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Expert and community based style advice

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ABSTRACT

We propose a knowledge framework for garment recommendations, which is based on two pillars. The first pillar incorporates knowledge about aspects of fashion, such as materials, garments, colours, body types, facial features, social occasion etc., as well as their interrelations, with the purpose of providing personalised recommendations. The said knowledge is encoded in the form of an OWL ontology, the origin of which is attributed to fashion experts. Moreover, in commercial fashion sites, customers purchase garments of various types. Because of that, interesting patterns in their purchase behaviour can be sought, and thus groups of garments that tend to be purchased together can be discovered. This forms the second pillar, that can be used to enhance the first pillar with community based garment recommendations. This paper is the description and integration of the aforementioned pillars in a knowledge framework.

1. Introduction

Personalisation in the fashion industry is a new trend that tries to produce garments respecting the idiosyncrasy of every customer and doing so cost effectively, whilst at the same time adding value to the services provided. Typically, a personalised fashion service recognises its users, collects information about their interests, their needs, as well as their personal physical characteristics (such as body type), and subsequently recommends products based on this information.

The recommender system should be able to create and maintain efficiently user information, and this is typically performed by means of user models. There are two types of information sources that are exploited for the creation of user models in the fashion domain. The first type is in the form of generic style advice rules that are defined by fashion experts. These rules provide some guidance about the appropriate style and fit for garments for different occasions, body types, facial features, etc. The second type of information source is in the form of customer's data which is collected by fashion oriented web sites or social networking sites; they contain users' preferences or purchases of garments. This information can be exploited to discover important patterns that denote general user tendencies.

An important issue for the creation of user models is the organisation and handling of the heterogeneous, quantitative and qualitative information that characterises the fashion industry. In particular, material properties, human morphology, garment styles, and the occasion for wearing a garment are among the factors that influence style advice. Although, there are associations between the concepts in the fashion domain (in the form of loose guidelines), they are not usually expressed in a way that could form a fashion oriented knowledge base. Thus, there is the requirement for processing this information, extracting the available knowledge and representing it in a more structured and manageable form.

1.1. Contribution of our work

We propose a hybrid recommender system for style advice in the fashion domain. The knowledge of the proposed system is based on domain expertise and user interaction data with fashion sites.

Domain expertise is expressed through a fashion ontology that also includes generic style advice. The ontology is represented in OWL constructs or SWRL rules that encode stereotypes of users. Stereotypes associate users' characteristics of various sorts with generic garments. The users' characteristics refer to (among others): somatometric data, and information about the facial features including skin tone. Generic garments are abstractions of real garments, but it is expected that their features are representative of real garments. Moreover, the stereotypes associate social occasions with appropriate generic garments.

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As users interact with the commercial sites of manufactures, they typically provide body measurements and then they order real garments, as opposed to the generic ones. Each interaction, followed by some preprocessing, forms an individual user model that can be stored in a personalisation server (PSERVER). PSERVER, with the aid of integrated data mining algorithms, can subsequently discover common purchase patterns of real garments (of the sort: *users who purchased this also purchased that*).

A typical user will first interact with the system that provides generic advice. She will provide her body type, facial features or a special occasion, and then she will receive generic advice. This is implemented by the reasoning mechanism of the fashion ontology. Next, based on the similarity of generic garments with real ones, she will receive recommendations about real garments. Finally, she will be assigned to a *community* of users and subsequently she will receive purchase advice about the preferred garments of the community. We should stress, that advice is offered to her, without seeing or selecting any garment (generic or real). This is important, especially for new users, where the so called cold start problem appears, i.e. generating item recommendations for a person that has not expressed interest in any item yet.

Concerning knowledge representation, the proposed system handles symbolic knowledge in the form of OWL but it also handle subsymbolic representations and performs relevant data mining with the aid of PSERVER. Moreover, the subsymbolic knowledge is used to enrich the ontology, and thus to entice the ontology to perform community based recommendation. The subsymbolic part is an information source external and unrelated to the symbolic part.

PSERVER is a general-purpose personalisation engine under development at NCSR "Demokritos".[1] It has been used for personalization in a variety of fields (Paliouras, Mouzakidis, Moustakas, & Skourlas, 2008). PSERVER operates as a web service, accepting http requests and returning XML documents with the results.

PSERVER separates user modelling from the rest of the application and features a flexible, domain-independent data model that is based on four entities: *users*, that are represented by some identifier; *attributes*, that represent persistent user-dependent characteristics; *features*, that are application-dependent characteristics, which may or may not attract user preference and *user models*. PSERVER offers three types of user models: *personal*, *stereotypes* and *communities*. Additionally, PSERVER provides the option of exploiting user interactions with the system and in particular, frequency counts or histories of actions in order to update the feature values of personal user models and user stereotypes. In this manner, it is possible to infer the level of interestingness of each user in a certain feature. Then communities can be discovered with the aid of data mining algorithms as explained next.

The above work was carried out in the context of the EU-FP7, Servive project[2] that aimed at tapping the potential of the combination of massively produced and tailor made cloths in the European market.

