DNSC 6290 Customer Analytics, Fall 2021

Lecture 5

Revenue & Customer Economics

Instructor: Ali Pilehvar, Ph.D.

GW | Business

9/30/2021

Agenda for today

- 10 min discussion from last week
- Latency metric
- **Calculating Marketing ROI**
- **Customer lifetime value**
- **RFM (recency, frequency, monetary) customer scoring**
- **Case Study [a real deep dive into an actual business problem]**
- Group Project review
- Homework 4 to be posted after the class

Office hour moving forward

- Wednesday 7pm-8 pm EST
- Monday 7:30-8:30 am EST

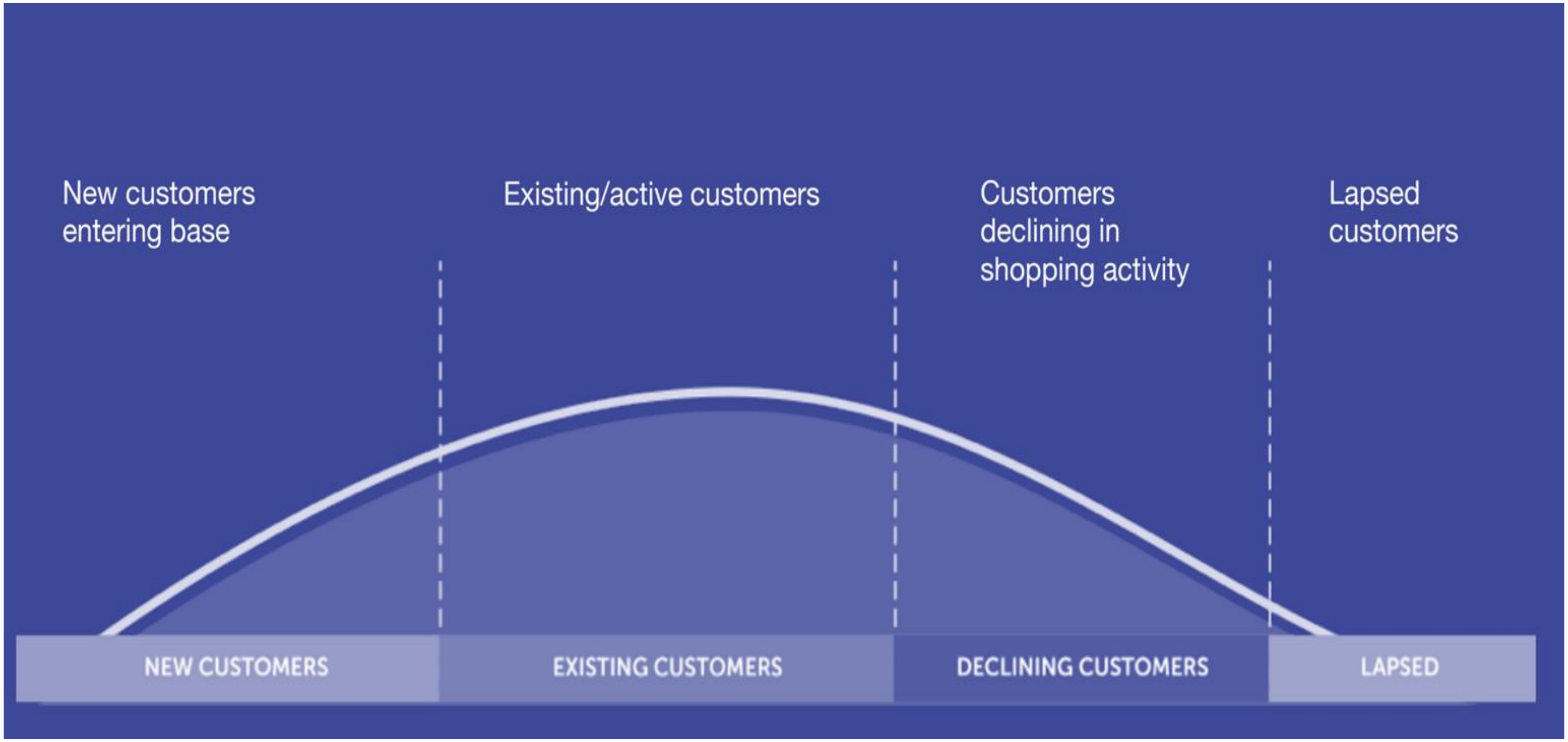
10-min round discussion for last week

- **Reading:** The Power User Curve: The best way to understand your most engaged users
- **Podcast:** The Basics of Growth — Engagement and retention
- **Video:** How to Get Users and Grow - Alex Schultz (Facebook Growth)
- **Video:** You are calculating Retention Wrong: RETENTION RATE FORMULA AND TOP MISTAKES

Latency Metric

Customer lifecycle refers to all changes in customer behavior over time and is the clue to customer's future behavior

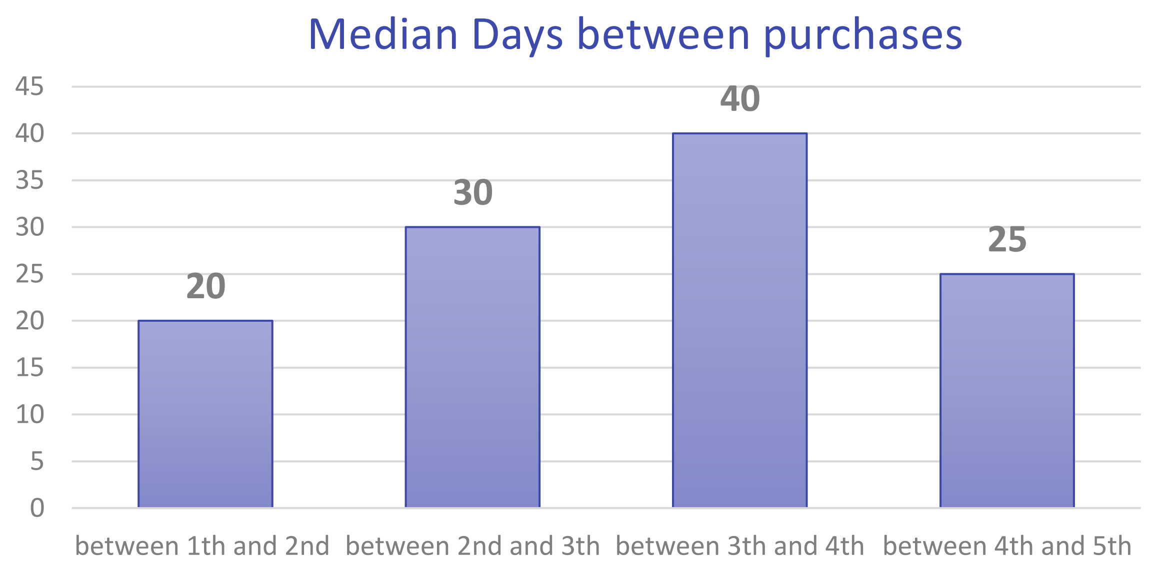
➢ **Without knowing the Lifecycle, it's impossible to find Lifetime Value (LTV).**



https://www.slideshare.net/LitmusApp/datadriven-lifecycle-email-for-ecommerce?from_action=save

