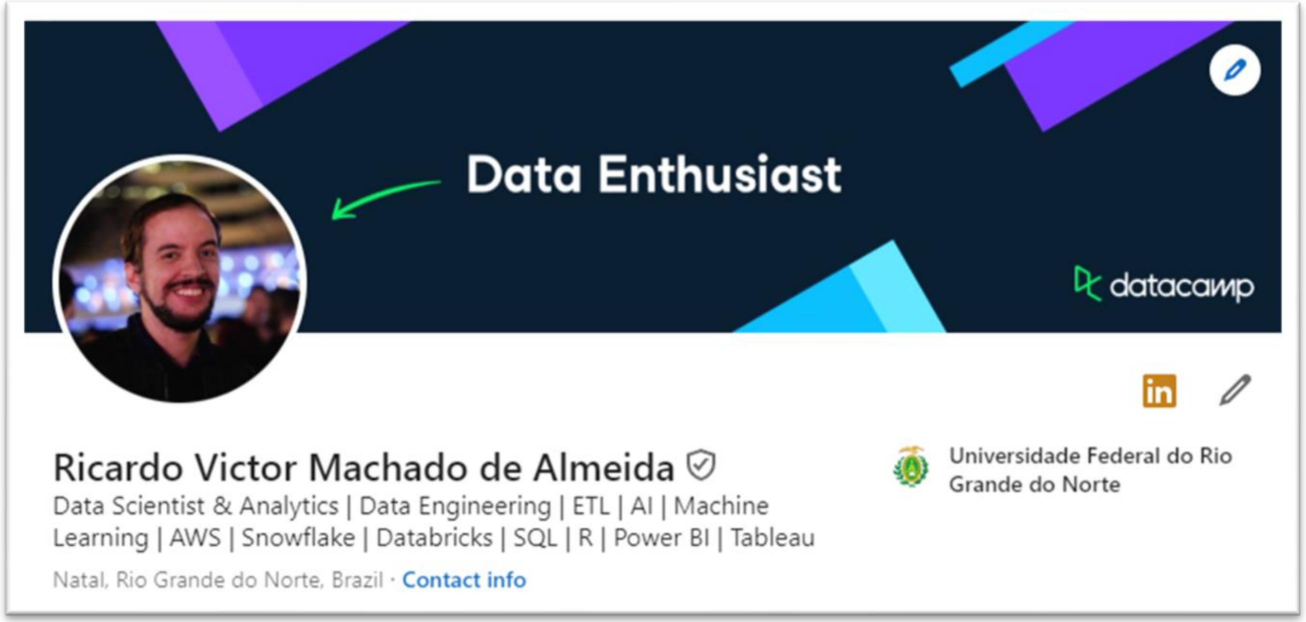
Marketing Business Intelligence *Insights & Strategies*

Leveraging Data for Enhanced Marketing Effectiveness

Ricardo V M Almeida | BI Analyst (*candidate*)

3rd January 2024

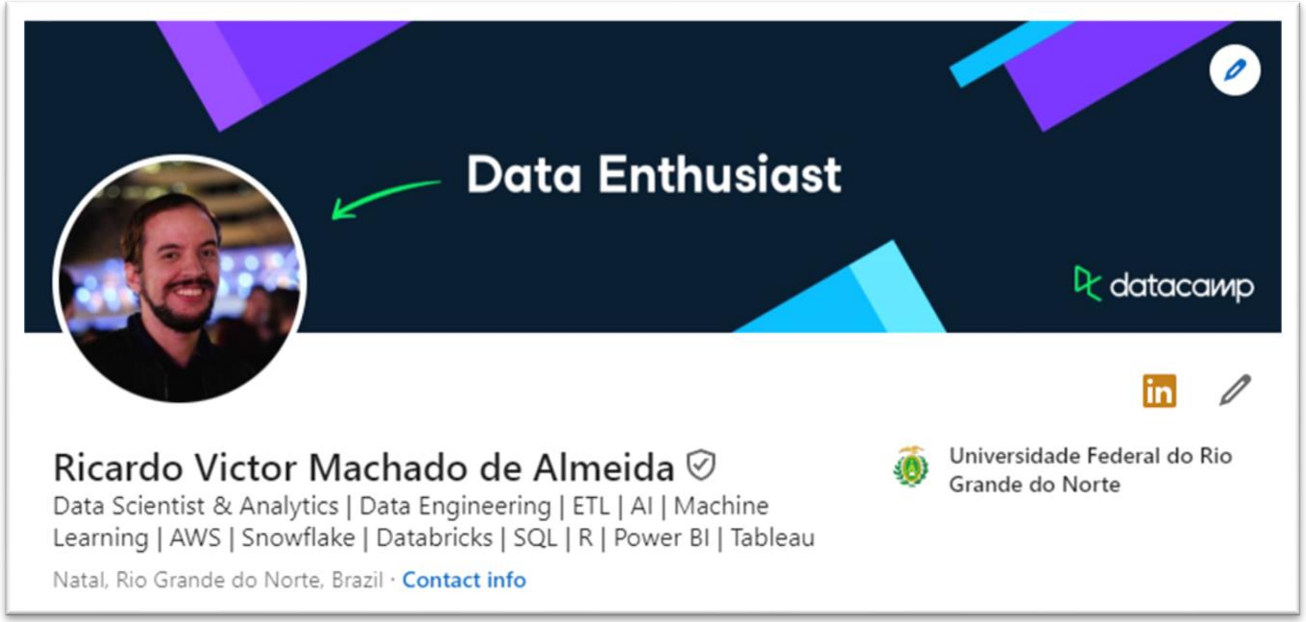
About Me



Professional experience

- Data Scientist / BI Analytics on Ioasys/Alpargatas SA:
  - "At *ioasys*, I managed E-commerce and OMNI model pipelines, using Python, PySpark and SQL."
  - Keywords: E-commerce, OMNI, Python, PySpark, SQL.
- Research at Alana AI and Federal University of Rio Grande do Norte:
  - "My experience in research and as a Data Manager at Alana AI gave me unique skills in..."
  - Keywords: AWS, Confluence, Bitbucket, ML, AI.

About Me



- My experience in querying and extracting data via SQL from *Data Warehouses*, and analysis via *Google Analytics* aligns with...
  - **Keywords:** SQL, Data Warehouse, Google Analytics.
- Developed and maintained advanced dashboards in...
  - **Keywords:** Google Data Studio, Tableau, PowerBI.
- My background includes presenting analysis and insights to support...
  - **Keywords:** Business Evolution, Project Initiatives, Strategic Decisions.

Agenda

Overview of key points and sections of the presentation.

01. Introduction to Data Analysis

02. Product Pricing Strategy

03. Brand Positioning and Inventory Management

04. Customer Engagement

05. Temporal Patterns in Customer Behavior

06. Data-Driven Decision Making

07. New Dataset | Makeup

08. Consumer Category Behavior

09. Conclusion

10. Q&A and *feedback*

Introduction

Brief overview of the data and analysis methodology.

Property	Description	Type	Note
event_time	Time when event happened at (in UTC).	*time*	**20692840** total values
event_type	Four kinds of event: view, cart, purchase, remove from cart	*string*	**65.92%** view, **6.22%** purchase, **27.86** cart
product_id	ID of a product.	*integer*	**54571** distinct products
category_id	Product's category ID.	*integer*	**525** category IDs
category_code	Product's category taxonomy, code name (can be missing).	*string*	**12** different taxonomies
brand	Downcased string of brand name (can be missing).	*string*	**273** different brands
price	Float price of a product. Present.	*float*	min: **-7.937**, max: **3.278**, mean: **8.534**
user_id	Permanent user ID.	*integer*	**1639358** total users
user_session	Temporary user's session ID. Changed after pauses.	*string*	

This dataset includes behavioral data from a mid-sized cosmetics online store from *Oct. 2019 to Jan. 2020*. Each entry in this dataset represents an event related to products and users. The events consist of different types such as views, items added to cart, items removed from cart, and purchases.

Introduction

Brief overview of the data and analysis methodology.

```
[ ]
# Show a general view of data
# Look at the first 10 rows.
df.head(10)
```

	event_time	event_type	product_id	category_id	category_code	brand	price	user_id	user_session
0	2019-11-04 18:50:11+00:00	view	5885574	1487580013950664926	None	markell	8.78	523808159	0f68fc68-3600-4feb-8bd1-9f89d96229c2
1	2020-02-10 10:53:30+00:00	view	5713017	1487580008011531230	None	coifin	63.48	599102798	bddfe4ee-1ebd-4cd6-af33-6788efee01d8
2	2020-01-30 02:28:22+00:00	view	5910417	1487580008053474272	None	dewal	22.19	607954171	a214b8fe-4d16-4857-bc9f-670f8e4aa71e
3	2019-12-22 17:47:03+00:00	purchase	5913387	1487580008112194531	None	dewal	7.57	459377142	86ee6c63-a4c7-41bb-993a-8df9679d06eb
4	2020-01-17 12:37:43+00:00	view	5862564	1487580008145748965	None	roubloff	1.71	561581928	c83b714c-25be-4db9-8231-1656b6e8341c
5	2019-10-22 10:25:53+00:00	view	5587656	1487580008145748965	None	roubloff	3.65	140457461	7ea68ac1-9f0b-499f-b9e0-d8226fe872ac
6	2019-11-12 12:02:21+00:00	view	5851710	1487580008246412266	None	kaypro	25.00	440370278	c0c1316c-183f-4921-8718-afef2102cbc9
7	2020-02-01 11:45:48+00:00	cart	5862721	1487580008246412266	None	keune	21.00	604164445	534255a9-7b0c-4f9a-a483-140cd12b989e
8	2019-11-10 16:23:00+00:00	view	5852312	1487580008246412266	None	kaypro	15.00	569787907	f178c74a-89da-4b9a-b213-c3344ec02f9a
9	2020-01-02 10:12:08+00:00	purchase	5873315	1487580008246412266	None	likato	7.89	416846267	c0e952f3-8afb-41df-9204-ae4c53caba16

Introduction

Brief overview of the data and analysis methodology.

