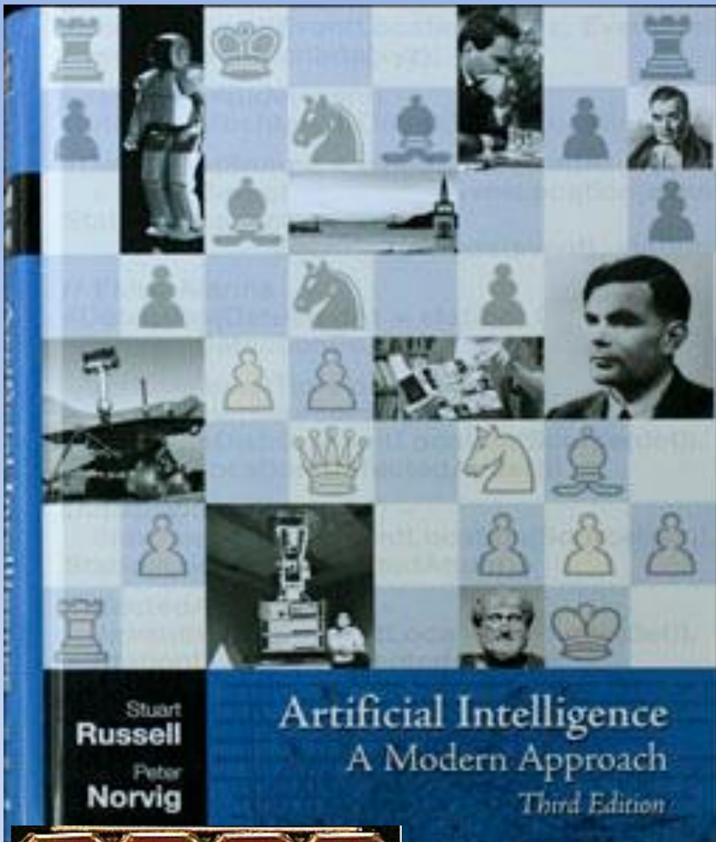
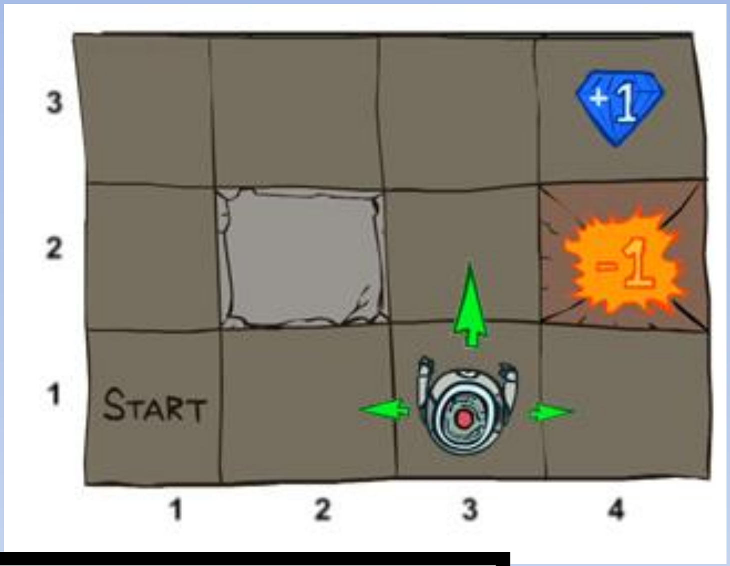
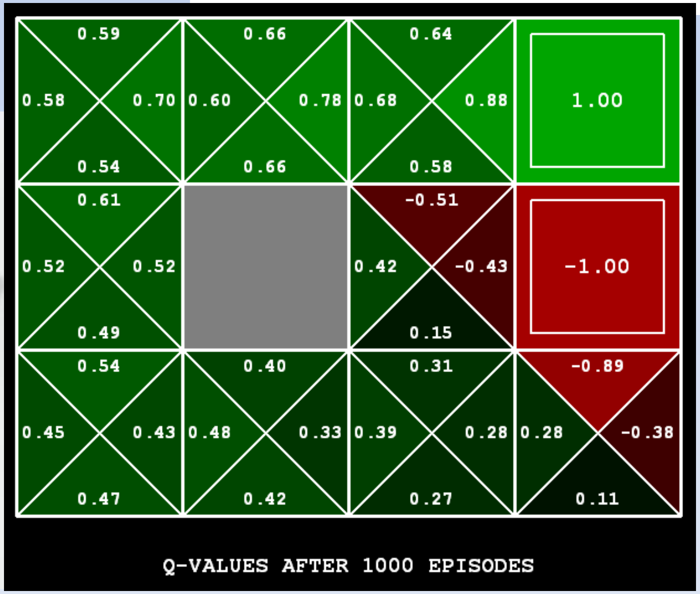
Artificial Intelligence







Grading

Period	Presentations/Examinations/Assignments	Points
Various	In-Class Participation/Presentations	125
	Search	125
	Probabilistic Reasoning	125
	Quizzes	125
	Midterm	200
	Final	300

Assignments (Programming)

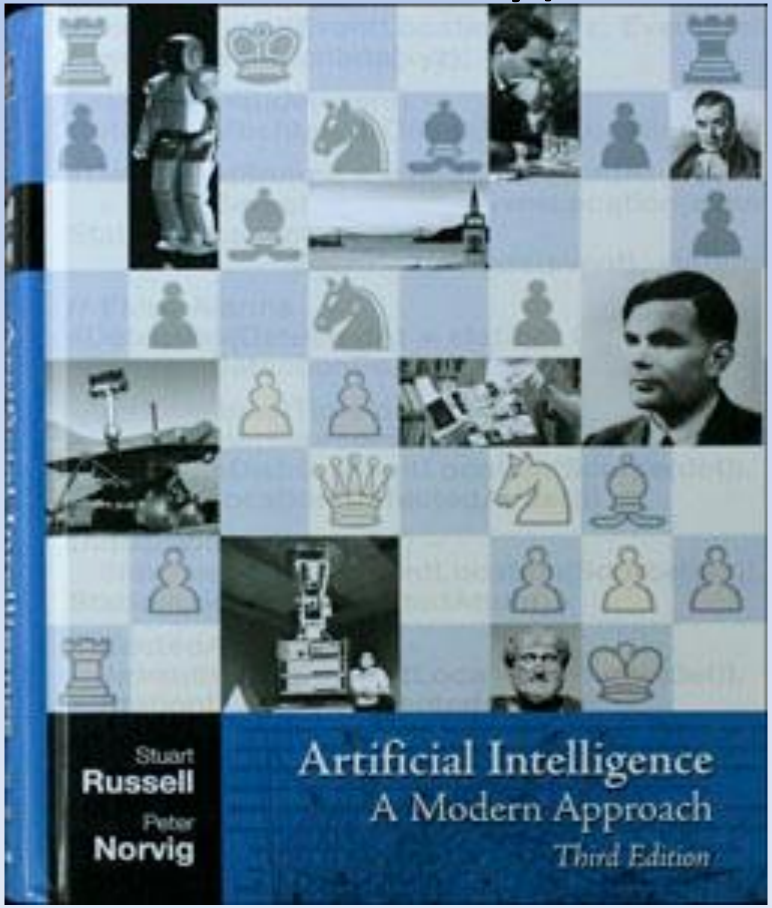
- Assignment 1: Search
- Assignment 2: Probabilistic Reasoning

Tests

- Midterm (20%)
- Final (30%)

Textbook

- The 22nd most cited computer science publication on Citeseer (and 4th most cited publication of this century).



Dr. Stuart Russell

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Education

B.A. (Hons.) 1st Class, Physics, Wadham College, University of Oxford, 1979--82.
Ph.D., Computer Science, Stanford University, 1982--86.

Employment history

2012--present, Professeur Invité, Université Pierre et Marie Curie, Paris
2012--present, Professeur, Fondation de l'École Normale Supérieure, Paris
2008--present, Adjunct Professor, Department of Neurological Surgery, University of California, San Francisco
2008--2010, Chair, Department of Electrical Engineering and Computer Sciences, University of California, Berkeley
2006--2010, Chair, Computer Science Division, University of California, Berkeley
1996--present, Professor, Computer Science Division, University of California, Berkeley
1991--96, Associate Professor, Computer Science Division, University of California, Berkeley
1986--91, Assistant Professor, Computer Science Division, University of California, Berkeley
1986, Summer employee, MCC, Austin, Texas, Machine learning research in the Large Scale KB Project (CYC)
1985--86, Research Assistant, Computer Science Dept., Stanford University
1983, Teaching Assistant, Computer Science Dept., Stanford University
1981, Programmer, graphics research project, IBM Los Angeles Scientific Center
1978--80 (1 year total), Programmer, IBM Systems Engineering Centre, Warwick, UK

Dr. Peter Norvig

Professional Employment (Full-Time)

2001-now	Google	Director of Research (2006-now); formerly Director of Search Quality (2002-2006) and Machine Learning (2001).
1998-2001	NASA Ames Research Center	Division Chief, Computational Sciences
1996-1998	Junglee Corp.	Chief Scientist
1994-1996	Harlequin, Inc.	Chief Designer
1991-1994	Sun Microsystems Labs	Senior Scientist
1986-1991	University of California, Berkeley	Research Faculty Member
1985-1986	University of Southern California	Assistant Professor
1978-1980	Higher Order Software, Inc.	Member of Technical Staff
1977-1977	Woods Hole Oceanographic Institute	Summer Programming Intern

I also have served as an advisory board member for various companies, including: Root-1, Fetch, CleverSet, Ask Jeeves, Thinking Software, PersonalGenie.com.

Education

1980-1985	Ph.D.	Computer Science	University of California, Berkeley
1974-1978	B.S.	Applied Mathematics	Brown University

Personal Information

Citizen: U.S.
Raised: RI, MA, CA.
Status: Married with 2 children.
Erdos #: 3 (Erdos to Peter Cameron to Stuart Russell to me)

Additional Materials

- AAAI
- KDD

www.aaai.org/Conferences/AAAI/aaai16.php

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Program Overview
Program Grid
Accepted Papers
Program (PDF)
AAAI Program Schedule
IAAI Schedule
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Guidebook Online Program

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Conference Committee

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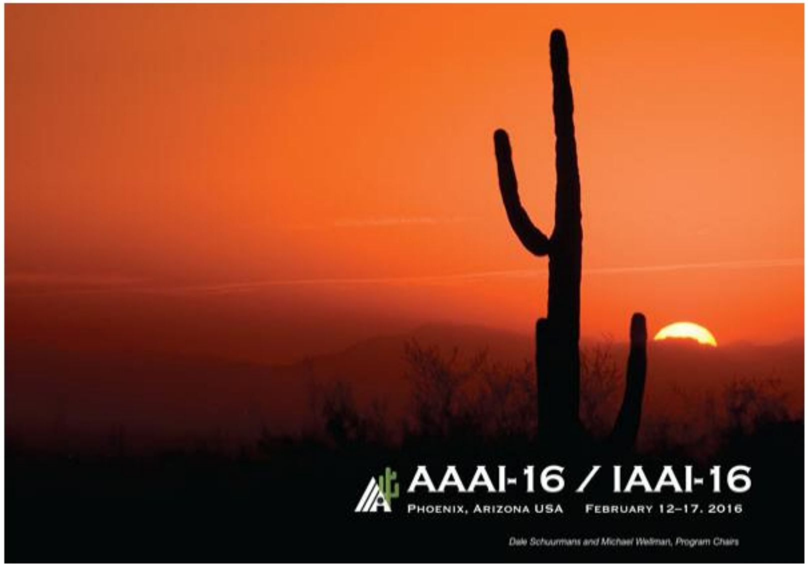
Student Programs
Student Poster Program
DC Call for Applications
Student Volunteer Program



PLEASE JOIN US FOR THE THIRTIETH AAAI CONFERENCE (AAAI-16)!

February 12–17, 2016, Phoenix, Arizona USA

NEW! **Registration Information!**

The Thirtieth AAAI Conference on Artificial Intelligence (AAAI-16) will be held February 12–17 at the Phoenix Convention Center, Phoenix, Arizona, USA. Please note the alternate day pattern for AAAI-16. The workshop, tutorial, and doctoral consortium programs will be held Friday and Saturday, February 12 and 13, followed by the technical program, Sunday through Wednesday (at noon), February 14–17.

http://www.aaai.org/Library/AAAI/aaai16contents.php

Technical Papers: Applications

Inferring Multi-Dimensional Ideal Points for US Supreme Court Justices / 4
Mohammad Raihanul Islam, K. S. M. Tozammel Hossain, Siddharth Krishnan, Naren Ramakrishnan

Little Is Much: Bridging Cross-Platform Behaviors through Overlapped Crowds / 13
Meng Jiang, Peng Cui, Nicholas Jing Yuan, Xing Xie, Shiqiang Yang

Scientific Ranking over Heterogeneous Academic Hypernetwork / 20
Ronghua Liang, Xiaorui Jiang

MUST-CNN: A Multilayer Shift-and-Stitch Deep Convolutional Architecture for Sequence-Based Protein Structure Prediction / 27
Zeming Lin, Jack Lanchantin, Yanjun Qi

Hospital Stockpiling Problems with Inventory Sharing / 35
Eric Lofgren, Anil Vullikanti

Predicting ICU Mortality Risk by Grouping Temporal Trends from a Multivariate Panel of Physiologic Measurements / 42
Yuan Luo, Yu Xin, Rohit Joshi, Leo Celi, Peter Szolovits

Learning to Generate Posters of Scientific Papers / 51
Yuting Qiang, Yanwei Fu, Yanwen Guo, Zhi-Hua Zhou, Leonid Sigal

Face Behind Makeup / 58
Shuyang Wang, Yun Fu

Social Role-Aware Emotion Contagion in Image Social Networks / 65
Yang Yang, Jia Jia, Boya Wu, Jie Tang

Survival Prediction by an Integrated Learning Criterion on Intermittently Varying Healthcare Data / 72
Jianfei Zhang, Lifei Chen, Alain Vanasse, Josiane Courteau, Shengrui Wang

On the Minimum Differentially Resolving Set Problem for Diffusion Source Inference in Networks / 79
Chuan Zhou, Wei-Xue Lu, Peng Zhang, Jia Wu, Yue Hu, Li Guo

Registration Information
Registration Form

Program

Program Overview
AAAI Guidebook Schedule
Accepted Papers
Program (PDF)
AAAI Program Schedule *New!*
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Invited Speakers

Conference Organization

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AAAI-17 SAN FRANCISCO

PLEASE JOIN US FOR THE THIRTY-FIRST AAAI CONFERENCE (AAAI-17)!

Register! 4 – 9 February – San Francisco, California USA

- AAAI Guidebook Schedule

Selected lectures and programs from this conference have been posted at VideoLectures.Net.

The Thirty-First AAAI Conference on Artificial Intelligence (AAAI-17) will be held February 4–9 at the Hilton San Francisco, San Francisco, California, USA. The workshop, tutorial, and doctoral consortium programs will be held Saturday and Sunday, February 4 and 5, followed by the technical program, Monday through Thursday, February 6–9.

The chairs of AAAI-17 are Satinder Singh (University of Michigan) and Shaul Markovitch (Technion-Israel Institute of Technology).

The purpose of the AAAI conference is to promote research in artificial intelligence (AI) and scientific exchange among AI researchers, practitioners, scientists, and engineers in affiliated disciplines. AAAI-17 will have a diverse technical track, student abstracts, poster sessions, invited speakers, tutorials, workshops, and exhibit and competition programs, all selected according to the highest reviewing standards. AAAI-17 welcomes submissions on mainstream AI topics as well as novel crosscutting work in related areas.

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THIRTY-FIRST AAAI CONFERENCE ON ARTIFICIAL INTELLIGENCE

Sponsored by the Association for the Advancement of Artificial Intelligence

Satinder Singh and Shaul Markovitch, Program Cochairs.

February 4 –9, 2017, San Francisco, California USA. Published by The AAAI Press, Palo Alto, California. This proceedings is also available in book format.

Please Note: Abstracts are linked to individual titles, and will appear in a separate browser window. Full-text versions of the papers are linked to the abstract text. PDF file sizes may be large!

