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Analysis of Subjective Conceptualizations towards Collective Conceptual Modelling

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This work is conducted as a preliminary study for a project where individuals' conceptualizations of domain knowledge will thoroughly be analyzed across 150 subjects from 6 countries. The project aims at investigating how humans' conceptualizations differ according to different types of mother languages, cultural backgrounds, gender, generations, etc., when domain-specific terms are expressed in a common language, i.e. English. In this work, we analyze a publicly available dataset [De Deyne, 2008] representing semantic structures of domain knowledge possessed by four people. The method applied in this work is based on a non-parametric relational model, Infinite Relational Model [Kemp, 2006] that in parallel analyzes concept-feature relations across the four people. The model identifies an optimal grid that are common to the four datasets considered, from there the individual semantic differences are analyzed. The results show that the identified common grid visualizes subject specific patterns among the extracted concept-feature clusters. The work further discusses our future perspectives for modeling a collective ontology across subjects according to different subjects' profiles.

1. Introduction

In the history of computer sciences and the philosophy of ontology, knowledge has often been considered as static at a certain temporal point. In this mindset, a standardized ontology defined by a third party [Gruber 92][Madsen 04][Declerck 10] has been playing an important role to establish a common ground that can facilitate mutual understandings among different communicating parties. However, the patterns of communication in our real life cannot be accounted for solely by standardized knowledge that is defined in a top-down manner. Scientists in semiotics [Pierce 58] [Durst-Andersen 11], cognitive pragmatics [Sperber 86] and cognitive sciences [Rosch 75][Storms 97] put emphasis on mental representations of knowledge that are constructed differently due to differences in our close environment and our different cognitive abilities. Hence, it is challenging but also fascinating to explore how differences in subjective conceptualization should be treated for the purpose of cross-cultural communication and collaboration. This work attempts to identify a common semantic structural grid where different patterns of conceptualizations are represented in a bottom-up manner.

In this work, an unsupervised learning method known as Infinite Relational Model (IRM) [Kemp 06] is employed. A framework of applying the IRM in this work is primary based on the design described in [Mørup 10]. The model in parallel analyzes concept-feature relations across the four people and eventually identifies an optimal grid that are common to the four datasets considered, from there the individual semantic differences are analyzed. In other words, the clusters are the same for each of the multiple datasets, whereas the relations between concepts and features are specific to each subject. Through this optimally identified grid, differences across individual semantic structures possessed by the respective subjects can be inspected. For visualization we apply an extended version of IRM, the normal Infinite Relational model (n-IRM) [Herlau 12] in order to further organize the subject specific patterns of interactions obtained from the optimally identified common grid. This enables one to analyze different patterns of conceptualization by the four subjects.

In the next section, the methods employed in this work are reviewed. Section 3 presents the results obtained by the IRM and the n-IRM, followed by the data analysis in Section 4. Section 5 further discusses future research perspectives, followed by the conclusions in Section 6.

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2. Methods

2.1 Semantic Structures

In cognitive sciences, a semantic structure of domain knowledge possessed by each human subject is often represented by a binary matrix consisting of objects (concepts) and attributes (features). De Deyne et al. [De Deyne 08] developed and verified a data matrix frame representing the domain of *clothing*. In [De Deyne 08], the reliability of concepts to be listed in the matrix has been validated with a number of human subjects based on multiple approaches, among others: typicality ratings, goodness ratings, exemplar generation frequency, exemplar and category associative strength, familiarity ratings, imaginability ratings, and pairwise similarity ratings. After the validation of the concepts list, De Deyne et al. [De Deyne 08] implemented feature-generation tasks and feature-importance ratings for each concept. The generated features for each concept are listed in a concept-feature matrix and its applicability has eventually been assessed by four individual human subjects in [De Deyne 08]. The clothing matrix framework developed in this way by [De Deyne 08] consists of 29 concepts, such as *sweater*, *mitten*, *blouse*, and 258 features, e.g. *used as accessory*, *made of cotton*, *worn at a special occasions*. The four binary matrices provided in [De Deyne 08] are structured in a way that, if a feature is considered relevant to a specific concept, a binary value 1 is assigned, otherwise 0 is assigned.

2.2 The Infinite Relational Model

The aim of the infinite relational model [Kemp 06] is to divide objects into groups in a way that the number of groups are automatically inferred using a Chinese Restaurant Process (CRP)[Pitman 02] which defines a distribution having support over all conceivable partitions. We currently focus on bipartite relational data constituting the relationship between two entities, i.e. clothing items and features defining various properties. We currently analyze multiple such matrices given by individual subject's perception of clothing items, thus the data is given by a set of binary matrices.

The CRP can be thought of as a iterative process in which items are assigned consecutively to clusters such that the probability of being assigned to an existing cluster is proportional to how many items are already assigned to that cluster. A new cluster can be generated with a probability proportional to a parameter γ which specifies the extend in which new clusters are preferred.

