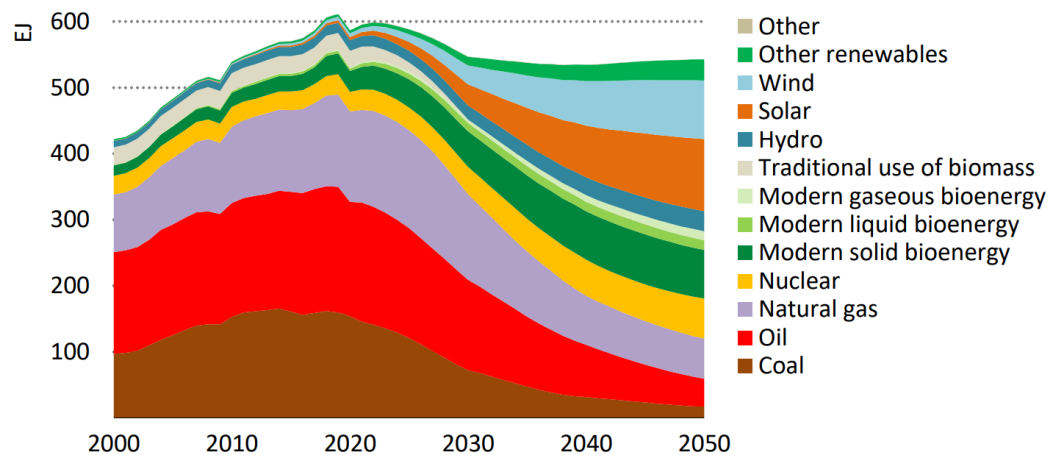


# Analyzing the Global Energy Discourse with Machine Learning

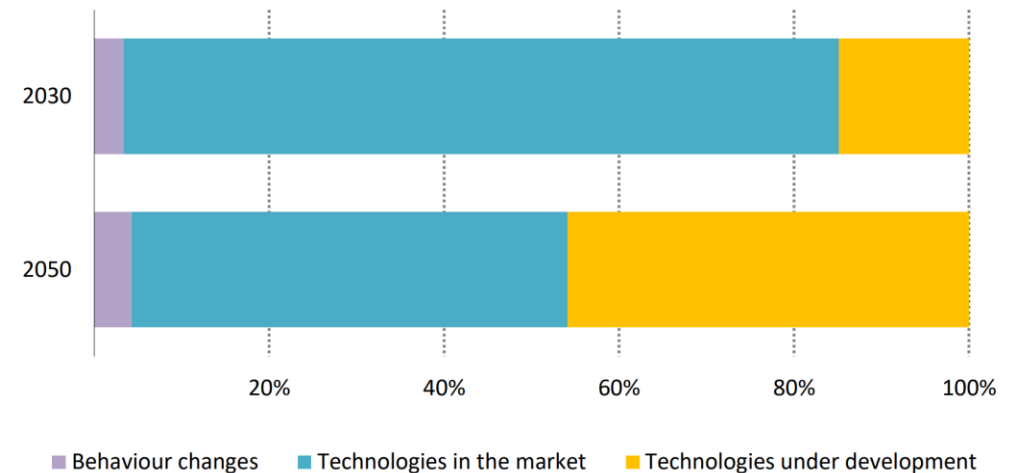
Malte Toetzke, Benedict Probst, Yasin Tatar, Stefan Feuerriegel, Volker Hoffmann

# Rapid innovation and diffusion of clean energy technologies is crucial to replace fossil energy and capture unavoidable emissions

Total energy supply in the Net-Zero Emissions by 2050 Scenario (IEA)



Annual CO2 emissions savings in the net zero pathway, relative to 2020



Source: IEA (<https://www.iea.org/reports/net-zero-by-2050>)

# The media plays an **important role** in the energy transformation with the potential to both **accelerate** and **regress** industrial development

## Displaying the energy transformation:

- Reflecting **public** opinions
- Describing the **political** discourse
- Featuring **technological** and **economic** trends
- ...

