

# Information Theory

<http://www.inf.ed.ac.uk/teaching/courses/it/>

## Week 1

Introduction to Information Theory

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School of Informatics, University of Edinburgh

# Course structure

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## Constituents:

- ~17 lectures
- Tutorials starting in week 3
- 1 assignment (20% marks)

## Website:

<http://tinyurl.com/itmasc>

<http://www.inf.ed.ac.uk/teaching/courses/it/>

Notes, assignments, tutorial material, news (optional RSS feed)

**Prerequisites:** some maths, some programming ability

**Maths background:** This is a theoretical course so some general mathematical ability is essential. Be very familiar with logarithms, mathematical notation (such as sums) and some calculus.

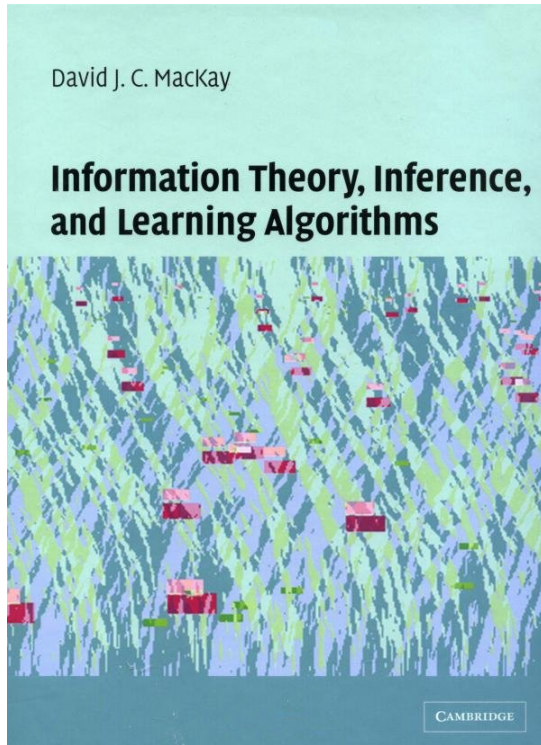
**Probabilities are used extensively:** Random variables; expectation; Bernoulli, Binomial and Gaussian distributions; joint and conditional probabilities. There will be some review, but expect to work hard if you don't have the background.

**Programming background:** by the end of the course you are expected to be able to implement algorithms involving probability distributions over many variables. However, I am not going to teach you a programming language. I can discuss programming issues in the tutorials. I won't mark code, only its output, so you are free to pick a language. Pick one that's quick and easy to use.

The scope of this course is to understand the applicability and properties of methods. Programming will be exploratory: slow, high-level but clear code is fine. We will not be writing the final optimized code to sit on a hard-disk controller!

# Resources / Acknowledgements

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## Recommended course text book

Inexpensive for a hardback textbook

(Stocked in Blackwells, Amazon currently cheaper)

Also free online:

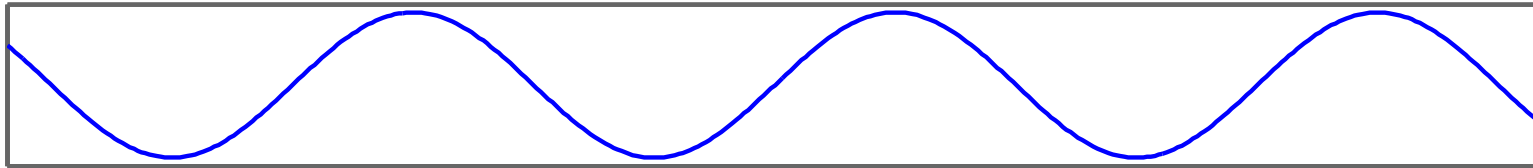
<http://www.inference.phy.cam.ac.uk/mackay/itila/>

Those preferring a theorem-lemma style book could check out:  
*Elements of information theory*, Cover and Thomas

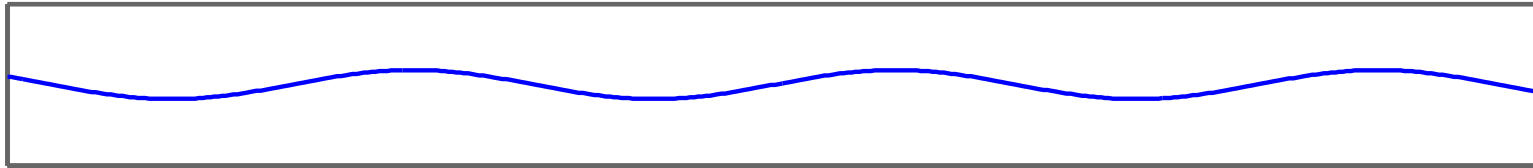
I made use of course notes by MacKay and from CSC310 at the University of Toronto (Radford Neal, 2004; Sam Roweis, 2006)

# Communicating with noise

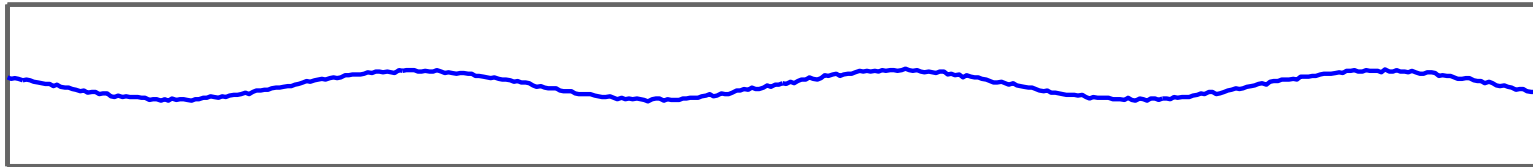
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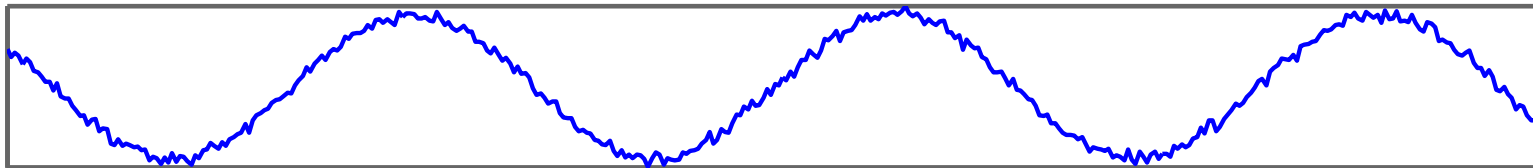
Signal



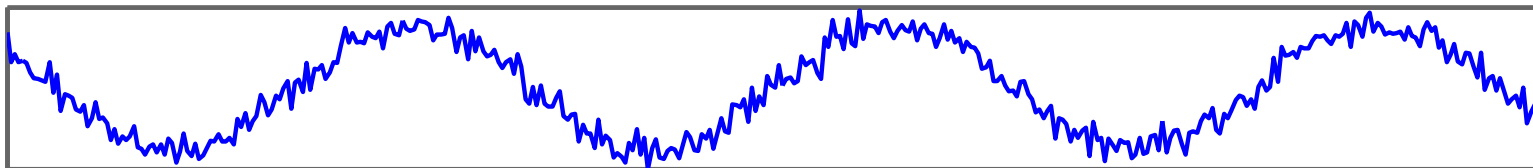
Attenuate



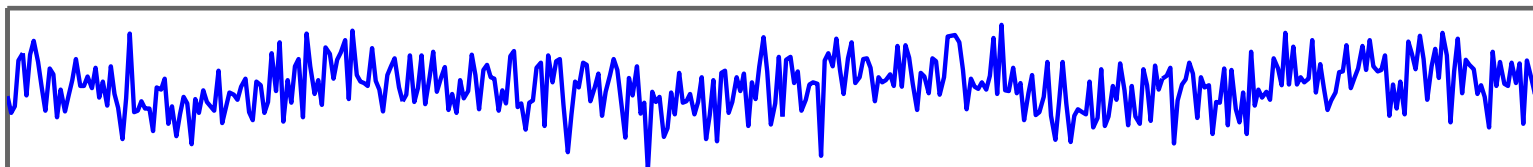
Add noise



Boost



5 cycles



100 cycles

Consider sending an audio signal by *amplitude modulation*: the desired speaker-cone position is the height of the signal. The figure shows an encoding of a pure tone.

A classical problem with this type of communication channel is attenuation: the amplitude of the signal decays over time. (The details of this in a real system could be messy.) Assuming we could regularly boost the signal, we would also amplify any noise that has been added to the signal. After several cycles of attenuation, noise addition and amplification, corruption can be severe.

