Introduction to Demand Planning & Forecasting

MIT Center for Transportation & Logistics

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	• Business Planning • Capacity Planning • Investment Strategies
Tactical	Quarterly	• Brand Plans • Budgeting • Sales Planning • Manpower Planning
	Months/Weeks	• Short-term Capacity Planning • Master Planning • Inventory Planning
Operational	Days/Hours	• Transportation Planning • Production Planning • Inventory Deployment

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 . . .

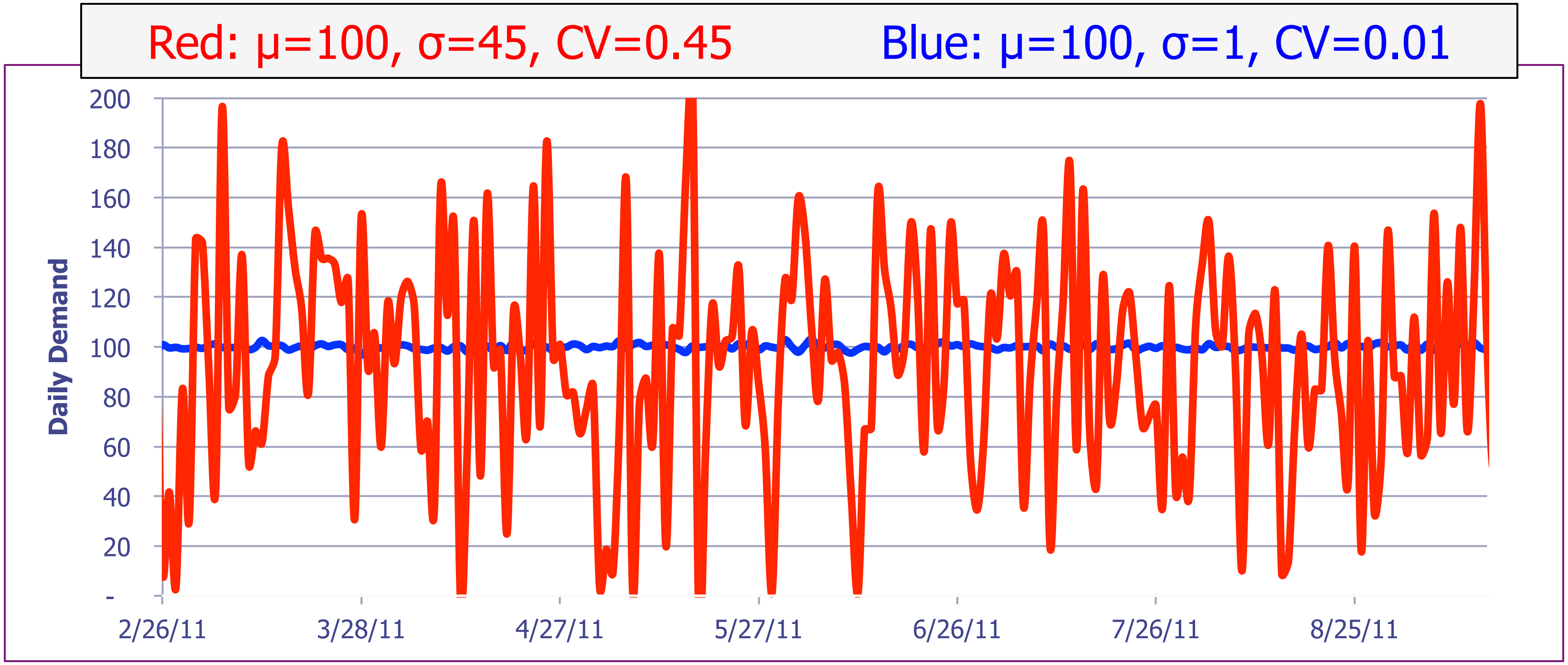
OK, so what can we do?

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

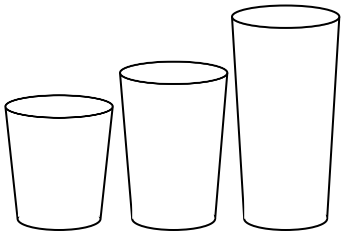
Forecasting Truisms 2:
Aggregated forecasts are more accurate

