

ABSTRACT

MCQUIGGAN, SCOTT W. An Inductive Approach to Modeling Affective Reasoning in Interactive Synthetic Agents (Under the direction of James C. Lester).

Recent years have witnessed significant progress on synthetic agents. With a broad range of applications in education, training, and entertainment, foundational work on synthetic agents has yielded expressive models of embodied cognition and behavior that support rich interaction. Complementing advances in cognition and behavior, affective reasoning has begun to play a central role in synthetic agents. A key challenge posed by affective reasoning in synthetic agents is devising empirically informed models of affect that enable synthetic agents to accurately respond in social situations.

This thesis presents an inductive affective modeling paradigm for learning models of affect by observing human-human social interactions. First, in training sessions, one trainer directs a synthetic agent to perform a sequence of tasks while another trainer manipulates a synthetic agent's affective states to produce appropriate behaviors. These include spoken language, gestural behaviors, and posture. Second, the model generator tracks observable situational attributes pertaining to locational, intentional, and temporal information to induce a model of affect. Finally, at runtime, a synthetic agent applies the model by tracking precisely the same observable attributes and using them to drive situation-appropriate behaviors.

The inductive affective reasoning framework has been implemented in a model generator that induces models of empathy for synthetic agents. A 31-subject experiment indicates that a data-driven approach can generate models of empathy that are both efficient

and accurate. In the experiment, naïve Bayes affective classifiers and decision tree affective classifiers were learned to model situational assessment (when to perform an affective behavior) and interpretation (which affective behavior to select). Results suggest that inductively generated models satisfy the real-time performance requirements of interactive environments and can provide the basis for empirically informed affective reasoning in synthetic agents.

An Inductive Approach to Modeling Affective Reasoning in Interactive Synthetic Agents

by

SCOTT W. MCQUIGGAN

A thesis submitted to the Graduate Faculty of
North Carolina State University
in partial fulfillment of the
requirements for the Degree of
Master of Science

COMPUTER SCIENCE

Raleigh

2005

APPROVED BY:

Dr. Munindar P. Singh
Committee Member

Dr. R. Michael Young
Committee Member

Dr. James C. Lester
Chair of Advisory Committee

*To Mother, Pops,
and
Jamie.*

Biography

Scott William McQuiggan was born in Elizabethtown, Pennsylvania, in 1980. He attended Elizabethtown Area High School, graduating in 1999. He then obtained a Bachelor of Science degree in computer science from Susquehanna University in Selinsgrove, Pennsylvania in 2003. He has been a graduate student at North Carolina State University since the fall of 2003. As a graduate student, Scott joined the IntelliMedia Center for Intelligent Systems, led by his advisor, Dr. James C. Lester. Scott has expressed interest in investigating the application of psychological findings coupled with techniques prevalent in computer science to create new paradigms to supplement a variety of applications with affective reasoning. His future endeavors most likely will focus on such affective reasoning applications, using artificial intelligence and machine learning techniques, particularly in assistive and educational domains.

Acknowledgements

I would like to first thank the members of my committee, Dr. Munindar P. Singh and Dr. R. Michael Young for their academic enthusiasm and support.

I am immensely thankful for the opportunity to be a student of my advisor, Dr. James C. Lester, who has given continuous guidance, support, and confidence throughout this work. Dr. Lester has bestowed many lessons in academia and insightful discussions for which I am genuinely grateful.

I am also appreciative of the generosity and help offered by the members of the IntelliMedia Center for Intelligent Systems. I would like to especially thank Sueng Lee, Sunyoung Lee, and Bradford Mott for considering me a peer. Discussions with fellow graduate students have often led to a better understanding of my own work and its application. For this I owe thanks to Leo Bae, Yuna Cheong, Neha Jain, Arnav Jhala, and Ben Rose.

I would like to additionally thank SAS Institute, Inc., particularly the JMP™ division and Dr. Richard Potter, for allowing me to gain valued experience in the development of first-class statistical software while prioritizing academics throughout the course of this research.

I am grateful to Dr. Boris Roussev, who engraved much confidence and motivation at SU, leading me to pursue the graduate studies I have come to treasure so deeply.

I would like to express my sincere appreciation to my sister, Kelly, my brother, Steven, and the rest of my family and friends who have, at some time or another, crafted a

piece of who I am. Furthermore, it is with the loving support, ready advice and unending encouragement gifted to me by my parents, William and Carol McQuiggan that has enabled me to pursue my interests and flourish in whatever makes me happy.

Finally, I would like to express my gratitude for the unconditional understanding, patience, and emotional support of my best friend and future wife, Jamie.

Table of Contents

| | |
|---|-------------|
| List of Figures..... | viii |
| List of Tables | ix |
| 1. Introduction..... | 1 |
| 1.1 Overview of Research..... | 3 |
| 1.2 Thesis Organization | 4 |
| 2. Modeling Affect..... | 6 |
| 2.1 Computational Models of Affect | 7 |
| 2.1.1 Ortony, Clore and Collins' Structure of Emotion..... | 7 |
| 2.1.2 Smith and Lazarus' Appraisal Theory | 9 |
| 2.2 Empathy | 10 |
| 2.2.1 Defining Empathy | 11 |
| 2.2.2 Empathy Limitations in Computational Models of Affect | 13 |
| 3. An Inductive Model of Empathy | 15 |
| 3.1 The CARE Architecture | 15 |
| 3.2 Training and Learning..... | 17 |
| 4. Implementation | 25 |
| 4.1 The Treasure Hunt Virtual Environment | 25 |
| 4.2 Implementing CARE | 27 |
| 4.3 Example Scenario | 29 |
| 5. Evaluation..... | 32 |
| 5.1 Method | 32 |
| 5.1.1 Participants and Design..... | 33 |
| 5.1.2 Materials and Apparatus – Training Target | 33 |
| 5.1.3 Materials and Apparatus - Empathizer | 34 |
| 5.2 Procedure | 35 |
| 5.3 Results..... | 39 |
| 5.3.1 IRI Empathy Instrument Results..... | 39 |
| 5.3.2 Model Results | 43 |
| 5.4 Discussion | 50 |

| | |
|---|-----------|
| 6. Related Work | 53 |
| 6.1 Believable Characters | 54 |
| 6.2 Affective Agents | 56 |
| 6.2.1 Pedagogical Agents..... | 56 |
| 6.2.2 Learning Companions..... | 59 |
| 6.2.3 Embodied Conversational Agents..... | 60 |
| 6.3 Socially Intelligent Synthetic Agents..... | 61 |
| 6.3.1 Politeness | 61 |
| 6.3.2 Generating Empathetic Behaviors | 62 |
| 6.3.3 Eliciting Empathy from Users | 64 |
| 7. Conclusion and Future Work | 66 |
| 7.1 Summary | 67 |
| 7.2 Future Work | 67 |
| 7.2 Concluding Remarks..... | 72 |
| References..... | 73 |
| A. Extended Model Results | 79 |
| A.1 Decision Tree Model of Empathetic Assessment | 80 |
| A.2 Naïve Bayes Model of Empathetic Assessment | 81 |
| A.3 Decision Tree Model of Empathetic Interpretation - Emotion | 82 |
| A.4 Naïve Bayes Model of Empathetic Interpretation - Emotion | 83 |
| A.5 Decision Tree Model of Empathetic Interpretation - Arousal | 84 |
| A.6 Naïve Bayes Model of Empathetic Interpretation - Arousal..... | 85 |
| A.7 Decision Tree Model of Empathetic Interpretation - Valence..... | 86 |
| A.8 Naïve Bayes Model of Empathetic Interpretation - Valence | 87 |
| A.9 Decision Tree Model of Empathetic Interpretation - Quadrant | 88 |
| A.10 Naïve Bayes Model of Empathetic Interpretation - Quadrant | 89 |

List of Figures

| | |
|--|----|
| Figure 1-1: Treasure Hunt Virtual Environment | 5 |
| Figure 2-1: The OCC Model..... | 8 |
| Figure 2-2: The Smith and Lazarus Model | 10 |
| Figure 2-3: Empathy Construct..... | 12 |
| Figure 3-1: General CARE Architecture..... | 16 |
| Figure 3-2: Two-dimensional Affective Space..... | 19 |
| Figure 3-3: General Training and Learning Data Flow | 21 |
| Figure 4-1: A Relaxed Companion Agent in Treasure Hunt | 26 |
| Figure 4-2: An Excited Companion Agent | 30 |
| Figure 4-3: A Relaxed Companion Agent | 30 |
| Figure 4-4: A Frustrated Companion Agent in Treasure Hunt | 31 |
| Figure 5-1: Evaluation Data Flow..... | 38 |
| Figure 5-2: Individual Empathizer IRI Results..... | 40 |
| Figure 5-3: Individual Empathizer IRI Subscale Results | 40 |
| Figure 5-4: Average Empathizer IRI Subscale Results by Gender..... | 41 |
| Figure 5-5: Affective State Frequencies | 41 |
| Figure 5-6: Affective State Frequencies by Gender | 42 |
| Figure 5-7: Average Affective State Frequencies by Gender..... | 42 |
| Figure 5-8: ROC Curves for Empathetic Assessment | 44 |
| Figure 5-9: Partial Decision Tree for Empathetic Assessment..... | 44 |
| Figure 5-10: ROC Curves for Empathetic Interpretation (Emotions) | 46 |
| Figure 5-11: ROC Curves for Empathetic Interpretation (Valence)..... | 48 |
| Figure 5-12: ROC Curves for Empathetic Interpretation (Arousal) | 48 |
| Figure 5-13: ROC Curves for Empathetic Interpretation (Quadrant)..... | 49 |

List of Tables

| | |
|---|----|
| Table 5-1: Areas Under ROC Curves in Figure 5.10..... | 47 |
| Table 5-2: Areas Under ROC Curves in Figures 5.11 and 5.12 | 48 |
| Table 5-3: Areas Under ROC Curves in Figure 5.13..... | 49 |
| Table 5-4: Empathizer Suggested Empathetic Emotions..... | 51 |
| Table A-1: Empathetic Assessment Decision Tree Confusion Matrix..... | 80 |
| Table A-2: Empathetic Assessment Decision Tree Evaluation Measures..... | 80 |
| Table A-3: Empathetic Assessment Decision Tree Measurements of Error | 80 |
| Table A-4: Empathetic Assessment Naïve Bayes Confusion Matrix | 81 |
| Table A-5: Empathetic Assessment Naïve Bayes Evaluation Measures | 81 |
| Table A-6: Empathetic Assessment Naïve Bayes Measurements of Error..... | 81 |
| Table A-7: Empathetic Interpretation (Emotion) DT Confusion Matrix..... | 82 |
| Table A-8: Empathetic Interpretation (Emotion) DT Evaluation Measures..... | 82 |
| Table A-9: Empathetic Interpretation (Emotion) DT Measurements of Error | 82 |
| Table A-10: Empathetic Interpretation (Emotion) NB Confusion Matrix..... | 83 |
| Table A-11: Empathetic Interpretation (Emotion) NB Evaluation Measures | 83 |
| Table A-12: Empathetic Interpretation (Emotion) NB Measurements of Error | 83 |
| Table A-13: Empathetic Interpretation (Arousal) DT Confusion Matrix..... | 84 |
| Table A-14: Empathetic Interpretation (Arousal) DT Evaluation Measures..... | 84 |
| Table A-15: Empathetic Interpretation (Arousal) DT Measurements of Error | 84 |
| Table A-16: Empathetic Interpretation (Arousal) NB Confusion Matrix..... | 85 |
| Table A-17: Empathetic Interpretation (Arousal) NB Evaluation Measures..... | 85 |
| Table A-18: Empathetic Interpretation (Arousal) NB Measurements of Error | 85 |
| Table A-19: Empathetic Interpretation (Valence) DT Confusion Matrix | 86 |
| Table A-20: Empathetic Interpretation (Valence) DT Evaluation Measures | 86 |
| Table A-21: Empathetic Interpretation (Valence) DT Measurements of Error | 86 |
| Table A-22: Empathetic Interpretation (Valence) NB Confusion Matrix | 87 |
| Table A-23: Empathetic Interpretation (Valence) NB Evaluation Measures | 87 |
| Table A-24: Empathetic Interpretation (Valence) NB Measurements of Error..... | 87 |
| Table A-25: Empathetic Interpretation (Quadrant) DT Confusion Matrix..... | 88 |
| Table A-26: Empathetic Interpretation (Quadrant) DT Evaluation Measures..... | 88 |
| Table A-27: Empathetic Interpretation (Quadrant) DT Measurements of Error | 88 |
| Table A-28: Empathetic Interpretation (Quadrant) NB Confusion Matrix | 89 |
| Table A-29: Empathetic Interpretation (Quadrant) NB Evaluation Measures | 89 |
| Table A-30: Empathetic Interpretation (Quadrant) NB Measurements of Error | 89 |

Chapter 1

Introduction

Recent years have witnessed significant progress on synthetic agents. With a broad range of applications in entertainment, education, and training, foundational work on synthetic agents has yielded expressive models of embodied cognition and behavior that support rich interactions in virtual environments [André and Müller 2003; Bates 1994; Cavazza *et al.* 2002; Johnson and Rizzo 2004; Lester *et al.* 2000; Reilly and Bates 1992; Ryokai *et al.* 2003; Swartout *et al.* 2004]. Complementing advances in cognition and behavior, affective reasoning [Elliott 1992; Gratch and Marsella 2004b; Ortony *et al.* 1988; Picard 1997] has begun to play a central role in synthetic agents [Bickmore 2003; Burleson and Picard 2004; Marsella and Gratch 2003]. The community is now well positioned to investigate affective reasoning in the context of social interaction [Johnson and Rizzo 2004; Paiva *et al.* 2004; Paiva *et al.* 2005; Prendinger *et al.* 2003; Prendinger and Ishizuka 2005] and to apply affective reasoning to the relationships agents have with one another and with their users.

Transitioning affective synthetic agents into the social arena could yield companion

agents that provide motivating support and compassionate comfort to their users. *Companion agents* can facilitate social interaction, a critical capability in virtual environments for education [Burleson and Picard 2004; Conati and McLaren 2005; Conati 2002; Lester *et al.* 1999] and training [Prendinger and Ishizuka 2005]. Companion agents help users cope with frustration [Burleson and Picard 2004], deal with stress [Prendinger and Ishizuka 2005], and counsel children on social behaviors, such as bullying in schools [Paiva *et al.* 2004; Paiva *et al.* 2005].

Empathy is a key component of social interaction [Hoffman 2000]. Because empathetic companion agents hold much promise for socially engaging virtual environments, empathy modeling is a logical next step in the evolution of synthetic agents and their social roles. One can distinguish two fundamental approaches to modeling empathy: analytical and empirical. In the *analytical* approach, models of empathy can be constructed by analyzing the findings of the empathy literature. However, empathy is not well understood. It is only in the past two decades—this is very recent in the history of psychology—that empathy has become a focus of study for social psychologists [Davis 1994]. Perhaps as a result of its limited study, while we have expressive computational models of affect, e.g., the OCC model [Ortony *et al.* 1988], we do not have similarly rich, comprehensive models of empathy. While particular models of affect [Ortony *et al.* 1988; Smith and Lazarus 1990] do account for some empathetic behaviors, they are not conclusive at this time. Moreover, because empathetic reasoning requires drawing inferences about another’s intentions, her affective state, and her situational context [Davis 1994], devising a complete, and universal model of empathy seems to be well beyond our grasp at the current juncture.

An alternative to analytically devising models of empathy for affective synthetic agents is the *empirical* approach. If somehow we could create models of empathy that were derived directly from observations of “empathy in action,” we could create empirically grounded models based on human-human empathetic behaviors exhibited during the performance of a specific task within a given domain. While it is not apparent that this approach could produce a universal model of empathy—a universal model may not even be achievable, at least in the near term—the empirical approach could nonetheless generate models of empathy that significantly extend the communicative capabilities of socially intelligent companion agents. Socially intelligent companion agents should have the ability to relate to, understand and interact effectively with their users and other synthetic agents.

Many have reported on the benefits of equipping synthetic agents, such as pedagogical agents [Baylor 2005; Lester *et al.* 1999], with expressive affective abilities. While such benefits stem from the internal assessment used to determine affective state of synthetic agents, we have only begun to explore what the potential benefits might then be for socially intelligent, empathetic synthetic agents whom assess situational contexts from another’s point of view, considering too the affective state and goals of another to arrive at their (the agent’s) own affective state.

1.1 Overview of Research

The empirical approach calls for a data-driven framework for modeling empathy. This paper presents CARE (Companion-Assisted **R**eactive **E**mpathizer agent) a data-driven affective architecture and methodology for learning empirically informed models of empathy from

observations of human-human social interactions. CARE begins with training sessions. During training sessions, CARE monitors observable situational data including locational, intentional, and temporal information while one trainer (the *target*) directs her synthetic agent to perform a sequence of prescribed tasks in a virtual environment as another trainer (the *empathizer*) reactively manipulates her synthetic agent's affective state producing empathetic behaviors. These behaviors include spoken language, gestural behaviors, and posture. Inducing a model of empathy, CARE uses observable situational data as predictive features for *empathetic assessment* (when to exhibit an empathetic behavior) and for *empathetic interpretation* (which affective state should be chosen). The recorded observable attributes are reported to an empathy learner during the training phase. During the subsequent learning phase, CARE induces operational models for each empathetic assessment and empathetic interpretation. At runtime, CARE uses the resulting models to drive situation-appropriate empathetic behaviors by determining first when and then how a companion agent should be empathetic as it interacts with actual users.

1.2 Thesis Organization

This thesis is organized as follows: Chapter 2 provides background on affective reasoning and empathy with a focus on synthetic agents. Chapter 3 presents the CARE architecture and methodology, describing how CARE models of empathy are induced. Chapter 4 describes a CARE implementation and its generation of the empathy model for the companion agent inhabiting Treasure Hunt (Figure 1-1), a virtual environment in which a user and a companion agent search for treasures. Chapter 5 provides details of an evaluation reporting



Figure 1-1: Treasure Hunt virtual environment (companion agent, left, and the user's agent, right).

on a 31-subject training focus group experiment. Chapter 6 presents a comprehensive comparison of this work with related work from the affect reasoning and synthetic agent communities. Chapter 7 concludes the discussion and suggests directions for future work.

Chapter 2

Modeling Affect

Emotions are an intricate system in humans which influence our interactions, our behavior and even our thinking. Emotions are almost always being expressed by the words we say, our facial expressions, our posture, and our actions. If computer systems are going to achieve high levels of believability, immersion, and more effective interaction, then emotion clearly needs to be incorporated into games, educational software, user-interfaces, and virtual environments. The field of *affective computing*, which focuses on the ability of computers to recognize, model, understand, express and respond to emotion effectively, is applicable in a wide range of application areas. Affective computing has found that emotions play a role in decision making, perception, learning and rational thinking and could positively affect the success of a broad range of computer systems.

