Visualizing Medical Coding Practices Using Transformer Models

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Abstract: In the United States, diagnostic codes are a key component of medical records that document the process of patient care. It has long been a common belief that there are inherent orders to the sequences of diagnosis codes in medical records. However, because of the complexities in medical records, there have been few tools that can automatically distill and make sense of the implicit ordering characteristics of the diagnostic codes within medical records. With the advent and fast advancement of the Transformer architecture, in this work we develop and demonstrate a transformer based model named DgPg. DgPg can automatically learn the patterns in the ordering of diagnostic codes in any given corpus of medical records, for example, those obtained from the same hospital or those from different hospitals but collected and organized around particular clinical scenarios. Using DgPg, we can flexibly visualize the coding patterns and context around any particular diagnostic code. Our results from DgPg further demonstrate that the model learned from one dataset can be unique to that dataset and, from this respect, confirm that medical coding practices have unique dependencies on the provider or the clinical scenarios. Our work uses three well known datasets: MIT's MIMIC-IV dataset, and CDC's NHDS and NHCS datasets. Our DgPg transformer models are only 2.5 MB in size. Such compact footprint enable flexibility in how the models can be deployed for real world use.

1 INTRODUCTION

The Transformer architecture, since first appearing in 2017 (Vaswani, 2017), has had a transformative effect on language models. A plethora of subsequent works have led to rapid further development. In 2018, bidirectional encoder representations from transformers (BERT) (Devlin, 2018) enabled models to understand context from both the left-to-right and right-to-left directions. In 2020, T5 (Raffel et al., 2020) proposed that flexible transfer learning can be achieved by treating all natural language based tasks in a unified text-to-text format. All of these culminated in the creation and widespread adoption of LLM models (Brown, 2020), which have fundamentally changed the landscape of how AI models are conceived, designed, used, and perceived.

Our research revolves around medical records, which are complex, specialized, and messy. In the United States, a key component in medical records are the diagnostic codes, which essentially is a "translation" from unstructured descriptions into structured labels that characterize the essence of the descriptions. In theory, the sequence of diagnostic codes documented per each patient should provide an accurate, accountable, and actionable summary that drives the coordination of that patient's care.

However, while the step of coding distills information, it is a step performed manually, very often based on experience and intuition. Standardization and quality-control are hard. Furthermore, even though there are often coding manuals to follow, those manuals have not been designed for ease of use and hence introduce significant cognitive barriers for the users, who are already overly task-burdened and at risk of workplace burnout. Worse yet, different hospital, or different units within the same hospital, may have differing coding practices due to nuances in their unique work processes, as well as clinicians' personal preferences in how they work.

Due to these reasons of variation, even though most medical professionals can agree that there must be inherent patterns among the coding sequences, few can articulate those patterns with confidence. In addition, even though coding manuals exist, those cannot reflect the reality of nuanced patient care and practical constraints faced by each clinician. From this respect, no one person truly knows the common coding practices. In result, it's hard for a hospital's lead physicians and administrators to have a shared under-

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standing of how patient care is carried out at their hospital. This further hampers quality control, process improvement, or burnout prevention.

In this work, we hypothesize that the Transformer architecture can be used to build an AI model to learn the most representative patterns in coding sequences, automatically and purely from a corpus of medical records. Our prototype called DgPg ("Diagnosis Progression") is successful. We show that the learned patterns can be visualized flexibly as AI-generated visual summaries of the representative coding practices. The trained transformer models within DgPg are about 2.5 MB in size. DgPg have been trained on three publicly accessible datasets: MIMIC-IV (Johnson et al., 2023), NHDS (US CDC NCHS, 2010), and NHCS (US CDC NCHS, 2020).

Our contributions in this paper are as follows. To the best of our knowledge, (1) DgPg is the first to demonstrate that the Transformer architecture can learn representative patterns in the code sequences in real-world medical records. (2) This paper is also the first work that uses AI generated visualizations to serve as visual summaries of representative patterns within a dataset, without the otherwise lengthy process of requiring a human user to explicitly go through the raw data to select features or create human-provided labels.

