AI Gone Astray: Technical Supplement

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1 Introduction

This study is a technical supplement to "AI gone astray: How subtle shifts in patient data send popular algorithms reeling, undermining patient safety." from STAT News, which investigates the effect of time drift on clinically deployed machine learning models. We use MIMIC-IV, a publicly available dataset, to train models that replicate commercial approaches by Dascena and Epic to predict the onset of sepsis, a deadly and yet treatable condition. We observe some of these models degrade over time; most notably an RNN built on Epic features degrades from a 0.729 AUC to a 0.525 AUC over a decade, leading us to investigate technical and clinical drift as root causes of this performance drop.

2 Methods

Dataset We investigate time drift using the MIMIC-IV database [1], which includes electronic health records of over 50,000 patients admitted to the intensive care units at the Beth Israel Deaconess Medical Center (BIDMC) between the years 2008-2019. We filter for patients over the age of 15, with an ICU stay between 24 hours and 10 days, and take each patient's first ICU stay (see Figure 1). After all filtering, we end up with 50k patients in our dataset.

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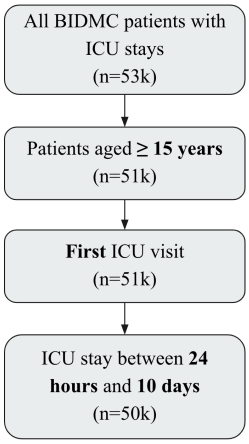

Figure 1: Cohort filtration process for MIMIC-IV

Sepsis Prediction Task Sepsis is a potentially life-threatening condition where a body's reaction to an infection triggers damage in organ systems. Following recent work [2, 3], we predict the onset of Sepsis-3 within 6 hours given 24 hours of ICU data. Sepsis-3 defines sepsis onset as an increase in SOFA-score of >= 2 points within a window of 48 hours before and 24 hours after a Suspicion of Infection, which occurs when there are concomitant orders of antibiotics and microbiological samples taken. We follow the implementation of Moor et al. [2], and use the SOFA value in the first hour of a patient's ICU stay as the baseline score for later comparisons.

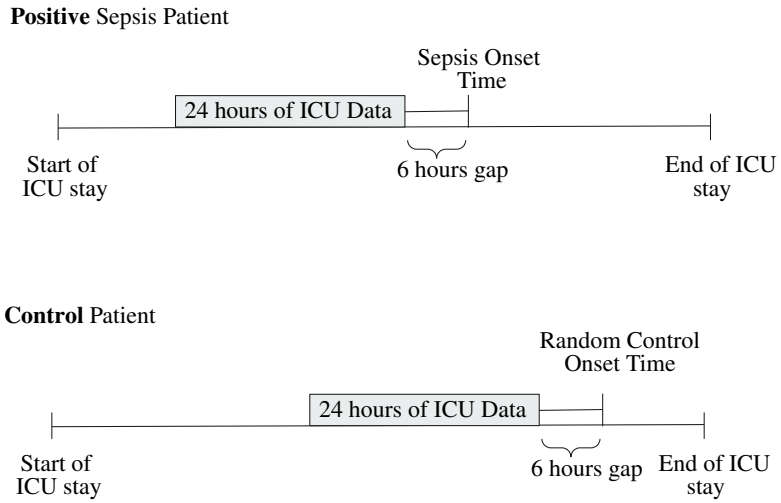

Figure 2: Top: data construction process for a positive sepsis patient, taking their first sepsis onset time during their ICU stay. Bottom: data construction process for a control patient with no sepsis onset during their ICU stay, assigning a random "onset" time for data extraction purposes.

Cohort Construction See Figure 2 for our cohort construction procedure. For patients with a positive sepsis label, the first instance of sepsis onset was taken to be the sepsis onset time. Following prior work by the Dascena group, [4], we assign a random "onset" time for control patients with no sepsis onset during their stay. For both positive and control samples, we extract 24 hours of ICU data preceding a 6 hour gap period before their onset time. We eliminate all patients with an onset

time before 6 hours. For patients who have less than 24 hours of data after extraction, we left pad all non-existent hours with zeros.

