

# UNIVERSIDAD POLITECNICA DE YUCATÁN

Machine Learning

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### Of course! Here's the simplified explanation in English:

### 1. Overfitting and Underfitting:

# Overfitting:

When a learning model focuses too much on training data and learns weird things that aren't helpful. It works great with that data but fails with new data.

Imagine a basketball player who spends hours practicing three-point shots on his local court. He knows every imperfection in the floor and can make almost every shot there. But when he goes to play on a different court in a real game, his skills are not as impressive because he got too used to his local court.

### Underfitting:

Happens when a model is too simple and can't handle training data properly. It performs poorly with both known and new data.

On the other hand, think of a player who hardly practices and doesn't take training seriously. When the game arrives, they can't make simple shots or dribble correctly. Here, underfitting would be like not having prepared enough.

### 2. Outliers:

These are unusual data points that stand out and can confuse analysis or predictions.

Let's say you're analyzing the scoring statistics of a basketball team. Most players score around 10-20 points per game, but there's a player who occasionally scores more than 50 points in a single game. That player is an outlier in your dataset because their performances are significantly different from those of their teammates.

## 3. Solutions for Overfitting, Underfitting, and Outliers:

### Overfitting:

Simplify your model.

Set rules to prevent the model from going crazy.

Test the model in different situations.

If a basketball team is overtrained in a specific tactic, like full-court press, they may become vulnerable to teams with different strategies. To address it, the coach could vary their tactical approach based on the opponent and balance their playing style.

### **Underfitting:**

Make the model smarter or use more information.

Get more data if needed.

Make the model more useful.

If a team doesn't practice enough and struggles in every game, they could improve their performance by increasing practice time, enhancing individual skills, and working together as a cohesive team.

# Outliers:

Find and fix unusual data or get rid of it if it's problematic.

Use models that aren't too sensitive to unusual data.

If in a basketball team's points-per-game statistics, the outlier player who scores more than 50 points negatively impacts the analysis, the coach might consider analyzing the team's performance by excluding those exceptional games to get a more representative picture of the overall performance.

Modify the data to reduce the impact of unusual values.

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When you have too many features in your data, and it becomes challenging to manage.

# 5. Dimensionality Reduction:

Reducing the number of features in your data to simplify it and make it easier to handle.

## 6. Bias-Variance Trade-Off:

It's like finding a balance between being very stubborn in your beliefs (bias) and changing your mind all the time (variance). You need to find the middle ground to make accurate decisions.

https://www.nrigroupindia.com/e-

book/Introduction%20to%20Machine%20Learning%20with%20Python%20(%20PDFDrive.com%20)-min.pdf



