



K Nearest Neighbors



- KNN (K nearest neighbors) is one of the simplest algorithms we will learn about!
- Section Overview
 - KNN Theory and Intuition
 - KNN Classification Coding Example
 - KNN Exercise Overview
 - KNN Exercise Solution



- While KNN can be used for regression tasks, its performance can be quite poor **and** less efficient than other algorithms, so we've decided not to exhibit its use for regression.
- However if you do want to use it for regression it is very easy to swap in the KNNRegressor model with scikit-learn.



- You may have also heard of K means algorithm.
- K means is unrelated to KNN, be careful not to confuse the two due to their similar sounding names!



- ISLR Relevant Reading
 - Chapter 2
 - Formula 2.12 starts discussion on KNN for classification.

$$\Pr(Y = j|X = x_0) = \frac{1}{K} \sum_{i \in \mathcal{N}_0} I(y_i = j).$$



KNN Classification

Theory and Intuition



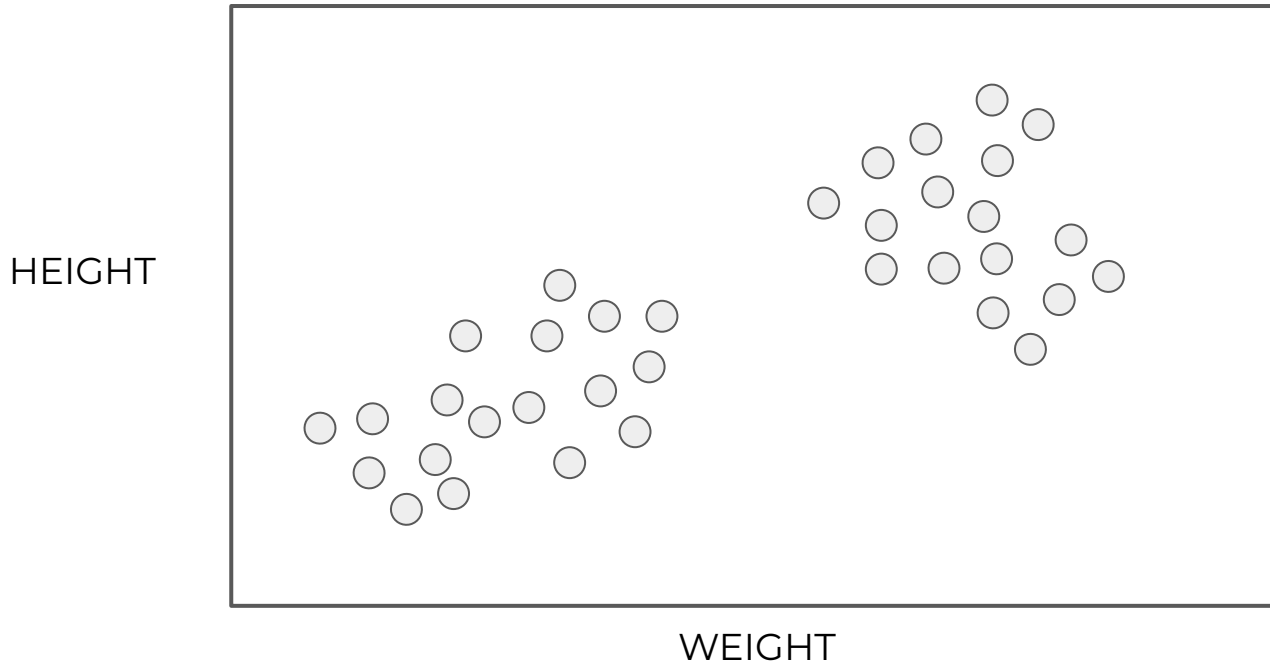
- K nearest neighbors is one of the simplest machine learning algorithms.
- It simply assigns a label to new data based on the **distance** between the old data and new data.
- Let's go through the intuition with an example use case...



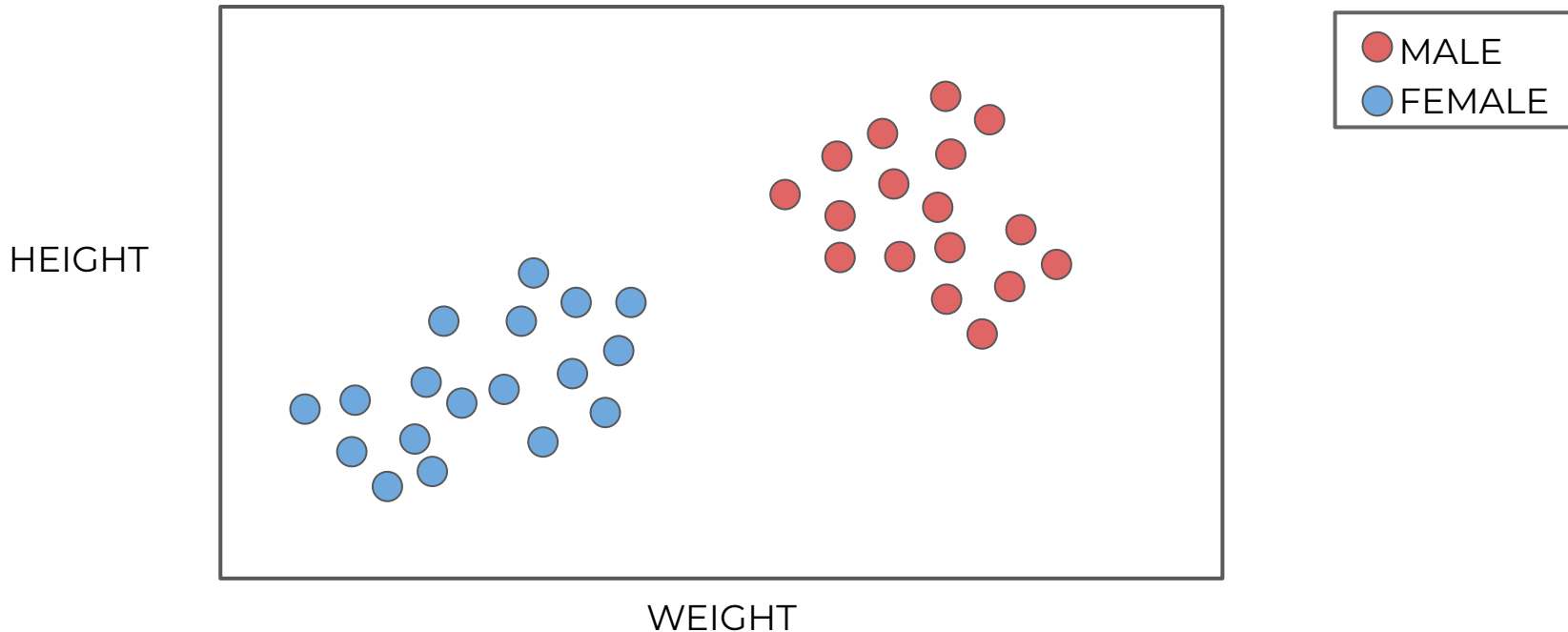
- Sexing chicks is still a very manual process:
 - en.wikipedia.org/wiki/Chick_sexing
- Let's imagine we gathered a dataset of baby chick heights and weights.
- How could we train an algorithm to identify the sex of a new baby chick based on historical features?



