# Beyond Clothing Ontologies: Modeling Fashion with Subjective Influence Networks

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## ABSTRACT

Extracting knowledge and actionable insights from fashion data still presents challenges due to the intrinsic subjectivity needed to effectively model the domain. Fashion ontologies help address this, but most existing such ontologies are "clothing" ontologies, which consider only the physical attributes of garments or people and often model subjective judgements only as opaque categorizations of entities. We address this by proposing a supplementary ontological approach in the fashion domain based on subjective influence networks. We enumerate a set of use cases this approach is intended to address and discuss possible classes of prediction questions and machine learning experiments that could be executed to validate or refute the model.

## Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous; I.2.4 [**Artificial Intelligence**]: Knowledge Representation Formalisms and Methods—*Semantic networks*; I.2.6 [**Artificial Intelligence**]: Learning—*Knowledge acquisition*; D.3.1 [**Programming Languages**]: Formal Definitions and Theory—*Semantics*

## General Terms

Ontologies, Knowledge Graph, Fashion, Subjectivity

## Keywords

Ontology, Temporal Networks, Social Networks, Fashion, Subjectivity, Influence

## 1. INTRODUCTION

As on-line fashion retail industry has been growing rapidly against traditional physical shopping, there has been a corresponding shift to a much more data-driven paradigm for business operations including manufacturing, merchandising, and marketing. In particular, future-focused data analysis has become a particularly important activity, such as predicting fashion trends, price forecasting, construction of recommender systems, and identification of consumer influencers. Often, these activities are approached using statistical, machine learning or other data-driven techniques. However, much of the data in the fashion domain comes from deep, diverse, cultural entities and phenomena. While fashion in itself is part of and can define culture, it also borrows from other cultural domains, such as music, language, film, religion, mythology, local folklore and many others. In most cultural domains, it is important to understand the narrative of history and contemporary subjective judgements and opinions. For example, in music, Italian words are used to contextualize abstract musical concepts (e.g., *allegro, largo, presto*). However the meaning of these words in the context of music has evolved and diverged from their original, common definitions. Knowing the history as well as the current interpretation of these words by the composers who use them is required to fully understand their musical meaning. Similarly, fashion is an inherently subjective, cultural notion. It is defined not by quantitative, testable measures, but by its history and the perceptions of people who care enough to form opinions about it. Therefore, in order to understand fashion in any rigorous way, this subjectivity must be an intrinsic part of the model.

One of the techniques for addressing the subjective, cultural parts of a knowledge domain is to use ontologies. Schemas, ontologies and its data population through knowledge graphs (KGs) are formal tools for expressing organized meaning and provide sense or context to a domain. More concretely, ontologies often integrate common-sense and human expert knowledge as well other external knowledge sources into machine readable computational models. Unfortunately however, most existing ontological work in fashion partially avoids subjectivity by simply focusing on "clothing ontologies" rather than fashion as a whole. Clothing ontologies primarily model the structure of physical feature values (e.g., sleeve length, colors, fabric). A particular garment can be represented in a multidimensional feature space chosen from such an ontology. Usually each garment class (e.g., top, bottom, shoe, hat) is considered to have a distinct feature space from other classes. When they do include subjective elements, clothing ontologies often do this through the inclusion of non-objective features (e.g., expected occasion, style category), but these features are usually opaque categorizations of entities, with no explicit semantics. Despite the limitations, these clothing features spaces are still useful because they provide semantic structure to data that can be used when applying analytic/prediction techniques (e.g., similarity measures, classifiers, function estimators).

We believe that deeper, richer representations of the subjective features of fashion data is possible and would help in many important use cases. In this paper, we propose an architectural augmentation to traditional clothing ontologies that includes the notion of a subjective influence network in a way that may be able to capture subjective semantics that simple categorical features do not. We enumerate a set of potential use cases, and propose types of measurements and applications that can be carried out to measure the usefulness of our approach.

