

Relating Dominance of Dialogue Participants with their Verbal Intelligence Scores

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Abstract

In this work we investigated whether there is a relationship between dominant behaviour of dialogue participants and their verbal intelligence. The analysis is based on a corpus containing 56 dialogues and verbal intelligence scores of the test persons. All the dialogues were divided into three groups: H-H is a group of dialogues between higher verbal intelligence participants, L-L is a group of dialogues between lower verbal intelligence participant and L-H is a group of all the other dialogues. The dominance scores of the dialogue partners from each group were analysed. The analysis showed that differences between dominance scores and verbal intelligence coefficients for L-L were positively correlated. Verbal intelligence scores of the test persons were compared to other features that may reflect dominant behaviour. The analysis showed that number of interruptions, long utterances, times grabbed the floor, influence diffusion model, number of agreements and several acoustic features may be related to verbal intelligence. These features were used for the automatic classification of the dialogue partners into two groups (lower and higher verbal intelligence participants); the achieved accuracy was 89.36%.

Keywords: Spoken language dialogue system, verbal intelligence, dominance, k-means clustering, verbal and nonverbal behaviour

1. Introduction

Automatic verbal intelligence estimation of users in a Spoken Language Dialogue System (SLDS) may help to change the style of the interaction for different users and adapt to them, increase its communicative competence and influence on systems acceptability. For a precise verbal intelligence estimation of the user we need to know language cues which reflect cognitive processes of speakers.

Verbal intelligence (VI) is the ability to use language for accomplishing certain goals (Goethals et al., 2004; Cianciolo and Sternberg, 2004). In other words, verbal intelligence is "the ability to analyse information and solve problems using language-based reasoning" (Logsdon, 2012). When a person is engaged in an interaction, he tries to show his opinion, to find convinced arguments and simultaneously not to offend the listener. On the other hand, the same thought may sound differently depending on which words and expressions the speaker uses. Proper phrases may help a person to start a smooth conversation with his dialogue partner and to keep it going for a long time. Life-experience, educational background, the richness of vocabulary and abilities to clearly express thoughts and feelings allow a speaker to be a leader in a conversation. According to (Goethals et al., 2004), verbal intelligence of a speaker and his or her dominant behaviour in a conversation are depended. This means that certain features used for identifying dominance in interactions may be applied to automatic estimation of verbal intelligence. In this work we investigated to what degree dominance in conversations and cues that reflect leading behaviour depend on verbal intelligence of dialogue participants and whether these features may be used for the classification task.

2. Related work

Dominance is a typical social behaviour explicitly shown by humans in group conversations, meetings and gatherings (Dunba and Burgoon, 2005). Psychologists describe dominance as a behavioural expression to seek attention, influence the others and to assert the authority. Dominance may be viewed as either a personality trait, i.e. the personal tendency to influence the others, or it may also be used to describe the role of a person in a group, i.e. group hierarchy (Mast, 2002). A person is dominant when his attempts to assert control and authority are accepted by the partners in an interaction (Rogers-Millar and Millar, 1979). Such kinds of situations may contribute either positively or negatively to the discussion. Positive contributions comprise of actions such as keeping the conversation going, task orientation, taking quick decisions, making conclusions, etc. Negative contributions may include not giving enough space to others to express their ideas, disturbing the team work, not being open to criticism, expressing the power verbally or physically, that may be found offensive and unjustified by other interaction partners.

Many approaches exist for identifying dominant behaviour in social interactions. In a conversation, dominance can be conveyed through verbal and nonverbal behaviour. Nonverbal cues include, for example, facial expression, gaze, smiling frequency, body intensity/relaxation, shifting posture, body composure, relative percentages of looking while speaking and looking while listening, etc. (Buller et al., 1984; Dovidio and Ellyson, 1982; Dunba and Burgoon, 2005). Several studies showed that nonverbal cues such as speaking duration, speaking intensity, pitch and voice control are important factors in perception of dominance (Cashdan, 1998; Burgeon and Hoobler, 2002).

