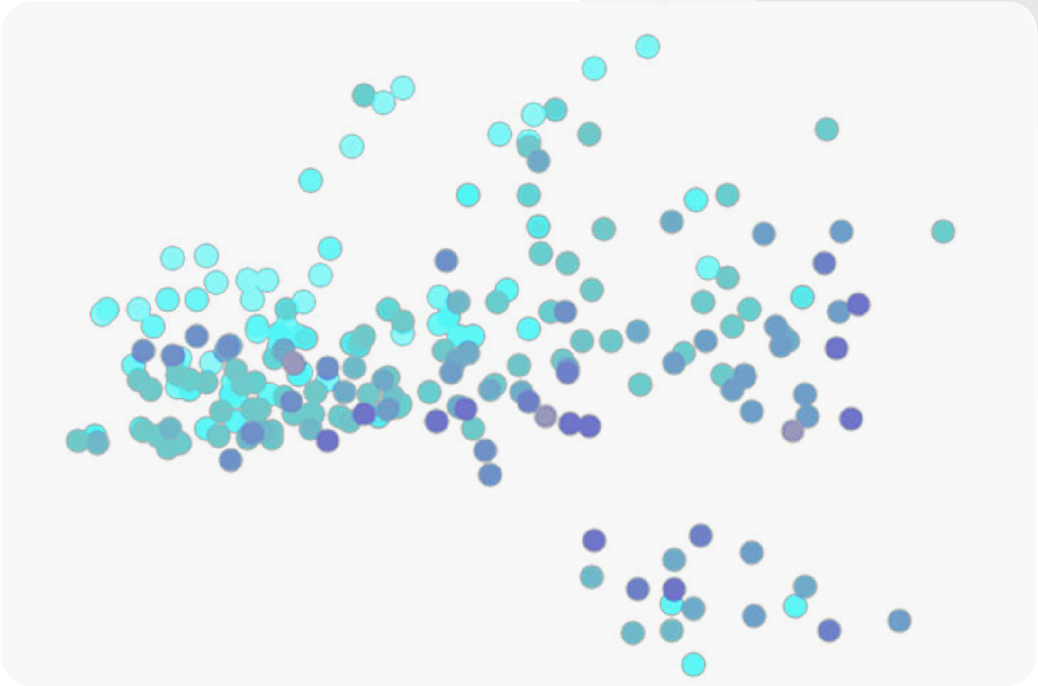
WHITE PAPER

Taste Graph Overview



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PRECISE TARGET

Taste-Aware Recommendations Drive Higher Conversion

A consumer purchase, otherwise referred to as a conversion, happens at the intersection of three forces: Need, Selection, and Urgency. Expressed as a mathematical model it appears as:

Need x Selection x Urgency = Conversion

Need is defined as the consumers wish to satisfy a recognized need. This might come in the form of a desire to look better at Monday's staff meeting, the attire required for next month's prom, or that you need a looser-fitting bathing suit after a winter of TV watching. Selection is the presentation of the retailer's options, whether it's this season's sweater collection, or the new shoe styles available for the spring. Urgency can be driven by either the consumer ("Oh no! Prom is next month!") or the retailer ("50% off Apparel - Sale ends Sunday!"). Retail marketers live in this mathematical equation, trying to influence the three forces. Their marketing departments attempt to stimulate your needs, present a superior selection, and impose urgency with promotions and sales.

At this stage of the Internet revolution, retailers have concluded that product recommendations rarely improve conversion. In the early stages of e-commerce, retailers added clickstream recommendation engines, which provided the functionality of "people who clicked on that product, also clicked on this one." Amazon and Netflix pioneered this approach, and there was a rush of vendors promising Amazon-like recommendations to retailers. In fact, one company, Rich Relevance, was founded by former Amazon people with the promise they could deliver Amazon-like recommendations to retailers. Unfortunately, the systems didn't work,

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Three Forces of Conversion

1. **Need:** consumers wish to satisfy a recognized need
2. **Selection:** the presentation of the retailer's options
3. **Urgency:** when a buyer feels like they need to act quickly

as evidenced by the lack of enthusiasm expressed by retailers. You could spend all day surveying retailers at a conference without finding a satisfied customer.

What's the Problem?

PreciseTarget has learned that predicting products a consumer will like is far more difficult than finding associations between product clicks. Retail customers have trusted us with more than 5 billion taste events, providing a rich data set for research. One important conclusion of our research is that consumers have far weaker affinities to brands than expected. In one study, we segmented consumers by brand affinity, by creating ranked deciles of people based on their frequency of purchasing a brand over a three-year period. The highest decile earned our "brand fan" designation, which for most brands meant they purchased more than six items of that brand. If it was Cole Haan, this person purchased six pairs in the past three years. We then compared the brand fans to other consumers who shared the same demographics as the brand fans. It was brand fans versus people like the fans. Clearly the brand fans would purchase more of the brand, right? No. Our research showed that brand fans were no more likely to re-purchase the brand than other similar people in a cohort group.

