

Hello and Welcome to AI Camp



XGBOOST

EXTREME GRADIENT BOOSTING WITH XGBOOST

HARIS BEL.
TURKI

LET'S TALK ABOUT ENSEMBLE TECHNIQUES FIRST



ENSEMBLE TECHNIQUES :

- **BAGGING :**

- **Random forest classifier**

- **Random forest regressor**

- **BOOSTING :**

- **Adaboost**

- **Gradient boosting**

- **XGBoost**

BOOSTING :

- WHAT IS BOOSTING :
 - Ensemble sequential meta-algorithm used to convert many weak learners into a strong learner
- HOW BOOSTING WORKS :

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TRAINING DATA

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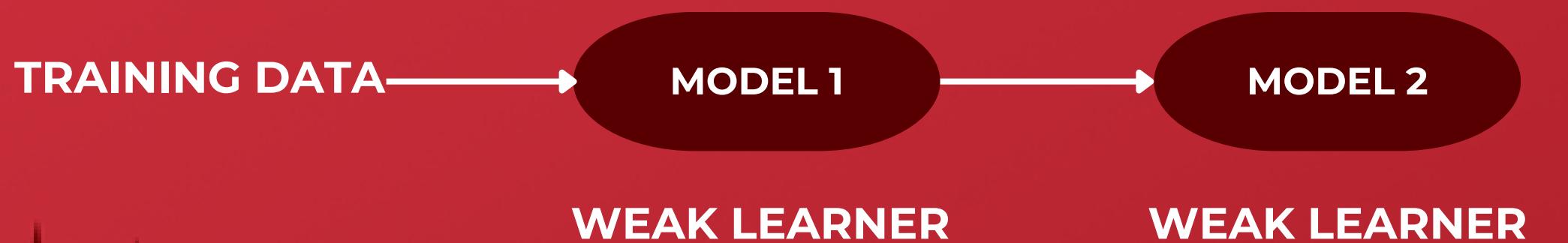
TRAINING DATA →

MODEL 1

WEAK LEARNER

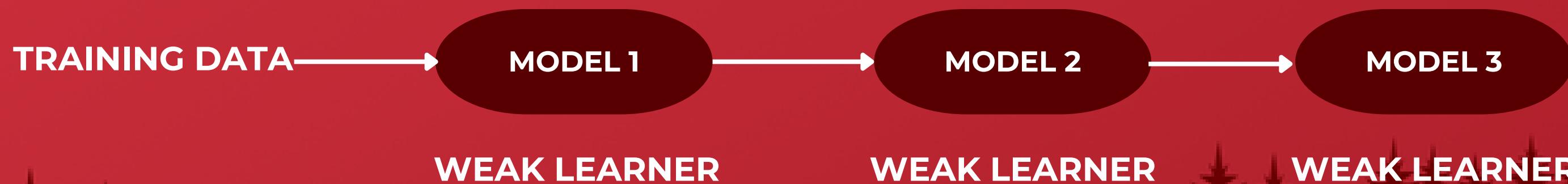
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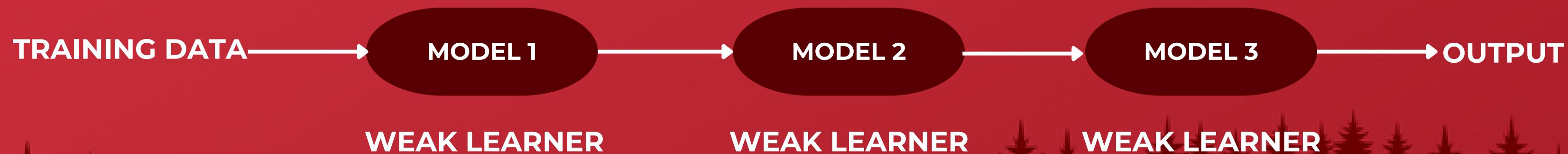
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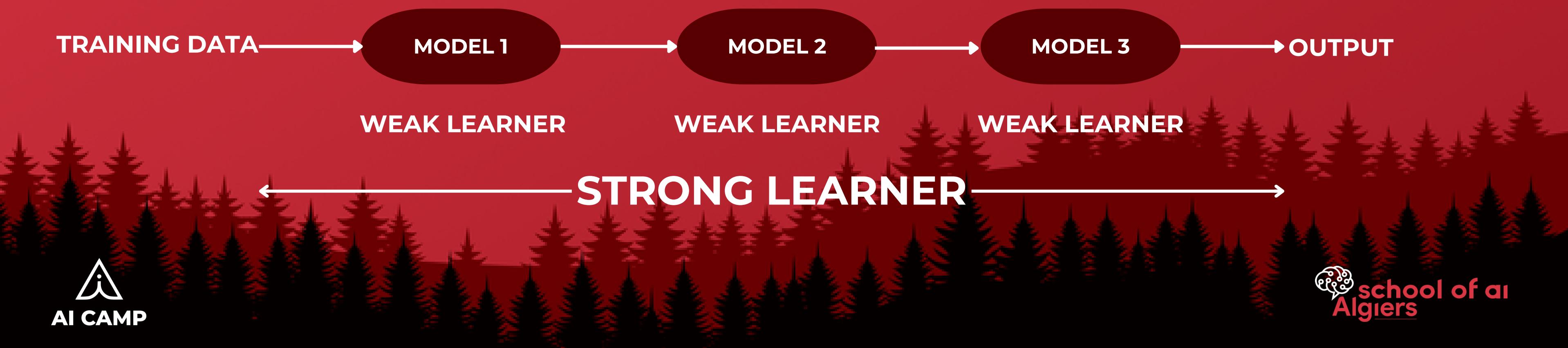
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WEAK LEARNERS AND STRONG LEARNERS :

- **WEAK LEARNER :**
 - ML algorithm that is slightly better than chance
 - Slightly better than chance means we are always going to have an error rate which is less than $1/2$
- **STRONG LEARNER :**
 - Any algorithm that can be tuned to achieve good performance

LET'S TALK ABOUT XGBOOST!

EXTREME GRADIENT BOOSTING WITH XGBOOST



WHAT IS XGBOOST (eXtreme Gradient Boosting) :

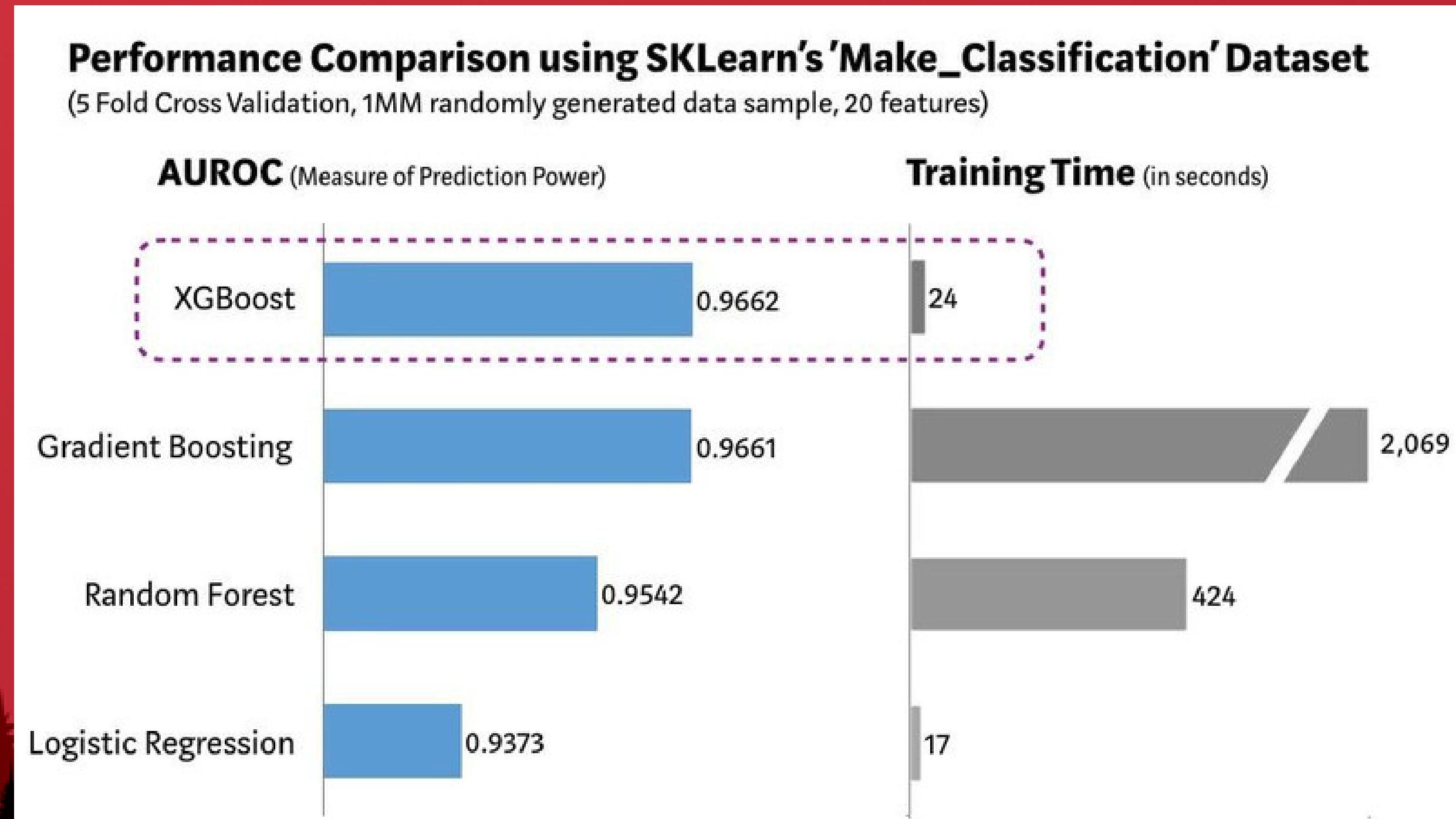
- Open source implementation of boosted trees
- Optimized gradient-boosting machine learning library
- Originally written in C++
- Has API's in several languages :
 - Python
 - R
 - Java

WHAT MAKES XGBOOST SO POPULAR :

- Fast & Efficient Implementation
- Speed and performance
- Core algorithm is parallelizable
- Consistently outperforms single-algorithm methods
- State-of-the-art performance in many ML tasks
- Built in regularization to prevent overfitting
- Highly competitive algorithm for machine learning competitions (eg: kaggle competitions)

WHAT MAKES XGBOOST SO POPULAR :

- Comparison between XGBoost and other models :



WHAT MAKES XGBOOST SO POPULAR :

- Comparison between XGBoost and Keras :

| Category | XGBoost | Keras Deep Learning | Winner? |
|---|---|---|---|
| Performance on test set | | | |
| Accuracy | 80.1% | 78.1% | |
| recall: true positive / (true positive + false negative) | 0.89 | 0.68 | XGBoost |
| false negatives | 1,200 | 3,500 | |
| Training time | 1 minute 24 seconds | 2 minutes – 3 minutes for 50 epoch experiment depending on hw env and call back patience setting | Inconclusive – deep learning training time varies |
| Code complexity | <ul style="list-style-type: none">• Extra steps required to transform data coming out of pipeline• 1 line to build model | <ul style="list-style-type: none">• Data from pipeline ready to train model• Complex model build | Inconclusive |
| Flexibility | Handles continuous & categorical columns | Handles continuous, categorical and text columns | Deep learning |

XGBOOST STEPS :

- XGBoost is an implementation of gradient boosting that goes through cycles to iteratively add models into an ensemble

XGBOOST STEPS :

- XGBoost is an implementation of gradient boosting that goes through cycles to iteratively add models into an ensemble
- It begins by initializing the ensemble with a single model, whose predictions can be pretty naive. (even if its predictions are wildly inaccurate, subsequent additions to the ensemble will address those errors.)

BASE / INITIAL
MODEL

XGBOOST STEPS :

- Then, we start the cycle:
- First, we use the current ensemble to generate predictions for each observation in the dataset. To make a prediction, we add the predictions from all models in the ensemble.



XGBOOST STEPS :

- Then, we start the cycle:
- First, we use the current ensemble to generate predictions for each observation in the dataset. To make a prediction, we add the predictions from all models in the ensemble.
- These predictions are used to calculate the errors(residuals) based on the previous model residuals for each observation in the dataset.



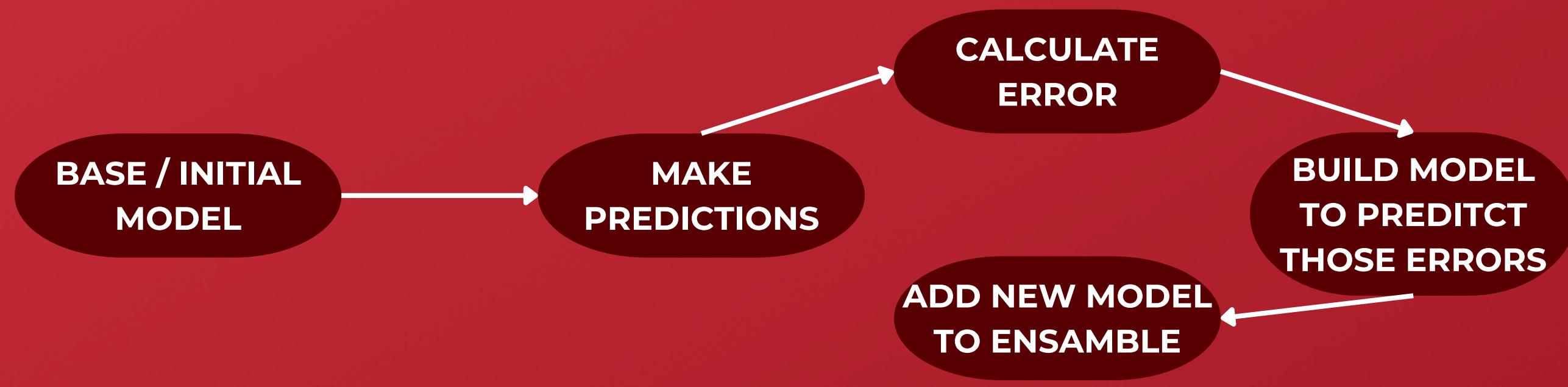
XGBOOST STEPS :

- Then, we build a new model to predict those errors (residuals)



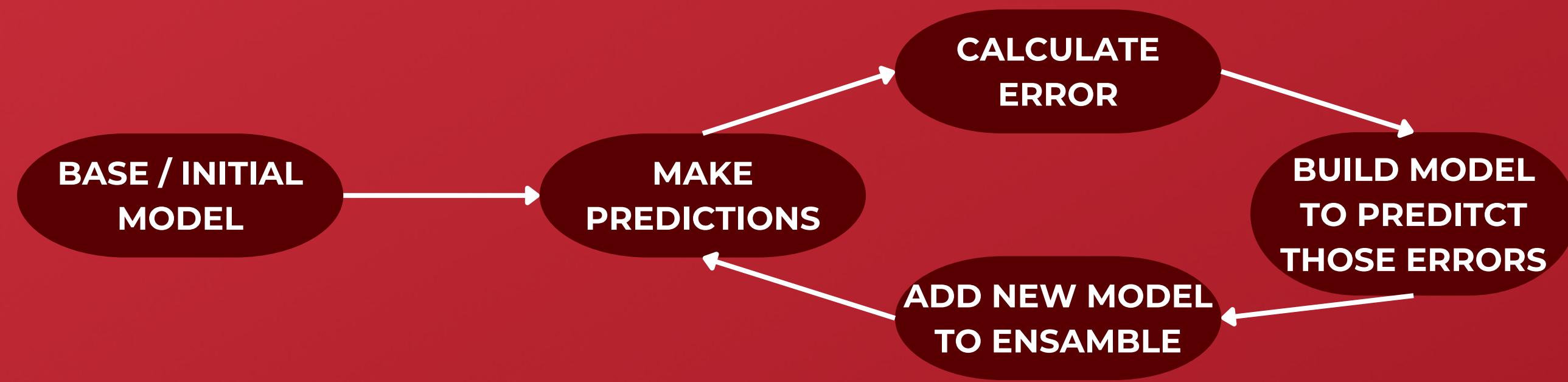
XGBOOST STEPS :

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- Finally, we add the new model to ensemble, and ...



XGBOOST STEPS :

- Then, we build a new model to predict those errors (residuals)
- Finally, we add the new model to ensemble, and ...
- ... repeat!



LET'S BEGIN USING XGBOOST!

