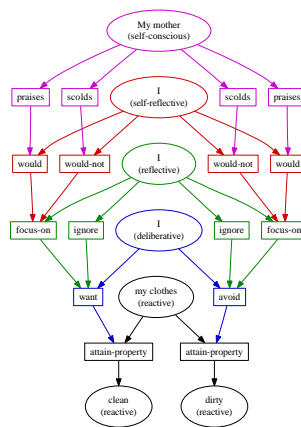


BO MORGAN

A REFLECTIVE COGNITIVE ARCHITECTURE
FOR COMBINING DIFFERENT WAYS OF
LEARNING

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BO MORGAN



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Don't do anything that isn't play.

— Joseph Campbell

Dedicated to the loving memory of Push Singh.

1972 – 2006

ABSTRACT

Recently, there have been two directions of research with the goal of building a machine that explains intelligent human behavior. The first approach is the machine learning approach and the second is the pattern recognition approach. Each of these solutions has benefits and drawbacks. The machine learning approach attempts to build a machine that learns to accomplish goals by learning the effects of its actions by interacting with its environment. The pattern recognition approach is given large amounts of knowledge and finds statistical regularities within this knowledge in order to generate more knowledge. Machine learning is good for dealing with novel problems, but these problems are necessarily simple because complex problems require background knowledge. Pattern recognition deals well with complicated problems requiring a lot of background knowledge, but fails to adapt to changing environments, for which the algorithm has not already been trained.

We are working on an algorithm that combines these two extremes into an algorithm that inherits cultural language knowledge, while recognizing the failures of this knowledge through failures and successes when this knowledge is used. We develop a definition of the utility of cultural knowledge in a domain that is grounded in goal-oriented action that corrects this knowledge by learning in the context of failure and success.

PUBLICATIONS

Some ideas and figures have appeared previously in the following publications:

Put your publications from the thesis here.

*Though there be no such thing as Chance in the world;
our ignorance of the real cause of any event
has the same influence on the understanding,
and begets a like species of belief or opinion.*

— David Hume [2]

ACKNOWLEDGMENTS

Put your acknowledgments here.

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ACRONYMS

Part I

THE SOCIAL COMMONSENSE LEARNING
PROBLEM

INTRODUCTION

Problem-solvers must find relevant data. How does the human mind retrieve what it needs from among so many millions of knowledge items? Different AI systems have attempted to use a variety of different methods for this. Some assign keywords, attributes, or descriptors to each item and then locate data by feature-matching or by using more sophisticated associative data-base methods. Others use graph-matching or analogical case-based adaptation. Yet others try to find relevant information by threading their ways through systematic, usually hierarchical classifications of knowledge—sometimes called “ontologies”. But, to me, all such ideas seem deficient because it is not enough to classify items of information simply in terms of the features or structures of those items themselves. This is because we rarely use a representation in an intentional vacuum, but we always have goals—and two objects may seem similar for one purpose but different for another purpose.

— Marvin Minsky [3]

1.1 COMMONSENSE REASONING

Part II

REFLECTIVE LAYERS OF GOALS, LEARNING, AND KNOWLEDGE

INTRODUCTION

In this chapter we will describe a sequence of scenarios that will demonstrate the top three layers of our theory: (1) reflective, (2) self-reflective, and (3) self-conscious.

First, we will describe examples critics and selectors in the top layers of our model.

2.1 BASIC FORMS OF FAILURE MUST BE DEBUGGED

A plan to use a resource is executed and that resource is no longer available when that step is about to be executed. This could be due to a number of types of reasons:

World Model Failure: The model of the world was incorrect. Miscategorized preconditions and postconditions for an action.

Planning Failure: The plan was incorrect. The agent had the correct knowledge regarding the actions involved in the plan, but the knowledge was not used when the plan was created.

- Control of Planning Failure:

2.2 SELF-CONSCIOUS REFLECTION

Self-conscious reflective critics look for conflicts between self- and other-models in stories and select resources that can debug those types of conflicts.

For example, when a person plans to use a resource and then another person uses that resource.

Part III

A PROGRAMMING LANGUAGE FOR SIMULATING A VARIETY OF REFLECTIVE THOUGHT PROCESSES

Part IV

A COGNITIVE ARCHITECTURE FOR
COORDINATING A VARIETY OF WAYS OF
LEARNING

EXAMPLES

Part V

AN EXAMPLE OF A SOCIAL COMMONSENSE REASONING DOMAIN INVOLVING MULTIPLE WAYS OF LEARNING

Ei choro aeterno antiopam mea, labitur bonorum pri no. His no decore nemore graecis. In eos meis nominavi, liber soluta vim cu. Sea commune suavitate interpretaris eu, vix eu libris efficiantur.

