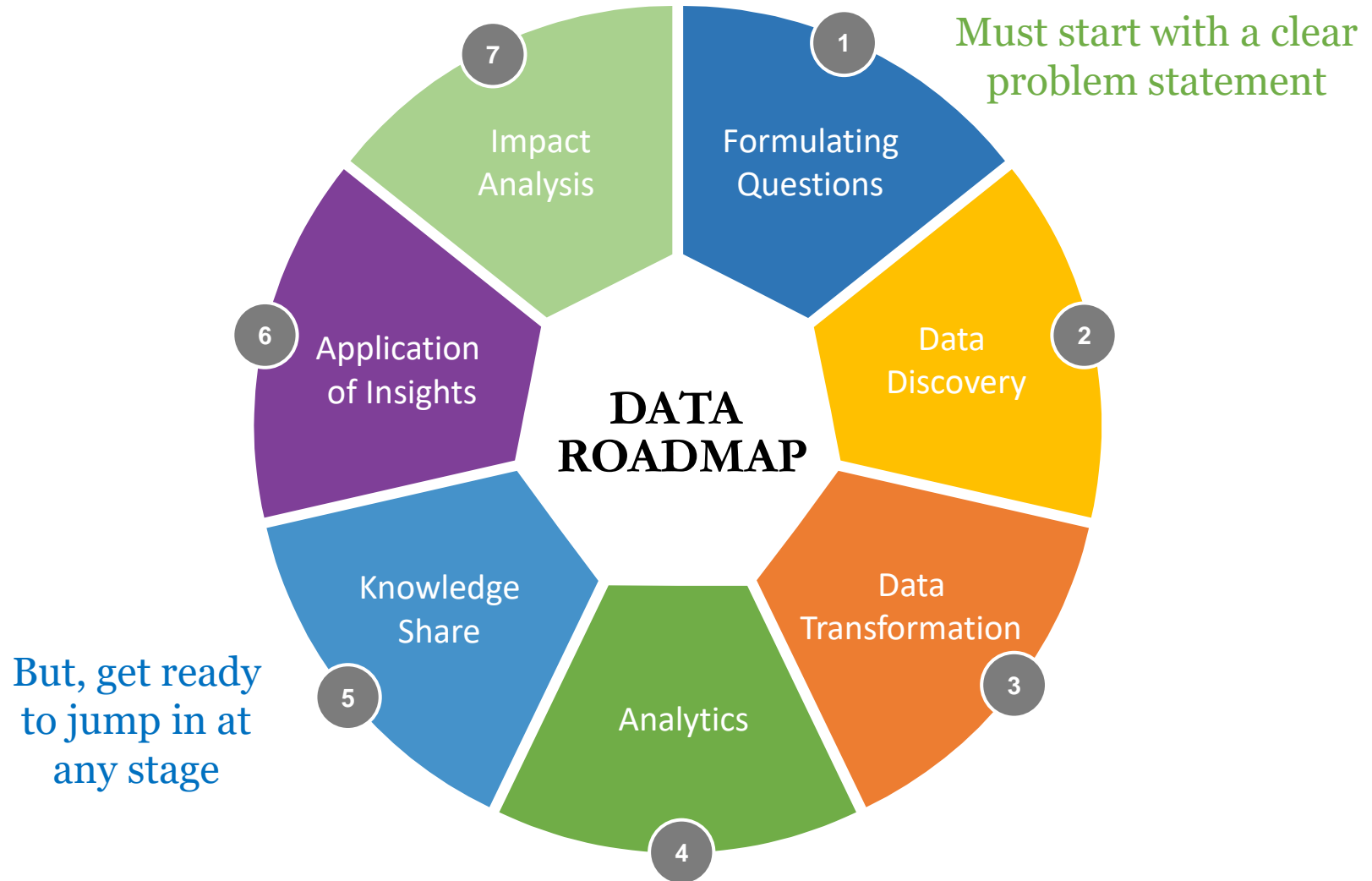


*A database is not just a sum of all data sources, and
Analytics is not just an array of statistical techniques*

1. Business Goals
2. Answers via Analytics/Modeling
3. Databases Optimized for Analytics

→ **Solution design based on business goals, not around capabilities**

Goal-Oriented Step-by-Step Approach



Big Data Must Get Smaller

Usable information is:

- Easily understandable without deep knowledge in analytical techniques or mathematics
- Digestible small bits of information, not mounds of data
- Consistent, accurate, effective, and easy-to-use tool
- Useful in most cases, not just limited instances
- Readily accessible through users' preferred devices and channels



Users need “Answers to Questions”. So,

1. Cut down the noise
2. Provide insights, not data through Analytics

Pillars of Data and Analytics

DATA PLAYERS MUST EXCEL IN:

Collection

- Data Collection by Channel
- Rapid Data Retrieval
- Basic Dashboard

Refinement

- Data Hygiene and Standardization
- Consolidation and Summarization
- Advanced Analytics including Statistical Modeling

Delivery

- Comprehensive Dashboard and BI Reporting
- Ad hoc Reports
- Campaign Targeting and Management
- Personalization

Insights are derived from data through the refinement process

Different Types of Analytics

“ANALYTICS” MEANS DIFFERENT THINGS...



Business Intelligence Reporting:

KPI Reports/Dashboards,
Digital Analytics,
Product/Channel Reports,
Campaign Performance Analysis



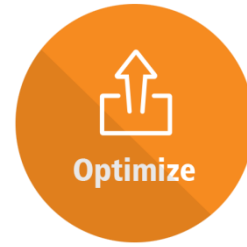
Predictive Modeling:

Propensity Models, Personas,
Response Models,
Customer Value Projection,
Churn Prediction,
Demand Forecasting



Descriptive Analytics:

Customer Profiling,
Segmentation & Clustering,
Customer Journey Analysis

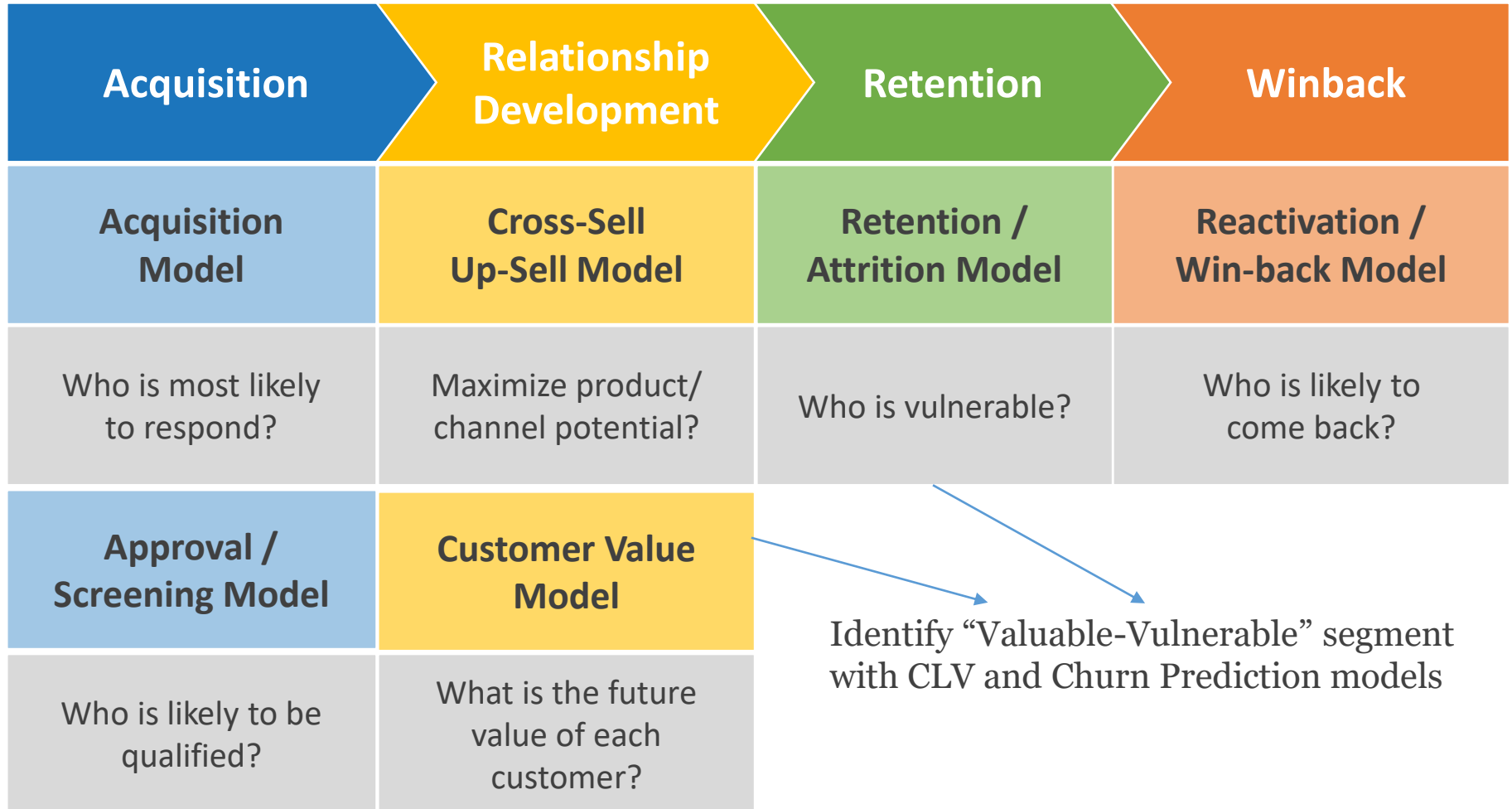


Optimization:

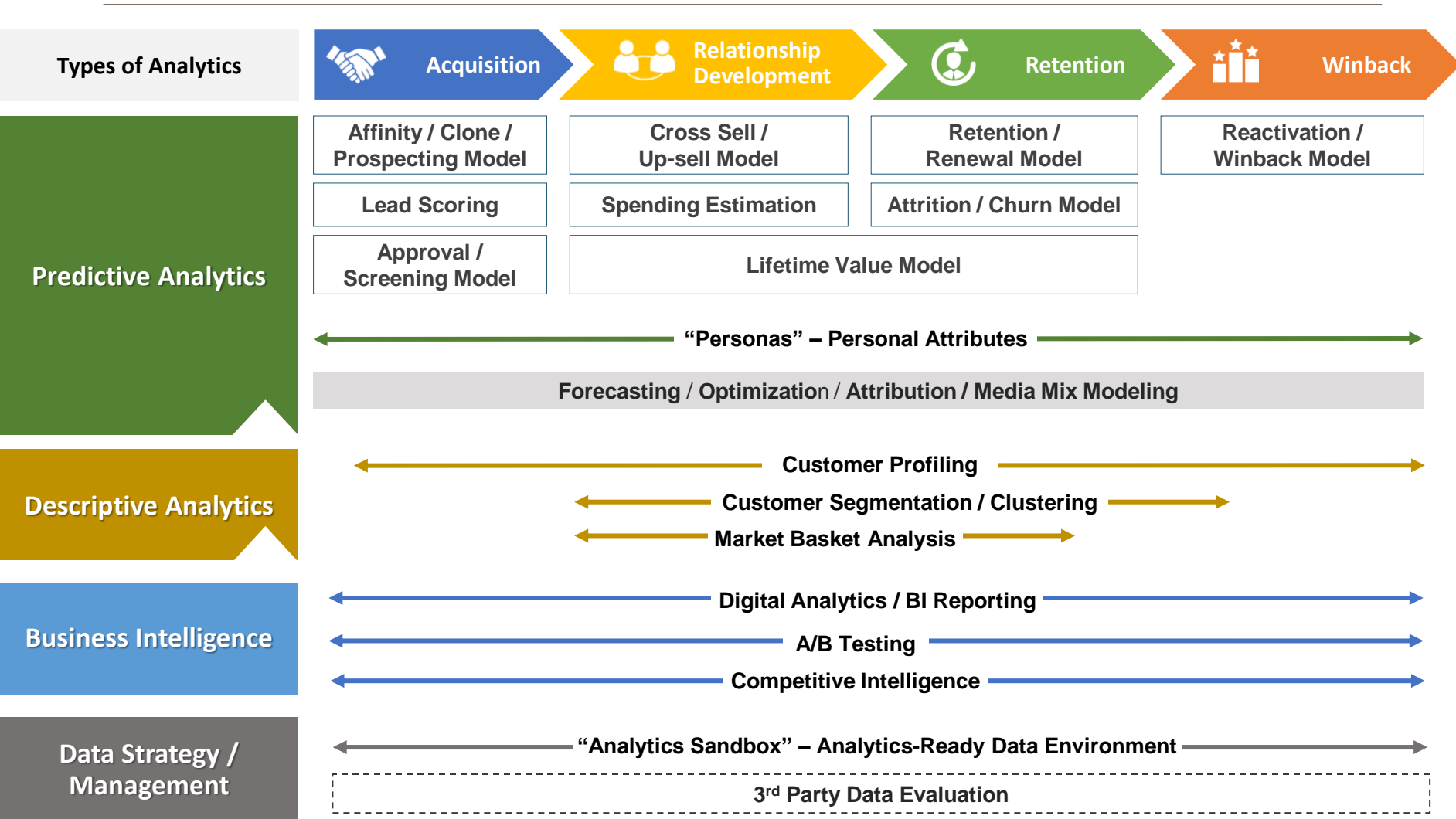
Channel Optimization,
Marketing Spending Analysis,
Marketing Mix Modeling,
Attribution, Pricing Models

