Improved hierarchical patient classification with language model pretraining over clinical notes

Jonas Kemp*  Alvin Rajkomar  Andrew M. Dai
Google Health
{jonasbkemp,alvinrajkomar,adai}@google.com

Abstract

Clinical notes in electronic health records contain highly heterogeneous writing styles, including non-standard terminology or abbreviations. Using these notes in predictive modeling has traditionally required preprocessing (e.g. taking frequent terms or topic modeling) that removes much of the richness of the source data. We propose a pretrained hierarchical recurrent neural network model that parses minimally processed clinical notes in an intuitive fashion, and show that it improves performance for discharge diagnosis classification tasks on the Medical Information Mart for Intensive Care III (MIMIC-III) dataset, compared to models that treat the notes as an unordered collection of terms or that conduct no pretraining. We also apply an attribution technique to examples to identify the words that the model uses to make its prediction, and show the importance of the words' nearby context.

1 Introduction

With the rapid deployment of electronic health records (EHRs) in the US, clinicians routinely enter patient data electronically, mostly in unstructured, free-text clinical notes. Because clinicians frequently employ non-standard, ambiguous shorthand phrases or organize their notes in unpredictable ways, automated parsing for downstream use can be quite challenging. Traditional natural language processing (NLP) techniques relying on hand-crafted rules [1] or feature engineering can be difficult to apply in this context. In practice, machine learning models tend to make more use of structured fields such as medications and diagnoses that can be straightforwardly extracted from the EHR [2], and clinical notes are often ignored outright [3-11]. Models that do use notes frequently reduce them to an unordered set of words [12-14] or topics [15, 16], which ignores many subtleties of language and context and can therefore obscure the meaning of the note.

Recent advances in deep learning have led to major improvements in a wide variety of NLP applications [17, 18]. Building on this work, we propose a model employing sequential, hierarchical, and pretraining (SHiP) techniques from deep NLP to improve EHR predictive models by automatically learning to extract relevant information from clinical notes. Specifically, our model employs a hierarchical attention network [19], augmented with a language model pretraining objective [20], to read notes with minimal assumptions about the text. We evaluate our model on standard classification tasks for EHRs, and compare performance against existing state-of-the-art baselines [14]. We also evaluate the sensitivity of the model’s outputs to different phrases in the text using deep learning attribution methods [21]. To our knowledge, the effectiveness of language model pretraining has not been previously demonstrated for hierarchical classification models.

*Work completed in part during the Google AI Residency.
2 Methods

2.1 Dataset and Prediction Tasks

We developed our models using critical care data from the Medical Information Mart for Intensive Care (MIMIC-III) [22,23]. We represented patients’ medical histories as a time series according to the Fast Healthcare Interoperability Resources (FHIR) specification, as described in previous work [14]. The study cohort included all patients in MIMIC-III hospitalized for at least 24 hours. (See supplementary table 2 for cohort summary statistics.) From these records, we extracted basic encounter information (admission type, status, and source), diagnosis and procedure codes, medication orders, quantitative observations (lab results and vital signs), and free-text clinical notes. For each continuous feature, we standardized values to Z-scores using training set statistics, with any outliers more than 10 standard deviations from the mean capped to a score of ±10. For each hospitalization, we developed models for the following classification tasks, using the patient’s full history up to the specified time in the current admission (including all past hospitalizations):

- Inpatient mortality prediction (predicted 24 hours after admission).
- Primary CCS [24] discharge diagnosis code (predicted at the moment of discharge).
- All ICD-9 [25] discharge diagnosis codes (predicted at the moment of discharge).

2.2 Model Architecture

We built on a core embedding scheme and top-level LSTM architecture described in previous work [14]. In this framework, we embedded discrete features from the patient record (e.g. diagnosis codes) and trained these jointly with the model. To reduce sequence length, we grouped observations into fixed-length timesteps, or “bags,” and averaged all embeddings or continuous values for observations of the same feature within the same bag; additionally, we collapsed all observations occurring prior to the most recent \( t \) timesteps into a single bag (with bag duration and \( t \) tuned as hyperparameters). Finally, we concatenated the bagged embeddings or values for all features into a single representation of each timestep in the patient history, and we fed this embedded sequence into a long short-term memory (LSTM) network [26], generating predictions from the final hidden state.

