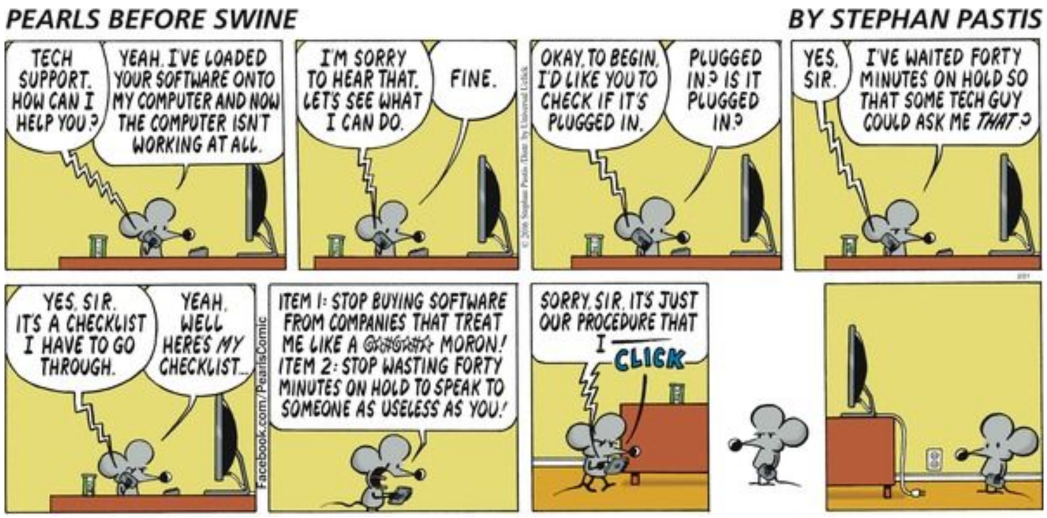
CSCI 3202

Lecture 11

September 17, 2025



Pearls Before Swine. https://www.gocomics.com/pearlsbeforeswine

Announcements

- HW #3 is due this Friday by 11:59 pm
- HW #3, Question 2d has the answer mistakenly below it. In your HW, rewrite the answer in your own words and submit it
- Switching schedule up a bit
  - Moved Hill Climbing and Beam Finding to 10/1
  - Homework has same schedule
  - Midterm still on same date, Wednesday 10/8
- Updated schedule posted on Canvas

5	**9/15**	**M**	Probability Review	Class Notes, 12.1, 12.2				
		W	Bayes Networks	13.1				
		F	Bayes Networks	13.2-13.3	**Quiz 4**		HW3	
6	**9/22**	**M**	Conditional Independence	12.4		HW 4		
		W	Bayes Examples	4.1				
		F	Bayes Summary	Class Notes	**Quiz 5**			
7	**9/29**	**M**	Solving Networks	13.3		HW 5	HW 4	
		W	Optimization: Hill Climbing	4.1				
		F	Beam Finding, Simulated Annealing	4.1	**Quiz 6**			
8	**10/6**	**M**	Review				HW 5	
		W	**Midterm**					**In class Midterm**
		F	Games	5.1				

Probability

- Bayesian Classifier
- Want to classify something
  - For spam filtering, we have "spam" and "ham"
  - Want to find P(E-Mail is "spam") or P(E-Mail is "ham") then classify based on which one is largest
  - Have features from the E-Mail, such as the individual words used in the message
  - Get a tranche of E-Mails, say n=100,000, then look at words and classify the message as either "spam" or "ham"
  - This is our training sample or training data
  - Assume conditional independence and calculate P(words|message is "spam") or P(words|message is "ham")
  - For new, unclassified messages, use Bayes rule to calculate P(message is "spam"|words) and P(message is "ham"|words).
  - Classify based on which probability is largest
- For our messages, let $\mathbf{X}$ be a collection of *features*, such as:
  - The individual words in an E-Mail
  - Common or uncommon phrases
  - The time or date an E-Mail was sent
  - The domain from which the E-Mail was sent
- There can be hundreds or thousands of features for a message
  - You may want to think of them like X values in a regression
- We calculate the $P(\mathbf{X}|"spam")$ and the $P(\mathbf{X}|"ham")$
  - We know which messages are spam and which are ham because we have paid someone to read the messages and assign a value to them
  - We know the words in the message
  - We assume *conditional independence* between the words: $P(x_1, x_2|"spam") = P(x_1|"spam") * P(x_2|"spam"))$ in general

