Zero-Shot Clinical Acronym Expansion with a Hierarchical Metadata-Based Latent Variable Model

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Abstract
We introduce Latent Meaning Cells, a deep latent variable model which learns contextualized representations of words by combining local lexical context and metadata. Metadata can refer to granular context, such as section type, or to more global context, such as unique document ids. Reliance on metadata for contextualized representation learning is apropos in the clinical domain where text is semi-structured and expresses high variation in topics. We evaluate the LMC model on the task of clinical acronym expansion across three datasets. The LMC significantly outperforms a diverse set of baselines at a fraction of the pre-training cost and learns clinically coherent representations.

Keywords: clinical acronyms, representation learning, variational inference

1. Introduction
Pre-trained language models have yielded remarkable advances in multiple natural language processing (NLP) tasks. The blueprint of pre-training a deep neural network on a massive, unlabeled corpus before fine-tuning on a smaller, labeled corpus has reset the state of the art for many NLP tasks in the general domain. Probabilistic models such as LDA (Blei et al., 2003), on the other hand, can uncover latent document-level topics. In topic models, words are drawn from shared topic distributions at the document level, whereas in language models, word semantics arise from co-occurrence with other words in a tighter window.

In this paper, we build upon both approaches and introduce Latent Meaning Cells (LMC), a deep latent variable model which learns a contextualized representation of a word by combining evidence from local context (i.e., the word and its surrounding words) and document-level metadata. We use the term metadata to generalize the framework because it may vary depending on the domain and application. Metadata can refer to a document itself, as in topic modeling, document categories (i.e, articles tagged under *Sports*), or structures within documents (i.e. section headers). Incorporating latent factors into language modeling allows for direct modeling of the inherent uncertainty of words. As such, we define a latent meaning cell as a Gaussian embedding jointly drawn from word and metadata prior densities. Conditioned on a central word and its metadata, the latent meaning cell identifies surrounding words as in a generative Skip-Gram model (Mikolov et al., 2013a; Brazinskas et al., 2018). Based on the variational autoencoder (Kingma and Welling, 2013; Rezende et al., 2014), we devise an amortized variational distribution over the
latent meaning cells, which enables approximation of posterior densities. The approximate posterior can best be viewed as the embedded word sense based on local context and metadata. In this way, the LMC is non-parametric in the number of latent meanings per word type.

We develop and motivate the LMC model for the task of clinical acronym expansion. Clinical texts are highly structured, with established section headers across note types and hospitals (Weed, 1968). They convey rich information, but their robust processing is challenging (Demner-Fushman and Elhadad, 2016), partly because clinicians frequently use acronyms and abbreviations (Meystre et al., 2008) with diverse meanings across contexts. For instance, the abbreviation Ca is more likely to stand for calcium in a Medications section whereas it may refer to cancer under the Past Medical History section. Consequently, section header information can provide complementary evidence to local word context. In experiments, we define metadata as section headers and evaluate the LMC and several baselines across three clinical datasets.

We summarize our primary contributions as: (1) We devise a contextualized language model which jointly reasons over words and metadata. Previous work has learned document-level representations. In contrast, we explicitly condition the meaning of a word on these representations; (2) Defining metadata as section headers, we evaluate our model on zero-shot clinical acronym expansion and demonstrate superior LMC performance. With relatively few parameters and rapid convergence, the LMC model offers an efficient alternative to more computational intensive models on the task.

2. Related Work

Clinical Acronym Expansion. Acronym expansion—mapping a Short Form (SF) to its most likely Long Form (LF)—is a task within the problem of word-sense disambiguation (Camacho-Collados and Pilehvar, 2018). For instance, the acronym PT refers to “patient” in “PT is 80-year old male,” whereas it refers to “physical therapy” in “prescribed PT for back pain.” Traditional supervised approaches to clinical acronym expansion consider only the local context (Joshi et al., 2006). Recent work leverages contextualized embeddings from ELMo, in tandem with attention over topic embeddings, to achieve strong performance after fine-tuning on a randomly sampled MIMIC dataset (Li et al., 2019). In the related task of biomedical entity linking, the LATTE model (Zhu et al., 2020) uses a similar architecture to ELMo for mapping natural language to standardized entities in the UMLS meta-thesaurus (Bodenreider, 2004). Skreta et al create a reverse substitution dataset and address class imbalances by sampling additional examples from related UMLS terms (Skreta et al., 2019).

Word Embeddings. Pre-trained language models learn contextual embeddings through masked, or next, word prediction (Peters et al., 2018a; Devlin et al., 2019; Yang et al., 2019; Bowman et al., 2019; Liu et al., 2019; Radford et al., 2019). Recently, SenseBert (Levine et al., 2019) leverages WordNet (Miller, 1998) to add a masked-word sense prediction task as an auxiliary task in BERT pre-training. While these models represent words as point embeddings, Bayesian language models treat embeddings as distributions. Word2Gauss defines a normal distribution over words to enable the representation of words as soft regions (Vilnis and McCallum, 2014). Other works directly model polysemy by treating word embeddings as mixtures of Gaussians (Tian et al., 2014; Athiwaratkun and Wilson, 2017; Athiwaratkun et al., 2018). Mixture components correspond to the different word
senses. But most of these approaches require setting a fixed number of senses for each word. Non-parametric Bayesian models enable a variable number of senses per word (Neelakantan et al., 2014; Bartunov et al., 2016). The Multi-Sense Skip Gram model (MSSG) creates new word senses online, while the Adaptive Skip-Gram model (Bartunov et al., 2016) uses Dirichlet processes. The Bayesian Skip-gram Model (BSG) proposes an alternative to modeling words as a mixture of discrete senses (Bražinskas et al., 2018). Instead, the BSG draws latent meaning vectors from center words, which are then used to identify context words.

Embedding models that incorporate global context have also been proposed (Le and Mikolov, 2014; Srivastava et al., 2013; Larochelle and Lauly, 2012). The generative models Gaussian LDA, TopicVec, and the Embedded Topic Model (ETM) integrate embeddings into topic models (Blei et al., 2003). ETM represents words as categorical distributions with a natural parameter equal to the inner product between word and assigned topic embeddings (Dieng et al., 2019); Gaussian LDA replaces LDA’s categorical topic assumption with multivariate Gaussians (Das et al., 2015); TopicVec can be viewed as a hybrid of LDA and PSDVec (Li et al., 2016). While these models make inference regarding the latent topics of a document given words, the LMC model makes inference on meaning given both a word and metadata.

3. Latent Meaning Cells

3.1. Motivation

In domains where text is semi-structured and expresses high variation in topics, there is an opportunity to consider context between low-level lexical and global document-level. Clinical texts from the electronic health record represent a prime example. Metadata, such as section header and note type, can offer vital clues for polysemous words like acronyms. Consequently, we posit that a word’s latent meaning directly depends on its metadata. We define a latent meaning cell (lmc)1 as a latent Gaussian embedding jointly drawn from word and metadata prior densities. The lmc represents a draw of an embedded word sense based on metadata. In a Skip-Gram formulation, we assume that context words are generated from the lmc formed by the center word and corresponding metadata. Context words, then, are conditionally independent of center words and metadata given the lmc.

3.2. Notation

A word is the atomic unit of discrete data and represents an item from a fixed vocabulary. A word is denoted as $w$ when representing a center word, and $c$ for a context word. $c$ represents the set of context words relative to a center word $w$. In different contexts, each

1. Lowercase lmc refers to the latent variable in the uppercase LMC graphical model.
word operates as both a center word and a context word. For our purposes, metadata are pseudo-documents which contain a sequence of \( N \) words denoted by \( m = (w_1, w_2, ..., w_N) \) where \( w_n \) is the \( n^{th} \) word. Please refer to \ref{fig:plate} for a graphic depiction. A corpus is a collection of \( K \) metadata denoted by \( D = \{m_1, m_2, ..., m_K\} \).

### 3.3. Latent Variable Setup

We rely on graphical model notation as a convenient tool for describing the specification of the objective, as is commonly done in latent variable model work (e.g., (Bražinskas et al., 2018)). Using the notation from Section 3.2, we illustrate the pseudo-generative\(^2\) process in plate notation and story form.

