Org Notebook for the IDEM project

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1 Import the Project

```
from IDEM import *
from utilities import create_grid
```

2 Constructing the Process Grid and Kernel

Closely following (Wikle, Christopher K and Zammit-Mangion, Andrew and Cressie, Noel, 2019);

We then define the transition kernel; as an example, this is using a Gaussian kernel

$$\kappa(\mathbf{s},\mathbf{x};\alpha,\pmb{\mu},\pmb{\Sigma}) = \alpha \exp\left[-(\mathbf{s}-\mathbf{x}-\pmb{\mu})\pmb{\Sigma}^{-1}(\mathbf{s}-\mathbf{x}-\pmb{\mu})\right].$$

Implemented as a JAX function,

```
return kappa_vmap
#example values
alpha = 1
mu = jnp.array([0,0])
sigma = jnp.array([[1,0],[0,2]])
s_{vec} = jnp.array([[1,1],[2,2]])
x_{vec} = jnp.array([[-1,2],[-2,2]])
result = kappa_vmap(s_vec, x_vec, alpha, mu, sigma)
   Lets first try to recreate the results in the original R book; here, the dimension is 1, and we consider the
point s = 0.5 for the following parameter options
thetap1 = (jnp.array(40),jnp.array([0]),jnp.array([[0.0002]]))
thetap2 = (jnp.array(5.75),jnp.array([0]),jnp.array([[0.01]]))
thetap3 = (jnp.array(8),jnp.array([0.1]),jnp.array([[0.005]]))
thetap4 = (jnp.array(8), jnp.array([-0.1]), jnp.array([[0.005]]))
   when we apply kappa_outer, we can unpack these by *thatap1, for example.
   Lets make a 1D grid with the create_grid function;
s_grid_1D = create_grid(jnp.array([[0,1]]), jnp.array([0.01]))
kappa_1 = make_kernel(*thetap1)
k_x_1 = kappa_1(jnp.array([[0.5]]),
                     s_grid_1D)
import matplotlib.pyplot as plt
plt.plot(s_grid_1D, k_x_1)
plt.title('k_x_1')
plt.xlabel('x')
plt.show()
plt.close()
   We should also define \eta_t. Being independent in time, this is simply a multivariate Gaussian with some
covariance matrix \Sigma_{\eta}. In the R book examples, they define this covariance as an exponential function as
follows;
sigma_eta = 0.1 * jnp.exp(-jnp.abs(
    s_grid_1D - s_grid_1D.T)/0.1
   and then simulation can be done through the jax.random.multivariate_normal operation (or other-
wise, of course).
key = jax.random.PRNGKey(seed=3)
sim = rand.multivariate_normal(key, jnp.zeros(100), sigma_eta)
plt.plot(s_grid_1D, sim)
plt.show()
plt.close()
```

3 Simulation of the Process

We can now consider how to actually simulate a realisation of such a system. In the R book, they do this with a for loop; this simply won't do. Instead, we define how the model should step forward with a function, which we can then iterate across.

```
def forward_step(Y,
                 s_grid,
                 key):
    sigma_eta = 0.1 * jnp.exp(-jnp.abs(
        s_{grid} - s_{grid}.T)/0.1)
    eta = rand.multivariate_normal(key, jnp.zeros(100), sigma_eta)
    ds=0.01 # for now :(
    Y_next = (M @ Y)*ds + eta
    return Y_next
Y_init = jnp.zeros(100)
kappa_1 = make_kernel(*thetap1)
kappa_3 = make_kernel(*thetap3)
M = kappa_3(s_grid_1D, s_grid_1D)
def step(carry, key):
        nextstate = forward_step(carry, M, s_grid_1D, key)
        return(nextstate, nextstate)
key = jax.random.PRNGKey(seed=2)
keys = rand.split(key, T)
simul = jl.scan(step, Y_init, keys)[1]
# Create the Hovmöller plot
plt.figure(figsize=(100, 6))
plt.contourf([jnp.arange(T),s_grid_1D.flatten()], simul, cmap='viridis', levels=200)
plt.colorbar(label='process')
plt.xlabel('Space')
plt.ylabel('Time')
plt.title('Hovmöller Plot')
# Show the plot
plt.show()
plt.close()
```