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Towards Understanding Climate Change Perceptions: A Social Media Dataset

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Tackling Cimate Change with Machine Learning:
NeurIPS Workshop 2023

www.uni-siegen.de

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Why do we need climate change datasets?

- Insights into climate change communication on Twitter.
- Increased effectiveness of climate change communication, public engagement, and climate change education.
- Challenging image classification datasets comprised of real-world climate change images.

How do we perceive climate change?

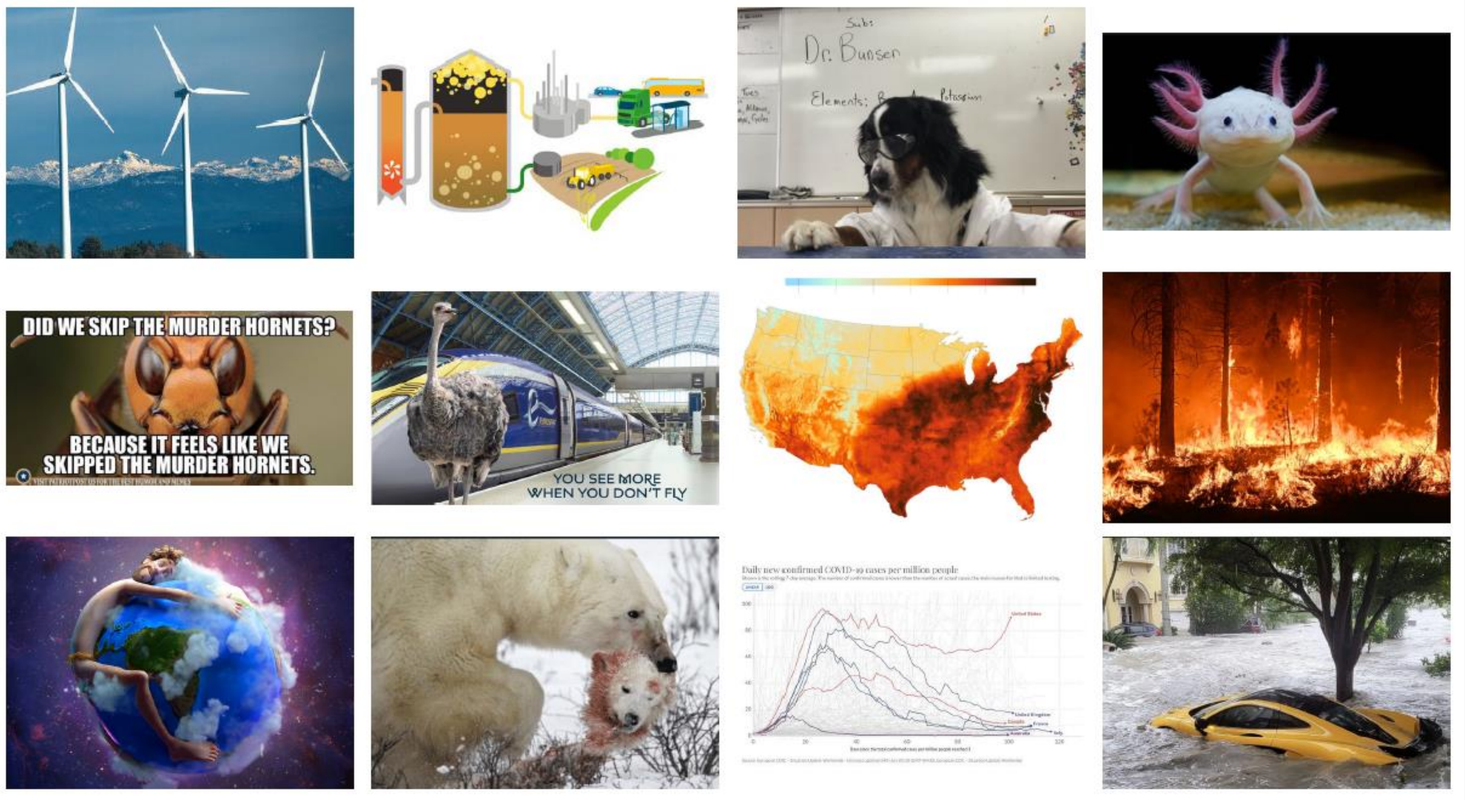

Figure 1: Example images contained in our datasets

Our datasets pose challenging classification tasks

ClimateTV

- Images tweeted between 01/01/2019 – 12/31/2019
- Hashtag #climatechange or mention „climate change“ or “climatechange“
- **Hashtag-based annotations** for **700,000 images** based on SONAR embeddings[1]
- Suitable for large vision and language models

ClimateCT

- Popular images tweeted between 01/01/2019 – 12/31/2022
- Hashtag #climatechange or mention „climate change“ or “climatechange“
- **Manual annotations** for **1,000 images** by two independent annotators
- Suitable for qualitative analysis of classification results

[1] P.-A. Duquenne, H. Schwenk, and B. Sagot. Sonar: Sentence-level multimodal and language-agnostic representations. arXiv preprint arXiv:2308.11466, 2023.

