MIMIC-Extract: A Data Extraction, Preprocessing, and Representation Pipeline for MIMIC-III

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Abstract

Robust machine learning relies on access to data that can be used with standardized frameworks in important tasks and the ability to develop models whose performance can be reasonably reproduced. In machine learning for healthcare, the community faces reproducibility challenges due to a lack of publicly accessible data and a lack of standardized data processing frameworks. We present MIMIC-Extract, an open-source pipeline for transforming raw electronic health record (EHR) data for critical care patients contained in the publicly-available MIMIC-III database into dataframes that are directly usable in common machine learning pipelines. MIMIC-Extract addresses three primary challenges in making complex health records data accessible to the broader machine learning community. First, it provides standardized data processing functions, including unit conversion, outlier detection, and aggregating semantically equivalent features, thus accounting for duplication and reducing missingness. Second, it preserves the time series nature of clinical data and can be easily integrated into clinically actionable prediction tasks in machine learning for health. Finally, it is highly extensible so that other researchers with related questions can easily use the same pipeline. We demonstrate the utility of this pipeline by showcasing several benchmark tasks and baseline results.

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1. Introduction

Machine learning from observational health datasets holds the potential to improve healthcare in many ways, e.g., by delivering better patient treatments, improving operations, or answering fundamental scientific questions (Ghassemi et al., 2018). To realize this potential, efforts have begun to make real healthcare datasets available to credentialed researchers with human subjects training, such as the Medical Information Mart for Intensive Care (MIMIC-III) dataset (Johnson et al., 2016). While MIMIC-III is publicly available, working with MIMIC-III data remains challenging due to the high complexity of health data and the myriad choices that must be made to extract a specific, clinically meaningful cohort for modelling and analysis. These difficulties also present barriers to reproducibility in machine learning studies on MIMIC-III data because researchers develop independent code and processes to extract, preprocess, and represent a task-appropriate labeled cohort. Many papers do not share code used to extract study-specific data (Johnson et al., 2017a), leading to unnecessary variance in reported results.

Prior works have targeted the creation and distribution of extraction pipelines aimed at canonical benchmark prediction tasks (Harutyunyan et al., 2019; Purushotham et al., 2018), but these pipelines and benchmarks have limited extensibility, include tasks of questionable clinical utility (e.g., the prediction of billing codes which ultimately have poor diagnostic value (Agniel et al., 2018)), or include temporal prediction tasks with no prediction gap, allowing label leakage and reducing the utility of models in real clinical deployment.

In this paper, we introduce MIMIC-Extract: a novel open source pipeline to extract, preprocess, and represent data from MIMIC-III v1.4, including static features and time-varying labs, vitals, and interventions. Our structured approach yields a rich cohort na"ively well suited to a number of meaningful benchmark tasks—several of which we profile in this paper—while simultaneously providing flexibility in cohort selection, missingness thresholding, outlier detection, and representation choice. Extracted data can be read directly into a Pandas DataFrame (McKinney et al., 2010), in a manner consistent with approaches used in many recent papers (Ghassemi et al., 2014, 2015, 2016, 2017; Suresh et al., 2017; Raghu et al., 2017; McDermott et al., 2018). We also provide Jupyter Notebooks (Pérez and Granger, 2007) that demonstrate the use MIMIC-Extract output in benchmark prediction tasks, including steps for data loading and preprocessing, and baseline model building. Lastly, MIMIC-Extract’s default output representation enables building highly performant and concept-drift resilient models (Nestor et al., 2019) through its aggregation of the raw features of MIMIC-III together into clinically meaningful buckets. Our code is available at https://github.com/MLforHealth/MIMIC_Extract.

The rest of this work is structured as follows: in Section 2, we give a detailed description of the MIMIC-Extract data extraction and processing pipeline, including summaries of features extracted and examples of how the system can be extended. In Section 3, we compare our data pipeline to other extraction systems. Section 4 profiles the default cohort extracted from the pipeline. In Section 5, we use standardized feature representations on the resulting cohort in several risk and clinical intervention prediction models. Section 6 discusses some limitations of this data pipeline and Section 7 concludes.

**Technical Significance** MIMIC-Extract is an open source, easy-to-use, and extensible pipeline to ingest MIMIC-III database and yield Pandas DataFrames (McKinney et al.,
2010) containing static and time series data over a standardized cohort. This approach can be easily integrated into many prediction tasks using MIMIC-III data and will be of significant utility to the broader research community.

**Clinical Relevance**  With a focus on clinically aggregated features and temporal dynamics, **MIMIC-Extract** is well-suited for a variety of actionable clinical prediction tasks, such as dynamic intervention predictions (Ghassemi et al., 2016, 2017; Suresh et al., 2017; Raghu et al., 2017; McDermott et al., 2018). Predicting needs for interventions over time is an important clinical problem, as small changes in the timing of onset and offset of devices like mechanical ventilators can make meaningful differences in patient outcomes (Tobin, 2006).

2. Data Pipeline Overview

Figure 1 summarizes the workflow in **MIMIC-Extract**. From the MIMIC relational database, SQL query results are processed to generate four output tables. These tables, as summarized in Table 1, maintain the time series nature of clinical data and also provide an aggregated featurization of the cohort selected.

