deLearyous: Training Interpersonal Communication Skills Using Unconstrained Text Input

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Abstract: We describe project deLearyous, in which the goal is to develop a proof-of-concept of a serious game that will assist in the training of communication skills following the Interpersonal Circumplex (also known as Leary′s Rose) –a framework for interpersonal communication. Users will interact with the application using unconstrained written natural language input and will engage in conversation with a 3D virtual agent. The application will thus alleviate the need for expensive communication coaching and will offer players a non-threatening environment in which to practice their communication skills. We outline the preliminary data collection procedure, as well as the workings of each of the modules that make up the application pipeline. We evaluate the modules' performance and offer our thoughts on what can be expected from the final "proof-of-concept" application.
To get a firm grasp on the structure and dynamics of human-to-human conversations, we first gathered data from a series of 〝Wizard of Oz〞 experiments in which the virtual agent was replaced with a human actor. All data was subsequently transcribed, analysed and annotated. This data functioned as the basis for all modules in the application pipeline: the NLP module, the scenario engine, the visualization module, and the audio module.
The freeform, unconstrained text input from the player is first processed by a Natural Language Processing (NLP) module, which uses machine learning to automatically identify the position of the player on the Interpersonal Circumplex. The NLP module also identifies the topic of the player′s input using a keyword-based approach. The output of the NLP module is sent to the scenario engine, which implements the virtual agent′s conversation options as a finite state machine. Given the virtual agent′s previous state and Circumplex position, it predicts the most likely follow-up state. The follow-up state is then realized by the visualization and audio modules. The visualization module takes care of displaying the 3D virtual agent′s facial and torso animations, while the audio module looks up and plays the appropriate pre-recorded audio responses.
In terms of performance, the NLP module appears to be a bottleneck, as finding the position of the player on the Interpersonal Circumplex is a very difficult problem to solve automatically. However, we show that human agreement on this task is also very low, indicating that there isn't always a single "correct" way to interpret Circumplex positions. We conclude by stating that applications like deLearyous show promise, but we also readily admit that technology still has a way to go before they can be used without human supervision.

Keywords: communication training, natural language, virtual agents, interpersonal communication

1. Introduction

For many people, interacting with co-workers and clients is an important part of their professional activities. Employers often require those responsible for sales or customer services to partake in training activities to improve their interpersonal communication skills. These training activities are often led by professional actors who act out different personalities in different situations, thereby helping trainees deal with a wide range of communicative scenarios. Communication coaching allows for a personalized hands-on experience for each trainee, but this flexibility comes at a cost. For most companies, providing training opportunities for employees is a significant investment, both in terms of time and money. An additional disadvantage is that some trainees experience these training sessions as a source of considerable stress. The expectation that they act out certain scenarios –often in the presence of colleagues– may limit the ways in which they dare to express themselves. Given a less threatening environment in which to practice, trainees might be more inclined to experiment with the full range of possible communicative options.

The goal of the deLearyous project is to develop a proof-of-concept of an application that will alleviate these problems. We aim to create a serious game in which the player can interact with an autonomous virtual agent using unconstrained text input. Based on the player input and a predetermined scenario, the virtual agent will formulate a response, appropriate both in terms of conversation topic and emotional register. This will allow the players to experiment with different approaches to a conversation in their own time, without the pressure of having to “act” in public, and at a fraction of the cost of professional coaching.
It is important to note that we do not believe that interacting with virtual agents can (or indeed should) fully replace more traditional forms of communication training. We merely see applications like deLearyous as extra tools for trainees to make use of. Human supervision and human interaction will remain essential.

1.1 Leary’s Rose

Several frameworks have been developed to describe the dynamics involved in interpersonal communication (Wiggins, 2003; Benjamin, 2006). We chose to use the Interpersonal Circumplex, also known as Leary’s Rose (Leary, 1957). The Interpersonal Circumplex maps the range of emotions one can experience while communicating onto a two-dimensional space, defined by a “dominance” and an “affinity” dimension. Figure 1 shows a common representation of the Interpersonal Circumplex.