EXTREME GRADIENT BOOSTING WITH XGBOOST



LET'S START WITH XGBOOST FOR CLASSIFICATION

EXTREME GRADIENT BOOSTING WITH XGBOOST



XGBOOST CLASSIFICATION :

- Dataset :

| SALARY | CREDIT | APPROVAL | RES |
|--------|--------|----------|-----|
| <=50K | B | 0 | |
| <=50K | G | 1 | |
| <=50K | G | 1 | |
| >50K | B | 0 | |
| >50K | G | 1 | |
| >50K | N | 1 | |
| <=50K | N | 0 | |

Pr =0.5

BASE / INITIAL
MODEL

- STEPS :

- Calculate Residuals and Construct tree with root
- Calculate Similarity Weight = $\frac{\sum(\text{Residuals})^2}{\sum(\text{Pr}(1-\text{Pr}))+\lambda}$
- Calculate the gain = SWL+SWR-SW(ROOT)

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| Pr =0.5 | BASE / INITIAL MODEL | | |
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Salary

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BASE / INITIAL
MODEL

Salary

$\leq 50K$

-0.5 , 0.5 , 0.5 ... , -0.5

$>50K$

-0.5 , 0.5 , 0.5 , -0.5

-0.5 , 0.5 , 0.5

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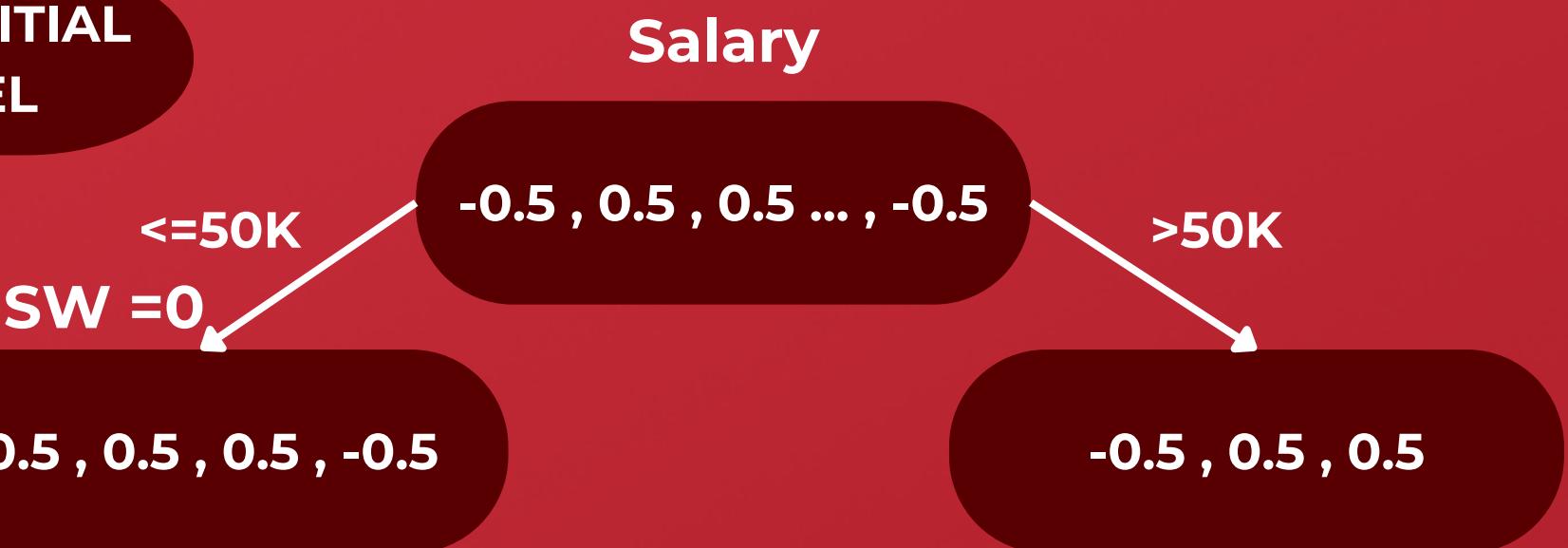
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BASE / INITIAL
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<=50K

-0.5 , 0.5 , 0.5 ... , -0.5

SW =0

-0.5 , 0.5 , 0.5 , -0.5

SW =0.14

>50K

SW =0.33

-0.5 , 0.5 , 0.5

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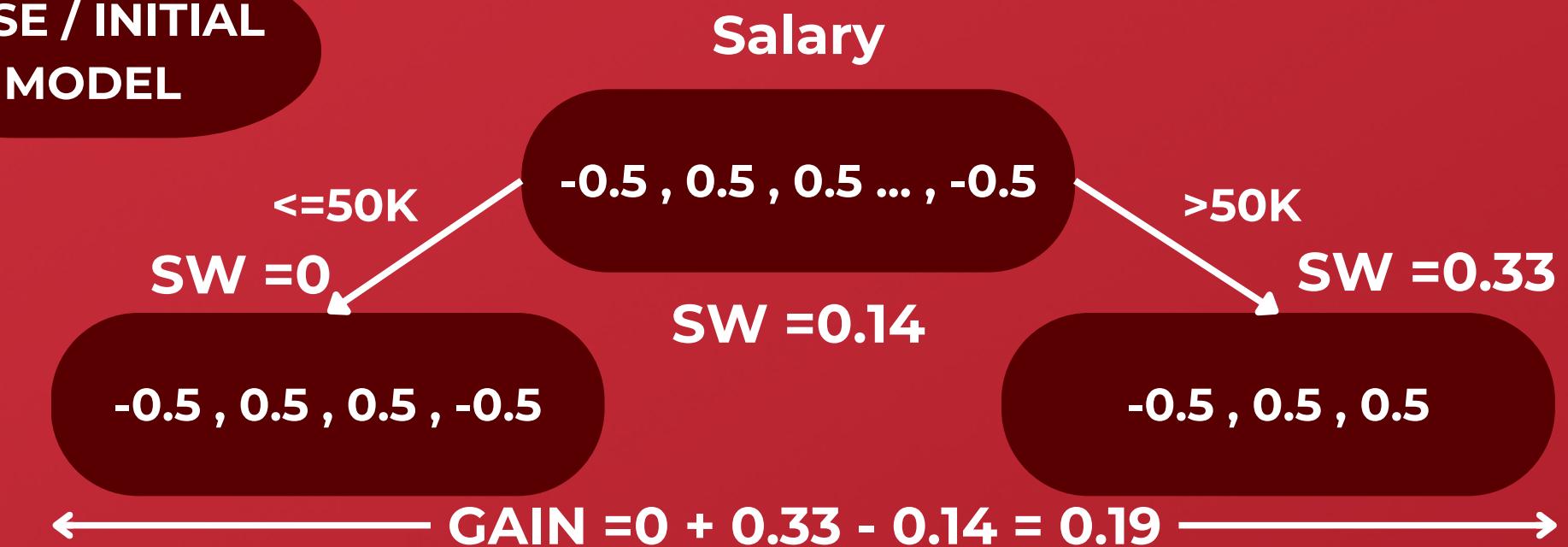
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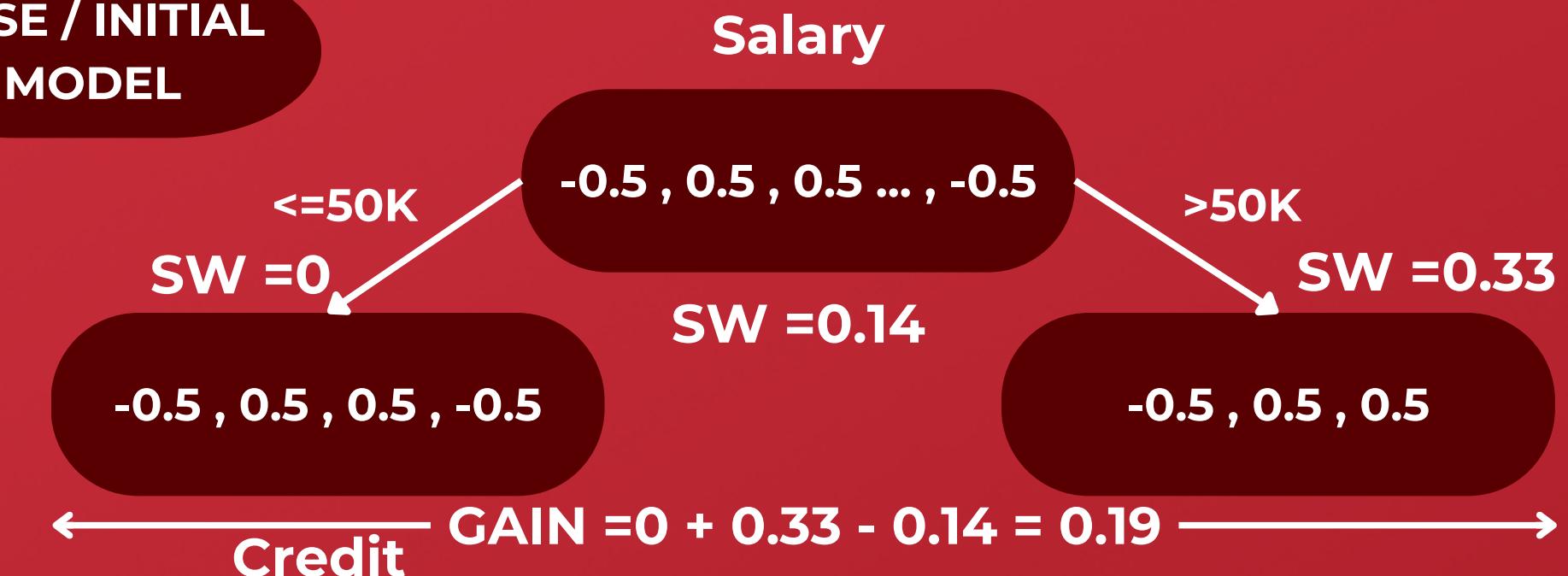
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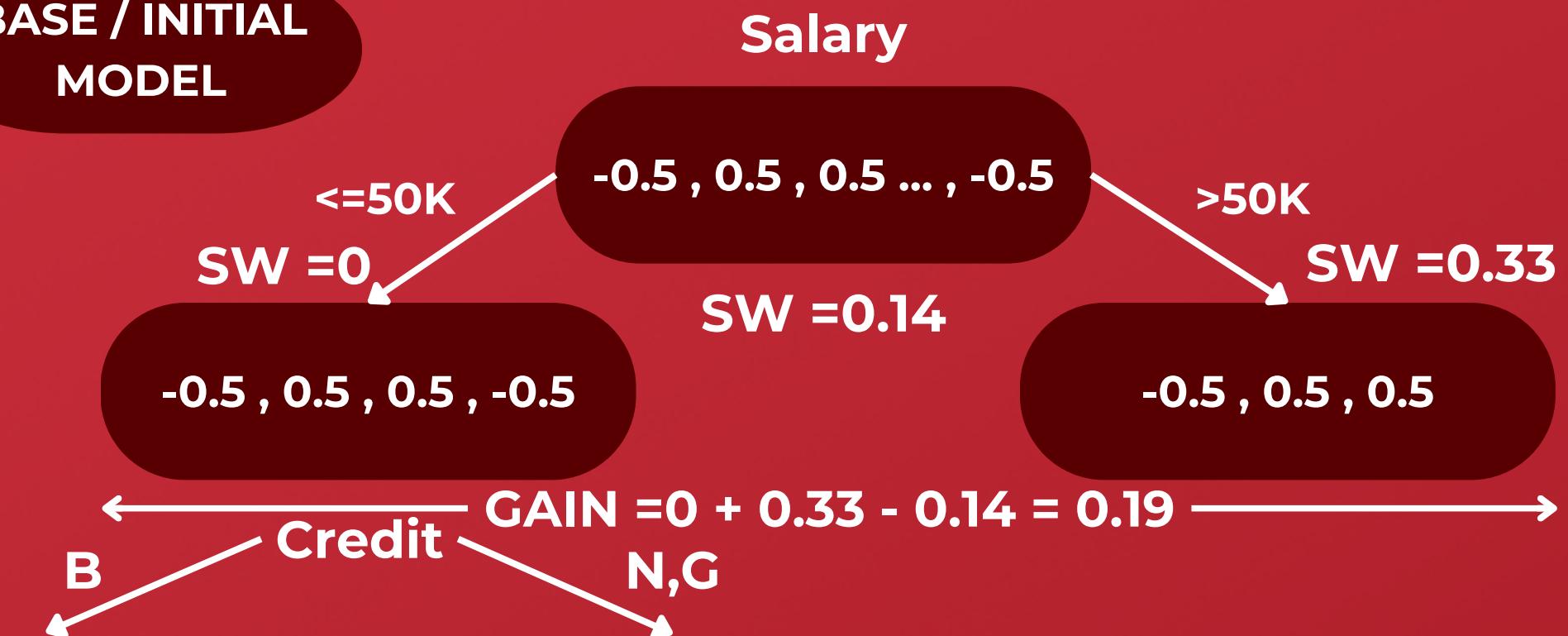
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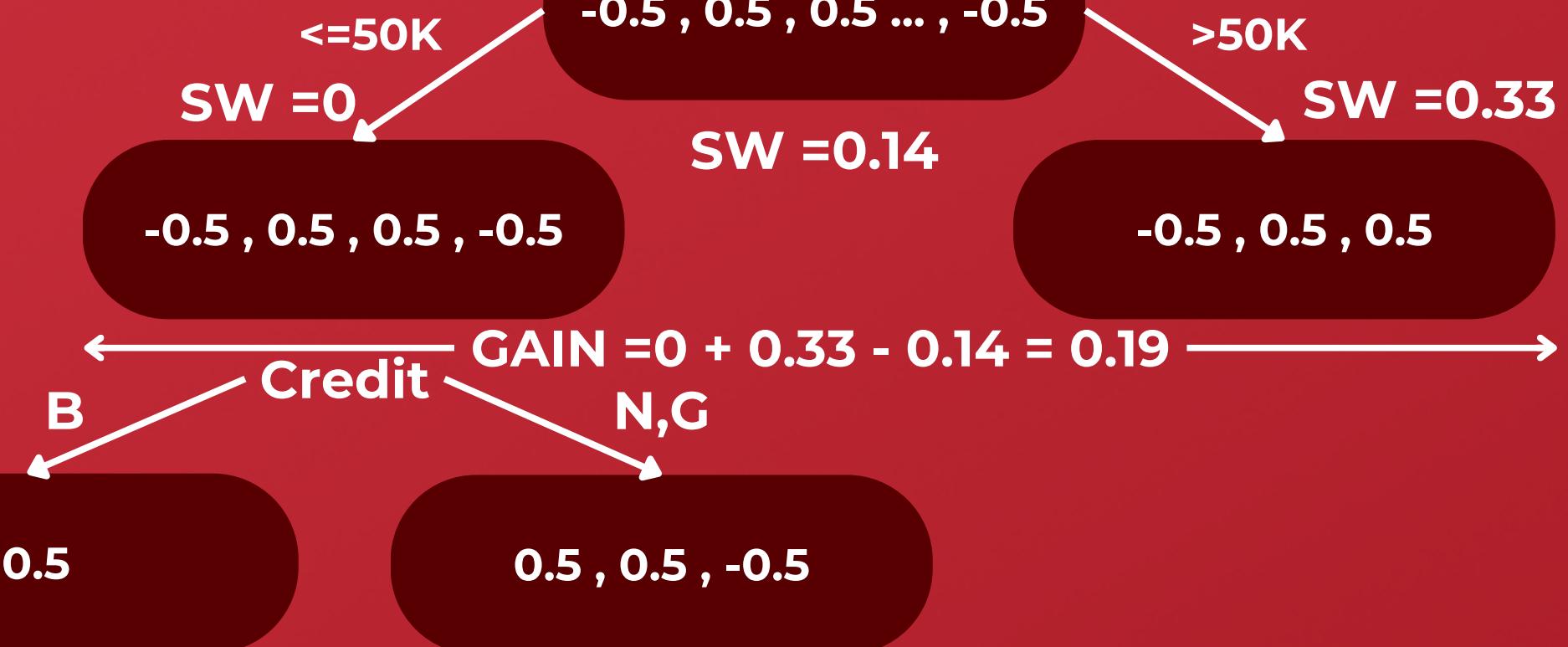
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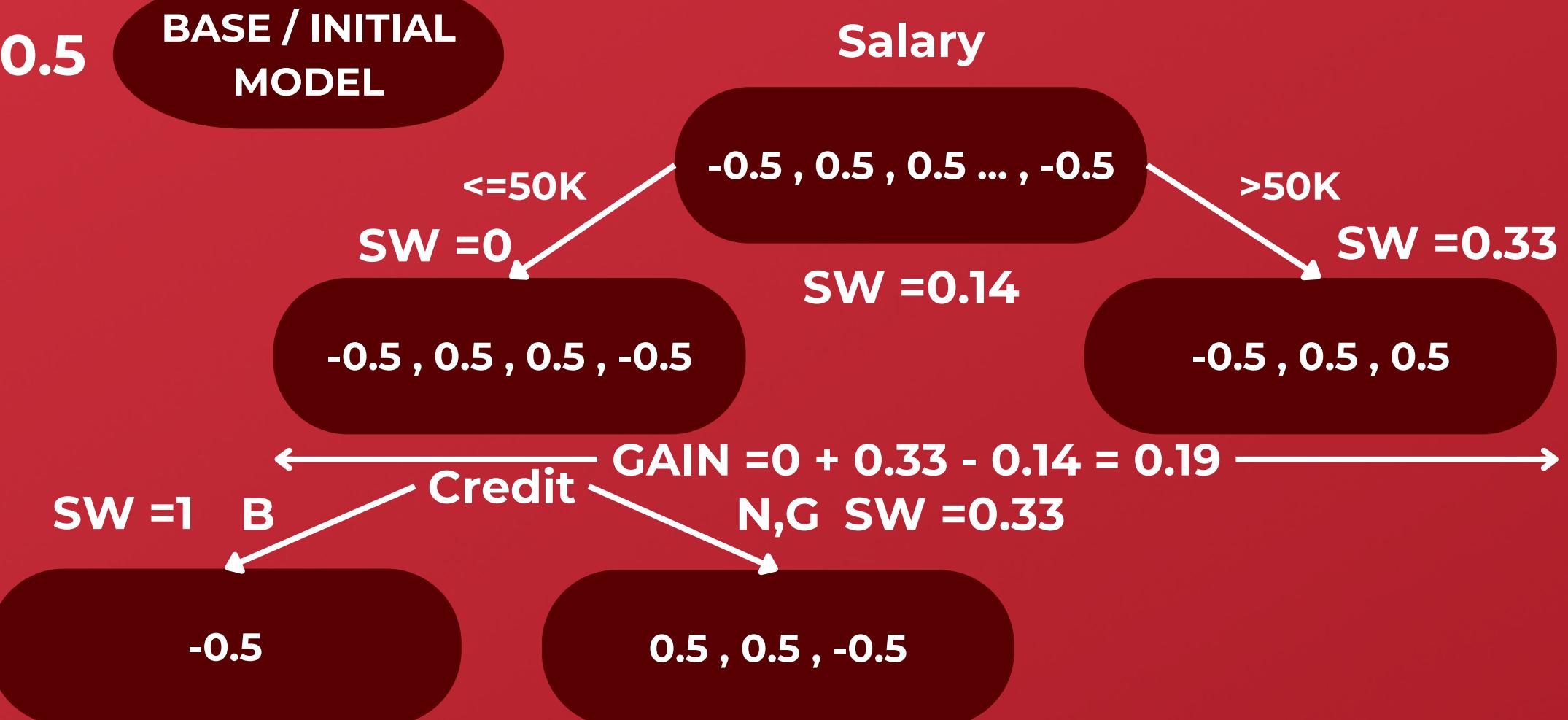
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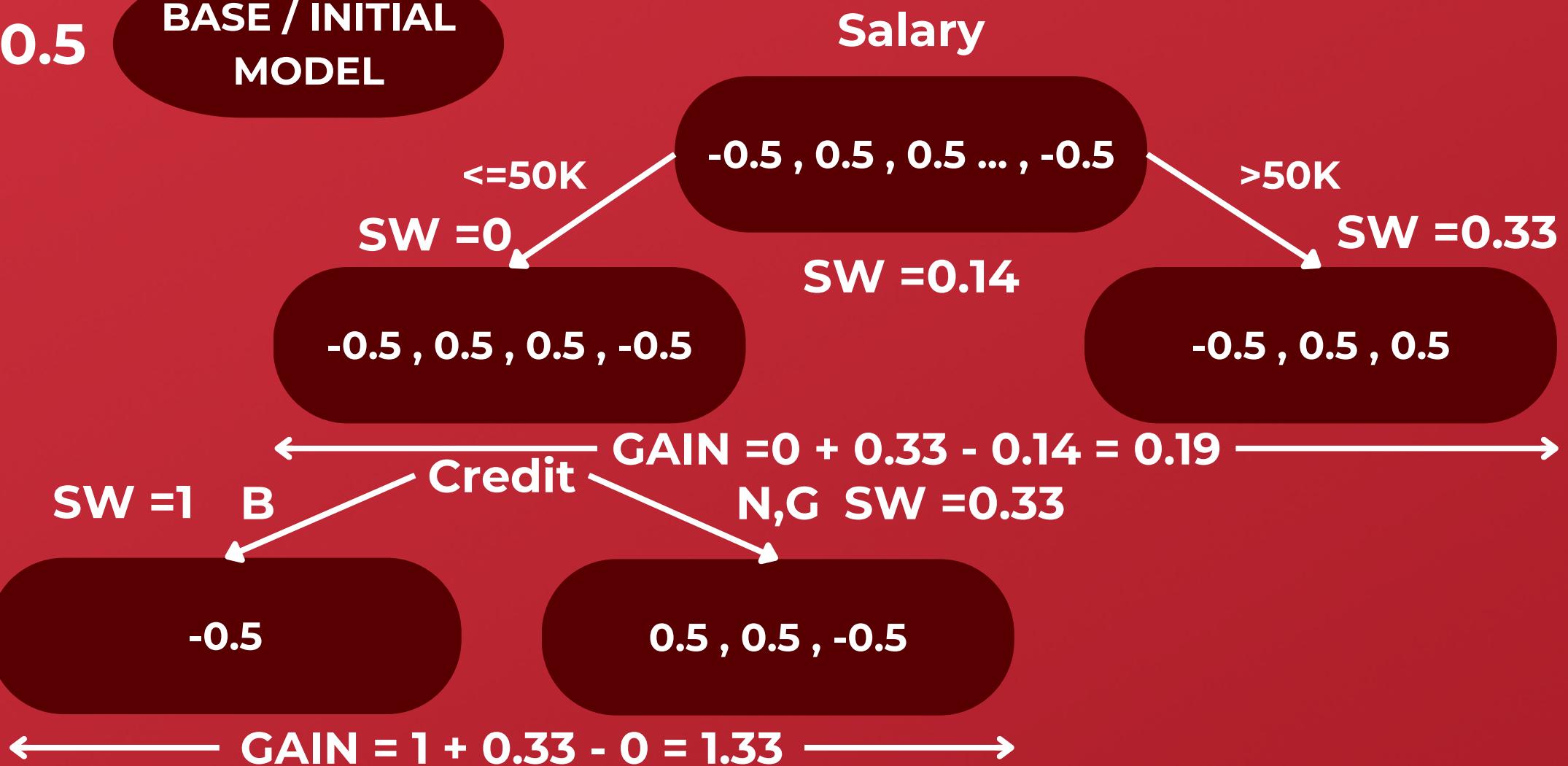
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BASE / INITIAL MODEL