The rest of the paper is organized as follows. In Section 2 we review ontologies and style advice systems. Then in Section 3 we present the ontology developed for the fashion domain, followed by expert and community style advice in Sections 4, and 5 respectively. In Section 6 we elaborate on the origin of community style advice rules, and the role of PSERVER. Next, in Section 7 we expose the architecture of the proposed system that encompasses expert and community style advice, followed by evaluation of the knowledge base in Section 8. Finally conclusions are drawn in Section 9.

[1] http://www.iit.demokritos.gr/skel/.
[2] http://www.servive.eu/.

2. Background knowledge and related work

2.1. Stereotypes and user modelling

User modelling technology aims to make information systems user friendly, by adapting the behaviour of the system to the needs of the individual. A user model primarily contains information that characterise the interaction of the user with the system and possibly with other users (Pierrakos, Paliouras, Papatheodorou, & Spyropoulos, 2003). In the fashion domain, each personal user model consists of demographic information, such as: age, body type, etc., and style preferences. In order to distinguish between the two, we will refer to demographic information as the *attributes* of the user model, whilst the style preferences will be represented by user model *features*. An example of user model is depicted in Table 1, where the numbers denote the degree of user preference.

One of the earliest types of user model is the stereotype (Rich, 1979). Stereotypes are collective user models that similarly to personal user models consist of two types of information. The *stereotype attributes* represent knowledge external to the application, usually demographics, such as body type, age, level of expertise in a domain etc. On the other hand, the *stereotype features*, refer to entities of the application, such as garment types. A stereotype can be interpreted as "users with certain attribute values, are recommended or prefer certain features". For example, the stereotype in Table 2 states that for women of average body type pleated skirts are highly recommended, but the recommendation for military jackets is not very strong. Stereotypes are central in implementing the expert-based style advice. The attributes of a personal user model, will be matched against the attributes of available stereotypes, and the features of the best matching stereotype will be suggested to the user. This is applicable to new users, addressing thus the cold start problem of recommender systems.

Yet another type of collective model is the garment-centred community, which can be thought of as a set of garments preferred by a group of users. Table 3 presents such a community of pleated skirts and jackets, where the numbers represent the strength of the relevant features in a [0, 1] scale. Communities can also be used in personalisation. For example it could be inferred that a user who likes pleated skirts will probably like jackets. Communities are usually produced by data mining algorithms when applied to

Table 1
Example of a user model (personal).

Attributes			Features	
User	bodyType	gender	skirt.pleated	jacket.military
Mary	Average	f	1	0.5

Table 2
Example of a stereotype (collective model).

Attributes	Features		
bodyType	skirt.pleated	jacket.military	jacket.peplum
Average	1	0.5	−1

Table 3
Example of a garment-centred community (collective model).

skirt.pleated	jacket
0.9	0.8

users' transaction data. Garment-centred communities are central in implementing the real garments recommendation.

2.2. Recommendation systems

A popular application of user modelling, especially on the web is item recommendation. A recommendation system (RS), is any system that produces personalised recommendations or guides a user towards interesting or useful items in a large space of possible options (Adomavicious & Tuzhilin, 2005). Two of the major categories of RS are: the *content based* and the *collaborative based*. In the former, the user is recommended items similar to the ones he preferred in the past; whereas in the latter, the user will be recommended items that people with similar tastes and preferences favour. Moreover, *rule based* recommender systems also play in important role, where the rules typically represent users' stereotypes.

Fashion recommender systems use a number of parameters to provide recommendations, such as demographic information (e.g. age, gender, height, weight), as well as information related to style, fashion trends, etc. With that information they build a user's profile and subsequently suggest clothing items that are appropriate for that profile; or even clothing items that can be combined, something that is known as coordination.

Rule-based systems represent fashion style advice in the form of *if-then* rules, either crisp or fuzzy. *Shirt-MC* is a rule based system for the mass customisation of garments, and in particular of shirts (Liu, Choi, Yuen, & NG, 2009). In that system, the user provides information about height, weight, complexion, as well as some subjective pieces of information. Then the user receives a suggestion, which is followed by a second range of user options concerning the trendiness and the freshness of the garment. The knowledge of the system is encoded in an expert data base. In *MyShoppingPal.com* a user submits information about his body type features and style preferences. This information is used for suggesting shoes. A similar system is *MyShape*.[3] On the other hand in *My VirtualModel*[4] each customer "dresses" her virtual model, based on her body type and style preferences. Subsequently the recommendation system suggests to the customer garments that fit this virtual model.

In another approach, supervised learning is combined with rules to suggest matching or coordinated clothing items. This is tackled at two levels. First, the relevant attributes of clothes are detected and recorded by experts. Then a rule-based system is built to evaluate the degree of coordination of pairs of clothing attributes. At the second level, the coordination degree of various clothing attributes is combined to provide the degree of coordination (i.e. how well they fit) between complete garments. At this level, a TG fuzzy neural network is employed (Wong, Zeng, & Au, 2009). Collaborative filtering has been used by the *Levis Style Finder*, which provides recommendations related to the company's garments. Each customer submits only gender information and subsequently rates a set of product categories.

