CSE 250A. Principles of AI

Probabilistic Reasoning and Decision-Making

Lecture 1 – Introduction

Lawrence Saul
Department of Computer Science and Engineering
University of California, San Diego

Fall 2021

Welcome to CSE 250A

Let's get started:

> *I've always considered the most boring 20 minutes of the semester the time I spend reading the syllabus on the first day of class. Students come in, potentially excited about getting started, only to end up listening to me read aloud. I imagine them paraphrasing in their heads one of my favorite Woody Allen lines: Thanks, but I've been doing my own reading since about the first grade.*

Source:

`http://chronicle.com/article/The-Promising-Syllabus/46748/`

Zoom protocol

1. Please stop your video and mute your sound.
2. Type questions (as they occur to you) in the chat!
3. Class-related messages and comments are also okay.
4. TAs may respond in real time; I will also monitor.
5. I will pause at regular intervals for questions.

Outline

1. Administrivia
2. Course overview
    - Probabilistic reasoning
    - Learning from data
    - Sequential modeling
    - Planning and decision-making
3. Conclusion

Web site

CSE 250A. Principles of Artificial Intelligence: Probabilistic Reasoning and Decision-Making

Subject

Probabilistic methods for reasoning and decision-making under uncertainty. Topics include: inference and learning in directed probabilistic graphical models; prediction and planning in Markov decision processes; applications to computer vision, robotics, speech recognition, natural language processing, and information retrieval.

Prerequisites

The course is aimed broadly at advanced undergraduates and beginning graduate students in mathematics, science, and engineering. Prerequisites are elementary probability, multivariable calculus, linear algebra, and basic programming ability in some high-level language such as Python, Matlab, R, Julia, Java, or C. Programming assignments are completed in the language of the student's choice.

Relation to other courses

CSE 250a covers largely the same topics as CSE 150a, but at a faster pace and more advanced mathematical level. The homework assignments and exams in CSE 250A are also longer and more challenging. In general you should not take CSE 250a if you have already taken CSE 150a.

Administrivia

1. **Instructor:** Lawrence Saul
   Office hour: Wed 3-4 pm (zoom)
2. **Teaching assistants:**
   1. Aditi Mavalankar
   2. Dongxia (Allen) Wu
   3. Htut Khine Win
   4. Pan Xia
   5. Shubham Chaudhary
   6. Umesh Singla
   7. Xinghan Wang
3. **Lectures:**
   Tue/Thu 3:30-4:50 pm (zoom)
4. **TA discussion sessions**
   1. Aditi: TBA
   2. Dongxia: TBA
   3. Htut Khine: TBA
   4. Pan: TBA
   5. Shubham: TBA
   6. Umesh: TBA
   7. Xinghan: TBA
5. **TA office hours**
   1. Aditi: TBA
   2. Dongxia: TBA
   3. Htut Khine: TBA
   4. Pan: TBA
   5. Shubham: TBA
   6. Umesh: TBA
   7. Xinghan: TBA
6. **Grading:**
   (75%) best 8 of 9 homework assignments
   (25%) take-home final exam

Textbooks

The course does not closely follow a particular text; the lectures are meant to be self-contained. Nevertheless, the following texts (though not required) may be useful as general references:

1. Artificial Intelligence: A Modern Approach (Russell & Norvig, 2020)
2. Probabilistic Machine Learning (Murphy, 2021)
3. Mathematics for Machine Learning (Deisenroth, Faisal & Ong, 2020)
4. Reinforcement Learning: An Introduction (Sutton & Barto, 2018)
5. Pattern Recognition and Machine Learning (Bishop, 2006)

Canvas

Enrolled students should monitor Canvas for more information, including course announcements, homework assignments, and additional resources.

