SynSUM – Synthetic Benchmark with Structured and Unstructured Medical Records

Paloma Rabaey[1], **Henri Arno**[1], **Stefan Heytens**[2], **Thomas Demeester**[1]

[1] Department of Information Technology, Ghent University - imec, Ghent, Belgium
[2] Department of Public Health and Primary Care, Ghent University, Ghent, Belgium

Abstract

We present the SynSUM benchmark, a synthetic dataset linking unstructured clinical notes to structured background variables. The dataset consists of 10,000 artificial patient records containing tabular variables (like symptoms, diagnoses and underlying conditions) and related notes describing the fictional patient encounter in the domain of respiratory diseases. The tabular portion of the data is generated through a Bayesian network, where both the causal structure between the variables and the conditional probabilities are proposed by an expert based on domain knowledge. We then prompt a large language model (GPT-4o) to generate a clinical note related to this patient encounter, describing the patient symptoms and additional context. We conduct both an expert evaluation study to assess the quality of the generated notes, as well as running some simple predictor models on both the tabular and text portions of the dataset, forming a baseline for further research. The SynSUM dataset is primarily designed to facilitate research on clinical information extraction in the presence of tabular background variables, which can be linked through domain knowledge to concepts of interest to be extracted from the text - the symptoms, in the case of SynSUM. Secondary uses include research on the automation of clinical reasoning over both tabular data and text, causal effect estimation in the presence of tabular and/or textual confounders, and multi-modal synthetic data generation.

Code & Dataset — https://github.com/prabaey/SynSUM

1 Introduction

Electronic health records (EHRs) are a gold mine of information, containing a mix of structured tabular variables (medication, diagnosis codes, lab results…) and free unstructured text (detailed clinical notes from physicians, nurses…) (Ford et al. 2016). These EHRs form a valuable basis for training clinical decision support systems, (partially) automating essential processes in the clinical world, such as diagnosis, writing treatment plans, and more (Peiffer-Smadja et al. 2020; Mujtaba et al. 2019; Rasmy et al. 2021; Li et al. 2020; Xu et al. 2019). While large language models can help leverage the potential of the unstructured text portion of the EHR (Zhang et al. 2020; Liu et al. 2022; Huang, Altosaar, and Ranganath 2019; Lehman and Johnson 2023; Singhal et al. 2023; Labrak et al. 2024), these black box systems lack interpretability (Quinn et al. 2022; Zhao et al. 2024; Tian et al. 2024). In high-risk clinical applications, it can be argued that one should prefer more robust and transparent systems built on simpler, feature-based models, like regression models, decision trees, or Bayesian networks (Rudin 2019; Sanchez et al. 2022; Lundberg et al. 2020). However, such models cannot directly deal with unstructured text and require tabular features as an input. For this reason, automated clinical information extraction (CIE) (Ford et al. 2016; Wang et al. 2018; Hahn and Oleynik 2020) is an essential tool for building large structured datasets that can serve as training data for such systems.

However, CIE remains a challenging task due to the complex nature of clinical notes. These often leave out important contextual details which an automated system would need in order to correctly extract concepts from the text. Existing systems do not fully exploit the available medical domain knowledge to fill in this gap. We propose that CIE could benefit from leveraging two additional sources of information, apart from the unstructured text itself. On the one hand, a range of tabular features are already encoded in the EHR. These contain information related to a particular patient visit (e.g. partially encoded symptoms or diagnosis codes), as well as information on the medical history of the patient. On the other hand, we can connect this encoded background information with the concepts we are trying to extract from the text, using a Bayesian network (BN) that represents medical domain knowledge. A visual example that helps illustrate this idea is shown in Figure 2 in Appendix A.

To investigate and implement the described research idea, we need a clinical dataset which (i) contains a mix of tabular data and unstructured text, where (ii) the tabular data and the concepts we aim to extract from the text can be linked through domain knowledge. While open-source datasets like MIMIC-III (Johnson et al. 2016) and MIMIC-IV (Johnson et al. 2023) contain this mix, they are not a perfect fit. First, the area of intensive care in which the data was collected is very extensive, making it hard to isolate a specific small-scale use-case for which the domain knowledge could be listed. Second, the portion of the dataset which is encoded into tabular features is often driven by billing needs, rather than completeness or accuracy, and does not contain any en-

coded symptoms, which are concepts that could be interesting to extract from the text for application in clinical decision support systems. Third, the link between the tabular features and the concepts mentioned in the text might be inconsistent due to system design or human errors (Kwon et al. 2024). Finally, the EHRs in MIMIC being time series adds another layer of complexity. Other existing datasets linking unstructured clinical text to structured features include BioDEX (D'Oosterlinck et al. 2023), a large set of papers describing adverse drug events, as well as TCGA-Reports (Kefeli and Tatonetti 2024), a set of cancer pathology reports, both accompanied by tabular patient descriptors and extracted biological features. However, in both cases, it is not trivial to devise a BN representing the relevant expert knowledge, partially because that knowledge is not fully understood yet.

In this work, we build a synthetic yet sufficiently realistic dataset that addresses some of these shortcomings, enabling research on incorporating domain knowledge for improved CIE in the presence of tabular variables. Our dataset, called SynSUM (Synthetic Structured and Unstructured Medical records) is a self-contained set of synthetic EHRs in a primary care setting, fulfilling the following requirements:

- It mixes structured tabular data and unstructured text.
- By design, clinical concepts expressed in the text and encoded in the tabular portion of the dataset are connected through a Bayesian network representing domain knowledge. In this case, the domain is respiratory diseases, with their associated symptoms and underlying conditions.
- Each EHR is a static snapshot of a single patient encounter, eliminating the time aspect for simplicity.
- The text contains additional context on some of the encoded tabular variables.

SynSUM is constructed in the domain of respiratory diseases, simulating patient visits to a primary care doctor. We mimic the scenario where the doctor notes down the patient's symptoms in a clinical note, along with some additional context, and stores this in the EHR together with the encoded diagnosis, as well as the encoded symptoms. Additionally, the EHR stores tabular background information on the underlying health conditions of the patient.

Section 2 describes how we generated 10,000 fictional patient encounters by sampling from an expert-defined BN and prompting a large language model. Section 3 describes the expert evaluation conducted by a panel of five primary care physicians on a subset of the generated notes. Section 4 then runs some simple symptom predictors on both the tabular and textual portions of our dataset, which form a baseline to be exceeded by future research. Finally, Section 5 discusses the potential use of our dataset in various areas of research (including but not limited to CIE), while also highlighting its limitations.

2 Data generation

Our general methodology for generating the artificial patient records is shown in Figure 1. We now zoom in on the two major parts of this data generating process. First, Section 2.1 describes how we generated the structured tabular variables through an expert-defined Bayesian network (BN). Then, Section 2.2 dives into the clinical note generation by the large language model.

2.1 Modeling structured tabular variables with a Bayesian network

Causal structure We asked an expert to define a Directed Acyclic Graph (DAG) which (partially) models the domain of respiratory diseases in primary care, shown in Figure 1. In this DAG, a directed arrow between two variables models a causal relation between them. Central to the model are the diagnoses of *pneumonia* and *common cold*, which may give rise to five symptoms (*dyspnea*, *cough*, *pain*, *fever* and *nasal*). The expert also modeled some relevant underlying conditions which may render a patient more predisposed to certain diagnoses or symptoms: *asthma*, *smoking*, *COPD* and *hay fever*. Based on the symptoms experienced by a patient, a primary care doctor decides whether to prescribe *antibiotics* or not. The presence and severity of the symptoms, as well as the prescription of antibiotics as a treatment, influence the outcome, which is the total number of days (*# days*) that the patient eventually stays home as a result of illness. Finally, there are some non-clinical variables which exert an external influence on the diagnoses, treatment and outcome (*season*, *policy* and *self-employed*). Table 3 in Appendix B summarizes all variables and their meaning, as well as their possible values. While this model does not completely describe the real world, we do believe it to be sufficiently realistic for the purpose of generating a useful artificial dataset.

Probability distribution We turn the DAG into a BN by defining a joint distribution, which factorizes into 16 conditional distributions, one for each variable. We use four different approaches to define these conditionals, after which we can sample synthetic patients from the BN in a top-down fashion.

For each of the variables *asthma*, *smoking*, *hay fever*, *COPD*, *season*, *pneumonia*, *common cold*, *fever*, *policy* and *self-employed*, we ask our expert to define a **conditional probability table** (CPT). When a variable has many parents, it becomes infeasible to manually fill in the CPT in a clinically meaningful way. For this reason, we use a **Noisy-OR distribution** for the symptoms *dyspnea*, *cough*, *pain* and *nasal*, which assumes an independent causal mechanism behind the activation of a symptom through any of its parents. We model the prescription of *antibiotics* through a **logistic regression model**, mimicking the way the clinician's suspicion of pneumonia (which needs to be treated with antibiotics) rises when a higher number of symptoms is present in the patient, with some symptoms weighing more than others, eventually exceeding a threshold. These weights are defined by the expert and validated with a set of test cases. In a similar fashion, we model the *# days* the patient stays home as a result of their complaints with a **Poisson regression model**. These weights are learned through maximum likelihood estimation over a set of train cases provided by the expert. The full specification of our BN can be found in Appendix B.

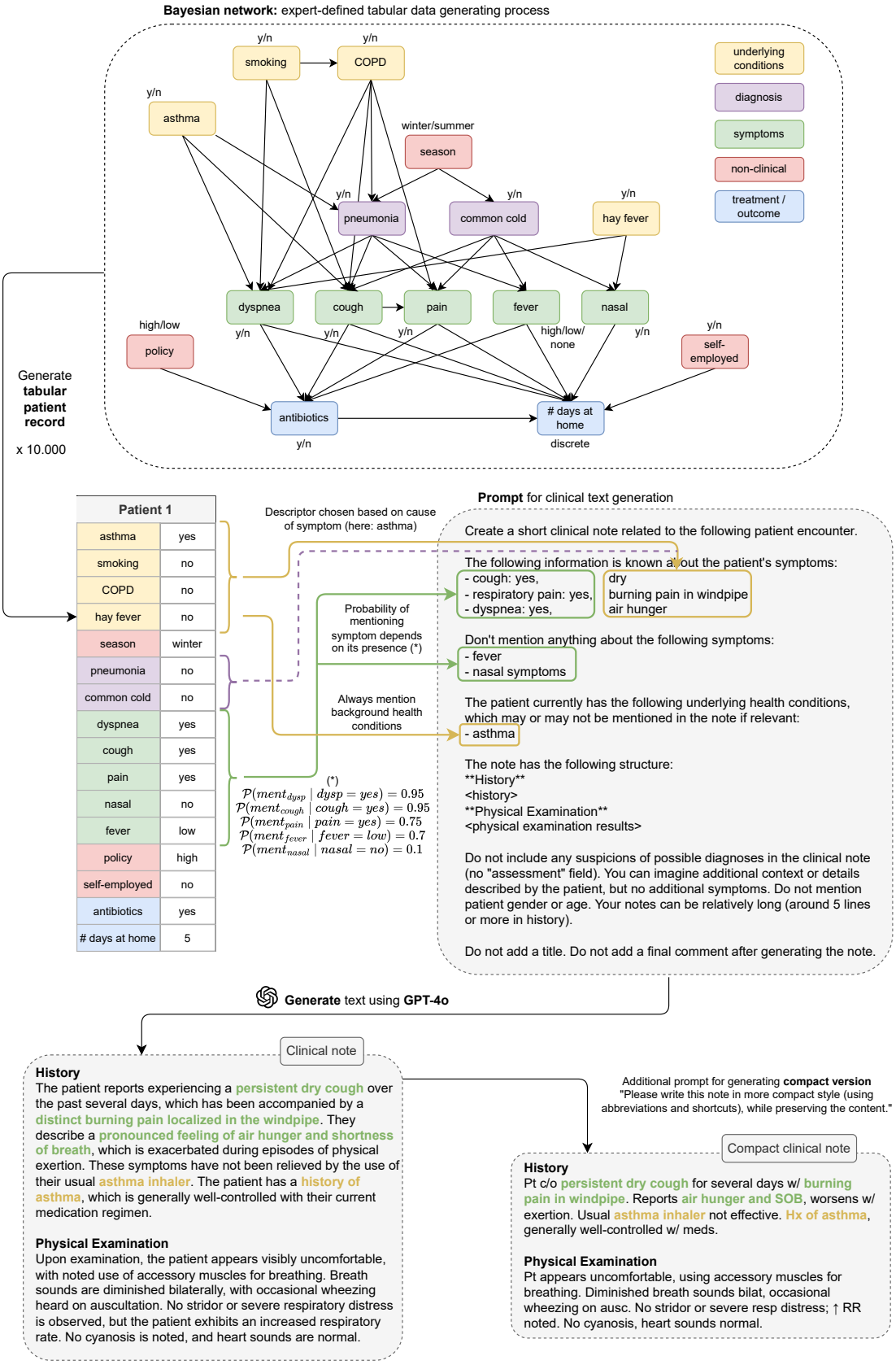


Figure 1: Overview of the full data generating process for the SynSUM dataset. First, the tabular portion of the synthetic patient record is sampled from a Bayesian network, where both the structure and the conditional probability distributions were defined by an expert. Afterwards, we construct a prompt describing the symptoms experienced by the patient, as well as their underlying health conditions (but no diagnoses). We ask the GPT-4o large language model to generate a clinical note describing this patient encounter. Finally, we ask to generate a more challenging compact version of the note, mimicking the complexity of real clinical notes by prompting the use of abbreviations and shortcuts. We generate 10,000 of these synthetic patient records in total.