![Figure 1: MIMIC-Extract Workflow](image)

2.1. Variable Selection

**Static Variables**  By default, our extraction code extracts all 10 static demographic variables listed in Appendix A, along with static outcomes including in-ICU mortality, in-hospital mortality, and the patient’s total length-of-stay (LOS), in hours.
Table 1: Description of Output Tables Generated by MIMIC-Extract

| Table Name       | Index                                                                 | Variables                                                                 |
|------------------|----------------------------------------------------------------------|---------------------------------------------------------------------------|
| patients         | subject_id, hadm_id, icustay_id                                       | static demographics, static outcomes                                        |
| vitals_labs      | subject_id, hadm_id, icustay_id, hours_in                            | time-varying vitals and labs (hourly mean, count and standard deviation)   |
| vitals_labs_mean | subject_id, hadm_id, icustay_id, hours_in                            | time-varying vitals and labs (hourly mean only)                            |
| interventions    | subject_id, hadm_id, icustay_id, hours_in                            | hourly binary indicators for administered interventions                     |

**Time-Varying Vitals and Labs** By default, our extraction code extracts 93 variables (listed in Appendix B) related to vital signs (e.g., heart rate, blood pressure, urine output) and laboratory test results (e.g., white blood cell counts). These were selected as a comprehensive set of possible signals for prediction algorithms with input from clinical care teams. We include 15 of the 17 predictors used Harutyunyan et al.’s recent pipeline. Importantly, unlike Purushotham et al. (2018), we do not include any prescription drugs such as aspirin—this is an intentional omission, because of the unclear quality of the prescription signals in the MIMIC-III database. Without additional insight into the prescriptions a patient actually took, which may differ from all prescriptions ordered for a patient, we feel the inclusion of prescriptions can induce significant confounding effects on the resulting models.

Practitioners can optionally choose to output only a subset of these variables that meet certain minimum percentages of non-missingness, as explained in Section 2.5.

**2.2. Unit Conversion and Outlier Detection**

Sometimes vitals and labs are taken with different measuring units. Our data pipeline standardizes measurements into consistent units, including weight into kilograms, height into centimeters, and temperature into degrees Celsius. This process is easily extensible if any additional unit-classes are added by downstream users which need conversion.

To handle outliers, we make use of a list of clinically reasonable variable ranges provided in the source code repository of Harutyunyan et al. (2019),\(^1\) which was developed in conversation with clinical experts, based on their knowledge of valid clinical measure ranges.

Each numerical variable is associated with thresholds for detecting outliers. If a raw value falls outside these thresholds, it is treated as missing. Additionally, each variable is associated with more refined thresholds for detecting a **physiologically valid** range of measurements. Any non-outlier value that falls outside the physiologically valid range is replaced with the nearest valid value. In generating the default cohort, we replace 35,251 (0.05%) non-valid outliers with nearest valid values and remove 5,402 (0.008%) extreme outliers.

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1. [https://github.com/YerevaNN/mimic3-benchmarks/blob/master/mimic3benchmark/resources/variable_ranges.csv](https://github.com/YerevaNN/mimic3-benchmarks/blob/master/mimic3benchmark/resources/variable_ranges.csv). Accessed 2019-03-29.
outliers. Appendix B lists the proportion of outliers detected at an aggregated feature level.

At the time of writing, outlier detection is unique to our benchmarking system—e.g., the public benchmarks of Harutyunyan et al. (2019) do not use any outlier detection and replacement. Changing this is not easy (e.g., it requires editing source code rather than changing a command-line option).

2.3. Hourly and Clinical Aggregation

MIMIC-III provides a high time-resolution of when labs and vitals were collected. To account for this, after unit conversion and outlier detection, MIMIC-Extract merge labs and vitals into hourly buckets. By default, MIMIC-Extract also merges labs and vitals together according to a manually curated clinical taxonomy, designed to group similar measurements together. This grouped representation also reduces overall data missingness and reduces the presence of duplicate measures. Appendix B details the proposed clinical taxonomy and includes statistics about the MIMIC-Extract featurization. A parallel work shows that aggregating according to this clinical taxonomy in this way yields significant benefits to the robustness of downstream models with respect to clinical concept drift over time (Nestor et al., 2019).

2.4. Time-Varying Treatment Labels

Our code extracts hourly indicators of when (if ever) common treatments were provided to each patient over time. We include device treatments such as mechanical ventilation, as well as drug treatments such as vasopressors and fluid boluses.

We target these interventions because they are commonly used in the ICU (Yang and Tobin; Müllner et al., 2004) and, despite medical necessity, they can present notable harms to the patients (Tobin, 2006; D’Aragon et al., 2015). We include fluid boluses of two types as interventions (crystalloid and colloid) but do not predict them in this work as they are often considered as less aggressive alternatives to vasopressors (Malbrain et al., 2014). The output stores binary indicators of whether an intervention was applied (1) or not applied (0) within a given hour. We treat any missing data as a non-treatment (0).

Note that we extracted both individual vasopressors (e.g., adenosine, dopamine, norepinephrine, vasopressin, etc.) and overall vasopressor usage, consistent with the MIMIC-III codebase (Johnson et al., 2017b). A comprehensive list of extracted interventions is provided in Appendix C.

2.5. Extensibility of Data Pipeline

While MIMIC-Extract promotes reproducibility by providing a default cohort for common benchmark tasks, it is also able to to extract data tailored to specific research questions. In this section, we demonstrate four possible modifications and extensions of this pipeline to enable customized extraction.

2. Note in README: “Outlier detection is disabled in the current version” https://github.com/YerevaNN/mimic3-benchmarks/commit/2da632f0d#diff-04c6e90faac267baa89e2176d2ec7d8
Keywords  Functions in MIMIC-Extract use keywords to control admission cohort and time-varying features selection. Overwriting default values for the following keywords allows researchers to modify default extraction:

min_age specifies a floor on patients’ age to be included in the cohort,
min_duration and max_duration specify restrictions on ICU LOS,
group_by_level2 specifies the granularity of vital and lab variables extracted, and
min_percent excludes vital and lab variables that contain high proportions of missing values.

Configurable Resource Files  The extraction code relies on information in associated resource files for variable grouping and extraction (itemid_to_variable_map.csv) and outlier correction (variable_ranges.csv). By modifying these files, researchers can extract sets of variables that are best suited for specific studies.

