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Exploring the Effect of a User's Personality Traits on Tactile Communication with a Robot using Bayesian Networks

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Abstract

Because robots are physically embodied agents, touch is one of the important modalities through which robots communicate with humans. Among the several factors that affect human-robot interaction, this research focuses on the effect of a user's personality traits on tactile interactions with a robot. Participants interacted freely with a robot and their tactile interaction patterns were analyzed. Several classifiers were used to examine the effect of a participant's degree of extroversion on tactile communication patterns with the robot and our results showed that a user's personality traits affected the way in which they interacted with the robot. Specifically, important features of Bayesian networks, such as the Markov blanket and what-if/goal-seeking power were tested and showed the effect of personality on tactile interaction with respect to where and how participants touched the robot. We also found that, by using Bayesian network classifiers, a user's personality traits can be inferred based on tactile communication patterns.

Keywords: Human-robot interaction, tactile interaction, Personality, General Bayesian network, Markov blanket

Exploring the Effect of a User's Personality Traits on Tactile Communication with a Robot using Bayesian Networks

Touch is one of the important modalities for communication in human social interactions as well as in human-robot interactions (HRI). Previous studies (Hertenstein, 2002; Hertenstein, Verkamp, Kerestes, & Holmes, 2006) have shown the communicative functions of touch in human social interactions, such that touch can convey emotions and intentions and can also reveal one's personality (Deethardt & Hines, 1983). Due to the tangible characteristics of robots, touch is a particularly important modality by which they communicate with humans. Many studies (Bainbridge, Nozawa, Ueda, Okada, & Inaba, 2011; Nakagawa et al., 2011; Salter, Dautenhahn, & Boekhorst, 2006; Yohanan & MacLean, 2012) have demonstrated the importance of touch as a means of communication for robots. Similarly, other studies (Salter et al., 2006; Salter, Michaud, Letourneau, Lee, & Werry, 2007; Wada, Shibata, Saito, & Tanie, 2004) also emphasized the importance of natural touch in social interactions with a robot.

There are several factors that affect human-robot tactile interaction. Physical characteristics of robots, such as size and appearance, have been recognized to have effects on human-robot tactile interaction. For example, Wada et al. (2004) introduced a baby seal robot called Paro. The robot was designed to communicate with users through touch. In order to facilitate tactile interactions with the robot, they designed it with a soft body covered with white fur. Users' characteristics, such as emotions and intentions, also have effects on human-robot tactile interactions. Yohanan and MacLean (2012) introduced a social robot called The Haptic Creature and showed how humans expressed their emotions towards the robot through touch.

To the best of our knowledge, however, there has been no research on the effect of a user's personality on natural tactile communication with a robot. Because personality affects how a person behaves in human social interactions, it is reasonable to assume that personality will also have an influence on such behavior as touch in human-robot tactile interactions. Many previous studies (Isbister & Nass, 2000; K. M. Lee, Peng, Jin, & Yan, 2006; Takayama & Pantofaru, 2009; Tapus, Ţăpuş, & Matarić, 2008; Walters et al., 2005) have shown that a user's personality played an important role in HRI. Tapus et al. (2008) examined the effect of user-robot personality matching for post-stroke rehabilitation therapy and found that extroverted participants spent more time with an extroverted robot. Walters et al. (2005) showed that a user's personality had an effect on establishing physical proximity to a robot. However, the effect of personality on tactile interactions with a robot has not yet been explored fully.

In this work, we investigated the relationship between a user's personality and tactile interaction with a robot. We focused in particular on the following two issues: how a user's personality traits affect tactile interaction with a robot and how personality traits can be inferred from tactile interaction patterns. Social robots provide an ideal platform to investigate these issues, as they are embodied agents and interact with humans physically. Pianesi, Mana, Cappelletti, Lepri, and Zancanaro (2008) stated that "social interaction is an ideal context to conduct automatic personality assessment." Furthermore, previous studies have shown that the tactile information acquired during human-robot social interaction can capture different levels of interactional context, such as the user's current behavior (Koo, Lim, & Kwon, 2008), modes of interaction (Salter et al., 2007) and emotion (Yohanan & MacLean, 2012). No research, however, has examined the effect of a user's personality on human-robot tactile interaction, although personality has effects on HRI. In this research, we focused specifically on the extroversion factor in the Big Five model of personality (John & Srivastava, 1999). Several previous studies have shown that the extroversion dimension is a particularly critical factor in interpersonal interactions as well as in human-robot interactions (Isbister & Nass, 2000; K. M. Lee et al., 2006; Nass & Lee, 2000). For example, Tapus and Matarić (2008) argued that the extroversion dimension is important in assistive robotics. Furthermore, the extroversion dimension has been also reported to be the most accurately observable factor in the Big Five taxonomy (Lippa & Dietz, 2000). Previous studies have revealed that the extroversion dimension showed the highest correlation among the different measurements (Gosling, Rentfrow, & Swann Jr, 2003) as well as the highest recognition rate among the dimensions (Mohammadi, Vinciarelli, & Mortillaro, 2010). Further, there are some similarities between the extroversion dimension and other dimensions, such that extroversion is dominant and friendly (Isbister & Nass, 2000; Trapnell & Wiggins, 1990; Wiggins, 1979). In order to investigate the effects of the degree of extroversion on human-robot tactile interaction, we employed several machine learning techniques to analyze the relationship between a user's personality and the patterns of tactile interaction with a robot. We focused in particular on the General Bayesian Network (GBN) classifier, as it has several advantages over other classifiers. We first compared the classification performance of several classifiers. Then we examined the causal relationship between personality traits and touch patterns by employing the GBN classifier.

One example of the possible applications of the results of this study is the development of a context-aware ubiquitous robotic system (Mastrogiovanni, Sgorbissa, & Zaccaria, 2010). In Scalmato, Sgorbissa, and Zaccaria (2012), context awareness was described as “the process of formalizing the state of the world, understanding what is going on at a given time instant, and adapting the system to behave accordingly.” The ability to detect and adapt its behavior to a user is crucial for sociable robots (Salter, Boekhorst, & Dautenhahn, 2004). By using tactile information acquired during natural interactions, the robot can understand the user (i.e., environment) and adapt its behavior.