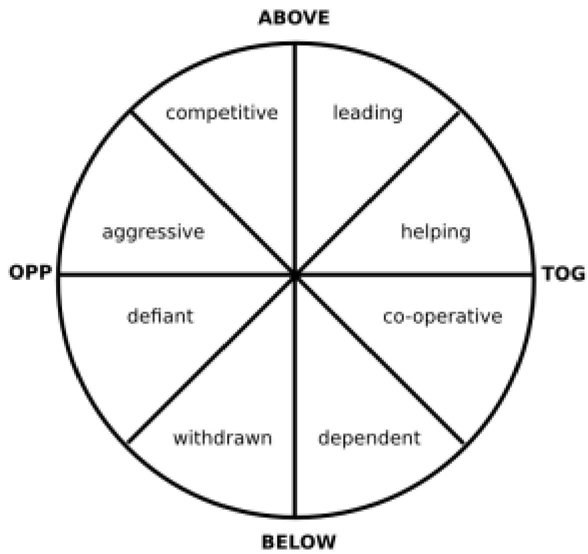

Figure 1: The Interpersonal Circumplex, AKA Leary’s Rose

The position of a speaker on the vertical “dominance” (above-below) axis tells us whether they are taking on a more dominant or submissive stance towards the listener. The horizontal (opposed-together) axis says something about the speaker’s willingness to co-operate with the listener. The two axes divide the Circumplex into four quadrants, and each quadrant is again divided into two octants.
What makes the Circumplex especially interesting for interpersonal communication training is that it allows one to predict (to some extent) what position the listener is going to take in reaction to the way the speaker positions himself. Two types of interactions are at play in Leary’s Rose: one of complementarity and one of similarity. Dominant behaviour triggers a (complementary) submissive response and vice versa, while *together*-behaviour triggers a (similar) response from the “together” zone and *opposed*-behaviour triggers a (similar) response from the “opposed” area of the Circumplex. The speaker can thus influence the listener’s emotions (and consequently, their response) by consciously positioning himself in the quadrant that will likely trigger the desired reaction.
The goal of deLearyous is to teach the player how to use these dynamics to their advantage. This learning process can be divided into three stages, which will be realized as different difficulty levels in the application. On the simplest level, the player should learn to identify a speaker’s (or indeed their own) position on the Circumplex. On a second level, they should be made aware of the reaction this position will most likely trigger in the listener. At the highest difficulty, they should learn to keep their own instinctive response in check and to consciously position themselves on the Rose in function of the reaction they want to provoke in the listener.

1.2 Scenario

For the purposes of the deLearyous proof-of-concept we chose to implement a single scenario to be played out by the player and the virtual agent (VA). In this scenario, the player takes on the role of a manager who just announced that the company's parking facilities are no longer free. It is the player's task to deal with the reactions of an employee (played by the VA). Using this well-defined scenario allows us to limit the number of responses the virtual agent needs to be able to interpret to a workable number.

There are several different realizations of this scenario, depending on the starting position of the virtual agent on the Interpersonal Circumplex. For instance, the employee can be angry about the fact that parking facilities have become payable, in which case the player will need to try to get the VA to calm down and to become more cooperative –which translates to moving the VA from the top left to the bottom right quadrant of the Circumplex. In another realization, the virtual agent may be withdrawn, and it will be up to the player to get the VA to open up and speak their mind – a move from bottom left to top right on the Circumplex. These different realizations allow players to train their understanding of all the positions on the Interpersonal Circumplex.

Our scenario was realized in Dutch, as our partners in the deLearyous project were primarily interested in a Dutch training environment. All of the techniques described in this paper, however, are entirely language-independent. The same procedures can be followed for English, or indeed for any other language.

1.3 Overview

The following paragraphs will describe the different steps we took to develop the application prototype. We first describe the data collection procedure (section 2), which was an essential first step, as it allowed us to identify key problems and focus points for the subsequent phases of development. The application was conceived as a pipeline of modules, and each module will be described in detail in section 3. We will evaluate each module and its contribution to the overall performance of the application. In section 4, we will formulate our conclusions and evaluate the feasibility of using applications like deLearyous for communication training.

