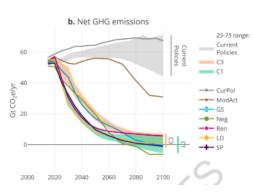
What is the evidence on climate mitigation policies, and to what extent can it be identified and classified using Machine Learning?

Max Callaghan



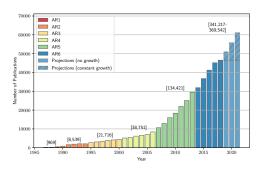
#### Context



AR6 WGIII Fig 3.6

 Meeting Paris goals requires an extremely rapid reversal of >100 years of rising emissions, going far beyond existing policies

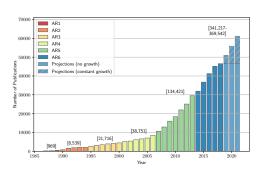
#### Context



Callaghan et al. (2020)

- Meeting Paris goals requires an extremely rapid reversal of >100 years of rising emissions, going far beyond existing policies
- The amount of climate policies, and the size of the scientific literature on policies is growing fast

#### Context



Callaghan et al. (2020)

- Meeting Paris goals requires an extremely rapid reversal of >100 years of rising emissions, going far beyond existing policies
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What instruments are studied where? How does this match with enacted instruments and emissions data?

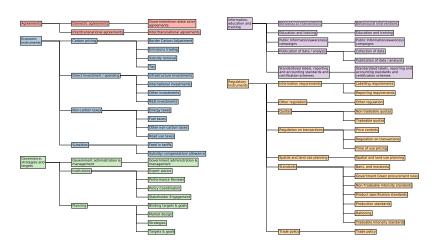
### Plan

What is the evidence on climate mitigation policies, and to what extent can it be identified and classified using Machine Learning?

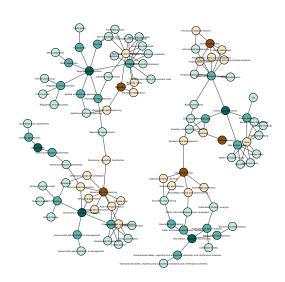
A machine-learning-assisted systematic map

- Develop a typology of climate policy instruments
- Screen and code documents by hand
- Predict labels for all other documents
- Extract geolocations
- Produce a map of what types of instruments we study in what places
- Bring this information together with policy databases / emissions

# **Typology**

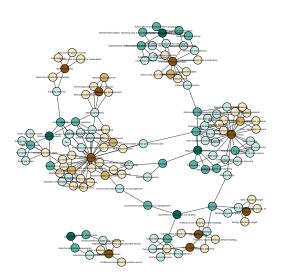


# Typology in context



 Our typology is more detailed than (Grantham Research Institute on Climate Change and the Environment and for Climate Change Law, 2022)

## Typology in context



- Our typology is more detailed than (Grantham Research Institute on Climate Change and the Environment and for Climate Change Law, 2022)
- We provide slightly more detail than (New Climate Institute, 2020) with a [subjectively] clearer hierarchy

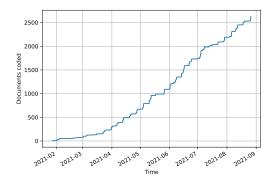
# Screening

 In addition to the policy type, we coded sector, scale, and study type (ex-post/ex-ate + qual/quantitative)



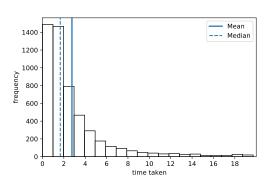
# Screening

- In addition to the policy type, we coded sector, scale, and study type (ex-post/ex-ate + qual/quantitative)
- We double coded around 2,500 documents



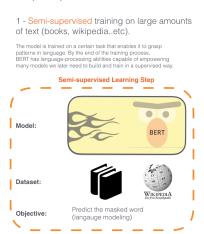
# Screening

- In addition to the policy type, we coded sector, scale, and study type (ex-post/ex-ate + qual/quantitative)
- We double coded around 2,500 documents
- Each document took on average <3 minutes to code, total work is 310 person hours (just initial coding)



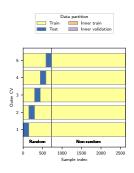
#### ClimateBert

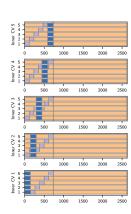
BERT (Bidirectional Representations from Transformers) is trained (by Google) on huge text corpora, and can be "fine tuned" on custom tasks. Webersinke et al. (2021) perform additional pre-training on texts from the climate domain.