Figure 2: LMC Plate Notation.

\begin{center}
\begin{tikzpicture}
\node[latent] (m) at (0,0) {$m_k$};
\node[obs, right=of m] (w) {$w_{ik}$};
\node[latent, above=of w] (z) {$z_{ik}$};
\node[latent, right=of z] (c) {$c_{ijk}$};
\node[obs, below=of z] (2S) {2S};
\node[obs, right=of 2S] (Nk) {$N_k$};
\factor[l m] at (m) {m \rightarrow w \rightarrow z \rightarrow c \rightarrow 2S \rightarrow N_k};
\end{tikzpicture}
\end{center}

**Algorithm 1** Pseudo-Generative Story

\begin{algorithmic}
\For{\( k = 1 \ldots K \)}
\EndFor
\For{\( i = 1 \ldots N_k \)}
\EndFor
\For{\( j = 1 \ldots 2S \)}
\EndFor
\State Draw metadata \( m_k \sim \text{Cat}(\gamma) \)
\State Draw word \( w_{ik} \sim \text{Cat}(\alpha) \)
\State Draw lmc \( z_{ik} \sim p(z_{ik} | w_{ik}, m_k) \)
\State Draw context word \( c_{ijk} \sim p(c_{ijk} | z_{ik}) \)
\end{algorithmic}

\(^2\) We use \textit{pseudo} because the LMC is a latent variable model, not a conventional generative model. As with the Skip-Gram model, due to the re-use of data (center and context words), we cannot use LMC to generate new text, but we can specify an objective function on existing data.

\[ S \] is the window size from which left-right context words are drawn. The factored joint distribution between observed and unobserved random variables \( P(M, W, C, Z) \) is:

\[ \prod_{k=1}^{K} p(m_k) \prod_{i=1}^{N_k} p(w_{ik})p(z_{ik} | w_{ik}, m_k) \prod_{j=1}^{2S} p(c_{ijk} | z_{ik}) \]

(1)

### 3.4. Distributions

We assume the following model distributions: \( m_k \sim \text{Cat}(\gamma) \), \( w_{ik} \sim \text{Cat}(\alpha) \), and \( z_{ik} | w_{ik}, m_k \sim \mathcal{N}(nn(w_{ik}, m_k; \theta)) \). \( nn(w_{ik}, m_k; \theta) \) denotes a neural network that outputs isotropic Gaussian parameters. \( p(c_{ijk} | z_{ik}) \) is simply a normalized function of fixed parameters \((\theta)\) and \( z_{ik} \). We choose a form that resembles Bayes’ Rule and compute the ratio of the joint to the marginal:

\[ p(c_{ijk} | z_{ik}) = \frac{\sum_{m} p(z_{ik} | c_{ijk}, m)p(m | c_{ijk})p(c_{ijk})}{\sum_{m} \sum_{c} p(z_{ik} | c, m)p(m | c)p(c)} \]

(2)

We marginalize over metadata and factorize to include \( p(z_{ik} | c_{ijk}, m) \), which shares parameters \( \theta \) with \( p(z_{ik} | w_{ik}, m_k) \). \( p(m | c) \) and \( p(c) \) are defined by corpus statistics. Therefore, the set of parameters that define \( p(z_{ik} | w_{ik}, m_k) \) completely determines \( p(c_{ijk} | z_{ik}) \), making for efficient inference.

### 4. Inference

Ideally, we would like to make posterior inference on lmc’s given observed variables. For one center word \( w_{ik} \), this requires modeling

\[ p(z_{ik} | m_k, w_{ik}, c_{ik}) = p(z_{ik}, m_k, w_{ik}, c_{ik}) \int p(z_{ik} | m_k, w_{ik}, c_{ik}) dz_{ik} \]

Unfortunately, the posterior is intractable because of the integral. Instead, we use variational Bayes to minimize the KL-Divergence (KLD) between an amortized variational family and the posterior:
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\[ \min_{\phi, \theta} D_{KL}(Q_\phi(Z|M, W, C) || P_\theta(Z|M, W, C)) \]

4.1. Deriving the Final Objective

At a high level, we factorize distributions (A.2.1) and then derive an analytical form of the KLD to arrive at a final objective (4.1.1). We then explain the use of approximate bounds for efficiency: the likelihood with negative sampling (4.1.2), and the KLD between the variational distribution and an unbiased mixture estimation (4.1.3).

4.1.1. Final Objective

To avoid high variance, we derive the analytical form of the objective function, rather than optimize with score gradients (Ranganath et al., 2014; Schulman et al., 2015). For each center word, the loss function we minimize is:

\[ L_{\phi, \theta}(m_k, w_{ik}, c_{ik}) = \sum_{j=1}^{2^S} \max \left( 0, \right. \]

\[ D_{KL}(q_{ik} || \sum_m p_\theta(z_{ik} | c_{ijk}, m) \beta_m | c_{ijk}) \]

\[ - D_{KL}(q_{ik} || \sum_m p_\theta(z_{ik} | \bar{c}, m) \beta_m | \bar{c}) \]

\[ + D_{KL}(q_{ik} || p_\theta(z_{ik} | m_k, w_{ik})) \]  

(3)

where \( q_{ik} \) denotes \( q_\phi(z_{ik} | m_k, w_{ik}, c_{ik}) \). \( \bar{c} \) represents a negatively sampled word. We denote the empirical likelihoods of metadata given a context / negatively sampled word as \( \beta_{m | c_{ijk}} / \beta_{m | \bar{c}} \). Intuitively, the objective rewards reconstruction of context words through the approximate posterior while encouraging it not to stray too far from the center word’s marginal meaning across metadata. Please see A.2.3 for the full derivation.

4.1.2. Negative Sampling

As in the BSG model, we use negative sampling as an efficient lower bound of the marginal likelihood from Equation 2. \( \bar{c} \) is sampled from the empirical vocabulary distribution \( p(\bar{c}) \) to construct an unbiased estimate for \( E_{\bar{c}} \left[ \sum_m p_\theta(z_{ik} | \bar{c}, m) \beta_{m | \bar{c}} \right] \). Finally, we transform the likelihood into a hard margin to bound the loss and stabilize training.

4.1.3. KL-Divergence for Mixtures

The objective requires computing the KLD between a Gaussian \( (q_{ik}) \) and a Gaussian mixture \( (\sum_m p_\theta(z | c, m) \beta_{m | c}) \). To avoid computing the full marginal, for both context words and negatively sampled words, we sample ten metadata using the appropriate empirical distribution: \( \beta_{m | c_{ijk}} \) and \( \beta_{m | \bar{c}} \), respectively. Using this unbiased sample of mixtures, we form an upper bound for the KLD between the variational family and an unbiased mixture estimation:

\[ D_{KL}(f || g) \leq \sum_{a,b} \pi_a \omega_b D_{KL}(f_a || g_b) \]

where \( \pi_a \) is the mixture weight of \( f \) and \( \omega_b \) is the mixture weight of \( g \). \( f \) is the variational distribution formed by a single Gaussian and \( g \) is the mixture of interest. Thus, the upper-bound is simply the weighted sum of the KLD between the variational distribution and each mixture component.

4.2. Training Algorithm

**Algorithm 1: LMC Training Procedure**

Randomly initialize parameters: \( \phi, \theta \) while not converged do

Sample mini-batch \( m_k, w_{ik}, c_{ik} \sim D \)

\( \delta \leftarrow \nabla_{\phi, \theta} L_{\phi, \theta}(m_k, w_{ik}, c_{ik}) \)

\( \phi, \theta \leftarrow \text{Update using gradient } \delta \)

end
The training procedure samples a center word, context word sequence, and metadata from the data distribution and minimizes the loss function from Equation 3 with stochastic gradient descent. In Algorithm 1, we jointly update the variational family and model parameters, \( \phi \) and \( \theta \) respectively.

