Logistics Engineering & Management

FORECASTING IN LOGISTICS

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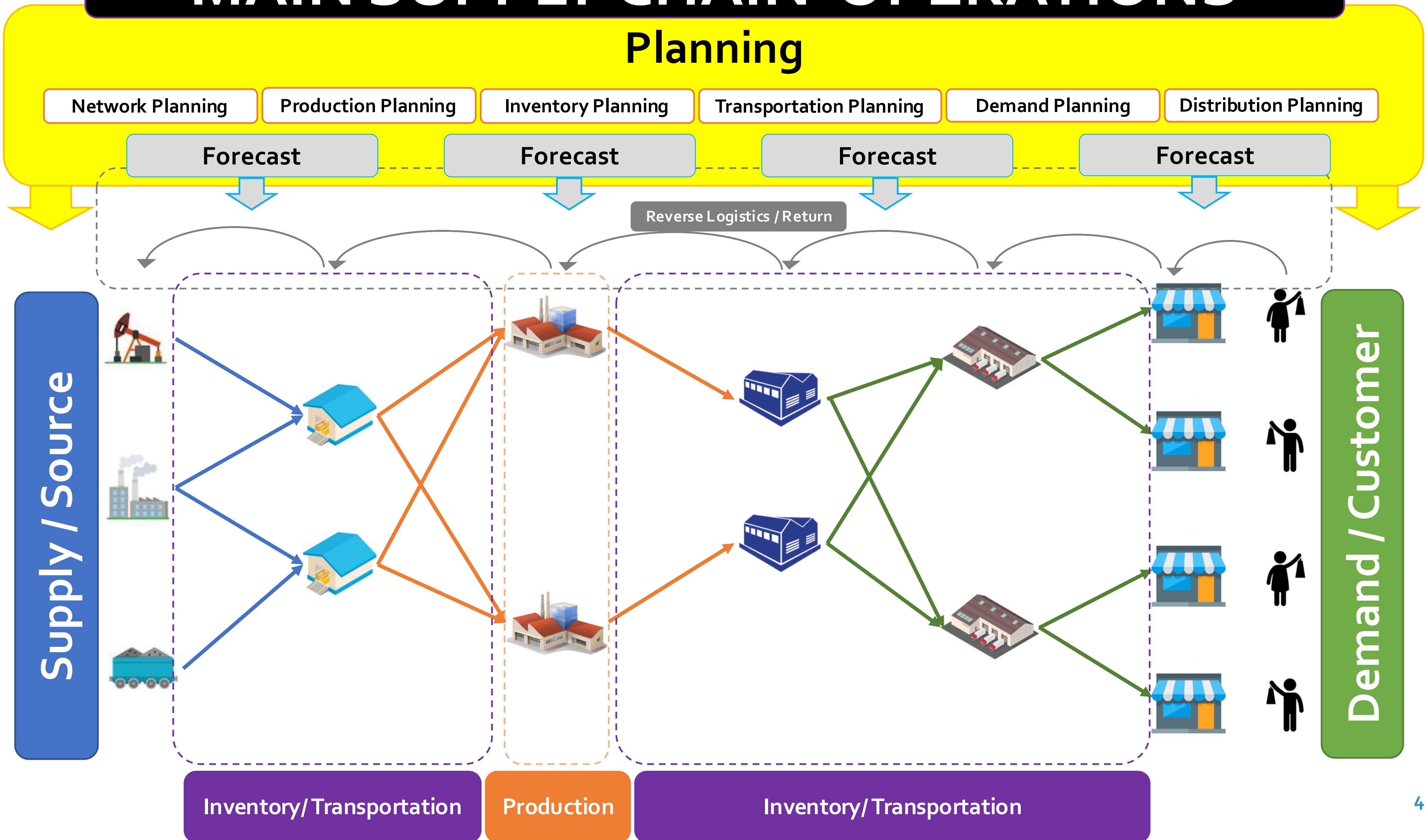
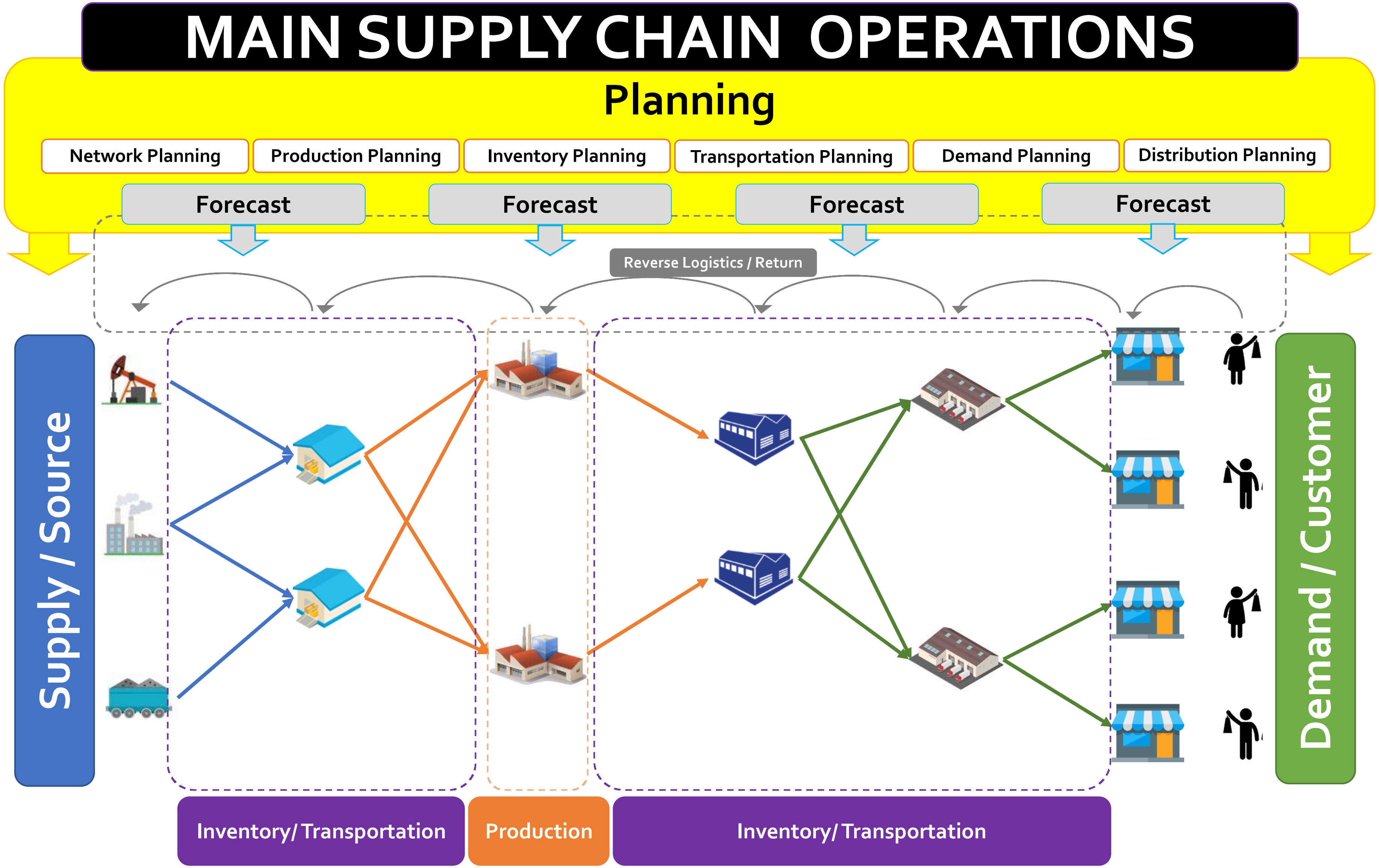
MAIN SUPPLY CHAIN OPERATIONS



Importance of Forecasting

- The future is uncertain
- Uncertainties at the core of demand and supply
- Improving profitability, productivity, and customer service
- Controlling costs
- Managing changes

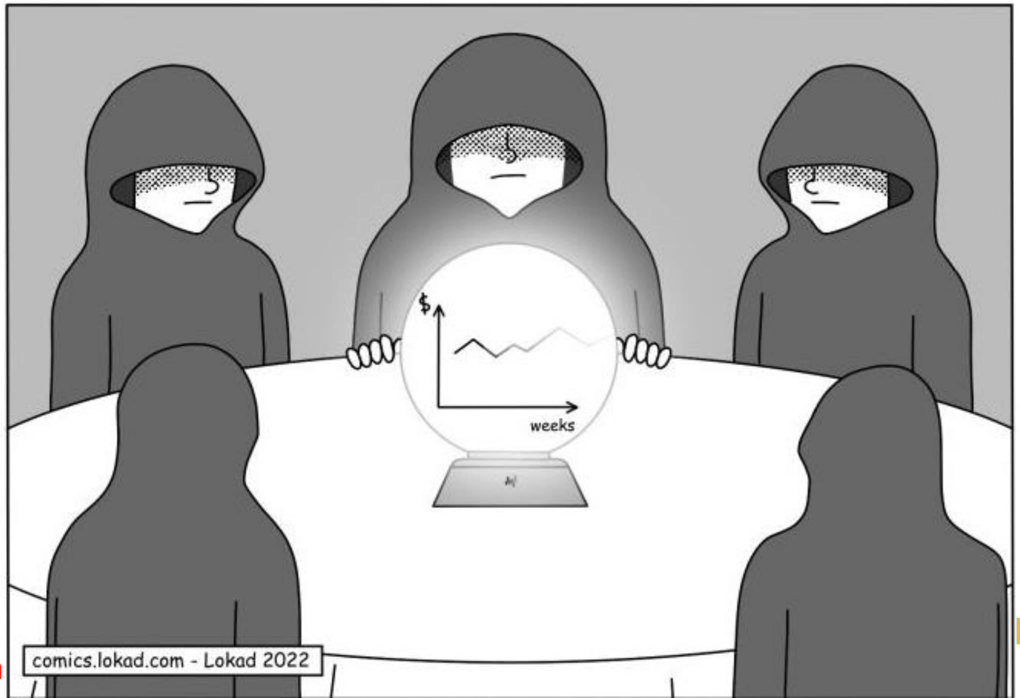


Role of Planning in Logistics Management

Definition

- An attempt to determine in advance the most likely outcome of an uncertain variable
- An objective estimate of future demand by projecting the past into the future

> "the business function that attempts to predict sales and use of products so they can be purchased or manufactured in appropriate quantities in advance."
>
> APICS Dictionary



Importance of Forecasting

Any 1% improvement in visibility on forecasting and inventory leads to…

Connect to www.wooclap.com/RMEGSK

????
Question

Which one do you think is a better forecasting?

The most accurate

The most useful

Forecasting Aggregation Level

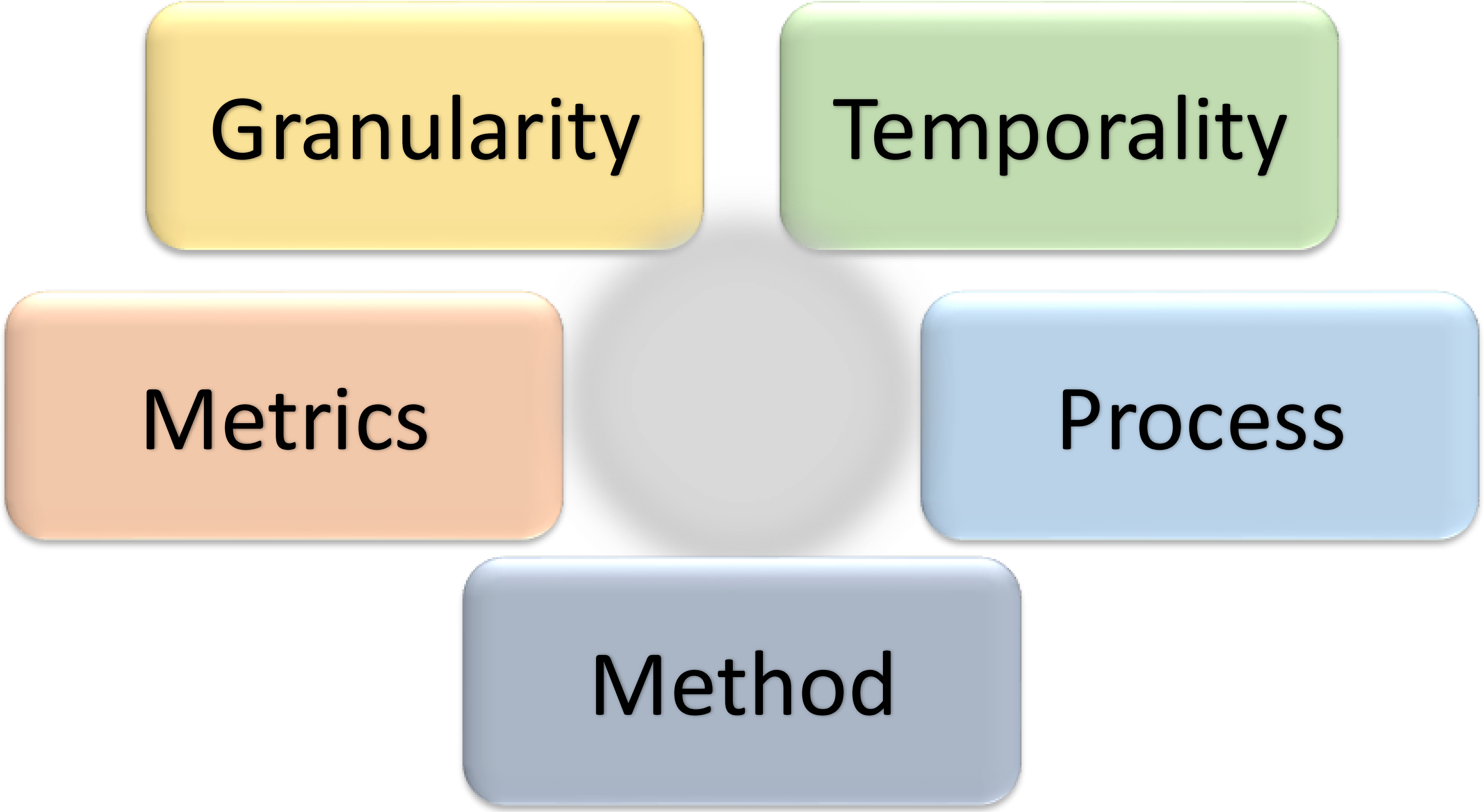
Material ⟷ Geographical ⟷ Temporal

Make proper Decisions -------- Take efficient Actions

- Right aggregation level
- Relevant metrics
- Efficient review process
- Accurate method

How to build a forecasting model

Forecasting Framework



Granularity

- How much to produce?
- Where to deploy inventory?
- Whether open/close plants?