 Plus, **Prescriptive Analytics** can be applied to any stage

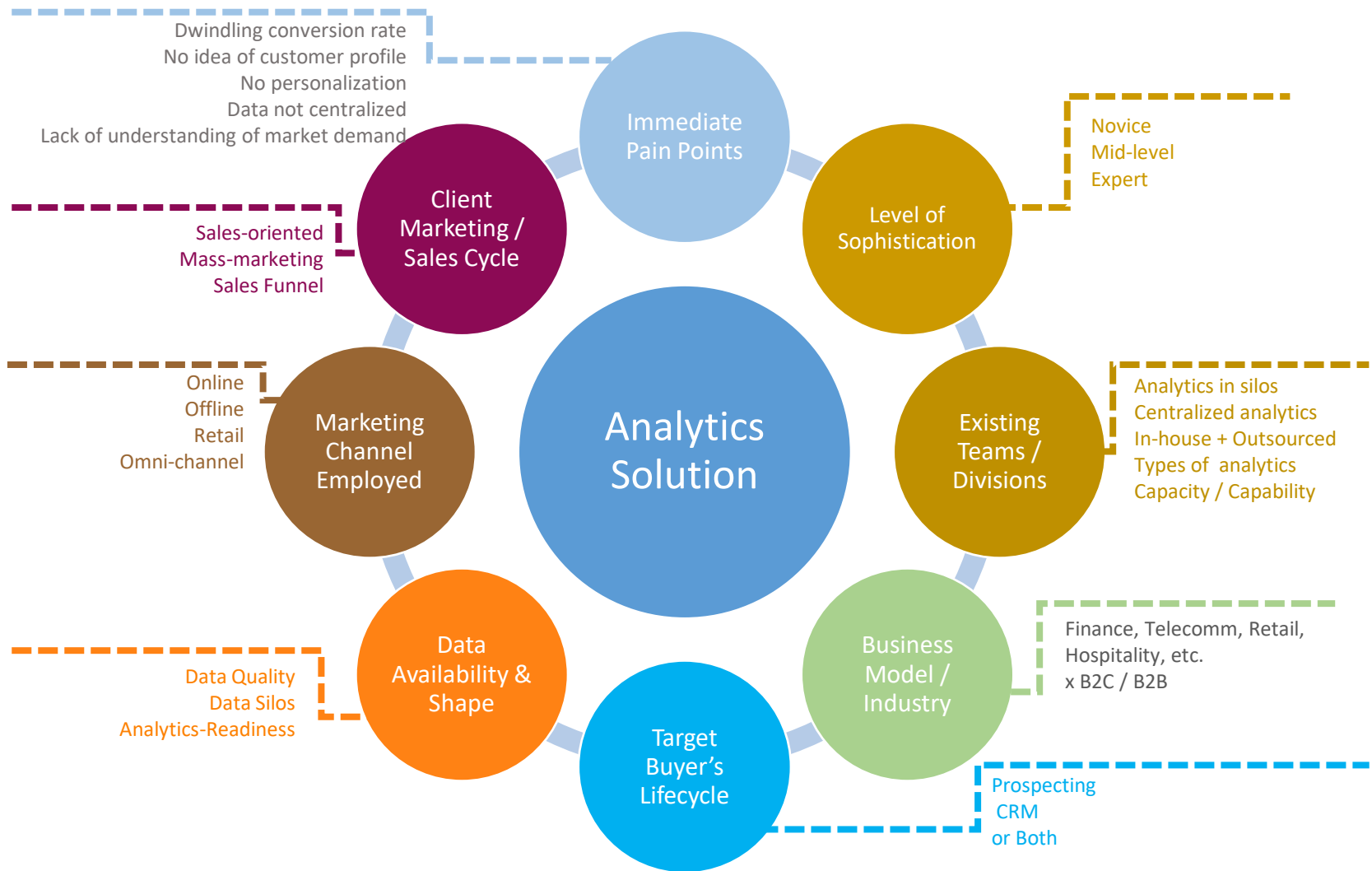
Matching Analytics to Marketing Cycle



Analytics Solutions by Marketing Cycle



8 Dimensions of Solutioning



Different Goals & Data for Different Industries



**Banking, Finance &
Credit Card**



**Travel, Hospitality &
Entertainment**



**Retail – Online &
Offline**



Publications



**Telecommunications
& Utilities**



Non-Profit



Catalog

B2B Paths to Conversion

End-to-End B2B Sales Journey – from Prospecting to Nurturing

Key Questions

What are the key marketing levers that attract more prospects?

Of the respondents, who are the most likely to convert?

What % of leads are active, stagnant, or lost in the funnel? What are their profiles, and which factors move them forward?

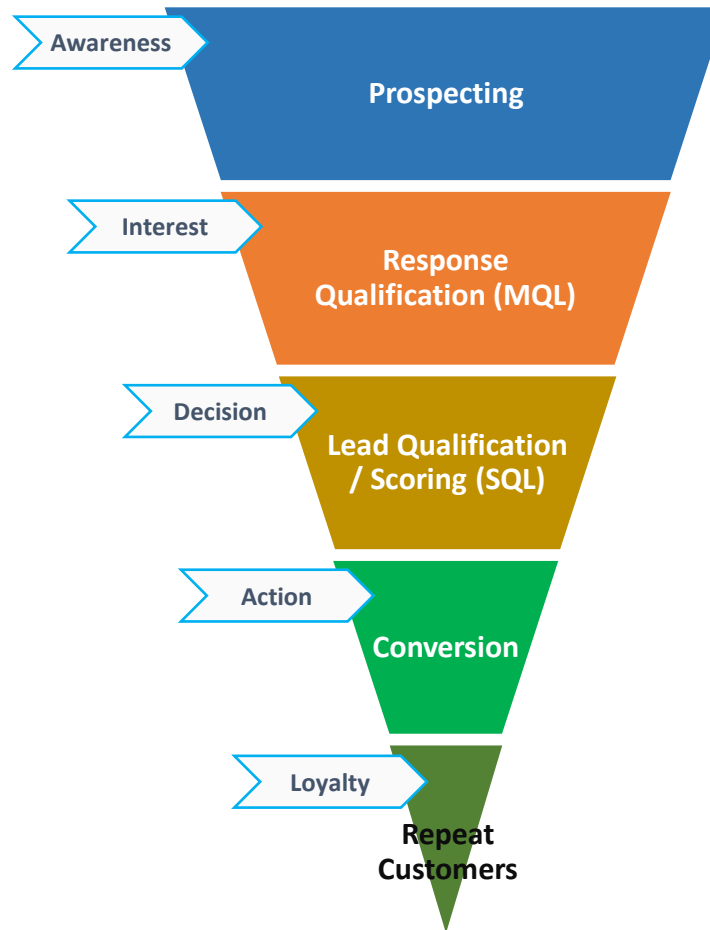
What are the optimal number of touchpoints required for conversion? What are the key channels and offers for these touchpoints? Is there a specific path that results in higher conversion?

What are the key drivers of sales? (e.g., promotion, price, offer, sales engagement, channels, creative, deal size, etc.)

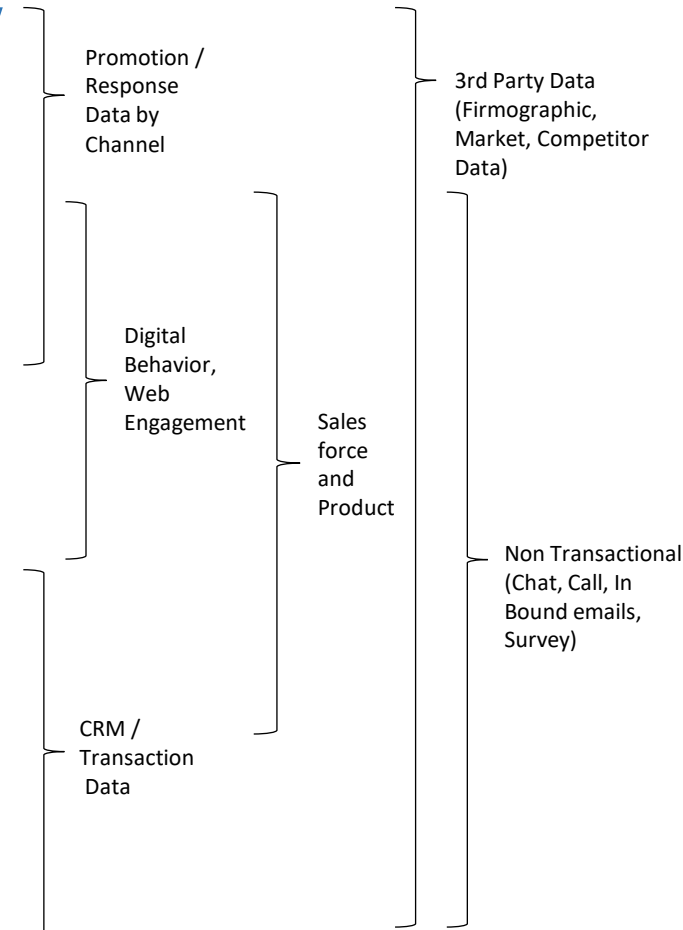
What specific cross-sell / up-sell opportunities should we pursue on a customer level?

Who are the customers more likely to churn? Where are 'valuable-vulnerable' segments?

Marketing & Sales Funnel



Data Assets



Why Model?

Converting Complex Data into Answers to Questions

Why Model?

- Increase targeting accuracy
- Reduce costs by contacting less/smart
- Stay relevant with target customers
- Achieve consistent results
- Reveal hidden patterns in data
- Reach marketing automation faster
- Expand the target universe
- “Supposedly” save time and effort



Models summarize complex data into simple-to-use “scores”, and fill in the gaps by converting “unknowns” to “potentials”

Why NOT Model?

- Universe too small
- Predictable data not available
- 1:1 marketing channels not in plan
- Tight budget
- Lack of resources

Really? Remember

1:1 Marketing is about:

- Knowing whom to engage
- Knowing what to offer if you decided to engage someone



Models provide answers for both

Data to Answers via Modeling

Raw Data

- » Demographic / Firmographic
- » Transaction Data / RFM Data
- » Products & Services Used
- » Promotion / Response History
- » Channel Usage Data
- » Lifestyle / Survey Responses
- » Delinquency history
- » Call / Communication Log
- » Movement Data
- » Survey / Social Media / Sentiments

Actionable Answers

- » Likely to buy a luxury car
- » Likely to be an early-adopter
- » Likely to be a wine enthusiast
- » Likely to have a home office
- » Likely to be a risk-averse investor
- » Likely to respond to free shipping offers
- » Likely to be a high value customer
- » Likely to be qualified for credit
- » Likely to upgrade/leave/come back

■ Formulate the answers through modeling

Problems with Rule-based Segmentation

Variable Selection

- What variables to use? Same old RFM?
- Data overload – Too many variables to choose from
- Resorting back to a few popular variables like Income & Age

Weight Factor

- Not all variables are equally important
- Variables interact – Dynamics hard to detect by intuition
- Some are even negatively correlated

Banding

- How high is high enough?
- Popular banding (e.g., income over \$100k) may not work
- Grouping categorical variables is difficult

 Do not just rely on your gut feelings – Employ advanced analytics

What is a Model?

“Model is a mathematical expression of differences between groups”

Target vs. Non-Target, such as

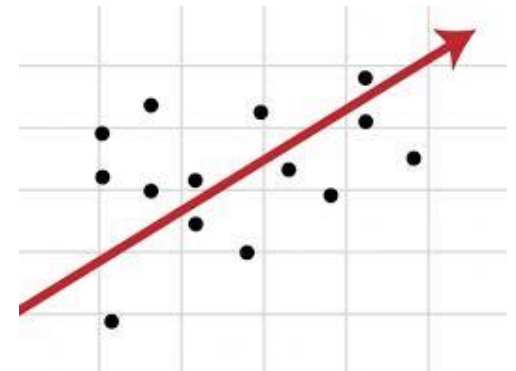
- Buyer vs. Non-Buyer
- Responder vs. Non-Responder
- Loyal vs. Attrition
- High Value vs. Low Value



→ Defining target and non-target are equally critical

Regression - Overview

- Powerful Statistical Technique
 - Less Predictive Error
 - Greater Discrimination
- Identifies **Combinations** of Characteristics that best predicts a specific behavior
- Result - Regression Equation
 - **Tool to Score & Rank Customers or Prospects**
- Types of Regression Techniques
 - *Logistic Regression* - for Dichotomous Dependent Variable
 - Yes/No Type of Behavior (*e.g.* Response/Non-Response, Buyer/Non-Buyer, etc.)
 - *Multiple Regression* - Dependent Variable is Not Dichotomous
 - Continuous or Ranges (*e.g.* Revenue \$ Amount)



Modeling Strategies for Marketing

- Acquire New Customers
 - “Clone” Current/Best Customers
 - Maximize Response/Net Acquisition
- Predict Approval/Payment/Activation
- Increase Revenue/Donation Amount
- Increase Profitability – per Contact or Customer
- CRM Applications
 - Increase Retention
 - Reduce Attrition
 - Predict Switching
- Minimize Risk
 - Bad Debt Prediction
 - Fraud Detection



Sample Regression Equation

<i>Effect</i>	<i>Weight (Coefficient)</i>		<i>Model Variables</i>	<i>Variable Description & Recode</i>	<i>Data Source</i>
=	- 5.4821		Constant		
-	0.6630	X	Length of Residence (LOR)	Actual value if LOR \leq 5 years, if LOR > 5 years then it is set = 5.	3 rd Party Consumer Database
+	0.2235	X	% HH Income \$30,000+	The percentage of HH's in neighborhood earning incomes \geq \$30,000 is recoded by taking the square root of the value.	Census Data
+	0.000865	X	PPI – Purchasing Power Indicator	A statistical estimate of the probable spending power of each HH based on regional cost of living variables. Actual values are used in the equation.	3 rd Party Consumer Database
+	0.0259	X	% Some College	The % of persons aged 25+ that have completed 1-3 years of college is recoded by setting all values \geq 50% = 50. If % < 50, actual value used.	Census Data
+	0.6448	X	Presence of Mobile Age Person	If one or more family members are aged 18 - 29 years, then value set = 1, otherwise the value set = 0.	3 rd Party Consumer Database