A variety of analogue encodings are possible, but whatever is used, no ‘boosting’ process can ever return a corrupted signal exactly to its original form. In digital communication the sent message comes from a discrete set. If the message is corrupted we can ‘round’ to the nearest discrete message. It is possible, but not guaranteed, we’ll restore the message to exactly the one sent.

# Digital communication

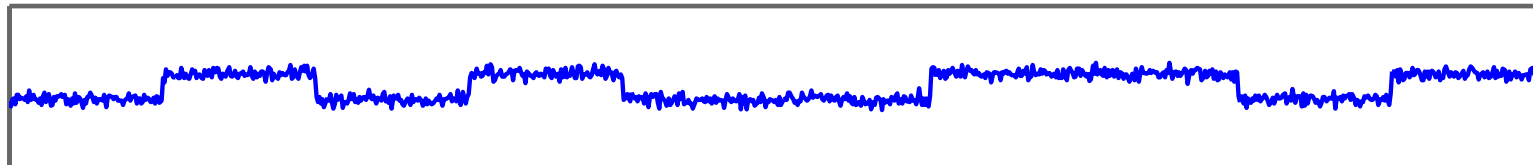
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**Encoding:** amplitude modulation not only choice.  
Can re-represent messages to improve signal-to-noise ratio

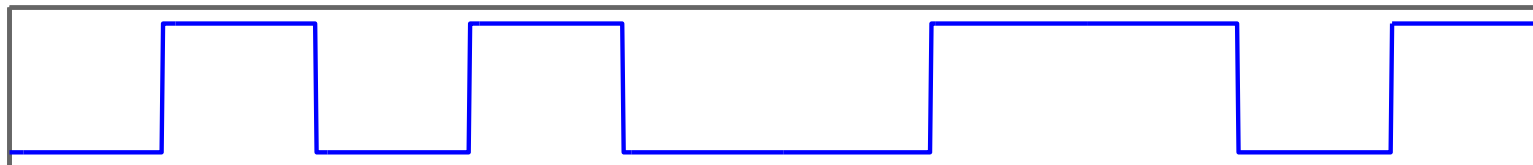
**Digital encodings:** signal takes on discrete values



Signal



Corrupted



Recovered

# Communication channels

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modem → phone line → modem

Galileo → radio waves → Earth

finger tips → nerves → brain

parent cell → daughter cells

computer memory → disk drive → computer memory



# The challenge

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Real channels are error prone

**Physical solutions:**

£ £ £

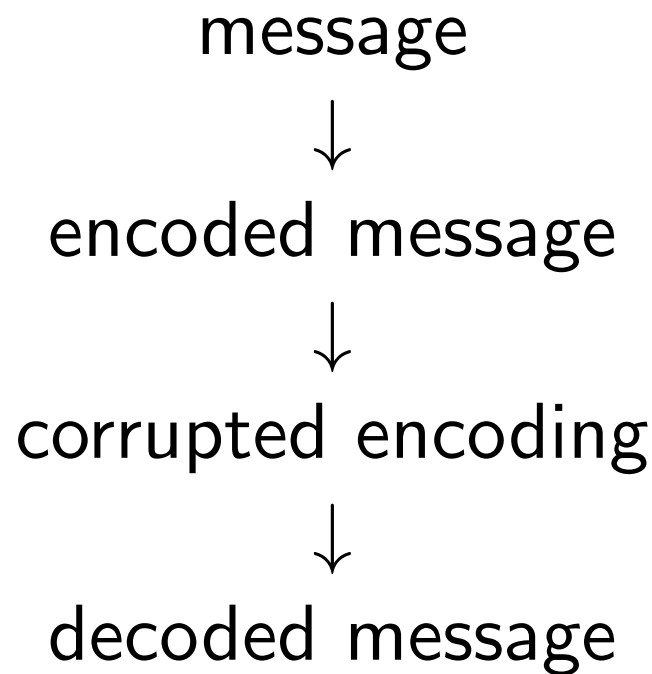
Change the system to reduce probability of error.

Cool system, increase power, . . .

# System solution

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Send more robust encodings over *existing* channel



But how is reliable communication possible at all?

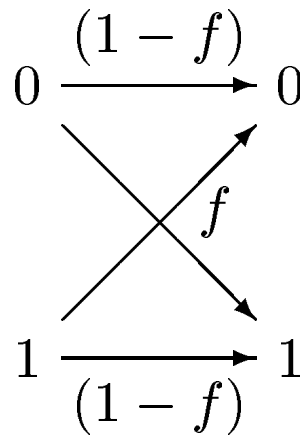


# Binary symmetric channel

Binary messages: 0010100111001...

Each 0 or 1 is flipped with probability  $f = 0.1$

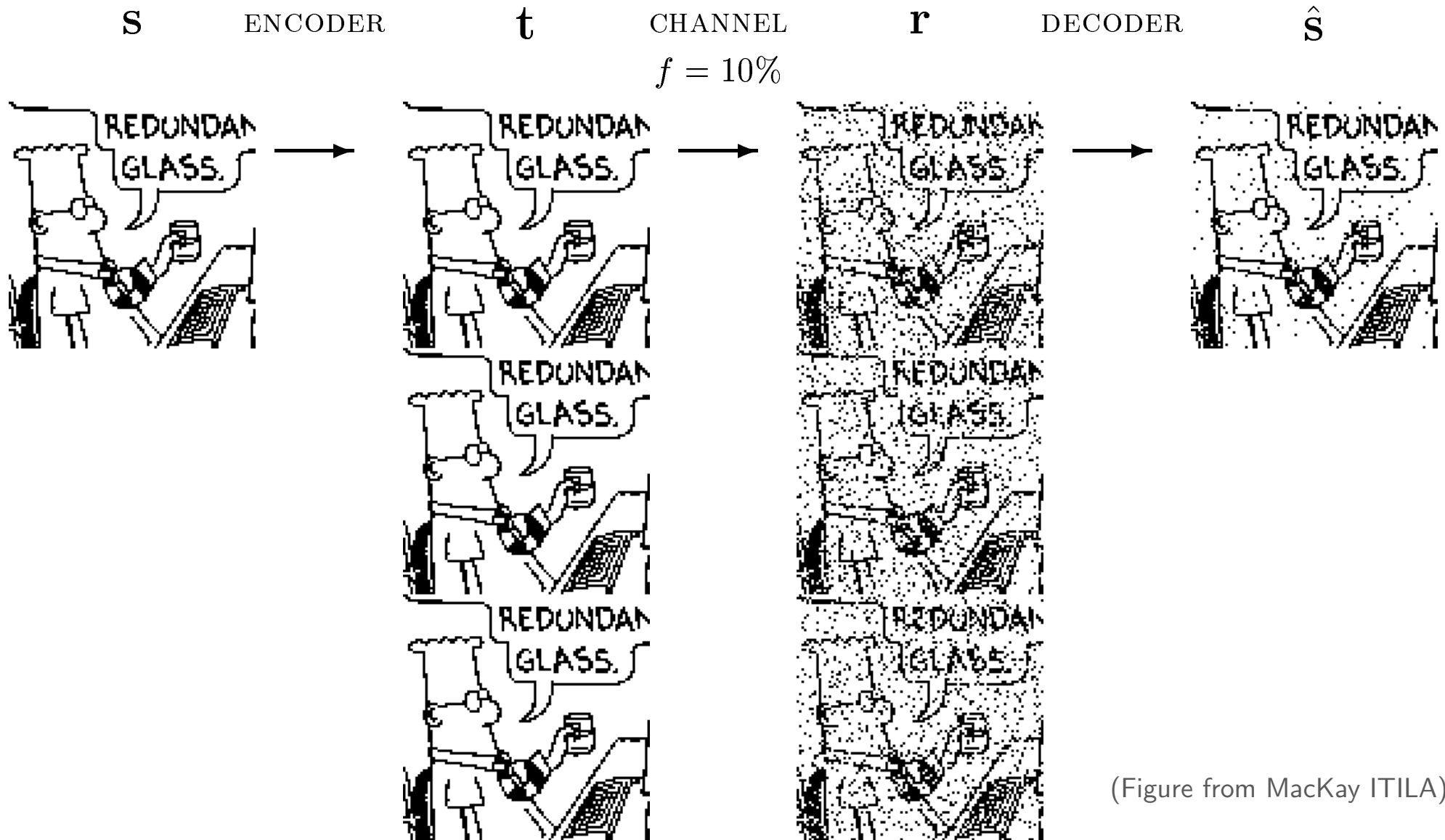
$$\begin{array}{ccc} \begin{array}{c} x \\ 0 \rightarrow 0 \\ 1 \rightarrow 1 \end{array} & \begin{array}{c} y \\ 0 \\ 1 \end{array} & \begin{array}{l} P(y=0 | x=0) = 1-f; \\ P(y=1 | x=0) = f; \end{array} \end{array} \quad \begin{array}{l} P(y=0 | x=1) = f; \\ P(y=1 | x=1) = 1-f. \end{array}$$



(Figure from MacKay ITILA)

Can repetition codes give reliable communication?

