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Customer Churn Prediction Using Hybrid Machine Learning Models: Implications for Customer Retention Strategy

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Abstract

Churn prediction is one of the most mature applications of machine learning in marketing, yet two gaps persist: the incremental value of hybrid (ensemble-of-ensembles) models over their components is rarely quantified in economic terms, and the link between a model's ranking quality and the design of the retention campaign that consumes its scores is often left implicit. This paper addresses both gaps using a simulation harness that generates 8,000 subscription customers from a logistic process with a known interaction between price increases and contract status. A stacked hybrid that combines logistic regression, random forest and gradient boosting through a logistic meta-learner is compared with its three components on discrimination, calibration, top-decile lift and the net value of a retention campaign under four contact budgets. The hybrid achieves the highest top-decile lift (4.50) and the highest campaign net value at every budget, although its AUC (0.803) is marginally below that of logistic regression (0.807), illustrating that global discrimination and campaign value can diverge. Net value peaks when the top 10% of customers are contacted and declines at wider budgets. The paper derives a budget-setting rule from the gains curve and discusses how calibrated churn probabilities, responsiveness estimates and customer value should be combined in retention strategy.

Keywords: Customer churn; stacked generalisation; ensemble learning; customer retention; lift; profit-driven evaluation.

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Introduction

Retaining an existing customer is generally cheaper than acquiring a new one, and subscription businesses therefore devote substantial budgets to retention campaigns aimed at customers likely to defect. Churn prediction models rank customers by their probability of leaving so that the campaign can be targeted. The field has a long history, with early comparative studies establishing that model choice affects accuracy [1], and later work shifting attention from accuracy to profit [2], [3] and from prediction to intervention effectiveness [4].

Hybrid models, in which several base learners are combined through a meta-learner, are frequently reported to outperform individual learners on churn tasks. Stacked generalisation [5] provides the general mechanism, and ensemble theory explains why combining diverse learners reduces variance [6]. What is less often reported is whether the improvement survives translation into campaign value: a hybrid that improves the area under the ROC curve by half a point may or may not change which customers are contacted under a fixed budget, and it is the latter that determines profit.

This paper contributes a transparent evaluation of a stacked hybrid against its components on four criteria that matter to retention strategy: discrimination, calibration, top-decile lift and net campaign value across contact budgets.

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A simulation harness with a known data-generating process is used so that results are reproducible and the mechanisms are inspectable. The paper then draws implications for how retention budgets should be set and how scores should be combined with other information.

Literature Review

Churn modelling

Neslin et al. [1] organised a churn-modelling tournament and found that the method used accounted for meaningful differences in predictive accuracy and that the top-decile lift was a useful managerial metric. Verbeke et al. [2] extended evaluation to a profit-driven framework in which the value of a model depends on customer lifetime value, the campaign's

success rate and contact cost; Verbraken et al. [3] formalised the expected maximum profit criterion. These contributions established that discrimination metrics are insufficient for selecting churn models.

Ensembles and stacking

Random forests [7] and gradient boosting [8] are the dominant base learners in churn applications. Stacking [5] trains a meta-learner on the out-of-fold predictions of the base learners, so that it learns how much to trust each base learner in different regions of score space. The approach is attractive when base learners have complementary strengths, for example a linear model that extrapolates smoothly and tree models that capture interactions.

From prediction to retention action

Ascarza [4] showed that targeting the customers with the highest churn probability can be ineffective because those customers are often the least responsive to retention offers; the quantity that should guide targeting is the uplift from intervention. Calibrated churn probabilities remain essential inputs, because expected campaign value is a function of churn probability, uplift, customer value and cost.

Drivers of subscription churn

Across telecommunications, media and software subscriptions, the drivers of churn fall into three groups: relationship variables such as tenure and contract type, which capture switching costs; experience variables such as complaints, support contacts and satisfaction, which capture accumulated dissatisfaction; and trigger events such as price increases and competitor offers, which precipitate the decision. Interactions among the groups are common: a price increase is far more consequential for an out-of-contract customer than for one locked into a term. A credible simulation of churn must therefore contain at least one such interaction, and the ability of models to capture it is one reason tree ensembles and hybrids are popular in the domain.

