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CUSTOMER DATA

The KEY to unlock Customer VALUE

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AGENDA

Introduction

How do we collect data?

What do we do?

How do we use data?

Online Data

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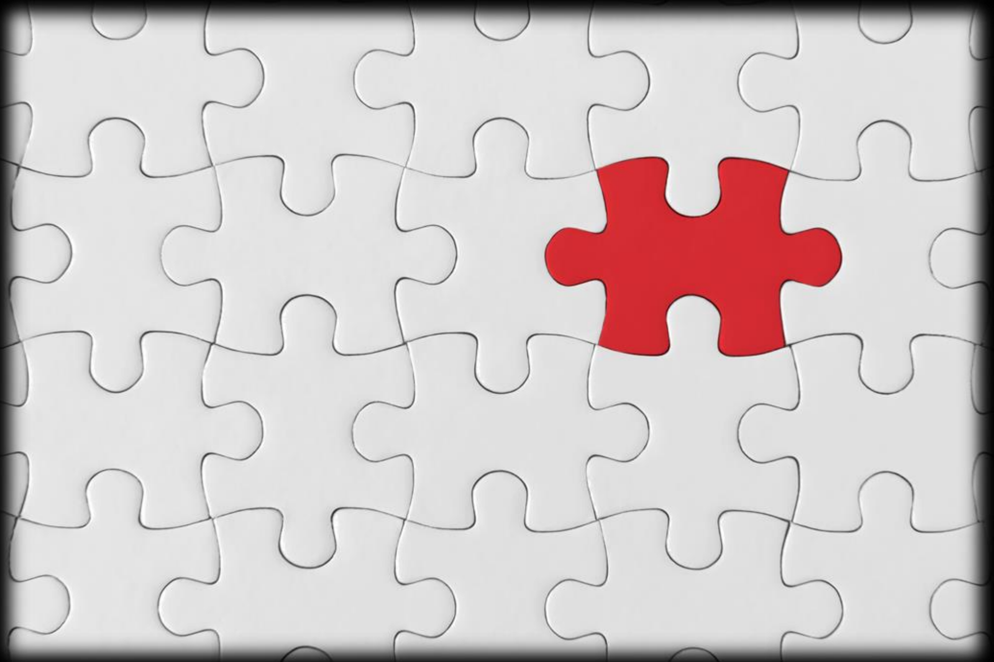
INTRODUCTION

KNOWING OUR CUSTOMERS

In other contexts, where businesses are smaller and local, business owners know their customers:



- Their product/brand preferences
- Financial availability
- Family structure
- Other aspects from their lives that could influence their choices

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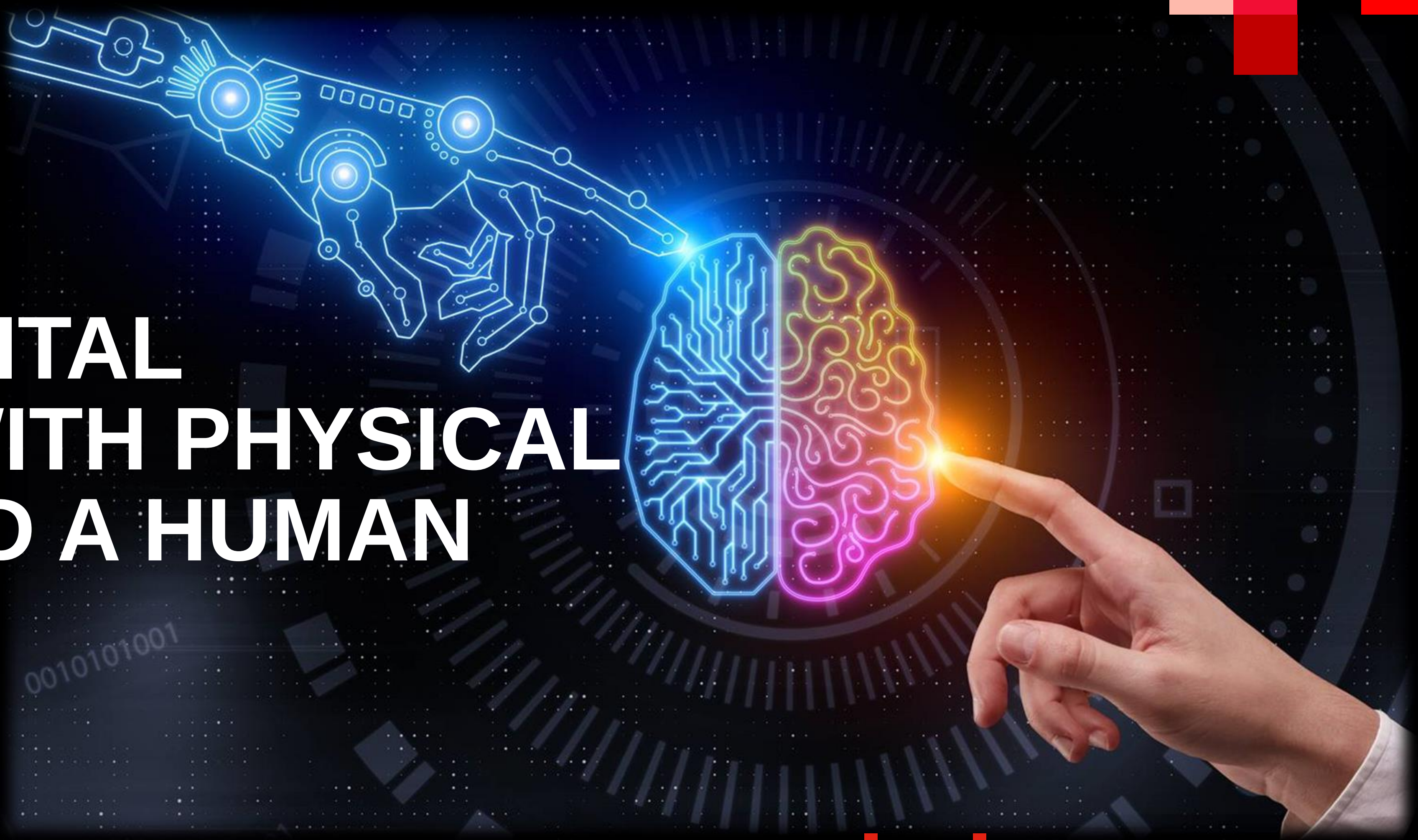
WHAT DO CUSTOMERS WANT?

- **Simplicity**
- **Convenience**
- Save **Time** and **Money**
- Feel **unique**

OUR VISION



» TO BE A DIGITAL RETAILER WITH PHYSICAL STORES AND A HUMAN TOUCH

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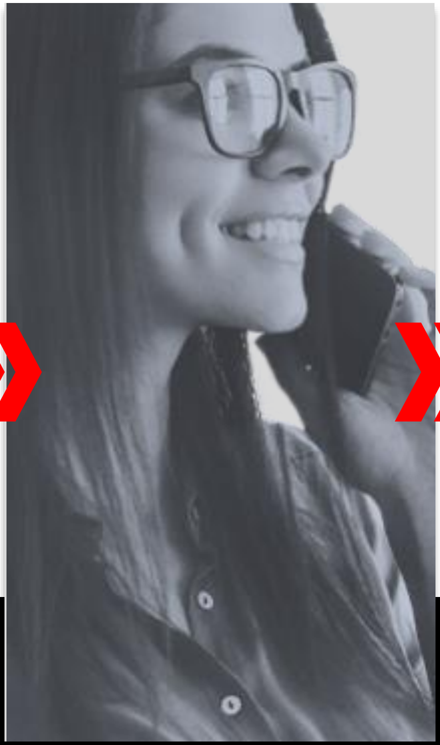
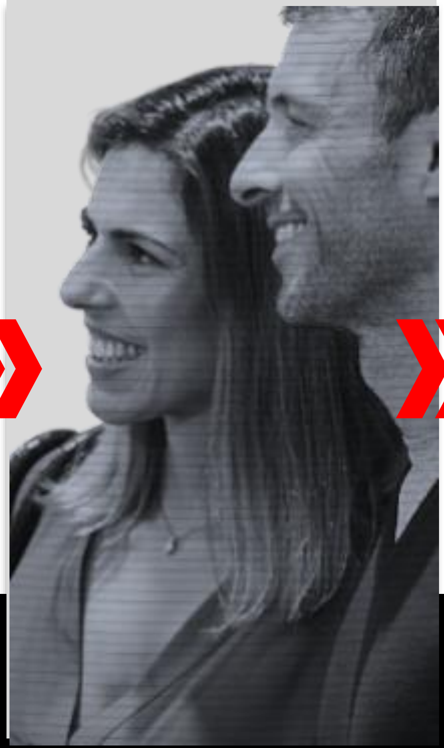
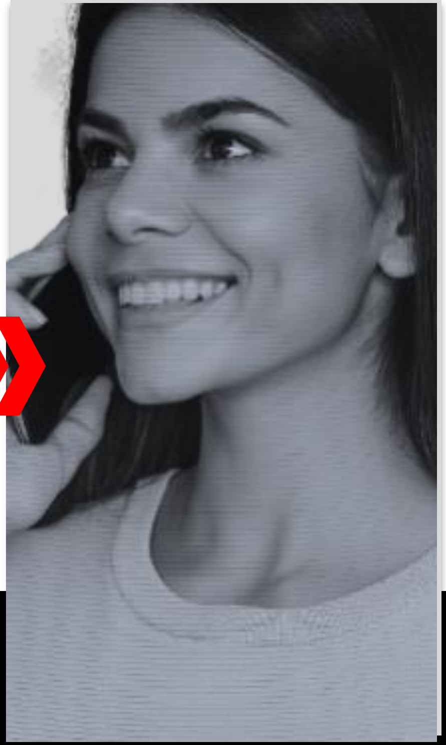
ONE ONGOING CONVERSATION

Effortless interactions, which may flow over different moments and different channels

Each interaction must flow from the last as if it was an **uninterrupted** conversation



CONSISTENCY

AGILITY

CONVENIENCE

PRO-ACTIVITY

ONE LONG

UNINTERRUPTED CONVERSATION

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DATA ANALYSIS

Transforming data into knowledge

To

Create a 360º view of customers.