Latency refers to the average time between different events or activities for different group of customers or cohorts

- Many small companies and marketers **intuitively use latency** as a metric for **retention campaigns**



Example

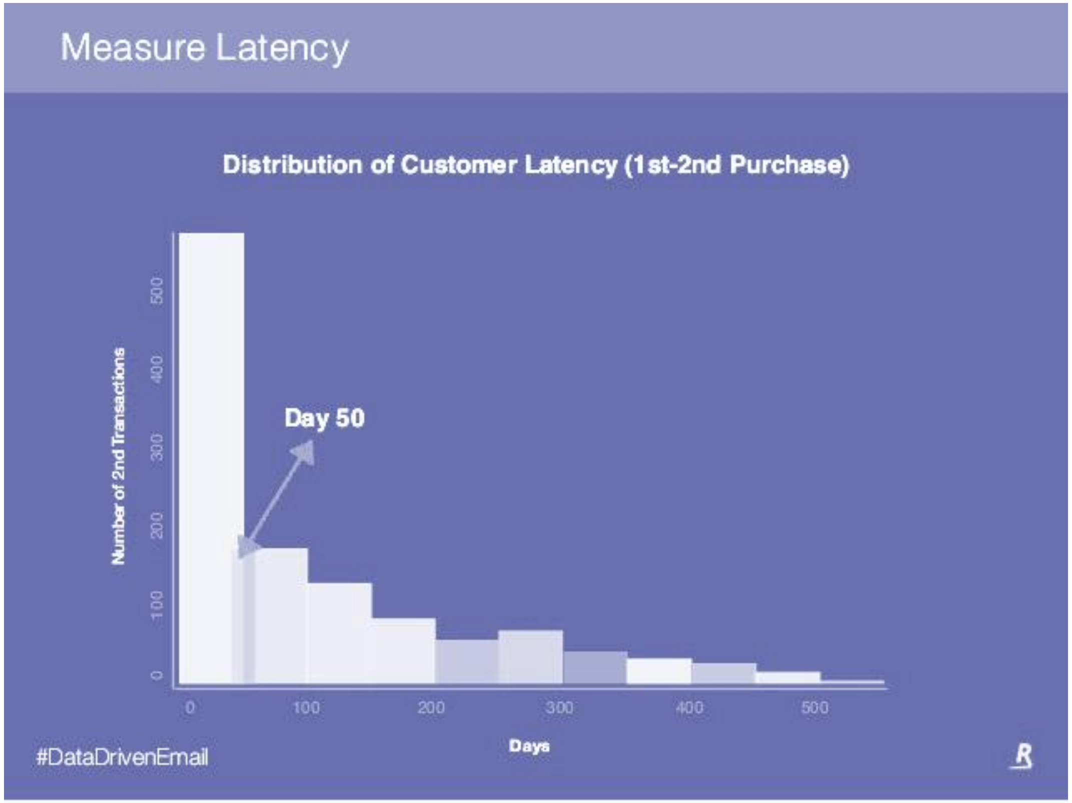
- You don’t go to your hair-stylist for a while and it took you longer than average to schedule your next appointment, **so your stylist will call you!**

- The longer the stylist waits to contact you after your average visit to your stylist passed, the more likely that you have been **churned (defected)**

In E-commerce one typical latency metric is the time between *n*th purchase and *(n+1)* th purchases

- Suppose that in below example, the avg time between first and second purchase is **around 50 days.**

- If you examine a customer and finds she goes beyond 50 days without making a second purchase, **what can we say about that customer?**



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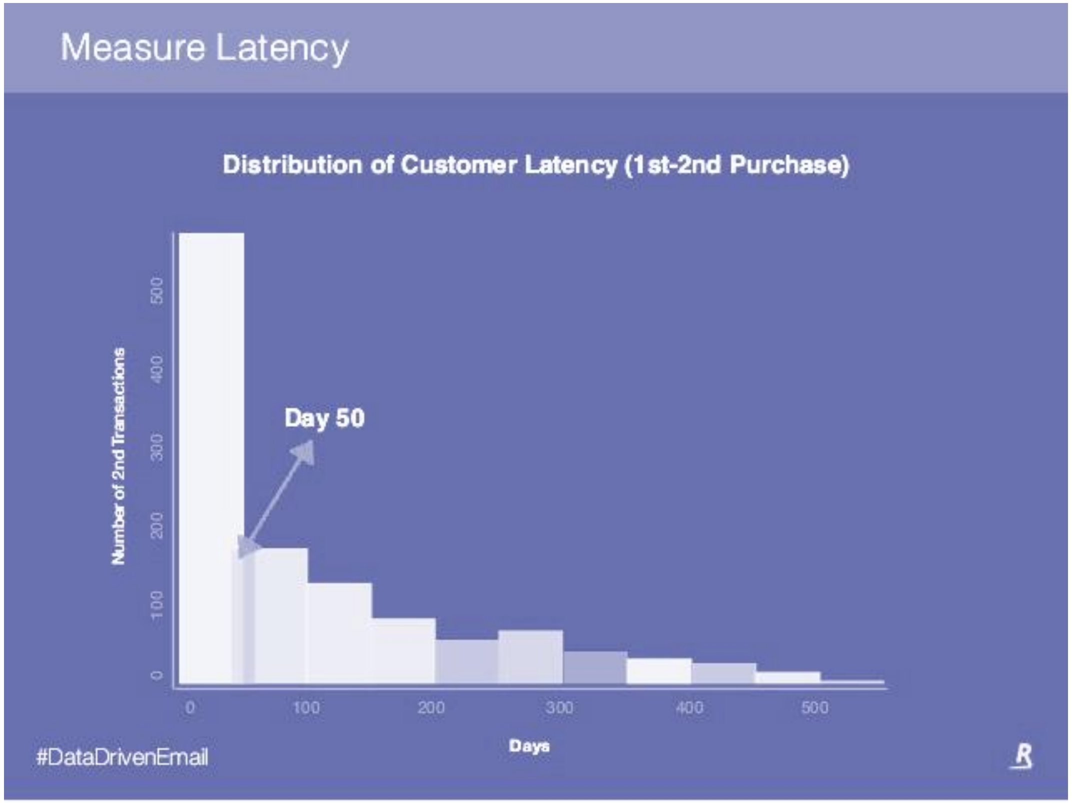
- If you examine a customer and finds she goes beyond 50 days without making a second purchase, **what can we say about that customer?**

- **Latency metrics** help marketers to apply the right triggers at the right time in customer life-cycle.