Regression – Sample Gains Chart

ACQUISITION MODEL

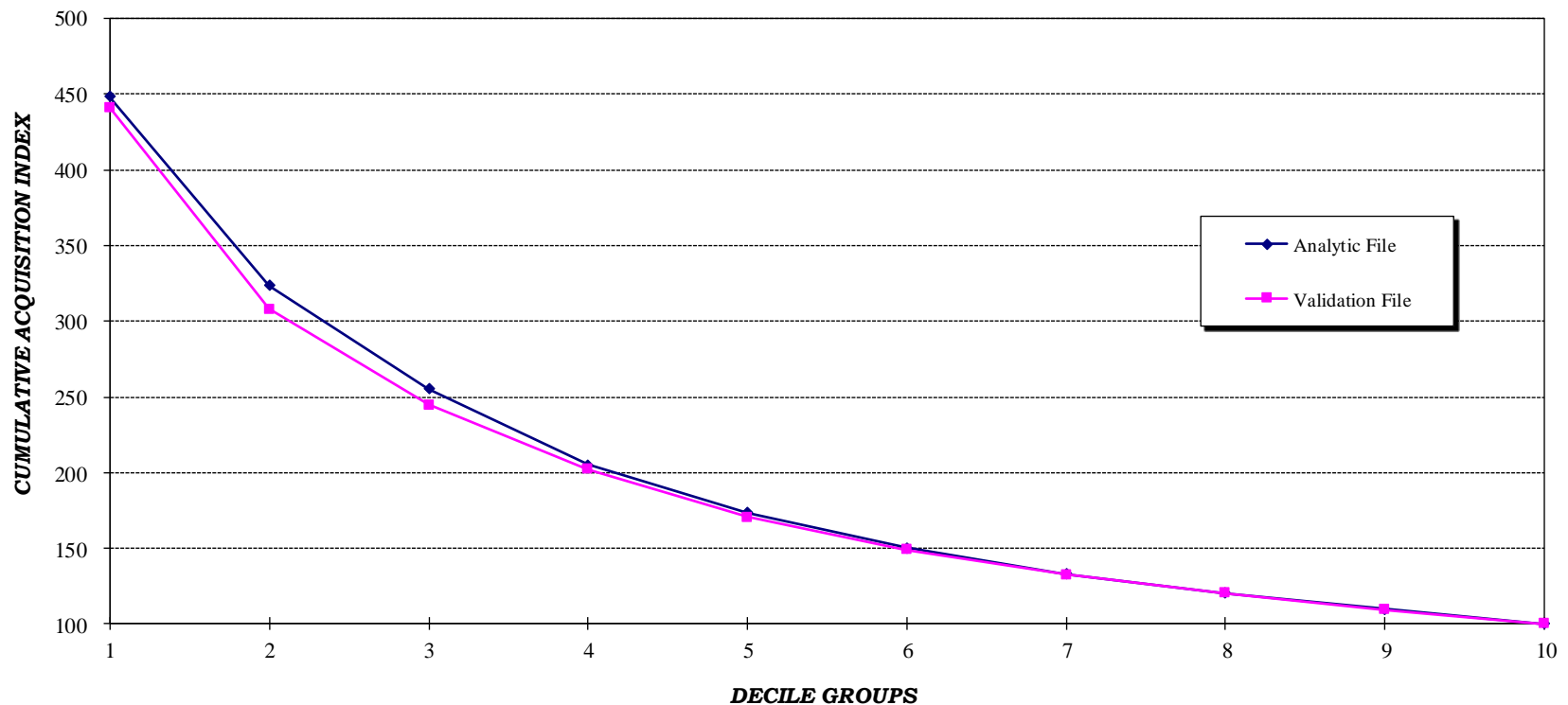
Development Sample

Decile Group	Count	# New Customers	Acquisition Rate	Acquisition Index
1	10,049	479	4.77	448
2	10,048	212	2.11	199
3	10,049	127	1.26	119
4	10,047	59	0.59	55
5	10,049	49	0.49	46
6	10,049	37	0.37	35
7	10,048	32	0.32	30
8	10,047	33	0.33	31
9	10,048	26	0.26	24
10	10,048	14	0.14	13

Cumulative			
Count	# New Customers	Acquisition Rate	Acquisition Index
10,049	479	4.77	448
20,097	691	3.44	323
30,146	818	2.71	255
40,193	877	2.18	205
50,242	926	1.84	173
60,291	963	1.60	150
70,339	995	1.41	133
80,386	1,028	1.28	120
90,434	1,054	1.17	110
100,482	1,068	1.06	100

Regression – Sample Efficiency Curves

EFFICIENCY CURVES - DEVELOPMENT VS VALIDATION SAMPLES



When Outsourcing Analytics, Consider

- 1 **Consulting Capability:** Translate marketing goals into mathematics
- 2 **Data Manipulation:** Standardization, hygiene, categorization, consolidation
- 3 **Track Record in the Industry:** Not in rocket science, but in marketing
- 4 **Types of Models Supported:** Watch out for one-trick ponies
- 5 **Speed of Execution:** Turnaround time measured in days, not weeks
- 6 **Pricing Structure:** Model development is only one part
- 7 **Documentation:** Full disclosure of algorithms, gains charts and reports
- 8 **Scoring Validation:** Job not done until fully scored and validated
- 9 **Back-end Analysis:** For true “Closed-loop” marketing
- 10 **Ongoing Support:** Periodic review and update

The Art of Targeting

Targeting is a Business Decision

Art of Targeting

Remember T, C, M

1.Target

2.Comparison Universe

3.Methodology

- Defining the proper target is most critical, even more than the methodology
 - Yes, even for Machine Learning
- Marketers must get involved in Target Definition
 - State the goals and usages clearly
 - Don't be a bad patient demanding specific prescriptions

“Some targets are not what they seem...”

Start by hanging the target in the right place



Defining the Target (or Targets) (1/4)

➤ Continuous Target

- How frequent is frequent enough?
 - How much is high enough value?
 - How big is the size of the ideal target?
- Do not make arbitrary cut-off lines, and follow the real value
- Employ Multiple Regression

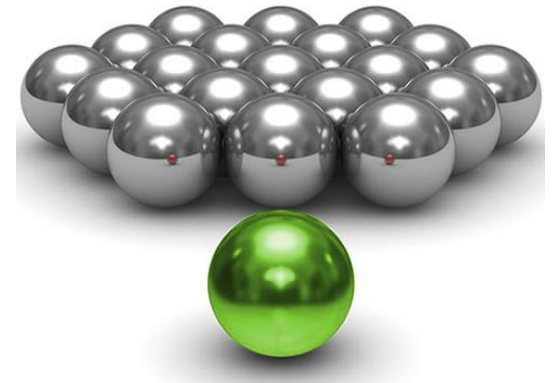


Defining the Target (or Targets) (2/4)

➤ Multiple Targets

Multiple distinctive segments such as:

- Infrequent Big Spenders
- Frequent Small Spenders
- Introductory Product Buyers
- Loyal Customers
- Recent Buyers
- Dormant Customers
- Geographic Targets (e.g., regions, cities, etc.)
- Demographic Segments (e.g., Millennials, Young & Upcoming, Soccer Moms, Middle-age Blues, Empty-nesters, Golden Years, etc.)



Defining the Target (or Targets) (3/4)

➤ Target within a Target

- Multi-step approach for multi-step sales/marketing
 - B-to-B Sales pipeline (various stages of lead qualification, sales, and conversion)
 - Open, Click, Browse, Convert, Repeat Purchase cycle
- Very narrow target in a big universe
- Sub-targets within major segments



Defining the Target (or Targets) (4/4)

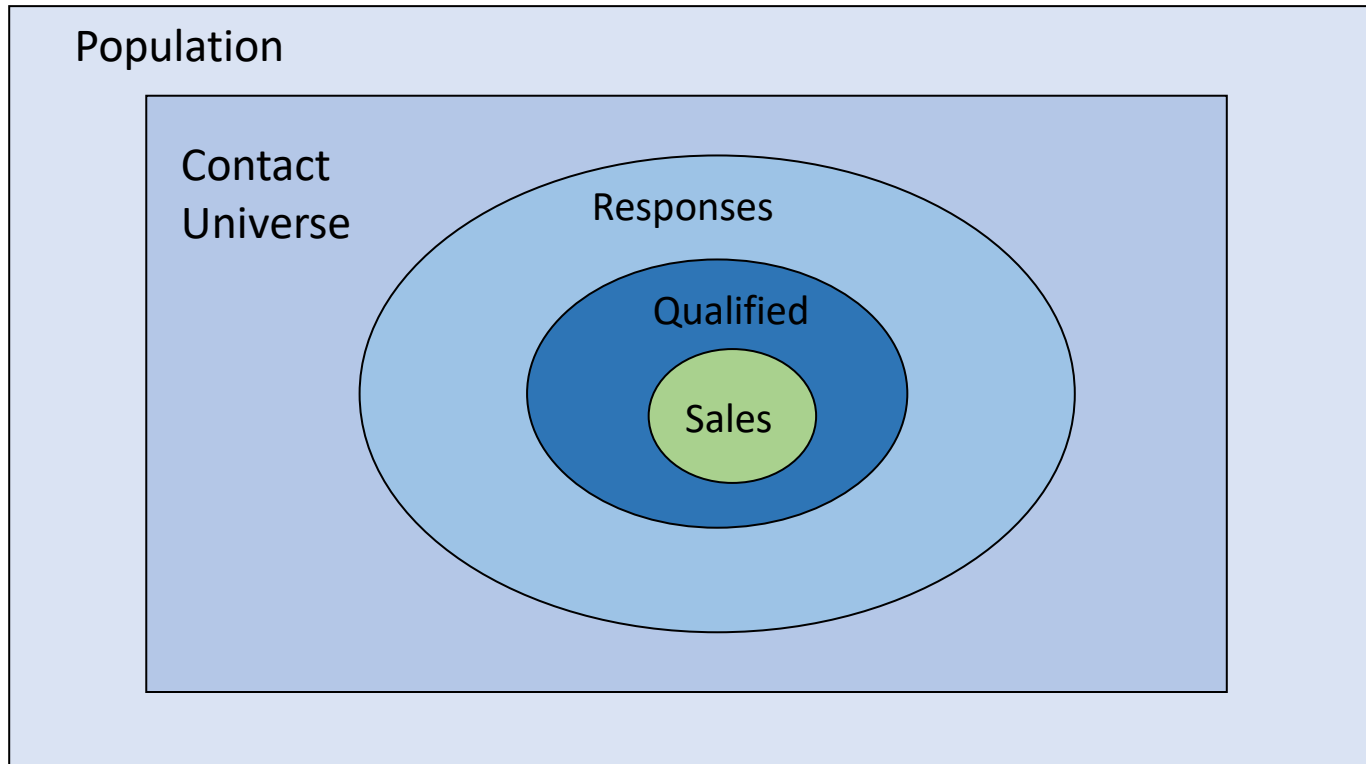
➤ Inversely Related Targets

For example,

- Frequent shoppers with low average spending
 - Responsive prospects with bad credit
- Build multiple models and find cross-sections



Multiple Model Approach Illustrated



More than 1 model may be necessary, if there is any inverse relationship among subsets

For example:

- Response Model: Target=Responders Comparison=Non-Responders
- Qualification Model: Target=Qualified Comparison=Non-Qualified among Responders

Sample Double Model Matrix

Response x Revenue										
Response Decile	Revenue Model Decile									
	1	2	3	4	5	6	7	8	9	10
1										
2	High Response, High Revenue							High Response, Low Revenue		
3										
4										
5			Average Response & Revenue							
6										
7										
8	Low Response, High Revenue							Low Response, Low Revenue		
9										
10										


 High-High is an obvious target, and Low-Low may be ignored.
 The rest depends on the targeting and messaging strategies.

Analytics-Ready Environment

Analytics Sandbox for Speed and Accuracy

Any Pain Implementing Models?

- Modelers are fixing data all the time
- Repeatedly rely on a few popular variables
- Always need more variables
- Takes too long to build models and deploy them
- Inconsistencies shown when scored
- Disappointing results, even with machine learning



Most troubles happen before or after the modeling process.

What does your database support?

You must have databases for...

- Order Fulfillment
- Contact Management
- Standard Reports / Dashboards
- Ad hoc Reports and Queries
- Campaign Execution
- Response Analysis
- Trend Analysis



But does any of them support predictive modeling and scoring?