The rest of the paper is organized as follows. Section 2 exhaustively summarizes the state of the art on existing fashion ontologies and frameworks and Section 2.4 describes machine learning applications as motivating use cases for our fashion ontological modelling approach. Section 3 proposes the theoretical foundations of the subjective model of influence, entities, relations and the mechanisms to quantify influence and subjectivity. Section 4 discusses evaluation approaches and utility of the model once populated with empirical data. Section 5 concludes with further insights.

# 2. RELATED WORK

## 2.1 Related Fashion Ontologies and Schemas

Ontologies have been used to represent knowledge in a large set of real-life problems, from genetics[1] to decision support systems, optimization, matchmaking and human activity recognition [4]. In the fashion world, ontologies have sporadically been used for recommendation systems. For example, ontologies have been combined with fuzzy logic for personalized garment design, where fuzzy decision trees serve in learning a set of representative samples. Fuzzy cognitive maps model complex relations between sensory descriptors and fashion themes given by consumers to provide more fine grained recommendations as well as the evaluate how much a specific body shape is relevant to a desired emotional fashion theme [16].

An important existing ontology is the Garment Style Advice Ontology SERVIVE (SERVice Oriented Intelligent Value Adding nEtwork for Clothing-SMEs embarking in Mass- Customisation)[2][13]. The Servive Fashion Ontology (SFO) includes relations among different categories of entities such as *colors, companies, garment features, materials*, etc. and provides a similarly structured and unified vocabulary to represent human, fashion and manufacturing concepts. The project includes the design of a Virtual Customer Advisor (VCA) which expresses preferences for a given garment that is evaluated via SWRL rules and Pellet reasoner. Fig. 1 shows the most abstract or top layer classes as well as the highest hierarchical layer of object properties modelled in SERVIVE ontology. Despite being the most complete ontology publicly available to the best of our knowledge, except for the subjective season labels (*hasHumanStyleColour*) and suitability classifications (*isForOccasion*), the ontology consists only of physical object hierarchies.

Ontologies per se act primarily as a modelling tool, and for

[1]http://geneontology.org/
[2]SERVIVE EU Project http://www.servive.eu/

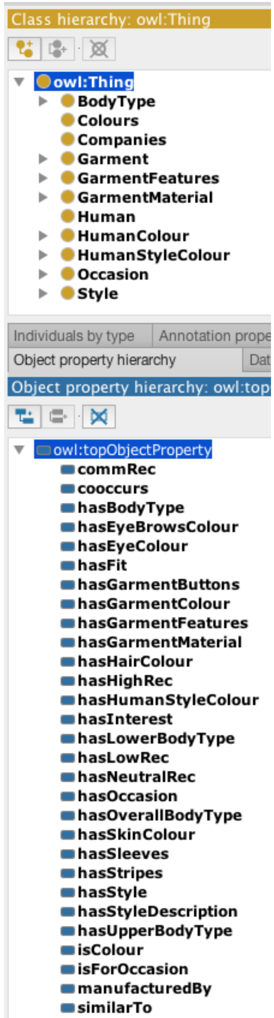


Figure 1: SERVIVE Ontology main entity classes (above) and main object properties (below) [13]

them to be useful, they are to be integrated into some kind of application (be it search, recommendation, classification or decision making applications). For instance, ontologies have also been integrated into probabilistic and media-rich approaches for personalized garment recommendation systems. Expert subjective knowledge from public online media is used to compute compatibility among products and user profiles according to context and probabilistic reasoning. [1] concretely focuses on dresses (*sarees*) and its evaluation of several individuals' fashion preferences and celebrities' actual choices compared with automated recommendations. The format of the ontology is MOWL, that *enables the analysis of visual properties of garments with respect to fashion concepts*, but it is not publicly available.

Another ontology, which considers designers, models, trends, seasons and celebrities is in [9], which exploits lexico-syntactic patterns as NLP tools for ontology learning, relation extraction and curation through domain experts. Table 1 summarizes the main ontologies' concepts and relations modelled.