CUSTOMER - CENTRIC CULTURE

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HOW DO WE **COLLECT** DATA?

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CUSTOMER DATA

FROM DIFFERENT SOURCES

What they tell us
(NPS/NSS and other surveys)

Their purchase habits (On&Offline)

Browsing, Reviews and Favourites

Other interactions
(repairs, complaints, installations…)

THERE ARE **MANY** OPPORTUNITIES

TO COLLECT **RELEVANT** DATA

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WHAT DO WE **DO?**

CUSTOMER

VALUE MANAGEMENT

WELCOME

DEFINE STRATEGIES TO MAXIMIZE THE CUSTOMER VALUE

- Analyze and understand customer segments
- Test targeted communications along the customer’s lifecycle
- Share gathered insights with the company

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CAMPAIGN MANAGEMENT

DIRECT MARKETING

SMS AND NEWSLETTERS COMMUNICATION

CUSTOMER DATA

TARGETED SEGMENTATION & COMMUNICATION

INSIGHTS INCORPORATION

RESULTS MONITORIZATION

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CAMPAIGN MANAGEMENT

DIRECT MARKETING

SMS AND NEWSLETTERS COMMUNICATION

CUSTOMER SEGMENTATION

- VALUE
- PRODUCT
- LIFECYCLE
- PURCHASE CHANNEL

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HOW DO WE **USE** DATA?

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DATA ANALYSIS

- They should be integrated so that they maximize the return (value) they bring to a company

Descriptive
What happened?

Diagnosis
Why did it happen?

4 TYPES OF DATA ANALYSIS

Predictive
What will happen?

Prescriptive
How can we make it happen?

BIG DATA

AI & MACHINE LEARNING

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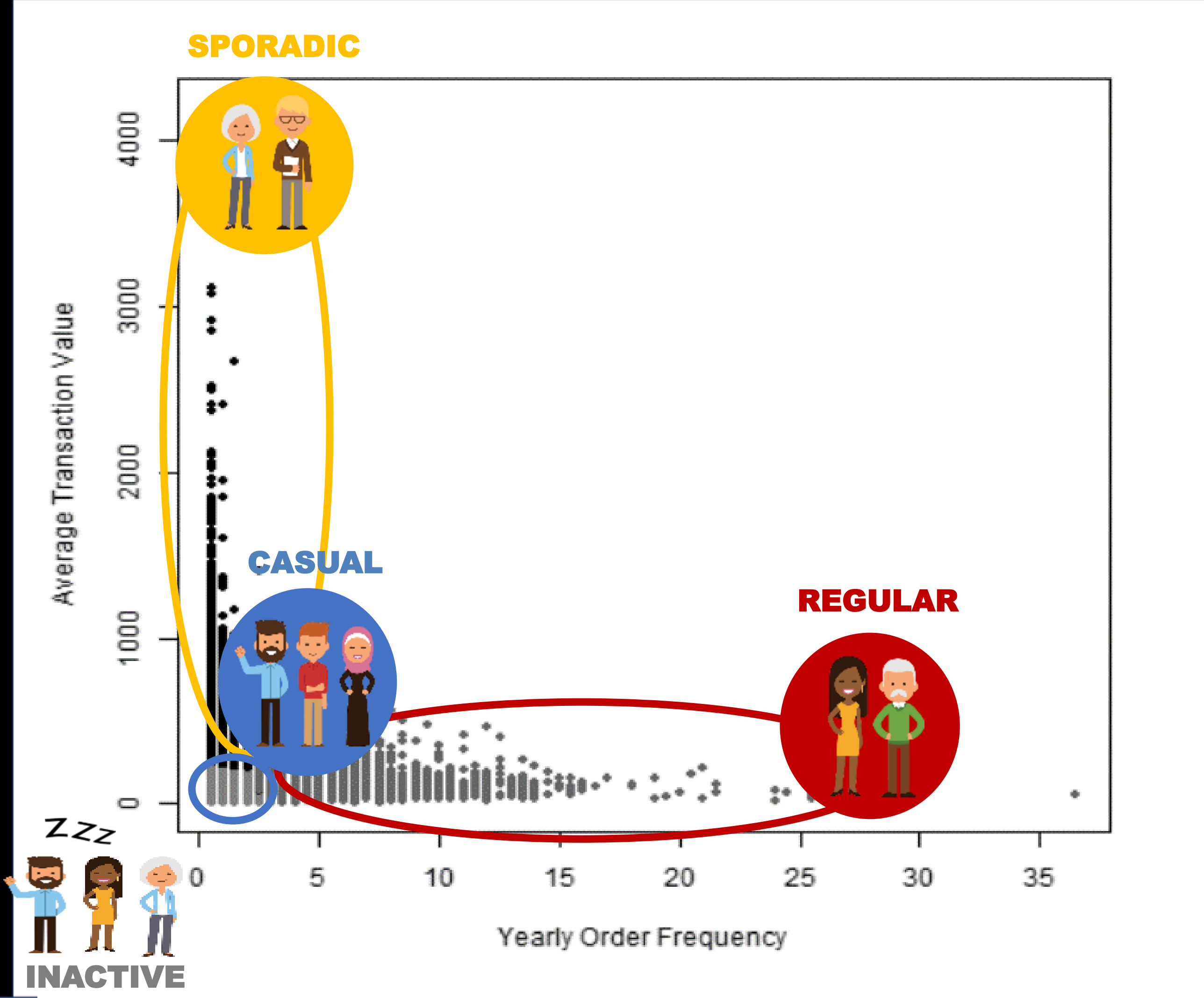
FREQUENCY & BASKET VALUE PREDICTION

Identifying customers moves between purchases allows us to:

Predict **how much** and **what** the customer will purchase in the future

Identify and **incentivize customer behavior**



CUSTOMER SEGMENTATION

To have a consistent and simple customer description we defined several approaches to customer segmentation. These are 3 of them:

- **Value/Frequency Segments**: based on order frequency and average basket value;
- **Product Interest Segments**: based on the types of product the customers buy;
- **Trend Segments**: a classification of customer activity/recency;

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CUSTOMER SEGMENTATION

Value/Frequency

The Value/Frequency segment is computed by a **k-medoids** algorithm – a ‘k-means’ but where the cluster centroids have to be part of the sample.

This process runs on these variables:

- Average Yearly Order Frequency (# Orders)
- Average Basket Value (€)

The resulting clusters are the following:

- Casual: a customer with low frequency and basket value
- Sporadic: a customer with high basket value
- Regular: a customer with high frequency

A high frequency and high basket value cluster didn’t show up because the basket value tends to decrease with frequency since it essentially is computed as $\text{Avg Basket Value} = \frac{Total\ Value}{Order\ Frequency}$