https://www.slideshare.net/LitmusApp/datadriven-lifecycle-email-for-ecommerce

Turning the latency data into profit

- **Two ways to increase the value of customers**

1

Extend the customer lifecycle

- Leaving more time for the customers to increase the value
- **Needs investment in loyalty program and can be expensive**
- If a loyalty program works, it can become extremely profitable

2

Increase the value of customers within existing lifecycle

- Do anything to increase their value before defection (churn)
- Needs anti-defection and retention program
- **Use customer Latency data and create Latency-based promotion**

Creating latency-based Promotion

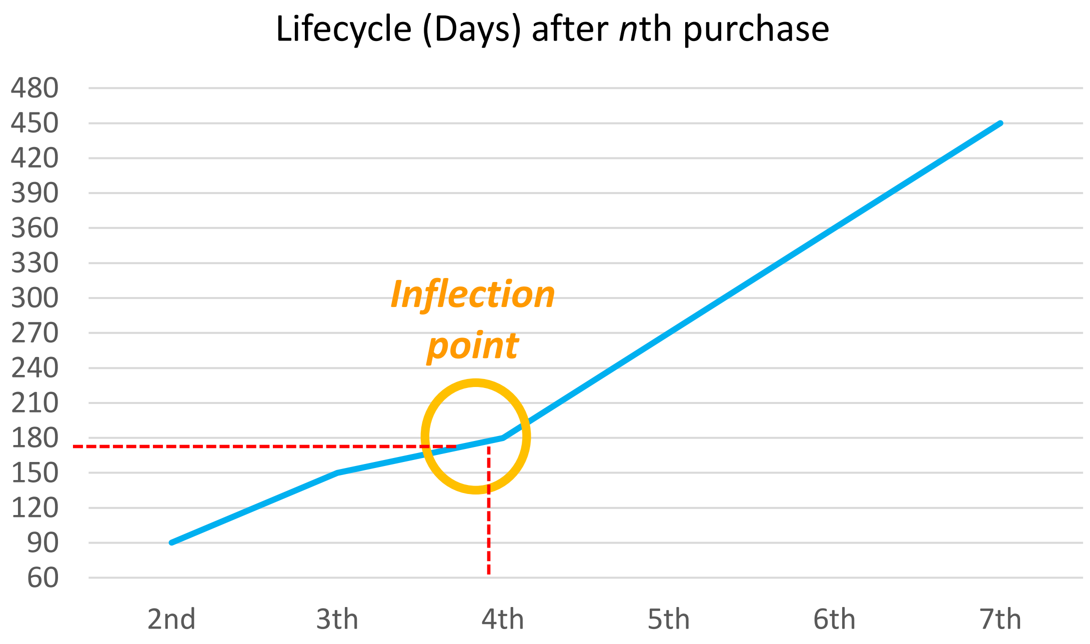
- Suppose that below is a customer **AVG life Cycle** for purchase event in a typical ecommerce site

Time between events (latency)		Time to date
Time between 1st and 2nd event	90 days	90
Time between 2nd and 3rd event	60 days	150
Time between 3rd and 4th event	30 days	180
Time between 4th and 5th event	90 days	270
Time between 5th and 6th event	90 days	360
Time between 6th and 7th event	90 days	450

- **If you need to focus on a specific customers in their lifecycle and easiest segment to make them purchase faster, where do you focus on?**

Creating latency-based promotion, *cont'd*

- Any customer who is 180 days old and has not yet make the 4th purchase **should be targeted!**
- Even if this can save just a small % of customers from churning, **ROI can be very high** since otherwise you would not have made a penny!



Calculating Marketing ROI

Marketing **ROI** enables companies to measure the degree to which marketing efforts contribute to revenue growth

- **Marketing ROI (Return on Investment) is the practice of attributing profit and revenue growth to the impact of marketing initiatives**

Why calculating marketing ROI?

1. **Justify Marketing Spend**
2. **Distribute Marketing Budgets (channel allocation optimization)**
3. **Measure Campaign Success and Establish Baselines**
4. **Competitive Analysis**

How to calculate the marketing ROI?

Marketing ROI=

(Sales Growth - Marketing Cost) / Marketing Cost

Assuming all sales growth is NOT tied to paid marketing efforts:

Marketing ROI=

(Sales Growth - Organic Sales Growth - Marketing Cost) / Marketing Cost

As a rule of thumb

- Marketing ROI more than 0 is considered profitable
- Marketing ROI bell curve is typically a **200%**
- Exceptional ROI being considered at around a **500%**.

In-class example

- **You decide to run a mailing promotion campaign to as many people you can afford to make them purchase from your online site while making the campaign profitable.**

Assumptions:

- It would cost $300 to mail promotion per thousand customers
- The average order value (AOV) on the site is $40
- Profit margin is 10%
- Let's assume the response rate the mail is 3.5% (only 35 customers out of 1000 will come to the site and purchase)

a) **What would be the ROI of this campaign?**
b) **At which response rate would campaigns reach to break-even point?**

Solution

Parameters			
	base model	mode 1	mode 2
1. Number Mailed	1000	1000	1000
2. Response Rate	3.50%	6%	8%
3.Responses	35	60	80
4. Net Margin @4$	$140	$240	$320
5. Mail Cost @0.3$	$300	$300	$300
6. ROI	-53%	-20%	7%

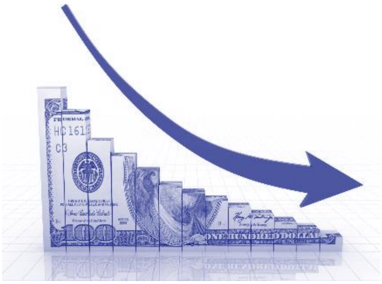
Break-even response rate is between 6%-8**%, how to calculate the exact number?**

Calculating Lifetime Value (LTV) or

Customer Lifetime Value (CLV)

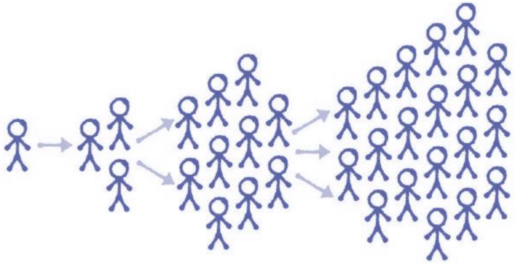
Customer Lifetime Value (CLV) revisited

- **Total profit (net revenue) of entire relationship with a customer**



Total cost to attract, service and maintain

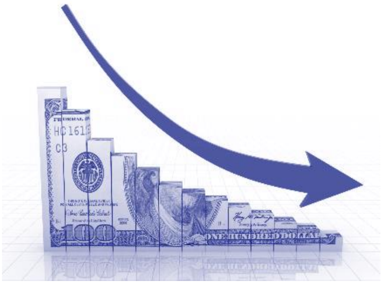
Total transactions and revenue (number and value)



Customer network effects (e.g., word-of-mouth)

Customer lifetime value (CLV) is revisited

- **Total profit (net revenue) of entire relationship with a customer**



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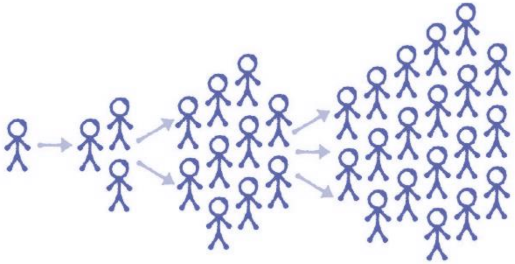


Customer network effects (e.g., word-of-mouth)

The focus of many CLV models is on the revenue side. The reason for this is that revenue is more difficult to forecast than the cost.

