Improving forecasting with sub-seasonal time series patterns

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XIXI LI
Joint work with Fotios Petropoulos and Yanfei Kang
xixi.li@manchester.ac.uk
https://xixili-2.wixsite.com/personal
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Outline

- Big time series $\rightarrow$ difficulty in identifying reliable models
- Model selection: information criteria or cross-validation
  - based on past performance on a hold-out set of observations
  - however, data generation processes and time varying patterns
- Model combination
  - all models are wrong and selecting just one of these maybe not enough (Box et al.,1987)
  - there is never a best method that fits in all situations. (Wolpert, 1996)
  - reduce the variance of the forecasts.(Bates and Granger, 1969; Hibon and Evgeniou, 2005)

Three uncertainties of forecasting (Petropoulos et al., 2018)

- Model uncertainty
  - ETS: error, trend and seasonality components
  - ARIMA: AR, MA and seasonality term
- Parameter uncertainty: smoothing parameters of ETS
- Data uncertainty: the variation of the inherent random component of the series

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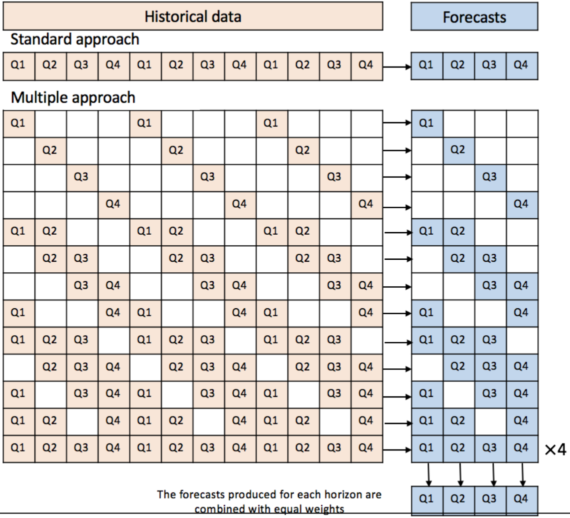
- Fiorucci et al. (2016) change the local curvatures of the seasonally-adjusted data →Theta: a first place in the M3-competition.
- Athanasopoulos et al. (2017): multiple temporal aggregation level of targeted series.
- Bergmeir et al. (2016) and Petropoulos et al. (2018): new time series generation with bootstrapping.

	Original series	Processed series
Multiple models	Model combination	Model combination
Single model	Model selection	Model selection/combination

What we do?

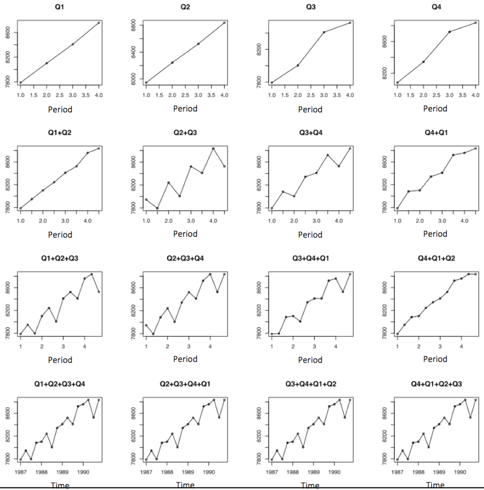
- Seasonal patterns: the data is influenced by seasonal factors (Hyndman, 2011).
- Seasonal methods: Seasonal Naive method, Holt-Winters' Exponential Smoothing, Damped Trend Seasonal Method, SARIMA
- One season of the historical data can be used to forecast the corresponding season.
- Our conjecture: several adjacent seasons also could be predicted by the respective past observations.
- What we do?
  - Construct sub-seasonal series $\rightarrow$ leveraging sub-seasonal patterns of the original time series.
  - Extrapolate these sub-seasonal series with ETS and ARIMA.
  - Forecasts combination $\rightarrow$ tackling model and parameters uncertainty.

A graph example visualizing the methodology



Constructing multiple time series with sub-seasonal patterns

Taking Q520 from M3 competition as an example.

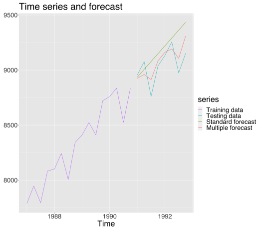


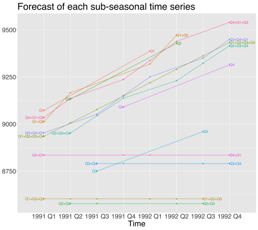
Making extrapolation forecasts for each sub-seasonal series

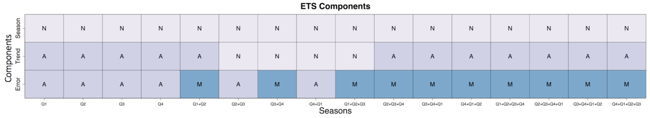
- ETS → capture the level, trend and seasonality automatically.
- Automatic and optimal model and parameter selection → local optimal predictions.
- Model-free: our framework can be plugged into any existing model.