We summarize background in Section 2 and present our research in Section 3. Results from our experiments and examples of our visualization are in Section 4. We conclude in Section 5.

2 BACKGROUND

DgPg's scope is to create organization-level analytics using an AI model that can learn representative coding practices within medical records and help hospital administrators gain operational insights. While that organizational analytics scope of research is new, we have drawn inspirations from a plethora of prior research that have analyzed medical records using AI methods for various clinical use cases.

Some of the best clinical use cases include: to predict patient readmission and in-hospital mortality (Hsu et al., 2020), to predict occurrences of sepsis hours before human clinicians are able to (Henry et al., 2015), early detection of diabetic retinopathy (Abràmoff et al., 2018), and cardiovascular disease diagnosis and prediction (Krittanawong et al., 2017). Besides clinical outcomes, clinical cost has been studied too. For example, to correlate a patient's medical records across multiple visits in order to reveal patterns of patients developing conditions that require costly procedures (Malhotra et al., 2015).

Specific to sequences pattern mining from medical records, past work have centered around inter visit patterns, i.e. across multiple visits by the same patient. In a large part because there is then a natural time variable. The most typical data structure used for modeling is graph (Malhotra et al., 2015). To the best of our knowledge, our work is the first to examine representative sequence patterns within the records of a single visit by a patient.

The medical coder's job is to understand the implicit reasons behind diagnoses and procedures (Hu et al., 2021). This job is time consuming. Kim et al. report that inpatient coders achieve a rate of 2.5 medical charts per hour (Kim and Ganapathi, 2021). The job is also cognitively intensive, because medical records involve large sets of synonymous words; there is rarely a single word that is used to describe one particular concept (Koleck et al., 2021).

Past researchers have incorporated external knowledge banks, such as Wikipedia (Bai and Vucetic, 2019) and UMLS (Chanda et al., 2022) in an effort to improve AI's coding capabilities. In a related manner, not all parts of patient visit summaries are equally important; using a restricted, high-quality set of text is more effective than using all available text (Hsu et al., 2020). Incorporating attention, a means of assigning importance to different parts of the text, has also become a common method (Mullenbach et al., 2018).

Lastly, it is worth noting that the direct use case of DgPg is not to improve medical coding or clinical predictions. Instead, our use case is to let AI curate how a complex process is actually implemented in reality based on data. The ensuing insights can be used for a variety of purposes. A relevant example of this use scenario is our prior work, eCamp (Raji et al., 2018), which is a system that learns and visualizes how university students navigate through 100s of potential degree programs at a typical major research university in the US. All purely based on anonymized electonic student records. The insights revealed by eCamp can be used generally by university administrators, academic advisors, faculty, students, and parents for their different purposes. We intend DgPg's insights about each hospital's coding practices to have a similar level of generality and can help disparate stakeholders in the hospital ecosystem as well. The work of eCamp predated transformers. To this end, DgPg is the first attempt of using transformers for such organization-level analytics.

Next, we describe the design process and technical details of DgPg in Section 3.

3 THE DgPg TRANSFORMER MODEL

3.1 Overview

Scope of Use. Every year the United States Center of Medicare & Medicaid Services (CMS) publishes the official ICD-10-CM (International Classification of Disease) coding guidelines (CMS, 2024), which details specific conventions and rules that guide coding and sequencing of codes. The sequence of codes can be due to temporal ordering, etiological ordering, or situation-specific guidelines.

The codes and sequencing of codes are both significant. It's fraudulent to change coding for the purpose of increasing medical claim payment. Any revision of coding must be done with proper support of documentation, including documentation of causal relationship between codes and medical events.

While it is possible, and common practice, for a human expert to read through the complete medical records of a patient's visit to audit each instance of the coding practice, a computational tool is needed to systematically understand the coding practice shared among a unit of healthcare providers. DgPg's scope of use is in this context. While DgPg's overall scope can include all medical codes, we have chosen to start with diagnostic (DX) codes in this work to reduce the complexities.