Syllabus

Thu Sep 23	Administrivia and course overview.	
Tue Sep 28	Modeling uncertainty, review of probability, explaining away.	HW 1 out.
Thu Sep 30	Belief networks: from probabilities to graphs.	
Tue Oct 05	Representing conditional probability tables. Conditional independence and d-separation.	HW 1 due. HW 2 out.
Thu Oct 07	Probabilistic inference in polytrees.	
Tue Oct 12	More algorithms for inference: node clustering, cutset conditioning, likelihood weighting.	HW 2 due. HW 3 out.
Thu Oct 14	Markov Chain Monte Carlo algorithms for inference. Learning from complete data.	
Tue Oct 19	Maximum likelihood estimation. Markov models of language. Naive Bayes models of text.	HW 3 due. HW 4 out.
Thu Oct 21	Linear regression and least squares. Detour on numerical optimization.	
Tue Oct 26	Logistic regression, gradient descent, Newton's method. Learning from incomplete data.	HW 4 due. HW 5 out.
Thu Oct 28	EM algorithm for discrete belief networks: derivation and proof of convergence.	
Tue Nov 02	EM algorithms for word clustering and linear interpolation.	HW 5 due. HW 6 out.
Thu Nov 04	EM algorithms for noisy-OR and matrix completion. Discrete hidden Markov models.	
Tue Nov 09	Computing likelihoods and Viterbi paths in hidden Markov models.	HW 6 due. HW 7 out.
Wed Nov 10	**Make-up lecture.** Forward-backward algorithm in HMMs. Gaussian mixture models.	
Thu Nov 11	**Veterans Day holiday**.	
Tue Nov 16	Linear dynamical systems. Reinforcement learning and Markov decision processes.	HW 7 due. HW 8 out.
Thu Nov 18	State and action value functions, Bellman equations, policy evaluation, greedy policies.	
Tue Nov 23	Policy improvement and policy iteration. Value iteration. Algorithm demos.	HW 8 due. HW 9 out.
Thu Nov 25	**Thanksgiving holiday**.	
Tue Nov 30	Convergence of value iteration. Model-free algorithms. Temporal difference prediction.	
Thu Dec 02	Q-learning, RL in large state spaces. Bonus topics. Course wrap-up.	HW 9 due.
Mon Dec 06	**Remote (take-home) final exam**.	

`http://cseweb.ucsd.edu/classes/fa21/cse250A-a/`

Enrollment priority

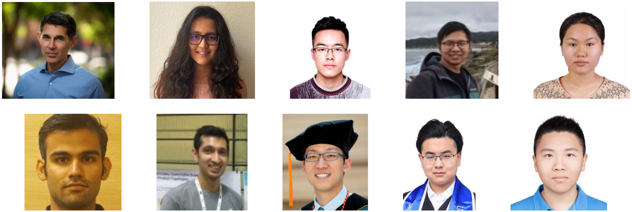
Roughly speaking, priority goes to:

- MS & PhD students in CSE
- PhD students in other departments
- MS students in other departments
- Undergraduate students ($*$)
- Exchange students

We try to take all interested students (and mostly succeed). But the course is limited by our TA capacity.

($*$) Undergraduates are advised to take CSE 150a.
Most graduate students take 3 courses per term, not 4 or 5.

Instructors



- **Professor:** Lawrence Saul
- **TAs:** Aditi Mavalankar, Dongxia Wu, Htut Khine Win,
  Pan Xia, Shubham Chaudhary, Umesh Singla
  Xinghan Wang, Zihao Zhou, Zhuowen Zou
- **My office hours:** Wed 3-4 pm.
- **Discussion sessions:** TBA
- **TA office hours:** TBA

We are here to help!

Textbooks

The course does not follow a textbook; lectures are self-contained. Though not required, the following texts may be useful:

- **Artificial Intelligence: A Modern Approach** (Russell & Norvig, 2020)
- **Probabilistic Machine Learning** (Murphy, 2021)
- **Mathematics for Machine Learning** (Deisenroth, Faisal, & Ong, 2020)
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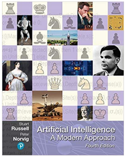
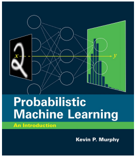
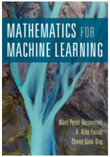
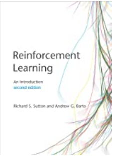
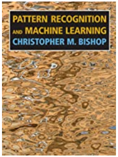
- **Pattern Recognition and Machine Learning** (Bishop, 2006)











Syllabus

What we do cover:

- Inference and learning in Bayesian networks
- Markov decision processes for reinforcement learning (RL)

What we don't cover (not exhaustive):

- Purely logical reasoning
- Heuristic search (A*)
- Theorem proving
- Genetic algorithms
- Philosophy of AI

Syllabus

What we do cover:

- Inference and learning in Bayesian networks
- Markov decision processes for reinforcement learning (RL)

Why these topics?

