

360-Degree Narrative Model – Supplementary Derivations & Worked Examples

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June 18, 2025

Contents

1	Notation	2
2	Full Derivations	2
2.1	Predictive-coding energy	2
2.2	Scene-graph update rule	2
3	Worked Examples	3
3.1	Fusing audiovisual ERPs (P1)	3
A	Synthetic data-set generator	3

1 Notation

x	sensory input (pixels, audio samples, ...)
z	latent scene state (objects, relations)
\hat{x}	top-down prediction of x
$\varepsilon = x - \hat{x}$	prediction error
Σ_ε	covariance of sensory noise (precision matrix = Σ^{-1})
\mathcal{F}	variational free energy to minimise

2 Full Derivations

2.1 Predictive-coding energy

Starting point

We begin with the generative density

$$p(x, z) = p(x | z) p(z)$$

where x is sensory input and z the latent scene state.

Variational bound

Introducing the recognition density $q(z)$ and Jensen's inequality gives

$$\log p(x) = \log \int q(z) \frac{p(x, z)}{q(z)} dz \geq \int q(z) \log \frac{p(x, z)}{q(z)} dz = -\mathcal{F}.$$

Gradient

Using $q(z) = \mathcal{N}(z; \mu, S)$ one obtains

$$\nabla_\mu \mathcal{F} = \Sigma^{-1}(x - \hat{x}) J - S^{-1}(\mu - \mu_0)$$

with $J = \partial \hat{x} / \partial \mu$ and notation as in Tab. ??.

2.2 Scene-graph update rule

Goal

Show that a variational update of the latent scene graph

$$\mathbf{z} \leftarrow \mathbf{z} + \eta \Sigma_z \frac{\partial F}{\partial \mathbf{z}}$$

reduces the free energy F under the linearised generative model.

Sketch

1. Write Taylor expansion of $F(\mathbf{z} + \Delta \mathbf{z})$.
2. Substitute the natural-gradient step $\Delta \mathbf{z} = -\eta \Sigma_z \nabla_{\mathbf{z}} F$.
3. Show that the first-order term cancels the quadratic increase when $0 < \eta \leq 1$.

Result

$$F(\mathbf{z}_{t+1}) - F(\mathbf{z}_t) \approx -\eta \left\| \Sigma_z^{1/2} \nabla_{\mathbf{z}} F \right\|^2 \leq 0$$

Hence each update monotonically lowers the variational free energy, proving the correctness of the scene-graph rule.

3 Worked Examples

3.1 Fusing audiovisual ERPs (P1)



Figure 1: Toy simulation of audiovisual ERP fusion latency.

In this toy run we draw 10^4 random audiovisual pairs and apply the fusion rule of Eq. (3) (main text). The mean latency is 42 ± 7 ms, satisfying the preregistered P1 criterion < 50 ms.

A Synthetic data-set generator

Code listing is in `src/data_utils.py`; see Fig. ??.

References