Computational Theories of Collaboration

Mohammad Shayganfar

PhD Comprehensive Exam
Summer 2015

Professor Charles Rich
Professor Candace L. Sidner
Professor Stacy C. Marsella
Professor John E. Laird

Collaboration Theories > Introduction

Collaboration is a special type of coordinated activity in which the participants work jointly, together performing a task or carrying out the activities needed to satisfy a shared goal.

- Participants possess:
  - different beliefs and capabilities,
  - partial knowledge of the collaborative activities.

- Collaborators need to:
  - maintain mutual beliefs about their shared goal throughout the collaboration,
  - be able to communicate with others effectively,
  - commit to the group activities and to their role in it,
  - commit to the success of others,
  - reconcile between commitments to the existing collaboration and their other activities.

- Collaborative plans are more than the sum of individual plans.

Collaboration Theories > SharedPlans Theory: *Overview*

- **Shared Plans & Recipes:**
  - Shows how a group of agents can incrementally form and execute a shared plan,
  - Allows the process of expanding partial plans into full plans,
  - Describes how a shared plan coordinates agents' activities towards achieving a shared goal,
  - Agents have a library of how to do their actions (recipes),

- **Beliefs & Intentions:**
  - Emphasizes that collaborative plans are an interleaving of mutual beliefs and intentions about the actions in the plan,

- **Communication:**
  - Agents communicate their beliefs and intentions about the actions they can contribute to the shared plan,
  - Communication makes the agents mutually believe that:
    - there is an agent responsible to execute an action in the plan,
    - that agent has intention to do so,
    - the actions in the plan contribute to the goal.

Collaboration Theories > SharedPlans Theory: *Full & Partial Shared Plans*

- **Full Shared Plan (FSP):** A complete plan in which agents have fully determined how to perform an action.

- The required conditions for FSP:
  - All collaborators mutually believe that they have intention to do an action.
  - All collaborators mutually believe that they have a recipe for that action.
  - For each individual action in the recipe:
    - A subgroup has an FSP for that step using the corresponding part of the recipe.
    - Other members of the group believe that there is a recipe for this particular step that the above subgroup can use and have an FSP for the corresponding set of actions.
    - Other members of the group have intention that the above subgroup can do the mentioned set of action using the associated recipe.

- **Partial Shared Plan (PSP):** used as a snapshot of the collaborators' mental states to modify and evolve the partial plan, which leads to communication and planning to fulfill the above (FSP's) conditions.

Collaboration Theories > Joint Intention Theory: *Overview*

- Based on the idea of individual and joint intentions to act as a team member.
- Joint Intentions theory describes how a team of agents can jointly act together by sharing mental states about their actions while an intention is viewed as a commitment to perform an action.
- A joint intention is a shared commitment to perform an action while in a group mental state.
- Once an agent entered into a joint commitment with other agents, the agent should communicate its private beliefs with other team members.
- Team members are committed to inform other team members when they reach the conclusion that a goal is *achievable*, *impossible*, or *irrelevant*.

Collaboration Theories > Joint Intention Theory: *Joint Commitment & Joint Intention*

- **Weak Achievement Goal (WAG):** shows the state of a team member nominally working on a goal. An agent has a WAG about ***p*** if either of the following conditions holds:
  - The agent does not yet believe that ***p*** is true and wants ***p*** to be true as a goal.
  - The agent believes that ***p*** is true, will never be true, or is irrelevant, but has as a goal that the status of ***p*** be mutually believed by all the team members.

- **Joint commitment** or Joint Persistent Goal (JPG) requires all team members to mutually believe that ***p*** is currently false and want ***p*** to eventually be true.

- A JPG guarantees that team members cannot decommit until ***p*** is mutually known to be achieved, unachievable or irrelevant.

- JPG requires team members to each hold ***p*** as a WAG.

- A team of agents jointly intends to do an action if and only if the members have a JPG of them having the action completed, and having it completed knowingly.

Collaboration Theories > STEAM – A Hybrid Approach

- Uses joint intentions as the basic building block of teamwork (formalizes commitment):
  - Reasoning about coordination and communication in a team.
  - Guidance for monitoring and maintenance of a team activity.
  - Reasoning about team activity and member's contribution.
  - To reinforce the teamwork coherency to build team members' mental states.

- It is informed by key concepts from SharedPlans theory (formulates team's attitude):
  - Mutual belief in a shared recipe and shared plans (adds coherency within the teamwork).
  - The limited required information about recipe to perform an action (only tracking who is responsible).
  - Uses the concept of intention-that for communication.

- **Novel aspects:**
  - Has team (expressing joint activities) vs. individual (individual's activities) operators.
  - Team synchronization protocol.
  - Constructs to monitoring team performance.
  - Communication's (based on joint intention) overhead and risks.

Collaboration Theories > Similarities: ***SharedPlans & Joint Intentions***

1. Both specify executing actions as a team.
2. Both based on BDI model and Bratman's view of intention.
3. In both joint actions are not collection of individual actions (agents need to share beliefs).
4. Both emphasize on communication.
5. Both are concerned about commitment.

Collaboration Theories > Differences: ***SharedPlans & Joint Intentions***

1. **SharedPlans** theory is based on mutual beliefs and notion of intention-that, while **Joint Intentions** theory is based on joint intentions.