Related Works

The Effect of Personality on Social Interactions with a Robot

There is no universally agreed-upon definition of personality. Warren (1922) defined personality as “the entire mental organization of a human being at any stage of his development,” while John, Robins, and Pervin (2010) described personality as that which “represents those characteristics of the person that account for consistent patterns of feeling, thinking, and behaving.” Most agree that personality is a key factor in human social interaction. In clinical and social psychology, human behavior has been explained by the concept of personality (Pianesi et al., 2008), and researchers have shown the relationship between personality and behavior (Ewen & Ewen, 2009; Morris, 1979). Morris (1979) emphasized the importance of personality in understanding human behavior by stating the consistency, stability, and uniqueness of personality. Several researchers have investigated the quantification of personality, such as the Big Five taxonomy (John & Srivastava, 1999), the Eysenck model of personality (Eysenck, 2013), and the Myers-Briggs model (Murray, 1990). The Big Five taxonomy assumes that personality consists of five dimensions: extroversion, neuroticism, agreeableness, conscientiousness, and openness (John & Srivastava, 1999). In the Eysenck model of personality (PEN), personality consists of three factors: psychoticism (P), extroversion (E), and neuroticism (N). The Myers-Briggs Type Indicator (MBTI) describes personality in terms of four dimensions: extroversion-introversion, sensation-intuition, thinking-feeling, and judging-perceiving (Murray, 1990).

One example of the effect of personality on human social interactions is a personality-based social attraction rule that consists of two competing rules: complementary and similarity attraction rules. The complementary attraction rule assumes that people tend to be attracted to those who are different from themselves. In contrast, the similarity attraction rule posits that people prefer to interact with those who are similar to themselves. Several researchers have examined whether these social attraction rules could be applied in the field of human-computer and human-robot interactions. Isbister and Nass (2000) examined what type of personality-based social attraction rule could be established in a social interaction between a user and a computer character. Their results demonstrated the complementary attraction rule, in that the participants were attracted to a computer character with a personality complementary to their own. The complementary social attraction rule was also discussed in Lee et al. (2006). In their experiment, participants played with either an extroverted or introverted AIBO. The results showed that the AIBO was evaluated as more intelligent and attractive when its personality was complementary to that of the participant (degree of extroversion). On the other hand, the similarity attraction rule has also found support in the field of HCI and HRI. Tapus et al. (2008) examined the effect of user-robot personality matching for post-stroke rehabilitation therapy and found that extroverted participants spent more time with an extroverted robot, supporting the similarity social attraction rule. The findings of Nass and Lee (2000) also supported this rule. Similarly, other studies have shown the effects of a user's personality in establishing physical proximity to a robot (Syrdal, Dautenhahn, Woods, Walters, & Koay, 2006; Takayama &

Pantofaru, 2009; Walters et al., 2005). For example, Walters et al. (2005) showed that a user's personality profile had an influence on establishing physical proximity to a robot.

Tactile Communication with a Robot

In this paper, tactile communication refers to the use of touch to communicate and interact with a robot. The role of touch as a communicative function in human social interactions has been studied by several researchers. Hertenstein, Keltner, App, Bulleit, and Jaskolka (2006) investigated whether touch could convey distinct emotions and whether such emotions could be identified. They found that the various emotions were characterized by different properties, such as duration and intensity. They also found that participants were able to decode distinct emotions accurately. Several researchers have investigated the relationship between personality traits and tactile communication in human social interaction. Malphurs, Raag, Field, Pickens, and Pelaez-Nogueras (1996) studied the tactile interaction behaviors of depressed adolescent mothers and their infants and found that mothers with depressive symptoms directed more negative touches to their infants than did non-depressed mothers. Riggio and Friedman (1986) also showed that extroverted and introverted people exhibited different non-verbal cues, such as gestures.

Robots have physical bodies and are present in the real world, so people often interact with robots physically. Several researchers have investigated the effect of touch on human robot interactions. Nakagawa et al. (2011) reported that a robot's active touch could improve a user's motivation. Yohanan and MacLean (2012) introduced a social robot called The Haptic Creature. The robot was designed with a focus on tactile interaction and the authors argued that users could communicate their emotions to the robot through touch. Similarly, Bainbridge et al. (2011) also showed that tactile interaction measures, such as pressure and force, could reveal a user's feelings. A thorough review on human-robot tactile interaction can be found in Argall and Billard (2010).

However, previous studies (Bainbridge et al., 2011; Yohanan & MacLean, 2012) have examined touch primarily as the communicative function of emotions and the effect of a user's personality traits on tactile communication has not yet been investigated thoroughly. Therefore, this study focused on identifying the effect of people's personality traits on tactile interactions with a robot. Tactile communication is private and outside of awareness (Clay, 1968), so touch could reveal a user's personality traits in interactions with a robot.

General Bayesian Network and Markov Blanket

A Bayesian Network is a directed acyclic graph that describes a probabilistic causal relationship among variables (Yaramakala & Margaritis, 2005). There are several types of Bayesian networks, such as Naïve Bayesian Network (NBN), Tree Augmented Naïve Bayesian Network (TAN) and General Bayesian Network (GBN). The NBN has the simplest shape, in which a class node—a node of interest—is linked with all other nodes. NBN does not explain the causal relationship between the children nodes. TAN is an extended version of the NBN in which the nodes form a tree.

In the General Bayesian Network (GBN), a class node is not differentiated from other nodes (variables) in the network. A class node can have a parent node and the causal relationships between variables can be expressed. GBN has several advantages. First, the nodes in the Markov Blanket (MB) of the class node can assist in efficient analysis. Nodes in MB consist of parents of a class node, children of a class node and any parents of children of a class node. Fig. 1 illustrates an example of a GBN structure which consists of 1 class node (Class) and 12 descriptive nodes (N#). The nodes that belong to the MB of the class node are filled with gray. Previous studies (Aliferis, Tsamardinos, & Statnikov, 2003; Yaramakala & Margaritis, 2005) have shown that nodes in MB can effectively and efficiently describe the causal relationship between a class node and other variables. Thus, similar to the feature selection technique, analyzing a few relevant variables in the MB of the class node could show the causal relationship among variables without analyzing all other descriptive variables (Aliferis et al., 2003; Koller & Sahami, 1996). In addition, GBN provides excellent analysis techniques, e.g., what-if and goal-seeking analyses (K. C. Lee & Cho, 2010). In what-if analysis, the change in the class node can be predicted by modulating the values of other nodes. In goal-seeking analysis, the necessary conditions for other variable to achieve a specific status of a class node (i.e., goal) can be examined. In this paper, we focused particularly on using the GBN to investigate causal relationships between users' personality traits (degree of extroversion) and their tactile interaction patterns.

