Experiment Log 10.11~

1 Overall plan

1.1 Current stage

- Choose a well studied downstream task (mortality prediction, length-of-stay prediction), select features, form a sub-dataset by joining tables and filtering (refer to MIMIC docs)
- Build an NN for it (better easy to perform DD on, e.g. temporal convolutional network)
- Get a distilled dataset **that has the same structure as the original selected sub-dataset**
- Evaluate the DD on traditional classifiers as well as NN on the same objective

1.2 Future work

- Try different DD strategies
- Explore how to perform DD with traditional classifiers

2 Preliminary verification

2.1 Problem setup

- **Objective**: In-hospital mortality prediction based on the first 48hr of an ICU stay
- **Data**: ~20 selected features (variables), all in tabular format, from MIMIC (III or IV)
- **Motivation**:
    - Mainly inspired by the foundamental benchmark study on MIMIC-III: H. Harutyunyan et al. - Multitask learning and benchmarking with clinical time series data (2019)
    - Mortality is a primary outcome of interest in acute care: ICU mortality rates are the highest among hospital units (10% to 29% depending on age and illness), and early detection of at-risk patients is key to improving outcomes
    - The study selected out only **17** variables for all the 4 tasks, including mortality prediction, which is a relatively simple selected sub-dataset

Variable	MIMIC-III table	Impute value	Modeled as
Capillary refill rate	chartevents	0.0	categorical
Diastolic blood pressure	chartevents	59.0	continuous
Fraction inspired oxygen	chartevents	0.21	continuous
Glascow coma scale eye opening	chartevents	4 spontaneously	categorical
Glascow coma scale motor response	chartevents	6 obeys commands	categorical
Glascow coma scale total	chartevents	15	categorical
Glascow coma scale verbal response	chartevents	5 oriented	categorical
Glucose	chartevents, labevents	128.0	continuous
Heart Rate	chartevents	86	continuous
Height	chartevents	170.0	continuous
Mean blood pressure	chartevents	77.0	continuous
Oxygen saturation	chartevents, labevents	98.0	continuous
Respiratory rate	chartevents	19	continuous
Systolic blood pressure	chartevents	118.0	continuous
Temperature	chartevents	36.6	continuous
Weight	chartevents	81.0	continuous
pH	chartevents, labevents	7.4	continuous

- For MIMIC-III, H. Harutyunyan et al. provided the code base; doing the similar thing on MIMIC-IV should not be too hard

2.2 Data processing

2.2.1 Feature selection

Useing the exact same pipeline of H. Harutyunyan et al., we have:

- **Size**
  - ~18k training subjects / stays
  - ~3k evaluating subjects / stays
- **Format**
  - Episodes (ICU stays) of **time series** of 48hr events, without a fixed sample rate (new timestamp is added each time a new lab/chart event happens)

Hours	Capillary refi	Diastolic blo	Fraction insp	Glascow com	Glascow com	Glascow com	Glascow com	Glucose	Heart Rate	Height	Mean blood	Oxygen satu	Respiratory r	Systolic bloo	Temperature	Weight	pH
0.9013888888888889													18				
1.3180555555555555		126	0.5								138		0	177			
1.3347222222222221												100					
1.3513888888888888									107				19				
1.4513888888888888			1										0				
1.4847222222222222								196									6
1.7847222222222222									113				16		35.77777777777778		
1.9013888888888888		89							108		102	98	14	154			
2.0847222222222222				To Pain	Localizes Pain		No Response-ETT										
2.2013888888888889																	7.31
2.9013888888888889		94							98		108	98	20	147			
3.1513888888888889									98			97	19		36.111111111111114		
3.2680555555555557		108									118			152			
3.3680555555555556											127						
3.3847222222222224		108												154			
3.4013888888888889		110							98		127	94	18	155	36.111111111111114		
3.7013888888888889																	7.33
3.9013888888888889		119		To Pain	Flex-withdraws		No Response-ETT		99		135		18	160	36.22222222222222		
3.9180555555555556												94					
4.118055555555555			0.5										22				
4.6513888888888889		104							88		118	100	22	141	36.111111111111114		
4.9013888888888889		100							87		89		22	137	36.333333333333336		
5.4513888888888888												96					
5.7347222222222222																	7.36
5.9013888888888889		109							86		98	100	22	153	36.166666666666664		
6.9013888888888889		111							78		127	100	22	158			
7.9013888888888889		120	0.5	To Pain	Flex-withdraws		No Response	135	85		133	100	22	163	36.44444444444444		
8.90138889		106		Spontaneous	Obeys Commands		No Response-ETT		78		129	100	22	169			
9.634722222222223																	7.48
9.90138889		101							67		123	100	22	159			
10.901388888888889		101							70		123	100	18	161	36.55555555555556		
11.901388888888889		92		To Pain	Localizes Pain		No Response-ETT		66		115	100	18	158	36.5		
12.084722222222222																	7.43
12.901388888888889		98							67		124	100	18	165			
13.401388888888889			0.5										16				
13.901388888888889		103						175	78		130	100	16	170	37.5		
14.484722222222222																	7.37
14.901388888888889		89							74		108	100	16	150			
15.901388888888889		92	0.5	To Speech	Obeys Commands		No Response-ETT		73		111	100	16	151			

