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 Φ 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.

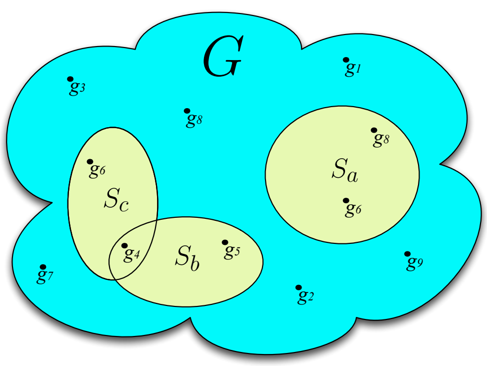

Figure 2: Traditional clothing feature space

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:

$$\forall x, y \in \Phi, \exists e(x, y) \quad (1)$$

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

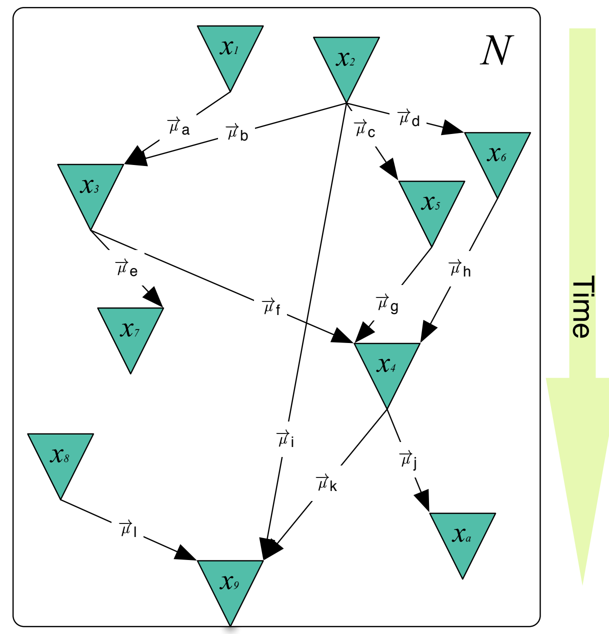

Figure 3: Influence Network

Each element of $\overrightarrow{\mu}$ 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