Human and Machine Learning II

Cognitive Modeling

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Outline

• Human and Machine Learning II
  • Advanced Learning abilities
    – Cognitive Learning Theories
    – Imitation Learning / Learning by Demonstration
    – Social Interactive Learning
    – Learning in ACT-R
Advanced Learning abilities

- Learning by observation, imitation, demonstration, explanation, discovery, ...
- Social learning (result of socialization and social interaction)
- 24/7 Life-long learning

- Not covered by basic machine learning
  - No generic algorithms to recognize and model behavior
  - Require multiple different skills and knowledge (e.g. body tracking, natural language understanding, ontologies, ...) to derive information for higher mental processes, Require measuring of relevance of derived information,...
Piaget’s Cognitive Learning Theory

• Cognitive learning theory
  • Explain behavior by higher mental processes (information processing, decision making, knowledge, ...)

• Jean Piaget (1896-1980)
  famous developmental psychologists

• Learning is adaptation to the environment

• How to classify and structure children development?
  • Piaget describes four stages in development of children
  • Increasing adaptation level
  • From sensorimotor (age <2) to formal operation (age >12)
What are the features enabling children to adapt to their environment?

*Assimilation*: Reaction based on already learned or innate schemes
  - Generalization and abstraction of schemata
  - Example: After seeing different kinds of dogs and a child is able to classify previously unseen kinds of dogs

*Accommodation*: Modify mental schemes to meet environment
  - Specialization and discrimination of schemata
  - Example: After seeing a cow not fitting into the dog scheme create new cow scheme
  - Shows up in imitation

*Equilibration of assimilation and accommodation*
  - Successful learning must consist of both assimilation and accommodation
Vygotsky cultural-cognitive theory

- Lev Vygotsky (1896-1934)
- Social constructivistic approach
  - Individual learners construct mental models to understand the world around them
- External influences
  - Culture
  - Speech
    - Cognitive development is mainly due to verbal interaction
    - Enables higher cognitive processes (thinking)
    - Development: social/external (control actions of others; age <3), egocentric (control own actions; age 3-7), internal (silent soliloquizing; age >7)
- Relation between trainer and trainee
  - Learning has social components
  - Zone of proximal development: things a person can potentially learn with guidance → scaffolding
Implications of Piaget and Vygotskyan on ML

- **Piaget**
  - Continuously learning of schematic models
  - Accommodation is connected to imitation (→ imitation learning)
  - Generalization of learned schemata (Assimilation)
  - Equilibrium (i.e. specialization and generalization) is important for machine learning e.g. to avoid overfitting

- **Vygotsky**
  - Use language as a cognitive tool
  - Learning through social interaction
  - Scaffolding: Allow the machine to learn more complicated behavior by human support
Imitation Learning

- Learn new skills by observing actions of others
- E.g. Tennis teacher shows how to serve
- Often interactive: Teacher gives important cues
  (-> no lengthy trial-and-error process)
- Growing interest in robotics:
  Imitation Learning / Programming by Demonstration
- Fundamental structure
  - Observation
  - Representation
    - Build internal model
    - Correspondence problem: mapping between teacher’s and student’s body parts
  - Reproduction
Programming by Demonstration

- PbD training center
Programming by Demonstration Cycle

from Dillmann /Jäkel
Programming by Demonstration

- Goal: Represent demonstrated action by elementary operations
- Elementary operations: Grasping, moving, ungrasping
- Segmentation using Dynamic Bayesian Network
- Hierarchical task representation of elementary operations

-> Finding of constraints, Abstraction and generalization

Flexibilität wichtig

Kühlschrank öffnen

Becher greifen, Flasche greifen, Einschenken, Becher abstellen und Flasche abstellen

Kühlschrank schließen from Dillmann /Jäkel
Tutelage and Socially guided robot learning

- Humanoid robot Leonardo (MIT)
- 65 degrees of freedom
- Designed for social interaction
- Learn task from human in intuitive and efficient way

- Interaction loop to communicate mutual understanding of the task (e.g. express understanding, confusion, attention, etc.)
- Can generalize task goal and apply to new configurations
- Vygotsky’s Scaffolding (tutelage)
  - Human can interactively structure the task in learning steps (teach seminal tasks -> teach complete task)
  - Robot can learn something it couldn’t accomplish independently
  - Narrows down the hypothesis space

Lockerd, et al. (2004): Tutelage and Socially Guided Robot Learning
Leo’s Learning Scenario

- Learning scenario consists of
  - Several buttons
  - Pressing activates/deactivates
- Human can interact with Leo to teach him simple *tasks*
- Example:
  - “This is the green button”
  - “I show you how to turn the green button on”
  - “Now the button is on”
Socially Guided Learning

