Hypersonic Glide Vehicle Trajectories:
A conversation about synthetic data in T&E

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Motivation

‘Most of the time, [AI-generated] synthetic data doesn’t work.

Synthetic data only works under the tightest conditions.

There must be an empirical basis to synthetic data.

If you have physics that is so well understood and a “fantastically true physics model…”

Why would you use AI to make synthetic data?’

-paraphrased remarks of DoD Chief Digital and AI Officer, Dr. Craig Martell at 2023 CDAO Industry Day and 2024 “Advantage DoD 24” Defense Data & AI Symposium.

Outline

The HGV kinematic model.

On modeling data for synthetic data generation.

The HGV kinematic model transformed.

Acceptability Criteria for AI-Generated Synthetic Data

This presentation is based on

Narrow Digital Twins for High Throughput High Fidelity Models

- 2024 National Fire Control Symposium

Using Generative Artificial Intelligence to Explore Defense against Hypersonic Glide Vehicles

- 2024 American Institute of Aeronautics and Astronautics
- 2023 Space and Missile Defense Symposium
- 2023 National Fire Control Symposium

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Connecting GenAI to Missile Defense T&E

Missile Defense is a difficult mission to test.

- Heavily reliant on detailed modeling and simulation (M&S).
- High-quality input data is critical path for studies and analyses.
- High-resolution, high-quality M&S is slow.

Current Missile Defense T&E processes incorporate M&S products.

Commercially popular “generative AI” is notoriously low-quality and not suitable for serious studies. (see Figure left)

We assert that narrow, physics-based generative AI applications <u>can</u> support M&S and T&E in a rigorous and valid way.

Hypersonic Kinematic Model

Equations of Motion

Velocity

$$\dot{V} = -\frac{D}{m} - g\sin\gamma + \Omega^2 r\left(\sin\gamma\cos\phi - \cos\gamma\sin\phi\cos\psi\right)\cos\phi$$

Flight Path

$$\dot{\gamma} = \frac{L\cos\sigma}{(\quad V)} - \frac{g\cos\gamma}{V} + \frac{V\cos\gamma}{r} + 2\Omega\cos\phi\sin\psi + \frac{\Omega^2 r\cos\phi\left(\cos\gamma\cos\phi + \cos\psi\sin\phi\sin\gamma\right)}{V}$$

$$\dot{\psi} = \frac{L\sin\sigma}{(\quad V\cos\gamma)} + \frac{V\cos\gamma\sin\psi\tan\phi}{r} - 2\Omega\left(\tan\gamma\cos\phi\cos\psi - \sin\phi\right) + \frac{\Omega^2 r\sin\phi\cos\phi\sin\psi}{(V\cos\gamma)}$$

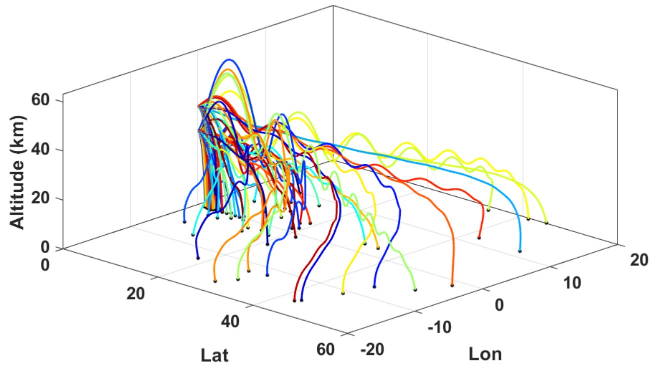
Coordinates with respect to Earth.

$$\dot{r} = V\sin\gamma$$

$$\dot{\theta} = \frac{(V\cos\gamma\cos\psi)}{(r\cos\phi)}$$

$$\dot{\phi} = \frac{(V\cos\gamma\sin\psi)}{r}$$

Exemplar Trajectories



Physical Constraints

Dynamic pressure, normal load, heating rate...

