

1906003132015

# Doğal Dil İşleme

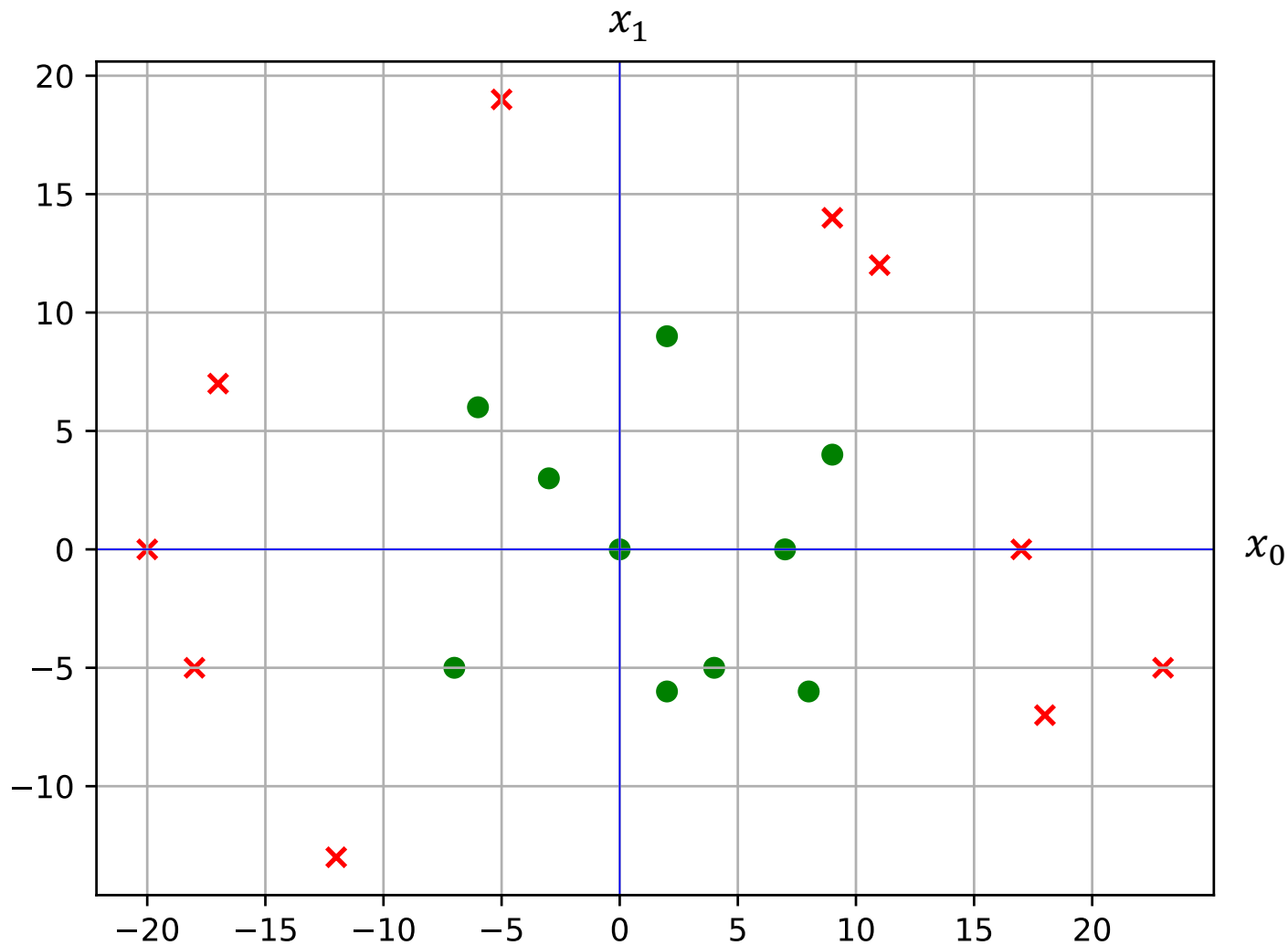
BAİBÜ Bilgisayar Müh.

Dr. Öğr. Üyesi İsmail Hakkı Parlak

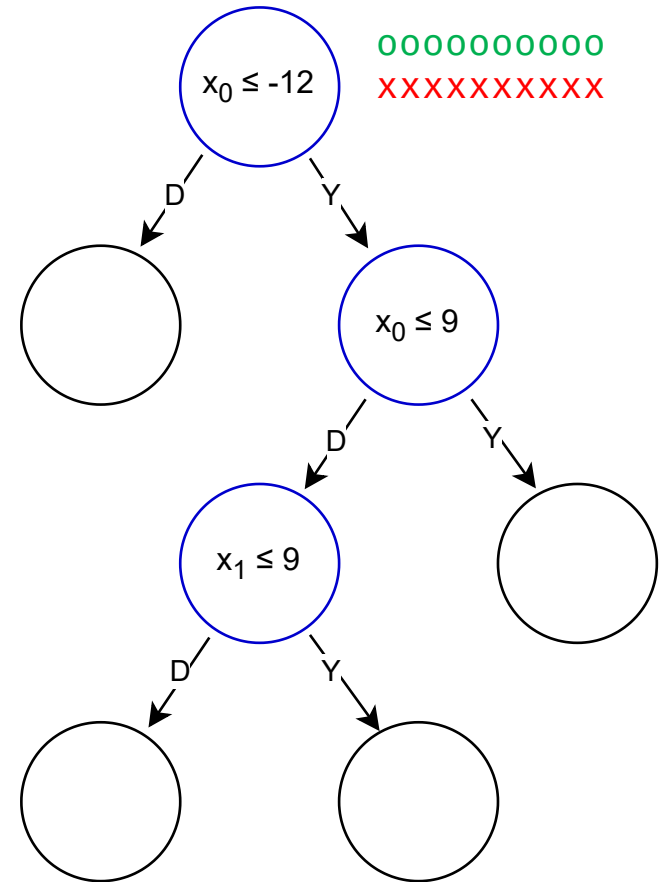
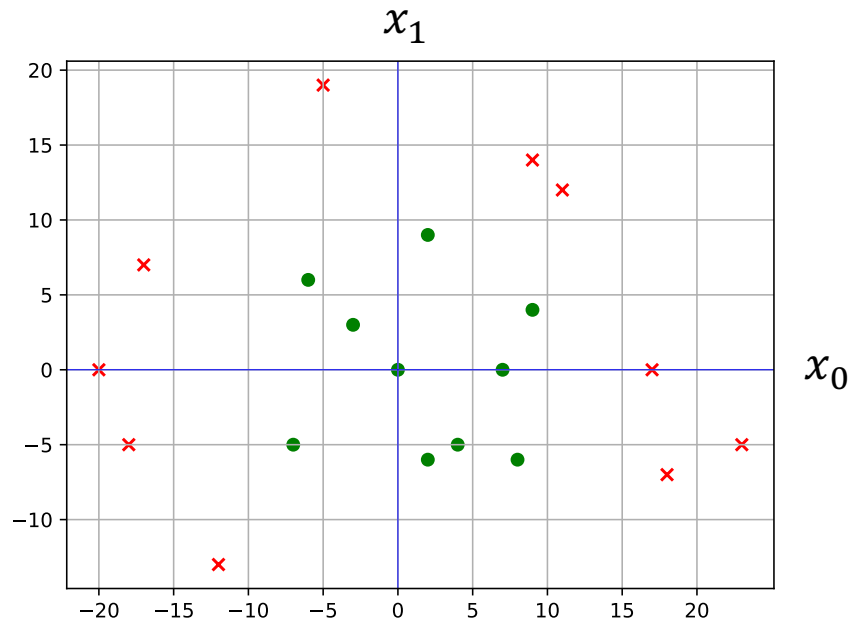
[ismail.parlak@ibu.edu.tr](mailto:ismail.parlak@ibu.edu.tr)

