

Introduction to Demand Planning & Forecasting



Demand Process – Three Key Questions

What should we do to shape and create demand for our product?



What should we expect demand to be given the demand plan in place?



How do we prepare for and act on demand when it materializes?

Demand Planning

- Product & Packaging
- Promotions
- Pricing
- Place

Demand Forecasting

- Strategic, Tactical, Operational
- Considers internal & external factors
- Baseline, unbiased, & unconstrained

Demand Management

- Balances demand & supply
- Sales & Operations Planning (S&OP)
- Bridges both sides of a firm

Material adapted from Lapide, L. (2006) Course Notes, ESD.260 Logistics Systems.

Forecasting Levels

Level	Horizon	Purposes
Strategic	Year/Years	<ul style="list-style-type: none">• Business Planning• Capacity Planning• Investment Strategies
	Quarterly	<ul style="list-style-type: none">• Brand Plans• Budgeting• Sales Planning• Manpower Planning
Tactical	Months/Weeks	<ul style="list-style-type: none">• Short-term Capacity Planning• Master Planning• Inventory Planning
	Days/Hours	<ul style="list-style-type: none">• Transportation Planning• Production Planning• Inventory Deployment
Operational		

Material adapted from Lapide, L. (2006) Course Notes, ESD.260 Logistics Systems.

Agenda

- Forecasting Truisms
- Subjective vs. Objective Approaches
- Forecast Quality
- Forecasting Metrics

Forecasting Truisms 1:

Forecasts are always wrong

1. Forecasts are always wrong

Why?

- Demand is essentially a continuous variable
- Every estimate has an “error band”
- Forecasts are highly disaggregated
 - ◆ Typically SKU-Location-Time forecasts
- Things happen . . .

OK, so what can we do?

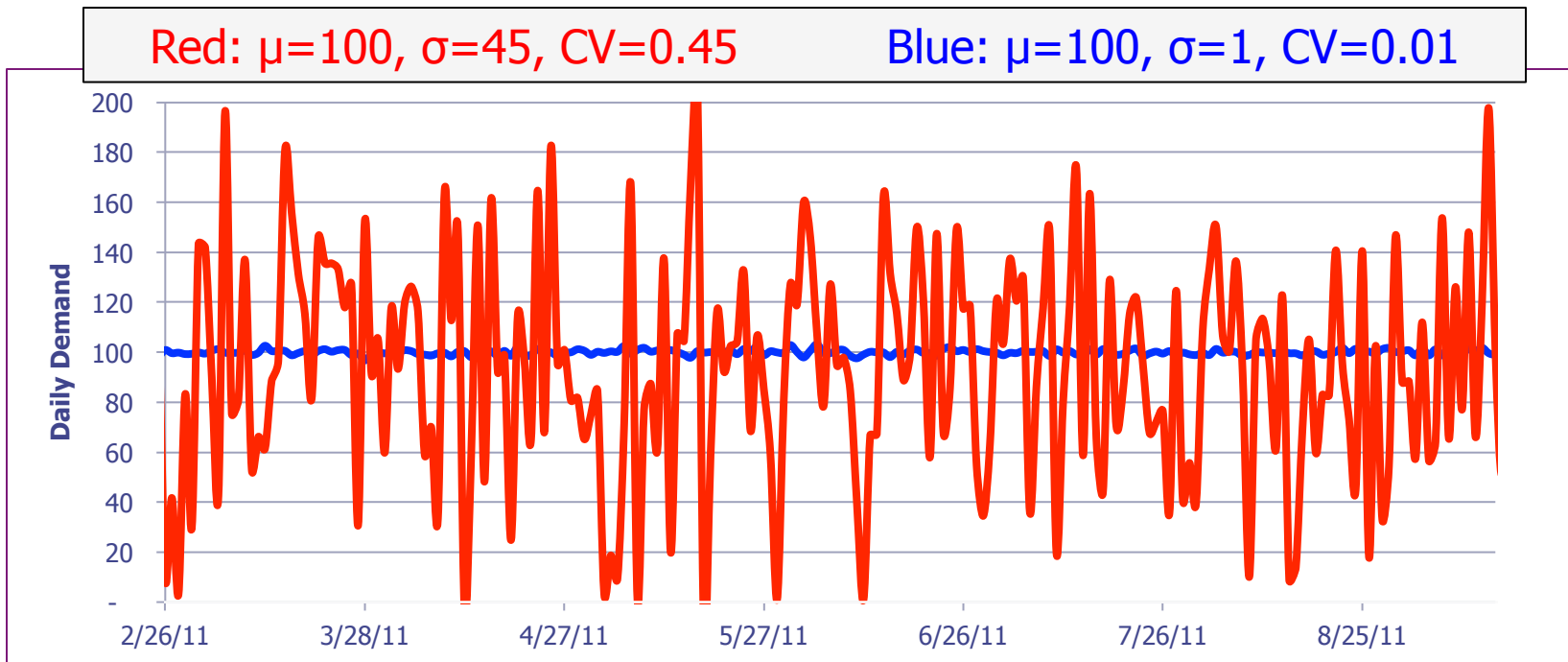
- Don't fixate on the point value
- Use range forecasts
- Capture error of forecasts
- Use buffer capacity or stock

