# 📌 Explanation of Each Metric Example

This document provides real-world examples demonstrating when to use specific metrics in Linear Regression models.

## 1️⃣ Mean Absolute Error (MAE) - House Price Prediction 🏠

\*\*When to Use MAE?\*\*  
✅ If you need an easily interpretable error metric (same units as the target variable).  
✅ If you don’t want to penalize large errors too much.

\*\*Example Scenario:\*\*  
A real estate company wants to predict house prices based on square footage.  
- \*\*Independent Variable (X):\*\* Square footage of the house.  
- \*\*Target Variable (Y):\*\* House price in dollars ($).  
- \*\*Model:\*\* Linear Regression.

📉 \*\*Result:\*\*  
\*\*MAE = $4,193.70\*\* → On average, our model’s predictions are \*\*$4,193.70 off\*\* from actual house prices.

🔹 \*\*Why MAE?\*\*  
Since we deal with \*\*dollar values\*\*, MAE is a good metric because it tells us the average error \*\*in the same unit as house prices ($)\*\*, making it easy to interpret.

## 2️⃣ Root Mean Squared Error (RMSE) - Stock Price Prediction 📈

\*\*When to Use RMSE?\*\*  
✅ If large errors need to be penalized more than small ones.  
✅ When dealing with stock prices, where large prediction mistakes can be costly.

\*\*Example Scenario:\*\*  
A trading firm wants to predict a stock’s closing price based on its opening price.  
- \*\*Independent Variable (X):\*\* Opening price of the stock.  
- \*\*Target Variable (Y):\*\* Closing price of the stock.  
- \*\*Model:\*\* Linear Regression.

📉 \*\*Result:\*\*  
\*\*RMSE = $10.41\*\* → The model’s stock price predictions have an \*\*average error of about $10.41\*\*.

🔹 \*\*Why RMSE?\*\*  
Stock prices are \*\*highly volatile\*\*, so a \*\*larger-than-expected error\*\* can be costly. RMSE penalizes larger errors more, making it useful for predicting stock prices \*\*where large errors should be avoided\*\*.

## 3️⃣ Mean Absolute Percentage Error (MAPE) - Sales Forecasting 📊

\*\*When to Use MAPE?\*\*  
✅ If relative error (percentage) matters more than absolute error.  
✅ Best for financial forecasting (e.g., revenue, sales predictions).

\*\*Example Scenario:\*\*  
A marketing team wants to predict daily sales revenue based on ad spending.  
- \*\*Independent Variable (X):\*\* Daily advertising budget ($).  
- \*\*Target Variable (Y):\*\* Sales revenue ($).  
- \*\*Model:\*\* Linear Regression.

📉 \*\*Result:\*\*  
\*\*MAPE = 509.46%\*\* → On average, our model’s sales predictions have an \*\*error of 509.46%\*\* compared to actual sales.

🔹 \*\*Why MAPE?\*\*  
Since revenue numbers \*\*vary in scale\*\*, absolute errors don’t always make sense. \*\*MAPE provides an error in percentage form\*\*, making it \*\*easier to compare across different budgets\*\*.

## 4️⃣ Adjusted R-Squared - GDP Prediction 💰

\*\*When to Use Adjusted R²?\*\*  
✅ If using multiple independent variables.  
✅ If trying to explain the relationship between multiple economic factors.

\*\*Example Scenario:\*\*  
An economist wants to predict a country’s GDP based on inflation rate, interest rate, and investment levels.  
- \*\*Independent Variables (X):\*\* Inflation rate (%), Interest rate (%), Investment ($).  
- \*\*Target Variable (Y):\*\* GDP ($).  
- \*\*Model:\*\* Multiple Linear Regression.

📉 \*\*Result:\*\*  
\*\*Adjusted R² = 0.69\*\* → Our model explains \*\*69% of the variation in GDP\*\* using inflation, interest rates, and investment.

🔹 \*\*Why Adjusted R²?\*\*  
Since we have \*\*multiple predictors\*\*, regular R² can be misleading because it always increases when adding variables. \*\*Adjusted R² accounts for the number of variables and only increases if they add real predictive power.\*\*

## 📌 Final Takeaways

✅ \*\*Use MAE for house prices\*\* → When errors should be interpretable in dollar amounts.  
✅ \*\*Use RMSE for stock prices\*\* → When large errors need to be penalized more.  
✅ \*\*Use MAPE for financial forecasting\*\* → When percentage errors matter more than absolute errors.  
✅ \*\*Use Adjusted R² for GDP prediction\*\* → When using multiple predictors and need to measure the model's overall explanatory power.