



SubTab

Subsetting Features of **Tab**ular Data for
Self-Supervised Representation Learning

Talip Uçar

Ehsan Hajiramezanali

Lindsay Edwards



Outline

I. Abstract

- ☐ Summary of our work

II. Motivation / Background

- ☐ Comparing data types
- ☐ Challenges in tabular data
 - ☐ Data augmentation
 - ☐ Parameter sharing

III. SubTab

- ☐ Framework
- ☐ Results
- ☐ Applications
- ☐ Summary



Abstract

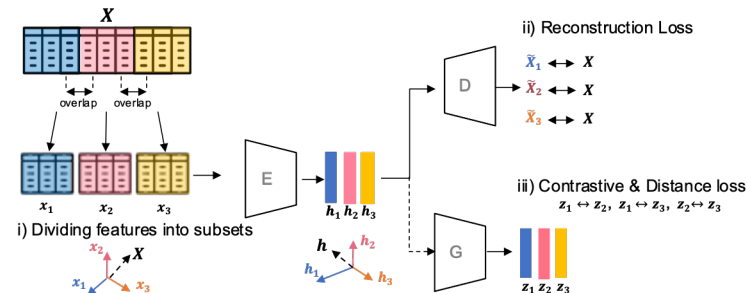
Problem:

- ❑ It is not easy to design effective data augmentation methods in tabular domain
- ❑ Self-supervised representation learning in tabular data is understudied:
 - ❑ Lack of effective data augmentation methods
 - ❑ Lack of specialized architectures for tabular data

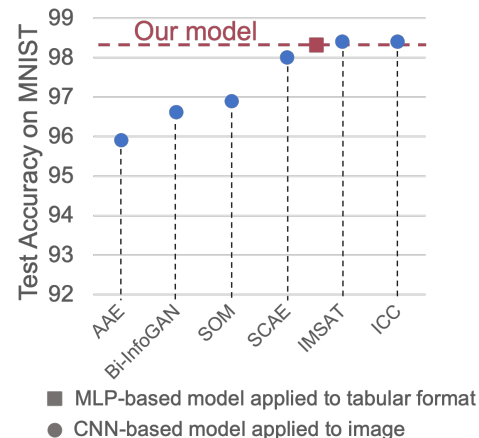
Our work - SubTab:

- ❑ Introduces effective methods for tabular data
- ❑ Achieves 98.31%, **the state of the art (SOTA)**, on MNIST data in tabular format.
- ❑ Makes a simple MLP-based model perform on par with CNN-based SOTA models

SubTab:



Result on MNIST:



Motivation / Background

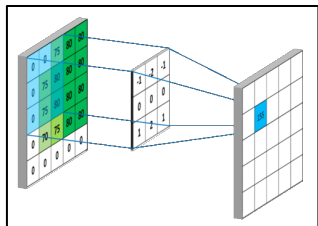


Types of Data

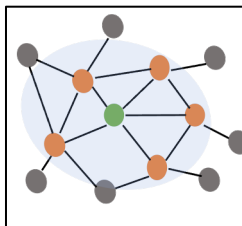
Tabular Data

Age	Gender	BMI	Insulin	...
50	M	26.6	0	...
31	F	33.6	94	...

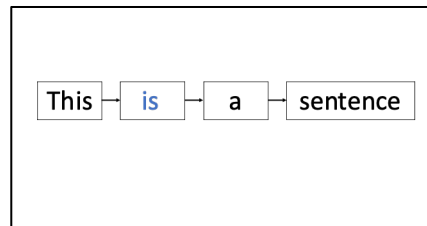
Images



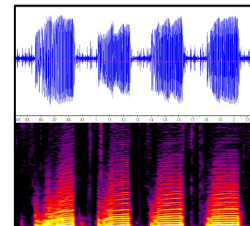
Graph



Text



Audio



?

- ☐ Sequence of pixels
- ☐ CNNs*
- ☐ Parameter sharing

- ☐ Neighboring nodes
- ☐ GNNs
- ☐ Parameter sharing

- ☐ Sequence of words
- ☐ LSTMs*
- ☐ Parameter sharing

- ☐ Sequence of samples
- ☐ CNNs / LSTMs*
- ☐ Parameter sharing

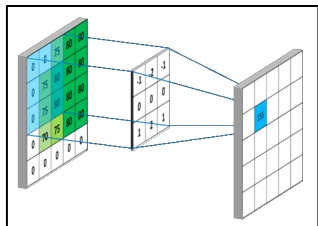


Types of Data

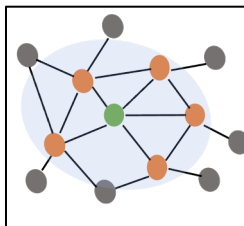
Tabular Data

Age	Gender	BMI	Insulin	...
50	M	26.6	0	...
31	F	33.6	94	...

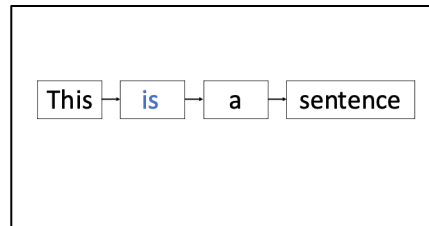
Images



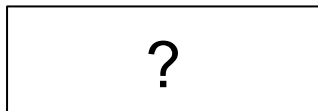
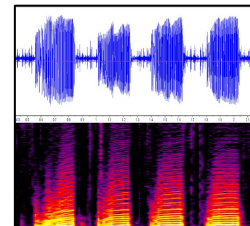
Graph



Text



Audio



- ☐ Sequence of pixels
- ☐ CNNs*
- ☐ Parameter sharing

- ☐ Neighboring nodes
- ☐ GNNs
- ☐ Parameter sharing

- ☐ Sequence of words
- ☐ LSTMs*
- ☐ Parameter sharing

- ☐ Sequence of samples
- ☐ CNNs / LSTMs*
- ☐ Parameter sharing

Common factors:

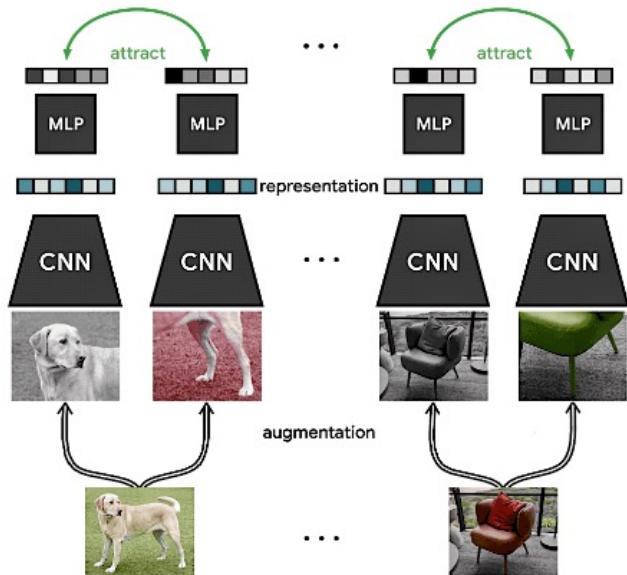
- ☐ Data augmentation can take advantage of structure in the data
- ☐ Parameter sharing through specialized architectures



Prominent Works in Representation Learning

- ❑ Most prominent works are done in Computer Vision and NLP
- ❑ They take advantage of **Data Augmentation**

Computer Vision: SimCLR



NLP: BERT

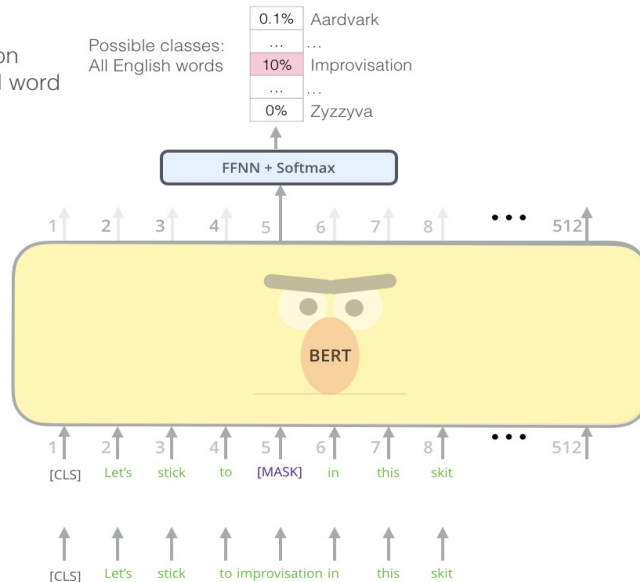
Use the output of the masked word's position to predict the masked word