2.2 Generating unstructured text with a large language model

Once the tabular patient record has been generated, we prompt a large language model (LLM, in our case GPT-4o) to write a clinical note based on the tabular variables associated with this fictional encounter. For this, we use a prompt which is generally structured like the example shown in Figure 1 (except for some special cases, which are addressed in Appendix C). Additional example prompts can be found in Appendix D. Only the background variables and symptoms may be directly mentioned in the prompt, while the diagnoses *pneumonia* and *common cold* would not yet be known to a clinician who is taking notes during a consultation and are therefore left out. They can still influence the content of the note through the descriptions of the symptoms that are included in the prompt. The treatment and outcome are left out of the prompt as well, just like the non-clinical variables, as all of these are typically either unknown or irrelevant at the time of writing the note.We ask the LLM to generate both a "history" portion and a "physical examination" portion, to encourage variation and complexity of the generated notes.

In general, the prompt is constructed as follows. For more details, we refer to Appendix C. First, we list the **symptoms** which are experienced by the patient. We do not exhaustively list the full set of symptoms, but rather sample the probability that a symptom is mentioned according to a distribution defined by the expert. This renders the notes more realistic, since real notes do not exhaustively mention the presence or absence of all possible symptoms, but rather follow the narrative of the patient and the subsequent probing of the clinician. While we encourage the LLM to invent additional context around the patient's symptoms, we want this to at least partially relate to the underlying cause of the symptom. For this reason, we include a **descriptor** next to each symptom, which is randomly sampled from a set of expert-defined phrases that describe the symptom in the case where it results from a particular cause. This way, the diagnoses can influence the content of the note, even when they are not mentioned explicitly in the prompt. The full list of descriptors, as well as further information on how we sample them, is included in Appendix C. The next part of the prompt lists the **underlying health conditions**, which are assumed to be known up-front, and could therefore influence the content of the note. Finally, the prompt lists some **additional instructions**, which we motivate in Appendix C. There, we also outline an alternative prompting strategy, which is used to generate clinical notes for the patient records where none of the respiratory symptoms are present, which is the case for around one third of our dataset. In these cases, we encourage the LLM to imagine an alternative reason for the patient visit, unrelated to the respiratory domain.

Real clinical notes can be challenging, often containing abbreviations, shortcuts and denser sentence structure. To make the notes more challenging, we ask the LLM to create a **compact version** of each note through an additional prompt, as can be seen in Figure 1. Our dataset contains both the original note and the compact version of the note.

	Normal				Compact	
	Consistency	Realism (hist)	Realism (phys)	Clinical accuracy	Content	Readability
mean	4.69	4.53	4.15	4.92	4.88	4.02
std	0.12	0.21	0.30	0.07	0.10	0.31

Table 1: Results of the expert evaluation study. We report average scores (ranging from 1-5) over 30 notes, together with their standard deviation over the five evaluators.

3 Expert evaluation

We asked five general practitioners to evaluate the quality of a random sample of 30 generated notes. The evaluators got to see the two versions of the generated note (normal and compact), as well as the prompt that was used to generate them. They were asked to evaluate four aspects:

1. **Consistency**: The description of the patient's symptoms and underlying health conditions must correspond with the instructions provided in the prompt.
2. **Realism**: The context and details invented by the LLM and added to the "history" portion of the note should be realistic given the symptoms experienced by the patient, as detailed in the prompt. Furthermore, the elements that are checked in the "physical examination" must be realistic in light of the patient information described in the "history". We evaluate both aspects separately, focusing on content (what information is included in the note), rather than format (how the information is written down).
3. **Clinical accuracy**: The findings described in the "physical examination" must be clinically accurate, both in a standalone fashion and in relation to the patient's symptoms described in the "history".
4. **Quality of compact version**: The content of the compact version of the note must correspond well with the original note, and remain readable despite the use of abbreviations and shortcuts. We evaluate both aspects separately.

To measure consistency, the evaluators were asked to assign a penalty for every element in the note that does not correspond with the requested information in the prompt, and for every requested symptom that was missing from the generated note. These penalties were then turned into ratings from 1 (>3 penalties) to 5 (0 penalties). All other aspects were directly rated on a scale of 1 (very bad) to 5 (perfect). Table 1 shows the results. For each rated aspect, we calculate the average score over all 30 notes, and report the mean and standard deviation over the five evaluators. For more details on the meaning of each rating in each aspect, as well as inter-annotator agreement scores, we refer to Appendix E.

Our artificial notes were rated as highly consistent with the prompt, and therefore with the information present in the tabular portion of the dataset. As shown in Appendix E.2, a large majority of the inconsistencies arise from a violation of the additional instructions (usually by inventing additional symptoms), while the key information included in the prompt was still conveyed correctly in the note.

The evaluators also deem the notes sufficiently realistic,

though the realism of the history section is rated higher on average than the realism of the physical examination. Out of those notes that scored worse, many included a clinical test that seemed unnecessary to the evaluators, while a few forgot a test that was deemed important. At the same time, the very high score for clinical accuracy is an important indication that the notes do not contain falsehoods.

Multiple evaluators mentioned that while the content of the notes seemed realistic, the format did not, as their own notes would be more complex as opposed to the artificial notes, which use clean language and full sentences. This underscores the fact that the dataset should not be used to train any systems which will later be deployed on real notes, and should instead fulfill the role of a research benchmark only.

The compact versions of the notes score very well on content, mostly conveying the same information as the original. They score a little lower in terms of readability, which evaluators often attributed to the extensive use of abbreviations.

4 Symptom predictor baselines

In order to set a baseline for future information extraction tasks, we run various prediction models on both the tabular and textual parts of the dataset. These models are trained to predict each of the five symptoms: *dyspnea*, *cough*, *pain*, *fever* and *nasal*.

Two of our baselines only get to see the tabular portion of the dataset at the input: Bayesian network (**BN-tab**) and XGBoost (**XGBoost-tab**). We use these models to predict each symptom in three settings, differing from one another in the set of tabular features that are taken as an input, which we call the evidence:

- $\mathcal{P}(sympt \mid all)$: Predict the symptom given all other tabular features as evidence. This set includes the background, diagnoses, non-clinical, treatment and outcome variables, as well as the other symptoms.
- $\mathcal{P}(sympt \mid no\text{-}sympt)$: Predict the symptom given all other tabular features as evidence, except for the other symptoms. This mimics the setting where we have tabular features available in the patient record, but have not extracted any symptoms from the text yet. This set includes the background, diagnoses, non-clinical, treatment and outcome variables.
- $\mathcal{P}(sympt \mid realistic)$: Predict the symptom given a more realistic set of tabular features as evidence. We do not expect *policy*, *self-employed* and *#days* to be recorded in any kind of realistic patient record, and therefore leave them out of this evidence set. As in the *no-sympt* setting, we do not include the symptoms either. In other words, this set includes the background, diagnoses, season and treatment variables.

Apart from the tabular-only baselines, we also train some baselines that get to see the text. Our **neural-text** classifier takes only the text as an input (in the form of a pretrained clinical sentence embedding) and outputs the probability that a symptom is mentioned in the text. We extend this text-only baseline by concatenating a numerical representation of the tabular features to the text embedding at the input, forming the **neural-text-tab** baseline. Again, we do this for each of the three evidence settings outlined above. Note that this is the only model that combines both the background knowledge available in the tabular features with the unstructured text, and it does so in a naive way. Future work will focus on improving the performance of this model by exploiting the relations between any of the tabular concepts, as envisioned in Figure 2.

	dyspnea	cough	pain	nasal	fever
BN-tab					
- all	<u>0.7370</u>	0.7816	0.2386	<u>0.7146</u>	<u>0.4864</u>
- no-sympt	0.7153	0.7776	0.1312	<u>0.7146</u>	0.4384
- realistic	0.6698	0.7763	0.0280	<u>0.7146</u>	0.3594
XGBoost-tab					
- all	0.6639	<u>0.7848</u>	<u>0.4070</u>	0.7130	0.4111
- no-sympt	0.6612	0.7779	0.3638	<u>0.7146</u>	0.4015
- realistic	0.6626	0.7798	0.3698	<u>0.7146</u>	0.3951
neural-text					
- normal	**0.9660**	**0.9595**	**0.8415**	**0.9602**	**0.9125**
neural-text-tab					
- normal + all	0.9526	0.9481	0.8096	0.9598	0.8804
- normal + no-sympt	0.9592	0.9530	0.8078	0.9550	0.9014
- normal + realistic	0.9544	0.9543	0.8303	0.9575	0.9101
neural-text					
- compact	0.9383	**0.9480**	0.7828	0.9583	**0.9073**
neural-text-tab					
- compact + all	**0.9535**	0.9384	0.7675	0.9566	0.8987
- compact + no-sympt	0.9363	0.9240	**0.7984**	**0.9638**	0.8991
- compact + realistic	0.9442	0.9422	0.7880	0.9606	0.9051

Table 2: F1-score obtained over the test set for each of our baseline models. The results for the text classifiers trained over the normal vs. the compact version of the notes are grouped together for readability. We report results for the *mean* embedding type, while results for the other embedding types can be found in Table 8. We <u>underline</u> the best result obtained by the tabular-only models, while the best overall result per symptom is in shown in **bold**.

4.1 Models

BN-tab We provide the causal structure in Figure 1 to the BN, and learn all parameters in the conditional probability tables (CPTs), Noisy-OR distributions, logistic regression model and Poisson regression model from the training data. In each case, we use maximum likelihood estimation to estimate the parameters. Where we don't directly learn a CPT (for the variables *dyspnea*, *cough*, *pain*, *nasal*, *antibiotics* and *#days*), we evaluate the learned distribution for each combination of child and parent values to obtain a CPT. For more details, we refer to Appendix F.1. We then use variable elimination over the full joint distribution to evaluate the capability of the learned BN to predict each of the symptoms, taking different variables as evidence according to the three settings described earlier (*all*, *no-sympt* and *realistic*).

XGBoost-tab We train an XGBoost classifier for each symptom in combination with each of the three evidence settings, meaning each classifier sees a different set of tabular features at the input. We optimize the hyperparameters separately for each combination (15 in total) using 5-fold cross-validation. For more details, we refer to Appendix F.2.

Neural-text We train a neural classifier that takes only the text as an input and is trained to predict the probability a symptom is mentioned. We train separate classifiers for each symptom. We first split the text into sentences, and transform these into an embedding using the pretrained clinical representation model BioLORD-2023 (Remy, Demuynck, and Demeester 2024). We explore 4 settings for turning these sentence embeddings into a single note embedding:

- *hist*: We average all sentence embeddings for the sentences in the "history" portion of the note.
- *phys*: We average all sentence embeddings for the sentences in the "physical examination" portion of the note.
- *mean*: To get a single representation for the full note, we take the average of the *hist* and *phys* embeddings.
- *concat*: Idem as previous, but now the embeddings for the two portions are concatenated.

The note embedding is then fed into a multi-layer perceptron with one hidden layer, followed by a Sigmoid activation for the symptoms *dyspnea*, *cough*, *pain* and *nasal*, and a Softmax activation with 3 outputs heads for the symptom $fever$. We optimized the parameters of each model (i.e. each combination of symptom and embedding type) using the binary or multiclass cross-entropy objective over the symptom labels. For more details, we refer to Appendix F.3.