A combination of collaborative and content-based filtering is used by FDRAS (Jung, Na, Park, & Lee, 2004). In this system each user rates garments, and based on the ratings similar garments can be suggested. Moreover, similar ratings of the same garments by different users can be used for collaborative filtering.

Common sense ontologies have also been used in clothing recommendations. An interesting application of that is in scenario-oriented recommendation (Kobayashi, Fumiaki, Takayuki, & Tojo, 2008; Shen, Lieberman, & Lan, 2007), where the user requests a garment for a social occasion in natural language. Furthermore, his personal wardrobe, has been characterised according to some criteria (such as brand, material, and occasion). The system discovers a relation between the occasion described in the user's input and the occasion of an existing garment with the aid of ConceptNet ontology.

In yet another approach, ontologies are used in conjunction with recommender systems. A popular method is to enhance the user's interest profile, with ontological concepts that are close to the user's expressed interests. For instance, the user's interest in a concept can be propagated to the super-concept, which can be integrated into the user's interest profile (Middleton, Shadbolt, & Roure, 2004). This approach has been evaluated in the domain of recommending research articles, but it is equally applicable to a fashion ontology.

In the current work we separate generic garments from real garments, this facilitates the work of style advisors, where they can state generic style advice, which is not bound to specific manufactured garments. Next, the fashion domain knowledge, that also includes style advice rules, is encoded in OWL, a language of choice for semantic web, and it is a first attempt to build such an ontology to the best of our knowledge.

Apart from the ontology, there are also usage data that refer to purchases of real garments by users. The usage data are *a priori* unrelated to the ontology. The usage data form the personal profiles of the corresponding users, and they are stored in PSERVER. Based on those profiles, and using data mining, PSERVER can discover interesting purchase patterns of real garments or garment-centred communities. Those communities can mapped to the ontology, in order to enrich it. The enriched ontology, can provide additional advice of the form: *users who are interested in this garment are also interested in that garment*. This also departs from the systems mentioned in the literature review.

3. Servive Fashion Ontology

Knowledge about garments, materials, various human styles, human morphology and social occasion are among the things pertinent in fashion advice. Although there are informal associations between the above types of information sources, most of it is in anecdotal, in non-machine readable or proprietary data formats.

The *Servive Fashion Ontology (SFO)* provides a structured and unified vocabulary to represent human, fashion and manufacturing concepts. The ontology shares a number of common terms and concepts from the above domains. This part of the SFO has originated from human experts.

Furthermore, SFO can be enriched, or *evolved* to handle knowledge that stems from users' purchase patterns. This, represents the data intensive or social part of ontology. It is changeable, and originates from users' interaction with the system.

The SFO was developed in OWL 2 (Horrocks, Patel-Schneider, & van Harmelen, 2003), with the aid of the Protégé 4.1 ontology editor.[5] The ontology serves two functions. The first is to represent a human expert style advisor, henceforth called *expert style advice*; and the second is to represent the *opinion of a community of users*.

The expert style advice, could be stated in abstract terms as follows: given some *body measurements* and some *facial features* infer the body type, and subsequently suggest some *garment types* and *garment colours* pertinent to an *occasion*. In the current work, garments concern women's clothes, and they fall into the following categories: knitwear, skirts, jackets, and two-piece business suits. SFO is not meant to be a final and complete ontology, but an

[3] http://www.myshape.com/.

[4] http://www.mvm.com/.

[5] http://protege.stanford.edu/.