Embedded SQL Queries  Researchers can modify the code or add SQL queries in the extraction code to include additional static variables, vitals and labs measurements and treatment labels in the output tables. For example, acuity score can be queried and added to the patients table, and treatment fluid amount can be extracted to the interventions table by querying respective tables in the MIMIC relational database. We plan to maintain and update this codebase regularly to reflect additional research needs and improve the extensibility and ease of adding new SQL queries.

Additional Dataframes  By using a consistent cohort for all output dataframes, MIMIC-Extract reduces the workload on subsequent data processing in downstream tasks. While it currently extracts static variables, vital signs, lab measurements, and treatment interventions, MIMIC-III contains more clinical information such as prescriptions. Researchers can extend the pipeline to output additional groups of variables. This pipeline can also be extended to extracting unstructured data such as caregiver notes to enable multi-modal learning.

3. Comparison to Other Extraction Systems

A particular reproducibility challenge that the machine learning for health community faces is the lack of standardized data preprocessing and cohort specification (McDermott et al., 2019). We focus here on the two most similar efforts to ours in addressing this challenge with MIMIC-III: the benchmarks released contemporaneously by Harutyunyan et al. (2019) and Purushotham et al. (2018). While both efforts have released public code that transforms MIMIC-III into processed dataset views suitable for timeseries machine learning prediction tasks, they differ from our work in several important dimensions, including

1. Which patients are included in the output cohort,
2. How the output data is featurized, and
3. What benchmark tasks are emphasized.

All works also differ with regards to which patient-specific features are exported and used in prediction, but we will not dive into these details as they are largely surface level.
Patient Inclusion Criteria  Our system exports a single cohort, which can be used in a variety of ways under different paradigms for various tasks. Purushotham et al. (2018) also establishes a single cohort, though with differing inclusion criteria. In contrast, Harutyunyan et al. (2019) establishes effectively four, task specific cohorts, each using different minimum duration inclusion criteria for their four tasks: in-hospital mortality; next-24 hour mortality, which they term “decompensation;” LOS prediction; and diagnostic code classification.

Output Featurization  Our system exports two possible featurizations: a “raw” featurization, which matches the input representation schema of MIMIC (at the ItemID level), and a “clinical aggregation” featurization, where outputs are bucketed together according to a manual taxonomy based on clinical knowledge (See Section 2.3 for more details). This representation induces a robustness to underlying temporal concept drift in the representation space Nestor et al. (2019). Our pipeline also performs unit conversion and optional outlier detection, similar to Purushotham et al. (2018) and Harutyunyan et al. (2019).

Output Tasks  In this work, we profile MIMIC-Extract against three classification benchmark tasks: mortality prediction (both in-hospital and in-ICU), long LOS prediction (both greater than three and seven days), and intervention onset/offset prediction (for both mechanical ventilation and vasopressor administration). Intervention onset/offset prediction has not been included in prior benchmark works by Harutyunyan et al. or Purushotham et al., and we choose to highlight it here as it is a very clinically relevant task and has a stronger temporal nature than do the other benchmark tasks analyzed, which largely have their labels sourced from a single, per-timeseries output (either mortality, LOS, or diagnostic codes), whereas an intervention may be used and weaned many times over the course of a patient’s stay. Both other tasks (mortality and long LOS prediction) have been explored historically and used in prior pipelining/benchmarking efforts; however, to the best of our knowledge neither Harutyunyan et al. nor Purushotham et al.’s works employ proper gap times when structuring these prediction tasks, risking temporal leakage of label information into the train dataset. For example, in either of the tasks with fixed 48-hour input windows, suppose a patient died at hour 48.5. It is likely that some signals of imminent decline (e.g. last-minute aggressive treatments) would be present before hour 48 and thus included as input, leading the predictor to identify what the care team obviously already knows about the patient’s poor health. This is a limitation of these tasks; in this work, all tasks presented use a temporal gap time to ensure no such label leakage.

4. Output Cohort Characterization

MIMIC-Extract defaults to extract first ICU admissions for adult patients (i.e. age > 15) only, where the lengths of stay are between 12 hours and 10 days. The resulting cohort of 34,472 patients has a diverse demographic and admission coverage, as summarized in Table 2. This cohort selection is consistent with many papers using MIMIC-III (Ghassemi et al., 2014, 2015, 2016, 2017; Suresh et al., 2017; Raghu et al., 2017; McDermott et al., 2018).

In addition to this default cohort, MIMIC-Extract provides flexibility for researchers to adjust inclusion criteria based on admission age and length of stay through simple changes of parameters. For example, researchers can define cohorts consistent with what were used in
|                  | Gender |         |         |
|------------------|--------|---------|---------|
|                  | F      | M       | Total   |
| **Ethnicity**    |        |         |         |
| Asian            | 370    | 472     | 842 (2%)|
| Hispanic         | 448    | 689     | 1,137 (3%)|
| Black            | 1,448  | 1,219   | 2,667 (8%)|
| Other            | 2,061  | 3,122   | 5,183 (15%)|
| White            | 10,651 | 13,992  | 24,643 (71%)|
| **Age**          |        |         |         |
| <30              | 748    | 1,084   | 1,832 (5%)|
| 31-50            | 2,212  | 3,277   | 5,489 (16%)|
| 51-70            | 4,888  | 8,054   | 12,942 (38%)|
| >70              | 7,130  | 7,079   | 14,209 (41%)|
| **Insurance Type**|       |         |         |
| Self Pay         | 125    | 352     | 477 (1%)|
| Government       | 402    | 648     | 1,050 (3%)|
| Medicaid         | 1,186  | 1,596   | 2,782 (8%)|
| Private          | 4,415  | 7,431   | 11,846 (34%)|
| Medicare         | 8,850  | 9,467   | 18,317 (53%)|
| **Admission Type**|      |         |         |
| Urgent           | 409    | 528     | 937 (3%)|
| Elective         | 2,282  | 3,423   | 5,705 (17%)|
| Emergency        | 12,287 | 15,543  | 27,830 (81%)|
| **First Careunit**|      |         |         |
| TSICU            | 1,777  | 2,725   | 4,502 (13%)|
| CCU              | 2,185  | 3,008   | 5,193 (15%)|
| SICU             | 2,678  | 2,842   | 5,520 (16%)|
| CSRU             | 2,326  | 4,724   | 7,050 (20%)|
| MICU             | 6,012  | 6,195   | 12,207 (35%)|
| **Total**        | 14,978 (43%) | 19,494 (57%) | 34,472 (100%) |

Table 2: Default Cohort Summary by Static Demographic and Admission Variables

Harutyunyan et al. (2019) in which there is no minimum stay requirement for the diagnosis task, only a 4 hour minimum for LOS prediction task, and a 48-hour minimum for the mortality prediction task.