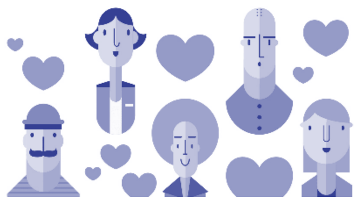
Portfolio approach for Customer Value Management

- **The sum of current value and potential value is CLV**
- Retention program should focus on **upper left and lower right** customers
- Win-back programs should focus on accidental and one-off customers

Current Value	Low Potential value High current value **Grow these customers**	High Potential value High current value **Keep these customers** **"ROCKET FUEL"**
	Low Potential value Low current value **Should you spend money here?** **"Accidental customers"**	High Potential value Low current value **Grow these customers**

Potential value

Why do we care about CLV?



- Customer segmentation to identify the **most profitable (loyal) customers**

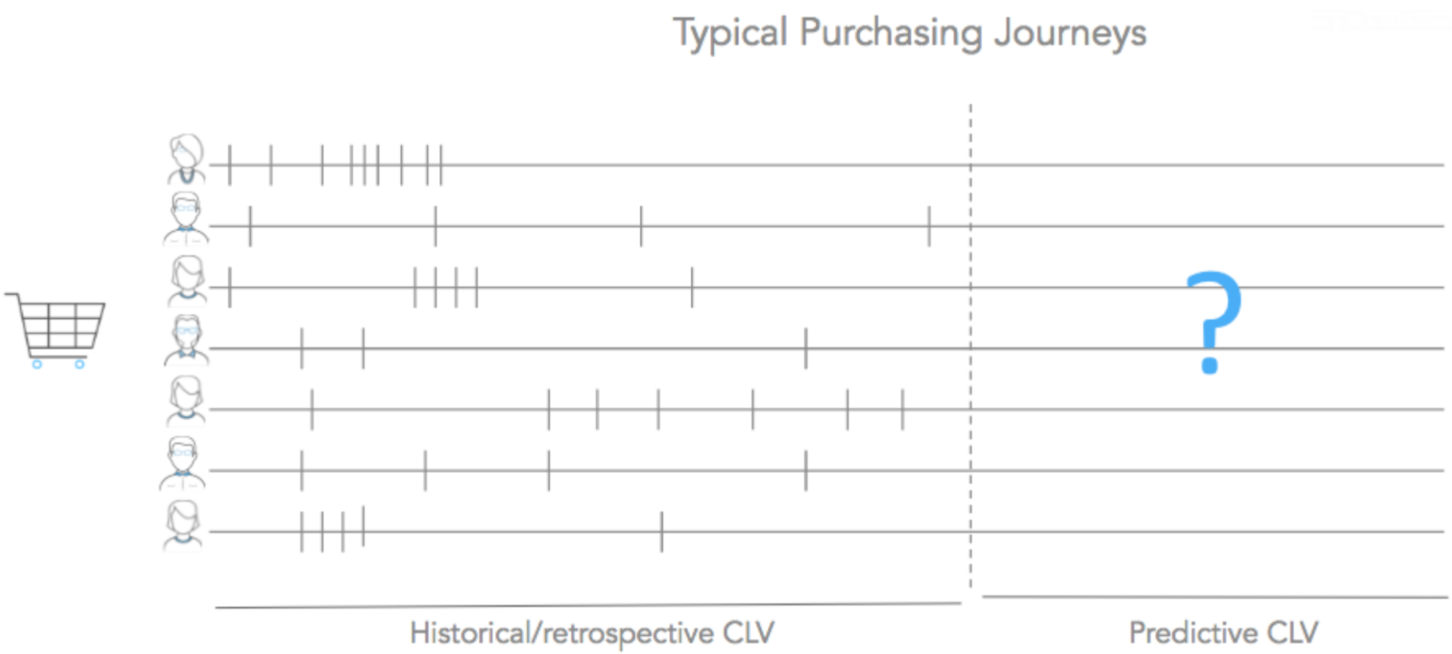
- **Identify the common characteristics** and attributes associated to the most profitable customers

- To maximize the impact of marketing retention programs targeting the **right segment** at the **right time**

- Direction and guideline on how much a company should **pay at most for CAC**

There are two main class of CLV methodologies: **predictive** versus **historical**

- **Historical CLV** models look at past data and calculate the LTV only based on past transactions (*no prediction about future!*)
- **Predictive CLV** is to model the purchasing behavior of customers in order to infer what their future actions will be.



https://www.datascience.com/blog/intro-to-predictive-modeling-for-customer-lifetime-value

Predictive CLV across different business settings

Contractual model (membership model)

Customer death can be observed

Non-contractual model (E-commerce)

Customer death cannot be observed

Discrete purchases

Purchase happens at some fixed period or frequency

Continuous purchases

Purchase can happen at any given time

CLV across different business contexts

	Non-contractual Settings	Contractual Settings
Continuous Purchases	• movie rentals • medical appointments • hotel stays • grocery purchases • amazon.com	• Costco membership • credit cards
Discrete Purchases	• prescription refills • charity fund drives • event attendance	• magazine/newspaper subscriptions • fitness clubs • most insurance policies • streaming services: netflix, hulu, etc. • most cell phone plans

https://www.datascience.com/blog/intro-to-predictive-modeling-for-customer-lifetime-value

CLV across different business contexts

	Non-contractual Settings	Contractual Settings
Continuous Purchases	• movie rentals • medical appointments • hotel stays • grocery purchases • amazon.com Hardest to model	• Costco membership • credit cards
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Predicting Customer Lifetime Value with **"Buy 'Til You Die" (BTYD)** probabilistic models in non-contractual settings (e-commerce)

Transaction Flow Model

The probabilistic **"Buy til you die"** models (the most well-known and commonly used methodology in the industry) estimate the purchasing behavior of a consumer through **two stochastic** processes:

(1) drop-out process: Probability of a consumer quitting and never purchase again

- Each consumer has an unobserved dropout propensity
- Dropout propensity vary across different consumers

