Decision Tree and Random Forest Implementations for fast Fitlering of Sensor Data

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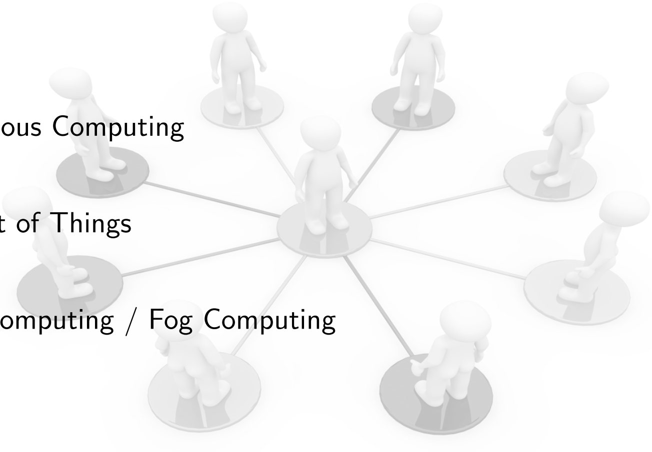
So... Distributed computation hype?

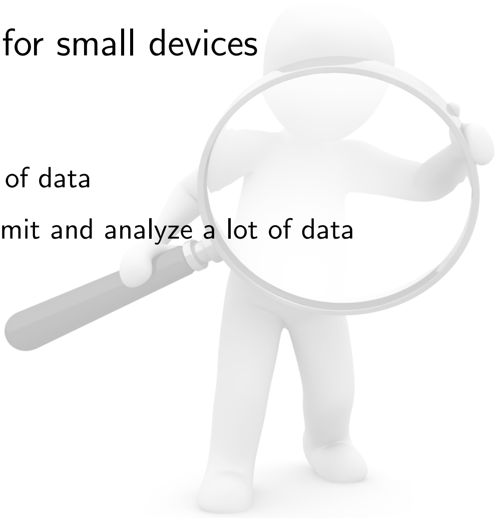


1991 Ubiquitous Computing

1999 Internet of Things

2015 Edge Computing / Fog Computing

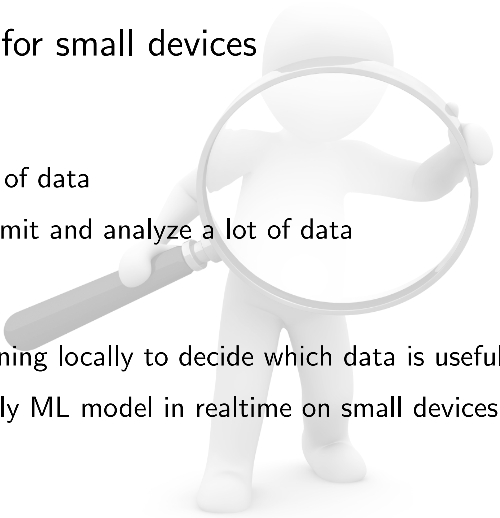
Machine Learning for small devices



Fact We measure a lot of data

Thus We need to transmit and analyze a lot of data

Machine Learning for small devices



Fact We measure a lot of data

Thus We need to transmit and analyze a lot of data

Idea Use Machine Learning locally to decide which data is useful

Thus Continuously apply ML model in realtime on small devices

Random Forest

Fact Random Forest is one of the best performing ML model

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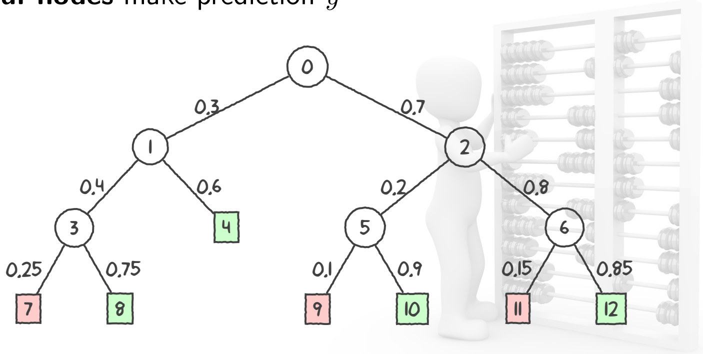
What system is needed for a given tree / forest?

What is the best way to implement a Decision Tree?

Decision Tree

- **Inner nodes** make decision $x_i < t$
- **Leaf nodes** make prediction $\widehat{y}$



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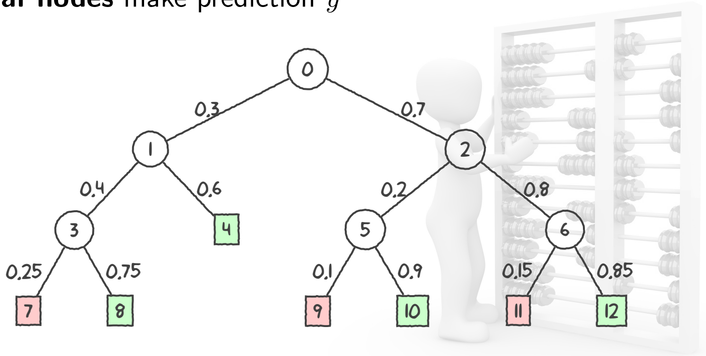

