

# CT111 Intro to Communication Systems

## Lecture 4: Weak Law of Large Numbers and Typical Sets

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# Overview of Today's Talk

## 1 WLLN



# Overview of Today's Talk

- 1 WLLN
- 2 Typical Sets



# Overview of Today's Talk

- 1 WLLN
- 2 Typical Sets
- 3 Compression of Digital Data



# Average of $N$ Data Points

- *Weak Law of Large Numbers (WLLN)* states that the average

$$\mu_M = \frac{1}{M} \sum_{m=1}^M X_m \text{ of } N \text{ samples } \{X_1, X_2, \dots, X_M\} \text{ of a random}$$

variable  $X$  with a finite variance  $\text{Var}[X]$  converges to its expected value  $E[X]$  as  $M \rightarrow \infty$ .

- Specifically, for an arbitrarily small positive scalar  $\epsilon$ ,  
 $\lim_{M \rightarrow \infty} P(|\mu_M - E[X]| \geq \epsilon) = 0$ .
- Use the Chebyshev's inequality

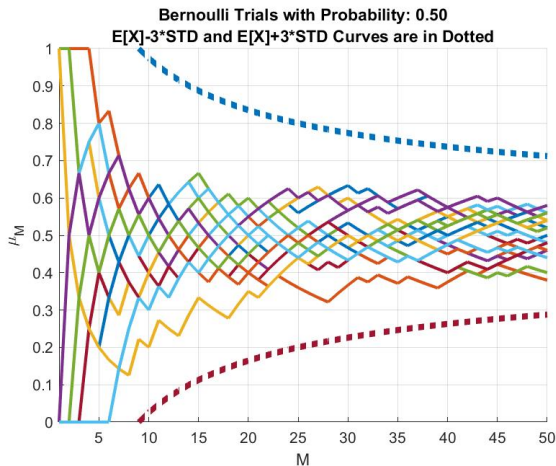
$$P(|\mu_M - E[\mu_M]| \geq \epsilon) \leq \frac{\text{Var}[\mu_M]}{\epsilon^2}$$

to prove the WLLN.