Possible classes:
All English words

0.1%	Aardvark
...	...
10%	Improvisation
...	...
0%	Zyzyva

Randomly mask 15% of tokens

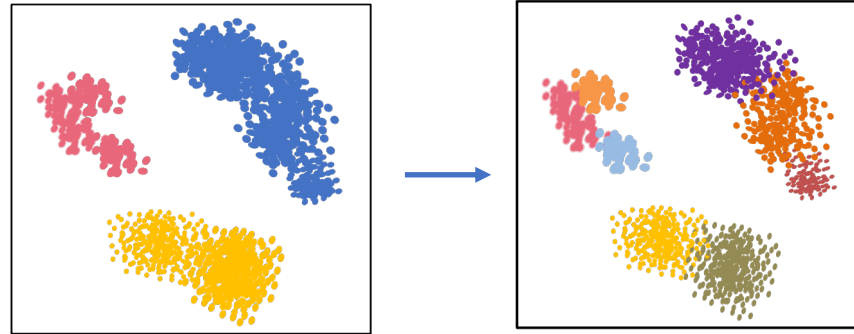
Input



Data Augmentation in Tabular Data



Tabular Data



$X = \textit{Patient records}$

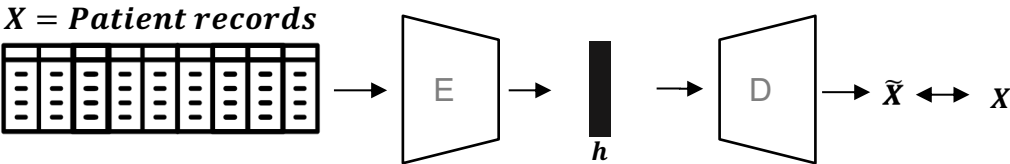
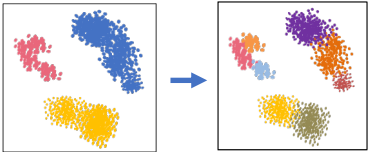
-	-	-	-	-	-	-	-	-	-
-	-	-	-	-	-	-	-	-	-
-	-	-	-	-	-	-	-	-	-

\equiv

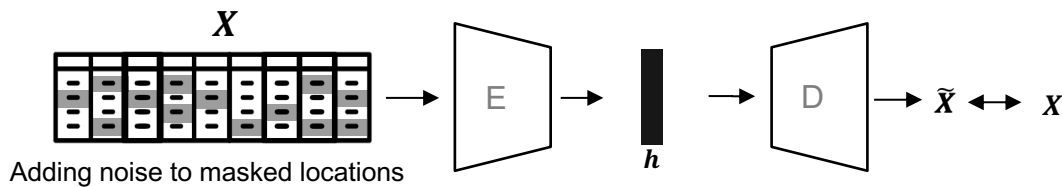
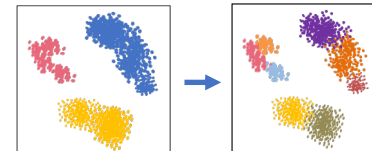
Age	Gender	BMI	Insulin	...
50	M	26.6	0	...
31	F	33.6	94	...



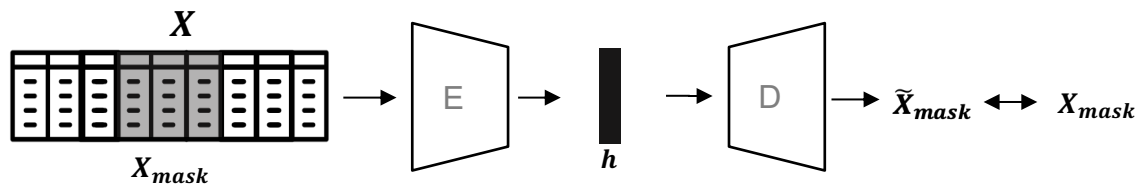
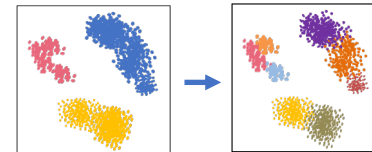
Autoencoder

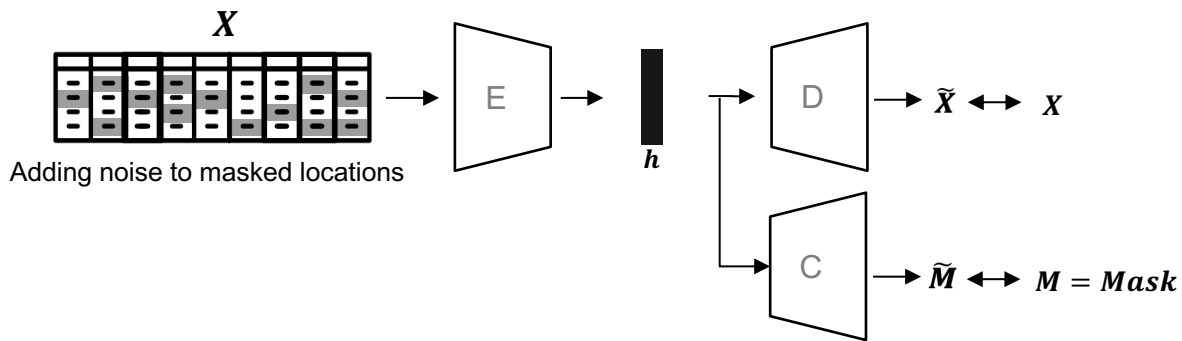
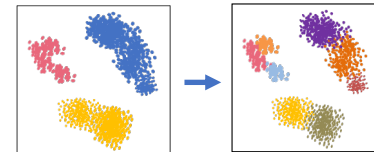


De-noising Autoencoder



Context Encoder

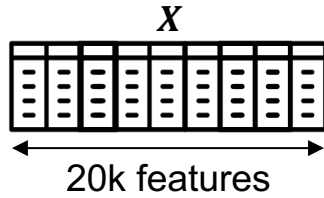




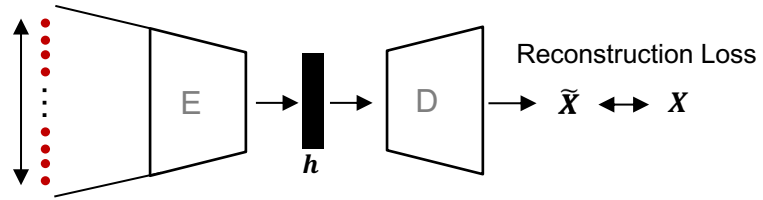
Parameter sharing in Tabular Data



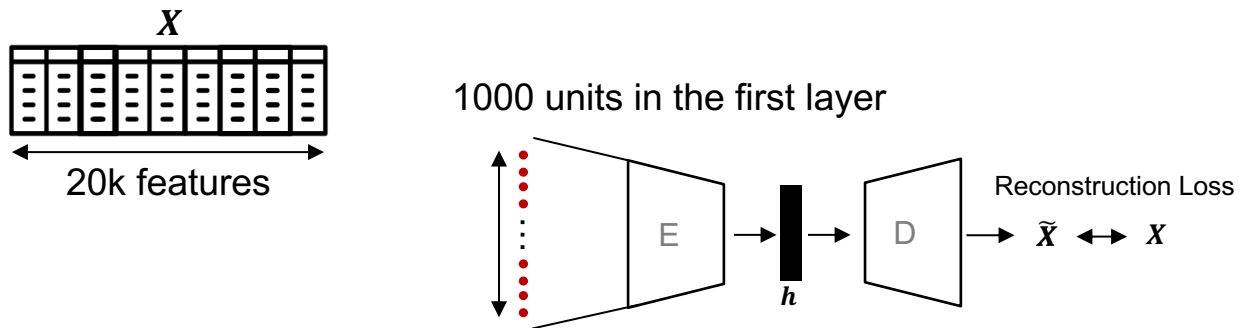
Parameter sharing (or lack of it) in Tabular Data



1000 units in the first layer



Parameter sharing (or lack of it) in Tabular Data



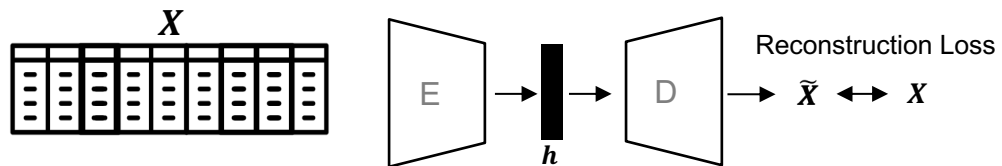
20 million parameters in the first layer alone