[FIGURE 1 ABOUT HERE]

Method

Robot

In this experiment, we used a Pleo (Fig. 2), a dinosaur-like robot developed by Innvo Labs. Pleo contains 14 motors that allow it to walk and move its body and it is equipped with a CCD camera, microphones, and various sensors for interacting with its user. However, Pleo's auditory and vision processing capabilities are limited, so it interacts with users primarily through touch. The eight capacitive touch sensors embedded in Pleo's body enable the robot to sense touches from humans. Four touch sensors are located on each of the legs and two are located on the back. There are also two touch sensors on the top and bottom of the head. Pleo is covered with rubber skin so that the touch sensors are invisible to a user. Prior to the experiment, we manipulated Pleo to manifest one of two personality types (extroverted or introverted). The later analysis showed that participants could distinguish between the two different personalities, indicating that the manipulation was successful.

[FIGURE 2 ABOUT HERE]

[FIGURE 3 ABOUT HERE]

Participants

A total of 31 university students were recruited for the experiment, (11 females, 20 males; average age = 24.03 years, SD = 2.18). Fig. 3 illustrates the distribution of the participants' personality traits (degree of extroversion); later analysis showed that the distribution was normal. The majority of participants (81%) reported that they had no previous exposure to Pleo or other types of animal-like robots. The participants were assigned randomly to play with either an extroverted or introverted Pleo.

Measurements

Personality Traits. Wiggins (1979) eight personality adjective items were used to measure the degree of extroversion of the participants. The eight items ($\alpha = 0.87$) used in the experiment were cheerful, enthusiastic, extrovert, bold, introvert (reverse coded), inward (reverse coded), shy (reverse coded), and quiet (reverse coded). A fivepoint Likert scale was used for each item, with responses ranging from 1 (strongly disagree) to 5 (strongly agree).

Tactile Interaction Patterns. To capture a participant's tactile interaction patterns with Pleo, we set up a camcorder in the experimental room and recorded the experiment. As the presence of the experimenter in the same room with a participant might hinder the natural interactions with Pleo, the experimenter left the room during the video recording. For the analysis, a participant's touch patterns with Pleo were coded into two categories (location touched and type of touch). Regarding the location touched, we included Pleo's body parts with the touch sensors as well as the body parts without the touch sensors in order to capture various tactile interaction patterns. With respect to the types of touch, we adopted and modified the touch patterns listed in two previous studies (Koo et al., 2008; Yohanan & MacLean, 2012) so that those touch patterns could fit to Pleo. The locations touched and types of touch were coded together with the time at which they occurred. Table 1 shows the coded elements for each category.

Table 1. *The coded categories and their elements*

Categories	*Elements*
Touched Location	Head, mouth, jaw, front legs, rear legs, neck, back, tail, belly, side, (any) two places at one time, undistinguishable location
Types Of Touch	Tickle, patting, slap, pick up, hold, shake, poke, push, pull, hug, kiss, undistinguishable type

[FIGURE 4 ABOUT HERE]

Procedure

The participants signed an informed consent upon arrival in the experimental room. They were then given the questionnaire, which was used to obtain information on their demographics and personality traits (degree of extroversion). After completing the questionnaire, a PowerPoint tutorial was shown to each participant. The tutorial gave a brief introduction to Pleo, including information on its sensors and functions. However, detailed information, such as the exact location of the touch sensors, was not given because such information could elicit “button-push” behavior and limit the types of touch patterns. The tutorial also contained two short video clips about Pleo. The first lasted 32 seconds and showed Pleo acting alone, i.e., exhibiting autonomous behavior only. The second video clip was 40 seconds long and showed Pleo interacting with a person. The person in the second video clip interacted naturally with Pleo. That is, the person showed various touch behaviors, but did not exhibit any touch behavior that revealed the location of Pleo’s sensors. After the participants watched the tutorial, Pleo was placed on the table in front of them, and each participant was asked to play with the robot for five minutes as freely as s/he wished. Previous studies (Kanda, Ishiguro, Ono, Imai, & Nakatsu, 2002; Melson et al., 2005; Tanaka, Cicourel, & Movellan, 2007) showed that people’s social behavior towards robots can be assessed in a period of time as short as five minutes. The experiment was conducted freely in an unstructured environment. No specific tasks or instructions were given to the participants. Before the interaction began, the experimenter started the timer and video recording, and left the room. After five minutes of interaction with Pleo, the experimenter returned to the room and gave the post-session questionnaire to the participant. This questionnaire was designed to measure participants’ judgments of the Pleo’s personality and the participants’ previous experience with Pleo. Fig. 4 shows two examples of interactions between a participant and Pleo during the experiment.

Analysis Tools

Waikato Environment for Knowledge Analysis (WEKA; Hall et al. (2009)) was used to model and examine several classifiers for predicting a participant's personality traits based on his/her touch interactions with the robot. WEKA provides several classification techniques, such as Bayesian networks, neural networks, and decision trees. In this paper, we focused on the use of the GBN classifier to explore the causal relationship between personality traits and tactile communication patterns. The structure of the GBN was learned using K2 algorithms, setting no limitation on the maximum number of parent nodes. The conditional probability among the variables was learned by SimpleEstimator provided in WEKA. We also compared the performance of the GBN classifier with other classifiers provided in WEKA: NBN, TAN, Neural Network (NN), Support Vector Machine (SVM), and Decision Tree classifiers (DT). The NBN has the simplest shape and does not explain the causal relationship among the children nodes. TAN is an extended version of the NBN in which the nodes form a tree. The NN classifier mimics the neuronal structure of the human brain and performs classification with knowledge stored in connections between nodes in the network (Liao, Paulsen, Reid, Ni, & Bonifacio-Maghirang, 1993). The SVM classifier is "a binary classifier which looks for an optimal hyperplane as a decision function in a high-dimensional space" (Cristianini & Shawe-Taylor, 2000). The DT classifier is also a binary tree in which every non-leaf node is related to a predicate (Jin & Agrawal, 2003).

