Predation model
Hybridisation_A

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This reports the hybridisation of the predation model with the ACF implementation of the policy model. It outlines how the models were hybridised and goes through the initialisation of the models and the experiments that will be run using these models.

1 The problem tree

Overall, the problem tree is given as follows:

- Policy core problems:
  1. Sheep - The amount of sheep on the grid.
  2. Wolf - The amount of wolves on the grid.
  3. Fully grown grass - The amount of fully grown grass on the grid.
- Secondary problems:
  1. Net sheep population change - This is the difference between initial and final amount of sheep.
  2. Net wolf population change - This is the difference between initial and final amount of wolves.
  3. Net grown grass patch change - This is the difference between initial and final amount of grown grass patches.

Note that the secondary issues and the policy core issues are the same. The main reason behind this choice is the simplicity of the model. The model is so simple that the it is difficult to find any different policy core issues.

2 The policy instruments

The policy instruments within the policy tree are implemented using incremental increases and decreases in the following exogenous parameters.

1. Change sheep reproduction [CR-0.01/+0.01]
2. Change wolf reproduction [WR -0.01/+0.01]
3. Change grass regrowth [GR-2/+2]

3 The steps for model integration

This section presents the steps that are needed to connect a policy context model, in this case the predation model, to the policy process model.

1. Before any coding, define what the belief tree and the policy instruments will be for the predation model.
2. Copy the policy emergence model files into the same folder.
3. In `runbatch.py`, replace the policy context items by the predation model.
4. In `runbatch.py`, make sure to initialise the predation model appropriately.
5. Change the `input goalProfiles` files to have the appropriate belief tree structure of the predation model.
6. In `model module interface.py`, construct the belief tree and the policy instrument array.
7. Make sure that the step function in the `model predation.py` returns the KPIs that will fit in the belief system in the order DC, PC and S. If no DC is considered, then include one value of 0 at least. All KPIs need to be normalised.
8. Modify the step function of the `model predation.py` to include a policy implemented.
9. Introduce the changes that a policy implemented would have on the model in `model predation.py`.

4 The steps for model simulation

This section presents the steps that are needed to connect a policy context model, in this case the predation model, to the policy process model.

1. For the policy process:
   (a) Define a set of hypotheses to be tested
   (b) Define scenarios that will be needed to assess the hypotheses
   (c) Choose the agent distribution based on the scenarios constructed
   (d) Set the preferred states for the active agents and the electorate along with the causal beliefs to be used. This should all be based on the scenarios that have been constructed.
2. For the predation model:
   (a) Define the initial values for the main parameters
   (b) Define the parameters that will be recorded
3. Save the right data from the model.

5 Model hypotheses

Because of the complexity of the model, there are a lot of hypotheses that can be tested with this ACF policy emergence model. However, we will try not to demonstrate the same hypotheses that were demonstrated for the SM. This would be redundant. This includes all of the hypotheses that establish a causal relation between policy change and environment change. The focus will instead be placed on the impact that the new elements, for each of the model variations, has on policy change and on the dynamics of the model. This includes the impact of policy learning and coalitions on policy change.

5.1 The +PL model

The main research question that we want to answer with this model is:

What impact does policy learning have on policy change within the ACF+PL model?

Several hypotheses are considered to answer this question:

- H1: Policy learning leads to policy change.
- H2: The resources distribution will affect the speed and the direction of policy learning.
- H4: The balance of power will affect the speed and the direction of policy learning.

5.2 The +Co model

The main research question that we want to answer with this model is:

What impact do coalitions have on policy change within the ACF+Co model?

Several hypotheses are considered to answer this question:

- H1:

6 Model scenarios

We differentiate the scenarios that will be run for the +PL and the +Co models within this section. For each scenario, we have to consider the belief system of the agents, the agent distribution and the resource distribution. Though in the formalisation of the model we do not make a mention of affiliations (except when it comes to the electorate influence), we will still use affiliations here to simplify the initialisation of the agents for the policy emergence model.