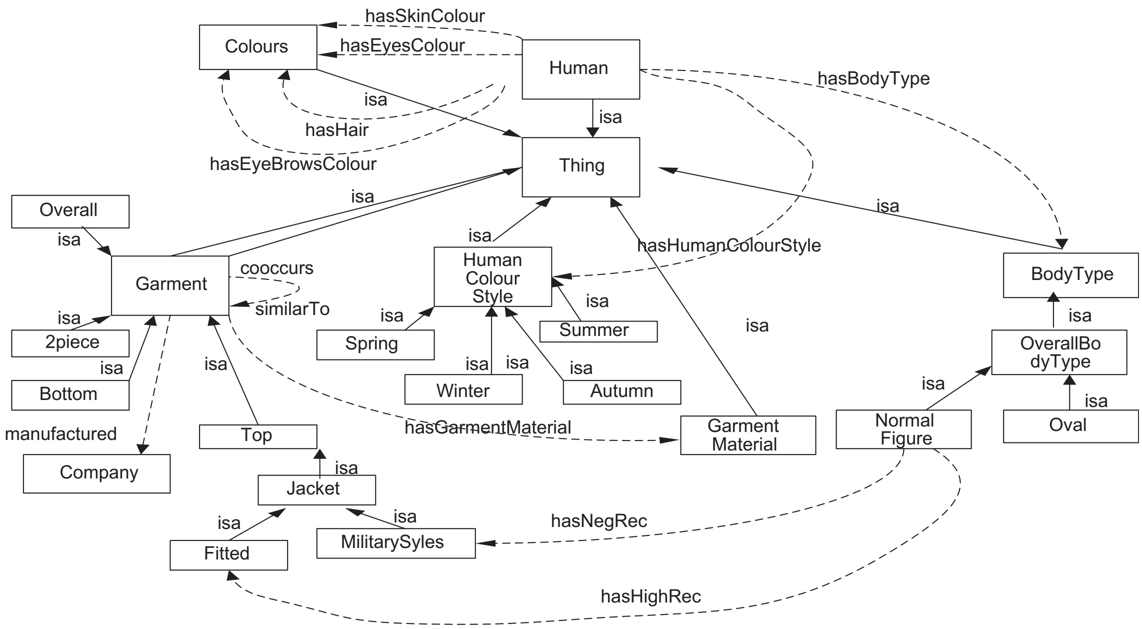

Fig. 1. Top level structure of the Servive Fashion Ontology. Solid lines denote `isa` relations, and dashed lines denote object properties.

ongoing effort. As such, it will be publicly available at the project web site.[6]

The main concepts in the ontology are *humans* and *garments*. Concerning humans, the related concepts are the body types, and facial features, such as skin colour, hair colour, eyes and eyebrow colour. Garments, are split into categories, such as garments for the top part of the body, the lower part or the whole body. Furthermore, there is the concept of *garment material*.

Based on these basic concepts we have formed a number of classes, object and data properties to encode the experts' knowledge. The top level of the ontology is depicted in Fig. 1. Henceforth, class names will have their first letter capitalized, while individuals' names will start will lower case. The basic classes of the ontology are:

- `class:BodyType`. It represents the concept of human body type, i.e., the general shape of a human. Based on the concept of "shape modelling driven by products", the human shape is described by its `LowerPart`, which corresponds to the body part from the waist to the legs, the `UpperPart`, which corresponds to the body part from the waist to the head and the `OverallBody` which corresponds to the human body shape as a whole. Eight different body shapes implement the `OverallBody` concept, `NormalFigure`, `BroadAtTop`, `BroadAtBottom`, `HourglassCurvy`, `OvalOverall`, `Narrow And Straight`, `BroadAndStraight` and `Atypical`. These concepts are defined as subclasses of the `OverallBody` concept.
- `class:Colours`. It represents various colours relevant to humans, fashion or garment domains. Individual colours, e.g. `navy`, `black`, `blue`, `grey` etc., are members of this class.
- `class:Garment`. This is the main class that models the domain of clothes. It has three main sub-classes that refer to the garment suited for the top part of the body, the bottom part and for the whole of the human body respectively.
- `class:GarmentFeatures`. It models the characteristics that can be used to distinguish the various types of garment, such as buttons, cut, pattern, number of pockets etc. These characteristics are represented as subclasses of the class.
- `class:GarmentMaterial`. It models the various types of fabric that are used to produce the garment. The different types of fabric, i.e., Cotton, Linen, Silk, Wool, etc., correspond to the subclasses of the class.
- `class:HumanStyleColour`. It models the categories that a human can be assigned, based on the Season Analysis Model (Kentner, 1979). There are four different categories of human colour style that are represented as subclasses of `Human Style Colour` class, i.e., `Spring`, `Summer`, `Autumn` and `Winter`.
- `class:Occasion`. The class `Occasion` models the cases that a human would select a particular garment. These cases, such as `Workwear`, or `Sportswear`, are the subclasses of the `Occasion` class.
- `class:Style`. The class models the various types of style that can be exploited to classify a human based on his/her dressing habits. These types can be `Casual`, `Eclectic`, etc., corresponding to the subclasses of the `Style` class.
- `class:Human`. It models the human in the fashion domain. The individuals of this class are the actual users that seek advice.
- `class:Companies`. This class includes companies that provide real garments. In the case of the Servive project there are three companies: MatteoDosso, Odermark and Munro, represented as individuals of the aforementioned class. Furthermore, there is another individual named *generic* to denote garments that are not produced by specific manufacturers.

The relations between the instances of classes are modelled using *object properties*. Examples of object properties are the following:

- `hasEyesColour`. This is an object property relating the `Human` class with the class `Colours`. Similarly, we have defined the object properties `hasHairColour`, `hasEyeBrowsColour`, `hasSkinColour`. These properties are employed by the first level of expert advice rules (see Section 4).
- `hasHighRec`. This is a property with domain in the `Human` class and range in the `Garments`. It associates humans with highly recommended garments. Similarly we have defined `hasLowRec` and `hasNegRec` object properties, to express low and negative recommendations respectively. These properties are employed by the second level of the expert advice rules (see Section 4).

[6] http://www.servive.eu/.

- `manufacturedBy`. This is an object type property with domain in the `Garments` and range in the `Companies`. It associates garments with manufacturers. It aims to distinguish between garments produced by specific manufacturer, and generic garments.
- `cooccurs`. An object property that associates two garments that tend to co-occur in the user purchases. It typically associates garments that come from specific manufacturers. For instance `munroJacket cooccurs munroVest`.
- `similarTo`. An object property that associates garments that are structurally similar. It aims to mark similarities between generic garments and real garments. For instance `creaseSkirt similarTo pleatedSkirt`.