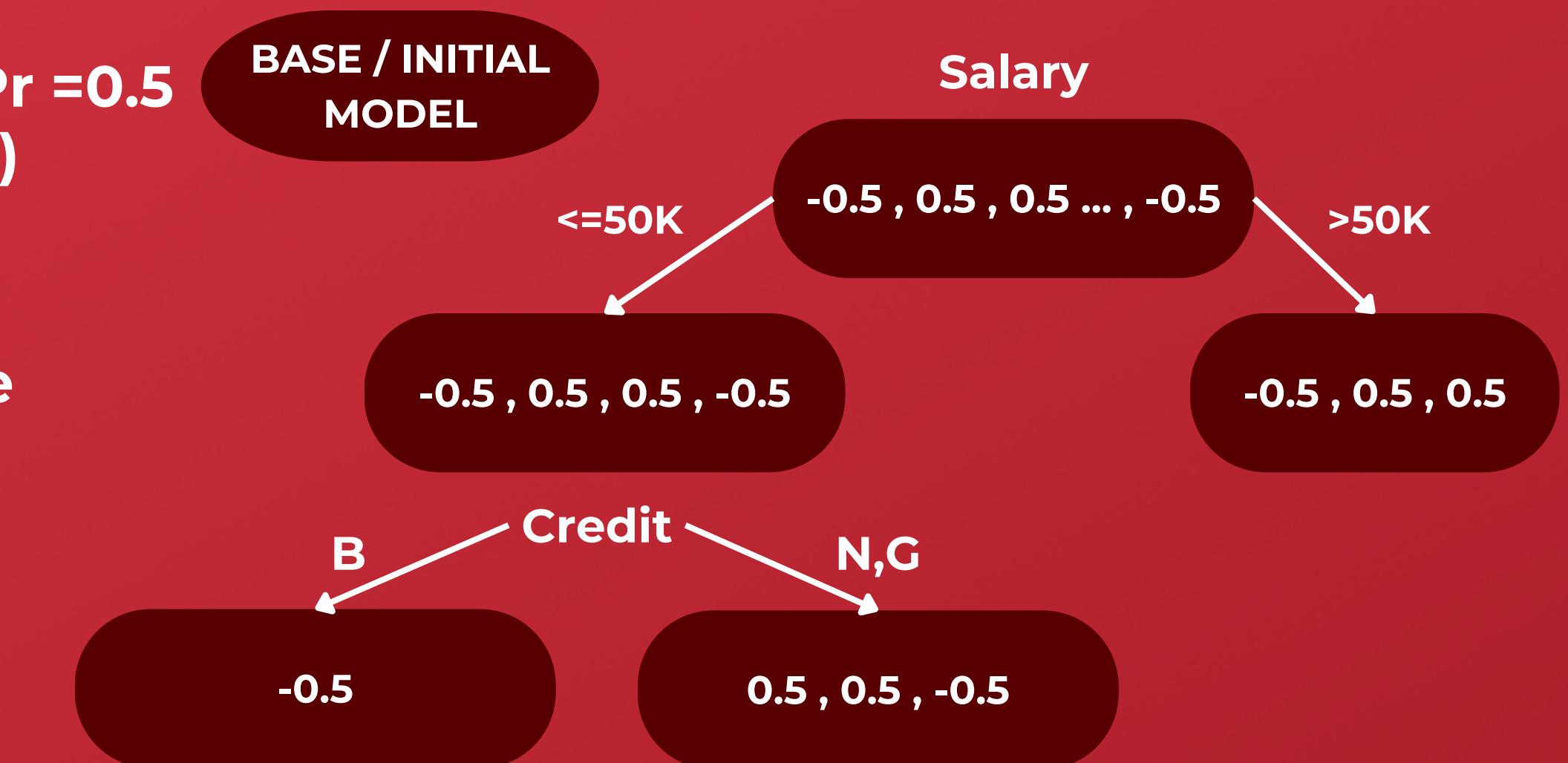


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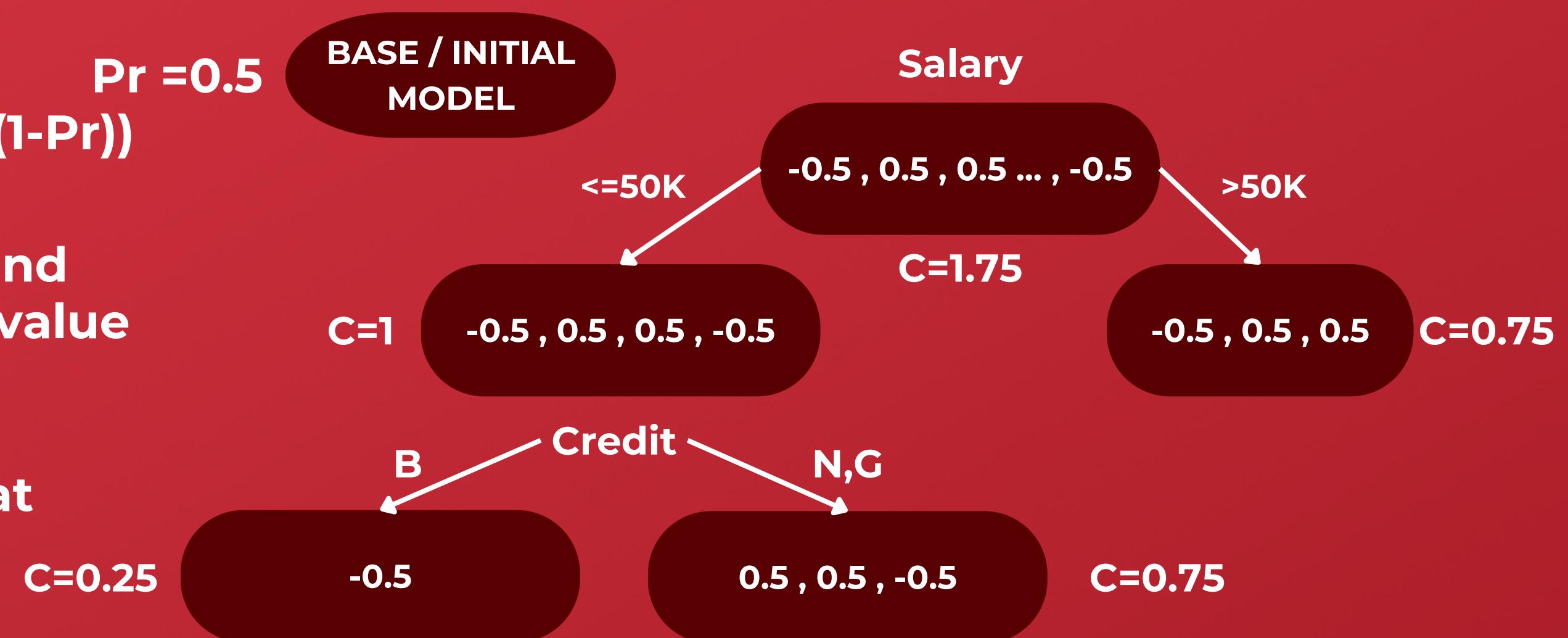
- STEPS (COVER) :
 - Calculate the cover = $\sum(Pr(1-Pr))$ for each leaf
 - Compare each leaf cover and and the default minimum value of the cover (which is by default = 1)
 - Eliminate all the leaves that have a cover < minimum cover



- Example Minimum Cover = 1:
- in Python :
By Default

XGBOOST CLASSIFICATION :

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Pr =0.5

BASE / INITIAL MODEL

C=1

-0.5 , 0.5 , 0.5 , -0.5

Salary

-0.5 , 0.5 , 0.5 ... , -0.5

C=1.75

>50K

-0.5 , 0.5 , 0.5

C=0.75

B Credit
-0.5

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XGBOOST CLASSIFICATION :

- **STEPS (COVER) :**

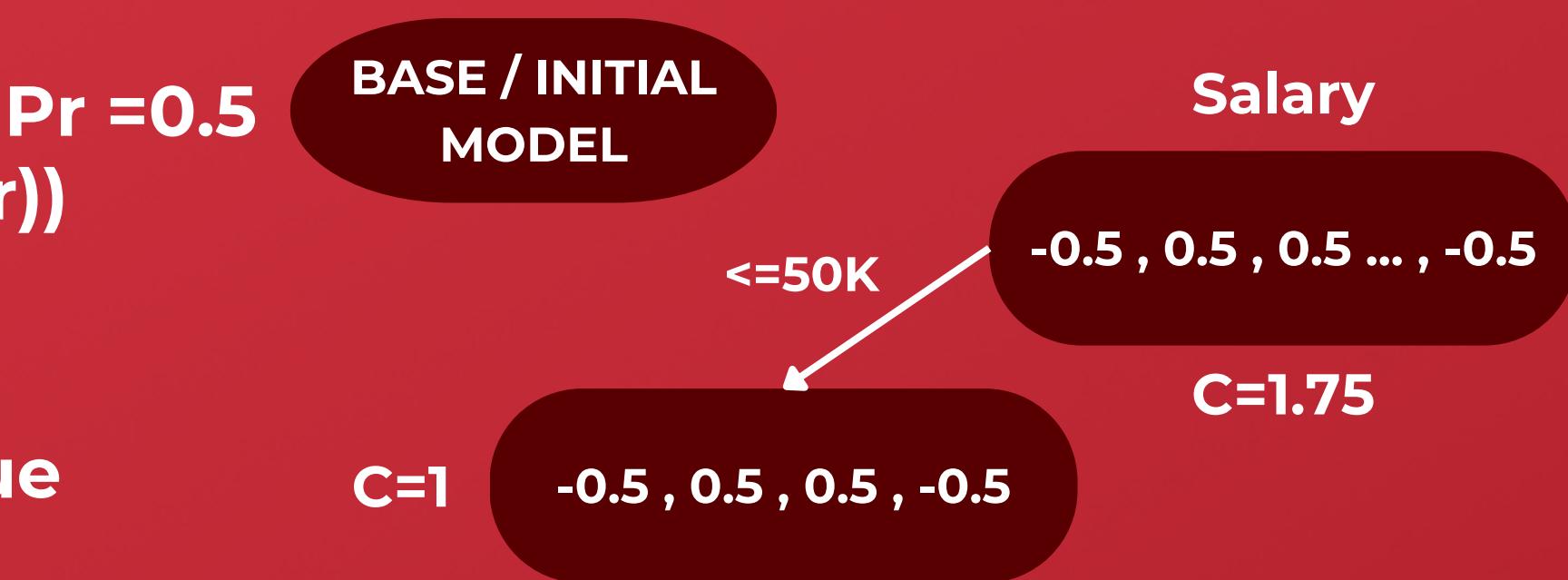
- Calculate the cover = $\sum(Pr(1-Pr))$ for each leaf

- Compare each leaf cover and and the default minimum value of the cover (which is by default = 1)

- Eliminate all the leaves that have a cover < minimum cover

- Example Minimum Cover = 1:

- in Python :
By Default



XGBOOST CLASSIFICATION :

- STEPS (COVER) :

- Calculate the cover = $\sum(\Pr(1-\Pr))$ for each leaf
- Compare each leaf cover and and the default minimum value of the cover (which is by default = 1)
- Eliminate all the leaves that have a cover < minimum cover

$\Pr = 0.5$

$C=0.25$

BASE / INITIAL MODEL

$C=1$

-0.5

Salary

$\leq 50K$

-0.5 , 0.5 , 0.5 , -0.5

$C=1.75$

B

Credit

N,G

0.5 , 0.5 , -0.5

$C=0.75$

$> 50K$

-0.5 , 0.5 , 0.5

$C=0.75$

- Example Minimum Cover = 3 :
- in Python :
`min_child_weight=3`

XGBOOST CLASSIFICATION :

- STEPS (COVER) :

Pr =0.5

BASE / INITIAL
MODEL

- Calculate the cover = $\sum(\text{Pr}(\text{l-Pr}))$ for each leaf
- Compare each leaf cover and and the default minimum value of the cover (which is by default = 1)
- Eliminate all the leaves that have a cover < minimum cover

- Example Minimum Cover = 3 :
- in Python :
`min_child_weight=3`

XGBOOST CLASSIFICATION :

- **STEPS (COVER) :**

- Calculate the cover = $\sum(\Pr(1-\Pr))$ for each leaf
- Compare each leaf cover and and the default minimum value of the cover (which is by default = 1)
- Eliminate all the leaves that have a cover < minimum cover

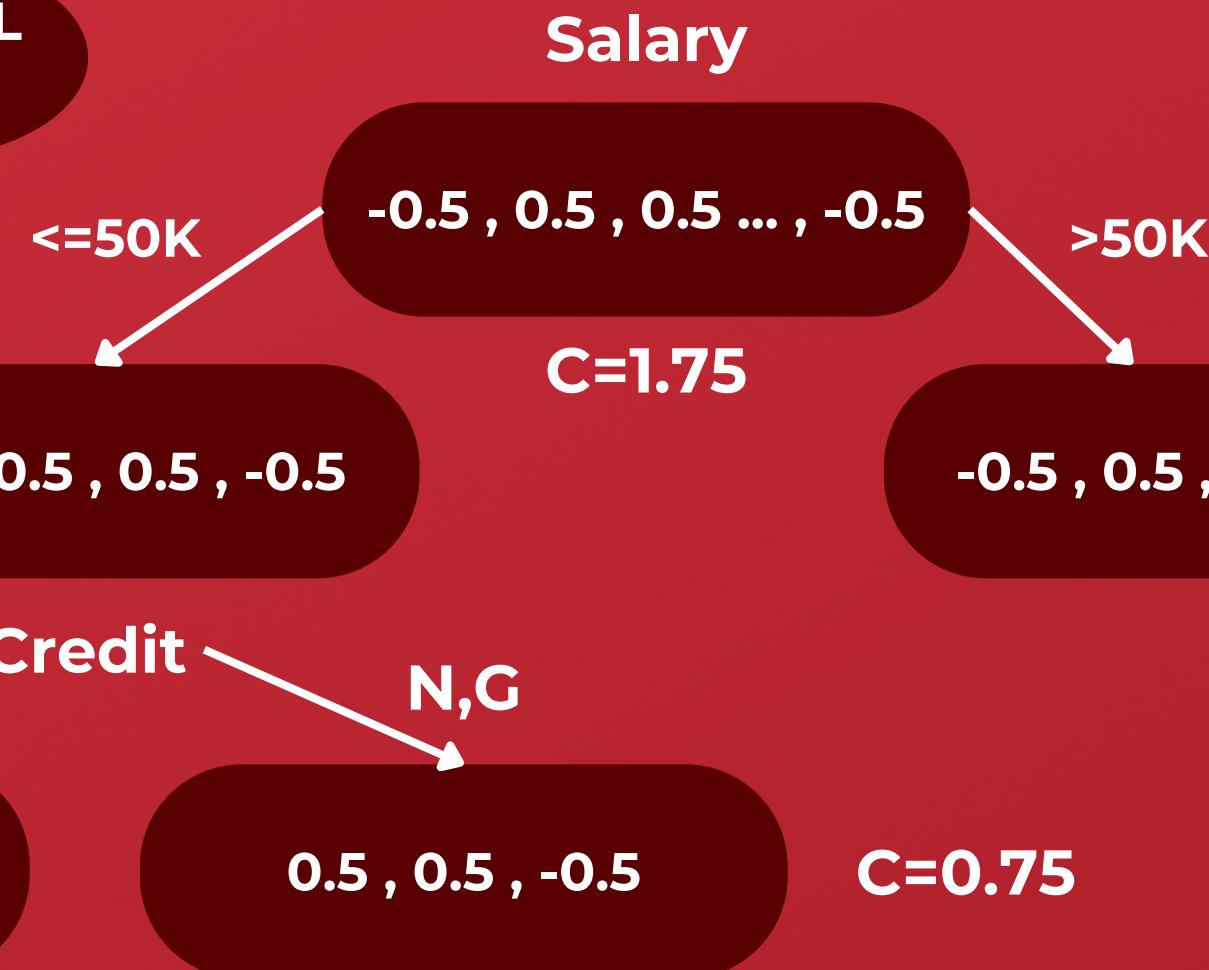
$\Pr = 0.5$

$C=0.25$

BASE / INITIAL MODEL

$C=1$

-0.5



- Example Minimum Cover = 0 :
- in Python :
`min_child_weight=0`

XGBOOST CLASSIFICATION :

