We consider the problem of churn prediction in real-time. Because of the batch mode of inference generation, the traditional methods can only support retention campaigns with offline interventions, e.g., test messages, emails or static in-product nudges. Other recent works in real-time churn predictions do not assess the cost to accuracy trade-off to deploy such models in production. In this paper we present RICON, a flexible, cost-effective and robust machine learning system to predict customer churn propensities in real-time using clickstream data. In addition to churn propensity prediction, RICON provides insights based on product usage intelligence. Through application on a real big data of QBO Advanced customers we showcase how RICON has achieved a top decile lift of 2.68 in the presence of strong class imbalance. Moreover, we execute an extensive comparative study to justify our modeling choices for RICON. Finally, we mention how RICON can be integrated with intervention platforms within Intuit to run large-scale retention campaigns with real-time in-product contextual helps.

1 INTRODUCTION

Objective: In the last decade, with the advancement of technology and software services, subscription business model has seen a rapid rise in various service-based industries, especially software and technology companies, e.g., Microsoft, Google, Adobe, Intuit, Salesforce etc. to name a few. In subscription business model, the objective is to maximise the lifetime value (LTV) of a customer and so, customer retention is one of the most important focus in Customer Relationship Management (CRM). Studies have shown the importance of customer churn prevention and how it is more profitable as compared to acquisition of new customers [13, 21].

QuickBooks: QuickBooks Online (QBO) Advanced is an Intuit cloud-based software product which provides various book-keeping and accounting related capabilities to mid-market business owners. QBO Advanced being a subscription-based software product, customer retention is one of the central focus area in CRM. Customer churn for QBO Advanced usually means either the customer has left the QuickBooks ecosystem or downgraded to one of the QuickBooks product with lower subscription renewal cost.

Figure 1: Percentage of churn by customer age at time of churn

Reducing churn by couple of percentage points for QBO Advanced will result in tens of millions of dollars of incremental revenue in customer LTV for Intuit. Hence, to prevent customer churn, the CRM team engages several retention campaigns, e.g., discount offers, feature recommendations, agent helps etc. Customer churn prediction can improve the success rate of these campaigns by identifying customers with high risk of churn as well as providing actionable insights to reduce the likelihood of churn. In Figure 1, we have presented the proportion of all the churners in last six month by the age of the companies at the time of cancelling the subscription. We have only considered those churn cases where the cancellation of subscription is voluntary and not based on payment failure or other possible passive reasons. It is clear from the picture that a significant portion of churns (33%) happens even before the first billing cycle i.e., before 31 days.

Motivation: Most of the studies in customer churn uses aggregated user profile and behavioural features and in some cases social attributes to predict the churn propensity. These models being trained and evaluated on a single temporal snapshot of the user data, can only be used as batch models, i.e. the model inference can happen in batches with a pre-defined time frequency and the customers who are eligible to be assessed for their churn risk are those who have already finished a pre-defined tenure in the product, e.g. one week, one month etc. at the time of inference generation. So, these models cannot identify customers who have high risk of churn but are at early stage of their subscription tenure. For
example, a batch model which requires a customer to be at least 21 days old to be eligible for risk scoring will miss out approx. 13% of the all churners as shown in Fig. 1. In addition, the features to these batch models being computed by aggregating several user behaviour attributes over a large historical window (at least 7 days), the predicted churn propensity is not sensitive to more recent (in last few hours) activities of the customers. Hence, the intervention campaigns run by CRM team to prevent customer churn using the batch churn model predictions can mostly be offline, e.g., emails, text messages or static in product nudges. Automated and scalable customer retention campaigns with real-time and contextual interventions cannot rely on batch churn propensity predictions. Though there are few recent articles on estimating churn propensity in real-time for online gaming and other subscription commerce, most of these studies do not provide a cost effective yet high performing and reusable real-time churn prediction system.

Contributions: In this paper, we present RICON (Real-Time Intervention for Customer RetentiON) – an ensemble approach of estimating churn propensity of customers in real-time using both aggregated user behavioural data in longer historical window (e.g., over the last week) as well as user activities over a short window (e.g., in last one hour) in recent past. In most of the data systems in industry, few datasets are available through Kafka and hence get updated and can be accessed in real-time, whereas most of the other datasets reside in datalake as hive tables and get updated with a frequency of more than 24 hours. Models built on only the real-time data are often not robust as the coverage and scope of real-time datasets are limited. On the other-hand, predictions coming from models trained on the datasets which gets updated daily are not sensitive to dynamic nature of the production environment. RICON by its design can incorporate both the real-time updated and daily updated datasets and predict churns in real-time robustly. The recent user interaction based features allow the churn propensity to vary in real-time based on user activities within product and thus, opens the opportunity for the CRM to design retention campaigns with more real-time, contextual and proactive interventions. On the other-hand, the features aggregated over a long historical window help to robustify the churn model by capturing churn signals based on overall product usage of the customers. In addition, RICON allows the featureization of the models to be completely automated and data-driven, making this approach reusable for other event detection problems. We have borrowed existing state-of-the-art machine learning and deep learning methodologies in binary classification and at the same time created a novel machine learning framework for churn prediction in real-time that addresses real world challenges and provides accurate churn prediction with contextual product usage-based insights.

2 RELATED WORK

Most of the churn prediction studies conducted in the last decade use hand-engineered customer-level aggregated usage-based features and customer profile information to predict the likelihood of churn. Apart from the applications of standard classification algorithms [7, 8], some of the novel methods proposed in this genre of static churn predictions are: locally trained linear model tree-based classifier [6]; advanced rule induction-based churn detection [23]; Polynomial SVM in conjunction with Adaboost classifier [22]; GMDH-based multi-classifier ensemble [25] – to name a few.

