Global Model for Hierarchical Multi-Label Text Classification

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Outline

- Task Settings
- Previous Work
- Proposed Method
- Results and Discussion
- Conclusion

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Task: Multi-Label Text Classification

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	Journal of Wood Science
	Harvested wood products accounting in the post Kyoto commitment period
	An increase in the amount of harvested wood products (HWP) from sustainable forestry would help to reduce levels of atmospheric carbon. In the first commitment period of the Kyoto Protocol (2008-2012), this carbon stock effect of HWP is ignored, and forest harvesting is treated as an instantaneous emission of carbon dioxide. However, in the next commitment period of the United Nations Framework Convention on Climate Change from 2013, the carbon stock changes resulting from HWP will be taken into account in the national greenhouse gas inventories…

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Output:
A set of labels

- FF01020X (forestry policies)
- SA01020V (environmental problems)

Task: Hierarchically Organized Labels

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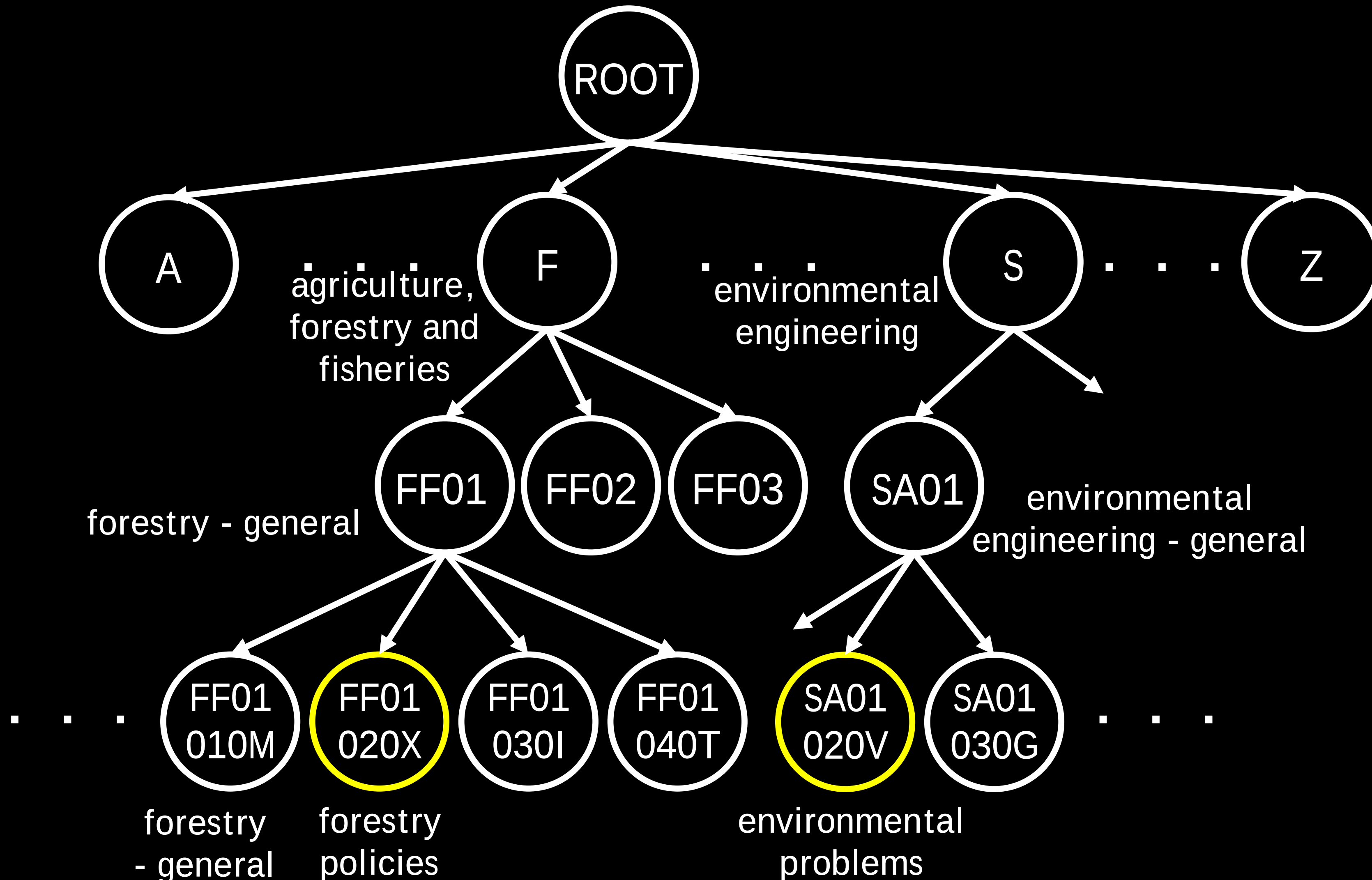

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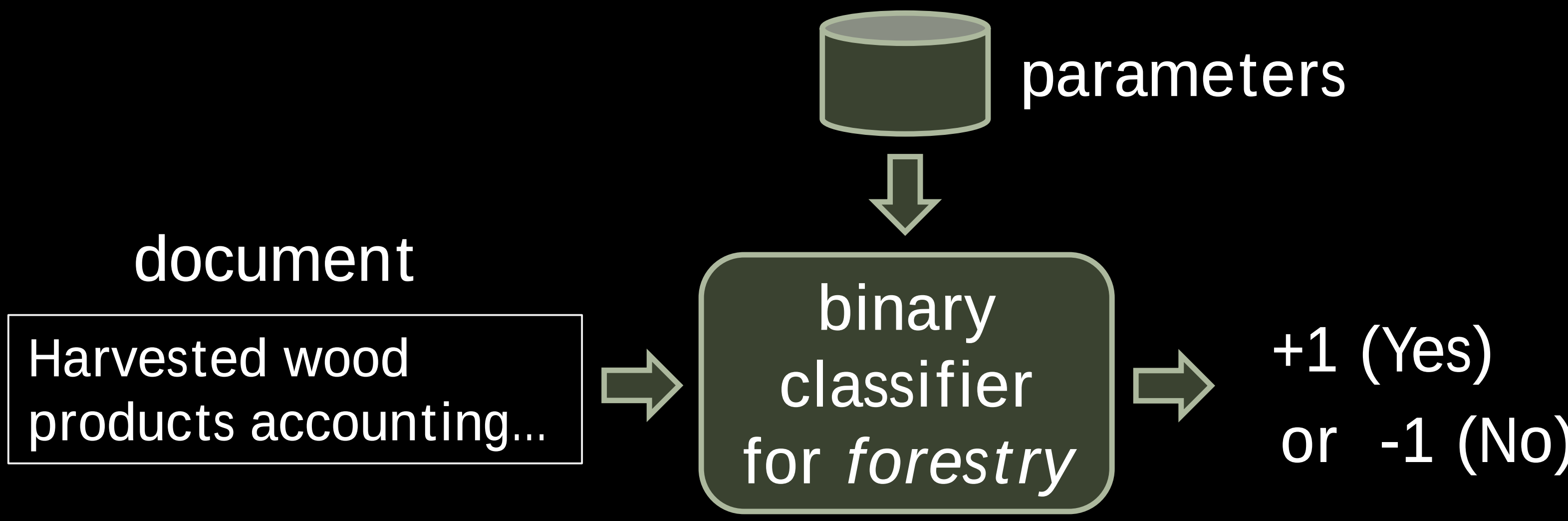
2. **Pruning**: Top-down pruning for speed, often in exchange for accuracy
3. **Parameter Sharing**: Share parameters according to the hierarchy to improve accuracy
4. **Proposed Method**: To capture dependencies among multiple labels to be output

Building Block: Binary Linear Classifier 1/2



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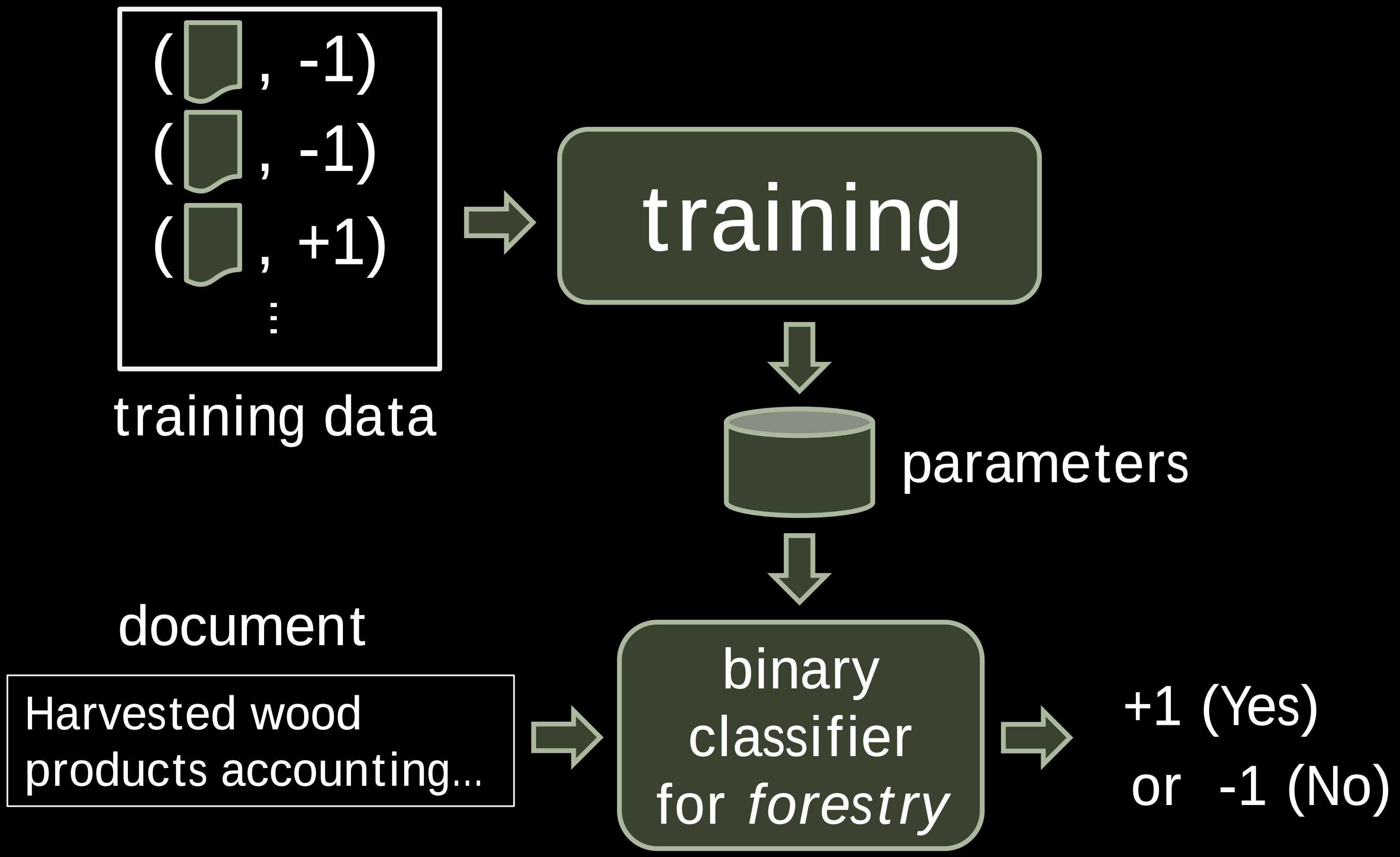

Building Block: Binary Linear Classifier 1/2

document

Harvested wood products accounting...

Building Block: Binary Linear Classifier 1/2

feature vector

$$\begin{bmatrix} 0 \\ 0 \\ 1 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \\ 0 \\ \vdots \end{bmatrix}$$

document

Harvested wood products accounting...

Building Block: Binary Linear Classifier 1/2

document

Harvested wood
products accounting...

feature vector

$$\begin{array}{cl} \begin{bmatrix} 0 \\ 0 \\ 1 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \\ 0 \\ \vdots \end{bmatrix} & \begin{array}{l} \text{algorithm} \\ \text{dolphin} \\ \text{wood} \\ \text{products} \\ \\ \\ \\ \\ \\ \\ \\ \end{array} \end{array}$$

Building Block: Binary Linear Classifier 1/2

document

Harvested wood products accounting...

weight vector

(-0.5, -0.2, 0.8, ...)

algorighm dolphin wood

feature vector

$$
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\left[\begin{array}{c} 0 \\ 0 \\ 1 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \\ 0 \\ \vdots \end{array}\right] &
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>0 ? then +1
otherwise -1

Building Block: Binary Linear Classifier 1/2

This is the parameters to be learned

document

Harvested wood products accounting...

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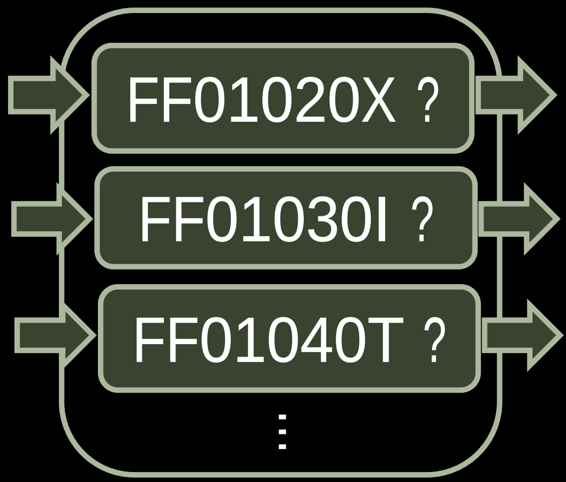

set of binary classifiers

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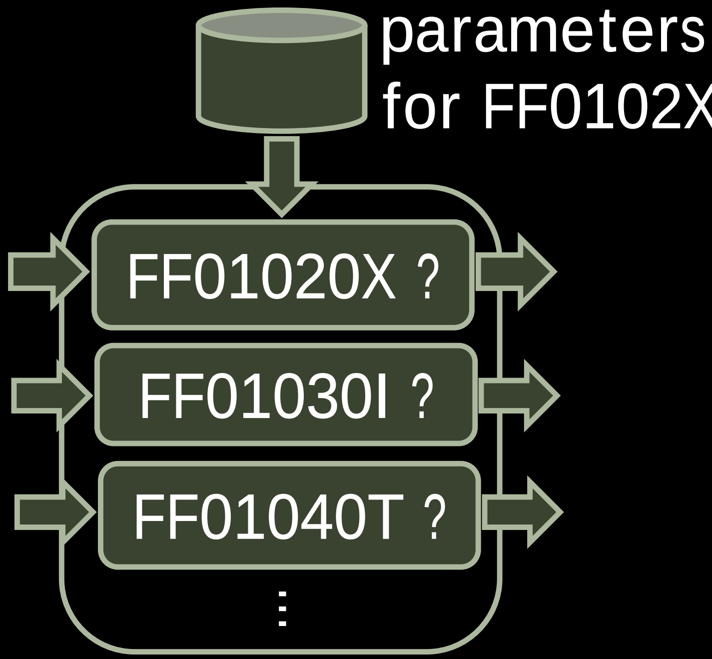

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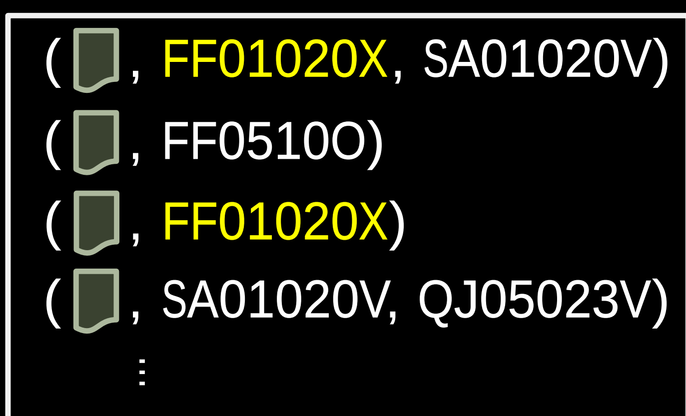
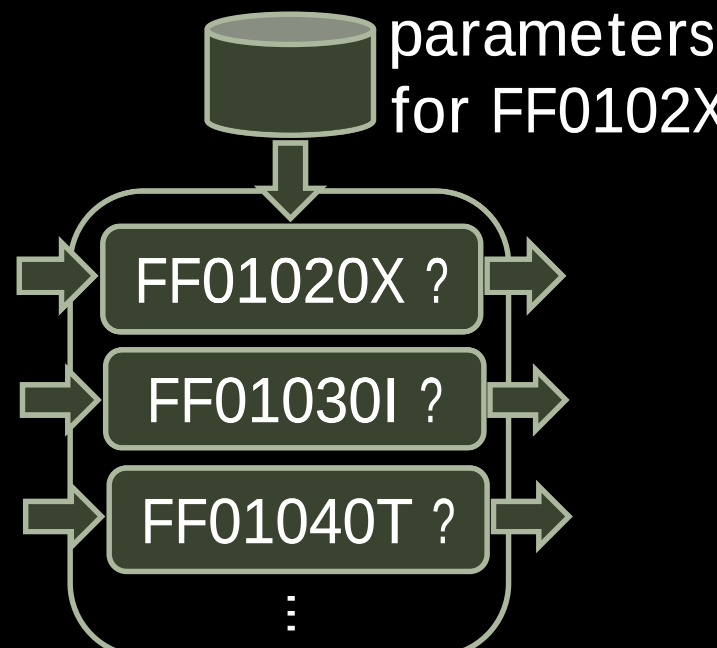


