Case-Based Reasoning and the Upswing of AI

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The history and evolution of AI has shaped Case-Based Reasoning (CBR) research and applications. We are currently living in an upswing of AI. To what degree does that mean an upswing of CBR as well? And what buttons should we push in order to increase the influence of CBR within the current AI summer, and beyond?

Artificial Intelligence as a scientific field was established at a Dartmouth College seminar in 1956, but ever since ancient times the idea of thinking as a formal and mechanistic process has occupied people’s minds. After the firing of the starting shot in 56, the field has experienced both summers and winters, including two serious AI winters up to now. The causes behind these shifts in seasons have been subject to substantial discussion, and a compelling question of course is what to learn from this.

Case-Based Reasoning has had its own development history within the broader AI field. The grouping of AI methods into data-driven AI and knowledge-based AI [1] is also a familiar distinction in CBR. Recent trends in AI has clearly favoured the data-driven methods, and the well-known successes of Deep Neural Networks is a justification for that. But in order to widen the scope of AI methods, and be able to address a wider range of problems and applications, there are reasons to believe that a stronger knowledge-based influence will be needed in the years to come. Several authors have claimed we should look beyond the current upswing of AI, some have argued for methods inspired by human cognition, and others for a need to revitalize symbol-processing based on explicit knowledge representation. Pat Langley started the Cognitive Systems Movement [5], aimed at getting AI back to its roots of studying artefacts that explore the full range of human intelligence. The Artificial General Intelligence initiative addresses thinking machines with full human capabilities and beyond [3]. A focus on symbolic AI and knowledge representation issues has been strongly advocated by Hector Levesque [6], who also warns us to not to be blinded by short-term successes of particular methods.

Initiatives such as these are important to be aware of when we discuss future paths for CBR, and AI more generally. Moreover, the upswing of AI has created in the public, media, and decision makers a great confusion as to what AI is, where numerous concepts — AI, robots, ML, deep learning, and big data, together with the “smart” adjective before almost anything — are conflated and used interchangeably.

So, where is CBR in the overall AI landscape today? Does it live its own life alongside other main subareas, or are there sufficient similarities at the foundational level to group CBR with other methods? With a focus on machine learning, a division of the ML field into five “tribes” has been suggested [2], within which one such tribe is the “Analogizers”, united by their reliance on similarity assessment as the basis for learning. It is a diverse tribe covering analogical reasoning, instance-based methods, and support vector machines. For

Invited talk, extended abstract
each of the five tribes a unifying ‘master algorithm’ is proposed, and some people may fall off their chairs when kernel machines is assigned as the unifying method for this tribe. Anyway, views like this may trigger discussions that will lead to a better understanding of CBR in relation to other AI methods.

Given the growing interest in cognitive foundations of AI, we recall the notions of System 1 and System 2 in human cognition presented by Kahneman [4]. System 1 is a model of human memory capable of ‘fast thinking’, basically performing recognition of new inputs and responding intuitively, while System 2 models the deliberate, explicit reasoning performed by humans. An important issue to discuss is how they could be related to an integrated view of CBR encompassing both data-driven and knowledge-intensive processes.

All these considerations open up some important future challenges and opportunities for CBR, including: How to interpret the revitalized cognitive turn in the paradigm of CBR? How can data-driven CBR be competitive with current ML developments? Can CBR offer a new kind of synergy of data-driven and knowledge-intensive approaches for AI?

References
CBR and the Upswing of AI

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Institut d’Investigació en Intel·ligència Artificial
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Our slot

• Why did we become CBR-ers?
• A bit of AI history – through changing seasons
• CBR history snippets
• The current success of AI – and prospects ahead
  • Data-driven vs. Knowledge-based AI
• How will/may CBR contribute to future AI?
• Discussion
So: Why, oh why, did we choose CBR?
BARCELONA DECLARATION FOR THE PROPER DEVELOPMENT AND USAGE OF ARTIFICIAL INTELLIGENCE IN EUROPE

