servicenow.

TACTIS

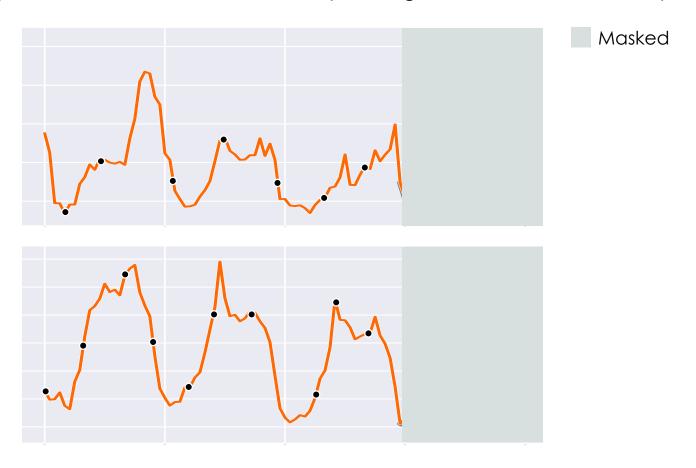
Transformer-Attentional Copula for Time Series



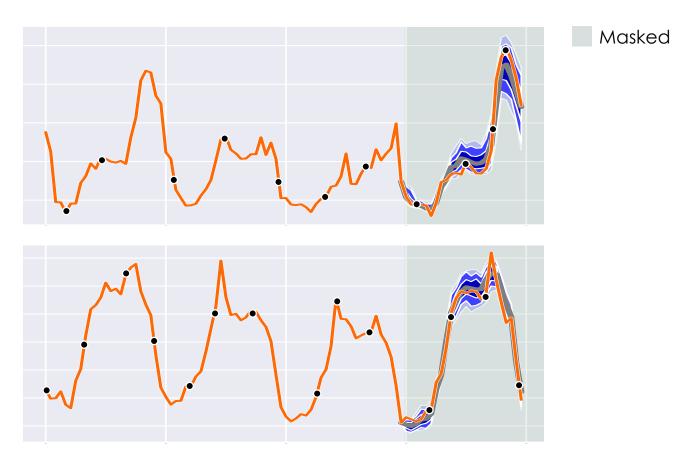




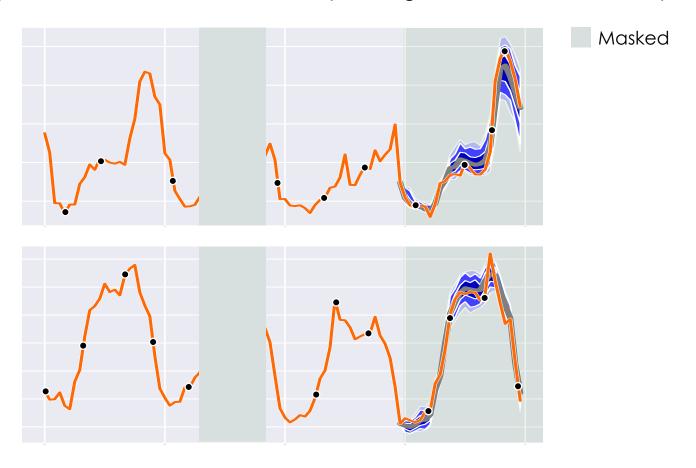
Goal: Infer the joint distribution of masked time points, given the observed time points



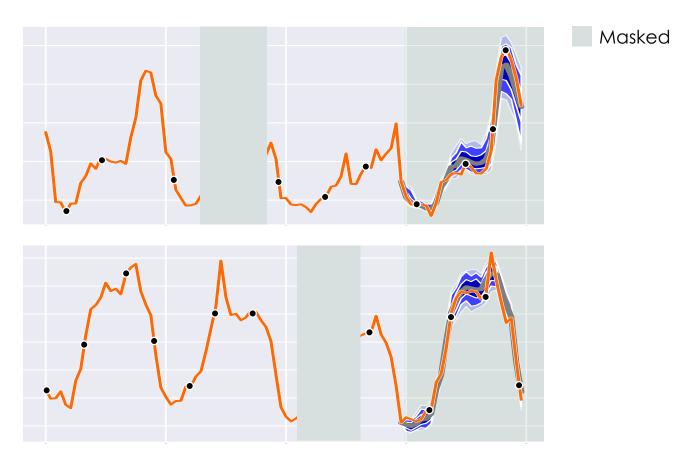
Goal: Infer the joint distribution of masked time points, given the observed time points



