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Decision Tree For Regression

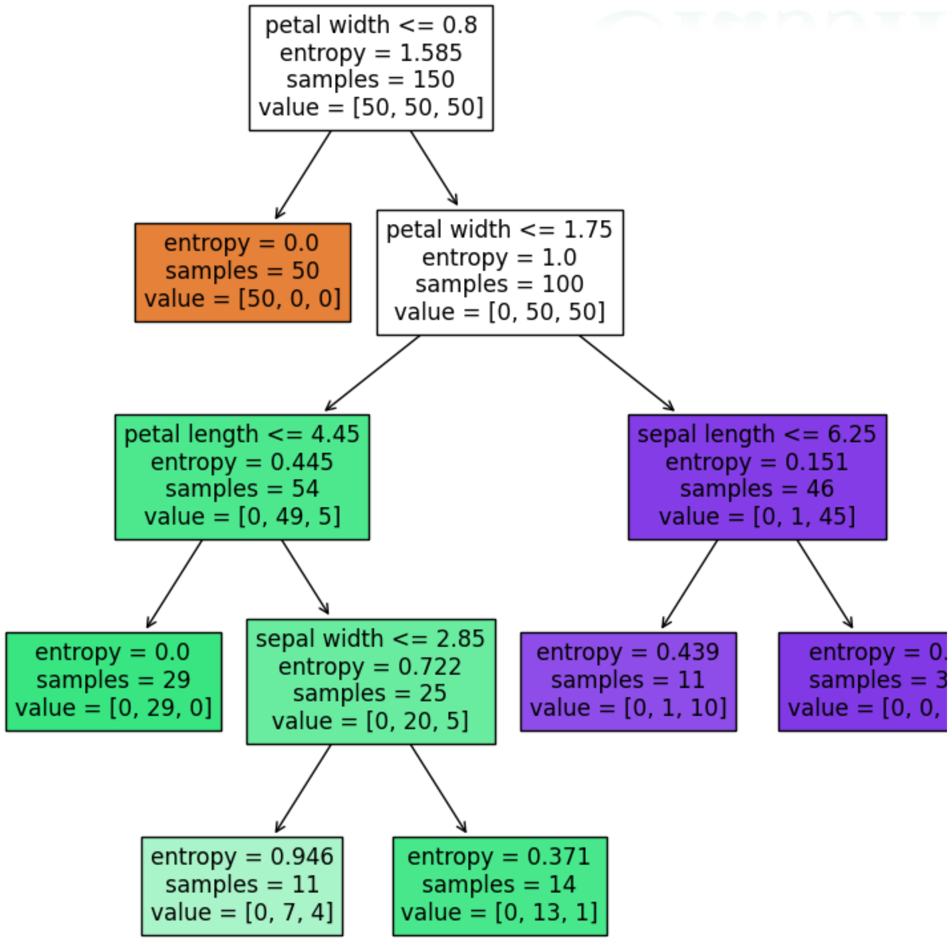
(Basic, Advanced Concepts and Its Applications)

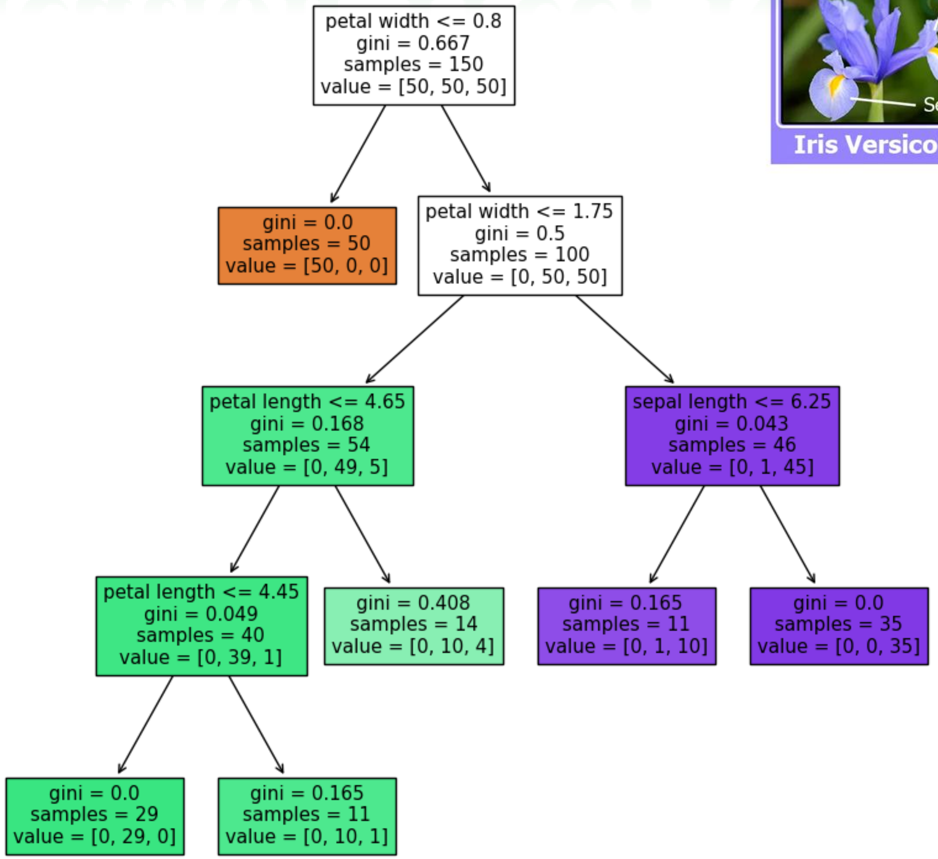
Vinh Dinh Nguyen
PhD in Computer Science

Outline

- ➢ **Classification Tree: Review**
- ➢ **Regression Tree: Motivation**
- ➢ **Regression Tree: Clearly Explain**
- ➢ **Regression Tree: Overfitting Problem**
- ➢ **Examples**

Classification Tree: Review



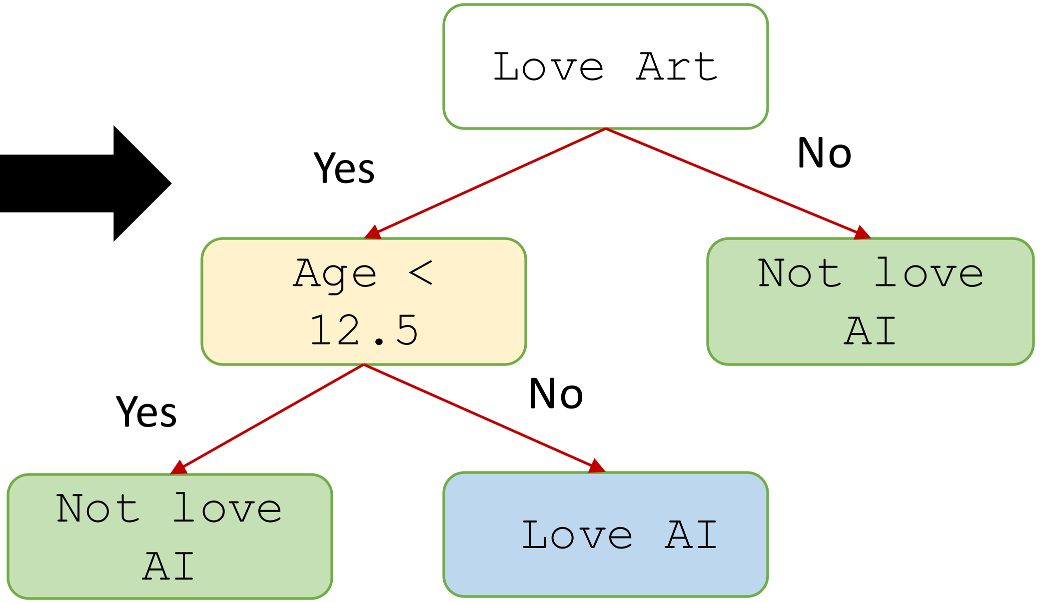


Classification Tree: Review

Love Math	Love Art	Age	Love AI
Yes	Yes	7	No
Yes	No	12	No
No	Yes	18	Yes
No	Yes	35	Yes
Yes	Yes	38	Yes
Yes	No	50	No
No	No	83	No

Features

Labels



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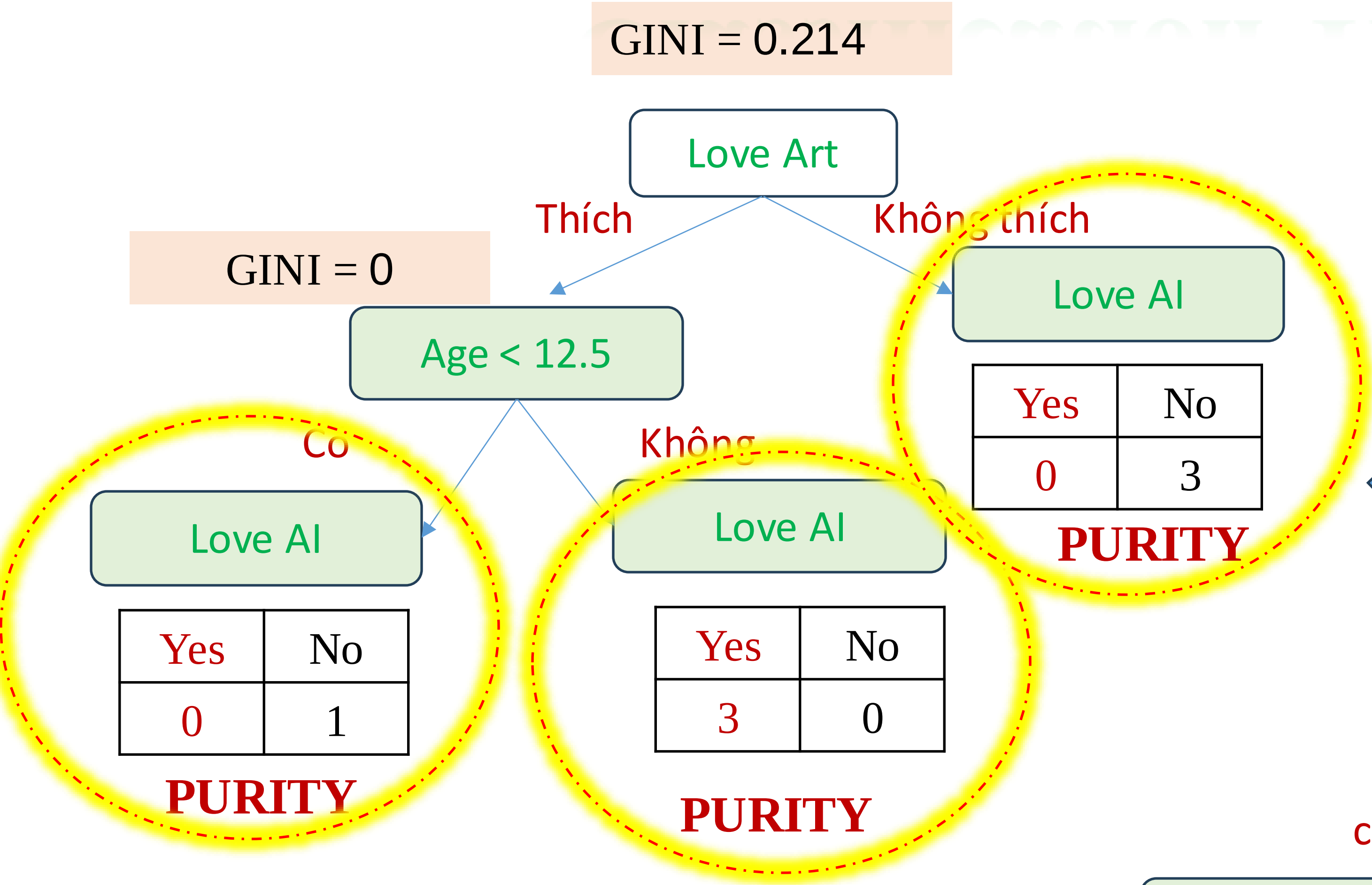
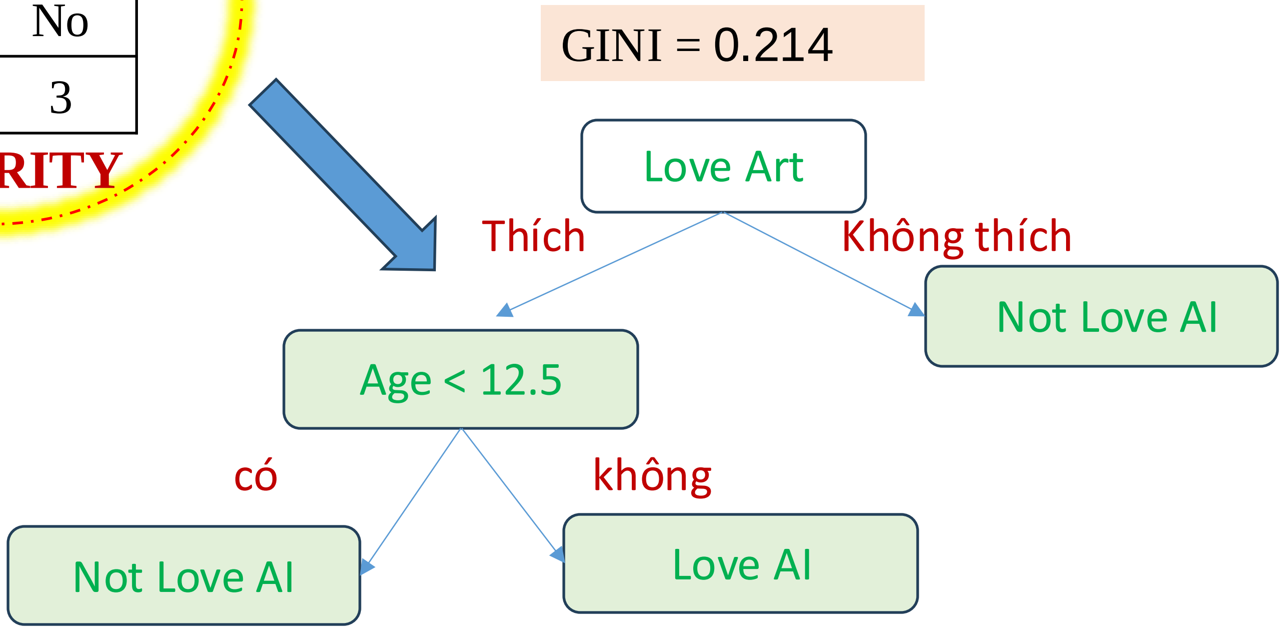
Classification Tree: Review



Previous Open Question: How can we handle overfitting?



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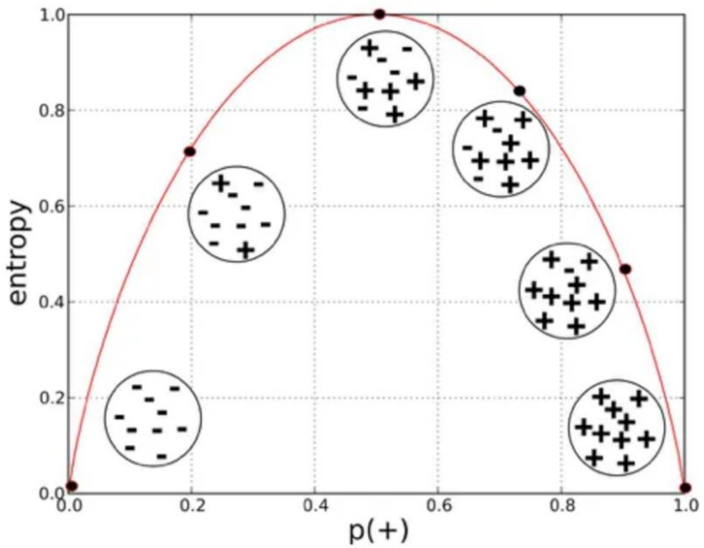
Evaluation Metric: Review

When should I use Gini Impurity as opposed to Information Gain (Entropy)

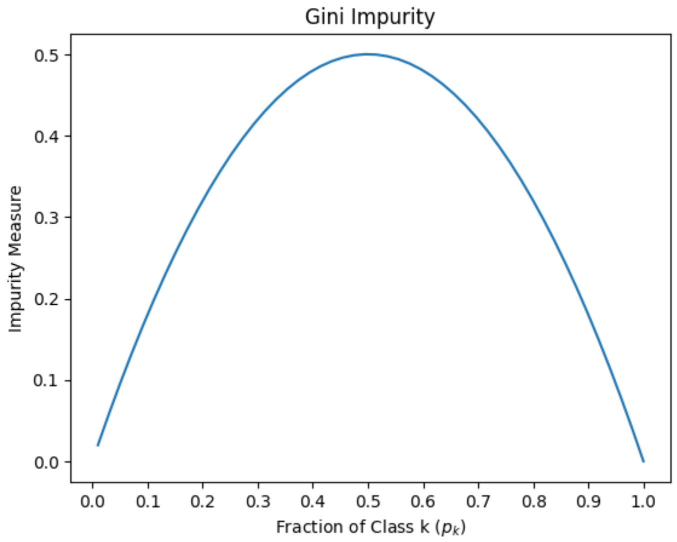
Entropy – Information Gain

$$GAIN_{split} = Entropy(p) - \left(\sum_{i=1}^{k} \frac{n_i}{n} Entropy(i) \right)$$



GNI IMPURITY

$$Gini = 1 - \sum_{i=1}^{c} (p_i)^2$$



GINI Vs. Entropy

Laura Elena Raileanu and Kilian Stoffel compared both in "Theoretical comparison between the gini index and information gain criteria". The most important remarks were:

•It only matters in 2% of the cases whether you use gini impurity or entropy.

•Entropy might be a little slower to compute (because it makes use of the logarithm).

Study the behavior of the Gini Index and Information Gain, to give an exact mathematical description of the situations when they are choosing the same test to split on and when they are choosing different tests.

Found that they disagree only in 2% of all cases, which explains why most previously published empirical results concluded that it is not possible to decide which one of the two tests performs better

Published: May 2004

Theoretical Comparison between the Gini Index and Information Gain Criteria

Laura Elena Raileanu & Kilian Stoffel

Annals of Mathematics and Artificial Intelligence **41**, 77–93 (2004) | Cite this article

Abstract

Knowledge Discovery in Databases (KDD) is an active and important research area with the promise for a high payoff in many business and scientific applications. One of the main tasks in KDD is classification. A particular efficient method for classification is decision tree induction. The selection of the attribute used at each node of the tree to split the data (split criterion) is crucial in order to correctly classify objects. Different split criteria were proposed in the literature (Information Gain, Gini Index, etc.). It is not obvious which of them will produce the best decision tree for a given data set. A large amount of empirical tests were conducted in order to answer this question. No conclusive results were found. In this paper we introduce a formal methodology, which allows us to compare multiple split criteria. This permits us to present fundamental insights into the decision process. Furthermore, we are

https://link.springer.com/article/10.1023/B:AMAI.0000018580.96245.c6

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Classification Tree: Review

	Sepal length	Sepal width	Petal length	Petal width	Class
1	5.1	3.5	1.4	0.2	setosa
2	4.9	3.0	1.4	0.2	setosa
3	4.7	3.2	1.3	0.2	setosa
⋮	⋮	⋮	⋮	⋮	⋮
150	5.9	3.0	5.1	1.8	virginica

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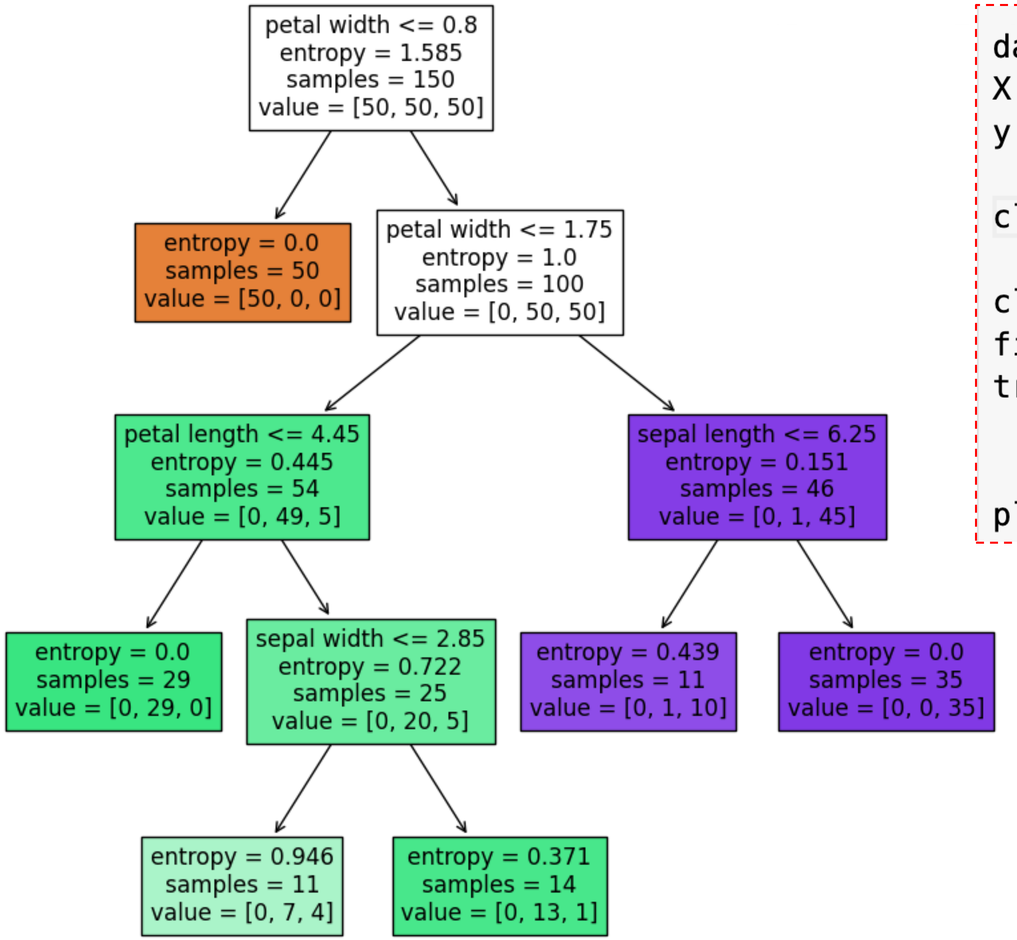
Iris Flower Classification (Entropy)



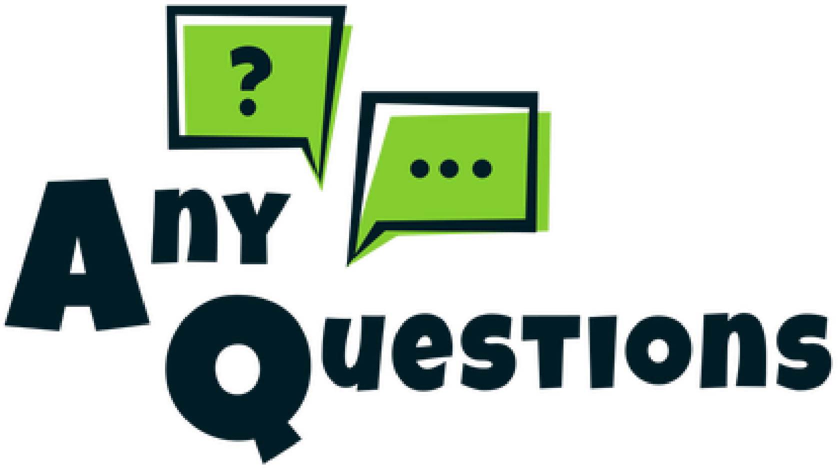
$$\text{Entropy} = \sum \log\left(\frac{1}{p(x)}\right) p(x)$$

Surprise

The probability of the Surprise.

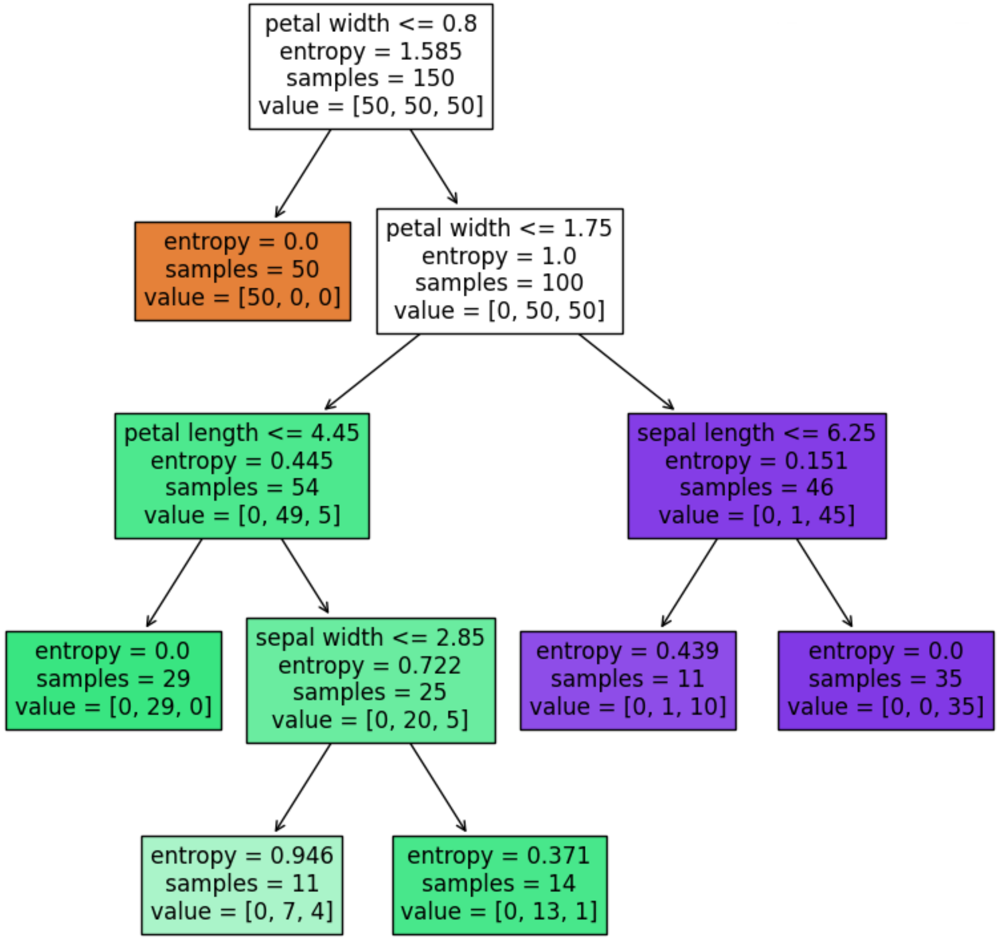
$$E(S) = \sum_{i=1}^{c} -p_i \log_2 p_i$$

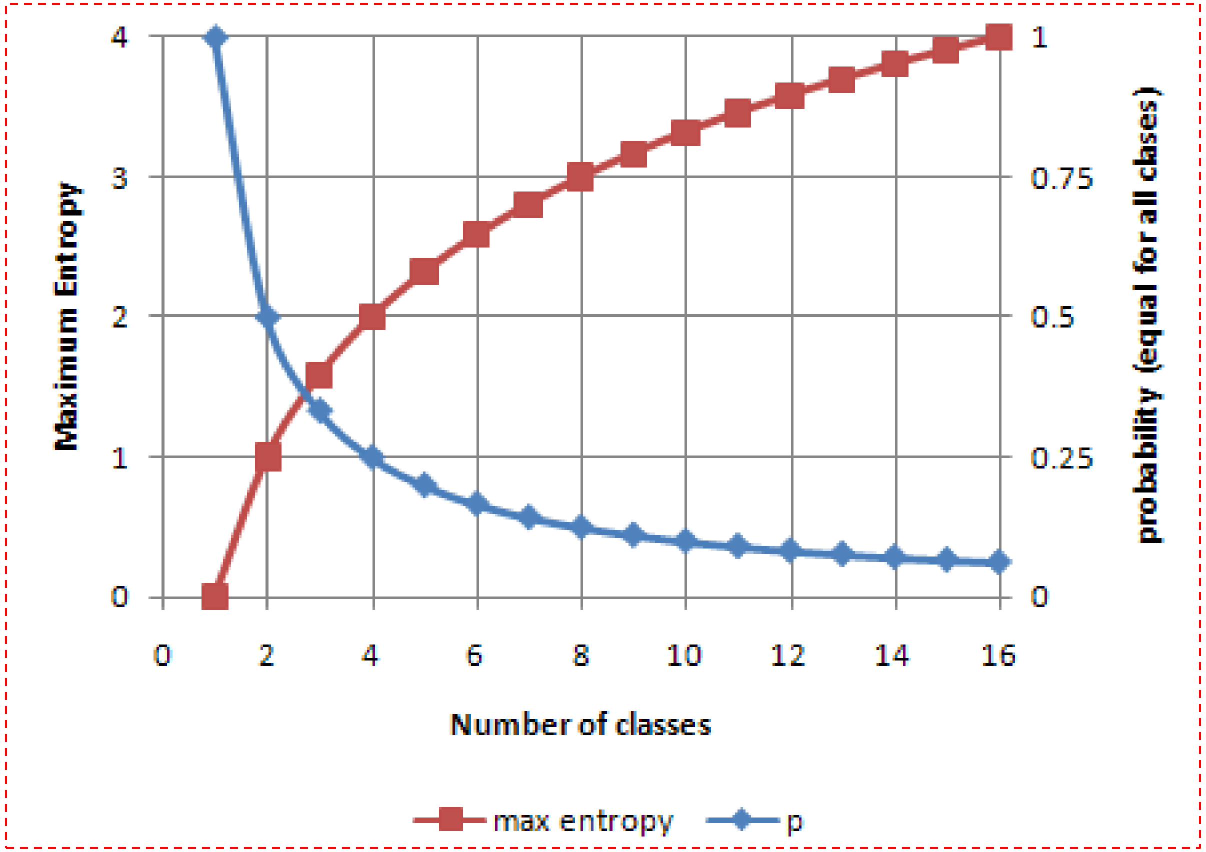
```
dataset = load_iris()
X = dataset.data
y = dataset.target

classifier = tree.DecisionTreeClassifier(criterion="entropy",
                                         max_depth=4, min_samples_leaf=10)
classifier.fit(X,y)
fig, ax = plt.subplots(figsize=(10,10))
tree.plot_tree(classifier,ax=ax, feature_names=["sepal length", "sepal width",
                                                "petal length", "petal width"],
                                                 filled=True)
plt.show()
```



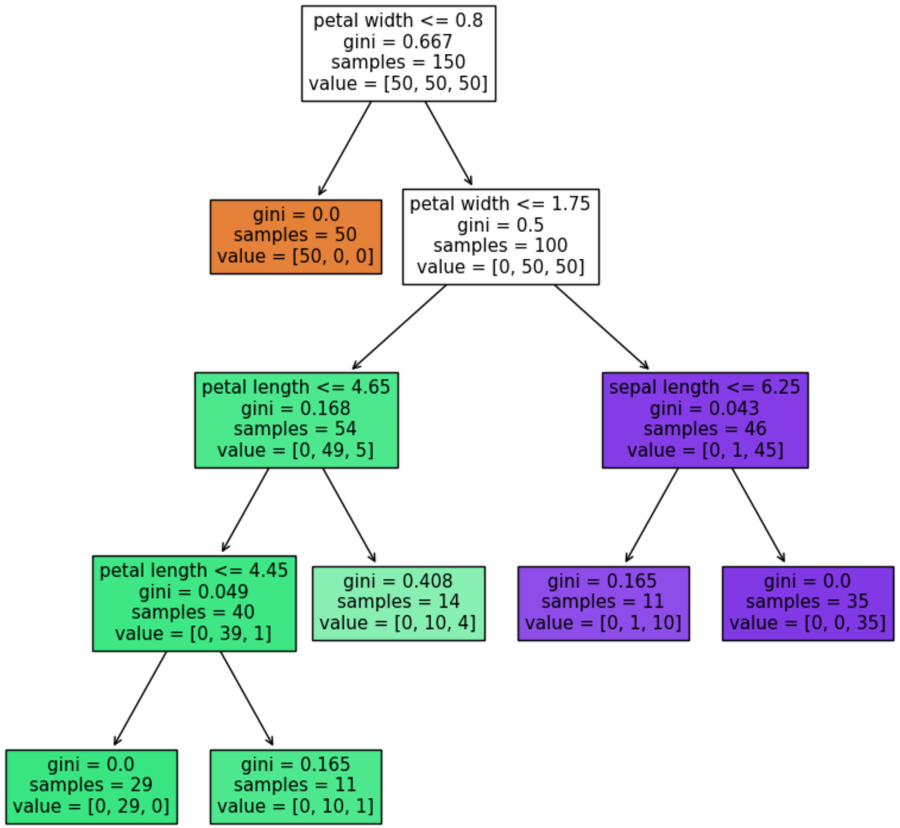
Các bạn có thấy điều gì bất thường ở đây không?

Iris Flower Classification (Entropy)





Iris Flower Classification (GINI)




```
dataset = load_iris()
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tree.plot_tree(classifier,ax=ax, feature_names=["sepal length", "sepal width",
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                                                 filled=True)
plt.show()
```
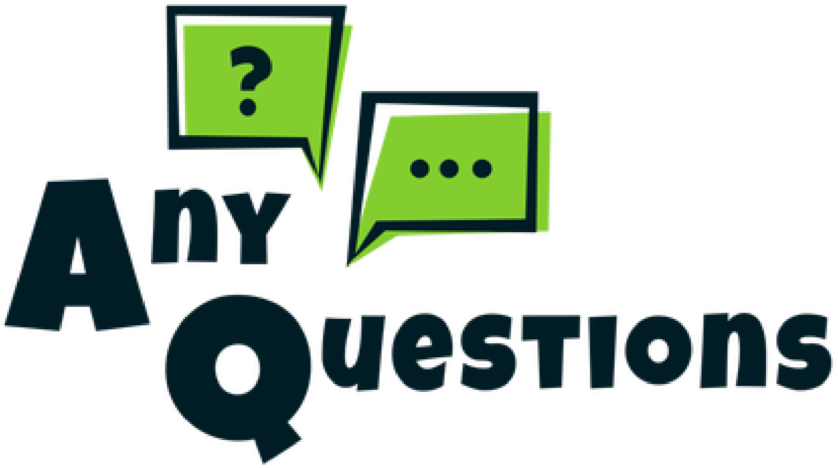

$$Gini = 1 - \sum_{i=1}^{C} (p_i)^2$$



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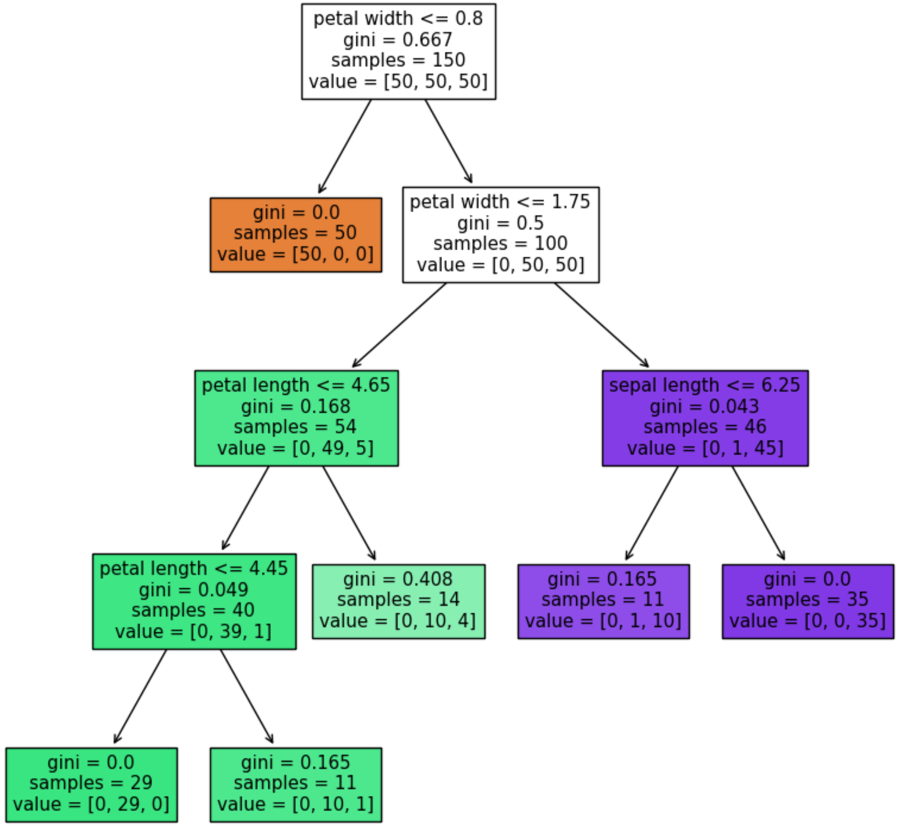
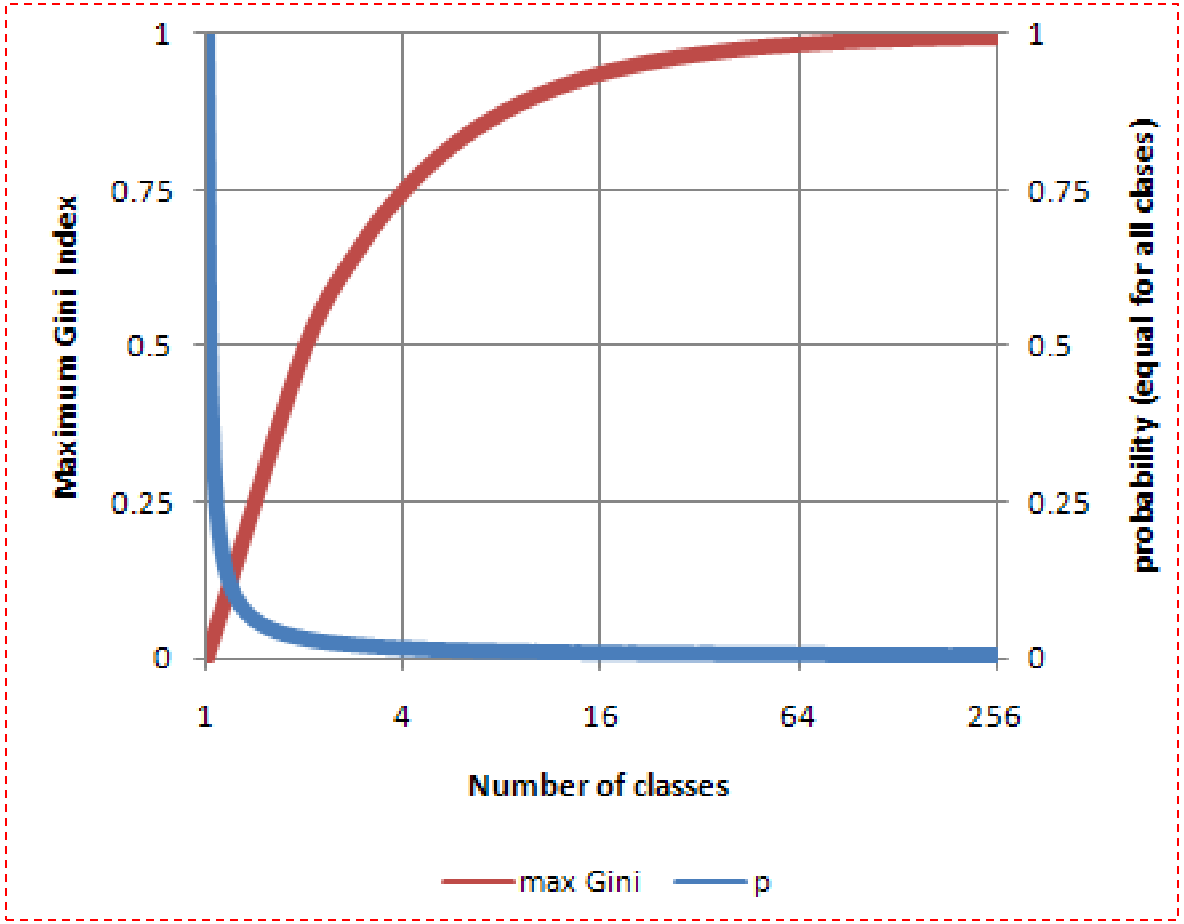
Iris Flower Classification (GINI)





