An Overview of Rule-Based Forecasting

Monica Adya
Department of Management
Marquette University

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Outline

- Background of RBF
  - what is RBF
  - the development of RBF
  - enhancements to RBF
- Elements of RBF
- Evidence on the value of RBF

What is RBF?

- Expert system that uses domain knowledge to combine forecasts
- Production rules determine weights to be assigned to four component methods.
- Rules rely on features of time series to suggest weights.
- E.g. IF there is a change in the basic trend THEN add 15% to the weight on random walk AND subtract it from the other three methods.

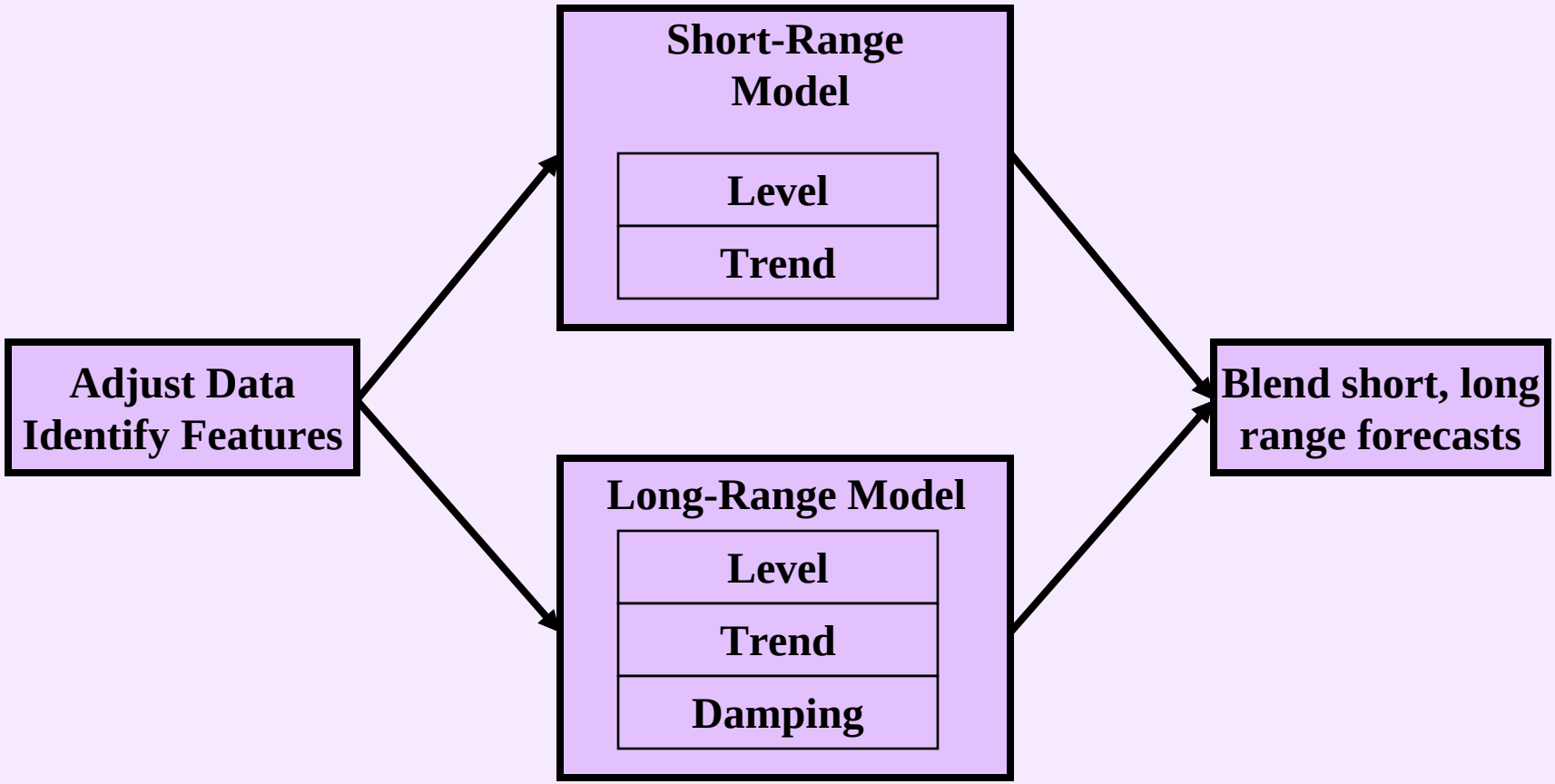
Gathering Rules

- Rules gathered from
  - literature
  - interviews and surveys of forecasters, and
  - protocol analysis of 5 experts.
- Rules calibrated and tested on 90 time series.
- Rules validated on 36 time series.