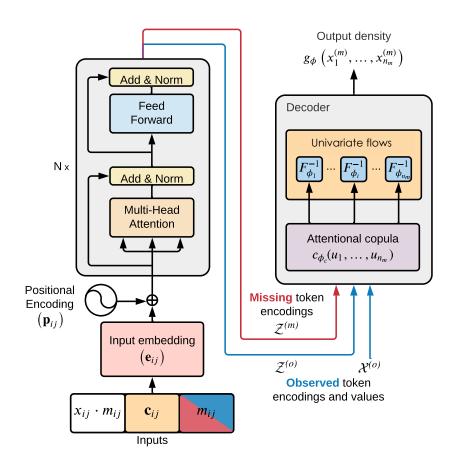
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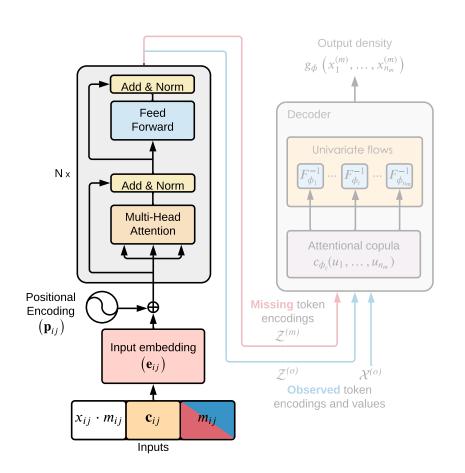
Goal: Infer the joint distribution of masked time points, given the observed time points



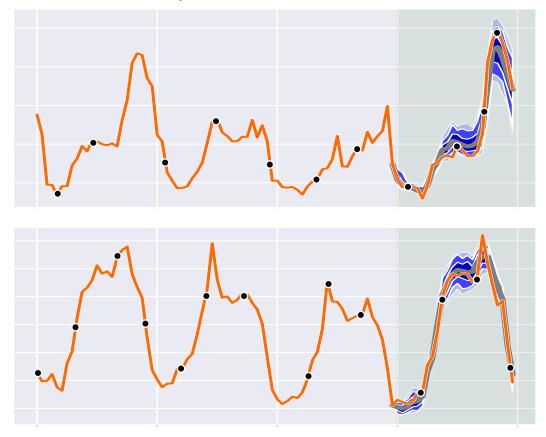
TACTIS is an encoder-decoder model, similar to standard transformers.



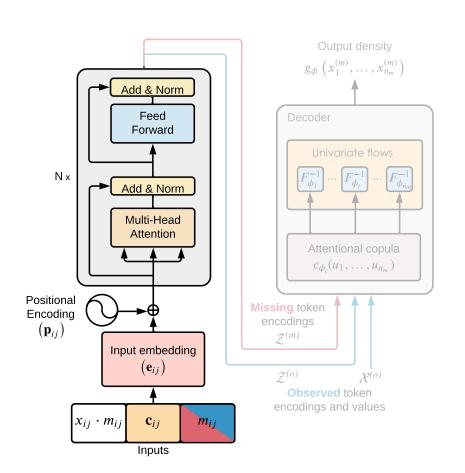
TACTIS is an encoder-decoder model, similar to standard transformers.



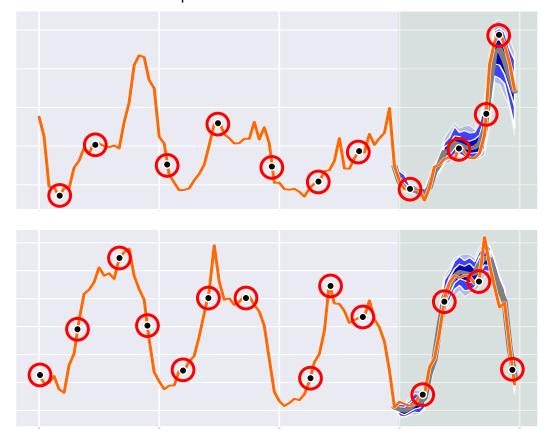
Encoder: each point in each time series is a token



