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RDSF: Everything at Same Place All at Once - A Random Decision Single Forest

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Summary

- Decision Trees and Random Forest
- Mapping a Random Forest in a single Decision Graph
    - Random Decision Single Forest (RDSF)
    - BIt adder Function, Majority and Priority Encoder
    - Binary Decision Diagram BDD
- Experimental Results
- Conclusion

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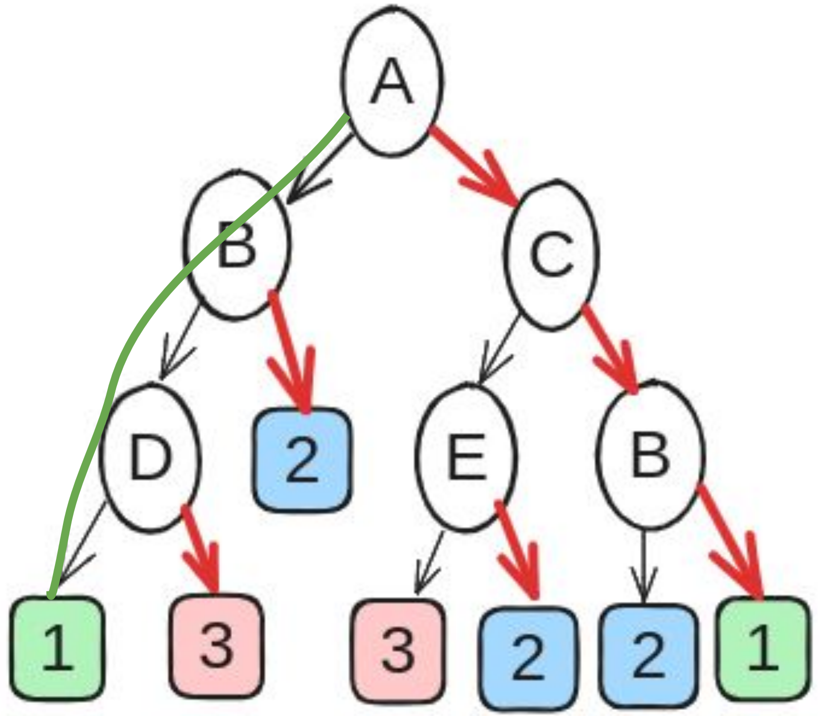
Decision Tree and Boolean Equations: Three Classes



3 Classes: 1, 2, and 3

$$\boxed{1} = \bar{A}\bar{B}\bar{D}$$

A= Length > 15.2 ?

B= Depth > 3.8 ?

…

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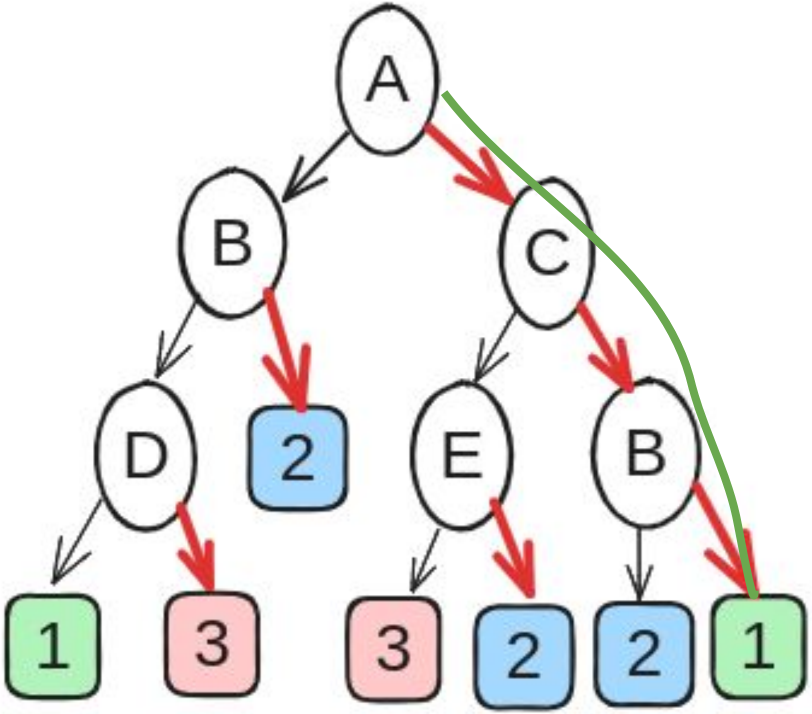
Each path generates one product term



3 Classes: 1, 2, and 3

$\boxed{1} = \overline{A}\,\overline{B}\,\overline{D}$ or ABC

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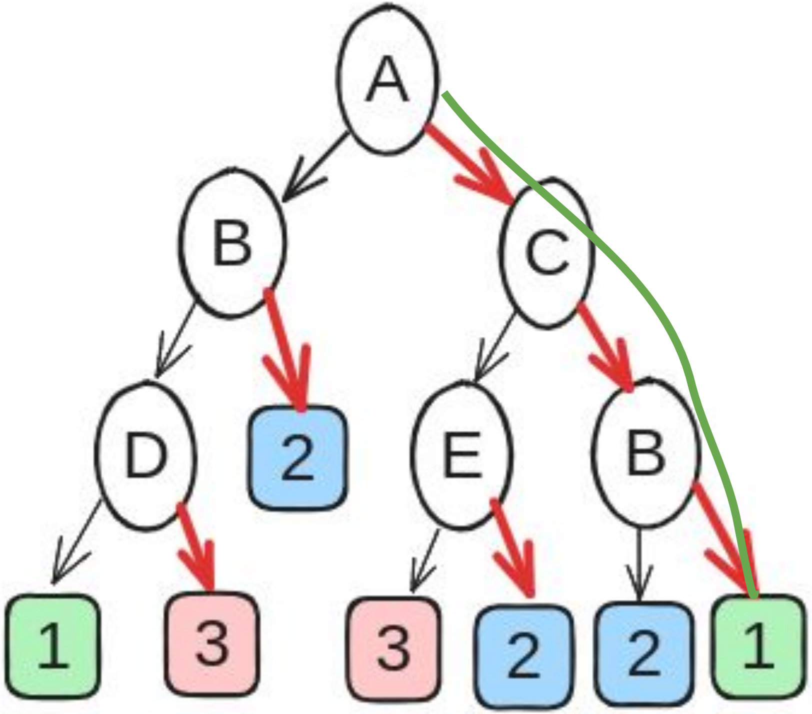
Each class has a conjunctive logic equation



