# Introduction to <br> <br> Information 

 <br> <br> Information}

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For the course "Data Compression"

## The Goal

## Represent information from using lesser amount of data that the original



It is actually a representation change

## Representation Changes


several representation changes may occur before obtaining output data
here is an example from Communications course
idea $\rightarrow$ words $\rightarrow$ speech/voice $\rightarrow$ electrical signals $\rightarrow$ bits $\rightarrow$ electrical signals

## Chessboard


method-3

1. ...
2. ...
3. ...

Question: how would you describe a chessboard?

1. Describe a black square
2. Tell what a square is
3. Give size
4. Describe what black is
5. Describe what filling with black is
6. 
7. Describe a white square
8. Describe an array of black \& white squares
9. Describe a filling pattern
10. Describe what a pixel is
method-2
11. Describe white pixel
12. Describe black pixel
13. Describe creating a square array of pixels
14. Describe an array of black \& white squares
15. ...
method-n
16. Tell the word "chessboard" because everybody knows what it is

## Question: how about this one?



Question: how much detail would you require to give?
Question: Will you be giving all the information about cracks, scratches, view, ?

Question: What is information?

## Representation Example



Fact 1 : if it is always 'True', then nobody needs to share this information, that is there is no information to share

Fact 2 : Information user must know what the representation mean (speak same language/symbols/signals etc)

## Simple Example

## A sentence : "The sun will rise tomorrow"

meaning : The star that the earth rounds around will continue to exist and earth will continue to spin and no catastrophic event will occur to prevent that and our side of the earth will complete a considerable part of its rotation cycle, facing towards the sun. (probability=1)

The opposite of the above event has the probability of 0 .
It turns out that there is no point of sharing this sentence as it does not contain any information unless the sentence has some epic meaning. For other meanings, of course, both sides must speak the same language.

So, what is information?

## Information and Data

Fact : In order for an event to be counted as informative event, its probability must be between $(0,1)$ excluding both ends
So: To have a probability within $(0,1)$ a complementing probability (opposite of the event) must exist

* So that the occurring event might change in the future
* So that the representative data might change in the future



## Information

$P(E)$
"Stocks will drop 0.5\% tomorrow" low information (happens everyday) "Stocks will drop 25\% tomorrow" high information (rarely happens)

information is [unit]less quantity.
But in order to compare quantities we use the base of the logarithm as if it is a unit

$$
I(E)=-\log _{2}(P(E)) \quad[\text { bits }] \text { (information value in bits) }
$$

## Example

Expected grades in Communications Course (approximately)
AA : 5\%

$$
I_{\mathrm{AA}}=-\log _{2}\left(P_{A A}\right)=-\log _{2}(0.05) \sim 4.32 \mathrm{bits}
$$

BA: 10\%
BB: 15\%
CB : 20\%
CC : 20\%
$I_{\mathrm{CC}}=-\log _{2}\left(P_{C C}\right)=-\log _{2}(0.2) \sim 2.32$ bits
DC: 15\%
DD:5\% .. so on
FF : 10\%

Meaning : When someone said "I got an AA", he/she actually transferred 4.32 bits worth of information to us.

Question: How much information does he/she transfer by telling all the grades?

Answer: SumOf(All_Info) = Info_Student1 + Info_Student2 + ... = Number_of_students X Average_Info_Per_Grade?

Question: What is the Average_Info_Per_Grade?

## Average Information Per Source Output

```
Information
Generator
```

Since we know the probabilities, we can calculate

$$
I_{a v g}=\sum_{n=1}^{N_{s y m}} p_{n} I_{n} \quad \text { (weighted average) }
$$

$N_{s y m}$ : the number of possible grades (8 in our example)
$I_{a v g}=-\sum_{n=1}^{N_{s y m}} p_{n} \log _{2}\left(p_{n}\right)$
we give it a special name : entropy of the source which depends only on the symbol probabilities
and denote it as $H(z)$ where $z=\left\{p_{n}, n=1, \ldots, N_{s y m}\right\}$

$$
\text { ( in our example } z=\{0.05,0.1,0.15,0.2,0.2,0.15,0.05,0.1\})
$$

## Examples

We have 2 possible events : H , T with equal probabilities (like a coin drop)

$$
\begin{aligned}
& I_{H}=-\log _{2}(0.5)=1 \quad \text { and } \quad I_{T}=-\log _{2}(0.5)=1 \quad \text { bit } \\
& H(z)=I_{\text {avg }}=\sum_{n=1}^{2} p_{n} I_{n}=0.5 \times 1+0.5 \times 1=1 \text { bit per symbol }
\end{aligned}
$$

H can be represented by binary $0 \quad$ T can be represented by binary 1


Question: What if the coin is not a fair one (probs are not equal)?
example : $z=\{0.25,0.75\}$
$I_{H}=-\log _{2}(0.25)=2 \quad I_{T}=-\log _{2}(0.75) \cong 0.415$ bits oops, how do we use 0.415 bits ?