Turing Prize 2011

Turing Award Citation:

> *Judea Pearl is credited with the invention of* **Bayesian networks**, *a mathematical formalism for defining complex probability models, as well as the principal algorithms used for inference in these models. This work not only revolutionized the field of AI, but also became an important tool for many other branches of engineering and the natural sciences.*

Breakthroughs in RL

HOW THE ARTIFICIAL-INTELLIGENCE PROGRAM ALPHAZERO MASTERED ITS GAMES

By James Somers

December 28, 2018

In 2016, a Google program soundly defeated Lee Sedol, the world's best Go player, in a match viewed by more than a hundred million people. Photograph by Ahn Young-joon / AP

Chess commentators have praised AlphaZero, declaring that the engine "plays like a human on fire." Photograph Courtesy DeepMind Technologies

Real-world impact

- **Search & Advertising** — Google, Microsoft, Yahoo
- **Sales & Recommendations** — Amazon, Netflix, Etsy
- **Social Media** — Facebook, Twitter, LinkedIn
- **Gaming and Graphics** — XBox, Playstation, Disney
- **Forensics & signal analysis** — FBI, NSA
- **Data science & analytics**

"Every company is a data company."

Calling all data scientists ...

Prerequisites

Programming:

- Most homeworks (HWs) will involve some coding.
- Many HWs require basic data analysis and visualization.
- Solutions are accepted in any programming language.
- Most common languages are Python and MATLAB.
- We can help with algorithmic and conceptual issues.
- We cannot help with installing, compiling, plotting, etc.

Non-CS backgrounds are welcome.

Prerequisites

Elementary probability:

- Random variables — discrete and continuous
- Expected values (via sums and integrals)

Multivariable calculus:

- Chain rule
- Gradients and partial derivatives
- Computing maxima and minima
- Constrained optimization with Lagrange multipliers

Prerequisites

Linear algebra:

- Vectors and matrices
- Matrix multiplication, inverses, determinants
- Systems of linear equations

Mathematical maturity:

- Patience and persistence
- Willingness to fill in gaps

Readings versus lectures

Readings:

- No required texts.
- Some handouts (on Canvas).

Lectures:

- Designed to be self-contained.
- Crucial for homework assignments.
- Emphasis on mathematical development.
- Slides will be posted (generally, in advance).

Grading

Breakdown:

- best 8 of 9 homework assignments (75%)
- take-home (24 hour?) final exam (25%)
- rubric: A (93-100), A- (90-92.$\bar{9}$), B$+$ (87-89.$\bar{9}$), etc.
- **But I reserve the right to be more generous.**

Academic dishonesty:

- Neither ethical nor in your self-interest.
- Always credit your sources.
- Suspected plagiarism will be reported to campus.

Homeworks

Once a week, every week:

- Your lowest assignment will be automatically dropped.
- Submit assignments electronically by gradescope.
- Solutions will be posted two days after the due date.
- Late assignments will be accepted without penalty, but only until the beginning of the next lecture after they are due.
- No credit will be given after solutions are posted.
- No further extensions will be granted.
- Difficult personal circumstances? **Email me.**

Best practices:

- Keep up, or lectures will be hard to digest.
- Handwritten solutions are fine (except for source code).

Rules of the game

What is allowed:

- Working in groups to start problems (but not to finish them).
- Working in groups to solve problems (but not to write them up).
- Comparing solutions after you have written them up yourself.
- Consulting published texts, online tutorials, Wikipedia, etc.

What is not allowed:

- Using or recycling old course materials in any way.
- Copying from current or former students.
- Uploading course materials to Web archives.

Canvas

https://canvas.ucsd.edu/courses/29580

This is where to find everything:

- Lectures slides (before class) and video (after class)
- Course announcements
- Homework assignments and solutions
- Links to Zoom, Piazza, Gradescope, etc.
- Handouts and supplementary resources

Questions?

What's next

The rest of today's lecture is like a movie trailer:

- It is not meant to be perfectly understood.
- It is designed to pique your interest.
- It will raise more questions than answers.
- It is only a preview of many things to come.

Outline

1. **Administrivia**
2. **Course Overview**
   - **Probabilistic reasoning**
   - Learning from data
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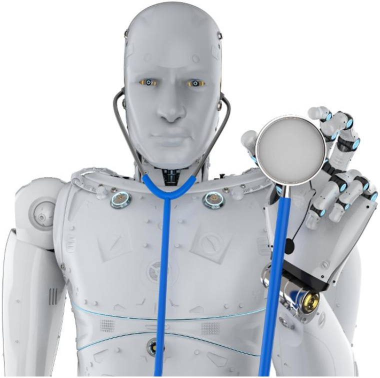
Probabilistic reasoning

How should intelligent agents cope with **uncertainty?**

These problems are best illustrated by example.