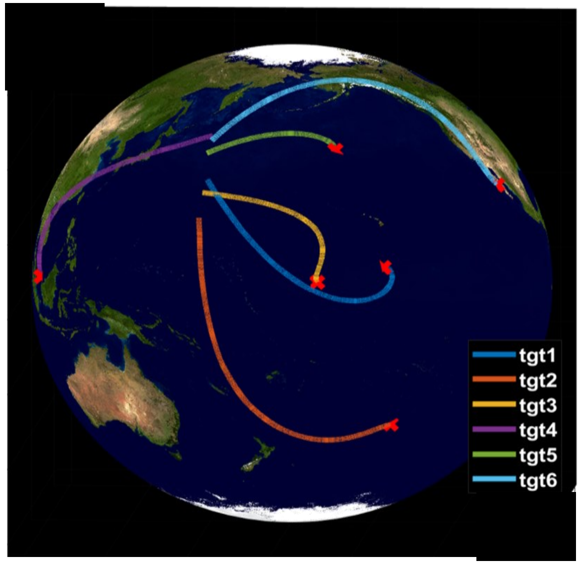
$$q \leq q_{\max}$$

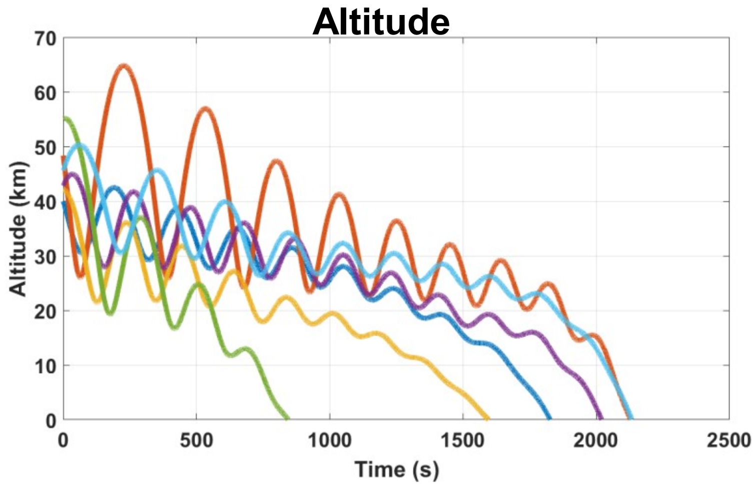
$$n = \frac{\sqrt{D^2+L^2}}{g} \leq n_{\max}$$

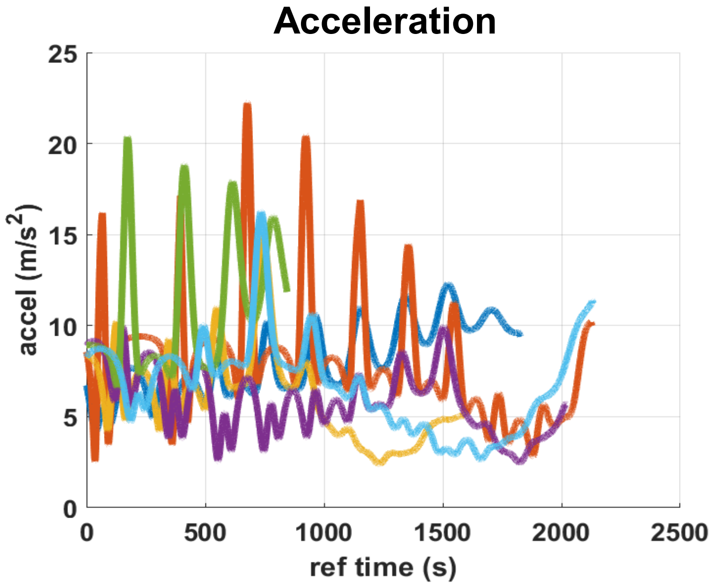
$$\dot{Q} = K\left(\frac{\rho}{\rho_0}\right)^{0.5}\left(\frac{V}{V_c}\right)^{3.15} \leq \dot{Q}_{\max}$$

