Multi-seasonal time series decomposition

Time series decomposition

Multi-seasonal decomposition methods

Decomposition methods

These directly try to break the time series into a trend, multiple seasonalities, and a remainder.

- MSTL (Multiple seasonal-trend decomposition using Loess) [1]
- STR (Seasonal-trend decomposition using Regression) [2]
  - Useful if external regressors impact the time series (e.g., spikes during promotions) or change the seasonality (e.g., public holidays act like weekends).

Forecasting models for decomposition

These extract multiple seasonal components as part of fitting a forecasting model.

- Prophet [3]
- TBATS [4]

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MSTL: What is it?

- **M**utliple **S**easonal-**T**rend decomposition using **L**oess (MSTL).

MSTL: A Seasonal-Trend Decomposition Algorithm for Time Series with Multiple Seasonal Patterns

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Abstract

The decomposition of time series into components is an important task that helps to understand time series and can enable better forecasting. Nowadays, with high sampling rates leading to high-frequency data (such as daily, hourly, or minutely data), many real-world

[1] Bandara, K., Hyndman, R.J. and Bergmeir, C., 2021. MSTL: A Seasonal-Trend Decomposition Algorithm for Time Series with Multiple Seasonal Patterns. *arXiv preprint arXiv:2107.13462.*

MSTL: What is it?

- **M**utliple **S**easonal-**T**rend decomposition using **L**oess (MSTL).
- A method to decompose a time series into a trend component, multiple seasonal components, and a residual component by repeatedly applying STL.

$$y_t = \underbrace{\hat{T}_t}_{\text{Trend component}} + \underbrace{\hat{S}_t^{(1)} + \hat{S}_t^{(2)} + \cdots + \hat{S}_t^{(N)}}_{\text{Seasonal components}} + \underbrace{\hat{R}_t}_{\text{Residual component}}$$

- MSTL, like STL, assumes the time series can be broken into an additive decomposition.
- Transform the time series (e.g., using Box Cox) if it is not additive.

MSTL: Why use it?

- The authors in [1] benchmarked MSTL to other methods: Prophet [2], TBATS[3], STR [4].
- Accurate, MSTL typically produced the lowest RMSE on a range of benchmark time series.

Table 4: The RMSE over 100 bootstrapped versions of the hourly electricity demand time series. Bold values indicate results that are significantly different from the MSTL values.

Method	Trend RMSE	Daily RMSE	Weekly RMSE	Remainder RMSE
STR	**399.4**	**408.0**	**214.8**	**580.9**
TBATS	**742.1**	**348.9**	**383.1**	**614.1**
PROPHET	**243.7**	**371.1**	**403.9**	**605.4**
MSTL	207.6	149.2	180.5	312.7

Table from Bandara, K., Hyndman, R.J. and Bergmeir, C., 2021. MSTL: A Seasonal-Trend Decomposition Algorithm for Time Series with Multiple Seasonal Patterns. *arXiv preprint arXiv:2107.13462.*

MSTL: Why use it?

- The authors in [1] benchmarked MSTL to other methods: Prophet [2], TBATS[3], STR [4].
- Computationally efficient, MSTL had the lowest execution time of all the methods compared.

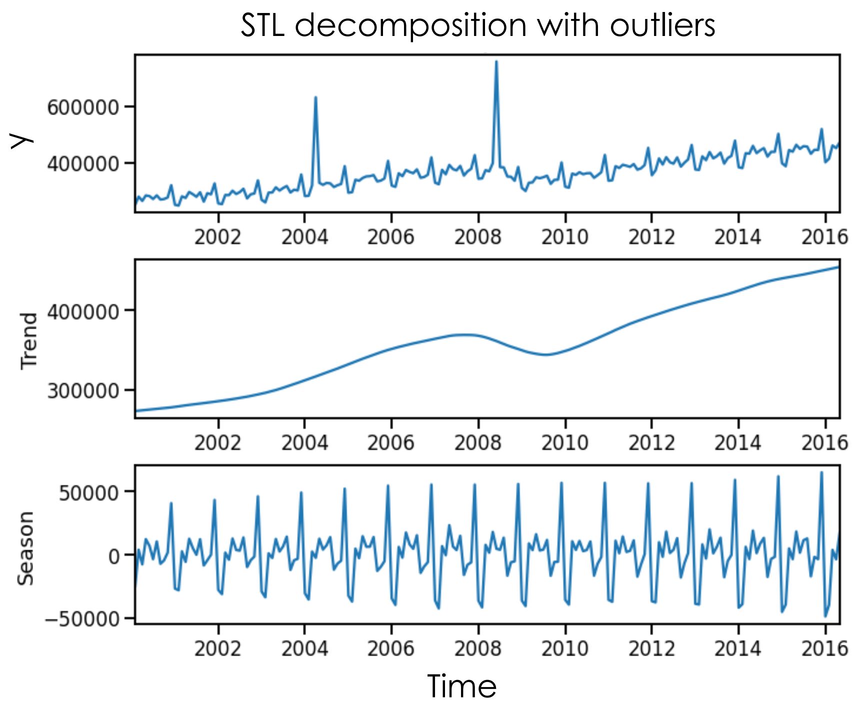
Table 5: The total computational cost of the decomposition methods for the electricity demand dataset, measured in seconds.

