Adding Time and Subject Line Features to the Donor Journey

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Abstract: The donor journey is the path a charitable constituent takes on their way to making a donation. Charities are moving towards more electronic communication and most appeals are now sent via email. The donor journey can be followed electronically, monitoring constituent and charity actions. Previous research has shown that it is possible to use past actions of a donor to predict their next gift within $25. We build on this research by adding new features that capture the time between actions, as well as new email features, including subject lines features in such a way as to isolate their effect on model accuracy. These additions show a small improvement in accuracy of recurrent neural network models for most charities, showing these features do indeed help deep learning methods understand the donor journey.

1 INTRODUCTION

On a day to day basis, the most asked question within charities is typically “What do we do next?”, and this question is asked about individual constituents (people in the charity’s database). The goal of a charity is to maximize how much money it raises in the long term, so simply answering this question with “ask them for money” is an oversimplification, since constituents are not going to give gifts to a charity every day. Instead, the charity might want to send a thank you letter (an example of stewardship) or wait and let the constituent take an action on their own, such as visiting the charity’s website.. While sending a solicitation email is likely the right action at some point along the donor journey, it is not necessarily the right action at any given time.

The donor journey is the set of chronological actions a constituent and a charity take while the constituent interacts with a charity. These include the charity sending emails and the constituent opening these emails, clicking links, and of course, donating to the charity. Charities seek to optimize the donor journey by performing the right actions at the right times to maximize a donor’s lifetime value (i.e., maximize how much money the donor gives to the charity). This is best achieved not only by maximizing donations, but reducing costs and donor fatigue. All appeals have associated costs which must be subtracted from the revenue in order to calculate the actual gain for the charity. In addition, when donors are asked for money too often, they can become less likely to donate in the future (Canals-Cerda, 2014).

Previous research on the donor journey (Lee et al., 2022; Lee et al., 2020b) has shown that a constituent’s donation amount can be estimated within a $25 mean absolute error (MAE) using deep learning methods on a chronological set of actions described by features of their associated email. Sample data could be the action *opened* with associated email features of 311 words, 3 paragraphs, and 2 variables. Window sizes varied between 1 and 25 for these experiments. Here the window size is how many past actions the deep learning algorithm is allowed to consider when trying to predict the donation amount.

We extend the work of the authors of (Lee et al., 2022; Lee et al., 2020b) by adding time and email subject line, and other email features for machine learning in order to see if these features can help deep learning algorithms improve their accuracy in terms of predicting which sequence of actions will generate the greatest lifetime value across a database of constituents.

As the authors did in (Lee et al., 2022; Lee et al., 2020b), we focus on email appeals and a sample charitable email as shown in Figure 1. Here, a university foundation makes an appeal to members of the university community (alumni, faculty, staff, and friends) in an effort to help students adversely affected by the COVID-19 pandemic. This email was one of 27 sent

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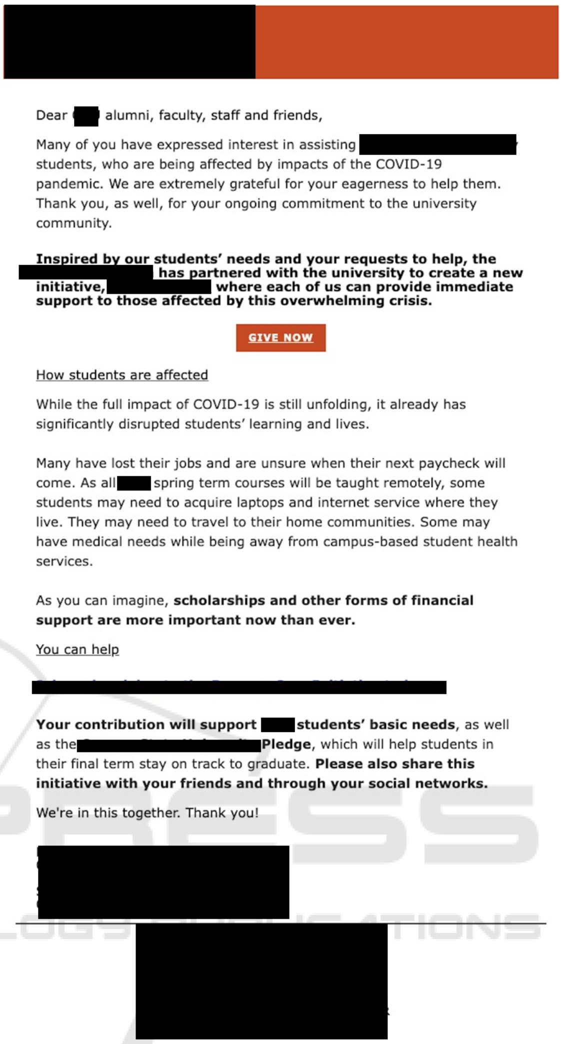
over an 8 month period and statistics were gathered concerning how often the email got to constituents, how often they opened it, and various other actions we describe later. Note that many of the 27 emails were sent to very specific groups of constituents (e.g., foundation board members or those who did not open a previous email) so no constituent received more than a few emails concerning this cause.