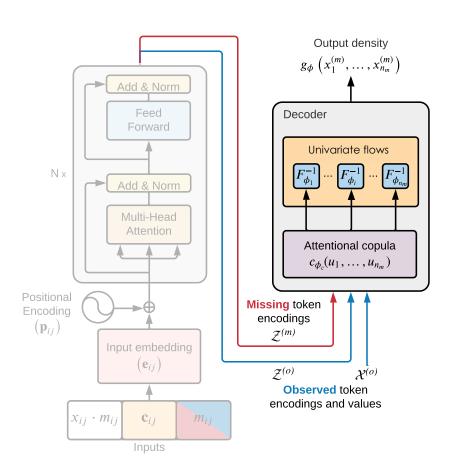
TACTIS is an encoder-decoder model, similar to standard transformers.



Encoder: each point in each time series is a token



TACTIS is an encoder-decoder model, similar to standard transformers.



Decoder: a copula-based autoregressive decoder

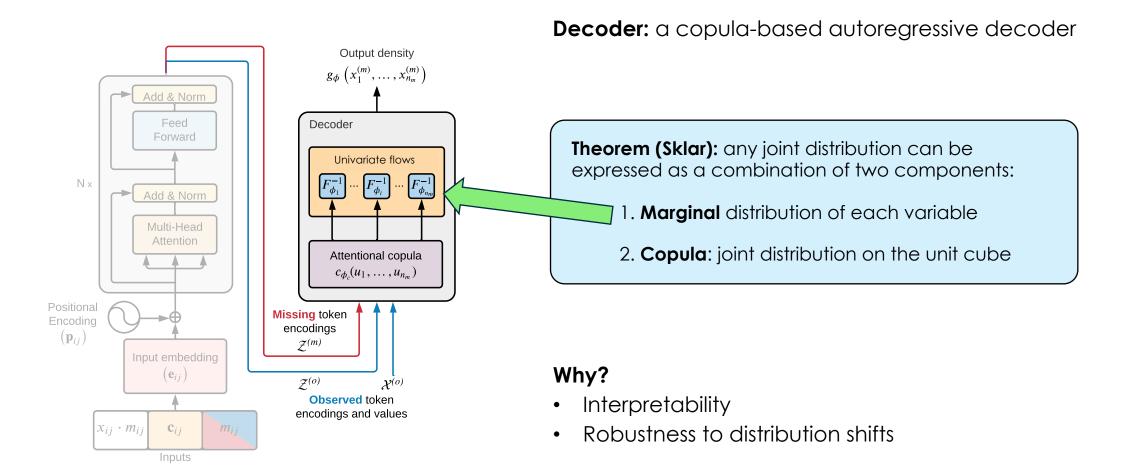
Theorem (Sklar): any joint distribution can be expressed as a combination of two components:

- 1. Marginal distribution of each variable
- 2. Copula: joint distribution on the unit cube

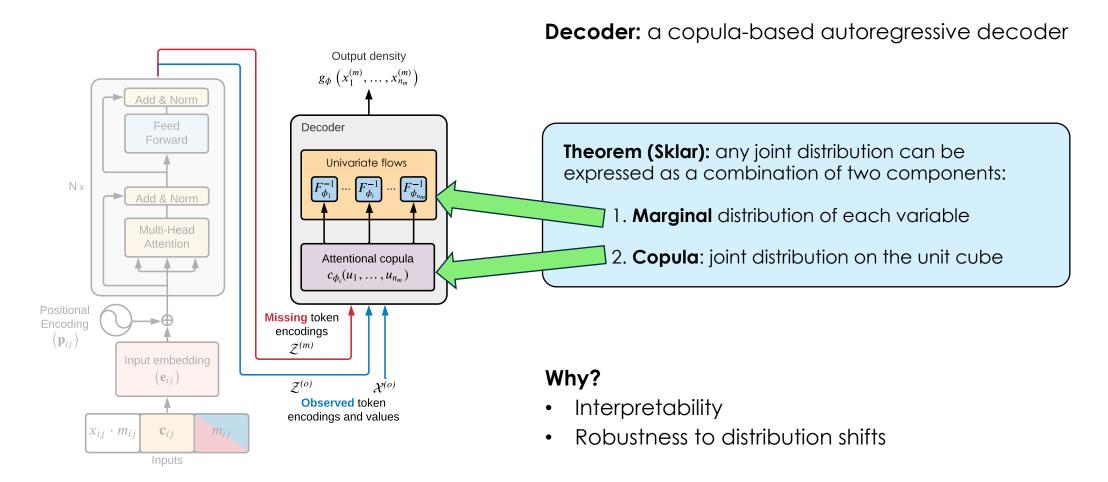
Why?