Forecasting method	Description	**R** implementation
ETS	The exponential smoothing state space model (Hyndman et al., 2002).	`forecast::ets()`
ARIMA	The autoregressive integrated moving average model automatically estimated in the **R** package **forecast**(Hyndman and Khandakar, 2008).	`forecast::auto.arima()`

- ETS components of each sub-seasonal series.
- Capture different existing patterns and components effectively.







Datasets

75 thousand real time series from M1, M3 and M4 datasets

Frequency	Source	Number of series	h
Quarterly	M1-Competition	203	8
	M3-Competition	756	8
	M4-Competition	24000	8
Total		24959	
Monthly	M1-Competition	617	18
	M3-Competition	1428	18
	M4-Competition	48000	18
Total		50045	

Standard versus multiple forecasts

Mean result

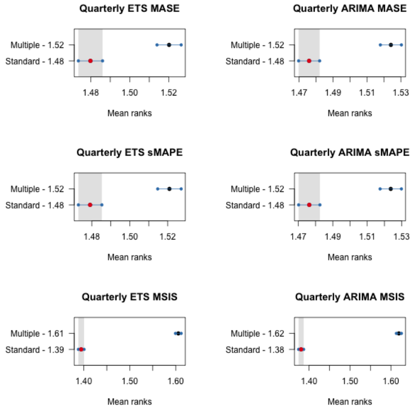
		Quarterly					Monthly				
		MASE									
		h=1	1-3	4-6	7-8	1-8	h=1	1-6	7-12	13-18	1-18
ETS	Standard	0.599	0.774	1.261	1.607	1.165	0.454	0.651	0.965	1.225	0.947
	Multiple	0.644	0.797	**1.252**	**1.567**	**1.160**	**0.451**	**0.633**	**0.936**	**1.173**	**0.914**
ARIMA	Standard	0.596	0.779	1.273	1.605	1.171	0.441	0.627	0.953	1.213	0.931
	Multiple	0.641	0.807	1.274	**1.584**	1.177	0.442	0.628	**0.932**	**1.172**	**0.911**
		sMAPE									
		h=1	1-3	4-6	7-8	1-8	h=1	1-6	7-12	13-18	1-18
ETS	Standard	5.985	7.469	11.070	13.515	10.331	6.872	10.001	13.650	17.031	13.560
	Multiple	6.265	7.558	**10.859**	**13.058**	**10.171**	**6.812**	**9.550**	**13.098**	**15.996**	**12.881**
ARIMA	Standard	5.987	7.602	11.250	13.578	10.464	6.790	9.703	13.627	17.364	13.565
	Multiple	6.326	7.768	**11.170**	**13.315**	**10.431**	**6.763**	**9.506**	**13.129**	**16.161**	**12.932**
		MSIS									
		h=1	1-3	4-6	7-8	1-8	h=1	1-6	7-12	13-18	1-18
ETS	Standard	4.729	6.154	10.354	13.585	9.587	3.698	5.137	8.493	11.143	8.258
	Multiple	5.046	6.253	**10.004**	**12.908**	**9.323**	**3.645**	**5.023**	**8.109**	**10.409**	**7.847**
ARIMA	Standard	5.543	7.221	12.230	15.787	11.241	4.045	5.470	9.132	11.640	8.747
	Multiple	**5.480**	**7.159**	**11.848**	**15.176**	**10.921**	**3.936**	**5.458**	**8.909**	**11.119**	**8.495**

Median result

		Quarterly					Monthly				
		MASE									
		h=1	1-3	4-6	7-8	1-8	h=1	1-6	7-12	13-18	1-18
ETS	Standard	0.360	0.572	0.912	1.129	0.887	0.245	0.501	0.709	0.877	0.736
	Multiple	0.421	0.598	**0.911**	**1.106**	0.892	0.250	**0.491**	**0.687**	**0.847**	**0.715**
ARIMA	Standard	0.363	0.578	0.920	1.126	0.895	0.235	0.481	0.699	0.877	0.728
	Multiple	0.421	0.609	0.927	**1.114**	0.907	0.244	0.485	**0.683**	**0.846**	**0.711**
		sMAPE									
		h=1	1-3	4-6	7-8	1-8	h=1	1-6	7-12	13-18	1-18
ETS	Standard	2.177	3.516	5.614	6.866	5.627	1.945	4.337	6.777	8.467	7.131
	Multiple	2.525	3.715	5.634	**6.731**	5.670	2.063	4.522	**6.717**	**8.311**	**7.109**
ARIMA	Standard	2.186	3.572	5.690	6.848	5.646	1.877	4.230	6.827	8.471	7.177
	Multiple	2.523	3.748	5.762	**6.798**	5.722	2.055	4.478	**6.694**	**8.260**	**7.096**
		MSIS									
		h=1	1-3	4-6	7-8	1-8	h=1	1-6	7-12	13-18	1-18
ETS	Standard	3.044	3.975	6.180	7.644	5.955	1.953	3.234	4.914	6.313	5.027
	Multiple	3.556	4.209	6.188	**7.446**	5.960	2.288	3.334	**4.625**	**6.112**	**4.821**
ARIMA	Standard	2.701	3.664	5.452	6.596	5.311	1.933	3.220	4.592	5.842	4.727
	Multiple	3.131	3.848	5.552	**6.528**	5.361	2.238	3.348	**4.501**	5.902	**4.720**