Oda: 335

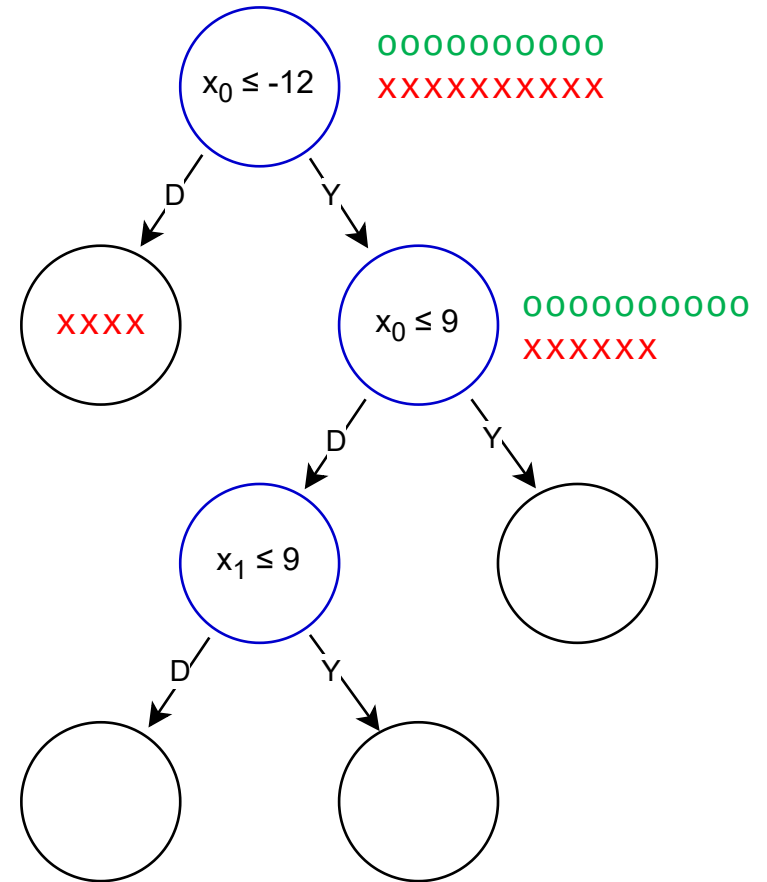
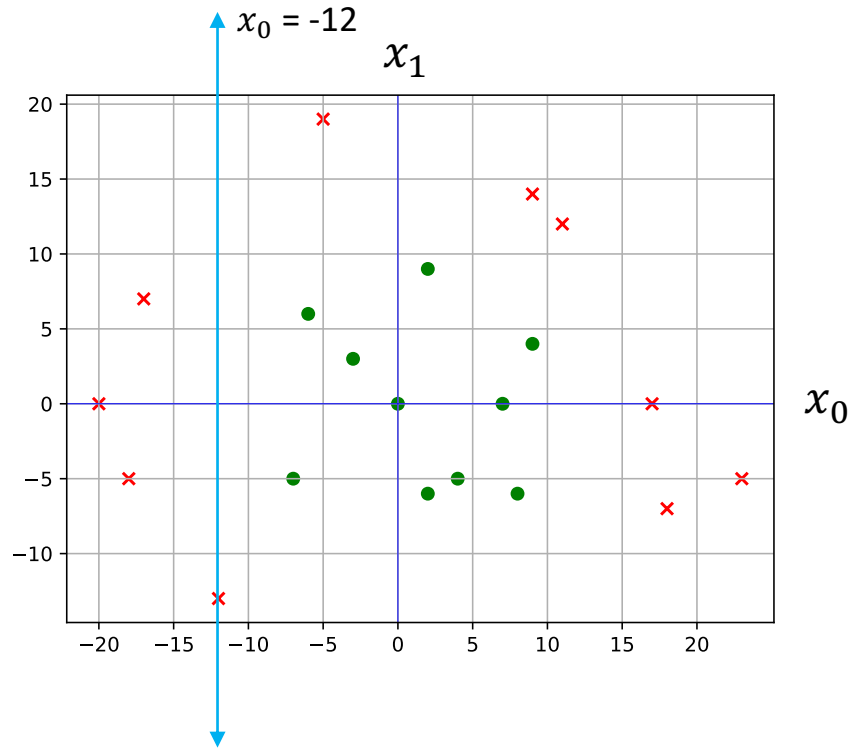
# Karar Ağacı (Decision Tree)



