Gradient Boosting Explained

(Classification Example)

| | | Favorite Color | Loves Troll 2 |
|-----|----|-------------------|------------------|
| Yes | 12 | Blue | Yes |
| Yes | 87 | Green | Yes |
| No | 44 | Blue | No |
| Yes | 19 | Red | No |
| No | 32 | Green | Yes |
| No | 14 | Blue | Yes |

When we use **Gradient Boost for Classification**, the initial **Prediction** for every individual is the **log(odds)**.

I like to think of the log(odds) as the Logistic Regression equivalent of the average.

| | | Favorite Color | Loves Troll 2 |
|-----|----|-------------------|------------------|
| Yes | 12 | Blue | Yes |
| Yes | 87 | Green | Yes |
| No | 44 | Blue | No |
| Yes | 19 | Red | No |
| No | 32 | Green | Yes |
| No | 14 | Blue | Yes |

...which we will put into our initial leaf.

$$\log(\frac{4}{2}) = 0.7$$

And let's save that up here for now.

| Yes | 12 | Blue | Yes |
|-----|----|-------|-----|
| Yes | 87 | Green | Yes |
| No | 44 | Blue | No |
| Yes | 19 | Red | No |
| No | 32 | Green | Yes |
| No | 14 | Blue | Yes |

Probability of Loving =
$$\frac{e^{\log(4/2)}}{1 + e^{\log(4/2)}} = 0.7$$
Troll 2

| Yes | 12 | Blue | Yes |
|-----|----|-------|-----|
| Yes | 87 | Green | Yes |
| No | 44 | Blue | No |
| Yes | 19 | Red | No |
| No | 32 | Green | Yes |
| No | 14 | Blue | Yes |

NOTE: These two numbers, the **log(4/2)** and the **Probability** are the same only because I'm rounding. If I allowed **4** digits passed the decimal place...

$$\log(\frac{4}{2}) = 0.6931$$

$$\frac{e^{\log(4/2)}}{1 + e^{\log(4/2)}} = 0.6667$$

Probability of Loving Troll 2 = 0.7

| | | Favorite Color | Loves Troll 2 |
|-----|----|-------------------|------------------|
| Yes | 12 | Blue | Yes |
| Yes | 87 | Green | Yes |
| No | 44 | Blue | No |
| Yes | 19 | Red | No |
| No | 32 | Green | Yes |
| No | 14 | Blue | Yes |

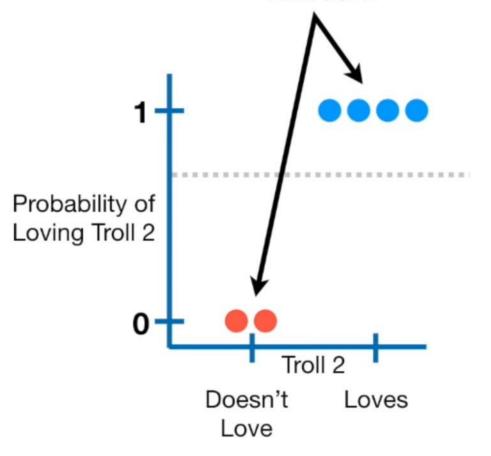
We can measure how bad the initial **Prediction** is by calculating **Pseudo Residuals**, the difference between the **Observed** and the **Predicted** values.

Residual = (Observed - Predicted)

Probability of Loving Troll 2 = 0.7

| Yes | 12 | Blue | Yes |
|-----|----|-------|-----|
| Yes | 87 | Green | Yes |
| No | 44 | Blue | No |
| Yes | 19 | Red | No |
| No | 32 | Green | Yes |
| No | 14 | Blue | Yes |

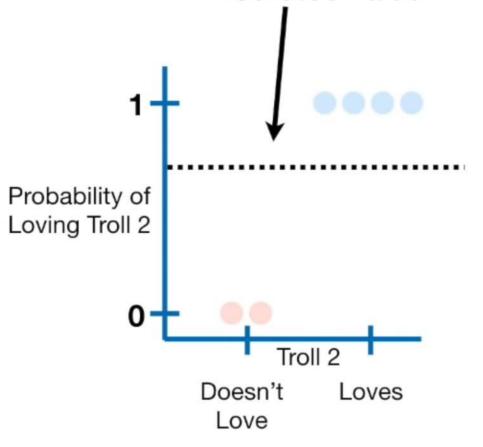
In other words, the **Red** and **Blue** dots are the **Observed** values...



Probability of Loving Troll 2 = 0.7

| Yes | 12 | Blue | Yes |
|-----|----|-------|-----|
| Yes | 87 | Green | Yes |
| No | 44 | Blue | No |
| Yes | 19 | Red | No |
| No | 32 | Green | Yes |
| No | 14 | Blue | Yes |

...and the dotted line is the **Predicted** value.

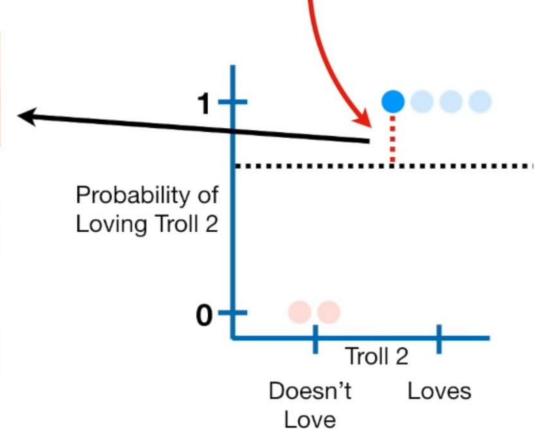


Probability of Loving Troll 2 = 0.7

...and we save the **Residual** in a new column.