BARCELONA DECLARATION FOR THE PROPER DEVELOPMENT AND USAGE OF ARTIFICIAL INTELLIGENCE IN EUROPE

- Prudence
- Reliability
- Accountability
- Responsability
- Constrained autonomy
- Human role
知识型人工智能（Knowledge-based AI）：自上而下的推理和问题解决策略、语言处理，以及洞察学习。

数据驱动人工智能（Data-driven AI）：自下而上的统计机器学习算法，用于预测、完成部分数据或模仿行为。
AI Seasons

SUMMER  WINTER  SUMMER  WINTER  SUMMER


Dartmouth '56

Methods

Drivers
Rule-based expert systems (Dendral)

Knowledge-based systems

Expert system tools

Commercial expert systems (XCON)

Methods

Optimism/Summer

Winter

Summer

Early cognitive models

General Problem Solver

Formal logical reasoning

Neural basis for learning

Semantic networks

Knowledge-based systems focus

Revival of expert systems (Mycin)

Robot planning (Shakey)

Expert systems successes boosted new interest and funding

Report on limits of neural networks (Perceptrons)

Negative US NRC report on nat. lang. understanding

US funding based on AI prospects and researcher excellence

Negative US DARPA report on future of AI

UK Lighthill report

Schank & Abelson’s scripts

Machine learning for scientific discovery (Meta-Dendral, AM)

Cover & Hart’s K-NN classifier

Rule-based expert systems (Dendral)

Semantic networks

Dartmouth ’56

Samuel’s checker player “rote learning”

Optimism/Summer

Winter

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Report on limits of neural networks (Perceptrons)
DARPA:

Mansfield Amendment (1969): DARPA should fund “mission-oriented research, rather than basic undirected research”

American Study Group (1973): “AI research is unlikely to produce military applications in the foreseeable future.”
Configuration with R1/XCon (1978)

- Knowledge domain: Configuring VAX computers, to customers' specifications.
- Input: Required characteristics of the computer system.
- Output: Specification for the computer system.
- Inference engine: Forward chaining; the output specification was assembled in working memory.
- Knowledge representation: Production rules.
- DEC attempted to write a conventional program to do this task, with no success, then invited McDermott to write an AI system to do it. McDermott wrote R1/XCON. By 1986, it had processed 80,000 orders, and achieved 95-98% accuracy. It was reckoned to be saving DEC $25M a year.
- R1/XCON suffered from the shortcomings of simple production-rule-based systems. Expensive rewriting was needed to restore the operation of the system.

American Study Group (1973): “AI research is unlikely to produce military applications in the foreseeable future.”
- **1980**
  - **Japan’s 5th generation project**
  - **US DARPA Strategic Computing Initiative**
  - **Knowledge Acquisition/Engineering**
  - **Lisp machines**
  - **Case-based reasoning**

- **1990**
  - **KBS development tools**
  - **ANN revival (backprop.)**
  - **Genetic algorithms**
  - **Reinforcement learning**
  - **New methods from critique of (traditional) AI**

- **2000**
  - **Bayesian networks**
  - **MIT Cog project (humanoid robot)**
  - **Support vector machines**
  - **Bio-inspired AI**
  - **Ensemble learning methods**
  - **Combined DL/RL**
  - **Google car**

- **2010**
  - **IBM Watson**
  - **Deep learning (ANN)**
  - **Deep Mind’s AlphaGo**
  - **Critique of pure data-driven AI**
  - **Domingo’s Master Algorithm**

**Methods**
- **BIG DATA**
- **Ensemble learning methods**
- **Extreme computer power**
- **Very strong role of AI expected in the future digitalization of society**

**Drivers**
- **DARPA: Explainable AI**
- **UK: Royal Society initiative**

**Critique of pure data-driven AI**
- **Severe US DARPA SCI cuts**
- **Limited success of rule-based expert systems**
- **Japan’s 5th generation below expectations**
- **Norwegian AI Society (NAIS) established**
- **Severe US DARPA SCI cuts**
- **Sintef group of Knowledge Technology established, in co-operation with NTNU IDI**
- **MIT Cog project (humanoid robot)**

