Course Wrap-up

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Customer Analytics

Date	Class #	Class Title	Assignments Due (Ind.=Individual-based; Grp.=Group-based)
January 14	1	Customer Analytics Overview; Quantifying Customer Value	
January 16	2	Using Python for Basic Customer Analysis; How to Tell Good Analytics from Bad Analytics	
January 21	3	Case Analysis: "Home Alarm, Inc.: Assessing Customer Lifetime Value," A/B Test, and Beyond	**Home Alarm LTV (Ind.)**
January 23	4	Statistics Review	
January 28	5	Predicting Response with RFM Analysis	**Using Python for Basic Customer Analysis (Ind.)**
January 30	6	Directed Acyclic Graph (DAG)	
February 4	7	Case Analysis: "Tuango: RFM Analysis for Mobile App Push Messaging"; Lift and Gains	**Tuango RFM (Ind.)**
February 6	8	Linear Regressions and its applications; Interpreting Interaction Effects; Diff-in-Diff Regression	**Using DAG for Bias Diagnosis (Ind.)**
February 11	9	Predicting Response with Logistic Regression	
February 13	10	Case Analysis: "Diff-in-Diff Analysis"; K-means and segmentation	**Diff-in-Diff Analysis (Ind.)**
February 18	11	Predicting Binary Response with Neural Networks	
February 20	12	Case Analysis: "BookBinders: Predicting Response with Logistic Regression"	**BookBinder Logistic Regression (Ind.)**
February 25		***No class***	
February 27		**In-class Midterm**	
March 18	13	Cross-selling and Upselling: Learning from Purchases	
March 20	14	Predicting Binary Response with Decision Tree	
March 25	15	Case Analysis: "Pentathlon: Cross-selling/Upselling;" Predicting Attrition	**Pentathlon: Cross-selling/Upselling (Grp.)**
March 27	16	Matching	
April 1	17	Case Analysis: "V-Mobile: Churn Management;" From Prediction to Prescription	**V-Mobile: Churn Management (Grp.)**
April 3	18	***Videos of matching codes; No In-person Class***	
April 8	19	Synthetic Control Method	**V-Mobile: Causal Analysis using Matching (Grp.)**
April 10	20	Instrumental Variable	
April 15	21	Recommendation Overview	
April 17	22	Synthetic Diff-in-Diff	**Synthetic Control (Grp.)**
April 22	23	Double Machine Learning (DML)	
April 24	24	Course Wrap-up	**Instrumental Variable Estimation (Grp.)**

The information revolution has given firms the possibility to know much more about their customers than before

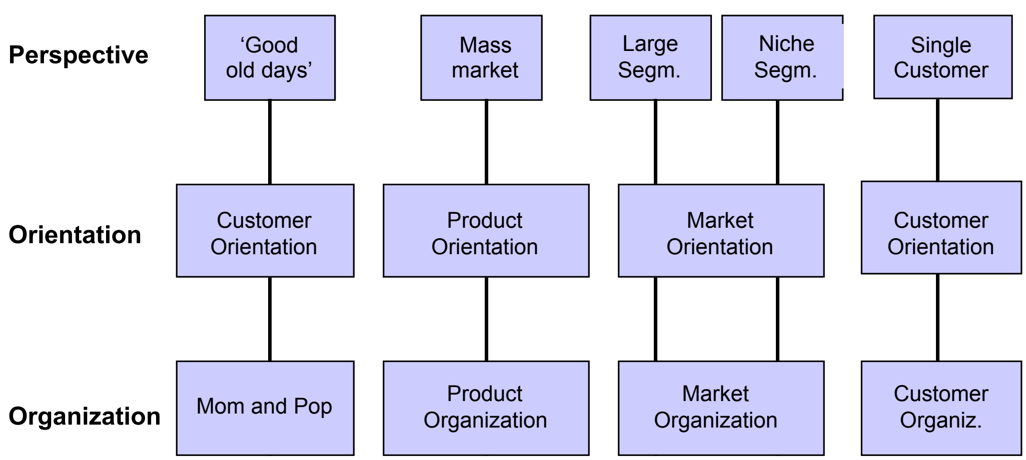
WHAT INFORMATION TRAIL DO WE LEAVE?

