# Understanding and Implementing Novelty and Outlier Detection



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#### Overview

Understanding outliers and novelties

Novelty and outlier detection uses

Algorithms for outlier and novelty detection

**Local Outlier Factor** 

**Elliptic Envelope** 

**Isolation Forest** 

## Outlier and Novelty

A data point that differs significantly from other data points in the same data set.

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## Novelty

A data point encountered in prediction that differs significantly from any data points encountered during training.

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#### Outliers and Novelties

**Outliers** 

Anomalous points in training dataset

Unsupervised

Outliers, by definition, will never form a dense cluster

**Novelties** 

Anomalous points in test dataset

Semi-supervised

Novelties could possibly form a dense cluster

#### Outlier Detection

Fit regions in the dataset where data points are the most concentrated, deviant observations are outliers.

## Novelty Detection

Training data not polluted by outliers, try to detect whether new observations are deviant.

#### Uses of Outlier and Novelty Detection

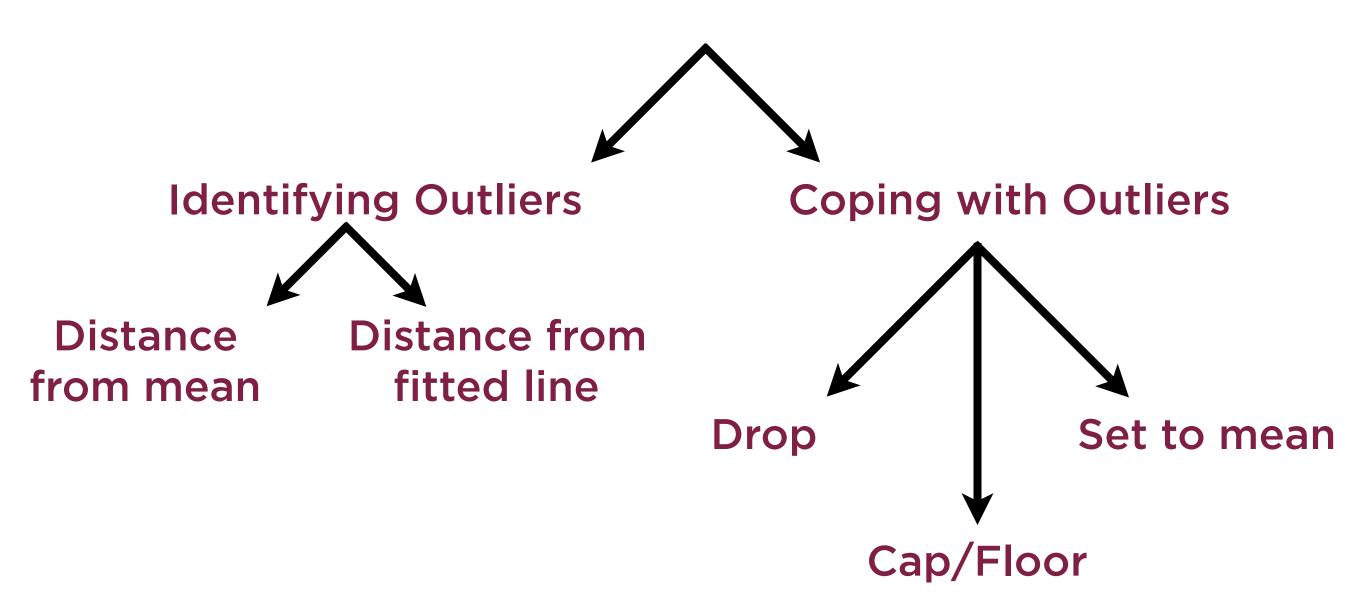


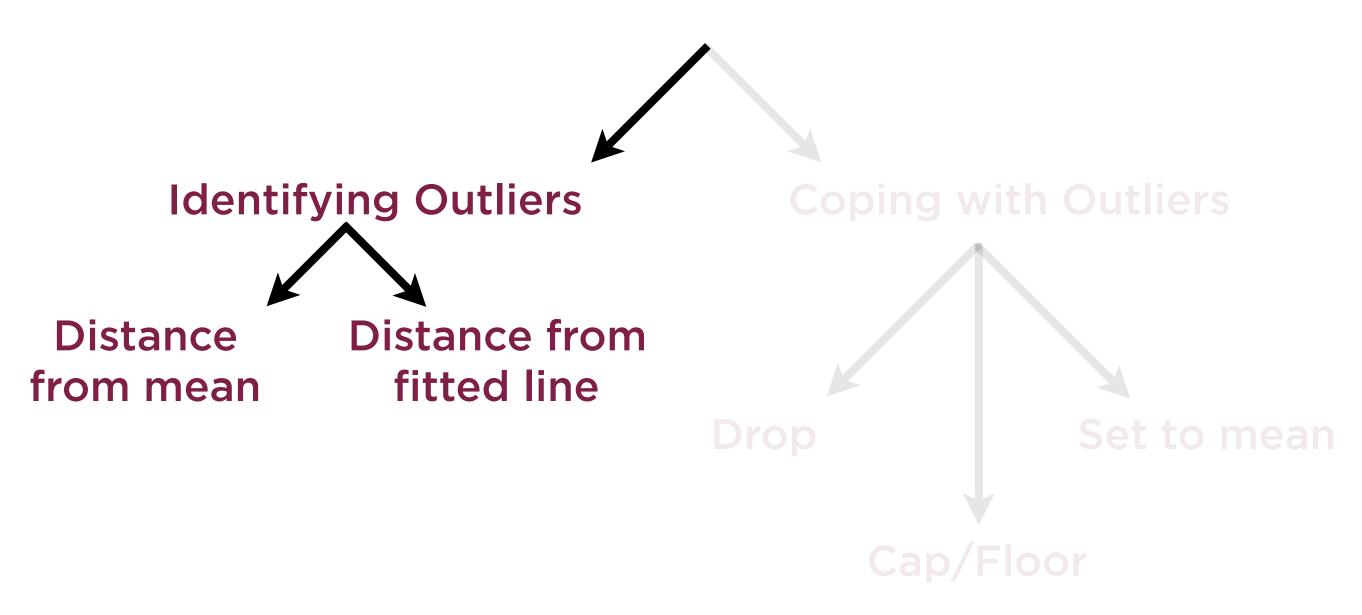
Detecting anomalous data i.e. fraudulent credit card transactions

