

Modern Machine Learning for Macroeconomic Forecasting

An Introductory Course for Central Bank Economists

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Course Overview

This intensive course bridges classical econometric forecasting with modern machine learning approaches, focusing on practical applications for central banking. The course emphasizes understanding the fundamental tradeoffs between classical and ML methods, hands-on implementation with state-of-the-art tools (AutoGluon, Chronos-2, TabPFN), and production deployment considerations.

Target Audience: Central bank economists familiar with ARIMA, ETS, VAR

Prerequisites: Time series econometrics, basic Python

Computational: Desktop/Laptop with Python 3.10+, 16GB RAM (GPU recommended for Lecture 3); Jupyter Notebook

Learning Objectives

By completing this course, participants will:

- Understand when ML methods outperform classical approaches for macro forecasting
- Implement ML forecasting pipelines using AutoGluon
- Apply foundation time series models (Chronos-2, TimesFM) and tabular models (TabPFN) via transfer learning
- Evaluate forecasts using metrics appropriate for policy decision-making
- Handle practical challenges: mixed-frequency data, structural breaks, limited samples
- Communicate ML forecast uncertainty to non-technical policy audiences

Course Outline

Lecture 1: From Classical to ML Forecasting - Foundations (3 hours)

Session 1.1: Why Machine Learning? (1 hour)

- Evolution from Box-Jenkins to AutoML; the data revolution in forecasting
- Global vs. local models; point vs. probabilistic forecasts
- Bias-variance tradeoff; when classical vs. ML models excel
- *Hands-on:* AutoGluon installation

Session 1.2: Statistical Models in AutoGluon (1.5 hours)

- Classical baselines: AutoARIMA, AutoETS, Theta, SeasonalNaive
- Model configuration, hyperparameter tuning within AutoGluon
- Backtesting: expanding/rolling windows, proper temporal cross-validation
- Evaluation metrics: RMSE, MAE, MASE, CRPS
- *Hands-on:* Comprehensive backtest on FRED-MD; statistical testing (Diebold-Mariano)

Session 1.3: Deep Learning Fundamentals (30 min)

- Why deep learning for time series? Automatic feature learning, flexibility
- Key architectures: DeepAR (probabilistic RNN), Temporal Fusion Transformer (attention)
- When deep models help: large N , long T , complex patterns, rich covariates

- *Hands-on:* Train DeepAR/TFT on cross-country inflation; compare to ARIMA

Lecture 2: Modern ML Architectures for Macro Forecasting (3 hours)

Session 2.1: Tree-Based Models (1 hour)

- Gradient boosting (LightGBM, XGBoost) for time series; advantages and challenges
- Feature engineering: lags, rolling stats, date features, cyclical encoding
- Avoiding data leakage; hyperparameter tuning (depth, learning rate, regularization)
- *Hands-on:* GDP nowcasting with high-frequency indicators; feature importance

Session 2.2: Deep Learning for Multi-Horizon Forecasting (1.5 hours)

- Multi-horizon strategies: recursive, direct, encoder-decoder
- Sequence-to-sequence models: LSTM encoder-decoder, DeepAR architecture
- Attention mechanisms: Temporal Fusion Transformer components, interpretability
- Covariate handling: static features, known future inputs, observed variables
- *Hands-on:* Global TFT for multiple countries; analyze transfer learning and attention weights

Session 2.3: Practical Challenges (30 min)

- Mixed-frequency data: aggregation, MIDAS, state-space, direct ML approaches
- Structural breaks: robust models, adaptive learning, regime modeling
- Cold start problem: transfer learning, hierarchical models, feature-based priors
- *Hands-on:* COVID as structural break; model robustness comparison

Lecture 3: Foundation Models and Applications (3 hours)

Session 3.1: Transfer Learning with Foundation Models (1.5 hours)

- Foundation model revolution: pre-training on massive datasets, zero-shot forecasting
- **Time Series Foundation Models:**
 - Chronos-2: 120M-parameter model supporting univariate, multivariate, and covariate-informed forecasting with group attention mechanism
 - TimesFM: Google’s 200M-parameter decoder-only model trained on 100B time points
 - Why they matter: cold start, robustness to crises, strong zero-shot performance
- **TabPFN for Tabular Data:** Transformer trained on 130M synthetic datasets; achieves SOTA on small datasets (<10K samples) in seconds without hyperparameter tuning; applications in recession prediction and nowcasting
- Fine-tuning approaches: full, LoRA (parameter-efficient), prompt tuning
- *Hands-on:* Zero-shot Chronos-2 with covariates; TabPFN for recession prediction

Session 3.2: Production Deployment and Case Studies (1 hour)

- Deployment essentials: batch forecasting, monitoring accuracy, model versioning
- Communicating uncertainty to policymakers: fan charts, scenario analysis
- **Central Bank Case Studies:**
 - Bank of England: ML nowcasting platform with ensemble methods
 - Banco Central do Brasil: RNN inflation forecasts
- *Hands-on:* Deploy simple forecasting pipeline with monitoring

Session 3.3: Future Directions and Q&A (30 min)

- Research frontiers: causal ML, multimodal models, hierarchical reconciliation, explainable AI
- Open discussion: Challenges and opportunities for ML in central banking

Essential References

Machine Learning for Forecasting

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Evaluation and Forecast Combination

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Foundation Models and Transfer Learning

15. Ansari, A.F., et al. (2024). “Chronos: Learning the Language of Time Series.” *arXiv:2403.07815*.
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Practical Challenges

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Production ML and Central Bank Applications

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Textbooks and Online Resources

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30. Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The Elements of Statistical Learning* (2nd ed.). Free: <https://hastie.su.domains/ElemStatLearn/>
31. Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning*. Free: <https://www.deeplearningbook.org/>
32. AutoGluon Time Series Documentation: <https://auto.gluon.ai/stable/tutorials/timeseries/>
33. Chronos Forecasting: <https://github.com/amazon-science/chronos-forecasting>
34. TabPFN Documentation: <https://github.com/PriorLabs/TabPFN>

Software and Datasets

Required packages: autogluon.timeseries, chronos-forecasting, tabpfn, statsmodels, pandas, numpy, matplotlib, scikit-learn, fredapi

Key datasets: FRED-MD (US macro), IMF IFS (cross-country), OECD MEI, Philadelphia Fed real-time data, ECB SDW

Course materials, code repositories, and additional resources available at course website

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