Neural-text-tab We extend the **neural-text** baseline by concatenating the mean text embeddings with the tabular variables at the input of each neural classifier. All categorical tabular variables were first transformed to a one-hot encoding, while the variable *#days* was preprocessed using standard scaling. We used the same architecture as the **neural-text** baseline (only changing the dimension of the input layer), and again trained separate classifiers for each symptom combined with each evidence setting (*all*, *no-sympt* and *realistic*). For more details, we refer to Appendix F.4.

4.2 Results

We use a random $8{,}000/2{,}000$ split to obtain a train and test set. We use cross-validation on the train set to tune any hyperparameters, and report the final F1-score over the test set after training. For the binary symptoms, we use a 0.5 decision threshold. For fever, which has three possible categories, the class with the highest predicted probability is chosen. In that case, we report the macro F1-score.

Table 2 compares the results obtained for all baselines. The tabular-only baselines (**BN-tab** and **XGBoost-tab**) perform consistently worse than the baselines that include text (**neural-text** and **neural-text-tab**). The evidence setting where *all* other features are included as evidence usually performs best for the tabular-only baselines.

The **neural-text-tab** baseline does not perform better than the **neural-text** baseline for the normal notes. While there is little room for improvement in the dyspnea, cough and nasal classifiers, the symptoms pain and fever are harder to predict. We also note a consistent gap in performance between the normal and compact notes, which can be attributed to the higher complexity of the latter. In that case, the **neural-text-tab** classifier manages to marginally improve over the **neural-text** classifier by including the tabular features.

Table 8 in Appendix F.3 further breaks down the results for the **neural-text** classifier over the different embedding types. Using only the *hist* embedding outperforms the *phys*-only setting for the symptoms cough, pain and fever. While the score for *hist* comes close to those for *mean* and *concat*, the latter usually still outperform the former for the normal notes, showing that there is some complementary information in the "history" and "physical examination" portions.

5 Discussion

Symptom extraction Our analysis of simple tabular and textual baseline models revealed that the symptoms pain and fever are hardest to predict in both the tabular-only and the text-only setting. Combining both settings, i.e. integrating tabular background features in the extraction of the concepts from the text, and linking them through domain knowledge, may have potential for improved information extraction. Future work will focus on realizing this hybrid approach to improve upon the baseline results presented in Table 2.

Potential uses The dataset is primarily designed to facilitate research on clinical information extraction in the presence of tabular background variables. Future work will focus on realizing the idea presented in Figure 2, where the tabular features aid in more accurately extracting concepts from the text by linking them through domain knowledge. Apart from this, we also foresee multiple secondary uses of the dataset. First, the dataset could facilitate research on the automation of clinical reasoning over tabular data and text, following the example of Rabaey et al. (2024). Second, it could be used to benchmark causal effect estimation methods in the presence of textual confounders, similar to Veitch, Sridhar, and Blei (2020), thanks to the purposeful inclusion of both a treatment and outcome variable in our dataset. Third, there has been increasing interest in clinical synthetic data (Hernandez et al. 2022), where a set of patient characteristics is turned into a synthetic version that is meant to protect the privacy of individuals in the original dataset. Our dataset could serve as a benchmark for comparing synthetic data generation methods that jointly generate tabular variables and text (Lee 2018; Ceritli et al. 2023; Guan et al. 2019). In short, any area of research focusing on the intersection of tabular data and text in healthcare can potentially benefit from our proposed benchmark.

Limitations While the dataset we constructed is meant to have realistic properties, we also intentionally simplify reality to make the design and generation process feasible. The dataset is purely meant as a research benchmark where the ground truth relations are known, and results obtained on it are not meant to transfer to real clinical notes or datasets. This is confirmed by the evaluators in our expert study, who warned that the writing style used in the text notes is not in accordance with reality, even if the content is mostly realistic. We therefore advise strongly against using the dataset for training prediction models which will be deployed in real settings. Furthermore, our dataset contains static patients that do not evolve over time. While this is a reasonable simplification to make in the realm of primary care, time series are a crucial modality in more complex settings, such as intensive care.

Acknowledgments

Paloma Rabaey and Henri Arno's research is funded by the Research Foundation Flanders (FWO Vlaanderen) with grant numbers 1170124N and 11Q2C24N. This research also received funding from the Flemish government under the "Onderzoeksprogramma Artificiële Intelligentie (AI) Vlaanderen" programme. The authors would like to thank Géraldine Deberdt, Thibault Detremerie, An De Sutter, Veerle Piessens en Florian Stul for participating in the expert evaluation of the artificial clinical notes.

References

Ankur Ankan; and Abinash Panda. 2015. pgmpy: Probabilistic Graphical Models using Python. In *Proceedings of the 14th Python in Science Conference*, 6 – 11.

Ceritli, T.; Ghosheh, G. O.; Chauhan, V. K.; Zhu, T.; Creagh, A. P.; and Clifton, D. A. 2023. Synthesizing mixed-type electronic health records using diffusion models. *arXiv preprint arXiv:2302.14679*.

D'Oosterlinck, K.; Remy, F.; Deleu, J.; Demeester, T.; Develder, C.; Zaporojets, K.; Ghodsi, A.; Ellershaw, S.; Collins, J.; and Potts, C. 2023. BioDEX: Large-scale biomedical adverse drug event extraction for real-world pharmacovigilance. *arXiv preprint arXiv:2305.13395*.

Ford, E.; Carroll, J. A.; Smith, H. E.; Scott, D.; and Cassell, J. A. 2016. Extracting information from the text of electronic medical records to improve case detection: a systematic review. *J Am Med Inform Assoc*, 23(5): 1007–1015.

Guan, J.; Li, R.; Yu, S.; and Zhang, X. 2019. A method for generating synthetic electronic medical record text. *IEEE/ACM transactions on computational biology and bioinformatics*, 18(1): 173–182.

Hahn, U.; and Oleynik, M. 2020. Medical information extraction in the age of deep learning. *Yearbook of medical informatics*, 29(01): 208–220.

Hernandez, M.; Epelde, G.; Alberdi, A.; Cilla, R.; and Rankin, D. 2022. Synthetic data generation for tabular health records: A systematic review. *Neurocomputing*, 493: 28–45.

Huang, K.; Altosaar, J.; and Ranganath, R. 2019. Clinicalbert: Modeling clinical notes and predicting hospital readmission. *arXiv preprint arXiv:1904.05342*.

Johnson, A. E.; Bulgarelli, L.; Shen, L.; Gayles, A.; Shammout, A.; Horng, S.; Pollard, T. J.; Hao, S.; Moody, B.; Gow, B.; et al. 2023. MIMIC-IV, a freely accessible electronic health record dataset. *Scientific data*, 10(1): 1.

Johnson, A. E.; Pollard, T. J.; Shen, L.; Lehman, L.-w. H.; Feng, M.; Ghassemi, M.; Moody, B.; Szolovits, P.; Anthony Celi, L.; and Mark, R. G. 2016. MIMIC-III, a freely accessible critical care database. *Scientific data*, 3(1): 1–9.

Kefeli, J.; and Tatonetti, N. 2024. TCGA-Reports: A machine-readable pathology report resource for benchmarking text-based AI models. *Patterns*, 5(3).

Koller, D.; and Friedman, N. 2009. *Probabilistic Graphical Models: Principles and Techniques*. Adaptive computation and machine learning. MIT Press. ISBN 9780262013192.

Kwon, Y.; Kim, J.; Lee, G.; Bae, S.; Kyung, D.; Cha, W.; Pollard, T.; Johnson, A.; and Choi, E. 2024. EHRCon: Dataset for Checking Consistency between Unstructured Notes and Structured Tables in Electronic Health Records. *arXiv preprint arXiv:2406.16341*.

Labrak, Y.; Bazoge, A.; Morin, E.; Gourraud, P.-A.; Rouvier, M.; and Dufour, R. 2024. Biomistral: A collection of open-source pretrained large language models for medical domains. *arXiv preprint arXiv:2402.10373*.

Lee, S. H. 2018. Natural language generation for electronic health records. *NPJ digital medicine*, 1(1): 63.

Lehman, E.; and Johnson, A. 2023. Clinical-t5: Large language models built using mimic clinical text. *PhysioNet*.

Li, Y.; Rao, S.; Solares, J. R. A.; Hassaine, A.; Ramakrishnan, R.; Canoy, D.; Zhu, Y.; Rahimi, K.; and Salimi-Khorshidi, G. 2020. BEHRT: transformer for electronic health records. *Scientific reports*, 10(1): 7155.

Liu, S.; Wang, X.; Hou, Y.; Li, G.; Wang, H.; Xu, H.; Xiang, Y.; and Tang, B. 2022. Multimodal data matters: language model pre-training over structured and unstructured electronic health records. *IEEE Journal of Biomedical and Health Informatics*, 27(1): 504–514.

Lundberg, S. M.; Erion, G.; Chen, H.; DeGrave, A.; Prutkin, J. M.; Nair, B.; Katz, R.; Himmelfarb, J.; Bansal, N.; and Lee, S.-I. 2020. From local explanations to global understanding with explainable AI for trees. *Nature machine intelligence*, 2(1): 56–67.

Mujtaba, G.; Shuib, L.; Idris, N.; Hoo, W. L.; Raj, R. G.; Khowaja, K.; Shaikh, K.; and Nweke, H. F. 2019. Clinical text classification research trends: Systematic literature review and open issues. *Expert Syst Appl*, 116: 494–520.

OpenAI. 2024. Models – GPT-4o. https://platform.openai.com/docs/models/gpt-4o. Online; accessed 12 August 2024.

Peiffer-Smadja, N.; Rawson, T.; Ahmad, R.; Buchard, A.; and et al. 2020. Machine learning for clinical decision support in infectious diseases: A narrative review of current applications. *Clin Microbiol Infect*, 26(5): 584–595.

Quinn, T. P.; Jacobs, S.; Senadeera, M.; Le, V.; and Coghlan, S. 2022. The three ghosts of medical AI: Can the black-box present deliver? *Artificial intelligence in medicine*, 124: 102158.

Rabaey, P.; Deleu, J.; Heytens, S.; and Demeester, T. 2024. Clinical Reasoning over Tabular Data and Text with Bayesian Networks. In *International Conference on Artificial Intelligence in Medicine*, 229–250. Springer.

Rasmy, L.; Xiang, Y.; Xie, Z.; Tao, C.; and Zhi, D. 2021. Med-BERT: pretrained contextualized embeddings on large-scale structured electronic health records for disease prediction. *NPJ digital medicine*, 4(1): 86.

Remy, F.; Demuynck, K.; and Demeester, T. 2024. BioLORD-2023: semantic textual representations fusing large language models and clinical knowledge graph insights. *Journal of the American Medical Informatics Association*, ocae029.

Rudin, C. 2019. Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. *Nature machine intelligence*, 1(5): 206–215.

Sanchez, P.; Voisey, J. P.; Xia, T.; Watson, H. I.; O'Neil, A. Q.; and Tsaftaris, S. A. 2022. Causal machine learning for healthcare and precision medicine. *Royal Society Open Science*, 9(8): 220638.

Singhal, K.; Azizi, S.; Tu, T.; Mahdavi, S. S.; Wei, J.; Chung, H. W.; Scales, N.; Tanwani, A.; Cole-Lewis, H.; Pfohl, S.; et al. 2023. Large language models encode clinical knowledge. *Nature*, 620(7972): 172–180.

Tian, S.; Jin, Q.; Yeganova, L.; Lai, P.-T.; Zhu, Q.; Chen, X.; Yang, Y.; Chen, Q.; Kim, W.; Comeau, D. C.; et al. 2024. Opportunities and challenges for ChatGPT and large language models in biomedicine and health. *Briefings in Bioinformatics*, 25(1): bbad493.

Veitch, V.; Sridhar, D.; and Blei, D. 2020. Adapting text embeddings for causal inference. In *Conference on Uncertainty in Artificial Intelligence*, 919–928. PMLR.

Wang, Y.; Wang, L.; Rastegar-Mojarad, M.; Moon, S.; Shen, F.; Afzal, N.; Liu, S.; Zeng, Y.; Mehrabi, S.; Sohn, S.; et al. 2018. Clinical information extraction applications: a literature review. *Journal of biomedical informatics*, 77: 34–49.

Xu, K.; Lam, M.; Pang, J.; Gao, X.; Band, C.; Mathur, P.; Papay, F.; Khanna, A. K.; Cywinski, J. B.; Maheshwari, K.; et al. 2019. Multimodal machine learning for automated ICD coding. In *Machine learning for healthcare conference*, 197–215. PMLR.

Zhang, D.; Yin, C.; Zeng, J.; Yuan, X.; and Zhang, P. 2020. Combining structured and unstructured data for predictive models: A deep learning approach. *BMC Med Inform Decis Mak*, 20(1): 280.