Detecting errors in data collection or processing

Cleaning and preparing data for ML models

#### Outlier and Novelty Detection





#### Identifying Outliers

Distance from mean

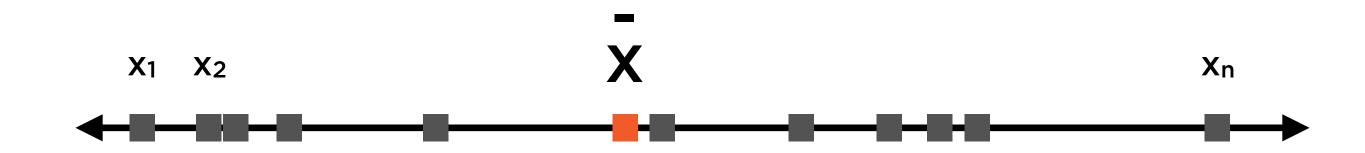
Distance from fitted line

#### Identifying Outliers

Distance from mean

Distance from fitted line

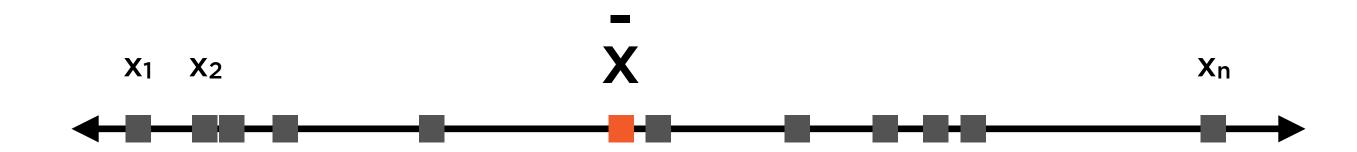
#### Mean and Variance



# Mean and variance succinctly summarize a set of numbers

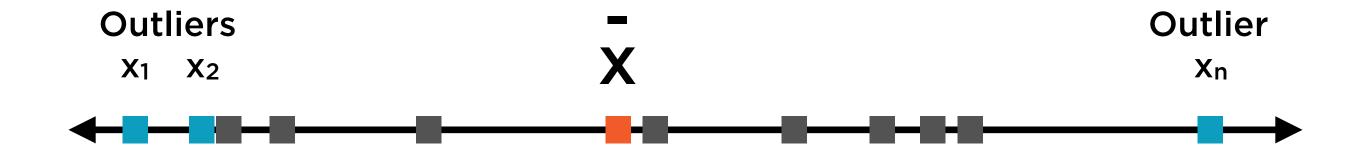
$$\frac{1}{x} = \frac{x_1 + x_2 + ... + x_n}{n}$$
 Variance =  $\frac{\sum (x_i - \overline{x})^2}{n-1}$ 

#### Variance and Standard Deviation



Standard deviation is the square root of variance

Variance = 
$$\frac{\sum (x_i - \overline{x})^2}{n-1}$$
 Std Dev = 
$$\sqrt{\frac{\sum (x_i - \overline{x})^2}{n-1}}$$



Points that lie more than 3 standard deviations from the mean are often considered outliers

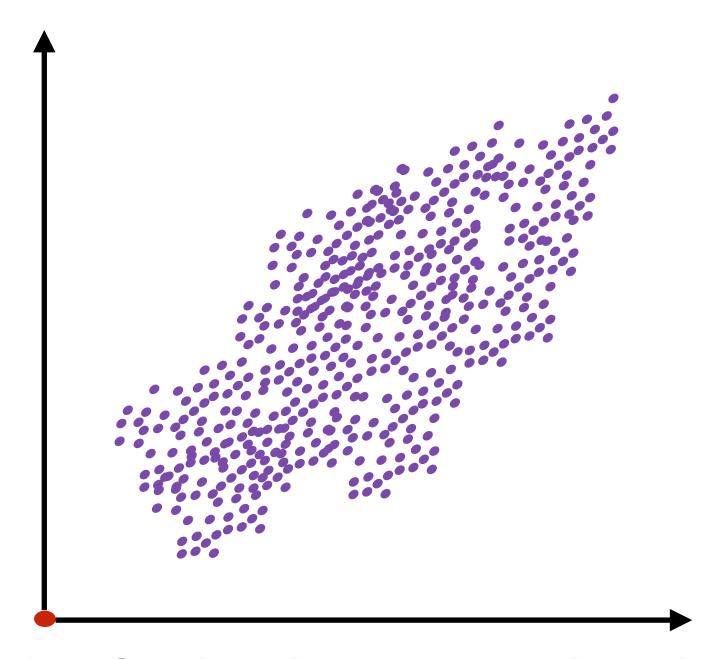


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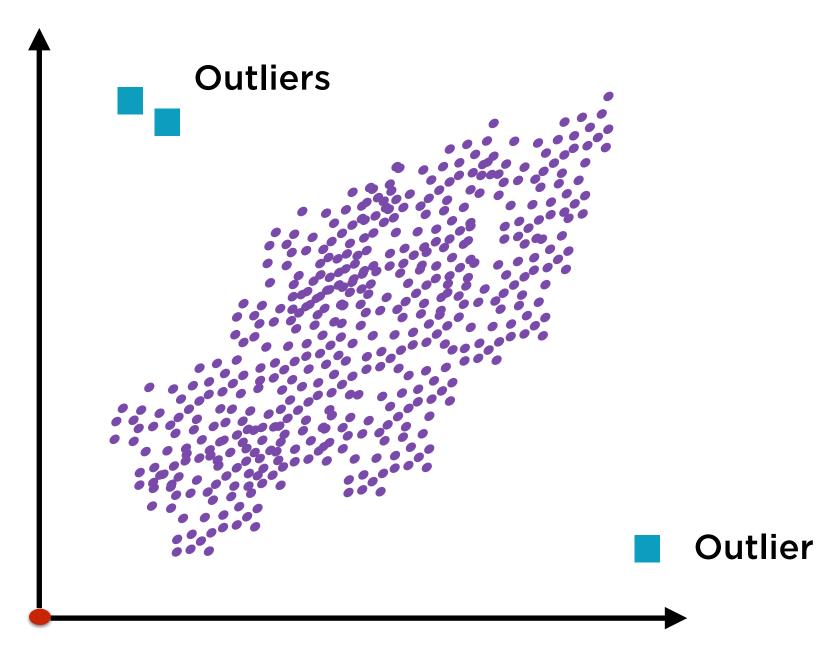
#### Identifying Outliers