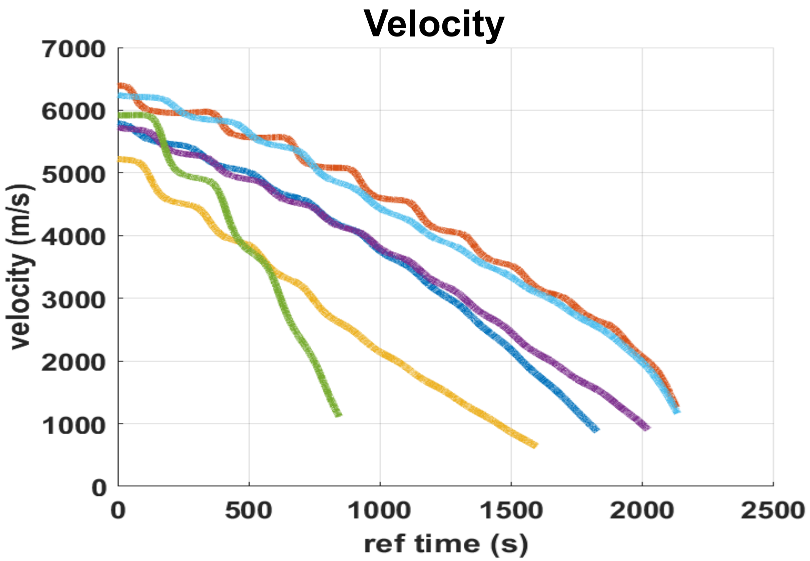
Chern, J-S.(1980) *Optimum reentry trajectories of a lifting vehicle. Vol 3236.* National Aeronautical and Space Administration, Scientific and Technical Information Office.

Exemplar HGV Trajectories



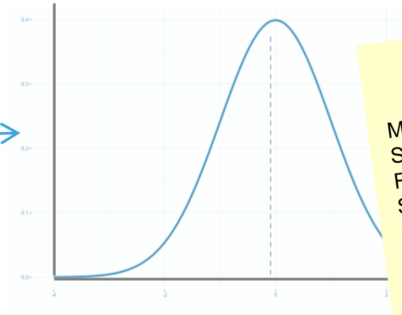






Modeling Data for Synthetic Generation

	Var 1	Var 2	Var 3	Var 4
0	112.7	101.2	59.1	34.3
1	103.6	106.3	55.1	49.6
2	107.9	101.2	50.7	9.7
3	116.3	108.4	58.0	22.0
4	96.8	103.0	42.6	26.2
5	85.8	80.6	56.7	32.4
6	94.1	105.2	34.8	10.9
7	83.5	104.1	45.2	27.2
8	102.1	105.6	34.2	27.6
9	95.0	105.1	30.4	19.0
10	91.9	114.8	49.0	32.0
11	112.6	115.0	50.3	32.4
12	99.9	118.0	34.4	23.8
13	90.4	91.8	57.8	32.3
14	100.7	109.9	63.6	37.3
15	87.6	89.8	52.5	28.1
16	100.4	95.3	44.5	32.3
17	78.2	126.8	45.9	23.6
18	[illegible]3.6	100 3	56.5	49.6
19	[illegible]	[illegible]	33.0	36.9
[illegible]			59.1	31.0
			[illegible]	[illegible]5.8



Mean, Median, Mode
Standard Deviation,
Range,
Skewness, Kurtosis
Shape Factor(s)
Etc…

=NORM.INV(RAND(), mean, standard_deviation) * (1 + (skewness * ((1 - (kurtosis - 3) / 4)) ^ 0.5))