- credit card transactions
- travel
- catalog/online purchases
- web surfing
- audio/video streaming
- DVR watching habits
- reactions to mail/e-mail offers
- customer support calls
- self-provided information on preferences, income, demographics
- location information
- usage information (machine sensors)
- social network posts and links

This information seems to create great opportunities for marketing

Marketing based on customer analytics is not really a new idea -- but a new way to implement it

CHANGING PERSPECTIVES ON MARKETING



Customer analytics has made customer-centric marketing <u>scalable</u>

Step 1: To introduce the customer as the unit of analysis

COURSE OBJECTIVES IN STEP 1

- To understand the customer lifecycle
- To understand the concept of customer profitability
- To understand the basics of causality

Step 2: To introduce the key strategic initiatives using customer information

COURSE OBJECTIVES IN STEP 2

- To understand how to acquire customers
- To understand how to do customer development
  - To understand how to cross-sell
  - To understand how to up-sell
- To understand how to manage customer churn (attrition)

Step 3: To introduce analytical and statistical modeling of customer information

COURSE OBJECTIVES IN STEP 3

- RFM Analysis (Heuristics)
- Linear/Logistic Regression (Statistical Model)
- Neutral Nets & Decision Trees
- Market Basked Analysis/Recommendation Systems (Algorithmic Models)
- Causal Inference Models

Step 4: To understand when analytical methods are appropriate and when they fail

COURSE OBJECTIVES IN STEP 4

- To understand why customer analytics has sometimes failed
- To learn how to avoid common mistakes in implementing customer analytics

What you have learned in these four steps enables you to implement "Customer Analytics" in practice

Where is customer analytics applicable?

REQUIREMENTS FOR customer analytics

Where customers are differentiated in terms of

- Value to the organization
- Their needs and wants

In organizations with

- Capability to customize communications with customers
- Production and logistics flexibility
- Capability to gather, process, and interpret customer information

What is at the core of customer analytics?

GOAL OF CUSTOMER ANALYTICS

Acquire → **Develop** → **Retain** → **The RIGHT Customer**

Acquire

1. Acquisition strategy
   - which lists?
   - what criteria?

-> Predict and change LTV and response from limited information

Develop

1. Targeting
2. Cross-selling
3. Up-selling

-> Predict/Change LTV and response from behavior

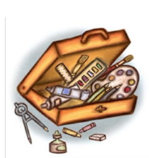
Retain

1. Prevent attrition
   - preemptive intervention
   - win-back offers
2. Allow attrition/fire cust.

-> Predict/Change LTV from behavior

The RIGHT Customer

1. Inherently high LTV or can be made so



1. Basic statistic descriptions
2. RFM/K-Means
3. Linear/Logistic Models
4. Neural Net/Random Forest
5. Causal Models
   - Diff-in-diff
   - Matching
   - Synthetic Control
   - Synthetic Diff-in-diff
   - DML

How to decide which models to use?

Purpose of the Analysis

Purpose	Model Types
Prediction	Linear/Logistic Regression, Random Forest, Neural Nets, RFM, K-Means
Causal Inference	Diff-in-Diff, Matching, Synthetic Control, Synthetic DiD, DML

How to decide which models to use?

