

# **Universal Stochastic Predictor**

## **Phase 3: Core Orchestration**

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# Capítulo 1

## Phase 3: Core Orchestration Overview

Phase 3 implements the physical orchestration layer in `stochastic_predictor/core/`. This layer fuses heterogeneous kernel outputs using Wasserstein gradient flow (JKO) and entropic optimal transport (Sinkhorn) with volatility-coupled regularization.

### 1.1 Scope

Phase 3 covers:

- **Sinkhorn Regularization:** Volatility-coupled entropic regularization for stable optimal transport
- **Wasserstein Fusion:** JKO-weighted fusion of kernel predictions and confidence scores
- **Simplex Sanitization:** Enforced simplex constraints for kernel weights
- **Core API:** Exported fusion and Sinkhorn utilities via `core/__init__.py`

### 1.2 Design Principles

- **Zero-Heuristics Policy:** All parameters injected via `PredictorConfig`
- **JAX-Native:** Stateless functions compatible with JIT/vmap
- **Determinism:** Bit-exact reproducibility under configured XLA settings
- **Volatility Coupling:** Dynamic regularization tied to EWMA variance

## Capítulo 2

# Sinkhorn Module (core/sinkhorn.py)

### 2.1 Volatility-Coupled Regularization

The entropic regularization parameter adapts to local volatility according to the specification:

$$\varepsilon_t = \max(\varepsilon_{\min}, \varepsilon_0 \cdot (1 + \alpha \cdot \sigma_t))$$

where  $\sigma_t = \sqrt{\text{EMA variance}}$  and  $\alpha$  is the coupling coefficient.

```
1 def compute_sinkhorn_epsilon(ema_variance, config):
2     sigma_t = jnp.sqrt(jnp.maximum(ema_variance, config.numerical_epsilon))
3     epsilon_t = config.sinkhorn_epsilon_0 * (1.0 + config.sinkhorn_alpha * sigma_t)
4     return jnp.maximum(config.sinkhorn_epsilon_min, epsilon_t)
```

### 2.2 Entropy-Regularized OT

```
1 def run_sinkhorn(source_weights, target_weights, cost_matrix, epsilon):
2     geom = geometry.Geometry(cost_matrix=cost_matrix, epsilon=float(epsilon))
3     problem = linear_problem.LinearProblem(geom, a=source_weights, b=target_weights)
4     out = sinkhorn.Sinkhorn()(problem)
5     return SinkhornResult(
6         transport_matrix=out.matrix,
7         reg_ot_cost=jnp.asarray(out.reg_ot_cost) if out.reg_ot_cost is not None else jnp.
8         array(0.0),
9         converged=bool(out.converged),
10         epsilon=jnp.asarray(float(epsilon)),
11     )
```

## Capítulo 3

# Fusion Module (core/fusion.py)

### 3.1 JKO-Weighted Fusion

The fusion step normalizes kernel confidences into a simplex and performs a JKO proximal update on weights:

$$\rho_{k+1} = \rho_k + \tau(\hat{\rho} - \rho_k)$$

```
1 def fuse_kernel_outputs(kernel_outputs, current_weights, ema_variance, config):
2     predictions = jnp.array([ko.prediction for ko in kernel_outputs]).reshape(-1)
3     confidences = jnp.array([ko.confidence for ko in kernel_outputs]).reshape(-1)
4     target_weights = _normalize_confidences(confidences, config)
5
6     sinkhorn_epsilon = compute_sinkhorn_epsilon(ema_variance, config)
7     cost_matrix = compute_cost_matrix(predictions, config)
8     sinkhorn_result = run_sinkhorn(
9         source_weights=current_weights,
10        target_weights=target_weights,
11        cost_matrix=cost_matrix,
12        epsilon=sinkhorn_epsilon,
13    )
14
15    updated_weights = _jko_update_weights(current_weights, target_weights, config)
16    PredictionResult.validate_simplex(updated_weights, config.validation_simplex_atol)
17
18    fused_prediction = jnp.sum(updated_weights * predictions)
19    return FusionResult(
20        fused_prediction=fused_prediction,
21        updated_weights=updated_weights,
22        free_energy=sinkhorn_result.reg_ot_cost,
23        sinkhorn_converged=sinkhorn_result.converged,
24        sinkhorn_epsilon=sinkhorn_result.epsilon,
25        sinkhorn_transport=sinkhorn_result.transport_matrix,
26    )
```

### 3.2 Simplex Sanitization

The simplex constraint is validated using the injected tolerance:

```
1 PredictionResult.validate_simplex(updated_weights, config.validation_simplex_atol)
```

# Capítulo 4

## Core Public API

```
1 from .fusion import FusionResult, fuse_kernel_outputs
2 from .sinkhorn import SinkhornResult, compute_sinkhorn_epsilon
```

### 4.1 Compliance Checklist

- **Zero-Heuristics:** All parameters injected via config
- **Volatility Coupling:** Implemented per specification
- **Simplex Validation:** Config-driven tolerance enforced
- **JAX-Native:** Pure functions and stateless modules

## Capítulo 5

### Phase 3 Summary

Phase 3 delivers a concrete orchestration layer for Wasserstein fusion and JKO weight updates. The core layer is now physically present and ready for integration with the prediction pipeline.