Contents

Applications

SnapNETS: Automatic Segmentation of Network Sequences with Node Labels / 3
Sorour E. Amiri, Liangzhe Chen, B. Aditya Prakash

Taming the Matthew Effect in Online Markets with Social Influence / 10
Franco Berbeglia, Pascal Van Hentenryck

A Leukocyte Detection Technique in Blood Smear Images Using Plant Growth Simulation Algorithm / 17
Deblina Bhattacharjee, Anand Paul

Partitioned Sampling of Public Opinions Based on Their Social Dynamics / 24
Weiran Huang, Liang Li, Wei Chen

Novel Geometric Approach for Global Alignment of PPI Networks / 31
Yangwei Liu, Hu Ding, Danyang Chen, Jinhui Xu


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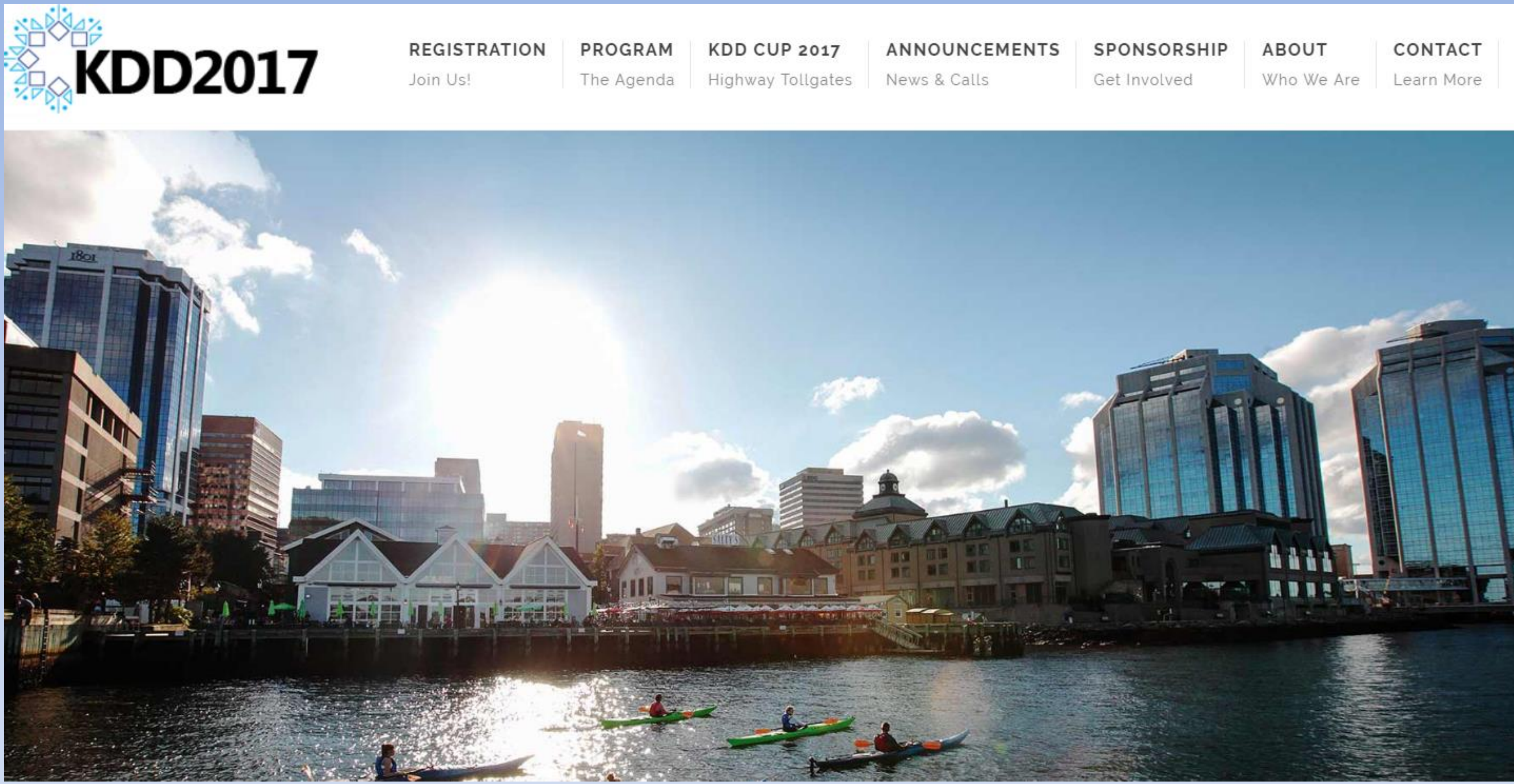
RESEARCH TRACK PAPERS - ORAL

Title & Authors
NetCycle: Collective Evolution Inference in Heterogeneous Information Networks Author(s): Yizhou Zhang*, Fudan University; Xiong Yun, ; Xiangnan Kong, Worcester Polytechnic Institute; Yangyong Zhu, Fudan University
Lexis: An Optimization Framework for Discovering the Hierarchical Structure of Sequential Data Author(s): Payam Siyari*, Georgia Institute of Technology; Bistra Dilkina, Georgia Tech; Constantine Dovrolis, Georgia Institute of Technology
Skinny-dip: Clustering in a Sea of Noise Author(s): Samuel Maurus*, Helmholtz Zentrum München; Claudia Plant
Goal-Directed Inductive Matrix Completion Author(s): Si Si*, Ut austin; Kai-Yang Chiang, UT Austin; Cho-Jui Hsieh, UT Austin; Nikhil Rao, Technicolor Research; Inderjit Dhillon, UTexas
Sampling of Attributed Networks From Hierarchical Generative Models Author(s): Pablo Robles Granda*, Purdue University; Sebastian Moreno, ; Jennifer Neville, Purdue
Joint Community and Structural Hole Spanner Detection via Harmonic Modularity Author(s): Lifang He*, ; CHUN-TA LU, UIC; Jiaqi Ma, Tsinghua University; Jianping Cao, NUDT; Linlin Shen, ; Philip S. Yu, UI Chicago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BEST PAPER AWARD

Winner

Accelerating Innovation Through Analogy Mining

Tom Hope (Hebrew University of Jerusalem);Joel Chan (Carnegie Mellon University);Aniket Kittur (Carnegie Mellon University);Dafna Shahaf (Hebrew University of Jerusalem)

Runner Up

Toeplitz Inverse Covariance-Based Clustering of Multivariate Time Series Data

David Hallac (Stanford University);Sagar Vare (Stanford University);Stephen Boyd (Stanford University);Jure Leskovec (Stanford University)

Best Reviewers

- Karthik Raman, Google
- Kevin Small, Amazon
- Zoran Obradovic, Temple University
- Pauli Miettinen, Max Planck Institute

- Monday
- Wednesday

Important Dates

- **Camera Ready Deadline**
  June 9, 2017
- **Startup Grant Deadline**
  June 16, 2017
- **Student Grants Deadline**
  June 17, 2017
- **Promotional Video Deadline**
  June 18, 2017
- **Tutorials**
  August 13, 2017
- **Workshops**
  August 14, 2017
- **Main Conference**
  August 15 - 17, 2017

Program

- Keynote Speakers
- Applied Data Science Invited Panels
- Applied Data Science Invited Talks
- Plenary Panel

KDD Topics

Home / Topics

Graph Mining and Social Networks

Curated by: Christos Faloutsos

Have you ever wondered how Google finds the best page for your question? How would you spot the most important people on faceBook? How would you spot fake followers on Twitter? In a who-contacts- whom network, which is the best nodes to immunize, to stop a flu epidemic?

All these problems, and myriad more, use "graph mining" methods. But graph mining is not restricted to social networks: in computer-to- computer communication networks we want to find whether a computer is under cyber-attack (and protect it, before-hand); in a user-product review system, we want to find fake reviews; in a prey-predator ecological system, we want to find the most important species, to protect the system from unraveling.

Graph mining uses sophisticated mathematical methods ("linear algebra", "eigenvalue analysis", "matrix factorizations", "tensors"), which pay off spectacularly - Google's PageRank algorithm being the most obvious example.

Link: http://www.cs.cmu.edu/~christos/TALKS/16-graph-mining-intro-kdd/

Robust Influence Maximization

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ABSTRACT

In this paper, we address the important issue of uncertainty in the edge influence probability estimates for the well studied influence maximization problem — the task of finding k seed nodes in a social network to maximize the influence spread. We propose the problem of robust influence maximization, which maximizes the worst-case ratio between the influence spread of the chosen seed set and the optimal seed set, given the uncertainty of the parameter input. We design an algorithm that solves this problem with a solution-dependent bound. We further study uniform sampling and adaptive sampling methods to effectively reduce the uncertainty on parameters and improve the robustness of the influence maximization task. Our empirical results show that parameter uncertainty may greatly affect influence maximization performance and prior studies that learned influence probabilities could lead to poor performance in robust influence maximization due to relatively large uncertainty in parameter estimates, and information cascade based adaptive sampling method may be an effective way to improve the robustness of influence maximization.

Keywords

social networks, influence maximization, robust optimization, information diffusion

algorithmic framework to find the most influential seeds, and they propose the *independent cascade* model and *linear threshold* model, which consider the social-psychological factors of information diffusion to simulate such a random process of adoptions.

Since Kempe et al.'s seminal work, extensive researches have been done on influence maximization, especially on improving the efficiency of influence maximization in the independent cascade model [11, 10, 16, 4, 28], all of which assume that the ground-truth influence probabilities on edges are exactly known. Separately, a number of studies [26, 27, 15, 25, 24] propose learning methods to extract edge influence probabilities. Due to inherent data limitation, no learning method could recover the exact values of the edge probabilities, and what can be achieved is the estimates on the true edge probabilities, with confidence intervals indicating that the true values are within the confidence intervals with high probability. The uncertainty in edge probability estimates, however, may adversely affect the performance of the influence maximization task, but this topic has left mostly unexplored. The only attempt addressing this question is a recent study in [18], but due to a technical issue as explained in [18], the results achieved by the study is rather limited.

In this paper, we utilize the concept of robust optimization [3] in operation research to address the issue of influence maximization with uncertainty. In particular, we con-

Robust Influence Maximization

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ABSTRACT

Uncertainty about models and data is ubiquitous in the computational social sciences, and it creates a need for *robust* social network algorithms, which can simultaneously provide guarantees across a spectrum of models and parameter settings. We begin an investigation into this broad domain by studying robust algorithms for the Influence Maximization problem, in which the goal is to identify a set of k nodes in a social network whose joint influence on the network is maximized.

We define a Robust Influence Maximization framework wherein an algorithm is presented with a set of influence functions, typically derived from different influence models or different parameter settings for the same model. The different parameter settings could be derived from observed cascades on different topics, under different conditions, or at different times. The algorithm's goal is to identify a set of k nodes who are simultaneously influential for all influence functions, compared to the (function-specific) optimum solutions.

We show strong approximation hardness results for this problem unless the algorithm gets to select at least a logarithmic factor more seeds than the optimum solution. However, when enough extra seeds may be selected, we show that techniques of Krause et al. can be used to approximate the optimum robust influence to within a factor of $1 - 1/e$. We evaluate this bicriteria approximation algorithm against natural heuristics on several real-world data sets. Our experiments indicate that the worst-case hardness does not necessarily translate into bad performance on real-world data sets; all algorithms perform fairly well.

Categories and Subject Descriptors

[**Human-centered computing**]: Social networks

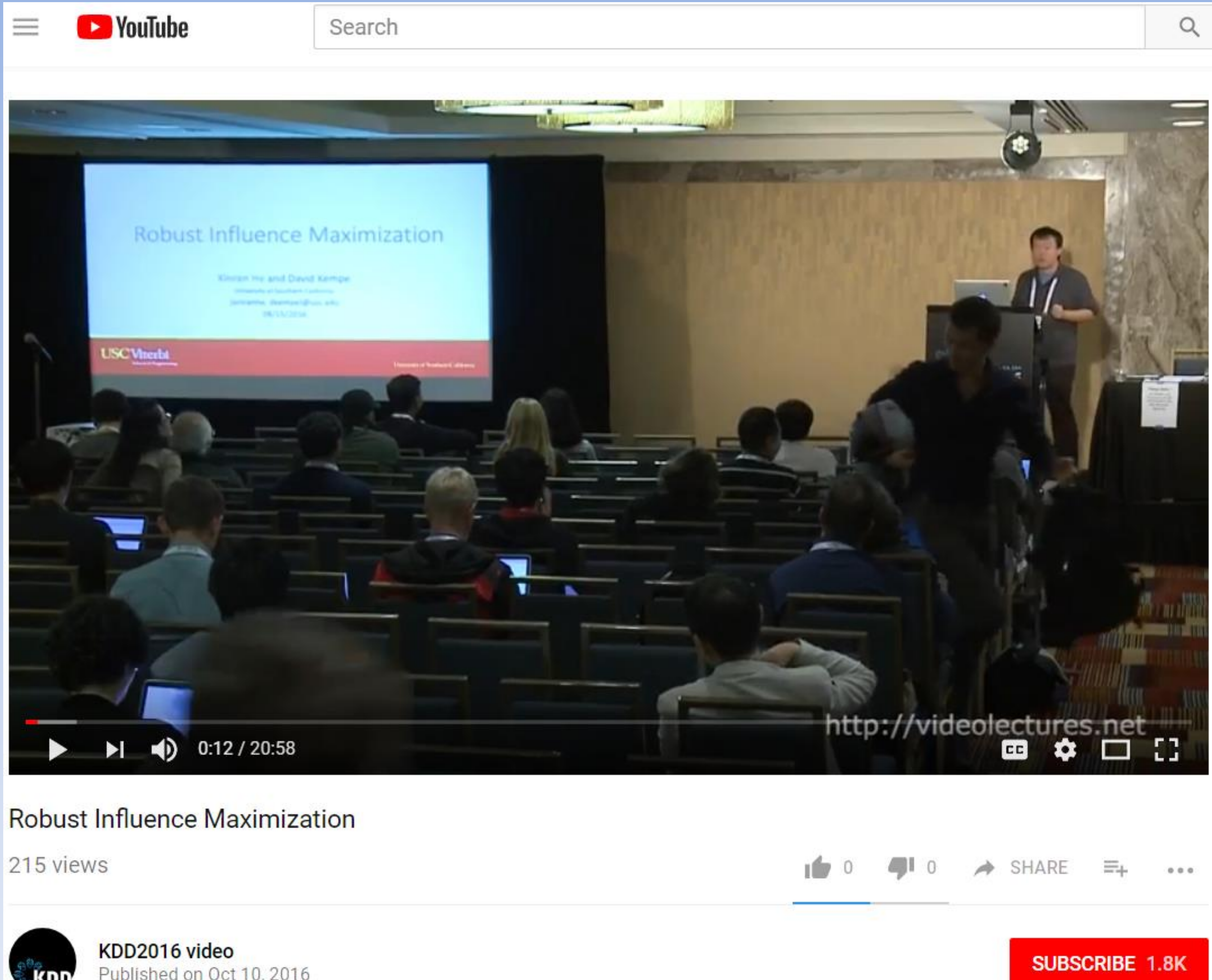
approaches and computational models. It has emerged as an important application of data mining and learning, while also invigorating research in the social sciences. Computational social science is frequently envisioned as a foundation for a discipline one could term "computational social engineering," wherein algorithmic approaches are used to change or mitigate individuals' behavior.

Among the many concrete problems that have been studied in this context, perhaps the most popular is Influence Maximization. It is based on the observation that behavioral change in individuals is frequently effected by influence from their social contacts. Thus, by identifying a small set of "seed nodes," one may influence a large fraction of the social network. The desired behavior may be of social value, such as refraining from smoking or drug use, using superior crops, or following hygienic practices. Alternatively, the behavior may provide financial value, as in the case of viral marketing, where a company wants to rely on word-of-mouth recommendations to increase the sale of its products.