Design Goals. First, functionally, DgPg needs to create summaries. We draw inspiration from transformers, especially because of its ability to produce patterns that can be used as summaries. Mechanistically, our goal is to identify and present patterns that can represent the shared practices. Our aim is not to report all deviations from the shared practice nor to evaluate or label a coding practice as good or bad.

Second, we aim for the DgPg model to be small in size and fast to train. The compactness affects deployment flexibility, but more importantly, affects the time to train the model. We prefer the model to be able to train quickly because, from what we have observed, different healthcare providers do have highly specialized and unique practices because of the kind of care they provide to patients. We believe a smaller and more specialized AI agent is easier to optimize, control and audit. In principle, this has been proven in the context of predicting an order sequence of characters in information theory (Grassberger, 2012), where a distinction is made between algorithmic complexity and statistical complexity. A sequence can be statistically complicated but if it's generated by a simple algorithm, then its information can be quantified by the complexity of the algorithm (Grassberger, 2012). Even though the transformer architecture is new, we believe the same principle still applies.

Table 1: An example of the ICD-10-CM code scheme being inherently hierarchical.

code	desc
S	Injury, poisoning and certain other consequences of external causes
S5	Injuries to the elbow and forearm
S52	Fracture of forearm
S52.5	Fracture of lower end of radius
S52.52	Torus fracture of ...
S52.521	... of right radius
S52.521A	Initial encounter for closed fracture

We aim to use the DgPg model in the following way: given a starting point, e.g. a particular DX code, we aim for DgPg to generate a graph of the most related DX codes that can be visualized as visual insights to users. The formulation of our research problem is next.

3.2 Problem Formulation

A Unified Format. ICD-10-CM codes are inherently hierarchical. Table 1 shows an example hierarchy, where one can trace an exact arm injury through seven levels of details. The first level of the hierarchy is encoded within the first character of the code, second level in the second character, etc. DgPg needs an architecture that can learn such coding schemes.

Typically, to use a *transformer* (Vaswani, 2017) model requires one to restructure their problem at hand as a sequence-to-sequence problem. Hence, given our need for a model that learns the hierarchical coding schemes, the transformer architecture is a natural choice. It allows our model to learn a code piece-by-piece instead of all-at-once. In essence, we will train our model to learn the first character, then learn the next character based on the first character, and iterate further recursively.

Baseline Memory Model. In contrast, let's examine the problem of learning the relationship between pairs of codes in a traditional way, where one has to represent these codes as numeric indices. For example, if the code `A41.9` is the 123rd code out of $12,039$ codes, then it would be encoded as the integer 123. With this traditional formulation, a memory model can be created as a matrix of $12,309 \times 12,309$. There are two consequences: (1) the model is large (around 290 MB of `float16` values), and (2) the model is not generalizable.

Table 2: Our data come from three datasets. In MIMIC-IV, each record represents a single patient. For NHCS and NHDS, a record can represent multiple patients. Hence, we show the number of records and the number of patients represented by the datasets as two separate columns.

From	Name	# Records	# Patients
MIT	MIMIC-IV	430,812	430,812
CDC	NHCS	123,565	33,595,765
CDC	NHDS	756,953	111,514,788
	Combined	1,277,400	145,507,435

As a specific example, consider a dataset where 60 % of the time the code `A41.9` is followed by `I10.0`; and 40 % of the time it is followed by `I59.1`. Ideally, we want the model to learn that 100 % of the time, it should predict `I` as the first character.

For this example, a memory model, will lose the hierarchy information of the codes. Hence we choose to build a unified text-to-text model on the character-level, so that the model can learn the hierarchical coding schemes naturally as shown in Table 1.

Datasets. Our requirement for input data is minimal. As we are only interested in the sequence of DX codes, any dataset that has ordered sequences of DX codes is sufficient. In this work, we use three datasets: MIMIC-IV, NHDS, and NHCS. Table 2 details these datasets.

The MIMIC-IV (Johnson et al., 2023) dataset is an anonymized collection of medical records from the Beth Israel Deaconess Medical Center. The data spans multiple years. Within MIMIC-IV, we use the `hosp/diagnoses_icd` data which has four columns: admission number, sequence number, ICD version, and ICD code.