Medical diagnosis



https://adigaskell.org/2019/06/21/would-you-trust-an-automated-doctor/

Medical diagnosis

- What is knowledge in this domain?
  How do we represent that knowledge?

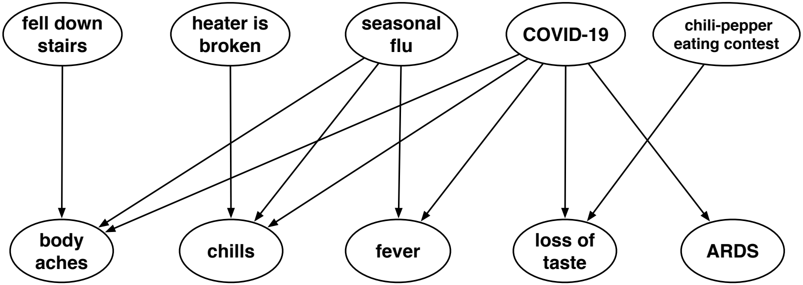
Diseases cause symptoms.

- What is uncertain in this domain?
  How do we model that uncertainty?

Some diseases are more likely than others.

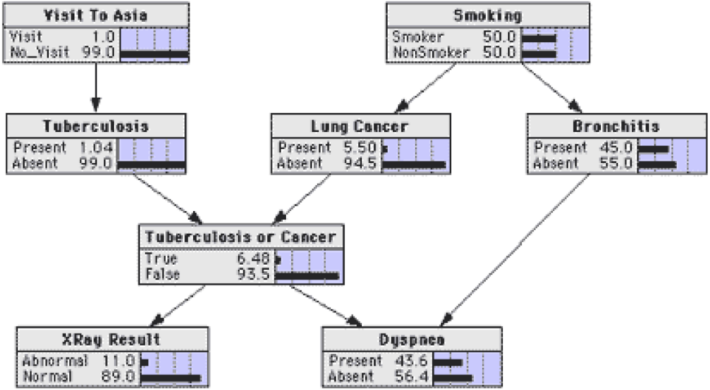
Some symptoms are more likely than others.

Graphical model for medical diagnosis



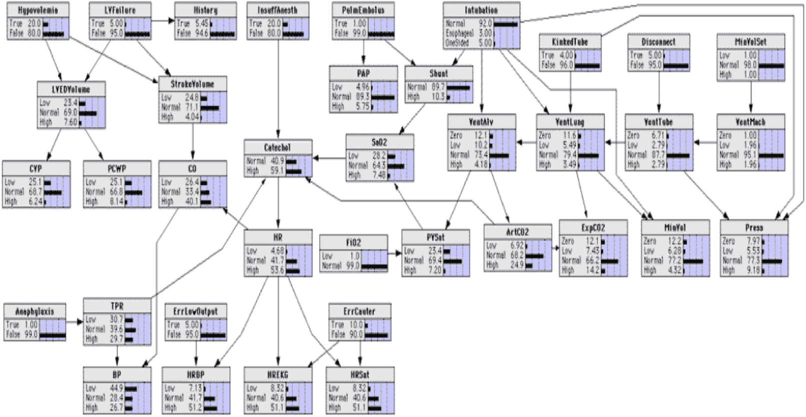
ARDS = acute respiratory distress syndrome

Real-world models



https://www.norsys.com/netlibrary/index.htm

Real-world models



https://www.norsys.com/netlibrary/index.htm

Key questions

- How do graphs represent ...
  - causation?
  - correlation?
  - independence?

- How to update beliefs in light of new evidence?

Graphical models are a marriage of graph theory and probability theory.

Questions?

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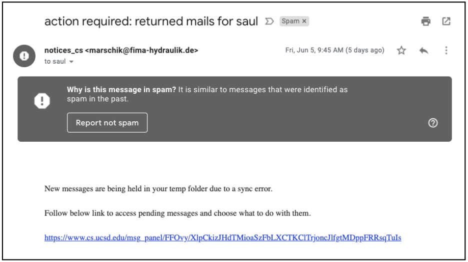
Learning from data

Graphical models can help us reason under uncertainty.

But how do we create useful models for real-world applications?

Often we must learn them from data.