To an **Exploratory Data Analysis (EDA)** is a critical step in understanding your data, identifying patterns, spotting anomalies, and testing hypotheses. Let's delve into the importance of analyzing specific aspects such as products with zero prices, the relationship between prices and brands, and the patterns in event times:

```
[ ]  1 # Summarize the dataset
     2 df.describe()
```

	product_id	category_id	price	user_id
count	20692840.0	20692840.0	2.069284e+07	20692840.0
mean	5484296.739535	-30478489757.482208	8.534735e+00	521552663.55997
std	1305715.731109	169103784917515008.0	1.938142e+01	87443121.502008
min	3752.0	1487580004807082752.0	-7.937000e+01	465496.0
25%	5724650.0	1487580005754995456.0	2.060000e+00	481830633.25
50%	5810720.0	1487580008263189504.0	4.050000e+00	553129688.0
75%	5857864.0	1487580013506068736.0	7.060000e+00	578857321.0
max	5932595.0	2242903426784559104.0	3.277800e+02	622090237.0

To get a better understanding of the data, I will perform the following analyses:

- **Basic statistics** (*count, mean, etc.*) for numerical columns like `price`.
- **Distribution** of `event_type` to see the frequency of each event.
- Check for **missing values** in important columns like `category_code`, `brand`, and `event_type`.
- **Summary of unique values** in columns like `product_id`, `user_id`, and user_session.

Introduction

Brief overview of the data and analysis methodology.

To an **Exploratory Data Analysis (EDA)** is a critical step in understanding your data, identifying patterns, spotting anomalies, and testing hypotheses. Let's delve into the importance of analyzing specific aspects such as products with **zero prices**, the **relationship between prices and brands**, and the **patterns in event times**:

First Observations to Next Steps to Market Analysis

1. **Products with Zero Prices**: Analyzing products with zero prices helps identify potential data quality issues or special cases like promotions or giveaways. This is crucial for accurate revenue projection and understanding marketing strategies. Zero-priced items could skew average pricing metrics and need careful handling in any analysis.
2. **Prices and Brands**: This analysis focuses on understanding the relationship between product prices and their associated brands. It provides insights into brand positioning (premium vs. budget), consumer behavior (which price ranges are popular for certain brands), and competitive market dynamics. It's also key for assessing pricing strategies and understanding price elasticity across different brands
3. **Events of Time**: Analyzing temporal patterns in customer events (like purchases or views) helps identify trends, seasonality, and customer engagement times. This is vital for planning marketing initiatives, managing inventory, and predicting future demand. It also assists in anomaly detection, revealing unusual activity that might indicate system issues or market shifts.

Each area provides significant ***insights*** into business operations and customer behavior, guiding strategic decision-making.

OBS.: For the functionality of this presentation, it is necessary to view the descriptive analysis of the data through **Google Colab Notebook [Link].**

Data Analysis with Market Insights

- This study presents a comprehensive analysis of consumer behavior and product performance in an **online cosmetics store**, covering the *period from October 2019 to February 2020*. By leveraging advanced analytics techniques, the report aims to unearth patterns, trends, and actionable insights from complex datasets.
- In the dynamic realm of online retail, the role of **a marketing business intelligence analyst** is pivotal in steering strategic decisions through data-driven insights.
- Such analyses are indispensable for a marketing business intelligence analyst, as they illuminate aspects like customer preferences, purchasing behavior, product popularity, and overall market dynamics.
- The insights derived from the report are expected to inform crucial marketing strategies, optimize customer engagement, and drive business growth, ensuring that the company remains competitive and responsive to consumer needs in a constantly evolving digital marketplace.

Product Pricing Strategy

Data findings on product pricing.

Products with Zero-prices

```
# Filter products with 0-price and less
zero_price = df[df['price'] <= 0]
zero_price.head()
```

	event_time	event_type	product_id	category_id	brand	price	user_id	user_session
3502	2020-02-06 21:00:59+00:00	cart	5814734	1783999068909863670	None	0.0	345824591	35eda300-9c23-4d87-96a4-1da53bd142f7
3755	2020-01-29 13:09:54+00:00	view	5923293	1487580013145358517	None	0.0	493481951	69878e7a-72f3-42f6-8fbc-4815cfa5e5c0
3875	2020-01-17 09:03:13+00:00	cart	5920432	1487580011652186237	None	0.0	352394658	dee05e29-f331-48dc-b1b3-547985fc2aa4
4195	2020-02-01 07:35:38+00:00	remove_from_cart	5838756	1487580006962955182	None	0.0	403905011	fc7282ef-2bba-f8b0-90fa-2ea6abd747af
4205	2019-12-23 16:04:41+00:00	view	5899868	1487580013170524342	None	0.0	563047849	e26b063a-473a-4301-ac09-bd73d276cae5

It seems like those 0-price product has **no brand** and some others with less than zero, almost as if they had a **discount**?

Product Pricing Strategy

Data findings on product pricing.

With this, we observe that all the **zero-price** products have **no brand**, accounting for **40.31%** of total products. However, it's important to note that **not all no-brand** products are priced at 0; the number of products with no brand accounts for **65.47%** of the total. Additionally, 0-price products may be attributed to the following factors:

1. **Missing Information**: The unknown brand and zero price might indicate that these products are placeholders or items for which complete information hasn't been entered into the dataset.
2. **Free or Promotional Items**: A zero price might intentionally indicate that the product is not being sold but rather offered as a promotion.
3. **Special Cases**: Some products might genuinely have a zero price due to unique circumstances. For example, a software product with a freemium model might have a free version with a zero price. Or products that have not shown prices can be considered as **placeholder prices**.

Products with Zero-prices

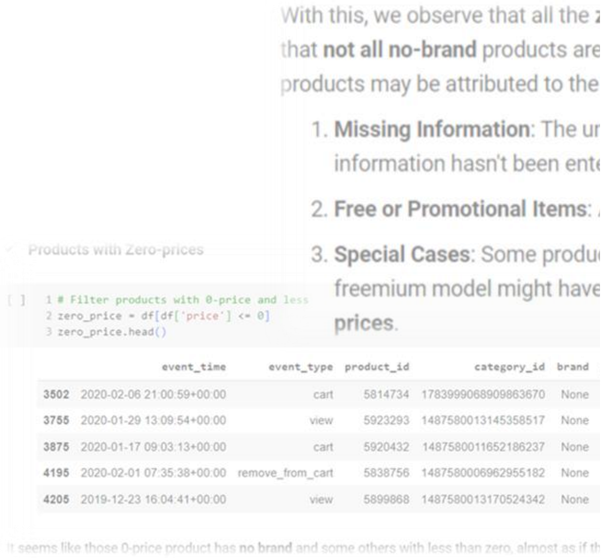
```
1 # Filter products with 0-pr
2 zero_price = df[df['price']
3 zero_price.head()
```

	event_time							
3502	2020-02-06 21:00:59+00:00	cart	[illegible]	[illegible]	None	0.0	[illegible]	[illegible]
3755	2020-01-29 13:09:54+00:00	view	5923293	1487580013145358517	None	0.0	493481951	69878e7a-72f3-42f6-8fbc-4815cfa5e5c0
3875	2020-01-17 09:03:13+00:00	cart	5920432	1487580011652186237	None	0.0	352394658	dee05e29-f331-48dc-b1b3-547985fc2aa4
4195	2020-02-01 07:35:38+00:00	remove_from_cart	5838756	1487580006962955182	None	0.0	403905011	fc7282ef-2bba-f8b0-90fa-2ea6abd747af
4205	2019-12-23 16:04:41+00:00	view	5899868	1487580013170524342	None	0.0	563047849	e26b063a-473a-4301-ac09-bd73d276cae5

It seems like those 0-price product has **no brand** and some others with less than zero, almost as if they had a **discount**?

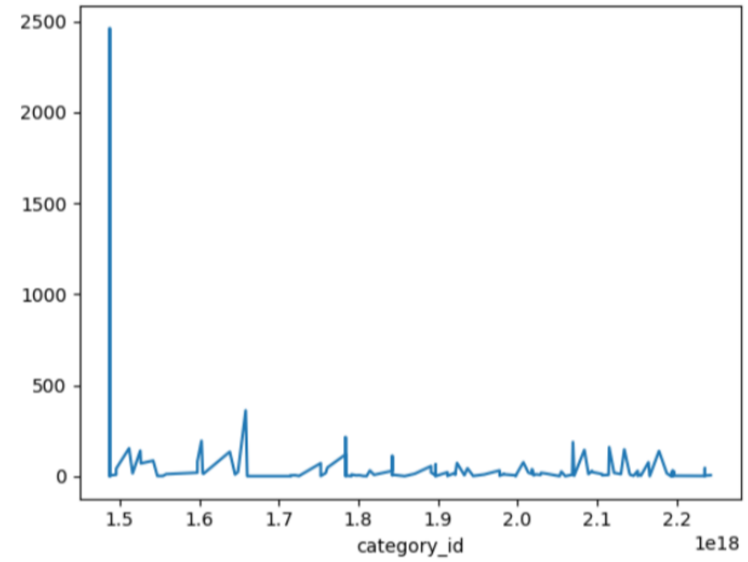
Product Pricing Strategy

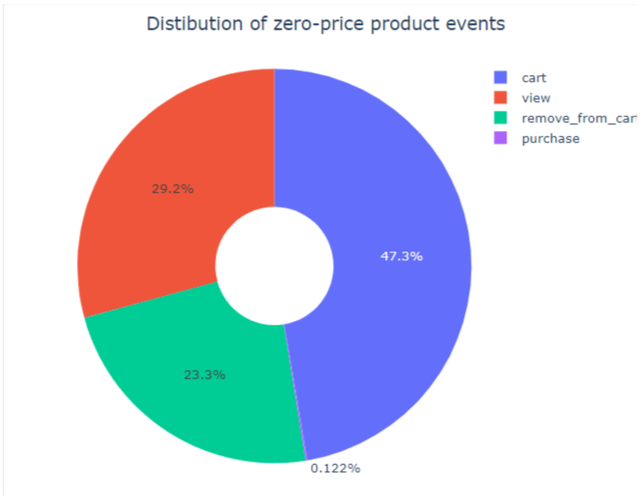
Data findings on product pricing.




```
[ ]  # See the distribution
     zeroprice_mainCat.plot()
```