2. Preliminary data collection

Prior to starting the development of deLearyous, a few important questions needed answering. Given our scenario ("parking facilities are no longer free"), what kind of arguments do people bring up in a conversation? What are the different possible emotional reactions, and how do they map to the Interpersonal Circumplex? How does the realization of an argument change depending on the speaker's position on Leary's Rose? How is the speaker's emotional state reflected in their facial expressions, their body language, or their tone of voice? Before we could think of simulating a conversation using a virtual agent, we needed to gather an inventory of real-life conversations.

2.1 Wizard of Oz tests

To approximate the final application as closely as possible, we carried out a series of Wizard of Oz tests, in which the virtual agent was replaced with a professional communication coach. The rest of the setup was similar to that of the finished application. The player and the coach were located in different rooms, and communicated using instant messaging software. The coach, however, could not see or hear the player and could only read the player's text input. The player, on the other hand, could see and hear the coach, but could only reply using text.

We carried out a total of eleven Wizard of Oz tests, iterating over three possible realizations of the scenario. Each time, the player was given a short description of the scenario they were meant to act out, and were given the starting conditions and the goals they had to achieve. Table 1 gives an overview of the three possible scenario realizations players were asked to act out.

Table 1: Scenario realizations used in the Wizard of Oz tests

	Starting conditions	Goal
Realization 1	Employee is aggressive	Employee is in a "together" octant
Realization 2	Employee is withdrawn	Employee is in an "above" octant
Realization 3	Employee is leading	Employee is in a "below" octant

After each conversation, the player joined the coach for a discussion. Player and coach were asked about their feelings concerning the naturalness of the conversation. This allowed us to get an impression of the advantages and disadvantages of communicating using only text. The coach was also asked to give feedback on the player's communication skills. This information increased our understanding of the dynamics at play in the Interpersonal Circumplex.

2.2 Transcription and annotation

Both the conversations and the ensuing discussions were recorded. A text log was kept of all player input, and the audio and video stream for both player and coach were captured. The coach's audio was transcribed and this transcription was interleaved with the player's text log, in effect reconstructing a full transcript of the conversation. We used this transcript to make an inventory of the possible arguments one can use within our scenario. This collection of arguments was later used to build the finite state machine for the scenario (see section 3.2).
The transcript was also annotated for the position of both player and coach on the Interpersonal Circumplex. Using all available material (audio, video and text log), four different annotators each annotated a part of the dataset. They were asked to place every sentence on the Circumplex using a simple GUI (figure 2).

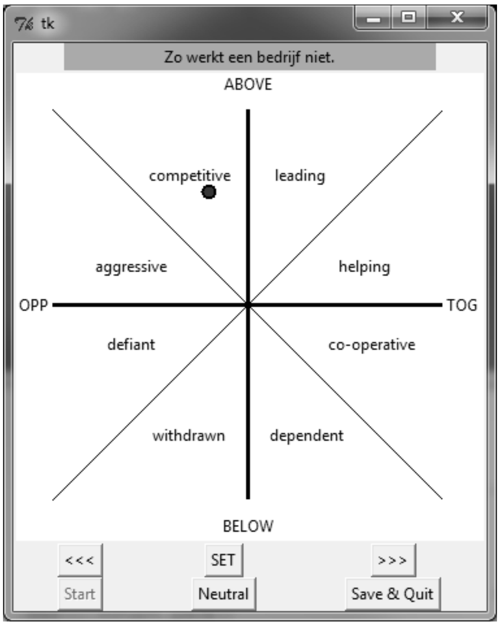

Figure 2: GUI for position annotation on the Interpersonal Circumplex

Annotators were told to use the following questions to assist in the annotation task:
- Is the current sentence more task-oriented (*opposed*) or relationship-oriented (*together*)?
- Does the speaker position himself more as the dominant partner in the conversation (*above*) or is the speaker more submissive (*below*)?
- Which of the above two dimensions (affinity or dominance) is most strongly present?

These questions allowed annotators to place sentences in one of the eight octants of the Rose. A "neutral" option was also provided should a sentence show no significant bias on either axis.

To evaluate the quality of the annotation, a random sample of 50 sentences were annotated by all four annotators. Annotators were asked to position these sentences out of context, based on their transcription only. Table 2 shows Fleiss' kappa score as well as the average pairwise overlap calculated on the quadrant and the octant level.

