Should I Call Them?

Measuring Marketing Effectiveness using Multi-Touch Attribution

MIT Management Business Analytics | Manulife

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Problem Statement

Problem

Manulife sells **financial products** to **financial advisors**; its sales team relies on various marketing **channels** to drive sales. To **optimize** and **personalize** its **marketing strategies**, Manulife wishes to understand the **value** of each channel. To do this we will determine the following:

Predict	Whether a customer journey will end in a sale
Attribute	The effect of each marketing channel on sales
Prescribe	The next best action for a salesperson to make a sale

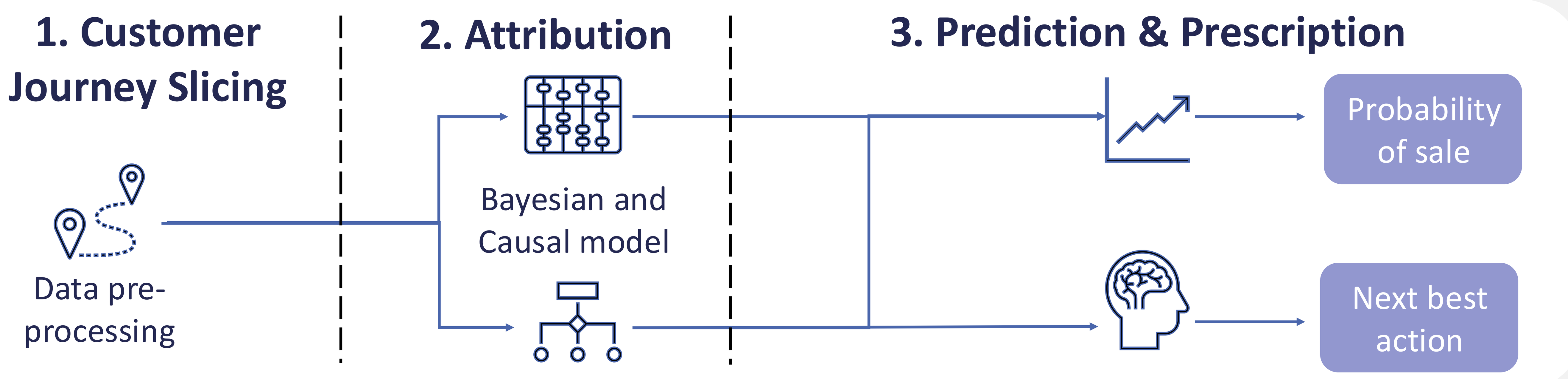
Data

Marketing engagements and sales and the date when they occurred

Objective

Our **goal** is to develop a **multi-touch attribution** framework that allows Manulife to evaluate the **efficacy** of its marketing strategies and **optimize** its approach to sales.

Methodology



300k+ Journeys

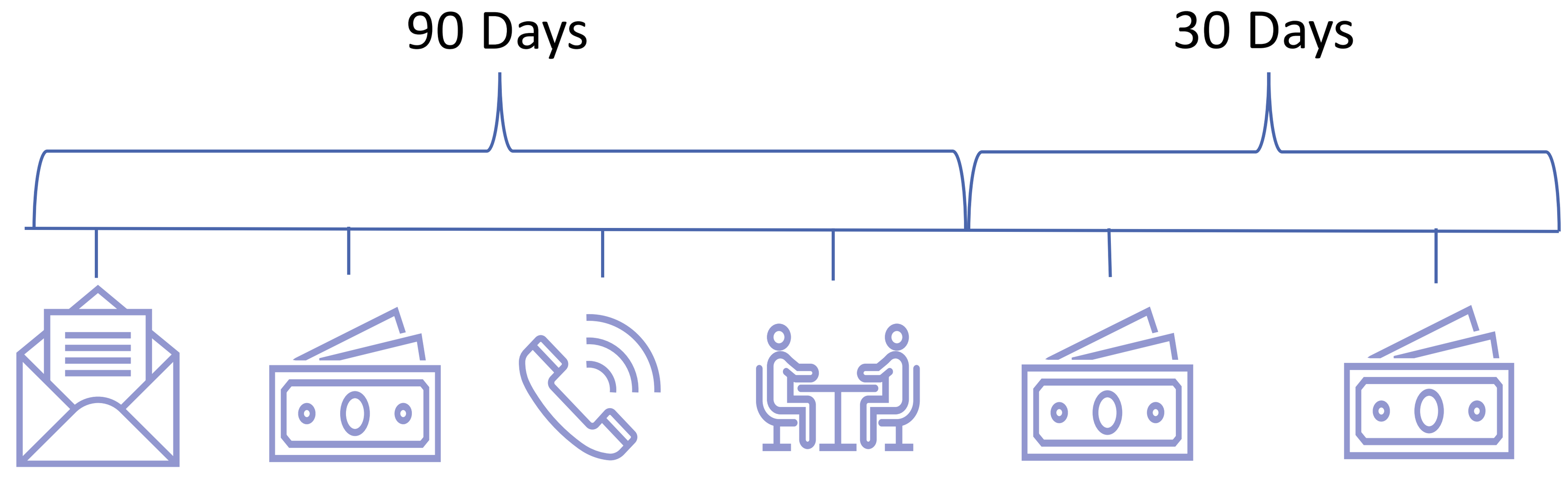
Generalizable to all lines of business

14 Engagement Types

Modeling

1. Customer Journey Slicing

We sliced the journeys to include a **marketing** period followed by an **observation** period.



2. Attribution

Causal Model

Output: The **expected difference** in outcomes of adding a **channel** and not adding it

Use Case: Confounders, time not a factor

Bayesian Classification

Output: The **change in probability** of sale from adding an **engagement** to the **end of a journey**

Use Case: No Confounders, Time Decay

3. Prediction & Prescription

We're predicting the **probability of a sale** given a journey

Bayesian Classification

[Journey, Time] → $sig\left(\sum_{i=1}^{n}\left[\beta_{a_i}\omega_{a_i}^{t_i} + \sum_{j\neq i}\gamma_{ij}\beta_{a_i}\beta_{a_j}\right]\right)$ → Probability of sale

Bayesian Logistic Regression

Causal Model

[Journey, Time, Profile] → Linear Double Machine Learning with XGBoost → Probability of sale

Prescription

Retrieve attribution and **conversion probabilities** from the causal model. Focus on instances with **high conversion potential** → **Rank** actions by **cost** and choose the **cheapest one** that boosts conversion probability **above** the **threshold** → **Recommend** this action as the **next best step**

Results & Impact

Results

- **Bayesian Classification** achieved an **42%** improvement from baseline
- **Causal Model** achieved an **64%** improvement from baseline

Impact

16,500	5%	300 million
Hours saved per year	Increase in productivity	Additional revenue generated

Next Steps

- Apply framework to **other lines of business**
- Recommend **sequences** of actions for journeys
- Create **interactive tool** for salespeople to use results
- Factor in **redemptions** into prediction