Formulating Rules

- Separate considerations are given to level and trend
- Simple extrapolation methods are used
- Forecasts are combined
- Different models are used for short and long term forecasts
- As uncertainty increases, trend is damped

Structure of RBF



The Features

- The IF… part of the rules rely on features of time series
  - domain knowledge
  - historical features
- RBF relies on 28 features

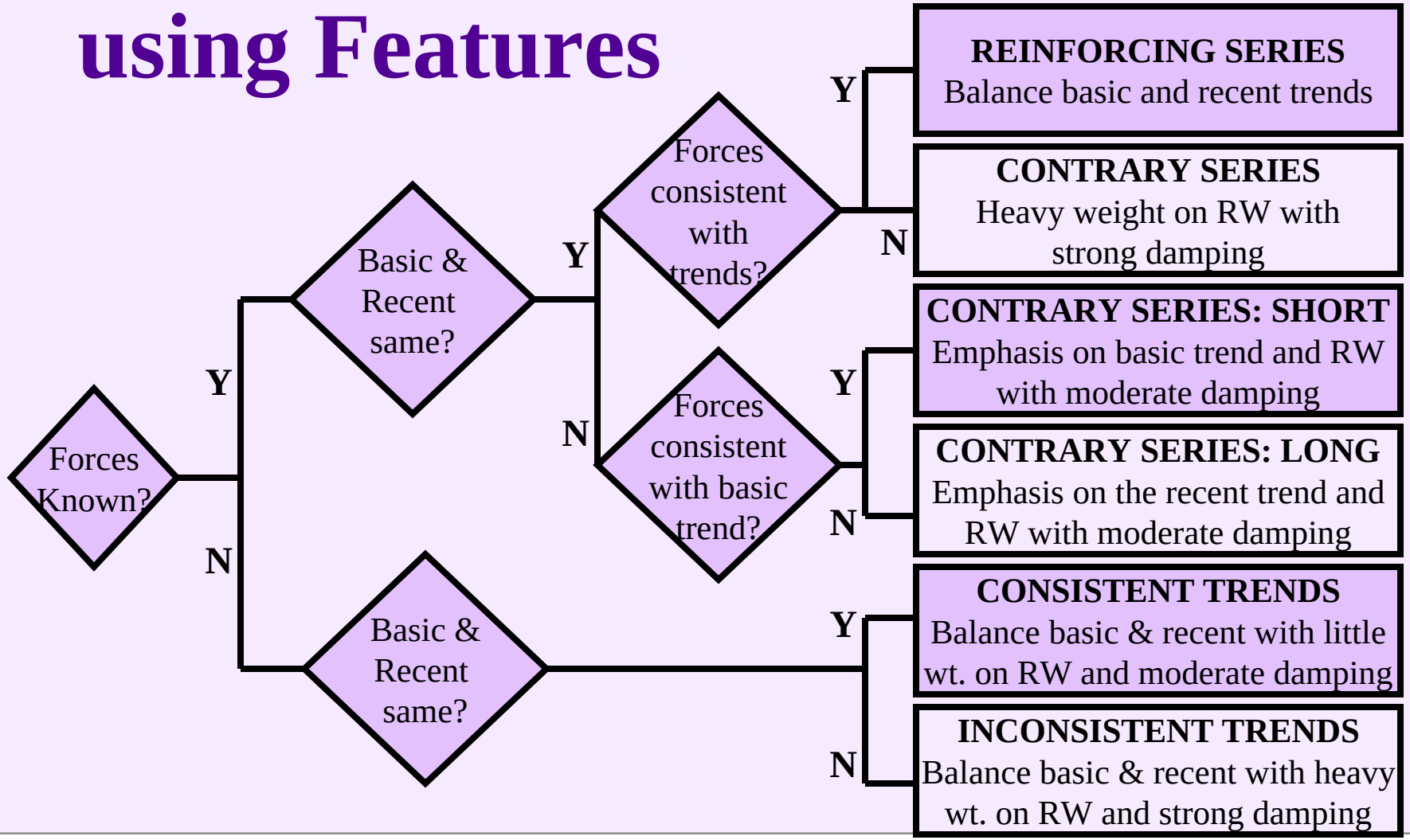
RBF uses 28 Features

Domain Knowledge	Historical Data	
• Causal Forces • Functional form • Cycles expected • Forecast horizon • Subject to events • Start-up series • Related to other series	**Types of Data** • Only positive values • Bounded • Missing observations **Level** • Biased **Trend** • Direction of basic trend • Direction of recent trend • Significant basic trend **Length of series** • Number of observations • Time interval **Seasonality**	**Uncertainty** • Coeff of variation about trend • Basic and recent trends differ **Instability** • Irrelevant early data • Suspicious pattern • Unstable recent trend • Outliers present • Recent run not long • Near a previous extreme • Changing basic trend • Level discontinuities • Last observation unusual