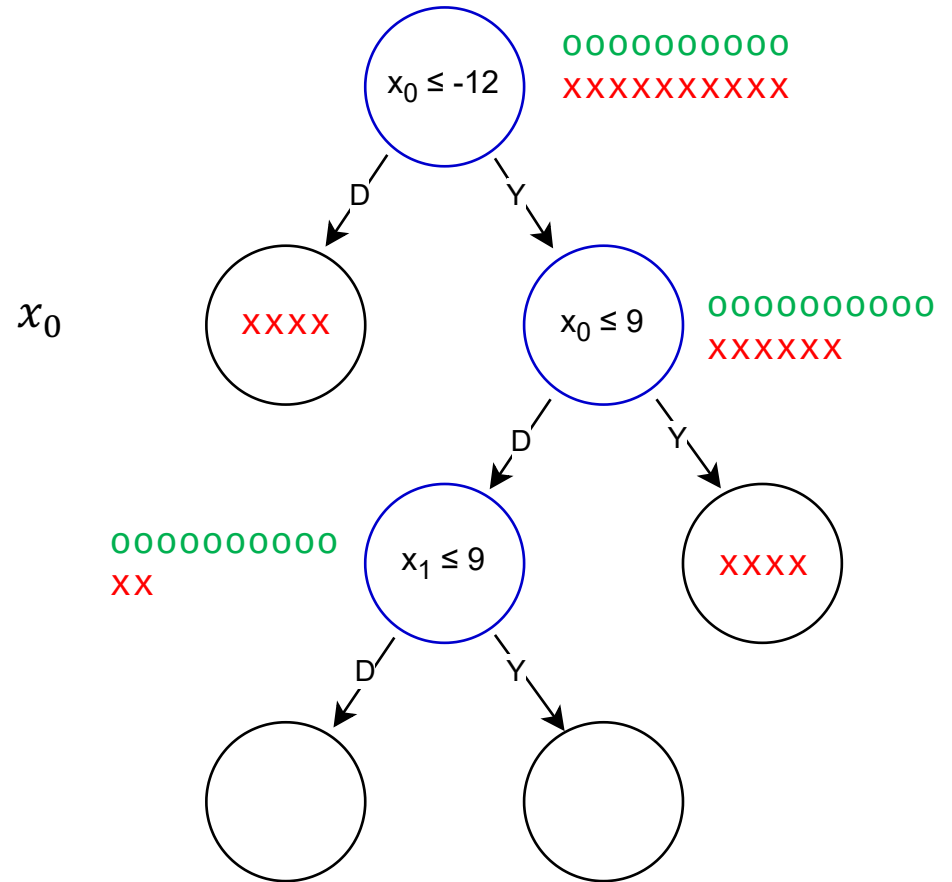
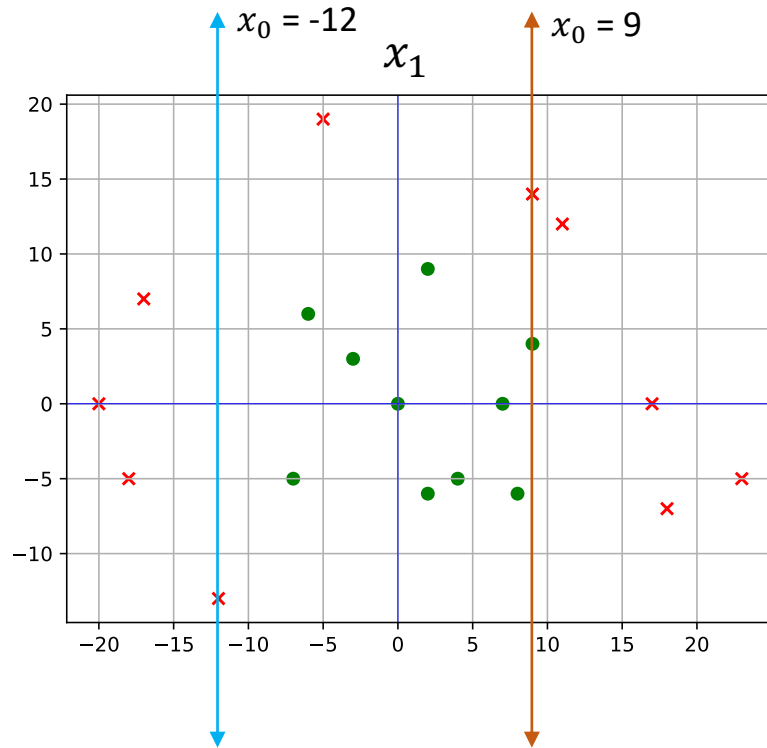
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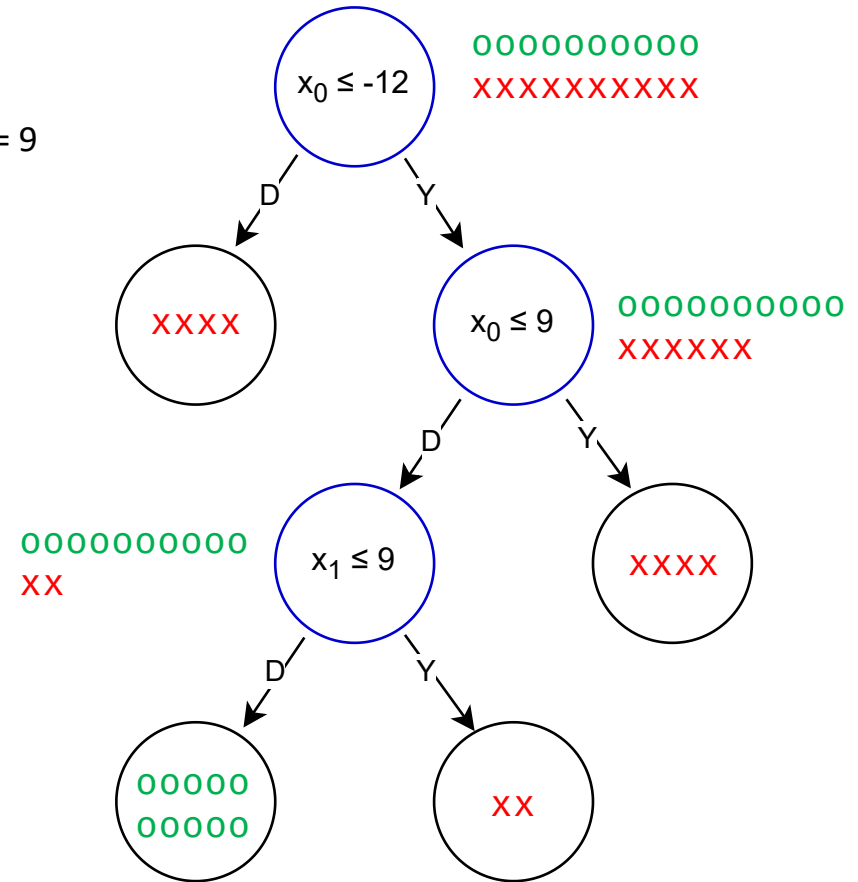
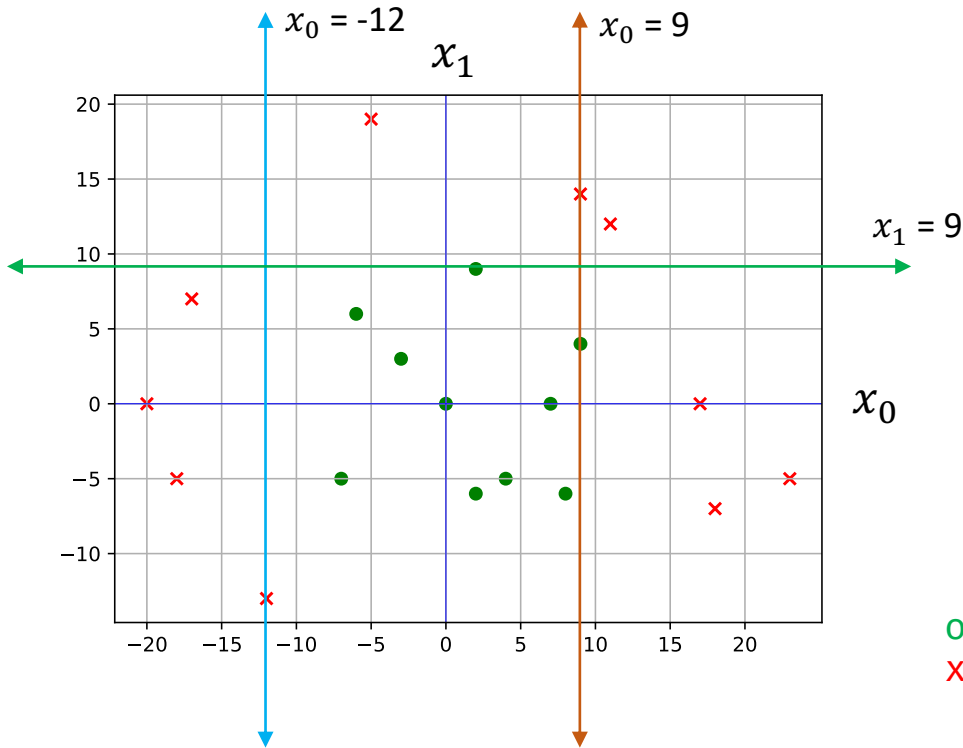
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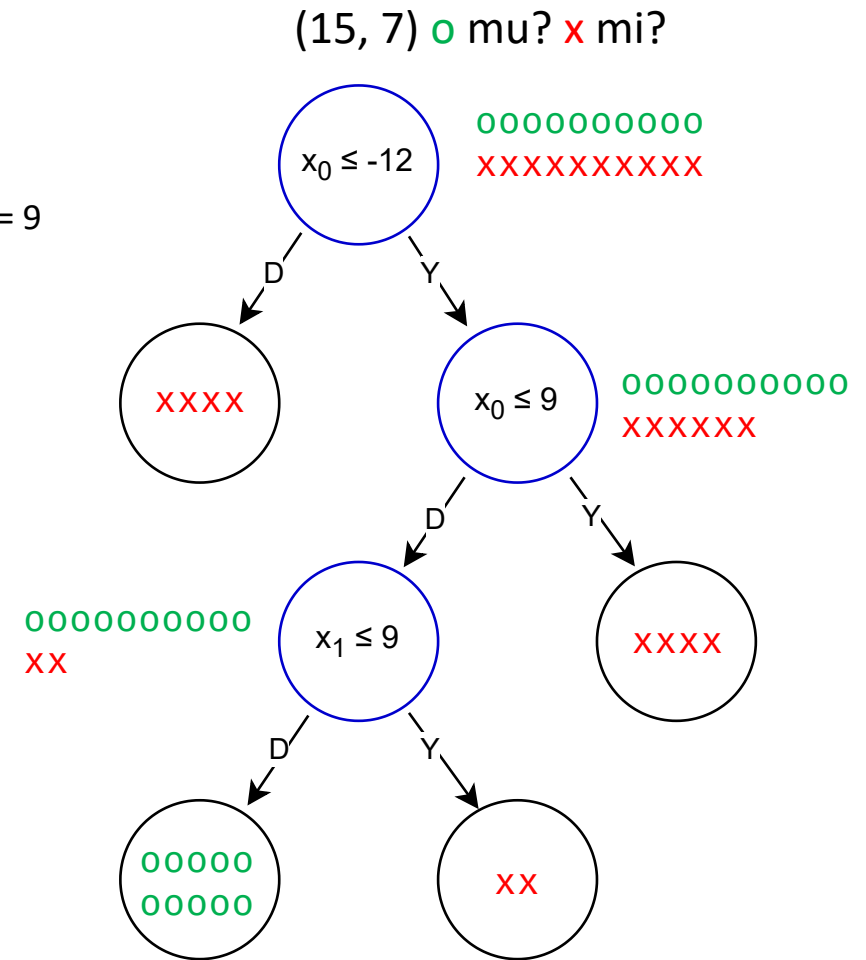
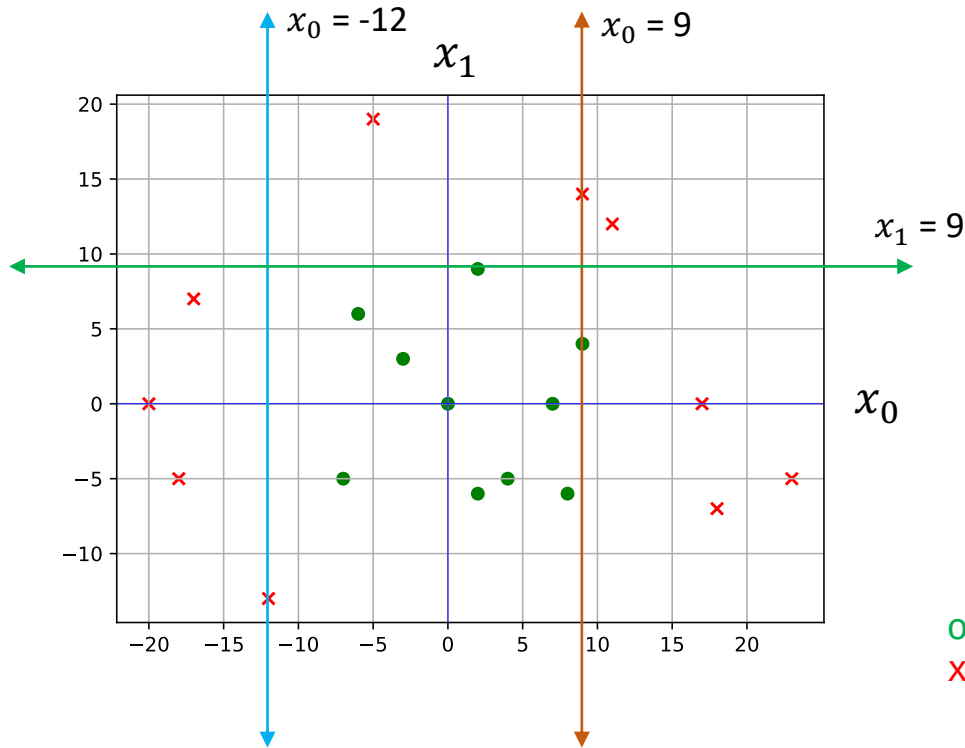