<Axes: xlabel='category_id'>





We can observe that zero-price products are present across all product ranges. It is also important to analyze the events associated with these zero-price products:

Product Pricing Strategy

Insight:

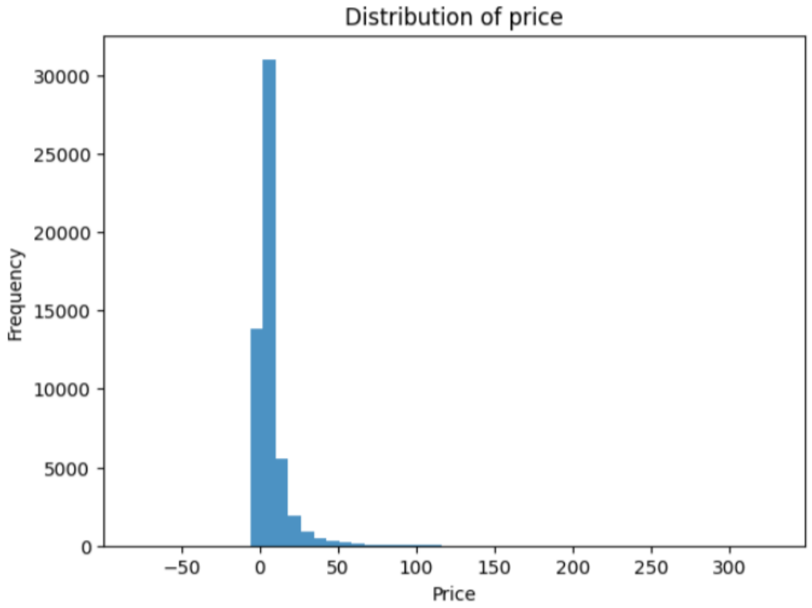
The presence of a large number of zero-priced and low-priced products suggests potential data quality issues or unique pricing strategies like promotions or giveaways.

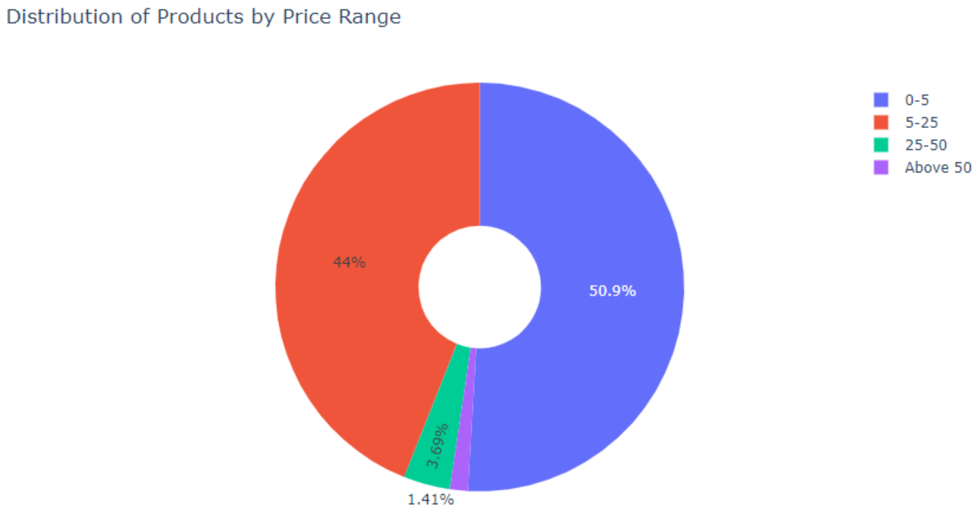
Suggestion:

Regularly review and clean product pricing data to ensure accuracy. Consider segmenting products into different pricing tiers for targeted marketing and pricing strategies.

Brand Position and Inventory Management

Analysis of brand-related pricing patterns.



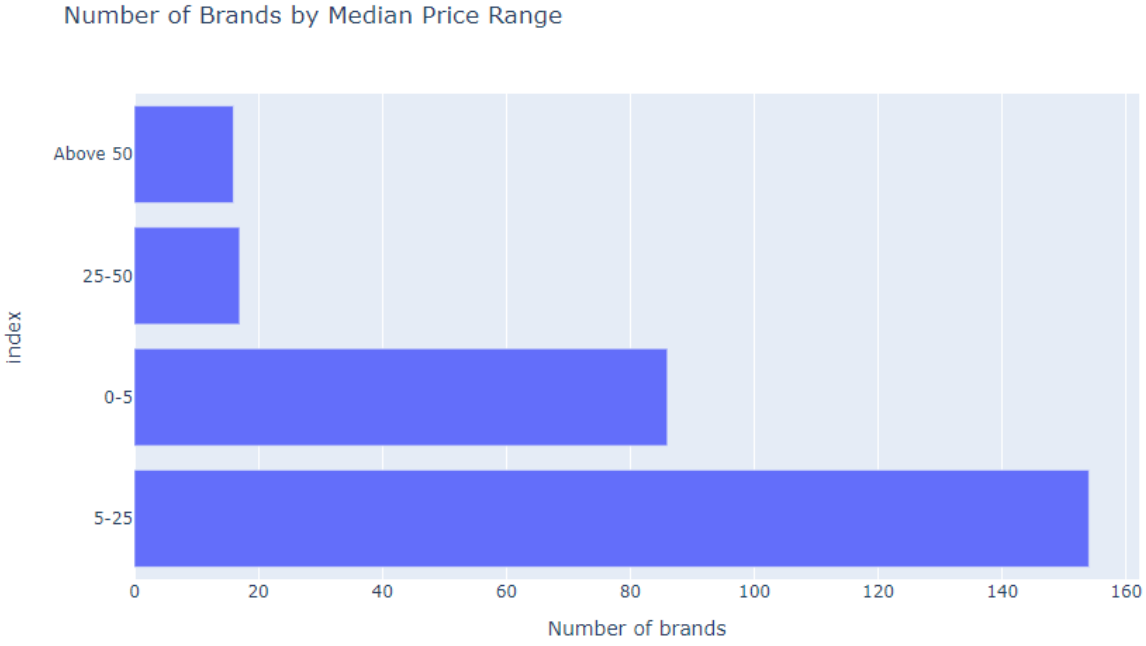


Most frequent prices fall in the range from **0 to 5** (almost 52% of all products). In constrast, product with price that **above 500 accounts for less than 2%** of the products. How about the brand? The price range of each brand are be segmented by using *median price values:*

The prices on the shopping website are **left-skewed**, with almost all falling **below 50**. The distribution shows that prices close to zero have the highest frequency. We can create a pie chart by segmenting the prices into 4 ranges: *0-5, 5-25, 25-50, and above 50*.

Brand Position and Inventory Management

Analysis of brand-related pricing patterns.



The presence of a significant number of brands in the **5-25 range** suggests a consumer demand for **mid-range products** with advanced features.

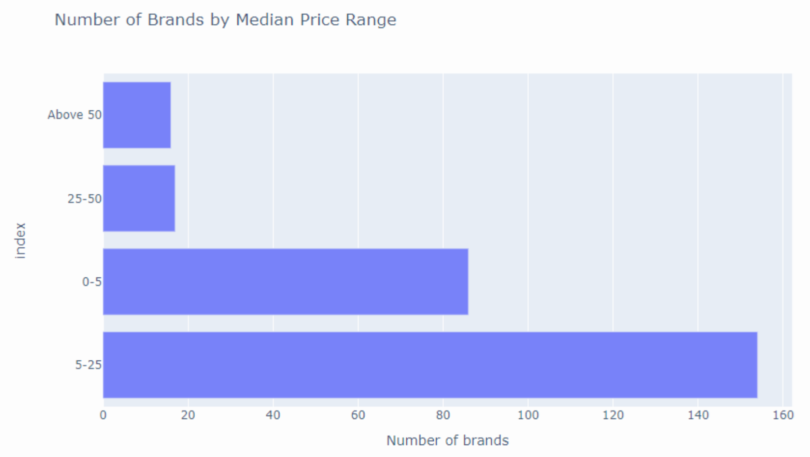
Brand Position and Inventory Management

Insight:

The data shows variations in product prices across different brands, indicating different market positioning (*premium vs. budget brands*).

Suggestion:

Tailor marketing messages according to brand positioning. For premium brands, focus on quality and exclusivity, while for budget brands, highlight value and affordability. Adjust inventory based on brand popularity and pricing trends



The presence of a significant number of brands in the **5-25 range** suggests a consumer demand for **mid-range products** with advanced features.

Customer Engagement

Engagement levels in different stages of the sales funnel.

