Food Wholesales Prediction: What is Your Baseline?

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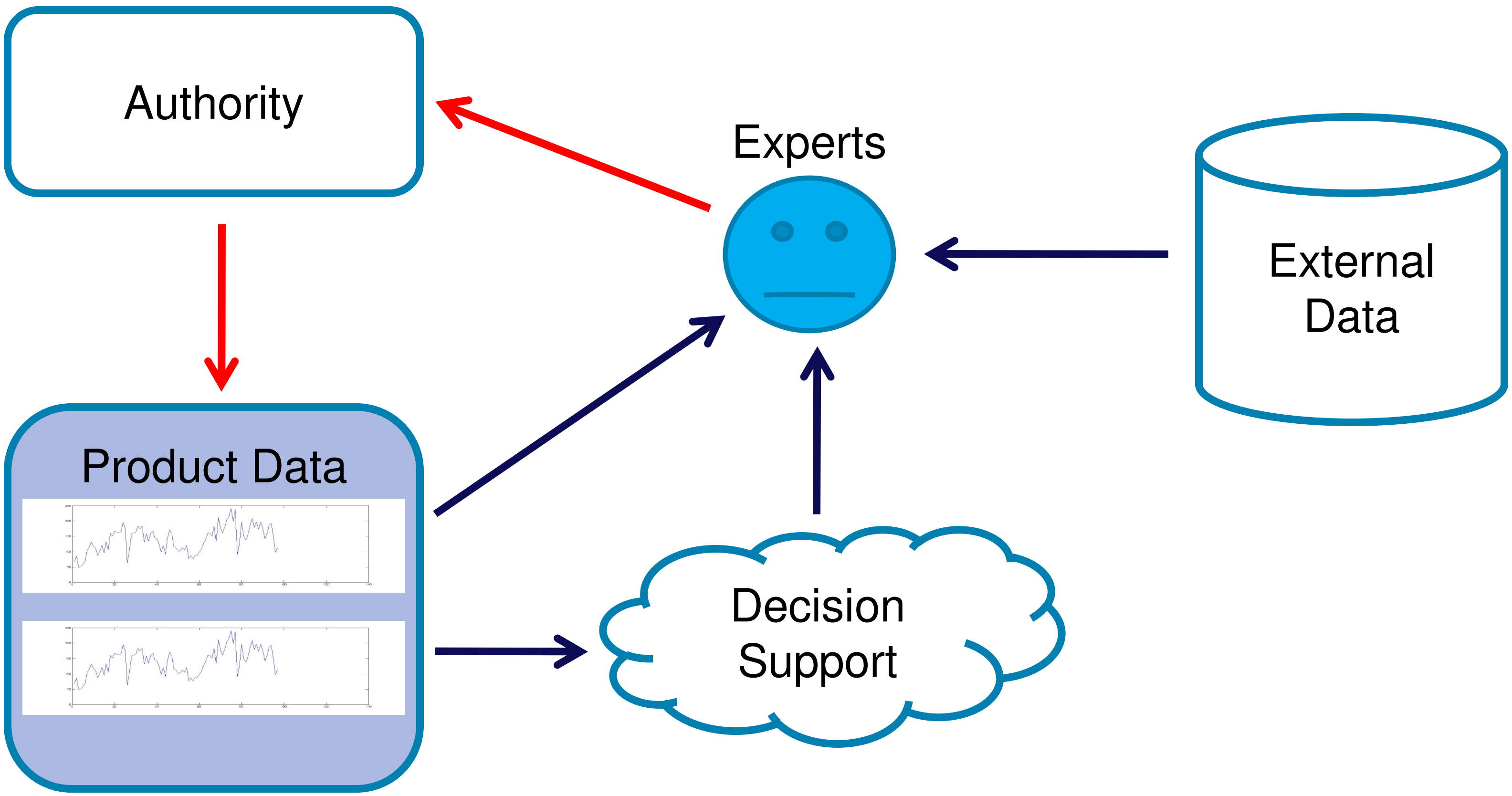
ISMIS 2009, Prague

Netherlands Organisation for Scientific Research

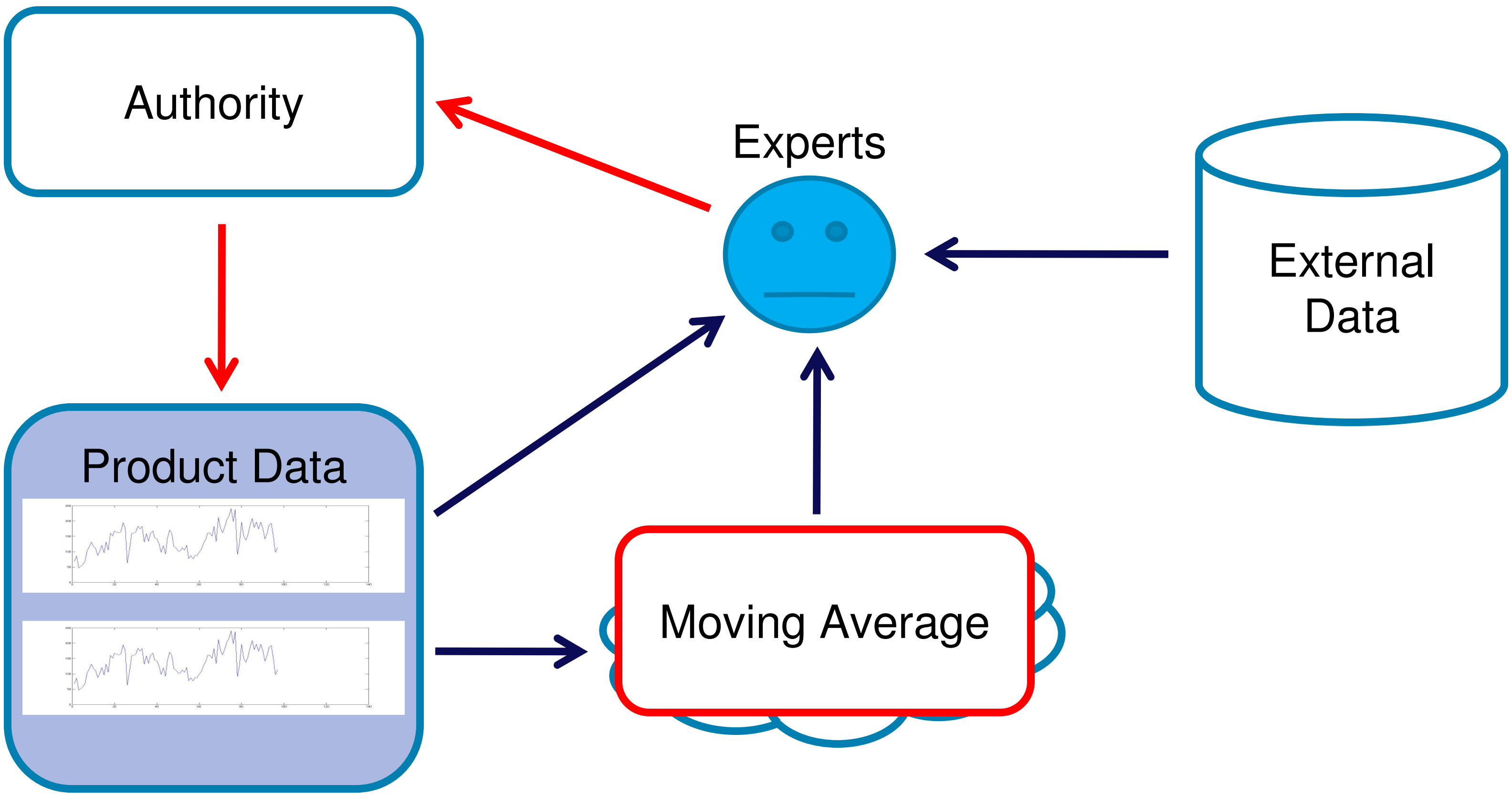
Technische Universiteit Eindhoven University of Technology

