The Sustainability of Reinforcement Learning Models Predicting Wildfire Movement

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Description of dataset and baseline

Chosen dataset and model

Sriram Ganapathi Subramanian and Mark Crowley discuss modeling the spread of wildfires using reinforcement learning. Subramanian and Crowley focused on two fires in particular, the 2011 Richardson fire and 2016 Fort McMurray fires, which took place in Northern Alberta. Data used to address the problem included satellite imagery (RGB and thermal) and weather data (Subramanian & Crowley, 2018).

The data collected for this problem came from several sources. Satellite imagery was collected from the USGS Earth Explorer data portal. By processing the RGB and thermal imagery, the researchers determined the date of the photo, coordinates, land cover, and temperature of specific areas. Weather data was collected from both the Canada Information Portal and World Clim datasets. Weather data included wind speed, wind direction, rainfall, and relative humidity. This information was then collated into a singular dataset (Subramanian & Crowley, 2018).

The researchers identified five reinforcement learning algorithms, and compared results of each to a gaussian process classifier baseline. The specific model focused on in this paper is Asynchronous Advantage Actor-Critic (A3C), which was one of the best performing models of the research (Subramanian & Crowley, 2018).

A3C is a specific RL algorithm which utilizes agents acting in parallel over an environment. Each agent explores different parts of the environment independently and updates a global network asynchronously (Mnih et al., 2016). The advantage in the wildfire problem is A3C's ability to use multiple agents (Subramanian & Crowley, 2018). If multiple fires are happening in the same satellite image, A3C will be able to deploy multiple agents for each independent task.

Assess its documentation

Subramanian and Crowley refer to another paper when discussing pre-processing steps. They do not, however, discuss if every step taken in the referenced paper should be followed or if they used certain steps. When referring to determining local temperatures based on thermal images, there is no direct reference to what steps need to be taken to get the exact values, rather only a mention of processing the data using a geoprocessing software (Subramanian & Crowley, 2018). The authors also discuss data cleaning saying "all images were corrected for missing values and outliers" (Subramanian & Crowley, 2018). There is no mention as to the techniques used in this case. A replication of these data cleaning and pre-processing techniques may be difficult due to missing key points. Subramanian and Crowley do provide in depth explanations of the final data values for each feature. Overall, a detailed explanation of pre-processing steps is necessary for exact replication of their dataset, but an approximate replication may be achieved with the current information.

For the A3C model, the authors provide a general overview of their implementation. As there is a good amount of resources available on the development of A3C models, the information provided in this paper seems sufficient. They discuss specific convolutional layers, activation functions, and kernel parameters. The model should be replicable by an individual with prior knowledge of A3C structure.

Connection to SDGs

Related goals and targets

Two goals have been identified as strongly relating to modeling the spread of wildfire using reinforcement learning. In particular, Goal 13 (Climate Action) and Goal 15 (Life on Land) (*THE 17 GOALS | Sustainable Development*, n.d.). Within Goal 13, the model impacts target 13.b, which references the promotion of mechanisms for effective climate change-related management. Within Goal 15, the model also impacts target 15.2, which promotes the implementation of sustainable management of all types of forests. As this paper, and the model created from it, are focused on the prediction and mitigation of wildfires, it has a strong relationship with the goals mentioned above. The model can have a positive impact on both disaster mitigation and sustainable management.

SDG enabler and inhibitor

By combining both satellite imagery and weather data into a single dataset, and using this dataset to predict wildfire movements, the model and dataset enable progress of goals 13 and 15 through promoting effective climate-change management and implementations of sustainable forestry management.

The main risk of this model and dataset is the danger a false prediction poses to first responders and people within a close proximity to a wildfire. This specific case would make the model and dataset an inhibitor of Goal 3 (Good Health and Wellbeing), and potentially Goal 6 (Clean Water and Sanitation) depending on the impact of the false prediction. It is important to remember that this is a conditional inhibitor depending on the overall reliance of individuals on the model.

Impact on Sustainability

Social Sustainability

<u>Who has access to the AI Application? Could unequal access impact social sustainability?</u>

The application is restricted to those with access to satellite imagery and weather data, specific to their area of interest. For underdeveloped communities, both access to high-quality data and the resources to model the data can be limited. Developed communities would have a greater benefit from this model, whereas underdeveloped communities would have a limited ability to use the model.

<u>Are responsibilities for possible damage and liability cases documented? Would this be relevant to ensure social sustainability in this case?</u>

There are risks to simulating wildfire movement. As the technology has been around for some time (not using reinforcement learning), there are certain guidelines simulation organizations attempt to follow. Timothy Neale and Daniel May argue the public's understanding of simulations as having "abilities to foresee and forestall disastrous or impactful fires" poses moral dilemmas for simulation organizations when those simulations are imperfect and produce suboptimal results (Neale & May, 2020). Some agencies opt to withhold uncertain predictions, while others disclose them, which can mislead those impacted by the fire (Neale & May, 2020).

