Measuring the incrementality of Paid Search on a customer-level

Introduction

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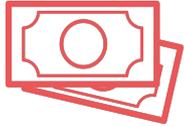**Mitch Komen - Lead Digital Marketing**

- Focusing on profitable growth, increasing **customer value** and trading efficiency
- Background in Paid Search
- Skiing, cycling, tennis and football

Introduction Wehkamp (Retail Group)

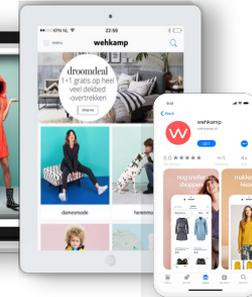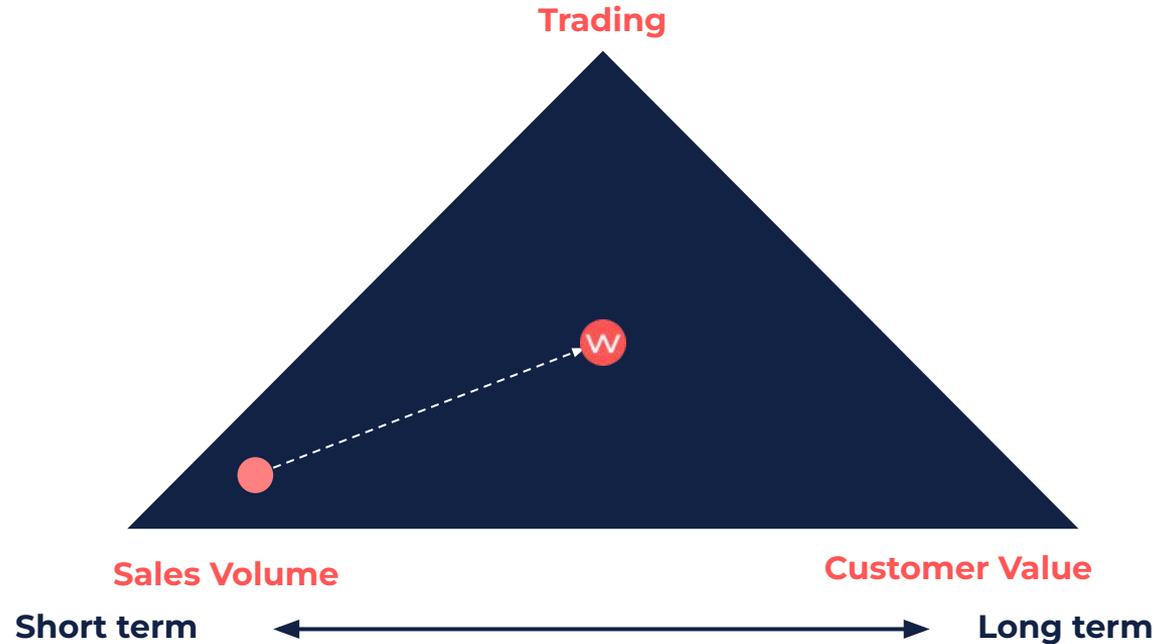**1952** - first advertisement   **1955** - first catalogue   **1995** - first steps online   **2010** - completely online   **2018** - mobile first   **2021** - Acquisition kleertjes.com

Introduction Paid Search @ Wehkamp

Trading

Sales Volume

Customer Value

Short term ⟵⟶ **Long term**

- Integrate trading insights into the paid search strategy rather then only push (profitable) volume.

- Take **customer value** into account while managing the paid search campaigns.

Incrementality & Elasticity

**What is incrementality for Paid Search advertising?**

Incrementality in Paid Search advertising refers to the incremental lift or additional impact on a campaign's performance, specifically on conversions or other key performance indicators (KPIs), that can be attributed to the specific ads that were paid for and shown, over and above what would have happened without those ads.

In other words, incrementality measures the additional value that Paid Search ads bring to a campaign, beyond what would have occurred through organic search results or other channels. This metric helps advertisers understand the true return on investment (ROI) for their Paid Search campaigns and the effectiveness of their ad spend.

To determine the incrementality of a Paid Search campaign, marketers can use methods such as A/B testing, where they compare the performance of a group that saw the ads with a control group that didn't, or multi-touch attribution models, which aim to identify the contribution of each marketing touchpoint along the customer journey.