Forecasting Truisms 2:

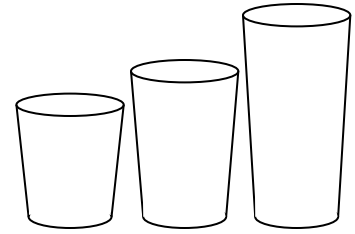
*Aggregated forecasts
are more accurate*

2. Aggregated forecasts are more accurate

- Aggregation by SKU, Time, Location, etc.
- Coefficient of Variation (CV)
 - Definition: Standard Deviation / Mean = σ/μ
 - Provides a relative measure of volatility or uncertainty
 - CV is non-negative and higher CV indicates higher volatility

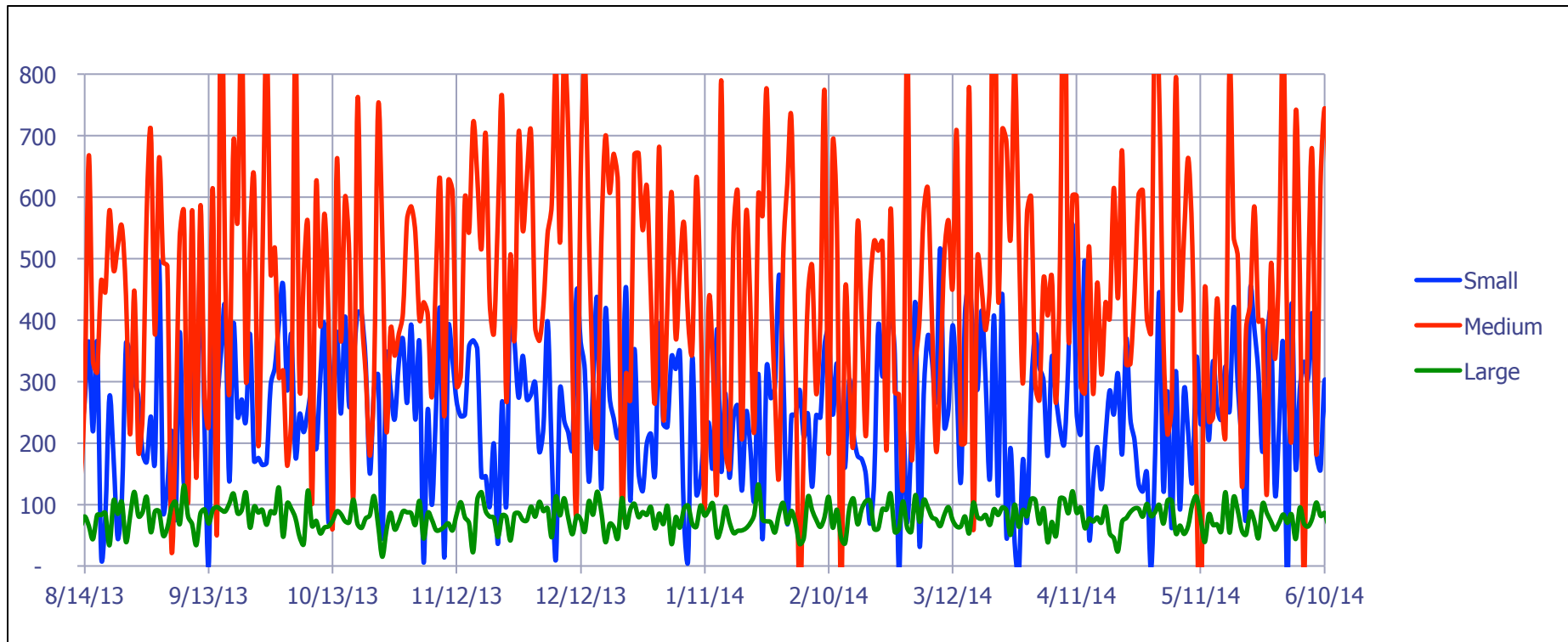


Aggregating by SKU



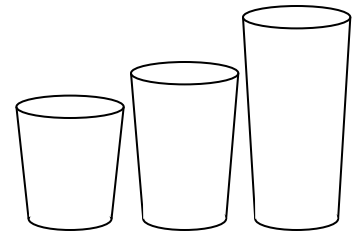
- Coffee Cups and Lids @ the Sandwich Shop

- Large $\sim N(80, 30)$ CV = 0.38
- Medium $\sim N(450, 210)$ CV = 0.47
- Small $\sim N(250, 110)$ CV = 0.44

