found to have a well visible [O II] λ 3727 Å emission line (Fig. 2) and the red objects have a rather large 4000 Å break amplitude.

The redshift of the galaxies show that we are not observing a cluster at the same redshift as the quasar. Seven objects out of nine could be in a cluster or a loose structure at $z \sim 0.3$ and two blue objects have the same redshift as the quasar (Table 1). Galaxy No. 6 is physically linked by an O II bridge to the quasar (Guzzo et al., 1988).

Perhaps the most surprising point is not that the cluster and the quasar are at different redshifts. The singularity is that this apparent cluster has such a peculiar population. Firstly it has a large blue excess, secondly it does not contain a core of very bright elliptical galaxies, thirdly the velocity spread is higher than expected. If giant elliptical galaxies were born in high density peaks of the initial density distribution, their absence suggests that there is not here a strong gravitational potential. There are indeed 10 red galaxies in the range $20.7 \leq V \leq 22$, implying the presence of a cluster. But the velocity range of the blue galaxies and the apparent compactness of the structure also suggests that we are observing a filament in the line-of-sight. Understanding the geometry of this structure would require more spectroscopic work.

The measurements of the [O II] λ 3727 Å equivalent width E(W) show that four of the blue objects have E(W) > 25 Å indicating that they are "bursting" objects or have nuclear activity. The absolute magnitudes of these galaxies are similar to those of the 6 "bursting" objects in Cl 0500-24. But in that case the redshift range $0.314 \leq z \leq 0.333$ is compatible with that of a rich cluster at $z = 0.32$. Possible explanations on the nature of these objects include galaxy interactions, environment dependent bursting, nuclear processes. Good spatial resolution imaging can tell us whether the star formation is across the entire disk, nuclear, associated with companions.

An example of an emission-line galaxy at $z = 0.2$, observed with EFOSC2 at the NTT (March 1990), is shown in Figure 3. Also shown is a red galaxy at $z = 0.3$. The V image (Fig. 2a, seeing 0".81) is slightly more extended than the I band image (Fig. 2b, seeing 0".85) indicating that the star-forming region is larger than the old component. A grey scale of the V-I colour (Fig. 2c) shows that the bluest part is in the central region implying that activity close to the nucleus plays a role in this object.

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Artificial Intelligence for Astronomy

ESO course held in 1990

H.-M. ADORF, ST-ECF/ESO

Introduction

To many people "Artificial Intelligence" is as fascinating as astronomy, to some it is a mystery and to some simply an annoyance. By constructing appropriate computer software, researchers in artificial intelligence laboratories around the world attempt to solve a variety of tasks generally considered to require some form and degree of intelligence. Among these tasks we find natural (written) language processing, speech processing, vision, symbolic computation (as opposed to numeric computation), various forms of formal reasoning such as theorem proving and uncertainty reasoning, learning, game playing and so on. A number of interesting results have been obtained in the past, but progress has been generally slower than anticipated by early enthusiasts, a phenomenon not unknown in other scientific areas.

A formal definition of artificial intelligence cannot be provided, but for our purpose it suffices to say that "AI", as it is often simply called, consists of the science of processing symbols by computers. What exactly is subsumed under the AI umbrella changes with time, a fact which has nicely been summarized in Tesler's law: "AI is whatever hasn't been done yet."

A Brief Excursion Into History

The roots of today's AI adventure can be traced back several centuries. The ancient Greeks already explored the rules governing our everyday logic. In the 17th century Blaise Pascal and Gottfried Wilhelm Leibniz dreamt of machines that could perform intellectual tasks. Boole and DeMorgan in the 19th century devised "the laws of thought" (i.e. propositional calculus) and developed rules for formal reasoning by manipulating symbols. Early in our century the eminent German mathematician David Hilbert posed several difficult problems, among them the question whether mathematics could eventually be completely formalized using a logical calculus. This conjecture was refuted through subsequent important discoveries by the logicians Kurt Gödel (1931) and Alonzo Church (in the 1930s) and one of the legendary fathers of computers, Alan Turing (1930s–50s).