Considering work that is more general than the fashion do-

Table 1: Existing Clothing Ontologies

| Ontology/Model and Language | Main Entities | Relations |
|---|---|---|
| SERVIVE [13], OWL | Body type, colors, companies, garments (features, material), human colour categories, seasonal human style color, occasion, style | Co-occurs, hasInterest, hasHigh/Low/NeutralRecommendation. hasBodyType/Fit/EyeColour, hasGarmentButtons/Colour/Feature/Material/ HumanStyleColour, hasOcassion, hasSleeves/Stripes/Style/styleDescription, isForOccasion, manufacturedBy, similarTo, isColour |
| Fashion ontology [9], RDF | Celebrity, designer, model, clothing term, trend, season | |
| Indian garment ontology [1], MOWL | Craft (stitch, print, embroidery), material, textile categories, | Celebrity validation |
| Fashion cognitive model [7] | Garment parts (silhouette, waist, length, collar, sleeve, ornaments, symmetry) | |
| Fashion cognitive model [16] | Body shape, desired emotional theme | Effectiveness, acceptability, realizability |

main, open data portals such as Dbpedia and Freebase [2] contain 1K topics and 3K facts around fashion, clothing and textiles[3]. Despite the richness and structure found in these formal base resources, the creative and subjective, contextual part of fashion is missing from these knowledge bases.

## 2.2 Cognitive Models for Fashion Modelling

In the literature there are non-ontological models which frame similar problems. They blend human and machine models for evaluating specific body shapes' relevance to a desired emotional fashion theme or intention to be transmitted. For instance, in [16], *effectiveness* evaluates whether recommended styles are relevant to the design objective or desired fashion theme, *acceptability* refers to whether the best recommended style is accepted by the expert, and *realizability* assesses if the proposed recommender system can be applied to the fashion [16].

An example of a cognitive model for fashion style decision making is in [7], where Genetic Algorithms enhanced with Multi-alternative Decision Field Theory (MDFT) tackle the context and choice set problem in decision making by using *psychological distance* between alternatives. The latter is based on the Euclidean distance among positions in a multi-attribute-dimensional subjective evaluation space.

## 2.3 Subjectivity in other domains

We identify a lack of a *subjective style* schema in the related work that goes beyond the biology or mechanics of clothing, and that expresses a more wholistic personal approach than the existing *inventory* clothing ontologies. By *inventory ontologies*, we mean those based on static attribute-based or physical feature spaces.

Other subjective and hard to describe domains such as music also benefit from having taxonomical classifications in form of ontologies. For instance, projects such as MusicBrainz [4] collects music metadata, and the Music Ontology[5][10] is a formal framework to deal with music-related information on the Semantic Web including editorial, cultural and acoustic information. Just like in music, a fashion ontology can integrate fashion-related data across multiple sources, or enrich search-engine results around decades, styles or influencers. Because of this, musicians might be useful allies for the fashion industry, (e.g., *thanks to their status as bohemian individuals*) and music industry might need fashion [8], e.g., to model music taste or predict fashion cliques.

Another similar natural phenomenon is language, where influence networks, among many other factors in time, model organically the evolution of its spread, its vocabulary, grammar rules, tonality, etc. In all, music, fashion and languages, influence and subjectivity are inherent to the domain and for them to fully be considered into machine learning systems, they need to be modelled quantitatively.

## 2.4 Fashion Ontology Use Cases

In fashion, the human component of algorithm evaluation is necessary [12, 14]. Guided by this, we identify candidate applications where a fashion ontology enhanced with a better subjective data representation would likely be helpful.

1. Defining stylistic rule guides and recommendations or predicting specific trends. For instance, to answer questions on: how to be edgy and ahead of the fashion trend without being too far off, or how to predict the Oscars' ceremony outfits?[6].

2. Predicting mass production trends. For example, the problems of cost-efficient budget and resource allocation as well as market demand optimization.