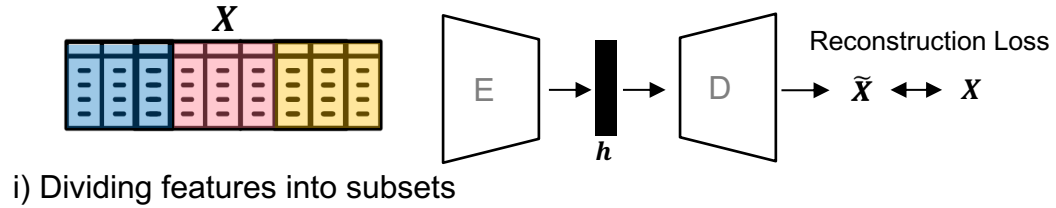
SubTab



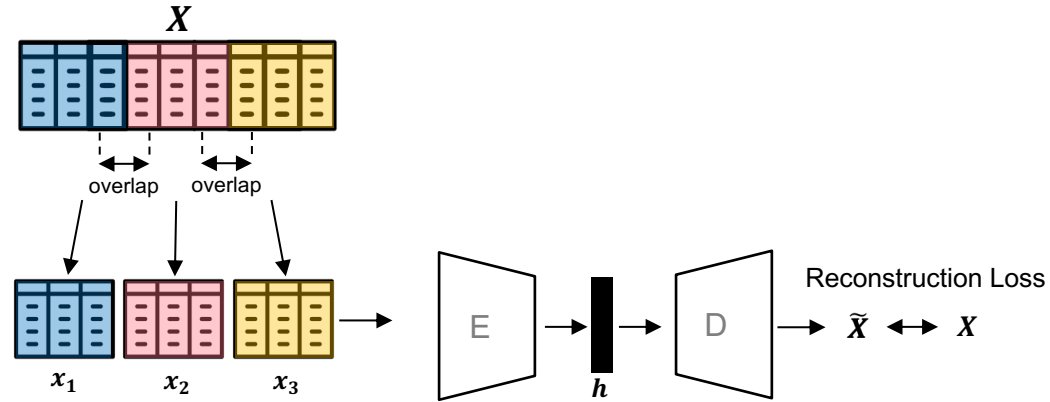
Self-Supervised Representation Learning in SubTab



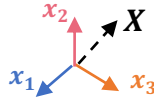
Self-Supervised Representation Learning in SubTab



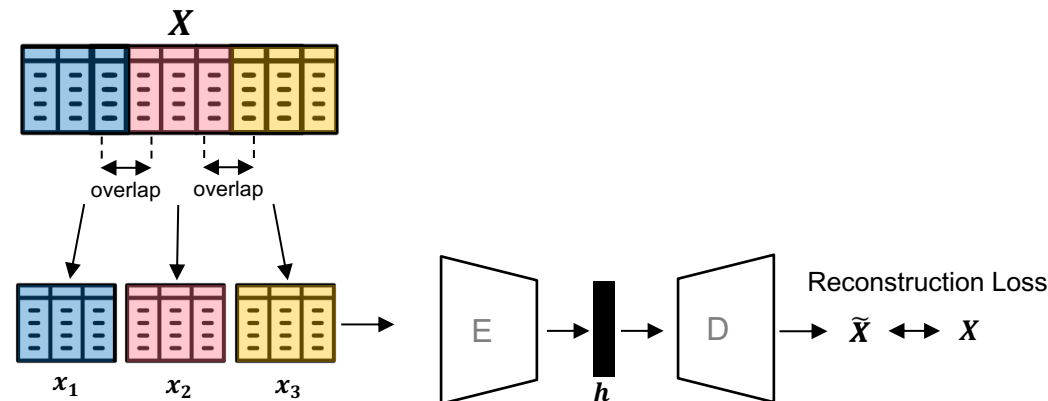
Self-Supervised Representation Learning in SubTab