Observation Some path in tree have higher frequency than others

Probabilistic Analysis of Decision Trees

Idea Each decision is a Bernoulli Experiment with probability $p_{i \to j}$

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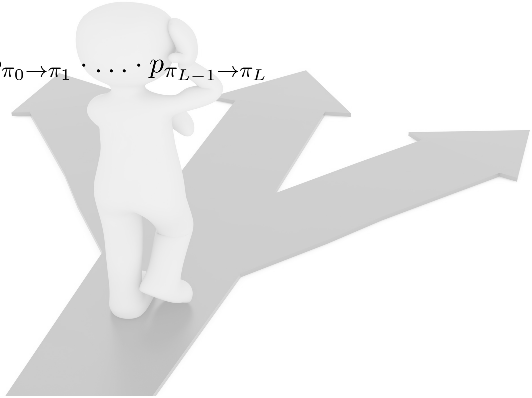
Path probability

$$p(\pi) = p_{\pi_0\to\pi_1} \cdot \ldots \cdot p_{\pi_{L-1}\to\pi_L}$$



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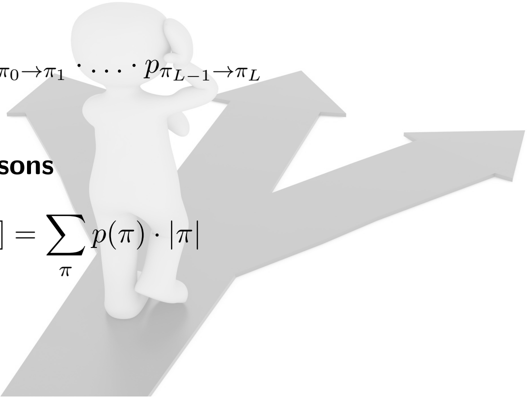
Expected no. of comparisons

$$\mathbb{E}[L] = \sum_{\pi} p(\pi) \cdot |\pi|$$



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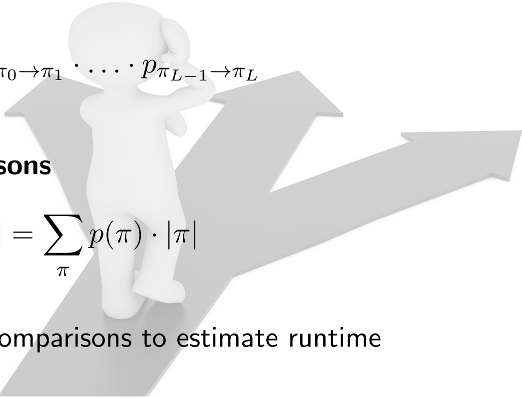
Idea Use expected no. of comparisons to estimate runtime



There are many ways to implement a Decision Tree

For Example: NativeTree

```
bool predict(short const * x){
    unsigned int i = 0;
    while(!tree[i].isLeaf) {
        if (x[tree[i].f] <= tree[i].split) {
            i = tree[i].left;
        } else {
            i = tree[i].right;
        }
    }
    return tree[i].prediction;
}
```

There are many ways to implement a Decision Tree

For Example: If-Else-Tree

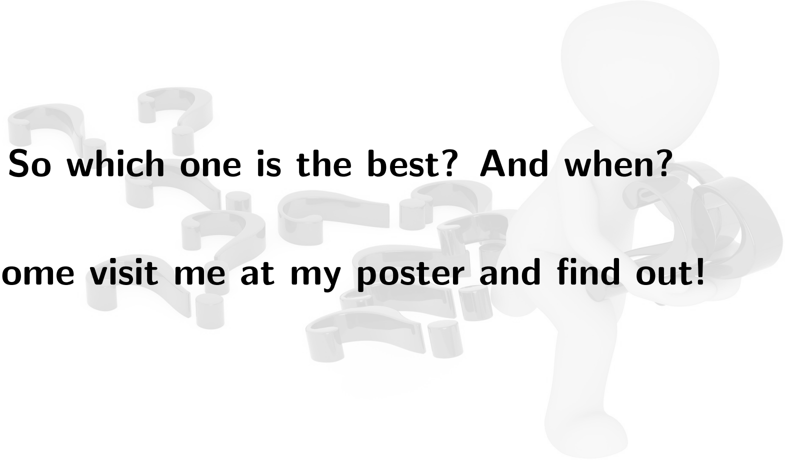
```
bool predict(short const * x){
    if(x[0] <= 8191){
        if(x[1] <= 2048){
            return true;
        } else {
            return false;
        }
    } else {
        if(x[2] <= 512){
            return true;
        } else {
            return false;
        }
    }
}
```

There are many ways to implement a Decision Tree

For Example: Vectorized Tree

```
bool predict(short const * x){
    unsigned int i = 0;
    unsigned int mask;
    void * tmp;
    while(!tree[i].isLeaf) {
        load_vectorized(tree[i],tmp);
        mask = compare_vectorized(tmp, x);
        i = mask_to_index(mask);
    }
    return tree[i].prediction;
}
```

Results



So which one is the best? And when?

Come visit me at my poster and find out!