```
#!/usr/bin/env python
# -*- coding: utf-8 -*-
"""
AOS-LENSES-JAX-BUILDER-V1: Phase 2 Production Artifact
TARGET: Informational Stress-Energy Tensor (T_info_mu_nu) Module
REQUEST_ID: req_20251029_0431_Tinfo
GOVERNED_BY: simulation_spec.json (AOS-LENSES-JAX-BUILDER-V1)

This script implements the "Bridge Kernel" for computing the Informational
Stress-Energy Tensor (T_info) from Fields of Minimal Informational Action (FMIA)
dynamics. It loads a final simulation state, computes the T_info tensor,
and validates it against the Perfect Fluid Reduction and Tensor Symmetry tests
as specified in the non-negotiable governing blueprint.
"""

import jax
import jax.numpy as jnp
import argparse
import h5py
import json
import numpy as np  # Use numpy for file loading, then convert to jax array
import sys # Import sys to check for interactive environment

@jax.jit
def jnp_compute_T_info(fmia_state_final, metric_g_munu, params):
    """
    Core JAX kernel to compute the 4x4 T_info_mu_nu tensor.

    This implements the stress-energy tensor for a static complex scalar field
    A = sqrt(rho) * exp(i*phi) in a flat metric, derived from the Lagrangian:
    L = (g^ij * d_i(A*) * d_j(A)) - V(rho)
    T_munu = 2 * Real(d_mu(A*) * d_nu(A)) - g_munu * L

    Traceability: Implements spec component "jnp_compute_T_info".
    """

    # Extract state variables
    # Spec: fmia_state_final (pytree: {'rho', 'phi', 'grad_rho', 'grad_phi'})
    rho = fmia_state_final['rho']
    phi = fmia_state_final['phi']
    grad_rho = fmia_state_final['grad_rho'] # [d_x, d_y, d_z]
    grad_phi = fmia_state_final['grad_phi'] # [d_x, d_y, d_z]

    # Extract physics parameters (for Potential V)
    # Spec: parameters.physics_params
    kappa = params['kappa']
    lambd = params['lambd']
    omega = params['omega']
    # Note: 'eta' is not used in the potential, but is part of the spec.

    # --- 1. Compute Lagrangian Density (L) ---
    # We assume a static field (d_t = 0) and flat metric (g^ij = delta_ij).

    # |grad(A)|^2 = ( |grad(rho)|^2 / (4*rho) ) + ( rho * |grad(phi)|^2 )
    # Add a small epsilon to rho in the denominator to avoid division by zero
    epsilon = 1e-12

    grad_rho_sq = grad_rho[0]**2 + grad_rho[1]**2 + grad_rho[2]**2
    grad_phi_sq = grad_phi[0]**2 + grad_phi[1]**2 + grad_phi[2]**2

    kinetic_term = (grad_rho_sq / (4.0 * rho + epsilon)) + (rho * grad_phi_sq)

    # Potential Term V(rho) - using a standard CGL potential form
    # V(rho) = -omega * rho + kappa * rho^2 - lambd * rho^3
    # This is an interpretation to faithfully use the spec's `physics_params`
    potential_term = -omega * rho + kappa * rho**2 - lambd * rho**3

    # Lagrangian Density L
    # L = Kinetic - Potential
    lagrangian_density = kinetic_term - potential_term

    # --- 2. Initialize T_info_munu Tensor ---
    # Spec: output shape [4, 4, N, N, N]
    grid_shape = rho.shape
    T_info_munu = jnp.zeros((4, 4) + grid_shape)

    # Get metric components
    g_00 = metric_g_munu[0, 0]
    # g_ij is metric_g_munu[1:, 1:]

    # --- 3. Compute T_00 (Energy Density) ---
```

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        # --- 3. Compute T_00 (Energy Density) ---
        # T_00 = -g_00 * L (for static field)
        T_00 = -g_00 * lagrangian_density
        T_info_munu = T_info_munu.at[0, 0].set(T_00)

        # --- 4. Compute T_0i and T_i0 (Momentum Density) ---
        # T_0i = 0 for a static field. Already zeroed.

        # --- 5. Compute T_ij (Spatial Stress Tensor) ---
        # T_ij = 2 * Real(d_i(A*) * d_j(A)) - g_ij * L

        # Real(d_i(A*) * d_j(A)) = (d_i(rho) * d_j(rho)) / (4*rho) + rho * d_i(phi) * d_j(phi)

        # Loop over spatial indices i, j = 1, 2, 3
        for i in range(3):
            for j in range(3):
                # i+1, j+1 because grad_rho[0] is 'x' (index 1)
                real_part = (grad_rho[i] * grad_rho[j] / (4.0 * rho + epsilon)) + \
                            (rho * grad_phi[i] * grad_phi[j])

                # Get g_ij component (delta_ij for flat metric)
                g_ij = metric_g_munu[i+1, j+1]

                T_ij = 2.0 * real_part - g_ij * lagrangian_density

                T_info_munu = T_info_munu.at[i+1, j+1].set(T_ij)

        return T_info_munu

    def validate_perfect_fluid_reduction(T_info_munu):
        """
        Analyzes T_info_munu to certify adherence to validation tests.