More recently, churn prediction has seen a shift towards application of more cutting-edge machine learning and big data techniques in most of the subscription-based commerce, e.g., big data mining techniques for churn detection in telecom industries [1, 9]; difficulty-aware churn prediction framework [15] and survival ensemble-based multi-dimensional churn prediction in online gaming [2]; Deep-CNN and autoencoder based churn analyses [24]; churn prediction by forecasting non-churn events by WTTE-RNN [18]; ML-based churn identification in retail banking [5] etc.

Though the above-mentioned studies assess the importance of big data and several machine learning algorithms for churn prediction, the literature on churn prediction in real-time is sparse. A recent study [4] describes how real-time transaction data can be consumed to make the churn prediction more accurate and interpretable. In this paper, we propose a reusable end-to-end machine learning framework for churn prediction in real-time that addresses real world challenges and provides accurate churn prediction with contextual product usage-based insights.

3 RICON: AN ENSEMBLE METHOD TO ESTIMATE CHURN PROPENSITY IN REAL-TIME

Similar to most of the existing literature, we have formulated the churn prediction as a binary classification problem. But for real-time detection of customers with high risk of churn while the customer is still online in the product, the requirement can be to evaluate the model continuously and hence, model training, evaluation and deployment need to be designed accordingly. In this section, we
provide an in-depth description of the end-to-end real-time churn prediction methodology of RICON.

3.1 Model Architecture: Stacked Ensemble

As shown in Fig. 2, RICON has three components: (1) a machine learning classifier with features computed by aggregating user activities over a long historical time window and user profile information – we call it Long Window Model (LWM), (2) a machine learning classifier based on sequence of user activities performed in a recent short window – Short Window Model (SWM) and finally, (3) a stacked ensemble layer which combines the SWM and LWM model outputs to give the final churn propensity output. Fig. 2 presents the flow of inference for RICON. We discuss the individual components in the later subsections.

3.2 Target Variable

Mechanism to define target variable is an important design choice in churn prediction system. Largely, there can be three approaches to define the target variable for churn prediction.

(a) Static binary outcome: Define the target variable at the customer level, i.e. the target is 1 if the customer have churned and 0 if not, given a constant time frame [11]. This approach of defining the target at a customer level do not take the dynamic nature of the product and usage behavior into account.

(b) Time to event: Instead of modeling churn as a binary event, the time to event can also be modeled as a survival regression problem [5, 18]. This model predicts a survival function for each customer which can be converted to a churn propensity by computing the probability of the event within a given time period from the reference time point.

(c) Sliding-box method: In this method, given a reference time point \( t \) for \( i \)th customer, define the target variable \( Y_i(t) \) as follows:

\[
Y_i(t) = \begin{cases} 
1 & \text{if the } i \text{th customer churns within } (t, t + \delta], \\
0 & \text{otherwise},
\end{cases}
\]

where, \( \delta > 0 \) is a pre-defined time-window.

For RICON we have chosen the Sliding-box approach. Similar to the other approaches, this method has some advantages and disadvantages. Sliding box method allows the target variable to change over time and thus it is a better approach as compared to method (a) for capturing the dynamic nature of the systems. Moreover, as the sliding-box method formulates the problem as a binary classification, the existing machine learning literature is more dense as compared to the survival learning approaches in (b) and hence, makes the sliding box method more flexible in terms of modeling choices. On the other-hand, the data processing pipeline for sliding box method is dependent on the length of the look-ahead sliding box (\( \delta \)) and hence, modifying the window requires rebuilding the entire model from scratch unlike the case for method in (b). We have opted for the sliding box method as there are more flexibility for modeling and the length of the box is pre-defined from business as 24 hours – the minimum time required for intervening and thus retaining the customers with high risk of churn. In Sec. 4, we have also compared the performance of RICON with survival regression model for detecting customer churns to justify this choice of target variable generation.

3.3 Featurization

For RICON, the main data source for feature engineering is the clickstream data, which stores user click events that happen when the user is interacting with the product. Clickstream also stores timestamp of the event and some other relevant information e.g., country of accessing the product website, page url, ip-address, event description, device info etc. The main three fields that we have used are following:

(a) Customer identifier: Unique numeric identifier to join all the information for one user across multiple datasets.

(b) Click event: String describing the event that the user has performed in the product. Every action in the product has a unique click event string, e.g. if the user clicks on the option for viewing the quick report for their account, the corresponding click event is denoted as \([qbo|reports-|report|:ACCTLQUICKREPORT\]. As prominent from the example, this click event records the page hierarchy of the product as well as the actual event that happened.

(c) Timestamp: This a datetime field which records the time at which the click event happened.

This clickstream data is available in both real-time through Kafka and as Hive tables in datalake (AWS S3) which gets updated multiple times a day. Other than clickstream data, there exists company status data generated by the analytics teams which records the customer profile information, e.g. their subscription start datetime in QBO Advanced, end datetime if they have churned, through which channels they have started their subscription, type of the customer: whether the customer is new to the QuickBooks franchise or, they have upgraded to QBO Advanced from one of the other product streams within QuickBooks etc. These tables are stored in datalake as Hive tables and gets updated daily.

LWM features: For LWM, for a given customer and a given reference time point \( t \), we have considered all the click events that have happened in \( (t - 7 \text{ days}, t - h] \), where \( h \) is the lag in getting the updated click events in datalake. For our use-case, \( h \) can be in between one to two hours. By incorporating this lag in featurization we ensure that the LWM is not highly sensitive to most recent click events and rather captures the user behavior over a longer historical window. As there can be thousands of clicks for a single user in a period of 7 days, we have converted the long list of clicks to a fixed...
dimensional feature vector by computing daily average count of clicks over a set of most frequently occurred click events across the entire dataset. So, the feature vector of LWM for \( t \)th customer at a reference time point \( t \) is defined as:

\[
X_{ij}^t(t) = (c_1(t), \ldots, c_m(t), C(t)),
\]

where, \( c_j(t) \) is the daily average count of click event \( j \), and \( C(t) \) is the daily average total count of click events over a period of \((t-7, t-h)\). Here \( j \in \{1, \ldots, m\} \) denotes the \( m \) most frequent click events across the entire dataset. The advantage of this featurization is three-fold: (a) this featurization can easily be performed at scale by using PySpark ML CountVectorizer operation, (b) the length of the feature vector is uniform across multiple observations and hence easy to use in any kind of machine learning classifiers, (c) the daily average click counts are comparable across customers at different stage of their subscription tenures in QBO Advanced while the total counts might be affected if the tenure is less than 7 days at feature computation time. Through this featurization we ensure that the features are interpretable, easy to compute and implement, yet captures the overall pattern of user activities in the last week. Increasing feature window beyond one week did not yield any improvements in model metrics.