The clustering of clothing items and their features are respectively specified by mode specific partitions $\mathbf{z}^{(1)}$ and $\mathbf{z}^{(2)}$. These partitions are shared across subjects, however, the probability of observing a binary relation between entities of group a in mode 1 and group b of mode 2 is individually defined for each subjects by the parameter $\eta_{ab}^{(s)}$. Thereby the generative model for the considered specification of the IRM can be written as:

$$
\begin{aligned}
\mathbf{z}^{(1)} &\sim \mathrm{CRP}(\gamma^{(1)}) && \textit{clothing items,}\\
\mathbf{z}^{(2)} &\sim \mathrm{CRP}(\gamma^{(2)}) && \textit{features,}\\
\eta_{ab}^{(s)} &\sim \mathrm{Beta}(\beta_0^+, \beta_0^-) && \textit{relation probability,}\\
R_{ij}^{(s)} &\sim \mathrm{Bernoulli}\left(\eta^{(s)}_{z_i^{(1)} z_j^{(2)}}\right) && \textit{relation.}
\end{aligned}
$$

In the above generative model, the clothing items and features are first partitioned into groups $\mathbf{z}^{(1)}$ and $\mathbf{z}^{(2)}$. Next, $\eta_{ab}^{(s)}$ defines how the a^{th} group of clothing items relate to the b^{th} group of features for the s^{th} human subject. Finally, binary relations between the i^{th} clothing item and the j^{th} features $R_{ij}^{(s)}$ is generated according to a Bernoulli distribution dependent on the two partitions and their relation probability. For the model we set the parameters of the prior distibutions to $\beta_0^+ = \beta_0^- = 1$, and $\gamma^{(\alpha)} = \log(J_\alpha)$ where J_α is the size of the α^{th} mode. We perform parameter inference using the Markov Chain Monte Carlo procedure described in [Mørup 10] and ran the sampler for a total of 1000 samples and discarded the first 500 samples for burnin. The solutions we display in the following are the realization with highest value of the posterior.

2.3 The normal Infinite Relational Model

The n-IRM [Herlau 12] generalizes the IRM to continuous data by replacing the Bernoulli likelihood with a Normal distribution which depends on mean and precision parameters $m_{ab}^{(s)}$, $\lambda_{ab}^{(s)}$ that are drawn from a Normal-Gamma prior. We apply the n-IRM to the multi-array eta-value $\eta_{ab}^{(s)}$ matrices, where $\eta_{ab}^{(s)}$ is defined as the expected value of $\eta_{ab}^{(s)}$ obtained from the realization having highest value of the posterior. The prior values for the n-IRM was set to $\kappa_0 = 1$, $\alpha_0 = 15$ and $\beta_0^{-1} = 1$. We used the same number of iterations as in the above IRM. To summarize, the generative model for the n-IRM presently considered is given by

$$
\begin{aligned}
\mathbf{z}^{(1)} &\sim \mathrm{CRP}(\gamma^{(1)}) && \textit{first mode,}\\
\mathbf{z}^{(2)} &\sim \mathrm{CRP}(\gamma^{(2)}) && \textit{second mode,}\\
\lambda_{ab}^{(s)} &\sim \mathrm{Gam}(\alpha_0, \mathrm{rate} = \beta_0) && \textit{precision,}\\
m_{ab}^{(s)} &\sim \mathrm{Normal}(m_0, (\kappa_0 \lambda_{ab}^{(s)})^{-1}) && \textit{mean,}\\
R_{ij}^{(s)} &\sim \mathrm{Normal}(m^{(s)}_{z_i^{(1)} z_j^{(2)}}, \lambda^{(s)\,-1}_{z_i^{(1)} z_j^{(2)}}) && \textit{links.}
\end{aligned}
$$

For further details regarding the n-IRM see also [Herlau 12].

3. Results

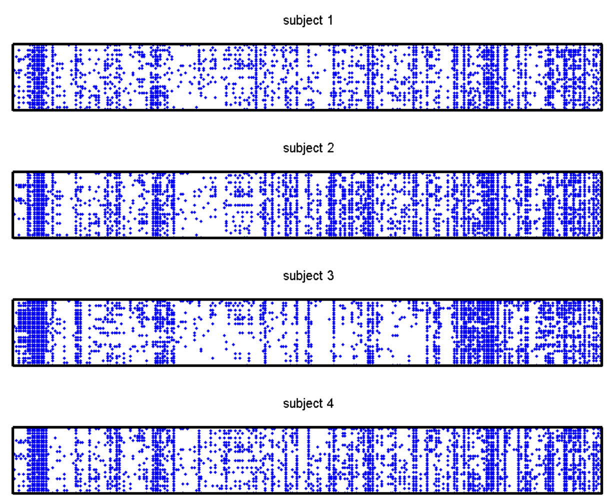

Figure 1: Original binary matrices representing the semantic structures of the four subjects

Figure 1 depicts the original binary matrices representing the semantic structures of the four subjects prepared by [De Deyne 08]. The y axis, x axis and blue dots of each graph respectively represent 29 clothing concepts, 258 characteristic features and their binary values where each subject assigned 1 if a feature is applicable to a concept in question. These four graphs indicate that the semantic