Methodology

Data-generating process

The harness simulates N = 8,000 customers with eight predictors: tenure in months (exponential, mean 24), monthly usage (log-normal), complaint count (Poisson, mean 0.6), a price-increase indicator (Bernoulli, 0.25), a contract indicator (Bernoulli, 0.5), support-call count (Poisson, mean 1.2), a standardised satisfaction score and a competitor-offer indicator (Bernoulli, 0.2). Churn follows

$$\text{logit } P(C = 1) = -2.0 - 0.02\,\textit{tenure} - 0.4\,\ln(\textit{usage}) + 0.5\,\textit{complaints} + 0.8\,\textit{price} - 1.0\,\textit{contract} + 0.25\,\textit{calls} - 0.6\,\textit{sat} + 1.1\,\textit{offer} + 0.9\,\textit{price}\cdot(1 - \textit{contract}), \quad (1)$$

so that a price increase is much more damaging for customers without a contract. The realised churn rate is 8.8%. Each customer also has an average revenue per user (ARPU) drawn from a log-normal distribution, used only for the economic evaluation.

Models

Three base learners are trained: logistic regression with standardised inputs, a 400-tree random forest and gradient boosting. The hybrid is a stacking classifier that uses the three base learners and a logistic-regression meta-learner trained on five-fold out-of-fold predictions. Data are split 70/30 with stratification; all implementation uses scikit-learn [9].

Evaluation criteria

Discrimination is measured by AUC and average precision, calibration by the Brier score, and ranking quality at the top by top-decile lift, defined as the churn rate among the 10% highest-scored customers divided by the overall churn rate. Campaign value is simulated as follows: the top q fraction of customers by score is contacted at a cost of 15 currency units each; 30% of contacted customers who would have churned are retained; each retained customer preserves 12 months of ARPU. Net value is retained revenue minus contact cost, and return on investment (ROI) is net value divided by cost. Budgets of q = 5%, 10%, 20% and 30% are evaluated. The retention success rate and contact cost are design parameters, not empirical estimates.

Results

Discrimination, calibration and lift

Table 1 reports the hold-out metrics. Logistic regression attains the highest AUC (0.807) and average precision (0.401), reflecting the additive structure of the process, with the hybrid close behind (0.803, 0.394). On top-decile lift, however, the hybrid is best at 4.50, ahead of logistic regression (4.41), gradient boosting (4.31) and random forest (4.17). Brier scores are nearly identical for the hybrid and logistic regression (0.066). The pattern shows that the meta-learner improves the ranking at the top of the score distribution, which is where a budget-constrained campaign operates, even though it does not improve global discrimination.

Figure 1 presents the cumulative gains curves. All four models capture roughly 40% of churners within the first 10% of contacts and 60% within the first 20%, and the curves separate only slightly, with the hybrid and logistic regression above the tree ensembles through most of the range.

Campaign economics

Table 2 reports net campaign value by model and budget. Two findings matter for strategy. First, the hybrid produces the highest net value at every budget, with a margin over logistic regression of 2–3% and over random forest of 13–31%. Second, net value is not monotone in budget: it rises from the 5% budget to the 10% budget and then declines, because the marginal customers contacted at wider budgets

Table 1: Hold-out performance of base learners and the stacked hybrid (synthetic subscribers, churn rate 8.8%)

Model	*AUC*	*Average precision*	*Brier score*	*Top-decile lift*
Logistic regression	0.807	0.401	0.066	4.41
Random forest	0.778	0.353	0.069	4.17
Gradient boosting	0.795	0.359	0.067	4.31
Hybrid (stacked)	0.803	0.394	0.066	4.50

have low churn probability and their contact cost exceeds the expected retained revenue. ROI, by contrast, declines monotonically with budget, from 2.5 at 5% to 0.43 at 30% for the hybrid.

Sensitivity to campaign assumptions

Because retained revenue is proportional to the retention success rate *r*, the breakeven value of *r* at which net value is zero can be computed directly for the hybrid: it is 0.085 at the 5% budget, 0.111 at 10%, 0.173 at 20% and 0.210 at 30%. Equivalently, the breakeven contact cost, holding *r* at 0.30, is 52.9 units per contact at 5%, 40.7 at 10%, 26.1 at 20% and 21.4 at 30%. The campaign therefore remains profitable at the 10% budget unless the offer converts fewer than about one in nine would-be churners or costs more than about 40 units per contact, whereas the 30% budget is profitable only under considerably more favourable assumptions. These breakeven values follow algebraically from the design parameters and the model's ranking, and they give campaign managers a direct way to test the robustness of a proposed budget.