Zhao, H.; Chen, H.; Yang, F.; Liu, N.; Deng, H.; Cai, H.; Wang, S.; Yin, D.; and Du, M. 2024. Explainability for large language models: A survey. *ACM Transactions on Intelligent Systems and Technology*, 15(2): 1–38.

Appendix

A Clinical Information Extraction with Background Knowledge

Clinical information extraction can be improved by exploiting tabular background information that is present in the EHR, next to the text from which we are extracting clinical concepts (e.g. the symptoms). Figure 2 illustrates this idea with two practical examples. The SynSUM benchmark enables future research to explore this idea, by linking structured tabular features with unstructured text describing a fictional patient encounter.

B Bayesian network

To define a data generating mechanism from which we can sample synthetic patients, we turn the DAG from Figure 1 into a Bayesian network by defining a joint probability distribution. In a Bayesian network, this joint distribution factorizes into the product of conditional probability distributions for each variable, as shown in Equation (1). We parameterize these using four different approaches.

Conditional probability table When the variable is discrete and has a limited number of parents, we define a conditional probability table (CPT). Each entry of the table contains the probability for a particular value of the variable, conditional on the combination of values of the parent variables. If the variable has no parents, we just define a prior probability. The probabilities in the tables were filled in by the expert based on experience, as well as demographics in Belgium and the expert's local general practice. While we do not expect these probabilities to generalize to the global patient population as a whole, a realistic-looking distribution suffices for our use-case. We provide these tables for the variables *asthma*, *smoking*, *hay fever*, *COPD*, *season*, *pneumonia*, *common cold*, *fever*, *policy* and *self-employed* in Figure 3.

Noisy-OR distribution For categorical variables with many parents, it becomes infeasible to manually fill in the CPT in a clinically meaningful way, because of the large number of possible combinations of parent values. This is the case for the symptoms *dyspnea*, *cough*, *pain* and *nasal* in our Bayesian network. To circumvent this problem, we define a Noisy-OR distribution (Koller and Friedman 2009). The Noisy-OR model is commonly used to define the distribution of a variable Y which depends on a set of causes $\{X_1, \ldots, X_k\}$. It rests on the assumption that the combined influence of the possible causes $\{X_1, \ldots, X_k\}$ on Y is a simple combination of the influence of each X_i on Y in isolation. This is a reasonable assumption to make in the case of symptoms with multiple possible causes (parents in the Bayesian network): a symptom arises in a patient if any of its possible causes succeeds in activating the symptom through its own independent mechanism. As shown in Equation (2), the parameterization of the noisy-OR distribution rests on choosing the parameters p_i, which is the probability that a possible cause X_i activates symptom Y. As a special case, p_0, also known as the leak probability, is the probability that symptom Y is activated as the result of another unmodeled cause (ouside of all X_i's). Note that x_i in the equation is 1 when the cause X_i is present in the patient, and 0 if not. Equations (3) through (6) define such a Noisy-OR distribution for the symptoms *dyspnea*, *cough*, *pain* and *nasal*. Note that the symptom *fever* is fully defined through a CPT, since the expert was able to provide intuition on all possible combinations of its two parent values, eliminating the need for a Noisy-OR distribution.

$$\begin{aligned}
&\text{Noisy-OR}(p_0, p_1, \ldots, p_k) \coloneqq \\
&\qquad \mathcal{P}(Y = 1 \mid X_1, \ldots, X_k) \\
&\quad = 1 - \mathcal{P}(Y = 0 \mid X_1, \ldots., X_k), \text{ with} \\
&\quad \mathcal{P}(Y = 0 \mid X_1 = x_1, \ldots, X_k = x_k) \\
&\quad = (1 - p_0)(1 - p_1)^{x_1} \ldots (1 - p_k)^{x_k} \\
&\qquad\qquad \text{and } x_1 ... x_k \in \{0, 1\} \qquad (2)
\end{aligned}$$

$$\begin{aligned}
&\mathcal{P}(\textit{dysp} \mid \textit{asthma, smoking, COPD, hayf, pneu}) \\
&= \text{Noisy-OR}(p_0 = 0.05, p_{\textit{asthma}} = 0.9, p_{\textit{smoking}} = 0.3, \\
&\qquad p_{\textit{COPD}} = 0.9, p_{\textit{hayf}} = 0.2, p_{\textit{pneu}} = 0.3) \qquad (3)
\end{aligned}$$

$$\begin{aligned}
&\mathcal{P}(\textit{cough} \mid \textit{asthma, smoking, COPD, pneu, cold}) \\
&= \text{Noisy-OR}(p_0 = 0.07, p_{\textit{asthma}} = 0.3, p_{\textit{smoking}} = 0.6, \\
&\qquad p_{\textit{COPD}} = 0.4, p_{\textit{pneu}} = 0.85, p_{\textit{cold}} = 0.7) \qquad (4)
\end{aligned}$$

$$\begin{aligned}
&\mathcal{P}(\textit{pain} \mid \textit{COPD}, \textit{cough}, \textit{pneu}, \textit{cold}) \\
&= \text{Noisy-OR}(p_0 = 0.05, p_{\textit{COPD}} = 0.15, p_{\textit{cough}} = 0.2, \\
&\qquad p_{\textit{pneu}} = 0.3, p_{\textit{cold}} = 0.1) \qquad (5)
\end{aligned}$$

$$\begin{aligned}
&\mathcal{P}(\textit{nasal} \mid \textit{hayf, cold}) \\
&\quad = NoisyOR(p_0 = 0.1, p_{\textit{hayf}} = 0.85, p_{\textit{cold}} = 0.7) \qquad (6)
\end{aligned}$$

Logistic regression Whether or not to prescribe antibiotics depends on whether the clinician suspects pneumonia in the patient. Their suspicion raises with the number of symptoms present in the patient, with some symptoms weighing more than others. Once their level of suspicion reaches a certain threshold, they decide to prescribe treatment. This process can be modeled using a logistic regression model taking the symptoms *dyspnea*, *cough*, *pain* and *fever*, as well as the variable *policy*, as an input, as shown in Equation (7). Here, x_{po} (*policy*) can take on the values 1 (high) or 0 (low), x_d (*dyspnea*), x_c (*cough*) and x_{pa} (*pain*) can take on the value 1 (yes) or 0 (no), and x_f (*fever*) can be 2 (high), 1 (low) or 0 (none). The bias of -3 was set based on the following constraint: if there's no symptoms at all, and *policy* is low, then the probability of prescribing antibiotics (due to some other unmodeled cause) should be around 5%. Similarly, the coefficient for *policy* was set to fit the following constraint: if there's no symptoms at all, and *policy* is

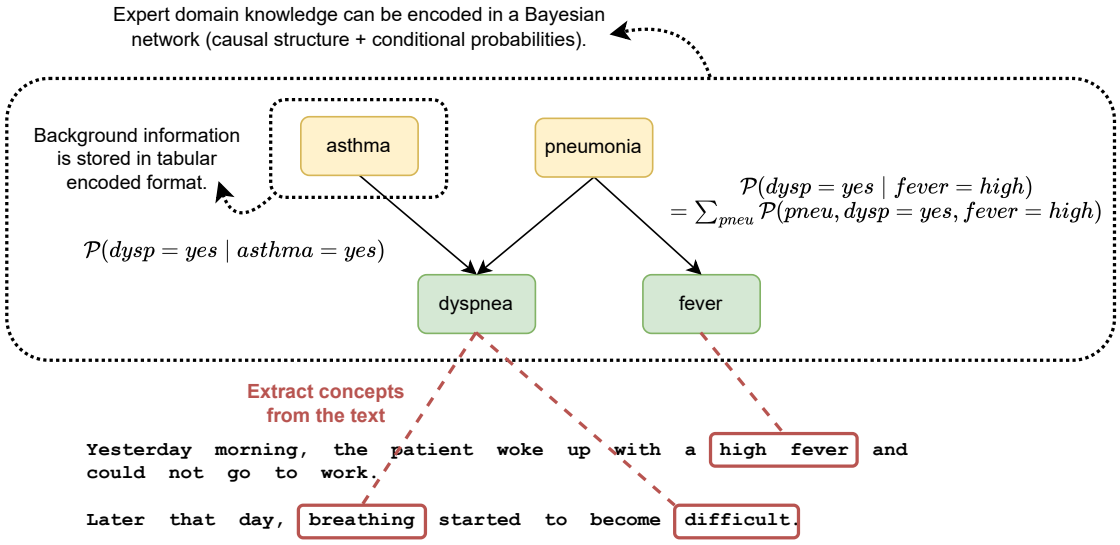


Figure 2: We have a clinical description of a patient encounter from which we want to extract some concepts, in this case the symptoms experienced by the patient. Some symptoms might be easy to extract using text-matching, like "high fever". Other symptoms are not mentioned verbatim and are therefore harder to extract, like dyspnea. In this case, additional information on the patient, present in encoded format in the tabular portion of the EHR, together with domain knowledge, may help.
Example 1: We know that the patient has asthma. Domain knowledge tells us that the probability of experiencing dyspnea when one has asthma is 90%. This can increase the confidence of the information extraction module for the concept of dyspnea being mentioned in the text.
Example 2: We know that the patient is experiencing high fever. Domain knowledge tells us that a high fever often co-occurs with dyspnea due to their common cause, which is pneumonia. Even if we do not know that the patient has pneumonia, the probability of dyspnea being mentioned in the text increases as a result of observing high fever. If we model the joint probability of dyspnea, fever and pneumonia using a Bayesian network, we can get the exact probability of $\mathcal{P}(dyspnea = yes \mid fever = high)$ by summing over the presence of pneumonia.

$$\begin{aligned}\mathcal{P}_{joint}(asthma, smoking, ..., antibio, \#\,days) = \mathcal{P}(asthma)\mathcal{P}(smoking)\mathcal{P}(COPD \mid smoking)\\ \mathcal{P}(hayf)\mathcal{P}(season)\mathcal{P}(pneu \mid asthma, COPD, season)\mathcal{P}(cold \mid season)\\ \mathcal{P}(dysp \mid asthma, smoking, COPD, pneu, hayf)\mathcal{P}(cough \mid asthma, smoking, COPD, pneu, cold)\\ \mathcal{P}(pain \mid cough, pneu, COPD, cold)\mathcal{P}(fever \mid pneu, cold)\\ \mathcal{P}(nasal \mid cold, hayf)\mathcal{P}(policy)\mathcal{P}(self\text{-}empl)\mathcal{P}(antibio \mid policy, dysp, cough, pain, fever)\\ \mathcal{P}(\#days \mid antibio, dysp, cough, pain, fever, nasal, self\text{-}empl) \quad (1)\end{aligned}$$

Name	Type	Description	Values
Asthma	underlying condition	Chronic lung disease in which the airways narrow and swell	yes/no
Smoking	underlying condition	Whether the patient is a regular smoker of tobacco	yes/no
COPD	underlying condition	Chronic Obstructive Pulmonary Disease, where airflow from the lungs is obstructed	yes/no
Hay fever	underlying condition	Allergic rhinitis, irritation of the nose caused by an allergen (e.g. pollen)	yes/no
Season	non-clinical	Season of the year	winter/summer
Pneumonia	diagnosis	Infection that inflames the air sacs in one or both lungs	yes/no
Common cold	diagnosis	Upper respiratory tract infection, irritation and swelling of the upper airways	yes/no
Dyspnea	symptom	Shortness of breath, the feeling of not getting enough air	yes/no
Cough	symptom	Any type of cough, no distinction between non-productive (dry) or productive (bringing up mucus or phlegm)	yes/no
Pain	symptom	Pain related to the airways or chest area	yes/no
Fever	symptom	Elevation of body temperature	high/low/none
Nasal	symptom	Nasal symptoms, such as runny nose or sneezing	yes/no
Policy	non-clinical	Whether the clinician has higher or lower prior inclination to prescribe antibiotics. Can be influenced by many factors, such as local policy in their general practice, their own caution towards antibiotics or level of experience.	high/low
Self-employed	non-clinical	Whether the patient is self-employed, rendering them less inclined to stay home from work for longer periods.	yes/no
Antibiotics	treatment	Whether any type of antibiotics are prescribed to the patient	yes/no
# Days at home	outcome	How many days the patient ends up staying home as a result of their symptoms and treatment	discrete $(0 - ...)$

