Global cooperation AI climate challenge : knowledge graphs and the attention mechanism

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1 Introduction

Climate change is the rapid increase of global temperature and depreciation of the ozone layer caused by burning of fossil fuels from factories, buildings, transportation, and other human activity. Global cooperation by different nations on climate change is necessary in order to reduce greenhouse gases emitted by various nations and ensure that climate change can be slowed down. The effects of climate change include extreme weather events, the adverse conditions for growing crops, sea-level rise, and more.

The successful global cooperation is modeled by a game-theoretic reinforcement learning problem. There are n agents which represent each country or region. The agents implement policies to optimize their own economic or climate incentives, and also implement actions related to other agents such as trade and investments. Agents interact with each other by trading, investing, and other actions. We want to achieve successful cooperation through agreements and negotiation, and use AI to train the policy for negotiation.

2 Background

The UNFCCC of 1992 is an international treaty on countering climate change which has the objective of prevention of human interferences with the global climate state [1]. The Kyoto Protocol of 1997 agreed on reducing emissions by an average of 5 percent below 1990 levels from 2008-2012, and reducing emissions by 18 percent below 1990 levels from 2013-2020. 192 of the UNFCCC parties agreed on the Kyoto Protocol but numerous major emission countries aren't part of it so it covers only 12 percent of global emissions [1]. In 2015, the Paris Agreement set a framework to avoid dangerous climate change by trying to lower warming below 2 degrees Celcius and to reach net zero emissions globally. It requires all countries to pledge to reduce their emissions by setting targets known as nationally determined contributions (NDCs) [2]. However, many agree that the Paris Agreement is not a negotiation that will be successful enough to limit the temperature rise that was agreed upon [2].

3 Proposed Solution

This solution is based on the bilateral negotiation protocol, but adding conditions such as how much each region pays attention to certain features as well as how much each region pays attention to other regions. The attention one region pays to another may be influenced by the proximity between the regions, how important their trade is, how much they value their political alliance, and other factors. If region a's actions are very detrimental to region b, then region b could also pay more attention to region a.

If one region's monitoring and proposals to another region is not sufficiently improving that region's emissions, then, that region could pay more attention to another region's proposals. We quantify the attention paid from region i to region j as a variable e_{ij} called attention coefficents, also defined in graph attention networks [3].

I focused on the relevant actions given by

['mitigation_rate', 'savings', 'export_action', 'import_actions', 'tariff_actions', 'proposal_actions', 'evaluation_actions'] to compare the regions, which reduced the computation of the correlation matrix and the graph representation of the regions' actions.

The attention mechanism is used in neural networks such as graph attention networks [4],[3]. In a Graph Attention Network, the input to the layer is a set of node features and the output is a new set of node features [3]. To be able to transform the input features to higher level features, at least one learnable linear transformation is needed. A shared linear transformation given by a weight matrix W is applied to each node.

The mechanism is divided into steps for computing the alignment scores, the weights, and the context vector. We are interested in the first two steps which correspond to computing normalized attention coefficients which computes $e_{ij} = a(Wh_i, Wh_j)$ where a is a feedforward NN, and then applies softmax to e_{ij}.

The entries of W are set to $c(i,j) = corr(i,j)$ where i and j are actions, state variables, or both,

$$W = \begin{bmatrix} c(1,1) & c(1,2) & ... & c(1,n) \\ c(2,1) & c(2,2) & ... & c(2,n) \\ \cdots & & & \\ c(n,1) & c(n,2) & ... & c(n,n) \end{bmatrix} \tag{1}$$

The vector h_i is the aggregated vector of region i, taking the mean over the levels of that action.

We use a graph structure to create a knowledge graph representation of the network of real-world entities. Here, the nodes represent the regions and the edges represent the scores or probabilities of accepting proposals or actions between regions. Knowledge graphs are popularly used for data governance, fraud detection, knowledge management, recommendation and intelligent systems across different organizational units [5].