Spam filters



action required: returned mails for saul Spam ×

notices_cs <marschik@fima-hydraulik.de> Fri, Jun 5, 9:45 AM (5 days ago)
to saul

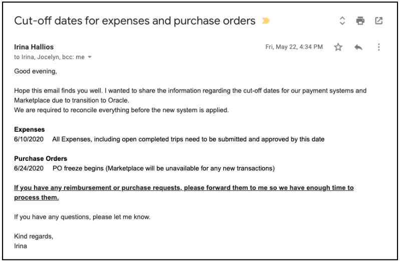
Why is this message in spam? It is similar to messages that were identified as spam in the past.

Report not spam

New messages are being held in your temp folder due to a sync error.

Follow below link to access pending messages and choose what to do with them.

https://www.cs.ucsd.edu/msg_panel/FFOvy/XlpCkizJHdTMioaSzFbLXCTKClTrjoncJlfgtMDppFRRsqTuIs



Cut-off dates for expenses and purchase orders

Irina Hallios Fri, May 22, 4:34 PM
to Irina, Jocelyn, bcc: me

Good evening,

Hope this email finds you well. I wanted to share the information regarding the cut-off dates for our payment systems and Marketplace due to transition to Oracle.
We are required to reconcile everything before the new system is applied.

Expenses
6/10/2020 All Expenses, including open completed trips need to be submitted and approved by this date

Purchase Orders
6/24/2020 PO freeze begins (Marketplace will be unavailable for any new transactions)

If you have any reimbursement or purchase requests, please forward them to me so we have enough time to process them.

If you have any questions, please let me know.

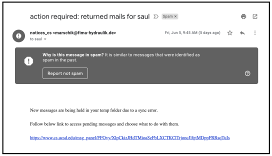
Kind regards,
Irina

- **Input:** email messages
- **Output:** binary decision – spam or not spam?

Graphical model for spam filter

- **How to represent input?**

  Convert messages to fixed-length vectors of word counts:


action required: returned mails for saul
Spam ×
notices_cs <marschik@fima-hydraulik.de>
to saul
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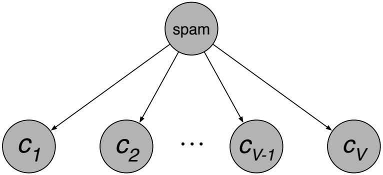
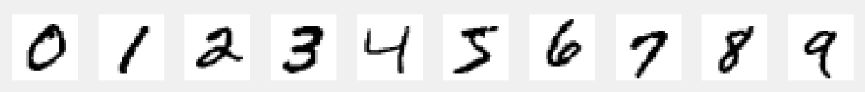
$$\longrightarrow \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_V \end{bmatrix} \qquad \begin{aligned} V &= \text{vocabulary size} \\ c_i &= \text{count of } i\text{th word} \\ & \text{in dictionary} \end{aligned}$$

- **How to make predictions?**

  Certain words are more likely to appear in spam than others. How to quantify?



Character recognition



- **Input:** grayscale image (20×20) of handwritten digit
- **Output:** label from $\{0, 1, 2, 3, 4, 5, 6, 7, 8, 9\}$

Useful to read zip codes on envelopes, dollar amounts on checks, etc.

Fashion item recognition

- **Input:** grayscale image (20×20) of fashion item
- **Output:** label from $\{$T-SHIRT, PANTS, PULLOVER, etc.$\}$

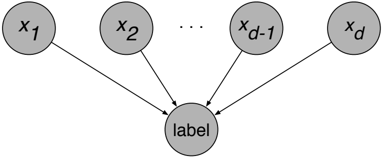
Useful to scrape web sites, profile user purchases, etc.

Graphical model

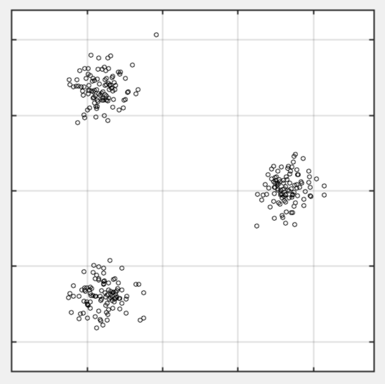
- **How to represent input?**
  Map each image to a real-valued vector of pixel values:

$$\longrightarrow \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_d \end{bmatrix} \qquad \begin{aligned} d &= \text{number of pixels} \\ x_i &= \text{grayscale value} \\ &\quad\ \text{of } i\text{th pixel} \end{aligned}$$

- **How to make predictions?**
  Certain patterns of pixels are more likely to appear for certain labels.