Since the only action a charity can take within an email campaign is to send an email, we also query the most accurate models found with a range of email parameters and observe which parameters values are most commonly regarded as those that will lead to higher donations. Given that some of the features we use were not used in previous work, charities now will have suggestions for email parameters they could not access previously, such as how many words to put in a subject line and how many font colours to use.

The rest of the paper is organized as follows. We next describe related research, followed by formulating the problem. Following this, we describe our approach and describe our experimental setup. The paper concludes with empirical results and conclusions and future work.


[redacted]

Dear [redacted] alumni, faculty, staff and friends,

Many of you have expressed interest in assisting [redacted] students, who are being affected by impacts of the COVID-19 pandemic. We are extremely grateful for your eagerness to help them. Thank you, as well, for your ongoing commitment to the university community.

Inspired by our students' needs and your requests to help, the [redacted] has partnered with the university to create a new initiative, [redacted] where each of us can provide immediate support to those affected by this overwhelming crisis.

GIVE NOW

How students are affected

While the full impact of COVID-19 is still unfolding, it already has significantly disrupted students' learning and lives.

Many have lost their jobs and are unsure when their next paycheck will come. As all [redacted] spring term courses will be taught remotely, some students may need to acquire laptops and internet service where they live. They may need to travel to their home communities. Some may have medical needs while being away from campus-based student health services.

As you can imagine, **scholarships and other forms of financial support are more important now than ever.**

You can help

[redacted]

Your contribution will support [redacted] students' basic needs, as well as the [redacted] **Pledge**, which will help students in their final term stay on track to graduate. **Please also share this initiative with your friends and through your social networks.**

We're in this together. Thank you!

[redacted]

Figure 1: A sample email solicitation, redacted to maintain anonymity.

2 RELATED RESEARCH

In this research, we learn to model the donor journey by predicting donation amounts based on past actions and query that model to select best actions and email parameters. This is relatively new field and little work has been done prior to this research. Most donor journey advice amounts to bullet points on websites (McLellan, 2022).

A few articles have investigated direct mail content through trials with Red Cross mailings. The authors found that enrollment cards lead to repeat donations, while providing donors with gifts hurt retention (Ryzhov et al., 2015). Email campaigns are generally evaluated based on demographics, interest and social network influence of constituents and external time-related factors using best practices shared. While for-profit organizations have been using machine learning models for predicting the customer journey (Lemon and Verhoef, 2016), charities are having trouble adapting to these techniques.

Machine learning has been applied to predicting donations to charities. In (Lee et al., 2022; Lee et al., 2020b) the donor journey is studied extensively in terms of adding constituent features, experimenting with multiple deep learning algorithms, combining data across charities We build on this research in this paper. Machine learning has also been applied to individual predictions, such as "who is lapsed, but most likely to return". These predictions provide charities with lists of constituents whom they can act on in a uniform matter, since machine learning algorithms predict they will all take a given action. These are point in time predictions that ignore the time aspect of the donor journey (Lee et al., 2020a).

Recurrent neural networks (RNNs) are specialized artificial neural networks that can use sequential data to learn based on chronological events. They can make use of long short-term memory (LSTM) in order to keep track of relevant events from the past while discarding less important events, through learning. RNNs have been used to predict customer churn, which is related to lapsed donors in charitable giving (Sudharsan and Ganesh, 2022). Bidirectional RNNs with LSTMs (BDLSTMs) can consider time series data in either direction, essentially looking both forward and backward with two separate RNNs, using backpropagation (Moolayil, 2019).

Convolutional neural networks (CNNs) are widely used on image and video classification, but can be used on sequential data as well (Xia and Kiguchi, 2021). CNNs can extract features from sequential data and map the internal features of the sequence to the previous layer for each convolutional layer in the model. This network is effective for deriving features from a fixed length segment of the overall dataset (Kim, 2014). CNN LSTMs were developed for predicting visual time series problems as well as to generate text from sequence of images (Wang et al., 2018). They have been used in various time series prediction tasks, such as predicting air quality (Yan et al., 2021).