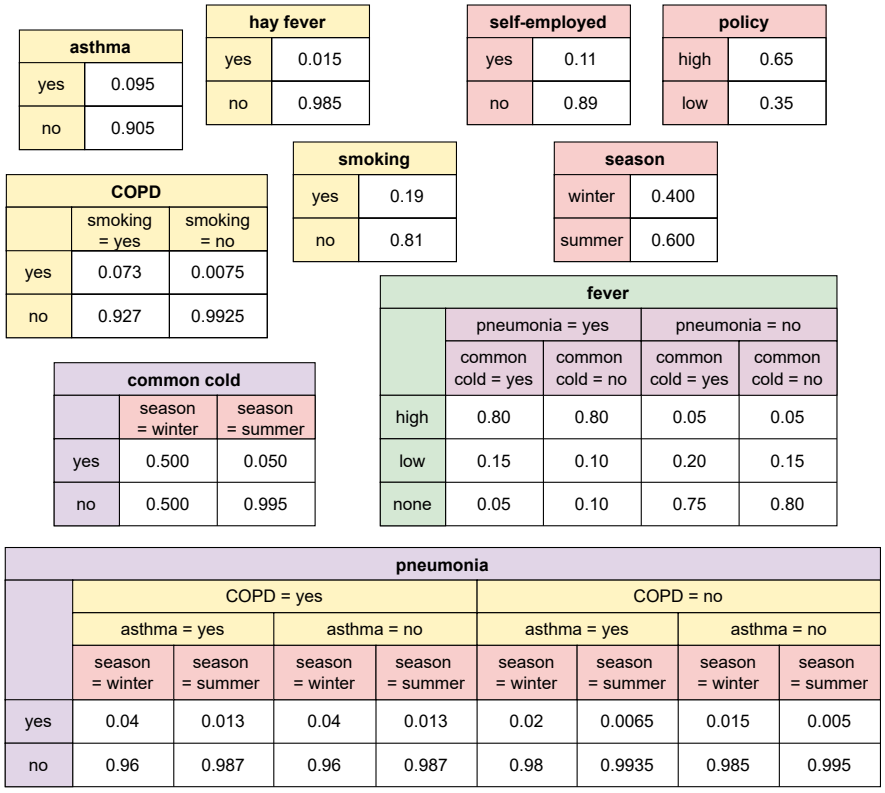
Table 3: Description of tabular variables in our dataset.

high, the probability should be around 10%. All other coefficients were then chosen by the expert based on the relative importance of the symptoms when deciding to prescribe antibiotics, taking the coefficient for *policy* as a starting point. As a final sanity-check, we asked the expert to label a set of test cases with whether they would prescribe antibiotics or not, allowing us to compare with the probability predicted by the model. Table 4 shows these results. We see that the predictions made by the model mostly correspond well with the clinician's intuition, confirming that the proposed coefficients make sense.

$$\begin{aligned}\mathcal{P}(&\textit{antibio} = \textit{yes} \mid \textit{policy} = x_{po}, \textit{dysp} = x_d,\\ &\textit{cough} = x_c, \textit{pain} = x_{pa}, \textit{fever} = x_f)\\ &= \text{Sigmoid}(-3 + 1 \times x_{po} + 0.8 \times x_d + 0.665 \times x_c\\ &+ 0.665 \times x_{pa} + 0.9 \times (x_f == 1) + 2.25 \times (x_f == 2)),\\ &\text{with } x_{po}, x_d, x_c, x_{pa} \in \{0, 1\}, \text{and } x_f \in \{0, 1, 2\} \quad (7)\end{aligned}$$

Poisson regression Finally, we need to model the number of days the patient ends up staying home due to their complaints. This depends on the symptoms experienced by the patient, as well as whether they received antibiotics as a treatment. Since the outcome is discrete, with most patients staying home for a low number of days, we decided to model this using a Poisson regression. Assuming that the effect of getting treatment would be non-linear in relation to the presence or absence of the symptoms, we defined two separate Poisson models: one where no antibiotics were prescribed (Equation (8)), and one where they were prescribed (Equation (9)). Both models take the symptoms *dysp*, *cough*, *pain*, *nasal* and *fever* as an input, as well as the variable *self-employed*, and predict a mean number of days λ, which parameterizes the Poisson distribution. The coefficients for each model were tuned using gradient descent based on the train cases shown in Table 5. Like before, the expert was asked to (loosely) label these cases for how long they suspected the patient to stay home on average as a result of these symptoms. The coefficient for the variable *self-employed* was tuned manually, based on the assumption that being self-employed would shave some days off the predicted number, regardless of the particular symptoms experienced by the patient. As a sanity check, we compared the mean number of days predicted by the model (parameter λ in the Poisson model) with the number of days estimated by the expert for a small test set of cases which were not seen during training. The results are shown in Table 6.

$$\begin{aligned}\mathcal{P}(&\textit{\# days} \mid \textit{dysp} = x_d, \textit{cough} = x_c, \textit{pain} = x_{pa},\\ &\textit{nasal} = x_n, \textit{fever} = x_f, \textit{self-empl} = x_{se}, \textit{antibio} = \textit{no})\\ &= Poisson(\lambda_0)\\ \lambda_0 &= exp(0.010 + 0.64 \times x_d + 0.35 \times x_c + 0.47 \times x_{pa}\\ &+ 0.011 \times x_n + 0.81 \times (x_f == 1)\\ &+ 1.23 \times (x_f == 2) - 0.5 \times x_{se})\\ &\text{with } x_d, x_c, x_{pa}, x_n, x_{se} \in \{0, 1\}, \text{and } x_f \in \{0, 1, 2\} \quad (8)\end{aligned}$$



asthma	
yes	0.095
no	0.905

hay fever	
yes	0.015
no	0.985

self-employed	
yes	0.11
no	0.89

policy	
high	0.65
low	0.35

smoking	
yes	0.19
no	0.81

season	
winter	0.400
summer	0.600

COPD	smoking = yes	smoking = no
yes	0.073	0.0075
no	0.927	0.9925

common cold	season = winter	season = summer
yes	0.500	0.050
no	0.500	0.995

fever	pneumonia = yes		pneumonia = no	
	common cold = yes	common cold = no	common cold = yes	common cold = no
high	0.80	0.80	0.05	0.05
low	0.15	0.10	0.20	0.15
none	0.05	0.10	0.75	0.80

pneumonia	COPD = yes				COPD = no			
	asthma = yes		asthma = no		asthma = yes		asthma = no	
	season = winter	season = summer	season = winter	season = summer	season = winter	season = summer	season = winter	season = summer
yes	0.04	0.013	0.04	0.013	0.02	0.0065	0.015	0.005
no	0.96	0.987	0.96	0.987	0.98	0.9935	0.985	0.995

Figure 3: Conditional probability tables for the variables *asthma*, *smoking*, *hay fever*, *COPD*, *season*, *pneumonia*, *common cold*, *fever*, *policy* and *self-employed*.

$$\begin{aligned}
&\mathcal{P}(\#\,days \mid dysp = x_d, cough = x_c, pain = x_{pa},\\
&nasal = x_n, fever = x_f, selfempl = x_{se}, antibio = yes)\\
&\qquad = Poisson(\lambda_1)\\
&\lambda_1 = exp(0.16 + 0.51 \times x_d + 0.42 \times x_c + 0.26 \times x_{pa}\\
&\qquad + 0.0051 \times x_n + 0.24 \times (x_f == 1)\\
&\qquad + 0.57 \times (x_f == 2) - 0.5 \times x_{se})\\
&\text{with } x_d, x_c, x_{pa}, x_n, x_{se} \in \{0, 1\}, \text{ and } x_f \in \{0, 1, 2\} \quad (9)
\end{aligned}$$

Sampling The joint probability distribution from Equation (1) is now fully specified. We can use this Bayesian network to randomly sample the tabular portion of a patient record top-down, starting from the root variables without parents at the top and continuing further down. Each value is sampled conditionally on the variable's parents' values, using the conditional distributions we have defined. We repeat this process 10,000 times, leaving us with 10,000 artificial patient records consisting of 16 tabular features.

C Prompting the large language model

Starting from the tabular portion of the patient record, we aim to generate a text describing this fictional patient encounter. The scenario we simulate artificially is as follows. The patient goes to the primary care physician, telling them their symptoms and possible underlying conditions, along with additional context on the severity of these symptoms, when they started, among other details. The physician takes descriptive notes during this consultation, writing down the (recent) history prescribed by the patient. Then, based on the patient's described complaints, they conduct a physical examination, writing down all findings. Both parts together then form the textual description of the patient encounter.

Presence of symptoms The first block of information in the prompt concerns the symptoms experienced by the patient. We do not list the full set of symptoms exhaustively. Even if a patient might experience a certain symptom, there is a possibility that they do not mention it to the clinician, or that the clinician does not find it noteworthy to write down. On the other hand, if a patient does not experience a symptom, it is not very likely that they will mention this to the physician, and the physician does not always have a reason to ask for the symptom either. We therefore ask our expert to list the probability of mentioning the symptom in a clinical note when the symptom is positive and when it is negative. Of course, this would not generalize to all physicians, but it helps to bring some variety and realism in the notes we generate. The probabilities are as follows:

- $\mathcal{P}(ment_{dysp} = yes \mid dysp = yes) = 0.95$, $\mathcal{P}(ment_{dysp} =$

Symptoms				Antibiotics	
dysp	cough	pain	fever	label	pred.
no	yes	no	high	no	0.48
no	yes	yes	high	yes	0.64
yes	yes	no	high	yes	0.67
yes	yes	yes	high	yes	0.80
yes	no	no	high	yes	0.51
no	no	yes	high	yes	0.48
no	no	no	high	no	0.32
no	no	no	low	no	0.11
no	yes	no	low	no	0.19
yes	yes	no	low	no	0.35
no	yes	yes	low	no	0.31
yes	yes	yes	low	yes	0.51
yes	yes	yes	none	yes	0.30
yes	no	yes	none	no	0.18
yes	yes	no	none	no	0.18
yes	no	no	none	no	0.10
no	yes	no	none	no	0.09
no	no	yes	none	no	0.09

Table 4: Test cases labeled by the expert on whether to prescribe antibiotics or not (all assume *policy* = *low*). "label" indicates the expert's decision, while "pred" indicates the model's predicted probability (based on Equation (7)).

$yes \mid dysp = no) = 0.75$

- $\mathcal{P}(ment_{cough} = yes \mid cough = yes) = 0.95$, $\mathcal{P}(ment_{cough} = yes \mid cough = no) = 0.9$
- $\mathcal{P}(ment_{pain} = yes \mid pain = yes) = 0.75$, $\mathcal{P}(ment_{pain} = yes \mid pain = no) = 0.3$
- $\mathcal{P}(ment_{fever} = yes \mid fever = high) = 0.95$, $\mathcal{P}(ment_{fever} = yes \mid fever = low) = 0.7$, $\mathcal{P}(ment_{fever} = yes \mid fever = none) = 0.4$
- $\mathcal{P}(ment_{nasal} = yes \mid nasal = yes) = 0.95$, $\mathcal{P}(ment_{nasal} = yes \mid nasal = no) = 0.1$

For each symptom, we sample whether it is to be mentioned in the prompt, conditional on its value, according to the probabilities stated above. As can be seen in Figure 1, we explicitly tell the model what symptoms to mention and which to steer clear from. We randomly permute the ordering of the symptoms in each prompt.

Symptom descriptors To make the note realistic, the LLM must invent some context regarding the patient's symptoms when writing the history portion of the note. We want this context to indirectly relate to the cause of these symptoms, as they would in a real patient encounter. For example, a cough induced by asthma would likely be momentarily and attack-related, while a cough resulting from pneumonia might be more persistent over the longer term. We therefore ask the expert to write down a list of adjectives or phrases describing each symptom, conditioned on the cause of the symptom. These descriptors can be found in Table 7. The list of possible causes for a symptom is simply the list of parents in the Bayesian network.

For each symptom which is present in the patient and selected to be mentioned in the note, we check the tabular patient record for the possible causes. For example, for the symptom cough, the possible causes are asthma, smoking, COPD, pneumonia and common cold. In the example in Figure 1, asthma is the only cause which is "on". We therefore randomly sample a descriptor from the list of descriptors for cough in the presence of asthma, in this case the adjective "dry". This adjective is added in the prompt. If multiple causes are "on", we find the strongest cause, and sample from that list. The strongest cause is pneumonia, followed by common cold, followed by all other causes. If neither pneumonia nor common cold is part of the multiple causes, we simply make a bag of all descriptors associated to the causes which are "on", and sample from that bag. In the rare event that no causes are "on", yet a symptom is still observed (which is possible due to the leak probability in the Noisy-OR distribution), we do not add a descriptor. Note that while the diagnoses pneumonia and common cold should not be mentioned explicitly, they indirectly and subtly influence the content of the note through the descriptors, adding another realistic dimension to the content of the note.

