You're your own best teacher: A Self-Supervised Learning Approach For Expressive Representations

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NC-VQVAE is able to capture the conditional distribution of the data significantly better than naive VQVAE for a wide variety of. For datasets with few training samples, it can be prone to overfitting. We see our model as a step in the right direction, but further development is needed to ensure better intraclass diversity, possibly through a more refined sampling procedure.

NC-VQVAE is better able to mimic the training data. When data is abundant, then our model better captures the entire distribution, while covering

0.1 Stage 1

In this section we present the results of the tokenization model, in particular the reconstruction loss and the downstream classification accuracy. We address research question 1 and 2, if the proposed NC-VQVAE is able to reconstruct on par with the naive VQVAE and if the learned latent representations are more expressive, in the sense that they simultaneously improve the downstream classification accuracy. We see that some configuration of NC-VQVAE is the top performer on the majority of datasets for both metrics, and provides significant increase in probe accuracy.

0.1.1 Reconstruction

We present top 1 and mean reconstruction loss across the four runs in table **??** and table **??** respectively.

Mean validation reconstruction error

Dataset	**Baseline**	**SSL Method**					
	Regular	Barlow Twins			VIbCReg		
	None	Warp	Slice	Gauss	Warp	Slice	Gauss
FordA	0.217	0.127	0.134	**0.108**	0.173	0.169	0.203
ElectricDevices	**0.041**	0.067	0.044	0.049	0.105	0.042	0.049
StarLightCurves	**0.032**	0.042	0.069	0.071	0.052	0.050	0.068
Wafer	0.044	0.037	0.048	0.049	**0.035**	0.042	0.039
ECG5000	**0.048**	0.083	0.170	0.104	0.093	0.205	0.064
TwoPatterns	0.197	0.201	**0.184**	0.230	0.214	0.186	0.207
UWaveGestureLibraryAll	0.190	**0.172**	0.190	0.245	0.189	0.178	0.237
FordB	0.150	0.115	0.122	0.123	**0.114**	0.121	0.142
ShapesAll	**0.045**	0.056	0.066	0.102	0.064	0.069	0.073
SonyAIBORobotSurface1	0.402	0.509	0.494	0.491	**0.360**	0.363	0.418
SonyAIBORobotSurface2	0.623	0.622	0.618	0.640	0.487	**0.454**	0.589
Symbols	0.110	0.143	0.134	0.173	0.078	**0.067**	0.105
Mallat	0.066	0.081	0.091	0.096	0.066	0.067	**0.060**

Top 1 validation reconstruction error

Dataset	**Baseline**	**SSL Method**					
	Regular	Barlow Twins			VIbCReg		
	None	Warp	Slice	Gauss	Warp	Slice	Gauss
FordA	0.158	0.108	0.111	**0.087**	0.130	0.134	0.113
ElectricDevices	0.036	0.060	0.034	0.043	0.092	**0.031**	0.045
StarLightCurves	**0.026**	0.037	0.057	0.055	0.043	0.048	0.065
Wafer	0.038	0.031	0.045	0.043	**0.027**	0.031	0.038
ECG5000	**0.044**	0.069	0.156	0.084	0.080	0.181	0.056
TwoPatterns	0.181	0.184	**0.169**	0.208	0.200	0.172	0.185
UWaveGestureLibraryAll	0.159	**0.145**	0.167	0.201	0.155	0.169	0.233
FordB	0.117	0.094	0.090	0.103	**0.082**	0.094	0.102
ShapesAll	**0.035**	0.043	0.046	0.092	0.061	0.063	0.067
SonyAIBORobotSurface1	0.381	0.473	0.472	0.465	0.329	**0.328**	0.408
SonyAIBORobotSurface2	0.513	0.577	0.536	0.588	0.444	**0.414**	0.470
Symbols	0.088	0.111	0.122	0.150	0.062	**0.059**	0.090
Mallat	0.061	0.075	0.076	0.088	0.059	0.059	**0.057**

From the tables we see that NC-VQVAE reconstructs on par with the baseline model, and that some configuration outperforms the naive VQVAE on mean reconstruction loss for 9 out of 13 datasets. In figure **??** observe that the difference in reconstruction loss is small for most datasets, both across SSL methods and augmentations. The use of gaussian augmentation introduces less of a regularizing effect compared to the two others, with the exception of Slice and shuffle on ECG5000. These results show that the introduction of a non contrastive loss does not hurt the reconstruction capabilities of our model compared to naive VQVAE.