- STEPS (PRUNING) :

- Calculate the :

- Gain of the branch - γ (Gamma)**

- γ (Gamma) is Tree Complexity parameter

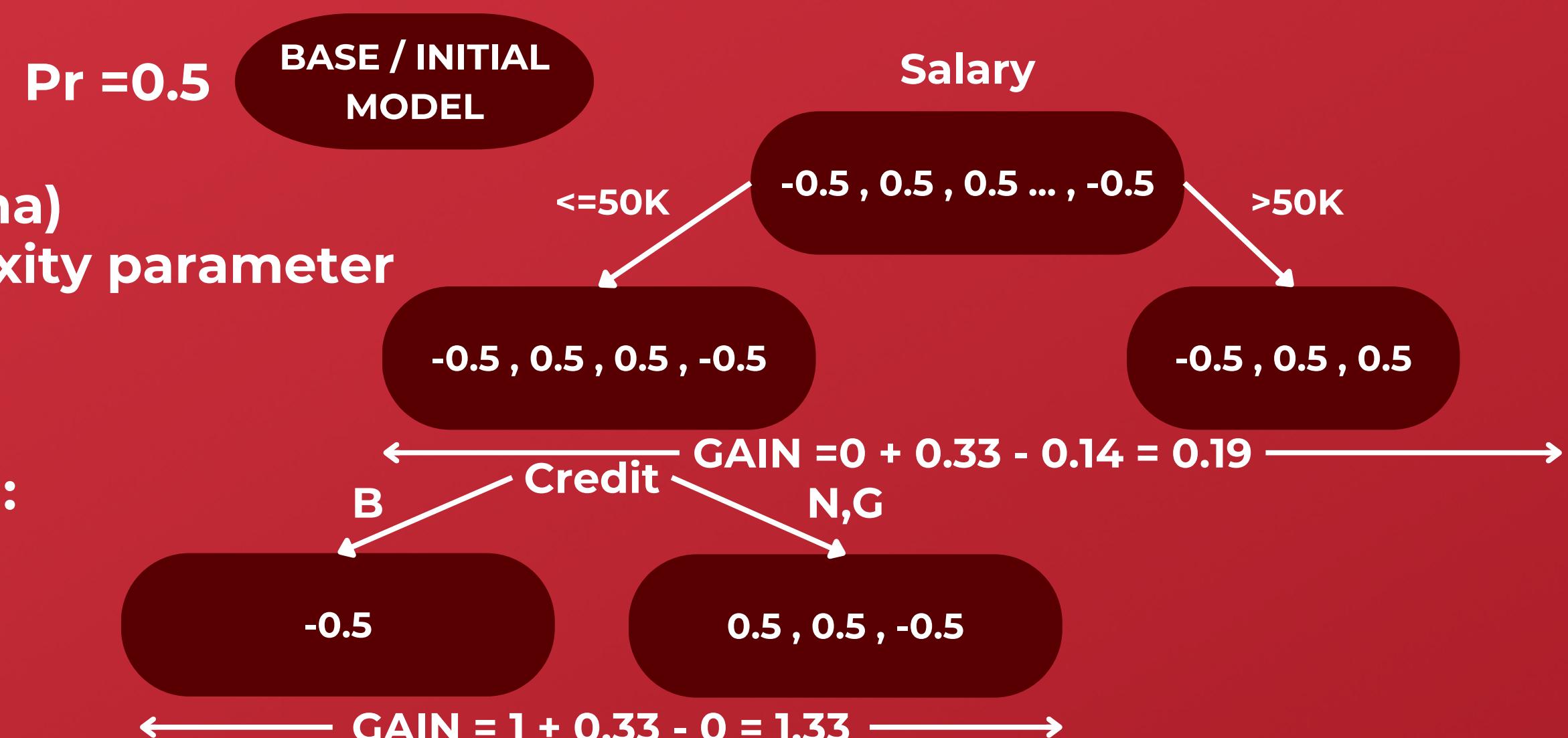
- If The Gain - $\gamma < 0$:

- We Prune the branch

- If we Prune we Calculate the :

- Next Gain - γ

- Etc ...



- Example $\gamma = 2$:

XGBOOST CLASSIFICATION :

- STEPS (PRUNING) :

- Calculate the :

- Gain of the branch - γ (Gamma)**

- γ (Gamma) is Tree Complexity parameter

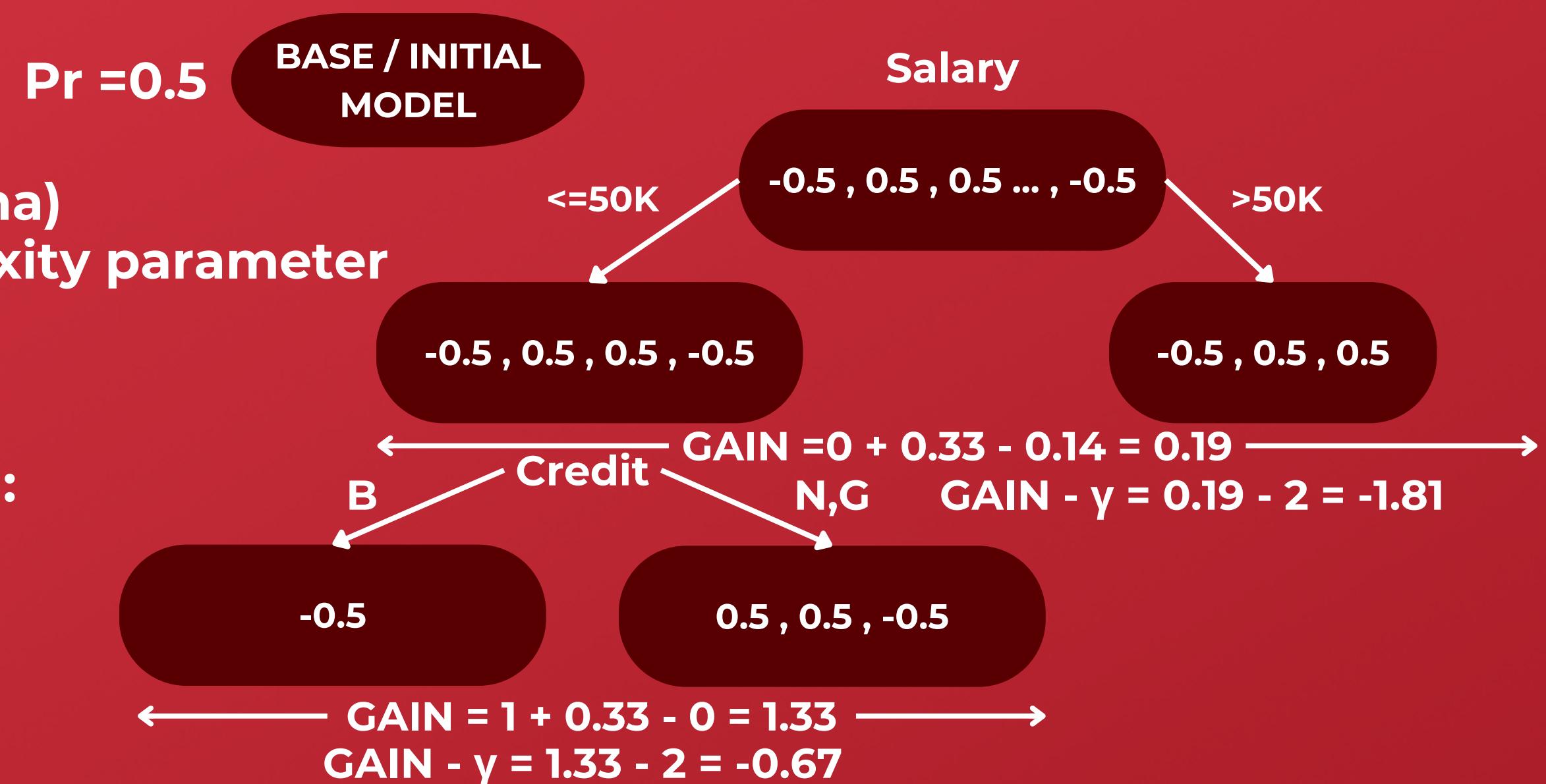
- If The Gain - $\gamma < 0$:

- We Prune the branch

- If we Prune we Calculate the :

- Next Gain - γ

- Etc ...



- Example $\gamma = 2$:

XGBOOST CLASSIFICATION :

- STEPS (PRUNING) :
 - Calculate the :
Gain of the branch - γ (Gamma)
 - γ (Gamma) is Tree Complexity parameter
 - If The Gain - $\gamma < 0$:
 - We Prune the branch
 - If we Prune we Calculate the :
Next Gain - γ
 - Etc ...
- Example $\gamma = 2$:

Pr =0.5

BASE / INITIAL
MODEL

XGBOOST CLASSIFICATION :

- STEPS (PRUNING) :

- Calculate the :

- Gain of the branch - γ (Gamma)**

- γ (Gamma) is Tree Complexity parameter

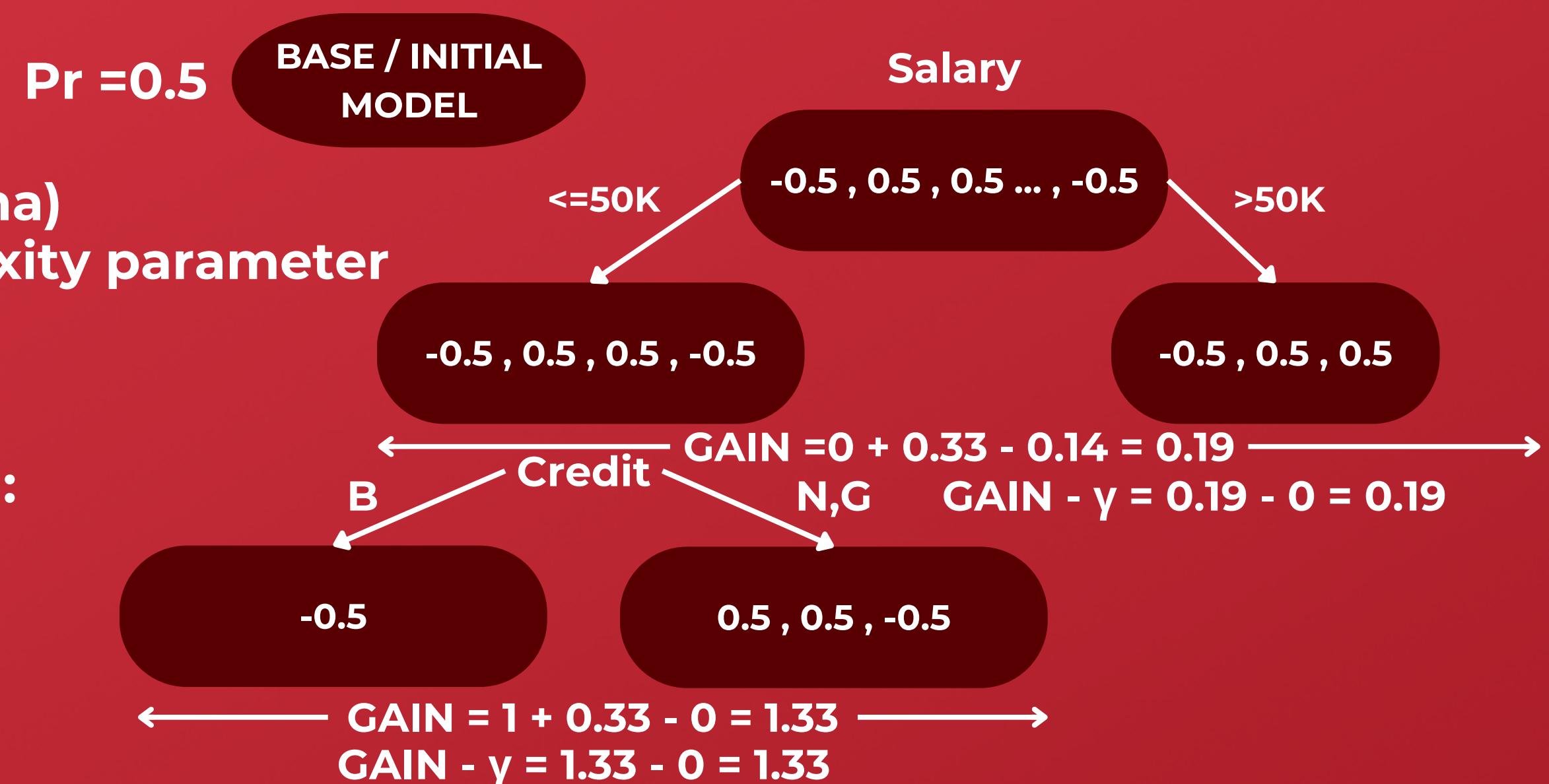
- If The Gain - $\gamma < 0$:

- We Prune the branch

- If we Prune we Calculate the :

- Next Gain - γ

- Etc ...



- Example $\gamma = 0$:

XGBOOST CLASSIFICATION :

- STEPS (PRUNING) :

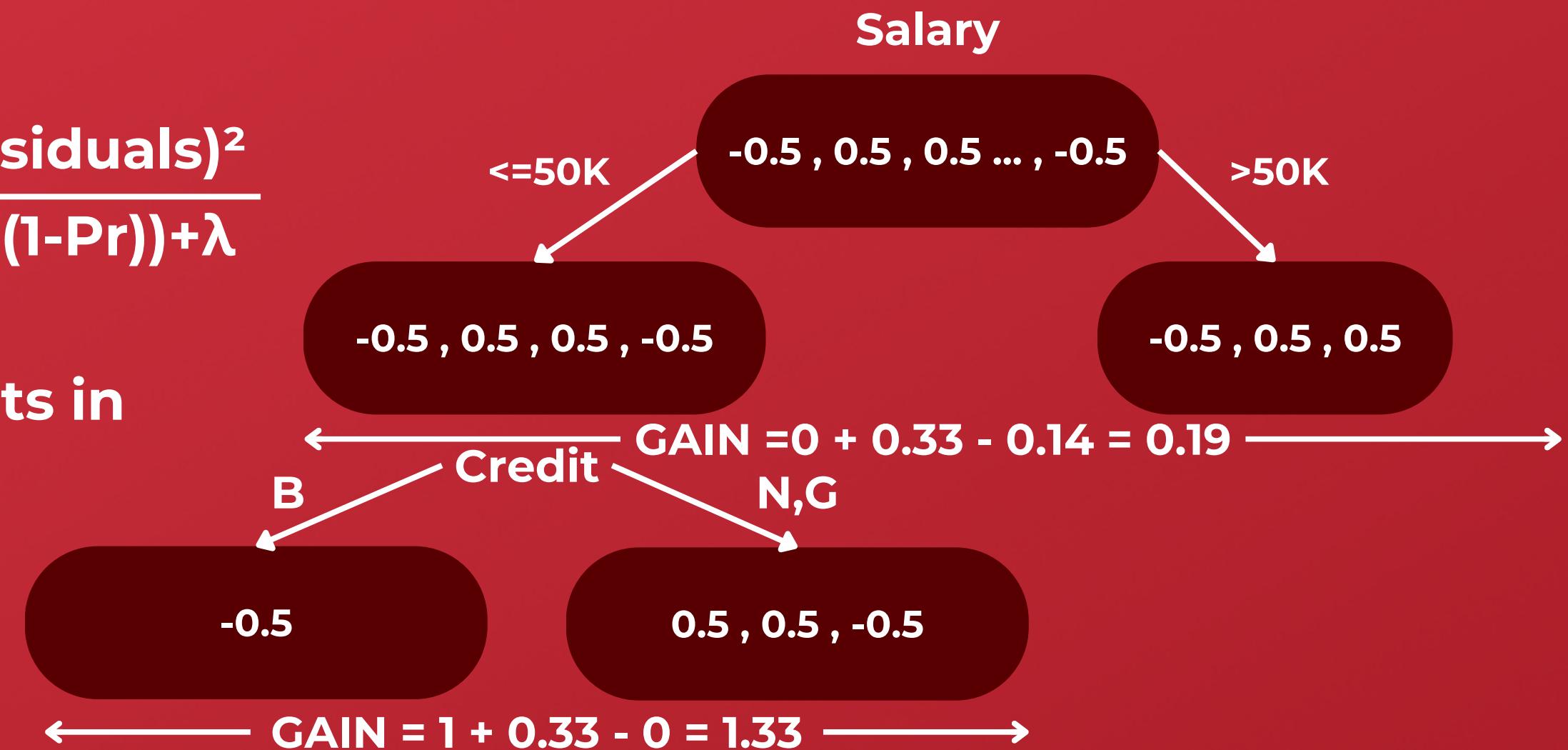
- Lastly, We Know That $SW = \frac{\sum(\text{Residuals})^2}{\sum(\text{Pr}(1-\text{Pr}))+\lambda}$

- So λ (Lambda) is a Regularization Parameter and when $\lambda > 0$, it results in more pruning by shrinking the Similarity Weights and branches gains .