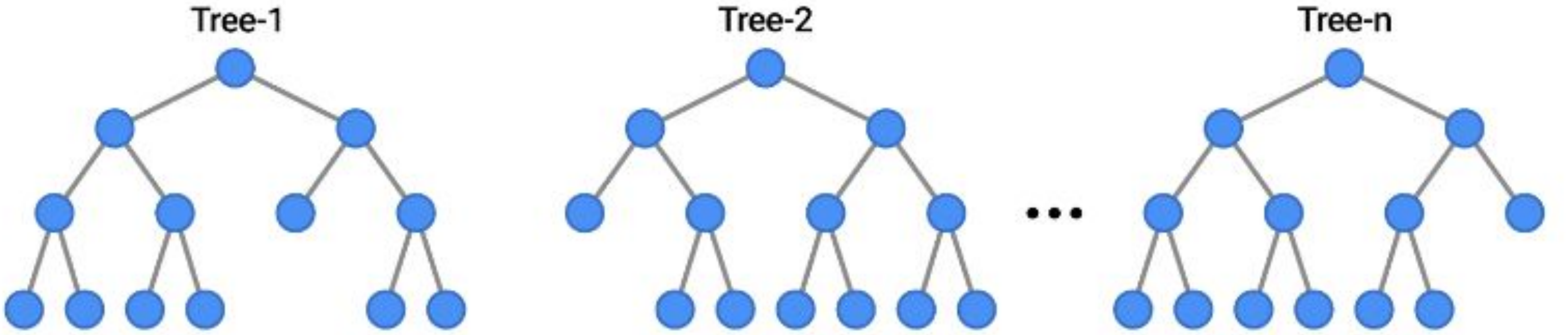
3 Classes: 1, 2, and 3

$\boxed{1}$ $= \bar{A}\bar{B}\bar{D}$ or ABC

$\boxed{2}$ $= \bar{A}B$ or $A\bar{C}E$ or $AC\bar{B}$

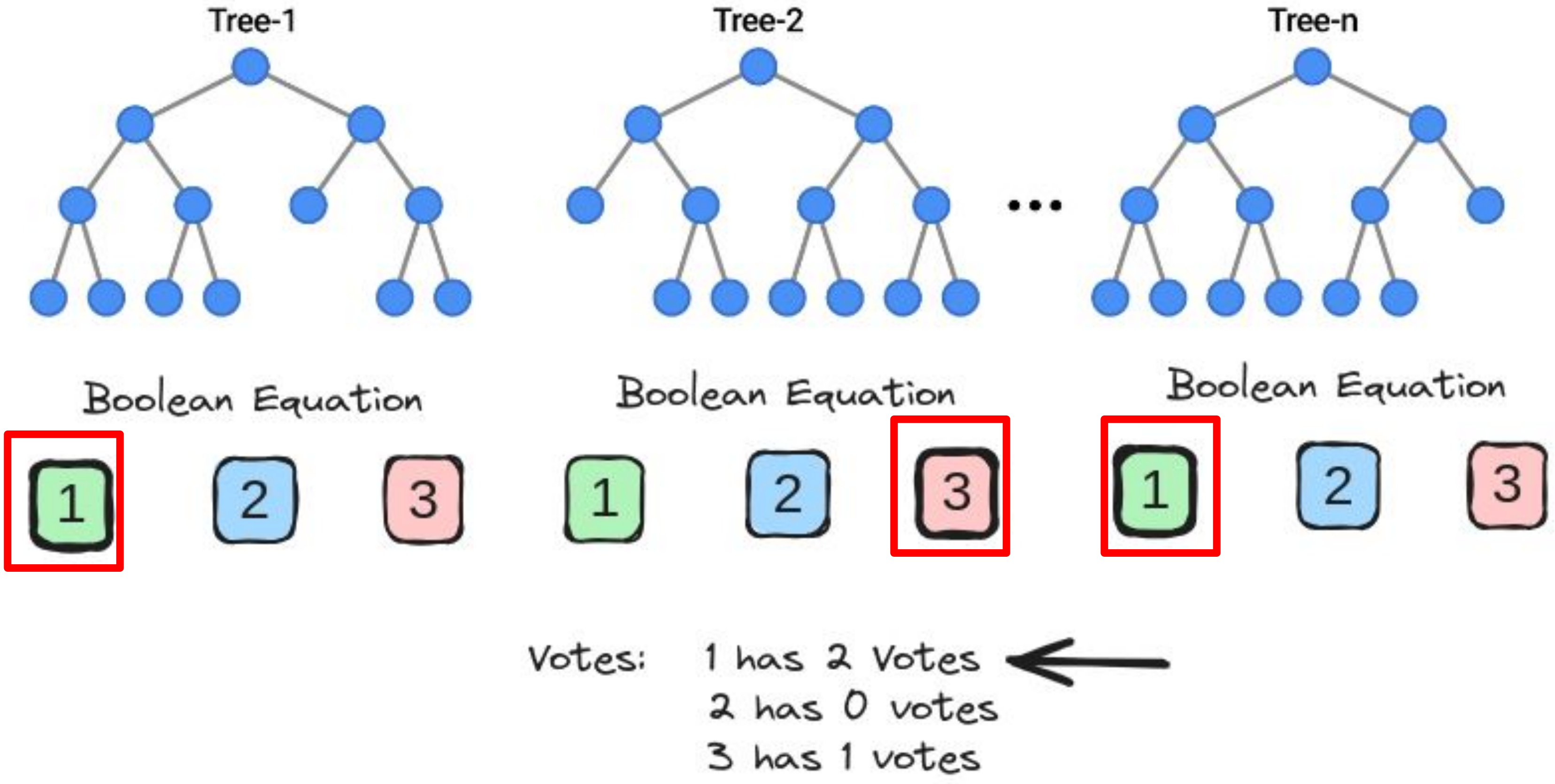
$\boxed{3}$ $= \bar{A}\bar{B}D$ or $A\bar{C}\bar{E}$