Modeling Commercial Tools We model two commercial sepsis detection systems: Dascena's [4] and Epic Systems'. Their specific model implementations are not publicly available, so we use their known features to build our own models on MIMIC-IV and experiment with different model architectures. Dascena's sepsis models include a combination of six vital signs – systolic blood pressure, diastolic blood pressure, heart rate, respiratory rate, peripheral oxygen saturation (SpO2), and temperature – and patient age. Epic's sepsis models include more than 40 high level features, generally divided into 6 categories: Demographics, Vital Signs, Recent Lab Results, Chronic Illness Diagnoses, Medication Orders, and Active Drains, Airways or Wounds.

These models leveraged two types of patient features: static demographic features, and time-varying features. For the former, one value per feature is included for each patient. For the latter, we follow prior work [5, 2] and aggregate multiple irregularly-measured values into hourly buckets for each hour of a patient's ICU stay. Vital sign measurements are aggregated by taking the average of all measurements in the hour, while events such as medication, infusions or drainages are aggregated by taking the sum across the hour. For each feature, we simply take their raw representation, as identified by each feature's unique item ID from the MIMIC-IV dataset. To account for data missingness in time-varying features, we implement simple imputation [6], which involves forward-filling each feature for each patient by hour, then concatenating binary flags for whether a feature was originally missing and another value for the time it was last recorded. A detailed list of the features we used and their Item ID's in MIMIC-IV can be found in Appendix A.

2.1 Model Details

To investigate the impact of model architecture on performance degradation, we experimented with both Logistic Regression models and Elman RNNs[7]. Reference our code repository for specific model implementation and training details.

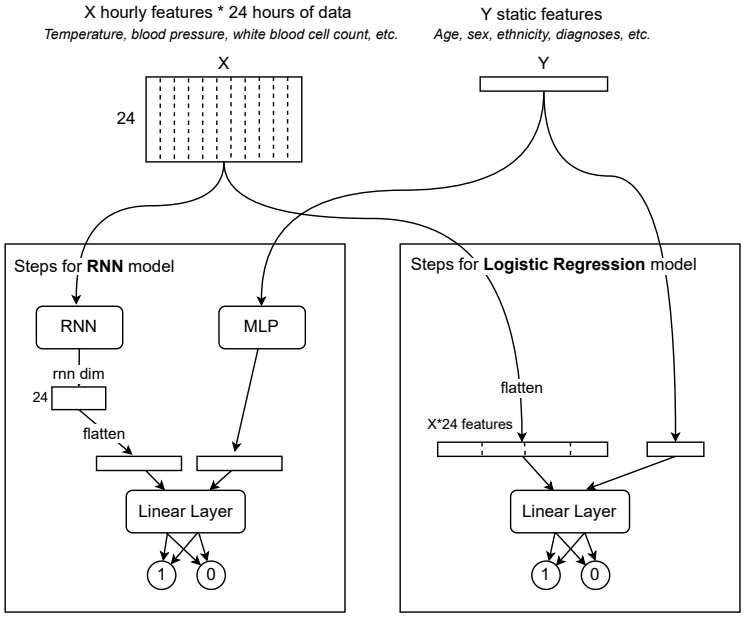

Figure 3: Model architectures for Logistic Regression and RNN models

Logistic Regression Our Logistic Regression baseline is illustrated in Figure 3. Following Nestor et al.[5]'s work, we first flatten all hourly features, treating each measurement at each hour as a separate column. We then concatenate the result with the patient's static features to form the overall feature vector for the patient. In the context of Dascena features, static features include age, and hourly

features include all vital sign measurements. In the context of Epic features, static features include demographic features and diagnoses codes, and hourly features include all vital sign measurements, medications, and lab measurements.

RNN To capture recurrent features, we implement an Elman RNN[7]. As depicted in Figure 3, static features are first fed through a separate 4-layer MLP (of 32 neurons in each layer, preceded by batch-normalization and succeeded by ReLU activation), while hourly features are fed directly through the Elman RNN. Then, the output hidden representations from the MLP are concatenated with the output hidden representations of the RNN before feeding everything through a final linear layer.

3 Experiments

3.1 Time Drift Experiments

We seek to investigate how different models replicating commercial feature sets would age in clinical settings. To understand why model performance may change over time, we investigate technical and clinical sources of data shift.