More details about the distribution of various features over this cohort can also be found in Appendix B, which details, among other things, the relative rates of missingness for both the individual raw ItemIDs and the grouped clinical aggregates over this cohort.

5. Benchmark Tasks and Models

In this section, we profile several benchmark tasks, ranging in complexity, across several types of models using data extracted with MIMIC-Extract, in efforts to both provide meaningful benchmarks and baseline results for the community and to demonstrate the utility of this extraction system. Code to run these benchmarks is available in the form of Jupyter Notebooks.
We specifically endeavor to highlight tasks of varying complexity, each with a broad clinical intervention surface. Accordingly, we break our benchmarks into two low complexity tasks and one high complexity task. Our low complexity tasks are both static, binary classification tasks, each broken into two variants: mortality prediction (either in-hospital or in-ICU) and long length-of-stay (LOS) prediction (either > 3 day or > 7 day). Our high complexity task is the continuous prediction of the onset and offset of various interventions, as performed in, e.g., Suresh et al. (2017).

Notably, we do not include any tasks based on billing code prediction; while such tasks were included as benchmarks by Harutyunyan et al. (2019), and are commonly used as a target (Lipton et al., 2016; Choi et al., 2016, 2018), we argue that predicting diagnosis code is of minimal value clinically, given the lack of temporal association linking a diagnosis to a particular point in the record, and the fact that such codes are more associated with the billing of a patient than the treatment of said patients (Agniel et al., 2018).

We use a non-zero time gap between the most recent feature measurement time and a relevant forecasted event in all tasks. A gap is needed to allow practitioners time to respond to a predicted risk; suddenly warning that a patient is in instant critical need is not viable in medical practice. Additionally, time is needed to assemble care teams or fetch necessary drugs or equipment.

5.1. Mortality and Length-of-stay (LOS) Predictions

Risk prediction tasks like mortality and long LOS predictions are highlighted as benchmark tasks in both Purushotham et al. (2018) and Harutyunyan et al. (2019). Though common, they are often well-known to be relatively easy tasks, with performance saturating given only minimal data and even under relatively modest models, such as random forests (Che et al., 2018b; Nestor et al., 2019).

5.1.1. Task Definitions

We consider several varieties of these tasks, including in-ICU mortality, in-hospital mortality, LOS > 3 days prediction, and LOS > 7 days prediction. For all tasks, we use our systems clinically grouped time-varying labs and vitals features alone to predict these targets as binary classification task. In all cases, we use the first 24 hours of a patient’s data, only considering patients with at least 30 hours of present data. This 6 hour gap time is critical to prevent temporal label leakage, and must be included in any valid benchmarking tasks.

5.1.2. Data Pre-processing

For all data, values were mean centered and scaled to univariance, then imputed missing data using a variant of the “Simple Imputation” scheme outlined in (Che et al., 2018a), in which we represent each variable via a mask (1 if the value is present at this timestep, 0 otherwise), the imputed variable, and the time since the last observation of this feature (with values which have never been observed being given a sentinel large value). In particular, variable values are first forward filled and then set to individual-specific mean if there is no previous values. If the variable is never observed from the patient, its value is set to training set global mean.
5.1.3. Models Benchmarked

For all tasks, we profiled logistic regression (LR), random forest (RF), and gated recurrent unit with delay (GRU-D) (Che et al., 2018a) models. As the point of this work is not to make strong statements about the workings or efficacy of these models, but rather to introduce our extraction pipeline and demonstrate its use on benchmark tasks, we will not discuss the details of these models here, but refer the reader to external sources for more model details.

Models were tuned using random hyperparameter search under broad parameter distributions, with 60 hyperparameter samples for RF and LR models, and a variable number of samples for GRU-D (less than 60 in all cases) as GRU-D is significantly more computationally intensive. Note that this likely induces a small bias against GRU-D in these baseline results.

5.1.4. Results

Results for these models are shown in Table 3. Our AUROCs are very much in line with the literature for these tasks, showing robustly high performance for GRU-D and RF models, as expected. One interesting observation is that random forest models often have very poor F1 scores, even while maintaining competitive AUPRC scores. This may indicate that these models are more sensitive to the initial choice of threshold than are other models. Similarly, GRU-D often displays stronger performance under the AUPRC metric than the AUROC metric relative to other models, which likely speaks in its favor here given the strong rates of class imbalance in these tasks.

| Task                  | Model | AUROC | AUPRC | Accuracy | F1   |
|-----------------------|-------|-------|-------|----------|------|
| In-ICU Mortality      | LR    | 88.7  | 46.4  | 93.4%    | 38.4 |
|                       | RF    | 89.7  | 49.8  | 93.3%    | 12.6 |
|                       | GRU-D | 89.1  | 50.9  | 94.0%    | 43.1 |
| In-Hospital Mortality | LR    | 85.6  | 49.1  | 91.1%    | 42.1 |
|                       | RF    | 86.7  | 53.1  | 90.7%    | 19.6 |
|                       | GRU-D | 87.6  | 53.2  | 91.7%    | 44.8 |
| LOS > 3 Days          | LR    | 71.6  | 65.1  | 68.6%    | 59.4 |
|                       | RF    | 73.6  | 68.5  | 69.5%    | 59.5 |
|                       | GRU-D | 73.3  | 68.5  | 68.3%    | 62.2 |
| LOS > 7 Days          | LR    | 72.4  | 18.5  | 91.9%    | 7.2  |
|                       | RF    | 76.4  | 19.5  | 92.3%    | 0.0  |
|                       | GRU-D | 71.0  | 17.9  | 91.2%    | 10.7 |