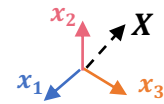
i) Dividing features into subsets



Self-Supervised Representation Learning in SubTab

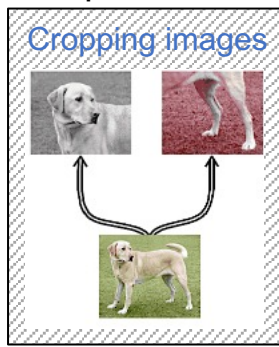


i) Dividing features into subsets

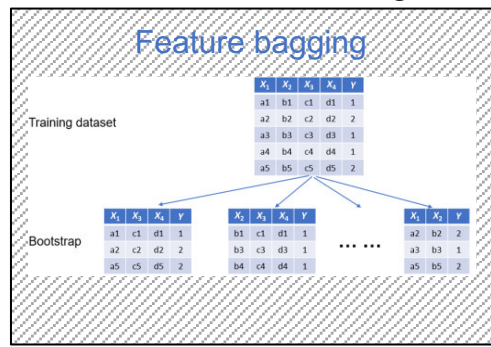


Similar to

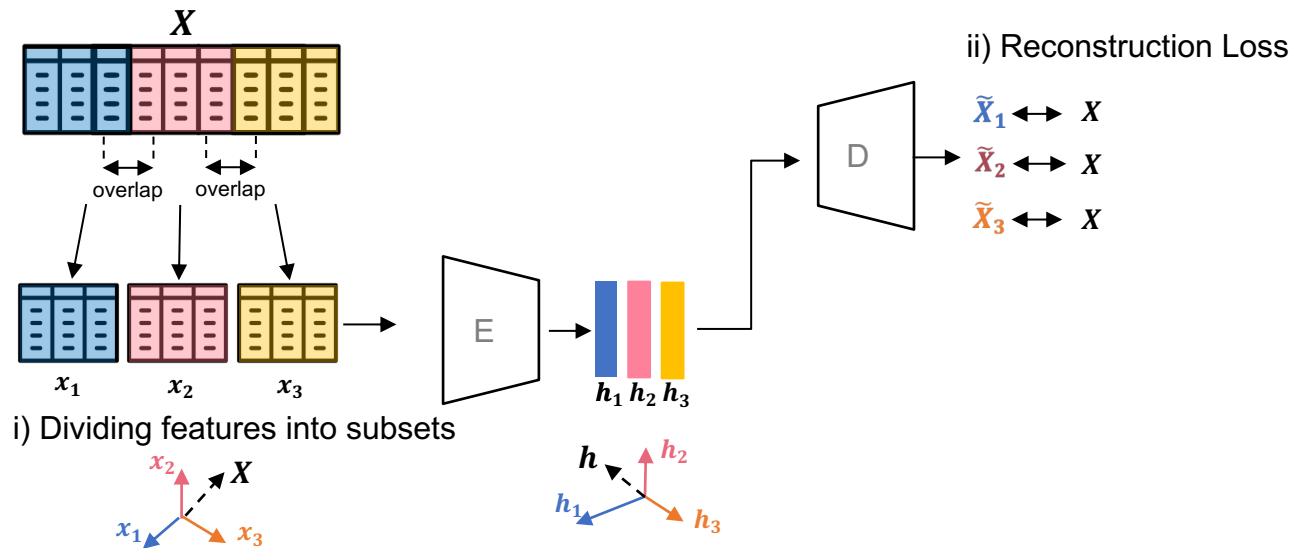
Computer Vision



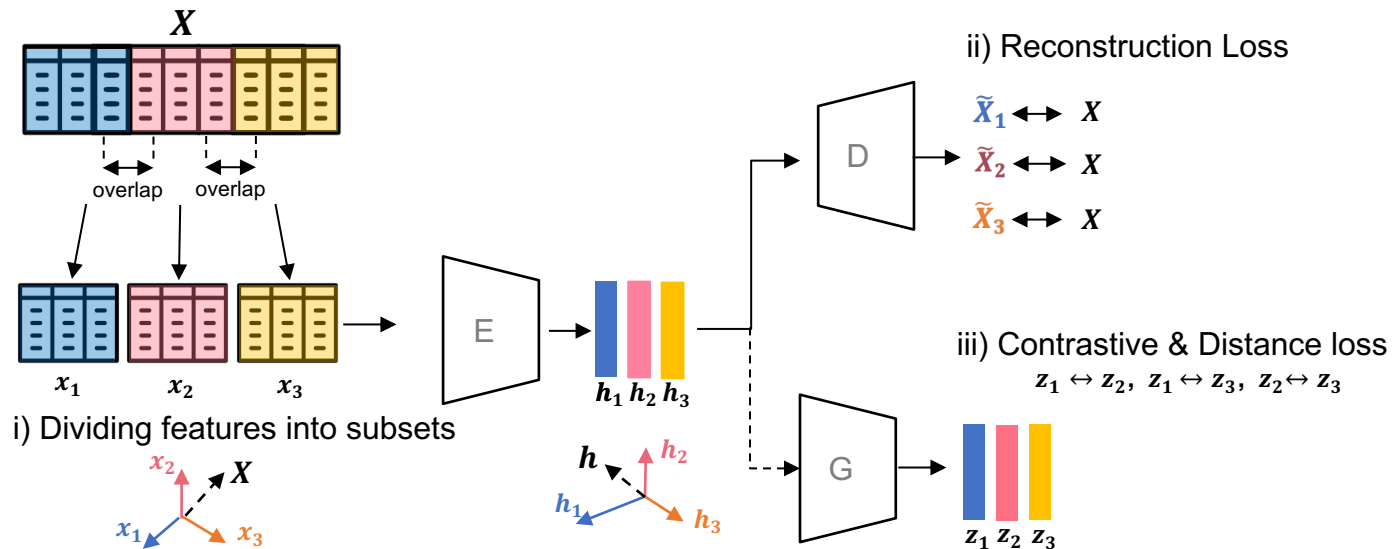
Ensemble Learning



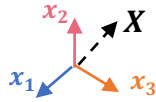
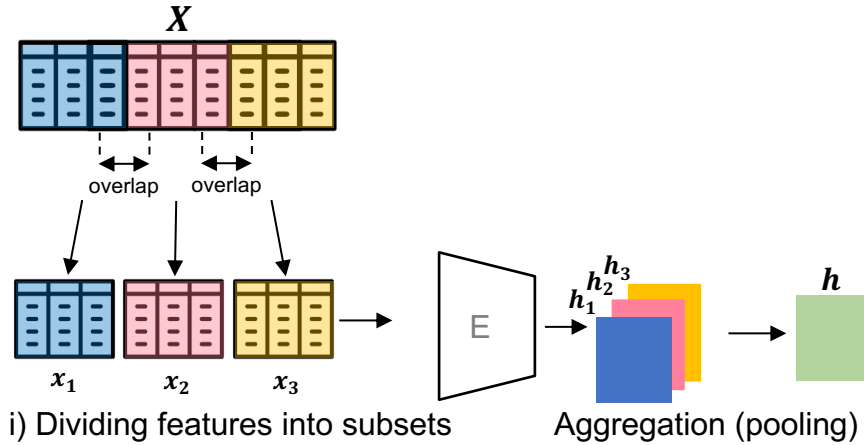
Self-Supervised Representation Learning in SubTab



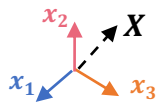
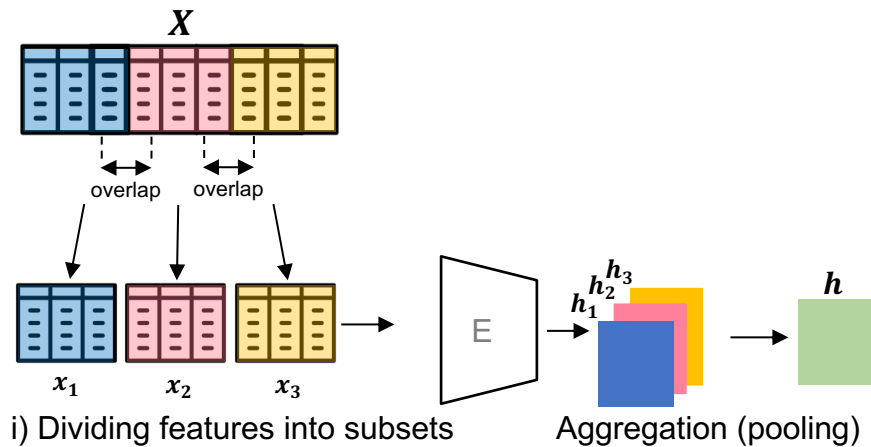
Self-Supervised Representation Learning in SubTab



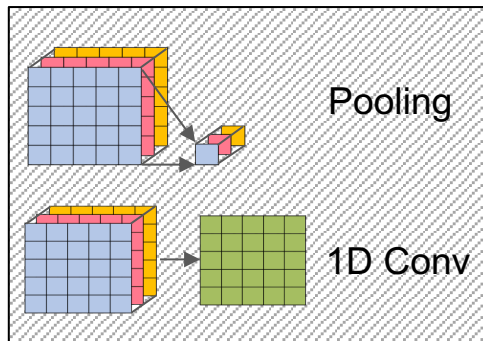
SubTab at test time



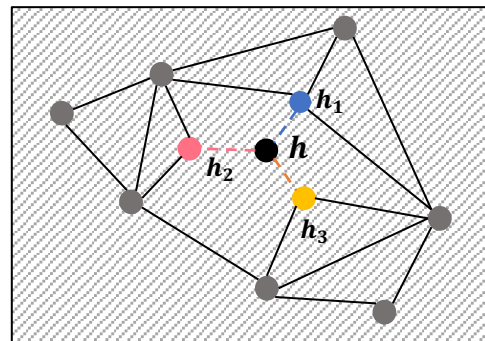
SubTab at test time



Pooling / 1D Convolution in CNNs



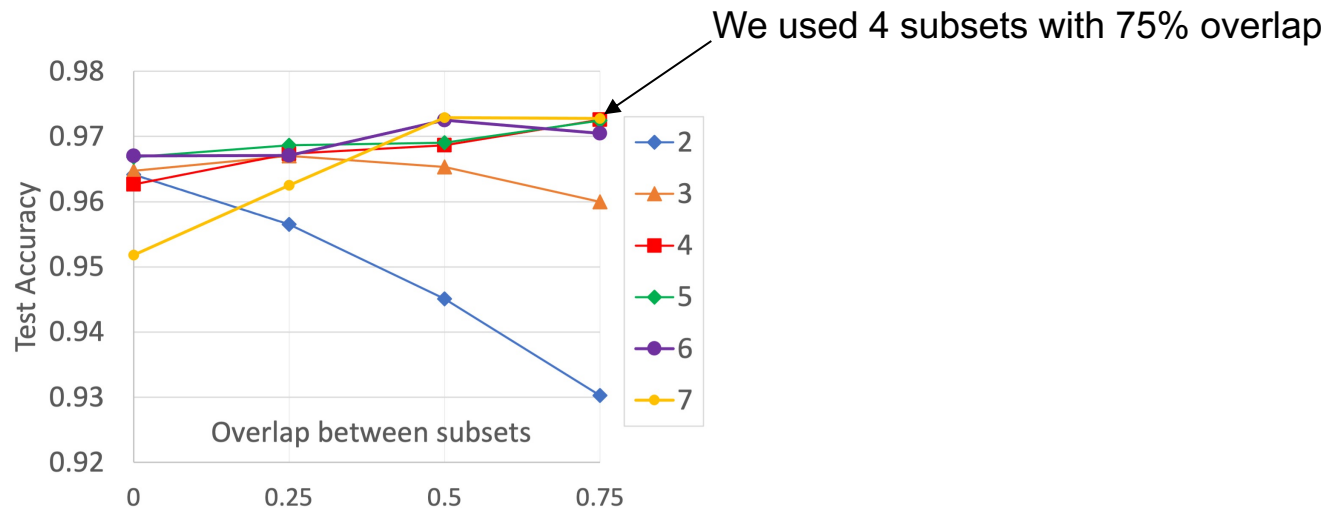
Neighbor aggregation in GNNs



Results & Summary

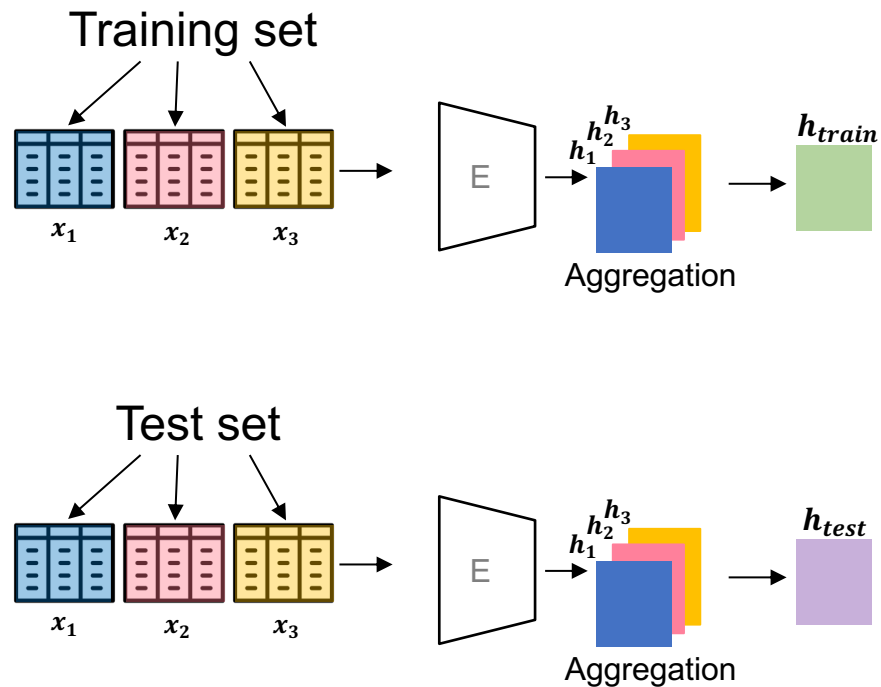


Performance over different number of subsets and overlap for MNIST



Evaluation

I. Extract embeddings



II. Evaluate representation



Results on 5 datasets

Table 1: Accuracy scores for all models for various datasets. The abbreviations in the table; NC: Neighbour columns used, RF: Random features used, G: Gaussian noise used, S: Swap noise used.