Material

product, segment, brand, value, weight, type of raw material required

Geographical

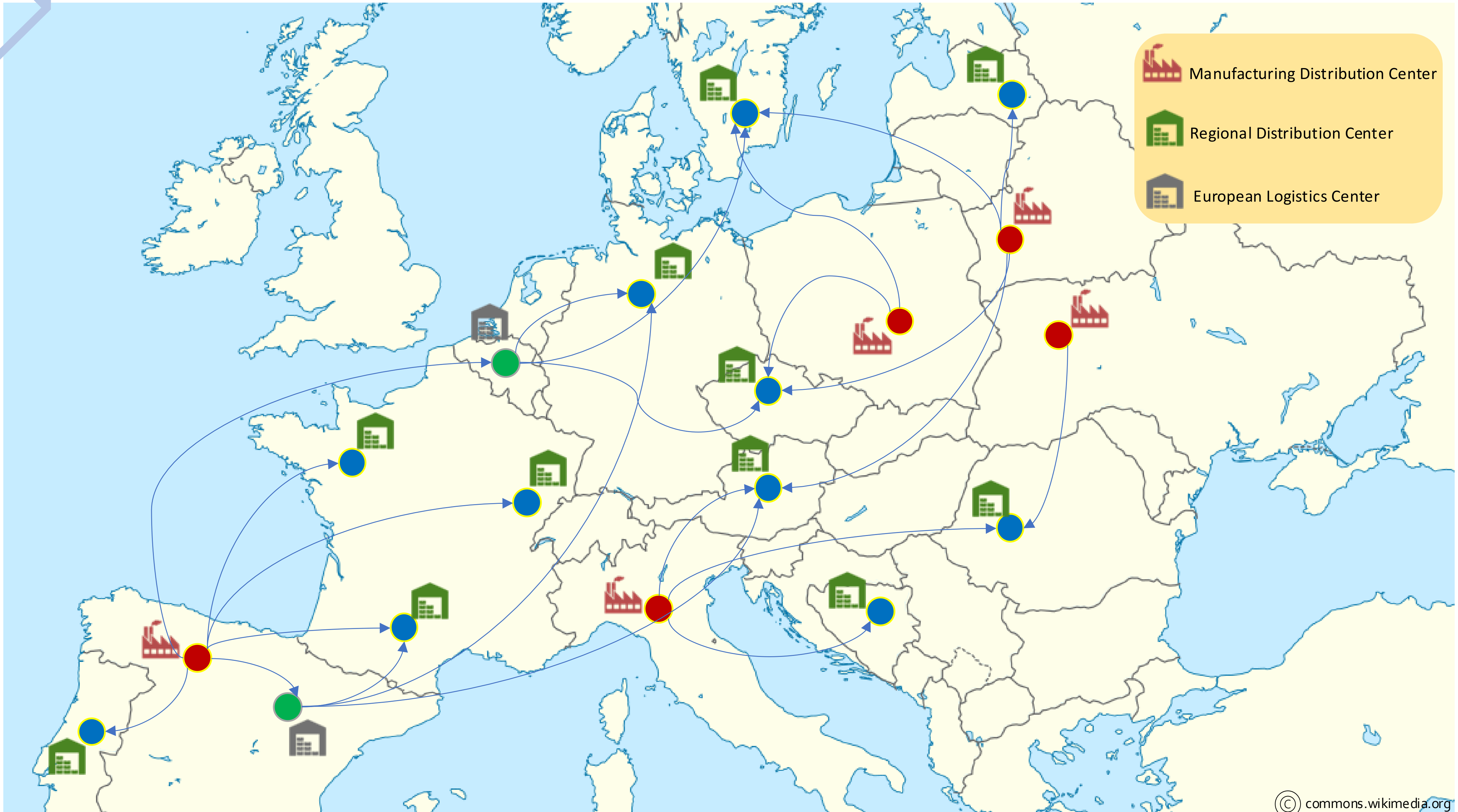
country, region, market, channel, customer segment, warehouse, store

$x_1, x_2, \ldots, x_n$ → same expected value μ_x and the same standard deviation σ_x

$y = x_1 + x_2 + \cdots + x_n$ → expected value and variance (standard deviation²) are, respectively, $\mu_y = n\mu_x$ and $\sigma^2_y = n\sigma^2_x$ →

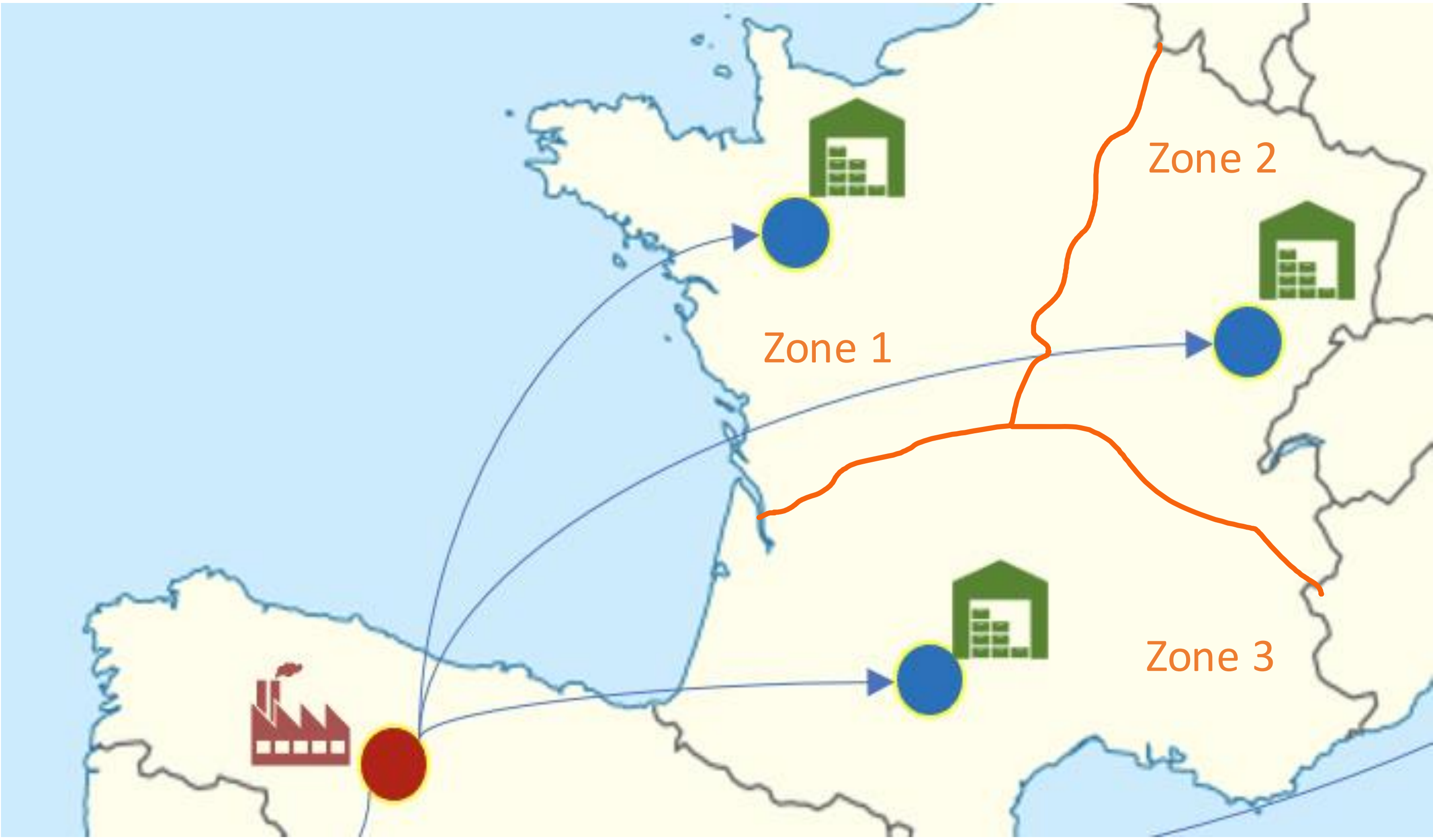
$$\frac{\sigma_y}{\mu_y} = \frac{1}{\sqrt{n}} \frac{\sigma_x}{\mu_x}.$$

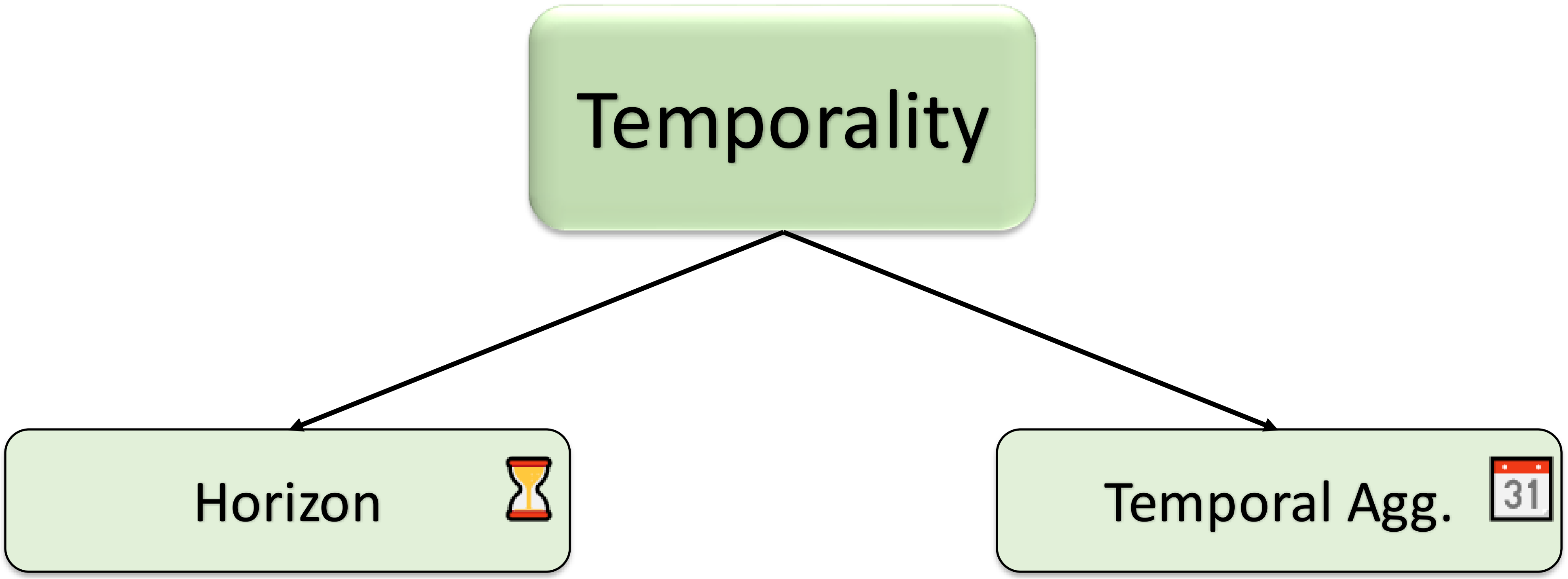
Question


Manufacturing Distribution Center
Regional Distribution Center
European Logistics Center
commons.wikimedia.org

Q1: If we need to decide which products and how much to ship from our plant to our regional warehouses

Q2: If we need to decide which products and how much to produce in our plant?



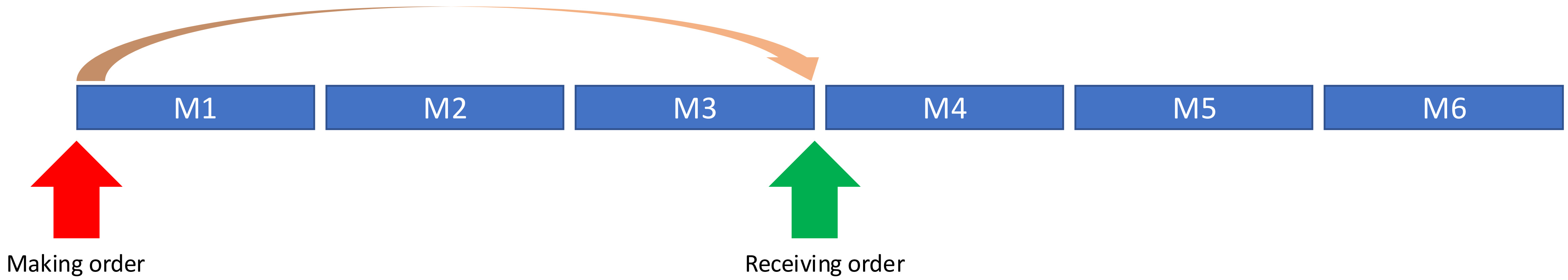


one month, six months, two years?

daily, weekly, monthly, quarterly, or yearly?

