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MASTERS THESIS

Using machine learning to model the temporal patterns of music listeners

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Declaration of Authorship

I, Badrul ALOM, declare that this thesis titled, “Using machine learning to model the temporal patterns of music listeners” and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
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- I have acknowledged all main sources of help.
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Abstract

Faculty Name
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Master of Science

Using machine learning to model the temporal patterns of music listeners

by Badrul ALOM

While areas of customer recommendation have received a lot of attention in recent years, predicting users behaviour, particularly the timing of their actions, has not had as much focus. The modeling of temporal processes representing human behaviour can be applied across many industries. In this research we examine different methods for predicting a user generated event based on analyzing the timing of their past interactions. Our context is that of music listening and we examine a Bayesian inference model, logistic regression, a linear and RBF SVM, and a RNN-LSTM model. We find that none of these beat our baseline which assumes event at time t matches event at time $t-1$. However this suggests a need to define the problem to detection of the start and end of a sequence of play events.

We find that precision and recall pose a trade-off, with a linear SVM being better at the former and an RBF model being better at the latter. We also find that an RNN model achieves relatively good result with a low amount of training data and expect that as computaitonal power improves it will lead to top in class results in this area.

Chapter 1

Introduction

The modeling of events is useful across industries. For instance the times at which a customer makes an online purchase can help determine the optimal periods for target marketing. The times at which public transport users tend to travel can help better manage resources to meet demand. The times at which a medical illness reoccurs can help predict future episodes. In all these cases modeling the temporal behaviour of the system is important in predicting the occurence of the next event.

Within the field of recommender systems, the area of predicting *what* a user would be interested in has received extensive attention in recent years, but *when* they would be interested in it, less so. In this research we look at how we can model the temporal behaviour of users, in order to help guage their interest in an event at current time t, conditional on their history, h. More formally this is known as a temporal point process and we examine the existing methods for modeling such problems as well as recent experimentations with applying deep learning to the problem.

We compare various classicial linear and non-linear techniques, but find they struggle to exceed our simplistic baseline model, suggesting a need to reframe the problem being solved. The research also suggests achieving a high precision and recall score on temporal point process problems requires a non-linear model with an RBF SVM model performing well. Our experiments with an RNN-LSTM model were inconclusive. Further investigation with additional features such as introducing a dropout may help the model to generalize better across more iterations.

1.1 Context

We take as our context for this research, the goal of estimating the probability that a user of a home-audio device would like to listen to music at a time period t, given their play history h. One application of this research would be to allow home audio devices to recommend music to a user at an ooportune time. It could then also be extended for other activities.

The goal was to evaluate the effectiveness of several different machine learning methods. The research was guided by Emotech Ltd., a home audio hardware and software company and the creators of Olly [14].

1.2 Data

The dataset being used in this analysis is the LastFM1k dataset, which is freely available online and contains the listening history of a thousand LastFM listeners. It consists of a series of timestamps denoting when a user started playing a song. We wish to learn the temporal patterns of a user's behaviour in order to predict the next item in the sequence - a play or non-play event.

The dataset contains the timestamp, user ID, and track ID of users listening habits over a number of years (2005-2009).

1.3 Structure of the report

In the next chapter we perform a brief review of existing methods of modeling temporal point processes. In Chapter 3 we detail the design of the experiments performed. Chapter 4 then presents the results of the preliminary analysis that helped shape the experimental design, before presenting the main results themselves and discussing each model in turn. Chatper 5 then concludes the report with a summary of insights and suggestions for how the research could be progressed.

Chapter 2

Literature Review

Analyzing event data presents its own unique challenges and questions. What are the ways to represent the data? What types of stochastic models are appropriate for explaining the structure in the data? How can we measure how well the data is described by a particular model? Within literature the problem is referred to as event prediction, sequence prediction, or temporal point process modeling.

When modelled as a temporal point process, the data can be represented as a sequence of fixed period intervals in one of three ways: as an ordered list of event times $T_i, ...T_n$, as inter-event times $U_1, ...U_n$ where $u + i = T_i - T_{i-1}$, or as a counting process where $N(t)$ is a count of the number of events occuring before time t [1].

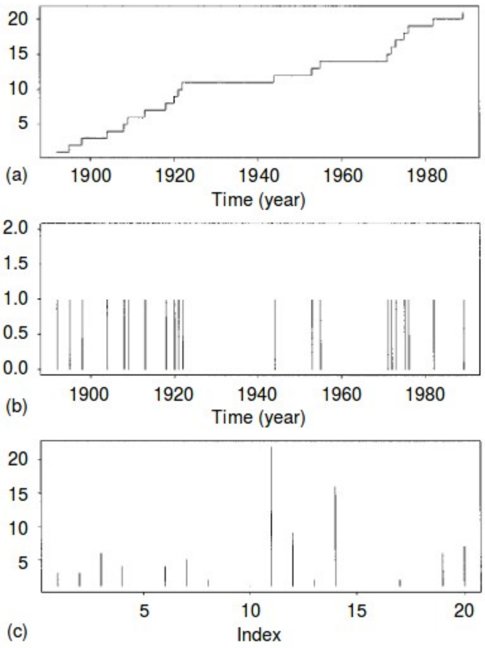


FIGURE 2.1: Three different representations of the same point-process
a) event count b) date of occurence c) inter-event time

Of these, inter-event time is the most commonly used, for example in the times between financial transactions [7]. An example of the counting process is the socring of goals in soccer [9]. In the case of music listening, we can model a sequence of events and non-events, where t_i can either be 0 (did not play music) or 1 (played music). This is the form we use in all but the Bayesian model as described in the next chapter.