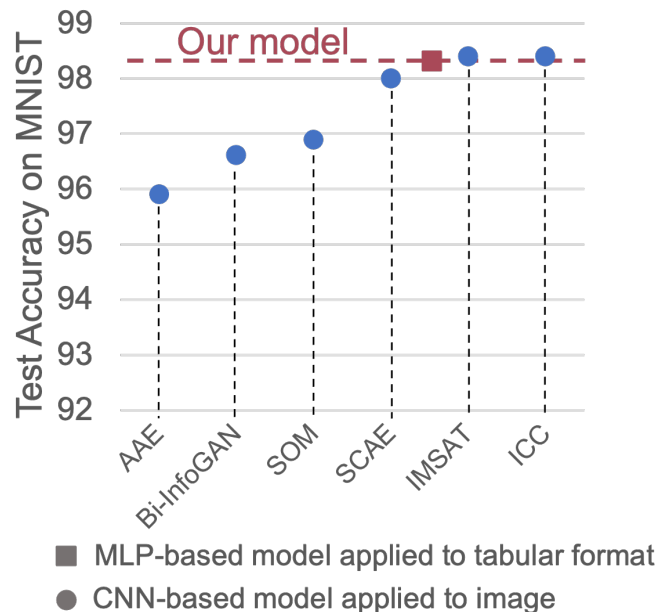
Type	Models	MNIST	Income	Blog	Obesity	TCGA
Supervised baseline	Logistic Regression	92.60±0.03	84.68±0.05	84.15±0.12	62.35±4.02	36.98± 1.25
	Random Forest	96.96±0.06	84.62±0.07	83.61±0.15	67.45±2.23	61.62± 1.02
	XGBoost	98.02±0.086	86.11±0.20	84.29±0.23	64.05±4.52	72.61±1.31
Autoencoder baseline	AE	92.77±0.32	84.67±0.07	84.06±0.24	61.96±3.28	55.16±0.75
	AE w/ Dropout (p=0.2)	94.31±0.28	85.00±0.10	84.18±0.20	62.74±4.38	56.87±2.26
Self-supervised	DAE (RF)	96.30±0.14 (S)	84.37±0.36 (G)	84.12±0.29 (G)	56.43±5.79 (G)	54.31±1.39 (G)
	CAE (NC)	96.39±0.20 (S)	84.24±0.18 (G)	84.3±0.31 (G)	62.26±5.01 (G)	54.20±1.17 (G)
	VIME-self	95.23±0.17 (S)	84.43±0.08 (G)	84.11±0.27 (G)	66.45±4.54 (G)	55.11±1.37 (G)
	SubTab with:					
	Base model (No noise)	97.26±0.2	85.31±0.08	84.29±0.26	68.01±3.07	57.02±1.50
	+Noise	97.47±0.18 (S)	85.34±0.07 (G)	84.47±0.15 (G)	71.13±4.08 (G)	58.25±1.36 (G)
	+Distance loss	97.52±0.14 (S)	85.35±0.06 (G)	84.64±0.19 (G)	69.25±4.19 (G)	58.15±1.56 (G)
	+LatentDim=512	97.86±0.07 (S)	-	-	-	-



Shallow vs Deep Architecture

Table 3: Comparing shallow and deep SubTab architectures.

Model	MNIST	Income	Blog	Obesity	TCGA
Deep SubTab	97.86 \pm 0.07	85.35 \pm 0.06	84.64 \pm 0.19	71.13\pm4.08	58.25 \pm 1.36
Shallow SubTab	98.31\pm0.06	85.34 \pm 0.03	84.64 \pm 0.09	66.88 \pm 5.35	61.41\pm1.11

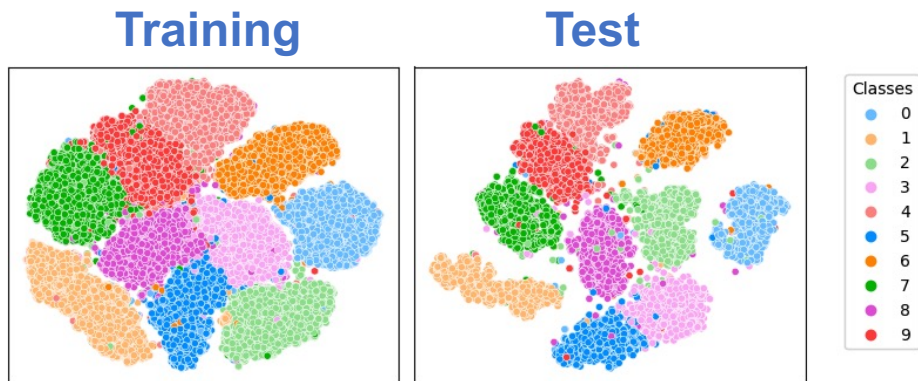


- ❑ Shallow architecture performs better in some datasets
- ❑ MLP-based SubTab performs on par with CNN-based SOTA models.



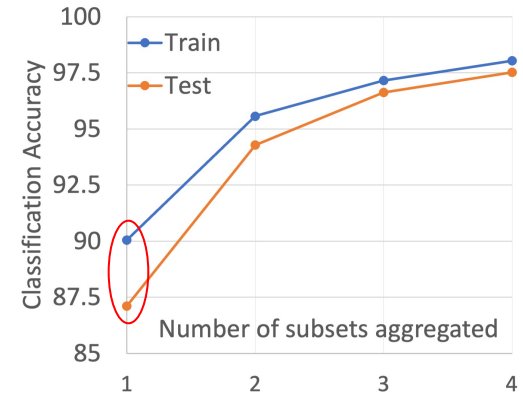
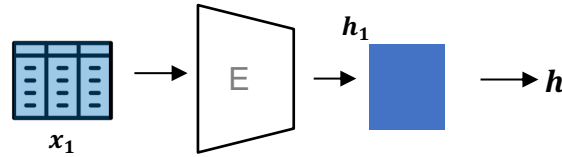
Representation Quality of SubTab

t-SNE plots for training and test set of MNIST for 4 subsets with 75% overlap



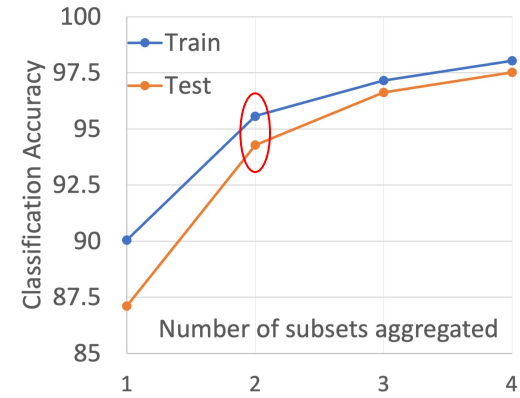
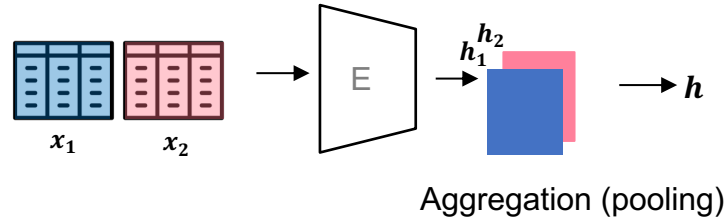
Information content in the joint embedding

E = Encoder trained on 4 subsets with 75% overlap



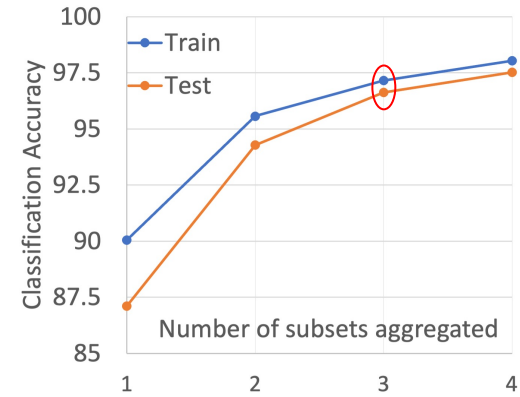
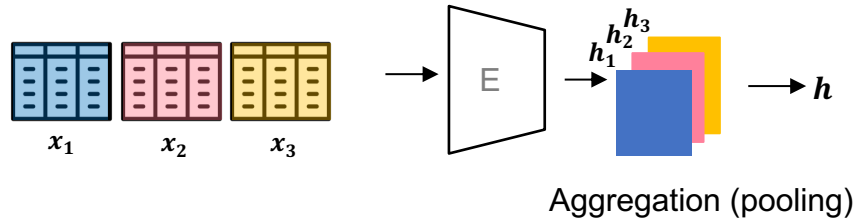
Information content in the joint embedding

