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

Jonathan Harris harrij15@rpi.edu Rensselaer Polytechnic Institute Troy, New York, USA Mohammed J. Zaki zaki@cs.rpi.edu Rensselaer Polytechnic Institute Troy, New York, USA

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

ACM Reference Format:

Jonathan Harris and Mohammed J. Zaki. 2022. Towards Neural Numeric-To-Text Generation From Temporal Personal Health Data. In *Proceedings of Workshop on Applied Data Science for Healthcare (DSHealth '22)*. ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/nnnnnnnnnnnn

DSHealth '22, August 14, 2022, Washington, D.C.

© 2022 Association for Computing Machinery.

ACM ISBN 978-x-xxxx-x/YY/MM...\$15.00

https://doi.org/10.1145/nnnnnnnnnnnn

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-selfers (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-selfers 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 \langle quantifier \rangle \langle sub-time window \rangle in the past \langle time window \rangle , 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

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

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 endto-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 proofof-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 datato-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.

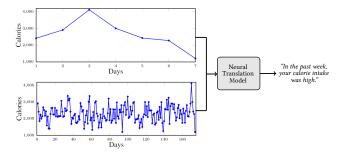


Figure 1: Learning Task Overview: A subsequence (top left) and the entire time series of a user's calorie intake (bottom left) are fed as input into a neural translation model, which outputs a natural language summary describing a pattern or trend in the numeric personal health data.

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

1. Here, the input is numeric time-series data comprising the subsequences 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 encoder-decoder models for numeric-to-text translation. The input to all three models comprises the the short-term (x_{short}) and long-term (x_{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 $x_{long} = (x_1, x_2, ..., x_N)$ where $x_i \in \mathbb{R}$ and N is the length of the entire time series, and the short-term representation as $x_{short} = (x_i, x_{i+1}, ..., x_j)$ where $1 \le i, j \le N$ and i < j. The length of x_{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_{long}) to be useful.

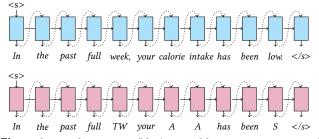


Figure 2: Decoder outputs: (blue) natural language summary, and (pink) protoform template.

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_{short} and x_{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 $y_{pred} = "s_1 \ s_2 \ ... \ s_n"$ where *n* is the number of tokens generated by the LSTM for the resulting natural language summary, while the template decoder generates the predicted template tokens $y_{proto} = "t_1 t_2 \dots t_n"$ for the resulting protoform. These template tokens are generated directly from the summary tokens y_{pred} for input. It may seem that the same y_{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_{proto} . Summary tokens y_{pred} and template tokens y_{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 summary 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 template 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 process 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: $L(\hat{y}_s, \hat{y}_t) = \sum_{i=1}^n CE(y_{s_i}, \hat{y}_{s_i}) + m \sum_{i=1}^n CE(y_{t_i}, \hat{y}_{t_i})$, where *CE* is the cross entropy loss per token, *n* is the summary length, y_{s_i} and \hat{y}_{s_i} represent the actual and predicted summary tokens from the summary decoder, y_{t_i} and \hat{y}_{t_i} 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 convolutional 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 generation) to construct a model for numeric-to-text generation. The input to TST encoder is the concatenation of x_{short} and x_{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 separately and evaluate their performance using the BLEU score and

Summary Type	Accuracy			BLEU Score		
	CNN-LSTM	TST-Transformer	TST-LSTM	CNN-LSTM	TST-Transformer	TST-LSTM
Standard Evaluation (TW granularity)	1	0.98	1	0.9999	0.998	1
Standard Evaluation (sTW granularity)	1	0.96	1	0.999	0.996	0.9998
Day-Based Pattern	1	0.846	1	0.9998	0.987	0.9999
Goal Evaluation	0.98	0.5	0.92	0.997	0.954	0.991
Goal Assistance	0.86	0.745	0.87	0.854	0.778	0.866
Standard Trend	1	0.29	1	0.9999	0.919	0.9999
If-Then Pattern	1	0.998	1	0.9999	0.9999	0.9998
Day If-Then Pattern	0.1	0.07	0.14	0.845	0.955	0.853
Evaluation Comparison	0.97	0.8	0.97	0.99	0.968	0.99
Goal Comparison	0.97	0.59	0.73	0.994	0.953	0.944
Cluster-Based Description	0.43	0.74	0.97	0.894	0.98	0.995
Cluster-Based Pattern	0.43	0.26	0.71	0.861	0.925	0.931
Standard Pattern	0.85	0.3	0.82	0.977	0.915	0.961
Average	0.815	0.621	0.856	0.955	0.948	0.964

Table 1: Experiment Results: Comparing the Numeric-to-Text Encoder-Decoder Models

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 the 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 0.59 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 w. 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. Towards Neural Numeric-To-Text Generation From Temporal Personal Health Data

DSHealth '22, August 14, 2022, Washington, D.C.

