Towards Neural Numeric-To-Text Generation From Temporal Personal Health Data

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ABSTRACT

With an increased interest in the production of personal health technologies designed to track user data (e.g., nutrient intake, step counts), there is now more opportunity than ever to surface meaningful behavioral insights to everyday users in the form of natural language. This knowledge can increase their behavioral awareness and allow them to take action to meet their health goals. It can also bridge the gap between the vast collection of personal health data and the summary generation required to describe an individual’s behavioral tendencies. Previous work has focused on rule-based time-series data summarization methods designed to generate natural language summaries of interesting patterns found within temporal personal health data. We examine recurrent, convolutional, and Transformer-based encoder-decoder models to automatically generate natural language summaries from numeric temporal personal health data. We showcase the effectiveness of our models on real user health data logged in MyFitnessPal [34] and show that we can automatically generate high-quality natural language summaries. Our work serves as a first step towards the ambitious goal of automatically generating novel and meaningful temporal summaries from personal health data.

CCS CONCEPTS

- Computing methodologies → Machine translation; Natural language generation; Supervised learning; Neural networks;
- Applied computing → Consumer health; Health informatics.

KEYWORDS

neural networks, natural language generation, personal health data, time-series data, Transformer, convolutional networks

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1 INTRODUCTION

It is now easier than ever to collect personal health data due to the increase in the production of smart devices designed to track data from multiple inputs. Target demographics of these products can be designated as quantified-sellers (those who maintain their own health records as a hobby), people with chronic health conditions, and everyday individuals who wish to maintain a healthy lifestyle. Quantified-sellers strive to record as much of their lives as possible using the health technologies available to them and are eager to track and learn from their own data. On the other hand, those with chronic health conditions (e.g., Type II diabetes) mainly use this information to make decisions related to future food consumption, physical activity, and so on [29]. Everyday individuals who are health-conscious may also utilize a health app or device to track their progress and learn what works for them. Unfortunately, many users of these personal health technologies tend to abandon them after a short period of time due to a lack of support when it comes to decision-making and a lack of sufficient interpretation of their data [4]. Users will then lose interest in learning from their own data and begin to record it less often. This results in a sparse dataset that becomes more difficult to interpret and the users end up becoming even more disengaged [6]. Non-expert users may also incorrectly interpret their data, leading them to make unfavorable health decisions [23]. With increasingly more data collected over longer periods of time, it becomes more and more difficult to understand it. In light of this, there is a need for an automated system that can interpret and surface meaningful insights to aid users in their progress towards their health goals. This problem was partially addressed previously by works [11–14, 35, 36] (inspired by [38, 39]) designed to generate natural language summaries of temporal data using summary templates, or “protoforms.” A protoform is essentially a summary with special “blanks” to be filled with specific types of words, such as summarizers (conclusive phrases), quantifiers (phrases that specify how often a conclusion is true), attributes (variables of interest), time windows (e.g., weeks, months), and days of the week (e.g., Friday). The structure of an example protoform is:

On ⟨quantifier⟩ ⟨sub-time window⟩ in the past ⟨time window⟩, your ⟨attribute⟩ was ⟨summarizer⟩.

This could generate the following example summary: “On most of the days in the past week, your calorie intake was high.” We call this a standard evaluation summary at the daily granularity. In recent work [10], we created a comprehensive hierarchy of twelve different protoforms to summarize different types of patterns of interest in time-series data. The summaries range from simple (e.g., standard evaluation and comparison) – those that focus on observations that are more apparent to the everyday individual – to more complex (e.g., if-then and cluster-based patterns) – those that describe longer patterns discovered using
more advanced data-mining techniques. We use the hierarchy to generate summaries (via our summarization framework) describing behavioral patterns in real user health data.

Although rule-based approaches can be effective, the reliance on the use of protoforms limits the diversity of the summary output. Furthermore, extending the summarization framework requires manually defining new temporal patterns (and subsequently creating new protoforms) to generate new summaries. In contrast, we aim to train deep learning models to both learn and fill the protoform templates presented in our framework. We believe that a transition to deep learning gives our framework more freedom to grow on a summarization and pattern mining level. Deep learning models may discover temporal patterns that we cannot see and present those patterns in natural language. We present an end-to-end neural approach for time-series summarization, exploring the spectrum of recurrent, convolutional, and Transformer-based models to automatically generate natural language summaries from numeric temporal personal health data. To our knowledge, this is the first such approach in the personalized health domain. Given the lack of publicly available ground-truth summaries from personal health data, we rely on the summaries generated from our protoform-based summarization framework to train the models. We showcase summaries generated from real user data from MyFitnessPal [34], and show that the automatically generated summaries are both personalized and of high quality. Our models achieve good accuracies and high BLEU scores [22] for many summary types. In other words, our models can effectively learn to generate understandable natural language summaries automatically from numeric time-series data. Our work should thus be considered as a proof-of-concept that opens up the tantalizing possibility of generating new temporal summary types and bypassing the need to manually extend rule-based approaches.