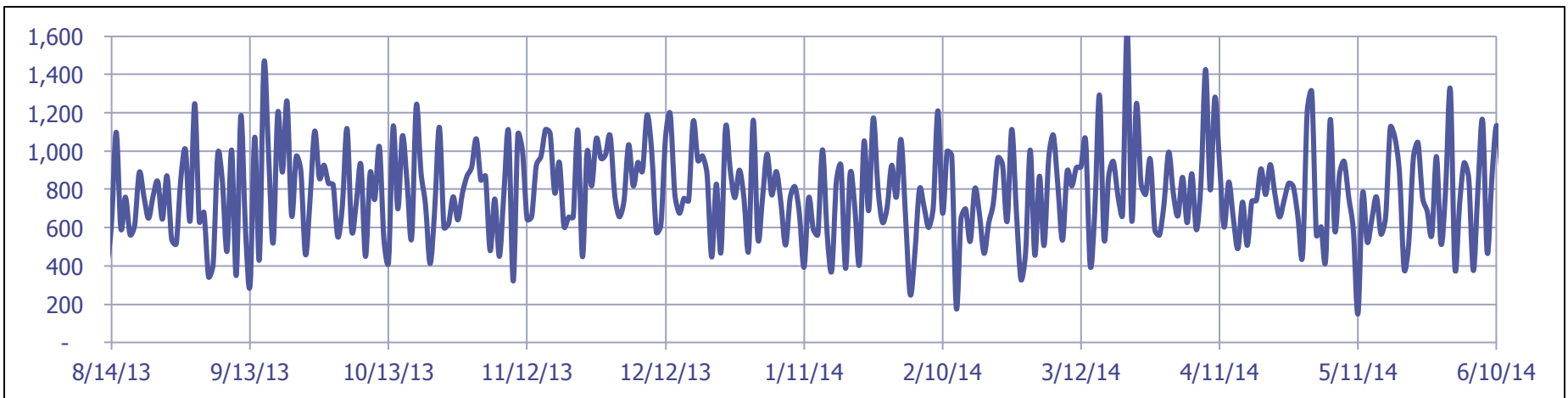


Aggregating by SKU

- What if I design cups with a common lid?
- Common Lid $\sim N(780, 239)$ $CV = 0.31$
 - $\mu = (80 + 450 + 250) = 780$ units/day
 - $\sigma = \sqrt{30^2 + 210^2 + 110^2} = 239$ units/day



Large $\sim N(80, 30)$ $CV=0.38$
Med. $\sim N(450, 210)$ $CV=0.47$
Small $\sim N(250, 110)$ $CV=0.44$
Lids $\sim N(780, 239)$ $CV=0.31$

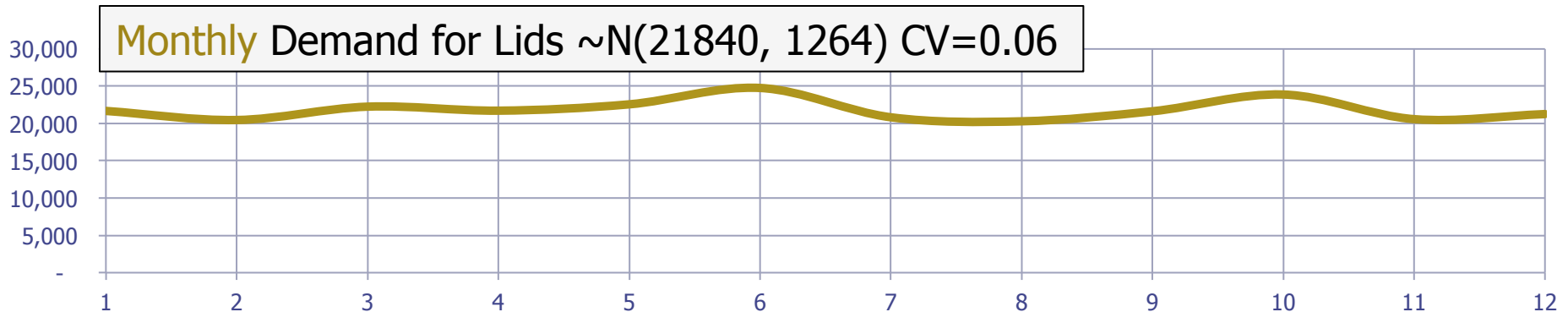
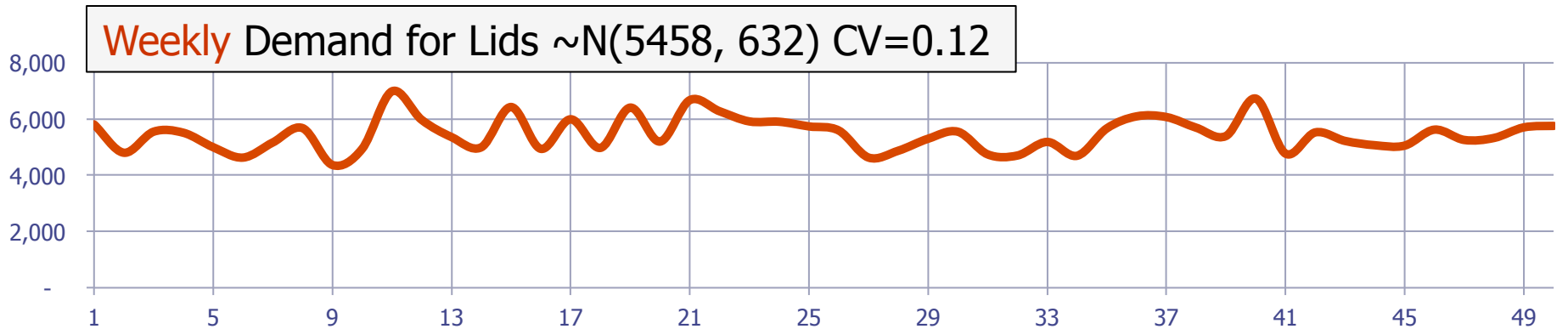
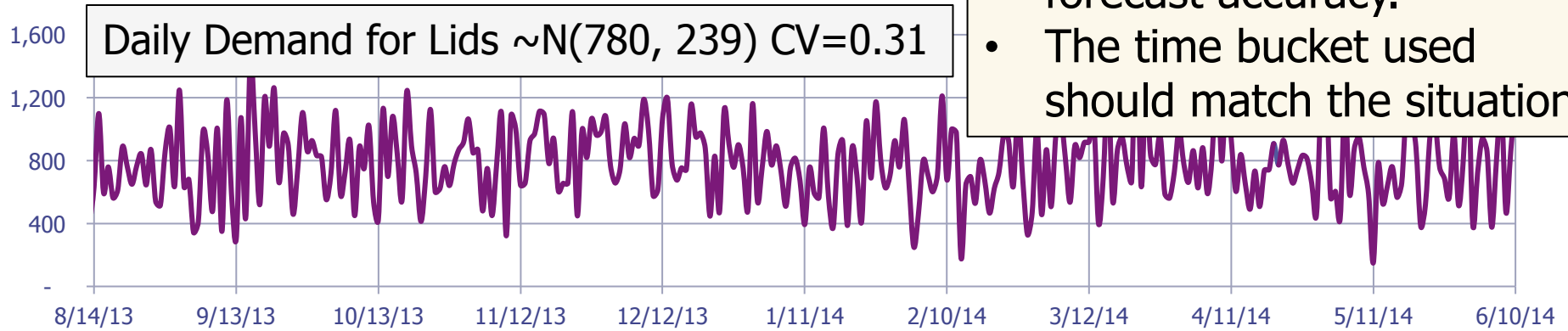


