The Devil Wears Data: Creating a Dataset for the Fashion Industry

Prof. A. Diamond & Prof. A. Hadavand

CP194: Capstone Directed Study II

Executive Summary

Background

Fashion research suffers from a methodological gap, with scholarly information fragmented across disparate sources. A trillion-dollar industry that employs millions worldwide, fashion remains conspicuously under-analyzed compared to other sectors where advanced data analytics are standard. Traditional academic databases typically provide limited quantitative insights, lacking comprehensive longitudinal datasets that can support rigorous empirical analysis.

Aims

This project addresses this critical gap by developing a **comprehensive fashion dataset** that enables both quantitative analysis and causal inference. **Part I** focused on identifying the need for a fashion dataset and **Part II** (the main goal) focused on creating a structured collection of variables tracking luxury fashion houses. The stretch goal (**Part III**) successfully demonstrated the dataset's utility through causal analysis.

Approach overview

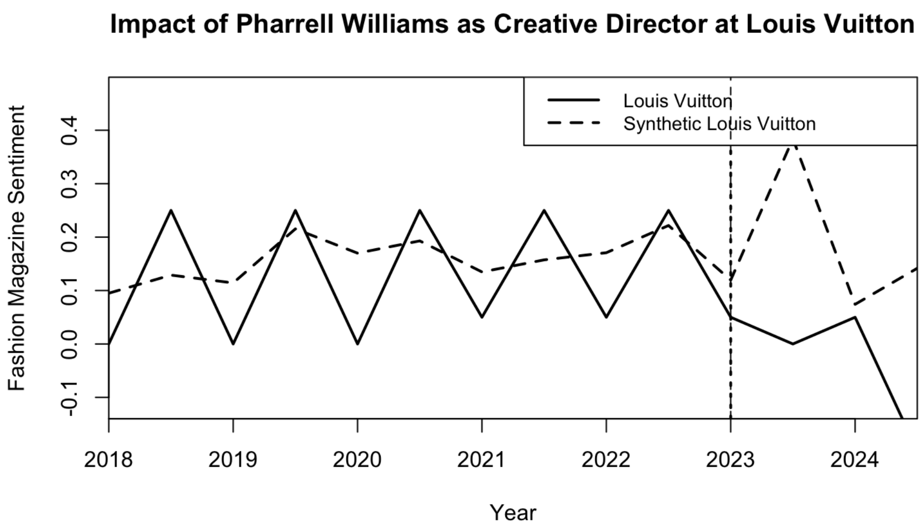
Part I: Problem Identification The project established the limitations of current fashion research methodologies, highlighting the need for fashion mindfulness—considering both fashion's rich heritage and its dynamic nature. I examined existing digital solutions, including social media analytics platforms like Data But Make It Fashion, identifying their correlational limitations.

Part II: Dataset Creation I curated data from 14 luxury fashion houses spanning 2018-2024, tracking variables including: creative directorship changes, participation in major fashion weeks, parent company associations, and online sentiment analysis of fashion magazine content using NLP techniques.

Part III: Causal Analysis Implementation (Stretch Goal) Employs a synthetic control methodology. I analyzed the causal impact of Pharrell Williams' appointment as creative director at Louis Vuitton. This demonstrated how the dataset enables rigorous causal inference beyond mere correlational analysis. Example shown in Figure A.

Figure A.

This graph shows Louis Vuitton's online sentiment (solid line) versus a synthetic control (dashed line) following Pharrell Williams' 2023 appointment, demonstrating how the dataset enables causal analysis of creative leadership changes in luxury fashion as one of the many potential use cases.



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Contents

Abstract

The landscape of fashion research is currently constrained by significant data accessibility challenges, with scholarly information often fragmented across disparate sources, proprietary databases, and industry-specific archives. Traditional academic databases typically provide limited quantitative insights, often lacking comprehensive, longitudinal datasets that can support rigorous empirical analysis. Fashion research suffers from a unique informational asymmetry, where rich contextual data exists but remains largely siloed within industry reports, fragmented social media archives, and disconnected digital platforms. By creating a consolidated, multi-variable dataset, this research addresses a critical methodological gap, providing researchers with a structured, accessible resource that can bridge the current quantitative limitations in fashion scholarship. The proposed dataset not only aggregates scattered information but also standardizes diverse data points, enabling more robust, reproducible, and comprehensive fashion research across multiple academic and industry domains. This dataset aims to take a stab at the solution, providing access for more research, more intellectual discussions, and practicing what we value as fashion mindfulness.

Part I: The World Needs a Fashion Dataset

In an era where technology dissects everything from social media trends to global economic patterns, fashion remains conspicuously under-analyzed—a glaring oversight for an industry that quite literally clothes the global economy. As Miranda Priestley from The Devil Wears Prada would sardonically remind us, it's sort of "comical" when we think that we've made a choice that exempts us from the fashion industry when, in fact, we're wearing a sweater from all the people in a tiny room that we call a pile of "stuff" (Frankel, 2006). This capstone project emerges from a simple yet provocative premise: if we can algorithmically predict stock markets and consumer behaviors, why haven't we developed a robust, quantitative approach to understanding fashion's complex dynamics?

The fashion industry—generating over trillions of dollars annually and employing millions worldwide—exists at a fascinating intersection of creativity, economics, and cultural signification. Yet, our current research methodologies remain frustratingly analog in a digital age. This project isn't just another academic exercise; it's a technological intervention designed to transform how we understand fashion as a complex, data-rich system of cultural and economic exchange. By developing a comprehensive dataset that enables causal inference, we're not just studying fashion—we're reimagining how we conceptualize its global impact.

The motivation behind this research stems from two critical observations: first, the persistent methodological limitations in fashion research that reduce a multi-billion dollar industry to surface-level trend analyses, and second, the urgent need to develop a more nuanced, technologically informed approach to understanding fashion's intricate ecosystems. Just as technology has revolutionized understanding in fields like finance and marketing, this project seeks to bring similar rigor to fashion research—proving that those cerulean blue sweaters aren't just chosen by chance, but are the result of complex, trackable, and potentially predictable systems of creative and economic decision-making.

Previous work and its inadequacies in a fast fashion dominated society

In the academic database world, there has been multitudes of work regarding macro-level analysis of the luxury fashion industry: from business decision and executive standpoints to cultural, artistic, and philosophical significance of changes in the fashion industry. The historical work proves to be valuable in helping recognize, shape, and verbalize brand identity and heritage over time. These conversations integrate many years of change intertwining with key moments of culture, coupled with the individual identities of directors and people with power in fashion (Skillen, 2019).

However, the fashion landscape is constantly changing, with many arguing that its evolution is increasingly dynamic while constantly cyclical in nature. This comes from the intersection between cycles of fashion. The 2020s have noticed the rise of Y2K culture, old money, and tradwife aesthetic, etc. intertwining with monthly and yearly microtrends, e.g.

"Miu Miu boy," "blueberry nails," "The Row Margaux bag," only to name a few. The accelerating pace at which we engage in fashion is compounded by the constant development of fast fashion and the rise of social media, providing significantly easier access to information, sharing of ideas, and purchasing of products means that fashion will always keep moving, according to specialists from SVRN, a San Francisco-based curated fashion space. No longer a collection of snapshots, fashion now shifts into a flow state, one that constantly asks for newer ideas, newer concepts, and newer ways of organizing these ideas and concepts that constantly impact the way we consume fashion.

Current digital solutions and their inadequacies

Capturing all of these dynamics would require a digital solution, which meant digital discourses in a digital space. These days, digital solutions are beyond fashion blogs: we can talk about social media, short-form content, fashion podcasts, fashion influencers, and content creators. They range anywhere from capturing trends and rising popularity through an influential perspective or providing insightful, intellectually engaging, and culturally significant discourses and commentaries (Le, 2022). While this is helpful, there is room to complement all these analyses on a more quantitative front.

Statistics and machine learning, coupled with social media, became promising. Data But Make it Fashion is an Instagram account that employs data analysis and machine learning techniques. Data But Make It Fashion is an initiative started by Made Lapuerta, a Harvard graduate and the Vice President of Global Technology Strategy at McKinsey, where she makes data-driven claims and predictions on upcoming micro-trends, from anywhere between colors, types of clothing, and brand sentiments, turning these statistics into visualizations on Instagram reels, as shown in this example below. Works by Lapuerta (2024) gradually became an online phenomenon, for its success lies in its analytical captures of fashion's consistently dynamic space, allowing for trends to be instantly visible to potential fashion consumers.

As innovative and valuable as this analysis can be for the fashion industry, what is exactly wrong with it? In fact, what exactly is wrong with analyzing micro-trends?

Microtrends, changes, and the need for fashion mindfulness in a digital world

A microtrend in fashion represents a hyper-localized, ephemeral style phenomenon that emerges and dissipates rapidly, typically lasting between a few weeks to a few months. According to trend forecaster Lyn Slater, these microtrends are characterized by their intense but short-lived popularity, often emerging from niche communities, social media subcultures, or localized fashion scenes. Unlike broader fashion trends that might persist for several seasons, microtrends represent a true emergent property of the modern fashion ecosystem—their hyper-accelerated lifecycle cannot be understood by examining any single component in isolation. The rapid rise and equally swift decline of these trends emerges specifically from the non-linear interactions between fast fashion production capabilities, digital amplification through platforms like TikTok and Instagram, and shifting consumer psychology. Arguments from Yip (2025) would also support that a microtrend is an emergent property of a collective yearning to outperform and establish originality, showing high-level patterns of constantly yielding new trends and learning what is the "next big thing." This high-level property is reinforced by the rise of fast fashion, which taps into not only different designer collections but the most minuscule rise of a microtrend. The trend then dies, because its accessibility is now easily given and becomes an antithesis to its originality. This emergent pattern of trend volatility could not be predicted by simply adding together the effects of each individual factor; rather, it manifests only when these elements interact in a complex system, creating a fundamentally new pattern of consumption that transcends the sum of its parts and reshapes the entire industry's temporal dynamics.

Looking beyond microtrends reveals the deeper sociological and economic significance of fashion as a complex system of cultural communication and economic value creation. Scholars like Pierre Bourdieu and Elizabeth Wilson have long argued that fashion is not merely about clothing, but a sophisticated language of social signaling, identity construction, and power dynamics (Bourdieu, 1984; Wilson, 2003). By examining fashion through broader lenses—considering factors like production networks, cultural diffusion, technological innovation, and socio-economic implications—researchers can uncover rich insights into global interconnectedness, labor practices, sustainability challenges, and the intricate relationships between individual expression and systemic structures.

Yip (2024) also highlighted a need to look at macro-level changes in fashion, especially creative directorship, through practicing what he defines as fashion mindfulness: the integration of micro-level changes into bigger pictures into what defines a brand, rather than just promoting direct comparisons between short time periods after one collection. Le (2022) and Yip (2024) both argue that fashion creators and sometimes even fashion brands themselves make top-down executive decisions that would harm fashion mindfulness because of short-term utility framing. Whether it be Sean McGirr's controversial, Balenciaga-reminiscent debut collection at Alexander McQueen, or Peter Do's inability to fully revive Helmut Lang's popularity despite his impressive collection, short-term framing disrupts the delivery and perception of a fashion brand as a mark of culture and heritage (Friedman, 2024; Silbert, 2024). The concern for fashion mindfulness becomes particularly relevant when examining the pressures faced by creative directors in today's industry. The fashion world has seen numerous high-profile departures of creative directors in recent years, reflecting the immense pressures of "competing with a hurtling trend cycle, online pundits, accelerated fashion week calendars, and high expectations for business performance in quick turnarounds" (Doupnik, 2024). These rapid transitions disrupt the delivery and perception of fashion brands as marks of culture and heritage.

A critical engagement in luxury fashion then, requires an analytical solution that captures two main ideals that correspond to an interpretation of fashion mindfulness: static enough that allows for personal, grounded, and critical evaluation of fashion, considering eras and collections as archival snapshots within fashion, yet dynamic enough that constantly allows for movement, flow, and the constantly incoming influx of information that social media and the internet provides to fashion enthusiasts and consumers.

The need for a technological solution is also argued for by Crepax and Liu (2024), as they argue that technology becomes a vehicle for "affect in fashion and popular culture". We come to a novel approach, one that balances between thoughtful scientific analysis and a technological solution: a centralized dataset.

The proposed fashion dataset addresses critical methodological limitations in contemporary fashion research by providing a comprehensive, multi-dimensional approach to analyzing fashion dynamics. Unlike existing datasets that often focus on singular metrics or isolated snapshots of fashion trends, this dataset integrates multiple variables across temporal, geographical, and socio-economic dimensions. By incorporating granular data points such as production details, market penetration, consumer demographics, social media engagement, and cultural context, the dataset enables researchers to move beyond surface-level trend analysis and conduct robust causal inference studies that can unpack the complex mechanisms driving fashion phenomena.