2 RELATED WORK

According to van der Lee et al. [32], there are three families of data-to-text generation methods: statistical machine translation [16, 20, 28, 31], neural machine translation [5, 8, 15, 17, 19, 24, 25, 30, 40], and rule-based linguistic summarization [2, 10, 27]. Neural and statistical methods generally involve training models to automatically generate natural language summaries of data, while rule-based methods depend on the use of protoforms to model their summary output. There are definite benefits and drawbacks between each family, especially between the machine translation methods and the rule-based methods. Rule-based methods tend to have better performance and higher textual quality; however, these methods require manual creation or extension which can be considerably time-intensive. Most rule-based approaches find simple conclusions based on the trend/concavity of a time series and relay this to the user in a templatized natural language summary. In our previous work [10], we employed various data mining algorithms to discover hidden patterns within temporal personal health data and generated summaries via different rule-based protoforms. They are evaluated by humans, and make use of objective measures [2], such as summary length and relevance.

In the field of neural machine translation [8, 9, 24, 25, 30, 37, 40], neural and statistical methods bypass the need for manual rule creation, but they rely on large datasets and are generally lacking in performance and text quality. The models’ reliance on large datasets can be especially difficult in certain domains, such as in personal health. For evaluation, these models are typically compared using the BLEU score, which is designed to measure the agreement between the model output and the reference sentences. Notable examples include Murakami et al. [21] and Aoki et al. [1] who present the Market Reporter model, which can handle inter-market relationships for stock market data (e.g., relationships between stock trends for the Nikkei and Dow Jones indices). The authors paired time series sequences gathered from Thomson Reuters DataScope Select with associated market comments from Nikkei Quick News (NQN). The summaries generated by this model were limited to simpler conclusions, such as a continual rising trend that could be easily viewed in the data. In contrast to the works mentioned above, our aim is to construct neural sequence-to-sequence (i.e., numeric-to-text) generation models for temporal personal health data to generate summaries of meaningful and interesting patterns.

3 LEARNING TASK

Before delving into the encoder-decoder architectures, we define the learning task for numeric-to-text neural models. A main challenge is the lack of suitable ground-truth training data pairing personal health data with high-quality summaries that can be used for training. On the other hand, we do have relatively high-quality summaries from our recently proposed summary type hierarchy. We also conducted a user study to evaluate the output summaries by their readability, their comprehensiveness, their usefulness, and how well they align with the data they are describing. Thus, given the lack of publicly available domain expert summaries for personal health data, as a first step, we use the summaries produced from our rule-based framework as the ground truth to train our neural models. We believe this is an effective strategy since we can train our models on a variety of summary types, establishing a suitable state-of-the-art method for this task. Further, this also showcases the proof of concept, that it is indeed possible to automatically generate high-quality natural language summaries from numeric data using deep learning models. In the future, our aim is to generate free-form summaries.

The learning task is to translate raw or numeric time-series subsequences into natural language summaries, as reflected in Figure 1: Learning Task Overview: A subsequence (top left) and the entire time series of a user’s calorie intake (bottom left) are fed as input into a neural translation model, which outputs a natural language summary describing a pattern or trend in the numeric personal health data.
1. Here, the input is numeric time-series data comprising the sub-
sequences comprising the past week (top) and the entire user history
(bottom). The neural network models are then expected to generate
a natural language summary, as shown. Our models receive training
pairs containing a time series subsequence of personal health data
(e.g., calorie intake), the natural language summary generated for it,
and the associated protoform for that summary. The summary type
is selected prior to training and the learning models are evaluated
based on their accuracy and BLEU score for each summary type.

4 NUMERIC-TO-TEXT MODELS

We introduce CNN-LSTM, Transformer, and Transformer-LSTM
coder-decoder models for numeric-to-text translation. The input
to all three models comprises the (bottom). The neural network models are then expected to generate
a natural language summary, as shown. Our models receive training
pairs containing a time series subsequence of personal health data
(e.g., calorie intake), the natural language summary generated for it,
and the associated protoform for that summary. The summary type
is selected prior to training and the learning models are evaluated
based on their accuracy and BLEU score for each summary type.