Distance from mean

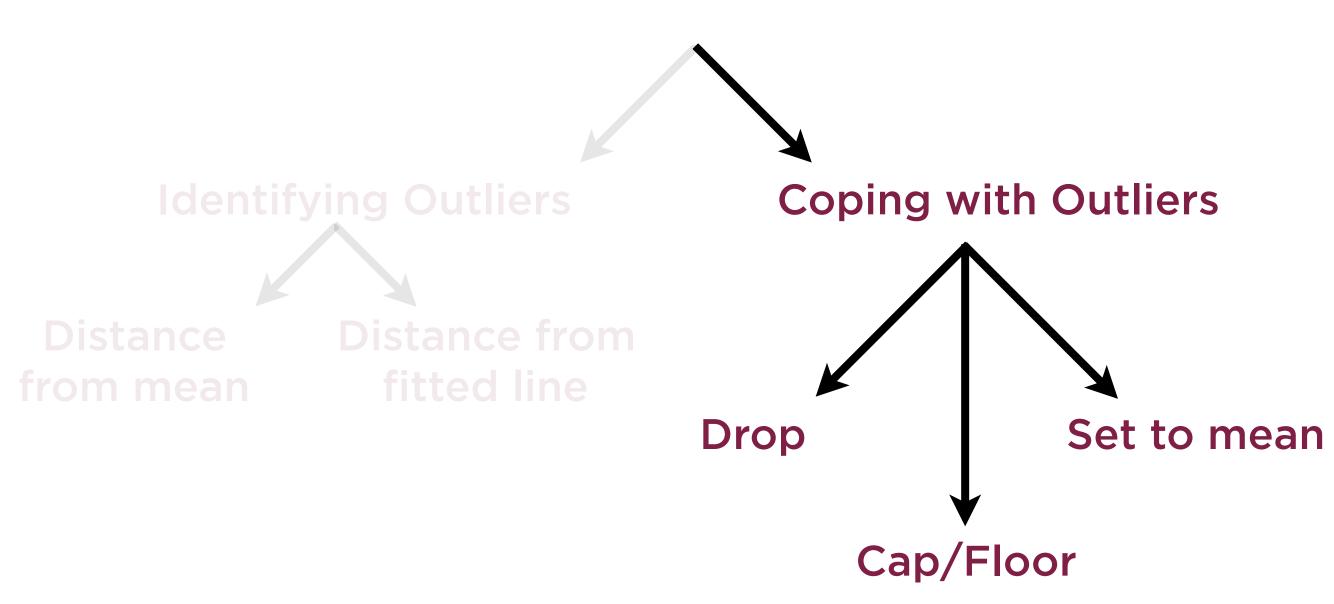
Distance from fitted line



Outliers might also be data points that do not fit into the same relationship as the rest of the data



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# Coping with Outliers

# Always start by scrutinizing outliers If erroneous observation

- Drop if all attributes of that point are erroneous
- Set to mean if only one attribute is erroneous

# Coping with Outliers

#### If genuine, legitimate outlier

- Leave as-is if model not distorted
- Cap/Floor if model is distorted
  - Need to first standardize data
  - Cap positive outliers to +3
  - Floor negative outliers to -3

scikit-learn algorithms can be used for both outlier as well as novelty detection

# Outlier and Novelty Detection Algorithms in scikit-learn

Local Outlier Factor

Elliptic Envelope

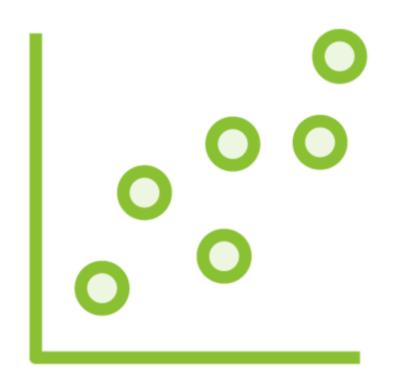
**Isolation Forest** 

# Outlier and Novelty Detection Algorithms in scikit-learn

Local Outlier Factor

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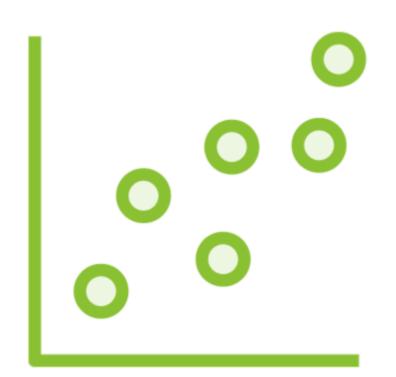
Isolation Forest



# For each point, compute a score called the Local Outlier Factor (LOF) score

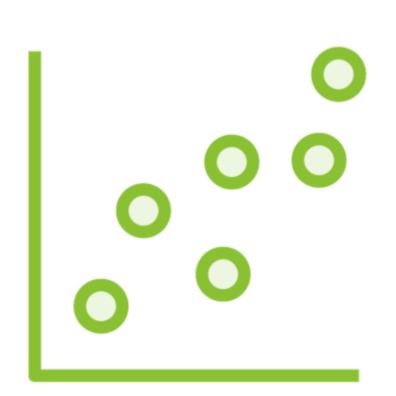
#### Flag as outlier if

- Point is far from its nearest neighbors
- Those neighbors are close to each other



Use K-nearest neighbors algorithm to find neighbors

Number of neighbors to be considered is a parameter



# Calculate the average density of neighbors

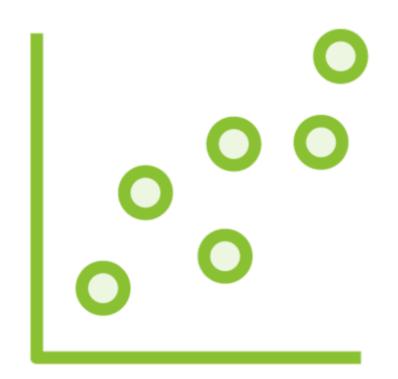
How close the neighbors are to each other, on average

