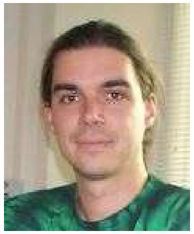
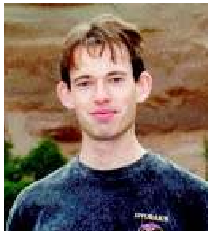
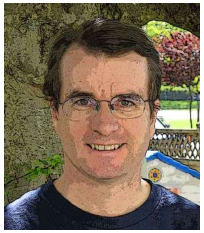
LCI Open House

Computational Statistics,
Empirical Algorithmics,
and Game Theory

Introduction







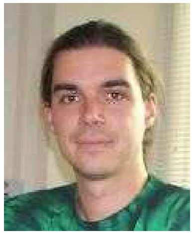
- Five LCI faculty members:
  - Nando De Freitas
  - Holger Hoos
  - Kevin Leyton-Brown
  - Kevin Murphy
  - David Poole
- Three interlocking research areas:
  - Probabilistic Reasoning & Machine Learning
    - De Freitas, Murphy, Poole
  - Empirical Algorithmics
    - Hoos, Leyton-Brown
  - Game Theory
    - Leyton-Brown, Poole

Nando De Freitas

Holger Hoos

- Hard combinatorial problems from AI and Bioinformatics
- Design and characterisation of stochastic local search algorithms for such problems
- Human-centred information management
- Computer music

The Propositional Satisfiability Problem (SAT)

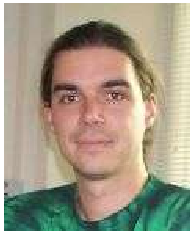


- *Given:* Propositional formula

$$
\begin{aligned}
F := \quad & (\neg x_1) \\
& \wedge (\neg x_2 \vee x_1) \\
& \wedge (\neg x_1 \vee \neg x_2 \vee \neg x_3) \\
& \wedge (x_1 \vee x_2) \\
& \wedge (\neg x_4 \vee x_3) \\
& \wedge (\neg x_5 \vee x_3)
\end{aligned}
$$

- *Question:* Satisfiable? no

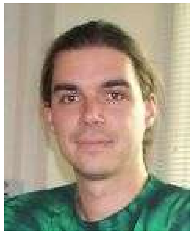
The Weighted MAX-SAT Problem



- *Given:* Propositional CNF formula with clause weights

$$
\begin{array}{rlr}
F' := & (\neg x_1) & w = 2 \\
& \wedge\ (\neg x_2 \vee x_1) & w = 1 \\
& \wedge\ (\neg x_1 \vee \neg x_2 \vee \neg x_3) & w = 7 \\
& \wedge\ (x_1 \vee x_2) & w = 3 \\
& \wedge\ (\neg x_4 \vee x_3) & w = 7 \\
& \wedge\ (\neg x_5 \vee x_3) & w = 7
\end{array}
$$

- *Question:* Minimum total weight of unsatisfied clauses? 1 (*e.g.*, $x_1 := \bot, x_2 := x_3 := x_4 := x_5 := \top$)



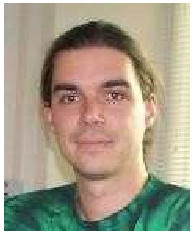
Why study SAT and MAX-SAT?

- prototypical $\mathcal{NP}$-hard problems
- many applications in AI and other areas
- conceptual simplicity facilitates algorithm design and analysis
- Weighted MAX-SAT facilities studies of characteristic differences between decision and optimisation problems

Some research questions:

- How to solve SAT and MAX-SAT as efficiently as possible?
- What makes SAT / MAX-SAT instances hard?
- Can efficient algorithms for SAT / MAX-SAT be generalised to other problems?

Stochastic Local Search (SLS)



- General method for solving combinatorial problems:

  determine initial candidate solution s
  (often based on random guess)
  repeat:
  apply small modification to s guided by
  evaluation function (often randomised)
  until termination criterion is satisfied

- Underlies state-of-the-art for many hard combinatorial problems in AI, such as MAX-SAT, scheduling, ...

