예시 Beamer 타입의 LaTeX문서

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Beamer 작성 시 유의할 점

- Beamer는 프레젠테이션을 위한 LaTeX 클래스입니다.
- SNU Beamer 테마를 사용한 템플릿입니다.
- 도큐먼트와 다르게, 해당 파일도 같이 있어야 합니다.
  - beamerthemesnubeam.sty
  - snucode.sty
  - ref.bib
- 각 파일의 쓸모는 알아서 잘 찾아보세요...

Brief Introductions about TabPFN

- TabPFN: A Transformer that solves small tabular classification problems in a second [3]
- TabPFNv2: Accurate predictions on small data with a tabular foundation model [4]
- Fast tabular statistical model using transformer.
- The distribution of the prediction is calculated in this formula.

$$p(y|x, D) = \int_{\Phi} p(y|x, \phi)p(D|\phi)p(\phi)d\phi$$

Structure of TabPFN

1. Pre-training
   - Model is trained on synthetic datasets (created by SCM) by minimizing the discrepancy between the predicted label of the test instance and its true label
   - We don't know the pre-training phase's structure : In the pip library, it just downloads pre-trained parameters and performs the inference phase.
2. Inference
   - For given data (training set + test set), TabPFN performs a single forward pass to generate predictions for all test samples.
   - In inference phase, model only do in-context learning, not backpropagation

TabPFN Example

Here is an example for fitting and making a prediction using TabPFN:

```
> from tabpfn import TabPFNRegressor
> ....
> train_1 = pd.DataFrame(data = [[-2, -2], [-1, -1], [1, 1], [2, 2]],
lumns = ['x', 'y'])
> test = pd.DataFrame(data = [[0]], columns = ['x'])
> regressor = TabPFNRegressor(device = 'cuda')
> regressor.fit(train_1[['x']], train_1[['y']]) // Forward pass
> regressor.predict(test) // Prediction
  array([0.1495245], dtype=float32)
```

$$\begin{array}{|c|}\hline \mathbf{x}\\\hline -2\\\hline -1\\\hline 1\\\hline 2\\\hline\end{array}, \begin{array}{|c|}\hline \mathbf{y}\\\hline -2\\\hline -1\\\hline 1\\\hline 2\\\hline\end{array} \xrightarrow{\text{TabPFNRegressor}} \text{regressor}, \begin{array}{|c|}\hline \mathbf{x}\\\hline 0\\\hline\end{array} \xrightarrow{\text{regressor}} \begin{array}{|c|}\hline \mathbf{y}\\\hline 2\\\hline\end{array}$$

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Is TabPFN better then traditional statistical models?

- In the past, many studies show that traditional statistical models (XGBoost, Random Forest, etc.) still outperform most deep learning models on tabular data. [6], [2]
- But TabPFN claims that their model is a state-of-the-art model for tabular data.

Why does this happen?

- TabPFN excels in handling small- to medium-sized datasets with up to 10,000 samples and 500 features. For larger datasets and highly non-smooth regression datasets, approaches such as CatBoost, XGB or AutoGluon are likely to outperform TabPFN. [4]
- The model was trained on a synthetic dataset generated via an SCM with about 130 million dataset samples.
- Since the dataset covered only a limited value range, the model did not learn to generalize beyond that domain.

TabPFN-TS

- Hoo et al., 2025 proposed TabPFN-TS, a TabPFN variant specific for time series.
- Proposes optimal transformation (preprocess) strategies tailored for TabPFN with time series data.

TabPFN-TS: Preprocessing

- Running index: chronological order
- Calendar features: second, minute, hour, weekday, day (month), day (year), week (year), year
- Seasonal features:
  - Additional cycles (e.g., lunar, non-calendar periodicities)
  - FFT top-k frequency features ($k = 5$)
- Cyclic features: sin / cos transformation

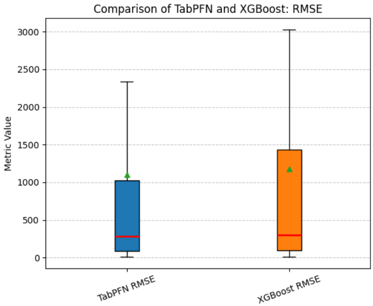
$$\Phi(t) = \left(\cdots, \cos\left(\frac{2\pi t}{P_i}\right), \sin\left(\frac{2\pi t}{P_i}\right), \cdots \right)$$

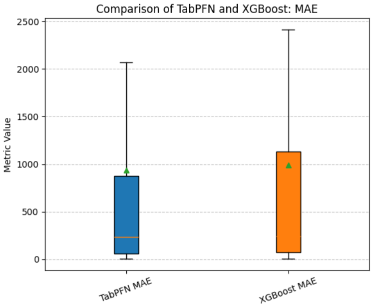
TabPFN-TS vs XGBoost

- In the paper, there is no comparison with XGBoost
- We conducted experiments using the Chronos [1] m4_hourly 100 time series datasets, predicting the last 48 data points.
- For a fair comparison, XGBoost was trained with the same feature set as TabPFN-TS.

TabPFN-TS vs XGBoost

- hi

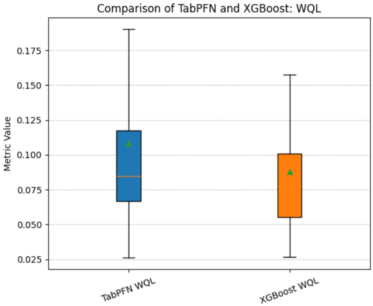




- hello

TabPFNv2 vs others

- Hello



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Conclusion

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Thank you!

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[7] Han-Jia Ye, Si-Yang Liu, and Wei-Lun Chao.
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