The National Hospital Discharge (and Care) Surveys (US CDC NCHS, 2010; US CDC NCHS, 2020) cover different years: NHDS from 1996 to 2010, and NHCS for only 2020.

These two CDC datasets follow a similar structure with $1+N$ columns: a weight column w, and N columns of DX codes. NHDS has $N = 7$ DX codes; NHCS has $N = 30$ DX codes. We treat the column ordering as the representative order of the codes, i.e. `DX1` is the first code, `DX2` is the second, etc.

The weight column w serves as a frequency multiplier, to indicate one record in the dataset can represent multiple patients. For each input record, we emit w copies as actual records for DgPg to learn.

Different datasets have different levels of specificity of the codes they use. In addition, to test the generality of our data and our models, we choose a common encoding scheme for all codes. Even though MIMIC-IV has up to seven characters in the DX codes and abides by ICD-10-CM standard, NHDS has DX codes limited to four characters and are under the ICD-9-CM standard. Hence we have converted ICD-9-CM codes to ICD-10-CM codes, using the National Bureau of Economic Research (NBER) ICD-9/10 crosswalk. We've also truncated the length of the DX codes in MIMIC-IV to four characters as well. Every ICD-10-CM code is normalized to four characters, truncating and/or padding with hyphens as necessary.

These data processing is to compare DgPg's model results across the MIMIC-IV dataset and the two CDC datasets. DgPg's capability is not limited to four characters.

The DgPg Model: $T(D)$**.** Notationally, we consider $T(D)$, where T is a DgPg transformer model trained on some dataset D.

For a given model and dataset pair, we measure the performance PERF using the standard approach for transformer models: fixed-length sequence perplexity (Radford et al., 2019). To get an average model performance, the PERF function gets applied to 10 K samples from the validation split and are aggregated via an arithmetic mean.

Specifically, we evaluate on sequences of codes. For example, for a sequence of two codes, (`M542,G441`), the DgPg model would see the sequence `•M542G441`. For each character in this sequence, the transformer model returns a probability of that character occurring, $\mathbf{p} = (p_1, \cdots, p_9)$. We are only interested in the model's predictive power, so that $\text{PERF}(\mathbf{x} \mid T(D))$ is calculated only on the 2nd code.

$$\log(\text{PERF}) = -\frac{1}{4}\sum_{i=5}^{9} \log P(x_i \mid x_1, \cdots, x_{i-1}) \qquad (1)$$

We show experimentation results in Section 4.

$$T : \mathrm{A}^n \times \mathrm{A} \to \mathbb{R}$$

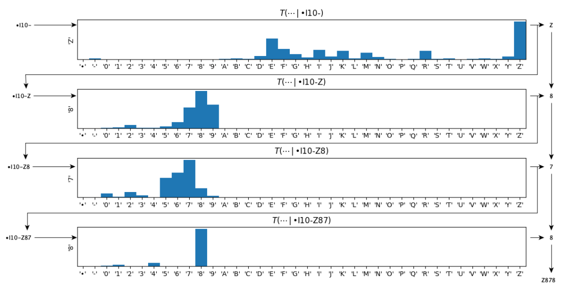


Figure 1: Starting from `I10-`, we predict the most likely code to follow: `Z878`.

Table 3: An example of the data used to train our models.

Original Codes	Training Sequence
DX1,DX2,DX3	•----N12-
N12,Q610,N179	•N12-Q610
A419,E119,""	•Q610N179
	•N179----

T reports the probability that a character in an alphabet A follows a sequence of characters. *T* is intended to be used iteratively: starting with a 4 character code, predict the 1st character of the second code. Then, starting with $4+1$ characters, predict the 2nd character of the second code. A complete example is shown in Figure 1.

Table 3 is an example of the kind of input the model is trained on.

4 RESULTS AND DISCUSSIONS

4.1 Configurations and Training

Base Model Configuration. We trained our models using a modified version of the `nanoGPT` project[1]. We based our model configuration on nanoGPT's included configuration for character-level training on a dataset of Shakespeare's plays. This configuration for our base model is in Listing 1. We also experimented with different model sizes (Section 4.3).