By optimizing for incrementality, advertisers can focus on generating the maximum value from their Paid Search ads and allocate their budgets more effectively.
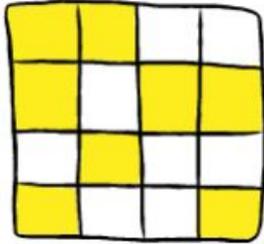
impressions
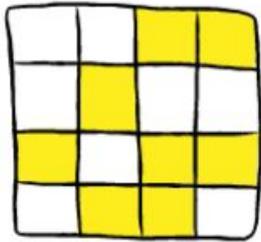
no impressions
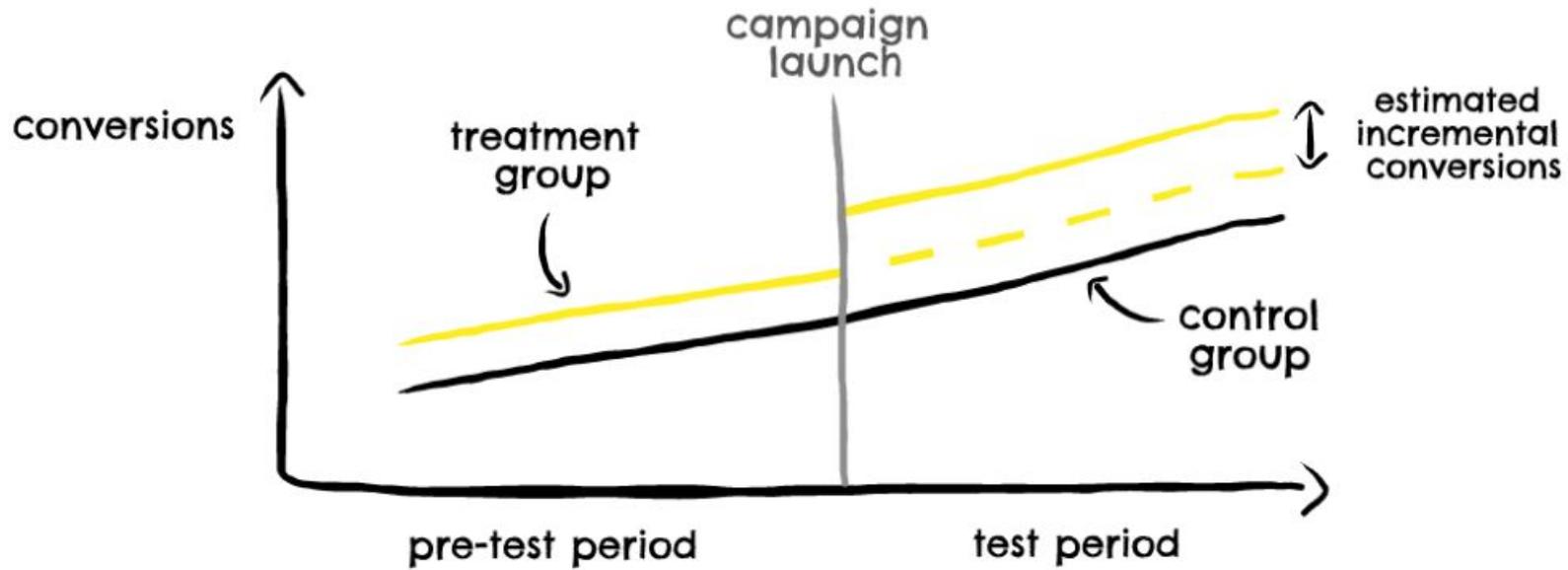
What's the real value of our Paid Search spend?