Our climate change annotation scheme

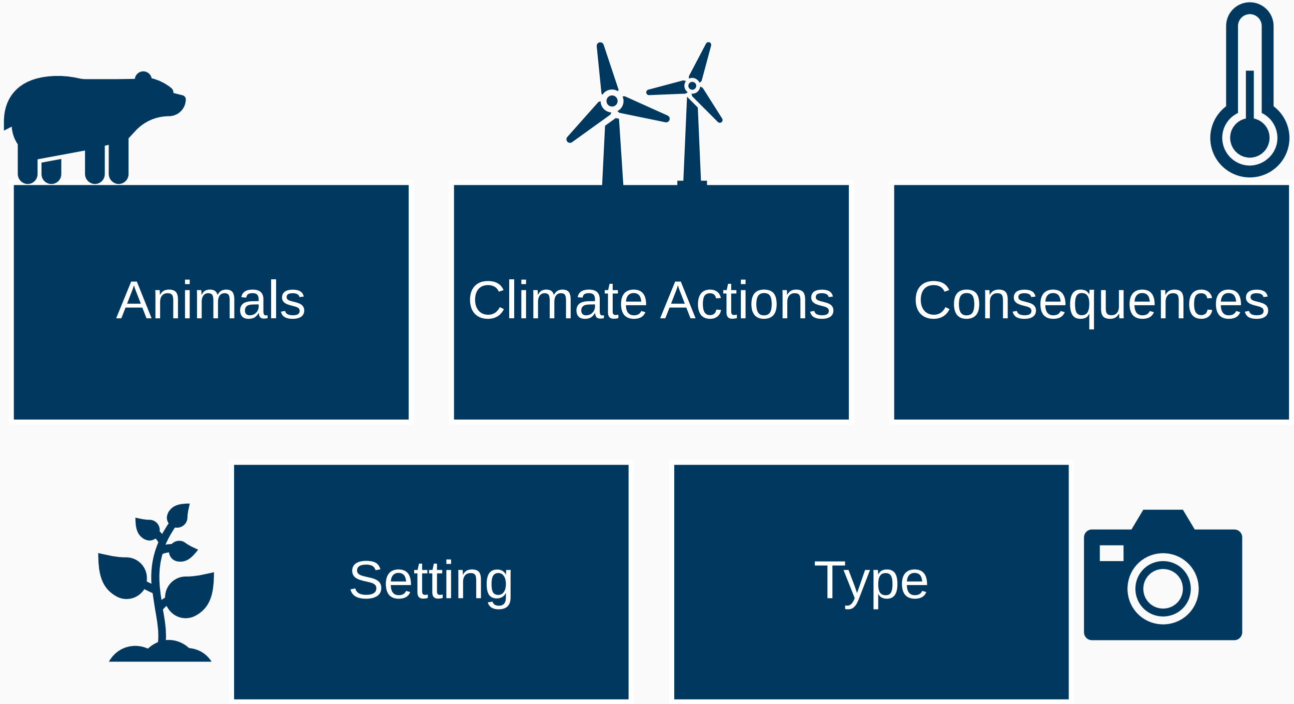

Figure 2: Annotation scheme designed on basis of climate change literature

Class Prevalences within Climate Change Consequences

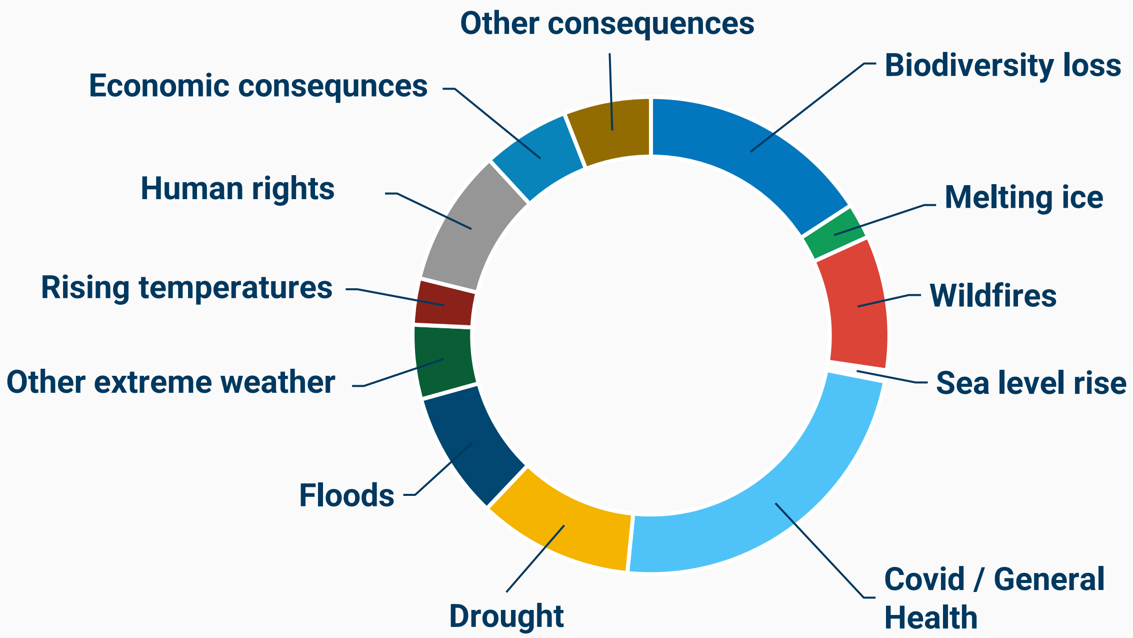

Table 3: **ClimateTV** class overview for the category Consequences

Baseline results & analysis

Model	CLIP		CoCoOp	
Dataset	**CT**	**TV**	**CT**	**TV**
Animals	64.68	28.52	58.94	9.32
Climate action	46.95	31.26	58.68	59.76
Consequences	40.51	23.62	69.52	33.06
Setting	26.04	27.66	49.38	9.84
Type	51.64	49.82	76.70	69.90
Average	45.96	32.18	54.08	36.38

Table 1: Classification accuracies for CLIP[2] and CoCoOp query optimization[3]

[2] A. Radford, J. W. Kim, C. Hallacy, A. Ramesh, G. Goh, S. Agarwal, G. Sastry, A. Askell, P. Mishkin, J. Clark, G. Krueger, and I. Sutskever. Learning transferable visual models from natural language supervision, 2021.

[3] K. Zhou, J. Yang, C. C. Loy, and Z. Liu. Conditional prompt learning for vision-language models. In IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2022.

Thank You!

Contact

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