Causal Forces

Type of CF	Causal Force Direction when trend has been up	Causal Force Direction when trend has been down	Example
Growth	up	up	Sales
Decay	down	down	Production costs
Regressing	toward a known mean value	toward a known mean value	Inventory as % of sales
Supporting	up	down	Real estate prices
Unknown	?	?	Exchange rates

Triggering Rules using Features



Trend Forecasting

- Use full trend extrapolation for reinforcing series
- Place little weight on trends in contrary series
- If expected trends from causal forces are contrary to historically estimated trends, do not use the historical trend

Trend Forecasting (cont.)

- Use a conservative trend estimate if the basic and recent trends are inconsistent
- Tailor extrapolation weights to the time interval of the series
- To estimate the levels for the short-term model, heavily weight the latest observations
- Adjust the estimate of the level in the direction implied by the causal forces.

Evidence from RBF

Data From M-Competition

	Median Absolute Percentage Errors							
	One-ahead forecasts				Six-ahead forecasts			
Method	**V1**	**V2**	**V3**	**W**	**V1**	**V2**	**V3**	**W**
RW	6.4	5.7	5.6	5.8	30.1	24.7	25.2	26.0
TM	5.5	4.3	4.9	4.8	23.3	18.0	18.0	19.0
EW	2.8	3.1	4.3	3.5	22.8	21.9	18.4	20.7
RBF	2.5	3.1	3.2	3.0	13.0	9.1	14.2	11.9

(V1, V2, and V3 represent the three validation samples as used in Collopy and Armstrong, 1992. W represents the weighted average.)

Results of the M3 Competition

- Annual Series
  - Short-term forecasts: RBF(A) wins over all other methods by small margin
  - Long term forecasts: RBF(A) wins over all methods by progressively wider margin
  - Overall - RBF(A) best method on annual data
- Short Period Series
  - Short-term forecasts: RBF(A) ranks third.
  - Long-term forecasts: RBF(A) progressively improves till it is the best method.
  - Overall - RBF(A) ranks second.

When is RBF Useful?