In the standard bag-of-words (BOW) approach to these models, notes are treated just as any other discrete feature, with individual words embedded and aggregated without regard to ordering. Our SHiP models augmented this approach in two ways. First, we maintained the sequential order of embeddings within each note and fed these to a second LSTM to generate a context-sensitive representation for each word. We computed the final output vector for each note by applying hierarchical dot product attention [19] over this output sequence, placing higher weight on the portions of the notes most important for downstream prediction. Second, we used unsupervised language model pretraining [20] to pretrain the notes LSTM: before optimizing the prediction loss, we trained an auxiliary objective such that, for each word in the note, the LSTM learned to predict the next word (and, if bidirectional, the previous word).

In addition to the core BOW and SHiP models, we also compared several variants of the above, including: a model without notes; models using only notes; a BOW model with unigram and bigram embeddings; and hierarchical attention models without pretraining.

2.3 Attribution Methods

To compute attribution scores over the text of notes, we used the path-integrated gradients technique [21]. For clarity in these attributions, we ran a notes-only model over only the selected note, omitting the rest of the notes in the patient’s record. We computed attribution scores with respect to each word embedding, relative to a zero-vector baseline, using \( m = 20 \) steps to approximate the path integral.

3 Results

3.1 Training and Evaluation Approach

We split our cohort by patient ID into 80% train, 10% validation, and 10% test splits. Models were optimized using Adam [27], and regularized using dropout [28,29] and Zoneout [30]. We
used a Gaussian process bandit optimization algorithm [31] to select hyperparameters maximizing performance for each task on the validation set. (See supplementary material B, particularly Table 3 for additional details.) Following hyperparameter tuning, we report mean (standard deviation) test set metrics over five runs from random initialization. Where reported, we also compute the statistical significance of pairwise differences in models’ performance using a two-tailed Welch’s t-test.

### 3.2 Model Performance

Table 1: Model performance results on the tasks of interest. Best values for each metric are bolded.

| Model                  | Mortality |          |          |          |          |          |          |          |          |          |          |          |          |          |
|------------------------|-----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|
|                        | AUPRC     | AUROC    | Top-1    | Top-5    |          | AUPRC    | AUROC,  |
|                        |           |          | Recall   | Recall   |          | weighted |          |          |
| No notes               | 0.449     | 0.869    | 0.526    | 0.796    | 0.305    | 0.873    |
| (0.006)                | (0.001)   | (0.006)  | (0.003)  | (0.001)  | (0.001)  | (<0.001) |
| Bag-of-words           |           |          |          |          |          |          |          |          |
| (notes only)           | 0.383     | 0.832    | 0.591    | 0.849    | 0.328    | 0.880    |
| (0.004)                | (0.003)   | (0.004)  | (0.002)  | (0.002)  | (0.001)  | (0.001)  |
| Unigrams (all features)| 0.479     | 0.880    | 0.592    | 0.842    | 0.331    | 0.883    |
| (0.008)                | (0.001)   | (0.003)  | (0.001)  | (0.001)  | (0.001)  | (0.001)  |
| Unigrams and bigrams   | 0.460     | 0.872    | 0.587    | 0.829    | 0.325    | 0.881    |
| (all features)         | (0.005)   | (0.002)  | (0.008)  | (0.005)  | (0.002)  | (<0.001) |
| Hierarchical           |           |          |          |          |          |          |          |          |
| (without pretraining)  | Notes only| 0.351    | 0.825    | 0.606    | 0.850    | 0.345    | 0.887    |
| (all features)         | 0.471     | 0.876    | 0.591    | 0.833    | 0.301    | 0.868    |
| (0.006)                | (0.003)   | (0.008)  | (0.006)  | (0.004)  | (0.001)  | (0.001)  |
| SHiP                   |           |          |          |          |          |          |          |          |
| (without pretraining)  | Notes only| 0.353    | 0.825    | 0.667    | 0.897*   | 0.352†   | 0.891†   |
| (0.005)                | (0.004)   | (0.006)  | (0.003)  | (0.001)  | (0.001)  | (0.001)  |
| All features           | 0.479     | 0.882    | 0.671†   | 0.890    | 0.345    | 0.889    |
| (0.007)                | (0.001)   | (0.004)  | (0.001)  | (0.005)  | (0.002)  | (0.002)  |

*p < 0.001 for difference compared to corresponding hierarchical model without pretraining.
†p < 0.001 for difference compared to best bag-of-words model.