Year Agnostic Similar to common model development practices, we report numbers from models trained and tested on the full set of MIMIC-IV patient data from 2008-2019, with patients randomly assigned to either training, validation or testing regardless of the year of care.

Year Buckets To measure temporal model drift, we train on a subset of patient data in the 2008-2010 bucket, then test on patient data from the unseen portion of the 2008-2010 bucket as well as the entirety of the data in the subsequent three year buckets 2011-2013, 2014-2016, and 2017-2019.

3.2 Investigating Cause of Time Drift

We investigate two causes of model drift: technical drift, and data drift. To investigate technical drift, we analyzed the effect of Beth Israel's switch in use of diagnoses codes from ICD-9 to ICD-10 in October 2015. We investigate the impact of these changing codes on model performance by removing all features from the Epic feature set that rely on ICD codes (HIV, obesity, coronary artery disease, congestive heart failure, chronic obstructive pulmonary disease, chronic kidney disease, chronic liver disease, diabetes, and hypertension), and retraining a new model with all other hyper-parameters kept constant. To investigate data shift over time, we plotted sepsis onset times, microbiology samples, and antibiotic usage trends over the years.

4 Results

We ran each combination of feature set, model, and training regime three times to measure the models' performance. The average AUCs from the three runs are reported in Tables 1 and 2. Overall, we observe a large drop in performance for models trained on the Epic feature set, especially the RNN. The models trained on the Dascena model also experienced some performance degradation, but on a much smaller scale.

4.1 Time Drift Experiments

		Year Buckets			
Model	Year-Agnostic	2008-2010	2011-2013	2014-2016	2017-2019
Dascena Features					
RNN	0.764	0.723	0.726	0.730	0.707
Logistic	0.731	0.687	0.696	0.682	0.640
Epic Features					
RNN	0.787	0.729	0.723	0.578	0.525
Logistic	0.724	0.706	0.701	0.679	0.626

Table 1: Time agnostic and year bucket results (average test AUCs of three runs) from RNN and Logistic Regression models trained on the Epic and Dascena feature sets.

We observe in Table 1 that the models trained on Epic's feature set dropped from 0.729 to 0.525 for the RNN model, and from 0.706 to 0.626 for the Logistic Regression model. This amounts to a 0.08 to 0.20 difference in test AUC over the years. These results indicate that several Epic features vary over time. In contrast, models built on Dascena features, which contain mainly vital signs, perform significantly better over time. We found a small temporal drop in AUC from 0.723 to 0.707 for the RNN model and a slightly larger AUC drop from 0.687 to 0.640 for the Logistic Regression model. In addition, we note that the choice in model architecture impacts performance drop, as we found that there is a much larger drop for the RNN model than the Logistic Regression model trained on Epic's feature set, while the opposite was true for models trained on the Dascena feature set. We also include results for two additional time drift experiments, Length of Stay and ICU Mortality prediction, in Appendix B.

4.2 Time Drift Investigations

		Year Buckets			
Model	Year-Agnostic	2008-2010	2011-2013	2014-2016	2017-2019
RNN	0.783	0.716	0.731	0.721	0.671
Logistic	0.669	0.715	0.702	0.692	0.633

Table 2: Average test AUCs from models trained on the Epic feature subset without ICD codes.

Technical Change Investigation In Table 2, we report the results of models trained on a subset of the Epic feature set without ICD codes. We found that without the ICD codes, the AUC drop across the entire time period is now 0.08 for the Logistic Regression model and 0.045 for the RNN. Compared to the RNN model trained on the full Epic feature set, this represents a significant improvement of around 0.15 for the last year bucket. Because models trained on the first year bucket only observed ICD-9 codes, they were unable to leverage ICD-10 features when the transition occurred.

We notice that the introduction of the ICD codes did not contribute to higher overall model performance, as seen by the year-agnostic numbers in Table 1 and Table 2. However, the inclusion of these features instead led to significant model degradation.

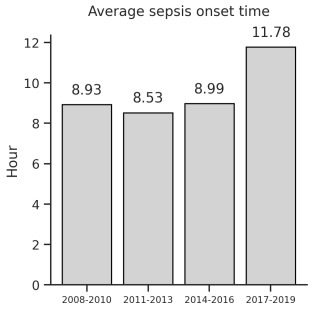

Figure 4: Sepsis onset time in the ICU by year bucket groups.

