

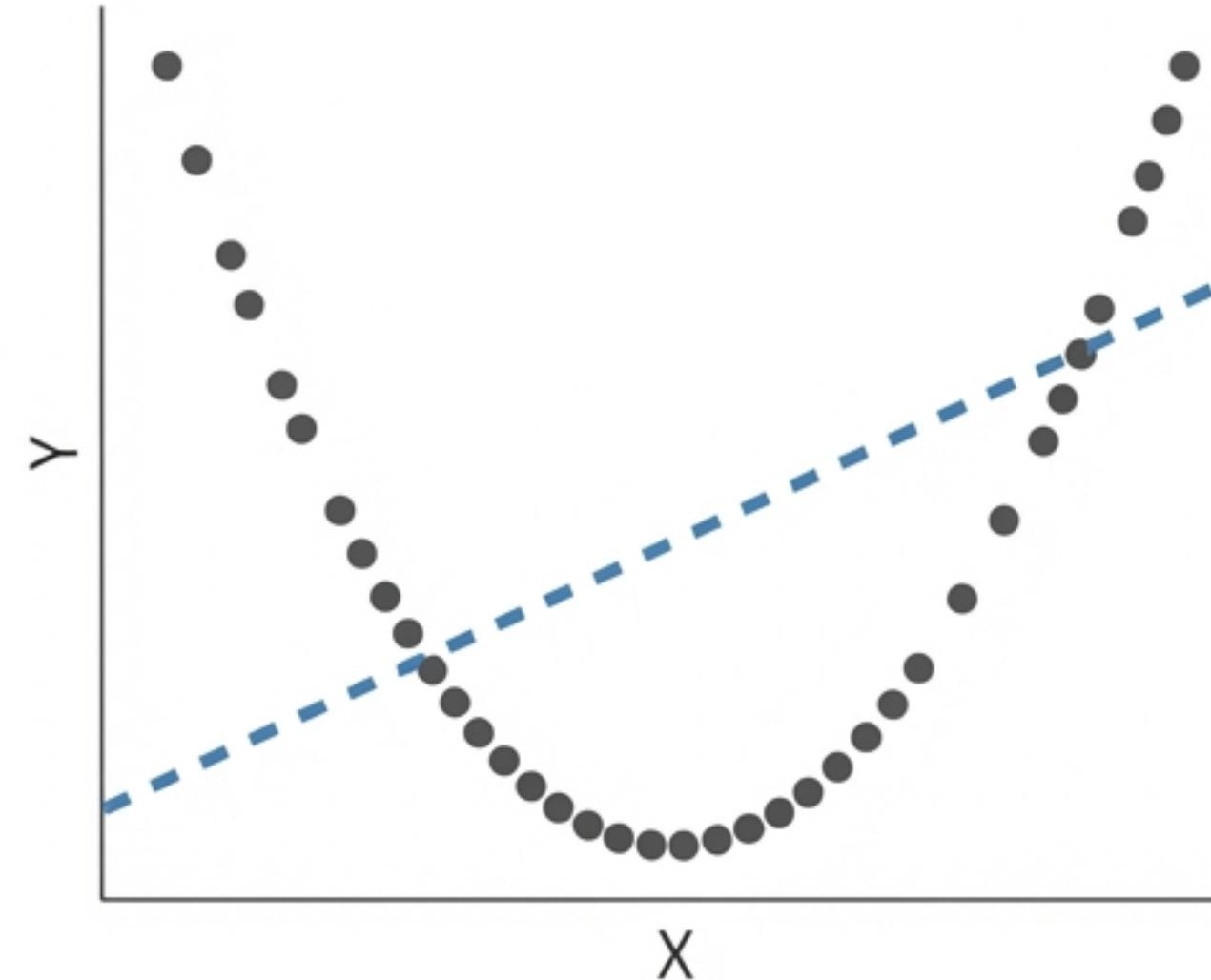
# Polynomial Regression

# Modeling the Curves in Your Data

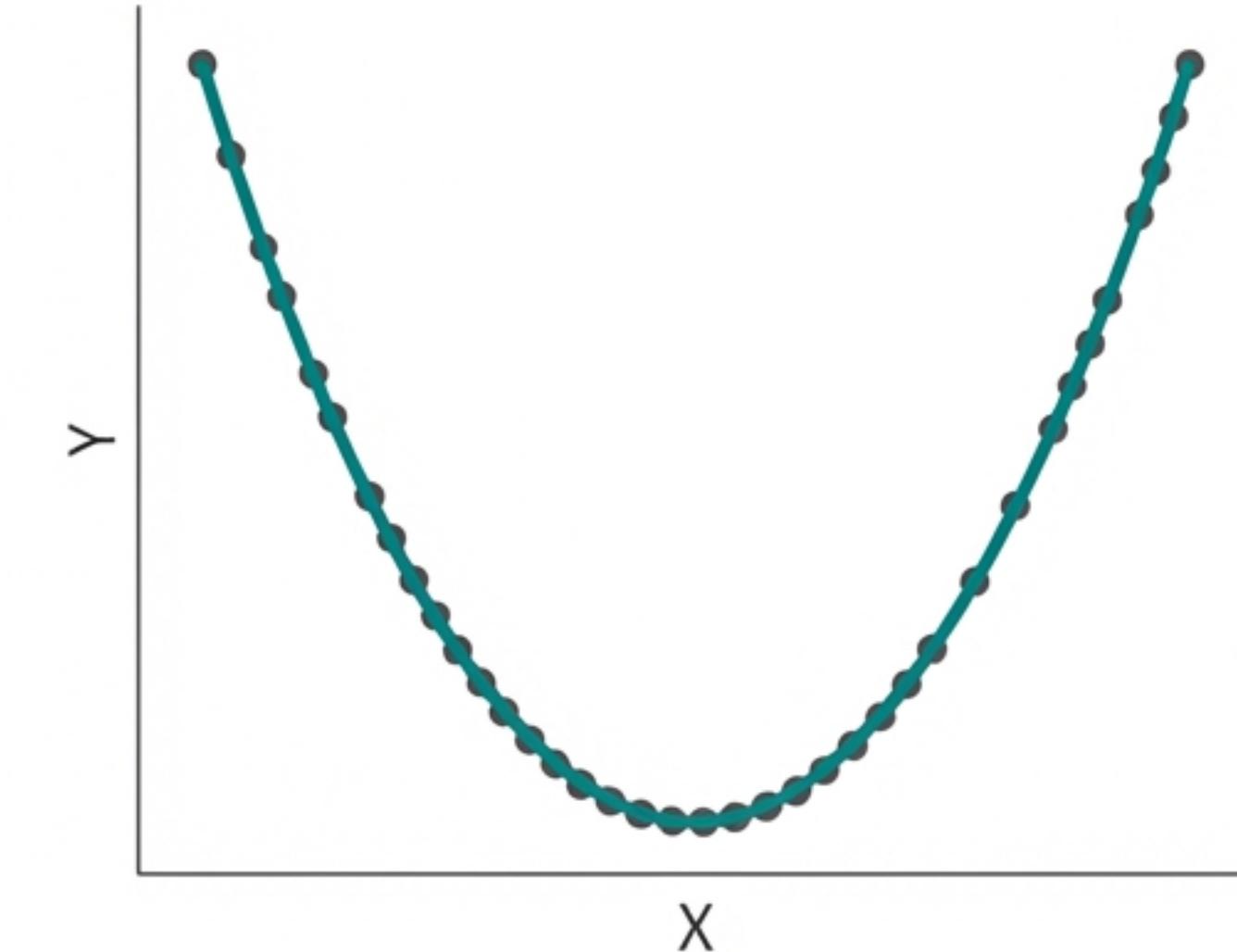
$$y = \beta_0 + \beta_1 x + \beta_2 x^2 + \cdots + \beta_n x^n + \epsilon$$

- An extension of linear regression used to model **non-linear relationships** between an independent variable ( $x$ ) and a dependent variable ( $y$ ).
- It works by transforming the input variable, adding higher-degree polynomial terms ( $x^2, x^3$ , etc.) to the model. This allows the regression line to become a flexible curve.
- Despite fitting a non-linear curve, it is considered a **linear model** because the regression function is linear in the unknown coefficients ( $\beta$ ) being estimated.