Verbal cues include criticism, suggestions, demands, rea-

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soning, ignoring, etc. However, it is very difficult to automatically measure such features and their perception highly depends on the context of the interaction. That’s why most investigations of dominance are based on nonverbal features. For example, Rienks and Heylen (2006) used such nonverbal features as number of interruptions, number of questions asked, number of words spoken, etc. for estimating dominance in conversations and reached the accuracy of 75%. Jayagopi et al. (2009) showed that by using nonverbal audio and video cues, it is possible to estimate dominant behaviour of individuals in groups. They used features such as total speaking energy, visual activity, total visual activity length, total visual activity turns, etc. They concluded that by using different combinations of these features, it is possible to estimate dominant behaviour in conversation with up to 91.2% using supervised models for classification and 85.3% using unsupervised models.

3. Corpus Description

The work is based on a speech data corpus described in (Zablotskaya et al., 2010), which consisted of 56 monologues (descriptions of a short film), 30 dialogues (two-person discussions about the same topic) and verbal intelligence scores of the test persons. For this work we have enlarged our corpus, which now contains 100 monologues (6 hours), 56 dialogues (12 hours) and verbal intelligence scores of all the participants. In this research only the dialogues were analysed. The topic of the dialogues was the German education. The participants were asked to discuss its problems, to compare it with the European education systems, to talk about advantages and disadvantages of the school system, the quality of higher education in universities, etc. They were asked to feel as relaxed as possible as if they were talking to their relatives or friends. Some test persons were asked to engage several two-person conversations with different dialogue partners. The others participated in a dialogue only once. The test persons were also asked to take the verbal part of the Hamburg Wechsler Intelligence Test for Adults (HAWIE) (Wechsler, 1982). Using this test, we estimated their verbal intelligence. The collected dialogues were transcribed according to the transcription standards by Mergenthaler (Mergenthaler, 1993).

4. Dominance and Verbal Intelligence

In this section we analysed whether dominance in conversations and verbal intelligence of dialogue partners are related to each other.

4.1. Dialogue Labelling

Based on the verbal intelligence scores of the test persons, they were partitioned into two clusters using the k-means algorithm: the first cluster contained test persons with lower verbal intelligence scores, the second cluster contained test persons with higher verbal intelligence scores. Using these clusters, each dialogue was labelled as L-L if both partners belonged to the first cluster (had a lower verbal intelligence), H-H if both partners belonged to the second cluster (had a higher verbal intelligence), L-H if the dialogue partners belonged to different clusters (a dialogue

between a higher verbal intelligence person and a lower verbal intelligence person).

4.2. Dominance Analysis

Three judges were asked to estimate dominance of each dialogue partner using a 10-point scale (1 means that a test person wasn’t dominant at all, 10 means that a test person was very dominant). For comparing the verbal intelligence of the participants and their dominance in conversations, the following experiments were performed.

- *Experiment 1.* For each group (H-H, L-L and L-H) we analysed the percentage of discussions in which a candidate with a greater verbal intelligence coefficient dominated his dialogue partner. Let’s name these values X_{H-H} , X_{L-L} and X_{L-H} . According to our results, $X_{H-H} = 52\%$, $X_{L-L} = 72\%$ and $X_{L-H} = 85\%$.
- *Experiment 2.* Let $D(A_1)$ and $D(B_1)$ be dominance scores of the dialogue partners from the first dialogue, $D(A_2)$ and $D(B_2)$ be dominance scores of the dialogue partners from the second dialogue, etc. For each dyadic conversation the differences $|D(A_1) - D(B_1)|$, $|D(A_2) - D(B_2)|$, etc. were calculated. The averaged values of the differences $|D(A_1) - D(B_1)|$, $|D(A_2) - D(B_2)|$, etc. for each group L-L, H-H and L-H were compared to each other using the one-way analysis of variance (ANOVA) and its nonparametric equivalence, the Kruskal-Wallis one-way analysis of variance. However, these tests did not show any significant results.
- *Experiment 3.* Let $\mathbf{D} = (|D(A_1) - D(B_1)|, |D(A_2) - D(B_2)|, \dots, |D(A_N) - D(B_N)|)$ be a vector containing differences between dominance scores of the dialogue partners, $\mathbf{VI} = (|VI(A_1) - VI(B_1)|, |VI(A_2) - VI(B_2)|, \dots, |VI(A_N) - VI(B_N)|)$ be a vector containing differences between verbal intelligence scores of the dialogue partners, N is the number of dialogues in the corpus. The Pearson correlation coefficient was calculated for measuring statistical dependence between \mathbf{D} and \mathbf{VI} . However, the value of the correlation coefficient was not statistically significant. Then we decided to calculate the Pearson correlation coefficient between \mathbf{D} and \mathbf{VI} separately for each group (L-L, H-H and L-H). For the group with lower verbal intelligence dialogue partners, L-L, the correlation coefficient was 0.75.

