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, Φ, 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 ν 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 ι 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 ι_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.