2. Aggregated forecasts are more accurate

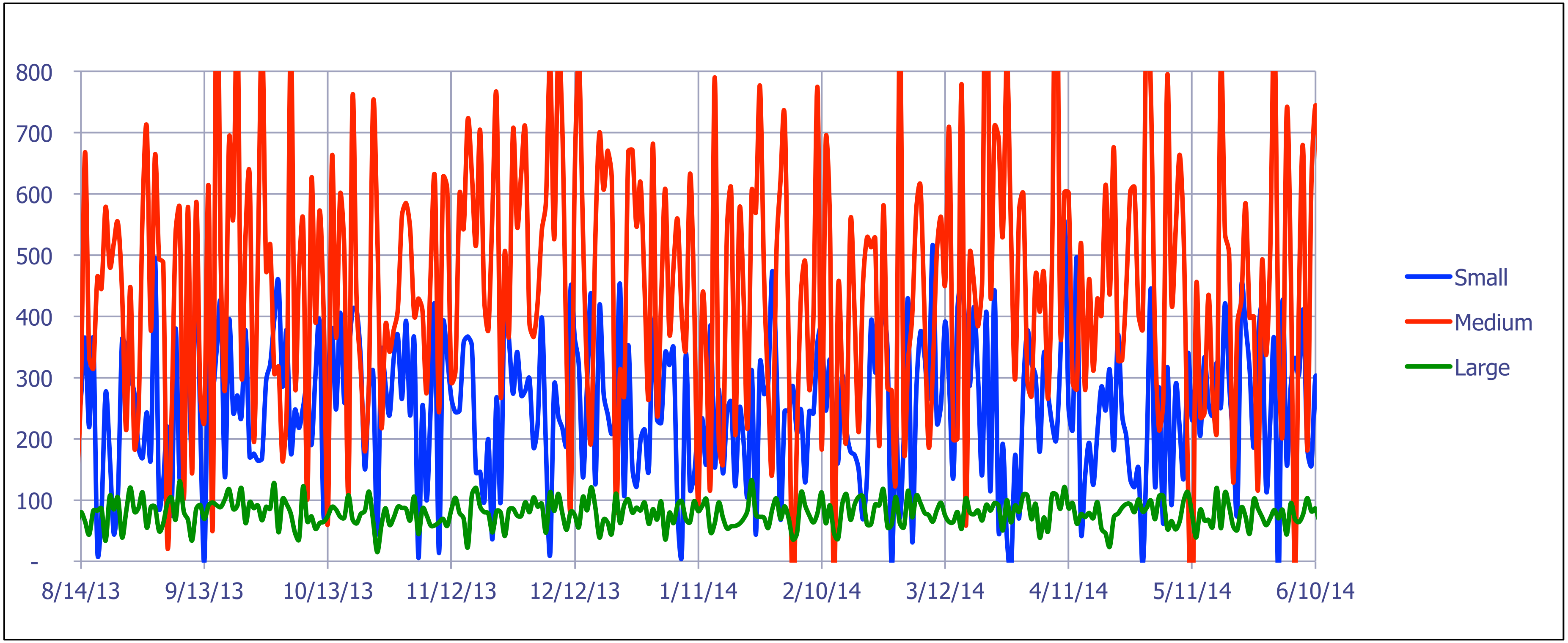
- Aggregation by SKU, Time, Location, etc.
- Coefficient of Variation (CV)
  - Definition: Standard Deviation / Mean = σ/μ
  - Provides a relative measure of volatility or uncertainty
  - CV is non-negative and higher CV indicates higher volatility



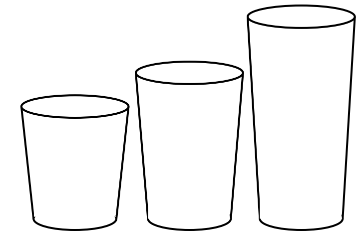
Aggregating by SKU



- Coffee Cups and Lids @ the Sandwich Shop
  - Large ~N(80, 30) CV = 0.38
  - Medium ~N(450, 210) CV = 0.47
  - Small ~N(250, 110) CV = 0.44