1.1 Prevalence of Uncertainty and Noise

Contrary to the "hard" sciences, the study of social networks — whether using traditional or computational approaches — suffers from massive amounts of noise inherent in the data and models. The reasons range from the fundamental to the practical:

- At a fundamental level, it is not even clear what a "social tie" is. Different individuals or researchers operationalize the intuition behind "friendship", "acquaintance", "regular" advice seeking, etc. in different ways (see, e.g., [4]). Based on different definitions, the same real-world individuals and behavior may give rise to different mathematical models of the same "social network."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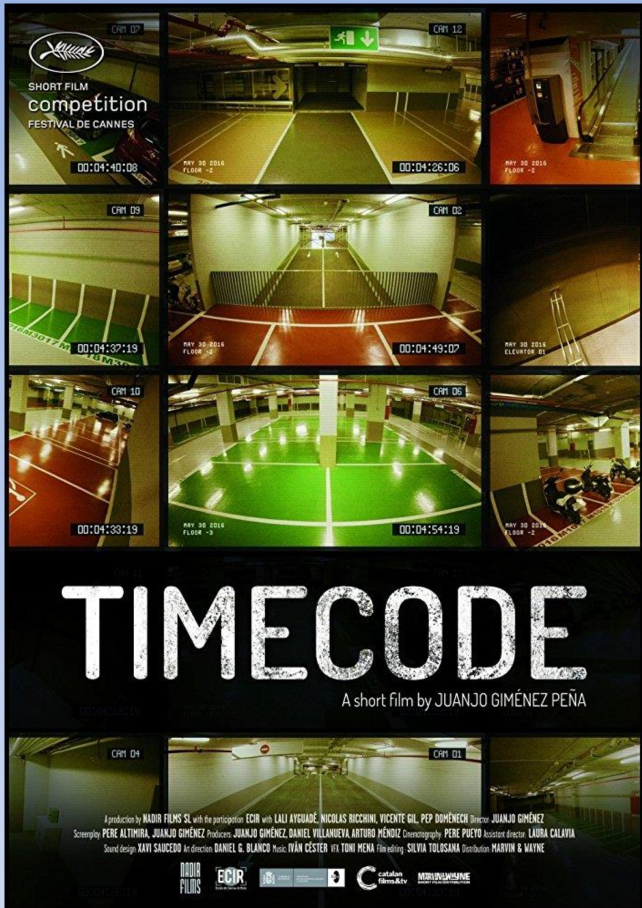

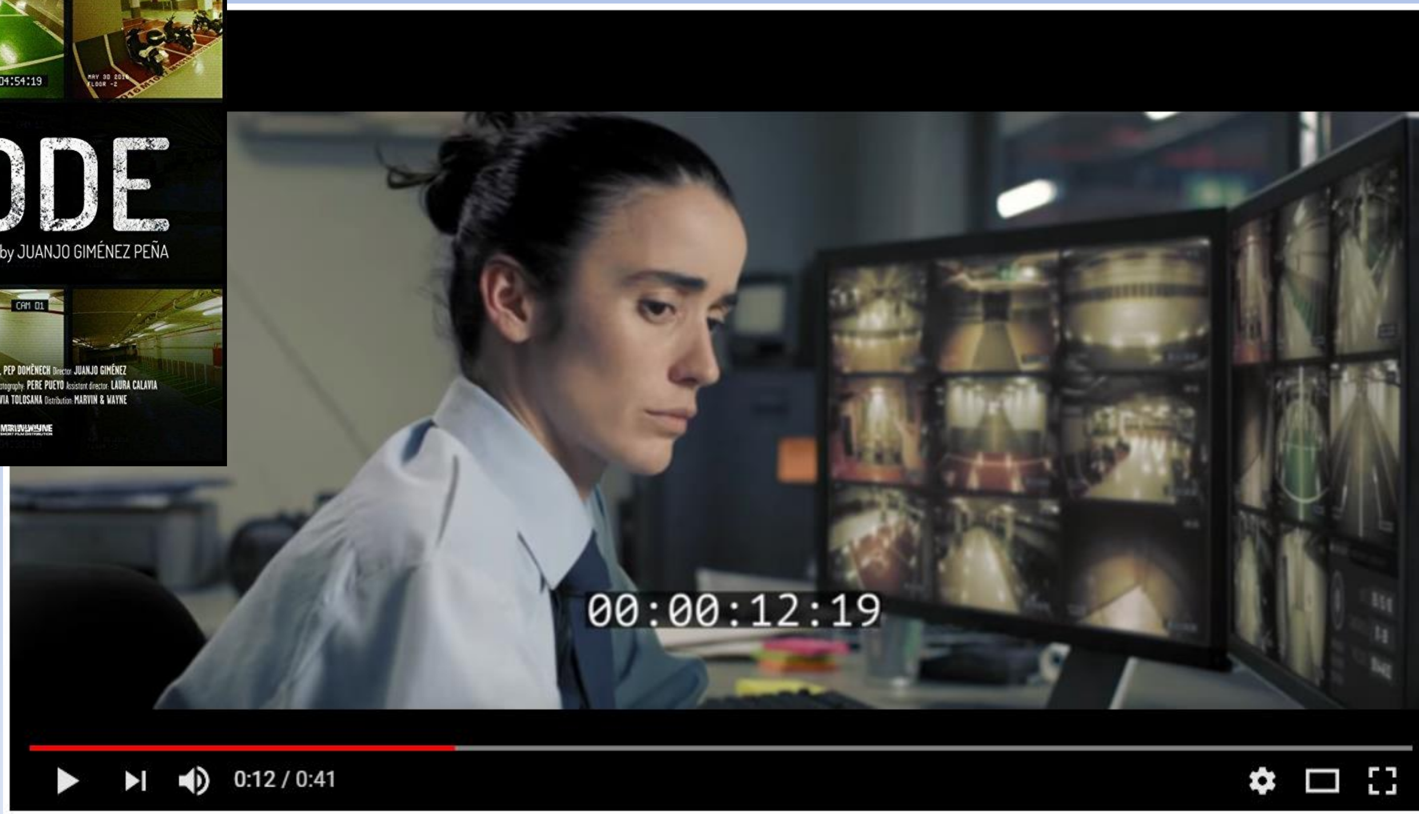

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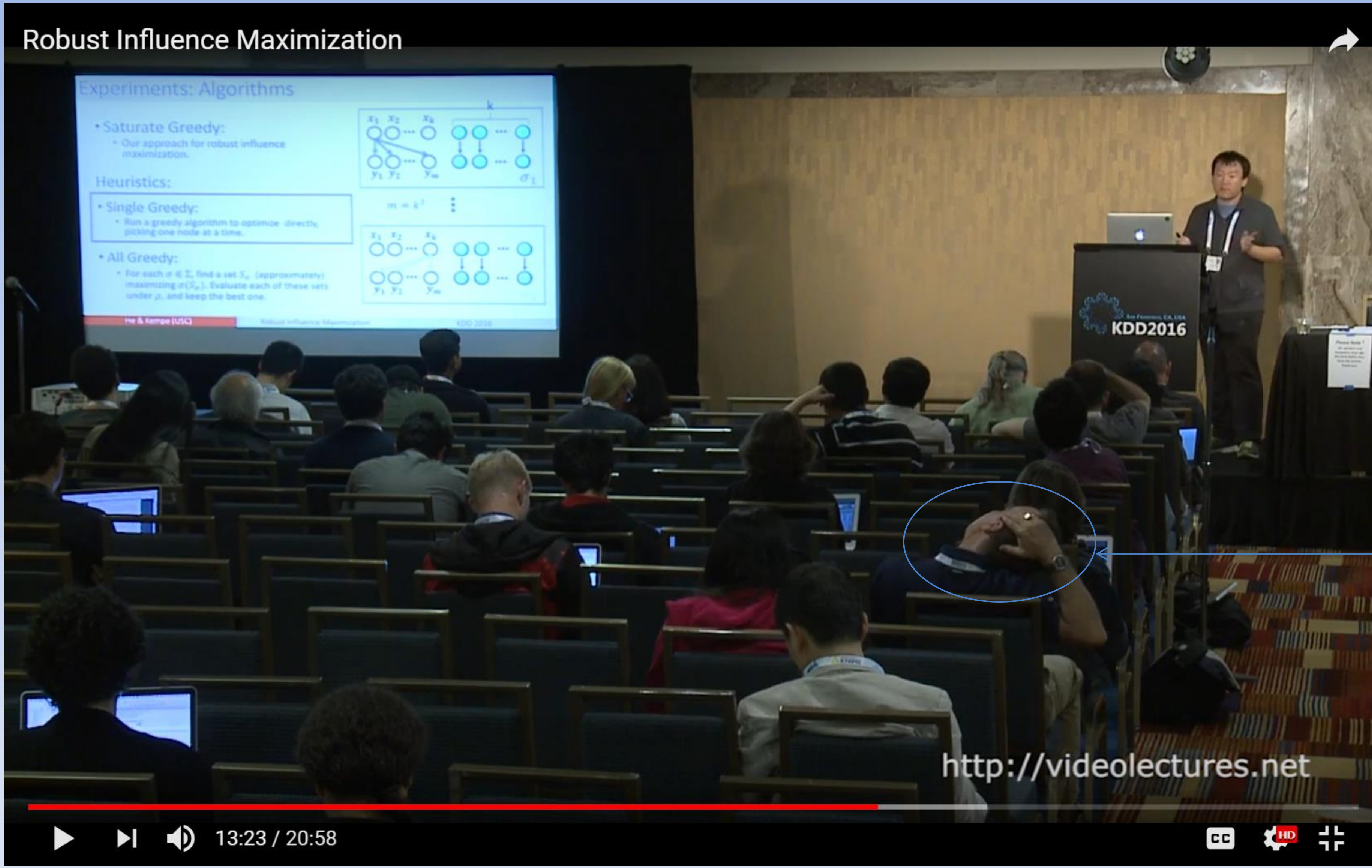
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Our approach for robust influence maximization.
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Personal Computer Science Focus

CSCI 164. Artificial Intelligence Programming

Prerequisite: CSCI 117. Introduction to problem-solving methods from artificial intelligence. Production systems. Knowledge-based systems. Machine learning. Topics chosen from fuzzy logic, neural network models, genetic algorithms. Verification, validation, testing.

Units: 3

CSCI 166. Principles of Artificial Intelligence

Prerequisite: CSCI 164. Analysis of knowledge-based and neural models, including self-organization, sequential learning models, neurally inspired models of reasoning and perception. Integration of different paradigms.

Units: 3

CSCI 126. Database Systems

Prerequisites: CSCI 124. Database concepts; hierarchical and relational network models; object-oriented data models. Data normalization, data description languages, data manipulation languages, and query design.

Units: 3
Course Typically Offered: Spring

CSCI 174. Design and Analysis of Algorithms

Prerequisites: CSCI 115, CSCI 119. Models of computation and measures of complexity, algorithms for sorting and searching, set representation and manipulation, branch and bound, integer and polynomial arithmetic, pattern-matching algorithms, parsing algorithm, graph algorithm, NP-complete problems.

Units: 3

Personal Computer Science Focus

- Search
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- Data
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- Puzzles
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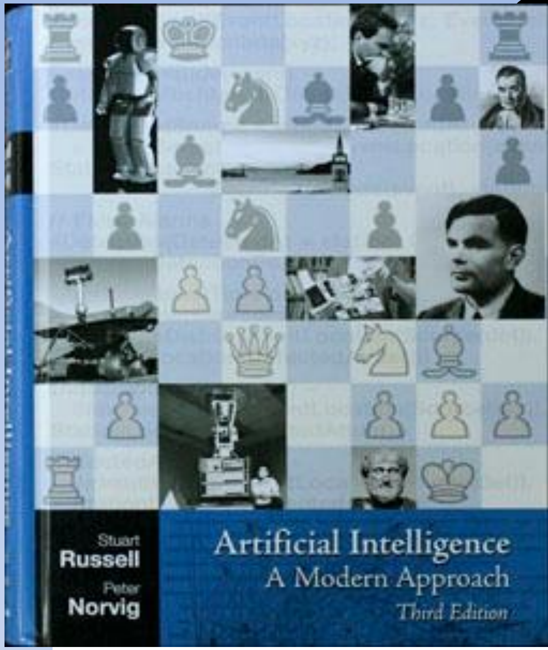
- **Books…**

Computer Science



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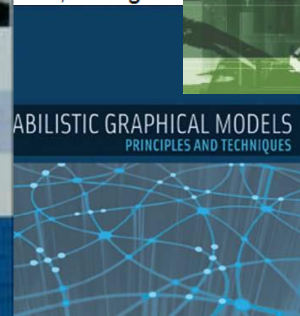

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Prerequisites: CSCI 124. Data
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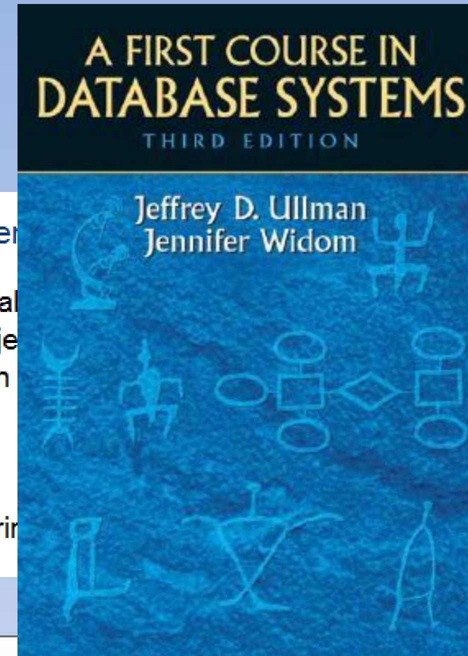

CSCI 174. Design and Analysis of Al

Prerequisites: CSCI 115, CSCI 119. Mo
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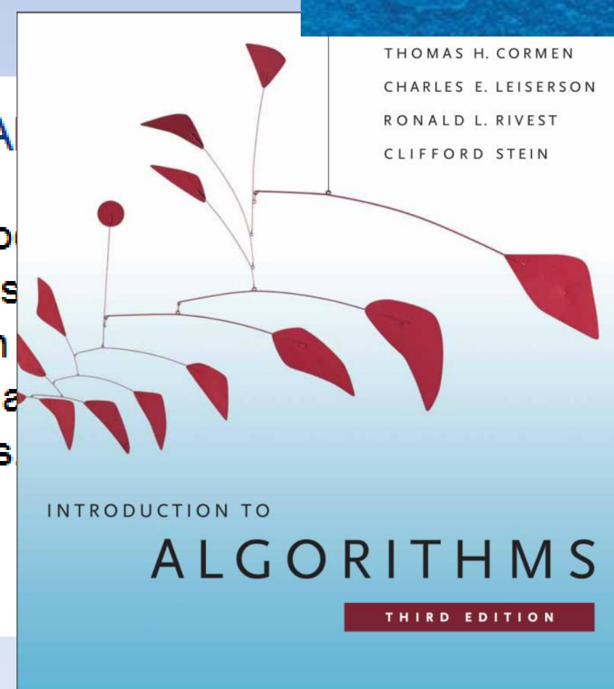
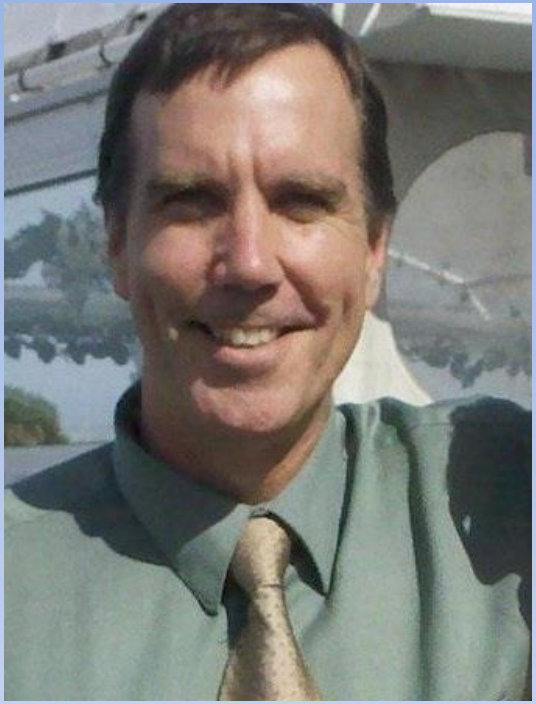




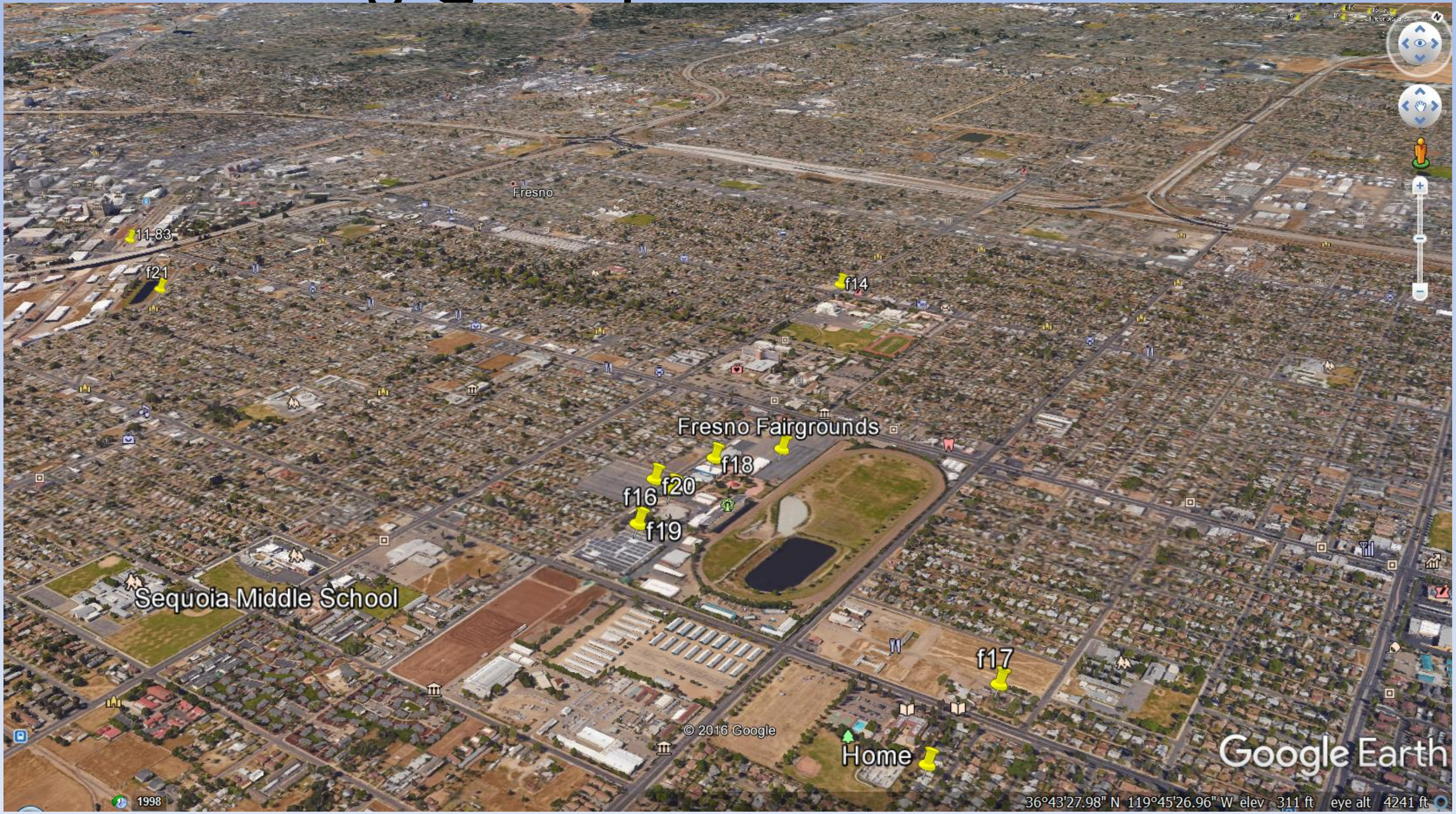
Class Instructor

- Office
  - Science II – 273
- Email:
  - druby@csufresno.edu

David Ruby

- First-Generation College Student
- How PhD?