- Expression and gestual communication of social cues for scaffolding
  - Mutual understanding of the learning process between human and robot

<table>
<thead>
<tr>
<th>Context</th>
<th>Leo’s Expression</th>
<th>Intention</th>
</tr>
</thead>
<tbody>
<tr>
<td>Human points to object</td>
<td>Looks at Object</td>
<td>Shows Object of Attention</td>
</tr>
<tr>
<td>Executing an Action</td>
<td>Looks at Object</td>
<td>Shows Object of Attention</td>
</tr>
<tr>
<td>Human: ”Let’s learn task X”</td>
<td>Subtle Head Nod</td>
<td>Confirms start of task X</td>
</tr>
<tr>
<td>Human: ”Task X is done”</td>
<td>Subtle Head Nod</td>
<td>Confirms end of task X</td>
</tr>
<tr>
<td>Any speech</td>
<td>Perks ears</td>
<td>Conveys that Leo is listening</td>
</tr>
<tr>
<td>Unconfident task execution</td>
<td>Glances to human frequently</td>
<td>Conveys uncertainty</td>
</tr>
<tr>
<td>Completion of demonstration</td>
<td>Perks ears, lean forward</td>
<td>Soliciting feedback from teacher</td>
</tr>
<tr>
<td>Human: ”Can you...?”</td>
<td>Perform or Nod/Shake</td>
<td>Communicates task knowledge</td>
</tr>
<tr>
<td>Human: ”Do task X”</td>
<td>Performs X</td>
<td>Demonstrating hypothesis for X</td>
</tr>
<tr>
<td>Task done; Human: ”Not quite...”</td>
<td>Subtle nod</td>
<td>Confirms feedback, expects refinement</td>
</tr>
<tr>
<td>Task done; Human: ”Good!”</td>
<td>Nods head</td>
<td>Confirms task hypothesis</td>
</tr>
<tr>
<td>Turn-taking Dialog</td>
<td>Eye contact</td>
<td>Making/breaking eye contact frames turns</td>
</tr>
</tbody>
</table>
• Visual perception
  • Tracking people and objects, Pointing gestures, ...
  • Deictic reference and shared attention
    – Track robot’s and human’s focus of attention

• Attention system
  • Model of human attention and model of robot attention
  • Joint attention
  • Compute level of saliency maps containing objects and events

• Speech processing
  • ASR and Speech understanding
  • Referencing of entities (button), features (color), actions (press)
  • Dialog skills (turn taking)
• Belief System (i.e. world model or memory)
  • Integrates visual information, attention and speech processing over time
  • Belief is state of the features of an object
    E.g. [type=button, color=red, location=xyz, ...]

• Mutual understanding with the teacher about the task state
  • Human gets model of robot’s state (what is understood)
  • Signaled by gestures and back-channels
  • E.g. express confusion if not understand, looking back to teacher if confidence is low, ...
  • Allows just-in-time correction
Leo’s Cognitive Architecture

[Diagram showing the cognitive architecture with various components such as Vision, Attention, Belief System, Action System, Motor System, Learning, Telemetry, Speech Understanding, and Speech Recognition.]
Leo’s Perception and Attention

- Associates gestures and objects
- Parses text output from ASR into meaningful entities for the cognitive system
Leo’s Beliefs, Learning, and Actions

Aggregates information from Speech and Vision

Learned by demonstration using telemetry suit

Execute robot behavior
Leo’s Task Learning

- Task Model
  - Hierarchical representation of actions, sub-tasks, and tasks
  - Consist of executable *task hypothesis*
  - To complete a task all its sub-tasks and actions must be completed
  - Task hypos have hierarchical goal-oriented task representation
    - Leo tries to infer the ‘goal’, when an action or task is successfully completed
      - Compare world state before and after action
      - What has changed? What is constant?
      - Goal is represented as set of beliefs
  - Execute Task hypothesis with highest Bayesian likelihood
    \[ P(h|D) \propto P(D|h)P(h) \]
    - \( h \) task hypothesis, \( D \) set of examples seen for this task
    - \( P(D|h) \) is percentage of examples where the world state change is consistent with goal of the task
    - \( P(h) \) controls preference for most specific task representations
Learning Example: “Buttons-On-and-Off” task

- **Scenario:** Teacher (T), Leo (L), and three buttons
- **Teacher (T) asks to do the task “Buttons-On-and-Off”**
  - Leo (L) indicates that he does not know the task
  - T says that the task starts with “Buttons-On”
  - L indicates that he does not know the task
  - T presses button1
  - L notices change of world state (belief system)
    - Encodes it as goal of the press action of button1
    - Stores press action in subtask “Buttons-On”
  - Analog for the other buttons
  - T says that “Buttons-On” is done
Learning Example: “Buttons-On-and-Off” task