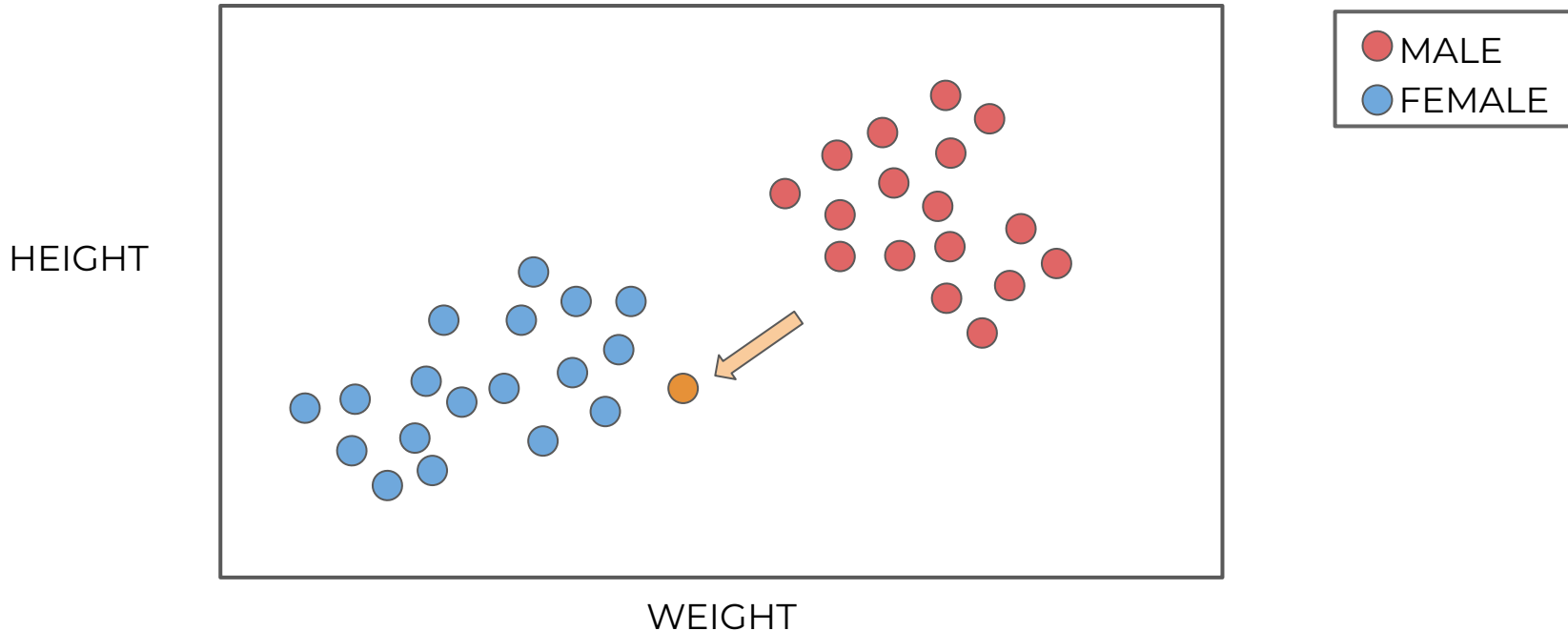
- Imagine a height and weight data set



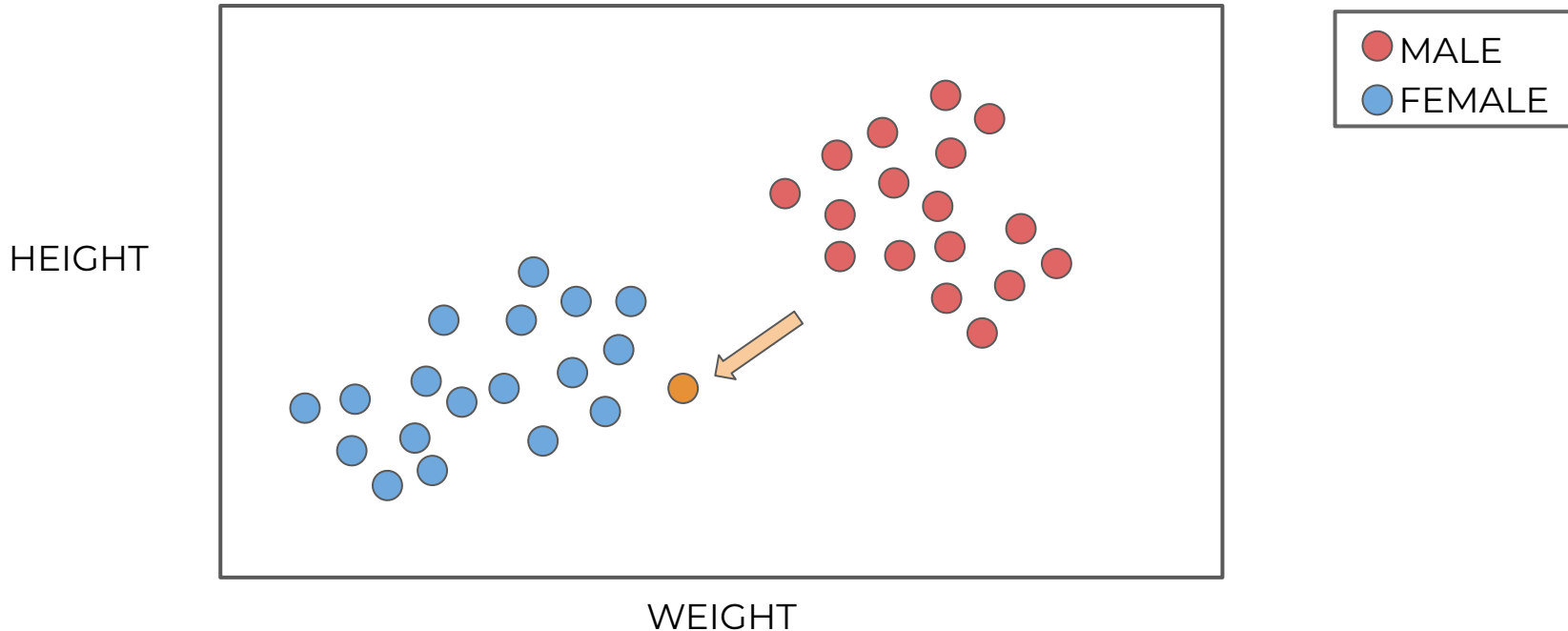
- We historically know the sex of the chicks:



- How would we assign sex to a new point?

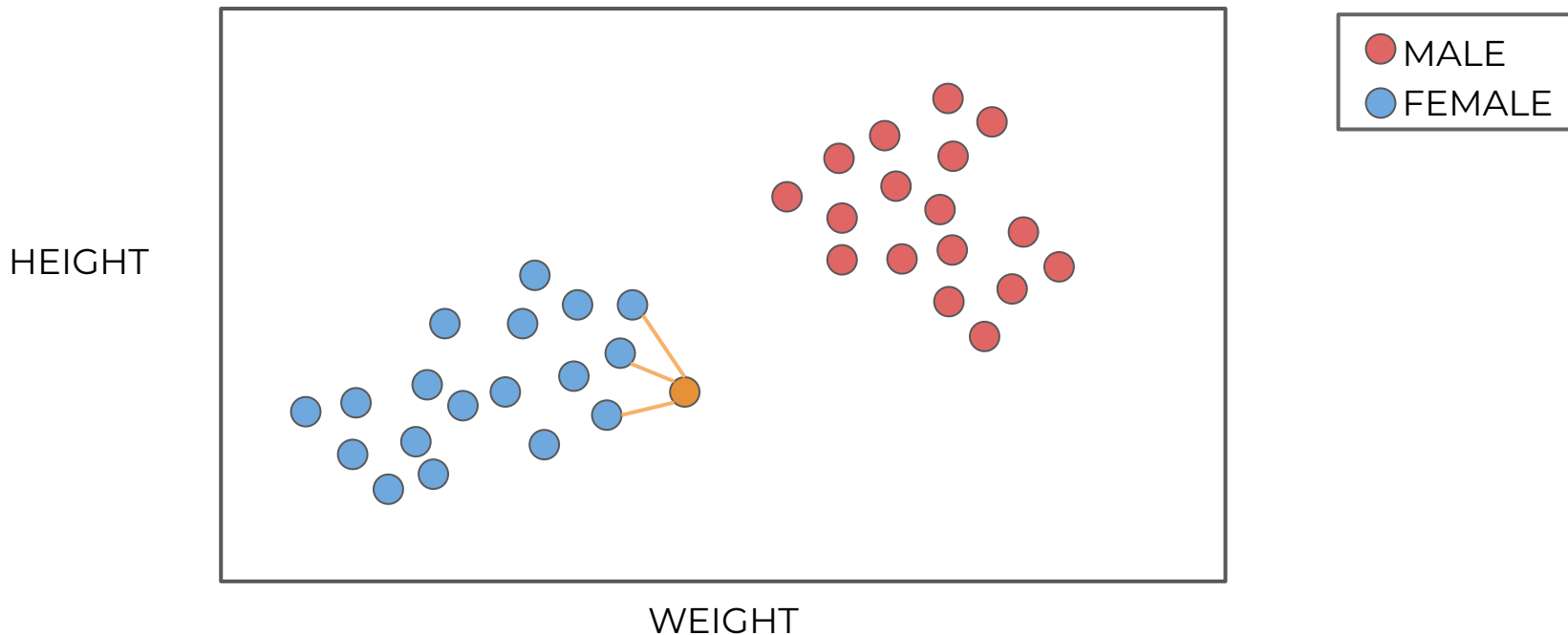


- We intuitively “know” this is likely female.