Dataset

We removed the data for one participant because later video analysis revealed that the subject did not interact with Pleo. Consequently, the data on the touch patterns of 30 participants were included in the analysis. The dataset containing five minutes of interaction was processed further into five different datasets, each representing different durations of the interaction: from the time of a first touch to one minute, to two minutes, to three minutes, to four minutes, and to five minutes of interaction. Similar to Pianesi et al. (2008), a participant's personality (degree of extroversion) was discretized into three groups to represent extroversion, introversion, and neither extroversion nor introversion based on the mean and standard deviation. All other variables in the dataset were discretized into the optimal number of equal-width bins using the leave-one-out method provided in WEKA.

Nodes in Classifiers

In the analysis, a total of 38 nodes were examined for classification. The 12 nodes representing the frequency of occurrence of each location touched and 12 nodes representing the frequency of occurrence of each type of touch were included in the network. We also added three nodes representing the frequency of three different affective touch types: positive, negative, and normal touches. Positive touches consisted of tickling, patting, hugging, and kissing, whereas negative touches consisted of slapping, shaking, and poking. All other types of touch were categorized as normal touches. There were also seven nodes representing the characteristics of the touch pattern: total number of touches, number of locations touched, number of touch types, standard deviation of the frequency of locations touched, standard deviation of frequency of touch type, discontinuity of locations touched, and discontinuity of touch type. The total number of touches represented how many touches occurred within the given duration of interaction and were calculated by summing the number of touches exhibited by a subject. The number of locations touched showed how many different body parts were touched during the interaction. Similarly, the number of touch types represented how many different types of touch patterns were exhibited by a subject. The standard deviation of the frequency of locations touched was calculated to represent how evenly a subject touched Pleo. The standard deviation of the frequency of touch type was calculated in a similar manner. For example, if both the standard deviation of the frequency of locations touched and touch type were high, then it implies that the participants touched some particular parts of Pleo in the same way. The discontinuity of locations touched and touch type represented the degree of monotony of the touch pattern. The discontinuity of locations touched and touch types were calculated by comparing two consecutive touches. For example, a higher discontinuity in touch type implied that a participant changed the type of touch frequently. Finally, four nodes were included to represent the participant's gender, Pleo's personality type, the participant's tendency to form a parasocial relationship with Pleo, and the participant's degree of extroversion. Table 2 shows the entire set of variables in the GBN examined in this research.

Table 2. *Variables in the General Bayesian Network*

Category	*Variables and Description*	
Touched Location	freqHead* freqMouth* freqJaw* freqFrontLegs* freqRearLegs*, freqNeck* freqBack* freqTail* freqBelly* freqSide* freqTwo* freqEtcBody*	
	Description. 12 variables representing the frequency of occurrence of each Pleo's body parts	
Types of Touch	freqTickle*, freqPatting* freqSlap* freqPickUp*, freqHold*, freqShake* freqPoke* freqPush*, freqPull* freqHug* freqKiss* freqEtcTouch*	
	Description. 12 variables representing the frequency of occurrence of each types of touch	
Affective Touch	freqPosTouch**, freqNegTouch**, freqNorTouch**	
	Description. 3 variables representing the frequency of three different affective touches. Positive touch consists of tickling, patting, hugging, and kissing whereas negative touch consists of slapping, shaking, and poking. All other types of touch were categorized as a normal touch.	
General Characteristics of Touch	numTotalTouch*,	Total number of touches occurred during interaction
	numKindsLocation*,	Total number of touched location during interaction
	numKindsTouch*,	Total number of types of touch exhibited during interaction
	stdFreqLocation*	Standard deviation of frequency of touched location
	stdFreqType*,	Standard deviation of frequency of touch type
	rawDiscontinuityLoc*	Discontinuity with respect to touched location
	rawDiscontinuityType*	Discontinuity with respect to touch type
Other variables	gender*,	Participant's gender
	PLEOpersonality**,	Manipulated Pleo's personality (extroverted/introverted)
	subjectParaTendency*,	Participant's tendency to form parasocial relationship
	subjectPersonality***	Participant's degree of extroversion

Notes. * Variables acquired by coding or questionnaire. ** Variables manipulated by the authors. *** Target variable (class node)

Results

Study 1: Comparison of Classification Performance

In Study 1, we compared the accuracy of six different classifiers. The classification accuracy in this paper refers to the network's accuracy in classifying participants' personality traits (degree of extroversion) into those self-reported by the participants based on their patterns of tactile interaction. Table 3 shows the classification accuracy (mean and standard deviation) of each classifier. The accuracy shown in the table is the average of 100 iterations in the validation process. In the validation process, we used the training-testing split method. In each validation process, 90% of the data (i.e., subject) were selected randomly for training and the remaining 10% of data were used for testing. As shown in Table 3, the GBN classifier generally elicited better classification accuracy than other classifiers. The average classification accuracy of GBN over the entire dataset was higher than for those of other classifiers. Further, GBN elicited the best classification performance (59.75%) among the other networks in the first minute of the interaction. There was a general tendency for the classification accuracy to decrease over time (Fig 5). Many classifiers generally showed higher accuracies in the first minute of interaction and the accuracies of those classifiers also generally decreased over time. This implies that the tactile information patterns acquired in the first minute of interaction can be a better predictor of the user's personality traits than those acquired in the entire five minutes of interaction. Based on the data obtained from all durations of the interaction, we further conducted pairwise t-tests at the 5% significance level to compare the average accuracy of each classifier. The GBN classifier outperformed all other classifiers and the differences in performance were statistically significant in all cases.

[FIGURE 5 ABOUT HERE]

Table 3. *The classification accuracy (%) of each classifier (mean and standard deviation)*

Duration of Interaction	*NBN*	*DT*	*SVM*	*GBN*	*TAN*	*NN*
1 minute	46.00 (31.17)	56.67 (28.60)	47.75 (28.30)	59.75 (29.90)	36.33 (29.10)	46.75 (31.27)
2 minutes	48.17 (24.23)	44.42 (23.00)	41.33 (27.95)	45.00 (26.00)	33.58 (28.31)	35.00 (26.51)
3 minutes	30.17 (23.50)	36.42 (25.28)	26.50 (25.88)	51.08 (24.00)	25.67 (22.18)	26.83 (25.23)
4 minutes	36.00 (27.24)	35.08 (23.96)	34.67 (26.53)	32.75 (24.51)	26.67 (25.46)	28.67 (23.34)
5 minutes	34.91 (26.82)	34.33 (25.96)	32.67 (27.54)	38.50 (26.87)	28.67 (26.07)	33.25 (26.81)
Average	39.05 (27.50)	41.38 (26.70)	36.58 (28.12)	45.42 (27.87)	30.18 (26.55)	34.10 (27.55)

Study 2: Causal Relationship between Personality and Touch

Based on the findings of Study 1, we used GBN to investigate further the effect of a participant's personality traits on the tactile interaction patterns. We chose the GBN for the following reasons. First, compared to the other classifiers, GBN can not only classify the participants' personality traits, but it can also reveal the causal relationship—the effect of personality trait (degree of extroversion)—on the tactile interaction pattern. Second, MB nodes in GBN can be used effectively to understand the causal relationship among variables. Finally, GBN is suitable for conducting typical decision support functions, such as what-if analyses (K. C. Lee & Cho, 2010).