# Repetition code performance



(Figure from MacKay ITILA)

Probability of error per bit  $\approx 0.03$ . What's good enough?

Consider a single 0 transmitted using  $R_3$  as 000

Eight possible messages could be received:

000 100 010 001 110 101 011 111

Majority vote decodes the first four correctly but the next four result in errors. Fortunately the first four are more probable than the rest!

Probability of 111 is small:  $f^3 = 0.1^3 = 10^{-3}$

Probability of two bit errors is  $3f^2(1-f) = 0.03 \times 0.9$

Total probability of error is a bit less than 3%

How to reduce probability of error further? Repeat more! ( $N$  times)

Probability of bit error = Probability  $>$  half of bits are flipped:

$$p_b = \sum_{r=\frac{N+1}{2}}^N \binom{N}{r} f^r (1-f)^{N-r}$$

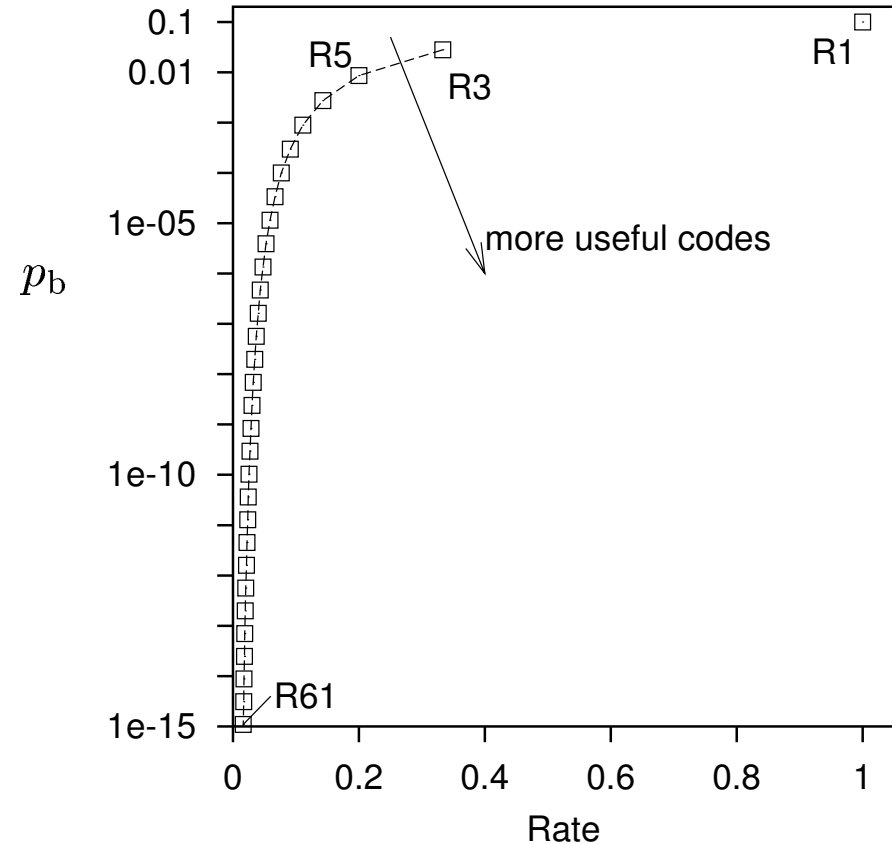
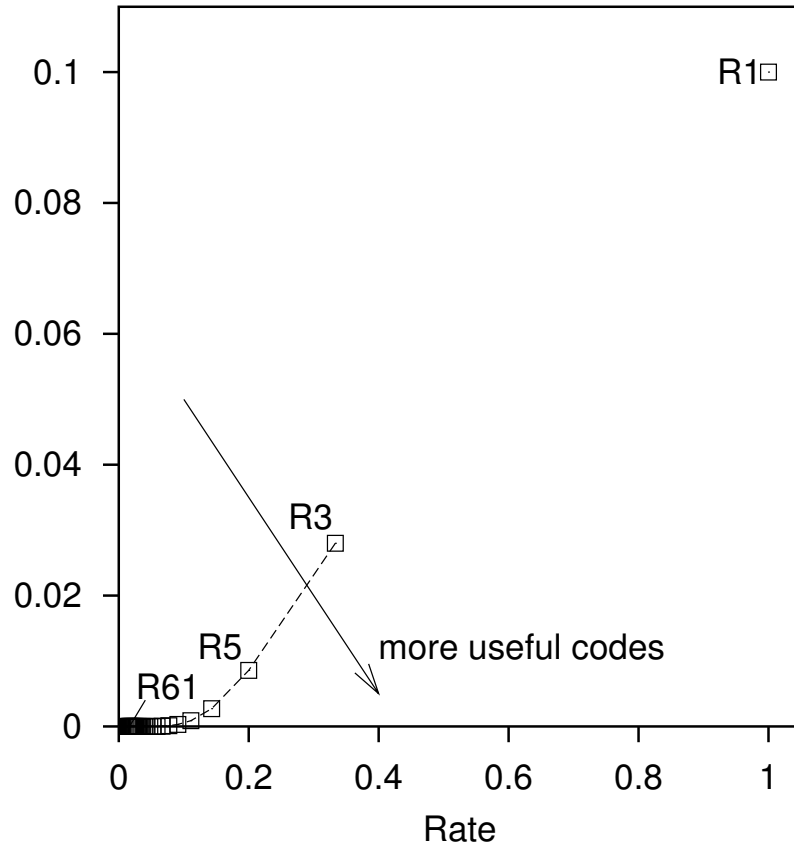
But transmit symbols  $N$  times slower! *Rate* is  $1/N$ .

# Repetition code performance

Binary messages: 0010100111001...

Each 0 or 1 is flipped with probability  $f = 0.1$

(Figure from MacKay ITILA)



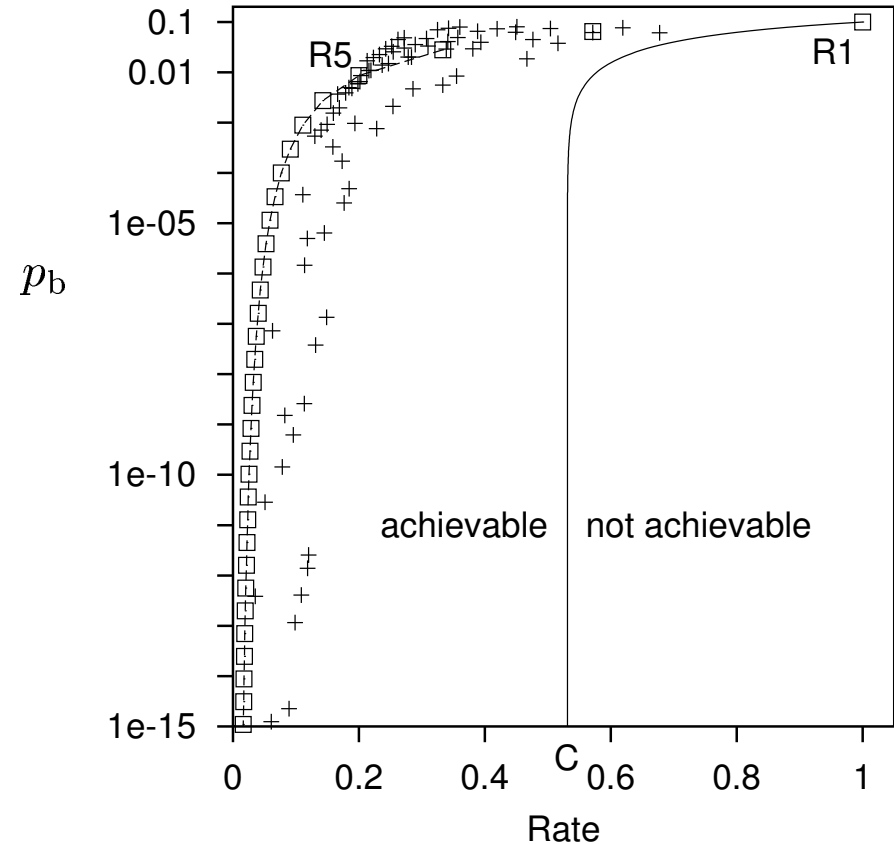
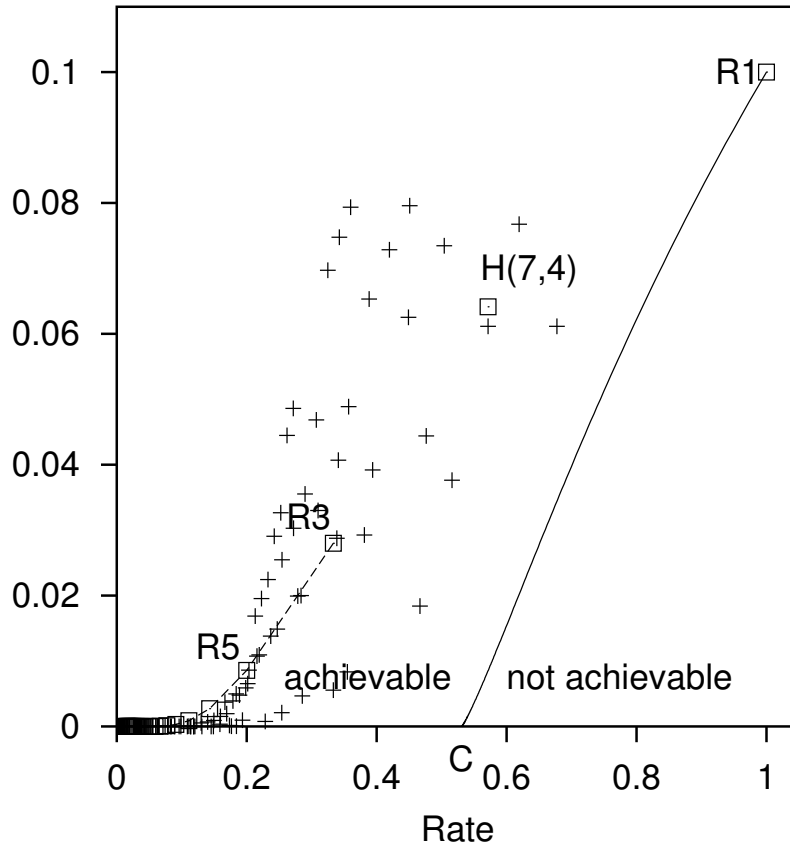
$p_b$  = probability of error at each bit of message