Symptoms					Days at home antibio = no		Days at home antibio = yes	
dysp	cough	pain	nasal	fever	label	pred.	label	pred.
no	no	no	no	none	1.5	1	1	1.1
no	yes	no	no	high	4	4.9	3.5	3.2
no	yes	no	no	low	2	3.2	2	2.3
no	yes	yes	no	high	9	7.9	4	4.1
yes	yes	no	no	high	10	9.3	5	5.3
yes	yes	yes	no	high	14	14.9	7	6.9
no	yes	yes	no	low	5	5.2	3	2.9
yes	yes	no	no	low	6	6.1	4	3.8
yes	yes	yes	no	low	10	9.8	5	4.9
yes	yes	yes	no	none	4	4.3	3.5	3.9
no	yes	yes	no	none	2	2.3	2	2.3
yes	yes	no	no	none	3	2.7	3	3
yes	no	yes	no	none	3	3.1	3	2.5
no	no	no	yes	none	2	1	2	1.2
no	yes	no	yes	high	4	4.7	3.5	3.2
no	yes	no	yes	low	2	3.3	2	2.3
no	yes	yes	yes	high	9	8	4	4.1
yes	yes	no	yes	high	10	9.4	5	5.3
yes	yes	yes	yes	high	14	15.1	7	6.9
no	yes	yes	yes	low	5	5.2	3	3
yes	yes	no	yes	low	6	6.2	4	3.8
yes	yes	yes	yes	low	10	9.9	5	4.9
yes	yes	yes	yes	none	4	4.4	3.5	3.9
no	yes	yes	yes	none	2	2.3	2	2.3
yes	yes	no	yes	none	3	2.7	3	3
yes	no	yes	yes	none	3	3.1	3	2.6

Table 5: Train cases labeled by the expert on how many days they expect a patient to stay home on average (all assuming *self-employed* = *no*), with and without prescribing antibiotics. "label" indicates the expert's estimation, "pred" indicates the model's predicted mean number of days λ (based on Equation (8) and (9)).

Underlying health conditions While the diagnoses should not be mentioned directly in the note, it is realistic to assume that the note would mention underlying health conditions the patient may have. Since these health conditions are assumed to be known up-front, as they are part of the history of the patient, they may contribute a lot to the interpre-

Symptoms					Days at home antibio = no		Days at home antibio = yes	
dysp	cough	pain	nasal	fever	label	pred.	label	pred.
yes	no	no	no	high	6	6.5	3.5	3.5
no	no	yes	no	high	6	5.5	3	2.7
yes	no	yes	no	high	12	10.5	5	4.5
yes	no	no	no	low	4	4.3	3	2.5
no	no	yes	no	low	4	3.7	3	1.9
yes	no	yes	no	low	6	6.9	5	3.2

Table 6: Test cases (not part of training set) labeled by the expert on how many days they expect a patient to stay home on average (all assuming *self-employed* = *no*), with and without prescribing antibiotics. "label" indicates the expert's estimation, while "pred" indicates the model's predicted mean number of days λ after training (based on Equations (8) and (9)).

tation of the symptoms by both the patient themselves and the clinician writing down the note. We therefore add them to the prompt as well, as can be seen in Figure 1. We do not force the LLM to explicitly mention these in the note, since it seems feasible that a clinician would not mention them every time. Should there be more than one underlying condition, we mention them all, randomly permuting the order in each prompt. If there are no underlying health conditions, we simply remove this part of the prompt.

Additional instructions We tell the LLM that the note must be structured with a "History" portion and a "Physical examination" portion. While the "History" portion describes the patient's self-reported symptoms and underlying health conditions, which are in large part dictated by the prompt, the "Physical examination" portion leaves the LLM with more freedom to imagine additional clinical examinations which were performed on the patient. As such, the "Physical examination" portion has a lot of potential for adding complexity, clinical terminology and realism to the note.

We also add some additional instructions to the prompt, asking it not to mention any suspicions of possible diagnoses. We further tell the LLM it can imagine context or details, but no additional symptoms. We noticed that if we left this part out, the LLM would sometimes mention the symptoms we specifically asked to leave out. We ask not to mention patient gender or age, because preliminary testing revealed that the LLM often used the same age and gender (34-year old woman), which could confound or bias the notes. Finally, we add that the notes may be long (around 5 lines or more), to avoid the LLM being too succinct.

Special case: no respiratory symptoms There are 3629 out of 10,000 patients where all symptoms in the tabular record are "no", meaning the patient does not experience any respiratory symptoms. If we used the same prompt as before, this would result in an unrealistic clinical note, since the note would simply list all symptoms the patient does not have, without giving an actual reason for the patient's visit. Furthermore, there would be little variation in these notes. An example is shown in Figure 4. For these cases, it makes more sense to assume that the patient visits for a complaint unrelated to the respiratory domain, such as back pain, stomach issues, a skin rash, etc. To generate these special cases, we use a special prompt, telling the LLM the patient does not experience any of the 5 respiratory symptoms. When the patient has at least one underlying health condition (which is the case in 239 out of 3629 special cases), we add this to the prompt in the same way as before, like the example in Figure 5. If not (i.e., for the remaining 3390 out of 3629 special cases), we tell the LLM not to mention any of those health conditions either, see the prompt in Figure 6. The latter prompt asks for three clinical notes at once, encouraging the LLM to be more creative and not repeat the same scenario every time, as well as being a little more cost-effective. This is possible because of the prompt being non-specific to any of these 3390 patients. We then randomly distribute all generated texts to each tabular patient record within this subset.

Prompting details As a large language model, we opted for OpenAI's GPT-4o model, using the version released in May 2024 (OpenAI 2024). We set the temperature to 1.2 to encourage some more variation in the notes, while at the same time keeping them realistic. Before providing the case-specific prompt, we set the following system message: "You are a general practitioner, and need to summarize the patient encounter in a clinical note. Your notes are detailed and extensive." We set the *max_tokens* parameter to 1000. All other parameters were kept as their default value. Generating all 10,000 notes and their compact version cost around 130$.

D Additional example prompts

Figures 7 and 8 show two additional example prompts.

E Expert evaluation

We picked a random subset of 30 generated notes and show them to 5 general practitioners, in a random order. All evaluators got to see the same 30 notes, together with the prompts that were used to generate them. All evaluators received detailed instructions on what was expected of them in the form of a PDF[1], which was orally explained by the researchers. The researchers then sat together with each evaluator separately to complete three example notes (different from the 30 notes that were to be evaluated). Afterwards, the evaluators were asked to rate the notes in their own time, without the researchers' involvement. Since it is infeasible to evaluate the whole dataset of 10,000 notes, we opted for a small subset of 30 notes, each going through a relatively extensive evaluation process that considered various measures of quality (evaluators took around $5 - 10$ minutes to evaluate each note). We decided to show all 5 evaluators the same set of 30 notes, to get a broader range of expert opinions in the evaluation of each note. This also allowed for the calculation of inter-annotator agreement.

We now provide further details on each dimension along which we evaluated the notes and the specific meaning as-

[1] https://github.com/prabaey/SynSUM/blob/main/eval/Instructions_clinical_evaluation.pdf

Symptom	Cause	Descriptors
dyspnea	asthma	attack-related, at night, in episodes, wheezing, difficulty breathing in, feeling of suffocation, nighttime stuffiness, provoked by exercise, light, severe, not able to breathe properly, air hunger
	smoking	during exercise, worse in morning, mild
	COPD	chronic, worse during flare-up, worse when lying down, difficulty sleeping, air hunger
	hay fever	light, mild, stuffy feeling, all closed up
	pneumonia	light, mild, severe, no clear cause
cough	asthma	attack-related, dry
	smoking	productive, mostly in morning, during exercise, gurgling
	COPD	phlegm, sputum, gurgling, worse when lying down
	pneumonia	for over 7 days, light, mild, severe, non-productive at first and later purulent
	common cold	prickly, irritating, dry, phlegm, sputum, light, mild, severe, constant, day and night
pain	asthma	tension behind sternum
	COPD	light, mild
	cough	muscle pain, burning pain in trachea, burning pain in windpipe, scraping pain in trachea, scraping pain in windpipe
	pneumonia	light, mild, severe, localized on right side, localized on left side, associated with breathing
	common cold	burning pain in trachea, burning pain in windpipe, scraping pain in trachea, scraping pain in windpipe, light, mild

Table 7: Descriptors used in the prompt to describe each symptom when it is present in the patient. Depending on the cause(s) of the symptom (as listed in the tabular patient record), we randomly sample from a different set of descriptors.

signed to each rating. The aspects of consistency, realism and clinical accuracy are only evaluated based on the normal note, while the quality of the compact note is evaluated using the last two dimensions (content and readability).

E.1 Evaluation aspects

Consistency We subdivided the prompt into four different sections, and asked the evaluators to assign penalties for each section. A penalty was assigned if the requested information in that section was incorrectly mentioned in the note (e.g. a particular symptom was said to be present in the patient, when the prompt particularly requested the symptom to be absent), or if the requested information was absent from the note (e.g. a symptom descriptor is not mentioned in the text). The four parts of the prompt were as follows: (i) the symptoms to mention (can be present or absent), (ii) the symptoms not to mention, (iii) the underlying health conditions, and (iv) the additional instructions.

As explained in Section 2.2, around one third of the notes were generated using a second type of prompt, where the LLM is told that the patient does not suffer from any respiratory symptoms or underlying health conditions. Following the prompt in Figure 6, there are three parts of the prompt which can be violated (leading to penalties): (i) the respiratory symptoms, which the patient does not have, (ii) the underlying conditions, which the patient does not have, and (iii) the additional instructions. In our random set of 30 notes, 20 notes belonged to the first type, and 10 to the second type.

Once penalties were assigned, we summed them into a total number of penalties, and converted these into scores from 1 to 5. Notes with no penalties get a perfect score of 5, one penalty corresponds to 4, two penalties to 3, three penalties to 2 and more than three penalties to 1.

Realism The LLM is allowed to invent context and details in light of the information it receives in the prompt, but this must be realistic and relevant to the symptoms experienced by the patient. While some clinical facts might not seem technically incorrect, one might not expect to see them in the note, or it might be unlikely that they would be written down by a real physician. For example, if a patient has a runny nose and no other complaints, most clinicians would not check for abnormalities in lung capacity. Another example is asking whether the patient has recently traveled to an exotic destination because they have a cough.

We ask to score realism of the "history" section using the ratings below. The evaluators are specifically instructed to take into account the information mentioned in the prompt.

5 – All pieces of additional context and details (i.e. outside of the symptoms and background provided in the prompt) are realistic and seem like they belong in the note.

4 – There are one or two pieces of additional context or details that I would not have mentioned as a physician, or that do not seem relevant (even though they do seem like they belong).

3 – There are one or two pieces of additional context or details that do not seem like they belong in the note, or do not seem relevant, given the symptoms and background provided in the prompt.

2 – There are multiple pieces of additional context or details that do not seem like they belong in the note, or do not seem relevant, given the symptoms and background provided in the prompt.

1 – (Almost) all of the additional context is nonsensical given the symptoms and background provided in the prompt.

We ask to score realism of the "physical examination" section using the ratings below. The evaluators are specifically instructed to take into account the information men-

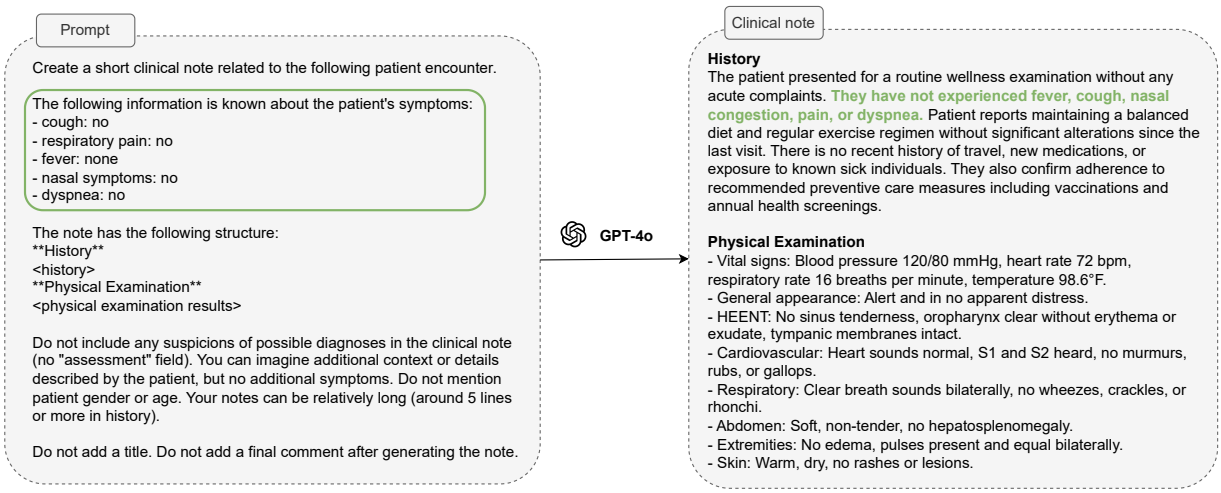


Figure 4: Example of what would happen if we simply extended the general prompt to the 3629 cases where the patient does not experience any respiratory symptoms. There would be little variation in these notes, as these patients seem to visit the doctor's office for no reason. It is more realistic to encourage the LLM to generate a note which describes a patient visiting for a non-respiratory complaint, like the prompts shown in Figures 5 and 6.

tioned in the "history" section of the note.