[3] `https://developers.google.com/freebase/`

[4] The Open Music Encyclopedia `https://musicbrainz.org/`

[5] `http://www.musicontology.com`

[6] `http://www.usatoday.com/story/life/entertainthis/2016/02/23/oscar-fashion-predicting-what-stars-wear-red-carpet/80747356/`

3. Providing organizing structure, e.g., taxonomy or folksonomy, for fashion annotation systems that leverage crowd-sourced online data (e.g., [18, 17]).

In next section we specify our augmentation for clothing ontologies, including a description of modeling obligations needed to make it useful and examples of first order measurements of represented data.

# 3. MODELING SUBJECTIVE INFLUENCE

## 3.1 Styles as Regions in a Feature Space

So how can subjectivity semantics be modeled as an influence network? Let us first consider a somewhat traditional interpretation of features of garments, based on physical properties from a clothing ontology. A particular garment $g$ can be represented as a point in a clothing feature space $G$ (see Figure 2). Let there be a theoretical set of all clothing styles $\Phi$ such that $\forall g \in G$ a subjective judge function $s()$ assigns a classification $s(g)$ such that $s(g) \in \Phi$. We define a distinct "style" $x$ to be a region $S_x \subset G$ such that $\forall g \in S, s(g) = x$.

Because the $S_x$ depends only on a single subjective function $s()$, it does not consider the fact that for any $x$, there may be multiple subjective functions that are contradictory. However, we believe this reflects the actual messiness of the real world.

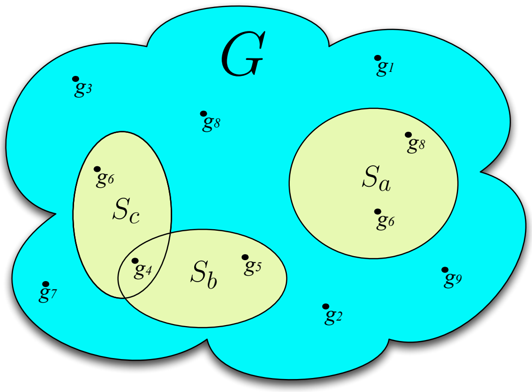


Figure 2: Traditional clothing feature space

## 3.2 Styles in a Network

Styles represented as a collection of points in a physical clothing feature space do little to capture the (subjective) semantics of fashion beyond the opaque categorical $s(g)$ features. To capture richer semantics, first consider a style as the human perception of the physical features of a single garment (or entire style region). Each style can then be described as a coherent aesthetic entity in the mind of an observer. While traditionally this style may be quantitatively described by its physical features, consider the alternative aspect of its subjective qualities shared with other cultural entities. These entities could be other clothing styles, or could be from other cultural domains external to fashion (e.g., music, sports, film, art, literature). We model this subjectivity as a network of influence.

We treat each style $x$ as a node in an acyclic graph/network $N$ (see Figure 3) such that there is a temporally directional edge function $e(x, y)$ that specifies the influence between nodes. Moving backward in time ($y$ to $x$) , an edge between styles describes the stylistic borrowing that occurs. Moving forward in time ($x$ to $y$), the edge represents the influence from older to newer styles. This influence is not a single measure, but rather a collection of influences of different mechanisms. The strength of each mechanism can be represented as a single positive number. More formally:

$$\forall x, y \in \Phi, \exists e(x, y) \tag{1}$$

such that $e(x, y) = \overrightarrow{\mu_{xy}}$ where $\overrightarrow{\mu_{xy}}$ is the influence vector from $x$ to $y$,