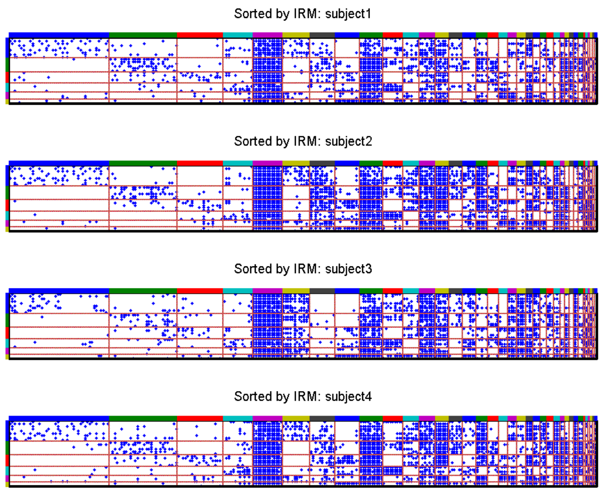

Figure 2: Individual semantic structures contrasted via a common grid

structures possessed by the four subjects are slightly diferent. Figure 2 illustrates individual semantic structures of the four subjects which are contrasted via a common grid optimally computed by the IRM. The graphs show that the 29 clothing concepts and the 258 features are respectively partitioned into 6 and 36 clusters. In Figure 2, the lines partitioning the concepts and features are considered as an optimal grid that is common across the four subjects. When observing individual blocks of the grid, different patterns across the four subjects become visible. The four plots in the left in Figure 3 shows the density (η-values) of each interaction between a concept-cluster and a feature-cluster, where the darkest gray indicates the highest density and vice versa. These four η matrices are further partitioned by the n-IRM in the plots of the right column. Here, the n-IRM has been applied in order to co-cluster the η-value matrices displayed in the left column for further visualizing what group of feature clusters influence the formation of the concept-clusters as well as the differentiation of the semantic structures possessed by the four subjects.

Figure 4 illustrates the results of the η-value partitions achieved by the n-IRM across the four subjects. For example, the four plots of the mean values of the normal distributions indicate that *feature-cluster cluster 3* (referred to as *fc3*) consisting of feature clusters f5, f9, f13, f21, f26 and f27, and *fc5* consiting of feature clusters f1, f2, f3, and f4 are relatively uniform across the four subjects. On the other hand, *fc2* (feature clusters: 12, 19, 22, 31, 32, 33, 34) and *fc4* (feature clusters: 16, 23, 25, 30, 35, 36), *fc6* (feature cluster: 28), *fc7* (feature cluster: 7), *fc8* (feature cluster: 29) are irregular across the four subjects. The four plots in the right giving the variance of the normal distributions in 4 show that, for example *fc1* (feature clusters: 6, 8, 10, 11, 14, 15, 17, 18, 20, 24), *fc2* (feature clusters: 12, 19, 22, 31, 32, 33, 34) and *fc4* (feature clusters: 16, 23, 25, 30, 35, 36) result in larger variances for all the four subjects. This

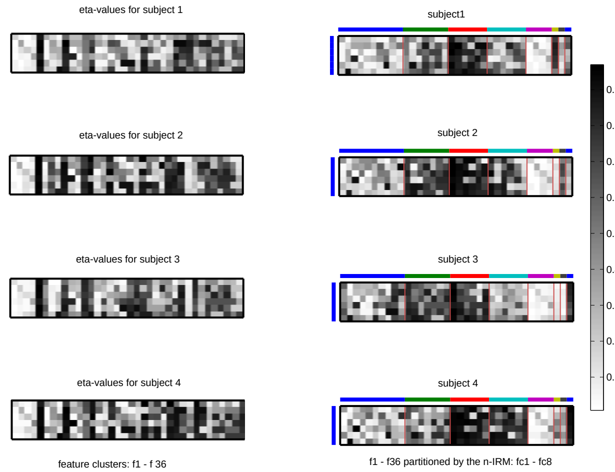

Figure 3: Individual semantic structures contrasted by η-values: left - feature clusters are extracted by the IRM; right - feature clusters are partitioned by the n-IRM

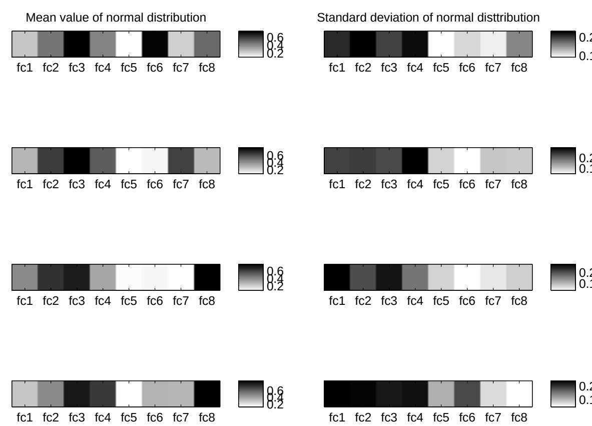

Figure 4: Mean values and standard deviations for the feature-cluster clusters (fc) extracted by the n-IRM across the four subjects

indicates that these *feature-cluster clusters* consist of the feature clusters that have stronger influence on distinguishing concept clusters in each semantic structure.

In this way, Figures 2, 3 and 4 overview the patterns of the semantic structures possessed by the four subjects by contrasting an interaction between a concept-cluster and a feature-cluster through the common grid that have optimally been computed by the IRM. In the next section, the contents of the obtained clusters are further analyzed in details.