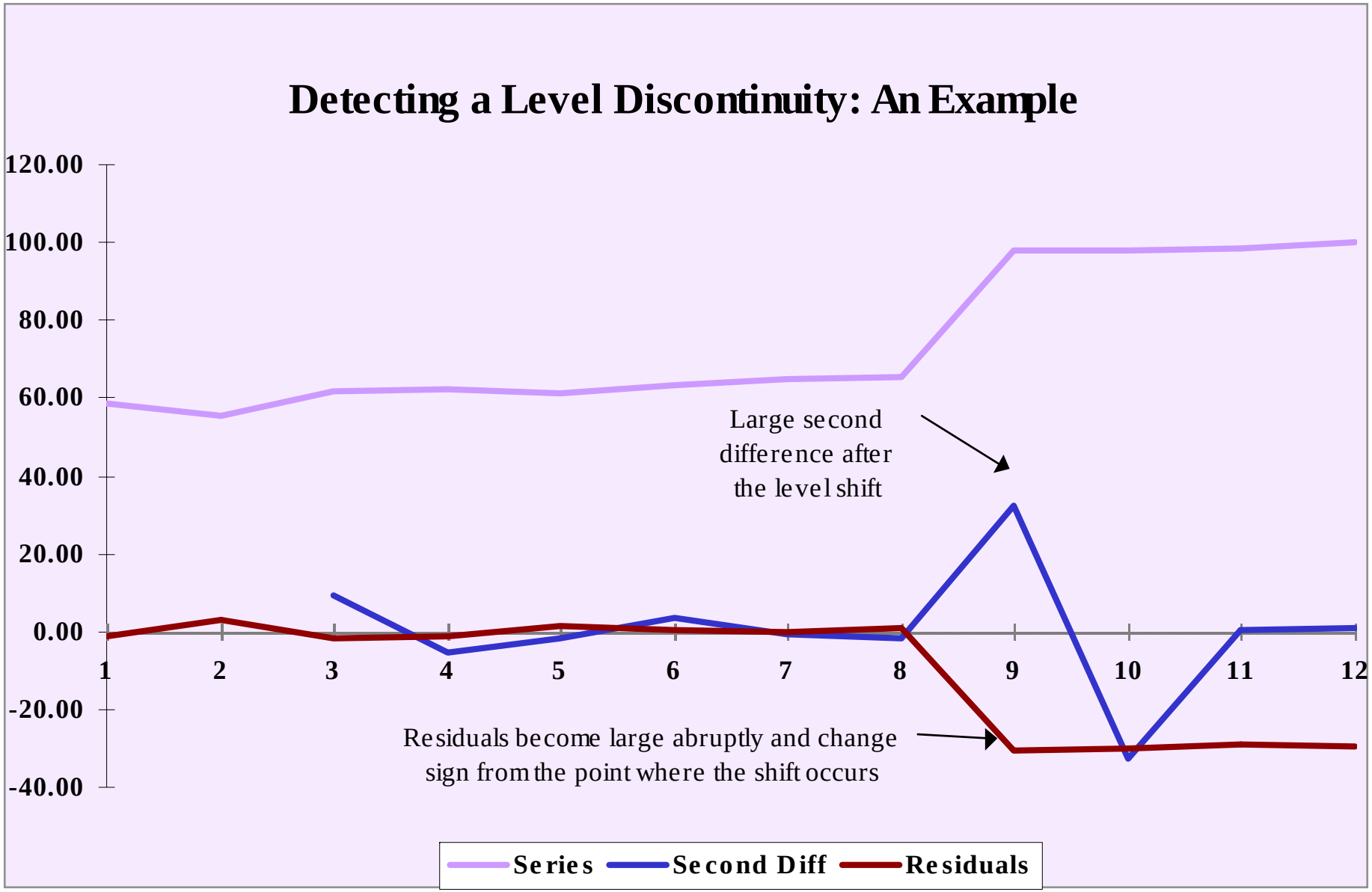
- Long-interval data are used
- good domain knowledge is available
- causal forces are clearly identifiable
- domain knowledge conflicts with historical trend
- long range forecasts are needed
- significant trend exists
- uncertainty is modest to low
- instability is modest to low