**SWM features:** In case of SWM, we use the click events in its most raw form, i.e. we use the sequence of click events in the last one hour and use that as our feature vector, i.e.,

\[
X_{ij}^{(s)}(t) = (e(t_1), \ldots, e(t_k)),
\]

where \((t-1) \leq t_1 < t_2 < \cdots < t_k \leq t\) are timestamps at which the click events \(\{e(t)\}\) occurred. The length of this feature vector can be anything in between 1 to a few hundreds. As the elements of this feature vector is not numeric in nature, we use this feature vector along with tokenizer and padding before passing to a sequence model with embedding with trainable weights.

**Ensemble model features:** Each of the LWM and SWM model outputs a probability score which are used as primary features for the stacked ensemble model. Along with the LWM and SWM model scores, we also include the customer profile information, e.g. type of the customer, age of the customer in QBO Advanced, channels through the customer onboarded in QBO Advanced as features for the ensemble model.

### 3.4 Model Training: Data and Models

To capture the dynamic nature of the product usage and customer behavior, we use multiple observations at different reference time points for one customer, as defined in Eq. 1. We have used 6 months of historical data, out of which first 5 months is our ‘train-period’ and last month is our ‘test-period’ (used to back-test the model). To define the reference points for a customer in the training period, we look at the following time frame: from the date the customer started their subscription with QBO Advanced to the date they are 31 days old in the product or, the date they have cancelled the subscription ~ which ever occurs early. The main goal of RICON within QBO Advanced is to reduce the rate of early churns and hence, we have restricted our study till the customers are 31 days old or in other words, they have finished one billing cycle. But the methodology is generic in nature and can easily be extended beyond 31 days.

**Reference points for train data:** For LWM, as the features are aggregated over a long window, the feature values are mostly static within a day and hence, we have used 24 hours as the time gap between two training reference points. Whereas for the SWM, the features being the raw sequence of click-events, reference points are taken to be hourly separated. To ensure that the modeling is not biased by the periodicity of the reference points, we have added random time shifts to the reference points making sure that it does not exceed the next or the previous reference time point.

For LWM, there can be at the most 31 reference time points for a customer, whereas for SWM there can be as much as \(31 \times 24 = 744\) reference time points. To maintain sign ambiguity, lets assume we want to train this model on 100k customers, then we can have upto 74 million reference points for SWM customers and up to 3 million reference points for LWM. Dealing this huge data is a bottleneck for many systems and is not cost-effective. To tackle this problem, we have introduced a time series block down-sampling technique.

**Time series block down sampling:** Instead of selecting random reference points for one customer, we divide the reference points into temporal blocks, where a block is a group of \(k\) consecutive reference points for a customer. Next we randomly select a subset of blocks and all the reference points within the selected blocks (see Fig. 5 in Supplement). This technique is inspired by the time series block bootstrap methodology used for estimation of higher order statistic for time series data [14]. So, if \( T = \{t_1, \ldots, t_n\} \) is the set of all reference time points for a customer, then the down-sampled set of reference points will be:

\[
\{t_1', \ldots, t_m'\} = \bigcup_{i \in \mathbb{B}_k} \{t : t \in \mathbb{B}_i\}
\]

where \( \mathbb{B}_i \) for \( i \in \{1, \ldots, B\} \) are \( B\)-many blocks in which the entire set of reference time points \( T \) has been divided into (i.e., \( \bigcup \mathbb{B}_i = T \)), \( s_k \) is a random sample of size \( b \) without replacement from \( \{1, \ldots, B\} \). For our use case, we have taken the blocks to be non-overlapping, i.e. \( \mathbb{B}_i \cap \mathbb{B}_j = \emptyset \) for any \( i \neq j \). By this block down-sampling methodology, we make sure that some consecutive reference points are selected for model training and that improves the robustness of the models, as showcased in Sec. 4. Moreover, this methodology allows to take multiple reduced size samples from the entire dataset of reference points and finally create an ensemble of models trained on different parts of the data. We refer this methodology as Time Series Block Down Sampling (TS-BDS).

**LWM model:** To model the churn propensity of a customer at a given reference time point using the long window user activity we have used a Gradient-boosting ensemble of decision trees. Through several experimentation we have justified the choice of this model.

**SWM model:** To model the churn propensity from the recent sequence of click events we have used a two layer BiLSTM model as shown in Fig. 3. The embedding layer has trainable weights so that the featurization can happen by maximizing the likelihood over the training data.

**Ensemble model:** Finally, while creating the stacked ensemble of SWM and LWM scores along with other customer level profile features, we first convert the SWM and LWM scores to negative log scale and then generate higher order polynomial features and use a regularized logistic regression with L1 penalty. By including
higher order polynomials we allow the estimation of churn propensity to be more flexible while the L1 penalty parameter restricts the model from overfitting.

**Threshold selection for churn prediction:** A threshold on final churn propensity score is required to classify observations (at reference time points) as ‘High’ propensity of churn vs ‘Low’ propensity of churn. The retention campaigns deploy the interventions and assist towards the predicted ‘High’ propensity cases. Due to resource, budget and user experience related constraints usually the retention campaigns try to target a small fixed percentage (say, p% = 10% or 20%) of the total customer-base and the predictive churn models help to identify the set of customers by selecting top p% in terms of predicted churn propensity scores. By this mechanism, the threshold is chosen based on back-testing results such that the percentage of customers falling in ‘High’ group is approximately p%.