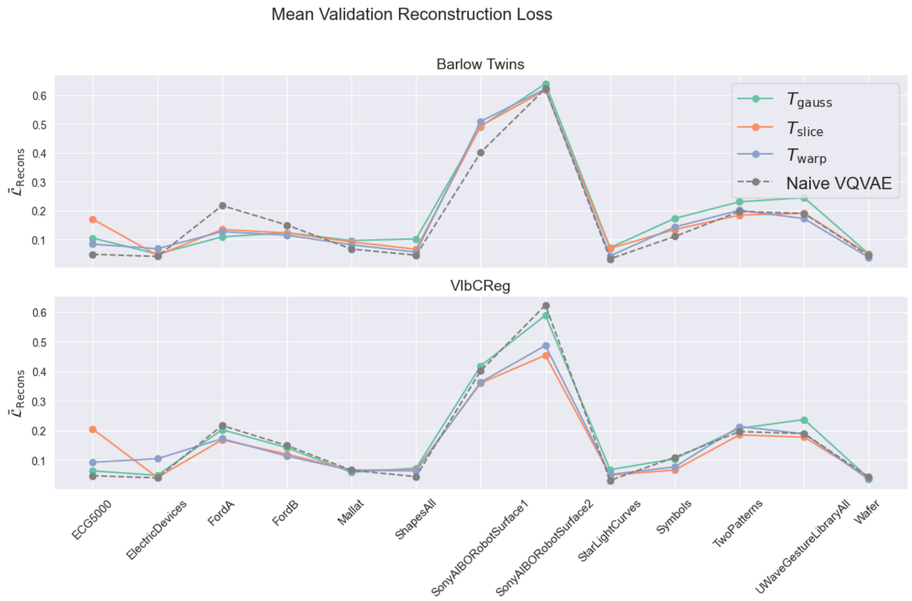


Figure 1: Mean validation reconstruction loss for the two models, compared to naive VQVAE

The right configuration for NC-VQVAE acts as a regularizer, in figure **??** we see how the validation reconstruction loss developes on FordA during training.

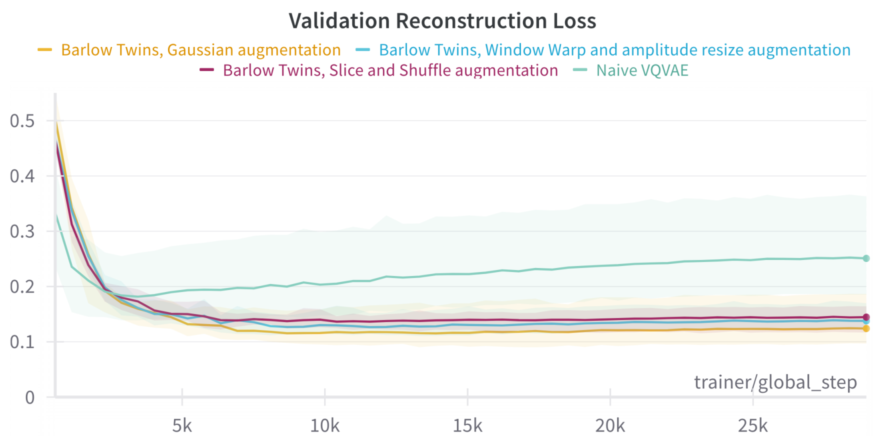


Figure 2: Development of the validation reconstruction loss for FordA during training. Averaged across all four runs.

0.1.2 Classification

We present the mean and max downstream classification accuracy in table **??** and **??** respectively.

Mean linear probe accuracy

Dataset	**Baseline**		**SSL Method**											
	Regular		Barlow Twins						VIbCReg					
	None		Warp		Slice		Gauss		Warp		Slice		Gauss	
	KNN	SVM	KNN	SVM	KNN	SVM	KNN	SVM	KNN	SVM	KNN	SVM	KNN	SVM
FordA	0.70	0.74	0.83	0.84	**0.91**	**0.89**	0.80	0.83	0.80	0.74	0.87	0.86	0.76	0.78
ElectricDevices	0.35	0.41	0.35	**0.44**	0.38	0.41	**0.40**	0.42	0.33	0.38	0.36	0.39	0.39	0.43
StarLightCurves	0.87	0.89	0.93	0.93	**0.94**	**0.94**	0.88	0.88	0.92	**0.94**	0.91	0.93	0.89	0.89
Wafer	0.93	0.89	0.96	**0.94**	0.96	**0.94**	0.96	0.93	**0.97**	0.94	0.96	0.92	**0.97**	0.92
ECG5000	0.80	0.83	0.85	0.81	**0.88**	0.84	0.86	**0.84**	0.86	0.82	**0.88**	**0.84**	0.84	0.82
TwoPatterns	0.34	0.53	**0.69**	**0.91**	0.66	0.82	0.47	0.71	0.64	0.90	0.68	0.80	0.55	0.72
UWaveGestureLibraryAll	0.31	0.40	**0.62**	0.70	0.56	0.63	0.40	0.54	**0.62**	**0.73**	0.55	0.66	0.44	0.55
FordB	0.58	0.60	0.64	0.67	0.74	0.76	0.64	0.68	0.63	0.64	0.70	0.70	0.61	0.64
ShapesAll	0.29	0.30	0.49	0.55	0.53	**0.60**	0.40	0.48	0.48	0.56	**0.54**	**0.60**	0.40	0.46
SonyAIBORobotSurface1	0.56	0.68	0.54	0.70	**0.61**	**0.74**	0.53	0.70	0.48	**0.74**	0.58	0.71	0.54	0.69
SonyAIBORobotSurface2	**0.81**	**0.86**	0.77	0.79	0.80	0.80	0.80	0.81	0.77	0.85	0.80	0.85	0.80	0.85
Symbols	0.50	0.60	**0.59**	0.60	0.50	**0.66**	**0.59**	**0.66**	0.45	0.61	0.42	0.62	0.43	0.63
Mallat	0.63	0.77	0.72	0.81	0.76	0.83	0.68	0.78	**0.79**	**0.87**	0.77	0.85	0.69	**0.86**