Where innovation starts

Food sales stock management



Food sales stock management



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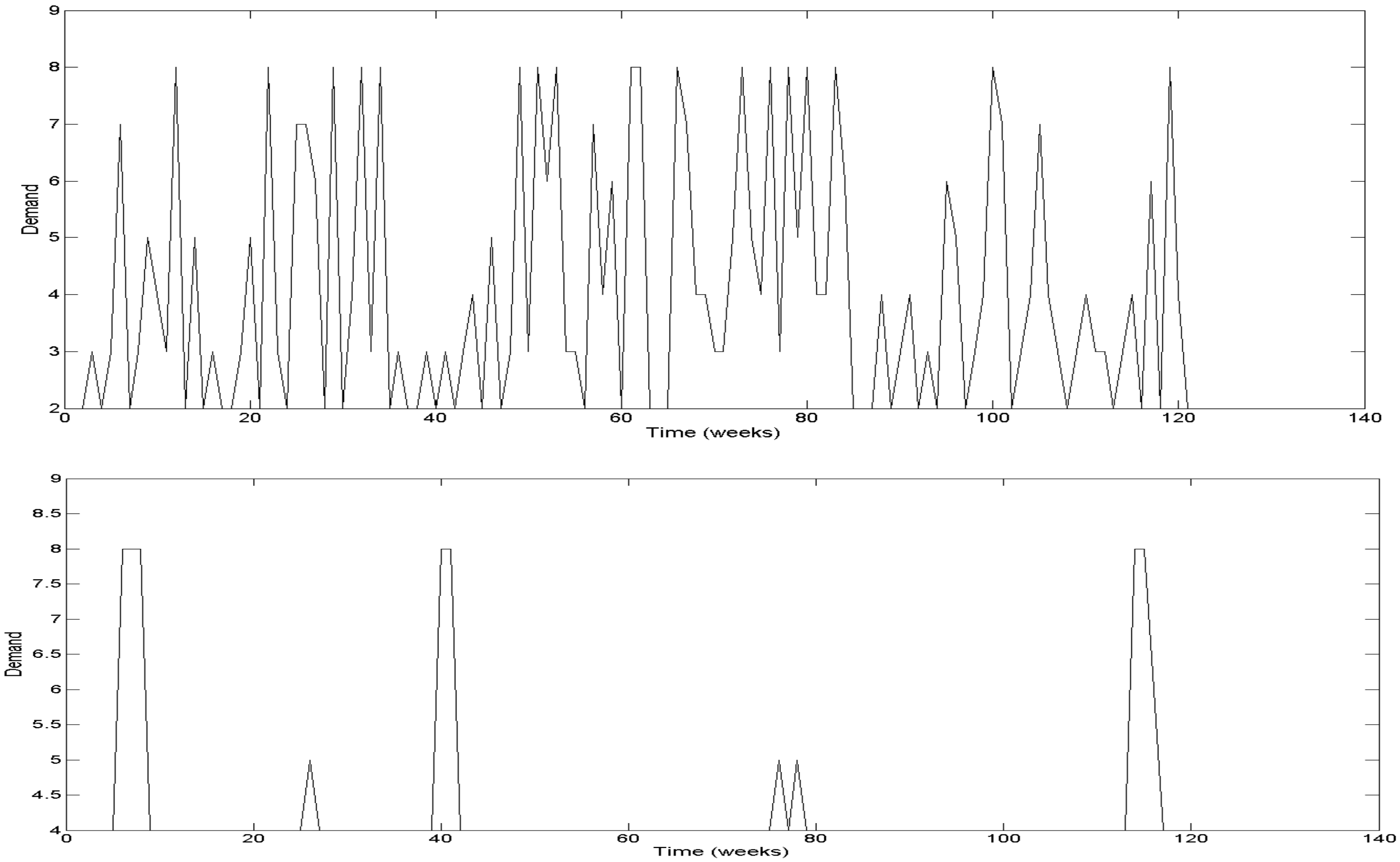

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Overview

- Foodsales prediction
- Evaluation issues
- Error measures
- Alternative visualizations
- Conclusion

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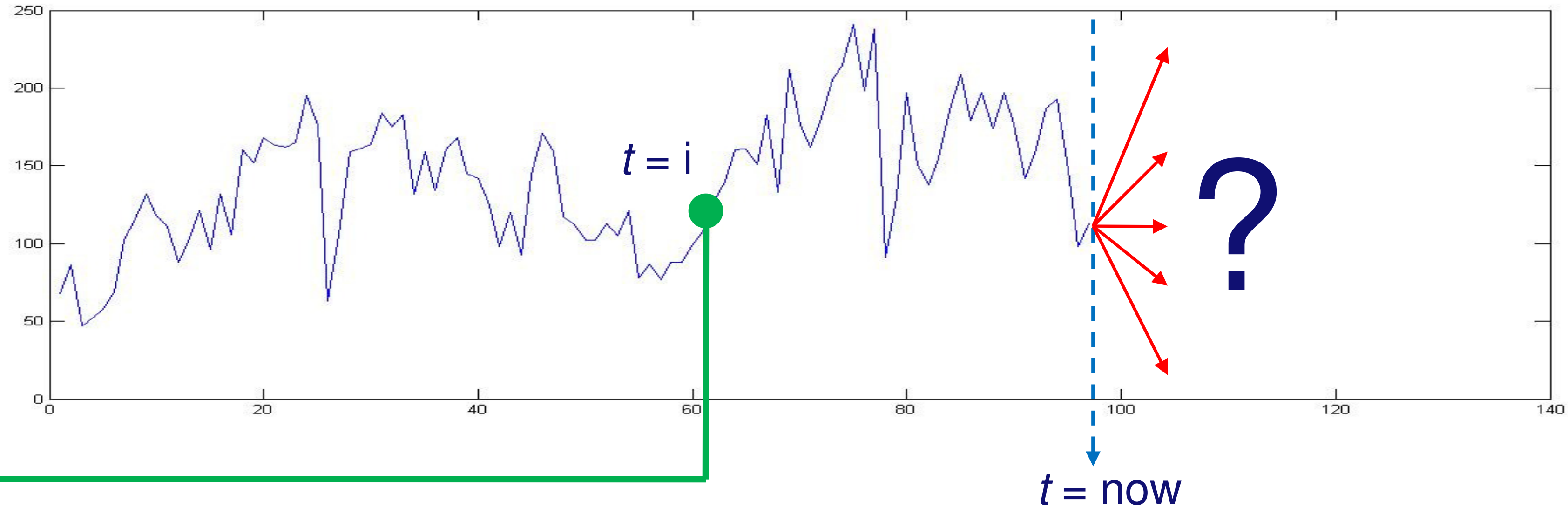
Food sales prediction



t	History	Temp	Holiday	Promo
1				
.				
i				
.				
n				

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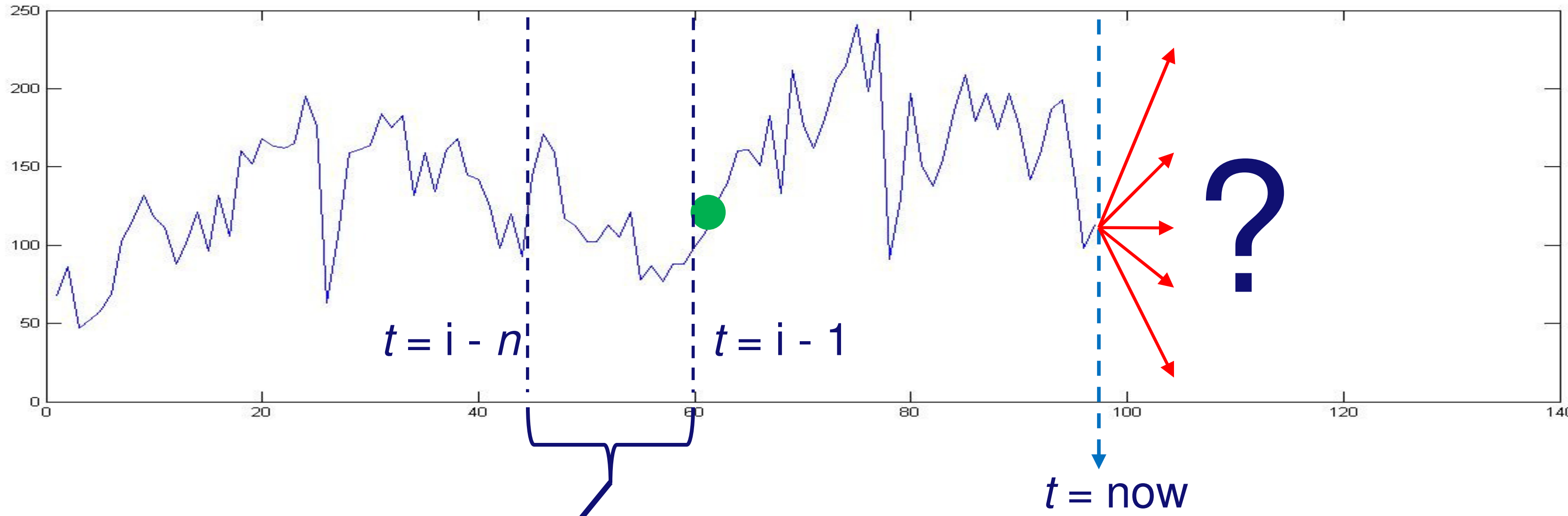
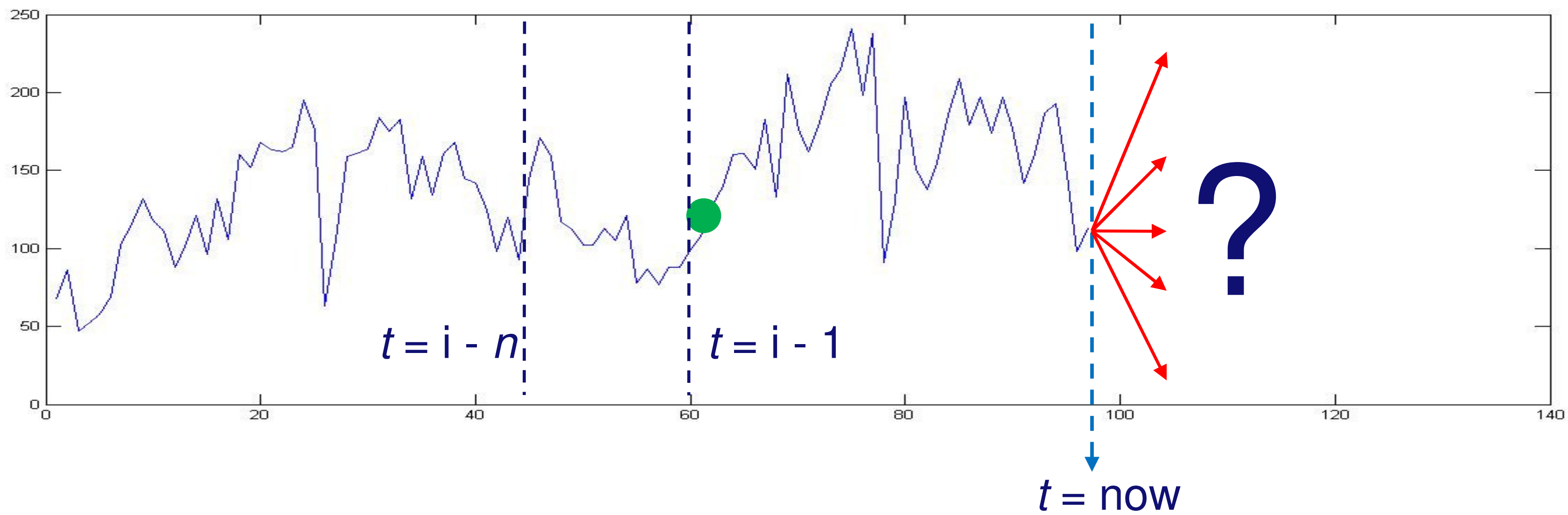
Food sales prediction