Conditional Intensity Function

The conditional intensity function, $\lambda(t)$, represents the infinitesimal rate at which events are expected to occur around a particular time t, conditional on the prior history of the point process prior to time t. A Poisson process [10] is a simple point process in which the probability of an event at time t is assumed to be independent from all other times, and where the conditional intensity function follows a Poisson distribution based on λ. λ may be estimated parametrically [6] or via a parametric model. With the Poisson process, λ depends only on t, where as in other point process models it would depends on the history preceding t.

If the conditional intensity remains constant over time it is referred to as a homogenous or stationary point process [5]. If however it can vary with time it is inhomgenous, such as the self-exciting (Hawkes) process where the intensity is determined by previous events through the parametric form $\lambda(t) = \mu + \beta \sum_{t_i < t} g(t - t_i)$ and where g is a non-negative kernel function. Note that the logit function used in generalized linear model, can also be thought of a conditional intensity function and has been used to develop sophisticated models such as [2] and [18].

However, as noted by Wass et. al [22], point process models using a condictional intensity function often make various parametric assumptions about the latent dynamics governing the generation of the observed point patterns. As a consequence, model mis-specification can cause significantly degraded performance in point process models.

Deep Learning

In recent years deep learning has demonstrated the power to learn hierarchical nonlinear patterns on large-scale datasets [12] through multiple layers of abstraction (e.g. multi-layer feedforward neural networks). It has achieved state-of-the-art performances on a wide range of applications, such as computer vision [11], natural language processing [20], and protein structure prediction [13].

However it has not been applied to temporal point processes until recently with Xiao et. al [22] applying Generative Adversarial Networks (GANS) to the problem. GANs consist of two neural network models - a generator tasked with generating (i.e. predicting) a future sequence of events based on the history, and a discriminator tasked with detecting the true (ground truth) sequence amongst the generated ones.

For measuring the loss between a generated and true sequence, the authors found the Wassertein-Distance [15] performed better than Maximum Likihood Estimate (MLE) which they remarked "may suffer from mode dropping or get stuck in an inferior local minimum".

Their findings showed that while parametric point process models work better with problems where a parametetric form exists, with real world data a GAN model with Wasserterin-Distance outperforms all other models.

2.0.1 Recurrent Neural Networks (RNN)

RNNs are a type of artificial neural network designed to recognize patterns in sequences of data, such as text, genomes, handwriting, the spoken word, or numerical times series data emanating from sensors, stock markets and government agencies. Whilst a traditional Feed-Forward network [19] has input nodes, hidden layers, and an output layer, with data flowing in one direction only, RNNs allow for the hidden state from one timestep of the neural net to be an input into the next (see fig. 2.2).

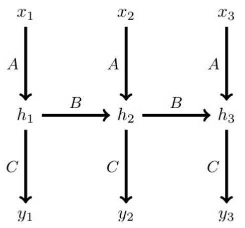


FIGURE 2.2: RNN with 3 timesteps

RNN models can employ different methods for the propogration of the hidden state over time. One such well known method is Long Short-Term memory (LSTM) [17]. Here the hidden state is the product of a further four layers that interact in a way as to learn what information to retain and what information to throw away.

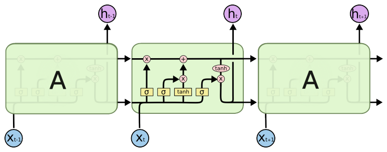


FIGURE 2.3: LSTM

Recently [23] attempts have been made to combine concepts of temporal point processes with that of an RNN. The authors viewed the conditional intensity function of a point process as a non-linear mapping between the predicted transient occurrence intensity of events with different types, and the model input information of event participators, event profile and the system history.

They model this non-linear mapping by utilizing two RNNs: one for modeling the time-series data and associated features and a second to model long-range dependency over history with arbitary time intervals; specifically a sequence of event type and the time since the previous event. In this way they can capture both the temporal based patterns, as well as the non-temporal, event-correlations which approximates to a conditional intensity function based on inter-event time.

The favoured evaluation metrics in their research were precision, recall, f1 score, and a confusion matrix, with a logistic regression model used as a baseline to compare against.

2.1 Summary

While not an exhaustive review of techniques we have seen some of the ways in which point processes can be modelled using traditional conditional intensity based models, as well as more recent areas of experimentation using deep learning. In the next chapter we layout the approach and methods we wish to explore in the context of this research.

Chapter 3

Experimental Design

In this chapter we describe the different methods that were assessed. The methods, in order of gradually increasing sophistication, are as follows:

1. Baseline model
2. Bayesian Inference
3. Binary Logistic Regression
4. Linear SVM Classifier
5. Non-Linear SVM Classifier
6. Recurrent Neural Networks

All methods, except for the Bayesian Inference method, require the data to be structured as a time-series. The Bayesian method adopts a different approach that requires the data to be aggregated into half-hourly buckets of a week. The data preparation that was performed is described in the next section, followed by an explanation each method, and the evaluaion criteria for assessing the methods in the sections that follow.

3.1 Data preparation

3.1.1 Data transformation

The analysis was carried out in Python (via Jupyter notebooks) running on Ubuntu. The raw data consisted of timestamps of when a song was played and a user ID. These were loaded as-is into a SqlLite3 database in order to reduce the need to repeat data preparation steps. The methods themselves utilized Scikit-learn for all models, save for the RNN model which used Tensorflow.

UserIDs were converted to integer (e.g. 'User0005' became '5') and a period lookup table was created at n minute intervals, against which all timestamps in our main dataset were mapped to. n was chosen to be a period of 30 minutes.

The data, which contained entries for the times at which each user listened to music, was supplemented with all the times they did *not* listen to music, between their date of their first and last play. This was required in order to generate a sequence of play and non-play events.