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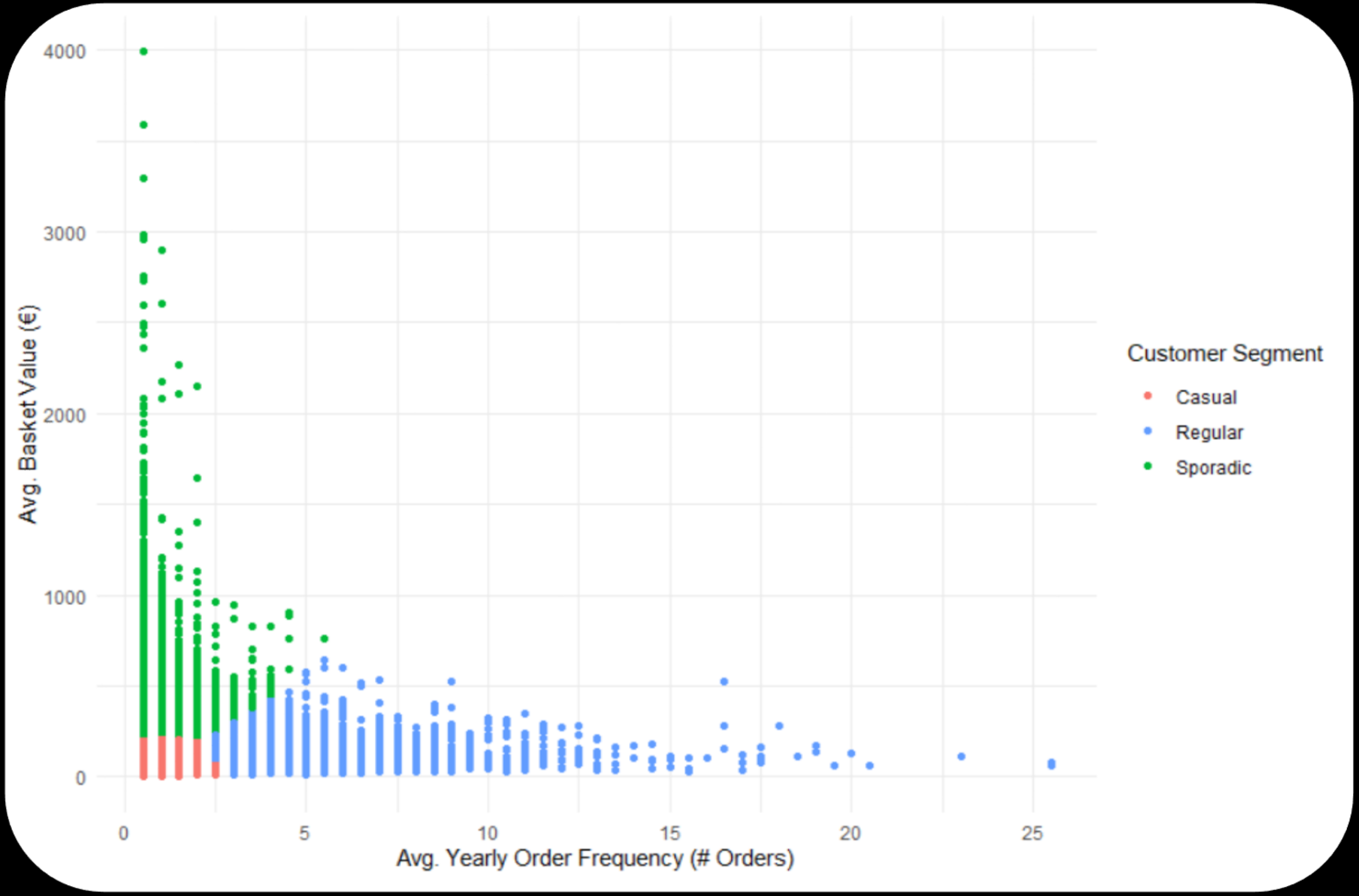
CUSTOMER SEGMENTATION

Value/Frequency



A look into the three segments for a sample of 20.000 customers

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CUSTOMER SEGMENTATION

Value/Frequency

Migrating **Casual** customers to higher segments is very much of interest as the smaller **Sporadic** and **Regular** segments make up more than 80% of the value spent by all customers. This means creating a relationship where the customers trust us with their high value purchases and frequently visit our stores.

Customers per segment

Total value spent (€) per segment

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CUSTOMER SEGMENTATION

Product Interest

To measure customer interest for product categories we divided our products into 14 categories:

- Big appliances
- Small appliances
- Telecom
- TV
- IT
- Audio
- Services
- Accessories
- Tickets
- Gaming
- Entertainment
- Photography
- Outdoors
- Marketplace Only

We found that interests would be skewed to be higher for expensive items like big appliances if we focused on value and higher for cheap things like accessories if we focused on number of items bought.

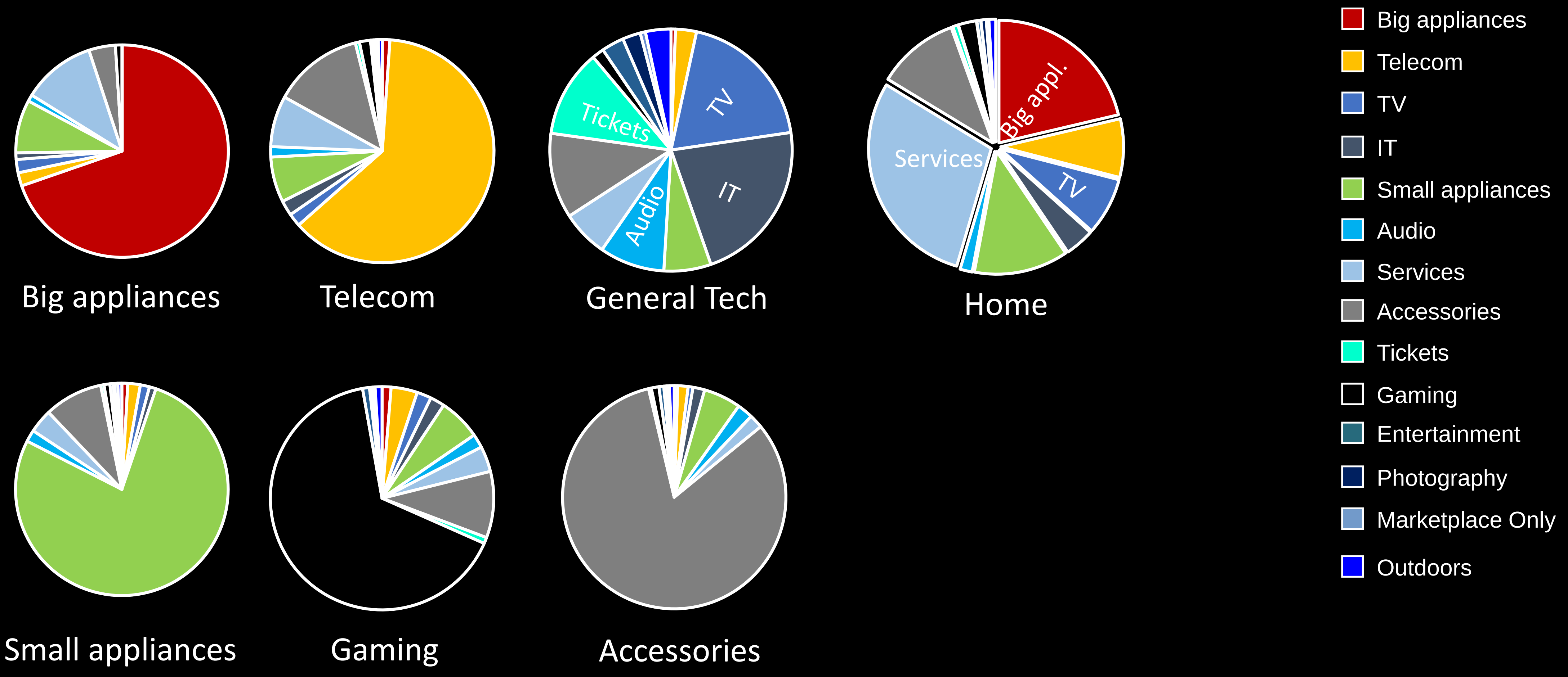
To balance this, for customer U we compute the interest for a certain category C as follows:

Interest =
(% of items U bought that belong to C) × (% of value spent by U that belongs to C)

Then we apply a k-means algorithm on this 14-dimensional space.

CUSTOMER SEGMENTATION

Product Interest – Cluster Centroids



CUSTOMER SEGMENTATION

Trend

To add to the information given by the value/frequency segments and the product interest segments, we classify the customers according to their activity based on the last 24 months with these labels:

Segment	12 to 24 months ago	Last 12 months
New	Unregistered	First Purchase!
Recent	First purchase!	
Escaping	Active (made purchases)	Inactive (no purchases)
Regained	Inactive	Active
Lost	Inactive	Inactive
Stable	Active	Active (same Value/Frequency Segment as the other period)
Rising	Active	Active (stronger V/F segment)*
Declining	Active	Active (weaker V/F segment)*
		* Casual < Sporadic < Regular

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CUSTOMER SEGMENTATION

In the end these approaches together form a simple but accurate description of the customer's history

Customer	Value/Frequency	Product Interest	Trend
#001	Sporadic	Gaming	New
#002	Regular	Home	Recent
#003	Casual	Accessories	Stable
#004	Sporadic	Big Appliances	Regained
#005	Inactive	Telecom	Lost

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NEXT BASKET
PREDICTION

Frequent Itemsets

- **Simplest question:** Find sets of items that appear together "frequently" in baskets
- ***Support*** for itemset I: Number of baskets containing all items in I
  - (Often expressed as a fraction of the total number of baskets)
- Given a ***support threshold*** s, then sets of items that appear in at least s baskets are called ***frequent itemsets***

TID	*Items*
1	Bread, Coke, Milk
2	Beer, Bread
3	Beer, Coke, Diaper, Milk
4	Beer, Bread, Diaper, Milk
5	Coke, Diaper, Milk

Support of {Beer, Bread} = 2

NEXT BASKET
PREDICTION

Association Rules

- **Association Rules:**
  If-then rules about the contents of baskets
- $\{i_1, i_2, \ldots, i_k\} \rightarrow j$ means: "if a basket contains all of $i_1, \ldots, i_k$ then it is ***likely*** to contain j"
- **In practice there are many rules, want to find significant/interesting ones!**
- ***Confidence*** of this association rule is the probability of j given $I = \{i_1, \ldots, i_k\}$

$$\operatorname{conf}(I \rightarrow j) = \frac{\operatorname{support}(I \cup j)}{\operatorname{support}(I)}$$

NEXT BASKET
PREDICTION

- Average Yearly Order Frequency - 1.71
- Average Number of Distinct Products per Transaction – 1.45
- **PREDICTIONS USING STANDARD METHODS ARE VERY DIFFICULT TO OBTAIN**