original training data



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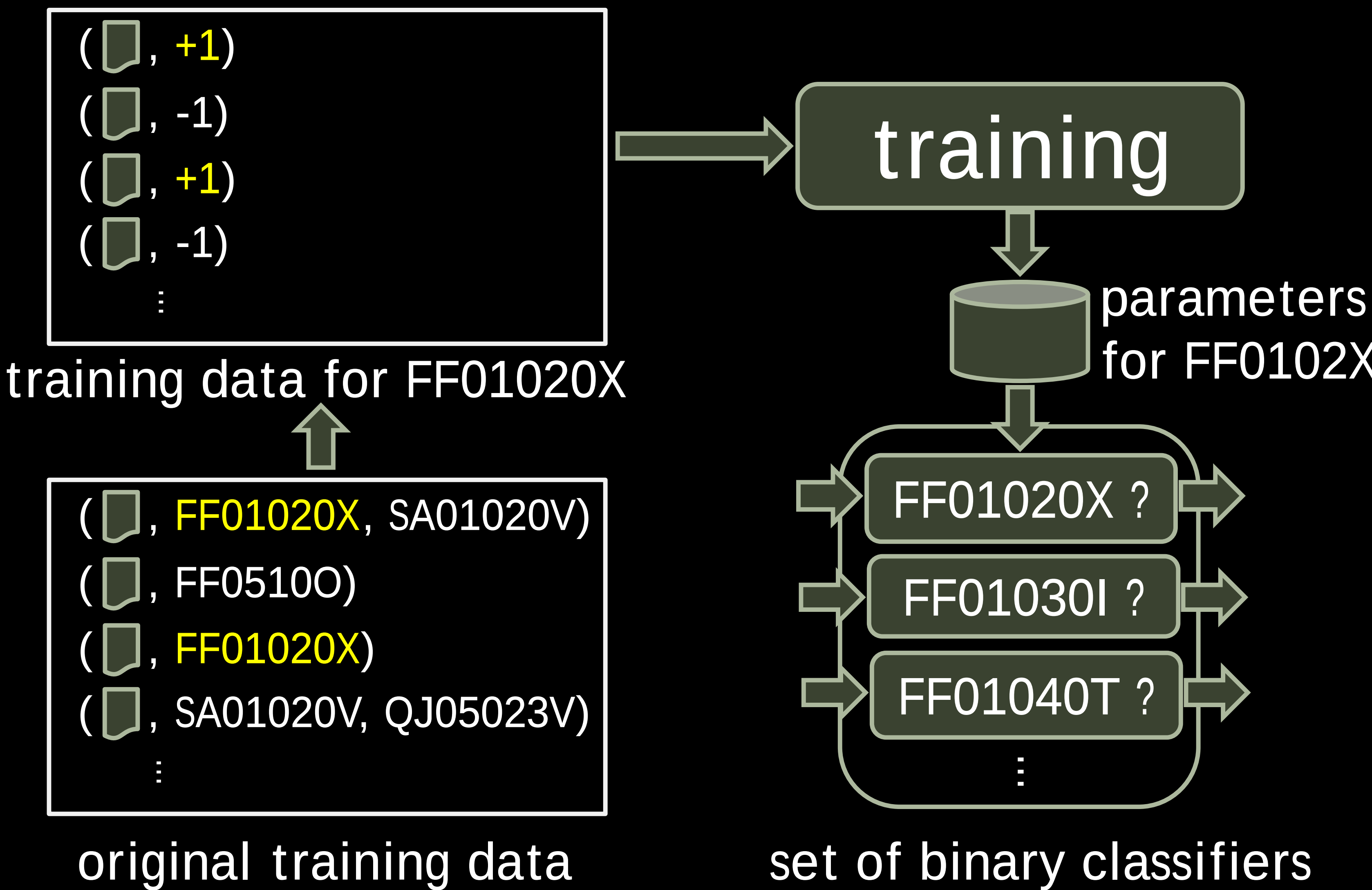
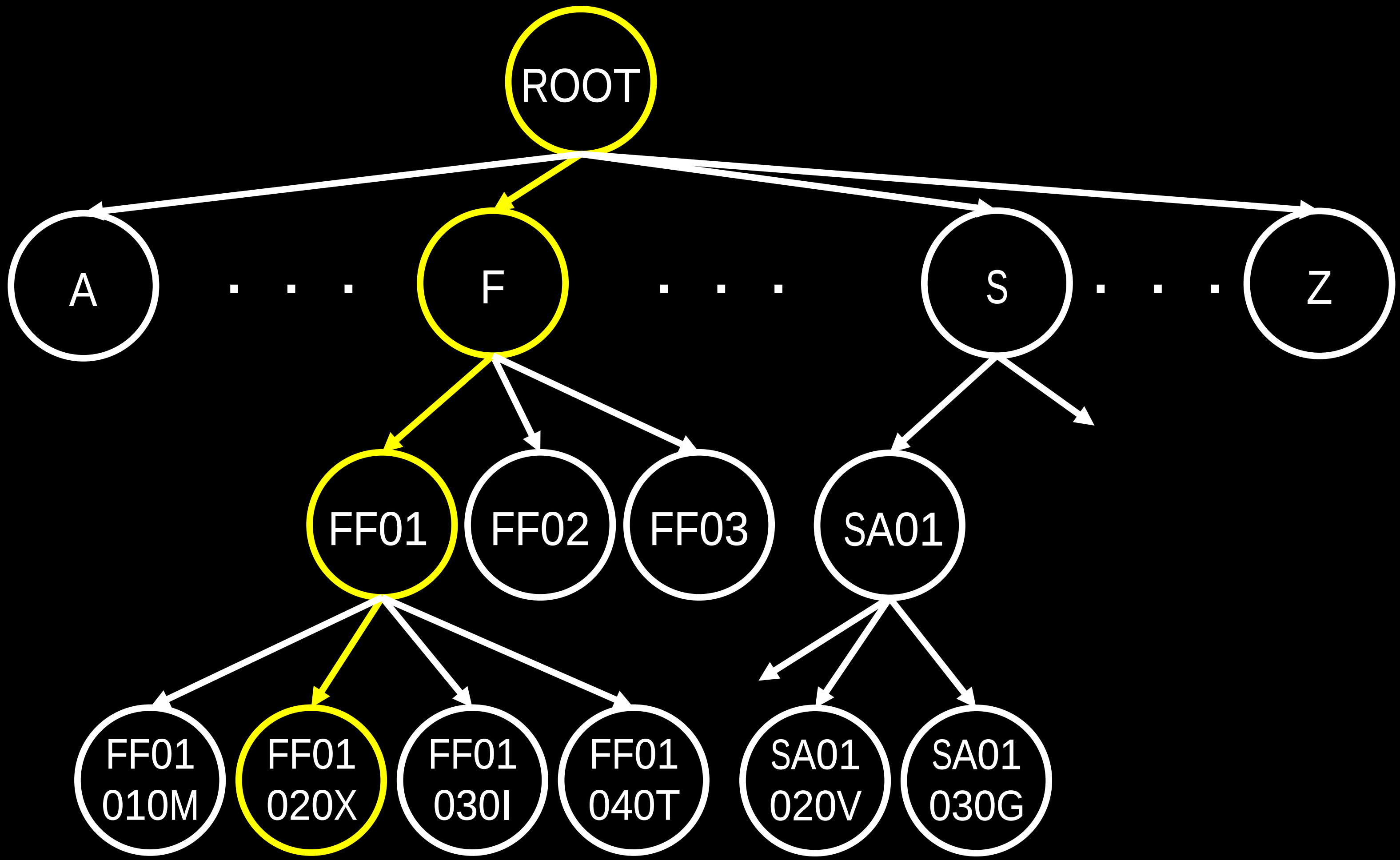


Tree Models 1/2



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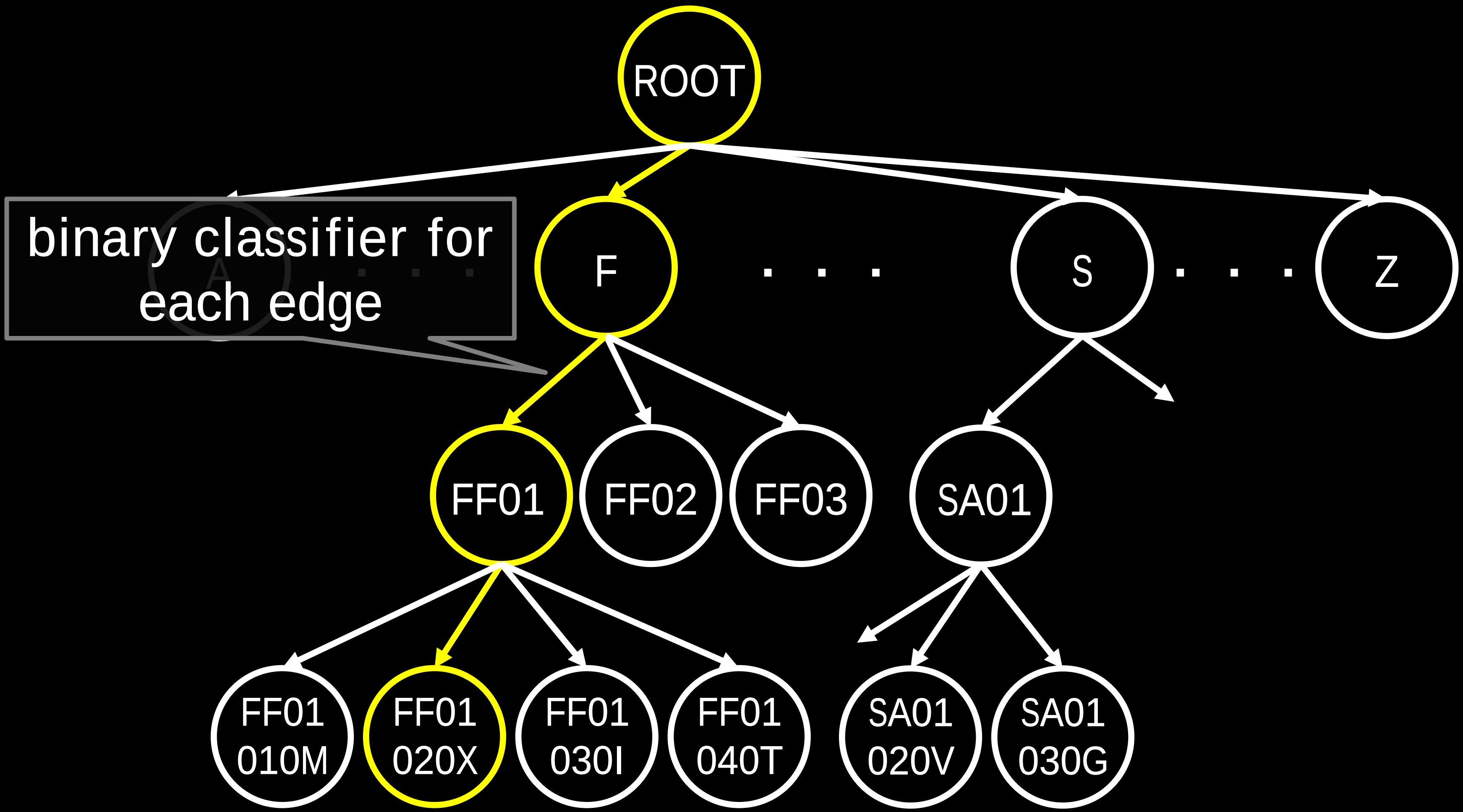
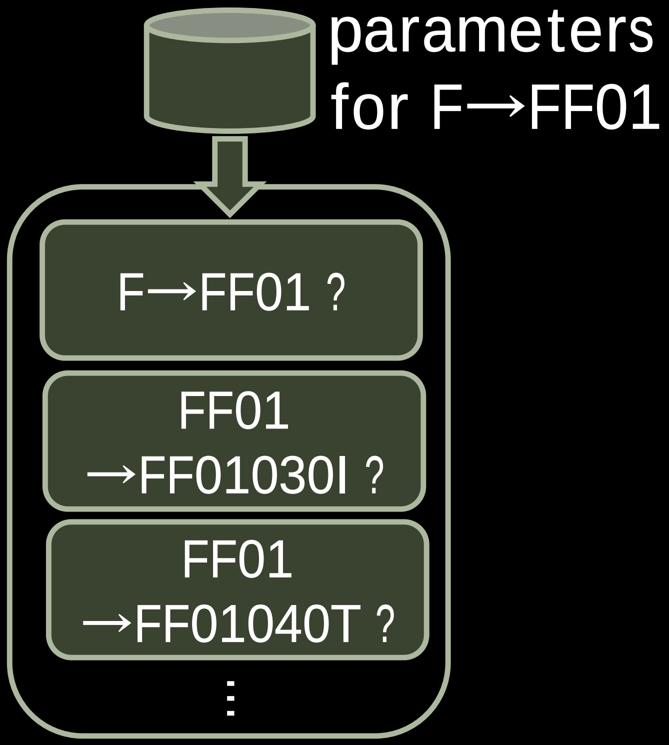


Tree Models 2/2

(, FF01020X, SA01020V)
(, FF0510O)
(, FF01020X)
(, SA01020V, QJ05023V)
⋮

original training data



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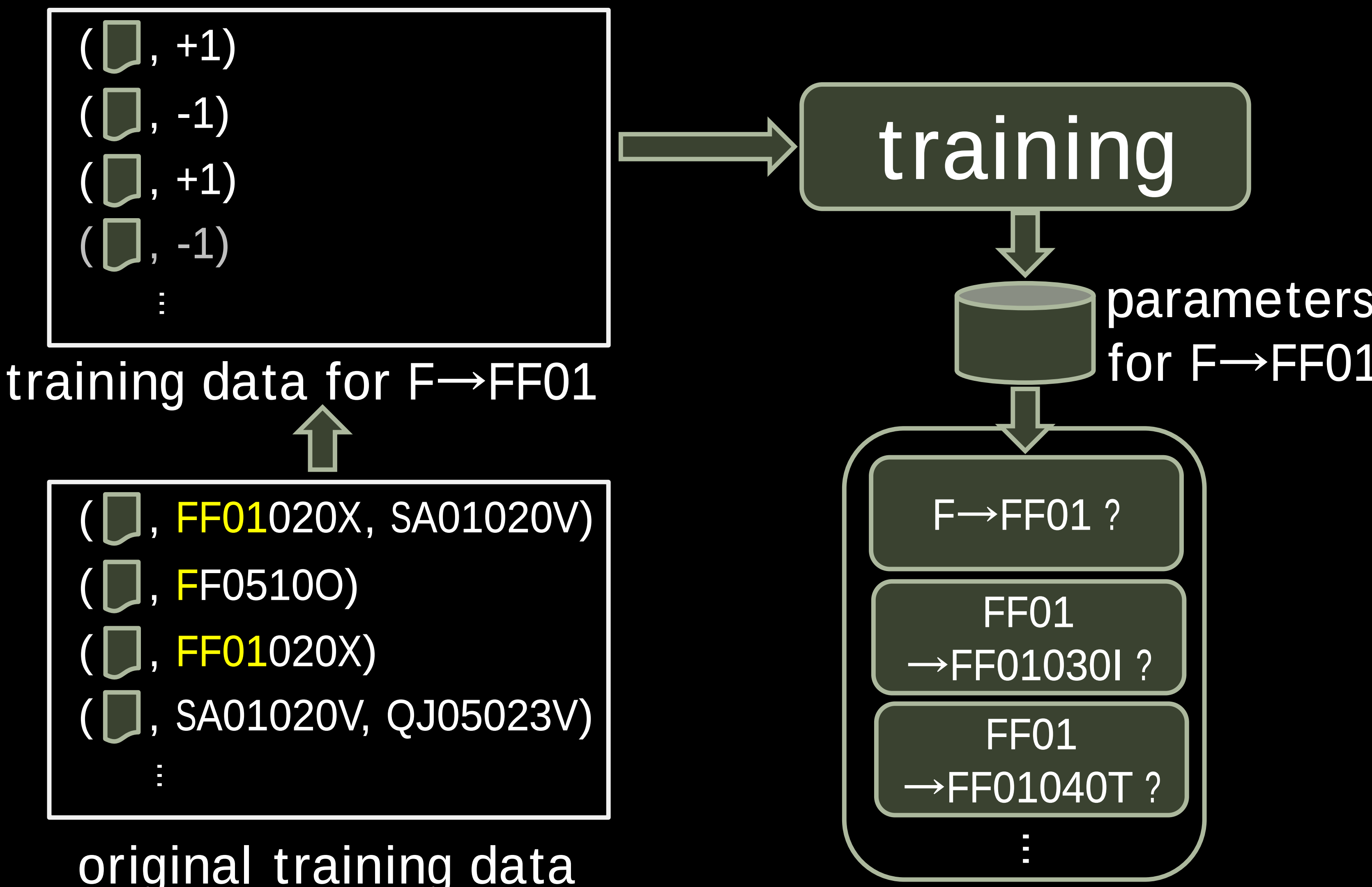

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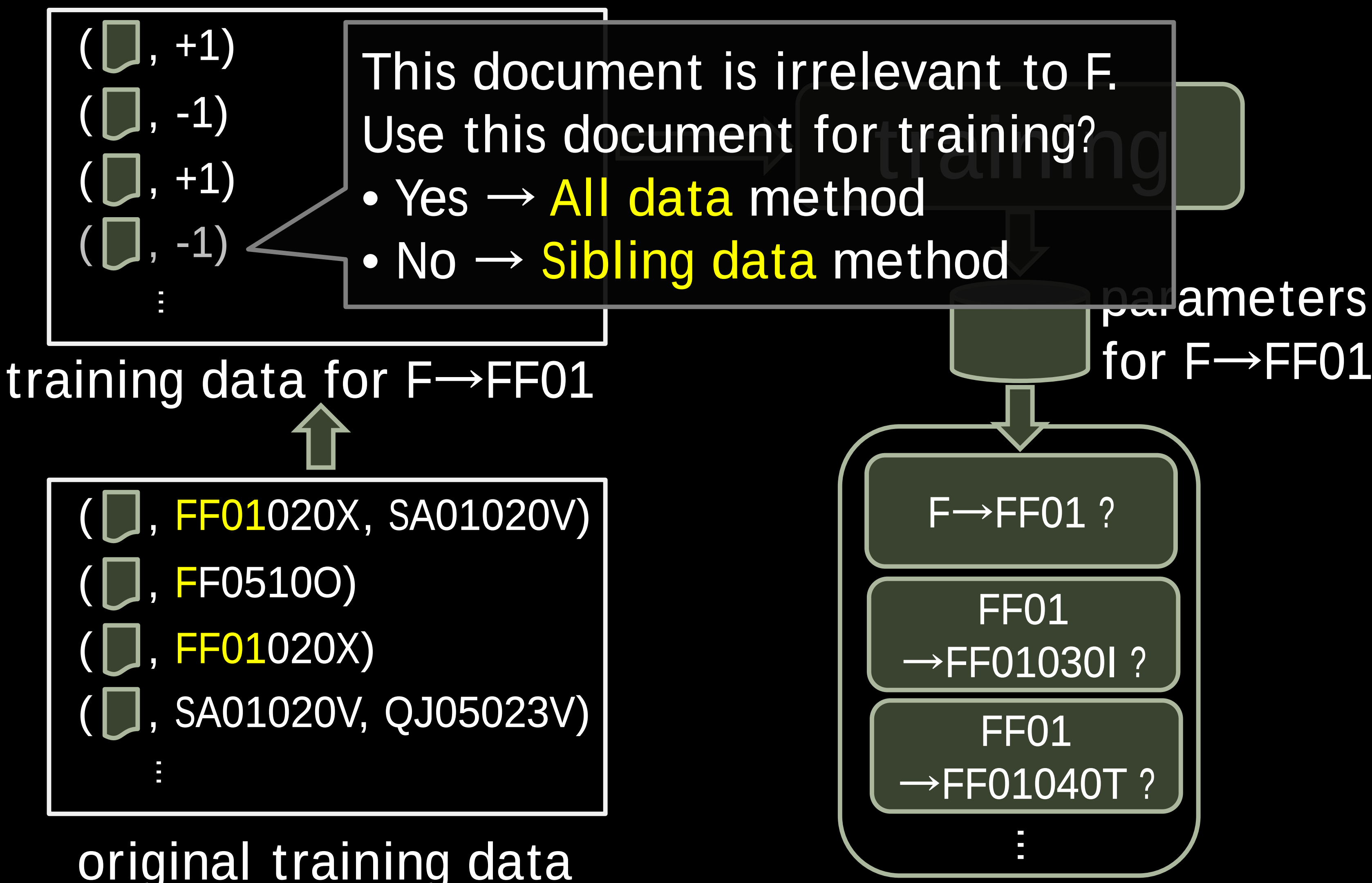
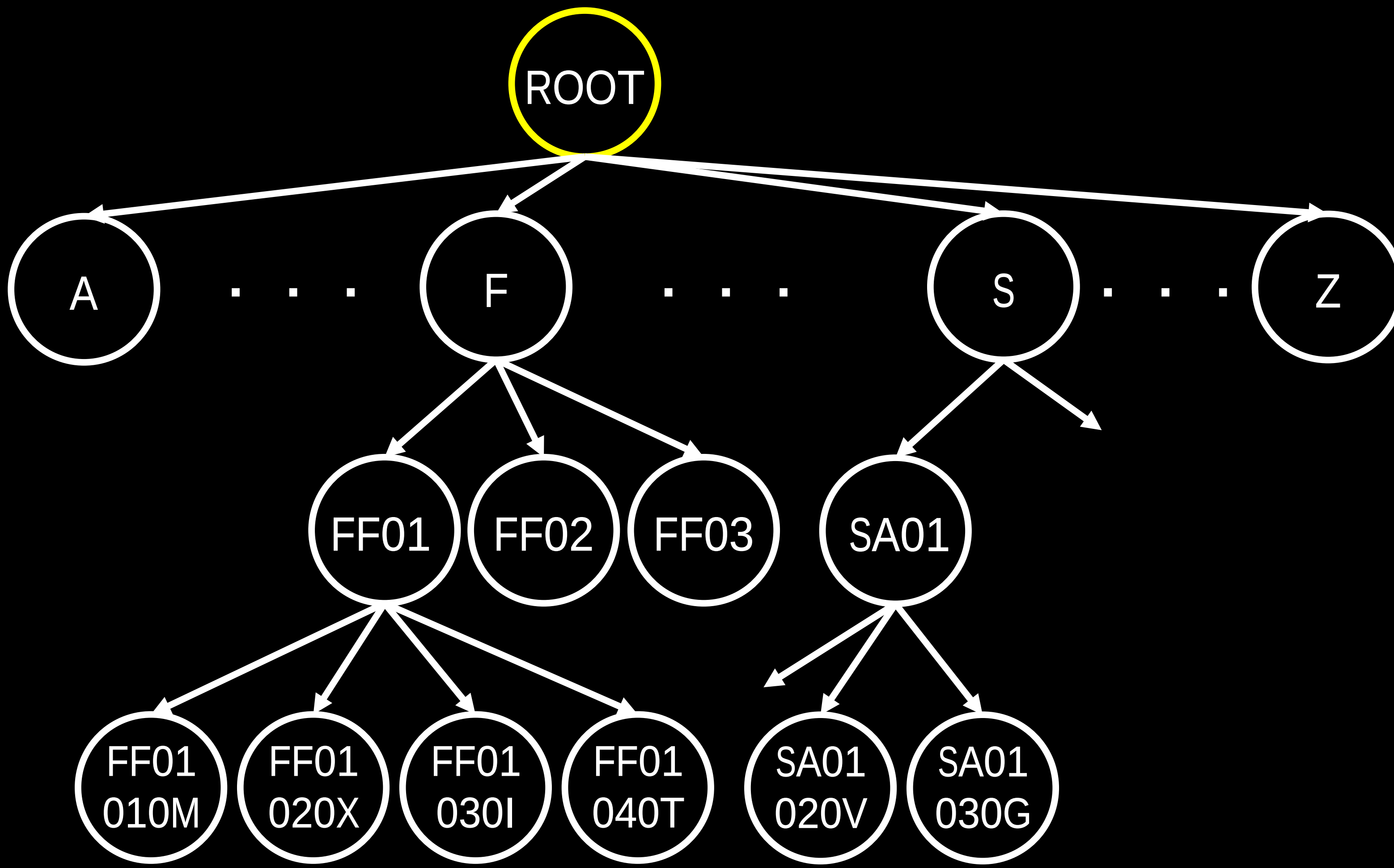


