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INFORMATION THEORY

Problem 1

CALCULATE ENTROPIES

A discrete source transmits message x_1, x_2, x_3 with the probabilities 0.3, 0.4 and 0.3. The source is connected to the channel as shown in fig. Calculate all entropies



Theorem 2.7.3 (Concavity of entropy) $H(p)$ is a concave function of p .

Proof

$$H(p) = \log |\mathcal{X}| - D(p||u), \quad (2.107)$$

where u is the uniform distribution on $|\mathcal{X}|$ outcomes. The concavity of H then follows directly from the convexity of D . \square

Information Theory: Entropy

Relationship between conditional, joint and marginal entropy.

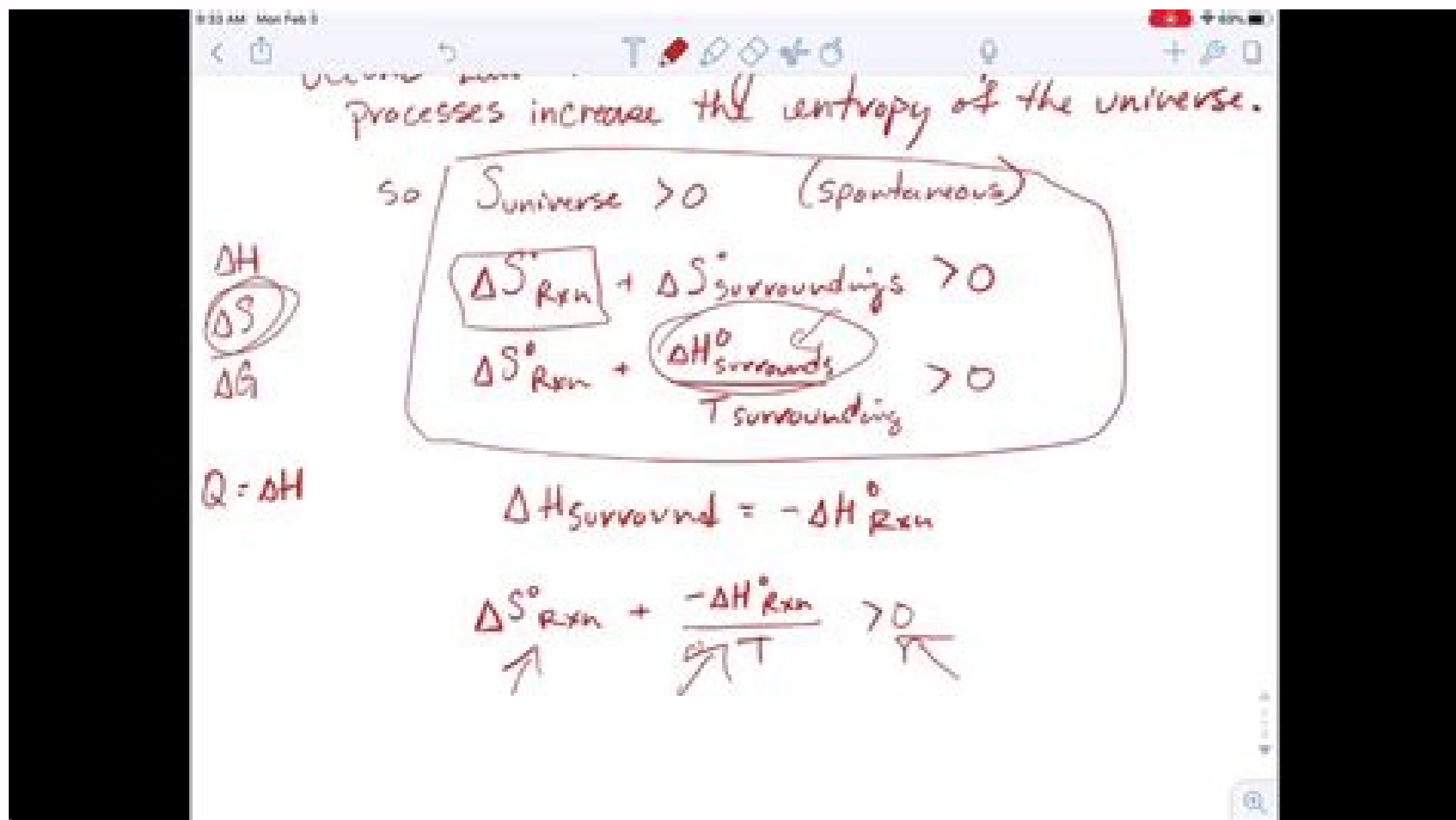
$$H(X, Y) = H(X|Y) + H(Y)$$
$$H(X, Y) = H(Y|X) + H(X) \text{ (Equivalently)}$$

Re-arranging these equations

$$H(X, Y) - H(Y) = H(X|Y)$$
$$H(X, Y) - H(X) = H(Y|X)$$

Shannon's entropy equation:

$$H(X) = - \sum_{i=0}^{N-1} p_i \log_2 p_i$$



What is entropy in systems theory. What is entropy for dummies. What is the theory of entropy. Entropy in information theory. Entropy information theory example.

