An Experimentation Engine for Data-Driven Fashion Systems

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Abstract

Data-driven fashion systems of the future will revolutionize the way consumers shop for clothing and choose outfits: imagine an automated personal stylist that ships clothes straight to your door based on their compatibility with your existing wardrobe, the upcoming events on your calendar, and style trends learned from the web. To build such systems, we must identify the fashion activities that are the largest consumer pain points, the interventions necessary to alleviate those pains, and the computational models that enable those interventions.

To guide the design of these next-generation tools, we propose an experimentation engine for fashion interfaces: leveraging social media platforms to run multivariate design tests with thousands to millions of users. Social platforms are already home to dedicated communities of fashion enthusiasts, and expose programmable agents — chatbots — that can be used to rapidly prototype data-driven design interfaces. Measuring the number of followers and user engagement amongst these prototypes can inform the design of future standalone fashion systems. At the workshop, we will sketch the design space of fashion experiments, and present preliminary results from deploying our "fashion bots."

Data-Driven Fashion Systems

"The clothes on the hanger do nothing; the clothes on the woman do everything."

– Stephen Breyer

Humans have a complex relationship with clothes. Beyond choosing which pair of pants to wear on any given day, people continually grapple with fashion-related problems ranging from "how much will this new jacket extend the versatility of my wardrobe?" to "how should I dress to convey strength and competence in this business meeting?" to "can I achieve the same 'look' as that celebrity with a vastly inferior budget?"

We posit that, in the future, computational systems will help everyday people solve many of these problems. In this short position paper, we sketch the space of fashion activities that are ripe for technological intervention; discuss a few promising classes of system interventions; identify a set of data-driven models that might be used to back them; and propose an experimentation engine that leverages popular social media platforms to rapidly prototype, deploy, and test the next generation of fashion interfaces.

Fashion Activities

Outfit Creation. The most fundamental fashion activity is deciding what to wear each day. When creating outfits, people optimize for both form and function, balancing practical considerations such as weather, occasion, and budget with personal preferences around style, silhouettes, and material. To choose an outfit, one must assemble a set of individual clothing items that are compatible with each other and come together to form a cohesive concept.

Computation can help find combinations of compatible items that meet constraints. Fashion systems of the future will assist users as they deal with the diverse situations and constraints of daily life, helping them find an outfit for a "business casual dinner," achieve the "same look for less," or create an outfit that transitions from "workwear" to "partywear" with just a few modifications.

Wardrobe Management. In addition to selecting items *from* their wardrobe, users must regularly curate *for* their wardrobe by adding and removing pieces. People add new clothes for a variety of reasons: to complement their existing wardrobe, diversify the types of outfits they create, to reinforce their existing style, or to experiment with a new look or trend.

Computational systems can help people assess whether new items are good investments: versatile in the context of their existing wardrobe, appropriate for a special event, a classic that will never go out of style, or on trend to signal that a user is keeping up with the fashion Joneses.

In addition to adding new items to one's wardrobe, people regularly remove old items because they have worn out, no longer fit, or have gone out of style. In the age of *fast fashion*, where brands produce new styles frequently and inexpensively, "consumers can afford to buy ... in quantities" never seen before (Zarroli 2013). Computation can help users pare down their wardrobes in an optimal manner to make way for new pieces.

In response to fast fashion's rampant consumerism, some fashion-savvy and cost-conscious people have embraced concepts like *capsule collections*, in which one intentionally limits their wardrobe to make dressing simpler, save

Figure 1: An automated personal stylist taking descriptions of outfit needs in natural language as input to produce item recommendations.

money, and focus on pieces that evoke strong emotions. Although Steve Jobs' black turtlenecks and blue jeans are an extreme example, these mini-wardrobes typically comprise thirty or forty pieces that are both versatile and well-loved by their owners (Rector 2014). While there are many instructional guides online for capsule neophytes, computational systems could greatly enhance the capsule-building process by identifying highly-compatible collections that minimize the number of pieces while maximizing the number of potential outfits.

Social Feedback. While the affluent can avail themselves to personal stylists for targeted fashion advice, many users look to friends when they consider buying new items or put together an outfit for a new event. The desire for this sort of social feedback underscores the role of fashion as a vehicle for *social signaling*: people wear clothes to send messages to others[1].

Signaling theory in fashion (Donath 2007) explores the way people use clothing to indicate wealth and status (Nelissen and Meijers 2011), sexual motivations (Grammer, Renninger, and Fischer 2004), and self-defined roles (Piacentini and Mailer 2004). These signals present another opportunity for computational systems to find ways to capture the intent behind certain outfits and to provide flexible platforms for self-expression.

System Interventions

Nudges. Small “nudges” from computational systems — interventions that provide information without advocating for specific action — may result in substantive behavioral changes in fashion. For example, many users fall into regular patterns of dressing and fail to explore even the well-matched options already present in their wardrobes. Tsujita et al. suggest a computational system that shows users items from their wardrobe while blurring clothing which has been recently worn (Tsujita et al. 2010). They note that one user “was apt to wear her favorite clothes many times ... [and] didn't wear the clothes stored in the back of her closet,” but substantially varied her choices and became more conscious of repetition once using the system.