Gödel, for instance, found the then shocking "Incompleteness Theorem" (see e.g. Hofstadter, 1979) which essentially says that within every formal theory there will be some conjecture which is *undecidable;* using predicate logic, neither its truth nor its falsity can be proved within the set of notions and axioms used for their formulation. This discovery ended speculations about the possibility of doing mathematics solely by mechanical theorem provers.

Turing made a number of important contributions to the general field of computing. In 1936, before the invention of 'real' computers, he posed the *halting problem:* "Is it possible to (mechanically) prove for every computer programme whether it will eventually stop?" His answer was "no", i.e. there are "undecidable" computer programmes, a result closely related to Gödel's incompleteness theorem. During World War II Turing participated in the very successful British endeavour of breaking the code of the German Enigma machine by developing and using the first real computers. Turing, a broad-minded mathematician, was the first to programme computers to play chess. In 1950, he attempted to define artificial intelligence by an operational test, which later became known as the "Turing test".

It took eight further years until the American computer scientist John McCarthy called for the first conference solely devoted to the subject of artificial intelligence. (It was actually at this conference that the notion "artificial intelligence" was coined.) Around this time McCarthy had conceived the LISP computer language, which was particularly suited for symbol manipulation. One of the founding principles of LISP is "recursion", a concept previously explored by Church in his so-called lambda calculus of recursive functions.

Another important result relevant to AI was discovered not too long ago by the computer scientist Steven Cook, who in 1971 showed that proving theorems using propositional logic is computationally intractable; in practice it takes exponential time (see e.g. Garey and Johnson, 1979). This result was generalized by others who showed many important practical problems (e.g. scheduling) to be as difficult as theorem proving.

This brief excursion into history provides us with two insights: Firstly, the AI-endeavour is deeply rooted in history and secondly, AI builds upon – and conversely is restricted by – many solid results obtained in neighbouring disciplines.

AI Methods and Techniques

Artificial intelligence researchers have always been very creative in inventing new tools and techniques in order to facilitate their work towards far reaching and ambitious goals. I will concentrate on three of these, namely languages, expert systems and artificial neural networks.

Languages. A basic tool for any computer scientist is an appropriate formal *language*. We already came across the LISP language, which actually is (after FORTRAN) the second-oldest high-level programming language still in use. However, contrary to other pioneering languages, LISP did not calcify, since it was not widely used and not standardized early on. Instead it underwent a continuous development by a breed of young enthusiastic computer specialists. LISP, a language built around the concept of manipulating lists (of symbols), has remained amazingly modern. Its simple syntax – every statement is itself a list of an operator followed by zero or more operands – allowed the easy construction of language sensitive text editors and comprehensive programme development environments. Another feature which is a direct consequence of LISP's syntactical simplicity is the ability of programmes to manipulate themselves. The language is also easily extensible and allows quick emulation of other special purpose computer languages.

For those who have never seen a statement in LISP (and may never have a chance to see one again), here is the complete recursive definition of a function which, when called, will calculate "n factorial", i.e. the product of the first n integers:

```
(defun factorial (n)                          ;define function
  (if (= n 0)                                 ;if argument equals 0
   1                                          ;then return 1
   (* n (factorial (- n 1)))))                ;else recurse with n-1
```

The programme works as follows: when called with some numerical argument n, the argument is first tested whether it is equal to zero (2nd line). If it is, the value 1 is returned (3rd line), since factorial of 0 is 1. Otherwise the factorial function is recursively called, but with an argument decremented by 1, and the result is multiplied by n (4th line).

Here is another interesting LISP programme, which calculates the "wondrous" function, defined as follows: Take an integer. If it is divisible by 2, divide; otherwise multiply by 3 and add 1. Continue with the division test. If you encounter the value 1, stop. The corresponding recursive LISP programme reads:

```
(defun wondrous (n)                                 ;define function
  (print n)                                         ;output value of n
  (cond ((= n 1) t)                                 ;if n = 1 then stop
        ((evenp n) (wondrous (/ n 2)))  ;if n even, rec. with n/2
        (t (wondrous (+ 1 (* 3 n))))))  ;else recurse with 3n+1
```

This programme prints a series of integers and, at least for all positive integers tested so far, eventually stops at 1. But, simple and short as the programme code looks, it is an open mathematical problem, whether for every positive integer n the programme will eventually halt.