Father Floyd Fresno Career Custodian Ending @ Sequoia Middle School

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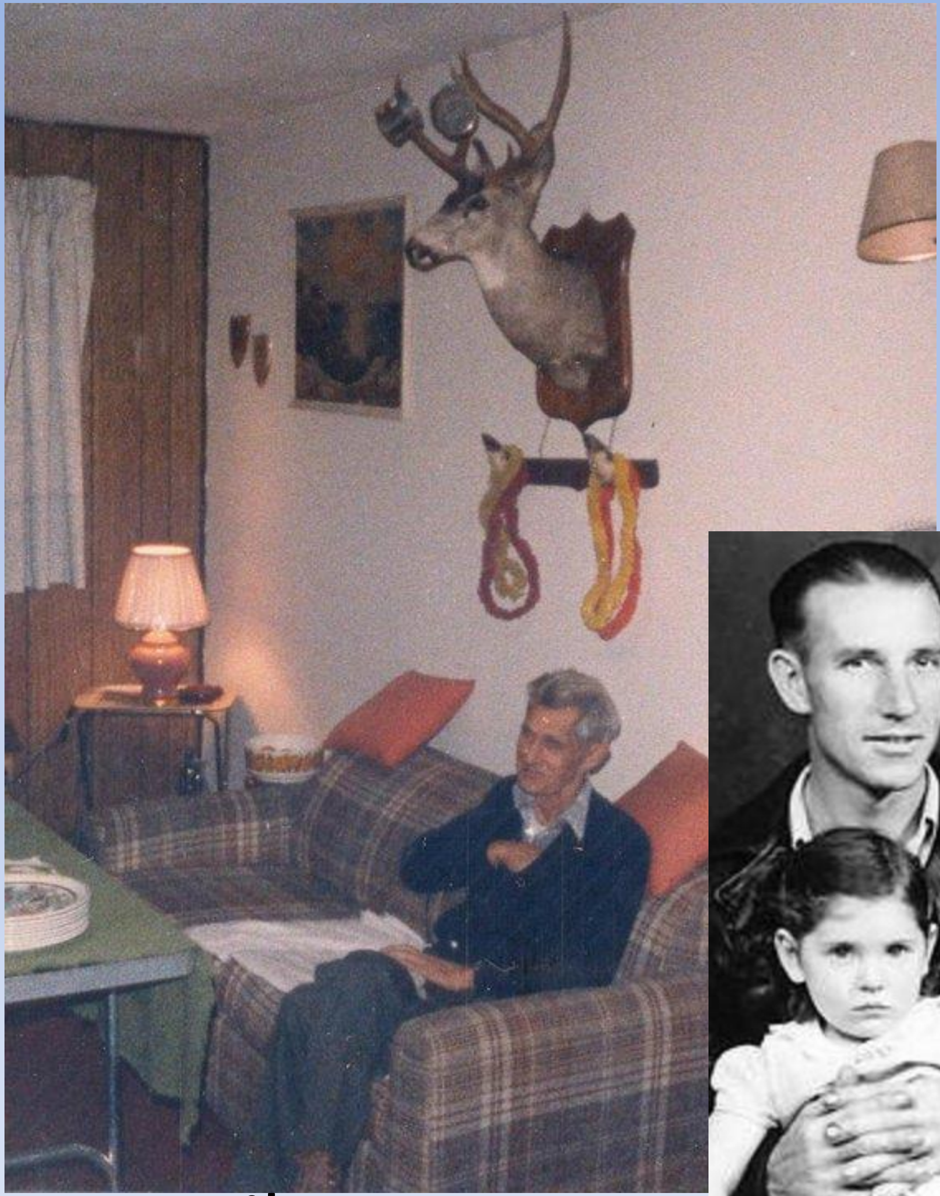
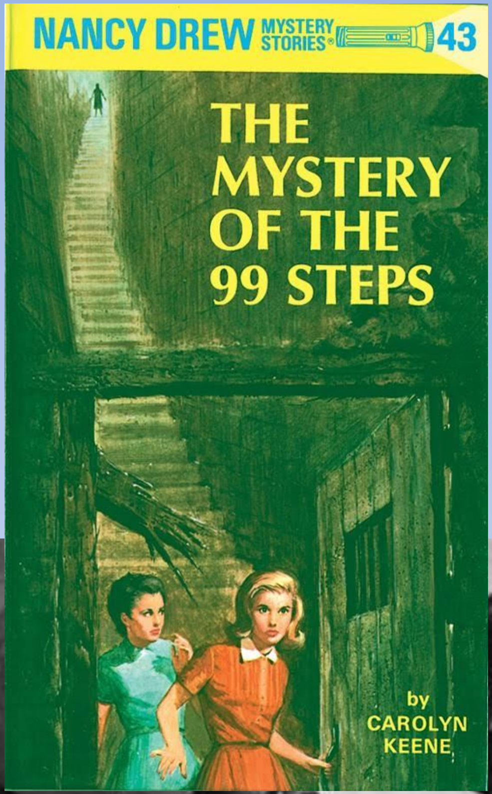




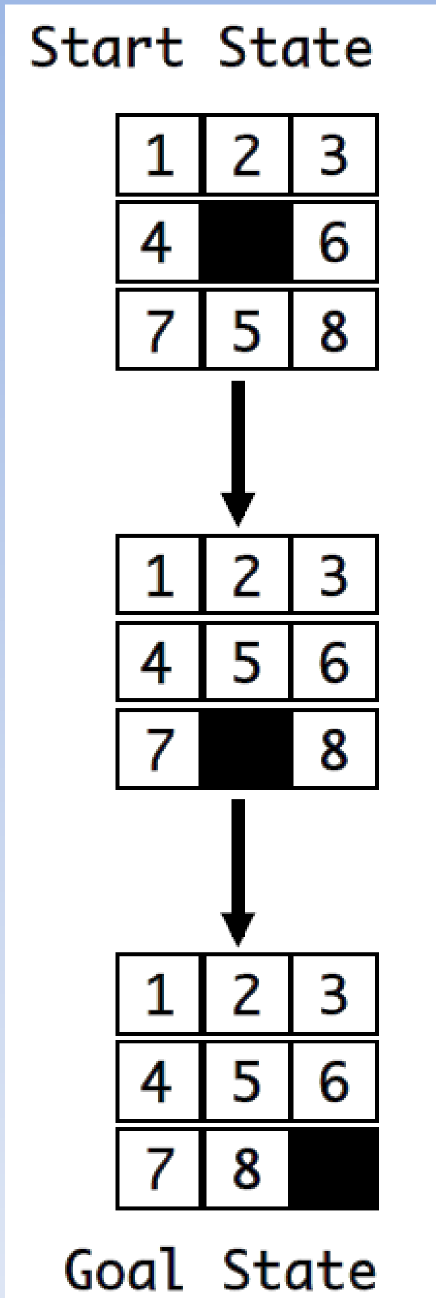
Interest In Puzzles

- Family Memories

Memories..
eXciting Puzzles !

- Home Hedges Maze Crawwwwwl !
- Also – First time w/ Sliding Tile Puzzle

Thesis: Tile-Sliding Puzzle



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StepppingStone: An Empirical and Analytical Evaluation*

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druby@ics.uci.edu

Abstract

Decomposing a difficult problem into simpler subproblems is a classic problem solving technique. Unfortunately, the most difficult subproblems can be as difficult, if not more difficult, than the original problem. This is not an obstacle to problem solving if the difficult subproblems recur in other problems. If the difficult subproblems recur often, then its solution need only be learned once and reused. SteppingStone is a learning problem solver that decomposes a problem into simple and difficult-but-recurring subproblems. It solves the

SteppingStone operates on problems defined with a state space representation consisting of a set of goals, a set of operators, and an initial state. The goal orderer takes as input a set of goals. It orders these goals so that the constrained search method will likely solve them. It does this by ordering them so as to reduce the likelihood of subgoal interactions using a domain independent heuristic we call *openness* [Ruby and Kibler, 1989]. It produces an ordered set of subgoals as output.

The constrained search component takes as input an

My Idea…

Memories are constructed..
Not stored complete!

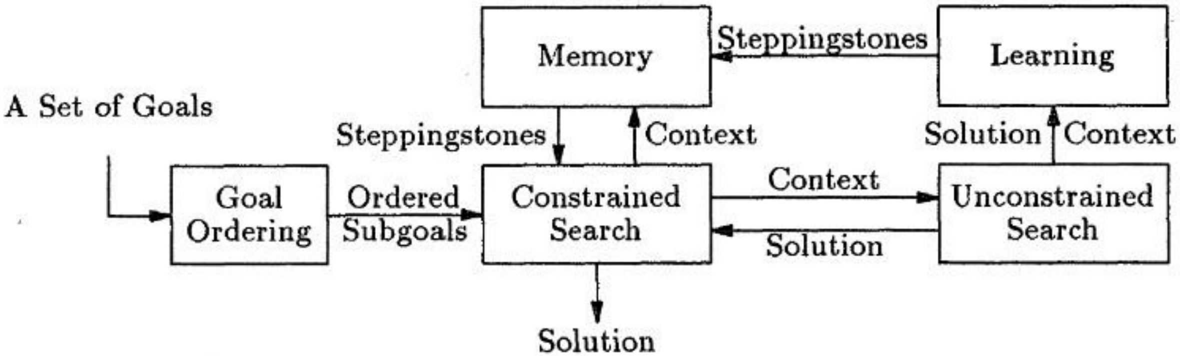


Figure 1: Overview of SteppingStone

the original impasse state.

When memory fails to return any useful steppingstones the constrained search component calls the unconstrained search component. The unconstrained search component takes as input a context, just as the memory component did. Unconstrained search relaxes the protection on the solved subgoals in its search for a solution. If it resolves the impasse, it returns the sequence of moves found to the constrained search component. The unconstrained search component also sends its impasse solution, along with the context, to the learner.

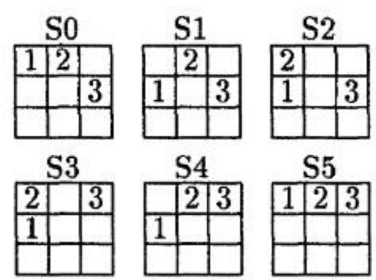
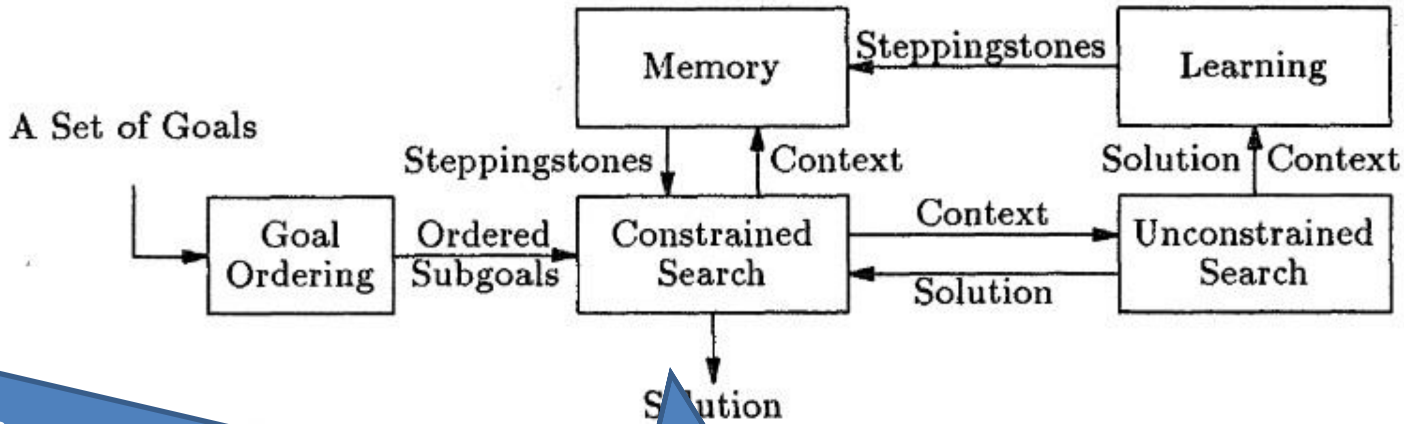


Figure 2: Steppingstones from Memory

Thesis: Tile Sliding Domain



1: Overv f SteppingStone

Memories have gaps!!!

When ... stones the constra... constrained search compo... search component takes as input a con... memory component did. Unconstrained search re... the protection on the solved subgoals in its searc... a solution. If it resolves the impasse, it returns t... quence of moves found to the constrained search c...po- nent. The unconstrained search component also sends its impasse solution, along with the context, to the learner.

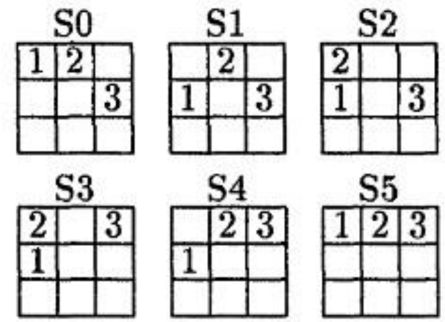
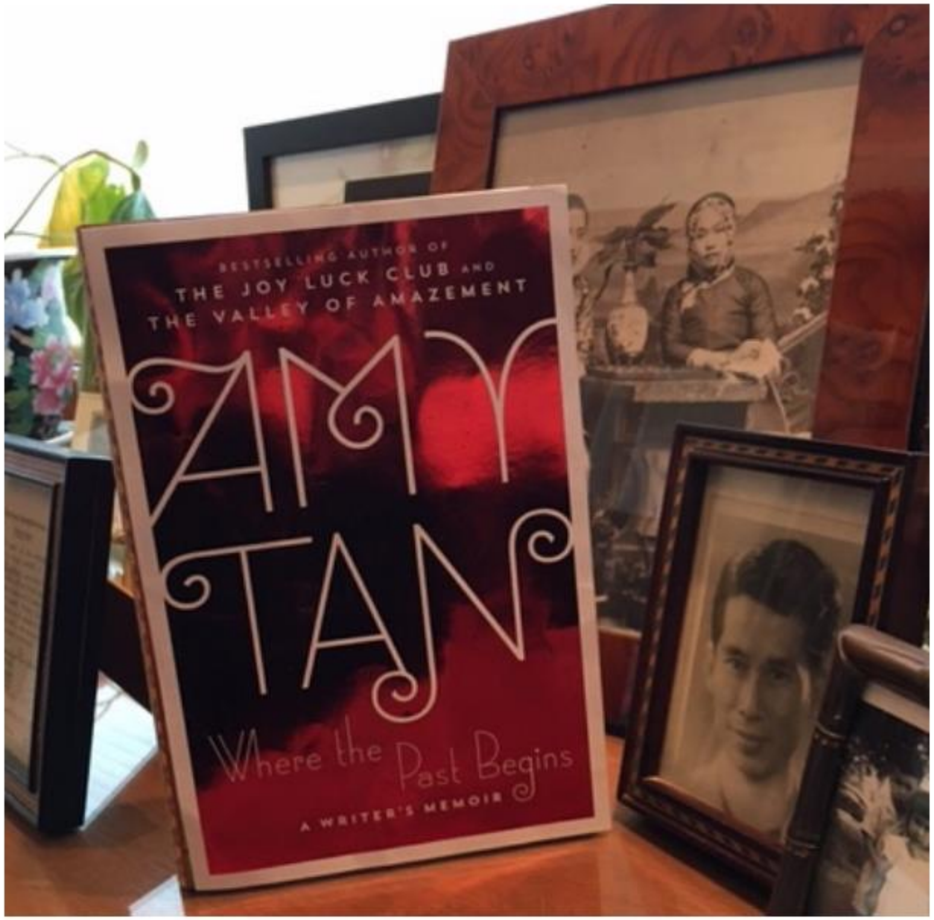
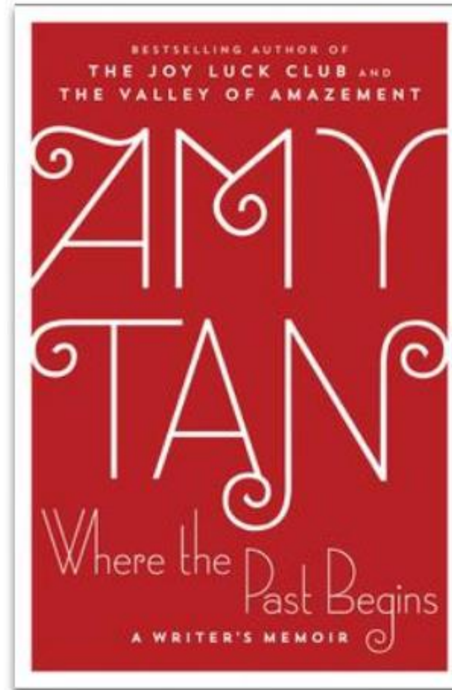


