Marketing | Telecom | Predictive forecasting | Natural language processing

Machine Learning Methods for Churn Prediction and Infrastructure Resilience

BUSINESS PROBLEM

Telecom companies seek to reduce customer churn through both short-term marketing strategies and long-term network reliability. The current forecasting approaches can be enhanced to better inform operational decisions around customer retention, upgrade promotions, and infrastructure resilience planning. The goal is to accurately forecast churn and proactively mitigate infrastructure-related churn risk.

APPROACH

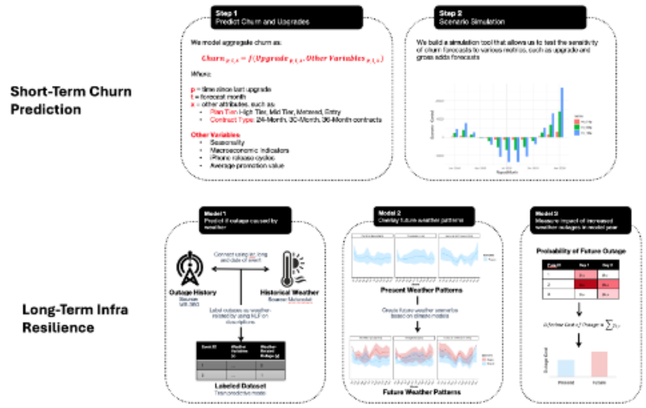
I created a cohort-based churn forecasting model integrating customer upgrade patterns, used synthetic data generation (MICE) for sparse cohorts, and applied interpretable linear regression with macroeconomic variables. For long-term resilience, I built predictive neural network models linking weather data to network outages and projected climate risk scenarios using clustering and simulations.

DATA SOURCES

I used aggregated customer churn, upgrades, and contract tenure data provided by the company, alongside macroeconomic indicators from the Bureau of Labor Statistics (e.g., CPI). Infrastructure outage data came from the Company's internal systems, enriched with external weather data from Meteostat and future climate scenarios (CMIP5) via Openmeteo.

Data Types and Format

Data included structured numerical customer records (monthly churn/upgrade rates, promo tenure), spatial-temporal outage incidents, qualitative incident descriptions, and hourly weather time series.



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IMPACT

My churn model improves forecasting accuracy, enhancing operational efficiency and enabling targeted marketing, thereby optimizing marketing spend. Stakeholders gain clear, interpretable insights into churn drivers, fostering internal alignment between marketing and finance teams. Improved forecasting significantly impacts customer retention and financial performance. For infrastructure resilience, predictive modeling anticipates future climate-induced outages, enabling proactive planning and targeted hardening investments. By identifying and quantifying vulnerabilities through robust climate scenario modeling, the Company gains a competitive edge, mitigating long-term risk and ensuring reliable service delivery during extreme weather events. This proactive resilience strategy also enhances the Company's market reputation and customer trust, potentially improving market share in the long term. Together, these solutions position the Company as a leader in applied AI, integrating machine learning deeply into strategic decisions around customer retention and network resilience, which are critical for sustained market competitiveness and growth.

DRIVERS	Increasing market commoditization and intense competition require the Company to prioritize customer retention via predictive insights. Concurrently, rising climate-related extreme weather events have exposed telecom infrastructure vulnerabilities. These industry pressures drive the strategic imperative to integrate AI-driven predictive analytics for immediate customer retention and long-term resilience planning.
BARRIERS	Key barriers included data sparsity for newer contract types, requiring synthetic data techniques. Organizational dynamics between various teams posed challenges, demanding significant efforts in trust-building and stakeholder alignment. Additionally, limited integration of existing outage datasets with real-time network performance data restricted detailed outage attribution modeling.
ENABLERS	Verizon's strategic commitment to becoming a leading AI-driven company provided strong organizational support. The Impact Analytics team's cross-functional position bridging AI and business operations was pivotal, facilitating stakeholder engagement and rapid operationalization of models. Additionally, Verizon's extensive historical customer data and structured outage records were foundational for modeling efforts.
ACTIONS	I first cleaned and synthesized data using regression-based imputation and MICE, then developed an interpretable linear regression churn model, validated rigorously against recent forecasts. I also built neural network-based predictive models linking weather variables to outages, applied DBSCAN clustering for event attribution, and integrated Monte Carlo simulations with climate projections to predict future risks.
INNOVATION	Innovations include the cohort-based churn model explicitly incorporating upgrade behaviors, and advanced imputation techniques for sparse datasets. Additionally, combining DBSCAN clustering with neural network modeling for weather-event attribution, integrated with CMIP5-driven climate scenario simulations, provides Verizon a cutting-edge framework for strategic infrastructure resilience planning.
IMPROVEMENT	My churn model notably improves forecasting, directly enabling more effective marketing strategies and optimized customer retention efforts. Infrastructure modeling clearly quantifies long-term climate risk, allowing targeted investments in network resilience, thus significantly reducing vulnerability to future extreme weather disruptions and associated customer churn impacts.
BEST PRACTICES	Prioritize stakeholder engagement and interpretability, particularly in enterprise contexts. Use cohort-based modeling to capture customer lifecycle dynamics, applying advanced imputation for data gaps. For resilience modeling, leverage robust spatio-temporal clustering methods combined with neural networks and climate scenario analysis, emphasizing transparency and explainability for practical business alignment.
OTHER APPLICATIONS	This methodology can extend to other subscription-based industries (streaming, SaaS) for churn and upgrade analytics. Infrastructure resilience techniques can similarly apply to energy grids, water utilities, transportation networks, and critical supply chains facing climate risks. Predictive modeling frameworks can inform insurance underwriting, urban resilience planning, and governmental policy development for climate adaptation strategies.