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STEP: Learning Structured Embeddings for Progressive Time Series

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Predictive maintenance of complex systems

Time series from critical systems capture progressive trajectories: from an initial to a terminal state.

Aircraft operate critical systems where a failure is extremely costly: operational, financial, and safety.

Two hard facts:

- **Sensors are sparse and noisy,** the physics is only partially observable.
- **The true health state is hidden,** many degradations unfold at once.

Central question:

From partial observations, can we learn a latent that reveals the underlying progressive latent structure?



Credits Safran, Adrien Daste.

Context and Contributions

- Structure collapses in complex systems
- Prior methods don’t provide health indicators (HI), or don’t learn possible failure pathways
- Estimating the underlying hidden state is crucial for critical systems
- Observations x, unobserved state s_t, $t = 1,...,T$ following a non regressive transition
- As t increases, s_t will also progress, but the evolving quantities of $s_t \neq t$
- Remaining Useful Life (RUL): the system will degrade through time, but at varying rates whereas t is monotonous

1. Contrastively learned progressive paths in a latent space

2. A readout tool, the *Latent Compass* providing HIs

3. Competitive performance, from simpler architectures

STEP: a latent compass for progressive series

Self-supervised contrastive objective that anchors each trajectory between two orthogonal prototypes.

The geometry of the latent becomes the interpretation.

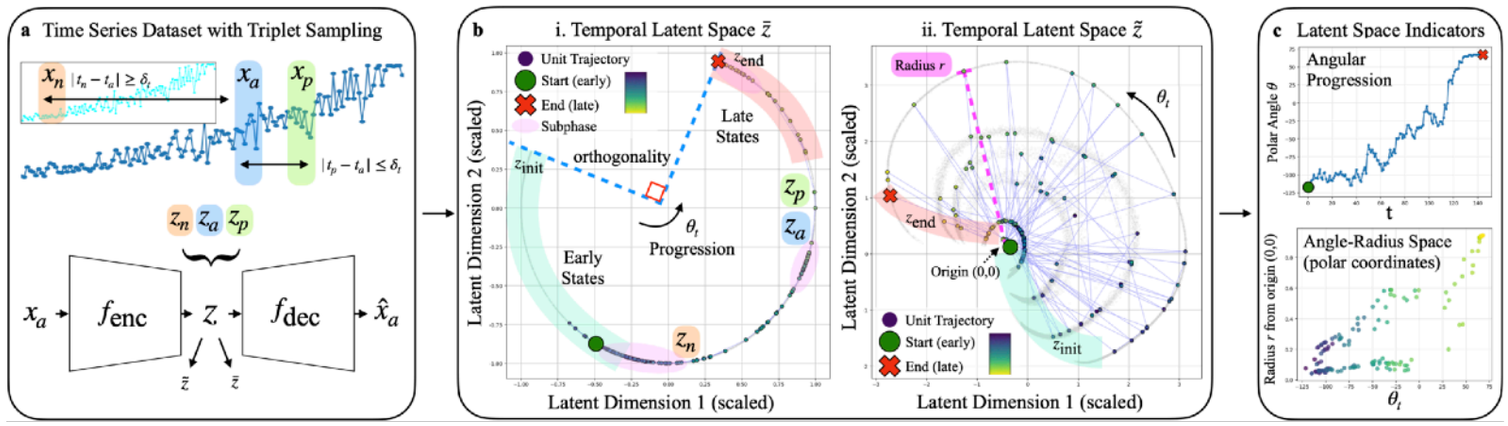


Figure 1. Overview: a. Contrastive SSL approach in three terms with triplet loss function, b. Geometric views with t-SNE of the latent. c. Health indicators emerging from the representation.

$$\mathcal{L}_{\text{trip}} = \frac{1}{N}\sum_{i=1}^{N} \max\big(0,\ \cos(z_a, z_n) - \cos(z_a, z_p) + m\big)$$

$$\mathcal{L}_{\text{recon}} = \frac{1}{N}\sum_{i=1}^{N} \|x_i - \hat{x}_i\|_2^2, \qquad \hat{x}_i = f_{\text{dec}}(f_{\text{enc}}(x_i))$$

$$\mathcal{L}_{\text{proto}} = \mathbb{E}_{x\in X_{\text{init}}}\left[\|f_{\text{enc}}(x) - z_{\text{init}}\|^2\right] + \mathbb{E}_{x\in X_{\text{end}}}\left[\|f_{\text{enc}}(x) - z_{\text{end}}\|^2\right]$$