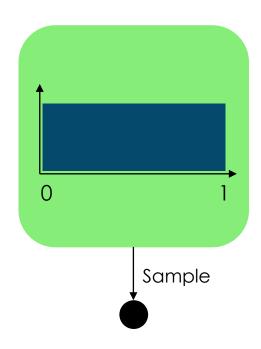
- Interpretability
- Robustness to distribution shifts

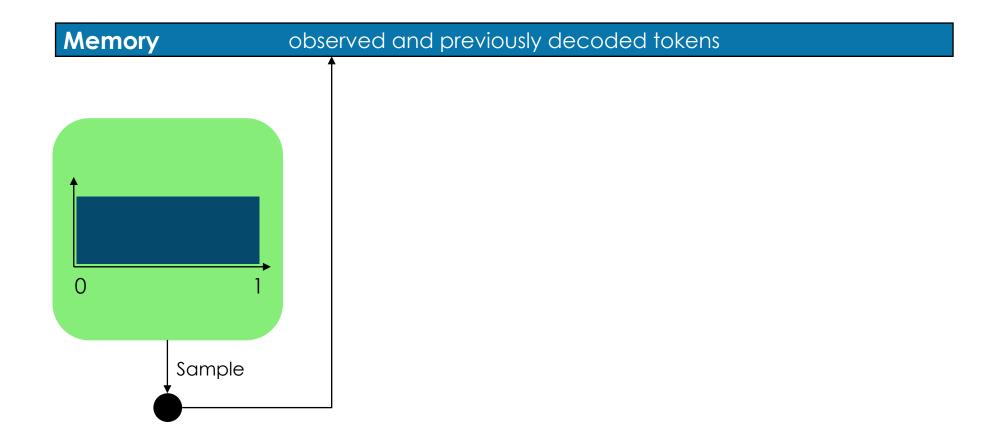
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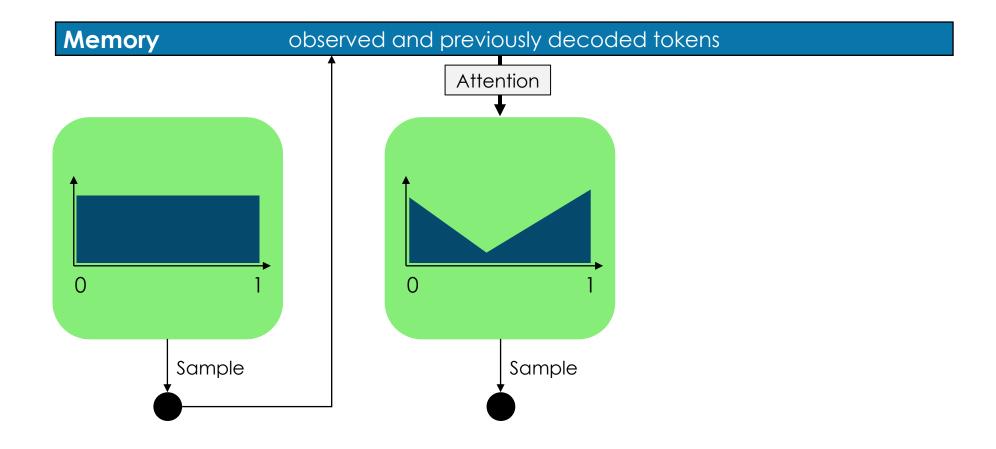