Table 1: Summary of mean linear probe accuracy by SSL Method and Augmentation. Average across 4 seeds. Best result for KNN and SVM are highlighted in bold.

Top 1 linear probe accuracy

Dataset	**Baseline**		**SSL Method**											
	Regular		Barlow Twins						VIbCReg					
	None		Warp		Slice		Gauss		Warp		Slice		Gauss	
	KNN	SVM	KNN	SVM	KNN	SVM	KNN	SVM	KNN	SVM	KNN	SVM	KNN	SVM
FordA	0.75	0.78	0.84	0.88	**0.93**	**0.92**	0.85	0.87	0.81	0.77	0.88	0.90	0.86	0.85
ElectricDevices	0.35	0.43	0.36	0.45	0.39	0.43	**0.45**	**0.46**	0.34	0.42	0.39	0.42	0.42	0.45
StarLightCurves	0.89	0.91	0.94	0.95	**0.96**	**0.96**	0.90	0.91	0.95	0.95	0.93	0.95	0.90	0.90
Wafer	0.94	0.89	**0.97**	**0.95**	**0.97**	**0.95**	**0.97**	0.93	**0.97**	**0.95**	**0.97**	**0.95**	**0.97**	0.94
ECG5000	0.83	0.84	0.88	0.86	**0.90**	**0.88**	**0.90**	**0.88**	0.88	0.85	0.89	0.86	0.86	0.85
TwoPatterns	0.37	0.62	**0.75**	**0.96**	0.68	0.85	0.55	0.75	0.70	0.92	0.71	0.81	0.63	0.76
UWaveGestureLibraryAll	0.34	0.43	**0.67**	0.74	0.60	0.67	0.43	0.54	**0.67**	**0.76**	0.58	0.67	0.48	0.58
FordB	0.60	0.63	0.67	0.71	**0.76**	**0.80**	0.69	0.74	0.67	0.65	0.74	0.77	0.63	0.68
ShapesAll	0.33	0.34	0.53	0.59	**0.59**	**0.65**	0.44	0.50	0.50	0.56	0.57	0.63	0.44	0.48
SonyAIBORobotSurface1	0.67	**0.80**	0.61	0.77	0.76	**0.80**	0.60	0.74	0.51	0.79	0.63	0.75	0.63	0.75
SonyAIBORobotSurface2	**0.84**	**0.89**	0.80	0.86	0.82	0.84	0.83	0.82	0.81	0.88	0.81	0.88	0.83	0.87
Symbols	0.56	0.66	0.65	0.69	0.55	0.73	**0.64**	**0.71**	0.51	0.65	0.45	0.67	0.46	0.69
Mallat	0.54	0.88	0.57	0.87	0.74	0.89	0.66	0.80	0.74	**0.92**	0.72	0.88	0.62	**0.90**

Table 2: Summary of max linear probe accuracy by SSL Method and Augmentation. Maximum value across 4 seeds. Best result for KNN and SVM are highlighted in bold.

From the tables we see a significant improvement in probe accuracy with NC-VQVAE compared to naive VQVAE. Some configuration is best on 12 out of 13 datasets, while the one where our model falls short, the difference is one percent for both svm and knn. The largest differences are seen on FordA, FordB, Mallat, ShapesAll, TwoPatterns and UWaveGestureLibraryAll.