[FIGURE 6 ABOUT HERE]

We analyzed the GBN structure for each duration of interaction. Fig. 6 illustrates the MB nodes of the GBN structures for each duration of interaction. In the first minute of interaction, the MB of the class node (subjectPersonality) consisted of 7 nodes: freqMouth, freqPull, stdFreqLocation, freqPush, freqPosTouch, freqHead, freqBelly. During the first two minutes of interaction, the MB consisted of freqPush, stdFreqLocation, freqPull and freqHead. There was only one variable (freqNorTouch) in the MB during the first three minutes of interaction. During the first four minutes of interaction, there were seven nodes in the MB: freqTwo, rawDiscontinuityType, freqPush, stdFreqTouch, freqPull, freqEtcTouch and freqPosTouch. Finally, there were five nodes in the MB in the five minutes of interaction: freqPull, freqPosTouch, gender, freqTwo, rawDiscontinuityType. As can be seen in Fig. 6, only a few variables were related directly to the user's personality traits (subjectPersonality) and those variables varied across the duration of the interaction. In order to investigate the effect of the user's degree of extroversion on tactile interaction patterns further, we conducted a what-if analysis by testing two scenarios.

[FIGURE 7 ABOUT HERE]

Scenario #1: *During the first minute of interaction with Pleo, if a user did not pull Pleo, but pushed Pleo frequently, and touched Pleo's head often, but not its mouth and belly, then how extroverted would a user be?*

Fig. 7 illustrates the original network structure and the prior probability of a user's personality traits (subjectPersonality) according to Scenario 1. When the MB nodes were set to the values in the scenario, the prior probability of a high degree of extroversion became the largest probability (High: 69.4%). This implied that a person showing the tactile interaction patterns described in the scenario above during the first minute of interaction would probably be extroverted.

Scenario #2: *What kinds of different tactile interaction patterns would be exhibited by extroverted and introverted users?*

In the second scenario, we conducted the analysis on the first four minutes of interaction with Pleo. As can be seen from Fig. 8, the introverted and extroverted users were expected to show different types of tactile behavior. A large difference in rawDiscontinuityType was particularly notable. The extroverted user might show a higher value in rawDiscontinuityType, whereas the introverted user might show a lower value. That is, the extroverted user might change the types of touch frequently while interacting with Pleo compared to the introverted user. Also, the frequency of touching Pleo with both hands (freqTwo) showed some differences, with the extroverted user touching Pleo with both hands more than the introverted user. This difference was also observed in freqEtcTouch. The extroverted user exhibited a higher probability in freqEtcTouch, which implies that they might exhibit some tactile behaviors that do not belong to the type of touch category.

[FIGURE 8 ABOUT HERE]

Discussion

The findings of Study 1 suggest that it is possible to predict a user's personality traits based on the types of touch patterns they direct to a robot. The GBN classifier elicited the highest classification performance (59.75%) and performed better than almost all other classifiers examined in the paper. In particular, the results of Study 1 supported a “thin slice” approach for the prediction of personality. Previous studies (Ambady & Rosenthal, 1992; Pianesi et al., 2008) showed that a short interaction was sufficient to predict a person’s personality traits. In our experiment, participants were given five minutes to interact with Pleo, which is a relatively short amount of time. Fig. 5 shows that the classification accuracy of all classifiers was above the chance level (33%) throughout the entire interaction. However, the highest classification performance was observed in the first minute of the interaction. This result is consistent with the findings of Pianesi et al. (2008), which showed the highest classification accuracy in the first part of the interaction.

However, the classification accuracy of the GBN and other classifiers was lower than we expected. This could be due to several reasons. First, the novelty effect might influence the subjects’ tactile interaction patterns and consequently, result in low classification accuracy. There was an overall tendency for the classification performance to decrease over time. During the video analysis, we observed that many participants showed the greatest interest in Pleo in the beginning and interacted actively with the robot. However, the participants seemed to lose interest over time, resulting in monotonous patterns of tactile interaction. Thus, we could assume that these monotonous patterns of touch may have hindered the revelation of participants’ true personality traits in the later stages of the interaction. Similarly, Gockley et al. (2005) showed that time spent interacting with a robot decreased because the novelty effect faded. Another reason that may have accounted for the low accuracy is the limitation in observational data. Salter et al. (2004) compared observational data with sensor readings that were both acquired during natural interactions between children and a robot. They showed that the observational data (children playing with a robot) provided results less clear than the robot's sensor readings when inferring the psychological classification of children.

The results of Study 1, however, still imply the possibility of using tactile interaction patterns to predict users' degree of extroversion. By using touch data, as well as other multi-modal features, such as acoustic features, the classification accuracy would likely be enhanced. Several previous studies have shown that multimodal features, such as acoustic and visual, can be used to detect personality traits (Batrinca, Lepri, & Pianesi, 2011; Pianesi et al., 2008). As the robotic system can be equipped with other sensory devices, such as a microphone and camera, classification based on tactile, as well as multimodal cues, would be likely to improve classification accuracy.