There are different ways to represent the entities in the graph. We considered different graphical representations, especially what nodes, edges, and their attributes represent. One representation (i) involves the global state where nodes are regions and edges are vectors of accepting proposal actions between the nodes. Another representation (ii) involves defining each graph to be a separate region, where nodes are their actions and edges are correlations between actions. A related representation (iii) where each graph is a region involves defining each node as a state variable related to that region such as gdp and each edge involves correlations between different state variables. Another representation (iv) has both state variables and actions as nodes and the edges involve correlations between them.

A graph kernel compares two input graphs and outputs a similarity score of the graphs, and it is a positive definite function. The most basic graph kernel function may be the vertex histogram or the edge histogram kernels. The vertex histogram kernel is given two vectors from two graphs and taking the inner product of the vectors, where the i-th entry of a vector is the count of label i in that graph. Similarly, the edge histogram kernel depends on the edge labels to construct vectors.

A node-attributed graph is a graph that has real-valued vectors assigned to vertices of the graph, as specified by a function $f : V \rightarrow R^d$. An edge-attributed graph has vectors assigned to the edges of the graph. Graphs that are both node and edge attributed can be input into the propagation kernel framework. This framework considers a sequence of graphs with evolving node information based on information propagation. They are built on the idea of the propagation of label information between nodes of the graph. The node attributes correspond to one-hot-vectors of the dictionary of labels. The graph is represented by a distribution P of size $n \times d$ (n is number of nodes, d is size of attributes) and the node information is propagated with a diffusion process given by $P_{t+1} \leftarrow TP_t$ where T is the transition matrix with the default value of $T = D^{-1}A$ where $D = diag(\sum_j A_{ij})$ and A is the adjacency matrix of the graph [6]. In this method, the node attributes are converted into labels by a locally sensitive hashing method that bins the nodes.

I calculated the correlation between the different regions' states and actions where I took a subset of actions or states that have the most impact. These quantities are used as the edge attributes. They are also used as the weight matrix W in attention coefficients. This addresses the distributional analysis part that can benefit the current Integrated Assessment Model limitations.

In the evaluation step, I compared the kernel scores between each pair of regions with the mean and 0.2 percentiles of kernel score array, which is updated at each timestep. I then flipped the proposal decision to 1 between regions if their graph kernel score of the graphs of i and j is above the mean, and flipped it to 0 if the graph kernel score is below the 20th percentile of all kernel scores.

In the evaluation step, I added the reward/punishment based on the kernel scores. It rewards or punishes the 'current_balance_all_regions' variable. Assuming the higher mitigation rate is better for the climate, we add a reward punishment step in the evaluation step which rewards positive change in miti-

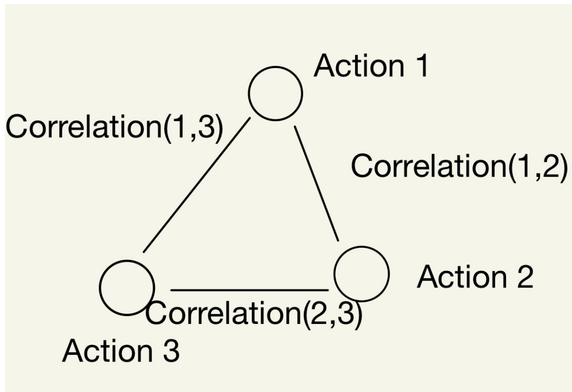

Figure 1: Knowledge Graph of a region

gation rate and punishes negative change by a factor from 0.10 to 0.35.

For the alternative solutions, I considered a graph attention network to compute the attention coefficients, but the pytorch geometric library did not work with the python version 3.7.

I considered using Bayesian probability theory to calculate the probability that an action should have a certain confidence level to define the action mask, rounding down to each tenth percent. For any action B, we can calculate its probability with Bayesian statistics: $P(B) = P(B|A_1)P(A_1) + \cdots + P(B|A_n)P(A_n)$. We can set $P(A_i)$ as a uniform probability $1/N_{actions}$. But the issue is that the correlation between B and A_i is not equivalent to the conditional probability $P(B|A_i)$, and also the computation cost of calculating the probabilities for each action would be high.