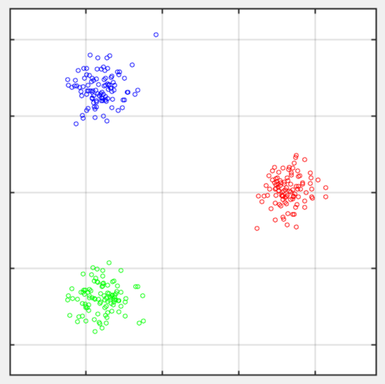


Clustering



How to cluster these points in the xy-plane?

Clustering

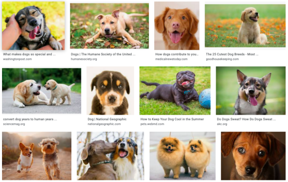


Visually it's obvious.

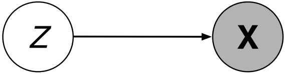
But what if the points are not in the xy-plane?

Clustering

What if the points are documents, represented as vectors of word counts?



What if the points are images, represented as vectors of pixels?



More generally:

how to infer labels $z \in \{1, 2, \ldots, k\}$
from inputs $\mathbf{x} \in \mathbb{R}^d$
without any labeled examples?

Collaborative filtering

How to build a movie recommendation system?

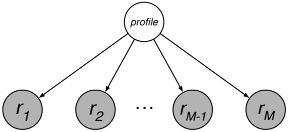
- Collect a data set of movie ratings:

$$\begin{bmatrix} + & - & + & - & ? & ? & + \\ - & ? & ? & + & + & ? & ? \\ + & + & + & + & + & + & + \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ - & - & - & - & - & ? & - \\ ? & ? & + & ? & ? & ? & - \end{bmatrix}$$

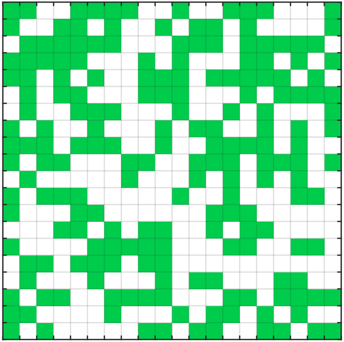
$+$	liked
$-$	disliked
?	not seen

(user-item matrix)

- Build a model of user profiles and fill in the missing ratings.



Matrix completion



How to complete a partially observed matrix?
Given some elements, how to infer the rest?

Questions?

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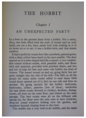
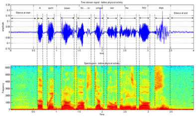
Sequential modeling

How do we model systems whose **state** *changes over time (or has some equivalently extended representation)?*

Examples:

- Traffic patterns
- Biological sequences
- Natural language
- Spoken utterances





Language modeling

We use sequences of words to create sentences.
A language model tells us which sentences are more or less likely.

Language modeling

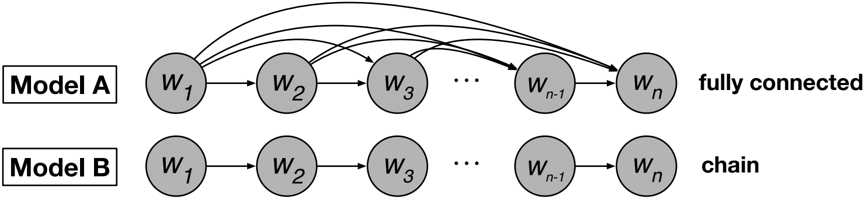
Which sentence is most/least likely?

1. `Mary had a little lamb.`
2. `Colorless green ideas sleep furiously.`
3. `Furiously sleep ideas green colorless.`

We can use a model to decide:

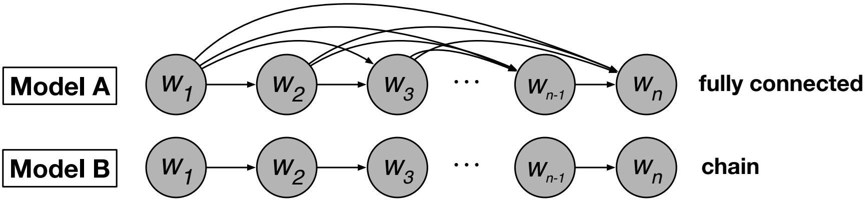
- Let w_n denote the n^{th} word in a sentence.
- A model will assign probabilities to sequences $w_1\, w_2 \ldots w_n$.