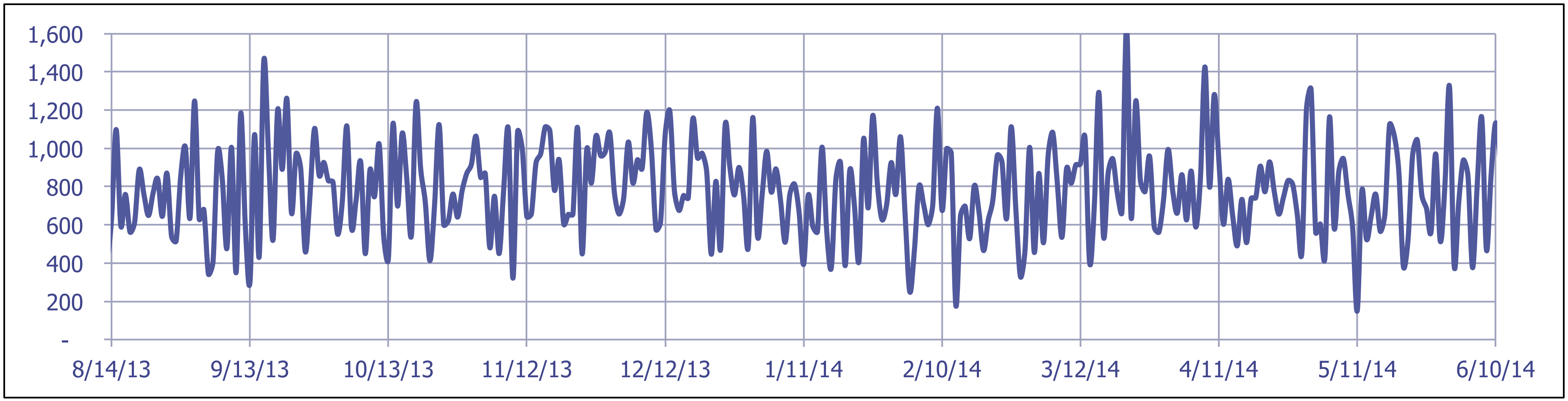


Aggregating by SKU



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

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

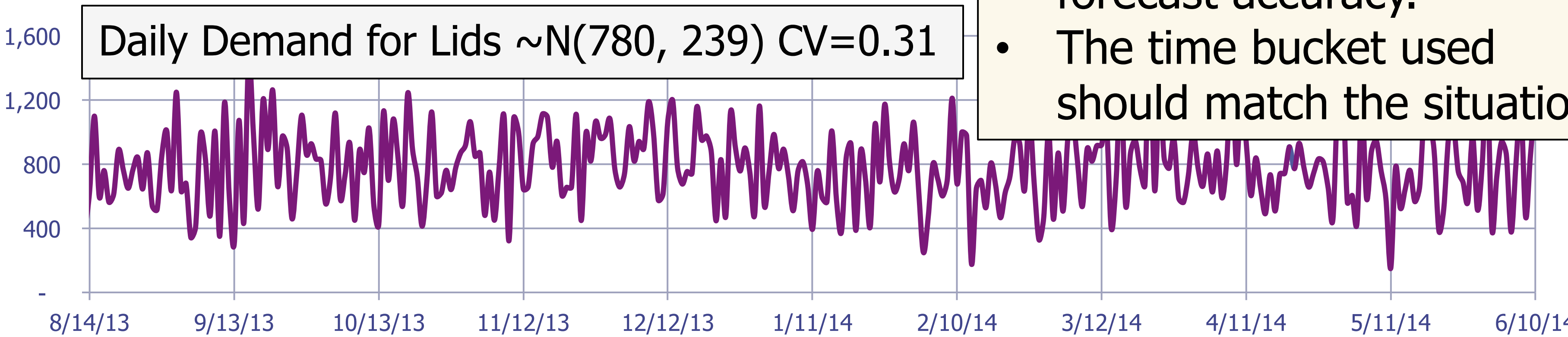


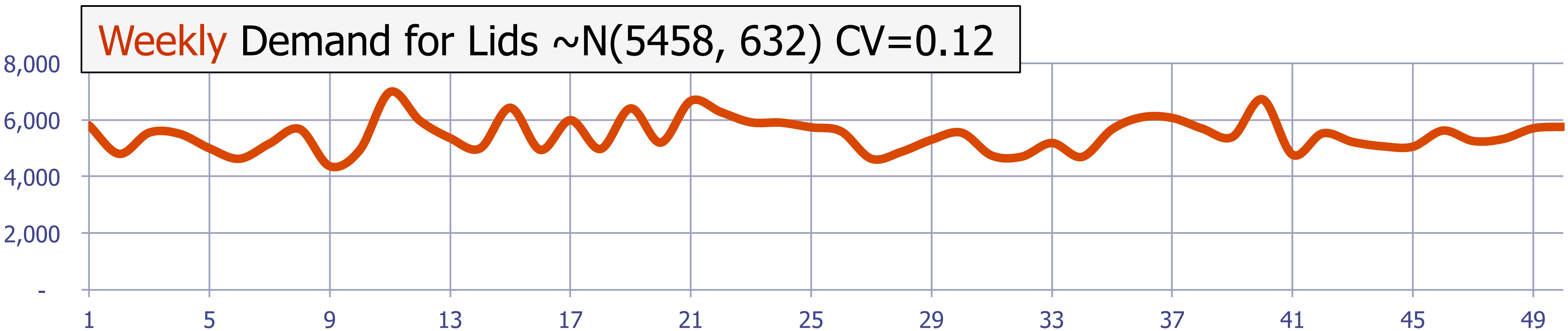
Example of Modularity or Parts Commonality

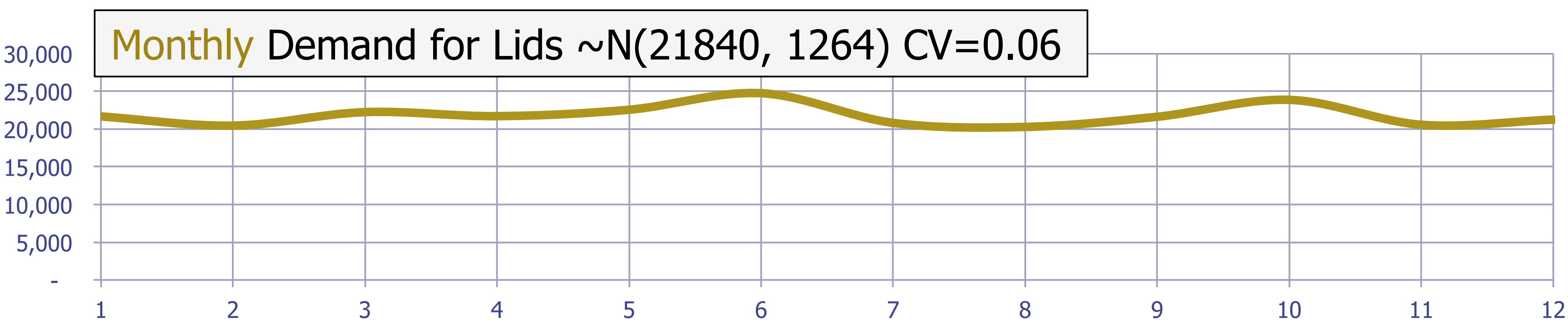
- Reduces the relative variability
- Increases forecasting accuracy
- Lowers safety stock requirements