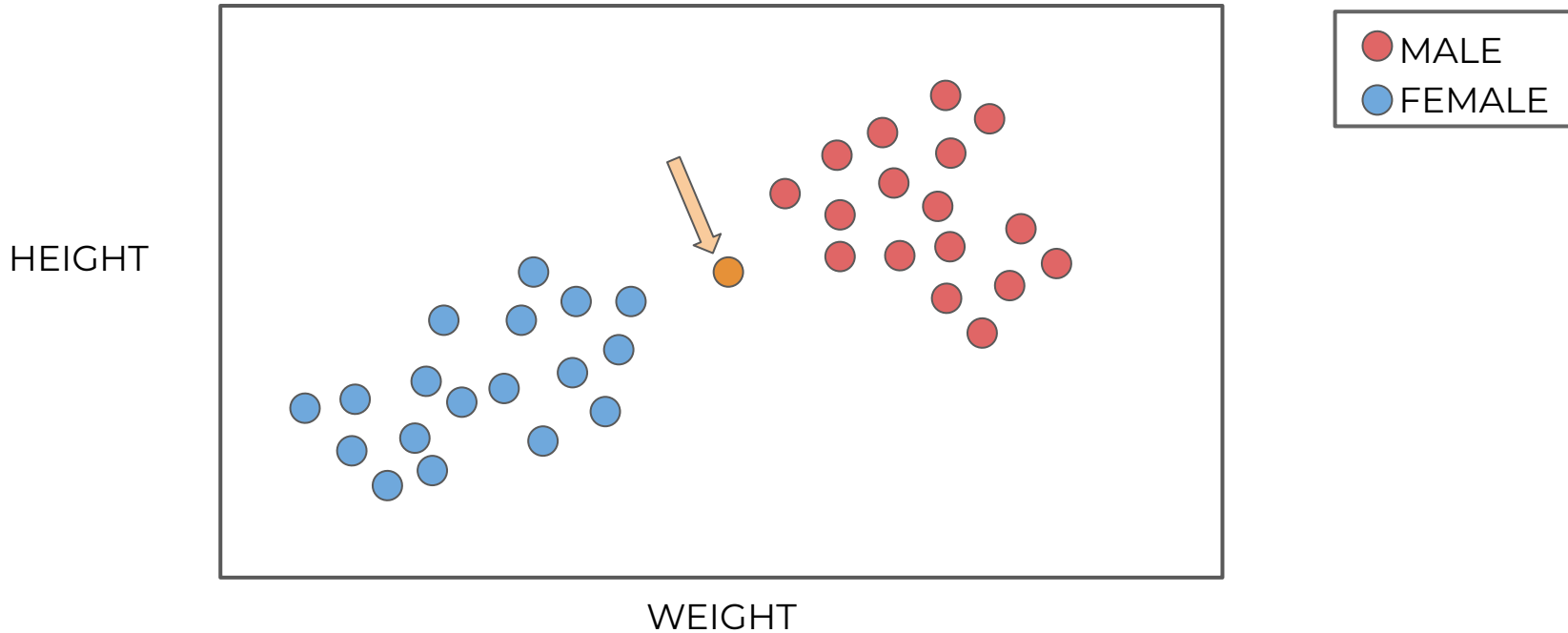




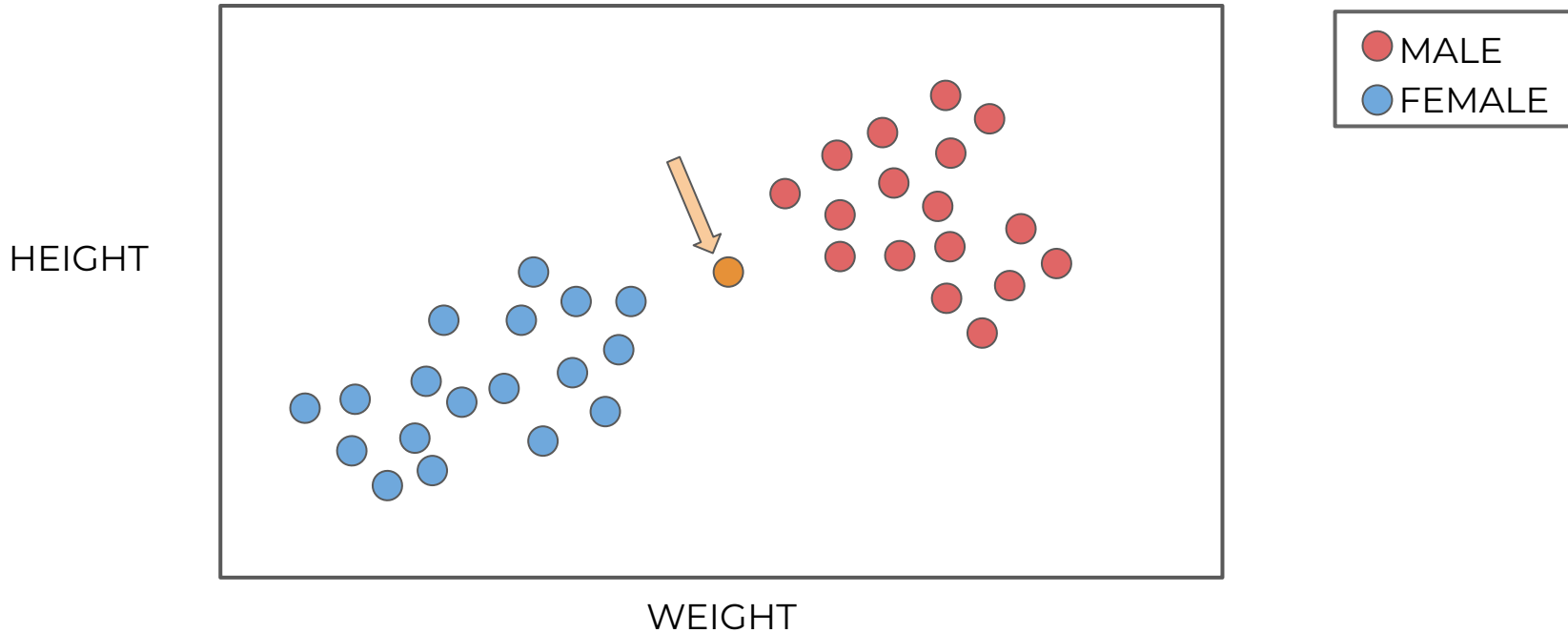
- Intuition comes from **distance** to points!



- What about a less obvious point?