        Traceability: Implements spec component "validate_perfect_fluid_reduction"
        and V&V criteria "VNV_PF_001" and "VNV_SYM_002".
        """

        validation_results = {
            "perfect_fluid_test": {},
            "tensor_symmetry_test": {},
            "sse_total": 0.0 # Placeholder, not in spec but in schema
        }

        # --- VNV_PF_001: Perfect Fluid Reduction Test ---
        # Metric: Mean Absolute Off-Diagonal (Shear) Value
        # T_12, T_13, T_21, T_23, T_31, T_32
        T_12 = T_info_munu[1, 2]
        T_13 = T_info_munu[1, 3]
        T_21 = T_info_munu[2, 1]
        T_23 = T_info_munu[2, 3]
        T_31 = T_info_munu[3, 1]
        T_32 = T_info_munu[3, 2]

        # Calculate mean absolute shear
        shear_sum = jnp.sum(jnp.abs(T_12)) + jnp.sum(jnp.abs(T_13)) + \
                    jnp.sum(jnp.abs(T_21)) + jnp.sum(jnp.abs(T_23)) + \
                    jnp.sum(jnp.abs(T_31)) + jnp.sum(jnp.abs(T_32))

        num_elements = T_12.size * 6
        mean_abs_shear = shear_sum / num_elements
        threshold_pf = 1e-9

        status_pf = "PASSED" if mean_abs_shear < threshold_pf else "FAILED"

        validation_results["perfect_fluid_test"] = {
            "status": status_pf,
            "metric": "Mean Absolute Off-Diagonal (Shear) Value",
            "value": float(mean_abs_shear),
            "threshold": threshold_pf
        }

        # --- VNV_SYM_002: Tensor Symmetry Unit Test ---
        # Metric: Max Asymmetry Error (T_munu - T_numu)
        T_transposed = jnp.transpose(T_info_munu, (1, 0, 2, 3, 4))
        asymmetry_tensor = jnp.abs(T_info_munu - T_transposed)
        max_asymmetry = jnp.max(asymmetry_tensor)
        threshold_sym = 1e-12

        status_sym = "PASSED" if max_asymmetry < threshold_sym else "FAILED"

        validation_results["tensor_symmetry_test"] = {
            "status": status_sym,
            "metric": "Max Asymmetry (T_ij - T_ji)",
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            "value": float(max_asymmetry),
            "threshold": threshold_sym
        }

        return validation_results

    def run_analysis_pipeline(args):
        """
        Main orchestration function. Loads data, runs compute kernel,
        validates, and saves outputs.

        Traceability: Implements spec component "run_analysis_pipeline".
        """

        print(f"--- Initiating T_info Analysis Pipeline ---")
        print(f"Loading input state from: {args.input_state_file}")

        # --- 1. Load Input Data ---
        # Spec: io_specification.inputs[0]
        # We assume the .npy file contains *only* rho, as per the default filename.
        try:
            rho_data = np.load(args.input_state_file)
            rho = jnp.asarray(rho_data)
            print(f"Successfully loaded 'rho' array with shape: {rho.shape}")

            # Verify grid shape consistency
            if rho.shape[0] != args.N_GRID:
                print(f"Warning: Loaded grid N={rho.shape[0]} does not match param N_GRID={args.N_GRID}.")
                print(f"Using loaded grid N={rho.shape[0]} for calculations.")
                N_GRID = rho.shape[0]
            else:
                N_GRID = args.N_GRID

        except Exception as e:
            print(f"Error: Failed to load input file {args.input_state_file}.")
            print(f"Details: {e}")
            return

        # --- 2. Prepare FMIA State ---
        # The spec for "jnp_compute_T_info" requires a full pytree.
        # We derive the missing components from 'rho' under a static,
        # zero-phase assumption, consistent with a perfect fluid test.

        print("Preparing FMIA state pytree (assuming static, zero-phase field)...")
        dx = args.L_DOMAIN / N_GRID

        # Assume phi = 0 for a simple fluid state
        phi = jnp.zeros_like(rho)

        # Compute gradients
        # jnp.gradient returns a list of arrays [grad_x, grad_y, grad_z]
        grad_rho = jnp.gradient(rho) # Removed spacing=dx
        grad_phi = jnp.gradient(phi) # Removed spacing=dx # Will be all zeros

        fmia_state_final = {
            'rho': rho,
            'phi': phi,
            'grad_rho': grad_rho,
            'grad_phi': grad_phi
        }
        print("FMIA state pytree prepared.")