2. In **SharedPlans** theory teammates agree on the shared plan, whereas in **Joint Intentions** theory teammates agree on intentions.

3. **SharedPlans** theory employs hierarchical structures over intentions (in contrast to **Joint Intentions** theory).

4. **SharedPlans** theory describe a way to achieve a shared goal whereas **Joint Intentions** theory only describes the shared goal.

5. **Joint Intentions** theory assumes knowledge about the teammates is always available (in contrast to partial plan in **SharedPlans** theory).

6. In **SharedPlans** theory communication requirements are derived from intention-that concept whereas it is "hard-wired" in **Joint Intentions** theory.

Collaboration Theories > Applications

- Assistant robots
- Emotional awareness (COCHI)
- Communication
- Joint actions and commitments
- Task-based planning
- Discourse generation and interpretation (COLLAGEN)
- Conversational agents
- Network management
- Proactive behaviors and information exchange (CAST)
- Instructional systems
- Group decision support systems
- Authors' assistant
- Sociable robots
- Combat air missions
- Robot soccer
- Rescue responses

Collaboration Theories > Conclusion

- **SharedPlans** is more convincing than the others.
  - Inclusive explanation of collaboration structure.
  - Association to discourse structure (improve communicative aspects).
- Joint Intentions theory is clearly defined and fulfills most of the key collaboration requirements.
- Hybrid approaches are valuable and make the theories closer to applications.
- The lack of underlying domain-independent collaboration processes which can construct and evolve the collaboration structure.

Affective Computing

Mohammad Shayganfar

PhD Comprehensive Exam
Summer 2015

Professor Charles Rich
Professor Candace L. Sidner
Professor Stacy C. Marsella
Professor John E. Laird

Affective Computing > Introduction

- Four categories of computational emotion modeling:
  - Detecting and recognizing human emotions,
  - Interpreting and understanding human emotions,
  - Generating artificial emotions,
  - Expressing human-perceivable emotions.

- Major emotion theories:
  - Appraisal
  - Dimensional
  - Discrete (basic)

- We majorly focus on Appraisal and Dimensional theories.

Affective Computing > Appraisal Theory: ***Overview***

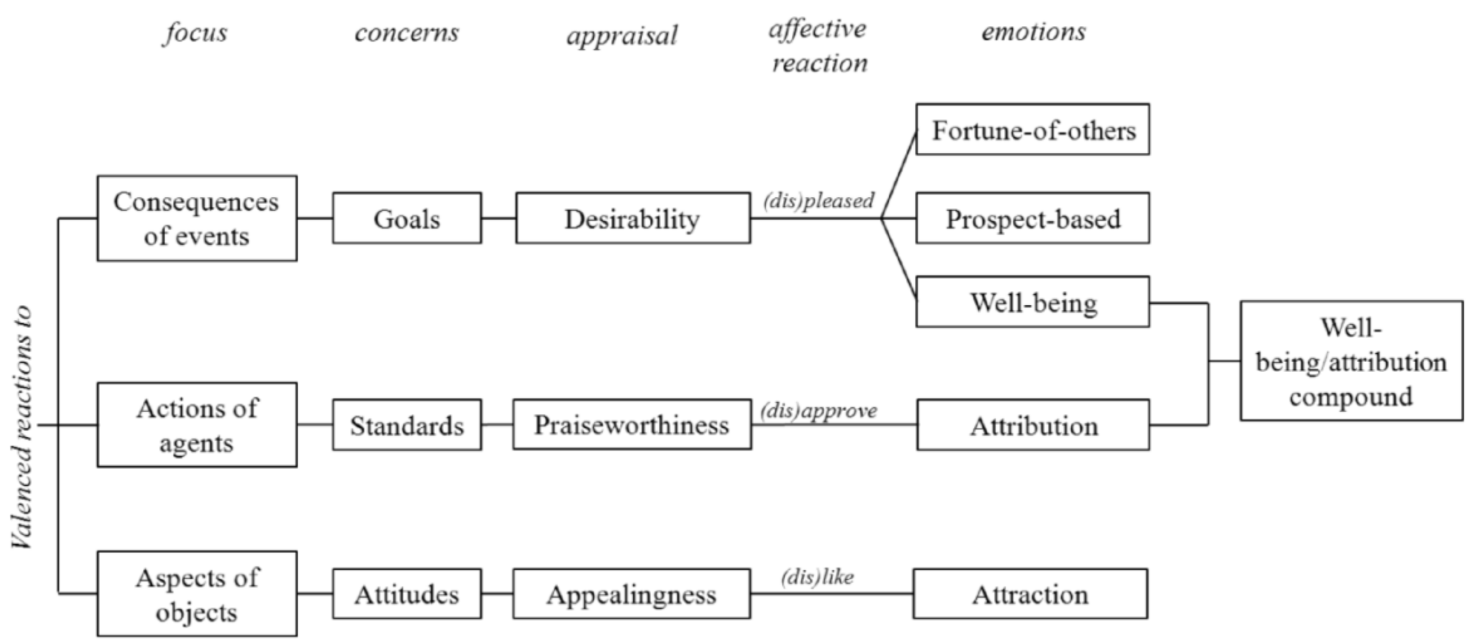
- **Appraisal theory** describes the cognitive process by which an individual evaluates the situation in the environment with respect to the individual's well-being and triggers emotions to control internal changes and external actions.
- Cognitive appraisal process:
  - Distinct components of emotions,
  - Components are called appraisal variables,
  - Agent Evaluates the stimuli with respect to their consequences;
    - According to Scherer's appraisal objectives (i.e., relevance, implication, coping, and normative significance),
    - Objectives include different appraisal variables,
  - Specific values will be assigned to appraisal variables,
  - Determined appraisal variables are mapped onto a particular emotion,
    - Appraisal variables are the semantic primitives for representing emotions.