Predictive Modeling is all about “Ranking”



Ultimately, models must properly “Rank”

- Households
- Individuals
- Companies
- Email Addresses
- Products

Define the level of data accordingly

- Relational or unstructured databases won't cut it
- Must create “Descriptors” that fit the level that needs to be ranked

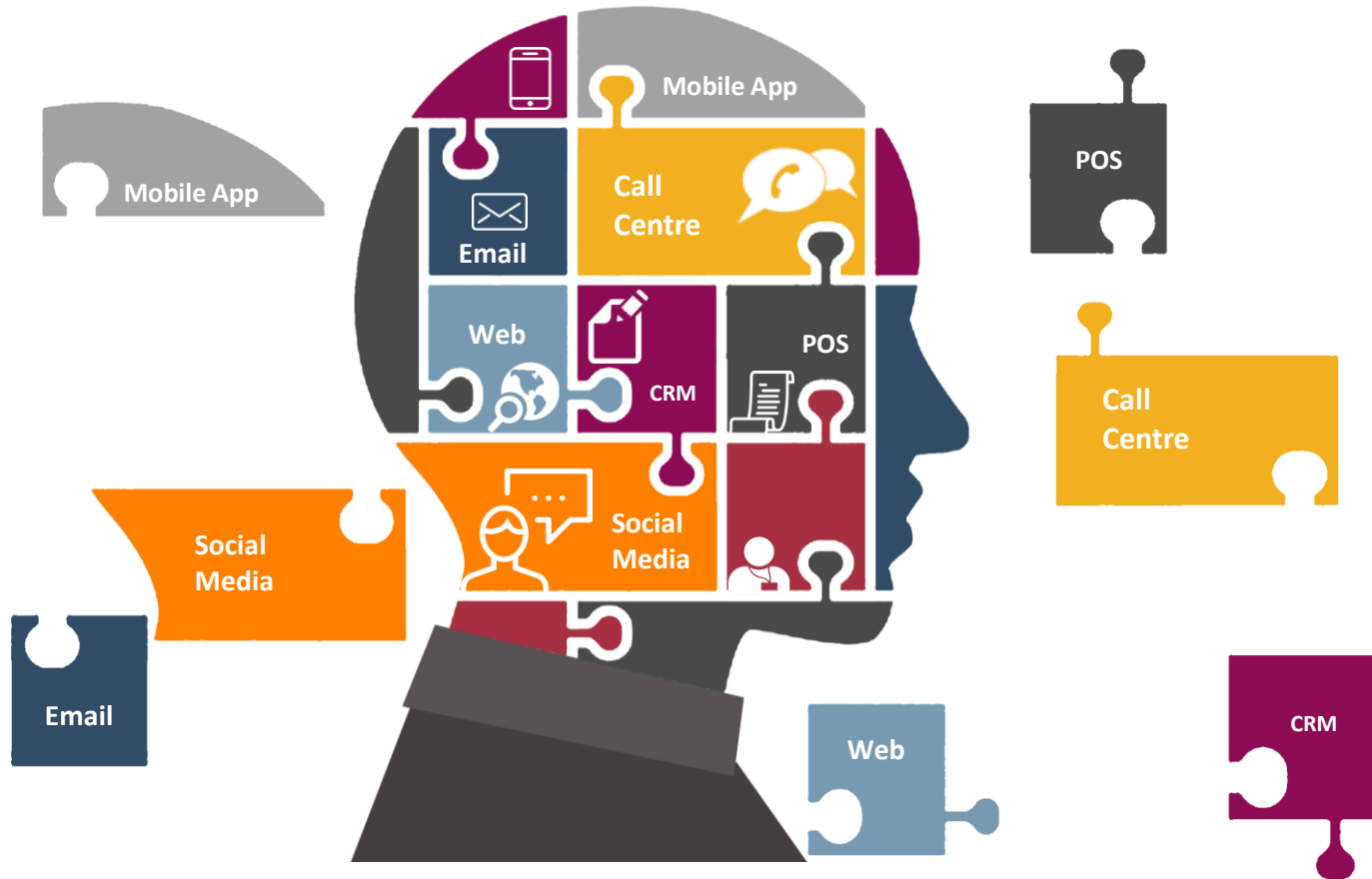
For Analytics, Clean the Data First

“Garbage-in, garbage-out”

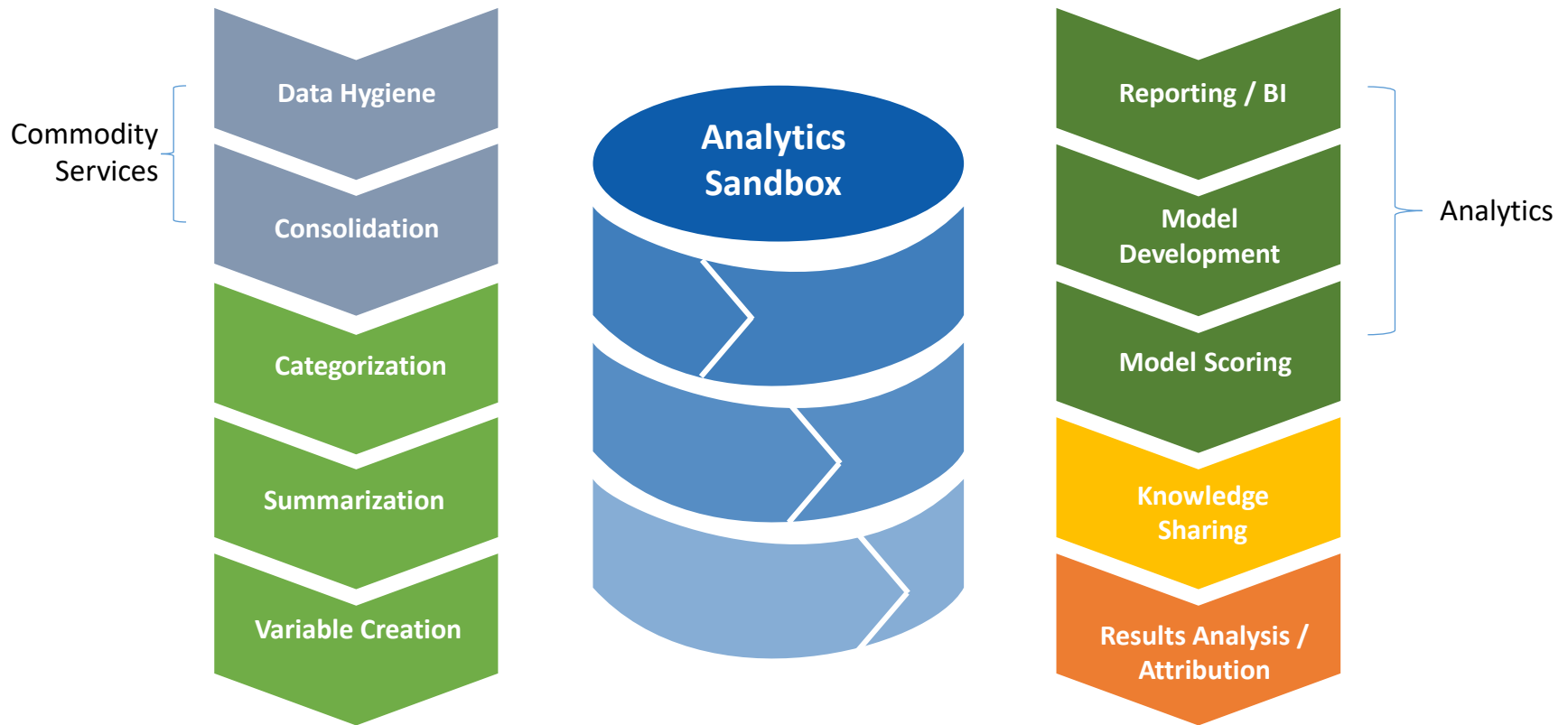
- Most data sets are “unrefined” and “unstructured”
- Over 80% of model development time goes to data prep work
 - Most databases are NOT analytics-ready
- Modeling & Scoring
 - Extension of database work
 - Consistency is “the” key



Single View of Customer for CRM



Holistic View of Analytics-Readiness



More than 80% of analytics work goes into data refinement

Why Front-end Data Work Important?



Many analysts spend majority of time doing the data work
→ Modeling work at the last minute!



Creative “intelligent” variables enhance model performance
→ Even for machines

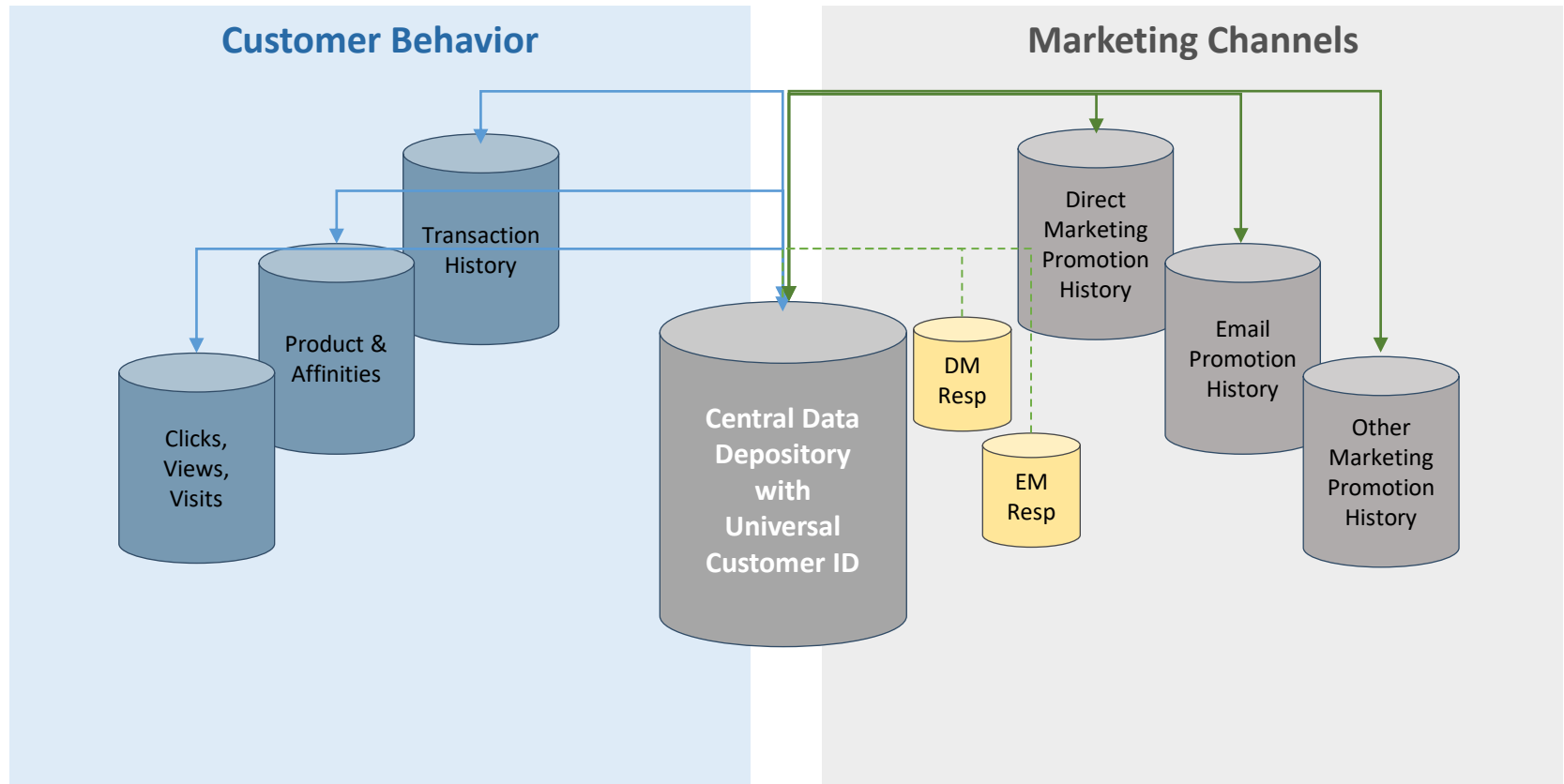


Inconsistent data create chain reactions to melt-downs
→ Most trouble happens before and after modeling steps



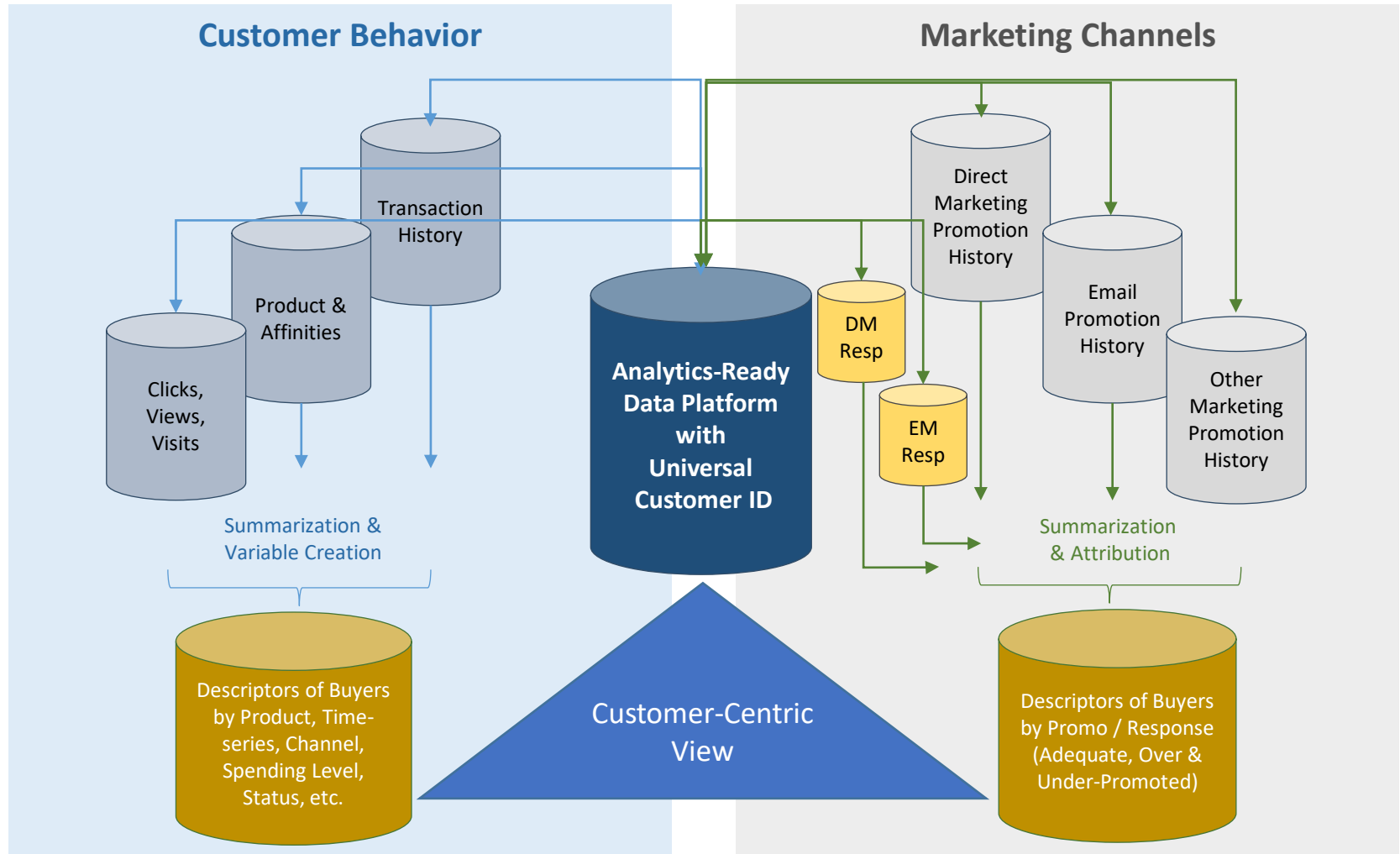
Data match and consolidation become ineffective
→ Consistent target identification and tracking is the key