In Study 2, we used the GBN classifier to investigate further the causal relationship between the degree of extroversion and the tactile interaction patterns. The findings of Study 2 were as follows. First, we observed that several key variables (i.e., nodes in the MB) were related directly to a participant's personality traits. Although we employed more than 30 variables in the network, the analysis showed that there were generally 5 to 6 key variables related directly to the subject's degree of extroversion and those variables varied over time. In the context of the feature selection problem, our findings suggested that only a few aspects of tactile interaction can be used to predict personality traits. Second, the what-if analysis revealed direct causal relationships between the degree of extroversion and the tactile interaction patterns. According to the scenarios, the prior probability of the MB nodes changed and consequently, it revealed the relationship between the personality traits and touch characteristics. In our first scenario, the prior probability of the nodes in the MB of the class node (i.e., degree of extroversion) was modulated and the GBN predicted the prior probability of the user's degree of extroversion. This result implies that the user's personality traits could be inferred by means of the GBN. This supported the findings of Study 1, in which we showed the classification accuracy of a subject's degree of extroversion based on tactile interaction patterns. In the second scenario, an analysis with two different personality traits (extroverted and introverted) was conducted and GBN forecasted that they might exhibit different interaction patterns. The GBN predicted that an extroverted user might exhibit more active tactile interaction (e.g., frequent use of both hands and frequent changes in types of touch) than an introverted user. This result is consistent with previous studies (Isbister & Nass, 2000; Salter et al., 2006) that demonstrated that extroverts exhibit more active behavior than introverts.

Our findings showed that tactile information can be used in a robotic system so that it can detect and adapt its behavior to users with different personalities. Previous authors (Salter et al., 2006; Tapus & Matarić, 2008; Tapus et al., 2008) have argued that detecting individual differences is important in HRI. The adaptation capability is also one of the most desirable functions for sociable robots (Salter et al., 2004). Previously, Yohanan and MacLean (2012) introduced social robots that could recognize users' emotions and adapt to them through the modality of touch. Similarly, we might be able to create a robot that can detect a user's personality and adapt its behavior accordingly. Unlike psychometric instruments, such as multiple questionnaires, the method of predicting a user's personality traits based on tactile communication patterns does not require much time or effort on the part of the user, but predicts traits during natural interactions instead. Once the user's personality traits are inferred or detected from the tactile information, the robotic system can adapt its behavior to manifest its own personality, which could enhance the quality of interactions. For example, the robot could adapt its behavior to manifest the same personality traits as its user's when the similarity attraction rule holds. Detecting the user's personality traits based on tactile information can be integrated further into other context-aware ubiquitous robotic systems (Mastrogiovanni et al., 2010; Scalmato et al., 2012).

Concluding Remarks

In this research, we investigated the effect of users' personality traits (degree of extroversion) on tactile interaction with a robot. We examined whether tactile communication patterns with a robot could reveal a user's personality traits in terms of the extroversion dimension. Based on the observational data acquired through the HRI experiment, we first compared the classification performance of the GBN classifiers with other classifiers. The results showed that the extroversion dimension could be classified from a user's touch patterns. Next, we investigated the causal relationship between the degree of extroversion and touch patterns by means of the MB nodes and what-if analysis provided by the GBN classifier. We found that a user's tactile communication patterns, such as where and how participants touched Pleo, could reveal a participant's personality traits. To the best of our knowledge, this work is the first attempt to employ the GBN classifier to predict a user's personality traits based on tactile communication with a robot.

Our suggestions for future research are as follows. First, different types of robots should be considered, because a robot's appearance might affect the user's patterns of tactile interaction. People generally exhibit different interaction or communication styles depending on the person with whom they interact. Therefore, it may be assumed that people will exhibit different tactile communication styles when interacting with robots having a different appearance (e.g., humanoid or machine-like robots). Second, other dimensions of personality need to be examined in other to broaden our insights on the effect of personality on tactile communication, even though previous studies (Trapnell & Wiggins, 1990) have shown similarities between extroversion and other dimensions of personality.

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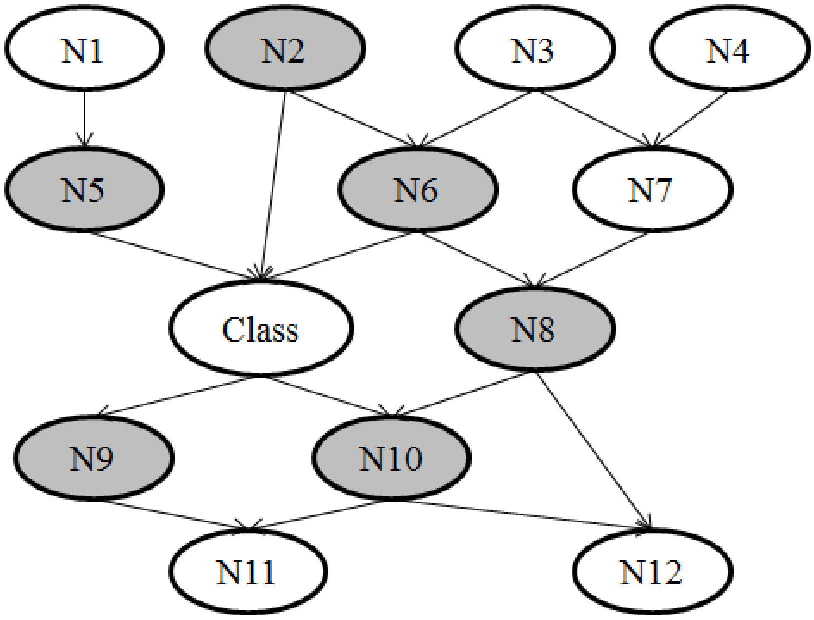


Figure 1. An example of General Bayesian Network (GBN) structure. The nodes belong to the Markov Blanket of the class node are filled with gray.

Figure 2. A dinosaur-like robot Pleo

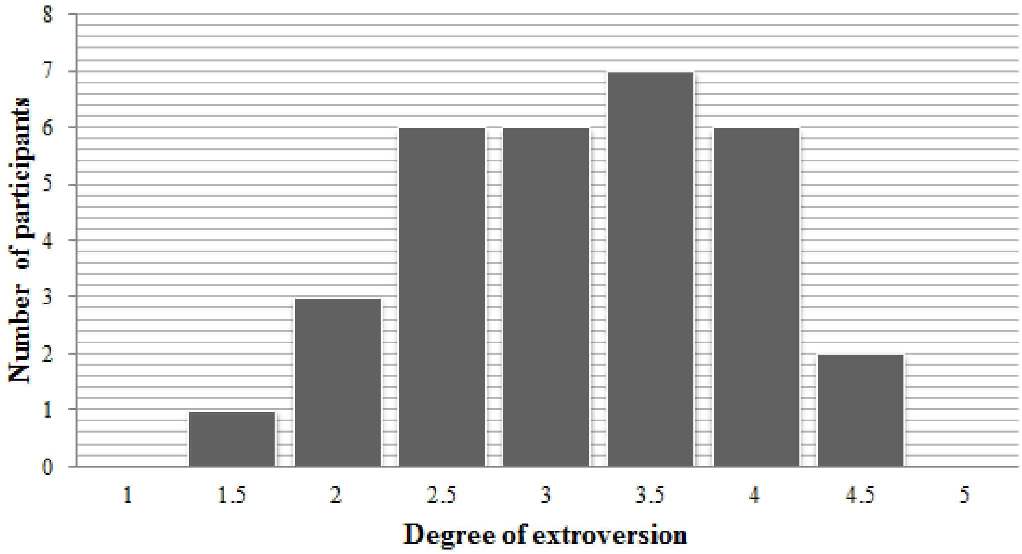


Figure 3. Personality distribution of the participants

Figure 4. The experiment setting.