Affective Computing > Appraisal Theory: *Appraisal & Coping processes*

- Appraisals are separable antecedents of emotions.
- Overall process:
  - Evaluation of the environment according to the internalized goals,
    - Systematic assessment of several elements.
  - Outcome triggers emotions and coping strategies.
- Appraisal variables, e.g., relevance, desirability, expectedness, controllability.
- Coping process:
  - Determines whether and how agent should respond to an event.
  - Coping strategies control (enable or suppress) cognitive processes operate on causal interpretation of the appraisals.
- Coping strategies can be grouped into different categories:
  - Problem-focused (e.g., planning)
  - Emotion-focused (seeking social support for instrumental reasons)

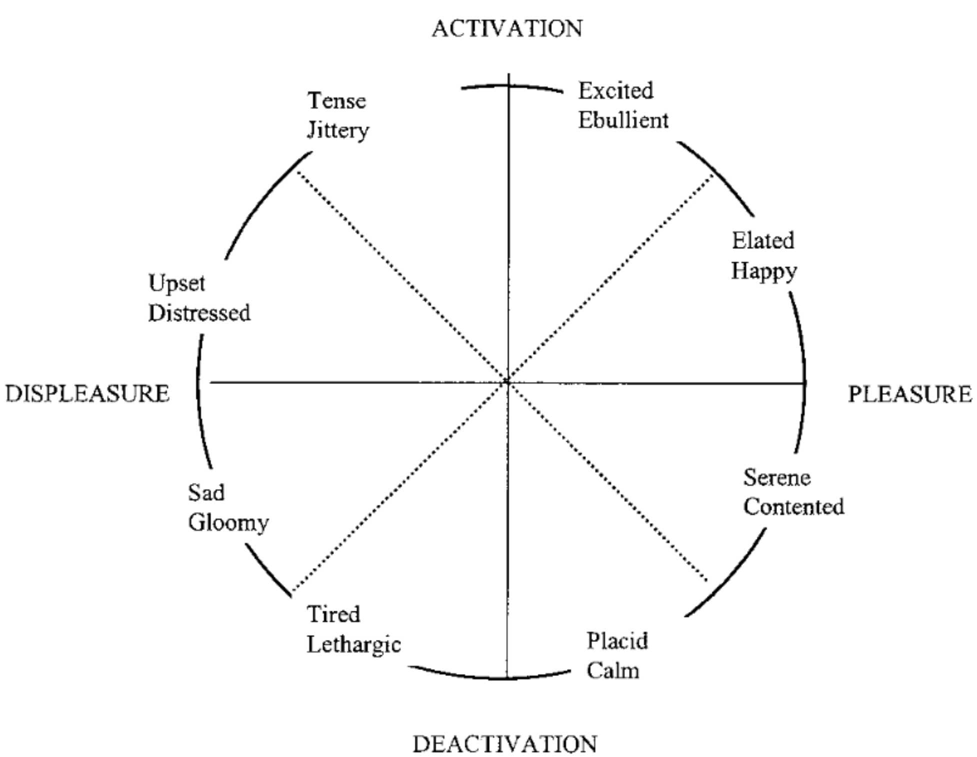
Affective Computing > Appraisal Theory: *OCC – A structural Appraisal Theory*

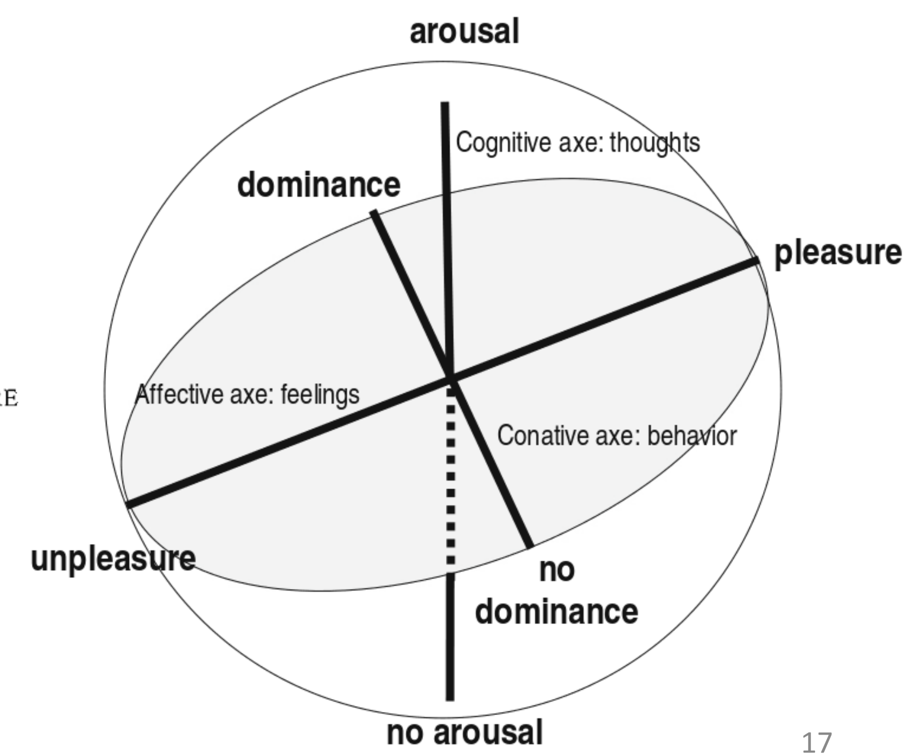
- The model categorizes emotions based on their underlying appraisal patterns.
- Patterns are fundamental criteria and involve:
  - One's focus of attention,
  - One's concern,
  - One's appraisals.
- OCC model introduces some global variables of an emotion's intensity to distinguish all types of emotions (e.g., sense of reality, and arousal).



