

Huffman Codes

<https://cs.pomona.edu/classes/cs140/>

Outline

Topics and Learning Objectives

- Introduce Huffman Codes for compression

Exercise

- None

Extra Resources

- Algorithms Illuminated Part 3, Chapter 14

Huffman Codes

- This will be our final greedy algorithm / application
- Huffman Codes are used for compression
- In general they can be thought of as:
 - A mapping of some set of characters/symbols to binary strings
- For example: let's encode the letters [a-z] and {., ?, !, ,, :}.
- How many bits would you use?
- Does this type of encoding sound familiar at all?

Huffman Codes

- In general we use Σ to represent the set of characters
- Let $\Sigma = \{A, B, C, D\}$
- What is one possible binary encoding?

| A | B | C | D |
|----|----|----|----|
| 00 | 01 | 10 | 11 |

- How many bits does it take to store 100 characters?

Huffman Codes

Can we do better than this **fixed-length** encoding (use fewer bits)?

| $\Sigma =$ | A | B | C | D |
|-------------------------|----|----|----|----|
| Fixed Encoding | 00 | 01 | 10 | 11 |
| (Bad) Variable Encoding | 0 | 01 | 10 | 1 |

What does the string 001 encode?

| | | |
|-----|-----|-----|
| AB | CD | AAD |
| 001 | 101 | 001 |

Huffman Codes

The problem with this encoding is called **prefixing**.

| $\Sigma =$ | A | B | C | D |
|-------------------------|----|----|----|----|
| Fixed Encoding | 00 | 01 | 10 | 11 |
| (Bad) Variable Encoding | 0 | 01 | 10 | 1 |

- This is **not** a **prefix-free** encoding.
- Problem: we don't know where one character ends and the next begins.
- Solution: ensure that the encoding is **prefix-free**.

Example Prefix-Free Encoding

| $\Sigma =$ | A | B | C | D |
|----------------------|----|----|----|----|
| Fixed Encoding | 00 | 01 | 10 | 11 |
| Prefix-free Encoding | | | | |

Example Prefix-Free Encoding

| $\Sigma =$ | A | B | C | D |
|----------------------|----|----|-----|-----|
| Fixed Encoding | 00 | 01 | 10 | 11 |
| Prefix-free Encoding | 0 | 10 | 110 | 111 |

Now, we know exactly when one character ends and another starts.

Why would this be a good idea?

- What if we needed to store a bunch of A's but only a few C's?

Example Prefix-Free Encoding

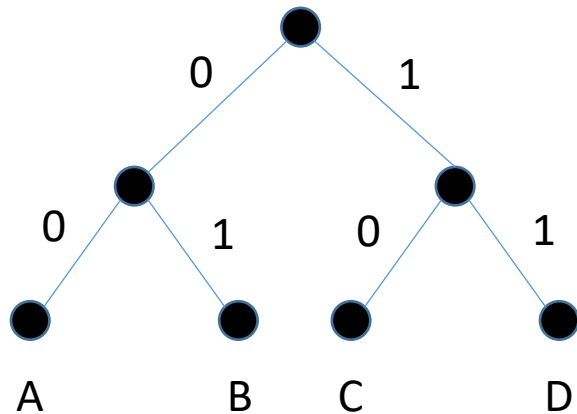
| $\Sigma =$ | A | B | C | D |
|----------------------|------------|------------|------------|-----------|
| Fixed Encoding | 00 | 01 | 10 | 11 |
| Prefix-free Encoding | 0 | 10 | 110 | 111 |
| Frequency | 60% | 25% | 10% | 5% |

What are the **average bit lengths** for these two encodings?