As we may see from the results, speakers with a higher verbal intelligence were able to dominate in the conversations independently on the verbal intelligence of their dialogue partners. When test persons with a lower verbal intelligence were talking to dialogue partners with approximately the same verbal intelligence levels, in 72% of dialogues they were able to dominate and influence the opinion of the dialogue partner. When lower verbal intelligence participants talked to higher verbal intelligence partners, it was not always easy for the former ones to dominate in the discussions (only in 15% of dialogue). The correlation coefficient

between dominance and verbal intelligence differences (**D** and **VI**) for L-H was not significant. This means that when the distance between verbal intelligence scores of the dialogue partners was getting greater, their dominance difference stayed the same. A strong positive correlation between **D** and **VI** may be seen only for the group L-L (lower verbal intelligence participants).

In (Goethals et al., 2004) it was concluded that "leaders are likely to be more intelligent, but not much more intelligent than the people they lead." A leader has the abilities to communicate effectively, to get dialogue partners round to his way of thinking and make them think that he or she is right. These abilities are based on language proficiency and accuracy related to a high verbal intelligence. In the following sections we will compare verbal intelligence and features that reflect dominance of the dialogue partners.

5. Features related to Dominance

In this work we also extracted features related to dominance to compare them with the verbal intelligence scores of the test persons. For this purpose we created two feature sets: the former one was based on features automatically extracted from the dialogue transcripts (non-acoustic features) and the latter one was based on acoustic/prosodic features. These features are described below.

Non-Acoustic Features: number of turns; number of words; influence diffusion model (number of words reused by a speaker from his dialogue partner) (Rienks and Heylen, 2005); number of questions asked; number of successful and unsuccessful interruptions; total duration of speaking; number of times a dialogue participant grabs the floor (starts speaking after a pause longer than 1.5 sec.); number of incomplete and repeated words; number of paraverbal expressions; number of agreements; number of short utterances (shorter than 1.5 sec.); number of long utterances (longer than 10 seconds).

Acoustic Features: These features were extracted using Praat (Boersma and Weenink, 2011) and consisted of: energy, power, mean, root-mean-square (rms), pitch (mean, median, minimum, maximum and standard deviation), pulse (number of pulses, periods, mean value of periods and standard deviation), unvoiced frames (fraction of locally unvoiced frames), voice breaks (number of voice breaks and degree of voice breaks), jitter, shimmer and harmonicity features.

The extracted features may be used for estimating dominance of dialogue participants. As dominance and verbal intelligence are related to each other, some of these features may be used for automatic estimation of verbal intelligence of speakers.

6. Feature Analysis

As stated above (Section 4.1.), the k-means algorithm partitioned the test persons into two clusters. The average values of the features described in Section 5. were compared to each other using ANOVA (Figure 1). Relevant features were *influence diffusion model*, *number of long utterances*, *shimmer*, *pitch*, *harmonicity*, *standard deviation of period*, etc. For further analysis, the test persons were partitioned into three clusters: first cluster - lower verbal intelligence,

second cluster - average verbal intelligence, third cluster - higher verbal intelligence (Figure 2). In this case we took into account that there may exist one more cluster which may contain test persons with average verbal intelligence scores. For the three clusters, significant features were *influence diffusion model* and also some acoustic features like *pitch*, *shimmer*, *degree of voice breaks*, etc. Differences in acoustic features may show that, when a test person did not know how to keep the conversation going, his voice was shivering, he was less confident, calm, etc. On the other hand, strong and loud speech reflected test person's self-reliance and firm belief that his opinion was right. These differences in acoustic features for test persons with different verbal intelligence levels should be further investigated. However, they may be used for the classification.