- Example $\gamma=0$ & $\lambda=0$:

- WHY PRUNING ? :

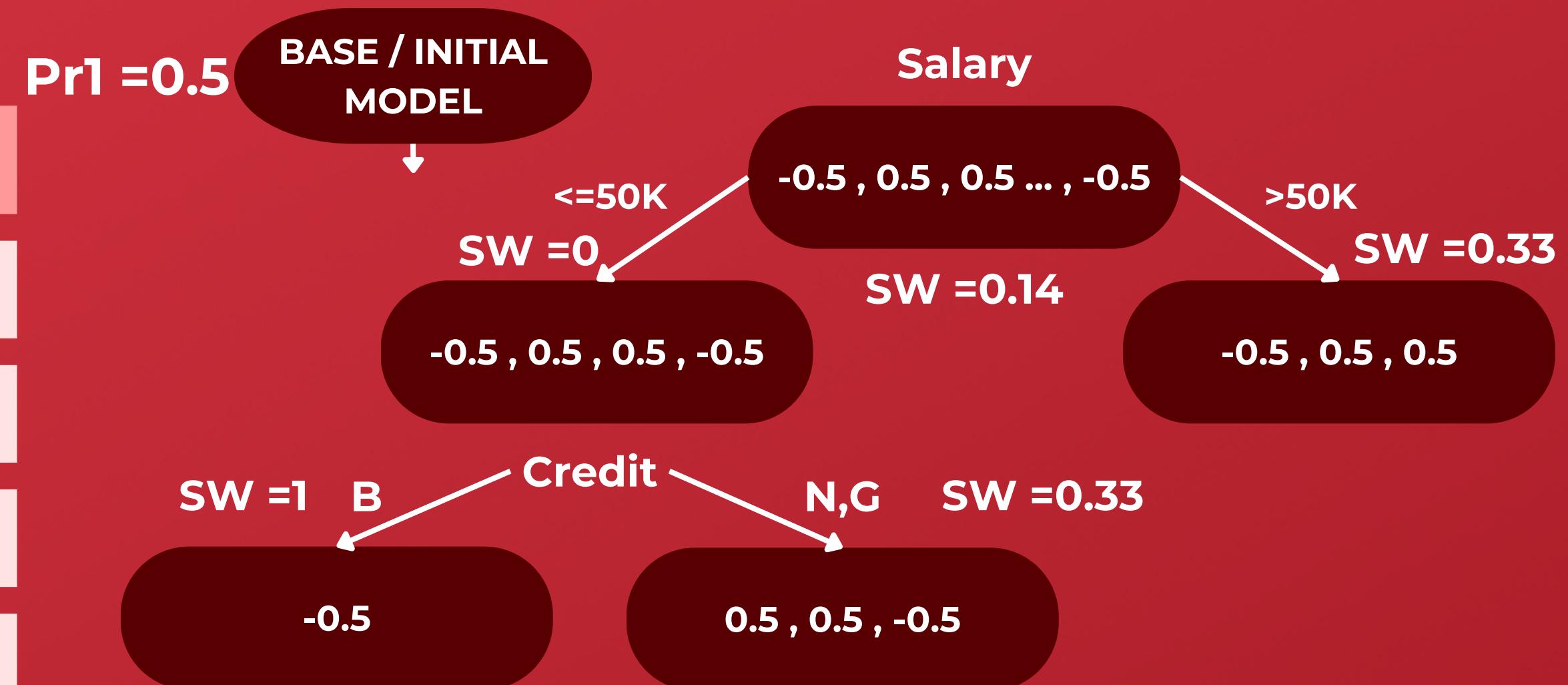
- Pruning removes less important branches of decision trees, reducing complexity and making the model less likely to overfit and also, smaller pruned trees are often easier to understand and interpret



XGBOOST CLASSIFICATION :

- Dataset :

| | SY | CR | AP | R1 | Pr2 | R2 |
|-------|----|----|------|----|-----|----|
| <=50K | B | 0 | -0.5 | | | |
| <=50K | G | 1 | 0.5 | | | |
| <=50K | G | 1 | 0.5 | | | |
| >50K | B | 0 | -0.5 | | | |
| >50K | G | 1 | 0.5 | | | |
| >50K | N | 1 | 0.5 | | | |
| <=50K | N | 0 | -0.5 | | | |



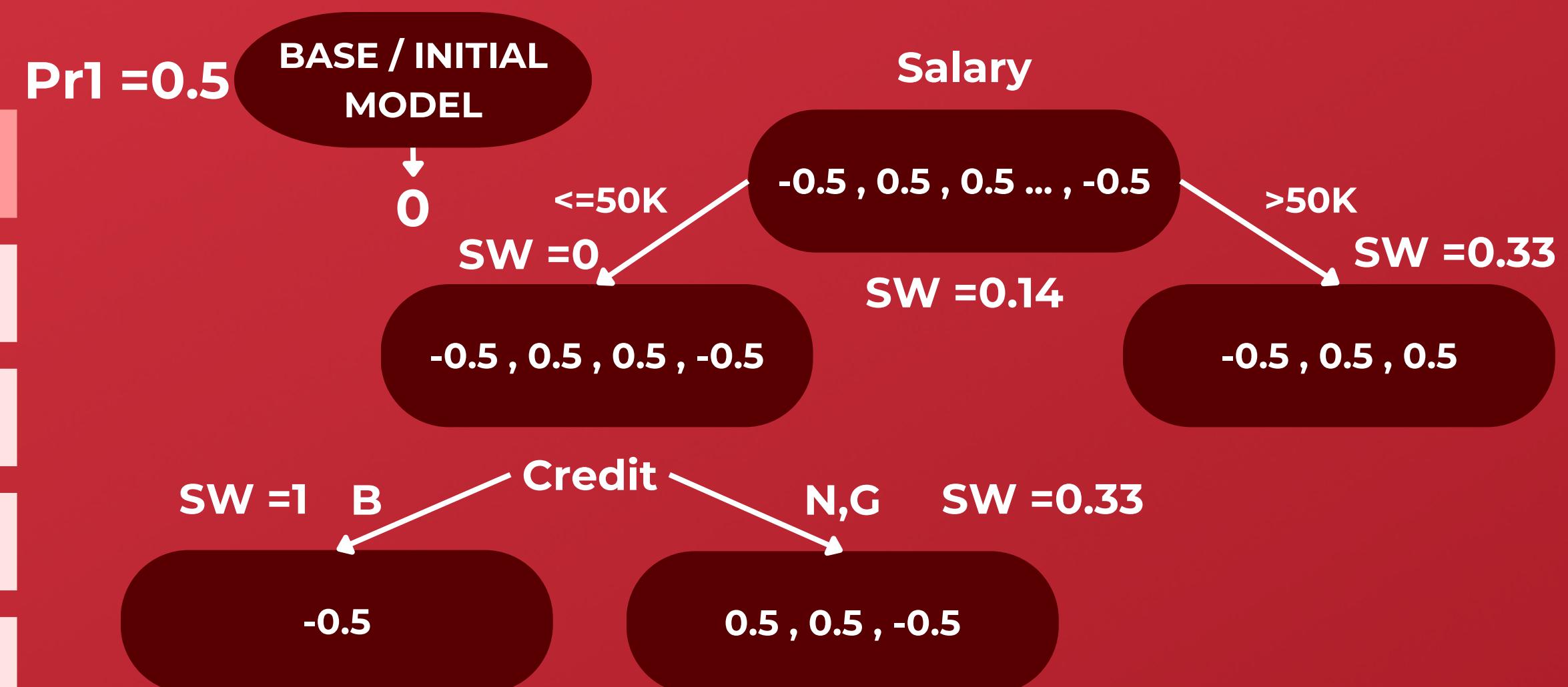
- FINAL STEPS :

- Calculate the output of the Base Model using : $\log(\text{odds}) = \log(\text{Pr}/1-\text{Pr})$. In our case it is 0
- Calculate the new probability of each record using : $\sigma(0 + \alpha(\text{DT 1}) + \alpha(\text{DT 2}) + \dots + \alpha(\text{DT N}))$

XGBOOST CLASSIFICATION :

- Dataset :

| SY | CR | AP | R1 | Pr2 | R2 |
|-------|----|----|------|-----|----|
| <=50K | B | 0 | -0.5 | | |
| <=50K | G | 1 | 0.5 | | |
| <=50K | G | 1 | 0.5 | | |
| >50K | B | 0 | -0.5 | | |
| >50K | G | 1 | 0.5 | | |
| >50K | N | 1 | 0.5 | | |
| <=50K | N | 0 | -0.5 | | |



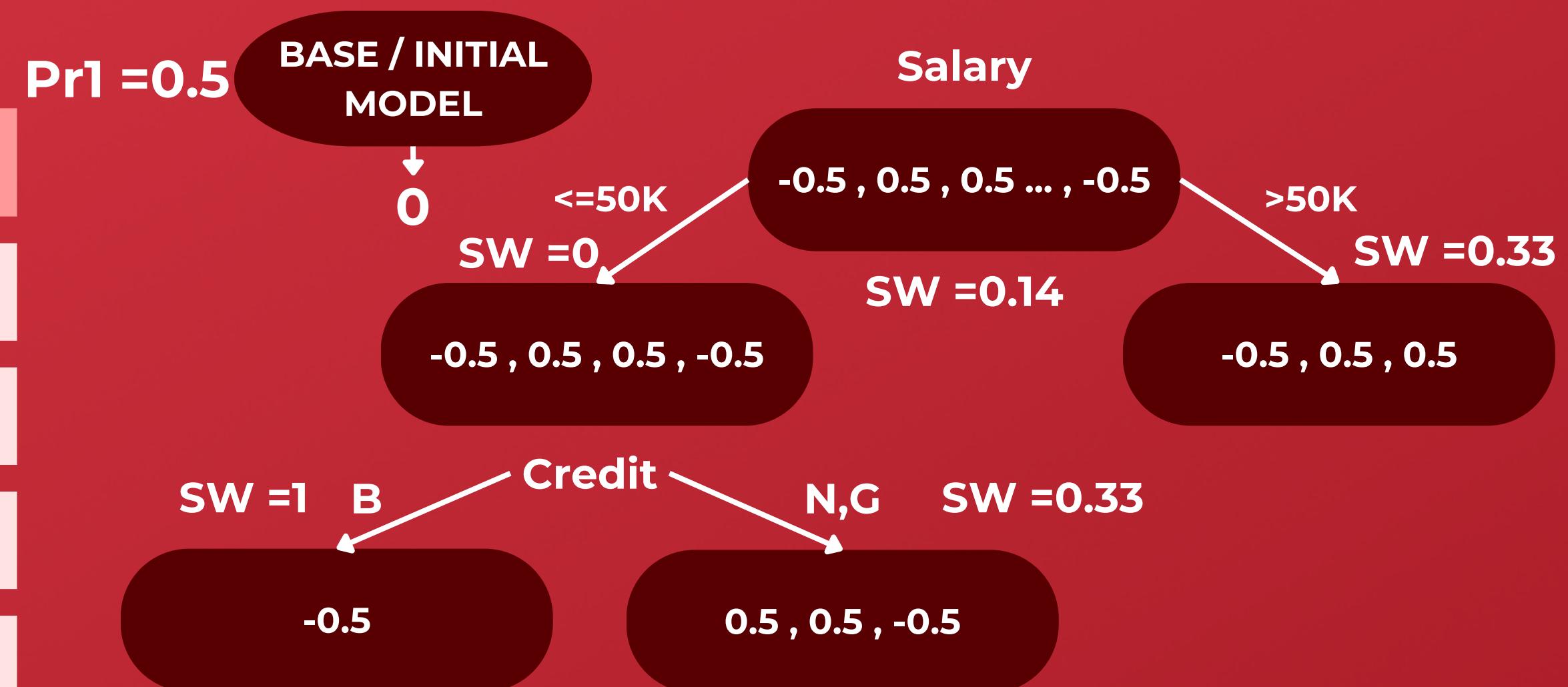
- FINAL STEPS :

- Calculate the output of the Base Model using : $\log(\text{odds}) = \log(Pr/1-Pr)$. In our case it is 0
- Calculate the new probability of each record using : $\sigma(0 + \alpha(DT 1) + \alpha(DT 2) + \dots + \alpha(DT N))$

XGBOOST CLASSIFICATION :

- Dataset :

| SY | CR | AP | R1 | Pr2 | R2 |
|-------|----|----|------|------|----|
| <=50K | B | 0 | -0.5 | 0.52 | |
| <=50K | G | 1 | 0.5 | | |
| <=50K | G | 1 | 0.5 | | |
| >50K | B | 0 | -0.5 | | |
| >50K | G | 1 | 0.5 | | |
| >50K | N | 1 | 0.5 | | |
| <=50K | N | 0 | -0.5 | | |



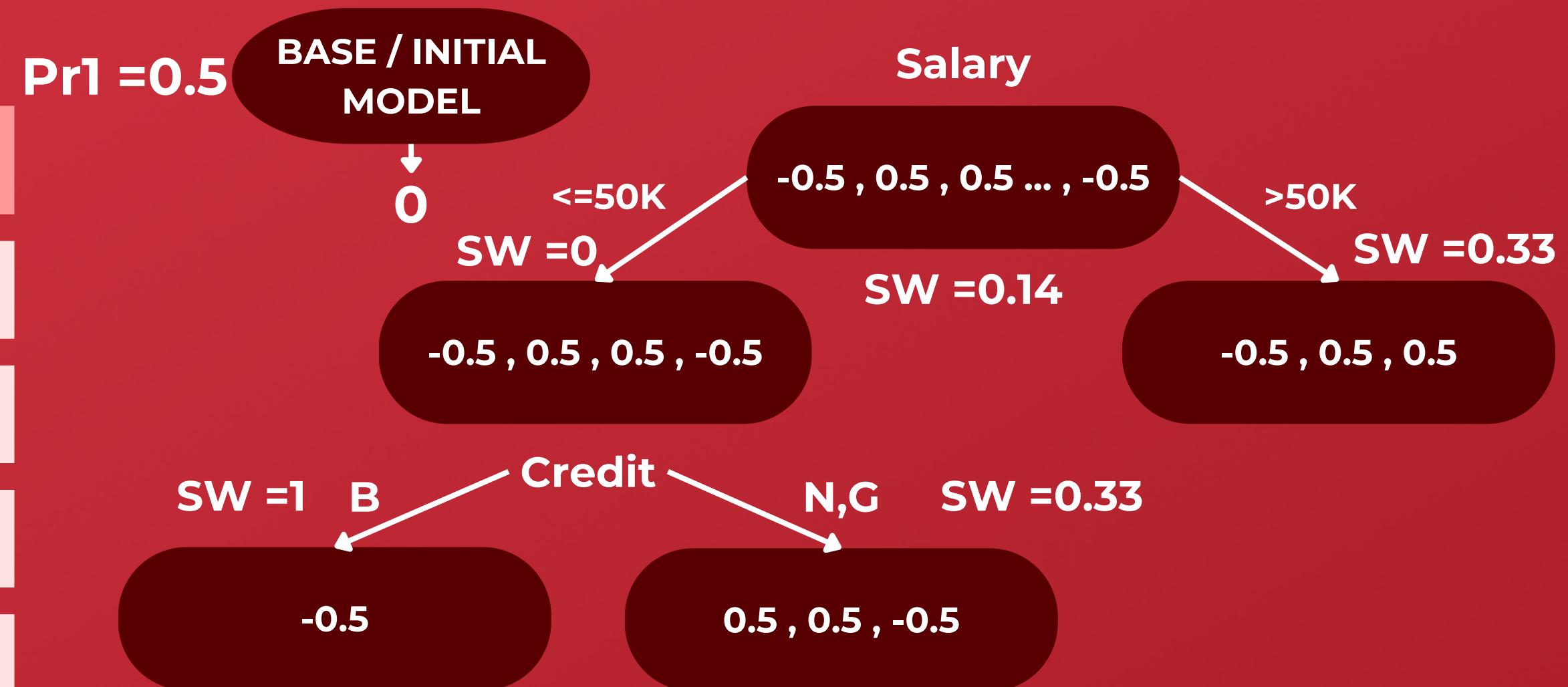
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XGBOOST CLASSIFICATION :

- Dataset :

| SY | CR | AP | R1 | Pr2 | R2 |
|-------|----|----|------|------|----|
| <=50K | B | 0 | -0.5 | 0.52 | |
| <=50K | G | 1 | 0.5 | 0.5 | |
| <=50K | G | 1 | 0.5 | 0.5 | |
| >50K | B | 0 | -0.5 | 0.5 | |
| >50K | G | 1 | 0.5 | 0.5 | |
| >50K | N | 1 | 0.5 | 0.5 | |
| <=50K | N | 0 | -0.5 | 0.5 | |



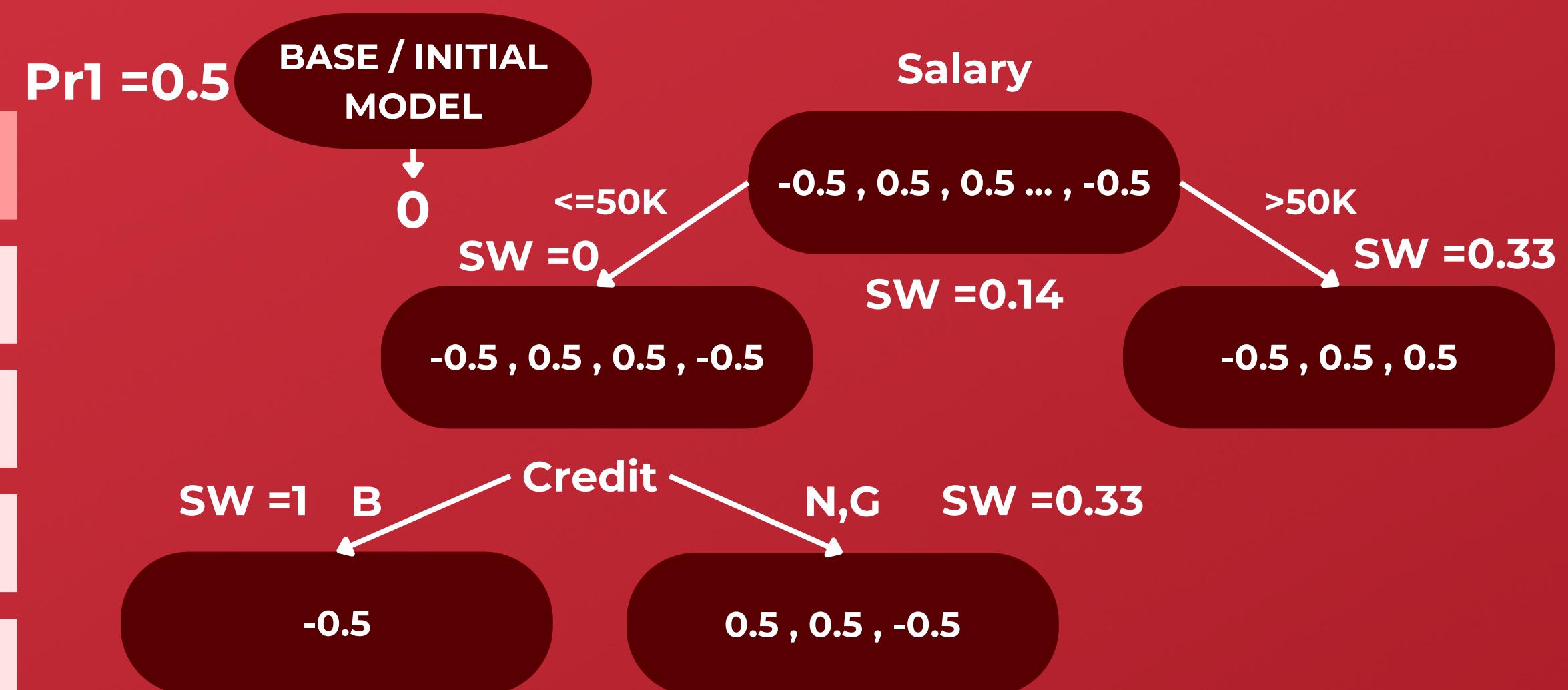
- FINAL STEPS :

- Calculate the output of the Base Model using : $\log(\text{odds}) = \log(\text{Pr}/1-\text{Pr})$. In our case it is 0
- Calculate the new probability of each record using : $\sigma(0 + \alpha(\text{DT 1}) + \alpha(\text{DT 2}) + \dots + \alpha(\text{DT N}))$