In recent years, there has been a shift in research on models of emotion, based on the discovery that emotion is founded in perception and decision-making processes. Prior to 1990 it was believed that perception and decision-making were primarily cortical (part of the

brain nearest the surface) processes [Cytowic 1989]. Cytowic discovered that the limbic systems of the brain (thought to lie beneath the cortex) were triggered during perception and decision-making processes in addition to the cortex. The limbic systems are thought to be responsible for emotion, memory and attention [Cytowic 1989]. This finding blurs the line between “thinking” and “feeling” and has led to the development of cognitive appraisal theories of emotion which will be introduced in the next section. Such computational models of emotion have been the heart of affective computing, which relies heavily on the notions of the OCC model [Ortony *et al.* 1988] and the Smith and Lazarus model [Smith and Lazarus 1990; Lazarus 1991].

2.1 Computational Models of Affect

Several computational models of affect have been developed in the last two decades. However, only two models, OCC [Ortony *et al.* 1988] and Smith and Lazarus [Smith and Lazarus 1990; Lazarus 1991] have been implemented in synthetic agent architectures. These are discussed in the following sections.

2.1.1 Ortony, Clore and Collins’ Structure of Emotion

The OCC model of affect was never intended to be used for reasoning about emotional synthesis; its focus was exclusively on recognizing an emotional state. The OCC model distinguishes itself from previous models because it is not strictly based on a fixed set of basic emotions, nor is it explicitly grounded on a two- or three-dimensional emotional space,

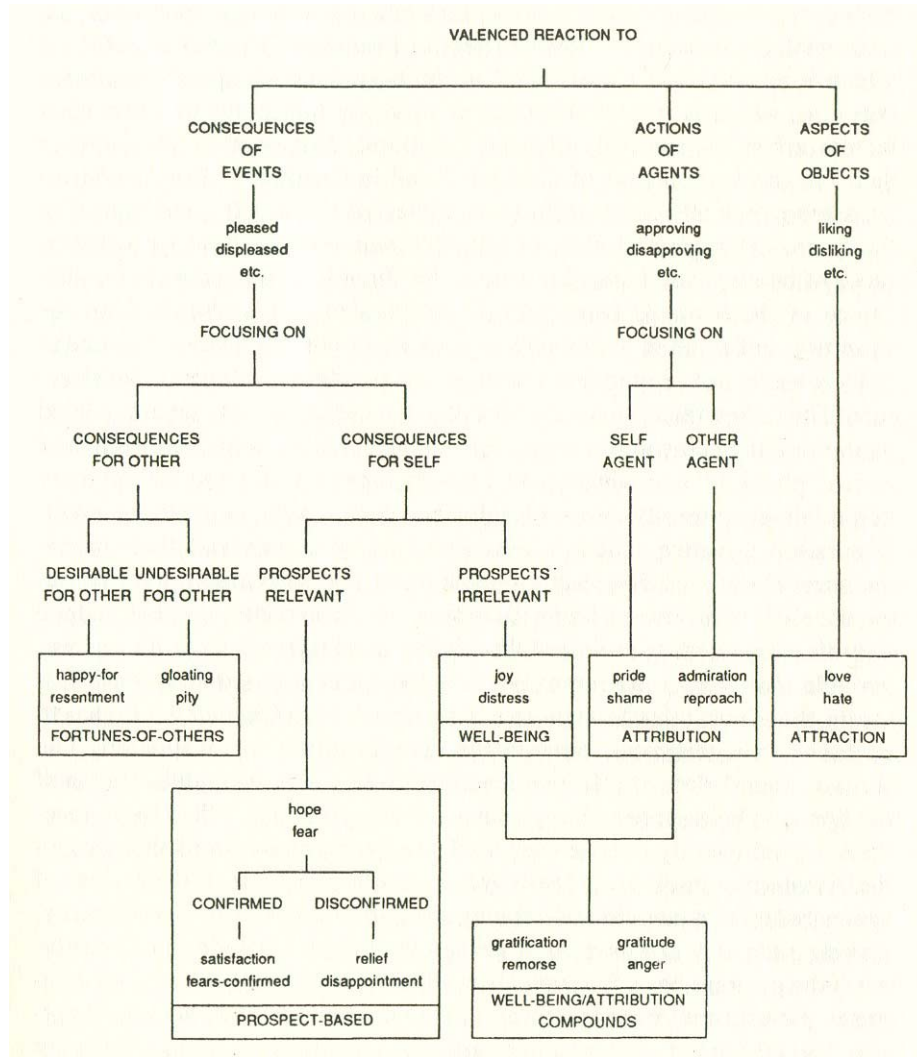


Figure 2-1: The OCC Model (from Figure 2.1 of [Ortony et al. 1988]).

although others (e.g., [Lang 1995]) have derived such notions from the OCC model [Ortony et al. 1988]. Instead, the OCC model groups emotions based on cognitive conditions. These conditions were formulated as a rule-based system by OCC [Ortony et al. 1988] (Figure 2-1). The OCC model supports twenty-two affective states; each individual emotional state is bolded in the boxes along the bottom of the rule-tree. The emotions arise from valenced

reactions, positive and negative, to appraised situations consisting of events, agents, and objects [Ortony *et al.* 1988]. The outcome of situations in the OCC model is a synthesized emotional state.

2.1.2 Smith and Lazarus' Appraisal Theory

The Smith and Lazarus appraisal theory of emotion (Figure 2-2) characterizes emotion as a two-staged cognitively informed process consisting of appraisal and coping [Smith and Lazarus 1990]. *Appraisal* refers to one's interpreted relationship with her surrounding physical and social environment. Appraisal is a cognitively-constructed representation of events and how these events relate to internal goals. *Coping* is the process by which one considers actions that either maintain or manipulate their existing relationship with the environment based on affective behavioral tendencies, current affective state, desired affective state, and physiological factors [Lazarus 1991]. Coping determines the response to appraised situations based on past, present and future events.

There are two types of coping strategies: those that motivate change in the environment, which are known as *problem-focused coping strategies*, and those that change the interpretation of the person-environment relationship, which are known as *emotion-focused coping strategies*. Behavior thus arises from the collection of cognition, emotion and coping strategies [Gratch and Marsella 2004b]. Note that this theory focuses on the underlying cognitive processes that produce emotions and not a theory seeking to define affective states, like that of the OCC model.

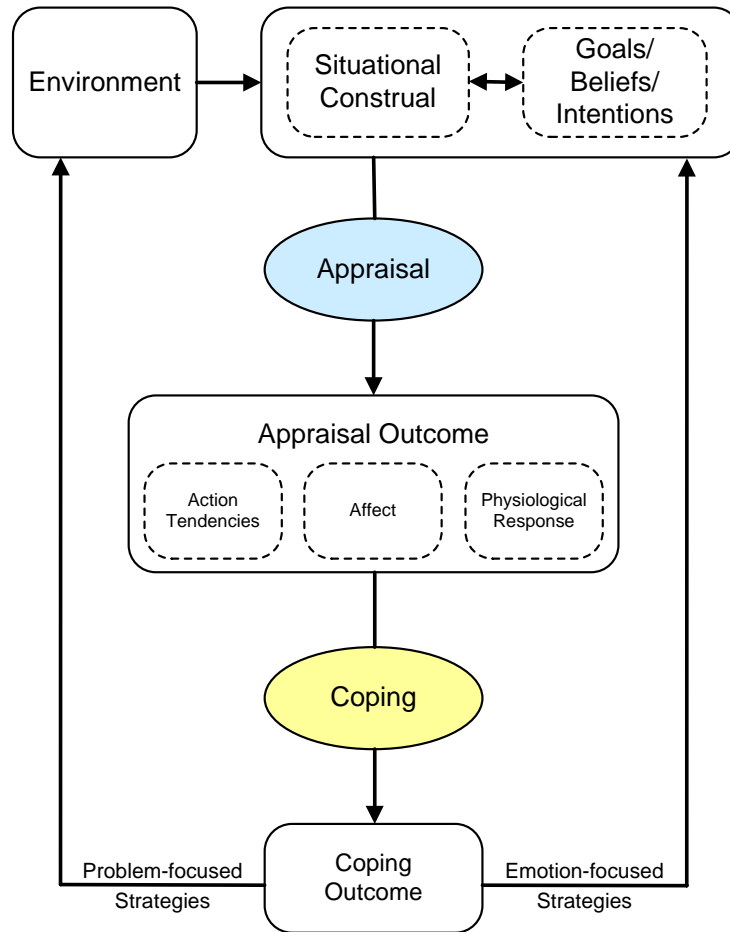


Figure 2-2: The Smith and Lazarus Model [Smith and Lazarus, 1990].

2.2 Empathy

Empathy is receiving more attention from social psychologists now than ever before [Davis 1994; Hoffman 2000]. Empathy is not comprehensively addressed in computational models of affect, perhaps because of the recentness with which it has been a focus in social psychology. Although recent developments in computational models of affect have reported success, their limited empathetic abilities suggest a need for enhanced computational models

focused on empathy to drive social interactions in synthetic agents.

Devising computational models of empathy contributes to the broader enterprise of modeling affective reasoning [Picard 1997]. Beginning with Elliott's implementation [Elliott 1992] of the OCC model [Ortony *et al.* 1988], advances in affective reasoning have accelerated in the past few years, including the appearance of a sophisticated theory of appraisal [Gratch and Marsella 2004b] based on the Smith and Lazarus appraisal theory [Lazarus 1991; Smith and Lazarus 1990]. We have also begun to see probabilistic approaches to assessing users' affective state in educational games [Conati 2002] and investigations of the role of affect and social factors in pedagogical agents [Baylor 2005; Burleson and Picard 2004; Elliot *et al.* 1999; Johnson and Rizzo 2004; Lester *et al.* 1999; Porayska-Pomsta and Pain 2004]. Recent work on empathy in synthetic agents has explored their affective responsiveness to biofeedback information and the communicative context [Prendinger *et al.* 2003]. It has also yielded agents that interact with one another and with the user in a virtual learning environment to elicit empathetic behaviors from its users [Paiva *et al.* 2005].

2.2.1 Defining Empathy

Empathy is a complex socio-psychological construct (Figure 2-3). Defined as “the cognitive awareness of another person's internal states, that is, his thoughts, feelings, perceptions, and intentions” [Ickes 1997], empathy enables us to vicariously respond to another via “psychological processes that make a person have feelings that are more congruent with

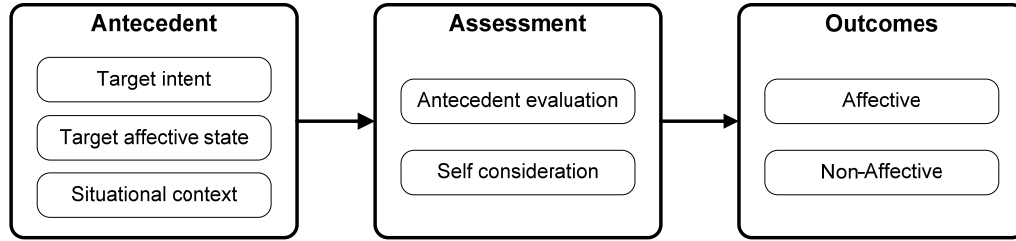


Figure 2-3: Empathy construct (modified from [Davis 1994]).

another's situation than with his own situation" [Hoffman 2000].

Social psychologists describe three constituents of empathy. First, the *antecedent* consists of the target's intent and affective state, and the situation at hand. Second, *assessment* consists of evaluating the antecedent and the empathizer's consideration of herself. Third, *empathetic outcomes*, e.g., behaviors expressing concern, are the products of assessment [Davis 1994] including both affective and non-affective outcomes (e.g., judgment, cognitive awareness). Two types of affective outcomes may occur: parallel and reactive.

- In *parallel* outcomes, the empathizer mimics the affective state of the target. For example, the empathizer may become fearful when the target is afraid.
- In *reactive* outcomes, empathizers exhibit a higher cognitive awareness of the situation to react with empathetic behaviors that do not necessarily match those of the target's affective state. For example, empathizers may become frustrated when the target does not meet with success in her task, even if the target herself may not be frustrated.

2.2.2 Empathy Limitations in Computational Models of Affect

The OCC model accounts for empathetic emotions, although it is somewhat limited with respect to the definition of empathy presented in Section 2.2.1. The OCC model refers to this set of emotions as “fortune-of-others” emotions [Ortony *et al.* 1988]. These emotions do consider what has happened to other people and arrives at an emotional reaction based on that assessment [Ortony *et al.* 1988]. However, this assessment only has 4 potential outcomes: “self-pleasing and target-desired”, “self-pleasing and target-undesired”, “self-displeasing and target-desired”, and “self-displeasing and target-undesired.” These four outcomes respectively, translate into the following emotions defined by [Ortony *et al.* 1988]: *happy-for*, *gloating*, *resentment*, and *sorry-for*. These *fortune-of-other* emotions do not capture the essence of the definition of empathy which allows for any emotion to be felt by the empathizer.

Smith and Lazarus do not address empathy specifically. Instead they address compassion. The definitions of empathy and compassion clearly overlap; compassionate behaviors entail those defined by empathy. Compassion refers to being aware of another’s suffering and wishing to relieve it. Essentially, this is “reactive empathy.” Smith and Lazarus do not accommodate “parallel empathy.”

These limitations, together with those presented in the OCC discussion, indicate the need for more accurate models of empathy. Clearly, accurately modeling parallel and reactive empathetic reasoning presents significant challenges. Foremost among these is the fact that empathetic outcomes are not restricted to a general emotional state consisting of several potential emotions; any affective state can be the product of empathetic assessment

and interpretation. The lack of well defined analytical models of empathy call for data-driven approaches which induce empirically informed models of empathy.

Chapter 3

An Inductive Model of Empathy

The prospect of creating an “empathy learner” that can induce empirically grounded models of empathy from observations of human-human social interactions holds much appeal. To this end, we propose CARE, an affective data-driven paradigm that learns empathetic assessment (when to be empathetic) and empathetic interpretation (how to be empathetic). CARE consists of a trainable agent architecture and a two-phase methodology of training and learning.

3.1 The CARE Architecture

The CARE architecture operates in two modes: empathetic model induction in which it interacts with two trainers, the target and the empathizer, (denoted in the diagram with dotted lines), and runtime operation, in which it manages empathetic behaviors for a companion

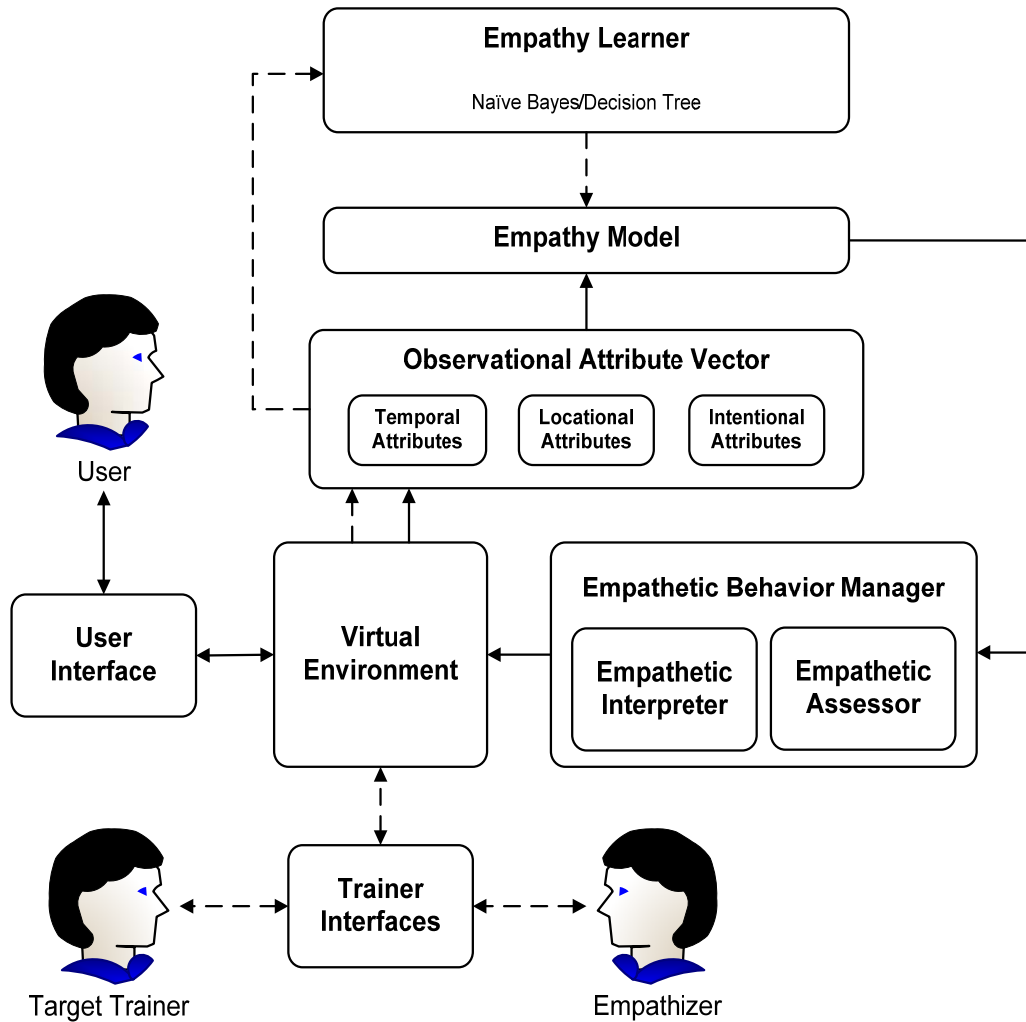


Figure 3-1: General CARE Architecture

agent interacting with a user (denoted in the diagram with solid lines) (Figure 3-1):

- **Empathetic Model Induction:** Trainers interact with CARE via interfaces through which they direct synthetic agents in the virtual environment. The virtual environment tracks all activities in the world and reports observable attributes pertaining to temporal,

locational, and intentional information. These are passed to the empathy learner during the training phase. During the subsequent learning phase, the learner induces a model of empathy that is operational, i.e., it will be used at runtime.

- **Runtime Operation:** Users interact with CARE via an interface through which they direct a synthetic agent in the virtual environment. Throughout their experience, they interact with a companion agent controlled by CARE. The virtual environment again tracks all activities in the world and monitors the same observable attributes reported to the empathy learner during empathetic model induction. The induced model is used by the empathetic behavior manager to (1) assess the situation to determine *when* to be empathetic, and (2) interpret situations deemed “empathy-worthy” to decide *how* to be empathetic. When a situation calls for empathy, a suitable empathetic behavior (including speech, gesture, and posture) is selected for sequencing in the virtual environment for execution by the companion agent to react empathetically to the user’s situation.

3.2 Training and Learning

In the training phase, CARE’s trainable agent must be exposed to social situations similar to the ones it will encounter at runtime. Because empathy by its very nature involves multiple actors (here we focus on two), the training experience should revolve around the interaction of multiple subjects in situations that elicit empathetic behaviors.

CARE training sessions are therefore situated in task-oriented scenarios involving two trainers, a *target* and an *empathizer*, each of whom is represented by a synthetic agent in the

3D virtual environment where training takes place. The target, whom is given a multi-objective mission to complete, controls her agent to navigate and perform tasks in the virtual environment from a first-person point-of-view (POV). It is the task of the empathizer, who looks on from a third-person POV, to monitor the target's activities and select suitable empathetic affective states based on the target's observed behaviors. Selecting an affective state causes her agent to perform an empathetic behavior.