REFERENCES

- Tatsuya Aoki, Akira Miyazawa, Tatsuya Ishigaki, Keiichi Goshima, Kasumi Aoki, Ichiro Kobayashi, Hiroya Takamura, and Yusuke Miyao. 2018. Generating Market Comments Referring to External Resources. In International Conference on Natural Language Generation.
- [2] Fatih Emre Boran, Diyar Akay, and Ronald R Yager. 2016. An overview of methods for linguistic summarization with fuzzy sets. *Expert Systems with Applications* 61 (2016), 356–377.
- [3] Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language Models are Few-Shot Learners. arXiv:2005.14165 [cs.CL]
- [4] Eun Kyoung Choe, Nicole B. Lee, Bongshin Lee, Wanda Pratt, and Julie A. Kientz. 2014. Understanding quantified-selfers' practices in collecting and exploring personal data. In ACM Conference on Human Factors in Computing Systems.
- [5] Edward Choi, Mohammad Taha Bahadori, Elizabeth Searles, Catherine Coffey, Michael Thompson, James Bost, Javier Tejedor-Sojo, and Jimeng Sun. 2016. Multi-Layer Representation Learning for Medical Concepts. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (San Francisco, California, USA) (KDD '16). Association for Computing Machinery, New York, NY, USA, 1495–1504. https://doi.org/10.1145/2939672.2939823
- [6] James Codella, Chohreh Partovian, Hung-Yang Chang, and Ching-Hua Chen. 2018. Data quality challenges for person-generated health and wellness data. *IBM Journal of Research and Development* 62, 1 (Jan 2018), 3:1–3:8.
- [7] Max Cohen. 2019. Maxjcohen/transformer: Implementation of transformer model (originally from attention is all you need) applied to time series. https://github. com/maxjcohen/transformer.
- [8] Thiago Castro Ferreira, Chris van der Lee, Emiel van Miltenburg, and Emiel Krahmer. 2019. Neural data-to-text generation: A comparison between pipeline and end-to-end architectures. arXiv:1908.09022 [cs.CL]
- [9] Shen Gao, Xiuying Chen, Piji Li, Zhangming Chan, Dongyan Zhao, and Rui Yan. 2019. How to Write Summaries with Patterns? Learning towards Abstractive Summarization through Prototype Editing. ArXiv abs/1909.08837 (2019).
- [10] Jonathan J. Harris, Ching-Hua Chen, and Mohammed J. Zaki. 2021. A Framework for Generating Summaries from Temporal Personal Health Data. ACM Trans. Comput. Healthcare 2, 3, Article 21 (jul 2021), 43 pages. https://doi.org/10.1145/ 3448672
- [11] Janusz Kacprzyk and Anna Wilbik. 2008. Linguistic summarization of time series using fuzzy logic with linguistic quantifiers: a truth and specificity based approach. In International Conference on Artificial Intelligence and Soft Computing. 241–252.
- [12] Janusz Kacprzyk, Anna Wilbik, and Slawomir Zadrozny. 2008. Linguistic summarization of time series using a fuzzy quantifier driven aggregation. *Fuzzy Sets* and Systems 159, 12 (2008), 1485–1499.
- [13] Janusz Kacprzyk, Anna Wilbik, and Slawomir Zadrozny. 2010. An Approach to the Linguistic Summarization of Time Series Using a Fuzzy Quantifier Driven Aggregation. Int. J. Intell. Syst. 25, 5 (May 2010), 411–439.
- [14] Janusz Kacprzyk, Ronald R. Yager, and Slawomir Zadrozny. 2002. Fuzzy Linguistic Summaries of Databases for an Efficient Business Data Analysis and Decision Support. Springer US, Boston, MA, 129–152. https://doi.org/10.1007/0-306-46991-X 6
- [15] Guillaume Klein, Yoon Kim, Yuntian Deng, Jean Senellart, and Alexander M. Rush. 2017. Open-MT: Open-Source Toolkit for Neural Machine Translation. *CoRR* abs/1701.02810 (2017). arXiv:1701.02810
- [16] Philipp Koehn, Hieu Hoang, Alexandra Birch, Chris Callison-Burch, Marcello Federico, Nicola Bertoldi, Brooke Cowan, Wade Shen, Christine Moran, Richard Zens, Chris Dyer, Ondrej Bojar, Alexandra Constantin, and Evan Herbst. 2007. Moses: Open Source Toolkit for Statistical Machine Translation. In ACL Companion Volume: Demo and Poster Sessions.
- [17] Scott H. Lee. 2018. Natural language generation for electronic health records. npj Digital Medicine 1, 1 (Nov 2018). https://doi.org/10.1038/s41746-018-0070-0
- [18] Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Ves Stoyanov, and Luke Zettlemoyer. 2019. BART: Denoising Sequence-to-Sequence Pre-training for Natural Language Generation, Translation, and Comprehension. arXiv:1910.13461 [cs.CL]
- [19] Irene Li, Jessica Pan, Jeremy Goldwasser, Neha Verma, Wai Pan Wong, Muhammed Yavuz Nuzumlah, Benjamin Rosand, Yixin Li, Matthew Zhang, David Chang, R. Andrew Taylor, Harlan M. Krumholz, and Dragomir Radev. 2021. Neural Natural Language Processing for Unstructured Data in Electronic Health Records: a Review. arXiv:2107.02975 [cs.CL]
- [20] Adam Lopez. 2008. Statistical Machine Translation. Comput. Surveys 40, 3, Article 8 (aug 2008), 49 pages. https://doi.org/10.1145/1380584.1380586

