

Laplace Smoothing

$$\underline{P(w_i | S=1)} = P(\text{today, is, a, good, day} \dots | S=1)$$

$$= \boxed{P(\text{today} | S=1)} P(\text{is} | S=1) \dots P(\text{day} | S=1)$$

$$P(\text{today} | S=1) = \left(\frac{0}{1000 (\text{span})} \right)$$

$$\Rightarrow P(S=1 | w_i) \approx 0$$

$$K=1$$

$$P(w_i | C) = \frac{\# \text{ words } \neq 1}{\#}$$

$$P(w_i | C=S) = \frac{\# \text{ of times } w_i \text{ appears in class } (S) + K}{\# \text{ of words in class } (S) + (Kn)}$$

n \equiv number of classes

K \equiv smoothing value

$$P(\text{today} | S=1) = \frac{0+1}{1000 + (1)(2)}$$

$$= \frac{1}{1002}$$

$$P(\text{day} | S=1) = \frac{20}{1000} \quad (\text{original})$$

$$\frac{20+1}{1000+(1)(2)} = \frac{21}{1002}$$

$$k = 0.01 \quad (\text{smoother})$$

$$P(\text{today} | S=1) = \frac{0 + 0.01}{1000 + (0.01)(2)}$$

Decision Tree

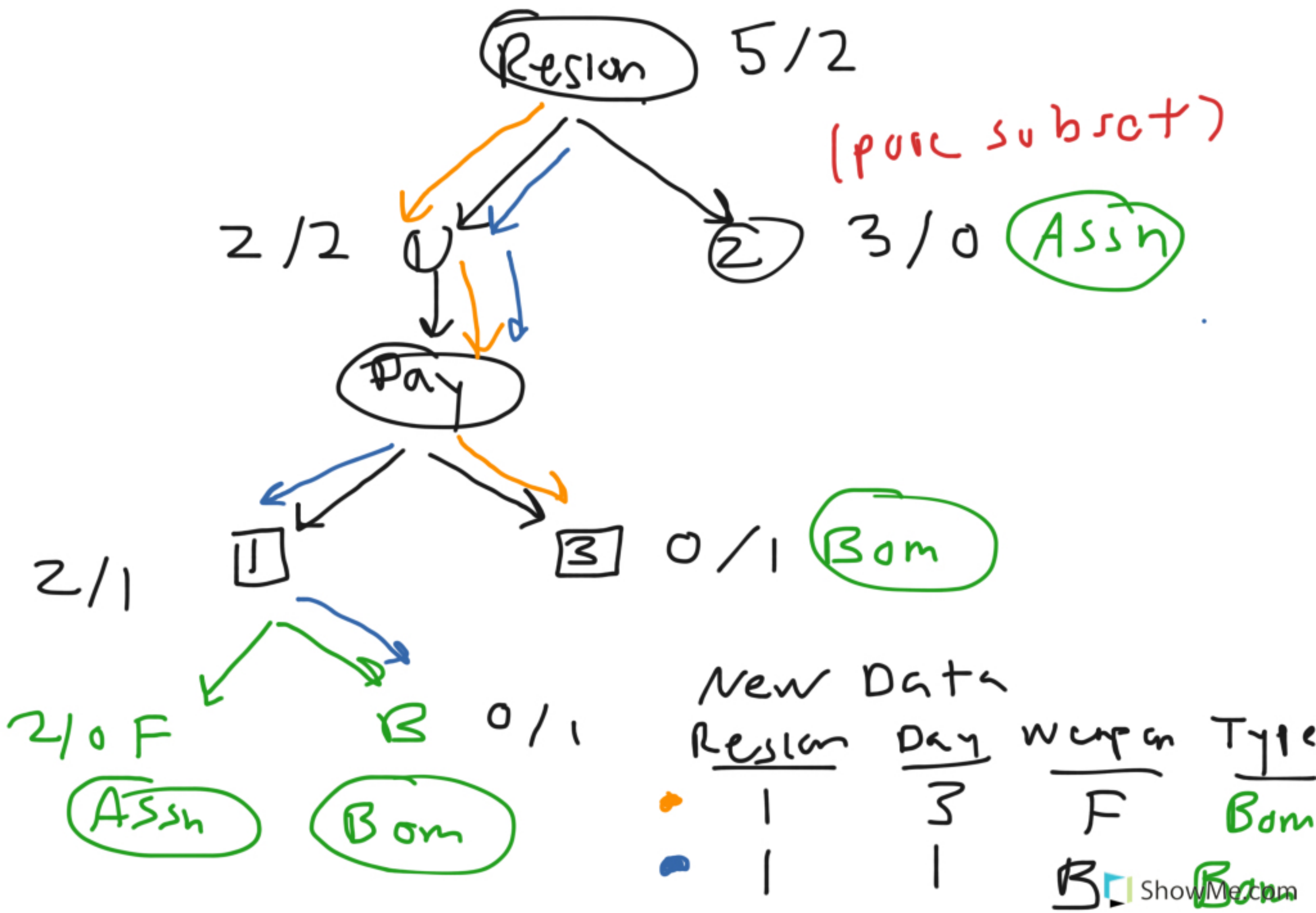
- divide & conquer
- Build a classifier that will predict attack type
 - Features: Region, Day, Weapon
 - Target: Attack type $\hat{y} = \hat{f}(x)$
(Assn, Bom)