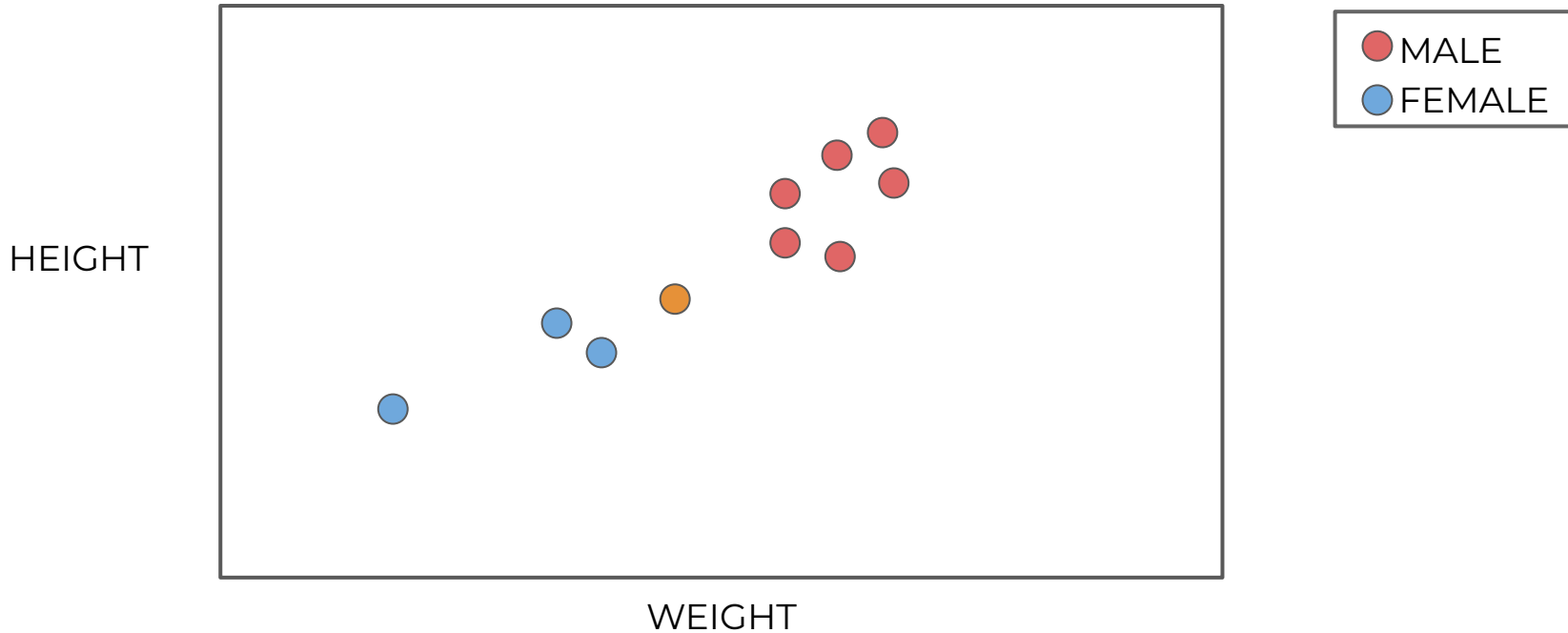


- How many points to we consider?





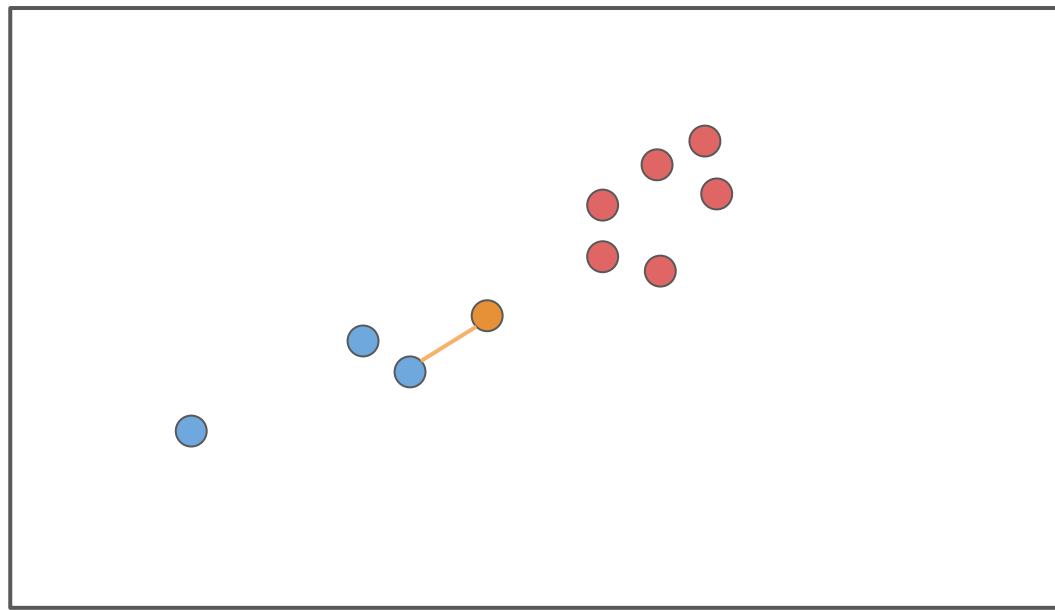
- Let's imagine a situation like this:





- $K=1$

HEIGHT

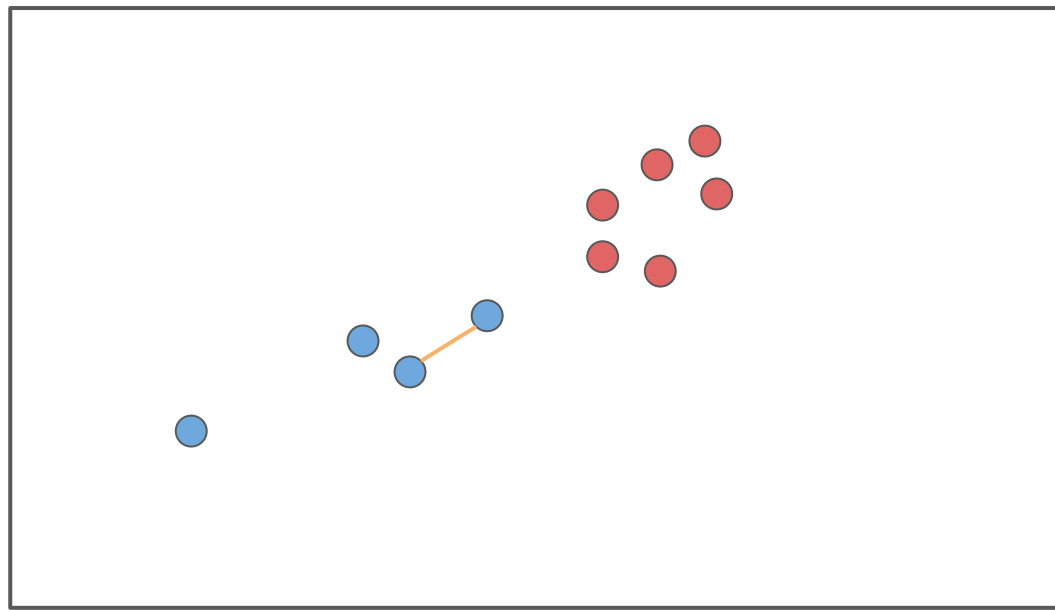


WEIGHT



- $K=1$

HEIGHT



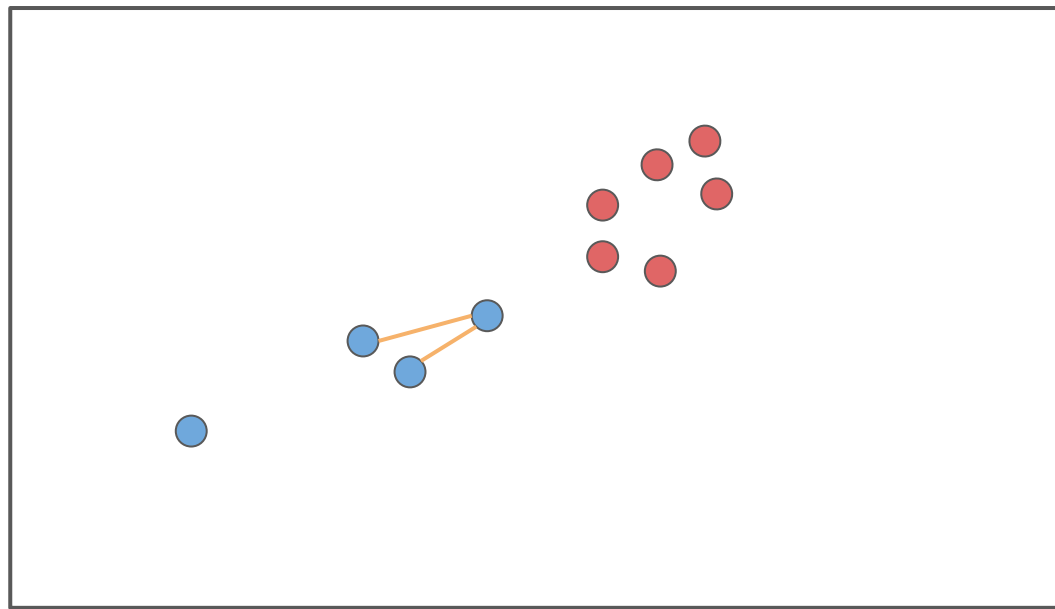
WEIGHT

● MALE
● FEMALE



- $K=2$

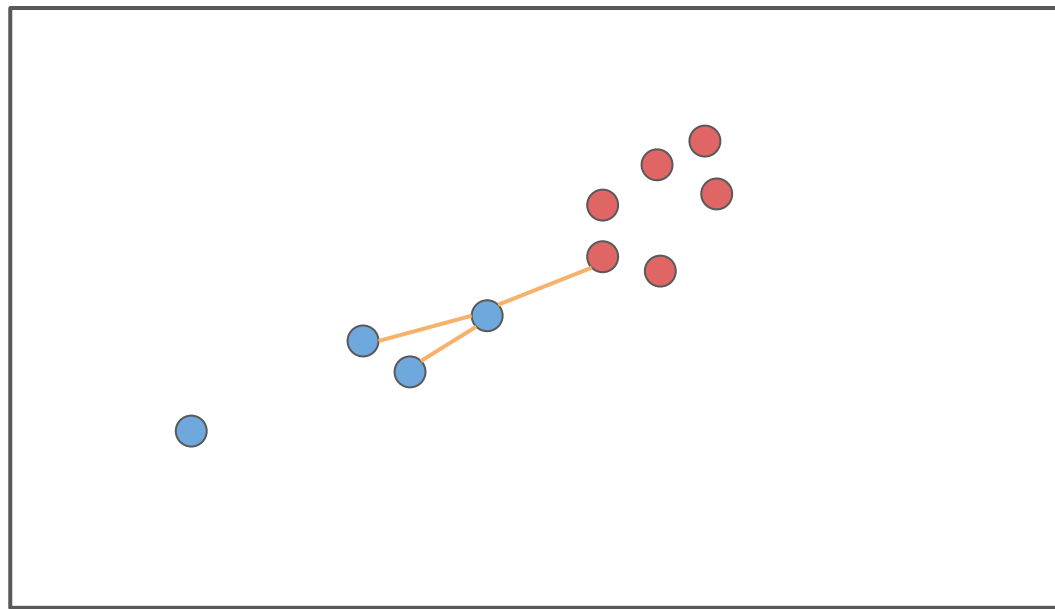
HEIGHT





- $K=3$

HEIGHT

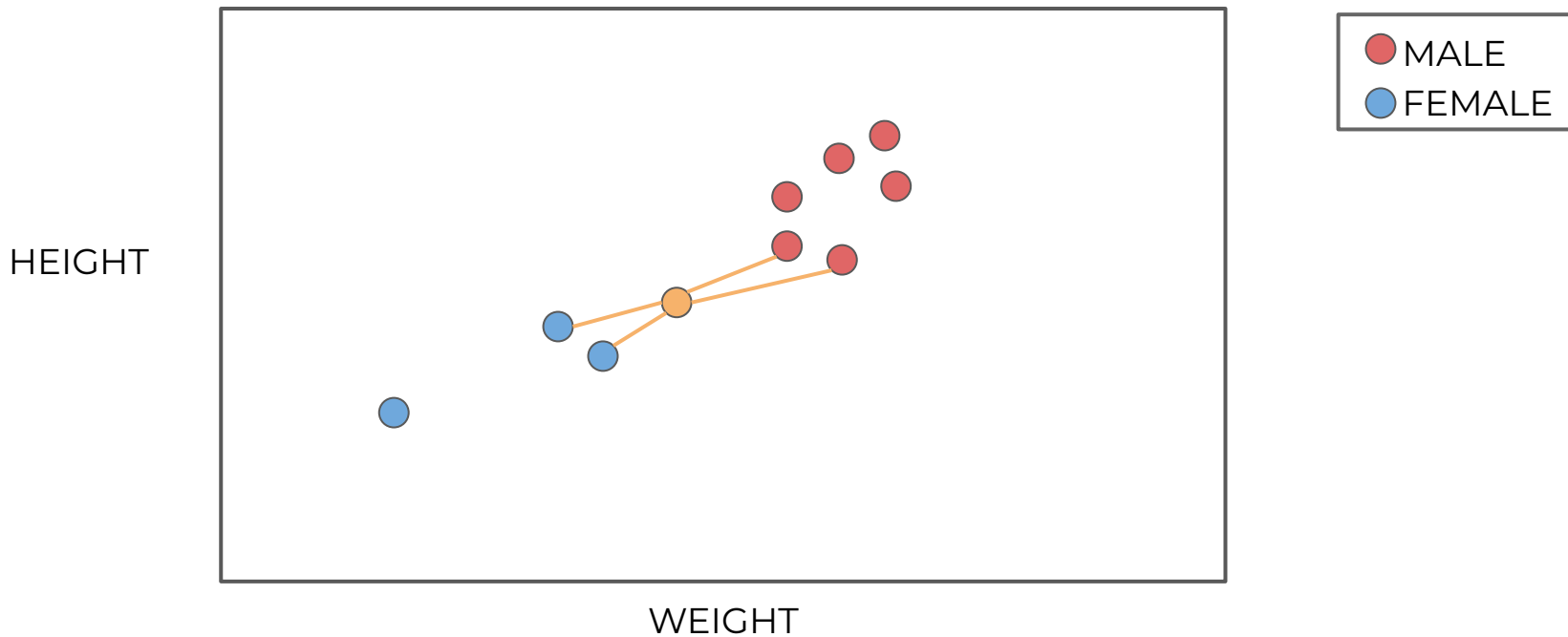


WEIGHT

MALE
FEMALE



- K=4 leads to a tie!





- Tie considerations and options:
 - Always choose an odd K .
 - In case of tie, simply reduce K by 1 until tie is broken.
 - Randomly break tie.
 - Choose nearest class point.



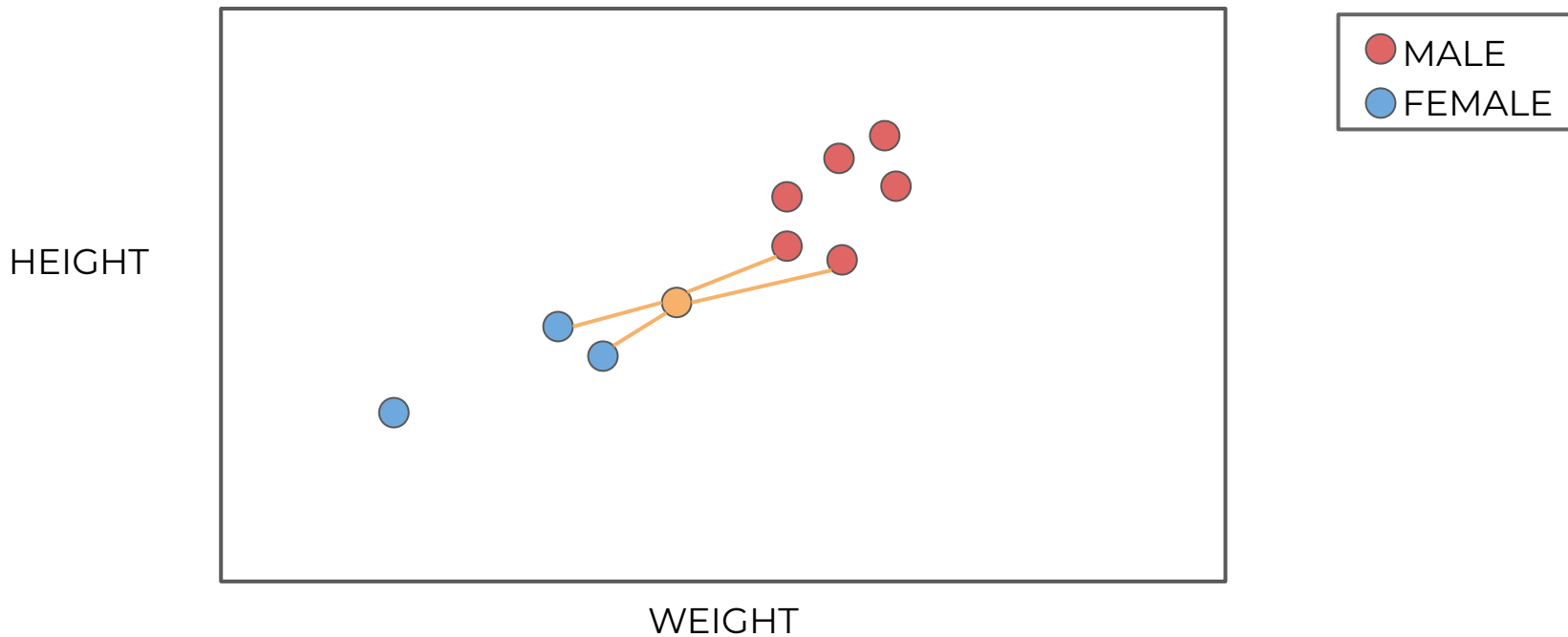
- What does Scikit-Learn do in case of tie?
 - *Warning: Regarding the Nearest Neighbors algorithms, if it is found that two neighbors, neighbor $k+1$ and k , have identical distances but different labels, the results will depend on the ordering of the training data.*