5. Neural Networks

The LMC model requires modeling two Gaussian distributions, \( q(\mathbf{z}_{ik}|\mathbf{m}_k, \mathbf{w}_{ik}, \mathbf{c}_{ik}) \) and \( p(\mathbf{z}_{ik}|\mathbf{c}_{ijk}, \mathbf{m}) \). We parametrize both with neural networks, but any black-box function suffice. We refer to \( q \) as the variational network and \( p \) as the model network.

5.1. Variational Network \((q_\phi)\)

The variational network accepts a center word \( w_{ik} \), metadata \( m_k \), and a sequence of context words \( \mathbf{c}_{ik} \), and outputs isotropic Gaussian parameters\(^3\): a mean vector \( \mu_q \) and variance scalar \( \sigma_q \). Then, \( q_\phi \sim N(\mu_q, \sigma_q) \). At a high level, we encode words with a bi-LSTM (Graves et al., 2005), summarize the sequence with metadata-specific attention, and then learn a gating function to selectively combine evidence. Please see A.3 for full specification.

5.2. Model Network \((p_\theta)\)

The model network accepts a word \( w_{ik} \) and metadata \( m_k \) and projects them onto a higher dimension with embedding matrix \( \mathbf{R} \). \( \mathbf{R}_{w_{ik}} \) and \( \mathbf{R}_{m_k} \) are combined:

\[
    h = \text{ReLU}((\mathbf{R}_{w_{ik}}; \mathbf{R}_{m_k}) + b) \quad (4)
\]

The hidden state \( h \) is then separately projected to produce a mean vector \( \mu_p \) and variance scalar \( \sigma_p \). Then, \( p_\theta \sim N(\mu_p, \sigma_p) \).

6. Experimental Setup

We design experiments to test our hypothesis:

On a relevant clinical task, metadata complements local word-level context to improve performance. Also, metadata and the LMC are synergistic: its success is a combination of more data (section headers) and a novel inference procedure.

We are primarily interested in the representation learning power of lmc's. As such, we focus on the zero-shot scenario: evaluating a models ability to align the meaning of an acronym in context to its target expansion. This is particularly useful for acronyms in the clinical setting, which have been shown to rapidly evolve and contain many rare forms (Skreta et al., 2019; Townsend, 2013). Out of fidelity to the data, we do not adjust the natural class imbalances. We explicitly test a model’s ability to handle rare expansions for which shared statistical strength from metadata may be critical\(^4\).

6.1. Pre-Training

MIMIC-III contains de-identified clinical records from patients admitted to Beth Israel Deaconess Medical Center (Johnson et al., 2016). It comprises two million documents spanning sixteen note types, from discharge summaries to radiology reports. Section headers are extracted through regular expressions. We pre-train all models for five epochs in PyTorch (Paszke et al., 2017) and report results on one test set using the others for validation. Please see A.4 for more details.

\(^4\) Because we focus on the zero-shot scenario, we restrict baselines to contextualized embeddings. It would be unfair, and in conflict with our focus on rare / unseen expansions, to include models pre-trained on clinical NED / WSD datasets.
6.2. Evaluation Data

It is difficult to acquire annotated data for clinical acronym expansion, especially with relevant metadata. One of the few publicly available datasets with section header annotations is the Clinical Abbreviation Sense Inventory (CASI) dataset (Moon et al., 2014). Considering 74 common clinical abbreviations, human annotators assign expansion labels to acronyms in context. Ambiguous examples (based on local word context alone) are removed. After cleaning the data, our experimental test set comprises 27,209 examples across 41 unique acronyms and 150 expansions. Please see A.4.2 for full details.

To evaluate performance across a range of institutions, we use the same acronym sense inventory from CASI to construct two new synthetic datasets via reverse substitution (RS). RS involves replacing long form expansions with their corresponding short form and then assigning the original expansion as the target label (Finley et al., 2016). 44,473 tuples of (short form context, section header, target long form) extracted from MIMIC comprise the MIMIC RS dataset. The second RS dataset consists of 22,163 labeled examples from a corpus of 150k ICU/CCU notes collected between 2005 and 2015 at a Large Metropolitan Institution RS (LMIRS). For each RS dataset, we draw at most 500 examples for each acronym-expansion pair. For the non-MIMIC datasets, in the event a section header does not map directly to one in MIMIC, we choose the closest corollary based on intuition. We extract long forms with a robust regex-based toolkit, which we will publish with the rest of our training, testing, and RS dataset construction code.

5. We found removing all documents in the test set from pre-training degraded performance no more than one percentage point across models. For consistency, we pre-train on all notes.
6. Most are trivial: Chief Complaint → Chief Complaints

6.3. Baselines

Dominant & Random Class. Acronym expansion datasets are highly imbalanced. Dominant class accuracy, then, tends to be high and is useful for putting metrics into perspective. Random performance provides a crude lower bound.

Section Header MLE. To isolate the discriminative power of section headers, we include a simple baseline which selects LFs based on \( p(LF|section) \propto p(section|LF) \). We compute \( p(section|LF) = \frac{C(section, LF)}{C(LF)} \) on held-out data.

Bayesian Skip-Gram (BSG). We implement our own version of the BSG model so that it uses the same variational network architecture as the LMC, with the exception that metadata is unavailable.

Metadata BSG Ensemble (MBSGE). To isolate the added-value of metadata, we devise an ensembled BSG. MBSGE maintains an identical optimization procedure with the exception that it treats metadata and center words as interchangeable observed variables. During training, center words are randomly replaced with metadata, which take on the function of a center word. For evaluation, we average ensemble the contextualized embeddings from metadata and center word. We train on two metadata types: section headers and note type, but for experiments, based on available data, we only use headers. Please see A.5 for the full algorithm.

ELMo. We use the AllenNLP implementation with default hyperparameters for the Transformer-based version (Gardner et al., 2018; Peters et al., 2018b). We pre-train the model for five epochs with a batch size of 3,072. We found optimal performance by

7. We choose the MLE over MAP estimate because the latter would never select rare LFs.
taking the sequence-wise mean rather than selecting the hidden state from the SF index.

**BERT.** Due to compute limitations, we rely on the publicly available Clinical BioBERT for evaluation (Alsentzer et al., 2019; Lee et al., 2020). We access the pre-trained model through the Hugging Face Transformer library (Wolf et al., 2019). The weights were initialized from BioBERT (which introduces Pubmed articles) before being fine-tuned on the MIMIC-III corpus. We experimented with many pooling configurations and found that taking the average of the mean and max pool from the final layer outperformed. Another ClinicalBERT uses this configuration (Huang et al., 2019).

### 6.4. Task Definition

For both test sets, we focus on the zero-shot scenario in which models are only trained on a language modeling objective. We rank each candidate acronym expansion (LF) by measuring similarity between its context-independent representation and the contextualized acronym representation. Table 1 shows the ranking functions we used. $ELMO_{avg}$ represents the mean of final hidden states. For the LMC scoring function, $\sum_m p(z|LF_k, m)\beta_m|LF_k)$ represents the smoothed marginal distribution of a word (or phrase) over metadata (as detailed in A.10). When an LF is a phrase, we take the mean of individual word embeddings.

| Model   | Ranking Function                                      |
|---------|-------------------------------------------------------|
| BERT    | $Cosine(BERT_{avg}^{max}(SF; c), BERT_{avg}^{max}(LF_k))$ |
| ELMo    | $Cosine(ELMO_{avg}(SF; c), ELMO_{avg}(LF_k))$          |
| BSG     | $D_{KL}(q(z|SF, c)||p(z|LF_k))$                        |
| MBSGE   | $D_{KL}(Avg_{x \in \{SF, m\}}(q(z|x, c)||p(z|LF_k))$ |
| LMC     | $D_{KL}(q(z|SF, m, c)||\sum_m p(z|LF_k, m)\beta_m|LF_k)$ |

Table 1: $LF_k$ represents the $k^{th}$ LF.

### 7. Results

For space, we report only quantitative results below. For a discussion on model efficiency and qualitative evaluation of learned representations, please refer to A.7 and A.8.