Table 2: Inter-annotator agreement on a random sample of 50 sentences, 4 annotators

# of classes	κ	Avg. pairwise overlap
4	0.37	51.3%
8	0.29	36.0%

Though the interpretation of kappa scores is in itself subjective, scores between 0.20 and 0.40 are usually taken to indicate "fair agreement". The low kappa scores indicate that even for humans, identifying the position of a speaker on the Interpersonal Circumplex is very difficult, especially given the lack of contextual and extra-textual information. However, this "blind" annotation is not unrealistic, as our application will need to predict positions on Leary's Rose based on text input only, and its awareness of context is also limited (see section 3.1).
From this preliminary evaluation, we can conclude that the automatic prediction of the Circumplex positions is likely to be one of the biggest challenges for deLearyous, as even human annotators find it difficult to agree. However, since the goal of the application is to simulate human behaviour, these results also imply that it is not critical for the final application to reach a perfect level of prediction – in fact, due to the subjective nature of the annotation process, an objectively "correct" result likely does not exist.

3. Application pipeline

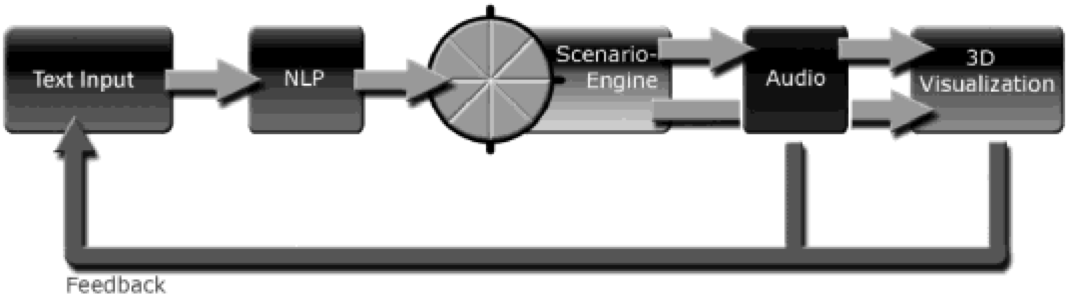

Figure 3: deLearyous application pipeline

The deLearyous application is conceived as a pipeline of modules (figure 3). The NLP (Natural Language Processing) module processes the player's text input and identifies its topic and the player's position on the Interpersonal Circumplex. Given this information, the scenario engine determines the appropriate follow-up state for the virtual agent. This state is then realized by the audio and 3D visualization modules.
In the next few sections, each module will be described individually, and their performance will be evaluated.

3.1 Natural language processing

The Natural Language Processing (NLP) module processes the player's raw text input. It has the important task of trying to determine the position of the player on the Interpersonal Circumplex, but it is also tasked with identifying what exactly the player is trying to say. Both functions are described and evaluated in the following paragraphs.

3.1.1 Circumplex position prediction

Our approach to the prediction of the player's position on the Interpersonal Circumplex falls within the domain of automatic text categorization (Sebastiani, 2002), which focuses on the classification of text into predefined categories. Starting from a training set of sentences labelled with their position on the Interpersonal Circumplex, we train a machine learner to pick up on cues that will allow the classification of new sentences into the correct section of the Circumplex (Vaassen F. and Daelemans W., 2011, 2010).
We use the dataset of annotated conversations from section 2 as our training corpus. This collection of 11 conversations contains a total of 1143 Dutch sentences. An extra 948 sentences were added from various teaching materials on Leary's Rose (van Dijk and Moes, 2005; van Dijk, 2007) and from training scripts created by deLearyous partner Opikanoba, a company specialized in e-learning. This brings the total up to 2091 sentences annotated with their position on the Interpersonal Circumplex.
From this training set, we extract feature vectors that can be interpreted by the machine learner. We first automatically annotate the sentences with linguistic information using Frog, a Dutch language parser (van den Bosch et al., 2007). From the parsed output, features of different types are generated using a "bag of n-grams" approach (Sebastiani, 2002). This implies that for each sentence, a vector is generated representing how many times each possible n-gram of a feature is present in the current

sentence. To capture part of the context of the sentence, we also include features referring to the player's and the virtual agent's previous Circumplex position. With these newly generated training vectors and their associated position on the Circumplex, we trained a Support Vector Machine classifier (Joachims, 1999).