Statistical language processing



Model A is very powerful but hard to estimate.
Model B is overly simple but easy to estimate.

Statistical language processing



Sometimes Model B is enough:

$$\mathrm{Prob}_B(❶) \gg \mathrm{Prob}_B(❷) \gg \mathrm{Prob}_B(❸)$$

1. `Mary had a little lamb.`
2. `Colorless green ideas sleep furiously.`
3. `Furiously sleep ideas green colorless.`

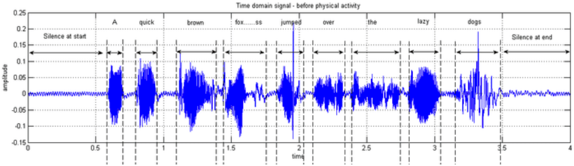
Colorless green ideas sleep furiously

Where simple models fail:

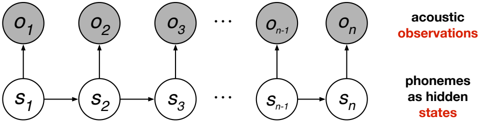
> It can only be the thought of verdure to come, which prompts us in the autumn to buy these dormant white lumps of vegetable matter covered by a brown papery skin, and lovingly to plant them and care for them. It is a marvel to me that under this cover they are laboring unseen at such a rate within to give us the sudden awesome beauty of spring flowering bulbs. While winter reigns the earth reposes but these **colorless green ideas sleep furiously**.
>
> — C. M. Street

Speech recognition

We speak in sequences of phonemes (i.e., the basic sounds of language). But how do we infer words from waveforms?



One approach is to use hidden Markov models:



Questions?

Outline

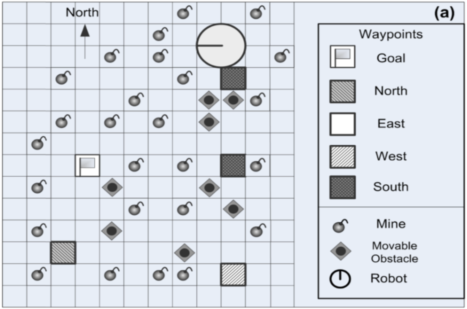
1. **Administrivia**
2. **Course Overview**
    - Probabilistic reasoning
    - Learning from data
    - Sequential modeling
    - **Planning and decision-making**
3. **Conclusion**

Planning and decision-making

How do we create **intelligent autonomous** agents?
What should we expect of such an agent?

It must do more than passively model its environment.
It must **act** in the world and **learn** from that experience.

Robot navigation

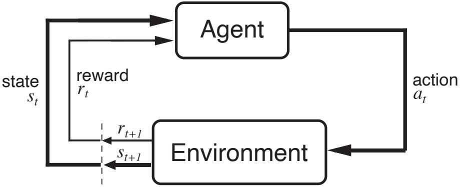


Thangavelautham & D'Eleuterio (2007)

How to navigate a 2D grid world with goals and obstacles?

Reinforcement learning (RL)

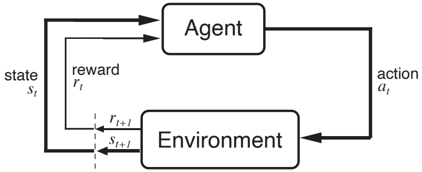
How can an autonomous agent learn from experience (whether it is real or simulated)?



Many applications:

- *Embodied* agents: robots, drones, self-driving cars, etc.
- *Embedded* agents: game-playing AIs, virtual assistants, etc.

Challenges of RL



- **Stochastic environments**
  Actions change the agent's state, but not deterministically.
  Agents must cope with uncertainty.

- **Sparse feedback**
  Rewards may be *delayed* rather than *immediate*.
  Feedback is *evaluative* rather than *instructive*.

Questions?

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Conclusion

Themes of CSE 250A:

1. Probability as a computational model of uncertainty
2. Principles versus heuristics:
   - Inference and reasoning as calculations
   - Learning and decision-making as optimizations
3. Power versus tractability:
   How to develop compact representations of complex worlds?
4. Unity of methods
   AI is no longer a hodgepodge of siloed sub-areas.

Questions?