Residual = (1 - 0.7) = 0.3

| Likes Popcorn | Age | Favorite Color | Loves Troll 2 | Residual |
|------------------|-----|-------------------|------------------|----------|
| Yes | 12 | Blue | Yes | 0.3 |
| Yes | 87 | Green | Yes | |
| No | 44 | Blue | No | |
| Yes | 19 | Red | No | |
| No | 32 | Green | Yes | |
| No | 14 | Blue | Yes | |

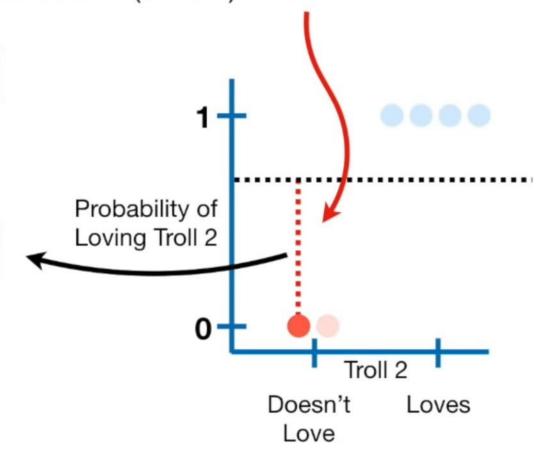


Probability of Loving Troll 2 = 0.7

Then we calculate the rest of the **Residuals**...

Residual = (0 - 0.7) = -0.7

| Likes Popcorn | Age | Favorite Color | Loves Troll 2 | Residual |
|------------------|-----|-------------------|------------------|----------|
| Yes | 12 | Blue | Yes | 0.3 |
| Yes | 87 | Green | Yes | 0.3 |
| No | 44 | Blue | No | -0.7 |
| Yes | 19 | Red | No | |
| No | 32 | Green | Yes | |
| No | 14 | Blue | Yes | |



Probability of Loving Troll 2 = 0.7

| Likes Popcorn | Age | Favorite Color | Loves Troll 2 | Residual |
|------------------|-----|-------------------|------------------|----------|
| Yes | 12 | Blue | Yes | 0.3 |
| Yes | 87 | Green | Yes | 0.3 |
| No | 44 | Blue | No | -0.7 |
| Yes | 19 | Red | No | -0.7 |
| No | 32 | Green | Yes | 0.3 |
| No | 14 | Blue | Yes | 0.3 |

Hooray! We've calculated the **Residuals** for the leaf's initial **Prediction**.

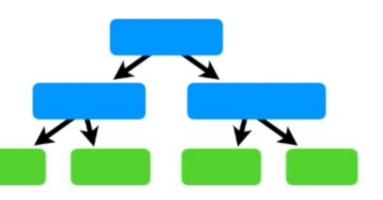
Now we will build a **Tree**, using **Likes Popcorn**, **Age** and **Favorite Color**...





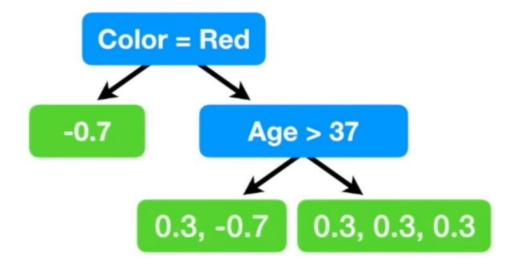






...to **Predict** the **Residuals**.

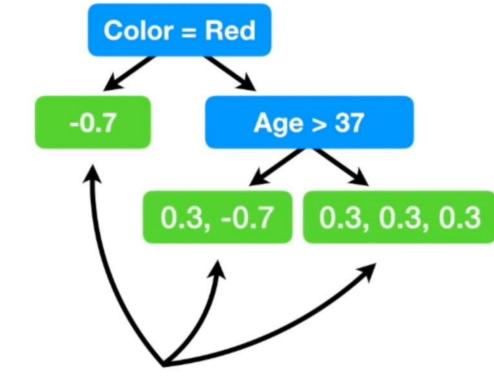
| Likes Popcorn | Age | Favorite Color | Loves Troll 2 | Residual |
|------------------|-----|-------------------|------------------|----------|
| Yes | 12 | Blue | Yes | 0.3 |
| Yes | 87 | Green | Yes | 0.3 |
| No | 44 | Blue | No | -0.7 |
| Yes | 19 | Red | No | -0.7 |
| No | 32 | Green | Yes | 0.3 |
| No | 14 | Blue | Yes | 0.3 |



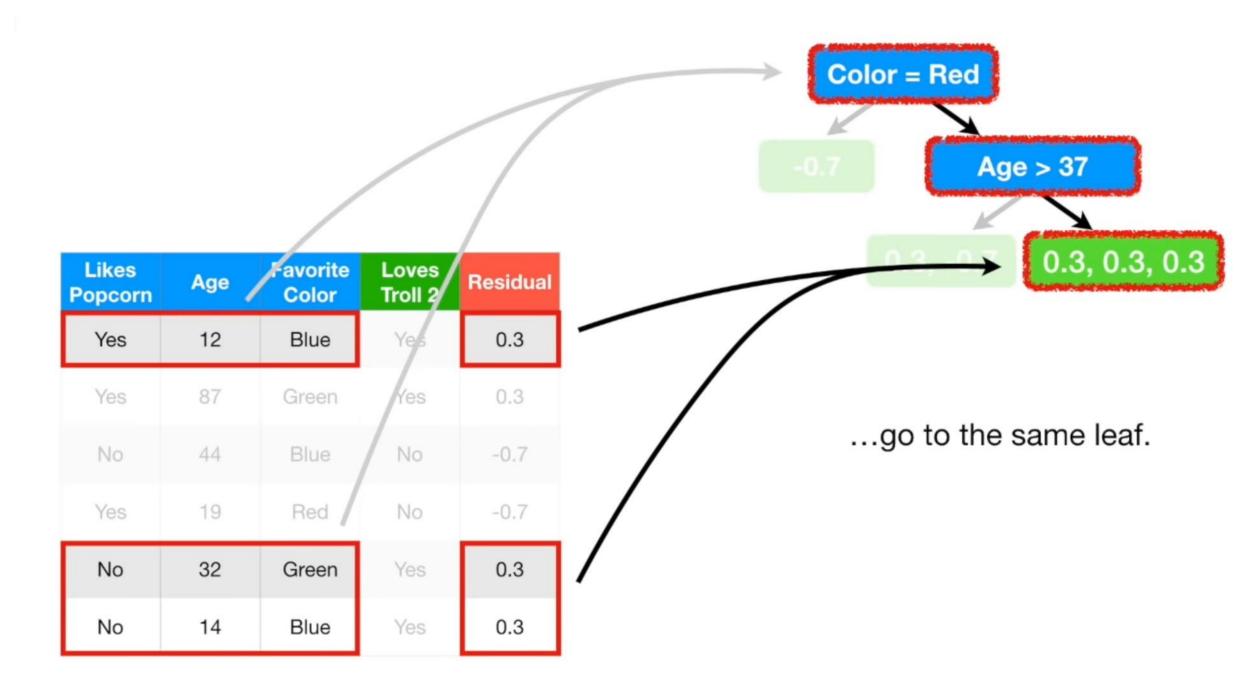
In this simple example, we are limiting the number of leaves to **3**.