Random Forest

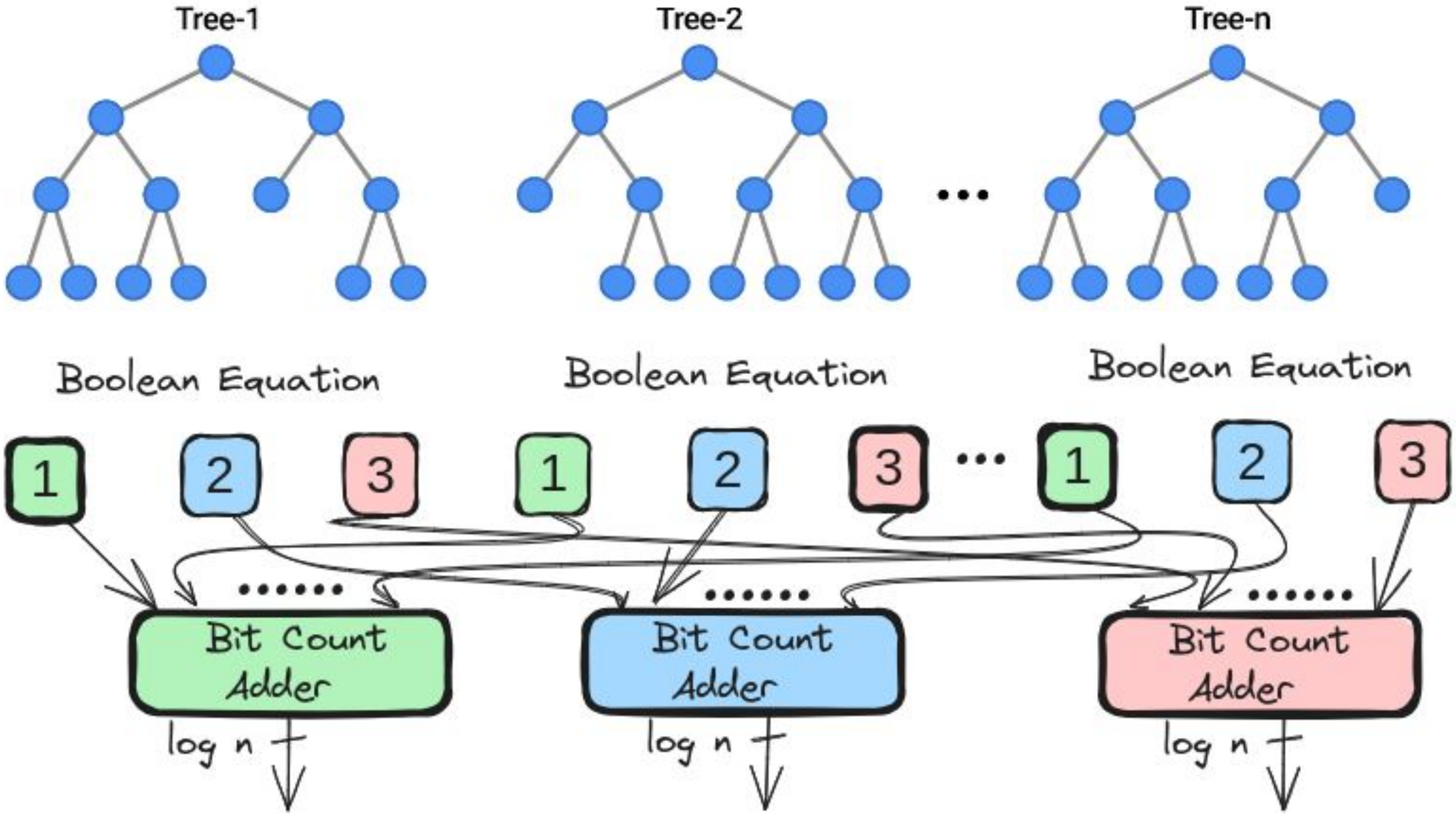


- Resilience against outliers and noisy data.
- By employing an ensemble of decision trees, Random Forest effectively reduces the vulnerability of individual trees to overfitting
- Enhancing its prediction accuracy.