3.1.2 Feature selection

The features that were chosen were based on the preliminary analysis (see next chapter) and consisted of time-seried and non-time series features. The time-series features were binary, representing play (1) or non-play (0) events at $t, t-1, t-2, t-3, t-4, t-5, t-12hrs, t-23.5hrs, t-24hrs, t-24.5hrs, t-1wk, t-2wks, t-3wks$, and $t-4wks$.

$t-1$ to $t-5$ represent user activity in the previous 2.5 hours. The remaining time-lags were chosen to represent half-day, daily, and weekly cycles, with additional empahsis around the -24 hour mark due to the daily patterns observed in the preliminary analsysis.

The non-time lag features were binary features representing the day of the week (isMon, isTue etc.) and the number of hours away from 5pm in either direction - so a timestamp at 4pm and 6pm would both be 1. Again this was based on the observations in the preliminary analysis of 5pm being a peak listening hour.

3.2 Validation and Test dataset selection

Our working dataset was a subset of the full 1000 user dataset, and comprised of 4,217,228 rows of training data across 97 users. Of this a random sample of 100,000 rows was taken and 5-fold cross-validation emplyoyed.

Data Imbalance

A data imbalance is when the training data is when one or more of the classes is under-represented in the dataset. Of the 4,217,228 rows in our working data set, 361,081 (8.6%) were play events and 91.4% were non-play events. This can result in models that achieve a high accuracy score by following either of the following two heuristcs:

- Predict non-event for everything
- Predict t will be the same as $t-1$

There are several methods for dealing with data imbalance [3] including restricting input data, having a weighted loss function, and using recall as an evaluation measure. We used recall as well as weighting. Both class weights and sample weights were employed in the scikit learn models. The class weights were inversely proportional to play & non-play frequencies in the input data, while the sample weights were a hyper-parameter. In the RNN model only sample weighting was used.

The effect of class weighting is to encourage the model to predict play events. The effect of the sample weighting is to encourage the model to predict play events while minimizing the number of false-positives.

3.3 Methods

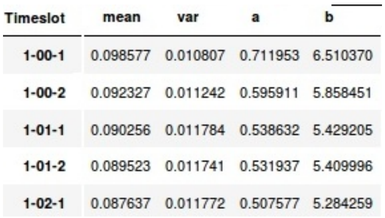
3.3.1 Baseline Model

Our baseline model will be to assume $t = t-1$. That is to say a person will listen to music at period t if, and only if, they listened to music in the period immediately priod. As music listening events tend to be clustered (people listen to music in batches) the accuracy of the baseline model is will be fairly high. However it will not be able to predict the first play of a listening session, or where the listening session duration lasts no longer than a single periodm, which in the experiments is defined as a 30 minute period.

3.3.2 Bayesian Inference

Here we employ a simple Bayesian Inference approach by utilizing the Beta-Binomial model. The Beta-Binomial model is built upon the weekly patterns observed in the preliminary analysis. Conceptually it seeks to build up a users personalized weekly listening profile using a Beta-Binomial probability distribution. The priors for which are based on the population as a whole, and the observations are history T_h. We then assess how effective this profile is at predicting listening outcome at time t for that user.

Prior probabilities were calculated for each half-hourly period in a week (24*2*7=336 timeslots). Fig 3.1 shows the calculations for the first 2.5 hours of a Sunday (d-hour-hh format).



Timeslot	mean	var	a	b
1-00-1	0.098577	0.010807	0.711953	6.510370
1-00-2	0.092327	0.011242	0.595911	5.858451
1-01-1	0.090256	0.011784	0.538632	5.429205
1-01-2	0.089523	0.011741	0.531937	5.409996
1-02-1	0.087637	0.011772	0.507577	5.284259

FIGURE 3.1

The liklihood function which represents the probability of a user listening to music was defined as a binomial distribution, where k is the number of plays in a given period, n is the sum of plays and non-plays, and θ is the unknown probability parameter for the binomial distribution.

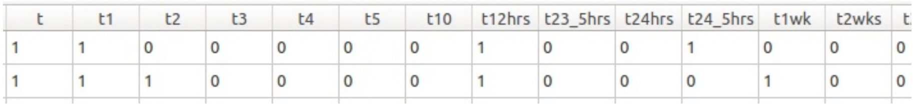
$$\binom{n}{k} p^k (1-p)^{n-k}$$

As the Beta distribution is a conjugate prior to the Binomial the model can be reduced to: $Beta(\alpha + P, \beta + Q)$ where P is the count of plays and Q is the count of non-plays. For which the parameters α and β, are derived from the training set, with an estimate of the mean for each half-hourly time period as shown in fig 3.1. To do this we first calculate the probability of a play (total plays in period / count of plays and non-plays) per user, then take the mean and variance across users. a and b are then determined as: $a = (\frac{(1-\mu)}{\sigma} - \frac{1}{\mu})\mu^2$ and $\beta = \alpha\left(\frac{1}{\mu} - 1\right)$.

Finally we convert the probabilites into a binary outcome by optimizing for a threshold λ at which we predict a play event.

