# TSMix: time series data augmentation by mixing sources

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## Introduction

- Data augmentation is a common strategy for improving generalisation capability of ML models such as neural networks.
- Data augmentation **alters existing data to produce realistic perspectives on data that might be expected during inference**.
- Data augmentation is widespread for image data because it is relatively trivial to construct automatic augmentation strategies (e.g., horizontal flipping, colour augmentation, mixup [1], etc.).
- Data **augmentation for time series is challenging because an individual datum is not an independent quantity, but a variable dependent on past data**. Individual time series data points are not necessarily independent and identically distributed (i.i.d.).
- In this paper we **propose and evaluate the idea that an individual time series (univariate or multivariate) can be considered as an i.i.d. sample from a wider set of time series**. We evaluate this idea through TSMix, a simple **method to combine multiple univariate time series to increase training dataset size and thereby improve forecast model generalisation.**

## Use-case: FaaS

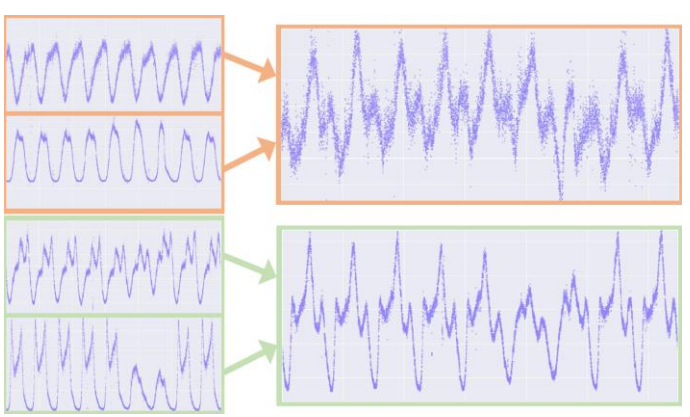
- **TSMix is motivated by and applied to serverless computing**, a cloud computing model where computational resources are transparently allocated by a cloud provider on-demand for the user.
- Function as a Service (FaaS) platforms such as Huawei FunctionGraph, Microsoft Azure Functions and Google Cloud Functions allow customers to run code in the form of single stateless event-driven functions. FaaS platforms execute thousands of concurrent function requests by different users.
- **These individual functions each result in multivariate time series**, allowing the collection of functions to be seen as a large set of independent time series.
- This work considers function requests, which are the incoming function request invocations per-minute as the common univariate time series. **FaaS requests of top functions tend to have daily periodicity and may tend to resolve into similar patterns.** Therefore, it is possible to produce qualitatively similar pseudo-function datasets by simply averaging two or more real time series from different functions.

## Algorithm

- N univariate time series (e.g. time series from different function calls in FaaS framework) are **combined by averaging their standardised versions (i.e., zero mean and unit standard deviation).**
- The final mixed version is **unnormalized by the average of incoming means and standard deviation** to ensure scale invariance with respect to the input series.

**Input:** $X$ = list of $N$ time series, length $L$
**Output:** $y$ = mixed time series, length $L$

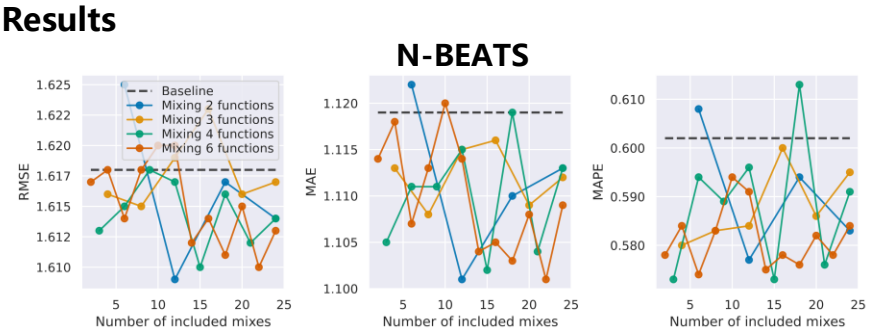
$Y :=$ vector of zeros, length $L$
$\mu := 0$
$\sigma := 0$
**for** $x_n$ *in* $X$ **do**
  $\mu_n = \text{mean}(x)$
  $\sigma_n = \text{std}(x)$
  $y+ = (x_n - \mu_n)/\sigma_n$
  $\mu+ = \mu_n$
  $\sigma+ = \sigma_n$
$\mu = \mu/N$
$\sigma = \sigma/N$
$y = (y/N) \times \sigma + \mu$

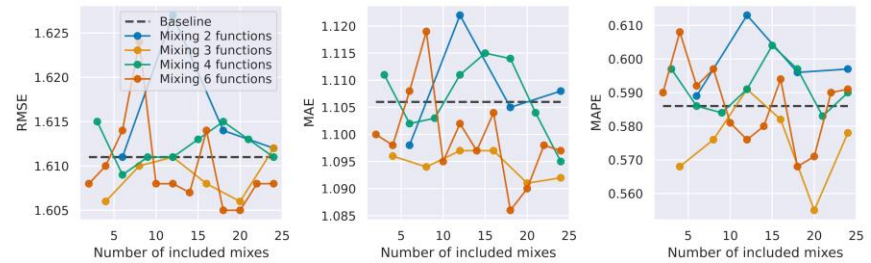


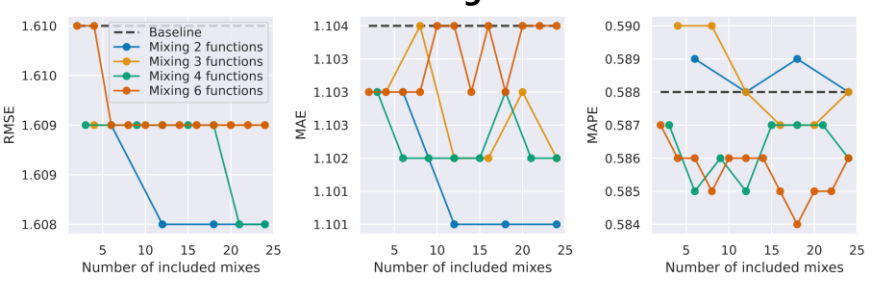
## Experimental setup

- Used top 12 functions from Azure 2019 (by median) [2]
- 14 days per function (9 for training and 5 for testing)
- Predictions over the 5 test days computed autoregressively
- Evaluate 3 models: N-HiTS [3], N-BEATS [4], linear regression
- The following 31 experiments were conducted for each model:
  - Training on original 12 functions only.
  - For N=2 we ran 4 experiments whereby we created 6, 12, 18, and 24 mixed pseudo functions. The original 12 functions were always included. We sampled mixes such that they were always unique. Increments of 6 are needed for N=2 in order to ensure equal sampling of the original 12 functions.
  - Other mixing combinations for N=3, 4, 6

## Results




## Future work

- Mixing different functions in this way can be expanded to include an informed version of TSMix using mutual information or cosine similarity as a metric to combine dissimilar functions.
- Decomposition into trend, seasonal, and residual components and applying TSMix to those and then recombining may also be a straightforward yet promising option.

## References

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3. Cristian Challu, Kin G Olivares, Boris N Oreshkin, Federico Garza, Max Mergenthaler, and Artur Dubrawski. 2022. N-hits: Neural hierarchical interpolation for time series forecasting. *arXiv preprint arXiv:2201.12886* (2022).
4. Boris N Oreshkin, Dmitri Carpov, Nicolas Chapados, and Yoshua Bengio. 2020. N-BEATS: Neural basis expansion analysis for interpretable time series forecasting. In *International Conference on Learning Representations*.