Basic CDP Data Modeling



! Datasets are in one place, but the work isn't nearly done

Analytics-Ready CDP Data Modeling



What CDPs Must be

- Cover omnichannel sources
- Connected on an individual level
- Clean and reliable
- Up-to-date
- “Analytics-Ready”
- Campaign-ready
- Designed to support omnichannel attribution



Holistic data journey
from Data Hygiene and Consolidation
to Model-Based Targeting and Attribution

Beware of One-Size-Fits-All CDP Solutions

Your business goals and challenges are unique:

- Don't forget the basics
 - Clean PII is a-must, but the definition of “clean” varies
- Match sensitivity must be customized
 - Tight, loose, or medium?
 - Combinations of Name, Address, Email, Phone, and Digital IDs
- Transaction data are unique to your business
 - Who, what, when, how much, through what channel
 - Unique to industries (e.g., subscription model)
- Behavioral data are complex and diverse
 - Online and Offline (i.e., Digital vs. POS)
 - Heavy dependency on employed toolsets

“Exception Management” is the key



Benefits of Analytics Sandbox

Analytics-Ready



Refined datasets with analytics-ready variables

Hundreds of Intelligent variables maximizing predictive power

Zero effort for data hygiene in analytics stages

360-degree View



Summary of all activities around the individual target

Variables as descriptors of customers, not transactions or events

Consistent metrics for casual users and advanced analytics

Speed



Over 10x speed gain in deployment of analytics

Expedited data-based decision making, campaign support and attribution

Ready for customer-centric personalization in real-time

Where to Begin with Analytics Sandbox

Spec it out:

- Project Goals
- Data Source List (as detailed as possible)
- Final Variable List (for the analysts)
- Project Flow:
 - Data Collection
 - Conversion / Standardization
 - Categorization
 - Consolidation / Summarization
 - Variable Creation
 - External Data Append
 - Sampling
 - Modeling
 - Scoring
 - Storage / Sharing
 - Application / Campaign
 - Backend Analysis / Attribution



Who Will Build the Sandbox?

- In-house vs. Outsourcing – Consider:
 - Platform
 - Software
 - Programming
 - Staffing – Never the analysts!
- Cost it out
 - Don't forget the Update & Maintenance Cost
- Involve Analysts for Variable List Review
- **Don't be shy and ask for help from specialists or consultants**



Scope It Out

- Don't try to boil the ocean right away
→ “Analytics is making the most of available data”



- Take a phased approach
 - Watch your budget, and start with low hanging fruits
(Hint: Transaction data are the most powerful predictors)
 - Phased approach: **Proof of Concept** to full commitment in steps
 - **Think Long-term** – Avoid redesigns and redevelopments
 - Maintain **Consistency**
 - Keep the Historical Data

Data Refinement & Management

Going beyond Simple Event & Transaction Data

3 Major Types of Data for Marketing



Descriptive Data

- Demographic Data
 - Firmographic Data
 - Geo-demographic Data
- (All from 3rd-Party Sources)



Behavioral Data

- Transaction Data
- Online Behavior Data
- Movement Data
- Lifestyle Data



Attitudinal Data

- Surveys
- Primary Research
- Sentiments (via Social Media, etc.)

3-Dimensions in Predictive Analytics

Data Source Evaluation Criteria

1. **Depth:** Content & uniqueness of data
2. **Width:** Data coverage
3. **Accuracy:** Free of errors or false positives
4. **Recency:** Fresh data / minimal data atrophy
5. **Consistency:** Matters more than sheer accuracy
6. **Connectivity:** To other data sources/systems
7. **Delivery Mechanism:** Query, drilldown, visualization
8. **User-friendliness:** Intuitive & meaningful data values
9. **Cost:** Development & maintenance costs



Not all data sources are created equal

Create Data Menu

- Base it on Companywide Need-Analysis
- Ask the Users & Analysts first:

What types of predictions are required?

- Affinity/Look-alike Models
 - Promotion/Response Models
 - Time-series Models
 - Attrition Models
 - Etc., etc.,...
- Consider non-analytics departments and users
 - Maintain only the ones that fit the objective
- Don't be afraid to throw out “noises”



Data Menu



Check the ingredients

- What do you have today?
- What can be bought?
- What can be created?

Cost - *Can you afford to maintain it?*

- Storage/Platform – Consider the scoring part, too
- Programming/Processing Time
- Software
- **Update/Maintenance**
- **External Data**

Organizational Data Inventory



You may have more than you thought:

- **PII** (Personally Identifiable Data): Name, Address, Email, Phone Number, etc. Key to Geo/Demographic Data
- **Order/Transaction Data**: “RFM”, Payment Methods
- **Item/SKU Level Data**: Products, Price, Units
- **Promotion/Response History**: Source, Channel, Offer
- Life-to-Date/Past “x” Months **Summary Data**
- **Customer Status** Flags: Active, Dormant, Delinquent
- **Surveys/Product Registration**: Attitudinal/Lifestyle
- **Customer Communication** History Data: Call-center, Web
- **Online Behavior**: Open, Click-through, Page views, etc.
- **Social Media**: Sentiment/Intentions

Need Standardization, Categorization, & Summarization

Maximize the Power of Transaction Data

Past Behavior is the Best Predictor of the Future Behavior

Most databases describe shopping baskets

→ Start describing your targets



- RFM Data must be Summarized (or De-normalized)
- Turn RFM data into individual / household level “Descriptors”
- Combine with essential categorical variables (e.g., product, offer, channel, etc.)

Data Summarization – Matching the Level of Data

Transactions

Cust ID	Trans ID	Order Date	\$ Amount
000123	100011	2016-05-06	\$199.99
000123	100128	2017-08-30	\$50.49
000123	103082	2018-12-21	\$128.60
003859	100036	2017-06-06	\$43.99
003859	101658	2018-01-20	\$43.99
003859	102189	2018-04-15	\$119.45
003859	106458	2019-02-18	\$43.99
004593	104535	2019-04-30	\$354.72
016899	107296	2018-07-14	\$199.99
019872	102982	2017-09-07	\$128.60
019872	103826	2018-04-30	\$499.99
019872	109056	2019-03-12	\$59.99

Individual Level Summary

Cust ID	# Orders	\$ Total	First Order Date	Last Order Date
000123	3	\$379.08	2016-05-06	2018-12-21
003859	4	\$251.42	2017-06-06	2019-02-18
004593	1	\$354.72	2019-04-30	2014-04-30
016899	1	\$199.99	2018-07-14	2018-07-14
019872	3	\$688.58	2017-09-07	2019-03-12

RFM Data Summary - Timeline

Life-to-date Summary provides the historical view

May create bias towards tenured customers

Put time limit on variables (e.g. 12-month, 24-month, etc.)

May require higher number of variables and complicate the process

For Lifetime Value & Time Series Models

Must create historical arrays (daily, weekly, monthly counts of events)



Raw Data Coming into Summarization

Merchandizing

- Who: Customer ID / PII
- What: Product SKU / Category
- When: Purchase Date
- How much: Total Paid, Net Price, Discount/Coupon, Tax, Shipping, Return
- Channel/Device: Store, Web, App, etc.
- Payment Method

Promotion Data

- Promotion Channel
- Source of Data / List
- Offer Type
- Creative Details
- Segment/Model (for selection/targeting)

Subscription

- Who: Subscriber ID / PII
- Brand / Title / Property
- Dates: First Subscription, Renewal, Payment, Delinquent, Cancellation, Reactivation, etc.
- Paid Amounts by Pay Period
- Number of Payments / Turns
- Payment Method
- Auto Payment Status
- Subscription Status
- Number of Renewals
- Subscription Terms
- Acquisition Channel / Device
- Acquisition Source

Hotel/Hospitality

- Who: Guest ID / PII
- Brand / Property
- Region
- Booking Site / Source
- Transaction Channel / Device
- Booking Date/Time/Day of Week
- Travel(Arrival) Date/Time
- Travel Duration
- Transaction Amount: Total Paid, Net Price, Discount, Coupon, Fees, Taxes
- Number of Rooms/Parties
- Room Class/Price Band
- Payment Method
- Corporate Discount Code
- Special Requests

Sample Variables after Summarization

Recency

- Weeks since first transaction date
- Weeks since last transaction date
- Years since first sign-up
- Last transaction channel
- Average number of days between transactions
- Transactions done in past 12, 24, 36 months

Frequency

- Number of transactions
- Number of items purchased
- Average transactions by month
- LTD returns and adjustments
- Transactions by payment method
- Transactions by dollar range [\$1-\$49.99], [\$50- \$99.99] ..
- # Full-price transactions

Monetary

- Life-to-date \$ spending
- Total \$ past 12, 24, 48 months
- Average dollars by channel
- Average dollars by payment method
- Highest transaction \$ amount
- Lowest transaction \$ amount
- Last transaction \$ amount

Brand Category

- Transactions made by brand
- Total \$ past 48 months by brand
- Average dollars by brand
- Weeks since first & last transaction date by brand

Product Category

- Transactions made by product category
- Total \$ past 48 months by category
- Average dollars by product category
- Weeks since first & last transaction date by product category

Data Categorization & Tagging

Freeform data comes to life through categorization

- Hidden data in:
 - Product, Service, Offer, Channel, Source, Status, Titles, Surveys, etc.
- Have categorization guideline?
- Who will do it?
 - **Consider Machine Learning**
- What to throw out?
 - Keep data mainly for analytics and predictive modeling



Categorical Data

Any Non-numeric Data

- Product
- Service
- **Offer**
- Transaction Channel
- Promotion Channel
- Source
- Market
- Region
- Business Title
- Member Status
- Payment Method
- etc...

Offer Code

For example:

- Flat Dollar Discount
- % Discount
- Buy 1, Get 1 Free
- Free Shipping
- No Payment Until...
- Free Gift
- Discount Coupon
- Friends & Family Discount
- etc...

→ Create standard codes



Categorize as much as possible at the data collection stage

Categorization Guidelines



- Define the key categories first
- Categorize during data collection
- Categorize buyers, not products
 - Not the products, but the intentions
 - Products change, but affinities rarely do
- More specific the better
 - Don't settle with general categories
 - Be as specific as possible (e.g., "Home Theater Speakers", not just "Home Electronics")
- Consistency over accuracy
- Automate as much as possible →
Via Machine Learning

Categorization Guidelines *(continued)*

Create rules and DON'T deviate from them



Create “Code” Structure
Training & Automation

Be consistent throughout



Surveys, Data Entry, Product
Taxonomy, Database, Analytics

Don't allow too many variations
(over 20) in one category



Break into multiple categorical
variables if necessary

Don't forget the end goals and
don't over-do it



Must be “relevant”



Data Hygiene & QC

Maintain accuracy and consistency

- Create consistency
 - Consistency via Standardization
 - Proper data conversion & edit
 - Purge bad data mercilessly
- Cover all basis
 - PII (Name, Address, Email, Phone)
 - Transaction data (#, \$, Dates)
 - Categorical data (everything else)
- Develop firm rules and enforce them
 - Data players – All of them
 - Everyone who touches data (e.g., retail stores)



Missing Values

“Missing Data can be meaningful”

Showing up as predictors in models

- For Numeric Data (e.g., \$, Counters, Dates, etc.)
 - Incalculable vs. Non-matches when joined
 - Missing is missing: DO NOT fill in with 0's
- For Categorical Data (e.g., Codes, Text, etc.)
 - Leave room for “N/A” (e.g., blank, “N/A”, “0”, “.”, etc.)
 - Code “Non-matches” to external files differently



Caution! Some “unstructured” non-relational databases only store what’s available.

More on Missing Data



- Agree on Imputation Rules
 - Across divisions and user groups
 - Do it upfront
 - Must be part of scoring codes
- Educate non-analysts
 - Hard to undo when combined with other values
 - Train data partners and vendors
- Always check % missing
 - Development Samples vs. Main Databases

PII – Gateway to External Data

What is hidden behind simple name & address?

- Standardize Name & Address first
 - Maintain PII (Personally Identifiable Information)
 - Hygiene via periodic NCOA and standardization
- First & Last Name – Ethnic, Gender
- Name, Address, Email – Demographic Data
- Address – Geo-demographic, Census Data
- Zip – County, Market Region, DMA



Watch out for Privacy Laws such as GDPR, when exchanging PII

Use Cases for 3rd-Party Demographic Data

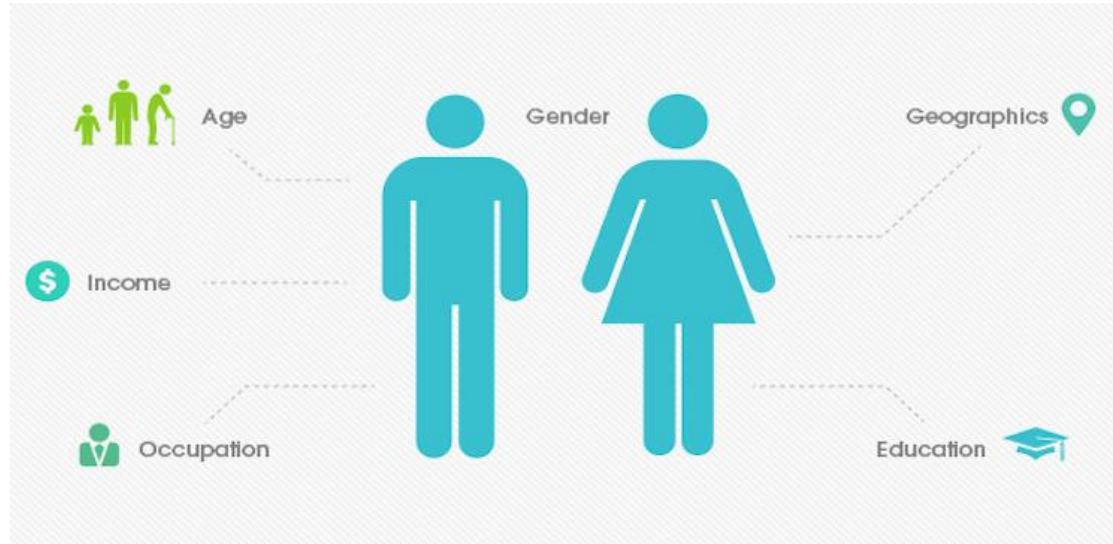
Data Append

- Add extra dimensions to existing customer data for:
 - Customer Profiling – with views against normative data (U.S. sample)
 - Modeling & Segmentation – for cross-sell/upsell, CLV, loyalty, etc.
 - Bring consistency factors to advanced analytics
 - Filtering based on key variables such as age, income, family type, etc.