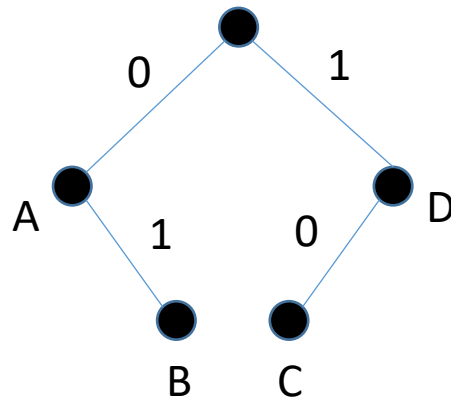
Discovering the Best Encoding

Let's think of Huffman Codes as trees. $\Sigma = A, B, C, D$

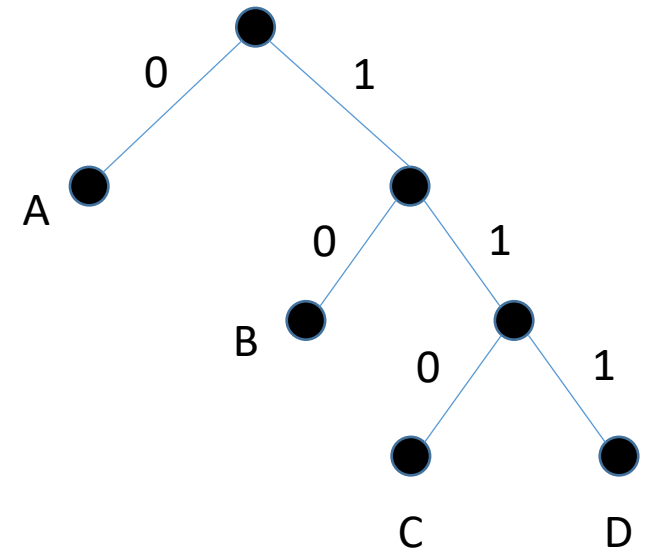
Fixed Encoding
{00,01,10,11}



First Variable Encoding
{0,01,10,1}



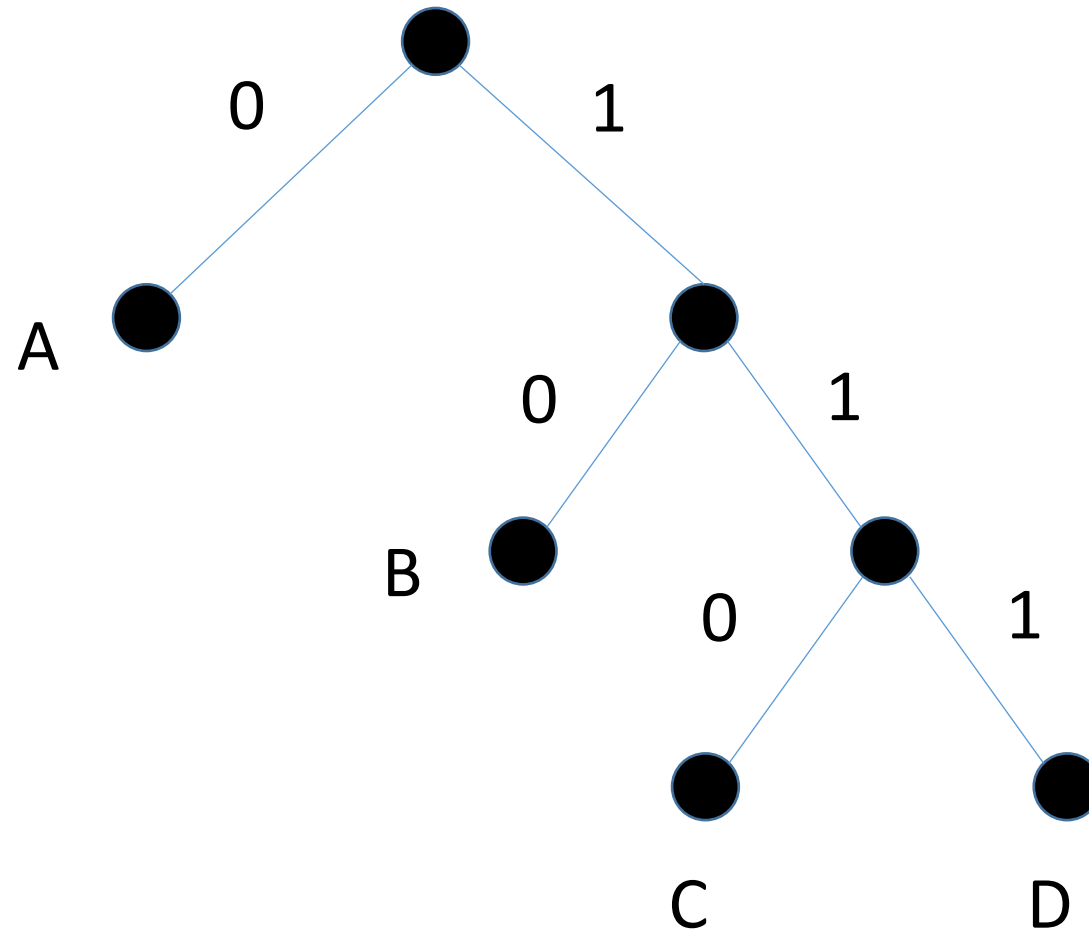
Prefix-Free Encoding
{0,10,110,111}



Huffman Codes as Trees

- Go to left child on a '0'
- Go to right child on a '1'
- For each **symbol** in Σ , exactly one node should be labeled **x**
- **Prefix-free** encoding require all labeled nodes to be **leaves**
- Trees are just a tool for helping us construct optimal encodings
- Decode: follow the input string until you reach a leaf
