## **On Stance Detection in Image Retrieval for Argumentation**

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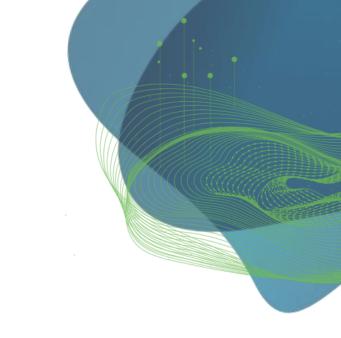
MARTIN-LUTHER-UNIVERSITÄT HALLE-WITTENBERG

**ScaDS** 

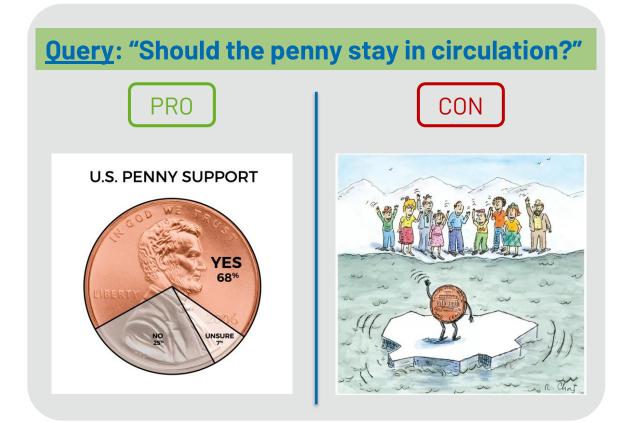
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# What is Image Retrieval for Argumentation?



- → The user enters a controversial topic
- $\rightarrow$  Search for

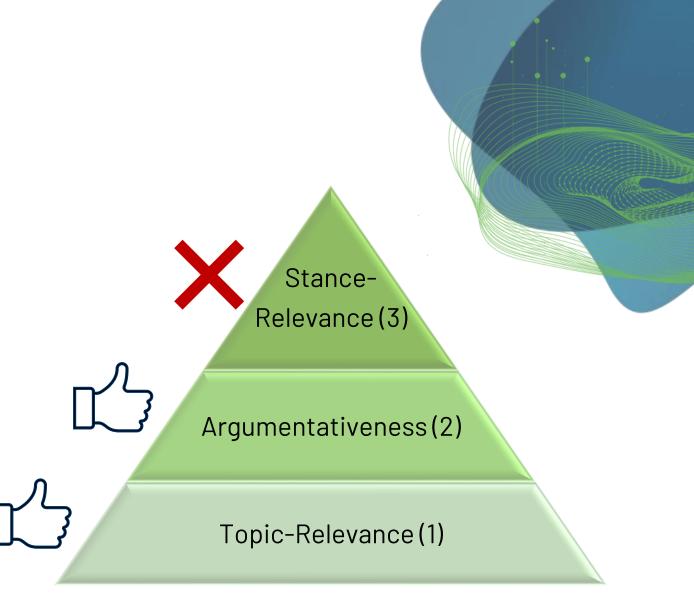
argumentative images

→ Division of images into pro and con



# Work Done So Far

 → First shared task at the Touché lab of the CLEF conference in 2022
→ Three-stage evaluation
→ Very good results for (1) and (2)
→ Unsatisfactory results for (3)