# What is achievable?

Binary messages: 0010100111001...

Each 0 or 1 is flipped with probability  $f = 0.1$

(Figure from MacKay ITILA)



$p_b$  = probability of error at each bit of message



# Course content

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## **Theoretical content**

- Shannon's noisy channel and source coding theorems
- Much of the theory is non-constructive
- However bounds are useful and approachable

## **Practical coding algorithms**

- Reliable communication
- Compression

## **Tools and related material**

- Probabilistic modelling and machine learning

# Storage capacity

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3 decimal digits allow  $10^3 = 1,000$  numbers: 000–999

3 **binary digits or bits** allow  $2^3 = 8$  numbers:

000, 001, 010, 011, 100, 101, 110, 111

8 bits, a 'byte', can store one of  $2^8 = 256$  characters

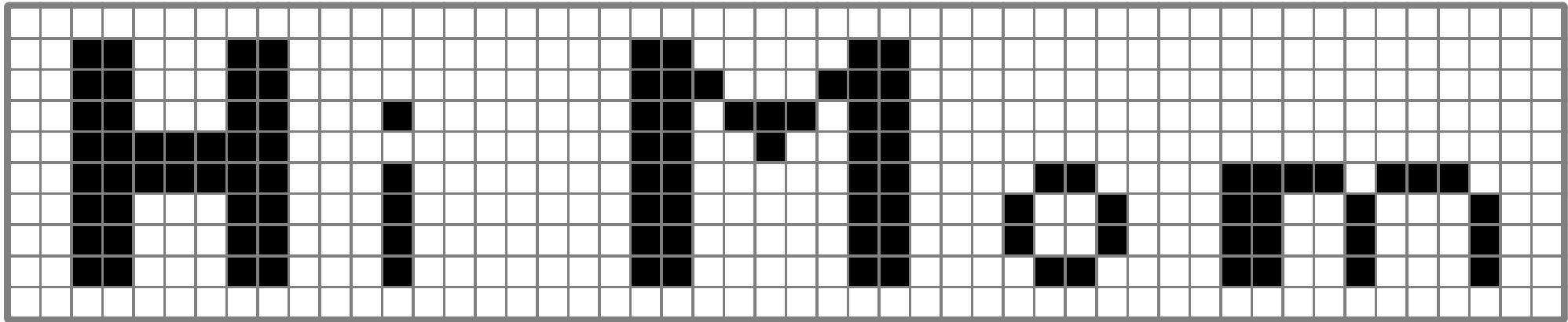
Indexing  $I$  items requires at least  
 $\log_{10} I$  decimal digits or  $\log_2 I$  bits

Reminder:  $b = \log_2 I \Rightarrow 2^b = I \Rightarrow b \log 2 = \log I \Rightarrow b = \frac{\log I}{\log 2}$

# Representing data / coding

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**Example:** a  $10 \times 50$  binary image



Assume image dimensions are known

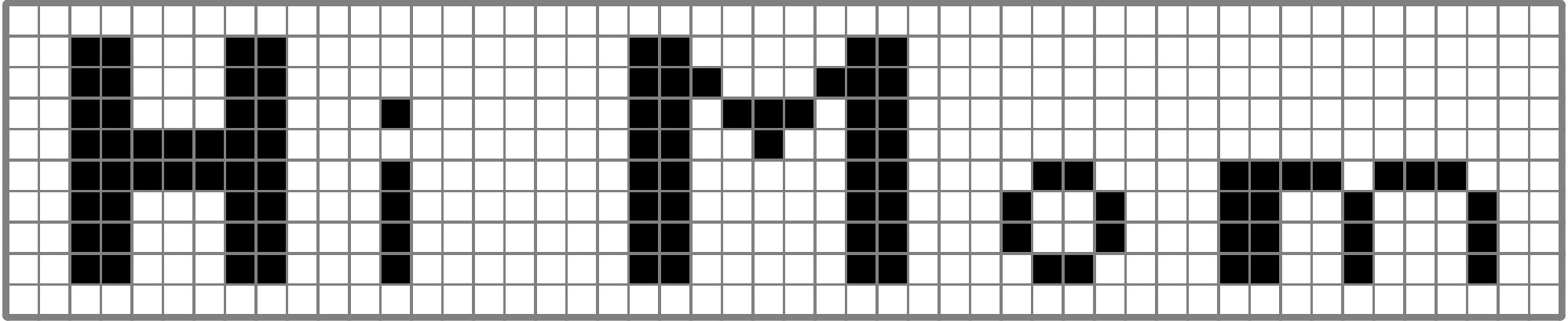
Pixels could be represented with 1s and 0s

This encoding takes **500 bits** (binary digits)

$2^{500}$  images can be encoded. The universe is  $\approx 2^{98}$  picoseconds old.

# Exploit sparseness

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As there are fewer black pixels we send just them.

Encode row + start/end column for each run in binary.

Requires  $(4+6+6) = 16$  bits per run (can you see why?)

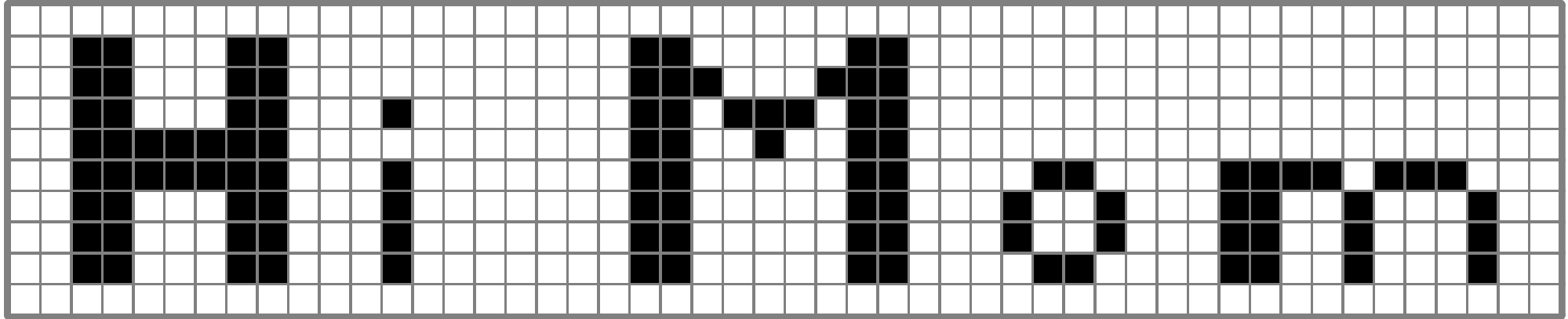
There are 54 black runs  $\Rightarrow 54 \times 16 =$  **864 bits**

That's worse than the 500 bit encoding we started with!