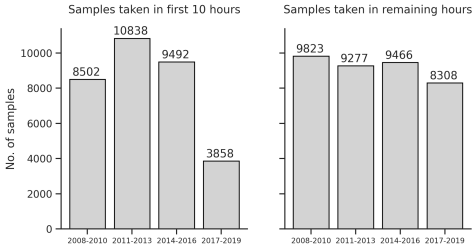

Figure 5: Microbiology samples across year buckets and time into ICU stay.

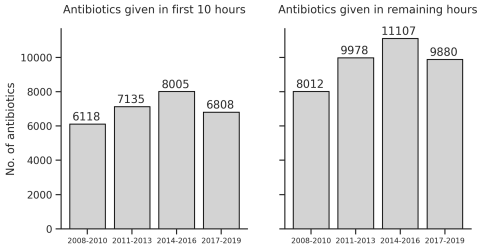

Figure 6: Antibiotics administered across year buckets and time into ICU stay.

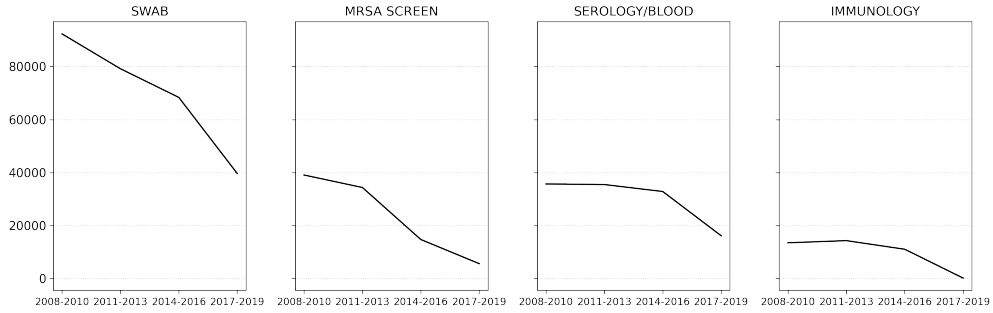

Figure 7: Microbiological culture types with the largest drop in number of samples taken across year bucket groups.

Specimen Type	2008-2010	2011-2013	2014-2016	2017-2019	Change	% Change
SWAB	92304	79169	68363	39677	-52627	-57%
MRSA SCREEN	39086	34375	14766	5657	-33429	-86%
BLOOD CULTURE	171630	158924	163711	144620	-27010	-16%
SPUTUM	52437	39027	40078	32135	-20302	-39%
SEROLOGY/BLOOD	35713	35489	32866	16187	-19526	-55%
STOOL	47316	38649	38166	28502	-18814	-40%
IMMUNOLOGY	13524	14336	11085	209	-13315	-98%
URINE	221335	211626	263363	234576	+13241	+6%
BONE MARROW - CYTOGENETICS	7442	3643	5	0	-7442	-100%
TISSUE	21455	26311	32957	28481	+7026	+33%
Immunology (CMV)	5921	5278	4285	42	-5879	-99%
CATHETER OR LINE	6862	3653	2014	1397	-5465	-80%
CSF;SPINAL FLUID	10725	8527	8601	6333	-4392	-41%
BRONCHIAL WASHINGS	2214	2577	5087	6442	+4228	+191%
Influenza A/B by DFA	4214	2771	532	0	-4214	-100%
ABSCESS	9597	11657	12734	13796	+4199	+44%
Blood (LYME)	0	4	2414	3815	+3815	+100%
PLEURAL FLUID	7560	7560	8834	9826	+2266	-30%
BRONCHOALVEOLAR LAVAGE	12772	10930	13205	10523	-2249	-18%
Staph aureus Screen	3609	9151	11949	5608	1999	+55%

Table 3: Specimen types with greatest absolute change between 2008-2010 and 2017-2019 year buckets. "Change" and "% Change" refers to the difference between the first and the last year buckets.