Methodologically, this dataset represents a significant advancement in fashion research by facilitating interdisciplinary investigations that transcend traditional disciplinary boundaries. Researchers from fields including sociology, economics, cultural studies, and data science can leverage this comprehensive resource to explore nuanced questions about fashion's role in social signaling, economic value creation, and cultural transformation. The multi-variable approach allows for sophisticated analytical techniques like causal inference models, which can help illuminate the often opaque relationships between design innovation, consumer behavior, cultural trends, and broader economic and social structures. By providing a rich, contextually grounded dataset, this research tool opens new pathways for understanding fashion not just as a aesthetic phenomenon, but as a complex, dynamic system of cultural and economic exchange. As the dataset has the ability to be hosted on a live online and digital space, it allows more a greater flow of intellectual and academic discourse on fashion: beyond just research papers, future content creators, fashion students, can also quickly analyze and keep up with the pacing of the fashion industry.

This is not to render microtrends and their analysis useless, but having a dataset on a macro scale provides a much greater quantitative analysis to anyone who can and will take a deeper look into fashion history, the brand, the house, and the heritage. Just like how Miranda Priestley once said that a "cerulean top fished out from a pile of stuff" represents "millions of dollars and countless jobs," one simple line of R code and causal inference analysis may represent an important insight on a change that unveils a whole corner of the fashion industry.

Correlational data and the Fundamental Problem of Causal Inference in fashion

What then, differentiates between the importance of a comprehensive dataset, as compared to the beautiful data visualizations that Lapuerta provided for the fashion world? On the statistical front, these data visualizations are anything but correlational. The attribution of correlational patterns and confirming causal hypotheses can be purely fallacious. This Fundamental Problem of Causal Inference has been captured by (Rubin, 2005) with a great possibility of having multiple covariates and other causal mechanisms explaining a correlational relationship. Any differences that we observe in the outcomes that may simultaneously happen when there is a change in one variable may not mean that this variable causes this change. Causal language when observing correlation is often widely used in fashion criticism, which engages itself in qualitative, small-n methods. Take a look at the example of the attribution of the rise of the "old money" aesthetic, something that could be attributed to the rising popularity of brands like Ralph Lauren, the rising popularity of baggy pants, and the post-Covid demand for comfort, but it could also be causal to a rise in the increasingly conservative values that the social media space is experiencing. All this means is that there needs to be consideration for multiple variables and covariates at once to verify any potential hypotheses there could be. From a practical front, the dataset can be analogous to the raw materials that allow for more exploratory challenges to be explored. A centralized dataset with multiple variables and covariates means that fashion enthusiasts, data science students, and analysts can utilize many correlational and causal relationships, with countless possibilities for answered questions, self-made data visualizations, and grounds for multiple causal frameworks. We can track online sentiments over time, changing creative directorships over time (in the midst of the 2025 creative director "musical chairs" between fashion houses), or analyze any difference between Paris-based brands compared to Milano ones; the possibilities are truly endless. The paper later showcases one empirical example to establish a causal mechanism in Louis Vuitton's creative directorship change, which is one example of the many that users of the dataset can freely explore.

Part II: The Dataset

As the dataset is quantitative and fresh in the fashion industry, the project aims to produce a dataset that could be analyzed by a large audience, including but not limited to, fashion students beginners to advanced, business students in luxury and fashion research, social science students, arts and humanities researchers, marketing personnel, amongst others. This is viable through the dataset's use of multiple types of variables, allowing multiple levels of familiarity and knowledge with the fashion industry be able to engage in the dataset, the analysis and the research work.

The project considers the following variables in mind, after considering the previous works by Yip (2024) and Skillen (2019):

- Year
- Season / Collection
- Home base (Geographical)
- Parent group
- Participation in New York Fashion Week

- Participation in Paris Fashion Week
- Participation in Milan Fashion Week
- Participation in London Fashion Week
- Participation in Met Gala
- Creative director
- Number of years creative director was active
- Number of brands creative director has been a part of
- Fashion magazine perception of collection

Overview & Justification for choice of variables

The project provides an overview of how the data for the variables are collected. Clear details on data types, definitions, and how specifically data for the variable is collected, can be seen in the GitHub.

Year, Home base, and Parent Company

These introductory variables form the foundation for contextualizing each fashion house within a temporal, geographical, and corporate framework.

Year: The business year of the company serves as a fundamental temporal anchor, allowing for time-series analysis of creative and commercial changes. This enables researchers to track trends over time, identifying potential correlations between market conditions, creative directorship changes, and brand performance.

Home Base: A categorical variable representing the country of origin for a fashion house. This is crucial because fashion is deeply influenced by regional aesthetic traditions, cultural capital, and economic conditions. Paris-based brands, for instance, often align with haute couture traditions, while New York-based brands may have a stronger emphasis on ready-to-wear and commercial viability.

Parent Company: The parent company exerts a significant influence on brand operations, ranging from financial decision-making to supply chain management. In the oligopolistic structure of high fashion, where conglomerates like LVMH, Kering, and Richemont control multiple brands, the ownership structure can impact creative freedom, pricing strategies, and market positioning. Tracking whether a brand transitions from an independent label to being acquired by a conglomerate allows for analysis of whether such transitions affect pricing models, creative output, and consumer perception.

Creative directorship

The creative director of the brand, in any given time frame, is compiled through information on Vogue articles and fashion blogs, and is a categorical variable.

The inclusion of the "creative director" variable represents a crucial analytical lens for understanding fashion's complex ecosystem of creative production and brand identity. Creative directors serve as pivotal agents of cultural and aesthetic transformation, wielding significant influence over brand narratives, design philosophies, and market positioning. Skillen (2019), using her case study of Dior, further reinforced reinvention of brand identity through charismatic succession and heritage, repositioning the brand's luxury standing while weaving the director's personal story into the brand identity.

By tracking the creative director as a variable, researchers can trace patterns of aesthetic innovation, examine the impact of individual creative leadership on brand trajectories, and illuminate the complex dynamics of creative labor, cultural production, and brand evolution in the fashion industry.

This data is collected based on reports of Vogue articles and interviews with the creative director. Coupled with creative director as a variable, the dataset also provides extra variables on the director, namely the number of luxury houses and the number of years of experience in the luxury fashion space that the director has been a part of. This is also collected based on fashion magazine articles including informational interviews with the directors through Vogue, L'Officiel, BOF, amongst others.

Number of Luxury Houses Worked At: This variable, a quantitative continuous variable taking only positive integer values, captures the experience level of creative directors within the luxury fashion ecosystem. A designer who has transitioned through multiple houses (e.g., Kim Jones at Louis Vuitton, Fendi, and Dior) may bring a more commercially viable design language, whereas a first-time director might introduce riskier, avant-garde aesthetics.

Years of Experience in Luxury Fashion: A quantitative continuous variable, taking only positive integer values, the variable measuré experience in luxury fashion provides insight into whether tenure influences creative output. A director with decades of experience may rely on established motifs, whereas an emerging talent may introduce radical innovation. Tracking creative directorship through these lenses allows for an empirical exploration of how leadership changes influence brand evolution, consumer perception, and financial performance.

Participation in fashion weeks

The inclusion of fashion week participation variables represents a critical metric for understanding a fashion brand's global visibility, market positioning, and industry recognition. By tracking participation in major international fashion weeks—New York, Paris, Milan, and London—the dataset captures a nuanced view of a brand's strategic positioning and cultural capital within the global fashion ecosystem. Besides being the four largest fashion weeks in the world, we also infer certain cultural and strategic significance. *Paris Fashion Week* can be associated with heritage luxury, haute couture, and high-concept fashion narratives. *Milan Fashion Week* carries a strong focus on craftsmanship, material innovation, and wearable luxury. *London Fashion Week* showcases hub for experimental, avant-garde, and emerging designers, while *New York Fashion Week* is commercially driven, emphasizing accessibility and market-ready collections. Analyzing a brand's presence over multiple seasons can reveal insights into its market evolution. For example, a brand transitioning from Milan to Paris may be attempting to reposition itself towards a more couture-oriented image.

Fashion weeks serve as more than mere showcasing platforms; they are pivotal spaces of cultural and economic exchange where brands communicate their creative narratives, establish industry relationships, and signal their artistic and commercial ambitions. The decision to participate in specific fashion weeks is not arbitrary but reflects complex strategic considerations involving brand identity, target market, and international positioning.

For instance, participation in Paris Fashion Week might signal a brand's aspiration towards haute couture and luxury positioning, while inclusion in New York Fashion Week could indicate a focus on commercial ready-to-wear and contemporary fashion trends. The geographical diversity of these fashion weeks allows researchers to explore how different fashion capitals influence brand strategies and creative expressions.

Moreover, these variables provide a quantitative lens into a brand's international reach and industry legitimacy. Consistent participation, frequency of appearances, and the specific fashion weeks chosen can reveal intricate patterns of brand evolution, market adaptation, and creative positioning. Scholars in fashion studies, marketing, and cultural analysis can leverage this data to understand broader trends in global fashion production and representation.

The Met Gala participation, while distinct from traditional fashion weeks, offers an additional layer of analysis. As a high-profile cultural event that intersects fashion, art, and celebrity culture, Met Gala participation can be interpreted as a marker of a brand's cultural relevance, artistic innovation, and ability to engage with broader cultural narratives beyond traditional runway shows. This is also a golden opportunity for the brands as a form of marketing and cementing its soft power, testable through further analysis and usage of the dataset, e.g., how Loewe's appearance at the Met Gala 2024 (Ariana Grande) might impact its social media popularity or brand perception.

Data for these variables is meticulously collected through comprehensive reviews of fashion industry publications, official fashion week schedules provided by organizations like the de la Haute Couture et de la Mode (2024), brand archives, verified media reports, and official live TikTok red carpet interviews for newer collections. This ensures a robust and reliable documentation of each brand's fashion week journey.

All these variables in the dataset are represented as Boolean variables, taking either a value of 1 (which indicates participation) or 0 (indicating non-participation).

Online perception of runway collection

Tying in with the discussion on creative direction, the presence of social media has also been a central issue in the digitalization of fashion, where Yip (2024) noted this as one of "the biggest things that ever happened to the fashion industry." Through the works of Yip, the diffusion of fashion criticism on social media may also have effects on decisions made towards the brand. In the case of Daniel Lee for example, while unsure of whether this was causal, but after a wave of controversy and disapproval on the Internet over his debut collection for Burberry in 2022 that was claimed to be contrarian to the Burberry brand identity, the adjustments he spent on his second Fall-Winter collection was more favorably received. Again, not causal, but something to think about.

Leveraging on the previous work by Lapuerta (2024), her Instagram analysis on fashion, and her public GitHub repository where she provided a sample code for the algorithm she used for Data But Make It Fashion, the project decides to use sentiment analysis on blog posts, magazine articles, and Google searches.

Overview of Sentiment Analysis

Sentiment analysis is a natural language processing (NLP) method used to systematically evaluate textual data to classify the emotional tone, typically as positive, neutral, or negative (Hutto & Gilbert, 2014). This project leverages sentiment analysis to assess perceptions expressed in fashion blogs, online reviews, news articles, and other digital sources, which provide insights into consumer and critic reactions to a brand's design changes, leadership shifts, and overall direction over time. For example, examining shifts in sentiment toward Burberry following the appointment of Daniel Lee could reveal how consumer perceptions have evolved in response to his creative influence.

Mathematically, sentiment for a document S_i can be quantified as

$$S_i = \sum_{j=1}^{n} w_j f_j$$

where f_j represents the frequency of sentiment-related terms within the document, and is the w_j weight or sentiment polarity score of each term, determined from a predefined lexicon or sentiment model. This formula effectively aggregates the weighted sentiment of terms to produce an overall sentiment score for the document. By calculating these scores over time and aggregating them, we can track sentiment trends, offering insights into how the public's perception of a brand like Burberry changes with new creative directions or brand strategy shifts.

Data Collection via Google Search API and Custom Dataset Generation

Given the lack of readily available fashion industry datasets specific to causal analysis, this project involves generating a custom dataset. Using the Google Search API, we construct targeted queries to retrieve relevant articles, blog posts, and reviews focusing on Burberry and select competitors like Dior, Gucci, and Loewe. The timeframe for these queries is chosen to encompass key moments of creative directorship transitions, enabling us to capture sentiment shifts that may correlate with these leadership changes.