5 – All elements in the physical examination are things I would check, given the history and symptoms of the patient, and no important elements are missing.

4 – There are one or two elements in the physical examination that I probably would not have checked, given the history and symptoms of the patient, but I could see it happen. Some minor elements might be missing, but nothing major.

3 – There are one or two elements in the physical examination that I would not have checked, or some important elements are missing, given the history and symptoms of the patient.

2 – There are multiple elements in the physical examination that make no sense given the history and symptoms of the patient, or many important elements are missing.

1 – The physical examination portion of the note seems totally unrealistic.

Clinical accuracy While the previous section talks about evaluating the realism of the presence of all examinations described in the "physical examination" section, here we talk about evaluating the clinical accuracy of these findings. Clinical inaccuracies may depend on the context, like physical findings which are not congruent with the history and symptoms of the patient. For example, if the "history" portion mentions that the patient has a no fever, then this should not be contradicted in the "physical examination" portion with a temperature of 39°C. Clinical inaccuracies may also stand alone. For example, a blood pressure reading of 20/10 mm Hg is impossible to encounter in any patient.

We ask the evaluators to score clinical accuracy of the findings that are mentioned in the "physical examination" portion of the note, using the ratings below.

5 – There are no mistakes, all reported clinical information is plausible in light of the patient's symptoms and history.

4 – There are one or two minor mistakes, or some details seem less plausible in light of the patient's symptoms and history, while the overall picture painted by the note is still correct.

3 – There are more than two minor mistakes, or multiple details which seem implausible in light of the patient's symptoms and history, but no major inaccuracies.

2 – There is a major mistake (on top of possibly some minor ones), or many details seem implausible given the patient's symptoms and history.

1 – There are multiple major mistakes and many details seem totally implausible given the patient's symptoms and history.

Quality of compact version While all the previous evaluations concerned the original note, here we evaluate the quality of the compact version of the note.

The **content** of the compact version should convey the same information as the original text, albeit in a shorter format. This is evaluated jointly for "history" and "physical examination" using the scoring system below.

5 – The compact version conveys the exact same information as the original text.

4 – The compact version conveys all key points of the original text, leaving out some details here and there.

3 – The compact version conveys some of the key points of the original text, but misses some as well.

2 – The compact version conveys some of the same information as the original text, but misses many key points.

1 – The compact version does not convey the same information as the original text, leaving out almost all key points.

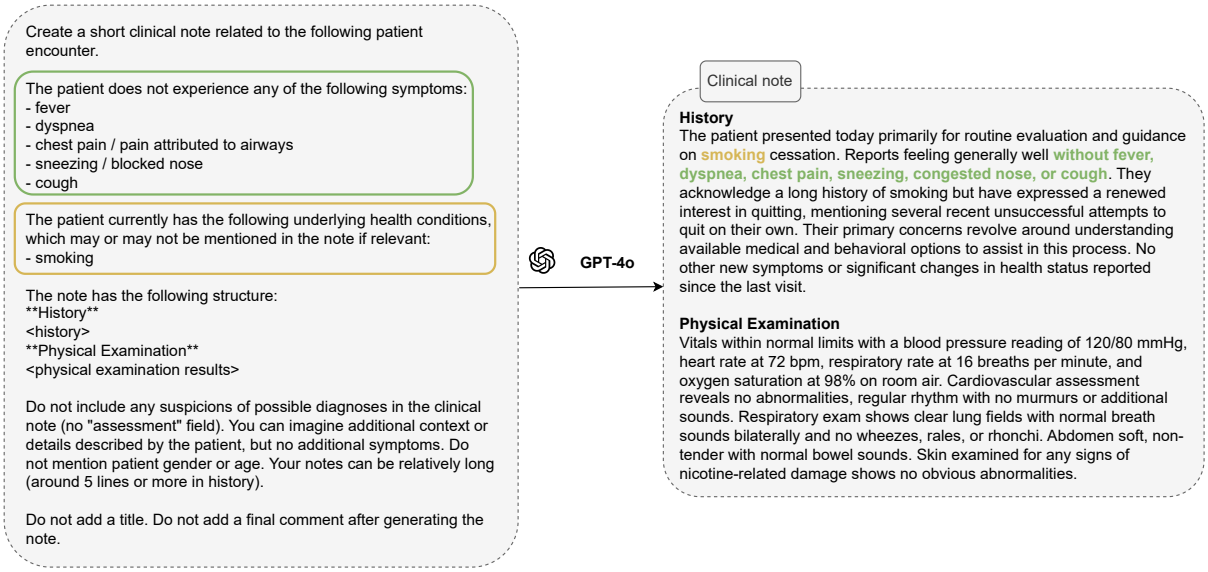


Figure 5: Example prompt and generated note for case where patient does not experience any respiratory symptoms, but does have an underlying respiratory health condition (here: smoking).

While we purposefully want these notes to be harder to read and understand for both humans and machines, mimicking the complexity of some real clinical notes, the use of abbreviations should not be excessive. We evaluate **readability** jointly for "history" and "physical examination", using the scoring system below.

5 – The compact version seems understandable without seeing the original.

4 – The compact version seems mostly understandable without seeing the original, though there are some abbreviations that I would not immediately understand.

3 – Some parts of the compact version seem understandable without seeing the original, but other parts are not. There are some abbreviations that seem far-fetched or are used incorrectly (i.e. these are known to refer to other clinical terms than the way they are used in the text).

2 – Many parts of the compact version would not be understandable without seeing the original. Many abbreviations seem far-fetched or are used incorrectly (i.e. these are known to refer to other clinical terms than the way they are used in the text).

1 – The compact version is impossible to understand without seeing the original.

E.2 Results

Extended results for consistency We list the total number of penalties assigned by all evaluators to each of the prompt sections. For the 20 notes belonging to the first prompt type, 41 penalties were assigned in total for section (iv) of the prompt, which are the additional instructions. Sections (i), (ii), and (iii), which describe the symptoms and underlying health conditions of the patients, received no penalties at all. For the 10 notes belonging to the second prompt type, 1 penalty was assigned for part (i), 2 penalties for part (ii) and another 2 penalties for part (iii).

From this, we can conclude that a large majority of the inconsistencies arise from a violation of the additional instructions (usually by inventing additional symptoms), while the key symptom information included in the prompt was still conveyed correctly in the note. High consistency between the tabular variables and the concepts mentioned in the text makes our dataset a reliable resource for information extraction tasks.

Inter-Annotator Agreement We calculate Krippendorff's alpha with ordinal distance measure to get an idea of the inter-annotator agreement in our study. We get the following results:

- Consistency: 0.44
- Realism (history): 0.25
- Realism (physical examination): 0.32
- Clinical accuracy: 0.21
- Content of compact version: -0.02
- Readability of compact version: 0.36

With an alpha of 1 indicating perfect agreement, we can say that there is some agreement between the 5 evaluators. Especially for consistency, readability and realism of the physical examination, the agreement is fair. Only the ratings for content of the compact version shows no indication of agreement. We hypothesize that this is at least partially due to the high scores assigned by all evaluators (mostly 4 and 5), with a deviation from 5 being assigned to random chance rather than to a common opinion of the evaluators. The lower standard deviations in Table 1 show that the evaluators con-

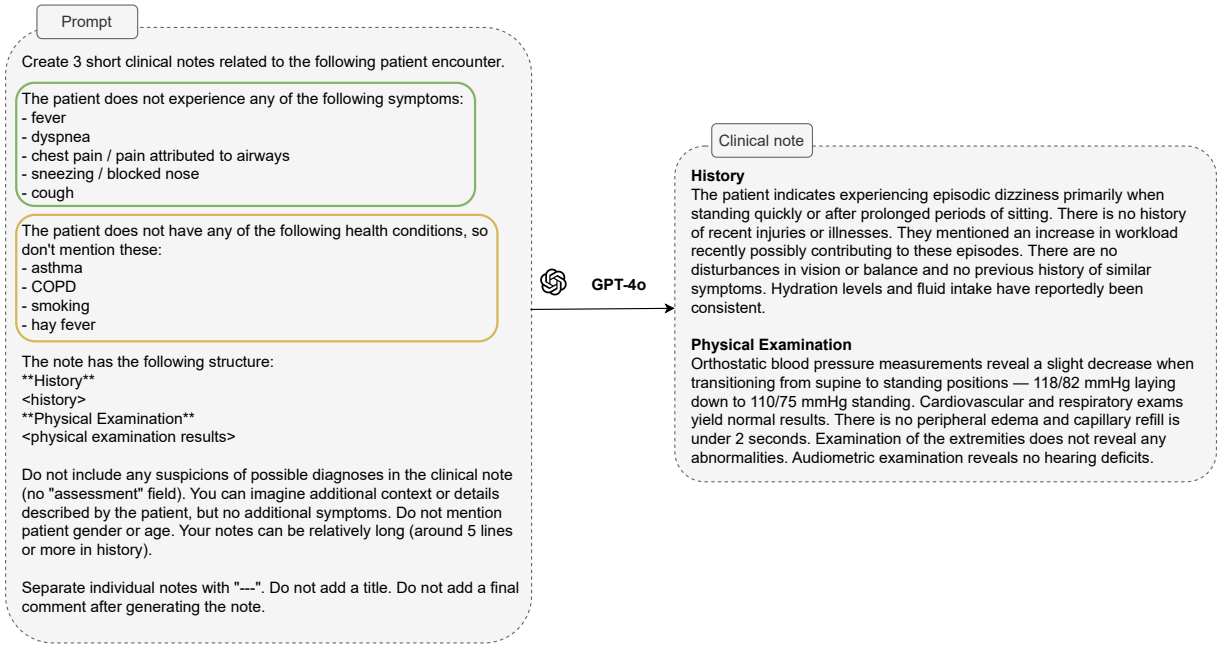


Figure 6: Prompt used for cases where patient does not experience any respiratory symptoms or have any underlying respiratory health condition. We show one of the three generated notes.

sistently assign high scores to all aspects of the evaluation, even if they don't agree on which particular notes deviate from these higher scores.

F Symptom predictor baselines

F.1 BN-tab

We learn a Bayesian network over the training data, providing the structure over all variables as in Figure 1. For the variables *asthma*, *smoking*, *hay fever*, *COPD*, *season*, *pneumonia*, *common cold*, *fever* and *self-employed*, we learn the conditional probability tables (CPTs) from the training data using maximum likelihood estimation (which comes down to counting co-occurrences of child and parent values for each entry in the CPT). We use the `pgmpy` library (Ankur Ankan and Abinash Panda 2015) with a K2 prior as a smoothing strategy to initialize empty CPTs.

As support for learning Noisy-OR distributions is not provided in `pgmpy`, we learn these parameters with a custom training loop. We formulate the likelihood as in Equation (2), and learn the parameters p_i in Equations (3) through (6) for the variables *dyspnea*, *cough*, *pain* and *nasal* through maximum likelihood estimation by iterating over the train set for 10 epochs, using an Adam optimizer with a batch size of 50, a learning rate of 0.01 and random initialization of each parameter. To integrate the learned Noisy-OR distributions in the Bayesian network, we turn them into fully specified CPTs. To obtain these, we simply evaluate Equation (2) for all possible combinations of child and parent values. While this results in large and inefficient CPTs, the automated inference engine built into `pgmpy` library does not support Noisy-OR distributions directly. Note that both versions of the conditional distribution are equivalent, so we do not incur a loss in precision.