Table 3: Performance Results on In-ICU Mortality, In-Hospital Mortality, > 3 Day LOS, and > 7 Day LOS. (Note that due to their additional computational overhead, GRU-D models were undersampled during hyperparameter turning as compared to LR and RF models.)
5.2. Clinical Intervention Prediction

We also use MIMIC-Extract for intervention prediction tasks. A well-executed intervention prediction can alert caregivers about administering effective treatments while avoiding unnecessary harms and costs (Ghassemi et al., 2016, 2017). In a high-paced ICU, such decision-support systems could be a fail-safe against catastrophic errors. We argue that tasks like intervention prediction have a stronger timeseries focus and are more clinically actionable. Following prior work on clinical intervention prediction (Suresh et al., 2017; Ghassemi et al., 2017, 2016), we present several models for predicting two target interventions—invasive ventilation and vasopressors.

5.2.1. Task Definitions

To make clinically meaningful predictions, we extract from MIMIC-Extract clinically aggregated outputs a sliding window of size 6 hours as input features, then predict intervention onset/offset within a 4 hour prediction window offset from the input window by a 6 hour gap window. For each intervention at each prediction window, there are 4 possible outcomes:

- **Onset** When the intervention begins off and is turned on.
- **Stay On** When the intervention begins on and stays on.
- **Wean** When the intervention begins on and is stopped.
- **Stay Off** When the intervention begins off and stays off.

5.2.2. Data Pre-processing

Time-varying lab and vital data were preprocessed in a manner similar to that described in Section 5.1, except that the “time since last measure” column was also centered and rescaled as this was found to improve performance for our neural models. We also included 5 static variables (gender, age bucket, ethnicity, ICU type, and admission type) and time-of-day as additional features.

5.2.3. Models Benchmarked

We profile LR, RF, convolutional neural network (CNN) models, and Long Short-Term Memory (LSTM) models for this task. Hyperparameters for RF and LR models were tuned via random search, whereas for CNN and LSTM models, parameters were replicated from prior work by Suresh et al. (2017).

5.2.4. Results

Model performance is summarized in Table 4.

We find that CNN and LSTM models perform very similarly to prior studies—this is notable given we do not include notes, whereas many prior studies do. RF models perform surprisingly well, outperforming CNN and LSTM models and prior results reported in the literature.
6. Pipeline Limitations and Future Work

Though highly useful, MIMIC-Extract makes a number of assumptions and simplifications which naturally induce limitations in the pipeline.

Most notable among these limitations are the features we exclude. Notable such categories include prescriptions, certain labs and vitals, various treatments/interventions, and notes. Many of these features can be externally extracted and joined to our pipeline’s output (as we demonstrate in Section 5.2 for notes), and others we excluded intentionally due to concerns about their robustness (prescriptions), but other parties may wish to extend the pipeline to enable extraction of these features. As the pipeline is open source, we endeavor to make this as easy as possible.

In addition, our timeseries coarsening into hourly buckets can also be limiting for certain tasks. By bucketing data into hourly aggregates, we lose out on a level of granularity present in the raw data and force the irregular medical timeseries into a artificially regular representation. We also lose all granularity with regards to time-of-day, which has known effects on care delivery (Agniel et al., 2018). Similarly, our clinical groupings, while highly performant, are also manually curated and limit the extensibility of the pipeline to new labs/vitals.

7. Conclusion

MIMIC-Extract is a novel, open-source cohort selection and pre-processing pipeline for MIMIC-III labs and vitals. The system produces a large, rich cohort whose data is represented according to manually defined clinically meaningful groupings which show strong performance and robustness to care practice drift. We demonstrate how MIMIC-Extract works, describe in detail its output cohort, and demonstrate its performance and extensibility on several benchmark tasks using a variety of models. Ultimately, we hope MIMIC-Extract will enable easier and faster development of novel machine learning models over the MIMIC-III data.
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Appendix A. Static Variables

| Variable     | Concept                                                      |
|--------------|--------------------------------------------------------------|
| gender       | patient gender                                               |
| ethnicity    | patient ethnicity                                            |
| age          | patient age (masked as 300 for patients who are older than 89 years old in MIMIC-III) |
| insurance    | patient insurance type                                       |
| admittime    | hospital admission time                                       |
| dischtime    | discharge time                                               |
| intime       | ICU admission time                                            |
| outtime      | ICU discharge time                                            |
| admission_type | type of hospital admission                                    |
| first_careunit | first ICU the patient was cared for                         |
### Appendix B. Feature Set