PROJECTS & ANALYTICS

STATISTICAL MODELS
DEVELOPMENT
AND AI

PURCHASE PROPENSITY
PROFILING
RECOMMENDATION

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RECOMMENDER SYSTEMS

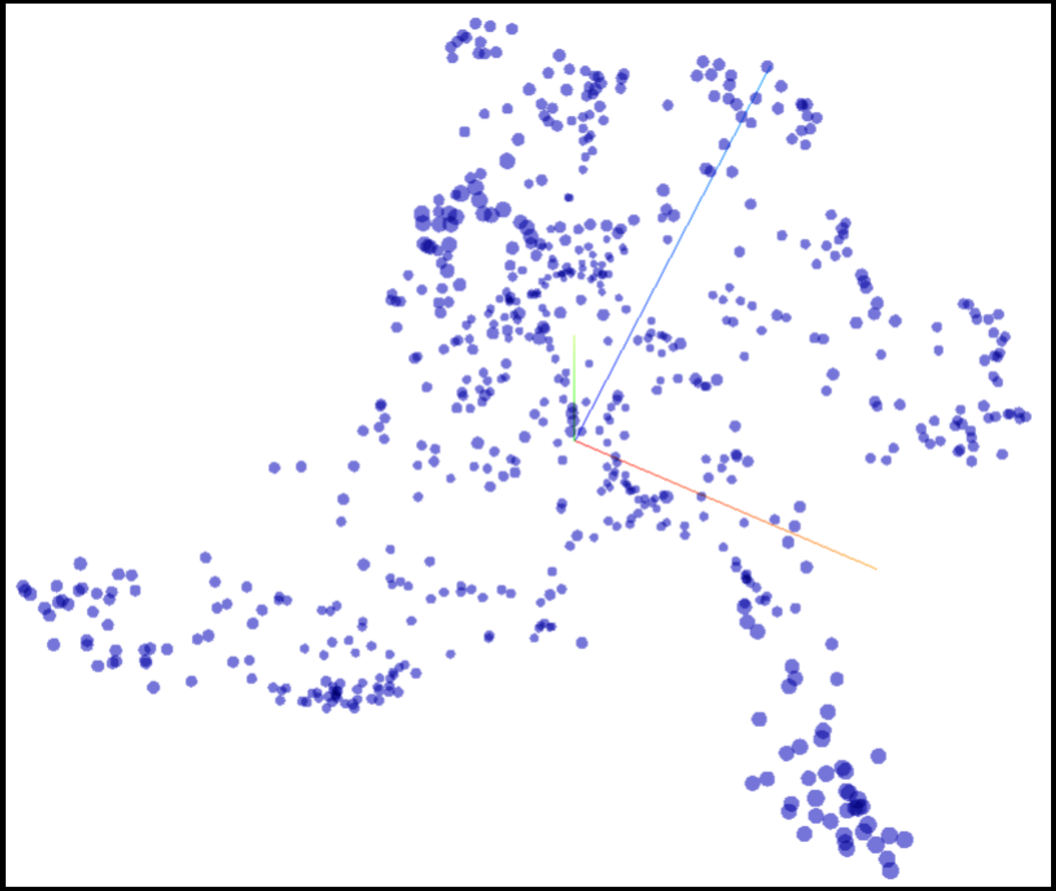
Some implemented/studied approaches:

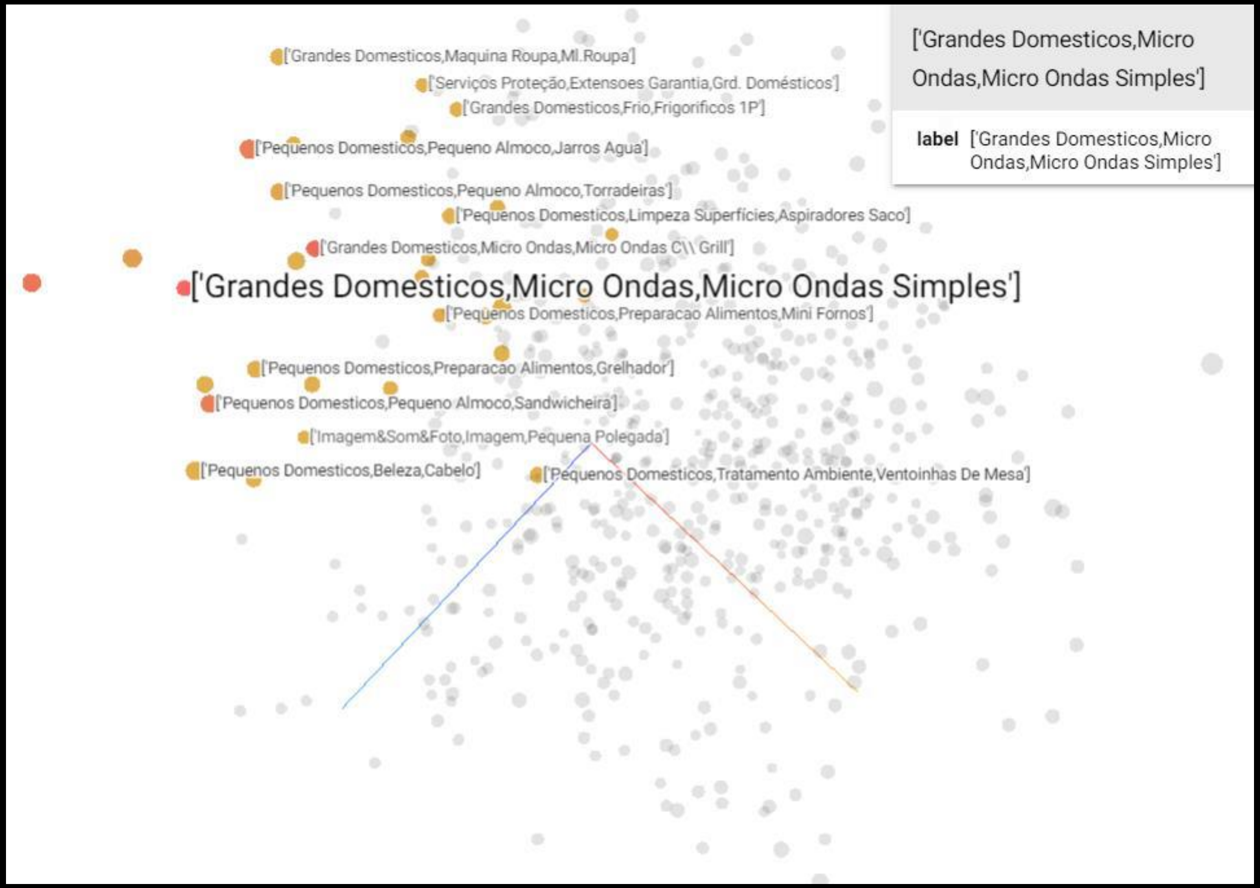
- Collaborative Filtering
- Sequential Collaborative Filtering (several variations)
- TransRec (He, Kang, McAuley – 2017)
- Item2vec (Barkan, Koenigstein – 2017)
- FPMC (Rendle, Freudenthaler, Schmidt-Thieme – 2010)

Software used: SAS, R, Python.

RECOMMENDER SYSTEMS

Item2Vec
Embeddings Visualization in Tensorflow





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RECOMMENDER SYSTEMS

Sequential Collaborative Filtering (item-to-item)

Purchase History

User	Date	Item
#001	1	A
#001	2	B
#001	2	C
#001	3	D
#002	1	C
#002	2	A
#002	2	D

$$\text{Similarity(i1,i2)} = \frac{\#users\ that\ bought\ i2\ \boldsymbol{after}\ buying\ i1}{\sqrt{\#\ users\ that\ bought\ i1} \times \sqrt{\#users\ that\ bought\ i2}}$$

Similarity Matrix

	A	B	C	D
A	-	0.707	0.5	0.5
B	0	-	0	0.707
C	0.5	0	-	1
D	0	0	0	-

This approach was found to capture the customers' **general interests** relatively better than others.

It generates recommended items based on the customer's **full purchase history.**

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RECOMMENDER SYSTEMS

Consecutive Collaborative Filtering (item-to-item)

Purchase History

User	Date	Item
#001	1	A
#001	2	B
#001	2	C
#001	3	D
#002	1	C
#002	2	A
#002	2	D

$$\text{Similarity(i1,i2)} = \frac{\#users\ that\ bought\ i1\ and\ i2\ in\ \boldsymbol{consecutive\ transactions}\ (i1\ first)}{\sqrt{\#\ users\ that\ bought\ i1} \times \sqrt{\#users\ that\ bought\ i2}}$$

Similarity Matrix

	A	B	C	D
A	-	0.707	0.5	0
B	0	-	0	0.707
C	0.5	0	-	1
D	0	0	0	-

This approach was found to capture the customers' **recent trends** relatively better than others.

It generates recommended items based on the customer's **latest order**.