Scan columns instead: 33 runs,  $(6+4+4) = 14$  bits each. **462 bits.**

# Run-length encoding

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Common idea: store lengths of runs of pixels

Longest possible run = 500 pixels, need 9 bits for run length

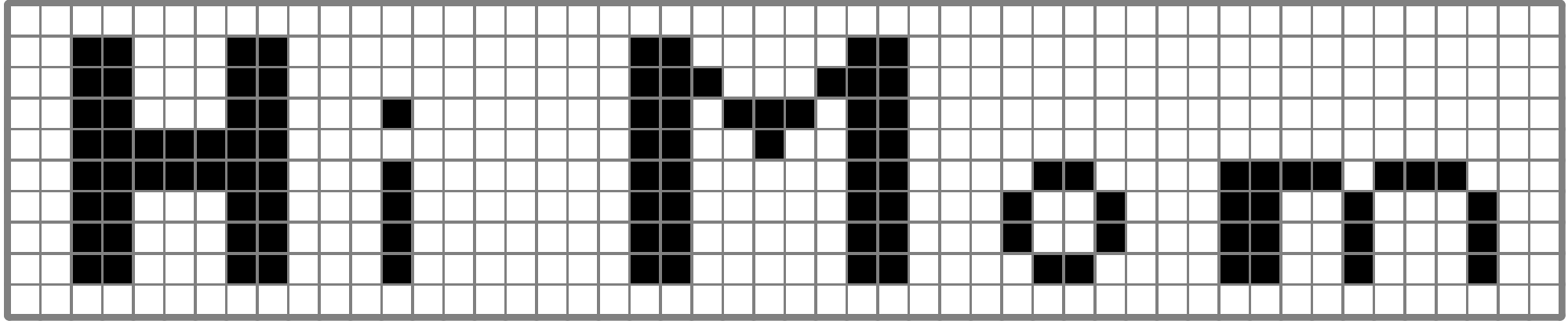
Use 1 bit to store colour of first run (should we?)

Scanning along rows: 109 runs  $\Rightarrow$  **982 bits(!)**

Scanning along cols: 67 runs  $\Rightarrow$  **604 bits**

# Adapting run-length encoding

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Store number of bits actually needed for runs in a header.  
 $4+4=8$  bits give sizes needed for black and white runs.

Scanning along rows: **501 bits** (includes  $8+1=9$  header bits)

55 white runs up to 52 long,  $55 \times 6 = 330$  bits

54 black runs up to 7 long,  $54 \times 3 = 162$  bits

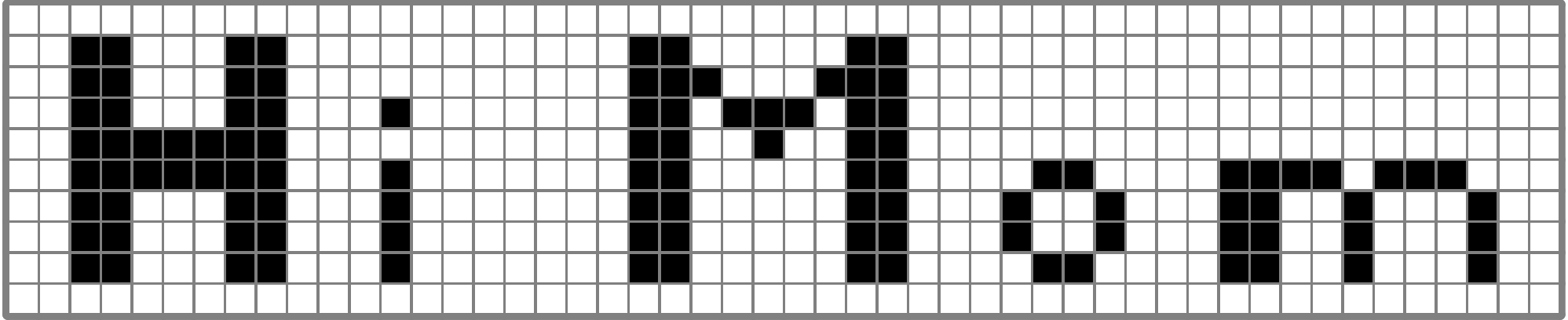
Scanning along cols: **249 bits**

34 white runs up to 72 long,  $24 \times 7 = 168$  bits

33 black runs up to 8 long,  $24 \times 3 = 72$  bits (3 bits/run if no zero-length runs; we did need the first-run-colour header bit!)

# Rectangles

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Exploit spatial structure: represent image as 20 rectangles

## Version 1:

Each rectangle:  $(x_1, y_1, x_2, y_2)$ ,  $4+6+4+6 = 20$  bits

Total size:  $20 \times 20 = \mathbf{400}$  bits

## Version 2:

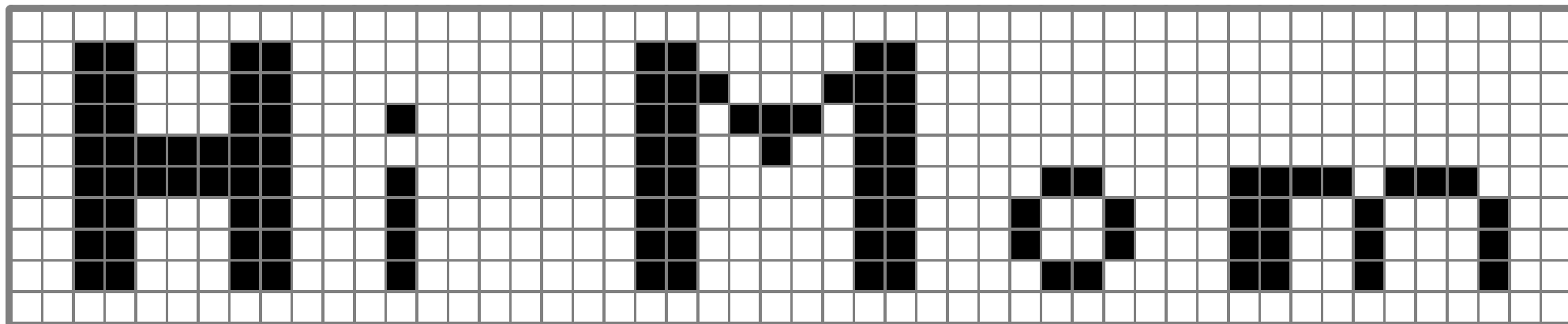
Header for max rectangle size:  $2+3 = 5$  bits

Each rectangle:  $(x_1, y_1, w, h)$ ,  $4+6+3+3 = 16$  bits

Total size:  $20 \times 16 + 5 = \mathbf{325}$  bits

# Off-the-shelf solutions?

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## Established image compressors:

Use PNG: 128 bytes = **1024 bits**

Use GIF: 98 bytes = **784 bits**

JBIG2: 108 bytes = 864 bits

DjVu: 124 bytes = 992 bits

**Unfair:** image is tiny, file format overhead: headers, image dims

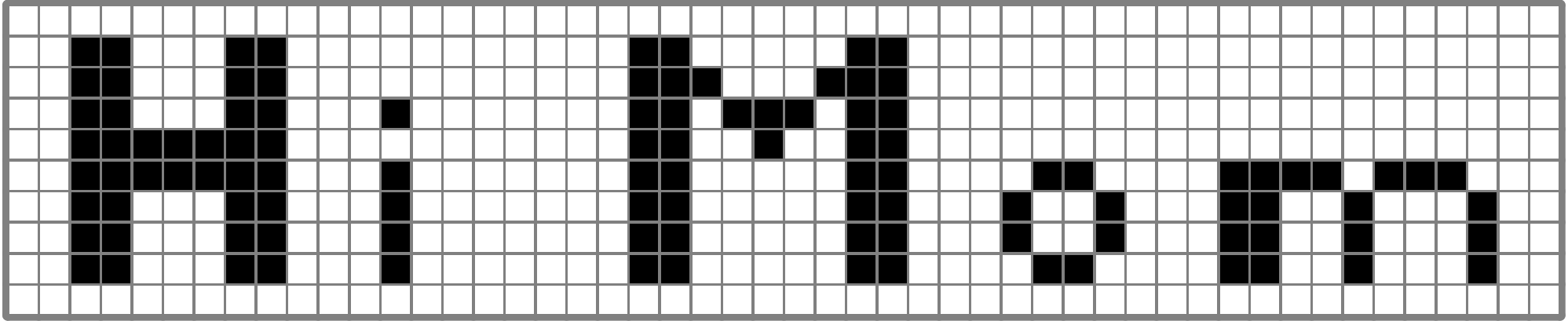
Smallest possible GIF file is about 35 bytes. Smallest possible PNG file is about 67 bytes.