# Calculate the average density of candidate point

- How close the point is to neighbors

#### Compare the two

# Determines how isolated a particular sample is with respect to its surrounding neighborhood

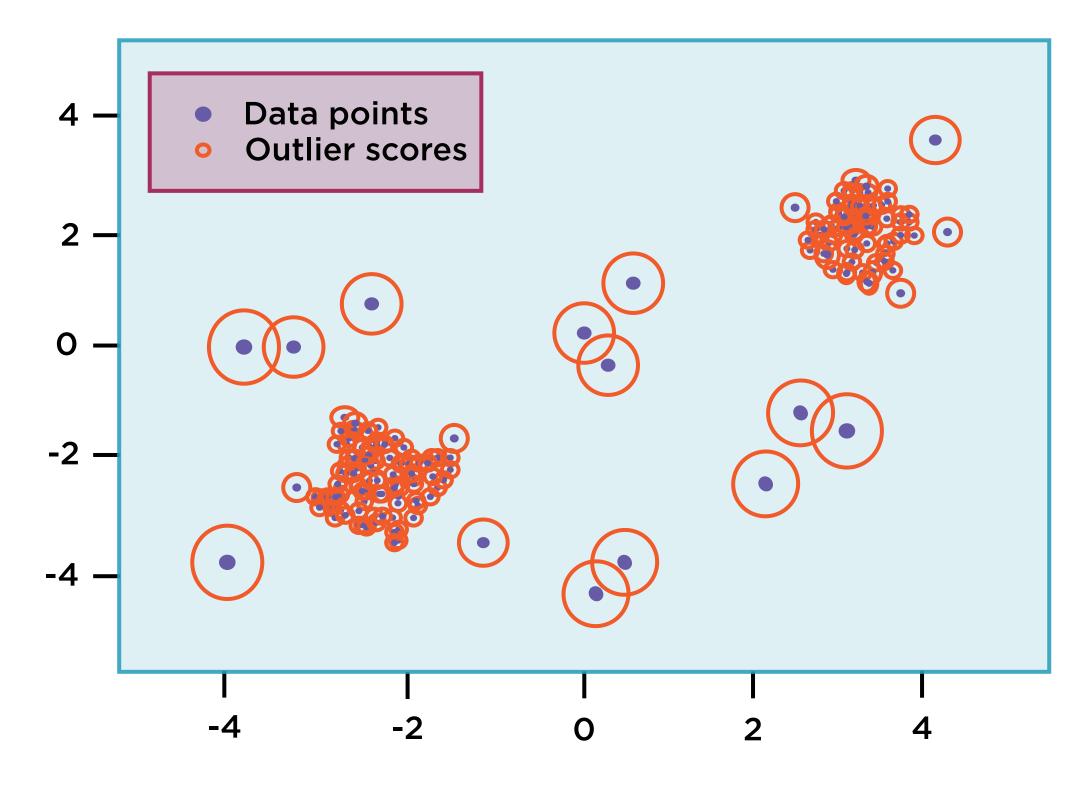


Works well with moderately high dimensionality data

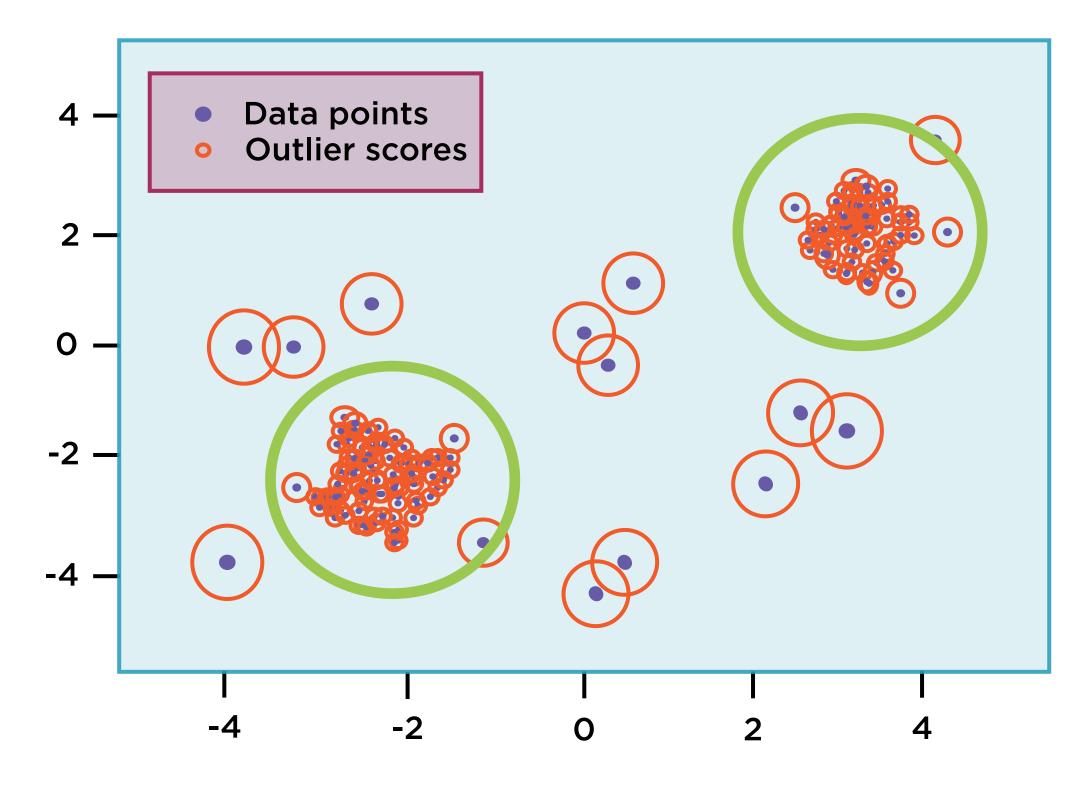
Considers both local and global properties

- Due to use of K-nearest-neighbors

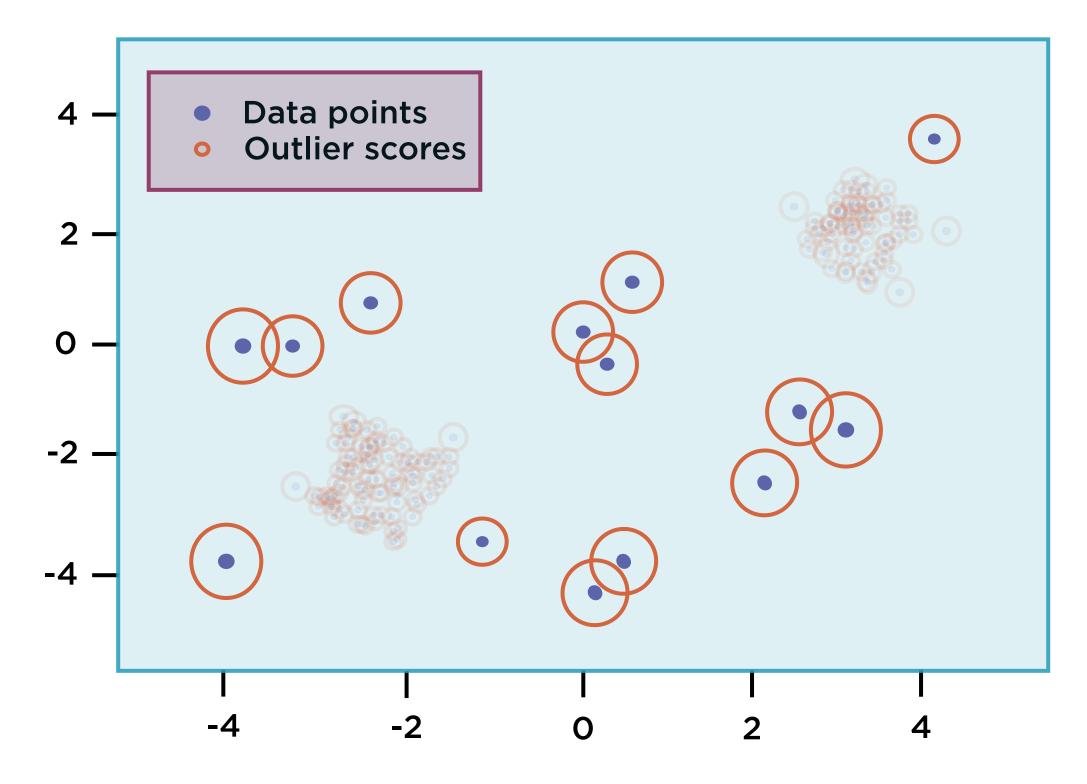
#### Outlier Detection with Local Outlier Factor