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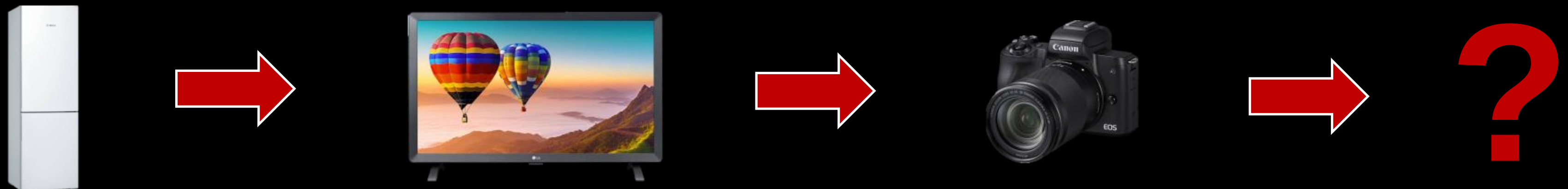
RECOMMENDER SYSTEMS

BEST RESULTS SO FAR



Sequential CF (to capture general interest)

Consecutive CF (to capture recent trend)

Ensemble Algorithm: Combined Similarities between Customers and Items from both models.
hit@10 = 34.8% for Regular Customers

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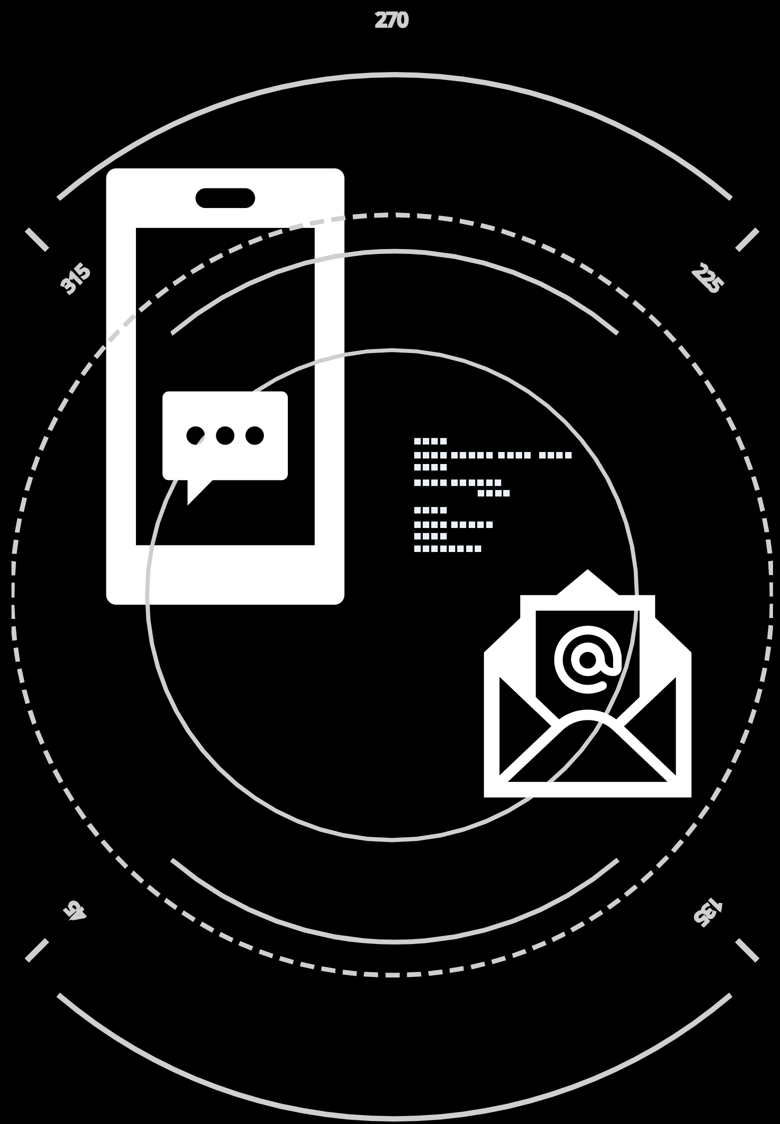
CAMPAIGN RESPONSE

PREDICTION



STUDYING CUSTOMERS' HISTORICAL RESPONSE TO CAMPAIGNS

Predict future response results to target the right customers

Maximize incremental sales

Maximize customer satisfaction

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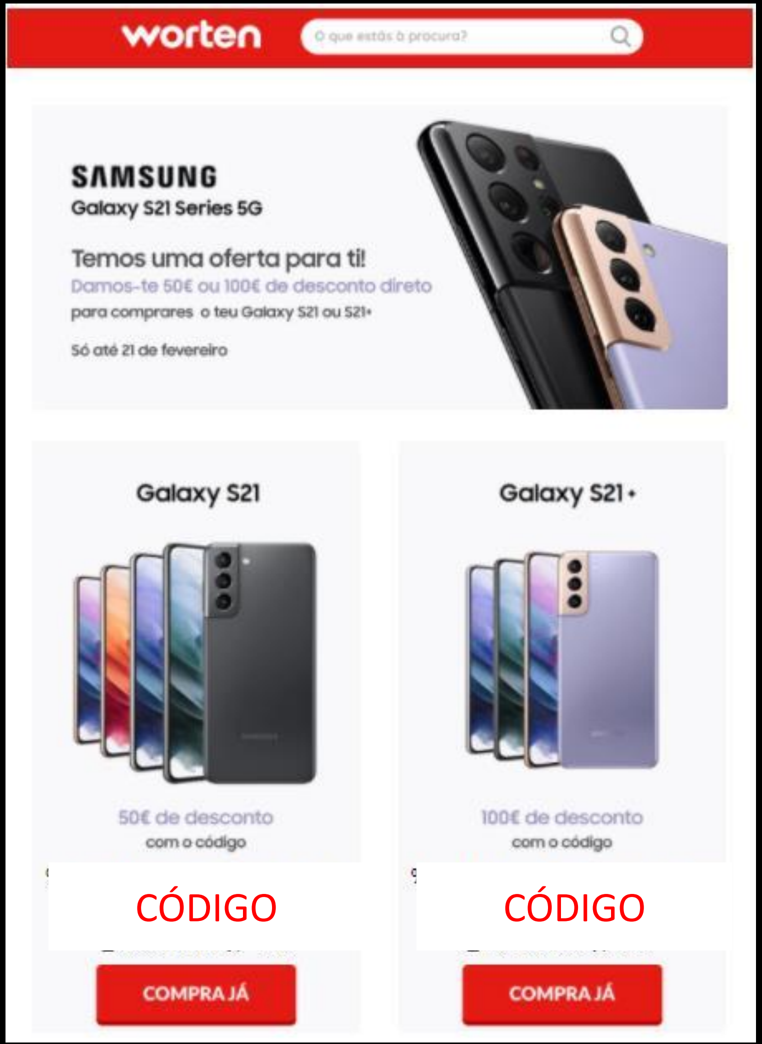
PERSONALIZATION

Personalized coupons



Cross-sell newsletters

ONLINE DATA

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SEARCH ENGINE

MARKETING

SEARCH ENGINE OPTIMIZATION (SEO)

+

SEARCH ENGINE ADVERTISING (SEA)

=

SEARCH ENGINE MARKETING (SEM)