Event Distribution

In the context of the provided dataset from an online cosmetics store, this analyze involves examining the frequency and types of interactions that users have with products on the website. These interactions are categorized into different types of events, each representing a specific action taken by the users. The main event types in this dataset are:

1. **View**: This event is recorded when a user views a product. It indicates initial interest or curiosity about the product.
2. **Cart**: This event occurs when a user adds a product to their shopping cart. It's a stronger indication of purchase intent than a view.
3. **Remove from Cart**: This event is logged when a user removes a product from their shopping cart. It often signifies a change of mind or a decision against purchasing the product.
4. **Purchase**: This event is the actual purchase of a product by a user. It's the most critical event as it directly relates to sales.

Customer Engagement

Engagement levels in different stages of the sales funnel.

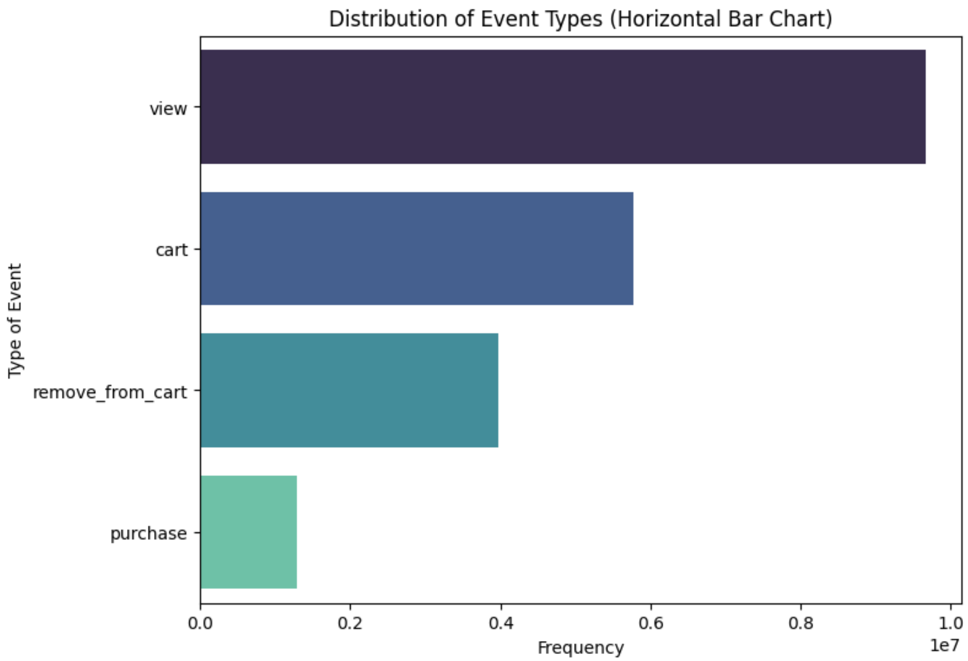
Analyzing the distribution of these events can provide valuable insights into consumer behavior and the effectiveness of the website's user interface and marketing strategies. Key aspects of this analysis might include:

- **Frequency of Each Event Type**: Understanding how often each type of event occurs can reveal which stages of the customer journey are the most and least engaged. For instance, a high number of views but low number of purchases might indicate a problem in converting interest into sales.
- **Conversion Rates**: Calculating the rate at which views convert to cart additions and purchases can help assess the effectiveness of the product listings and the overall sales funnel.
- **User Engagement**: Analysis can show how users interact with the website, including which products attract the most attention and which ones successfully lead to sales.
- **Strategic Insights for Marketing and Sales**: Understanding which products are frequently added to carts but not purchased might indicate pricing or product description issues. Similarly, products with high views but low cart additions might need better positioning or promotional strategies.

In summary, analyzing event distribution in this context is about understanding how users interact with the online store's products and identifying opportunities to enhance the shopping experience, thereby potentially increasing sales and customer satisfaction.

Customer Engagement

Engagement levels in different stages of the sales funnel.



Analyzing the
website's use

- Frequer journey problen
- Convers effectiv
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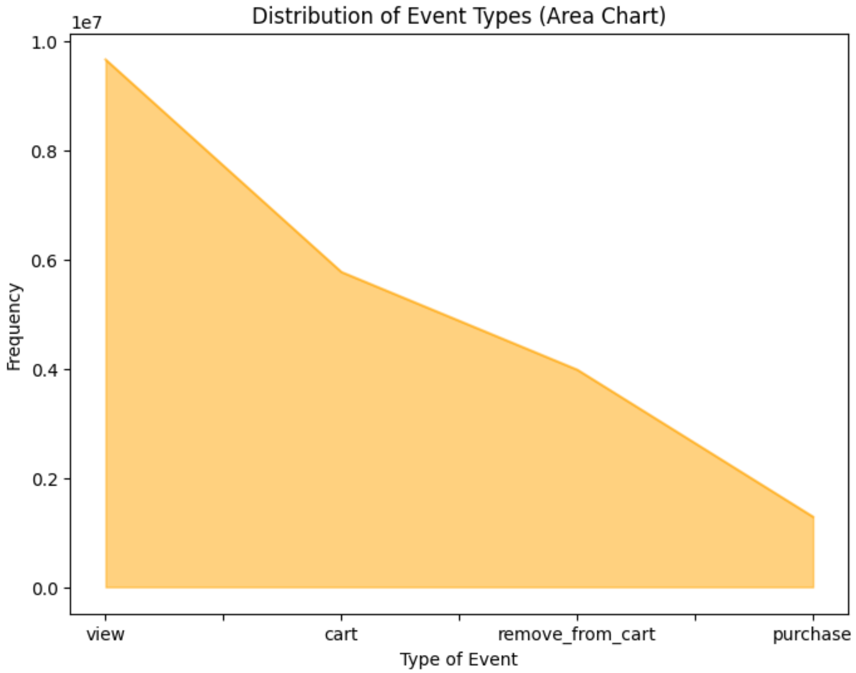
In summary, analyzing event distribution in this context is about understanding how users interact with the online store's products and identifying opportunities to enhance the shopping experience, thereby potentially increasing sales and customer satisfaction.



These charts would help illustrate the nature of user engagements with the site, enabling business analysts to identify opportunities to optimize the sales funnel, enhance customer experience, and increase conversion.

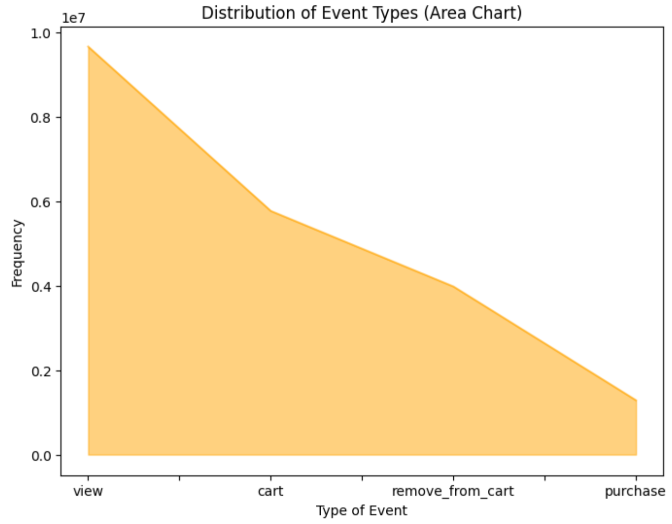
Customer Engagement

Insight:

Analysis of event types (views, carts, purchases) reveals how customers interact with the site, indicating different levels of engagement in the sales funnel.

Suggestion:

Develop strategies to move customers through the funnel more effectively. For example, target users who view products frequently with personalized recommendations or retargeting ads to encourage purchases.



These charts would help illustrate the nature of user engagements with the site, enabling business analysts to identify opportunities to optimize the sales funnel, enhance customer experience, and increase conversion.

Temporal Patterns in Customer Behavior

Trends and seasonality observed in customer interactions.

Each customer is assigned their own ID for the corresponding customer account/IP. The dataset reflects customer behavior based on the events that they interacted with on the e-commerce cosmetics store platform.

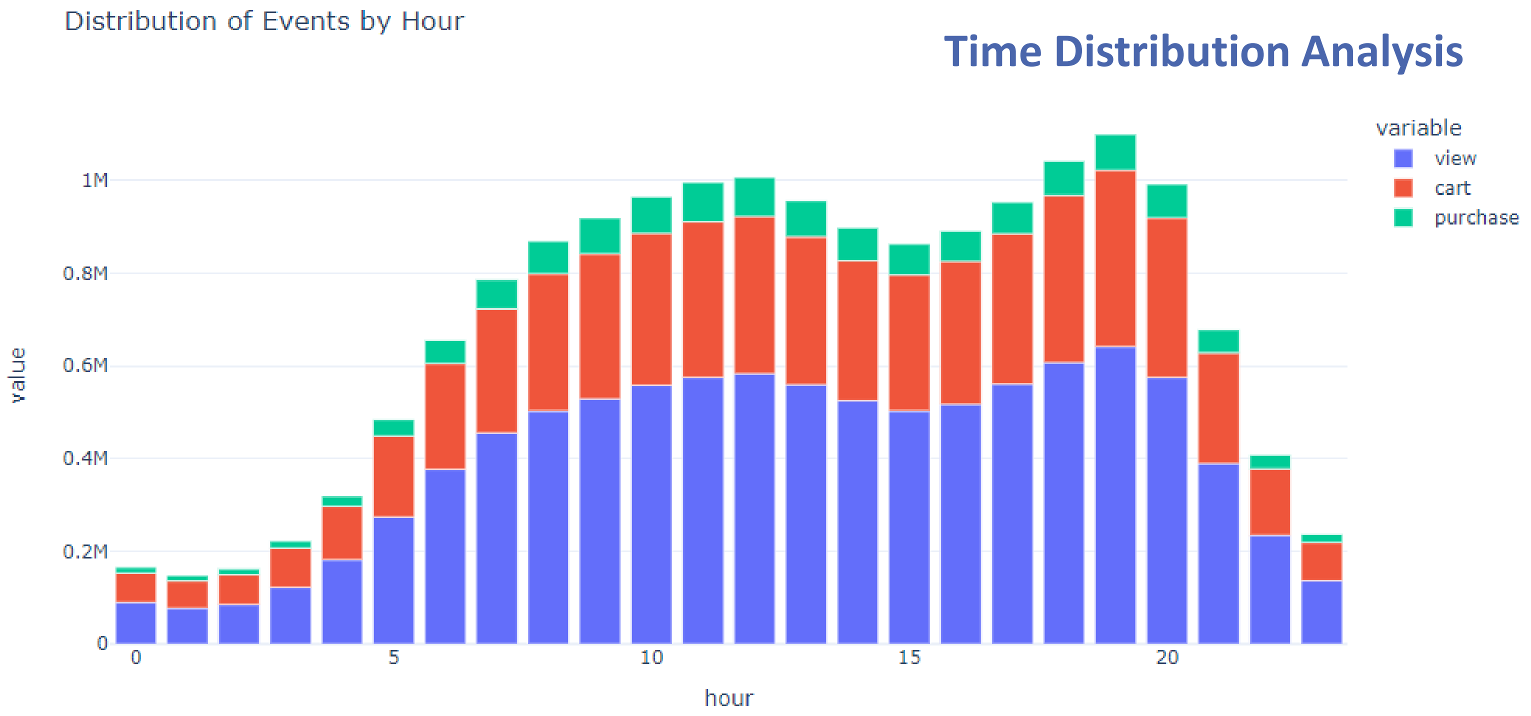
```
[ ]  1 df.loc[df.user_session == "25415286-97b2-4174-8d66-36cee689fd9a"].sort_values(by=['date', 'time'])
```