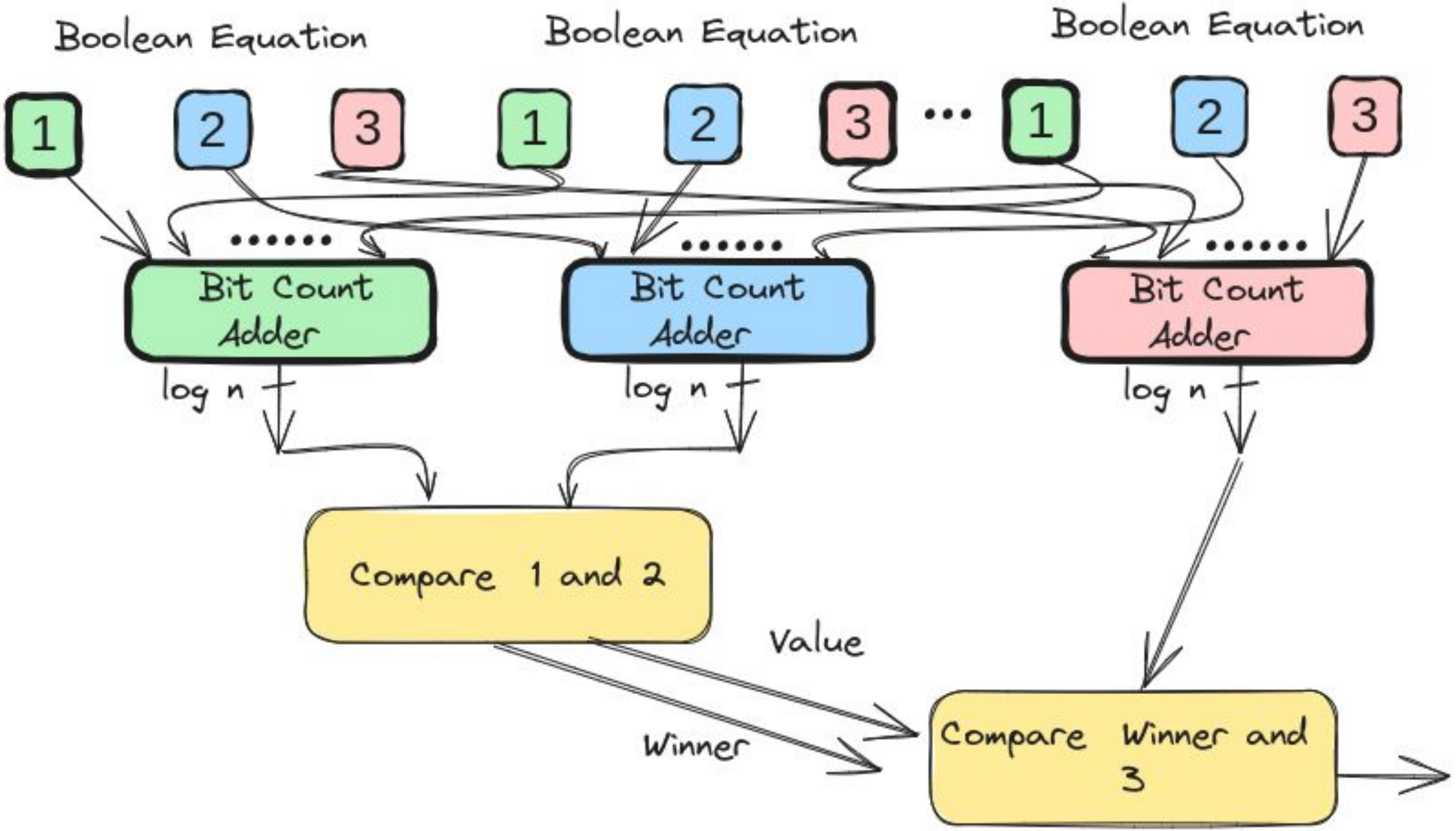
Random Forest



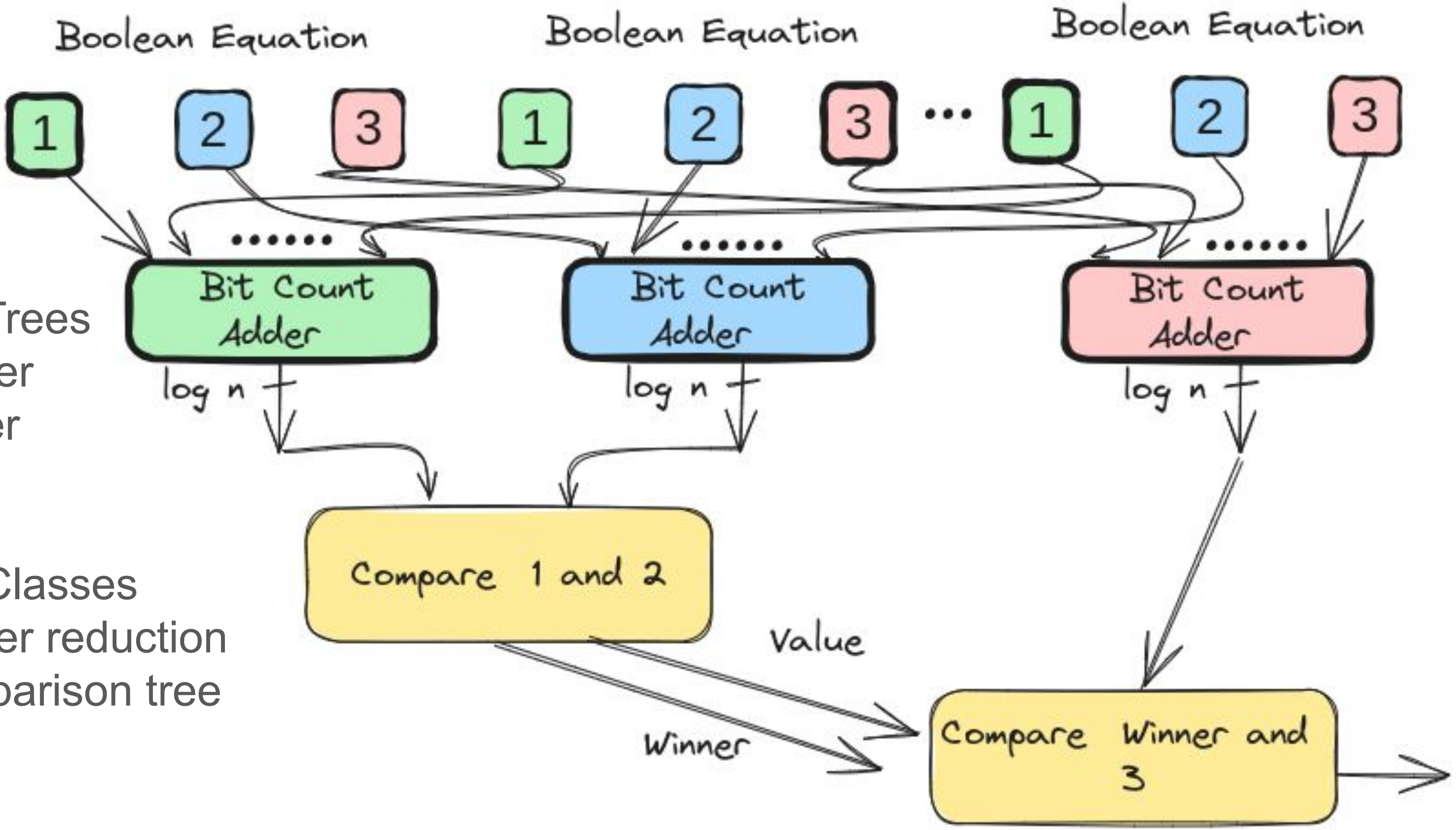
Random Forest



Random Forest



Random Forest



More Trees
= Larger
Adder

More Classes
= Larger reduction
comparison tree

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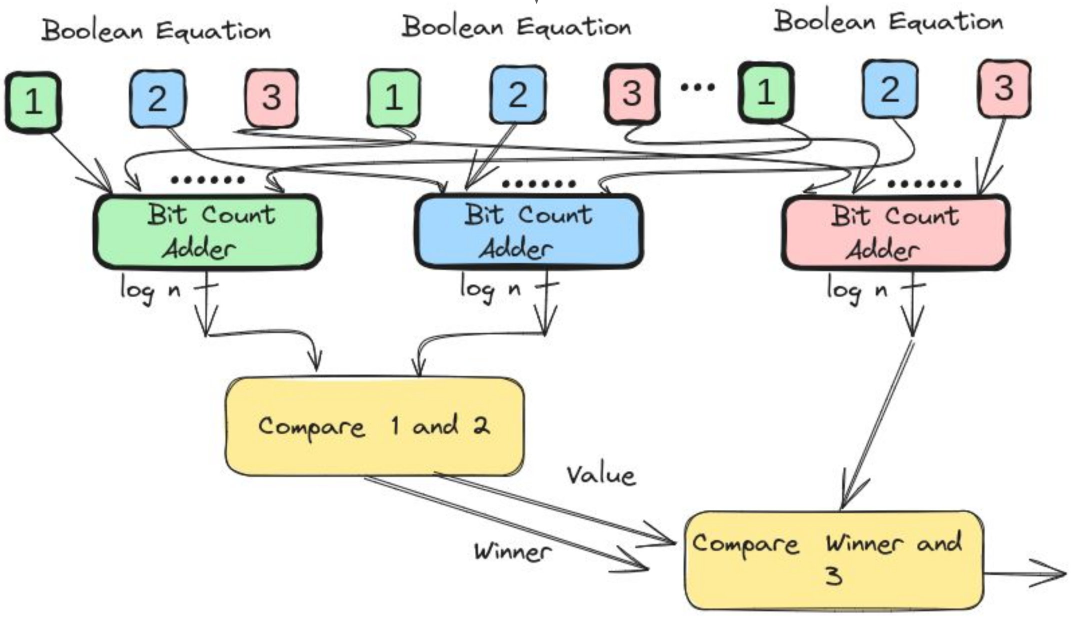
Our Proposal: Generate a single Boolean Function

