Propensity Modeling for an E-Commerce Company

Concept Guide

Contents:

Business Problem

Our Client is an early stage e-commerce company selling various products from daily essentials (such as Dairy & vegetables) to high end electronics and home appliances.

It is a one year old company and they are witnessing many people coming to their platform and searching products but only few end up purchasing.

To increase the number of purchases, the business is planning to send discounts or coupons to users to motivate them to buy.

But since it an early stage startup, they have only limited funds for this discount campaign. So, they have reached out to us seeking our help in building a model that would **predict the purchase probability of each users in buying a product**.

With this probability scores, the marketing team can then filter only those users who need the actual push (in terms of discounts or coupons) to make a purchase rather than sending coupons to users who would have bought the product anyways.

Data Summary

User_id	Session_id	DateTime	Category	SubCategory	Action	Quantity	Rate	Total Price
52243841613	d76fde-8bb3-4e00-8c23	01-10-2019 10:20	Electronic Appliances	Speakers	first_app_open			
52243841613	33dfbd-b87a-4708-9857	01-10-2019 10:22	Electronic Appliances	Speakers	search			
57314161118	6511c2-e2e3-422b-b695	01-10-2019 14:00	Men's Fashion	Jeans	search			
57314161118	90fc70-0e80-4590-96f3	01-10-2019 14:07	Men's Fashion	Jeans	product_view			
57314161118	bd7419-2748-4c56-95b4	01-10-2019 14:12	Men's Fashion	Jeans	read_reviews			
59221776934	0d91c2-c9c2-4e81-90a5	08-10-2019 17:00	Mobile & Accessories	Mobile	add_review			
51629142904	e811e9-91de-46da-90c3	09-03-2019 12:09	Cleaning supplies	Cleaning sprays	search			
51629142904	srtdf7-25c8-4147-901d	09-03-2019 12:12	Cleaning supplies	Cleaning sprays	product_view			
51629142904	vfgscx-91de-4da-90c4	09-03-2019 12:22	Cleaning supplies	Cleaning sprays	search			
51629142904	hgfhgf7-25c8-417-901d	09-03-2019 14:29	Cleaning supplies	Cleaning sprays	product_view			
51629142904	fhfvfb9-91de-46da-9055	09-03-2019 14:44	Cleaning supplies	Cleaning sprays	read_reviews			
51629142904	c1cd4e5-a3ce-4224-a2d1	09-03-2019 14:50	Cleaning supplies	Cleaning sprays	add_to_cart			
51629142904	6c46ed-90a4-4787-a43b	09-03-2019 18:04	Cleaning supplies	Cleaning sprays	checkout			
51629142904	b5bdd3-4ca2-4c55-939e	09-03-2019 18:10	Cleaning supplies	Cleaning sprays	purchase	5	300	1500
51629142904	e811e9-91de-46da-90c3	01-10-2019 15:00	Mobile & Accessories	Charging wire	search			
51629142904	yugfx7-25c8-4147-901d	01-10-2019 15:17	Mobile & Accessories	Charging wire	product_view			
51629142904	defgdf9-91de-46da-8425	01-10-2019 15:24	Mobile & Accessories	Charging wire	add_to_wishlist			
51629142904	rafgdf7-25c8-4147-7856	01-10-2019 17:31	Mobile & Accessories	Charging wire	search			
51629142904	e811e9-91de-44da-9863	01-10-2019 17:38	Mobile & Accessories	Charging wire	product_view			
51629142904	cxzfzgd-a3ce-4224-a2d1	01-10-2019 17:42	Mobile & Accessories	Charging wire	add_to_cart			
51629142904	gfdcvd90a4-4787-a43b	01-10-2019 21:05	Mobile & Accessories	Charging wire	checkout			
51629142904	fbdhyrt4ca2-4c55-939e	01-10-2019 21:08	Mobile & Accessories	Charging wire	purchase	2	2000	4000
52018010018	ghfty5940-41b2-baf3	01-10-2019 19:00	Digital Devices	Kindle eBook	search			
52018010018	98bfa0-d8fa-4b9d-8a71	01-10-2019 19:05	Digital Devices	Kindle eBook	product_view			
52018010018	72d76de-8bb3-4e00-8c23	01-10-2019 19:09	Digital Devices	Kindle eBook	read_reviews			
52018010018	7f62d8-ead0-4e0a-96f6	01-10-2019 19:17	Digital Devices	Kindle eBook	click_wishlist_page			
51613167885	dcxv0c-e9d7-42d3-9c87	01-10-2019 22:12	Mobile & Accessories	Mobile	first_app_open			
51613167885	cxzcx-a0c8fa-4d9d-8f71	01-10-2019 22:14	Mobile & Accessories	Mobile	search			
51613167885	5fb5d0c-e907-4293-9c87	01-10-2019 22:19	Mobile & Accessories	Mobile	product_view			
52028780773	175667-0a8f-4506-9f30	02-10-2019 12:00	Accessories	Watches	search			
52028780773	e31595-c355-4efa-acf6	02-10-2019 12:08	Accessories	Watches	product_view			
52028780773	901be3c-3f8f-4147-a442	02-10-2019 12:14	Accessories	Watches	click_wishlist_page			

Columns	Description
User_id	Unique identifier for each user
Session_id	Unique identifier generated every time an user comes to the platform
DateTime	Timestamp when an action is performed
Category	Product Category
SubCategory	Product Sub Category
Action	Actions that an user could do in the app such as product view, read reviews, purchase,add to cart etc.
Quantity	Number of products ordered
Rate	Price of a single product
Total Price	Total order price (Quantity X Rate)

Propensity Modeling - Concept

Propensity modeling is a set of approaches to building predictive models to forecast behavior of a target audience by analyzing their past behaviors. That is to say, propensity models help identify the likelihood of someone performing a certain action.