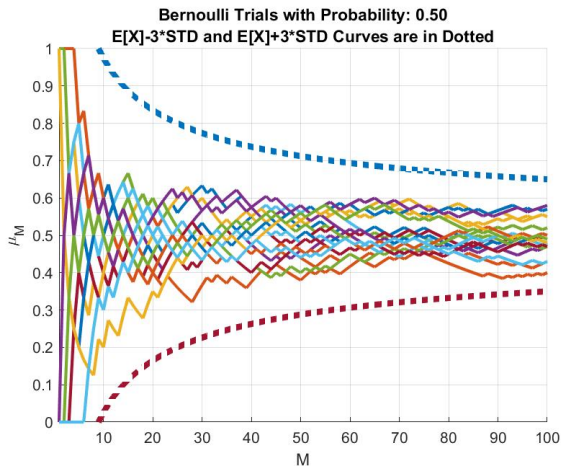
# Average of $M$ Data Points

$p = 0.5$ , up to  $M = 50$



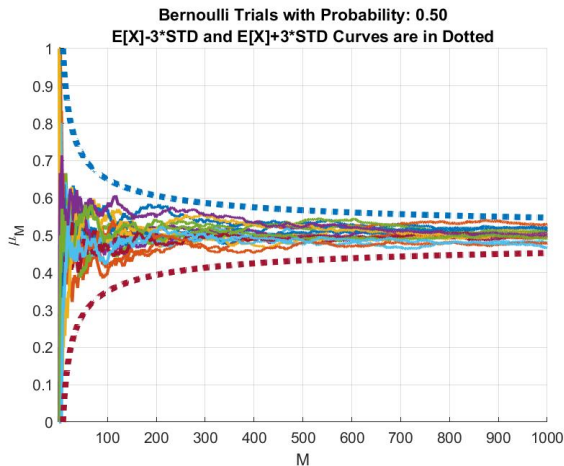
# Average of $M$ Data Points

$p = 0.5$ , up to  $M = 100$



# Average of $M$ Data Points

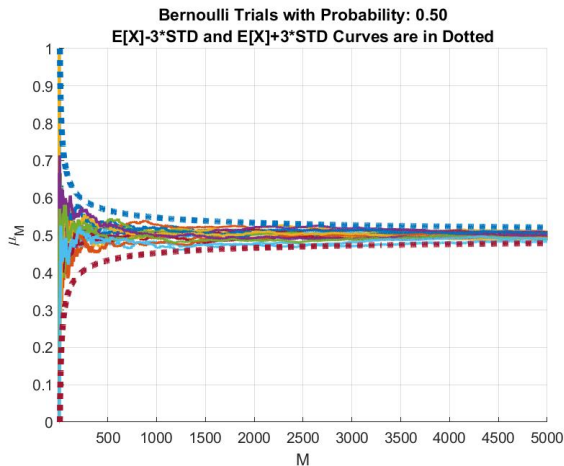
$p = 0.5$ , up to  $M = 1000$





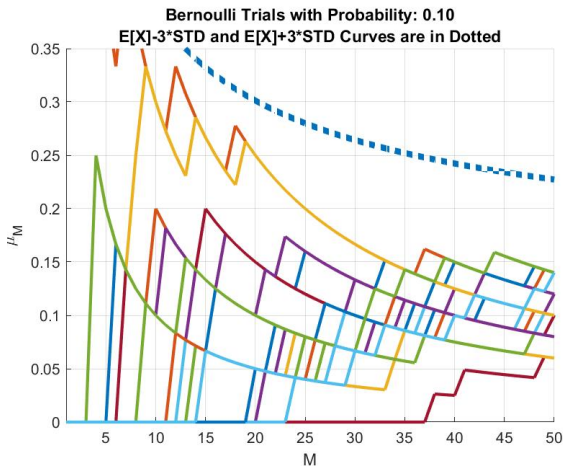
# Average of $M$ Data Points

$p = 0.5$ , up to  $M = 5000$



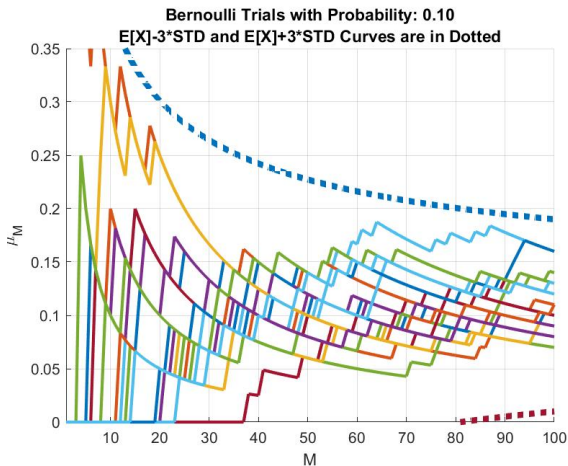
# Average of $M$ Data Points

$p = 0.1$ , up to  $M = 50$



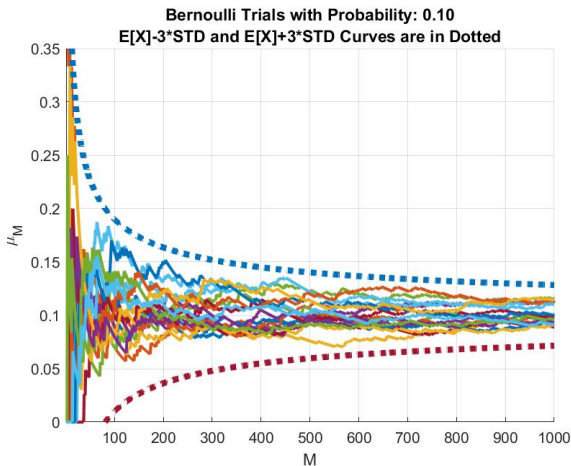
# Average of $M$ Data Points

$p = 0.1$ , up to  $M = 100$



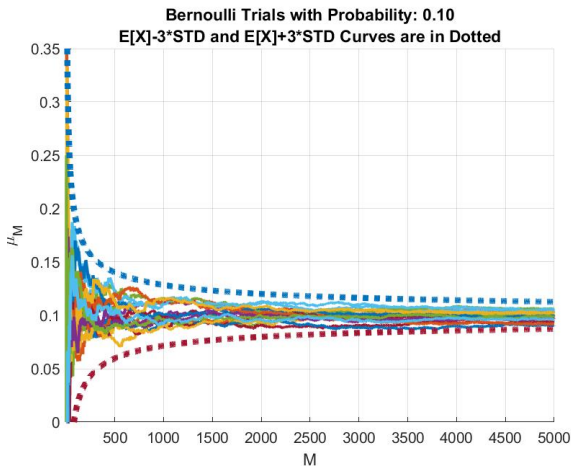
# Average of $M$ Data Points

$p = 0.1$ , up to  $M = 1000$



# Average of $M$ Data Points

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# A Sequence of $M$ bits

$$M = 2, p = 0.1$$

- Let us consider a sequence of  $M = 2$  consecutive bits generated by a random information source