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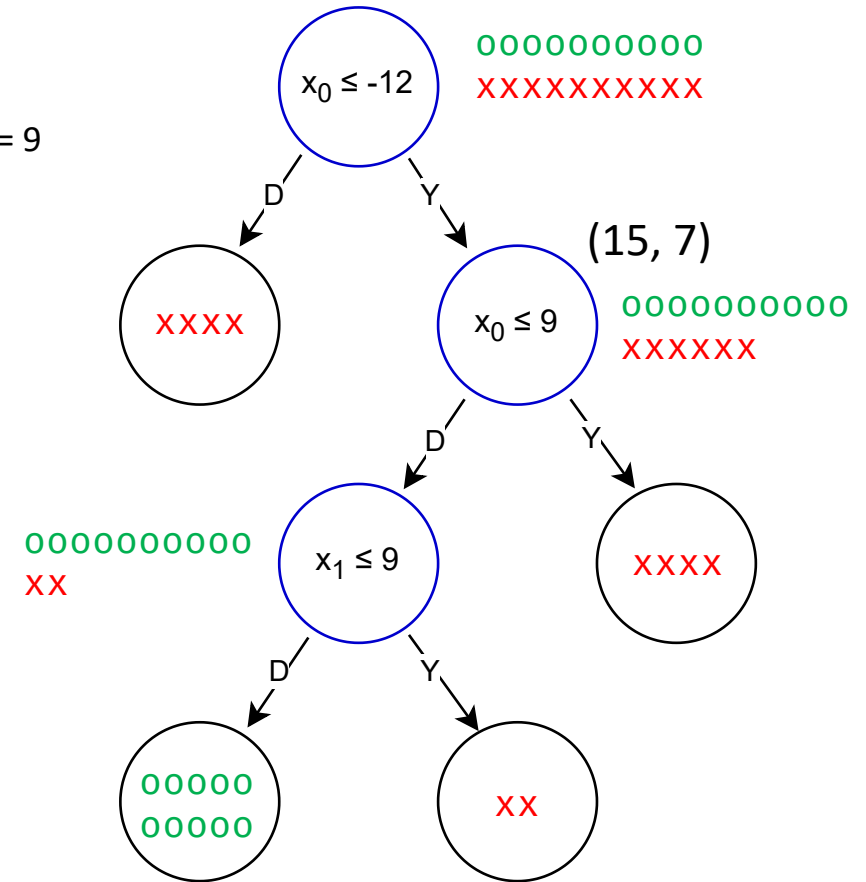
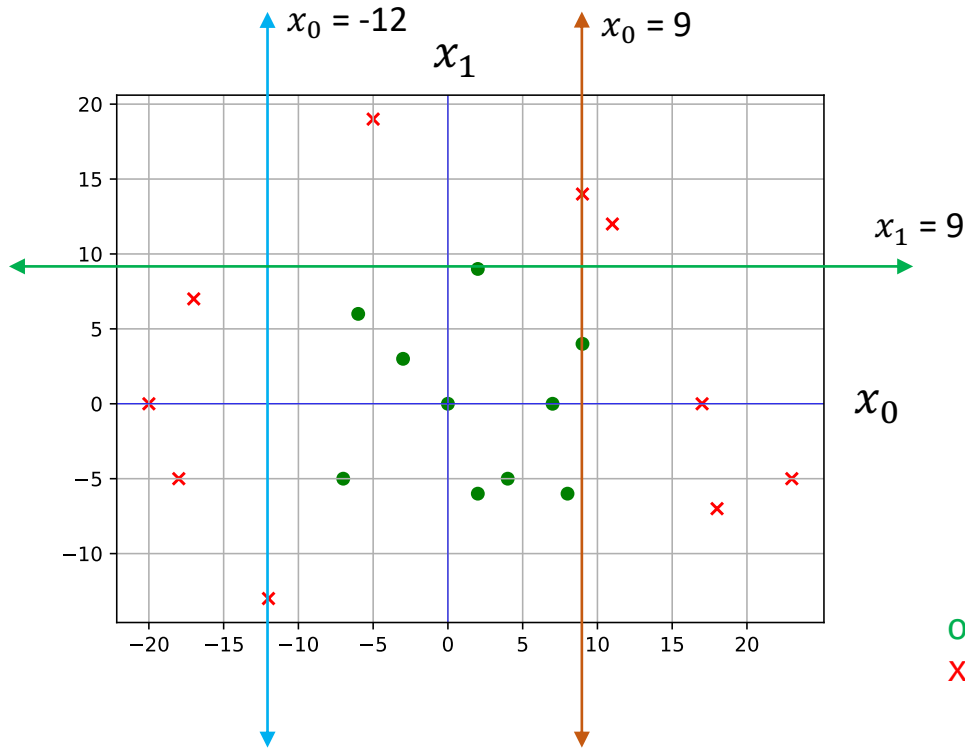