#### 7.1. Classification Performance

Recent work has shown that randomness in pre-training contextualized LMs can lead to large variance on downstream tasks (Dodge et al., 2020). For robustness, then, we pre-train five separate weights for each model class and report aggregate results. Tables 2 and 3 show mean statistics for each model across five pre-training runs. In A.6.1, we show best/worst performance, as well as bootstrap each test set to generate confidence intervals (A.6.2). These additional experiments add robustness and reveal de minimus variance between LMC pre-training runs and between bootstrapped test sets for a single model. Our main takeaways are:

**Metadata.** The MBSGE and LMC models materially outperform the non-metadata baselines. This suggests the explanatory power of metadata is complementary to local word context for the task.

**LMC Robust Performance.** The LMC outperforms all baselines and exhibits very low variance across pre-training runs. Given the same input and very similar parameters as MBSGE, LMC appears useful beyond the addition of a helpful feature.

**Dataset Comparison.** Unsurprisingly, performance is best on the MIMIC RS dataset because all models are pre-trained on MIMIC notes. While LMIRS and CASI are in-domain, there is minor performance degradation from the transfer.

**Lower CASI Spread.** The LMC performance gains are less pronounced on the CASI dataset. CASI was curated to only include
Table 2: Mean across 5 pre-training runs. NLL is neg log likelihood, W/M weighted/macro.

| Model  | NLL | Acc | W | F1 | M | F1 |
|--------|-----|-----|---|----|---|----|
| MIMIC  |     |     |   |    |   |    |
| BERT   | 1.36| 0.40| 0.40| 0.33| |
| ELMo   | 1.33| 0.58| 0.61| 0.53| |
| BSG    | 1.28| 0.57| 0.59| 0.52| |
| MBSGE  | 1.07| 0.65| 0.67| 0.59| |
| LMC    | 0.81| 0.74| 0.78| 0.69| |

| LMIRS  |     |     |   |    |   |    |
|--------|-----|-----|---|----|---|----|
| BERT   | 1.41| 0.37| 0.33| 0.28| |
| ELMo   | 1.38| 0.58| 0.60| 0.49| |
| BSG    | 9.04| 0.58| 0.58| 0.46| |
| MBSGE  | 6.16| 0.64| 0.64| 0.52| |
| LMC    | 0.90| 0.69| 0.68| 0.57| |

| CASI   |     |     |   |    |   |    |
|--------|-----|-----|---|----|---|----|
| BERT   | 1.23| 0.42| 0.38| 0.23| |
| ELMo   | 1.21| 0.55| 0.56| 0.38| |
| BSG    | 0.99| 0.64| 0.64| 0.41| |
| MBSGE  | 0.88| 0.70| 0.70| 0.46| |
| LMC    | 0.79| 0.71| 0.73| 0.51| |

Figure 3: Average accuracy @K across 5 pre-training runs.

Examples whose expansions could be unambiguously deduced from local context by humans. Hence, the relative explanatory power of metadata is likely dampened.

Poor BERT, ELMo Performance. BERT / ELMo underperform across datasets. They are optimized to assign high probability to masked or next-word tokens, not to align embedded representations. For our zero-shot use case, then, they may represent suboptimal pre-training objectives. Meanwhile, the BSG, MBSGE, and LMC models are trained to align context-dependent representations (variational network) with corresponding context-independent representations (model network). For evaluation, we simply replace context words with candidate LFs.

Non-Parametric Baselines. Random accuracy is 27%, 26%, and 31% for MIMIC, LMIRS, and CASI, respectively. Dominant-class accuracy is 42%, 47%, and 78% for MIMIC, LMIRS, and CASI, respectively. Section information alone proves very discriminative on MIMIC (85% accuracy), but, given the sparse distribution, it severely overfits. On CASI / LMIRS, the accuracy plummets to 48 / 46% and macro F1 to 35 / 33%. While a relevant baseline, distributional header representations are necessary for generalization.

8. Discussion

We hope the LMC framework and code base encourages research into metadata-based language modeling. We highlight potential directions: (1) New domains. the LMC can be applied to other domains, particular where discrete metadata provide informative contextual clues (e.g., document categories, sections, and documents themselves). (2) Linguistic Properties. A unique feature of the LMC is the ability to represent words as marginal distributions over metadata, and vice versa (as detailed in A.9). We motivate exploration into its linguistic implications. (3) Metadata Skip-Gram. Depending on the choice of metadata, the LMC model could be ex-
panded to draw context metadata from a center metadata. This might simulate metadata-level entailment.

9. Conclusion

We target a key problem in clinical text, introduce a helpful feature, and present a Bayesian solution that works well on the task. More generally, the LMC model presents a principled, efficient approach for incorporating metadata into language modeling.

10. Citations and Bibliography

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Appendix A. Appendix

A.1. Metadata Pseudo Document

For our experiments, metadata is comprised of the concatenation of the body of every section header across the corpus. Yet, when computing context windows, we do not combine text from different physical documents. Please see Figure 4 for a toy example.

A.2. Full Derivations

A.2.1. Factorize & Reduce

After factorizing the model posterior and variational distribution, we can push the integral inside the summation and integrate out latent variables that are independent:

$$\sum_{i,k} \int q_\phi(z_{ik}|m_k, w_{ik}, c_{ik}) \log \frac{q_\phi(z_{ik}|m_k, w_{ik}, c_{ik})}{p_\theta(z_{ik}|m_k, w_{ik}, c_{ik})} d_{z_{ik}}$$

(5)
The integral defines a KL measure between individual latent variables, which can be expressed as
\[
|W| \frac{1}{|W|} \sum_{i,k} E_{q_{ik}} \left[ \log \frac{q_{\phi}(z_{ik} | m_k, w_{ik}, c_{ik})}{p_{\theta}(z_{ik} | m_k, w_{ik}, c_{ik})} \right]
\]
where \(|W|\) represents the corpus word count. Dividing and multiplying by \(|W|\) does not change the result:
\[
E_{\tilde{p}} \left[ D_{KL} \left( q_{ik} || p_{ik} \right) \right]
\]
We ignore \(|W|\), as it does not affect the optimization, and denote the amortized variational distribution, model posterior, and the empirical uniform distribution over center words in the corpus as \(q_{ik}, p_{ik}, \) and \(\tilde{p},\) respectively.

### A.2.2. LMC Objective

In the main manuscript, we outline the steps involved to arrive at the variational objective. Here, we break it down into a more complete derivation. Because the posterior of the LMC model is intractable, we use variational Bayes and minimize the KLD between the variational distribution and the model posterior:
\[
\min D_{KL} \left( Q(Z|M,W,C) || P(Z|M,W,C) \right)
\]
KL-Divergence can also be expressed in expected value form:
\[
\min \mathbb{E}_Q \left[ \log \frac{Q(Z|M,W,C)}{P(Z|M,W,C)} \right]
\]
The expectation can be re-written in the integral form as follows:
\[
\min \int \log \frac{Q(Z|M,W,C)}{P(Z|M,W,C)} Q(Z|M,W,C) dZ
\]
Using the independence assumption of the latent random variables, we can factor \(Q\) and \(P\) as follows:
\[
\min \int \ldots \int \log \prod_{i,k} q(z_{ik} | m_k, w_{ik}, c_{ik}) \prod_{i,k} p(z_{ik} | m_k, w_{ik}, c_{ik}) q(z_{ik} | m_k, w_{ik}, c_{ik}) dz_{ik}
\]
Taking the product out of the logarithm yields
\[
\min \int \ldots \int \sum_{i,k} \log \frac{q(z_{ik} | m_k, w_{ik}, c_{ik})}{p(z_{ik} | m_k, w_{ik}, c_{ik})} \prod_{i,k} q(z_{ik} | m_k, w_{ik}, c_{ik}) dz_{ik}
\]
We can push the integral inside the summation by integrating independent latent variables out:
\[
\min \sum_{i,k} \int \log \frac{q(z_{ik} | m_k, w_{ik}, c_{ik})}{p(z_{ik} | m_k, w_{ik}, c_{ik})} q(z_{ik} | m_k, w_{ik}, c_{ik}) dz_{ik}
\]
Dividing the summation by the number of words in the corpus defines an expectation over the KL-Divergence for each independent latent variable. Here, $|W|$ denotes the number of words in the corpus. Multiplying the above expression by $|W|$ and dividing by $|W|$ doesn’t change the result. Thus,

$$\min |W| \frac{1}{|S|} \sum_{i,k} E_{q_{ik}} \left[ \log \frac{q(z_{ik}|m_k, w_{ik}, c_{ik})}{p(z_{ik}|m_k, w_{ik}, c_{ik})} \right]$$  \hspace{1cm} (14)$$

$$\frac{1}{|W|} \sum_{i,k} \text{defines an expectation over the observed data. Therefore, we can write the above expression as}$$

$$\min E_{m_k, w_{ik}, c_{ik}} \sim D \left[ E_{q_{ik}} \left[ \log \frac{q(z_{ik}|m_k, w_{ik}, c_{ik})}{p(z_{ik}|m_k, w_{ik}, c_{ik})} \right] \right]$$  \hspace{1cm} (15)$$

