

the recognition deserved to the pioneers of mathematics and computing that steered the path from these early crude machines to the **laptops** and **servers** of modern time is well beyond the scope of this book. Instead, we will leap forward in time, past all the technology-related creativity inspired by the **Second World War**, to the early 1960s, and the coining of the term ‘computer science’ by numerical analyst **George Forsythe**. By this time, the computer had many of the properties associated with contemporary machines: a **Central Processing Unit** (CPU) able both to manipulate numbers represented in binary and to execute a **program** to choreograph such manipulations; some form of **memory** in which to store data and programs; **back-up devices** to record the contents of memory when the device was switched off; connective infrastructure to allow the machine to communicate with devices other than itself; and various forms of input and output (screens, keyboards, *etc.*) to allow users to interact with the machine.

The first computer programs focused on solving mathematical problems (like finding large **prime numbers**) for which no equation existed that could simply be ‘solved’ by a human with pen and paper, but for which iterative algorithms could be devised that played to the computer’s strength of being able to mindlessly and repetitively ‘crunch’ numbers according to prescribed rules. Over time, programs were written to perform calculations that were related to more pragmatic ends: calculating payrolls and other business tasks, simulating engineering problems, and recording and searching over data about individuals for all manner of purposes. Today, computers perform innumerable jobs, from sending television programmes across **wireless networks**, to hand-held **mobile devices**, to autonomously guiding the trajectory of space probes visiting the outer reaches of our **solar system**.

Of course, this unashamedly selective, whirlwind tour of the history of computer science overlooks a multitude of incredible developments and technological innovations of the past few decades. On the face of it, many of these appear to be merely incremental improvements to existing ideas, resulting in something that is just a bit faster, smaller, bigger, greener, lighter – insert the adjective of your choice here – than before. Many of these improvements, however, are not just the result of ‘trying a bit harder’: often, development of the next generation of a particular technology has required considerable research and creative effort to overcome or circumvent what were previously considered unbreachable limits of engineering or physics. Other inventions have resulted in turning points in the way we live and work: the first machines ‘cheap’ enough to have on one’s desk, or efficient enough to run off a battery in one’s pocket; the early Internet as a connective infrastructure for commerce and research, and the Web as its more friendly front-end, with much broader appeal. More recently, **social networking**, wireless and mobile technology, and the ability to easily create and distribute audio and video, have changed how society interacts in ways that were inconceivable only a few years ago. Many of these technologies are now so integral to modern society that we fail to recognise they exist, much less the effort and thought that led to their creation.

1.3.2 Computer science meets bioinformatics

So, what has happened to allow today’s devices to quietly perform such diverse, incredibly complex tasks since the ‘primitive’ machines of the 1960s? Although faster, cheaper, smaller, less power-hungry, and in almost every way better, more sophisticated and interconnected than their older counterparts, the modern computer has very much the same basic components as its ancestors: its core remains a device for manipulating binary numbers. What has changed is our ability to use patterns of numbers to

represent increasingly complex and sophisticated things. Using a computer to calculate mathematical results is, in some ways, easy – this, after all, is what computers do. Determining which book someone is likely to want to buy next, based on the reading habits of people who have been established as having similar tastes, or – to bring this technological tale back to the life sciences – predicting whether individuals are likely to suffer from particular **diseases**, based on their genetic profiles, are altogether much more complex problems for computers to solve.

Here, then, is a gap: the vast gulf between a computer's ability to manipulate binary numbers, and our desire to use these machines to examine, understand and manipulate concepts – which, ostensibly, have no relationship to binary numbers at all. Bridging this gap, by devising techniques for representing our increasingly sophisticated knowledge in 'computable' form, is a fundamental challenge of modern computer science, one whose solution is poised to transform bioinformatics. Next to the very prominent developments we've just talked about, this is a much quieter revolution, but one that's already shaping how computers deal with data, and particularly **data representation**. In the early days of computing, **flat-file** databases, with their field-based searches, were the norm. In time, however, these were superseded by **relational database** systems that captured some of the structure of the information they modelled; and now we have **graph databases**, which attempt to model the meaning of data through the use of **controlled vocabularies**, allowing 'intelligent' data- and **text-mining** algorithms to scour them for nuggets of knowledge. This trend towards richer, more **semantic** (and thus 'computer friendly') data representation reflects our ongoing quest to make the growing volumes of data accessible to us as knowledge, knowledge that will touch innumerable aspects of our lives, from our relationships with each other and with our planet, to our future medical practice and health.

Albeit very much a thing of the past in the realms of computer science, the flat-file database was the cornerstone of early bioinformatics, playing a pivotal role in housing the gradually accumulating quantities of biomedical information. But modern high-throughput biology changed all this: its data explosion caught many bioinformaticians off-guard, and brought a growing realisation that the technologies underpinning the earliest databases were simply not up to the job. If storing the now-vast quantities of biological data was becoming increasingly demanding, reasoning over the data was becoming more difficult still. Consequently, in the aftershocks that followed, a gulf opened up between what we wanted to be able to do with bioinformatics on the one hand, and what we could actually do with it on the other.