- Encode(**x**): the path followed from the root to **x**
- The encoding length of **x** is the same as its depth

Decode the string: 0110111



Huffman Codes

Problem: *how do we choose/design our encodings?*

- Input: a set of symbols Σ and their probabilities/frequencies p_i
- Notation: if T is a tree with leaves as symbols of Σ , then let

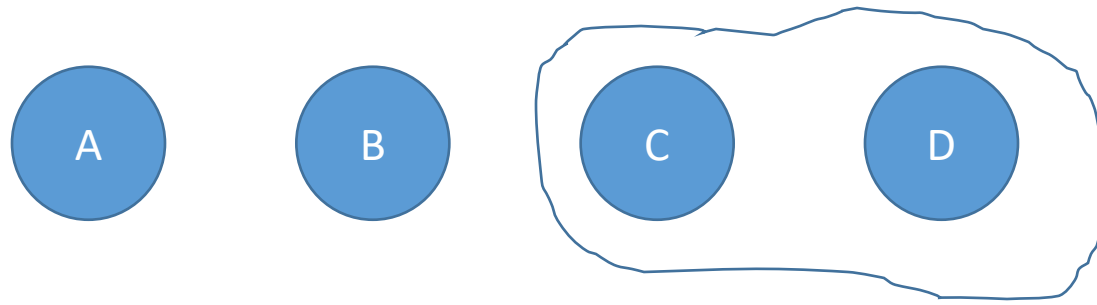
$$L(T) = \sum_{i=1}^{|\Sigma|} p_i * depth_i$$

- $L(T)$ is the average encoding length
- The output of our algorithm will be a binary tree T that minimizes $L(T)$

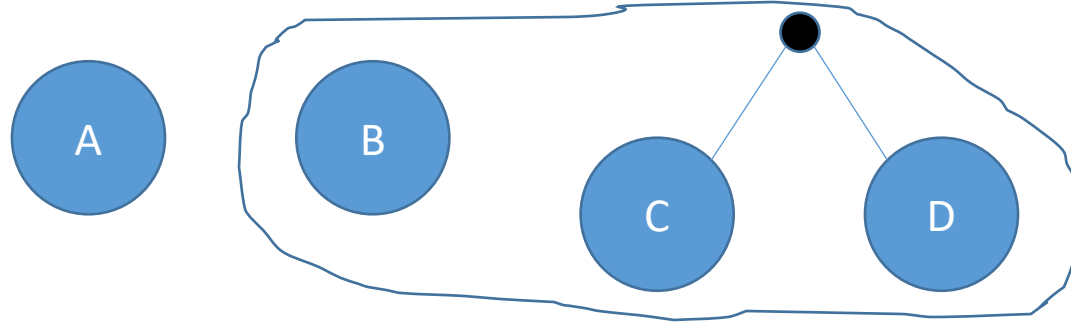
Huffman's Algorithm (compression)