Top-down Pruning



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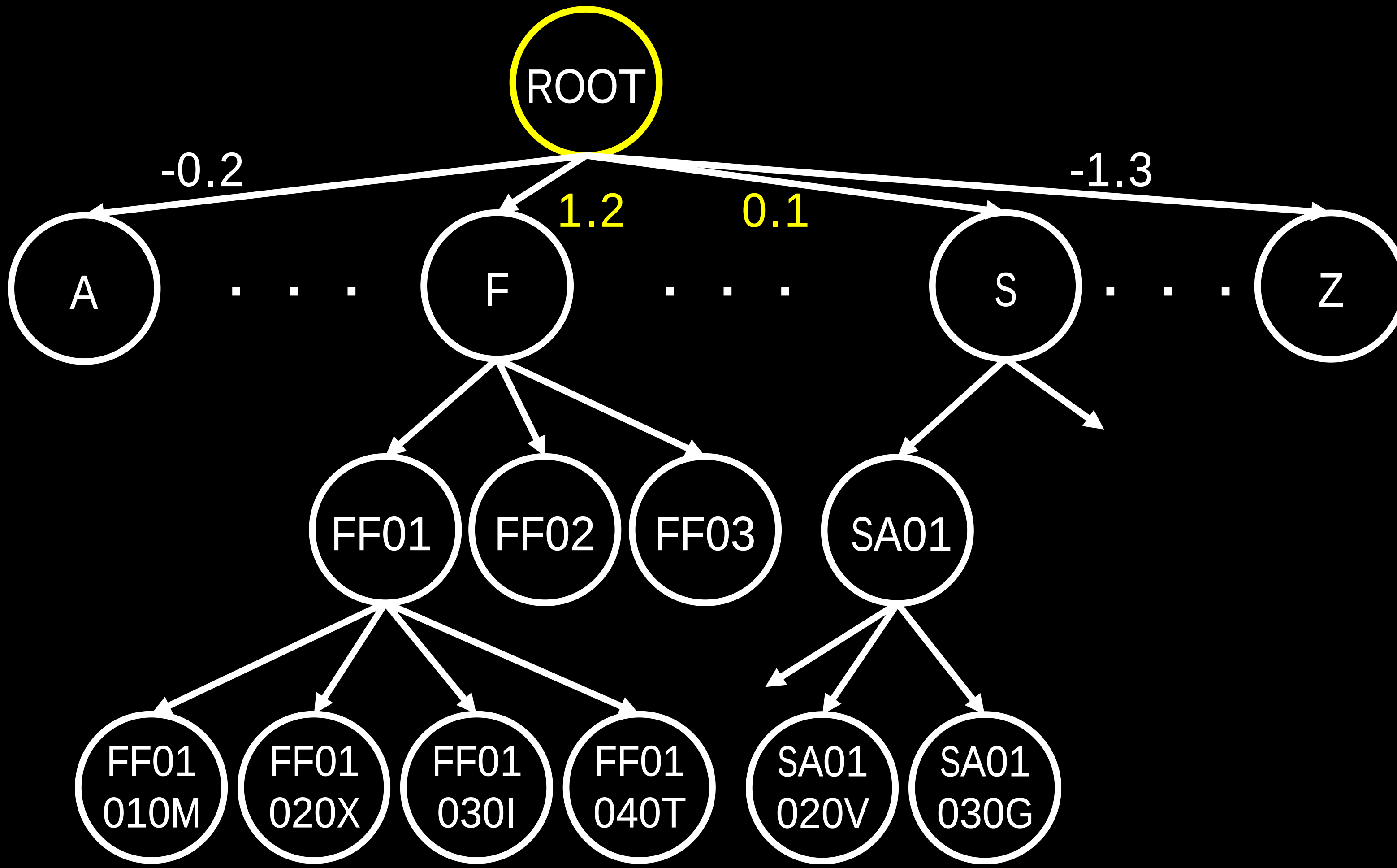

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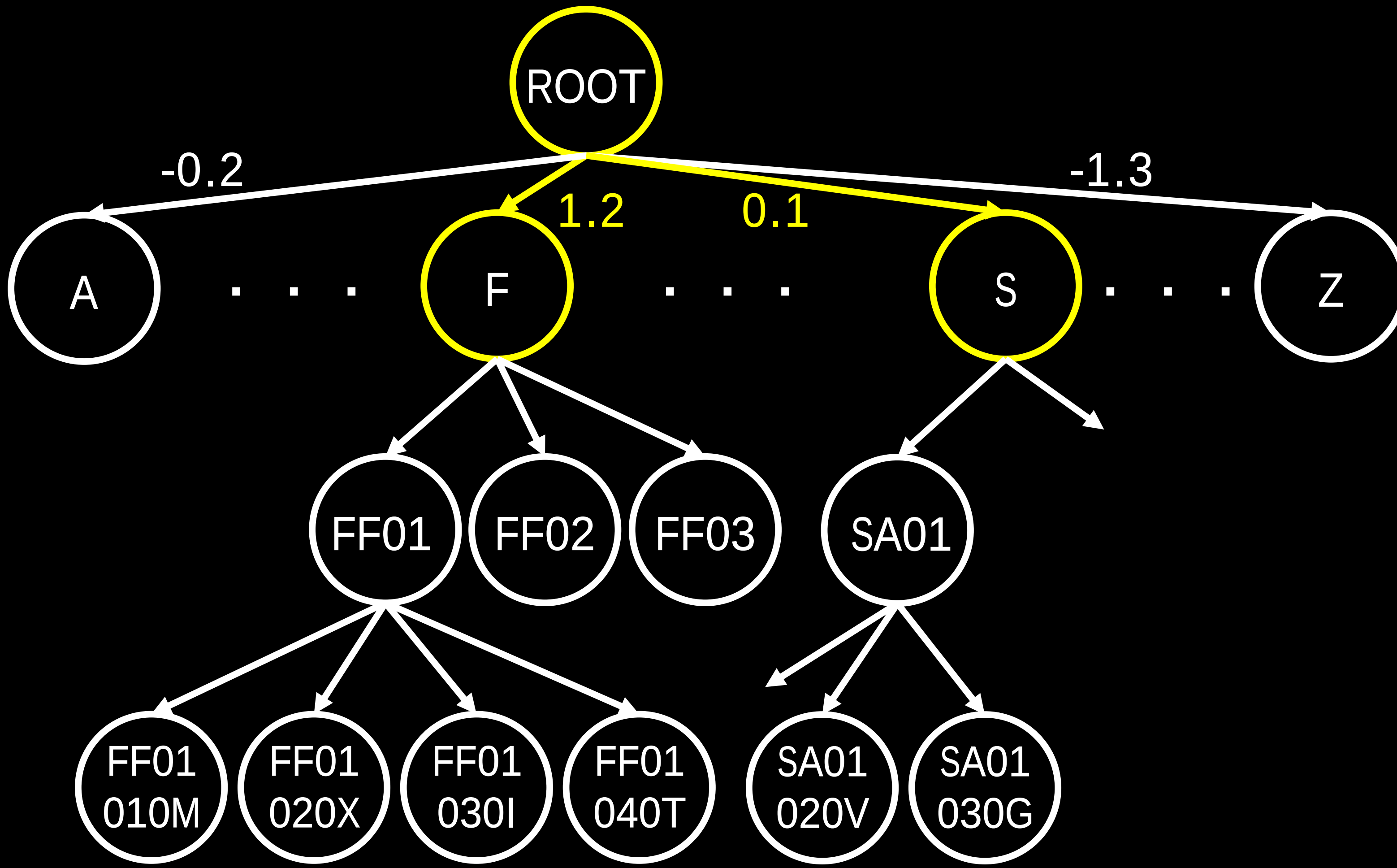

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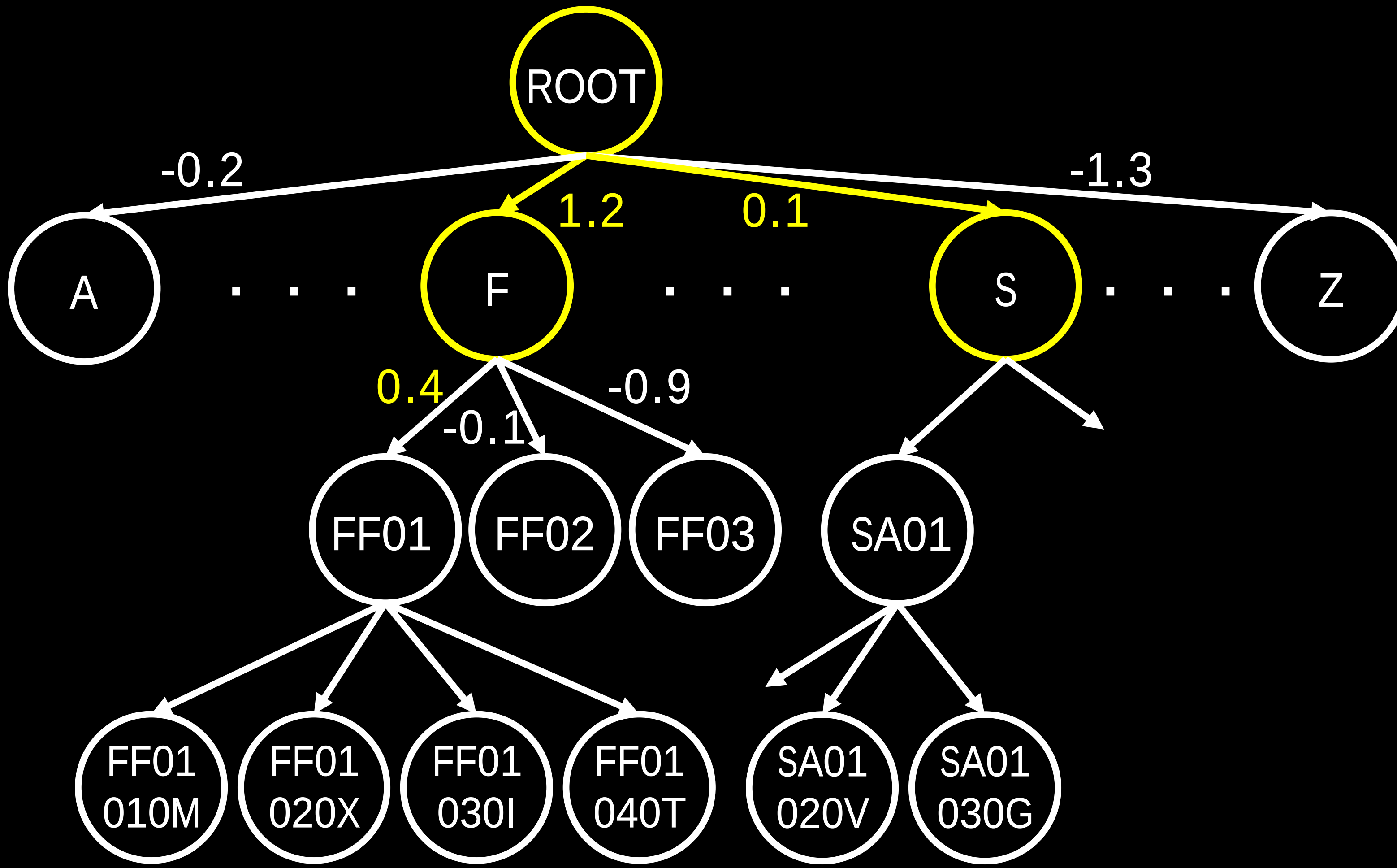

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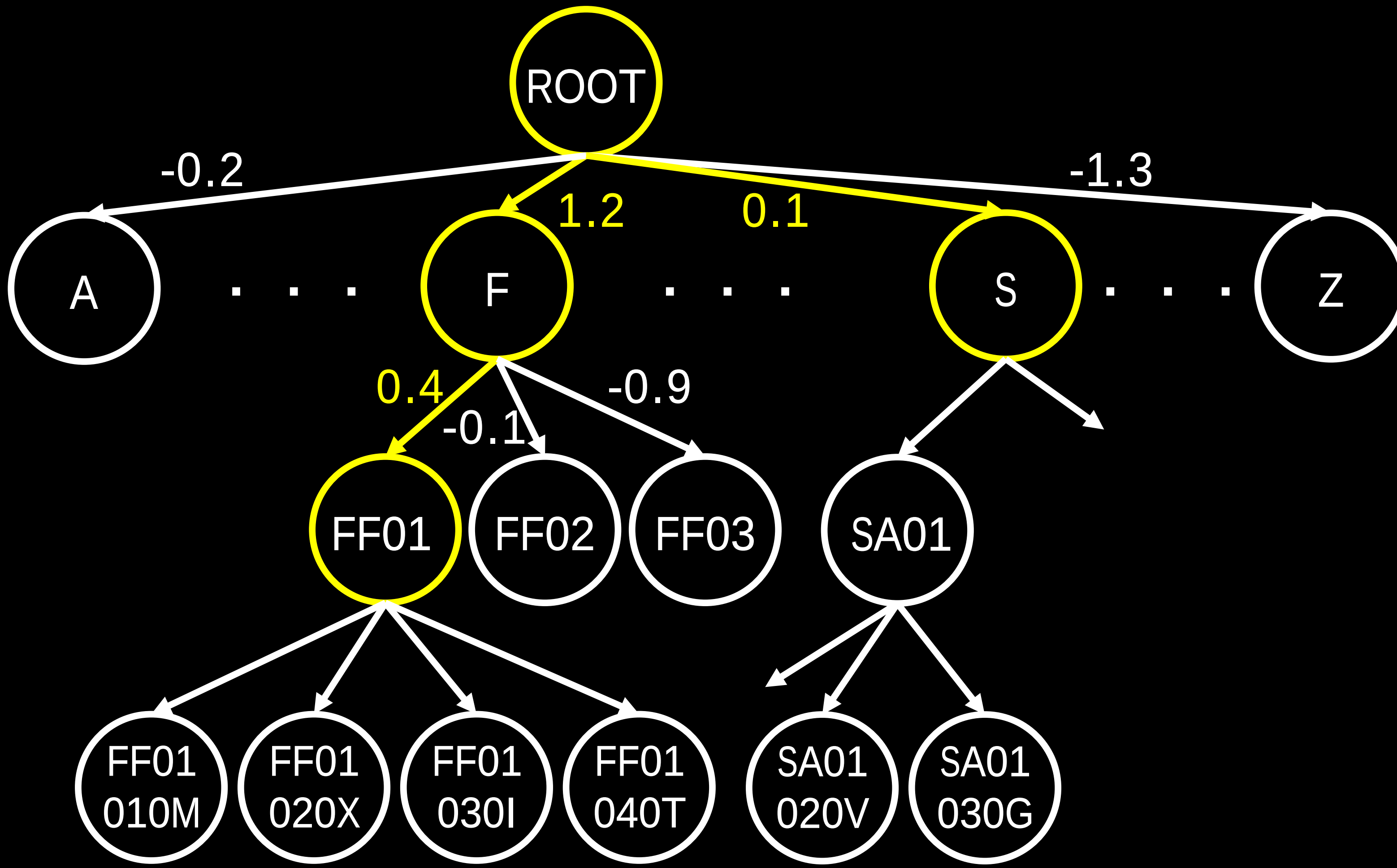

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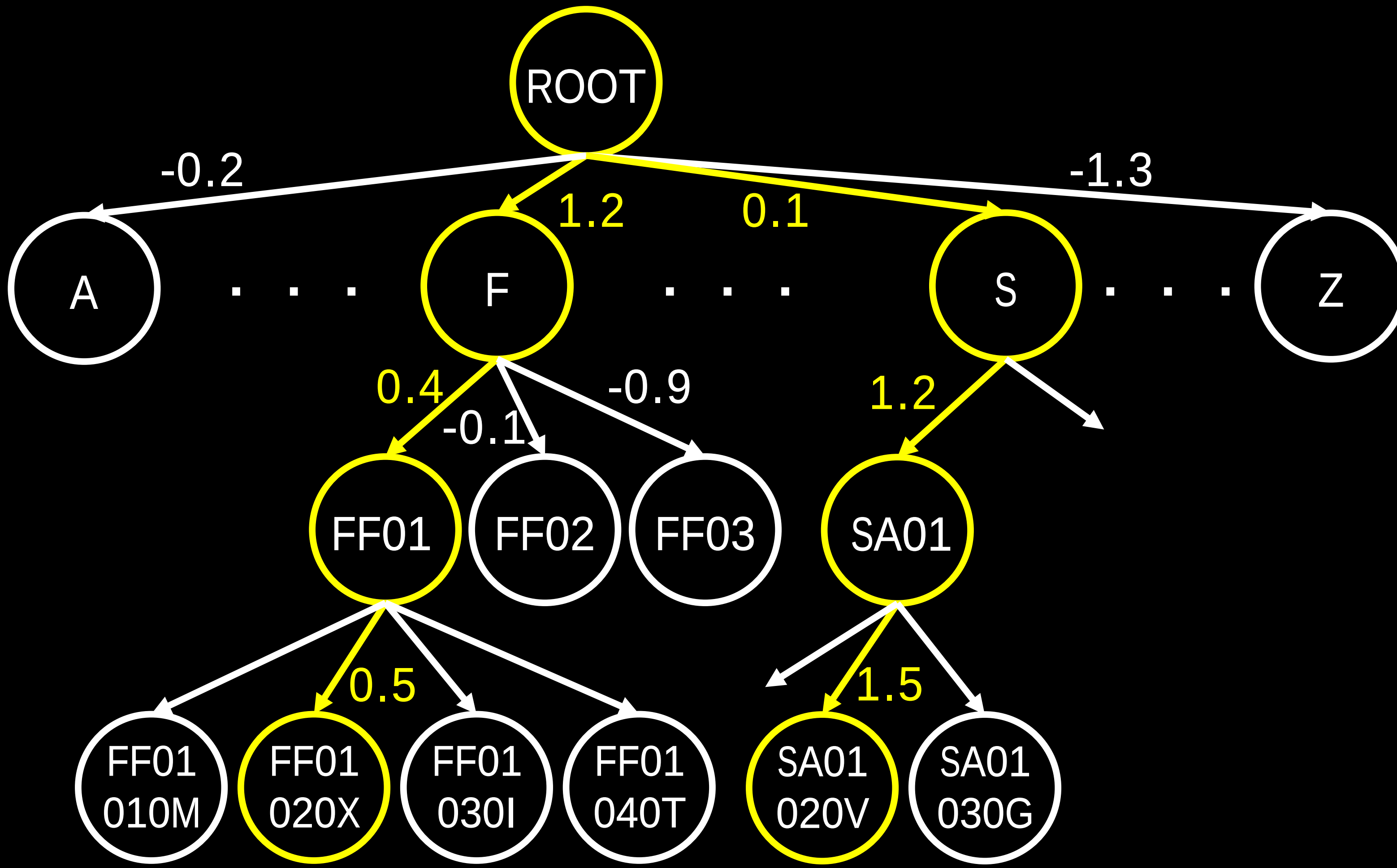