Saf düğümler (pure nodes) elde edilene kadar örnekler ayrıştırılır.

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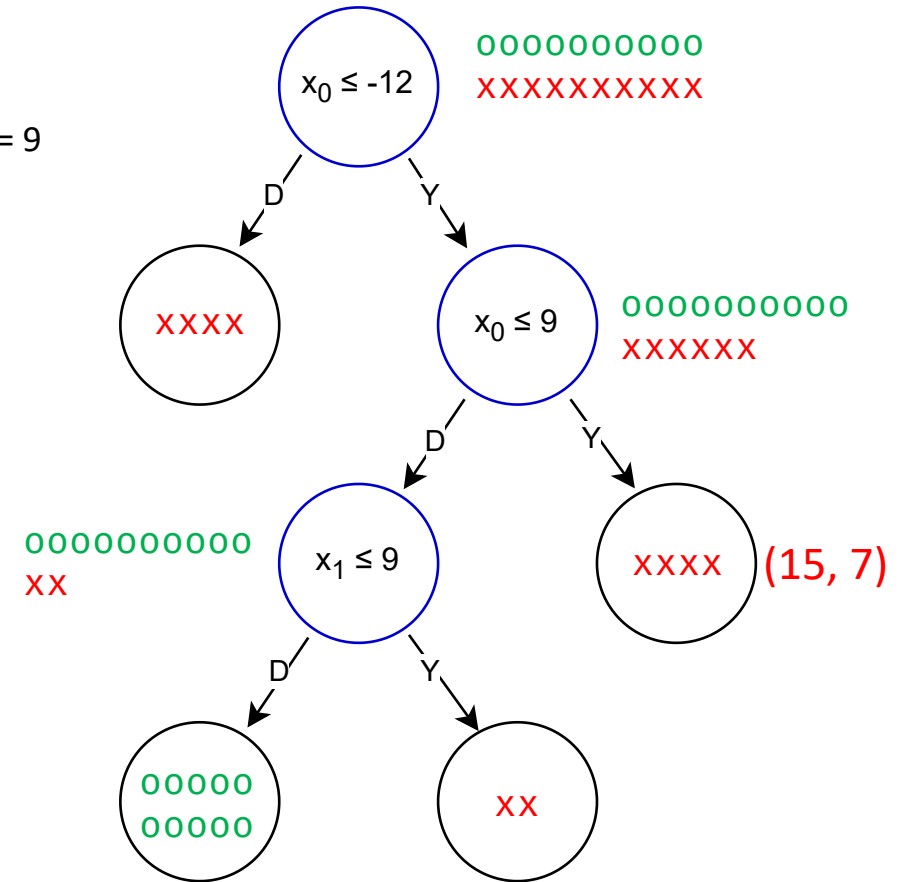
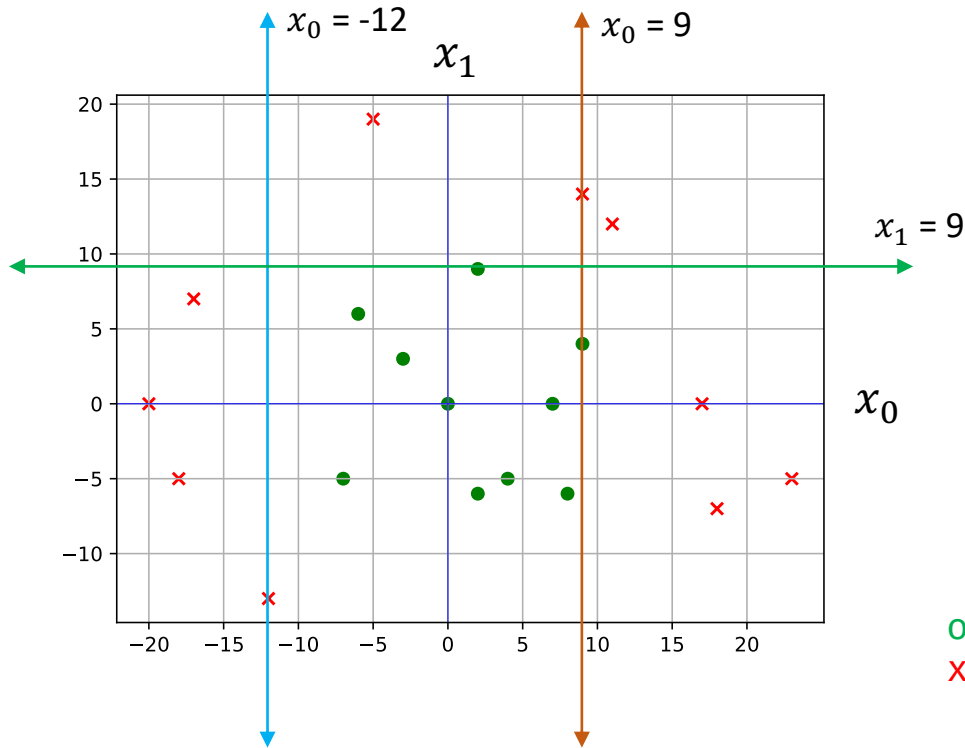