4.1 SOME FORMULAS

Due to the statistical nature of ionisation energy loss, large fluctuations can occur in the amount of energy deposited by a particle traversing an absorber element¹. Continuous processes such as multiple scattering and energy loss play a relevant role in the longitudinal and lateral development of electromagnetic and hadronic showers, and in the case of sampling calorimeters the measured resolution can be significantly affected by such fluctuations in their active layers. The description of ionisation fluctuations is characterised by the significance parameter κ , which is proportional to the ratio of mean energy loss to the maximum allowed energy transfer in a single collision with an atomic electron:

$$\kappa = \frac{\xi}{E_{\max}} ZNR$$

E_{\max} is the maximum transferable energy in a single collision with an atomic electron.

$$E_{\max} = \frac{2m_e\beta^2\gamma^2}{1 + 2\gamma m_e/m_x + (m_e/m_x)^2},$$

where $\gamma = E/m_x$, E is energy and m_x the mass of the incident particle, $\beta^2 = 1 - 1/\gamma^2$ and m_e is the electron mass. ξ comes from the Rutherford scattering cross section and is defined as:

$$\xi = \frac{2\pi z^2 e^4 N_{Av} Z \rho \delta x}{m_e \beta^2 c^2 A} = 153.4 \frac{z^2}{\beta^2} \frac{Z}{A} \rho \delta x \quad \text{keV},$$

where

- z charge of the incident particle
- N_{Av} Avogadro's number
- Z atomic number of the material
- A atomic weight of the material
- ρ density
- δx thickness of the material

κ measures the contribution of the collisions with energy transfer close to E_{\max} . For a given absorber, κ tends towards large values if δx is large and/or if β is small. Likewise, κ tends towards zero if δx is small and/or if β approaches 1.

You might get unexpected results using math in chapter or section heads. Consider the pdfspacing option.

¹ Examples taken from Walter Schmidt's great gallery:
<http://home.vrweb.de/~was/mathfonts.html>

The value of κ distinguishes two regimes which occur in the description of ionisation fluctuations:

1. A large number of collisions involving the loss of all or most of the incident particle energy during the traversal of an absorber.

As the total energy transfer is composed of a multitude of small energy losses, we can apply the central limit theorem and describe the fluctuations by a Gaussian distribution. This case is applicable to non-relativistic particles and is described by the inequality $\kappa > 10$ (i.e., when the mean energy loss in the absorber is greater than the maximum energy transfer in a single collision).

2. Particles traversing thin counters and incident electrons under any conditions.

The relevant inequalities and distributions are $0.01 < \kappa < 10$, Vavilov distribution, and $\kappa < 0.01$, Landau distribution.

4.2 VARIOUS MATHEMATICAL EXAMPLES

If $n > 2$, the identity

$$t[u_1, \dots, u_n] = t[t[u_1, \dots, u_{n-1}], t[u_n, \dots, u_n]]$$

defines $t[u_1, \dots, u_n]$ recursively, and it can be shown that the alternative definition

$$t[u_1, \dots, u_n] = t[t[u_1, u_2], \dots, t[u_{n-1}, u_n]]$$

gives the same result.

Part VI

CONCLUSIONS AND FUTURE DIRECTIONS

Part VII

APPENDIX



RELATED RESEARCH IN PSYCHOLOGY

“Theory of Mind: Simulation Theory versus Theory Theory”

“Emotion or affect versus goal-oriented cognition”

“Embarrassment, Guilt, and Shame”

RELATED RESEARCH IN NEUROSCIENCE

“Neural Correlates of Consciousness”

“Awareness”

“Positive and Negative Reinforcement Learning”



RELATED RESEARCH IN ARTIFICIAL INTELLIGENCE

“These systems use multiple representations including semantic networks, propositional and first-order probabilistic graphical models, case bases of story scripts, rule based systems, logical axioms, shape descriptions, and even English sentences.” — Push Singh’s webpage

RELATED RESEARCH IN COMPUTER SCIENCE

“Distributed Systems”

“Cloud Computing”

“Databases”

“Social Networks”

BIBLIOGRAPHY

- [1] Robert Bringhurst. *The Elements of Typographic Style*. Version 2.5. Hartley & Marks, Publishers, Point Roberts, WA, USA, 2002.
- [2] David Hume. *Enquiries concerning the human understanding: and concerning the principles of morals*, volume 921. Clarendon Press, 1902.
- [3] Marvin Minsky. Logical vs. analogical or symbolic vs. connectionist or neat vs. scruffy. In *Artificial intelligence at MIT expanding frontiers*, pages 218–243. MIT press, 1991.

COLOPHON

This thesis was typeset with $\text{\LaTeX}2_{\epsilon}$ using Hermann Zapf's *Palatino* and *Euler* type faces (Type 1 PostScript fonts *URW Palatino L* and *FPL* were used). The listings are typeset in *Bera Mono*, originally developed by Bitstream, Inc. as "Bitstream Vera". (Type 1 PostScript fonts were made available by Malte Rosenau and Ulrich Dirr.)

The typographic style was inspired by Bringhurst's genius as presented in *The Elements of Typographic Style* [1]. It is available for \LaTeX via CTAN as "*classicthesis*".

NOTE: The custom size of the textblock was calculated using the directions given by Mr. Bringhurst (pages 26–29 and 175/176). 10 pt Palatino needs 133.21 pt for the string "abcdefghijklmnopqrstuvwxyz". This yields a good line length between 24–26 pc (288–312 pt). Using a "double square textblock" with a 1:2 ratio this results in a textblock of 312:624 pt (which includes the headline in this design). A good alternative would be the "golden section textblock" with a ratio of 1:1.62, here 312:505.44 pt. For comparison, DIV9 of the `typearea` package results in a line length of 389 pt (32.4 pc), which is by far too long. However, this information will only be of interest for hardcore pseudo-typographers like me.

To make your own calculations, use the following commands and look up the corresponding lengths in the book:

```
\settowidth{\abcd}{abcdefghijklmnopqrstuvwxyz}
\the\abcd\ % prints the value of the length
```

Please see the file `classicthesis.sty` for some precalculated values for Palatino and Minion.

145.86469pt

DECLARATION

Put your declaration here.

Cambridge, August 2011

Bo Morgan