For RICON, as the model is going to be evaluated at multiple time points for one customer, choosing the threshold to ensure the percentage of targeted customers in production is upper-bounded by p is not straight-forward. To do so, we aggregate the model scores at a customer level by taking the maximum of the model scores obtained at different reference time points in the back-test data. The threshold is defined by (100 - p)-th percentile of the maximum scores across customers in the back-test data. If the maximum score is not higher than the threshold for one customer, then the model has never predicted the customer in ‘High’ group, whereas if the maximum score is higher than the threshold then the model has classified the customer at least once as ‘High’ risk of churn. Hence, the total number of customers targeted by the campaigns using this threshold will be approximately upper-bounded by p%, assuming the back-testing data is a good representation of the production environment.

Note that, the above-mentioned threshold selection methodology cannot control the number of times a customer can be classified as ‘High’ propensity cases. We rely on the capabilities of the intervention campaigns to control how many times the customer will be intervened to ensure a good user experience even for the cases where RICON predicts one customer with high risk of churn multiple times in short interval of time. Please refer to Sec. 5 and Sec. A.1 for additional details.

### 3.5 Model explainability

In addition to the churn risk score, RICON also provides a set of ‘explainability’ output which can provide actionable insights to the CRM team for intervening the customers in the product.

**LWM Explainability:** To generate the explainability output for LWM, a SHAP explainer [17, 19] is trained on the training and back-testing LWM dataset. Then for each of the inference cases, SHAP explainer shows the contribution of each of the features for that particular inferred churn risk score. The sign of the SHAP value for a feature being positive or negative denotes whether that feature has contributed to increase or decrease the churn propensity of the inference case. Moreover, the SHAP explainer also indicates whether the corresponding feature value for the inference case is ‘high’ or ‘low’ by comparing them with the population average (computed from the data on which the explainer has been trained). As for LWM, the features are daily average count of clicks at certain click points in the product, we can easily associate the feature contribution insights from SHAP to the corresponding feature in the product. For example, if for the feature (daily average count in last week) corresponding to ‘account settings help text’ is high and the corresponding SHAP value is significantly positive, that can be translated to the CRM team as the customer is using the account settings help option very frequently in the last week and that has increased the churn risk of the customer. We attach this insight along with the model score for LWM inference.

**SWM Explainability:** Currently the LIME textExplainer or the SHAP deepExplainer do not support sequence of clicks or models with embedding layers respectively. Hence, for SWM, we have manually generated the explainability by back-testing our model on the test data. We compare the frequency distribution of click events for high churn propensity cases (top decile ranked by descending order by churn probability) vs the low propensity cases (rest of the deciles), based on the chosen threshold. The list of click events for which the marginal proportion of occurrence is significantly different between high and low groups, forms the candidate event set for SWM explainability. During the real-time inference, most recent event from the candidate set is passed as explainability insight from SWM.

**Ensemble model Explainability:** Ensemble model combines the explainability insight from LWM and SWM to provide the final explainability output. Essentially, another SHAP explainer is trained on training and back-testing ensemble model dataset. To construct the final explainability output we look for features in the ensemble layer that have significantly positive SHAP values. If the SHAP values for any of the LWM or SWM score based features is significantly positive, we include the explainability insights from LWM or SWM models in the final explainability output. Moreover, if the user profile features also have positive contribution to increase the churn risk, we include them as well in the final explainability output. This output is automatically passed to the CRM agents helping the customers at the time of intervention or call-backs.

### 3.6 Model deployment in production

We have set up the data processing, model training and model inference as an end-to-end (e2e) automated pipeline. Without any
manual effort or intervention the data processing, featurization, model training and finally model inference happens automatically.

**Featurization:** There are two steps of featurization for RICON: (a) one batch featurization for generating features to be used for LWM, SWM and Ensemble model training (b) one real-time featurization to be used for SWM inference. We used PySpark for both batch and real-time domains of computation due to its proven performance characteristics at scale as well as familiarity with scientists and engineers alike.

The batch featurization processes millions of historical events along with other company status and analytic data from datalake (built over AWS S3) on a daily basis using PySpark jobs scheduled over Kubernetes. It generates and stores features to be used for model training in S3. The batch nature of job allows for massive parallelization across executors with ability to tune for cost and speed. The real-time featurization on other hand uses Spark’s Structured Streaming with executors running over Kubernetes. The featurization scales horizontally with available data partitions in source (Kafka) and can be tuned accordingly for factors such as size of time-domain split, latency requirements as well as volume of incoming clickstream events. Real-time featurization ingests the resulting features to a low-latency Feature Store built over AWS DynamoDB to be used by the SWM model for real-time inference.

**Model training pipeline:** All training and inference code is packaged into containers with CI (Continuous Integration) pipelines. The training is done using AWS SageMaker training jobs.

**Batch inference:** The LWM batch predictions are generated in parallel by executing inference code in parallel containers with different partitions of features. The resulting predictions from LMW are also ingested into Feature Store for low-latency access during real-time inference.

**Real-time inference:** Real-time inference is done by deploying code to AWS SageMaker Inference. The inference endpoints are placed behind an Intuit’s API Gateway providing Authentication and Authorization to model API. The inference works by fetching LWM predictions and SWM features from Feature Store’s DynamoDB on incoming request to evaluate the ensemble model and return response synchronously.

**Orchestration:** The entire pipeline for featurization, model training and deploying real-time inference endpoint is handled end-to-end using an internal ML framework. The framework uses Kubeflow for scheduling Spark jobs and allows to declaratively specify the pipeline steps for featurization, training and inference deployment, while handling CICD (Continuous Integration, Continuous Deployment), artefact storage and monitoring. Refer to Sec. A.3 for more details on deployment architecture.