This means a retailer has the same statistical probability of selling a pair of Cole Haan shoes, or Nike running Shoes, to a brand fan as others who match the demographics (the only observed exception was cosmetics, where we saw more predictive brand re-purchase behavior). As an incidental point, this may explain why retailers don't use their transaction history data for email marketing. One could hazard a guess

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that the embedded algorithms in the email marketing system are saying re-purchase data isn't helpful.

Our research indicates that brand re-purchase isn't likely, nor a promising predictive signal. Conversely, our research indicates that consumers are very consistent in expressing taste. While indifferent to brand (including the brand of the retailer), they are very consistent about staying within the white lines of their expressed taste. This might mean they love jeans $50 to $65, cashmere blend sweaters under $60, or A-line dresses in bright colors. By way of analogy, you may love contemporary-style home architecture, but its doubtful you'll give your real estate agent a list of architects to guide your home search. More realistically, you'll provide a list of "metadata" elements, that say three bedrooms, metal roof, large windows, and an open floor plan. In the same way that the apparel brand is secondary, the architect's name is typically unknown to the buyer.

If consumers are consistent in expressing taste, how does the retailer learn this critical information? Wouldn't the retail sales clerk, or the e-commerce algorithm, be more successful if he/it understood the consumer's taste?

How Do We Determine Taste?

PreciseTarget by the Numbers

5 billion
SKU-level transactions

50 million
SKUs we receive from major retailers daily

550
Number of sub-categories our taste graph defines

PreciseTarget started with the creation of a normalized taxonomy of products from nearly all large retailers. The retailers provided us with daily catalog feeds, providing fuel to our data engine. One early hurdle was the normalization problem, given that retailers routinely rename products, re-categorize products, and 'add value' by changing the description of the product. A tiger-striped Michael Kors scarf sold by retailer A becomes a leopard print wrap at retailer B, and a brown stole at retailer C. One retailer will use a different name to replace 'polyester,' and another will display the product in metric dimensions. This example is the norm, rather than the exception, often resulting in 10 different products at 10 different retailers. If your taste is defined by what you historically buy, we need a "normal" view of your purchases to learn about you.

Each day we receive over 50 million SKUs from major retailers, with each SKU fitted to our normalized taxonomy. In this form, our normalized cross-merchant catalog might be second only to Amazon in catalog breadth. Next, we must understand the metadata of each product. Our retail partners provide 20+ metadata elements for each product. Each metadata element becomes a taste attribute, including price, discount level, fabric, brand, style, cleaning instructions, release date, and whether it's made of sustainable materials.

With this normal taxonomy of products, informed with comprehensive product metadata, we can build the taste graph. We fit consumers to the graph by matching the products they've purchased to our product taxonomy. PreciseTarget uses machine learning, to understand the types of products you like, by understanding the metadata of each product. We've learned there's little observed relationship between categories,

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meaning you may have expensive taste in shoes, like discount jeans, and prefer high-end wool coats, but you always buy cheap synthetic fabric socks. Our taste graph defines consumer taste in 550 sub-categories, accommodating the diversity of preferences held by each consumer across their closet (we might find a Cadillac parked in front of the contemporary house).

Delivery to Consumers

PreciseTarget delivers products that match your taste in the form of product sets. This means we aren't a product recommender, rather we recommend sets of products. A typical product set is composed of 50 to 200 products, which could appear as 100 dresses at Macy's under $70 (from their catalog of 6,000 women's dresses), or 50% off 100 running shoes at Finish Line (from their catalog of 500 women's running shoes). We have the ability to personalize each product set for each user, which is natural given that everyone has a different and unique taste graph. This means the 100 Macy's dresses for consumer A will be different from the 100 dresses presented to consumer B.

Consumers like the selection and choice process and we believe product sets are a consumer-preferred approach than the single products solution provided by clickstream recommenders. Shopping remains a fun process for consumers, and we view our mission as helping consumers navigate the overwhelming selection of products in the market. Our retail customers now have new capabilities to acquire, expand, and reactivate customers.

We deliver the product sets via real-time APIs to our partners, including retailers, deal sites, content publishers, and credit card deal and loyalty systems. You can learn more about PreciseTarget at precisetarget.com.

About PreciseTarget

PreciseTarget is a retail data company focused on helping retailers drive higher conversion by using our innovative Taste Graph. The company has profiled the product tastes of over 200 million U.S. adults in the largest retail categories, including apparel, footwear, cosmetics, home goods, and electronics. Our customers have trusted us with over 5 billion SKU-level transactions, and more than 200 major retailers provide us with daily data feeds. Retailers, agencies, and ad-tech companies use our audiences and customer profile data for e-commerce, in-store, and customer insight applications. To learn more, please contact us at Sales@PreciseTarget.com.

Our Founder

Our team is led by Rob McGovern, an experienced entrepreneur who founded Careerbuilder.com. He has previously served in executive positions at Hewlett Packard and Legent Corporations, and has held many board directorships at private and public companies. He's a graduate of the Smith School of Business at the University of Maryland, and in his free time is a cyclist, airplane pilot, and mentor to young entrepreneurs.