## Examples

We have 8 possible symbols with equal probabilities of 0.125 each
$I_{s}=-\log _{2}(0.125)=3$ bits for each symbol (logical)

These can well be $\{000,001,010,011,100,101,110,111\}$
or $\{0,1,2,3,4,5,6,7\}$ or $\{a, b, c, d, e, f, g, h\}$ or $\ldots$
The point is : the symbols do not need to be represented in binary (although their info can be measured in bits)
However : we prefer binary since we use it all the time (in all digital systems). But that does not prevent us to create symbols like "01011" which might conveniently be represented by 01011 bit sequence.

Question: What if the symbol information values are not integers?
Answer: No problem. That all depends on what we want to do with them or how we represent them.

## Extensions

Extensions are constructed by having symbols together (side by side or in a bag)

$$
\begin{aligned}
\text { example } & A=\{0,1\} \\
\text { then } & B=\{000,001,010,011,100,101,110,111\} \text { (fixed length) }
\end{aligned}
$$

$$
\text { is a } 3^{\text {rd }} \text { extension of binary alphabet } A
$$

Why ? : To have more symbols to have more efficient representations

Probabilities of newly created symbols are

$$
\begin{aligned}
& u=\left\{p_{000}, p_{001}, p_{010}, p_{011}, p_{100}, p_{101}, p_{110}, p_{111}\right\} \\
& p_{a b c}=p_{a} p_{b} p_{c} \\
& \text { example } z=\{0.25,0.75\} \\
& \quad p_{011}=p_{o} p_{1} p_{1}=0.25 \times 0.75 \times 0.75 \cong 0.14
\end{aligned}
$$

## Extensions

Neither extensions nor original alphabet needs to have fixed length codes
example alphabet constructed of fixed length extensions of binary alphabet symbols

$$
B=\{000,001,010,011,100,101,110,111\}
$$

example alphabets constructed from variable length extensions of binary alphabet symbols

$$
\begin{aligned}
& C=\{00,01,011,1011,101,11001,110,111\} \\
& D=\{0,1,10,11,100,101,110,111\}
\end{aligned}
$$

We can have infinite number of alphabets representing the same source symbol-set

Question: So, What are their differences, advantages, disadvantages etc?

## Coding : Representations with Other Symbol Sets

| Symbol | Code-1 | Code-2 | Code-3 | Code-4 | Code -5 | Code -6 |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $S_{1}$ | 000 | 0 | 1 | 1 | 0 | 00 |  |
| $S_{2}$ | 001 | 1 | 01 | 10 | 01 | 01 |  |
| $S_{3}$ | 010 | 10 | 001 | 100 | 011 | 10 | $\cdots$ |
| $S_{4}$ | 011 | 11 | 0001 | 1000 | 0111 | 110 |  |
| $S_{5}$ | $100$ | 100 | 00001 | 10000 | 01111 | 111 |  |

Coding Representing symbols (or a sequence of symbols) from a symbol set with symbols (or a sequence of symbols) from another set
example
abc... $\longrightarrow$ 123...
it is also good to have
123... $\longrightarrow$ abc...

## Average Code Length

| $p_{i}$ | Symbol | Code-1 | Code-2 | Code-3 | Code-4 | Code -5 | Code -6 |  |
| :--- | :---: | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| 0.36 | $S_{1}$ | 000 | 0 | 1 | 1 | 0 | 00 |  |
| 0.18 | $S_{2}$ | 001 | 1 | 01 | 10 | 01 | 01 |  |
| 0.17 | $S_{3}$ | 010 | 10 | 001 | 100 | 011 | 10 | $\ldots$ |
| 0.16 | $S_{4}$ | 011 | 11 | 0001 | 1000 | 0111 | 110 |  |
| 0.13 | $S_{5}$ | 100 | 100 | 00001 | 10000 | 01111 | 111 |  |

$L_{\text {avg }}=\sum_{n=1}^{N_{s y m}} p_{n} l_{n}=3$ bits for Code-1
$L_{\text {avg }}=\sum_{n=1}^{N_{s y m}} p_{n} l_{n}=2.29$ bits for Code-6
so, using Code-6 is better

Why not use Code-2 then? It looks like it will result a shorter average code length
Because Code-2 is not uniquely decodable when transferred consecutively $123 \ldots \nrightarrow$ abc...