In our work, we experiment with each of RNNs, BDLSTMs, CNNs, and CNN LSTMs in order to see which algorithm can produce the best models for predicting the next best action to take in the donor journey, in terms of maximizing donations, given the addition of time and new email features.

3 PROBLEM FORMULATION

In general, the issue at hand is to help charities raise more money. This can be done on a point-in-time scale, by asking questions such as “who is likely to upgrade to a $500 gift?” and creating training data for machine learning algorithms based on constituents features at that given time. This would include features such as “maximum donation” and “number of emails opened”. We can make use of these features in our work, but focus more on the *order* of constituent and charity actions, and on what action to take next rather than which behaviour a constituent is likely to exhibit at some arbitrary point in the future.

The donor journey can be modeled by considering the past n actions of the constituent and the charity with respect to that constituent, and using that information to try to predict the next best action for the charity or constituent to take. Charities generally do this by hand with “common sense” rules, such as “do not send another solicitation email until 3 months after receiving a donation”. While many of the rules charities use likely work in many situations, we seek to eliminate bias and error from the process of understanding the donor journey, and use machine learning to arrive at data-driven rules for charities to follow, on an individual basis.

The actions considered in this and previous work in this area are shown in Table 1. For one of the charities used extensively in our experiments, extra actions were available in the data, shown in Table 2. Note that all actions are taken by the constituent except for the “delivered” action, which is taken by the charity. Since we are working with email campaigns, all actions in this experiment have an associated email, except for the ’no action’ action, for which all email features are set to 0. ’No action’ is necessary to pad donor journeys that are not n actions long (i.e., a constituent who is newer to the charity than most constituents), and since no action was taken, there cannot be an associated email. The email features used both in this work and previous work in this area are given in Table 3.

Table 1: The list of all actions used in our experiments for every charity.

Action	**Description**
No Action	Filler action when none happened
Delivered	Successfully delivered email
Opened	The constituent opened an appeal email
Pageview	The constituent viewed the donation portal
Donated	The constituent made a donation
Clicked	The constituent clicked on a email link
Complained	The constituent reported an appeal email as spam
Dropped	The appeal email did not reach the constituent
Bounced	The appeal email was blocked by the constituent
Unsubscribed	The constituent unsubscribed from a mailing list

Table 2: The list of all actions used in our experiments exclusively for a university foundation (C5).

Action	**Description**
Virtual Response	Made a social media comment
Attended	Attended a university event
Prospect Visit	A major gift officer visited the constituent
Volunteer Member	Volunteered for a foundation committee
Purchased	Purchased an event ticket
Recurring signup	Signed up for the same activity 2+ times
Volunteer	General volunteering
Participant	Participated in an advisory circle
Staff	Foundation staff action
Current	Continued volunteering
Mentors	Participated in accelerator mentoring
Ex Officio	Historic trustee action
Trustee Term	Alumnus trustee action
Participating Host	Off-campus event
Suppressed	Unknown email error
Opt out	Opted out of some email options
Failed	Email did not reach constituent
Trustee Liaison	Relevant board participation
Former	Former board member action

Table 3: Variable email parameters.

Parameter	**Description.**
Words	Number of words
Paragraphs	Number of paragraphs
Images	Number of images
Links	Number of HTML links
Blocks	Number of sections
Divs	Number of HTML content division elements
Editable Content Divs	Number of editable HTML divs

4 OUR APPROACH

To model the donor journey, we use deep learning algorithms that are sensitive to time steps, in order to take advantage of the chronological aspect of the donor journey. Opening an email and donating is not the same as donating and then opening an email, and thus we sought algorithms that can recognize this difference. An example of a sequence of actions leading to a donation would be a constituent receiving an email, opening it, opening it again, clicking a link in that email, clicking another link in that email, and viewing the donation portal, which would be registered as $\{$*Delivered, Opened, Opened, Clicked, Clicked, Pageview*$\}$. To each of these actions, we add the corresponding email features.

To build training data, each action is encoded as a one-hot encoded action with corresponding email features. In the experiments, this data is augmented with the features that we describe in Table 4 in order to observe the effect of the new features on model accuracy. An example of a set of actions is shown in Figure 2.

A1	A2	A2	A3	A10	A2	$150

A1	A2	A3	…	A10	E1	E2	E3	E4	…	E7
1	0	0		0	0	0	0	0		0
0	1	0		0	220	5	6	11		18
0	1	0		0	220	5	6	11		18
0	0	1		0	155	3	11	4		12
0	0	0		1	155	3	11	4		12
0	1	0		0	301	10	3	2		1

Figure 2: A sample set of six actions used as training data for deep learning models. The actions are one-hot encoded and have corresponding email features appended.