#### Outlier Detection with Local Outlier Factor



#### Outlier Detection with Local Outlier Factor



estimator cannot be used directly for novelty detection, need to set novelty=True

#### Elliptic Envelope

# Outlier and Novelty Detection Algorithms in scikit-learn

Local Outlier Factor

Elliptic Envelope

Isolation Forest

#### Elliptic Envelope



Assumes data is drawn from a normal i.e. Gaussian distribution

Draw an elliptical envelope through the central data points

All points outside the ellipse are considered outliers

#### Elliptic Envelope



Elliptic envelope is drawn using a Robust Covariance estimate

Assumes data is drawn from a known distribution e.g. Gaussian Normal

#### Robust Covariance



Covariance matrix simply summarizes pair-wise covariance of vectors

If greater values of one variable correspond to greater values in another

Or vice versa

Covariance is positive

#### Robust Covariance



#### Trivial to compute, but can be fragile

- Time-series data with illiquid stocks

Usually calculated using maximum likelihood estimate

Very sensitive to outliers in the dataset

#### Robust Covariance



### Use complex but robust procedure called Minimum Covariance Determinant

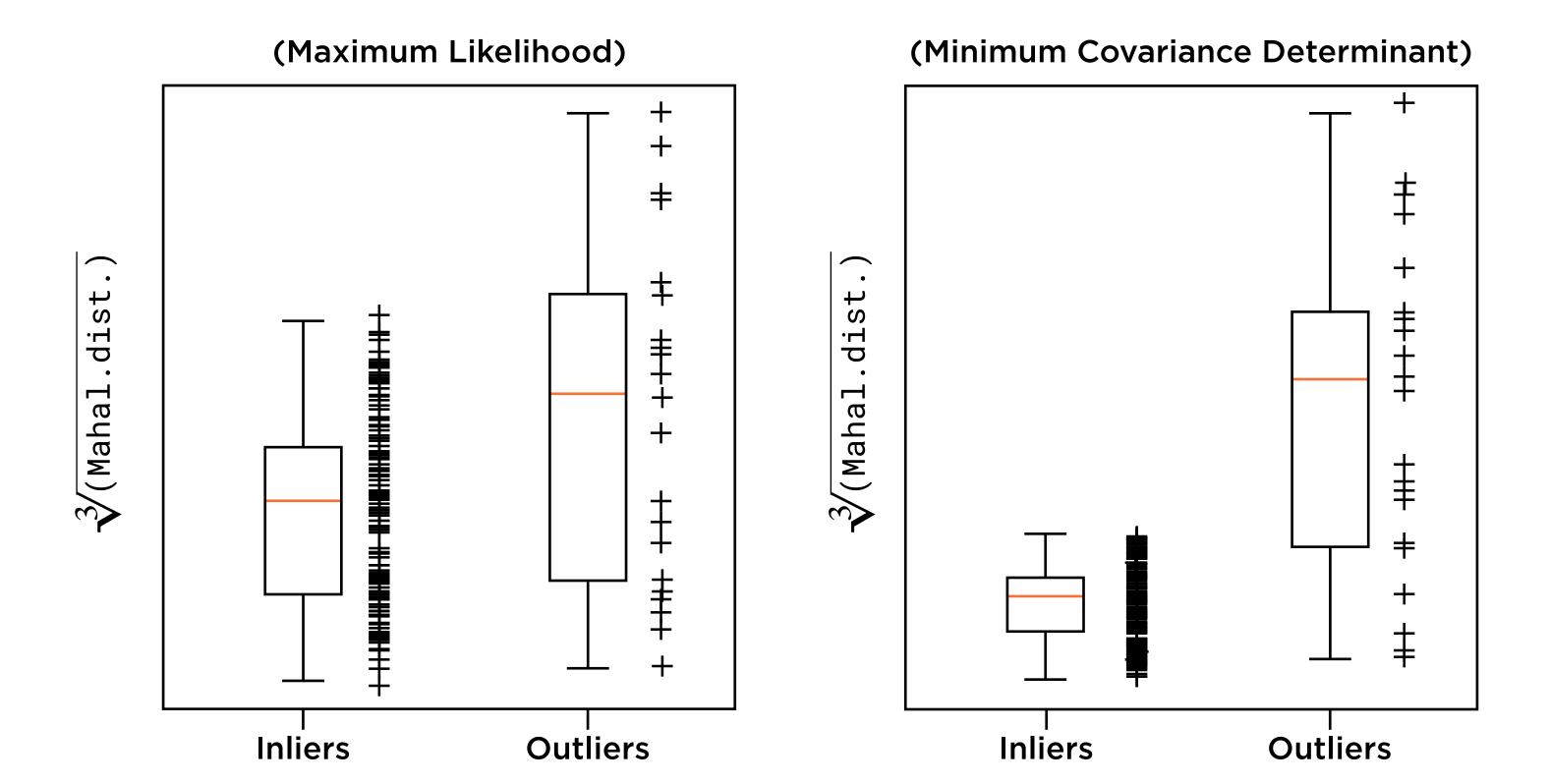
- Uses Mahalanobis Distance

Estimation is robust to outliers

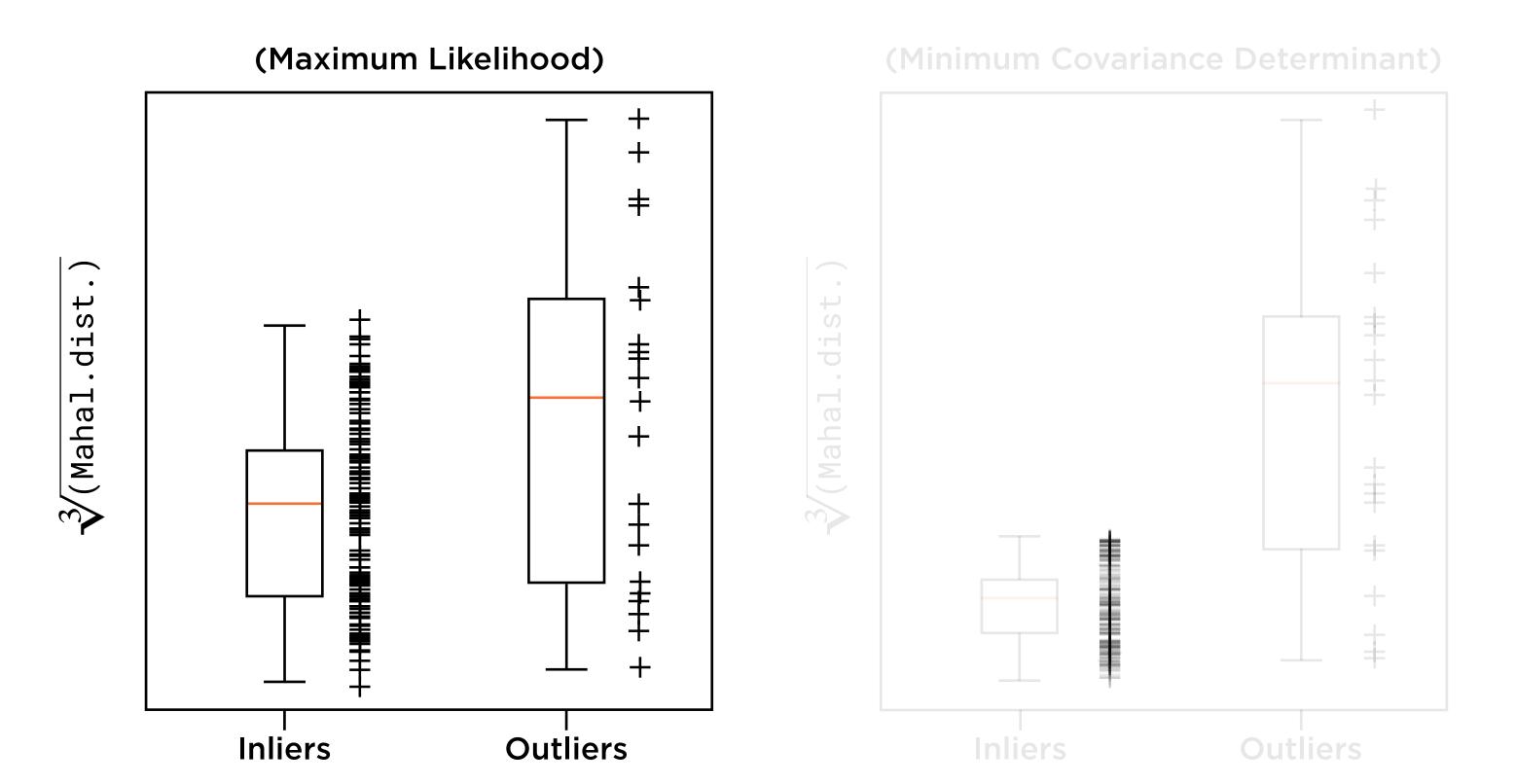
#### Mahalanobis Distance

Measure of distance between two points; similar to Euclidean (L2) distance, but with the difference that each dimension is normalized to have equal variance.

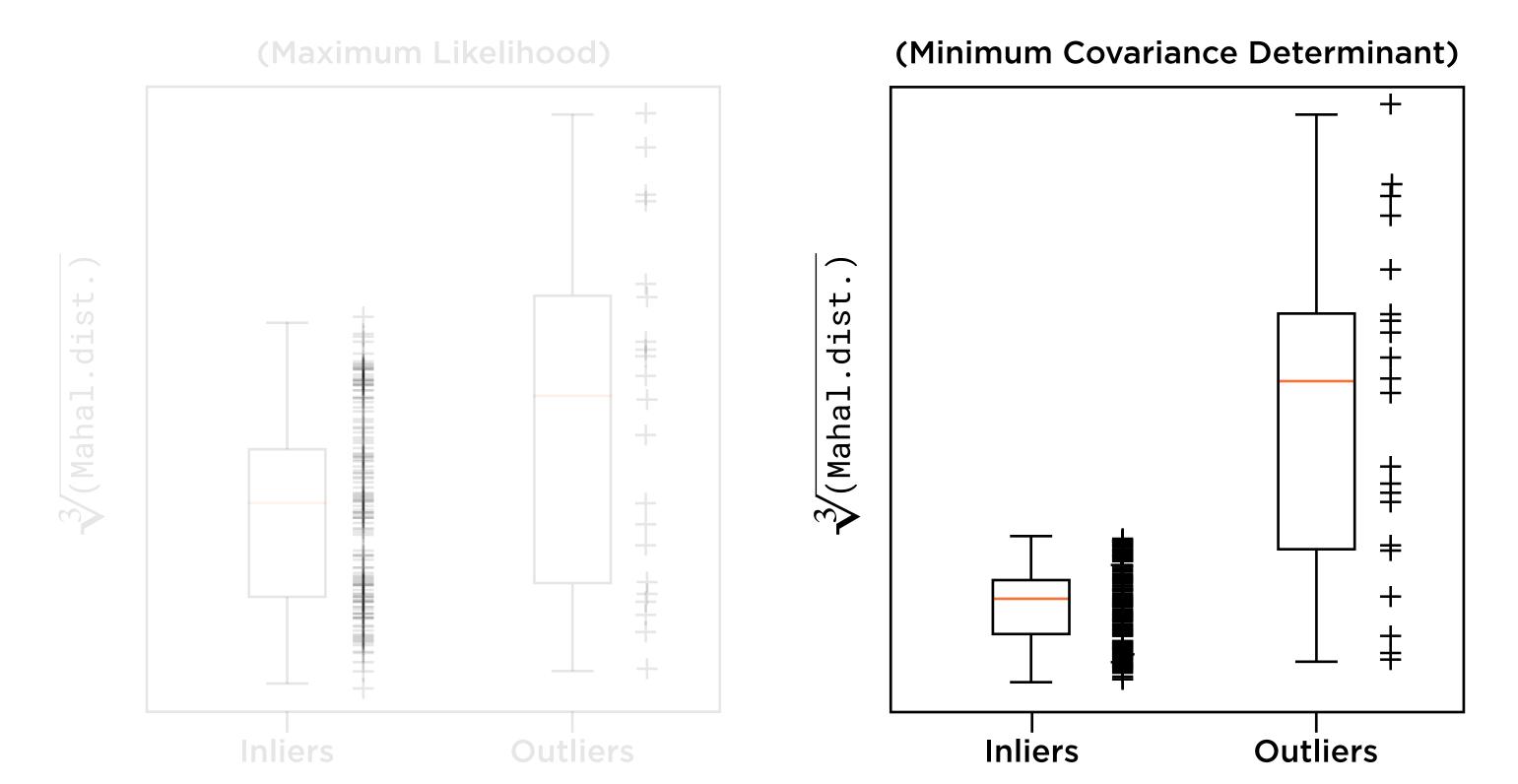
#### Mahalanobis Distances of a Contaminated Dataset