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- Let us consider a sequence of  $M = 2$  consecutive bits generated by a random information source
- We will see  $2^M = 4$  possible sequences
- These can be divided into  $M + 1 = 3$  different, non-overlapping, subsets of binary sequences
  - 1 Subset 1 is all-zero sequence (no ones)
    - Has one sequence  $[0, 0]$ , which occurs with a probability of  $(1 - p)^2 = 0.9^2 = 0.81$





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  - 2 Subset 2 is a set of all sequences with exactly one 1
    - Has  $\binom{M=2}{1} = 2$  sequences ( $[0, 1]$  and  $[1, 0]$ ), each of which occurs with probability of  $0.9 \times 0.1 = 0.09$ . Therefore, total probability of this subset is  $2 \times 0.09 = 0.18$ .



# A Sequence of $M$ bits

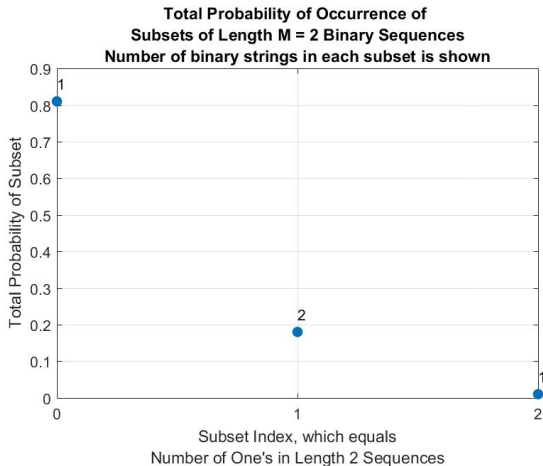
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  - 3 Finally, subset 3 is a set of all-ones sequences
    - Has one sequence  $[1, 1]$ , which occurs with a probability of  $(1 - p)^2 = 0.1^2 = 0.01$