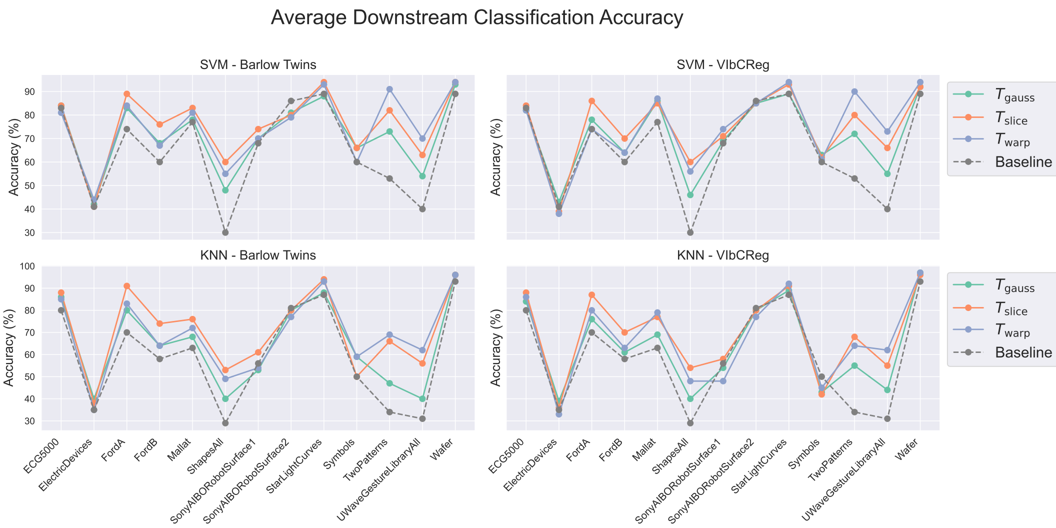


Figure 3: Mean probe accuracies.

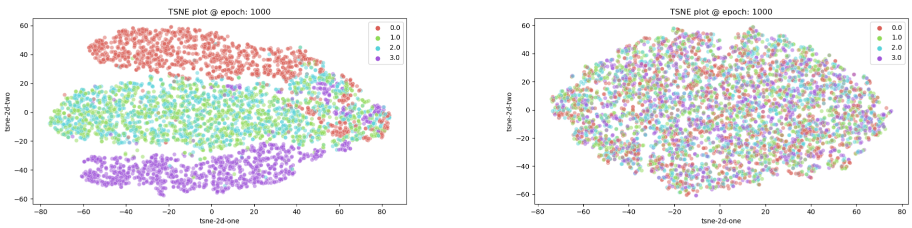


Figure 4: TSNE plot of discrete latent representations from VIbCReg with slice and shuffle (left) and naive VQVAE (right). Dataset is TwoPatterns.

The NC-VQVAE model is able to reconstruct on par with naive VQVAE, and in some cases improve the reconstruction loss, while significantly improving the probe accuracy for the discrete latent representations for most datasets. The NC-VQVAE produces representations that separates classes more effectively, and could in turn encode more class specific information.

Losses

TODO: How does the minimization of diffrerent losses influence linear probes/FID/IS?

SSL loss during training. Gauss is much easier to minimize. Probes seem to be better for warp and slice.

VQ-loss: VIbCReg minimizes a lot better than Barlow Twins. Gaussian augmentations results in the hardest minimization. Then windowwarp and then slice.

Augment recons: Is minimized very quickly. VIbCReg slightly more than Barlow. Slice produces the highest loss, which makes intuitive sense.

SSL loss: Gaussian is consistently more minimized than slice and warp. Which of slice and warp that is most minimized is dataset dependent, and are in many cases similar.

0.1.3 Visual inspection

TODO: PCA-TSNE-UMAP plots

TODO: Latent space plots

Illustrate the clustering in latent space

0.2 Stage 2

0.2.1 Generative quality

The generative quality of or models are evaluated according to FID, IS and CAS. We present the top 1 results in table **??**, and the mean score across the four runs in table **??**. From the tables we see that our model produces better IS score for 12 out of 13 datates, and better FID for 10 out of 13.

Top 1 FID and IS

Dataset	Baseline		SSL Method											
	Regular		Barlow Twins						VIbCReg					
	None		Warp		Slice		Gauss		Warp		Slice		Gauss	
	FID↓	IS↑	FID↓	IS↑	FID↓	IS↑	FID↓	IS↑	FID↓	IS↑	FID↓	IS ↑	FID↓	IS↑
FordA	2.59	1.30	1.93	**1.51**	2.13	1.48	1.80	**1.51**	2.83	1.38	2.50	1.43	**1.66**	1.41
ElectricDevices	12.05	3.97	11.82	4.20	**8.91**	4.07	9.89	3.86	12.38	**4.23**	11.08	3.94	13.96	3.71
StarLightCurves	**0.74**	1.99	0.89	**2.43**	1.50	2.36	0.75	2.39	0.92	2.39	0.85	**2.40**	0.79	2.26
Wafer	5.27	**1.39**	3.31	1.29	3.82	**1.26**	2.77	1.35	3.33	1.29	3.60	1.30	**2.52**	1.34
ECG5000	1.56	2.01	2.43	2.02	2.27	2.00	2.15	2.02	2.15	**2.03**	2.21	2.00	**1.52**	2.02
TwoPatterns	3.63	2.47	3.59	2.65	2.74	2.73	**2.24**	2.70	3.45	2.64	2.90	2.70	**2.19**	**2.77**
UWaveGestureLibraryAll	8.16	2.24	6.45	2.94	**6.26**	**3.13**	7.31	2.79	6.52	2.99	6.33	3.06	7.09	2.79
FordB	2.92	1.52	2.10	1.52	2.44	1.61	1.93	**1.67**	1.76	1.65	2.12	1.64	**1.66**	1.52
ShapesAll	**21.35**	4.32	35.89	**5.22**	29.61	5.16	27.91	4.83	30.03	4.95	31.59	4.92	27.20	4.94
SonyAIBORobotSurface1	18.21	1.27	26.20	1.32	28.90	1.28	21.63	1.32	21.98	1.36	25.20	1.38	**15.73**	**1.55**
SonyAIBORobotSurface2	3.85	1.69	2.50	1.82	3.34	1.79	**0.82**	1.82	2.61	1.81	2.75	1.83	1.24	**1.84**
Symbols	8.50	2.43	5.86	3.20	7.39	2.82	**4.25**	**3.50**	6.78	3.39	7.21	3.23	8.21	3.30
Mallat	**1.31**	3.41	2.01	3.67	2.24	3.72	1.85	3.66	1.87	3.34	2.30	3.05	**1.31**	**3.92**