**Summer**
- **Knowledge Acquisiton/Engineering**
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- **Case-based reasoning**

**Winter**
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- **ANN revival (backprop.)**
- **Genetic algorithms**
T. Moto-Oka, 1982

Feigenbaum/McCorduck, 1983

T. Moto-Oka, 1982

Alvey programme:
Annual Report

Note: This is not the actual book cover
Some early CBR developments

Main CBR foci:
• The Schankian school – theory of reminding and learning
• Instance-based learning
• Similarity
• Explanations
• Knowledge-intensive CBR
• Analogy reasoning

1980
Dynamic Memory (Schank 1982)
Precedence-based reasoning (Rissland 1983)
Concept learning in weak domains (Porter&Bareiss 1986)
Reconstructive Memory (Kolodner 1983)
Case-based problem solving (Simpson 1985)
CBR in law (Ashley 1987)
Derivational analogy (Carbonell 1985)
Memory-based reasoning (Stanfill&Waltz 1988)
Structure mapping (Gentner&Forbus 1983)
Case-based planning (Hammond 1986)
Analogical mapping (Keane 1986)

1985
Instance-based learning (Kibler&Aha 1987),
Knowledge acquisition and CBR (Althoff 1989),
Knowledge-intensive CBR (Aamodt 1989)
CBR and causal explanations (Koton 1988),
Case-based learning, fuzzy examples, strategies (Plaza&Lopez 1990)

1990
Similarity and uncertainty (Richter 1990)
Genetic algorithms

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Knowledge Acquisition/Engineering

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Knowledge Acquisition/Engineering

Knowledge Acquisition/Engineering
Knowledge-based vs. Data-driven CBR

Different approaches to how to capture experiences

Knowledge-intensive cases

- Substantial generalized knowledge
- Few, comprehensive cases
- A case is a user experience
- Complex case structures
- Similarity assessment is an explanation
- Knowledge-based adaptation
- Knowledge-based learning

Instances

- No explicit generalized knowledge
- Many cases
- A case is a data record
- Simple case structures
- Global similarity metric
- No adaptation
- Learning by storing cases

Integrated case-based and model-based reasoning

Instance-based Reasoning
Contentions

All currently successful AI techniques are not new: basic ideas at least a decade old (with only small improvements)

Success of “killer apps” supports AI, but main differences are:

1) lots of data
2) high performance computing
“Silver bulletism”

“As a field I believe that we tend to suffer from what might be called serial silver bullitism, defined as follows:

the tendency to believe in a silver bullet for AI, coupled with the belief that previous beliefs about silver bullets were hopelessly naïve.”

(Hector Levesque, Research Excellence Lecture, IJCAI 2013)
No tricks!

• We should avoid being overly swayed by what appears to be the most promising approach of the day.

• We need to return to our roots in Knowledge Representation and Reasoning for language and from language.

• We should carefully study how simple knowledge bases might be used to make sense of the simple language needed to build slightly more complex knowledge bases, and so on.

• It is not enough to build knowledge bases without paying closer attention to the demands arising from their use.

• We should explore more thoroughly the space of computations between fact retrieval and full automated logical reasoning.

(Levesque, 2013)
The Cognitive Systems Movement

Most of the original challenges still remain and provide many opportunities for research.

Because “AI” now has such limited connotations, we need a new label for research that:

A New Journal for Cognitive Systems

Pat Langley, Cognitive Systems Institute, Dec. 2015
Artificial General Intelligence

Artificial General Intelligence (AGI) is an emerging field aiming at the building of "thinking machines", that is, general-purpose systems with intelligence comparable to that of the human mind. While this was the original goal of Artificial Intelligence (AI), the mainstream of AI research has turned toward domain-dependent and problem-specific solutions; therefore it has become necessary to use a new name to indicate research that still pursues the "Grand AI Dream". Similar labels for this kind of research include "Strong AI", "Human-level AI", etc.