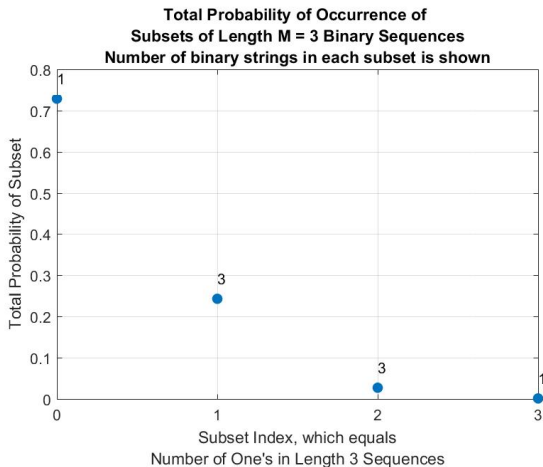
# A Sequence of $M$ DMS symbols

$$M = 2, p = 0.1$$



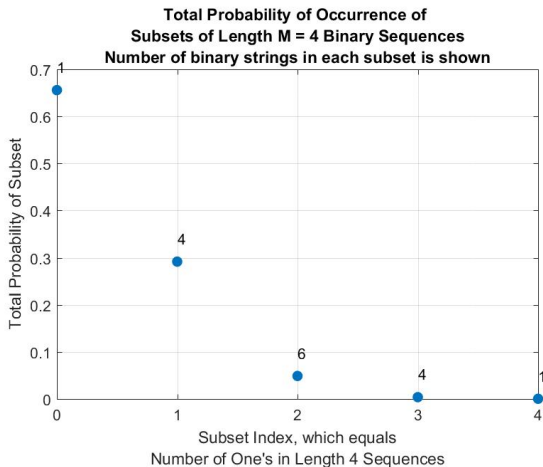
# A Sequence of $M$ DMS symbols

$$M = 3, p = 0.1$$



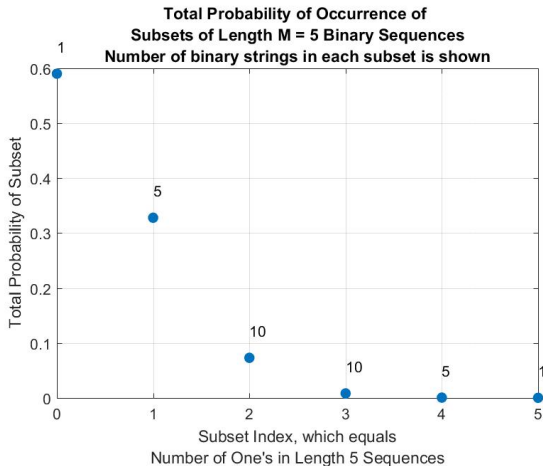
# A Sequence of $M$ DMS symbols

$$M = 4, p = 0.1$$



# A Sequence of $M$ DMS symbols

$$M = 5, p = 0.1$$



# A Few More Questions

- What do we expect to see as we keep on increasing  $M$ ?



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- A claim: only one subset will survive!





# A Few More Questions

- What do we expect to see as we keep on increasing  $M$ ?
- A claim: only one subset will survive!
- Which one?



# A Note

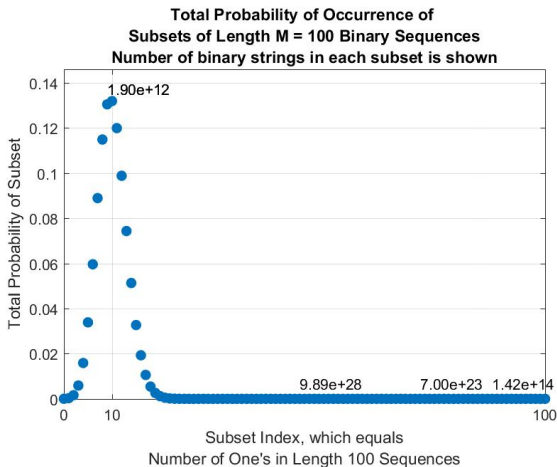
- As we keep on increasing  $M$ , the set of binary sequences, which has total  $2^M$  members, becomes *huge*
  - $M = 58$ ,  $2^M$  is the age of universe in seconds
  - $M = 171$ ,  $2^M$  is the number of electrons in the Earth
  - $M = 190$ ,  $2^M$  is the number of electrons in the solar system
  - $M = 266$ ,  $2^M$  is the number of electrons in the universe

(REF: David MacKay book: “Information Theory, Inference, and Learning Algorithms,” available on the web for free download)