Main research directions:

- Developing new SLS algorithms for SAT, MAX-SAT, ...
- Understanding and modelling SLS behaviour

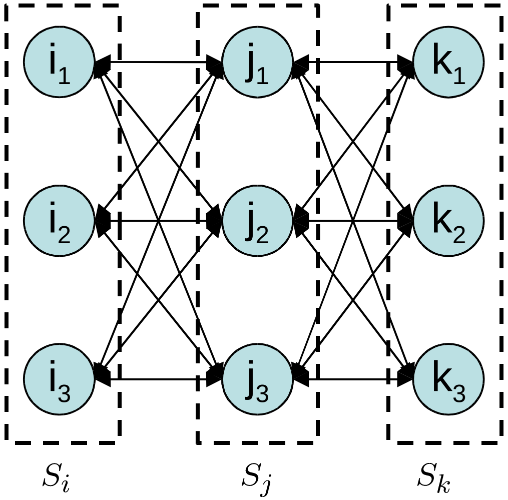
Kevin Leyton-Brown

- Research goals:
  - theoretical problems in **multiagent systems**
  - understanding **empirical properties of algorithms**

- Research areas:
  - Game Theory
  - Auction Theory, Mechanism Design
  - Empirical Hardness Models

Game Theory

- Formal model of interactions between multiple self-interested agents
  - can be competitive, cooperative, or a mix
- Central concept: Nash equilibrium
  - a set of strategies with the property that no single agent would prefer a different strategy



- Problem: compute equilibrium of games involving large numbers of players, actions
  - represent the game compactly
  - design an algorithm that leverages this structure

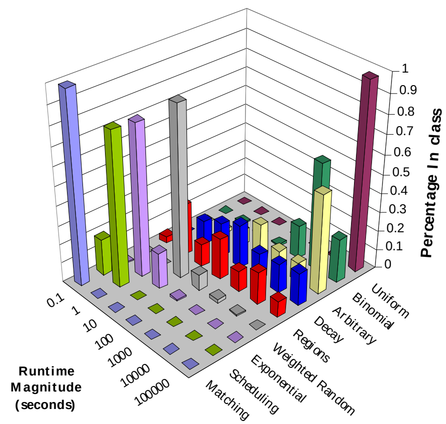
Auctions

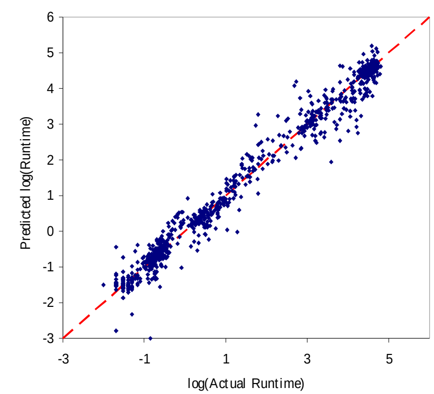
- A theoretical framework for resource allocation among self-interested agents
  - Imagine I want to give a new laptop to the grad student who would benefit the most from having it. How should I choose if students can exaggerate?

- Sample research problems:
  - design an auction to meet a set of both economic and computational requirements
  - predict or suggest strategies for a complex auction
  - facilitate or deter collusion between bidders
  - combinatorial auctions

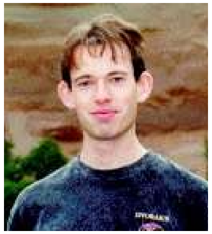
Empirical Hardness Models

- Often, empirical runtimes of identically-sized instances of NP-hard problems vary by many orders of magnitude
  - e.g., combinatorial auction winner determination
  - this graph: CPLEX runtimes for 9 CA test distributions, fixed problem size (note log scale)





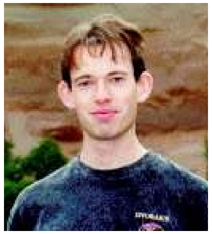
- Research agenda
  - use machine learning to build models of an algorithm's runtime for such a problem
  - analyze a model to understand sources of empirical hardness
  - model several algorithms and build an algorithm portfolio
  - use sampling to build harder benchmark distributions



Kevin Murphy

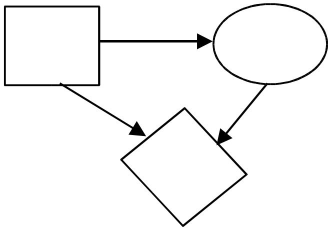
- Machine learning/ computational statistics
  - Probabilistic graphical models (PGMs)
- Applications to computer vision
  - Visual object detection and scene understanding