Affective Computing > Dimensional Emotion Theories

- They conceptualize emotions by defining where they lie in two or three dimensions.
- Russell's Circumplex model (Valence and Arousal).
- Mehrabian and Russell's PAD model (Pleasure, Arousal, Dominance).





Affective Computing > Discrete Emotion Theories

- These theories emphasize a small set of discrete and fundamental emotions.
- The underlying assumption is that these emotions are mediated by associated neural circuitry, with a hardwired component.
- Different emotions are characterized by stable patterns of triggers, behavioral expression, and associated distinct subjective experiences.
- The emotions are called basic emotions: *happiness, sadness, fear, anger, surprise,* and *disgust.*
- This universality has a production side and a recognition side.
- Computational models focus on low-level perceptual-motor tasks (fast and automatic vs. slower, reasoning-based).

Affective Computing > Similarities & Differences: *Dimensional Vs. Discrete*

- In contrast to **basic** emotions, **dimensional** theory is compatible with the differences in the behavioral responses to the stimuli.

- **Dimensional** theories can represent instances of **basic** emotions.

- In contrast to **basic** emotions, **dimensional** theory argues that emotion may not necessarily be aimed at a particular object.

- **Dimensional** models of emotion are capable of accounting for a wider range of affective phenomena.

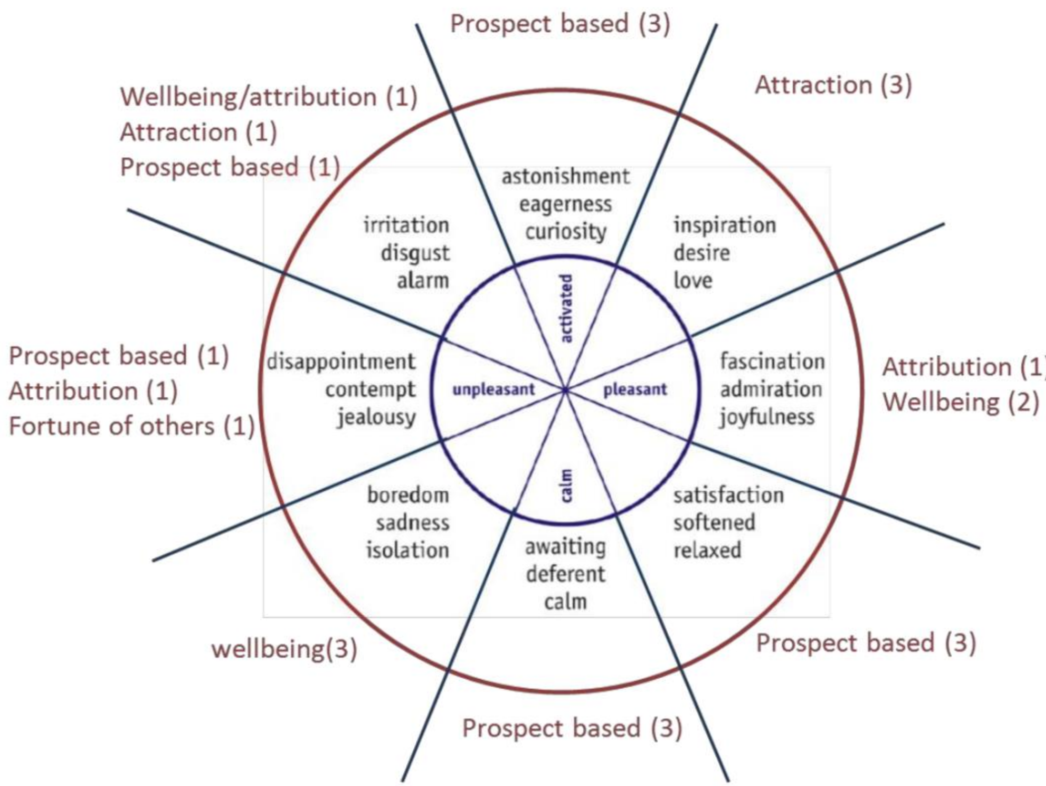
- In contrast to **dimensional** theory, **basic** emotion theory's categorization of emotions captures elicitation of a facial expression of the emotion.