To collect empathy data that is as representative as possible of that which will be encountered by the companion agent at runtime, training sessions must satisfy the following requirements:

Affective space coverage: At each stage of the mission, to promote the target's experiencing a range of emotions spanning the classic two-dimensional affective space defined by *valence* (degree of attraction, ranging from negative to positive) and *arousal* (level of stimulation, ranging from low to high) [Lang 1995] (Figure 3-2), the target should be faced with goals of varying degrees of difficulty: some should be very easy to achieve, while others should be very challenging. For example, in Treasure Hunt, the virtual environment that serves as a test bed for CARE, some treasures are in plain view of the target while others are partially occluded and some are hidden altogether. Some targets should be exposed to virtual environments in which goals are easy to achieve, and some should be introduced into worlds in which goals are difficult to achieve. Thus, in some Treasure Hunt worlds, targets can score a specified number of points by collecting treasures very easily, while other worlds pose significant challenges stemming from the accessibility and varying point values.

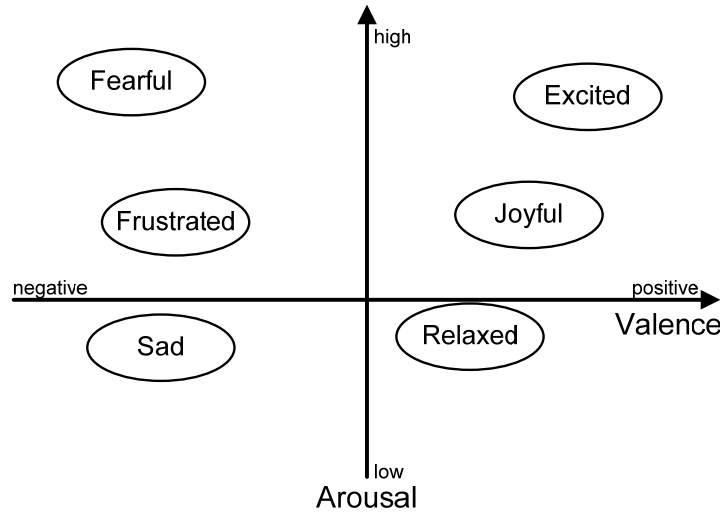


Figure 3-2: Two-dimensional Affective Space.

- **Double-blind training:** Training sessions should be conducted such that the target is unaware that an empathizer is at the controls of the empathetic behaviors of the companion agent in the virtual world. Likewise, restricting the empathizer's environment to the virtual world (i.e., without access to the target's facial or vocal expressions) enables empathetic decisions to be based solely on inferences from the observed virtual world.
- **Empathy-centered control:** The empathizer should be able to focus exclusively on empathy decision making. Thus, navigation control for the companion agent is provided by an autonomous path planning mechanism that ensures that the companion agent is always within a specified proximity to the target's agent in the virtual environment.
- **Training session length:** Each training session must strike a careful balance between

being long enough to yield a large body of data and short enough so that the trainers do not become overly fatigued. In the Treasure Hunt environment, experimentation indicated that 7-minute sessions satisfied this requirement.

- ***Controlled affective expression:*** Minimizing the complexity of the empathizer's task can be achieved by limiting the set of emotions at her disposal. For example, empathizers in Treasure Hunt have access to six affective states: excited, joyful, relaxed, fearful, frustrated, and sad. This particular set of emotions was chosen because it covers the four quadrants of the two-dimensional affective space [Lang 1995] and addresses three levels arousal (high, medium, and low) for each level of valence (positive or negative).
- ***Uniform agent personae:*** While investigating different personae is a promising direction for future work, e.g., pedagogical agent personae experiments [Baylor 2005], baseline training should control for personae by holding both the target's agent and the empathizer's agent constant throughout training sessions.
- ***Situation data collection intervals:*** Situation data should be collected at least as often as significant events occur, where an event is deemed significant if it can plausibly affect the empathizer's decisions. In Treasure Hunt, locational data were collected when events in the world indicated notable state changes, e.g., an agent's entering a room, while some temporal data were monitored continuously, e.g., the amount of time between goal achievement. A typical training session in Treasure Hunt yields approximately 6,000-9,000 data points. Figure 3-3 presents the general training and learning data flow.

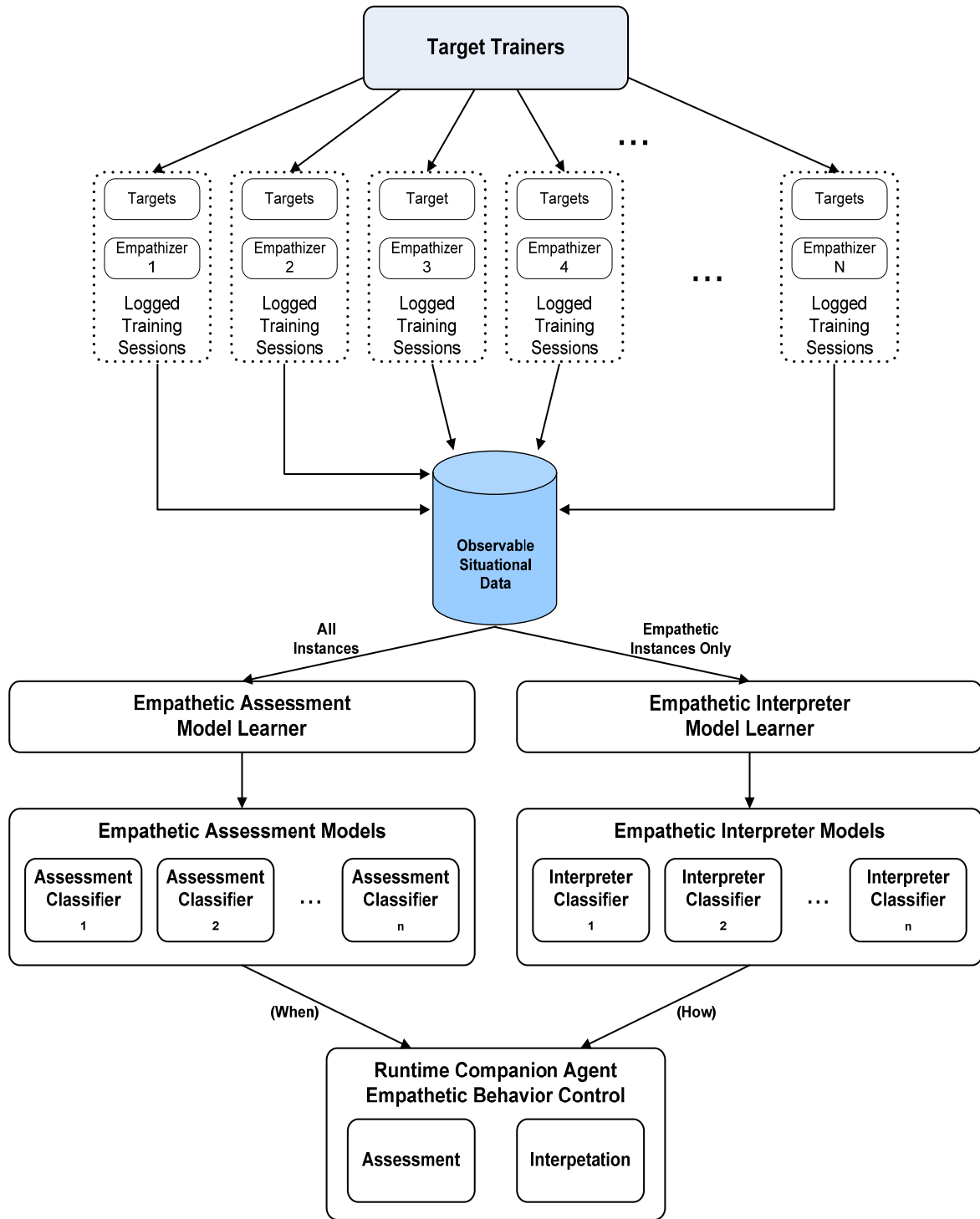


Figure 3-3: General Training and Learning Data Flow.

Accurately modeling empathy requires a representation of the situational context that satisfies two requirements. First, it must be sufficiently rich to support empathetic assessment and empathetic interpretation. Second, it must be encoded with features that are readily observable at runtime so that they may drive companion agents' empathetic decision making. CARE therefore employs an expressive representation of activities in the virtual environment by encoding them in an observational attribute vector, which is used in both modes of operation: during empathetic model induction, the *observational attribute vector* is passed to the empathy learner for model generation; during runtime operation, the attribute vector is monitored by the empathetic behavior manager for determining empathetic behavior. CARE's observable attribute vector represents three interrelated categories of features for making empathetic decisions:

- **Temporal features:** CARE tracks the amount of time that has elapsed since the target/user arrived at the current location, since the target/user achieved a goal, since the empathizer/companion agent last behaved empathetically, and since the target/user was last presented with an opportunity to achieve a goal.
- **Locational features:** CARE continuously tracks the location of all agents. It monitors locations visited in the past, locations recently visited, locations not visited, and locations being approached.
- **Intentional features.** CARE tracks goals being attempted (as inferred from locational and temporal features, e.g., approaching a location where a goal can be achieved), goals achieved, the rate of goal achievement, and the effort expended to achieve a goal (as inferred from recent exploratory activities and locational features).

In the CARE implementation for Treasure Hunt, the observational attribute vector encodes 192 features. During empathetic model induction, an instance of the vector is logged every time a significant event occurs. On average, vectors are updated several hundred times each minute. At runtime, the same features are updated continuously by the virtual environment and are used by the empathetic behavior manager to select situation-appropriate empathetic behaviors.

Finally, in the learning phase, CARE induces a dual model of empathy. One component will be used at runtime to support empathetic assessment, and the other will be used to support empathetic interpretation. CARE's empathy learner first uses all of the data collected in the training session to induce the empathetic assessment model. Induction may be based on any standard classifier learning technique. Two versions of CARE have been implemented in Treasure Hunt, one with naïve Bayes classifiers and one with decision trees. The evaluation reported in Section 5 discusses the performance of both approaches. CARE's empathy learner next uses a subset of the data collected in the training sessions to induce the empathetic interpretation model. Here, it only considers data instances in which empathy was in fact exhibited. The second induction produces a model of empathy interpretation that at runtime is used to instruct the agent which empathetic behaviors to perform.

Naïve Bayes and decision tree classifiers are excellent machine learning techniques for generating preliminary predictive models. Naïve Bayes classification approaches produce probability tables that can be implemented into the runtime system and used to continually update probabilities for empathetic assessment and empathetic interpretation. Decision trees provide interpretable rules and logic statements that enable intelligent decision

making. When the conditions of empathetic assessment rules are met other conditions are then checked to determine how to be empathetic. Both the naïve Bayes and decision tree machine learning classification techniques are useful for preliminary predictive model induction for large multidimensional data, such as the 192-observational attribute vector used in the implementation of CARE discussed in the next chapter. Since it is unclear which particular runtime variables are likely to be the most predictive, using advanced machine learning techniques (e.g., Bayesian networks) is much more difficult without the knowledge of a preliminary analysis and relies heavily on the authors own beliefs. Instead, by making all observable attributes available to the model learner it is more likely to induce models that better predict empathizer assessment and interpretation. As discussed in the future work of Chapter 7, analysis of naïve Bayes and decision tree classifications can lead to the identification of select attributes that can be used sufficiently for prediction, significantly reducing the dimensionality of monitored attributes.

The products of the learning phase are two classifiers used to determine when and how the companion agent should be empathetic as dictated by a generalized model induced from all of the empathizing trainers' empathetic behaviors. Because the classifiers employ features directly observable in the environment, they can be easily integrated into the runtime behavior control systems of companion agents.

Chapter 4

Implementation

The CARE paradigm has been used to train models of empathy and to control the behavior of a companion agent at runtime in Treasure Hunt, a virtual environment test bed in which targets/users are instructed to collect treasures in the allotted time. After introducing the Treasure Hunt virtual environment, we describe the implementation and present an illustrative example of CARE generating an empathetic behavior.

4.1 The Treasure Hunt Virtual Environment

Treasure Hunt is a prototype virtual environment featuring a synthetic agent controlled by the user and a companion agent whose empathetic behaviors are controlled by CARE. The user navigates the 3D virtual world in search of hidden (and some not-so-hidden) treasures. Each treasure box is labeled with the value of its contents, representing points obtained by collecting the associated treasure. Throughout the users' quest for treasure, the companion



Figure 4-1: A relaxed companion agent in Treasure Hunt with target/user agent (right).

agent follows along and expresses empathetic behaviors as appropriate situations arise (Figure 4-1).

The following description of Treasure Hunt was presented to target trainers in an effort to establish a controlled backstory. Each target trainer received a copy of the same backstory, verbatim.

You are about to find yourself on what appears to be an abandoned island with your companion, Alyx. On the island is an old warehouse, formerly used by pirates. The pirates have since left the island leaving some of their treasures behind! Scattered

throughout the island and particularly in the warehouse you may find boxes labeled by the value of their contents. Break open the boxes to collect the treasure within using your crowbar. Beware, some boxes may be unusually marked and have unknown contents. Collect such treasure at your own risk. You will have 7 minutes to explore the environment and collect treasure. The treasure you have collected, the number of remaining treasure boxes and the time left will be displayed in the bottom left corner of your display. Those that have ventured to the island before have left with treasure valued over 3,500!!!

4.2 Implementing CARE

CARE's empathetic assessment model and interpretation model have been implemented using naïve Bayes and decision tree approaches. A discussion of their relative performance follows in Section 5. The empathetic models were induced from a dataset consisting of a 192-dimensional observational attribute vector. Treasure Hunt is implemented using a high-performance 3D game platform from Valve Software. The virtual environment, observational attribute monitoring, and empathetic models have been implemented with Valve's Source™ engine and the accompanying 3D game platform for Half-Life 2.

As described in chapter 3, CARE models track temporal, locational and intentional features. Examples of those features include the following:

- *10-second score window.* A temporal feature which tracks whether the user has scored in the last 10 seconds of the interaction. Many time-window attributes are monitored because empathetic behaviors such as *excited* often happened within a 10

second window of time after a significant score, while empathetic emotions such as *frustrated* most frequently occurred after collecting a treasure worth a minuscule value took much longer. Time-windows for monitoring the last score are monitored at 5, 10, 15, 20, 30, 50, 75 and 100 second intervals.

- *Been to rocks on the beach.* A locational feature, the been-to-the-rocks-on-beach attribute monitors whether the user has visited a specific location where a known high-valued treasure is hidden behind a group of rocks. Other locational features track the user's navigation trends over time. For example, there are attributes to monitor where the user has been in a series of time-window attributes like those described above.
- *Moving towards high-valued treasure in sight.* This is an example of an intentional attribute that is monitoring whether or not there is a treasure in the user's view, if there is a treasure box, the value of the treasure and whether the user is navigating in the direction of the treasure. This represents the user's intent to approach and perhaps collect the treasure in sight.
- *Time left and total score.* The time remaining and the total score are displayed to both the target trainers and the empathizers. As time began to expire certain empathetic selections were made based on the performance of the target trainer. For instance, if the score was well below the expected value and the potential that the target would reach the goal based on the amount of time left empathizers chose different empathetic affective states (e.g., *frustrated* and *sad*). In contrast if, as time expired, the target had surpassed the expected goal then empathizers made empathetic

selections of *joyful* and *excited*, based on the target trainers overall success.

- *Last emotion.* Tracking the last emotion could prove to be quite predictive of the next empathetic interpretation. Especially in the male empathizers it was uncommon to move from highly-aroused, positive-valenced emotion (*excited*) to a low-aroused, negative-valenced emotion (*sad*). This exact example, however, was witnessed several times with female empathizers. Tracking the last emotion is also useful for determining how far in the two-dimensional affective space empathizers moved between empathetic interpretations.

As users interact with Treasure Hunt, the observational attribute vector monitors variables such as those noted above to update when and how to be empathetic. Figures 4-2 and 4-3 depict similar situations that have been assessed as a situation calling for empathy but have been interpreted differently. Notice that a treasure box is in the user's view in Figure 4-2 where the companion is *excited*, in an "easy" environment, but not in Figure 4-3 the companion is *relaxed*, in a challenging environment.

4.3 Example Scenario

To illustrate the empathetic behavior control posed by CARE, consider the following scenario in Treasure Hunt, which repeatedly played out in CARE training sessions. As we catch up with the user, she has navigated her synthetic agent throughout the virtual environment as she struggles to find significant, high-valued treasure. The user and empathizer are aware that the user has not yet met her expected treasure collection quota (as specified in the graphical HUD representation) and is quickly running out of time. Only 30 seconds remain.



Figure 4-2: An excited companion agent.



Figure 4-3: A relaxed companion agent.

Now, the user has found her agent’s way into a location on the beach, a location visited by the user’s agent in the early moments when the session began. The empathizer realizes that this particular location has been previously visited and was already determined to be an area without any treasure boxes. It has now been over one minute since the user last discovered any treasure at all.

Assessing the situation, the empathizer selects the frustrated affective state, igniting a behavioral sequence in which the companion agent announces her frustration, “This is becoming quite frustrating,” and using gestures and posture similar to Figure 4-4. (The agent’s speech segments are stored in high quality pre-rendered audio clips.) CARE’s empathy learner has monitored a variety of environmental characteristics, including those described above, during its training sessions. The resulting instances aid the empathetic models in inferring that the same response is suitable (“when” and “how”) to similar situations when time is running out, the user’s agent is in a previously visited location known



Figure 4-4: A frustrated companion agent in Treasure Hunt with target/user agent (right).

to be without treasure, the user's intended treasure collection goal is likely to fail, etc. Thus, given the same situation with CARE driving the empathetic behaviors of the companion agent at runtime, empathetic assessment and interpreter models are likely to make the appropriate empathetic decisions. The next section discusses how effectively the models learned by the agent are able to predict empathizer actions.

Chapter 5

Evaluation

This section presents a discussion of a user study, training sessions and the experiment conducted to create, implement, and evaluate CARE models of empathy for companion agents. The purpose of the experiment is to develop models of human-human social interaction by observing situational data changes in the Treasure Hunt virtual environment.

5.1 Method

A brief description of participants and the design of their participation are presented, followed by a presentation of materials and apparatus, first for empathizers and second for trainers. Section 5.2 discusses the procedures, which is followed by the details of the experiments results. Finally, a discussion of the experiment and evaluation responses concludes the chapter.

5.1.1 Participants and Design

In a formal evaluation, more than two hours of data were gathered from thirty-one subjects in an Institutional Review Board (IRB) of North Carolina State University approved user study. The subjects were divided into 25 targets and 6 empathizers. There were 20 male subjects serving as target trainers and 5 female subjects serving as target trainers varying in race, ethnicity, age and marital status who participated as training targets. There were 3 male and 3 female subjects participating as training empathizers. On average, empathizers completed 4 training sessions, each with a unique training target participant.