Training Data. In Section 4.4, we trained on four datasets: MIMIC, NHCS, NHDS datasets, and a 4th dataset, which we refer to as "Combine", which combines all three of the MIMIC, NHCS and NHDS datasets.

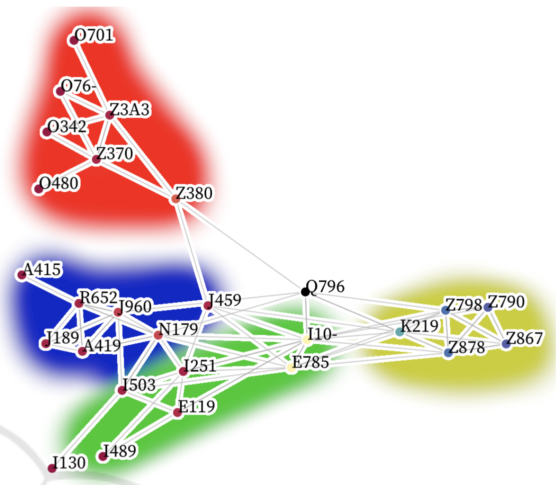
Compute Configuration and Training Time. All of our models were trained on Google Colab using a NVIDIA T4 GPU instance. On average, it took 1,092 S to train a model, at a cost of 0.16 USD/HR, which amounts to to about 0.05 USD per model. As is typical in transformer model training, DgPg uses half precision `f16` floating point numbers (Warner et al., 2024).

Summary. When training the base model and the variation models, the only technical difference is with how the training data is arranged. In terms of training time, we notice very minor differences among the DgPg base model and the variation models. Thus we conclude that the cost to train for all DgPg models can be regarded as the same. The reason to choose a particular DgPg model will solely depend on the use case at hand.

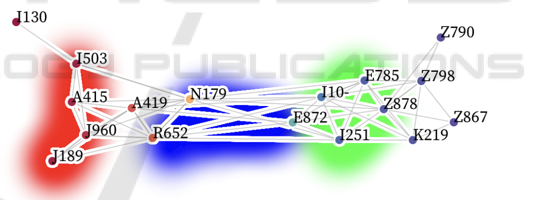
[1]https://github.com/karpathy/nanoGPT

```
learning_rate = 1e-3 ;    dropout = 0.2
lr_decay_iters = 30000 ; min_lr = 1e-4
beta2 = 0.99 ;          max_iters = 30000
batch_size = 256 ;          n_layer = 3
n_head = 3 ;                n_embd = 192
```

Listing 1: A summary of the base model configuration.



(a) Q79.6: Ehlers-Danlos Syndrome. Red 🟥 is pregnancy and childbirth; Blue 🟦 is other diverse diseases; Green 🟩 is circulatory, endocrine, and metabolic diseases; Yellow 🟨 is health status and personal history.

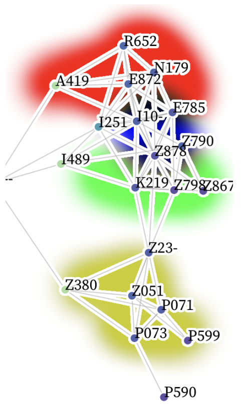


(b) A41.9: Sepsis. Red 🟥 is acute conditions; Blue 🟦 is symptoms and chronic conditions; Green 🟩 is metabolic and circulatory conditions.

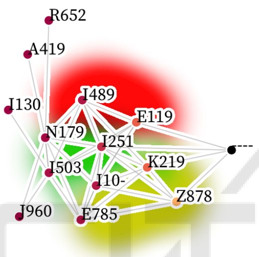
Figure 2: Visualization of diagnosis-specific coding patterns (Section 4.2).

4.2 Visualizing Coding Practices

We aim to visualize medical coding patterns using our DgPg model. We designed a generative algorithm to extract the most likely codes that follow or precede a "seed code." The generative approach to coding is critical as it allows our models to learn and reproduce the DX coding hierarchy. We then recursively conduct



(a) The diagnoses most likely to be coded first. Red 🟥 is infectious diseases; Blue 🟦 is circulatory system diseases; Green 🟩 is digestive diseases; Yellow 🟨 is health status and perinatal.