Table 1 compares the performance of all model variants. The SHiP models significantly improved over the BOW baselines on the two diagnosis tasks (p < 0.001 under Welch’s t-test): for CCS prediction, the best SHiP models improved top-1 recall by 7.9 percentage points and top-5 recall by 4.8 percentage points, respectively, over the best BOW models; for ICD-9 prediction, area under the precision-recall curve (AUPRC) increased by 2.1 percentage points and weighted area under the ROC curve (AUROC) increased by 0.8 percentage points. For mortality prediction, we saw negligible benefit from the SHiP architecture.

The SHiP models also improved over the corresponding hierarchical models without pretraining. For mortality, pretraining the all-features model increased AUPRC by 0.8 percentage points (p = 0.06) and AUROC by 0.6 percentage points (p = 0.04); for primary CCS, pretraining the all-feature model increased top-1 recall by 8.0 percentage points (p < 0.001), while pretraining the notes-only model increased top-5 recall by 4.7 percentage points (p < 0.001); for all ICD-9, pretraining the notes-only model increased AUPRC by 0.7 percentage points (p = 0.03) and weighted AUROC by 0.4 percentage points (p = 0.01).

### 3.3 Qualitative Analysis

Figure 1 shows examples of path-integrated gradients attribution from CCS prediction models, over discharge summaries from different patients. We observe that the SHiP model frequently concentrates
on just one or a few important phrases, even in very long notes. The choice of phrase is often informed by the nearby context: for example, we can see that the SHiP model is consistently most sensitive to the clinically-relevant words following the phrase “discharge diagnoses.” In fact, in each sample here, the patient’s diagnosis is restated elsewhere in the text in a less relevant context (e.g. stating that the patient has “no family history” of diabetes), but the model is sensitive only to the instance where the discharge context is made explicit. The bag-of-words model, by contrast, is incapable of making such contextual distinctions, and is generally more sensitive to key words and phrases throughout the text.

Figure 1: Visualization of integrated gradients attribution over excerpts from patient discharge summaries (primary diagnosis shown at left). For each excerpt, the left column shows attribution from the BOW baseline, and the right column shows attribution from the SHiP model. Below each word is the value of the attribution computed for that word, where a higher absolute value indicates greater importance. Red boxes highlight the patient’s stated diagnosis in the text, while blue boxes indicate relevant pieces of nearby context.

4 Conclusion

We demonstrate that SHiP, a novel combination of hierarchical modeling of clinical notes and language model pretraining, can improve discharge diagnosis classification over previous state-of-the-art models, with only minimal preprocessing of text. Our work builds on a substantial recent literature on applying deep learning techniques to analysis of electronic health records data [32], including many clinical NLP studies using more standard convolutional or recurrent architectures [33–37], or employing hierarchical models with limited or no pretraining [38–42]. Drawing on the respective successes of hierarchical attention networks [19, 43–46] and pretraining methods [18, 20, 47] in a wide variety of general NLP applications, we show the utility of these methods applied jointly, and specifically within a clinical context.
Acknowledgments

We thank Nissan Hajaj and Xiaobing Liu for developing the core framework used to implement our models. We thank Gerardo Flores, Kathryn Rough, and Kun Zhang for providing assistance with our data processing and evaluation pipelines. We thank Kai Chen, Michael Howell, and Denny Zhou for their comments and feedback on this manuscript.

Code Availability

A code sample illustrating our approach is available at https://github.com/google-health/records-research/tree/master/clinical-notes-prediction.

References

[1] Maxwell Taggart, Wendy W Chapman, Benjamin A Steinberg, Shane Ruckel, Arianna Pregenzer-Wenzler, Yishuai Du, Jeffrey Ferraro, Brian T Bucher, Donald M Lloyd-Jones, Matthew T Rondina, and Rashmee U Shah. Comparison of 2 natural language processing methods for identification of bleeding among critically ill patients. JAMA Netw Open, 1(6): e183451–e183451, October 2018.

[2] Michael J Pencina, Benjamin A Goldstein, Ann Marie Navar, and John P A Ioannidis. Opportunities and challenges in developing risk prediction models with electronic health records data: a systematic review. Journal of the American Medical Informatics Association, 24(1):198–208, 05 2016. ISSN 1067-5027. doi: 10.1093/jamia/ocw042. URL https://doi.org/10.1093/jamia/ocw042.