5.1.2 Materials and Apparatus – Training Target

For each target trainer pre-experiment paper-and-pencil materials consisted of a demographic survey, Half-Life 2 controls reference sheet, and a controlled backstory in preparation for interacting within the environment. The post-experiment paper-and-pencil materials consisted of a general survey about the training target's experience and opinions on affect in applications such as games. The demographic survey collected basic information such as gender, age, ethnicity, marital status, and number of children. The Half-Life controls reference sheet described which keys and mouse movements would be needed to manipulate the agent in both the practice task and the training task. The controlled backstory for the interactive environment was constructed in such a way that each participant would be given the same preparatory information.

The computerized materials for the target trainers consisted of three 3D Treasure Hunt virtual environments, each of varying degrees of difficulty, and the practice task drawn

directly from the game Half-Life 2. The easiest version of Treasure Hunt offered many opportunities to find treasures and meet the expectations that were set in the backstory. The most challenging version of Treasure Hunt made it difficult to find treasures; there were fewer treasures worth less value and more occluded treasure boxes making it difficult to meet backstory expectations. The practice task from the game Half-Life 2 was an opportunity for target trainers to become familiar with the required controls. The practice task required completing activities such things as climbing a ladder, stacking boxes, and jumping.

The target training apparatus consisted of a Gateway 7510GX laptop with a 2.4 GHz processor, 1.0 GB of RAM, 15-in. monitor and built-in speakers.

5.1.3 Materials and Apparatus - Empathizer

For each empathizer pre-experiment paper-and-pencil materials consisted of a demographic survey, Davis' Interpersonal Reactivity Index questionnaire, a two-paged background on emotions and empathy, and an empathizer controls reference sheet. Post-experiment paper-and-pencil materials consisted of a survey inquiring about the emotions used/unused, other emotions that could have been useful, and general opinions regarding affect in applications, such as games. The demographic survey collected basic information such as gender, age, ethnicity, marital status, and number of children. Before empathizers began training, they completed Davis's Interpersonal Reactivity Index (IRI) to gain a measure of their empathy [Davis 1983].

The IRI consists of 28 statements in which respondents are instructed to rate the degree to which each item describes them on a Likert scale of 0 to 4. The result is a set of 4

subscale values pertaining to the following qualities of empathy: fantasy, perspective taking, empathetic concern and personal distress [Davis 1994]. These empathetic qualities are described below:

- *Fantasy scale.* The fantasy scale refers to tendency one has to immerse themselves into fictional situations.
- *Perspective taking.* Perspective taking measure indicates tendency one has to adapt to the psychological point-of-view of others.
- *Empathetic concern.* Empathetic concern reflects tendencies to have feelings of sympathy and compassion when others experience unfortunate circumstances.
- *Personal Distress.* Person Distress describes the general discomfort and distress one experiences in response another's distress.

The computerized materials consisted of a spectator view (third person point of view) of the 3D virtual environment, Treasure Hunt, that target trainers would be interacting in. Empathizers did not view target trainer practice tasks and they were not informed of the degree of difficulty.

The empathizer apparatus consisted of a Gateway 7510GX laptop with a 2.4 GHz processor, 1.0 GB of RAM, 15-in. monitor and built-in speakers.

5.2 Procedure

Each training target participant entered a conference room and was seated in front of a laptop computer. First, target participants completed the demographic survey at their own rate. Concurrently, empathizers entered a second room and were seated in front of another laptop

computer. Training targets were unaware of the empathizer's participation at this point. Empathizers were only aware that a target training participant was in the next room. There was no contact between the participants at any point disabling the empathizers' ability to distinguish any characteristics of the target trainer other than those assumed from the interaction portrayed on their monitor. Empathizers also first completed the same demographic survey as the targets, also at their own pace. Next, empathizers completed Davis' IRI questionnaire at their own rate while targets were given the Half-Life 2 controls reference sheet to read until the practice task was loaded on the laptop in front of the target. Once loaded target trainers were able to complete the practice task at their own rate until the task was accomplished. At this point empathizers were given the emotion and empathy reference sheet and instructed to read over the definitions and empathizer controls. Next, one of the degrees of difficulty was randomly selected and that Treasure Hunt training environment was loaded on the target machine while the spectator view application was concurrently loaded on the empathizer machine.

Once the training environment was loaded target trainers had 7 minutes to explore the environment and collect treasure. Empathizers viewed the interaction and made empathetic behavior decisions by selecting the appropriate control for the affective state they desired the companion agent to have. When empathetic behaviors were selected by the empathizer, both participants had the opportunity to hear the companion agent's spoken language and see the associated gestural behaviors and posture. Upon completion of the 7 minute training session, both training targets and empathizers were given post-session surveys and were interviewed. Finally, target trainers were offered information about the details of the experiment and

informed about the presence of the empathizer during the training session.

The following procedural steps were used to generate models of empathy from the training sessions (Figure 5-1 presents the evaluation data flow):

- **Data Construction.** Each session log, containing 6,000 – 9,000 observation changes, was first translated into a full observational attribute vector. For example, if a treasure box came into view (and all other observable attributes remained constant) then the observational attribute vector would modify the previous vector to account for the noted change.
- **Data cleansing.** After data was converted into the observational attribute vector format the data was ready to be cleaned. This step included generating the dataset containing only records in which the empathizer selected an empathetic emotion.
- **Naïve Bayes classifier and Decision Tree analysis.** Once the dataset was ready it was loaded into the Weka machine learning package [Witten and Frank 2005], a naïve Bayes classifier and decision tree were learned, and tenfold cross-validation analyses were run on the resulting models. The entire dataset was used to generate models for empathetic assessment (when to be empathetic) and empathetic interpretation (how to be empathetic). Empathetic assessment is determined using the entire dataset, while empathetic interpretation is determined from a transformed dataset containing only empathetic records.

The following section presents the results of the naïve Bayes and decision tree classification models and describes statistical analyses of the training sessions.

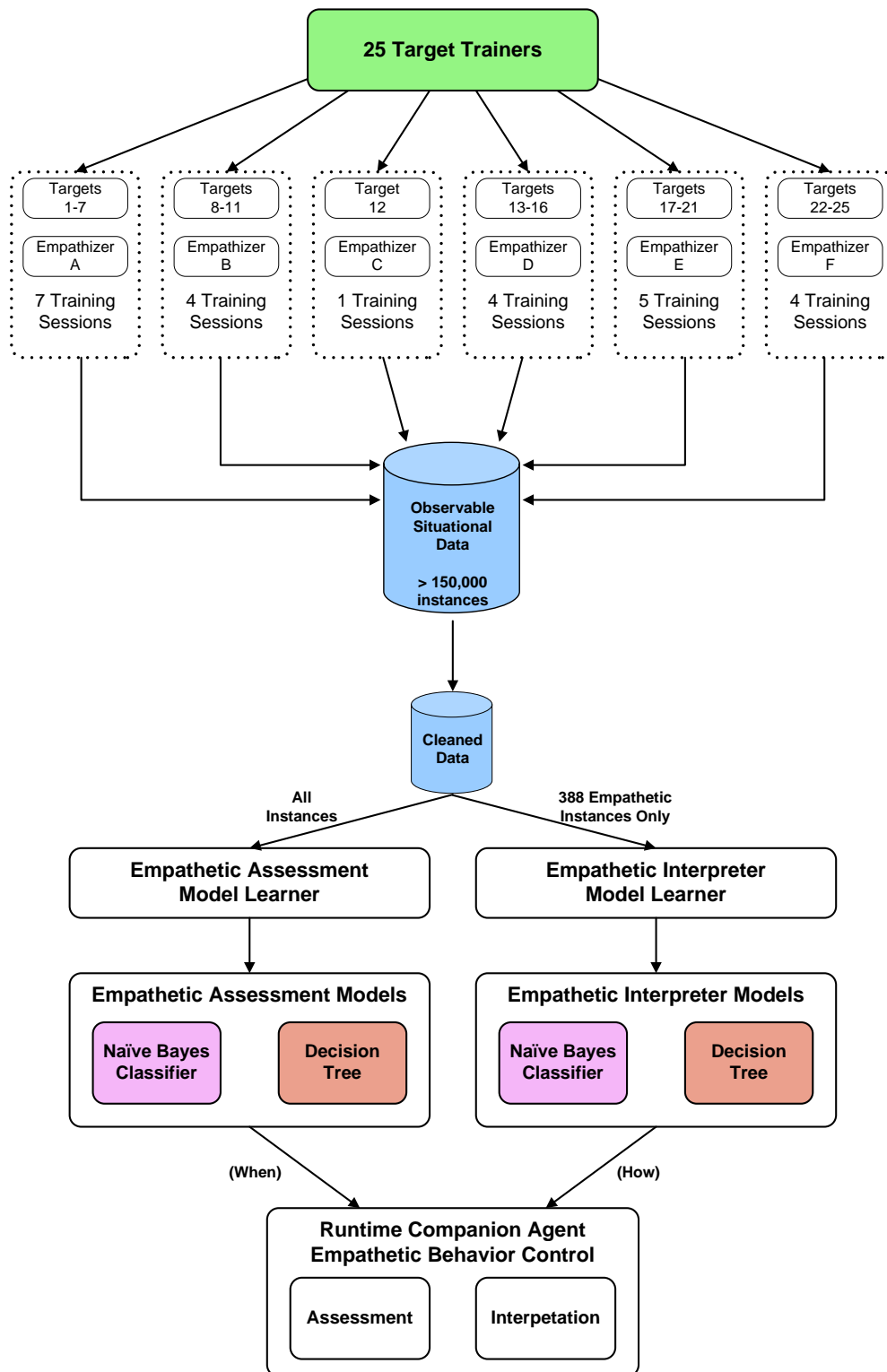


Figure 5-1 Evaluation Data Flow.

5.3 Results

The following sections report results from the training sessions and on the performance of constructed models of empathetic assessment and empathetic interpretation.

5.3.1 IRI Empathy Instrument Results

Female empathizers scored higher than male empathizers on the pre-experiment Davis Interpersonal Reactivity Index, in each quality except for perspective taking. Males averaged one-half point higher than the female empathizers for perspective taking. Subjects were found to be representative of the general population in empathetic characteristics [Davis 1983]. Figure 5-2 reports the IRI results for each empathizer. IRI results are also reported by subscale (Figure 5-3), and by subscale and gender (Figure 5-4). Empathizer 2 was deemed the most likely to be empathetic based on Davis' index. This empathizer chose to be empathetic 93 times over 4 training sessions, significantly more than the 72 empathetic selections of Empathizer 6 over 4 training sessions. Furthermore, Empathizer 2 chose to be "excited" 55 of 93 empathetic selections. In all, "excited" was chosen 119 times across the 25 training sessions, one-half stemming from Empathizer 2. All emotion frequencies are reported in Figure 5-5. Figures 5-6 and 5-7 examine affect frequencies by gender, and average emotion frequencies per training session by gender. From the figures on the following pages it is evident that female empathizers were more likely to be empathetic and more likely to use the extreme emotions: *excited*, representative of positive valence and high arousal, and *sad*, representative of negative valence and low arousal. Male empathizers were less likely to venture too far from the origin of the two-dimensional affective space, using the emotions fear, frustrated, relaxed and joyful much more than excited and sad.

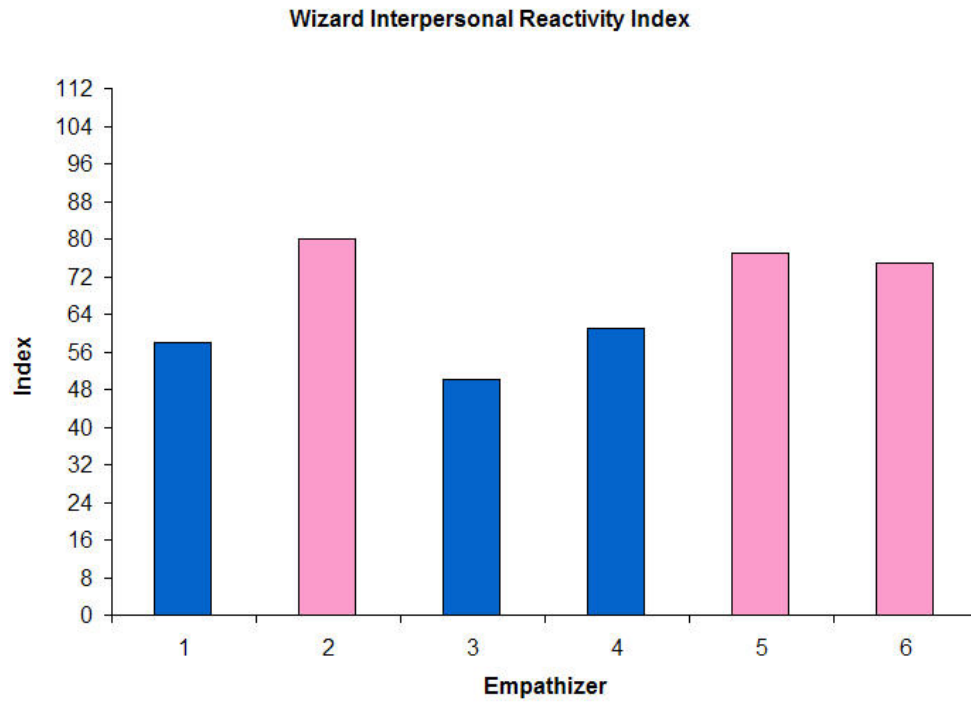


Figure 5-2: Individual Empathizer IRI Results.

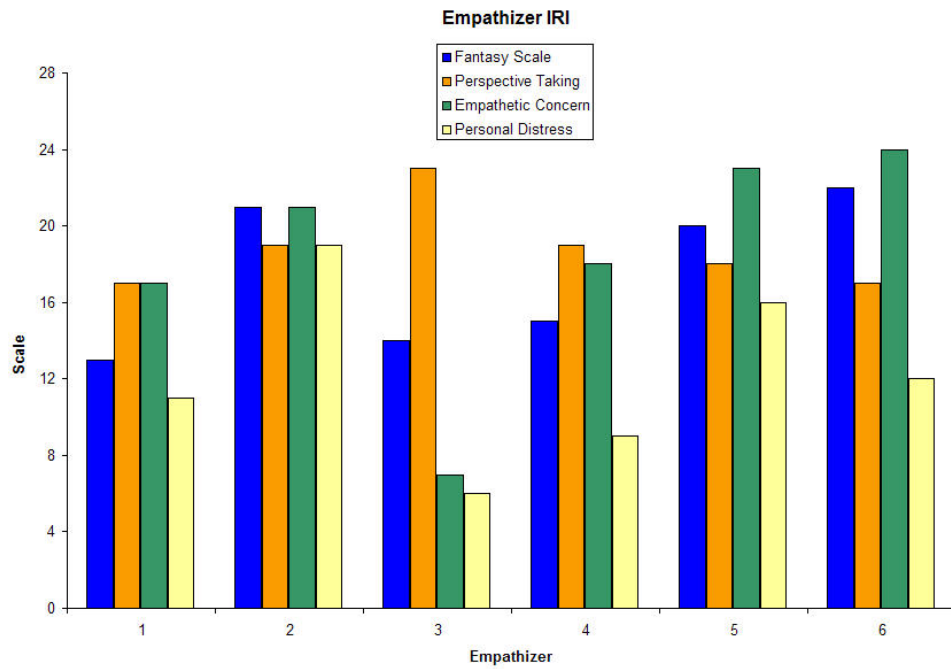


Figure 5-3: Individual Empathizer IRI Subscale Results.

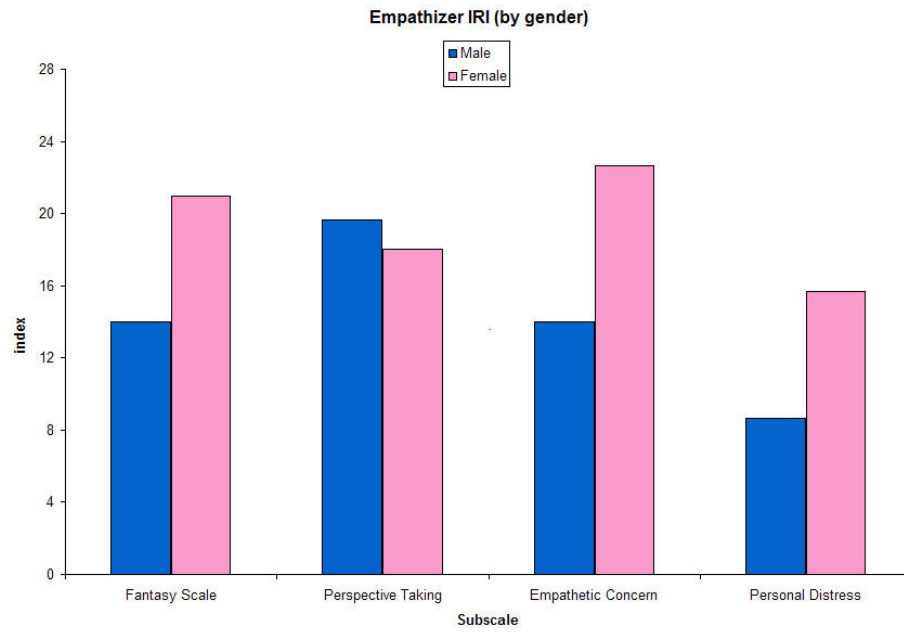


Figure 5-4: Average Empathizer IRI Subscale Results by Gender.

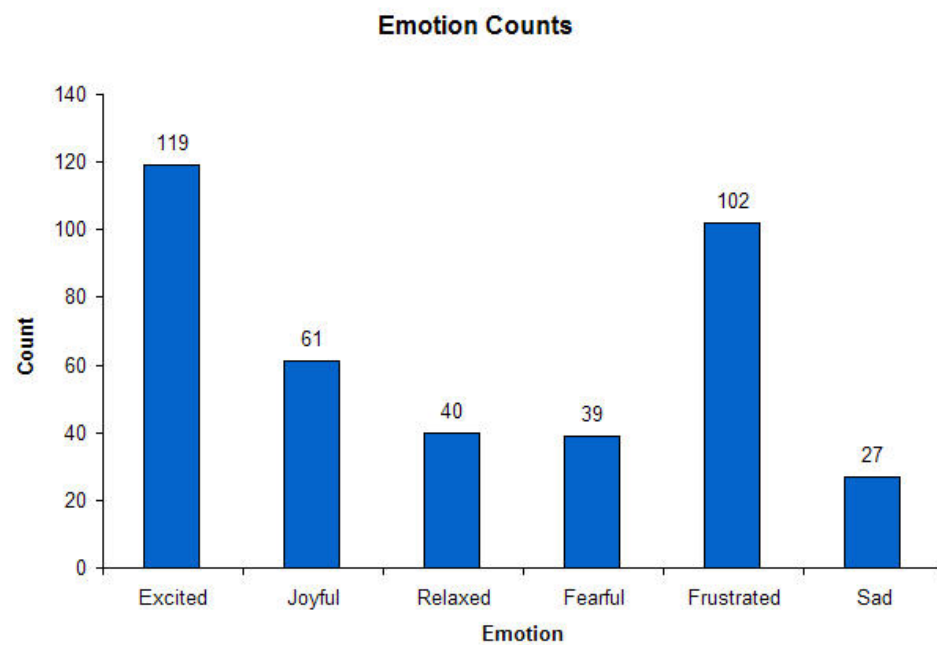


Figure 5-5: Affective State Frequencies from 25 Training Sessions.