t	History	Temp	Holiday	Promo
1				
.				
i	{y(i-n) .. y(i-1)}			
.				
n				

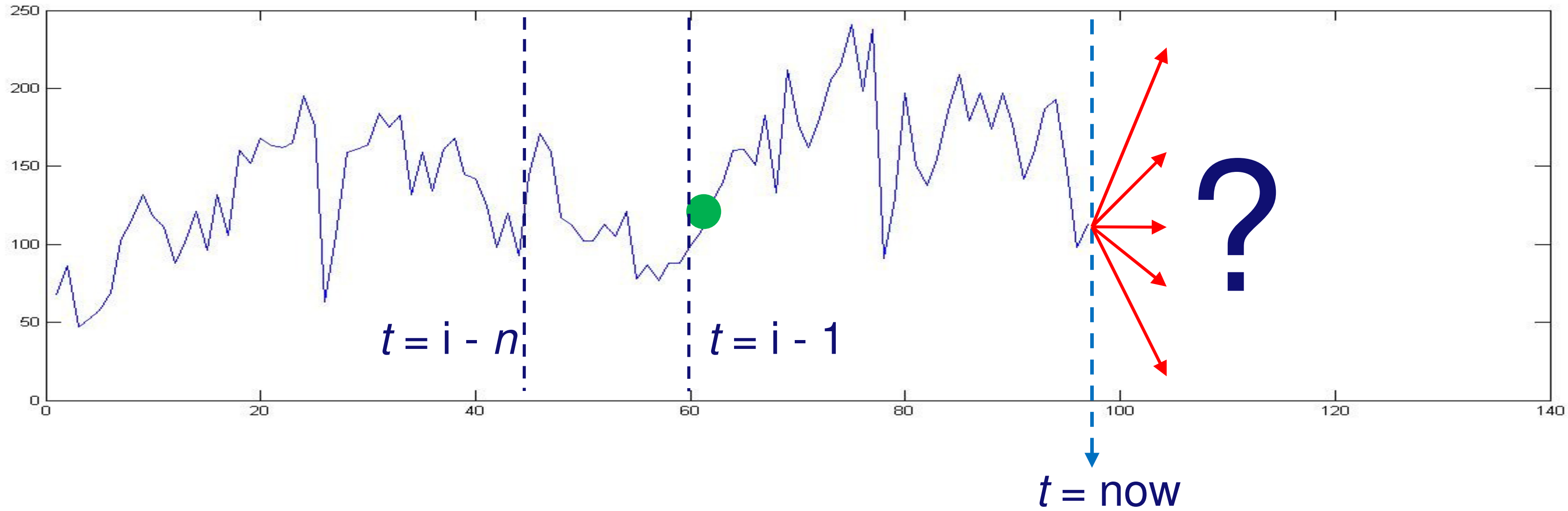
Food sales prediction



t	History	Temp	Holiday	Promo
1				
.				
i	{y(i-n) .. y(i-1)}			
.				
n				

External Features

Food sales prediction



t	History	Temp	Holiday	Promo
1				
.				
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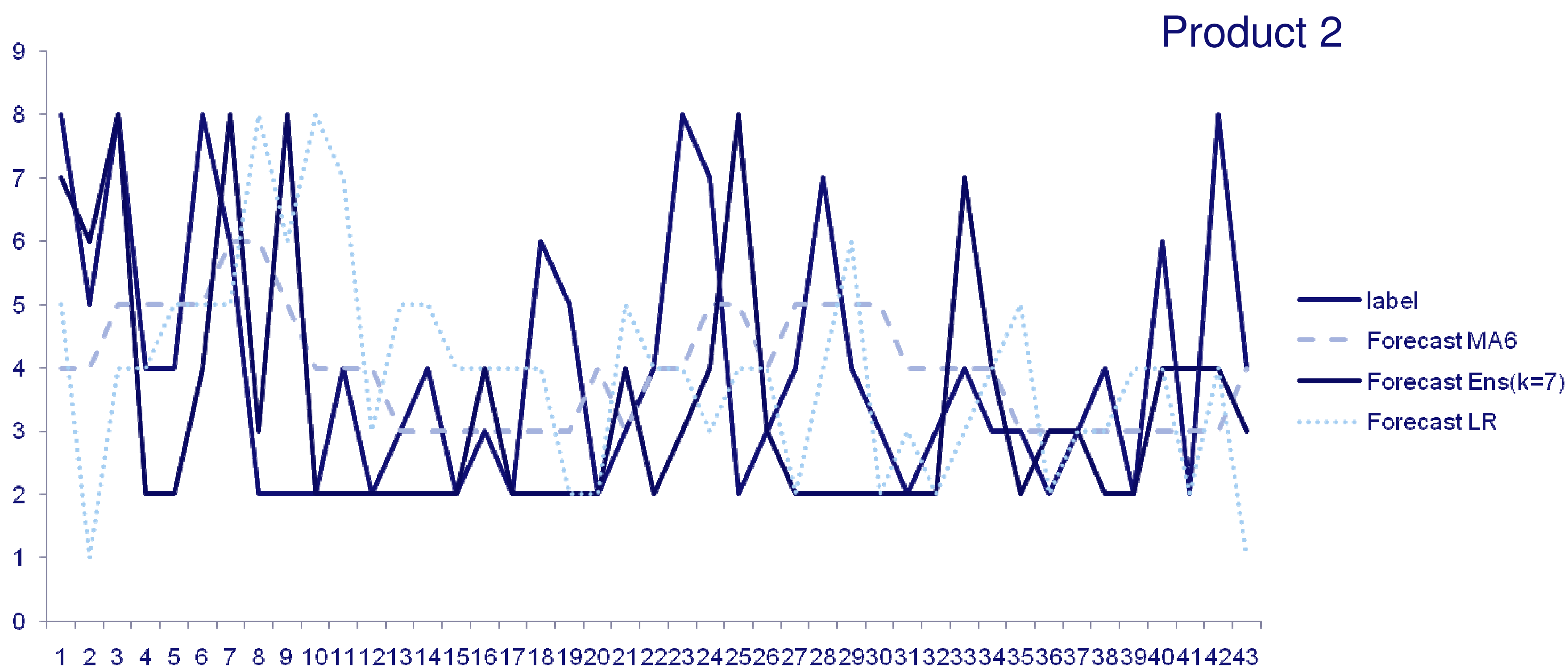
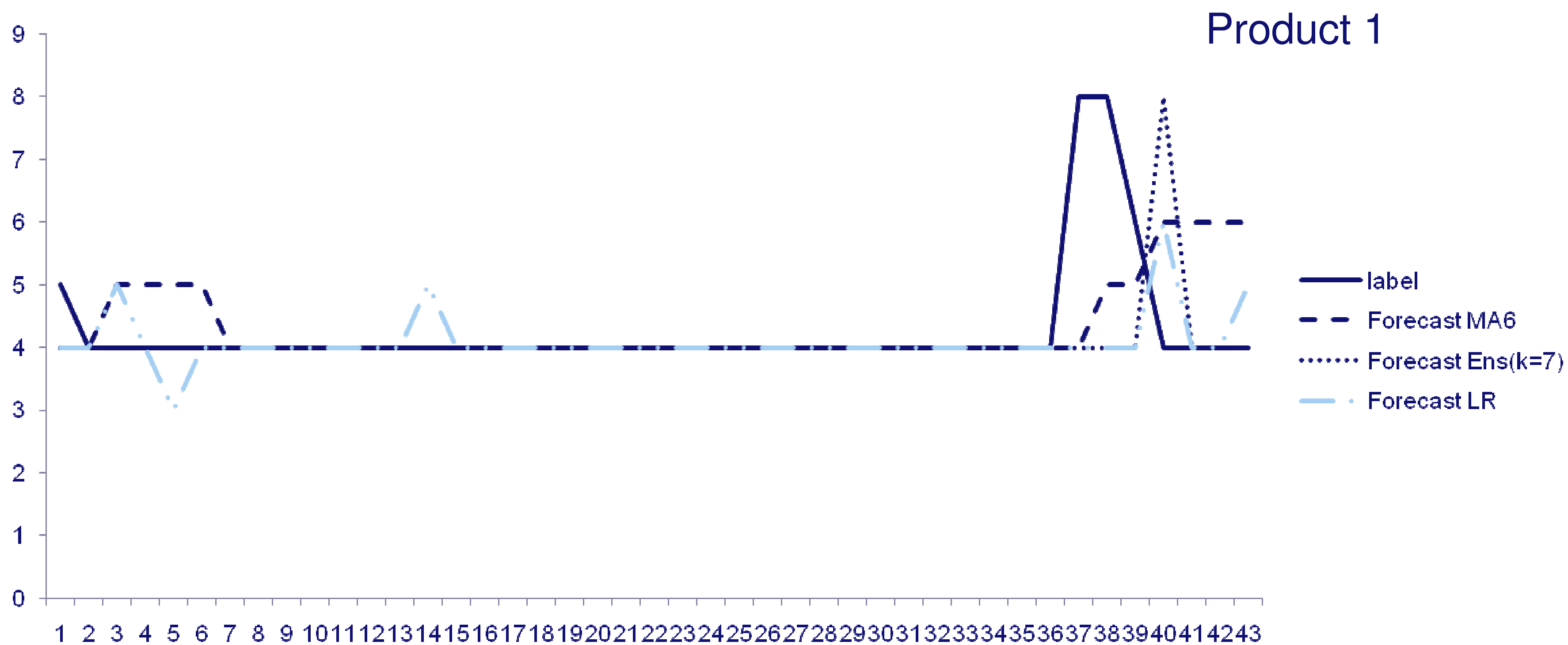
n				