Outline

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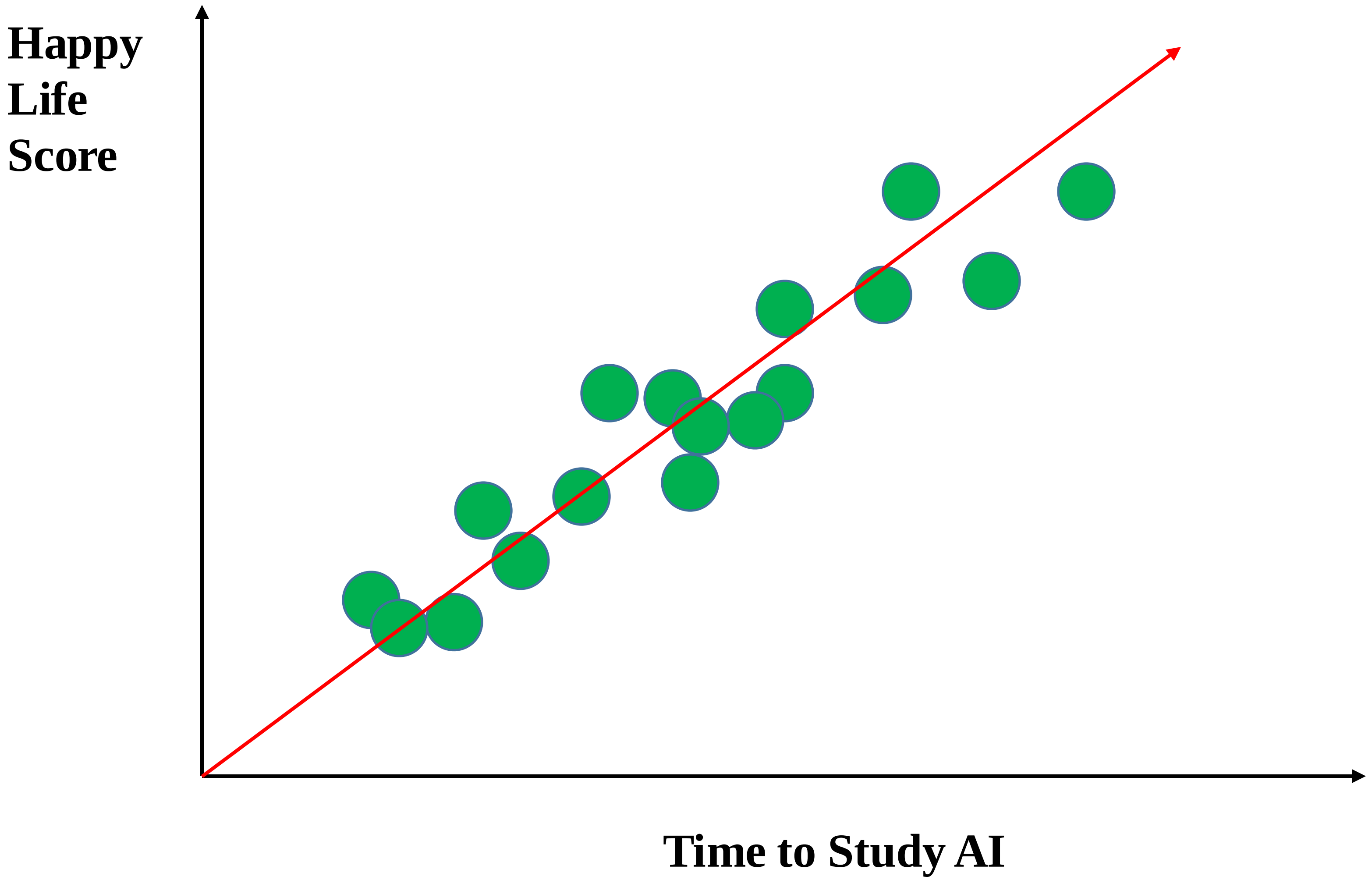
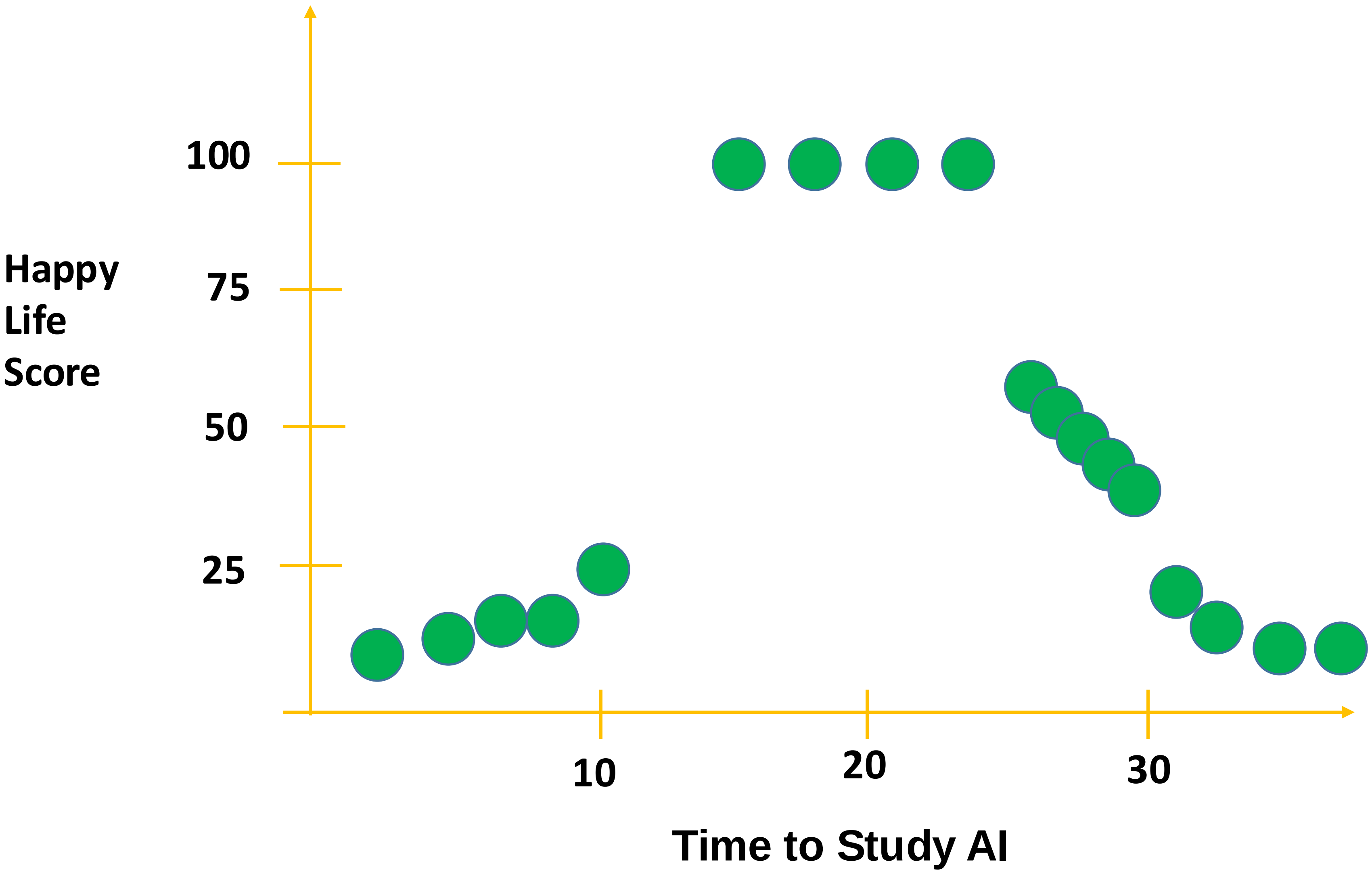
- ➢ Examples

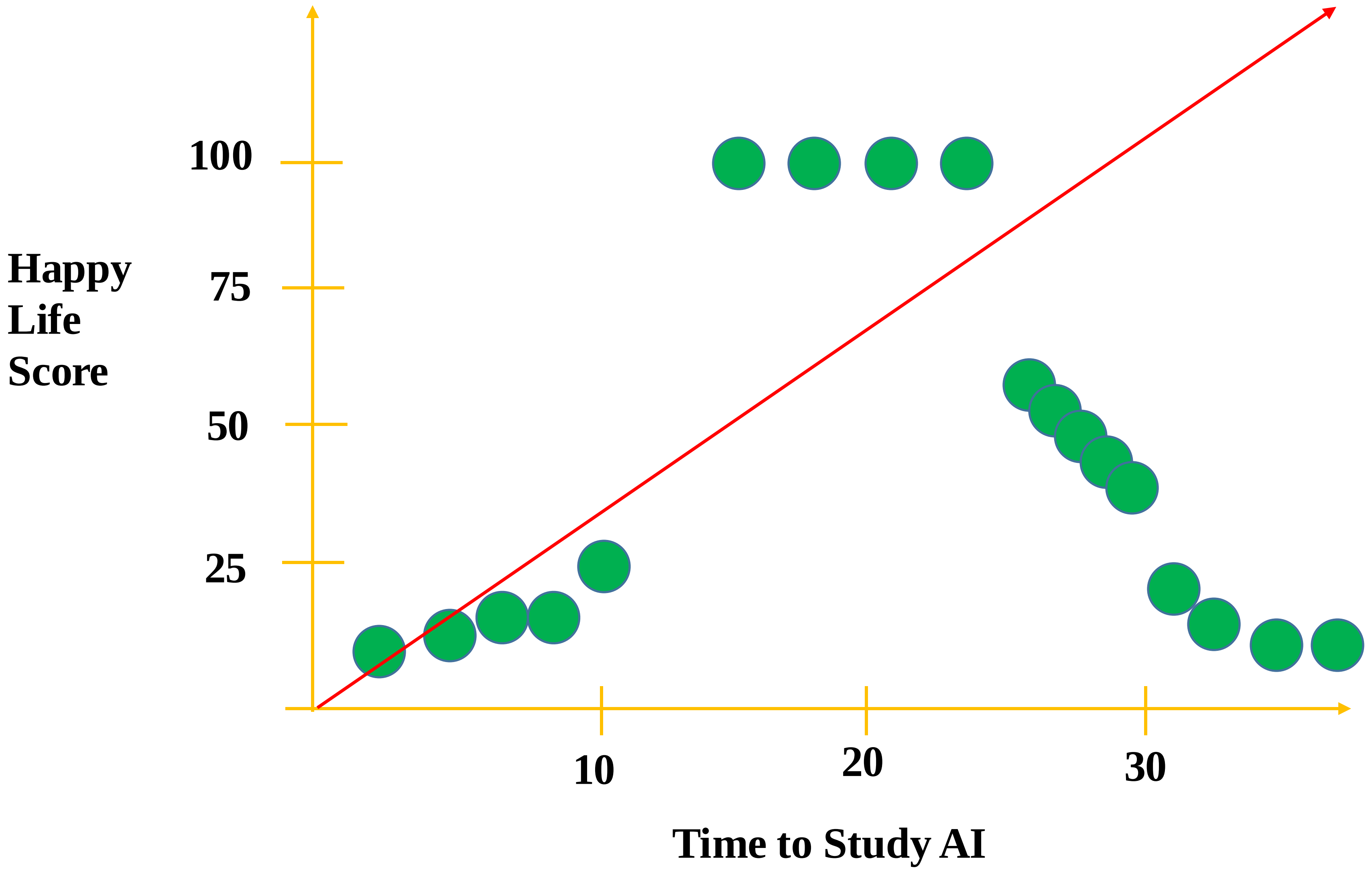
Linear Regression



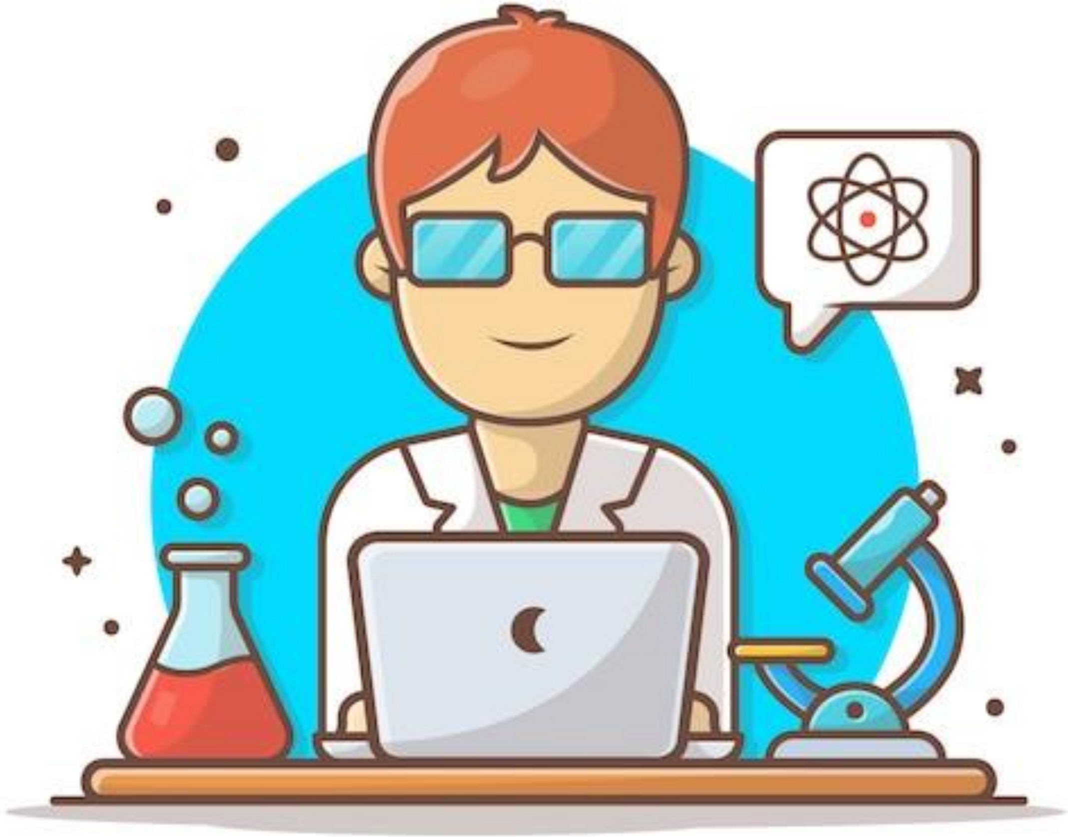
Linear Regression



Linear Regression: Problem

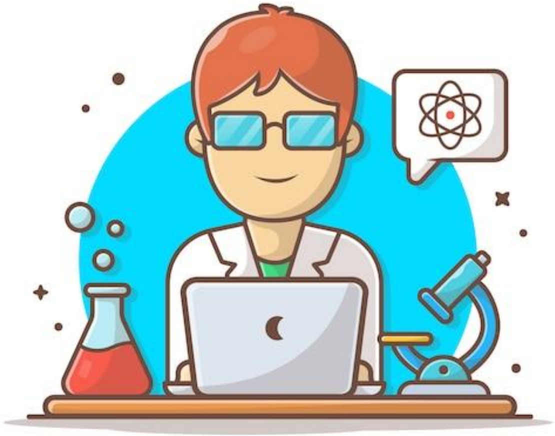


Case Study



Supposing that, you want to research and develop a new vaccine to cure the Covid-19

Case Study



Unit	Age	Sex	Effect (%)
10	25	Female	98
20	73	Male	0
35	54	Female	100
5	12	Male	44
…	…	…	…

Tiêm 5 đơn vị vaccine, 12 tuổi, giới tính nam

Hiệu quả vaccine: 44%

Khi có 1 vaccine ra đời, chúng ta muốn dự đoán xem nó hiệu quả bao nhiêu % ứng với liều lượng dùng cố định (unit), tuổi (age) và giới tính (sex) của bệnh nhân.

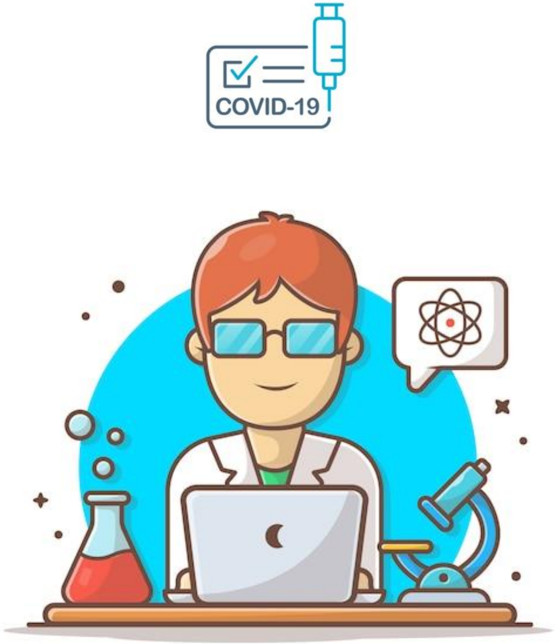
Can we use Decision Tree for solving this research?

Outline

- Classification Tree: Review
- Regression Tree: Motivation

- Regression Tree: Clearly Explain
- Regression Tree: Overfitting Problem
- Examples

Which Node Should be the Root?



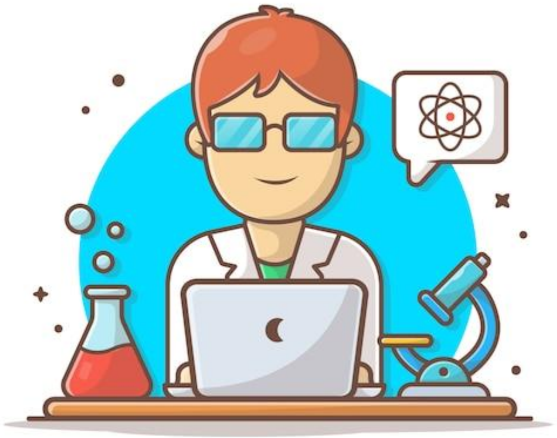
Unit(đơn vị)	Effect (hiệu quả) (%)
10	98
20	0
35	100
5	44
…	…

Tiêm 5 đơn vị vaccine

Hiệu quả vaccine: 44%

Khi có 1 vaccine ra đời, chúng ta muốn dự đoán xem nó hiệu quả bao nhiêu % ứng với từng liều lượng (unit) dùng trên bệnh nhân.

Which Node Should be the Root?



Age	Effect (hiệu quả) (%)
25	98
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…	…

12 tuổi

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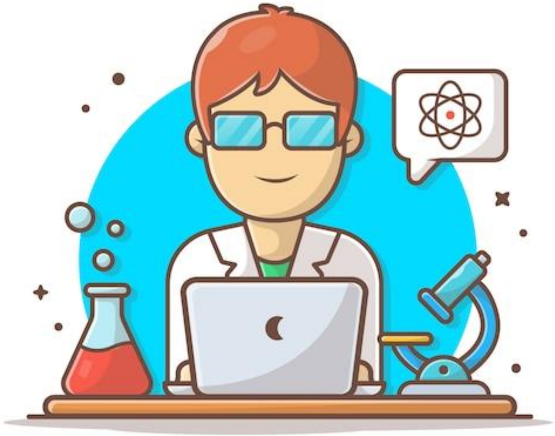

Sex	Effect (hiệu quả) (%)
Female	98
Male	0
Female	100
Male	44
…	…

Giới tính Male

Hiệu quả vaccine: 44%

Khi có 1 vaccine ra đời, chúng ta muốn dự đoán xem nó hiệu quả bao nhiêu % ứng với giới tính (sex) của bệnh nhân.

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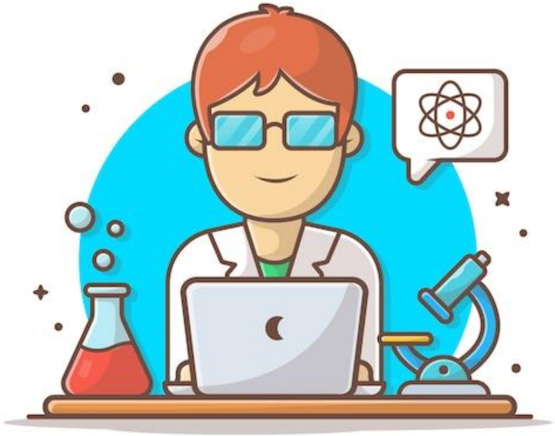
Unit is a Root Node



Unit(đơn vị)	Effect (hiệu quả) (%)
10	98
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5	44
…	…

Tiêm 5 đơn vị vaccine

Hiệu quả vaccine: 44%

Khi có 1 vaccine ra đời, chúng ta muốn dự đoán xem nó hiệu quả bao nhiêu % ứng với từng liều lượng (unit) dùng trên bệnh nhân.

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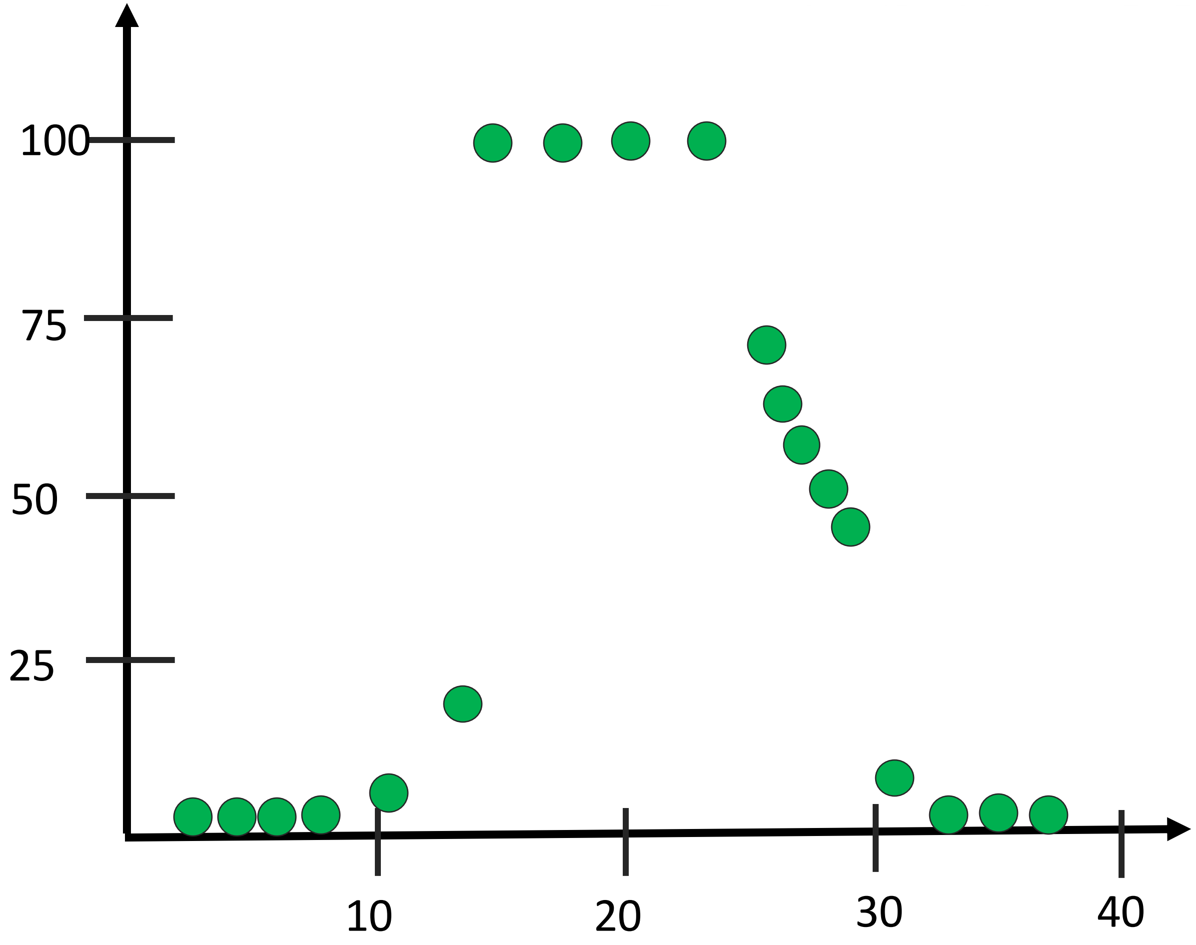

Tiêm 5 đơn vị vaccine

Hiệu quả vaccine: 44%

Khi có 1 vaccine ra đời, chúng ta muốn dự đoán xem nó hiệu quả bao nhiêu % ứng với từng liều lượng dùng (unit) trên bệnh nhân.

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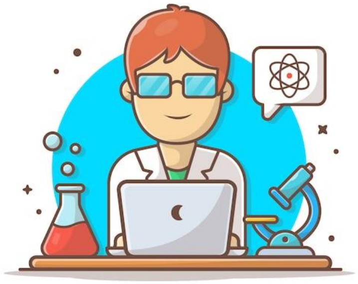
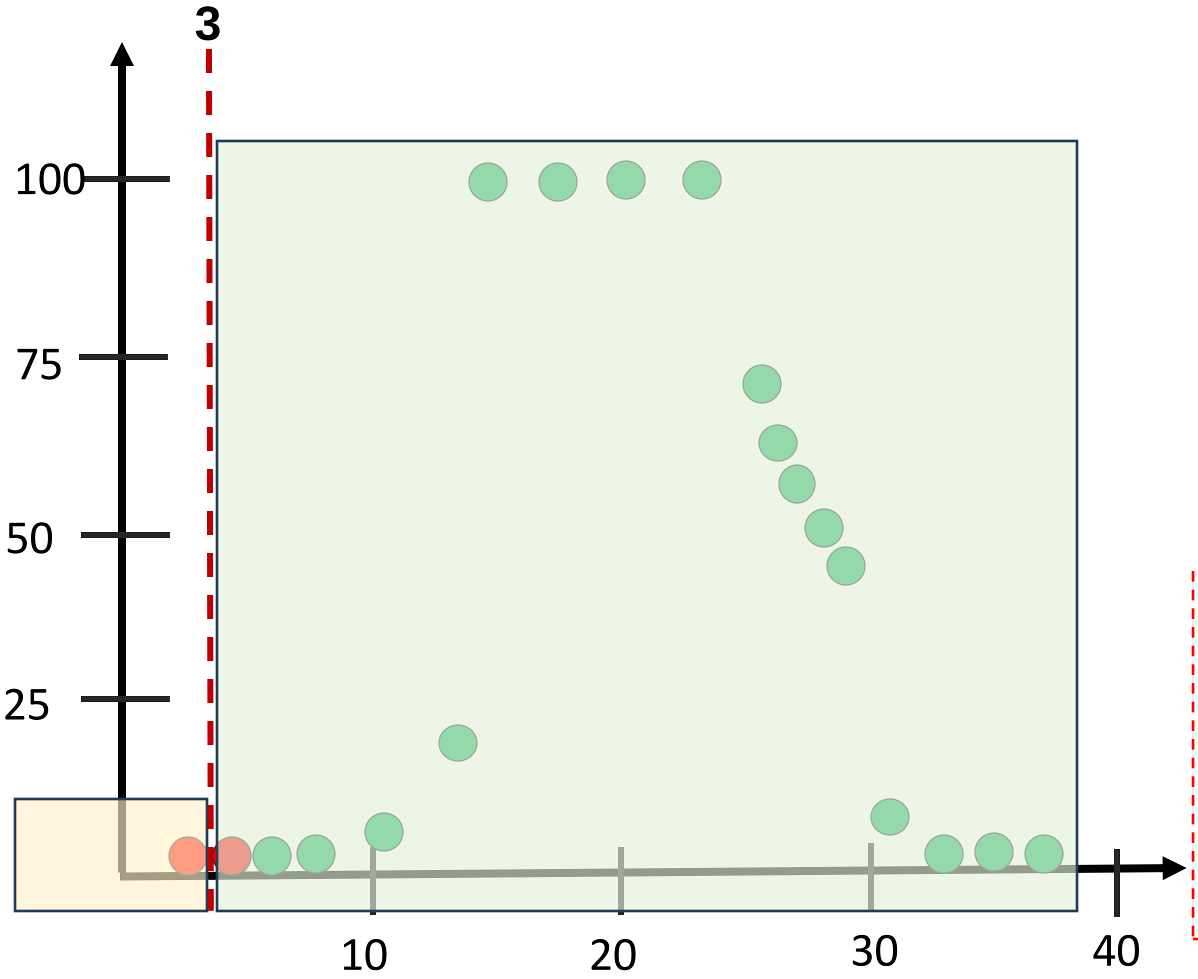


Effectiveness
(Hiệu quả)
(%)

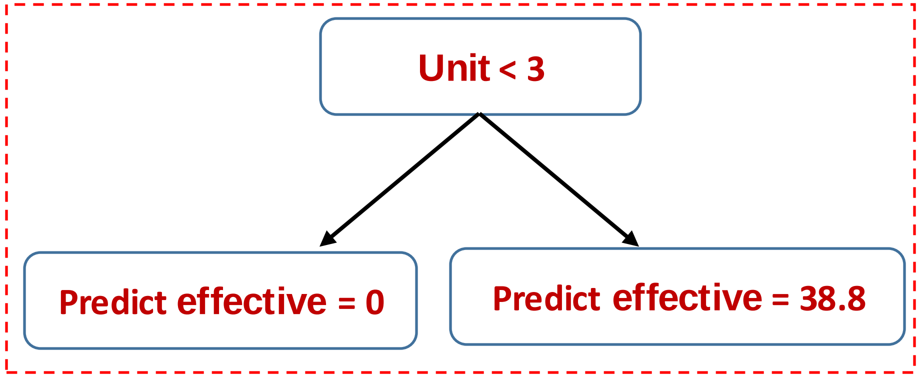


Unit (Đơn vị) vaccine

Average in unit(●●) = 3

Average in effectiveness( ) = 0

Average in effectiveness( ) = 38.8



Khi có 1 vaccine ra đời, chúng ta muốn dự đoán xem nó hiệu quả bao nhiêu % ứng với từng liều lượng dùng (unit) trên bệnh nhân.

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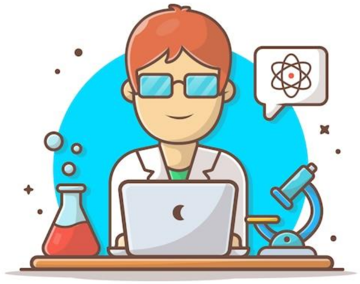
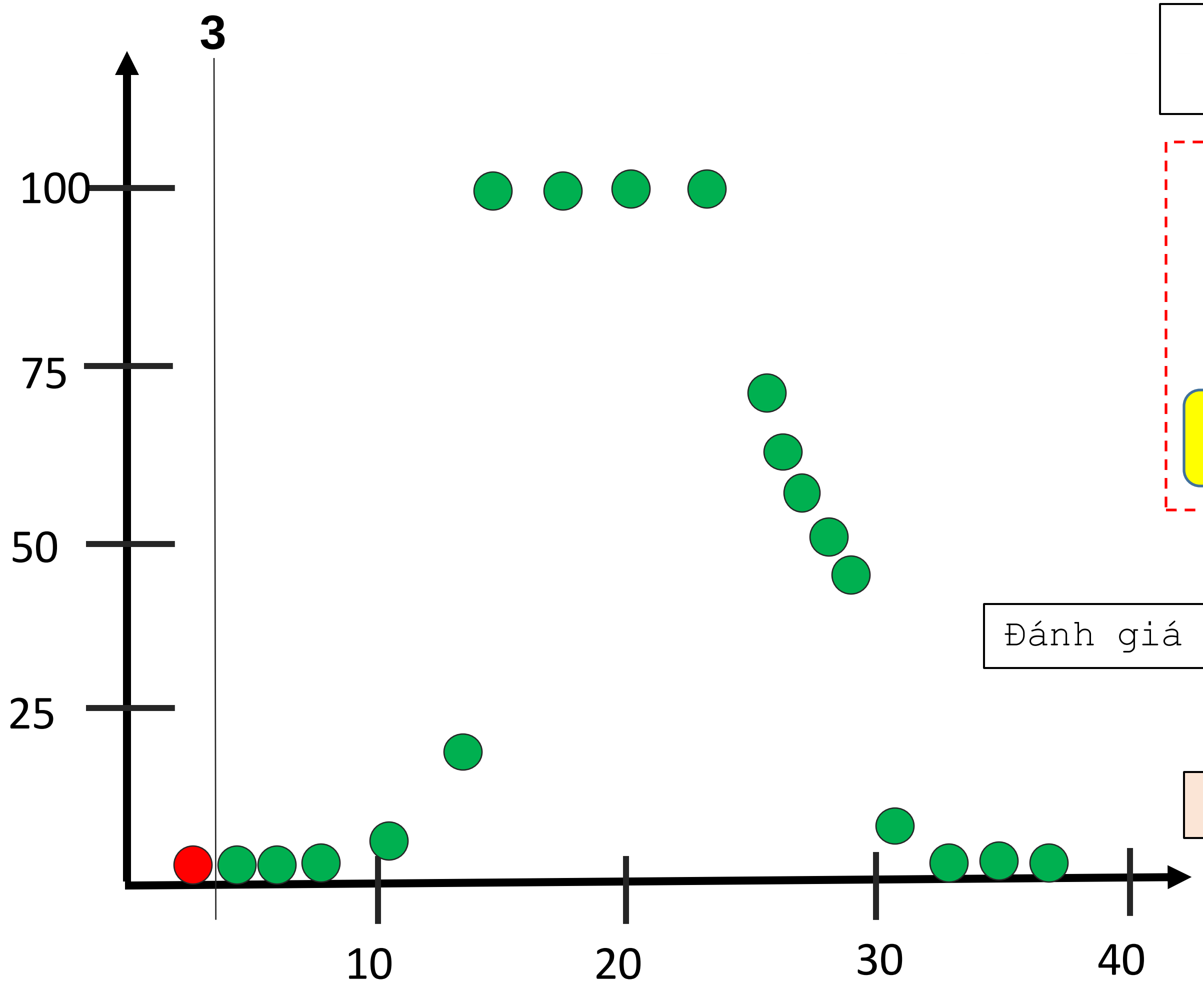
Unit is a Root Node





Effectiveness (Hiệu quả) (%)

Unit (Đơn vị) vaccine

Để đánh giá chất lượng cây mới tạo, chúng ta cần đánh giá residual error (lỗi) của nó

Unit < 3

Predict effective = 0

Predict effective = 38.8

Đánh giá residual error trong trường hợp unit < 3

Sum of Square Error (SSR) = 0

$$\underbrace{\sum_{i=1}^{\boxed{n}} (\boxed{Y_i} - \boxed{\hat{Y}_i})^2}_{\text{sum of the errors of all samples}}$$

number of samples

real value

predicted value

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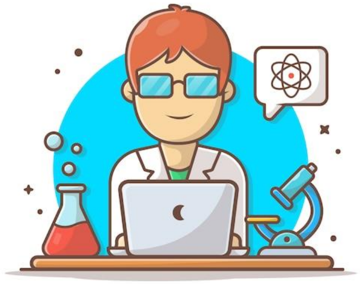
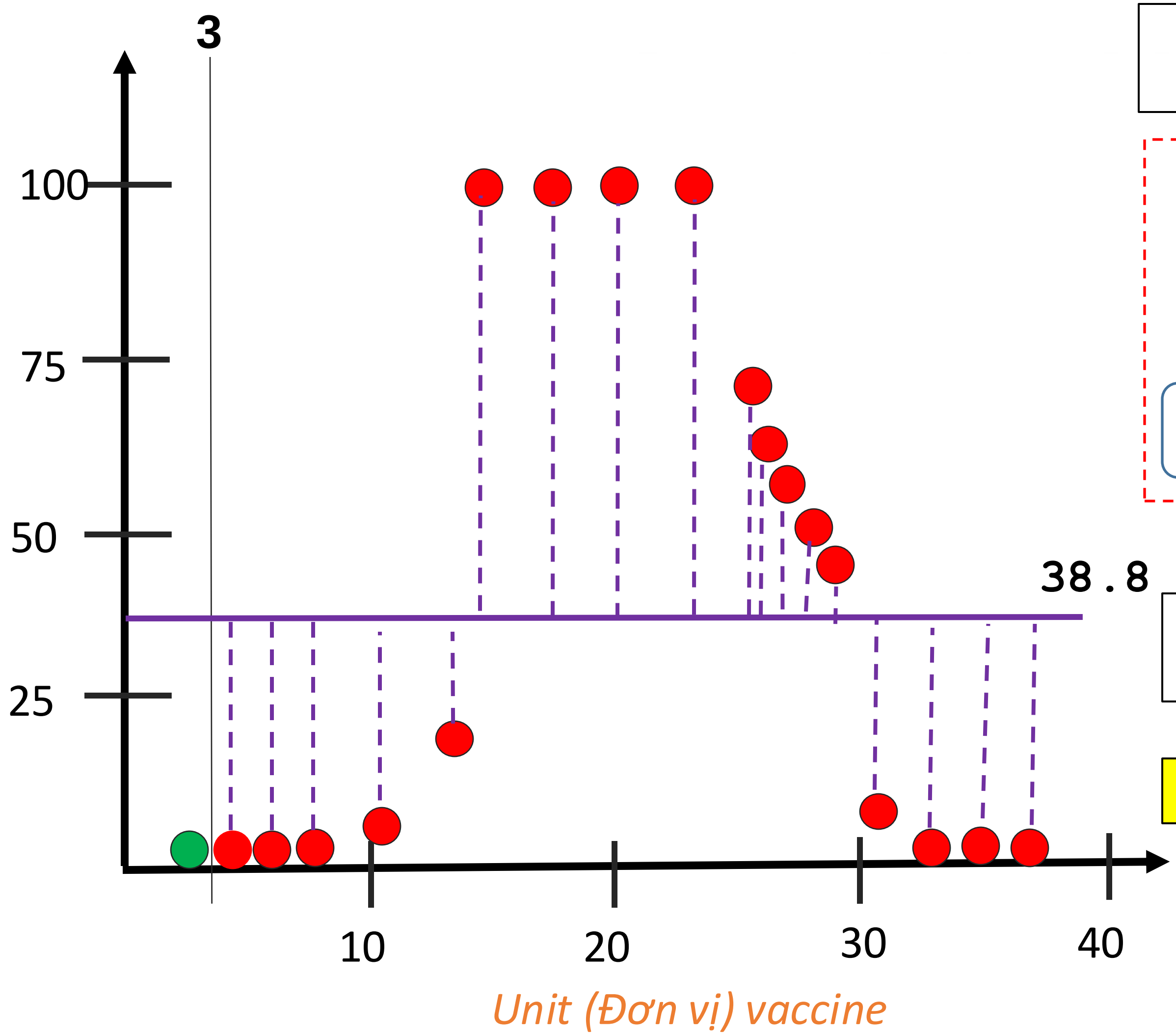
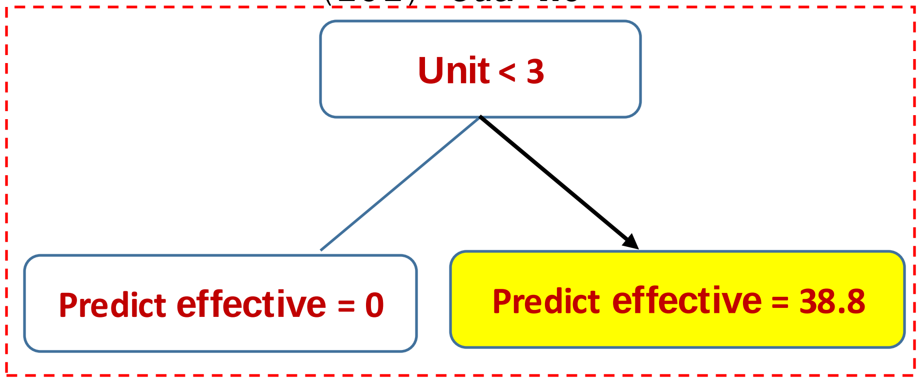
Unit is a Root Node