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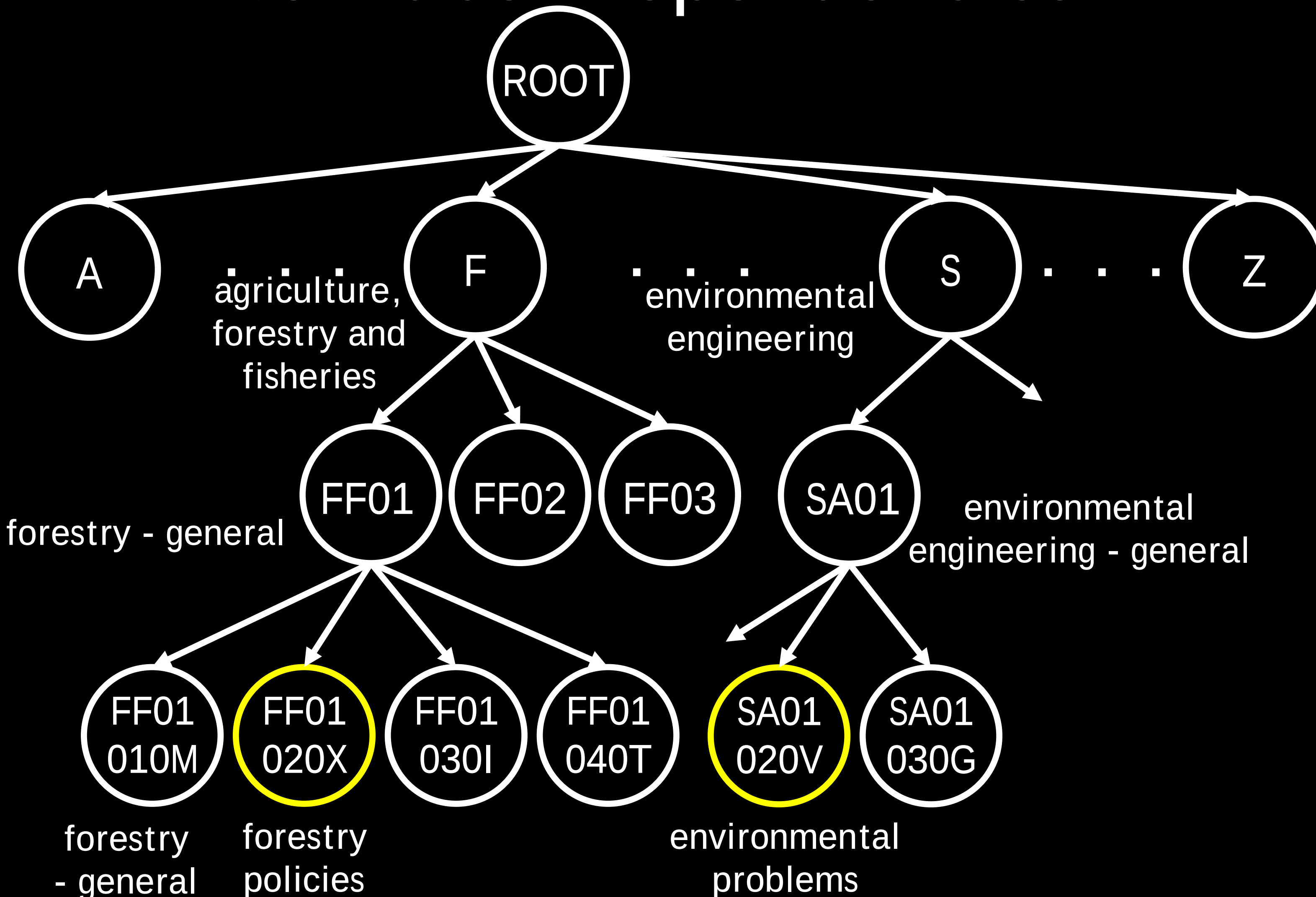
Proposed Method: Hierarchy for Multiple Labels

- Need to choose not just one best
- How many labels should we choose?
  A difficult question even for humans
- Our assumption: Human annotators do not select each label independently but consider the relative importance among competing labels by consulting the hierarchy

Intuition: Hierarchy Encodes Inter-label Dependencies



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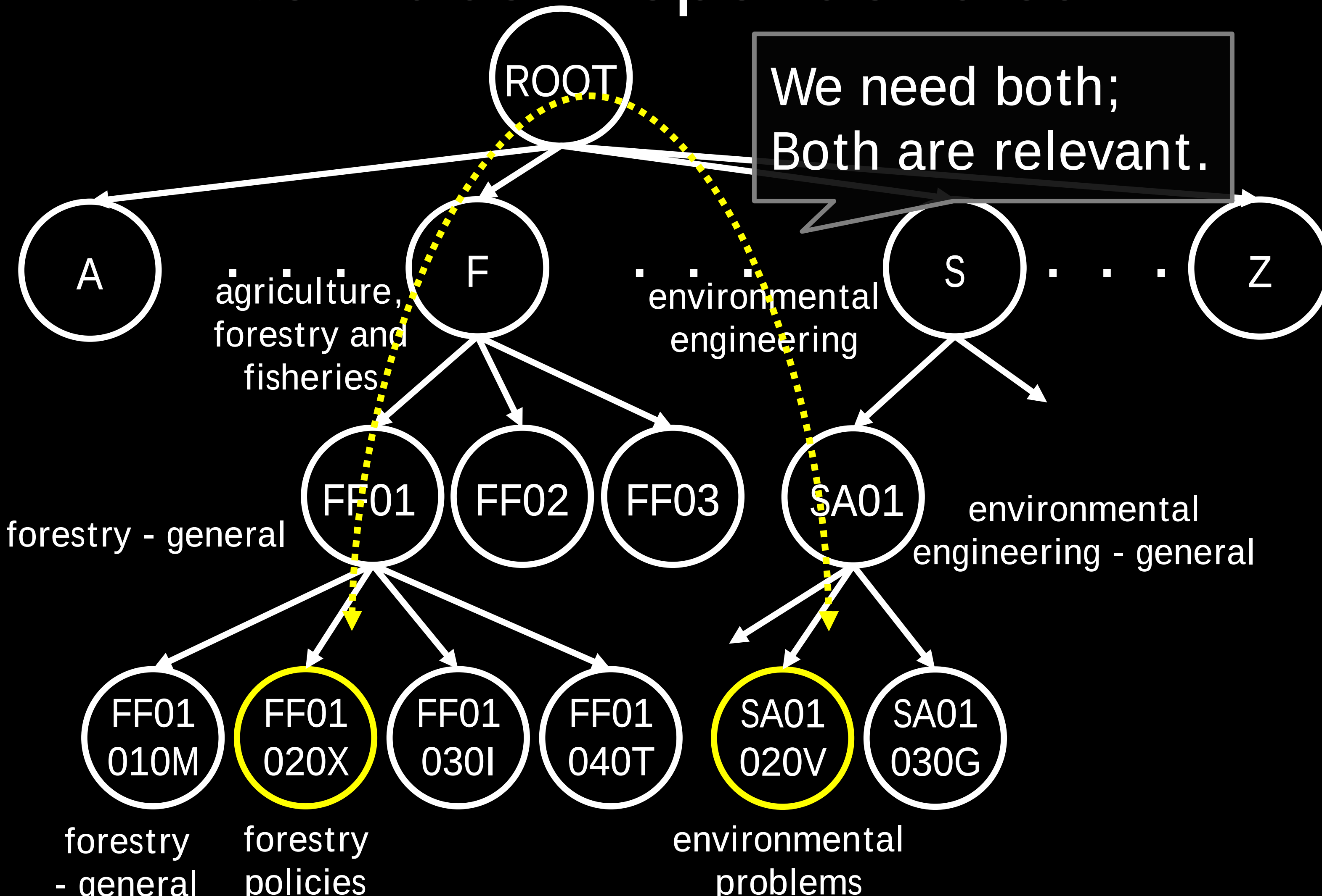

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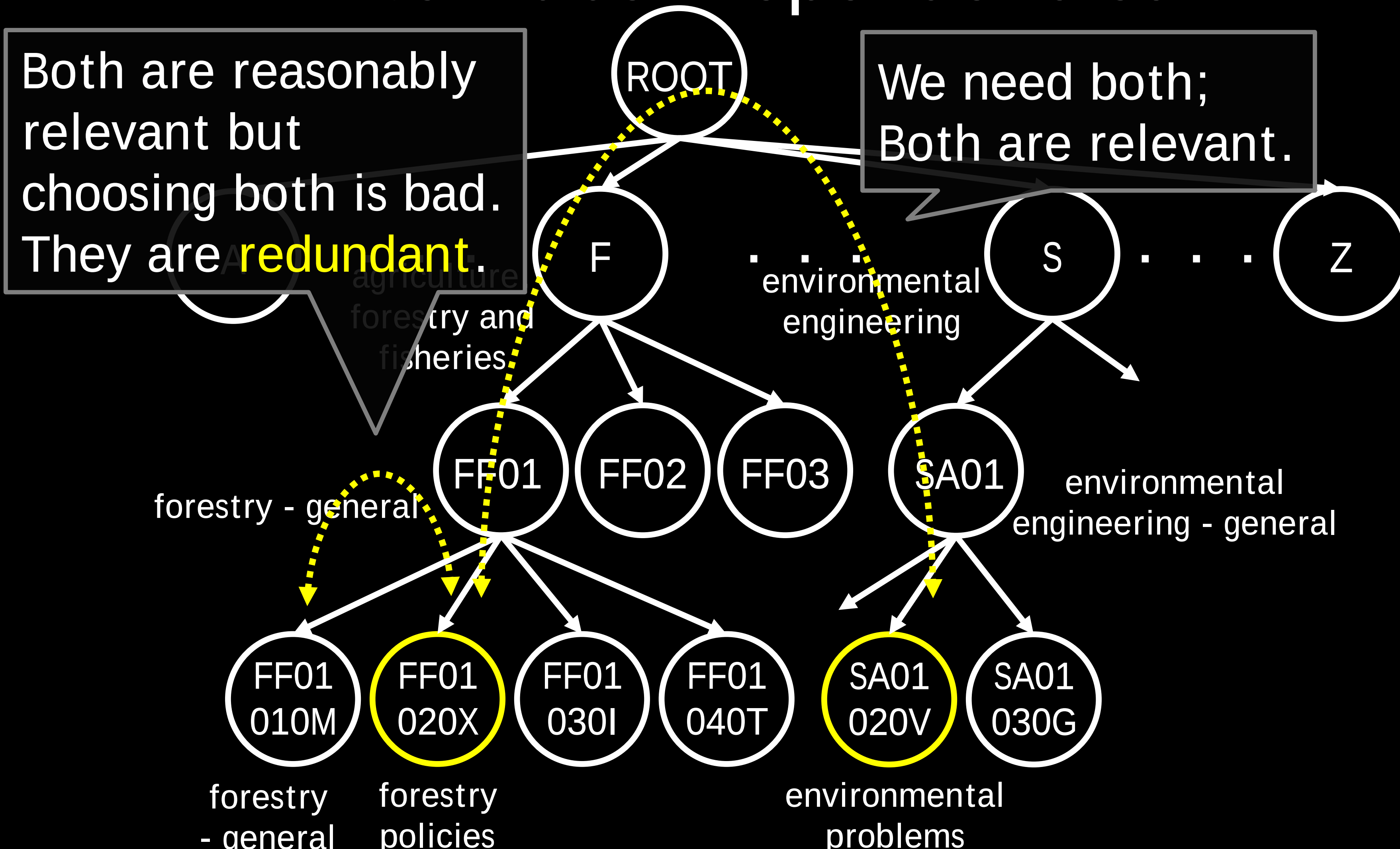

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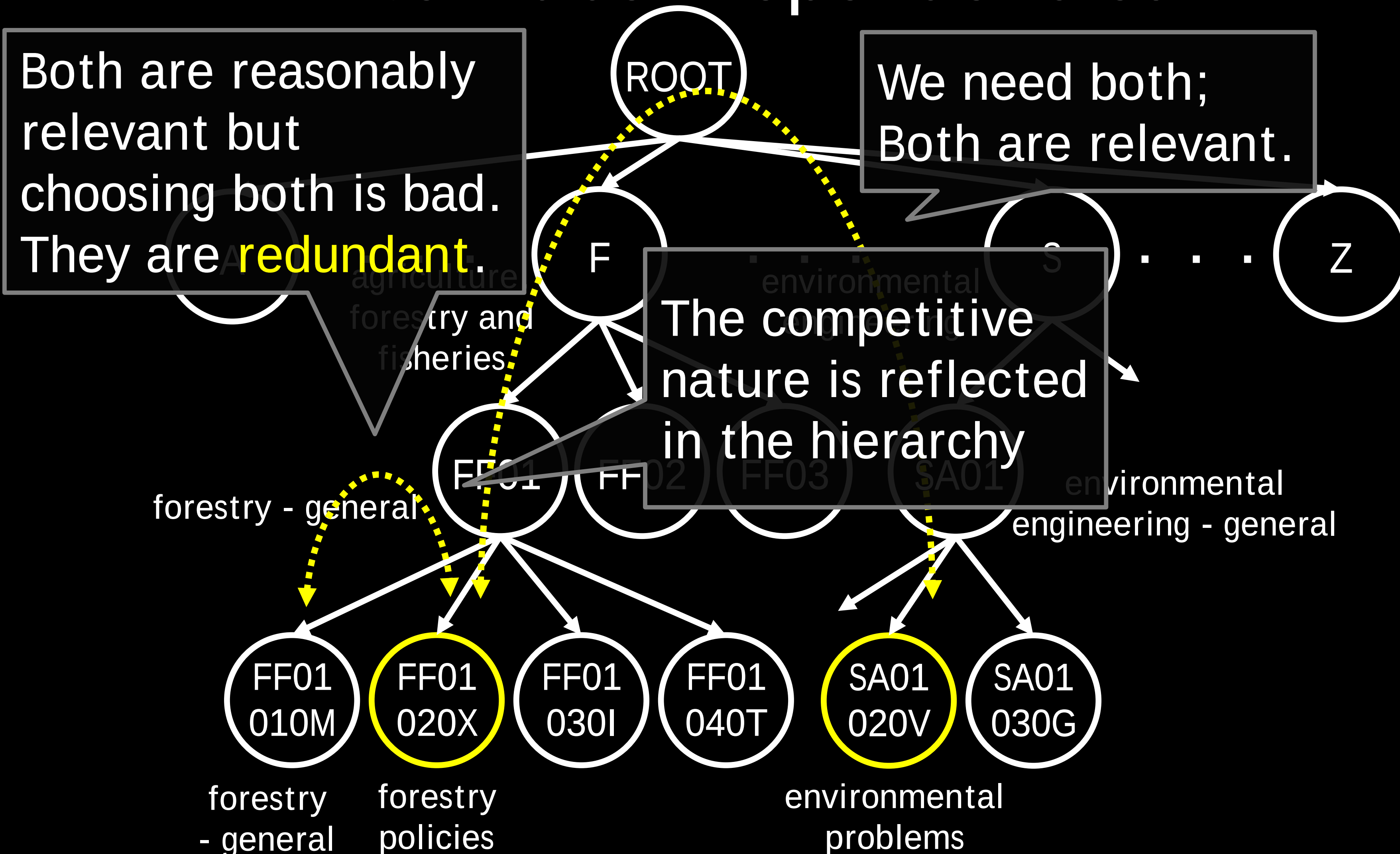
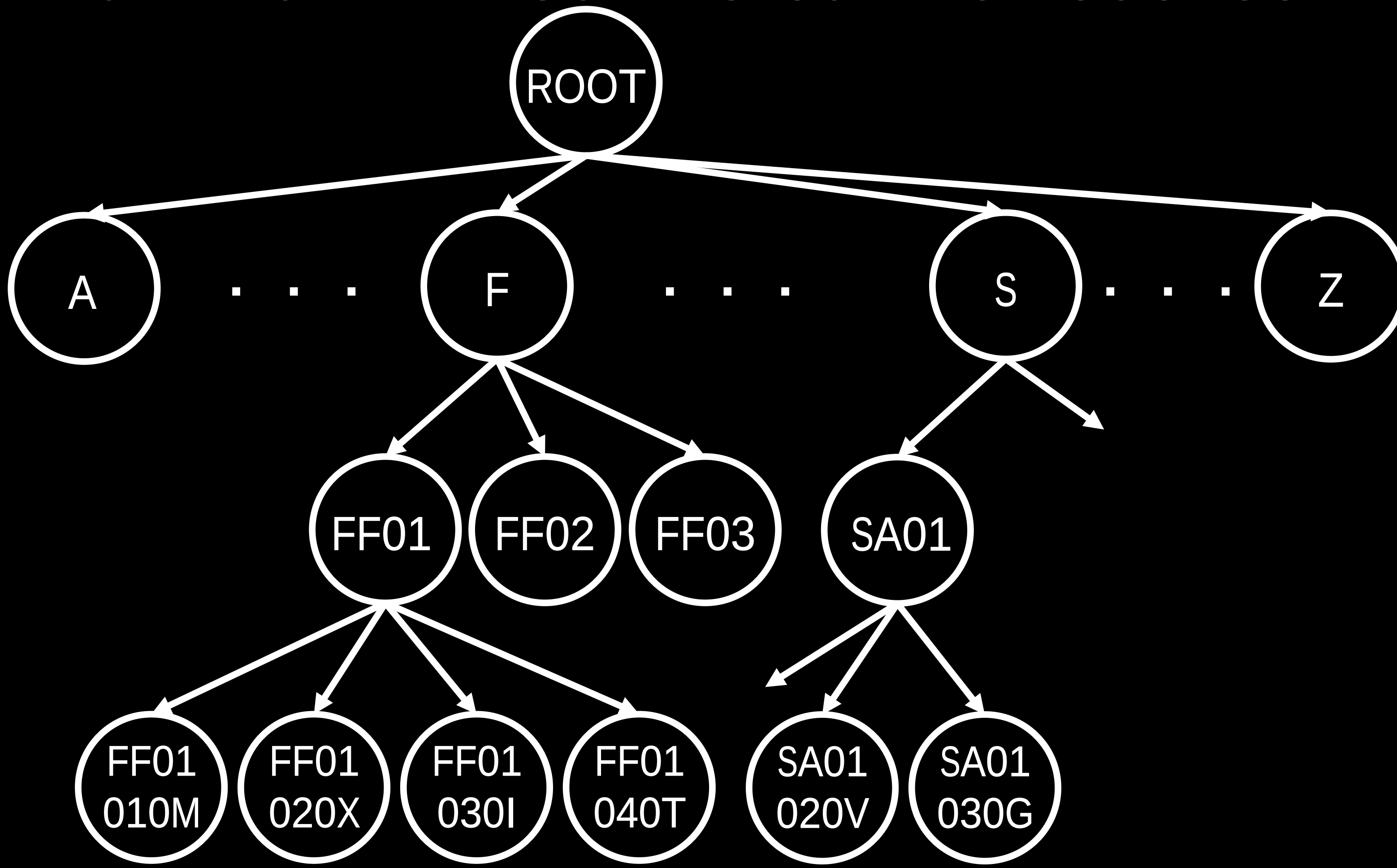