Expected amount of information needed to specify the output of a stochastic data source For other uses, see Entropy (disambiguation). This article needs additional citations for verification. Please help improve this article by adding citations to reliable sources. Unsourced material may be challenged and removed.Find sources: "Entropy" information theory - news - newspapers - books - scholar - JSTOR (February 2019) (Learn how and when to remove this template message) Information theory Entropy Differential entropy Conditional entropy Joint entropy Mutual information Conditional mutual information Relative entropy Entropy rate Limiting density of discrete points Asymptotic equipartition property Rate-distortion theory Shannon's source coding theorem Channel capacity Noisy-channel coding theorem Shannon-Hartley theorem vte In information theory, the entropy of a random variable is the average level of "information", "surprise", or "uncertainty" inherent to the variable's possible outcomes. Given a discrete random variable X (displaystyle X), which takes values in the alphabet \mathcal{X} (displaystyle {\mathcal {X}}) and is distributed according to $p: \mathcal{X} \rightarrow [0, 1]$ (displaystyle p: {\mathcal {X}} \to [0, 1]) ; $H(X) = - \sum_{i=1}^n p(x_i) \log P(X=x_i)$ (displaystyle \mathrm {H} (X)=-\sum _{i=1}^n {\mathrm {P} (X=x_i)} \log \mathrm {P} (X=x_i)) where Σ (displaystyle {\Sigma }) denotes the sum over the variable's possible values. The choice of base for log (displaystyle \log), the logarithm, varies for different applications. Base 2 gives the unit of bits (or "shannons"), while base e gives "natural units" nat, and base 10 gives units of "dits", "bans", or "hartleys". An equivalent definition of entropy is the expected value of the self-information of a variable.[1] Two bits of entropy. In the case of two fair coin tosses, the information entropy in bits is the base-2 logarithm of the number of possible outcomes, with two coins there are four possible outcomes, and two bits of entropy. Generally, information entropy is the average amount of information conveyed by an event, when considering all possible outcomes. The concept of information theory was introduced by Claude Shannon in his 1948 paper "A Mathematical Theory of Communication".[2][3] and is also referred to as Shannon entropy. Shannon's theory defines a data communication system composed of three elements: a source of data, a communication channel, and a receiver. The "fundamental problem of communication" - as expressed by Shannon - is for the receiver to be able to identify what data was generated by the source, based on the signal it receives through the channel.[2][3] Shannon considered various ways to encode, compress, and transmit messages from a data source, and proved in his famous source coding theorem that the entropy represents an absolute mathematical limit on how well data from the source can be losslessly compressed onto a perfectly noiseless channel. Shannon strengthened this result considerably for noisy channels in his noisy-channel coding theorem. Entropy in information theory is directly analogous to the entropy in statistical thermodynamics. The analogy results when the values of the random variable designate energies of microstates, so Gibbs formula for the entropy is formally identical to Shannon's formula. Entropy has relevance to other areas of mathematics such as combinatorics and machine learning. The definition can be derived from a set of axioms establishing that entropy should be a measure of how "surprising" the average outcome of a variable is. For a continuous random variable, differential entropy is analogous to entropy. Introduction The core idea of information theory is that the "informational value" of a communicated message depends on the degree to which the content of the message is surprising. If a highly likely event occurs, the message carries very little information. On the other hand, if a highly unlikely event occurs, the message is much more informative. For instance, the knowledge that some particular number will not be the winning number of a lottery provides very little information, because any particular chosen number will almost certainly not win. However, knowledge that a particular number will win a lottery has high informational value because it communicates the outcome of a very low probability event. The information content, also called the surprisal or self-information, of an event E (displaystyle E) is a function which increases as the probability $p(E)$ (displaystyle p(E)) of an event decreases. When $P(E)$ (displaystyle P(E)) is close to 1, the surprisal of the event is low, but if $P(E)$ (displaystyle P(E)) is close to 0, the surprisal of the event is high. This relationship is described by the function $\log (1/P(E))$ (displaystyle \log \left({\frac {1}{P(E)}} \right)) where log (displaystyle \log) is the logarithm, which gives 0 surprise when the probability of the event is 1.