Aggregating by Time

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



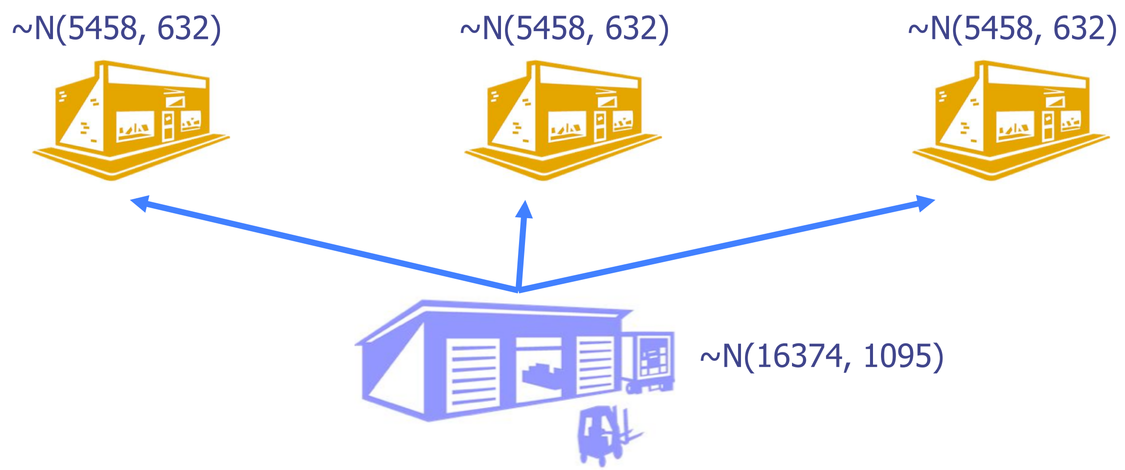




Aggregating by Locations

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

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



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

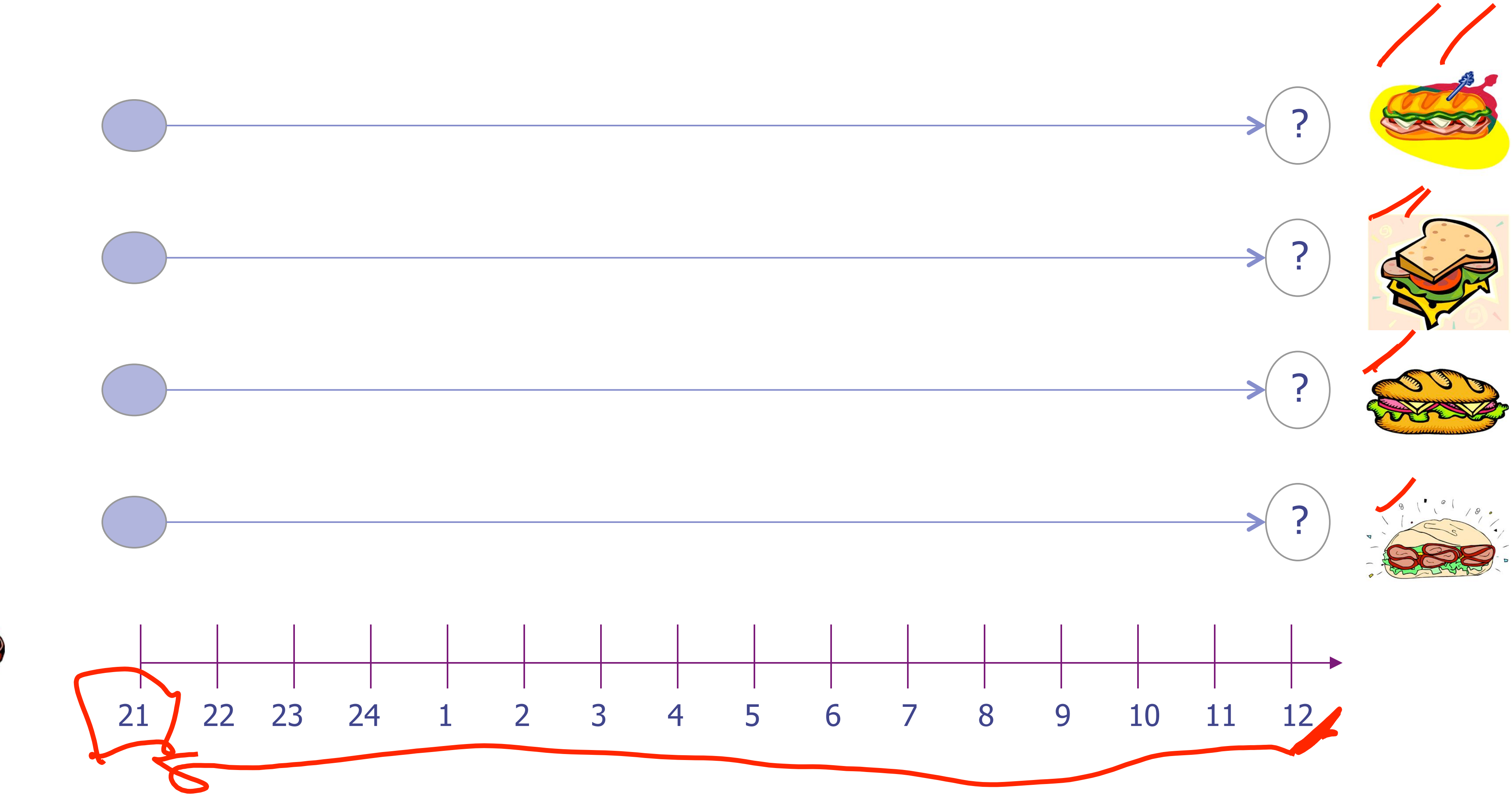
$$\boxed{CV_{ind} = \frac{\sigma}{\mu}}$$