Not strictly meaningful, but:  $(98-35) \times 8 = 504$  bits.  $(128-67) \times 8 = 488$  bits



# Store as text

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Assume we know the font

Encode six characters in a 64 character alphabet (say)

Total size:  $6 \times \log_2 64 = \mathbf{36 \text{ bits}}$

# “Overfitting”

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We can compress the ‘Hi Mom’ image down to **1 bit**:

Represent ‘Hi Mom’ image with a single ‘1’

All other files encoded with ‘0’ and a naive encoding of the image.

*. . . the actual message is one selected from a set of possible messages. The system must be designed to operate for each possible selection, not just the one which will actually be chosen since this is unknown at the time of design.*

— Shannon, 1948

## Summary of lecture 1 (slide 1/2)

**Digital communication** can work reliably over a noisy channel. We add *redundancy* to a message, so that we can try to infer what corruption occurred and undo it.

**Repetition codes** simply repeat each message symbol  $N$  times.

A majority vote at the receiving end removes errors unless more than half of the repetitions were corrupted. Increasing  $N$  reduces the error rate, but the *rate* of the code is  $1/N$ : transmission is slower, or more storage space is used. For the Binary Symmetric Channel the error probability is:  $\sum_{r=(N+1)/2}^N \binom{N}{r} f^r (1-f)^{N-r}$

**Amazing claim:** it is possible to get arbitrarily small errors at a fixed rate known as the *capacity* of the channel. *Aside:* codes that approach the capacity send a more complicated message than simple repetitions. Inferring what corruptions must have occurred (occurred with overwhelmingly high probability) is more complex than a majority vote. The algorithms are related to how some groups perform inference in machine learning.

## Summary of lecture 1 (slide 2/2)

First task: represent data optimally when there is no noise

### Representing files as (binary) numbers:

$C$  bits (binary digits) can index  $I = 2^C$  objects.

$\log I = C \log 2$ ,  $C = \frac{\log I}{\log 2}$  for logs of any base,  $C = \log_2 I$

In information theory textbooks “log” often means “ $\log_2$ ”.

### Experiences with the Hi Mom image:

Unless we’re careful, we can expand the file dramatically.

When developing a fancy method, always consider simple baselines.

The bit encodings and header bits I used were inelegant.

We’d like more principled and better ways to proceed. (See later).

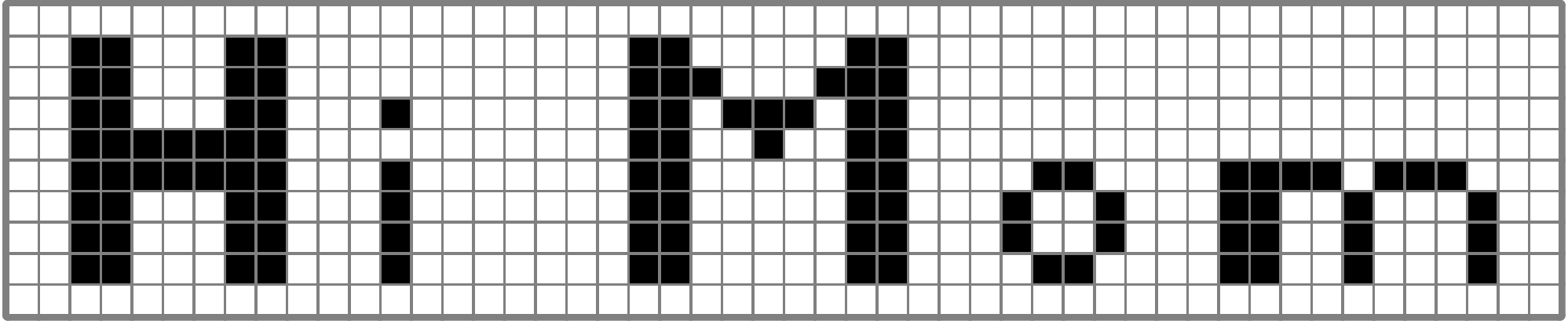
Summarizing groups of bits (rectangles, runs, etc.) can lead to fewer objects to index. Structure in the image allows compression.

Cheating: add whole image as a “word” in our dictionary.

Schemes should work on future data that the receiver hasn’t seen.

# Where now

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What are the fundamental limits to compression?

Can we avoid all the hackery?

Or at least make it clearer how to proceed?

**This course:** Shannon's information theory relates compression to *probabilistic modelling*

A simple probabilistic model (predict from three previous neighbouring pixels) and an *arithmetic coder* can compress to about **220 bits**.

# Why is compression possible?

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Try to compress *all*  $b$  bit files to  $< b$  bits

There are  $2^b$  possible files but only  $(2^b - 1)$  codewords

**Theorem:** if we compress some files we must expand others  
(or fail to represent some files unambiguously)

Search for the `comp.compression` FAQ currently available at:

<http://www.faqs.org/faqs/compression-faq/>

# Which files to compress?

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We choose to compress the **more probable** files

Example: compress  $28 \times 28$  binary images like this:



At the expense of longer encodings for files like this:



There are  $2^{784}$  binary images. I think  $< 2^{125}$  are like the digits

# Sparse file model

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Long binary vector  $\mathbf{x}$ , mainly zeros

Assume bits drawn independently

**Bernoulli distribution**, a single “bent coin” flip

$$P(x_i | p) = \begin{cases} p & \text{if } x_i = 1 \\ (1 - p) \equiv p_0 & \text{if } x_i = 0 \end{cases}$$

How would we compress a large file for  $p = 0.1$ ?

**Idea:** encode blocks of  $N$  bits at a time



## Intuitions:

‘Blocks’ of lengths  $N=1$  give naive encoding: 1 bit / symbol

Blocks of lengths  $N=2$  aren’t going to help

... *maybe* we want long blocks

For large  $N$ , some blocks won’t appear in the file, e.g. 111111111111...

The receiver won’t know exactly which blocks will be used

Don’t want a header listing blocks: expensive for large  $N$ .

Instead we use our probabilistic model of the source to guide which blocks will be useful. For  $N=5$  the 6 most probable blocks are:

00000 00001 00010 00100 01000 10000

3 bits can encode these as 0–5 in binary: 000 001 010 011 100 101

Use spare codewords (110 111) followed by 4 more bits to encode remaining blocks. Expected length of this code =  $3 + 4 P(\text{need 4 more})$   
 $= 3 + 4(1 - (1-p)^5 - 5p(1-p)^4) \approx 3.3$  bits  $\Rightarrow 3.3/5 \approx 0.67$  bits/symbol

# Quick quiz

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**Q1.** Toss a fair coin 20 times. (Block of  $N=20$ ,  $p=0.5$ )  
What's the probability of all heads?

**Q2.** What's the probability of 'TTHTTHHTTTHTTHTHHTTT'?

**Q3.** What's the probability of 7 heads and 13 tails?

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- |                           |          |                       |
|---------------------------|----------|-----------------------|
| you'll be waiting forever | <b>A</b> | $\approx 10^{-100}$   |
| about one in a million    | <b>B</b> | $\approx 10^{-6}$     |
| about one in ten          | <b>C</b> | $\approx 10^{-1}$     |
| about a half              | <b>D</b> | $\approx 0.5$         |
| very probable             | <b>E</b> | $\approx 1 - 10^{-6}$ |
| don't know                | <b>Z</b> | ???                   |

# Binomial distribution

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How many 1's will be in our block?