The Circumplex classifier was evaluated on the data set using 10-fold cross validation: ten different experiments, each time using a tenth of the sentences as test data. Table 3 shows the performance of the machine learner in terms of quadrants and octants.

	Quadrants (+neutral)		Octants (+neutral)	
	accuracy	F-score	Accuracy	F-score
SVM classifier	55.0%	38.0%	42.6%	18.5%
Random baseline	24.2%		13.0%	

Table 3: Circumplex classifier performance and baseline scores

The random baseline score is the accuracy one would achieve if every sentence in the data set was assigned to a class at random. It is clear that the classifier improves on this random baseline significantly, and while scores may seem low, considering the low agreement scores outlined in section 2.2, human performance appears within reach. However, since incorrect classifications will remain quite frequent, the NLP module will not simply pass on a single quadrant or octant to the scenario manager, but it will return a list of possible labels, accompanied by their estimated probabilities. This way, the scenario manager can still correct certain predictions if probabilities are too low.

3.1.2 Topic detection

To be able to determine the appropriate response from the virtual agent, it is essential that the application "understands" what it is the player is trying to say. To carry out this topic detection task, we use an extended keyword matching technique.

We provided every argument in our finite state machine (see section 3.2) with a set of keywords. When the player inputs a new sentence, the matching argument is calculated by finding the highest overlap between its keywords and the words in the input sentence.

To maximize the keywords' coverage, we first apply a WordNet-based expansion using the Cornetto database (Jijkoun and Hofmann, 2009) to add synonyms and related words to the base keyword sets. On the player input side, all words are lemmatized (i.e. reduced to their standard form) prior to matching, to avoid mismatches due to different grammatical forms of the same word (buses ⇔ bus).

Additionally, we implemented rudimentary negation detection to avoid cases where sentences would be matched to an argument that means the opposite of what the player intended to say. Words that are detected to fall within the scope of a negation marker will only match their antonyms.

The topic detection feature was evaluated on a set of 93 unseen sentences (one for each statement in the scenario FSM). When using keyword matching without any of the enhancements described above (lemmatization, negation detection and keyword expansion), only 33% of the sentences are matched to the correct argument. With the aforementioned enhancements, however, this score reaches 71%.

3.2 Scenario engine

The scenario engine requires two variables as input: the ID of the argument brought up by the player (as predicted by the NLP module's topic detection), and the player's most probable Circumplex position (also predicted by the NLP module). It then proceeds to finding the most probable follow-up state for the virtual agent, while attempting to avoid repetitions or illogical jumps in the conversation.

3.2.1 FSM – construction

At the core of the scenario engine is a Finite State Machine (FSM). This FSM was constructed based on the data gathered during the Wizard of Oz tests. Every possible argument in the conversation is given a single node in the network (separate realizations of an argument –on different octants of the Circumplex– are *not* given separate nodes). The FSM contains 93 nodes specific to the player and 111 nodes specific to the virtual agent (VA). Each VA node contains a specific phrasing for each

octant of the Circumplex (plus a neutral one), while player nodes contain a list of keywords for use in the NLP's topic detection.
Links between nodes only exist from player nodes to VA nodes, indicating the possible answers the VA might give in response to the player's argument. Because the player's input is unconstrained, links in the other direction cannot be determined; the player can say anything at any time, and we have no choice but to check every possibility when performing topic matching.
Links from player to VA nodes were created manually. They could not be determined based on the Wizard of Oz tests, because the conversations in these tests only contain a very small subset of all possible links. To prevent having to check 93 x 111 possible transitions, VA nodes were grouped into subject clusters, each of which contains arguments related to a specific subject (e.g. "alternate means of transportation", "ecological arguments", etc.). Each player node was then linked to its possible follow-up clusters.

3.2.2 FSM – special statements

The resulting scenario was further expanded with special statements. These come in two flavors: the first, *action statements*, are statements which have a specific trigger and may cause a special action in the system. Examples include announcing that the VA did not understand the player (if the NLP topic detection did not find a match) or reacting to inappropriate language (if at least one instance of profanity was detected in the player input). Action statements can either be specific to the current scenario, or applicable to any scenario. They can belong to the player, the VA, or both.
The second type of special statement is the *universal statement*. These are common statements which are not scenario-specific. Examples include greeting and saying goodbye, (dis)agreement, apologizing, etc.