XGBOOST CLASSIFICATION :

- Dataset :

| SY | CR | AP | R1 | Pr2 | R2 |
|-------|----|----|------|------|-------|
| <=50K | B | 0 | -0.5 | 0.52 | -0.48 |
| <=50K | G | 1 | 0.5 | 0.5 | |
| <=50K | G | 1 | 0.5 | 0.5 | |
| >50K | B | 0 | -0.5 | 0.5 | |
| >50K | G | 1 | 0.5 | 0.5 | |
| >50K | N | 1 | 0.5 | 0.5 | |
| <=50K | N | 0 | -0.5 | 0.5 | |



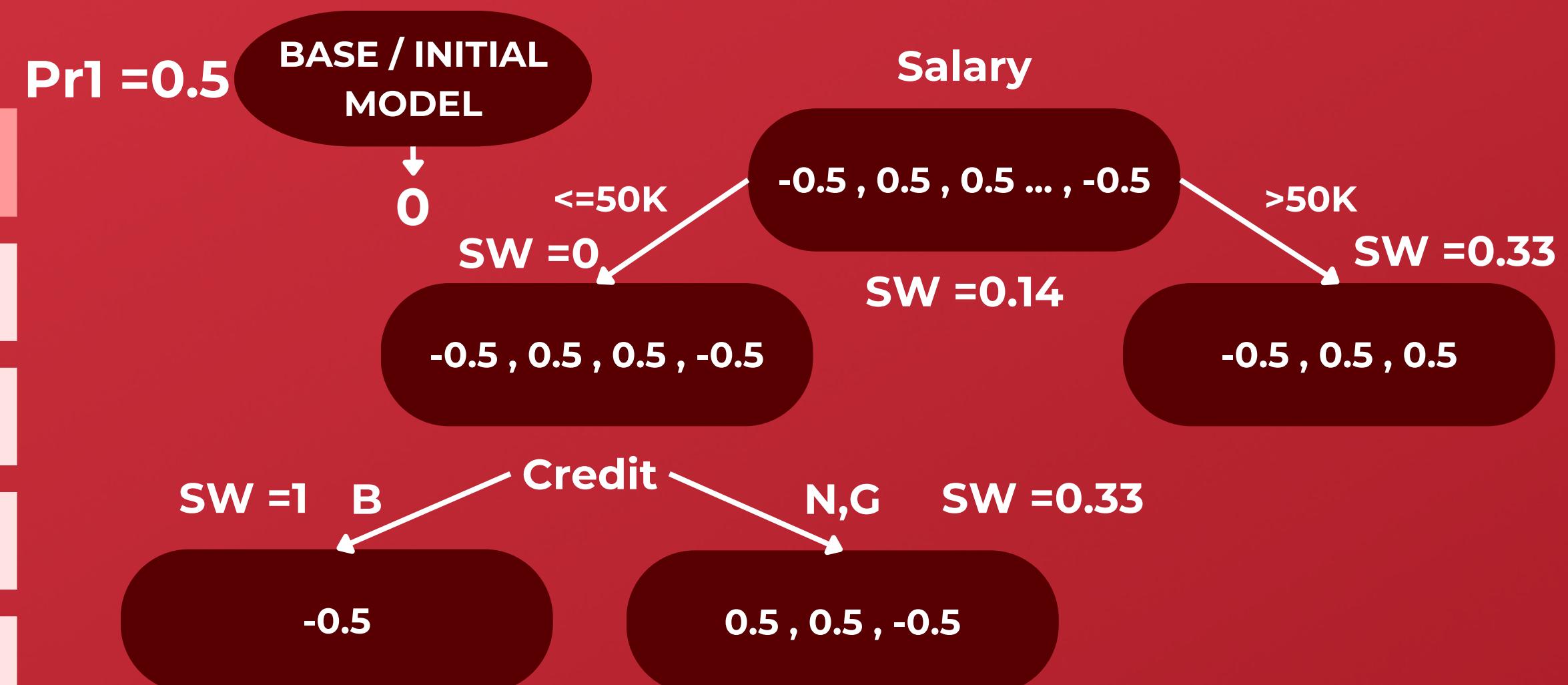
- FINAL STEPS :

- Calculate the output of the Base Model using : $\log(\text{odds}) = \log(\text{Pr}/1-\text{Pr})$. In our case it is 0
- Calculate the new probability of each record using : $\sigma(0 + \alpha(DT 1) + \alpha(DT 2) + \dots + \alpha(DT N))$

XGBOOST CLASSIFICATION :

- Dataset :

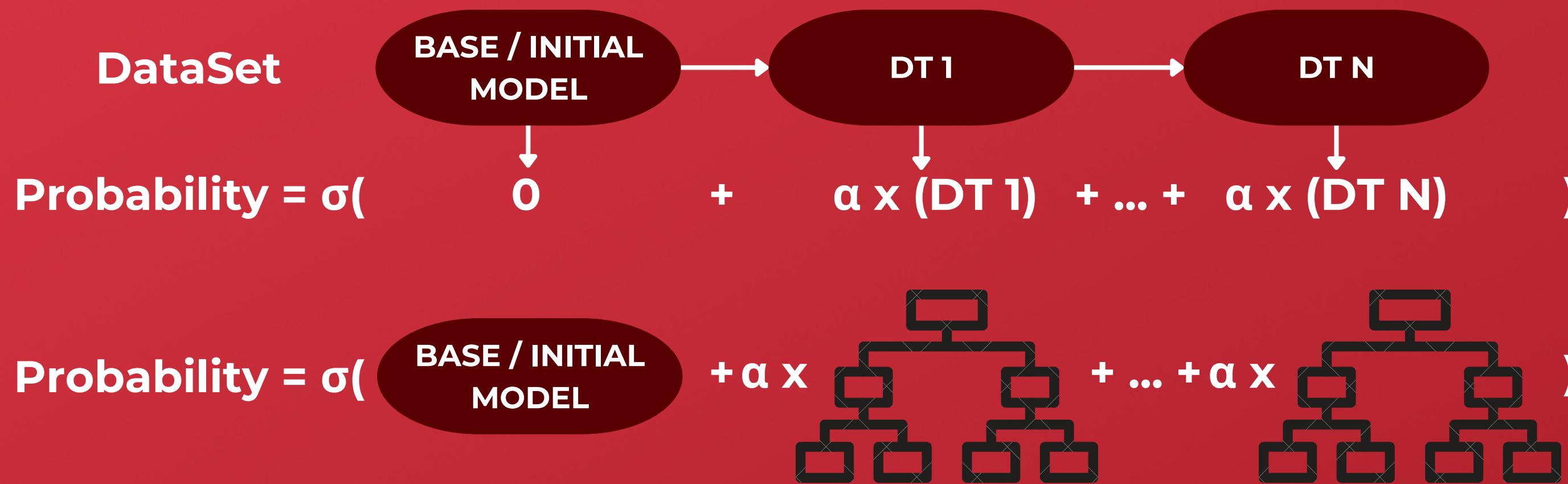
| SY | CR | AP | R1 | Pr2 | R2 |
|-------|----|----|------|------|-------|
| <=50K | B | 0 | -0.5 | 0.52 | -0.48 |
| <=50K | G | 1 | 0.5 | 0.5 | 0.5 |
| <=50K | G | 1 | 0.5 | 0.5 | 0.5 |
| >50K | B | 0 | -0.5 | 0.5 | -0.5 |
| >50K | G | 1 | 0.5 | 0.5 | 0.5 |
| >50K | N | 1 | 0.5 | 0.5 | 0.5 |
| <=50K | N | 0 | -0.5 | 0.5 | -0.5 |



- FINAL STEPS :

- Calculate the output of the Base Model using : $\log(\text{odds}) = \log(\text{Pr}/1-\text{Pr})$. In our case it is 0
- Calculate the new probability of each record using : $\sigma(0 + \alpha \times (\text{DT 1}) + \alpha \times (\text{DT 2}) + \dots + \alpha \times (\text{DT N}))$

XGBOOST CLASSIFICATION :



- **FINAL STEPS :**
 - Calculate the output of the Base Model using : $\log(\text{odds}) = \log(\text{Pr}/1-\text{Pr})$. In our case it is 0
 - Calculate the new probability of each record using : $\sigma(0 + \alpha \times (\text{DT 1}) + \alpha \times (\text{DT 2}) + \dots + \alpha \times (\text{DT N}))$

LET'S MOVE TO XGBOOST FOR REGRESSION

EXTREME GRADIENT BOOSTING WITH XGBOOST



XGBOOST REGRESSION :

- Dataset :

| | EXP | GAP | SALARY | RES |
|-----|-----|-----|--------|-----|
| 2 | Y | 40k | | |
| 2.5 | Y | 42k | | |
| 3 | N | 52k | | |
| 4 | N | 60k | | |
| 4.5 | Y | 62k | | |

Avg Salary= 51k

BASE / INITIAL
MODEL

- STEPS :
 - Construct tree with root
 - Calculate Similarity Weight = $\frac{\sum(\text{Residuals})^2}{\text{Nb of Res} + \lambda}$
 - Calculate the gain = $\text{SWL} + \text{SWR} - \text{SW(ROOT)}$

XGBOOST REGRESSION :

- Dataset :

| EXP | GAP | SALARY | RES |
|-----|-----|--------|------|
| 2 | Y | 40k | -11k |
| 2.5 | Y | 42k | |
| 3 | N | 52k | |
| 4 | N | 60k | |
| 4.5 | Y | 62k | |

Avg Salary= 51k

BASE / INITIAL
MODEL

- STEPS :
 - Construct tree with root
 - Calculate Similarity Weight = $\frac{\sum(\text{Residuals})^2}{\text{Nb of Res} + \lambda}$
 - Calculate the gain = $\text{SWL} + \text{SWR} - \text{SW(ROOT)}$

XGBOOST REGRESSION :

- Dataset :

| | EXP | GAP | SALARY | RES |
|-----|-----|-----|--------|-----|
| 2 | Y | 40k | -11k | |
| 2.5 | Y | 42k | -9k | |
| 3 | N | 52k | 1k | |
| 4 | N | 60k | 9k | |
| 4.5 | Y | 62k | 11k | |

Avg Salary= 51k

BASE / INITIAL
MODEL

- STEPS :
 - Construct tree with root
 - Calculate Similarity Weight = $\frac{\sum(\text{Residuals})^2}{\text{Nb of Res} + \lambda}$
 - Calculate the gain = $\text{SWL} + \text{SWR} - \text{SW(ROOT)}$

XGBOOST REGRESSION :

- Dataset :

| | EXP | GAP | SALARY | RES |
|-----|-----|-----|--------|-----|
| 2 | Y | 40k | -11k | |
| 2.5 | Y | 42k | -9k | |
| 3 | N | 52k | 1k | |
| 4 | N | 60k | 9k | |
| 4.5 | Y | 62k | 11k | |

Avg Salary= 51k

BASE / INITIAL
MODEL

Split 1
EXP

- STEPS :
 - Construct tree with root
 - Calculate Similarity Weight = $\frac{\sum(\text{Residuals})^2}{\text{Nb of Res} + \lambda}$
 - Calculate the gain = $\text{SWL} + \text{SWR} - \text{SW(ROOT)}$

XGBOOST REGRESSION :

- Dataset :

| | EXP | GAP | SALARY | RES |
|-----|-----|-----|--------|-----|
| 2 | Y | 40k | -11k | |
| 2.5 | Y | 42k | -9k | |
| 3 | N | 52k | 1k | |
| 4 | N | 60k | 9k | |
| 4.5 | Y | 62k | 11k | |

Avg Salary= 51k

BASE / INITIAL
MODEL

Split 1
EXP

-11 , -9 , 1 , 9 , 11

- STEPS :
 - Construct tree with root
 - Calculate Similarity Weight = $\frac{\sum(\text{Residuals})^2}{\text{Nb of Res} + \lambda}$
 - Calculate the gain = $\text{SWL} + \text{SWR} - \text{SW(ROOT)}$

XGBOOST REGRESSION :

- Dataset :

| | EXP | GAP | SALARY | RES |
|-----|-----|-----|--------|-----|
| 2 | Y | 40k | -11k | |
| 2.5 | Y | 42k | -9k | |
| 3 | N | 52k | 1k | |
| 4 | N | 60k | 9k | |
| 4.5 | Y | 62k | 11k | |

Avg Salary= 51k

BASE / INITIAL MODEL

Split 1
EXP

>2
-11, -9, 1, 9, 11

<=2

- STEPS :
 - Construct tree with root
 - Calculate Similarity Weight = $\frac{\sum(\text{Residuals})^2}{\text{Nb of Res} + \lambda}$
 - Calculate the gain = $\text{SWL} + \text{SWR} - \text{SW(ROOT)}$

XGBOOST REGRESSION :

- Dataset :

| Avg Salary= 51k | | | |
|-----------------|-----|--------|------|
| EXP | GAP | SALARY | RES |
| 2 | Y | 40k | -11k |
| 2.5 | Y | 42k | -9k |
| 3 | N | 52k | 1k |
| 4 | N | 60k | 9k |
| 4.5 | Y | 62k | 11k |

BASE / INITIAL MODEL

Split 1
EXP

-11 , -9 , 1 , 9 , 11

>2

-9 , 1 , 9 , 11

<=2

-11

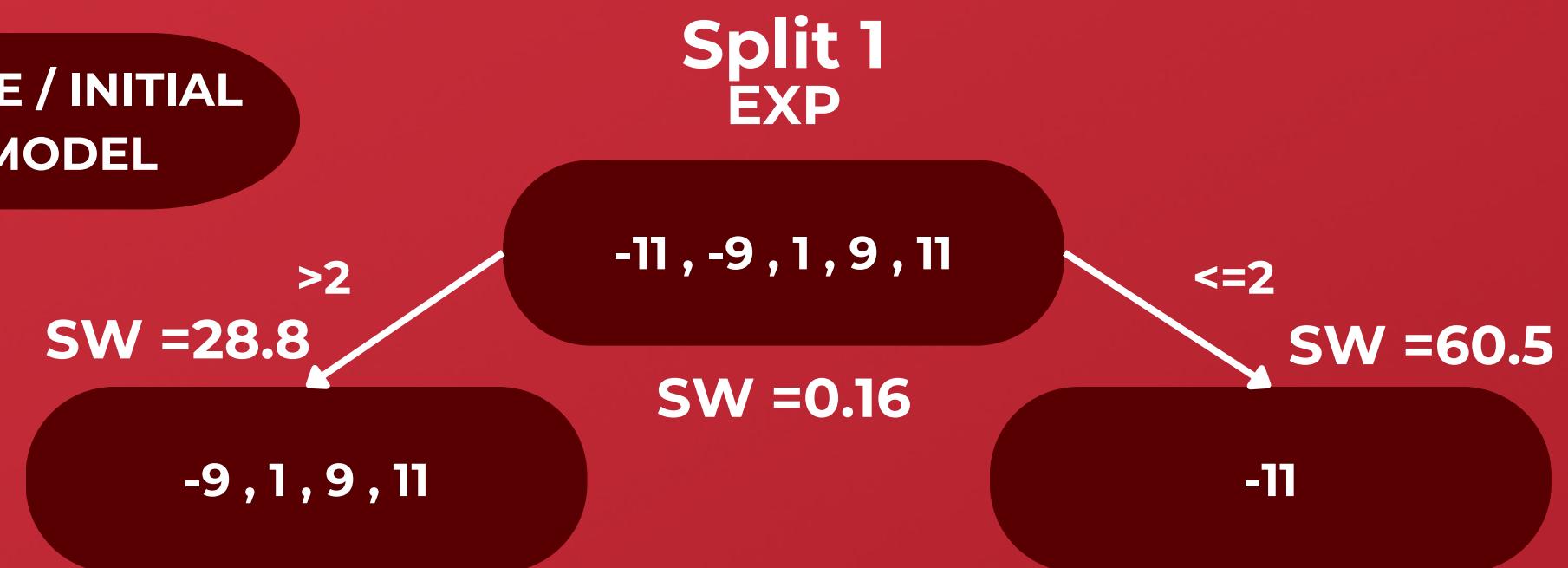
- STEPS :
 - Construct tree with root
 - Calculate Similarity Weight = $\frac{\sum(\text{Residuals})^2}{\text{Nb of Res} + \lambda}$
 - Calculate the gain = $\text{SWL} + \text{SWR} - \text{SW(ROOT)}$

XGBOOST REGRESSION :

- Dataset :

| Avg Salary= 51k | | | |
|-----------------|-----|--------|------|
| EXP | GAP | SALARY | RES |
| 2 | Y | 40k | -11k |
| 2.5 | Y | 42k | -9k |
| 3 | N | 52k | 1k |
| 4 | N | 60k | 9k |
| 4.5 | Y | 62k | 11k |

BASE / INITIAL MODEL



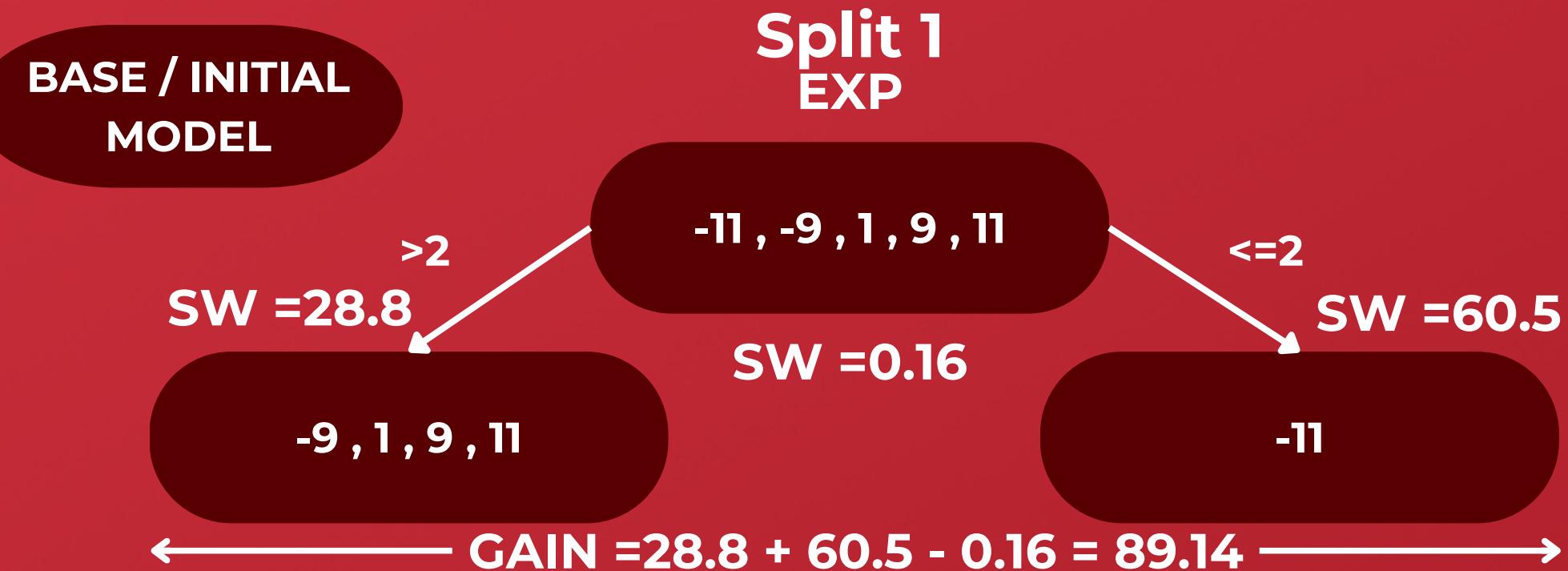
- STEPS :
 - Construct tree with root
 - Calculate Similarity Weight = $\frac{\sum(\text{Residuals})^2}{\text{Nb of Res} + \lambda}$
 - Calculate the gain = $\text{SWL} + \text{SWR} - \text{SW(ROOT)}$