Để đánh giá chất lượng cây mới tạo, chúng ta cần đánh giá residual error (lỗi) của nó

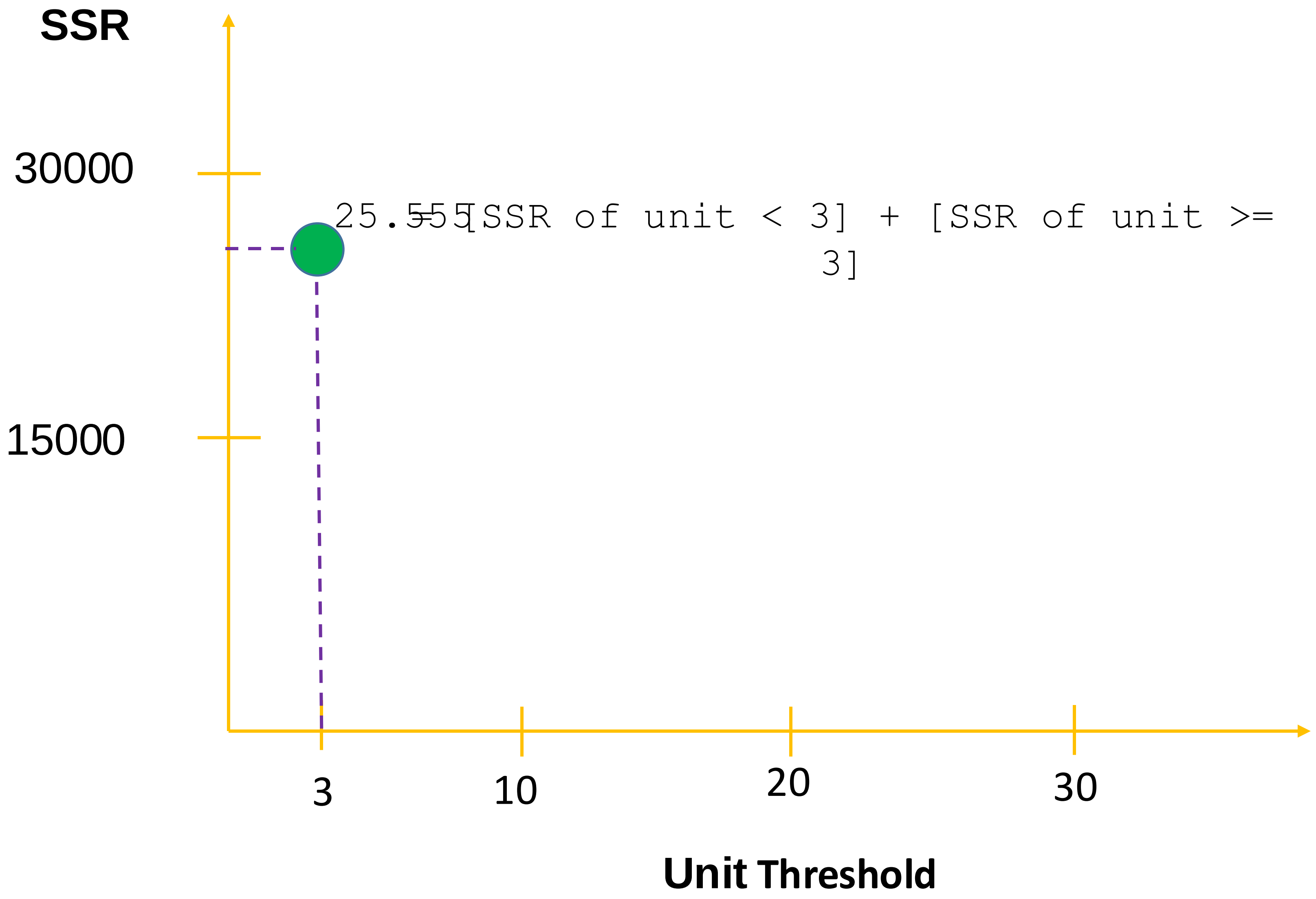


Đánh giá residual error trong trường hợp unit >= 3

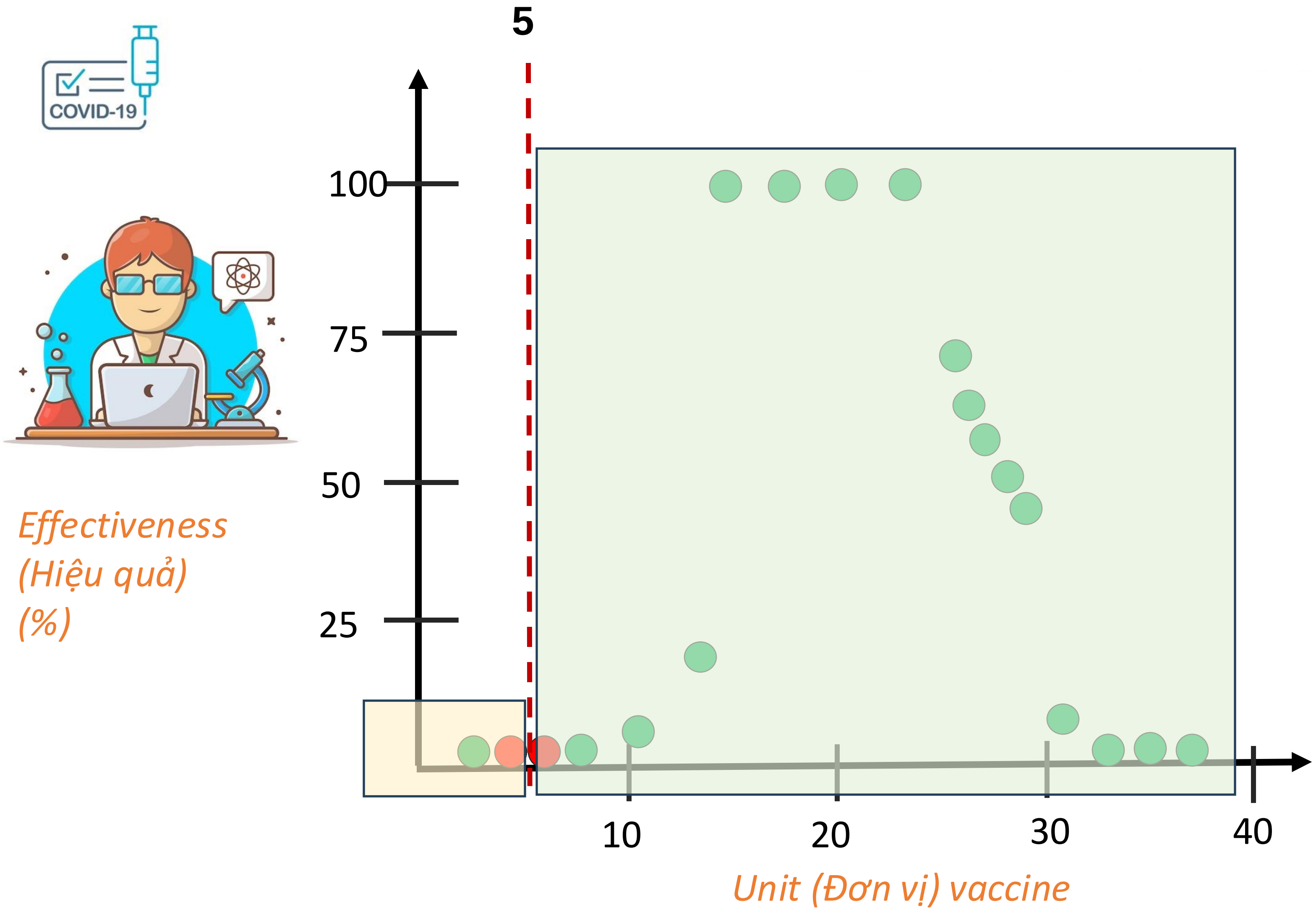
Sum of Square Error (SSR) = 25.555

$$\underbrace{\sum_{i=1}^{\boxed{n}} (\boxed{Y_i} - \boxed{\hat{Y}_i})^2}_{\text{sum of the errors of all samples}}$$

number of samples | real value | predicted value


SSR
30000
25.555
= [SSR of unit < 3] + [SSR of unit >= 3]
15000
3
10
20
30
Unit Threshold

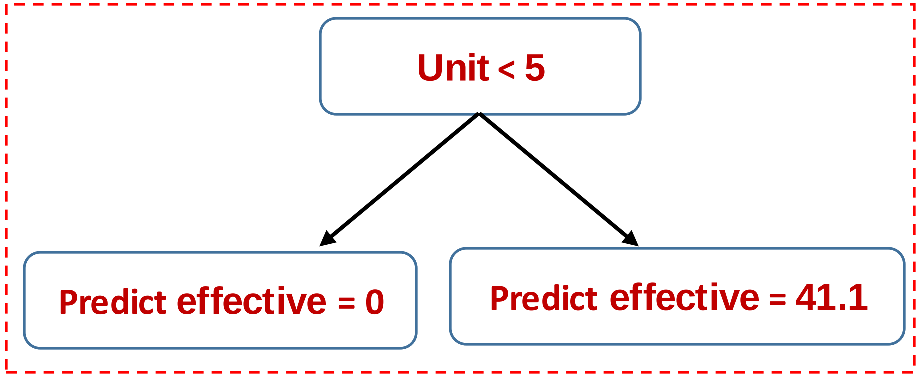
Unit is a Root Node



Average in unit( ) = 5

Average in effectiveness( ) = 0

Average in effectiveness( ) = 41.1



Compute SSR

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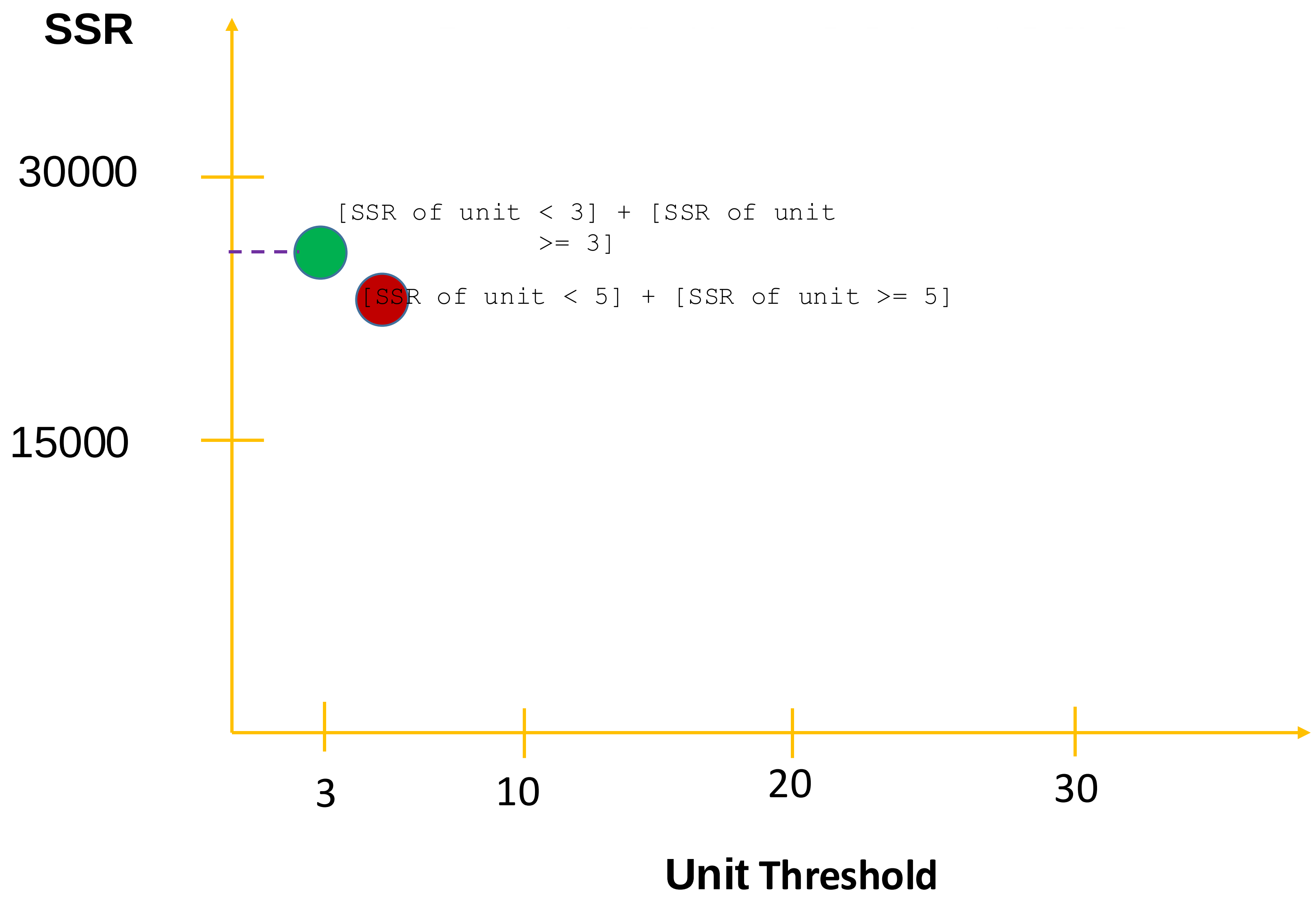
Unit is a Root Node



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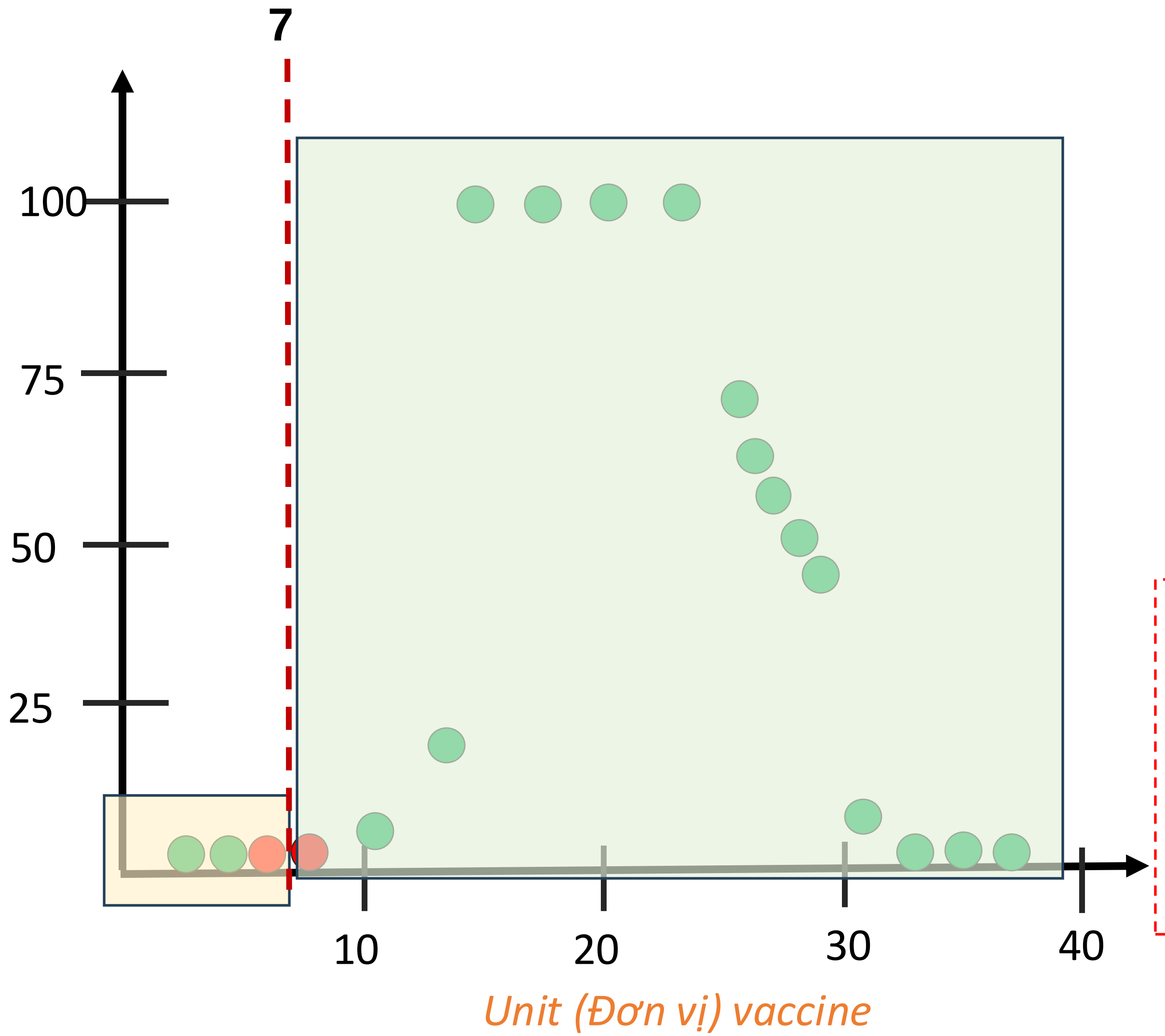
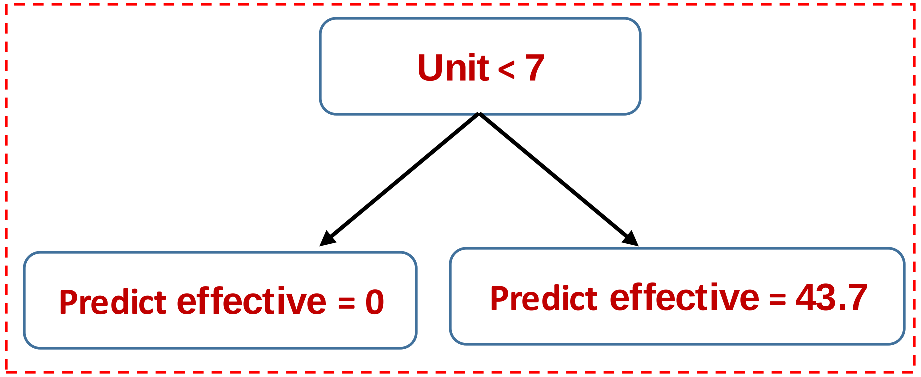


Average in unit( ) = 7

Average in effectiveness( ) = 0

Average in effectiveness( ) = 43.7



Compute SSR

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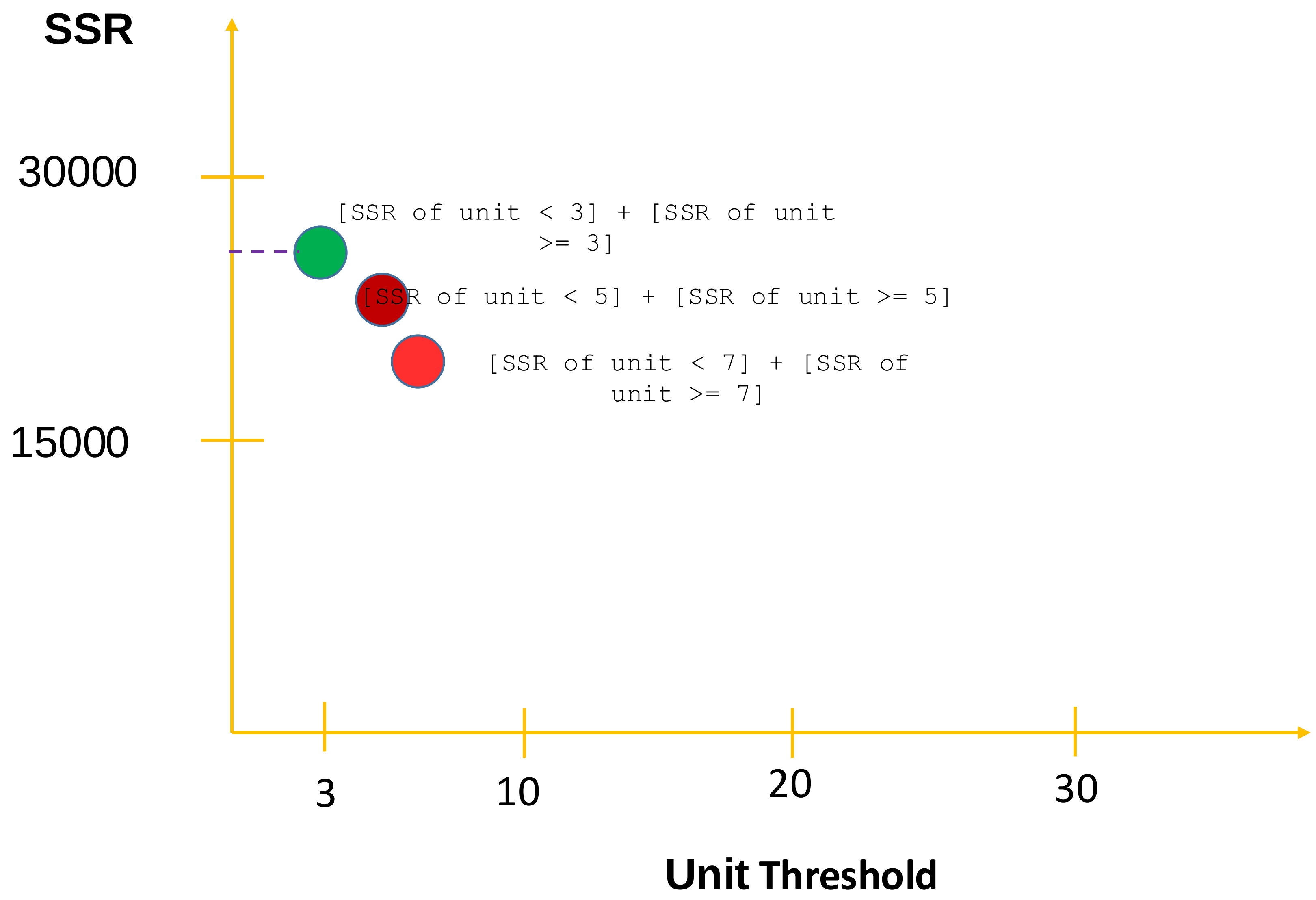

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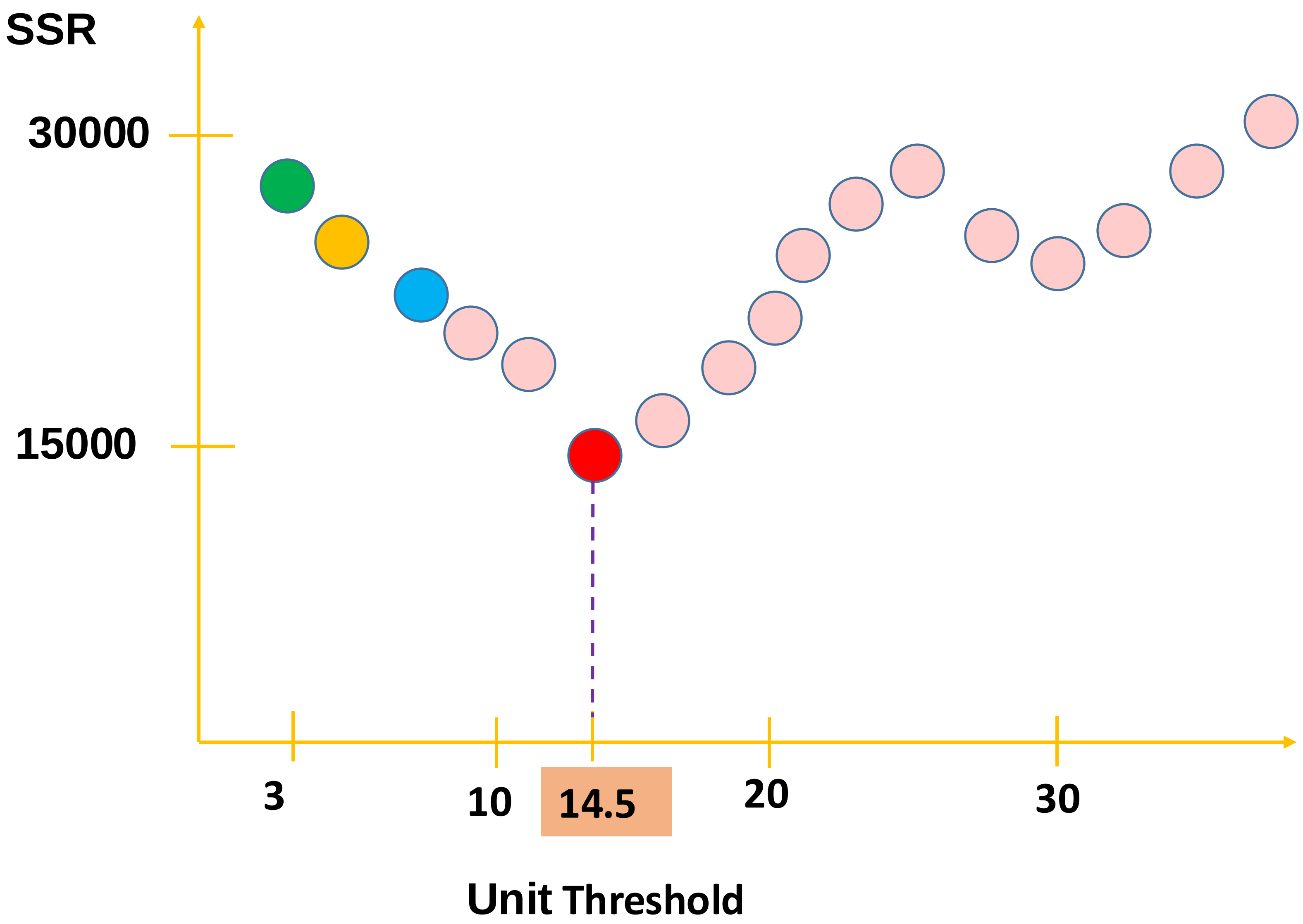

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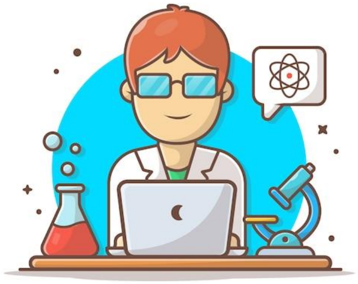
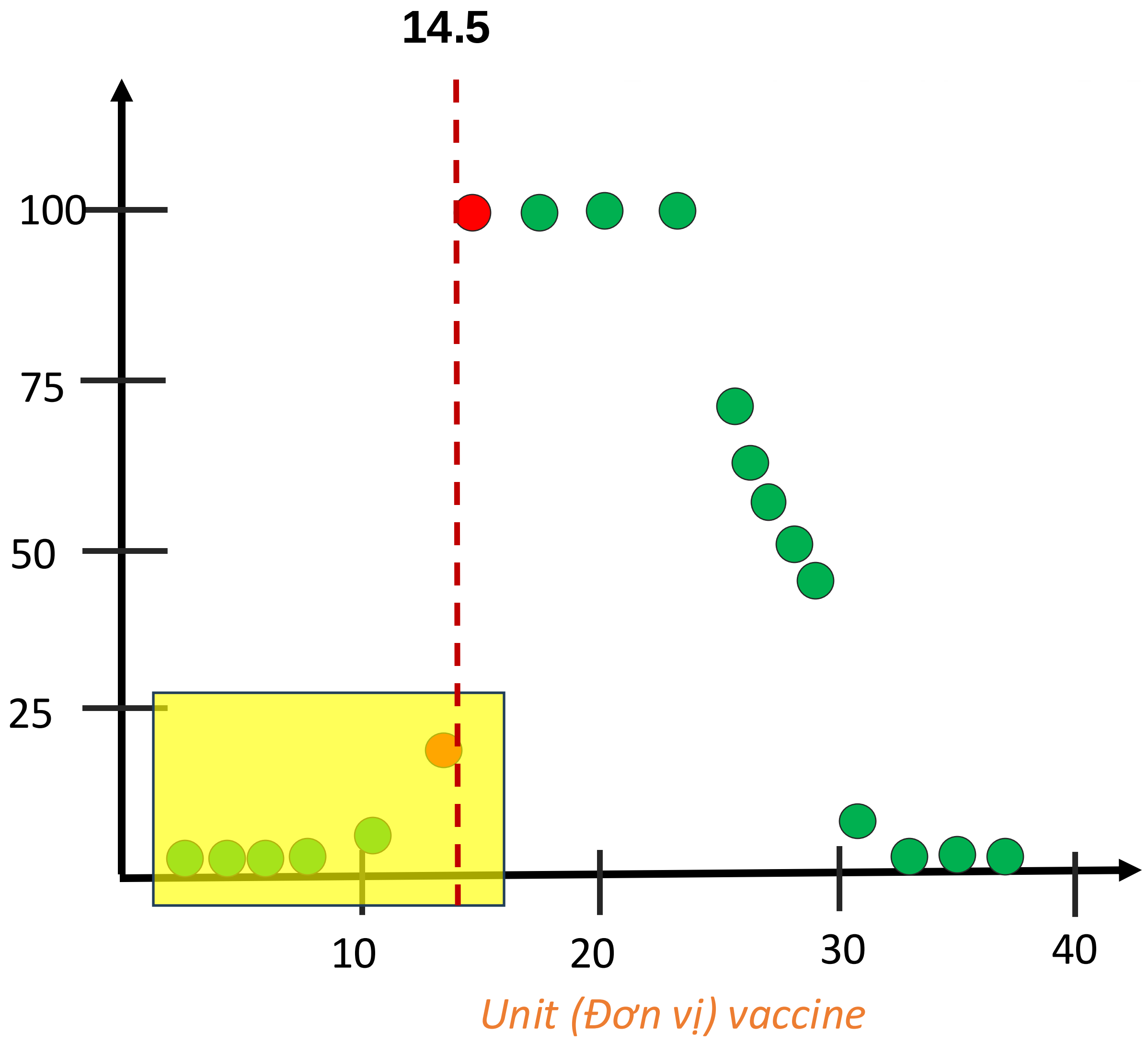
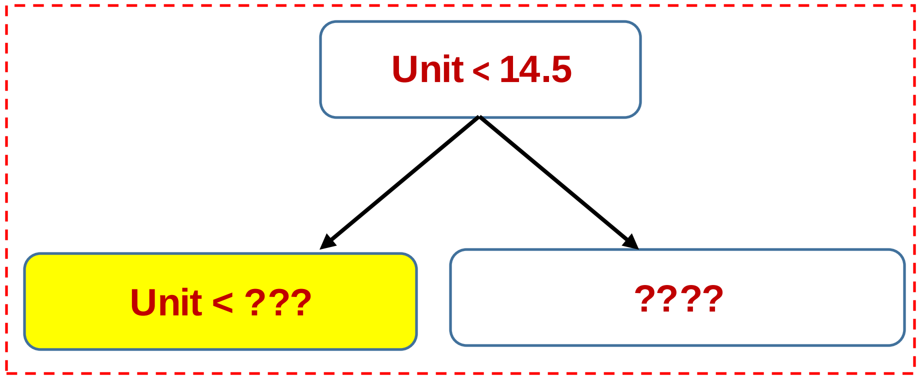
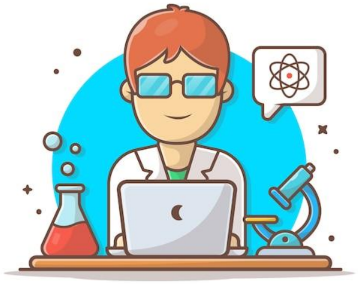