Finally, data properties are used to represent the parameters of the body shape analysis, as well as human characteristics such as height, age, etc. Examples of data properties are the following:

- `hasHeight`, is a property of the Human class, corresponding to human's height.
- `hasBMI`, is a property of the Human class, corresponding to the body mass index of a human.
- `hasAge`, is a property corresponding to the age of a human.

4. Reasoning with experts' rules

In addition to the representation of the main concepts and their relationships, SFO also represents rules for style advice on generic garments. The rules fall into two types: (a) *first level* or *attribute rules* and (b) *second level* or *style advice rules*. The first type of rules associates human characteristics with higher-level concepts (named attributes), whilst the second type associates higher-level concepts with garment types or garment colours. The two types of rule are meant to work in conjunction and they are defined by fashion experts[7] after examining various parameters, such as the available garment types, current fashion trends, etc. Next, we provide samples of those rules in a Prolog-like format as they were initially captured after contacting domain experts, as well as their final form in OWL.

4.1. Attribute rules (first-level rules)

Attribute rules are created by fashion experts to denote relations between characteristics of humans that are modelled in the ontology. They associate human facial features with "human style colours", i.e. summer, spring, autumn and winter. Such a rule could be stated as follows,

```
hasEyeBrowsColour (X,Y) and
hasEyeColour (X,Z) and
hasHairColour (X,W) and
hasSkinColour (X,N) and
(Y==light; Y = darkBlond; Y = Light) and
...
-> Spring (x)
```

In OWL, the above can be represented as a defined class. Thus, if an individual (a customer in our case), provides input relevant to object properties that appear in the rule, she will be classified to the Spring class by a reasoner supporting OWL 2, such as Pellet (Sirin, Parsia, Grau, Kalyanpur, & Katza, 2007). The rule above can be represented in OWL as follows:

```
Spring EquivalentTo
hasEyeBrowsColour some
  {Light, DarkBlond, GoldenNaturalBlond}
and hasEyeColour some
  {Aqua, Hazelnut, Green, Golden, LightBrown}
and hasHairColour some
  {Light, DarkBlond, GoldenNaturalBlond}
and hasSkinColour some
  {Light, Frekles, Golden}
```

Similarly, there are three additional definitions for the Summer, Autumn and Winter classes.

Another set of attribute rules allows the specification of a body type, based on body measurements, e.g.,

```
hasWaistHeight (X,Y), Y<=100.826 and
hasHeight (X,Z), Z > 68 ->
OvalBodyType (X)
```

In OWL, the above can described as a defined class with the aid of data properties:

```
OvalBodyType EquivalentTo
hasWaistHeight exactly 1 (float[<=100.825])
and
hasWeight exactly 1 (float[>"68"^^integer])
```

Similarly, there are seven more rules for the rest of the body types. Note that the values of object and data properties are expressed in OWL as class descriptions with property restrictions.

4.2. Style advice rules (second-level rules)

The style advice rules are also defined by fashion experts, and they are built to relate intermediate concepts with garment characteristics, but also to denote the degree of association. Statistics about the style advice rules are provided in Table 4. A rule such as the following captures the advice:

```
normalFigure (X) ->
  hasHighRecom (X, jacketFitted)
```

In OWL, we represent the style advice rules also as class definitions. For the above rule, and given the `NormalFigure` body type, and the `hasHighRec` object property, and the `jacketFitted` and

Table 4
Number of Stereotypes or second level rules.

Normal figure	39
Triangular	19
Hourglass	19
OvalRound	13
Narrow and Straight	17
Square	18
Summer	3
Winter	3
Spring	3
Autumn	3
Total	137

[7] The rules were provided by Prof. Sue Jankyn-Jones, of the London College of Fashion email:s.jenkyn-jones@fashion.arts.ac.uk.

`militaryStyles` individuals, the following specify what is highly appropriate (`hasHighRec`) and inappropriate (`hasLowRec`) for a human of normal body type:

```
NormalFigure EquivalentTo
  hasHighRec value jacketFitted
NormalFigure EquivalentTo
  hasNegRec value militaryStyles
```

Given the above definition, and `mary` being a member of the `NormalFigure` class it is inferred that:

```
(marry hasHighRec jacketFitted)
```

Moreover, we have rules that involve the *occasion* for a garment apart from the body type such as:

```
hasOccasion (X, dinnerParty),
  hasBodyType (X,average) ->
  hasHighRecom (X, dressShift)
```

The above cannot be handled in an elegant way in OWL. Instead extra OWL constructs are used, i.e. SWRL rules. Thus the above rule can be stated as:

$$\mathit{swrlRule} : \mathit{hasOccasion}(?u, \mathit{dinnerParty}),\\ \mathit{hasBodyType}(?u, \mathit{average}) \rightarrow\\ \mathit{hasHighRec}(?u, \mathit{dressShift})$$

There are rules that just state the occasion without reference to body type, e.g.

```
hasOccasion (X, dinnerParty) ->
  hasHighRecom (X, dressShift)
```

stated as

$$\mathit{swrlRule} : \mathit{hasOccasion}(?u, \mathit{dinnerParty}) \rightarrow\\ \mathit{hasHighRec}(?u, \mathit{dressShift})$$

Another type of a style advice rule is the association of *human colour style* or "seasons" with *garment colours*. In the following example, all users of the "Spring" type are recommended light, warm and bright colours for garments:

```
Spring EquivalentTo
  hasHighRec some {light, warm, bright}
```

5. Reasoning with community style rules

Once a user has received expert style advice, then he is assigned to a garment-centred community based on similarities between generic and real garments. Subsequently, this user will receive information about the real garment preferences of the community. This step is realised in the ontology, assuming that real garments have been mapped to corresponding generic garments, and that garment-centred communities have been discovered.