**Binomial distribution**, the sum of  $N$  Bernoulli outcomes

$$k = \sum_{n=1}^N x_n, \quad x_n \sim \text{Bernoulli}(p)$$

$$\Rightarrow k \sim \text{Binomial}(N, p)$$

$$\begin{aligned} P(k | N, p) &= \binom{N}{k} p^k (1-p)^{N-k} \\ &= \frac{N!}{(N-k)! k!} p^k (1-p)^{N-k} \end{aligned}$$

# Distribution over blocks

total number of bits:  $N$  ( $= 1000$  in examples here)

probability of a 1:  $p = P(x_i = 1)$

number of 1's:  $k = \sum_i x_i$

**Every block is improbable!**

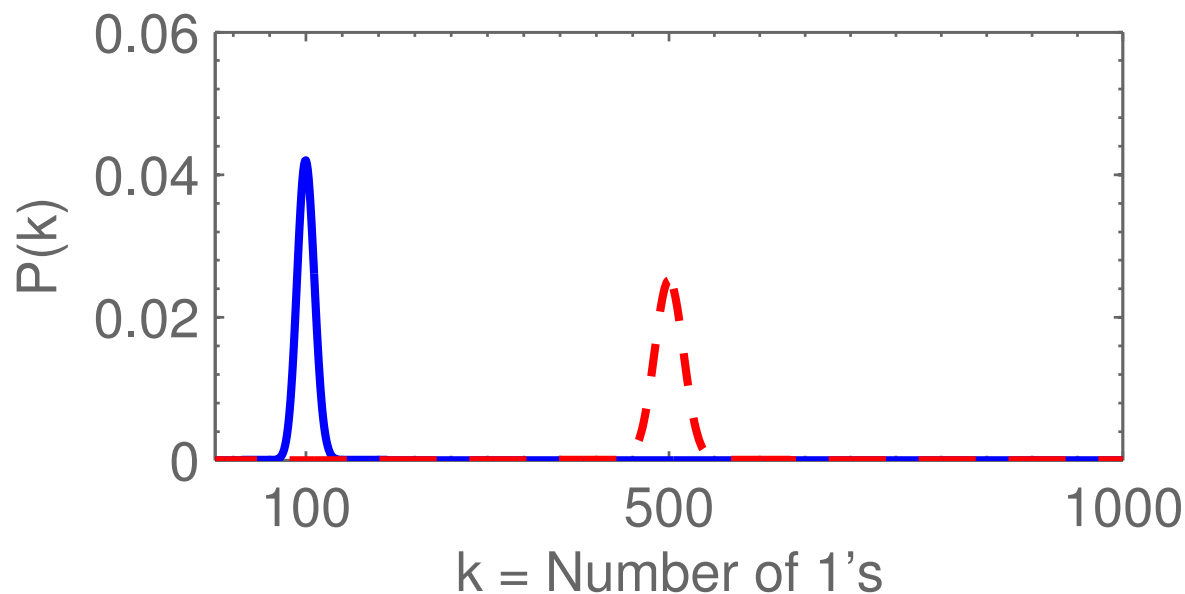
$$P(\mathbf{x}) = p^k (1 - p)^{N-k}, \quad (\text{at most } (1-p)^N \approx 10^{-45} \text{ for } p=0.1)$$

How many 1's will we see?

$$P(k) = \binom{N}{k} p^k (1 - p)^{N-k}$$

**Solid:**  $p=0.1$

**Dashed:**  $p=0.5$



**Intuitions:** If we sample uniformly at random, the number of 1s is distributed according to the **dashed** curve. That bump is where almost all of the bit-strings of length  $N = 1000$  are.

When  $p = 0.1$ , the blocks with the most zeros are the most probable. However, there is only one block with zero ones, and not many with only a few ones. As a result, there isn't much probability mass on states with only a few ones. In fact, most of the probability mass is on blocks with around  $Np$  ones, so they are the ones we are likely to see. The most probable block is not a typical block, and we'd be surprised to see it!

# Evaluating the numbers

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$$\binom{N}{k} = \frac{N!}{(N-k)! k!}, \quad \text{what happens for } N = 1000, k = 500? \\ \text{(or } N = 10,000, k = 5,000)$$

Knee-jerk reaction: try taking logs

**Explicit summation:**  $\log x! = \sum_{n=2}^x \log n$

**Library routines:**  $\ln x! = \ln \Gamma(x + 1)$ , e.g. `gammaaln`

**Stirling's approx:**  $\ln x! \approx x \ln x - x + \frac{1}{2} \ln 2\pi x \dots$

**Care:** Stirling's series gets *less* accurate if you add lots terms(!), but the relative error disappears for large  $x$  with just the terms shown.

There is also (now) a convergent version (see Wikipedia).

See also: more specialist routines. Matlab/Octave: `binopdf`, `nchoosek`

LIII: A Letter from the late Rev. Mr. Thomas Bayes F.R.S. to John Canton M.A. F.R.S.

Read at R.S.

S<sup>r</sup>

24 Novemb. 1763,

If the following observations do not seem to you to be too minute, I should esteem it as a favor if you would please to communicate them to the royal society

It has been asserted by some eminent Mathematicians, <sup>that</sup> the sum of  $n^{\text{th}}$  logarithms of ~~the~~ the numbers 1. 2. 3. 4. &c. to  $n$  is equal to

$\frac{1}{2} \text{Log}, c + \overline{2 + \frac{1}{2}} \times \text{Log}, z$  lessened by the series

$$z^{-2} - \frac{1}{12z} + \frac{1}{360z^3} - \frac{1}{1260z^5} + \frac{1}{1680z^7} - \frac{1}{1188z^9} + \&c \quad \text{if } c \text{ denote}$$

the circumference of a circle whose radius is unity. And it is true that this expression will very nearly approach to the value of that sum when  $z$  is large, & you take in only a proper number of the first terms of the foregoing series; but the whole series can never properly express any quantity at all; because after the 5<sup>th</sup> term the coefficients begin to increase, & they afterwards increase at a greater rate than what can be compensated by the increase of the powers of  $z$ : tho'  $z$  represent a number ever so large, & it will be evident in the following manner in which the coefficients of that

*XLIII. A Letter from the late Reverend Mr.  
Thomas Bayes, F. R. S. to John Canton,  
M. A. and F. R. S.*

S I R,

Read Nov. 24, <sup>1763.</sup> **I**F the following observations do not seem to you to be too minute, I should esteem it as a favour, if you would please to communicate them to the Royal Society.

It has been asserted by some eminent mathematicians, that the sum of the logarithms of the numbers 1. 2. 3. 4. &c. to  $z$ , is equal to  $\frac{1}{2} \log. c + \overline{z} + \frac{1}{2} \times \log. z$  lessened by the series  $z \frac{1}{12z} + \frac{1}{360z^3} + \frac{1}{1260z^5} + \frac{1}{1680z^7} - \frac{1}{1188z^9} + \&c.$  if  $c$  denote the circumference of a circle whose radius is unity. And it is true that this expression will very nearly approach to the value of that sum when  $z$  is large, and you take in only a proper number of the first terms of the foregoing series: but the whole series can never properly express



Discipuli Domini Colini Drummond qui vigesimo-septimo die  
Februarii MDCCXIX subscripserunt 1419

Arch Rennie 4	And: Beanel 3	Alexr Crokat 3
Edwa: Aukine 2	Geo: Carruthers 4	David Lindsay 1
Geo: Gordon 2	Geo: Dewar	Geo: Douglass 2
Geo: Inglis 4	Geo: McLenzie 2	Gul: Taylor 1
Gul: Horsburgh 3	Gul: Ramsay 3	Jo: Barclay 2
Hen: Ker 4	Gul: Adell 4	Jo: Pickhurst
Joan: Boston 3	John Connell 2	Jo: Howley
Jo: Carruthers 4	J <sup>r</sup> Gilechrist mair 2	John: Patoun 1
Joan Morison 3	John Gilson	John Rutherford 2
John Parton 2	Jo: Sharr 1	Jo: Smith 1
Jo: Faull 2	Jo: Jacques 1	Jo: Thomson 2
Mich: Robertone 2	Rich: Bell	Isa: Maddox
Pat: Murdock 3	Ro: Dalrymple 1	Rob: Cleland 4
Simon Elliot 2	Row: Dunbar 4	Rob: Douglass 1
Thomas Carmichael 2	Skinner Smith	Rob: Richarby 1
	Tho: Davidson 2	Th: Bayes
		Tho: Morison 2

**Familiarity with extreme numbers:** when counting sets of possible strings or images the numbers are *enormous*. Similarly the probabilities of any such objects must be *tiny*, if the probabilities are to sum to one.

**Learn to guess:** before computing a number, force yourself to guess a rough range of where it will be. Guessing improves intuition and might catch errors.

**Numerical experiments:** we will derive the asymptotic behaviour of large block codes. Seeing how finite-sized blocks behave empirically is also useful. Take the logs of extreme positive numbers when implementing code.

**Bayes and Stirling's series:** approximations of functions can be useful for analytically work. The images show copies of Bayes's letter about Stirling's series to John Canton, both handwritten and the original typeset version. Bayes studied at what became the University of Edinburgh. I've included a copy of a class list with his name (possibly not his signature) second from the end.