Here the expression $m_k, w_{ik}, c_{ik} \sim D$ denotes sampling observed variables of document, center word and context words from the data distribution. We ignore $|W|$ as it does not affect the optimization:

$$\min E_{m_k, w_{ik}, c_{ik}} \sim D \left[ D_{KL} \left( q(z_{ik}|m_k, w_{ik}, c_{ik}) || p(z_{ik}|m_k, w_{ik}, c_{ik}) \right) \right]$$  \hspace{1cm} (16)$$

The above expression represents the final objective function. To optimize, we sample $m_k, w_{ik}, c_{ik} \sim D$ and minimize the KL-Divergence between $q$ and $p$. Here $D$ represents the distribution of data from the corpus, which we assume is uniform across observed metadata and words.

**A.2.3. Analytical Form of KL-Divergence**

One can approximate KL-Divergence by sampling. Yet, such an estimate has high variance. To avoid this, we derive the analytical form of the objective function. From Section A.2.2, we seek to minimize the following objective function:

$$D_{KL} \left( q_{\phi}(z_{ik}|m_k, w_{ik}, c_{ik}) || p_{\theta}(z_{ik}|m_k, w_{ik}, c_{ik}) \right)$$  \hspace{1cm} (17)$$

The above equation can be expressed as

$$E_{q_{ik}} \left[ \log q_{\phi}(z_{ik}|m_k, w_{ik}, c_{ik}) - \log p_{\theta}(z_{ik}|m_k, w_{ik}, c_{ik}) \right] + \log p(m_k, w_{ik}, c_{ik})$$  \hspace{1cm} (18)$$

We can factorize $p_{\theta}(z_{ik}|m_k, w_{ik}, c_{ik})$ using the model family definition

$$E_{q_{ik}} \left[ \log q_{\phi}(z_{ik}|m_k, w_{ik}, c_{ik}) - \log p(m_k)p(w_{ik})p(z_{ik}|w_{ik}, m_k) \prod_{j=1}^{2S} p_{\theta}(c_{ijk}|z_{ik}) \right] + \log p(m_k, w_{ik}, c_{ik})$$  \hspace{1cm} (19)$$

Since, $p(m_k, w_{ik}, c_{ik}) = p(c_{ik}|m_k, w_{ik})p(w_{ik})p(m_k)$, we can re-write Equation 19 as

$$E_{q_{ik}} \left[ \log q_{\phi}(z_{ik}|m_k, w_{ik}, c_{ik}) - \log p(m_k) - \log p(w_{ik}) - \log p(z_{ik}|w_{ik}, m_k) \right. \left. - \sum_{j=1}^{2S} \log p_{\theta}(c_{ijk}|z_{ik}) \right] + \log p(c_{ik}|m_k, w_{ik}) + \log p(m_k) + \log p(w_{ik})$$  \hspace{1cm} (20)$$
\( \log p(m_k) \) and \( \log p(w_{ik}) \) can leave the expectation and cancel as they do not include any latent variables. Since KL-Divergence is always positive, and the function we are minimizing is the KL-Divergence between the variational family and the posterior, we can write the following inequality:

\[
E_{q_{ik}} \left[ \log q_\phi(z_{ik}|m_k, w_{ik}, \mathbf{c}_{ik}) - \log p_\theta(z_{ik}|w_{ik}, m_k) - \sum_{j=1}^{2S} \log p_\theta(c_{ijk}|z_{ik}) \right] + \log p(c_{ik}|m_k, w_{ik}) \geq 0
\]  

(21)

Pushing the observed variables to the right-hand side of the inequality and negating both sides yields

\[
E_{q_{ik}} \left[ -\log q_\phi(z_{ik}|m_k, w_{ik}, \mathbf{c}_{ik}) + \log p_\theta(z_{ik}|w_{ik}, m_k) + \sum_{j=1}^{2S} \log p_\theta(c_{ijk}|z_{ik}) \right] \leq \log p(c_{ik}|m_k, w_{ik})
\]

(22)

To construct a lower-bound for the likelihood of context words given center word and metadata, \( p(c_{ik}|m_k, w_{ik}) \), we minimize the negative left-hand side of Equation 22. That is, we minimize:

\[
E_{q_{ik}} \left[ \log q_\phi(z_{ik}|m_k, w_{ik}, \mathbf{c}_{ik}) - \log p_\theta(z_{ik}|w_{ik}, m_k) \right] - E_{q_{ik}} \left[ \sum_{j=1}^{2S} \log p_\theta(c_{ijk}|z_{ik}) \right]
\]

(23)

We can write \( E_{q_{ik}} \left[ \log q_\phi(z_{ik}|m_k, w_{ik}, \mathbf{c}_{ik}) - \log p_\theta(z_{ik}|w_{ik}, m_k) \right] \) as the KL-Divergence between \( q_\phi(z_{ik}|m_k, w_{ik}, \mathbf{c}_{ik}) \) and \( p_\theta(z_{ik}|w_{ik}, m_k) \). That is,

\[
D_{KL}(q_\phi(z_{ik}|m_k, w_{ik}, \mathbf{c}_{ik})||p_\theta(z_{ik}|w_{ik}, m_k)) - E_{q_{ik}} \left[ \sum_{j=1}^{2S} \log p_\theta(c_{ijk}|z_{ik}) \right]
\]

(24)

Using the definition of \( p(c_{ijk}|z_{ik}) \) and re-arranging terms,

\[
D_{KL}(q_\phi(z_{ik}|m_k, w_{ik}, \mathbf{c}_{ik})||p_\theta(z_{ik}|w_{ik}, m_k))
- \sum_{j=1}^{2S} E_{q_{ik}} \left[ \log \sum_{m} p_\theta(z_{ik}|c_{ijk}, m)p(m|c_{ijk})p(c_{ijk}) \right]
+ E_{q_{ik}} \left[ \log E_{\tilde{c}} \left[ \sum_{m} p_\theta(z_{ik}|\tilde{c}, m)p(m|\tilde{c}) \right] \right]
\]

(25)

Here, we re-write \( \sum_c \sum_d p_\theta(z_{ik}|c, d)p(d|c)p(c) \) in expected value form as \( E_{\tilde{c}} \left[ \sum_d p_\theta(z_{ik}|\tilde{c}, d)p(d|\tilde{c}) \right] \). In addition, \( p(c_{ijk}) \) is the empirical probability value which does not contain the latent variable \( z_{ik} \). Therefore, it can leave the expectation and
be ignored during optimization:

\[
D_{KL}\left(q_{\phi}(z_{ik}|m_k, w_{ik}, c_{ik})||p_{\theta}(z_{ik}|w_{ik}, m_k)\right) \\
- \sum_{j=1}^{2S} E_{q_{ik}}\left[\log \sum_{m} p_{\theta}(z_{ijk}, m)p(m|c_{ijk})\right] \\
+ E_{q_{ik}}\left[\log E_{\tilde{c}}\left[\sum_{m} p_{\theta}(z_{i\tilde{c}}, m)p(m|\tilde{c})\right]\right] 
\]