Table 4: The new features added to training data. These are divided into time features, subject line features, and email features for clarity.

Feature	Description
Time Features	
Time Since Last Action	Time in seconds since last action
Time Since Last Same Action	Time in seconds since last same action
Subject Line Features	
Subject Line Characters	Number of chars in the subject line
Subject Line Words	Number of words in the subject line
Subject Line Variables	Number of variables in the subject line
Email Features	
Special Characters	Number of special chars
Font Colours	The number of fonts
Background Colours	The number of background colours

In Figure 2 a window of 6 actions is used and select actions and email features are given for space reasons. The top of the figure shows the sequence of actions with the donation amount ($150), while the bottom shows the one-hot encoded actions with appended email features. The first action (A1) is the "no action" action and thus has no associated email features, which is why they are all 0 in the figure. The second action is a true action (A2), and has associated email features. Here, E1 could be 220 words and E4 could be 11 images. The third action is the same action as the second action (A2) and has the same associated email features. This could be a case where the constituent opened an email twice in a row. The fourth action (A3) is a different action from the second and third action and has a different associated email. The fifth action has the same associated email as the fourth action, but is a different action (A10). Finally, the sixth action is the same as the second and third actions (A2), but has different email parameter values, so this could be the constituent opening up a different email.

For all experiments, the deep learning algorithms are provided with training data in the form of Figure 2. Window sizes vary between 1 and 25. While CNN LSTMs were the best performing algorithm in previous research (Lee et al., 2022; Lee et al., 2020b), we experiment with RNNs, BDLSTMs, and CNNs as well to see the effect of the new features on these algorithms, and to see whether the new features can actually improve their accuracies to the point of matching or surpassing that of the CNN LSTMs. In particular, since RNNs and BDLSTMs are more suited to sequential data, we consider it important to continue to evaluate their performance on this task.

Donor actions are given in sequence, but the element of time is missing. In previous work, if action *B* followed action *A*, there could have been years between these actions, or seconds, and the data did not provide any information to allow the machine learning algorithms to distinguish between these situations. We introduce two new features - time since last action, and time since last same action. *Time since last action* measures the time between the current action and the previous action, while *time since last same action* measures how much time has elapsed since an action of the same type was taken (e.g., if the last action was 'delivered', how long it has been since the previous 'delivered' action). We hypothesize that these features could provide crucial information about the meaning of actions following each other in the donor journey. Figure 3 shows the data from Figure 2 augmented with these two features.

In Figure 3 we give the times in a readable format, but they are given as seconds in the training data. The deep learning algorithms are now given information about how long it has been since actions were taken. While the times given are fabricated, we can see how the sixth action happened 2 days after the last same action (the third action) by summing 1 day, 6 hours,

A1	A2	A3	…	A10	E1	E2	E3	E4	…	E7	TA	TSA
1	0	0		0	0	0	0	0		0	0	0
0	1	0		0	220	5	6	11		18	0	2 days
0	1	0		0	220	5	6	11		18	20 minutes	20 minutes
0	0	1		0	155	3	11	4		12	1 day	1 year
0	0	0		1	155	3	11	4		12	6 hours	5 days
0	1	0		0	301	10	3	2		1	18 hours	2 days

Figure 3: The action set from Figure 2 with TA (Time since last action) and TSA (Time since last same action) added.

and 18 hours between them in terms of *time since last action*. We can also see that the third action happened 20 minutes after the second action, but it was an entire day later that the fourth action happened. Also, the constituent has not taken A3 action in a year until they do so on their fourth action. Without time features, all of this information is not available to machine learning algorithms.

With emails, before the reader sees the email message, they typically see the subject line. Subject lines have been shown to affect response rates to surveys (Sappleton and Lourenço, 2016). We add 3 subject line features to the set of features describing an email associated with an action (Table 4. *Subject line characters* and *subject line words* are related, but it is possible to have many short words, or few long words and have the same number of characters. *Subject line characters* gives a measure of the overall length of the subject line, while *subject line words* help the algorithms know how split up these characters are. *Subject line variables* count how many variables there are in the subject line, where a variable is a placeholder for a value that can be personalized (e.g., the constituent's first name in "Hi (first name), we want to thank you for your donation!").