After collecting raw text data, preprocessing steps such as tokenization, lemmatization, and stop-word removal are applied to standardize the text. Tokenization breaks down text into individual words or phrases, lemmatization reduces words to their base forms, and stop-word removal eliminates common but non-informative words (e.g., "the," "and"). This processing makes the text more suitable for accurate and efficient sentiment analysis.

Sentiment Scoring Methodology: Lexicon-Based and Machine Learning Approaches

This project employs a hybrid sentiment analysis approach, combining lexicon-based techniques with machine learning models tailored to fashion-related language. Lexicon-based methods involve sentiment dictionaries, such as VADER or TextBlob, which assign sentiment polarity scores to words or phrases based on established lexicons. For instance, words like "luxurious" or "bold" might be weighted positively, while words like "dated" or "uninspired" might carry a negative score. The sentiment score S_i for a document iii is then calculated as:

$$S_i = \frac{1}{|D|} \sum_{t \in D} \text{score}(t) \tag{1}$$

where $|D|$ is the total number of sentiment-bearing terms in the document, and $\text{score}(t)$ represents the polarity score for each term t. This approach allows us to gauge sentiment even when individual terms are used sporadically (Elbagir & Yang, 2019).

Given the unique vocabulary of fashion media, this project also integrates machine learning techniques to better capture nuanced sentiment. A supervised learning approach is applied, where a sample dataset is manually labeled with sentiment classes (positive, neutral, negative), and a model such as a Support Vector Machine (SVM) or BERT (Bidirectional Encoder Representations from Transformers) is trained on these labeled data. Once trained, the model can predict sentiment on unlabeled documents. This additional layer enhances the accuracy of sentiment analysis, particularly when analyzing fashion-related language, which often includes subjective, highly specific terms.

By combining these approaches, we can calculate aggregate sentiment scores over time, allowing for a more nuanced understanding of how sentiment towards. This analysis serves as an essential component of our causal inference framework, helping to assess the impact of directorship changes on brand perception and providing actionable insights for the fashion industry.

The Data Set

As of the time this paper is written, the dataset contains data for 14 fashion houses spanning from 2018 to 2024. More data on additional brands will be incorporated in a future rendition of this Capstone project. The selected houses are Burberry, Dior, Loewe, Prada, Miu Miu, Louis Vuitton, Saint Laurent, Gucci, Bottega Veneta, Valentino, Hermès, Celine, Maison Margiela, and Versace. Each brand's dataset includes values for the selected variables per season—Spring/Summer (S/S) and Fall/Winter (F/W)—across seven years, yielding a total of 196 rows and 14 columns. At its current scale, the dataset provides a sufficient number of data points for meaningful quantitative analysis, with plans to expand as additional runway seasons allow for a richer dataset.

The selection of these brands is deliberate, while definitely not exhaustive, based on their cultural and commercial significance in shaping contemporary fashion. The chosen houses fall into distinct categories that reflect different facets of the luxury and high-fashion landscape.

The first criterion for the choice of the house is heritage and legacy (Dior, Louis Vuitton, Hermès, Versace, Valentino, Saint Laurent). These houses have a longstanding presence in the fashion industry, with established brand codes that evolve over time. Analyzing sentiment around their creative direction provides insight into how historical brand narratives are preserved or reinterpreted.

We note the second criterion, experimentation and avant-garde designs (Loewe, Maison Margiela, Bottega Veneta, Celine). These brands are known for pushing creative boundaries and often generate polarizing responses from critics and consumers. Studying sentiment trends here reveals how the industry and the public perceive innovation.

Lastly, many of the brands chosen are trend-setting brands with strong digital influence (Prada, Miu Miu, Gucci, Burberry). These houses have been at the forefront of digital and social media-driven trends. The online discourse surrounding their collections offers an opportunity to assess how viral fashion moments (e.g., Miu Miu's micro-mini, Gucci's maximalism) translate into overall sentiment shifts.

Furthermore, each selected house has experienced notable creative directorship changes or brand evolutions during the dataset's timeframe. This makes them particularly valuable for studying the relationship between creative shifts and public perception. For example, the dataset captures, Burberry's transition from Riccardo Tisci to Daniel Lee (Socha, 2010; Armstrong, 2023), Gucci's shift from Alessandro Michele to Sabato De Sarno (2022–2023), Celine's reinvention under Hedi Slimane (2018), Bottega Veneta's shift from Daniel Lee to Matthieu Blazy (Conti, 2021), and Jonathan Anderson's iconic run that revived Loewe's branding (Morgan, 2025).

By analyzing sentiment across these houses, the dataset aims to capture the impact of creative leadership transitions, brand repositioning, and evolving consumer expectations in the luxury fashion industry. The inclusion of additional brands in future updates will further strengthen the dataset's breadth and applicability in understanding long-term shifts in fashion perception.

As mentioned above, the list of brands chosen is deliberate and carries significant cultural impact within the fashion industry, but as more brands evolve in their identity, creative direction, and market share, the dataset hopes to include further additions of many other promising fashion houses, enriching the project's information and research/analytical potential.

Given the elaborated dataset, one can access the dataset using the GitHub repository **here**, along with the code that was used to gather data, and the detailed codebook that would have a detailed explanation on all of the variables being collected. This link will be mentioned again in Appendix A.

Part III: Using the Dataset

The dataset not only offers a rich foundation for advanced causal inference methodologies but also serves as an accessible entry point for students new to data analysis and causal inference. Its structured variables—ranging from seasonal revenues to social media sentiment—are intuitively connected to concepts like regression analysis, making it an ideal resource for learners. By exploring how fashion brand performance responds to changes in creative directorship, students can gain hands-on experience with statistical models while developing an understanding of the nuanced interplay between business decisions and market outcomes.

The dataset provides grounds for multiple types of data analysis for different exploratory questions, from time-series analysis tracking changes of different variables throughout fashion seasons to regression analysis that tests for association between the variables in the dataset, and even advanced causal inference techniques that help support or critique causal theories set out by fashion researchers.

In order to showcase the flexibility of the dataset, the report dives in with an empirical example, using a causal methodology for an observational study, that aims to attempt a normative question. When asking relevant questions about the impact of creative directorship change on brand sentiment, based on the theoretical grounds we had in Part I, we can generate a potential, general hypothesis such as the following, "Creative directorship changes in luxury fashion houses affect brand perception through the mechanism of aesthetic alignment with brand heritage, where greater misalignment between a new director's aesthetic vision and established brand identity results in more negative online sentiment."

Grounds for this hypothesis formation begín with the concept of fashion mindfulness, as developed in the earlier discussion, which provides a critical lens for understanding the complex interplay between creative directorship, brand identity, and market perception. Emerging from scholarly perspectives that view fashion as more than mere clothing—but as a sophisticated system of cultural communication—this approach challenges reductive, short-term evaluations of fashion brands.

As concluded by Le (2022), fashion mindfulness emphasizes the need to view brand transformations holistically. It recognizes that creative directorship is not simply about individual collections, but about navigating the delicate balance between heritage and innovation, tradition and contemporary relevance.

This hypothesis alone, has many general claims and terms that we have to suggest and variables that we can choose and curate. The dataset itself, while not completely able to answer this question fully, can provide quantitative grounds for one or more case studies. Up for interpretation, we can map certain key terms in this hypothesis into variables available in the dataset. Creative directorship can refer to the brand's standing creative director. Brand perception can be quantified using the dataset's online magazine perception or Google search perception. The misalignment between the director's vision and established identity can be tricky to target, but a reasonable simplification in an attempt to quantify, but we can also approach this from two of the many explantory variables: number of years that the director has worked for the brand (which, the fewer the years, the larger the misalignment), and presence in one of the fashion weeks (which has predominantly shown evidence as an identity and cultural hallmark of the brand). These variables become the covariates that we look at in the case study that we choose in an in-depth attempt to answer the question. The case study is Pharrell's controversial entry into Louis Vuitton in 2023.

Example of using the dataset: Synthetic control

One example that we could use for this data set could be a causal question on the change in creative directorship for these houses. In this case, the creative director variable becomes a treatment variable. With the current collection of Pharrell Williams in Louis Vuitton receiving mixed reviews from fans and critics, having large shoes to fill from the late Virgil Abloh, one could potentially pose a question, "What is the impact of Pharrell Williams' creative directorship on the online magazine perception on the brand?"

Motivation for the question & Connection to the thesis

Perhaps one of the most controversial menswear collections that was occurring during the Fall/Winter 2025 season is Pharrell's creation for Louis Vuitton. A fun, playful take on menswear that supposedly aims to balance between elegance, the brand's playfulness, and its long-standing French identity, Pharrell's collection features a collection of ready-to-wear pieces, with relaxed tailoring, accessories, lounge-wear, and streetwear aesthetics (Graves, 2025). As the brand answered to call for recent menswear trends for elegance and classiness, Pharrell's collection was met with heavy criticism from menswear enthusiasts and social media critics, many expressing confusion, disbelief, and disappointment. The question became interesting to study, as Louis Vuitton's change was not met with agreement, and its shift from a maximalist, streetwear, "hype beast" aesthetic from a few years black to now blending in with the current fashion climate, was not welcomed. Its counterparts, Amiri and Dior, on the other hand, experienced a similar branding change journey, and Amiri's collection was met with praise, and labeled by many as "one of the best collections" released during this season. The stark contrast between the reception of Louis Vuitton, Dior, and Amiri's perception, then leaves enthusiasts with a lingering yet obvious question, "Is it Pharrell's fault that we cannot be 'happy' [1] with his collection?" It would be easy to categorize this as a natural experiment, limiting our comparisons to just Dior, Louis Vuitton, and Amiri, and studying only the most recent collection. We could zoom into the quantitative data, collect qualitative data, and conduct small n case study analysis. As usual, these small, in-depth data points will always be valuable to facilitate fashionably mindful conversations about brand identities and brand revolutions. Its challenge, however, lies in its limited ability for external validity, generalizability, and most importantly, the lack of a fair, apples-to-apples comparison. This is where the dataset comes in.

Using other fashion houses to create a "synthetic" Louis Vuitton

We pose this as a causal question, with the creative director being the treatment variable, and the perception of brands on online magazines being the outcome variable. In this case, the "synthetic control" would be a "synthetic" Louis Vuitton, which could be

[1] "Happy" is the name of one of Pharrell's hits.

synthesized by using other covariates and other fashion houses. As established in Part I, a direct comparison between Louis Vuitton with one or more brands existing in the dataset, or a direct comparison of Louis Vuitton as a brand before and after S/S 2023, would be unfair and purely correlational, for there is the presence of potential confounders that disrupt the establishment of a causal theory. We target this problem by comparing the online sentiment of Louis Vuitton during the Pharrell era with that of a weighted combination of other fashion houses before Pharrell (SS2023). The idea is such that the weighted average of other fashion houses act as a "synthetic" Louis Vuitton without Pharrell ever stepping into the house (control unit), against which we compare with the actual Louis Vuitton with Pharrell (treatment unit). Following the synthetic control logic by Abadie et al. (2010), we let J be the number of available control fashion houses and $W = (w_1, w_2, \ldots, w_J)'$ be a $(J \times 1)$ vector of non-negative weights which sum up to 1, with $w_j (j = 1, 2, ..., J)$ representing the weight of fashion house j in synthetic Louis Vuitton. Mathematically, two following conditions about w_j must hold, which are the non-negative constraint, where

$$W_j \geq 0$$

$\forall j = 1, 2, \ldots, J$, and the sum-to-one constraint, where

$$w_1 + w_2 + \ldots w_j = 1$$

Of course, each vector W chosen will generate a different synthetic Louis Vuitton. The goal here, however, is to be able to resemble an experimental setting as much as possible, meaning that the synthetic Louis Vuitton should come as close to the real Louis Vuitton as much as possible before Pharrell. We let X_1 be a $(K \times 1)$ vector of pre-Pharrell values of K online sentiment predictors for Louis Vuitton, which are present as the columns in our dataset, and X_0 be a $(K \times J)$ matrix which contains the values of the same variables for the J possible control fashion houses. V would be a diagonal matrix with non-negative components, whose diagonal elements carry values that indicate the importance of different predictors. From here, we choose $W = W^*$, a value at which minimizes the following loss function

$$L(W) = (X_1 \breve{} X_0 W)' V (X_1 - X_0 W)$$

while still maintaining the constraints established for W. The choice of V, on the other hand, can be pretty subjective, but this paper chooses V in a way that the online sentiment for Louis Vuitton is best reproduced by the resulting synthetic Louis Vuitton. Further details can be seen in Appendix B. As established, we place two constraints on the choice of W to prevent extrapolation outside the support of the predictors for the control fashion houses: without such constraint (and V has all positive diagonal elements), X_1 would be perfectly fitted as long as the rank of X_0, or $\text{Rank}(X_0) = K$. It would be impossible to attain a perfectly fitted X_1 even if $\text{Rank}(X_0) = K$. Table ?? shows sentiment predictors for synthetic Louis Vuitton before Pharrell, where $X_1^* = X_0 W^*$.