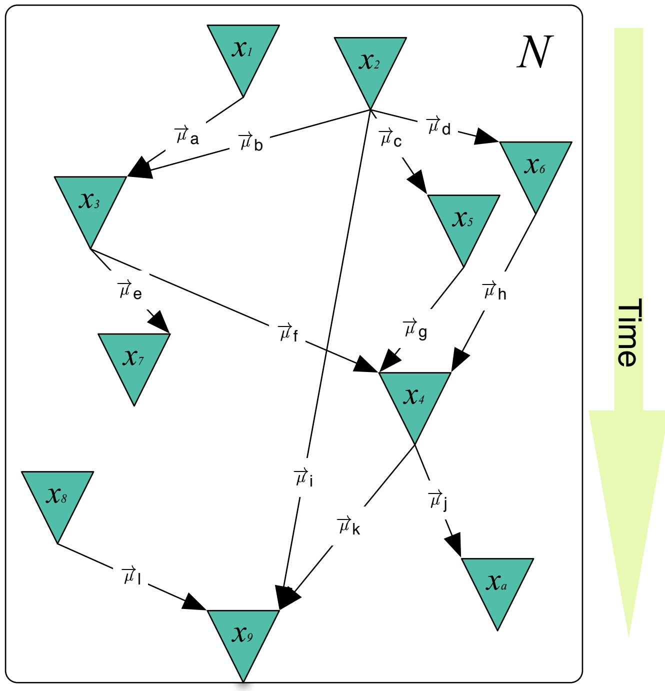


Figure 3: Influence Network

Each element of $\vec{\mu}$ can be treated as a quad $(t, i, m, a)$ where $t$ is the amount of elapsed time between the influencing and influenced style, $i$ is the intensity or strength of influence, $m$ is the mechanism of influence, and $a$ is the agent of influence. While $t$ and $i$ can both be represented as positive reals, $m$ is a class that exists in a (likely) vast space of possible mechanisms $M$. Some categories of $m \in M$ might be:

- *Explicit*: The creator of a style explicitly declares previous styles that have been influential in the current creative process.
- *Calculated*: Algorithmic or other mechanical means may estimate influence mechanism and strength based on garment features or causal cultural models.
- *Extrinsic*: The influence may be caused by cultural influences in one or more external parallel cultural influence networks (e.g music, religion, sports) For example, a musician that borrows musical style from a

revered earlier musician, may also borrow fashion elements for their own public image.

There are many different types of possible agents of influence $a$, including:

- *Well known individual persons or small groups*: These extrinsic influencers may be fashion designers, well known artists/performers, cultural icons, or celebrities who are admired for the artistic or political talents.
- *Organizations*: Corporations whose business is in the fashion create styles and attempt to maximize the desirability of the products they sell.
- *Emergent Social Networks*: In the age of almost-instant, wide information dissemination, feedback loops of influence among highly fashion-conscious groups of people may result in rapid evolution and exposure of styles.

## 3.3 Modeling Obligations

The subjective influence network model simply lays a framework for building an ontology that is capable of representing some aspects of subjectivity in fashion. In order for this model to be practically useful, a full ontology would need to be constructed, including:

- Enumerating (at least some of) the members in $G$, $\Phi$, $N$, and $M$.
- Characterizing a relevant set of subjective functions $s()$.
- Calculating, estimating, or assuming values for the quads $(t, i, m, a)$ for the edges between the nodes $x \in N$.
- Consideration of cycles. For example, 70's Disco fashion has come back in multiple times in past decades. The approach described here would model this return as a new style that is heavily influenced by the original. However, explicit modeling of this dynamic would be important.

## 3.4 First Order Interpretations of the Network

Interpreting an existing fashion network might allow us to make useful, testable judgements, including identification of important styles properties, including:

- *Novelty*: This is the subjective notion of a style that is different from previous styles in a pleasantly surprising way. Using our influence network model, one naive first order measure of a style's novelty is that the sum of intensity of influencing styles is low; i.e. that it is influenced only weakly by the combination of all previous styles. The novelty $\nu$ of $y$ could be defined as:

$$\nu_y = e^{-\sum_{x \neq y \in N} i_{xy}} \tag{2}$$

  where $N$ is our influence network, and $i_{xy}$ is the intensity element of $\overrightarrow{\mu_{xy}}$. In this case, when the sum of $i$ values is high , $\nu_y \approx 0$, and when $i$ is zero, $\nu_y = 1$. Other, more sophisticated measures of novelty could include deeper network analysis approaches or more nuances summing of intensity based on mechanism $m$ and or agent $a$. This measure of novelty requires there to be no missing nodes or links in the influence network. A more sophisticated variant that tolerates missing information and noise would likely be needed in a practical application.
- *Impact*: This is a measure of how much a particular style has influenced all other styles as a whole. A simple (and very naive) measure of impact $\iota$ of a style $x$ on the network $N$ could be:

$$\iota_x = \sum_{y \neq x \in N} i_{xy} \tag{3}$$

  If $x$ has little impact then $\iota_x \approx 0$ and if $x$ is heavily influential, then $\iota_x$ would be large. There is much previous, mature work on the topic of measuring influence in networks such the concepts of centrality, node influence metrics, page rank, etc. As such is beyond the scope here, and a likely important direction for future research.

# 4. EVALUATION APPROACHES

In this section, we propose quantitative evaluation strategies to assess the practical usefulness of representing knowledge in the fashion domain using the influence network model presented here. In particular, we suggest measurements on values of such representation and potential applications.

## 4.1 Quality Measurements

In order to assess practical values of the proposed approach, we describe a number of evaluation strategies to measure its quality. Specifically, we focus on data-driven and task-driven evaluations which have been applied to ontologies in other domains [11]. For the former, we aim to measure how well the ontology represents empirical data related to fashion. For the latter, we examine information retrieval and recommender systems which could be consumers of the ontology and data.

### *4.1.1 Domain data approximation*

This is a data-driven approach to quantify how well the proposed ontology approximates empirical data in the fashion domain. Since fashion is a highly non-static, subjective and high-dimensional domain, we propose a few metrics which may capture expressiveness, both in terms of topics and temporal evolution, including:

- **Categorical precision:** Count how many styles encoded in the influence network are real-world recognizable styles in empirical domain data.
- **Temporal bias:** If we repeat the above categorical measurements on datasets from different time spans, the resulting metrics might stay stationary if this property of influence network's is time-invariant; otherwise, a network which fails to represent future datasets could indicate variable predictive power. The length of time span before the divergence is the representativeness timescale of the network, and the scope indicates its robustness.

- **Semantic similarity:** This measurement provides a distance metric between a traditional ontology augmented with an influence network and the text data in fashion domain in terms of "meanings" they express. We project both labels (class names $O_c$ and property names $O_p$) in the ontology and the tokens in the text corpus $D$ in the same vector space (e.g., using word2vec). Then we compute the overall similarity based on all labels' distances weighted by their importance within the network:

$$\sum_{c_i \in O_c} \sum_{t \in c_i} Sim(t, D) * \theta(c_i) + \sum_{p_i \in O_p} \sum_{t \in p_i} Sim(t, D) \quad (4)$$

The importance score $\theta(c_i)$ is a normalized score $[0, 1]$ and can be defined depending on the context and usage. For example, $\theta(c_i)$ refers to how knowledgeable a network is w.r.t. class $c_i$, which can be approximated by the cumulative distribution function of its number of attributes $u_i$

$$\theta(c_i) = \sum_{u_m < u_i} P(U = u_m) \quad (5)$$

### 4.1.2 *Task-specific expressiveness*

This is a task-driven measurements to quantify how expressible the ontology is compared to user's mental representation in the context of a task. Here we use information retrieval in the fashion domain as an example task, and developed statistical measures of "expressiveness".