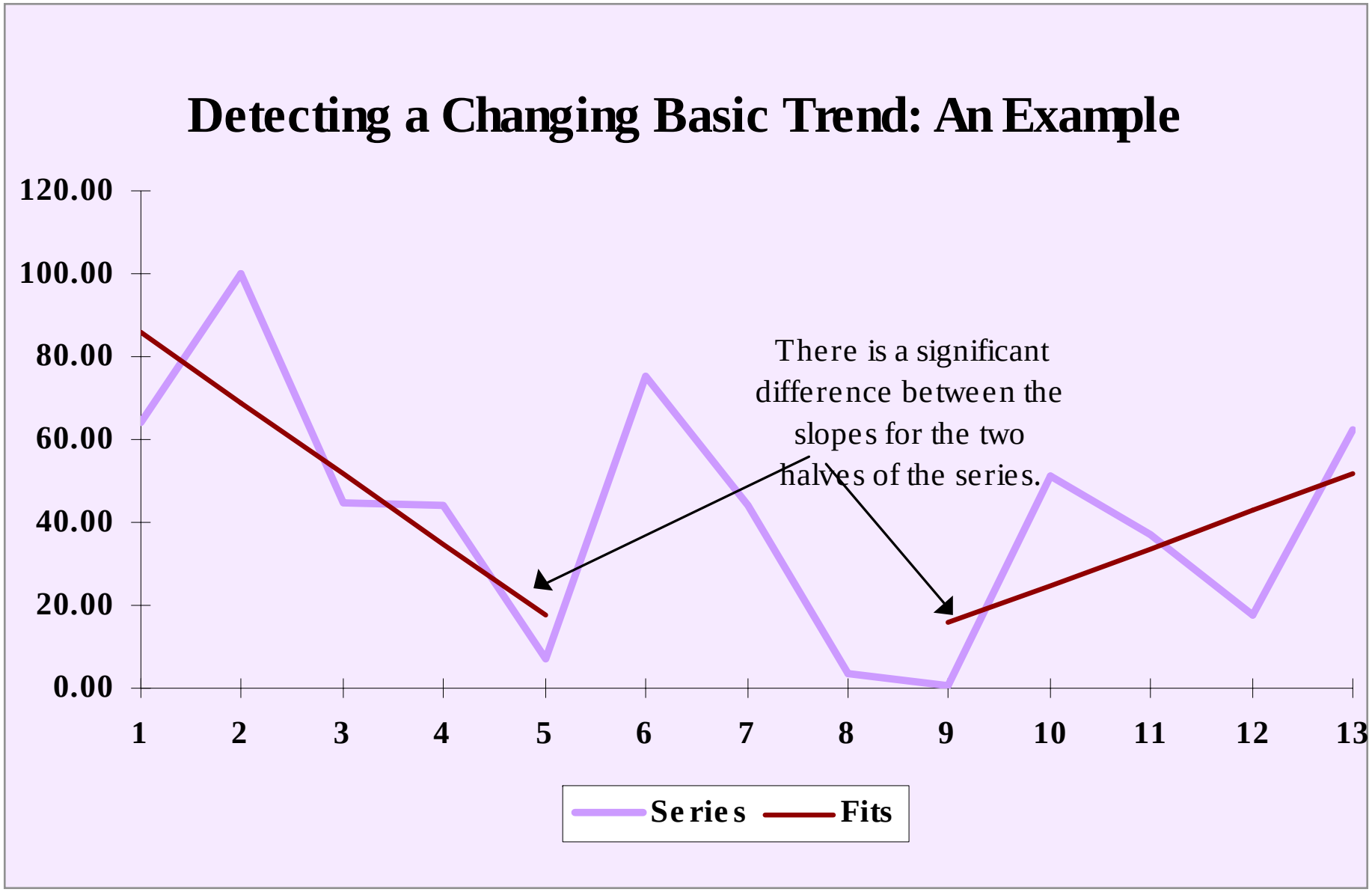
Automatic Feature Identification

- Objective of Automation
  - Consistent coding of features
  - Reduced costs: judgmental coding typically takes 4-5 minutes per series
- Which features were automated?
  - Those that were visually determined - outliers, level discontinuity, unusual last observation, changing basic trend, unstable recent trend, and functional form.
- How was feature identification automated?
  - Develop heuristics based on simple statistical procedures.

Development of the Heuristics

- Developed on 70 series used to develop RBF. Validated on 52 series.
- Identified a test that seemed most appropriate for the detection of the feature.
- Produce forecasts for development and validation sample.
- Compare forecast accuracy of RBF with judgmental and heuristic coding of features.


Detecting a Level Discontinuity: An Example
120.00
100.00
80.00
60.00
40.00
20.00
0.00
-20.00
-40.00
1
2
3
4
5
6
7
8
9
10
11
12
Large second difference after the level shift
Residuals become large abruptly and change sign from the point where the shift occurs
Series
Second Diff
Residuals


Detecting a Changing Basic Trend: An Example
120.00
100.00
80.00
60.00
40.00
20.00
0.00
1
2
3
4
5
6
7
8
9
10
11
12
13
There is a significant difference between the slopes for the two halves of the series.
Series
Fits

Automatic Identification Results

- Forecast accuracies were not significantly harmed as a result of automated feature detection.
- Significant reduction in coding time.
- 30% of series performed the same on all horizons.
- Of the remaining, as many series performed better with automated detection as did worse.

Ex Ante Evaluation of RBF(A) on Weatherhead II

Forecast Method	MAPEs			MdAPEs		
	1 yr	6 Yr	Cum	1 yr	6 Yr	Cum
Random Walk	9.37	26.15	19.91	5.05	17.31	12.20
Linear Regression	19.98	38.36	31.13	12.29	23.26	19.99
Holt's	9.73	31.04	22.57	3.38	12.62	9.79
Equal-Weights	11.18	26.36	20.77	5.61	13.07	10.25
RBF(A)	8.14	23.74	18.68	3.13	12.58	8.91

- Weatherhead II consists of 456 series collected in 1995. Description of series in this sample can be found at http://www-marketing.wharton.upenn.edu/forecast/researchers.html
- The RBF(A) version of RBF includes the modules for automated feature identification.

Future Research

- Address the issue of seasonality on short period data.
- Further examination of feature identification heuristics.
- Examine the impact of features on seasonality.
- Sensitivity analysis on rules.

Suggested Resources

- forecastingprinciples.com
- *Principles of forecasting: A handbook for researchers and practitioners*, J.S. Armstrong [ed.], Kluwer Academic Press