Forecasting Demand for Decarbonized Energy Grids

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About me

- Current OMSCS student
- Graduating this weekend!
- Lives in San Francisco, CA
- Works as a Data Scientist/Data Engineer at Modern Treasury
- Hobbies: landscape photography, chess, history, science fiction

Our goal: improve demand forecasting to improve grid operations

- Managing load is critical for grid operations
- Accurate forecasts improve economics of grids with renewable inputs
  - Improves long-term economics of renewable generation projects
- Matching demand with supply is key!

Credit: American Public Power Association

About the dataset: what is PSML?

- PSML is an open access dataset containing extensive time series data on grid load, renewable availability, and weather conditions
- Multiple possible use cases
  - Intended to drive ML-enabled research on improving electric grid operations
- Contains benchmarks for various traditional and ML approaches
- We use data from CAISO, which operates California's grid

Citation:
Zheng, X., Xu, N., Trinh, L. et al. A multi-scale time-series dataset with benchmark for machine learning in decarbonized energy grids. Sci Data 9, 359 (2022). https://doi.org/10.1038/s41597-022-01455-7

Hypothesis: newer deep learning architectures may outperform benchmarks

- ARIMA and exponential smoothing (ETS) both perform well on benchmarks
- We're interested to see if deep learning architectures can help push the envelope
- We chose 3 relatively new different deep learning methods to explore:
    - Spacetimeformer, DeepAR, Temporal Fusion Transformer

Why the Temporal Fusion Transformer?

- Architecture well suited to multi-horizon forecasting
  - Variable selection networks pick relevant features at each time step
  - Gating mechanisms skip irrelevant parts of the architecture for future predictions
  - Multi-head attention integrates information from any past time step to future predictions
- Better interpretability than previous DL-based forecasting methods
- Incredible name!

Citation:
Bryan Lim, Sercan O. Arik, Nicolas Loeff, Tomas Pfister, arXiv:1912.09363 [stat.ML],
https://doi.org/10.48550/arXiv.1912.09363

Experimental process: what worked, what didn’t

- Trained using the RTX 3080 on my gaming desktop - relatively efficient!
- Found pytorch-forecasting, a library with a TFT implementation
- Used optuna for more efficient hyperparameter tuning

- Academic code can be difficult to adapt
- Don’t try creating bespoke implementations, use off-the-shelf ones when possible
- Had to reduce scope given project constraints

Results: not state-of-the-art, but promising!

	2018 RMSE	2018 MAE	2019 RMSE	2019 MAE	2020 RMSE	2020 MAE
ARIMA	0.031	0.022	0.027	0.020	0.024	0.017
ETS	0.029	0.021	0.026	0.019	0.022	0.017
DeepAR	0.068	0.055	0.110	0.086	0.093	0.078
Transformer	0.108	0.086	0.132	0.095	0.086	0.101
TFT	*0.087*	*0.077*	*0.067*	*0.054*	*0.096*	*0.077*

Conclusions

- ARIMA and ETS still top the benchmarks for now
- TFT outperformed vanilla transformer benchmark and most other DL methodologies
- Transformers adapted to time series forecasting challenges show potential
- Need more research into models specifically tailored for energy demand forecasting and grid management
- Need to improve multi-horizon forecasting of availability of renewables

Acknowledgements and brief reflections on OMSCS

- Big thank you to my project teammates: Matt Carney and Pei Chao
- Overall, I’ve learned so much through structured academic coursework
- One of the only reasonably priced programs of its kind
    - Flip side: lack of synchronous components made it difficult to socialize with other students
- Excited to have my nights and weekends back!

Thank you