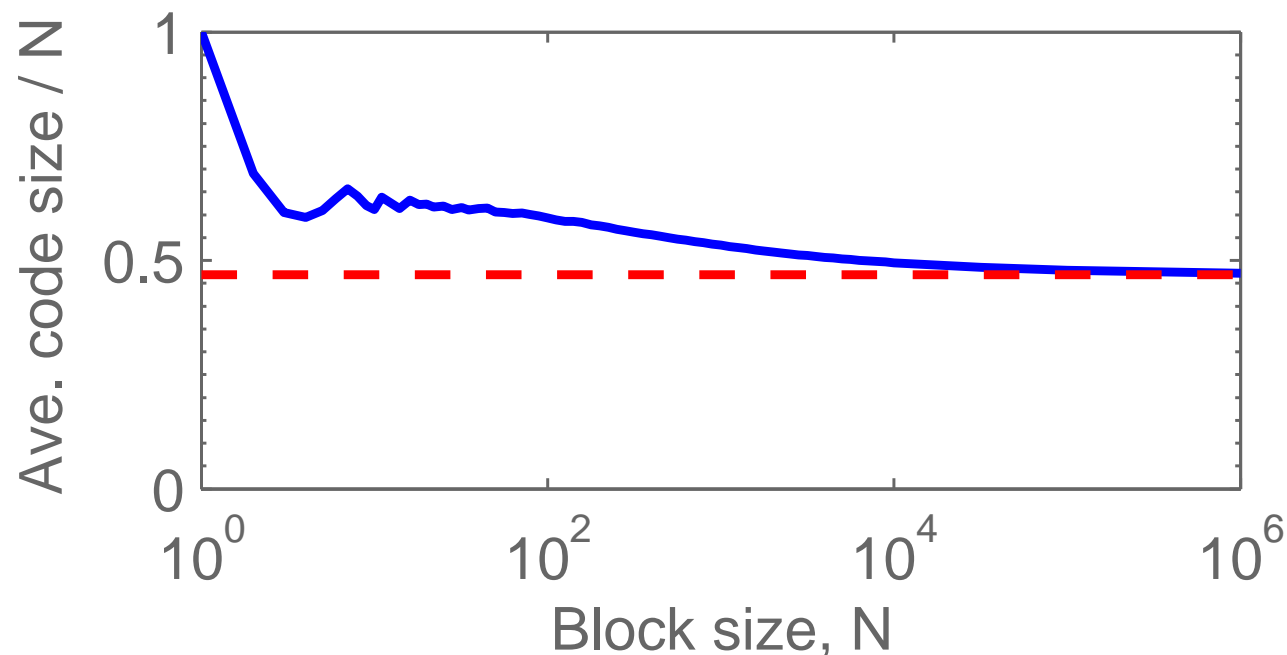
# Compression for $N$ -bit blocks

## Strategy:

- Encode  $N$ -bit blocks with  $\leq t$  ones with  $C_1(t)$  bits.
- Use remaining codewords followed by  $C_2(t)$  bits for other blocks.

Set  $C_1(t)$  and  $C_2(t)$  to minimum values required.

Set  $t$  to minimize average length:  $C_1(t) + P(t < \sum_{n=1}^N x_n) C_2(t)$



# Can we do better?

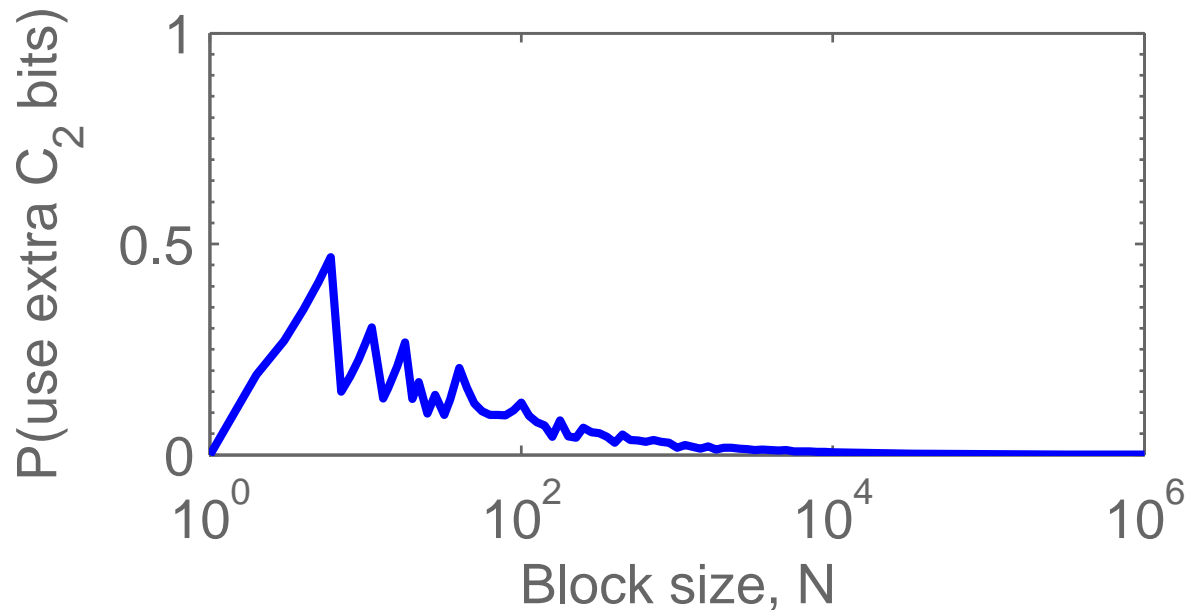
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**We took a simple, greedy strategy:**

*Assume one code-length  $C_1$ , add another  $C_2$  bits if that doesn't work.*

**First observation for large  $N$ :**

The first  $C_1$  bits index almost every block we will see.



*With high probability we can compress a large- $N$  block into a fixed number of bits. Empirically  $\approx 0.47 N$  for  $p=0.1$ .*

# Can we do better?

---

**We took a simple, greedy strategy:**

*Assume one code-length  $C_1$ , add another  $C_2$  bits if that doesn't work.*

**Second observation for large  $N$ :**

Trying to use  $< C_1$  bits means we *always* use more bits

At  $N = 10^6$ , trying to use 0.95 the optimal  $C_1$  initial bits

$\Rightarrow P(\text{need more bits}) \approx 1 - 10^{-100}$

*It is very unlikely a file can be compressed into fewer bits.*

## Summary of lecture 2 (slide 1/2)

**If some files are shrunk others must grow:**

# files length  $b$  bits =  $2^b$

# files  $< b$  bits =  $\sum_{c=0}^{b-1} 2^c = 1 + 2 + 4 + 8 + \dots + 2^{b-1} = 2^b - 1$

(We'll see that things are even worse for encoding blocks in a stream.

Consider using bit strings up to length 2 to index symbols:

A=0, B=1, C=00, D=01, E=11

If you receive 111, what was sent? BBB, BE, EB?)

**We temporarily focus on sparse binary files:**

Encode blocks of  $N$  bits,  $\mathbf{x} = 00010000001000\dots000$

Assume model:  $P(\mathbf{x}) = p^k (1 - p)^{N-k}$ , where  $k = \sum_i x_i = \text{"# 1's"}$

**Key idea: give short encoding to most probable blocks:**

Most probable block has  $k=0$ . Next  $N$  most probable blocks have  $k=1$

Let's encode all blocks with  $k \leq t$ , for some threshold  $t$ .

This set has  $I_1 = \sum_{k=0}^t \binom{N}{k}$  items. Can index with  $C_1 = \lceil \log_2 I_1 \rceil$  bits.

## Summary of lecture 2 (slide 2/2)

**Can make a lossless compression scheme:**

Actually transmit  $C_1 = \lceil \log_2(I_1 + 1) \rceil$  bits

Spare code word(s) are used to signal  $C_2$  more bits should be read, where  $C_2 \leq N$  can index the other blocks with  $k > t$ .

Expected/average code length =  $C_1 + P(k > t) C_2$

**Empirical results for large block-lengths  $N$**

- The best codes (best  $t$ ,  $C_1$ ,  $C_2$ ) had code length  $\approx 0.47N$
- these had tiny  $P(k > t)$ ; it doesn't matter how we encode  $k > t$
- Setting  $C_1 = 0.95 \times 0.47N$  made  $P(k > t) \approx 1$

**$\approx 0.47N$  bits are sufficient and necessary to encode long blocks (with our model,  $p=0.1$ ) almost all the time and on average**

No scheme can compress binary variables with  $p=0.1$  into less than 0.47 bits on average, or we could contradict the above result.

Other schemes will be more practical (they'd better be!) and will be closer to the  $0.47N$  limit for small  $N$ .