XGBOOST REGRESSION :

- Dataset :

| Avg Salary= 51k | | | |
|-----------------|-----|--------|------|
| EXP | GAP | SALARY | RES |
| 2 | Y | 40k | -11k |
| 2.5 | Y | 42k | -9k |
| 3 | N | 52k | 1k |
| 4 | N | 60k | 9k |
| 4.5 | Y | 62k | 11k |

• Gain Split 1 = 89.14



- STEPS :
 - Construct tree with root
 - Calculate Similarity Weight = $\frac{\sum(\text{Residuals})^2}{\text{Nb of Res} + \lambda}$
 - Calculate the gain = $\text{SWL} + \text{SWR} - \text{SW}(\text{ROOT})$

XGBOOST REGRESSION :

- Dataset :

| | EXP | GAP | SALARY | RES |
|-----|-----|-----|--------|-----|
| 2 | Y | 40k | -11k | |
| 2.5 | Y | 42k | -9k | |
| 3 | N | 52k | 1k | |
| 4 | N | 60k | 9k | |
| 4.5 | Y | 62k | 11k | |

Gain Split 1 = 89.14

Avg Salary= 51k

BASE / INITIAL
MODEL

Split 2
EXP

-11 , -9 , 1 , 9 , 11

- STEPS :
 - Construct tree with root
 - Calculate Similarity Weight = $\frac{\sum(\text{Residuals})^2}{\text{Nb of Res} + \lambda}$
 - Calculate the gain = $\text{SWL} + \text{SWR} - \text{SW(ROOT)}$

XGBOOST REGRESSION :

- Dataset :

| | EXP | GAP | SALARY | RES |
|-----|-----|-----|--------|-----|
| 2 | Y | 40k | -11k | |
| 2.5 | Y | 42k | -9k | |
| 3 | N | 52k | 1k | |
| 4 | N | 60k | 9k | |
| 4.5 | Y | 62k | 11k | |

Gain Split 1 = 89.14

Avg Salary= 51k

BASE / INITIAL
MODEL

Split 2
EXP

>2.5
-11, -9, 1, 9, 11

<=2.5

- STEPS :
 - Construct tree with root
 - Calculate Similarity Weight = $\frac{\sum(\text{Residuals})^2}{\text{Nb of Res} + \lambda}$
 - Calculate the gain = $\text{SWL} + \text{SWR} - \text{SW(ROOT)}$

XGBOOST REGRESSION :

- Dataset :

| | EXP | GAP | SALARY | RES |
|-----|-----|-----|--------|-----|
| 2 | Y | 40k | -11k | |
| 2.5 | Y | 42k | -9k | |
| 3 | N | 52k | 1k | |
| 4 | N | 60k | 9k | |
| 4.5 | Y | 62k | 11k | |

Gain Split 1 = 89.14

Avg Salary= 51k

BASE / INITIAL MODEL

Split 2
EXP

>2.5
-11, -9, 1, 9, 11

1, 9, 11

<=2.5

-11, -9

- STEPS :
 - Construct tree with root
 - Calculate Similarity Weight = $\frac{\sum(\text{Residuals})^2}{\text{Nb of Res} + \lambda}$
 - Calculate the gain = $\text{SWL} + \text{SWR} - \text{SW(ROOT)}$

XGBOOST REGRESSION :

- Dataset :

| Avg Salary= 51k | | | |
|-----------------|-----|--------|------|
| EXP | GAP | SALARY | RES |
| 2 | Y | 40k | -11k |
| 2.5 | Y | 42k | -9k |
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| 4 | N | 60k | 9k |
| 4.5 | Y | 62k | 11k |

• Gain Split 1 = 89.14

BASE / INITIAL MODEL

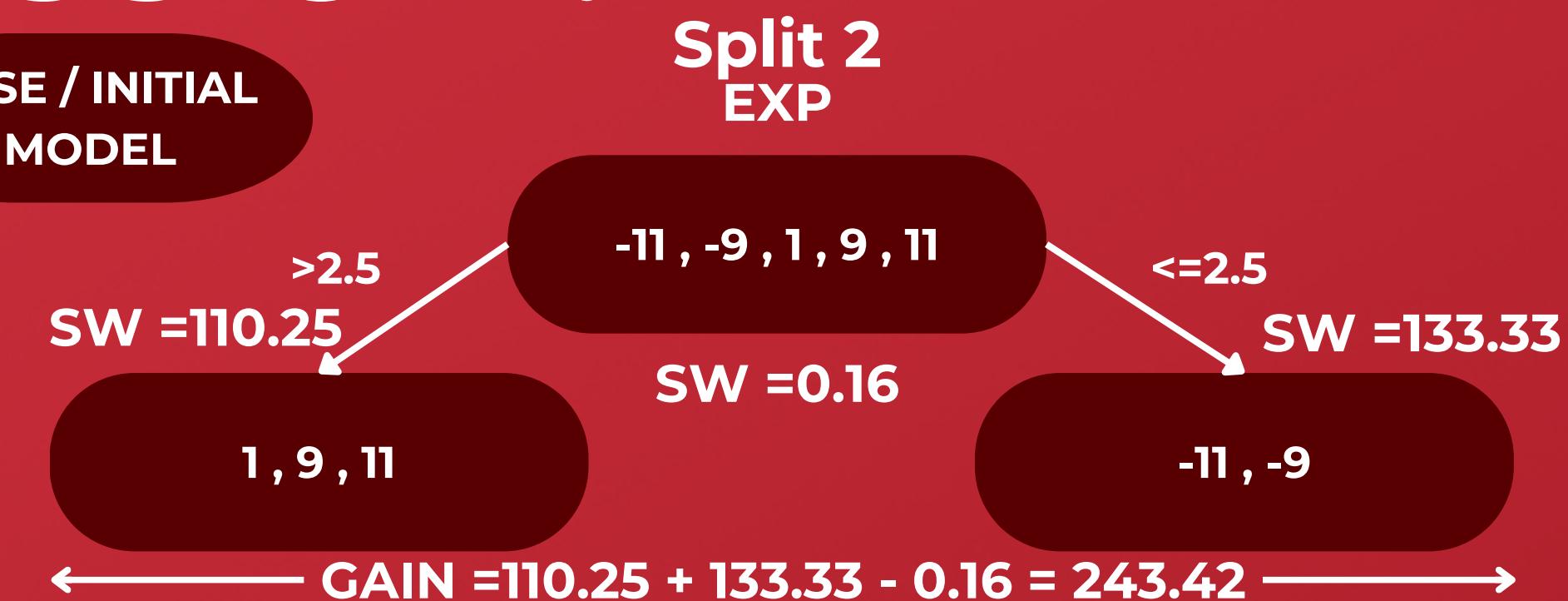


- STEPS :
 - Construct tree with root
 - Calculate Similarity Weight = $\frac{\sum(\text{Residuals})^2}{\text{Nb of Res} + \lambda}$
 - Calculate the gain = $SW_L + SW_R - SW(\text{ROOT})$

XGBOOST REGRESSION :

- Dataset :

| Avg Salary= 51k | | | |
|-----------------|-----|--------|------|
| EXP | GAP | SALARY | RES |
| 2 | Y | 40k | -11k |
| 2.5 | Y | 42k | -9k |
| 3 | N | 52k | 1k |
| 4 | N | 60k | 9k |
| 4.5 | Y | 62k | 11k |



- Gain Split 1 = 89.14
- Gain Split 2 = 243.42
- Gain Split 2 > Gain Split 1 So : We keep The Split 2

- STEPS :

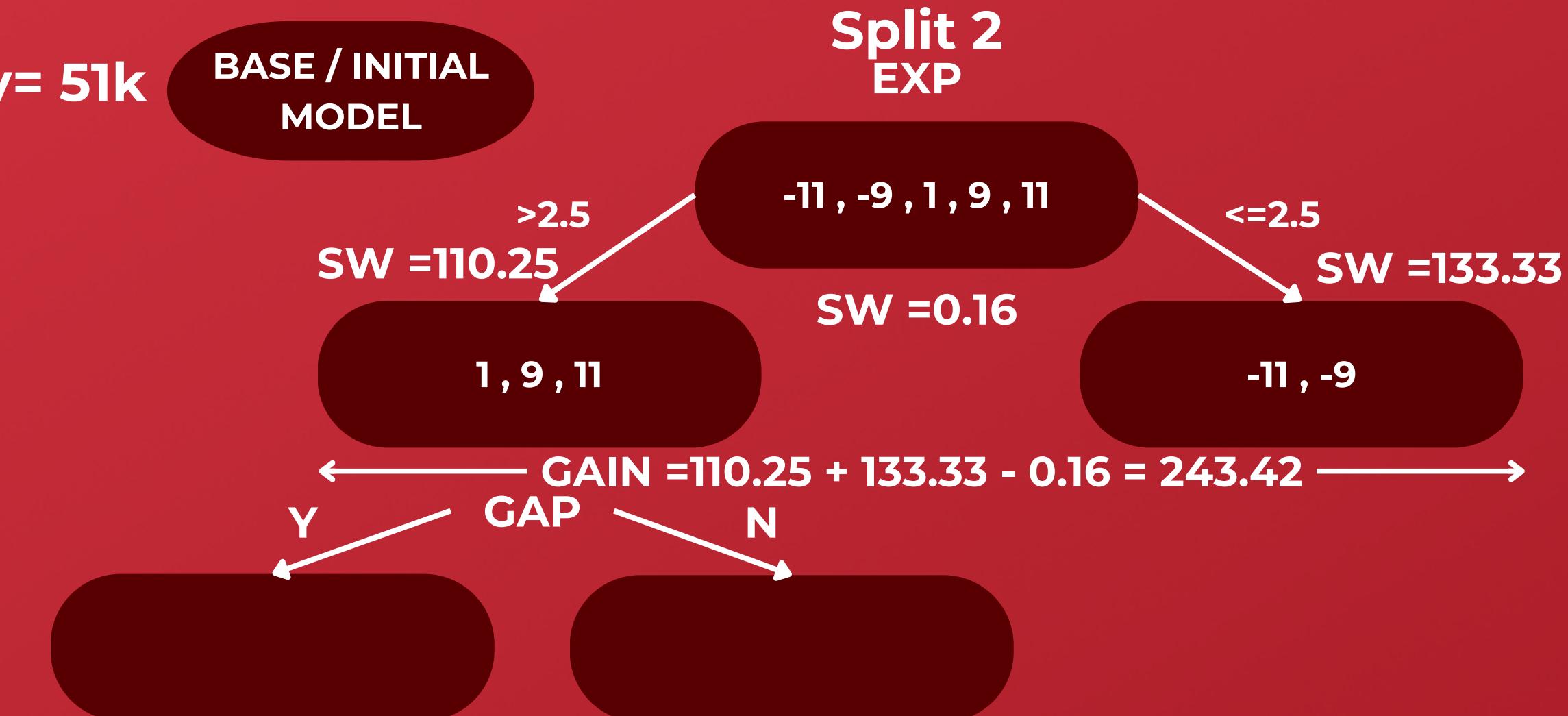
- Construct tree with root
- Calculate Similarity Weight = $\frac{\sum(\text{Residuals})^2}{\text{Nb of Res} + \lambda}$
- Calculate the gain = $\text{SWL} + \text{SWR} - \text{SW(ROOT)}$

XGBOOST REGRESSION :

- Dataset :

| Avg Salary= 51k | | | |
|-----------------|-----|--------|------|
| EXP | GAP | SALARY | RES |
| 2 | Y | 40k | -11k |
| 2.5 | Y | 42k | -9k |
| 3 | N | 52k | 1k |
| 4 | N | 60k | 9k |
| 4.5 | Y | 62k | 11k |

- Gain Split 1 = 89.14
- Gain Split 2 = 243.42
- Gain Split 2 > Gain Split 1 So :
We keep The Split 2



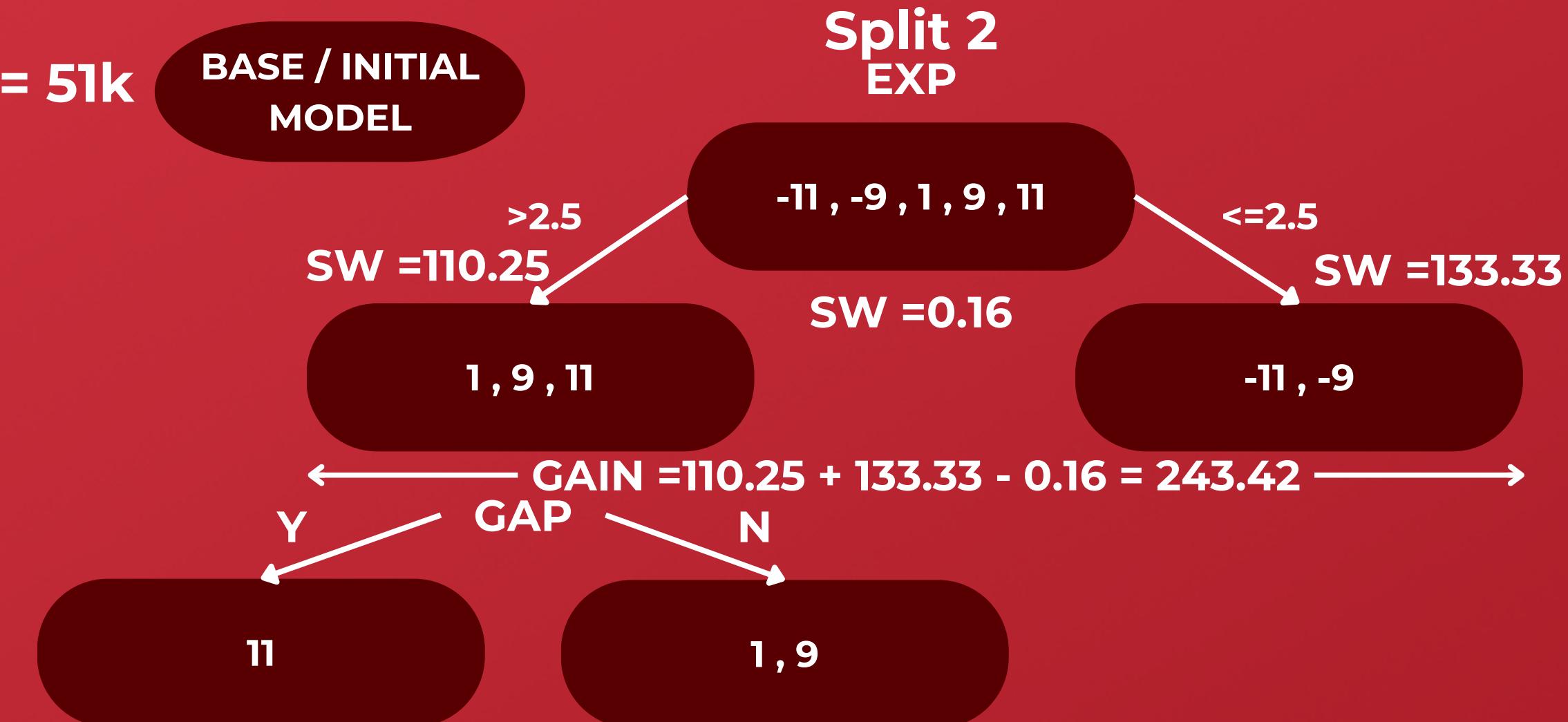
- STEPS :
 - Construct tree with root
 - Calculate Similarity Weight = $\frac{\sum(\text{Residuals})^2}{\text{Nb of Res} + \lambda}$
 - Calculate the gain = SWL+SWR-SW(ROOT)

XGBOOST REGRESSION :

- Dataset :

| Avg Salary= 51k | | | |
|-----------------|-----|--------|------|
| EXP | GAP | SALARY | RES |
| 2 | Y | 40k | -11k |
| 2.5 | Y | 42k | -9k |
| 3 | N | 52k | 1k |
| 4 | N | 60k | 9k |
| 4.5 | Y | 62k | 11k |

- Gain Split 1 = 89.14
- Gain Split 2 = 243.42
- Gain Split 2 > Gain Split 1 So :
We keep The Split 2