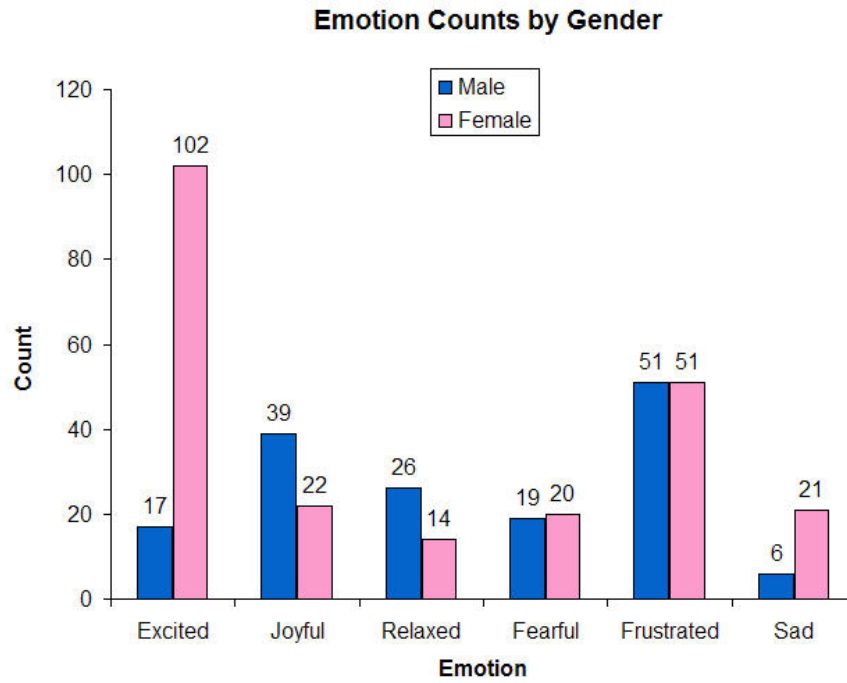


Figure 5-6: Affective State Frequencies by Gender.

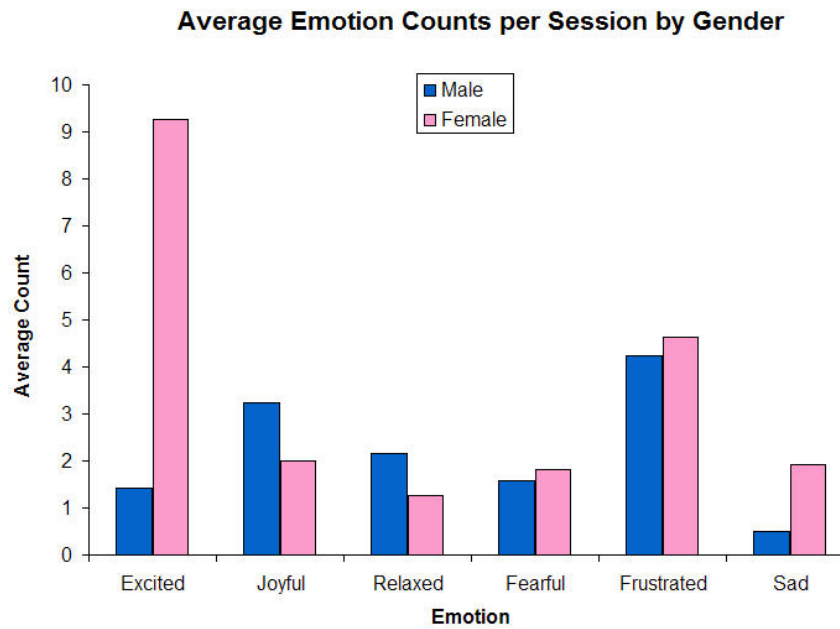


Figure 5-7: Average Affective State Frequencies by Gender.

5.3.2 Model Results

Models were induced from data collected in the training sessions described above. As noted earlier, 192 observational attributes were used to define the feature vectors. Figure 5-8 shows the ROC curves for CARE's naïve Bayes and decision tree approaches for modeling empathetic assessment. Figures 5-10 through 5-13 show ROC curves for CARE's naïve Bayes and decision tree approaches for empathetic interpretation modeling. Associated areas under the curve can be found in the figures' captions. Additional tables and figures reporting the statistical performance of the models below can be found in Appendix A.

Cross-validated ROC curves are useful for presenting the performance of classification algorithms for two reasons. First, the curve represents the positive classifications (true positives), included in a sample, as a percentage of the total number of positives along the vertical axis, against the negative classifications (false positives) as a percentage of the total number of negatives [Witten and Frank, 2005]. Second, the area under the ROC curve has widely been accepted as a generalization of the measure of the probability of correctly classifying an instance [Hanley and McNeil 1982].

Two categories of functionality can be distinguished. First, the decision tree classifier was best suited for modeling empathy assessment, i.e., it was better able to determine *when* to be empathetic (Figure 5-8). The first several levels of the decision tree for empathetic assessment are presented in Figure 5-9. The depth of the decision tree constructed for empathetic assessment surpasses 1,000-levels. However, many of the decision trees constructed for empathetic interpretation were much shallower. For instance, empathizers tended to select the affective state *fearful* most often when the target trainer appeared in the *dark*

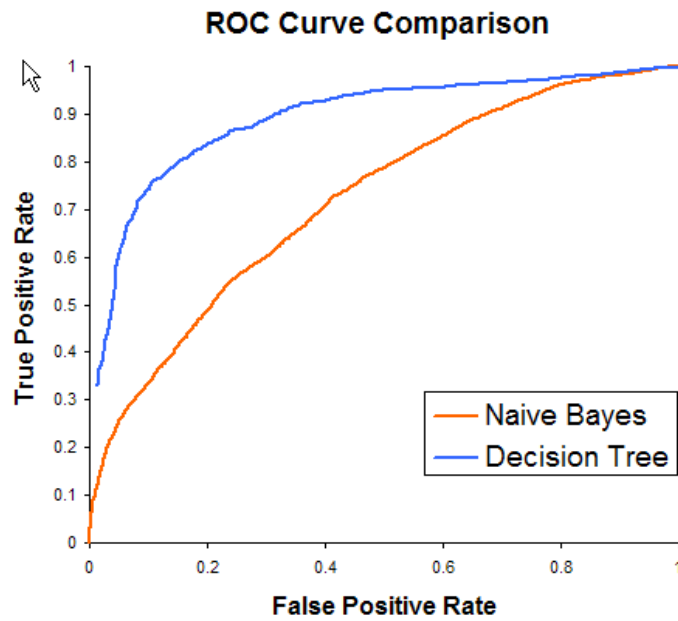


Figure 5-8: ROC Curves for Empathetic Assessment. The ROC curves for each model predicting assessed empathetic behavior triggers in a ten second interval. The area under the Naïve Bayes curve is 0.72 and the area under the Decision Tree curve is 0.89.

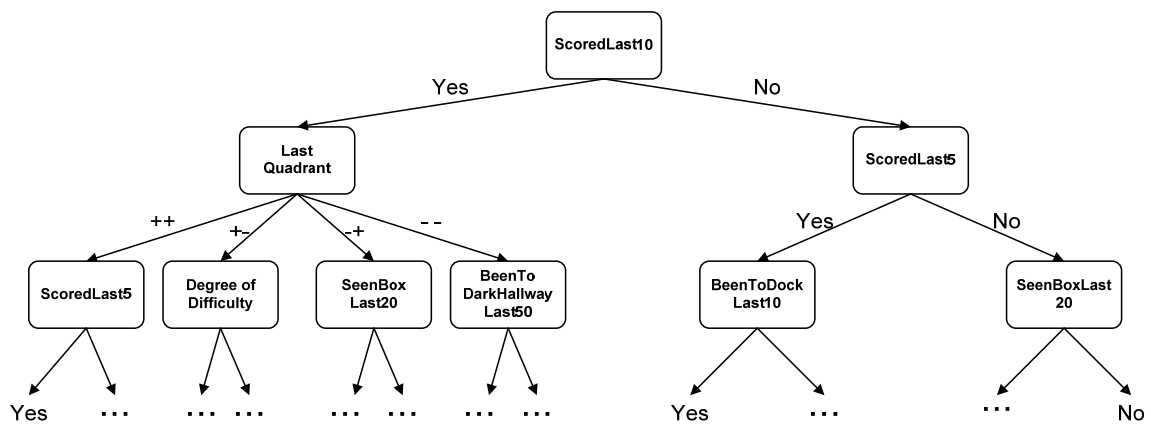


Figure 5-9: Partial decision tree for empathetic assessment.

hallway of the Treasure Hunt virtual environment. This locational feature coupled with several other observational attributes were used to construct shallower decision trees compared to the decision tree (Figure 5-9) for determining *when* to be empathetic.

Second, the naïve Bayes classifier was best suited to modeling empathy interpretation, i.e., it was better able to determine *how* to be empathetic. The smoothness of the curve in Figure 5-8 indicates that sufficient data seems to have been used for training empathy assessment, while the jaggedness of the curve in the empathetic interpretation ROC graphs (Figures 5-10 through 5-13) indicates that more data covering a larger space of situations is called for in training empathy interpretation.

Many empathizers only rarely used particular emotions, e.g., sad, and some trainers suggested that having more affective states available would have been helpful. In general, however, it appears that effective classifiers can indeed be learned for both empathy assessment and empathy interpretation.

All six emotions were evaluated and the naïve Bayes classifier bested the decision tree classifier in every case (Figures 5-10a through 5-10f). Areas under the curve can be found in Table 5-1.

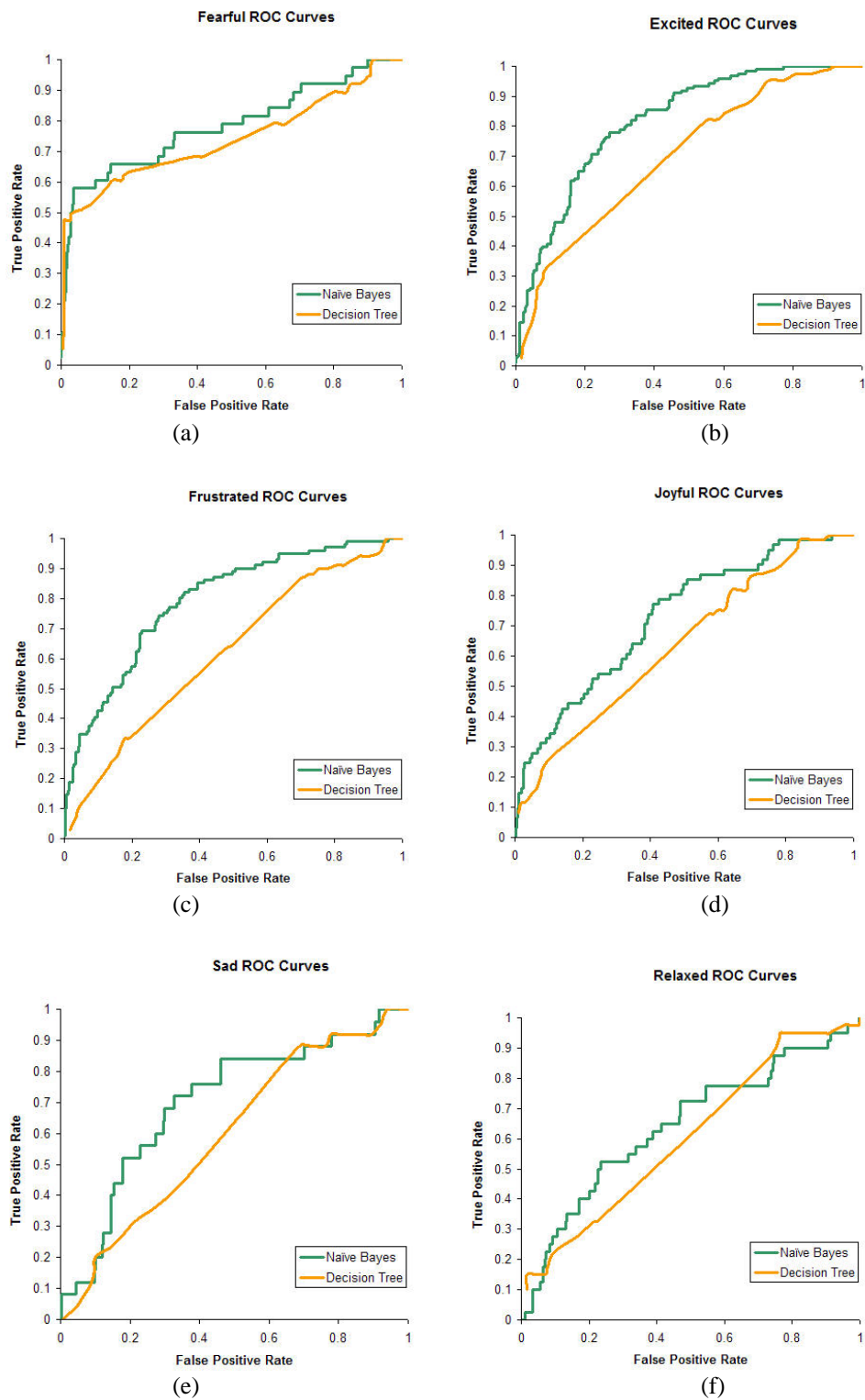


Figure 5-10: ROC Curves for Empathetic Interpretation (Emotions).

Table 5-1: Areas under ROC curves in Figure 5-10.

| Emotion | Area under naïve Bayes ROC curve | Area under decision tree ROC curve |
|----------------|---|---|
| (a) Fearful | 0.74 | 0.66 |
| (b) Excited | 0.80 | 0.56 |
| (c) Frustrated | 0.78 | 0.56 |
| (d) Joyful | 0.69 | 0.56 |
| (e) Sad | 0.69 | 0.50 |
| (f) Relaxed | 0.57 | 0.51 |

Of course, there are other ways to classify empathetic interpretation other than into individual the emotions. One such classification is to determine the valence (positive or negative) of the interpretation in conjunction with a separate model determining the arousal (High, Medium, or Low) (Figures 5-11 and 5-12). Areas under the curves present in the figures can be found in table 5-2. The naïve Bayes classifier also outperformed the decision tree for both determining valence and arousal, also likely due to the amount of data available.

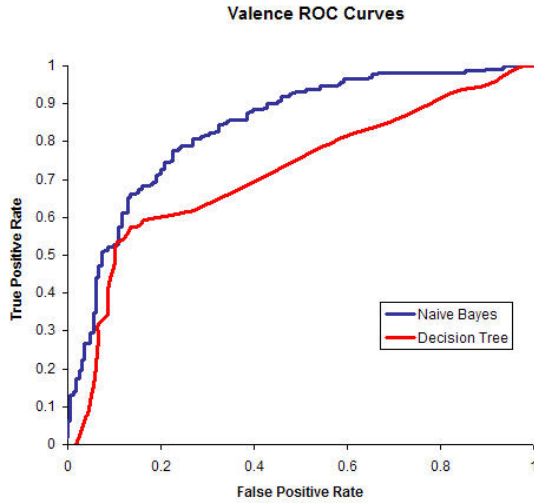


Figure 5-11: ROC Curves for Empathetic Interpretation (Valence). Prediction of positive valence.

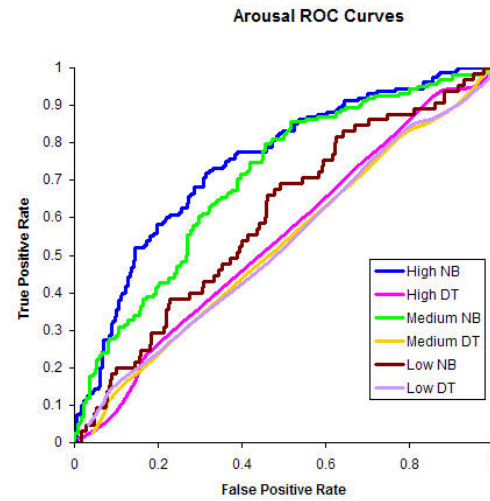


Figure 5-12: ROC Curves for Empathetic Interpretation (Arousal). Prediction of high, medium, or low arousal.

Table 5-2: Areas under ROC curves in Figures 5-11 and 5-12.

| Classification of: | Area under naïve Bayes ROC curve | Area under decision tree ROC curve |
|--------------------|----------------------------------|------------------------------------|
| Positive valence | 0.84 | 0.74 |
| Negative valence | 0.84 | 0.74 |
| High arousal | 0.75 | 0.54 |
| Medium arousal | 0.70 | 0.52 |
| Low arousal | 0.60 | 0.53 |

Yet another classification of emotions that can be used to determine how to be empathetic is by determining the quadrant of the two-dimensional affective space [Lang 1995] the affective state should come from (Figures 5-13a through 5-13d). Areas underneath these curves can be found in table 5-3.

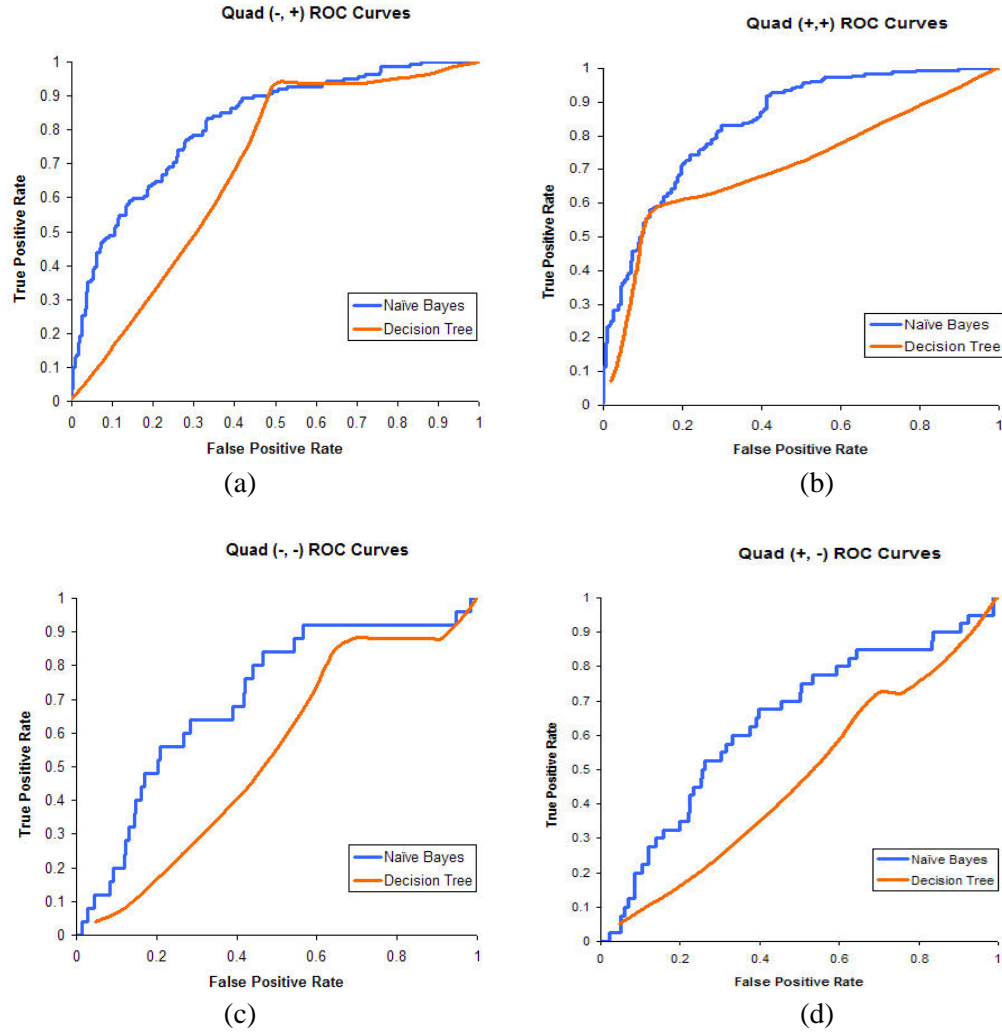


Figure 5-13: ROC Curves for Empathetic Interpretation (Quadrant). Predicting empathetic interpretation as a quadrant of the two-dimensional affective space.

