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Evolutionary Computation and Machine Learning for the Optimisation and Design of Physical, Chemical and Biological Systems

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Content

- Motivation & Overview of Problems, Methodologies and Computational challenges
  - 5 hours
- Introduction to Evolutionary Computing and Machine Learning
  - 7 hours
- Bioinformatics
- Systems Biology
- Chemoinformatics and Computational Physics
  - 4 hours
- Back to computing....
Motivation

Major advances in the rational design of large and complex systems have been reported in the literature and more recently, automated design and optimisation of these systems by modern AI and optimisation tools have been introduced.

It is unrealistic to expect every large and complex physical, chemical or biological system to be amenable to hand-made fully analytical designs/optimisations.

We anticipate that as the number of research challenges and applications in these domains (and their complexity) increase, we will need to rely even more on automated design and optimisation based on sophisticated AI & machine learning.

This has happened before in other research and industrial disciplines, e.g.:

• VLSI design
• Space antennae design
• Transport Network design/optimisation
• Personnel Rostering
• Scheduling and timetabling designs/optimisations.

That is, complex systems are plagued with NP-Hardness, non-approximability, uncertainty, etc. Yet, they are routinely solved by sophisticated optimisation and design techniques, like Evolutionary algorithms, etc.

Motivation
Automated Design/Optimisation is not only good because it can solve larger problems but also because this approach gives access to different regions of the space of possible designs (examples of this abound in the literature).
The Research Challenge

• For the Engineer, Chemist, Physicist, Biologist, etc:
  – To come up with a relevant (MODEL) SYSTEM $M^*$

• For the Computer Scientist:
  – To develop adequate sophisticated algorithms -beyond exhaustive search- to automatically design or optimise existing designs on $M^*$ regardless of computationally (worst-case) unfavourable results of exact algorithms.
My PhD students and Postdocs Team:

Lin Li
Jaume Bacardit
Danny Barthel
Itziar Frade
Mike Stout
Peter Siepman

Pawel Walera
German Terrazas
Scott Littlewood

Cuatro Nuevas Vacantes de Postdoctorando:
• 2X 2008
• 2X 2009

Evolutionary Computation & Machine Learning
Novel Computation, Complex systems
Bioinformatics
Physics
Chemistry

~ £14M Funded by EPSRC/BBSRC/EU/DTA

-Adam Sweetman (with P. Moriarty @ Physics)
Protein Structure Problems

Primary Structure = Sequence
MKYNNHDKIRDIIIEAYMFRFKKKVKPEVDMTIKEF ILLTYLFHQQENTLPFKKIIVSDLACYKQSDLVQHIKVL VKHSYISKVRSDERNTYISISEEQREKIAEVTLDQ QIIKQFNLADQSESQMIPKDSKEFLNLMMYTMIFK NIIKKHHTLSFVEFTILAIITSQNKIVLLKDLIETHHK YPQTVRALNLKKQGYLIKERTEDERKILIHMDDDAQ QDHAEQLLAQVNNQLLADKDHHLHLVFE

Secondary Structure

Tertiary

Local Interactions

Global Interactions
• In the native state atoms that are far away in the chain come close to each other and form *contacts*.

• These can be represented in a two-dimensional *contact map* (middle).

• CMs are used to compare pairs of proteins according to their USM *similarity*.

• Taking a set of proteins, a *similarity matrix* is computed and used to cluster proteins accordingly to their similarity (right).
Protein Structure Feature Prediction using Learning Classifier Systems

• PSP can be divided in several sub problems:
  – Secondary structure
  – Coordination number prediction
  – Solvent accessibility
  – Disulfide bonding prediction
  – etc

• The coordination number of a protein is a simplified profile of a protein's 3D structure

• CN indicates, for each residue in the protein, the number of other residues that are closer than a certain threshold to it
• Given the AA sequence of a protein chain we would like to predict the coordination number of each residue in the chain

• We have to transform the data into a regular structure so that it can be processed by standard machine learning techniques
Mechanics of Classification

- **Training Instances**
- **Learning Algorithm**
- **New Instance**
- **Inference Engine**
- **Rule Set**
- **Assigned Class**

Human Readable!
• We are developing cutting-edge Learning Classifier Systems (LCS) as the learning paradigm for these problems

• LCS are a very smart integration of evolutionary computation (robustness), reinforcement learning (quick convergence) and MDL (generalization)

• We also benchmark against other machine learning techniques e.g. Bayesian learning, decision trees, SVM, etc
We are building an integrated database containing (under a relational model):

- structural
- physicochemical
- functional
- biological
- evolutionary
- as well as genetic information of protein data.

Data is derived mainly from SCOP, PDB and DSSP databases and other web services out there.