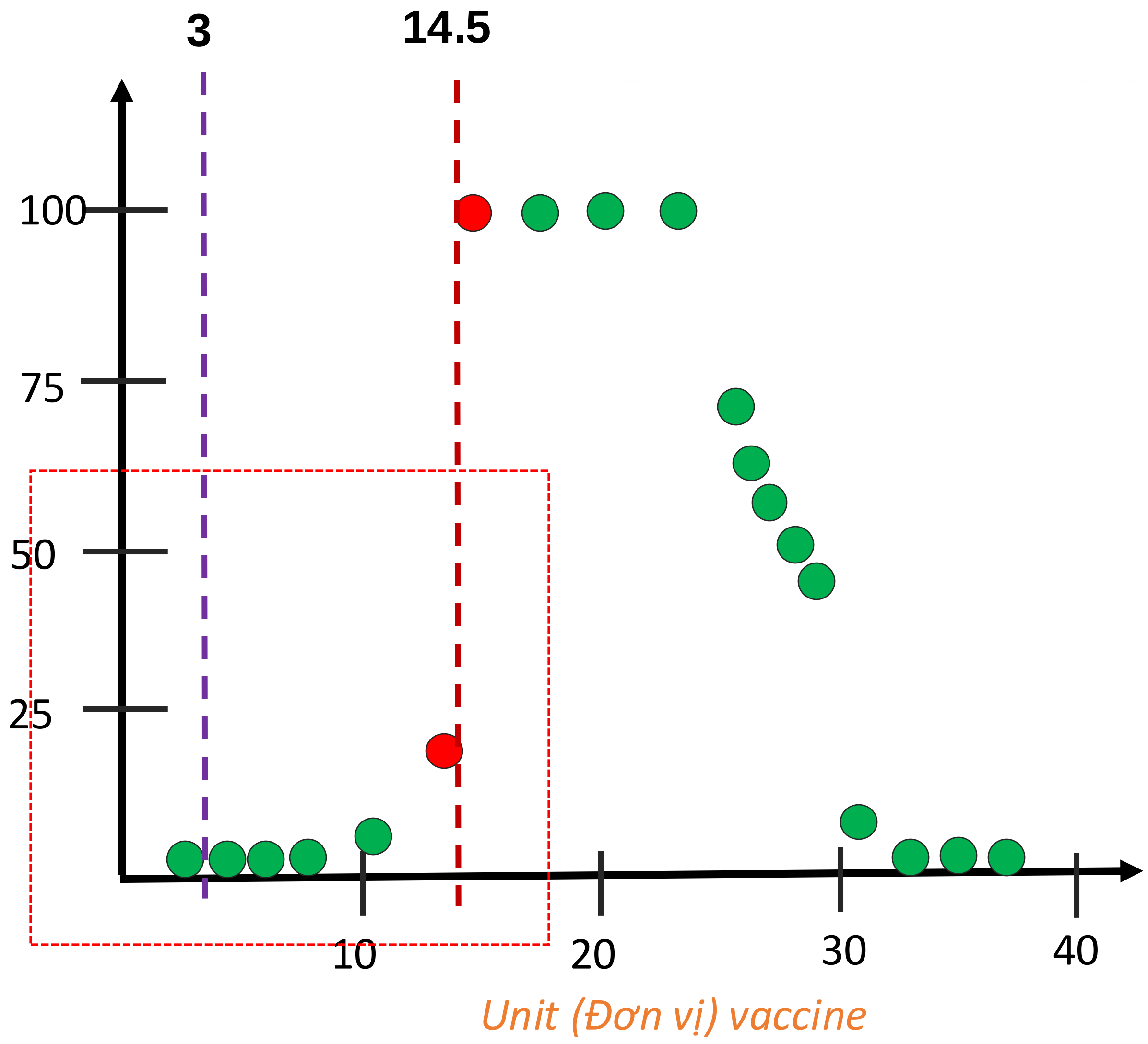


Average in unit( ) = 14.5

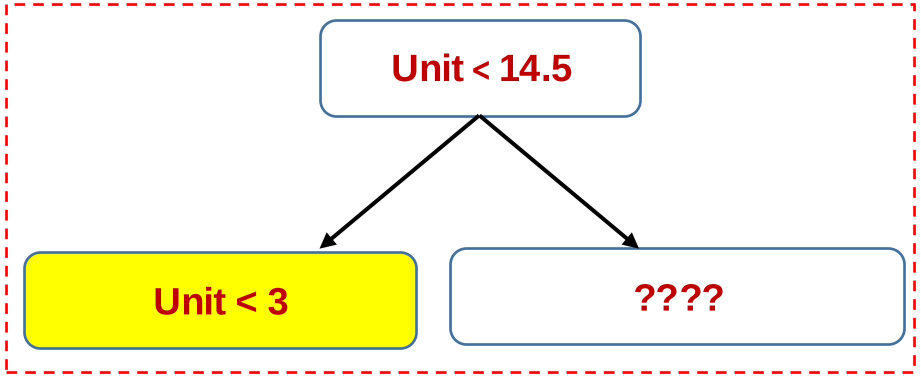


Unit is a Root Node



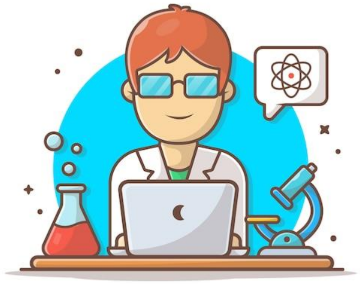


Average in unit( ) = 14.5

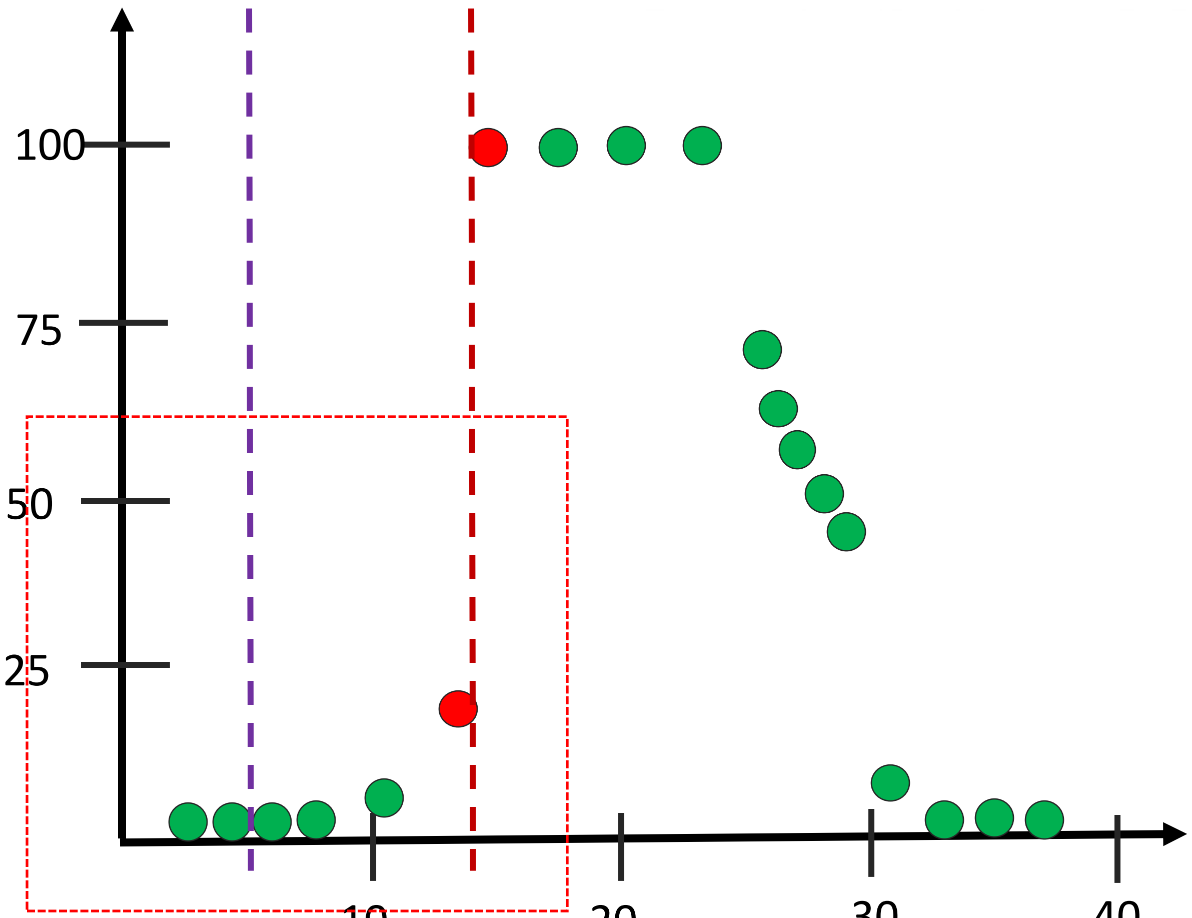


Compute SSR for unit 3

Unit is a Root Node

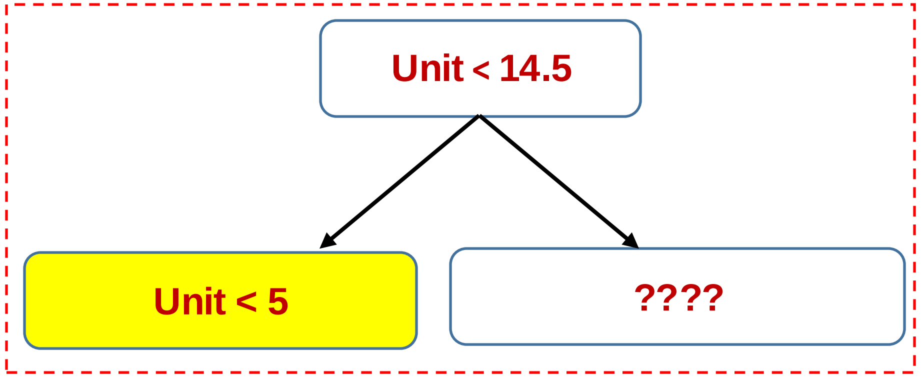


Effectiveness (Hiệu quả) (%)



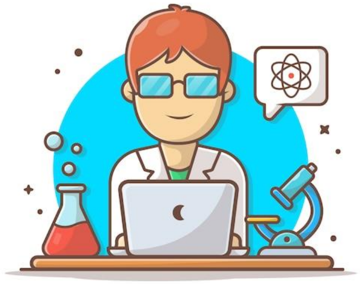
Unit (Đơn vị) vaccine

Average in unit(●●) = 14.5

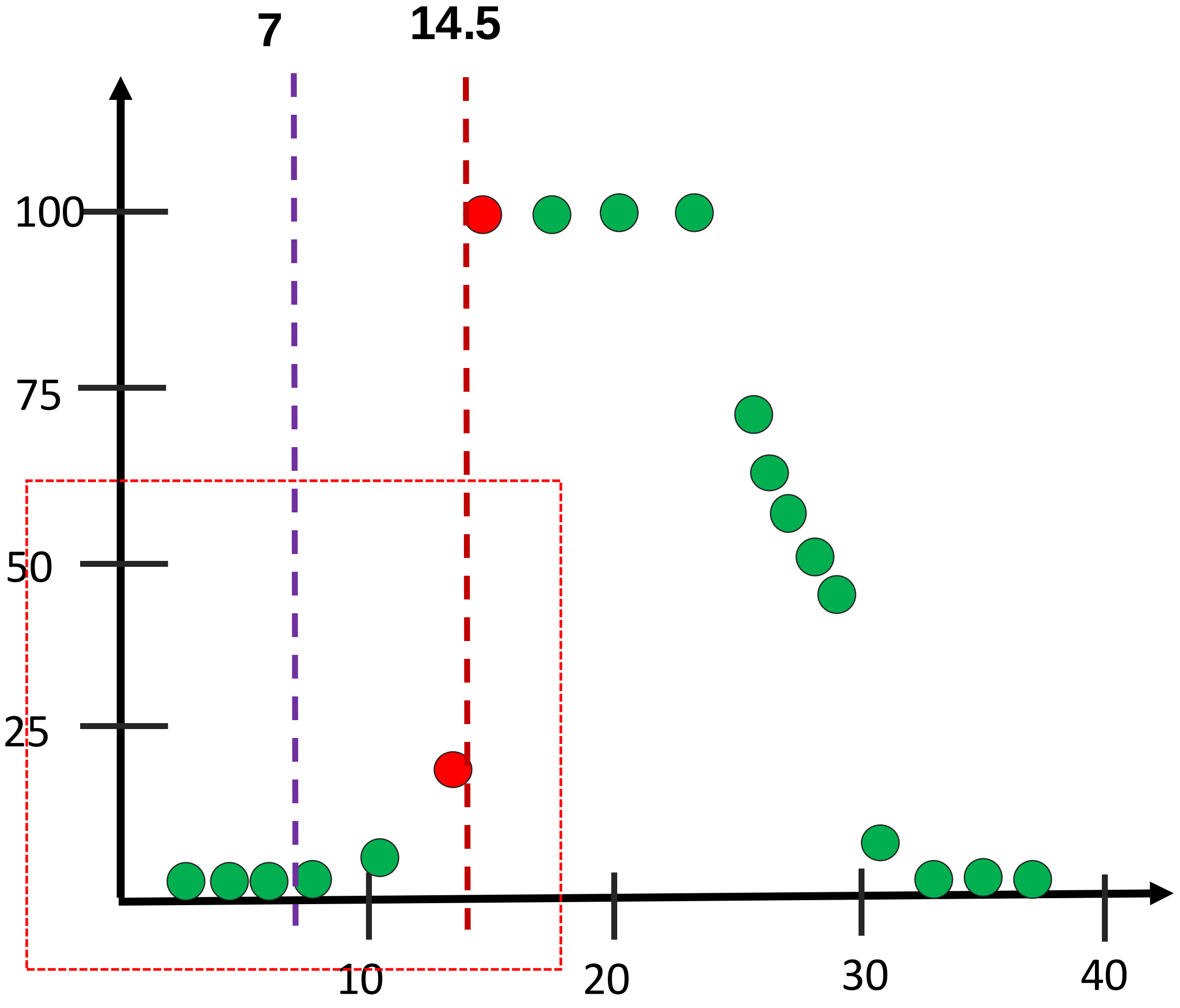


Compute SSR for unit 5

Unit is a Root Node

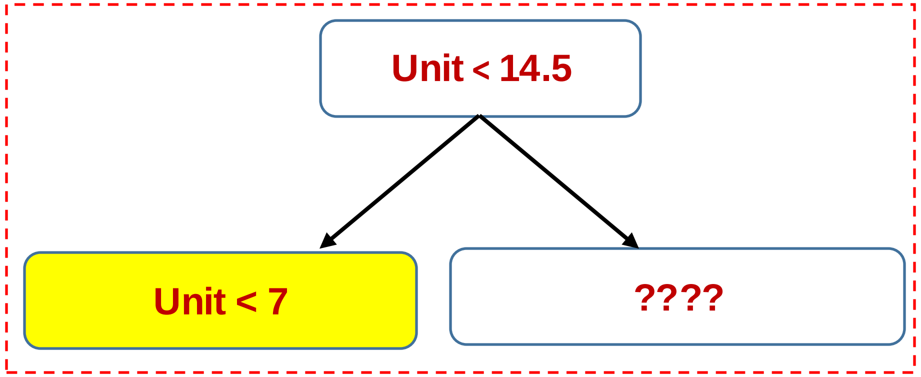


Effectiveness (Hiệu quả) (%)



Unit (Đơn vị) vaccine

Average in unit(●●) = 14.5



Compute SSR for unit

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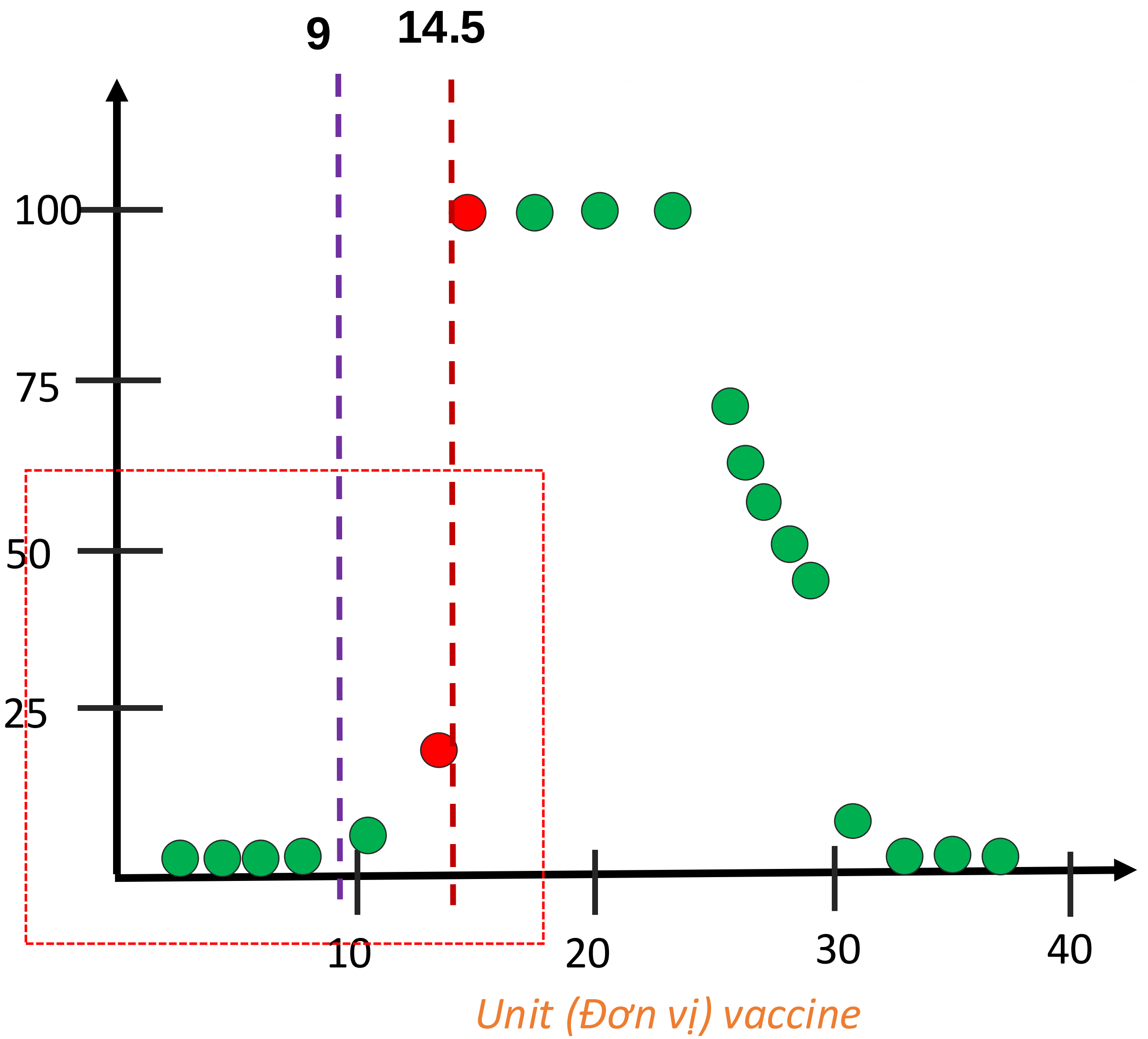
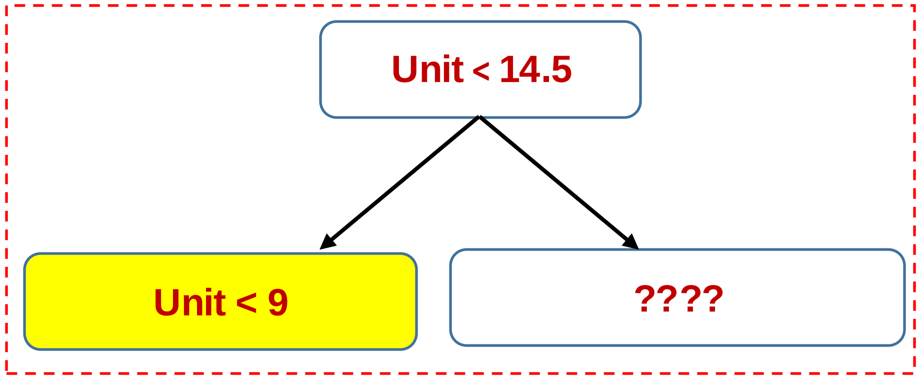
Unit is a Root Node

COVID-19

Effectiveness (Hiệu quả) (%)



Average in unit(●●) = 14.5



Compute SSR for unit 9

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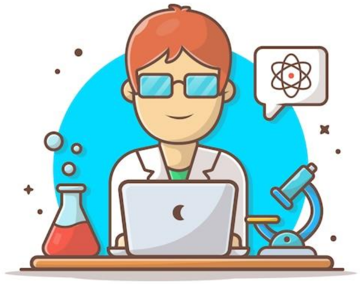
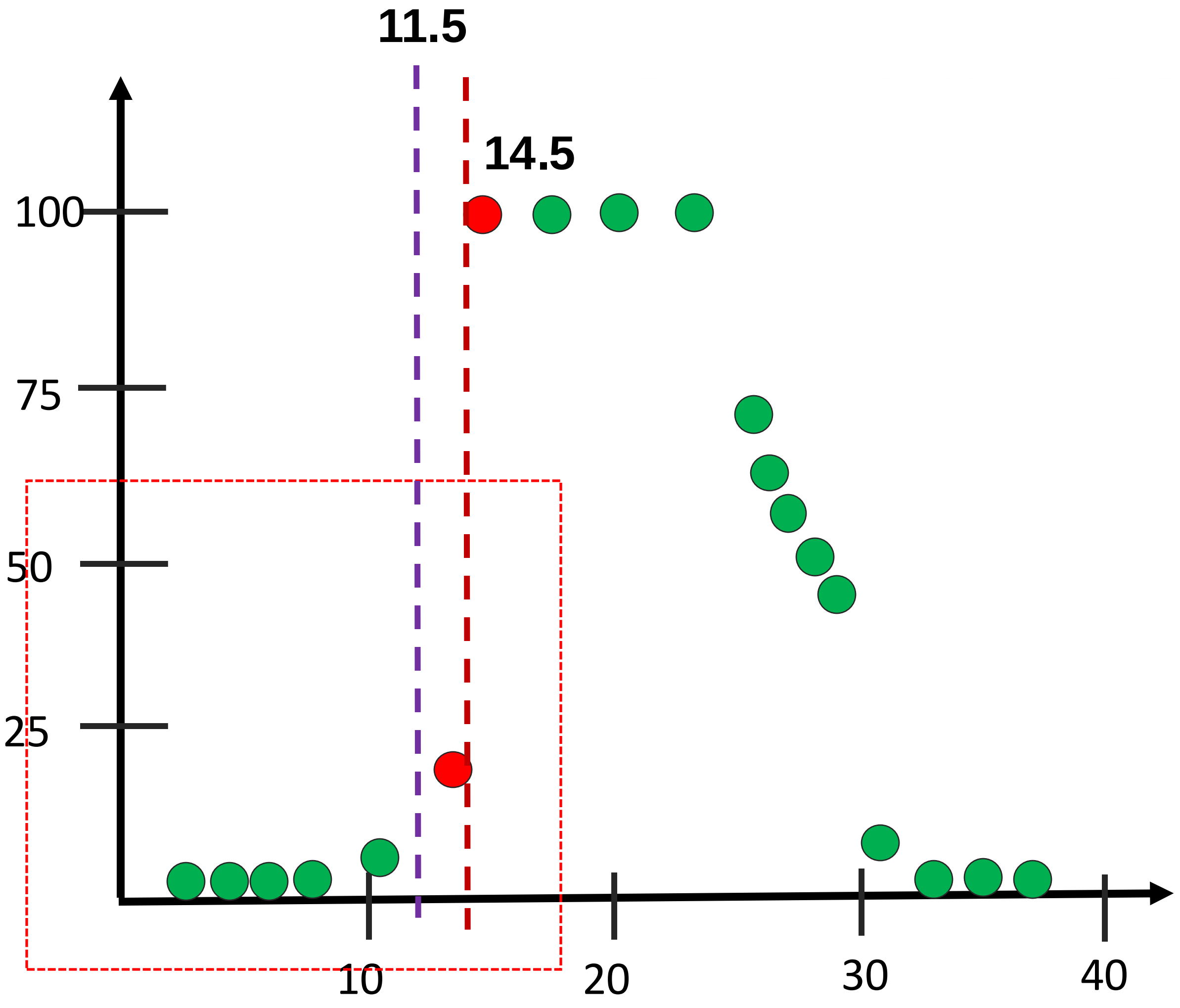
Unit is a Root Node

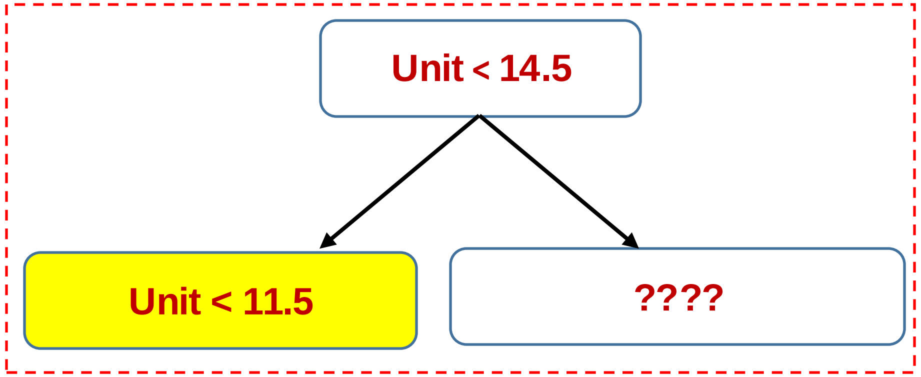


Effectiveness (Hiệu quả) (%)



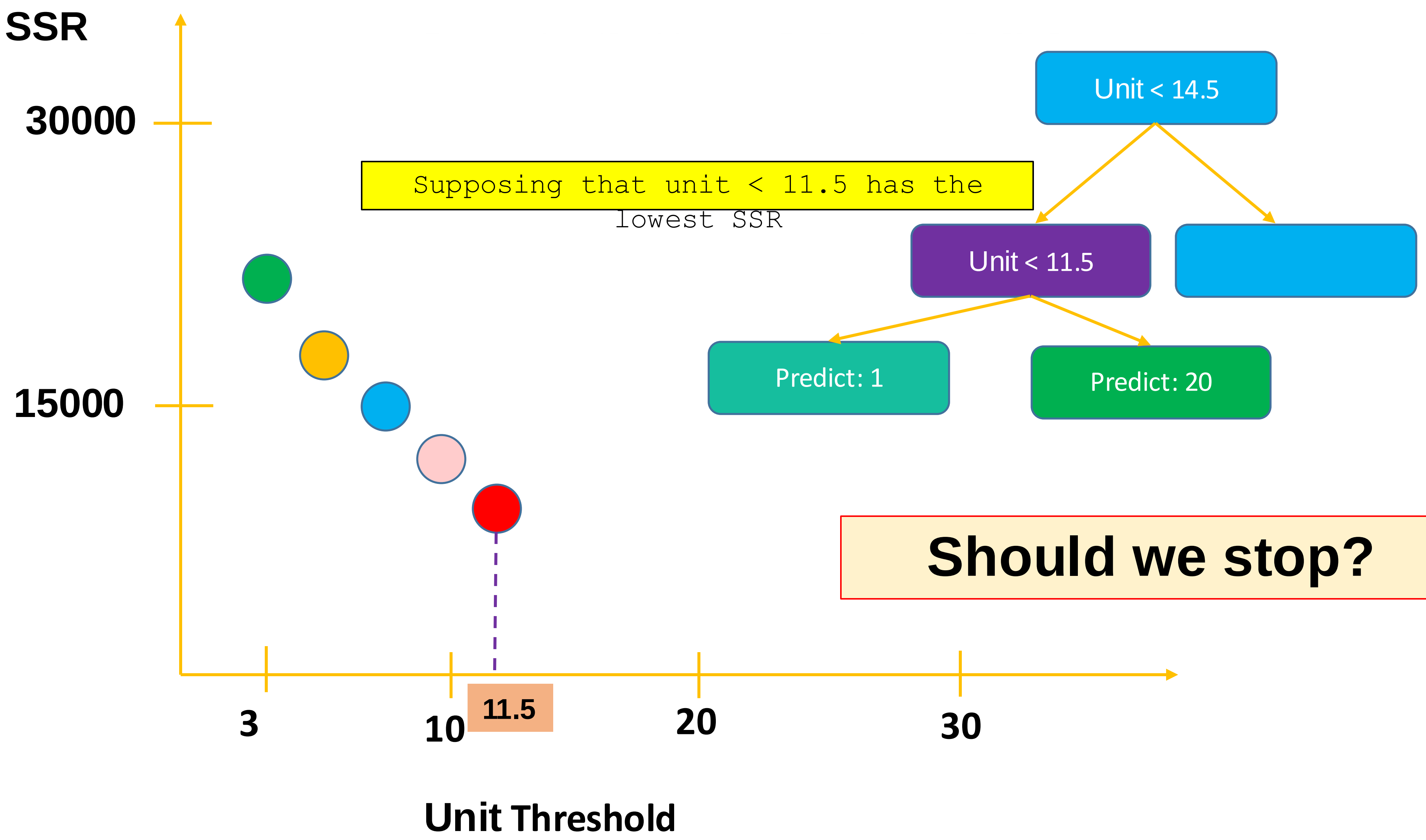
Unit (Đơn vị) vaccine

Average in unit(●●) = 14.5



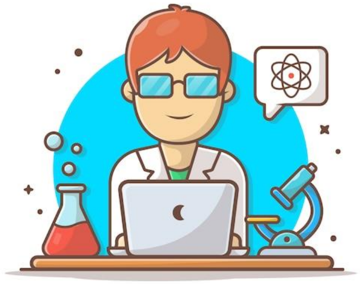
`Compute SSR for unit 11.5`

Unit is a Root Node

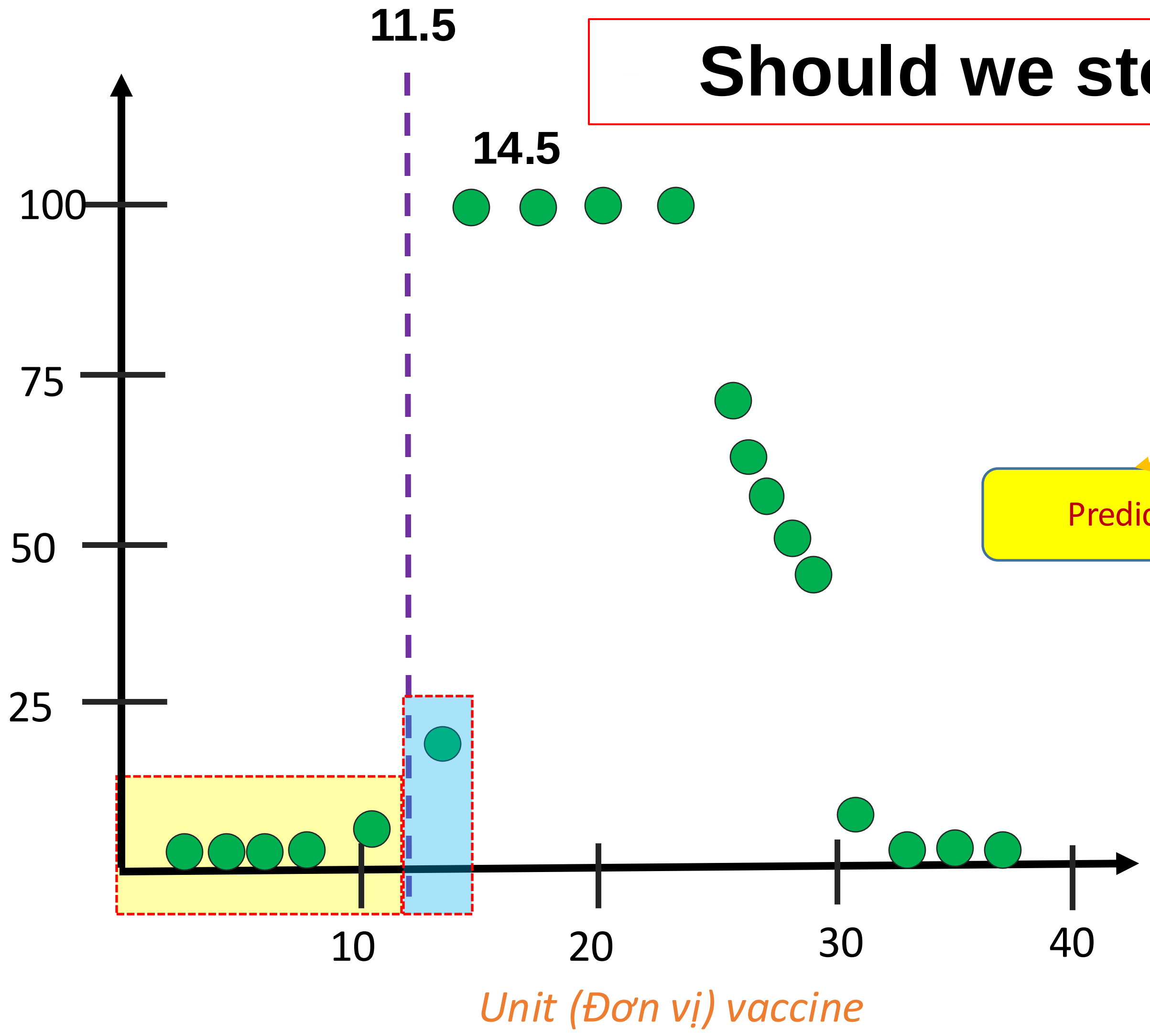


Should we stop?

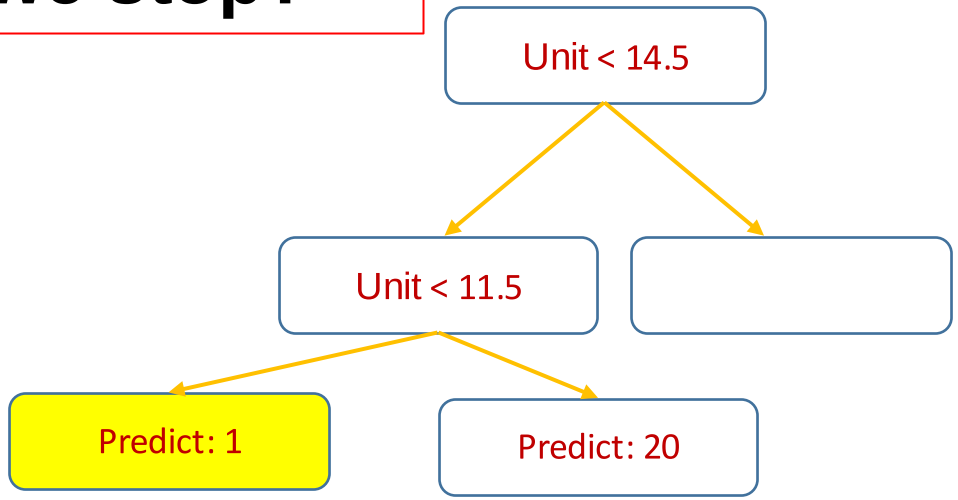
Unit is a Root Node



Effectiveness (Hiệu quả) (%)

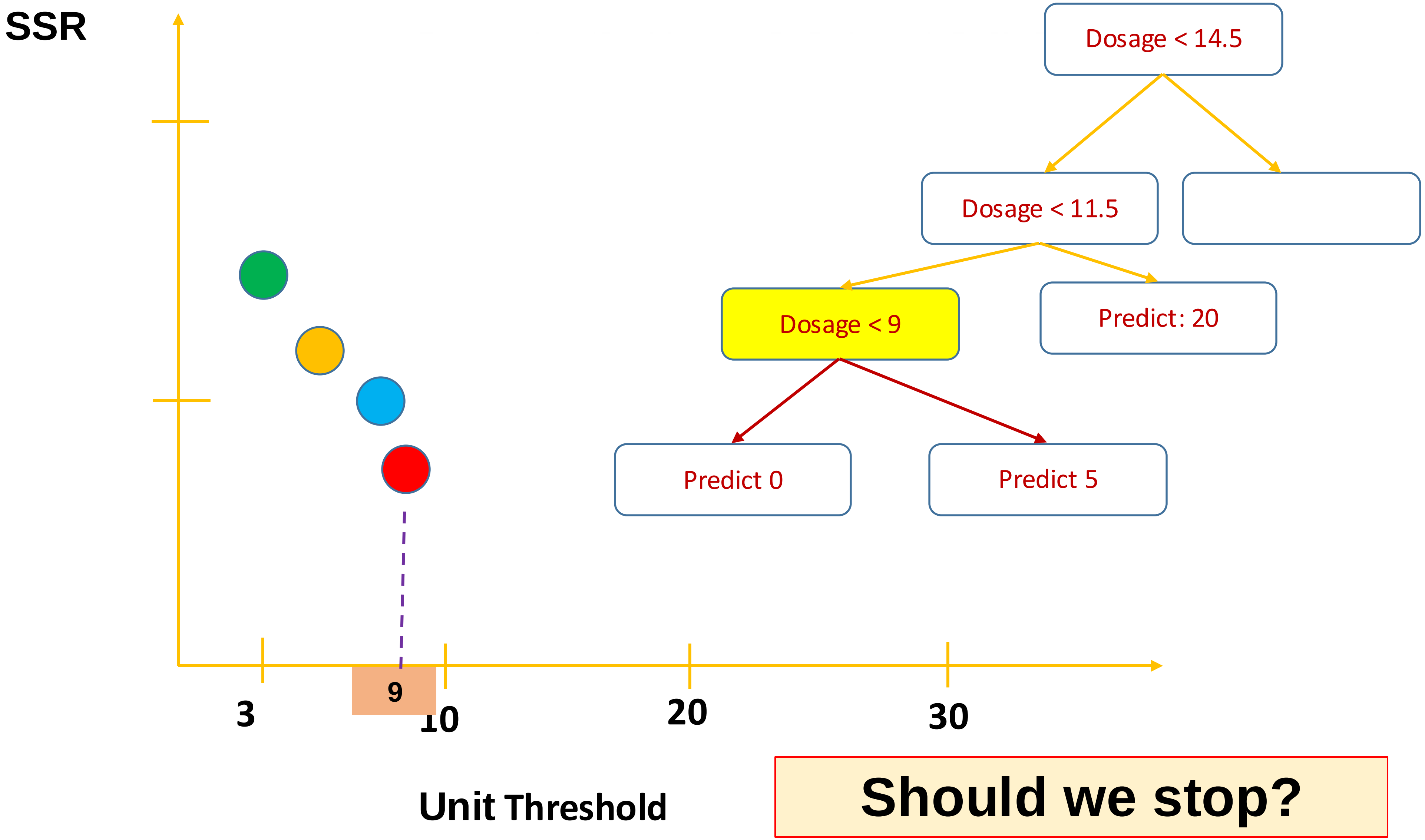


Should we stop?



Chúng ta xét trường hợp unit < 11.5. Kết quả vẫn còn có thể tiếp tục ???

Unit is a Root Node



Should we stop?

