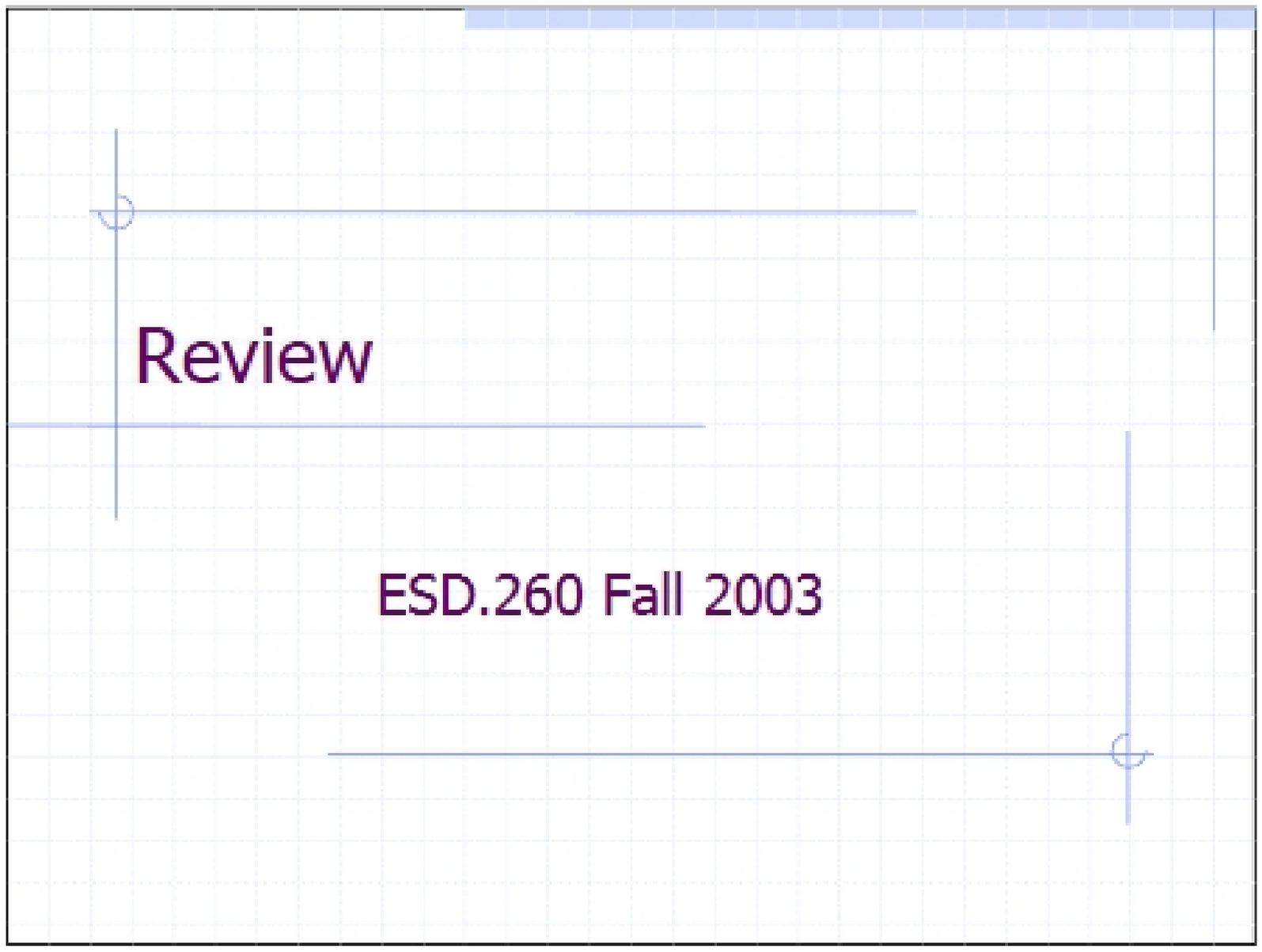
Review
ESD.260 Fall 2003


Demand Forecasting

Accuracy and Bias Measures

1. Forecast Error: $e_t = D_t - F_t$

2. Mean Deviation: $$MD = \frac{\sum_{t=1}^{n} e_t}{n}$$

3. Mean Absolute Deviation $$MAD = \frac{\sum_{t=1}^{n} |e_t|}{n}$$

4. Mean Squared Error: $$MSE = \frac{\sum_{t=1}^{n} e_t^2}{n}$$

5. Root Mean Squared Error: $$RMSE = \sqrt{\frac{\sum_{t=1}^{n} e_t^2}{n}}$$

6. Mean Percent Error: $$MPE = \frac{\sum_{t=1}^{n} \frac{e_t}{D_t}}{n}$$

7. Mean Absolute Percent Error: $$MAPE = \frac{\sum_{t=1}^{n} \frac{|e_t|}{D_t}}{n}$$

MD – cancels out the over and under – good measure of bias not accuracy

MAD – fixes the cancelling out, but statistical properties are not suited to probability based dss

MSE – fixes cancelling out, equivalent to variance of forecast errors, HEAVILY USED statistically appropriate measure of forecast errors

RMSE – easier to interpret (proportionate in large data sets to MAD) MAD/RMSE = SQRT(2/pi) for e~N

Relative metrics are weighted by the actual demand

MPE – shows relative bias of forecasts

MAPE – shows relative accuracy

Optimal is when the MSE of forecasts -> Var(e) – thus the forecsts explain all but the noise.

What is good in practice (hard to say) MAPE 10% to 15% is excellent, MAPE 20%-30% is average CLASS?