Features

A= Length > 15.2 ?, B= Depth > 3.8 ?, …, F = width > 1.2 ?



Random
Decision
Single
Forest

Boolean Function

1 0 = **Class 2**

no adder, no maj

How to do that ? embedded the adder …..

- Tree 1 generates “paths” equation Tree1Class1 = A & B | C
- Tree 2 generates “paths” equation Tree2Class1 = D’ & E | A
- By using an “adder function operator”, we could merge Trees 1 and 2
- For X and Y, sum = X ^ Y and carry on = X & Y

- S1 = (A&B|C) ^ (D’&E|A) = F(A,B,C,D,E)

- Con1 = (A&B|C) & (D’&E|A) = F(A,B,C,D,E)

What to do next to “adding the class trees” ?

- Each Class generates a Sum Function Vector with Log N bits, for N trees
- Assuming a simple example of 3 trees => 2 bits
  - Class1Sum = $\boxed{C1S1}\boxed{C1S0}$
  - Class2Sum = $\boxed{C2S1}\boxed{C2S0}$
  - Class3Sum = $\boxed{C3S1}\boxed{C3S0}$
- Compare Function
  - C1S1 = 1 means Class 1 has “**1**0” ou “**1**1” votes (2 or 3)
  - Therefore   Maj1 = C1S1 or ….
  - Maj2 = C2S1 or ….
  - Maj3 = C3S1 or …
- One-Hot Code Maj (C1,C2,C3) function(a,b,c,d,e)

What to do event of a tie in the voting process ?

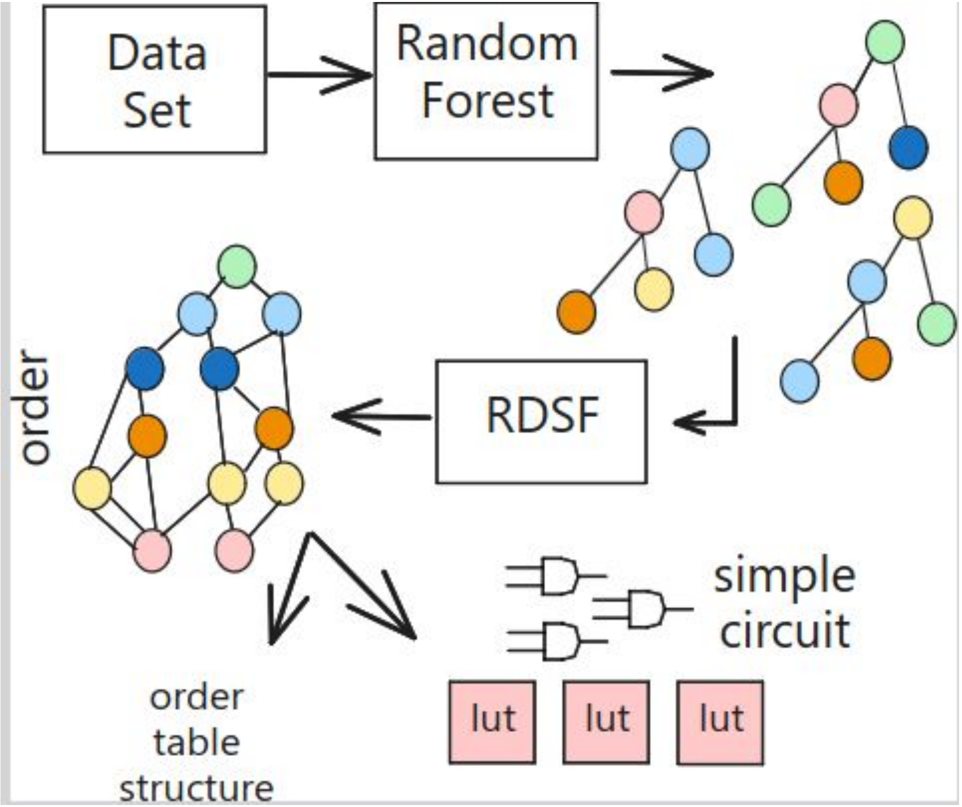
- Priority Encoder
- Assuming 4 class example One Hot Maj(c0,c1,c2,c3)
  - Encoder E1= C3 or C2
  - Encoder E0 = not E1 and C1 or C3
  - F= 0,0,1,1 E1E0 = 11 = C3
  - F= 1,0,1,0 E1E0 = 10 = C2
  - F= 1,1,0,0 E1E0 = 01 = C1

Embedded Boolean Function depends on the primary inputs

- Final = Encoder (Maj (Adding (primary input)))
- We use BDD to manipulate the Boolean Functions
  - compact
  - canonical representation
  - CUDD C++ efficient BDD package
  - Variable ORDER