(2) Transaction process: the expected number of his future transactions

- Given a consumer stay alive. A consumer purchase randomly around his mean transaction rate
- Transaction rates vary across different consumers

Model inputs

- **Recency** (derived from t_x): the consumer's age at the moment of his last purchase, equal to the duration between a consumer's first purchase and their last purchase.
- **Frequency** (x): the number of periods in which the consumer has made a repeat purchases
- **Monetary value** (M)**:** is the average monetary amount of each repeat purchase made by a consumer
- **Age of the consumer** (T): duration between a consumer's first purchase and the time of the analysis

https://towardsdatascience.com/predicting-customer-lifetime-value-with-buy-til-you-die-probabilistic-models-in-python-f5cac78758d9

CLV across different business contexts

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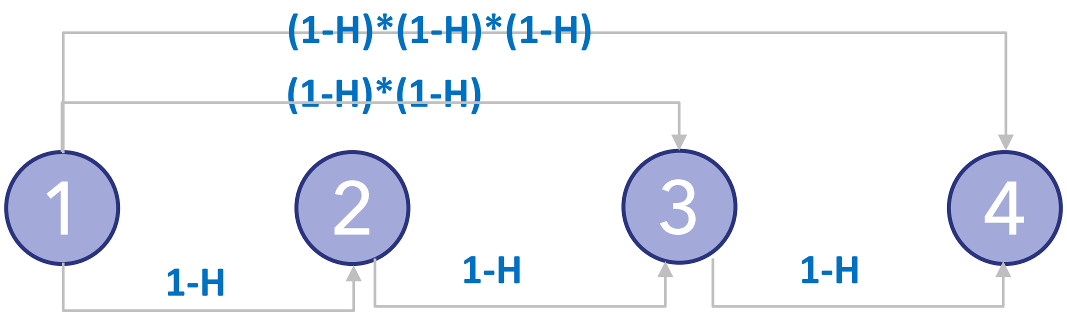
Continuous Purchases	• movie rentals • medical appointments • hotel stays • grocery purchases • amazon.com	• Costco membership • credit cards
Discrete Purchases	• prescription refills • charity fund drives • event attendance	• magazine/newspaper subscriptions • fitness clubs • most insurance policies • streaming services: netflix, hulu, etc. • most cell phone plans We focus on this

https://www.datascience.com/blog/intro-to-predictive-modeling-for-customer-lifetime-value

Basic equation of CLV: *Naïve model to calculate CLV for contractual setting*

Things we need:

- The probability of a customer churn (leaving the platform) in a given period *(t)*. **This is also called constant Hazard rate *(H)***



$$Survival\ probability\ in\ period\ t = (1-H)^{t-1}$$

- $\boldsymbol{v}$ (Nu): Expected revenue per customer which is net profit in a given period (t)
- $\boldsymbol{\delta}$ (Delta) is the stationary discount multiplier of capital for a given period
- $$Discount\ multiplier\ in\ period\ t = 1/(1+\delta)^{t-1}$$

Basic equation of CLV: *Naïve model to calculate CLV for contractual setting*

- **CLV for *n* periods**

$$v + \frac{v(1-H)}{(1+\delta)} + \frac{v(1-H)^2}{(1+\delta)^2} + \frac{v(1-H)^3}{(1+\delta)^3} + \ldots + \frac{v(1-H)^{n-1}}{(1+\delta)^{n-1}}$$

$$CLV_{1\ to\ n} = \sum_{t=1}^{n} v \frac{(1-H)^{t-1}}{(1+\delta)^{t-1}}$$

- **CLV for infinite periods**

$$\text{CLV} = \sum_{t=1}^{\infty} v \frac{(1-H)^{t-1}}{(1+\delta)^{t-1}} = v/(1-X)$$

$$X = (1-H)/(1+\delta)$$

$$\text{CLV} = v(1+\delta)/(H+\delta)$$

In-class CLV (LTV) example

Hazard rate (churn)	10%
Discount Rate	10%
Revenue ($)	$200
Cost	$100

Year	Hazard Rate	Retention Rate	Survival Rate	Discount Multplier	Discounted Expected Profit
1	0%	100%	100%	100%	$100
2	10%	90%	90%	91%	$82
3	10%	90%	81%	83%	$67
4	10%	90%	73%	75%	$55
5	10%	90%	66%	68%	$45
6	10%	90%	59%	62%	$37
7	10%	90%	53%	56%	$30
8	10%	90%	48%	51%	$25
9	10%	90%	43%	47%	$20
10	10%	90%	39%	42%	$16
			LTV after 10 yrs		$476
			LTV over infinite horizon		$550

$$CLV_{1\ to\ 10} = \sum_{t=1}^{n} v \frac{(1-H)^{t-1}}{(1+\delta)^{t-1}}$$

$$CLV = v(1+\delta)/(H+\delta)$$

Limitation with Contractual Naïve CLV models

- **We are treating all customers the same and all portions of time the same**

- The Hazard Rate is considered to steady (constant)

A customer who has been with a company for 2 periods likely to have the same churn rate as one who has been with a company for 6 periods!

- All customers are treated the same in terms of their revenues at different points of time in their lifecycle

There is no differentiation based on spending habits over time.

- **More sophisticated models** (like Recency Frequency Monetary, Markov Chains, Hazard Functions, Survival Regression, and Supervised Machine Learning using Random Forest) **should be used for accurate modeling.**

RFM Scoring

RFM refers to a modelling technique that utilizes **Recency Frequency** and **Monetary** (RFM) data from client records

- **R**ecency: Time since last purchase (or some valuable interaction).

- **F**requency**:** How many purchases an individual made within a given period (every month, quarter or year)

- **M**onetary**:** Cumulative total spent by client during the given period

RFM is one of the most basic behavioral models ever developed, yet so powerful to predict the future behavior.

RFM model can be used as a predictor of LTV of the customer
[we saw that in "Buy 'Til You Die" models]

RFM in actions: **Individual Customer Scores**

We group the data based on these metrics and give them scores

- Customers are split along each metric into quintiles (20% or 25% groupings) and assigned an ordinal label of 5 for the highest 20% of values, 4 to next highest etc.