Method	Total time
STL	7
STR	612
PROPHET	936
TBATS	2521

Table from Bandara, K., Hyndman, R.J. and Bergmeir, C., 2021. MSTL: A Seasonal-Trend Decomposition Algorithm for Time Series with Multiple Seasonal Patterns. *arXiv preprint arXiv:2107.13462.*

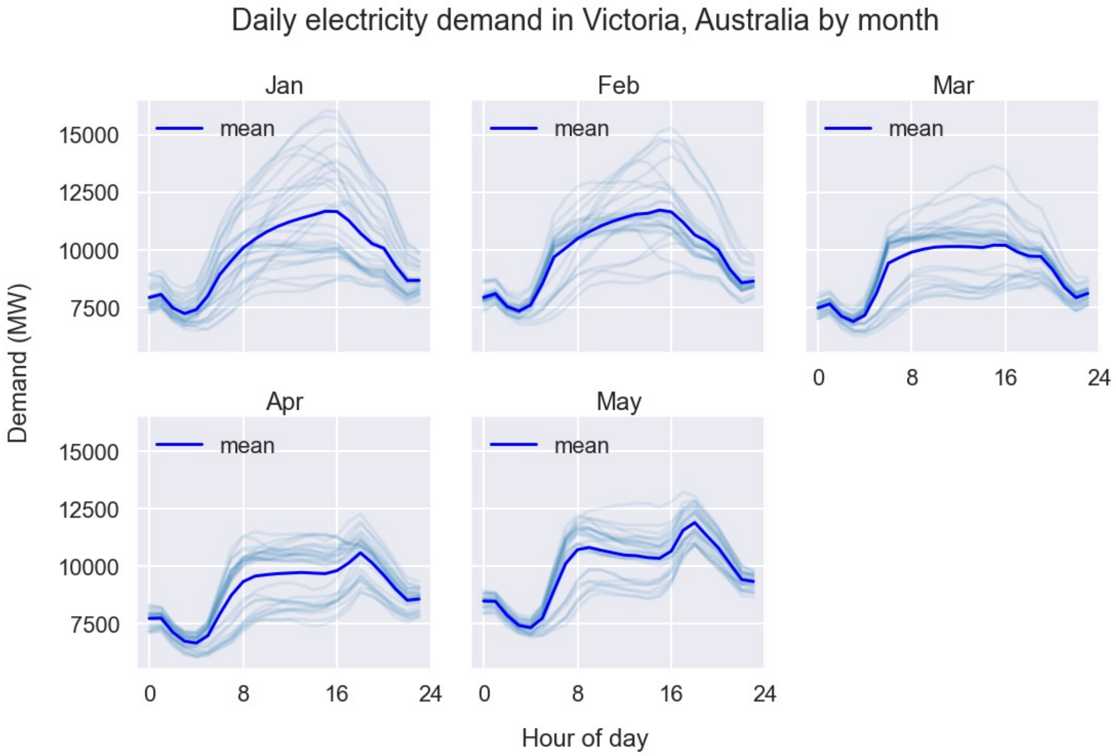
MSTL: Why use it?

- The authors in [1] benchmarked MSTL to other methods: Prophet [2], TBATS[3], STR [4].
- Robust to outliers, MSTL is able to use an outlier robust version of STL by passing a flag to the underlying STL fit.



MSTL: Why use it?

- MSTL can model seasonality which changes with time because STL can model seasonality which changes with time (e.g., the daily pattern of electricity demand will be different in the winter compared to the summer).



MSTL: Why use it?

- MSTL is simpler than using forecasting models (e.g., Prophet and TBATS).
- Forecasting models have more parameters to tune.
- Need to make a good forecasting model to get a good decomposition.
- Hence, forecasting models require the user to think about more factors (e.g., model complexity, outliers, changepoints).
- MSTL instead focuses entirely on decomposition.

```python
def __init__(
        self,
        growth='linear',
        changepoints=None,
        n_changepoints=25,
        changepoint_range=0.8,
        yearly_seasonality='auto',
        weekly_seasonality='auto',
        daily_seasonality='auto',
        holidays=None,
        seasonality_mode='additive',
        seasonality_prior_scale=10.0,
        holidays_prior_scale=10.0,
        changepoint_prior_scale=0.05,
        mcmc_samples=0,
        interval_width=0.80,
        uncertainty_samples=1000,
        stan_backend=None
):
```

Parameters for Prophet

References

[1] (MSTL) Bandara, K., Hyndman, R.J. and Bergmeir, C., 2021. MSTL: A Seasonal-Trend Decomposition Algorithm for Time Series with Multiple Seasonal Patterns. *arXiv preprint arXiv:2107.13462*.

[2] (STR) Dokumentov, A. and Hyndman, R.J., 2021. STR: Seasonal-Trend Decomposition Using Regression. INFORMS Journal on Data Science.

[3] (Prophet) Taylor, S.J. and Letham, B., 2018. Forecasting at scale. The American Statistician, 72(1), pp.37–45

[4] (TBATS) De Livera, A.M., Hyndman, R.J. and Snyder, R.D., 2011. Forecasting time series with complex seasonal patterns using exponential smoothing. Journal of the American statistical association, 106(496), pp.1513–1527.

Summary

- There are multiple methods to decompose multi-seasonal time series.
- Forecasting models can also be used to decompose a time series.
- MSTL is a performant method to extract multiple seasonal components.