Example of Modularity or Parts Commonality

- Reduces the relative variability
- Increases forecasting accuracy
- Lowers safety stock requirements

Aggregating by Time

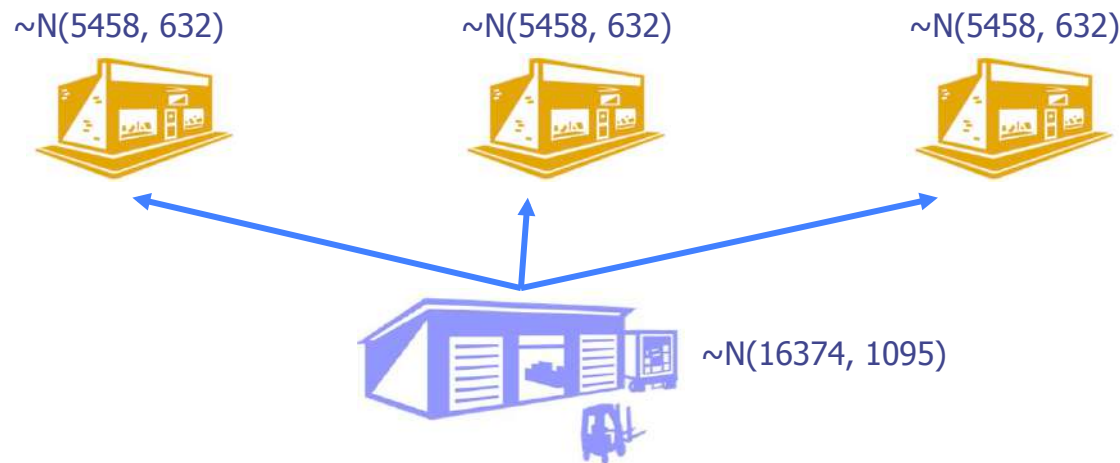
- Forecasts with longer time buckets have better forecast accuracy.
- The time bucket used should match the situation.



Aggregating by Locations

CV reduces as we aggregate over SKUs, time, or locations.

- Suppose we have three sandwich shops
 - Weekly lid demand at each $\sim N(5458, 632)$ $CV=0.12$



- What if demand is pooled at a common Distribution Center?
 - Weekly lid demand at DC $\sim N(16374, 1095)$ $CV=0.07$