Table 5-3: Areas under curves in Figure 5-13.

| Quadrant | Area under naïve Bayes ROC curve | Area under decision tree ROC curve |
|------------------------------------|----------------------------------|------------------------------------|
| Positive valence, Positive arousal | 0.84 | 0.71 |
| Positive valence, Negative arousal | 0.64 | 0.49 |
| Negative valence, Positive arousal | 0.82 | 0.69 |
| Negative valence, Negative arousal | 0.70 | 0.54 |

5.4 Discussion

The results clearly demonstrate that a decision tree classification approach is sufficient for modeling empathetic assessment and that significantly more training is needed to produce large quantities of empathetic instances for the same approach to have such compelling results for empathetic interpretation. Although, naïve Bayes makes the assumption that all attributes of the observational attribute vector are independent – this assumption is false – it nonetheless induces a model sufficient for controlling empathetic interpretation in companion agents.

Only 388 instances were available for modeling empathetic interpretation. Collecting more data would likely improve the predictability of the decision tree classifier for interpreting *how* to be empathetic. We speculate that for this reason, the decision tree classifier was outperformed by the naïve Bayes classifier for modeling empathetic interpretation. Although more data would likely improve decision tree classification it is unclear whether more data would increase the *true positive rate* of the decision tree model such that it would surpass that of the naïve Bayes classifier.

The empathetic assessment models had over 10,000 instances from which to learn from; a significantly larger dataset. There was a sufficient amount of collected data to generate naïve Bayes and decision tree models of empathetic assessment while the transformed dataset of empathetic records seems to have been insufficient for decision tree models of empathetic interpretation.

Table 5-4: Empathizer Suggested Empathetic Emotions.

| | |
|--------------------|-----------------|
| Angry (2) | Curious (2) |
| Annoyed (2) | Encouraging (1) |
| Bored (1) | Relieved (1) |
| Confused (3) | Worried (1) |
| Congratulatory (1) | |

Part of the post-experiment experience for target trainers was to answer several oral questions posed by the researcher. One such question concerned the target trainer's expectations of the companion agent's role contrasted with the role the companion agent portrayed in actual training. An overwhelming majority of target trainers expected the companion to play the role of a guide, or at least be able to make constructive comments concerning exploration by providing some form of assistance or advice. Some target trainers expected the companion agent to explore the world on her own, dividing the task between the user and the companion agent. Most target trainers described the companion agent as providing comic relief based on the current situation and still others commented that the companion agent provided emotional commentary throughout the interaction. We revisit this issue in the future work of Chapter 7.

In post-interviews with empathizers it was discovered that up to an additional set of 4 emotions, for a set of set of 10 emotions, would have been preferred. Only one empathizer responded that they would not have preferred any more empathetic emotions be available. Table 5.4 lists the additional empathetic affective states that empathizers expressed interest in having at their disposal. The number in parentheses represents the number of empathizers

suggesting the emotion as an additional empathetic affective state choice.

Three empathizers expressed, in post-experiment interviews, that they wished they could have experienced the target trainers' response. Empathizers expressed that from solely watching the interaction, assessing only situational context, it was difficult to judge the impact of their empathetic selections.

One empathizer expressed an interesting view in the process they used to determine which empathetic emotion to select. They described their thinking as follows, "I tried to think of what the user's (target trainer's) character was feeling and how my character (the companion agent) felt and should respond." This perspective is an interesting one because it points to immersion of not only the empathizer, but the target trainer as well, and that empathetic assessment and interpretation were embedded completely within the virtual environment. Another direction for future work discussed in Chapter 7 is to investigate the sense of immersion created when a user, in this case the empathizer, is thinking empathetically. It seems that eliciting users to be empathetic may draw them deeper into the virtual environment.

Chapter 6

Related Work

The complexity of empathy as a construct prohibits models of affect, such as OCC [Ortony *et al.* 1988] and Smith and Lazarus [Smith and Lazarus 1990; Lazarus 1991] from effectively covering the range of empathetic behaviors permitted by our definition of empathy [Hoffman 2000]. The OCC and Smith and Lazarus models are sufficiently expressive to model the affective state of an individual agent in situations inhabited solely by that same agent. As the complexity of social situation increases (e.g., more agents) so to does the complexity of empathetic assessment and interpretation, making it less deterministic as to how one should feel, or may feel. Thus, the empirical approach to modeling empathy in combination with either OCC [Ortony *et al.* 1988] or Smith and Lazarus [Lazarus 1991] may lead to more effective models of affect, especially for socially enriched situations where empathy occurs.

Section 6.1 presents work on believable characters and virtual humans. Section 6.2 discusses work on affective agents such as pedagogical agents, learning companion agents, and embodied conversational agents. Chapter 6 concludes with a discussion of socially

intelligent synthetic agents including several projects that have investigated empathy.

6.1 Believable Characters

The architecture of Oz [Bates *et al.* 1994; Bates 1994; Reilly and Bates 1992] includes and generates a simulated physical world, multiple characters, an interactor, a theory of presentation, and a drama manager. Oz also presents an emotion modeling system [Reilly and Bates 1992] which is based on OCC [Ortony *et al.* 1988]. The emotional model takes a clustering approach where emotions are placed into clusters of emotion types with other emotions that share similar causes [Reilly and Bates 1992]. For example, the distress emotional type includes the emotions of sad, distraught and lovesick which differ on intensity and situation types but share similar causes. The emotional model is based on three types of subject appraisals suggested in [Ortony *et al.* 1988]: (1) the pleasingness of events in respect to desired goals, (2) approval of actions with respect to a set of standard behaviors, and (3) the appraisal of liking certain objects with respect to attitudes. In addition [Ortony *et al.* 1988] proposed another set of emotions which are the result of other emotional combinations [Reilly and Bates 1992]. The emotions resulting from this model that [Reilly and Bates 1992] explores include: joy, distress, hope, fear, pride, shame, admiration, reproach, anger, gratitude, gratification, and remorse. The emotional model bases its decisions on the success or failure of goals and the events that may have led to the success or failure. The emotional model creates an affective state for an agent which is used to influence the agent's behavior. This work is one of the first attempts to apply emotional modeling schemes from outside disciplines to influence the behavior of agents in a computer system. The emotions explored

in the Oz project through the emotional model described by Reilly have led to increased believability in agents and a more intensive immersion in the virtual environments. We believe that introducing empirically-grounded models of empathy, such as CARE, into Oz-like environments would increase the believability of agents.

EMA, an emotional model based on Smith and Lazarus' Appraisal Theory of emotion has been implemented by [Gratch and Marsella 2001; Gratch and Marsella 2004a; Gratch and Marsella 2004b; Marsella and Gratch 2003]. Recall that Smith and Lazarus' theory centers on the cycle of event appraisal and selection of coping strategies. EMA has been implemented in Mission Rehearsal Exercise (MRE), a system that is designed to train military officer candidates in decision-making in highly volatile situations [Gratch and Marsella 2001; Gratch and Marsella 2004a; Gratch and Marsella 2004b; Marsella and Gratch 2003]. The user immersed in a virtual learning environment experiences typical sights, sounds and events found in mission circumstances [Gratch and Marsella 2001]. She acts as the commanding officer in the situation with all other soldiers, enemies and civilians controlled by agents. Each agent is controlled by the EMA emotional model, which increases the believability and realism of the characters, the environment and the situation [Gratch and Marsella 2001; Gratch and Marsella 2004b]. The point of the exercise is to compel the user to assess the situation and make an effective decision in a short amount of time. Adding emotional factors, such as a crying citizen upset by her son's (also a citizen) injury in the virtual Bosnian village, makes the training more life-like and as educational as possible without requiring the commanding officer to actually experience the mission physically.

MRE has several opportunities to exploit empathy: (1) in its users and (2) in its accompanying agents. Users of MRE are faced with tense, emotionally-high situations, like the one described above with the emotionally expressive mother. Whether commanding officers have the opportunity to be empathetic, they are faced with an empathetically assessable situation. There are additional agents in the MRE virtual environment exposed to the same situational context, witnessing the same events as the user.

Although Gratch and Marsella use Smith and Lazarus' model of affect they do not account for empathetic situations which seem readily available in MRE. There certainly is an opportunity to exploit empathy as a social construct in their work. Incorporating empirically grounded models of empathy into EMA would allow citizen agents to empathize with the soldiers in the environment and with the user.

6.2 Affective Agents

Several recent projects have been conducted on affective agents. Below we discuss pedagogical agents, learning companion agents, and embodied conversational agents.

6.2.1 Pedagogical Agents

The Soar Training Expert for Virtual Environments (STEVE) is a pedagogical agent cohabiting virtual environments with students learning to perform physical, procedural tasks such as operating complex devices [Johnson and Rickel 1998; Rickel and Johnson 1999]. Steve was developed in collaboration between the Center for Advanced Research in

Technology for Education, Lockheed AI Center and USC Behavior Technology Laboratories. Steve's goals for a particular situation may include engaging the user, and teaching the user so that the user performs better over time [Johnson and Rickel 1998]. From such goals Steve exhibits emotions of caring about the user and desiring to ensure successful learning. Steve is happy-for the student when the student successfully completes a task and is disappointed when the student fails. A goal of the user exhibiting caution is an indication that possible actions would include fear of possible future actions and/or hope of the user performing possible actions [Johnson and Rickel 1998]. Steve not only is able to simulate the expression of motion, but through its procedural tasks, it invokes emotions in the user.

Herman-the-Bug inhabits Design-A-Plant, a knowledge-based learning environment used to explore interactive problem solving in the domain of botanical anatomy and physiology, with an animated pedagogical agent [Elliott *et al.* 1999; Lester *et al.* 2000]. Herman-the-Bug employs an affective user modeling architecture [Lester *et al.* 2000]. Herman-the-Bug appraises the world allowing him to interpret situations that arise which may invoke emotional responses [Lester *et al.* 2000]. The agent maintains emotional models about the fortune of its users, including enjoyment and happiness when goals are met [Lester *et al.* 2000]. Herman-the-Bug maintains structures which monitor user goals, principles and preferences and supports inferences concerning motivations and pleasure which can be used by Herman-the-Bug to produce emotional expressions to encourage a user [Lester *et al.* 2000].

The Prime Climb educational game [Conati 2002; Conati and McLaren 2005; Conati and Zhao 2002; Conati and Zhao 2004] addresses affective reasoning with probabilistic

approaches. Prime Climb investigates using affective user models derived from probabilistic approaches in educational games [Conati 2002]. It makes use of dynamic Bayesian networks to detect a variety of affective states based on the OCC model [Ortony *et al.* 1988]. Prime Climb links detected personality traits (extraversion, agreeableness, and conscientiousness) directly to goals associated with the math game [Conati 2002]. Bodily expression of emotion is measured, including eyebrow tracking, skin conductivity and heartbeat, while probabilities determine which trait is portrayed by a given set of measurement values [Conati 2002]. While such techniques are very representative of internal affective states and, in this case, personality traits building deployable systems cannot rely on the “wiredness” required by this implementation. Using “wired” approaches are useful for inducing models based on internal system features.

To date six studies evaluating the impact of affective interface agents on both affective and motivational outcomes based a number of factors including gender, ethnicity and realism of the agent have been conducted by Amy Baylor [Baylor 2005]. The first study asked 183 participants (undergraduates) to select the desired instructor from eight pedagogical agents. Participants were immediately asked to explain their selection. The responses cited perceived demeanor, gender, instructor-looking characteristics and ethnicity. Regression results discovered that the participants tended to select an instructor who was the same ethnicity. The second test randomly assigned agents and examined motivational outcomes such as self-regulation and self-efficacy. Other studies focused on expert agents vs. motivating agents and investigated tradeoffs between genders and ethnicity. The final two studies focused on non-human-like agents categorized by color, shape aliveness and

complexity. The first looked into associated meanings of agent images by asking participants what they thought the displayed figure was. Responses were categorized as either an emotion-related (sad, happy) or word association (spoon, dinosaur) response. The more complex the agent the more likely participants were to match the agents with their intended meanings. The last study focused on the role of color and shape. Color was determined to have a very low impact if any while the more complex the shape (fish and dog, vs. a geometric shape) the more the likely the agent was perceived as instructor-like. All six of Baylor *et al.*'s studies indicate that characteristics such as gender, ethnicity, and realism are influential agent characteristics affecting student learning experiences, in particular student affect and motivation [Baylor 2005].

6.2.2 Learning Companions

The Affective Learning Companion project at MIT [Burleson and Picard 2004] is focused on monitoring user physiological signals to determine frustration, which is used to trigger learning support. This approach allows learners to sink into states of impasse and only intervening at points where the learner becomes “stuck” [Burleson *et al.* 2004; Burleson and Picard 2004; Picard 1997]. The affective learning companion makes use of input from a variety of affective and physiological sensors including cameras for facial feature expression and eye gaze detection, seat pressure pads to detect posture, galvanic skin response, pressure mouse and game state [Burleson and Picard 2004]. An affective agent in the learning environment is able to sense user's emotion and respond by expressing its own emotion. The Affective Learning Companion project focuses on motivating students through states of

failure and frustration, required phases for becoming an expert, and in particular focus on the characteristics of the affective agent that influence sustaining a high-level of motivation to continue through failure or a state of “stuck” [Burleson and Picard 2004]. This is accomplished through two approaches: (1) manipulating the environment to maintain an optimal experience for the user and (2) promoting self-awareness to users to empower them to self-regulate their own motivation [Burleson *et al.* 2004]. While this work is still in its beginning stages, initial results suggest that the detection mechanisms provide enough detail to determine user affect and that affective agents can positively influence users in maintaining their motivational state and self-awareness.

6.2.3 Embodied Conversational Agents

Focused on modeling multimodal interactions in conversation several projects lead by Justine Cassell, such as REA, have incorporated affect. Gestures, gaze, body posture and vocal intonation have been used in human-computer conversation to replicate the interactions of human-human conversation. The vocal intonation and body posture are bodily experiences that are influenced by emotion. At MIT Cassell along with Timothy Bickmore completed work on relational agents as a conjunction of the Affective Computing Group and the Gesture and Narrative Language Group. This work was interested in building computational relational agents designed to interact and build social-emotional relationships [Cassell and Bickmore 2003]. The work draws largely from materials found in affective computing and plans to investigate affective state recognition. [Cassell and Bickmore 2003] particularly cite

interest in investigating notions of caring and empathetic behaviors as they play an instrumental role in relational strategies and need be considered in their model of social relationships [Cassell and Bickmore 2003].

6.3 Socially Intelligent Synthetic Agents

With demonstrated models of emotion the logical next step for affective reasoning is to create socially intelligent synthetic agents that exploit constructs such as empathy. Below work on synthetic agents that use empathy and politeness are discussed.

6.3.1 Politeness

The Social Intelligence Project led by W. Lewis Johnson is dedicated to producing socially-skilled pedagogical agents. They strive to create agents that are expressive with regard to both emotion and attitude, sympathetic and sensitive to student's motivational states, and are polite, knowing how to appropriately interact in different social contexts. Johnson uses such agents to exploit Reeves and Nass' findings [Reeves and Nass 1996] that people tend to relate to and other media as if such mediums were people. Adele is one of the first agents developed by Johnson. Adele is used in a medical domain setting for teaching medical materials and as an assistant to doctors in clinical workups. Making use of a variety of deictic gestures and head movements Adele is able to communicate in social-normal ways [Johnson *et al.* 2005].

[Johnson and Rizzo 2004] report on a Wizard-of-Oz experiment used to evaluate the

effects of social techniques, in this case politeness strategies, on the self-confidence, interest and motivation of the learner. The results of the experiment will be used to construct models of politeness for pedagogical agents in intelligent tutoring applications [Johnson and Rizzo 2004]. Politeness is a technique used when a socially rich situation assessment calls for reactive empathy. In this case, understanding the need to use positively valenced emotions to effect the learner's motivation and self-confidence is deemed necessary. It is not the case that all instances of politeness can be handled by empathetic assessment and interpretation, but some can. Regardless, [Johnson and Rizzo 2004] and [Johnson *et al.* 2005] clearly identify the type of socially intelligent opportunities that are now available based on the rich models of affect [Ortony *et al.* 1988; Smith and Lazarus 1990; Lazarus 1991].

6.3.2 Generating Empathetic Behaviors

Clark Elliott completed his dissertation, entitled “The Affective Reasoner: A process model of emotions in a multi-agent system” [Elliott 1992], under the guidance of Andrew Ortony, of the OCC model [Ortony *et al.* 1988]. Elliott's Affective Reasoner was, for obvious reasons, based on the OCC model. However, Elliott expanded the OCC model to include 26 emotions, as opposed to the 22 emotions described in the rule-based system of the OCC model [Elliott 1992]. Elliott additionally included jealousy, envy, like, and dislike in his Affective Reasoner implementation. The Affective Reasoner incorporates these emotions into a rule-based system to model multiple software agent personalities and the existing social relationships between the agents [Elliott 1992; Ortony *et al.* 1998]. Elliott modeled three types of social relationships: friendship, animosity and empathy. A friendship among

agents prompts similar valenced emotions. For example, if an agent is *satisfied* with a good grade one could expect the agent's friends to be *happy-for* the agent, both are positive emotions, while *happy-for* is empathetic in nature. Animosity typically provokes oppositely valenced emotions between two agents. The emphasis of his system is work is reasoning about emotions for a social context. The Affective Reasoner does this by using a rule-based rule system for appraising events to determine its own emotions while modeling concern for other agents using a backward, case-based system [Elliott 1992]. It is notable, in the Affective Reasoner project emotional recognition is not solely based on the expression of other agents; rather, the significance of situational context is considered in conjunction with expression to determine other agent's emotions. This point is an important implementation consideration since humans derive their emotions from a number of factors such as past emotion, mood, the emotions of those nearby, and the mood of the environment. Elliott's Affective Reasoner is one the most comprehensive affective projects to date, particularly in a social interaction context.