4 EXPERIMENTATION RESULTS

4.1 Test Data

For evaluating RICON we selected a historical time frame of 181 days out of which the last 31 days is our ‘test-period’ and the first 150 days is our ‘train-period’. We selected a sample of 25,000 customers among all the customers who had active subscription for at least one day in the above-mentioned time frame. Out of them, approximately 6,000 customers had active subscription in the test period for at least one day. The baseline churn rate in the test-data, i.e. the ratio of number of customers who have churned voluntarily to the number of customers who had active subscription at least one day within the test-period, is 5%. Similar to other studies [3, 6] related to customer churn, the test-data for our experiment is highly imbalanced. As the objective of RICON is to detect the customer churns in real-time, the model needs to be evaluated multiple times within a day for one customer. Hence, to evaluate the ‘real-time’ performance of RICON we have constructed the test data by taking 24 hourly reference time points for all of the days the customers had active subscription in QBO Advanced. These 24 reference points are randomly selected within each hour, i.e. the first reference point is chosen randomly within 12:00 AM to 1:00 AM PST, the second one is a random time point within 1:00 AM to 2:00 AM PST and so on. The random sample of daily reference points are drawn separately for individual customers. Under this experimental design, based on the variable customer tenures within the test-period we have approximately 987,000 test reference time points to evaluate our models on. Out of these 987,000 observations, only 2872 reference time points have observed a churn within the next 24 hours. Hence, the test data is highly imbalanced in nature with proportion of positive cases to be 0.3%.

4.2 Evaluation criterion

In many studies [8, 22], authors have used the usual binary classification metrics e.g. accuracy, precision, recall, F1-score or the ROC-AUC score. But, for the experimental design mentioned in Sec. 4.1, some of these metrics might not be best suited to evaluate models. For example, if one model score is above threshold for a reference time point which is earlier than the 24 hours prior to the churn date of a customer, by the definition of sliding box target variable, the prediction will be taken as a false positive case. But, often the models can capture churn signals in customer behavior early (e.g., see Fig. 7 in Supplement) and so, the metrics which penalizes these cases is not optimal choice for this problem. Hence, instead of evaluating the binary classification models in isolation, we aggregate the scores at customer level (as mentioned in threshold selection part of Sec. 3.4) and compute the following metrics.

**Lift Metrics:** In problems, where the event of interest is rare in nature, e.g. customer churn, road accident, credit card fraud, loan default etc., and campaigns are designed to target the customers with high risk of these events, decile lift chart is a well-accepted metric both in industry and academia [6, 16, 20, 23]. The decile lift at decile d (DL@d) is defined as:

\[
\text{DL}@d = \frac{\text{Churn rate for top } (10 \times d)\% \text{ users}}{\text{Baseline churn rate for all users}}
\]

for d ∈ {1, ..., 10}. So, higher the lift at decile d, the more accurate a model is and hence, the more effective the customer retention campaign is to target customers who actually churned. For comparative study we have used DL@1 and DL@2 as most of the retention campaigns target top 10 to 20% of the customers. For a set of selected methods we have plotted the entire lift chart for all d ∈ {1, ..., 9}.

**Average time from detection to churn:** Though the DL@1, DL@2 and the lift chart capture the performance of the models for predicting customers who are going to churn, it does not capture the real-time prediction efficiency. One of the many advantages of real-time churn prediction is the early detection of future churn
events. The earlier one model detects the future churn of a customer, more time there is for the CRM team to engage with the user and take necessary actions to prevent the churn. To measure this, we have defined a metric named Average Time from Detection to Churn at decile d (ATDC@d). Suppose for \( i \)th customer in the top d-decile (based on the customer-wise maximum model scores) \( T_i = \{ t_{i0}, \ldots, t_{in} \} \) are the reference time points in the test-period and say \( t_{i0} \) is the first time the predicted churn propensity has crossed the threshold. Then Time from Detection to Churn (TDC) for this customer is defined as:

\[
TDC_i = \begin{cases} 
    t_{i0} - t_{ij} & \text{if } \text{ith customer churns at } t_{ij} \in (t_{in}, t_{in+24 \text{ hrs.}}] \\
    0 & \text{otherwise.}
\end{cases}
\]

Finally, the ATDC@d is defined as:

\[
\text{ATDC@d} = \frac{\sum^d_{i=1} TDC_i}{\text{total number of customers who churned}}.
\]

where, \( \Sigma^d \) is the summation taken over all the customers who are in the top d-decile based on customer-wise maximum predicted model scores. Clearly, the more customers who churned is grouped in the top decile bracket and the earlier the churn is detected by the predictive model, higher the value of ATDC@d will be. We have considered ATDC@1 for our studies and note that, it is similar to the recall metric where instead of adding indicators in the numerator we are adding the time the predictive model is providing to the CRM team to save the customer from churning. For comparative study, we have provided a baseline value of ATDC@1 by computing it for a model with no predictive power.

### 4.3 RICON system specification

To train components of RICON we have constructed separate training datasets for LWM, SWM and ensemble models. For each of these models we take an independent sample of 25,000 customers who have an active QBO Advanced subscription for at least one day in the training period of 150 days (as mentioned in Sec.4.1). For LWM model we take reference time points separated by a day, whereas for SWM and ensemble we take reference time points separated by an hour. To tackle the data volume and the high imbalance of class, we use TS-BDS to down-sample the negative cases, i.e. the reference time points where there is no churn in next 24 hours. The details of the hyper-parameters and other variables for LWM, SWM and ensemble are specified in the Supplementary Material (A).

In addition to RICON, we have also evaluated the LWM and SWM models individually, without the stacked ensemble. This is done to showcase the advantage we get by combining the SWM and LWM models scores to get the final estimate of churn propensity.

**Implementation resources and cost:** RICON is deployed on AWS, and as mentioned in Sec. 3.6, can be divided into five subsystems and corresponding resources: batch featureization, real-time featureization, model training, batch inference and real-time inference.