(b) The diagnoses most likely to be coded last. Red 🟥 is cardiovascular diseases; Green 🟩 is comorbidities; Yellow 🟨 is factors influencing health status.

Figure 3: Visualization of which codes are most likely to be coded (a) first and (b) last (Section 4.2).

a breadth-first search. For each code, we exhaustively check the PERF of all following codes. The top $k = 3$ performers get added to the working set. This continues until we reach a depth of $n = 3$.

The resulting graphs (Figure 2 and 3) can be used to understand the most common following and preceding codes for a given diagnosis.

One of those examples is in Figure 2a, which details the codes most likely to surround a Ehlers-Danlos diagnosis. Based on the graph, we can see that the diagnosis is often preceded by records of the patients birth, or the existence of other diseases. Our graph also highlights a few codes that are used in similar positions within the coding sequence, specifically the codes that represent systemic conditions.

Figure 2b shows that sepsis is often preceded by acute medical conditions that could have contributed to a patient becoming septic. Similarly, it is often followed by chronic, metabolic, and circulatory conditions that sepsis could adversely affect.

Table 4: We evaluated the performance of the model at four different levels of model complexities. NL is `n_layer`, NH is `n_head`, and NE is `n_embd`. The parameters in this table override the base configuration in Listing 1. We found that $T_{11\,\mathrm{M}}$ and $T_{1.3\,\mathrm{M}}$ perform similarly, despite a $10\times$ difference in model size.

Name	NL	NH	NE	Model Size	Loss
$T_{11\,\mathrm{M}}$	6	6	384	20. MB	1.16
$T_{1.3\,\mathrm{M}}$ *	3	3	192	2.5 MB	1.17
$T_{230\,\mathrm{K}}$	2	2	96	440 KB	1.19
$T_{30\,\mathrm{K}}$	1	1	48	58 KB	1.25

Figure 3a (and 3b) visualize the most likely diagnoses to be coded first (and last) in the diagnosis sequence. These graphs provide insight into what kinds of codes are the most significant when starting or ending the coding process.

The graphs we create can be of arbitrary size and constraints. For Figure 2 and 3, each graph took around 2 minutes to generate. Each graph is organized from left (earlier codes) to right (later codes).

4.3 Model Complexity

Here we report our ablation study to evaluate the effect of model configuration on the performance of DgPg. Specifically, we experiment with the size of the model. Because the tests are about model size, in this section we refer to models in the test by the size of the models, such as $T_{11\,\mathrm{M}}$ and $T_{1.3\,\mathrm{M}}$, which represents models with 11 M and 1.3 M parameters, respectively.

In the ablation study, we start with model configurations where we have no risk of overfitting the data. We note that there are 12.3 K suitable (4-character or less) diagnosis codes. Constructing a matrix of transition probabilities would require $12.3\,\mathrm{K} \times 12.3\,\mathrm{K}$ `float16` values, or around 290 MB. We limit our model sizes to a maximum of 10 % of this size. This limitation ensures that our models are learning generalizable patterns.

Table 4 shows the results of our ablation tests. In total, we tested four different model configurations. From these results, we observe that $T_{11\,\mathrm{M}}$ and $T_{1.3\,\mathrm{M}}$ perform similarly even though their sizes differ by a factor of $10\times$. With this result, we feel confident that the $T_{1.3\,\mathrm{M}}$ configuration represents the optimal trade-off between model size and performance. Results in Section 4.2 uses $T_{1.3\,\mathrm{M}}$.

We also note that even the $T_{230\,\mathrm{K}}$ configuration could be suitable because its performance is comparable to the other two best-performing models. $T_{30\,\mathrm{K}}$, however, is unsuitable as it is the worst performing model.