<u>Region</u>	<u>Day</u>	<u>Weapon</u>	<u>Type</u>
1	1	F	Assn
2	2	B	Assn
1	3	F	Bom
1	1	F	Assn
2	2	F	Assn
1	1	B	Bom
2	2	B	Assn

①
Region Day

②
Day Weapon

③
Region Weapon



CART / ID3 Algorithm

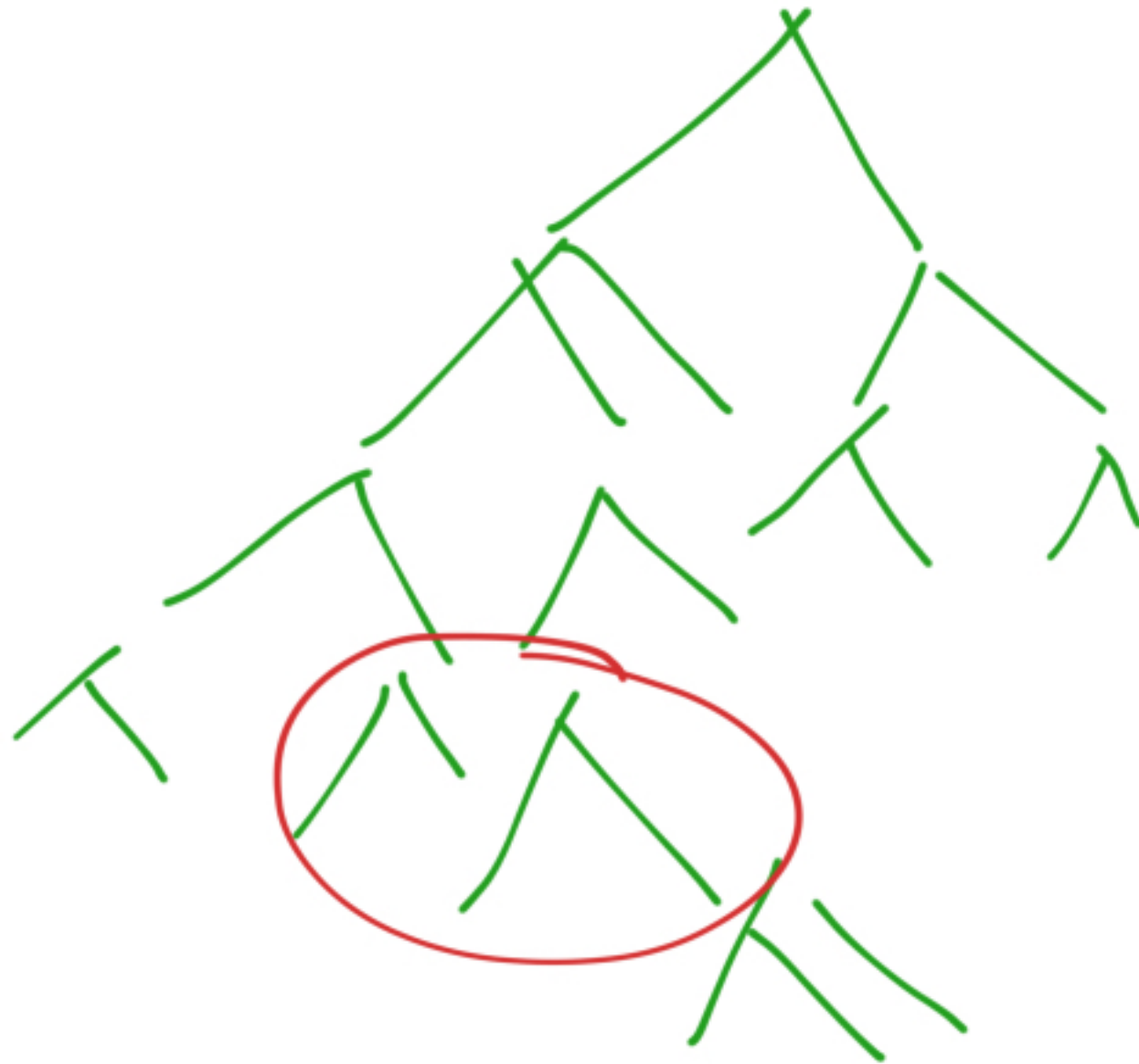
- choose the best feature on the basis of 'information gain'.
- create a new child node for each feature
- for each child node
 - if (subset is pure) { stop }
 - else split node, examples)