Table 3: Summary of FID and IS scores by SSL Method and Augmentation. Best achieved results are highlighted in bold

Mean FID and IS

Dataset	**Baseline**		**SSL Method**											
	Regular		Barlow Twins						VIbCReg					
	None		Warp		Slice		Gauss		Warp		Slice		Gauss	
	FID↓	IS↑	FID↓	IS↑	FID↓	IS↑	FID↓	IS↑	FID↓	IS↑	FID↓	IS ↑	FID↓	IS↑
FordA	5.15	1.16	2.59	1.41	2.36	**1.45**	**2.28**	**1.45**	3.01	1.34	2.90	1.41	3.73	1.29
ElectricDevices	13.48	3.75	16.51	3.95	**10.20**	3.93	11.54	3.75	13.99	**4.17**	11.82	3.85	15.20	3.55
StarLightCurves	**1.01**	1.93	1.29	2.35	1.91	2.32	1.08	2.25	1.07	2.35	1.19	**2.36**	1.05	2.22
Wafer	5.72	**1.33**	3.70	1.25	4.20	1.24	2.85	1.31	3.67	1.26	3.86	1.26	**2.84**	1.31
ECG5000	**1.62**	1.94	2.61	**2.00**	2.56	1.98	2.47	**2.00**	2.60	1.99	2.39	**2.00**	1.76	1.99
TwoPatterns	4.04	2.41	4.00	2.54	2.96	2.66	**2.44**	**2.67**	4.05	2.56	3.15	2.66	2.62	**2.67**
UWaveGestureLibraryAll	8.48	2.13	6.77	2.86	6.64	2.96	7.35	2.73	6.80	2.91	**6.49**	**2.99**	7.34	2.72
FordB	4.05	1.28	2.66	1.48	3.49	1.50	2.88	**1.52**	**2.49**	1.48	3.07	1.51	3.04	1.31
ShapesAll	**27.64**	4.22	38.22	5.07	32.54	**5.04**	32.25	4.56	36.59	4.72	35.79	4.76	31.56	4.71
SonyAIBORobotSurface1	23.71	1.20	30.65	1.22	31.97	1.21	25.29	1.28	26.11	1.32	28.20	1.32	**18.61**	**1.44**
SonyAIBORobotSurface2	5.42	1.62	3.35	1.77	4.41	1.74	**1.78**	**1.81**	4.43	1.74	3.32	1.79	2.36	1.79
Symbols	13.62	1.99	9.78	2.92	9.78	2.67	8.61	3.14	8.84	3.20	9.74	3.03	**8.58**	**3.24**
Mallat	2.09	3.01	2.54	3.29	3.68	2.94	2.12	3.53	2.11	3.18	2.40	2.96	**1.65**	**3.72**

Table 4: Summary of FID and IS scores by SSL Method and Augmentation. Best mean achieved FID and IS are highlighted in bold

In figure **??** we get a better overview of the results, and observe that both Barlow Twins and VIbCReg produces better samples than the naive VQVAE in terms of FID and IS. Additionally we see that the use of gaussian augmentation results in the largest improvements for most datasets. The high IS scores indicate that NC-VQVAE captures the conditional distributions better than naive VQVAE in many datasets. This will be explored further in section **??**. The improved FID scores indicates that the synthetic samples more closely resemble the test data. The moderate decrease in FID, compared to the increase in IS, could indicate that the generated samples does not generalize too well to the test data. The discrete latent representations from NC-VQVAE provides more information regarding the classes, as we saw from the improved downstream classification accuracy in stage 1. This additional class specific information seems to assist the prior learning in capturing class conditional distributions.