Preparation: Global Model

- Want to capture dependencies among multiple labels to be output
- First need to jointly predicts multiple labels
- Then capture inter-label dependencies by adding features to the global model

Global Model: Find a Subtree that maximizes the sum of scores



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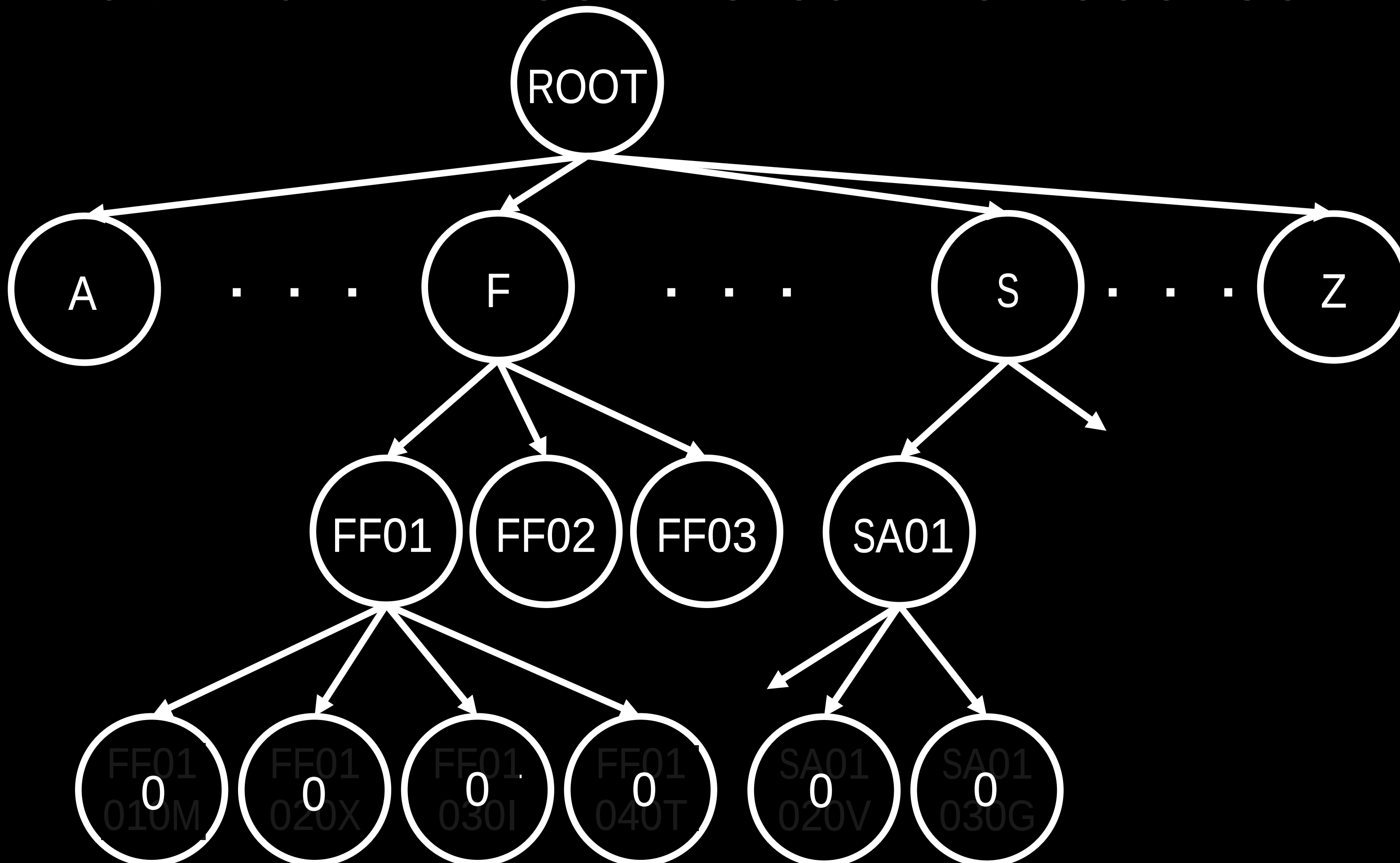

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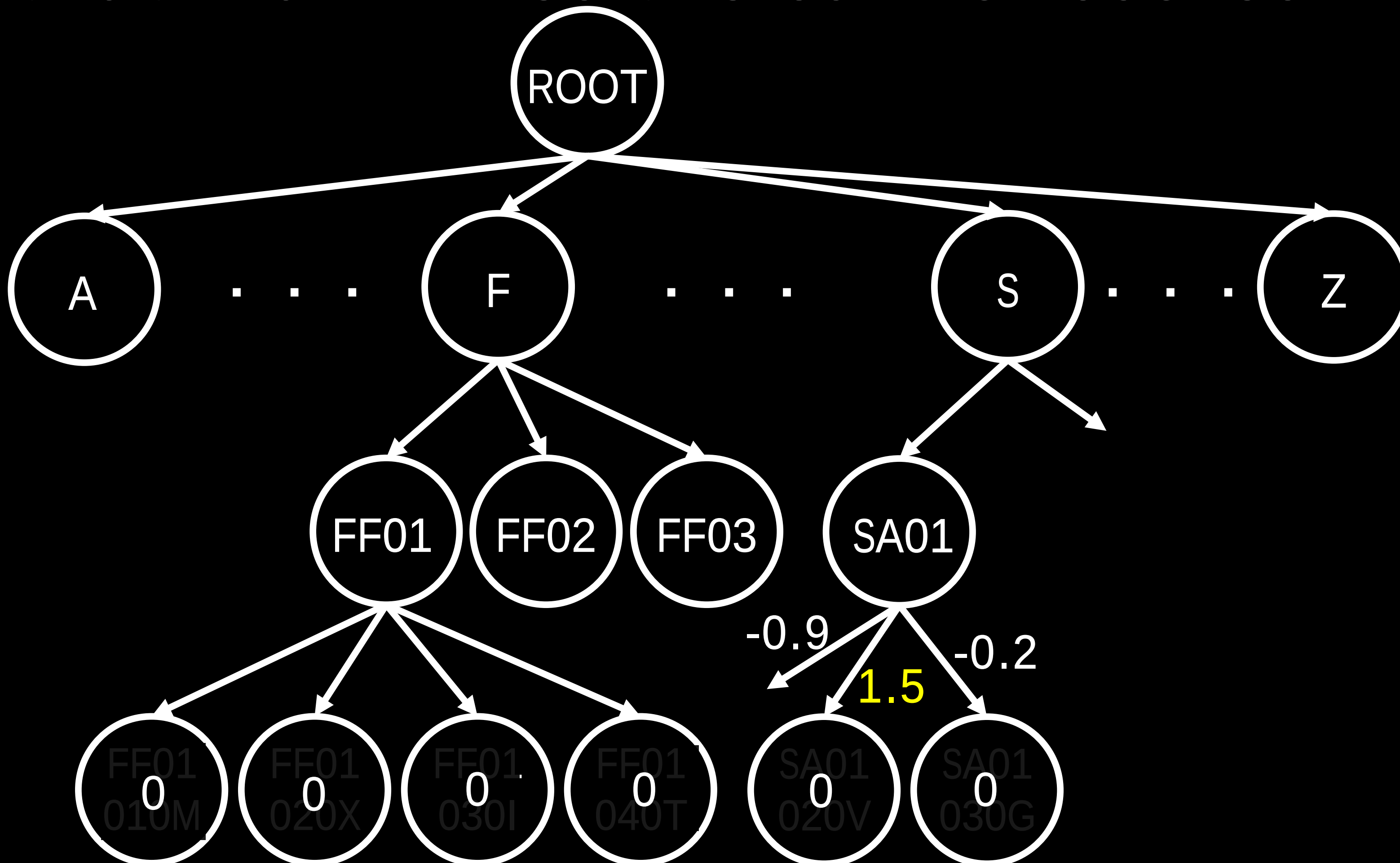

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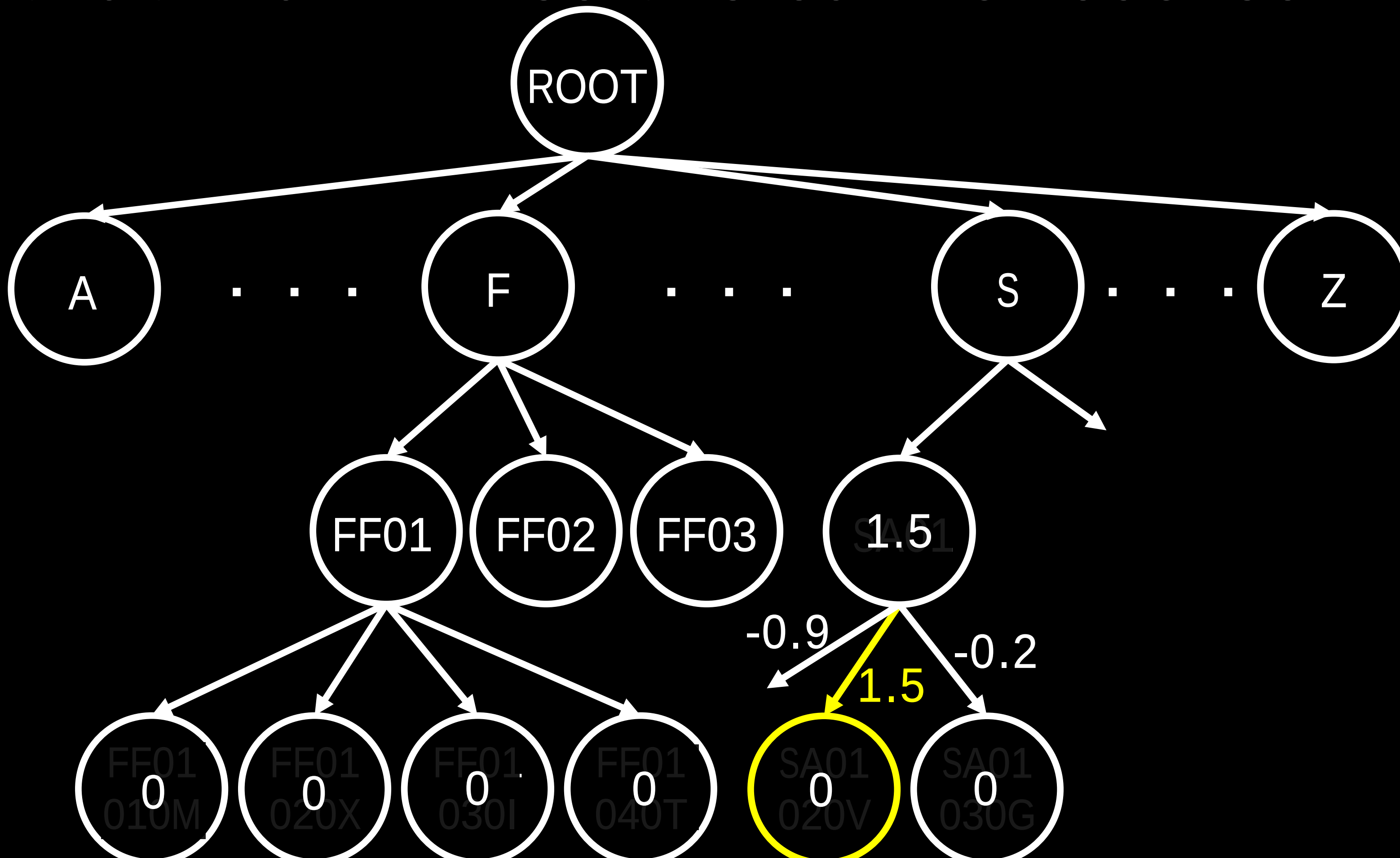

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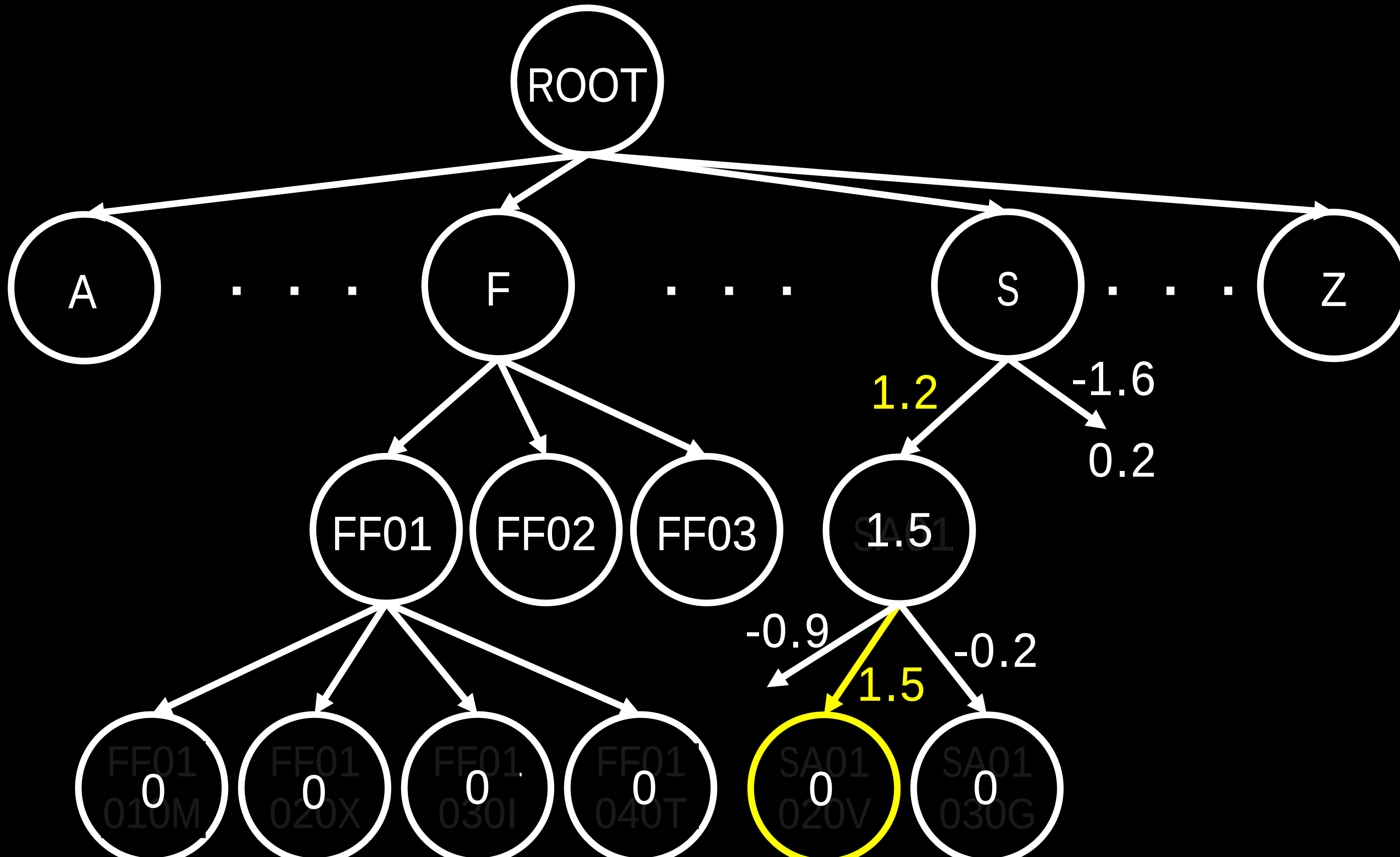

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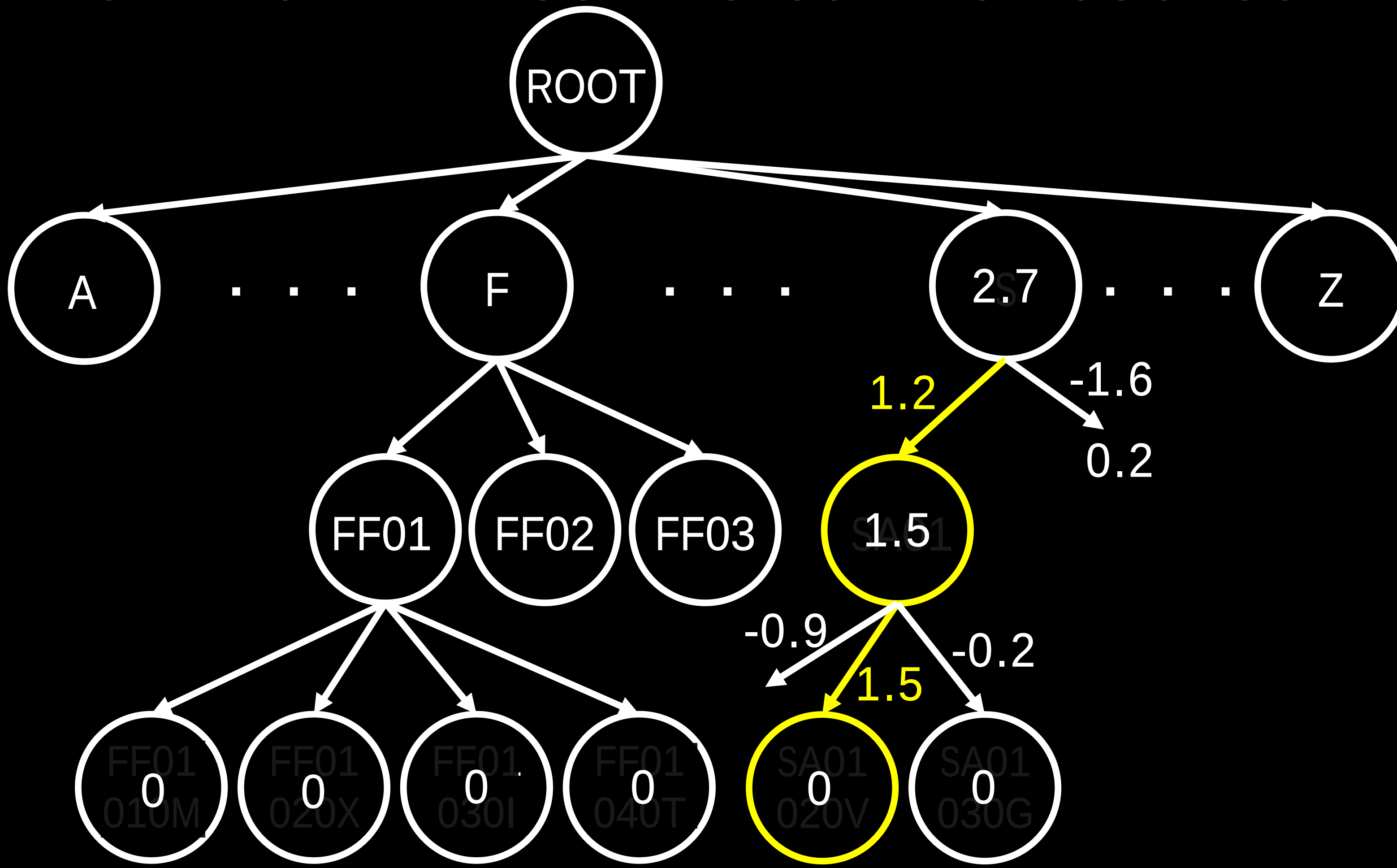