First, we introduce the object property `cooccurs`, which represents the discovery of a pattern that certain real products tend to be purchased together. The pattern is produced at the subsymbolic level in PSERVER, and is elaborated in Section 6. For example, the following three garments that co-occur are represented in the SFO as follows:

```
(odermarkTrendTrousers cooccurs odermarkVest)
(odermarkVest cooccurs odermarkTrendJacket)
```

In addition, the following chain property is defined:

```
hasHighRec o similarTo -> hasInterest
```

which expresses the fact that if a user has received an expert-based recommendation for a generic garment, and the recommended garment is similar to a real product, then it can be inferred that the user is also interested (`hasInterest`) in the latter garment. It actually connects the user to a real garment.

Second, the `similarTo` object property expresses a similarity between a generic garment and a real product. In the current work garments of the same type are considered similar. Thus a generic pleated trousers is `similarTo` odermark trousers. This relation can be made more elaborate once the properties of garments are quantified in such a way as to be comparable.

Third, in order to arrive at a community-based recommendation for user u, the following SWRL rule is used, where `commRec` is an object property that denotes the recommendation of a garment-centred community of users:

$$\mathit{swrlRule} : \mathit{hasInterest}(?u, ?x), \mathit{hasInterest}(?u, ?y),\\ \mathit{cooccurs}(?x, ?y), \mathit{cooccurs}(?y, ?z) \rightarrow\\ \mathit{commRec}(?u, ?z)$$

where $?u$ denotes a user, and $?x$, $?y$, $?z$ represent real garments. In essence this rule offer community centred advice. Fig. 2 depicts the passage from generic style advice to community style advice.

6. Origin of community rules or subsymbolic level

The interactions of customers with commercial sites, generally speaking, generate two sorts of data, the first being somatometric data (mostly body measurements), whereas the second type refers to garment purchases. Such data, after some preprocessing, can be stored and maintained in the form of personal user models in the PSERVER, and subsequently data mining algorithms can be applied to derive garment-centred communities of users.

CustoMax[8] provided us with a data set of anonymised customer garment purchases along with customer measurements. It included 818 customers, and 22 products of 3 companies (Matteo Dosso, Odermark and Munro). The products are: jackets, trousers, blouses, tops, waistcoats, overcoats, skirts and vests (see Table 5, where purchases of two users are depicted). Let us consider the set of features F denoting the normalised frequencies of garments the customer has purchased. Thus each customer can be represented in PSERVER by a feature vector as in the following example:

$$\mathit{user}_n = (\mathit{matteoDossoSkirt} = 0.9, \mathit{munroJacket} = 0.5,\\ \mathit{odermarkOvercoat} = 0.6)$$

[8] www.customax.com.