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

Forecasting Truisms 3:

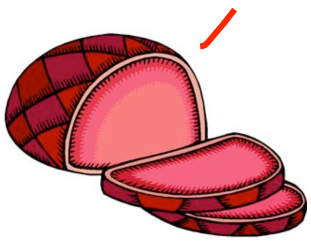
Shorter horizon forecasts are more accurate

3. Shorter horizon forecasts are more accurate

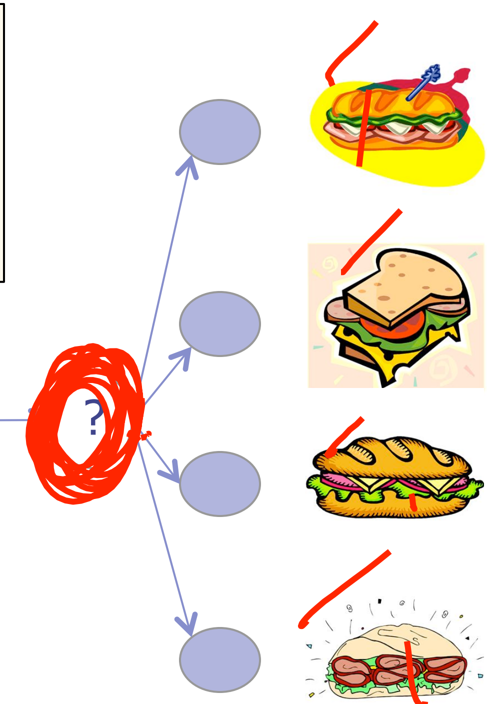


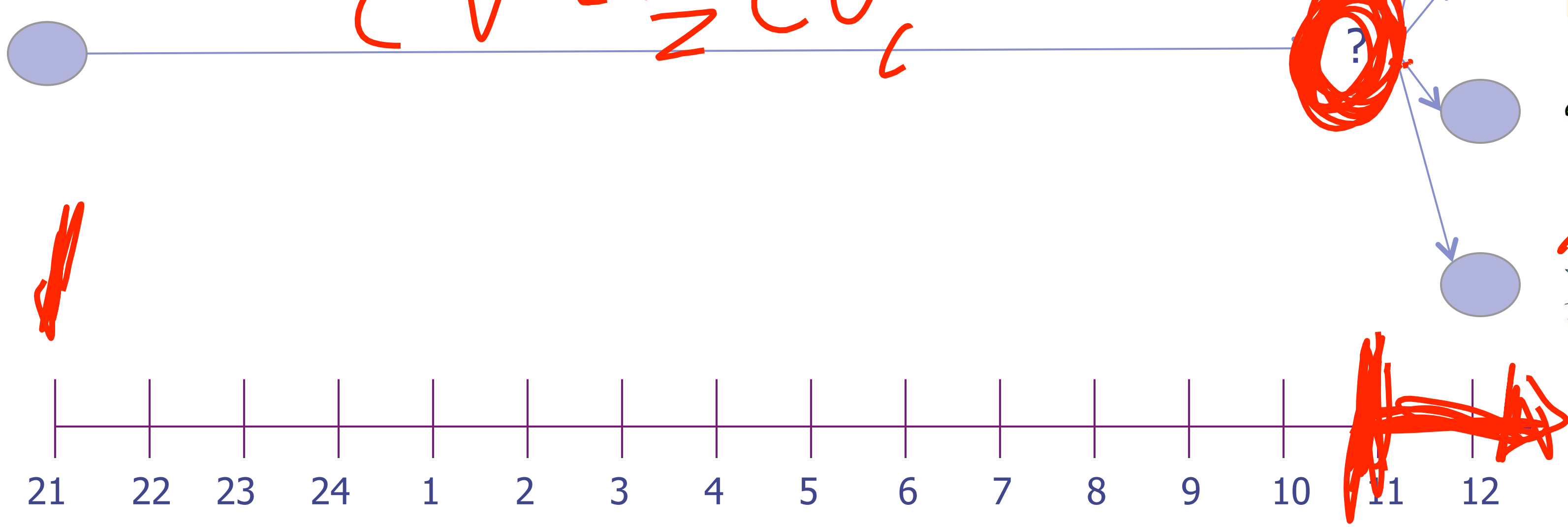
3. Shorter horizon forecasts are more accurate