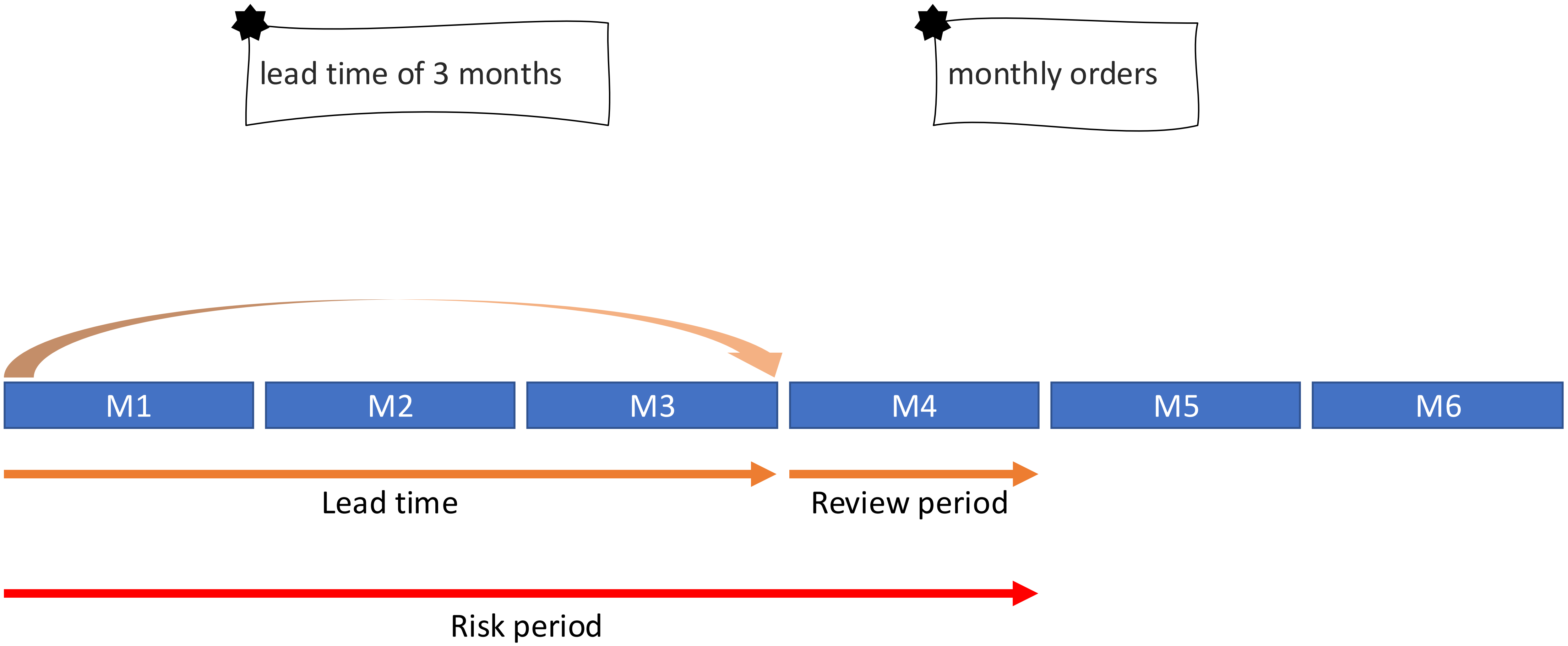
lead time of 3 months

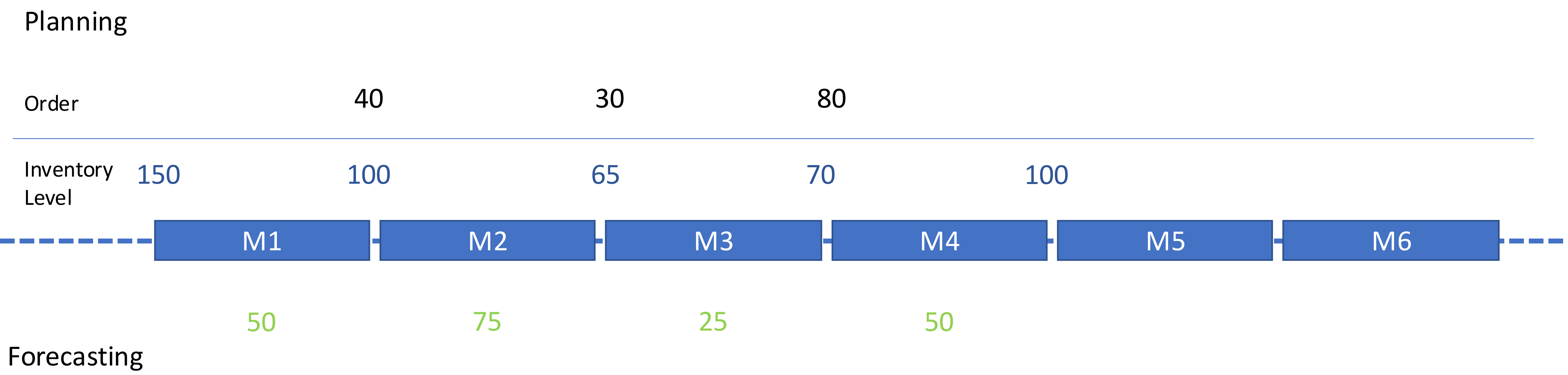
monthly orders



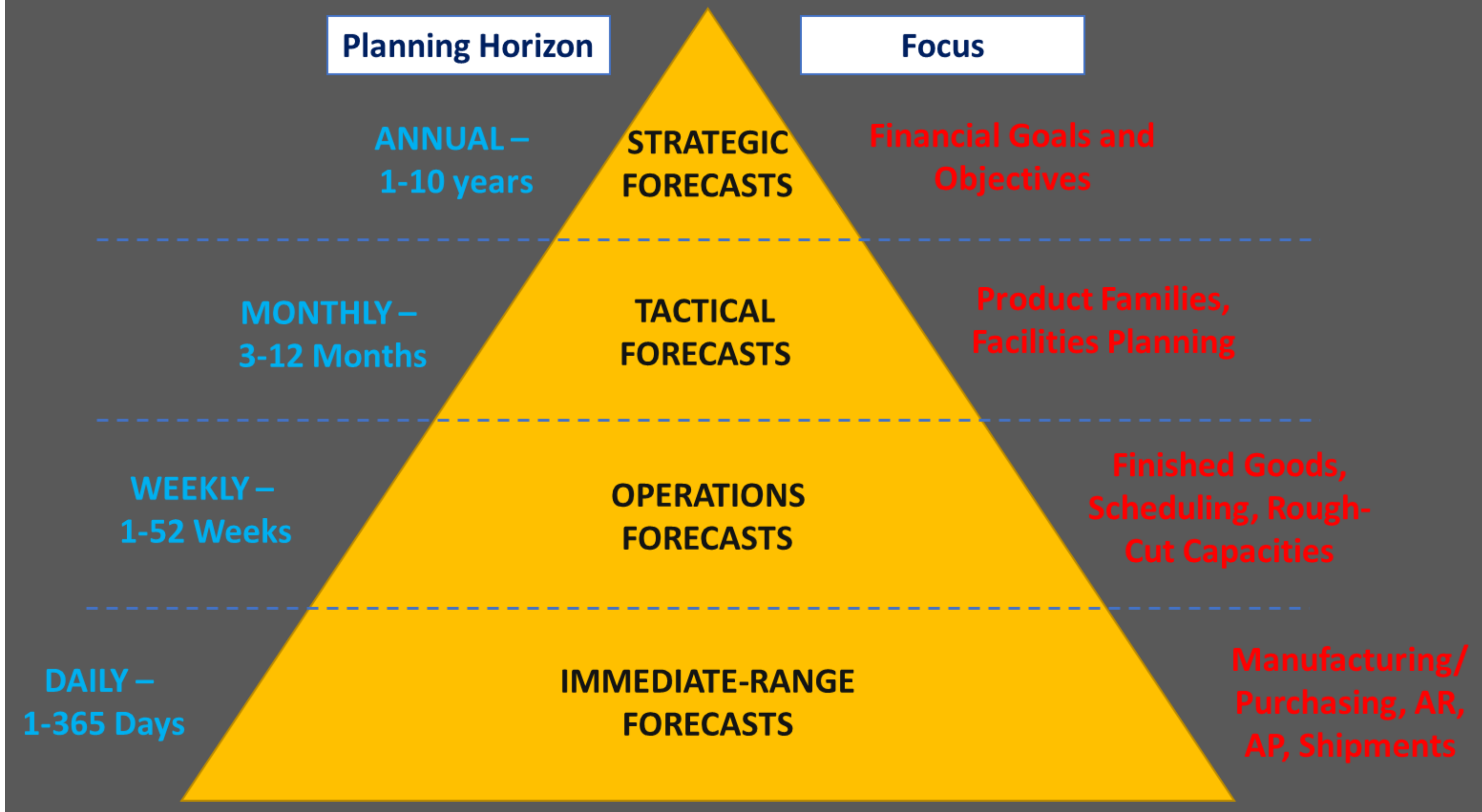
On which month(s) should we focus?

- Forecasting M+1?
- Forecasting M+3?
- Forecasting M+4?
- Forecasting M+1 to M+3?
- Forecasting M+1 to M+4?

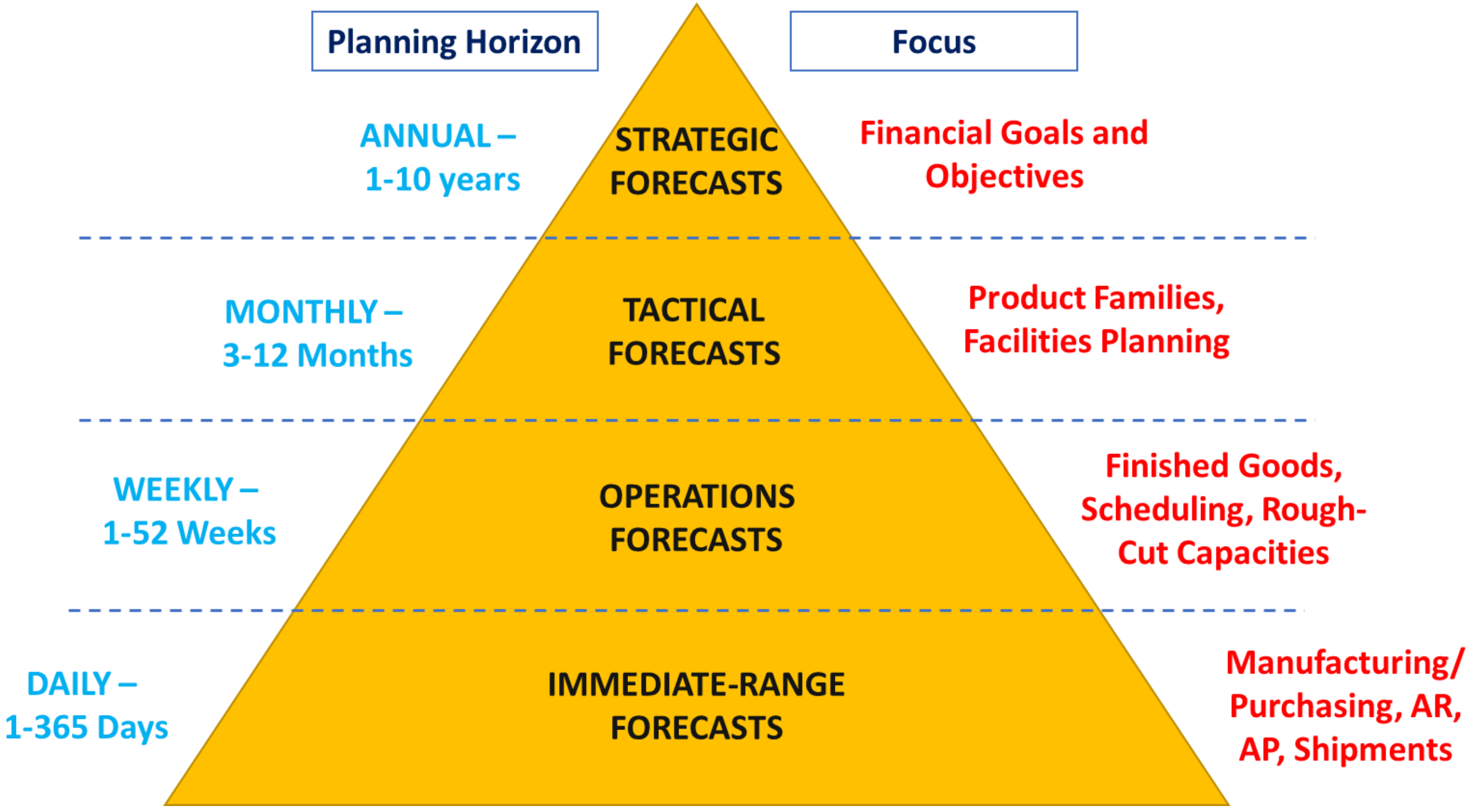

lead time of 3 months
monthly orders
M1
M2
M3
M4
M5
M6
Lead time
Review period
Risk period


Planning
Order
40
30
80
Inventory Level
150
100
65
70
100
M1
M2
M3
M4
M5
M6
50
75
25
50
Forecasting