#### Mahalanobis Distances of a Contaminated Dataset



#### Mahalanobis Distances of a Contaminated Dataset



# Outlier and Novelty Detection Algorithms in scikit-learn

Local Outlier Factor

Elliptic Envelope

**Isolation Forest** 

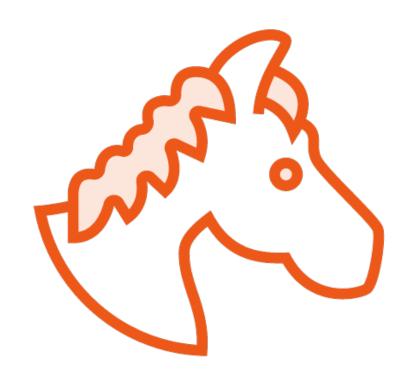


Use Random Forests (common ML technique) to identify outliers

**Forests of Decision Trees** 

Works particularly well for data of moderately high dimensionality

#### Jockey or Basketball Player?



**Jockeys** 

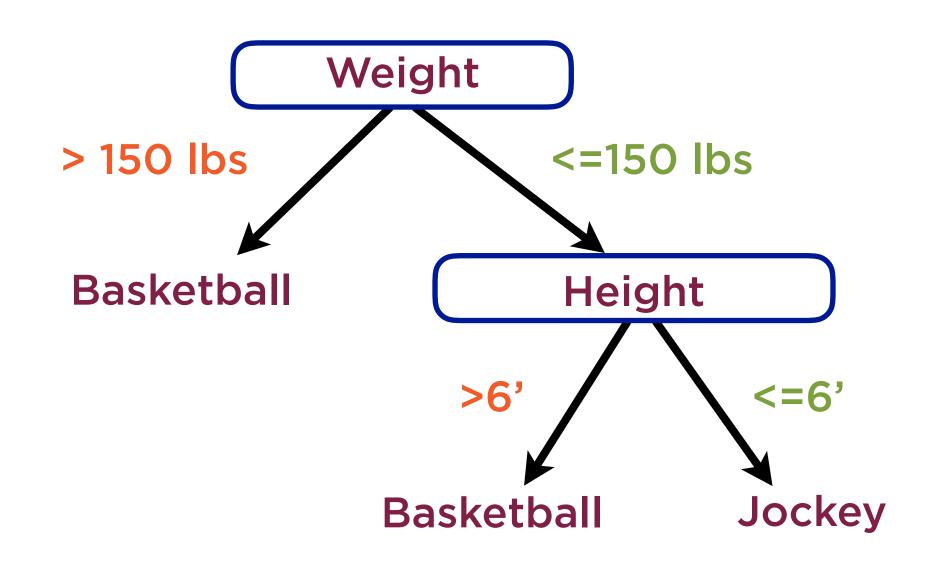
Tend to be light to meet horse carrying limits