We note that from the donor pool of control fashion houses in Table ??, three houses stand out as the main contributors to a synthetic Louis Vuitton: Loewe (38%), Bottega Veneta (28%), and Celine (33%). It is a generally interesting combination of primary donors. While Louis Vuitton does share a parent company with its two most significant donors, being under the LVMH umbrella, all these brands remain generally different in their identities. Loewe and Bottega, especially, primarily shift their focus on their heritage craftsmanship, something that Louis Vuitton is not known for. On a creative and archival front, these brands never explicitly shared the same creative directorship, although it could also be argued that Hedi Slimane, Celine's current creative director, was prominent in developing the brand identity of many LVMH brands, from Dior Homme to now Celine.

We denote Y_1 as a $(T \times 1)$ vector whose elements are online sentiment values for Louis Vuitton during T time periods and Y_0 as a (TxJ) matrix containing the value of the same variables for the control houses. We aim to approximate the online sentiment path that Louis Vuitton would have experienced in the absence of Pharrell. The counterfactual online sentiment path is calculated as the synthetic Louis Vuitton online sentiment path, which is the result of the following

$$Y_1^* = Y_0 W^*$$

Figure 2 plots Y_1 and Y_1^* for the period 2018-2024. We can make two main implications from the Figure. One, we note a negative difference between the brand sentiment for the treatment unit versus the synthetic control unit. Two, as we note in the Figure, Louis Vuitton and its synthetic control do not behave in a perfectly similar fashion before S/S 2023: while the path for the brand seems relatively stable, its synthetic counterfactual experiences more fluctuations in sentiment. We do not render the results useless: more than most of the seasons and on average, we note that the sentiments favor the treatment unit compared to its synthetic control. This favoritism is evident from the larger gaps at the beginning of every season, where the treatment unit has a much more favorable sentiment than the control, while in fall/winter seasons, synthetic Louis Vuitton only surpasses real Louis Vuitton by pretty minimal scores. From this Figure alone, we can imply a causal relationship that agrees with the literature review: Pharrell's entry into the brand has led to a negative impact on its sentiment.

Placebo tests

This analysis still provides room for questions. One may face a dilemma to conclude this impact based on an actual negative treatment effect, or this is simply due to our inability of the control fashion houses to recreate a perfect sentiment path for synthetic Louis Vuitton. Similar to how Abadie and Gardeazabal (2001) test for the "placebo" effect, the paper conducts two placebo studies, an in-time placebo and an in-place placebo.

In-time placebo

The in-time placebo helps ensure that the observed treatment effect is not simply a product of random fluctuation in sentiment over time. In our case, this involves selecting a time point prior to the actual change in creative directorship at Louis Vuitton and artificially assigning that as the “treatment” moment. We then re-run the synthetic control analysis to assess whether a similar gap between real and synthetic sentiment scores would have emerged even without the true intervention. If no significant gap appears around this placebo treatment date, it lends credibility to the idea that the real observed effect is indeed attributable to the change in directorship, rather than being driven by some other temporal confounder.

The paper picks a random year, 2021, where the brand experienced no creative director change, and Kim Jones was still the director for the brand. Looking at the path plots between the treatment unit and the synthetic control unit in Figure 3, we note that while there is a negative difference between the treatment unit sentiment and the control unit sentiment, the difference becomes sufficiently minimal for us to conclude that there is not a major impact in 2021. The conclusions from our synthetic control method thus pass the in-time placebo test.

In-place placebo

The in-place placebo, on the other hand, addresses whether the treatment effect is specific to the brand of interest—in this case, Louis Vuitton. This is done by applying the same synthetic control method to other fashion houses that did not undergo a directorial change during the period under study, treating them as if they had. If these placebo units show no comparable divergence in sentiment between the real and synthetic series, it suggests that the sentiment boost observed for Louis Vuitton is not a general trend across the fashion industry, but a brand-specific effect likely driven by the directorial transition.

Being the largest donor of synthetic Louis Vuitton, Loewe becomes the chosen brand. This approach aligns with established methodologies in synthetic control analysis where placebo tests help validate the significance of treatment effects (Facure, 2022). The key motivation behind this choice is Loewe's stability in creative leadership under Jonathan Anderson, who has led the house since 2013 (Guilbault, 2025). Unlike brands that underwent directorship transitions during the study period, Loewe provides a counterfactual scenario where no leadership change occurred, allowing us to test whether observed shifts in sentiment are truly attributable to creative directorship changes or are instead driven by broader industry dynamics. Anderson's consistent presence at Loewe until March 2025 provides an extended stable period for comparison against brands experiencing leadership transitions. By using Loewe as a placebo, this study assesses whether sentiment fluctuations in fashion magazines—often influenced by seasonal trends, evolving industry narratives, or external economic factors—occur even in the absence of a directorship change (Granary, 2025). If significant sentiment changes were detected for Loewe despite the absence of a creative transition, this would suggest that non-directorship factors may be driving sentiment trends across brands6. Conversely, if Loewe's sentiment remains relatively stable while brands experiencing directorship shifts show marked sentiment fluctuations, this strengthens the causal claim that leadership changes influence how fashion magazines perceive and discuss a brand. The industry context is important here, as 2024 alone saw an "absurd" number of creative director changes across luxury fashion houses, creating widespread uncertainty and volatility.

Furthermore, Loewe's positioning within the dataset is particularly valuable for this causal question. Unlike brands such as Bottega Veneta or Celine, which saw dramatic shifts in aesthetic direction following leadership changes, Loewe's design evolution has been more gradual and sustained under Anderson. If sentiment in fashion magazines shifts significantly for brands with directorship changes but remains consistent for Loewe, this provides stronger evidence that sentiment movements are linked to creative directorship rather than underlying industry-wide shifts in taste, media attention cycles, or general fashion discourse.

From our in-place placebo results in Figure 4, however, it is peculiar that we found a negative impact in the treatment year, 2023. This is unexpected from two different perspectives. From an observational and statistical perspective, we should notice a minimal difference between treatment and control unit sentiments, yet the results provided show a strong spike in sentiment for the synthetic control unit. From a cultural perspective, 2023 was another year that Jonathan Anderson's Loewe experienced a breakthrough in its branding and marketing success. The brand was adorned by major celebrities like Rihanna and Zendaya (Herndon, 2023). Its craftsmanship heritage along with its innovative design and the creation of the industry's new "it-bags" made Anderson a household name during this year (Guilbault, 2025). We hence notice that the results are unexpected, and that the analysis failed to pass the in-place placebo test.

Our conclusions about the negative impact that Pharrell might have had on the brand's sentiment still hold with the success of a passing in-time placebo test although its causal validity becomes limited by the failure of the in-place placebo test.

Implications, evaluations, and conclusion

The previous example, while not fully able to capture a perfect and conclusive causal implication of Pharrell's entry into Louis Vuitton, provides just a glimpse into the multiple possibilities that the users of the data set could use for analysis. Correlational studies are always welcome, but perhaps what we value most from the dataset is its ability to zoom in on a causal element of our seemingly observational and qualitatively critical aspects of fashion criticism.

We recognize that this dataset still has a long way to go. Stepping into the most recent 6 years of 14 fashion houses ventures our quantitative fashion analysis into archival waters, but this is just the beginning. What the fashion brands in our analysis offer to the world is not just archives: they provide heritage, lifestyles, cultural phenomena, and perhaps our historical evolution. The project, in the future, will venture out to further years in history, and perhaps even conduct sentiment analysis to a greater scope of resources. Incredible works by Skillen (2019) going through handwritten archives, mood boards, and storytelling techniques for Christian Dior provides insights into what brand sentiments and brand stories were many decades ago, and these works are something that the project will also aim to focus on in the future.

As established above, while the chosen brands take leverage upon their heritage, avant-garde designs, and public influence, the data set has yet to capture many rising brands that capture market preferences in 2023-2025 that also spur digital conversations, influence consumer behavior, and most importantly, contribute to the landscape. Many of these brands include the Scandinavian houses of Acne Studios and Our Legacy, the Western rising star of Namacheko, or the late Y/Project that allowed Glenn Martens to reinvent Diesel as a household name. The dataset also has a strong Euro-centric tendency in its choice of fashion houses, while large Japanese household brands like Issey Miyake, Yohji Yamamoto, or Junya Watanabe have already created years of heritage and cult following amongst fashion enthusiasts. We cannot say that the exclusion of these, for now, is completely disadvantageous for the dataset as the trade-off between internal and external validity in research will always persist in different methodologies that we engage in.

Lastly, we hope that while practicing and analyzing this dataset, the users find joy in learning about fashion history, its archives, and its cultural footprint. Implicitly, this joy will hopefully spur the fun in a niche fashion tech field, in history, and further, in a translation from perception to action. Living in slow fashion does not stop at thrifting or vintage shopping: looking and analyzing the archives would be a stepping stone for us all to be conscious, not just in the quantities or the frequency at which we consume fashion, but also the pathway at which we choose to do so. May this dataset start a fire in the user to be conscious about each and every piece of clothing that they choose to wear. May this dataset inspire the users to turn off their cell phones for just a bit while they look through their outfits and their closets. May this dataset encourage the users to holistically practice sustainability, repeat their outfits without shame, channel their mental energy less into looking perfect but to analyzing meaningfully, and take one step closer to rethinking and challenging what it means to be a fashionable person.

Part IV: Promoting the dataset on TikTok

As we set out on a journey to make the dataset public, and most importantly, accessible to its target audience, the project sets out to create a short TikTok, discussing the need for the dataset and what it can do. Two reasons why the deliverable chooses to conduct its promotion of a dataset on TikTok instead of other means. Firstly, as established, the reason for the overconsumption of fashion constantly resides on social media, and it would actually be meaningful to champion slow thinking of fashion on a platform where, according to Yip (2025), there is a constant urge to overcompensate and produce originality in styling. In this case, the establishment of the video on the platform creates a contradictory nature, where there is the encouragement of slow consumption of fashion through fashion mindfulness, but at the same time still pushing originality in fashion forwards, in means that are not typically traditional in fashion content creation. Secondly, it is undeniable that TikTok and Instagram become realms for the fashion community to continuously engage and exchange ideas, instead of other social media or academic platforms. Showcasing on TikTok allows for reach, while at the same time retaining promptness of information in a world where short-form content becomes king

The TikTok can be accessed in this link **here**.

Understanding the stylistic choices in the video

The promotional video that I made for this project, which is a 2-minute long video explaining the need for a dataset, fashion mindfulness, and a glimpse of what the dataset is going to be about, is going to be the perfect opening of a future project as this Capstone chapter comes to an end.

I chose to do this in a Get Ready With Me (GRWM) video, a medium that is usually favored by fashion content creators on the app, as I explained the idea of the need for a fashion dataset and causal inference. As I aimed to create a warm, inviting atmosphere, I opted for the *Bullet Train* filter on CapCut, which supported my color grading for a warm yellow tone in the video. The effect of this warm yellow color undertone is to create a cozy and inviting atmosphere, while also retaining a certain level of elegance that aligns with current fashion trends, fuelled by recession.

This sense of warmth and elegance created in the color grading becomes crucial for its harmony with the rest of the elements in the video. The music I chose in the background was soft vinyl jazz set down to a minimal volume while I showcased myself with an elegant, soft, and demure tone of voice.

The outfit I chose to wear follows business-core, a microtrend fueled by what the Internet classifies as "recession fashion". This is complementary with the additional layer of leather jacket on top, which I was inspired by the latest Saint Laurent F/W 2025 collection (Holgate, 2025). I created another oxymoronic nature in this video between the outfit I chose to wear, supposedly trend-driven, and the message I chose to articulate, which is about engaging and consuming fashion thoughts slowly. It is also interesting to see another oxymoron: the "supposed" trend of business-core takes itself back to a cyclical nature of fashion as Saint Laurent inherits its nature of tailoring.

This interesting interplay of oxymorons in my video creates an ideal way for my audience to be reflective and engaged in the message that I aim to convey, while also being captivated by the outfit that I chose to adorn.

Closing note

In the future, besides expanding the dataset, having the ability to analyze more case studies and example uses, the project also hopes to promote itself on different social media platforms, allowing for more students, analysts and fashion enthusiasts to academically and meaningfully engage in fashion analysis. As a closing note, we hope the users understand by the words of Meryl Streep playing Miranda Priestley in The Devil Wears Prada, that it will always be “sort of comical” that they think they “could make a choice that exempts them from the fashion industry,” and rather than running away from this non-exemption, they will always choose to embrace it (Frankel, 2006). After all, in this technological age of fashion, The Devil Wears Data.