3.3.3 Binary Logistic Regression

This method (and the subsequent methods) adopts a more classicial time-series approach to the prediction problem by constructing a dataset as a sequence of play events at time $T_t = 1$ and non-play events $T_t = 0$, with t representing a time period of a fixed interval of 30 minute chunks.



t	t1	t2	t3	t4	t5	t10	t12hrs	t23_5hrs	t24hrs	t24_5hrs	t1wk	t2wks	t
1	1	0	0	0	0	0	1	0	0	1	0	0	0
1	1	1	0	0	0	0	1	0	0	0	1	0	0

FIGURE 3.2: Example of times-series data

We seek to model the probability of an event in the current time period t, given the history of events: $p(Y_t = 1 \mid Y_h)$. Our binary logistic model is therefore defined as:

$$p(Y_t = 1|Y_h) = \sigma(w^T x + b)$$

$$p(Y_t = 1|Y_h) = 1 - p(Y_t = 1|Y_h)$$

with σ being the sigmoid function defined as:

$$\sigma(x) = \frac{e^x}{1 + e^x}$$

Determining the optimal weights and constant can be determined by maximization of the log-liklihood or the minimization of the negative log-liklihood.

In addition we will be using an L2 regularizer term, $+1/2w^T w$, to prevent overfitting:

3.3.4 Linear SVM Classifier

SVM models work by determining a separation plane between classes based on the support vectors - the data points closes to the decision boundary. A linear SVM regression model performs this through the Epsilon Intesive loss function [21]. The objective becomes to *minimize:*

$$max(0, \|(y_i - w_i x_i - b) - \epsilon\|)$$

In other words we ignore cost functions that are within a certain margin ϵ. In our case this may be of importance in cases where the probability of user listening to music is close to the decision boundary, which may be the case for the very first song played at the start of a session.

3.3.5 RBF SVM Classifier

Here we use a Gaussian RBF kernel in our SVM model. A Gaussian kernel is a popular method for modeling non-linear decision boundaries. Our model becomes:

$$p(E = 1) = b + \sum_{i=1}^{N} w_i RBF(x, x_i)$$

where the RBF kernel is defined as:

$$K(\mathbf{x}, \mathbf{x}') = \exp\left(-\frac{\|\mathbf{x} - \mathbf{x}'\|^2}{2\sigma^2}\right)$$

Note that actual implementations of this make use of more computationally efficient methods [16]. This restated method has a hyper-parameter γ that takes the place of $2\sigma^2$.

3.3.6 RNN-LSTM model

The construction of the RNN model requires a number of hyper-parameters. These are as follows:

- Time-steps: How many time steps to use (= batch depth)
  - Learning rate: Learning rate of backprop algorithm
- Hidden units: Number of units per hidden layer
- Layers: Number of hidden layers
- SampleWeighting: Weighting to apply in the cost function for labels that are a play event
- User iteration: How many random users to select for training)
- SamplesPerUser: How many mini-batches to select for each user
- BatchRows: How many random periods to select in each mini-batch (=batch height)
- Batch iterations: How many iterations to perform on one batch

Batch shape

We provide the RNN model with a sequence of historical data at times $t-1..t-n$ with $n > 1$). This is fed into the RNN as separate time steps in forward temporal order (earliest time-steps are processed first). The hidden state would propogate information forward at each time step, until it was used to predict the outcome at time t.

Practically speaking this meant feeding in the data with input shape (batch rows, time-steps, features). Some points of interest are:

1. The features dimension here only contains $t-1$ and no other feature.
2. The time-steps are 'unrolled' within Tensorflow and fed into the LSTM. In this research we experiment with different lengths of time-steps, with 48 (half-hour periods) representing a day, 336 for a week, and 672 for 2 weeks.
3. When the data is unrolled, time step t for all rows in the batches are processed together as one block, before moving onto the next time-step.
4. Constructing the 3-d shape often requires building them up in slices. A significant speed up was observed in Python when using a pre-allocated array vs. appending to it.

Samples and iterations

A challenge in testing the RNN model was to balance the number of users being samples from, with the number of samples to take from each user, and the numebr iterations to then do on each sample. A distinction between batch rows and samples per user was required for computational reasons to reduce the demand on RAM per mini-batch, vs. feeding in one large mini-batch per user.

Cost function and weighting

Both the logistic loss and a weighted softmax cross entropy loss function were tried in the model (the latter requires converting the output label into one-hot encoding format). Logistic loss was found to be the more effective of the two cost function and hence used for our results.

Secondly due to the imbalanced data, adding weighting to the costs of a Play event was found to be crucial in getting good results. The key snippet of code for the cost function is given below:

```
_logits = RNN(x, weights, biases,n_steps)
_prob = tf.sigmoid(_logits)
_weightstf.add(1,tf.multiply( _
tf.cast(tf.equal(y,1),'int32'),n_weighting))

_logloss =
tf.losses.log_loss(predictions=_prob, _ labels=y,epsilon=0.00001, _
weights=_weights)

_cost = tf.reduce_mean(_logloss)
```

3.4 Evaluation critera

Deciding on an approporiate evaluation measure requires careful consideration to the costs attached to different predictions. In our case the cost of suggesting music when the user is likely not interested is higher than not playing music when they are likely to be interested.

A number of possible evaluation criteria were looked at. The most-straight forward of which was *accuracy*. This computes the count of correct predictions as a fraction of the total number of predictions. While this is an intuitive measure, it would not distinguish between models that had a high accuracy on the play-events vs. a high accuracy on non-play events.

To do this we look at precision. Precision (P) is defined as the number of true positives over the number of true positives plus the number of false positives. A positive in this case is a play-event so our precision equation becomes:

$$Precision = \frac{CorrectPlayPredictions}{TotalPlayPredictions}$$

.

This will be measuring our models on how many of the 'Play' events predicted were correct. However it does not distinguish between models that predict a play event only on 'safe bets', such as when t-1 was also a play event, vs. those that are attempting to guess the start of a play sequence. For this we turn to recall.