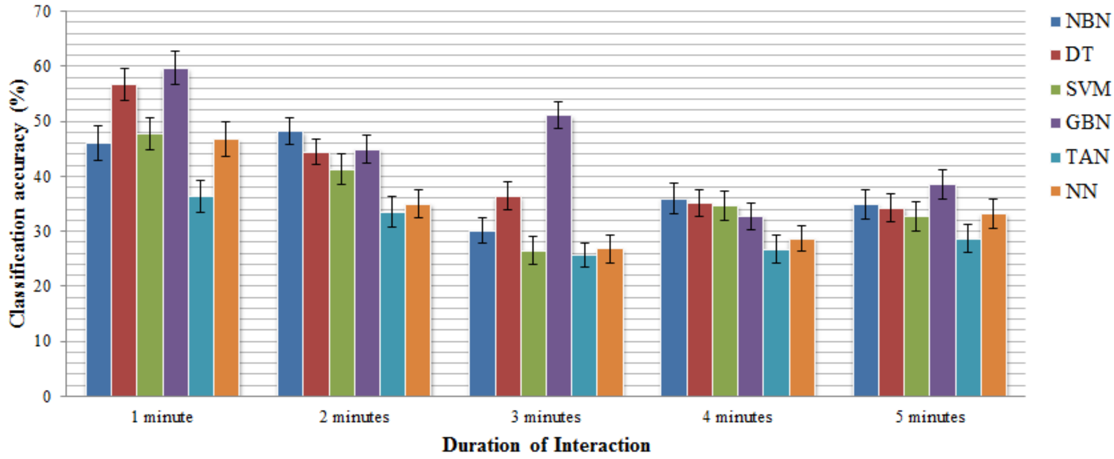


Figure 5. The classification accuracy of each classifier in each duration of interaction.

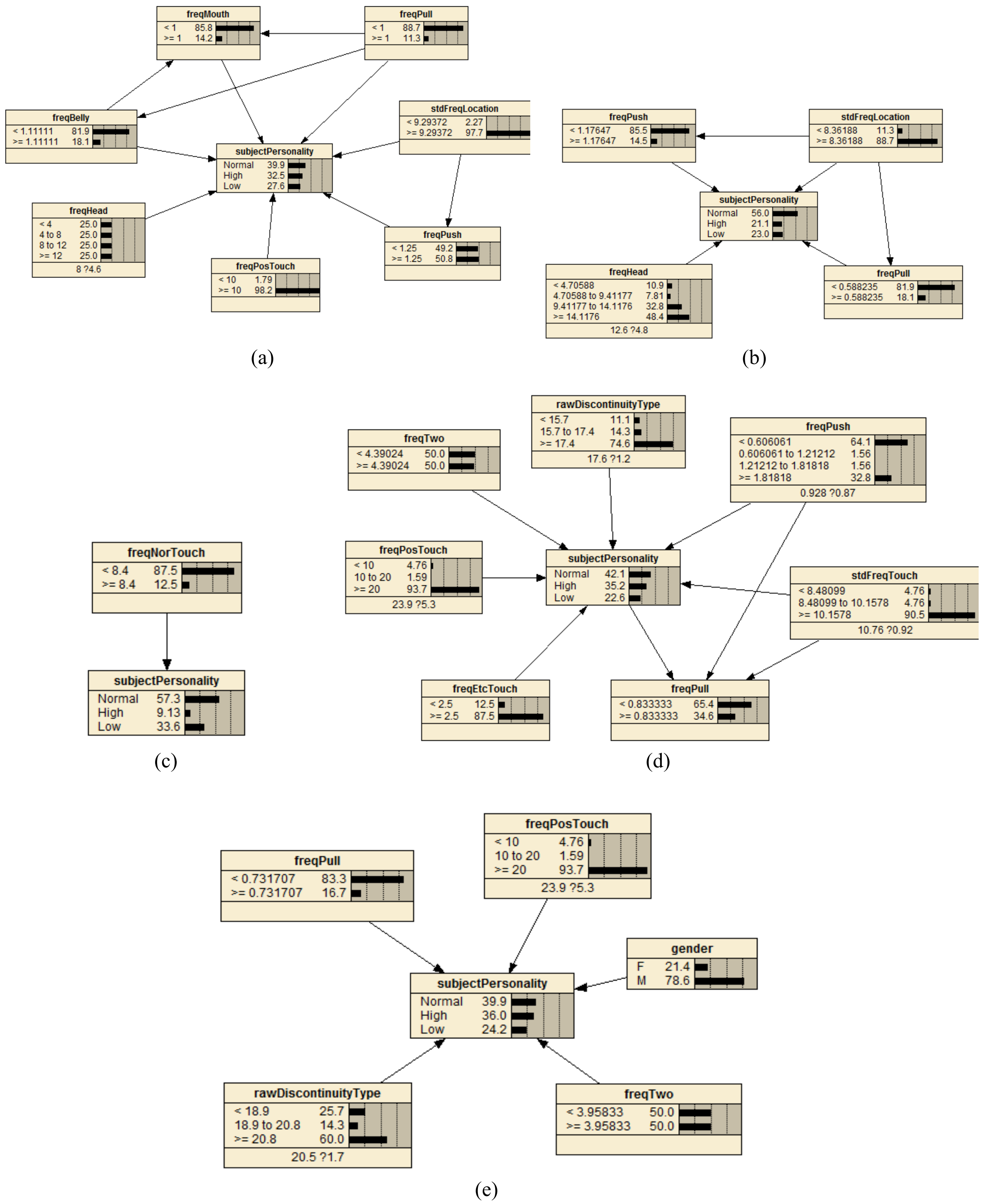


Figure 6. Nodes in the Markov Blanket (MB) of the class node (subjectPersonality). (a) one minute, (b) two minutes (c) three minutes (d) four minutes and (e) five minutes of interaction.