	date	weekday	time	event_type	product_id	category_id	brand	price	user_id	user_session
3123340	2019-12-24	1	10:39:59	view	5865141	1648815651034235876	rosi	4.13	591786331	25415286-97b2-4174-8d66-36cee689fd9a
111025	2019-12-24	1	10:40:52	view	5865130	1648815651034235876	rosi	4.13	591786331	25415286-97b2-4174-8d66-36cee689fd9a
9241599	2019-12-24	1	10:44:54	view	5780837	1487580005092295511	rosi	7.86	591786331	25415286-97b2-4174-8d66-36cee689fd9a
349138	2019-12-24	1	10:47:55	view	5915803	1648815651034235876	None	0.00	591786331	25415286-97b2-4174-8d66-36cee689fd9a
3152930	2019-12-24	1	10:48:05	view	5915804	1648815651034235876	None	0.00	591786331	25415286-97b2-4174-8d66-36cee689fd9a
8414181	2019-12-24	1	10:48:12	view	5915805	1648815651034235876	None	0.00	591786331	25415286-97b2-4174-8d66-36cee689fd9a
8172234	2019-12-24	1	10:48:25	view	5915807	1648815651034235876	None	0.00	591786331	25415286-97b2-4174-8d66-36cee689fd9a
1094598	2019-12-24	1	10:48:32	view	5915808	1648815651034235876	None	0.00	591786331	25415286-97b2-4174-8d66-36cee689fd9a
7915804	2019-12-24	1	10:48:51	view	5915992	1487580005092295511	None	0.00	591786331	25415286-97b2-4174-8d66-36cee689fd9a
1733978	2019-12-24	1	10:50:25	view	5865125	1648815651034235876	rosi	4.13	591786331	25415286-97b2-4174-8d66-36cee689fd9a

Temporal Patterns in Customer Behavior

Trends and seasonality observed in customer interactions.

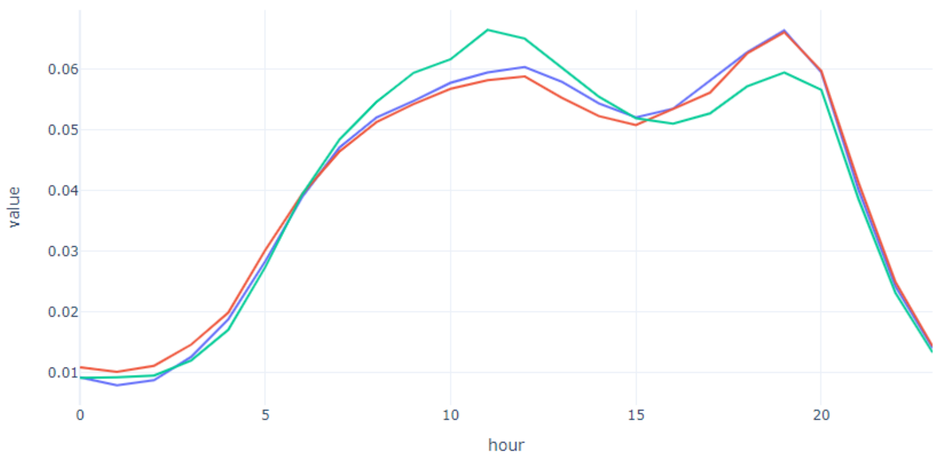
Time Distribution Analysis



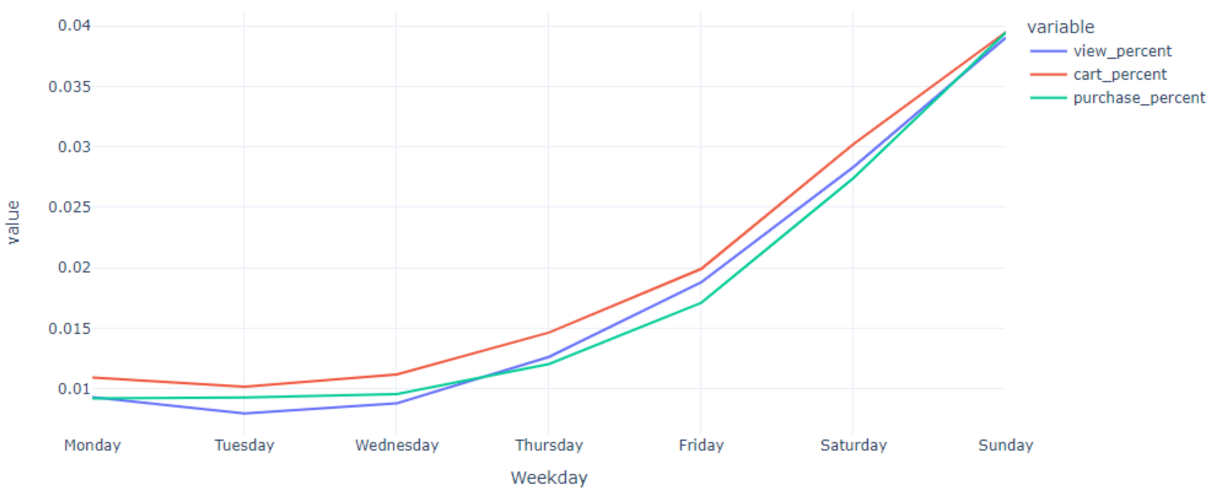
Temporal Patterns in Customer Behavior

Trends and seasonality observed in customer interactions.

Percentage Distribution of Events by Hour



Percentage Distribution of Events by Weekday



Temporal Patterns in Customer Behavior

Insight:

The time series analysis of product prices and customer events shows trends and seasonality in customer behavior.

Suggestion:

Leverage these insights for timing marketing campaigns, managing stock levels, and introducing dynamic pricing strategies during peak demand periods.

Data-Driven Decision Making

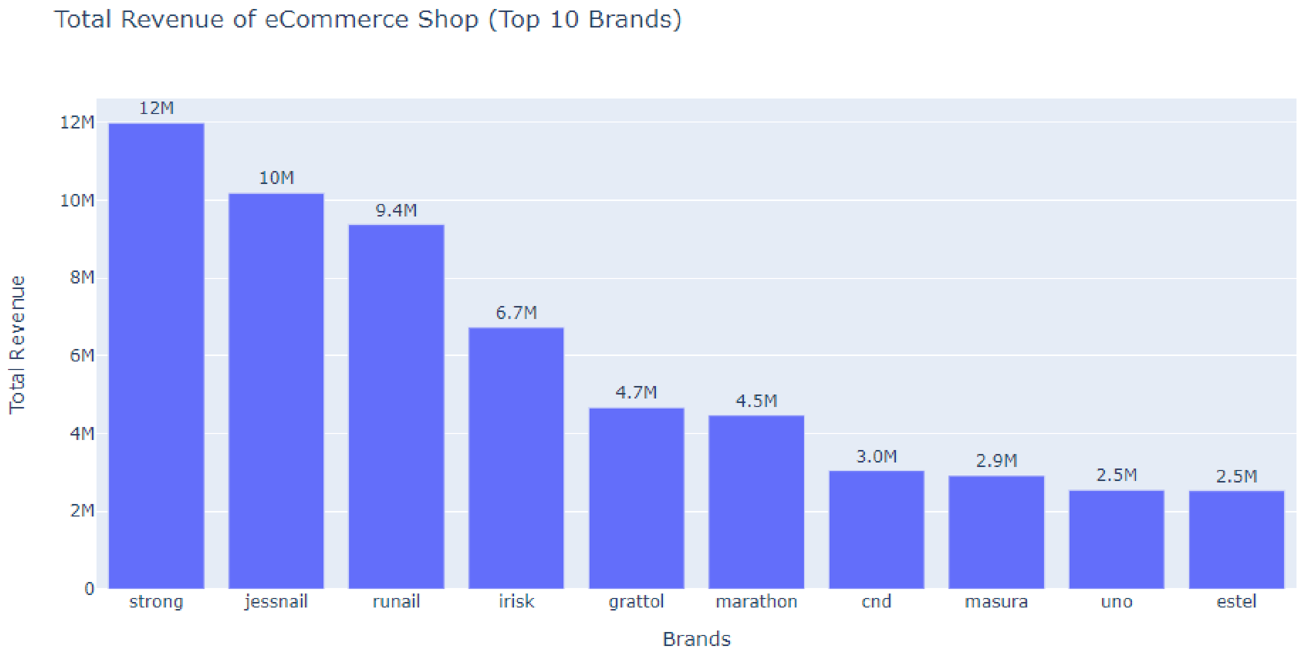
```
# Total order per time by brands
order_per_weekday = df[df.event_type == "purchase"].groupby(["weekday", "brand"])["event_type"].count().reset_index()
order_per_weekday.head(10)
```

	weekday	brand	event_type
0	0	airnails	1013
1	0	almea	21
2	0	ardell	117
3	0	arganoil	1
4	0	art-visage	621
5	0	artex	205
6	0	aura	16
7	0	avene	5
8	0	babyliss	11
9	0	balbcare	52

In the context of analyzing an e-commerce dataset, the ***Category and Brand Analysis*** focuses on understanding the dynamics and performance of different product categories and brands within the online store. This analysis involves examining how various categories and brands fare in terms of user engagement events such as views, cart additions, purchases, and removals from the cart. It helps identify which product categories and brands are most popular, which ones are leading in sales, and how they compare in terms of pricing strategies.