- What does Scikit-Learn do in case of tie?
 - *In the case of ties, the answer will be the class that happens to appear first in the set of neighbors.*
 - *Results are ordered by distance, so it chooses the class of the closest point.*

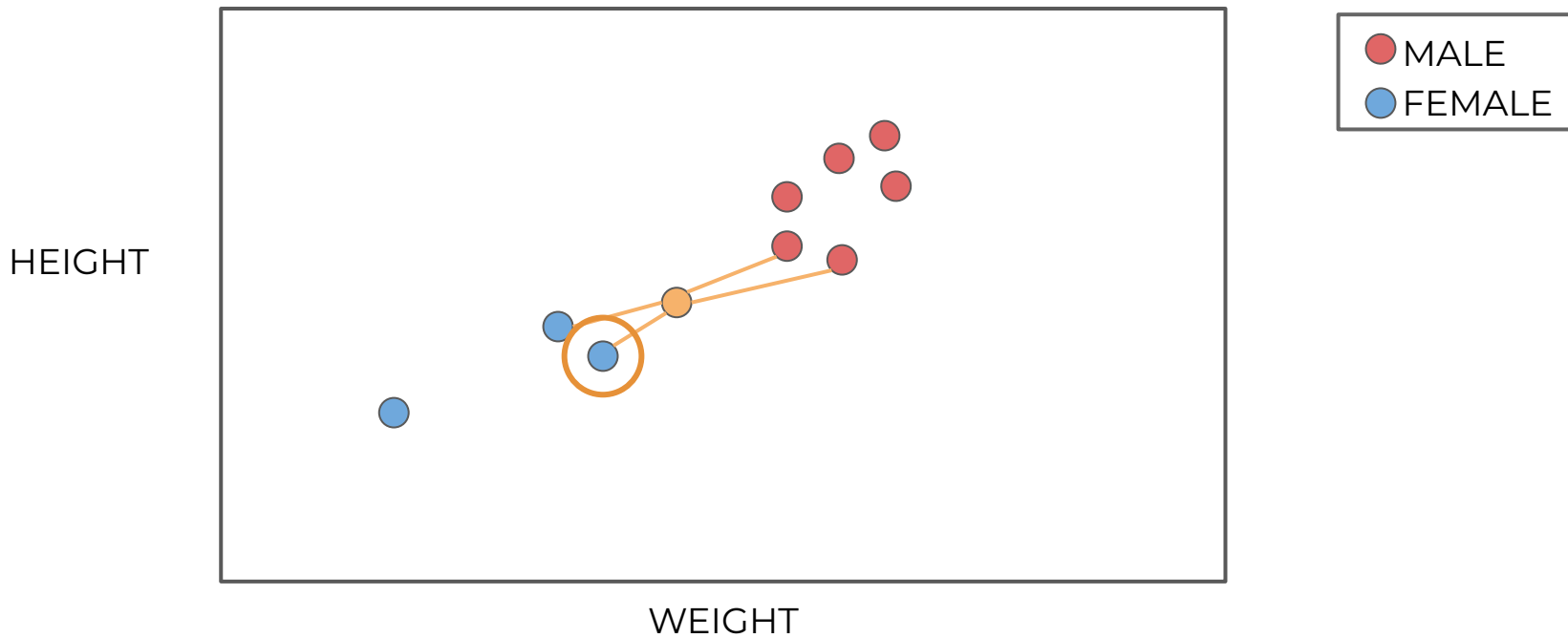


- K=4 leads to a tie!