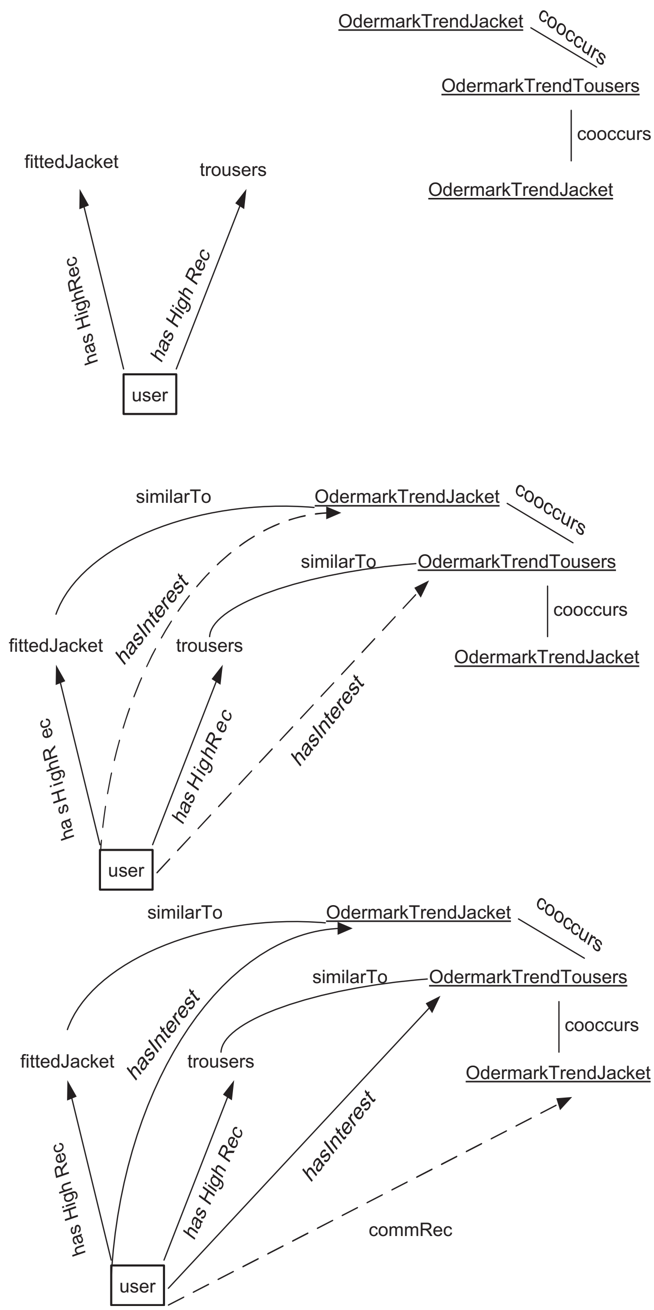

Fig. 2. Community advice combined with expert's advice. Underlined garments denote real garments. Dashed lines the current reasoning step.

Table 5
Customers' purchases.

ID	Product
1	Odermark trend jacket
2	Odermark trend trousers
1	Matteo Dosso jacket

Garments that co-occur often in the users' purchases form a *garment-centred community*. Such communities can be formed with the aid of various algorithms in PSERVER. In this work, the a priori algorithm performed well (confidence at least 0.9) and produced the garment associations that are depicted in Table 6, in form of *frequent* itemsets.

Table 6
Garment-centred communities represented as frequent item-sets. All items-sets refer to Odermark products.

trend trousers, trend jacket
trend overcoat, trend jacket
trend overcoat, trend trousers
trend trousers, trend jacket, overcoat
trend trousers, trend jacket, trend overcoat
trend overcoat, overcoat, trend jacket
trend trousers, trend overcoat, overcoat, trend jacket

7. System architecture

The style advisor provides generic and real garment recommendations, and it comprises *resources* and *processes*. The resources include the ontology, relevant SWRL rules, an external information source, and the learnt purchase patterns of garments. The processes include the overall manager, the reasoner, the ontology enrichment, and the data mining facilities of the PSERVER. The above are combined as follows (see also Fig. 3),

- Preliminary steps
  - *Original ontology design.* Fashion experts, with the aid of knowledge engineers, build-up an ontology that aims to provide style advice in the form of generic garments.
  - Identification and integration of an *external information source.* An external, to the ontology, information source is identified, that contains garment purchases. PSERVER is subsequently associated to that source, to discover groups of real garments to tend to be purchased together. That is described in chapter 6.
  - Operational mode
    * *User mapping to the ontology*. The first step is the association of a particular user to the classes and relations of the ontology. A set of user characteristics, such as her body measurements, facial features, and social occasion are submitted and represented as object properties, and an individual of the `Human` class is created in the ontology.
    * *Attribute rules*. Using the Pellet reasoner and the attribute rules, the particular individual is also assigned to intermediate level concepts. For instance, the user may be assigned to a class that describes her *season*, and her *body type*.
    * *Generic garment recommendation*. An appropriate style advice is provided in the form of generic garments. An individual being assigned to class `Spring`, and to class bodyType `Oval`, will be associated through inferencing to the following object properties and generic garments: `(mary hasHighRecom jacketLoose)`: and `(mary hasHighRec jacketColourAzur)`.
    * *Ontology enrichment.*
    The ontology is enriched with information from the external source. First, real garments are added to ontology to complement the generic garments. Second, similarities between generic garments and real ones are discovered and recorded with the `similarTo` object property. Third, the co-occurence of real garments with other real garments (as discovered by PSERVER) is recorded in the ontology with the `cooccurs` object property.

  - *Real garment recommendation*. Upon request of the user, the enriched ontology will suggest real garments, that are similar to the generic garments. Then the user will be assigned to a community of garments, and subsequently real garments will be suggested with the aid of relevant SWRL rules and the `communityRec` object property.