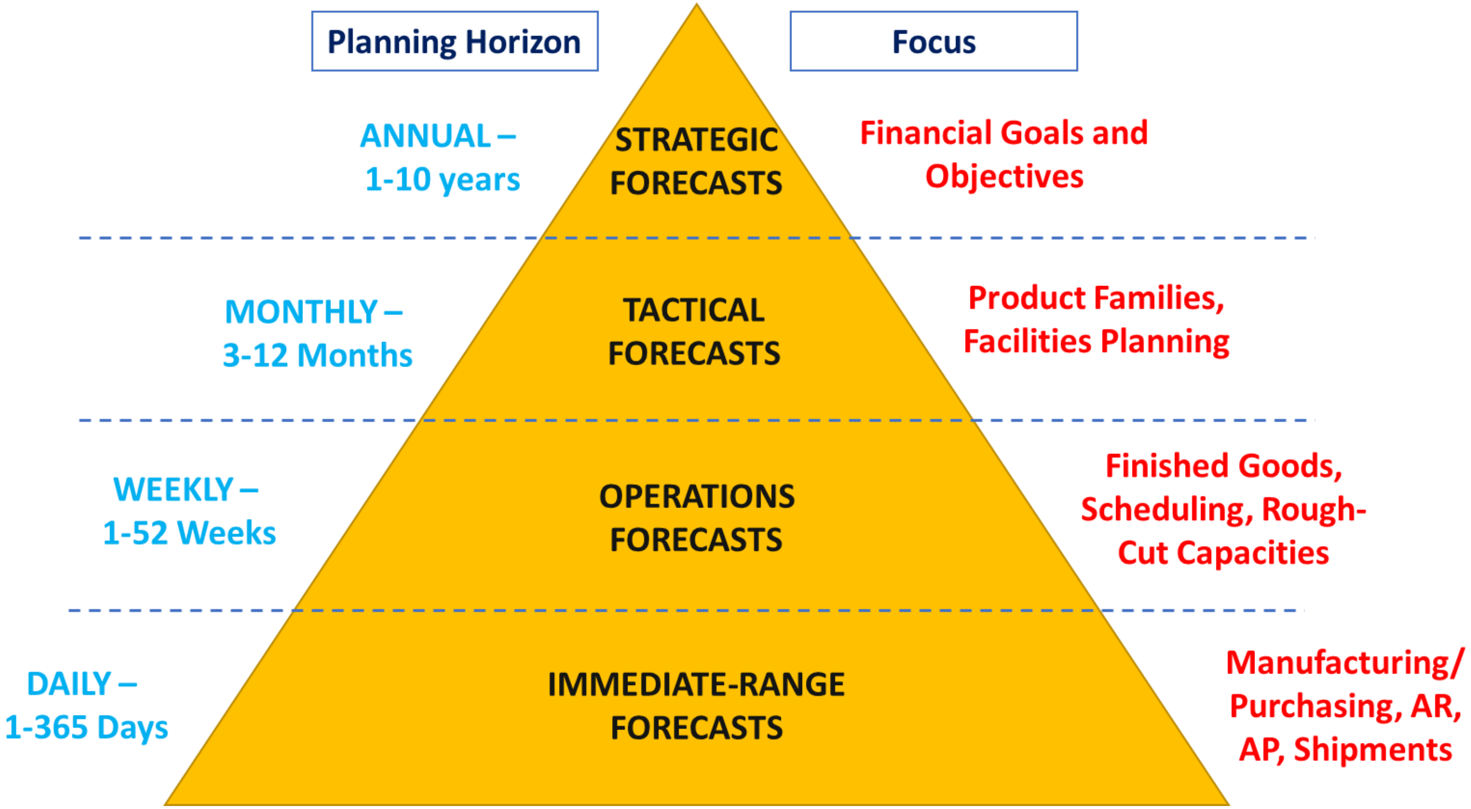
Forecasting Levels



*Long term/Short term definition may vary from one company to another

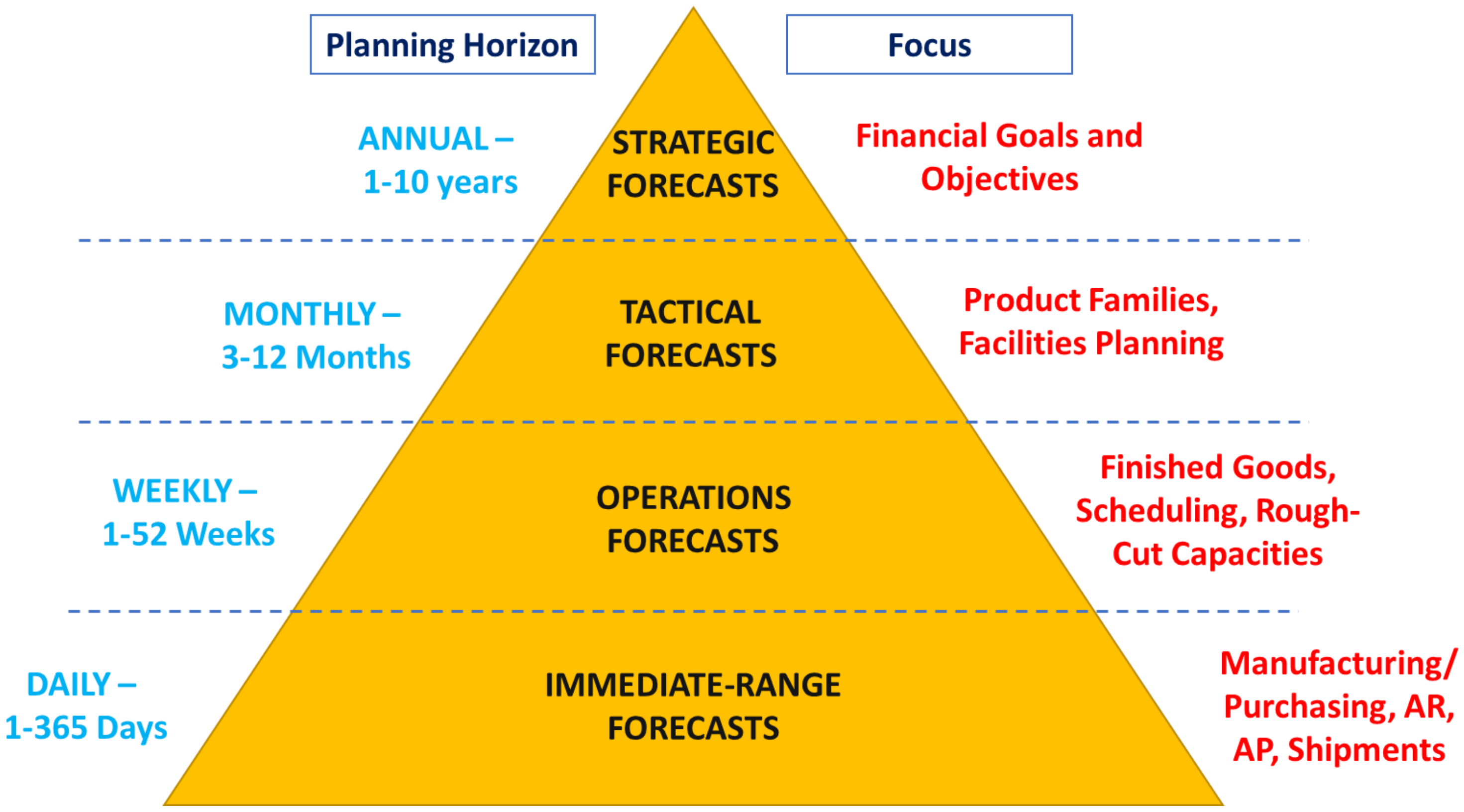


How much to ship?
How much to produce?
How much extra hours do we need?



How much to produce (seasonal products)?

How much interims should we hire?



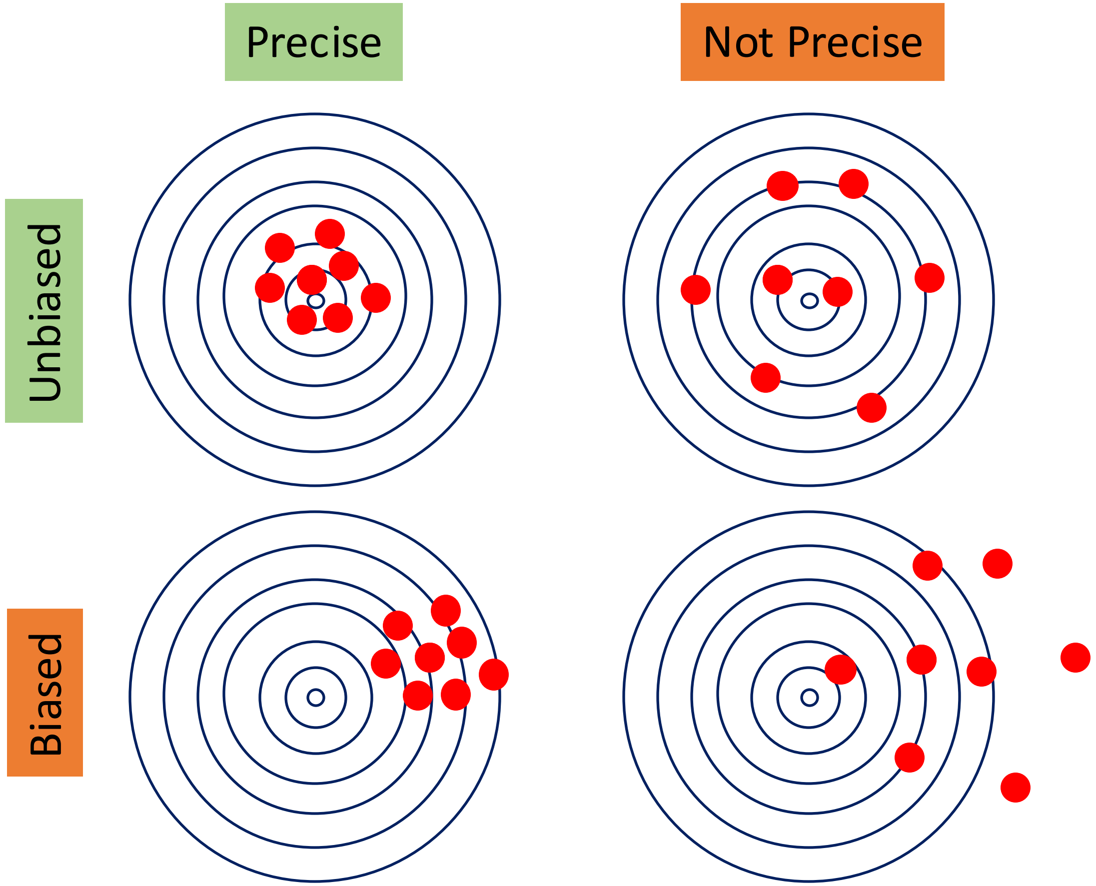
Should we launch this new product?
How much should we invest (in production, inventory)?
How many people should we hire?

Metrics

Track, Measure and Update forecasts

Precision measure the expected average error

Bias measure the forecast error spread



Measures of Forecast Error

I. Forecast error
II. Absolute Percent of Error (APE)
III. Bias
IV. Mean Absolute Error (MAE)
V. Mean Absolute Percent Error (MAPE)
VI. Root Mean Square Error (RMSE)
VII. Tracking Signal

Measures of Forecast Error

Calculating Forecast Error

$E_t = F_t - D_t$

E = the forecast error

F = the forecast

D = the demand

t = time

Measures of Forecast Error

Calculating the Absolute Percent of Error (APE)

How much the forecast deviates from the actual demand as a percent

$$APE = \frac{|f_t - d_t|}{d_t}$$

Measures of Forecast Error

Mean Absolute Percentage Error (MAPE)

The sum of the absolute percent error (as a percentage) for a given number of periods divided by the number of demand occurrences

$$MAPE = \frac{\sum_{t=1}^{N} \frac{|f_t - d_t|}{d_t}}{N}$$

1. Subtract the demand from the forecast to arrive at the forecast error for each period.
2. Convert the forecast error to an absolute value.
3. In each period, divide the absolute forecast error by the period's demand.
4. Multiply this value by 100 to arrive at the period APE.
5. Sum all of the period-level APEs.
6. Divide the sum APE by n periods to arrive at the MAPE percent

Measures of Forecast Error

Calculating Forecast Bias (Mean Error)

Consistent deviation of demand from the mean in one direction (high or low)

$$Bias = \frac{\Sigma(f_t - d_t)}{N}$$

$> 0 \rightarrow F > D$

$< 0 \rightarrow F < D$

1. Sum the total forecast and the total demand for n periods.
2. Subtract the demand from the forecast to arrive at the total forecast error.
3. Divide the sum of the forecast error by n periods.

Measures of Forecast Error

Mean Absolute Error (MAE)

deviation between the forecast and actual demand by ignoring whether the demand was above or below the forecast, and arriving at the average

$$MAE = \frac{\sum_{t=1}^{n} |F_t - D_t|}{n}$$

$$MAE\% = \frac{\sum_{t=1}^{n} |F_t - D_t|}{\sum_{t=1}^{n} D_t}$$

Measures of Forecast Error

Root Mean Square Error (RMSE)

The square root of the average squared error:

$$RMSE = \sqrt{\frac{1}{n}\sum(F_t - D_t)^2}$$

$$MSE = \frac{1}{n}\sum(F_t - D_t)^2$$

Period	Demand	Forecast
1	299	300
2	305	300
3	312	300
4	310	300
5	294	300
6	315	300
7	306	300
8	286	300
9	292	300
10	285	300
11	311	300
12	285	300

Process

- Who? → **Stakeholders**
- When? → **Periodicity**
- How? → **Review Process**
- What? → **Data**

Data

more data → better data → better forecast

Demand ≠ Sales 🤷‍♂

Question ???
What are the reasons causing difference between demand and sales?

- 🤝 Collaboration with clients
- ❌ Track Out-of-Stocks
- 😐 Products’ Cannibalization
- 📊 Analyze Demand Drivers
- 💻 Sales Order Management System

Data

Outliers

Mistakes & Errors

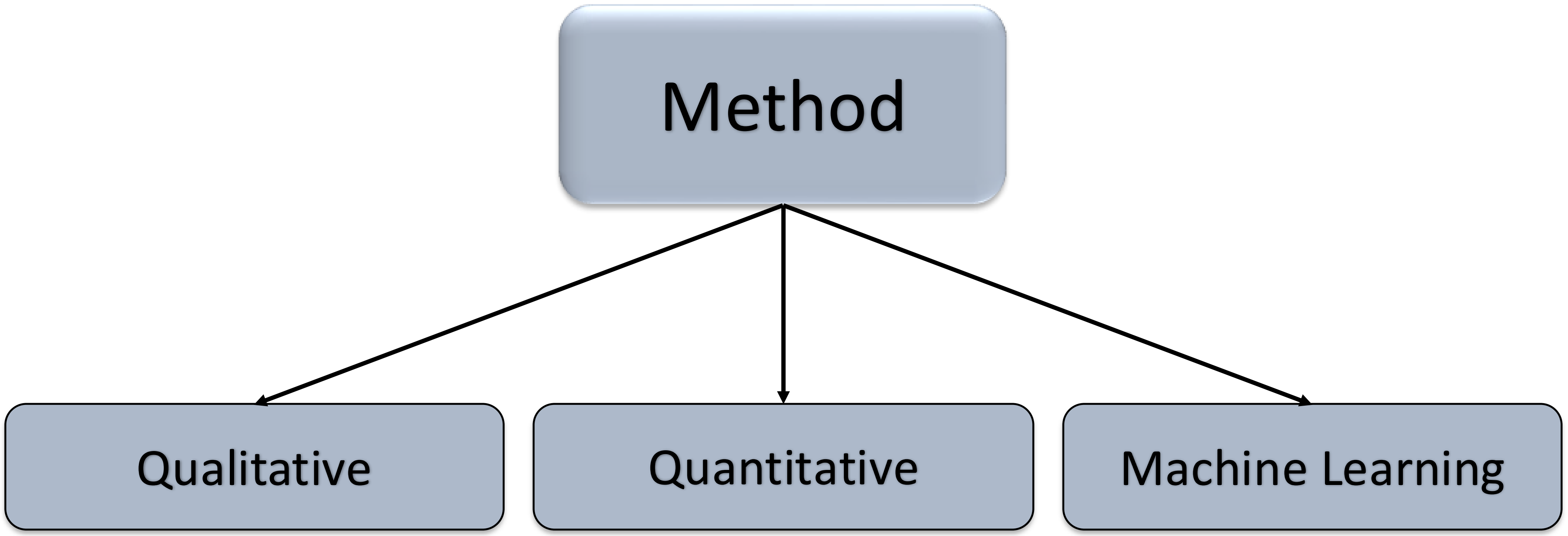
Exceptional demand

detection and cleaning

Winsorization

Error standard deviation

Standard deviation


Method
Qualitative
Quantitative
Machine Learning

Forecasting Techniques

Forecasting Techniques

Qualitative Techniques

Judgmental

- Expert opinion
- Sales force estimate
- Historical analogy
- Panel consensus
- Market research
- Delphi technique
- Visionary forecast
- Product life cycle analysis

Quantitative Techniques

Time Series (Intrinsic)

- Simple average
- Moving average
- Exponential smoothing

Associative (Extrinsic)

- Simple Regression
- Multiple Regression

Machine Learning

Bagging Models

- Random decision forests

Boosting Models

- Extreme Gradient Boosting

Deep Learning

- Neural Networks

Qualitative methods

- based on intuition or judgmental evaluation
- workforce experience or on surveys
- long- and medium-term forecasts
- insufficient history
  - new product or service

Delphi Method

1. Send questionnaires to experts
2. Gather anonymous answers
3. Send back the aggregated results to experts
4. Back to step 1 until agreement

Advantages

- Capabilities when no patterns and relationships
- Easily and quickly assembled

Disadvantages

- Lack of supporting evidence
- Overconfidence
- Possibility of over conformity of the individuals
- High cost of development and maintenance