Final Boolean Function depends on the primary inputs

BDD



Random Forest

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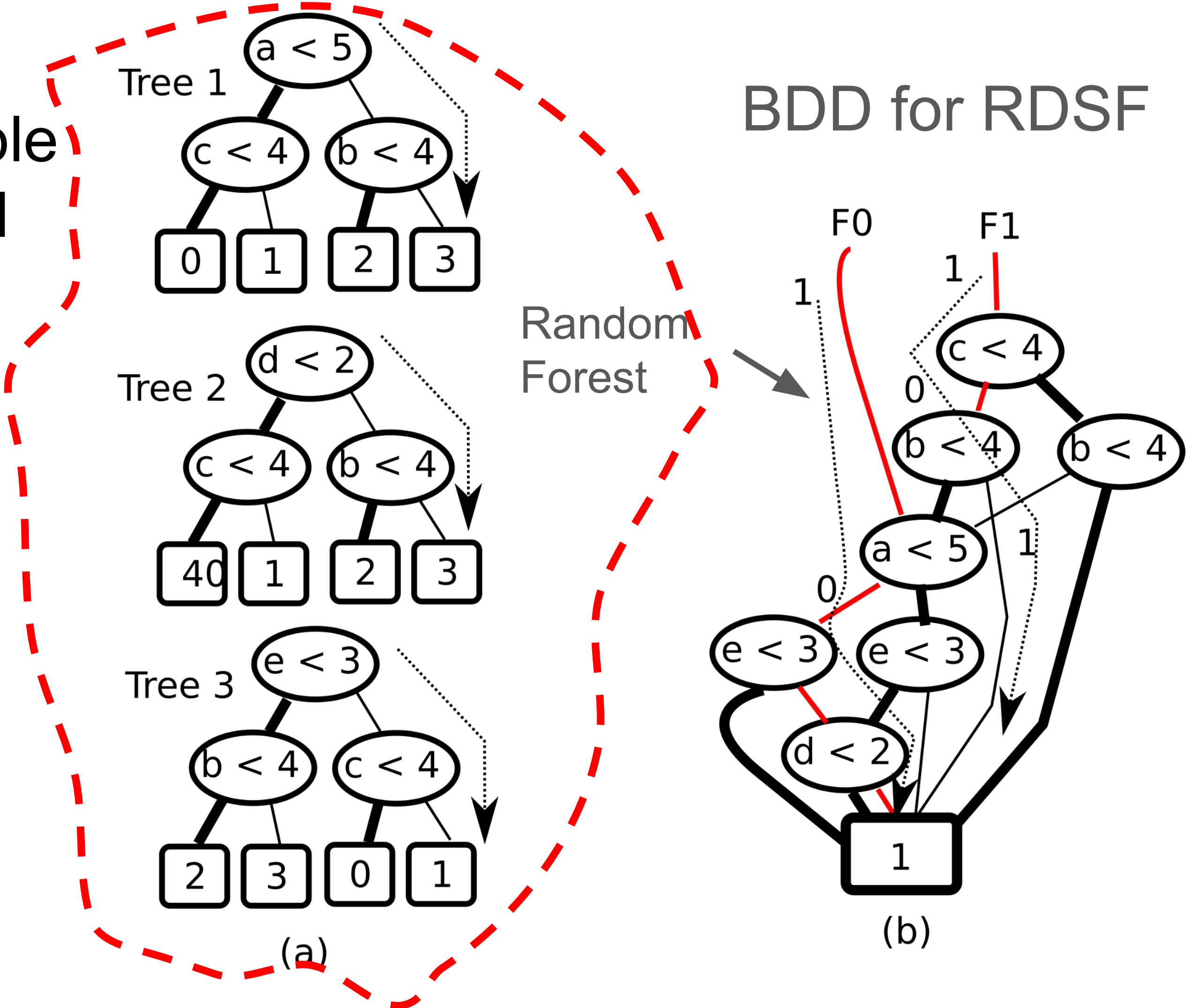
A simple example with 3 trees and 3 classes

BDD for RDSF



(a)

(b)