Figure 2: Steppingstones from Memory

Emotional Memory: Retrieving/Writing Stories





coming

Oct 17, 2017

Pre-order

Malleable Memory (Gaps)
Learning & Memory w/ Elizabeth Loftus

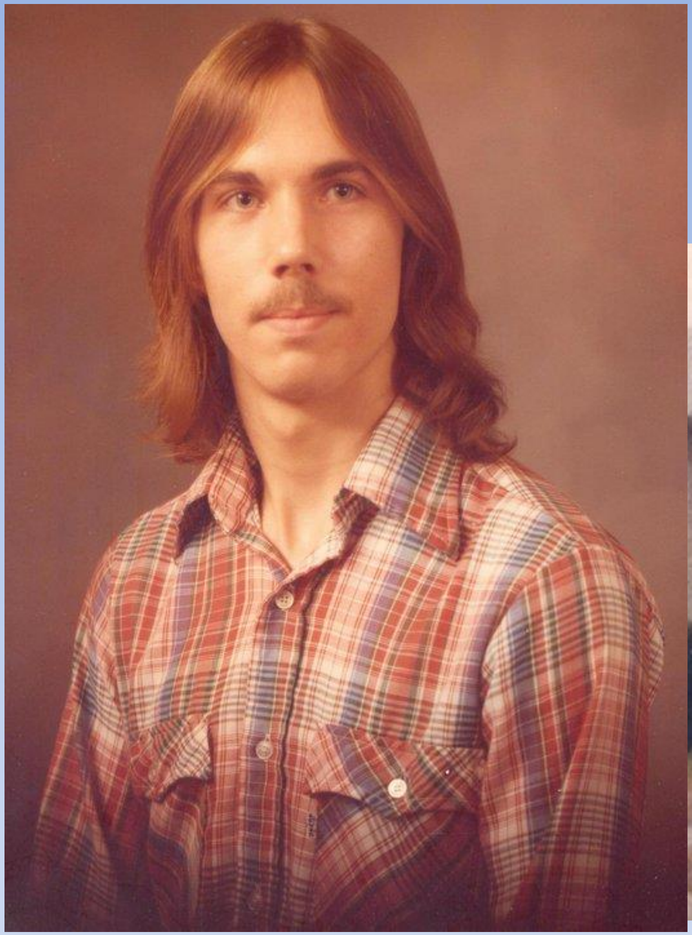
CORRUPTED MEMORY

Elizabeth Loftus has spent decades exposing flaws in eyewitness testimony. Her ideas are gaining fresh traction in the US legal system.

BY MOHEB COSTANDI

Elizabeth Loftus is a cognitive psychologist at the University of California Irvine.

eXciting Mazes Memories!



- ME:
  - Do you remember the FUN maze?
- NEIGHBOR:
  - Do YOU remember this other HORRIBLE thing??
- ME:
  - Hmmm .. I guess not.
- Language influencing memory ??

Memories & Learning

JOURNAL OF VERBAL LEARNING AND VERBAL BEHAVIOR 13, 585–589 (1974)

Reconstruction of Automobile Destruction: An Example of the Interaction Between Language and Memory[1]

ELIZABETH F. LOFTUS AND JOHN C. PALMER

University of Washington

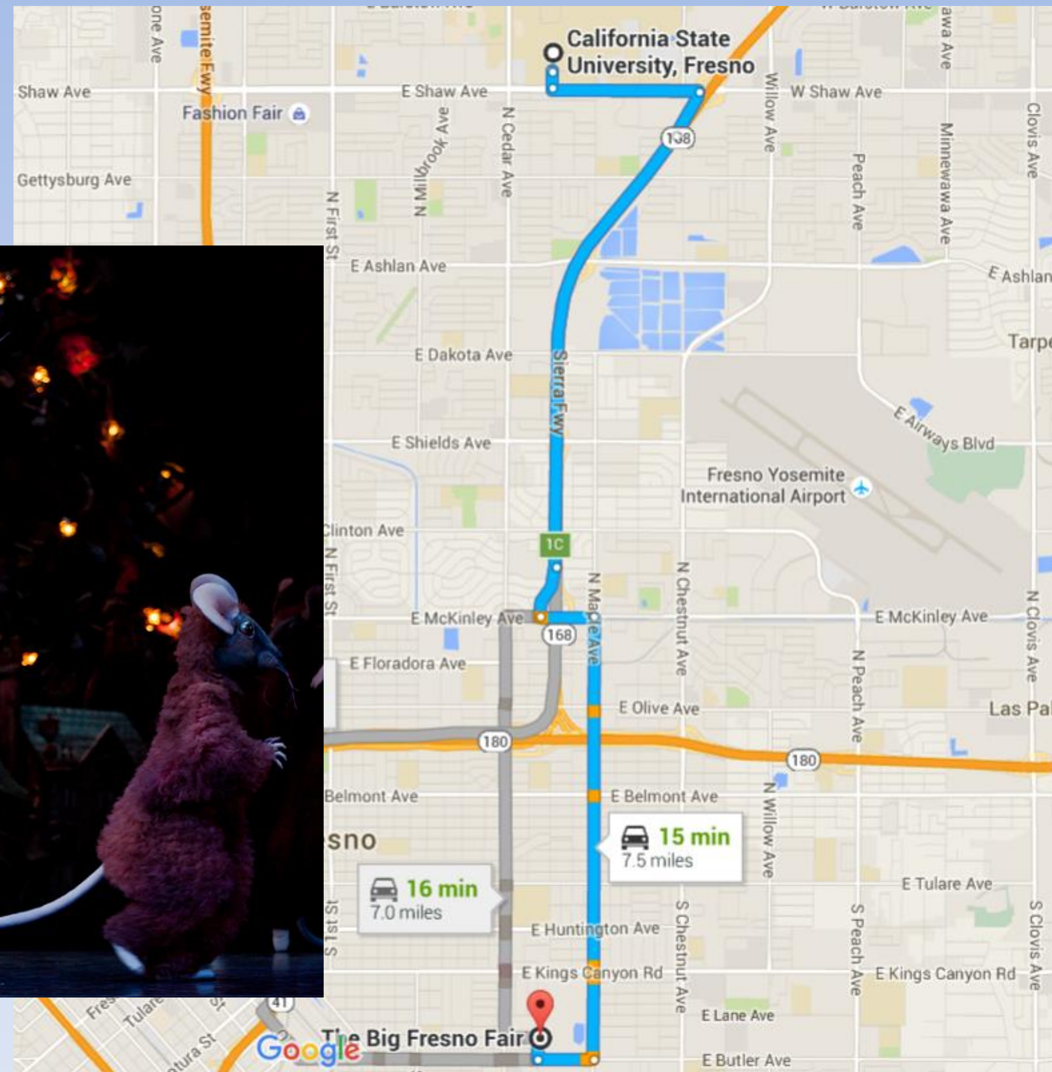
Two experiments are reported in which subjects viewed films of automobile accidents and then answered questions about events occurring in the films. The question, "About how fast were the cars going when they smashed into each other?" elicited higher estimates of speed than questions which used the verbs ***collided***, ***bumped***, ***contucted***, or ***hit*** in place of ***smashed***. On a retest one week later, those subjects who received the verb ***smashed*** were more likely to say "yes" to the question, "Did you see any broken glass?", even though broken glass was not present in the film. These results are consistent with the view that the questions asked subsequent to an event can cause a reconstruction in one's memory of that event.

Computer Science / Memories

- Puzzles
- Abstractions
- Memories

Current Interest: Abstraction

- Hello, World!



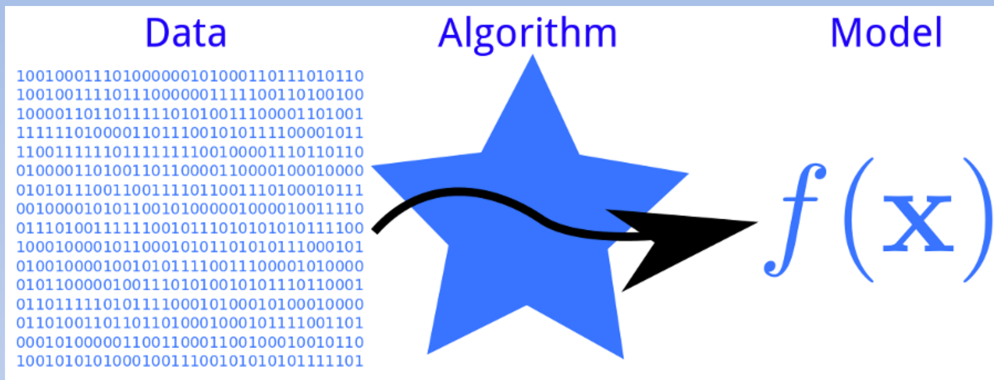
Abstraction: Computational Thinking

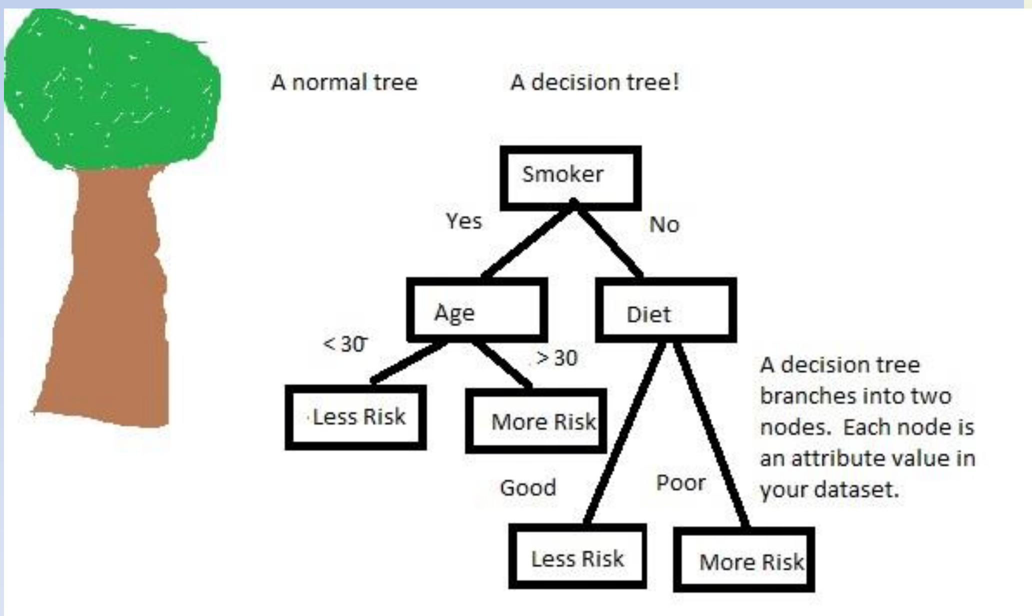
- Abstraction
- Automation
- Algorithms/Analysis

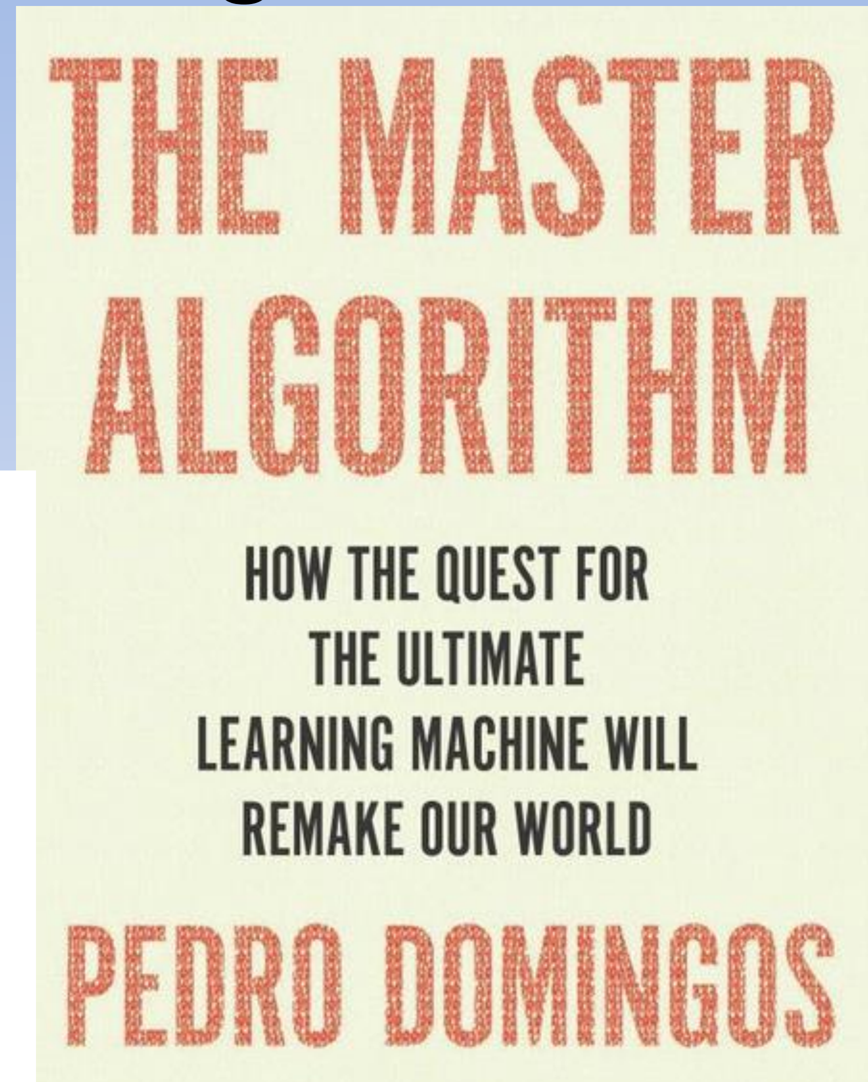
Intelligence (Problem Solving) Requires..
..Learning from Experiences

- Intelligence requires learning from experiences.

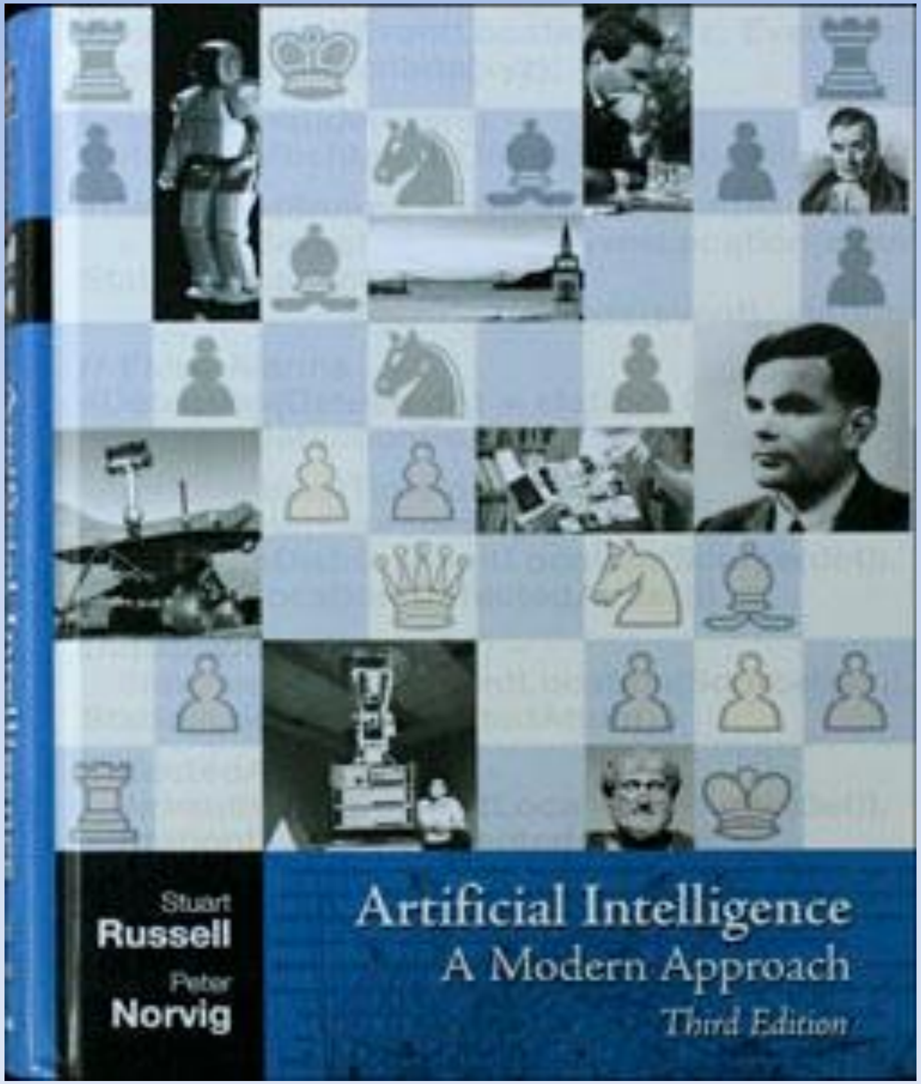
Machine Learning - AI







Tentative Course Schedule



- Chapters 1-7
- Chapters 13-15
- Chapters 17, 18, 20, 21

Chapter 1
What is AI?