Huffman's approach is to start at the leaves and build the tree bottom-up

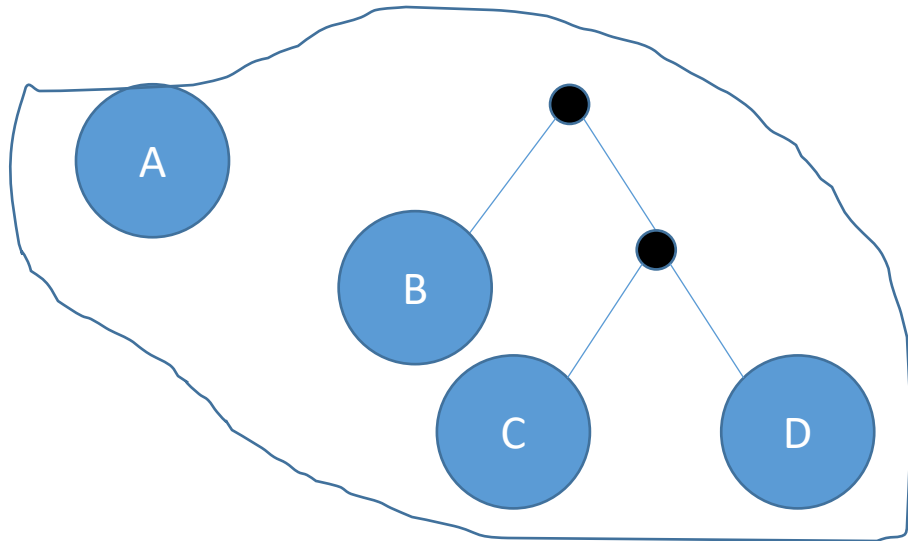
Iteration 1



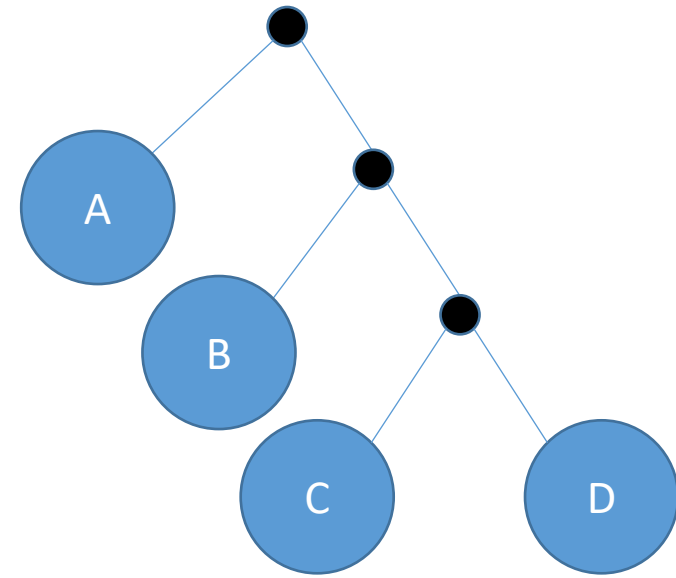
Iteration 2