Affective Computing > Similarities & Differences: *Appraisal & Dimensional*

- **Dimensional** theories might struggle to adequately distinguish emotions because of the existence of limited dimensions.
- Pleasure dimension roughly maps onto appraisal dimensions that characterize the valence of an appraisal-eliciting event (e.g., desirability).
- Dominance roughly maps onto the appraisal dimension of coping potential.
- Arousal can be considered as a measure of intensity.
- **Appraisals** are relational constructs (between an event and one's mental states), whereas emotions in **dimensional** are non-relational and just a unique overall state of individual.
- **Dimensional** emotion theory does not address affects' antecedents like appraisal and they question the causal linkage between appraisal and emotion.

Affective Computing > Similarities & Differences: *OCC & Dimensional*

- Both consider emotions to descend from valenced reactions to the stimuli.
- Both acknowledge the role of arousal in determining emotional reactions (as intensity in OCC model – as coping potential by Scherer).
- **Dimensional** theories and **OCC** model can relate to each other in terms of categorization of emotions.



Affective Computing > Applications

- Companion robots
- Expressive robots
- Robots with affective behaviors
- Robots with affect recognition capability
- Robots with adaptive behaviors
- Interactive robots
- Learning in robots
- Service robots
- Decision-making in robots
- Human-computer interaction

Affective Computing > Conclusion

- It is good to follow well-established computational models with theoretical foundations.
- They can explain more details of the structure or the processes involved in affective situations.
- It is not necessary to exactly follow only one theory and its descriptions.
- We believe the interpersonal functions of emotions should be our first concern.
- We can see the importance of interpretive, communicative and regulatory aspects of emotion functions in our proposed work.

Uncertainty in Modeling and Reasoning about Beliefs

Mohammad Shayganfar

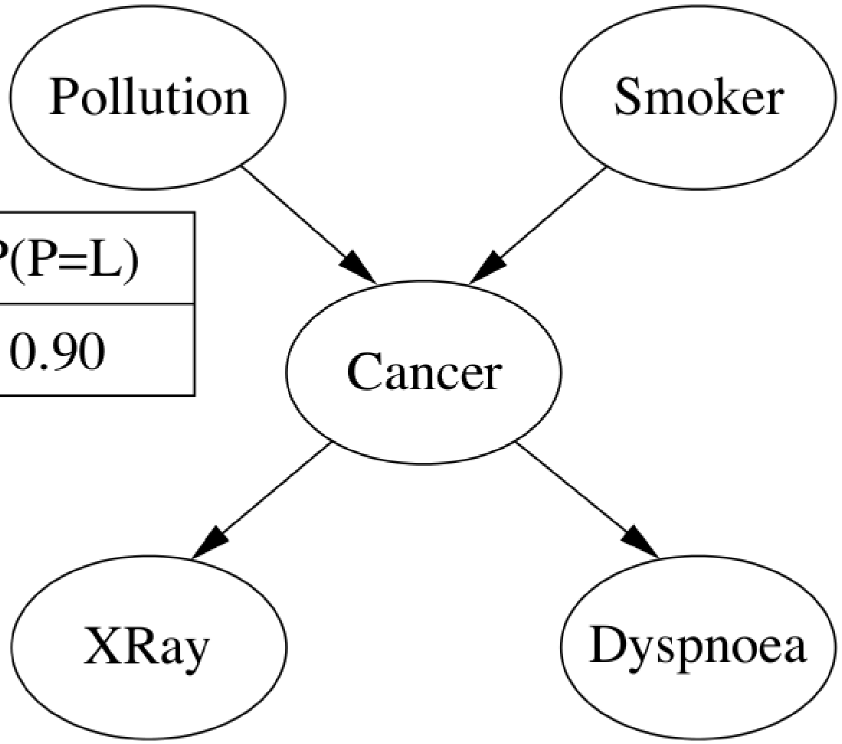
PhD Comprehensive Exam
Summer 2015

Professor Charles Rich
Professor Candace L. Sidner
Professor Stacy C. Marsella
Professor John E. Laird

Uncertainty in AI > Introduction

- Bayesian Belief Networks (probabilistic reasoning)
- Dempster-Shafer theory (evidential reasoning)
- Fuzzy logic (reasoning under ambiguity)

