PRINCIPLES OF DATA SCIENCE

CUSTOMER CHURN PREDICTION USING LLMs WITH SHAP AND BEHAVIOR SUMMARIES

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1. Introduction

Customer churn—the act of customers discontinuing a service—is a significant concern in the telecommunications industry. Retaining existing customers is generally more cost-effective than acquiring new ones, making churn prediction a valuable strategy for improving customer lifetime value. Anticipating churn allows companies to proactively address dissatisfaction through targeted offers, personalized support, or improved service quality.

This project introduces a machine learning approach that integrates structured tabular data with Natural Language Processing (NLP) to predict churn and provide interpretable insights.

2. Related Work

Churn prediction has traditionally relied on machine learning models such as logistic regression, decision trees, and random forests. These models, while effective, typically depend on manual feature engineering and offer limited interpretability. Deep learning models like multilayer perceptrons (MLPs) and convolutional networks have also been applied but often function as black boxes.

More recently, researchers have explored using transformer models for structured data by converting tabular records into natural language. Notable developments include **TabLLM** and **TABBIE**, which demonstrated that language models can learn from structured inputs when transformed into textual prompts.

3. Methodology and Results

This project follows a structured workflow to predict customer churn using transformer-based language models. The process includes data preparation, natural language prompt generation, model training, evaluation, and interpretability analysis.

Data Preparation:
The dataset included customer demographics, service usage, billing details, and churn labels. Preprocessing steps involved handling missing values (notably in TotalCharges), converting data types, encoding categorical features, and addressing class imbalance through stratified train-test splitting. Exploratory analysis showed that churn correlated strongly with contract type, tech support usage, and payment methods.

Prompt Engineering:
Structured records were converted into descriptive sentences. For example:

"A senior female customer on a month-to-month contract, paying $80 per month, with no tech support."
These prompts allowed models to understand the data contextually, similar to human reasoning.

Modeling:
Two models were employed:

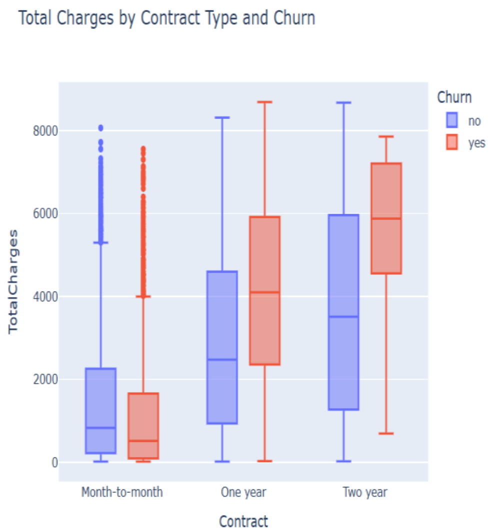
- **BERT** for binary churn classification.
- **T5** for generating concise summaries explaining churn risk.

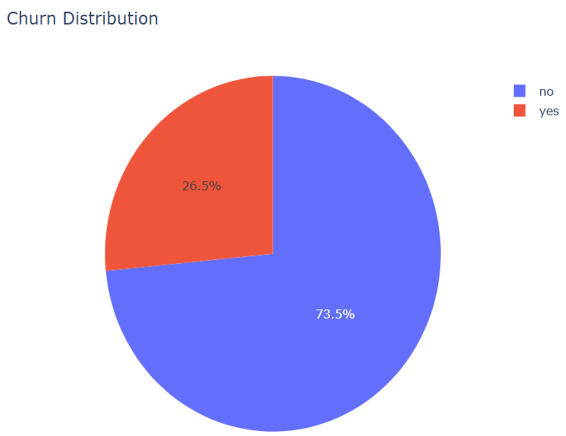
The data was tokenized, split 80/20, and trained over 3–5 epochs with tuned hyperparameters using GPU support.

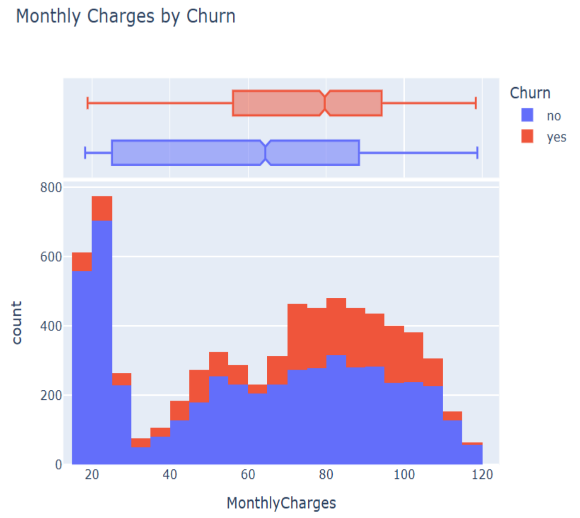
Evaluation:
Performance metrics such as accuracy, precision, recall, and F1-score showed that BERT effectively identified churn cases with balanced class performance. Confusion matrices validated its predictive reliability. T5 summaries were reviewed for clarity and relevance.

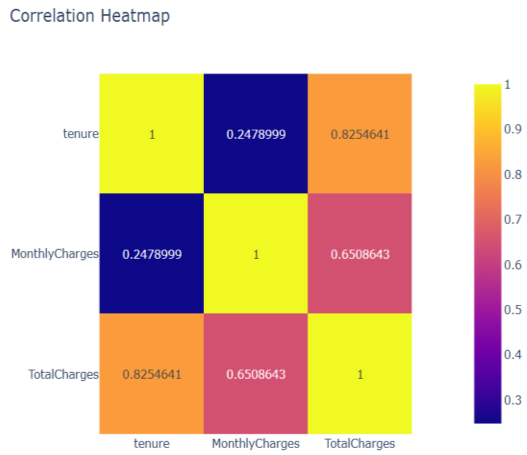
Explainability with SHAP:
SHAP visualizations highlighted the most impactful features—contract type, monthly charges, and tenure. These insights confirmed the model's alignment with real-world churn factors.

Key Results:
The BERT model achieved strong classification performance, while T5 generated human-readable summaries reflecting individual risk factors. This dual-output system improves transparency and usability, making it suitable for business teams who need both predictions and actionable insights.







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BERT Classification Report:
              precision    recall  f1-score   support

           0       0.85      0.87      0.86      1035
           1       0.62      0.57      0.59       374

    accuracy                           0.79      1409
   macro avg       0.73      0.72      0.73      1409
weighted avg       0.79      0.79      0.79      1409
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BERT Accuracy: 0.7927608232789212

5. Challenges and Future Work

Challenges:

Key challenges included handling class imbalance, designing effective prompts, and managing the high computational cost of training transformer models. Ensuring interpretability for non-technical users was also a significant concern. Additionally, training transformer models was computationally demanding, requiring access to GPUs and careful hyperparameter tuning.

Future Work:

Future enhancements may include support for multilingual data, integration of real-time customer feedback, automated prompt generation, and deployment as a web-based tool for easier access by business teams.

Automating prompt design with dynamic templates and evaluating T5 summaries using standardized NLP metrics like ROUGE or BLEU would also add robustness.

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