2 - Supervised training on a specific task with a labeled dataset Supervised Learning Step 75% Spam Classifier 25% Not Spam Model: (pre-trained BERT in step #1) Buy these pills Spam Dataset: Win cash prizes Spam Dear Mr. Atreides, please find attached. Not Spam

#### Validation

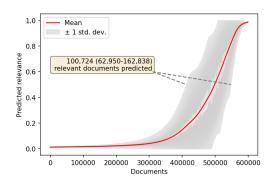




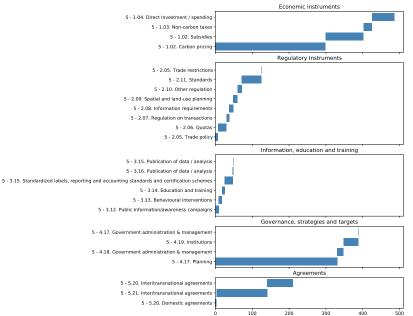
- Nested
  cross-validation
  separates
  hyperparamter
  optimisation from
  evaluation
- Less subject to random selection of test set in a test-validation-train setting
- Allows use of more data in a data-scarce setting

## Uncertain predictions

- In a previous study we made multiple predictions with multiple subsets of the data, and calculated the mean ± standard deviation for each sample.
- This captures some uncertainty from sensitivity of model to training data, but uses no information about model performance
- How to express uncertainty about model performance?

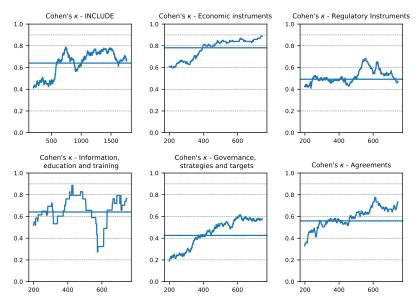


## Results

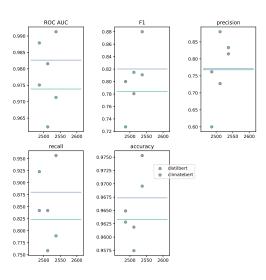




# Human accuracy

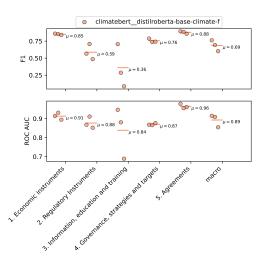


### CV results



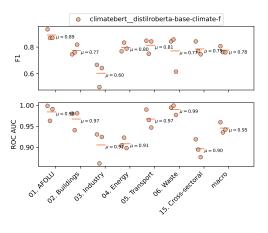
 Inclusion is pretty well predicted

## CV results



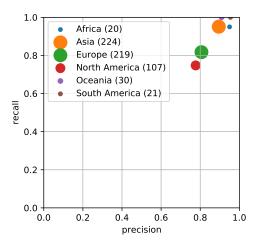
- Inclusion is pretty well predicted
- We are poor at predicting classes with fewer samples

### CV results



- Inclusion is pretty well predicted
- We are poor at predicting classes with fewer samples
- Sectors are relatively well predicted

## Geoparsing accuracy



- A combination of a geoparser for places, and a simple dictionary of country adjectives achieves good results
- That results are more accurate for Africa and Asia than Europe and North America is a pleasant surprise

# Possible questions

- How does policy literature relate to policy databases?
- How does policy literature (+ policy databases) relate to emissions?
- Can learning across domains (policy + scientific docs) improve classifiers?

# Bibliography and further resources

- Callaghan, M. W., Minx, J. C., and Forster, P. M. (2020). A topography of climate change research. *Nature Climate Change*, 10(2):118–123. Number: 2 Publisher: Nature Publishing Group.
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