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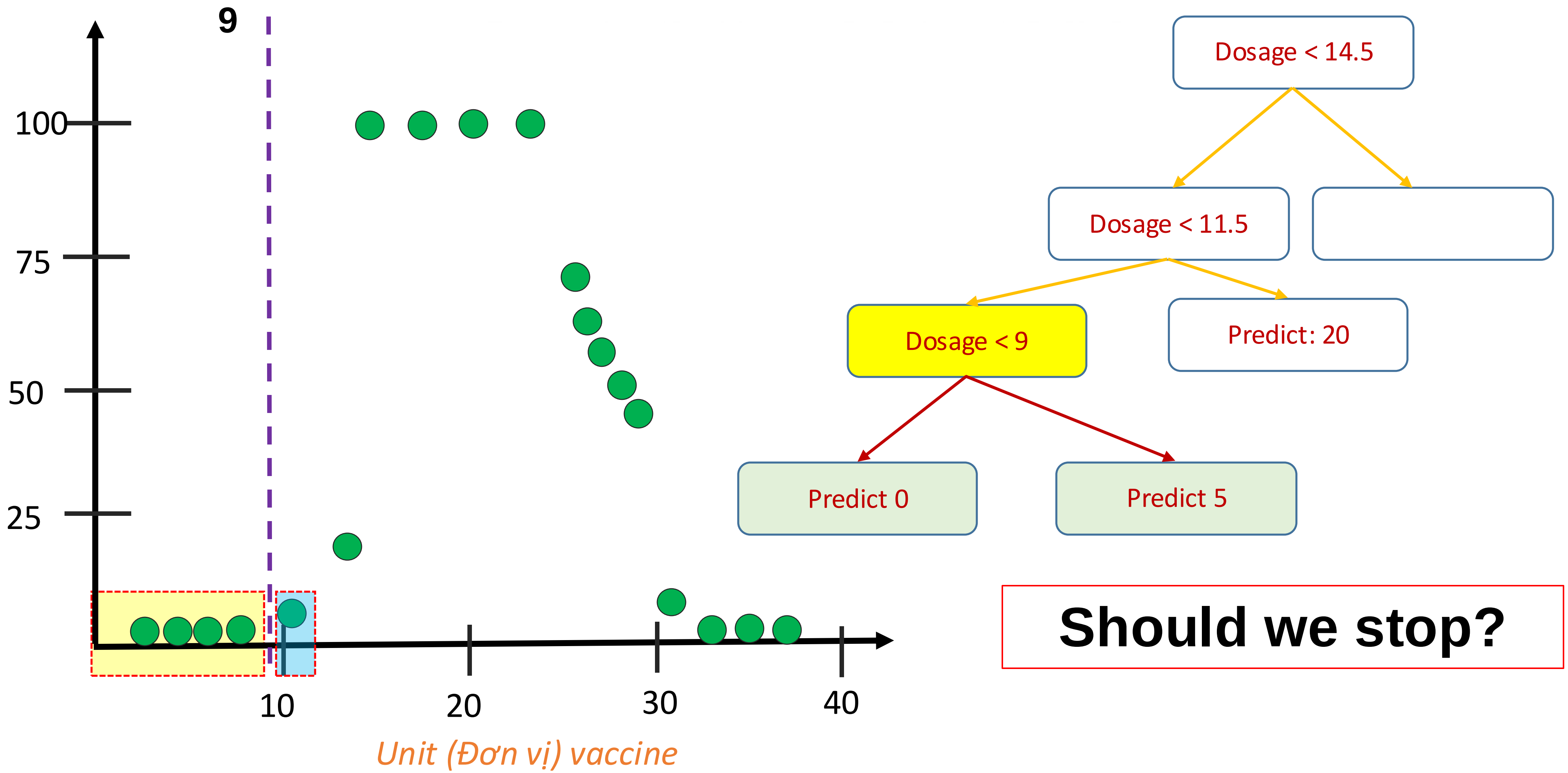
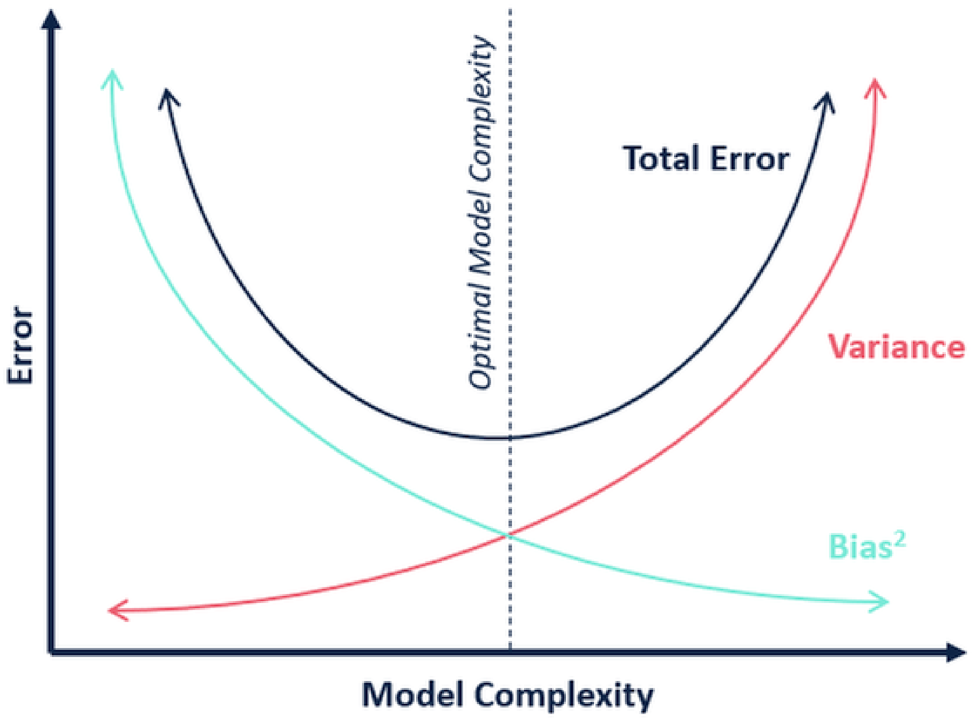
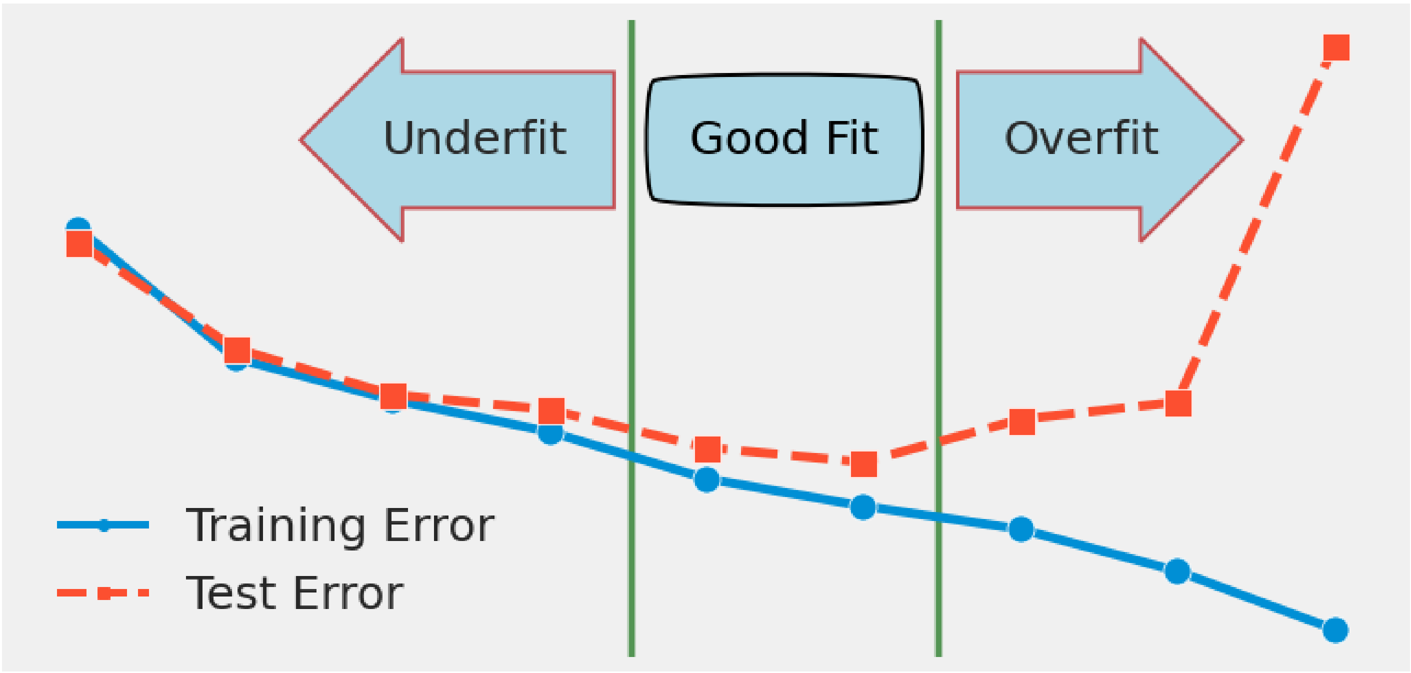
Unit is a Root Node



Should we stop?

Overfitting Problem





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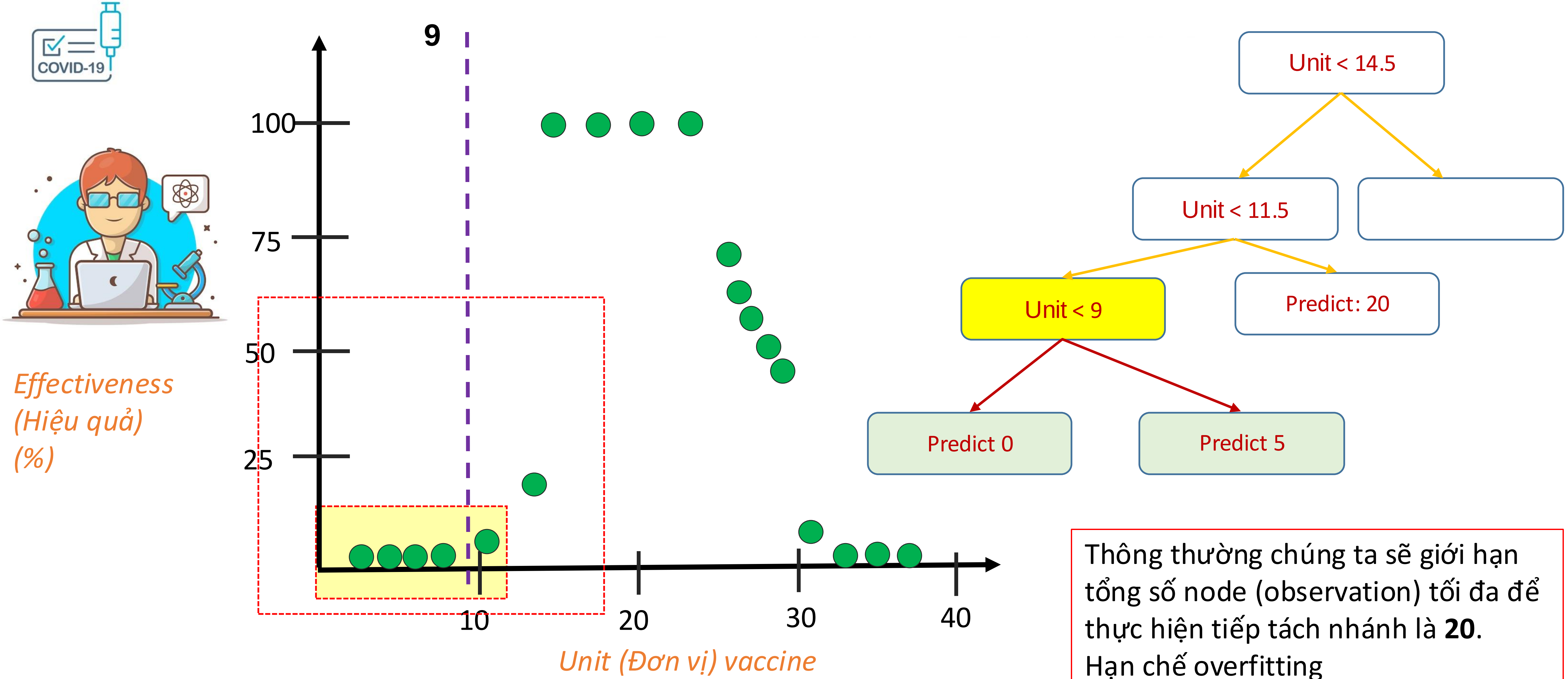
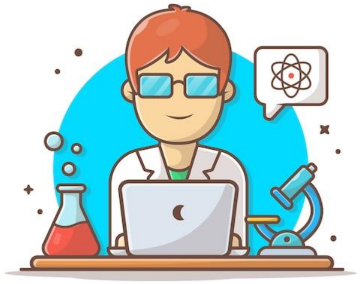
Unit is a Root Node



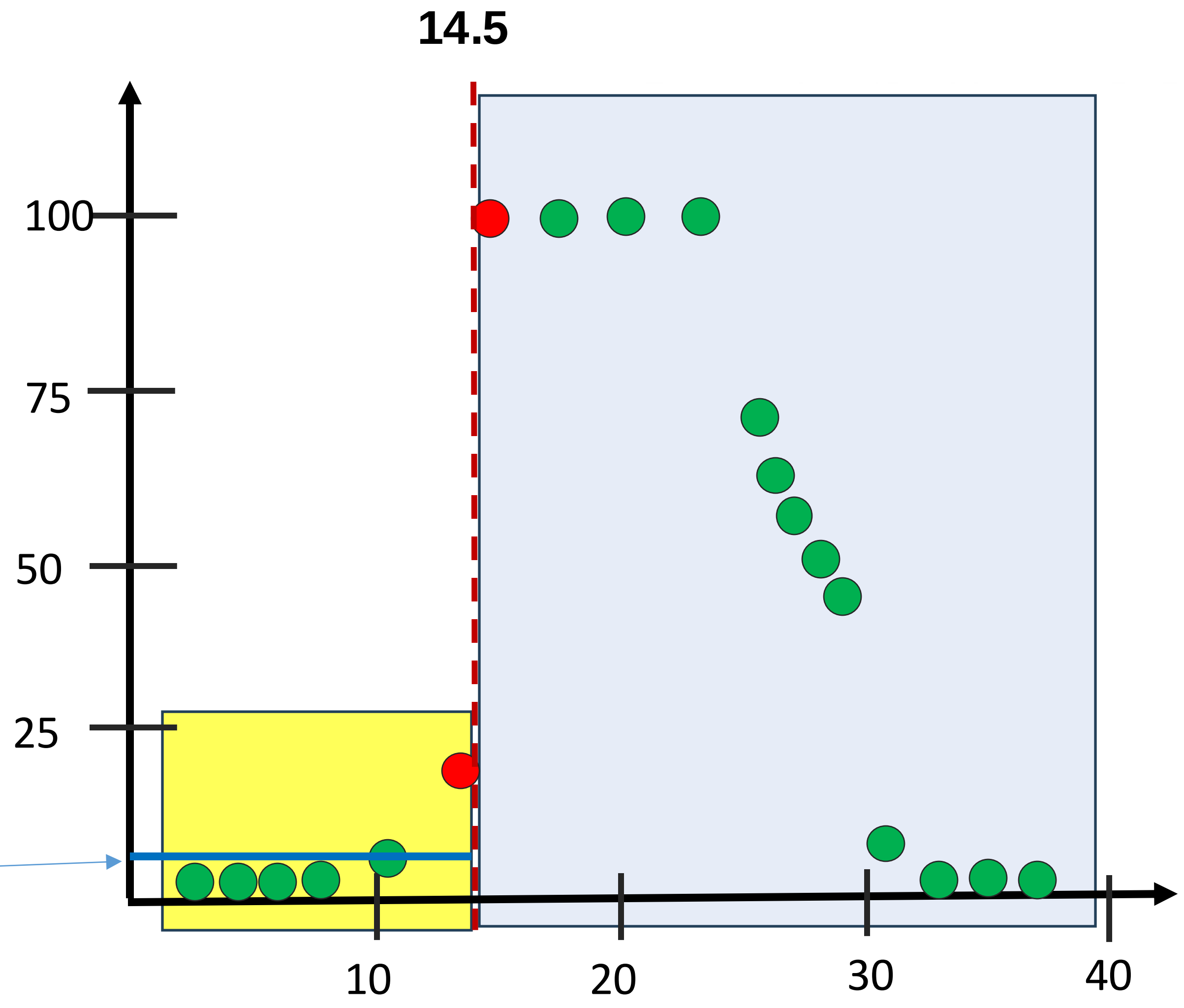
Thông thường chúng ta sẽ giới hạn tổng số node (observation) tối đa để thực hiện tiếp tách nhánh là **20**.
Hạn chế overfitting

Unit is a Root Node

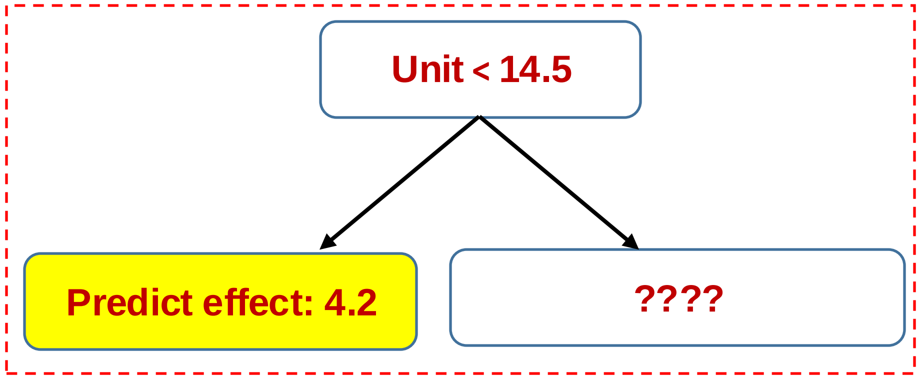


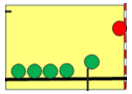
Effectiveness
(Hiệu quả)
(%)

Kết quả dự đoán
cho unit < 14.5



Unit (Đơn vị) vaccine



Average in effect.() = 4.2

Vì nhánh unit < 14.5 có tổng số nodes < 7 . Dừng triển khai tách nhánh

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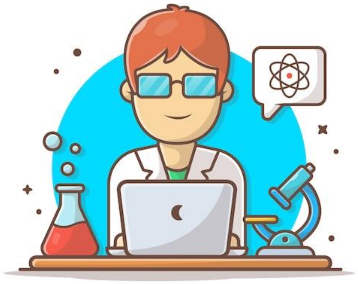
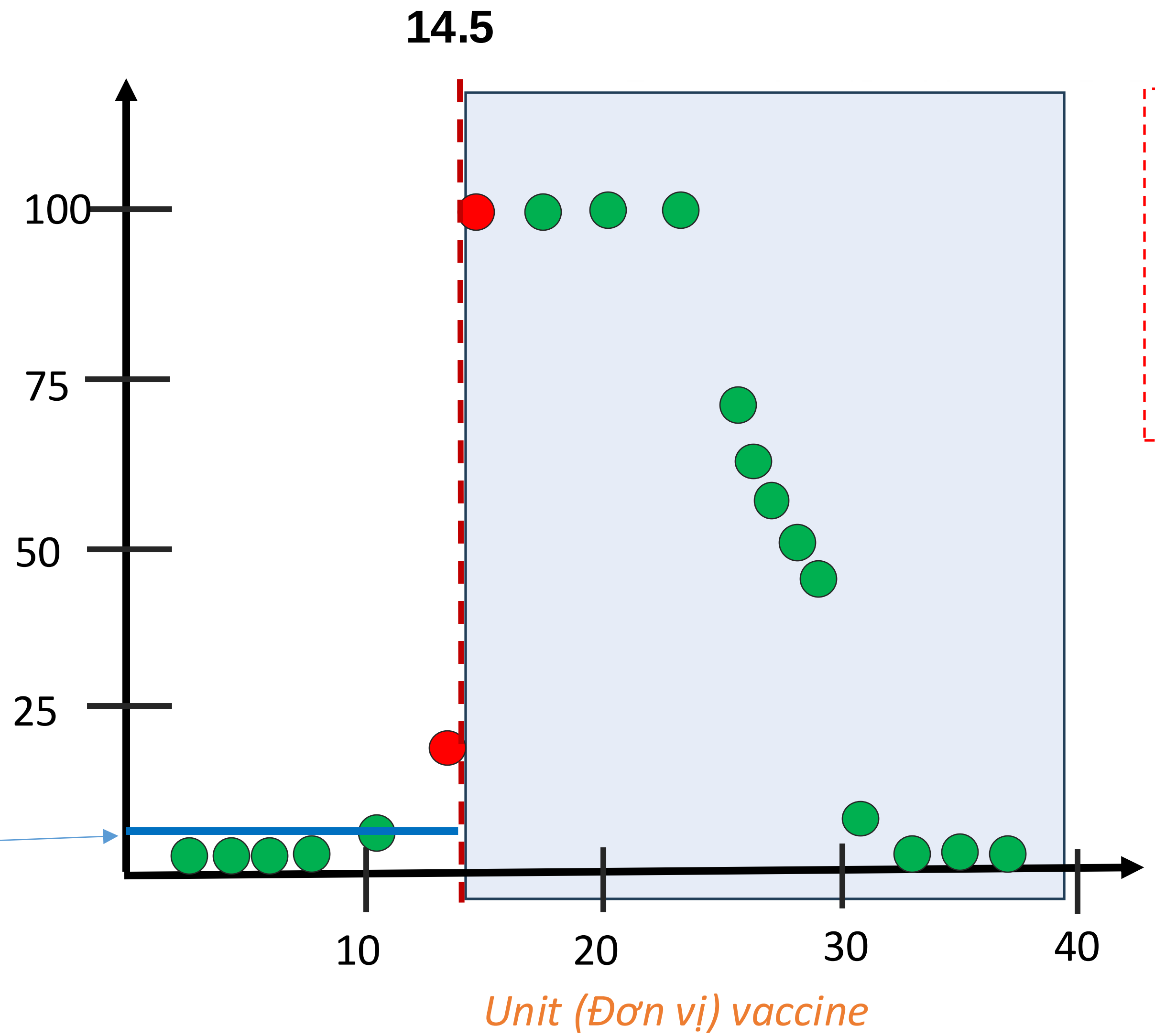
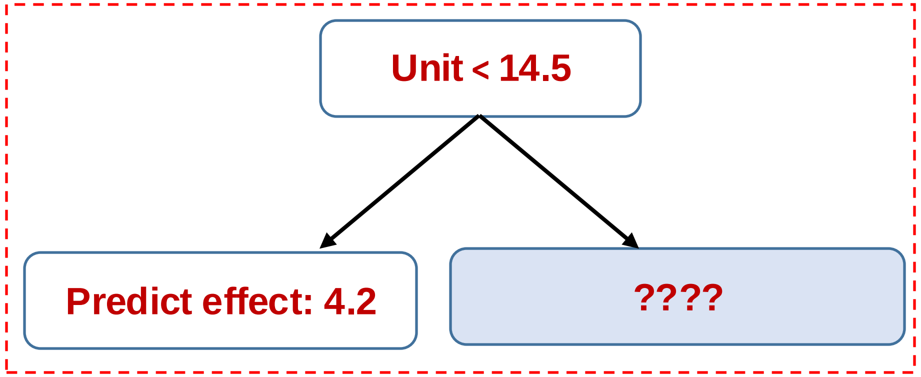
Unit is a Root Node







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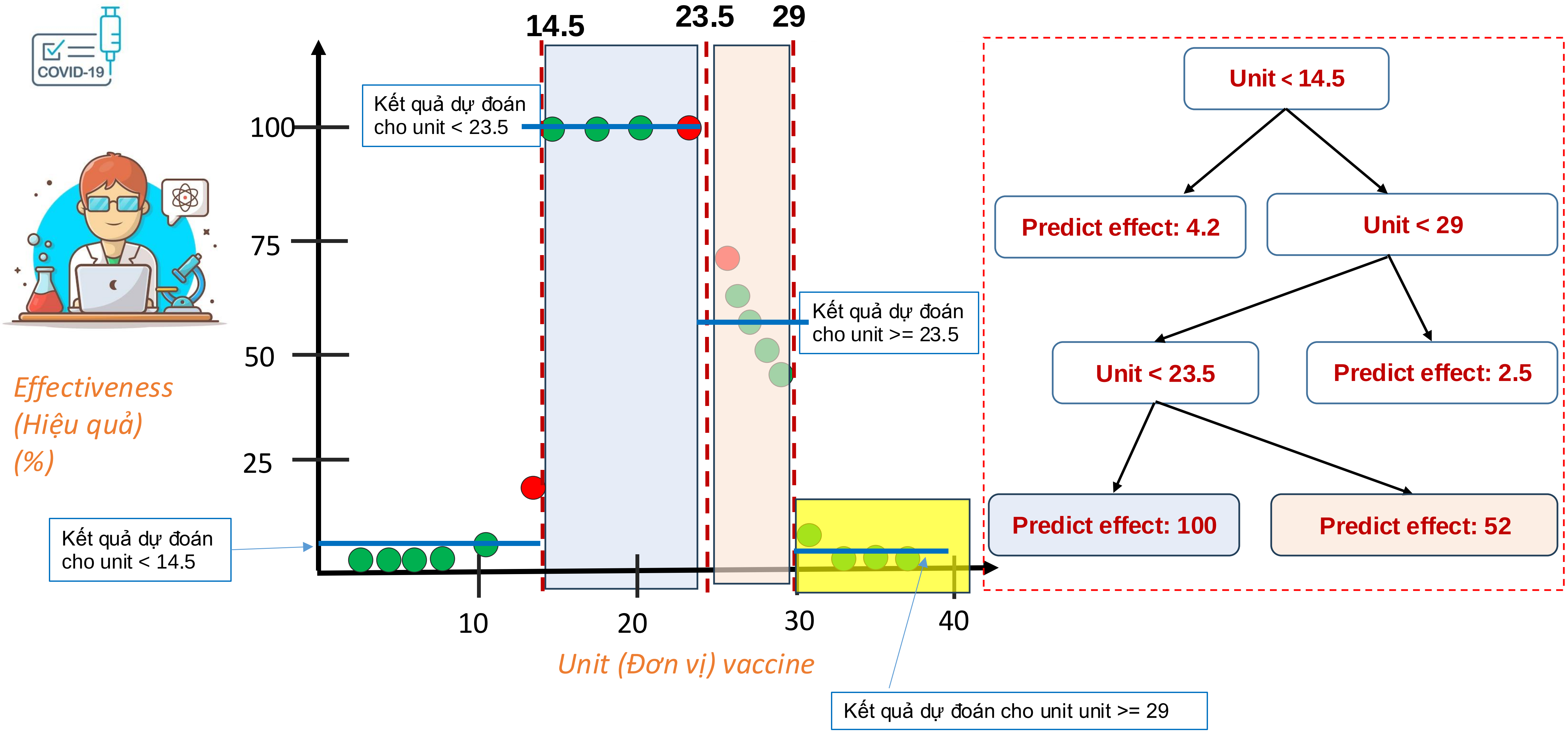
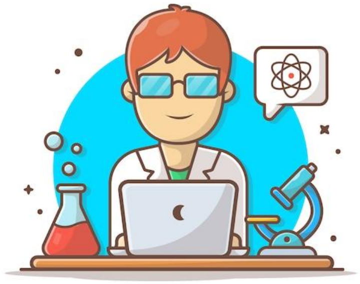
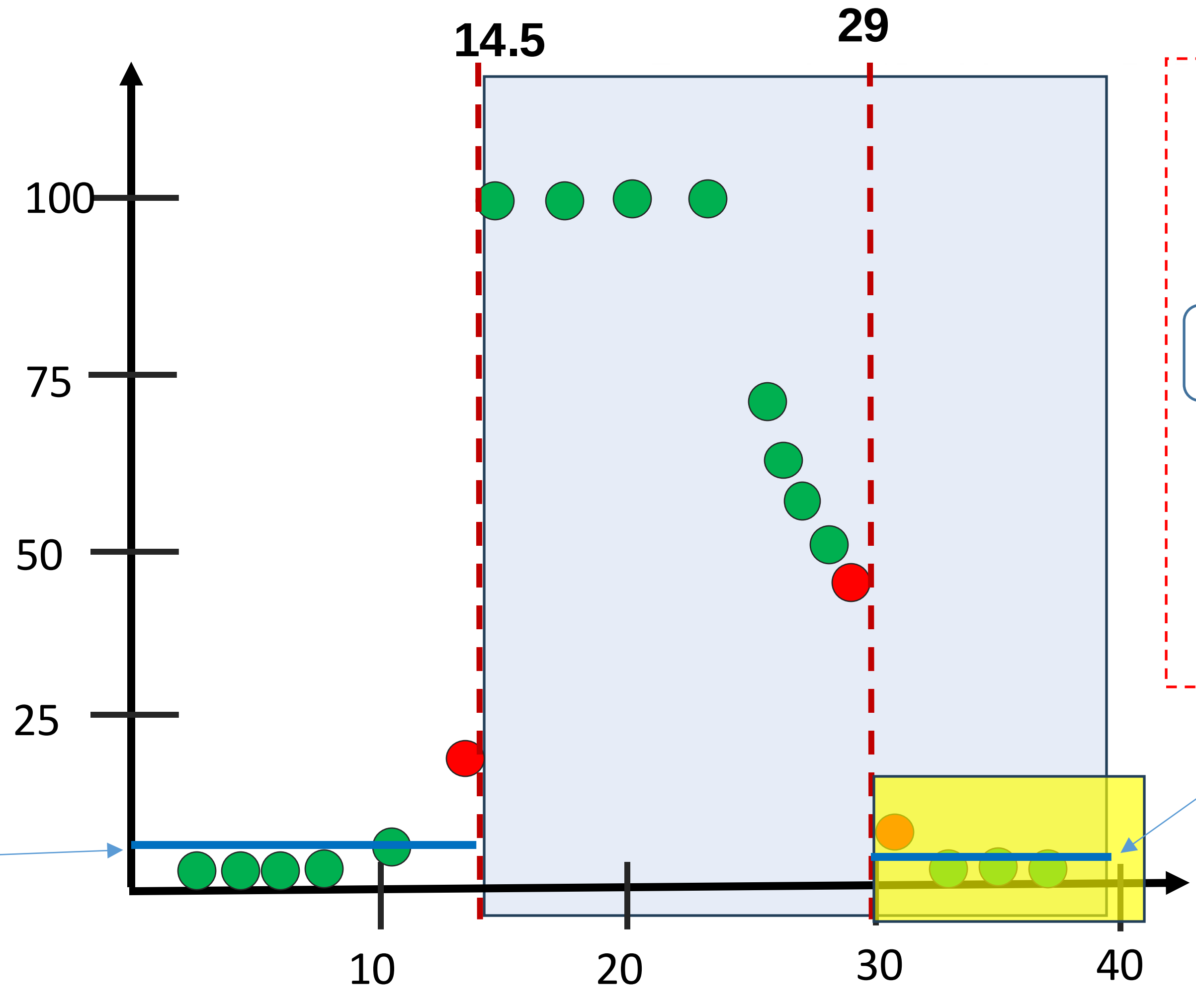
Unit is a Root Node



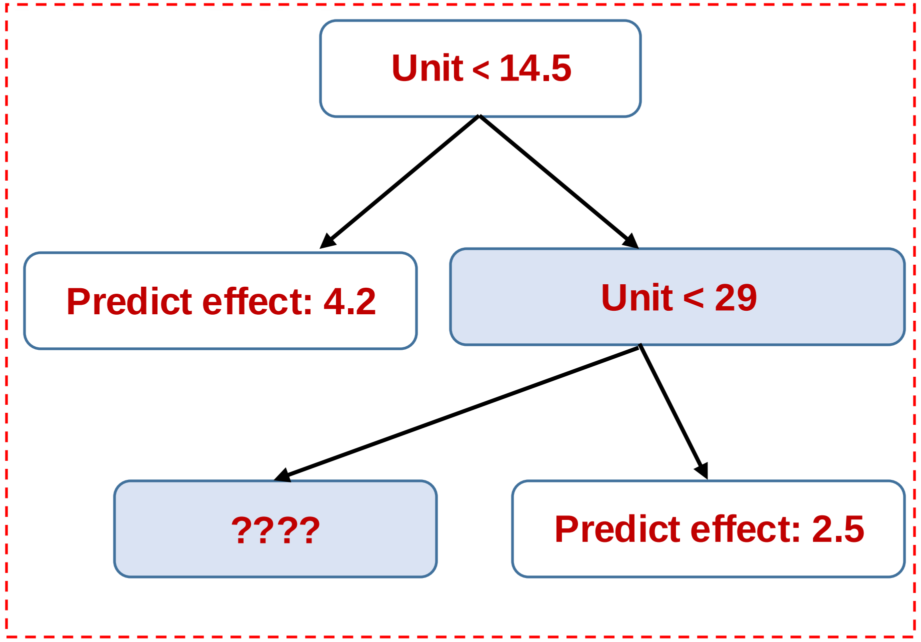
Unit is a Root Node





Effectiveness (Hiệu quả) (%)

Unit (Đơn vị) vaccine



Bây giờ, chúng ta cài đặt mininum nodes cho tách nhánh là 20? What's happen?

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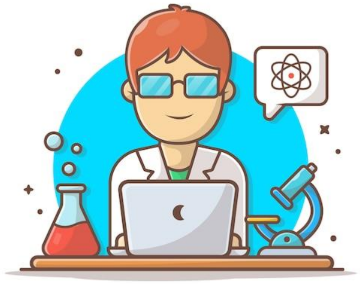
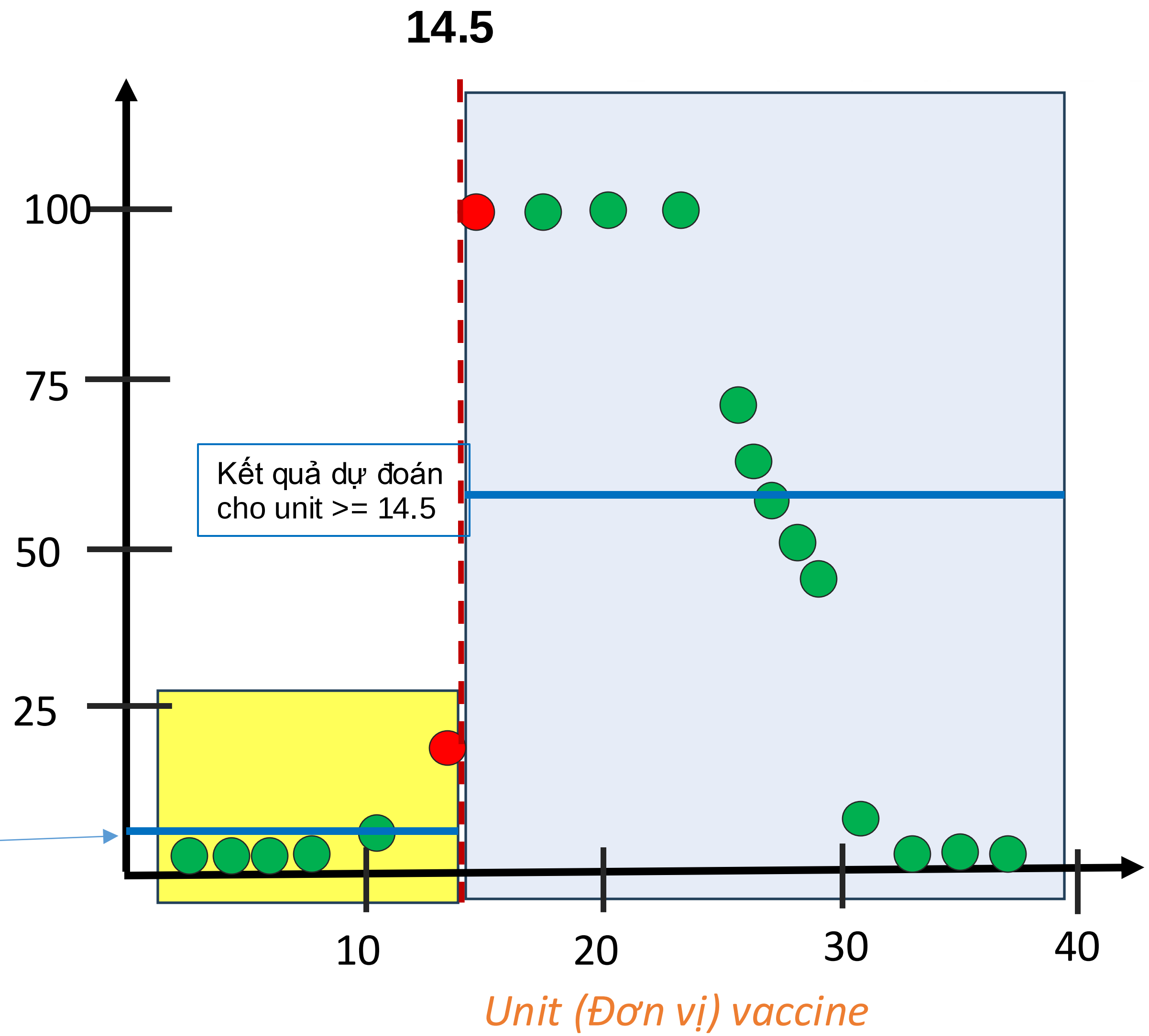
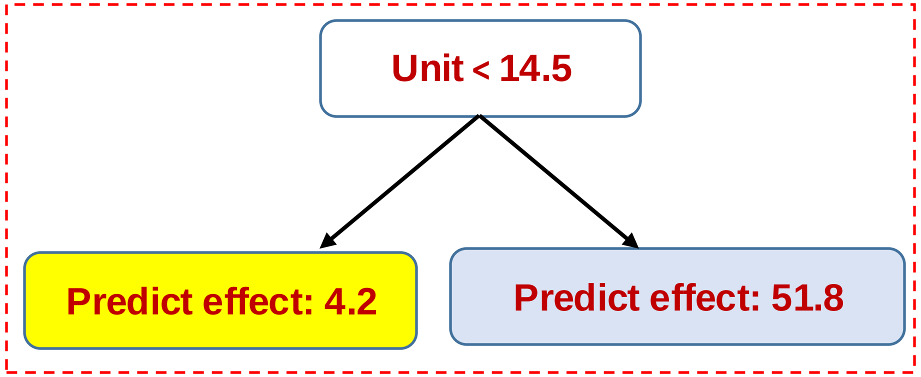
Unit is a Root Node



Effectiveness (Hiệu quả) (%)

Kết quả dự đoán cho unit < 14.5





Compute SSR for this case
SSR ~ 19.000

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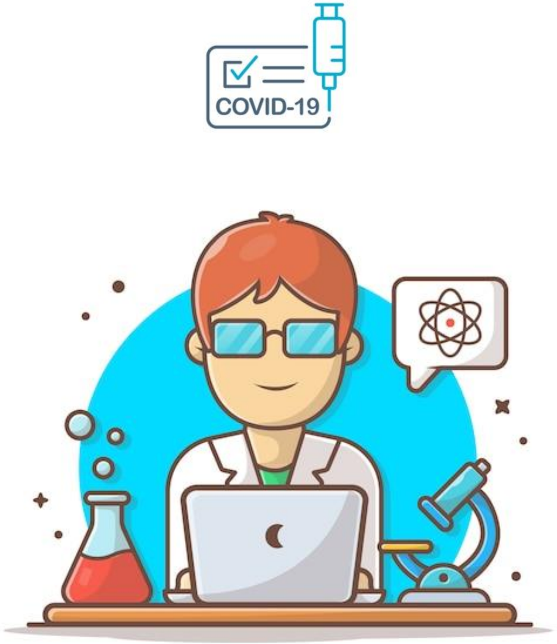
Case Study



Unit	Age	Sex	Effect (%)
10	25	Female	98
20	73	Male	0
35	54	Female	100
5	12	Male	44
…	…	…	…

Tiêm 5 đơn vị vaccine, 12 tuổi, giới tính nam

Hiệu quả vaccine: 44%

Khi có 1 vaccine ra đời, chúng ta muốn dự đoán xem nó hiệu quả bao nhiêu % ứng với liều lượng dùng cố định, tuổi và giới tính của bệnh nhân.

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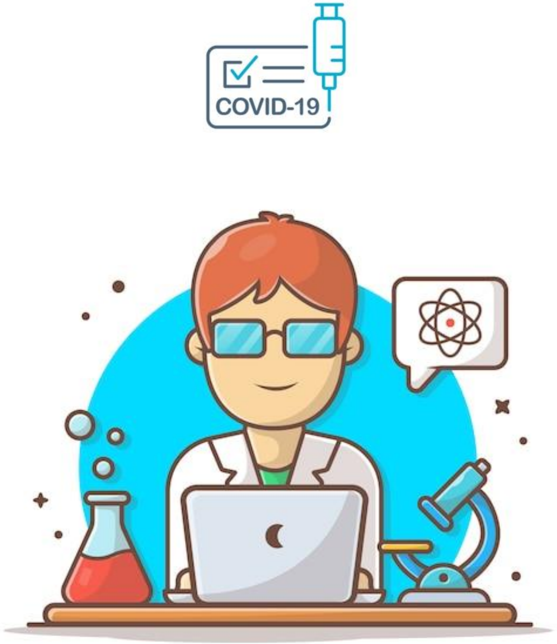
Age note is a root?



Age	Effect (hiệu quả) (%)
25	98
73	0
54	100
12	44
…	…

12 tuổi

Hiệu quả vaccine: 44%

Khi có 1 vaccine ra đời, chúng ta muốn dự đoán xem nó hiệu quả bao nhiêu % ứng với tuổi (age) của bệnh nhân.