Uncertainty in AI > Bayesian Belief Networks: *Overview*



P(S=T)
0.30

P(P=L)
0.90

P	S	P(C=T|P,S)
H	T	0.05
H	F	0.02
L	T	0.03
L	F	0.001

C	P(X=pos|C)
T	0.90
F	0.20

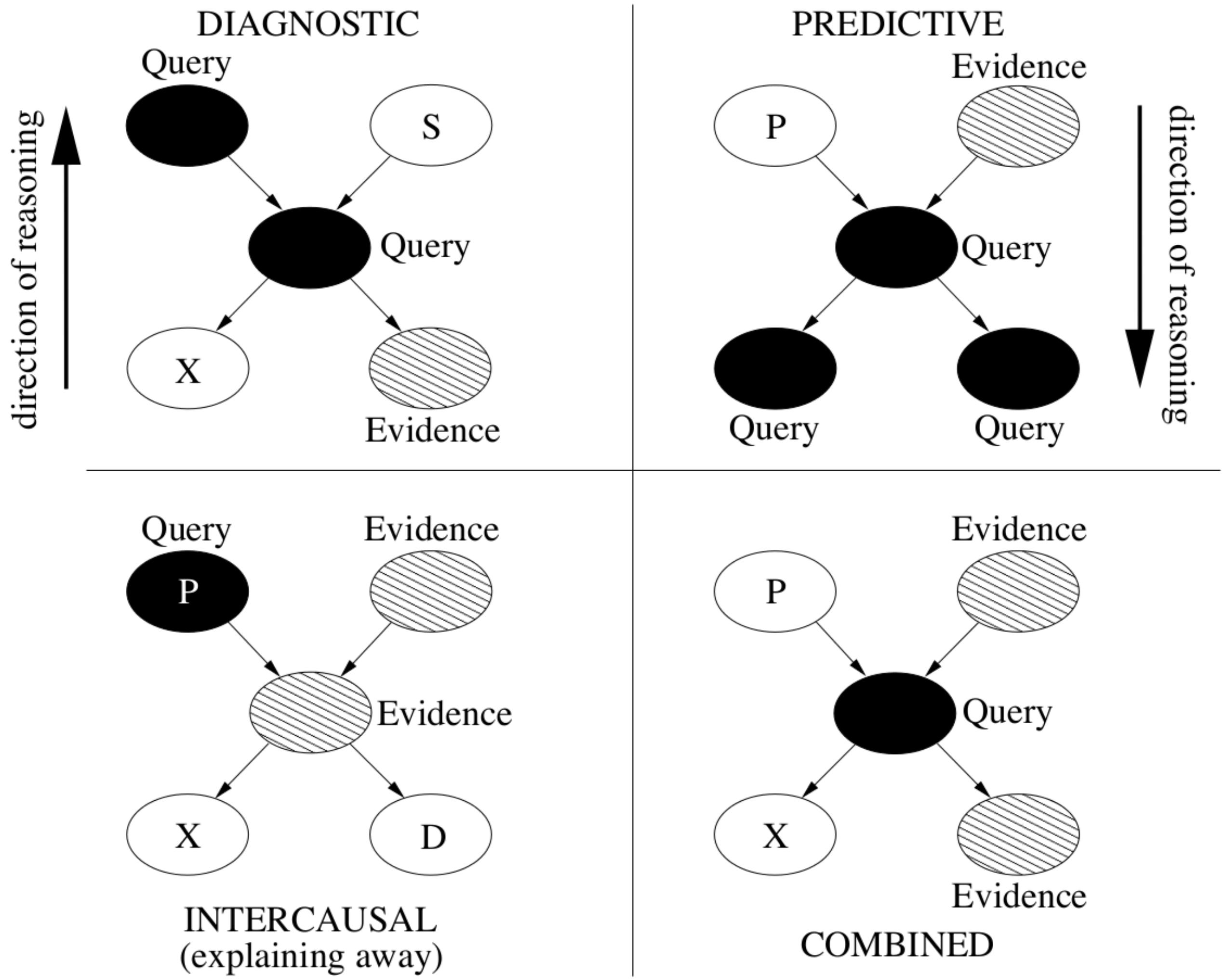
C	P(D=T|C)
T	0.65
F	0.30

Uncertainty in AI > Bayesian Belief Networks: *Joint Probability Distribution*

Given Markov property, the product of only the appropriate elements (parent nodes) of the CPTs in the network represents the value of each individual entry in the joint probability distribution.

$$P(x_1, x_2, \ldots, x_n) = \prod_{i=1}^{n} P(x_i | parents(X_i))$$

Uncertainty in AI > Bayesian Belief Networks: *Reasoning in BBNs*



Uncertainty in AI > Dempster-Shafer Theory: *Overview*

- Dempster-Shafer theory is designed to deal with the distinction between uncertainty and ignorance.
- Rather than computing the probability of a proposition, it computes the probability that the evidence supports the proposition.
- The set of hypotheses (frame of discernment) represent all of the possible states of the system considered.
- The relation between a piece of evidence and a hypothesis corresponds to a cause-effect chain.
- There are three basic functions required for modeling purposes: mass function, belief function, and plausibility function.

Uncertainty in AI > Dempster-Shafer Theory: *important functions*

- **Mass Function:** A Basic Probability Assignment (BPA) or mass function is a function $2^{\Theta} \rightarrow [0,1]$ such that:

$$m(\emptyset) = 0, \text{ and } \sum_{x \in 2^{\Theta}} m(x) = 1$$

- **Belief Function:** It is the measure of total belief committed to $A \subseteq \Theta$ that can be obtained by simply adding up the mass of all the subsets of *A*, denoted by $Belief(A)$. It is a function $Belief : 2^{\Theta} \rightarrow [0,1]$:

$$Belief(A) = \sum_{B \subseteq A} m(B) \qquad \text{for all } A \subseteq \Theta$$

- **Plausibility Function:** It represents the maximum possibility that a set *A* is true given all the evidences. It is a function $Plausible : 2^{\Theta} \rightarrow [0,1]$:

$$Plausible(A) = \sum_{B \cap A \neq \emptyset} m(B) \qquad \text{for all } A \subseteq \Theta$$