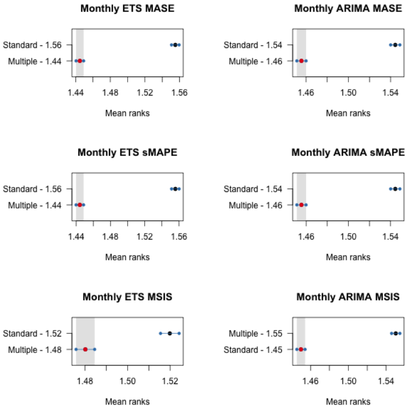
MCB significance tests for Quarterly datasets

- MCB: Multiple Comparisons from the Best
- Comparisons of averaging ranking
- Not significantly better: Quarterly datasets



MCB tests for Monthly datasets

- MCB: Multiple Comparisons from the Best
- Comparisons of averaging ranking
- Significantly better: Monthly datasets



DM significance tests

- DM: Diebold-Mariano
- Comparisons of forecasts
- The entries: percentage of times the multiple forecasts are significantly better or worse than the standard forecasts.
- The test result is consistent with MCB test.

			Quarterly					Monthly				
			h=1	1-3	4-6	7-8	1-8	h=1	1-6	7-12	13-18	1-18
ETS	Multiple	better	15.313	11.007	6.754	7.913	8.639	33.276	20.786	17.605	10.599	16.330
	Multiple	worse	18.611	14.924	11.663	11.373	12.814	24.464	14.392	11.923	8.285	11.533
ARIMA	Multiple	better	13.566	10.141	6.794	7.490	8.223	30.884	17.984	13.942	9.964	13.964
	Multiple	worse	17.749	14.122	11.007	11.034	12.182	24.886	14.030	11.618	9.037	11.561

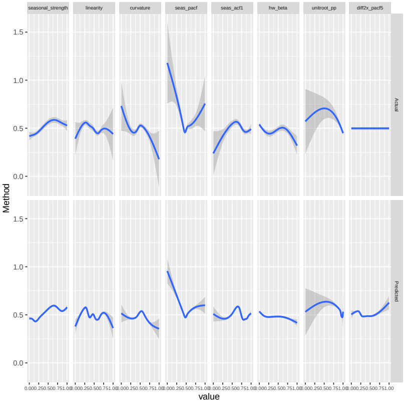
What kind of time series is our method more suitable for?

- X: 42 features (Montero-Manso et al., 2020).
- Y: method label: 0 is Standard and 1 is Multiple.

		MASE		
		decision tree	random forest	logistic regression
Quarterly	ETS	56.29%	**62.06%**	54.33%
	ARIMA	55.89%	**61.66%**	56.49%
Monthly	ETS	57.59%	**64.13%**	56.79%
	ARIMA	58.51%	**65.85%**	57.51%
		sMAPE		
		decision tree	random forest	logistic regression
Quarterly	ETS	56.41%	**64.06%**	57.61%
	ARIMA	58.09%	**63.86%**	58.41%
Monthly	ETS	56.83%	**63.95%**	57.67%
	ARIMA	56.95%	**64.17%**	56.79%
		MSIS		
		decision tree	random forest	logistic regression
Quarterly	ETS	62.02%	**69.39%**	63.46%
	ARIMA	60.66%	**68.47%**	63.06%
Monthly	ETS	65.53%	**73.96%**	67.53%
	ARIMA	61.89%	**70.02%**	63.69%

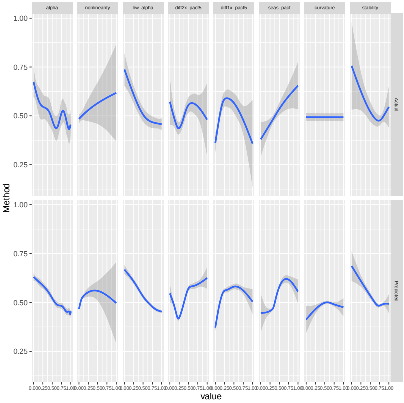
What kind of time series is our method more suitable for?

- 8 important features selected based on Mean Decrease in Gini.
- Predicted responses vs actual responses for each features in point prediction over Monthly dataset.



What kind of time series is our method more suitable for?

- 8 important features selected based on Mean Decrease in Gini.
- Predicted responses vs actual responses for each features in point prediction over Quarterly dataset.



Why our method works?

- Manipulating the data $\rightarrow$ sub-seasonal series $\rightarrow$ amplifying the sub-seasonal patterns of the original series.
- Model combination$\rightarrow$ mitigating the importance of single model selection when forecasting each sub-series.

Conclusion

- We zoom in on sub-seasonal patterns of the original series that are simpler to model.
- Mitigating the importance of model selection by combining forecasts across many sub-seasonal series.
- Simple, transparent, and model-free. Our proposed framework can be plugged into any existing model.

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Thanks!

xixi.li@manchester.ac.uk
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