## Influencing the energy transformation:

- Attracting **demand** (e.g., for EVs, solar)
- Instigating **resistance** (e.g., against wind parks, nuclear plants)
- Putting **pressure** decision makers in industry, finance, and politics
- ...



<https://www.pexels.com/>

# Existing literature analyzing the media discourse around the energy transformation has limitations



<https://www.pexels.com/>

- **Qualitative** assessment
  - ❑ **No quantitative conclusions** about associations between real-world outcomes and the media discourse possible
  
- **Exploratory** approaches
  - ❑ **Lack of detail** from analyses with unsupervised models due to noisy data
  
- **Single country or single media outlet** analysis
  - ❑ Difficult to **generalize** or **contrast** observations between countries and media outlets

# We create a **comprehensive dataset** covering global newspaper articles on energy technologies



## **13 Energy technologies:**

Biofuels, biomass, carbon capture, coal, gas, heat pumps, hydrogen, EVs, nuclear, oil, solar, synthetic fuels, wind



## **14 newspaper outlets:**

2 major outlets of each country by circulation



## **7 countries:**

China, USA, India, Japan, Canada, Germany, United Kingdom



**~ 5 million articles**



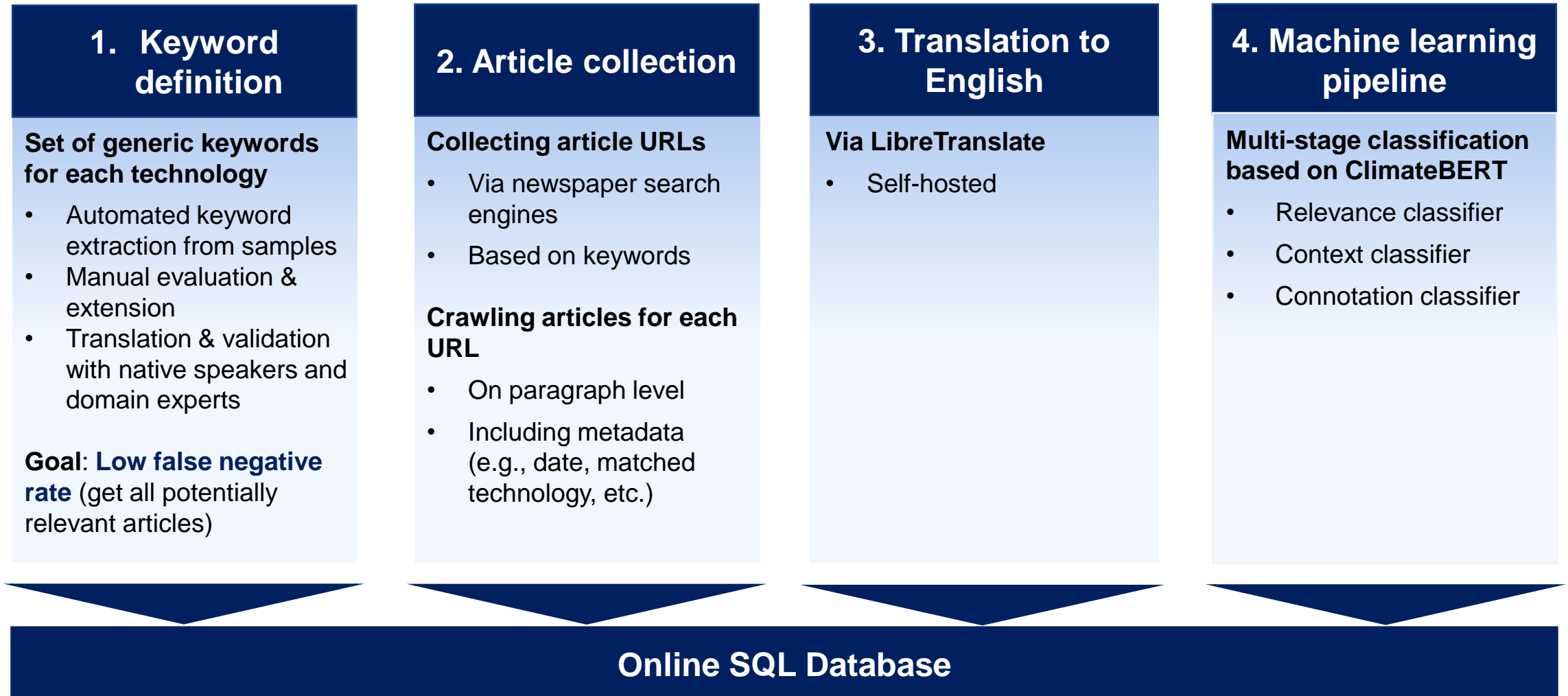
## **~22 years:**

2000—2022



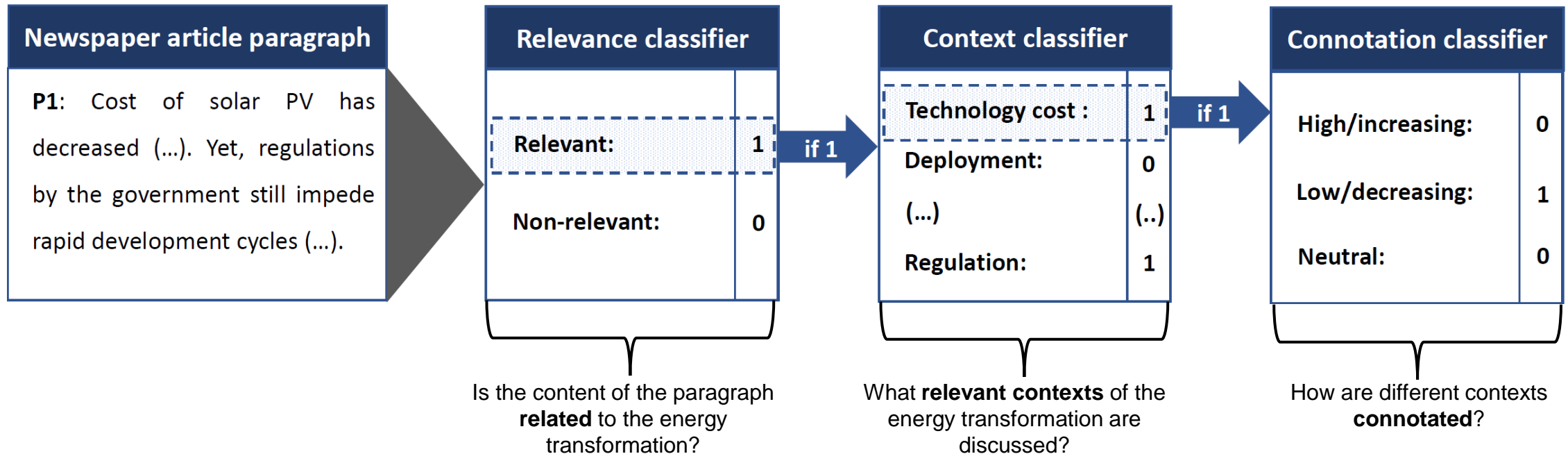
**~ 40 million paragraphs**

# We **collect** and **process** the data in 4 steps



# The machine learning pipeline: we classify newspaper articles on paragraph level regarding relevance, context, and related connotation