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



$CV = \frac{1}{2} CV_i$





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

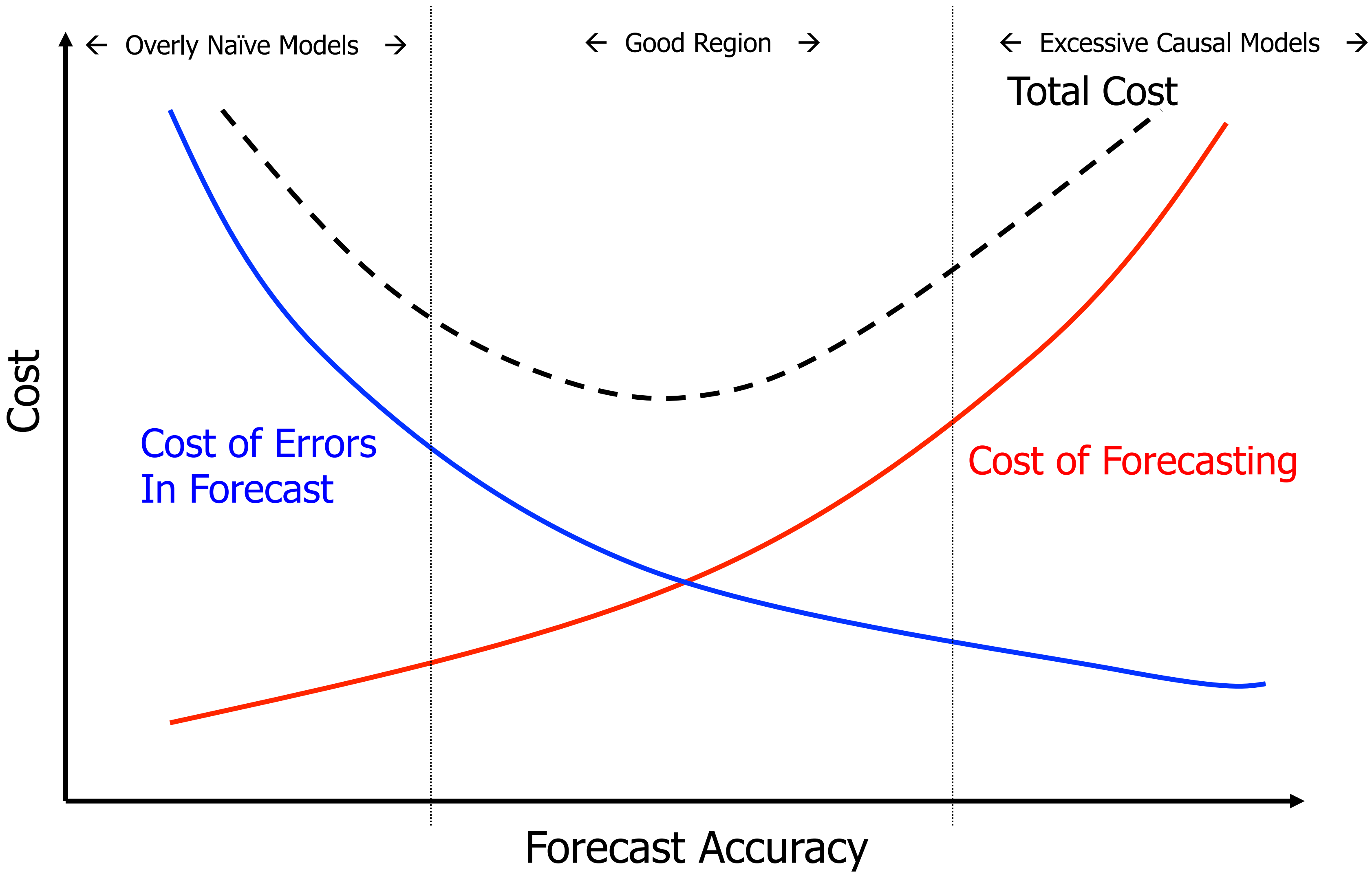
Fundamental Forecasting Approaches

Subjective	Objective
Judgmental	**Causal / Relational**
▪ Sales force surveys	▪ Econometric Models
▪ Jury of experts	▪ Leading Indicators
▪ Delphi techniques	▪ Input-Output Models
Experimental	**Time Series**
▪ Customer surveys	▪ "Black Box" Approach
▪ Focus group sessions	▪ Past predicts the future
▪ Test marketing	▪ Identify patterns