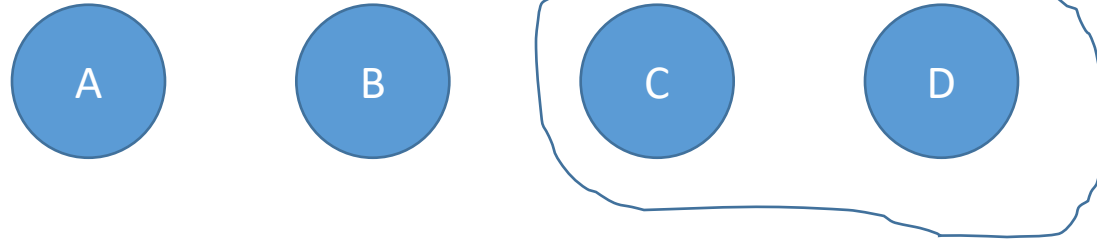
Iteration 3



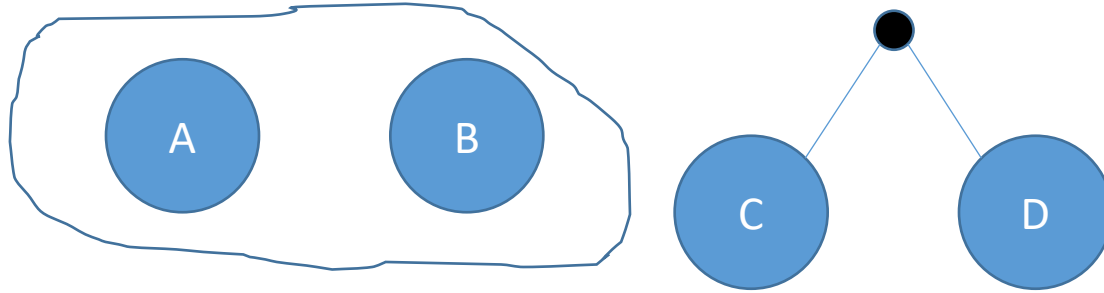
Iteration 4



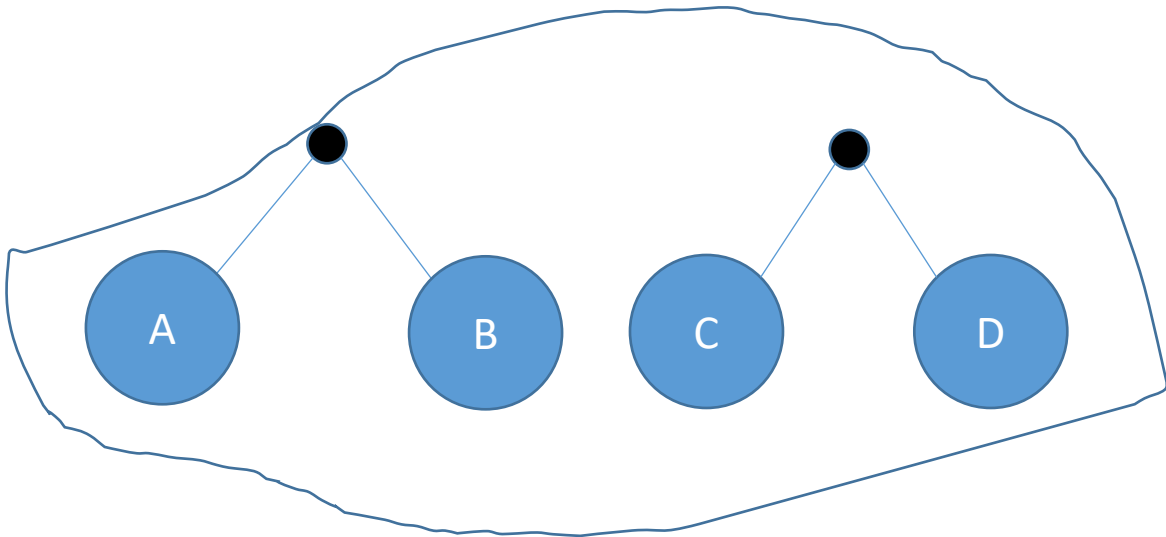
Iteration 1



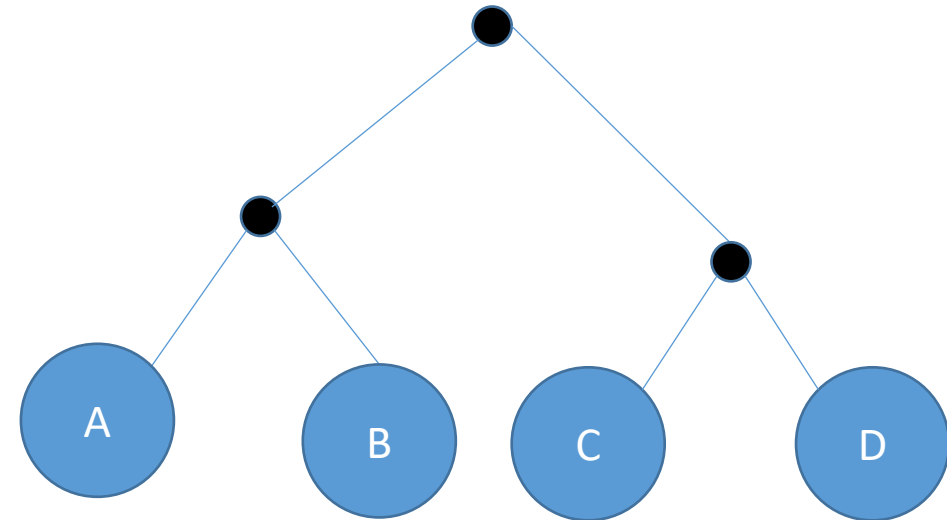
Iteration 2