- [21] Soichiro Murakami, Akihiko Watanabe, Akira Miyazawa, Keiichi Goshima, Toshihiko Yanase, Hiroya Takamura, and Yusuke Miyao. 2017. Learning to Generate Market Comments from Stock Prices. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics.
- [22] Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a Method for Automatic Evaluation of Machine Translation. In Annual Meeting of the Association for Computational Linguistics.
- [23] Elizabeth Peel, Margaret Douglas, and Julia Lawton. 2007. Self monitoring of blood glucose in type 2 diabetes: longitudinal qualitative study of patients' perspectives. *BMJ* 335, 7618 (Sep 2007), 493.
- [24] Ratish Puduppully, Li Dong, and Mirella Lapata. 2019. Data-to-Text Generation with Content Selection and Planning. *Proceedings of the AAAI Conference on Artificial Intelligence* 33, 01 (July 2019), 6908–6915. https://doi.org/10.1609/aaai. v33i01.33016908
- [25] Ratish Puduppully, Li Dong, and Mirella Lapata. 2019. Data-to-text Generation with Entity Modeling. arXiv:1906.03221 [cs.CL]
- [26] Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2020. Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer. arXiv:1910.10683 [cs.LG]
- [27] Ehud Reiter. 1995. NLG vs. Templates. arXiv:cmp-lg/9504013 [cmp-lg]
- [28] Lauren Sanby, Ion Todd, and Maria C. Keet. 2016. Comparing the Template-Based Approach to GF: the case of Afrikaans. In Proceedings of the 2nd International Workshop on Natural Language Generation and the Semantic Web (WebNLG 2016). Association for Computational Linguistics, Edinburgh, Scotland, 50–53.
- [29] Si Sun and Kaitlin L. Costello. 2018. Designing decision-support technologies for patient-generated data in type 1 diabetes. In AMIA Annual Proceedings. 1645–1654.
- [30] Yui Uehara, Tatsuya Ishigaki, Kasumi Aoki, Hiroshi Noji, Keiichi Goshima, Ichiro Kobayashi, Hiroya Takamura, and Yusuke Miyao. 2020. Learning with Contrastive Examples for Data-to-Text Generation. In *Proceedings of the 28th International Conference on Computational Linguistics*. International Committee on Computational Linguistics, Barcelona, Spain (Online), 2352–2362. https://doi.org/10.18653/v1/2020.coling-main.213
- [31] Kees Van Deemter, Emiel Krahmer, and Mariët Theune. 2005. Real versus Template-Based Natural Language Generation: A False Opposition? Computational Linguistics 31, 1 (March 2005), 15-24. https://doi.org/10.1162/ 0891201053630291
- [32] Chris van der Lee, Emiel Krahmer, and Sander Wubben. 2018. Automated learning of templates for data-to-text generation: comparing rule-based, statistical and neural methods. In International Conference on Natural Language Generation.
- [33] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Ł ukasz Kaiser, and Illia Polosukhin. 2017. Attention is All you Need. In Advances in Neural Information Processing Systems, I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett (Eds.), Vol. 30. Curran Associates, Inc. https://proceedings.neurips.cc/paper/2017/file/ 3f5ee243547dee91fbd053c1c4a845aa-Paper.pdf
- [34] Ingmar Weber and Palakorn Achananuparp. 2016. Insights from Machine-Learned Diet Success Prediction. In *Pacific Symposium on Biocomputing*.
- [35] Anna Wilbik and Uzay Kaymak. 2015. Linguistic Summarization of Processes -a research agenda. In Conference of the International Fuzzy Systems Association and the European Society for Fuzzy Logic and Technology.
- [36] Anna Wilbik, James M. Keller, and Gregory Lynn Alexander. 2011. Linguistic summarization of sensor data for eldercare. In 2011 IEEE International Conference on Systems, Man, and Cybernetics. 2595–2599. https://doi.org/10.1109/ICSMC. 2011.6084067
- [37] Sam Wiseman, Stuart M. Shieber, and Alexander M. Rush. 2018. Learning Neural Templates for Text Generation. In *EMNLP*.
- [38] Ronald R. Yager. 1982. A new approach to the summarization of data. Information Sciences 28, 1 (1982), 69 – 86.
- [39] Lotfi A. Zadeh. 2002. A prototype-centered approach to adding deduction capability to search engines-the concept of protoform. In *IEEE Symposium on Intelligent* Systems.
- [40] Chao Zhao, Marilyn Walker, and Snigdha Chaturvedi. 2020. Bridging the Structural Gap Between Encoding and Decoding for Data-To-Text Generation. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics. Association for Computational Linguistics, Online, 2481–2491. https://doi.org/10.18653/v1/2020.acl-main.224