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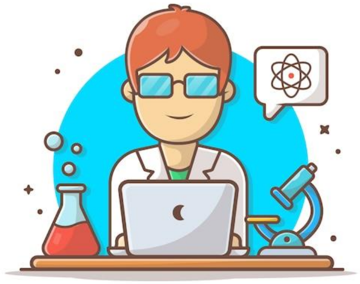
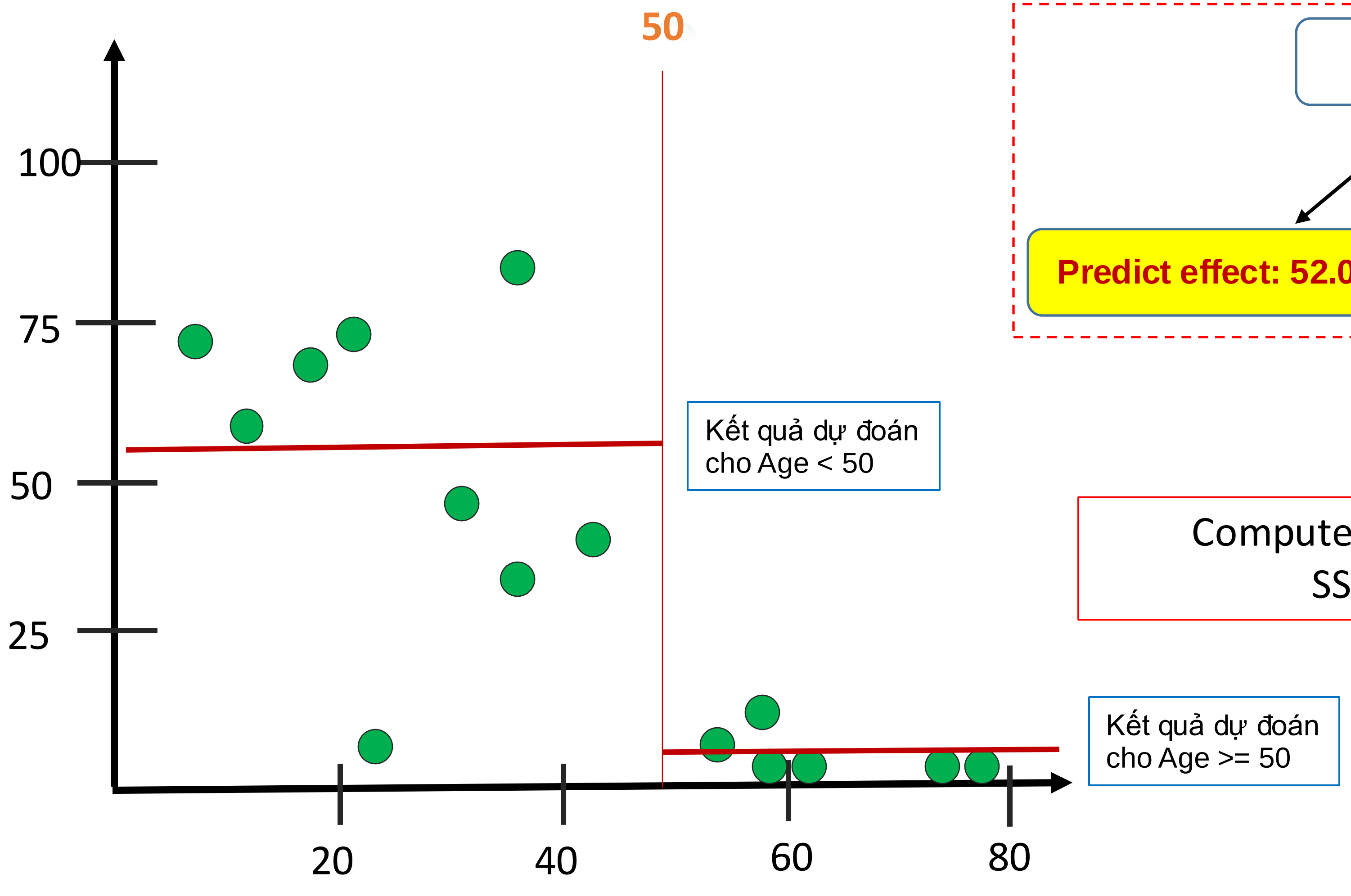
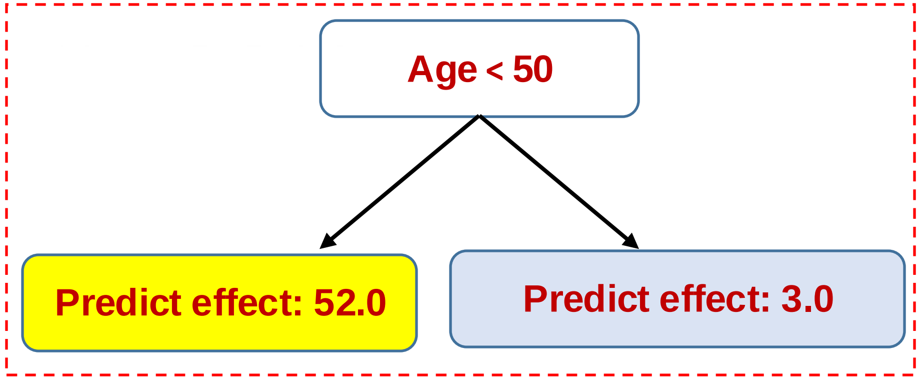
Age note is a root?



Hiệu quả (%)

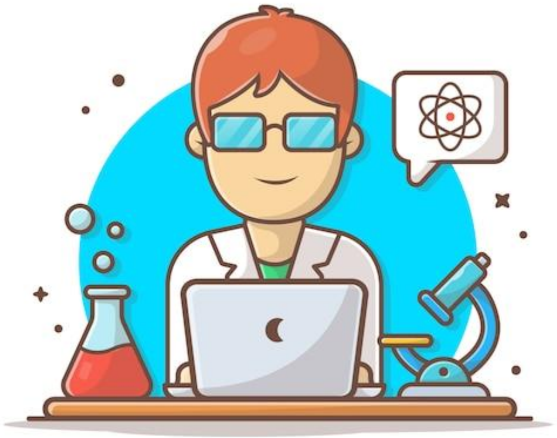




Compute SSR for this case
SSR ~ 12,000

Khi có 1 vaccine ra đời, chúng ta muốn dự đoán xem nó hiệu quả bao nhiêu % ứng với từng liều lượng dùng trên bệnh nhân.

Case Study



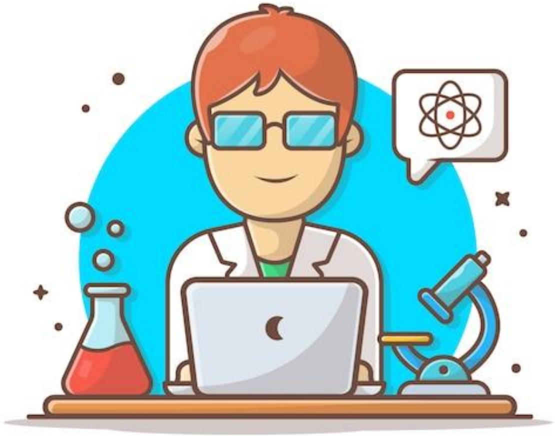
Unit	Age	Sex	Effect (%)
10	25	Female	98
20	73	Male	0
35	54	Female	100
5	12	Male	44
…	…	…	…

Giới tính nam

Hiệu quả vaccine: 44%

Khi có 1 vaccine ra đời, chúng ta muốn dự đoán xem nó hiệu quả bao nhiêu % ứng với liều lượng dùng cố định, tuổi và giới tính của bệnh nhân.

Sex note is a root?



Sex	Effect (hiệu quả) (%)
Female	98
Male	0
Female	100
Male	44
…	…

Giới tính Male

Hiệu quả vaccine: 44%

Khi có 1 vaccine ra đời, chúng ta muốn dự đoán xem nó hiệu quả bao nhiêu % ứng với giới tính (sex) của bệnh nhân.

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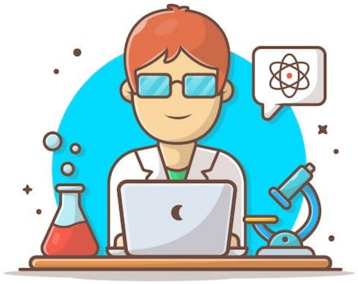
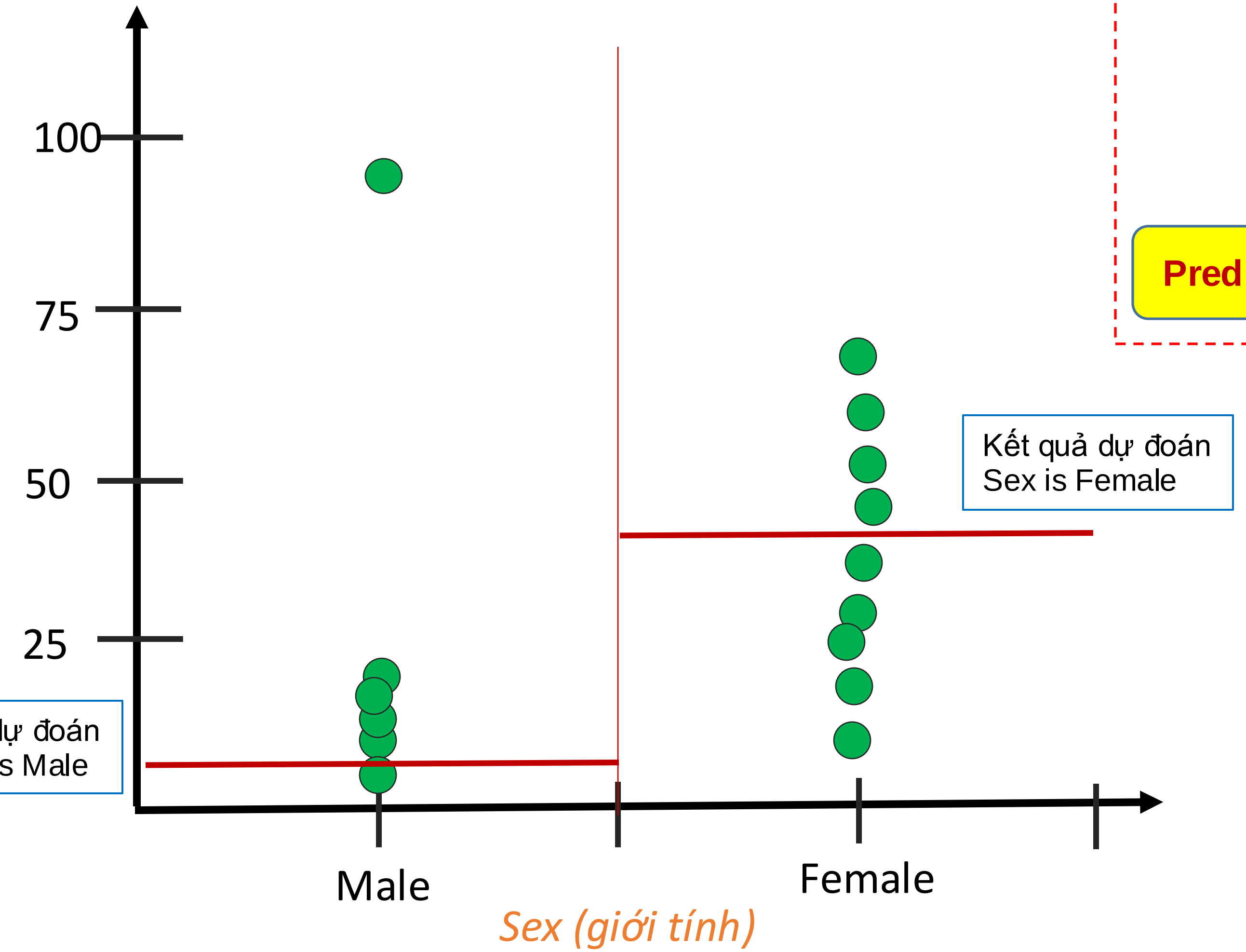
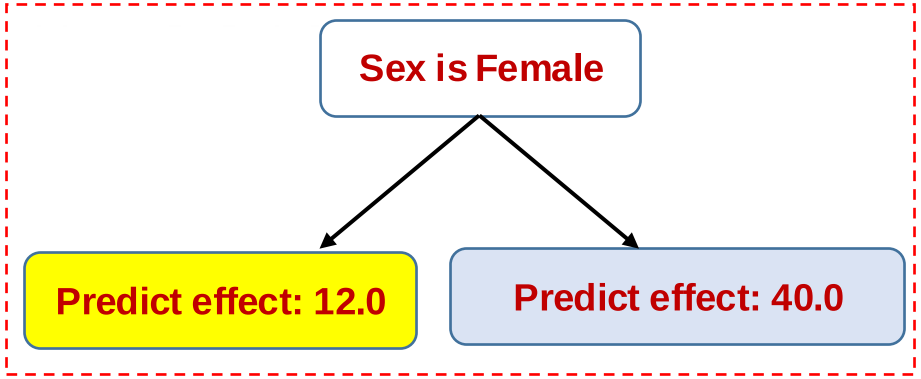
Sex note is a root?

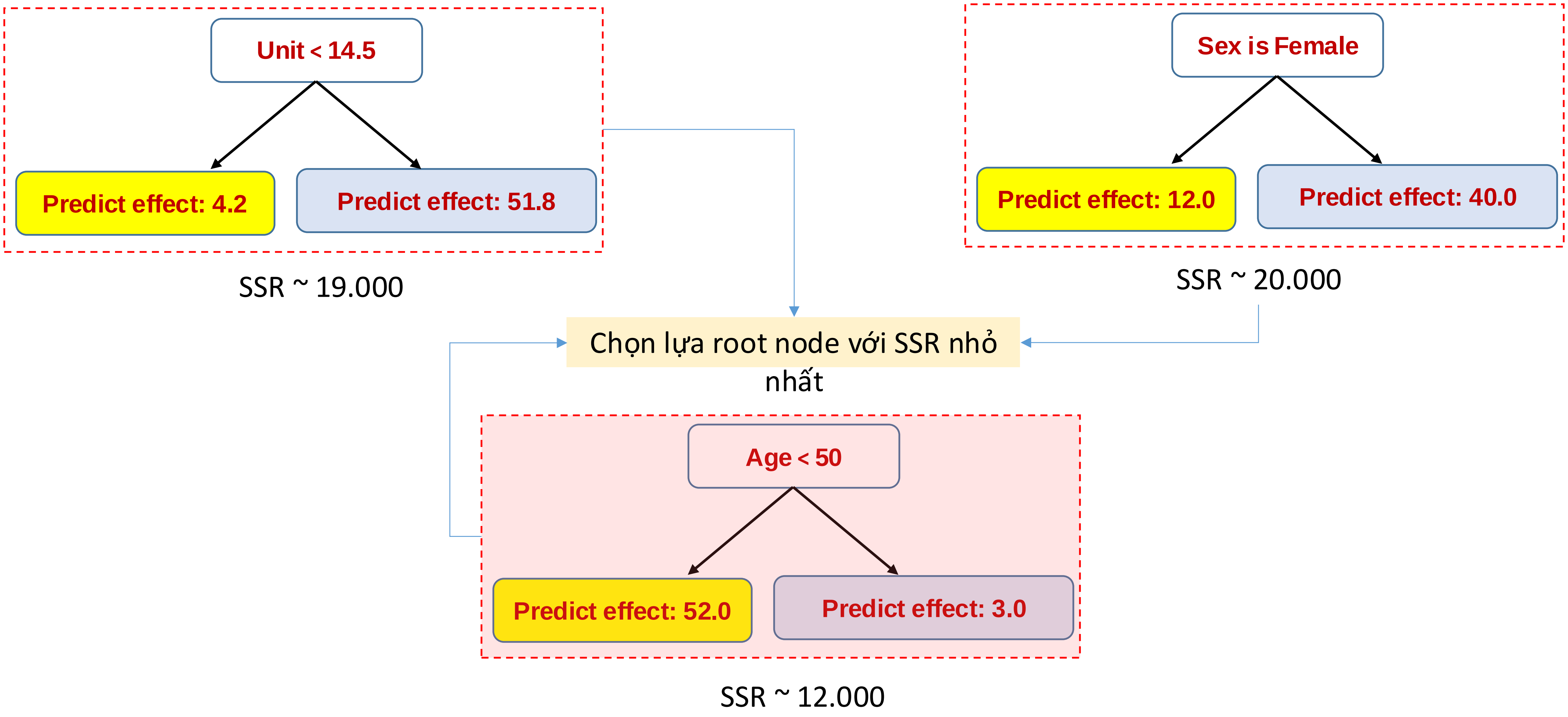




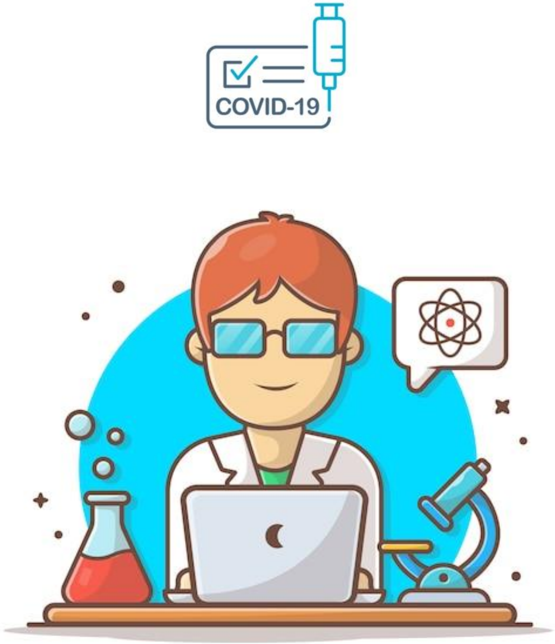


Compute SSR for this case
SSR ~ 20,000

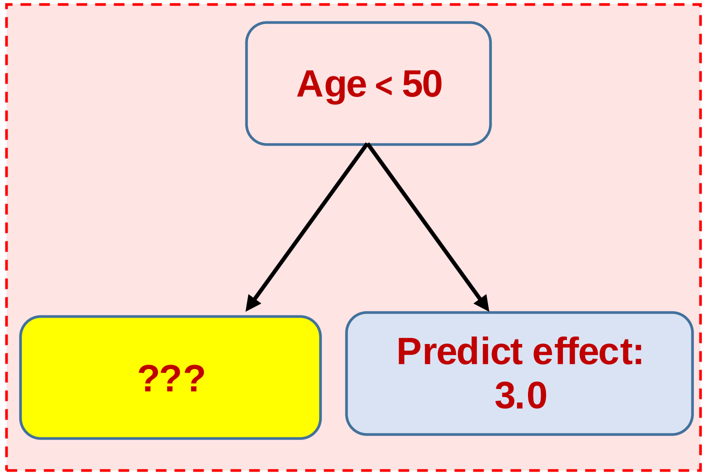
Khi có 1 vaccine ra đời, chúng ta muốn dự đoán xem nó hiệu quả bao nhiêu % ứng với từng liều lượng dùng trên bệnh nhân.


Unit < 14.5
Predict effect: 4.2
Predict effect: 51.8
SSR ~ 19.000
Sex is Female
Predict effect: 12.0
Predict effect: 40.0
SSR ~ 20.000
Chọn lựa root node với SSR nhỏ nhất
Age < 50
Predict effect: 52.0
Predict effect: 3.0
SSR ~ 12.000

Case Study



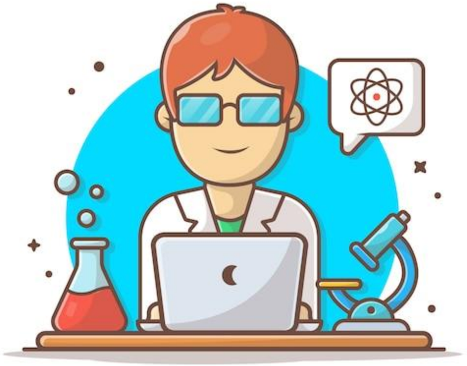
Unit	Age	Sex	Effect (%)
10	25	Female	98
20	73	Male	0
35	54	Female	100
5	12	Male	44
7	80	Male	5
…	…	…	…



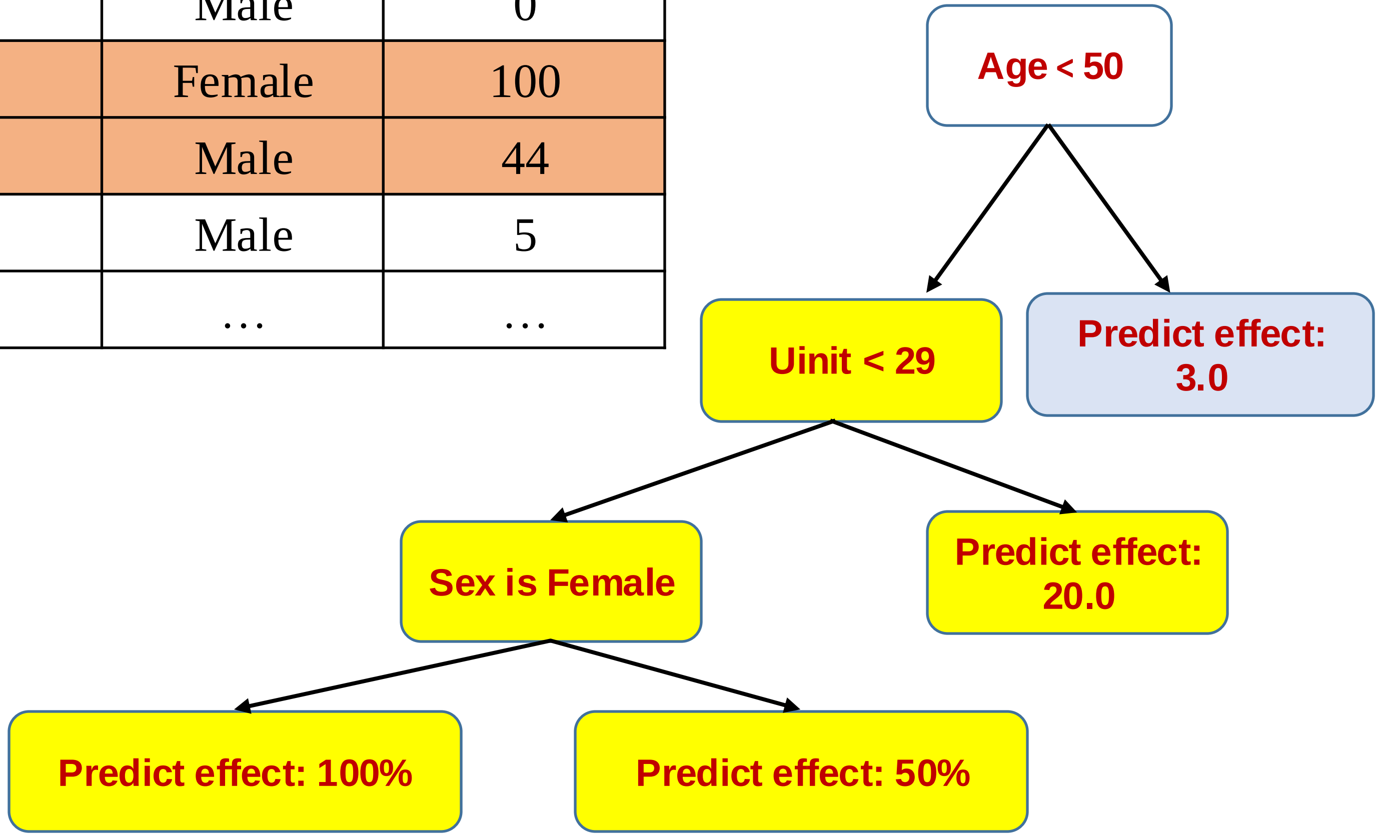
Tiếp tục mở rộng cho trường hợp Age < 50

Unit hoặc **Sex** là node kế tiếp???

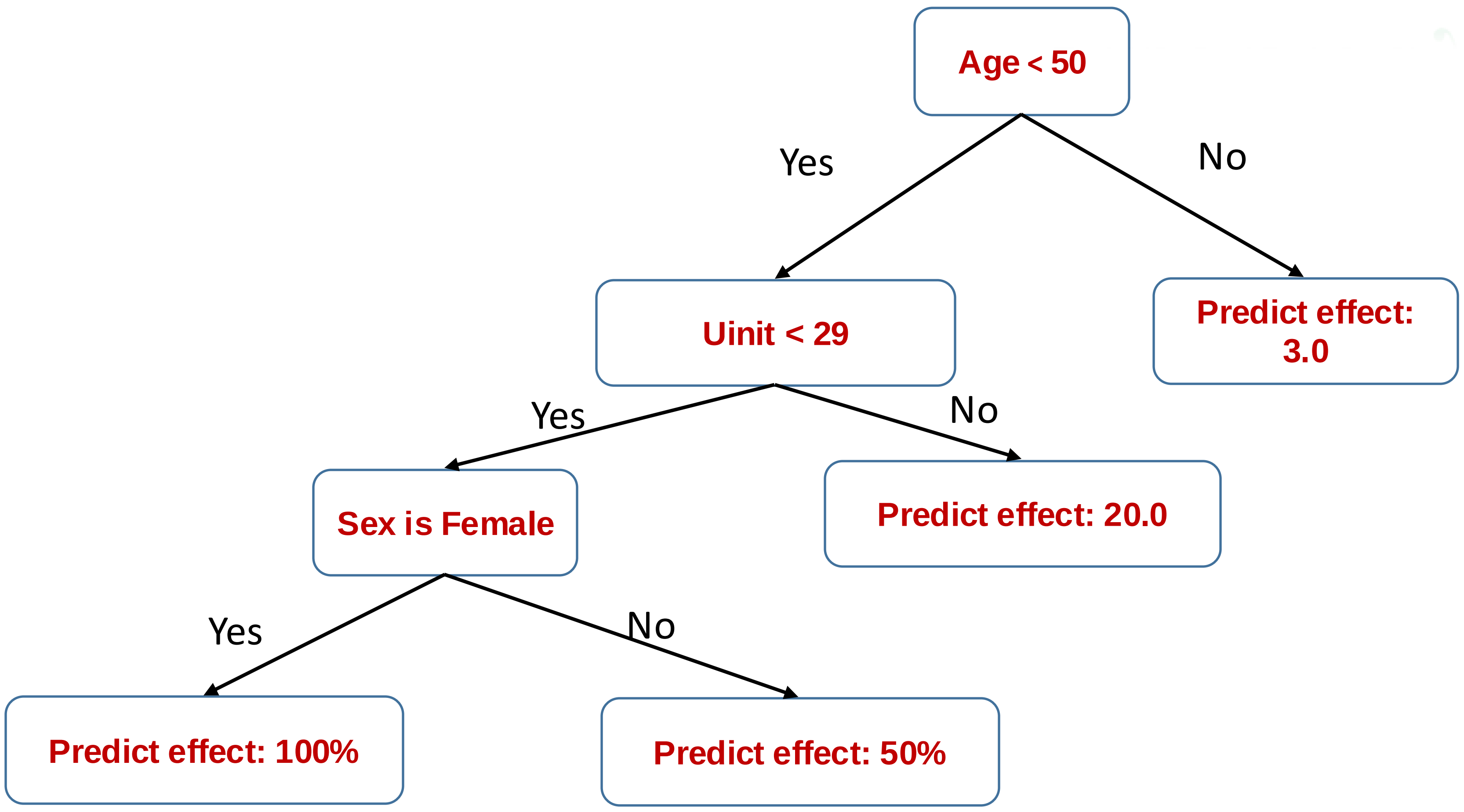
Case Study



Unit	Age	Sex	Effect (%)
10	25	Female	98
20	73	Male	0
35	54	Female	100
5	12	Male	44
7	80	Male	5
…	…	…	…



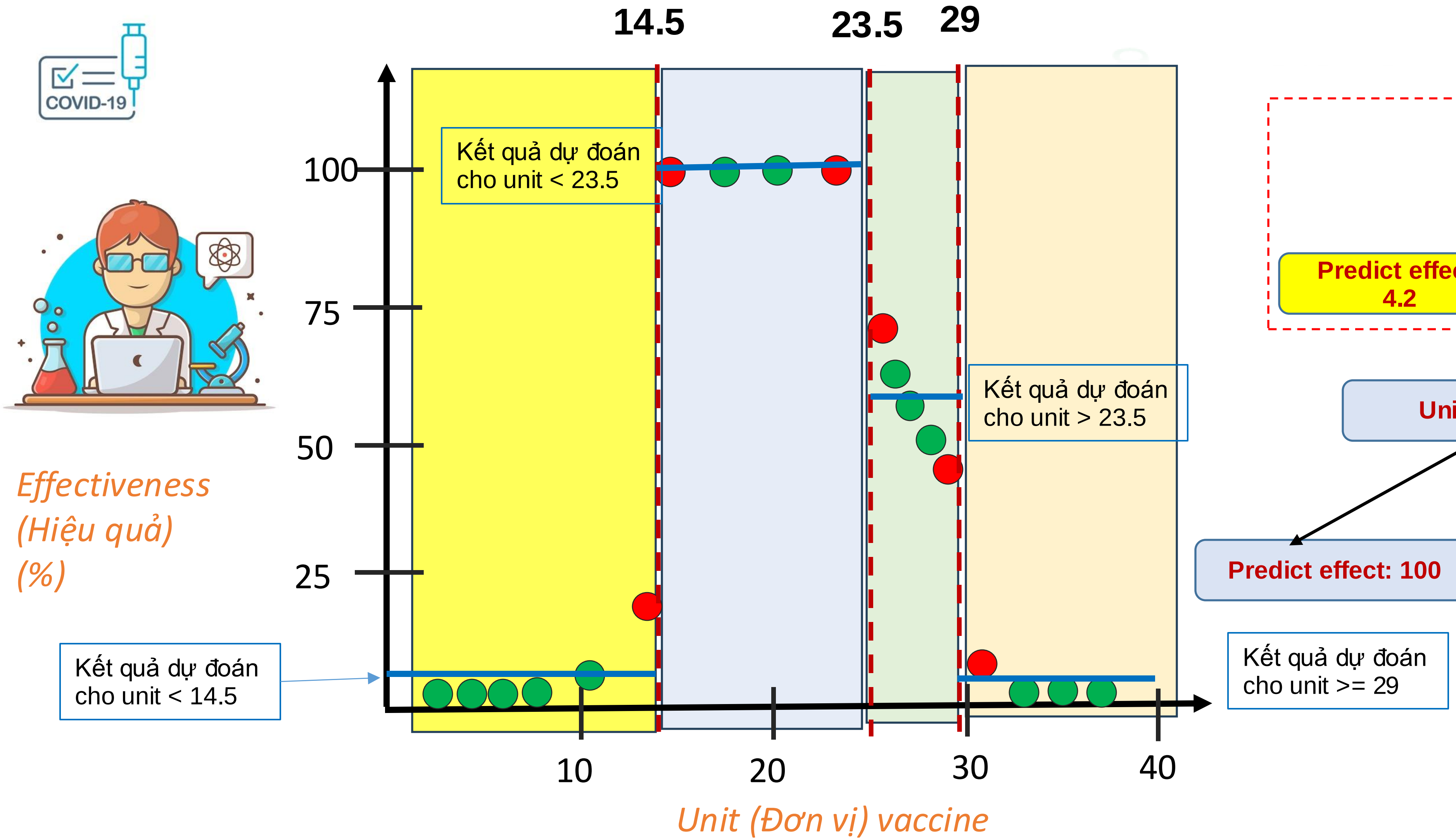
Case Study

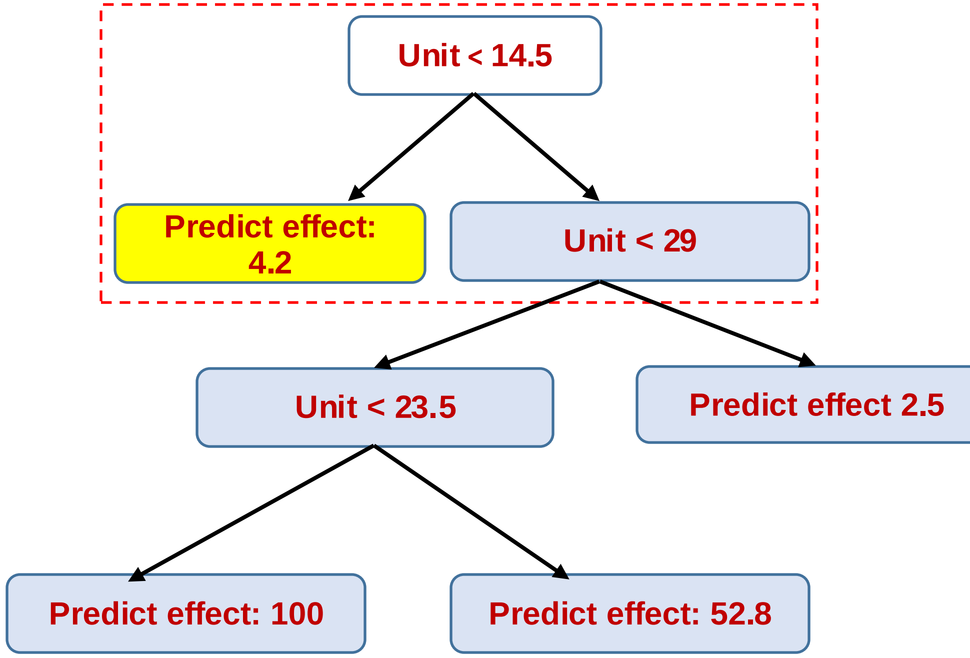

Age < 50
Yes
No
Uinit < 29
Predict effect: 3.0
Yes
No
Sex is Female
Predict effect: 20.0
Yes
No
Predict effect: 100%
Predict effect: 50%

Outline

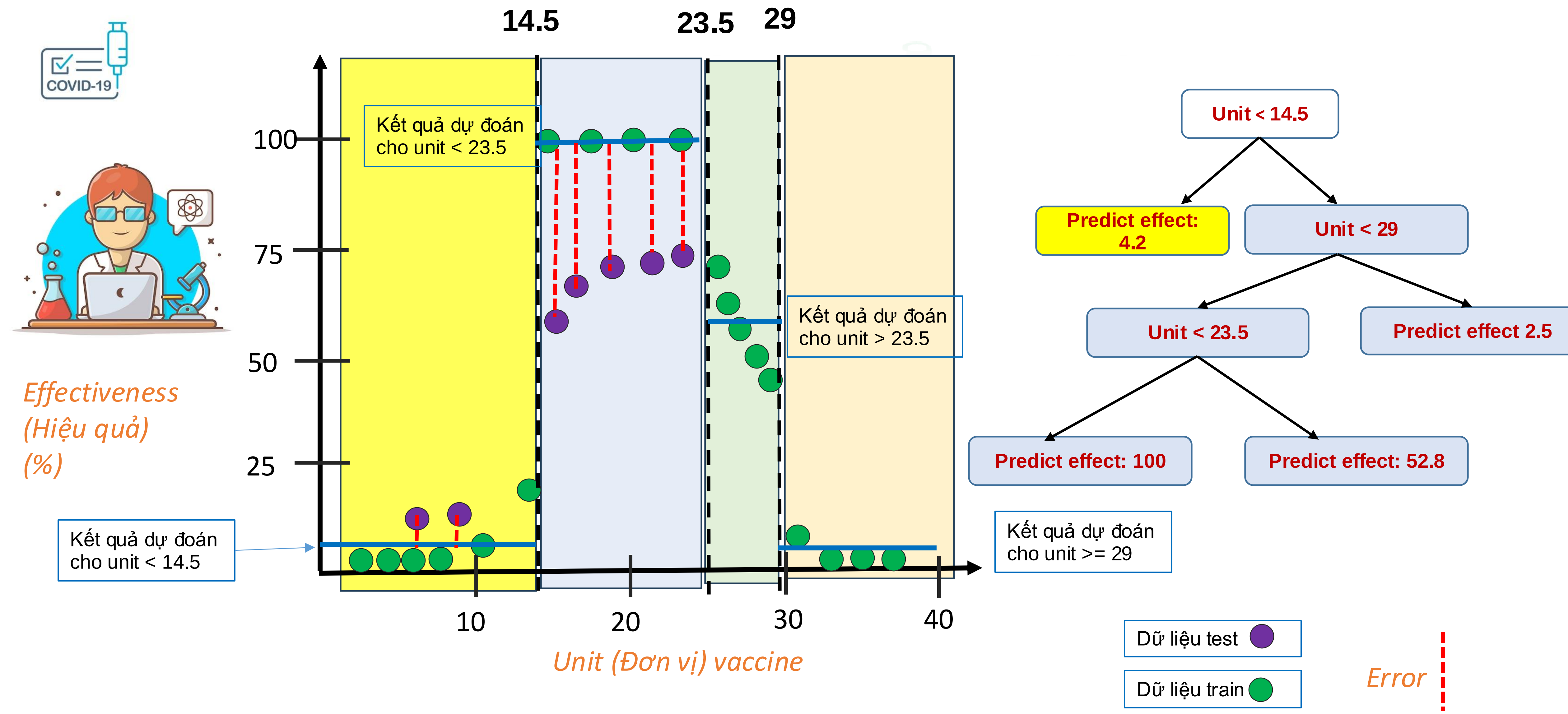
- ➢ Classification Tree: Review
- ➢ Regression Tree: Motivation
- ➢ Regression Tree: Clearly Explain
- ➢ Regression Tree: Overfitting Problem
- ➢ Examples