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

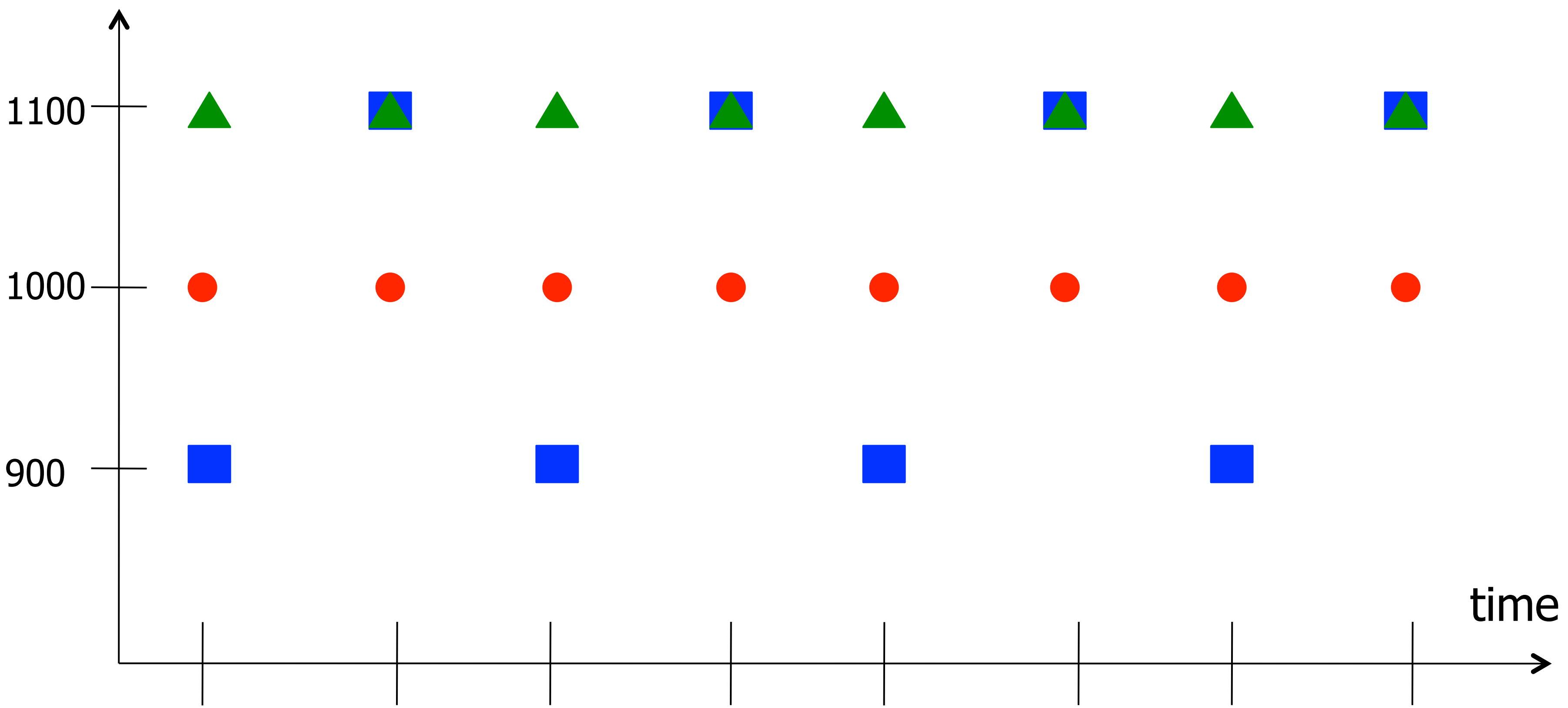
Forecasting Quality

Cost of Forecasting vs Inaccuracy



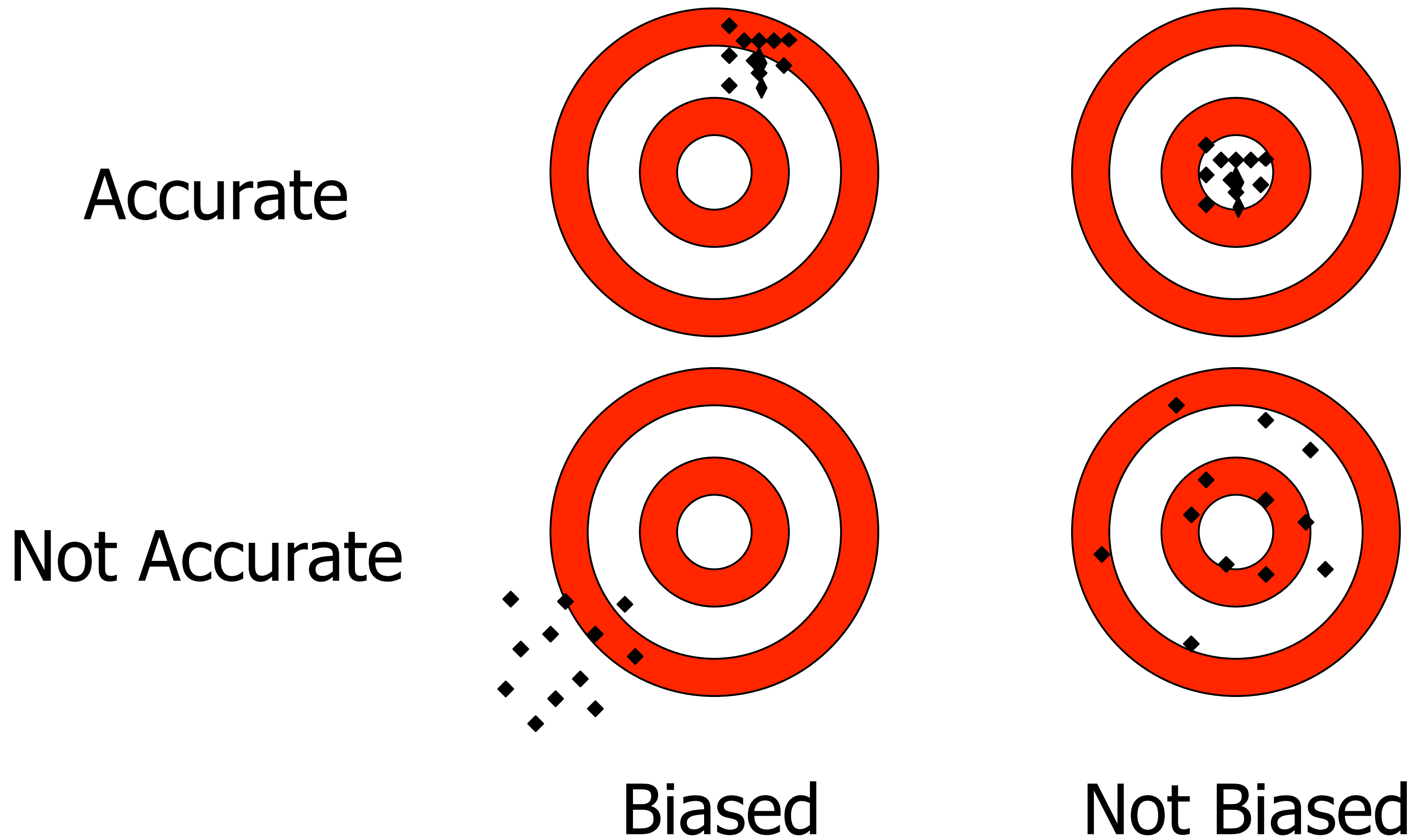
How do we determine if a forecast is good?

- 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



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