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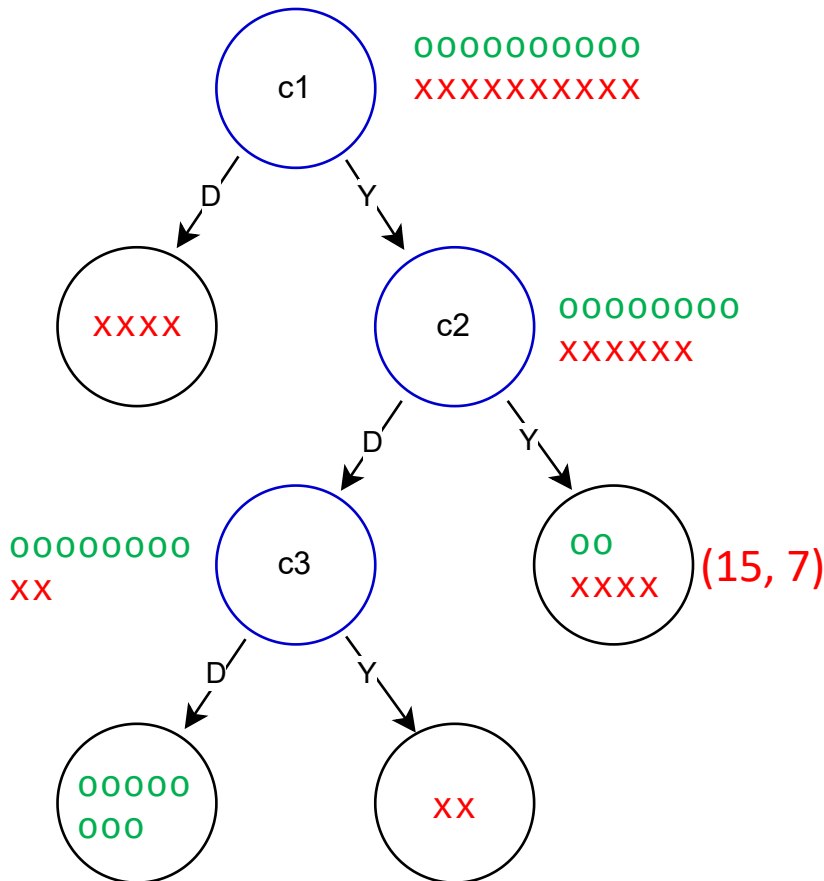


# Karar Ağacı (Decision Tree)



# Karar Ağacı (Decision Tree)

Eğer düğümler saf değilse çoğunluk oylaması yapılır.



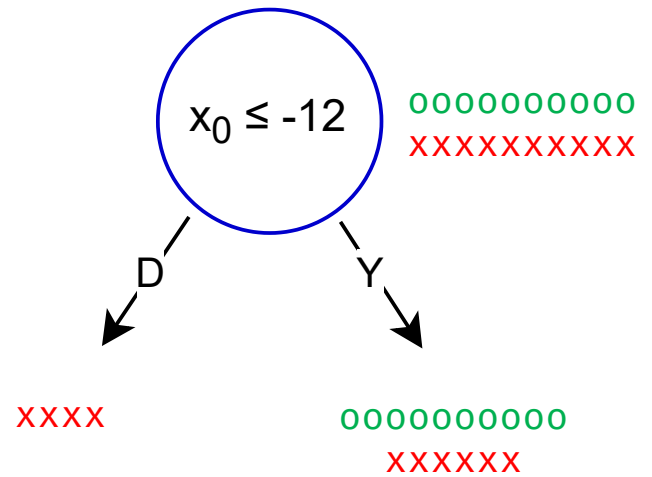
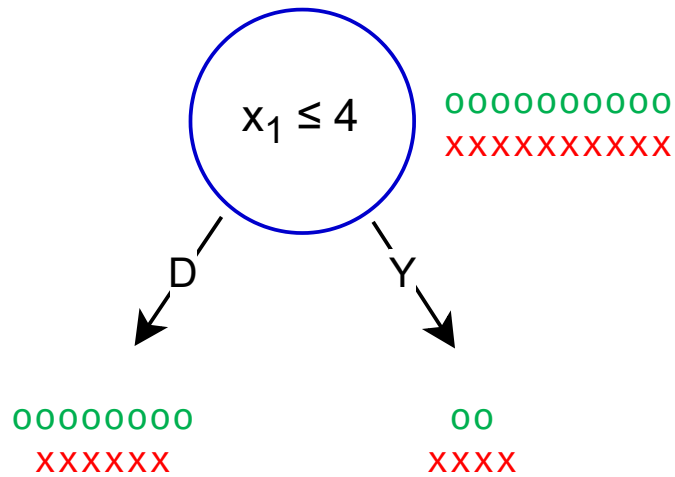
# Karar Ağacı (Decision Tree)

- Bir veri setinde karar ağaçları ile sınıflandırma (classification) yaparken birden çok çözüm olabilir.
- Diğer bir deyişle, sınıfları uygun şekilde birbirinden ayırabilen birbirinden farklı, birden çok karar ağacı bulunabilir.
- Karar ağaçları karar düğümlerinde hangi koşulu kullanması gerektiğini nasıl hesaplar?