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Features Order

Tree1

A, C, B

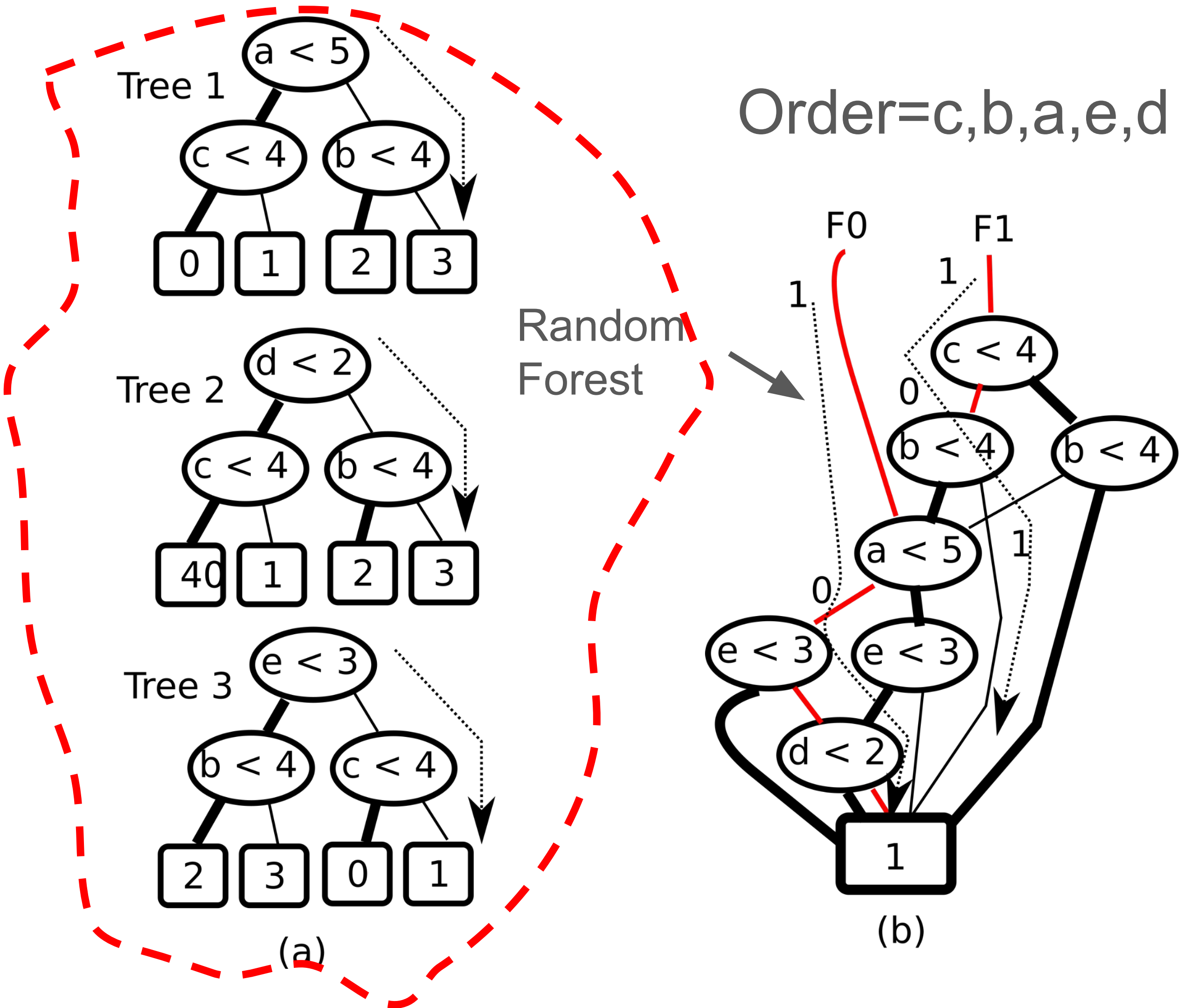
Tree 2

D,C, B

Tree 3

E, B, C

Order=c,b,a,e,d



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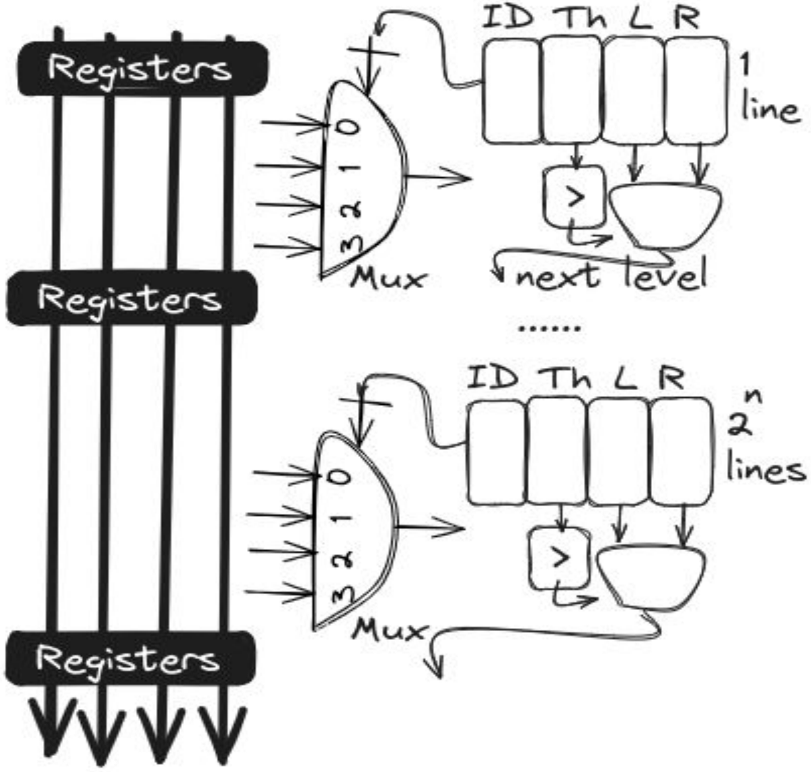
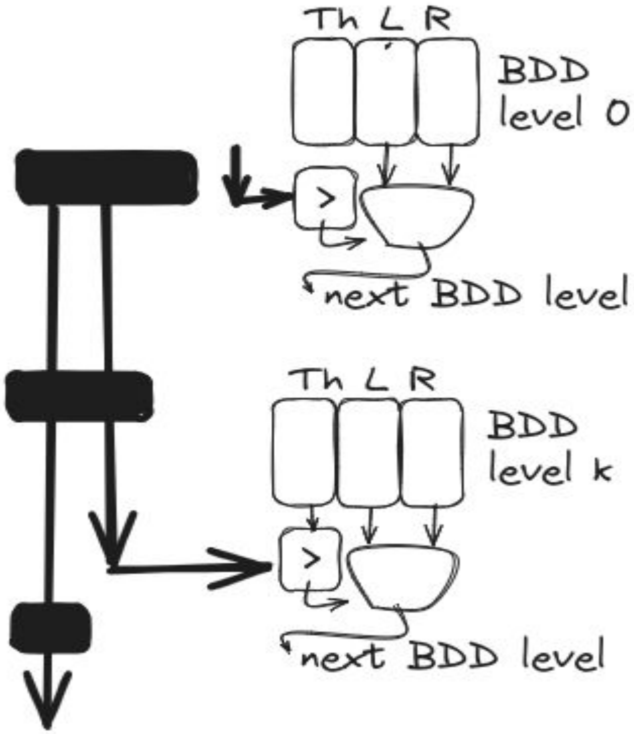
Random Forest

Order=c,b,a,e,d





Experimental Results BDD versus Previous Approach

Execution Time (ms)					
		Generate		Inference	
Trees	Depth	CUDD	ADD-lib	CUDD	ADD-Lib
3	3	9	77	78	509
3	7	9	895	110	918
3	-	9	-	290	-
7	3	9	269	94	745

Dry beam Dataset 13K samples, 16 features, 4 classes

Experimental Results BDD generation Size

Tree	Depth	Var	Eq	Add	Vote	All
3	3	15	30	72	74	51
3	7	91	136	1364	1387	1006
3	-	271	377	29027	26059	20647
7	3	39	81	433	973	759
3	3	12	29	80	47	37

Dry beam Dataset 13K samples, 16 features, 4 classes

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Congress Voting, 16 attributes, 2 classes, 435 samples

Tree	Depth	Var	Eq	Add	Vote
3	3	16	10	16	10
3	7	16	93	265	117
3	-	16	99	431	222
7	3	16	21	66	24
7	7	16	225	1639	470
7	-	16	289	2057	552

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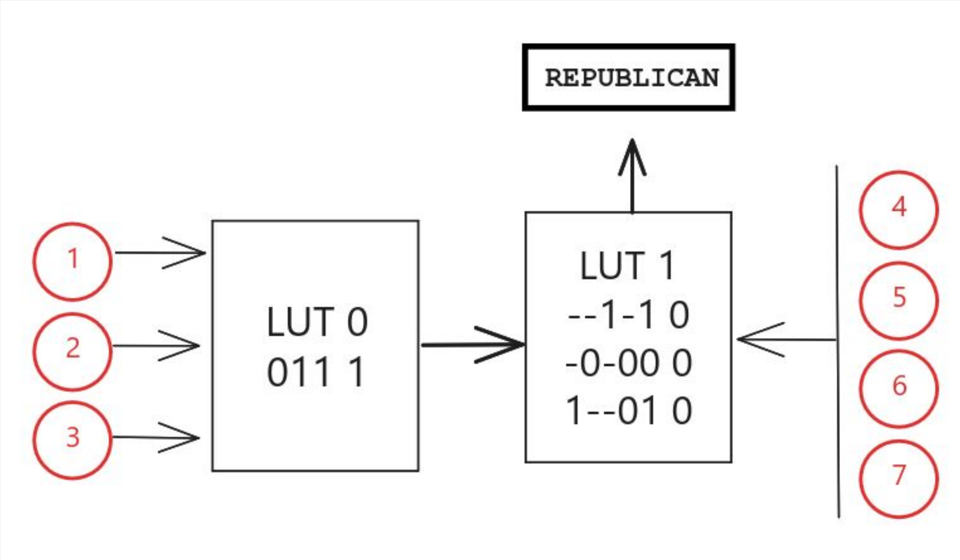
Congress Voting, 16 attributes, 2 classes, 435 samples