We also add the following email features – special character count, font colours, and background colour to investigate their effect on the donor journey. *Special character count* counts how many "$" and "&" characters are in the email. This can be thought of primarily as how often money is mentioned, but also how often the constituent is seeing symbols in the email. *Font colour* counts the number of fonts colours used in the email. Some emails have only one font colour (black) but many fundraising emails have several, in order to try to make the email appear more inviting and exciting. A similar story holds for *background colour*, where often the only background colour is white, but some emails have many backgrounds throughout, again to try to appear more enticing to the reader.

Architectures for the deep learning algorithms were kept the same as the best architectures in (Lee et al., 2022; Lee et al., 2020b) for consistency in terms of comparison, and because the authors stated that

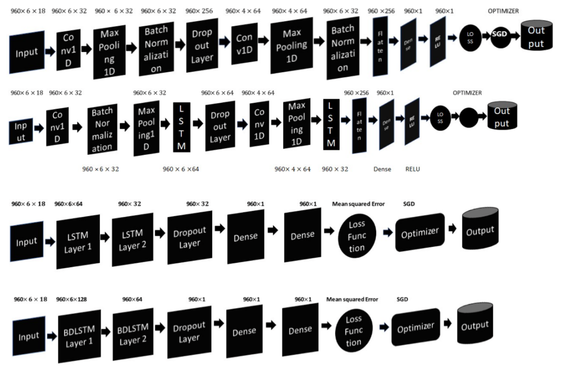


Figure 4: The best deep learning architectures discovered empirically and used in our experiments. From top to bottom they are: CNN, CNN LSTM, RNN, and BDLSTM.

those architectures had been optimized for the data at hand. The best deep learning architectures are shown in Figure 4.

5 EMPIRICAL EVALUATION

Our experiments involve comparing the performance of four deep learning algorithms (CNNs, CNN LSTMs, RNNs, and BDLSTMs) using the features in previous work to their performance with those features + the features described in Table 4. We seek to understand if these new features can help any charities better model the donor journey for their constituents. In order to try to isolate the effect of the new features we are adding, we omit constituent features from the data. In previous researchers work on this data (Lee et al., 2022; Lee et al., 2020b) constituent features generally helped lower MAE, but did not have a large effect on it, so omitting them should not have a large effect on the overall measurements. We also do not combine data across charities, since for most charities this is not an option, since they do not have access to other charities' data. We believe this comparison gives a more accurate assessment of whether the features we are adding help deep learning algorithms learn more accurate donor journey models.

All experimental results are averaged over 25 cross validation runs, where at each run we balance donors and non donors. This is done by selecting all of the smaller set (donors) and an equal random number of the larger set (non-donors) for the training set, and choosing a different subset of the larger set at each subsequent iteration. While this is a regression problem, it is as important for charities to distinguish between donors and non-donors as it is to determine how much a donor may give. Data is split into 75%

Table 5: Summary of training data from five charities.

	C1	**C2**	**C3**	**C4**	**C5**
Donors	640	229	316	27	1258
Non-Donors	195669	195688	50811	60	173363
Total Raised	$54,387	$55,952	$130,034	$6,285	$364,133
Mean Don.	$85	$245	$409	$233	$290
Median Don.	$50	$100	$100	$100	$100
Standard Dev.	$105	$514	$1520	$585	$1,035
Min Don.	$5	$1	$1	$10	$5
Max Don.	$1,000	$5,000	$10,000	$3,000	$25,000

training and 25% testing.

5.1 Preliminary Experiments

The charitable data used in our preliminary experiments is the same data used in previous research (Lee et al., 2022; Lee et al., 2020b). This data is described in Table 5. C1 is a wildlife charity, C2 is a disease charity, C3 is a youth charity, C4 is a disease charity and C5 is a university foundation. This data comes from Fundmetric (www.fundmetric.com), a machine learning platform that provides anonymized data that mirrors the real world completeness of most data sets for nonprofits.

Table 6: Preliminary experiment using all 5 charities, with window size 20 and a CNN.

	C1	**C2**	**C3**	**C4**	**C5**
Without Time Features	**$26**	$490	$195	$59	**$46**
With Time Features	$35	**$290**	**$138**	**$57**	$52

Tables 6 compares the MAE for the five charities when time features are added to the action data to the MAE without time features, using window size 20 for each charity, and the CNN algorithm. The MAE for C2 and C4 saw a 41% and a 29% drop respectively when adding time features to the data. This still constitutes a $290 and $138 MAE for these charities, which is too high of an error to use the model for suggesting email parameters for those charities. For C1 and C5, where the MAEs were lower in previous experiments, there was a slight increase in MAE with the addition of time features.