[3] Zachary C. Lipton, David C. Kale, Charles Elkan, and Randall Wetzel. Learning to Diagnose with LSTM Recurrent Neural Networks. arXiv e-prints, art. arXiv:1511.03677, Nov 2015.

[4] Edward Choi, Mohammad Taha Bahadori, Andy Schuetz, Walter F Stewart, and Jimeng Sun. Doctor AI: Predicting clinical events via recurrent neural networks. In Machine Learning for Healthcare Conference, pages 301–318, December 2016.

[5] Cristobal Esteban, Oliver Staeck, Stephan Baier, Yinchong Yang, and Volker Tresp. Predicting clinical events by combining static and dynamic information using recurrent neural networks. In 2016 IEEE International Conference on Healthcare Informatics (ICHI), 2016.

[6] Paul Nickerson, Patrick Tighe, Benjamin Shickel, and Parisa Rashidi. Deep neural network architectures for forecasting analgesic response. Conf. Proc. IEEE Eng. Med. Biol. Soc., 2016: 2966–2969, August 2016.

[7] Trang Pham, Truyen Tran, Dinh Phung, and Svetla Venkatesh. DeepCare: A deep dynamic memory model for predictive medicine. In Advances in Knowledge Discovery and Data Mining, pages 30–41. Springer, Cham, April 2016.

[8] Edward Choi, Andy Schuetz, Walter F Stewart, and Jimeng Sun. Using recurrent neural network models for early detection of heart failure onset. J. Am. Med. Inform. Assoc., 24(2):361–370, March 2017.

[9] Zhengping Che, Sanjay Purushotham, Kyunghyun Cho, David Sontag, and Yan Liu. Recurrent neural networks for multivariate time series with missing values. Sci. Rep., 8(1), 2018.

[10] Yu Cheng, Fei Wang, Ping Zhang, and Jinying Hu. Risk prediction with electronic health records: A deep learning approach. In Proceedings of the 2016 SIAM International Conference on Data Mining, 2016.

[11] P. Nguyen, T. Tran, N. Wickramasinghe, and S. Venkatesh. DeepR: A convolutional net for medical records. IEEE Journal of Biomedical and Health Informatics, 21(1):22–30, Jan 2017. ISSN 2168-2194. doi: 10.1109/JBHI.2016.2633963.
[12] Ben J Marafino, Miran Park, Jason M Davies, Robert Thombley, Harold S Luft, David C Sing, Dhruv S Kazi, Colette DeJong, W John Boscardin, Mitzi L Dean, and R Adams Dudley. Validation of prediction models for critical care outcomes using natural language processing of electronic health record data. *JAMA Netw Open*, 1(8):e185097–e185097, December 2018.

[13] Olof Jacobson and Hercules Dalianis. Applying deep learning on electronic health records in swedish to predict healthcare-associated infections. In *Proceedings of the 15th Workshop on Biomedical Natural Language Processing*, 2016.

[14] Alvin Rajkomar, Eyal Oren, Kai Chen, Andrew M Dai, Nissan Hajaj, Michaela Hardt, Peter J Liu, Xiaobing Liu, Jake Marcus, Mimi Sun, Patrik Sundberg, Hector Yee, Kun Zhang, Yi Zhang, Gerardo Flores, Gavin E Duggan, Jamie Irvine, Quoc Le, Kurt Litsch, Alexander Mossin, Justin Tansuwan, De Wang, James Wexler, Jimbo Wilson, Dana Ludwig, Samuel L Volchenboum, Katherine Chou, Michael Pearson, Srinivasan Madabushi, Nigam H Shah, Atul J Butte, Michael D Howell, Claire Cui, Greg S Corrado, and Jeffrey Dean. Scalable and accurate deep learning with electronic health records. *npj Digital Medicine*, 1(1):18, May 2018.

[15] Riccardo Miotto, Li Li, Brian A Kidd, and Joel T Dudley. Deep patient: An unsupervised representation to predict the future of patients from the electronic health records. *Sci. Rep.*, 6: 26094, May 2016.

[16] Harini Suresh, Nathan Hunt, Alistair Johnson, Leo Anthony Celi, Peter Szolovits, and Marzyeh Ghassemi. Clinical intervention prediction and understanding with deep neural networks. In *Machine Learning for Healthcare Conference*, pages 322–337, November 2017.