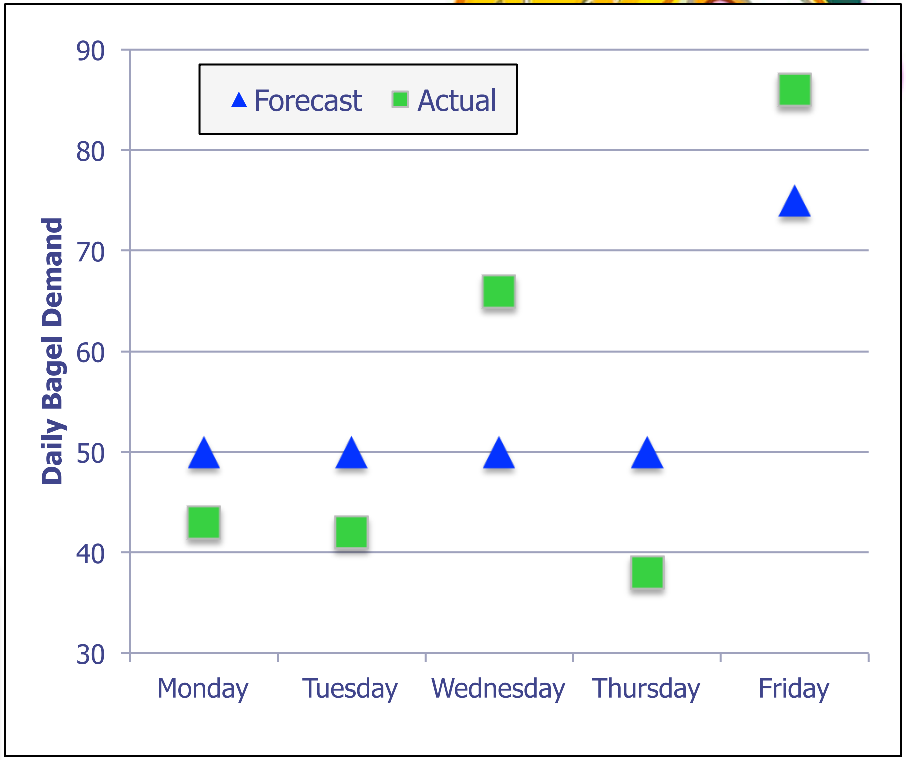
$$MAD = \frac{\sum_{t=1}^{n} |e_t|}{n}$$

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

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

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%

MAD = 54/5 = 10.8
RMSE = sqrt(126.8) = 11.3
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