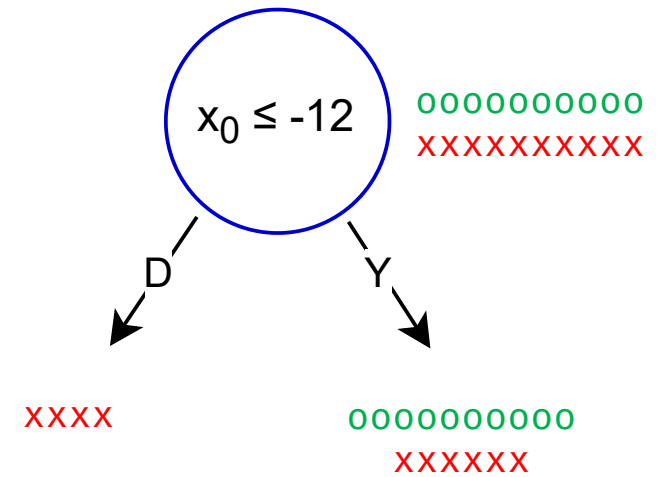
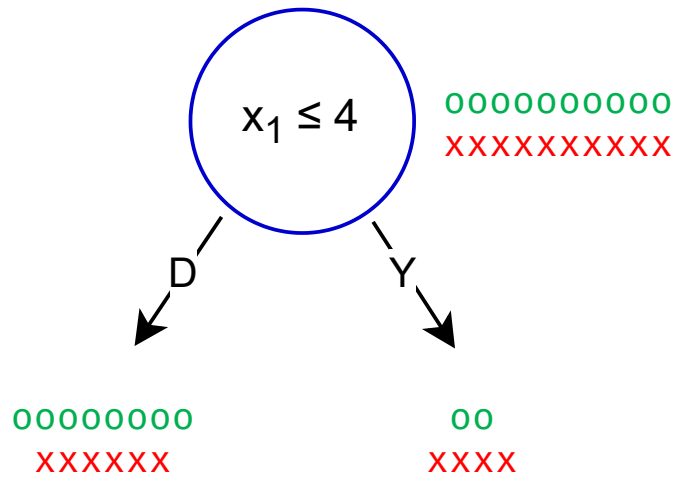
# Karar Ağacı (Decision Tree)

- Karar ağaçları karar düğümlerinde hangi koşulu kullanması gerektiğini nasıl hesaplar?
- Veri setinden rastgele 2 örnek seçilir ve bu örneklerin nitelikleri (features) karar mekanizmalarında kullanılarak bilgi kazanımları (information gain) hesaplanır.
- Bilgi kazanımı yüksek olan karar mekanizması kullanılarak işlem olabildiğince saf düğümler elde edilene kadar tekrarlanır.

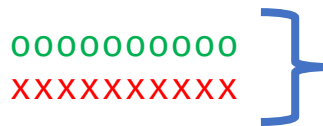
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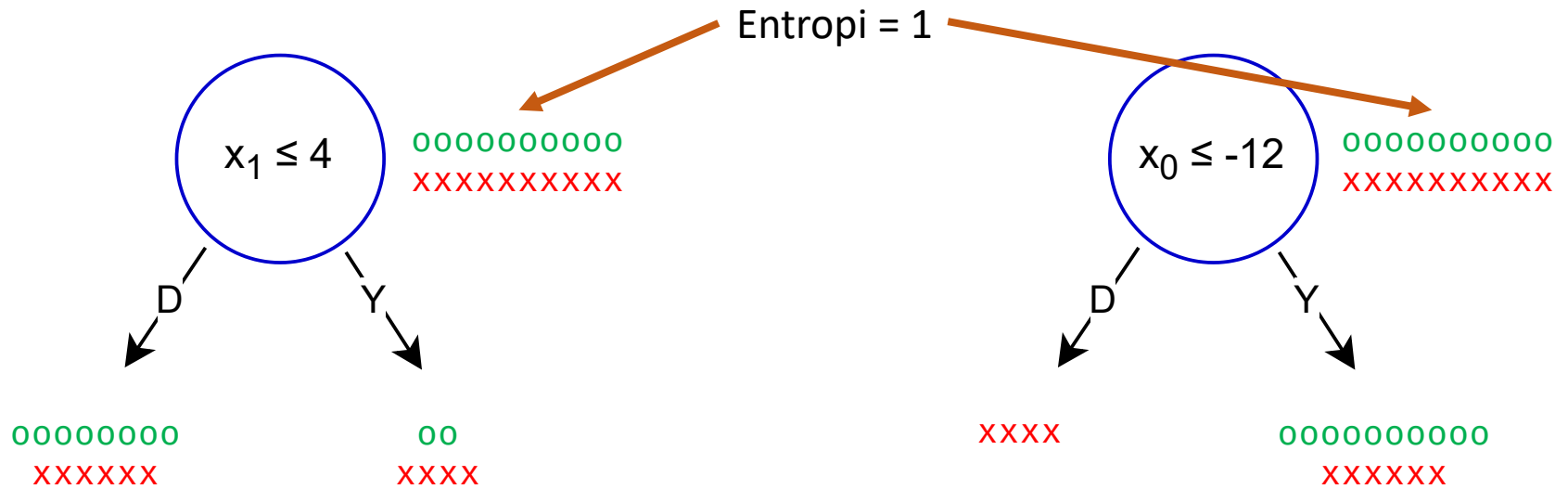
# Karar Ağacı (Decision Tree)



Entropi =  $\sum -p_i \log(p_i)$ ,  $p_i$ : p sınıfının olasılığı

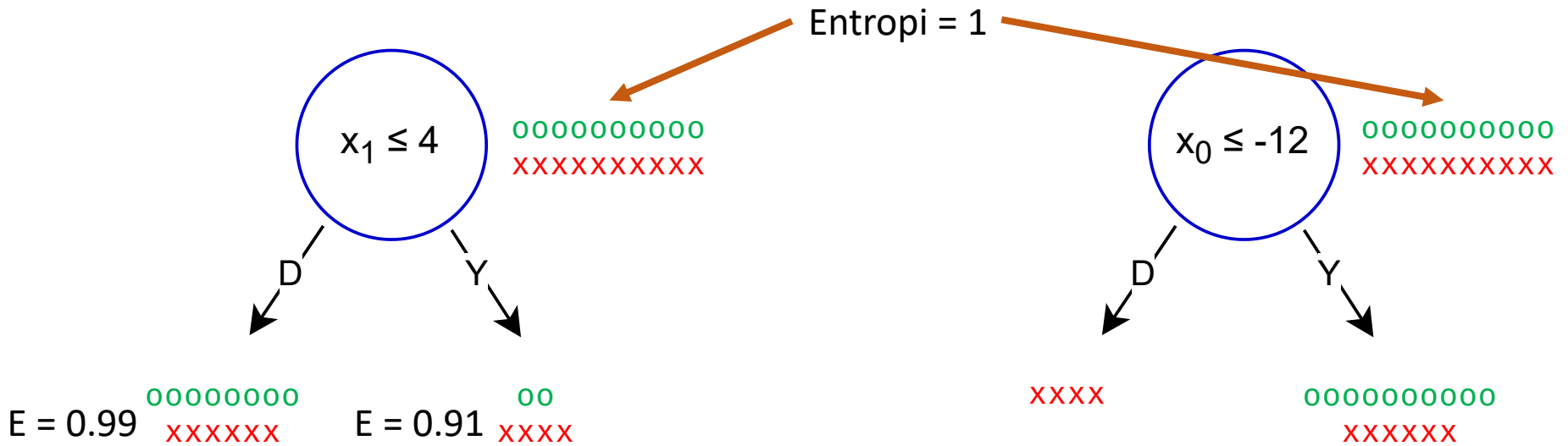
 Entropi (E) =  $(-0.5 \times \log(0.5)) + (-0.5 \times \log(0.5)) = -0.5 \times -1 + -0.5 \times -1 = 1$