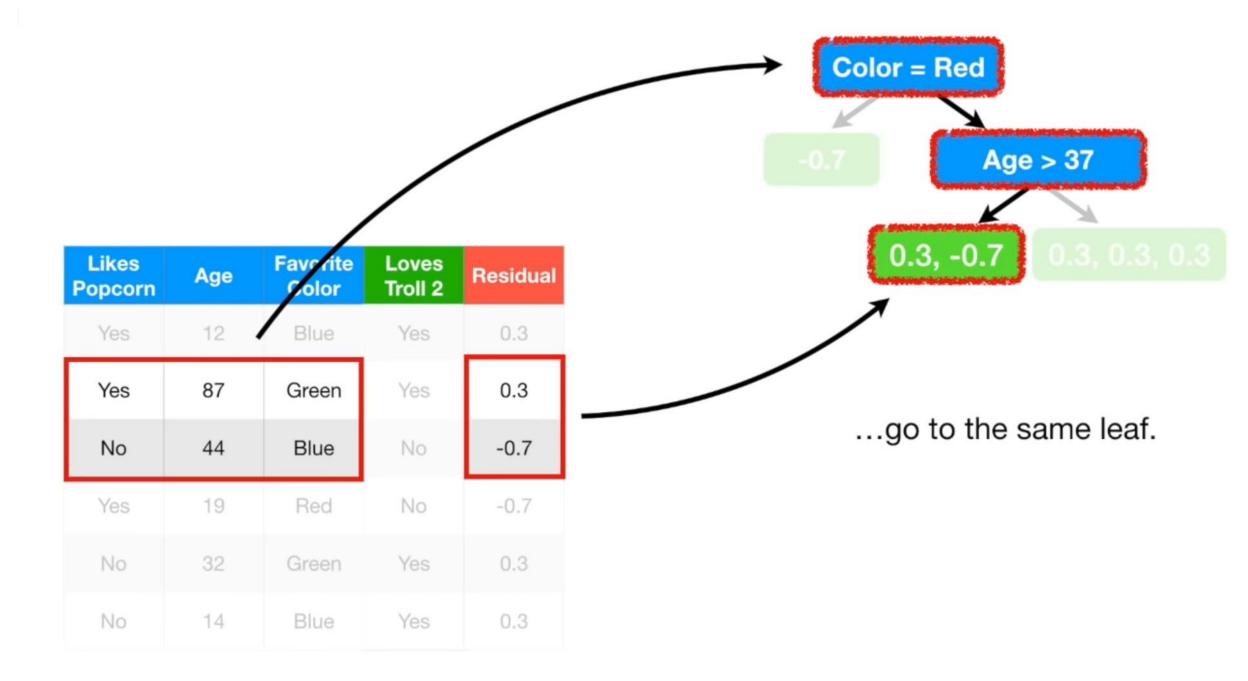
In practice people often set the maximum number of leaves to be between 8 and 32

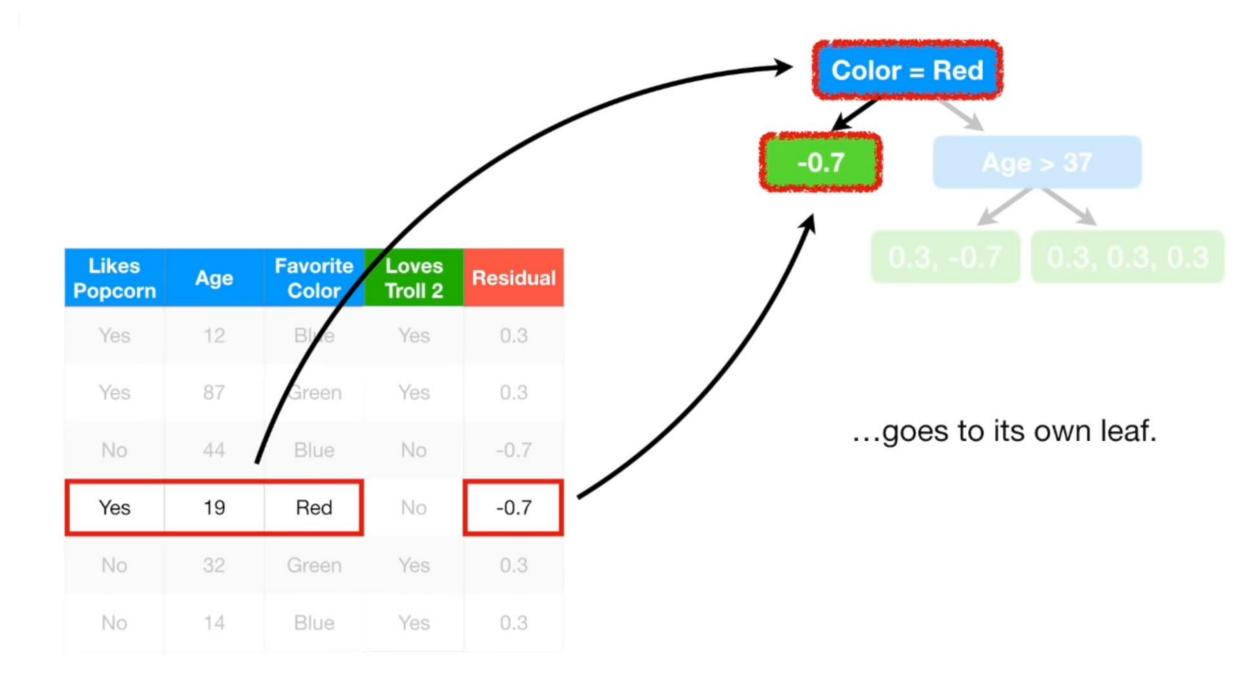
| Yes | 12 | Blue | 0.3 |
|-----|----|-------|------|
| Yes | 87 | Green | 0.3 |
| No | 44 | Blue | -0.7 |
| Yes | 19 | Red | -0.7 |
| No | 32 | Green | 0.3 |
| No | 14 | Blue | 0.3 |