1.4 What did we want to do with bioinformatics?

Because the origins of bioinformatics were rooted in sequence analysis, the earliest analyses aimed to understand what biomolecular sequences could tell us about the functions of **genes** and of their encoded proteins. Ultimately, scientists wanted to discover how amino acid sequences determined 3D **protein folds**, and what their sequences and structures could tell us about their evolutionary histories. Perhaps more importantly, researchers wanted to know how sequence and structure information could be used to elucidate the roles of particular genes and proteins in **pathogenic processes**, and how the assembled data could be used to design better, more efficacious **drugs**.

Later, with the advent of the human **genome-sequencing project**, the goals became increasingly ambitious, and the focus of attention turned more and more towards using bioinformatics to revolutionise molecular medicine. Researchers wanted to identify the

genetic determinants both of rare **syndromes** and of common, pervasive diseases like **cancer**; bioinformatics, it was claimed, would play a major role in the development of new approaches to eradicate such diseases, and would pave the way to **personalised therapies**, where an individual's **genome** could be used to determine which drug regime would offer maximal benefit with the minimum of **side-effects**. Ultimately, the goal was to integrate all molecular and cellular data in such a way as to be able to model **biochemical pathways** and, indeed, whole **cells**, and to understand not just how individual cells work, but how complete assemblies of cells work in whole **organs**, including the brain.

To put some of these aspirations in context, in the run up to the publication of the human genome, huge expectations were placed on what bioinformatics should or would be able to deliver. One commentator predicted that a bioinformatics revolution was afoot from which the next step in man's **evolution** would be

our acquisition of the power to control the evolution of our own **species** and all others on the planet...to **create plants that walk**², animals that can carry out **photosynthesis** and other unlikely **chimeras**..., [ultimately to] go beyond, in human-computer communication, anything we can remotely conceive of at present (Cantor, 2000).

Other predictions weren't quite so far-fetched. Yet there was a general belief that this new discipline would transform research in fields from **genomics** to **pharmacology**, and would probably 'reverse the long-standing **reductionist** paradigm that has held sway in molecular biology' for more than 50 years;

In addition, bioinformatics will likely provide the methodology finally to make highly accurate predictions about protein **tertiary structure** based on amino acid sequences and a viable means to design drugs based on computer simulation of the **docking** of small molecules to the predicted protein architecture...New computational methods will likely transform taxonomic and phylogenetic [sic] studies as well as our ability to understand and predict the results of complex **signal transduction** cascades and the **kinetics** of intricate **metabolic pathways** (Wallace, 2001).

Such views were not uncommon in this exciting new era. Genomics research was making it possible to investigate biological phenomena on a hitherto-impossible scale, amongst other things, generating masses of **gene expression**, gene and protein sequence, protein structure, and protein-protein interaction data.

How to handle these data, make sense of them, and render them accessible to biologists working on a wide variety of problems is the challenge facing bioinformatics...The 'post-genomic era' holds phenomenal promise for identifying the mechanistic bases of organisational development, metabolic processes, and disease, and we can confidently predict that bioinformatics research will have a dramatic impact on improving our understanding of such diverse areas as the regulation of gene expression, protein structure determination, comparative evolution, and **drug discovery** (Roos, 2001).

As this book unfolds, we'll touch on some of the predictions that have been made for the bioinformatics revolution, and consider how realistic they are in the context of the challenges that still lie ahead. The reality is that *in silico* approaches won't transport us to **Star Trek**³ futures quickly. Indeed, more than a decade ago, a rather prescient

²<http://en.wikipedia.org/wiki/Triffid>

³http://en.wikipedia.org/wiki/Star_Trek

Nature Biotechnology editorial suggested that the transformation we could expect genomics and *in silico* tools to have on traditional **empirical** medicine,

should take about 10 to 15 years (with a following wind) ... Thus, genomics will not rapidly improve the efficiency of drug development. In fact, it may make it even more complicated (Editorial, 2001).

In the chapters that follow, we will explore some of the complexities. We'll look at the transition from numeric to symbolic algorithms that was necessary to allow bioinformatics to move beyond the computation, say, of sequence comparison scores, to manipulation of concepts or entities, such as '**prion**', '**promoter**', '**helix**', and so on (Attwood and Miller, 2001). We'll touch on many of the emerging techniques that are being used to transform data into knowledge, exploring how **ontologies** can be used to give meaning to raw information, how **semantic integration** is beginning to make it possible to join up disparate data-sets, and how visualisation techniques provide a way of harnessing human intuition in situations where computational techniques fall short. As we navigate the [Grand Canyon](http://en.wikipedia.org/wiki/Grand_Canyon)⁴ interface between bioinformatics and computer science, we'll see why, despite the power of computers and progress in **information technology**, bioinformatics is still not as straightforward as it perhaps could or should be. In particular, we'll examine the gap between what we wanted to do with bioinformatics and what we can actually do with it, and why the 'following wind' will need to be very much stronger if we're to make substantial progress even in the next 10–15 years.