- What is Intelligence?

Chapter 1
What is AI?

- Introduce Science of Artificial Intelligence
- History of AI

Chapter 2:
Intelligent Agents

- Agents operate in world
- Is Agent Intelligent?

Chapter 2: Problem Characteristics

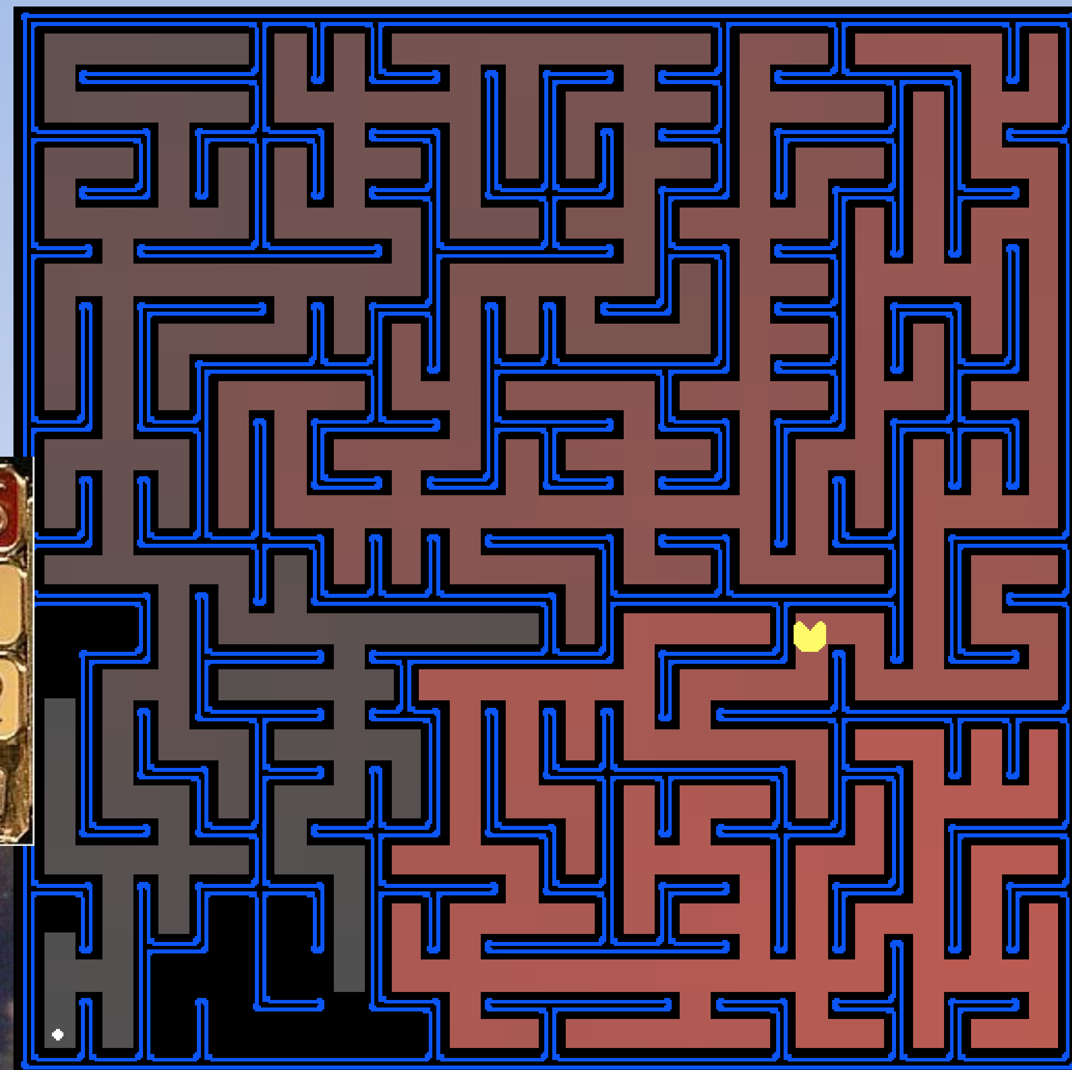
- Examine problems
  - Problems people solve
  - Problems not currently solved by computers
- Develop characteristics for describing problems.

Chapter 3:
State-Space Search

- Uniformed Search
- Heuristics
- Informed Search
  - A*

State-Space Search

- Uniformed Search
- Heuristics
- Informed Search



Chapter 4:
Beyond Classical Search

- Additional Search Methods
  - Beam Search
  - Genetic Algorithms
- Incomplete Knowledge
  - And/Or Trees

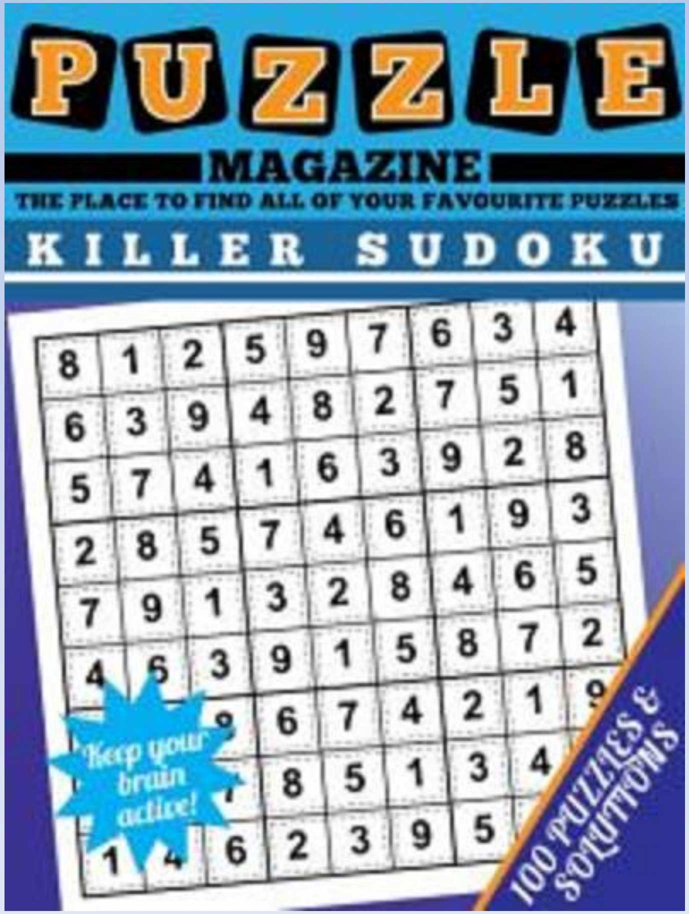
Chapter 5 Adversarial Search

- Multiplayer Games
- Minimax
- Alpha Beta Cutoff

Chapter 6: CSP

- Constraint Satisfaction Problems
- AC-3 Algorithm
- Cutsets
- Etc…

- Assignment 4: CSP



Chapter 7: Logical Agents

- Propositional Logic

P	Q	$\neg P$	$P \wedge Q$	$P \vee Q$	$P \Rightarrow Q$	$P \Leftrightarrow Q$
false	*false*	*true*	*false*	*false*	*true*	*true*
false	*true*	*true*	*false*	*true*	*true*	*false*
true	*false*	*false*	*false*	*true*	*false*	*false*
true	*true*	*false*	*true*	*true*	*true*	*true*

Figure 7.8 Truth tables for the five logical connectives. To use the table to compute, for
ie and Q is false, first look on the left for the row
w). Then look in that row under the $P \vee Q$ column

$$
\begin{aligned}
(\alpha \wedge \beta) &\equiv (\beta \wedge \alpha) \quad \text{commutativity of } \wedge \\
(\alpha \vee \beta) &\equiv (\beta \vee \alpha) \quad \text{commutativity of } \vee \\
((\alpha \wedge \beta) \wedge \gamma) &\equiv (\alpha \wedge (\beta \wedge \gamma)) \quad \text{associativity of } \wedge \\
((\alpha \vee \beta) \vee \gamma) &\equiv (\alpha \vee (\beta \vee \gamma)) \quad \text{associativity of } \vee \\
\neg(\neg \alpha) &\equiv \alpha \quad \text{double-negation elimination} \\
(\alpha \Rightarrow \beta) &\equiv (\neg \beta \Rightarrow \neg \alpha) \quad \text{contraposition} \\
(\alpha \Rightarrow \beta) &\equiv (\neg \alpha \vee \beta) \quad \text{implication elimination} \\
(\alpha \Leftrightarrow \beta) &\equiv ((\alpha \Rightarrow \beta) \wedge (\beta \Rightarrow \alpha)) \quad \text{biconditional elimination} \\
\neg(\alpha \wedge \beta) &\equiv (\neg \alpha \vee \neg \beta) \quad \text{De Morgan} \\
\neg(\alpha \vee \beta) &\equiv (\neg \alpha \wedge \neg \beta) \quad \text{De Morgan} \\
(\alpha \wedge (\beta \vee \gamma)) &\equiv ((\alpha \wedge \beta) \vee (\alpha \wedge \gamma)) \quad \text{distributivity of } \wedge \text{ over } \vee \\
(\alpha \vee (\beta \wedge \gamma)) &\equiv ((\alpha \vee \beta) \wedge (\alpha \vee \gamma)) \quad \text{distributivity of } \vee \text{ over } \wedge
\end{aligned}
$$

Figure 7.11 Standard logical equivalences. The symbols α, β, and γ stand for arbitrary sentences of propositional logic.

Chapter 7: Logical Agents w/ Wumpus World

- Wumpus World

238 Chapter 7. Logical Agents

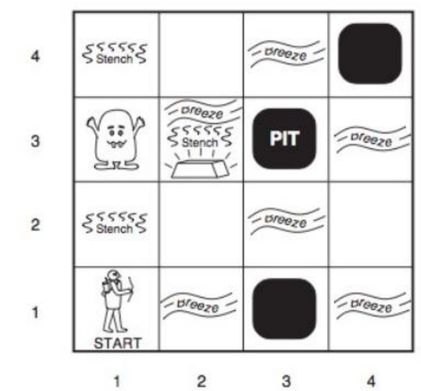
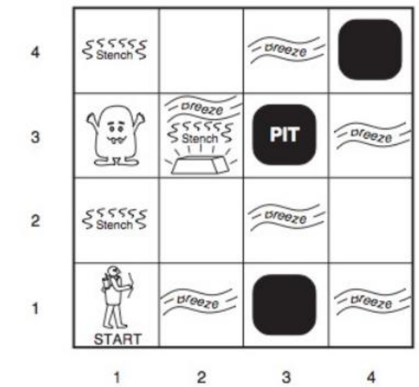


Figure 7.2 A typical wumpus world. The agent is in the bottom left corner, facing right.

$P_{x,y}$ is true if there is a pit in $[x, y]$.
$W_{x,y}$ is true if there is a wumpus in $[x, y]$, dead or alive.
$B_{x,y}$ is true if the agent perceives a breeze in $[x, y]$.
$S_{x,y}$ is true if the agent perceives a stench in $[x, y]$.

PROBLEMS!!!

238 Chapter 7. Logical Agents



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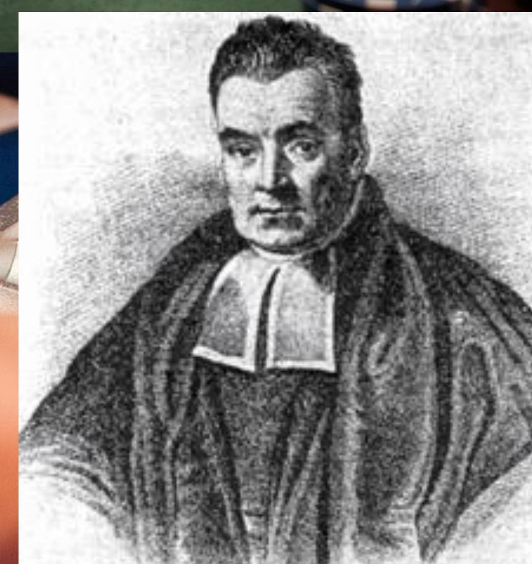
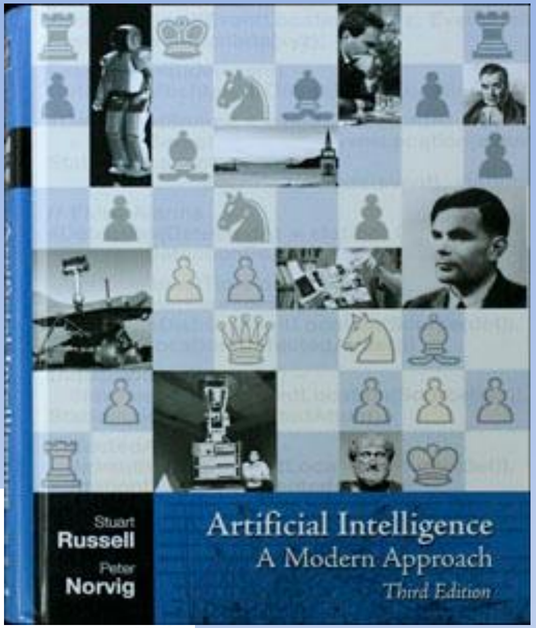
Uncertainty

Chapter 13: Dealing w/ Uncertainty

- Probability Review



Dealing w/ Uncertainty



IV Uncertain knowledge and reasoning

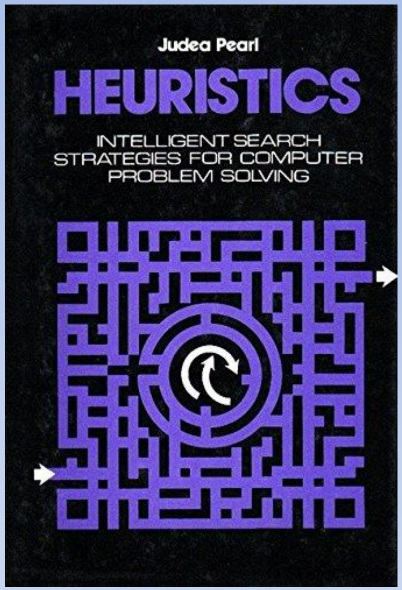
13 Quantifying Uncertainty

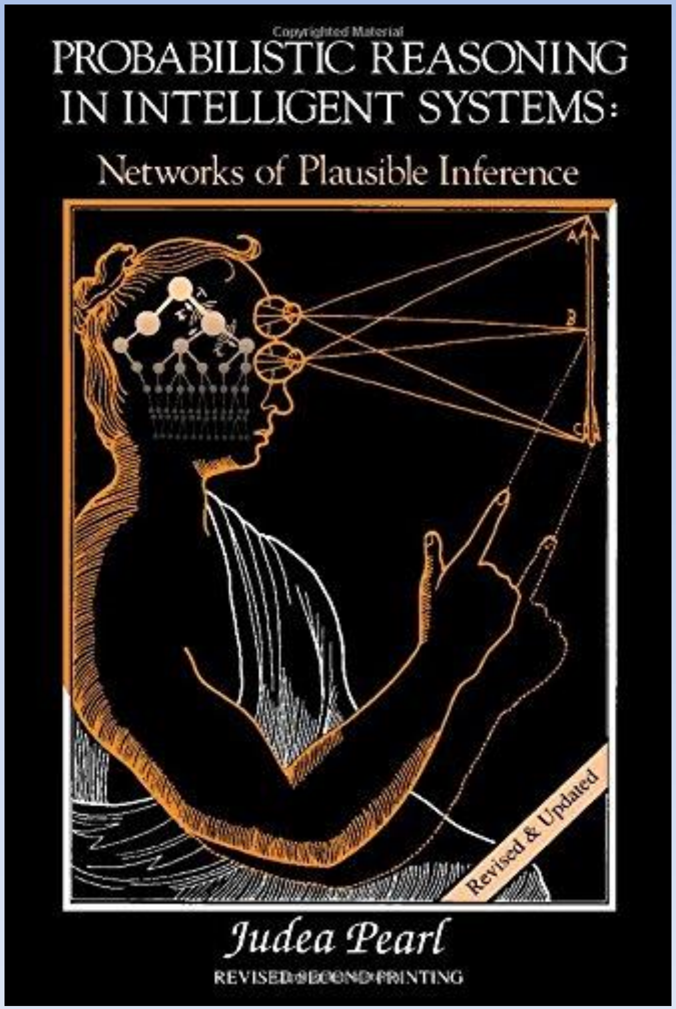
13.1 Acting under Uncertainty 480
13.2 Basic Probability Notation 483
13.3 Inference Using Full Joint Distributions 490
13.4 Independence 494
13.5 Bayes' Rule and Its Use 495
13.6 The Wumpus World Revisited 499
13.7 Summary, Bibliographical and Historical Notes, Exercises 503