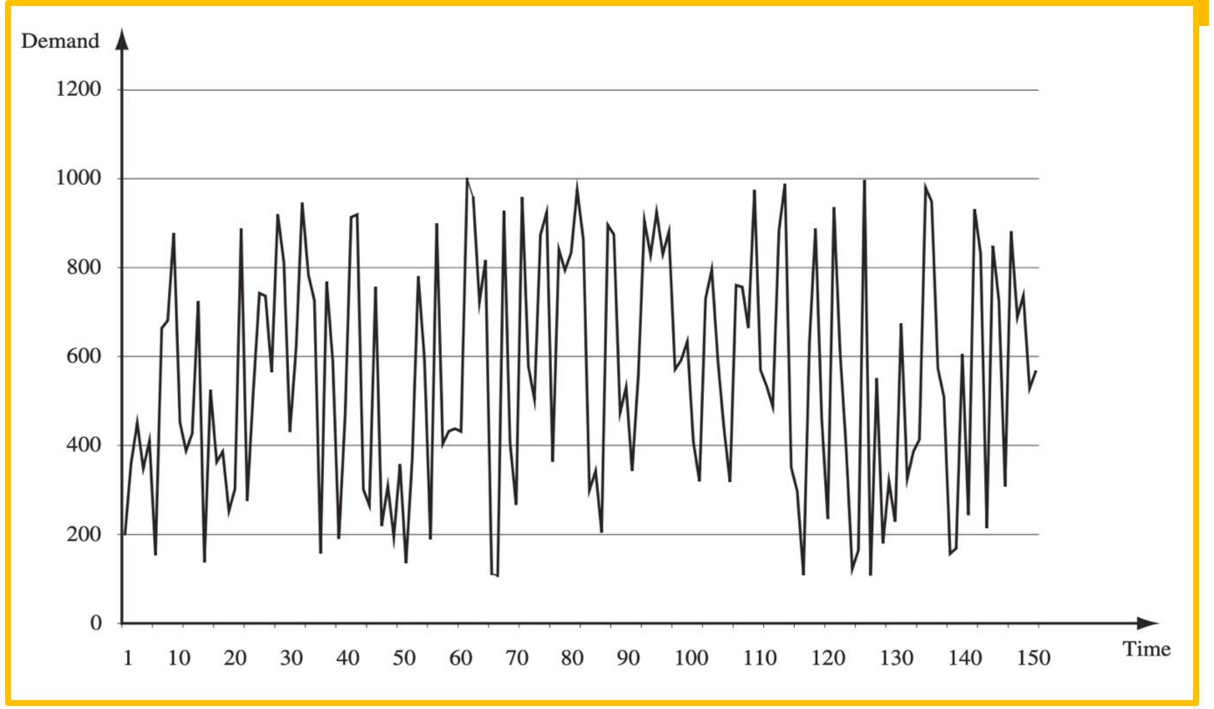
In qualitative forecasting pay attention to…

- Social pressure/Hierarchical/Political pressure
- Budget pressure
- Cognitive Bias

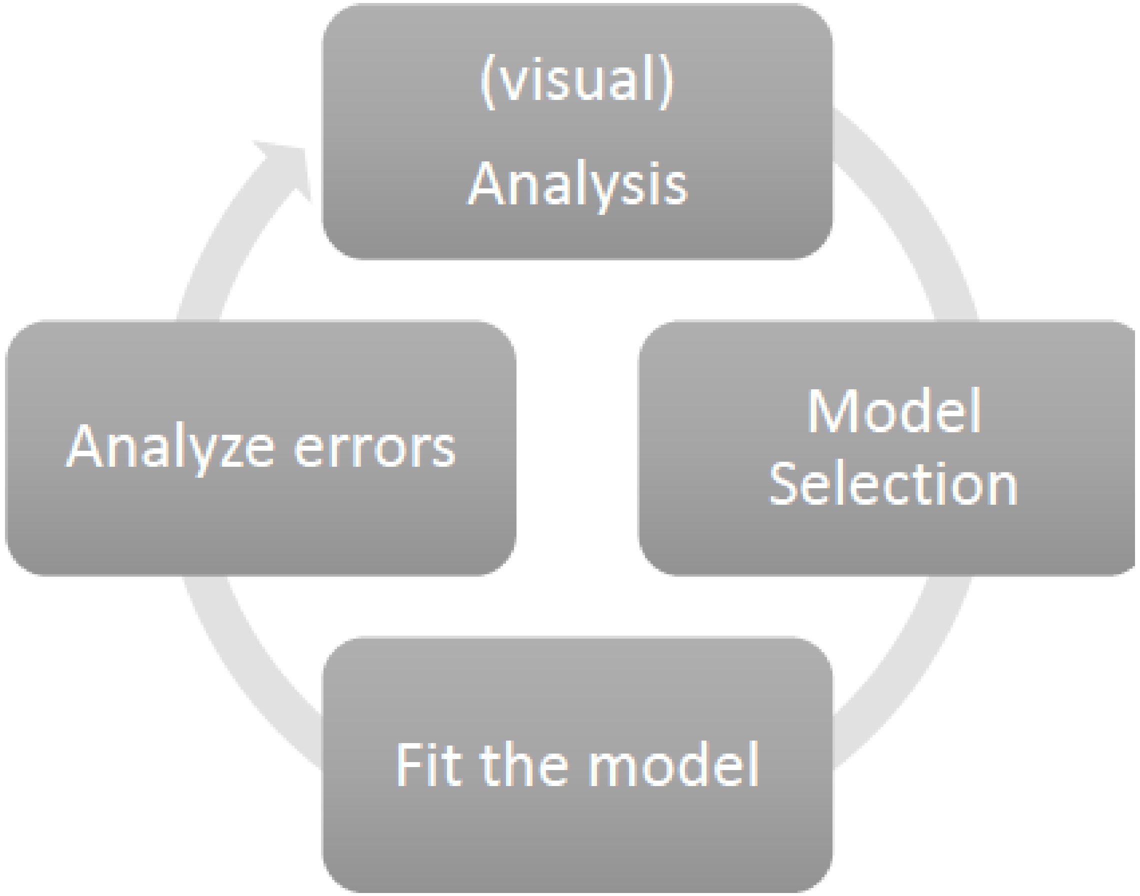
Forecast should not be done by the users

Quantitative methods

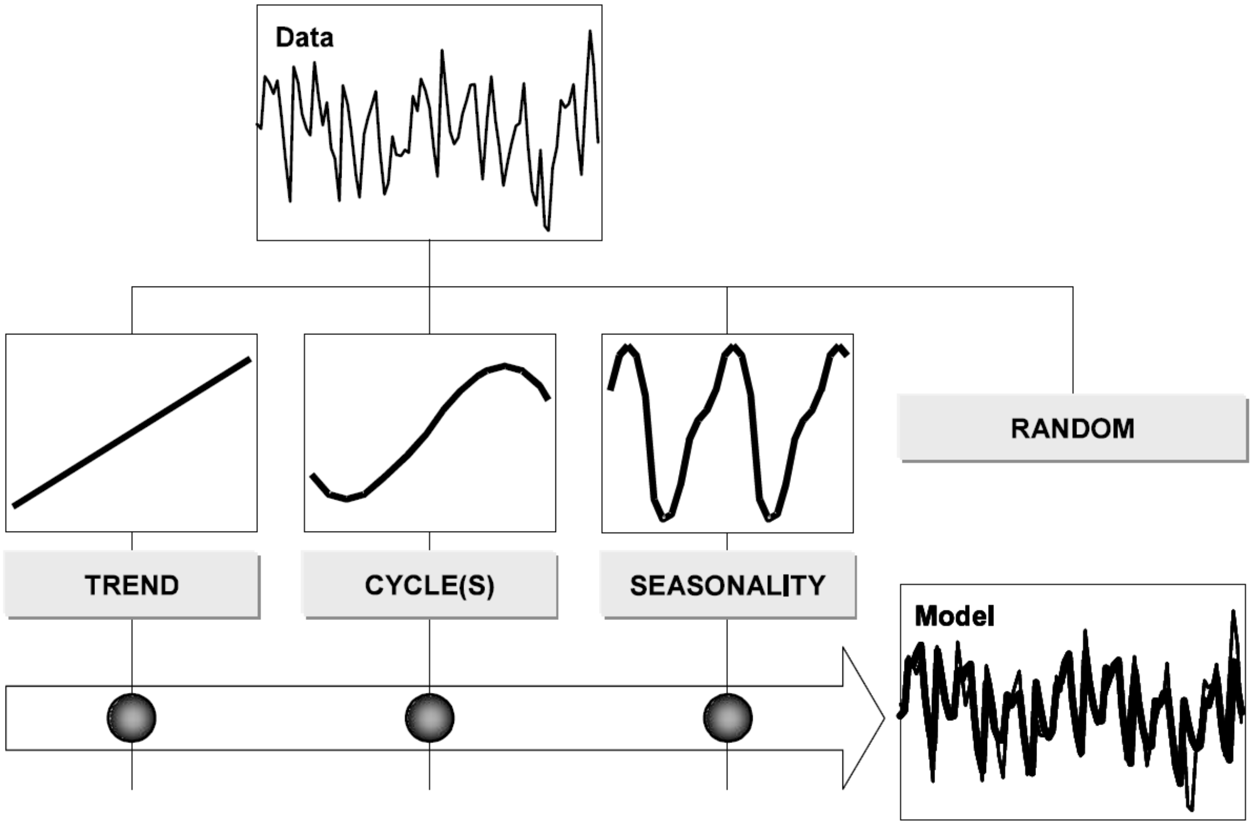
- Sizeable historical data
- Clear and stable relationships and patterns in data
- Short and medium-term forecasts



How to create a quantitative forecast model?



Components of Time Series



- Trend Variations
- Cyclical Variations
- Seasonal Variations
- Random Variations

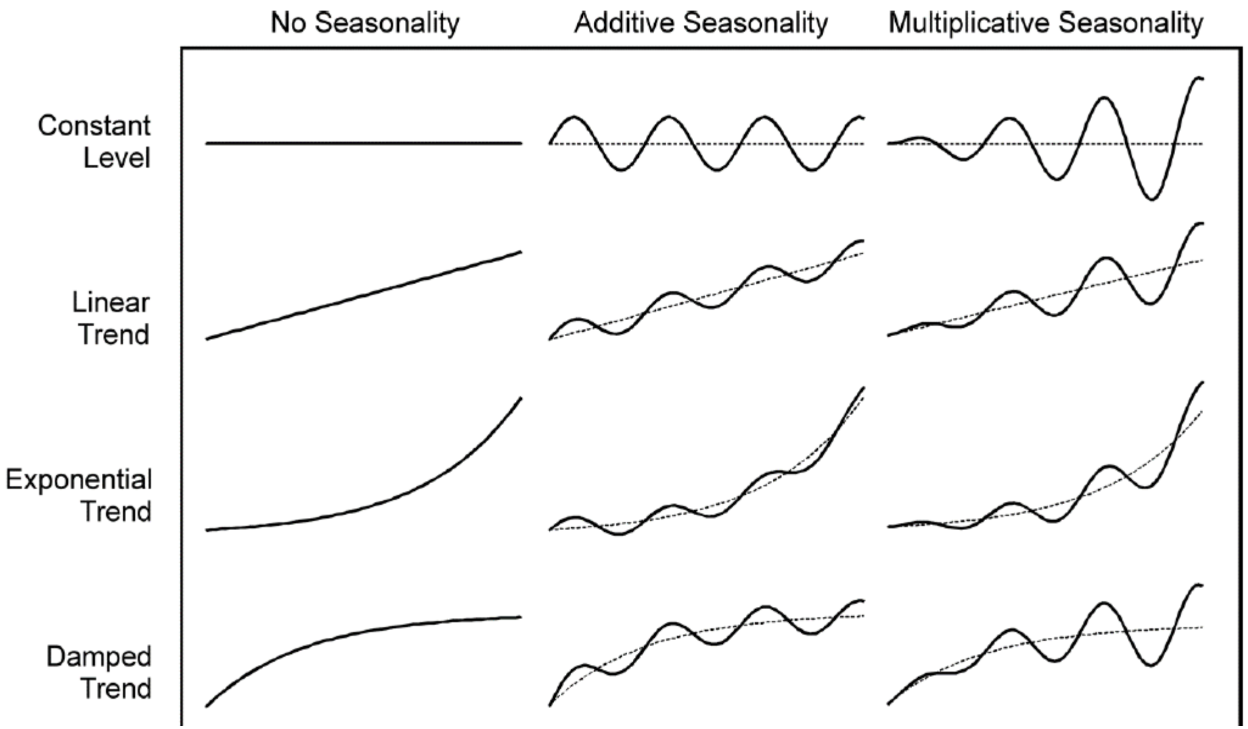
Decomposition of a Time Series

- **Additive**

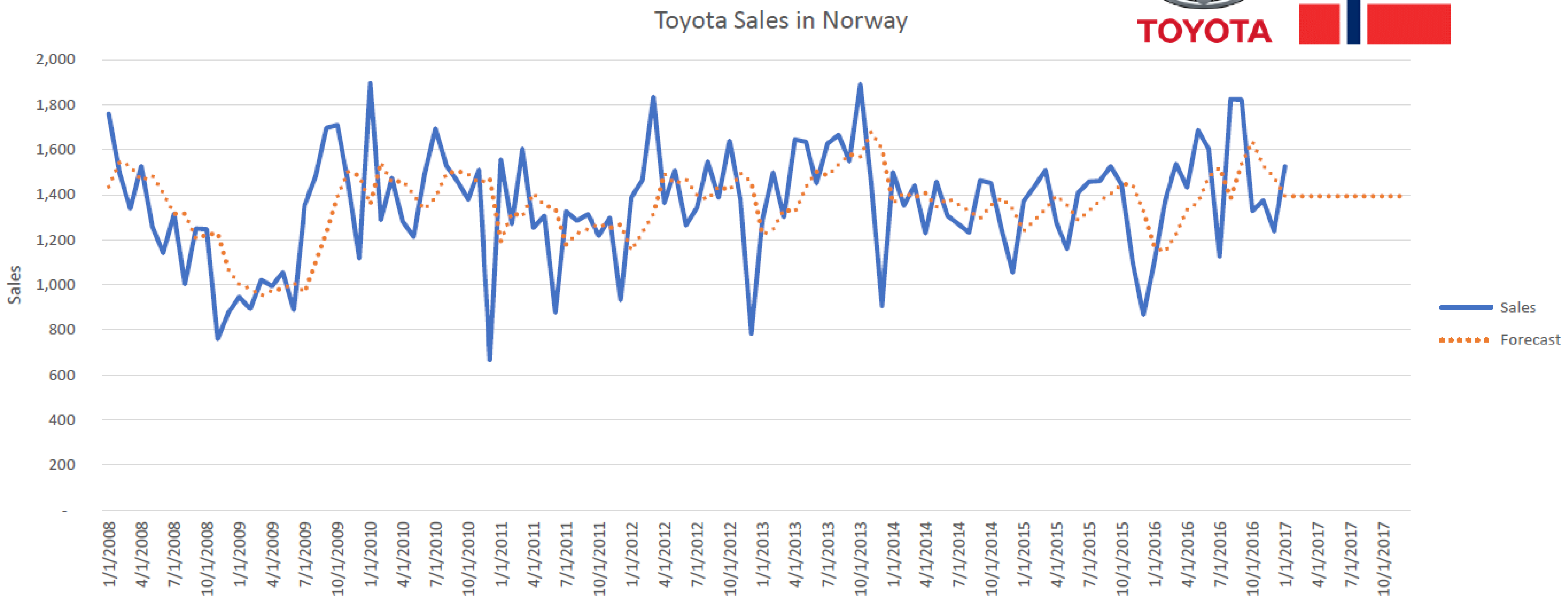
  level (base model) + trend quantity + seasonal factor.

