A direct approach to detection and attribution of climate change

Enikő Székely

Swiss Data Science Center

AI4Climate Seminar, Paris

January 24, 2020

Joint work with:

- Sebastian Sippel (Institute for Atmospheric and Climate Science, ETH Zürich)
- Reto Knutti (Institute for Atmospheric and Climate Science, ETH Zürich)
- Erich Fischer (Institute for Atmospheric and Climate Science, ETH Zürich)
- Nicolai Meinshausen (Seminar for Statistics, ETH Zürich)
- Guillaume Obozinski (Swiss Data Science Center)

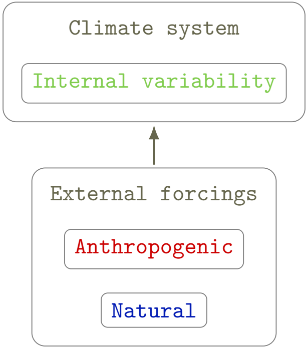
Outline

1. Introduction and motivation
2. Direct approach to D&A
3. Daily detection
4. Attribution
5. Summary

Outline

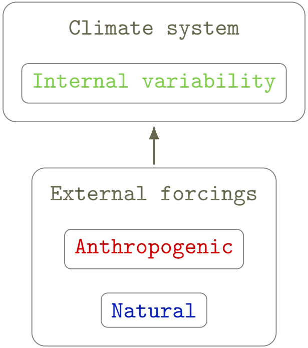
1. Introduction and motivation
2. Direct approach to D&A
3. Daily detection
4. Attribution
5. Summary

The climate system



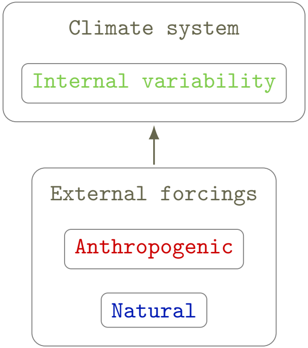
- The Earth is a complex system with highly nonlinear and unknown feedbacks between the components of the climate (atmosphere, ocean, land and ice)
- *Internal (natural, unforced) climate variability*: processes that occur naturally within the climate (El-Niño, North Atlantic Oscillation)
- *Forced climate variability*: external forcings (sun, volcanic activity, human influence)

The climate system



- Regionally, the internal (natural) variability is large enough to mask climate changes for possibly many decades to come.
- **Open questions**: What changes will happen on regional scales and on shorter timescales? How strongly will the Earth's temperature respond to increasing CO2 levels?

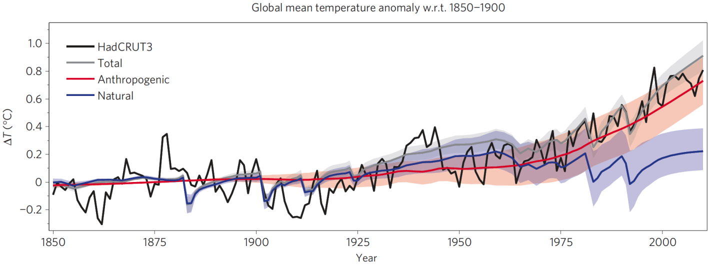
Detection and attribution (D&A) of climate change



D&A studies the causal links between external drivers of climate change and observed changes in climate variables.

- **Detection** aims to find if there is a change in the observations that cannot be explained by internal (natural) climate variability alone.
- **Attribution** tries to assign the detected change to a particular external forcing or a combination of forcings.