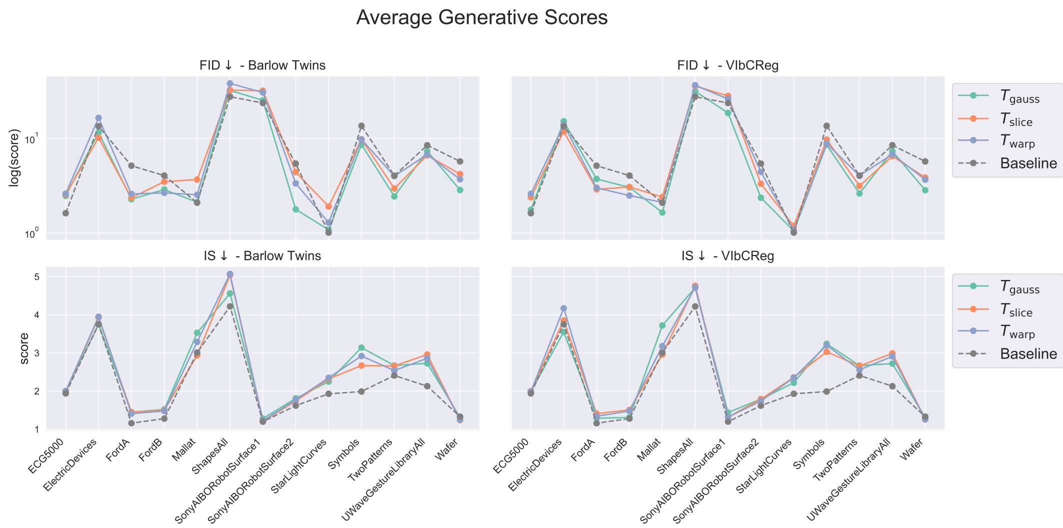


Figure 5: Mean FID and IS scores for Barlow Twins and VIbCReg VQVAE. FID is plotted on a log scale because of the large difference in values across datasets.

0.2.2 Class conditional sampling

Mean CAS

Dataset	Baseline	SSL Method					
	Regular	Barlow Twins			VIbCReg		
	None	Warp	Slice	Gauss	Warp	Slice	Gauss
FordA	0.864	0.884	**0.902**	0.878	0.864	0.895	0.870
ElectricDevices	0.614	0.588	0.607	0.599	**0.618**	0.610	0.594
StarLightCurves	0.960	0.953	0.955	**0.965**	0.962	0.954	0.964
Wafer	0.976	0.977	0.978	0.968	0.979	0.976	**0.984**
ECG5000	0.866	0.881	0.863	0.880	0.877	0.892	**0.910**
TwoPatterns	0.808	0.770	0.788	**0.847**	0.715	0.781	0.846
UWaveGestureLibraryAll	0.333	0.300	0.367	0.313	0.360	**0.401**	0.383
FordB	0.725	0.748	**0.756**	0.741	0.750	0.738	0.750
ShapesAll	0.361	0.344	0.329	**0.420**	0.379	0.367	0.404
SonyAIBORobotSurface1	0.975	0.933	0.957	0.979	0.982	0.976	**0.985**
SonyAIBORobotSurface2	0.929	0.956	0.951	0.969	0.960	**0.970**	0.964
Symbols	0.956	0.929	0.930	0.930	0.969	**0.974**	0.963
Mallat	0.471	0.642	0.563	0.661	0.827	0.876	**0.908**

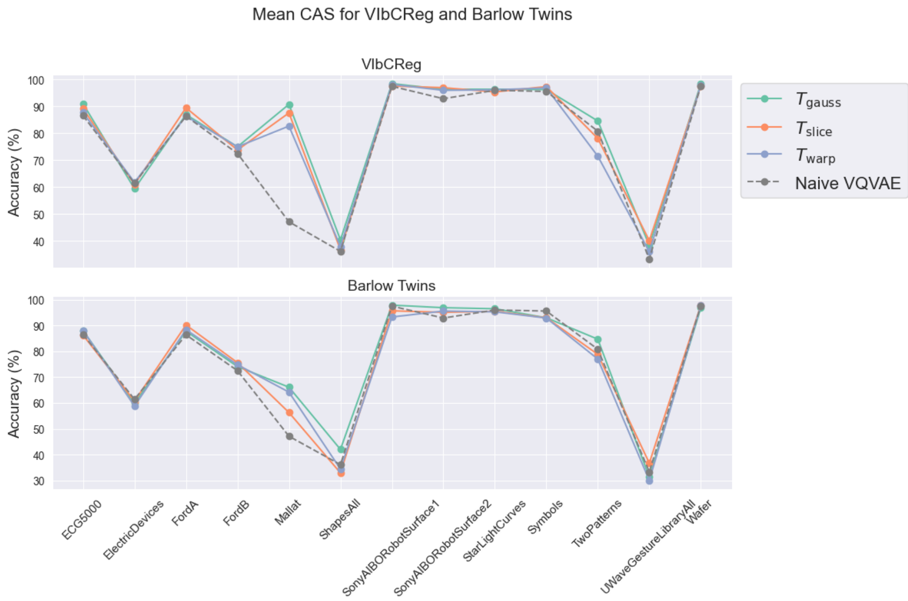
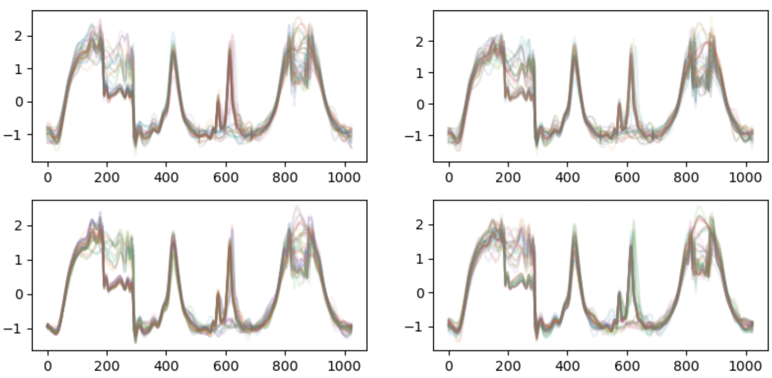


Figure 6: Mean probe accuracies for VIbCReg VQVAE

TODO: Plots that illustrate.