E = Encoder trained on 4 subsets with 75% overlap



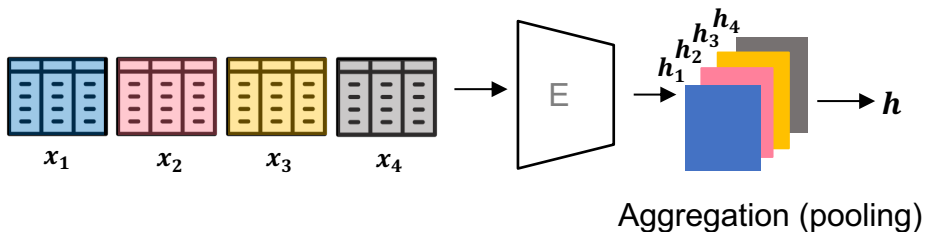
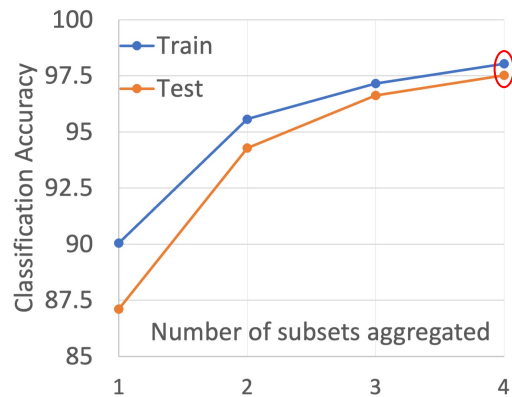
Information content in the joint embedding

E = Encoder trained on 4 subsets with 75% overlap

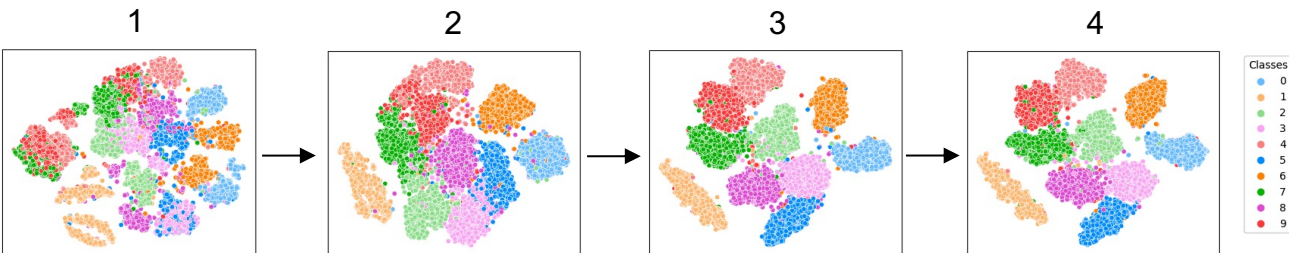


Information content in the joint embedding

E = Encoder trained on 4 subsets with 75% overlap



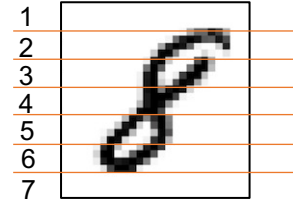
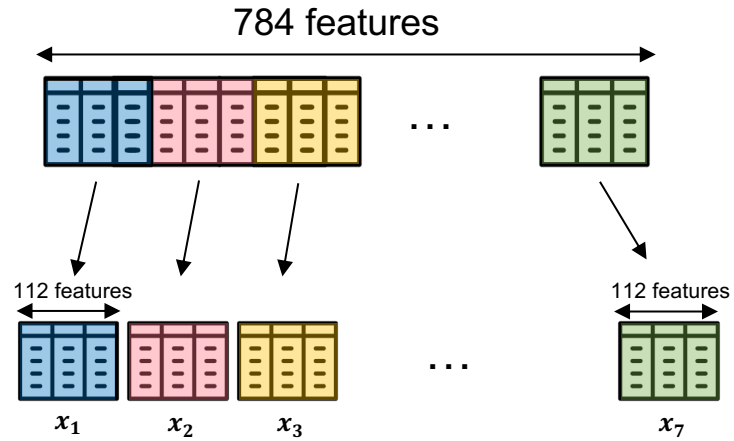
of Subsets:



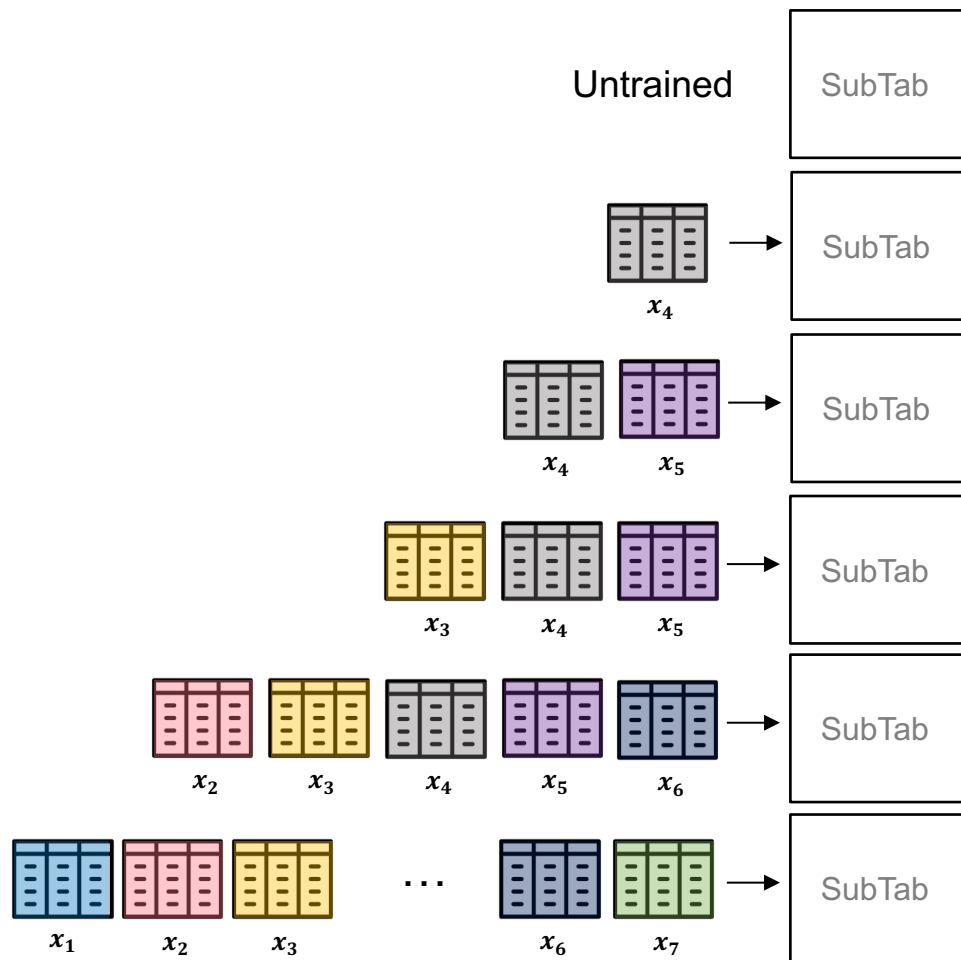
Additional Experiments with MNIST



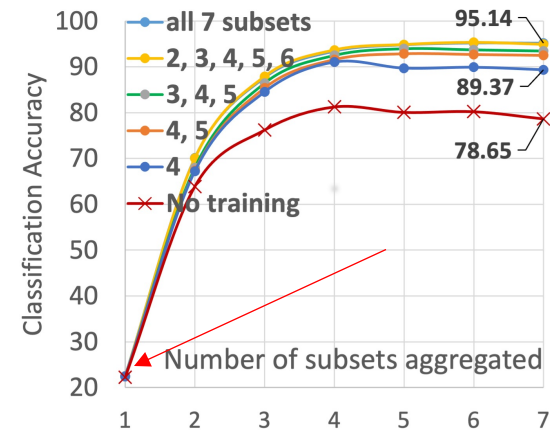
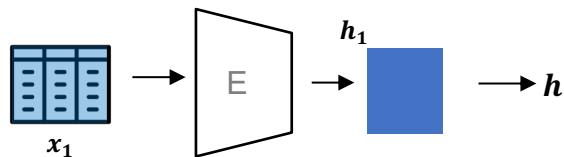
Slicing MNIST digits to 7 subsets