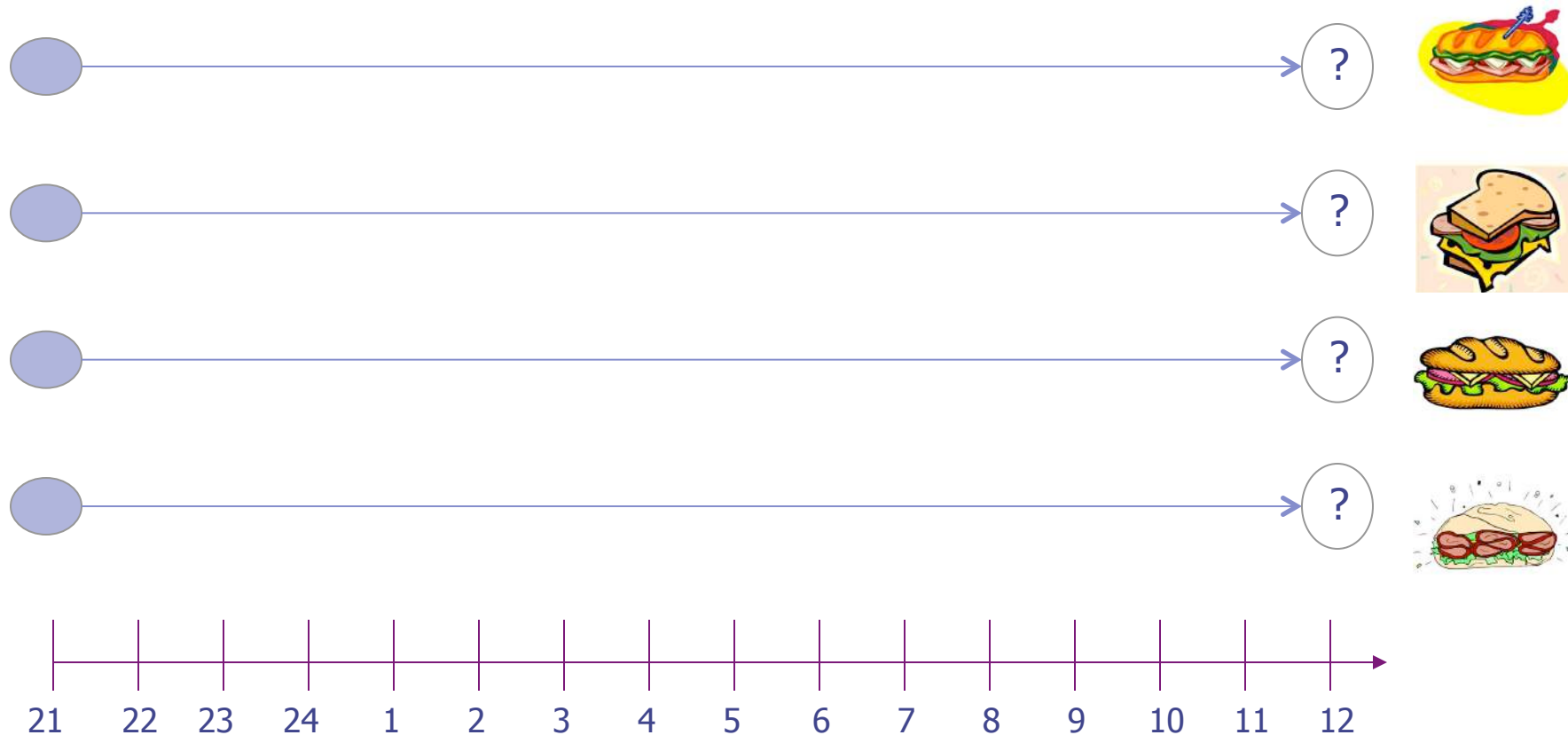
$$CV_{ind} = \frac{\sigma}{\mu}$$

$$CV_{agg} = \frac{\sigma\sqrt{n}}{\mu n} = \frac{\sigma}{\mu\sqrt{n}} = \frac{CV_{ind}}{\sqrt{n}}$$

Forecasting Truisms 3:

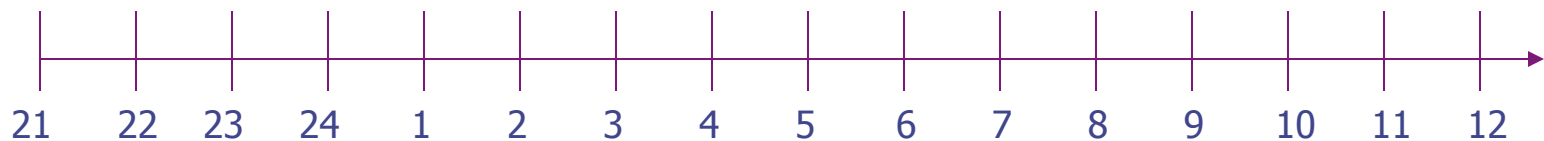
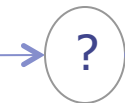
*Shorter horizon forecasts
are more accurate*

3. Shorter horizon forecasts are more accurate



3. Shorter horizon forecasts are more accurate

- Postponed final customization to closer time of consumption
- Risk pooling of component (e.g., ham) increases forecast accuracy.