Prediction Models Comparison

Model	When to Use	Strengths	Watch Out
Linear/Logistic Regression	Outcome is continuous or binary; relationships among covariates are transparent	Simple, interpretable, good baseline	Assumes linearity, may underperform with complex non-linearities
Neural Nets / Random Forest	Large dataset with complex non-linear patterns; focus on predictive accuracy	Flexible, handles complex interactions	Less interpretable, not ideal for causal inference without adjustment
RFM	Customer segmentation with purchase history data	Intuitive and effective for targeting	Doesn't use ML; static and rule-based
K-Means	Segment customers/ users based on features or behaviors	Simple, fast, effective with normalized numeric data	Requires K; sensitive to outliers and scaling

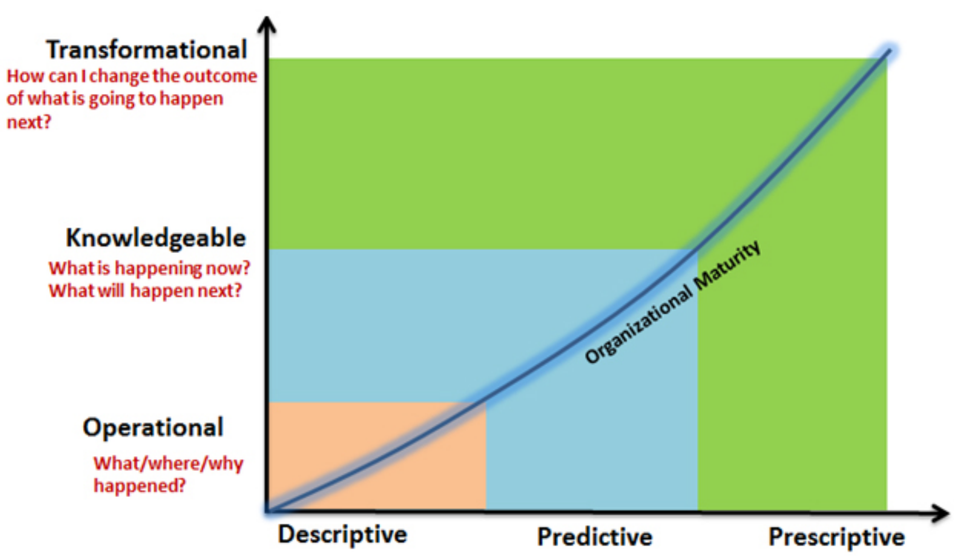
How to decide which models to use?

Causal Models Comparison

Method	When to Use	Strengths	Key Assumptions (SUTVA for All!)
Diff-in-Diff	Pre/post data with policy change and control group	Simple, intuitive	Parallel trends
Matching (KNN, PSM, IPW)	Rich covariate data, treatment selection on observables	Transparent, balances treatment/control groups	Unconfoundedness given obervables
Synthetic Control	Single treated unit with many controls/ donors over time	Controls for unobserved time-invariant confounders	No other shocks besides treatment
Synthetic Diff-in-Diff	Similar to SC and DiD; when SC alone too restrictive	Combines strengths of DiD and SC	Similar to SC
DML (Double Machine Learning)	High-dimensional covariates need to control for confounding	Robust to model misspecification	Unconfoundedness given obervables

We have also discussed concepts that extend far beyond marketing

EXAMPLE OF ANALYTICS MATURITY CURVE



Source: bdisys.com

Descriptive Analytics: *Describing Outcomes*

Descriptive statistics that **summarize data**,
often over time and /or by groups, geography, etc.

Predictive analytics: *Anticipating Outcomes*

Using data **that you have** to predict an **outcome you don't yet know**, using **statistical** or **machine learning** approaches.

Prescriptive analytics: *Changing Outcomes*

Using data that you **have** or **newly create** (e.g. by experimenting) to determine **whether** and **how** an action ***causes a change*** in the outcome you are predicting.

Interview Tips from Personal Experiences

Storytelling

- The STAR (or SOAR) method
  - **S**ituation, **T**ask (**O**bstacle), **A**ction, **R**esult
  - Example: Rapunzel (the Disney movie "Tangled")
  - A common mistake
    - Missing/Insufficient S & T
- Be comfortable with pauses
- Audience: Tailor your content and delivery