Expert systems. One of the practical applications of AI-research in theorem proving and symbolic reasoning are *expert systems*. These programmes have been devised for a variety of different fields, the paramount example being medicine. Expert systems, in their traditional and widespread form, combine a body of knowledge, which is coded in form of facts and rules, with an "inference engine", which allows the deduction of new facts from the known ones with the help of the rules. Some expert systems use exact logic, others use "fuzzy" inference indicating how to combine uncertain knowledge.

Quite enthusiastically greeted when they first arrived on the scene, expert systems are not the panacea which they have sometimes unduly been taken for. Particularly, they will not replace the "how to do" of procedural programming by the "what to do" of logic programming. Expert systems for sizeable real world problems often suffer from serious performance problems. But when applied to tasks which they are suited to, the reasoning techniques developed for expert systems are useful tools in the programmer's toolbox.

Artificial neural networks. Another area of artificial intelligence, which has already flourished several times, is associated with the notion of neural networks. Networks of neurons, axons and dendrites govern the functioning of mammalian brains. They are held responsible for performing the complex cognitive tasks which allow animals to survive in a hostile environment. The amazing speed performance of neural networks is seen to be a consequence of the huge number of neurons and their high interconnectivity, allowing a form of massively parallel computing unchallenged even by modern serial supercomputers. Another advantage of natural neural networks, when compared with traditional computers, is their ability to learn and generalize. Computers almost invariably need to be programmed in every detail.

These are some of the incentives which have lead AI-researchers to distil the essentials out of natural neural networks and to construct *artificial neural networks,* usually comprised of software models. The concept of artificial "treshold logic neurons" was conceived as early as in 1943 by W. McCulloch and W. Pitts. The recent upsurge of interest was spurred by two influential papers

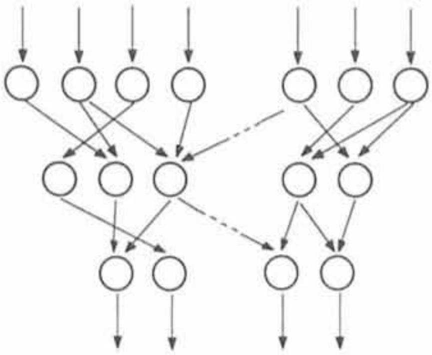

Figure 1: *Schematic view of a feed-forward neural network with three neuron layers, a topology frequently used for pattern recognition and classification. Input signals stimulate the neurons of the top layers. Their output is channelled through the middle layer and the bottom layer neurons finally produce the recognition/classification results.*

written by the physicist J.J. Hopfield in 1982 and 1984. Artificial neural networks are applied to a variety of tasks, among which we find adaptive control, image processing, natural language processing, scheduling, speech synthesis, and unsupervised and supervised classification (Fig. 1). For more details on the history and application of neural networks, consult the interesting book by Arbib (1987) and my own recent review (Adorf 1989).

Astronomical Applications of Artificial Intelligence

A few years ago, artificial intelligence entered astronomy. The prime account of current ideas and applications of AI in astronomy is the book *Knowledge-Based Systems in Astronomy*, initiated and edited by André Heck and Fionn Murtagh, to whom we all should be very grateful. As can be seen from the contributions to this book, AI has reached the fringes of astronomy, but barely the core.

Proposal processing and scheduling. The Hubble Space Telescope has served as a focal point for AI-oriented applications in the US and in Europe. A few years ago the Space Telescope-European Coordinating Facility launched its "Artificial Intelligence Pilot Project" with the aim of exploring AI-opportunities and to apply these new software techniques to a few selected areas of interest.