Divergence between AUC and value

The hybrid's lower AUC but higher net value is not an anomaly. AUC weights every pair of customers equally, including pairs far down the ranking that no campaign will ever reach. Net value depends only on the ordering within the contacted fraction. A model that sharpens the top of the ranking at the expense of the middle will lose AUC and gain value, which is exactly what stacking did here.

Implications for Retention Strategy

Setting the contact budget

The gains curve provides a direct budget rule. Contact customers in descending score order until the marginal expected retained revenue falls below the marginal contact cost, that is, until $p_i \cdot r \cdot V_i < c$, where p_i is the calibrated churn probability, r the retention success rate, V_i the customer's value at stake and c the contact cost. In the simulation this point lies near the 10% budget, which is why net value peaks there. Because the rule uses calibrated probabilities, calibration should be treated as a first-class model requirement rather than an afterthought.

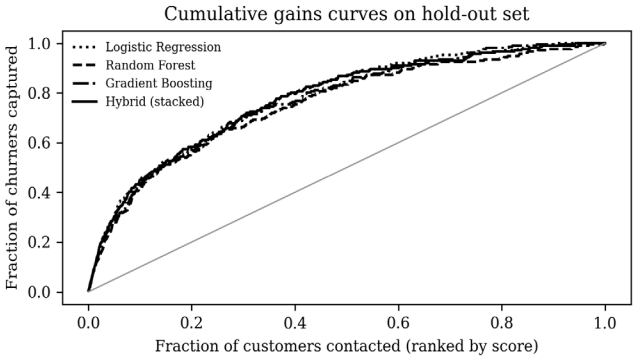

Figure 1: Cumulative gains curves on the hold-out set

Choosing the model

The choice should be made on the metric that matches the decision: top-decile lift or expected profit [3] when budgets are tight, and the full gains curve when budgets are flexible. On these metrics the hybrid was preferred, but the margin over a well-specified logistic model was small, and the hybrid's additional complexity should be weighed against the ease of explaining a logistic score to campaign managers.

Beyond churn probability

Churn probability answers "who is likely to leave", not "who can be persuaded to stay". The campaign value model used here assumes a uniform 30% retention rate; in reality responsiveness varies, and the highest-risk customers may

Table 2: Simulated net campaign value (currency units) and ROI by contact budget

Model	*5% budget*	*10% budget*	*20% budget*	*30% budget*
Logistic regression	4,724 (ROI 2.62)	6,003 (1.67)	5,292 (0.74)	4,547 (0.42)
Random forest	4,322 (2.40)	5,452 (1.51)	4,760 (0.66)	3,505 (0.32)
Gradient boosting	4,127 (2.29)	5,943 (1.65)	5,017 (0.70)	4,190 (0.39)
Hybrid (stacked)	4,549 (2.53)	6,158 (1.71)	5,316 (0.74)	4,609 (0.43)

be the least responsive [4]. A complete retention strategy therefore combines three estimates per customer: churn probability, uplift from intervention and value at stake. The hybrid model developed here supplies the first; the other two require experimental data from past campaigns.

Organisational process

Retention campaigns should be run as a closed loop: score, contact, observe, and feed outcomes back as training data for both the churn model and the uplift model. Randomised holdout groups within each campaign provide the counterfactual needed to estimate uplift and to verify that the campaign is creating, not merely predicting, retention.

Limitations

The data-generating process is additive on the logit scale apart from one interaction, which favours logistic regression and limits the advantage available to the hybrid. Retention success rate, contact cost and value at stake are fixed design parameters; in practice they vary by customer and offer. The evaluation uses a single random split rather than repeated cross-validation. All reported figures are outputs of the simulation harness and are not estimates for any real customer base.

Conclusion

A stacked hybrid of logistic regression, random forest and gradient boosting delivered the best top-decile lift and the highest simulated campaign value at every contact budget, despite a marginally lower AUC than its logistic component. The result shows that model selection for retention should rest on budget-aware metrics rather than global discrimination, and that net campaign value peaks at an intermediate budget determined by the gains curve and contact economics. Retention strategy should combine churn scores with uplift and value estimates in a closed experimental loop.

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