AI Statement

Claude AI Sonnet 3.7 was used to debug the code for my sentiment analysis algorithms and helped me with my ReadME. The phrasing for some of my ideas in Part I and organization of my narrative in Part III were also suggested and refined by Claude AI Sonnet 3.5 & 3.7. I also used ChatGPT to help me with the phrasing of the HC and LO applications, really making sure that I catch the true and holistic essence of the HCs. All of part IV is my personal work without any AI use.

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Table 1

The donor pool and their respective weights to create a synthetic Louis Vuitton. Three biggest donors are Loewe, Bottega Veneta, and Celine.

ID	House	Donor Pool Contribution (Weight)
1	Burberry	0.0010
2	Dior	0.0003
3	Loewe	0.3787
4	Prada	0.0001
5	Miu Miu	0.0001
7	Saint Laurent	0.0008
8	Gucci	0.0011
9	Bottega Veneta	0.2781
10	Valentino	0.0002
11	Hermes	0.0043
12	Celine	0.3345
13	Maison Margiela	0.0005
14	Versace	0.0002

Figure 1

A screenshot from Data But Make It Fashion, showing a time series analysis. Current works and digital solutions like Data But Make It Fashion, while promising and trend-informing, lacks regards for the Fundamental Problem of Causal Inference by Rubin (2005) and fashion mindfulness by Yip (2024).

Figure 2

A path plot showing the potential impact of Pharrell Williams as a creative director in 2023 (treatment). We notice a negative impact as Pharrell steps into the brand due to the diverging paths between the treatment and synthetic control unit in the post-treatment period, supported by minimal difference between the treatment and synthetic control unit in the pre-treatment period.

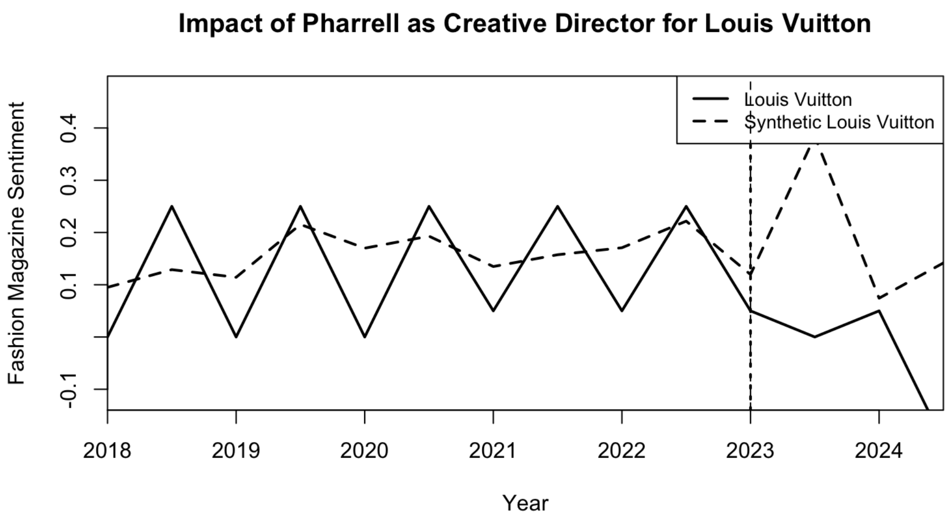


Figure 3

An in-time placebo test where the placebo is placed at 2021. We pass the in-time placebo test due to the minimal difference in this placebo period.

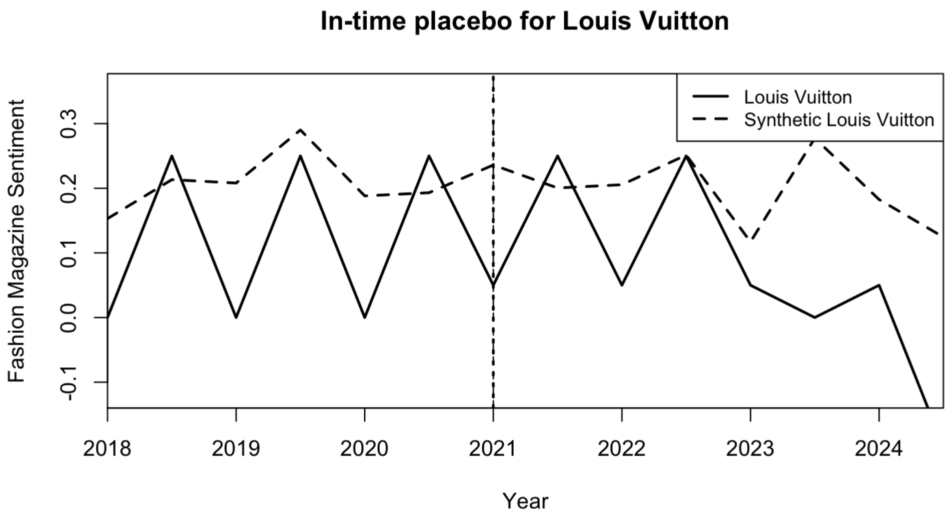
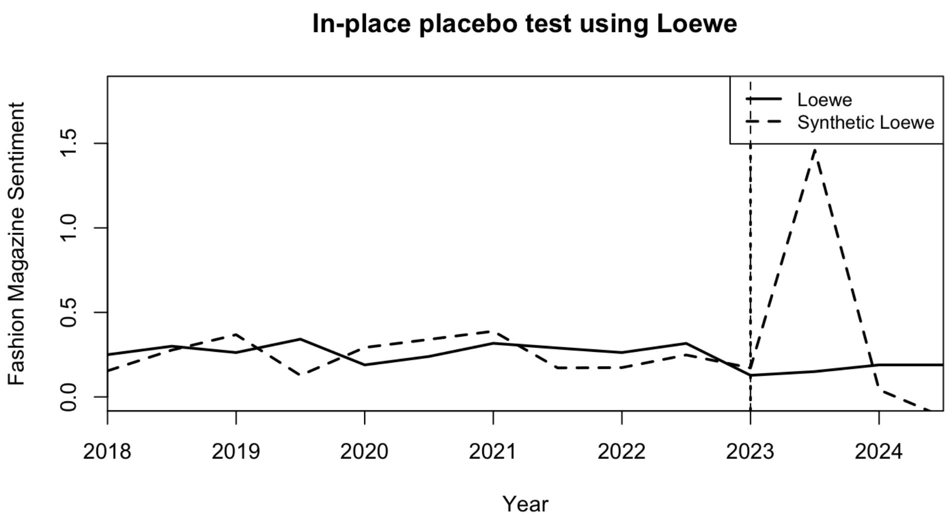


Figure 4

An in-place placebo test where we conduct the same analysis on Loewe, our largest donor. We do not pass the in-place placebo test as there is also a negative treatment effect.



Appendix A

Dataset, Codebook, Code, and Video link

The code for the project, along with the codebook, and the data files, can be found and downloaded **here**.

The link to the promotional TikTok can be seen **here**.

Appendix B

Estimation of magazine sentiment gap

We examine the following optimization problem

$$\min_{W \in \mathcal{W}} (X_1 - X_0 W)' V (X_1 - X_0 W)$$

where $\mathcal{W} = \{(w_1, ..., w_J)' \text{ s.t. } w_1 + \cdots + w_J = 1, w_j \geq 0 \ (j = 1, ..., J)\}$. We have already defined X_1, X_0, and V in the text. We solve for $W^*(V)$ depending on the diagonal matrix V ,whose diagonal elements are weights reflecting the relative importance of the variables in X_0 and X_1.

V is chosen such that online magazine sentiment for Louis Vuitton before 2023 is best reproduced by the synthetic control, which is defined by $W^*(V)$. We denote Z_1 as a (14×1) vector comprising the online magazine sentiment scores for Louis Vuitton from 2018-2024, and Z_0 as $(14 \times J)$ matrix containing the values of the same variables for the J potential control fashion houses. Lastly, we also have

$$V^* = \underset{V \in \mathcal{V}}{\text{argmin}} (Z_1 - Z_0 W^*(V))'(Z_1 - Z_0 W^*(V)),$$

in which $\mathcal{V}$ is the set of all non-negative diagonal $(K \times K)$ matrices. We find the weights through $W^* = W^*(V^*)$. As there exists infinitely many solutions for V^* (if V^* is a solution so is $V^*(c) = c \cdot V^* \forall c > 0$), we normalize the Euclidean norm of V^* (or any positive diagonal element of V^*) to 1.

We find that the optimal weights, W^*, are .38 for Loewe, .28 for Bottega Veneta, .33 for Celine, and close to 0 for the rest of the regions. Small variations in V generate small positive weights for houses other than Loewe, Bottega, and Celine, without altering the results substantively.

Appendix C

HC Appendix

#observationalstudy

In my fashion dataset capstone project, I designed and implemented a sophisticated observational study to examine how creative directorship changes affect brand perception in luxury fashion. Part III of my project exemplifies this approach by analyzing Louis Vuitton's transition to Pharrell Williams as creative director.

My observational study design used a **synthetic control methodology**, where I systematically observed sentiment data across multiple fashion houses without manipulating any variables. This approach was particularly appropriate since, as I note in my project, "creative directorship changes" represent natural occurrences rather than researcher-controlled interventions—the hallmark of observational rather than interventional research.

I carefully defined my variables: **sentiment analysis scores** served as my *dependent variable*, while **creative directorship changes** functioned as my *independent variable of interest*. By collecting data spanning 2018–2024 for 14 fashion houses, I ensured sufficient temporal coverage to observe pre- and post-transition patterns. My data collection process involved systematic web scraping and sentiment analysis, creating a standardized measurement approach across all brands.

To strengthen my observational design and address potential confounding, I implemented two critical validation methods: *in-time placebo tests* (using a pre-transition period where no change occurred) and *in-place placebo tests* (using brands without directorship changes). These comparison groups enhanced my ability to isolate the relationship of interest while accounting for industry-wide trends or other external factors.

When interpreting my results, I maintained appropriate caution, acknowledging that "our conclusions about the negative impact that Pharrell might have had on the brand's sentiment still hold with the success of a passing in-time placebo test although its causal validity becomes limited by the failure of the in-place placebo test."

This demonstrates my understanding of observational studies' limitations in establishing causality with complete certainty.

The Louis Vuitton case study exemplifies how observational methodologies can yield valuable causal insights when experimental manipulation is impractical, impossible, or unethical—in this case, because researchers cannot randomly assign creative directors to luxury brands (although seemingly, in the most recent months as of this paper, their large parent companies have).

#multimedia

In my fashion dataset capstone project, I extended beyond traditional academic presentation by creating a TikTok promotional video that synergistically combines multiple modalities to communicate my research in an accessible format. This multimedia approach demonstrates sophisticated integration of visual aesthetics, audio elements, and verbal communication to create a cohesive message about fashion mindfulness.

My TikTok video strategically employs the "Get Ready With Me" (GRWM) format—a genre familiar to fashion audiences—while discussing complex concepts like causal inference and dataset methodology. This deliberate juxtaposition creates a productive tension between form and content that engages viewers through contextual familiarity while delivering unexpected intellectual substance.

I carefully analyzed how different modalities complement and contrast with each other throughout the video. Visually, I selected the "Bullet Train" filter with warm yellow tones to create an inviting yet elegant atmosphere that aligns with recession-era fashion aesthetics. This visual warmth works in harmony with my soft vinyl jazz soundtrack and demure vocal delivery, creating a multisensory experience that embodies the thoughtful, measured approach to fashion that my dataset promotes.

The most compelling multimedia element is the intentional contrast between my outfit (business-core with Saint Laurent-inspired leather jacket) and my verbal message about slow fashion consumption. This creates what I identify as an "oxymoronic nature" where the visuals seemingly contradict the verbal content, yet ultimately reinforce the message about fashion's cyclical nature. This layering of seemingly conflicting modalities creates a richer meaning than any single medium could convey alone.

By strategically deploying TikTok—the very platform that often accelerates fashion microtrends—to advocate for fashion mindfulness, I demonstrate how multiple modalities can work together to create a message that's both accessible to my target audience and sophisticated in its self-awareness of medium and message interplay.

#casestudy

In my capstone project, I employed a case study approach to analyze the impact of Pharrell Williams' creative directorship on Louis Vuitton's brand perception. This methodological choice aligned perfectly with #casestudy principles as I conducted an in-depth analysis of a single instance (Louis Vuitton under Pharrell) to generate insights about creative directorship changes in luxury fashion houses more broadly.