why DTs are great

- ① high-performance ✓
- ② interpretable / transparent ✓

~~why DT's still~~

- ~~① overfit (pruning) ✓ (random forests)~~
- ~~② computationally intensive ✓~~
~~(gradient boosting)~~



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Random Forest

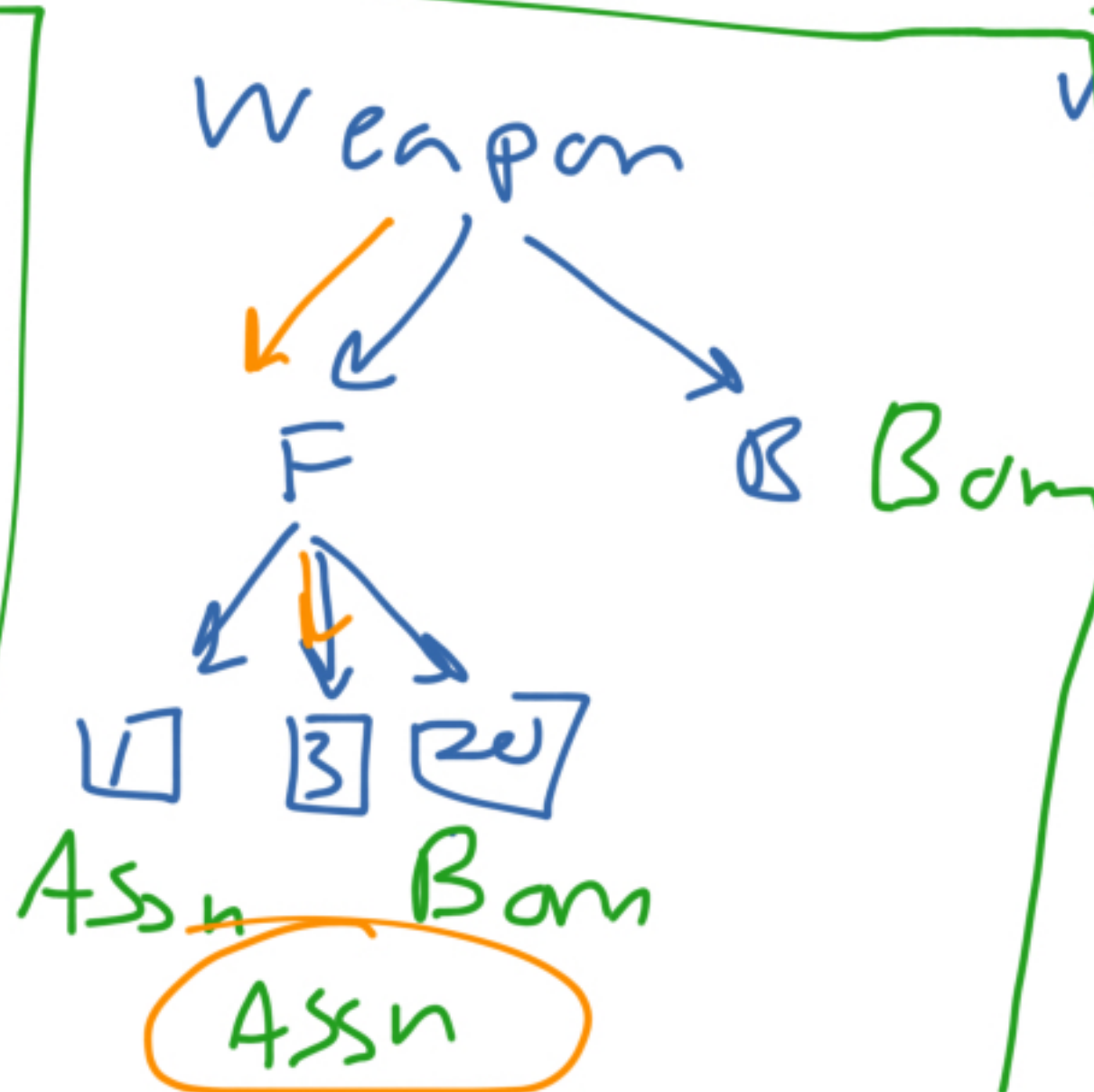
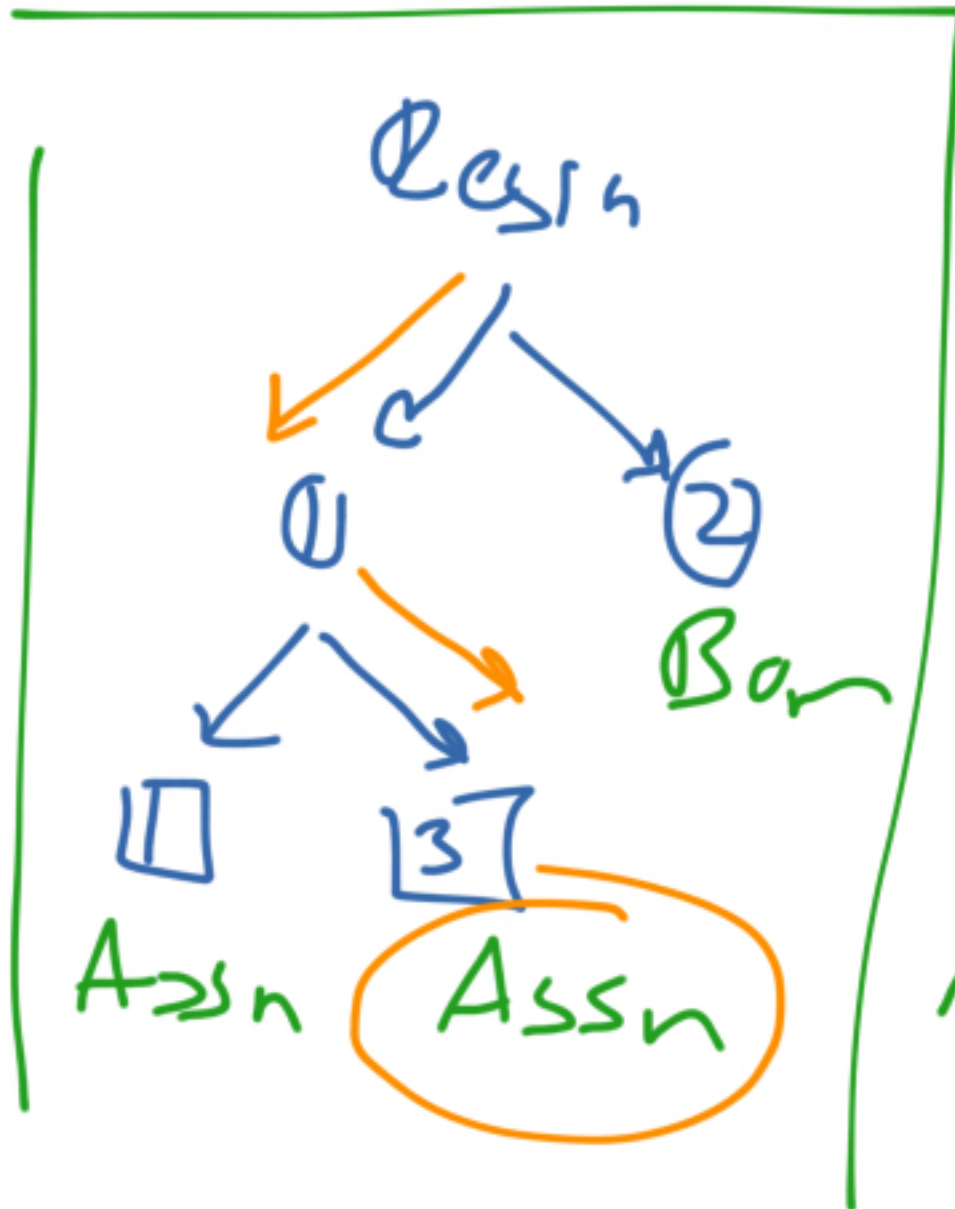
①

Resin/Dry

②

Pay/Victim Resin/Weapon

Resin 1, Dry 3,
Weapon 7
③ Assn



①
Assn
||

②
Assn
Bom

③
Bom
||

Label
Assn
Bom