Now let's calculate the **Output Values** for the leaves.







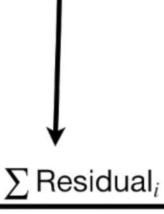


together to get a new

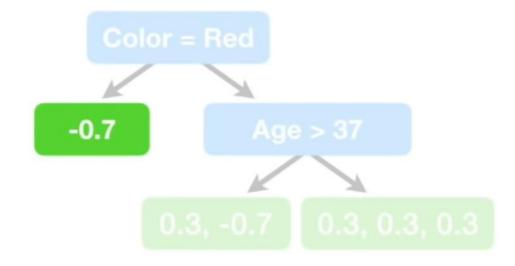
log(odds) Prediction without

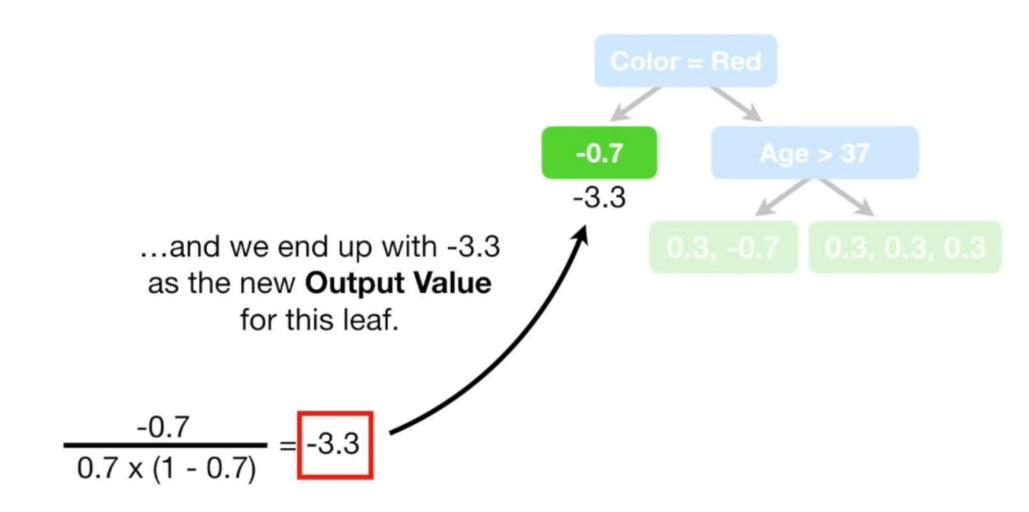
some sort of transformation.

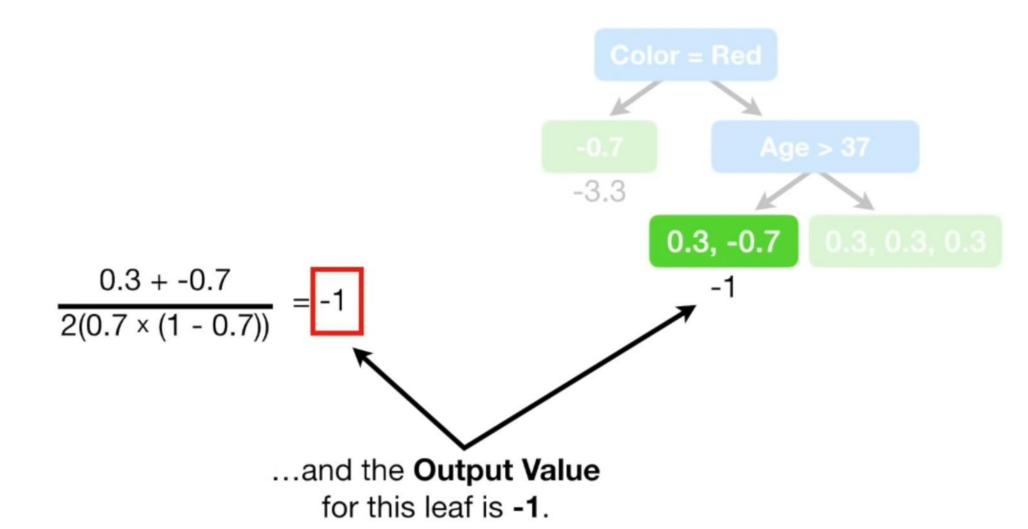
When we use **Gradient Boost** for **Classification**, the most common transformation is the following formula.