14 Probabilistic Reasoning **510**

14.1 Representing Knowledge in an Uncertain Domain 510
14.2 The Semantics of Bayesian Networks 513
14.3 Efficient Representation of Conditional Distributions 518
14.4 Exact Inference in Bayesian Networks 522
14.5 Approximate Inference in Bayesian Networks 530
14.6 Relational and First-Order Probability Models 539
14.7 Other Approaches to Uncertain Reasoning 546

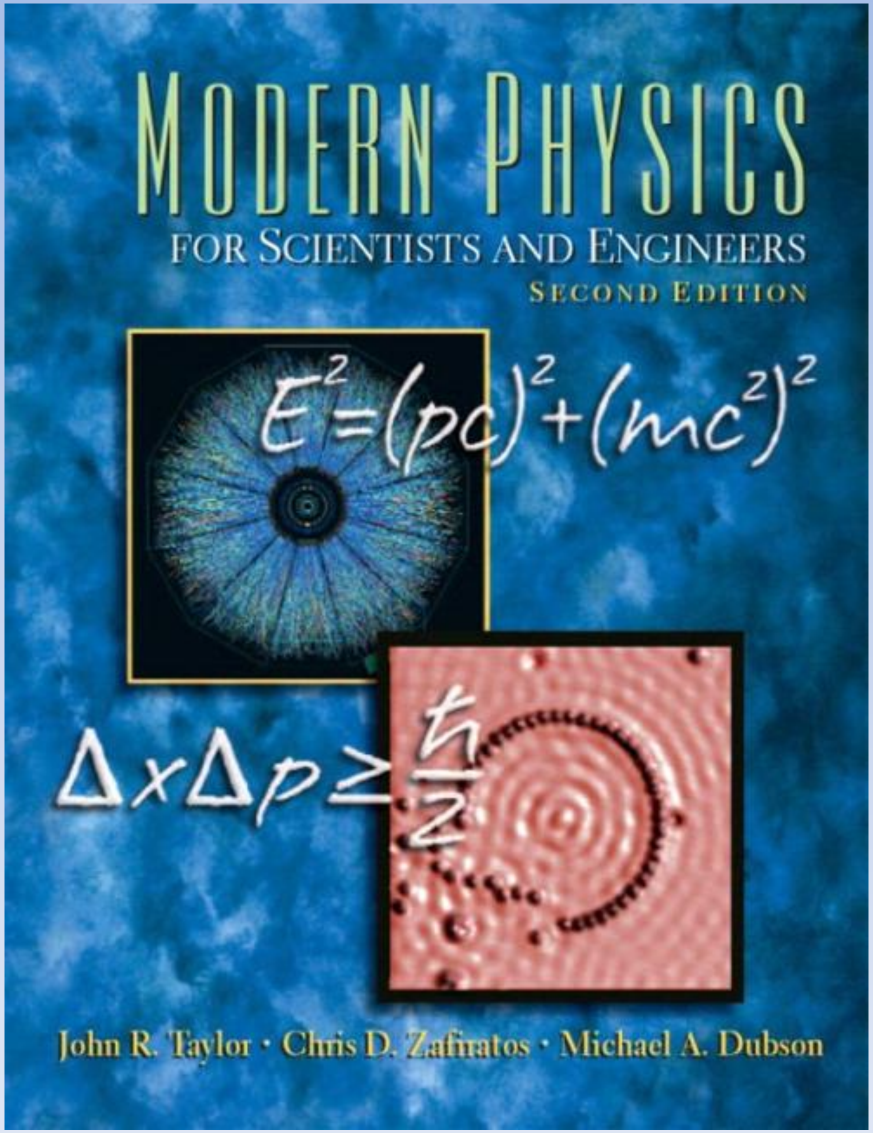
Judea Pearl
Heuristics -> Probabilistic Reasoning





- April 1984
- September 15, 1988

Uncertainty in Science



Classical Mechanics

Probability & Physics

- Albert Einstein
- Quantum mechanics is certainly imposing. But an inner voice tells me that it is not yet the real thing. The theory says a lot, but does not really bring us any closer to the secret of the "old one." **I, at any rate, am convinced that *He* does not throw dice.**
  - Letter to Max Born (4 December 1926); *The Born-Einstein Letters* (translated by Irene Born) (Walker and Company, New York, 1971) ISBN 0-8027-0326-7.
- In a 1943 conversation with William Hermanns recorded in Hermanns' book *Einstein and the Poet*, Einstein said: **"As I have said so many times, God doesn't play dice with the world."** (p. 58).

Uncertainty in Science

Schrödinger's Equation

$$i\hbar \frac{\partial}{\partial t}\psi(\mathbf{r},t) = -\frac{\hbar^2}{2m}\nabla^2\psi(\mathbf{r},t) + V(\mathbf{r},t)\psi(\mathbf{r},t)$$

i is the imaginary number, $\sqrt{-1}$.

$\hbar$ is Planck's constant divided by 2π: 1

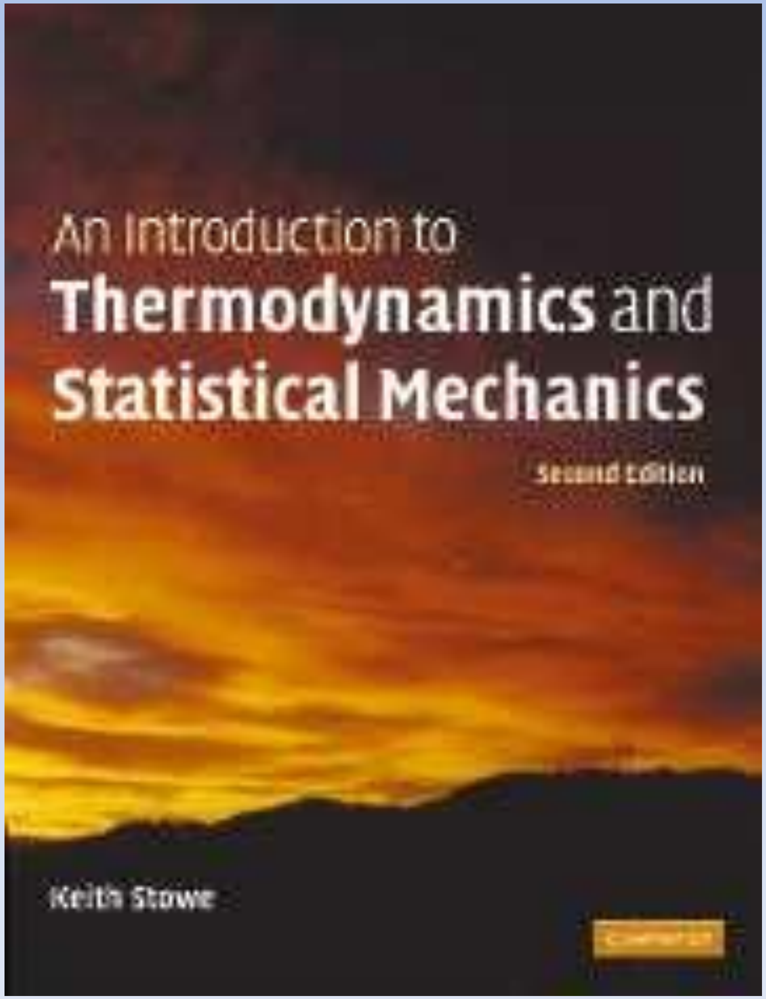
$\psi(\mathbf{r},t)$ is the wave function, defined ov

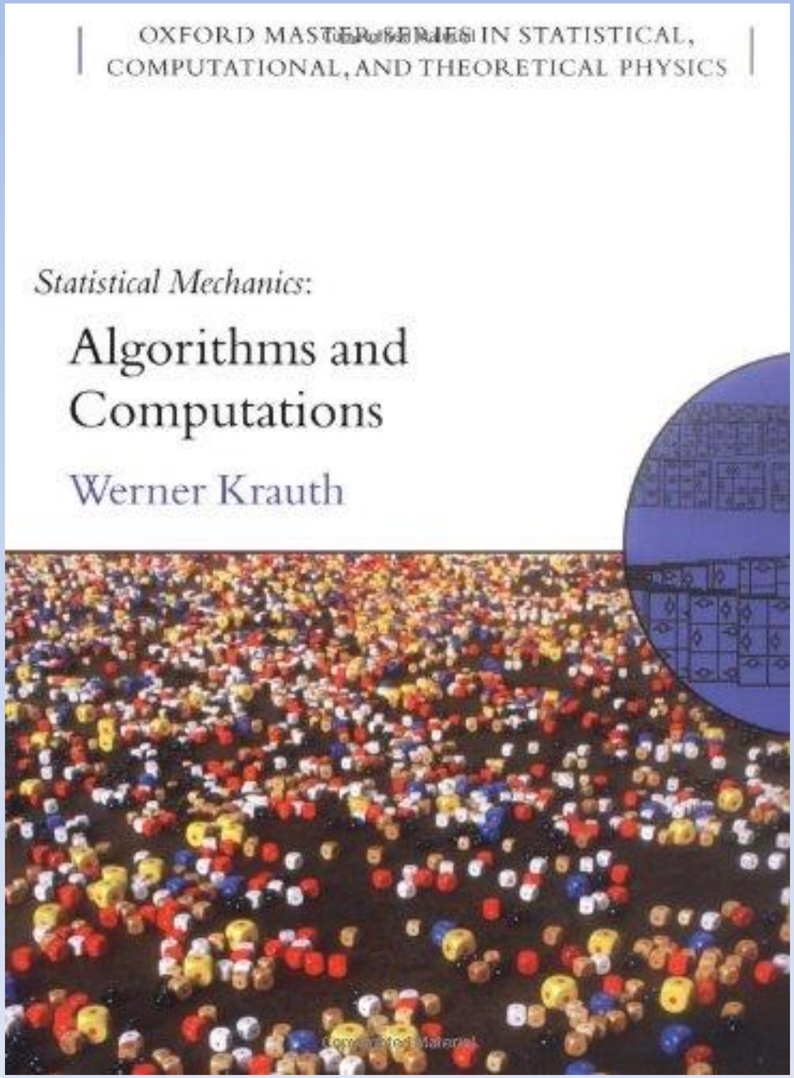
m is the mass of the particle.

∇^2 is the Laplacian operator, $\frac{\partial^2}{\partial x^2} + \frac{\partial}{\partial}$

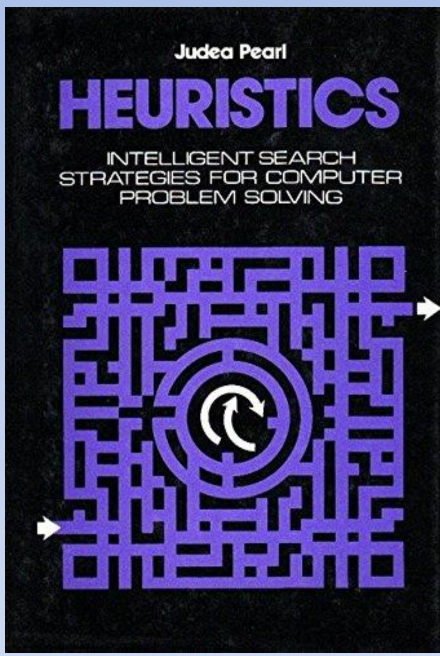
$V(\mathbf{r},t)$ is the potential energy influencin

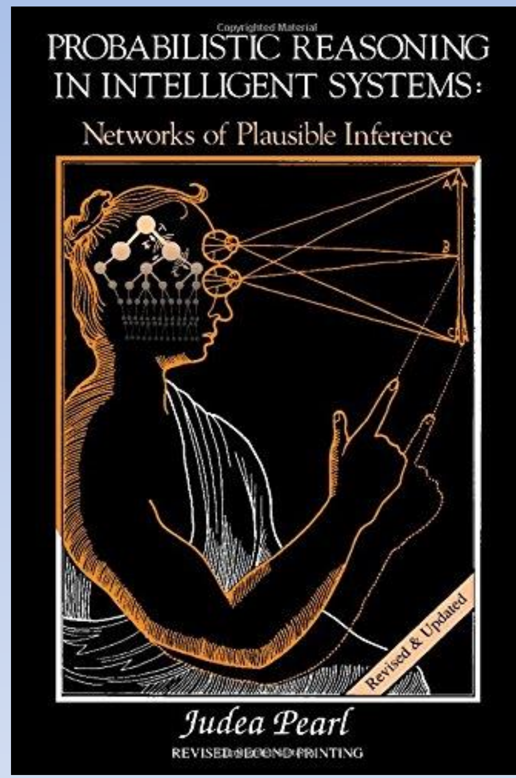
Uncertainty in Science
Classical Mechanics versus
Statistical Mechanics

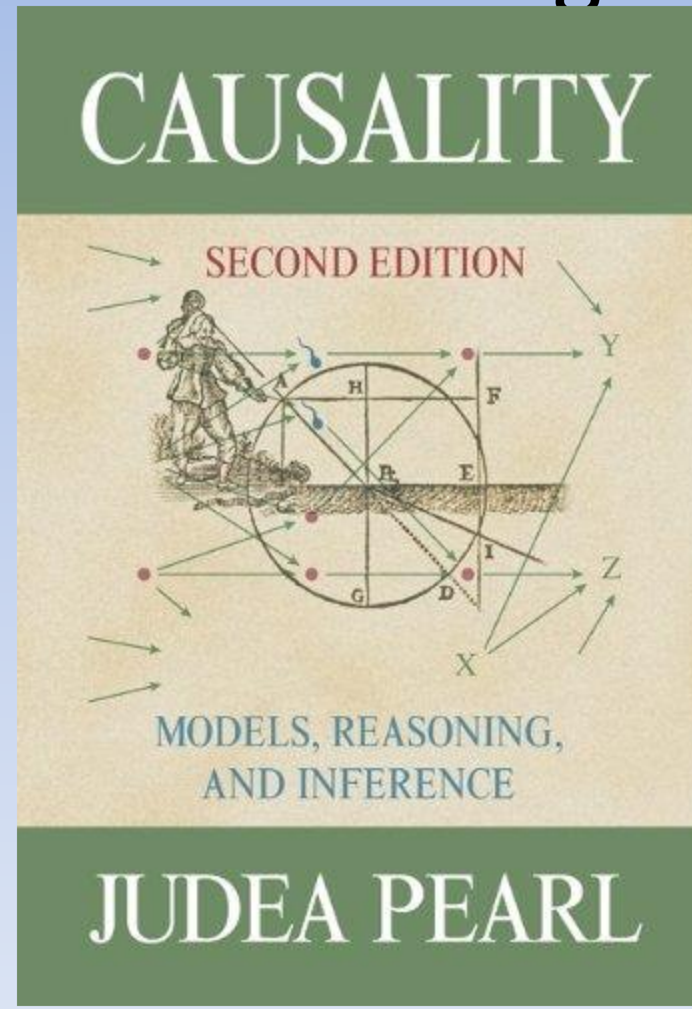




Judea Pearl
Heuristics -> Probabilistic Reasoning







- April 1984
- September 15, 1988
- September 14th, 2009

History of Probability (AI Text)

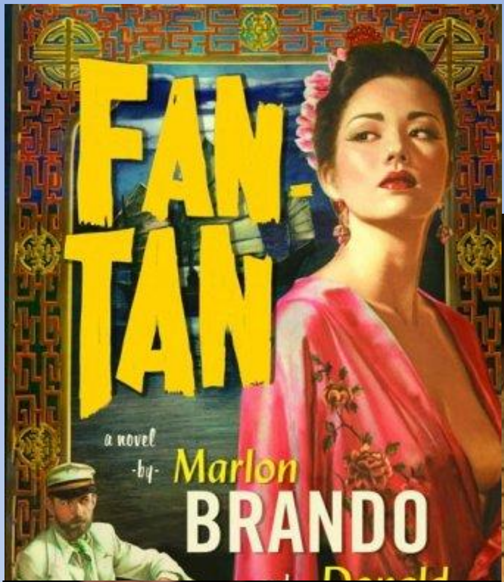
- In about 850 A.D. the Indian mathematician Mahaviracarya described how to arrange a set of bets that can’t lose (what we now call a Dutch book).

