Chapter 3 Motivation Driven Emotion Computing Model for Cognitive Dialogue System

(Psi and Micro Psi stuff)  
  
3.1 The Psi Model of Motivated Action  
  
3.2 Emotion and Personality in the Psi Model

3.3 Psi in Cognitive Dialogue System

3.4 Summary  
  
  
Chapter 4 Cognitive motivated Dialogue Control Mechanism using Speech Act Theory and Probabilistic Logic Network  
  
4.1 The Conceptual Model of the Cognitive Dialogue System  
  
4.2 Motivation Driven Dialogue Control Mechanism

   4.2.1 Configuring OpenPsi for Dialogue Control

(also mention Goals and Motivations for Dialogue)

   4.2.2 Motivation Driven Action Selection with Logic Inference

In our cognitive approach to dialogue, dialogue control occurs via the combination of multiple cognitive processes on a shared set of knowledge representations. The dynamics of dialogue control is guided by a motivational system, based on Dorner's Psi model, that chooses actions and allocates system resources according to a set of goals defined over multiple time scales.

The key steps in our Psi-based dialogue control process are as follows:

1. Perception
2. Evaluation of urges and desires
3. Evaluation of modulator values
4. Formulation of the current goals
5. Formulation of currently available actions
6. Action selection
7. Action orchestration

For the purpose of simple exposition, we will now step through these 7 steps in sequential order and explain how they come together to enable intelligent, motivation-driven responses in a dialogue context. However, we must emphasize that the actual dynamics in our model are not unidirectional. Alongside the feedforward dynamics in which perceptions trigger actions, the framework also allows for feedback dynamics in which the process of formulating actions guides perception. Diagram XX shows both the feedforward and feedback information flows involved in our model.

Step 1 (Perception) in our framework involves mapping linguistic and nonlinguistic perceptions into a common logic-based knowledge representation, which is the same one used to represent system goals and actions, and general background knowledge. In our conceptual model of dialogue control, we allow for cognitive dynamics to influence the nature of the mapping from sentences, or from e.g. visual perceptions, into logical representations. In our current prototype implementations, the transformation of linguistic surface forms and visual camera input into logical representations have been primarily feedforward and rule-based.

Step 2 (Evaluation of Urges and Desires), involves the dialogue control system estimating, at each point in time, the degree to which each of its top-level goals (Ubergoals) and explicitly represented subgoals is fulfilled. For some goals, this will depend only on various predicates evaluated based on the system's current situation. For other goals, this will also depend on internal variables associated with the particular goals (e.g. in a dialogue system with a high motivation to seek novelty, after it has not experienced any novelty for a certain period of time, its novelty Urge may gradually increase in value, representing a steadily increasing boredom).

The derivation of subgoals for the system's top-level Ubergoals is carried out by probabilistic logical inference. Often this inference will occur via system background processing, independently of the systems real-time dialogue-control behavior. However, in cases where complex and adaptive discourse planning is required (e.g. a debate against a crafty opponent) then inference can also be used in real-time to create new subgoals, which then have their degree of fulfillment evaluated alongside the base-level Urges and Desires and the higher-level goals.

In our prototyping work, we have generally worked with a relatively limited set of Ubergoals as appropriate for simple dialogic interaction, e.g.

* affiliation (positive social interaction), which has been measured in two ways
  + via a default assumption that any dialogue interaction in which some human responds to the system provides positive “affiliation”
  + via emotion recognition from text, facial expression and voice, so that positive emotional responses on the part of the human dialogue participant is perceived to provide an amount of extra “affiliation”
* novelty (exploration),
  + which has been measured using the probabilistic truth values of the logic expressions in our system's knowledge base (using the grounding of the psychological concept of “novelty” in the mathematics of information theory, according to which a dramatic shift in the truth value of a logical predicate may be considered as “novel”).
* knowledge (competence)
  + which is measured via the probabilistic truth value of new logical relationships entered into the system's knowledge base
* aesthetics
  + which we have estimated in a very rough way based on the variety of emotions expressed by the human dialogue participant, according to the simple assumption that emotional expression is intrinsically aesthetically positive to a small degree

Step 3 (Evaluation of Modulator Values) involves evaluation of the modulator parameters that, in accordance with the Psi model, guide the particulars of the system's action selection and action response.