At the Space Telescope Science Institute, Baltimore, the leading centre for the application of AI to astronomy, a number of successful AI-based computer programmes have been developed and are in operational use within the complex ground system of the Hubble Space Telescope. The TACOS natural language front end, for instance, provides easy access to the data base of proposals used by the HST time allocation committee. The "same science" duplication checker effectively acts as a stopgap for similar proposals from different research groups. A cornerstone in the sequence of proposal processing operations (see Adorf 1990 and references therein) is the "transformation" expert system, which disassembles observing proposals into scheduling units and re-merges them from a pool into larger entities for subsequent placement onto the observational timeline.

The most prominent example of the set of STScI's proposal processing tools is certainly SPIKE, a programme system written by Mark Johnston and his group for long-term scheduling of HST-observations (Johnston, 1989, 1990; Miller and Johnston, 1991 and references therein). After the science verification phase, HST is supposed to deliver the large quantity of some 10,000 exposures per year, which are subject to a variety of (partially interacting) scientific, political, operational, spacecraft and environmental constraints. Placing these exposures onto an observational timeline is a complex task – insurmountable, if it were tried manually. SPIKE (Fig. 2) combines a novel uncertainty reasoning mechanism with a very fast neural network-inspired, stochastic scheduling algorithm (Johnston and Adorf, 1989; Adorf & Johnston, 1990) to achieve an unparalleled performance, even on ordinary serial computers. The

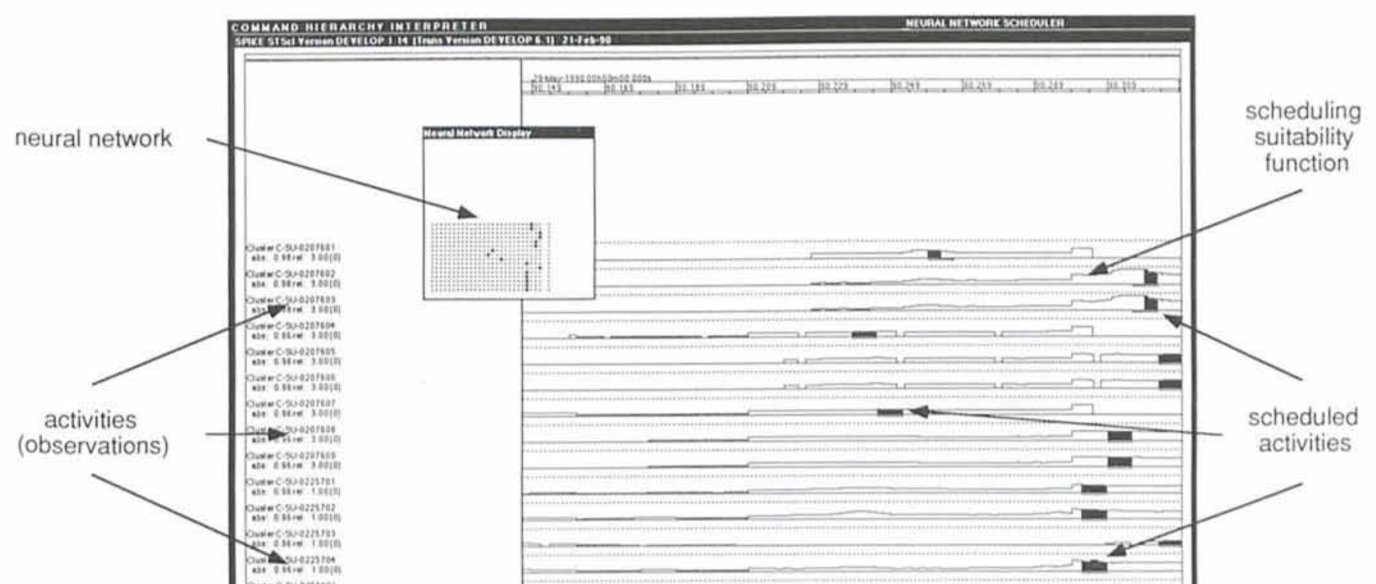

Figure 2: *Example screen from the long-range scheduler SPIKE showing the scheduling of HST observations. A number of activities (along the y-axis of the large window) have to be scheduled within a six-month scheduling interval (along the x-axis). For each activity the scheduling suitability function represents scheduling opportunities as a function of time. The small window in the upper left shows an artificial neural network used for the computation of the displayed schedule.*

SPIKE scheduler is not restricted to HST scheduling problems and has successfully been applied on a trial basis to schedule observations for the International Ultraviolet Explorer (IUE), the Extreme Ultraviolet Explorer (EUVE) and ESO's 3.6-m telescope.