| Grouping | low        | high       | strict     | avg | std | pres.     | pres. cv     | pres. mv     | ItemID | Table     | AVG  | DB  | ItemID | AVG  |
|----------|------------|------------|------------|-----|-----|-----------|---------------|---------------|--------|-----------|------|-----|--------|------|
| alanine aminotransferase | 1.7E-04 | 1.9E-04 | 3.9E-04 | 282.3 | 916.4 | 2.0E-02 | 1.5E-02 | 2.5E-02 | 769 | chartevents | cv   | 335.1 | 984.9 | 6.7E-03 |
| albumin | 0.0E+00 | 1.9E-05 | 0.0E+00 | 3.1 | 0.7 | 1.3E-02 | 1.1E-02 | 1.5E-02 | 1521 | chartevents | cv   | 3.0 | 0.6 | 3.8E-03 |
| alkaline phosphate | 4.1E-04 | 4.1E-04 | 4.1E-04 | 123.3 | 145.6 | 1.9E-02 | 1.5E-02 | 2.4E-02 | 774 | chartevents | cv   | 126.1 | 145.6 | 6.7E-03 |
| anion gap | 1.8E-04 | 2.1E-05 | 1.4E-05 | 13.7 | 4.9 | 8.3E-02 | 6.8E-02 | 1.0E-01 | 225612 | chartevents | mv   | 120.1 | 145.6 | 6.7E-03 |
| aspartate aminotransferase | 2.1E-04 | 2.1E-05 | 4.7E-05 | 348.1 | 1239.6 | 2.0E-02 | 1.5E-02 | 2.5E-02 | 763 | chartevents | cv   | 404.3 | 1299.0 | 6.7E-03 |
| bicarbonate | 0.0E+00 | 0.0E+00 | 6.1E-06 | 24.2 | 4.7 | 8.8E-02 | 6.8E-02 | 1.0E-01 | 220443 | chartevents | mv   | 24.4 | 4.7 | 3.8E-02 |
| bilirubin | 1.2E-03 | 4.1E-05 | 2.8E-05 | 26.2 | 21.8 | 2.0E-02 | 1.5E-02 | 2.5E-02 | 781 | chartevents | cv   | 26.6 | 22.1 | 3.8E-02 |
| calcium | NAN | NAN | NAN | 8.3 | 1.9 | 7.0E-02 | 5.1E-02 | 8.6E-02 | 1162 | chartevents | cv   | 26.4 | 22.0 | 3.8E-02 |
| calcium ionized | NAN | NAN | NAN | 1.3 | 5.1 | 5.1E-02 | 4.9E-02 | 4.7E-02 | 818 | chartevents | cv   | 1.5 | 7.3 | 3.8E-02 |
| cardiac index | NAN | NAN | NAN | 2.9 | 0.8 | 3.3E-02 | 5.8E-02 | 2.6E-04 | 116 | chartevents | cv   | 2.9 | 0.8 | 3.8E-02 |
| cardiac output fick | NAN | NAN | NAN | 5.7 | 2.9 | 7.3E-03 | 1.2E-02 | 9.5E-05 | 89 | chartevents | mv   | 5.7 | 2.9 | 3.8E-02 |
| cardiac output thermodilution | NAN | NAN | NAN | 5.7 | 1.9 | 3.0E-02 | 5.0E-02 | 2.1E-04 | 99 | chartevents | cv   | 5.7 | 1.9 | 3.8E-02 |
| central venous pressure | NAN | NAN | NAN | 11.6 | 16.1 | 2.0E-01 | 2.2E-01 | 1.3E-01 | 220074 | chartevents | mv   | 11.6 | 16.1 | 3.8E-02 |
| chloride | 1.1E-05 | 1.7E-06 | 0.0E+00 | 105.2 | 6.3 | 9.6E-02 | 7.3E-02 | 1.2E-01 | 1523 | chartevents | cv   | 105.8 | 6.2 | 3.8E-02 |
| cholesterol | 4.2E-04 | 9.4E-05 | 1.9E-04 | 161.9 | 51.3 | 1.8E-03 | 1.6E-03 | 1.7E-03 | 1244 | chartevents | cv   | 158.3 | 47.4 | 3.8E-02 |
| co2 | NAN | NAN | NAN | 24.1 | 4.8 | 3.4E-02 | 5.8E-02 | 3.5E-05 | 788 | chartevents | cv   | 24.1 | 4.8 | 3.8E-02 |
| co2 (etc02, pco2, etc.) | NAN | NAN | NAN | 25.2 | 5.3 | 8.2E-02 | 8.1E-02 | 7.5E-02 | 225698 | chartevents | cv   | 25.2 | 5.2 | 3.8E-02 |
| creatinine | 1.4E-05 | 0.0E+00 | 8.5E-05 | 1.4 | 1.5 | 8.9E-02 | 7.0E-02 | 1.1E-01 | 791 | chartevents | cv   | 1.5 | 1.5 | 3.8E-02 |
| diastolic blood pressure | 0.0E+00 | 0.0E+00 | 1.3E-05 | 60.9 | 14.1 | 8.7E-01 | 8.2E-01 | 7.7E-01 | 225410 | chartevents | cv   | 60.4 | 14.1 | 3.8E-02 |
| fibrinogen | NAN | NAN | NAN | 295.6 | 175.3 | 9.4E-03 | 8.0E-03 | 1.1E-02 | 225468 | chartevents | cv   | 288.7 | 175.5 | 3.8E-02 |