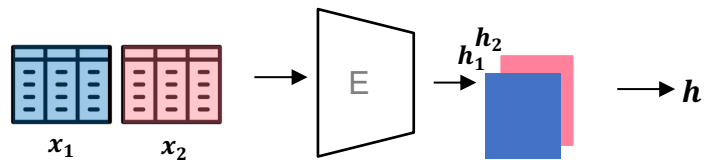
Trained 6 different models



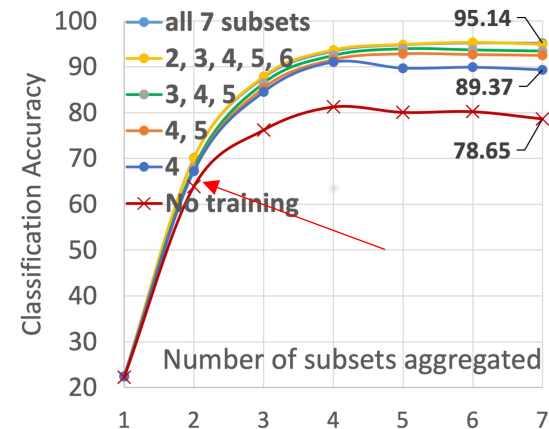
Information content in the joint embedding



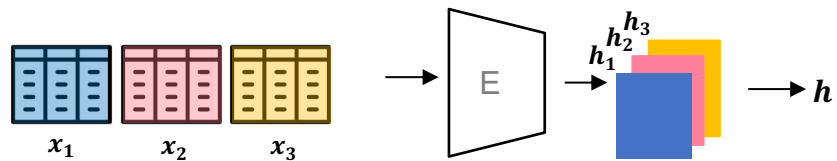
Information content in the joint embedding



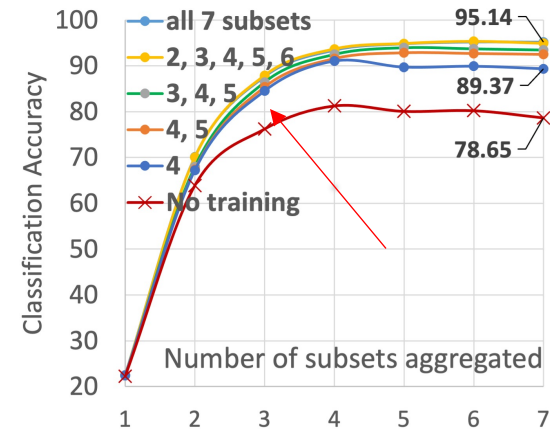
Aggregation (pooling)



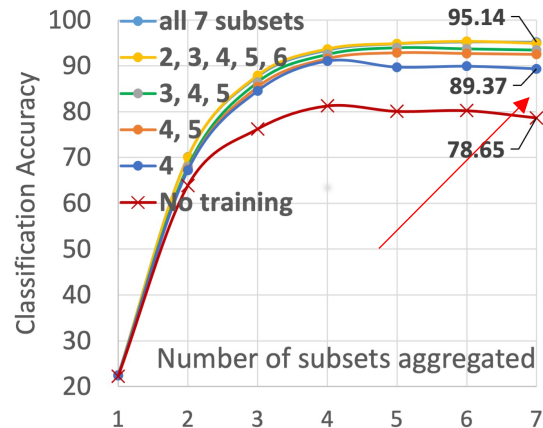
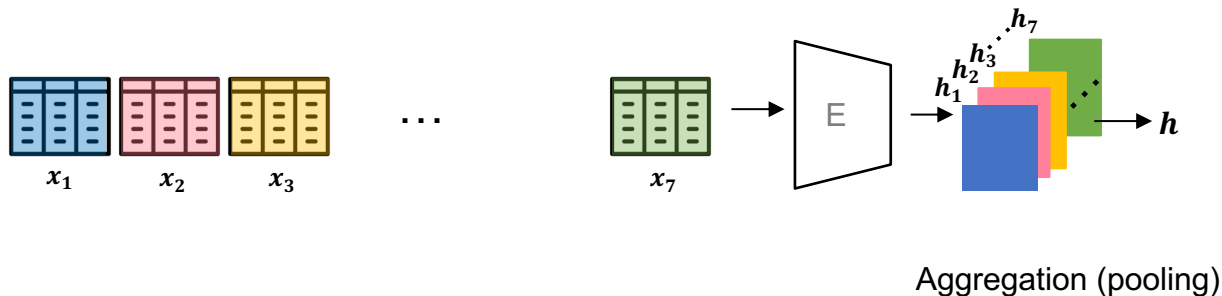
Information content in the joint embedding



Aggregation (pooling)



Information content in the joint embedding



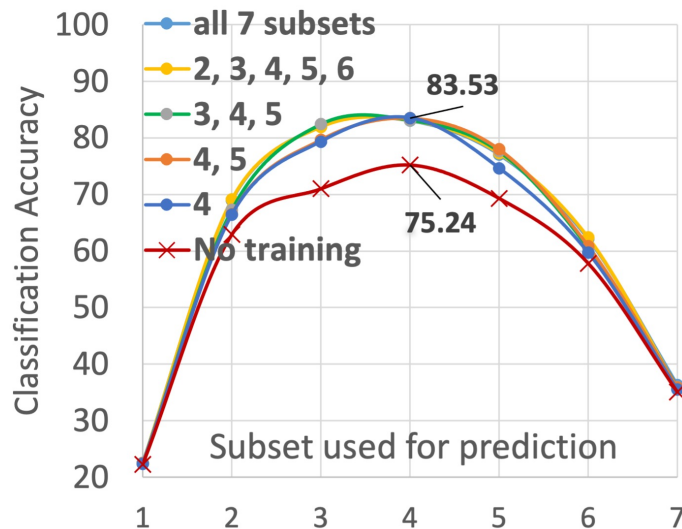
❑ We can have missing features during training and/or test time, and still perform well.



Experiment-2



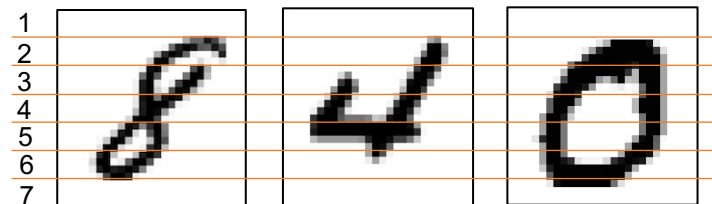
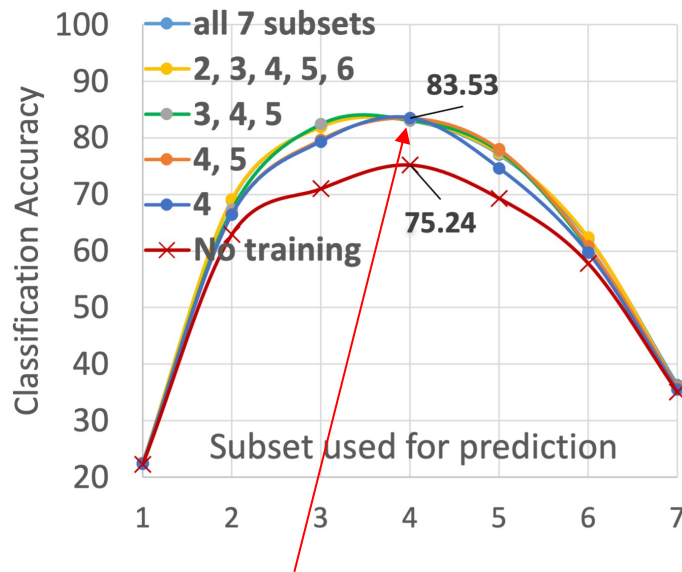
Information content of individual subsets



- ❑ We can discover informative subsets
- ❑ We can even use untrained model for discovering them



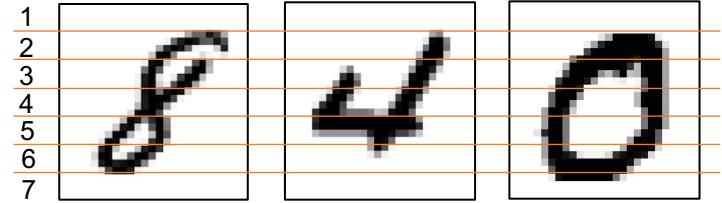
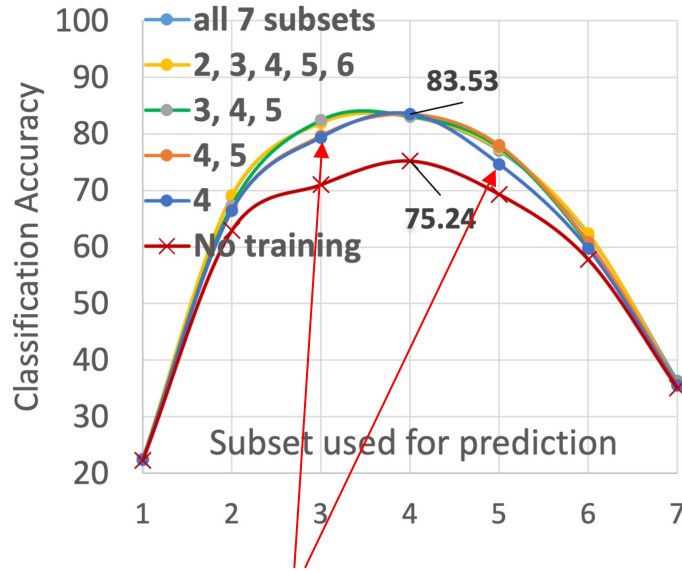
Information content of individual subsets