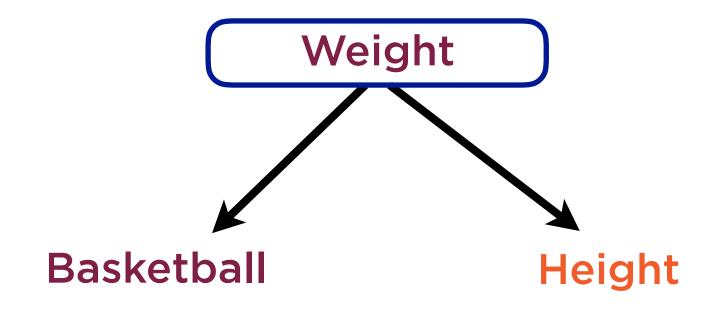
**Basketball Players** 

Tend to be tall, strong and heavy

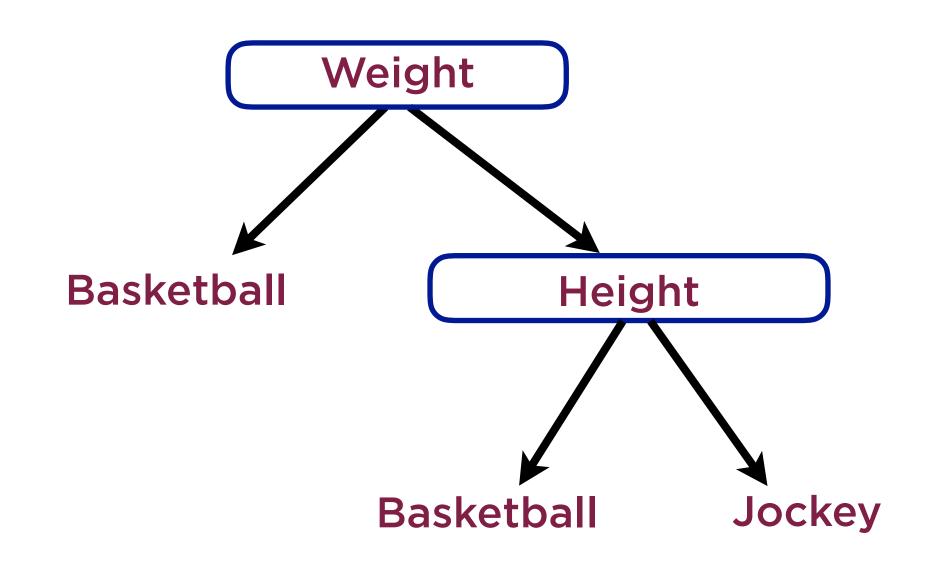
#### Fit Knowledge Into Rules



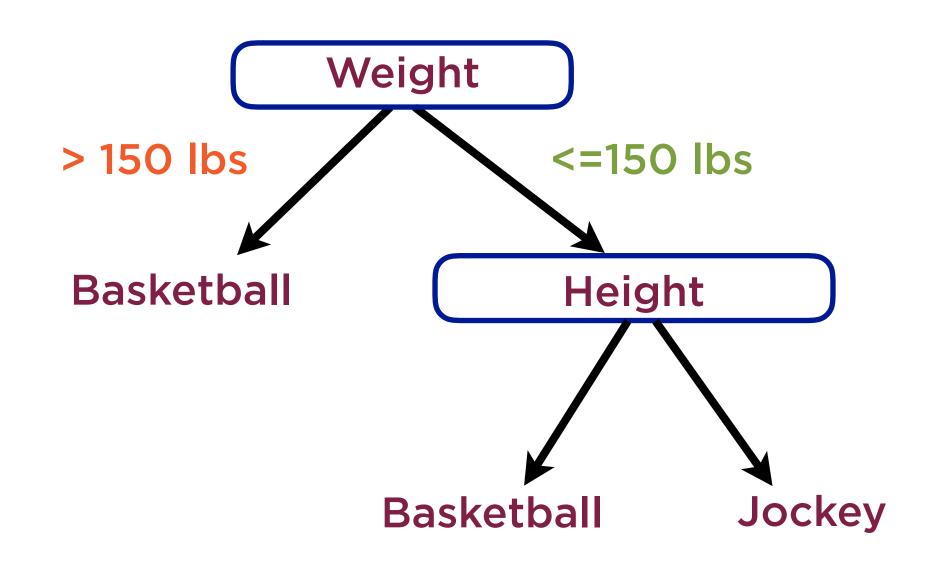
#### Decision Based on Weight



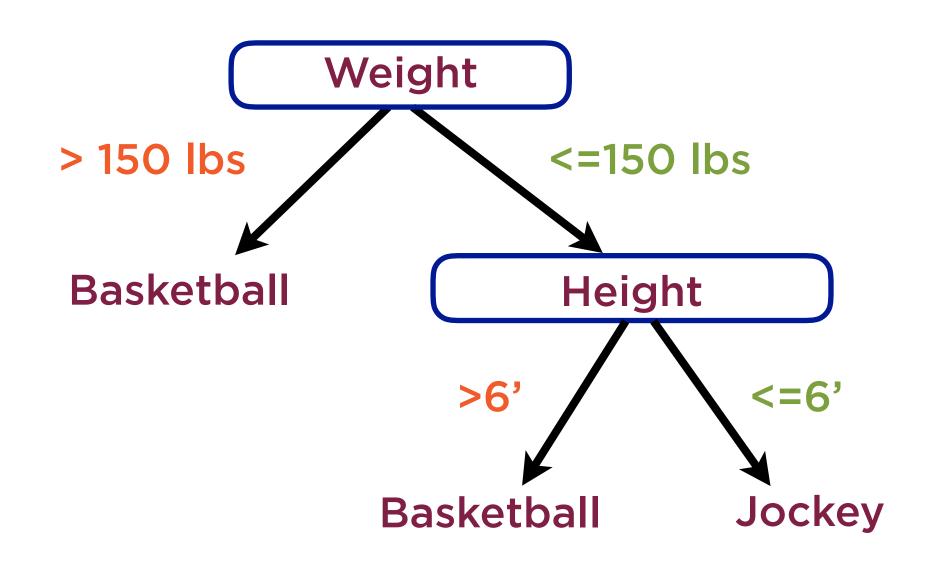
#### Decision Based on Height



#### Fit Knowledge Into Rules



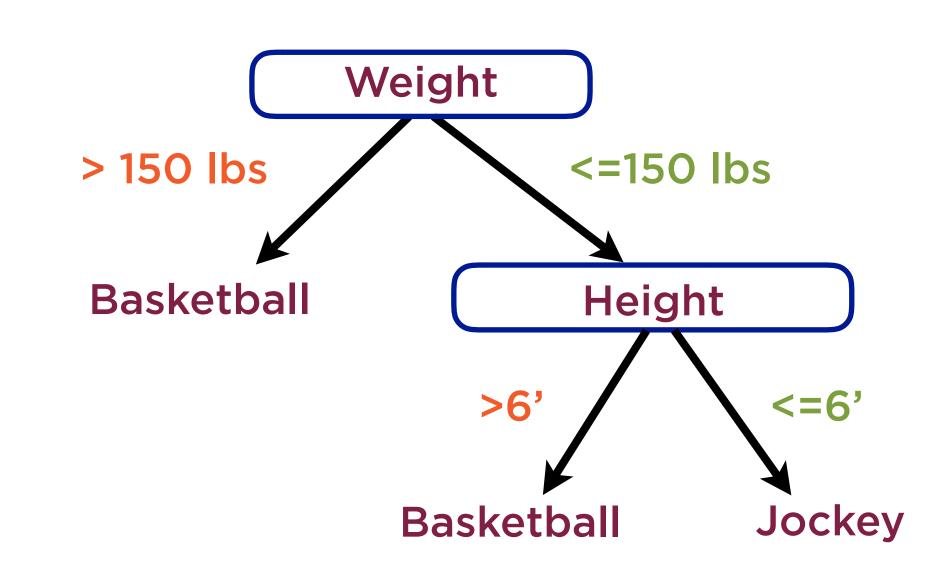
#### Fit Knowledge Into Rules



#### Decision Tree

Fit knowledge into rules

Each rule involves a threshold





Select a feature of the data point

Split records based on a randomly chosen value of the feature

Continue till a sample is isolated



## Find how many splits are needed to isolate a point

- Place the point in a category by itself

## Smaller the number of splits, the more likely the point is to be an outlier

- Smaller path length from root => greater probability of being outlier



Find how many splits are needed to isolate a point

Place the point in a category by itself

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# Path length averaged over a forest of random trees determines outliers

#### Demo

Detecting outliers in data using Local Outlier Factor, Isolation Forest and Elliptic Envelope

#### Demo

Novelty detection using Local Outlier Factor, Isolation Forest and Elliptic Envelope

#### Demo

Detecting outliers in the head-brain dataset

#### Summary

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