**Note:** Grouping categories include low, high, strict, and average values. Pres., pres. cv, and pres. mv refer to the mean, mean of mean, and mean of median, respectively.
| ItemID | Table | DB avg | std | pres. | cv pres. | mv pres. | ItemID | Table | DB avg | std | pres. | cv pres. | mv pres. |
|--------|-------|--------|-----|-------|---------|----------|--------|-------|-------|-----|-------|---------|----------|
| 189    | chartevents | 12.5  | 7.9  | 6.7E-05 | 0.0E+00 | 3.1E-06 | 727    | chartevents | 10.4  | 6.2  | 1.7E-03 | 0.0E+00 | 7.2E-05 |
| 223835 | chartevents | 0.6   | 0.2  | 1.7E-03 | 0.0E+00 | 4.3E-02 | 113    | chartevents | 0.4   | 0.2  | 7.2E-05 | 0.0E+00 | 5.2E-04 |
| 727    | chartevents | 0.4   | 0.2  | 7.2E-05 | 0.0E+00 | 1.7E-03 | 220621 | chartevents | 0.5   | 0.2  | 6.5E-02 | 0.0E+00 | 1.1E-01 |
| 190    | chartevents | 0.5   | 0.2  | 6.5E-02 | 0.0E+00 | 1.7E-03 | 220045 | chartevents | 0.5   | 0.2  | 8.4E-01 | 0.0E+00 | 8.1E-01 |
| 198    | chartevents | 12.5  | 3.6  | 1.7E-01 | 0.0E+00 | 2.8E-01 | 1529   | chartevents | 132.8 | 52.1 | 5.1E-02 | 0.0E+00 | 7.3E-03 |
| 807    | chartevents | 144.5 | 57.8 | 6.2E-02 | 0.0E+00 | 5.8E-01 | 811    | chartevents | 135.8 | 53.8 | 6.8E-02 | 0.0E+00 | 5.8E-01 |
| 818    | chartevents | 3.0   | 3.3  | 1.2E-02 | 0.0E+00 | 1.2E-01 | 225664 | chartevents | 2.5   | 2.3  | 1.3E-02 | 0.0E+00 | 2.5E-02 |
| 225668 | chartevents | 2.9   | 3.2  | 1.0E-02 | 0.0E+00 | 3.5E-02 | 1531   | chartevents | 2.9   | 3.2  | 1.0E-02 | 0.0E+00 | 3.5E-02 |
| 226707 | chartevents | 168.8 | 13.8 | 3.4E-03 | 0.0E+00 | 8.8E-05 | 226730 | chartevents | 168.8 | 13.9 | 3.4E-03 | 0.0E+00 | 8.8E-05 |

