# Quantifying Randomness Part 1: Introduction to Entropy <br> INFO-1301, Quantitative Reasoning 1 <br> University of Colorado Boulder 

October 3, 2016<br>Prof. Michael Paul<br>Prof. William Aspray

## How uncertain is a distribution?

One extreme: everything is equally likely
$\mathrm{P}(X=1)=0.2$
$\mathrm{P}(X=2)=0.2$
$\mathrm{P}(X=3)=0.2$
$\mathrm{P}(X=4)=0.2$
$\mathrm{P}(X=5)=0.2$

With this distribution, you are completely uncertain about what the outcome will be

## How uncertain is a distribution?

Another extreme: only one outcome is likely
$\mathrm{P}(X=1)=0.0$
$\mathrm{P}(X=2)=0.0$
$\mathrm{P}(X=3)=1.0$
$\mathrm{P}(X=4)=0.0$
$\mathrm{P}(X=5)=0.0$

With this distribution, you are completely certain about what the outcome will be

## How uncertain is a distribution?

Distributions in between these extremes:
$\mathrm{P}(X=1)=0.1$
$\mathrm{P}(X=2)=0.2$
$\mathrm{P}(X=3)=0.4$
$\mathrm{P}(X=4)=0.2$
$\mathrm{P}(X=5)=0.1$

$$
\begin{aligned}
& \mathrm{P}(X=1)=0.05 \\
& \mathrm{P}(X=2)=0.05 \\
& \mathrm{P}(X=3)=0.8 \\
& \mathrm{P}(X=4)=0.05 \\
& \mathrm{P}(X=5)=0.05
\end{aligned}
$$

Which one is more "certain"?

- Which one would be easier to base decisions on?


## Information Entropy

Entropy is a measurement of how evenly distributed a probability distribution is

- We can quantify the "uncertainty" of a distribution, using the concepts from the preceding examples

Entropy of a random variable $X$ is denoted $\mathrm{H}(X)$

- Entropy is non-negative (0 or higher)

Lower entropy means it is less even, more certain Higher entropy means it is more even, less certain

## Information Entropy

The lowest possible value of entropy is 0
This occurs when a distribution gives 0 probability to all but one outcome (called a point distribution)
$\mathrm{P}(X=1)=0.0$
$\mathrm{P}(X=2)=0.0$
$\mathrm{P}(X=3)=1.0$
$\mathrm{P}(X=4)=0.0$
$\mathrm{P}(X=5)=0.0$
$P(X=1)=1.0$
$\mathrm{P}(X=2)=0.0$
$\mathrm{P}(X=3)=0.0$
$\mathrm{P}(X=4)=0.0$
$\mathrm{P}(X=5)=0.0$

## Information Entropy

The highest possible value of entropy occurs when the distribution is uniform
$\mathrm{P}(X=1)=0.2$
$\mathrm{P}(X=2)=0.2$
$\mathrm{P}(X=3)=0.2$
$\mathrm{P}(X=4)=0.2$
$\mathrm{P}(X=5)=0.2$

## Logarithms

If: $2^{y}=x$
$\log _{2}(2)=1$
$\log _{2}(4)=2$
$\log _{2}(8)=3$
then: $\quad \log _{2}(x)=y$

$$
\begin{gathered}
\log _{2}(x)=y \\
1
\end{gathered}
$$

2 is the base of the log Entropy uses base 2

How many times can you divide by 2 until you get 1 ?
$16 / 2=8 / 2=4 / 2=2 / 2=1$
$>\log _{2}(16)=4$

## Logarithms

If: $2^{y}=x \quad$ then: $\quad \log _{2}(x)=y$
$\log _{2}(1)=0$
$\log _{2}(10)=3.32$
$\log _{2}(1.5)=0.58$ $\log _{2}(0.5)=-1$
$\log _{2}(0.2)=-2.32$ $\log _{2}(0)=n / a$ $\log _{2}(-0.5)=n / a$
$2^{0}=1$
Between $\log _{2}(8)$ and $\log _{2}(16)$
Between $\log _{2}(1)$ and $\log _{2}(2)$
$2^{-1}=1 / 2=0.5$
If $x<1$, then $\log (x)<0$
If $x=0$, there is no $\log (x)$
If $x<0$, there is no $\log (x)$

## Information Entropy

How to calculate $\mathrm{H}(X)$ ?
For every outcome of $X$, calculate:
$\mathrm{P}(X=\mathrm{a}) \times \log _{2} \mathrm{P}(X=\mathrm{a})$
Then sum the results for each outcome:
$\mathrm{P}(X=a) \times \log _{2} \mathrm{P}(X=\mathrm{a})+\mathrm{P}(X=\mathrm{b}) \times \log _{2} \mathrm{P}(X=\mathrm{b})$
Then multiply the final result by -1 :
$-\mathrm{P}(X=a) \times \log _{2} \mathrm{P}(X=a)-\mathrm{P}(X=b) \times \log _{2} \mathrm{P}(X=b)$

## Information Entropy

Example: coin flip
$\mathrm{P}(X=$ Heads $)=0.5$
$\mathrm{P}(X=$ Tails $)=0.5$
$0.5 \log _{2}(0.5)+0.5 \log _{2}(0.5)=-1$ $H(X)=1$

The highest possible entropy for a distribution with two outcomes is 1

## Information Entropy

Example: chance of rain
$\mathrm{P}(X=$ Sunny $)=0.9$
$\mathrm{P}(X=$ Rainy $)=0.1$
$0.9 \log _{2}(0.9)+0.1 \log _{2}(0.1)=-0.469$ $H(X)=0.469$

Entropy of this distribution is lower than a coin flip

## Information Entropy

General formula:
$\mathrm{H}(X)=-\sum_{\mathrm{a}} \mathrm{P}(X=\mathrm{a}) \log _{2} \mathrm{P}(X=\mathrm{a})$

Next time we'll look at where this formula comes from