- **multiplicative**

  level (base model) * trend factor * seasonal factor.



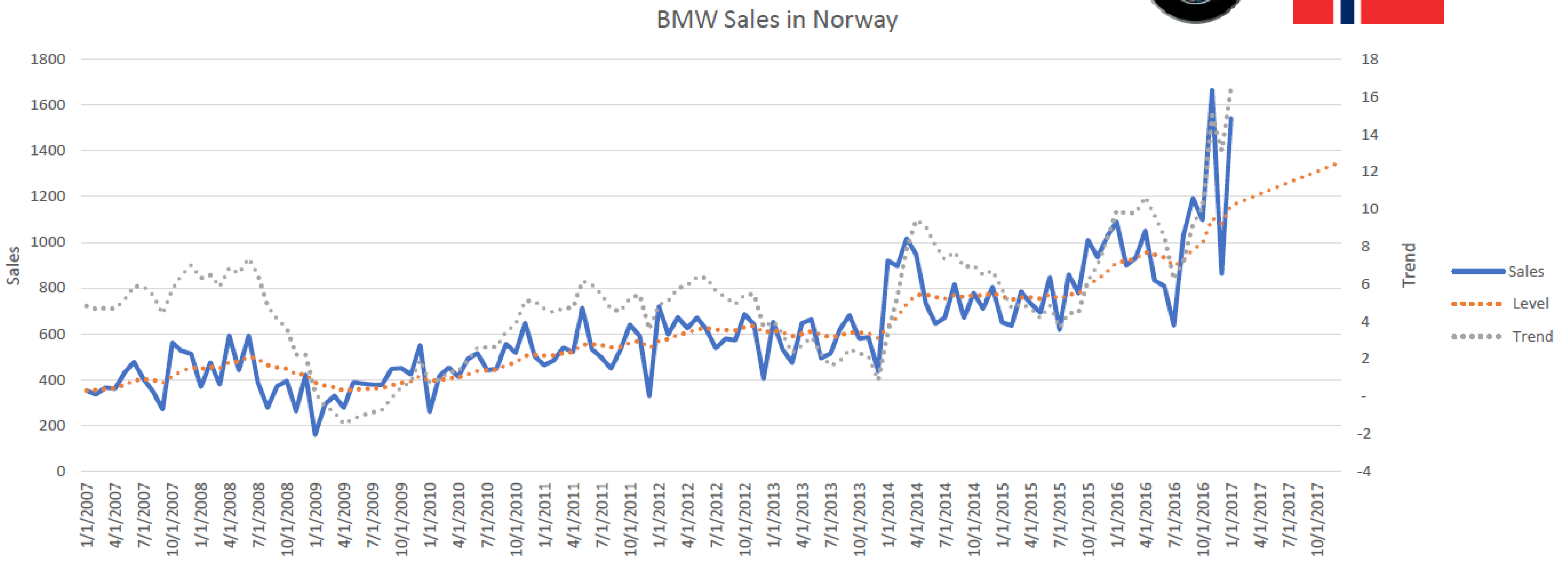
Visual Analysis – Level



Sales vary around an average amount (level)

$$Sales = level + noise$$

Visual Analysis – Level & Trend



Sales vary around an average amount (level) that changes over time (trend)

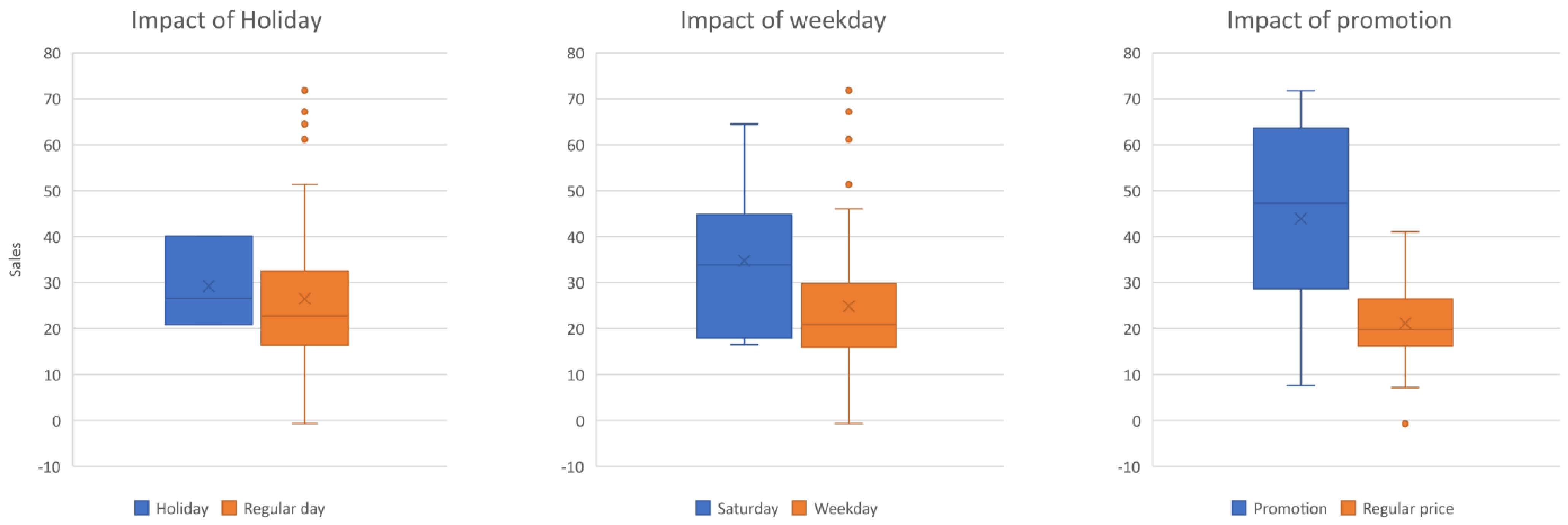
$$Sales = level + trend + noise$$

Visual Analysis – Level, Trend & Seasonality

Multiplicative trend with a multiplicative seasonality

$$Passengers = (level \times trend)seasonality + noise$$

Visual Analysis – Exogenous drivers



$$Sales = level + Saturday? + holiday? + Promotion? + noise$$

Quantitative Forecast Methods

- Classic time series methods
  - Simple Models
  - Exponential Smoothing
- Cause-and-effect
  - Linear/Nonlinear, Single/Multiple Regression
- Combination
  - ARIMA models

Time Series Forecasting Models

Pattern: Level + Noise

Naïve Forecast:

next period is equal to the actual demand for the immediate past period:

$$\boxed{f_{t+1} = d_t}$$

Where:

f_{t+1} = forecast for period t+1;

d_t = actual demand for period t

Time Series Forecasting Models

Pattern: Level + Noise

Simple Moving Average Forecast

$$f_{t+1} = \frac{\sum_{i=t-n+1}^{t} d_i}{n}$$

f_{t+1} = forecast for period t+1;

n = number of periods used to calculate moving average;

d_i = actual demand in period i

Historical data

Stable demand

Simple to use and easy to understand.

Inability to respond to trend changes quickly

Weighted Moving Average Forecast

- The weighted average of the n-period observations - unequal weights
- Nonnegative weights - sum to one

f_{t+1} = forecast for period $t+1$;

n = number of periods used in determining the moving average;

d_i = actual demand in period i;

w_i = weight assigned to period i; $\Sigma wi = 1$.

$$\boxed{f_{t+1} = \sum_{i=t-n+1}^{t} w_i d_i}$$

$F_t = 0.5\ A_{t-1} + 0.3\ A_{t-2} + 0.2\ A_{t-3}.$

Exponential Smoothing Forecast

- The forecast for next period's demand is the current period's forecast adjusted by a fraction of the difference between the current period's actual demand and forecast
- Requires less data

✓ **Adaptive Exponential Smoothing** ➡ $\boxed{\alpha = \frac{2}{(n+1)}}$

For *alpha* of 0.1 : $n = (2/0.1) - 1 = 19$ period average
For *alpha* of 0.3 : $n = (2/0.3) - 1 = 5.67$ period average
For *alpha* of 0.6 : $n = (2/0.6) - 1 = 2.33$ period average
For *alpha* of 0.9 : $n = (2/0.9) - 1 = 1.22$ period average

$f_{t-1} = \alpha d_{t-2} + (1 - \alpha) f_{t-2}$

$f_t = \alpha d_{t-1} + (1 - \alpha) f_{t-1}$

$f_{t+1} = f_t + \alpha (d_t - f_t)$
or

$$\mathbf{f_{t+1} = \alpha d_t + (1 - \alpha) f_t}$$

where f_{t+1} = forecast for period t + 1;
f_t = forecast for period t;
d_t = actual demand for period t;
α = smoothing constant ($0 \le \alpha \le 1$)

Why is it called *exponential* smoothing?!

period	moving average					Exponential Smoothing				
	n=5	n=4	n=3	n=2	n=1	alpha=0.2	alpha=0.4	alpha=0.6	alpha=0.8	alpha=1
t = 1	0,2	0,25	0,33	0,5	1	0,2	0,4	0,6	0,8	1
t = 2	0,2	0,25	0,33	0,5		0,16	0,24	0,24	0,16	
t = 3	0,2	0,25	0,33			0,13	0,14	0,1	0,03	
t = 4	0,2	0,25				0,1	0,09	0,04	0,01	
t = 5	0,2					0,08	0,05	0,02		

Time Series Forecasting Models

Pattern: Level + Trend + Noise

Double exponential smoothing

Two smoothing factors, α and β

The components are updated at each period based on:

1- The most recent Observation

2- The previous estimation

$$a_t = \alpha d_t + (1-\alpha)(a_{t-1} + b_{t-1})$$

$$b_t = \beta(a_t - a_{t-1}) + (1-\beta)\, b_{t-1}$$

$$f_{t+1} = a_t + b_t$$

$$f_{t+\lambda} = a_t + \lambda\, b_t$$

- f_{t+1} : Forecast for the following period performed in the current period,
- a_t : Level estimation,
- b_t: Trend estimation
- λ: Number of periods for which we are making the forecast

Time Series Forecasting Models

Pattern: Level + Trend + Noise

Double exponential smoothing (with Damped Trend)

$$a_t = \alpha d_t + (1 - \alpha)(a_{t-1} + \phi b_{t-1})$$

$$b_t = \beta(a_t - a_{t-1}) + (1 - \beta)(\phi b_{t-1})$$

ϕ: Dampening Factor

$$f_{t+1} = a_t + \phi b_t$$

$$f_{t+\lambda} = a_t + b_t \sum_{i=1}^{\lambda} \phi^i$$

Example: $f_{t+3} = a_t + b_t\phi + b_t\phi^2 + b_t\phi^3$

Time Series Forecasting Models

Pattern: (Level + Trend) * Seasonality + Noise

Triple exponential smoothing

$$a_t = \alpha(\frac{d_t}{s_{t-p}}) + (1-\alpha)(a_{t-1} + \phi b_{t-1})$$

$$b_t = \beta(a_t - a_{t-1}) + (1-\beta)(\phi b_{t-1})$$

$$s_t = \gamma\left(\frac{d_t}{a_t}\right) + (1-\gamma)\, s_{t-p}$$

$$f_t = (a_{t-1} + \phi b_{t-1}) * s_{t-p}$$

$$f_{t+\lambda} = (a_t + b_t \sum_{i=1}^{\lambda} \phi^i) * s_{t-p}$$

Without damping factor:

$$f_{t+\lambda} = (a_t + \lambda\, b_t)\, s_{t-p}$$

Simple Linear Regression Forecast

✓ Only one explanatory variable

$\hat{Y} = b_0 + b_1 x$

Where:

$\hat{Y}$: forecast or dependent variable;

x : explanatory or independent variable;

b_0 : intercept of the vertical axis;

b_1 : slope of the regression line.

$$\boxed{b_1 = \frac{\sum xy - n\bar{x}\bar{y}}{\sum x^2 - n\bar{x}^2}}$$

$$\boxed{b_0 = \bar{y} - b\bar{x}}$$

Multiple Regression Forecast

✓ Several explanatory variables

$$\hat{Y} = b_0 + b_1 x_1 + b_2 x_2 + \ldots + b_k x_k$$

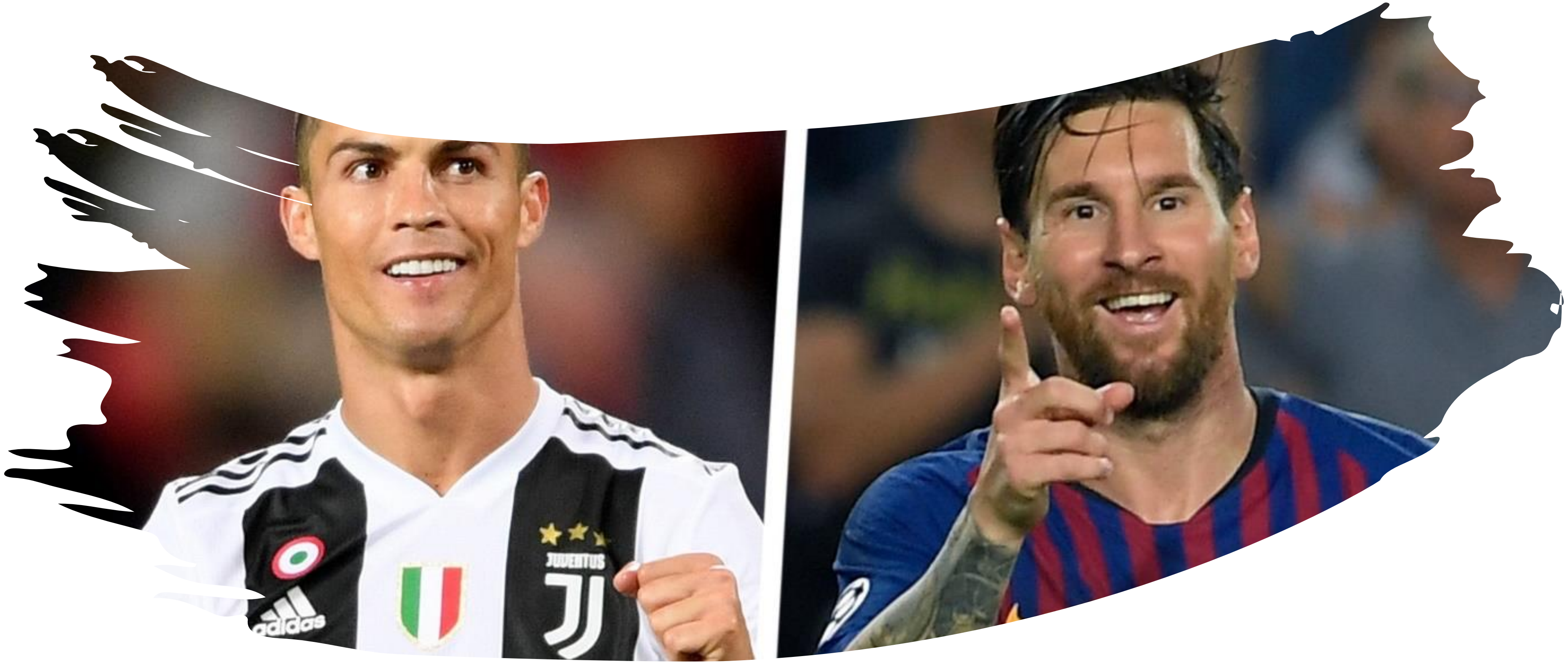
Where:

$\hat{Y}$: forecast or dependent variable;

x_k : kth explanatory or independent variable;

b_0 : constant;

b_k : regression coefficient of the independent variable x_k.