Traditional D&A



[Huber & Knutti (2011)]

$$X_{obs} = f(X_{ant}, X_{nat}, \varepsilon_X)$$

- *Unsupervised* fingerprint (EOF) extraction
- Empirical Orthogonal Functions (EOF) $\Leftrightarrow$ Principal Component Analysis (PCA)

$$\hat{X}_{obs}^{EOF} = \alpha_{ant} X_{ant}^{EOF} + \alpha_{nat} X_{nat}^{EOF}$$

Outline

1 Introduction and motivation

2 Direct approach to D&A

3 Daily detection

4 Attribution

5 Summary

Direct D&A

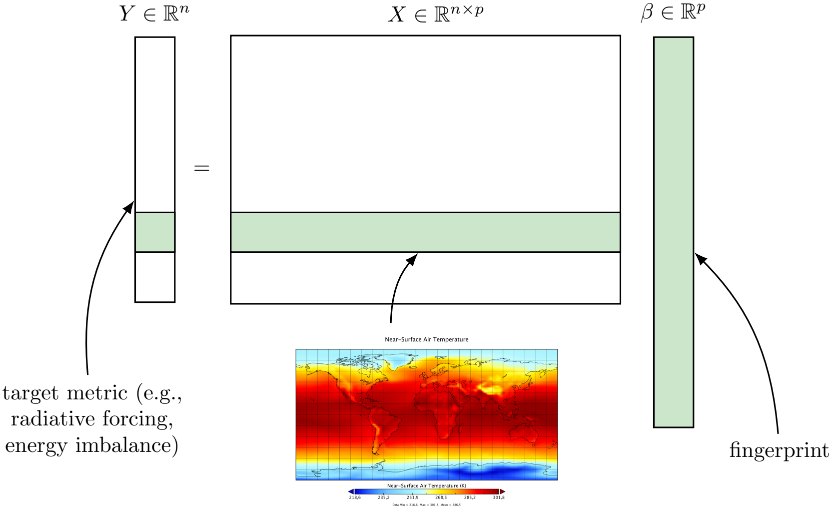
x = climate variable (temperature, humidity, precipitation)
y = external forcing (anthropogenic, solar, volcanic)

$$\hat{\beta} = \underset{\beta}{\operatorname{argmin}} \, \mathbb{E}_{(x,y)\sim P} \left[l(y, f_\beta(x)) \right]$$

$$\hat{y}_{new} = f_\beta(x_{new})$$

- *Supervised* fingerprint (β) extraction
- The predicted forcing $\hat{y}$ used as a test statistic for D&A

Direct D&A (linear setting)



Detection and attribution as hypothesis testing

Detection:

- *Null hypothesis*: absence of an externally forced climate change
- The predicted forcing $\hat{y}$ is indistinguishable from internal variability, e.g., not significantly different from zero

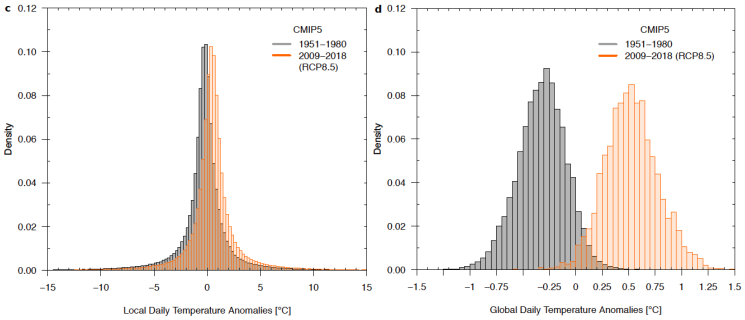
Attribution:

- If the true forcing y lies within the confidence intervals of the predicted forcing $\hat{y}$, then we attribute the detected change to the respective forcing

Outline

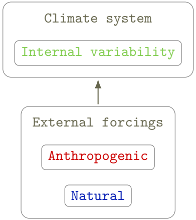
1. Introduction and motivation
2. Direct approach to D&A
3. Daily detection
4. Attribution
5. Summary