Data is extracted through a variety of scripts that need to parse, compute, filter, etc gigabytes of data at a time.

Currently PDB and DSSP have about 34626 proteins. The above information requires monthly re-computation & updating and several tens of GB to run and store hence I/O is crucial here.
Complex Physico-Chemical Systems Design

Evolutionary algorithms

chemical platforms or models/simulations

parameters

working with CHELLnet
http://www.chellnet.org
&
working with Prof. P. Moriarty’s group

Our software evolves a set of parameters such that the Physico-chemical complex system produces a specified target behaviour.

patterns & computation in the BZ reactions

Nano-particle self-organisation

Vesicles/miscelles formation

Patterns & computation in the BZ reactions

Nano-particle self-organisation

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Current Cluster use

- We use simulations to model the physico-chemical systems.
- These simulations can take a long time.
- Even a small population of 10 candidate solutions may take days to evaluate.

Solution?

- Parallelise the evaluation of a population – evaluate each solution on a separate processor/node.
- Produce multiple runs with different random seeds
- Subdivide parameter search space

Note that even once we tie the GA to the platform we will still require horse power to evaluate heavy objective functions
Automated Software Self-Assembly Programming Paradigm (ASAP$^2$)

- Software self-assembly takes a set of human-made software components and integrate these components to yield a desired architecture to satisfy a given goal.
- New automatic paradigm for automatic program discovery. Aims: investigate, and analyze the behaviour of software self-assembly.
  - What and how software self-assembly can be affected by various factors.
  - How software self-assembly differs from other automatic programming approaches such as genetic programming.
Current work

- Software must be embedded into a simulated physical world. We define the rules of the world as to make ASAP efficient & effective.

- Kinetic theory on perfect gas is used as a metaphor, i.e., the embedding:
  \[ PV = nRT \]

- Three sorting algorithms are used as initial software components repository.

- Components are put in the virtual world \((V,T,n)\) and let to interact.

- We measure the diversity \((D_\varepsilon)\), Time to equilibrium \((T_\varepsilon)\) against three free environment parameters \((V \in [400, 500, 600, 700], \ T \in [0.25, ..., 4.0] \text{ with an increment in value of 0.25, } n \in [1,2,3,4,8,16,24,32])\).

- Using components from the three different software repositories, we use cluster to run the experiments in \((V, T, n)\) in distributedly.

- We aim at further parallelizing each individual run.
Automated Software Self-Assembly Programming Paradigm (ASAP$^2$)

Programming Wang Tiles Self-Assembly

- Given a target shape (e.g. 10x10 tile square)
- Given a Wang Tile “world” model
- Goal: To evolve sets of tiles that self-assemble in the target shape under the dynamics of the model
Generations 0, 15, 30, 45 ...
Generations ... 60, 75, 90, 99
Conclusions

• The best science today is interdisciplinary

• Computer science is at the heart of it all!

• Essentially all our work heavily depends on sophisticated algorithms and state of the art hardware, e.g. cluster computers, STM/ATM microscopes, etc.

• Today we can do science that was unimaginable a few years ago

• Different types of jobs:
  – Purely distributed jobs (√)
  – Purely parallel jobs, e.g. vesicle formation (√)
  – Low CPU, Heavy I/O load (√)
  – Mixture of distributed & parallel (X)
  – Mixture of distributed & parallel & Heavy I/O (X)

√ already running
X to run within 6 months time
Introduction to EC & ML

- **Evolutionary Computing**
- Evolutionary Machine Learning
  - Introduction to Learning Classifier Systems (Part 1)
  - Advanced LCS (Part 2)
Bioinformatics

- Conceptos Elementales de Biologia
  - Pelicula
  - Presentacion

- Introduction to Protein Structure Prediction
  - Simple Models and Algorithms

- Real-world Protein Structure Prediction Problems
  - Predicting Folding/Non Folding
  - Contact Number Prediction:
    - Part 1
    - Part 2
  - Post Synaptic Activity

- Protein Structure Comparison
  - Models, Measures, Metrics and Methods and the Procksi Server
Systems Biology

• **An (Unorthodox) Introduction**
• **Modelling Quorum Sensing**
  – The biology of QS in *P. aeruginosa*
  – Mathematical Modelling
  – A Natural Computation Mechanism derived from QS
  – Towards a formal language based model
Chemoinformatics and Computational Physics

• Evolutionary Design of Physicochemical Systems
  – Evolutionary Design of Complex Systems
  – Evolutionary Design for Surface nanoscience
Back To Computing…

• The Automated Self-Assembly Programming Paradigm (ASAP^2)
  – ASAP for programs dynamic synthesis
  – ASAP for Wang Tile’s programming