## **Re-Using the Touché'22 Dataset**



#### Included for each image:

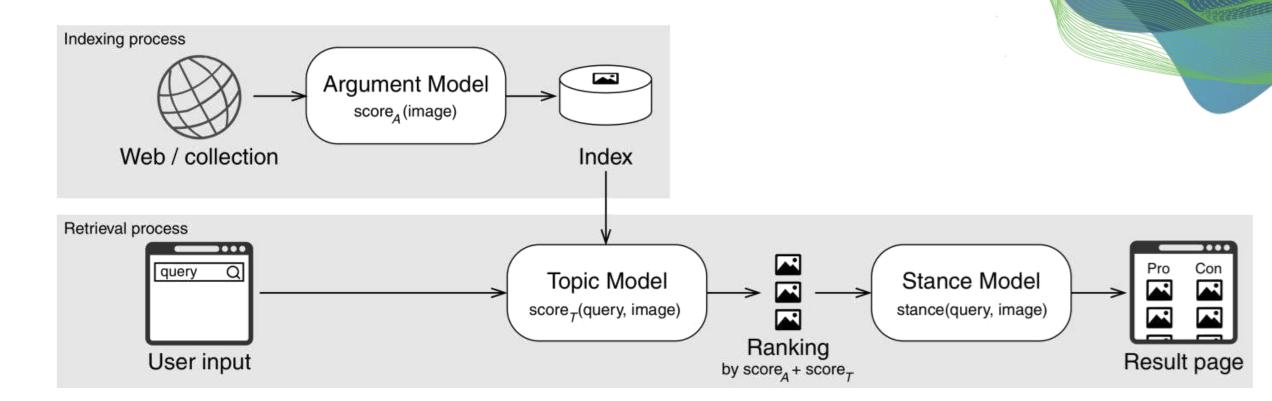
- Image pixel values
- Web page screenshot
- Web page text and HTML source code

• Etc.

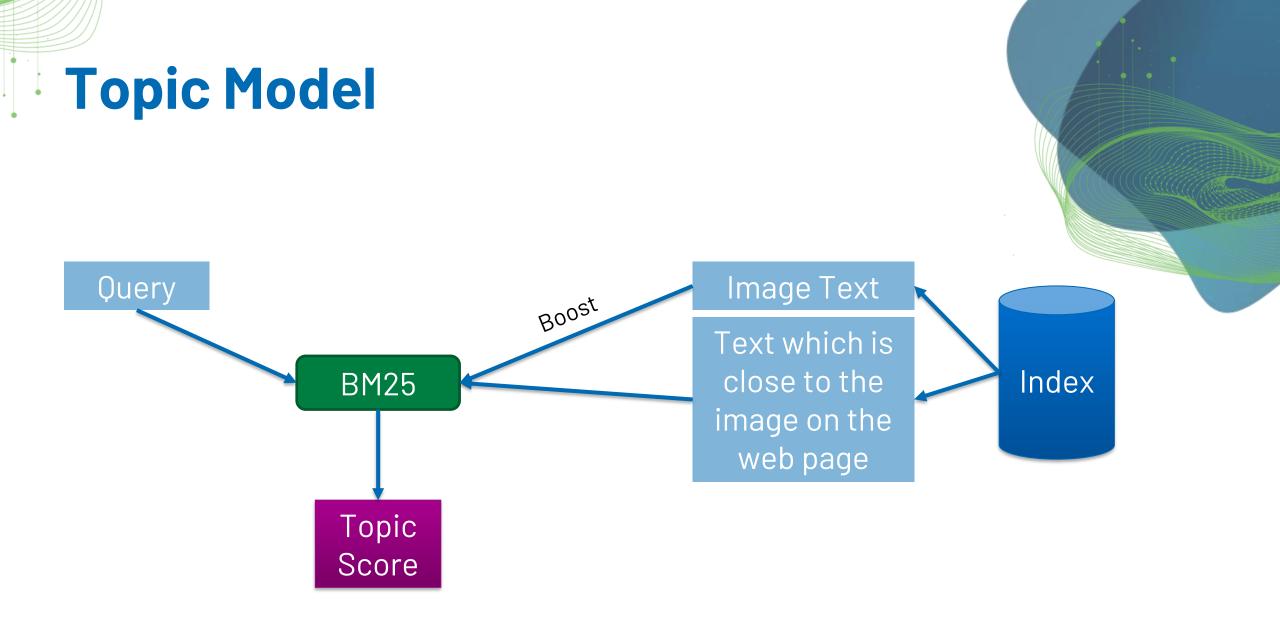
### Relevance ratings for **6,607** images