Overfitting Problem





Overfitting Problem



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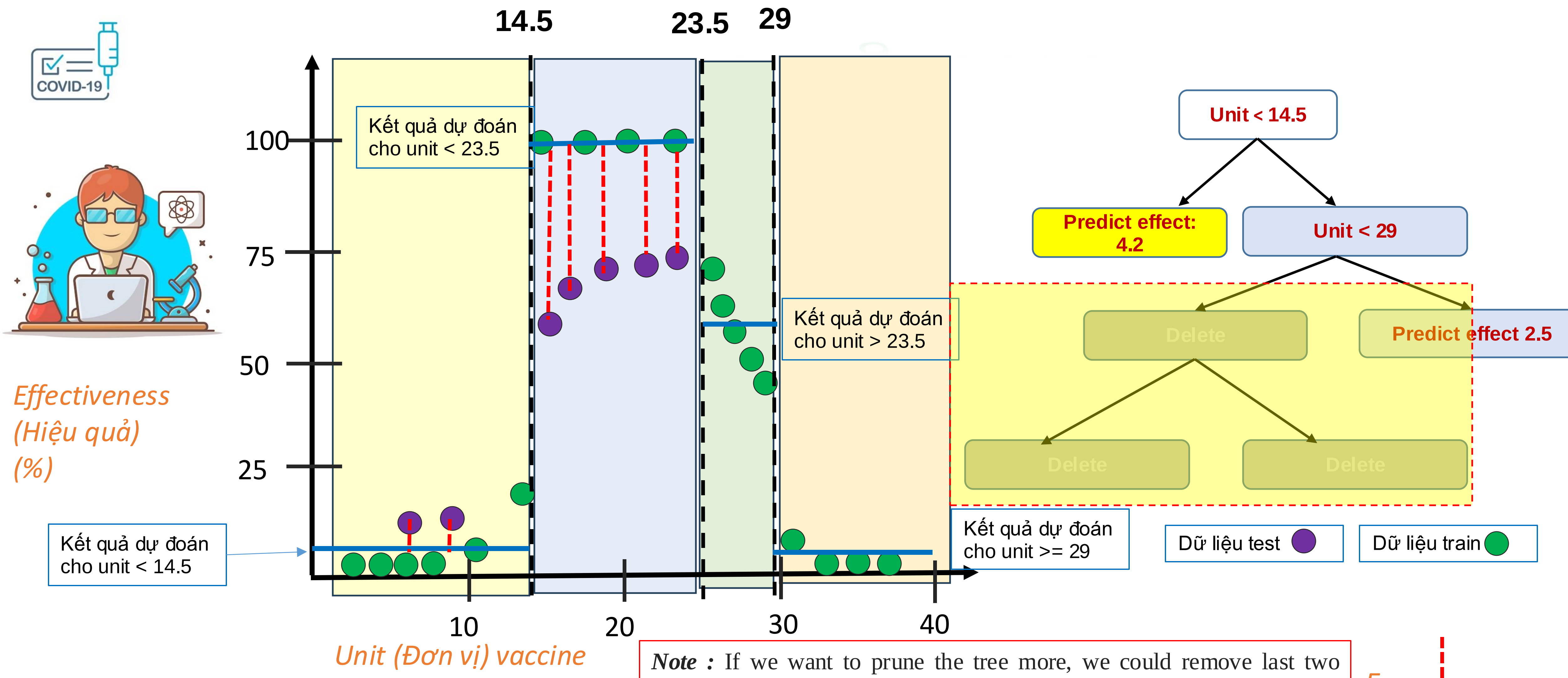
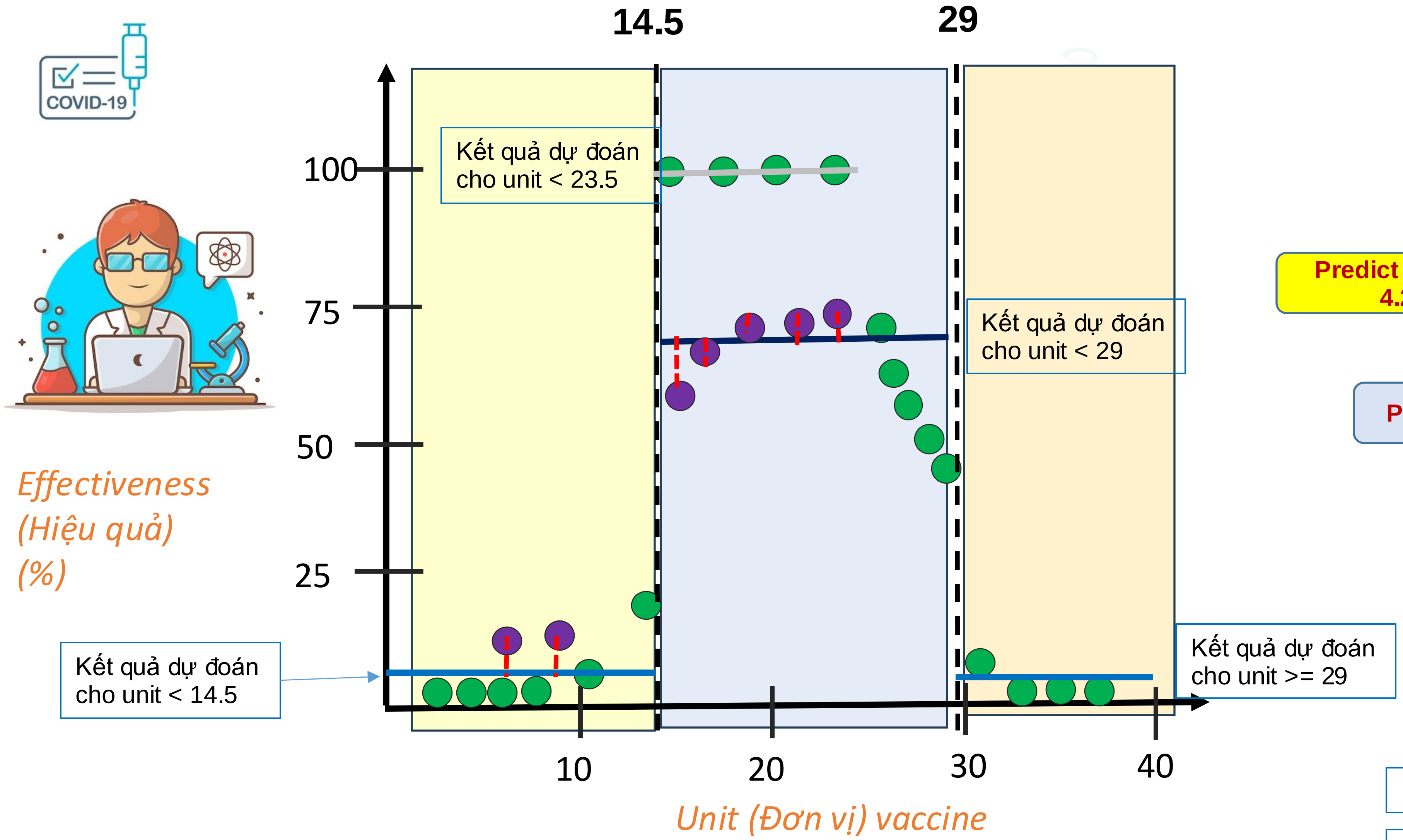
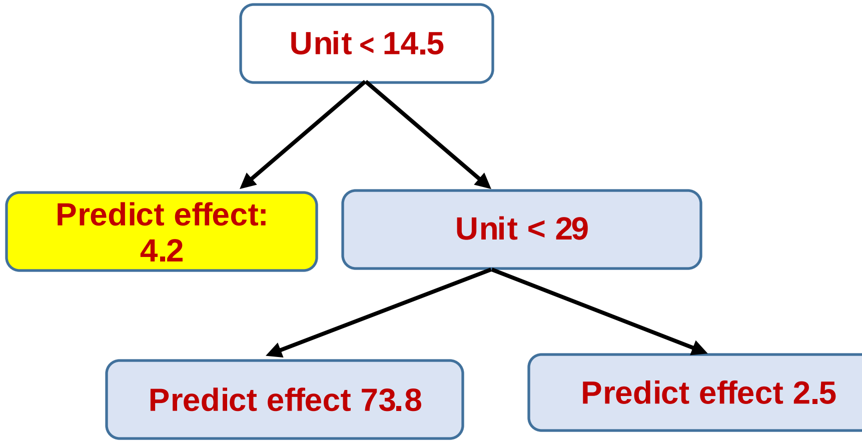
Pruning Solution



Note **:** If we want to prune the tree more, we could remove last two leaves and replace the split with a leaf that is the average of all of the observations

Pruning Solution





Dữ liệu test
Dữ liệu train
Error

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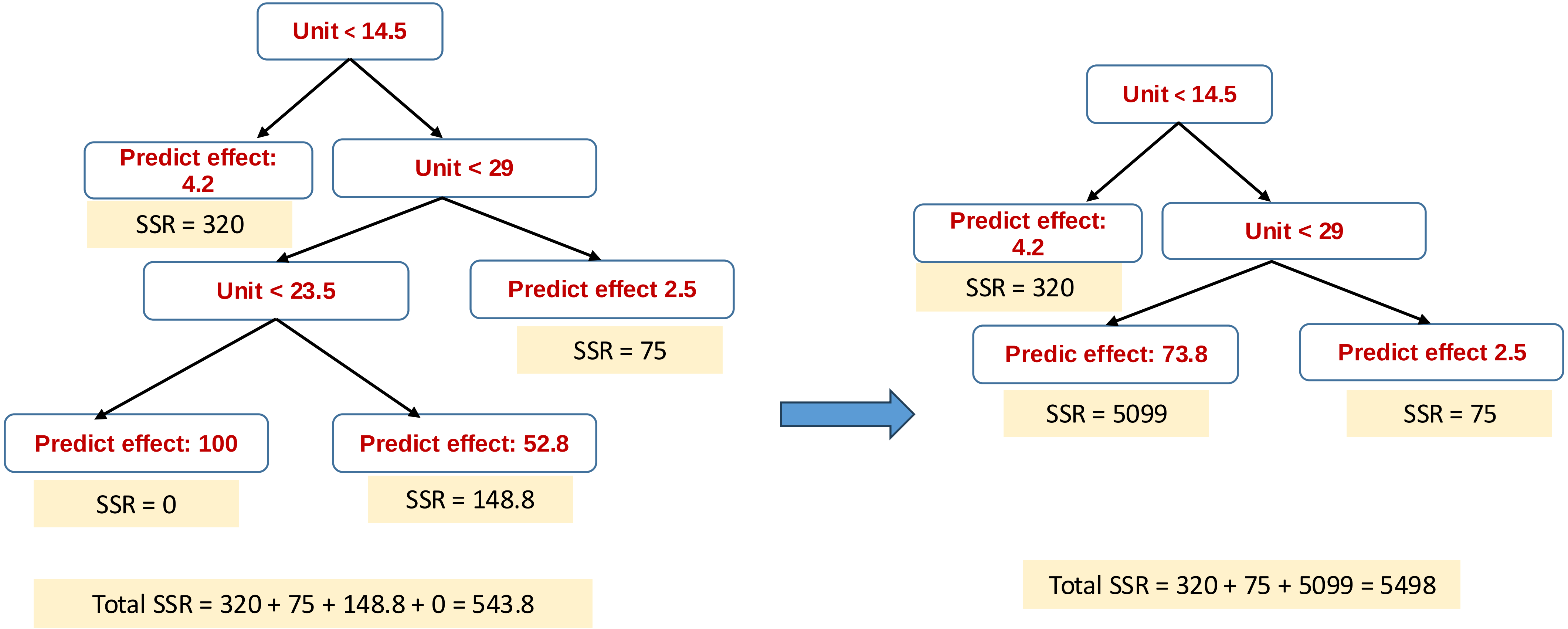
How to Select an Optimal Tree



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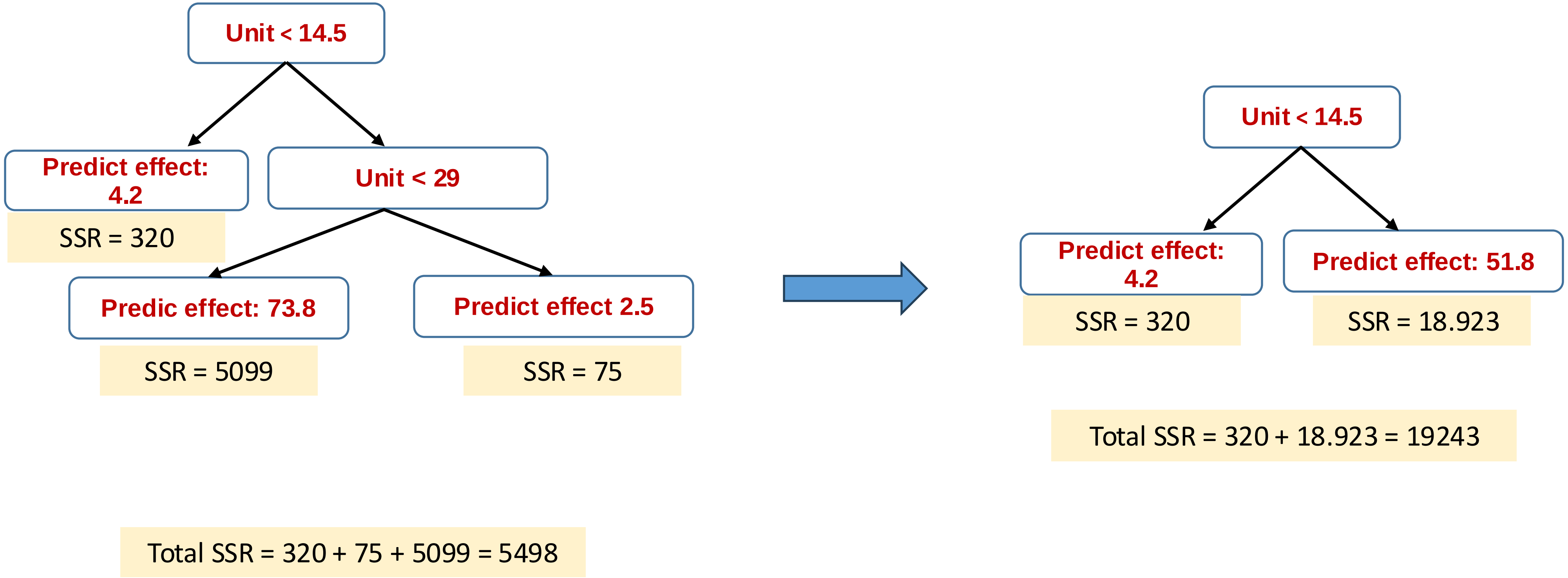
How to Select an Optimal Tree



How to Select an Optimal Tree

Unit < 14.5

Predict effect: 4.2

SSR = 320

Predict effect: 51.8

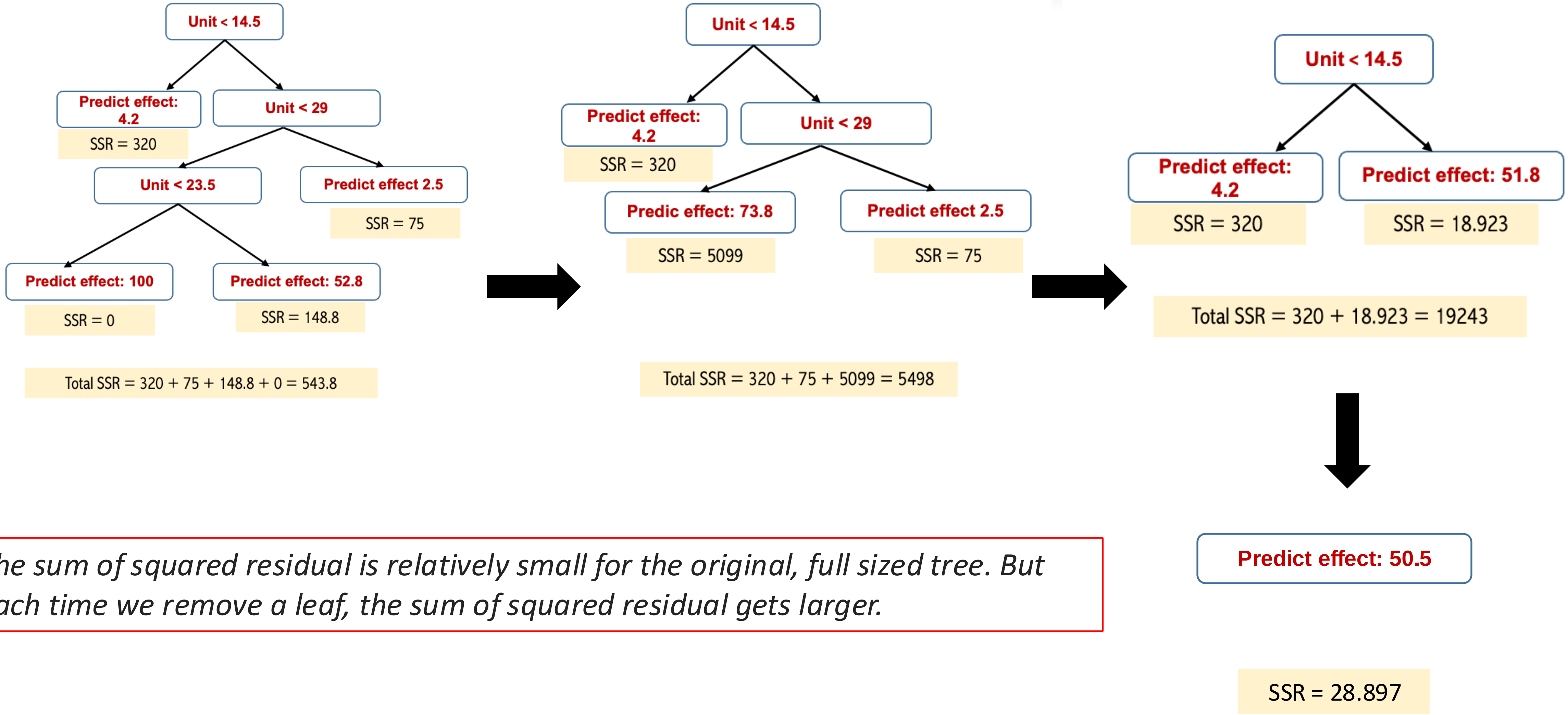
SSR = 18.923

Total SSR = 320 + 18.923 = 19243

Predict effect: 50.5

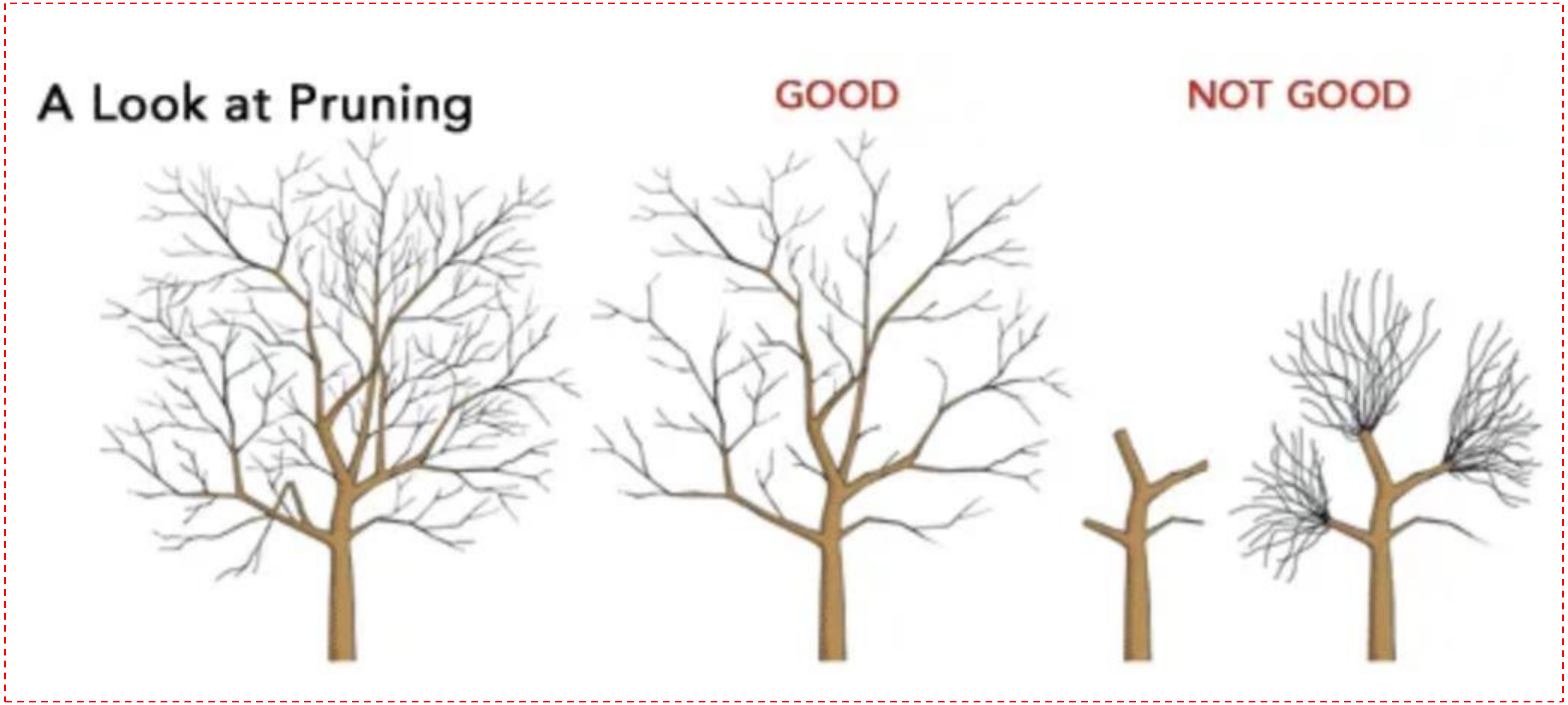
SSR = 28.897

How to Select an Optimal Tree



The sum of squared residual is relatively small for the original, full sized tree. But each time we remove a leaf, the sum of squared residual gets larger.

Decision Tree-Pruning-Cost Complexity Method



Tree Complexity Penalty

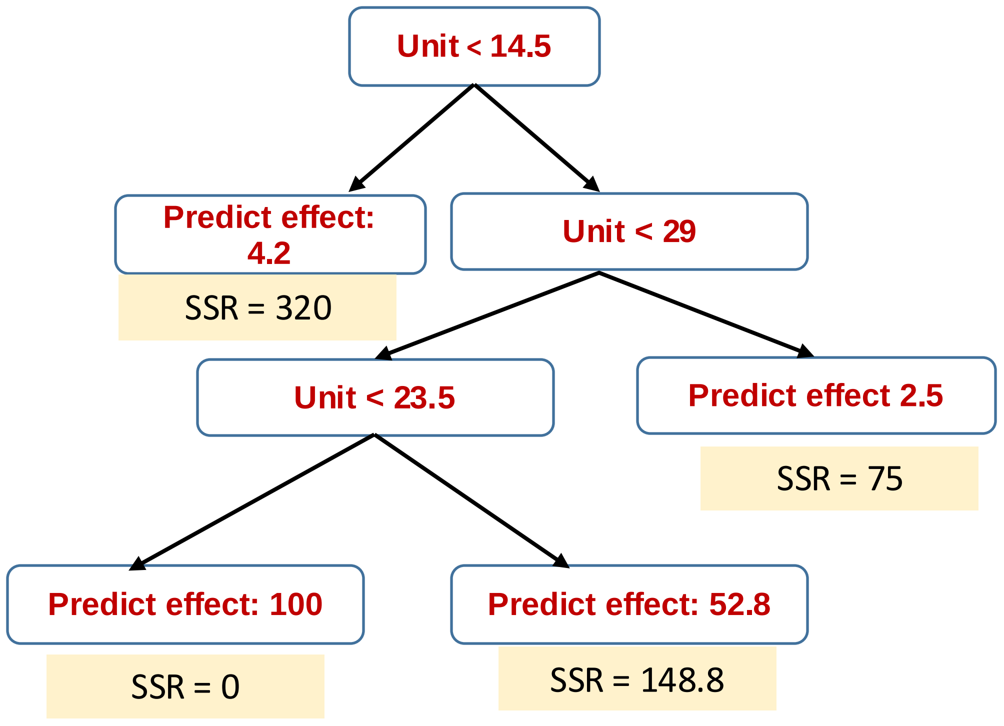
The tree complexity penalty compensates for the difference in the number of leaves.

Tree Score = sum of squared residual + αT

α (alpha) is a tuning parameter that we finding using cross validation.
T is the total number of terminal nodes/the total number of leaves

For now, let's let α = 10,000 and calculate tree score for each tree.

Tree Score



Total SSR = 320 + 75 + 148.8 + 0 = 543.8

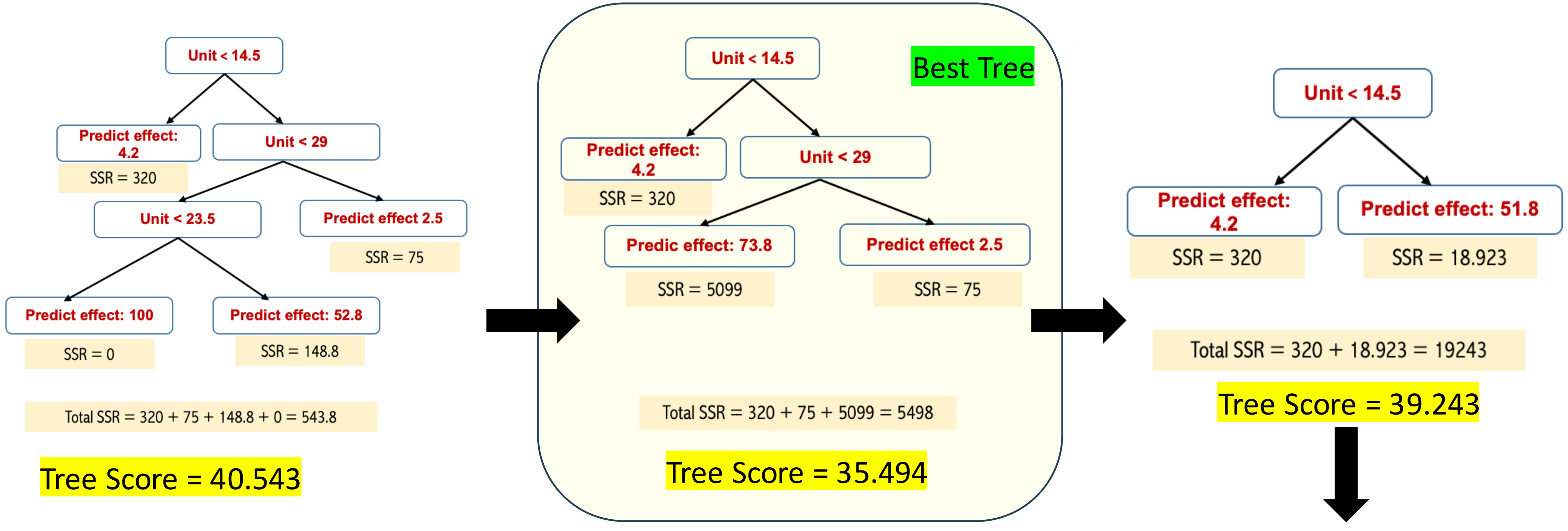
$\alpha = 10000, T = 4$

Tree Score = Total SSR+ αT

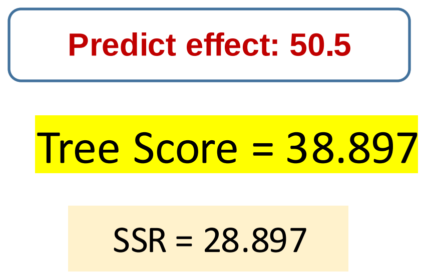
Tree Score = 543 + αT = 40.543

Tree Score

$\alpha = 10.000$



The sum of squared residual is relatively small for the original, full sized tree. But each time we remove a leaf, the sum of squared residual gets larger.



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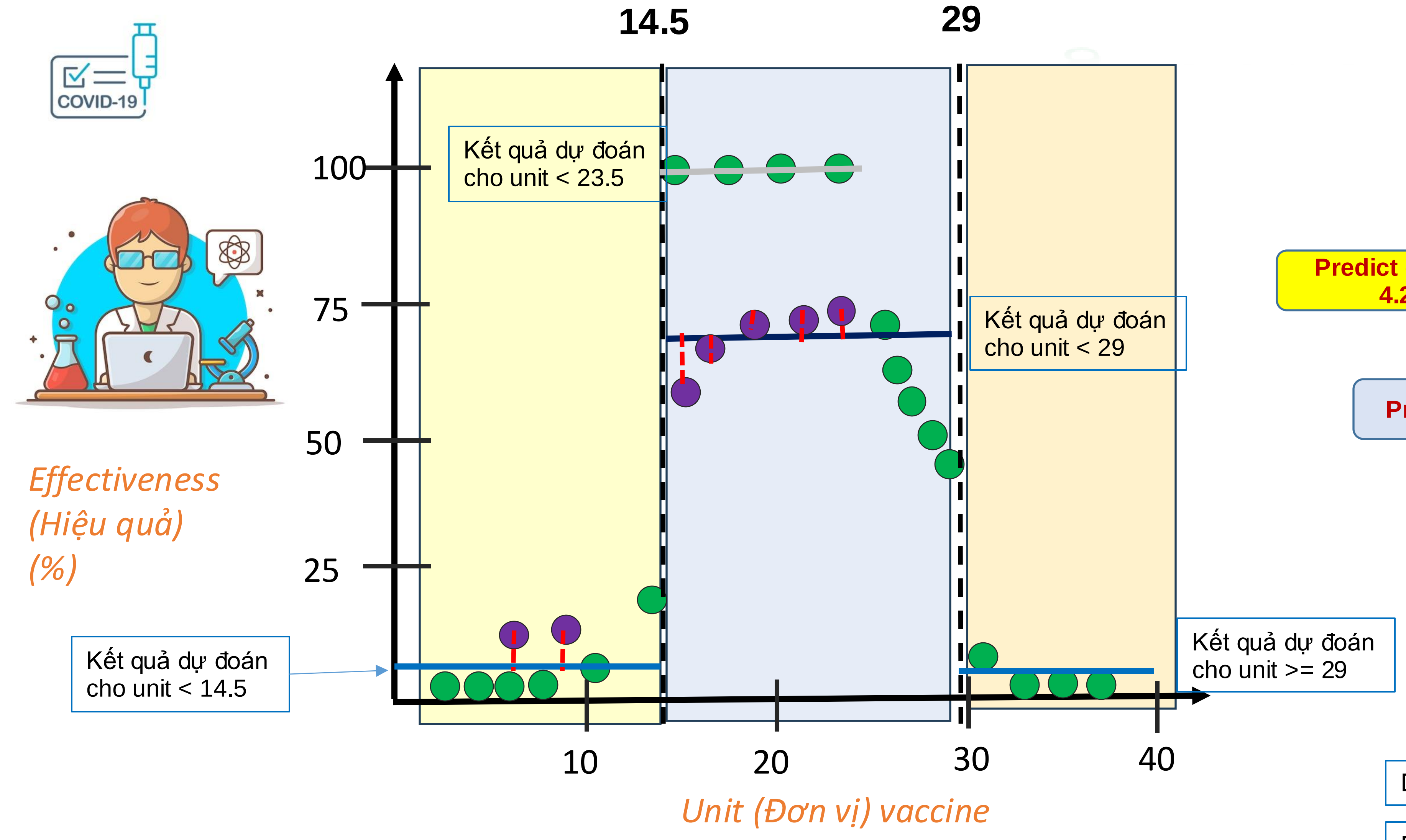
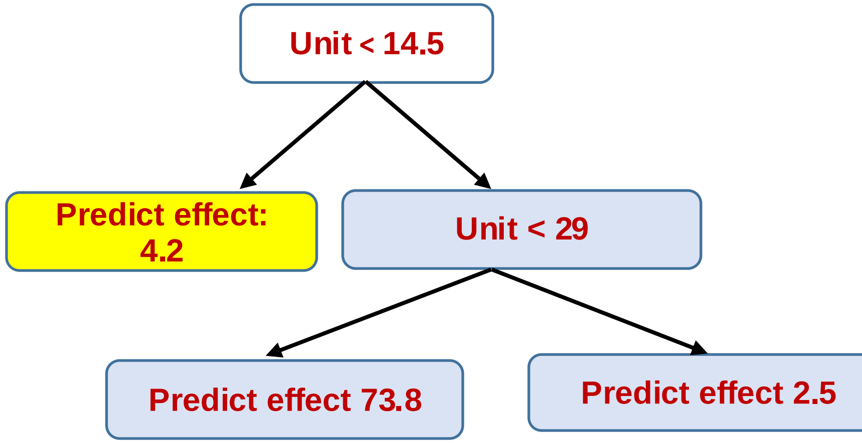
Pruning Solution





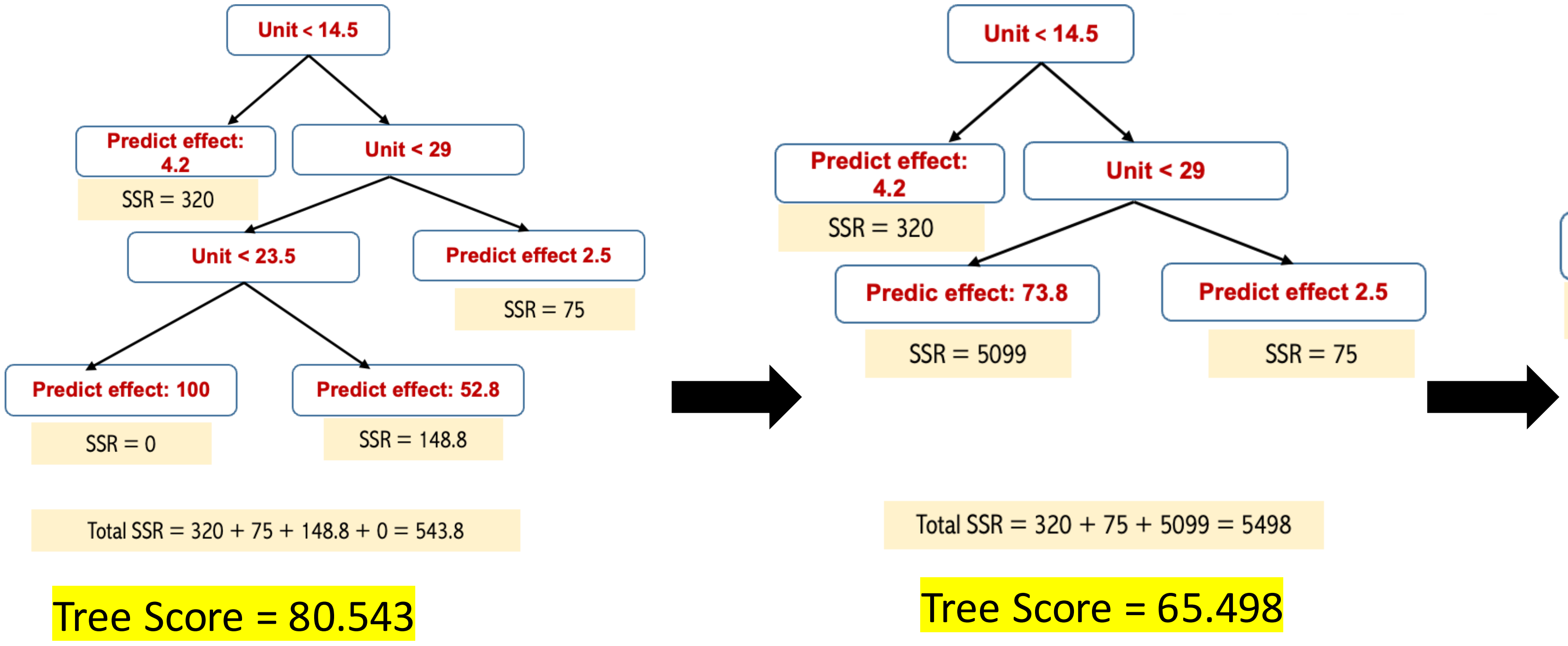
Dữ liệu test

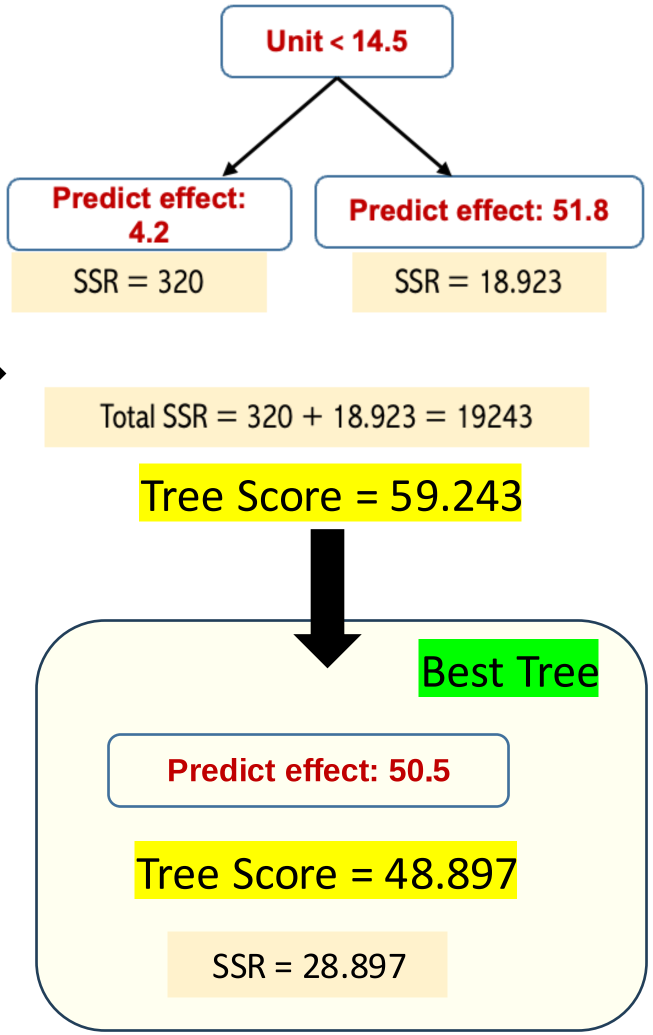
Dữ liệu train

Error

Tree Score

α = 20.000





The sum of squared residual is relatively small for the original, full sized tree. But each time we remove a leaf, the sum of squared residual gets larger.

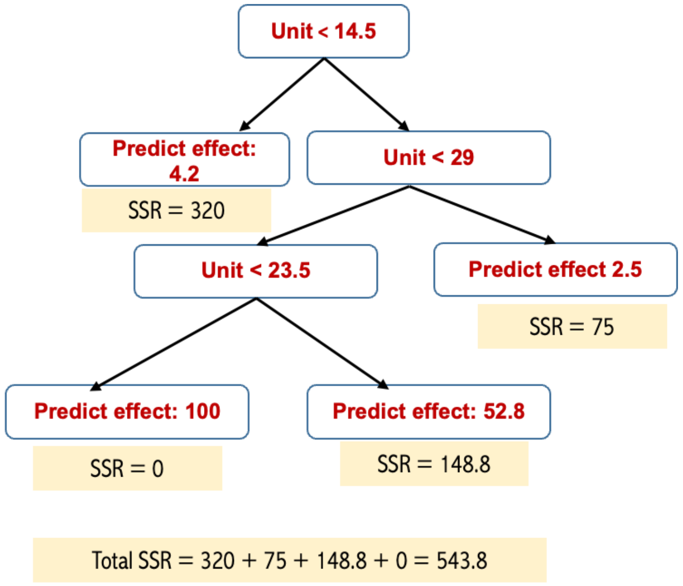
How to Select α

1

Entire dataset

Unit	Age	Sex	Effect (%)
10	25	Female	98
20	73	Male	0
35	54	Female	100
5	12	Male	44
7	80	Male	5
…	…	…	…

Full size Tree



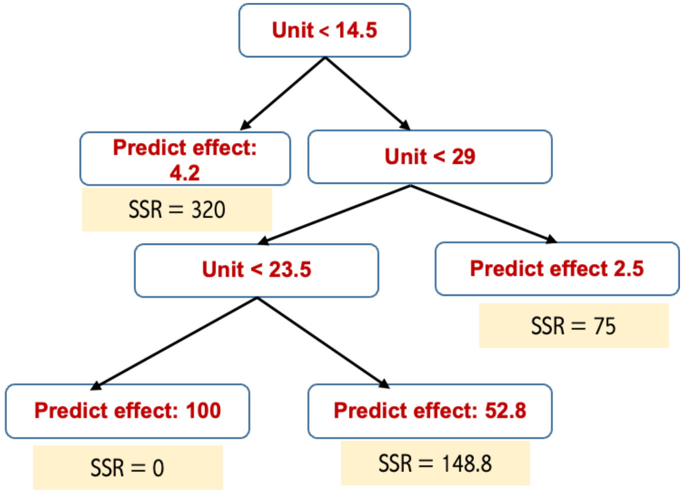
Tree Score = sum of squared residual + αT

This full size tree has lowest Tree Score when α = ??