Local *vs.* global daily weather



Signal *vs.* noise problem

Detection of externally forced climate change

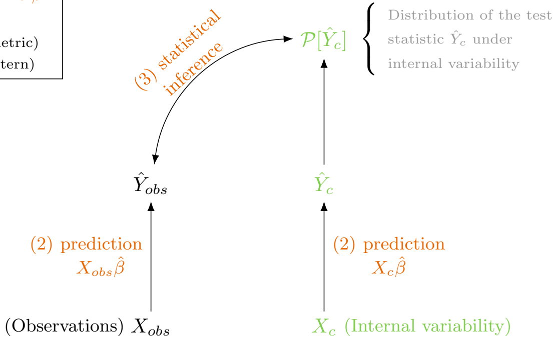


(1) extraction of fingerprint $\hat{\beta}$

$$Y = X\hat{\beta} + \epsilon$$

Y (annual global climate metric)

X (daily global spatial pattern)



Daily detection in global weather

- Assess whether externally forced climate change can be detected on shorter timescales (daily) if the detection is based on a *global* spatial pattern

nature climate change
LETTERS
https://doi.org/10.1038/s41558-019-0666-7

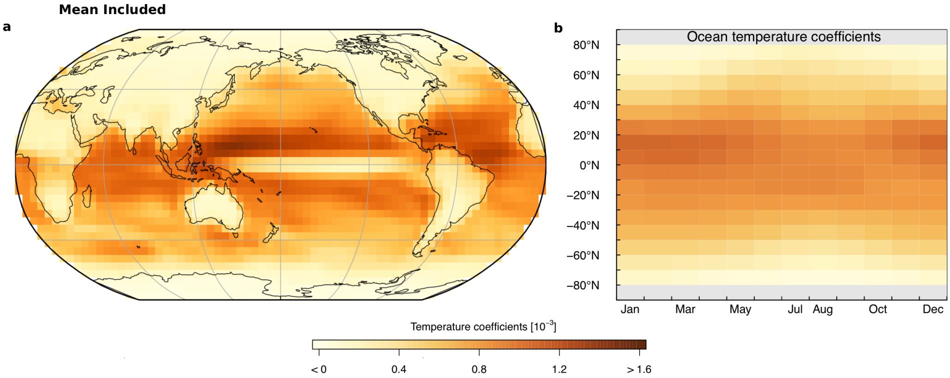
Climate change now detectable from any single day of weather at global scale

Sebastian Sippel[1,2,3]*, Nicolai Meinshausen[2], Erich M. Fischer[1], Enikő Székely[4] and Reto Knutti[1]

For generations, climate scientists have educated the public that 'weather is not climate', and climate change has been framed as the change in the distribution of weather that slowly emerges from large variability over decades[1–7]. However, weather when considered globally is now in uncharted territory. Here we show that on the basis of a single day of globally observed temperature and moisture, we detect the fingerprint of externally driven climate change, and conclude that Earth as a whole is warming. Our detection approach invokes statisti-

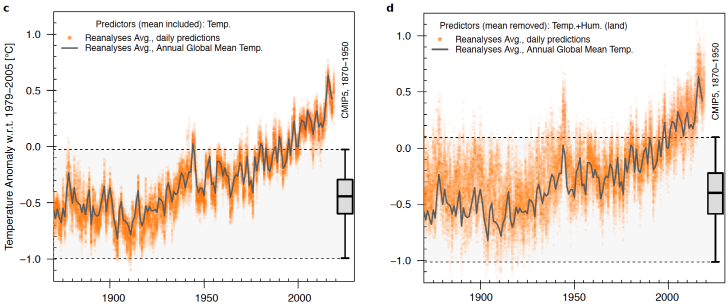
We start with a simple example to illustrate the difference in warming experienced locally and globally (Fig. 1). The past decade (2009–2018) has been on average 0.7 °C warmer than an earlier period (1951–1980). Locally, deseasonalized daily temperature anomalies fluctuate due to internal weather-related variability with a magnitude of up to 30 °C (Fig. 1a,c), depending on region and season. This substantial variation implies that despite an overall warmer climate, cold anomalies or even cold records can still occur and are to be expected[15]. However, at the global scale, weather-

Daily detection in global weather



Daily detection in global weather

- The fingerprint of climate change is detected from any single day in the observed global record since early 2012, and since 1999 on the basis of a year of data
- While changes in weather locally are emerging over decades, global climate change is now detected instantaneously