4. Analysis

Figures 5, 6 and 7 summarize the aforementioned results with concrete concept- and feature labels. The concept-clusters obtained across the four subjects from the IRM analysis are: cluster 1 (hat, boots, beanie, cap, belt, shoes, scarf, socks, mittens); cluster 2 (bra, dress, skirt, panties, top, bathing suit); cluster 3 (tracksuit, pyjamas, dungarees, shorts, t-shirt); cluster 4 (blouse, tie, shirt, suit); cluster 5 (coat, sweater, pullover); and cluster 6 (pants, jeans). From the common sense intuition, the IRM has reasonably partitioned 29 concepts into 6 clusters that could respectively characterized as: 1) accesories; 2) items targeted for female, 3) casual items, 4) formal items, 5) items used outside, and 6) items covering legs. This motivate us to further investigate how these clusters have been formed based on the distribution of 258 features whose associations are individually assessed by the four subjects.

In Figures 5, 6 and 7, the IRM results, i.e. 6 concept-clusters and 36 feature-clusters, are re-ordered computed by the n-IRM.

Figure 5 depicts *fc1* that consists of feature clusters f6, f8, f10, f11, f14, f15, f17, f18, f20 and f24. As described in the previous section, the variances in *fc1* are high, while the mean values are low in all the four subjects. This indicates that these 10 feature-clusters have, in general, strong influences on the formation of specific concept-clusters. For example, f18 consists of features *is worn on top of a T-shirt*; *has long sleeves*; *has sleeves; has two sleeves* that mainly describes about concept-cluster 5 but also some items in concept-clusters 3 and 4 for all the four subjects. Similarly, there are strong links between f8 with the concept cluster 6; f10 with the concept-cluster 4 and so on. Another tendency identified from Figure 5 is that the feature-clusters (e.g. f8, f18) that consist of features describing physical characteristics, e.g. *has sleeves*, *has zipper* etc. have similar patterns of associations possessed by the four subjects, while the feature-clusters (e.g. f15, f24) that consist of features describing impressions, e.g. *is feminine*, *can be a status symbol*, *fashionable* are rather subject-dependent.

In Figure 4, the mean values for *fc2* are generally higher than those of *fc1* for all the four subjects. This indicates that the feature-clusters are linked with several concept-clusters. At the same time, both the mean values and the variance indicate that the pattern of feature associations to the concept-clusters are different across the four subjects. For example, the feture-cluster f19 (is used to keep you warm; gives warmth; is warm; is warm in winter) in *fc2* clearly indicates that the patterns of association to the concept-clusters are different especially for the subject 3 in 6. Most of the features included in *fc2* describe functionality such as *is worn to keep you warm* and impression such as *worn by elderly*, *is loose* etc.

The mean values for *fc3* are all very high in Figure 4, while there are some slight differences in variances across the four subjects. The high mean values indicate that each feature-cluster contained in *fc3* has tendency to form stronger links with majority of the concept clusters. In other words, the features listed in these feature-clusters, e.g. *bought in a store*, *exists in different kinds* etc., are rather common to most of concepts so that they have little influence on the formation of the concept-clusters.

As it can be observed from both Figures 4 and 6, *fc4*, *fc6*, *fc7* and *fc8* respectively consist of the feature-clusters that are rather subject-dependent. For example, subjects 2 and 4 showed different association patterns for features such as *is comfortable*, *is fun to wear*, *is sexy* from the patterns indicated by subjects 1 and 3. On the contrary, for *fc7* consisting of features such as *is hygienic*, *is beautiful*, and *smells like washing powder*, subjects 1 and 4 indicated similar patterns, while subject 2 and subject 3 showed compretely different association patterns in 6.

Finally, Figure 7 represents an overview of *fc5* that consists of very sparse feature-clusters, i.e. f1, f2, f3 and f4. These feature-clusters consist of features that describe specific clothing items rather than the all items in a specific concept-cluster. For example, the feature *keep your feet warm* in f1 specifically associates with the concepts *boots*, *shoes* and *socks* that are members of the concept-cluster 1, while the feature *keep your head warm* in f1 specifically associate with the concepts such as *beanie*, *hat*, *scarf* and *cap* in the same concept-cluster 1.

The approach of applying the IRM to the multi-array matrices enables one to first identify a common semantic structural grid across multiple human subjects, from which different patterns of semantic structures possessed among the human subjects can be analyzed in details. By applying the n-IRM to the four η-value matrices obtained from the IRM, it is further possible to roughly estimate hierarchical structure of 29 clothing items via the item-specific features shown in *fc5*, the concept-cluster specific features shown in *fc1*, and the features that cover multiple concept-clusters such as *fc2*. This indicates an interesting potential for learning ontological structures of a collective domain knowledge possessed by multiple people. Future perspectives of this approach are further discussed in the next section.

5. Discussion and Future Perspectives

The work presented in the previous sections demonstrates that semantic representations of domain knowledge are slightly different across the four individual human subjects. For example, subject 2 and 4 indicated similar pattern of association to a specific feature-cluster, while, for another feature-cluster, the same subject 2 indicated different pattern of association from subject 4 but similar pattern possessed by subject 3. One of the main limitation in this work is that the publicly available datasets made by [De Deyne 08] do not disclose the profiles of each subject. Hence it is impossible to investigate if the identified differences in the association patterns are caused by aspects of the subjects' profiles such as gender.