## Example:

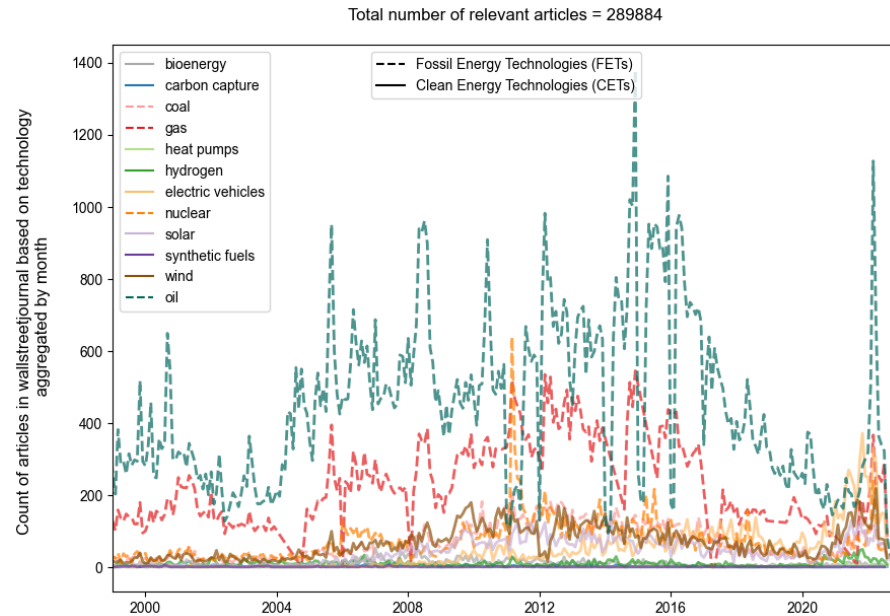


# Context labels based on literature and an expert user study

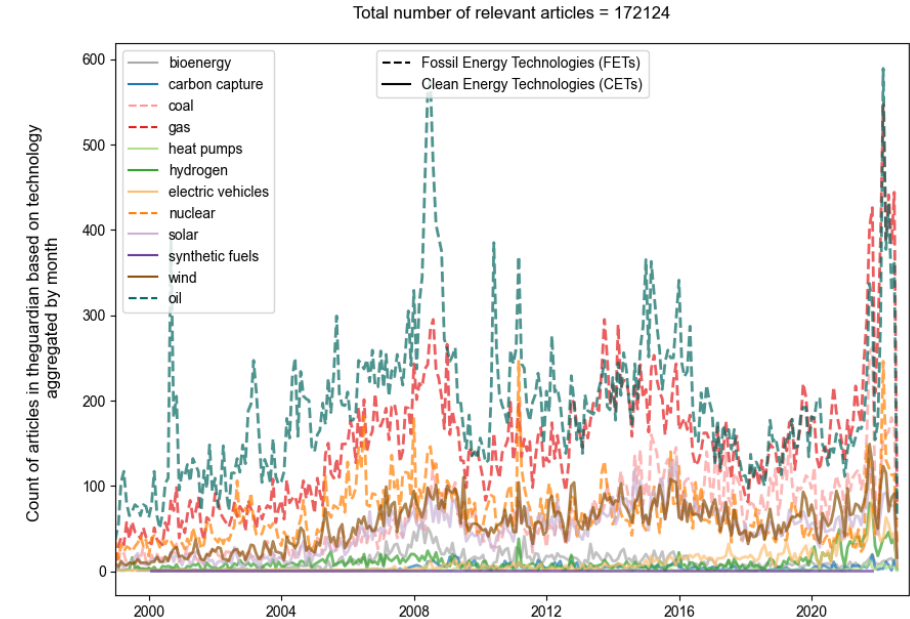
Industry	Politics	Society	Technology	Climate
Manufacturing & production	Political targets & agendas	Social impact	Technology cost & price	Ghg emissions
Deployment	Climate & energy policies	Energy security	Technology efficiency	Climate change
Private investment	Regulation	Employment	Technology characteristics	
Companies	Trade	Public perception	Infrastructure	
Revenues & firm values	Science & public research	Disasters & health risks	Raw materials	
Partnerships	Public finance & investment			
Competition & markets				
Research & development				
Industry transformation				



# Number of **article occurrences** per technology after relevance classification



Wallstreetjournal



The Guardian

What are these articles discussing?

# Current **project status** and **next steps**

## **Article Collection and preprocessing**

- ✓ Defining the keywords
- 🚩 Crawling the articles
- 🚩 Translating paragraphs

## **Machine learning pipeline**

- ✓ Training the relevance classifier
- 🚩 Training the context classifier
- 📅 Training the connotation classifier

## **Data analysis:**

- 📅 Comparing patterns across countries and technologies
- 📅 Forecasting technology investment and deployment based on news data