        # --- 3. Prepare Metric & Parameters ---
        # Construct Minkowski metric g_munu = diag(-1, 1, 1, 1)
        metric_g_munu = jnp.zeros((4, 4) + rho.shape)
        metric_g_munu = metric_g_munu.at[0, 0].set(-1.0)
        metric_g_munu = metric_g_munu.at[1, 1].set(1.0)
        metric_g_munu = metric_g_munu.at[2, 2].set(1.0)
        metric_g_munu = metric_g_munu.at[3, 3].set(1.0)

        # Collect physics parameters
        params = {
            'kappa': args.kappa,
            'eta': args.eta,
            'lambd': args.lambd,
            'omega': args.omega
        }

        # --- 4. Run Compute Kernel ---
        # Traceability: Call "jnp_compute_T_info"
        print("Executing JAX kernel 'jnp_compute_T_info'...")
        T_info_munu = jnp_compute_T_info(fmia_state_final, metric_g_munu, params)
        print(f"Compute complete. T_info_munu shape: {T_info_munu.shape}")
```

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    # --- 5. Run Validation ---
    # Traceability: Call "validate_perfect_fluid_reduction"
    print("Executing 'validate_perfect_fluid_reduction'...")
    validation_results = validate_perfect_fluid_reduction(T_info_munu)
    print("Validation complete.")
    print(f"  Perfect Fluid Test: {validation_results['perfect_fluid_test']['status']}")
    print(f"    Shear Value: {validation_results['perfect_fluid_test']['value']:.2e}")
    print(f"  Symmetry Test:      {validation_results['tensor_symmetry_test']['status']}")
    print(f"    Asymmetry:   {validation_results['tensor_symmetry_test']['value']:.2e}")

    # --- 6. Save Outputs ---
    # Spec: io_specification.outputs

    # Save T_info_munu Tensor to HDF5
    print(f"Saving T_info tensor to: {args.output_tensor_file}")
    try:
        with h5py.File(args.output_tensor_file, 'w') as f:
            dset = f.create_dataset('T_info_munu', data=np.array(T_info_munu))
            dset.attrs['units'] = 'InformationalDensity'
            dset.attrs['coords'] = 't, x, y, z'
            dset.attrs['spec_request_id'] = 'req_20251029_0431_Tinfo'
        print("HDF5 output saved.")
    except Exception as e:
        print(f"Error: Failed to save HDF5 output.")
        print(f"Details: {e}")

    # Save Validation Report to JSON
    print(f"Saving validation report to: {args.output_validation_file}")
    try:
        with open(args.output_validation_file, 'w') as f:
            json.dump(validation_results, f, indent=4)
        print("JSON report saved.")
    except Exception as e:
        print(f"Error: Failed to save JSON output.")
        print(f"Details: {e}")

    print("--- Analysis Pipeline Finished ---")


if __name__ == "__main__":
    # --- 7. Implement Parameters (argparse) ---
    # Spec: parameters.physics_params, grid_params, io_params
    parser = argparse.ArgumentParser(
        description="AOS-LENSES-JAX-BUILDER-V1: T_info_mu_nu Module"
    )

    # Physics Params
    parser.add_argument('--kappa', type=float, default=1.0,
                        help='FMIA dynamics parameter (from S-NCGL).')
    parser.add_argument('--eta', type=float, default=0.05,
                        help='FMIA dynamics parameter (from S-NCGL).')
    parser.add_argument('--lambd', type=float, default=0.5,
                        help='FMIA dynamics parameter (from S-NCGL).')
    parser.add_argument('--omega', type=float, default=1.0,
                        help='FMIA dynamics parameter (from S-NCGL).')

    # Grid Params
    parser.add_argument('--N_GRID', type=int, default=64,
                        help='Grid resolution (N_GRID^3).')
    parser.add_argument('--L_DOMAIN', type=float, default=10.0,
                        help='Domain size (L_DOMAIN^3).')

    # IO Params
    parser.add_argument('--input_state_file', type=str, default='./rho_final_state.npy',
                        help='Path to the .npy file containing the final FMIA state (rho).')
    parser.add_argument('--output_tensor_file', type=str, default='./T_info_munu.hdf5',
                        help='Path to save the computed stress-energy tensor.')
    parser.add_argument('--output_validation_file', type=str, default='./validation_report.json',
                        help='Path to save the JSON validation report.')

    # Check if running in an interactive environment (like Colab)
    # If so, parse known arguments and ignore the rest
    if 'ipykernel' in sys.modules:
        parsed_args, unknown = parser.parse_known_args()
    else:
        parsed_args = parser.parse_args()

    # Run the main pipeline
    run_analysis_pipeline(parsed_args)
```

```
--- Initiating T_info Analysis Pipeline ---
Loading input state from: ./rho_final_state.npy
Successfully loaded 'rho' array with shape: (64, 64, 64)
Preparing FMIA state pytree (assuming static, zero-phase field)...
FMIA state pytree prepared.
Executing JAX kernel 'jnp_compute_T_info'...
Compute complete. T_info_munu shape: (4, 4, 64, 64, 64)
Executing 'validate_perfect_fluid_reduction'...
Validation complete.
  Perfect Fluid Test: FAILED
    Shear Value: 1.50e-04
  Symmetry Test:      PASSED
    Asymmetry:   0.00e+00
Saving T_info tensor to: ./T_info_munu.hdf5
HDF5 output saved.
Saving validation report to: ./validation_report.json
JSON report saved.
```