One of our future plans is to collect data from a larger number of human subjects with different profiles, such as cultural backgrounds, genders, generations, social environments, different expertise etc. To be more specific, a group at Copenhagen Business School is planning to study patterns of semantic structures of a specific knowledge domain, possessed by 150 subjects in 6 countries, i.e. Denmark, Japan, China, Russia, Spain and UK, and investigate how a conceptualization differs according to the different types of mother languages [Durst-Andersen 11], cultural backgrounds, social status, gender, English proficiency level, etc., when domain-specific terms are expressed in a common language, i.e. English. The work demonstrated here indicates that the application of the IRM seems to be an interesting starting point for analyzing such semantic structures of people having different profiles. The results presented above also imply some exciting future potentials for: i) the unsupervised construction of hierarchical ontologies of the domain knowledge based on the analysis of the feature-concept structure; ii) the clustering of 150 subjects based on different patterns of concept-feature relations across 150 matrices; iii) the identification of a collective ontology across subjects belonging to a specific profile group; and iv) the alignment of the identified collective ontologies that belong to two respective profile groups. These attempts could eventually contribute to the bottom-up learning of collective knowledge which optimally represents individuals' knowledge naturally possessed by a group of people.

6. Conclusions

The work introduced an approach of combining the IRM and the n-IRM for optimally identifying a common semantic structural grid from multiple concept-feature matrices, from which the individual semantic structures possessed by the respective subjects are further contrasted to each other. The results indicated that the IRM reasonably partitioned the 29 concepts into 6 clusters that respectively characterized with common themes. By further applying the n-IRM to the concept- and feature clusters obtained by the IRM, the feature-clusters are further structured in three levels: feature-clusters consisting of item specific features; feature-clusters consisting of a concept-cluster specific features; and feature-clusters consisting of features that cover several concept-clusters. In addition, the identified common grid effectively visualized the different feature association patterns possessed by the four subjects. The work indicated several potential models to be considered in the future research in order to achieve the bottom-up learning of collective knowledge which optimally represents individuals' knowledge naturally possessed by a group of people.