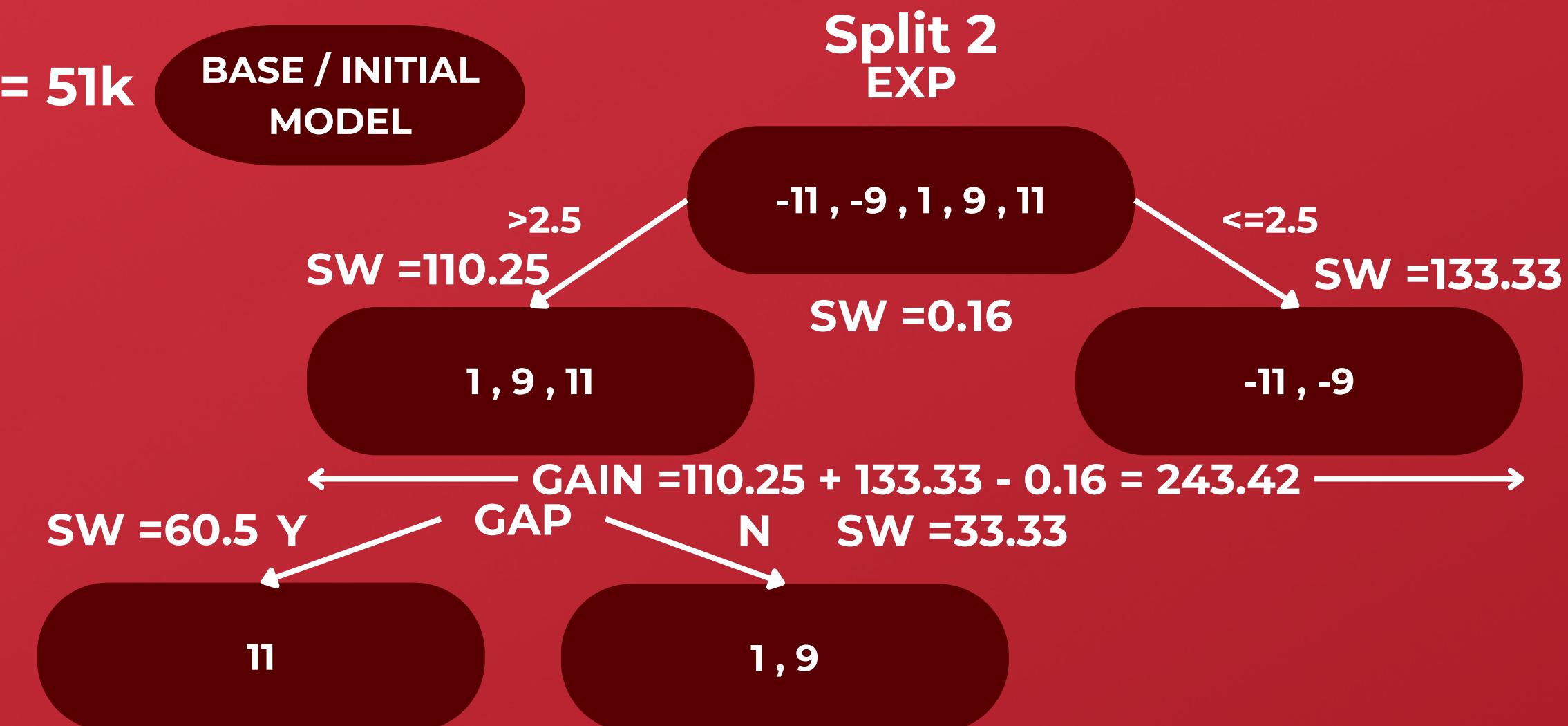
- STEPS :
 - Construct tree with root
 - Calculate Similarity Weight = $\frac{\sum(\text{Residuals})^2}{\text{Nb of Res} + \lambda}$
 - Calculate the gain = SWL+SWR-SW(ROOT)

XGBOOST REGRESSION :

- Dataset :

| Avg Salary= 51k | | | |
|-----------------|-----|--------|------|
| EXP | GAP | SALARY | RES |
| 2 | Y | 40k | -11k |
| 2.5 | Y | 42k | -9k |
| 3 | N | 52k | 1k |
| 4 | N | 60k | 9k |
| 4.5 | Y | 62k | 11k |

- Gain Split 1 = 89.14
- Gain Split 2 = 243.42
- Gain Split 2 > Gain Split 1 So :
We keep The Split 2



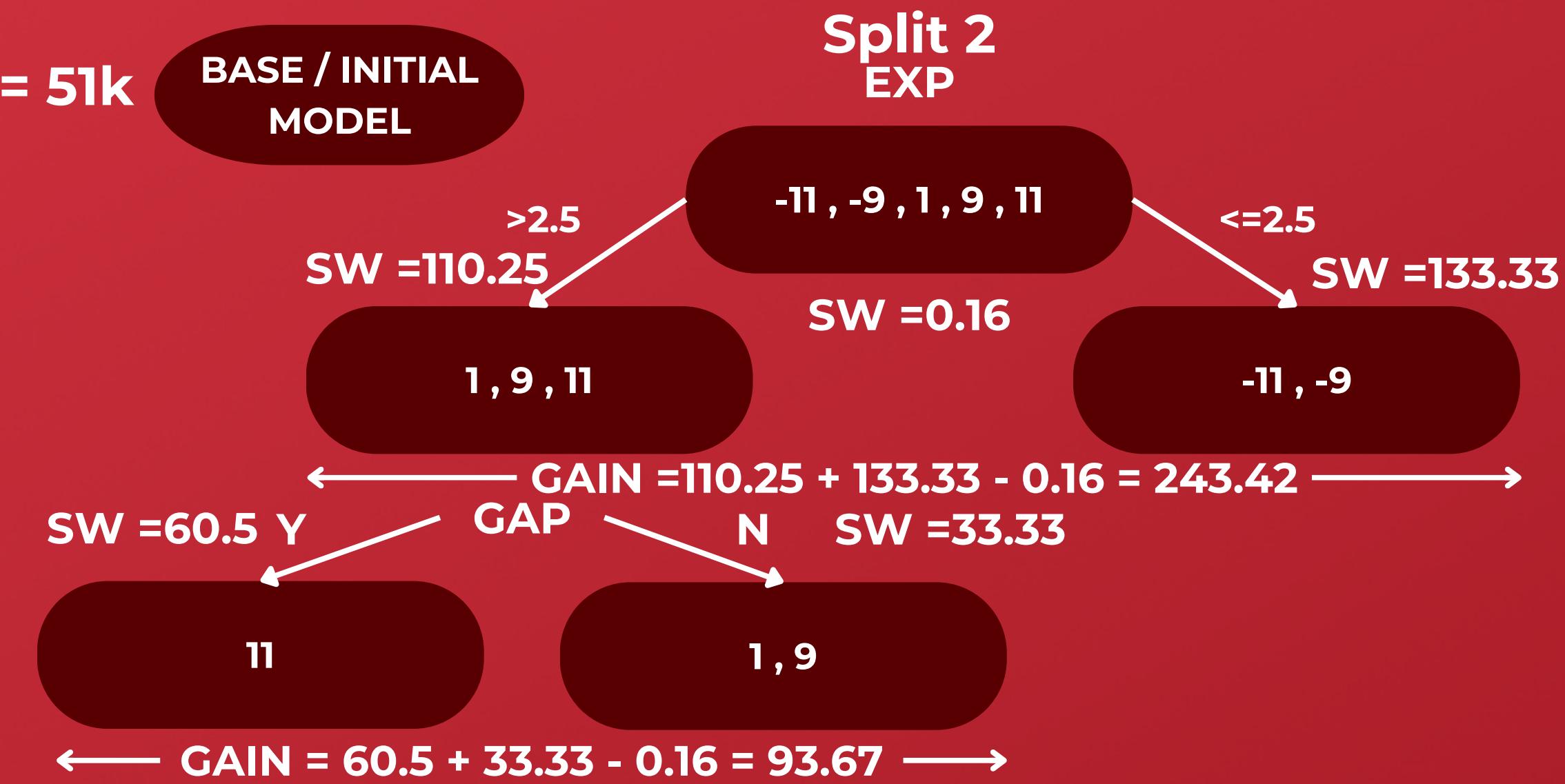
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- Calculate the gain = $\text{SWL} + \text{SWR} - \text{SW(ROOT)}$

XGBOOST REGRESSION :

- Dataset :

| | EX | GP | SY | RS1 | O/P | RS2 | Avg Salary= 51k |
|-----|----|----|-----|------|-----|-----|-----------------|
| 2 | Y | | 40k | -11k | | | |
| 2.5 | Y | | 42k | -9k | | | |
| 3 | N | | 52k | 1k | | | |
| 4 | N | | 60k | 9k | | | |
| 4.5 | Y | | 62k | 11k | | | |

BASE / INITIAL MODEL

Split 2
EXP

>2.5

-11, -9, 1, 9, 11

<=2.5

1, 9, 11

-11, -9

GAP

11

1, 9

- FINAL STEPS :

- Calculate the output of each bottom leaf using :

$$\text{Output} = \text{Avg of RES} = (\text{Sum Residuals}) / (\text{Nb Residuals})$$
- Calculate the new probability of each record using :

$$\text{O/P} = \text{Base Model} + \alpha(\text{DT 1}) + \alpha(\text{DT 2}) + \dots + \alpha(\text{DT N})$$

XGBOOST REGRESSION :

- Dataset :

| | EX | GP | SY | RS1 | O/P | RS2 | Avg Salary= 51k |
|-----|----|----|-----|------|-----|-----|-----------------|
| 2 | | Y | 40k | -11k | | | |
| 2.5 | | Y | 42k | -9k | | | |
| 3 | | N | 52k | 1k | | | |
| 4 | | N | 60k | 9k | | | |
| 4.5 | | Y | 62k | 11k | | | |

BASE / INITIAL MODEL

Split 2
EXP

>2.5

-11, -9, 1, 9, 11

<=2.5

1, 9, 11

-11, -9
Output = -10

GAP

11
Output = 11

N

1, 9

- FINAL STEPS :

- Calculate the output of each bottom leaf using :

$$\text{Output} = \text{Avg of RES} = (\text{Sum Residuals}) / (\text{Nb Residuals})$$
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XGBOOST REGRESSION :

- Dataset :

| | EX | GP | SY | RS1 | O/P | RS2 | Avg Salary= 51k |
|-----|----|----|-----|------|-----|-----|-----------------|
| 2 | | Y | 40k | -11k | | | |
| 2.5 | | Y | 42k | -9k | | | |
| 3 | | N | 52k | 1k | | | |
| 4 | | N | 60k | 9k | | | |
| 4.5 | | Y | 62k | 11k | | | |

BASE / INITIAL MODEL

Split 2
EXP

>2.5

-11, -9, 1, 9, 11

<=2.5

1, 9, 11

-11, -9
Output = -10

Y

GAP

N

11
Output = 11

1, 9
Output = 5

- FINAL STEPS :

- Calculate the output of each bottom leaf using :

$$\text{Output} = \text{Avg of RES} = (\text{Sum Residuals}) / (\text{Nb Residuals})$$
- Calculate the new probability of each record using :

$$\text{O/P} = \text{Base Model} + \alpha(\text{DT 1}) + \alpha(\text{DT 2}) + \dots + \alpha(\text{DT N})$$

XGBOOST REGRESSION :

- Dataset :

| | EX | GP | SY | RS1 | O/P | RS2 | Avg Salary= 51k |
|-----|----|----|-----|------|-----|-----|-----------------|
| 2 | | Y | 40k | -11k | 46k | | |
| 2.5 | | Y | 42k | -9k | | | |
| 3 | | N | 52k | 1k | | | |
| 4 | | N | 60k | 9k | | | |
| 4.5 | | Y | 62k | 11k | | | |

BASE / INITIAL MODEL

Split 2
EXP

>2.5

-11, -9, 1, 9, 11

<=2.5

1, 9, 11

-11, -9
Output = -10

Y

GAP

11
Output = 11

N

1, 9
Output = 5

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XGBOOST REGRESSION :

- Dataset :

| | EX | GP | SY | RS1 | O/P | RS2 | Avg Salary= 51k |
|-----|----|----|-----|------|-------|-----|-----------------|
| 2 | | Y | 40k | -11k | 46k | | |
| 2.5 | | Y | 42k | -9k | 46k | | |
| 3 | | N | 52k | 1k | 53.5k | | |
| 4 | | N | 60k | 9k | 53.5k | | |
| 4.5 | | Y | 62k | 11k | 56.5k | | |

BASE / INITIAL MODEL

Split 2
EXP

>2.5

-11, -9, 1, 9, 11

<=2.5

1, 9, 11

-11, -9
Output = -10

Y

GAP

N

11
Output = 11

1, 9
Output = 5

- FINAL STEPS :

- Calculate the output of each bottom leaf using :

$$\text{Output} = \text{Avg of RES} = (\text{Sum Residuals}) / (\text{Nb Residuals})$$
- Calculate the new probability of each record using :

$$\text{O/P} = \text{Base Model} + \alpha(\text{DT 1}) + \alpha(\text{DT 2}) + \dots + \alpha(\text{DT N})$$

XGBOOST REGRESSION :

- Dataset :

| | EX | GP | SY | RS1 | O/P | RS2 | Avg Salary= 51k |
|-----|----|----|-----|------|-------|-----|-----------------|
| 2 | Y | | 40k | -11k | 46k | -6k | |
| 2.5 | Y | | 42k | -9k | 46k | | |
| 3 | N | | 52k | 1k | 53.5k | | |
| 4 | N | | 60k | 9k | 53.5k | | |
| 4.5 | Y | | 62k | 11k | 56.5k | | |

BASE / INITIAL MODEL

Split 2
EXP

>2.5

-11, -9, 1, 9, 11

<=2.5

1, 9, 11

-11, -9
Output = -10

Y

GAP

N

11
Output = 11

1, 9
Output = 5

- FINAL STEPS :

- Calculate the output of each bottom leaf using :

$$\text{Output} = \text{Avg of RES} = (\text{Sum Residuals}) / (\text{Nb Residuals})$$
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XGBOOST REGRESSION :

- Dataset :

| | EX | GP | SY | RS1 | O/P | RS2 | Avg Salary= 51k |
|-----|----|-----|------|-------|-------|-----|-----------------|
| 2 | Y | 40k | -11k | 46k | -6k | | |
| 2.5 | Y | 42k | -9k | 46k | -4k | | |
| 3 | N | 52k | 1k | 53.5k | -1.5k | | |
| 4 | N | 60k | 9k | 53.5k | 6.5k | | |
| 4.5 | Y | 62k | 11k | 56.5k | 5.5k | | |

BASE / INITIAL MODEL

Split 2
EXP

>2.5

-11, -9, 1, 9, 11

<=2.5

1, 9, 11

-11, -9
Output = -10

Y
11
Output = 11

GAP
N
1, 9
Output = 5

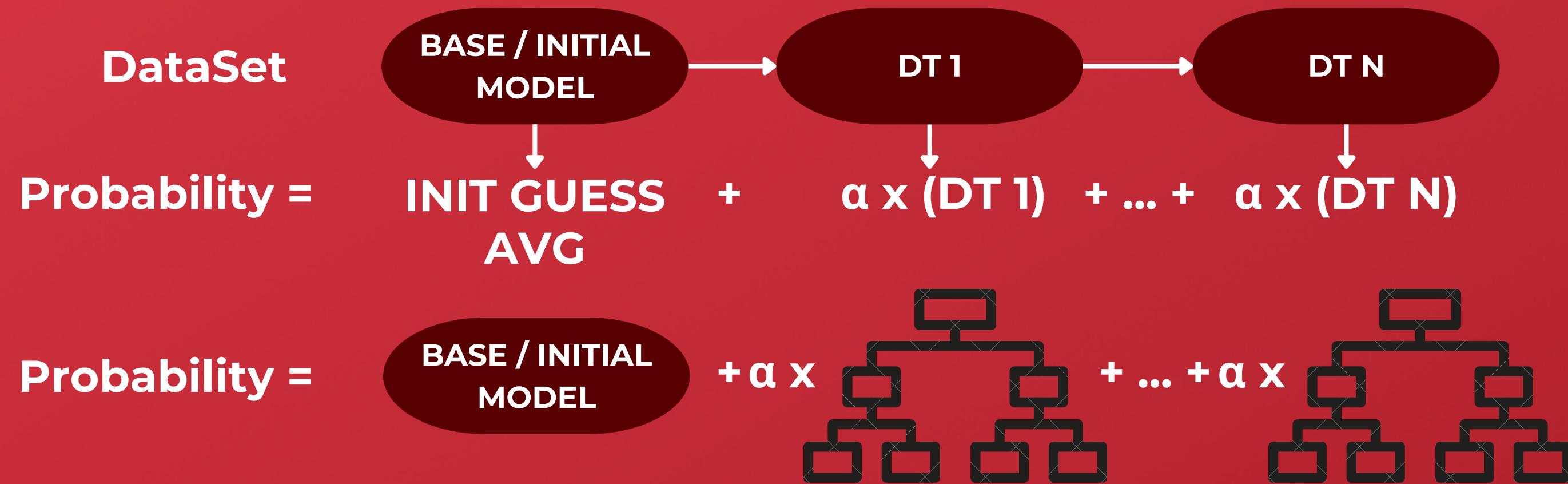
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$$\text{O/P} = \text{Base Model} + \alpha(\text{DT 1}) + \alpha(\text{DT 2}) + \dots + \alpha(\text{DT N})$$

XGBOOST REGRESSION :



- **FINAL STEPS :**
 - Calculate the output of each bottom leaf using :
Output = Avg of RES = (Sum Residuals)/(Nb Residuals)
 - Calculate the new probability of each record using :
O/P = Base Model + $\alpha(DT\ 1) + \alpha(DT\ 2) + \dots + \alpha(DT\ N)$

WHEN SHOULD I USE XGBOOST?

EXTREME GRADIENT BOOSTING WITH XGBOOST



WHEN TO USE XGBOOST :

- You have a large number of training samples
- Greater than 1000 training samples and less 100 features
- The number of features < number of training samples
- You have a mixture of categorical and numeric features

WHEN TO NOT USE XGBOOST :

- Image recognition
- Computer vision
- Natural language processing and understanding problems
- When the number of training samples is significantly smaller than the number of features

HOW XGBOOST IS IMPLEMENTED IN PYTHON

EXTREME GRADIENT BOOSTING WITH XGBOOST



HOW TO IMPLEMENT XGBOOST :

- Classification :

```
from xgboost import XGBClassifier  
model = XGBClassifier()  
model.fit(X_train, y_train)  
y_pred = model.predict(X_test)
```

- Regression

```
from xgboost import XGBRegressor  
model = XGBRegressor()  
model.fit(X_train, y_train)  
y_pred = model.predict(X_test)
```

LET'S PRACTICE!

EXTREME GRADIENT BOOSTING WITH XGBOOST



XGBOOST : SOME HELPFUL RSOURCES

- XGBoost Paper : <https://arxiv.org/pdf/1603.02754.pdf>
- XGBoost Docs : <https://xgboost.readthedocs.io>

XGBoost: A Scalable Tree Boosting System

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Carlos Guestrin
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guestrin@cs.washington.edu

ABSTRACT

Tree boosting is a highly effective and widely used machine learning method. In this paper, we describe a scalable end-to-end tree boosting system called XGBoost, which is used widely by data scientists to achieve state-of-the-art results on many machine learning challenges. We propose a novel sparsity-aware algorithm for sparse data and weighted quantile sketch for approximate tree learning. More importantly, we provide insights on cache access patterns, data compression and sharding to build a scalable tree boosting system. By combining these insights, XGBoost scales beyond billions of examples using far fewer resources than existing systems.

problems. Besides being used as a stand-alone predictor, it is also incorporated into real-world production pipelines for ad click through rate prediction [15]. Finally, it is the de-facto choice of ensemble method and is used in challenges such as the Netflix prize [3].

In this paper, we describe XGBoost, a scalable machine learning system for tree boosting. The system is available as an open source package². The impact of the system has been widely recognized in a number of machine learning and data mining challenges. Take the challenges hosted by the machine learning competition site Kaggle for example. Among the 29 challenge winning solutions³ published at Kaggle's blog during 2015, 17 solutions used XGBoost. Among these solutions eight solely used XGBoost to train the model.

Thank you for
attending
any questions ?