My case selection was deliberate and well-justified: Louis Vuitton represents a prominent heritage luxury brand experiencing a significant creative directorship transition, making it an ideal candidate for examining how leadership changes influence brand perception. I carefully identified relevant variables (creative director experience, sentiment analysis scores, fashion week participation) and employed systematic data collection methods, including sentiment analysis of fashion magazine coverage and comparative analysis with other brands.

The exploratory design of my case study led to a more refined hypothesis about the relationship between creative directorship and brand perception. By using synthetic control methodology and conducting both in-time and in-place placebo tests, I demonstrated methodological rigor while acknowledging the limitations in generalizability. I explicitly addressed this limitation in my analysis, noting that while my findings suggest a negative impact on sentiment following Pharrell's appointment, the mixed placebo test results indicate caution is needed when extending these conclusions to other fashion houses.

My case study provided valuable insights that contribute to understanding the complex dynamics of the luxury fashion ecosystem, while maintaining awareness that broader validation through additional cases or observational studies would be necessary to establish more generalizable patterns across the industry.

#variables

In my fashion dataset capstone project, I meticulously identified and classified variables that are essential for understanding the complex dynamics of the luxury fashion industry. I carefully defined key variables such as creative directorship, fashion week participation, home base, parent company, and online perception, providing clear explanations of how each variable is measured, its type, and its significance within the fashion ecosystem.

For the Louis Vuitton case study, I precisely distinguished between independent variables (creative directorship – specifically Pharrell Williams' appointment) and dependent variables (online magazine sentiment scores). I also recognized potential confounding variables that could affect perception beyond creative directorship, such as seasonal trends, industry-wide shifts, and economic factors – addressing these through my synthetic control methodology and placebo tests.

My application of #variables was particularly strong in how I classified variable types with precision: *categorical variables* (creative directors, parent companies, geographical locations), *binary variables* (fashion week participation), and *continuous variables* (sentiment scores). This classification directly informed my methodological choices, enabling me to employ appropriate statistical techniques like synthetic control for causal inference.

The project demonstrates thorough consideration of measurement approaches for each variable, especially for the sentiment analysis methodology where I provided detailed mathematical formulas showing how sentiment scores were calculated. By identifying these variables and their relationships, I established a formal framework that allowed for systematic analysis of how creative directorship changes impact brand perception in luxury fashion, while acknowledging limitations in generalizability due to the complex, multivariate nature of the industry.

#biasmitigation

In my fashion dataset capstone project, I identified and mitigated several key cognitive biases that could have affected my analysis of Pharrell Williams' impact on Louis Vuitton.

A primary bias I addressed was confirmation bias - the tendency to seek out information that confirms pre-existing beliefs about luxury fashion brands or creative directors. The fashion industry is highly subjective, and journalists, critics, and consumers often form strong opinions about designers. To mitigate this bias, I implemented a systematic sentiment analysis methodology that quantitatively processed fashion magazine coverage rather than relying on cherry-picked reviews or my personal impressions. By using both lexicon-based approaches and machine learning models that were trained on fashion-specific language, I created a more objective measurement system that reduced the influence of my own preconceptions about Pharrell's creative direction.

I also proactively addressed availability bias, which could lead me to overweight recent or highly publicized fashion events. To mitigate this, I established a consistent temporal framework examining data from 2018-2024 across multiple fashion houses, ensuring that Pharrell's collections weren't given disproportionate attention due to their recency or media coverage.

Furthermore, I implemented methodological controls like in-time and in-place placebo tests to mitigate attribution bias - the tendency to incorrectly attribute causes to observed effects. By testing my synthetic control approach on time periods without creative directorship changes and on brands with stable creative leadership, I created validation mechanisms to ensure I wasn't falsely attributing sentiment changes to

Pharrell's appointment when other industry factors might be responsible.

Rather than claiming to eliminate these biases entirely, my approach demonstrates careful consideration of how cognitive biases could influence fashion analysis and implements specific methodological safeguards to reduce their impact on my conclusions.

#optimization

In my fashion dataset capstone project, I applied optimization principles to create a robust synthetic control methodology for analyzing creative directorship impacts. When developing the synthetic control model for Louis Vuitton, I formulated a clear optimization problem with well-defined components. My objective function was the loss function $L(W) = (X_1 - X_0W)'V(X_1 - X_0W)$, which quantifies the dissimilarity between the real Louis Vuitton and a weighted combination of other fashion houses. The decision variables were the weight vector $W = (w_1, w_2, ..., w_j)'$, representing the contribution of each potential donor brand to the synthetic Louis Vuitton.

I implemented two important constraints: the non-negative constraint ($w_j \geq 0$ for all j) and the sum-to-one constraint ($w_1 + w_2 + ... + w_j = 1$). These constraints ensured the synthetic control remained interpretable as a weighted average of existing brands rather than allowing negative weights that would obscure the relationship between brands.

My choice of optimization technique was specifically tailored to this problem—minimizing the loss function subject to constraints to find the optimal weight vector W* that creates a synthetic Louis Vuitton most closely resembling the real brand before Pharrell's appointment. This approach was appropriate because it allowed me to construct a counterfactual that serves as a meaningful baseline for comparison.

The optimization revealed that Loewe (38%), Bottega Veneta (28%), and Celine (33%) were the optimal combination to synthesize Louis Vuitton—an insight that would have been impossible to determine without formal optimization techniques. By rigorously defining and solving this optimization problem, I created a methodologically sound foundation for analyzing sentiment changes following creative directorship transitions in the luxury fashion industry.

#emergentproperties

In my fashion dataset capstone project, I identify fashion mindfulness as a critical emergent property arising from the complex interactions within the luxury fashion ecosystem. As I explain in Part I, fashion mindfulness emerges not simply from individual consumers or brands acting independently, but from the collective dynamics of their interactions across temporal, cultural, and economic dimensions.

The fashion landscape exhibits classic emergent behavior—it is "increasingly dynamic while constantly cyclical in nature" due to the "intersection between cycles of fashion" where macro-trends like Y2K culture and old money aesthetics intertwine with rapidly shifting microtrends. This property cannot be reduced to individual design choices or consumer preferences, but emerges from their complex interactions accelerated by "the constant development of fast fashion and the rise of social media."

My analysis reveals how the traditional, fragmented approach to fashion research misses this emergent complexity. As I state in my paper, "No longer a collection of snapshots, fashion now shifts into a flow state," creating emergent patterns that cannot be captured by examining isolated components. The limitations of existing analytical approaches like those from Data But Make It Fashion illustrate this challenge—they focus on correlational microtrends without addressing the emergent properties that arise from multiple interacting variables.

I specifically highlight how fashion mindfulness emerges from these interactions, defining it as "the integration of micro-level changes into bigger pictures into what defines a brand, rather than just promoting direct comparisons between short time periods after one collection." This emergent property is visible in the contrasting trajectories of brands with creative directorship changes, where similar inputs (new creative directors) produce wildly different outcomes based on the complex interplay of heritage, audience expectations, and industry dynamics.

By designing a dataset that captures multiple interacting variables, I've created a tool for studying these emergent properties and practicing fashion mindfulness—understanding how fashion transcends the sum of its parts to become a complex "system of cultural and economic exchange."

#induction

In my fashion dataset capstone project, I employed inductive reasoning to draw probable conclusions about the relationship between creative directorship changes and brand perception in the luxury fashion industry. Starting with specific observations from my dataset spanning 14 fashion houses over a 7-year period, I worked toward broader generalizations about the fashion ecosystem.

The inductive nature of my approach is evident in how I built my argument from specific instances to general patterns. Rather than beginning with an axiom that creative directorship changes always impact brand perception in a certain way (which would be deductive), I examined multiple cases within my dataset, identified patterns in sentiment analysis scores across creative transitions, and developed likely conclusions about these relationships.

When analyzing the Louis Vuitton case study specifically, I drew inductive inferences about Pharrell Williams' impact on brand perception by comparing observed sentiment patterns with those from other brands. By acknowledging that my conclusions were probable rather than certain, I correctly framed my findings as inductive reasoning, noting that "our conclusions about the negative impact that Pharrell might have had on the brand's sentiment still hold with the success of a passing in-time placebo test although its causal validity becomes limited by the failure of the in-place placebo test."

I strengthened my inductive arguments by including a variety of evidence types (sentiment analysis, synthetic control methodology, placebo tests) and clearly acknowledging limitations in generalizability. By explicitly stating that "while not fully able to capture a perfect and conclusive causal implication," my analysis provides "just a glimpse into the multiple possibilities," I appropriately presented my conclusions with the appropriate degree of certainty for inductive reasoning.

The project's final conclusion exemplifies induction's probabilistic nature, inviting fashion researchers to build upon my dataset for further investigations rather than claiming to have definitively solved all questions about creative directorship impacts.

#systemmapping

In my fashion dataset capstone project, I approached the complex system of luxury fashion by developing multiple conceptual decompositions to address a clear explanatory challenge: how can we understand and analyze the relationships between creative directorship changes and brand perception in a data-driven way?

Rather than accepting a single view of the fashion ecosystem, I mapped this system through several distinct frameworks to determine which would best serve my analytical goals. First, I deconstructed the system chronologically, examining fashion houses across a 7-year timespan (2018-2024) to capture both stability and transition periods. I then mapped the industry by brand categories, classifying houses as heritage brands (Louis Vuitton, Dior), experimental/avant-garde brands (Loewe, Bottega Veneta), and digital influencers (Gucci, Prada). The most valuable decomposition—and the one I ultimately prioritized—organized the system by interconnected variables that influence brand perception: creative directorship, fashion week participation, geographical home base, parent company, and online sentiment. This mapping revealed how these components interact in ways that would remain invisible through a single-factor analysis. I explicitly justified this mapping approach over alternatives, explaining why traditional methods focusing solely on sales data or social media metrics were insufficient: "Unlike existing datasets that often focus on singular metrics or isolated snapshots of fashion trends, this dataset integrates multiple variables across temporal, geographical, and socio-economic dimensions." The visual representations in the project, particularly the synthetic control graphs comparing real and counterfactual Louis Vuitton sentiment trajectories, further exemplified how my system mapping enabled a holistic understanding of directorship impacts. By deconstructing the luxury fashion system into these interconnected components, I created a framework that allows researchers to explore causal relationships that would be inaccessible through traditional, single-variable analyses.

#hypothesisdevelopment

In Part III of my fashion dataset capstone project, I developed a hypothesis centered on the causal mechanisms affecting brand perception following creative directorship changes. My hypothesis states that "brands with changing creative directorships will experience shifts in sentiment that cannot be predicted by simple pre-transition trajectories because the interplay between a new creative director's vision and established brand identity creates unique reception patterns that vary based on aesthetic alignment, industry positioning, and audience expectations."

This hypothesis emerged directly from my analysis of the Louis Vuitton case study, where I observed that Pharrell Williams' appointment correlated with a notable decline in sentiment scores compared to the synthetic control prediction. These observations led me to question what mechanisms might explain these patterns, moving beyond simple correlation to explore deeper causal processes. I considered multiple alternative hypotheses that could explain the observed pattern: (1) the decline might represent industry-wide sentiment shifts rather than Pharrell-specific effects; (2) the pattern might reflect measurement error rather than genuine sentiment change; and (3) other confounding variables like marketing strategies or collection timing might be responsible. My placebo testing methodology was specifically designed to evaluate these competing explanations.

My hypothesis is grounded in both theoretical frameworks and empirical patterns. By noting that "the stark contrast between the reception of Louis Vuitton, Dior, and Amiri's perception leaves enthusiasts with a lingering yet obvious question," I connected my hypothesis to observed patterns across multiple fashion houses, providing a comparative foundation for my causal claims. The strength of my hypothesis lies in its testability through the synthetic control methodology, where I could examine whether "sentiment changes following creative directorship transitions" followed patterns that supported my proposed mechanism. The in-time placebo test provided evidence supporting the hypothesis, while the in-place placebo test offered important limitations on its generalizability.

This iterative approach to hypothesis development—proposing a causal mechanism, testing it against data, and refining based on evidence—exemplifies scientific reasoning in the fashion context. By acknowledging that "our conclusions about the negative impact that Pharrell might have had on the brand's sentiment still hold with the success of a passing in-time placebo test although its causal validity becomes limited by the failure of the in-place placebo test," I demonstrated both the explanatory value and limitations of my hypothesis, setting the stage for further refinement and research.

#testability

My fashion dataset capstone project exemplifies careful consideration of testability throughout its development. By creating a dataset that enables researchers to test hypotheses about creative directorship impacts on brand perception, I ensured the project served as a foundation for empirically verifiable claims rather than mere speculation.