Adding-subtracting \(E_{q_{ik}}[\log q_{\phi}(z_{ik}|m_k, w_{ik}, c_{ik})]\) to Equation 26 yields

\[
D_{KL}\left(q_{\phi}(z_{ik}|m_k, w_{ik}, c_{ik})||p_{\theta}(z_{ik}|w_{ik}, m_k)\right) \\
+ \sum_{j=1}^{2S} E_{q_{ik}}\left[\log q_{\phi}(z_{ik}|m_k, w_{ik}, c_{ik}) - \log \sum_{m} p_{\theta}(z_{ijk}, m)p(m|c_{ijk})\right] \\
- E_{q_{ik}}\left[\log q_{\phi}(z_{ik}|m_k, w_{ik}, c_{ik}) - \log E_{\tilde{c}}\left[\sum_{m} p_{\theta}(z_{i\tilde{c}}, m)p(m|\tilde{c})\right]\right] 
\]

This additional operation defines two KL-Divergence terms:

\[
D_{KL}\left(q_{\phi}(z_{ik}|m_k, w_{ik}, c_{ik})||p_{\theta}(z_{ik}|w_{ik}, m_k)\right) \\
+ \sum_{j=1}^{2S} D_{KL}\left(q_{\phi}(z_{ik}|m_k, w_{ik}, c_{ik})||\sum_{m} p_{\theta}(z_{ijk}, m)p(m|c_{ijk})\right) \\
- D_{KL}\left(q_{\phi}(z_{ik}|m_k, w_{ik}, c_{ik})||E_{\tilde{c}}\left[\sum_{m} p_{\theta}(z_{i\tilde{c}}, m)p(m|\tilde{c})\right]\right) 
\]

To approximate \(E_{\tilde{c}}[\sum_{m} p_{\theta}(z_{ik}|\tilde{c}, m)p(m|\tilde{c})]\), we sample a word using the negative word distribution (as in word2vec). As in the BSG model, we transform the second term into a hard margin to bound the loss in case the KL-Divergence terms for negatively sampled words are very large. The final objective we minimize is:

\[
D_{KL}\left(q_{ik}||p_{\theta}(z_{ik}|m_k, w_{ik})\right) + \\
\sum_{j=1}^{2S} \max\left(0, D_{KL}\left(q_{ik}||\sum_{m} p_{\theta}(z_{ik}|c_{ijk}, m)\beta_{m|c_{ijk}}\right) - D_{KL}\left(q_{ik}||\sum_{m} p_{\theta}(z_{ik}|\tilde{c}, m)\beta_{m|\tilde{c}}\right)\right) 
\]

Here, we denote \(q_{\phi}(z_{ik}|m_k, w_{ik}, c_{ik})\) as \(q_{ik}\). \(\tilde{c}\) is sampled from \(p(c)\) to construct an unbiased estimate for \(E_{\tilde{c}}[\sum_{m} p_{\theta}(z_{ik}|\tilde{c}, m)\beta_{m|\tilde{c}}]\).

A.3. variational network Architecture

Words \((w_{ik}, c_{ik})\), as well as metadata \((m_k)\), are first projected onto a higher dimension via an embedding matrix \(E\). The central word embedding \(E_{w_{ik}}\) is then tiled across each context.
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word and concatenated with context word embeddings $E_{cik}$. We then encode the combined word sequence:

$$h = LSTM(\{E_{cik}; E_{wik}\})$$ (30)

where ‘;’ denotes concatenation and $h$ represents the concatenation of the hidden states from the forward and backward passes at each timestep. The relevance of a word, especially one with multiple meanings, might depend on the section or document type in which it is found. To allow for an adaptive notion of relevance, we employ scaled dot-product attention (Vaswani et al., 2017) to compute a weighted-average summary of $h$:

$$h_{word} = \text{softmax}(\frac{E_{tm}^T h}{\sqrt{\text{dim}_e}})h$$ (31)

where $\text{dim}_e$ is the embedding dimension. The scaling factor $\frac{1}{\sqrt{\text{dim}_e}}$ acts as a normalizer to the dot product. We selectively combine information from the metadata embedding ($E_{mk}$) and attended context ($h_{word}$) with a gating mechanism similar to (Miyamoto and Cho, 2016). Precisely, we learn a relative weight $^8$:

$$p_{mk} = \text{sigmoid}(W_{\text{gate}}([E_{mk}; h_{word}] + b_{\text{gate}}))$$ (32)

We then use $p_{mk}$ to create a weighted average:

$$h_{joint} = p_{mk} E_{mk} + (1 - p_{mk})h_{word}$$ (33)

Finally, we project $h_{joint}$ to produce Gaussian parameters

$$\mu_q = W_{\mu} h_{joint} + b_{\mu}$$
$$\sigma_q = \exp(W_{\sigma} h_{joint} + b_{\sigma})$$ (34)

As in the BSG model, the network produces the log of the variance, which we exponentiate to ensure it is positive.

A.4. Additional Details on Experimental Setup

A.4.1. Preprocessing

Clinical text is tokenized, stopwords are removed, and digits are standardized to a common format using NLTK toolkit (Loper and Bird, 2002). The vocabulary comprises all terms with corpus frequency above 10. We use negative sampling with standard parameter 0.001 to downsample frequent words (Mikolov et al., 2013b). After preprocessing, the MIMIC pre-training dataset consists of $\sim 330m$ tokens, a token vocabulary size of $\sim 100k$, and a section vocabulary size of $\sim 10k$. We write a custom regex to extract section headers from MIMIC notes:

```
    r'(?:^|\s{4,}|\n)[\d.#]{0,4}\s*([A-Z][A-z0-9/ ]+[A-z]):\n\r
```

The search targets a flexible combination of uppercase letters, beginning of line characters,  

---

8. In practice, we compute separate relevance scores for word and metadata and apply the Tanh function before taking the softmax. We do this to place a constant lower bound of $\min(p_{mk}, 1 - p_{mk})$ and prevent over-reliance on one form of evidence.
and either a trailing ‘;’ or sufficient space following a candidate header. We experimented with using template regexes to canonicalize section headers as well as concatenate note type with section headers. This additional hand-crafted complexity did not improve performance so we use the simpler solution for all experiments. The code exists to play around with more sophisticated extraction schemes.

A.4.2. Constructing CASI Test Set

For clarity into the results, we outline the filtering operations performed on the CASI dataset. In Table 3, we enumerate the operations and their associated reductions to the size of the original dataset. The final dataset at the bottom produces the gold standard test set against which all our models are evaluated. These changes were made in the interest of producing a coherent test. Empirically, performance is not really affected by the filtering operations.

| Preprocessing Step                           | Examples |
|----------------------------------------------|----------|
| Initial                                      | 37,000   |
| LF Same as SF (just a sense)                 | 5,601    |
| SF Not Present in Context                    | 1,249    |
| Parsing Issue                                | 725      |
| Duplicate Example                            | 731      |
| Single Target                                | 1,481    |
| SFs with LFs not present in MIMIC-III        | 8,976    |
| **Final Dataset**                            | **18,233** |

Because our evaluations rely on computing the distance between contextualized SFs and candidate LFs, we manually curate canonical forms for each LF in the CASI sense inventory. For instance, we replace the candidate LF for the acronym CVS:

"customer, value, service" → "CVS pharmacy;brand;store"

where ';' represents a boolean or.

A.4.3. Hyperparameters

Our hyperparameter settings are shared across the LMC model and BSG baselines. We assign embedding dimensions of 100d, and set all hidden state dimensions to 64d. We apply a dropout rate of 0.2 consistently across neural layers (Srivastava et al., 2014). We use a hard margin of 1 for the hinge loss. Context window sizes are fixed to a minimum of 10 tokens and the nearest section/document boundary. We develop the model in PyTorch (Paszke et al., 2017) and train all models for 5 epochs with Adam (Kingma and Ba, 2014) for adaptive optimization (learning rate of $1e^{-3}$). Inspired by denoising autoencoders (Vincent et al., 2008) and BERT, we randomly mask context tokens and central words with a probability of 0.2 during training for regularization. The conditional model probabilities $p(w|d)$ and $p(d|w)$ are computed with add-1 smoothing on corpus counts.
**A.5. MBSGE Algorithm**

The training procedure for MBSGE is enumerated in Algorithm 2, where $m^1_k$ represents the note type for the $k$'th document and $m^2_{ik}$ represents the section header corresponding to the $i$'th word in the $k$'th document. Rather than train three separate models, we train a single model with stochastic replacement to ensure a common embedding space. We choose non-uniform replacement sampling to account for the vastly different vocabulary sizes.