In subsequent experiments, C1 and C5 were the focus, in an attempt to further lower the MAE for their donor journeys, since it was these charities for which MAE was at more acceptable levels in terms of a charity making decisions based on the results of donor journey experiments, and since C5 has extra actions making it a different dataset on which to train. We present the C2 and C3 results here to show that when MAE is high, time features can be added in order to move towards a more acceptable error. C4 has a small data set (only 60 donors) and we did not include it in further experiments as a result.

The following experiments show results for C1 and C5 when adding time features (Section 5.2), and then adding the new email features (Section 5.3), using window sizes from 1 to 25. We experiment with each of RNNs, BDLSTMs, CNNs, and CNN LSTMs for each experiment, to see the effect of the newly added features on their performance with respect to MAE.

5.2 Experiment 1: Adding Time Features

Tables 7, 8, 9, and 10 show the change in MAE when the two time features are added to the data compared to the MAE without these features for four deep learning algorithms. In all results tables, bold values show the lower MAE in a comparison of data, and bold italic values show the lowest value in the table for a given charity.

For CNNs and CNN LSTMs, there is an increase in MAE with almost every window size for both C1 and C5. On the contrary, for RNNs and BDLSTMs, there is a decrease in MAE for most windows sizes for both C1 and C5. Thus, the extra features seem to help RNN-based deep learning algorithms. In addition, the MAEs are generally lower for RNNs and BDLSTMs than they are for CNNs and CNN LSTMs, suggesting that adding time features and using RNN-based deep learning algorithms is a charity's best choice to obtain the most accurate donor journey model. We next experiment with adding subject line and other email features to the time features data.

Table 7: Comparing the performance of CNNs with new added time features to data without these features."TF" stands for time features being added to the data.

Window Size	1	3	6	10	15	20	25
C1	**$32**	**$33**	***$26***	**$34**	**$29**	**$27**	**$27**
C1TF	$43	$42	$44	$43	$39	$41	$40
C5	**$49**	**$49**	**$44**	$49	**$49**	**$50**	$57
C5TF	$52	$52	$46	***$41***	$52	$52	**$50**

Table 8: Comparing the performance of CNN LSTMs with new added time features to data without these features. "TF" stands for time features being added to the data.

Window Size	1	3	6	10	15	20	25
C1	**$41**	**$41**	**$36**	***$35***	**$36**	$42	**$33**
C1TF	**$41**	$42	$43	$41	$40	**$39**	$39
C5	**$49**	***$46***	**$47**	**$48**	**$47**	**$49**	***$46***
C5TF	$53	$52	$52	$53	$53	$52	$53

Table 9: Comparing the performance of RNNs with new added time features to data without these features. 'TF' stands for time features being added to the data.

Window Size	1	3	6	10	15	20	25
C1	$43	$31	$30	$28	$27	$26	$27
C1TF	**$25**	***$24***	***$24***	***$24***	**$25**	***$24***	***$24***
C5	$55	$55	$55	$54	$55	$50	$48
C5TF	**$44**	***$38***	**$40**	**$41**	**$40**	**$40**	**$41**

Table 10: Comparing the performance of BDLSTMs with new added time features to data without these features. "TF" stands for time features being added to the data.

Window Size	1	3	6	10	15	20	25
C1	$43	$31	$29	$28	$27	$28	$25
C1TF	**$28**	**$25**	**$28**	***$24***	**$25**	**$26**	***$24***
C5	$53	$52	**$42**	$41	$43	**$40**	$50
C5TF	**$39**	***$38***	$48	**$40**	**$40**	**$40**	***$38***

5.3 Experiment 2: Adding Subject Line Features and More Email Features

We next added new email features, including those describing the subject line for the email associated with each action. Tables 11, 12,13, and 14, show the change in MAE when these features are added to the data compared to the MAE without these features for four deep learning algorithms.

As with adding just time features, for CNNs and CNN LSTMs, there is an increase in MAE in with almost every window size for both C1 and C5. On the contrary, for RNNs and BDLSTMs, there is a decrease in MAE for most windows sizes for both C1 and C5. Thus, the extra features seem to help RNN-based deep learning algorithms.

For CNNs the MAEs are lowered when adding new email and subject line features to time features, while CNN LSTMs are unaffected. For RNNs the addition of new email and subject line features actually caused an increase in MAE compared to only adding time features, although these MAEs were still lower than not adding new features at all. For BDLSTMs, adding the new email and subject features had mixed results compared to only adding time features, but for C5 it was generally better to have all of the new features in terms of MAE.