Sales Volume
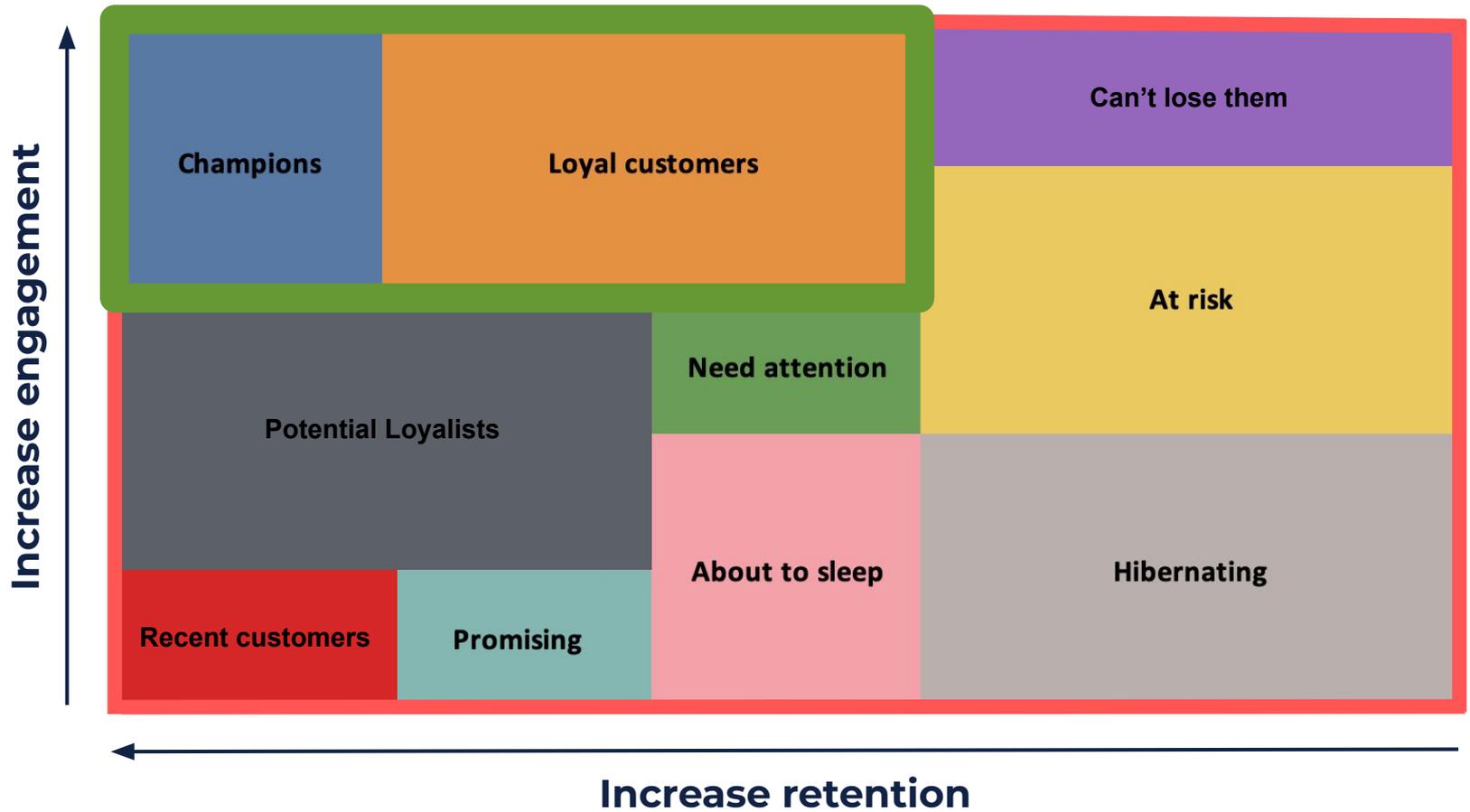Attribution

Profitable Growth

etc.

Trading
Category

Stock Data

etc.

Customer
Loyal

Not so Loyal

Inactives

But …. How much should we (optimal) bid per customer group?

A Customer Approach

Champions

Loyal customers

Can't lose them

At risk

Potential Loyalists

Need attention

About to sleep

Hibernating

Recent customers

Promising

Increase engagement

Increase retention

Segment name ↑	Type	Source	Match rate	Membership status
DB - rfm_01_champions DB - rfm_01_champions User list created from databricks	Customer list Customer contact information	Customer data	100% High	Open
DB - rfm_02_loyal_customers DB - rfm_02_loyal_customers User list created from databric	Customer list	Customer data	100% High	Open
DB - rfm_03_potential_loyalists DB - rfm_03_potential_loyalists User list created from databr		Customer data	100% High	Open
DB - rfm_04_promising DB - rfm_04_promising User list created from databricks		Customer data	100% High	Open
DB - rfm_05_recent_customers DB - rfm_05_recent_customers User list created from databr		Customer data	100% High	Open
DB - rfm_06_cant_lose_them DB - rfm_06_cant_lose_them User list created from databrick		Customer data	100% High	Open
DB - rfm_07_need_attention DB - rfm_07_need_attention User list created from databricks		Customer data	100% High	Open
DB - rfm_08_about_to_sleep DB - rfm_08_about_to_sleep User list created from databrick		Customer data	100% High	Open
DB - rfm_09_at_risk DB - rfm_09_at_risk User list created from databricks	Customer contact information	Customer data	100% High	Open
DB - rfm_10_hibernating DB - rfm_10_hibernating User list created from databricks	Customer list Customer contact information	Customer data	100% High	Open
DB - rfm_11_inactivate_customers DB - rfm_11_inactivate_customers User list created from databricks	Customer list Customer contact information	Customer data	100% High	Open