Forecasting Truisms

- Forecasts are always wrong
 - Use ranges & track forecast error
- Aggregated forecasts are more accurate
 - Risk pooling reduces CV
- Shorter time horizon forecasts are more accurate
 - Postpone customization until as late as possible

Subjective & Objective Approaches

Fundamental Forecasting Approaches

Subjective

Judgmental

- Sales force surveys
- Jury of experts
- Delphi techniques

Experimental

- Customer surveys
- Focus group sessions
- Test marketing

Objective

Causal / Relational

- Econometric Models
- Leading Indicators
- Input-Output Models

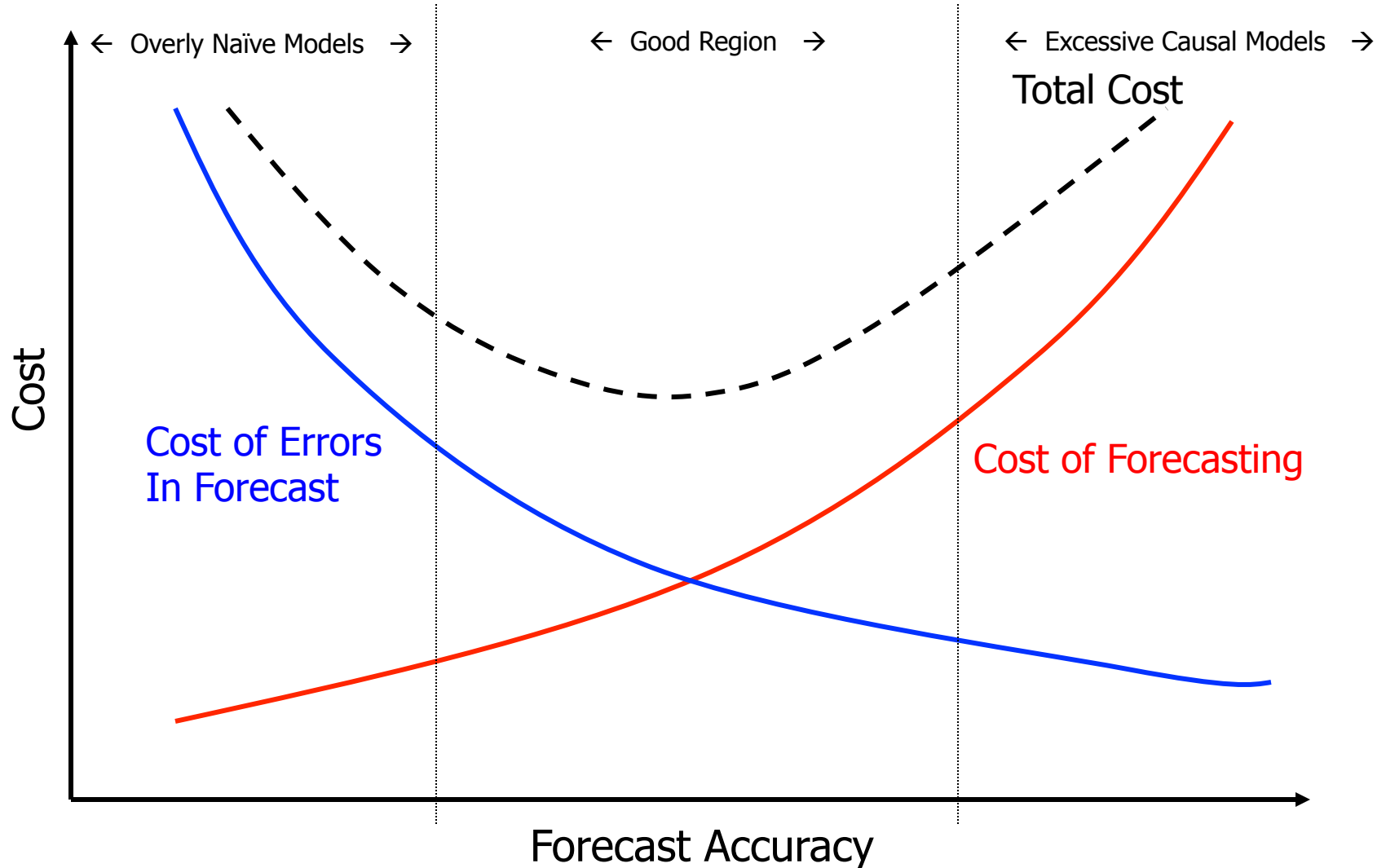
Time Series

- “Black Box” Approach