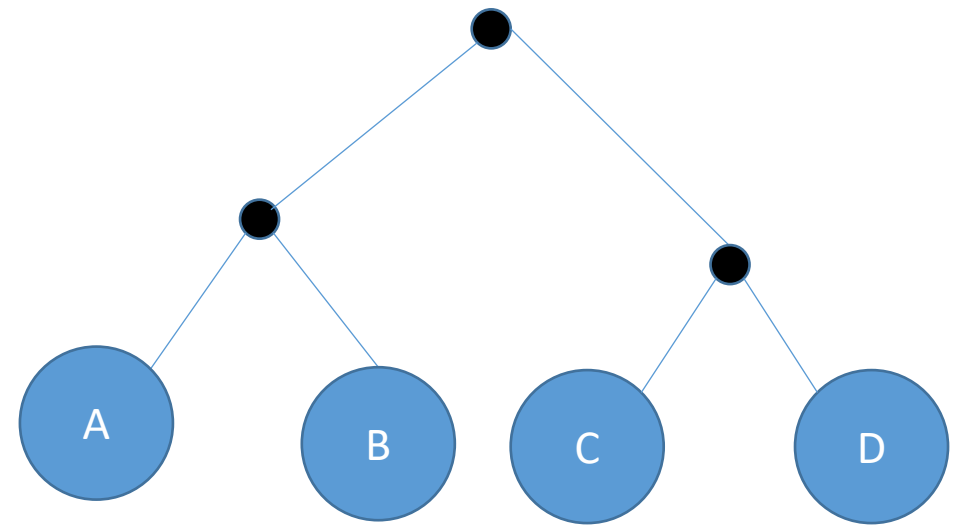
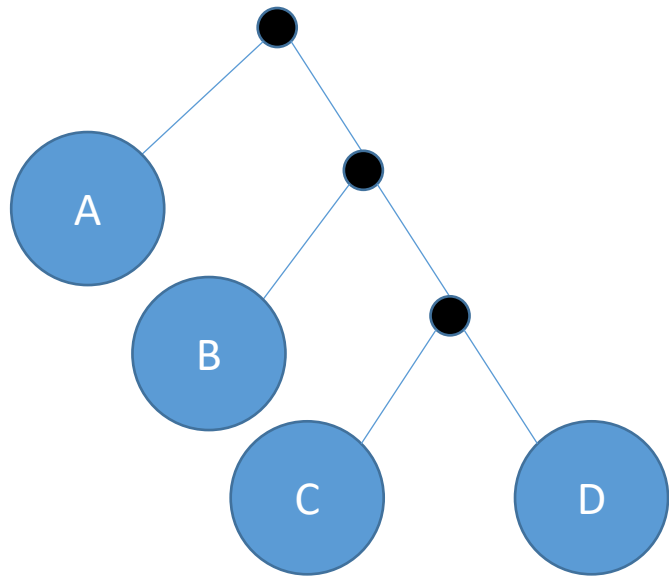
Iteration 3



Iteration 4



Which Tree is Better?



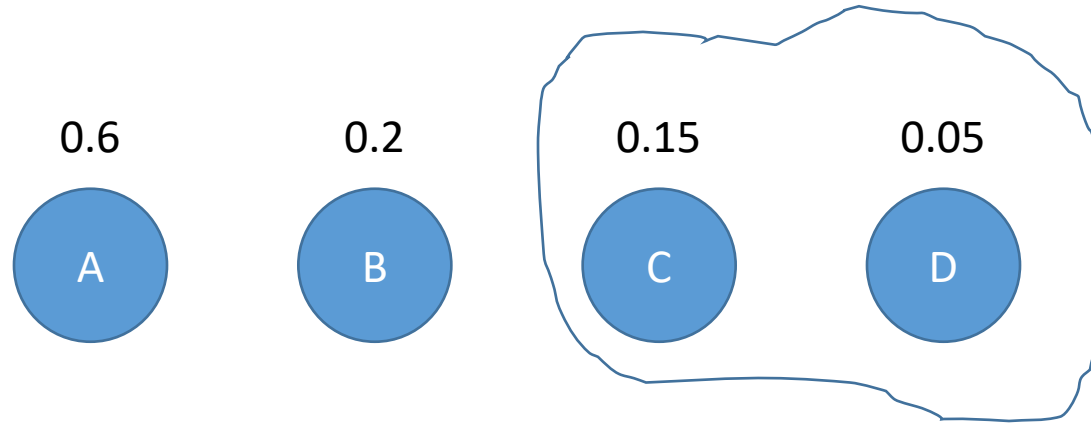
It depends on the frequencies!