4.4 Discussion

Transformer Model Variations. We have also experimented with several variations on the base DgPg model. Our base model can predict which DX codes directly follow other DX codes within a medical record. Related to but beyond this functionality, one might also want the capability to predict codes that precede other codes, and to expand the meaning of "follows" to include "broadly follows a code" instead of "immediately follows a code." To this end, it's useful to build models that can predict broadly-following codes can be used for normalizing the ordering of codes within a medical record.

Furthermore, although a single model could be used for all of these variations simultaneously via a unique prompt prefix, our experiments show that specialized models can be built very efficiently. That is because the DgPg framework is general, where the main difference between each model variation lies solely in the training data used. The format of the training data stays the same while the meaning behind each training sample varies. Due to this architectural advantage, every model variation trains in the same amount of time and using exactly the same DgPg training pipeline. Results from the variation models are not included in this publication due to the limit of space, however.

Applicability of Transformers. The first reason we chose the transformer architecture was because of the need to learn the coding hierarchies. There is a second reason as well. That is, generative models are also a natural fit for generating summaries and, in this paper, visual summaries, to explain large, messy real-world datasets. As shown in Figure 2 and Figure 3, the DgPg transformer model can perform well in such a generative setting. We believe there is a strong potential to extend DgPg's organization-level analytics use case into more clinically-oriented settings. From this respect, DgPg is simply a starting point.

Limited Transferability. With the evidence that patterns exist in all of our tested datasets, we also want to know if they have the same patterns or if there are unique patterns within each dataset. To evaluate this, we leverage our PERF metric to measure a model trained on one dataset when evaluated on another dataset.

Using our DgPg model with 1.3 M parameters as the example, Figure 4 shows how generalizable the patterns are between datasets. There are two takeaways from these results:

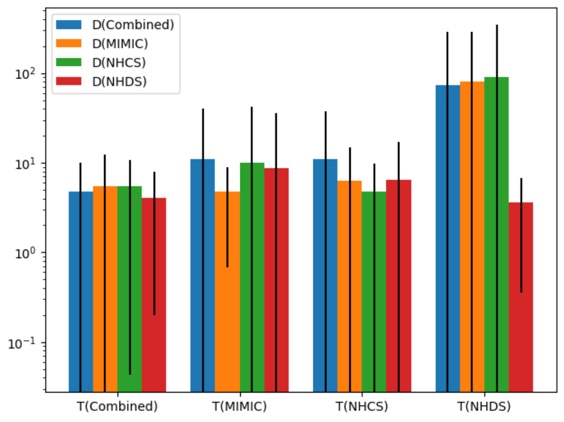


Figure 4: Evidence that the models have learned patterns within their respective datasets that aren't present in the other datasets. $T(\cdot)$ represents that the model was trained on a dataset, $D(\cdot)$ represents the dataset that was tested. For each dataset, 10 K samples were collected. For each sample, the model's performance PERF was calculated. The mean and standard deviation of the 10 K samples is shown in this chart. As expected, testing with the same dataset that was trained on yields a better PERF than testing on a different dataset than the model was trained on. MIMIC and NHCS are the most generalizable models, while NHDS is the least generalizable.

First, as expected, the model trained on the Combined data performs equally well on all of the other datasets that make it up. This reaffirms the generally held belief that training on an increased variety of datasets yields improved performance.

Second, the model trained only on NHDS data performs the worst when tested on all the other datasets. This is evidence that the patterns within NHDS are unique to that dataset and are less generalizable to other medical records datasets.

5 CONCLUSION

In this paper, we developed a transformer model, DgPg, that can learn organization-level analytics and summarize representative coding patterns based on any corpus of medical records. Training a DgPg model for a medical records dataset is both time- and cost-efficient. After training, the DgPg models are compact in size. We also demonstrate the use of DgPg models in a generative use case to visualize the representative coding patterns, as well as in a classification use case to evaluate how representative a code sequence is, given the context of any given dataset.

This work is only an initial step showing that transformer models can learn the representation of coding patterns. As future work, we aim to investigate possibilities to continuously improve the capabilities of DgPg and to use transformer models in a bigger variety of clinical use cases. In addition, as hallucination is a research priority for language models, we want to also study the issue of hallucination as it's applicable to DgPg transformer models too.

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