The Empathic Companion, an animated interface agent, resides in a simulated interview environment providing empathic feedback based on user's affective states [Prendinger and Ishizuka 2005]. Interestingly, the user's affective state is derived from only two physiological sensors measuring skin conductivity and electromyography in real time. Using a Bayesian network, signals distance measurements from a baseline determine user emotion [Prendinger and Ishizuka 2003]. Six emotions are associated with a job interview scenario: sad, frustrated and fear, relaxed, joyful and excited. The agent makes the user aware of negatively valenced emotions in response to interviewer questions. For example, if

the interviewer asks the interviewee if they would mind working unpaid overtime the interviewee may become frustrated and cause the Empathic Companion to intervene and make the user aware of their affective state so that they may cope with such a situation differently if actually presented with such a scenario. No study has yet been conducted to determine the effectiveness of the Empathic Companion; however, Prendinger *et al.* believe from a small experiment that the empathic feedback has a positive effect for the interviewee's management of stress [Prendinger and Ishizuka 2005]. A direction for future work discussed later in this thesis is the inclusion of biofeedback for determining target/user affective state, such as Prendinger has done. The empathetic behaviors used in this application are purely reactive to help cope with stressful questions in an interview. The focus is narrow and does not require the breadth of empathetic behaviors and particularly parallel empathetic behaviors. It would be interesting to see how their author structured model compares to an empirically constructed model of empathy.

6.3.3 Eliciting Empathy from Users

The *FearNot!* Project, headed by Ana Paiva has focused on eliciting empathetic responses in users responding to bullying scenarios depicted in on-screen interactions [Paiva *et al.* 2004; Paiva *et al.* 2005]. It has been reported that the young generation has experienced a decline in emotional intelligence [Goleman 1995], and applications such as [Paiva *et al.* 2005] aim to correct this by eliciting empathetic interaction from the application's users, in this case children. Their work is based on the assumption that creating emotionally charged situations which evoke empathy from users increases agent believability and immersion [Paiva *et al.*

2005]. Empathy in users accomplishes this objective because, by its very nature, empathy requires being immersed in another's perspective. If users are able to allow themselves to feel empathetic towards agents in the world, then they have achieved a level of immersion to be empathetic and increased the believability of the target agent. Using empirical approaches to model empathy for the synthetic agents inhabiting the *FearNot!* environment their approach would allow a greater reciprocation of empathy and further develop believability, because users would be able to recognize other agents as responding to their own affective state and situation.

This section has presented several projects related to the work reported in this thesis. Many successful applications have been constructed containing affective synthetic agents. Many of these agents are able to express emotion, while others are able to recognize emotion in their users and accompanying agents in virtual environments. Only a few of the projects have moved beyond models of affect to explore models that can be used to control intelligent social interactions of synthetic agents. As psychologists progress the understanding of social emotions and constructs, such as empathy, intelligent systems will be able to incorporate more effective models of appropriate social behavior. Without concrete understanding of empathetic assessment and interpretation data-driven approaches which induce empirically informed models of empathy, such as CARE, should suffice.

Chapter 7

Conclusion and Future Work

Recent advances in affective reasoning have demonstrated that emotion plays a central role in human cognition and should therefore play an equally important role in synthetic agents. A key affective capability of human social intelligence is empathy. Because empathy is paramount in successful human-human interactions, it would therefore be useful to endow companion agents who are to accompany users in interactive virtual environments with the ability to empathize. Empathy modeling requires accurately assessing a social context in order to determine (1) if an empathetic reaction is warranted, and (2) if so, what sort of empathetic behavior should be performed.

In addition, there is now a growing understanding and a variety of applications supporting affective behaviors of synthetic agents, such as those discussed in Chapter 6. Coupling models of socially intelligent constructs with expressive controls of agent behavior should promote a new generation of socially, emotionally intelligent synthetic agents in the coming years.

7.1 Summary

We have presented a data-driven approach to learning empirically grounded models of empathy from observations of human-human social interactions. In this approach, training data is first generated as a by-product of trainers' interactions with a virtual environment, and models of empathy are induced from the resulting data sets. Critically, the training data employs only observable features, i.e., features that can be directly observed in the environment, so that at runtime, the same features can be used by the empathy models to drive the behavior of companion agents interacting with users. An evaluation of an implemented data-driven empathy modeler suggests that this empirical paradigm offers a promising technique for extending the affective capabilities of synthetic agents.

7.2 Future Work

Several areas of future work have been uncovered throughout the course of this investigation:

- *Biofeedback.* It will be interesting to explore mechanisms for varying empathetic responses in a manner that is most appropriate for individual users, perhaps integrating them with tools such as socio-psychologically validated empathy response instruments. It will also be interesting to devise integrated methods for employing biofeedback mechanisms with empirically grounded models of empathy to further extend their range and increase their accuracy. Adding additional attributes to the observational attribute vector would supply the model with concrete evidence concerning the user's affective state. Current CARE models may have an assumed

user affective state incorporated since empathizers may or may not have made assumptions about the target's affective state during training sessions. Because considering target affective state is an integral part of the construct of empathy, biofeedback may lead to more robust models of empathy. Furthermore, including biofeedback as part of the empathizer's interface we could monitor the empathizers affective in comparison with the empathetic affective states they choose for their synthetic agent. This could suggest the degree to which the empathizer is immersed in the task indicating whether they are experiencing the emotions they select themselves.

- *Enhanced observation and empathizer interface.* Many technological devices are now available for monitoring physiological changes in addition to biofeedback devices. Such devices include eye gaze tracking, facial feature tracking, posture monitoring, etc. These devices would support an enriched observational attribute vector, although resulting systems would be less deployable. As additional situational data becomes available to the empathy model learner, so too must the information be made available to the training empathizer. This calls for an enhanced empathizer display. For example, if the environment is supplemented with devices to monitor target affective state, the empathizer needs to be supplied with the same information, perhaps as part of a HUD in the empathizer's view of the virtual environment.
- *An empathetic slider.* With only six empathizers it was difficult to conclude any significance made in pattern assumptions regarding empathizer IRI scores [Davis

1994]. However, with substantially more training sessions and additional empathizers one could model empathy based on IRI measures, thereby enabling empathetic companion agents to have their own IRI values manipulated as a basis for producing unique empathetic behaviors, perhaps increasing the number of empathetically appraised situations or controlling affective behaviors are selected. The system would then be empowered to adjust the companion agents internal IRI subscales which would be reflected in the empathetic assessment and interpretation of the agent. Using such manipulations in companions would allow systems to monitor characteristics such as user success and enjoyment and appropriately select proper IRI levels of empathy in agents for particular users.

- *Learning companion and pedagogical agent effectiveness.* Assessing the educational effectiveness of CARE models employed in learning companions and pedagogical agents is an interesting topic for exploration. It has been reported that agent affect has an impact on learners in pedagogical environments [Baylor 2005; Lester *et al.* 1999], which suggests that the addition of social intelligence to affective pedagogical agents, and perhaps to learning companions, may produce even better educational results including an increase in learning effectiveness and efficiency. Furthermore, many target trainers reported expectations that the companion agent in the Treasure Hunt test bed would provide advice or assistance of some form. Clearly, investigating an expansion of the communication functionalities of the companion is an interesting direction of future work.
- *Extending empathetic behavior expressiveness.* Extending CARE companion agents'

expressive abilities is a compelling direction of future work. While the behaviors were not a direct focus of this research because we were only investigating when and with which affective state to be empathetic, behaviors clearly have a strong effect on users. Synthetic agent behavior expression has been a subject of research for others and it is a promising direction here as well.

- *Larger and more expansive datasets.* A comprehensive evaluation of CARE empathetic behaviors requires significantly more training sessions. There were only 388 instances of empathetic affective state selection in the 25 training sessions. Also, if the availability of emotions is expanded, it will require proportionately more training sessions so that each emotion has enough instances for the empathetic interpreter to produce robust models.
- *Tuning machine learning approaches.* Naïve Bayes classifiers and decision tree techniques were used for generating preliminary predictive models of empathy. As we gain a better understanding of which variables are most predictive from these analyses we can narrow the observational attribute vectors dimensionality and pursue more advanced machine learning techniques such as Bayesian networks and neural networks for assessing *when* to be empathetic and then interpreting *how* to be empathetic. Certainly, collecting more data will enable other machine learning algorithms to be practiced.
- *Evaluating empathetic agent personae.* Evaluation of agent personae in conjunction with believability of empathetic reactions is a promising direction for future work. In general, females tend to be more empathetic. This stereotype held in the case of

CARE training sessions. A female empathizer sat at the companion agent controls for only one-half of the training sessions and yet Chapter 5 reported that the female empathizers generated approximately 60% of the empathetic instances from all training sessions. It is therefore interesting to consider the effectiveness of an empathizing companion agent based on the agent's personae.

- *Affective camera and path planning needed.* Whenever an empathetic behavior is performed by the companion agent the user is not forced to look at the companion and therefore may miss some of the effects the companion's display of empathy could have. Adding control for the companion agent to forcefully enter the user's view before performing the empathetic behavior is an interesting topic, perhaps worth future pursuit. Taking control of the user's view is a more intrusive form of enabling the companion agent to perform empathetic behaviors in view. A final approach could to use third-person-point-of-view opposed to the current first-person implementation thereby increasing the peripheral view of the user increasing the view area available to the companion agent.
- *Eliciting empathy.* Similar to Paiva's discoveries [Paiva *et al.* 2005], and empathizer's reports from CARE training sessions empathy in users creates a greater sense of immersion and increases the believability of characters. Eliciting empathy from users of CARE driven applications is an interesting direction for future work to consider, because it would allow empathy to be expressed in both directions creating companions who are empathetic to users and users who are empathetic to companions.

- *Integration of a CARE model of empathy with a computational model of affect.* OCC and Smith and Lazarus models have limited empathetic functionalities. Exploring how CARE models could be coupled with such models of emotions is a critical next step in producing affective, empathetic synthetic agents. Empathetic affective states comprise only a small subset of potential affective states. Thus, CARE could exploit the powerful capabilities of affect models such as OCC and Smith and Lazarus to deploy complete affective synthetic agents.

7.2 Concluding Remarks

Models of empathy for runtime synthetic agent affective behavior control offer significant potential for improving the quality of socially intelligent agent-human interaction and agent-agent interaction. Such models can be utilized in a wide variety of interactive systems inhabited by synthetic agents, including training, education, simulation and entertainment applications. As we begin to better understand the constructs of empathy and further develop models of affect, more complex, comprehensive models of social behavior will be attainable. The proposed inductive approach for modeling empathy in companion agents offers a promising technique for constructing socially intelligent synthetic agents.

References

[Aimeur *et al.*, 2000] Aimeur, E. Frasson, C. and Dufot, H. Cooperative learning strategies of intelligent tutoring systems, *Applied Artificial Intelligence*, 14: 465-489, 2000.

[André and Müller, 2003] André, E., and Müller, M. E. Learning affective behavior. In *Proceedings of the 10th International Conference on Human-Computer Interaction* (Heraklion, Crete, Greece, June 22-27, 2003). Lawrence Erlbaum, Mahwah, NJ, 512-516, 2003.

[Ball and Breese, 2000] Ball, G. and Breese, J. Emotion and Personality in a Conversational Agent. *Embodied Conversational Agents*. J. Cassell, J. Sullivan, S. Prevost and E. Churchill, eds. MIT Press: 189-219, 2000.

[Bates et al., 1994] Bates, J., Loyall, A.B., and Reilly, W.S. An architecture for action, emotion, and social behavior. In *Artificial Social Systems: Proceedings of fourth European Workshop on Modeling Autonomous Agents in a Multi-Agent World*. Springer-Verlag. 1994.

[Bates, 1994] Bates, J. *The role of emotion in believable agents*. Report CMU-CS-94-136, Carnegie Mellon University, 1994.

[Baylor, 2005] Baylor, A.L. The impact of pedagogical agent image on affective outcomes. In *Proceedings of Workshop on Affective Interactions: Computers in the Affective Loop, International Conference on Intelligent User Interfaces* (San Diego, CA January 9-12), 2005.

[Baylor, 2002] Baylor, A.L. Agent-based learning environments for investigating teaching and learning. *Journal of Educational Computing Research*. 26(3), 249-270, 2002.

[Baylor and Kim, 2004] Baylor, A.L., and Kim, Y. Pedagogical agent design: The impact of agent realism, gender, ethnicity, and instructional role. In *International Conference on Intelligent Tutoring Systems*, Maceió, Brazil, 2004.

[Baylor and Ryu, 2003] Baylor, A.L. and Ryu, J. The effects of pedagogical agent voice and animation on learning, motivation and perceived Persona. *ED-MEDIA*, Honolulu, Hawaii, 2003.

[Bickmore, 2003] Bickmore, T. *Relational agents: Effecting change through human-computer relationships*. Technical Report, PhD Thesis, MIT Media Lab, 2003.

[Burleson and Picard, 2004] Burleson, W. and Picard, R.W. Affective agents: Sustaining motivation to learn through failure and a state of stuck. In *Social and Emotional Intelligence in Learning Environments Workshop In conjunction with the 7th International Conference on Intelligent Tutoring Systems*, Maceio - Alagoas, Brasil, August, 2004.

[Burleson et al., 2004] Burleson, W., Picard, R.W., Perlin, K., and Lippincott, J. A platform for affective agent research. In *Proceedings of third international joint conference on Autonomous Agents and Multi-Agent Systems*, Columbia University, New York, NY, July 2004.

[Cassell and Bickmore, 2003] Cassell, J., and Brickmore, T. Negotiated collusion: Modeling social language and its relationship effects in intelligent agents. In *User Modeling and User-Adapted Interaction* 13(1-2), pp. 89-132, 2003.

[Cavalluzzi et al., 2003] Cavalluzzi, A., De Carolis, B., Carofiglio, V., and Grassano, G. Emotional dialogs with an embodied agent. *User Modeling* 2003: 86-95.

[Cavazza et al., 2002] Cavazza, M., Charles, F., and Mead, S.J. Interacting with virtual characters in interactive storytelling. In *Proceedings of the 1st International Conference on Autonomous Agents and Multi-Agent Systems* (Bologna, Italy, July 15-19). ACM Press, New York, NY, 318-325, 2002.

[Chan and Baskin, 1990] Chan, T.W. and Baskin, A.B. Learning companion systems. In Frasson, C. and Gauthier, G. (eds.), *Intelligent Tutoring Systems: At the Crossroads of Artificial Intelligence and Education*, chapter 1, 1990.

[Conati, 2002] Conati, C. Probabilistic assessment of user's emotions in educational games. *Applied Artificial Intelligence*, 16:555-575, 2002.

[Conati and McLaren, 2005] Conati, C., and McLaren, H. Data-driven refinement of a probabilistic model of user affect. In *Proceedings of the 10th International Conference on User Modeling* (Edinburgh, Scotland, UK, July 23-29). Springer-Verlag, New York, NY, 40-49, 2005.

[Conati and Zhao, 2004] Conati, C. and Zhao, X. Building and evaluating an intelligent pedagogical agent to improve the effectiveness of an educational game. In *Proceedings of International Conference on Intelligent User Interfaces*, Island of Madeira, Portugal, p. 6-13, 2004.

[Conati and Zhou, 2002] Conati, C. and Zhou, X. Modeling students' emotions from cognitive appraisal in educational games. In *Proceedings of the 6th International Conference on Intelligent Tutoring Systems*, Biarritz, France, 2002.

- [Cytowic, 1989] Cytowic, R.E. *Synesthesia: A Union of the Senses*. Springer-Verlag, New York, 1989.
- [Davis, 1983] Davis, M. H. Measuring individual differences in empathy: Evidence for a multidimensional approach. *Journal of Personality and Social Psychology*, 44, 113-126, 1983.
- [Davis, 1994] Davis, M. H. *Empathy: A Social Psychological Approach*. Brown and Benchmark Publishers, Madison, WI, 1994.
- [Elliott, 1992] Elliott, C. *The Affective Reasoner: A Process Model of Emotions in a Multi-agent System*. PhD thesis, Northwestern University, 1992.
- [Elliott et al., 1997] Elliott, C., Lester, J. and Rickel, J. Integrating affective computing into animated tutoring agents. In *Proceedings of the IJCAI Workshop on Animated Interface Agents*, Nagoya, Japan, 1997, pages pp. 113--121.
- [Elliott et al., 1999] Elliott, C., Rickel, J., and Lester, J. Lifelike pedagogical agents and affective computing: An exploratory synthesis. In *Artificial Intelligence Today*, Lecture Notes In Artificial Intelligence (Subseries of Lecture Notes in Computer Science), Special Volume 1600, M. Wooldridge & M. Veloso (Eds.), pp. 195-212, Springer-Verlag, Berlin, 1999.
- [Frijda, 1986] Frijda, N.H. *The Emotions*. Cambridge University Press, Cambridge, 1986.
- [Gardiner, 1918] Gardiner, H.N.. The psychology of the affections in Plato and Aristotle. *The Philosophical Review*, Vol. 27, No. 5 (September 1918), 469-488.
- [Gardiner, 1919] Gardiner, H.N. The psychology of the affections in Plato and Aristotle. *The Philosophical Review*, Vol. 28, No. 1 (January 1919), 1-26.
- [Goleman, 1995] Goleman, D. *Emotional Intelligence*, Bantam Books, New York, 1995.
- [Gratch and Marsella, 2001] Gratch, J., and Marsella, S. Tears and fears: Modeling emotions and emotional behaviors in synthetic agents,” in *Proceedings of the Fifth International Conference on Autonomous Agents*, Montreal, Canada, June 2001.
- [Gratch and Marsella, 2004a] Gratch, J., and Marsella, S. Evaluating the modeling and use of emotion in virtual humans. In *Proceedings of the Third International Joint Conference on Autonomous Agents and Multiagent Systems* (New York, NY), 2004.
- [Gratch and Marsella, 2004b] A domain-independent framework for modeling emotion. *Journal of Cognitive Systems Research*, 5(4):269-306, 2004.