[4] In fact, the log (displaystyle \log) is the only function that satisfies this specific set of characterization. Hence, we can define the information, or surprisal, of an event E (displaystyle E) by $I(E) = - \log 2 (p(E))$ (displaystyle I(E)=-\log _{2} (p(E)), or equivalently, $I(E) = \log 2 (1/p(E))$ (displaystyle I(E)=\log _{2}\left({\frac {1}{p(E)}} \right)) . Entropy measures the expected (i.e., average) amount of information conveyed by identifying the outcome of a random trial.[5]:67 This implies that casting a die has higher entropy than tossing a coin because each outcome of a die toss has smaller probability (about $p = 1/6$ (displaystyle p=1/6)) than each outcome of a coin toss ($p = 1/2$ (displaystyle p=1/2)). Consider a biased coin with probability p of landing on heads and probability $1 - p$ of landing on tails. The maximum surprise is when $p = 1/2$, for which one outcome is not expected over the other. In this case a coin flip has an entropy of one bit. (Similarly, one trit with equiprobable values contains $\log 2 3$ (displaystyle \log _{2}3) (about 1.58496) bits of information because it can have one of three values.) The minimum surprise is when $p = 0$ or $p = 1$, when the event outcome is known ahead of time, and the entropy is zero bits. When the entropy is zero bits, this is sometimes referred to as unity, where there is no uncertainty at all - no freedom of choice - no information. Other values of p give entropies between zero and one bits. Information theory is useful to calculate the smallest amount of information required to convey a message, as in data compression. For example, consider the transmission of sequences comprising the 4 characters 'A', 'B', 'C', and 'D' over a binary channel. If all 4 letters are equally likely (25%), one can't do better than using two bits to encode each letter. 'A' might code as '00', 'B' as '01', 'C' as '10', and 'D' as '11'. However, if the probabilities of each letter are unequal, say 'A' occurs with 70% probability, 'B' with 26%, and 'C' and 'D' with 2% each, one could assign variable length codes. In this case, 'A' would be coded as '0', 'B' as '10', 'C' as '110', and D as '111'. With this representation, 70% of the time only one bit needs to be sent, 26% of the time two bits, and only 4% of the time 3 bits. On average, fewer than 2 bits are required since the entropy is lower (owing to the high prevalence of 'A' followed by 'B' - together 96% of characters). The calculation of the sum of probability-weighted log probabilities measures and captures this effect. English text, treated as a string of characters, has fairly low entropy, i.e., is fairly predictable. We can be fairly certain that, for example, 'e' will be far more common than 'z', that the combination 'qu' will be much more common than any other combination with a 'q' in it, and that the combination 'th' will be more common than 'z', 'q', or 'qu'. After the first few letters one can often guess the rest of the word. English text has between 0.6 and 1.3 bits of entropy per character of the message.[6]:234 Definition Named after Boltzmann's H-theorem, Shannon defined the entropy H (Greek capital letter eta) of a discrete random variable X (textstyle X) with possible values $\{x_1, \dots, x_n\}$ (textstyle \left\{x_1, \ldots ,x_n\right\}) and probability mass function $P(X)$ as: $H(X) = E[-\log(P(X))]$. (displaystyle \mathrm {H} (X)=\operatornamename {E} [-\log(\mathrm {P} (X))]. Here E (displaystyle \operatornamename {E}) is the expected value operator, and I is the information content of X . [7]:11 [8]:19–20 $I(X)$ (displaystyle \operatornamename {I} (X)) is itself a random variable. The entropy can explicitly be written as: $H(X) = - \sum_{i=1}^n p(x_i) \log_b P(X=x_i)$ (displaystyle \mathrm {H} (X)=-\sum _{i=1}^n {\mathrm {P} (X=x_i)} \log _b {\mathrm {P} (X=x_i)}) where b is the base of the logarithm used. Common values of b are 2, Euler's number e , and 10, and the corresponding units of entropy are the bits for $b = 2$, nats for $b = e$, and bans for $b = 10$. [9] In the case of $P(x_i) = 0$ for some i , the value of the corresponding summand $0 \log(0)$ is taken to be 0, which is consistent with the limit: [10]:13 $\lim_{p \rightarrow 0} p \log(p) = 0$. (displaystyle \lim _{p\to 0^+} p\log(p)=0.) One may also define the conditional entropy of two variables X (displaystyle X) and Y (displaystyle Y) taking values x_i (displaystyle x_i) and y_j (displaystyle y_j) respectively, as: [10]:16 $H(X|Y) = - \sum_{i,j} p(x_i, y_j) \log p(x_i, y_j)$ (displaystyle \mathrm {H} (X|Y)=-\sum _{i,j} p(x_i,y_j) \log \left({\frac {p(x_i,y_j)}{p(y_j)}} \right)) where $p(x_i, y_j)$ (displaystyle p(x_i,y_j)) is the probability that $X = x_i$ (displaystyle X=x_i) and $Y = y_j$ (displaystyle Y=y_j). This quantity should be understood as the amount of randomness in the random variable X (displaystyle X) given the random variable Y (displaystyle Y). Measure theory Entropy can be formally defined in the language of measure theory as follows:[11] Let (X, Σ, μ) (displaystyle (X,\Sigma ,\mu)) be a probability space. Let $A \in \Sigma$ (displaystyle A\in \Sigma) be an event. The surprisal of A (displaystyle A) is $\sigma \mu(A) = - \ln \mu(A)$ (displaystyle \sigma _{\mu }(A)=-\ln \mu (A)) The expected surprisal of A (displaystyle A) is $h_{\mu}(A) = \mu(A) \sigma \mu(A)$ (displaystyle h_{\mu}(A)=\mu (A)\sigma _{\mu}(A)) μ (displaystyle \mu) -almost partition is a set family $\mathcal{P}(X)$ (displaystyle \mathcal {P}\subseteq \Sigma) such that $\mu(\cup P) = 1$ (displaystyle \mu (\cup P)=1) and $\mu(A \cap B) = 0$ (displaystyle \mu (A\cap B)=0) for all distinct $A, B \in \mathcal{P}$ (displaystyle A,B\in \mathcal {P}). (This is a relaxation of the usual conditions for a partition.) The entropy of \mathcal{P} (displaystyle \mathcal {P}) is $H_{\mu}(\mathcal{P}) = \sum A \in \mathcal{P} h_{\mu}(A)$ (displaystyle H_{\mu}(\mathcal {P})=\sum _{A\in \mathcal {P}} h_{\mu}(A)) Let \mathcal{M} (displaystyle \mathcal {M}) be a sigma-algebra on X (displaystyle X). The entropy of \mathcal{M} (displaystyle \mathcal {M}) is $H_{\mu}(\mathcal{M}) = \sup_{\mathcal{P} \subseteq \mathcal{M}} H_{\mu}(\mathcal{P})$ (displaystyle H_{\mu}(\mathcal {M})=\sup _{\{\mathcal {P}\subseteq \text{seteq } \mathcal {M}\}} H_{\mu}(\mathcal {P})) Finally, the entropy of the probability space is $H_{\mu}(\Sigma)$ (displaystyle H_{\mu}(\Sigma)) that is, the entropy with respect to μ (displaystyle \mu) of the sigma-algebra of all measurable subsets of X (displaystyle X). Example Entropy $H(X)$ (i.e. the expected surprisal) of a coin flip, measured in bits, graphed versus the bias of the coin $P(X=1)$, where $X=1$ represents a result of heads.[10]:14–15 Here, the entropy is at most 1 bit, and to communicate the outcome of a coin flip (2 possible values) will require an average of at most 1 bit (exactly 1 bit for a fair coin). The result of a fair die (6 possible values) would have entropy log26 bits. Main articles: Binary entropy function and Bernoulli process Consider tossing a coin with known, not necessarily fair, probabilities of coming up heads or tails; this can be modelled as a Bernoulli process. The entropy of the unknown result of the next toss of the coin is maximized if the coin is fair (that is, if heads and tails both have equal probability 1/2). This is the situation of maximum uncertainty as it is most difficult to predict the outcome of the next toss; the result of each toss of the coin delivers one full bit of information. This is because $H(X) = - \sum_{i=1}^n p(x_i) \log_b P(X=x_i) = - \sum_{i=1}^2 1/2 \log_2 1/2 = - \sum_{i=1}^2 1/2 \cdot (-1) = 1$ (displaystyle {\begin{aligned}\mathrm {H} (X)&=-\sum _{i=1}^n {\mathrm {P} (X=x_i)} \log _b {\mathrm {P} (X=x_i)} \\&=-\sum _{i=1}^2 \left({\frac {1}{2}} \right) \log _2 \left({\frac {1}{2}} \right) \\&=-\sum _{i=1}^2 \left({\frac {1}{2}} \right) \cdot (-1) \\&=1\end{aligned}}) However, if we know the coin is not fair, but comes up heads or tails with probabilities p and q , where $p \neq q$, then there is less uncertainty. Every time it is tossed, one side is more likely to come up than the other. The reduced uncertainty is quantified in a lower entropy: on average each toss of the coin delivers less than one full bit of information. For example, if $p=0.7$, then $H(X) = - p \log 2 (p) - q \log 2 (q) = - 0.7 \log 2 (0.7) - 0.3 \log 2 (0.3) = - 0.7 \cdot (- 0.515) - 0.3 \cdot (- 1.737) = 0.8816 < 1$ (displaystyle {\begin{aligned}\mathrm {H} (X)&=-p\log _2(p)-q\log _2(q) \\&=-0.7\log _2(0.7)-0.3\log _2(0.3) \\&\approx -0.7\cdot (-0.515)-0.3\cdot (-1.737) \\&=0.8816\end{aligned}})

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