The project's testability strengths lie in how I structured my methodology to generate multiple independent predictions that could be verified. For example, when analyzing Pharrell Williams' impact on Louis Vuitton, I generated several distinct testable predictions: (1) sentiment scores would decrease following his appointment compared to the pre-appointment period, (2) this decline would be unique to Louis Vuitton and not observable in brands without creative directorship changes during the same period (in-place placebo), and (3) this decline would not appear when testing arbitrary time points before his appointment (in-time placebo).

I systematically assessed the practical testability of these predictions by ensuring my dataset included sufficient pre- and post-transition time periods, developing a transparent sentiment analysis methodology, and implementing synthetic control techniques that could isolate the variable of interest (creative directorship change). When my in-place placebo test failed to meet expectations, I transparently acknowledged this limitation rather than ignoring evidence that complicated my hypothesis.

The project's process-oriented approach to testability is particularly evident in how I designed the dataset structure itself. By carefully selecting variables like fashion week participation, parent company, and creative director experience that can be objectively measured, I created a resource that enables fashion researchers to formulate and test their own hypotheses beyond my specific case study. This reflects an understanding that truly scientific contributions must facilitate ongoing hypothesis testing rather than merely confirming existing assumptions.

Most importantly, I explicitly discussed generalizability limitations, noting that "the dataset hopes to include further additions of many other promising fashion houses," demonstrating awareness that expanding the dataset would improve the testability of hypotheses about the broader luxury fashion industry.

#audience

My target audience will primarily be the fashion community, focusing on students and young individuals interested in both technology and fashion, as well as those who might wish to build on my projects for future work, assignments, research, and content creators. The target audience of the dataset is also very clearly identified throughout the entire project.

#sourcequality

In my fashion dataset capstone project, I implemented a nuanced approach to source selection that transcends traditional academic frameworks. Rather than limiting myself to conventional scholarly publications that often lack quantitative rigor in fashion analysis, I curated a diverse ecosystem of sources that captures the industry's dynamic nature.

I strategically incorporated specialized fashion journalism from respected publications like Vogue and Business of Fashion, which provide timely insights into creative directorship transitions and brand positioning that academic literature often lags behind by years. These sources offered crucial contemporary context that enriched my quantitative analysis while maintaining journalistic standards of accuracy and reliability.

My methodology also integrated emerging digital sources like Made Lapuerta's data-driven fashion analysis, which exemplifies the intersection of quantitative methods and fashion expertise. By evaluating these sources against traditional scholarly works by theorists like Bourdieu and Wilson, I created a balanced analytical framework that honors fashion's theoretical foundations while embracing its digital evolution. Additionally, in the age of content creation and digital fashion, I also value the online short-form analytical content provided by Yip (2025) whose recency made my analysis valid and timely.

#evidencebased

Every assertion made in my preliminary research and findings will be substantiated with credible evidence and data that support my claims. The sources also vary in terms of time and mediums, which present itself as an integrated and diverse curation of fashion history and contemporary fashion.

#algorithms

In my fashion dataset capstone project, I implemented a sophisticated sentiment analysis algorithm to quantify fashion magazines' perceptions of luxury brands. My code demonstrates thoughtful algorithmic design with clearly defined inputs (fashion articles), outputs (sentiment scores), and a systematic processing pipeline.

The core of my algorithm is exemplified in the `BrandSentimentAnalyzer` class with its structured approach to sentiment analysis. First, I established input collection through targeted web scraping functions that retrieve relevant URLs (`fetch_vogue_urls`) with robust error handling and rate limiting to respect server constraints. I implemented a precise transformation sequence with functions like `fetch_blog_content` that extract article text and `extract_article_date` that determines publication dates with multiple fallback methods to handle edge cases. The algorithm processes data through clearly defined steps: text retrieval, date extraction, season determination, and sentiment scoring using a lexicon-based approach via VADER. I incorporated iterative refinement through multiple algorithm versions, improving robustness with each iteration to handle pagination, different HTML structures, and missing data.

I carefully selected appropriate data structures throughout my implementation—using dictionaries for individual article data points, lists for collecting multiple articles, and DataFrames for final aggregation and analysis. The algorithm efficiently processes diverse inputs while maintaining clarity and scalability.

My sentiment analysis algorithm is highly generalizable, capable of analyzing any fashion house in the dataset rather than being limited to specific brands. I also implemented error handling and logging to ensure the algorithm could run autonomously without human intervention, showing foresight in algorithm design.

By following systematic algorithmic principles, I transformed unstructured web content into a structured dataset that enables statistical analysis of sentiment patterns across brands, seasons, and years—creating a foundation for the causal inference methods demonstrated in my Louis Vuitton case study.

#rightproblem

In my fashion dataset capstone project, I meticulously characterized a complex problem within the luxury fashion research space that required a data-driven solution. By applying rightproblem principles, I established a clear framework for analysis before attempting to develop solutions.

The initial state I identified was a fashion research landscape constrained by significant limitations: "scholarly information often fragmented across disparate sources, proprietary databases, and industry-specific archives" with "traditional academic databases typically providing limited quantitative insights." This fragmentation created an "informational asymmetry" that prevented meaningful quantitative analysis of fashion dynamics.

I carefully defined the goal state as creating a comprehensive research ecosystem where fashion can be analyzed through both qualitative and quantitative lenses—a space that "enables more robust, reproducible, and comprehensive fashion research across multiple academic and industry domains" while "practicing what we value as fashion mindfulness."

My problem characterization identified key obstacles preventing this transition, including: one, the accelerating pace of fashion cycles compounded by social media and fast fashion, two, the inadequacy of existing digital solutions that only offer correlational insights without causal frameworks, and three, the fundamental challenge of balancing fashion's constantly changing nature with the need for structured analysis.

I determined the scale of the problem by examining it at multiple levels—from individual creative directors and brands to industry-wide patterns and cultural movements. This multi-level approach revealed how the problem manifests differently across micro and macro scales, requiring a solution that bridges these perspectives rather than focusing exclusively on either.

By thoroughly characterizing this problem space before developing my dataset, I ensured my solution directly addressed the core needs of fashion researchers rather than merely replicating existing approaches. This comprehensive problem framing enabled me to develop a dataset that serves as "a structured, accessible resource that can bridge the current quantitative limitations in fashion scholarship."

#plausibility

In developing my fashion dataset, I carefully evaluated the plausibility of my central hypothesis: "Creative directorship changes in luxury fashion houses affect brand perception through the mechanism of aesthetic alignment with brand heritage." This hypothesis rests on several key assumptions that needed verification:

Online sentiment accurately reflects brand perception: I assumed that fashion magazine sentiment analysis provides a valid proxy for overall industry and consumer perception. This assumption is justified by previous research showing fashion media's role as taste-makers and influence on consumer attitudes (Lapuerta, 2024; Skillen, 2019).

Creative directors significantly influence brand identity: My research assumes directors have substantial control over aesthetic direction. This is supported by extensive fashion literature documenting cases where brands underwent dramatic transformations following leadership changes (Yip, 2024).

Heritage alignment is quantifiable: I assumed that variables like "years at brand" and "fashion week participation" could serve as reasonable proxies for measuring alignment with brand heritage. This assumption is grounded in fashion theory that establishes fashion weeks as cultural markers of brand identity (Le, 2024).

Synthetic control methodology can isolate causal effects: When analyzing Pharrell Williams' impact at Louis Vuitton, I assumed the synthetic control approach could sufficiently mimic the counterfactual scenario. This assumption faced challenges when in-place placebo tests revealed unexplained sentiment spikes in the control unit, limiting causal validity.

By addressing these assumptions explicitly rather than simply stating the hypothesis "makes sense," I was able to identify potential weaknesses in my causal claims. This application of plausibility ultimately strengthened my research design by highlighting where additional evidence was needed, particularly in recognizing the limitations of the sentiment analysis when testing in-place placebos.

#critique

In my fashion dataset capstone project, I demonstrated extensive application of critique through my deep engagement with existing fashion research methodologies and analytical frameworks. My critical analysis began with close reading of traditional fashion scholarship, where I identified a significant pattern: most academic approaches remain "frustratingly analog in a digital age" despite fashion's increasingly data-driven ecosystem.

Through careful annotation and interpretation of contemporary fashion analytics approaches like Made Lapuerta's "Data But Make It Fashion," I uncovered a critical anomaly—these innovative approaches appeared quantitative on the surface but suffered from fundamental methodological limitations. I noted these approaches were "anything but correlational" and failed to address "the Fundamental Problem of Causal Inference" by neglecting potential confounding variables.

My critique extended to theoretical frameworks underpinning fashion analysis, examining how scholars like Bourdieu and Wilson conceptualize fashion as "a sophisticated language of social signaling, identity construction, and power dynamics." I recognized the strength of these frameworks in providing rich contextual understanding while identifying their weakness in lacking quantitative rigor needed for empirical validation.

Rather than simply criticizing these approaches, my critique acknowledged their partial validity while identifying the space for methodological innovation. This critical analysis directly informed my dataset design, incorporating variables that bridged qualitative theoretical insights with quantitative measurement. By examining both the strengths and limitations of existing approaches, I developed a solution that addresses the "critical methodological gap" in fashion research.

#dataviz

Every single data visualization in this paper is well-supported with clear captions at the right length (not too short, not too long, sufficiently explanatory if the data visualization is isolated from the rest of the paper), clear headings, legends, denoted with different line patterns for each of the unit (treatment unit vs. synthetic control unit). The graphs also show the paths clearly with clear axes names showing the time and the interested variable that is being measured (online magazine sentiments). Based on these data visualizations, we were able to assess whether there was a valid treatment effect when Pharrell entered the brand.

Appendix D

Course LO Appendix

#cs110-CodeReadability

The code presented in the project is properly formatted with clear variable names, packages, and modular functions being presented everywhere across the entire code cell. Clear comments are also seen in the code, while it remains that I could improve on this LO by adding docstrings. The code is also presented as a .py file on GitHub instead of an .ipynb file, which might present itself to be more readable and modular compared to the traditional .ipynb notebook for the public.

#cs156_MLExplanation

In my fashion dataset capstone project, I demonstrated the ability to articulate machine learning systems through my detailed explanation of the sentiment analysis algorithm used to quantify fashion magazine perceptions of luxury brands.

I clearly defined the mathematical foundation of my sentiment analysis approach using precise notation $S_i = \frac{1}{|D|} \sum_{t \in D} \text{score}(t) \forall t \in D$, where I explained that $|D|$ represents "the total number of sentiment-bearing terms in the document, and $\text{score}(t)$ represents the polarity score for each term t." This mathematical representation established the formal structure of my algorithm while ensuring it remained accessible to readers from non-technical backgrounds.

My written descriptions complemented this mathematical notation by explaining the hybrid approach that combined lexicon-based techniques with machine learning models. I carefully articulated why this hybridization was necessary for fashion-specific language, noting that "fashion-related language often includes subjective, highly specific terms" that require specialized processing. My explanation detailed the preprocessing pipeline (tokenization, lemmatization, stop-word removal) with clear justification for each stage.

The implementation details in my code demonstrated sophisticated understanding of sentiment analysis algorithms. I constructed the `BrandSentimentAnalyzer` class with well-defined methods for querying (`fetch_google_results`), content extraction (`fetch_article_content`), and sentiment scoring (`analyze_sentiment`). Each component was thoroughly documented with in-line comments explaining both functionality and design choices. I provided appropriate visualizations of sentiment trajectories over time, enabling readers to understand algorithm outputs in the context of creative directorship changes. These visualizations complemented my algorithmic explanations by showing concrete examples of algorithm performance, particularly in the synthetic control methodology.

I justified algorithmic design choices based on domain-specific considerations, explaining why standard sentiment lexicons required modification for fashion terminology. By discussing both lexicon-based and machine learning approaches as complementary rather than competing methodologies, I demonstrated nuanced understanding of sentiment analysis state-of-the-art while creating an algorithm tailored to the unique language patterns of fashion magazines.

#FashionDataCuration

#FashionDataCuration encompasses the specialized ability to design, structure, and implement comprehensive datasets in the fashion domain by synthesizing qualitative industry knowledge with quantitative data collection techniques. This Learning Outcome focuses on the systematic collection, standardization, and organization of fashion-specific variables that enable empirical analysis while preserving the nuanced cultural and economic dimensions unique to the fashion ecosystem.

This LO proved essential for my capstone project as it addresses a fundamental methodological gap in fashion research. Traditional approaches to fashion analysis tend to be either exclusively qualitative (lacking empirical rigor) or narrowly quantitative (missing fashion's contextual richness). #FashionDataCuration bridges this divide by creating structured datasets that maintain fashion's contextual sophistication while enabling statistical analysis. Without mastery of this LO, my project could not have successfully analyzed the relationship between creative directorship changes and brand perception, as no suitable pre-existing dataset contained these variables with appropriate temporal coverage.