Uncertainty in AI > Dempster-Shafer Theory

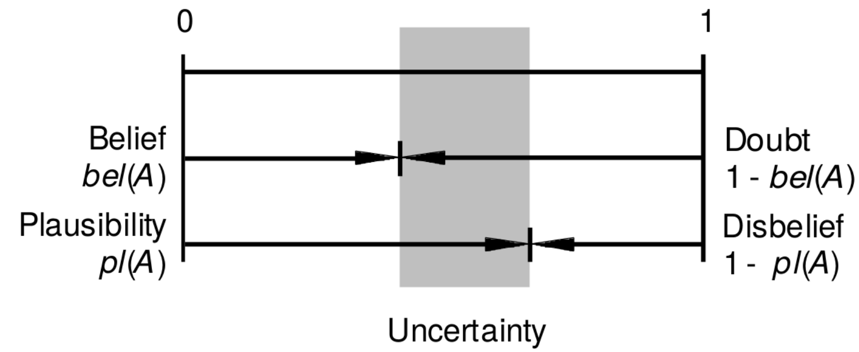
- The plausibility and belief functions have the following relationship:

$$Belief(A) = 1 - Plausible(\neg A) \qquad \text{and} \qquad Plausible(A) = 1 - Belief(\neg A),$$

- Uncertainty measure (belief interval):

$$[Belief(A),\ Plausible(A)]$$

Where: $Belief(A) \leqslant Plausible(A)$



- **Dempster's Rule of Combination:**
  - A method to combine the measures of evidence from different sources.

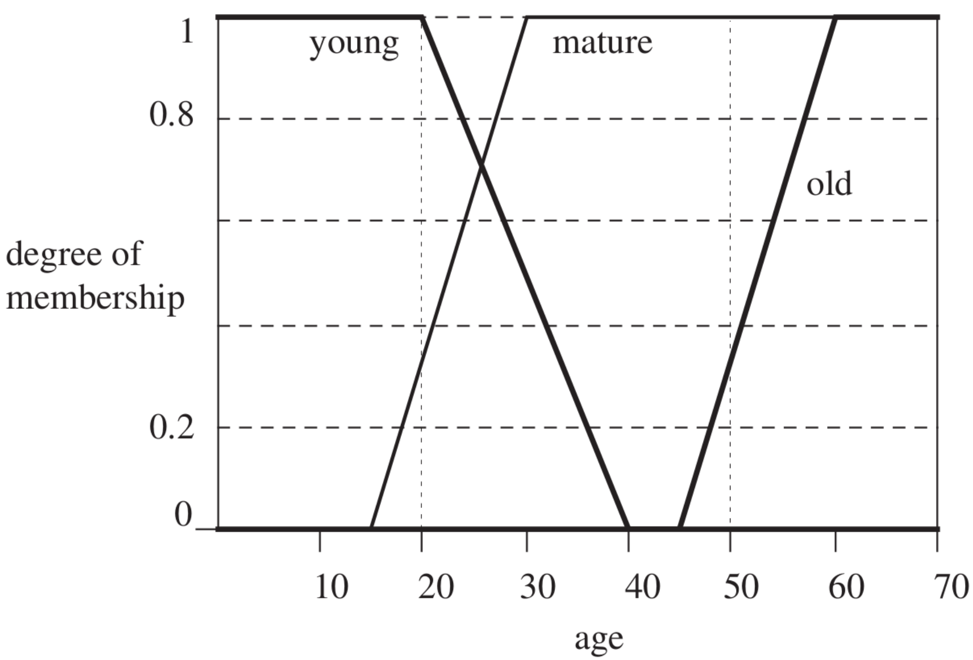
$$[m_1 \oplus m_2](y) = \begin{cases} 0, & y = \emptyset \\ \dfrac{\sum_{A \cap B = y} m_1(A) m_2(B)}{1 - \sum_{A \cap B \neq \emptyset} m_1(A) m_2(B)}, & y \neq \emptyset \end{cases}$$

Uncertainty in AI > Fuzzy Logic Theory: *Overview*

- Fuzzy Logic's ultimate goal is to provide foundations for approximate reasoning using imprecise propositions based on fuzzy set theory.
- In order to deal with such imprecise inference, Fuzzy Logic allows the imprecise linguistic terms such as:
  - fuzzy predicates (e.g., old, expensive),
  - fuzzy quantifiers (e.g., many, little),
  - and fuzzy truth values (e.g., unlikely false or unlikely true).
- **Fuzzy Sets:** A fuzzy set is a class of objects with a continuum of degrees of membership.
- A fuzzy set ***A*** is defined by a membership function μ_A from the universe of discourse ***X*** to the closed unit interval **[0,1]**. We interpret $\mu_A(x)$ as the degree of membership of ***x*** in ***A***.

Uncertainty in AI > Fuzzy Logic Theory: *Membership Functions*

- Membership functions are mathematical tools for indicating flexible membership to a set, modeling, and quantifying the meaning of symbols.
- Membership functions are used in the fuzzification and defuzzification steps of a Fuzzy Logic system.
- A membership function is used to quantify a linguistic term.