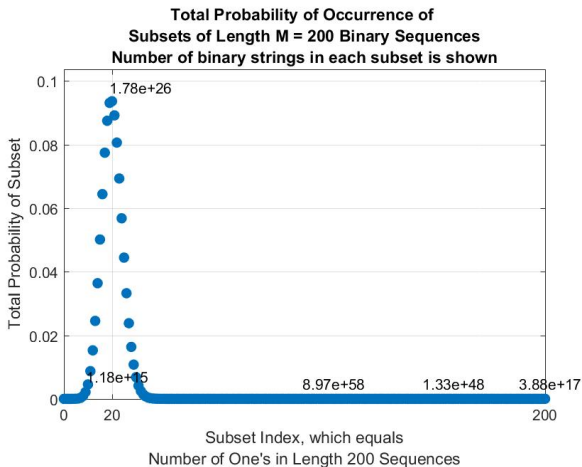
# A Sequence of $M$ DMS symbols

$$M = 100, p = 0.1$$



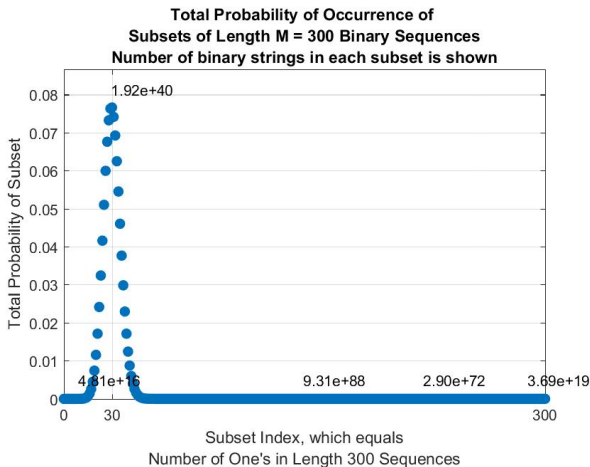
# A Sequence of $M$ DMS symbols

$$M = 200, p = 0.1$$



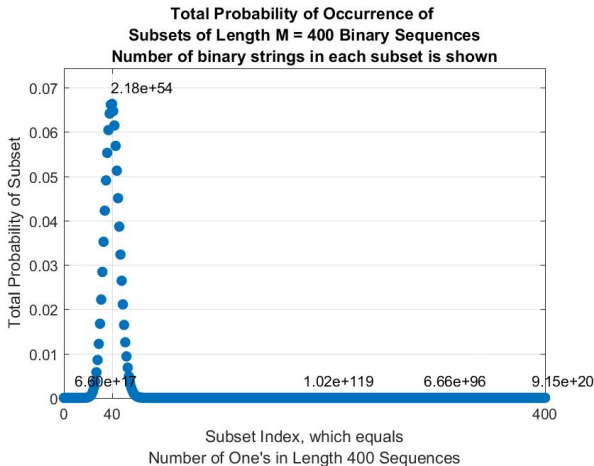
# A Sequence of $M$ DMS symbols

$$M = 300, p = 0.1$$



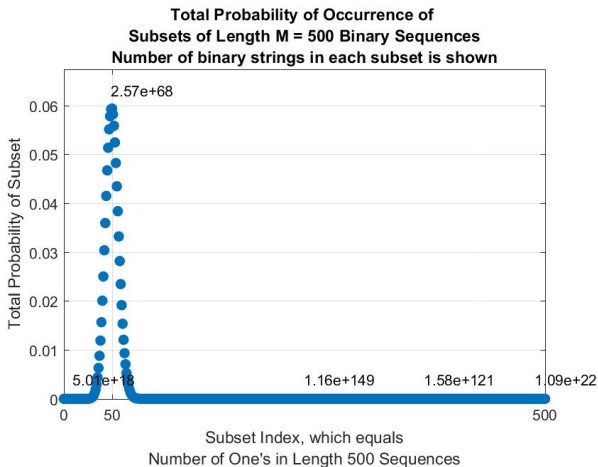
# A Sequence of $M$ DMS symbols

$$M = 400, p = 0.1$$



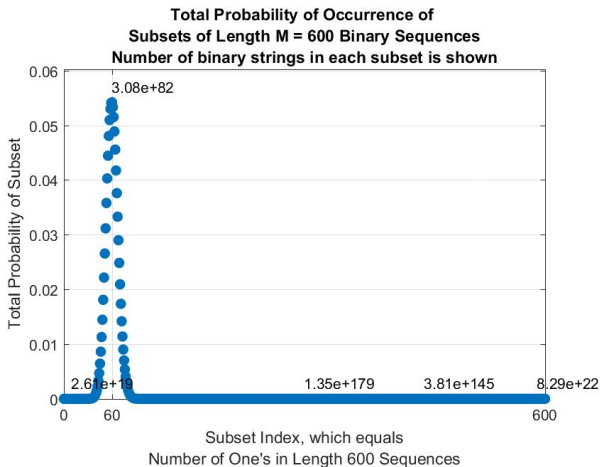
# A Sequence of $M$ DMS symbols

$$M = 500, p = 0.1$$



# A Sequence of $M$ DMS symbols

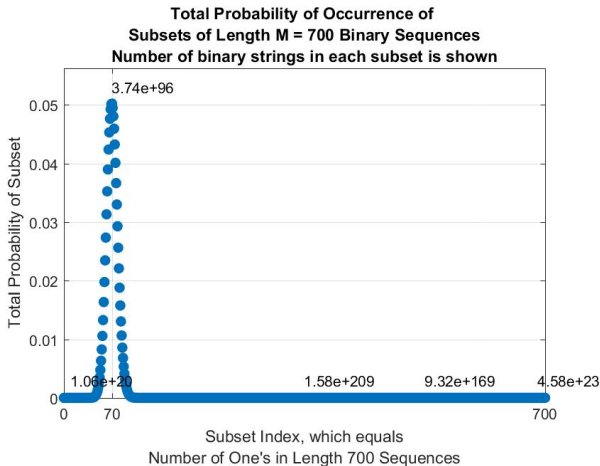
$$M = 600, p = 0.1$$





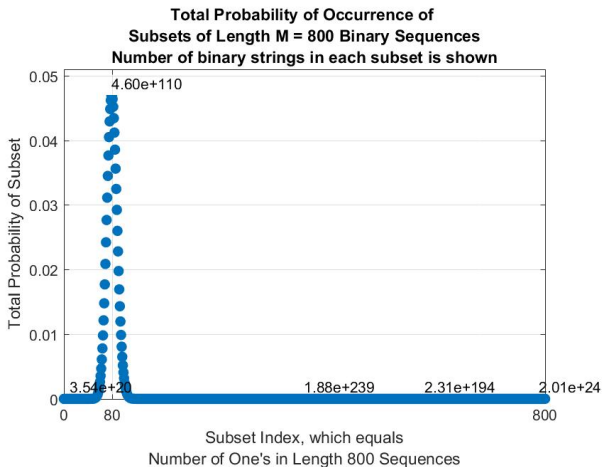
# A Sequence of $M$ DMS symbols

$$M = 700, p = 0.1$$



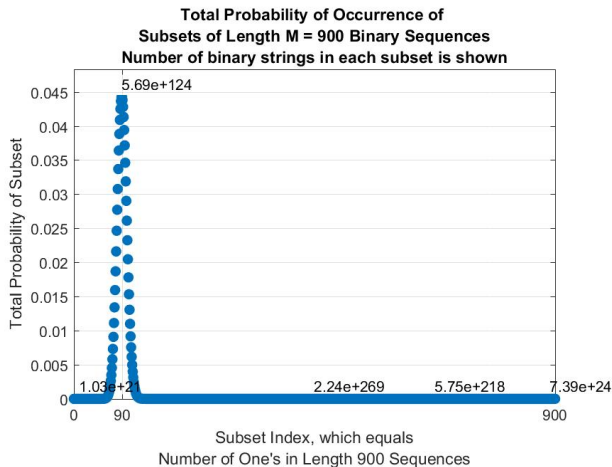
# A Sequence of $M$ DMS symbols

$$M = 800, p = 0.1$$



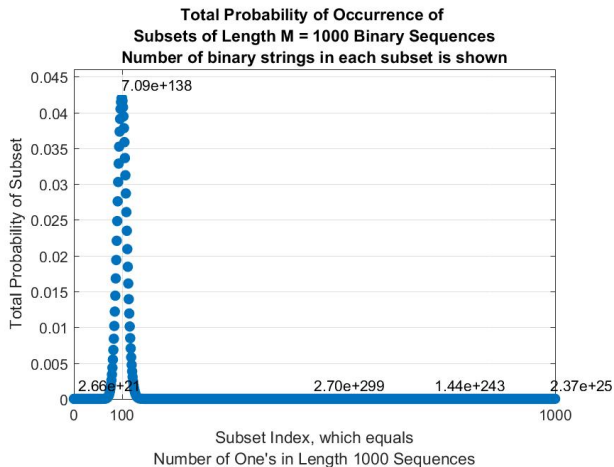
# A Sequence of $M$ DMS symbols

$$M = 900, p = 0.1$$



# A Sequence of $M$ DMS symbols

$$M = 1000, p = 0.1$$



# A Few More Questions

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## A Few More Questions

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- Which one?
- The subset formed by *all* binary sequences of length  $M$  which have  $M_1 = p \times M$  ones





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- A claim: only one subset will survive!
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- Why?



# A Few More Questions

- What do we expect to see as we keep on increasing  $M$ ?
- A claim: only one subset will survive!
- Which one?
- The subset formed by *all* binary sequences of length  $M$  which have  $M_1 = p \times M$  ones
- Why?
- Because that is *exactly* the definition of probability  $p$ :

$$p = \lim_{M \rightarrow \infty} \frac{M_1}{M}$$



# Coming to a Conclusion

- As  $M \rightarrow \infty$ , only one subset of  $2^M$  binary sequences survives
  - Total probability of this subset  $\rightarrow 1$
  - Total probability of all other (nonsurviving) subsets  $\rightarrow 0$
- No matter which binary sequence is picked from this subset,
  - it has  $p \times M$  ones and  $(1 - p) \times M$  zeros, and
  - therefore, the probability of each of these sequences is *identical* and equal to  $p^{pM}(1 - p)^{(1-p)M}$