[17] Melvin Johnson, Mike Schuster, Quoc V Le, Maxim Krikun, Yonghui Wu, Zhifeng Chen, Nikhil Thorat, Fernanda Viégas, Martin Wattenberg, Greg Corrado, Macduff Hughes, and Jeffrey Dean. Google’s multilingual neural machine translation system: Enabling Zero-Shot translation. *Transactions of the Association for Computational Linguistics*, 5:339–351, 2017.

[18] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. *arXiv e-prints*, art. arXiv:1810.04805, Oct 2018.

[19] Zichao Yang, Diyi Yang, Chris Dyer, Xiaodong He, Alex Smola, and Eduard Hovy. Hierarchical attention networks for document classification. In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, 2016.

[20] Andrew M Dai and Quoc V Le. Semi-supervised sequence learning. In *Neural Information Processing Systems (NIPS)*, November 2015.

[21] Mukund Sundararajan, Ankur Taly, and Qiqi Yan. Axiomatic attribution for deep networks. In *Proceedings of the 34th International Conference on Machine Learning - Volume 70*, ICML’17, pages 3319–3328. JMLR.org, 2017. URL http://dl.acm.org/citation.cfm?id=3305890.3306024.

[22] Alistair E W Johnson, Tom J Pollard, Lu Shen, Li-Wei H Lehman, Mengling Feng, Mohammad Ghassemi, Benjamin Moody, Peter Szolovits, Leo Anthony Celi, and Roger G Mark. MIMIC-III, a freely accessible critical care database. *Sci Data*, 3:160035, May 2016.

[23] T J Pollard and A E W Johnson. The MIMIC-III clinical database, 2016. Accessed: 2018-12-10.

[24] Anne Elixhauser. *Clinical Classifications for Health Policy Research, Version 2: Hospital Inpatient Statistics*. 1996.

[25] Vergil N Slee. The international classification of diseases: Ninth revision (ICD-9). *Ann. Intern. Med.*, 88(3):424, 1978.

[26] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural Comput.*, 9(8): 1735–1780, December 1997.
[27] Diederik P. Kingma and Jimmy Ba. Adam: A method for stochastic optimization. In 3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings, 2015. URL http://arxiv.org/abs/1412.6980

[28] Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. Dropout: A simple way to prevent neural networks from overfitting. J. Mach. Learn. Res., 15: 1929–1958, 2014.

[29] Yarin Gal and Zoubin Ghahramani. A theoretically grounded application of dropout in recurrent neural networks. In Advances in Neural Information Processing Systems, pages 1019–1027, 2016.

[30] David Krueger, Tegan Maharaj, János Kramár, Mohammad Pezeshki, Nicolas Ballas, Nan Rosemary Ke, Anirudh Goyal, Yoshua Bengio, Aaron Courville, and Chris Pal. Zoneout: Regularizing RNNs by Randomly Preserving Hidden Activations. arXiv e-prints, art. arXiv:1606.01305, Jun 2016.

[31] Thomas Desautels, Andreas Krause, and Joel W. Burdick. Parallelizing exploration-exploitation tradeoffs in gaussian process bandit optimization. Journal of Machine Learning Research, 15: 4053–4103, 2014. URL http://jmlr.org/papers/v15/desautels14a.html.

[32] Benjamin Shickel, Patrick James Tighe, Azra Bihorac, and Parisa Rashidi. Deep EHR: A survey of recent advances in deep learning techniques for electronic health record (EHR) analysis. IEEE Journal of Biomedical and Health Informatics, pages 1–1, 2017.

[33] Abhyuday Jagannatha and Hong Yu. Structured prediction models for RNN based sequence labeling in clinical text. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, 2016.

[34] Ankit Vani, Yacine Jernite, and David Sontag. Grounded Recurrent Neural Networks. arXiv e-prints, art. arXiv:1705.08557, May 2017.

[35] James Mullenbach, Sarah Wiegreffe, Jon Duke, Jimeng Sun, and Jacob Eisenstein. Explainable prediction of medical codes from clinical text. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 1101–1111, New Orleans, Louisiana, June 2018. Association for Computational Linguistics. doi: 10.18653/v1/N18-1100. URL https://www.aclweb.org/anthology/N18-1100.