Recall is defined as:

$$Recall = \frac{CorrectPlayPredictions}{TotalPlayPrectionsInDataset}$$

For example if we predicted 100 plays correctly but there were in fact 110 plays in the dataset, then recall would be 100/(100 + 10)= 91

3.5 Summary

We have described how our data was transformed to make it useful for our experiments. In particular how we had to convert our list of play events into a list of play and non-play events for every period. By doing this we are faced with an imbalance of data as non-play events make up 91% of the data and so we employ a weighting strategy to counteract this.

We then described the methods we will be utilizing in our experiments, consisting of a Baseline model which simply assumes $t = t - 1$, a Bayesian model which builds up a weekly profile of listening habits for each user, Logistic and SVM models that apply classical machine learning techniques to our time-series problem, and finally a deep learning model in the form of an RNN-LSTM where we seek to utilize its ability to learn temporal patterns through a hidden memory state.

Finally we looked at different ways for measuring the success of our problem, with precision and recall being the preferred choice.

In the next chapter we shall present the results of our experiements together with insights on each model.

Chapter 4

Results

We begin our discussion of the results with preliminary analysis of the data. Here we seek to understand some of the overarching patterns in listening habits and how these look at an individual level. After this we present a summary of our results followed by a discussion of the performance of each individual method.

4.1 Preliminary analysis

4.1.1 Daily play patterns

By grouping track plays into 30 min intervals and aggregating by periods within a day, we see a clear daily pattern with music listening hitting a peak at around 5pm and a trough at around 6am.

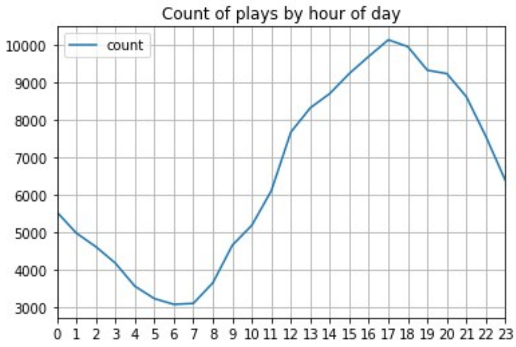


FIGURE 4.1: 5-5.30pm is peak listening time

Zooming out to view the pattern across an entire week in figure 4.2, we see that the daily pattern occurs across every day of the week with weekends having a lower total number of plays.

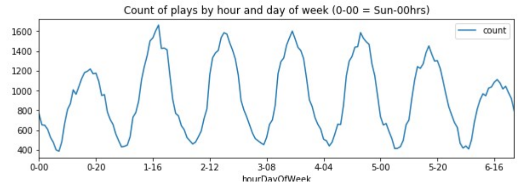


FIGURE 4.2: Most popular times to listen to music across all users

At an aggregate level therefore one can get good accuracy by simply anticipating music demand to peak at 5pm. However if we select two users at random (fig. 4.3), we see that these daily patters are not as strongly discernable. As we see later this is likely impacting the Bayesian Inference model as it begins with using the population distribution as the prior.

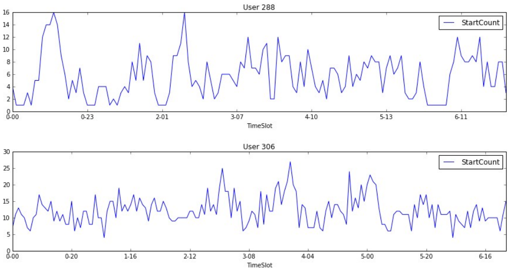


FIGURE 4.3: Most popular times to listen to music by individual user

4.1.2 Outlier analysis

The dataset contains a timestamp associated with each user. This does not necessarily mean the user played a song in its entirety. Analysis shows plenty of cases where the interval time between tracks was a few seconds suggesting the user skipped tracks.

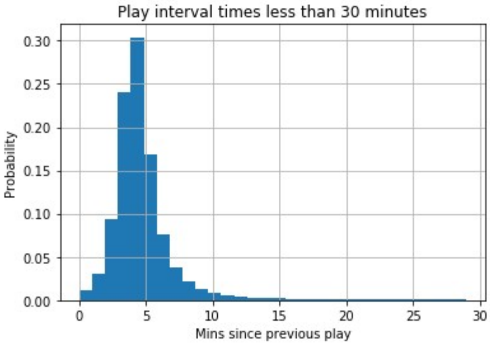


FIGURE 4.4

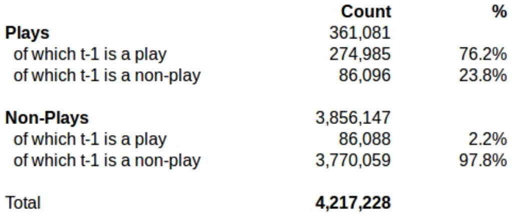
Figure 4.4 shows a frequency plot of intervals. Intervals beyond 30 minutes continue the exponential decrease and are not shown. We see that while the mode is on par with a typical song length, there is a significant number of plays that lasted under 5 minutes. For our purposes these are include as evidence that the user was interested in playing music at time t and therefore treated as a Play event.

Further analysis showed one user in particular with very high amount of plays, with very low durations, suggesting it was likely to have been generated by a bot, possibly a LastFM test. This was excluded from the dataset.

4.1.3 Time-series analysis

Here we examine our data once it has been transformed into a binary sequence of play events (1) and non-play events(0). We seek to understand better how an optimizer may perform based on traits of the data.

We begin with assessing how well our baseline model may perform. Fig 4.5 shows that the 76% of Plays, also had a play in $t-1$. However this rule also captures 2.2% of non-plays events.



	Count	%
Plays	361,081	
of which t-1 is a play	274,985	76.2%
of which t-1 is a non-play	86,096	23.8%
Non-Plays	3,856,147	
of which t-1 is a play	86,088	2.2%
of which t-1 is a non-play	3,770,059	97.8%
Total	**4,217,228**	

FIGURE 4.5

The 23.8% of Plays that did not have a play in the prior period are harder to predict, yet are of more interest as they represent the beginning of a listneing period.