Data → **Data Model** → **Generate Synthetic Samples** …

	Var 1	Var 2	Var 3	Var 4
0	112.7	101.2	59.1	34.3
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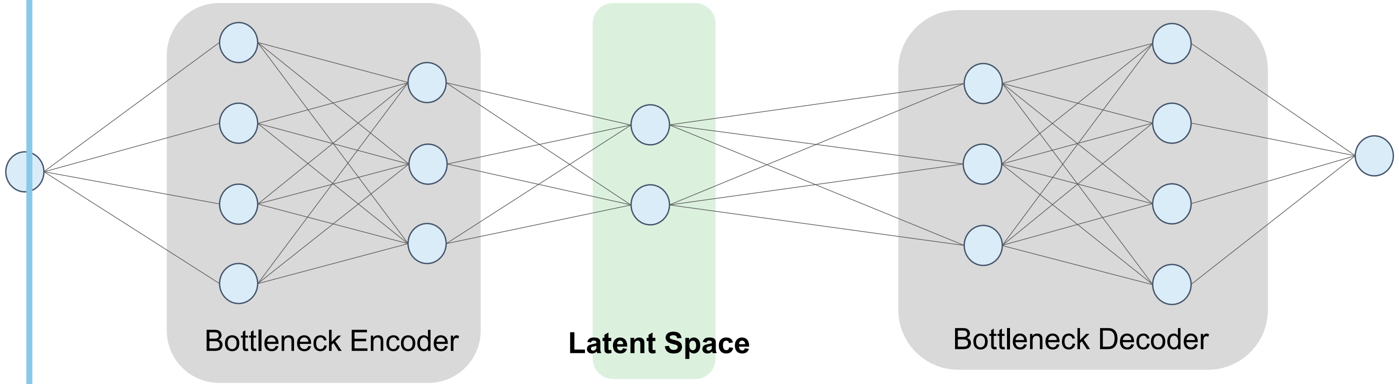
			[illegible]	[illegible]5.8

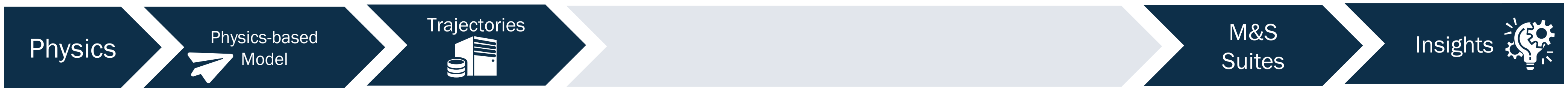
Conditional Variational Autoencoder (CVAA) with Attention



Autoencoders are unsupervised artificial deep neural networks that learn to compress and reconstruct complex data structures data by encoding it to a lower-dimensional representation, called the latent space, and then reconstructing the original data from latent space (decoding).

The conditional autoencoder allows the user to set conditions – such as coordinates or trajectory length.

HGV Trajectories for M&S



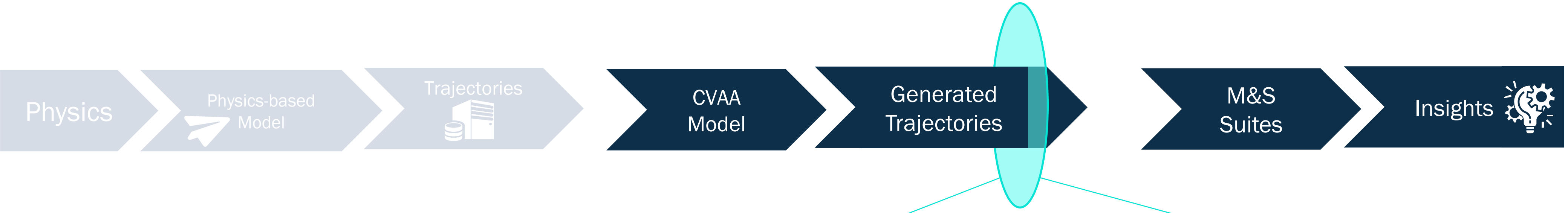
Millions of trajectories on disk from years of model runs…

Generative AI Option:

Model the repository of HGV trajectories with Conditional Variational Autoencoder with Attention (CVAA).

CVAA generates required trajectory >1000x faster than Physics-based Model.

Validating the Generated Trajectories



Filter With Physics

Apply logical tests derived from physics:

- ✓ Conservation of Energy
- ✓ Time Stamps
- ✓ Smoothness
- ✓ Internal consistency (ratios)
- ✓ Thresholds imposed by physical constraints and limits.