# Our unified image retrieval system for arguments

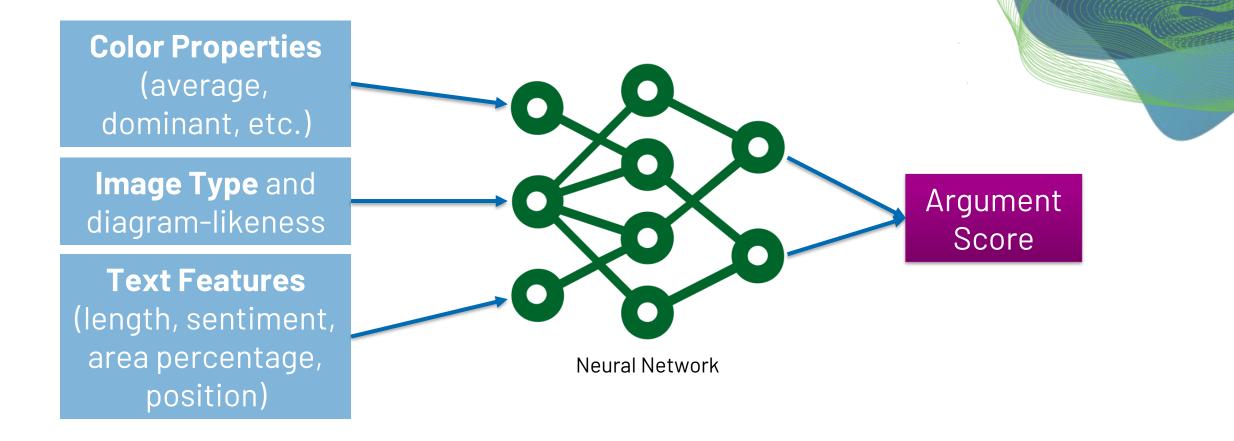








# **Argument Model**





# Stance Models (1/2)

Oracle	upper limit using the ground-truth stance labels			
Both-sides baseline	each image in pro and con			
Random baseline	each image in pro or con with equal probability			
Crawl query stance	labels each image based on which result list it was originally found while crawling (query was extended with pro/anti)			
CLIP query stance	uses CLIP to compute the image's similarity to the query extended with "good" for pro / "anti" for con			
BERT title sentiment	uses a BERT-model to classify the sentiment of the web page's title	>0 → pro		
AFINN text sentiment	sums up the AFINN sentiment score for each word of the web page's text	<0 → con		



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# Stance Models (2/2)

Aramis Formula	uses a heuristic formula that is based on 13 features (developed by Team Aramis)	
Aramis Neural	uses the same features as A <i>ramis Formula</i> as input for a NN, classifies images into pro/con/neutral	
Neural text+image 3class	combines a BERT model with a ResNet50V2 extended by some dropout layers; uses the image, the query, and the OCR text as input; 3 output neurons	
Neural text+image 2x2class	same as <i>Neural text+image 3class</i> but with a single output neuron, trained twice (for pro and for con independantly)	
Neural text 3class	same as <i>Neural text+image 3class</i> but with the title of the web page instead of the image	
Neural text+page 3class	same as <i>Neural text 3class</i> but additionally uses HTML text in the window around the image as input	



### **Performance** (precision@10)

	Topic-	Argumenta-	Stance-		
	relevance	Tiveness	relevance	-Pro	-Con
Oracle	1.000	1.000	0.901	1.000	0.802
Neural text+image 2x2class	0.873	0.798	0.485	0.660	0.310
BERT title sentiment	0.882	0.804	0.462	0.674	0.250
CLIP query stance	0.932	0.830	0.459	0.662	0.256
Aramis Formula	0.867	0.790	0.453	0.690	0.216
Both-sides baseline	0.926	0.832	0.447	0.662	0.232
Neural text+image 3class	0.895	0.815	0.443	0.660	0.226
Random baseline	0.891	0.814	0.443	0.664	0.222
Aramis Neural	0.685	0.654	0.433	0.588	0.278
Best of Touché'22 (Boromir)	0.878	0.768	0.425	0.594	0.256
Crawl query stance	0.779	0.719	0.412	0.610	0.214
AFINN text sentiment	0.837	0.761	0.393	0.564	0.222
Neural text+page 3class	0.630	0.579	0.329	0.504	0.154
Neural text 3class	0.668	0.602	0.324	0.458	0.190