Overall, the lowest MAE for C1 data was $24 which was achieved by both RNNs and BDLSTMs with time features and with time features and new email features. For C5, the lowest MAE was $36 which was achieved using a BDLSTM with both time features and new email features. These MAEs are lower than any achieved in previous work ((Lee et al., 2022; Lee et al., 2020b)) when constituent features and data combination were not used and thus show that the addition of time and new email features helps create deep learning models better capable of capturing the donor journey.

Table 11: Comparing the performance of CNNs with new features(time and new email features) to without new features."NewF" stands for new email and subject line features being added to the data.

Window Size	1	3	6	10	15	20	25
C1	**$32**	**$33**	***$26***	**$34**	**$29**	**$27**	**$27**
C1NewF	$40	$42	$42	$39	$40	$39	$38
C5	**$49**	**$49**	***$44***	**$49**	**$49**	**$50**	**$57**
C5NewF	$52	$58	$52	$53	$52	$52	$51

Table 12: Comparing the performance of CNN LSTMs with new features(time and new email features) to without new features. "NewF" stands for new email and subject line features being added to the data.

Window Size	1	3	6	10	15	20	25
C1	**$41**	**$41**	**$36**	**$35**	**$36**	**$42**	***$33***
C1NewF	**$41**	$42	$42	$42	$42	**$42**	$41
C5	**$49**	***$46***	**$47**	**$48**	**$47**	**$49**	***$46***
C5NewF	$51	$50	$52	$53	$54	$53	$53

5.4 Experiment 3: Querying the Most Accurate Models

In order to ensure the models learned were reasonable, we queried them to see which actions they thought would lead to the highest donation amount across donor journeys. This involved taking the last n actions associated with a constituent and shifting them back a position, and querying the model with each of the possible actions, as shown in Figure 5. Doing this resulted in the highest predicted gift amount being associated with *pageview*, *donated*, and *delivered* in 80% of cases and actions such as *complained* never being predicted to produce the highest donation amount. We interpreted this to mean the model had learned positive actions help increase do-

Table 13: Comparing the performance of RNNs with new features(time and new email features) to without new features. "NewF" stands for new email and subject line features being added to the data.

Window Size	1	3	6	10	15	20	25
C1	$43	$31	**$30**	$28	$27	$26	$27
C1NewF	***$24***	***$24***	$32	***$24***	***$24***	***$24***	***$24***
C5	$55	$55	$55	$54	$55	$50	**$48**
C5NewF	**$44**	***$39***	**$41**	**$40**	**$44**	**$46**	**$48**

Table 14: Comparing the performance of BDLSTMs with new features(time and new email features) to without new features."NewF" stands for new email and subject line features being added to the data.

Window Size	1	3	6	10	15	20	25
C1	$43	$31	**$29**	**$28**	$27	$28	$25
C1NewF	**$25**	**$25**	$30	$29	***$24***	**$25**	***$24***
C5	$53	$52	**$42**	**$41**	$43	**$40**	$50
C5NewF	***$36***	**$41**	$43	**$41**	**$41**	$42	**$41**

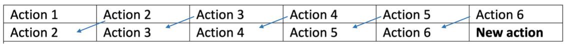


Figure 5: When querying the models, all actions are shifted back by 1 and a new action is inserted into the last position. The model is then queried for a predicted donation amount with this set of actions. Email and time features are included, but are not shown here.

nations and as a further sanity check on its reasoning.

Ultimately, since we cannot choose the actions of the constituent, we want to be able to optimize the action the charity can take, which is sending an email (*delivered*). We queried the most accurate models from Experiments 1–3 with the *delivered* action with a range of values for each email parameter, and observed which values led to the model suggesting the highest donation amount for each constituent. These results are shown in Tables 15, 16 show the mode, median, mean and standard deviation for the email parameter values deemed by BDLSTMs to be the best in order to maximize donation values for C1 and C5 constituents respectively. We used BDLSTMs with window size 20 in this experiment since this setup generally had the lowest MAEs in our experiments.

For C1, BDLSTMs suggest a larger number of paragraphs, while for C5 they suggest just 1 paragraph, perhaps picking up on a difference between the two charities. C1 is a wildlife charity and C5 is a university foundation and their donors may have different email preferences. Another difference is shorter subject line words for C1 vs longer ones for C5. For both charities, the model chose 5 words, but averaging their lengths using the number of characters selected gives us 4 letter words for C1 and almost 8 letter words for C5. Donors to C5 may need more information in their subject lines in order to be sufficiently interested to open an email.