**Algorithm 2** MBSGE Stochastic Training Procedure

\[
\text{while not converged do} \\
\quad \text{Sample } m_k, w_{ik}, c_{ik} \sim D \\
\quad \text{Sample } x \sim \text{Cat}\{w_{ik}, m^1_k, m^2_{ik}\}; \{0.7, 0.1, 0.2\} \\
\delta \leftarrow -\nabla D_{KL}(q_\phi(z_{ik}|x, c_{ik})||p_\theta(z_{ik}|x)) \\
\phi, \theta \leftarrow \text{Update parameters using } \delta
\]

For evaluation, we average ensemble the Gaussian parameters from the variational network ($q_\phi$), where $x$ separately stands for both the center word acronym ($w_{ik}$), and the section header metadata ($m^2_{ik}$).

**A.6. Additional Evaluations**

**A.6.1. Aggregate Performance**

In the main manuscript, we report mean results across the 5 pre-training runs. In Table 4, we include the best and worst performing models to provide a better sense of pre-training variance. Even though it is a small sample size, it appears the LMC is robust to randomness in weight initialization as evidenced by the tight bounds.

**A.6.2. Bootstrapping**

For robustness, we select the best performing from each model class and bootstrap the test set to construct confidence intervals. We draw 100 independent random samples from the test set and compute metrics for each model class. Each subset represents 80% of the original dataset. Very tight bounds exist for each model class as can be seen in Figure 5.
Table 4: Aggregated across 5 pre-training runs. NLL is neg log likelihood, W/M weighted/macro.

| Model   | MIMIC |       |       |       | LMIRS |       |       |       | CASI  |       |       |       |       |
|---------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
|         | NLL   | Acc   | W F1  | M F1  | NLL   | Acc   | W F1  | M F1  | NLL   | Acc   | W F1  | M F1  | NLL   | Acc   | W F1  | M F1  |
| Worst   |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |
| BERT    | 1.36  | 0.40  | 0.40  | 0.33  | 1.41  | 0.37  | 0.33  | 0.28  | 1.23  | 0.42  | 0.38  | 0.23  |
| ELMo    | 1.34  | 0.56  | 0.59  | 0.51  | 1.39  | 0.55  | 0.58  | 0.48  | 1.21  | 0.51  | 0.52  | 0.36  |
| BSG     | 2.06  | 0.43  | 0.42  | 0.38  | 12.2  | 0.48  | 0.48  | 0.36  | 1.38  | 0.58  | 0.56  | 0.33  |
| MBSGE   | 1.26  | 0.60  | 0.62  | 0.54  | 7.94  | 0.61  | 0.61  | 0.48  | 0.96  | 0.68  | 0.67  | 0.43  |
| LMC     | 0.82  | 0.74  | 0.77  | 0.68  | 0.91  | 0.69  | 0.68  | 0.56  | 0.80  | 0.71  | 0.73  | 0.50  |
| Mean    |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |
| BERT    | 1.36  | 0.40  | 0.40  | 0.33  | 1.41  | 0.37  | 0.33  | 0.28  | 1.23  | 0.42  | 0.38  | 0.23  |
| ELMo    | 1.33  | 0.58  | 0.61  | 0.53  | 1.38  | 0.58  | 0.60  | 0.49  | 1.21  | 0.55  | 0.56  | 0.38  |
| BSG     | 1.28  | 0.57  | 0.59  | 0.52  | 9.04  | 0.58  | 0.58  | 0.46  | 0.99  | 0.64  | 0.64  | 0.41  |
| MBSGE   | 1.07  | 0.65  | 0.67  | 0.59  | 6.16  | 0.64  | 0.64  | 0.52  | 0.88  | 0.70  | 0.70  | 0.46  |
| LMC     | 0.81  | 0.74  | 0.78  | 0.69  | 0.90  | 0.69  | 0.68  | 0.57  | 0.79  | 0.71  | 0.73  | 0.51  |
| Best    |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |
| BERT    | 1.36  | 0.40  | 0.40  | 0.33  | 1.41  | 0.37  | 0.33  | 0.28  | 1.23  | 0.42  | 0.38  | 0.23  |
| ELMo    | 1.33  | 0.61  | 0.65  | 0.58  | 1.38  | 0.62  | 0.64  | 0.50  | 1.21  | 0.59  | 0.60  | 0.42  |
| BSG     | 0.98  | 0.64  | 0.68  | 0.59  | 5.41  | 0.61  | 0.62  | 0.50  | 0.85  | 0.67  | 0.70  | 0.46  |
| MBSGE   | 0.96  | 0.68  | 0.71  | 0.62  | 4.81  | 0.67  | 0.67  | 0.57  | 0.83  | 0.72  | 0.73  | 0.50  |
| LMC     | 0.80  | 0.75  | 0.79  | 0.70  | 0.89  | 0.70  | 0.69  | 0.58  | 0.78  | 0.72  | 0.74  | 0.52  |

### A.6.3. Effect of Number of Target Expansions

For most tasks, performance deteriorates as the number of target outputs grows. To measure the relative rate of decline, in Figure 6, we plot the F1 score as the number of candidate LFs increases.
Figure 6: Effect of Number of Output Classes on F1 Performance. Best performing models shown.
We provide a breakdown of performance by SF on MIMIC RS between the LMC model and the ELMo baseline. There is a good deal of volatility across SFs, particularly for the macro F1 metric. We leave out the other baselines for space considerations.
Clinical Acronym Expansion via Latent Meaning Cells

| Acronym | Support | Targets | LMC | ELMo |
|---------|---------|--------|-----|------|
| AMA     | 471     | 3      | mPr | mR  |
| ASA     | 395     | 2      | mF1 | wPr |
| AV      | 491     | 3      | wR  | wF1 |
| BAL     | 485     | 2      | mPr | mR  |
| BM      | 488     | 3      | mF1 | wPr |
| CnS     | 432     | 5      | wR  | wF1 |
| CEA     | 497     | 4      | mPr | mR  |
| CR      | 499     | 6      | mF1 | wPr |
| CTA     | 495     | 4      | mR  | wF1 |
| CVA     | 474     | 2      | mF1 | wPr |
| CVP     | 487     | 3      | wR  | wF1 |
| CVS     | 237     | 3      | mPr | mR  |
| DC      | 455     | 5      | wR  | wF1 |
| DIP     | 492     | 3      | mPr | mR  |
| DM      | 484     | 3      | mF1 | wPr |
| DT      | 475     | 6      | mR  | wF1 |
| EC      | 473     | 4      | mR  | wF1 |
| ER      | 495     | 3      | mF1 | wPr |
| FSH     | 265     | 2      | mR  | wF1 |
| IA      | 171     | 2      | mR  | wF1 |
| IM      | 492     | 2      | mR  | wF1 |
| LA      | 454     | 3      | mR  | wF1 |
| LE      | 481     | 7      | mR  | wF1 |
| MR      | 492     | 5      | mR  | wF1 |
| MS      | 488     | 6      | mR  | wF1 |
| NAD     | 465     | 2      | mR  | wF1 |
| NP      | 463     | 4      | mR  | wF1 |
| OP      | 489     | 6      | mR  | wF1 |
| PA      | 412     | 6      | mR  | wF1 |
| PCP     | 488     | 4      | mR  | wF1 |
| PDA     | 478     | 3      | mR  | wF1 |
| PM      | 375     | 3      | mR  | wF1 |
| PR      | 241     | 4      | mR  | wF1 |
| PT      | 496     | 4      | mR  | wF1 |
| RA      | 490     | 4      | mR  | wF1 |
| RT      | 470     | 4      | mR  | wF1 |
| SA      | 454     | 5      | mR  | wF1 |
| SBP     | 489     | 2      | mR  | wF1 |
| US      | 290     | 2      | mR  | wF1 |
| VAD     | 482     | 4      | mR  | wF1 |
| VBG     | 483     | 2      | mR  | wF1 |