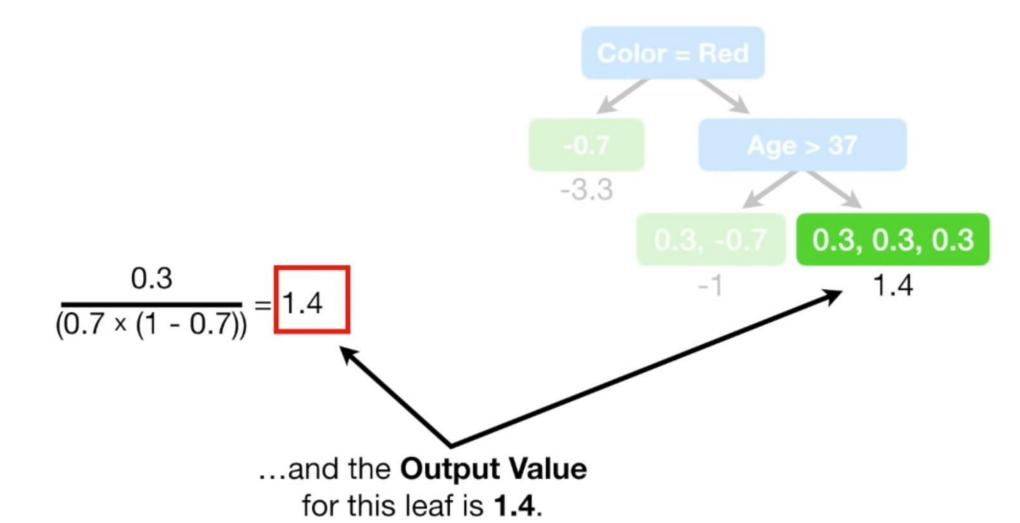


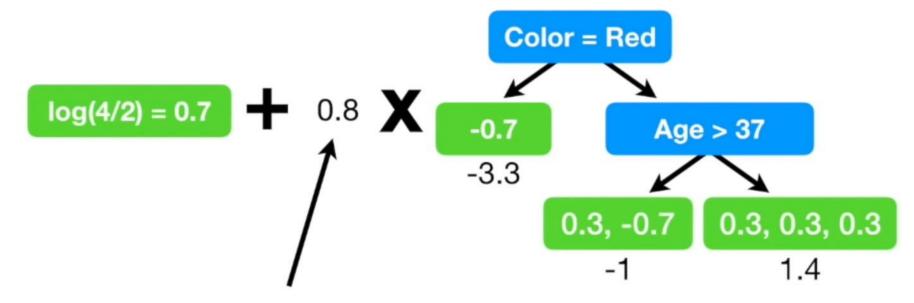
 \sum [Previous Probability_i × (1 – Previous Probability_i)]











NOTE: Just like before, the new tree is scaled by a Learning Rate.

This example uses a relatively large **Learning Rate** for illustrative purposes. However, **0.1** is more common.



| Likes Popcorn | Age | Favorite Color | Loves Troll 2 |
|------------------|-----|-------------------|------------------|
| Yes | 12 | Blue | Yes |
| Yes | 87 | Green | Yes |
| No | 44 | Blue | No |
| Yes | 19 | Red | No |
| No | 32 | Green | Yes |
| No | 14 | Blue | Yes |

...and the new log(odds)

Prediction = 1.8.

log(odds) Prediction =
$$0.7 + (0.8 \times 1.4) = 1.8$$

| Likes Popcorn | Age | Favorite Color | Loves Troll 2 |
|------------------|-----|-------------------|------------------|
| Yes | 12 | Blue | Yes |
| Yes | 87 | Green | Yes |
| No | 44 | Blue | No |
| Yes | 19 | Red | No |
| No | 32 | Green | Yes |
| No | 14 | Blue | Yes |

Now we convert the new log(odds) Prediction into a Probability...

Probability =
$$\frac{e^{\log(\text{odds})}}{1 + e^{\log(\text{odds})}}$$

 $\log(\text{odds})$ Prediction = 0.7 + (0.8 × 1.4) = 1.8

| Likes Popcorn | Age | Favorite Color | Loves Troll 2 | Predicted Prob. |
|------------------|-----|-------------------|------------------|--------------------|
| Yes | 12 | Blue | Yes | 0.9 |
| Yes | 87 | Green | Yes | |
| No | 44 | Blue | No | |
| Yes | 19 | Red | No | |
| No | 32 | Green | Yes | |
| No | 14 | Blue | Yes | |

We save the new **Predicted Probability** here.

Probability =
$$\frac{e^{1.8}}{1 + e^{1.8}} = 0.9$$

 $log(odds) Prediction = 0.7 + (0.8 \times 1.4) = 1.8$



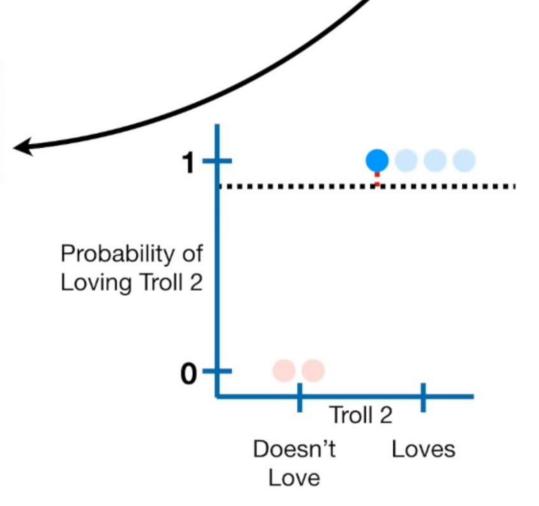
| Likes Popcorn | Age | Favorite Color | Loves Troll 2 | Predicted Prob. |
|------------------|-----|-------------------|------------------|-----------------|
| Yes | 12 | Blue | Yes | 0.9 |
| Yes | 87 | Green | Yes | 0.5 |
| No | 44 | Blue | No | 0.5 |
| Yes | 19 | Red | No | 0.1 |
| No | 32 | Green | Yes | 0.9 |
| No | 14 | Blue | Yes | 0.9 |

Then we calculate the **Predicted Probabilities** for the remaining people.

And we save that value here.