Before addressing the technical and philosophical issues that arise when we use computers to try to tackle biological problems, the next chapter will take a brief look at the biological context that provides the foundation for molecular sequence- and structure-based bioinformatics today.

1.5 Summary

This chapter explored the nature and roots of bioinformatics, and the origins of computer science. In particular, we saw that:

- 1 Bioinformatics has both service and research components;
- 2 The service side of bioinformatics involves storage, maintenance and retrieval of biological data;
- 3 The research side of bioinformatics largely involves analysis and conceptual modelling of biological data;
- 4 The term 'bioinformatics' originally had a different meaning, and pre-dates the discipline we recognise today;
- 5 The discipline evolved from labour-intensive manual technologies that aimed to deduce molecular sequences and structures, and from largely descriptive manual approaches to catalogue this information;
- 6 The first such catalogues were books;
- 7 Manual approaches for deriving molecular sequences were gradually superseded by powerful automatic processes;

⁴http://en.wikipedia.org/wiki/Grand_Canyon

- 8 Automation of sequencing technologies catalysed both the spread of databases to store, maintain and disseminate the growing quantities of data, and the development of algorithms and programs to analyse them;
- 9 Automation of DNA sequencing technologies generated data on a scale that was inconceivable 60 years ago, and even now is almost unimaginable;
- 10 Computer science involves finding ways of representing real-world problems such that they can be manipulated by machines;
- 11 The scale of modern bio-data production is demanding new computational approaches for data storage and knowledge representation;
- 12 There is currently a gap between what computers do (manipulate binary numbers) and what we want them to do (examine and manipulate concepts);
- 13 The impact of bioinformatics on drug discovery and personalised medicine has been slower to emerge than predicted;
- 14 Bridging the knowledge-representation gap will help to advance bioinformatics in future.

1.6 References

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1.7 Quiz

The following multiple-choice quiz will help you to check how much you've remembered of the origins of bioinformatics and computer science described in this chapter. Be mindful that in this and other quizzes throughout the book – just to keep you on your toes – there may be more than one answer!

- 1 Who first introduced the term bioinformatics?
 - A Fred Sanger
 - B Linus Pauling
 - C Paulien Hogeweg
 - D Margaret Dayhoff
- 2 Who first sequenced a protein?
 - A Fred Sanger
 - B Linus Pauling
 - C Paulien Hogeweg
 - D Margaret Dayhoff
- 3 How long did the determination of the sequence of insulin take?
 - A Five months
 - B Five years
 - C Eight years
 - D Ten years

- 4 Which was the first enzyme whose amino acid sequence was determined?
 - A Insulin
 - B Ribonuclease
 - C Myoglobin
 - D Haemoglobin

- 5 Which was the first protein whose structure was determined?
 - A Insulin
 - B Ribonuclease
 - C Myoglobin
 - D Haemoglobin

- 6 Which of the following statements is true?
 - A The first collection of protein sequences was at the National Center for Biotechnology Information
 - B The first collection of protein sequences was made by Fred Sanger
 - C The first collection of protein sequences was the *Atlas of Protein Sequence and Structure*
 - D None of the above

- 7 Who was responsible for the invention of the Difference Engine?
 - A John Napier
 - B Charles Babbage
 - C Joseph Marie Jacquard
 - D George Forsythe

- 8 What is the smallest number that could be represented using the Babylonian counting scheme?
 - A One
 - B Two
 - C 'Several'
 - D Zero

- 9 Binary representation was first conceived by:
 - A George Boole
 - B Pingala
 - C Alan Turing
 - D John Napier

- 10 Which of the following statements is true?
 - A There is a gap between the ability of computers to manipulate concepts and our desire to use them to manipulate binary numbers
 - B There is a gap between the ability of computers to manipulate primary numbers and our desire to use them to manipulate concepts
 - C There is a gap between the ability of computers to manipulate binary numbers and our desire to use them to manipulate concepts
 - D None of the above

1.8 Problems

- 1 Margaret Dayhoff was one of the pioneers of bioinformatics, actively working in the field in the 1960s, long before the discipline that we know today had even been named. In Section 1.2.3, we described how she was involved in producing the *Atlas of Protein Sequence and Structure*, the first published compendium of protein sequences, one that went on to give life to one of the first protein sequence databases. In addition, she is known for two other pivotal contributions to bioinformatics. What were they?
- 2 The NCBI, established in 1988, became the new home of the USA's first national nucleotide sequence database in October 1992. What was that database? How many sequences did the database contain when it was first released, and how many were contained in its first release under the auspices of the NCBI?⁵ How many sequences does the database contain today?
- 3 This book is about the gaps we encounter when we explore the interface of bioinformatics and computer science. The nature and types of gap we'll discuss are many and varied: some are subtle and small; others are large and frightening. What is the gap described by Fraser and Dunstan in their 2010 article (*The BMJ*, 342, 1314–15), and why is it especially disturbing?

⁵Hints: <http://www.youtube.com/watch?v=mn98mokVAXI>; <http://www.ncbi.nlm.nih.gov/genbank/statistics>