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		fc1																																																																			
		f6												f8											f10									f11							f14						f15						f17					f18				f20				f24		
		'protects against the cold'	'protects against the rain'	'protects against the wind'	'protects against the sun'	'is knit by your grandma'	'is used to protect you'	'is not worn in the summer'	'hung on hallstand'	'is to be used outside'	'can be worn as ornament'	'can be knit by yourself'	'used as accessory'	'is worn on your legs'	'has a button'	'has a zipper'	'has buttons'	'has long (trousers)legs'	'has (trousers)legs'	'has two (trousers)legs'	'has bags'	'is a pair of trousers'	'is long'	'you can put a belt in it'	'is worn to work'	'is worn at special occasions'	'gives a businesslike impression'	'is chic'	'for fancy occasions'	'used to look nicer'	'worn by business people'	'worn at parties'	'worn on gala balls'	'is worn to go for a run'	'is worn to go skiing'	'is worn by sportsmen'	'worn during sports'	'is cheap'	'is not expensive'	'can''t be worn in the church'	'is worn by cowboys'	'is small'	'is narrow'	'is tight around the body'	'is blown away by the wind'	'is tight'	'in in style'	'is fashionable'	'is hard to iron'	'can be a status symbol'	'is given a present'	'worn with a suit'	'is worn under a sweater'	'is refreshing in the summer'	'is airy'	'is made in a light fabric'	'worn underneath other clothes'	'is worn on top of a T-shirt'	'has long sleeves'	'has sleeves'	'has two sleeves'	'can have sequins'	'can be carried backwards'	'can be manufactured by yoursel	'shrinks when washed'	'worn by transvestites'	'is feminine'	'men think it is sexy'
subject 1	'hat'	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0
	'boots'	1	1	0	0	0	1	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	'beanie'	1	0	0	0	0	0	1	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0
	'cap'	0	0	0	1	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
	'belt'	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	1	1	1	1	0	0	0	0	0	0	0	1	0	1	1	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	'shoes'	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	1	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0
	'scarf'	1	0	1	0	1	0	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	1	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0
	'socks'	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	0	1	0	1	0	0	1	0	1	0	1	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0
	'mittens'	1	0	0	0	1	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	0	0
	'bra'	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	1	0	0	0	0	0	0	1	1	1	0	0	1	0	1	0	1	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	1	0	0	0	1	1	1
	'dress'	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	1	0	1	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	1	1	1	1	0	0	1	1	0	0	1	0	0	1	1
	'skirt'	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	0	0	0	0	1	1	1	0	0	0	0	0	0	1	1	0	0	1	1
	'panties'	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	1	1	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	1	1	1	1	0	1	1	1	1	0	1	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	1	0	0	1	0	0
	'top'	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	1	0	1	1	1	1	0	0	0	1	1	1	1	1	0	0	0	0	0	1	0	1	0	1	0
	'bathing suit'	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	1	0	0	0	1	0	1	0	0	0	0	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	1	0
	'tracksuit'	0	0	0	0	0	0	0	0	1	0	0	0	1	0	1	0	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	1	1	1	0	0	0	0	0	0	0
	'pyjamas'	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	1	1	0	0	0	0	0	0	0
	'dungarees'	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0
	'shorts'	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	1	1	0	0	0	0
	't-shirt'	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	1	0	0	1	1	0	1	0	0	0	0	0
	'blouse'	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	1	1	1	0	1	1	1	0	1	0	0	0	1	0
	'tie'	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	1	1	0	1	1	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	'shirt'	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	1	1	0	0	1	1	1	1	1	1	0	0	0	0	0	0	0
	'suit'	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	1	0	0	1	1	1	0	0	0	0	0	0	0
	'coat'	1	1	1	0	0	1	0	1	1	0	0	0	0	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0
	'sweater'	1	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	0
	'pullover'	1	0	1	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	1	0	1	0	0	0
	'pants'	1	0	0	0	0	0	0	0	1	0	0	0	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	1	1	1	1	1	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0
	'jeans'	1	0	0	0	0	1	0	0	0	0	0	0	1	1	1	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
subject 2	'hat'	1	1	1	1	0	0	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	1	1	1	0	0	0	0	0	0	0	1	1	1	0	0	1	1	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0
	'boots'	1	1	0	0	0	1	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	'beanie'	1	1	1	0	0	1	1	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	1	0	1	0	1	0	1	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0
	'cap'	0	1	0	1	0	0	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0	1	0	1	0	1	1	1	1	0	1	0	0	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0
	'belt'	0	0	0	0	0	0	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	1	0	1	0	1	1	0	1	1	1	1	0	1	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
	'shoes'	0	0	0	0	0	1	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	1	1	1	1	1	0	1	1	0	0	0	1	0	0	0	0	1	1	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
	'scarf'	1	0	1	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	1	0	0	1	0	0	1	1	0	0	0	1	0	1	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	1	0
	'socks'	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	0	1	0	0	0	0	1	1	0	0	0	0	1	0	0	0	0	0	0	1	0	1	0	0
	'mittens'	1	0	0	0	0	0	1	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	1	1	0	0	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
	'bra'	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	1	1	1	1	0	0	0	0	1	1	1	0	1	0	0	1	1	1	0	1	0	0	1	1	0	0	0	0	0	0	0	0	1	1	1
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	'skirt'	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	1	1	1	0	1	1	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	0	0	0	0	1	1	1	0	0	0	0	0	0	1	1	0	1	1	1
	'panties'	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	1	0	0	0	0	1	1	0	0	0	0	1	1	1	1	1	1	1	1	1	0	1	1	0	1	0	1	0	0	0	0	0	1	0	0	0	1	1	0	0	0	0	0	0	0	0	1	1	1
	'top'	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	1	0	0	0	0	1	1	1	0	1	1	1	0	1	1	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	1	0	1	1	1
	'bathing suit'	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	1	0	1	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	1	1	1
	'tracksuit'	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	1	0	1	1	1	1	1	0	0	0	0	0	0
	'pyjamas'	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1	0	0	1	1	1	0	0	0	0	1	0	1
	'dungarees'	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0
	'shorts'	0	0	0	0	0	0	1	0	0	0	0	0	1	1	1	0	0	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	1	0	1	1	1	0	1	0	0	0	0	0	0	1	1	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
	't-shirt'	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	1	1	0	1	1	1	0	1	0	0	1	1	0	0	1	0	0	0	0
	'blouse'	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	1	1	1	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	0	1	1	0	1	1	1	0	0	1	0	1	1	0
	'tie'	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	1	1	0	0	1	0	0	0	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