Predict label of i

Evaluation issues



Evaluation issues



Evaluation issues

Model 1 ….. **MA6** **Ensemble** ….. Model n

Product 1

Product 2

.

.

Product j

:

.

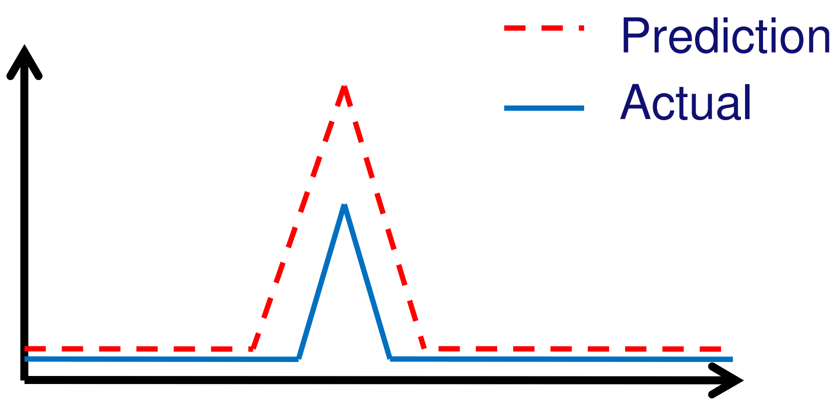
.

Product m

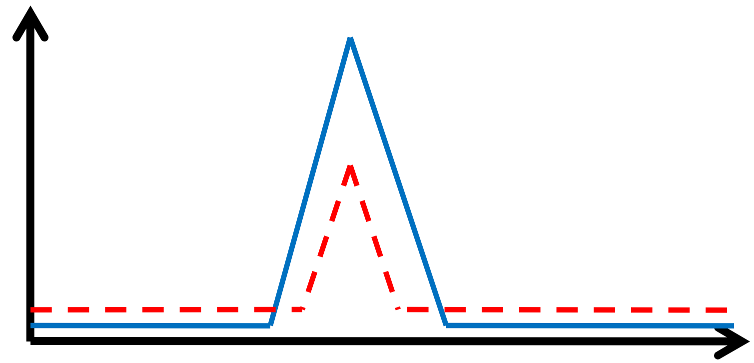
Evaluation issues

	Model 1	.....	MA6	Ensemble	.....	Model n
Product 1			1.09	1.23		
Product 2			3.79	5.88		
.						
.						
Product j						
:						
.						
.						
Product m						
			2.44	3.55		

Evaluation issues



Over prediction might lead to surplus and generate more costs



Under prediction might lead to shortage and loss of profits

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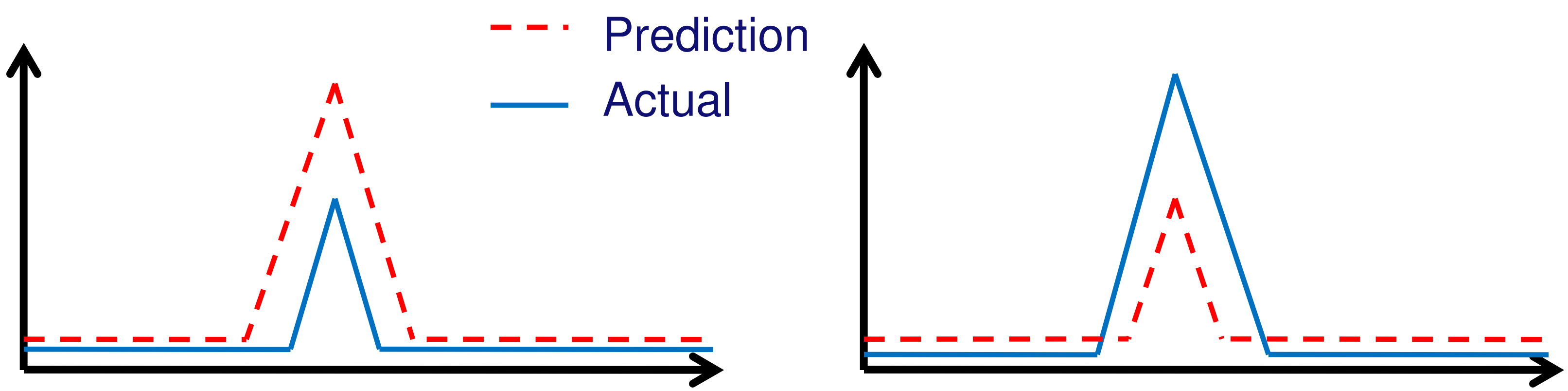
Evaluation issues

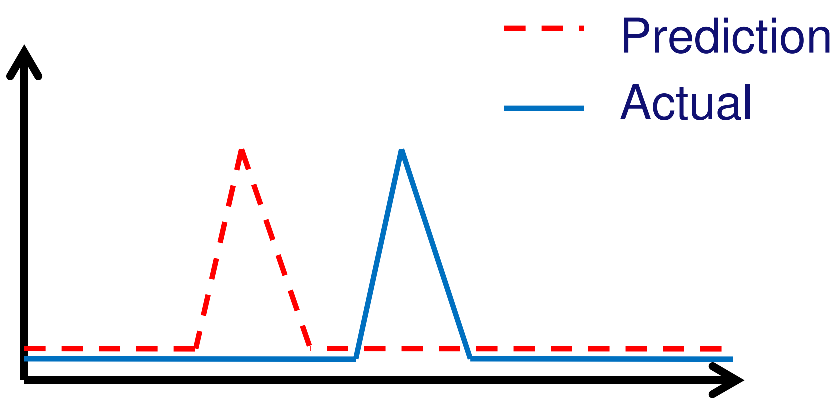


Over prediction might lead to surplus and generate more costs

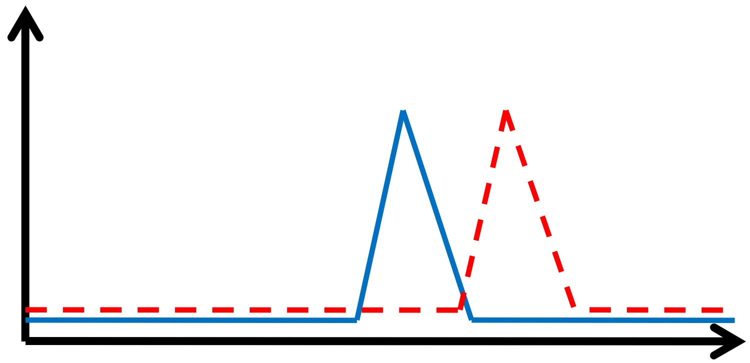
Under prediction might lead to shortage and loss of profits

Difference in impact!