I also considered linear sum assignment algorithms for assigning regions to certain actions. This was hard to implement because it is a large matrix of possible events and regions, the regions do not have to each choose one action (or set of actions) each, and it is not possible to explicitly assign the actions to the regions because they are trained by the ray library algorithms.

4 Effectiveness

The impact of the solution would let the different regions to compete with a subset of the total regions and this may give them more motivation to lower their emissions.

I tried to experiment with different variations of the computed graph kernel scores and pairwise attention scores. In my initial solution I only used the graph kernel scores for changing the evaluation step. Then, I tried adding the graph kernel scores together with the attention scores. I also changed the factors multiplying the reward or the threshold for changing the state.

The proposed solution will impact the regions or countries involved by organizing the features of interest and letting them understand which features are optimized.

Also, using the correlation between features can help the countries understand which features have a positive or negative correlation, and therefore how to account for the changes and balance out various features.

Over time, the state of the climate will probably align more with a good economy because more companies will switch to green technologies or sustainable energy.

5 Feasibility

The cost of running the protocol involves calculation of the feature properties from each of the regions. Maybe this protocol is not as feasible, because if the regions pay attention to each other it does not automatically make them switch proposal decisions for the benefit of the climate. Policymakers can make this policy more feasible if they make legal agreements, such as having fines if they fail to follow the policy. The incentives may also depend on the relationship between the two countries, such as their trade agreements or political relationship.

This protocol may need to be approved by participating countries, especially given data privacy regulations. Also, it must be approved for fairness to not give preference to the gains of certain countries over others.

6 Robustness

A challenge that I considered was how to relate the government with private companies or other organizations because their choice to try to become carbon neutral is also a big factor in climate change.

Also, a challenge lies in the relationship between actions and features, and how to correctly calculate their correlations. I used the pandas dataframe correlation function on the matrix but I could also try calculating the conditional correlations, or only relating certain actions and features.

A challenge is how to assess the importance that each region assigns to various variables such as emissions or gdp. Some countries may report that they care more about certain variables and may not be truthful. I was not sure how to calculate the regions' important categories. I considered utilizing the region yaml files to determine this; for example, the initial population of the regions can tell if a similar initial population lets regions understand each other better. But other properties did not help to determine which features were important to the regions.

A failure mode may occur if the country does not want to follow the proposal even if the negotiation recommended it. Maybe using the different levels it can more easily accept the proposals up to a certain extent.

7 Ethics and Climate Justice

Climate justice involves development that also addresses water, sanitation, health, and other human challenges that arise from climate change. The solution addresses these issues by helping represent different entities within the region, and understand the correlations between them. This can allow for a greater understanding of which variables are affected by which others.

8 Novelty

The novelty of this solution involves a knowledge graph representation of the environment and its actors and the kernel scores between two graphs representing two regions where the nodes are actions, the attention certain regions pay other regions, and how to involve these properties to accepting proposals and monetary rewards or punishments.

9 Conclusion

I found that I can use different representations of the state and action variables and use statistical quantities to group together regions that may be more similar and therefore more likely to cooperate together. I believe the factor and thresholds can be also determined through cross-optimization in training, or conditional probability calculations. I combined different techniques such as graph kernels and attention coefficients.

I added the variables but did not know how to simulate their dynamics: green energy investment, private company green investment, public transportation investment, research and development of methods to fight climate change, investment in planting trees/reforestation. It would also be knowledgeable to know how each country ranks how important each feature is on a scale from 1 to 10, and to include importance weighting.

Future directions may include adding the state variables as nodes. I considered actions in the representations of regions, and used the action as attributes to calculate the kernel scores as well as the attention mechanism scores, but I did not include the global state variables within their representation. Also, a direction involves using other graph kernels or designing other graph kernels, especially kernels that can consider both the node attributes and edge attributes.

The attention coefficient can be used as the importance given by each region to the various features to group the regions into separate groups. For example, group regions with similar interests into groups and let them accept the proposal decisions within the group, or group regions with different interests into groups. I think graph attention networks or Bayesian neural networks can be used, which involve the same concepts [7].

It would be interesting to see how countries following this policy would play out over time, and whether it is effective.

References

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