	'shirt'	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	1	1	1	1	0	1	0	0	1	1	1	0	1	1	1	0	0	1	0	0	0	0
	'suit'	0	0	0	0	0	0	0	1	0	0	0	0	1	1	1	0	1	1	1	0	1	1	1	1	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0
	'coat'	1	1	1	0	0	1	1	1	1	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	1	1	1	1	0	0	0	1	0	0	0
	'sweater'	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	1	1	1	1	1	1	0	1	0	0	0	0
	'pullover'	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	1	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0
	'pants'	0	0	0	0	0	0	0	0	1	0	0	0	1	1	1	0	1	1	1	1	1	1	1	1	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0
	'jeans'	0	0	0	0	0	1	0	0	0	0	0	0	1	1	1	0	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
subject 3	'hat'	1	1	1	1	0	1	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	1	1	0	0	0	0	0	0	0	0	1	0	0	1	1	1	1	0	1	1	1	1	0	0	0	0	0	0	0	0	0	1	1	1	1	0	1	0
	'boots'	1	1	1	1	0	1	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0
	'beanie'	1	1	1	1	1	1	0	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0
	'cap'	1	1	1	1	0	1	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	1	0	0	0	0	1	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0
	'belt'	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	0	1	1	1	1	0	0	1	0	0	0	0	0	0	0	1	0	1	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	1	1	1	0	0	1	0
	'shoes'	1	1	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	1	0	0	0	0	1	1	1	0	1	1	0
	'scarf'	1	1	1	1	1	1	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	1	0	1	0	0	1	0	1	0	0	0	1	0	0	0	1	1	0	0	0	1	1	0	0	1	0	0	1	0	0	0	0	0	1	1	0	1	1	1
	'socks'	1	0	0	1	1	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	1	1	1	1	1	0	1	0	1	1	1	0	1	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0	1	0	1	1	0
	'mittens'	1	0	1	0	1	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0	0
	'bra'	0	0	0	0	0	1	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	1	1	1	0	0	0	0	0	1	1	1	0	0	0	1	1	0	1	0	0	1	1	0	0	0	0	1	1	1	1	1	1	1
	'dress'	1	1	1	1	1	1	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	1	0	0	1	1	0	0	0	0	1	1	1	1	1	1
	'skirt'	1	1	1	1	1	1	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	1	1	0	0	0	0	1	1	0	0	0	1	1	1	1	0	1	1
	'panties'	0	0	0	0	0	1	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	1	0	0	0	0	1	1	0	1	0	0	0	1	1	0	0	0	1	1	1	1	0	1	1
	'top'	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	1	0	1	0	1	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	1	1	1	1	1	1	1
	'bathing suit'	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	1	0	1	0	0	0	1	0	0	0	1	1	1	1	0	0	0	0	1	0	0	0	1	1	1
	'tracksuit'	1	1	1	1	0	1	0	1	1	0	0	0	1	0	0	0	1	1	1	1	0	1	0	0	1	0	0	0	0	0	0	0	1	1	1	1	0	0	1	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	0	0
	'pyjamas'	0	0	0	0	0	1	1	0	0	1	0	0	1	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	1	0	1	1	1	1	1	1	0	0	1
	'dungarees'	1	1	1	1	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0
	'shorts'	0	0	0	0	0	1	0	0	1	0	0	1	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	0	1	0	0	0	0	1	1	1	0	0	1	1
	't-shirt'	1	0	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	1	0	0	0	1	1	1	1	1	1	0	0
	'blouse'	1	0	1	1	0	1	0	0	1	0	0	1	0	0	0	1	0	0	0	0	0	0	0	1	1	1	1	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0
	'tie'	0	0	0	0	0	0	1	0	0	1	1	1	0	0	0	0	0	0	0	0	0	1	0	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	1	1	1	1	0	0	1	1	1	0	0	0	1	1	1	0	0	0	0
	'shirt'	1	1	1	1	0	1	0	1	0	1	0	0	0	1	0	1	0	0	0	1	0	0	0	1	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	1	0	0	0
	'suit'	1	1	1	1	0	1	0	1	1	1	0	0	0	0	0	1	1	1	1	1	0	1	1	0	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	1	0	0	0	0	1	1	1	0	0	0	0	1	0	0
	'coat'	1	1	1	1	0	1	0	1	1	1	1	1	0	1	1	1	0	0	0	1	0	0	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1	1	0	0	0	0	0	1	1	1	1	1	1	1	1	0	1	0
	'sweater'	1	0	1	1	0	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0	0
	'pullover'	1	0	1	1	1	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0	0
	'pants'	1	1	1	1	0	1	0	0	1	0	0	0	1	1	1	1	1	1	1	1	1	1	1	0	0	1	1	0	1	1	1	1	1	1	1	1	0	0	1	1	0	0	0	0	0	1	1	1	1	1	1	1	0	0	0	1	0	0	0	0	1	0	1	0	1	0	0
	'jeans'	1	1	1	1	0	1	0	0	1	0	0	1	1	1	0	1	1	1	1	1	1	1	1	1	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	1	1	0	1	1	1	1	0	0	0	1	0	0	0	0	1	1	1	1	1	1	1
subject 4	'hat'	0	1	0	1	0	1	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	1	1	0	0	1	0	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	'boots'	0	1	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
	'beanie'	1	0	1	0	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	1	0	0
	'cap'	0	1	0	1	0	1	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1	1	1	0	1	0	1	1	1	1	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0
	'belt'	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	'shoes'	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	1	1	1	0	1	1	0	0	0	1	1	0	1	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
	'scarf'	1	0	1	0	1	1	1	1	1	0	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	1	0	1	0	1	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0
	'socks'	0	0	0	0	1	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	1	0	0
	'mittens'	1	0	0	0	1	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
	'bra'	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	1	1	1	1	1	1	1	0	0	0	0	1	0	1	0	1	0	0	1	0	1	0	1	0	1	1	1	0	0	0	0	0	0	0	0	1	1	1
	'dress'	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	1	1	1	0	1	1	0	0	0	0	0	0	0	0	0	1	1	1	0	0	1	0	1	0	0	0	0	1	1	0	0	0	1	1	0	0	0	0	1	1	1
	'skirt'	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	1	0	0	1	0	1	0	1	1	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	1	0	1	1	1
	'panties'	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	1	1	1	1	1	1	0	0	0	1	1	1	1	0	1	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	1	0	0	1	0	1
	'top'	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	1	1	1	0	1	0	0	0	0	0	0	1	1	0	1	1	0	0	0	0	0	1	0	0	0	1	1
	'bathing suit'	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	1	0	1	1	1	0	1	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	1	1
	'tracksuit'	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1	1	1	0	0	0	0	0	0
	'pyjamas'	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	1	1	1	0	0	0	0	0	0	0
	'dungarees'	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0
	'shorts'	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	1	1	0	1	0	0	0	0	1	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
	't-shirt'	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0	0	1	1	0	1	0	0	0	0	0
	'blouse'	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	1	0	1	1	1	0	0	1	1	1	1	0
	'tie'	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	1	0	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	1	1	0	1	1	0	0	0	1	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
	'shirt'	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	1	0	0	0	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	1	1	1	0	0	1	1	0	0	0	1	1	1	1	1	0	0	1	1	0	0	0
	'suit'	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0	0	0	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	1	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0
	'coat'	1	1	1	0	0	1	1	1	1	0	0	0	0	1	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	1	0	0
	'sweater'	0	0	1	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0
	'pullover'	1	0	1	0	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	1	1	1	0	1	1	1	1	0	0
	'pants'	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	1	0	1	1	0	1	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0
	'jeans'	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0