In terms of special characters and fonts, BDLSTMs suggested 5 each for both C1 and C5, but suggested 15 background colours for C1 vs 5 for C5. Similarly to the choice of larger words for C5, this is perhaps indicative of the BDLSTM learning that university foundation donors prefer larger words with fewer colours. For both C1 and C5, BDLSTMs chose

Table 15: Summary of email parameter values chosen by BDLSTMs for C1.

	Mode	**Median**	**Mean**	**St. Dev**
Words	150	150	134.43	132.47
Paragraphs	18	18	15.03	6.43
Images	15	15	13.54	3.32
Links	35	35	34.14	2.1
Blocks	9	9	9	0
Special chars	5	5	6.76	3.8
Font colours	5	5	5.14	1.18
Background colour	15	15	12.52	4.32
Divs	41	41	44.64	6.4
Editable Content	9	9	10.17	2.3
Subject line words	5	5	5.69	2.7
Subject line characters	20	20	22.53	5.74
Subject line variables	0	0	0.4	0.49

Table 16: Summary of email parameter values chosen by BDLSTMs for C5.

	Mode	**Median**	**Mean**	**St. Dev**
Words	150	150	124.8	56.23
Paragraphs	1	1	1	0
Images	15	15	13.4	3.3
Links	35	35	33.9	2.2
Blocks	9	9	9	0
Special chars	5	5	8.23	4.7
Font colours	5	5	9.9	5.03
Background colour	5	5	9.9	5.03
Divs	56	56	53.4	5.6
Editable Content	15	15	13.05	2.8
Subject line words	5	5	5	0
Subject line characters	38	38	29.12	9.06
Subject line variables	0	0	0.05	0.23

0 subject line variables except for in a few cases, indicating that having a constituent's name in the subject line is not advisable, according to the models.

6 CONCLUSIONS AND FUTURE WORK

This research builds on the work in (Lee et al., 2022; Lee et al., 2020b) by augmenting donor journey data with time features and more email features, including subject line features. The former provides needed context for the passage of time between actions, and the passage of time between similar actions, while the latter provides more information about the initial section of an email the reader sees (the subject line) and about the appearance of the email.

The addition of these features had a strong effect on two charities (C2 and C3), reducing the MAE by 41% for one charity and 34% for another. But these charities had high MAEs to begin with, so we focused on charities that had lower MAEs, including one that had extra actions compared to the other charities with data available, since these models are accurate enough to be used in practice.

Adding time features increased MAE for CNNs and CNN LSTMs in most cases, as those algorithm were perhaps less well-equipped to handle the time features and did not seem to learn from the new email features. In contrast, when time features were added to the data for RNNs and BDLSTMs, the MAE dropped, and was below that of the CNN and CNN LSTMs on data without time features. This showed adding time features can help deep learning achieve lower MAEs on the donor journey.

We next added subject line features and new email features to the data with time features and again compared to data without any new features. The results were similar as to when time features were added, although CNN and CNN LSTM MAEs improved with data containing these new features compared to their MAEs when only having time features added. For RNNs and BDLSTMs, there was not a significant change from only adding time features, but the lowest MAEs were achieved with data having all of time features, subject line features, and other new email features. This shows that the new features added in these experiments help create more accurate deep learning models for the donor journey.

When querying the most accurate model to select email parameters, the BDLSTM model suggested short emails for both C1 and C5, but many more paragraphs for C1, which is a wildlife charity. It also chose fewer background colours for C5, a university foundation and larger words for its subject lines compared to C1. This may reflect the level of language sophistication around university donors, since many of them are alumni of the university foundation, and thus have a post-secondary education.

In the future, we will add in constituent features to (hopefully) further lower MAE and see if deep learning algorithms can benefit from having all of actions, email features, constituent features, and all the features we added in this paper. We will also combine data across charities to see the effect, even though this combination of data is not realistic for most charities. We will continue to add new features to the data as they become available and as we create them.

In addition to understanding which features matter for machine learning the donor journey, understanding *why* such features matter is a possible avenue of research. For instance, background colours may have different effects on constituents from different cultures. We can also survey constituents to obtain direct answers concerning which email features actually made a different in their decision to donate or not, and in their decision concerning how much to donate.

Also in the future, the type of email sent will be a feature, which would be in the set of {acquisition, solicitation, stewardship, cultivation}. Acquisition emails seek donations from non-donors, while solicitation emails seek donations from previous donors. Cultivation emails seek to increase a donor's donation amount, while stewardship emails thank donors for their donations and keep them informed on the activities of the charity. While adding these features may seem straightforward, many emails fit more than one category. Charities always try to say thank you even when asking for money, so these features will likely need to be scaled in the [0,1] range and we will experiment to see which system works best for incorporating this information into the data.

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