SEO

Search Engine Optimization

SERP

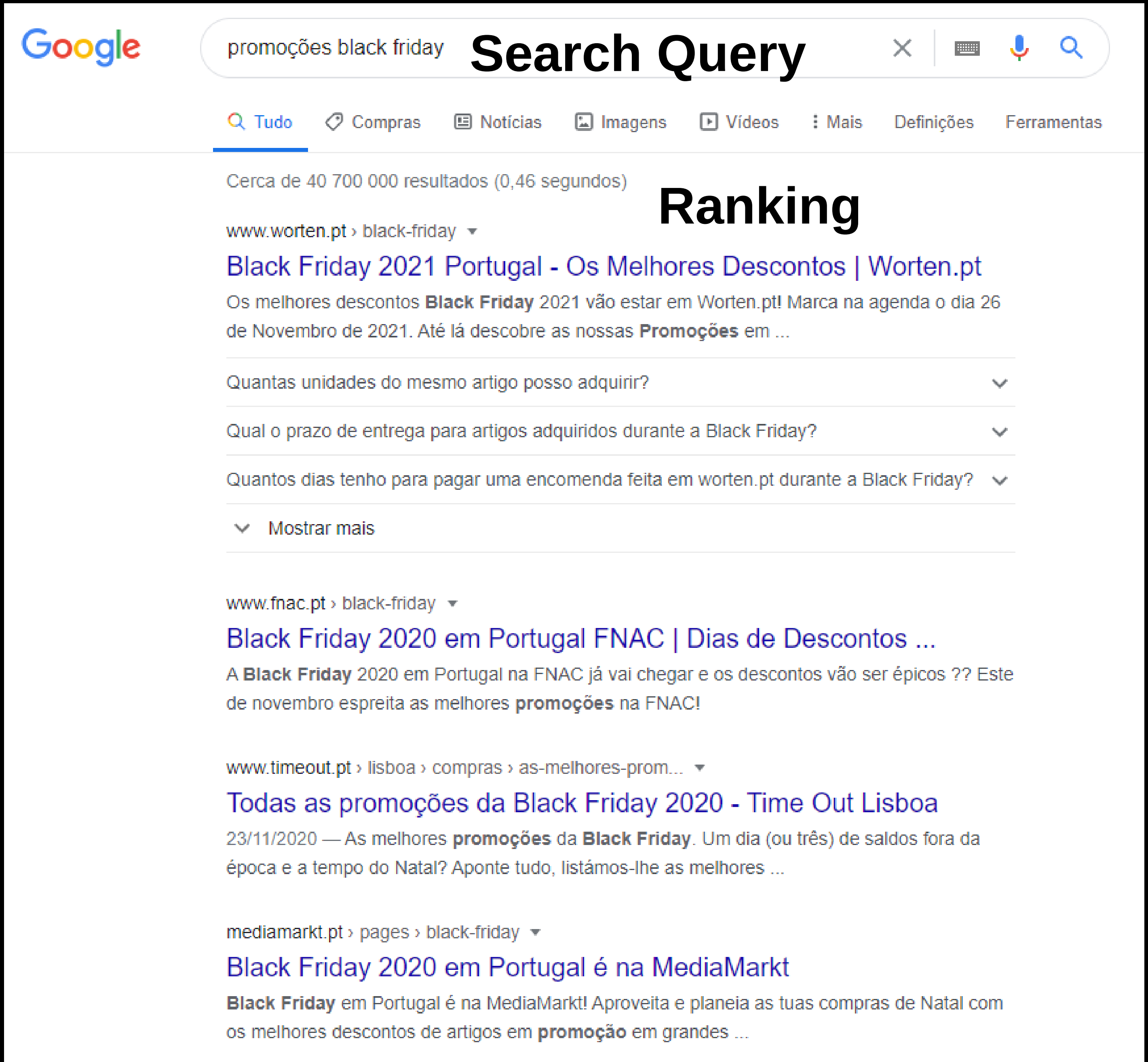
Search

Engine

Result

Page

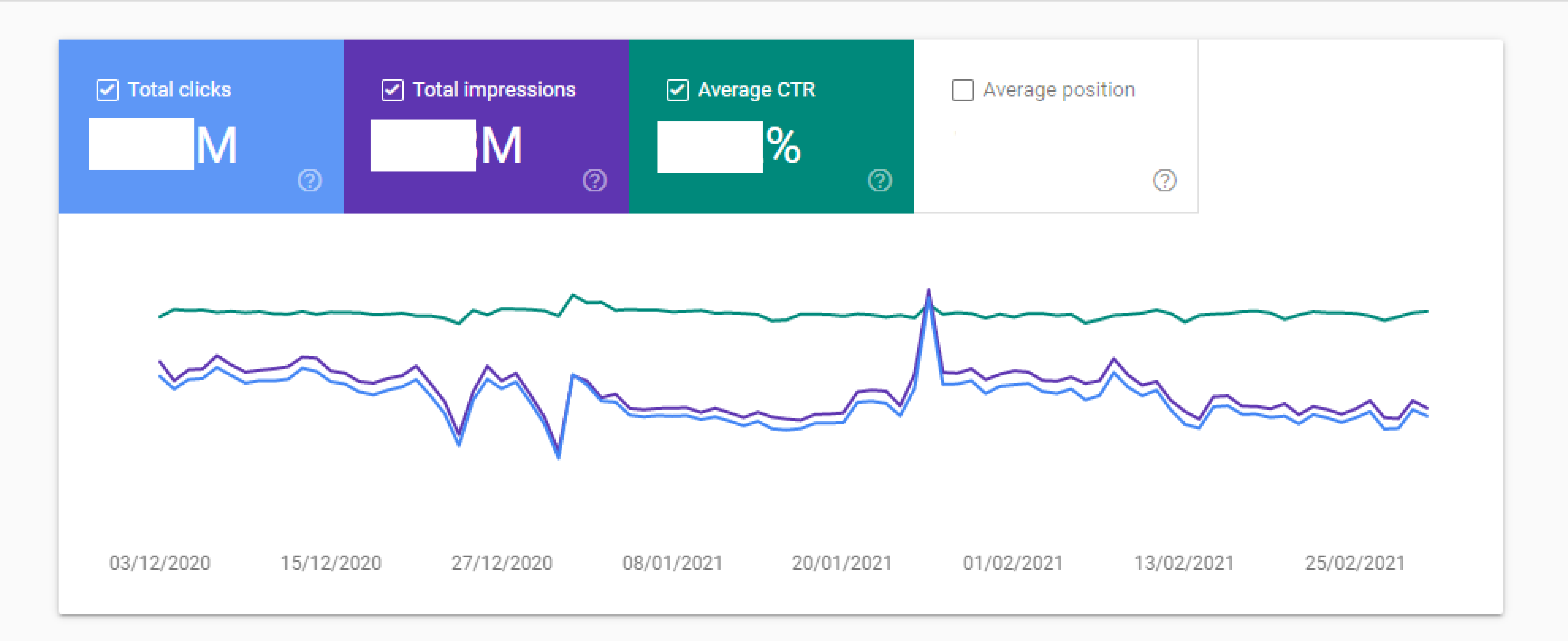
Based on KeyWords



SEARCH ENGINE

MARKETING

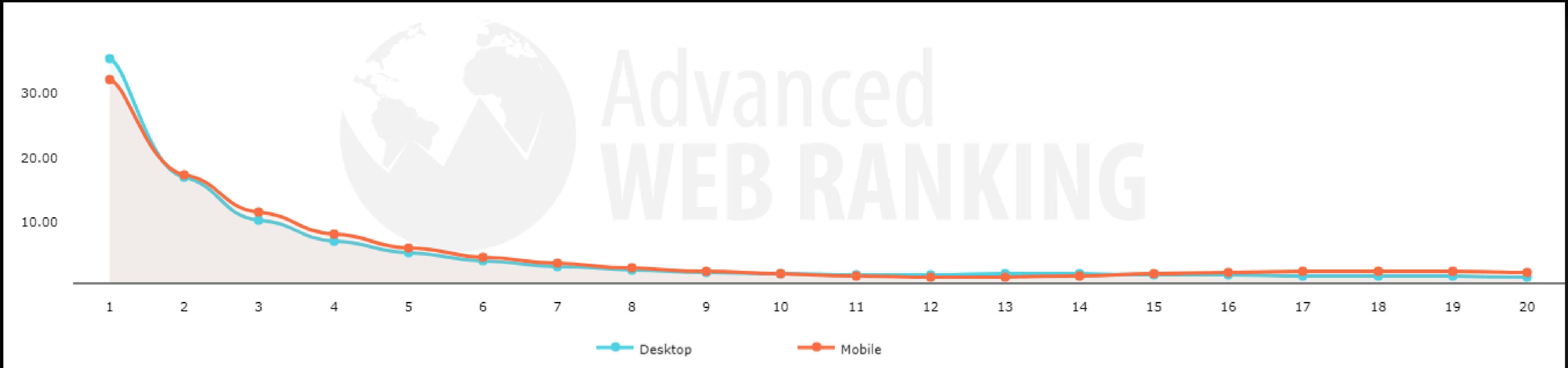
Google Search Console



SEARCH ENGINE

MARKETING

CTR – Click Through Rate



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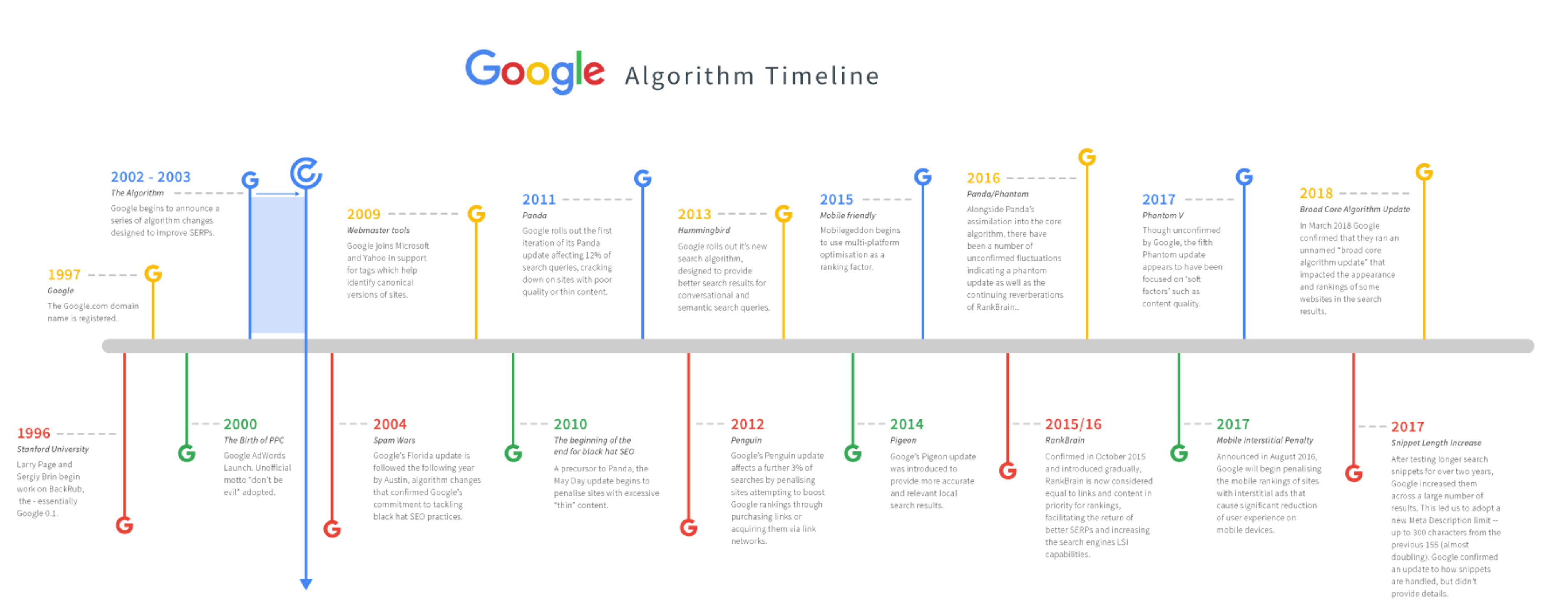
SEARCH ENGINE