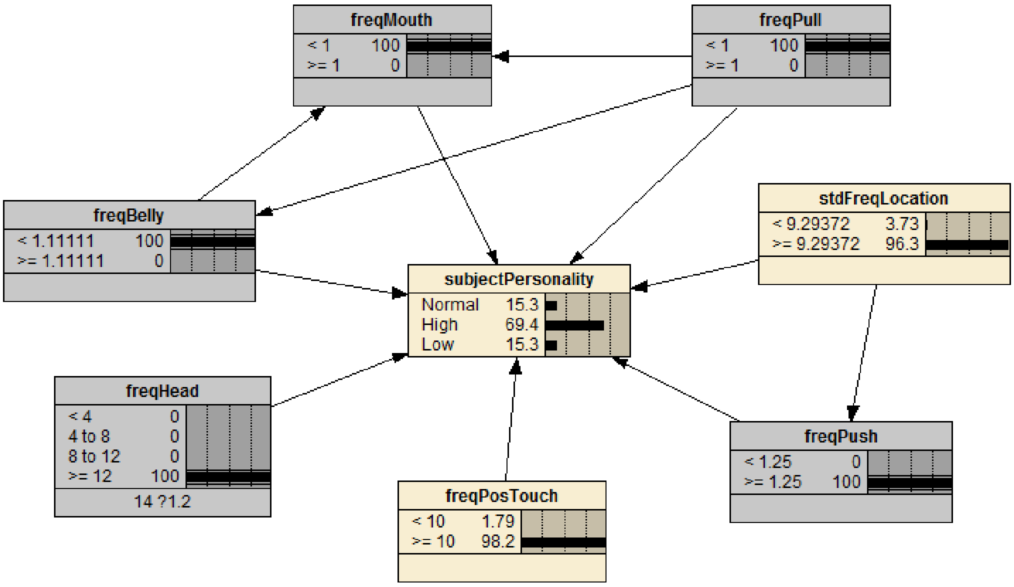
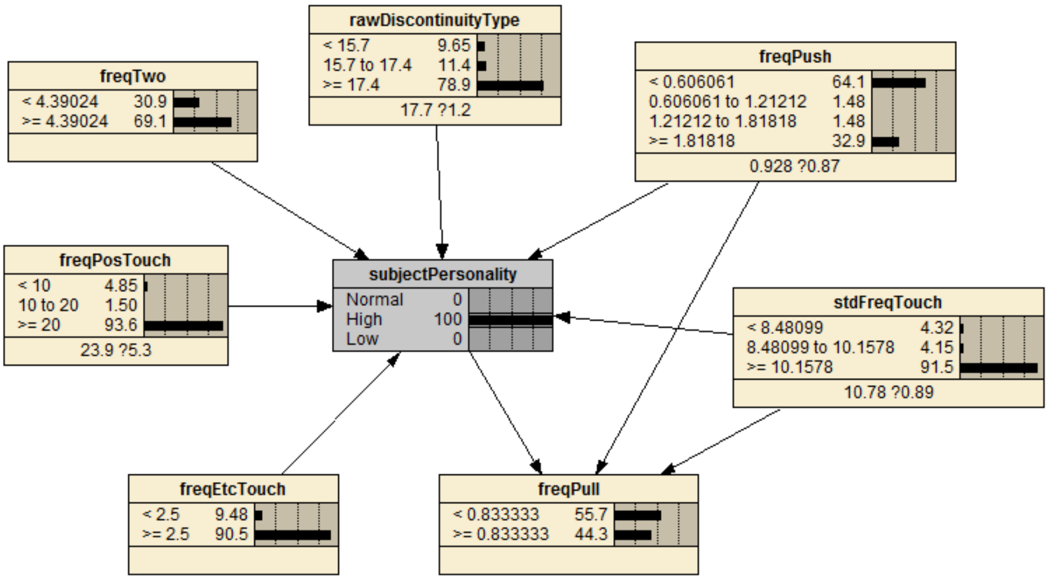
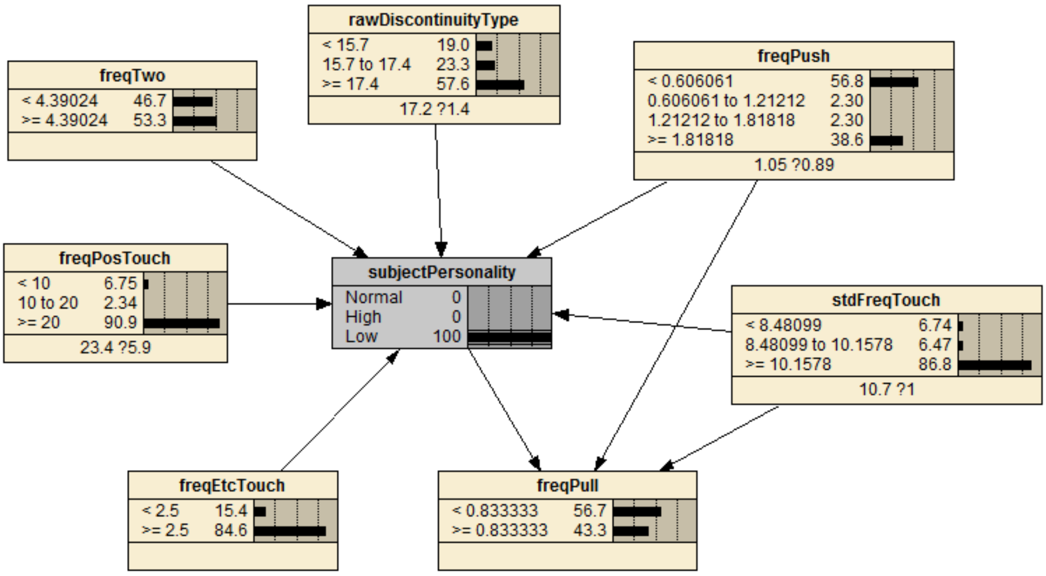


Figure 7. Probability distribution in a What-If analysis on Scenario 1.



(a)



(b)

Figure 8. Probability distribution in a What-If analysis on Scenario 2. (a) Extroverted (b) introverted