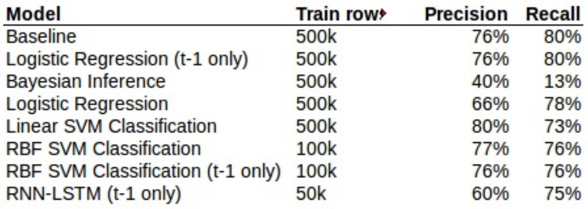
Given the daily patterns we have seen, it might be reasonable to assume that $t - 24hrs$ may help us to determine the start of an session. However analysis shows that in only 34% of play events was there also a play event in 24 hours prior.

What both of these results tell us is that fairly high precision score of around 76% ought ot be possible purely based on $t - 1$ but going above this will be a lot harder.

4.2 Main results

4.2.1 Summary

Fig. 4.6 shows the results from across all experiments after 5-fold cross validation.



Model	Train row	Precision	Recall
Baseline	500k	76%	80%
Logistic Regression (t-1 only)	500k	76%	80%
Bayesian Inference	500k	40%	13%
Logistic Regression	500k	66%	78%
Linear SVM Classification	500k	80%	73%
RBF SVM Classification	100k	77%	76%
RBF SVM Classification (t-1 only)	100k	76%	76%
RNN-LSTM (t-1 only)	50k	60%	75%

FIGURE 4.6: Summary of results

We see that none of the models score better than the Baseline model. The logistic regression model is able to match the Baseline model once we restrict the input to $t - 1$.

It may be that $t = t - 1$ is the only pattern that is consistently important across users, with all other time-lags having too much variance across users for them to be useful.

In a similar vein, the Bayesian Inference model performed poorly on both measures, suggesting that that the difference between the population and what is observed at an individual level differs too much for the prior probability to be accurate for any one individual user, something we saw some indications for in our preliminary analysis.

Our remaining models exhibit the the tension between good accuracy and good recall, with only the RBF SVM model demonstrating the ability to reach a balance score across both. The Logistic regression and RNN models perform below average on precision but well on recall, while the Linear SVM model scores better on precision. We will discuss each one model in turn next.

4.3 Bayesian Inference model

We outline here how the model was derived in order to aid understanding of its performance.

We can plot the prior probability for any given time period, as shown in fig 4.7.

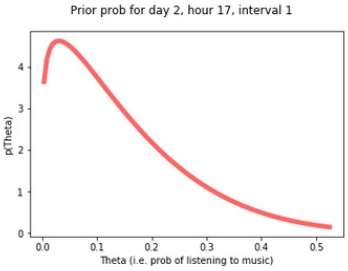


FIGURE 4.7

Here we see that θ, which represents the prior probability of listening to music in the specified timeslot, is likely to be less than 0.1. Notice that this timeslot is for hour 17 (i.e. 5pm) which, from our preliminary analysis, we know is the peak listening time at an aggregate level. The fact that the probablity is so low for this timeslot would likely be due to the presence of lots of 5pm periods in which music was not listened to at the individual user level. For instance - if our dataset contains large gaps between weeks in which music was listened to.

For our posterior function, the threshold at which we determine a play event was determined by comparing the false positive rates with the true positive rates using a ROC curve (4.8). From this, 0.4 was selected as the optimal threshold at which to determine a Play event across all users.

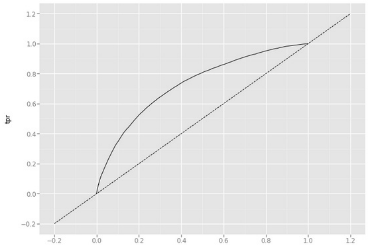
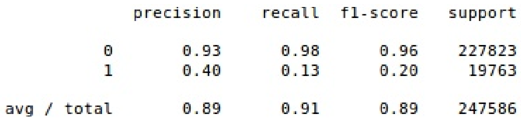


FIGURE 4.8: ROC curve showing 0.4 as the optimal threshold

The results from the model are shown in figure 4.9. We see that the recall and precision of play events (as denoted by 1) is very low. Clearly the approach of building up a weekly profile based on the population then updating it with individual observations is not very effective. This does not however rule some other form of Bayesian modeling such as Bayesian Logistic Regression.

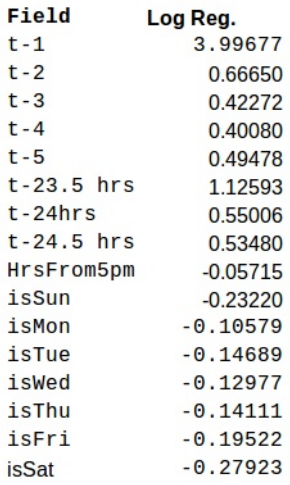


```
             precision    recall  f1-score   support

          0       0.93      0.98      0.96    227823
          1       0.40      0.13      0.20     19763

avg / total       0.89      0.91      0.89    247586
```

FIGURE 4.9: Beta-Binomial Model Results

4.4 Logistic regression analysis

For logistic regression we are able to examine the co-efficients to understnd how the model is making use of the input data.