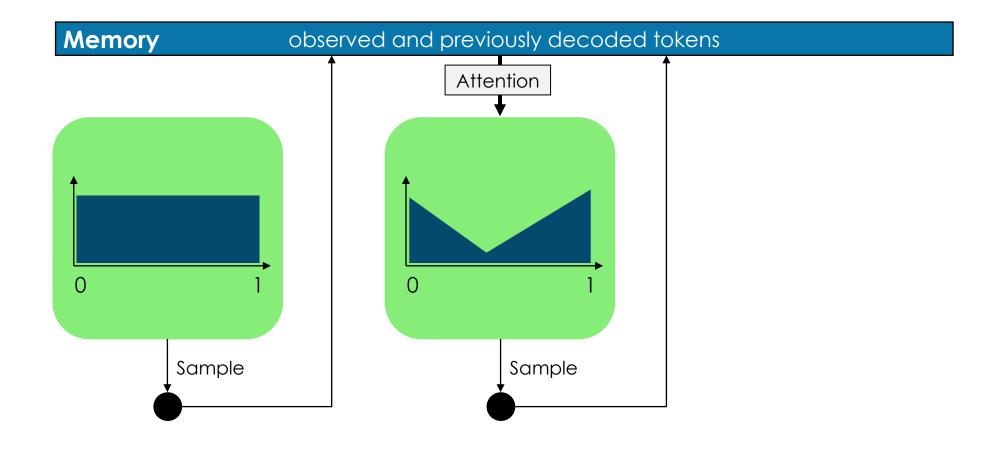
TACTIS is an encoder-decoder model, similar to standard transformers.