MARKETING

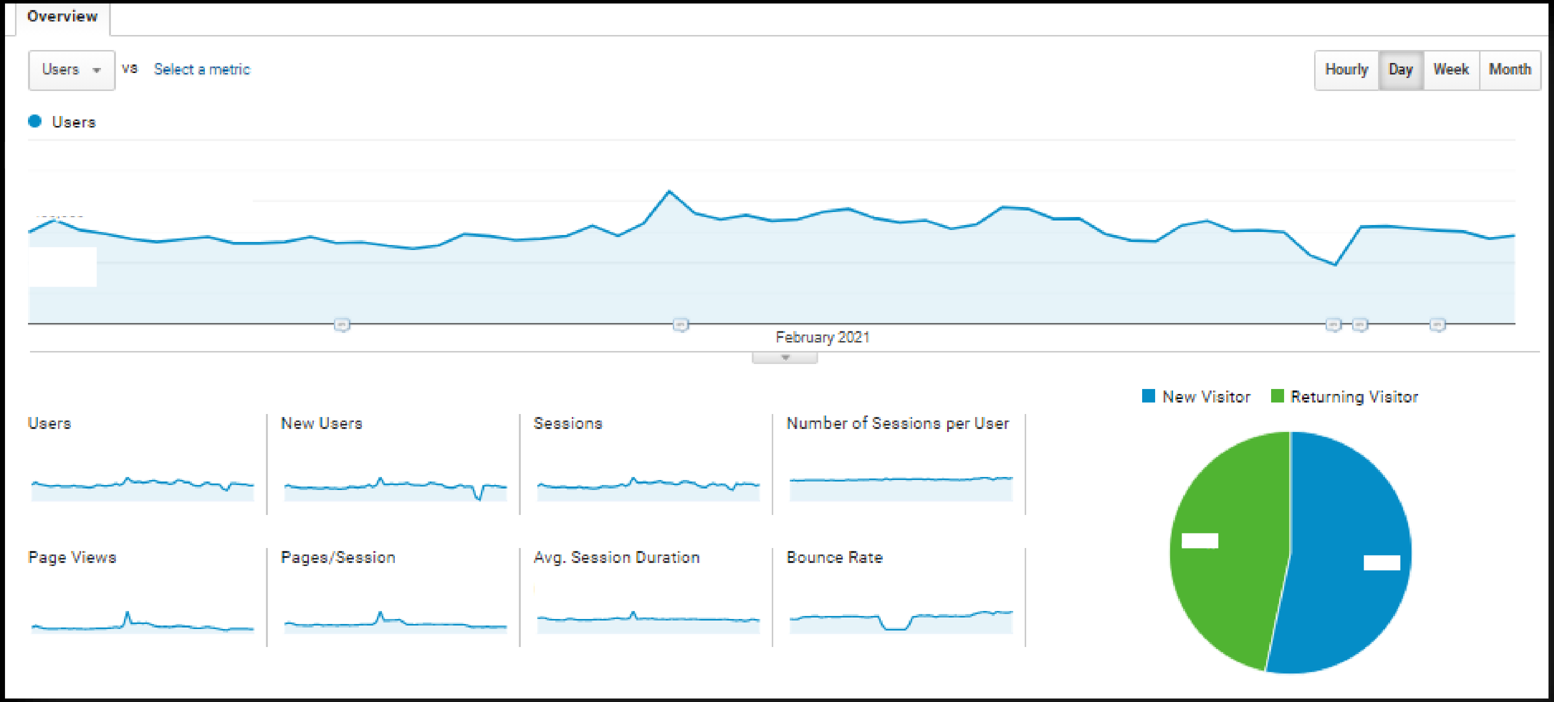
Algorithms are frequently changed and not completely known, so constant optimization is required.



SEARCH ENGINE

MARKETING

Google Analytics



The continuous optimization strategy aims at increasing relevant KPIs, such as PageViews, PageSessions and Avg Sessions

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SEA

Search Engine Advertising

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SEARCH ENGINE
MARKETING

A look on the Web Advertising providers' side of the problem…

Performance-based Advertising

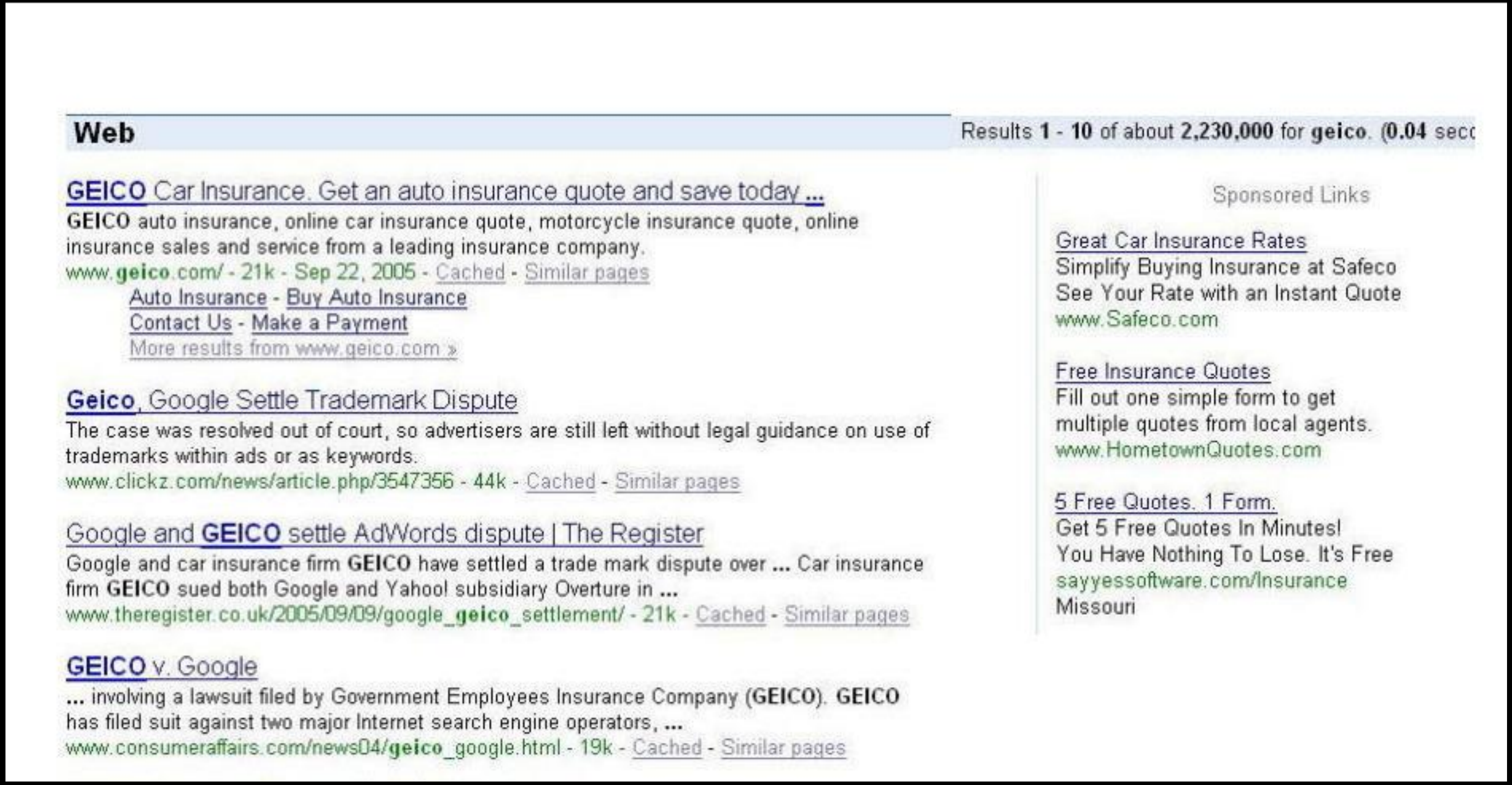
- **Introduced by Overture around 2000**
  - Advertisers **bid** on **search keywords**
  - When someone searches for that keyword, the **highest bidder's ad is shown**
  - Advertiser is charged only if the ad is clicked on
- Similar model adopted by Google with some changes around 2002
  - Called **Adwords**

J. Leskovec, A. Rajaraman, J. Ullman: Mining of Massive Datasets, http://www.mmds.org

SEARCH ENGINE
MARKETING

A look on the Web Advertising providers' side of the problem…

Ads vs. Search Results



Adwords Problem

- **Given:**
  - **1.** A set of bids by advertisers for search queries
  - **2.** A click-through rate for each advertiser-query pair
  - **3.** A budget for each advertiser (say for 1 month)
  - **4.** A limit on the number of ads to be displayed with each search query
- **Respond to each search query with a set of advertisers such that:**
  - **1.** The size of the set is no larger than the limit on the number of ads per query
  - **2.** Each advertiser has bid on the search query
  - **3.** Each advertiser has enough budget left to pay for the ad if it is clicked upon