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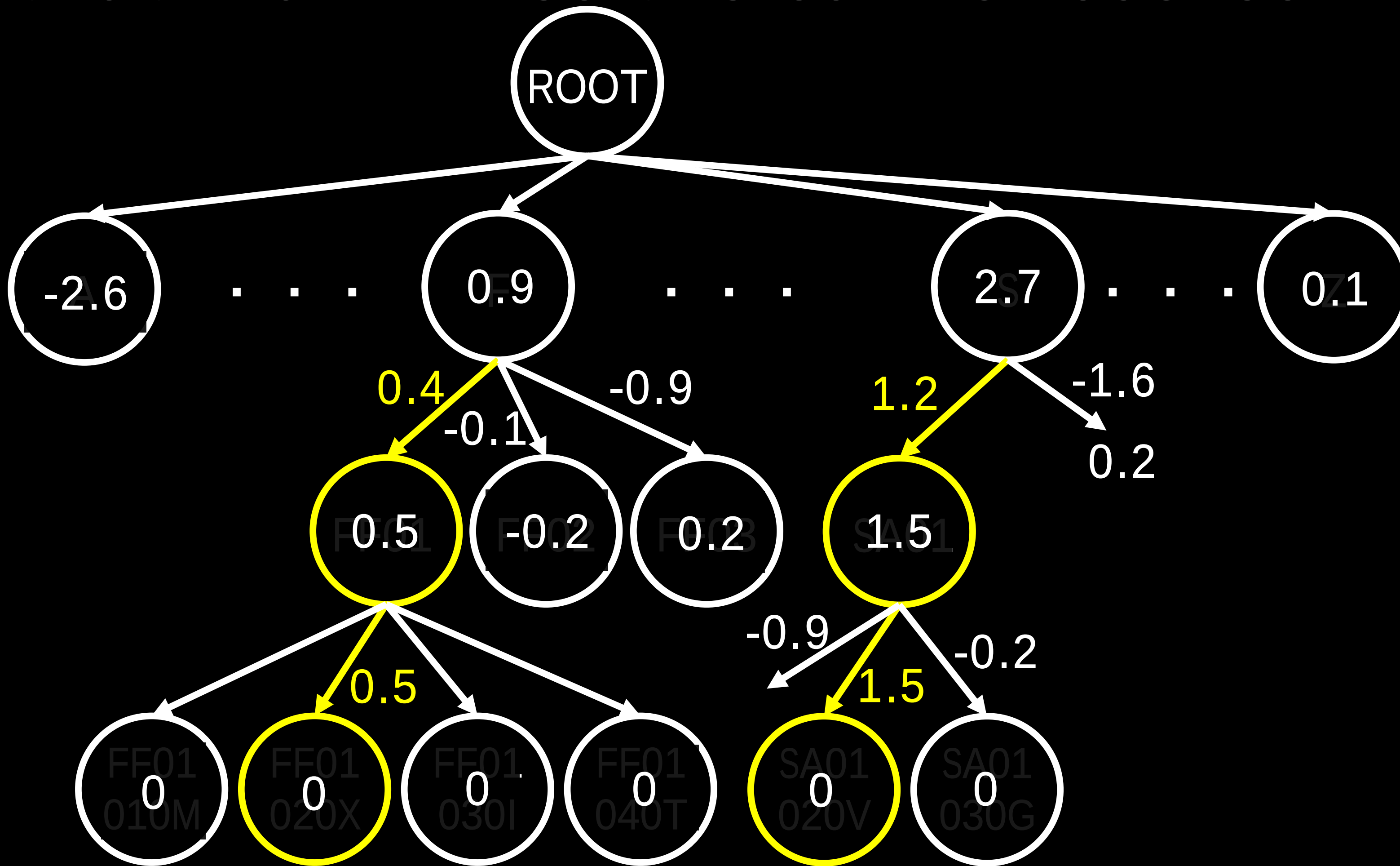

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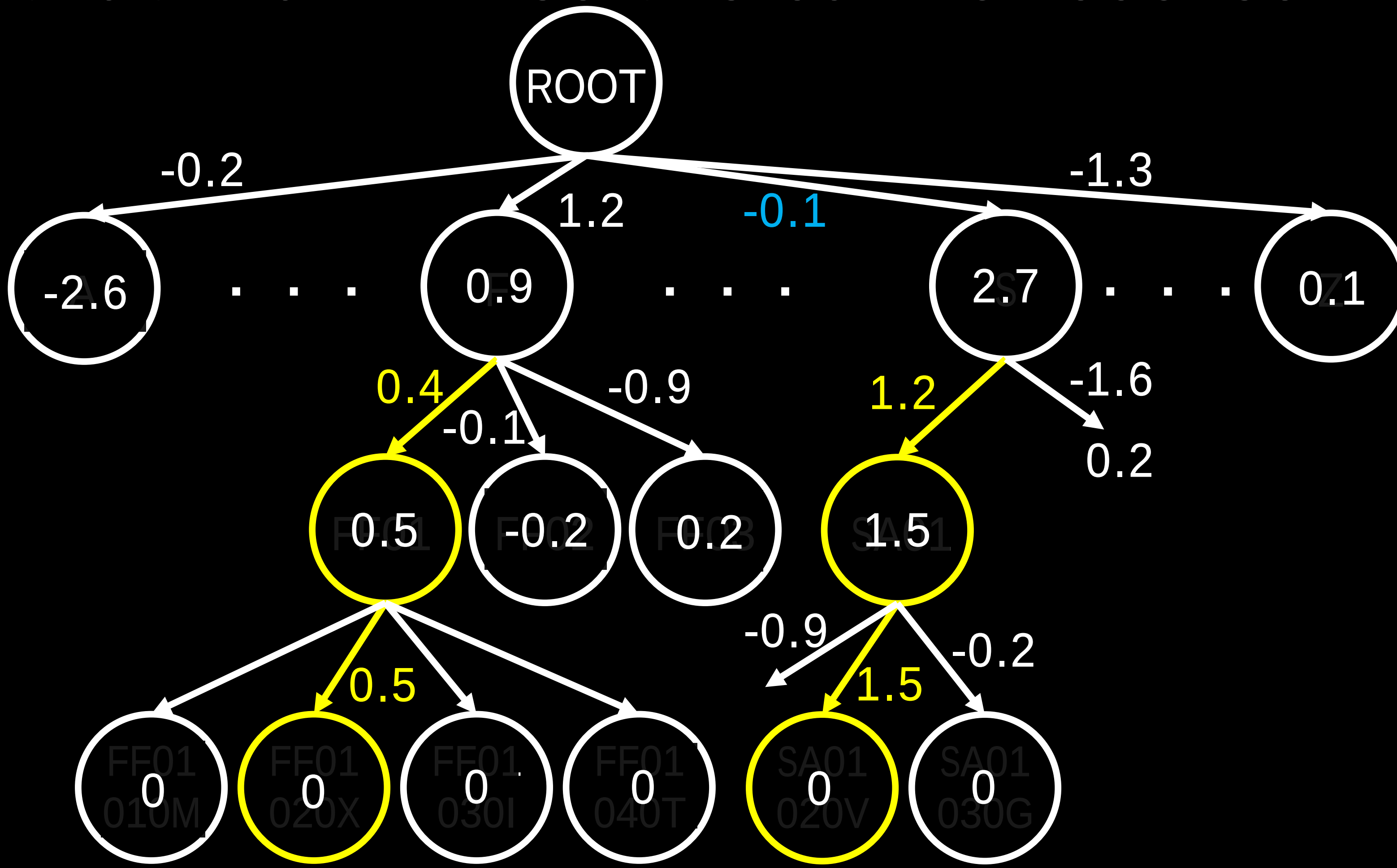

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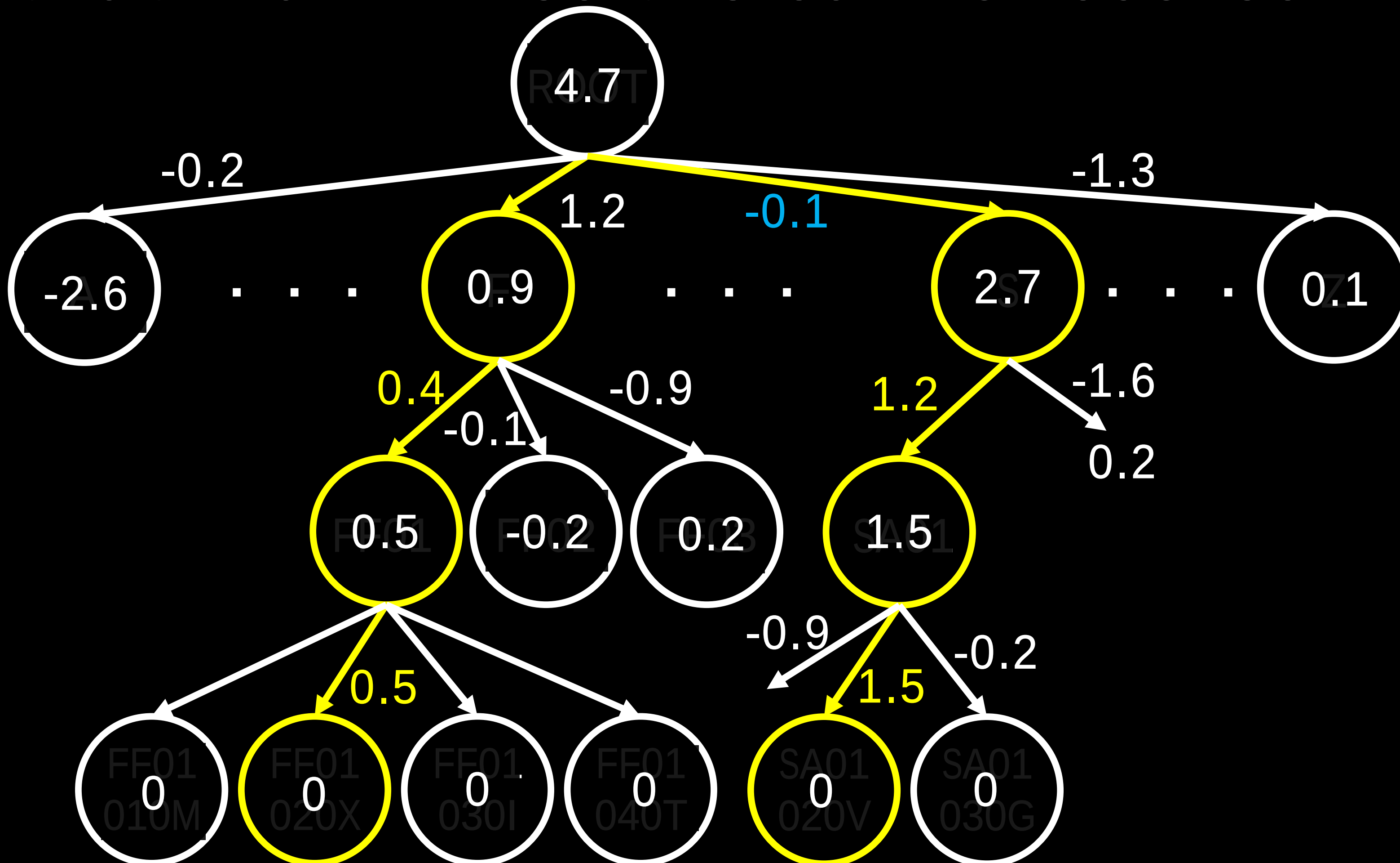

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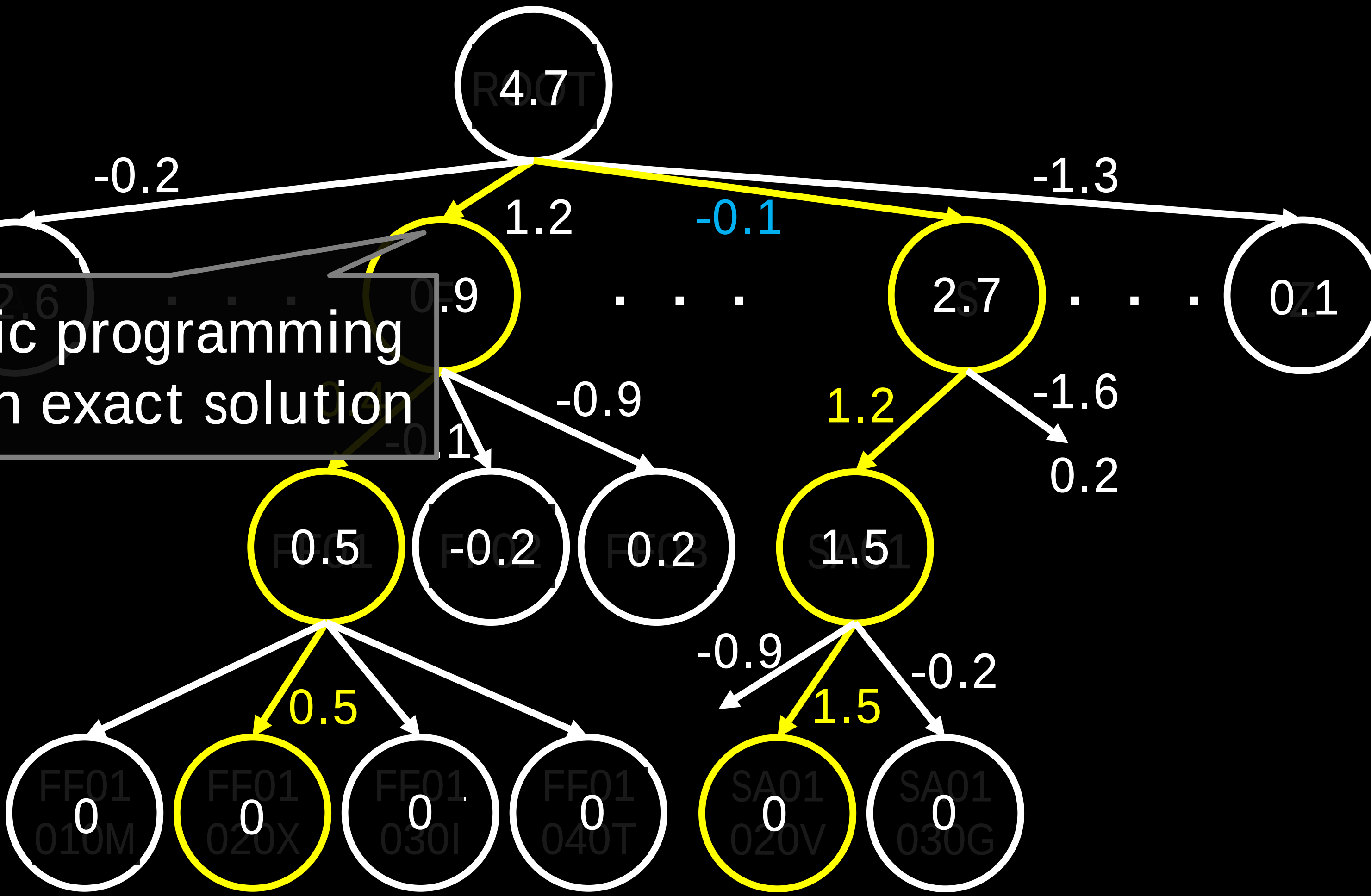
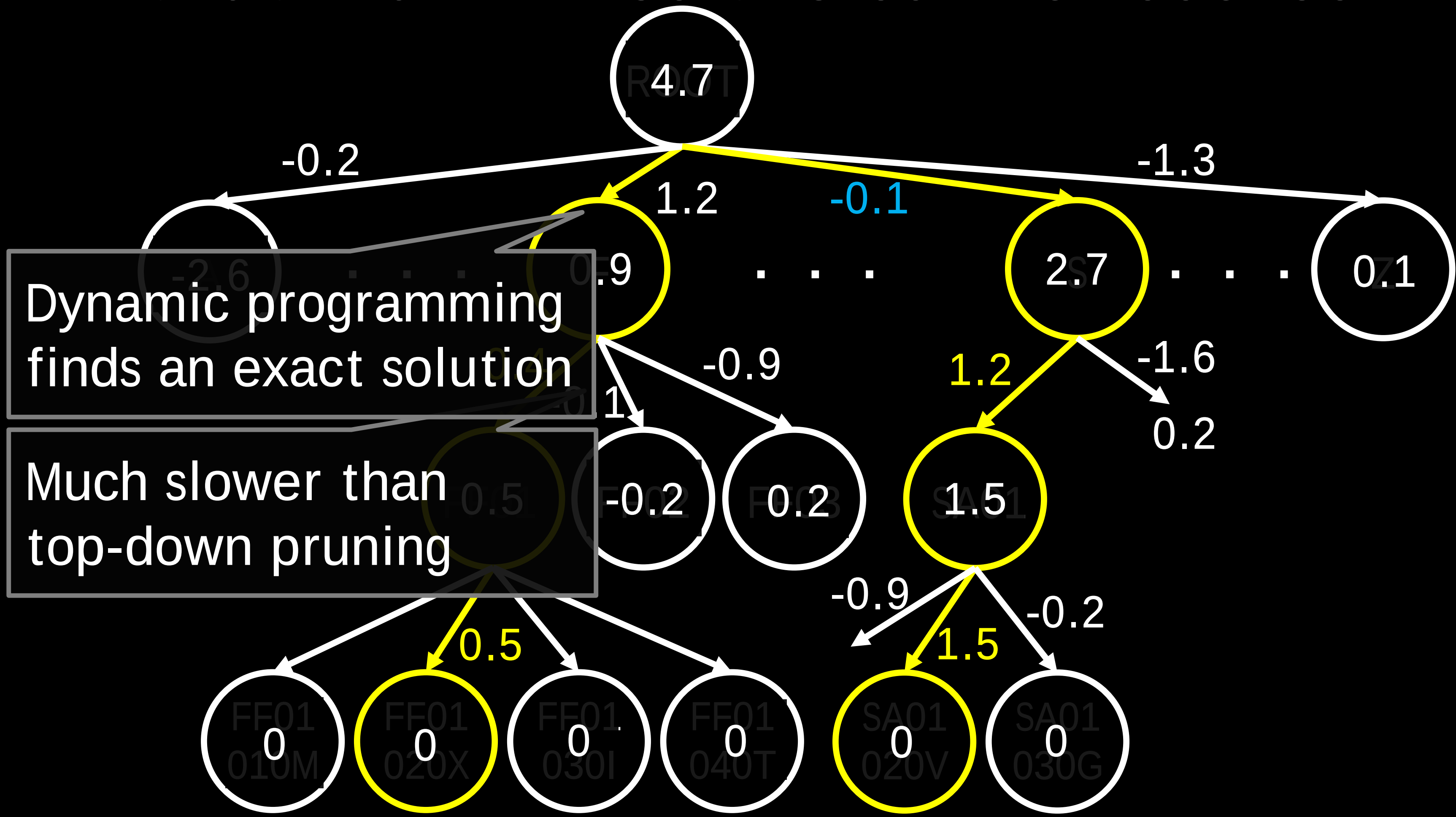
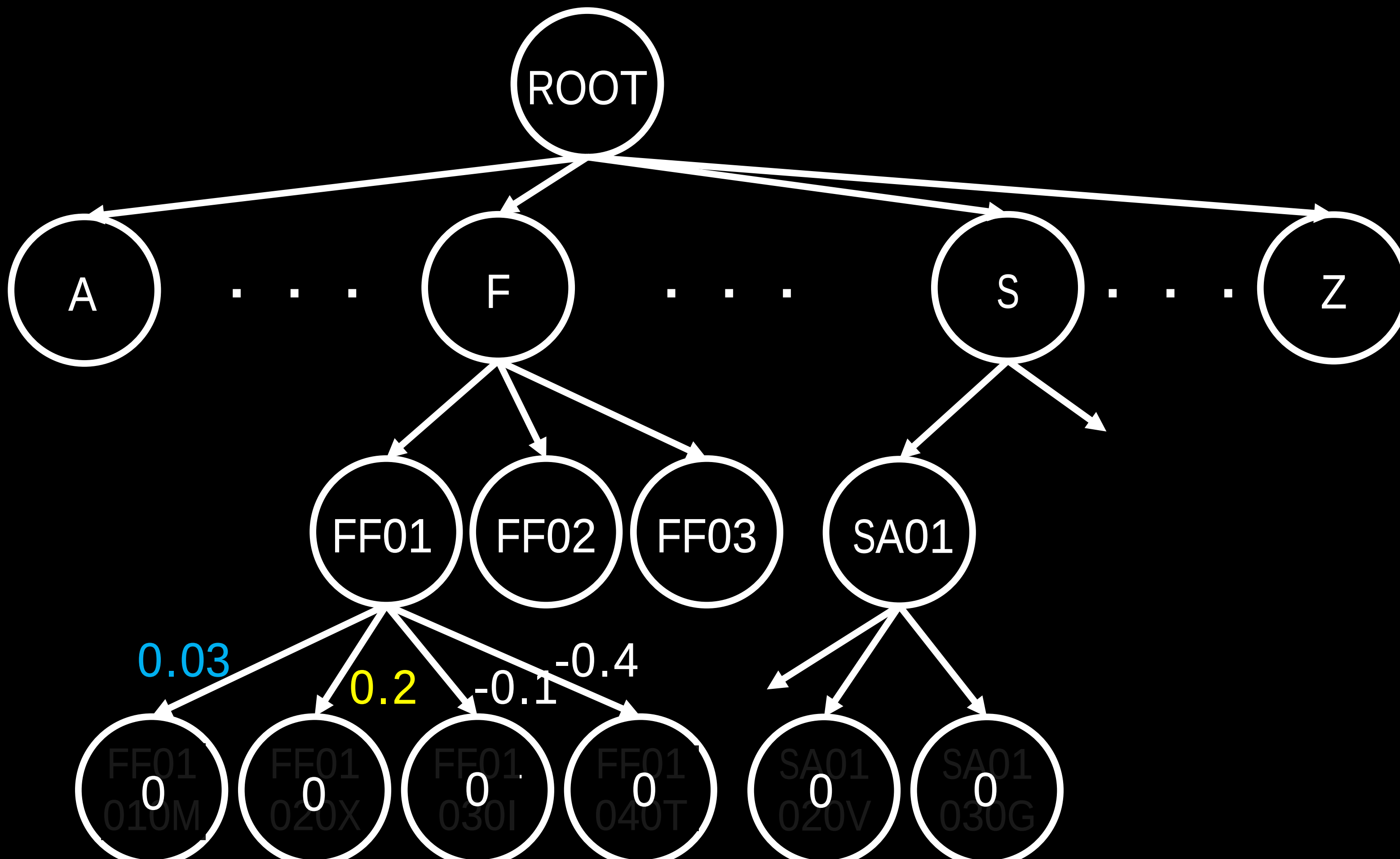