[36] Sebastian Gehrmann, Franck Dernoncourt, Yeran Li, Eric T. Carlson, Joy T. Wu, Jonathan Welt, John Foote, Jr., Edward T. Moseley, David W. Grant, Patrick D. Tyler, and Leo A. Celi. Comparing deep learning and concept extraction based methods for patient phenotyping from clinical narratives. PLOS ONE, 13(2):1–19, 02 2018. doi: 10.1371/journal.pone.0192360. URL https://doi.org/10.1371/journal.pone.0192360.

[37] Thanat Chokwijitkul, Anthony Nguyen, Hamed Hassanzadeh, and Siegfried Perez. Identifying risk factors for heart disease in electronic medical records: A deep learning approach. Proceedings of the BioNLP 2018 workshop, pages 18–27, 2018.

[38] Shang Gao, Michael T Young, John X Qiu, Hong-Jun Yoon, James B Christian, Paul A Fearn, Georgia D Tourassi, and Arvind Ramananth. Hierarchical attention networks for information extraction from cancer pathology reports. J. Am. Med. Inform. Assoc., November 2017.

[39] Tal Baumel, Jumana Nassour-Kassis, Raphael Cohen, Michael Elhadad, and No’emie Elhadad. Multi-Label Classification of Patient Notes a Case Study on ICD Code Assignment. arXiv e-prints, art. arXiv:1709.09587, Sep 2017.

[40] Mary Jane C Samonte, Bobby D Gerardo, Arnel C Fajardo, and Ruji P Medina. ICD-9 tagging of clinical notes using topical word embedding. In Proceedings of the 2018 International Conference on Internet and e-Business - ICIEB `18, 2018.

[41] Jingshu Liu, Zachariah Zhang, and Narges Razavian. Deep EHR: Chronic Disease Prediction Using Medical Notes. arXiv e-prints, art. arXiv:1808.04928, Aug 2018.
[42] Denis Newman-Griffis and Ayah Zirikly. Embedding transfer for Low-Resource medical named entity recognition: A case study on patient mobility. *Proceedings of the BioNLP 2018 workshop*, pages 1–11, 2018.

[43] Junyoung Chung, Sungjin Ahn, and Yoshua Bengio. Hierarchical Multiscale Recurrent Neural Networks. *arXiv e-prints*, art. arXiv:1609.01704, Sep 2016.

[44] K. Hwang and W. Sung. Character-level language modeling with hierarchical recurrent neural networks. In *2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 5720–5724, March 2017. doi: 10.1109/ICASSP.2017.7953252.

[45] Haonan Yu, Jiang Wang, Zhiheng Huang, Yi Yang, and Wei Xu. Video paragraph captioning using hierarchical recurrent neural networks. In *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016.

[46] Zhao Meng, Lili Mou, and Zhi Jin. Hierarchical RNN with static Sentence-Level attention for Text-Based speaker change detection. In *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management - CIKM ’17*, 2017.

[47] Zhilin Yang, Zihang Dai, Yiming Yang, Jaime Carbonell, Ruslan Salakhutdinov, and Quoc V. Le. XLNet: Generalized Autoregressive Pretraining for Language Understanding. *arXiv e-prints*, art. arXiv:1906.08237, Jun 2019.

[48] Martín Abadi, Ashish Agarwal, Paul Barham, Eugene Brevdo, Zhifeng Chen, Craig Citro, Greg S. Corrado, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Ian Goodfellow, Andrew Harp, Geoffrey Irving, Michael Isard, Yangqing Jia, Rafal Jozefowicz, Lukasz Kaiser, Manjunath Kudlur, Josh Levenberg, Dan Mane, Rajat Monga, Sherry Moore, Derek Murray, Chris Olah, Mike Schuster, Jonathon Shlens, Benoit Steiner, Ilya Sutskever, Kunal Talwar, Paul Tucker, Vincent Vanhoucke, Vijay Vasudevan, Fernanda Viegas, Oriol Vinyals, Pete Warden, Martin Wattenberg, Martin Wicke, Yuan Yu, and Xiaoqiang Zheng. TensorFlow: Large-Scale Machine Learning on Heterogeneous Distributed Systems. *arXiv e-prints*, art. arXiv:1603.04467, Mar 2016.