- **Query concept recall:** Given a query stream like "natural fabric button down from banana republic", we derive a mapping between concepts that appeared in the query and concepts encoded in the ontology. Specifically, we ask expert judges to identify important classes $\{c_i\}$ in the query. For each class being detected, we ask them to map it to the most similar label in the ontology. Then we compute the recall of concepts in the query as $\frac{\text{\# concepts mapped to ontology}}{\text{\# concepts detected}}$
- **Search result ranking:** We use rankings of search results for a given query as a proxy of "golden standards". Then the Normalized Discounted Cumulative Gain (NDCG) metric can be adapted to measure the ontology's relevancy to search quality. Specifically, the "gain" is quantified by the ontology's recall of concepts in search results. We examine the top $K$ returned search results. For each of them $D_p$ at position $p$, we compute the ontology's document concept recall, which is then discounted by its logarithmic rank $log(p)$.

$$\sum_{p=1}^{K} \frac{Recall(O, D_p)}{log(p)} \quad (6)$$

## 4.2 Applications

### 4.2.1 *Web Data Markup through schema.org*

There are massive data sources on the Web (including mobile applications). However, they are mostly unstructured, and there is no common vocabulary which facilitates collective curation of domain knowledge. Schema.org markup has been the major adoption for web data (about 31.3% of all pages by Dec 2015[5]) and is used by a variety of high traffic applications like search engines and news portal. Although it contains vertical specific schemas such as movies, music, medical and products, schema that can represent fashion content is absent.

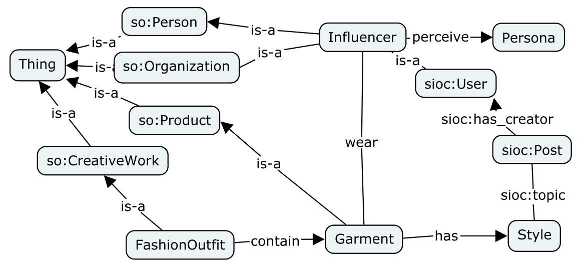


Figure 4: Integration with schema.org

In Figure 4 we illustrate that the proposed ontology framework can easily adapt to a lightweight ontology and integrated as an external extension of the core schema.org vocabulary, while also linking to other relevant common vocabularies such as the *GoodRelations* for E-commerce[6], *SIOC* for influence mechanisms on the social Web [3].

### 4.2.2 *Consumed by machine learning systems*

The data represented in a subjective influence network as proposed here could be used for a variety of different data analysis and processing efforts, including the following types:

- **General machine learning problems:** The knowledge base represented by a populated influence network would contain instances associated with high-quality categorical types, which provide labeled data to train models for entity recognition. Also, the edges on their own in the network contain both numeric and categorical features which can be used in whole-network modeling experiments.
- **Fashion data retrieval:** The integration with `schema.org` enables community content publishers to explicitly annotate their posts with their perceived subjectivity of fashion contents, which are basic building blocks of a crowd-sourcing system. As a result, the marked up Web data in return allows for information organizers such as search engines to index rich contents and answer queries which contain both entities and subjective projections.
- **Recommender systems:** The taxonomy defined in the ontology provides a perfect complement to recommendations learnt in a bottom-up fashion. Therefore, it could be a very useful approach to deal with data sparsity situations such as cold start problems.

# 5. CONCLUSIONS

In this paper we propose a new ontological augmentation in the fashion domain, which represents subjective feature information as an influence network. Because fashion (just like art, music or languages) strongly contains subjective information (cultural phenomena which are not designed nor engineered), we believe that such an augmentation might result in the construction of higher performing machine learning and data analysis systems.

Following the theoretical modeling, we suggest quantitative measures to assess the framework's utility to machine learning systems. Especially we focused on quantifying how well the ontology can represent domain data, and how the features from an influence network could be integrated into machine learning systems.

Future work will instantiate concrete machine learning problems into the proposed approach. For instance, an example can be quantifying fuzzy influence networks in social media opinions [15]. In this way we will validate our theoretical assumptions by incarnating and materializing different influence functions, distance and quality measures, scales and other parameters for our model assessment and evaluation in different machine learning problems. Ultimately, this will help refining the model's capability to effectively quantify influence and subjectivity in fashion and style.