Tree	Depth	Var	Eq	Add	Vote
3	3	16	10	16	10

1 - education spending
2 - immigration
3 - export administration act South Africa



4 - synfuels corporation cutback
5 - duty-free expor
6 - physician fee freeze
7 - adoption of the budget resolution

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Heart disease, 9 features, 400k samples

Tree	Depth	Var	Eq	Add	Vote
3	3	9	5	7	5
3	7	9	7	13	10
3	-	9	189	147	74
7	3	9	8	13	6
7	7	9	218	163	46
7	-	9	383	213	79

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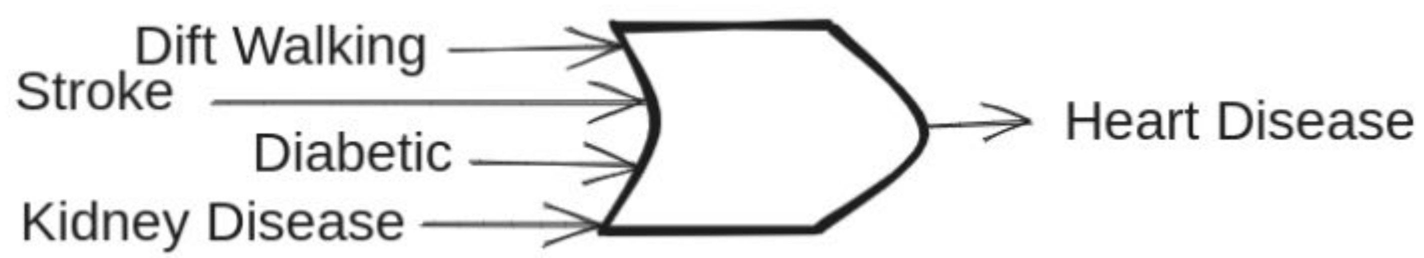
Heart disease, 9 features, 400k samples

Tree	Depth	Var	Eq	Add	Vote
3	3	9	5	7	5
3	7	9	7	13	10
3					
7					
7					
7					

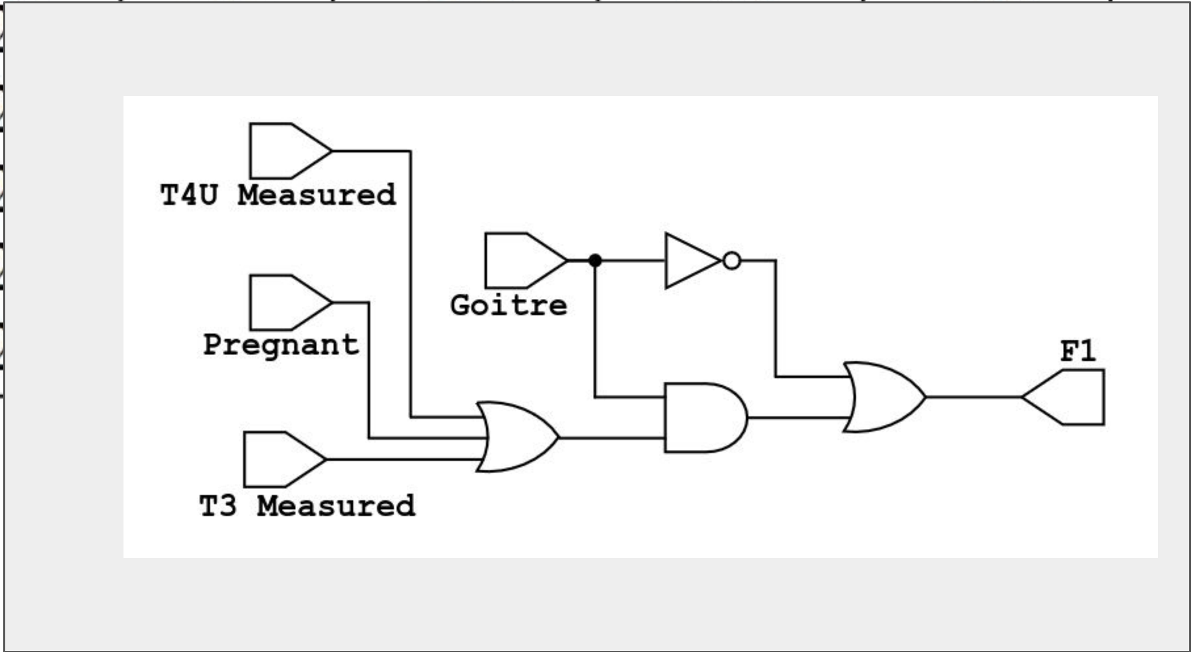


Thyroid, 20 features, 4 classes, 9k samples

Tree	Depth	Var	Eq	Add	Vote	All
3	3	20	5	7	5	5
3	7	20	105	282	132	109
3	-	20	364	875	333	287
7	7	20	18	53	19	15
7	7	20	252	2,612	868	718
7	-	20	968	7,055	1,383	1162

Thyroid, 20 features, 4 classes, 9k samples

Tree	Depth	Var	Eq	Add	Vote	All
3	3	20	5	7	5	5
3	7	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3	-	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
7	7	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
7	7	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
7	-	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]



Cluster Classification

- Maj vote (c0,c1,c2,c3,c4,c5,c6,c7)
- Maj vote (c0,c5,c6,c3,c4,c1,c2,c7)
- Maj vote (c0,c5,c6,c3,c4,c1,c2,c7)

Conclusions

- Random Decision Single Forest (RDSF)
- Improved scalability and reduced execution time compared to ADD approaches.

- Advantage of controlling input data order during inference
- Facilitating direct class clustering, enhancing its versatility.

- Numerical and categorical datasets.
- Mapping some datasets in simple functions for categorical ones

Questions ?

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