# Karar Ağacı (Decision Tree)



$$BK (IG) = E(anne) - \sum w_i E(\text{çocuk}), \quad w_i = \text{çocuğun anneye oranlı büyüklüğü}$$

# Karar Ağacı (Decision Tree)



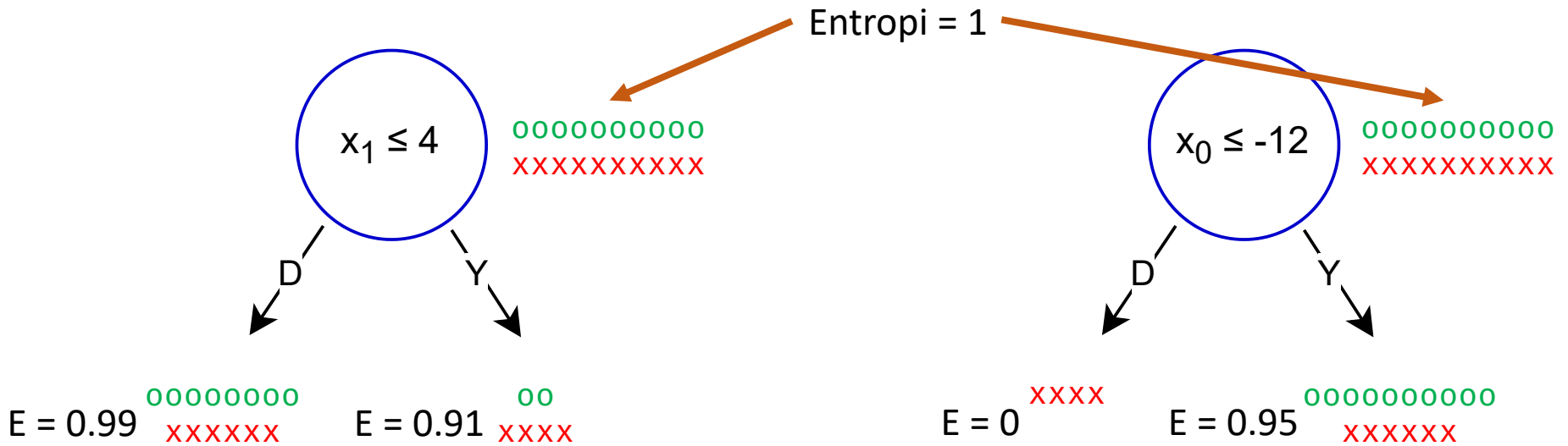
$$BK (IG) = E(anne) - \sum w_i E(\text{çocuk}), w_i = \text{çocuğun anneye oranlı büyüklüğü}$$

$\left. \begin{array}{c} \text{O O O O O O O O} \\ \text{X X X X X X} \end{array} \right\} \text{Entropi} = \frac{-8}{14} \log \left( \frac{8}{14} \right) + \frac{-6}{14} \log \left( \frac{6}{14} \right) = 0.99$

$\left. \begin{array}{c} \text{O O} \\ \text{X X X X} \end{array} \right\} \text{Entropi} = \frac{-2}{6} \log \left( \frac{2}{6} \right) + \frac{-4}{6} \log \left( \frac{4}{6} \right) = 0.91$



# Karar Ağacı (Decision Tree)

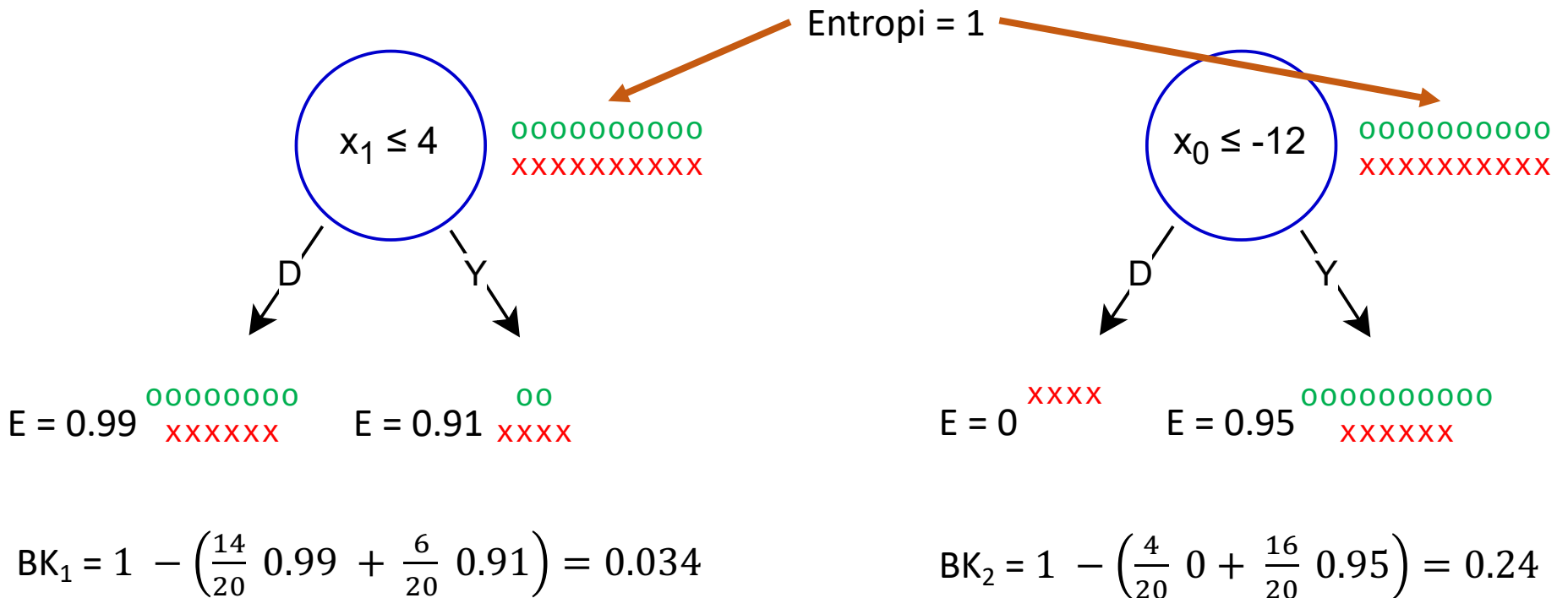


$$BK (IG) = E(anne) - \sum w_i E(\text{çocuk}), w_i = \text{çocuğun anneye oranlı büyüklüğü}$$

xxxx } Entropi =  $-1 \log(1) + 0 \log(0) = 0$

0000000000 } Entropi =  $\frac{-10}{16} \log\left(\frac{10}{16}\right) + \frac{-6}{16} \log\left(\frac{6}{16}\right) = 0.95$   
 xxxxxx

# Karar Ağacı (Decision Tree)



$BK_2$ ,  $BK_1$ 'den büyük olduğu için sağ taraftaki karar mekanizmasını kullanmak sol taraftakinden daha faydalıdır diyoruz.