Adwords Problem

- A stream of queries arrives at the search engine: $q_1, q_2, \ldots$
- Several advertisers bid on each query
- When query q_i arrives, search engine must pick a subset of advertisers whose ads are shown

- Goal: **Maximize search engine's revenues**
  - Simple solution: Instead of raw bids, use the "**expected revenue per click**" (i.e., **Bid*CTR**)

Adwords Problem

Advertiser	Bid	CTR	Bid * CTR
A	$1.00	1%	1 cent
B	$0.75	2%	1.5 cents
C	$0.50	2.5%	1.125 cents
		Click through rate	Expected revenue

Advertiser	Bid	CTR	Bid * CTR
B	$0.75	2%	1.5 cents
C	$0.50	2.5%	1.125 cents
A	$1.00	1%	1 cent

Adwords Problem

Complications: CTR

- **CTR: Each ad has a different likelihood of being clicked**
  - **Advertiser 1** bids \$2, click probability = 0.1
  - **Advertiser 2** bids \$1, click probability = 0.5
  - **Clickthrough rate (CTR)** is measured **historically**
    - **Very hard problem: Exploration vs. exploitation**
      Exploit: Should we keep showing an ad for which we have good estimates of click-through rate
      or
      Explore: Shall we show a brand new ad to get a better sense of its click-through rate

There are several algorithms used to solve this proble:

- Greedy Algorithm
- Balanced Algorithm
- …

ATTRIBUTION MODELS

In the **Last Interaction** attribution model, the last touchpoint—in this case, the *Direct* channel—would receive 100% of the credit for the sale.

In the **Last Non-Direct Click** attribution model, all direct traffic is ignored, and 100% of the credit for the sale goes to the last channel that the customer clicked through from before converting—in this case, the *Email* channel.

In the **Last AdWords Click** attribution model, the last AdWords click—in this case, the first and only click to the *Paid Search* channel —would receive 100% of the credit for the sale.

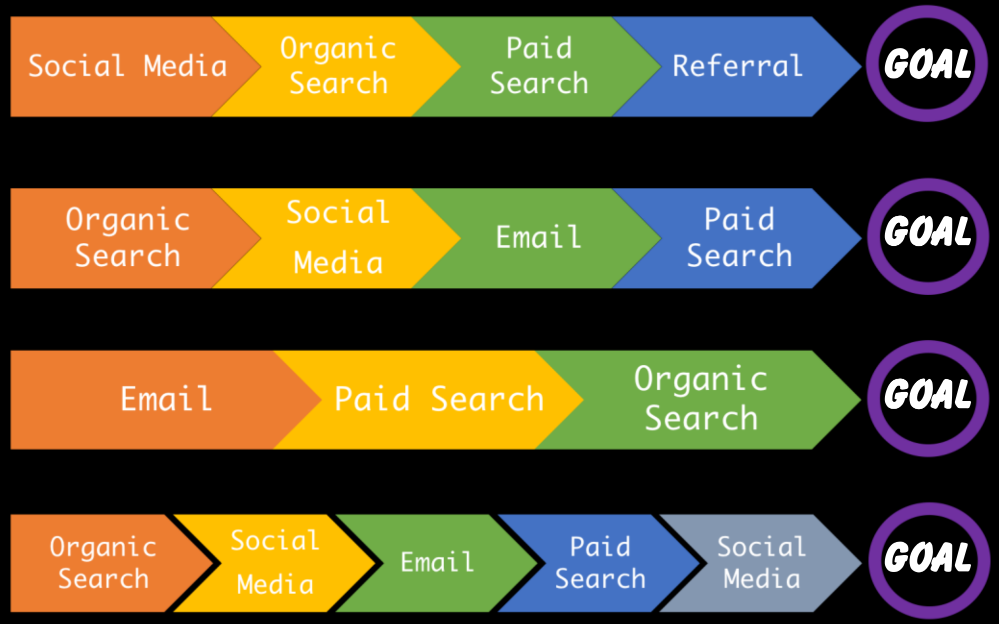
In the **First Interaction** attribution model, the first touchpoint—in this case, the *Paid Search* channel—would receive 100% of the credit for the sale.

In the **Linear** attribution model, each touchpoint in the conversion path—in this case the *Paid Search*, *Social Network*, *Email*, and *Direct* channels—would share equal credit (25% each) for the sale.

In the **Time Decay** attribution model, the touchpoints closest in time to the sale or conversion get most of the credit. In this particular sale, the *Direct* and *Email* channels would receive the most credit because the customer interacted with them within a few hours of conversion. The *Social Network* channel would receive less credit than either the *Direct* or *Email* channels. Since the *Paid Search* interaction occurred one week earlier, this channel would receive significantly less credit.

In the **Position Based** attribution model, 40% credit is assigned to each the first and last interaction, and the remaining 20% credit is distributed evenly to the middle interactions. In this example, the *Paid Search* and *Direct* channels would each receive 40% credit, while the *Social Network* and *Email* channels would each receive 10% credit.

Used to model customer behaviour and understand what drives visits and conversions.



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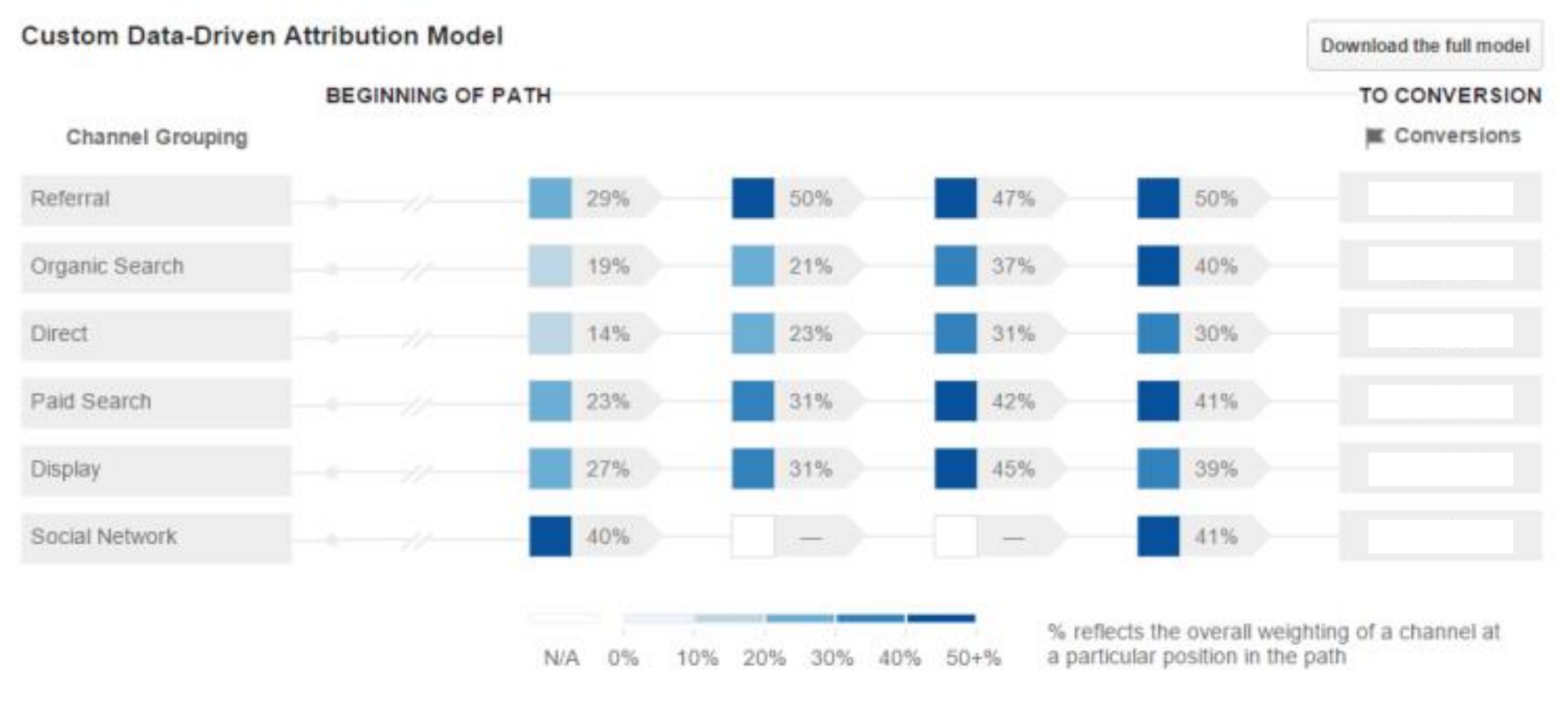
ATTRIBUTION MODELS

A continuous optimization problem…



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BIG DATA

Online customers' information

PAGEVIEWS

FAVOURITES & BANNER CLICKS

BEHAVIOURAL SHIFT

PANDEMIC CONTEXT ACCELERATED eCOMMERCE GROWTH

NEW DIGITAL CHANNELS & AI TOOLS

LARGER AMOUNT OF DATA TO PROFILE THE CUSTOMER

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QUESTIONS?

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