Residual =
$$(1 - 0.9) = 0.1$$

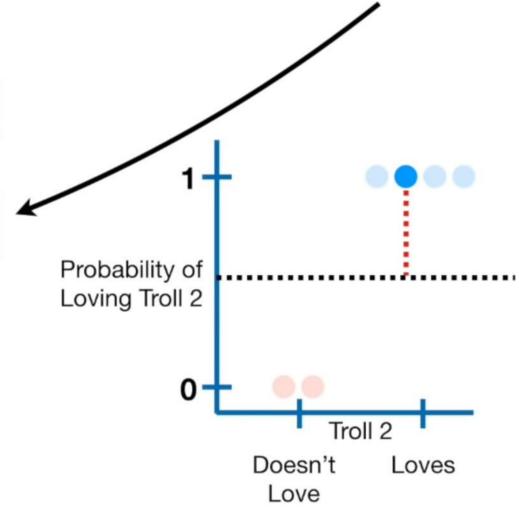
| | | Favorite Color | Loves Troll 2 | Predicted Prob. | Residual |
|-----|----|-------------------|------------------|-----------------|----------|
| Yes | 12 | Blue | Yes | 0.9 | 0.1 |
| Yes | 87 | Green | Yes | 0.5 | |
| No | 44 | Blue | No | 0.5 | |
| Yes | 19 | Red | No | 0.1 | |
| No | 32 | Green | Yes | 0.9 | |
| No | 14 | Blue | Yes | 0.9 | |



And we save that value here.

Residual =
$$(1 - 0.5) = 0.5$$

| | | Favorite Color | Loves Troll 2 | Predicted Prob. | Residual |
|-----|----|-------------------|------------------|-----------------|----------|
| Yes | 12 | Blue | Yes | 0.9 | 0.1 |
| Yes | 87 | Green | Yes | 0.5 | 0.5 |
| No | 44 | Blue | No | 0.5 | |
| Yes | 19 | Red | No | 0.1 | |
| No | 32 | Green | Yes | 0.9 | |
| No | 14 | Blue | Yes | 0.9 | |

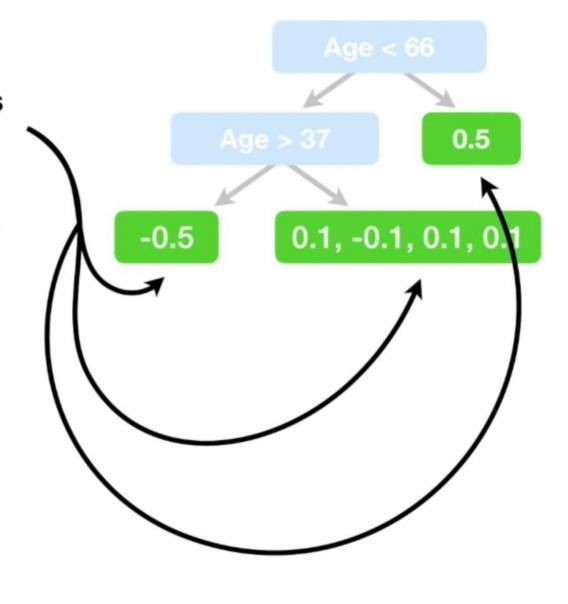




| Likes Popcorn | Age | Favorite Color | Loves Troll 2 | | Residual |
|------------------|-----|-------------------|------------------|-----|----------|
| Yes | 12 | Blue | Yes | 0.9 | 0.1 |
| Yes | 87 | Green | Yes | 0.5 | 0.5 |
| No | 44 | Blue | No | 0.5 | -0.5 |
| Yes | 19 | Red | No | 0.1 | -0.1 |
| No | 32 | Green | Yes | 0.9 | 0.1 |
| No | 14 | Blue | Yes | 0.9 | 0.1 |

...and then we need to calculate the **Output Values** for each leaf.

| Yes | 12 | Blue | Yes | 0.9 | 0.1 |
|-----|----|-------|-----|-----|------|
| Yes | 87 | Green | Yes | 0.5 | 0.5 |
| No | 44 | Blue | No | 0.5 | -0.5 |
| Yes | 19 | Red | No | 0.1 | -0.1 |
| No | 32 | Green | Yes | 0.9 | 0.1 |
| No | 14 | Blue | Yes | 0.9 | 0.1 |





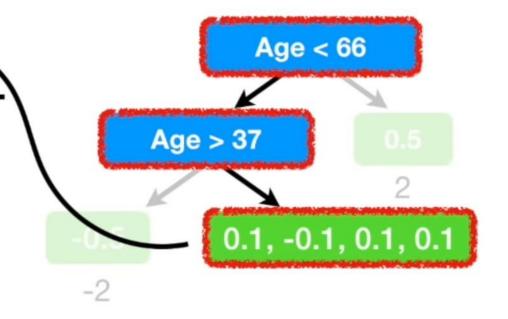
0.1 Yes 12 0.9 Blue Yes Yes 87 Yes 0.5 0.5 Green No 44 No 0.5 -0.5 Blue Yes 19 Red No 0.1 -0.10.9 0.1 No 32 Yes Green 0.9 0.1 No 14 Blue Yes

...and the Output Value for this leaf is 2.



 \sum Previous Probability, $\times (1 - \text{Previous Probability}_i)$

| Likes Popcorn | Age | Favorite Color | Loves Troll 2 | Predicted Prob. | Residual |
|------------------|-----|-------------------|------------------|--------------------|----------|
| Yes | 12 | Blue | Yes | 0.9 | 0.1 |
| Yes | 87 | Green | Yes | 0.5 | 0.5 |
| No | 44 | Blue | No | 0.5 | -0.5 |
| Yes | 19 | Red | No | 0.1 | -0.1 |
| No | 32 | Green | Yes | 0.9 | 0.1 |
| No | 14 | Blue | Yes | 0.9 | 0.1 |

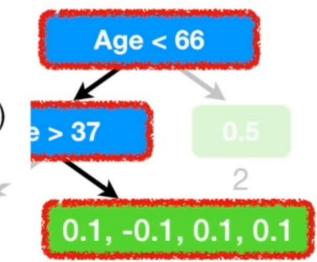


So we plug the **Residuals** into the formula for the **Output Values**...