Suggestions. While “nudges” can provide users with valuable information even when they are not actively looking for it, users may seek answers to well-formed fashion questions such as “what should I wear to dinner?” Suggestion interfaces — which answer user queries with recommended courses of action — can reduce the cognitive burden on users by helping them make decisions (Fig. 1).

Researchers have proposed a number of computational schemes for making fashion suggestions, either of particular items (McAuley et al. 2015; McAuley, Pandey, and Leskovec 2015; Veit et al. 2015; Di et al. 2013) or of complete outfits (Liu et al. 2012; Shen, Lieberman, and Lam 2007; Yu et al. 2012; Vartak and Madden 2013). Next generation fashion systems must personalize their recommendations by seamlessly[2] accounting for user preferences, purchase histories, and the contents of their wardrobes.

Autonomous Actions. Truly sophisticated computational fashion systems could even be trusted to take independent action on behalf of their users. Existing personal stylist services like TrunkClub and Stitchfix mail their subscribers clothing each month, with the goal that users will buy the items that are sent to them (Stitch Fix ; Trunk Club). While these services are presently driven by human curation, it is easy to imagine machine learning playing a more prominent role in curation.

Similarly, one could imagine a “magic closet” that lays out an outfit each morning (Liu et al. 2012) for a user to accept or reject. By engendering a tight feedback loop and correlating fashion choices with holistic data about a user's life (i.e., “I don't want to wear that white skirt because they're serving spaghetti for lunch today”), useful predictive systems could be constructed.

[1] Admittedly, one important social message is “I am not naked,” particularly when one is a head of state, or Emperor.

[2] Pun intended.

Data-Driven Models

Image parsing. Researchers in computer vision have had some success identifying items in outfits (Yamaguchi, Kiapour, and Berg 2013) and identifying attributes of individual items (Berg, Berg, and Shih 2010; Vittayakorn et al. 2015), leading to innovative search patterns for fashion data (Kovashka, Parikh, and Grauman 2012). They have even been able to evaluate outfit style, both for individuals (Kiapour et al. 2014; Song et al. 2011; Simo-Serra and Ishikawa 2016), groups (Kwak et al. 2013; Murillo et al. 2012), and clothing items (Di et al. 2013; Veit et al. 2015; McAuley et al. 2015). Recent work has measured overall outfit fashionability from images of outfits (Simo-Serra et al. 2015).

Outfit compatibility. Several existing systems measure outfit compatibility or generate compatible outfits, either via low-level hand-annotated features (Liu et al. 2012; **?**; Yu et al. 2012; Vartak and Madden 2013) or higher-order ones generated, for instance, via deep learning (McAuley et al. 2015; McAuley, Pandey, and Leskovec 2015; Veit et al. 2015; Di et al. 2013).

Styles. Existing fashion systems have also described items or outfits in terms of their styles (Kiapour et al. 2014; Song et al. 2011; Simo-Serra and Ishikawa 2016; Veit et al. 2015; Di et al. 2013; McAuley et al. 2015; Yu et al. 2012; Vaccaro et al. 2016). Simiarly, many systems that generate outfits do so with style constraints (Liu et al. 2012; McAuley et al. 2015; Shen, Lieberman, and Lam 2007; Yu et al. 2012).

Trends. The evolution of fashion over time has attracted a great deal of attention from fashion researchers (Au, Choi, and Yu 2008; Alon, Qi, and Sadowski 2001; Hidayati et al. 2014; He and McAuley 2015; Lin, Zhou, and Xu 2015; Vittayakorn et al. 2015). Trickle-down theories of fashion suggest that the middle-class adopted trends from the rich emulating them and signaling their wealth, while more recent trickle-up and trickle-across theories posit that trends come "from the street" (English 2007). The ability to identify emerging trends and accurately predict their life-cycles would greatly empower next-generation fashion systems (Trufelman 2016).

An Experimentation Engine

Designing the next generation of fashion systems is a complex task: one must identify a concrete problem in the domain, find a suitable system intervention, and pick an appropriate computational model to back it. *A priori*, it is impossible to predict which user pain points are the greatest, which system interventions provide the best user experiences, and which data models are the most suitable for a given task. Therefore, we propose to develop an *experimentation engine* for fashion systems that allows researchers to rapidly prototype, deploy, and test design variations.

To build an engine that can support multivariate design tests with thousands to millions of users, we turn to social media platforms. Platforms such as Facebook, Twitter, and Instagram are already home to dedicated communities of fashion enthusiasts, and expose programmable agents — chatbots — that can be used to rapidly prototype natural data-driven design interfaces. Measuring the number of followers and user engagement amongst these prototypes can inform the design of future standalone fashion systems.

These fashion chatbots can be built out in stages. Initially, the chatbots can be backed by humans instead of computational systems, and wizard-of-oz experiments can be run to understand which pain points and types of system interventions elicit the greatest user engagement. Perhaps users would be incentivized to take daily selfies after getting dressed, if a Twitter bot would then offer an opinion of the style and affect their outfit conveyed. Once — and only once — such an interaction was determined to be *useful*, researchers could develop the image parsing and style data models to support it.

Additionally, different social platforms naturally support different types of interactions. Facebook messenger bots are well-suited for private conversations similar to those one might have with a personal stylist, while Twitter bots could rapidly disseminate content like fashion editorials, using strategic hashtags to gain visibility and encourage broader community participation and discussion around fashion topics.

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