Match rate

100%

100% is high

0%   29%   62%   100%

Most advertisers' match rates are between 29% and 62%. To improve your match rate, make sure you're formatting and encrypting your list properly. Learn more

Segment name ↑		Match rate	Size: Search
☐	DB - test_lifecycle_churning_a DB - test_lifecycle_churning_a User list created from databricks	100% High	230,000

Match rate
100%

100% is **high**

| 0% | 29% | 62% | 100% |

Most advertisers' match rates are between 29% and 62%. To improve your match rate, make sure you're formatting and encrypting your list properly. Learn more

Your customer list has been successfully saved

- Of the 471,798 rows uploaded, 471,797 were formatted correctly (100%)
- Google Ads will match your data to your customers on Google's networks. Learn more
- You can add this list to your targeting now, but matching can take up to 24 hours to finish
- When matching is complete, your ads can start showing to your new audiences. Lists must have at least 1000 matched users for them to serve.

230K ÷ 472K = 49% = 🤨

Bid adjustments and Target ROAS

Bid adjustments allow you to show your ads more or less frequently based on where, when, and how people search. Because Target ROAS helps optimize your bids based on real-time data, your existing bid adjustments aren't used. There is one exception: You can still set device bid adjustments of -100%.

Note: You don't need to remove bid adjustments—they just won't be used.

	Index CPC *compared to avg. CPC*	**Index POAS** *compared to avg. POAS*
★★★ **Loyal Customers**	123	130
★★☆ **Not So Loyal Customers**	106	84
★☆☆ **Inactive Customers**	100	74

Primary condition

Select your rule's primary condition ⓘ

Audience 🔒

○ All audience segments

◉ Enter audience segment

Search	**Browse**	1 selected

← How they've interacted with your business | Customer lists

☐ DB - rfm_09_at_risk | DB - rfm_11_inactivate_customers ⊗

☐ DB - rfm_10_hibernating

☑ DB - rfm_11_inactivate_customers
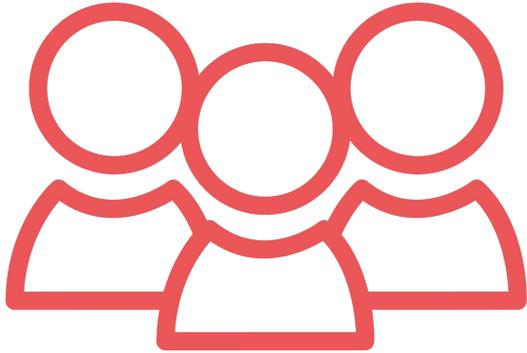
☐ DB - test_high_returners

Value

Select the value adjustment that will apply to your base conversion value ⓘ
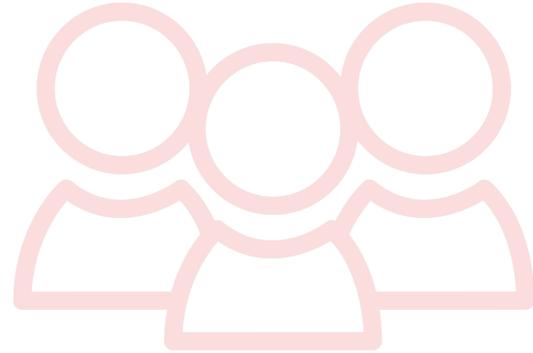
[Multiply ▾] [2]