How to Select α

2

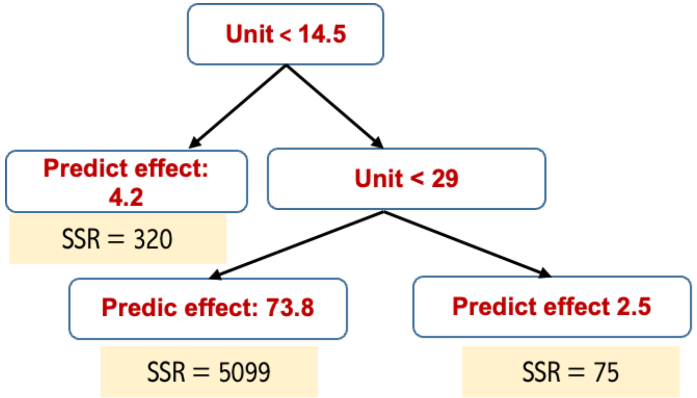
Full size Tree



Total SSR = 320 + 75 + 148.8 + 0 = 543.8

α = 0

Prunning Tree



Total SSR = 320 + 75 + 5099 = 5498

α = 10.000

Tree Score = sum of squared residual + αT

Increase untill pruning leaves will give us a lower Tree Score

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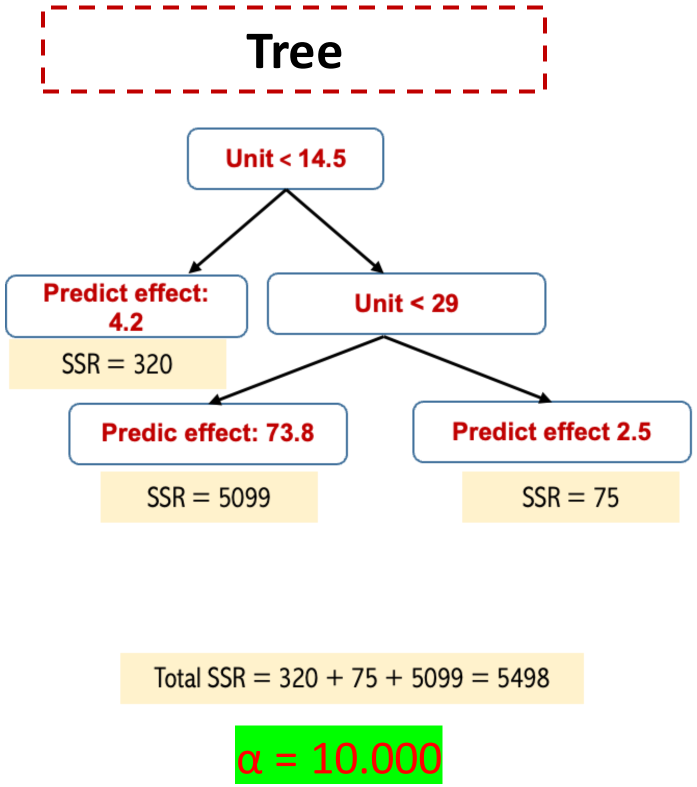
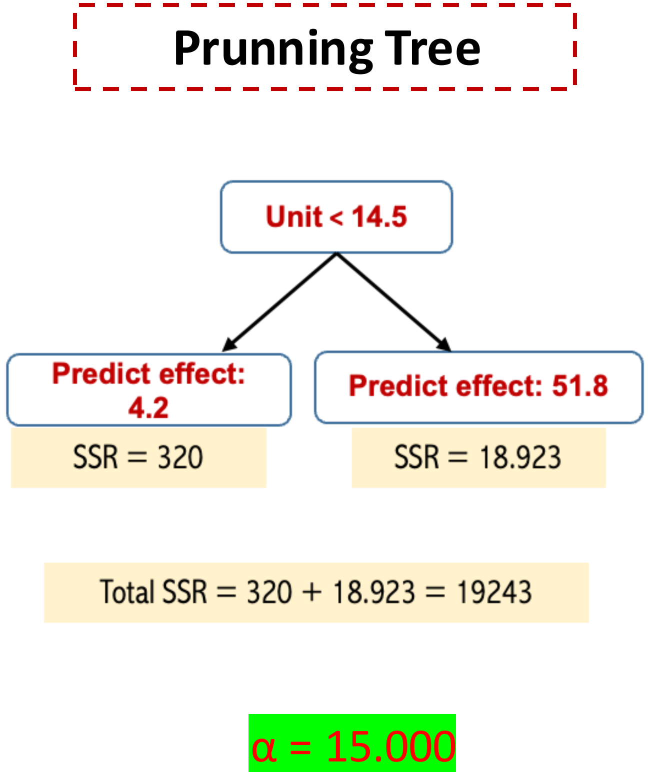
How to Select α

3





Tree Score = sum of squared residual + αT

Increase untill pruning leaves will give us a lower Tree Score

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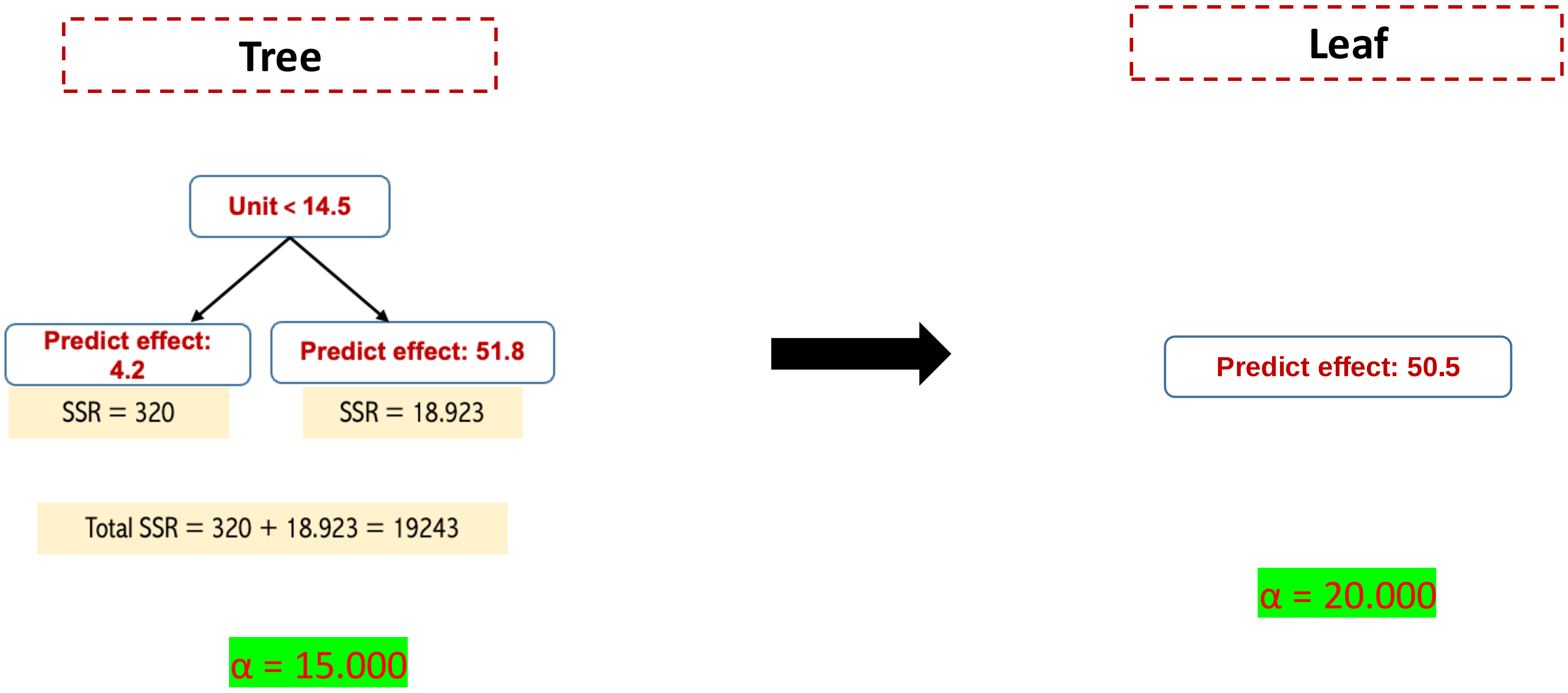
How to Select α

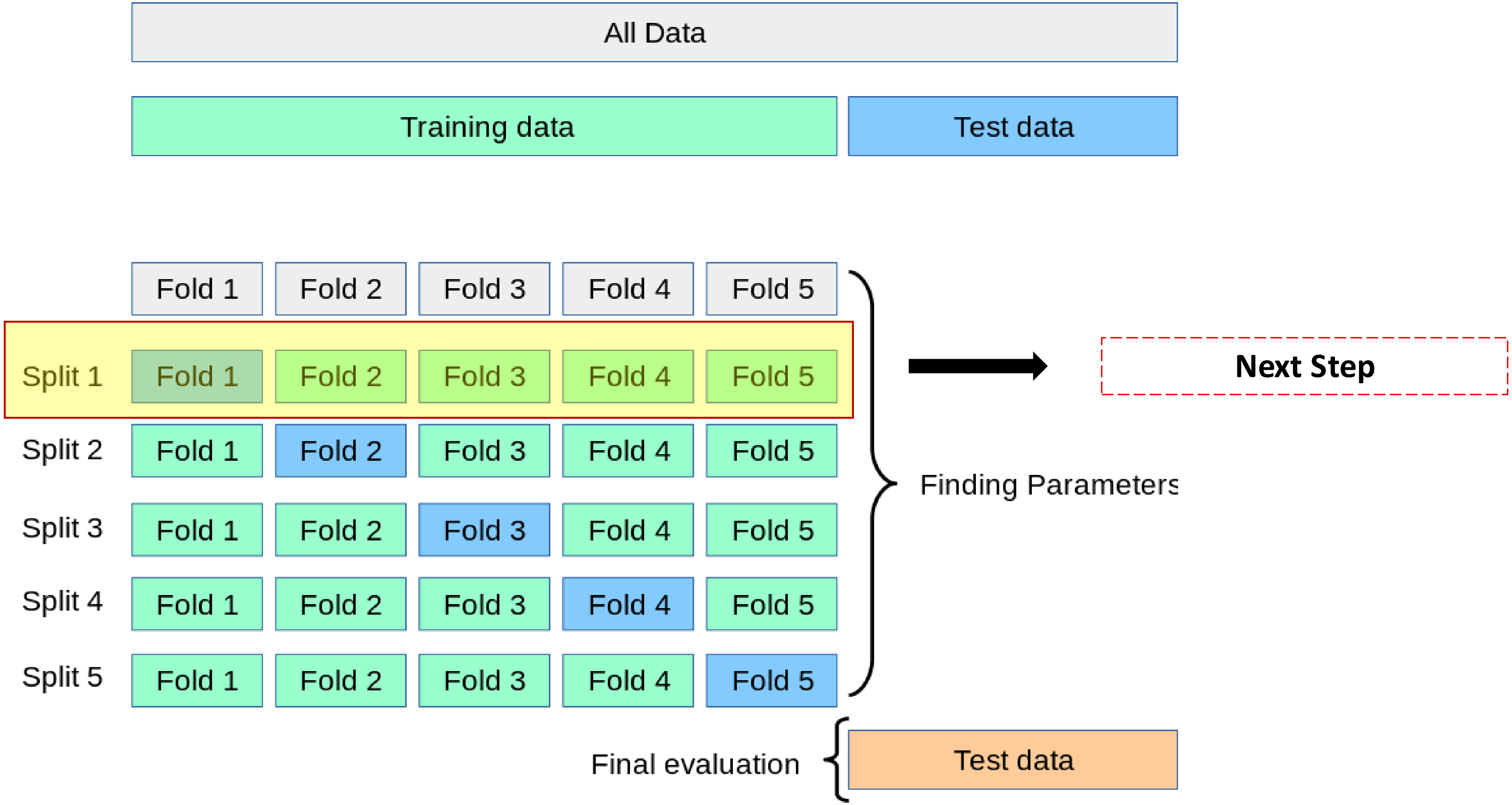
3



Tree Score = sum of squared residual + αT

Increase untill pruning leaves will give us a lower Tree Score

How to Select α



How to Select α

For each Split

Entire dataset

Unit	Age	Sex	Effect (%)
10	25	Female	98
20	73	Male	0
35	54	Female	100
5	12	Male	44
7	80	Male	5
…	…	…	…

Training dataset

Unit	Age	Sex	Effect (%)
10	25	Female	98
20	73	Male	0
…	…	…	…

Build Tree with $\alpha = 0$, $\alpha = 10000$, $\alpha = 15000$, $\alpha = 20,000$

Testing dataset

Unit	Age	Sex	Effect (%)
5	12	Male	44
7	80	Male	5
…	…	…	…

Tree Score with $\alpha = 0$, $\alpha = 10000$, $\alpha = 15000$, $\alpha = 20,000$

How to Select α

	α = 0	α = 10,000	α = 15000	α =20,000
Split 1	…	…	…	…
Split 2	…	…	…	…
Split 3	…	…	…	…
Split 4	…	…	…	…
Split 5	…	…	…	…
Average	50,000	5000	11,000	30,000

In this case, the optimal trees built with α = 10,000 had, on average, the lowest sum of square residuals. So α = 10,000 is our final value.

Outline

- ➢ Classification Tree: Review
- ➢ Regression Tree: Motivation
- ➢ Regression Tree: Clearly Explain
- ➢ Regression Tree: Overfitting Problem
- ➢ Examples

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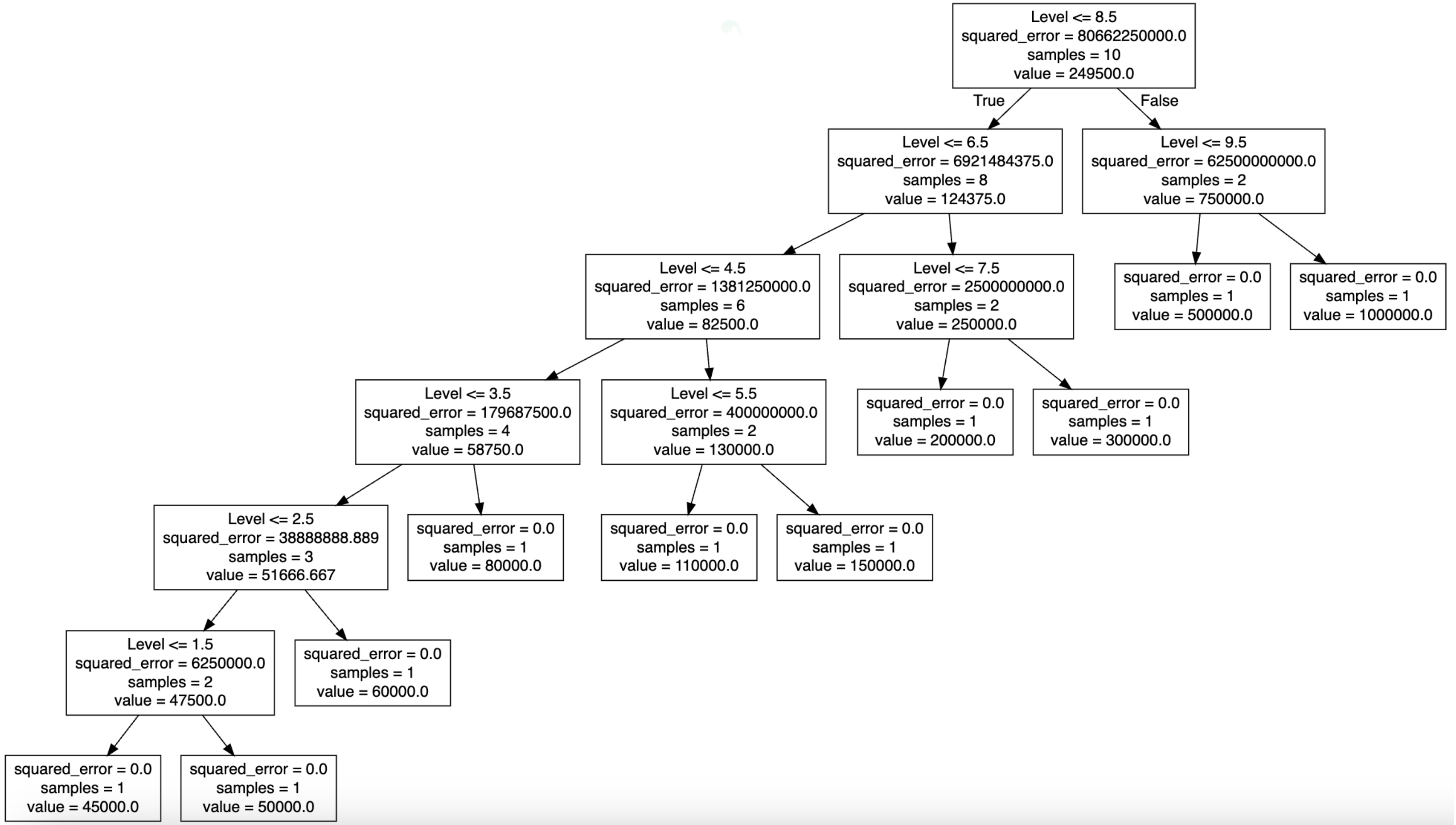
Case Study

Position_Salaries

Position	Level	Salary
Business Analyst	1	45000
Junior Consultant	2	50000
Senior Consultant	3	60000
Manager	4	80000
Country Manager	5	110000
Region Manager	6	150000
Partner	7	200000
Senior Partner	8	300000
C-level	9	500000
CEO	10	1000000



http://www.webgraphviz.com/

```
export_graphviz(regressor, out_file ='tree.dot',
feature_names =["Level"])
```

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Case Study

Position_Salaries

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Business Analyst	1	45000
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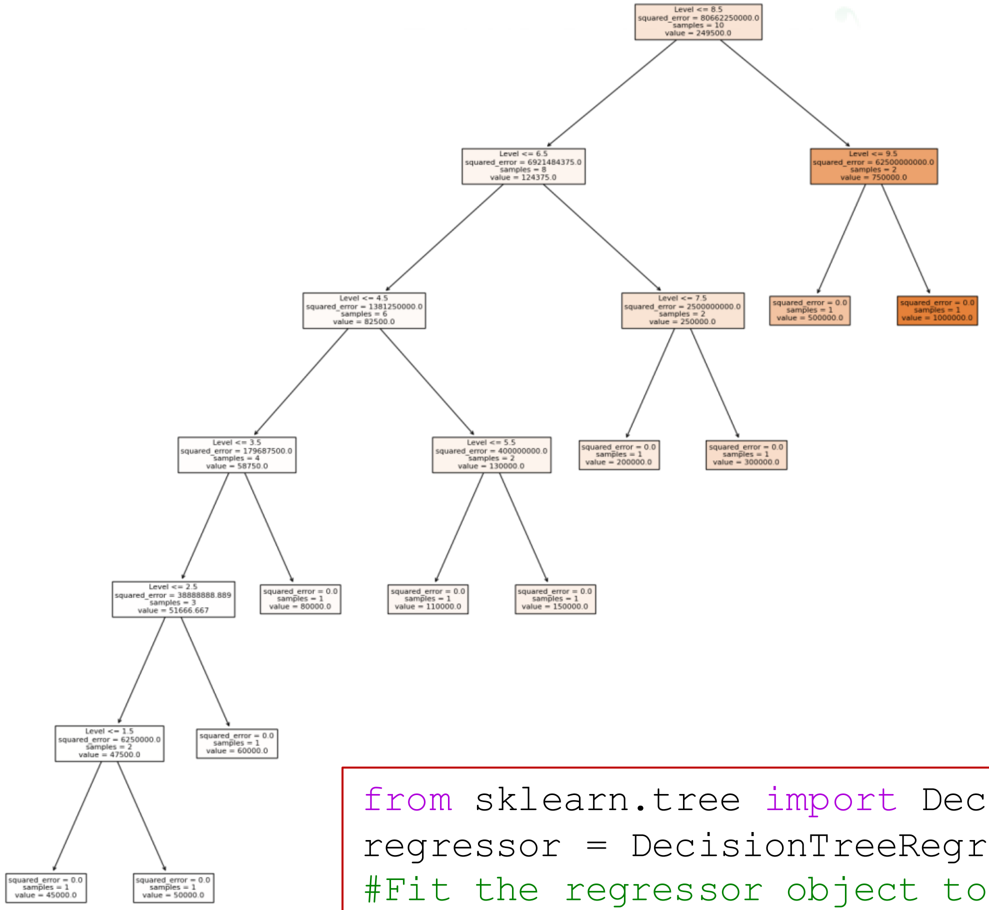


```python
from sklearn.tree import DecisionTreeRegressor
regressor = DecisionTreeRegressor(random_state=0)
#Fit the regressor object to the dataset.
regressor.fit(X,y)
```

```python
tree.plot_tree(regressor, ax=ax, feature_names = ["Level"],
               filled=True)
```

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Case Study

Position_Salaries

Position	Level	Salary
Business Analyst	1	45000
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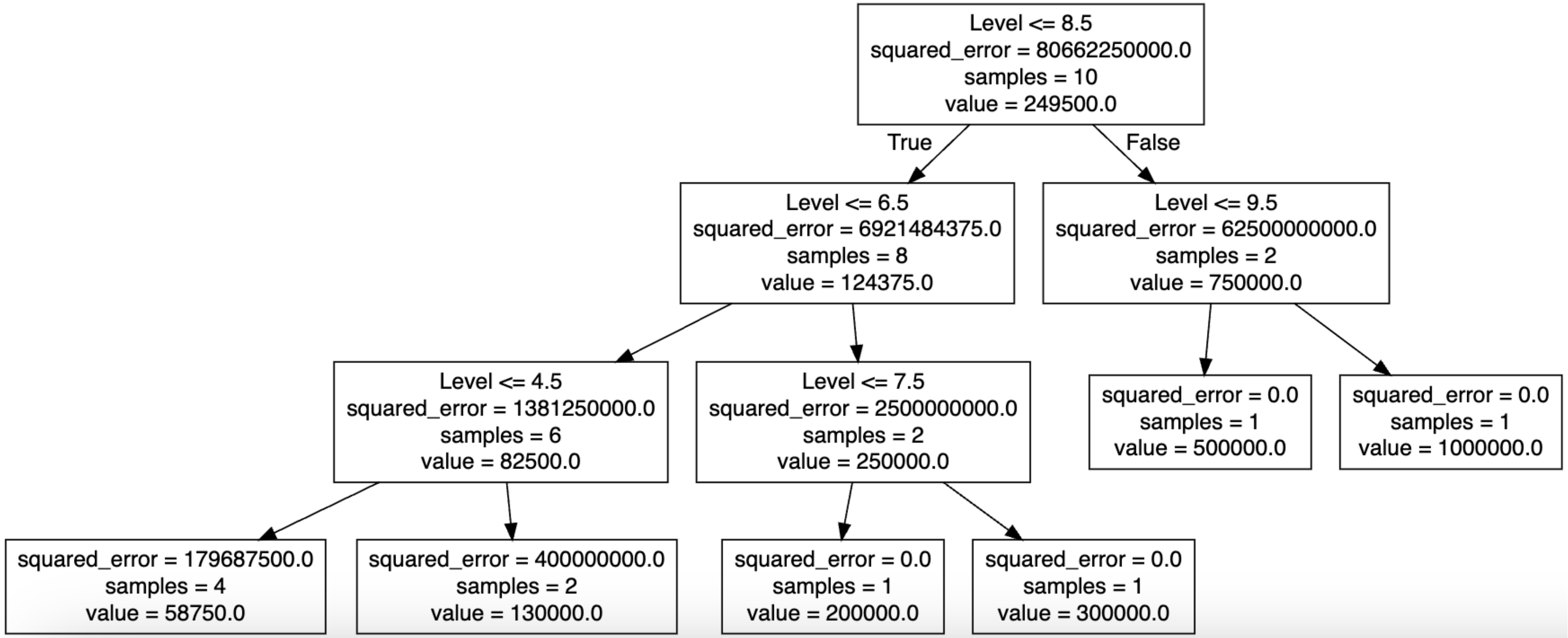


```
regressor = DecisionTreeRegressor(random_state=0,
max_depth=3)
```

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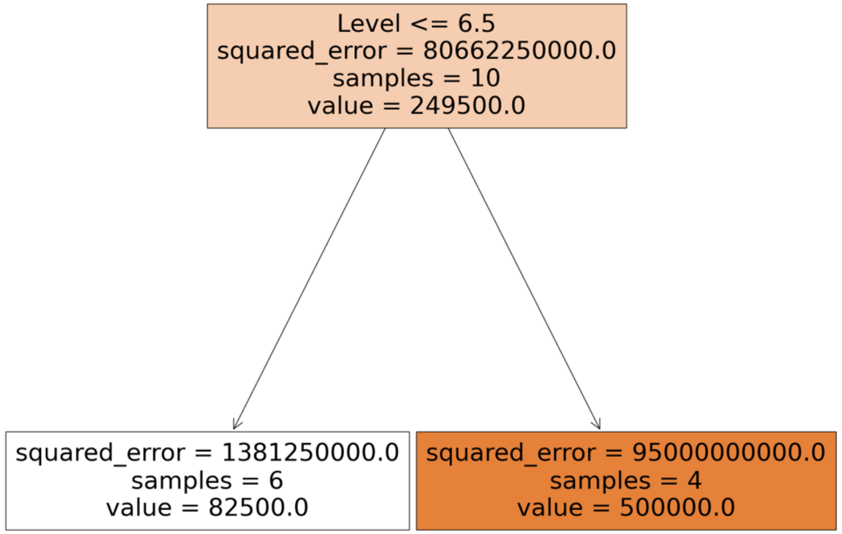
Case Study

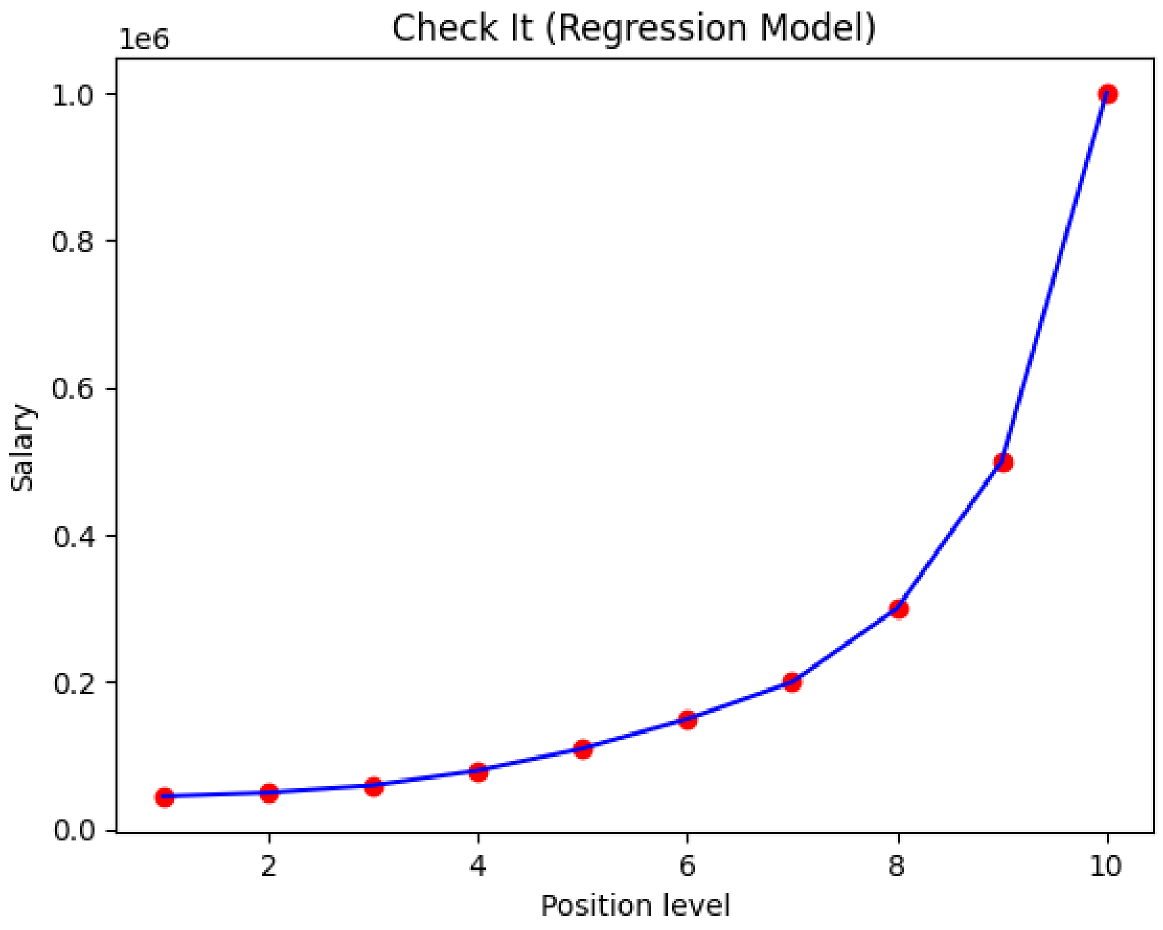
Position_Salaries

Position	Level	Salary
Business Analyst	1	45000
Junior Consultant	2	50000
Senior Consultant	3	60000
Manager	4	80000
Country Manager	5	110000
Region Manager	6	150000
Partner	7	200000
Senior Partner	8	300000
C-level	9	500000
CEO	10	1000000




```
regressor = DecisionTreeRegressor(random_state=0,
min_samples_leaf=4)
```

Case Study




```
Visualising the Decision Tree Regression results
plt.scatter(X, y, color = 'red')
plt.plot(X, regressor.predict(X), color = 'blue')
plt.title('Check It (Regression Model)')
plt.xlabel('Position level')
plt.ylabel('Salary')
plt.show()
```

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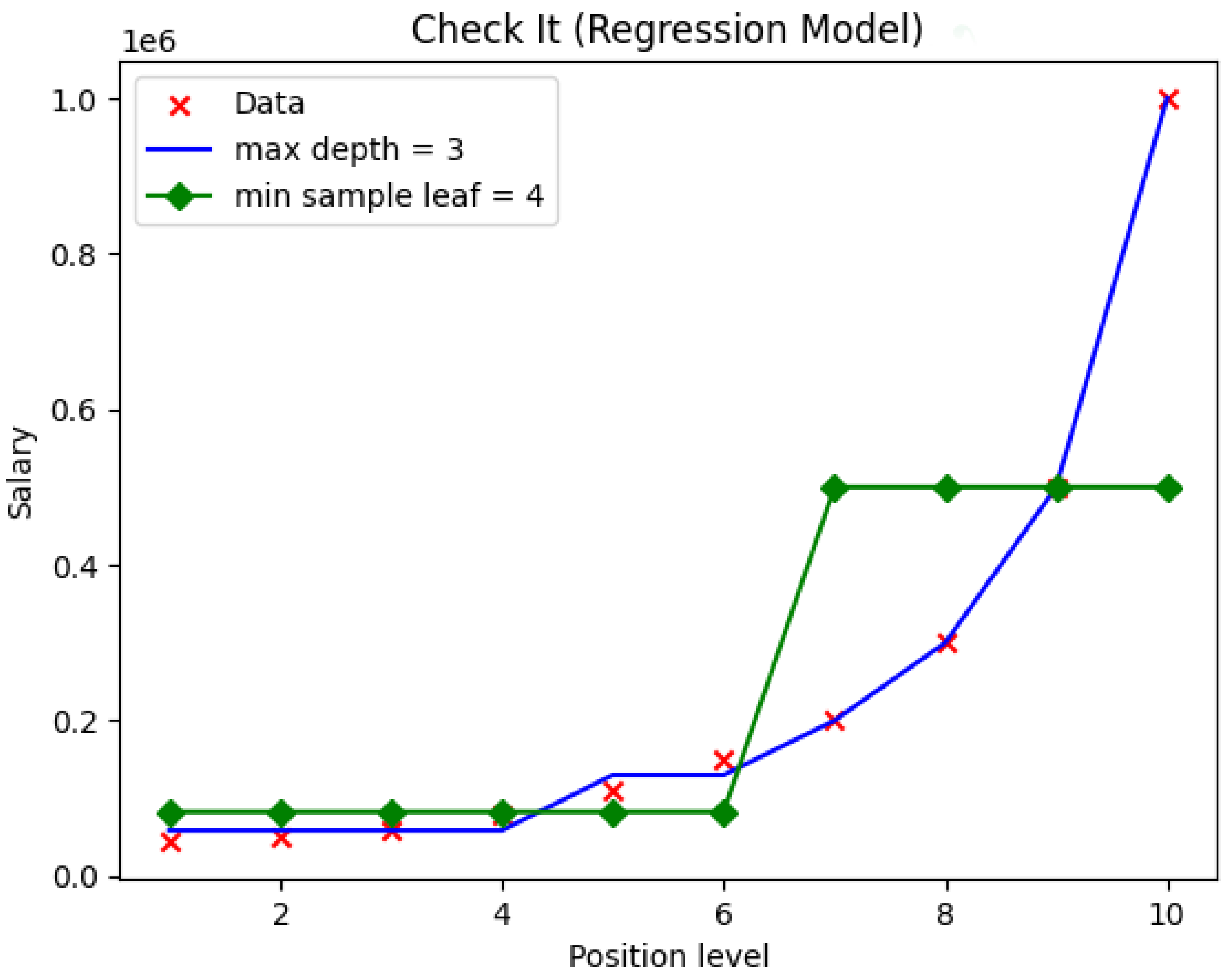
Case Study



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Microsoft Stock Price Prediction

1. Visit [Yahoo Finance]
2. Search for **“MSFT”**
3. Click on **“Historical Data”**
4. Click on **“Download”**

MSFT

Date	Open	High	Low	Close	Adj Close	Volume
2023-08-16	320.799988	324.420013	319.799988	320.399994	318.013000	20698900
2023-08-17	320.540009	321.869995	316.209991	316.880005	314.519196	21257200
2023-08-18	314.489990	318.380005	311.549988	316.480011	314.122192	24744800
2023-08-21	317.929993	322.769989	317.040009	321.880005	319.481964	24040000
2023-08-22	325.500000	326.079987	321.459991	322.459991	320.057648	16102000
2023-08-23	323.820007	329.200012	323.459991	327.000000	324.563812	21166400
2023-08-24	332.850006	332.980011	319.959991	319.970001	317.586182	23281400
2023-08-25	321.470001	325.359985	318.799988	322.980011	320.573761	21684100
2023-08-28	325.660004	326.149994	321.720001	323.700012	321.288422	14808500
2023-08-29	321.880005	328.980011	321.880005	328.410004	325.963287	19284600
2023-08-30	328.670013	329.809998	326.450012	328.790009	326.340485	15222100
2023-08-31	329.200012	330.910004	326.779999	327.760010	325.318146	26411000

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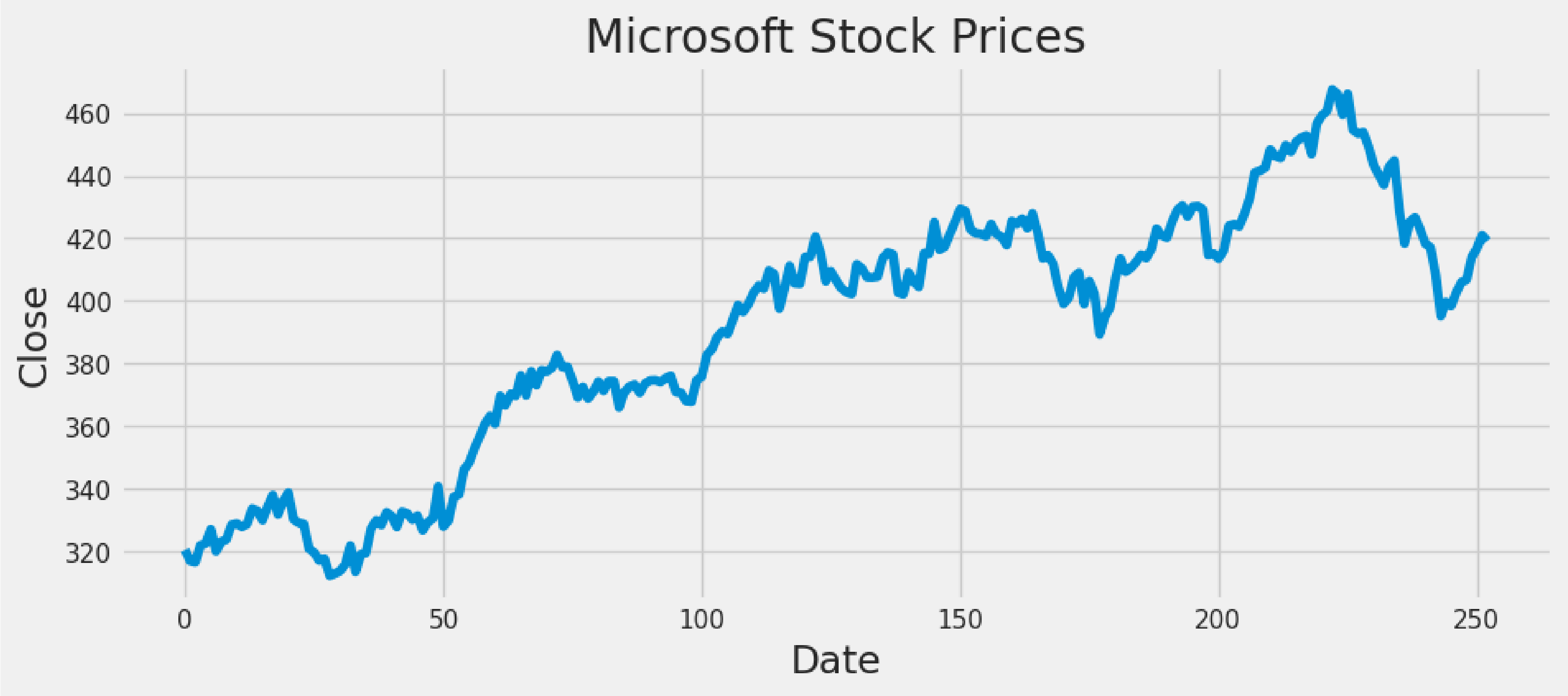
Microsoft Stock Price Prediction

```
plt.figure(figsize=(10, 4))
plt.title("Microsoft Stock Prices")
plt.xlabel("Date")
plt.ylabel("Close")
plt.plot(data["Close"])
plt.show()
```



Microsoft Stock Price Prediction

```
[5] x = data[["Open", "High", "Low"]]
    y = data["Close"]
    x = x.to_numpy()
    y = y.to_numpy()
    y = y.reshape(-1, 1)

    from sklearn.model_selection import train_test_split
    xtrain, xtest, ytrain, ytest = train_test_split(x, y, test_size=0.2, random_state=42)
```

```
from sklearn.tree import DecisionTreeRegressor
model = DecisionTreeRegressor()
model.fit(xtrain, ytrain)
ypred = model.predict(xtest)
data = pd.DataFrame(data={"Predicted Rate": ypred})
print(data.head())
```

```
   Predicted Rate
0      442.570007
1      326.670013
2      371.299988
3      424.589996
4      407.570007
```


Thank you