[49] Fabian Pedregosa, Gaël Varoquaux, Alexandre Gramfort, Vincent Michel, Bertrand Thirion, Olivier Grisel, Mathieu Blondel, Peter Prettenhofer, Ron Weiss, Vincent Dubourg, Jake Vanderplas, Alexandre Passos, David Cournapeau, Matthieu Brucher, Matthieu Perrot, and Édouard Duchesnay. Scikit-learn: Machine learning in python. *J. Mach. Learn. Res.*, 12(Oct):2825–2830, 2011.
Supplementary Material

A Additional details of patient cohort

Table 2: Descriptive statistics for patient cohort.

|                         | Train & validation | Test |
|-------------------------|--------------------|------|
| Number of patients      | 40,511             | 4,439|
| Number of hospital admissions* | 51,081             | 5,598|
| Gender, n(%)            |                    |      |
| Female                  | 22,468 (44.0)      | 2,548 (45.5) |
| Male                    | 28,613 (56.0)      | 3,050 (54.5) |
| Age, median (IQR)       | 62 (32)            | 62 (33)|
| Hospital discharge service, n (%) |                   |      |
| General medicine        | 21,350 (41.8)      | 2,354 (42.1) |
| Cardiovascular          | 10,965 (21.5)      | 1,175 (21.0) |
| Obstetrics              | 7,123 (13.9)       | 803 (14.3) |
| Cardiopulmonary         | 4,459 (8.7)        | 519 (9.3) |
| Neurology               | 4,282 (8.4)        | 457 (8.2) |
| Cancer                  | 2,217 (4.3)        | 223 (4.0) |
| Psychiatric             | 28 (0.1)           | 4 (0.1) |
| Other                   | 657 (1.3)          | 63 (1.1) |
| Discharge location, n (%)|                    |      |
| Home                    | 28,991 (56.8)      | 3,095 (55.3) |
| Skilled nursing facility| 6,878 (13.5)       | 794 (14.2) |
| Rehab                   | 5,757 (11.3)       | 653 (11.7) |
| Other healthcare facility| 3,830 (7.5)        | 448 (8.0) |
| Expired                 | 4,420 (8.7)        | 462 (8.3) |
| Other                   | 1,205 (2.4)        | 146 (2.6) |
| Previous hospitalizations, n (%) |              |      |
| None                    | 40,362 (79.0)      | 4,415 (78.9) |
| One                     | 6,427 (12.6)       | 721 (12.9) |
| Two to five             | 3,681 (7.2)        | 397 (7.1) |
| Six or more             | 611 (1.2)          | 65 (1.2) |
| Number of discharge ICD-9, median (IQR)** | 9 (8)             | 9 (8) |

* For primary CCS prediction, 1.3% of these admissions were excluded, where the primary diagnosis corresponded to a non-billable ICD-9 code.
** Includes only billable ICD-9 codes.
B Additional details of model training

For memory and performance reasons, in all hierarchical models we restricted the maximum amount of text used in the notes LSTM, keeping the most recent $N$ tokens per record (across all notes) and discarding any additional leading tokens. We tuned the level of truncation on the validation set, and found $N = 1000$ to be sufficient for training mortality models, but increased to $N = 2500$ for both diagnosis tasks and for pretraining. All models were implemented in Tensorflow 1.12 [48], and trained on Nvidia Tesla P100 GPUs.

Metrics for model selection included AUROC for mortality and ICD9, and top-5 recall for CCS. For multilabel ICD9 prediction, we computed a weighted AUROC, where the AUROC for each label is averaged according to the label’s prevalence. Evaluation metrics and statistical tests were calculated using scikit-learn 0.20 [49].
Table 3: Model hyperparameters. For the same task, all non-hierarchical models shared the BOW hyperparameters, and all hierarchical models shared the SHiP hyperparameters, except where noted. For the SHiP models, dropout was applied during both pretraining and training. All models were trained using the Adam optimizer with default constant values: $\beta_1 = 0.9, \beta_2 = 0.999, \epsilon = 1 \times 10^{-8}$.