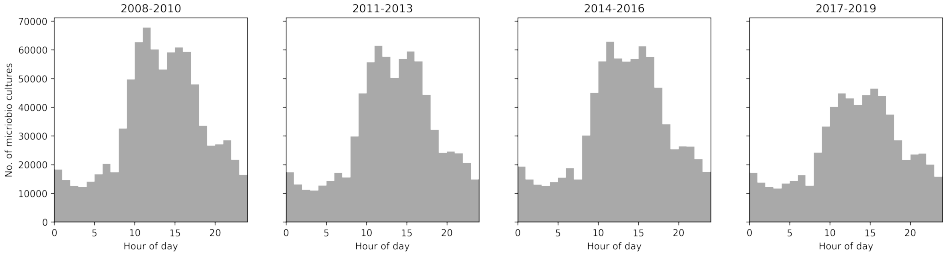

Figure 8: Amount of cultures drawn for each hour of the day, per year-bucket.

Data Change Investigation We plot all data changes in Figures 4-8 and Table 3. While we see no major changes in antibiotics administered, we see a large increase in average sepsis onset time from 9 hours to 12 hours by the last year bucket, accompanied by a drop in microbiology samples taken within the first 10 hours of a patient's ICU stay. Figure 7 shows a select few of the microbiological sample types with the largest changes across the years, and Table 3 shows the full numbers in detail. Since the definition of Sepsis-3 onset depends on a suspicion of infection, which is influenced by the timing of microbiology samples, we observe that these two changes are related. Finally, Figure 8 shows that the drop in number of samples occurs mainly during daytime hours (between 9 AM and 5 PM).

Clinical sources we interviewed explained that changing hospital demographics, caused by multiple new hospital acquisitions and partnerships, in recent years could have been the cause of changing clinical practices around microbiology sampling and other ICU procedures.

5 Conclusion

By replicating commercially produced sepsis prediction models on the MIMIC-IV dataset, we were able to observe the extent of model degradation over time. We found a significant AUC drop of 0.08 to 0.20 for models trained on the Epic feature set, while a smaller drop of 0.02 to 0.05 was observed

for models trained on the more stable Dascena feature set. We concluded that the technical shift of changing ICD codes from ICD-9 to ICD-10 in 2015 was a major cause of degradation in the former models, as the performance drop diminished by 0.15 after the models were retrained without ICD codes. Finally, we observed a data shift in later years from changing microbiology sampling practices in the ICU, which had an impact on delaying sepsis onset times in the last year bucket.

Limitations There are several limitations to this study. First, because the Epic and Dascena models are not publicly available, we trained our models leveraging their published feature sets on MIMIC-IV. These features can be found in Appendix A. Our results do not directly reflect the performance of Epic or Dascena's commercial models. Second, this study does not account for possible model retraining procedures a hospital could undertake to diminish the impact of model degradation in clinical settings.

Acknowledgements

We are grateful to BIDMC, the MIMIC team, Leo Anthony Celi and Brian Gow for their support of this project.

Data and Code Availability

The MIMIC-IV dataset is freely available provided you have completed CITI certification. It can be downloaded from `https://physionet.org/content/mimiciv/1.0/`.

All code used to reproduce the results in this report (including instructions on how to do so) is openly available at `https://github.com/mariehane/ai-gone-astray`.

References

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A Feature Lists and Origin Categories

Below are the features we found in MIMIC-IV that best approximate the feature categories used by Dascena and Epic's models, given that their code is not publicly available. For Epic's feature set, we were unable to find certain feature results in the MIMIC database, including medicines administered by category and the exact mapping of ICD codes for all diagnoses used.