## 6. ACKNOWLEDGMENTS

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## 7. REFERENCES

[1] S. Ajmani, H. Ghosh, A. Mallik, and S. Chaudhury. An ontology based personalized garment recommendation system. In *Web Intelligence (WI) and Intelligent Agent Technologies (IAT), 2013 IEEE/WIC/ACM International Joint Conferences on*, volume 3, pages 17–20. IEEE, 2013.

[2] K. Bollacker, C. Evans, P. Paritosh, T. Sturge, and J. Taylor. Freebase: A collaboratively created graph database for structuring human knowledge. In *Proceedings of the 2008 ACM SIGMOD International Conference on Management of Data*, SIGMOD '08, pages 1247–1250, New York, NY, USA, 2008. ACM.

[3] J. G. Breslin, A. Harth, U. Bojars, and S. Decker. Towards semantically-interlinked online communities. In *The Semantic Web: Research and Applications*, pages 500–514. Springer, 2005.

[4] N. Díaz-Rodríguez, M. P. Cuéllar, J. Lilius, and M. D. Calvo-Flores. A survey on ontologies for human behavior recognition. *ACM Comput. Surv.*, 46(4):43:1–43:33, Mar. 2014.

[5] R. Guha, D. Brickley, and S. Macbeth. Schema. org: Evolution of structured data on the web. *Communications of the ACM*, 59(2):44–51, 2016.

[6] M. Hepp. Goodrelations: An ontology for describing products and services offers on the web. In *Knowledge Engineering: Practice and Patterns*, pages 329–346. Springer, 2008.

[7] J. Li and Y. Li. Cognitive model based fashion style decision making. *Expert Systems with Applications*, 39(5):4972 – 4977, 2012.

[8] J. Miller. *Fashion and Music*. Bloomsbury Publishing, 2011.

[9] I. Novalija and G. Leban. Applying NLP for building domain ontology: Fashion collection. A:147–150, 2013.

[10] Y. Raimond, S. A. Abdallah, M. B. Sandler, and F. Giasson. The music ontology. In *ISMIR*, 2007.

[11] Y. Raimond and M. Sandler. Evaluation of the music ontology framework. In *The Semantic Web: Research and Applications*, pages 255–269. Springer, 2012.

[12] A. Steinfeld, S. R. Bennett, K. Cunningham, M. Lahut, P.-A. Quinones, D. Wexler, D. Siewiorek , J. Hayes, P. Cohen, J. Fitzgerald, O. Hansson, M. Pool, and M. Drummond. Evaluation of an integrated multi-task machine learning system with humans in the loop. In *NIST Performance Metrics for Intelligent Systems Workshop (PerMIS)*, 2007.

[13] D. Vogiatzis, D. Pierrakos, G. Paliouras, S. Jenkyn-Jones, and B. J. H. H. A. Possen. Expert and community based style advice. *Expert Syst. Appl.*, 39(12):10647–10655, Sept. 2012.

[14] C. Wah, S. Branson, P. Perona, and S. Belongie. Multiclass recognition and part localization with humans in the loop. In *Computer Vision (ICCV), 2011 IEEE International Conference on*, pages 2524–2531. IEEE, 2011.

[15] L. Wang and J. M. Mendel. Fuzzy opinion networks: A mathematical framework for the evolution of opinions and their uncertainties across social networks. *CoRR*, abs/1602.06508, 2016.

[16] L. Wang, X. Zeng, L. Koehl, and Y. Chen. Intelligent fashion recommender system: Fuzzy logic in personalized garment design. *Human-Machine Systems, IEEE Transactions on*, 45(1):95–109, 2015.

[17] S. Zoghbi, G. Heyman, J. C. Gomez, and M.-F. Moens. Cross-modal fashion search. In *MultiMedia Modeling*, pages 367–373. Springer International Publishing, 2016.

[18] S. Zoghbi, I. Vulić, and M.-F. Moens. I pinned it. where can I buy one like it?: Automatically linking pinterest pins to online webshops. In *Proceedings of the 2013 workshop on Data-driven user behavioral modelling and mining from social media*, pages 9–12. ACM, 2013.