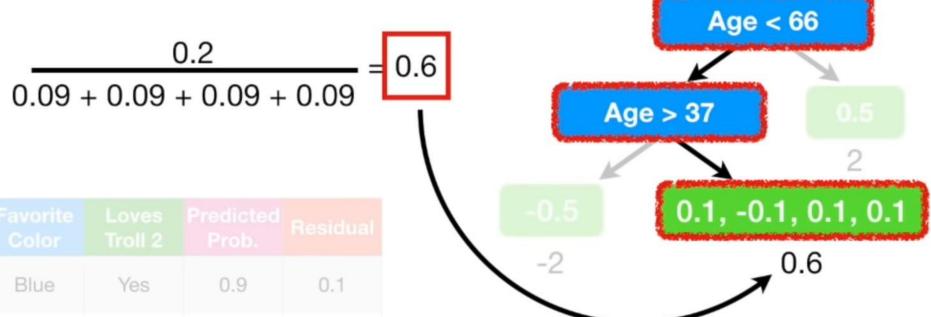
$$0.1 + -0.1 + 0.1 + 0.1$$

$$(0.9 \times (1 - 0.9)) + (0.1 \times (1 - 0.1)) + (0.9 \times (1 - 0.9)) + (0.9 \times (1 - 0.9))$$

| Yes | 12 | Blue | Yes | 0.9 | 0.1 |
|-----|----|-------|-----|-----|--------------|
| Yes | 87 | Green | Yes | 0.5 | 0.5 |
| No | 44 | Blue | No | 0.5 | /5/ |
| Yes | 19 | Red | No | 0.1 | / 6.1 |
| No | 32 | Green | Yes | 0.9 | 0.1 |
| No | 14 | Blue | Yes | 0.9 | 0.1 |



...and we plug in the **Predicted Probability** for each individual in the leaf...



Yes 12 Yes 87 Yes 0.5 0.5 Green No 44 No 0.5 -0.5 Blue Yes 19 Red No 0.1 -0.1 0.1 No 32 Yes 0.9 Green

Yes

0.9

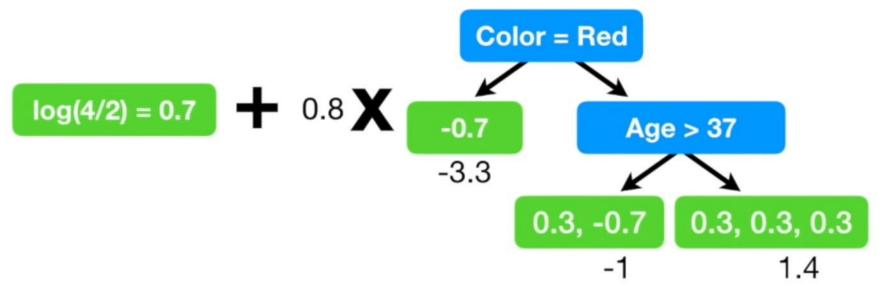
0.1

Blue

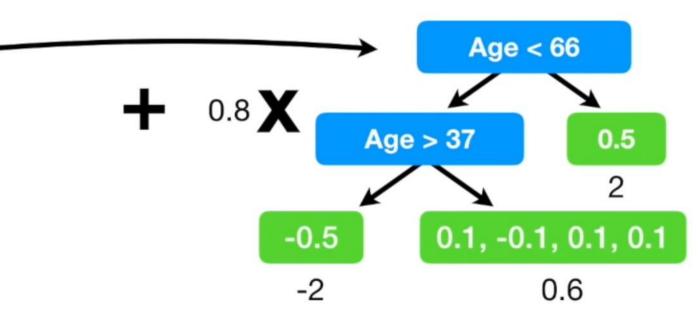
No

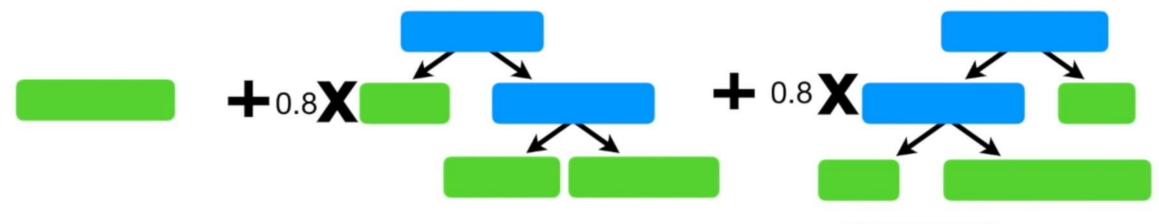
14

...and the **Output Value** for this leaf is **0.6**.

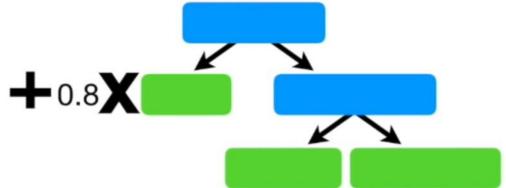


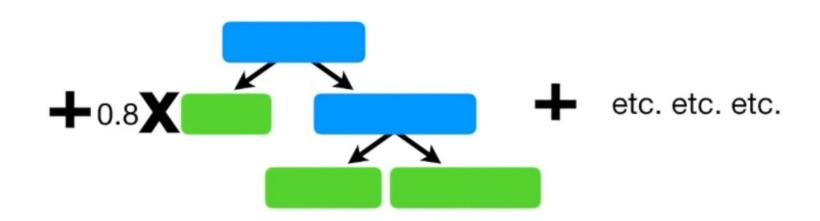
Then we built another tree based on the new Residuals, the difference between the Observed values and the values Predicted by the leaf and the first tree...