## Unique Decodability

Let us have an information source generating symbols from the alphabet

$$
A=\left\{s_{1}, s_{2}, s_{3}, s_{4}, s_{5}\right\}
$$

with the probabilities of $u=\{0.36,0.16,0.17,0.16 .0 .13\}$

Assume that the source has generated the sequence of $S_{1} S_{2} S_{3} S_{1} S_{1} S_{5} S_{4}$

Coding the symbols with Code-2, we would have : $0,1,10,0,0,100,11$ or a binary sequence of : 01100010011

We would like to decode the sequence 01100010011 back to $S_{1} S_{2} S_{3} S_{1} S_{1} S_{5} S_{4}$
remembering that we do not have symbol separators, we see that it is impossible to decode it back to original

So, the Code-2 is not uniquely decodable (that means it is nearly useless)

## Unique Decodability

How about using Code-6 on the same source

Sequence is $\quad S_{1} S_{2} S_{3} S_{1} S_{1} S_{5} S_{4}$
Code-6 coder output: 00, 01, 10, 00, 00, 111, 110
binary sequence without separators: 0001100000111110

On the receiver side we would like to decode the sequence 0001100000111110 back

## 0001100000111110

0: not in table, take another bit from the stream. Remaining : 01100000111110 00: in table, so output $S_{1}$
0 : not in table, take another bit from the stream. Remaining : 100000111110
01: in table, so output $S_{2}$
1: not in table, take another bit from the stream. Remaining : 0000111110
10: in table, so output $S_{3}$
...so on and so forth, up to the end of the stream

Therefore, Code-6 is uniquely decodable although the symbols are variable length

## Corollary

We need to have uniquely decodable codes with lower (than original) average code-lengths
Let us examine the previous code table again

| $p_{i}$ | Symbol | Code-1 | Code-2 | Code-3 | Code-4 | Code-5 | Code-6 |  |
| :---: | :---: | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| 0.36 | $S_{1}$ | 000 | 0 | 1 | 1 | 0 | 00 |  |
| 0.18 | $S_{2}$ | 001 | 1 | 01 | 10 | 01 | 01 |  |
| 0.17 | $S_{3}$ | 010 | 10 | 001 | 100 | 011 | 10 | $\ldots$ |
| 0.16 | $S_{4}$ | 011 | 11 | 0001 | 1000 | 0111 | 110 |  |
| 0.13 | $S_{5}$ | 100 | 100 | 00001 | 10000 | 01111 | 111 |  |

Code-1 : uniquely decodable, Lavg = 3, fixed-length
Code-2 : not uniquely decodable, Lavg = ?, variable-length, not instantaneous*
Code-3 : uniquely decodable, Lavg $=x$, variable-length
Code-4 : uniquely decodable, Lavg $=\mathrm{x}$, variable-length, not instantaneous*
Code-5 : uniquely decodable, Lavg $=\mathrm{x}$, variable-length, not instantaneous*
Code-6 : uniquely decodable, Lavg $=2.29$, variable-length

The code is considered instantaneous if the symbols can be determined when their last bits are received

## Minimum Average Code Length

We see that we can have infinite number of Codes that are uniquely decodable.
We also need to have efficient representation (smaller average code length)
Question : Is there a way to find a code with minimum average code length?
Answer: Yes for block codes
block code : symbol-to-binarycode representation (implying that there are other (non-block) codes as well)


## Example

| Symbols | Prob.s | New symbols /code |  |
| :---: | :---: | :---: | :---: |
| 00 | 0.49 | $?$ | We would like to determine a code for each |
| 01 | 0.21 | $?$ | symbol, which, for the given probabilities, best |
| 10 | 0.21 | $?$ | represents the self-information of the symbol. |
| 11 | 0.09 | $?$ |  |