In our prototyping work, we have evaluated the core Psi modulator values as follows:

* Valence: Recognition of positive and negative words and phrases in what the human dialogue participant says, and recognition of positive and negative tones in their voice (where the latter is determined by supervised learning models trained based on annotated data).
* Arousal:
  + Verbal communication with the dialogue system elicits arousal
  + Acoustic or verbal cues indicating urgency, or intensity of emotion, will elicit increased arousal
* Resolution level, in our prototyping work, has been left constant or set inversely proportional to arousal.
* Selection threshold:
  + The default selection threshold is a "personality parameter" which controls how "scatterbrained" the dialogue system appears
  + This parameter can also be adapted, so that e.g. the selection threshold is higher (and the system thus appears more persistent and single-focused) if it is detected that the human dialogue participant is especially serious in orientation in the particular interactions
* Goal-directedness:
  + In our experimentation so far, if the human dialogue participant is asking complex questions, then the goal-directedness is high; and if not, then it is assumed that more of a “casual conversation” mode is in place and the goal-directedness is lower.
  + In future work goal-directedness will need to be varied as part of dialogue planning
* Securing rate (frequency of background checks):
  + Some novel salient event occurring in the non-linguistic environment should increase the securing rate.
  + Being engaged in a conversation should decrease the securing rate

Step 4 (Formulation of the Current Goals) involves a weighting aspect, and a more creative and adaptive inference aspect. In the simplest cases, what is involved is just assigning weights to various system goals based on the current modulator values and any internal dynamics associated with the goals. However, in cases where more complex dialogue planning is required, then subgoals will need to be synthesized adaptively in response to the current context, via uncertain inference; the assignment of weights to these subgoals is then done as part of the subgoal learning process.

Step 5 (Formulation of Currently Available Actions) again involves a weighting aspect, and a more creative and adaptive inference aspect. In the simplest cases, what is involved is looking in the system's knowledge base for implications of the conceptual form CONTEXT and ACTION implies GOAL (which we call “Psi implications), and then weighting each such implication according to the current situation (according to mathematics we have outlined in Section XX above). But in cases where more complex dialogue planning is required, then new implications of this form will need to be synthesized based on available knowledge.

In our current prototyping work we have experimented with dynamic synthesis of such implications in a few situations, for instance when information about user state is only indirectly given and needs to be inferred. Primarily, however, we have relied upon Psi implications that correspond to commonly recognized speech act types, drawn from the SWBD-DAMSL speech act ontology as reviewed in Section XXX above. Via hand-coding Psi implications corresponding to different speech act types, we are able to create a dialogue system covering various everyday human interactions. This system then records its experiences in its logical knowledge base, and recognizes patterns in its experience, enabling it to ongoingly synthesize new Psi implications to guide its future actions.

XXX I think there are some specific examples from the previous dialogue-system draft that may fit in here XXXX

Step 6 (Action selection) occurs according to our adaptation of the Psi model, as we have outlined in Section XX above. The logical implications gathered in Step 5 are then evaluated, and actions are stochastically chosen based on multiple factors. Actions involving language production are executed via invocation of the microplanner, which in turn invokes the surface realizer.

Step 7 (Action orchestration) handles mediation between multiple potentially contradictory system actions. For instance, in a multi-user dialogue context, the system might be answering person A's question with a lengthy answer, and then person B interrupts with a simple Yes-No question. The action selector may suggest a “Yes” response to person B, but the job of deciding when to interrupt the response to A to utter this “Yes”, is left to the Action Orchestration process. In many cases some feedback between action orchestration, action formulation and action selection will be required, for truly flexible and intelligent dialogue behavior.

   4.2.3 Cognitive Discourse Management

Since the central role in this dialogue control dynamic is played by the system's goals and motivations, the achievement of complex dialogue management using this framework relies on the balancing of goals with multiple time-frames. For instance, if the dialogue system is interacting with person A and has a high-level goal of gathering information about A, it may nevertheless not be intelligent for the system to pursue this high-level goal directly via every utterance it makes. The system must be able to, for example, maintain “gather information about A” as a goal to be pursued over a 30 minute or one hour time-frame, but then be able to prioritize “make A happy” over “gather information about A” on a one-minute time-frame. In this case we simply have Psi implications that are making implications on different time scales, and the goal and action formulation phases of the dialogue process must be able to accommodate this (as they are, even in our current prototype system).

PLN as a logic system incorporates temporal reasoning, and is able to carry out planning and reasoning as parts of the same integrated cognitive process (XX). Real-world everyday dialogue structure also contains many “human” elements going beyond logic formalism, e.g. conventional narrative structures (XX); however, we do not attempt to encode these elements explicitly into our system, but rather endeavor that the system may learn these via uncertain inference based on its own experience.

4.3 Speech Act Schema  
  
  
4.4 The Design of our integrative cognitive dialogue system(Digram)

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