The batch featureization processes approximately 350 million click-events daily along with some other analytic data from data-lake and stores the features in S3 to be used for model training. The computation cost comes around $500 per month for this. On the other-hand the real-time featureization for real-time SWM inference costs around $4500 per month which processes on an average 100 thousand click-events hourly. The model training and batch inference on decently sized instance in AWS Sagemaker takes around 2 hours combined and costs approximately $200 per month. Finally, the real-time inference hosting costs around $250 per month to ensure a latency of 200ms handling up to 20 evaluate requests per second.

The above-mentioned prices are on-demand AWS EC2 equivalent of compute costs and can be lowered by using the discount methods provided by various cloud providers.

### 4.4 Baseline Approaches

We have compared the performance of RICON with a set of existing methods of churn prediction as described below.

**Batch binary classifiers:** For batch models, usually a customer churn prediction happens when they have completed a pre-defined tenure in the product, e.g., 7 days or one month. We have considered Random Forest (Batch-RF), Logistic Regression (Batch-LR) and a Feed Forward Neural Network (Batch-FNN) for our comparative study. These models take the click counts in different product features for the last 7 days as features. In the batch mode, the predictions are generated daily for the existing customers who have active subscriptions for more than last 7 days.

**Real-time binary classifiers:** For real-time models to detect churn, the model is pre-trained and the featureization for inference cases happens online in real-time. The only data that these models can make use of are the dataset that gets continuously updated and available in real-time. In this category we have considered the following set of sequence models: a LSTM model with one-hot encoded click sequences (LSTM-OH), a LSTM model with unsupervised skip-gram embeddings (LSTM-SG) and a Transformer model with token and positioning embeddings (Trans-TP). The feature to these models are same with the SWM model of RICON, i.e., the sequence of clicks in last one hour.

**Survival models:** Survival modeling is another approach for predicting churn as described in Sec. 3.2. First, we have considered Random Survival Forest (Batch-RSF) [10], a tree-based ensemble to estimate the survival function from censored data, in batch mode using same featureization as other batch models. Next, we have considered a real-time neural network-based survival model (Real-time-DeepSurv) where using the recent sequence of clicks we try to estimate the survival function. The architecture used has been borrowed from a deep learning based survival regression model known as DeepSurv [12]. For computing DL@d for survival models, we convert the survival probability scores to propensity of churn within next 24 hours and then group the top decile customers based customer-level maximum of predicted churn propensities.

The details of hyper-parameters for these baseline approaches are given in Sec. A.1.

### 4.5 Results

In this section, we record the performance of the experimented models and draw insights from the comparative study executed.

**Comparative analysis:** In Tab. 1, we have recorded the top two decile lifts along with ATDC at the top decile for all the models considered in this experiment. The DL@1 and DL@2 metrics measure
the performance of the model to group the customers who actually churned in the top two deciles, whereas the ROC-AUC score indicates the overall classification performance of the model. ATDC@1 in addition to the above three metrics, indicates the expected time the CRM team have to engage with the customers across all the actual churn cases.

| Model type       | Model name | DL@1 | DL@2 | ROC-AUC | ATDC@1 (hrs.) |
|------------------|------------|------|------|---------|---------------|
| Batch            | Batch-RF   | 1.84 | 1.33 | 0.54    | 44.00         |
|                  | Batch-LR   | 1.05 | 1.04 | 0.52    | 8.84          |
|                  | Batch-FNN  | 1.13 | 1.04 | 0.53    | 30.26         |
| Real-time        | LSTM-OH    | 1.01 | 0.96 | 0.49    | 10.81         |
|                  | LSTM-SG    | 2.04 | 1.45 | 0.51    | 32.65         |
|                  | Trans-TP   | 1.65 | 1.47 | 0.53    | 24.15         |
| Survival         | Batch-RSF  | 1.40 | 1.46 | 0.64    | 32.75         |
|                  | Real-time/DeepSurv | 0.91 | 0.81 | 0.49    | 14.55         |
| RICON Components | LWM        | 1.91 | 1.86 | 0.69    | 46.05         |
|                  | SWM        | 2.15 | 1.81 | 0.54    | 37.62         |
|                  | RICON      | 2.68 | 2.16 | 0.71    | 48.75         |
| Non-predictive baseline Random | 1 | 1 | 0.50 | 14.72 |

Table 1: Comparison of RICON with a set of alternative churn prediction methods in terms of decile lift, roc-auc and time given to the CRM team from first detection to churn.

Among the models for which the predictions are generated in batch mode, Random Forest (Batch-RF) has the best performance with a top decile lift (DL@1) of 1.84 and ATDC@1 of 44 hours. As the feature vector for these models are high dimensional (counts of clicks across 3000 different product features in last week), there can be strong correlation and internal dependance across the features and hence, Logistic Regression (even with L1 penalty) and FNN have failed to outperform the tree-based ensemble in this case.

For the real-time short window based models, the predictive model identifies customer reference time points with high risk of churn using the last one hour sequence of clicks. The first model considered in this category is LSTM-OH where instead of using an embedding layer we use one-hot encoded sequence of clicks and pass it through a LSTM model. As can be found in Tab. 1, LSTM-OH has very similar or worse accuracy as a non-predictive model. On the other-hand, other models in this category, i.e. LSTM-SG, Trans-TP and SWM of RICON have decent performance in top deciles and this justifies the importance of embedding layer in problems where sequence of clicks is considered as feature. LSTM-SG has shown very good accuracy in the top decile (DL@1) but the performance drops sharply from 2.04 to 1.45 as we move from DL@1 to DL@2. For the Transformer architecture with token-and-positioning embeddings (Trans-TP), though the top decile accuracy is not as good as LSTM-SG, the overall classification ability of the model is better than LSTM-SG in terms of ROC.

Next, we have considered two variants of survival models. The Batch-RSF is a tree-based random forest ensemble for estimating the survival step function and the predictions are generated in batches. Though the top decile performance of the Batch-RSF is not as good as Batch-RF, Batch-RSF is one of the best performing model in terms of overall classification ability (ROC and drop from DL@1 to DL@2). The other model considered in the experiment from survival models is Real-time-DeepSurv. It is a deep learning based model to estimate the time to event survival function. Though this model has shown promising results in many use-cases in biomedical sciences, for our problem of identifying customer churns in real-time, this has performed poorly.