Figure 5: Obtained concept-clusters and feature-clusters for fc1

Figure 6: Obtained concept-clusters and feature-clusters for fc2, fc3, fc4, fc6, fc7 and fc8

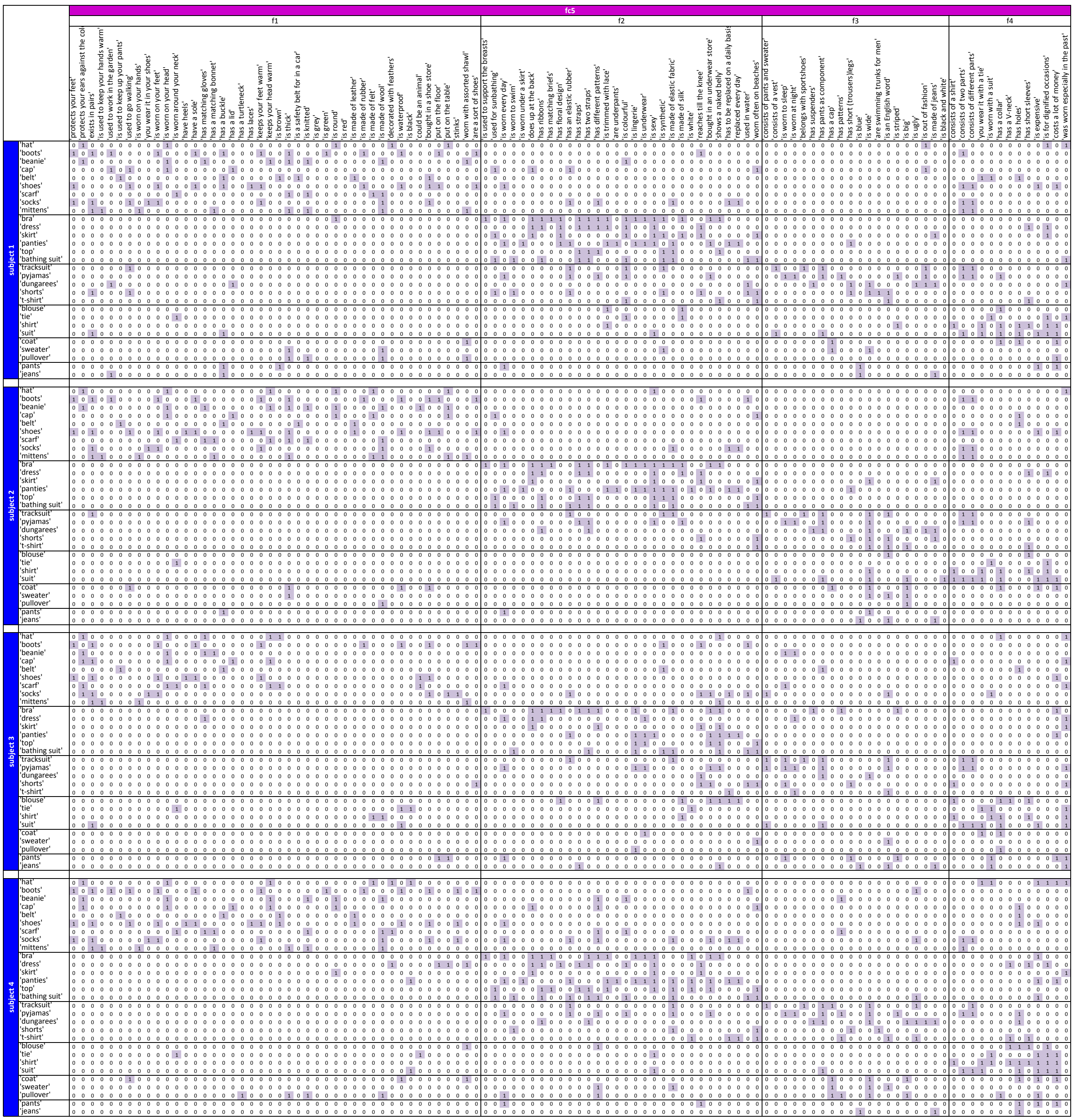

Figure 7: Obtained concept-clusters and feature-clusters for fc5