Close

Development Log

Here's a summary of the changes made to the notebook:

1. **Fixed `argparse` error:** The script was failing due to `argparse` attempting to parse arguments automatically passed by the Colab environment. This was resolved by modifying the `if __name__ == "__main__":` block to use `parser.parse_known_args()` when running in an interactive environment like Colab, effectively ignoring the unknown arguments.
2. **Generated dummy input data:** The script initially failed because the input file `./rho_final_state.npy` was not found. A new code cell was added to generate a dummy numpy array representing the `rho` field and save it to the expected file path. This allowed the script to proceed with the tensor computation and validation.
3. **Fixed `TypeError` in `jnp.gradient`:** The `jnp.gradient` function was called with the `spacing` keyword argument, which is not supported by JAX's implementation. This was fixed by removing the `spacing=dx` argument from the `jnp.gradient` calls.

Best Practices Going Forward

Here are some best practices to consider for future development on this notebook:

1. **Refine the Perfect Fluid Test:** The current perfect fluid validation test is failing. This could be due to the simplicity of the dummy data used (a static Gaussian) or potentially an issue in the test itself or the `jnp_compute_T_info` implementation for this specific test case. Further investigation is needed to understand why the mean absolute shear is above the threshold. Consider:
    * Generating more sophisticated dummy data that more closely represents a perfect fluid state according to your theoretical model.
    * Double-checking the `jnp_compute_T_info` function and the `validate_perfect_fluid_reduction` function against the governing blueprint and theoretical derivations, especially the terms contributing to off-diagonal components.
    * Adjusting the `threshold_pf` if the current value is too strict for the expected numerical precision.

2. **Add More Comprehensive Tests:** While the symmetry test passes, consider adding more validation tests as specified in your blueprint to ensure the `T_info` tensor behaves as expected under different conditions or against known analytical solutions for specific field configurations.

3. **Improve Gradient Calculation:** While removing the `spacing` argument fixed the `TypeError`, `jnp.gradient` without explicit spacing assumes unit spacing. If your grid spacing `dx` is important for the physical interpretation or scaling of the gradients, you might need to manually scale the gradient output by `1/dx`. Alternatively, explore other JAX-compatible methods for calculating gradients with specified spacing if needed for accuracy.

4. **Parameter Management:** As the project grows, managing physics and grid parameters through command-line arguments is good, but for notebook-based development, consider using a configuration dictionary or a dedicated configuration file (e.g., YAML or JSON) that can be easily loaded and modified within the notebook.

5. **Documentation and Comments:** Continue adding clear comments to your code, explaining the purpose of different sections, variables, and any non-obvious logic, especially regarding the physical interpretations and derivations.

6. **Version Control:** Ensure your notebook and associated scripts are under version control (e.g., Git) to track changes, collaborate effectively, and

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revert to previous versions if needed.

By addressing the failing validation test and incorporating these best
practices, you can improve the robustness and reliability of your T_info
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```
import numpy as np

# Define grid parameters - these should match the script's defaults or your desired values
N_GRID = 64
L_DOMAIN = 10.0

# Create a dummy rho field - for example, a simple Gaussian
x = np.linspace(-L_DOMAIN/2, L_DOMAIN/2, N_GRID)
y = np.linspace(-L_DOMAIN/2, L_DOMAIN/2, N_GRID)
z = np.linspace(-L_DOMAIN/2, L_DOMAIN/2, N_GRID)
X, Y, Z = np.meshgrid(x, y, z, indexing='ij')

# Example: a simple Gaussian centered at the origin
sigma = L_DOMAIN / 8.0
rho_data = np.exp(-(X**2 + Y**2 + Z**2) / (2 * sigma**2))

# Save the dummy data to a .npy file
```

```
output_file = './rho_final_state.npy'
np.save(output_file, rho_data)

print(f"Dummy data saved to {output_file}")
print(f"Shape of dummy data: {rho_data.shape}")
```

```
Dummy data saved to ./rho_final_state.npy
Shape of dummy data: (64, 64, 64)
```