Finally, we have recorded the performance of RICON. The LWM component of RICON alone has outperformed all the batch models considered in the experiment. Since LWM can also score customers who have not completed even a week in their subscription, it is superior than all the other batch models in terms of all the metrics. Similarly, the SWM component of RICON alone is also superior than other real-time models – which justifies the architecture choice for SWM. Finally, RICON – with the ensemble of SWM and LWM – achieves a top decile lift of 2.68 with an ROC-AUC score of 71%. As shown in Tab. 1, SWM has higher top decile lift but the lift drops sharply from decile 1 to 2, whereas LWM has more stable performance across top two deciles and the overall classification ability is higher. The ensemble of SWM and LWM has helped to retain the good performance of SWM yet the robust nature of LWM and thus achieved an improvement in all the metrics: DL@1, DL@2, ROC-AUC and ATDC@1. In Fig. 4, we have plotted the lift chart for all components of RICON and best performing models in each category. By achieving a top decile lift of 2.68 in a highly imbalanced dataset (with only approx. 5% customers churned), RICON has a state-of-the-art performance by comparing with existing novel techniques of churn predictions [6, 7].

**Effect of TS-BDS:** To showcase the efficacy of the TS-BDS based down-sampling mechanism, we compared it against the approach of random down-sampling of reference points. With similar training sample size, we observed 11% reduction in average of DL@1 and DL@2 for random sampling approach, as compared to TS-BDS approach. (more details in Tab. 2 in Supplement).

5 ML-BASED PROACTIVE AND REAL-TIME INTERVENTION IN QBO ADVANCED

**Real-time proactive intervention:** RICON can be integrated with Intuit’s in-product intervention platforms to run large scale retention campaigns with real-time, contextual and proactive interventions. A RICON evaluation (via a HTTP endpoint) at any given time for a customer provides the churn propensity of the user based on
the recent and long-window product usage. Each evaluation also provides set of explainability insights drawn from the customer’s product usage intelligence and profile information. RICON further classifies the customer at that time point to be at ‘High’ or ‘Low’ risk of churn depending on a threshold. This threshold is chosen based on back-testing results using previous month’s churn data is such a way that only top 10% of the customers are classified as ‘High’ risk. When a RICON evaluation returns ‘High’ risk of churn, a proactive chat window pops up in the product and presents relevant help article based on the explainability output from the model. For further help, customer is provided an option to directly chat or call a CRM agent (as shown in Fig. 8). The intervention platform in that case takes the explainability output from RICON and passes it to the connected agent to provide context and insight before-hand.

Event-based model trigger: RICON evaluates propensity in real-time. This allows service consumers to evaluate each customer by using a pre-defined frequency, e.g., every hour. For example, to evaluate 500K customers via RICON hourly would make almost one evaluate request every hour for every customer for a short burst of time. Batching requests is ineffective here since DynamoDB-based Feature Store is optimized more for point queries. This requires provisioning enough capacity for burst load. Continuous evaluation of the model for all customers for every time schedule hence is not cost effective due to reasons such as fixed-time evaluations, missing customer context due to time lag, increased inference hosting costs, non-uniform load on inference endpoint and caching requirements of inference results until next evaluation schedule for consumers. Since churn is a rare event and the models within RICON are trained to handle the data imbalance, the predicted churn propensity will rarely cross the threshold to be classified as ‘High’. Thus we proposed a click-event based RICON evaluation allowing consumers to request evaluation on certain events of interest. From our back-testing results, we created a super-set of such click-events which are likely to change the model scores by using the feature importances of LWM and SWM (as described in Sec. 3.5). The intervention platform then evaluates a customer using RICON endpoint whenever such an event is detected. This reduced the evaluation requirement from 500K requests per hour down to almost 70K requests per hour. This approach has the advantage of the customer being online in product at the time of inference (due to low latency of click events) as well removes any evaluation requests for users which are offline at a given time thus reducing inference costs. Further, this results in uniform inference request load to RICON endpoint as well removes any need for caching the predictions on consumer side.

6 CONCLUSION
We have proposed a cost-effective, robust methodology RICON for real-time churn prediction. RICON can use both slowly updated data and real-time streaming data for featureization and predict churn propensities in real-time. By using ensemble of small window and long window based product usage behavior, RICON has outperformed not only batch churn models, but also other possible real-time and survival models.

We have described how RICON can be used within Intuit for running large scale retention campaigns with real-time, contextual, within product and dynamic interventions. The application of RICON is not only limited to retention campaigns, but it can also be used for contextual feature recommendations, discount offerings, digital assistant-based helps etc to assist the customers in more automated fashion.

With the advancement of data mining and machine learning techniques, large-scale automated, real-time yet contextual retention campaigns are becoming a necessity in subscription-based commerce. Our work is a step towards enabling the CRM team to design such retention campaigns with the help of cutting-edge machine learning and data mining techniques.

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A SUPPLEMENTARY MATERIALS

A.1 Additional modeling details

RICON specifications: In this section we provide the details of the hyper-parameter and model choices made for training RICON for the experimental results stated in the main paper.

For LWM training, we have used TS-BDS to sample 5 blocks of 3 consecutive reference time points (as shown in Fig. 5) from non-event observations, which ensures at most 15 reference time points with target variable 0 per customer. We trained the LWM model on approximately 300,000 reference points with proportion of positive cases to be 2.9%. We further used Borderline SMOTE to over-sample the positive cases with oversampling proportion to be 10%. Finally gradient-boosted ensemble of decision trees from scikit-learn was trained and the chosen hyper-parameters based on maximizing 5-fold cross-validated ROC-AUC score are: \( n_{\text{estimator}} = 500, \text{learning rate} = 0.01, \text{max_depth} = 3, \text{max_features} = \sqrt{n_{\text{features}}}, \text{subsample} = 0.8 \).