Dynamic programming finds an exact solution

Global Model: Find a Subtree that maximizes the sum of scores



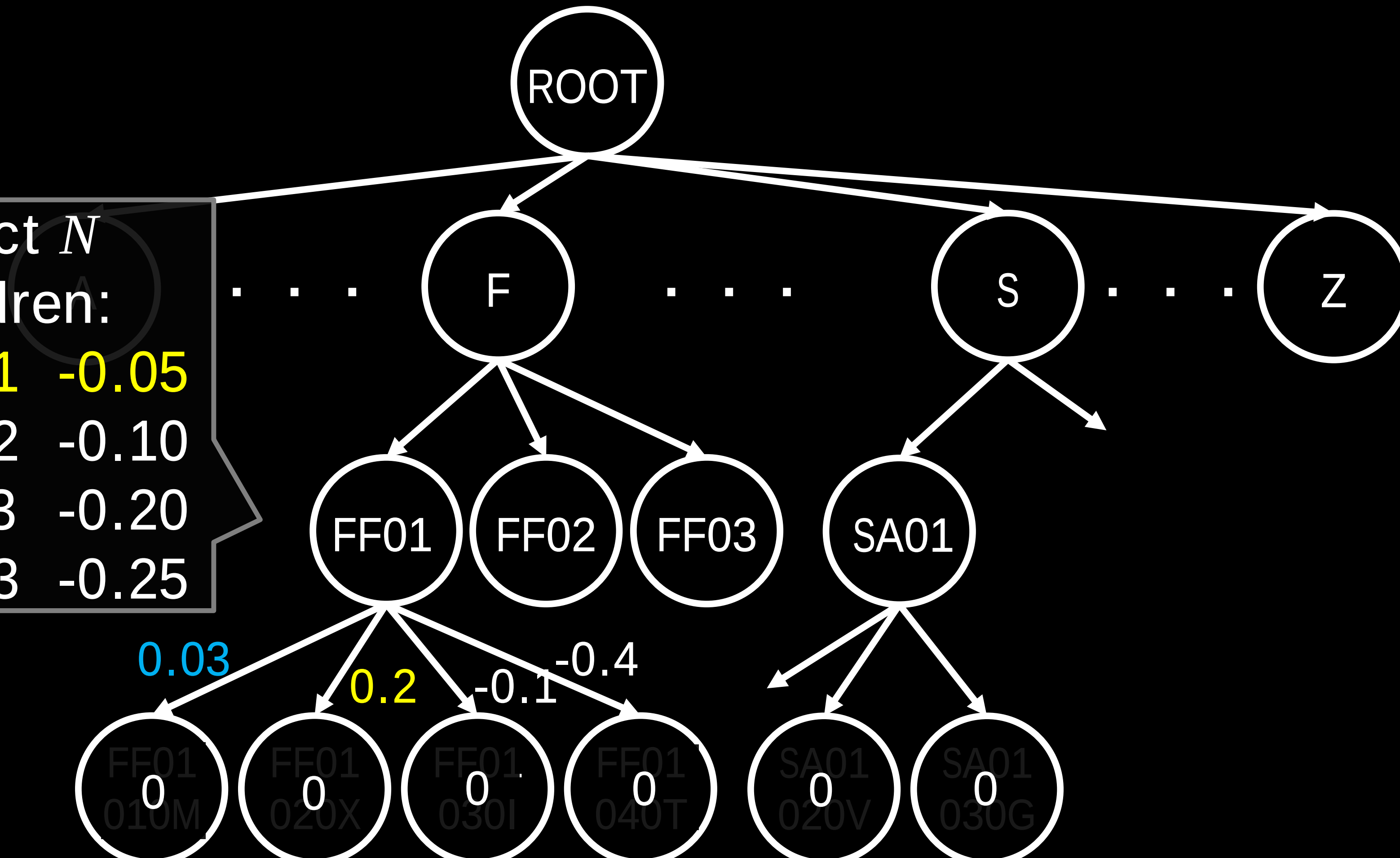
Additonal Scores by Branching Features



Additonal Scores by Branching Features

Select N children:

- N=1 -0.05
- N=2 -0.10
- N=3 -0.20
- N>3 -0.25



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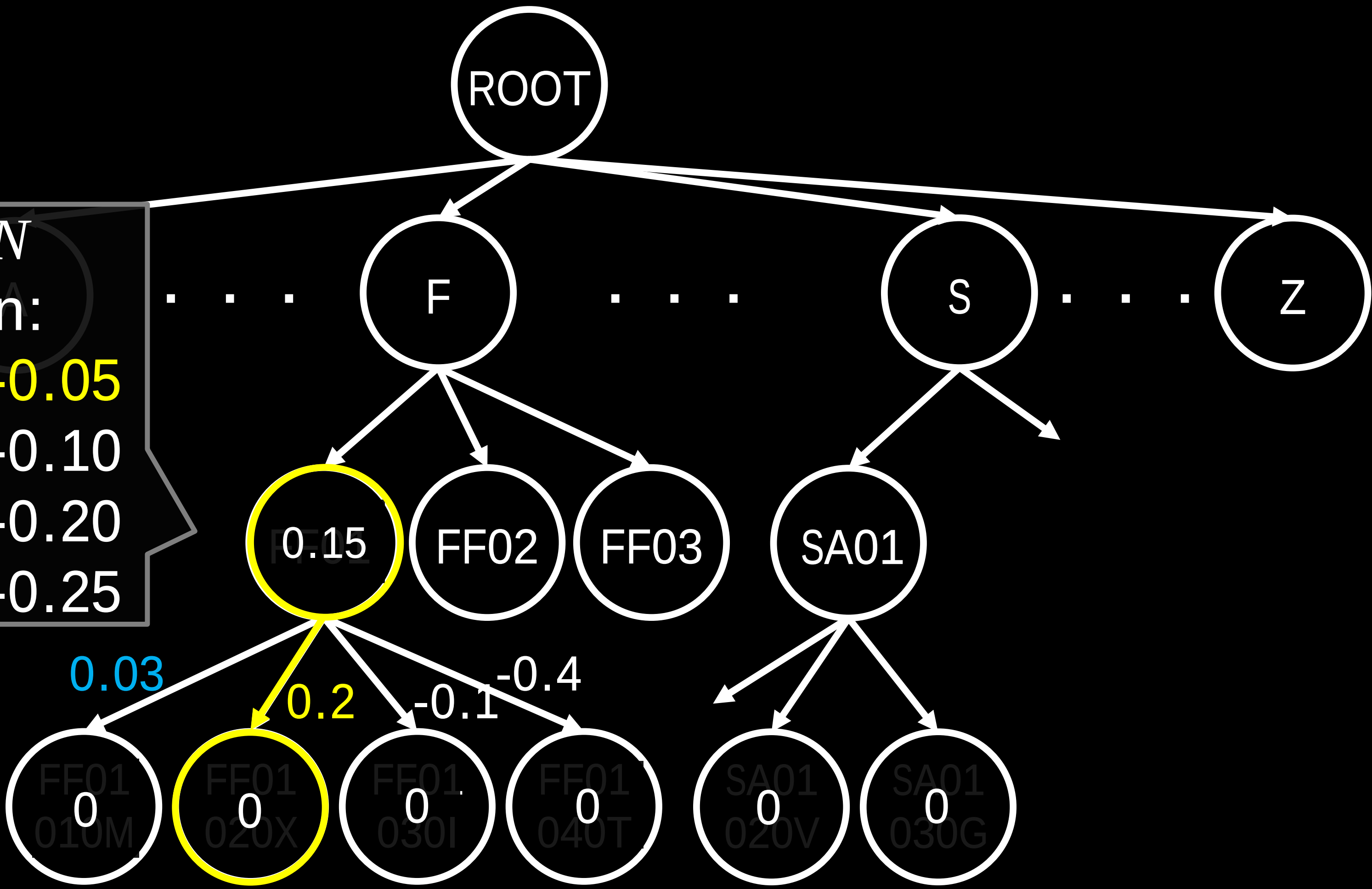

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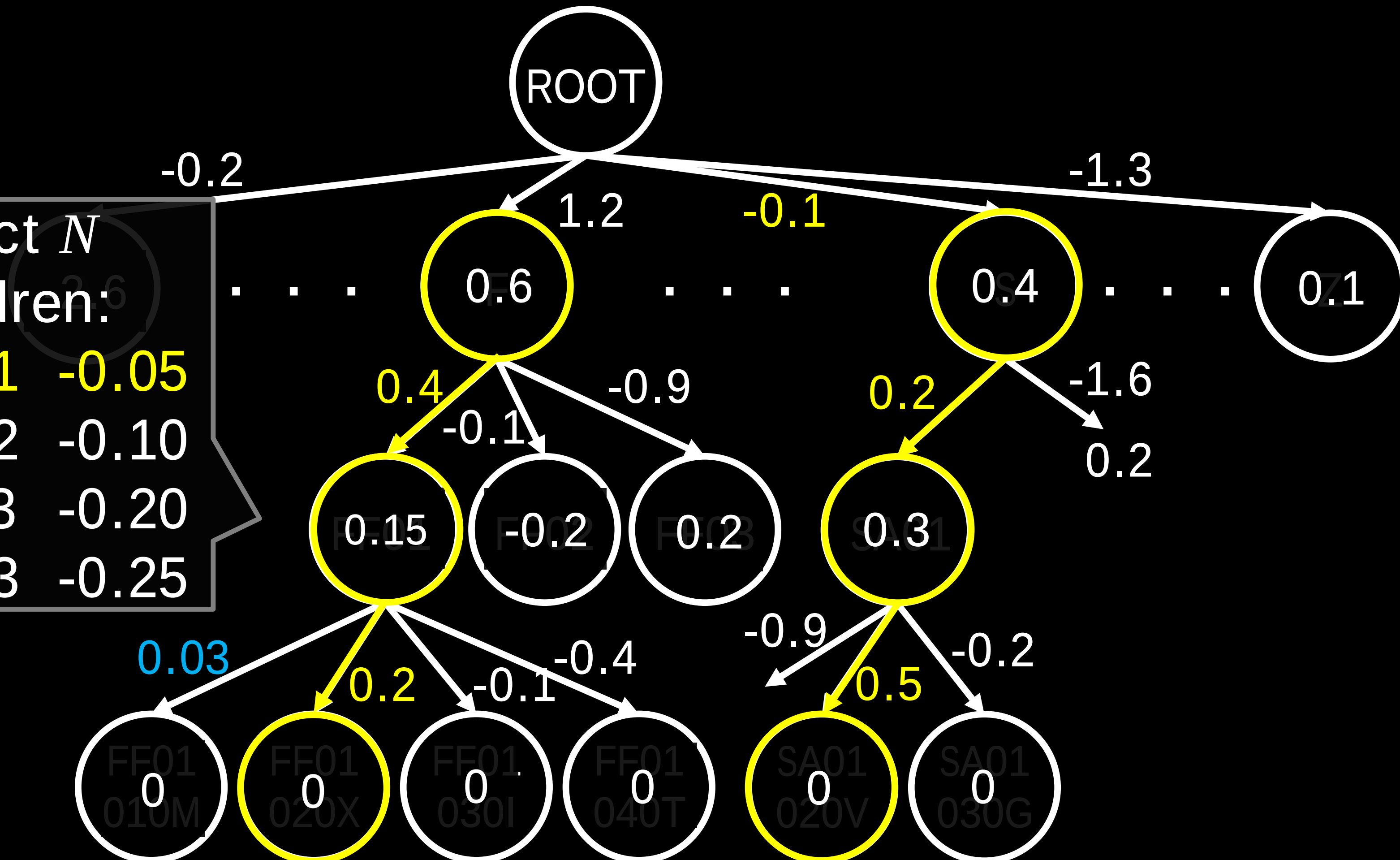

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Additional Scores by Branching Features

Select N children:
- N=1 -0.02
- N=2 -0.05
- N=3 -0.10
- N>3 -0.15

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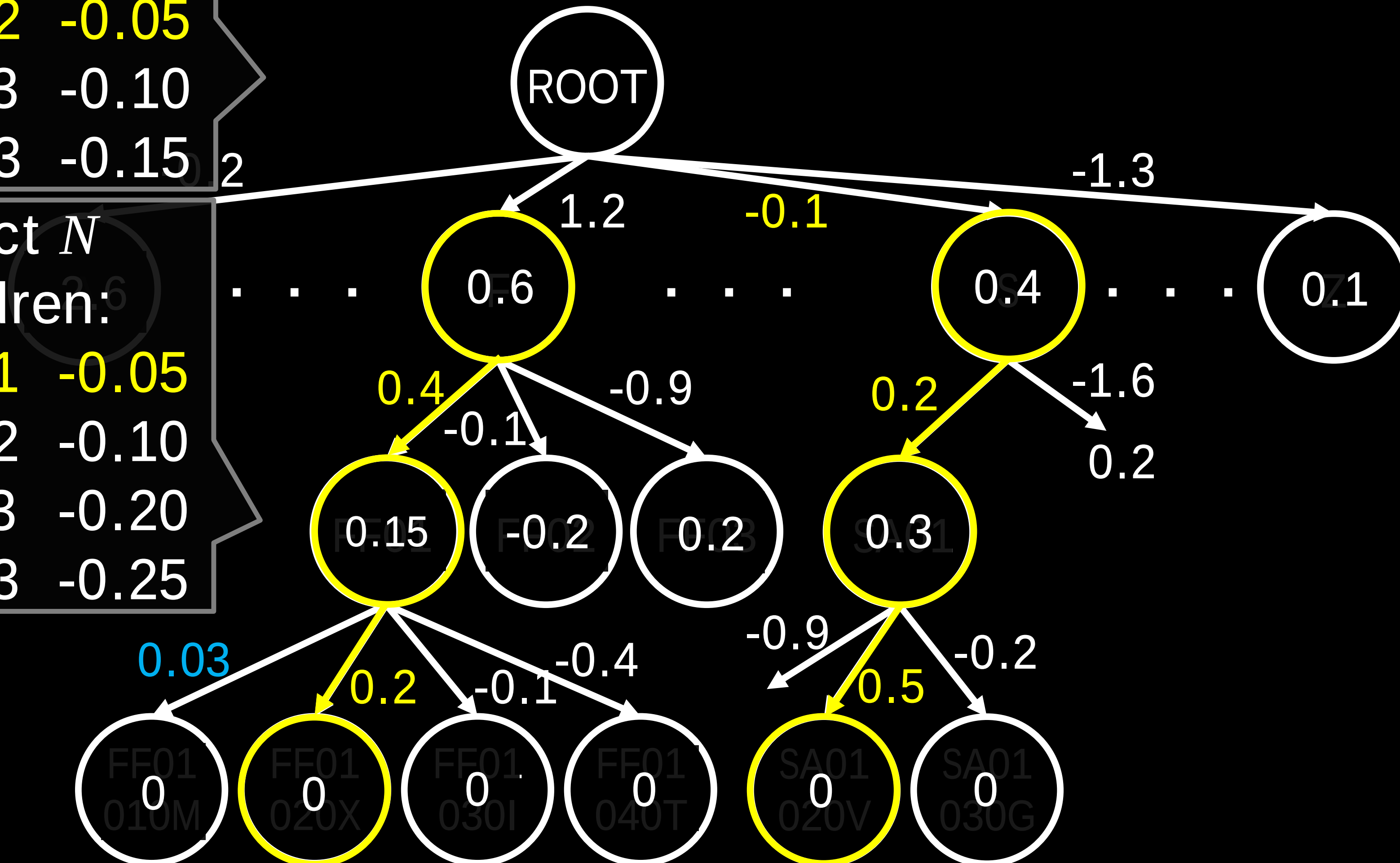