Huffman's Algorithm

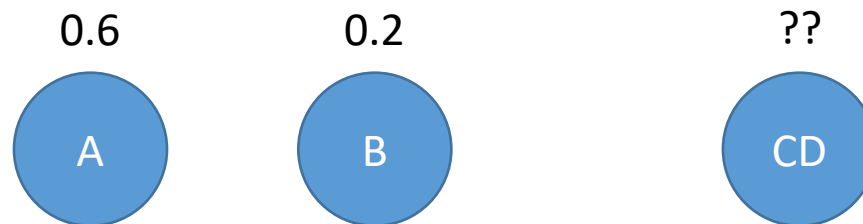
- We're building from the leaves up.
- How do we know which two symbols we should merge?
- How does the final encoding length of a given symbol in Σ relate to the number of merges it experiences?
- Each merge adds one node to the path from the root to x !
- So, how do we minimize the weighted average encoding length?
- Huffman's Greedy Criteria: Merge the least frequent characters first.

How do we compare nodes after a merge?

Iteration 1



Iteration 2



- a) $p_c + p_d$
- b) $\text{Min}[p_c, p_d]$
- c) $\text{Max}[p_c, p_d]$
- d) $p_c * p_d$

```
FUNCTION Huffman(symbols, frequencies)
```

```
    forest = [(f, s) FOR f, s IN Zip(symbols, frequencies)]  
    heapifyMin(forest)
```

```
WHILE forest.length  $\geq$  2
```

```
    treeA = extract_min(forest)
```

```
    treeB = extract_min(forest)
```

```
    treeMerged = merge(treeA, treeB)
```

```
    heap_add(forest, treeMerged)
```

```
# Only one tree remaining in forest
```

```
RETURN forest[0]
```

```
FUNCTION Huffman(symbols, frequencies)
```

```
    forest = [(f, s) FOR f, s IN Zip(symbols, frequencies)]  
    heapifyMin(forest)
```

```
WHILE forest.length  $\geq$  2  
    treeA = extract_min(forest)  
    treeB = extract_min(forest)  
    treeMerged = merge(treeA, treeB)  
    heap_add(forest, treeMerged)
```

```
# Only one tree remaining in forest
```

```
RETURN forest[0]
```

| $\Sigma =$ | A | B | C | D | E | F |
|------------|---|---|---|---|---|---|
| P = | 3 | 2 | 6 | 8 | 2 | 6 |

```
FUNCTION Huffman(symbols, frequencies)
```

```
    forest = [(f, s) FOR f, s IN Zip(symbols, frequencies)]  
    heapifyMin(forest)
```

```
WHILE forest.length  $\geq$  2  
    treeA = extract_min(forest)  
    treeB = extract_min(forest)  
    treeMerged = merge(treeA, treeB)  
    heap_add(forest, treeMerged)
```

```
# Only one tree remaining in forest
```

```
RETURN forest[0]
```

What is the running time?

Note: faster algorithms do exist for this problem

Correctness Proof

Theorem: Huffman's algorithm computes a binary tree that minimizes the average encoding length of all symbols

$$L(T) = \sum_{i=1}^{|\Sigma|} p_i * depth_i$$

Strategy:

- Induction
- Exchange argument

Proof by induction that $P(n)$ holds for all n

- Base Case: $P(1)$ holds because ...
- Inductive Hypothesis: Let's assume that $P(k)$ holds, where $k < n$
- Inductive Step: $P(n)$ holds because of $P(k)$ and ...
- Thus, by induction, $P(n)$ holds for all n

Inductive Proof

Base Case:

- If $n = 1$ or $n = 2$ there is only one option for average encoding length
- Thus the base cases are trivially true

Inductive Hypothesis:

- Huffman's algorithm produces the optimal coding with $\leq k$ symbols where $k < n$

Inductive Step...