Evaluation issues

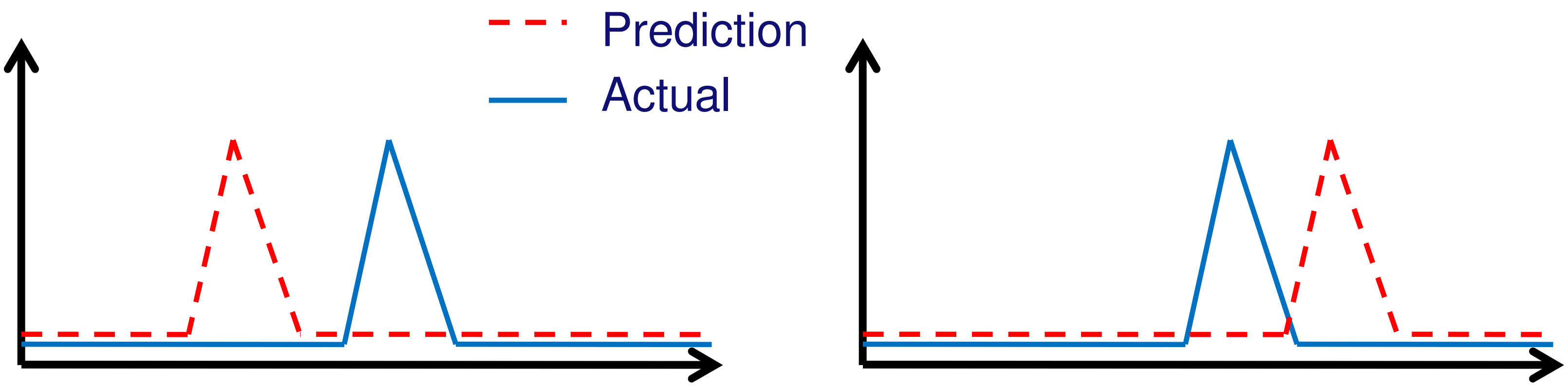


Early prediction might not be that bad



Late prediction might generate large costs

Evaluation issues



Early prediction might not be that bad

Late prediction might generate large costs

Difference in impact!

Error Measures

- **From: Hyndman and Koehler, 2006 [1]**

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

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

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

Error Measures

- **From: Hyndman and Koehler, *"Another look at measures of forecast accuracy"*, Int. Journal of forecasting 2006**

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

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

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

Not suitable

Error Measures

$$MASE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{e_t}{MAE(Baseline)}\right|$$

Baseline being the "naive predictor"

$$f_{WCScaled} = \frac{MSE(p(t'))}{MSE(f_{WC}(t'))}$$

Where *t'* is the set of points for which:

$$y_t \neq y_{t-1} \vee y_t - p_t \neq 0$$

Worst possible prediction strategy

Error measures

Mean Squared Error

	Product 1	Product 2
Ensemble	1.23	5.88
Moving Average 6	1.09	3.79

Mean Absolute Scaled Error (MA1)

	Product 1	Product 2
Ensemble	1.63	0.90
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Error measures

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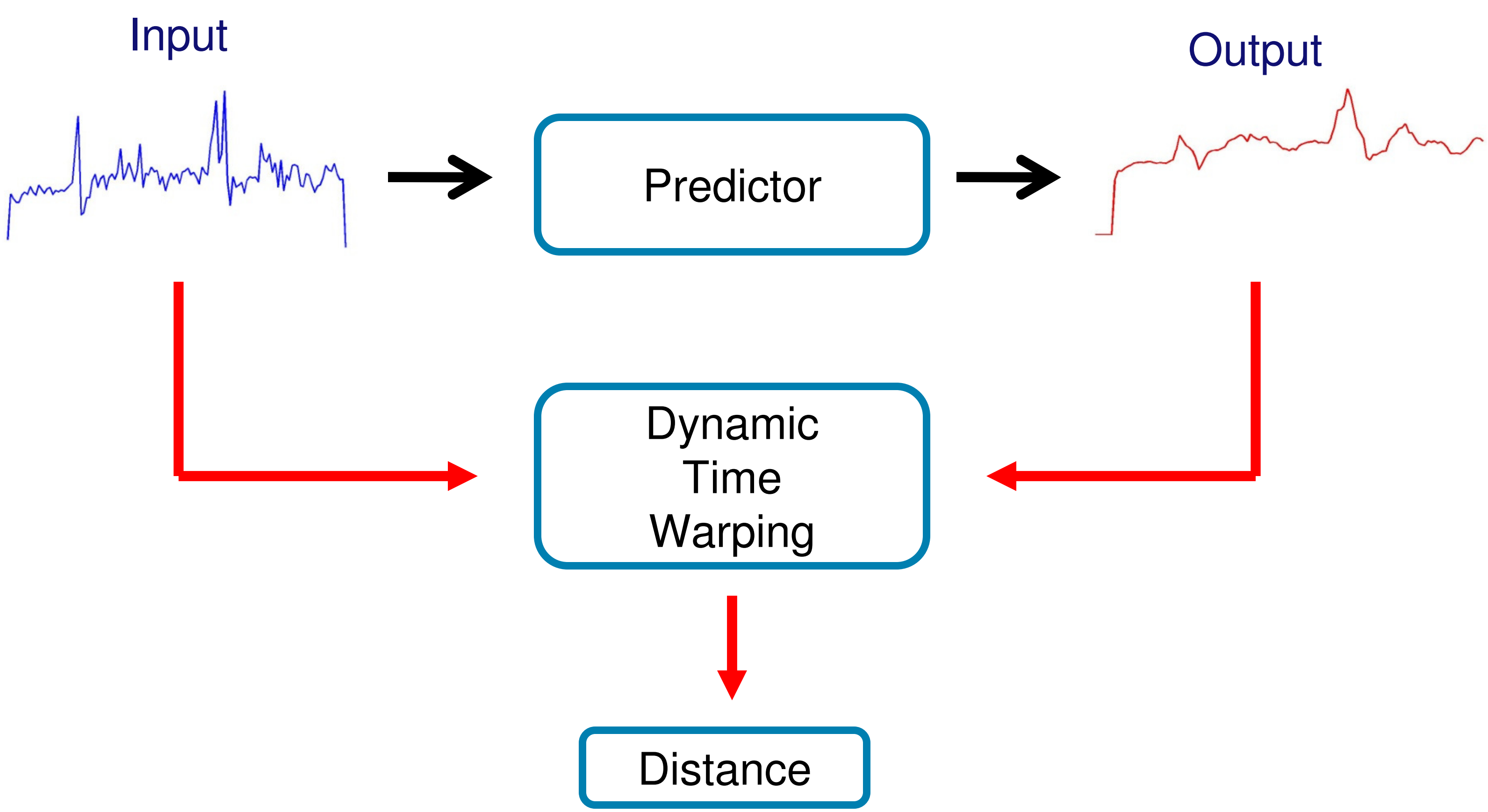
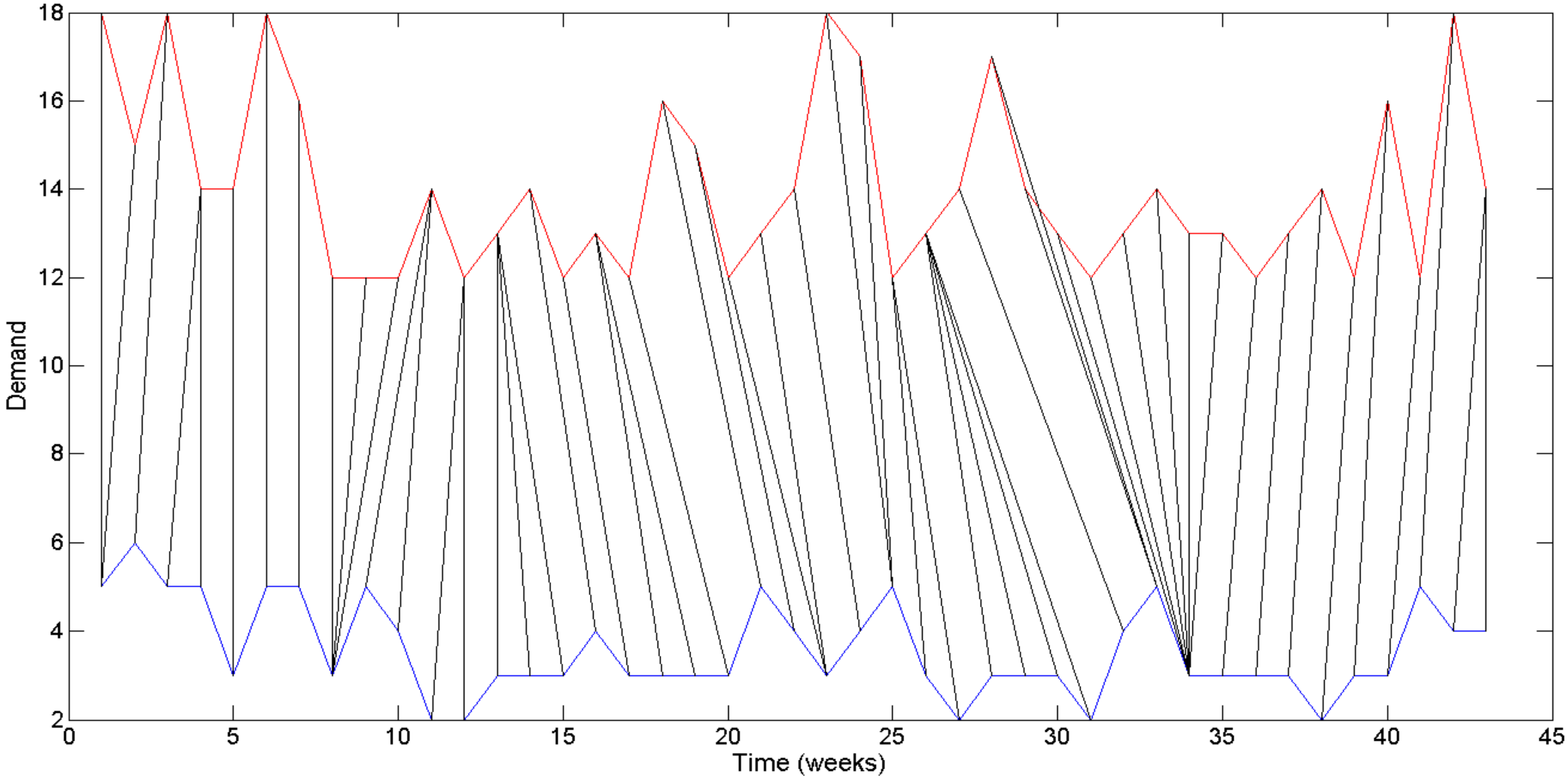
Alternative visualization