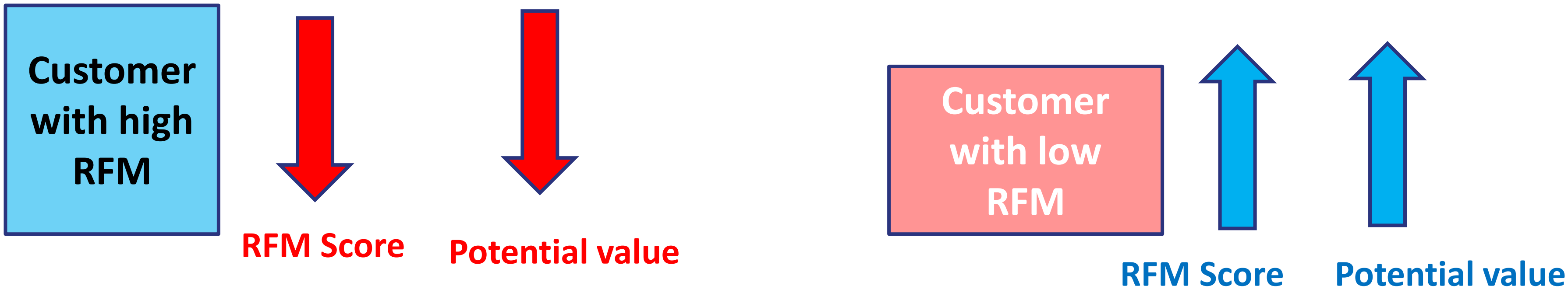
Recency	**F**requency	**M**onetary
=1 (highest 20%)	=1 (lowest 20%)	=1 (lowest 20%)
2	2	2
3	3	3
4	4	4
5 (lowest 20%) **[most recent]**	**5 (highest 20%)**	**5 (highest 20%)**

- These can then be concatenated (ex 454, 134, 555)
- **155** is a frequent purchaser who has spent a lot of money during this period but has not purchased in some time.

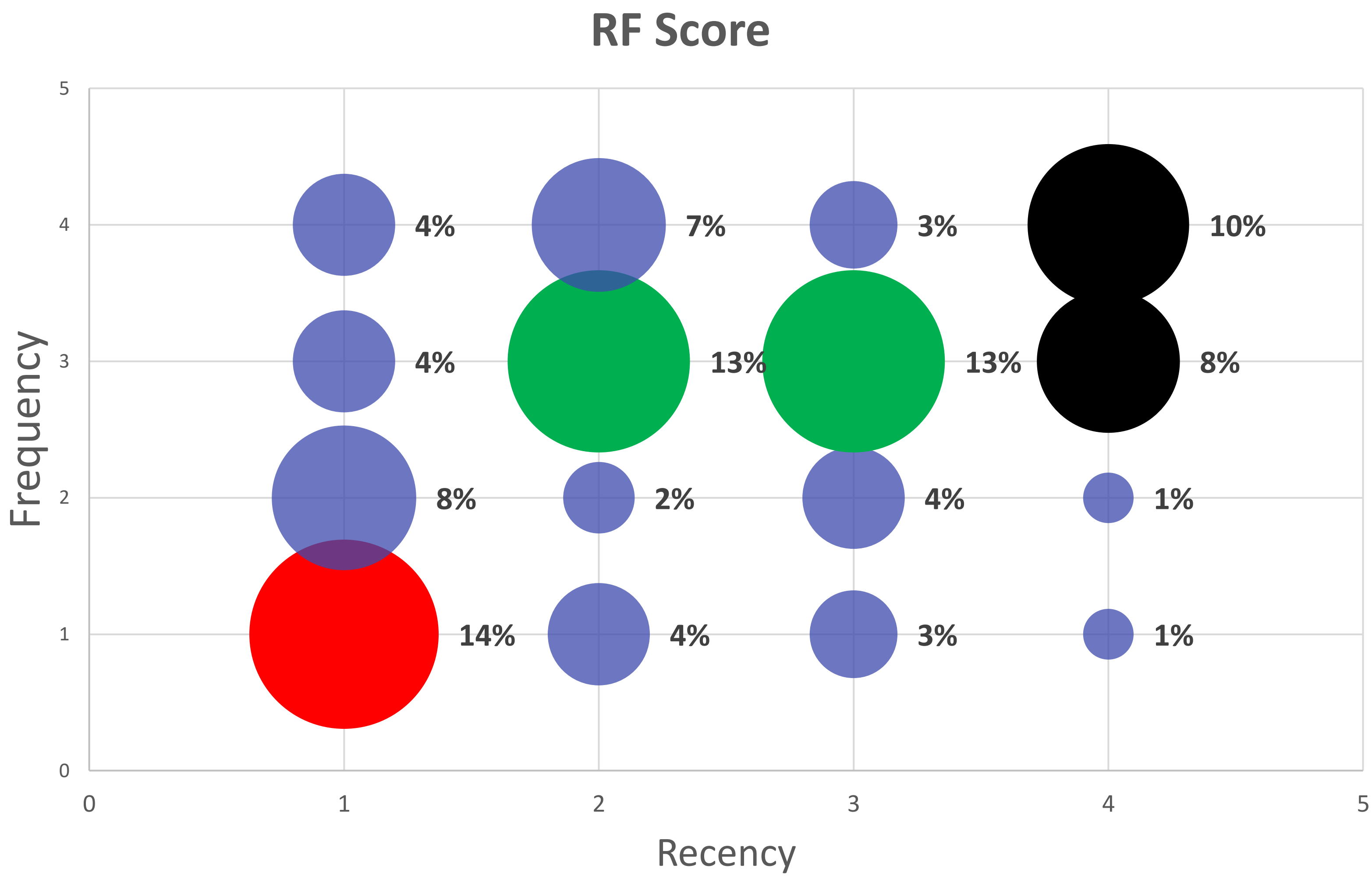
RFM can be used as a proxy for future profitability

- RFM scores can be used to assess the potential value of your business*, the higher RFM, the more likely the customers will repeat a behavior and respond to promotion*

- **RFM** can be used as a **proxy** for **future profitability** of your business: High RFM score customers will tend to have high LTV, and low RFM score customers will tend to have low LTV