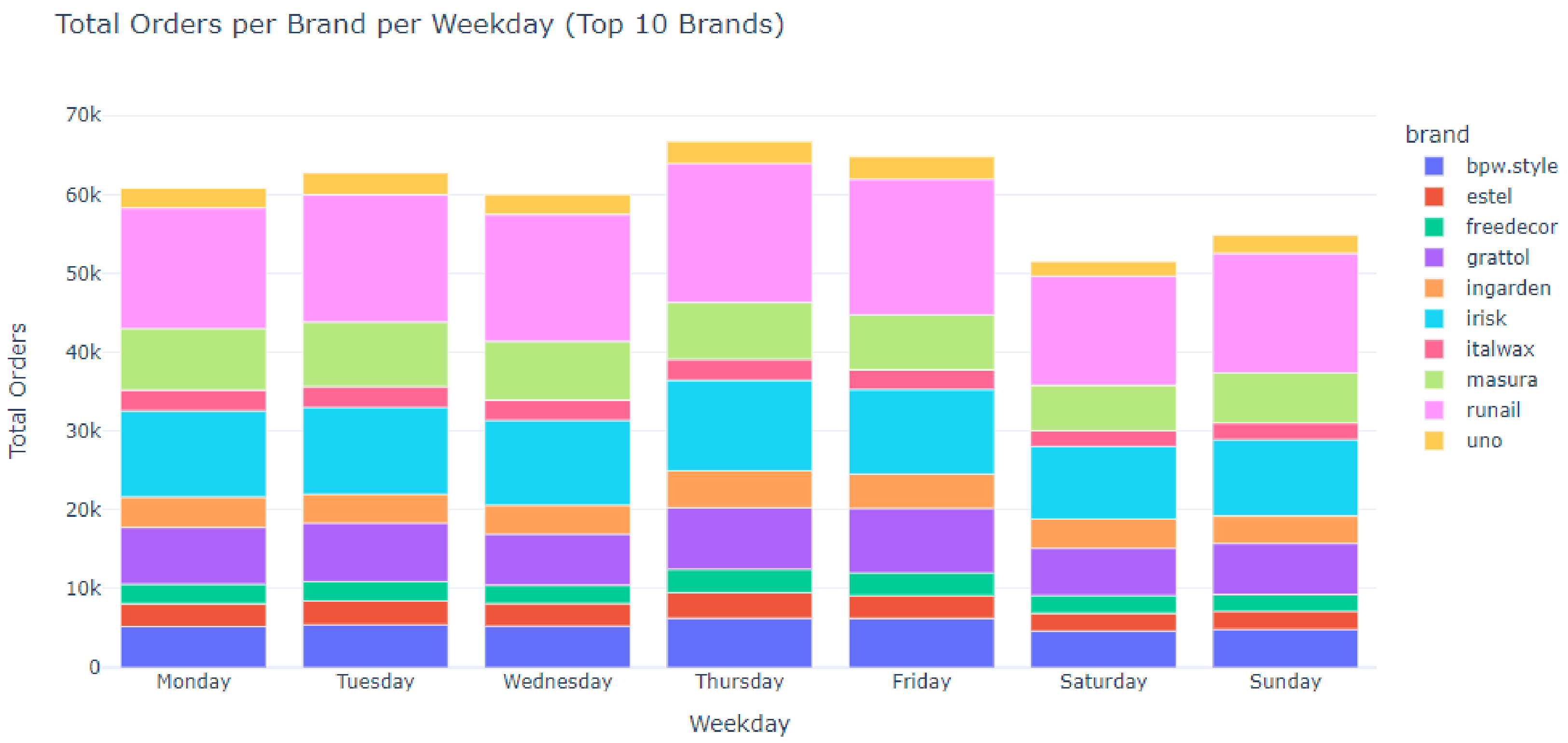
This analysis can reveal consumer preferences and trends, allowing for targeted marketing strategies, inventory management, and pricing optimizations. By understanding the performance of different categories and brands, businesses can make informed decisions to enhance product offerings, promote high-performing brands or categories, and improve customer engagement and satisfaction.

Data-Driven Decision Making



This analysis gives us an overview of how different categories and brands perform in terms of user engagement and price ranges. We can dig deeper to understand which categories and brands are more popular or generate more revenue, as well as study price trends in relation to popularity and conversion rate.

Data-Driven Decision Making



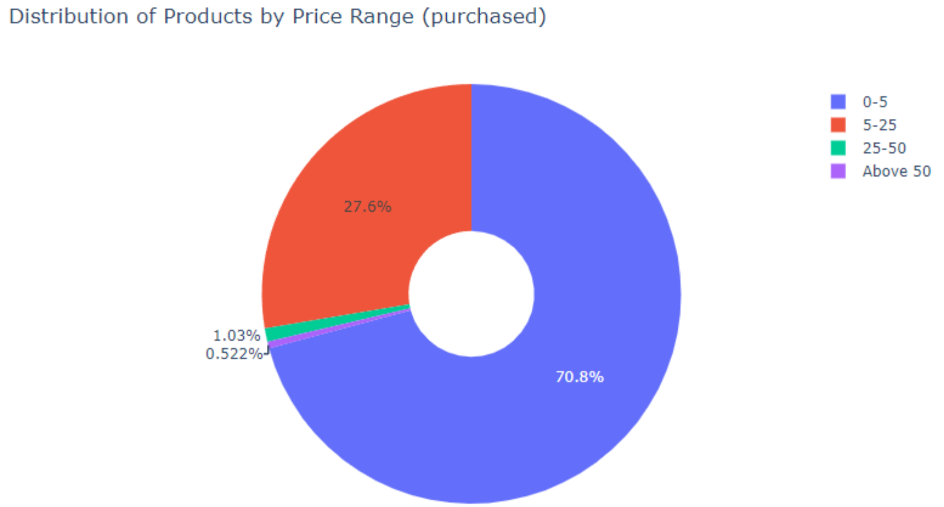
Data-Driven Decision Making

Insight:

The analysis demonstrates the power of data in uncovering insights about customer preferences, market trends, and operational efficiencies.

Suggestion:

Foster a culture of data-driven decision-making. Regularly analyze customer data to stay ahead of market trends, optimize marketing strategies, and enhance customer experience.



New Dataset | Makeup-api

> "Arbitrarily cross-reference product identifiers with the https://makeup-api.herokuapp.com/ API so that we have data about products and their respective categories."

	id	brand	name	price	currency	rating	category	product_type	created_at	updated_at
0	966	nyx	Cosmic Gel Liner	10.0	USD	NaN	gel	eyeliner	2017-12-24 02:32:26.896000+00:00	2017-12-24 02:32:27.267000+00:00
1	965	nyx	Gel Liner And Smudger	9.0	USD	NaN	gel	eyeliner	2017-12-24 02:32:25.619000+00:00	2017-12-24 02:32:25.974000+00:00
2	674	dior	FLASH LUMINIZER	29.0	GBP	NaN	highlighter	foundation	2017-12-03 23:22:20.685000+00:00	2017-12-23 20:59:04.893000+00:00
3	788	clinique	Chubby Stick™ Sculpting Highlight	23.0	USD	NaN	contour	foundation	2017-12-23 23:35:06.969000+00:00	2017-12-23 23:38:33.306000+00:00
4	787	clinique	Chubby Stick™ Sculpting Contour	23.0	USD	NaN	contour	foundation	2017-12-23 23:35:06.871000+00:00	2017-12-23 23:38:32.856000+00:00
5	786	clinique	Limited Edition Highlighting Kit	39.0	USD	NaN	contour	foundation	2017-12-23 23:35:06.486000+00:00	2017-12-23 23:38:32.270000+00:00
6	1001	glossier	Haloscope	27.0	USD	NaN	highlighter	foundation	2017-12-27 02:44:12.059000+00:00	2017-12-27 02:58:27.019000+00:00
7	1021	marienatie	Gel Liner	0.0	USD	NaN	gel	eyeliner	2018-06-30 19:19:30.898000+00:00	2018-09-02 22:52:06.494000+00:00
8	1040	zorah biocosmetiques	Eyeshadow	0.0	USD	NaN	None	eyeshadow	2018-06-30 19:19:32.252000+00:00	2018-09-02 22:52:06.714000+00:00
9	1038	sally b's skin yummies	B Smudged	0.0	USD	NaN	None	eyeshadow	2018-06-30 19:19:32.132000+00:00	2018-09-02 22:52:06.697000+00:00

Once again, since this is a **new dataset** with no correlation to the previous one, it is important to provide **an overview** of the information available about this data.