- ❑ Information content of a subset does not depend on other subsets
 - ❑ All models trained on subset 4 has same performance



Information content of individual subsets

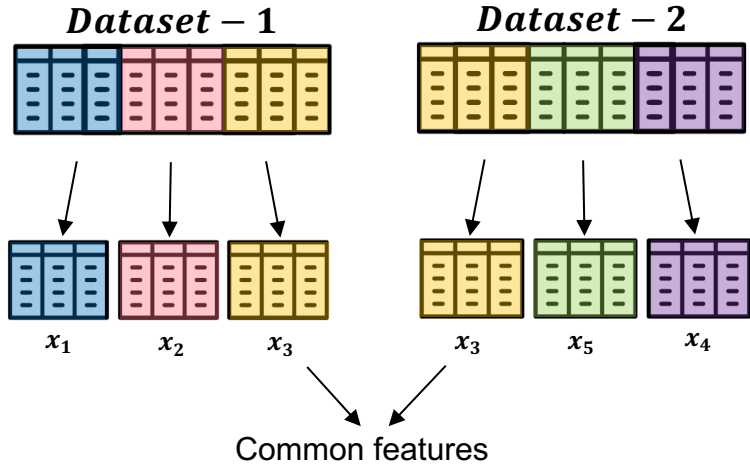


- ❑ Information content of a subset does not depend on other subsets
 - ❑ All models trained on subset 4 has same performance
 - ❑ Same can be seen for subset 3 and 5

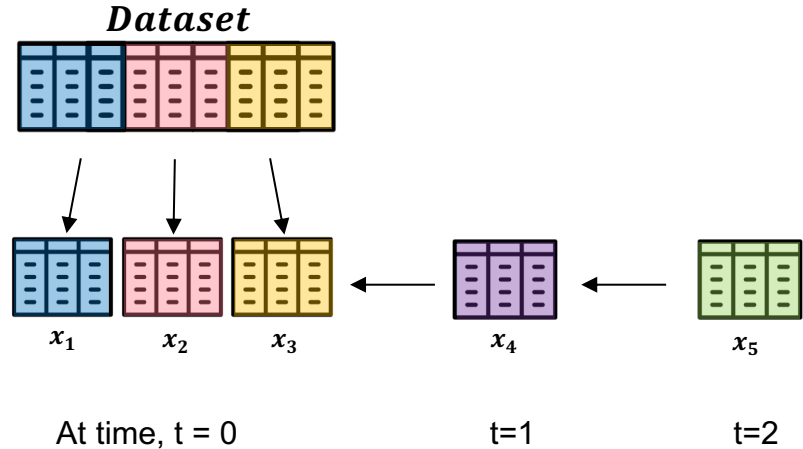


Possible applications

❑ Transfer learning



❑ Integrating new features over time



❑ And there are others such as distributed training, multi-modal learning and so on.



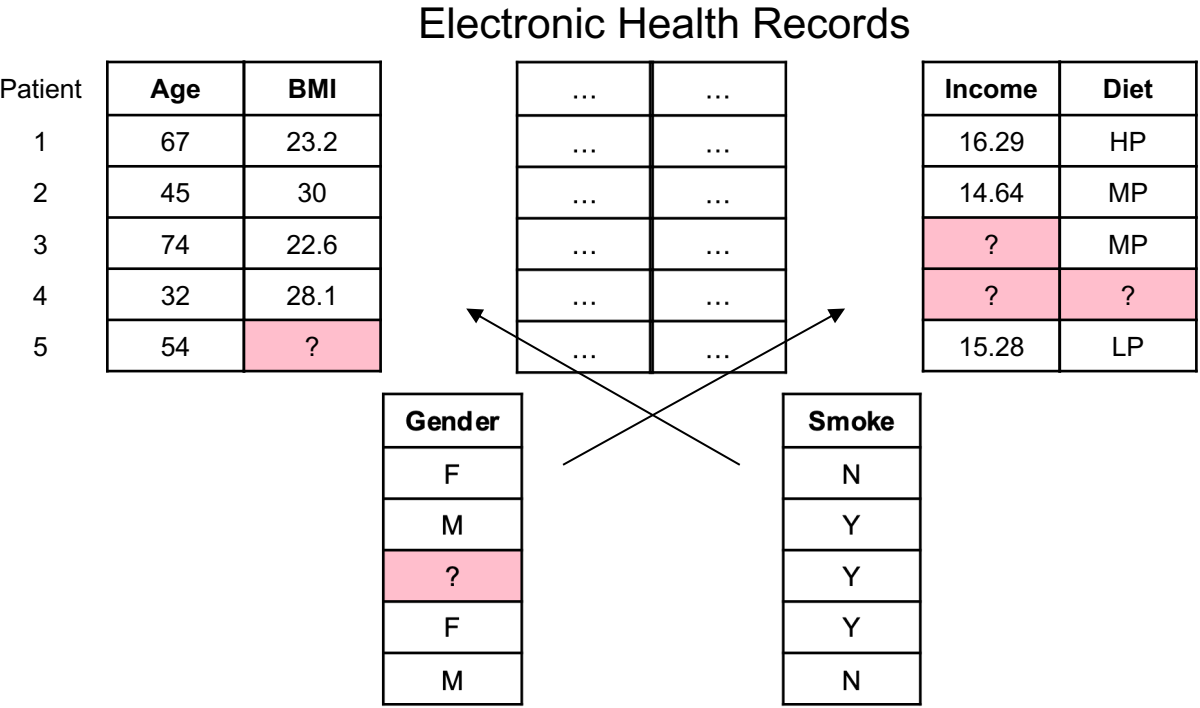
Possible applications – Tabular data with missing features

Electronic Health Records

Patient	Age	BMI	...	Gender	Smoke	...	Income	Diet
1	67	23.2	...	F	N	...	16.29	HP
2	45	30	...	M	Y	...	14.64	MP
3	74	22.6	...	?	Y	...	?	MP
4	32	28.1	...	F	Y	...	?	?
5	54	?	...	M	N	...	15.28	LP



Possible applications – Tabular data with missing features



Possible applications – Tabular data with missing features

Electronic Health Records

Patient	Age	BMI	Smoke	Gender	Income	Diet
1	67	23.2	N	F	16.29	HP
2	45	30	Y	M	14.64	MP
3	74	22.6	Y	?	?	MP
4	32	28.1	Y	F	?	?
5	54	?	N	M	15.28	LP



Possible applications – Tabular data with missing features

Electronic Health Records

Patient	Age	BMI	Smoke	Gender	Income	Diet
1	67	23.2	N	F	16.29	HP
2	45	30	Y	M	14.64	MP
3	74	22.6	Y	?	?	MP
4	32	28.1	Y	F	?	?
5	54	?	N	M	15.28	LP

Subset 1 ... Subset 2



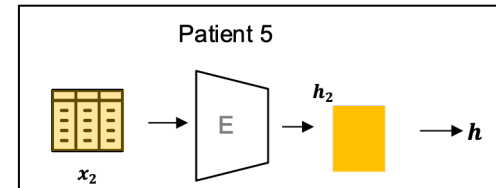
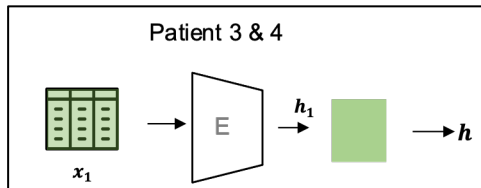
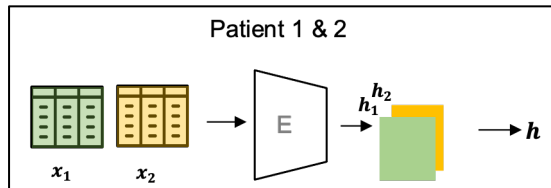
Possible applications – Tabular data with missing features

Electronic Health Records

Patient	Age	BMI	Smoke	Gender	Income	Diet
1	67	23.2	N	F	16.29	HP
2	45	30	Y	M	14.64	MP
3	74	22.6	Y	?	?	MP
4	32	28.1	Y	F	?	?
5	54	?	N	M	15.28	LP

Subset 1 ... Subset 2

Personalized modelling



Summary

- ❑ We showed a new method for representation learning using tabular data
- ❑ But the problem is no way solved:
 - ❑ Tabular data comes in many forms
 - ❑ There is no single solution that can fit all situations
- ❑ We will continue developing methods to address existing challenges

Thanks!

GitHub: <https://github.com/AstraZeneca/SubTab>