Alternative visualization



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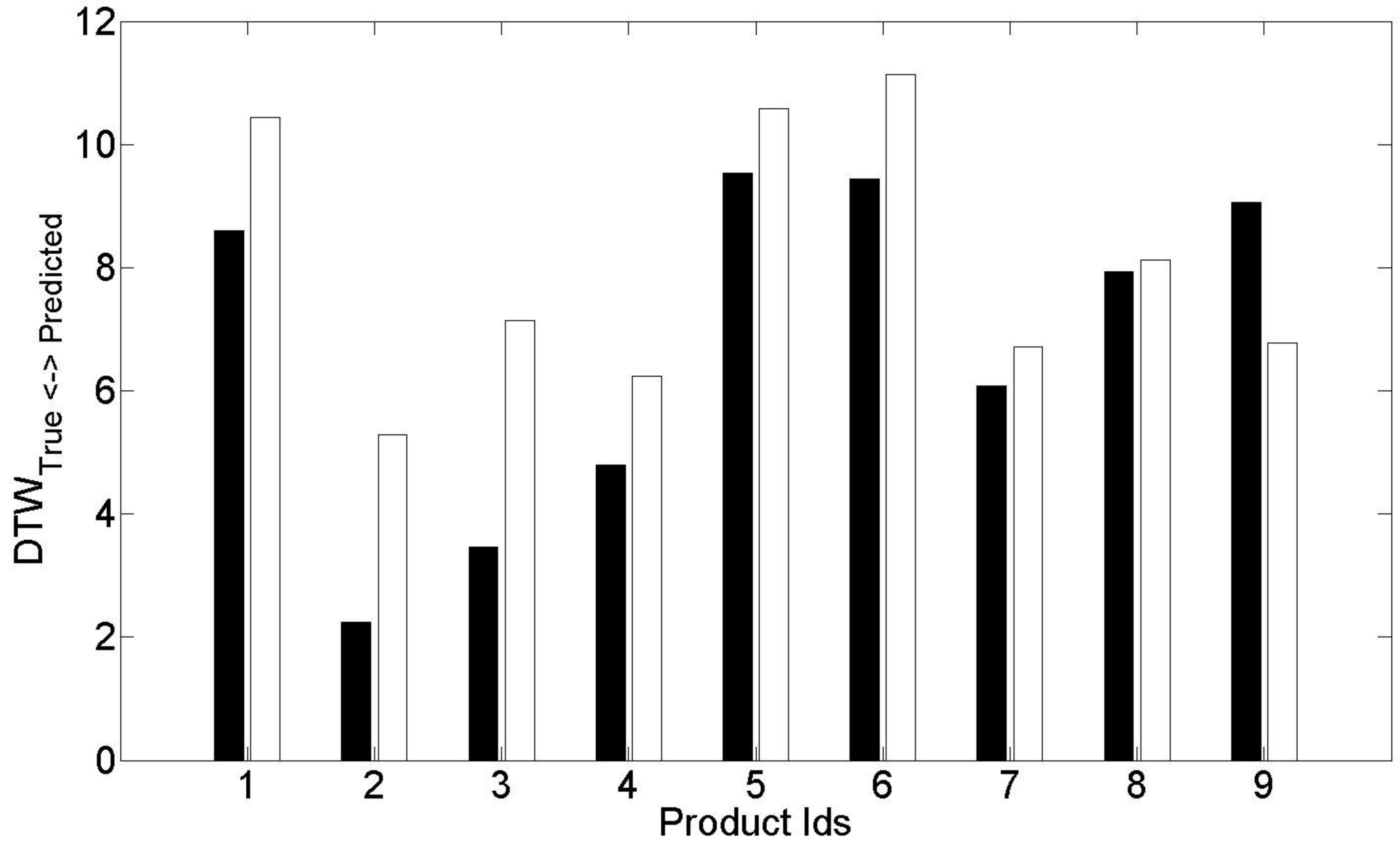

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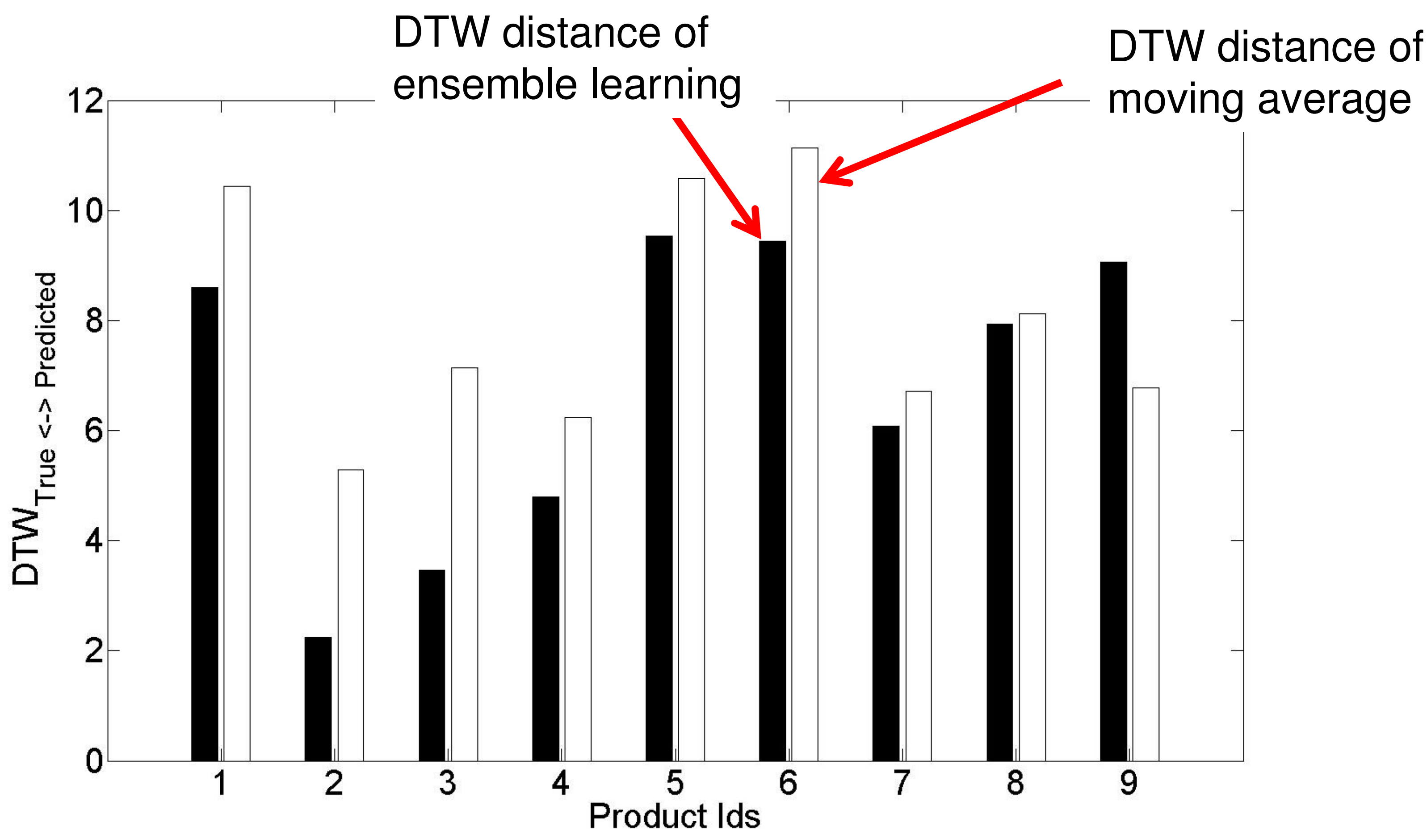