New Dataset | Makeup-api

- In order to randomly correlate product identifiers, a mapping can be established between the makeup set **id** and **product_id** from **all_events_2019_to_2020**. A random match will be created between these identifiers, associating each id in the makeup set with a random **product_id** in the first dataset;

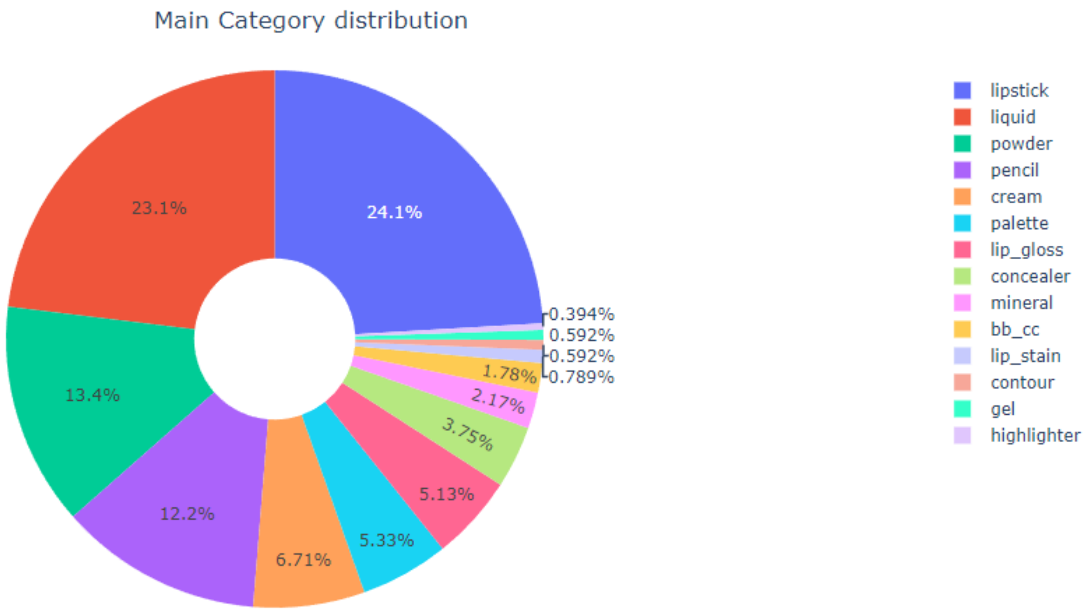
- The new dataset has been created successfully:

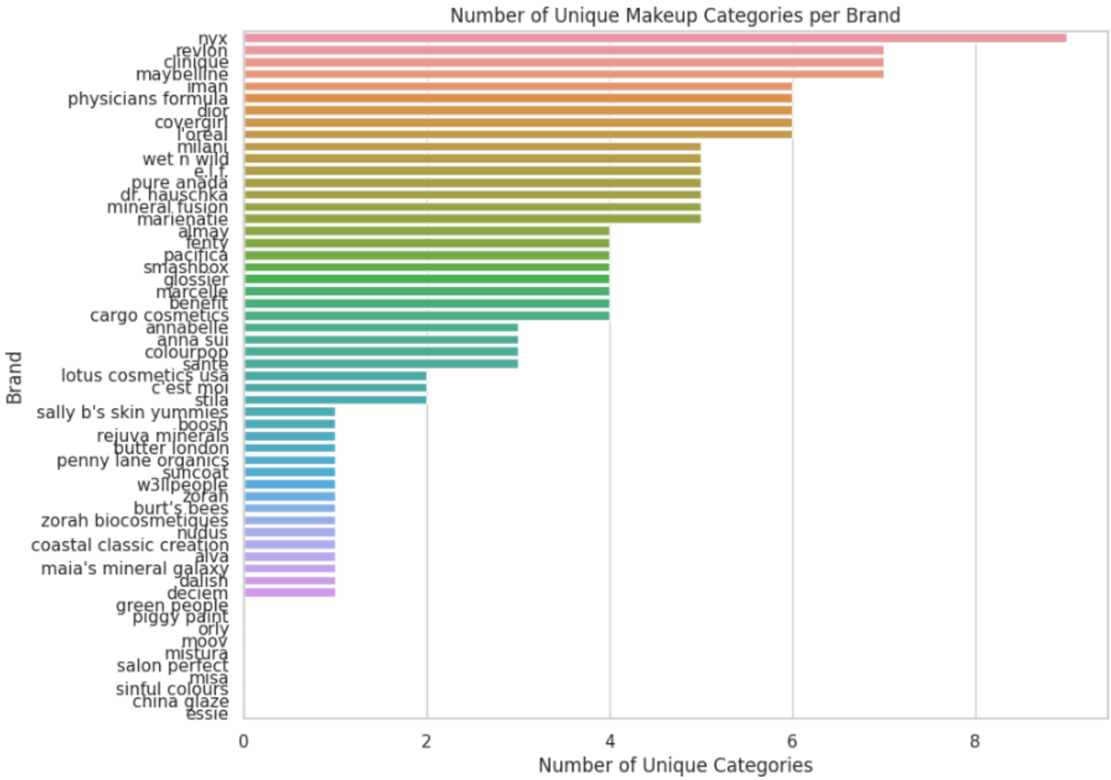
	makeup_id	makeup_brand	makeup_name	makeup_category	makeup_product_type	mapped_product_id	nov_category_id	nov_brand	nov_price
0	966	nyx	Cosmic Gel Liner	gel	eyeliner	5726394	1487580005092295511	None	5.56
1	966	nyx	Cosmic Gel Liner	gel	eyeliner	5726394	1487580005092295511	None	5.56
2	966	nyx	Cosmic Gel Liner	gel	eyeliner	5726394	1487580005092295511	None	5.56
3	966	nyx	Cosmic Gel Liner	gel	eyeliner	5726394	1487580005092295511	None	5.56
4	966	nyx	Cosmic Gel Liner	gel	eyeliner	5726394	1487580005092295511	None	5.56

- Now, this **table** can be used for **analyzes that consider both data sources**.

Consumer Category Behavior

- For new analyzes of the number of distinct categories per **Makeup Brand** (*only brands originating from makeup dataset*):

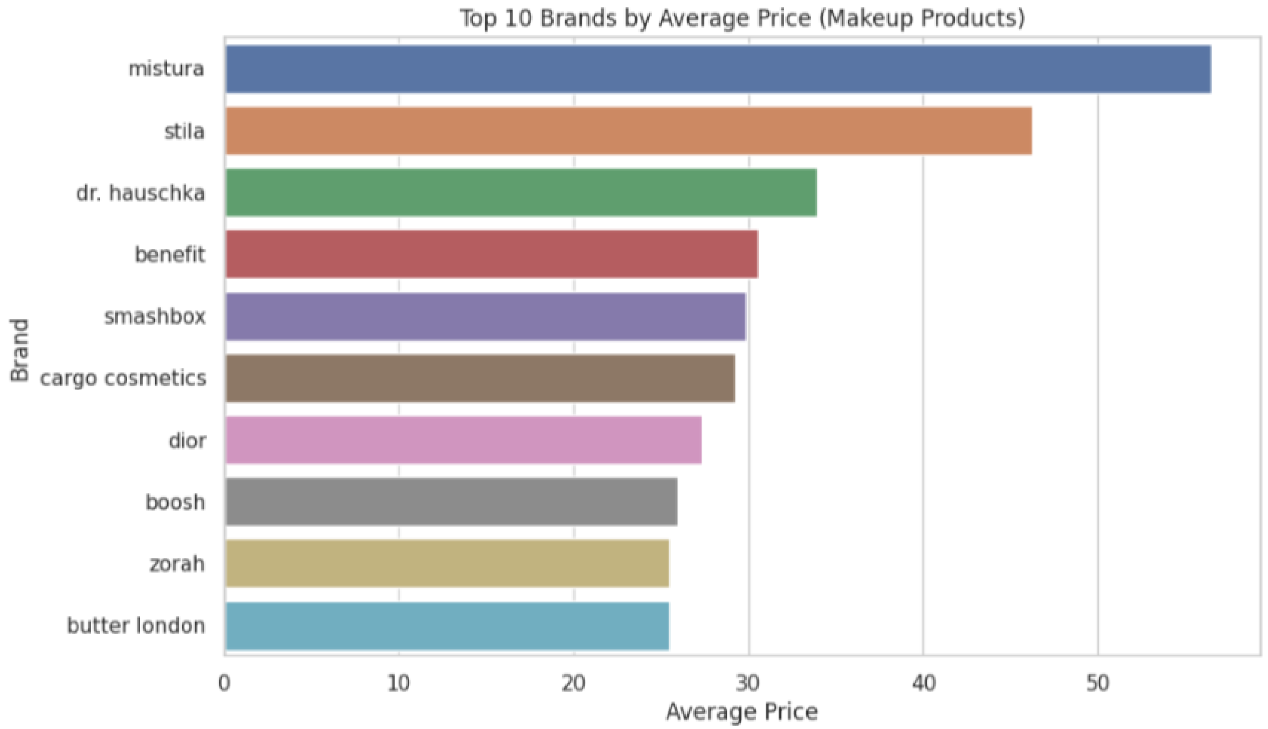




Consumer Category Behavior

Pricing and Brand Analysis

- To identify which **Premium Brands** and **Sales Volume** by *Brand* are possible. :