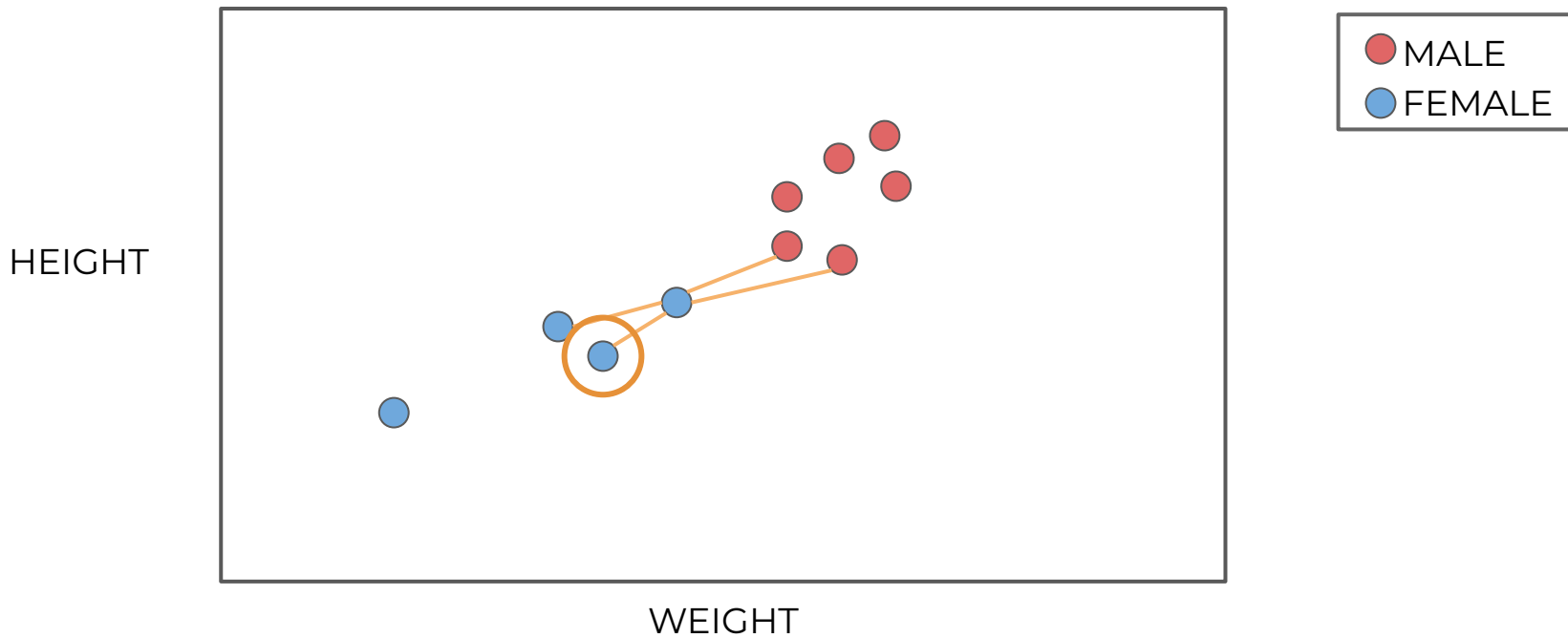


- Choose closest K



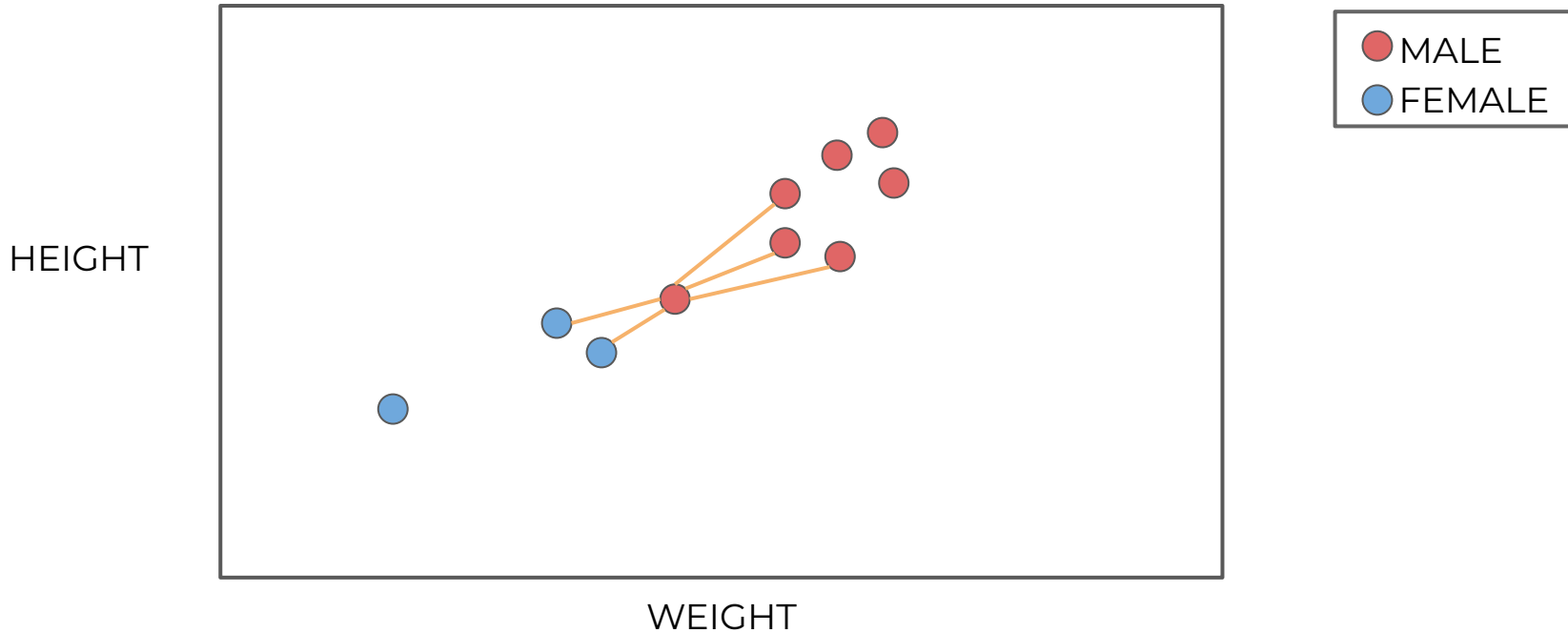


- Choose closest K



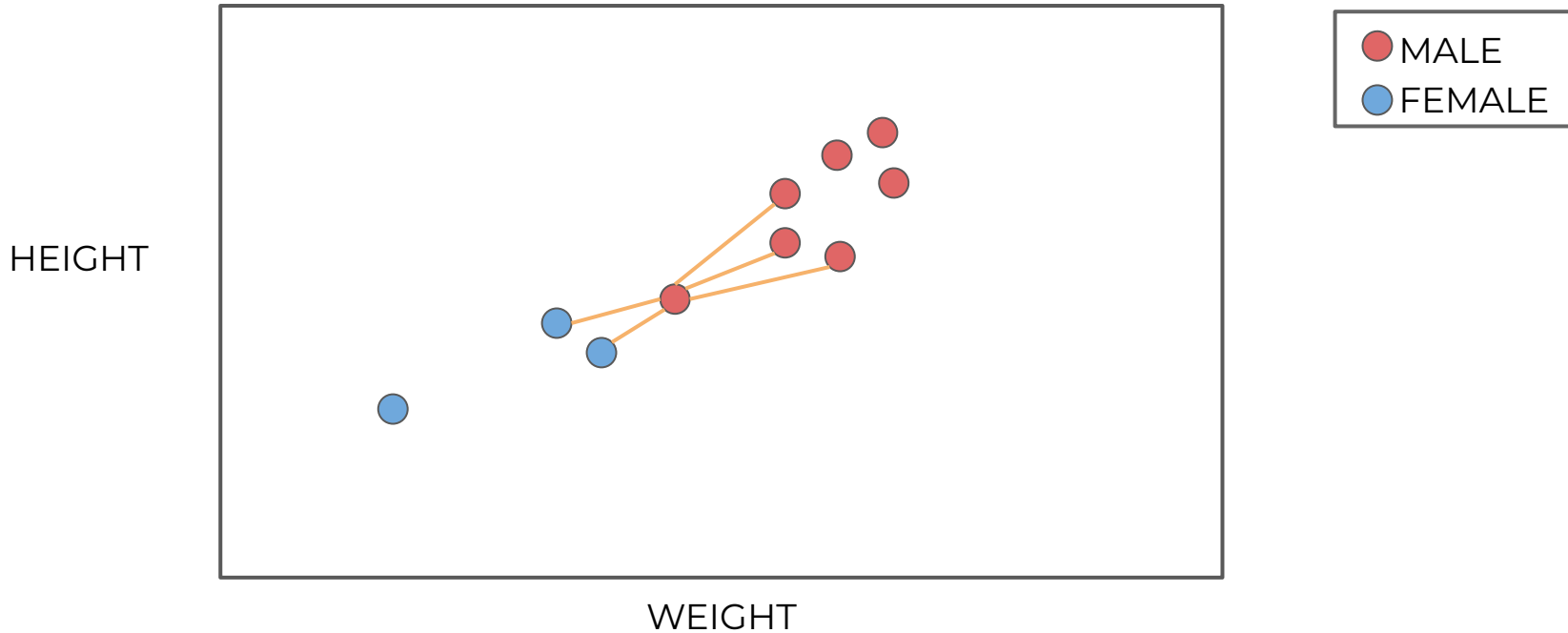


- K=5 causes a switch from previous K values.





- How to choose best K value?

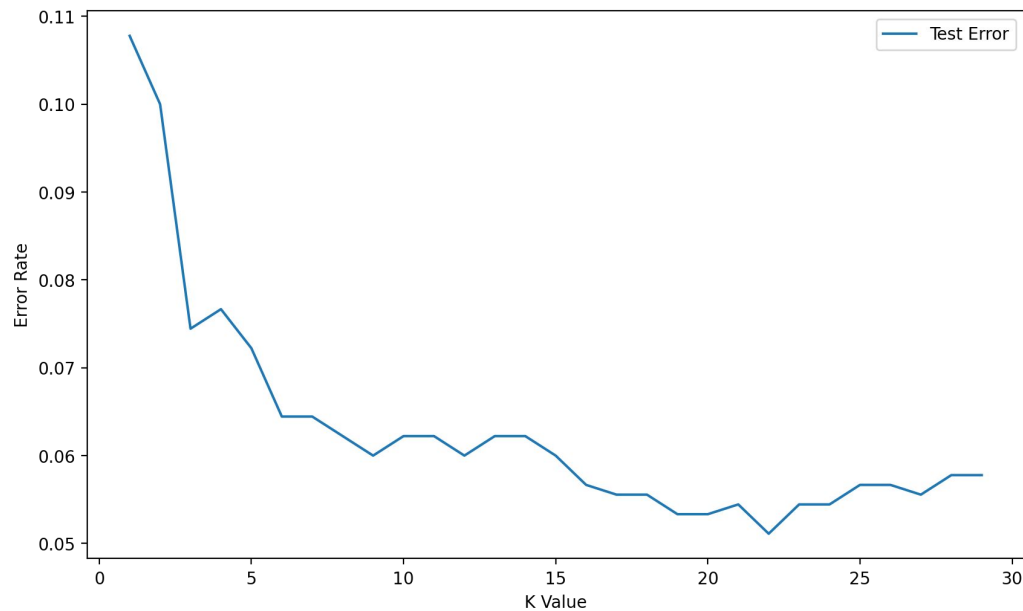




- We want a K value that **minimizes** error:
 - $\text{Error} = 1 - \text{Accuracy}$
- Two methods:
 - Elbow method.
 - Cross validate a grid search of multiple K values and choose K that results in lowest error or highest accuracy.