Full-text retrieval. Retrieval of astronomical bibliographic full-text information is another area, for which the application of AI-techniques has been proposed originally for the machine-readable version of Astronomy & Astrophysics Abstracts (Adorf and Busch, 1988) and is now being realized within the American Astrophysical Data System (ADS), a distributed database system which incorporates all major astronomical space-borne databases.

Symbolic computation. Symbolic computations are required e.g. in the process of solving integrals or differential equations. For quite some time, there exist computer programmes which can assist in carrying out such tasks. In physics, these programmes are mainly being used for elementary particle or general relativity computations. One of these programmes, available at ESO, is Mathematica, a comprehensive system for doing mathematics. It allows one to easily solve algebraic equations, to multiply matrices, to integrate complex formulae, etc., all on the symbolic level. Results can be cast into FORTRAN-, C- or $\mathrm{T_EX}$-form, or can be graphically represented. Arbitrary precision arithmetic can be used to solve problems, which can only be computed numerically. A convenient interface allows easy access to the functionality provided by this modern research tool. Mathematica has successfully been applied at ESO to optical design problems.

Classification. This seems to be a natural area for the application of artificial intelligence techniques to astronomy. Already in 1986 a rule-based classifier for the morphological classification of galaxies was devised by the French computer scientist Monique Thonnat (see Heck and Murtagh, 1989). Other classifiers have been designed for the classification of IUE low-dispersion spectra and of low-resolution spectra from the Infrared Astronomical Satellite (IRAS). Trainable neural networks offer some potential for difficult classification tasks such as the detection and discrimination of cosmic ray hits on images from solid-state detectors in space.

The Future

Artificial intelligence in astronomy has neither as bright a future as some see it, nor as dark a future as some others do. It is easy to imagine a number of areas, still outside the core of astronomy, where AI-techniques may play a role in the future.

The increased complexity of computer systems will require better human-computer interfaces. The operation of ground-based observatories also seems to increase in complexity, and may reach a stage beyond the level which can quickly and reliably be handled by humans. Absentee and split-schedule observing modes will become more common. Coordinated multi-frequency observations, which require the synchronization of several ground-based and satellite observatories, could be facilitated by the help of sophisticated schedulers. Planned planetary missions, if ever financed, will require autonomous observing capabilities. Retrieval by content of data from large image databases, adaptive control of "flexible" telescope optics or the optimization of arrays of telescopes may be possible using neural networks (see the discussion after Merkle, 1988, and Angel et al., 1990). There are already approved plans to provide assistance in the reduction and analysis of astronomical data by a computerized expert system (Millerj, 1990). All these areas may (and in the long run will) benefit in one way or other from methods and techniques developed in AI-research labs.

Conclusion

By considering a few examples we have seen that artificial intelligence techniques have already made an inroad into astronomy. The achievements described above have been established by few, dedicated people without monetary reasons as driving forces (as opposed to other areas such as geological oil exploration). It is fairly safe to expect more AI in astronomy in the future, related, of course, to the interest by the astronomical community and the amount of resources devoted to AI-research and astronomical application development.

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Editorial Note

The present *Messenger* issue exceptionally contains 84 pages, due to a late, unexpected influx of articles, reflecting an ever-increasing level of astronomical activity in and around ESO. It is, however, our intention to revert to the normal size (60–68 pages). This may mean that we will in the future be unable to accept contributions which are submitted after the stipulated deadlines, i.e. January 20, April 20, July 20 and October 20, for the March, June, September and December issues, respectively.