Discard any trajectories that are not physically-real.

Less than 1% are physically-unreal.

Validate

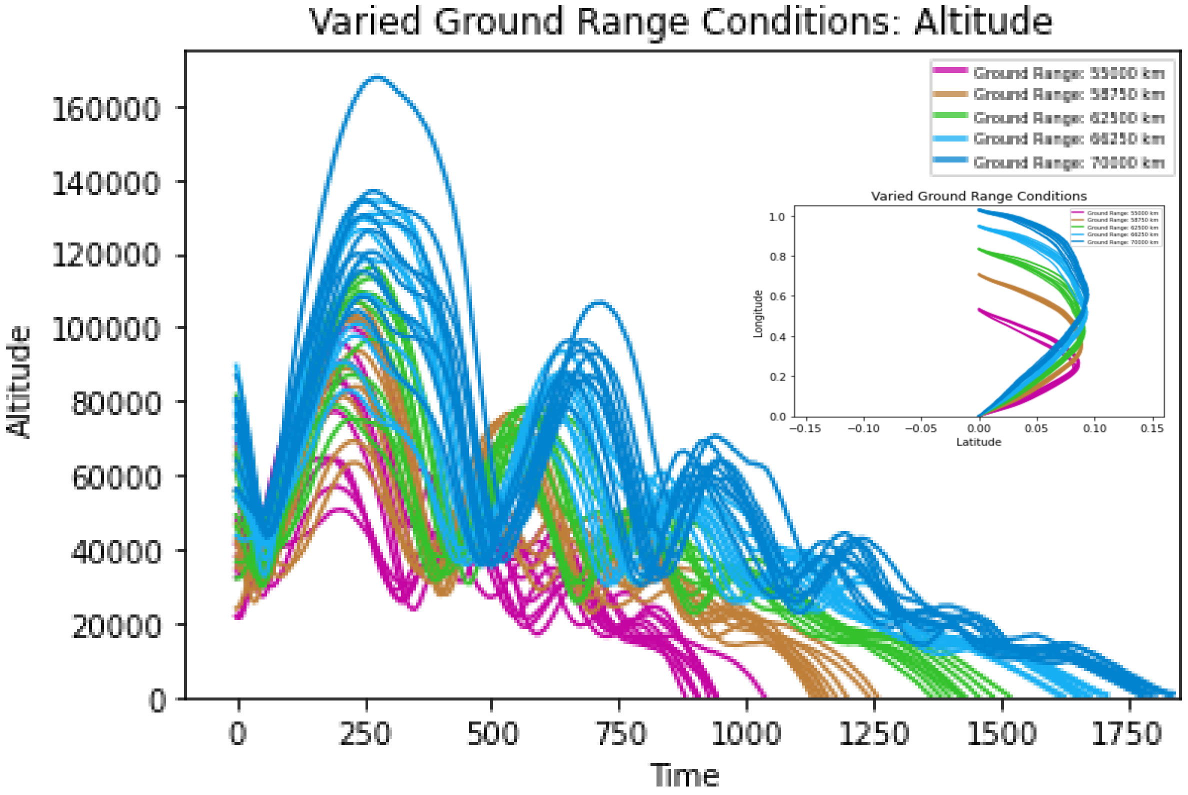
Check features of resultant trajectories against original distributions.