Uncertainty in AI > Fuzzy Logic Theory: *Algorithm*

```
1. Define the linguistic variables and terms (initialization)
2. Construct the membership functions (initialization)
3. Construct the rule base (initialization)
4. Convert crisp input data to fuzzy values
   using the membership functions (fuzzification)
5. Evaluate the rules in the rule base (inference)
6. Combine the results of each rule (inference)
7. Convert the output data to non-fuzzy values (defuzzification)
```

Linguistic Variables:

- Linguistic variables are the input or output variables of the system whose values (linguistic terms) are words or sentences from a natural language.

Fuzzy Rules:

- A rule-base is constructed to determine and control the output variable.

IF (a statement of conditions is satisfied)

THEN (a set of consequences can be inferred)

Uncertainty in AI > Fuzzy Logic Theory: *Algorithm*

```
1. Define the linguistic variables and terms (initialization)
2. Construct the membership functions (initialization)
3. Construct the rule base (initialization)
4. Convert crisp input data to fuzzy values
   using the membership functions (fuzzification)
5. Evaluate the rules in the rule base (inference)
6. Combine the results of each rule (inference)
7. Convert the output data to non-fuzzy values (defuzzification)
```

- **Fuzzification:** The process of obtaining one fuzzy value for each crisp input.
- **Reasoning:** The process of combining the results of the rules to obtain a final result.
- **Defuzzification:** The process of obtaining a crisp value by defuzzifying the final fuzzy result using the membership function of the output variable.

Uncertainty in AI > Advantages & Disadvantages: *Bayesian Networks*

Advantages:

- Transparent representation of causal relationships between variables.
- Relatively easy recognition of dependencies and independencies between various nodes.
- The ability to handle situations where the data set is incomplete since the model accounts for dependencies between all variables.
- Capable of being readily updated when a new evidence becomes available.
- Both predictive/deductive and diagnostic/abductive reasonings are possible.
- Computational tractability exists for most practical applications.

Uncertainty in AI > Advantages & Disadvantages: *Bayesian Networks*

Disadvantages:

- A high level of effort is required to build network models where a significant amount of probability data is required due to an increasing number of nodes and links in the structure (possible large CPT sizes).

- Computationally intensive if the conditional independencies are not properly considered among the variables.

- Challenging to obtain experts' knowledge in the form of probability to build the network.

- No feedback loops in the Bayesian network's structure, which has an acyclic nature. This structure prevents typical feedback loops in design of Bayesian network models.

Uncertainty in AI > Advantages & Disadvantages: *Dempster-Shafer Theory*

Advantages:

- Addressing the concept of possibility.
- The ability to represent the concept of ignorance to allow one to specify a degree of ignorance in a situation, instead of being forced to supply prior probabilities.
- Consistent with classical probability theory.
- Distinguishing randomness from missing information.
- No required a priori knowledge.
- Including an evidence combination rule which provides an operator to integrate multiple pieces of information from different sources.

Uncertainty in AI > Advantages & Disadvantages: *Dempster-Shafer Theory*

Disadvantages:

- Computational complexity grows exponentially with the number of hypotheses (in original formulation).

- Small modifications in the evidence assignments may lead to a completely different conclusion, which can lead to misleading and counter-intuitive results.

Uncertainty in AI > Advantages & Disadvantages: *Fuzzy Logic Theory*

Advantages:

- Describing algorithms in terms of a combination of numerics and linguistics.
- Capturing the concept of the ambiguity of information.
- Flexible and intuitive knowledge-base design.
- Easy computation.
- Relatively robust algorithms.

Uncertainty in AI > Advantages & Disadvantages: *Fuzzy Logic Theory*

Disadvantages:

- Determining the exact fuzzy rules and membership functions is a hard task.
- Requires manual tuning to obtain a better result.
- Requires tuning in many options in design of a system.
- The order of inference steps matters.
- After reasoning, it can be difficult to exactly interpret the membership value.
- Validation of a fuzzy knowledge-base is typically expensive.

Uncertainty in AI > Applications

- Robot’s motion control
- Sensory data fusion in robots
- Modeling domain knowledge
- Modeling human-robot interaction
- Modeling emotional state of the robot
- Modeling forward model of robot’s actions
- Modeling object affordances
- Robot’s navigation
- Learning robot’s decision function
- Learning imitative body motions of humans
- Intention recognition
- Mobile-robot localization
- Modeling cooperative agents
- Agent’s argumentation and decision making framework
- Modeling theory of mind

Uncertainty in AI > Conclusion

- Uncertainty is involved in collaboration, Different theories are concerned about teamwork and the involvement of others:
  - to form an intention,
  - to generate or evolve the shared plan,
  - or even to establish a single mutual belief.
- There is a certain amount of uncertainty, ambiguity and lack of evidence in perceiving others‘ behaviors.
- Processes involved in collaboration need to be designed to address the existence of uncertainty.
- Beliefs include certain amount of uncertainty independent of their source:
  - the lack of evidence about a counterpart's belief about an event,
  - the lack of evidence about the feeling of a counterpart for a collaborative action.
- Consequences can be mitigated by having a mechanism to deal with uncertainty in some level.
- It is for us to choose where to apply the appropriate mechanism to make more stable collaborative behaviors.

Thank You!