Who is the best?!

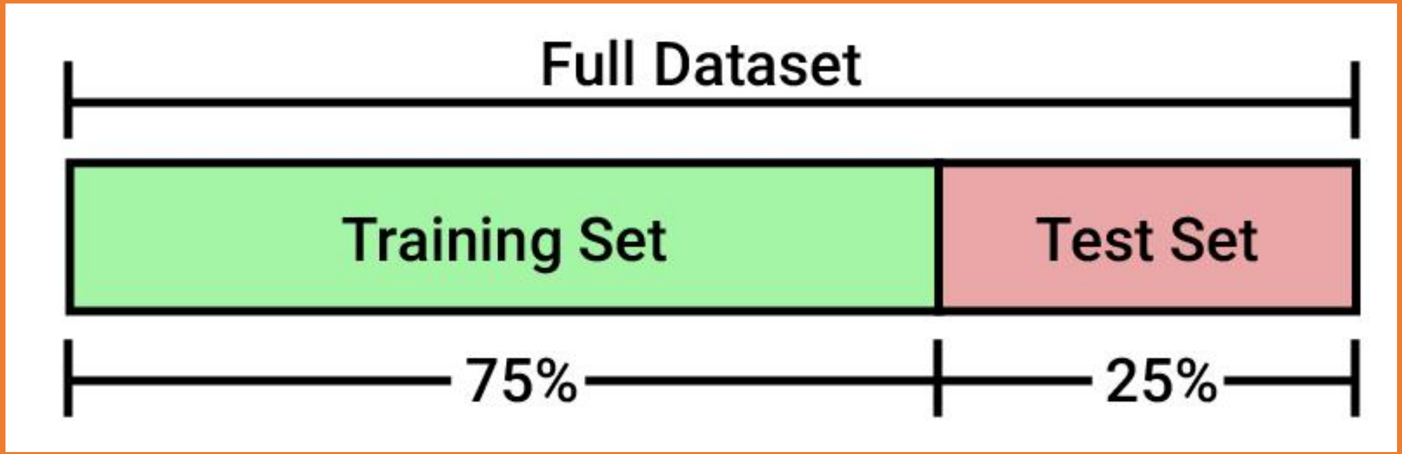
Quantitative or Qualitative methods

These forecasting methods are complementary and must be tested/combined to produce accurate and usable forecasts

Parameter Optimization

Parameter Optimization

Method	Parameter
Moving Average	n
Simple Exponential Smoothing	Alpha
Double Exponential Smoothing	Alpha and Beta
Double Exponential Smoothing with Damped Trend	Alpha, Beta and Phi



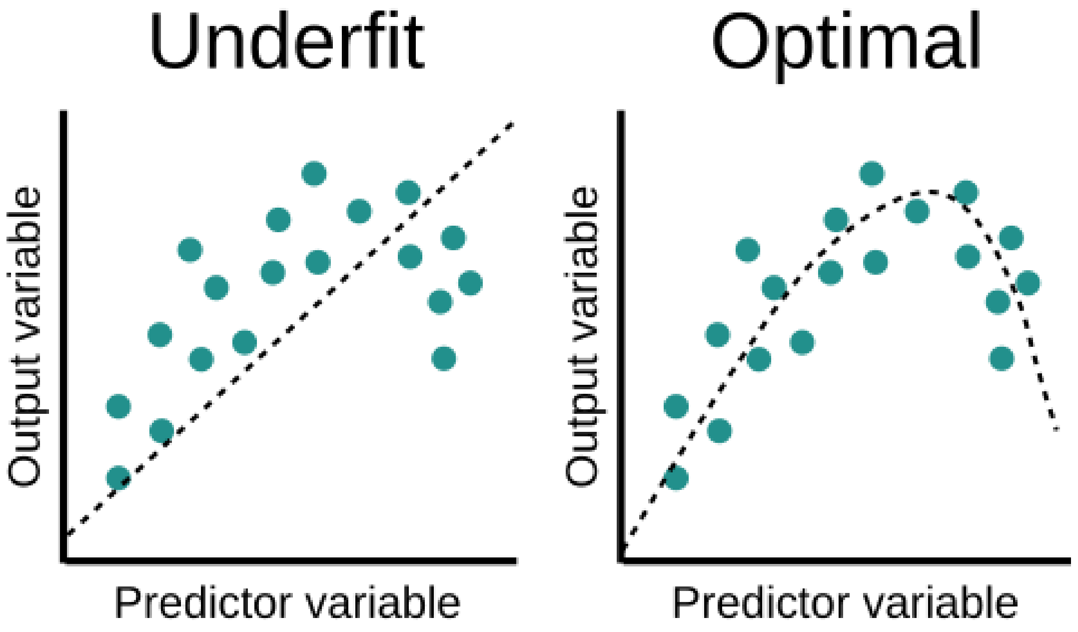
Training dataset ➡ optimize model parameters

Test dataset ➡ assess the accuracy of model

Don’t use test dataset to optimize the model

Underfitted model lacks a good understanding of the training dataset

Underfitting

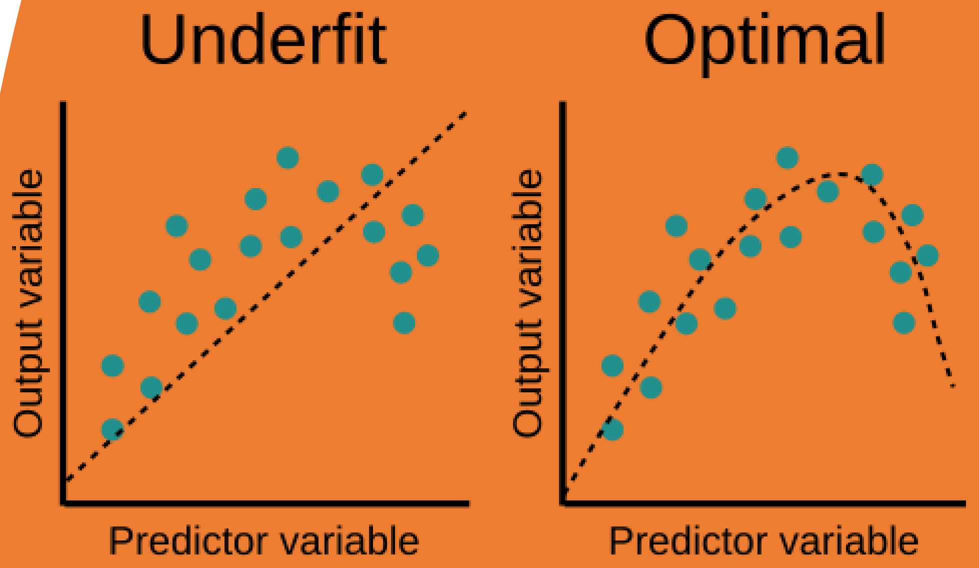


Some forecast models will not be able to properly predict or explain the reality

A model is underfitted if it does not explain reality properly enough

Cause of underfitting:
Model complexity is too low
Lack of explanatory variables

Solutions:
Change the model for a more complex one
Use more explanatory variables



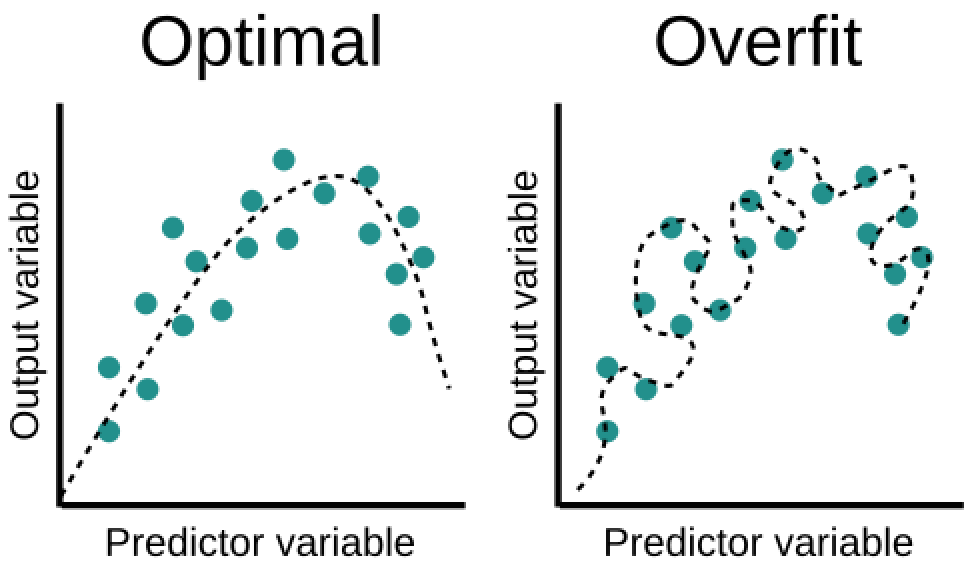
Overfitting

Recognizing patterns from the noise (randomness) of the training set.

Re-apply these patterns in the future.

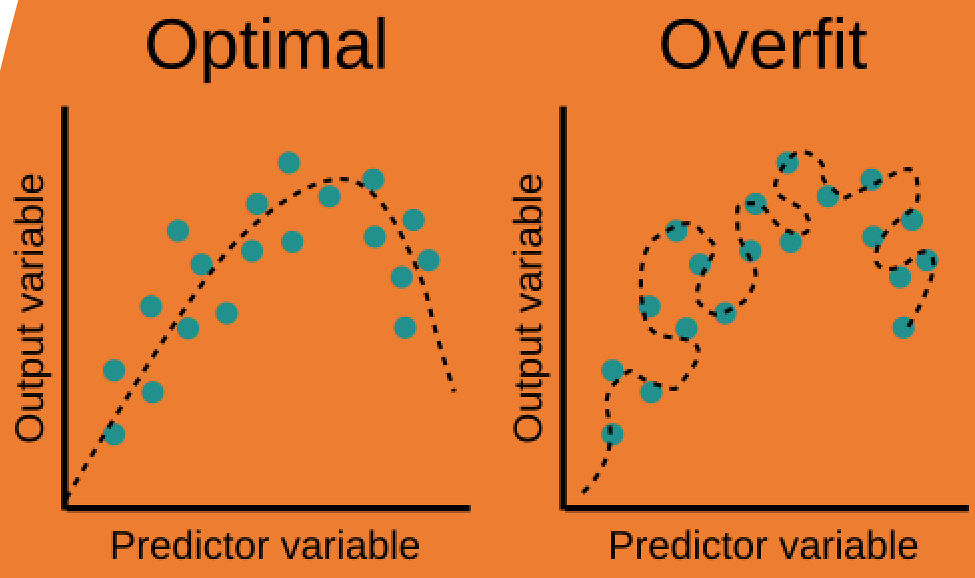
Good results on the training dataset.

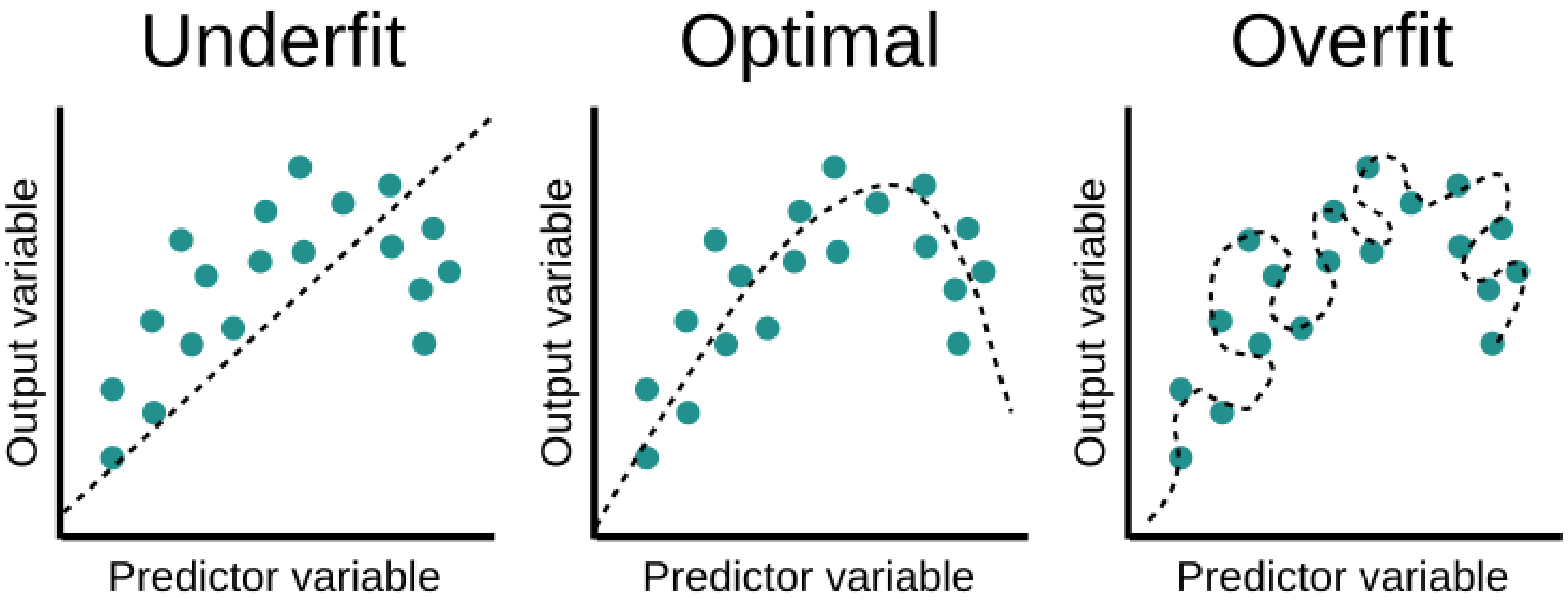
Fail to make good predictions on the test set.