Probabilistic Graphical Models

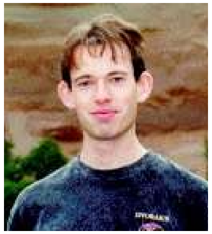


- Combines graph theory and probability theory

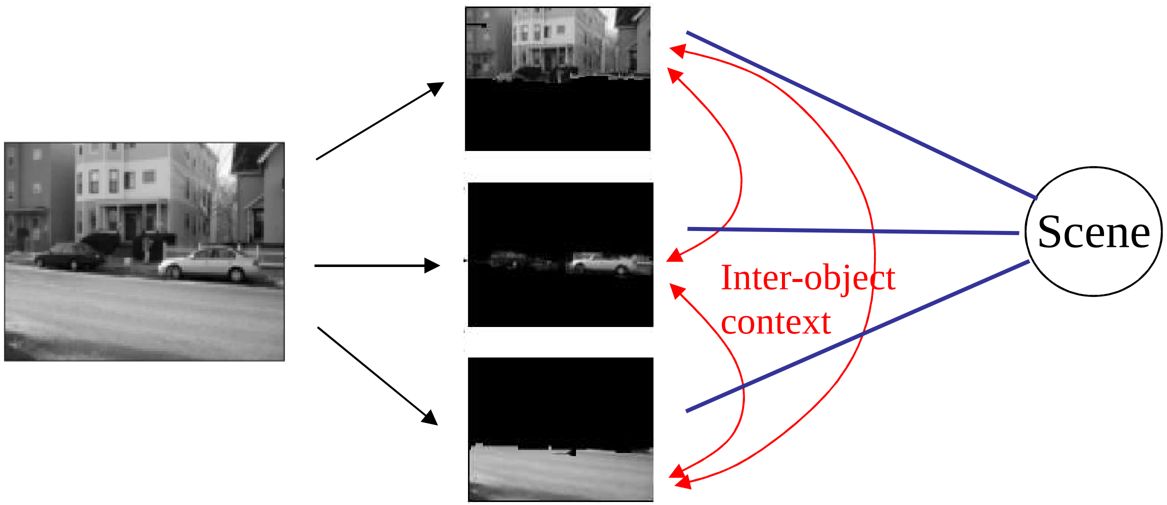
- Kevin’s focus:
  - Efficient (exact and approximate) inference algorithms
  - Flexible software toolkits (eg. BNT)



Visual Object Detection and Image Understanding

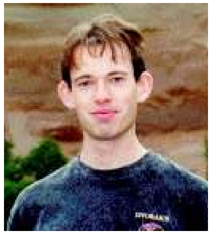


- Focus: model probabilistic relationships between objects and scenes.

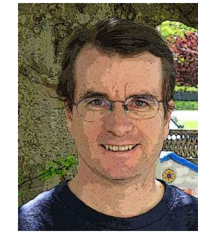


- Applications to wearable computing and mobile robotics.