# Conclusions

- As  $M \rightarrow \infty$ , only one subset of binary sequence survives
- Let the probability of occurrence of this subset be denoted as  $p_{typ}$ . As  $M \rightarrow \infty$ ,  $p_{typ} \rightarrow 1$ .
- Each of binary sequences picked from the surviving subset has
  - $p \times M$  ones and  $(1 - p) \times M$  zeros, and
  - probability of occurrence which is equal to  $p_i = p^{pM}(1 - p)^{(1-p)M}$
- Suppose the size of the surviving subset is  $K$  (i.e., it has  $K$  binary sequences)
  - $p_{typ} = K \times p_i = K \times p^{pM}(1 - p)^{(1-p)M} \rightarrow 1$
  - Therefore,  $K = p^{-pM}(1 - p)^{-(1-p)M}$



# Conclusions

- The size of surviving subset, which we will now call *typical set*, is  $K = p^{-pM}(1-p)^{-(1-p)M}$
- Each of its member sequences has equal probability of  $p_i = p^{pM}(1-p)^{(1-p)M}$
- Therefore, we can use *fixed-length* coding to represent these  $K$  sequences
- This fixed-length code will require *exactly*

$$\begin{aligned}\log_2 K &= \log_2 \left\{ p^{-pM}(1-p)^{-(1-p)M} \right\} \\ &= M \times (-p \log_2 p - (1-p) \log_2 (1-p)) \\ &= M \times H_b(p)\end{aligned}$$

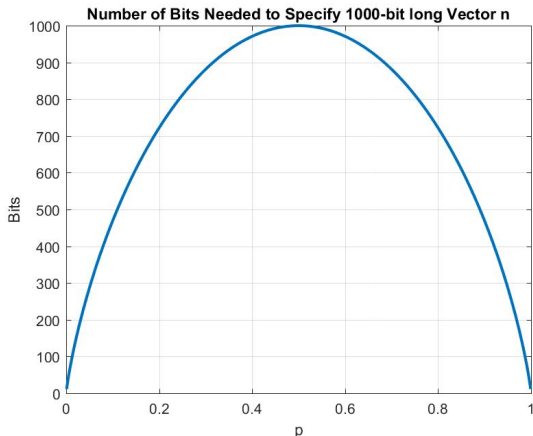
bits. Less than  $M \times H_b(p)$  bits will not be sufficient. More than  $M \times H(X)$  bits are too many.



# Binary Entropy Function

$$H_b(p)$$

- Entropy function for the binary set  $H_b(p) \times M$  ( $M = 1000$  bits):



# A Question

- 1 How is the binary Entropy function related to the combinatorial function  $\binom{M}{k}$ ?
- 2 Generalize: the derivation in the prior slides assumes that the information source generates bits 0 or 1 with probabilities  $p_1 = p$  and  $p_2 = 1 - p$ . Suppose the information source generates one of  $M$  symbols having probabilities  $p_m$ , where  $\sum_{m=1}^M p_m = 1$ . Derive the typical set formulation and the Entropy function for such non-binary ( $M$ -ary) information source.

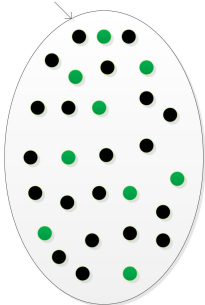


# Asymptotic Behavior

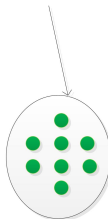
## of Random Binary Source of Information

- Green markers represent the members of the typical set

Before data compression:  
Requires  $M$  bits  
Total size of the set:  $2^M$



After data compression:  
Requires  $M \times H(X)$  bits  
Total size of the set:  $2^{M \times H(X)}$



● Members of the Typical Set

● Remaining, belong to subsets with vanishing probability as  $N$  becomes large





# Source Coding

## Solves the Problem of Data Compression

- Many digital data streams contain a lot of redundant information. For example, a digital image file may contain more zeros than ones:  
0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 1
- We wish to squeeze out the redundant information to minimize the amount of data needed to be stored or transmitted
- Definition of Data Compression Problem:
  - 1 What are the good algorithms that achieve the maximal data compression?
  - 2 What is the maximum data compression that can be achieved if we want to recover the exact bit sequence after decompression?
- Importance of Data Compression Problem:
  - ▷ Cannot be overstated given so much data is getting uploaded/downloaded and stored in today's world of YouTube, Facebook, etc.