As an artificial general intelligence technology, Nigel learns through an ever-growing neural network with nodes that can extend to any type of connected device and across any domain.

Google DeepMind publishes breakthrough Artificial General Intelligence architecture

DeepMind’s stab to become the first company to build the first, fabled, Artificial General Intelligence (AGI) solution.
Mapping the Landscape of Human-Level Artificial General Intelligence

Sam S. Adams, Itamar Arel, Josa Bach, Robert Coop, Rod Furlan, Ben Goertzel, J. Stairs Hall, Alexei Samsonovich, Matthias Schultz, Matthew Schlesinger, Stuart C. Shapiro, John F. Sowa

AI MAGAZINE  SPRING 2012

C1. The environment is complex, with diverse, interacting and richly structured objects.
C2. The environment is dynamic and open.
C3. Task-relevant regularities exist at multiple time scales.
C4. Other agents impact performance.
C5. Tasks can be complex, diverse and novel.
C6. Interactions between agent, environment and tasks are complex and limited.
C7. Computational resources of the agent are limited.
C8. Agent existence is long-term and continual.

Figure 1. Characteristics for AGI Environments, Tasks, and Agents.

R0. New tasks do not require re-programming of the agent
R1. Realize a symbol system
Represent and effectively use:
R2. Modality-specific knowledge
R3. Large bodies of diverse knowledge
R4. Knowledge with different levels of generality
R5. Diverse levels of knowledge
R6. Beliefs independent of current perception
R7. Rich, hierarchical control knowledge
R8. Meta-cognitive knowledge
R9. Support a spectrum of bounded and unbounded deliberation
R10. Support diverse, comprehensive learning
R11. Support incremental, online learning

Figure 2. Cognitive Architecture Requirements for AGI.
Daniel Dennett: Competence vs. Comprehension

“competence without comprehension”

Just as computers can perform complex calculations without understanding arithmetic, so creatures can display finely tuned behaviour without understanding why they do so.

Does comprehension matter?

Do we want post-comprehension “science”? Technological competence without comprehension? Or DARPA’s “explainable AI” initiative . . . ?

Should we try to make persons out of them?

PRO: So they can explain their reasoning to us. So they can develop their own imaginative curiosity, and epistemic goals.

CON: They will blur the lines of moral responsibility.
Recent initiatives

The US

**Broad Agency Announcement**
Explainable Artificial Intelligence (XAI)
DARPA-BAA-16-53
August 10, 2016
A DARPA Perspective on Artificial Intelligence (John Launchbury, Director I20, DARPA)
## Master Algorithm

The 5 “tribes” of ML (P. Domingos)

<table>
<thead>
<tr>
<th>Tribe</th>
<th>Origins</th>
<th>Problem</th>
<th>M.A.(solution)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Symbolists</td>
<td>Logic</td>
<td>Knowledge composition</td>
<td>Inverse deduction</td>
</tr>
<tr>
<td>Connectionist</td>
<td>Neuroscience</td>
<td>Credit assignment</td>
<td>Backpropagation</td>
</tr>
<tr>
<td>Evolutionaries</td>
<td>Evolutionary Biology</td>
<td>Structured discovery</td>
<td>Genetic Programmimg</td>
</tr>
<tr>
<td>Bayesians</td>
<td>Statistics</td>
<td>Uncertainty</td>
<td>Probabilistic Inference</td>
</tr>
<tr>
<td>Analogizers</td>
<td>Psychology</td>
<td>Similarity</td>
<td>Kernel machines</td>
</tr>
</tbody>
</table>

CBR? Clustering?
Master Algorithm

The 5 “tribes” of ML (P. Domingos)

Deep Learning (backpropagation) is most successful now. Why? What can we learn for its success?