**AVG** - 0.57, 0.65, 0.51, 0.9, 0.72, 0.73, 0.52, 0.54, 0.37, 0.83, 0.52, 0.52

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A.7. Efficiency

![Figure 7: Accuracy by pre-training hours.](image)

Task performance at the end of pre-training is an informative, but potentially incomplete, evaluation metric. Recent work has noted that large-scale transfer learning can come at a notable financial and environmental cost (Strubell et al., 2019). Also, a model which adapts quickly to a task may emulate general linguistic intelligence (Yogatama et al., 2019). In Figure A.7, we plot test set accuracy on MIMIC RS at successive pre-training checkpoints. We pre-train the models on a single NVIDIA GeForce RTX 2080 Ti GPU. We hypothesize that flexibility in latent word senses and shared statistical strength across section headers facilitate rapid LMC convergence. Averaged across datasets and runs, the number of pre-training hours required for peak test set performance is 6 for LMC, while 50, 51, and 55 for MBSGE, BSG, and ELMo. The non-embedding parameter counts are 169k for the LMC and 150k for both the BSG and MBSGE. ELMo has 91mn parameters. Taken together, the LMC efficiently learns the task as a by-product of pre-training.

A.8. Qualitative Analysis

A.8.1. Word-Metadata Gating Function

Inside the variational network, the network learns a weighted average of metadata and word level representations. We examine instances where more weight is placed on local acronym context vis-a-vis section header, and vice versa. Table 5 shows for a few examples
Clinical Acronym Expansion via Latent Meaning Cells

Figure 8: The latent word sense distribution changes when manually interpolating the variational network weight between the word “MG” and three different section headers.

that shorter sections with limited topic diversity (e.g., “Other ICU Medications”) are assigned greater relative weight. It can selectively rely on each source based on relative informativeness.

Table 5: variational network gating function weights.

| Target Label                  | Context Window                           | Section Weight |
|-------------------------------|------------------------------------------|----------------|
| patent ductus arteriosis      | Hospital Course:... echocardiogram showed normal heart structure with small PDA hemodynamically significant... | 0.12           |
| pulmonary artery              | Tricuspid Valve: physiologic tr pulmonic valve PA physiologic normal pr | 0.21           |
| no acute distress             | General Appearance: well nourished NAD   | 0.38           |
| morphine sulfate              | Other ICU Medications: MS ⟨digit⟩ pm     | 0.46           |

The gating function enables manual interpolation between local context and metadata to measure smoothness in word meaning transitions. We select three sections which a priori we associate with expansions of the acronym MG: “Discharge Medications” with milligrams, “Imaging” with myasthenia gravis, and “Review of Systems” with magnesium (deficiency). We compute the lmc conditioned on “MG” and each section m, ranking LFs by taking the softmax over $-D_{KL}(q(z|MG,m,c_\emptyset||p(z|LF,m_\emptyset)))$, where $c_\emptyset$ and $m_\emptyset$ denote null values. Figure 8 shows a gradual transition between meanings, suggesting the variational network is a smooth function approximator.

A.8.2. Latent Meaning Cells as Word Senses

A guiding principle behind the LMC model centers on the power of metadata to disambiguate meaning for words with multiple senses. We choose a generic target word “history” and enumerate five diverse types of patient history: smoking, depression, diabetes, cholesterol,
Table 6: Conditional latent meaning: history

| Section               | Most Similar Words       |
|-----------------------|--------------------------|
| Past Medical History  | depression, diabetes     |
| Social History        | smoking, depression      |
| Family History        | depression, smoking      |
| Glycemic Control      | cholesterol, diabetes    |
| Left Ventricle        | heart, depression        |
| Nutrition             | diabetes, cholesterol    |

Table 7: Section header embedding nearest neighbors.

| Section                         | Nearest Neighbors                  |
|---------------------------------|------------------------------------|
| Allergies                       | Social History, Prophylaxis, Disp  |
| Assessment                      | Response, Neuro, Action            |
| Chief Complaint                 | Reason, Family History, Indication |
| History of Present Illness      | HPI, Past Medical History, Total Time Spent |
| Meds on Admission               | Discharge Medications, Other Medications, Disp |
| Past Medical History            | HPI, Social History, History of Present Illness |

and heart. Then, we examine the proximity of lmcs for the target word under relevant section headers and compare to the expected representations of the five types of patient history. Section headers have a largely positive impact on word meanings (Table 6), especially for generic words with large prior variances like “history.”

A.8.3. Clustering Section Headers

In Table 7, we manually select ten prominent headers and examine nearest neighbors. In most cases, results are meaningful and even uncover a section acronym: "HPI” for "History of Present Illness”.

A.9. Words and Metadata as Mixtures

Consider metadata and its building blocks. A natural question to consider is the distribution of latent meanings given metadata. We can simply write this as

\[
p(z_{ik}|m_k) = \sum_{w_{ik}} p(z_{ik}|w_{ik}, m_k)p(w_{ik}|m_k)
\]  

(35)

\(w_{ik}\) denotes an arbitrary word in document \(k\) and the summation marginalizes it with respect to the vocabulary. \(p(w_{ik}|m_k)\) can be measured empirically with corpus statistics. We will denote this probability value as \(\xi_{w_{ik}|m_k}\). In addition, \(p(z_{ik}|w_{ik}, m_k)\) has already
been defined as $N(nn(w_{ik}, m_k; \theta))$. Therefore,

$$p(z_{ik}|m_k) = \sum_{w_{ik}} N(nn(w_{ik}, m_k; \theta))\xi_{w_{ik}|m_k} \tag{36}$$

The distribution of the latent space over metadata is a mixture of Gaussians weighted by occurrence probability in metadata $k$. One can measure the similarity between two metadata using KL-Divergence. This measure is computationally expensive because each metadata can be a mixture of thousands of Gaussians. Monte Carlo sampling, however, can serve as an efficient, unbiased approximation.

It is also a natural question to ask about the potential meanings a word can exhibit (Figure 9). That is,

$$p(z_{ik}|w_{ik}) = \sum_{m_k} p(z|m_k, w_{ik})p(m_k|w_{ik}) \tag{37}$$

$p(m_k|w_{ik})$ can also be measured empirically. We denote this distribution as $\beta_{m_k|w_{ik}}$.

$$p(z_{ik}|w_{ik}) = \sum_{m_k} N(nn(w_{ik}, m_k; \theta))\beta_{m_k|w_{ik}} \tag{38}$$

![Figure 9: The meaning of “Amazon” can be interpreted as a mixture of Gaussian distributions in different metadata.](image)

**A.10. Word and Metadata as Vectors**

With a certain trade-off of compression, we can represent metadata as a vector using its expected conditional meaning:

$$E_{z_{ik}|m_k}[z_{ik}] = \sum_{w_{ik}} \xi_{w_{ik}|m_k} \int z_{ik}N(nn(w_{ik}, m_k; \theta))dz_{ik} \tag{39}$$
Since $\int z_{ik} N(nn(w_{ik}, m_k; \theta))dz_{ik} = E_{z_{ik}|w_{ik}, m_k}[z_{ik}]$ The expectation can be simply written as the combination of the means of normal distributions that form metadata $k$:

$$E_{z_{ik}|w_{ik}, m_k}[z_{ik}] = \sum_{w_{ik}} \xi_{w_{ik}|m_k} E[z_{ik}|w_{ik}, m_k]$$  \hspace{1cm} (40)

The above equation sums the expected meaning of words inside a metadata weighted by occurrence probability. Following the same logic for words yields

$$E_{z_{ik}|w_{ik}}[z_{ik}] = \sum_{m_k} \beta_{m_k|w_{ik}} E[z_{ik}|w_{ik}, m_k]$$  \hspace{1cm} (41)