Cause of overfitting:
Model complexity is too High
More explanatory variables

Solutions:
Use less explanatory variables
Use a simpler model
Use more data
Don't fit on the test set




Underfit
Optimal
Overfit
Output variable
Output variable
Output variable
Predictor variable
Predictor variable
Predictor variable

Machine Learning

Old-school statistics

You must provide a model to get outputs

- You understand the model and its interpretation of reality
- The model cannot adapt itself to the task/data
- The model will only learn from the product we want to forecast

Machine Learning

You must provide outputs to get a model

- Model is unknown and mostly impossible to understand
- The model will adapt to the task/data
- The model will learn relationships from the whole dataset
- The model can learn complex relationships

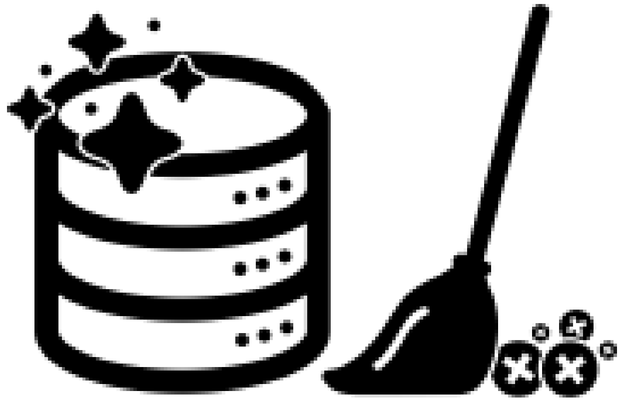
White Box

Black Box

Machine Learning

- Which data to feed the algorithm.
- Which machine learning algorithm to use.
- Which parameters to use.

Data Cleaning



Data Cleaning

The first step of any machine learning algorithm project

Better data beats fancier algorithms

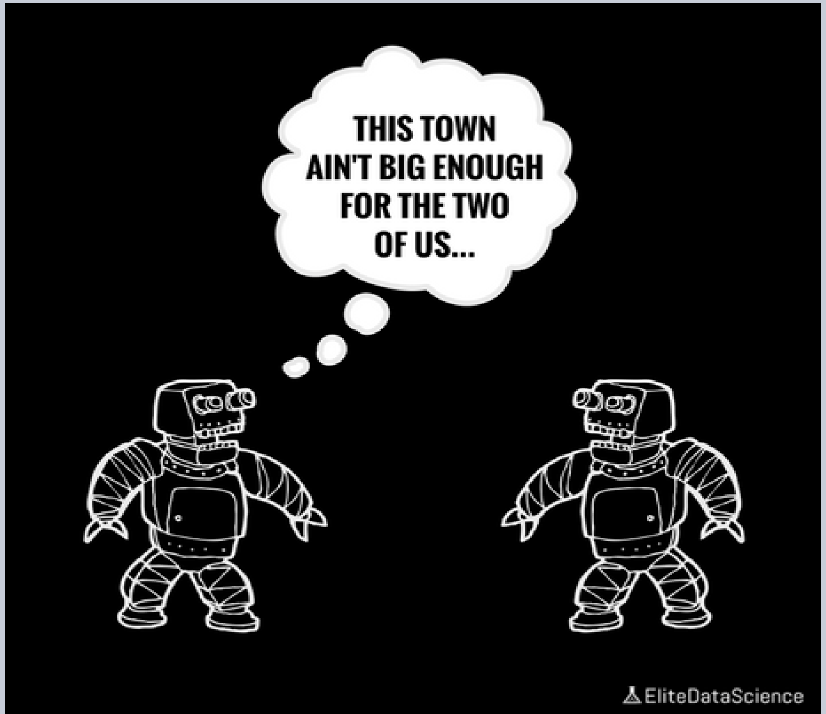
Garbage In → Garbage Out

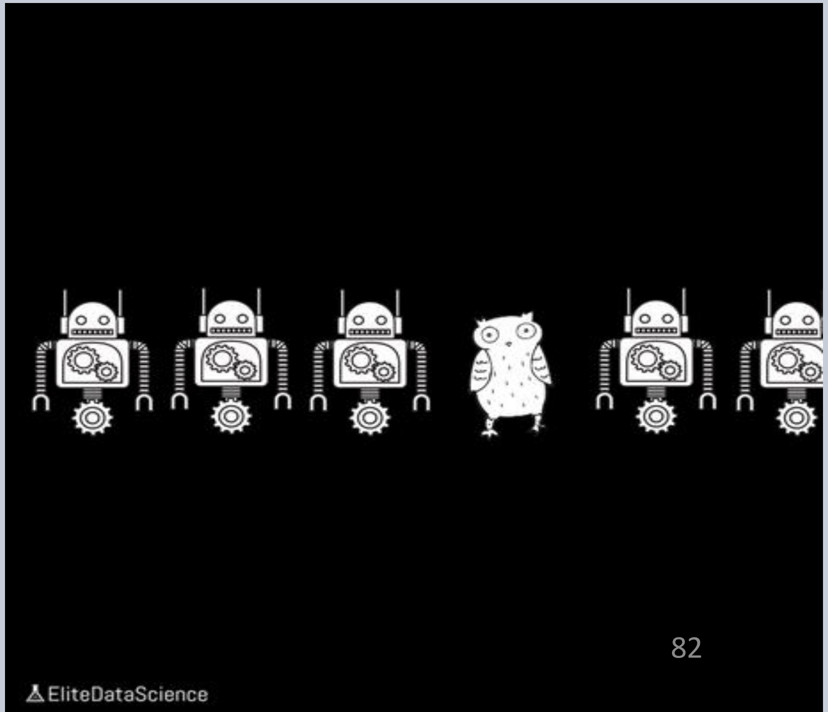
Data Cleaning

1 **Remove Unwanted observations**

Duplicate observations

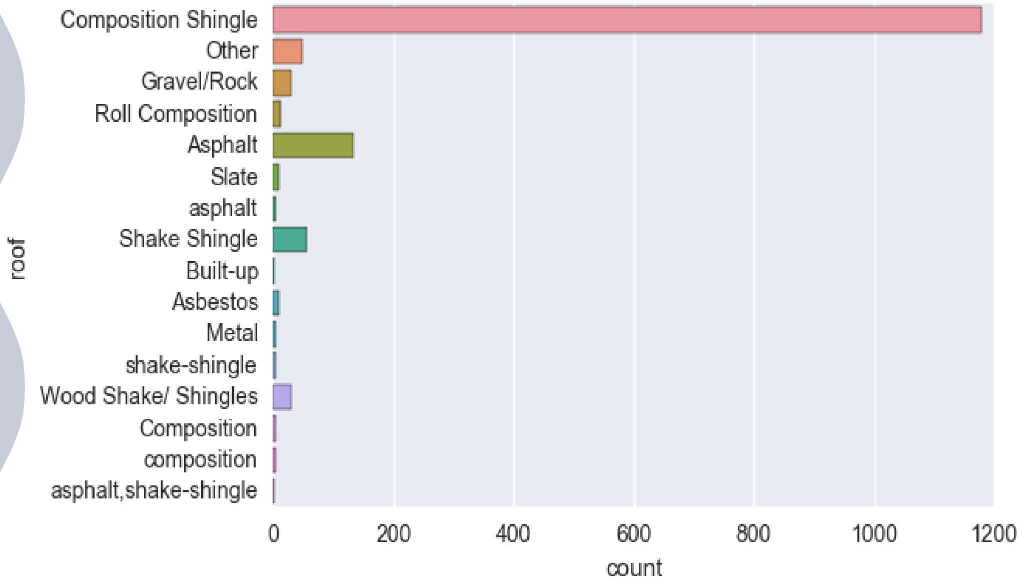
Irrelevant observations

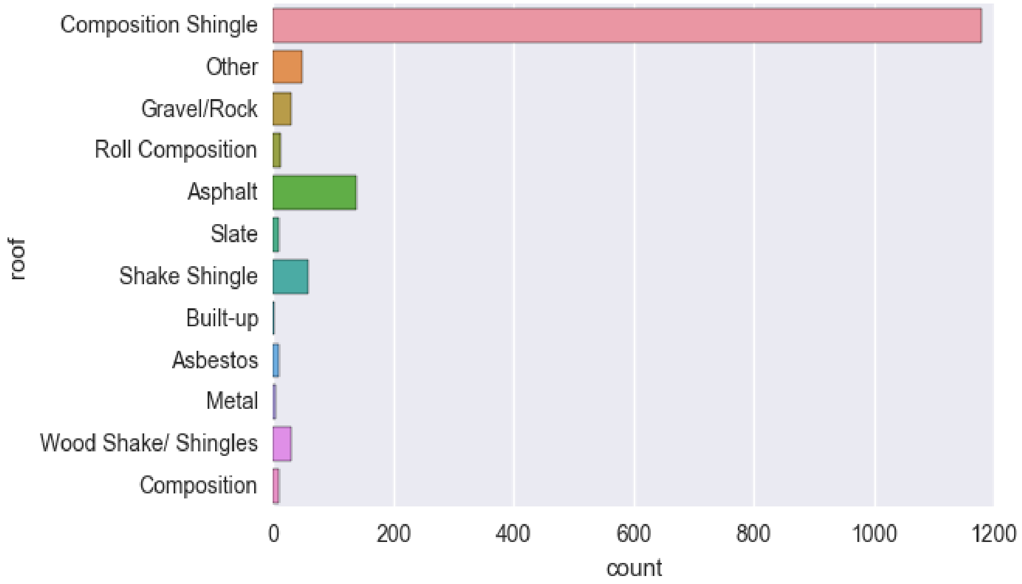


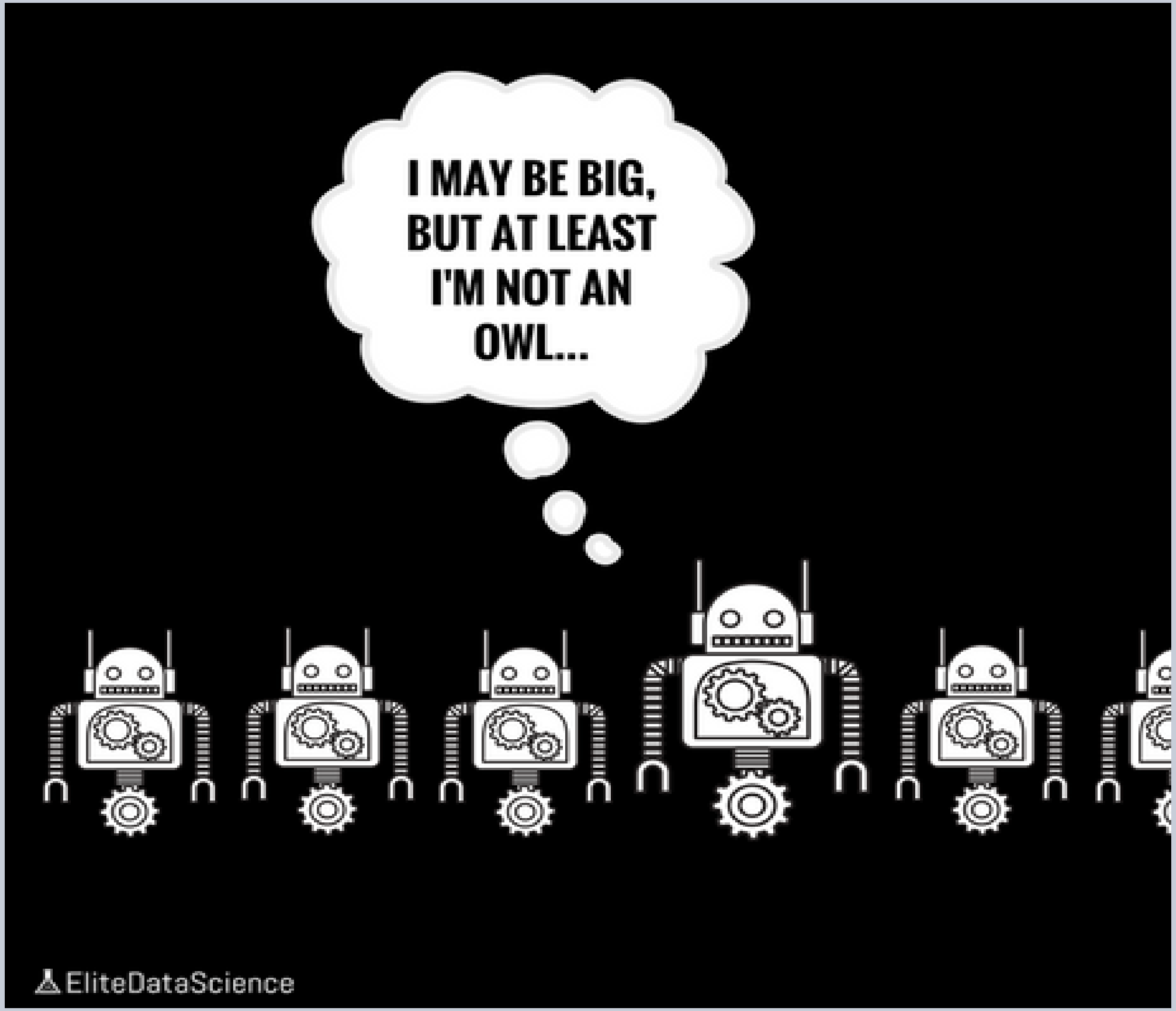


Data Cleaning

2 Fix Structural Errors







Data Cleaning

3 **Filter Unwanted Outliers**

Dropping observations that have missing values

Data Cleaning

4 **Handle Missing Data**

Imputing the missing values based on other observations

Q/A

Thank you…

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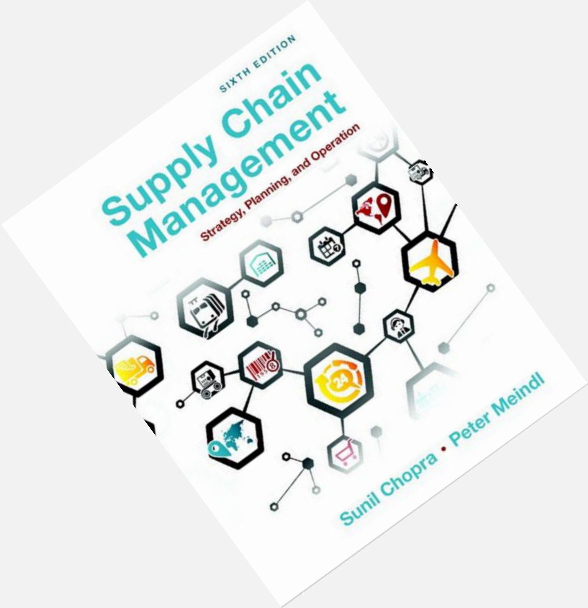
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