| Hyperparameters          | Mortality | Primary CCS | All ICD-9 |
|--------------------------|-----------|-------------|-----------|
|                          | BOW       | SHiP        | BOW       | SHiP      | BOW       | SHiP      |
| Training                 |           |             |           |           |           |           |
| Learning rate            | 0.00015   | 0.00011     | 0.00369   | 0.00067   | 0.00369   | 0.00048   |
| Batch size               | 128       | 16          | 128       | 16        | 128       | 16        |
| Pretraining steps        | –         | 30,000      | –         | 30,000    | –         | 40,000    |
| Gradient clip norm       | 37.5      | 37.5        | 0.125     | 0.125     | 0.125     | 0.125     |
| Variational vocabulary dropout* | 0.001  | 0.229       | 0.273     | 0.396     | 0.273     | 0.273     |
| Bag length, hours        |           |             |           |           |           |           |
| Notes only               | 1         | 1           | 1         | 1         | 1         | 1         |
| All features             | 1         | 1           | 8         | 8         | 8         | 8         |
| Maximum timesteps        |           |             |           |           |           |           |
| Notes only               | 1000      | 1000        | 1000      | 1000      | 1000      | 1000      |
| All features             | 1000      | 1000        | 200       | 200       | 200       | 200       |
| Record LSTM              | Hidden units |           |           |           |           |           |
|                          | 379       | 518         | 518       |           |           |           |
| Input dropout            | 0.466     | 0.246       | 0.246     |           |           |           |
| Hidden dropout           | 0.045     | 0.136       | 0.136     |           |           |           |
| Variational input dropout| 0.034     | 0.071       | 0.071     |           |           |           |
| Variational hidden dropout| 0.090     | 0.122       | 0.122     |           |           |           |
| Zoneout                  | 0.268     | 0.437       | 0.437     |           |           |           |
| Notes LSTM               | Bidirectional? | –         | Yes       | –         | Yes       | –         |
|                          | Hidden units | –         | 350       | –         | 325       | –         |
|                          | Input dropout   | –         | 0.052     | –         | 0.019     | –         |
|                          | Hidden dropout   | –         | 0.175     | –         | 0.391     | –         |
|                          | Variational input dropout | –     | 0.176   | –         | 0.291     | –         |
|                          | Variational hidden dropout | – | 0.061 | –         | 0.085     | –         |
|                          | Zoneout     | –         | 0.312     | –         | 0.336     | –         |

* The variational vocabulary dropout rate is shared across all features. For baseline models with bigrams, we increased the dropout rate on the notes vocabulary only to 0.75.
### C Additional experimental results

**Table 4:** Comparison of different bagging lengths for all-feature hierarchical CCS and ICD9 models. Reporting mean (standard deviation) test set results over five runs from random initialization.

|                  | Primary CCS | All ICD-9 |
|------------------|-------------|-----------|
|                  | Top-1 Recall | Top-5 Recall | AUPRC | AUROC, weighted |
| No pretraining   |             |            |        |                |
| 1-hour bagging, $t = 1000$ | 0.555 (0.020) | 0.812 (0.014) | 0.291 (0.010) | 0.869 (0.004) |
| 8-hour bagging, $t = 200$  | 0.591 (0.008) | 0.833 (0.006) | 0.301 (0.004) | 0.868 (0.001) |
| SHiP             |             |            |        |                |
| 1-hour bagging, $t = 1000$ | 0.660 (0.004) | 0.887 (0.003) | 0.332 (0.016) | 0.889 (0.002) |
| 8-hour bagging, $t = 200$  | 0.671 (0.004) | 0.890 (0.001) | 0.345 (0.005) | 0.889 (0.002) |

**Table 5:** Comparison of unidirectional vs. bidirectional notes LSTMs for SHiP models. Reporting validation set results for a single run.

|                  | Mortality | Primary CCS | All ICD-9 |
|------------------|-----------|-------------|-----------|
|                  | AUPRC     | AUROC       | Top-1 Recall | Top-5 Recall | AUPRC | AUROC, weighted |
| Unidirectional   | 0.490     | 0.895       | 0.651 | 0.888 | 0.342 | 0.887 |
| Bidirectional    | 0.497     | 0.896       | 0.663 | 0.896 | 0.326 | 0.878 |

**Table 6:** Comparison of pretraining time thresholds for all-feature SHiP mortality models. Reporting mean (standard deviation) test set results over five runs from random initialization.

|                  | AUPRC     | AUROC       |
|------------------|-----------|-------------|
| Pretrained to 24 hours | 0.478 (0.005) | 0.881 (0.001) |
| Pretrained to discharge | 0.479 (0.007) | 0.882 (0.001) |