# CMPSCI 240: "Reasoning Under Uncertainty" Lecture 9 

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## Reminders

- Check the course website: http://www.cs.umass.edu/ ~wallach/courses/s12/cmpsci240/
- Third homework is due on Friday


## Information Theory

## Communication

- Communication: representing and transmitting information


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- "The fundamental problem of communication is that of reproducing at one point either exactly or approximately a message selected at another point." - Claude Shannon
- Information theory: the math behind this


## Uses of Information Theory

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- Measuring information content
- Compressing data (e.g., images, video, text, etc.)
- Communicating without errors over noisy, imperfect communication channels (e.g., phone lines, disk drives, etc.)


## Information Content

## Probability and Information: Intuition

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- e.g., sun rising vs. professor making a TurBacHenDuckEn


## Desirable Properties of Information Content

- If $P(A)=1$ and $P\left(A^{c}\right)=0$, the information gained by learning that the outcome $x$ is in $A$ should be zero and the information gained by learning that $x \in A^{c}$ should be infinite


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- If $P(A)=1$ and $P\left(A^{c}\right)=0$, the information gained by learning that the outcome $x$ is in $A$ should be zero and the information gained by learning that $x \in A^{c}$ should be infinite
- If $P(A)=P\left(A^{c}\right)=1 / 2$, we are maximally uncertain about the outcome and we should gain one unit of information by learning that the event is in $A$ and similarly for $A^{c}$


## Asking Informative Questions

- If $A_{1}, \ldots, A_{n}$ have probabilities $P\left(A_{1}\right), \ldots, P\left(A_{n}\right)$ and partition $\Omega$, how would you identify the event containing outcome $x$ using as few yes/no questions as possible?


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- e.g., suppose $n=4$ and $P\left(A_{i}\right)=1 / 4$ for $i=1, \ldots, 4$


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- e.g., suppose $n=4$ and $P\left(A_{i}\right)=1 / 4$ for $i=1, \ldots, 4$
- e.g., suppose $n=4$ again but now we have $P\left(A_{1}\right)=1 / 2$, $P\left(A_{2}\right)=1 / 4, P\left(A_{3}\right)=1 / 8$, and $P\left(A_{4}\right)=1 / 8$


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- Ask the questions that will eliminate the most remaining possibilities regardless of the answers obtained, i.e., those questions that divide the remaining probability equally


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## Asking Informative Questions

- Think of the equiprobable yes/no questions as defining a (weighted, binary) tree with events $A_{1}, \ldots, A_{n}$ as leaves
- The depth of $A_{i}$ is equal to the number of equiprobable yes/no questions required to uniquely determine that $x \in A_{i}$
- Each yes/no question divides the remaining probability in half, so we know that if event $A_{i}$ is at depth $k$, its probability $P\left(A_{i}\right)$ must be equal to $(1 / 2)^{k}=\left(2^{-1}\right)^{k}=2^{-k}$


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- e.g., $I\left(A_{1}\right)=1, I\left(A_{2}\right)=2, I\left(A_{3}\right)=3, I\left(A_{4}\right)=3$


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$$
\begin{aligned}
I(A \cap B) & =\log _{2} \frac{1}{P(A \cap B)} \\
& =\log _{2} \frac{1}{P(A) P(B \mid A)}=I(A)+I(B \mid A)
\end{aligned}
$$

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- More probable events are identified via fewer equiprobable yes/no questions (i.e., shorter bit strings) while less probable events require more questions (i.e., longer bit strings)
- Information content is therefore measured in bits


## Examples of Information Content

- e.g., $P\left(A_{1}\right)=P\left(A_{2}\right)=1 / 2$
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- e.g., $P\left(A_{1}\right)=1 / 2, P\left(A_{2}\right)=3 / 8, P\left(A_{3}\right)=P\left(A_{4}\right)=1 / 16$
- e.g., $P\left(A_{1}\right)=1, P\left(A_{2}\right)=P\left(A_{3}\right)=P\left(A_{4}\right)=0$


## Entropy

- Entropy: average information content of a set of $n$ disjoint, mutually exclusive events $A_{1}, \ldots, A_{n}$ that partition $\Omega$

$$
H\left(A_{1}, \ldots, A_{n}\right)=\sum_{i=1}^{n} P\left(A_{i}\right) \log _{2} \frac{1}{P\left(A_{i}\right)}
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- Average number of equiprobable yes/no questions required to uniquely determine that outcome $x$ is in any event $A_{i}$
- Measure of uncertainty of the entire set of events


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- Entropy $H\left(A_{1}, \ldots, A_{n}\right)$ is the best achievable (lowest possible) information rate if events must be uniquely encoded


## Examples of Information Rate

- e.g., suppose $P\left(A_{1}\right)=1 / 2, P\left(A_{2}\right)=1 / 4$, $P\left(A_{3}\right)=P\left(A_{4}\right)=1 / 8$, what is the information rate of $A_{1}=11, A_{2}=10, A_{3}=01, A_{4}=10$ ?


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- e.g., $A_{1}=01, A_{2}=000, A_{3}=001, A_{4}=1$ ?


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## Communicating Perfectly

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- Want to make sure the correct message is received even if there are transmission errors (e.g., static, disk failure, ...)
- Probability of a single bit being flipped is $p$
- Error probability: overall probability of there being an undetected error when using some encoding scheme
[Got to here in class...]


## Examples of Error Probability

- e.g., 8 events represented as $000,001,010, \ldots 111$, probability of a single bit flip is $1 / 10$, what is the error probability?


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- Can use additional bits when encoding messages to ensure that they are "protected" against errors in transmission
- Error detecting codes vs. error correcting codes
- Fundamental trade-off: want encoding schemes that minimize both the error probability and the information rate


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- Append a parity bit to each binary string such that every binary string always contains an even number of ones
- e.g., 0000, 0011, 0101, ... , 1100, 1111
- Can detect error if an odd number of bits get flipped
- Cannot detect error if an even number of bits get flipped


## Examples of Parity Check Codes

- e.g., 8 events represented as $0000,0011, \ldots, 1111$, probability of a single bit flip is $1 / 10$, what is the error probability?


## For Next Time

- Check the course website: http://www.cs.umass.edu/ ~wallach/courses/s12/cmpsci240/
- Third homework is due on Friday
- IMPORTANT: check you can log into the EdLab in preparation for next week's homework