- **Fraction inspired oxygen**: 0.46E-05 0.0E+00 2.4E-03 0.5 0.2 4.5E-02 3.0E-03 9.1E-02
- **Glucose**: 2.8E-04 0.0E+00 3.1E-06 140.5 57.2 2.3E-01 2.2E-01 2.2E-01
- **height**: 0.0E+00 8.8E-05 1.8E-04 168.8 13.8 3.5E-03 2.1E-05 7.3E-03
- **hemoglobin**: 0.0E+00 1.0E-06 6.0E-06 10.6 1.9 9.3E-02 8.0E-02 1.0E-01
- **lactic acid**: NAN NAN NAN 2.7 2.8 2.4E-02 2.0E-02 2.5E-02
- **mean blood pressure**: 2.2E-04 2.0E-05 6.1E-05 79.4 15.5 8.6E-01 8.1E-01 7.8E-01
- **oxygen saturation**: 0.0E+00 6.6E-07 3.6E-06 96.7 3.6 8.6E-01 7.9E-01 7.9E-01
- **partial pressure of carbon dioxide**: 0.0E+00 2.0E-06 2.0E-06 41.2 9.6 9.3E-02 8.1E-02 7.5E-02
- **partial pressure of oxygen**: 2.8E-04 0.0E+00 0.0E+00 145.8 84.9 4.2E-02 6.8E-02 5.9E-04
- **partial thromboplastin time**: 4.0E-04 0.0E+00 5.2E-06 41.2 9.6 9.3E-02 8.1E-02 7.5E-02
- **peak inspiratory pressure**: 3.7E-04 3.0E-04 5.5E-04 22.8 6.6 5.2E-02 4.2E-02 5.6E-02
- **ph**: 0.0E+00 2.2E-06 4.5E-06 7.4 0.1 9.1E-02 9.0E-02 8.3E-02
- **Phosphate**: 0.0E+00 1.0E-06 5.1E-06 205.0 123.4 8.5E-02 6.9E-02 9.4E-02
- **pH**: 0.0E+00 1.0E-06 5.1E-06 205.0 123.4 8.5E-02 6.9E-02 9.4E-02
| Item ID          | Table | DB | avg | std | pres. | pres. | cv | pres. | mv | avg | std | pres. | pres. | cv | pres. | mv |
|------------------|-------|----|-----|-----|-------|-------|----|-------|----|-----|-----|-------|-------|----|-------|----|
| positive end-expiratory pressure | NAN   | NAN | 0.0E+00 | 1.6E-04 | 2.1E-04 | 7.2  | 3.5  | 1.6E-02 | 1.2E-02 | 2.0E-02 | 224700 | chartevents | mv | 7.4 | 3.5 | 6.5E-03 |
| positive end-expiratory pressure set | NAN   | NAN | NAN | NAN | 6.2  | 2.9  | 6.5E-03 | 506 | chartevents | cv | 6.2 | 2.9 | 7.5 | 1.9E-02 |
| post void residual | NAN   | NAN | NAN | NAN | 205.6 | 135.0 | 1.4E-03 | 2.3E-03 | 0.0E+00 | 512 | chartevents | cv | 205.6 | 135.0 | 1.4E-03 |
| potassium | NAM   | NAM | 0.0E+00 | 9.7E-06 | 1.6E-05 | 4.1  | 0.6  | 1.1E-01 | 1.1E-01 | 9.6E-02 | 1535 | chartevents | cv | 4.1 | 0.6 | 3.2E-02 |
| potassium serum | NAN   | NAN | NAN | NAN | 4.2  | 0.7  | 1.1E-02 | 227464 | chartevents | mv | 4.2 | 0.7 | 3.5E-03 |
| prothrombin time inr | NAN   | NAN | NAN | NAN | 1.5  | 1.2  | 5.9E-02 | 5.0E-02 | 6.6E-02 | 227467 | chartevents | mv | 1.5 | 1.2 | 1.9E-02 |
| prothrombin time pt | NAN   | NAN | NAN | NAN | 16.0 | 7.0  | 5.9E-02 | 5.0E-02 | 6.6E-02 | 1286 | chartevents | cv | 15.6 | 5.8 | 1.9E-02 |
| pulmonary artery pressure mean | NAN   | NAN | 38.1 | 12.3 | 9.6E-02 | 5.0E-02 | 6.5E-02 | 227405 | chartevents | mv | 38.1 | 12.3 | 5.0E-02 |
| pulmonary artery pressure systolic | NAM   | NAM | 15.6 | 8.0  | 4.6E-02 | 4.7E-02 | 8.3E-01 | 8.0E-01 | 7.8E-01 | 227403 | chartevents | mv | 15.6 | 8.0 | 4.7E-02 |
| respiratory rate | NAN   | NAN | 15.6 | 8.0  | 4.6E-02 | 4.7E-02 | 8.3E-01 | 8.0E-01 | 7.8E-01 | 227403 | chartevents | mv | 15.6 | 8.0 | 4.7E-02 |
| respiratory rate set | NAN   | NAN | 15.6 | 8.0  | 4.6E-02 | 4.7E-02 | 8.3E-01 | 8.0E-01 | 7.8E-01 | 227403 | chartevents | mv | 15.6 | 8.0 | 4.7E-02 |
| systemic vascular resistance | NAN   | NAN | 15.6 | 8.0  | 4.6E-02 | 4.7E-02 | 8.3E-01 | 8.0E-01 | 7.8E-01 | 227403 | chartevents | mv | 15.6 | 8.0 | 4.7E-02 |
| tidal volume observed | NAM   | NAM | 0.0E+00 | 0.0E+00 | 1.1E-06 | 121.8 | 22.0 | 8.7E-01 | 8.2E-01 | 7.8E-01 | 227243 | chartevents | mv | 123.7 | 26.5 | 1.4E-04 |
| tidal volume set | NAM   | NAM | 0.0E+00 | 0.0E+00 | 1.1E-06 | 121.8 | 22.0 | 8.7E-01 | 8.2E-01 | 7.8E-01 | 227243 | chartevents | mv | 123.7 | 26.5 | 1.4E-04 |
| tidal volume spontaneous | NAM   | NAM | 0.0E+00 | 0.0E+00 | 1.1E-06 | 121.8 | 22.0 | 8.7E-01 | 8.2E-01 | 7.8E-01 | 227243 | chartevents | mv | 123.7 | 26.5 | 1.4E-04 |
| temperature | NAM   | NAM | 8.0E-06 | 0.0E+00 | 0.0E+00 | 1.1E-06 | 121.8 | 22.0 | 8.7E-01 | 8.2E-01 | 7.8E-01 | 227243 | chartevents | mv | 123.7 | 26.5 | 1.4E-04 |
| troponin-i | NAM   | NAM | 0.0E+00 | 4.1E-04 | 0.0E+00 | 7.6  | 10.7  | 9.2E-04 | 1.5E-03 | 9.1E-05 | 851 | chartevents | cv | 7.7 | 10.7 | 6.2E-04 |
| troponin-t | NAM   | NAM | 2.1E-05 | 4.7E-04 | 1.7E-04 | 0.9  | 2.2  | 1.3E-02 | 8.8E-03 | 1.7E-02 | 229749 | chartevents | mv | 0.7 | 1.9 | 5.5E-03 |
| troponin-t set | NAM   | NAM | 0.0E+00 | 0.0E+00 | 0.0E+00 | 0.0E+00 | 5.2  | 2.2  | 8.9E-03 | 2.8E-02 | 2.0E-02 | 229749 | chartevents | mv | 0.0E+00 | 0.0E+00 | 0.0E+00 |
| Grouping          | low    | high   | strict | avg | std  | pres. | pres. cv | pres. mv | ItemID | Table       | DB | avg    | std  | pres. |
|-------------------|--------|--------|--------|-----|------|-------|----------|----------|--------|-------------|----|--------|------|-------|
| venous pvo2       | NAN    | NAN    | NAN    | 41.9| 14.9 | 4.3E-04| 7.0E-04  | 1.7E-05 | 859    | chartevents | cv | 43.9   | 14.9 | 4.3E-04|
| weight            | 0.0E+00| 0.0E+00| 2.1E-04| 83.1| 23.4 | 2.8E-02| 1.3E-02  | 4.2E-02 | 763    | chartevents | cv | 84.3   | 23.0 | 8.1E-03|
|                   |        |        |        |     |      |       |          |          | 224649 | chartevents | mv | 86.3   | 23.7 | 6.9E-03|
|                   |        |        |        |     |      |       |          |          | 236512 | chartevents | mv | 80.8   | 22.5 | 6.6E-03|
|                   |        |        |        |     |      |       |          |          | 236531 | chartevents | mv | 80.7   | 23.4 | 1.0E-02|
| white blood cell count | 0.0E+00| 0.0E+00| 2.5E-06| 11.9| 10.0 | 8.1E-02| 6.5E-02  | 9.6E-02 | 861    | chartevents | cv | 12.2   | 10.0 | 3.2E-02|
|                   |        |        |        |     |      |       |          |          | 1127   | chartevents | cv | 12.2   | 10.2 | 3.1E-02|
|                   |        |        |        |     |      |       |          |          | 1542   | chartevents | cv | 12.2   | 10.4 | 2.5E-02|
### Appendix C. Intervention Set

| Intervention      | Concept                          | Mean Hours |
|-------------------|----------------------------------|------------|
| vent              | mechanical ventilation administration | 12.20      |
| vaso              | vasopressor administration       | 8.10       |
| adenosine         | adenosine administration          | 0.00       |
| dobutamine        | dobutamine administration         | 0.36       |
| dopamine          | dopamine administration           | 0.95       |
| epinephrine       | epinephrine administration        | 0.60       |
| isuprel           | isuprel administration            | 0.01       |
| milrinone         | milrinone administration          | 0.87       |
| norepinephrine    | norepinephrine administration     | 2.72       |
| phenylephrine     | phenylephrine administration      | 4.06       |
| vasopressin       | vasopressin administration        | 0.90       |
| colloid_bolus     | colloid bolus administration      | 0.16       |
| crystalloid_bolus | crystalloid bolus administration   | 1.93       |
| nivdurations      | non-invasive ventilation administration | 25.81   |