Field	Log Reg.
t-1	3.99677
t-2	0.66650
t-3	0.42272
t-4	0.40080
t-5	0.49478
t-23.5 hrs	1.12593
t-24hrs	0.55006
t-24.5 hrs	0.53480
HrsFrom5pm	-0.05715
isSun	-0.23220
isMon	-0.10579
isTue	-0.14689
isWed	-0.12977
isThu	-0.14111
isFri	-0.19522
isSat	-0.27923

FIGURE 4.10

Fig 4.10 shows that $t-1$ was by far the most important feature and its importance crowds out the other features. Interestingly $t - 23.5$ is the second strongest time-lag and more significant than t-24hrs. As t-23.5 would be 24 hours prior to $t - 1$, it suggests that having a consistent $t-1$ is more important than simply knowing what t was 24 hours prior; which we know from our preliminary analysis is not very effective anyway.

The non-time lag features seem to have very little effect. We see this in the forward stepwise regressoin chart in fig 4.11which shows that the inclusion of addiitional features barely impacts the results.

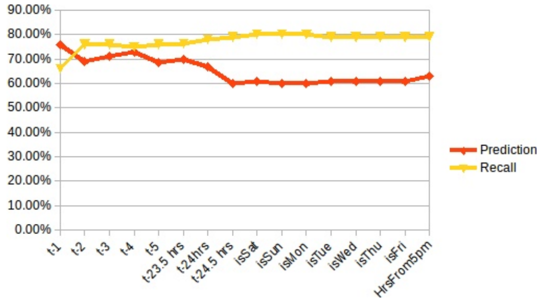


FIGURE 4.11: Stepwise regression, adding in fields from left to right

4.5 SVM analysis

That the Linear SVM performs well on precision but not recall may be due to it ignoring probabilities that fall within the margin of the decision boundary during optimization, such as the start of a play sequence or ad-hoc plays by a user that do not fit their regular listening pattern. Hence the model is more likely to only predict a play event when the probability is sufficiently high.

The RBF model on the other hand performs well on both metrics. Note that the RBF classifciation was restricted to 100k rows of training data as it was found the computational cost of 500k rows was too high.

An RBF kernel has two hyper-paramters that can significantly impact the results. The C parameter and the $gamma$. Intuitively, the gamma parameter defines how far the influence of a single training example reaches, with low values meaning ‘far’ and high values meaning ‘close’. A low C makes the decision surface smooth, while a high C aims at classifying all training examples correctly by giving the model freedom to select more samples as support vectors.

In order to determine optimal gamma and C values, a grid search was carried out with precision and recall of the test dataset plotted on a heatmap. In order to get through the many iterations of the data, the input data was reduced to 30,000 training samples. Fig 4.12 shows the final heatmap, after multiple iterations to home in on the optimal values, with precision on the left and recall on the right. The optimal values are deemed to be 0.6 for C and 0.76 for Gamma, although as the charts show there is some scope for movement around those values.

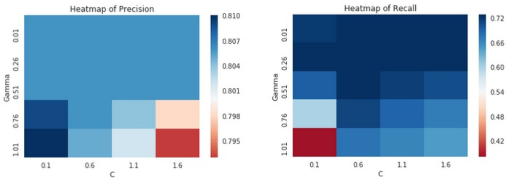


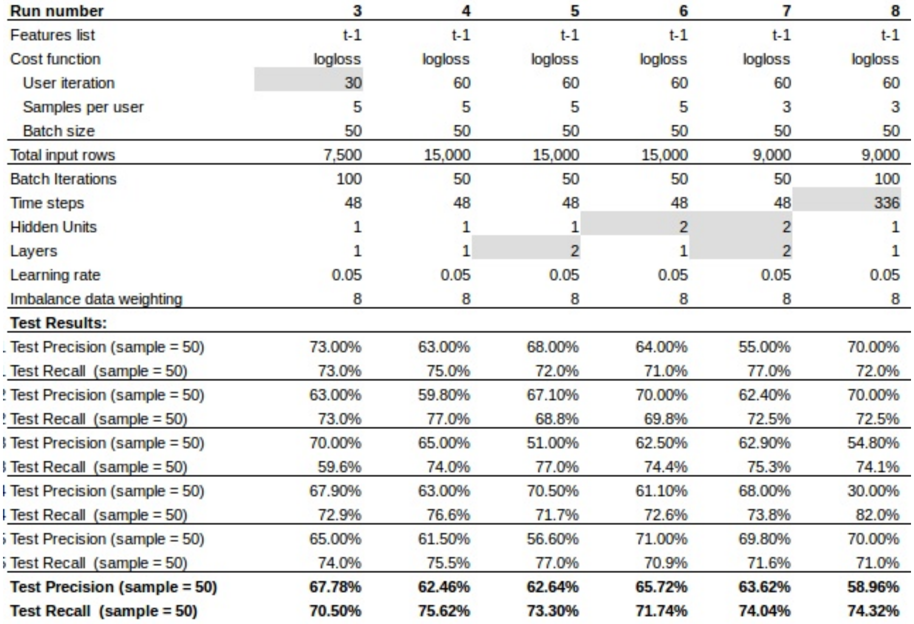
FIGURE 4.12: Heatmap of hyper-parameter search. Dark blue shade = better precision and recall

The final results for the RBF model (precision of 77%, recall of 76%) was about the same when only $t - 1$ was provided as an input, suggesting the RBF model is likely approximating to the $t = t - 1$ rule used in the baseline model.

Finally, a note on the computational complexity of the RBF model. The Scikit-Learn implementation of the RBF kernel is based on libsvm. The fit time complexity of this is more than quadratic to the number of samples, making it hard to scale to datasets with more than 10,000 samples [4]. While we managed to get as high as 100,000 in our training it was not considered a practical to go any higher thereby limiting the scalability of this approach and our ability to potentially obtain higher scores than what we already had.

4.6 RNN-LSTM analysis

The RNN model had a large number of hyper-parameters to search through resulting in significantly more time required to train than the other models. Fig 4.13 shows details of a few of these runs, including the model that gave the best set of results (run num. 4). Key differences between the runs are shaded in grey.