We extend the Time Series Transformer (TST) [7] encoder, and
focus on text-to-text machine translation. Thus, we replace the
input to TST encoder is the concatenation of
attention) to construct a model for numeric-to-text generation. The
encoder-decoder models for numeric-to-text translation. The input
to all three models comprises the short-term \(x_{\text{short}}\) and long-
term \(x_{\text{long}}\) representations of the temporal personal health data.
In our case, the short-term representation of the data is the input
time series subsequence of interest (shown on top left in Fig. 1),
while the long-term representation is the entire time series (shown
on bottom left). Formally, we define the long-term representation
as \(x_{\text{long}} = (x_1, x_2, \ldots, x_N)\) where \(x_i \in \mathbb{R}\) and \(N\) is the length of the
entire time series, and the short-term representation as \(x_{\text{short}} =
(x_i, x_{i+1}, \ldots, x_j)\) where \(1 \leq i, j \leq N\) and \(i < j\). The length of \(x_{\text{short}}\)
depends on the summary type the model is learning. Since we are
working with personalized summaries (e.g., medium sodium intake
for one user can be high intake for another user), they require the
context of the time series \(x_{\text{long}}\) to be useful.

![Figure 2: Decoder outputs: (blue) natural language summary, and
(pink) protoform template.](image)

For the CNN-LSTM model, we feed the two representations of the
input data into separate, yet similar, convolutional encoder layers
and concatenate the resulting hidden states with the original \(x_{\text{short}}\)
and \(x_{\text{long}}\) sequences before sending them through fully-connected
dense and dropout layers. For the decoding step, we utilize two
separate LSTM decoders: a summary decoder and an additional
template decoder. The summary decoder generates the predicted
summary tokens \(y_{\text{pred}} = s_1 \ldots s_n\) where \(n\) is the number of
tokens generated by the LSTM for the resulting natural language
summary, while the template decoder generates the predicted tem-
plate tokens \(y_{\text{proto}} = t_1 \ldots t_n\) for the resulting protoform.
These template tokens are generated directly from the summary
\(y_{\text{pred}}\) for input. It may seem that the same \(y_{\text{proto}}\) will be
fed as input for each example; however, any summary type capable
of generating summaries that vary in length (e.g., if-then pattern
summaries) will have varying inputs for \(y_{\text{proto}}\). Summary tokens
\(y_{\text{pred}}\) and template tokens \(y_{\text{proto}}\) are the two outputs of our model.
In essence, the model has two similar learning tasks: the translation
of a time series sequence with added context to a natural language
summary and its associated protoform. Whereas we are mainly
interested in the summary output, the template decoder allows the
model to learn the protoform structure which results in better sum-
mary output. Once it learns the protoform using the input template
tokens, it can automatically determine what the “blanks” should be.
For example, given the set of template tokens “In the past full TW,
your A A has been S,” it can generate a summary such as “In the past full week, your calorie intake has been moderate.” The tem-
plate tokens help the neural network focus on the special “blanks”
mentioned in Sec. 1, whereas the summary tokens can focus on the
final token-level natural language summary. The decoding pro-
cess is shown in Figure 2. The model utilizes a cross-entropy loss
with respect to the ground-truth summary and template tokens
at each position, which yields the combined loss for the summary
and template decoder output. The resulting loss function given
as: \(L(\hat{y}_S, \hat{y}_T) = \sum \sum CE(y_i, \hat{y}_i) + m \sum \sum CE(y_i, \hat{y}_i)\), where CE is
the cross entropy loss per token, \(n\) is the summary length, \(y_i\), and
\(\hat{y}_i\) represent the actual and predicted summary tokens from
the summary decoder, \(y_S\) and \(\hat{y}_S\) represent the actual and predicted
template tokens from the template decoder, and \(m\) represents the
number of incorrect “blanks” in the template decoder output (i.e.,
m provides a higher penalty).

Transformers are a viable alternative to recurrent and convolu-
tional networks via their use of attention; therefore, we decided to
test the summary generation task on a numeric-to-text Time Series
Transformer-Transformer model. The original Transformer [33]
focuses on text-to-text machine translation. Thus, we replace the
text encoder with one that can process numeric time-series data.
We extend the Time Series Transformer (TST) [7] encoder, and
pair it with a Transformer decoder (for natural language gener-
ation) to construct a model for numeric-to-text generation. The
input to TST encoder is the concatenation of \(x_{\text{short}}\) and \(x_{\text{long}}\), and it utilizes multi-head attention by dividing the queries, keys, and
values into chunks using a moving window (we use window size
12). For decoding, we employ dual Transformer decoders to train
the model on both the protoform structure and natural language so
that it can produce a more comprehensive output. Teacher forcing
is not used during training. We also experimented with the TST
encoder and an LSTM decoder model. We hypothesized that the
LSTM decoder could be a possible alternative to the Transformer
decoder, especially when receiving encodings from time-series data
since the Transformer decoder may not be the ideal pairing for the
TST encoder. The encoder-decoder connection between the TST
and LSTM is similar to that of the CNN-LSTM model.