“The analogizers are the least cohesive of the five tribes”

Pedro Domingos. “The Master Algorithm”.
“Perhaps in a future decade, machine learning will be dominated by deep analogy, combining in one algorithm the efficiency of nearest-neighbor, the mathematical sophistication of support vector machines, and the power and flexibility of analogical reasoning”

Pedro Domingos. “The Master Algorithm”
CBR strengths

Integrating learning and problem solving

Artificial Intelligence

Data-driven AI     Knowledge-intensive AI
CBR strengths

Artificial Intelligence

Data-driven AI  Knowledge-intensive AI

Human cognition

System 1  System 2

Thinking, Fast and Slow
Daniel Kahneman

Judgment under Uncertainty: Heuristics and Biases
Daniel Kahneman and Amos Tversky
## CBR and cognitive models

### Human cognition

<table>
<thead>
<tr>
<th>System 1</th>
<th>System 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fast, automatic, frequent,</td>
<td>Slow, effortful, infrequent,</td>
</tr>
<tr>
<td>emotional, stereotypic,</td>
<td>logical, calculating, conscious</td>
</tr>
<tr>
<td>subconscious</td>
<td></td>
</tr>
</tbody>
</table>

«Intuition is recognition»
(Herbert Simon)
CBR and cognitive models

Human cognition

System 1

Fast,
automatic,
frequent,
emotional,
stereotypic,
subconscious

Associative Memory
(Daniel Kahneman)

Episodes, Stories, Experience
CBR and cognitive models

Challenge

An archive/base of cases → Self-Organising Memory

data-driven similarity creation, feature reduction & invention, multi-level representation
Deep Learning Facts

(Joan Serrà, Telefonica R&D)
https://vimeo.com/album/4516480/video/211630902

- High Accuracy/performance
- **No Feature Engineering** (ML development speedup)
- Less “Complexity” and Specifications in Design
- Scale with Large Data (ML performance saturation)
- Transfer Learning (e.g. from numbers to letters)
- Flexibility (combining building blocks)
- “Unlikely” Learning (case-based learning of addition from images)
- Generative by Nature (generate new data similar to input date)
Supervised/Unsupervised Learning

• Unsupervised learning as dimensionality reduction

• Unsupervised learning as feature engineering

• the synergy of combining supervised /unsupervised learning
  
  • clustering + kNN

• MF (Matrix factorization) à la PCA

  • Unsupervised = (1) Dimensionality reduction + (2) clustering

  • Supervised (labeled targets ~ regression)

Xavier Amatriain (Quora)

10 More Lessons (Learned from building real-life Machine Learning Systems)
Supervised/Unsupervised Learning

• Core “trick” in Deep Learning is how to combine Supervised/Unsupervised Learning
  • E.g. Stacked Autoencoders
  • E.g. training convolutional nets

Xavier Amatriain (Quora)
10 More Lessons (Learned from building real-life Machine Learning Systems)
ConvNet

Training using Backpropagation

Process 1: convolution, ReLU (rectified linear unit) and pooling operations along with forward propagation in the Fully Connected layer

Process 2: measure total error and backpropagate (adjust weights)
ConvNet
Challenge 1

- Given
  - a task/goal specifying output/solution
  - cases/instances/examples/(i,o) pairs

- Discover *automatically* from the given data
  - similarity measure
  - relevant features
  - multilevel representation

Self-Organising Memory
Challenge 1

CBR is viewed as integrating “learning” and “problem solving”. We should widen the scope to integrate recognition tasks and deliberative tasks.
“To Generalize is to be an Idiot;
To Particularize is the Alone Distinction of Merit”

William Blake

(comment to Joshua Reynolds’ writings)
Analogy and categorization are the same: “There is no fundamental difference between a single memory trace (instance/entity) and a category (concept)”

E.g. “The moons of Jupiter”

Analogy as the core of cognition
Douglas Hofstadter
Challenge 2

• Today’s AI need thousands of examples.

• How to learn from only one or two?
  • Better understanding the relations between CBR and
    • Analogy?
    • ‘XAI’?
    • One-shot learning?
Discussion

• How relevant is the new cognitive turn for CBR?

• What role can CBR play in the current upswing of AI?

• Can CBR offer a new kind of synergy of data-driven and knowledge-intensive approaches to AI?

• Other new challenges for CBR should we focus on?