For SWM training, we have used TS-BDS with 4 blocks of 3 consecutive reference time points to down-sample the negative cases. SWM model architecture was implemented using keras framework from tensorflow-2.2. We trained the SWM model on approximately 500,000 reference points with proportion of positive cases to be 3%. The size of the tokenizer dictionary is set to 3000 and the maximum length of a sequence of clicks is set to 100 for pre-padding of the sequences. We train the model shown in Fig. 3 with embedding vector length equal to 10, two BiLSTM layers with 16 units, 10% spatial drop-out layers and finally a two layer feed forward network with width 30 and 15 with ReLu activation. The model weights including the embedding layer are estimated by minimizing binary cross-entropy loss using ADAM optimizer with learning rate equals to 0.001. To tackle the imbalance of the data, 5x more class weight was assigned on the positive classes while training.

For ensemble model, we used the trained SWM and LWM models to generate the LWM and SWM scores for ensemble training points. We used similar TS-BDS based down-sampling of negative cases with 4 blocks of 6 consecutive reference time points and Borderline SMOTE based over-sampling of positive cases before training the scikit-learn-based logistic regression with L1-penalty. The regularization parameter C has been chosen from a grid with 20 values varying from 0.001 to 2 by maximizing the 5-fold cross-validated ROC-AUC score.

Baseline models specifications: For Batch-RF and Batch-LR we have used a pre-defined hyper-parameter grid to choose the final hyper-parameters by maximizing 5-fold cross-validated ROC-AUC scores. For Batch-FNN, we have used keras framework within tensorflow-2.2 to train a model of depth 2 with width 30 and 15. The output layer has a sigmoid activation while the two hidden layers have ReLu activation. At each layer we allow a dropout of 0.2. Finally the weights of this model is estimated by minimizing binary cross-entropy loss with ADAM optimizer with learning rate 0.01.

For the LSTM-OH and LSTM-SG we have used the same neural network architecture as of SWM apart from the embedding layer. For LSTM-SG we have used a pre-defined embedding matrix obtained by unsupervised training of a Skip-Gram Word2vec model from package gensim with vector size = 10 and window length = 5. For Trans-TP we have replaced the two BiLSTM layers in SWM by a transformer block with two attention heads and 10 dimensional feed forward layer and substituted the embedding layer with a token-and-position embedding with vector size = 10.

For the Batch-RSF we have again chosen the hyper-parameters from a pre-specified grid to maximize the cross-validated concordance index. For Real-time-DeepSurv we have used the MLPVanilla model from the pycox package with two layers with 32 nodes each. The weights of this model are estimated to maximize Cox-proportional hazard likelihood with AdamWR optimizer.

A.2 Additional results from experimentation

In Tab. 2, we have recorded the incremental gain in accuracy in terms of average of DL@1 and DL@2 and training time if in place of TS-BDS a random down-sampling of the negative cases were performed. We executed this comparative study for training the LWM component of RICON on a AWS Sagemaker with ml.m5.2xlarge instance. From Tab. 2, it is clear that TS-BDS has advantage over ran-

| Method                  | % change w.r.t. TS-BDS | Avg.(DL@1, DL@2) | Training Time |
|-------------------------|------------------------|------------------|---------------|
| Rand-DS: same sample size | -11.29%                | -0.91%           |
| Rand-DS: 2x sample size  | -0.26%                 | 104.37%          |
| Rand-DS: 3x sample size  | 1.31%                  | 288.38%          |

Table 2: Accuracy and training time for random down-sampling in comparison with TS-BDS.

dom down-sampling for our experiment both in terms of accuracy gain and training time and cost reduction.

A.3 Additional details of production deployment

In Fig. 6, we present the deployment architecture for RICON as described in Sec. 3.6. At high level the architecture consists of three major components: a batch data processing jobs that process data stored in datalake, a real-time featureization job processing clickstream data from product, and model training & inference hosting using AWS SageMaker.

Datalake is built over AWS S3 with a central Hive Metastore maintaining all the associated metadata. Real-time featureization uses Structured Streaming in Spark to process clickstream events.
while consuming events from an internal Kafka cluster. The generated real-time features and LWM batch predictions are ingested in real-time to a Feature Store which is built around AWS DynamoDB with additional capability for metadata management, health monitoring and data governance. All Spark and SageMaker jobs are scheduled using Kubernetes with AWS EKS as control plane. An internal management service administers roles and policies for access control, isolation and security in a self-serve manner. The entire pipeline execution is managed end-to-end using an internal ML framework built around Kubeflow, which uses Argo Project for deploying over Kubernetes.

Next, we present some examples for the temporal profiles of the predicted churn propensity scores along with the chosen threshold (to target top 10% customers) in Fig. 7. Fig. 7 (a) and (b) are examples of ‘early’ detection of churn events. Specifically in Fig. 7 (b) RICON detected the user to have high risk of churn at very early stage of their subscription tenure and there was no activity in the product after first few days. Finally the churn happened after a few days – this is a classic example of ‘implicit churn’ where the user has already stopped using the product but the churn event happens once the user voluntarily cancels the subscription. Moreover, note that, RICON can put one customer in high propensity of churn for multiple consecutive evaluations and hence, under the current deployment mechanism the intervention campaign platform needs to manage the frequency of intervention for better user experience. To do that, based on domain-driven business logic a pre-defined lower-bound interval is defined and after one successful intervention next one does not happen till that specified interval passes.

In Fig. 8 we provide a screenshot of the proactive churn based intervention using RICON in QBO Advanced. The other possible ways of intervention includes digital assistant-based self-help articles, call from an agent if further assist is requested by the user. Based on the explainability output provided by RICON, digital-assistant based self-help articles are created for automated interventions in product. An option is provided to the user for further help if needed where agents are available for chat and call. The product-usage based explainability output provides a context for the agents to make the assistance experience better for the users.