- L notices change of world state before and after the sub-task “Buttons-On”
  - L encodes that goal of the sub-task is to have all buttons on
- Analog for “Buttons-Off” sub-task
- T tells that original “Buttons-On-and-Off” task is done
  - L sees that state of the world before and after is the same
  - L encodes overall task goal as a just-do-it goal
- Resulting hierarchical task representation:
Traditional vs. Socially Guided ML

- Comparison to traditional Machine Learning
  - Goal oriented task representation
    - Reinforcement Learning (RL) would learn a strategy (how) to achieve the goal
    - Leo learns the goal (what) and generates a way to achieve it
    - This makes generalization to other tasks possible
  - Transparent Learning
    - Leo maintains mutual belief about the learning state with the teacher (e.g. joint attention)
    - Adaptively narrowing down the hypothesis space
    - n/a in standard ML
  - Just-in-time correction
    - Resolve problems / correct errors in human robot-interaction
    - RL only can influence after execution of an action using reward
Learning in ACT-R

- ACT-R is advertised as “simple theory of learning and cognition”
- Has several different mechanisms that change its behavior from experience -> learning
- Implicit learning mechanisms are integral parts of the architecture
  - Not guided by learning intention
  - By-product of normal processing
  - Corresponds to unconscious human learning
  - Chunk from goal, production rules compilation, base activation of chunks, utility of production rules
- Explicit learning must be explicitly modeled
  - Example: Rehearsal (i.e. repeated access of chunks) can be implemented to increase base level activation
Reminder: ACT-R Operation Cycle

- Rough sketch of ACT-R’s operation cycle
  - Match production rules against current goal (on top of goal stack)
  - Conflict set = productions that match state of the current goal
  - Productions in conflict set are tested in the order of their utility
    - Chunks that occur in production condition are retrieved from declarative memory
      - Retrieval gives the chunk that matches the retrieval and has highest activation
    - If all conditional chunks can be retrieved
      - Execute production action
      - Can leave, modify, push, or pop current goal
Learning in ACT-R - Chunks

• Creation of chunks (declarative knowledge) from goals
  • When goal is popped from goal stack it becomes a chunk in declarative memory
  • Contains statement of the task and its solution
  • Next time the task arises it can be retrieved from declarative memory instead of being recomputed
  • Remember example adding two numbers by counting
    – Compute the sum of two numbers by counting
    – Next time this sum can directly be retrieved from the declarative module
Learning in ACT-R - Production Rules

- Productions contain procedural knowledge (actions)
  - Preconditions and bindings

- Creation of production rules (procedural knowledge)
  - Production compilation: combine 2 subsequently executed production rules (P1, P2) into new production rule (P3)
    - Combine the 2 sets of conditions and actions of both production rules
    - When P1 transforms a buffer that is condition of P2
      -> Test if condition of P2 can be omitted in P3
    - When P1 and P2 transform the same buffer
      -> Buffer change of P1 can be omitted in P3

- Buffers can have further restrictions on the compilation
  (e.g. motor and perceptual buffers usually do not allow compilation)
Learning in ACT-R Base - Activation

- Learning of base activation values in declarative memory

\[ B_i = \ln\left(\sum_{j=1}^{n} t_j^{-d}\right) \]

- \( t_j \) is age of \( j^{th} \) activation of chunk \( i \)
- \( d \) is constant parameter (e.g. \( d=2 \))
- \( B_i \) is large if \( t_j \) are small (activated short time ago)

- Increase activation when chunk is retrieved (t)

- -> Learning: Chunks used often become more active and are retrieved more likely
Learning in ACT-R - Utility

- Definition Utility: \( U_i = P_iG - C_i \)
- New Mechanism for learning the utility of production rules (ACT-R 6)
  - Principle of Reinforcement Learning
  - Suits human behavior in experiments and dopamin systems
  - Difference Learning Equation:
    \[
    U_i(n) = U_i(n-1) + \alpha [R_i(n) - U_i(n-1)]
    \]
    \( i \) Production, \( U_i \) Utility, \( \alpha \) Learning rate, \( R_i \) scalar Reward
  - -> Learning: Productions get higher (lower) utility, which get higher (lower) reward than expected
Comparison between Cognitive Theories and ML

- Piaget and Vygotsky are often referenced in ML literature
  - Very well known and accepted theories
  - Transfer of concepts, such as imitation, scaffolding, etc.
  - Representation of cognitive aspects of learning theories is rather limited machine learning approaches

- Performance of lower-level processes (body tracking, language understanding, ...) is still a limiting factor

- Learning theories are rather descriptive than generative
  - Describe how people learn
  - Only few instructions how to learn
Questions?