- Past predicts the future
- Identify patterns

Often times, you will need to use a combination of approaches

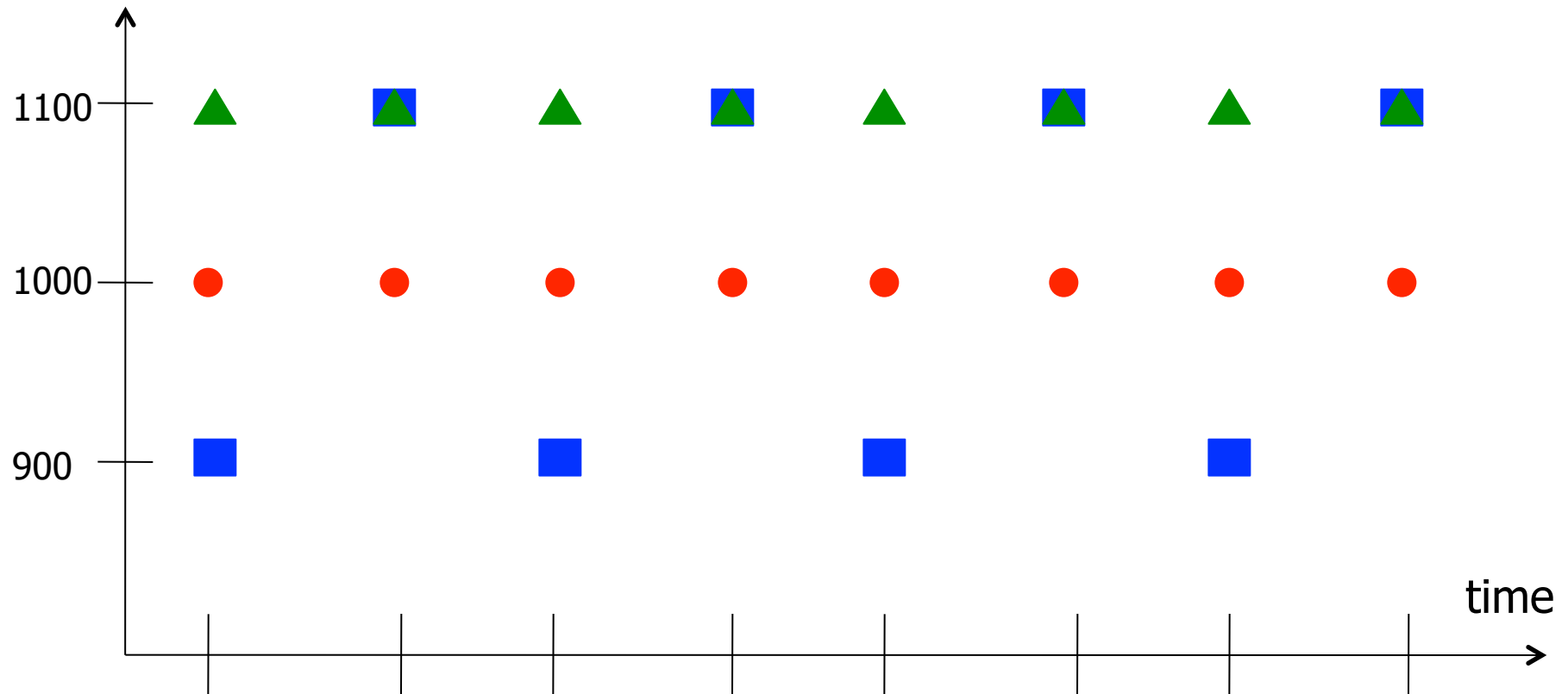
Forecasting Quality

Cost of Forecasting vs Inaccuracy



How do we determine if a forecast is good?

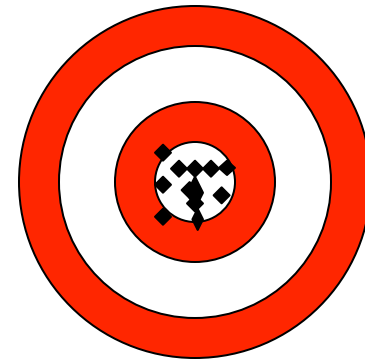
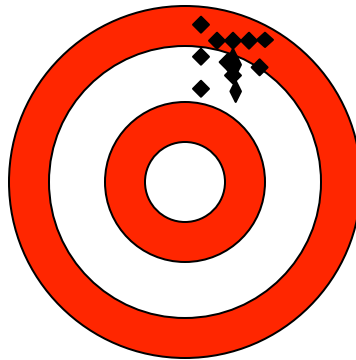
- What metrics should we use?
- Example - Which is a better forecast?
 - Squares & triangles are different forecasts
 - Circles are actual values



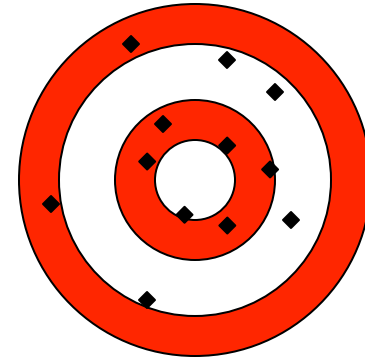
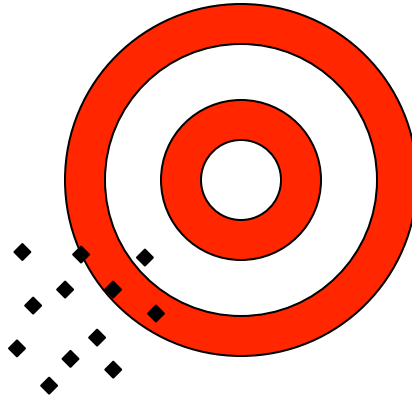
Accuracy versus Bias

- Accuracy - Closeness to actual observations
- Bias - Persistent tendency to over or under predict