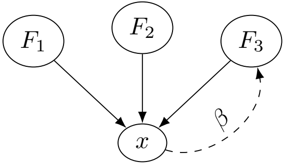


[Sippel *et al.* (2020)]

Outline

1 Introduction and motivation
2 Direct approach to D&A
3 Daily detection
4 Attribution
5 Summary

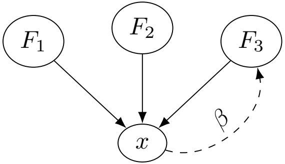
Distributional robustness



F_1 = solar forcing
F_2 = volcanic forcing
F_3 = anthropogenic forcing

$$y = F_3$$

Distributional robustness



F_1 = solar forcing
F_2 = volcanic forcing
F_3 = anthropogenic forcing

$y = F_3$

F_1, F_2, F_3 have a causal effect on x

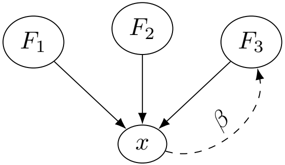
$$x = g(F_1, F_2, F_3, \varepsilon_X)$$

$$y = f_\beta(x)$$

$$(x, y) \sim P$$

- Changes in $p(F_1) \Rightarrow$ changes in $p(x, y)$ even if $p(y)$ remains the same
- Causal inference: *interventions* or *perturbations*

Distributional robustness



F_1 = solar forcing
F_2 = volcanic forcing
F_3 = anthropogenic forcing

$y = F_3$

Goal: Good prediction accuracy even under distributional changes of the external forcings (shift interventions).

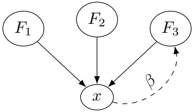
Observational distribution $(x, y) \sim P$:

$$\hat{\beta} = \underset{\beta}{\operatorname{argmin}} \, \mathbb{E}_{(x,y)\sim P} \left[l(y, f_\beta(x)) \right]$$

Class of distributions $(x, y) \sim Q$ where $Q \in \mathcal{Q}$:

$$\hat{\beta} = \underset{\beta}{\operatorname{argmin}} \, \sup_{Q \in \mathcal{Q}} \, \mathbb{E}_{(x,y)\sim Q} \left[l(y, f_\beta(x)) \right]$$

Anchor regression



Anchor regression estimator [Rothenhäusler *et al.* (2019)]:

$$\hat{\beta}^{\gamma} = \underset{\beta}{\operatorname{argmin}} \|(I_n - \Pi_A)(Y - X\beta)\|_2^2 + \gamma \|\Pi_A(Y - X\beta)\|_2^2$$

$$y = F_3$$

$$A = [F_1, F_2]$$

- $\Pi_A \in \mathbb{R}^{n \times n}$ is the matrix that projects on the column space of $A \in \mathbb{R}^{n \times q}$, i.e., $\Pi_A = A(A^T A)^{-1} A^T$
- $\gamma =$ **"causal" regularization** parameter that gives the strength of the intervention on the anchor variable A
- The causal regularization encourages orthogonality (uncorrelatedness) of the residuals with the anchor variable.

Anchor regression

$$\hat{\beta}^{\gamma} = \underset{\beta}{\operatorname{argmin}} \|(I_n - \Pi_A)(Y - X\beta)\|_2^2 + \gamma \|\Pi_A(Y - X\beta)\|_2^2$$

$\gamma = 0 \quad \Rightarrow \quad \hat{\beta}^{0} = \operatorname{argmin}_{\beta} \|(I - \Pi_A)(Y - X\beta)\|_2^2$ Partialling out A (PA)

$\gamma = 1 \quad \Rightarrow \quad \hat{\beta}^{1} = \operatorname{argmin}_{\beta} \|Y - X\beta\|_2^2$ Ordinary Least Squares (OLS)

$\gamma \to \infty \quad \Rightarrow \quad \hat{\beta}^{\infty} = \operatorname{argmin}_{\beta} \|\Pi_A(Y - X\beta)\|_2^2$ Instrumental variables (IV) $\Rightarrow$ Causality