Similarly, the coefficients in the logistic regression model for *antibiotics* and the Poisson regression model for *#days* are learned using maximum likelihood estimation over the training set of $8{,}000$ examples. The likelihood is expressed as in Equation (7) and Equations (8) and (9) respectively, with learnable parameters in place of each coefficient. We iterate over the train set for 15 epochs, again using an Adam optimizer with a batch size of 50, a learning rate of 0.01 and random initialization of each parameter. Finally, we turn the logistic regression and Poisson regression models into CPTs by evaluating Equations (7), (8) and (9) for all combinations of parent and child values. For the variable *#days*, we needed to turn each discrete number of days into a category, because `pgmpy` only provides automated inference for Bayesian networks consisting of exclusively categorical variables. This results in a large CPT containing one row per possible number of days, which range from 0 to 15 in our training dataset, and one column for each combination of the 7 parent variables. To allow for a possible larger maximum number of days in the test set, we create a category $\geq$ *15 days*, which is defined as one minus the summed probability of all other days.

Once we have learned all parameters in the joint distribution, we can evaluate the Bayesian network's ability to predict each of the symptoms. For each evidence setting (as defined in the main text), we apply variable elimination with each of the symptoms as a target variable. Looking at the causal structure in Figure 1, we note that the model never

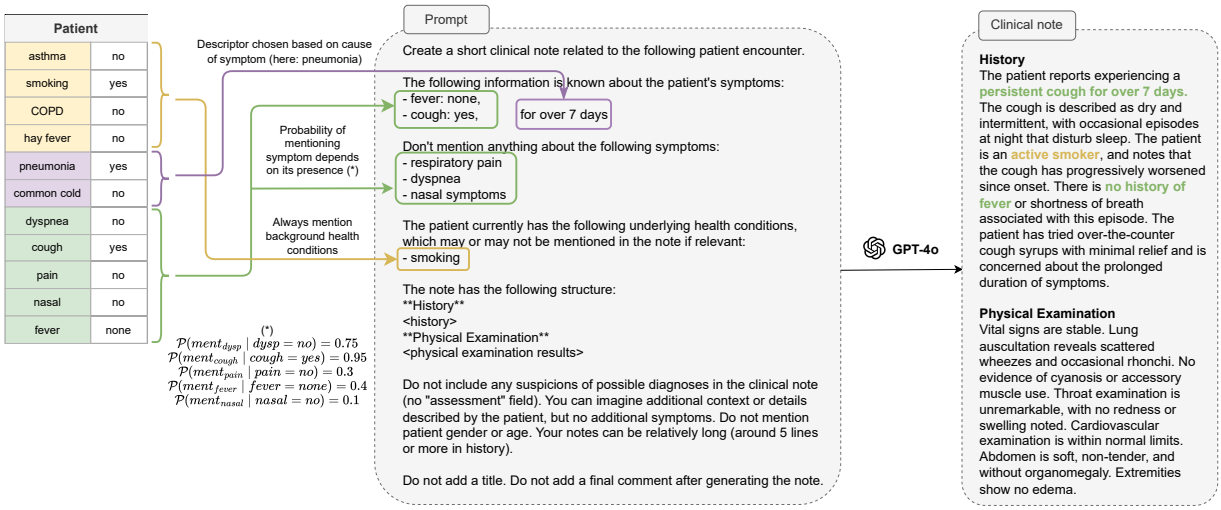


Figure 7: Additional example prompt with generated note.

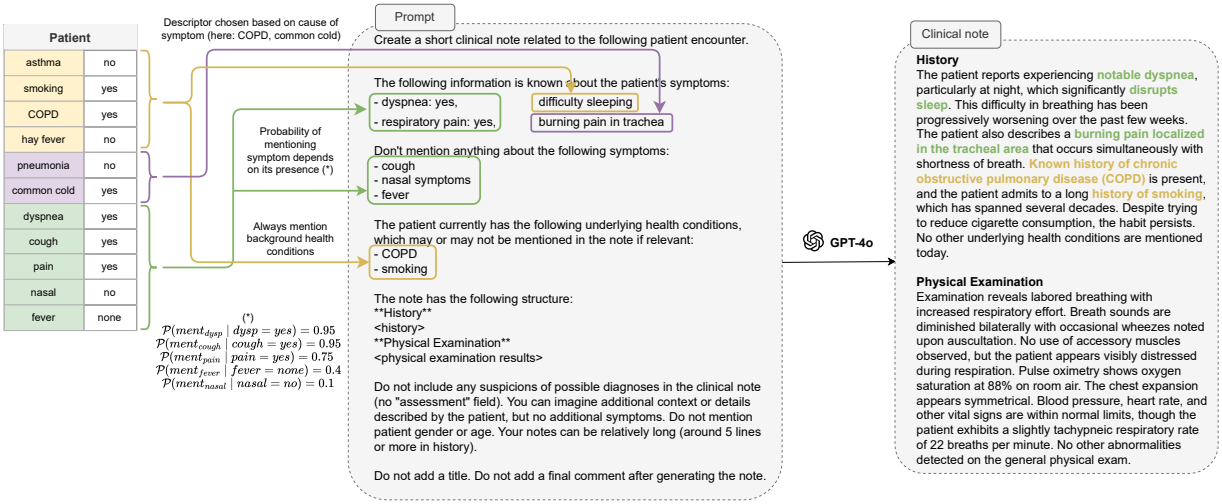


Figure 8: Additional example prompt with generated note. Since there are multiple causes for the symptom dyspnea (smoking, COPD) which are present in the patient, the descriptor "difficulty sleeping" was chosen randomly out of the bag of descriptors for smoking and COPD from table 7. For respiratory pain, the descriptor "burning pain in the trachea" was chosen randomly out of the descriptors for common cold. While cough and COPD are also possible causes for respiratory pain, and are present in the patient, common cold overrules the two according to our strategy outlined in Section 2.2.

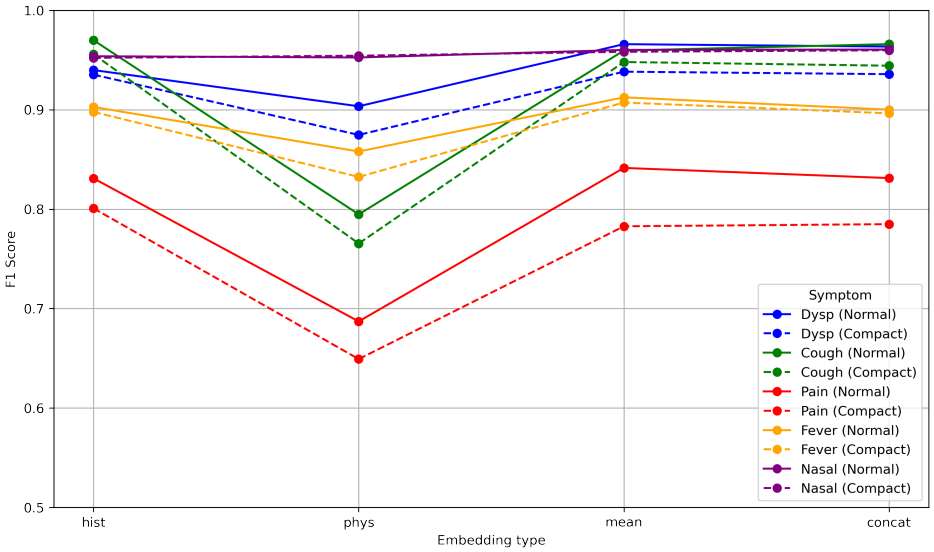


Figure 9: Results for the **neural-text** baseline for the different embedding types. We show F1-scores over the test set for both the normal and compact versions of the notes. Figure best viewed in color.

has to marginalize over the many rows in the learned *#days* CPT, since it is never a target variable. This makes automated inference feasible in our case.

F.2 XGBoost-tab

We use the `xgboost` library in combination with `sklearn`. We train separate classifiers per symptom, one for each setting, which means we train 15 classifiers total. We tune the hyperparameters separately for each classifier, using 5-fold cross validation with F1 as a scoring metric (macro-F1 for *fever*).

The classifiers for the symptoms *dysp*, *cough*, *pain* and *nasal* use a binary logistic objective and logloss as an evaluation metric within the XGBoost training procedure, while the classifiers for the symptom *fever* use the multi-softmax objective with multiclass logloss as an evaluation metric. The *scale_pos_weight* parameter is set to the ratio of negative over positive samples for the binary classifiers. For the *fever* classifier, we address class imbalance by setting *class_weight* = *balanced*, which ensures that samples from less frequent classes (in our case low and high fever) receive higher weight in the loss calculation. We use grid search to find the best hyperparameter configuration, where the following sets of options are explored:

- *n_estimators*: $\{50, 100, 200\}$
- *max_depth*: $\{2, 3, 4, 5\}$
- *learning_rate*: $\{0.01, 0.1, 0.2\}$
- *subsample*: $\{0.8, 1\}$
- *colsample_bytree*: $\{0.8, 1\}$
- *gamma*: $\{0, 0.1, 0.3\}$
- *min_child_weight*: $\{1, 5, 10\}$

F.3 Neural-text

The pretrained BioLORD encoder (Remy, Demuynck, and Demeester 2024) was obtained through the `huggingface` library. The encoder outputs 768-dimensional sentence embeddings. Since the full text did not fit into the context window, we embedded each sentence separately, and then combined them using our strategies outlined in the main text. To split the text into sentences, we used the `nltk` package. The settings *hist*, *phys* and *mean* all result in a text embedding of 768 dimensions, while the setting *concat* results in a text embedding of 2*768 dimensions.

These embeddings are fed into a linear layer with 256 neurons, followed by a ReLU activation. The hidden state is then transformed into a single output neuron, followed by a Sigmoid activation. For the classifiers that predict *fever*, three output neurons followed by a Softmax activation are used instead, one for each class. While the embeddings remain fixed, we learn the parameters in the hidden and output layers using cross-entropy as a loss function over the training set. We train a separate classifier for each symptom, setting and difficulty of the text (normal vs. compact). For the binary symptoms, we train for 15 epochs using the Adam optimizer with a batch size of 100, a learning rate of 0.001 and *weight_decay* set to $1e{-}5$. The classifier for $fever$ tended to collapse more easily, which is why we train it for 30 epochs with a lower learning rate of $5e-4$ instead. These hyperparameters were obtained using a mix of manual tuning and grid search with 5-fold cross validation over the training set.

Results for the different embedding types are reported numerically in Table 8, and shown visually in Figure 9. There is a significant gap in performance between the *hist* and *phys* settings for the symptoms cough, pain and fever. This makes sense, as the "history" section of the note outlines the symptoms experienced by the patient more clearly. The performance difference between the *mean* and *concat* settings is usually small.While the score for *hist* comes close to those for *mean* and *concat*, the latter usually still outperform the former for the normal notes, showing that there is some com-

	dyspnea	cough	pain	nasal	fever
normal					
- hist	0.9399	**0.9699**	0.8310	0.9538	0.9028
- phys	0.9035	0.7948	0.6871	0.9526	0.8580
- mean	**0.9660**	0.9595	**0.8415**	0.9602	**0.9125**
- concat	0.9635	0.9660	0.8313	**0.9606**	0.9001
compact					
- hist	0.9353	**0.9557**	**0.8008**	0.9522	0.8978
- phys	0.8747	0.7655	0.6492	0.9544	0.8324
- mean	**0.9383**	0.9480	0.7828	0.9583	**0.9073**
- concat	0.9358	0.9443	0.7849	**0.9598**	0.8964

Table 8: Results for the **neural-text** baseline using different embedding types at the input. We report F1-score over the test set for both the normal and compact versions of the notes. The best results per symptoms and per note version is shown in **bold**.

plementary information in the "history" and "physical examination" portions. For the compact notes, including the "physical examination" portion seems to confuse the model for the symptoms cough and pain, since the *hist* setting outperforms *mean* and *concat* there.

F.4 Neural-text-tab

For each evidence setting, we select the relevant set of tabular features and transform them into a numerical representation. We use a one-hot encoding for the categorical (binary or multiclass) features, and normalize the *#days* feature using the StandardScaler from `sklearn`. This tabular feature representation is then concatenated with the text representation we obtained in the previous baseline. Both are fed into the same architecture described in Section F.4, adapting the dimension of the input layer accordingly. For example, for the *dyspnea* classifier in the evidence setting *all*, the input dimension becomes $768 + 17$. We use the same hyperparameters as in the **neural-text** baseline to ensure a fair comparison. All other training details remain the same.