- [Hanley and McNeil 1982] Hanley, J.A. and McNeil, B.J. The meaning and use of the area under the Receiver Operating Characteristic (ROC) curve. *Radiology* (143):29-36, 1982.
- [Hoffman, 2000] Hoffman, M. L. *Empathy and Moral Development: Implications for Caring and Justice*. Cambridge University Press, Cambridge, UK, 2000.
- [Ickes, 1997] Ickes, W. *Empathy Accuracy*. New York: Guilford, 1997.
- [Johnson et al., 2005] Johnson, W.L., Kole, S., Shaw, E., and Pain, H. Socially intelligent learner-agent interaction tactics. In *Proceedings of the International Conference on Artificial Intelligence in Education*, 2005.
- [Johnson and Rickel, 1998] Johnson, W.L., and Rickel, J. Steve: An animated pedagogical agent for procedural training in virtual environments. *SIGART Bulletin* 8:16-21, 1998.
- [Johnson and Rizzo, 2004] Johnson, W.L., and Rizzo, P. Politeness in tutoring dialogs: "Run the factory, that's what I'd do". In *Proceedings of Seventh International Conference on Intelligent Tutoring Systems*, pages 67-76, 2004.
- [Lang, 1995] Lang, P.J. The emotion probe: Studies of motivation and attention. *American Psychologist*, 50(5):372-385, 1995.
- [Lazarus, 1991] Lazarus, R.S. *Emotion and Adaptation*. Oxford University Press, New York (1991).
- [Lester et al., 2000] Lester, J.C., Towns, S.G., Callaway, C.B., Voerman, J.L., and FitzGerald, P.J. Deictic and Emotive Communication in Animated Pedagogical Agents. In *Embodied Conversational Agents*, J. Cassell, S. Prevost, J. Sullivan, and E. Churchill (Eds.), pp. 123-154, MIT Press, Cambridge, 2000.
- [Lester et al., 1999] Lester, J.C., Towns, S.G., and FitzGerald, P.J. Achieving affective Impact: Visual emotive communication in lifelike pedagogical agents. *International Journal of Artificial Intelligence in Education*, 10(3-4), 278-291, 1999.
- [Marsella and Gratch, 2003] Marsella, S. and Gratch, J. Modeling coping behavior in virtual humans: Don't worry, be happy. In *2nd International Joint Conference on Autonomous Agents and Multiagent Systems*, 2003.
- [Nass et al., 1995] Nass, C., Moon, Y., Fogg, B.J., Reeves, B., and Dryer, D.C. Can computer personalities be human personalities," *International Journal of Human-Computer Studies*, 43, 223-239. 1995.

[Ortony et al., 1988] Ortony, A., Clores, G.L, and Collins, A. *The Cognitive Structure of Emotions*. Cambridge University Press, Cambridge, MA, 1988.

[Paiva et al., 2004] Paiva, A., Dias, J., Sobral, D., Aylett, R., Sobreperez, P., Woods, S., and Zoll, C. Caring for agents and agents that care: Building empathic relations with synthetic agents. In *Proceedings of the 3rd International Joint Conference on Autonomous Agents and Multi-Agent Systems* (New York, NY, July 19-23). ACM Press, New York, NY, 194-201, 2004.

[Paiva et al., 2005] Paiva, A., Dias, J., Sobral, D., Aylett, R., Woods, S., Hall, L., and Zoll, C. Learning by feeling: Evoking empathy with synthetic characters. *Applied Artificial Intelligence*, 19:235-266, 2005.

[Picard, 1997] Picard, R.W. *Affective Computing*. MIT Press, Cambridge, MA, 1997.

[Porayska-Pomsta and Pain, 2004] Porayska-Pomsta, K. and Pain, H. Providing Cognitive and Affective Scaffolding through Teaching Strategies, *Proceedings of the 7th International Conference on Intelligent Tutoring System*., Maceio, Brazil, August-September 2004.

[Prendinger and Ishizuka, 2005] Prendinger, H., and Ishizuka, M. The empathic companion: A character-based interface that addresses users' affective states. *Applied Artificial Intelligence*. 19:267-285, 2005.

[Prendinger et al., 2003] Prendinger, H., Mayer, S., Mori, J., and Ishizuka, M. Persona effect revisited: Using bio-signals to measure and reflect the impact of character-based interfaces. In *Proceedings of the 4th International Working Conference on Intelligent Virtual Agents* (Kloster Irsee, Germany, September 15-17). Springer-Verlag, New York, NY, 2003. 283-291.

[Reeves and Nass, 1996] Reeves, B. and Nass, C. *The Media Equation*. New York: Cambridge University Press, 1996.

[Reilly and Bates, 1992] Reilly, S. and Bates, J. *Building emotional agents*. Report CMU-CS-92-143, Carnegie Mellon University, 1992.

[Rickel and Johnson, 1999] Rickel, J. and Johnson, W.L. Animated agents for procedural training in virtual reality: Perception, cognition, and motor control. *Applied Artificial Intelligence* 13:343-382, 1999.

[Ryokai et al., 2003] Ryokai, K., Vaucelle, C., and Cassell, J. Virtual peers as partners in storytelling and literacy learning. *Journal of Computer Assisted Learning*, 19(2): 195-208, 2003.

[Smith and Lazarus, 1990] Smith, C.A. and Lazarus, R. Emotion and adaptation. In Pervin (Ed.), *Handbook of Personality: Theory and Research* (pp. 609-637). Guilford Press, New York, 1990.

[Swartout et al., 2004] Swartout, W., Gratch, J., Hill Jr., R. W., Hovy, E., Lindheim, R., Marsella, S., Rickel, J., and Traum, D. Simulation meets Hollywood: Integrating graphics, sound, story and character for immersive simulation. In Stock, O., and Zancznaro, M. (eds.), *Multimodal Intelligent Information Presentation*, Kluwer, 2004.

[Witten and Frank, 2005] Witten, I. and Frank, E. *Data Mining: Practical machine learning tools and techniques*. 2nd Edition, Morgan Kaufman, San Francisco, CA, 2005.

Appendix A

Extended Model Results

This appendix includes additional results concerning the performance of the naïve Bayes and decision tree classification approaches (Chapter 5) to modeling empathy. The tables included in this appendix for each model are described below.

- Confusion matrices. Confusion matrices report how misclassifications were errantly classified. Columns correspond to the model’s classifications and rows correspond to records’ actual class.
- Evaluation measures. These tables report *true positive* classification rates (e.g., classifying an empathetic interpretation as “excited” when the instance is “excited”), *false positive* classification rates (e.g., classifying an empathetic interpretation as “frustrated” when the instance is actually a different affective state), *recall* (the number of true positives divided by the total number of true’s), *precision* (the number of true positives divided by the total number of positives), and *f-measures* (derived from recall and precision).
- Estimates of error. There are several standard ways to measure error for machine learning approaches. A variety of error measurements are reported in these tables.

A.1 Decision Tree Model of Empathetic Assessment

Table A-1: Empathetic assessment decision tree confusion matrix.

| Classified As: | | |
|----------------|------|------|
| | Yes | No |
| Yes | 2708 | 975 |
| No | 634 | 5979 |

Table A-2: Empathetic assessment decision tree evaluation measures.

| Class | TP Rate | FP Rate | Precision | Recall | F-measure |
|-------|---------|---------|-----------|--------|-----------|
| Yes | 0.74 | 0.09 | 0.81 | 0.74 | 0.77 |
| No | 0.90 | 0.27 | 0.86 | 0.90 | 0.88 |

Table A-3: Empathetic assessment decision tree measurements of error.

| | |
|----------------------------------|----------------|
| Correctly Classified Instances | 84.37 % (8687) |
| Incorrectly Classified Instances | 15.63 % (1609) |
| Kappa statistic | 0.65 |
| Mean absolute error | 0.20 |
| Root mean squared error | 0.34 |
| Relative absolute error | 43.36 % |
| Root relative squared error | 71.31 % |
| Total Number of Instances | 10296 |

A.2 Naïve Bayes Model of Empathetic Assessment

Table A-4: Empathetic assessment naïve Bayes confusion matrix.

| Classified As: | | |
|----------------|------|------|
| | Yes | No |
| Yes | 1998 | 1685 |
| No | 1555 | 5058 |

Table A-5: Empathetic assessment naïve Bayes evaluation measures.

| Class | TP Rate | FP Rate | Precision | Recall | F-measure |
|-------|---------|---------|-----------|--------|-----------|
| Yes | 0.54 | 0.24 | 0.56 | 0.54 | 0.55 |
| No | 0.77 | 0.46 | 0.75 | 0.77 | 0.76 |

Table A-6: Empathetic assessment naïve Bayes measurements of error.

| | |
|----------------------------------|----------------|
| Correctly Classified Instances | 68.53 % (7056) |
| Incorrectly Classified Instances | 31.47 % (3240) |
| Kappa statistic | 0.31 |
| Mean absolute error | 0.32 |
| Root mean squared error | 0.51 |
| Relative absolute error | 70.33 % |
| Root relative squared error | 107.16 % |
| Total Number of Instances | 10296 |

A.3 Decision Tree Model of Empathetic Interpretation – Emotion

Table A-7: Empathetic interpretation (affective state) decision tree confusion matrix.

Classified As:

| | Excited | Joyful | Relaxed | Fearful | Frustrated | Sad |
|------------|---------|--------|---------|---------|------------|-----|
| Excited | 110 | 0 | 0 | 0 | 13 | 0 |
| Joyful | 56 | 0 | 0 | 0 | 5 | 0 |
| Relaxed | 35 | 0 | 0 | 1 | 4 | 0 |
| Fearful | 16 | 0 | 0 | 18 | 4 | 0 |
| Frustrated | 83 | 0 | 0 | 2 | 16 | 0 |
| Sad | 22 | 0 | 0 | 0 | 3 | 0 |

Table A-8: Empathetic interpretation (affective state) decision tree evaluation measures.

| Class | TP Rate | FP Rate | Precision | Recall | F-measure |
|------------|---------|---------|-----------|--------|-----------|
| Excited | 0.89 | 0.80 | 0.34 | 0.89 | 0.49 |
| Joyful | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Relaxed | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Fearful | 0.47 | 0.01 | 0.86 | 0.47 | 0.61 |
| Frustrated | 0.16 | 0.10 | 0.36 | 0.16 | 0.22 |
| Sad | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

Table A-9: Empathetic interpretation (affective state) decision tree measurements of error.

| | |
|----------------------------------|---------------|
| Correctly Classified Instances | 37.11 % (144) |
| Incorrectly Classified Instances | 62.89 % (244) |
| Kappa statistic | 0.10 |
| Mean absolute error | 0.21 |
| Root mean squared error | 0.33 |
| Relative absolute error | 93.64 % |
| Root relative squared error | 97.36 % |
| Total Number of Instances | 388 |

A.4 Naïve Bayes Model of Empathetic Interpretation – Emotion

Table A-10: Empathetic interpretation (affective state) naïve Bayes confusion matrix.

| Classified As: | | | | | | |
|----------------|---------|--------|---------|---------|------------|-----|
| | Excited | Joyful | Relaxed | Fearful | Frustrated | Sad |
| Excited | 73 | 23 | 5 | 3 | 19 | 0 |
| Joyful | 31 | 13 | 1 | 3 | 14 | 0 |
| Relaxed | 15 | 7 | 0 | 5 | 12 | 1 |
| Fearful | 6 | 1 | 1 | 22 | 6 | 2 |
| Frustrated | 15 | 7 | 3 | 11 | 64 | 1 |
| Sad | 7 | 1 | 1 | 1 | 14 | 1 |

Table A-11: Empathetic interpretation (affective state) naïve Bayes evaluation measures.

| Class | TP Rate | FP Rate | Precision | Recall | F-measure |
|------------|---------|---------|-----------|--------|-----------|
| Excited | 0.59 | 0.28 | 0.50 | 0.59 | 0.54 |
| Joyful | 0.21 | 0.12 | 0.25 | 0.21 | 0.23 |
| Relaxed | 0.00 | 0.03 | 0.00 | 0.00 | 0.00 |
| Fearful | 0.58 | 0.07 | 0.49 | 0.58 | 0.53 |
| Frustrated | 0.63 | 0.23 | 0.50 | 0.63 | 0.56 |
| Sad | 0.04 | 0.01 | 0.20 | 0.04 | 0.07 |

Table A-12: Empathetic interpretation (affective state) naïve Bayes measurements of error.

| | |
|----------------------------------|---------------|
| Correctly Classified Instances | 44.59 % (173) |
| Incorrectly Classified Instances | 15.63 % (215) |
| Kappa statistic | 0.27 |
| Mean absolute error | 0.16 |
| Root mean squared error | 0.38 |
| Relative absolute error | 71.91 % |
| Root relative squared error | 113.76 % |
| Total Number of Instances | 388 |

A.5 Decision Tree Model of Empathetic Interpretation – Arousal

Table A-13: Empathetic interpretation (arousal) decision tree confusion matrix.

| Classified As: | | | |
|----------------|------|--------|-----|
| | High | Medium | Low |
| High | 55 | 106 | 0 |
| Medium | 47 | 115 | 0 |
| Low | 17 | 48 | 0 |

Table A-14: Empathetic interpretation (arousal) decision tree evaluation measures.

| Class | TP Rate | FP Rate | Precision | Recall | F-measure |
|--------|---------|---------|-----------|--------|-----------|
| High | 0.34 | 0.28 | 0.46 | 0.34 | 0.39 |
| Medium | 0.71 | 0.68 | 0.43 | 0.71 | 0.53 |
| Low | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

Table A-15: Empathetic interpretation (arousal) decision tree measurements of error.

| | |
|----------------------------------|---------------|
| Correctly Classified Instances | 43.81 % (170) |
| Incorrectly Classified Instances | 56.19 % (218) |
| Kappa statistic | 0.04 |
| Mean absolute error | 0.31 |
| Root mean squared error | 0.40 |
| Relative absolute error | 99.26 % |
| Root relative squared error | 100.34 % |
| Total Number of Instances | 388 |

A.6 Naïve Bayes Model of Empathetic Interpretation – Arousal

Table A-16: Empathetic interpretation (arousal) naïve Bayes confusion matrix.

| Classified As: | | | |
|----------------|------|--------|-----|
| | High | Medium | Low |
| High | 112 | 46 | 3 |
| Medium | 47 | 109 | 6 |
| Low | 23 | 39 | 3 |

Table A-17: Empathetic interpretation (arousal) naïve Bayes evaluation measures.

| Class | TP Rate | FP Rate | Precision | Recall | F-measure |
|--------|---------|---------|-----------|--------|-----------|
| High | 0.70 | 0.31 | 0.62 | 0.70 | 0.65 |
| Medium | 0.67 | 0.38 | 0.56 | 0.67 | 0.61 |
| Low | 0.05 | 0.03 | 0.25 | 0.05 | 0.08 |

Table A-18: Empathetic interpretation (arousal) naïve Bayes measurements of error.

| | |
|----------------------------------|---------------|
| Correctly Classified Instances | 57.73 % (224) |
| Incorrectly Classified Instances | 42.27 % (164) |
| Kappa statistic | 0.29 |
| Mean absolute error | 0.21 |
| Root mean squared error | 0.44 |
| Relative absolute error | 68.08 % |
| Root relative squared error | 110.37 % |
| Total Number of Instances | 388 |

A.7 Decision Tree Model of Empathetic Interpretation – Valence

Table A-19: Empathetic interpretation (valence) decision tree confusion matrix.

| Classified As: | | |
|----------------|----------|----------|
| | Positive | Negative |
| Positive | 132 | 92 |
| Negative | 26 | 138 |

Table A-20: Empathetic interpretation (valence) decision tree evaluation measures.

| Class | TP Rate | FP Rate | Precision | Recall | F-measure |
|----------|---------|---------|-----------|--------|-----------|
| Positive | 0.59 | 0.16 | 0.84 | 0.59 | 0.69 |
| Negative | 0.84 | 0.41 | 0.60 | 0.84 | 0.70 |

Table A-21: Empathetic interpretation (valence) decision tree measurements of error.

| | |
|----------------------------------|---------------|
| Correctly Classified Instances | 69.59 % (270) |
| Incorrectly Classified Instances | 30.41 % (118) |
| Kappa statistic | 0.41 |
| Mean absolute error | 0.37 |
| Root mean squared error | 0.45 |
| Relative absolute error | 76.19 % |
| Root relative squared error | 90.86 % |
| Total Number of Instances | 388 |

A.8 Naïve Bayes Model of Empathetic Interpretation – Valence

Table A-22: Empathetic interpretation (valence) naïve Bayes confusion matrix.

| Classified As: | | |
|----------------|----------|----------|
| | Positive | Negative |
| Positive | 179 | 45 |
| Negative | 44 | 120 |

Table A-23: Empathetic interpretation (valence) naïve Bayes evaluation measures.

| Class | TP Rate | FP Rate | Precision | Recall | F-measure |
|----------|---------|---------|-----------|--------|-----------|
| Positive | 0.80 | 0.27 | 0.80 | 0.80 | 0.60 |
| Negative | 0.73 | 0.20 | 0.73 | 0.73 | 0.73 |

Table A-24: Empathetic interpretation (valence) naïve Bayes measurements of error.

| | |
|----------------------------------|---------------|
| Correctly Classified Instances | 77.06 % (299) |
| Incorrectly Classified Instances | 22.94 % (89) |
| Kappa statistic | 0.53 |
| Mean absolute error | 0.23 |
| Root mean squared error | 0.46 |
| Relative absolute error | 47.27 % |
| Root relative squared error | 93.52 % |
| Total Number of Instances | 388 |

A.9 Decision Tree Model of Empathetic Interpretation – Quadrant

Table A-25: Empathetic interpretation (quadrant) decision tree confusion matrix.

| Classified As: | | | | |
|----------------|-----|----|-----|----|
| | ++ | +- | -+ | -- |
| ++ | 107 | 0 | 77 | 0 |
| +- | 13 | 0 | 27 | 0 |
| -+ | 9 | 0 | 130 | 0 |
| -- | 4 | 0 | 21 | 0 |

Table A-26: Empathetic interpretation (quadrant) decision tree evaluation measures.

| Class | TP Rate | FP Rate | Precision | Recall | F-measure |
|-------|---------|---------|-----------|--------|-----------|
| ++ | 0.58 | 0.13 | 0.81 | 0.58 | 0.68 |
| +- | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| -+ | 0.94 | 0.50 | 0.51 | 0.94 | 0.66 |
| -- | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

Table A-27: Empathetic interpretation (quadrant) decision tree measurements of error.

| | |
|----------------------------------|---------------|
| Correctly Classified Instances | 61.08 % (237) |
| Incorrectly Classified Instances | 38.92 % (151) |
| Kappa statistic | 0.35 |
| Mean absolute error | 0.21 |
| Root mean squared error | 0.33 |
| Relative absolute error | 82.97 % |
| Root relative squared error | 91.67 % |
| Total Number of Instances | 388 |

A.10 Naïve Bayes Model of Empathetic Interpretation – Quadrant

Table A-28: Empathetic interpretation (quadrant) naïve Bayes confusion matrix.

| Classified As: | | | | |
|----------------|-----|----|----|----|
| | ++ | +- | -+ | -- |
| ++ | 153 | 2 | 29 | 0 |
| +- | 25 | 1 | 14 | 0 |
| -+ | 33 | 8 | 95 | 3 |
| -- | 8 | 0 | 17 | 0 |

Table A-29: Empathetic interpretation (quadrant) naïve Bayes evaluation measures.

| Class | TP Rate | FP Rate | Precision | Recall | F-measure |
|-------|---------|---------|-----------|--------|-----------|
| ++ | 0.83 | 0.32 | 0.70 | 0.83 | 0.76 |
| +- | 0.03 | 0.03 | 0.09 | 0.03 | 0.04 |
| -+ | 0.86 | 0.24 | 0.61 | 0.86 | 0.65 |
| -- | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 |

Table A-30: Empathetic interpretation (quadrant) naïve Bayes measurements of error.

| | |
|----------------------------------|---------------|
| Correctly Classified Instances | 61.18 % (249) |
| Incorrectly Classified Instances | 35.82 % (139) |
| Kappa statistic | 0.39 |
| Mean absolute error | 0.14 |
| Root mean squared error | 0.36 |
| Relative absolute error | 56.68 % |
| Root relative squared error | 102.09 % |
| Total Number of Instances | 388 |