Run number	3	4	5	6	7	8
Features list	t-1	t-1	t-1	t-1	t-1	t-1
Cost function	logloss	logloss	logloss	logloss	logloss	logloss
User iteration	30	60	60	60	60	60
Samples per user	5	5	5	5	3	3
Batch size	50	50	50	50	50	50
Total input rows	7,500	15,000	15,000	15,000	9,000	9,000
Batch Iterations	100	50	50	50	50	100
Time steps	48	48	48	48	48	336
Hidden Units	1	1	1	2	2	1
Layers	1	1	2	1	2	1
Learning rate	0.05	0.05	0.05	0.05	0.05	0.05
Imbalance data weighting	8	8	8	8	8	8
Test Results:						
Test Precision (sample = 50)	73.00%	63.00%	68.00%	64.00%	55.00%	70.00%
Test Recall (sample = 50)	73.0%	75.0%	72.0%	71.0%	77.0%	72.0%
Test Precision (sample = 50)	63.00%	59.80%	67.10%	70.00%	62.40%	70.00%
Test Recall (sample = 50)	73.0%	77.0%	68.8%	69.8%	72.5%	72.5%
Test Precision (sample = 50)	70.00%	65.00%	51.00%	62.50%	62.90%	54.80%
Test Recall (sample = 50)	59.6%	74.0%	77.0%	74.4%	75.3%	74.1%
Test Precision (sample = 50)	67.90%	63.00%	70.50%	61.10%	68.00%	30.00%
Test Recall (sample = 50)	72.9%	76.6%	71.7%	72.6%	73.8%	82.0%
Test Precision (sample = 50)	65.00%	61.50%	56.60%	71.00%	69.80%	70.00%
Test Recall (sample = 50)	74.0%	75.5%	77.0%	70.9%	71.6%	71.0%
Test Precision (sample = 50)	**67.78%**	**62.46%**	**62.64%**	**65.72%**	**63.62%**	**58.96%**
Test Recall (sample = 50)	**70.50%**	**75.62%**	**73.30%**	**71.74%**	**74.04%**	**74.32%**

FIGURE 4.13: Example of hyper-parameter search. Key settings shaded.

In total 50+ experiments were performed with different hyper-parameter settings. The following observations were made based on the results of all experiments.

Early stopping

Continued training of models eventually led to performance decrease, with predictions becoming either all play events or all non-play events depending on the weighting used. Possible measures to counteract this may be to use drop-outs, a form of regularization in neural networks. However this was not investigated. Instead models were trained upto around 15,000 rows of data.

More layers or units did not improve performance

Moving up from 1 hidden unit and 1 hidden layer did not result in performance improvement, and performance started to drop if it increased too high (10 units or 3+ layers). It appears that this was due to the model over-fitting the data.

The ideal sample weigh was 8

The amount of weighting required to deal with the data imbalance varies depending on how many rows of training data there are, but generally 8 was found to be the level at which precision and recall remained high across a training set of 15,000 rows.

Going beyond a 24hour timestep did not improve performance

Moving beyond a time-step of 48 (i.e. 24 hours) to 336 (1 week) or more led to a decrease in performance. This matches what we saw in the logistic regression model where periods beyond the 24 hour period had little impact in predicting outcome.

4.7 Summary

None of our models beat the baseline model. Furthermore from our examination of the co-efficients and experiments with the RNN model, it did not appear that time-lags beyond 24 hours were a useful predictor. Indeed logistic regression performed best, and on-par with the baseline, when $t-1$ was the only input feature. These results suggests that additional features make it harder for the models to attribute the right level of importance to $t-1$.

Chapter 5

Summary

5.1 Conclusion

Predicting the propensity of a user to listen to music at a certain time, based on their recent listening history can be applied to a range of other areas such as the propensity to purchase products, electricity usage, or the demands on a public transport system. The ability to accurately model these patterns is therefore of great significance to industry. Traditional temporal point processes modeling requires making assumptions about the data, such as the feature engineering done in this research, in order to build a prediction model and struggle with capturing highly non-linear patterns in a scalable manner.

We applied a range of techniques to the task of modeling temporal point processes and used precision and recall as our evaluation measure. Our Baseline model which simply assumes $t = t - 1$ performed the best, with a precision of 76% and a recall of 80%. As music listening is typically long periods of non-play events, followed by consequtive periods of play events, it is easy to achieve high scores using this heuristic. No models were able to exceed the baseline model. This points to the need to change the the problem definition. Rather than trying predict all Play events, it may be better to try and predict the start of a play sequence instead. Alternatively we may wish to predict the probability n steps into the future.

Secondly, achieving a good balance between precision and recall is a challenge, and the RBF SVM model was the only one of our initial model that achieved this.

Finally we experimented with an RNN-LSTM model. As our literature review showed, the application of deep learning to temporal point processes is still in its infancy but shows promising signs. Our own research is inconclusive though positive enough to warrant further research. As mentioned, careful thought needs to be given to the problem definition in order to perform a reasonable assessment.

5.2 Future research

There are seveal directions one could follow to take this research forward.

1. Attempt to predict the start of a play sequence
2. Attempt to predict events n steps into the future, where $t - 1$ to $t - 5$ are not available
3. Investigate the variance between the temporal patterns of individual users and that of the population and models that can better deal with these
4. Evaluation of more sophisticated RNN structures such as that described in our literature review [23].

5. Evaluation of advanced Bayesian models such as Bayesian Logistic regression
6. Application of Gaussian Point processes as way of getting around RBF scalability limitations
7. Investigation into how quickly models can learn to model the behaviour of new users

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