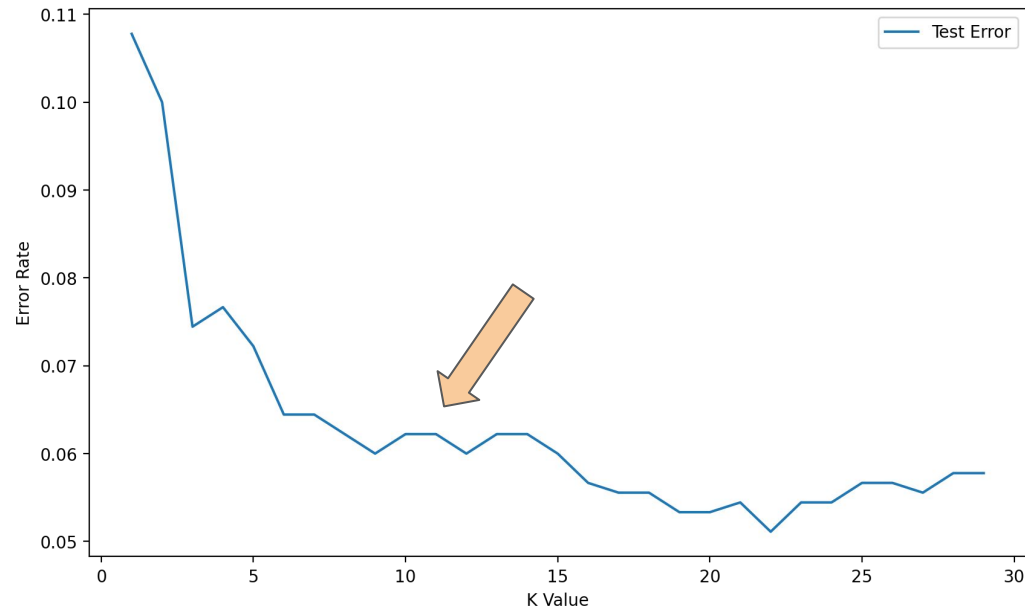


- Elbow method:



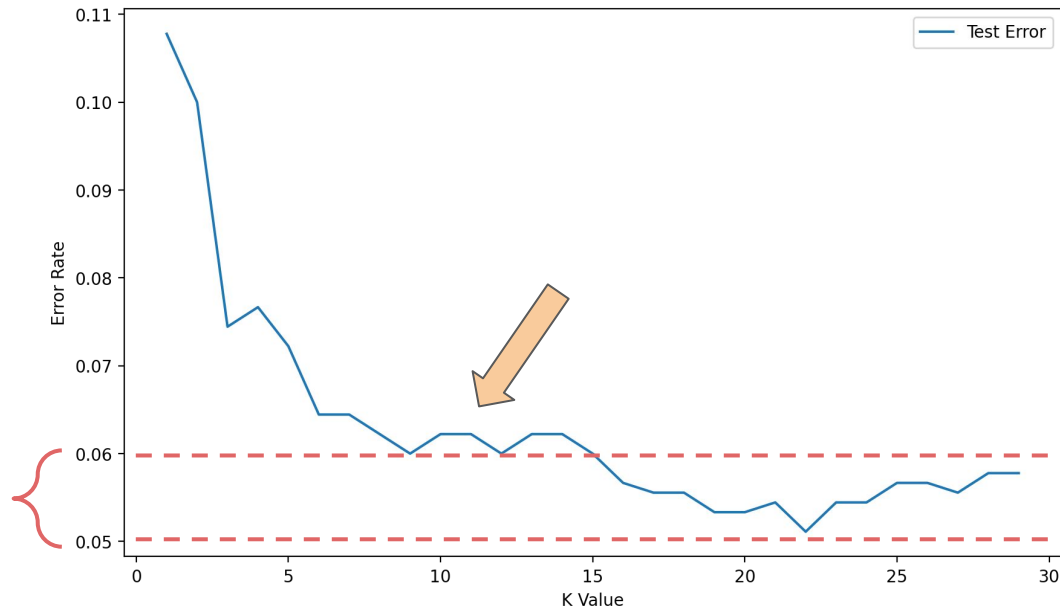


- Elbow method:





- Elbow method:





- Cross validation only takes into account the K value with the lowest error rate across multiple folds.
- This could result in a more complex model (higher value of K).
- Consider the context of the problem to decide if larger K values are an issue.



- KNN Algorithm
 - Choose K value.
 - Sort feature vectors (N dimensional space) by distance metric.
 - Choose class based on K nearest feature vectors.



- KNN Considerations:
 - Distance Metric
 - Many ways to measure distance:
 - Minkowski
 - Euclidean
 - Manhattan
 - Chebyshev



- KNN Considerations:
 - Scaling for Distance
 - Features could have vastly different value ranges!



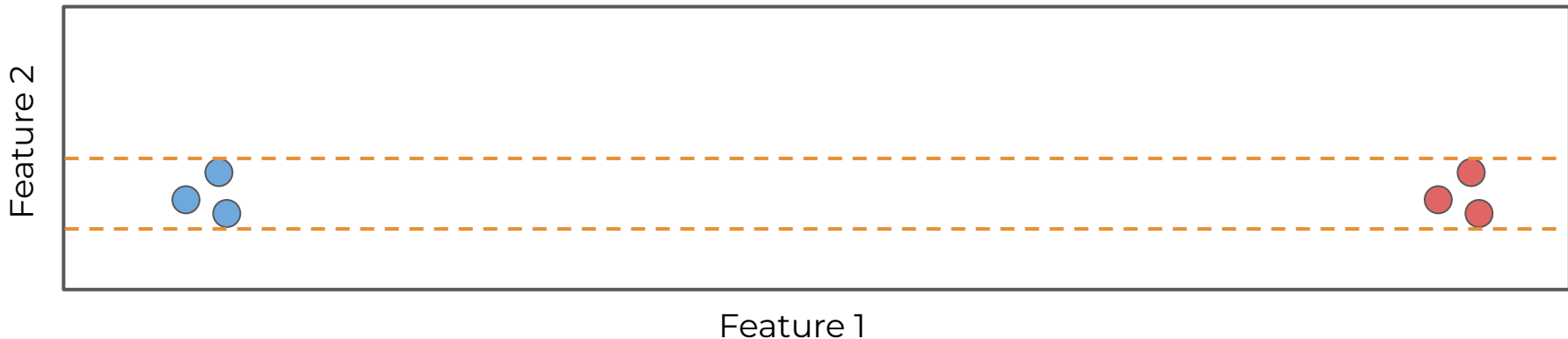


- KNN Considerations:
 - Scaling for Distance
 - Features could have vastly different value ranges!



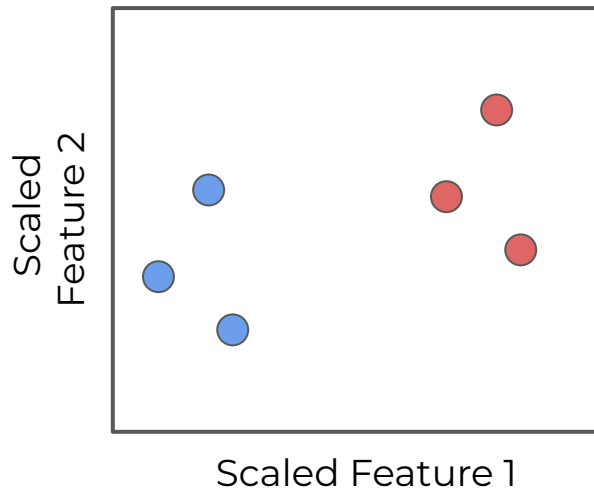


- KNN Considerations:
 - Scaling for Distance
 - Features could have vastly different value ranges!





- KNN Considerations:
 - Scaling is necessary for KNN.





- While the KNN Algorithm is relatively simple, keep in mind the following considerations:
 - Choosing the optimal K value.
 - Scaling features.
- Let's continue to explore how to perform KNN for classification!



KNN Classification

Coding Part Two: Choosing K



- A Pipeline object in Scikit-Learn can set up a sequence of repeated operations, such as a scaler and a model.
- This way only the pipeline needs to be called, instead of having to repeatedly call a scaler and a model.