Transformer■based Forecasting — Interview Brief (BGSU)

Scope

Forecast weekly demand for Learning Commons services (by subject and location) and early■risk signals (probability of course withdrawal) to staff proactively and trigger nudges. Context: Bowling Green State University (BGSU) Student Success Analytics. Cohort focus is first■year undergraduates. Primary KPI: next■term retention; secondary: term GPA, gateway pass rate, early-course engagement. Data sources: SIS, LMS, advising, Learning Commons outreach logs.

Business Questions

- What is the 1–4 week■ahead forecast of tutoring demand by subject/location?
- Which weeks/sections are at highest risk of withdrawal/no■show so we can intervene earlier?
- How much staffing buffer is needed to hit service■level targets?

Methodology (Plain)

- Construct spatiotemporal features: week■of■term, holidays, exam calendars, weather, sports/events; include leading indicators from LMS (logins, assignment submissions) aggregated pre■week.
- Models: baseline prophet/ARIMA and gradient■boosting; main model: Temporal Fusion Transformer or Informer with quantile loss for P10/P50/P90 forecasts.
- Evaluation: rolling■origin backtests; metrics = WAPE/MAE for demand, AUC/PR for risk; calibration for quantiles.
- Operationalization: convert P90 forecast into staffing plan; trigger nudges when predicted risk exceeds threshold with precision■recall guardrails.
- Drift monitoring and weekly re■training during term.

Tools

- Python: pandas, numpy, scikit■learn, pytorch■lightning or gluonts/tsflex, statsmodels for baselines.
- Experiment tracking with MLflow; simple API/cron for weekly batch forecasts.
- Dashboards showing capacity vs. forecast bands and alert queues.

Potential Results (Example framing)

- Demand WAPE improves from 18% (baseline) to 11% (transformer) across subjects.
- Staffing buffers derived from P90 cut peak waits by ~20% without adding headcount.
- Early■risk alerts lift tutoring bookings by 8% for flagged sections.

Interview Talking Points (60–90s)

- Emphasize simple outcomes: fewer surprises, shorter waits, earlier help.
- Note that we compare against strong baselines; we ship a schedule, not just a model.
- Guardrails: avoid feature leakage; respect privacy; explain predictions to coordinators.

Risks & Mitigations

- Data sparsity by subject/location → hierarchical pooling and shrinkage.
- Black■box concerns → provide backtest charts, SHAP■style drivers, and simple fallback rules.