Mahāvīra (mathematician)

From Wikipedia, the free encyclopedia

Mahāvīra (or **Mahaviracharya**, "Mahavira the Teacher") was a 9th-century Jain mathematician from Mysore, India.[1][2][3] He was the author of *Gaṇitasārasañgraha* (or *Ganita Sara Samgraha*, c. 850), which revised the Brāhmasphuṭasiddhānta.[1] He was patronised by the Rashtrakuta king Amoghavarsha.[4] He separated astrology from mathematics. It is the earliest Indian text entirely devoted to mathematics.[5] He expounded on the same subjects on which Aryabhata and Brahmagupta contended, but he expressed them more clearly. His work is a highly syncopated approach to algebra and the emphasis in much of his text is on developing the techniques necessary to solve algebraic problems.[6] He is highly respected among Indian mathematicians, because of his establishment of terminology for concepts such as equilateral, and isosceles triangle; rhombus; circle and semicircle.[7] Mahāvīra's eminence spread in all South India and his books proved inspirational to other mathematicians in Southern India.[8] It was translated into Telugu language by Pavuluri Mallana as *Saar Sangraha Ganitam*.[9]

Uncertainty w/ Gambling Games



Gambling Concepts

- Games of Chance
  - Poker
  - Roulette
  - Fan Tan
- Odds
  - Sports Book
  - Horse Racing

1565 Girolamo Cardano

- In Europe, the first significant systematic analyses were produced by Girolamo Cardano around 1565, although publication was posthumous (1663).

- Gambling Motivated

Meaning and Probability Theory

- 20 to 1 in the 5^{th}
  - What does 20 to 1 Mean?
  - Where does 20 come from?

Joints & Marginals

		Intelligence		
		low	high	
Grade	A	0.07	0.18	0.25
	B	0.28	0.09	
	C	0.35	0.03	
			0.3	1.0

- P(Intelligence=high) = ?

More Problems...

		Intelligence		
		low	high	
Grade	A	0.07	0.18	0.25
	B	0.28	0.09	
	C	0.35	0.03	
			0.3	1.0

- P(Intelligence=high) = ?

INTRACTABILITY

Computational Thinking!!!
Algorithms & Data Structures

- Representation
  - Bayesian Networks
- Algorithms
  - Exact Inference
  - Approximate Inference

PLAN
The Bayesian Network (Chapter 14)

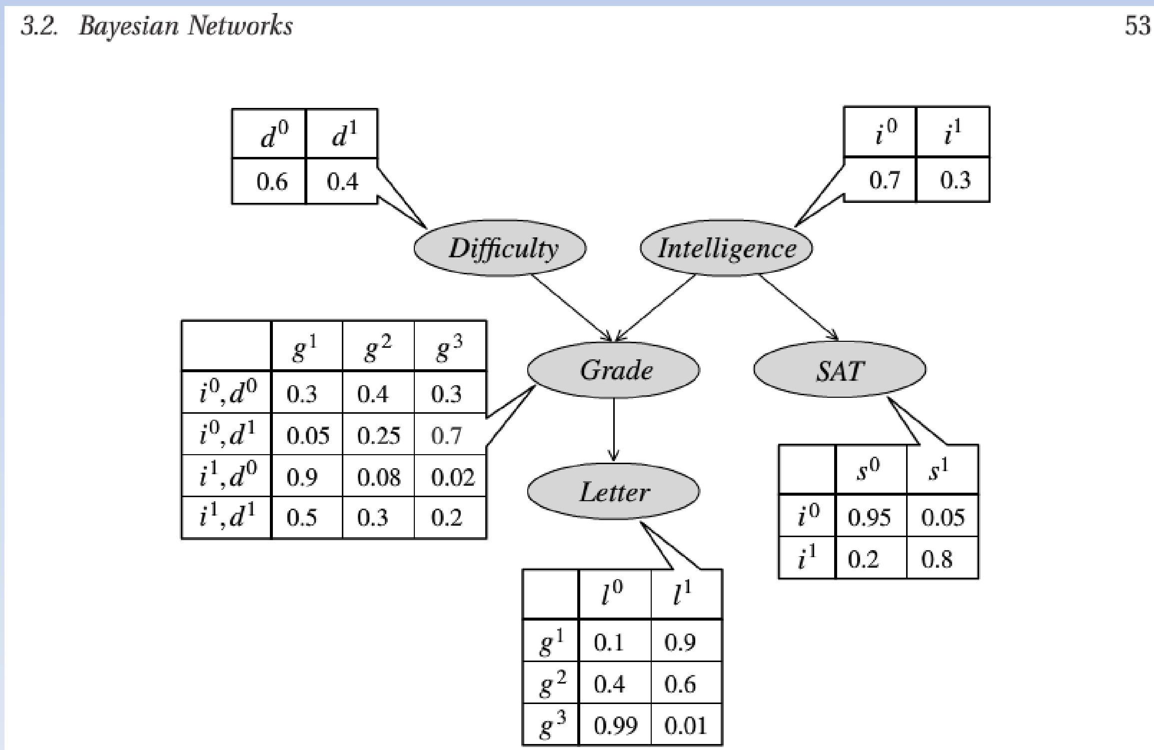
- Exploit Islands of Tractability in High Dimensional Space Probability Distributions
  - Worst Case is Intractable
  - Real World Frequently NOT Worst Case
  - Efficiently Exploit properties in Real World Probability Distributions to induce Tractability

- Primary Tool:

INDEPENDENCE!

Bayesian Networks : (CPD's)

- Each variable is associated with a conditional probability distribution (CPD) that specifies a distribution CPD over the values of X given each possible joint assignment of values to its parents in the model.
- For a node with no parents, the CPD is conditioned on the empty set of variables.



d^0	d^1
0.6	0.4

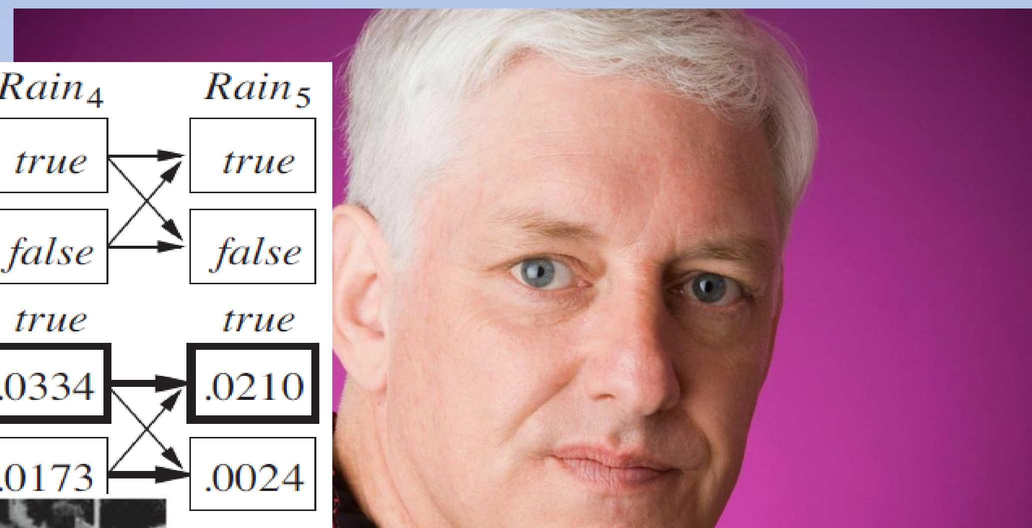
i^0	i^1
0.7	0.3

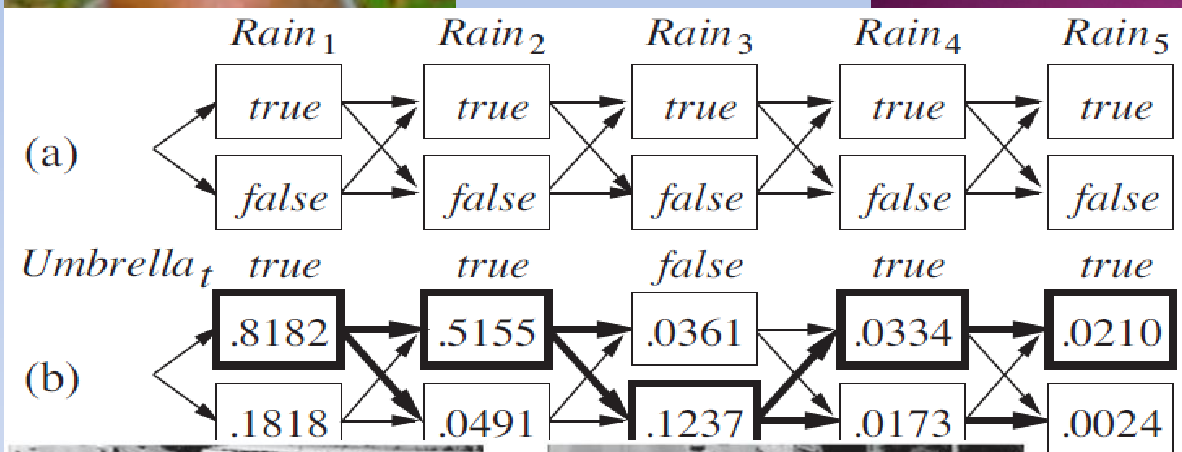
	g^1	g^2	g^3
i^0,d^0	0.3	0.4	0.3
i^0,d^1	0.05	0.25	0.7
i^1,d^0	0.9	0.08	0.02
i^1,d^1	0.5	0.3	0.2

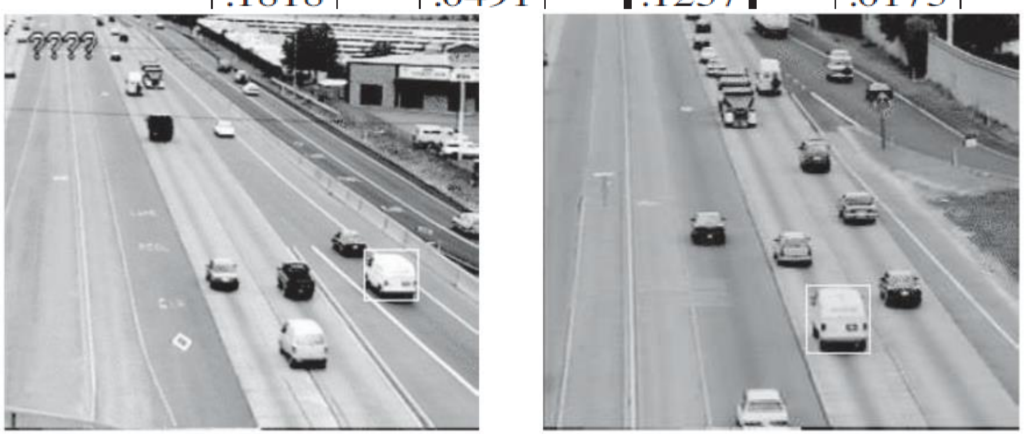
	s^0	s^1
i^0	0.95	0.05
i^1	0.2	0.8

	l^0	l^1
g^1	0.1	0.9
g^2	0.4	0.6
g^3	0.99	0.01

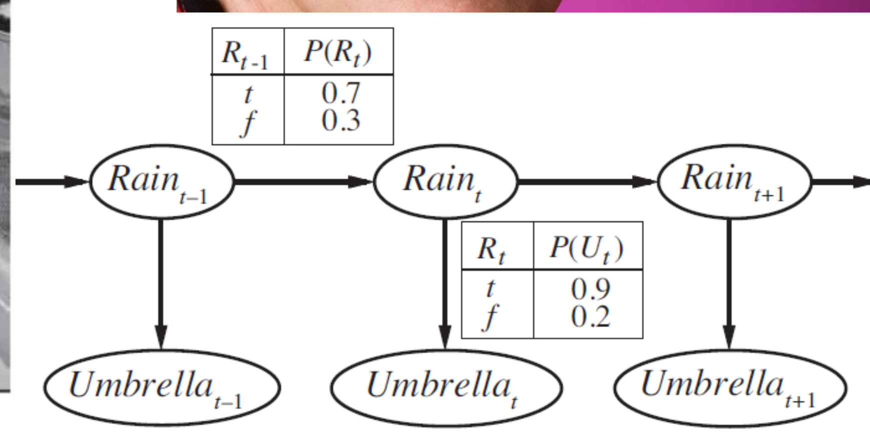
Chapter 15: Probabilistic Reasoning over Time





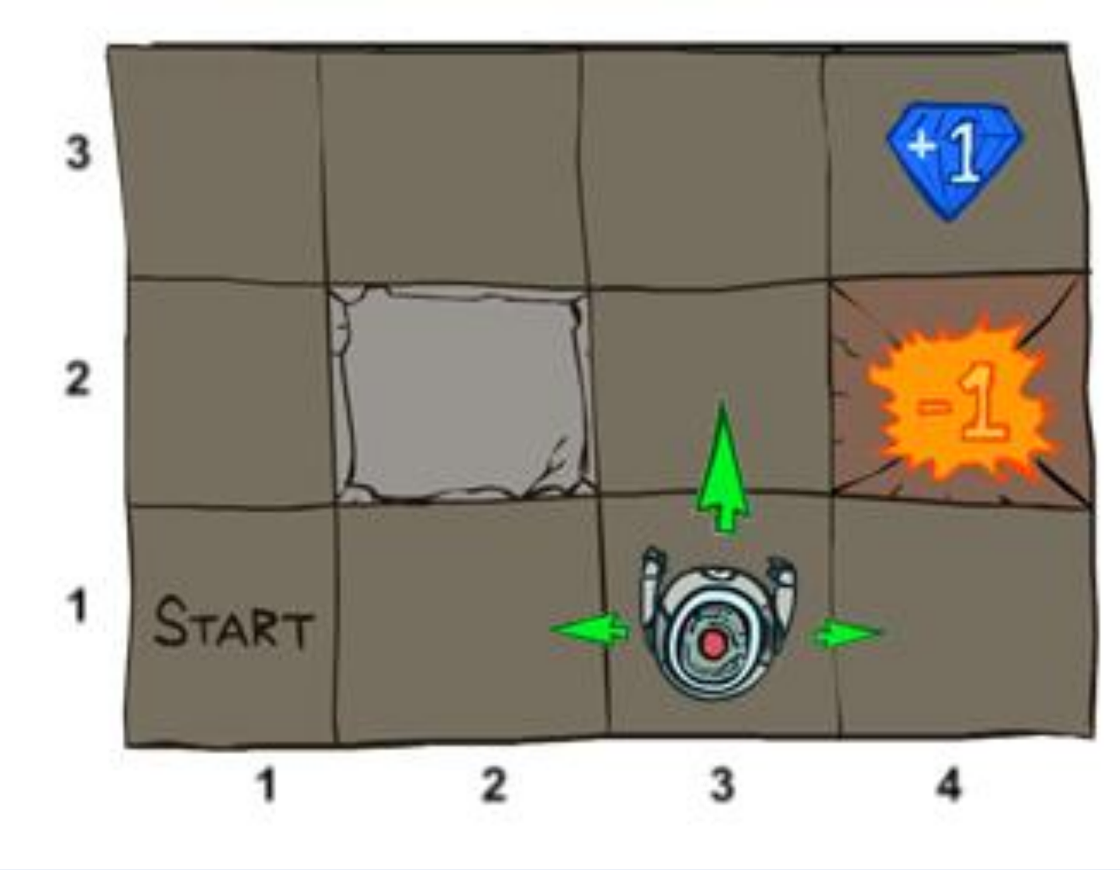


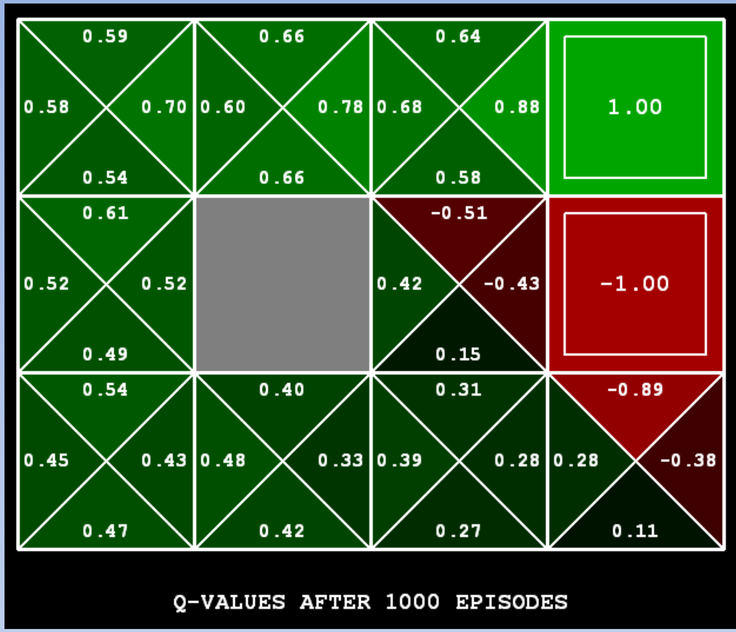
(a) (b)



Chapter 17: Making Complex Decisions

- Markov Decision Process





Chapter 21: Reinforcement Learning

- Q-Learning
- Approximate Q-Learning

Scientific Transitions

- Rational To Real
  - a/b
  - Ratio of Circle to Circumference
  - Hypotenuse of right triangle with two equal sides
- Logical To Approximation
  - Undecidable problems
  - Perfect Information
  - Uncertainty
  - Machine Learning/Neural Nets

Chapter 18: Learning from Examples

- Decision Trees
- Linear Models
- Neural Nets

Chapter 20 : Learning Probabilistic Models

- Naïve Bayes

Final

- Chapters 1-7
- Chapters 13-15
- Chapters 17, 18, 20, 21