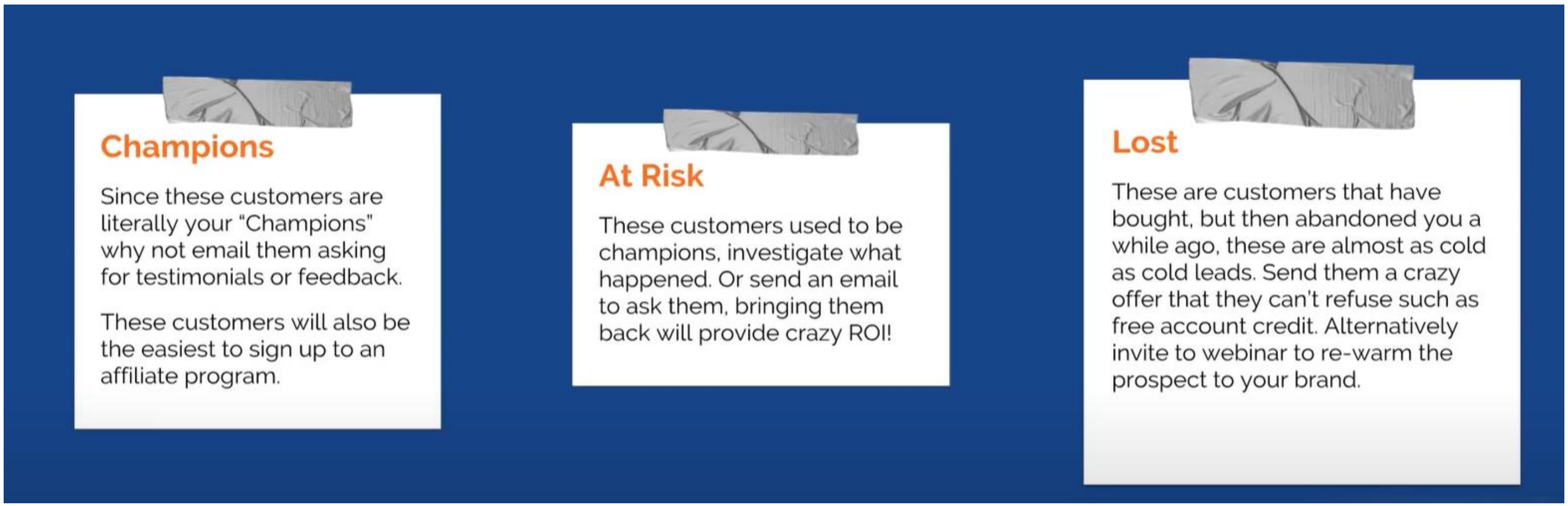


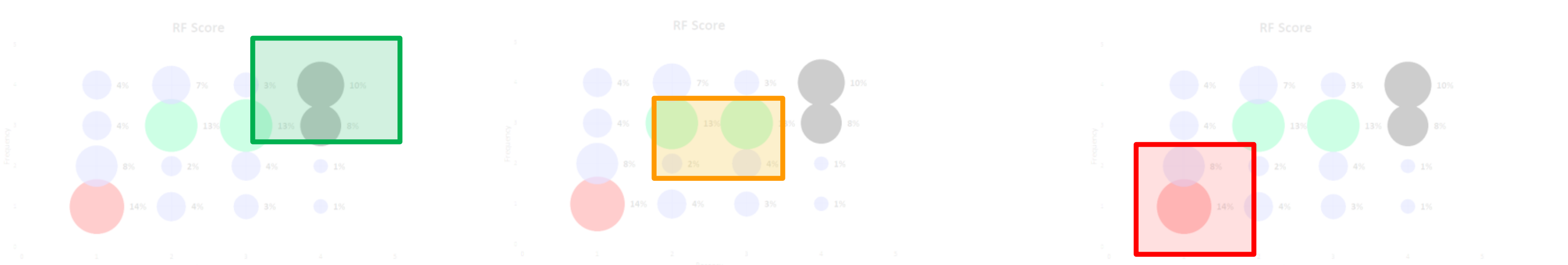
RF can be also used to drive insights about CLV and customer future values



Now that we have identified different group of customers (111 to 555), what do we next?

- **The next step will be to target them with marketing specific to their audience type.**





https://www.youtube.com/watch?v=Hv40TNfNPHY

RFM analysis explained, min 6:18-9

https://www.youtube.com/watch?v=Hv40TNfNPHY

In-class Example

We have the RFM data of 49 customers over the course of 1 year:

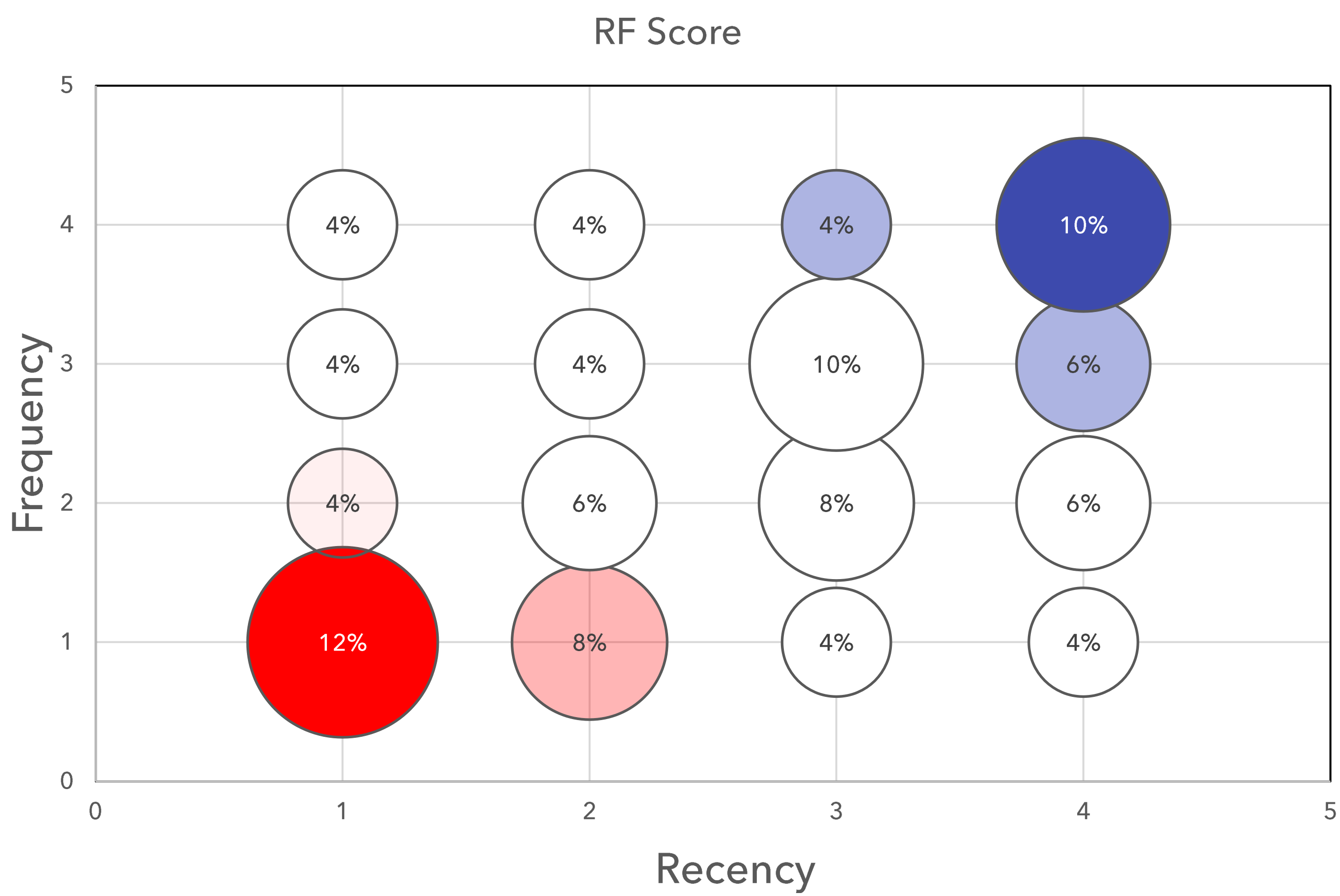
[See in-class example file]

a) Calculate the RFM score for all these 49 customers with 4 scores for each R, F, M based on 25%-50%-75% quantile

b) Identify the highest RFM customer, and calculate what % of total revenue is contributed by them?

c) If you only calculate the RF score, what % of customers has the lowest RF score (or 11)?