Experiments & Results

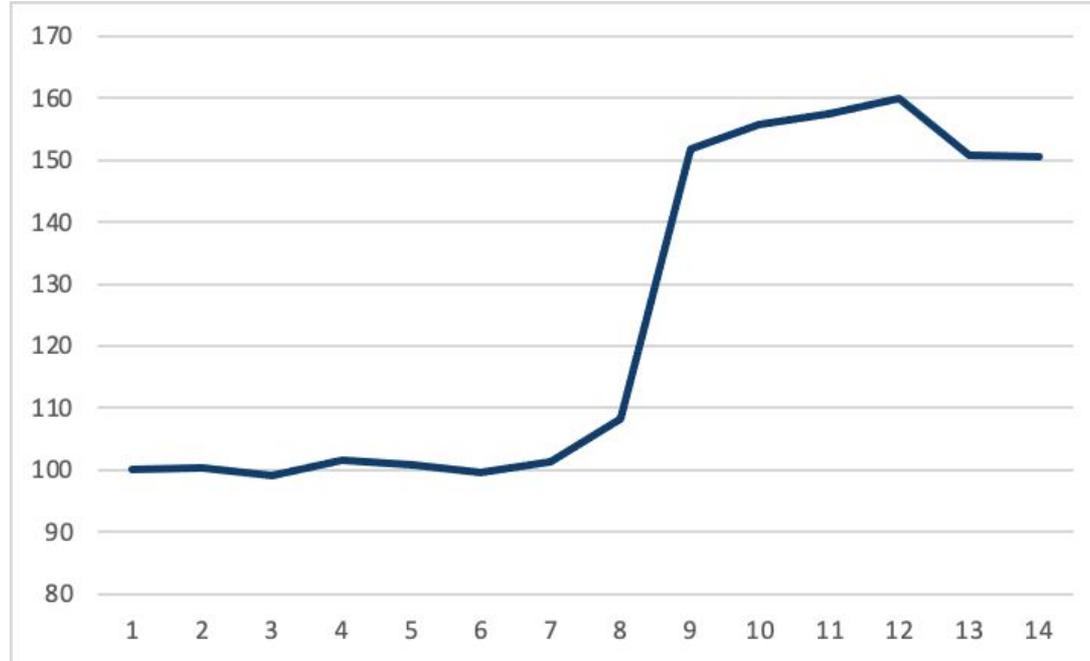# Split the segments into a test- and control group

Test Group
Use multiplier
e.g. 2 on inactives

Control Group
Do not use multiplier

Immediate effect on avg. CPC for inactive customers after implementation multiplier of 2

Experiment 1: Inactive Customers *(multiplier of 2)*

Test vs. Control	Clicks	Avg. CPC	Costs	Re-activated Customers	Customer Acquisition Cost
Attributed Results	**+140%**	**+57%**	**+276%**	**+69%**	**+119%**
Incremental Results				**+10%**	**+264%**

Additional CAC =
Additional Costs / Customers
Example: €144K / 4.6K = €31.30

>> Future Value
Based on cohort analysis
est. profit in NY after reactivation

Experiment 2: Loyal Customers *(multiplier of 0.75)*

Test vs. Control	Clicks	Avg. CPC	Costs	Loyal Customers	Customer Acquisition Cost
Attributed Results	-30%	-19%	-44%	-20%	-29%
Incremental Results				-0.04%	-43%

Experiment 3: Not So Loyal Customers *(multiplier of 1.5)*

Test vs. Control	Clicks	Avg. CPC	Costs	Not So Loyal Customers	Customer Acquisition Cost
Attributed Results	+69%	+31%	+122%	+39%	+59%
Incremental Results				+5%	+119%

Concluding

Optimal bidding point for **Loyal Customers** towards incrementality

Invest *"saved"* €€ from Loyal Customers towards **not so Loyal Customers**

Powerful tool to **re-activate customers**, but it's expensive

Next steps
&
Takeaways

Next steps

Implement in Offline Conversion Import

Instead of Conversion Value Rules, _concern_: how will affect this (non) customers that are not in the customer match lists based on the smart bidding signals like demographics, geographics etc.

Improve Multi Touch Attribution

Should we implement the "Customer Value" into our MTA model?
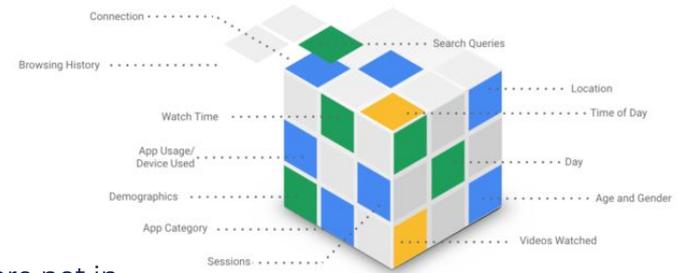
Increase "Targetable" Customers

How can we increase the amount of targetable customers in the Customer Match lists?

Test with fixed multipliers

For example within the "inactive" customer base

Implement in other channels

How can we adopt this way of steering into other (digital) channels?

Takeaways

First-party-data

Use first-party data, like customer match lists for more in depth steering and insights on a customer level

Challenge your attribution model

Even when it's a DDA / MTA model - it does not always takes "Customer Value" into account

Measure incrementality without attribution on a total-level

Look at the total impact of an ad click, so not only on the channel were the click (and attributed conversion) came from

Take long term value into account when you evaluating your spend efficiency

Most important for your new and reactivated customers

Incrementality ≠ Elasticity

Incrementality is great, but it does not tell you what the optimal bidding point is

Thanks!
Any questions?

wehkamp