θ Angle = progression of the state (healthy → degraded)

r Radius = residual structure (e.g., operating regimes)

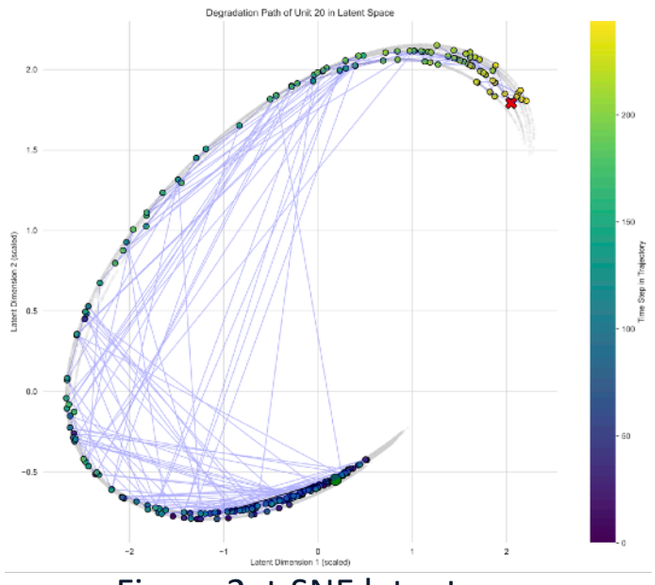


Figure 2. t-SNE latent representation of FD002 with dim(z)=4 on CMAPSS

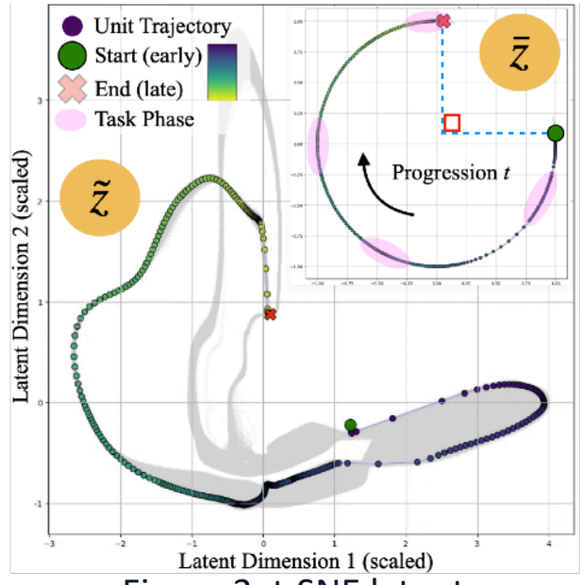


Figure 3. t-SNE latent representation of NVIDIA GR00T Isaac Can2Drawer.

Downstream RUL estimation

Geometry alone explains performance

Model	HI	FD001	FD002	FD003	FD004	Trend.
Prob. CNN	-	12.42	13.72	12.16	15.95	-
I-GLIDE (healthy data only)	✅	**9.47**	16.18	**8.29**	**12.32**	-
Autoencoder	-	17.15±0.19	18.13±0.21	20.72±1.41	20.76±0.68	0.41
SoftCLT	-	15.50±0.61	19.73±1.25	14.87±1.06	23.09±2.08	-
Tr.STEP z=32	✅	13.27±0.38	11.57±0.34	12.66±0.51	13.13±0.69	0.69
LR.STEP z=32 (linear head)	✅	13.09±0.42	**11.44±0.04**	12.48±0.48	13.26±0.39	0.69

RUL RMSE on C-MAPSS (lower is better). Even with a linear regressor and providing new HIs, STEP improves. Proof that the representation is accessible and the underlying measured state captured.

Model	RMSE	Trend
N-CMAPSS, AE only	9.39	0.06
N-CMAPSS, STEP	**2.2–2.9**	0.86–0.92
Battery (held-out cells) STEP vs best classical	-	0.95 vs 0.97

Trendability of STEP's representations.