We can then use this likelihood or probability score to create personalized targeting campaigns to the users thus reducing our total cost (targeting only small set of users) and increasing our ROI.

Propensity Modeling - Real world examples

Barack Obama reelection campaign: Voters segmentation

During Barack Obama's 2012 reelection campaign, a team of data scientists was hired to build propensity-to-convert models. The task was to predict which undecided voters could be encouraged to vote for democrats and which type of political campaign contact such as a door knock, call, flyer, etc., would work best for each voter. The use of Big Data predictive analytics contributed to the Obama reelection win.

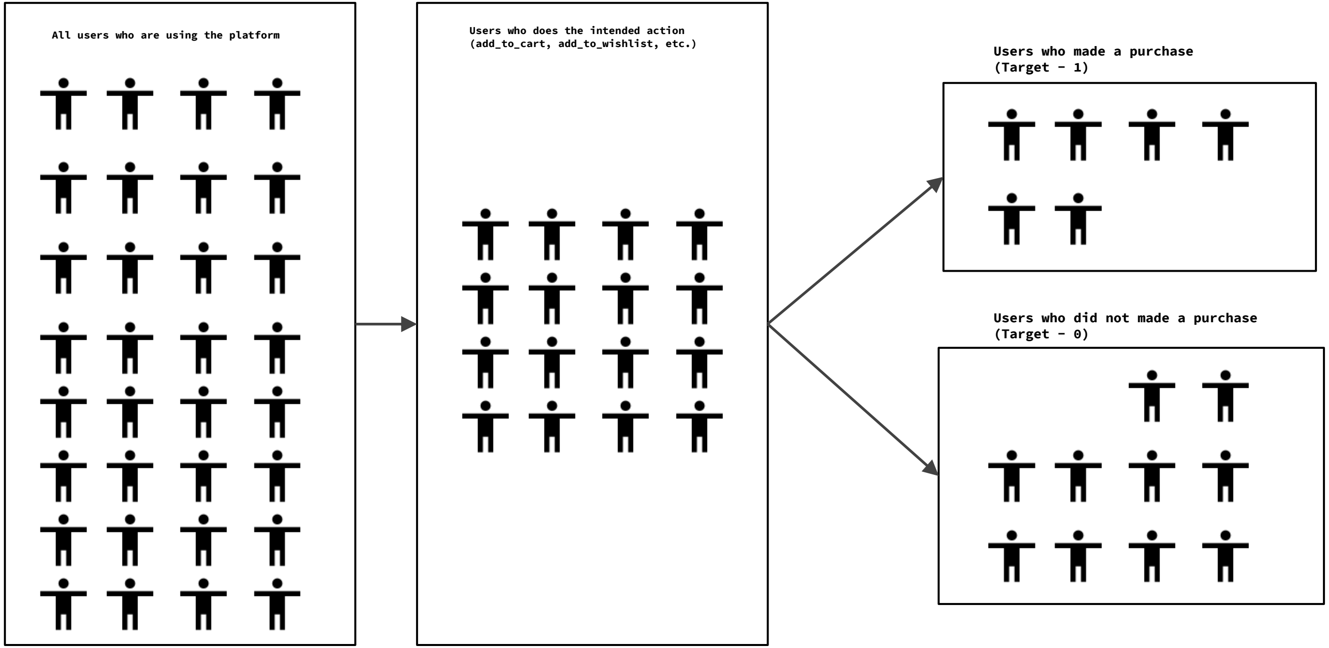
Scandinavian Airlines: Personalized communication with customers

Scandinavian Airlines (SAS) leverages machine learning and predictive analytics to calculate a customer's propensity to book a flight ticket. Armed with this data, they can provide timely offers for customers who are more willing to buy a flight and avoid having empty seats.

Vodafone: Customer churn risks identification

Vodafone is the second-largest mobile operator in Ukraine providing services to more than 23 million users. The company was looking for a way to reduce customer churn rate and improve their targeting with a final goal to outpace their top competitor. The company called on SAS Customer Intelligence, which leverages artificial intelligence opportunities, to build more accurate propensity models and make better decisions. With the help of outputs provided by ML-powered propensity modeling, marketers at Vodafone Ukraine managed to form accurate customer segments and determine which products perfectly match the next-best offers. The strategy resulted in the 30 percent customer churn reduction, increasing incremental revenue by 2 percent.

Propensity Modeling - Trigger based Model



Training:

Taking all the user who does the intended action as our base population. In the next ‘t’ hour, if those users make a purchase then Target for those users will be 1 else 0. Using this target and the behavioural features of the users we create an ML model.

Inference:

Whenever a user does an intended action (such as add_to_cart, add_to_wishlist, etc.) the ML model gets triggered and it scores each user on their propensity to buy a product in the next ‘t’ hours.