Accurate



Not Accurate



Biased

Not Biased

Forecasting Metrics

Forecasting Metrics

$$e_t = A_t - F_t$$

Mean Deviation
(MD)

$$MD = \frac{\sum_{t=1}^n e_t}{n}$$

Mean Absolute
Deviation (MAD)

$$MAD = \frac{\sum_{t=1}^n |e_t|}{n}$$

Mean Squared
Error (MSE)

$$MSE = \frac{\sum_{t=1}^n e_t^2}{n}$$

Root Mean
Squared
Error (RMSE)

$$RMSE = \sqrt{\frac{\sum_{t=1}^n e_t^2}{n}}$$

Mean Percent
Error (MPE)

$$MPE = \frac{\sum_{t=1}^n \frac{e_t}{A_t}}{n}$$

Mean Absolute
Percent Error (MAPE)

$$MAPE = \frac{\sum_{t=1}^n \frac{|e_t|}{A_t}}{n}$$

Notation:

A_t = Actual value for obs. t
 F_t = Forecasted value for obs. t

e_t = Error for observation t
 n = Number of observations

Example: Forecasting Bagels



- For the bagel forecast and actual values shown below, find the:
 - Mean Absolute Deviation (MAD)
 - Root Mean Square of Error (RMSE)
 - Mean Absolute Percent Error (MAPE)

	Forecast	Actual
Monday	50	43
Tuesday	50	42
Wednesday	50	66
Thursday	50	38
Friday	75	86

$$MAD = \frac{\sum_{t=1}^n |e_t|}{n}$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^n e_t^2}{n}}$$

$$MAPE = \frac{\sum_{t=1}^n \frac{|e_t|}{A_t}}{n}$$

Example: Forecasting Bagels



- Solution:

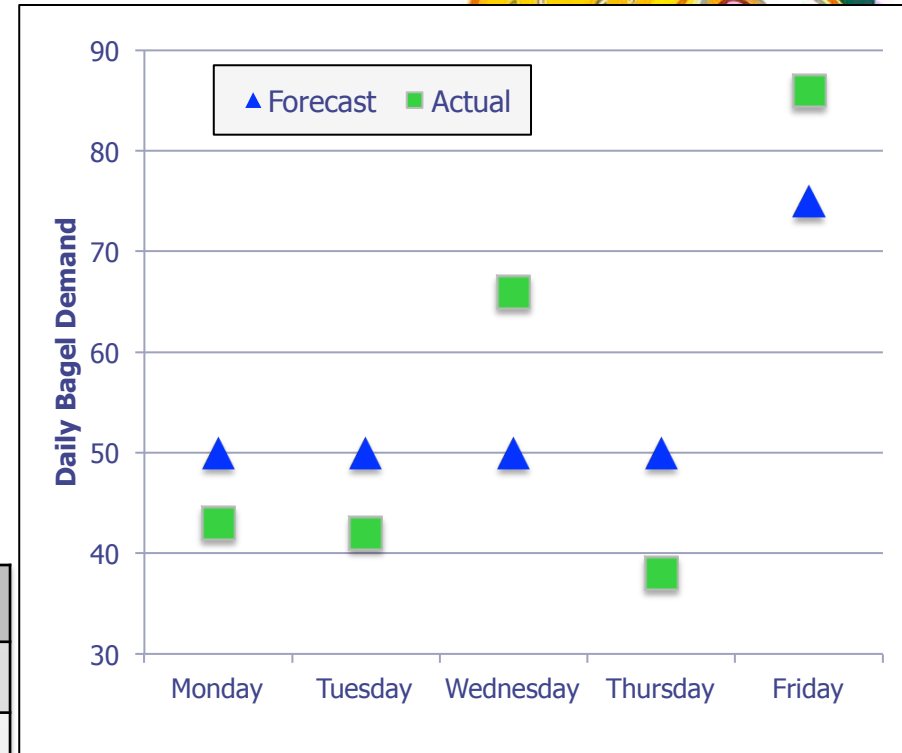
1. Graph it.

2. Extend data table:

- ◆ Error: $e_t = A_t - F_t$
- ◆ Abs[error] = $|e_t|$
- ◆ Sqr[error] = e^2
- ◆ AbsPct[error] = $|e_t/A_t|$

3. Sum and find means

	F_t	A_t	e_t	$ e_t $	e^2	$ e_t/A_t $
Monday	50	43	-7	7	49	16.3%
Tuesday	50	42	-8	8	64	19.0%
Wednesday	50	66	16	16	256	24.2%
Thursday	50	38	-12	12	144	31.6%
Friday	75	86	11	11	121	12.8%
Sum			0	54	634	104%
Mean			0	10.8	126.8	21%



$$\text{MAD} = 54/5 = 10.8$$

$$\text{RMSE} = \sqrt{126.8} = 11.3$$

$$\text{MAPE} = 104\%/5 = 21\%$$

Key Points from Lesson

Key Points

- Forecasting is a means not an end
- Forecasting Truisms
 - Forecasts are always wrong
 - Aggregated forecasts are more accurate
 - Shorter horizon forecasts are more accurate
- Subjective & Objective Approaches
 - Judgmental & experimental
 - Causal & time series
- Forecasting metrics
 - Capture both bias & accuracy
 - MAD, RMSE, MAPE

Questions, Comments, Suggestions? Use the Discussion!



"Janie"

Photo courtesy Yankee Golden
Retriever Rescue (www.ygrr.org)



MIT Center for
Transportation & Logistics

caplice@mit.edu