A.1 Dascena Features

High-level feature	Itemid	Low-level label	Origin
diastolic blood pressure	8441	nbp [diastolic]	chartevents
	8368	arterial bp [diastolic]	chartevents
	220180	non invasive blood pressure diastolic	chartevents
	220051	arterial blood pressure diastolic	chartevents
	225310	art bp diastolic	chartevents
	8555	arterial bp #2 [diastolic]	chartevents
	8440	manual bp [diastolic]	chartevents
	224643	manual blood pressure diastolic left	chartevents
systolic blood pressure	455	nbp [systolic]	chartevents
	51	arterial bp [systolic]	chartevents
	220179	non invasive blood pressure systolic	chartevents
	220050	arterial blood pressure systolic	chartevents
	225309	art bp systolic	chartevents
	6701	arterial bp #2 [systolic]	chartevents
	442	manual bp [systolic]	chartevents
	224167	manual blood pressure systolic left	chartevents
	227243	manual blood pressure systolic right	chartevents
heart rate	211	heart rate	chartevents
	220045	heart rate	chartevents
temperature	678	temperature f	chartevents
	677	temperature c (calc)	chartevents
	223761	temperature fahrenheit	chartevents
	679	temperature f (calc)	chartevents
	676	temperature c	chartevents
	223762	temperature celsius	chartevents
respiratory rate	618	respiratory rate	chartevents
	220210	respiratory rate	chartevents
	615	resp rate (total)	chartevents
	614	resp rate (spont)	chartevents
	224689	respiratory rate (spontaneous)	chartevents
	224690	respiratory rate (total)	chartevents
	651	spon rr (mech.)	chartevents
	224422	spont rr	chartevents
oxygen saturation	646	spo2	chartevents
	220277	o2 saturation pulseoxymetry	chartevents
	834	sao2	chartevents
	220227	arterial o2 saturation	chartevents

Table 4: Full Dascena feature set

A.2 Epic Features

Feature	Origin
age	patients
ethnicity	admissions
martial status	admissions
gender	patients

Table 5: Static demographical features used by Epic's model

High-level feature	Itemid	Low-level label	Origin
creatinine	791	creatinine (0-1.3)	chartevents
	1525	creatinine	chartevents
	220615	creatinine	chartevents
heart rate	211	heart rate	chartevents
	220045	heart rate	chartevents
hematocrit	813	hematocrit	chartevents
	220545	hematocrit (serum)	chartevents
hemoglobin	814	hemoglobin	chartevents
	220228	hemoglobin	chartevents
platelets	828	platelets	chartevents
	227457	platelet count	chartevents
red blood cell count	833	rbc	chartevents
respiratory rate	614	resp rate (spont)	chartevents
	615	resp rate (total)	chartevents
	618	respiratory rate	chartevents
	651	spon rr (mech.)	chartevents
	220210	respiratory rate	chartevents
	224422	spont rr	chartevents
	224689	respiratory rate (spontaneous)	chartevents
	224690	respiratory rate (total)	chartevents
respiratory rate set	619	respiratory rate set	chartevents
	224688	respiratory rate (set)	chartevents
temperature	676	temperature c	chartevents
	677	temperature c (calc)	chartevents
	678	temperature f	chartevents
	679	temperature f (calc)	chartevents
	223761	temperature fahrenheit	chartevents
	223762	temperature celsius	chartevents
white blood cell count	861	wbc (4-11,000)	chartevents
	1127	wbc (4-11,000)	chartevents
	1542	wbc	chartevents
	220546	wbc	chartevents
Band neutrophils	51144	Bands	labevents
Base excess	50802	Base Excess	labevents
Lymphocyte	51244	Lymphocytes	labevents
Mean corpuscular hemoglobin concentration	51249	MCHC	labevents
Monocytes	51254	Monocytes	labevents
Neutrophils	51256	Neutrophils	labevents
Nucleated red blood cell count	51257	Nucleated Red Cells	labevents
Red Blood Cell morphology	52171	RBC Morphology	labevents
Red Blood Cell distribution width	52204	RBCDist	labevents
reticulocyte count	51282	Reticulocyte Count, Absolute	labevents
Segmented neutrophil count	51232	Hypersegmented Neutrophils	labevents