  - Episode-level information (patient age, gender, ethnicity, height, weight) and outcomes (mortality, length of stay, diagnoses) are also available

- **Balance**
  - ~86% negative (safe)
  - ~14$ positive (mortality)

2.2.2 Preprocess

1. Resample: just like in the original paper, **resample** the timeseries to a fixed sample rate (1h), so that the length is unified
2. Recover missing variables: recover by **imputation** (forward filling), add mask columns for each feature column, representing whether the datapoint is imputed or real
3. Normilize each column using **Z-score normalization**
4. Each tensor is sized 48 (time steps) * 59 (num features, mask columns included)

2.3 Model

Mainly 2 types models to do the binary classification:

- `1DCNN`: 1-D CNN, with 2 conv layers and 2 fc layers (given that the temporal data has 1-D translational invariance)
- `MLP`: 3 fc layers

2.4 Experiments

2.4.1 Model capacity verification

This stage is to verify whether the dataset is good, and whether the model trained on train set can generalize onto test set.

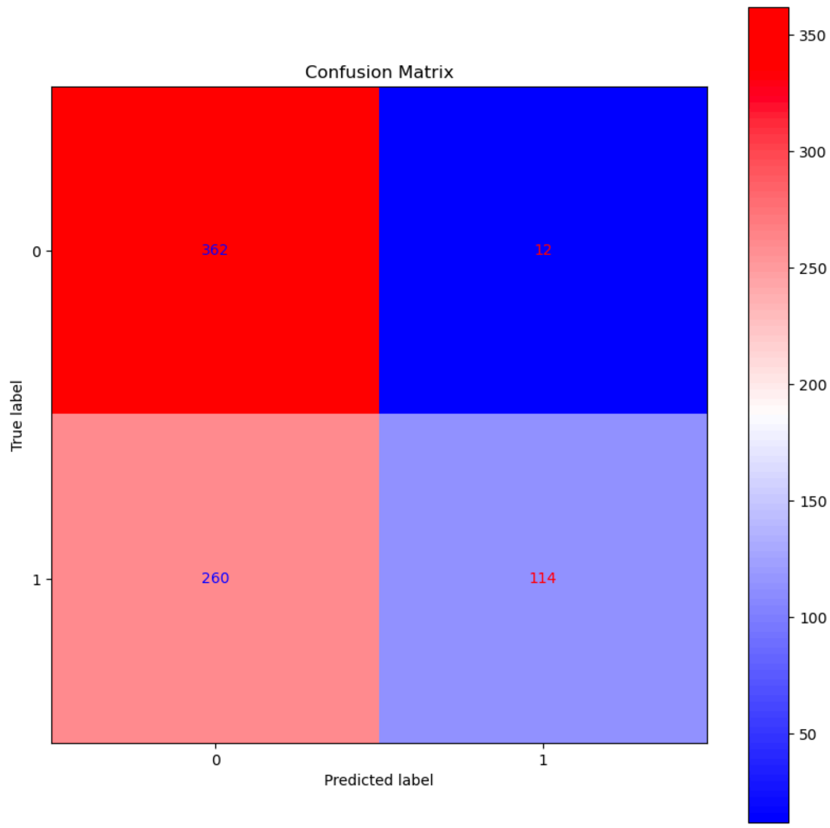
Training setup:

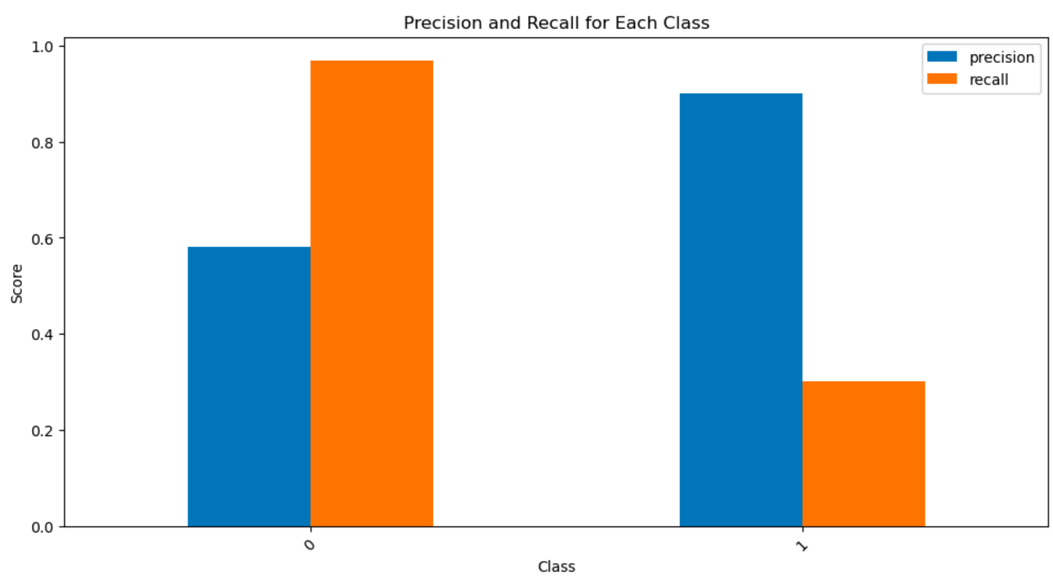
- lr = 0.001
- Optimizer = Adam
- Epoch = 100
- Data = unbalanced

On both models, test loss stops to decrease within 3 epochs, and then rise all the way up, which points to **severe overfitting**.

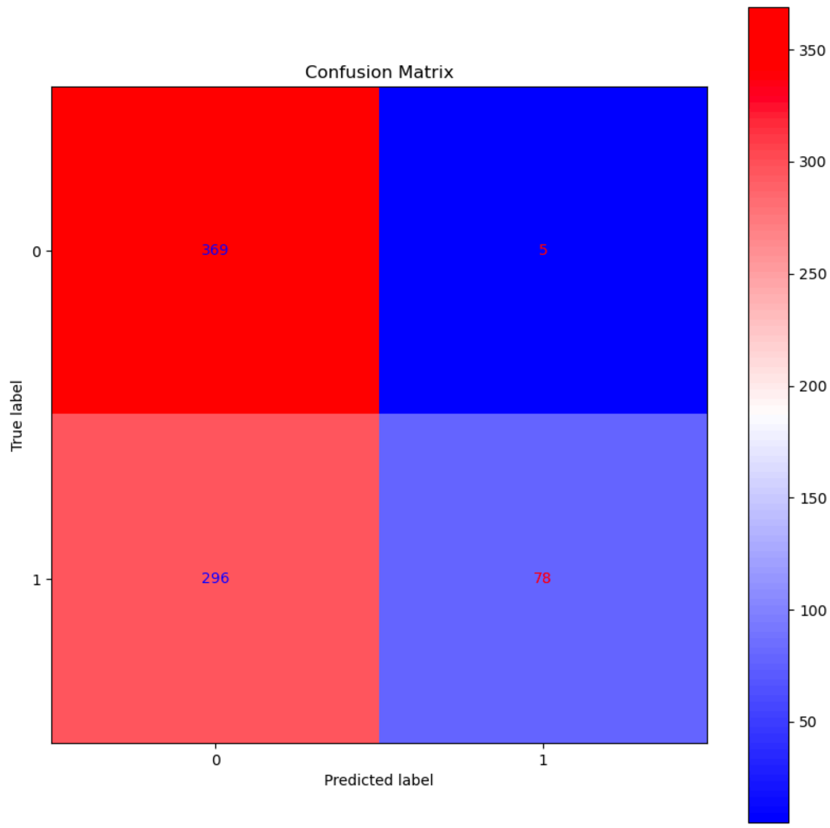
Pick the best performing epoch (overall acc ~90%), generate a classfication report, on a **balanced test set**:

1DCNN:

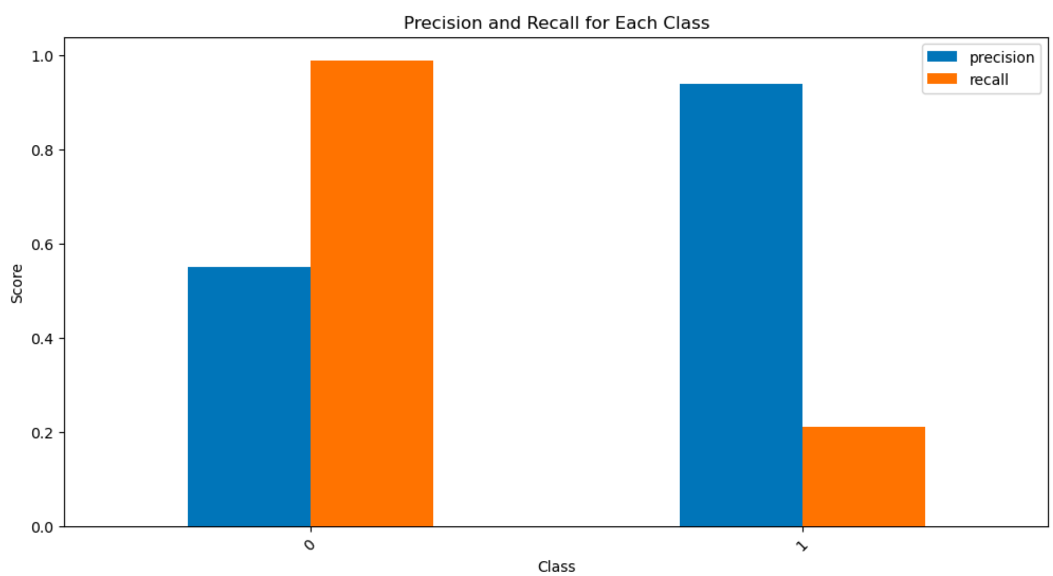

Confusion Matrix
True label
Predicted label
0
1
362
12
260
114
350
300
250
200
150
100
50


Precision and Recall for Each Class
Score
Class
precision
recall
0.0
0.2
0.4
0.6
0.8
1.0
0
1

MLP:



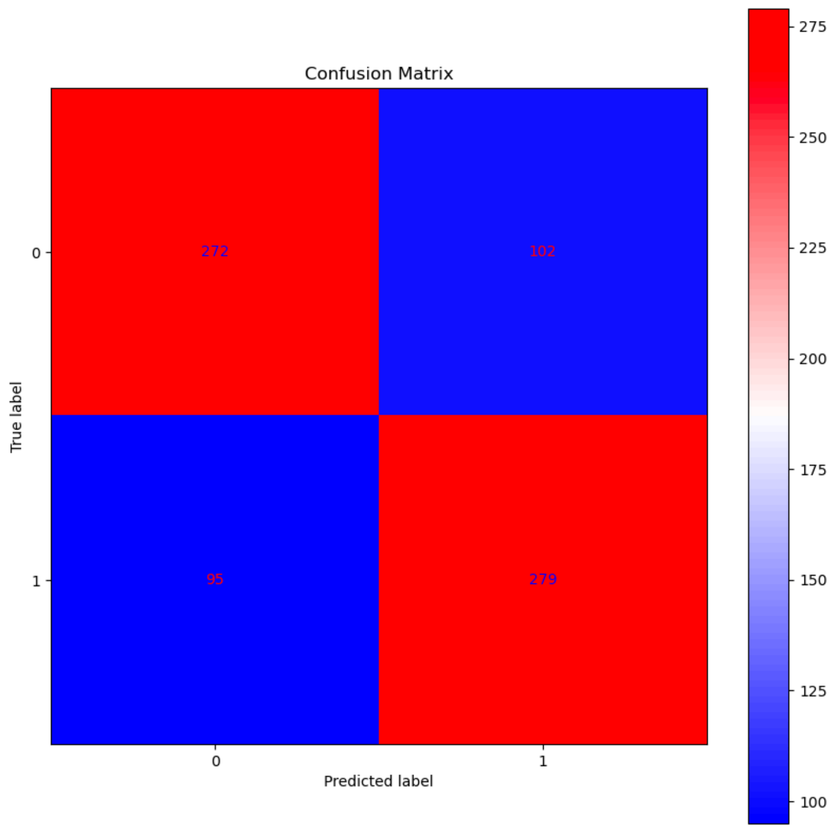
Confusion Matrix
369
5
296
78
0
1
True label
Predicted label
350
300
250
200
150
100
50