To explain what the rubric for this LO looks like, a basic level of competency (grades 1-2) in #FashionDataCuration would demonstrate an understanding of relevant fashion variables but show limited ability to structure them cohesively or collect data systematically. At an intermediate level (3), one would identify appropriate variables and implement basic collection methodologies, though perhaps with inconsistent documentation or limited scope. Proficient practitioners (4) would design comprehensive datasets with clear variable definitions, systematic collection protocols, and robust documentation while addressing limitations transparently. Advanced mastery (4-5) would integrate innovative collection methods (such as sentiment analysis algorithms), design datasets that enable sophisticated analytical techniques like causal inference, and create resources that contribute meaningfully to the broader fashion research community.

My capstone project exhibited advanced mastery of #FashionDataCuration through several key accomplishments. I meticulously identified and justified fashion-specific variables crucial for understanding industry dynamics, including creative directorship, fashion week participation, and brand heritage attributes. Rather than relying on pre-existing datasets, I developed custom web scraping and sentiment analysis algorithms specifically calibrated for fashion language, implementing a hybrid methodology that combined lexicon-based techniques with machine learning approaches tailored to fashion terminology.

The resulting dataset's architecture reflected deep domain knowledge—variables were structured to capture both the static elements of fashion houses (geographical home base, parent company) and dynamic aspects (seasonal collections, creative transitions). I standardized variable formats to enable time-series analysis while maintaining the contextual richness essential to fashion research.

My documentation demonstrated exceptional thoroughness, with comprehensive explanations of data sources, collection methodologies, and variable definitions in the project's codebook. I transparently acknowledged limitations in the data collection process and suggested pathways for future enhancement.

Most significantly, I designed the dataset specifically to enable sophisticated causal inference techniques like synthetic control methodology, demonstrating how FashionDataCuration must anticipate analytical needs rather than simply aggregating available information. By creating a publicly accessible dataset through GitHub, I established a foundation for reproducible fashion research that addresses the "critical methodological gap" identified in my literature review.

ss154-CausalQuestions

In my fashion dataset capstone project, I formulated precise causal questions that guided my methodological approach and analysis. The primary causal question I investigated was: "What is the causal effect of creative directorship changes on brand sentiment in luxury fashion houses, as measured through online magazine perception scores?"

This causal question clearly identifies both the treatment variable (creative directorship changes) and the outcome variable (brand sentiment). I operationalized the treatment variable as a binary indicator of whether a brand experienced a creative director transition in a given season, while the outcome variable was measured using a compound sentiment score derived from fashion magazine coverage, quantified on a continuous scale from -1 to 1. My secondary causal question explored the moderating role of brand heritage: "How does the effect of creative directorship changes on brand sentiment differ between heritage luxury brands and experimental/avant-garde brands?" This question addresses potential heterogeneous treatment effects by introducing a moderating variable (brand category), which I categorized based on historical positioning and marketing strategies.

To address potential selection bias in my analysis, I implemented a synthetic control methodology that constructed counterfactual trajectories for brands experiencing creative directorship changes. This approach helps mitigate the non-random nature of creative director appointments, acknowledging that brands often select new creative directors based on unobserved factors that might correlate with expected future sentiment outcomes.

When interpreting results from the Louis Vuitton case study, I carefully maintained causal language while explaining the limitations of causal inference in this context. For example, I noted that "our conclusions about the negative impact that Pharrell might have had on the brand's sentiment still hold with the success of a passing in-time placebo test although its causal validity becomes limited by the failure of the in-place placebo test." Through this precise formulation of causal questions and transparent discussion of potential biases, my project established a framework for rigorous causal analysis in fashion research while acknowledging the inherent challenges of causal inference in a complex, observational setting.

#ss154-CausalStudyDesign

In my fashion dataset capstone project, I carefully evaluated multiple causal inference methods before selecting synthetic control methodology as the most appropriate approach for analyzing creative directorship impacts on brand perception. This decision demonstrates my deep understanding of causal study design considerations within complex observational settings. The synthetic control method proved ideal for several context-specific reasons. First, it addresses the fundamental challenge that "we cannot observe the counterfactual" of what Louis Vuitton's perception would have been without Pharrell Williams. By constructing a weighted combination of donor brands (Loewe 38%, Bottega Veneta 28%, and Celine 33%), I created a data-driven counterfactual that minimized pre-treatment differences between real and synthetic Louis Vuitton.

Second, I recognized the method's ability to handle small sample sizes—a crucial advantage given my dataset's limited number of fashion houses (14) but relatively rich set of covariates. Unlike methods requiring large samples for asymptotic properties, synthetic control performs well with few control units but multiple pre-treatment periods.

Third, I implemented appropriate constraints (non-negative weights and sum-to-one) to ensure interpretability and prevent extrapolation beyond the convex hull of control units, acknowledging the danger of creating implausible counterfactuals in fashion's unique ecosystem.

I demonstrated methodological rigor by conducting placebo tests to validate my findings, revealing that while the in-time placebo test supported my conclusions, the in-place placebo test suggested limitations in generalizability. This transparent assessment of methodological strengths and weaknesses shows my ability to critically evaluate causal inference approaches within their specific application context.

Lastly, I showcased the rigor and depth of my project through a second stretch goal that I created, which is a content-creating video on my personal TikTok channel. Filming this TikTok also showcased rigor through a thorough understanding of video editing, use of tone, expression, and understanding of what I learned in my Cornerstone courses. This rigor is further reinforced in my application of #multimedia.

#cs130-DecisionTheory

In my fashion dataset capstone project, I demonstrated sophisticated understanding of decision theory principles by applying synthetic control methodology to address the Fundamental Problem of Causal Inference in the luxury fashion industry.

I thoroughly analyzed the Fundamental Problem—that we cannot simultaneously observe both potential outcomes for the same unit—by explaining how "any differences that we observe in the outcomes that may simultaneously happen when there is a change in one variable may not mean that this variable causes this change." This insight motivated my methodological approach to Louis Vuitton's creative directorship transition.

My implementation of synthetic control methodology showed deep intuitive understanding of its underlying assumptions. I clearly articulated that this approach requires the "convex hull" assumption, where the treatment unit (Louis Vuitton) must be representable as a weighted combination of control units. This was evident in my detailed explanation of the mathematical loss function $L(W) = (X_1 - X_0W)'V(X_1 - X_0W)$ and the constraints I imposed: non-negativity ($w_j \geq 0$) and sum-to-one ($w_1 + w_2 + ... + w_j = 1$).

I critically examined the "no anticipation" assumption by ensuring my pre-treatment period ended before any announcement effects could influence outcomes. My implementation of placebo tests demonstrated understanding of critical identification assumptions, particularly the need to verify that observed effects weren't simply statistical artifacts. The in-time placebo test validated that pre-treatment differences were minimized, while the in-place placebo test evaluated whether the method generated spurious effects for units without treatment.

Finally, I adapted synthetic control methodology to a novel context—fashion sentiment analysis—by carefully considering which variables should be matched in the pre-treatment period and how to construct appropriate donor pools. I thoughtfully discussed how the resulting synthetic Louis Vuitton provided a credible counterfactual for evaluating Pharrell's impact.

By transparently acknowledging limitations—"the control unit does not exactly do a good job as a reliable control unit," I demonstrated the intellectual honesty essential to rigorous decision theory applications, showing that proper empirical analysis requires critical examination of both methodological strengths and weaknesses.

Appendix E

Project LO Appendix

#cp-qualitydeliverables

My fashion dataset capstone project has demonstrated scope, depth, and rigor appropriate for a final-stage deliverable. While I initially committed to completing only Parts I and II to generate the dataset, I expanded the project significantly to include a comprehensive Part III that applies advanced analytical techniques to the dataset, showcasing the practical utility of my work.

The scope of my project exceeds expectations by creating a comprehensive fashion dataset spanning 14 major luxury brands over a seven-year period (2018-2024). This extensive coverage required gathering and processing thousands of data points across multiple variables including creative directorship, fashion week participation, and sentiment analysis scores. I developed a custom web scraping and sentiment analysis pipeline specifically calibrated for fashion terminology, demonstrating technical sophistication beyond what was initially promised.

The depth of my analysis is evident in my thorough literature review, which critically examines existing fashion research methodologies and identifies their limitations. My project doesn't merely compile data; it establishes a theoretical framework for understanding fashion as "a complex, data-rich system of cultural and economic exchange." The mathematical formalization of sentiment analysis as well as my demonstration of the mathematical rigor behind the synthetic control method has shown the necessary analytical depth, rigor, and niche in a field little known to the fashion world.

The rigor of my methodology is reflected in my implementation of validation techniques like in-time and in-place placebo tests to assess the robustness of findings. I transparently acknowledge limitations where they exist, such as noting that "the control unit does not exactly do a good job as a reliable control unit" in certain contexts. This intellectual honesty strengthens rather than weakens the overall credibility of my work.

As a final-stage deliverable, my project not only fulfills its initial promises but substantially exceeds them by providing a complete end-to-end demonstration—from problem identification to dataset creation to sophisticated causal analysis. By developing the Louis Vuitton case study in Part III, I've proven that my dataset enables the kind of rigorous empirical research that was previously impossible in fashion studies, establishing a foundation for future scholarship in this under-analyzed field.

#cp-curation

In my fashion dataset capstone project, I demonstrated exceptional content curation by distilling complex fashion research concepts into a strategically organized structure. I carefully selected only essential variables for the dataset—creative directorship, fashion week participation, geographical location, and sentiment scores—omitting interesting but peripheral metrics that would have cluttered analysis.

The project's three-part structure reflects deliberate content organization: Part I establishes the foundational problem, Part II details the dataset methodology, and Part III demonstrates practical application—creating a logical progression that guides readers from problem recognition to solution implementation. This architecture ensures each section builds meaningfully on previous content.

My literature review exemplifies selective curation, focusing exclusively on works that highlight the methodological gap rather than providing an exhaustive history of fashion research. Similarly, my Louis Vuitton case study was chosen from numerous possibilities because it perfectly illustrated the dataset's analytical capabilities while maintaining narrative coherence, as well as showed relevance to the courses that I took in Minerva.

I also became really intentional when building my second stretch goal, which is my TikTok promoting my dataset. The curation of what to include in this TikTok was an intentional use of #curation, where I had to make decisions on what to include in the video, the Capcut filters I could use, the choice of music in the video, and the right visuals that align with both my personal style and my audience.

#cp-outcomeanalysis

In my fashion dataset capstone project, I employed sophisticated evaluation frameworks by utilizing Habits of Mind and Learning Outcomes as structured rubrics to assess my work at each stage. This approach ensured comprehensive coverage of both technical aspects (like algorithms, variables, and optimzation) and methodological considerations (such as gapanalysis and biasmitigation), creating a multidimensional evaluation framework tailored to fashion analytics. I also curated my own custom LO, #FashionDataCuration. This custom rubric established specific criteria for evaluating fashion dataset design, including variable selection appropriateness, collection methodology robustness, and analytical utility

The project demonstrates empirical validation through the Louis Vuitton case study, where I implemented rigorous testing protocols including in-time and in-place placebo tests to evaluate causal inferences. These validation measures directly assessed whether the dataset could reliably identify treatment effects from creative directorship changes, providing quantifiable metrics of performance rather than relying on subjective assessments.

#cp-navigation

In my fashion dataset capstone project, I exemplified strategic project management by consistently underpromising and overdelivering. While I initially committed to developing only Parts I and II—establishing the need for a fashion dataset and creating the dataset structure—I strategically planned my workflow to enable significant extension beyond these requirements.

By front-loading the literature review and dataset development phases, I created space to develop the comprehensive Part III case study analyzing Louis Vuitton's creative directorship transition. This wasn't a spontaneous addition but a carefully planned expansion that I had privately targeted from the beginning of this year with the new menswear collection, allowing me to demonstrate the real-world utility of my dataset rather than merely theorizing about its potential applications.

I also even went as far as adding a second stretch goal to my project, which I also completed. This stretch goal showcases my content-creating skills, but I also showed genuine excitement and effort to film, explain, and promote my dataset.

Most importantly, I hope that you can see that through this navigation process of my project, this is a project that I genuinely loved to do. I enjoyed every single second of it, being able to learn, read, network, and struggle through every single step of the way, but this was made possible because I know fashion is a calling that I have in my life, and I fuel every step that I take with the passion and the fire I have. To me, this is the most important aspect of navigation, and I hope this is evident throughout the project.