High-level feature	Itemid	Low-level label	Origin
Peripherally inserted central catheters	224264	PICC Line	procedureevents
Central venous catheters	225315	Tunneled (Hickman) Line	procedureevents
Drains	225447	percutaneous drain insertion	procedureevents
	225456	ventricular drain	procedureevents
	226475	intraventricular drain inserted	procedureevents
	229523	subdural drain	procedureevents
	229524	lumbar drain	procedureevents
Feeding tube	224007	gi #1 intub site	chartevents
	224441	gi #2 intub site	chartevents
	224442	gi #3 intub site	chartevents
Incision	227472	incision site #1	chartevents
	227473	incision site #2	chartevents
	227474	incision site #3	chartevents
	227475	incision site #4	chartevents
	227476	incision site #5	chartevents
	227477	incision site #6	chartevents
	228559	incision #1- location	chartevents
	228560	incision #2- location	chartevents
	228561	incision #3- location	chartevents
	228562	incision #4- location	chartevents
	228563	incision #5- location	chartevents
	228564	incision #6- location	chartevents
	229015	incision #7- location	chartevents
	229016	incision #8- location	chartevents
	229017	incision #9- location	chartevents
	229018	incision #10- location	chartevents
Pressure Ulcers	228506	pressure ulcer #1- location	chartevents
	228507	pressure ulcer #2- location	chartevents
	228508	pressure ulcer #3- location	chartevents
	228509	pressure ulcer #4- location	chartevents
	228510	pressure ulcer #5- location	chartevents
	228511	pressure ulcer #6- location	chartevents
	228512	pressure ulcer #7- location	chartevents
	228513	pressure ulcer #8- location	chartevents
	228514	pressure ulcer #9- location	chartevents
	228515	pressure ulcer #10- location	chartevents
Active penicillin orders	008880	Penicillin V Potassium	prescriptions
	043350	Penicillin G Benzathine	prescriptions
Active vancomycin orders	043952	Vancomycin	prescriptions
	009331	Vancomycin	prescriptions
	009328	Vancomycin	prescriptions
	009329	Vancomycin	prescriptions
	067111	Vancomycin	prescriptions
	020611	Vancomycin	prescriptions

Table 6: Time-varying Epic features.

Feature	ICD Code	ICD Version	Origin
Diabetes	E11	ICD-10	diagnoses_icd
	E10	ICD-10	diagnoses_icd
Hypertension	I10	ICD-10	diagnoses_icd
HIV	42	ICD-9	diagnoses_icd
	B20	ICD-10	diagnoses_icd
Obesity	27800	ICD-9	diagnoses_icd
	E66	ICD-10	diagnoses_icd
Coronary Artery Disease	41400	ICD-9	diagnoses_icd
	I251	ICD-10	diagnoses_icd
Congestive Heart Failure	I502	ICD-10	diagnoses_icd
	I503	ICD-10	diagnoses_icd
	I504	ICD-10	diagnoses_icd
Chronic Obstructive Pulmonary Disease (COPD)	J44	ICD-10	diagnoses_icd
Chronic Kidney Disease	I13	ICD-10	diagnoses_icd
	I12	ICD-10	diagnoses_icd
Chronic Liver Disease	5719	ICD-9	diagnoses_icd
	K76	ICD-10	diagnoses_icd

Table 7: Epic features based on ICD-codes.

B Other Prediction Tasks

To validate our results of temporal drift with Nestor et al.'s [5] experiments on MIMIC-III, we followed a similar setup to run experiments on Length of Stay and ICU Mortality prediction tasks on MIMIC-IV, with results in Table 8 and Table 9. The length of stay prediction task involves taking the first 24 hours of data of a patient's stay in the ICU, and predicting whether this patient's specific stay in the ICU would last >= 3 days (a binary prediction task). The ICU mortality task uses the same feature set as the LOS prediction task, and likewise uses the first 24 hours of data of a patient's ICU stay to predict whether a patient would die in the ICU during this particular stay. The features used for both prediction tasks were the same 8 demographic variables and 141 vital signs from the chartevents table used by Nestor et al.

B.1 Length-of-stay (LOS) Results

		Trained on 2008-2010			
Model	All data	2008-2010	2011-2013	2014-2016	2017-2019
RNN	0.658	0.661	0.635	0.623	0.564
Logistic	0.601	0.620	0.600	0.585	0.549

Table 8: Results from Length-of-stay prediction on MIMIC-IV, trained on raw data representations

B.2 ICU Mortality Results

		Trained on 2008-2010			
Model	All data	2008-2010	2011-2013	2014-2016	2017-2019
RNN	0.830	0.745	0.760	0.776	0.777
Logistic	0.680	0.696	0.684	0.693	0.690

Table 9: Results from ICU Mortality prediction on MIMIC-IV, trained on raw data representations