# From Straight Lines to Best-Fit Curves

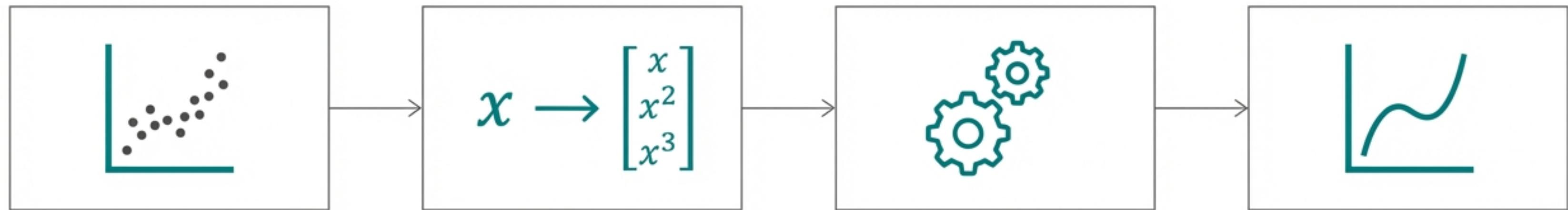


**Linear Regression:** Underfits the data due to high bias, failing to capture the underlying curved pattern.



**Polynomial Regression:** Flexibly captures the non-linear trend by increasing model complexity, resulting in a much better fit.

# Transforming Features to Model Complexity



## Observe Data

Start with independent (x) and dependent (y) variables that show a non-linear relationship.

## Transform Features

Create new polynomial features from the original independent variable:  $x \rightarrow [x, x^2, x^3 \dots]$ . These are treated as distinct independent variables.

## Fit Linear Model

Use the transformed features to fit a multiple linear regression model, which learns the optimal coefficients ( $\beta$ ) for each polynomial term.

## Predict Curve

The final model produces a non-linear curve that can predict y for new values of x.

# The Power and the Pitfalls



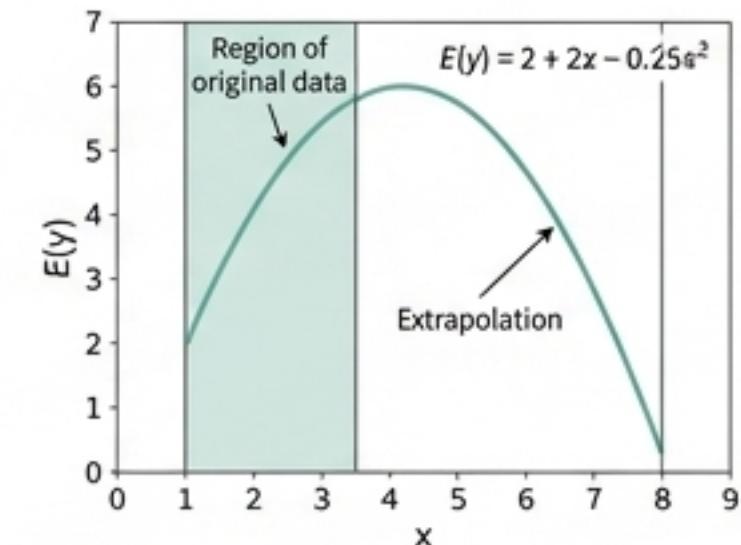
## Advantages

- **Flexibility:** Captures a wide range of complex, non-linear relationships that linear models miss.
- **Broad Applicability:** Useful across diverse domains where data isn't linear, such as biology, finance, and physics.
- **Intuitive Extension:** Builds directly upon the well-understood mathematical framework of multiple linear regression.



## Disadvantages

- **Overfitting Risk:** High-degree polynomials can fit the noise in the training data (high variance), leading to poor performance on new data. This is the primary trade-off.
- **Extrapolation Danger:** Predictions outside the range of the original training data can be wildly inaccurate and unreliable, as the curve may turn in unanticipated directions.
- **Difficult Interpretation:** Individual coefficients ( $\beta_2$ ,  $\beta_3$ , etc.) are often hard to interpret meaningfully, as the monomial terms ( $x$ ,  $x^2$ ,  $x^3$ ) can be highly correlated.



# Where Polynomial Regression Makes an Impact



## Epidemiology

Modeling the sub-exponential (polynomial) growth patterns of disease outbreaks, such as the 2014 Ebola epidemic and the historical spread of HIV/AIDS.



## Biology

Predicting non-linear biological processes, such as tissue and tumor growth rates over time.



## Industrial Processes

Optimizing outputs in manufacturing and chemical processes by modeling the relationship between variables like temperature, concentration, and yield.



## Finance & Economics

Analyzing and forecasting cyclical market trends and economic growth patterns that do not follow a linear path.

# Key Takeaway

Polynomial Regression offers the flexibility to model complex, curved relationships, but its power must be balanced with careful model selection to avoid overfitting.

This embodies the classic bias-variance trade-off: as the polynomial degree increases, bias decreases, but the model becomes more sensitive to noise, increasing variance.