A method : divide the pre-ordered set of probabilities into two so that sum of probabilities on both sides are as close as possible. Continue doing that until there is only one in each division


## Generated code table

000
$01 \quad 10$
$10 \quad 110$
11111

Code is variable length and uniquely decodable. The method is called

Shannon-Fano

## Example

| $p_{i}$ | code table |  |
| :---: | :--- | :---: |
| 0.49000 |  |  |


| 0.21 | 01 | 10 |  |
| :---: | :---: | :---: | :---: |
| 0.21 | 10 | 110 | $L_{\text {avg }}=\sum_{i=1}^{4} P\left(s_{i}\right) L\left(s_{i}\right) \quad 0.49 \times 1+0.21 \times 2+0.21 \times 3+0.09 \times 3=1.81$ |
| 0.09 | 11 | 111 | a single input bit is now represented by |
|  |  |  |  |
|  |  |  |  |
|  |  |  |  |

Notice that this distribution is actually $2^{\text {nd }}$ extension of the ensemble $(A, z)$ where $z=\{0.7,0.3\}$

Shannon states that "wider the extension, better the representation"

Let us now test this argument with the $2^{\text {nd }}$ extension of the $2^{\text {nd }}$ extension (or the $4^{\text {th }}$ extension of the original binary alphabet)

## Example

| Probs | code table |  |
| :--- | :--- | :--- |
| 0.2401 | 0000 | 00 |
| 0.1029 | 0001 | 010 |
| 0.1029 | 0010 | 0110 |
| 0.1029 | 0011 | 0111 |
| 0.1029 | 0100 | $1 \ldots$ |
| 0.0441 | . | $1 \ldots$ |
| 0.0441 | . | $1 \ldots$ |
| 0.0441 | . | $1 \ldots$ |
| 0.0441 | . | $1 \ldots$ |
| 0.0441 | . | $1 \ldots$ |
| 0.0441 | . | $1 \ldots$ |
| 0.0189 | . | $1 \ldots$ |
| 0.0189 | . | $1 \ldots$ |
| 0.0189 | . | $1 \ldots$ |
| 0.0189 | . | $1 \ldots$ |
| 0.0081 | 1111 | $1 \ldots$ |

$L_{\text {avg }}=3.5948$ bits/symbol
a single input bit is now represented by $3.5948 / 4=0.8987$ bits
we see that it is getting better

The entropy is $H(u)=3.5252$
so, we still have room for improvement

It is guaranteed that extensions of $n>4$ will have better representations

But cannot be lower than $H$
hmw: complete the table

## Huffman

It is proven that Huffman's code generates smallest ACL among dictionary-based statistical block codes

## Example

```
    Probs
S S 0.49
s
S 0.21 --_Let these symbols with smallest
S 0.09 probabilities be a single symbol }\mp@subsup{S}{5}{
                                    Its probability would be 0.30
```

But they are actually two symbols and when its code is seen at the decoder we need to have a bit to differentiate them
additional bit
$\begin{array}{lllll}s_{3} & 0.21 & 0 & \cdots & \\ s_{4} & 0.09 & 1 & & \end{array}$

Now we have three symbols. Continue combining symbols with smallest probs and prepending differentiating bit marks.


Now, from right to left, follow the paths for each symbol and find assigned bits to them by appending each bit to the right (LSB)


One can create the tree first and assign bits later

We see that the ACL is same as the code found using Shannon-Fano. It is guaranteed that Huffman method generates shorter or same length codes

$$
L_{\text {avg }}=\sum_{i=1}^{4} P\left(s_{i}\right) L\left(s_{i}\right) \quad 0.49 \times 1+0.21 \times 2+0.21 \times 3+0.09 \times 3=1.81
$$

Here is an Example where two methods generate different code lengths

\[

\]

## Flow of Dictionary Coding

(Compression/Decompression)


## Summary

## What we have seen/learned

1. Information is the entity we need to preserve/communicate
2. We measure the information using probabilities of events/symbols
3. Average information of a source is the weighted (by their probabilities) self-information of events/symbols
4. Average Info Per source output is called Entropy of the source
5. Unique decodability is a requirement but instantaneous decodability is not.
6. Block codes are the simplest but not the only coding method.
7. Efficiency of block coding can be improved by extensions.
8. $\mathrm{ACL} \geq$ Entropy

## Related

$\sum \Delta$-Coding

## END