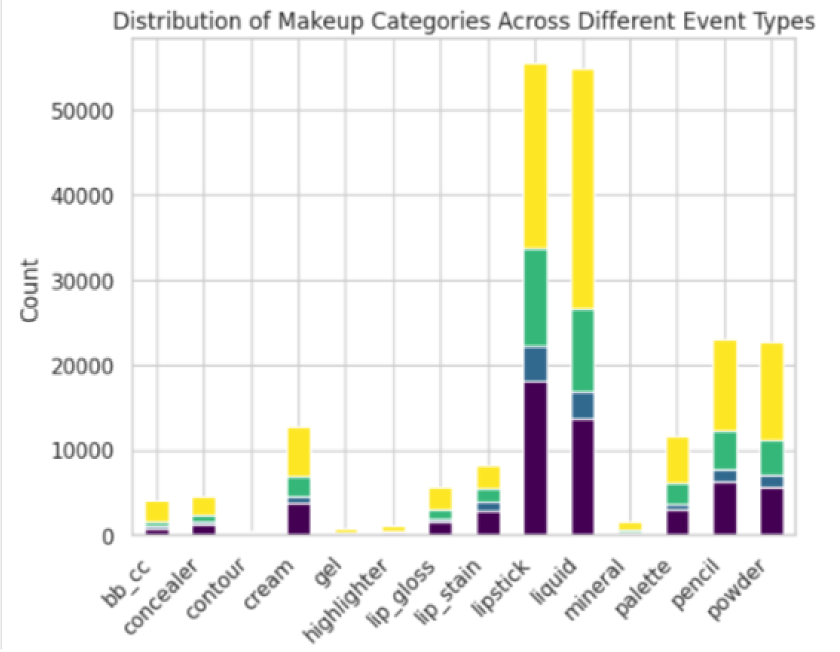


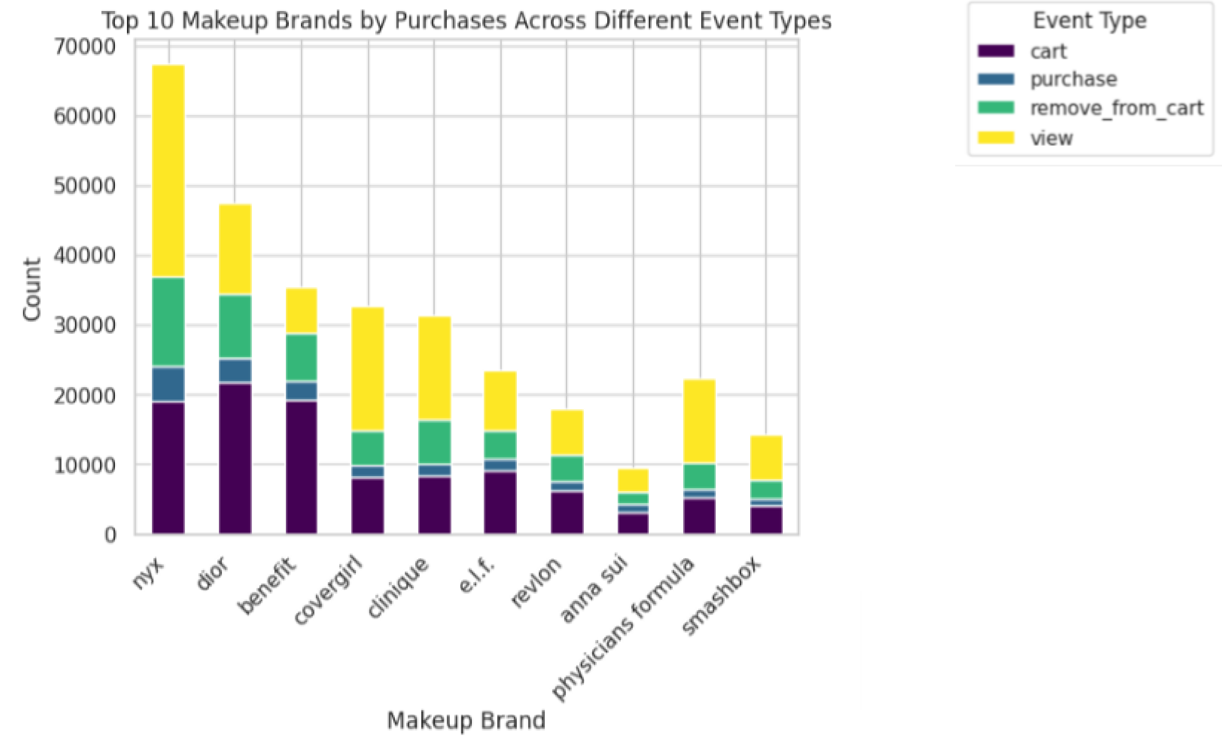
	Brand	Average Price
34	mistura	56.490000
51	stila	46.247500
18	dr. hauschka	33.916667
4	benefit	30.536585
50	smashbox	29.847826

Consumer Category Behavior

Purchase Events and Purchase Patterns

- These charts offer different perspectives on which **makeup categories are most popular** in terms of purchases:





Consumer Category Behavior

Insight:

How makeup brands are interacted with by users in different contexts, such as shopping, views, and interactions with the shopping cart.

Suggestion:

Create personalized marketing campaigns based on purchasing behavior. Studying the consumer's path from viewing to purchasing to understand purchasing patterns better.

Conclusion

Summary of the key insights and recommendations.

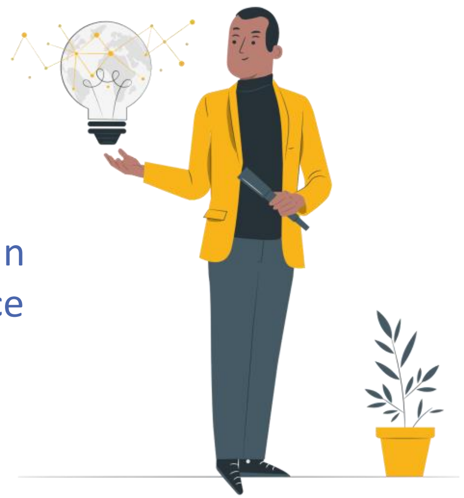
The impact of these strategies on overall marketing effectiveness.

So... What can you do?

In conclusion, the **analysis offers a roadmap for refining marketing strategies in the cosmetics e-commerce domain**. Implementing these data-driven strategies is expected to significantly bolster the overall marketing effectiveness, leading to increased sales, customer satisfaction, and brand loyalty.

Conclusion

So… What can you do?



So, based on our analysis of this dataset, several key insights and strategic recommendations can be drawn to enhance the overall effectiveness of marketing efforts in the cosmetics e-commerce sector:

Key Insights:

1. **Product Engagement**: Products that were most viewed, added to cart, and purchased provided insights into consumer preferences. These items are likely to resonate with the target market.
2. **Shopping Patterns**: Identification of peak shopping times highlighted when consumers are most active online, offering optimal times for marketing campaigns and promotions.
3. **Pricing Strategy**: Analysis of average product prices across various categories and brands revealed the price points that are most appealing to consumers.
4. **Brand Popularity**: Recognizing popular brands within the dataset helped in understanding brand loyalty and preferences.

Conclusion

So... What can you do?

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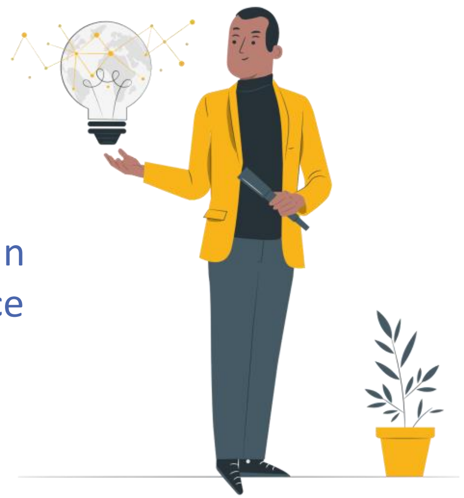
Recommendations:

1. **Targeted Promotions:** Focus marketing efforts on the most engaged products to capitalize on existing consumer interest.
2. **Optimized Timing for Campaigns:** Schedule marketing campaigns during peak shopping hours to maximize visibility and engagement.
3. **Dynamic Pricing Models:** Adjust pricing strategies based on the average price points that attracted the most consumer attention, balancing profitability and competitiveness.
4. **Brand-Centric Marketing:** Leverage the popularity of certain brands in marketing campaigns to attract brand-loyal customers.
5. **Optimize the Checkout Page:** Make the checkout process simpler, offer more payment options, and be transparent about any additional costs.
6. **Remarketing:** Use remarketing strategies to re-engage customers who have abandoned their cart.
7. **Feedback Analysis:** Conduct surveys or A/B tests on product pages for categories with high cart abandonment to improve presentation, and gather user feedback to comprehend the reasons for cart abandonment.
8. **Offer Personalization and Recommendations:** Base personalized product recommendations and offers on categories that show high engagement and conversion.

Conclusion

So... What can you do?



So, based on our analysis of this dataset, several key insights and strategic recommendations can be drawn to enhance the overall effectiveness of marketing efforts in the cosmetics e-commerce sector:

Key Insights:

1. **Product Engagement**: Products that were most viewed, added to cart, and purchased

Impact on Marketing Effectiveness:

- **Increased Conversion Rates**: By aligning marketing strategies with consumer behavior and preferences, conversion rates are likely to improve.
- **Enhanced Customer Engagement**: Understanding peak times and preferred products can lead to more effective and engaging marketing campaigns.
- **Optimized Marketing Spend**: Focusing on what works (popular products/brands, optimal times) can lead to more efficient use of the marketing budget.
- **Competitive Edge**: A dynamic pricing strategy can provide a competitive edge in the market, making the products more appealing to a price-sensitive audience.

Thank you for the opportunity to show my qualifications in this process.

Feedback is always welcome! ^^

Looking forward to the invitation to become a Racer at **Autoforce**.

Ricardo V M Almeida | Data Analytics & Science

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