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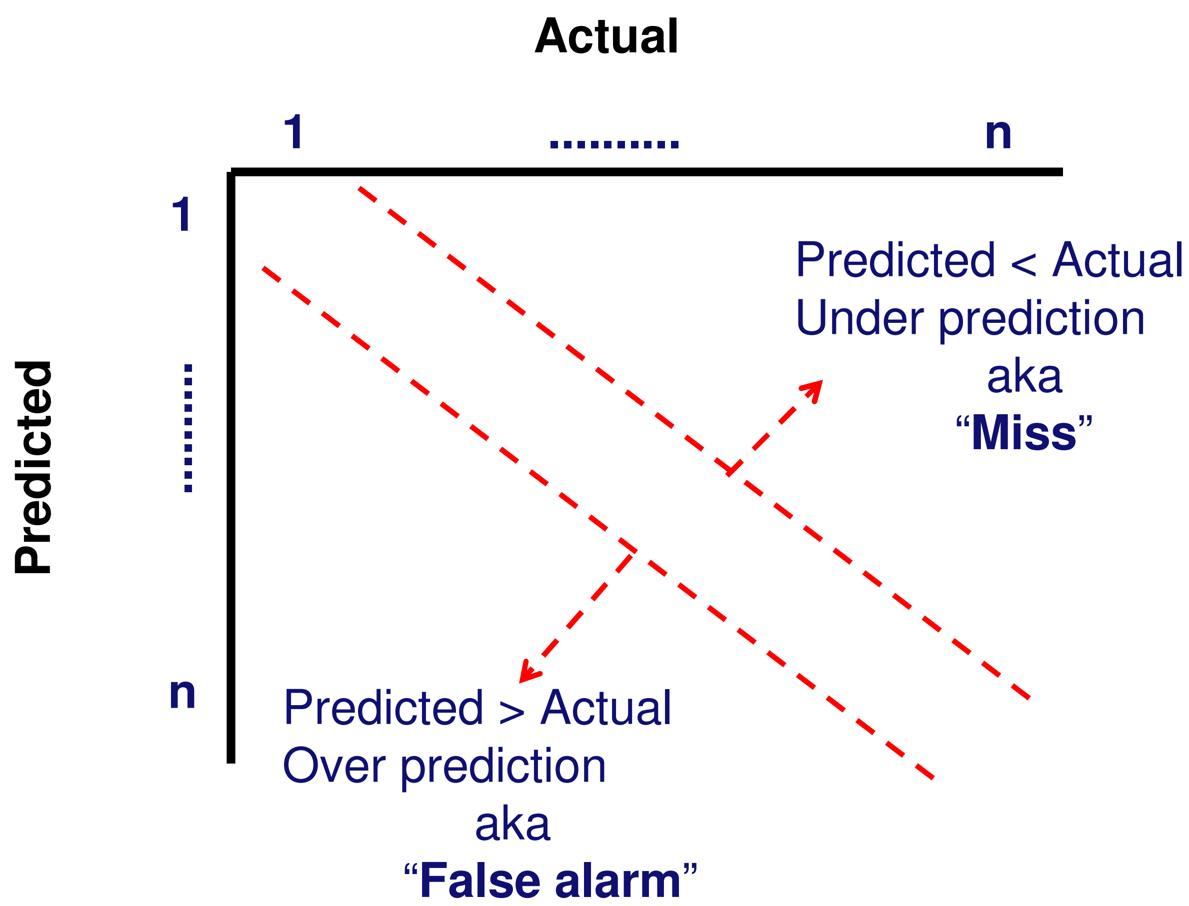

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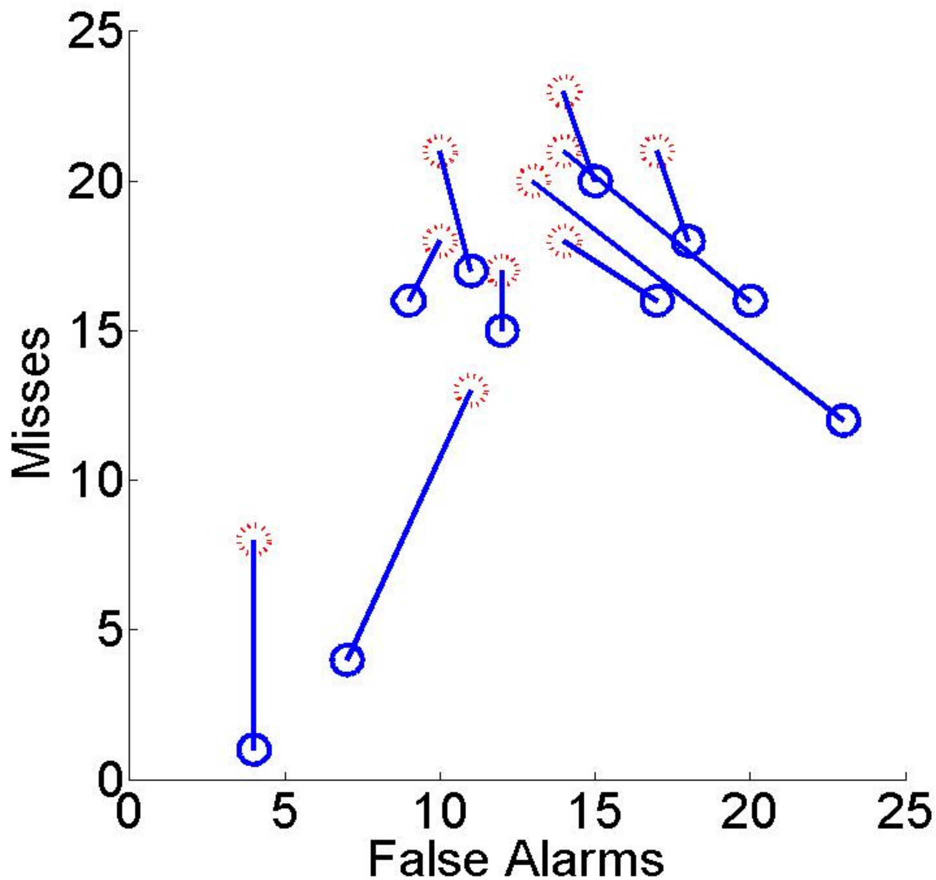