Prospecting

- Create new customer base using all available data sources
 - Define various “Best Customer” types using data assets in CDP
 - 3rd-party vendor builds “look-alike” models using the Best Customers as targets
 - Have the vendor deploy email campaigns and/or produce contact lists for targeted campaigns

External Data



Always consider buying data before collecting and building

- Compiled Demographic / Firmographic Data
- Behavioral / Transaction / Co-op Data
- Lifestyle / Attitudinal / Survey
- Census / Geo-Demographic Data

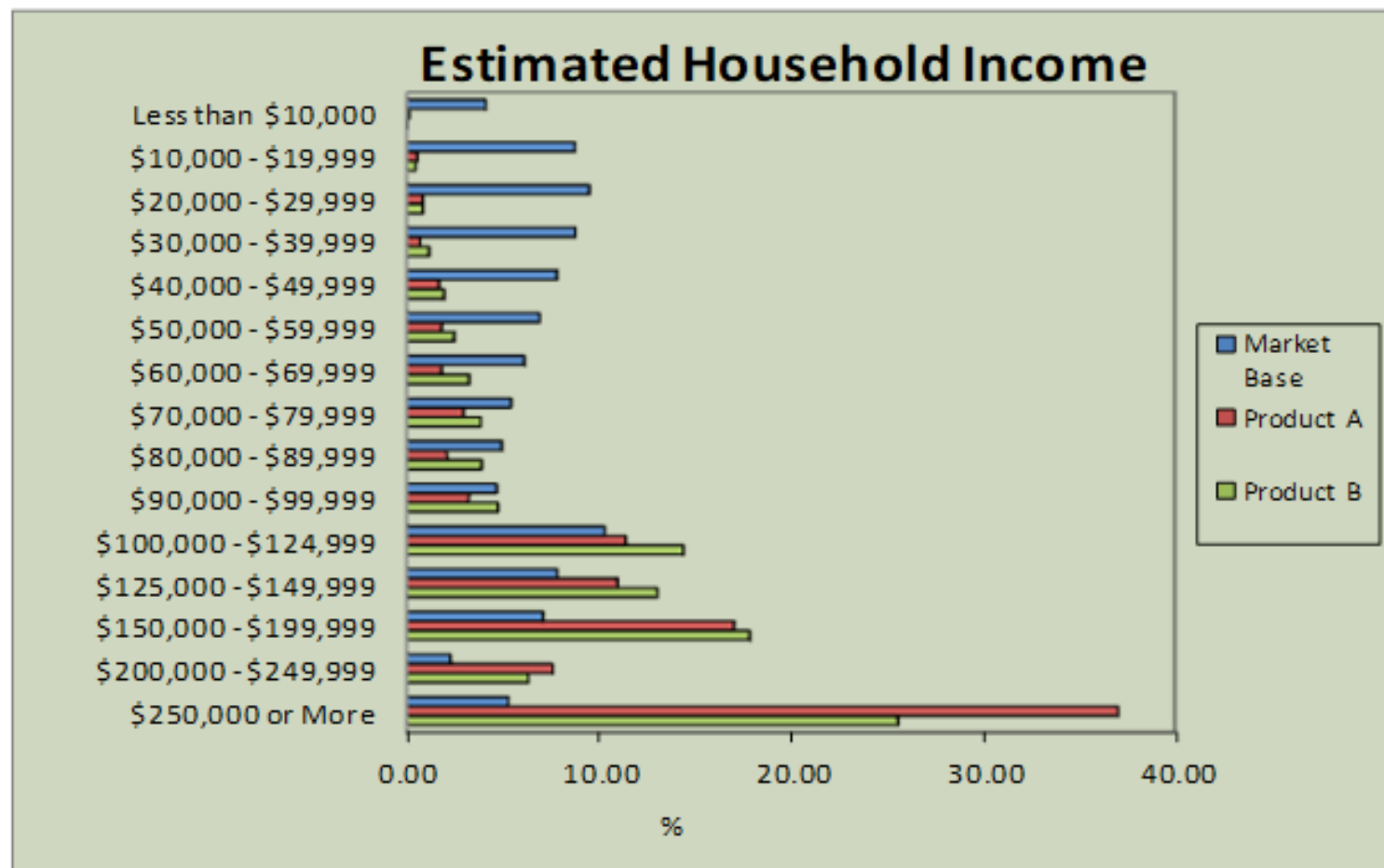
Evaluating External Data



- Test multiple data sources
 1. Depth of information / Uniqueness
 2. Coverage / Match Rate
 3. Consistency / Update Cycle
 4. Accuracy
 5. Price
 6. User-friendliness
 7. Delivery Options – Real-time via API

- Learn about the data sources
 - What's real and what's imputed?
 - Don't stop at Demographic: Consider "Behavioral" data

Sample Demographic Profile Report



Sample Multi-Column Profile Report

		Customers				Prospects					
Market Base		Post 2002		Pre 2002		Lost to Competition		Still Interested		Special Project	
%		%		%		%		%		%	
		Index		Index		Index		Index		Index	
ESTIMATED HOUSEHOLD INCOME											
Less Than \$30,000	10.40	1.06	10	0.83	8	1.42	14	1.69	16	0.79	8
\$30,000 - \$39,999	10.12	1.07	11	0.82	8	0.91	9	1.61	16	2.38	24
\$40,000 - \$49,999	8.70	1.53	18	1.36	16	1.04	12	1.61	19	3.17	36
\$50,000 - \$59,999	8.00	2.02	25	1.78	22	2.85	36	2.55	32	1.59	20
\$60,000 - \$69,999	7.36	2.34	32	2.28	31	2.72	37	3.23	44	4.76	65
\$70,000 - \$79,999	6.68	2.98	45	2.67	40	2.72	41	4.50	67	4.76	71
\$80,000 - \$89,999	6.41	3.57	56	3.40	53	3.17	49	4.33	68	4.76	74
\$90,000 - \$99,999	5.91	3.93	66	3.85	65	4.08	69	5.27	89	8.73	148
\$100,000 - \$124,999	11.86	11.44	96	11.18	94	12.89	109	12.91	109	26.98	227
\$125,000 - \$149,999	8.40	12.25	146	11.81	141	13.47	160	14.87	177	14.29	170
\$150,000 - \$199,999	7.24	15.89	219	13.46	186	20.34	281	17.76	245	19.84	274
\$200,000 - \$249,999	4.45	13.73	309	15.10	339	13.08	294	13.17	296	5.56	125
\$250,000 or More	4.46	28.21	633	31.49	706	21.31	478	16.48	370	2.38	53
PURCHASING POWER INDICATOR (PPI)											
Less than \$20,000	6.44	0.68	11	0.58	9	1.03	16	1.10	17	0.79	12
\$20,000 - \$29,999	13.26	1.17	9	0.86	6	1.10	8	2.04	15	2.38	18
\$30,000 - \$39,999	11.16	2.05	18	1.68	15	1.88	17	2.12	19	3.17	28
\$40,000 - \$49,999	10.11	2.58	26	2.52	25	3.37	33	3.06	30	5.56	55
\$50,000 - \$59,999	8.95	3.75	42	3.26	36	3.69	41	4.50	50	3.97	44
\$60,000 - \$69,999	8.44	4.61	55	4.45	53	4.40	52	7.14	85	5.56	66
\$70,000 - \$79,999	7.37	5.42	74	5.10	69	5.70	77	6.37	86	14.29	194
\$80,000 - \$89,999	6.42	6.07	95	5.93	92	6.80	106	7.31	114	14.29	223
\$90,000 - \$99,999	5.45	6.55	120	6.32	116	7.19	132	7.65	140	9.52	175
\$100,000 - \$124,999	9.56	15.94	167	15.94	167	17.49	183	17.08	179	18.25	191
\$125,000 - \$149,999	5.69	13.93	245	14.44	254	15.87	279	15.12	266	16.67	293
\$150,000 - \$199,999	4.81	18.11	377	19.63	408	18.52	385	16.06	334	3.97	83
\$200,000 - \$249,999	1.33	9.08	683	9.56	719	7.12	535	5.52	415	0.79	59
\$250,000 or More	1.00	10.07	1007	9.73	973	5.83	583	4.93	493	0.79	79

Model Score Quality Control

Most troubles happen after the models are built...

Check:

- Model Group Distributions
- Variable distributions (values and indices)
- Missing Values
- Match rate for appended data
- Scoring codes, including score breaks
- Compare to previous runs – Check Deterioration



Set parameters for acceptable differences and
Enforce them

Scoring – Sample vs. Database

- Development Sample vs. Live Database

- Database Structure
- Variable List/Names
- Variable Values
- Imputation Assumptions



Lead to disasters if “anything” is different

- **Never** alter model group definitions that are set in the development samples

Share the Model Scores

Model scores are summaries of large and complex data in a compact form

- Sync model scores with other databases and data-marts
- Plan ahead:
 - Reserve spaces
 - Educate the users & [Evangelize](#)
- Store raw scores, not just model groups
- Match the Levels of Scores
 - Household
 - Individual
 - Company
 - Email
 - Product



Personalization

Road to Holistic Personalization

About Personalization

Personalization is the big buzzword now, but what does it mean to you?

- Addressing your customers by their first names?
- Collecting explicitly expressed preferences and treating them accordingly?
- Customizing emails and landing pages based on customer profiles and behaviors?
- Knowing when to contact, and through what channel?
- Keeping in touch with your customers constantly?
- Suggesting more of the same products that they just purchased via collaborative filtering?

Some efforts are better than mindless batching and blasting, but...

- Maybe you are:
 - “Personally” annoying your customers and prospects
 - Personalizing a fraction of your target base, while completely ignoring others
 - Personalizing sporadically only when obvious trigger data becomes available
 - Mismatching offers to targets customers more often than not

Personalization is about the Person

Look at it from the customer's point of view...



- No one is just an “online” or an “offline” person
- “Personalization Engines” are often overrated (especially when product level collaborative filtering is on “auto-drive” mode)
- Raw SKU level data sets are utterly inadequate for personalization

“Personalization is about the Person”

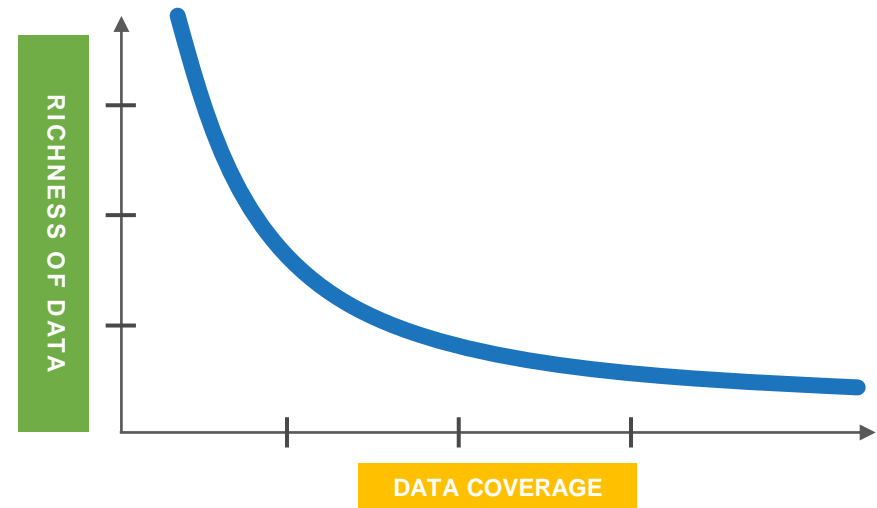


- Transform transaction, event, or product level data to:
 - Describe people, not products
 - Create a 360-degree Single Customer View (“Analytics Sandbox”)
- Develop “Personas”, then match products to them
 - Not the other way around
 - Fill in the gaps with modeling

Even now, real data are hard to come by

Verified “known” explicit data can be scarce, even in this age.