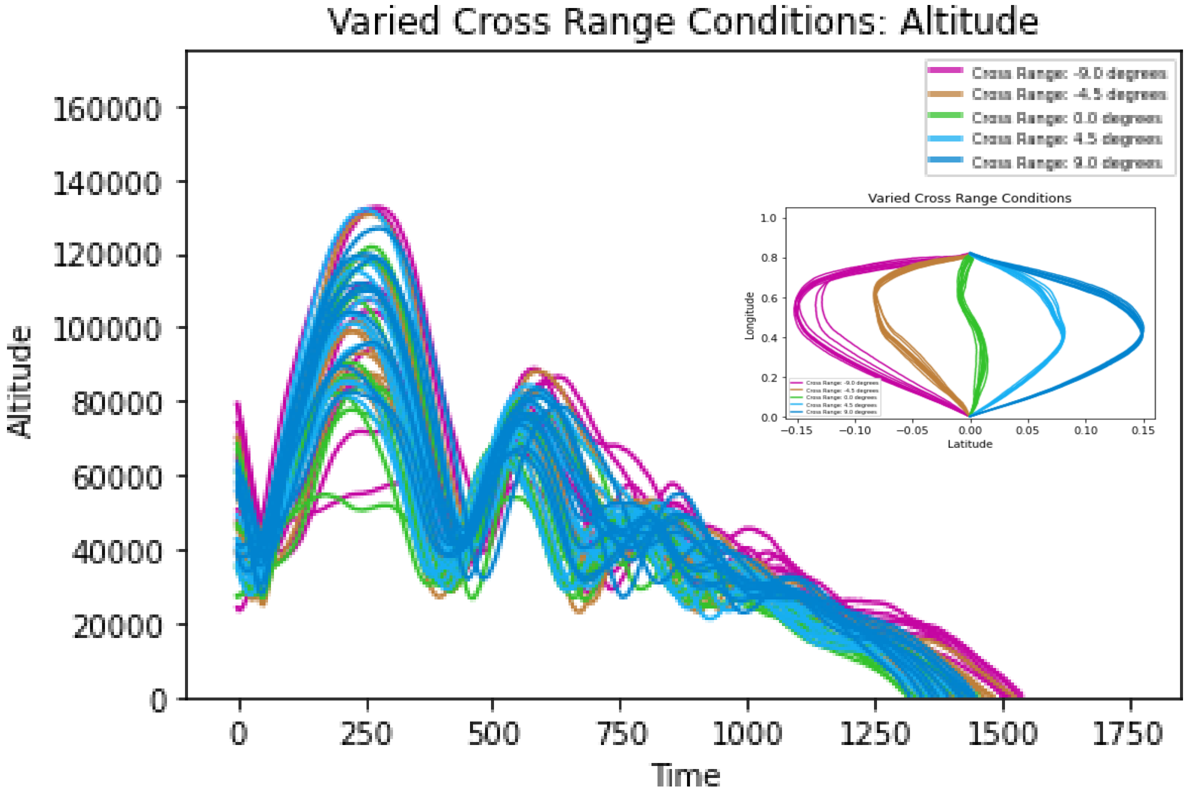
- ✓ Peak Curvatures
- ✓ Position of Peak Curvatures

… or a functional principal component analysis

- ✓ Check downstream M&S results to detect differences & sensitivity.

Sample CVAA Output for Narrow Twin





Toward Acceptability Criteria for AI-Generated Data

Narrowness	Phenomenology	Statistical Confirmation
✓ A single or limited number of phenomena are modeled.	✓ Well-understood and described by governing equations. ✓ Significant empirical foundation.	✓ Output is satisfactorily consistent with the characteristics of the training data. ✓ Downstream uses are insensitive to any differences.
A single kinematic model and a single aerodynamic profile in this case.	*Logical tests can be derived and applied to the generated output.*	*Generated output is compellingly like the original.*

Q: Why Would You Use AI to Make Synthetic Data?

The trained CVAA Generative AI model produces trajectories >1,000x faster than the standard physics modeling.

- ✓ Trade a small amount of resolution* for weeks or months of computational savings.
- ✓ Generative nature allows efficient creation of random trajectories that satisfy the required conditions.
- ✓ Conditional architecture allows for specification of ground range and cross range.

A: To support high-quality M&S studies at the speed of relevance.

A: To provide more trajectories than can typically be produced due to schedule constraints.

If physics-based acceptability criteria exist, then synthetic data sourced from Generative AI models could be verified and validated for use in T&E (via M&S studies).

*small enough that downstream uses of the trajectories are insensitive to the difference.

Thank you!!

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