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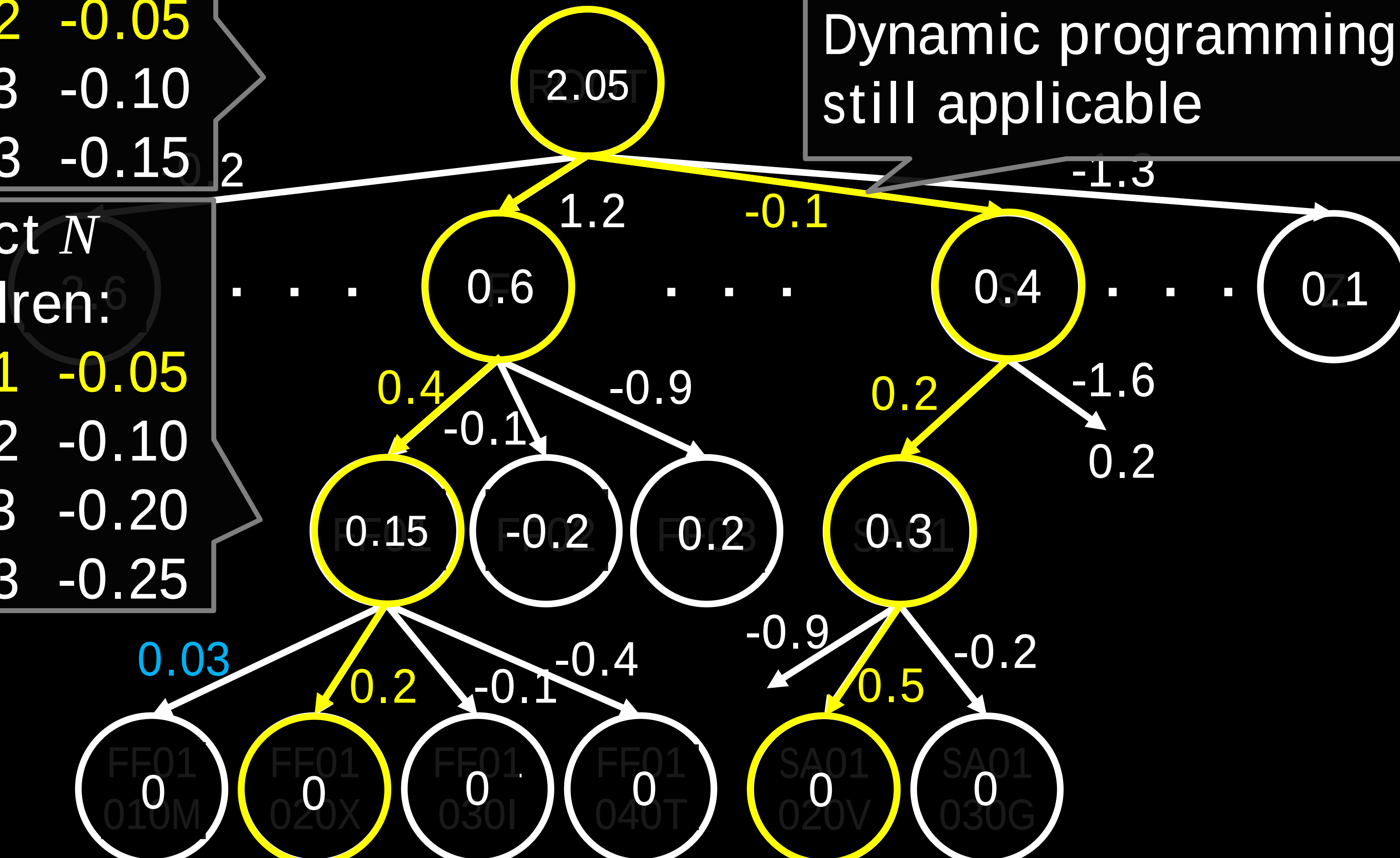
Dynamic programming still applicable



Training

- Global optimization
  - Instead of training edge classifiers separately, we directly optimize the global model
- Parallelization by iterative parameter mixing (McDonald+, 2010)
  - Global optimization is too slow
  - Parallelize training by splitting training data into small “shards” and mix the models per iteration

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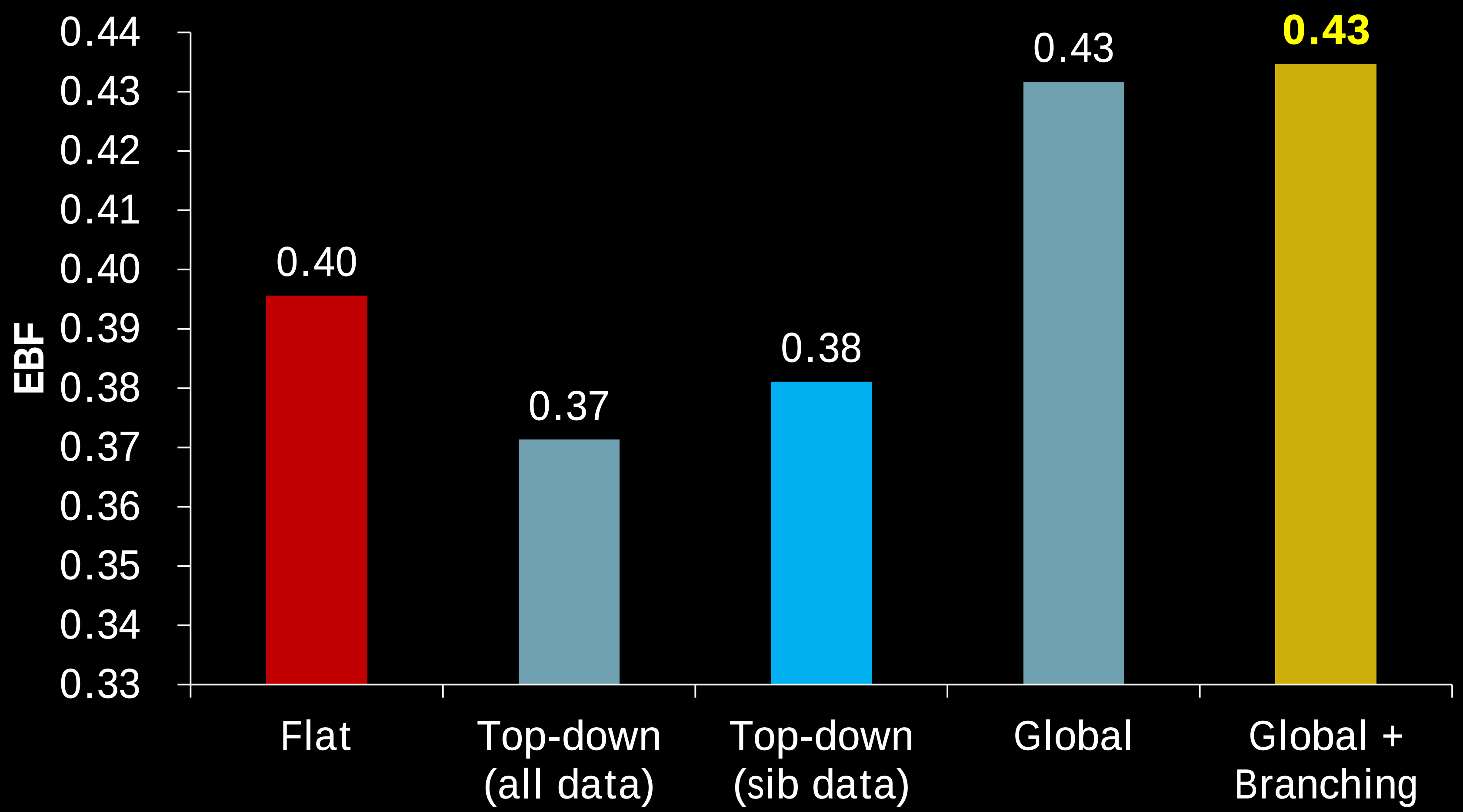
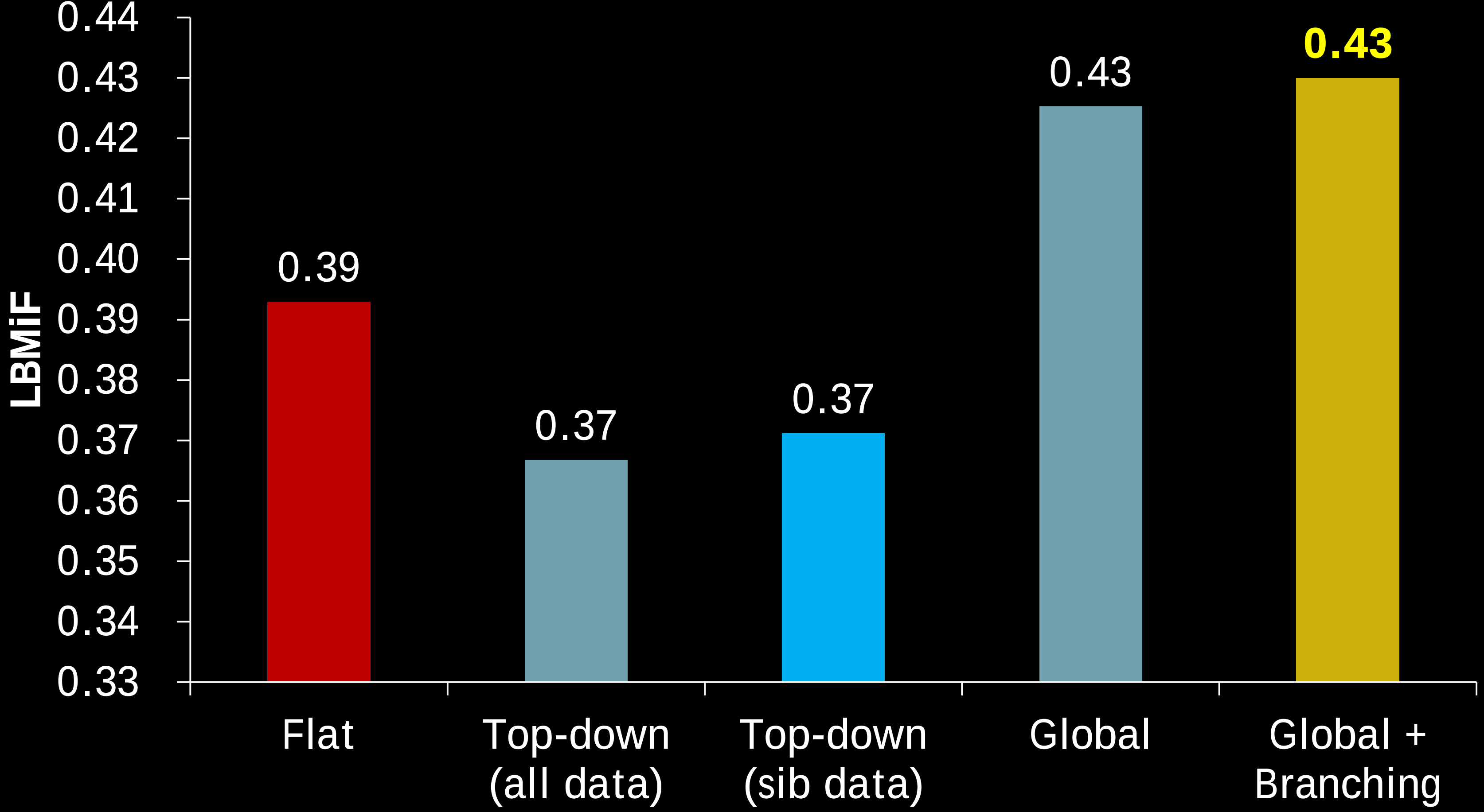
Experimental Settings

- Portion of JSTPlus (Japanese academic bibliographic database)
  – Training: 409,892 documents
  – Evaluation: 45,419 documents
- Features: content words & journal name
- Training:
  – Online passive-aggressive algorithm
  – 10 iterations

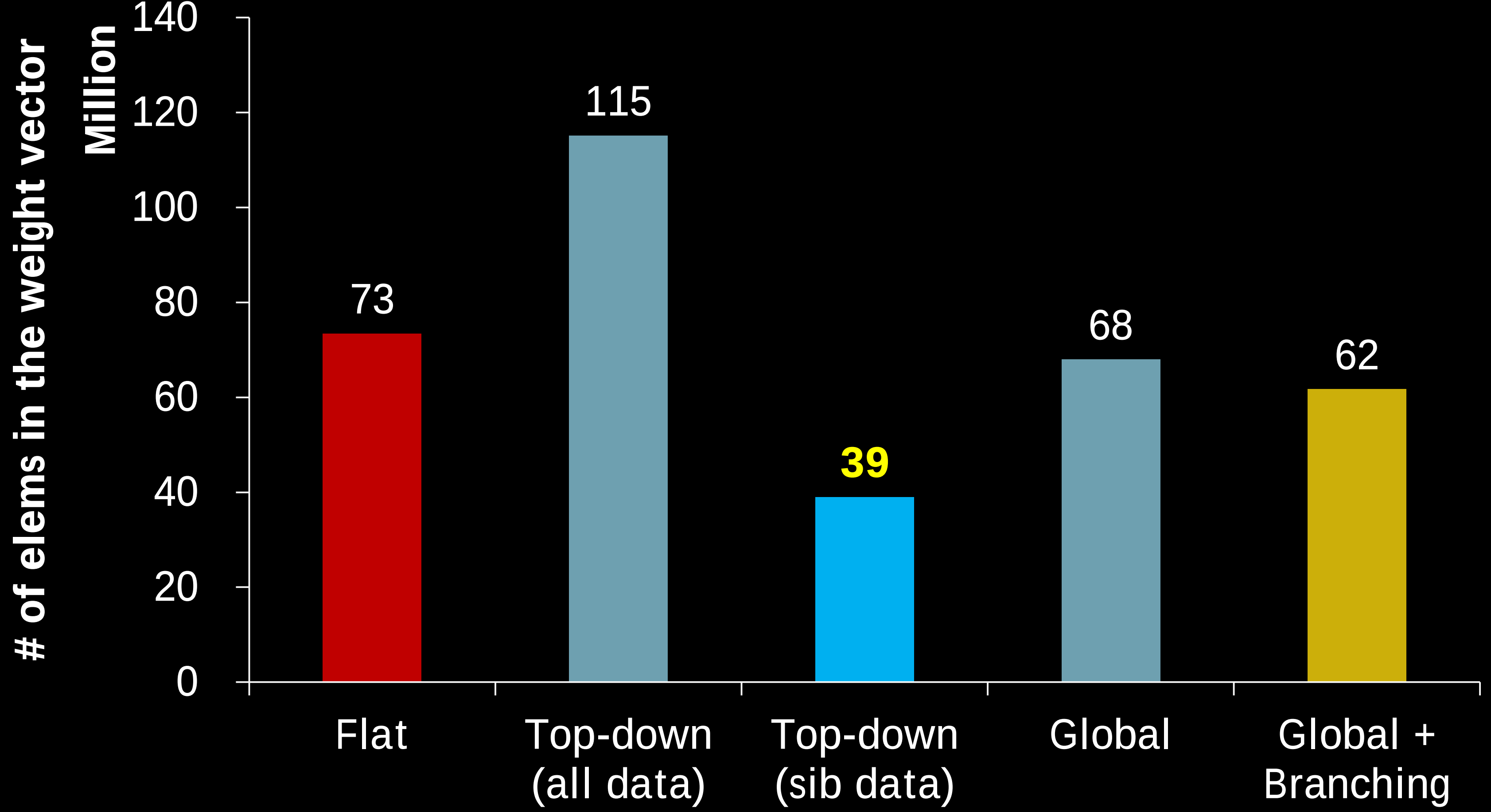
Example-based F Measure



Label-based Micro-average F Measure

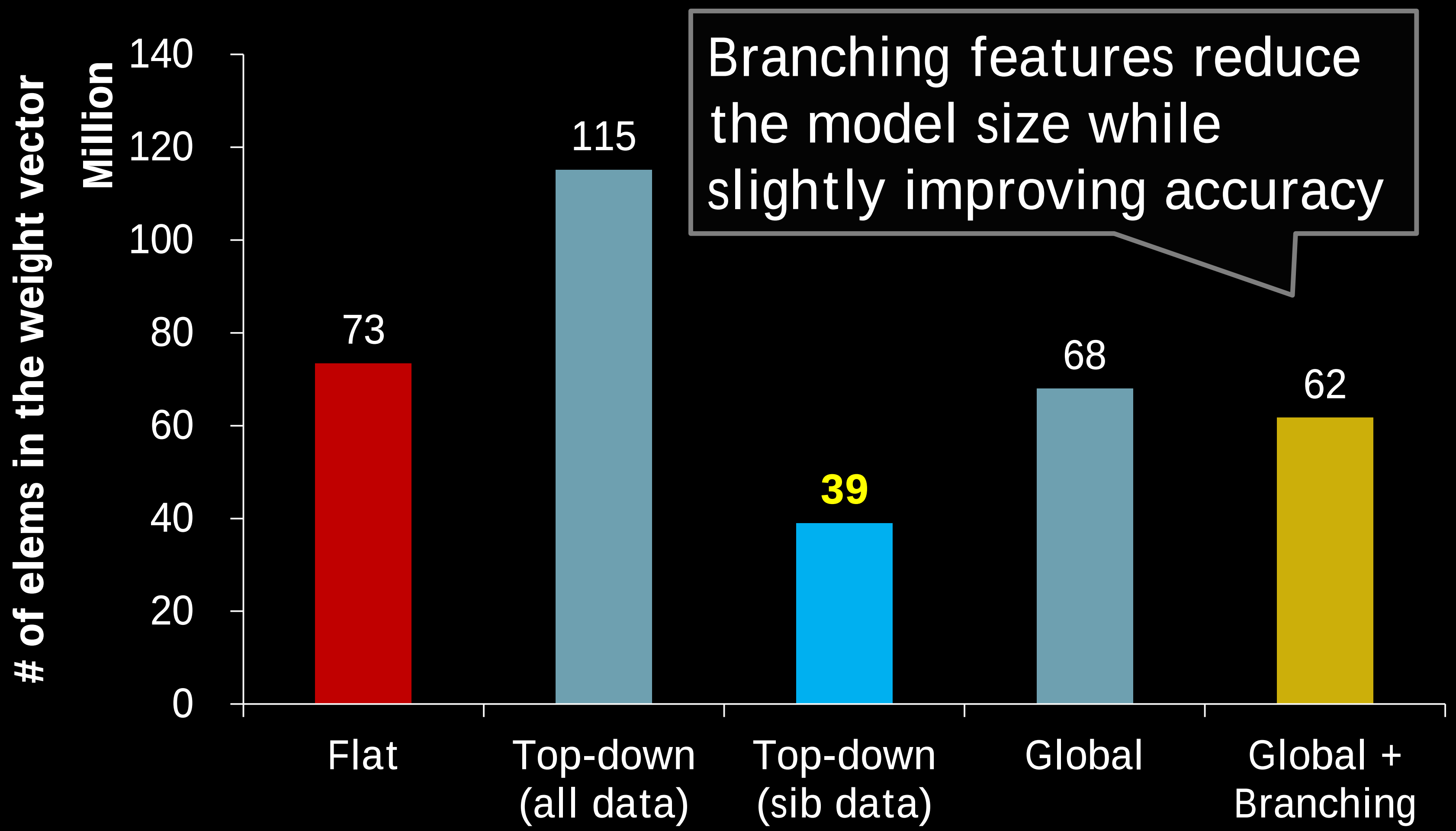


Model Size



# of elems in the weight vector
Million
140
120
100
80
60
40
20
0
73
115
39
68
62
Flat
Top-down (all data)
Top-down (sib data)
Global
Global + Branching

Model Size



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Top-down (sib data)
Global
Global + Branching
Branching features reduce the model size while slightly improving accuracy

Conclusions & Future Work

- Exploit the label hierarchy to capture inter-label dependencies
- Branching features reduce model size while slightly improving accuracy
- Future work
  - Extension to directed acyclic graphs
  - Improving scalability