Anchor regression

Let $X \in \mathbb{R}^{n \times p}$, $Y \in \mathbb{R}^n, \beta \in \mathbb{R}^p$, n = number of samples, p = dimensionality

$$\tilde{X} = (I_n - \Pi_A)X + \sqrt{\gamma}\Pi_A X$$

$$\tilde{Y} = (I_n - \Pi_A)Y + \sqrt{\gamma}\Pi_A Y$$

$$\hat{\beta}^\gamma = \underset{\beta}{\operatorname{argmin}} \| \tilde{Y} - \tilde{X}\beta\|_2^2$$

Anchor regression

Let $X \in \mathbb{R}^{n \times p}$, $Y \in \mathbb{R}^n, \beta \in \mathbb{R}^p$, n = number of samples, p = dimensionality

$$\tilde{X} = (I_n - \Pi_A)X + \sqrt{\gamma}\Pi_A X$$

$$\tilde{Y} = (I_n - \Pi_A)Y + \sqrt{\gamma}\Pi_A Y$$

$$\hat{\beta}^{\gamma} = \underset{\beta}{\operatorname{argmin}} \|\tilde{Y} - \tilde{X}\beta\|_2^2$$

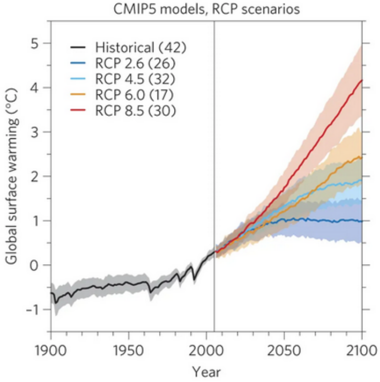
- Ridge regularization allows to handle the multicollinearity of the predictors

$$\hat{\beta}^{\gamma} = \underset{\beta}{\operatorname{argmin}} \|\tilde{Y} - \tilde{X}\beta\|_2^2 + \lambda\|\beta\|_2^2$$

Data

Climate simulations:

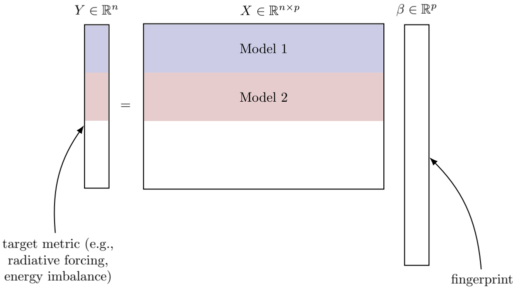
- CMIP5 (Coupled Model Intercomparison Project)
- control runs (climate simulations with no external forcings, only internal variability)
- Representative Concentration Pathways (RCP) (climate simulations with all external forcings)



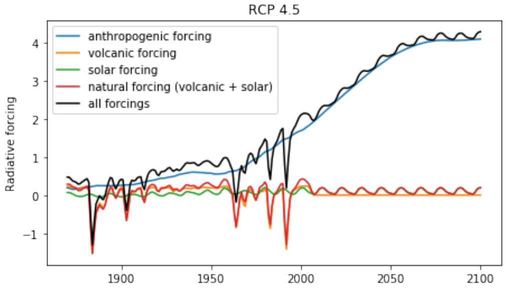
[Knutti & Sedlácek (2013)]

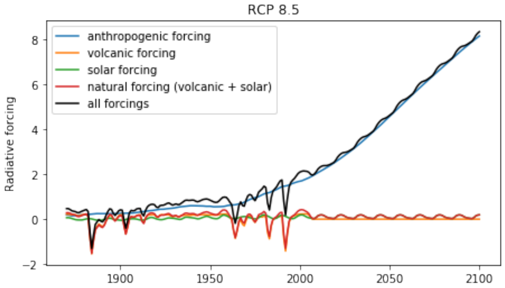
Data

- Climate simulations
  - 42 RCP 8.5 and 40 control runs
  - Temperature and precipitation
- Temporal resolution
  - annual (1870-2100)
  - $n = 82 \times 231 = 18,942$ samples
- Spatial resolution
  - $p = 144 \times 72 = 10,368$ dimensions