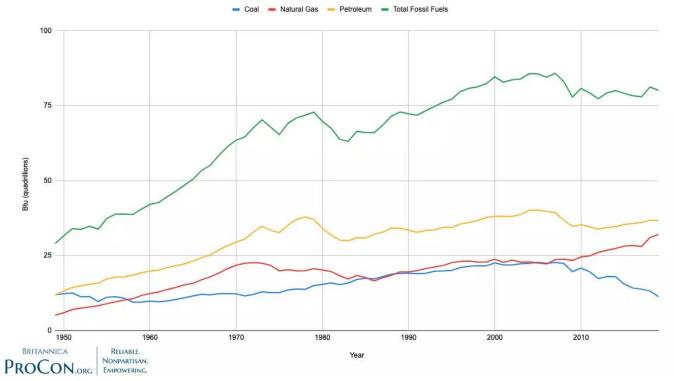


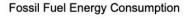




## 1. Semantic Gap for Diagrams

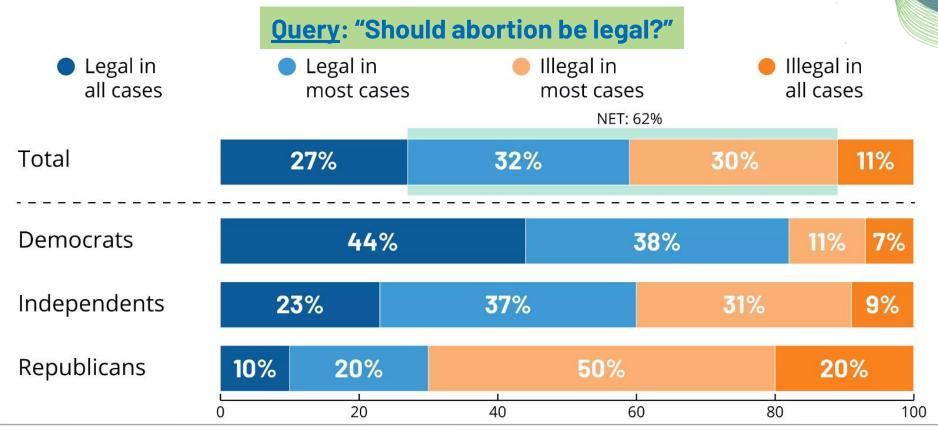
### <u>**Ouery</u>: "Can alternative energy effectively replace fossil fuels?"**</u>







# 2. Different valuations cause stance ambiguity





# 3. Image understanding depends on background knowledge

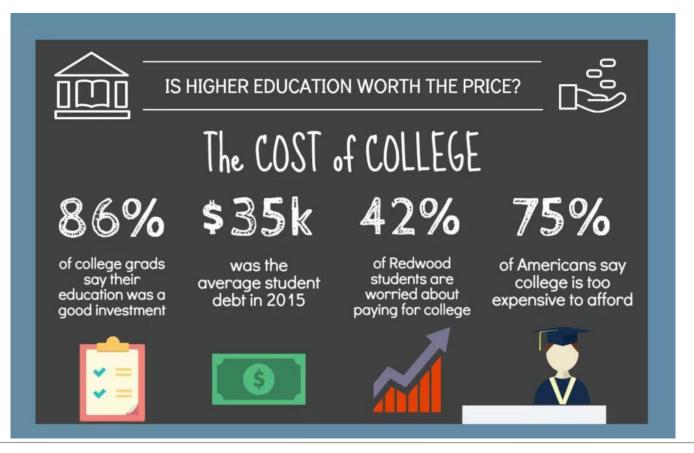
**<u>Query</u>: "Is human activity primarily responsible for global climate change?"** 