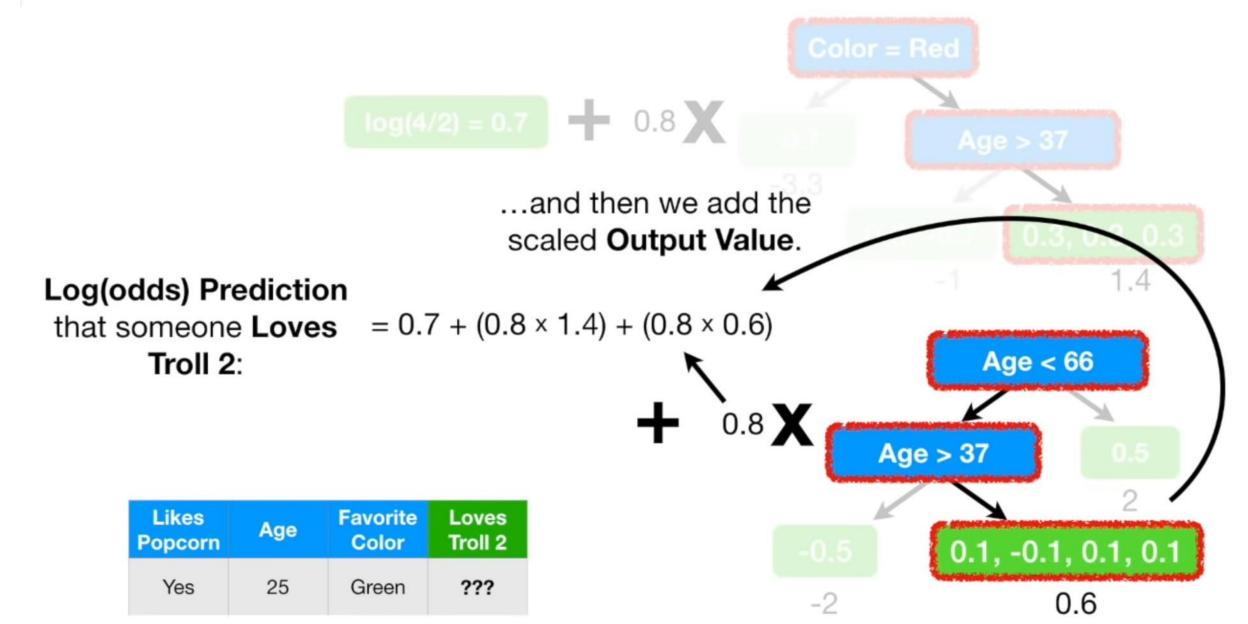


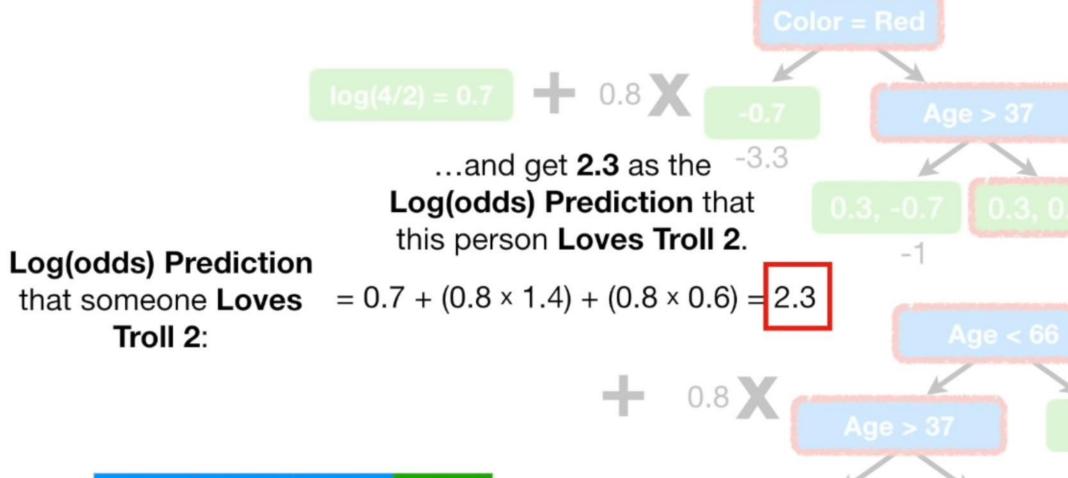


This process repeats until we have made the maximum number of trees specified, or the residuals get super small.









| Likes opcorn | Age | Favorite Color | Loves Troll 2 |
|-----------------|-----|-------------------|------------------|
| Yes | 25 | Green | ??? |

| ^ [| | | | |
|-----|---|---|----|---|
| | K | 1 | | 2 |
| | | | | |
| -2 | | | 0. | 6 |

Now we need to convert this **Log(odds)** into a **Probability**.



Log(odds) Prediction

| Likes | Age | Favorite | Loves |
|---------|-----|----------|---------|
| Popcorn | | Color | Troll 2 |
| Yes | 25 | Green | ??? |

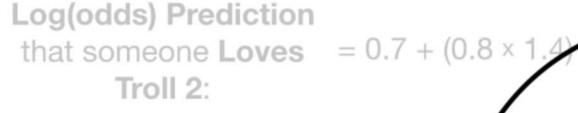
...and the **Predicted Probability** that this individual will **Love Troll 2** is **0.9**.

Log(odds) Prediction that someone **Loves**
$$= 0.7 + (0.8 \times 1.4) + (0.8 \times 0.6) = 2.3$$
 Troll 2:

Probability =
$$\frac{e^{2.3}}{1 + e^{2.3}} = 0.9$$

| Likes | Age | Favorite | Loves |
|---------|-----|----------|---------|
| Popcorn | | Color | Troll 2 |
| Yes | 25 | Green | ??? |

...we will **Classify** this person as someone who **Loves Troll 2**.



$$= 0.7 + (0.8 \times 1.4) + (0.8 \times 0.6) = 2.3$$

| Probability = | e ^{2.3} | = 0.9 |
|----------------|------------------|-------|
| 1 Tobability = | $1 + e^{2.3}$ | - 0.5 |