Naive VQVAE. Real (Top) vs synthetic (Bottom)

VIbCReg with Gaussian augmentation. Real (Top) vs synthetic (Bottom)

Figure 7: Difference in synthetic samples between the top performing naive VQVAE and VIbCReg VQVAE with Gaussian augmentation. The VIbCReg VQVAE samples are more varied in the first 300 timesteps, which from figure **??** contains much class specific information.

0.2.3 Prior loss

Mention that during experiments with our stage 2 modification, embed / finetune, we observed that the val prior loss with our modification was higher, but with similar shape as without. If we had time and computational resources to rerun the experiments, then we would omit the stage 2 modification. The FID/IS in our main experiments are in many cases better than baseline VQVAE, despite higher val prior loss.

0.2.4 Token usage

Include something on the differences in sampling/token usage between naive VQVAE and NC-VQVAE. NC-VQVAE has a tendency to be more certain of tokens selected. For small datasets such as Mallat, the certainty is close to 1 for most sampled tokens.

TODO: Investigate this further. Compare/relate the selected probability histograms with token usage histograms / perplexity

Would be interesting to investigate different values for T in maskgit iterative sampling.

Higher masking ratios during training etc.

0.2.5 Visual inspection

Simple patterns, such as sinusoids, are very easily captured. Sharp changes in modularity and frequency are

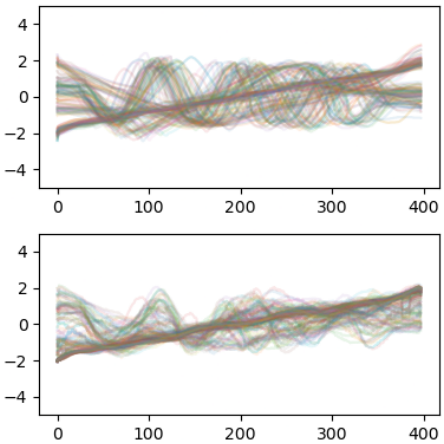
Symbols

Naive VQVAE: Does not capture the entire underlying distribution, some classes are not represented/not recognizable. Global consistency for the sinusoids are poor, particularly towards the end.
VIbCReg: Good mode coverage, but underrepresents the sinusoids or lacks diversity in each class.

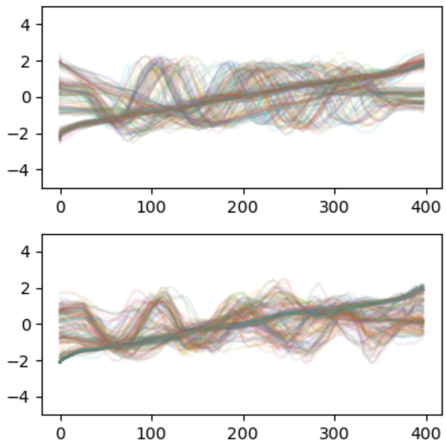
Barlow Twins: windowwarp: little variability in sinusoids, could it be that the ssl loss makes these too close in latent space?

Does the high IS scores correlate with good mode covarage? For symbols our model cover the modes much better than naive. But produces many very similar samples. Does this have something to do with the selected token histograms. Seems like our models select tokens with higher probability, sometimes much higher!

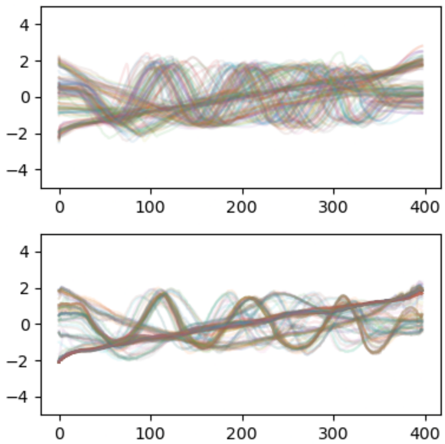
IS has a flaw in that it does not take intraclass diversity into account. Thus a model which generates the mode at each class will get a high IS score. Thus it can give high scores to models that overfit.