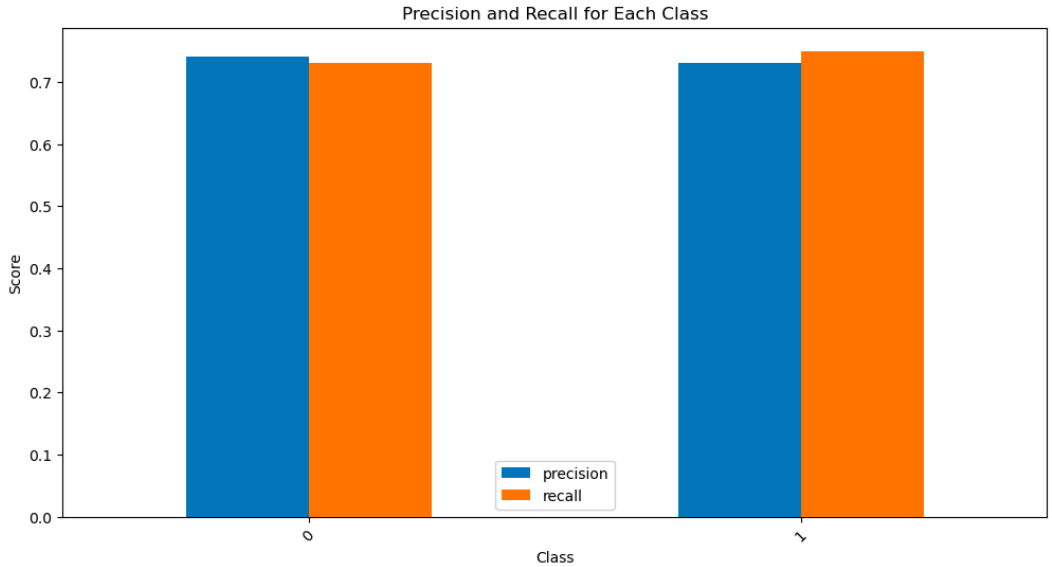


Precision and Recall for Each Class
precision
recall
Score
Class
0
1
0.0
0.2
0.4
0.6
0.8
1.0

Further moves

- After configuring `weight_decay` to Adam (which allows L2 regularaztion), the overfitting is postponed, but not improving the best performance on test set (loss ~0.27)
- After taking out mask columns from training data, performance is slightly better (loss ~0.26)
- Also tried **training on balanced training set** and **evaluating on balanced test set** (by under-sampling)
    - Test acc is up to ~72%, which better than random guess for binary classification, but not impressive
    - Still suffer from overfitting: test loss starts to rise at around epoch 3





Observation summary

- Models generally suffer from overfitting
- Maybe the data itself just isn't good enough

2.4.2 Synthetic dataset distillation

Distilled dataset using Matching Gradients, 100 iterations.

Evaluate by:

- Train 2 models simultaneously, syn model trained on synthetic dataset, and real model trained on real dataset (balanced)
- Both models are evaluated (computing loss and accuracy) on real dataset after each epoch
- Compare both models' performance
- Result: syn model isn't learning anything, acc near 0.5 (random guess)

Next move

Vanilla dataset distillation ("train on synth, val on real, backward loss all the way to the synth data"): working on this