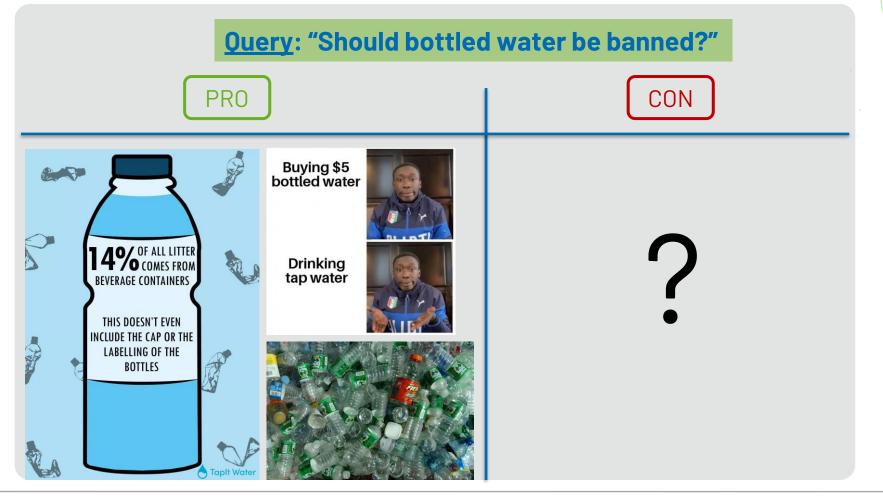
## 4. Regional images

#### **<u>Ouery</u>: "Is a college education worth it?"**





### 5. Unbalanced image stance distribution





## 6. Both stances in one image

#### <u>Query</u>: "Should adults be allowed to carry a concealed handgun?"

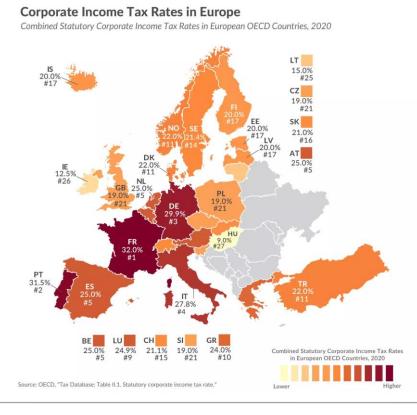
YES	NO		
1.) Criminals less likely to attack someone that they believe might be armed.	1.) Concealed handguns are not an effective form of self-defense. Someone carrying a gun for self-defense is 4.5 times more likely to be shot during an assault than a victim without a gun.		
2.) Concealed-carry laws reduce murders by 8.5%, aggravated assaults			
by 7%, rapes by 5%, and robberies by 3%	2.) Concealed-carry laws lead to increases in rates of rape, robbery, and violent crime.		
3.) The right to carry concealed			
handguns is guaranteed by the	3.) Ability to carry a concealed handgun		
Second Amendment ("Right to Bear	NOT guaranteed by the Constitution.		
Arms")	Second Amendment for military and militia purposes, not personal carry.		
4.) "Guns don't shoot people; People shoot people."	4.) Guns are a primary tool used by people to kill people.		

"Should adults have the right to carry a concealed handgun?"



## 7. Neutral images

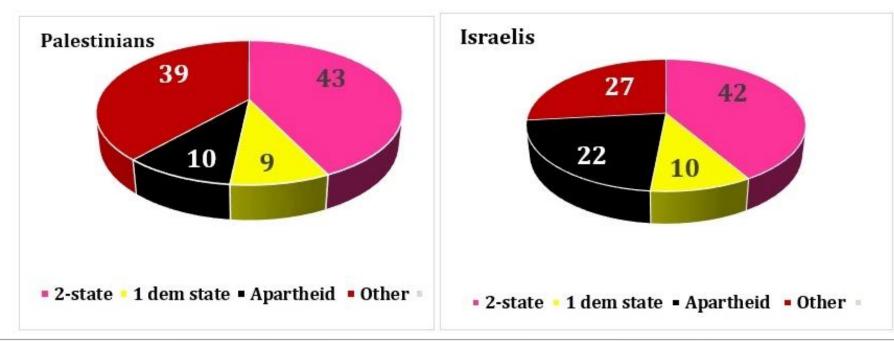
## <u>Query</u>: "Does lowering the federal corporate income tax create jobs?"





### 8. More than two stances

#### <u>Query</u>: "Is a two-state solution an acceptable solution to the Israeli-Palestinian conflict?"



Support for the two-state solution and two alternative options among Palestinians and Israeli Jews, 2020



## 9. Irony and Jokes

<u>**Ouery</u>: "Do violent video games contribute to youth violence?"**</u>

violence is introduced to humanity for the first time (1978)





## **Lessons learned**

- →A modular image retrieval system works very well for finding topic-relevant and argumentative images (new state-of-the-art)
- →None of the 14 reproduced or new approaches can significantly beat a random baseline at stance detection
- $\rightarrow$ Stance detection of images is an unsolved problem
- $\rightarrow$  The task provides many different challenges