The RL model proposed by Subramanian and Crowley also falls into this gray area. There is a social responsibility to share potentially life saving information with first responders and people impacted by wildfire, yet at the same time, uncertain predictions can mislead people causing them to take actions they normally wouldn't have used.

Environmental Sustainability

Does the application protect us against risks related to climate instability and disasters?

This application is specifically designed to track and mitigate wildfire, a type of climate disaster. Through this research and model creation the authors designed a model that can be used by first responders to counteract the risks of wildfire.

Could the application cause damage to plants or animals in any way?

While the model has no direct ability to harm plants or animals, it can indirectly affect both groups. As mentioned previously, if the model incorrectly predicts the movement of wildfire, fire managers relying on its prediction may make a suboptimal choice if the prediction is uncertain or incorrect. This choice can cause more harm to plants and animals in the path of the wildfire than if another decision, uninformed by the model, was made.

Economic Sustainability

Is the model open-source? How could that impact our economy, especially if the solution can be deployed and reutilised in a scalable fashion to other problems?

The model architecture is described in the journal article, and descriptions of how to replicate it are provided. While the code is not provided, it is somewhat straightforward to replicate. By having a low/no-cost solution to wildfire modeling, governments can save significant amounts of money used in predicting and mitigating wildfire movement.

What could be the economic impact of the application?

If the application was flushed out enough to be deployable in the field, it would likely save money. Wildfire simulations are currently being used which are costly and slow compared to the RL approach (Subramanian & Crowley, 2018). However, it can also displace the current wildfire simulation market. There would likely be a positive economic impact through saving resources and time.

Other Sustainability Factors

Critical questions we should be asking

Does the model encapsulate all major factors that affect wildfire spread?

There are a few critical factors not considered in the model, which can assist in the prediction of wildfire spread. Namely, the intervention of firefighters, terrain topography, and ground moisture (Subramanian & Crowley, 2018).

Does the application need significant amounts of data to train and use?

The advantage of using reinforcement learning in this context is that it can provide reasonably effective predictions with sparse data, meaning only a few images and features are needed to train the model.

How could a poor prediction impact economic sustainability?

If a poor prediction is used for decision making, it can affect economic sustainability by the decision needing more resources than necessary and human-made/urban areas such as buildings and agriculture can be destroyed.

Interactions between SDGs

By directly affecting Goal 15 (Life on Land), through promoting the implementation of sustainable management in forests, there will be an enabling influence on Goal 3 (Good Health and Wellbeing), as modeling the spread of wildfire enables firefighters to effectively combat the fire. By mitigating the fire, air pollution will also be mitigated which helps target 3.9 of Goal 3, reduce illness and death from hazardous chemicals and pollution.

Another interaction from promoting Goal 15 is a reinforcement of Goal 14 (Life Below Water). Specifically, by effectively combating wildfire, there will be less of an effect of ocean acidification (target 14.3). Debris from wildfires can pollute oceans, as seen with higher levels of carbon on the Pacific Ocean's surface during and after wildfires from 2020 in Western United States (Coward et al., 2022). By minimizing wildfires, carbon levels on water will decrease as well.

Promoting Goal 15 can also reinforce target 6.6 of Goal 6 (Clean Water and Sanitation), which is focused on protecting and restoring water-related ecosystems. Wildfires pose a risk to the drinking water of areas damaged by the fires (Solomon et al., 2021). By reducing pollution from wildfires in water-related ecosystems, there is less risk of drinking water contamination.

Speculative Solutions

Changes to dataset

One of the sustainability issues identified previously was the encapsulation of essential features, as improving the model's performance can improve its sustainable impact. By adding in additional data, specifically topographical features of land, historical wildfire data, and firefighting plans, the model will likely have better performance.

Changes to ML model

This research was completed in late 2017, and published in 2018 (Subramanian & Crowley, 2018). At the same time, a paper which first created the algorithm Proximal Policy Optimization (PPO) was published (Schulman et al., 2017). The implementation of PPO for this specific task may be beneficial for this task as PPO generally has superior flexibility and training stability compared to A3C (del Río Ponce et al., 2024).

Technology governance

Specifically for mitigating risks of social sustainability, it is important to consider governance over the releasing of simulated predictions. While there is some debate and gray area in this regard, there should be strict guidelines about what gets released. Moreover, adding in a threshold for simulation accuracy over multiple wildfires should be required before allowing these models to affect decision making. Currently, this model has only been trained on two wildfires, adding a minimum amount of wildfires trained on is also another solution to mitigating social sustainability risks.

Speculating on the ideal scenario/dataset/task

The most important features to add are historical wildfire data and concurrent human interventional data. By adding historical wildfire data, the model would be able to consider what land areas burn at what rates, the speed of which fires spread based on historical weather data, and how wildfire consumes urban areas. Concurrent human interventional data is also necessary to improve the model. The model would take into account the likelihood of human intervention slowing the spread of wildfire in certain areas. This would increase accuracy and potentially minimize the risk of firefighters' health and safety.

References

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