- Data sets are often missing for targets who are:
 - New to the business
 - Dormant
 - New to specific channels
 - Hiding their tracks

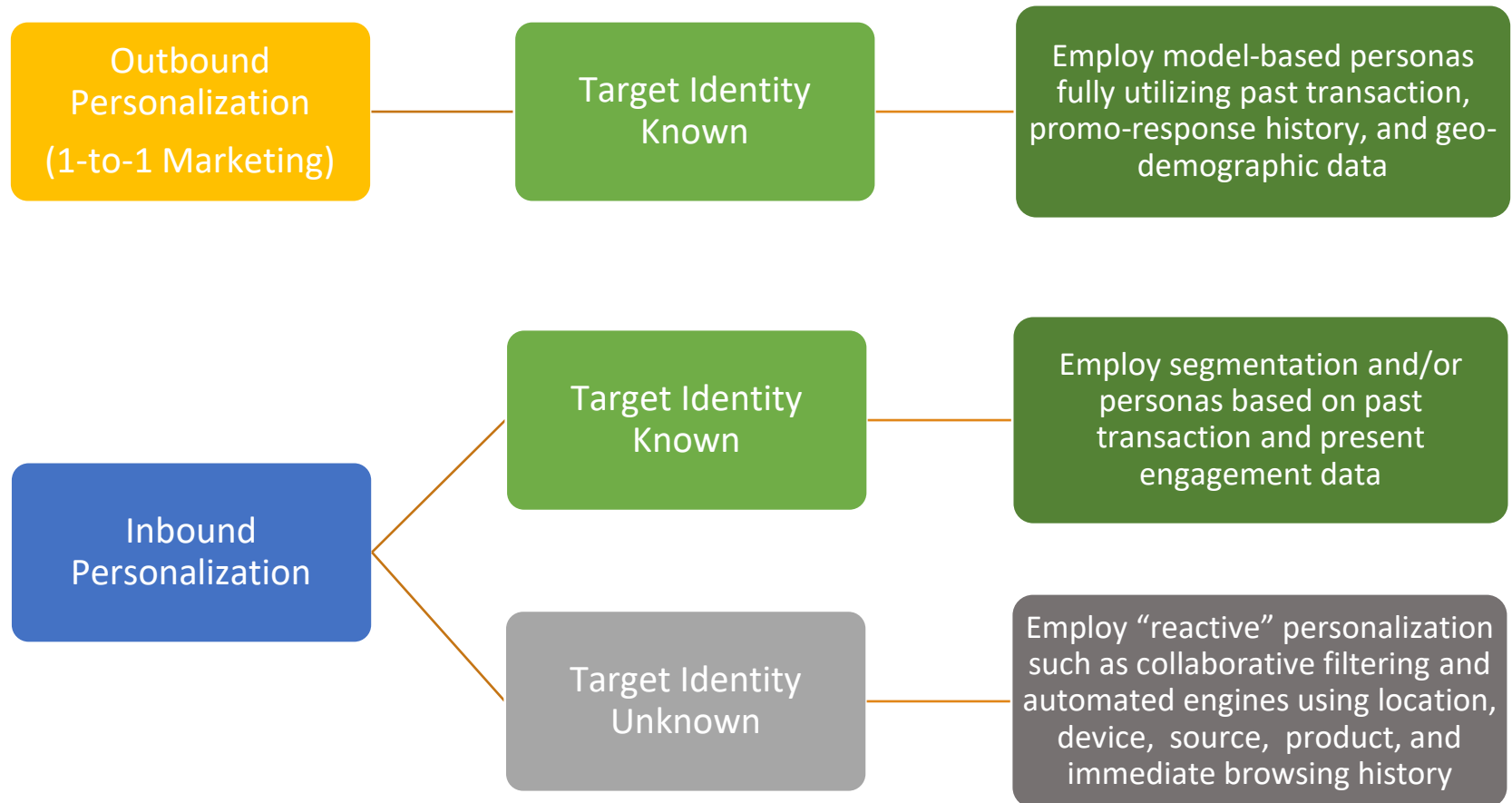


But, most personalization efforts are done based only on “known” explicit data!

- Need to maximize the value of available data, even implicit or anonymous data

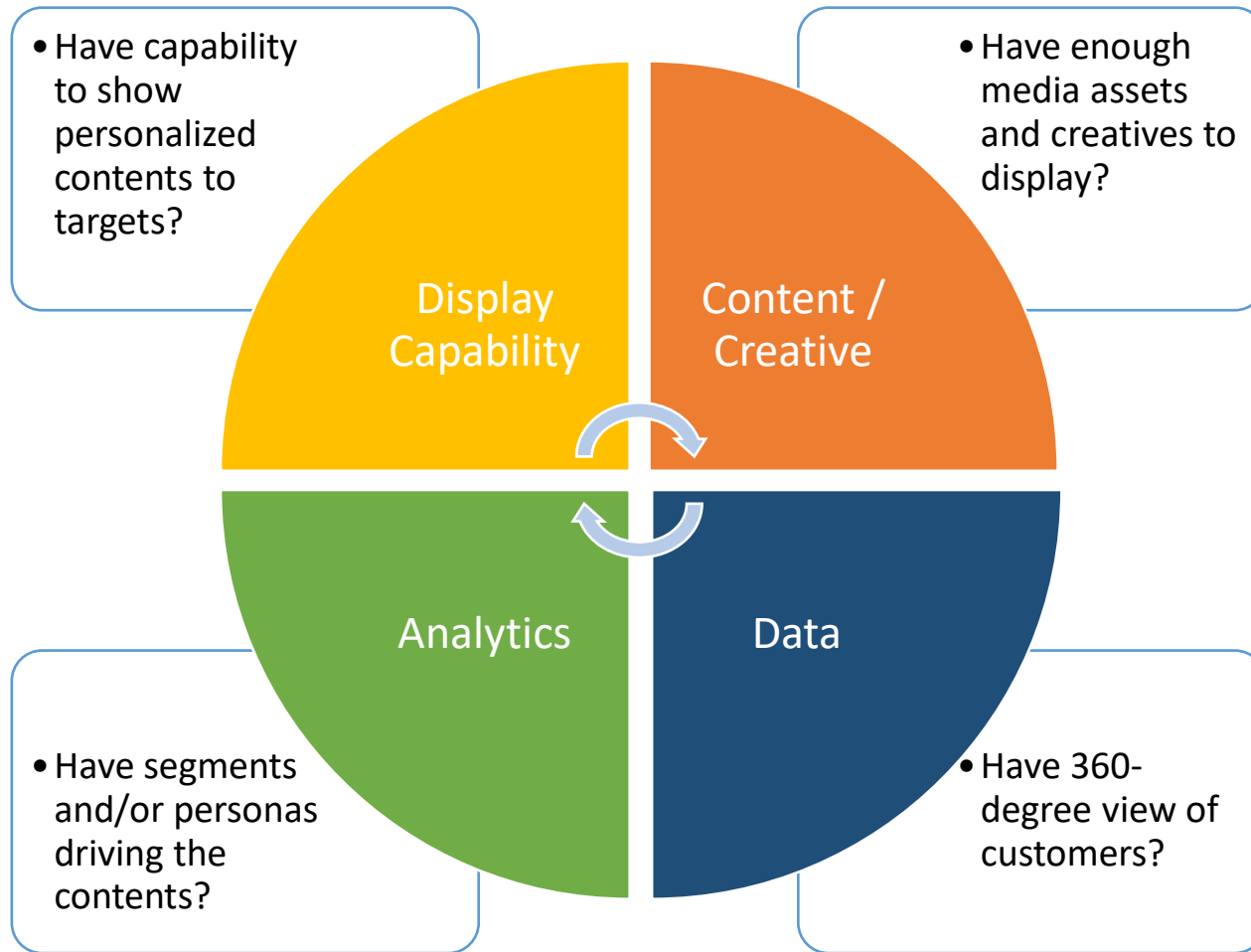
Personalization Framework

Differentiate “Planned” and “Reactionary” Personalization Efforts

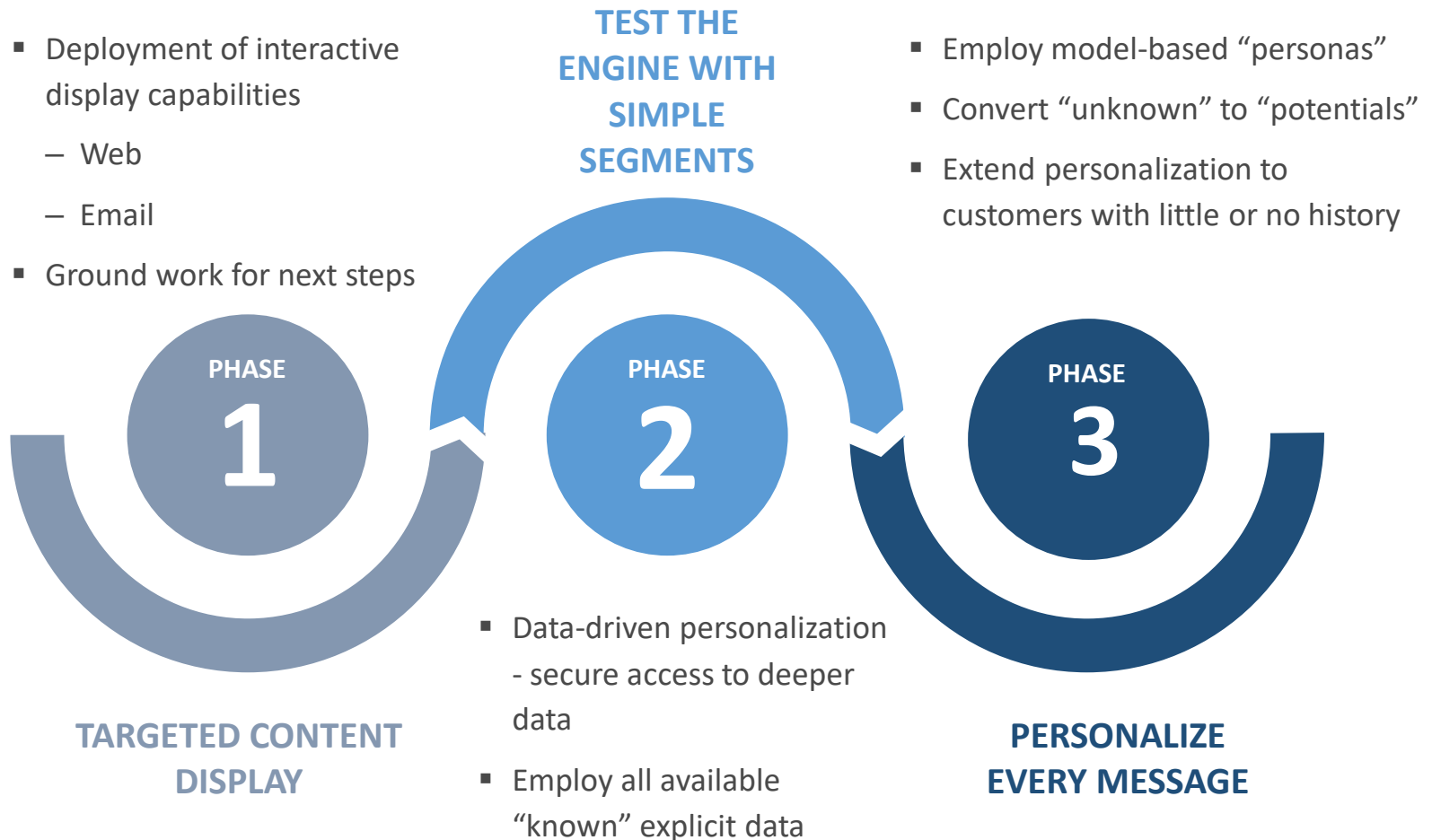


Elements of Holistic Personalization

Personalization is about connecting the dots among these elements

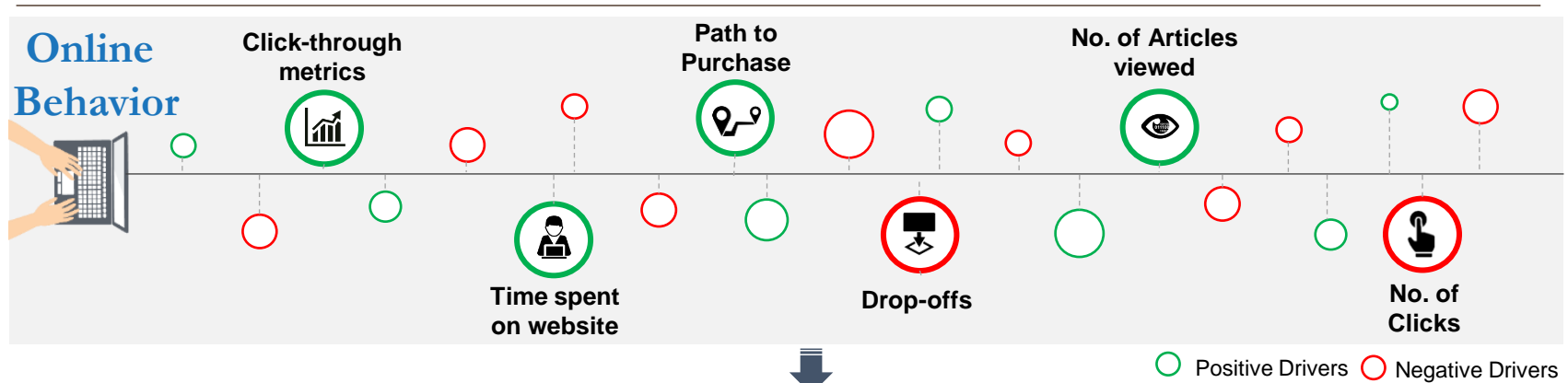


Step-by-Step Approach to Personalization

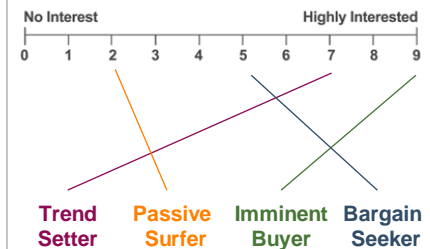
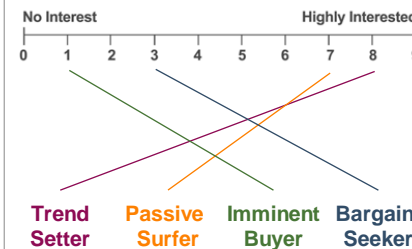
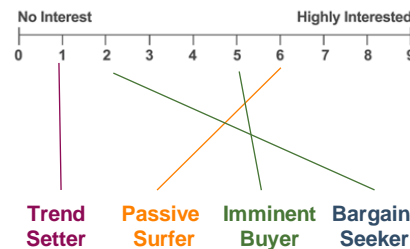
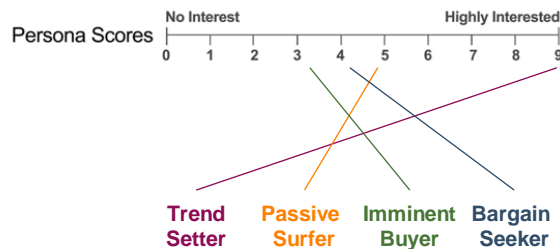