3.2.3 FSM – follow-up state prediction

When the scenario manager receives the predicted topic (or node) and Circumplex position from the NLP module, the decision process to determine the next VA statement is started. First, trigger conditions for all action statements are evaluated. If one or more of these evaluate to true, the resulting action with the highest priority is taken. If no action statement is triggered, a reply is selected at random from the possible follow-up nodes to the current player node. Follow-up nodes which already appear in the conversation history are ignored unless no other option exists.
Finally, the resulting reply and the VA's Circumplex position are passed to the audio and visualization modules.

3.3 Audio

The audio module collaborates with the 3D visualization module to output audio-visual feedback to the user. For each node in the finite state machine of the scenario engine, a professional actor will be asked to voice nine different realizations of the argument, following the different octants on the Interpersonal Circumplex in addition to a neutral version. The end result will be a database of pre-recorded responses to be used by the virtual agent.
We initially considered using text-to-speech software to automatically generate the virtual agent's speech, but it quickly became clear that in a task where the identification of subtle emotions is key, using artificial speech would simply not be sufficient, and we chose to use pre-recorded audio instead. Despite the higher cost and time requirements, recording human speech is currently the only way to gather natural sounding emotive utterances.
The audio module receives input from the scenario engine and searches through its internal database of audio files, selecting the one which most closely matches the response sentence and the emotional state of the virtual agent. This file is then played back while the 3D visualisation module renders the corresponding animations.

3.4 3D visualization

The 3D visualization module is responsible for rendering a convincing 3D representation of the virtual agent. It contains a database of poses and body animations, each of which is linked to a certain position on the Circumplex. Based on the output of the scenario engine, a pose and one or more animations will be selected and played during playback of the audio file.
The visualization engine is also responsible for the facial animation of the virtual agent. Facial animation is achieved by analysing which phonemes occur in the sound file selected by the audio module, and then creating an animation morph based on the head meshes for the corresponding

visemes (mouth, lip and tongue positions for a certain phoneme). While the results are less impressive than more advanced techniques (Cao et al, 2005; Müller et al, 2005), this approach has the benefit of simplicity and can be applied in real time. The resulting animation is further blended with a facial representation of the virtual agent's emotional state (Knutson, 1996). The head and body animations are subsequently combined into the final representation.

4. Conclusions and future research

We have described the design of deLearyous, a proof-of-concept of a serious game for the training of interpersonal communication skills. We have outlined the application pipeline and have described the individual modules in detail, evaluating them where possible.
The goals of project deLearyous are ambitious: to attempt to create a virtual agent that "understands" free-form natural language input, interprets its emotional contents (in terms of a position on the Interpersonal Circumplex) and responds in a manner that makes conversation possible.
These ambitions were partially realized. The virtual agent was developed, and a full scenario was implemented. Carrying out a conversation with the virtual agent using natural (written) language is indeed possible given a narrow definition of the conversation topic. Automatically identifying the emotional contents of written text is more challenging, however. The accuracy of the system's predictions is low, but given the low agreement of humans on the same task, this is not in itself worrying. We expect players to unconsciously reinterpret "incorrect" responses to logically fit the conversation. We therefore believe it will be more important for the system to correctly classify key turning phrases, and that raw accuracy is of secondary importance.
Given the application's imperfect output, we recommend it be used under the supervision of a coach. The deLearyous application should be used as a tool, a playground for interpersonal communication training, but it shouldn't be seen as a providing a gold standard.

Future research in the deLearyous project will involve extensive focus testing of the application. Players will be asked to test the application, and their responses will be recorded and evaluated. Based on player feedback, the various modules can still be tweaked and improved.
When the application is in a sufficiently stable state, we will test to which extent the application can help achieving our learning goals: do player effectively learn to work with the Interpersonal Circumplex? Can they learn to recognize their interlocutor's position on the Rose? Can they estimate their own position? And finally, can they keep their own emotions in check so as to consciously trigger a reaction in their conversation partner?

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