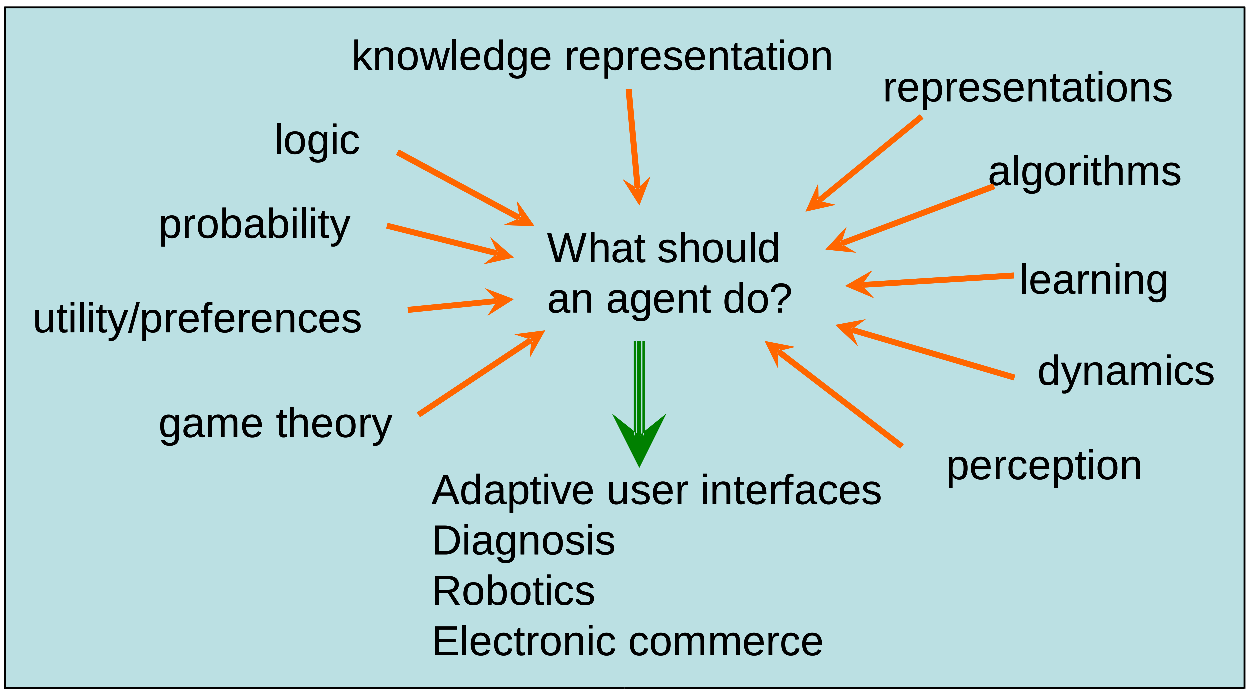
Demo of Car Detection using Local and Global Image Features



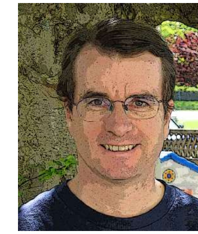
David Poole



"What should an agent do based on its prior knowledge, what it observes about the world, and its values or goals?"



Probabilistic Reasoning

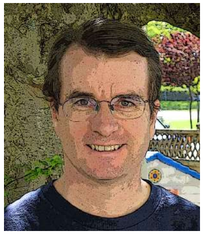


- Search algorithms for Bayesian Networks
  - enumerate very likely possible worlds; estimate probabilities
  - works well for skewed probability distributions

- Exploiting Contextual Independence in Probabilistic Inference
  - a rule-based representation of Bayes nets, which can leverage contextual independence for exponential computational gain

- Decision Making Under Uncertainty
  - sequential decision making under imperfect sensors
  - represent the problems as influence diagrams or partially observable Markov decision processes (POMDPs).

Combining Logic and Probability



- Probabilistic Horn Abduction
  - an early combination of logic and probability with a very weak logic (e.g., no disjunction)

- Independent Choice Logic
  - a semantic framework allowing for independent choices by multiple agents, and a logic program to give consequences of their choices
  - an expansion of Probabilistic Horn abduction to include a richer logic and choices by multiple agents
  - extends logic programs, Bayesian networks, influence diagrams, MDPs, and game theory representations

- Central issues:
  - representation (e.g., introducing a notion of time)
  - inference algorithms that leverage compactness in representation
  - learning
  - applications (e.g., diagnosis, robotics, user modeling)

Related Grad Courses

Term 1:

- CS532c: Graphical Models – Murphy

Term 2:

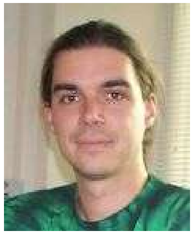
- CS532a: Multiagent Systems – Leyton-Brown
- CS532d: Stochastic Search Algorithms – Hoos
- CS540: Machine Learning – de Freitas

LCI Forum: alternate Fridays at noon (with food!)

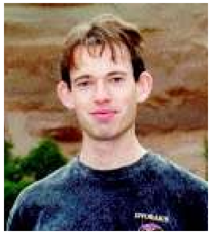
– next forum: September 17

Summary

- People:
  - Nando De Freitas
  - Holger Hoos
  - Kevin Leyton-Brown
  - Kevin Murphy
  - David Poole



- Research areas:
  - Probabilistic Reasoning & Machine Learning
    - De Freitas, Murphy, Poole
  - Empirical Algorithmics
    - Hoos, Leyton-Brown
  - Game Theory
    - Leyton-Brown, Poole



- …and now it's time to meet some students,
  and see some cool demos!