Data, analytics, content management and delivery working in conjunction

Reactive Personalization w/ Online Behavior



Online Personas



Identify Personas

Heuristic or statistical personas based on visitor's online behavior, converting "unknowns" to "potentials"

Identify Levers

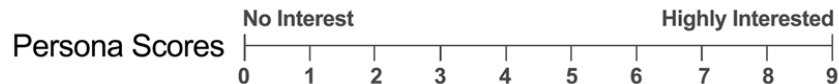
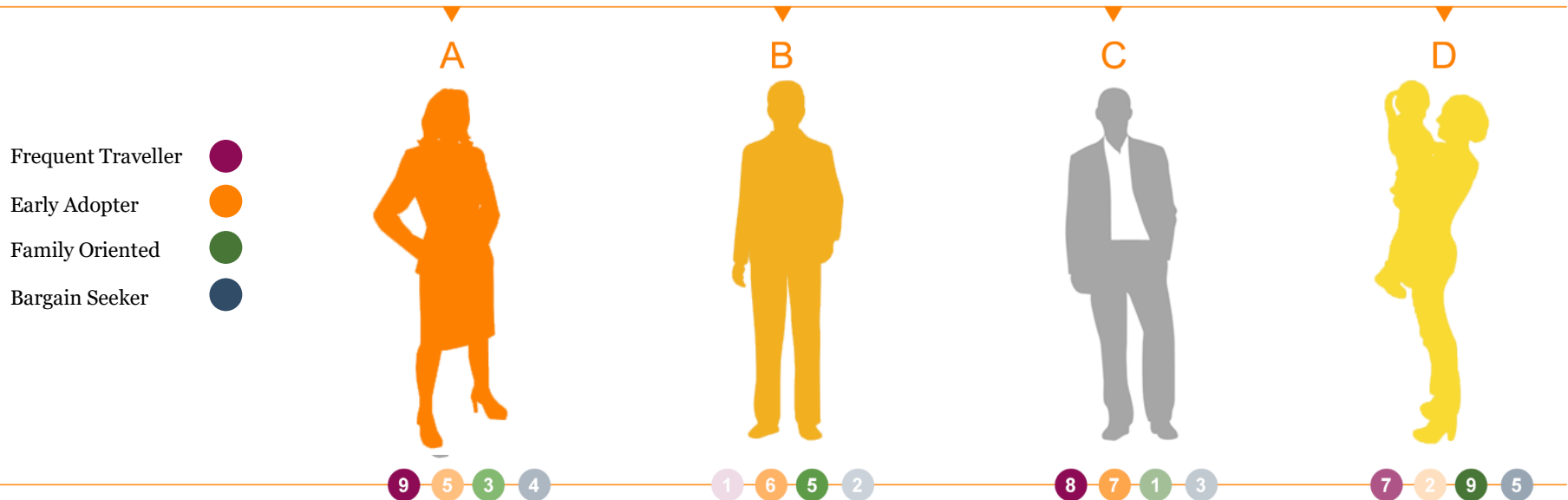
Connect the dots between the visitor behavior and desired business outcome

Personalize

Extend personalization to new visitors in real-time, driving them towards desired outcome

Personas Based-on Full Set of Data

Customer



Extend personalization to customers with limited data using model-based personas

- Convert “unknown” to “potentials”
- Go beyond rudimentary segments
- Match best products/offers to each target

Examples of Personas

For Hospitality Industry

- Frequent Flyer
- Foreign Traveler
- Luxury Hotel
- Gourmet
- Wine Enthusiast
- Adventure Seeker
- Young Family
- Budget Conscious

For Gift Industry

- Family Oriented
- Romantic
- High-end / Luxury
- Seasonal
- Frequent Small Gifts
- Pre-packages
- Bargain Seekers
- Specialty Items

For Business Solutions

- Corporate Purchase
- Home Office
- Consumables / Repeat Purchase
- Big Ticket Items
- Technology Buyers
- Early Adopters
- Trend Followers

Examples of Personas

For Telco Industry

- Home office
- Family with kids
- Heavy download
- Gamer
- Mobile phone only
- VOIP user
- International Caller
- Pay-per-view Movie
- Pay-per-view Sports
- Season ticket holder

For Financial Industry

- Frequent trader
- Do-it-yourself investor
- High value investor
- Institutional investor
- Annuity investor
- Risk-averse investor
- Safety conscience
- Credit revolver
- Credit card transactor

For Women's Interest

- Fashion enthusiast
- High-end accessories
- Beauty / Skincare
- Children's interest
- Gardening enthusiast
- Organic food
- Weight-loss / Diet
- Gourmet cooking
- Spa / Day-spa
- Family entertainment
- Foreign vacation
- Bargain seeker / Value shopper
- Coupon collector

Segments vs. Personas

Clustering/Segmentation/Cohorts

- More about messaging than targeting
- Pin a target individual into one segment at a time
- Hard to update algorithms with reliable consistency – Most just keep rescoreing new data using dated formula
- Group them first, describe them later
 - End up calling everyone in a segment the same way

Personas

- Built for 1 attribute at a time
- Describe an individual with multiple attributes
- Identifies dominant characteristics of a person via side-by-side comparison
- Each persona represents diverse array of data
- Easy to update, 1 persona (i.e., one model) at a time with consistency
- Ready for multi-channel marketing

Personas for Personalization

“Personas” built for specific attributes

- Project small “known” attributes to large universes of “unknowns” in form of model scores
- Fill in data gaps leaving no missing value – Scores for every record using all available data
- Enable side-by-side comparison of attributes – Quickly find dominant characteristics of an individual
- Simplify matching process between individuals and best suitable products/services
- Support message “rotation” for an individual customer using multiple personas
- Lead to marketing automation – Simple scores are no burden to personalization engines



Post-Campaign Analysis and Attribution

Close the Loop Properly

Closed-Loop Marketing



- 1-to-1 Marketing is a Continuous Loop
- Analytics “before” and “after” campaigns → What really worked?
- Last-click attribution is seriously limited
 - Digital channels only
 - Limited view of customer journey

→ Again, it is about commitment, not technology

What worked, and what didn't?

In the Multi-Channel Marketing Environment, pinpointing “What Worked” is difficult:

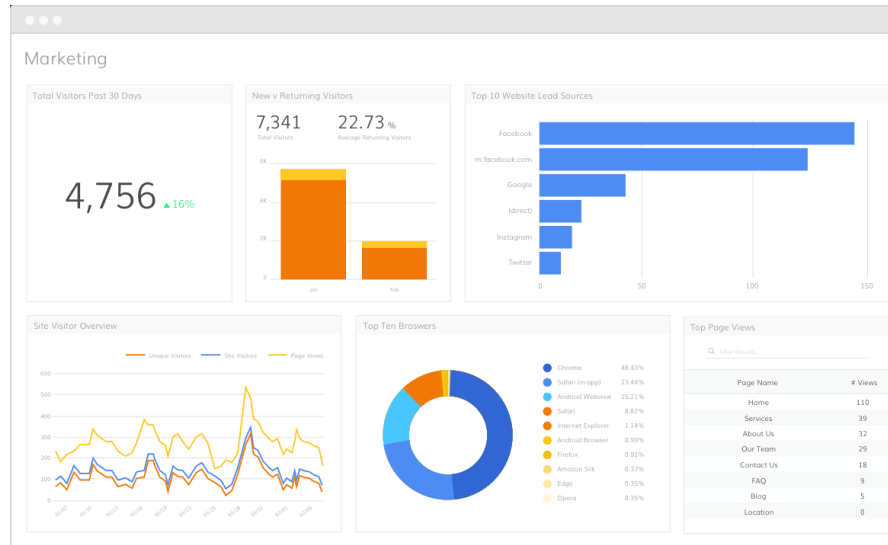
- Escape channel-centric view, and consider other elements
- Don't settle with “Last Touch” attribution
- Retain Customer-Centric view
- Continuously apply learnings to the next campaign

What did *you* do?

Target	Offer/Message
<ul style="list-style-type: none">• Target List Source• Primary Segments• Selection Rules• Model Score Group / Clusters	<ul style="list-style-type: none">• Promotion Channel• Campaign• Drop• Primary Offer(s)• Feature Product(s)• Creative Version(s)

Always maintain promotion and response history on a transaction and an individual customer level

Response Reports & BI Analytics



- Start with “Canned” Reports and BI Dashboards from vendors
- Don’t insist real-time for every report
- Get ready to create “Custom” reports and dashboard views
 - Prioritize what you want
- Format and Delivery
- Timing and Interval
- Timeline to be covered and pulled (YTD, 12-mo, 3-mo, 2-weeks, daily, etc.)

Key Performance Indicators

Set KPIs upfront:

- Open, Click-through, Conversion Rates
 - “Denominator” for each rate?
- Revenue
 - Per 1,000 Mailed/Contacts
 - Per Order/Transaction
 - Per Display, Email, Click-through, Conversion
- By
 - Source, Campaign, Drop, Season, Day-part, Segment, Model Group, Offer, Creative, Featured Products, Channels (in & outbound), Ad server, Publisher, Affiliate, Key word, Script/Copy, etc.
- Key variables must reside in the database
 - Most digital tags are NOT in consistent format
 - Keep them in “report-ready” forms



1:1 Channels and Customer Journey

Allocation Methods:

- Last Touch
- First Touch
- Double Credit
- Equal Credit
- Proportional Split (based on touches)
- Weighted Value
- Modeled Weighted Value

Also Consider:

- Direct Click and/or Look-back Attribution
- Go beyond Google UTM tags and consider non-digital Channels
- Time Duration – depending on the channel in question

Touch Channels Regardless of Order

Outbound	Inbound
<ul style="list-style-type: none">• Email• Direct Mail	<ul style="list-style-type: none">• Direct• Organic Search• Paid Search• Social Media• Display Ads• Referrals• Affiliates

Assume every target is exposed to multiple channels.

Consider 2-step summary process:

1. Transaction Level Attribution
2. Individual Level Attribution

Future of Data & Analytics

What will we be doing in the future?

Personalized Ad in the Future



The Future Is Here Already

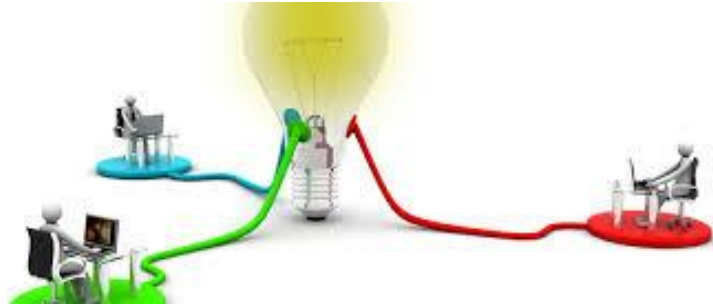
A Scene from the Movie “Minority Report” - Personal Advertising in the Future

What just happened in this scene?

1. Machine identified the target individual
 2. Retrieved the target’s past transaction data
 3. Algorithm chose suitable products to offer
 4. Displayed images of selected products to the target individual in real-time
- We can do all this now – albeit more slowly
 - Cannot skip these steps even with AI & automation – Different algorithms for each step
 - It is about the target individuals and their data, not product, channel, or display technology



Information Must Flow



In the world of ubiquitous data and AI:

- It is really about organizational commitment to harness the power of data
 - Higher values are created when information is freely exchanged – among divisions, brands, companies and individuals
 - Predictive power increases as multiple types of data are joined together
 - Speed of data exchange and processing is the only game left in town
 - It will require less human intervention, and more AI & Machine Learning
- *Will most humans even be relevant or necessary in the near future?*

Humanizing the Data

- Data play is people business in the end
 - Customer-centric mindset, not business-, division-, product-, or channel-centric
 - Make data usage easier, not more complicated
- Don't do it just because you can
 - Respect people's privacy
 - Gentle nudges, not hard-sells
 - Don't be creepy – TMI is bad
- Try not to get replaced by machines
 - Command machines with purposes
 - Think logically even as end-users
 - Don't be a Data Plumber and go beyond data and statistical knowledge – Look at things from multiple perspectives



Only human factors and mathematics will remain unchanged.

Consumer Bill of Rights

Consumer Bill of Rights for Online Engagement (1999)

by Lester Wunderman, the Father of Direct Marketing

1. Tell me clearly who you are and why you are contacting me.
2. Tell me clearly what you are—or are not—going to do with the information I give.
3. Don't pretend that you know me personally. You don't know me; you know some things about me.
4. Don't assume that we have a relationship.
5. Don't assume that I want to have a relationship with you.
6. Make it easy for me to say "yes" and "no."
7. When I say "no," accept that I mean *not this, not now*.
8. Help me budget not only my money, but also my TIME.
9. My time is valuable, don't waste it.
10. Make my shopping experience easier.
11. Don't communicate with me just because you can.
12. If you do all of that, maybe we will then have the basis for a relationship!

Key Takeaways

1. Business first; it is not about data or technology
2. Invest in analytics – Models pack large amount of data into simple answers to questions
3. Databases must be optimized for analytics – “Analytics Sandbox” for consistency and speed
4. Start small with a proof of concept – Don’t take a big bite
5. Consider every data source, but don’t wait for a perfect dataset
6. Don’t settle for simple segments – Employ personas for personalization through every channel
7. Close the loop properly – Always conduct post-campaign analyses with proper channel attribution
8. Don’t get lost among machines – Give them purposes
9. Ask for help



Q&A



Further Questions?

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For comprehensive data and analytics solutioning, check our website:

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For further details on this presentation, please read my series in [Adweek](#):

Complete list of my articles, webinars and interviews is at:

<https://www.willowdatastrategy.com/articles-and-publications>