In-class Example



Case Study [a real deep dive into an actual business problem]

https://towardsdatascience.com/yammer-investigating-a-sudden-drop-in-user-engagement-7c9c4093c038

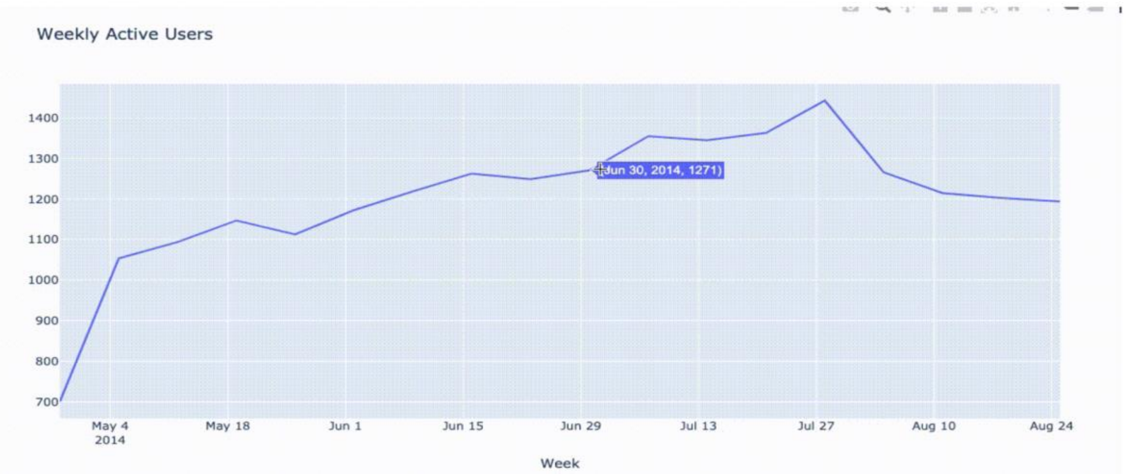
How did the weekly engagement drop 21% in a month?!

It's Monday morning…you sit down at your desk with a cup of coffee — your eyes barely open. Suddenly the head of product taps you on your shoulder and slams his laptop down on your desk.

"How did our weekly engagement drop 21% in a month?!"

Sighhhhhhh

You crack your knuckles, and put down your coffee — "let's take a look".



https://towardsdatascience.com/yammer-investigating-a-sudden-drop-in-user-engagement-7c9c4093c038

Never forget about Segmentation!

Root Cause: Decline in email CTR In US

Course Project, 40 points

(Final presentation Oct 14th between 7:10-9:40)

Each group has 25 min to present

Group project (Presentation Oct 14)

	Group 1	Group 2	Group 3	Group 4
Member 1	Alex Coffin	Vi Pham	Haelim Kim	Calvin Ji
Member 2	Veta Dennis-Umoja	Peijia Wu	Dahyun Choi	Alexis Yang
Member 3	Peterson	Weike Zhou	Sunpil Howang	Chen
Member 4	Adeyemi			

Deadline to submit final presentation ppt is end of day Wednesday Oct 13 2pm at the project folder on BB

25 min each group in Oct 14

7:25-7:50	**7:55-8:20**	**8:25-8:50**	**9:00-9:25**

Group Project

Avocci LLC. is a Canadian e-commerce company which acquires customers from multiple channels (examples include Search, Display Ads, Social Media etc.) across different device types.

As the customer analytics group, our focus is on providing the best customer experience to help them find the right product and make the purchase process easy.

Customer journey includes:

- Finding and viewing the products
- Adding product to cart
- Placing the order

Group project, cont'd

We should utilize customer data captured at different steps to build short term funnel improvement and long-term customer engagement strategies.

There are 2 attached tab in the **(find it in the project folder)**

Customer data	Customer Funnel and Spend data by category at monthly level
• Customer ID – unique identifier at customer level. • Acquisition Date – date when customer was acquired via email capture. • Acquisition Channel – channel that was used to acquire customer. • Acquisition Device – customer's device at the time of acquisition.	• Customer ID – unique identifier at customer level. • category Name – category for the product / SKU. • SKUs Viewed - # SKUs viewed in that month by the customer in that category • SKUs Added to Cart - # SKUs added to cart in that month by the customer in that category • SKUs Purchased - # SKUs purchased in that month by the customer in that category • Revenue Generated ($) – total revenue generated from the sale of SKUs purchased in that month by the customer in that category

What is the ask?

Focusing to utilize customer acquisition, spend and funnel performance data across different channels and product category:

- What do you learn and derive from current status and trends?
- How do you propose potential long-term engagement strategies for different customer groups to the leadership team?

Some hints on analyzing the provided dataset

• Understand the underlying data and definitions.

• Describe specific metrics you would use to draw business insights and build strategy

• Build a narrative with proper visuals to communicate the information effectively.

Some hints on the flow of your presentation and grading

- Underlying data and metrics for the given problem [10 points]
- Acquisition channels and device Performance [10 points]
- Different product category Performance [10 points]
- **List of recommendations and next steps [10 points]**

Deliverable (power point presentation)

- **During 25 min group presentation,** you should present your analysis approach, metrics and trends you observed along with business insights to drive strategy.

- While no specific format is required, keep in mind that you will be assessed on the content, clarity, and conciseness of your presentation.

- **Presentation should be in power point and not more than 15 slides at the most.**

- **Finishing up the presentation on time is a MUST! You should be able to present your analysis, findings and recommendations within your allocated 25 min.**

Reading/listening

Last HW (HW4)

HW4 will be posted in the assignment section of BB, 9/30, 8pm EST **[Due 10/7, 7pm EST]**

Relevant readings, articles, podcasts and videos

10-min round discussion for next week

- **Reading**: Calculating CLV
- **Reading:** An Introduction to Predictive Customer Lifetime Value Modeling
- **Video:** The RFM Principal Template
- **Podcast,** RFM Modeling 101: Predict Churn, Purchase, & Retention with Simple Segmentation – Caren Carrasco
- **Video:** Peter Fader, Wharton, Customer lifetime value using BG/NBD model

Extra interesting and relevant content

- **Reading:** Latency and Loyalty in Retail Ecommerce
- **Reading:** Drilling Down: Turning Customer Data Into Profits with a Spreadsheet [Chapters 5-27]
- **Reading:** https://towardsdatascience.com/yammer-investigating-a-sudden-drop-in-user-engagement-7c9c4093c038

Questions

Email me @ Alipilehvarm@GWU.edu