$$P(x_1, x_2, \ldots, x_n|"spam") = \prod_{i=1}^{n} P(x_i|"spam")$$

  - The same is true for "ham"
  - Why do we need to make this assumption?
  - This is known as *training* the classifier
- For an unknown E-Mail, we use Bayes Rule to calculate $P(\mathbf{X}|"spam")$ and the $P(\mathbf{X}|"ham")$ using the training data from our 100,000 E-Mails
- According to Bayes Rule,

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

- For our data, this results in:

$$P(\text{"}spam\text{"}|\mathbf{X}) = \frac{P(\mathbf{X}|\text{"}spam\text{"}) * P(\text{"}spam\text{"})}{P(\mathbf{X})}$$

  - We calculate P("ham"|\bold{X}) in a similar fashion
  - We can get $P(\text{"}spam\text{"})$ from talking to an expert or estimating it from our data. This is the *prior probability*
  - $P(\mathbf{X})$ can be difficult to calculate
  - If we look at the ratio:

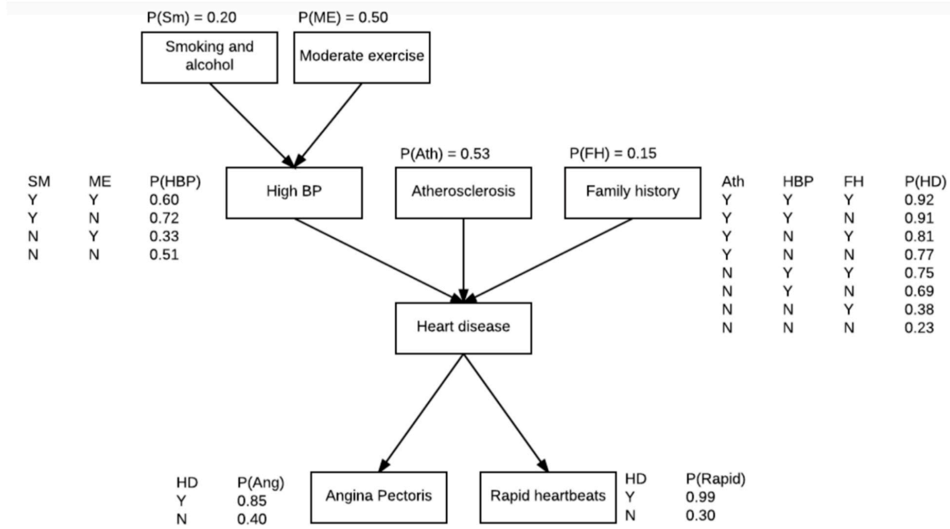
$$\lambda = \frac{\frac{P(\mathbf{X}|\text{"}spam\text{"}) * P(\text{"}spam\text{"})}{P(\mathbf{X})}}{\frac{P(\mathbf{X}|\text{"}ham\text{"}) * P(\text{"}ham\text{"})}{P(\mathbf{X})}}$$

    we can see that $P(\mathbf{X})$ mostly cancels out. We comapare λ to 1.0. If $\lambda > 1.0$ then we classify a message as "spam" otherwise we classify it as spam"ham"
  - In reality, we may find some messages with values near λ that we can't classify correctly. For this reason, we may choose to classify as spam any message where $\lambda > 1.2$ or something similar
- Probability Review.pdf

Bayesian Networks

- Bayesian networks are an extension of the Bayesian Classifier ideas
- The networks allow us to solve complex problems such as the relationship between exercise and heart disease in ways we could not solve them before

The following Bayesian network is based loosely on a study that examined heart disease risk factors in 167 elderly individuals in South Carolina. Note that this figure uses Y and N to represent Yes and No, whereas in class we used the equivalent T and F to represent True and False Boolean values.



- Bayes Nets Intro.pdf

Readings

- AIMA Section 13.1

Upcoming

- More Introduction to Bayes Networks
- Quiz #4 on Friday will cover Probability, Bayes Rule
- HW #4 released on Monday
  - Covers probability, Bayes Rule