5 EXPERIMENTS

The models were trained using PyTorch, on a Linux-based machine
with an NVIDIA Tesla V100 GPU. For reproducibility purposes, our
open source implementation is available from https://github.com/
neato47/Neural-Numeric-To-Text-Generation. We conducted our
experiments using the MyFitnessPal food log dataset [34], which
contains 587,187 days of real food log data across 9.9K users (389
of them were selected), each tracking up to 180 days worth of food
and nutrient intake data. Users were expected to log the food items
they consumed and their daily calorie goals, while the MyFitnessPal
database added in the associated nutrient information and total
daily intake. We train our models on each summary type sepa-
ately and evaluate their performance using the BLEU score and
the model’s prediction accuracy. The accuracy is determined by how exactly each summary in the predicted output matches the expected output on a token-to-token basis. In terms of hyperparameters, we used the Adam optimizer with a learning rate of 0.0001 and cross-entropy loss for all three models. For the CNN-LSTM model, the hidden encoder/decoder size is 180 and the encoder’s output size is 256. The CNN kernel size is 1 × 3, with a stride of 1 and padding of 1 for both convolutional layers. The max pooling layers have a kernel size of 2 and a stride of 2. Only one linear layer is used before the output neurons. The output dimension of the decoder is the length of the largest ground-truth summary. The CNN-LSTM model is trained in batches of size 180 for 78 epochs. For the Transformer-based models, the input embeddings are 64 dimensional (d_model), with query, key and value dimensionality of 8, with 4 heads. There are four stacks encoder and (summary and template) decoder layers. A dropout probability of 0.2 is used for both the encoder and decoder layers. The TST-LSTM model was trained in batches of size 8 for 30 epochs.

We ran experiments on the users’ calorie intake data; the comparative results for the three models, for each summary type, are reported in Table 1. The CNN-LSTM’s average prediction accuracy across all of the summary types is around 0.814, the TST-Transformer’s average accuracy is around 0.621, and the TST-LSTM’s is around 0.856. The TST-LSTM model also has the highest exact match accuracy for 10 out of the 13 summary types. The BLEU score [22] measures the agreement between the model output and the reference sentences by calculating the n-gram overlap between the output and reference sentences. A score of 1 indicates identical sentences. The CNN-LSTM model has an average BLEU score of 0.955, the TST-Transformer model has an average of 0.948, and the TST-LSTM model has an average of 0.964. The TST-LSTM model also has the highest BLEU score for 9 out of 13 summary types. Based on average accuracy and BLEU score alone, the TST-LSTM model performs better when it comes to matching the exact summary output and it makes predictions that are closer to the target summary output more often. This shows that the TST-LSTM model is the better model. Looking at the summary types, it seems that the models had the most trouble with day if-then pattern, goal comparison, cluster-based pattern, and standard pattern summaries. Please refer to [10] for more information on these summary types. All three models mainly struggled to correctly guess the days of the week (e.g., Friday) for the day if-then pattern summaries. It may be difficult to keep track of the days based on the data. Goal comparison summaries compare a user’s adherence to a goal between two time windows at the weekly granularity. It appears that the TST-Transformer had trouble factoring in the calorie intake goal for the comparison, which may point to the raw input. It only had an accuracy of 0.3 for this type, while it had an accuracy of 0.8 for evaluation comparison summaries. Standard trend summaries describe how often a time series changes slope from one day to the next; however, the CNN-LSTM struggles for this summary type with an accuracy of 0.29. It is possible that the CNN encoder is having trouble detecting the change in slope. Cluster-based pattern summaries explain what happened directly after weeks that are most similar to the most recent week. This information helps predict what could happen in w′, the week after week w. The cluster-based description summary type is a description of the similar week that is most recent. The x_short of both summary types is the most recent week. This may hinder the CNN-LSTM’s and TST-Transformer’s ability to find the connections between the most recent week and the weeks similar to it since the CNN-LSTM only had an accuracy of 0.43 for both summary types, while the TST-Transformer had an accuracy of 0.26 for the cluster-based pattern summary type. It may be beneficial to add more information to the x_short (i.e., similar weeks and the weeks after them). The standard pattern summary type is very similar to the cluster-based pattern summary type, except it only uses the most recent similar week to predict the user’s behavior in week w′ and its x_short contains the most recent similar week, the week directly after, and w. The CNN-LSTM also struggled with this summary type, resulting in an accuracy of 0.3.

### 6 CONCLUSION

In this paper, we present and compare neural numeric-to-text machine translation models designed to translate raw temporal personal health data into natural language summaries. With these models, we surface hidden, meaningful patterns in a user’s personal health data and provide them with the knowledge required to work closer to their health goals. This work is a proof-of-concept demonstrating the feasibility of generating explanations and summaries from personal health data. For future work, we plan to construct joint models that can be trained on all of the summary types at once. We also plan to explore generative models [3, 18, 26] to generate novel summaries from time-series data using machine translation. Finally, we wish to look more into how we could make real-life applications of our work despite limited training data.