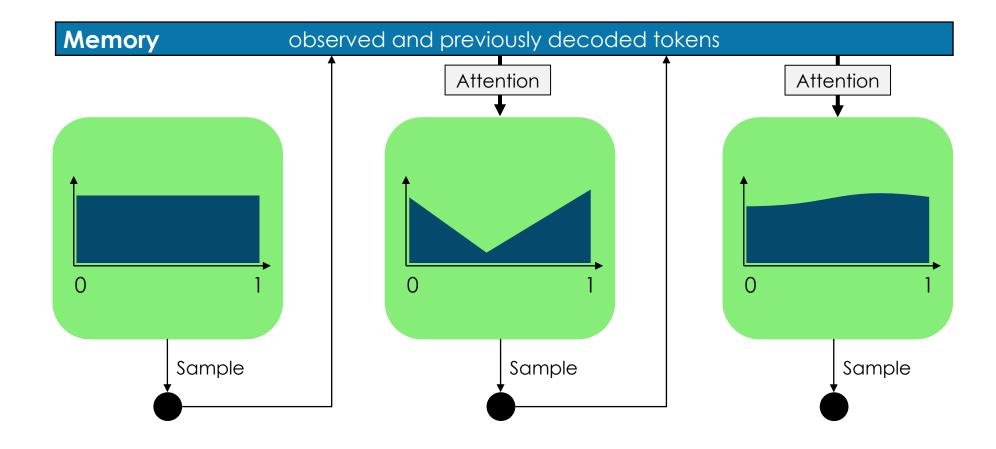


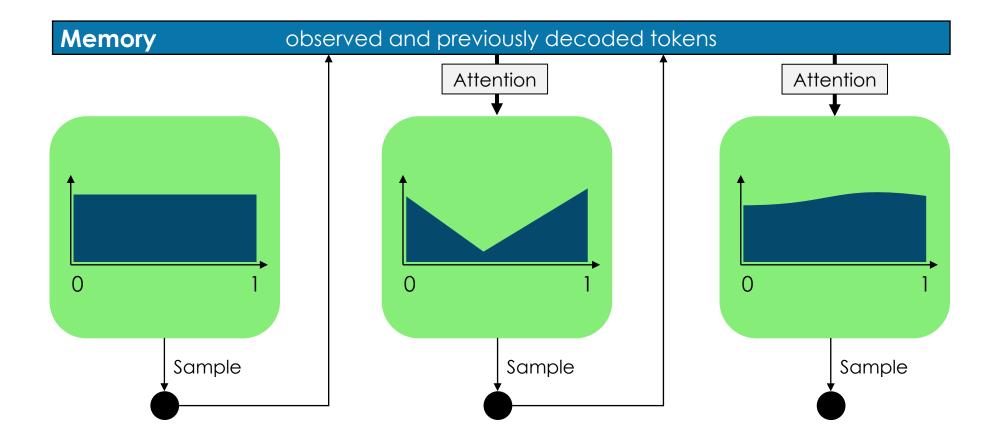












Theorem: decoding in a random order guarantees convergence to valid copulas

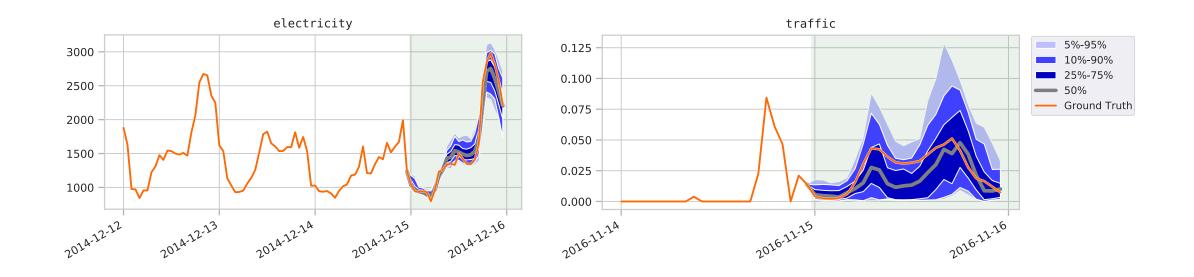
State-of-the-art forecasting performance

CRPS-Sum means (± standard errors). Lower is better. Best results in bold.

| Model | electricity | fred-md | kdd-cup | solar-10min | traffic | Avg. Rank |
|------------|-------------------|--------------------------------|--------------------------------|-------------------|-------------------|---------------------------------|
| Auto-ARIMA | 0.077 ± 0.016 | 0.043 ± 0.005 | 0.625 ± 0.066 | 0.994 ± 0.216 | 0.222 ± 0.005 | 4.7 ± 0.3 |
| ETS | 0.059 ± 0.011 | $\boldsymbol{0.037 \pm 0.010}$ | 0.408 ± 0.030 | 0.678 ± 0.097 | 0.353 ± 0.011 | 4.4 ± 0.3 |
| TempFlow | 0.075 ± 0.024 | 0.095 ± 0.004 | 0.250 ± 0.010 | 0.507 ± 0.034 | 0.242 ± 0.020 | 3.9 ± 0.2 |
| TimeGrad | 0.067 ± 0.028 | 0.094 ± 0.030 | 0.326 ± 0.024 | 0.540 ± 0.044 | 0.126 ± 0.019 | 3.6 ± 0.3 |
| GPVar | 0.035 ± 0.011 | 0.067 ± 0.008 | 0.290 ± 0.005 | 0.254 ± 0.028 | 0.145 ± 0.010 | 2.7 ± 0.2 |
| TACTiS-TT | 0.021 ± 0.005 | 0.042 ± 0.009 | $\boldsymbol{0.237 \pm 0.013}$ | 0.311 ± 0.061 | 0.071 ± 0.008 | $\textbf{1.6} \pm \textbf{0.2}$ |

TACTIS outperforms state-of-the-art models on real-world datasets with hundreds of time series

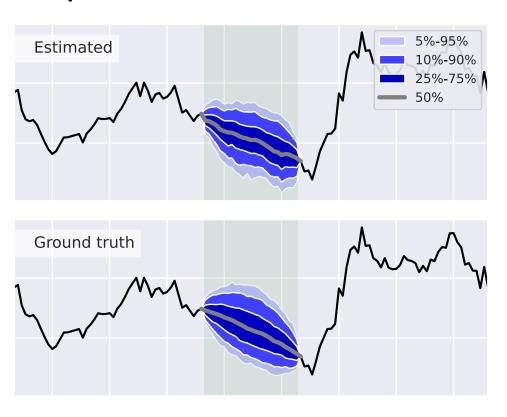
State-of-the-art forecasting performance



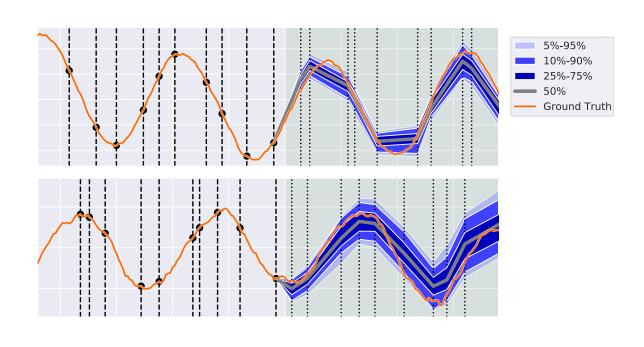
TACTIS outperforms state-of-the-art models on real-world datasets with hundreds of time series

TACTiS is very flexible

Interpolation



Unaligned and non-uniformly sampled data



Thank you!

Please come by our poster!

Code: https://github.com/ServiceNow/TACTiS