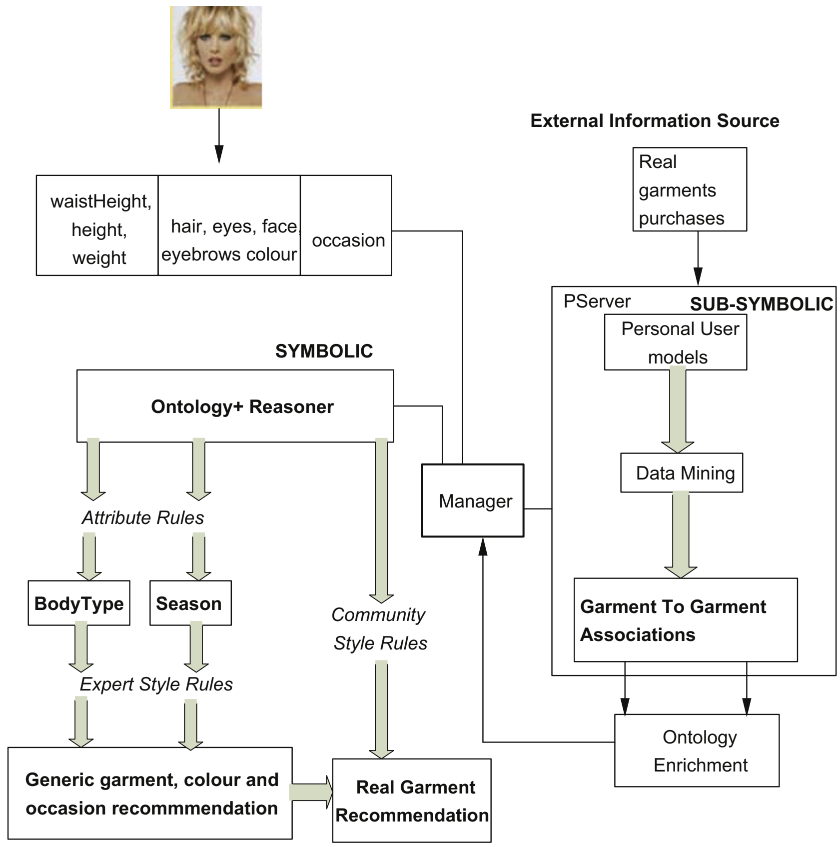

Fig. 3. Ontology and external source integration through PSERVER.

– *Manager*. The manager is responsible for the overall co-ordination of the style advice process. It controls user input, the ontology, the inferencing mechanism, and the ontology enrichment process.

8. Evaluation or knowledge validation

The evaluation of the system has focused on the verification of the knowledge base, i.e the Servive Fashion Ontology. Verification can be thought of as a way to address the question, "is the system being built in the right way?" (see Hicks, 1996). In particular, we focus on structural verification, which examines the following issues: conflicting, subsumed, circular and missing rules.

Circles do not occur because of the form of attribute and style advice rules. Attribute rules connect user measurements, or facial features to intermediate level concepts, such as body types and 'seasons'; on the other hand style advice rules, connect the intermediate level concepts to generic garments or to garment colours. Thus, two levels of rules, with no feedbacks preclude circles.

Contradictions would occur, if the same body type would lead to the same generic garment, with different degrees of recommendation. For instance, the following would lead to a contradiction,

```
NormalFigure EquivalentTo
  hasHighRec value jacketFitted
```

```
NormalFigure EquivalentTo
  hasLowRec value jacketFitted
```

The knowledge base can be checked for such inconsistencies, with the aid of Pellet reasoner (provided that the following has been defined).

```
ObjectProperty: hasLowRec
    DisjointWith: hasHighRec
```

Missing rules could occur when a customer's input cannot be matched against the condition of some rule. This is not the case here, because the users are classified into 8 body types which cover all the possible cases, the same holds for the facial features.

Finally, subsumed rules do not pose a problem, because in any case the most specific style rule is activated. For instance, in the following example, if both the BodyType and the Occasion have been provided, only the third rule will be considered relevant.

```
BodyType -> garment
Occasion -> garment
BodyType, Occasion-> garment
```

9. Conclusion and future work

The aim of our work was to provide personalised clothing recommendations to users. To achieve that we combined knowledge derived from fashion experts with the preferences of users towards garments. The experts' knowledge was encoded in the form of an

OWL ontology, that included information about body types, generic garments, and social occasion, as well as their relationships. In particular, the ontology represents user stereotypes that associate body types, facial features, and social occasion with generic garments. The stereotypes, are represented as equivalence relations or as SWRL rules. An inference engine, such as Pellet, activates the stereotypes upon the addition of a user in the ontology, together with her relevant body type, facial features and social occasion.

Furthermore, there is an external information source, where the purchase behaviour of some users is recorded. This is represented in PSERVER under the form of personal user models, that contain as features the purchased garments, and as feature values the frequency of purchases. PSERVER through data mining, allows the construction of data driven (or learnt) garment-centred communities. The garment centred communities can be used to enrich the original ontology, and subsequently to enhance the kind of advice the user (who has been added to the ontology) receives. Thus, a user will not only receive information about pertinent generic garments, but also suggestions about real garments that are similar to the generic ones; and even more importantly, the user will be assigned to a community, and because of that she will receive recommendations about real garments favoured by the community.

In the current work, the discovery of similarities between real and generic garments (as captured by the `similarTo`) object property is rather simplistic, and it is due to the lack of the available features of the real garments. Once they become available, a more elaborate comparison will be possible.

An important open issue is the presentation of recommendations to the end user. The authors have worked into enriching domain ontologies with linguistic structures, in order to generate natural language descriptions (15). Let us consider a very simple example, provided the following individual `(mary hasHighRec jacketFitted)`, and a relevant microplan (linguistic) annotation for the `hasHighRec` property then, the sentence `A very good recommendation for mary is a fitted jacket` will be produced.

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