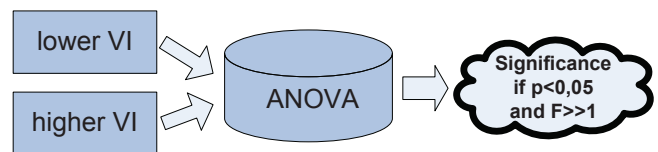


Figure 1: ANOVA for 2 clusters

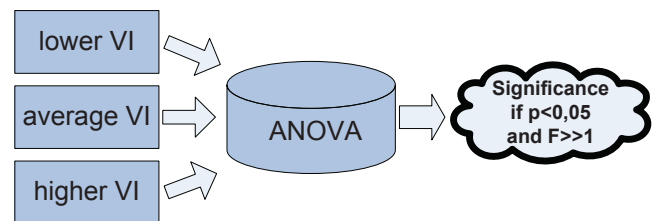


Figure 2: ANOVA for 3 clusters

Based on the two clusters, we obtained new variables and used them for performing four ANOVA experiments (Figure 3). In *Experiment 1*, the first variable contained test persons yielding a higher verbal intelligence if they talked to lower verbal intelligence test persons. The second variable contained participants yielding a higher verbal intelligence if they carried out discussions with higher verbal intelligence participants. In *Experiment 2*, the first variable contained test persons yielding a lower verbal intelligence if they talked to test persons yielding a lower verbal intelligence. The second variable contained participants yielding a lower verbal intelligence if they engaged discussions with participants yielding a higher verbal intelligence. The same procedure was performed in *Experiments 3* and *4*.

For each experiment, *Variable 1* and *Variable 2* were compared to each other using ANOVA to investigate if some of these features were somehow related to the verbal intelligence of the test persons.

For *Experiment 1* (Figure3), the significant features were:

- *number of interruptions* ($AV_1 = 0.17$, $AV_2 = 0.35$, $p = 0.017$, $F = 6.18$);
- *number of times grabbed the floor* ($AV_1 = 0.25$, $AV_2 = 0.1$, $p = 0.02$, $F = 5, 53$).

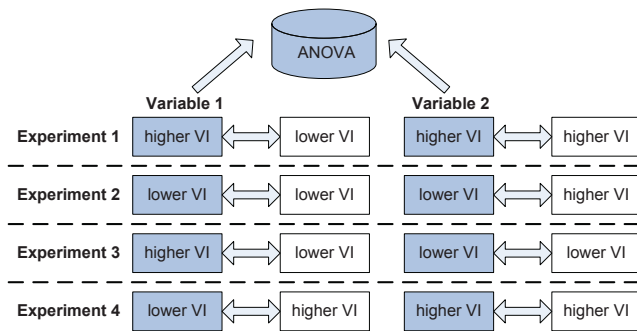


Figure 3: ANOVA experiments

This means that higher verbal intelligence test persons interrupted their dialogue partners more often if these dialogue partners also had a high verbal intelligence. This may happen because, when two higher verbal intelligence dialogue partners are talking to each other, expressing their opinions and trying to persuade each other, the discussion may be more lively, exciting and contradictory. Also, talking to lower verbal intelligence dialogue partners, test persons with a high verbal intelligence more often started talking after long pauses in the discussions.

For *Experiment 4* significant features were:

- *influence diffusion model* ($AV_1 = 0.09$, $AV_2 = 0.03$, $p = 0.003$, $F = 9.74$);
- *number of agreements* ($AV_1 = 0.62$, $AV_2 = 0.38$, $p = 0.006$, $F = 8.28$).

This means that, when talking to higher verbal intelligence speakers, lower verbal intelligence test persons reused more words of their partners and more often agreed with their opinions than higher verbal intelligence test persons.

7. Classification Results and Conclusions

Bayesian Logical Regression (BLR) classifier was trained for the automatic classification of the dialogue partners into two groups (lower and higher verbal intelligence test persons). As we did not have sufficient data points for training and testing, leave-one-out cross-validation was used for the classification. Features which were significant according to ANOVA were chosen for the classification. The achieved accuracy for the data set was 89.36%. In contrast, the achieved accuracy of BLR with all the features described in this paper was 68.08%; the achieved accuracy with only audio features was 72.34%. The investigation showed that there is a dependency between verbal intelligence and dominant behaviour of dialogue participants. Features that reflect dominance in conversations may be successfully used for automatic estimation of verbal intelligence of speakers.

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