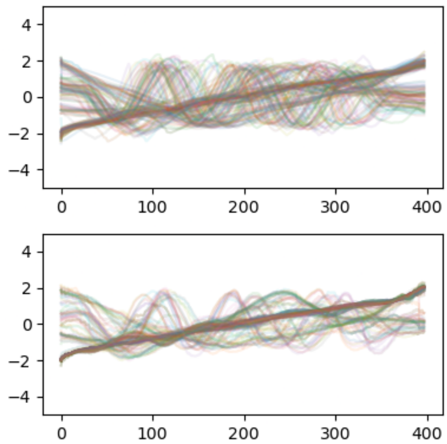
Collapse of global consistency for Naive VQVAE



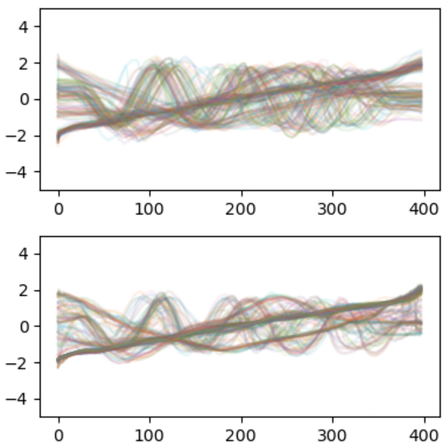
Best Naive VQVAE in terms of FID and IS



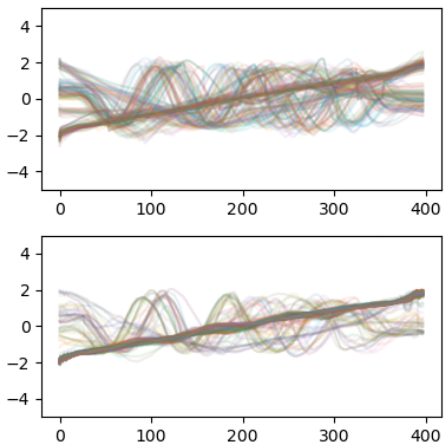
Barlow Twins with Gaussian augmentation, the best performing BT model in terms of FID and IS



Barlow Twins with Gaussian augmentation, the wors performing BT model in terms of FID.



VIbCReg with Slice and Shuffle augmentation, the best performing BT model in terms of FID. Among top performers in terms of IS



VIbCReg with Slice and Shuffle augmentation, the worst performing VIbCReg model in terms of FID and IS.

Sony2 is interesting

ShapesALL

A LOT BETTER class conditional sampling!
Generated vs real.

UWaveGestureLibraryAll

Our model follows the training data quite closely. It might be susceptible to generate outlier data.

The bias introduced by augmentation

0.3 The influence of stage 1 on stage 2

The best performing datasets in terms of probe accuracies: "FordA", "FordB", "Mallat", "ShapesAll", "TwoPatterns", "UWaveGestureLibraryAll"

Relationship between reconstruction in stage 1 and FID/IS/CAS: Does better reconstruction capabilities in stage 1 improve the generative model?

Relationship between probes in stage 1 and FID/IS/CAS: Does better probe accuracies (class separation) in stage 1 improve the generative model?

How does the best performing models from stage 1 transfer to stage 2?

Look at FordA, FordB, Mallat, ShapesALL, TwoPatterns and UWaveGestureLibraryAll. The datasets where probe accuracies are good compared to baseline. Slice is aug with best performance overall on these datasets.

0.3.1 Thoughts

Better inception score and CAS of our models indicate that the class separability learned in latent space makes the conditional distributions more distinct easier to classify. The FID is variable, but in many cases better, which indicated that the generative distributions are closer to the ground truth.

Gaussian noise aug seems to result in a lot easier the BT/VIbCReg loss to minimize.
Slice and shuffle is harder to minimize, but could seem to push representations for different classes further apart resulting in better linear probes.

Talk about the difficulty/ease in minimizing the SSL loss for the different augmentations. Does this affect linear probes / reconstruction / FID / IS / Prior loss

For datasets of smaller size with classes of different characteristics (a clear distributional difference in visual inspection [Sony2 and Symbols]) NC-VQVAE seems to perform better both in terms of FID and IS.

The biases introduced by augmentations in stage 1 seems to be included in the generated samples to some degree. In particular datasets with high frequency components, when applying Gaussian noise (easier to spot), has substantially better FID score.

Is there correlation between CAS and linear probe accuracy??

Temporal vs frequency influence of augmentations. We compress only along temporal axis in the encoder. Could this be a reason for Gaussian artifacts in generation and not slice?

0.4 Discussion

The added flexibility of NC-VQVAE, with possibility of choosing dataset specific augmentations, can in some applications be beneficial.

0.5 Further work

[**morningstar2024augmentations**] suggest that focus on augmentations is of great importance. The hunt for good augmentations in the time series domain is ongoing and should probably get more attention.
HF-LF split - augmentations tailored for HF and LF, as they often have quite different characteristics.
Wavelet transform to improve HF-LF split.

Further optimize the relationship between aug recon loss and choice of augmentations.

Improving on the stage 2 learning to better handle the expressive representations, and be able to create more diverse samples. Higher masking ratio during training, lower value for T etc.