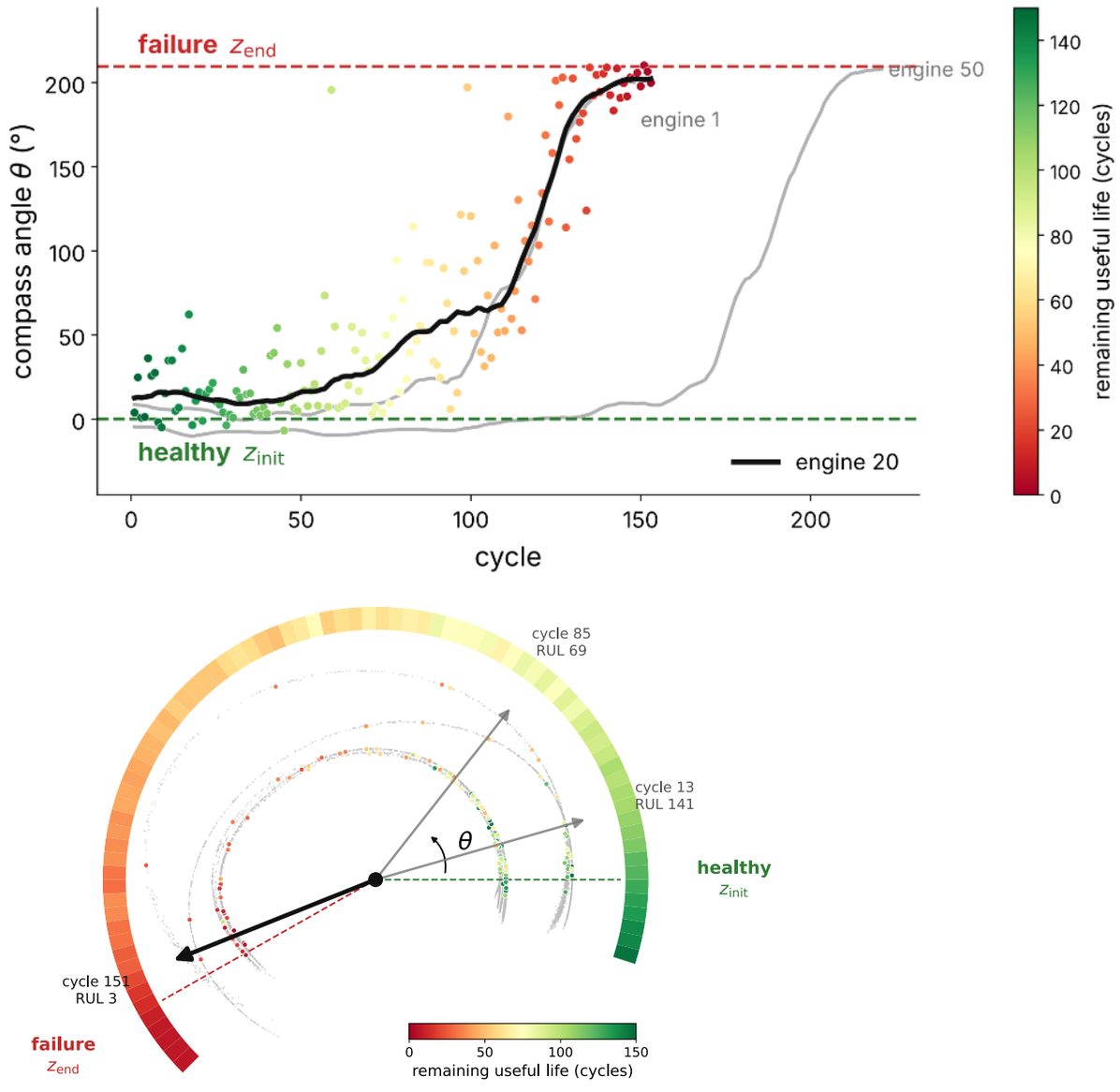
×2 trendability over the same backbone trained for reconstruction

Linear head = transformer head → the state is linearly readable

4 encoders (CNN, GRU, LSTM, PatchTST) on N-CMAPSS: RMSE 2.2–2.9 vs 9.4 for reconstruction only

Discussion

Learning state or time?



- θ follows health, not the clock. Engine 50 lives longer and turns later.
- On held-out engines, θ carries remaining-life information beyond elapsed cycles.
- Operating regimes stay off the angle but remain in the latent.

Takeways

✓ A readable progression angle, no supervised progression target

✓ Competitive RUL, and a linear head is enough

✓ Same objective across encoders, and on robot task phases

Next: reversible states (maintenance), and how controls shape the degradation rate

Come see our poster!

In Room: Hall 1-4 Wed 17:00 in Sydney Poster Session 4.

Project's page