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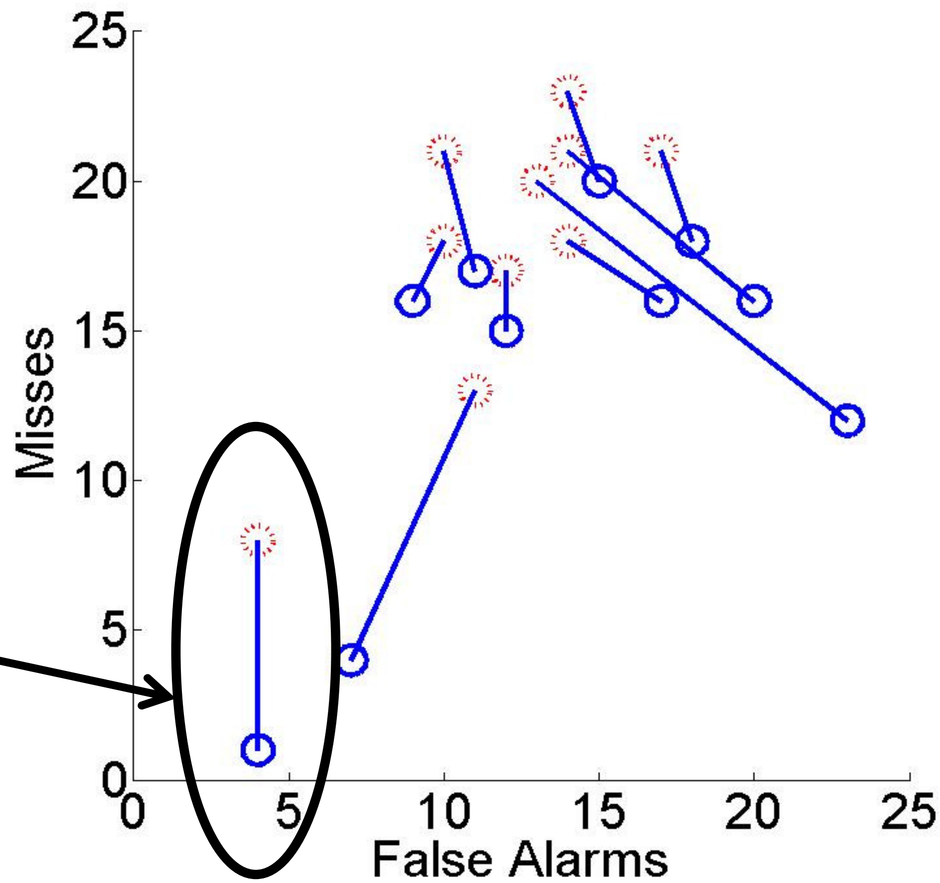
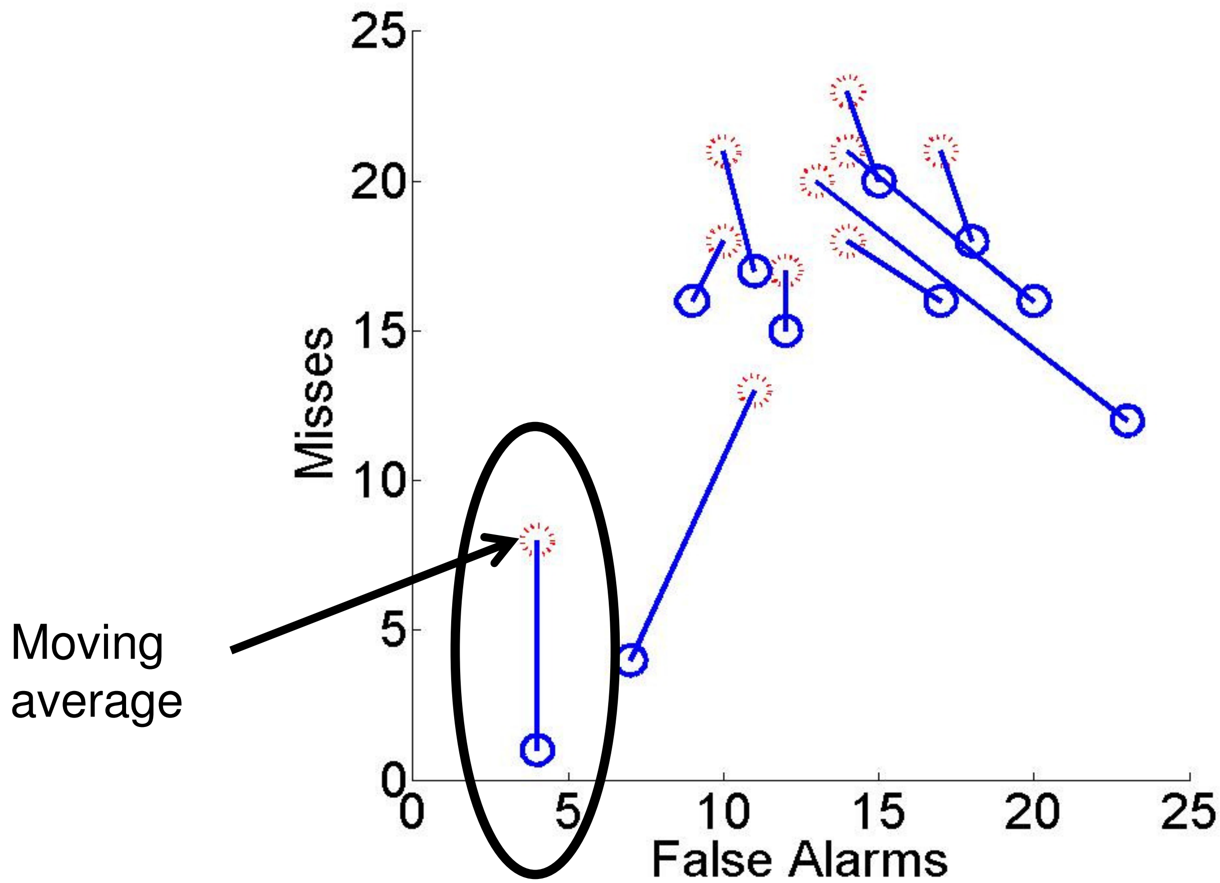
Alternative visualization

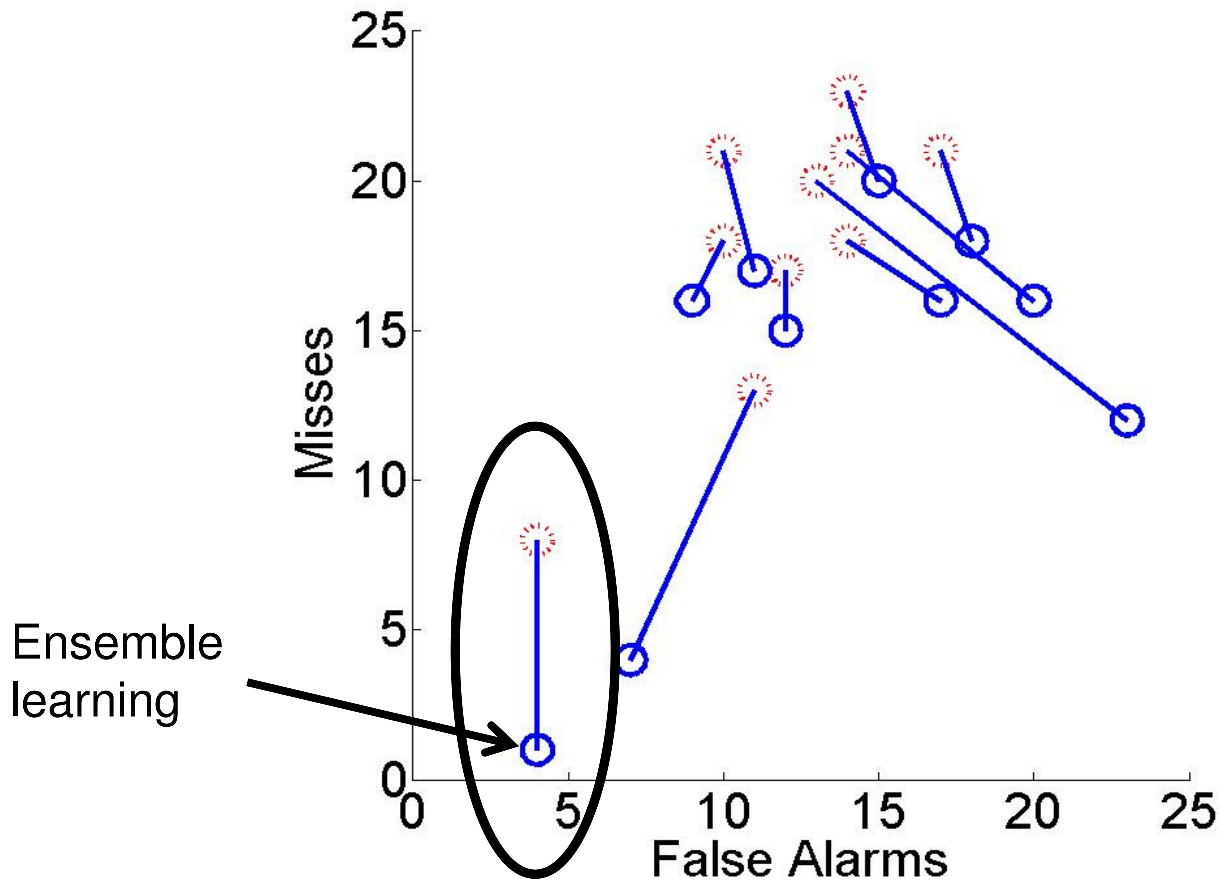


Experiment for one product

Alternative visualization



Alternative visualization



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Conclusion

	Quantitative	Qualitative	Memory
MASE	-	+	-
MSE WC scaled	+	-	-
DTW	-	+	-
Misses/False Alarms	-	+	-

Conclusion

	Quantitative	Qualitative	Memory
MASE	-	+	-
MSE WC scaled	+	-	-
DTW	-	+	-
Misses/False Alarms	-	+	-
Cost Sensitive	+		+

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The end