Proof by induction that $P(n)$ holds for all n

- Base Case: $P(1)$ holds because ...
- Inductive Hypothesis: Let's assume that $P(k)$ holds, where $k < n$
- Inductive Step: $P(n)$ holds because of $P(k)$ and ...
- Thus, by induction, $P(n)$ holds for all n

Main Ideas for Inductive Step

Let symbols \emptyset and π be the symbols with the smallest and second smallest frequencies, respectively

1. Huffman's Algorithm outputs the optimal tree in which \emptyset and π are siblings
 - Out of all possible trees where \emptyset and π are siblings
2. The optimal tree is the one in which \emptyset and π are siblings
 - Out of all possible trees in general

Part 1

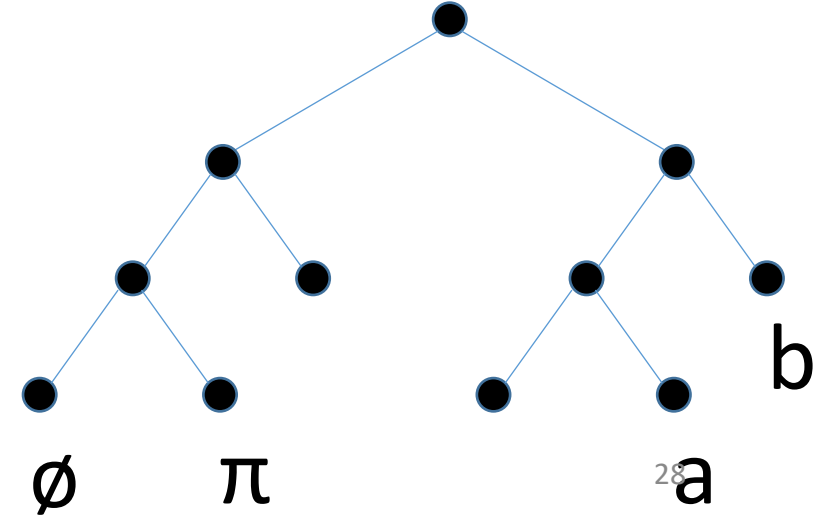
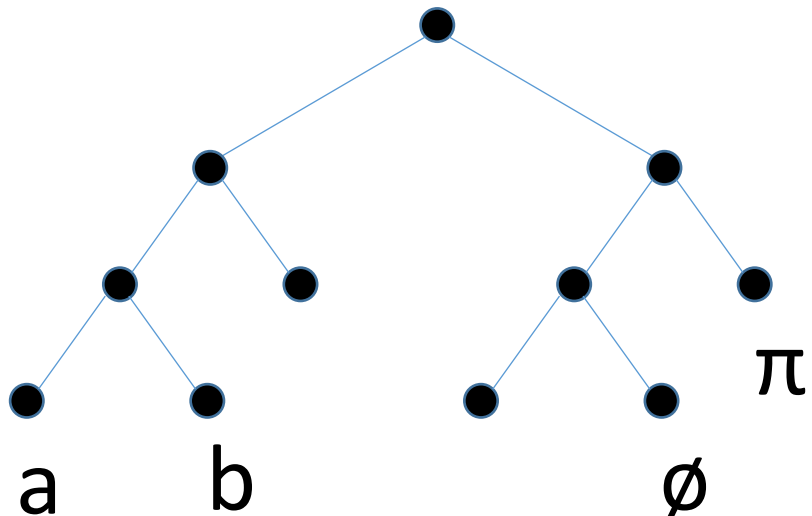
Huffman's outputs the optimal tree in which \emptyset and π are siblings

- After combining symbols \emptyset and π into a single " $\emptyset\pi$ " symbol we have reduced the total number of symbols by 1
- Given our inductive hypothesis, we know that Huffman's algorithm outputs the optimal tree for k symbols where $k < n$
- Thus, Huffman's outputs the optimal tree after combining \emptyset and π

Part 2

The optimal tree is the one in which \emptyset and π are siblings

- Consider the case where \emptyset and π are not siblings
- And we then exchange \emptyset and π with two nodes that are siblings
- The average encoding length goes down (or stays the same)!



Summary

- Prefix-free, variable-length binary codes have smaller average encoding lengths (per symbol) than fixed-length codes
- These Huffman Codes can be visualized as a binary tree
- Huffman's Algorithm works by greedily combining trees in the forest until you are left with a single tree in $O(n \lg n)$ time
- We proved correctness with induction and an exchange argument