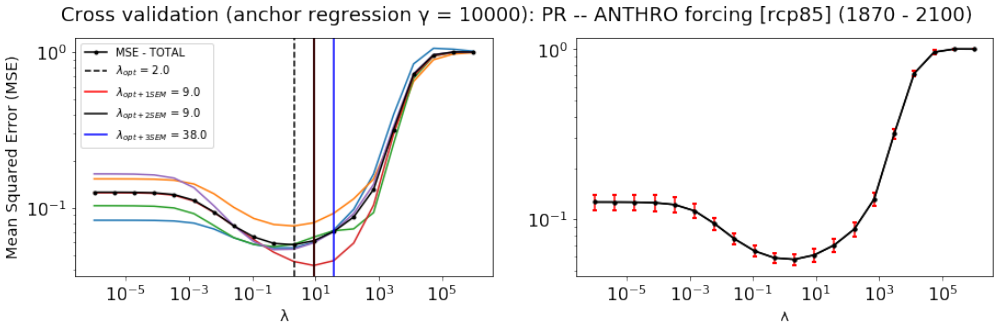


Radiative forcing



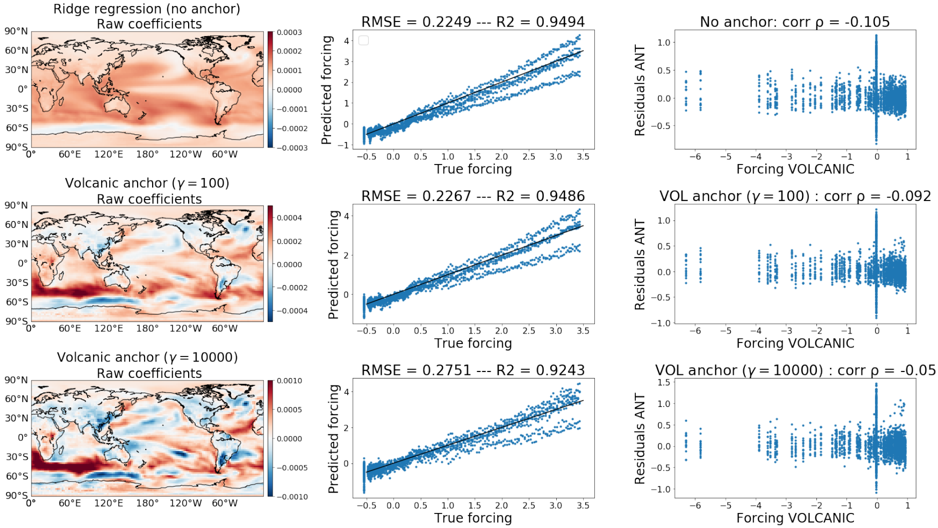


Cross validation

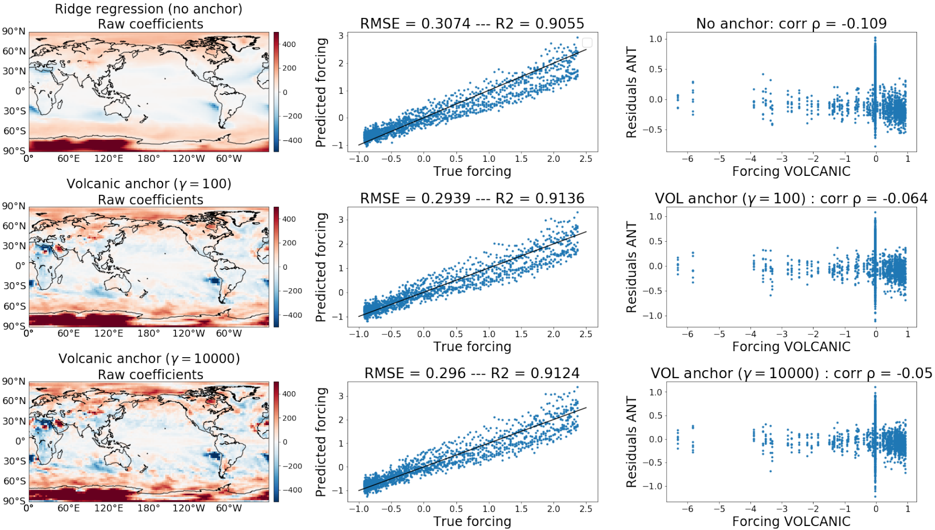


Model-wise splitting for training - testing - folds.

Temperature - y = ANT, A = VOL

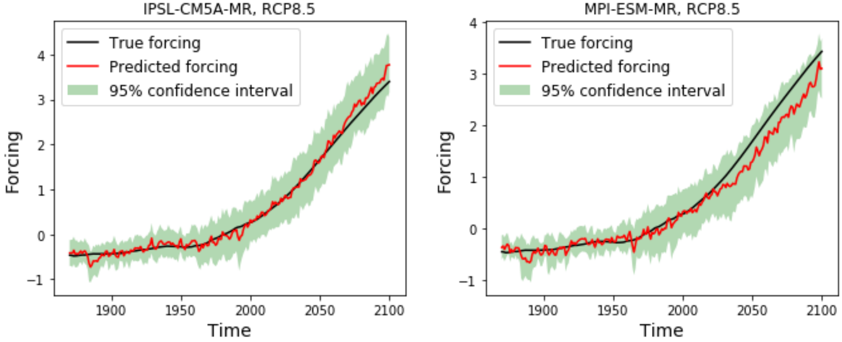


Precipitation - y = ANT, A = VOL



Attribution of externally forced climate change

- If the true forcing y lies within the confidence intervals of the predicted forcing $\hat{y}$



Outline

1 Introduction and motivation

2 Direct approach to D&A

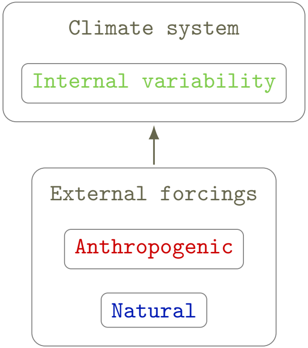
3 Daily detection

4 Attribution

5 Summary

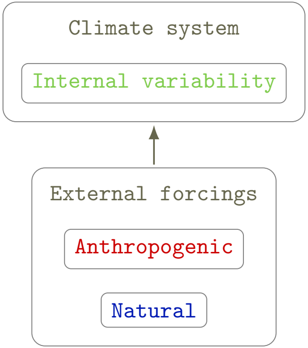
Summary

- Introduced a novel statistical learning approach for D&A that fits into the framework of supervised methods
- We can now detect the signal of externally forced climate change in any single day since 2012 when considering the weather globally
- Distributional robustness protects us against future distributional changes allowing us to do attribution



Future work

- Apply the direct D&A approach to observations, other climate variables, multivariate relationships (temperature and precipitation)
- Relationship between external forcings and the water cycle is more complex than temperature because of larger internal variability which can mask externally forced climate changes
- Daily detection has implications for extreme events attribution



Thank you!

References:

- S. Sippel, N. Meinshausen, E. M. Fischer, E. Székely, R. Knutti (2020). Climate change now detectable from any single day of weather at global scale. *Nature Climate Change*, **10**, 35-41
- E. Székely, S. Sippel, R. Knutti, G. Obozinski, N. Meinshausen (2019). A direct approach to detection and attribution of climate change. *Proceedings of the 9th International Workshop on Climate Informatics: CI2019 (No. NCAR/TN-561+PROC)*, 119-124
- D. Rothenhäusler, N. Meinshausen, P. Bühlmann, J. Peters (2019) Anchor regression: heterogeneous data meets causality, *arXiv:1801.06229*