6.1 The +PL model

For now only the benchmark scenario and scenario 1 are considered. These basically test the different impact of a change of resources on policy learning and the associated effect on policy change, if any. For each of the scenario, the preferred states of the agents are shown in Table 1, their causal relations are provided in Table 2 and the agents and resources distribution are provided in Table 3.

Note that for now we only allow the agents to influence one another on their preferred states and not on their causal beliefs.

- Scenario 0 - No interactions

  Scenario 0 is a scenario where no interactions are taken into account. It is the SM simulation. This is used to compare with the results from the model with the interactions introduced.

- Scenario 1 - Benchmark interactions

  The benchmark scenario is to be used as a benchmark. It is a simulation of the predation model with the policy emergence model. Two affiliations are considered. Affiliation 0 consists of two policy makers and four policy entrepreneurs (2 PM and 4 PE) with high resources and a preference for sheep favouring policies. Affiliation 1 consists of one policy maker and four policy entrepreneurs (1 PM and 4 PE) with low resources and a preference for wolf favouring policies. The preferred states for the agents are provided in Table 1. The causal beliefs used as given in Table 2.

- Scenario 2 - Demonstrating policy learning but not policy change

  The aim of this scenario is to demonstrate that policy learning does not always lead to policy change by having a resource rich set of agents not be the dominant set of agents for the agenda selection and the policy implementation.

  Two affiliations are considered. Affiliation 0 consists of two policy makers and four policy entrepreneurs (2 PM and 4 PE) with low resources and a preference for sheep favouring policies. Affiliation 1 consists of one policy maker and four policy entrepreneurs (1 PM and 4 PE) with high resources and a preference for wolf favouring policies. The preferred states for the agents are provided in Table 1. The causal beliefs used as given in Table 2.

- Scenario 3 - External event on a preferred state

  Introduce an external event on one of the preferred states of all agents to influence their beliefs and observe whether that makes a difference in their choice of policy selection.

	PC1 Sheep	**PC2** Wolves	**PC3** Grass	**S1** Sheep growth	**S2** Wolves growth	**S3** Grass growth
Scenario 0/1/2						
Affiliation 0 - Pro sheep						
Value	400	50	2000	75	-50	200
Norm.	0.80	0.10	0.80	0.88	0.25	0.70
Affiliation 1 - Pro wolves						
Value	200	175	1700	50	25	120
Norm.	0.40	0.35	0.68	0.75	0.63	0.62

Table 1: Preferred states for the policy makers on a the interval [0,1] for scenarios 0 and 1.

Scenario 0/1/2			
	PC1	PC2	PC3
-S1	1.00	0.75	-0.75
-S2	-0.75	1.00	0.25
-S3	0.50	0.75	1.00

Table 2: Causal beliefs for the policy makers. These causal relations can be read as: an increase of 1 in S2 will lead to a decrease of 0.75 in PC1. They are all given on the interval [-1,1].

Scenarios	**0**		**1**	
Affiliations	0	1	0	1
Policy makers	2	1	2	1
Policy entrepreneurs	4	4	4	4
Resources	50	25	25	50

Table 3: Agents and resource distribution for each of the scenarios. Resources values will have to be adjusted - the current values are only temporary.

6.2 The +Co model

7 Initialisation of the predation model

The parameters that need to be initialised for the predation model are given by:

- Grid height: 50
- Grid width: 50
- Initial amount of grass: about 50% of the grid
- Initial number of sheep: 250
- Sheep reproduce rate: 4%
- Sheep gain from food: 6
- Initial number of wolves: 25
- Wolf reproduce rate: 5%
- Wolf gain from food: 35
- Grass regrowth time: 30

Note that the initial parameter as chosen such that if only the predation model is run, it has a stable configuration. Furthermore the onus is placed on the simulation of the policy process, therefore no scenarios are placed on the predation model side of the simulation.

8 Initialisation of the policy emergence model

Conflict level thresholds ...

Resources spent

9 Results

There are a number of results we can look at:

1. Predation model results (count of sheep and wolves)

2. Policy selection

3. Belief evolution (both policy core and secondary preferred states) per affiliation of course - This is the new part in this part of the simulation - This can be used to track the policy learning happening within the system.