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From Unstructured Data to Digital Twins: From Tweets to Structured Knowledge

Sergej Schultenkämper, M.Sc.; Bielefeld University of Applied Sciences and Arts Dr. Frederik Simon Bäumer; Bielefeld University of Applied Sciences and Arts Dr. Yeong Su Lee; University of the Bundeswehr Munich

Prof. Dr. Michaela Geierhos; University of the Bundeswehr Munich





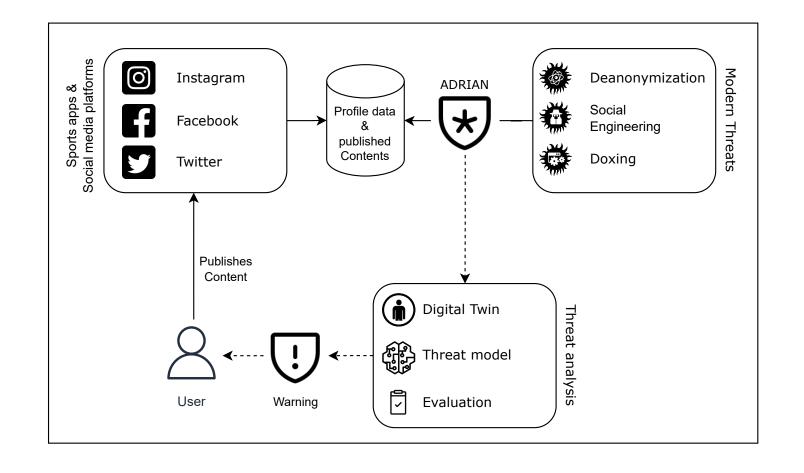








ADRIAN RESEARCH PROJECT





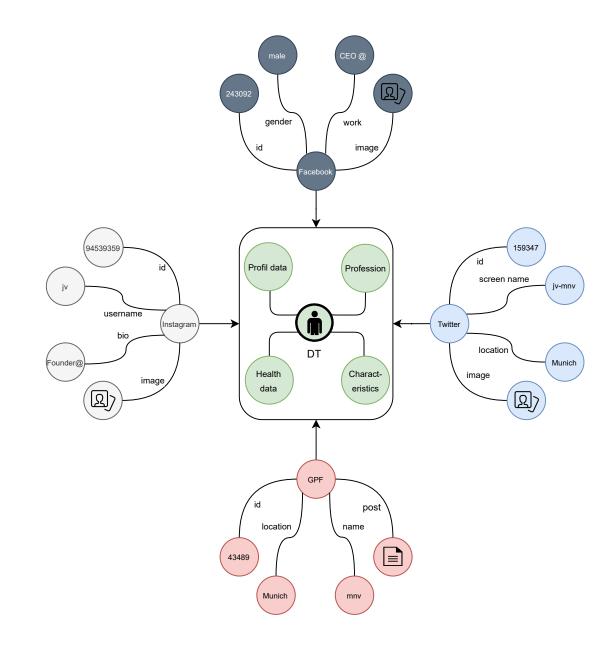
RELATED WORK

- I Traditional Methods: Rule-Based Systems, and Language Model Techniques (Named Entity Recognition & Relationship Classification)
- I Latest Research: Large Language Models (LLMs) combined with In-Context Learning (ICL) capabilities offer promising ways to extract relational data as a single task
- I Recent Studies: Xu et al. (2023) emphasized instructional prompts in ICL. Wan et al. (2023) introduced GPT-RE, emphasizing quality demonstrations and improved reasoning



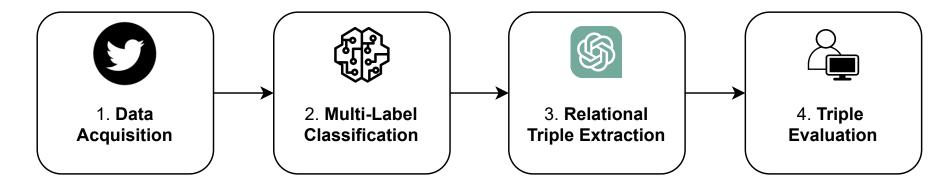
HUMAN DIGITAL TWIN (HDT)

- I There is **no standard definition** for HDT
- In the ADRIAN project, the HDT is defined as a digital representation of a real person, instantiated through available web-based information
- I The HDT is used to **store** and **analyze** relevant **characteristics** of an individual
- I The vulnerability of a person can be modeled and measured





APPROACH



- I Data Acquisition: 870,000 Tweets from 246 Users
- I Multi-Label Classification: XLM-RoBERTa Training for 7 classes of interest
- I Relational Triple Extraction: GPT-4 to analyze 5,000 tweets from 100 users
- I Triple Evaluation: Manual Triple Evaluation



DATASET

I Data Source: Twitter API

I Collection Date: May 2023

I Data Challenges: Tweets have character restrictions and often contain very limited information

I User-generated content: Suffers from spelling and grammar errors, lacks context

Dataset Feature	Count
No. of Users Searched	300
No. of Users Found	246
Avg. Tweets/User	3,532
Median Tweets/User	546
Min. Tweets/User	1
Max. Tweets/User	80,689
Total Tweets	869,069
Top Languages	EN, DE, FR, ES, TR
No. of Reply Tweets	274,504
No. with Attachments	106,997
No. with Geolocation	43,138
No. of Retweets	236,553



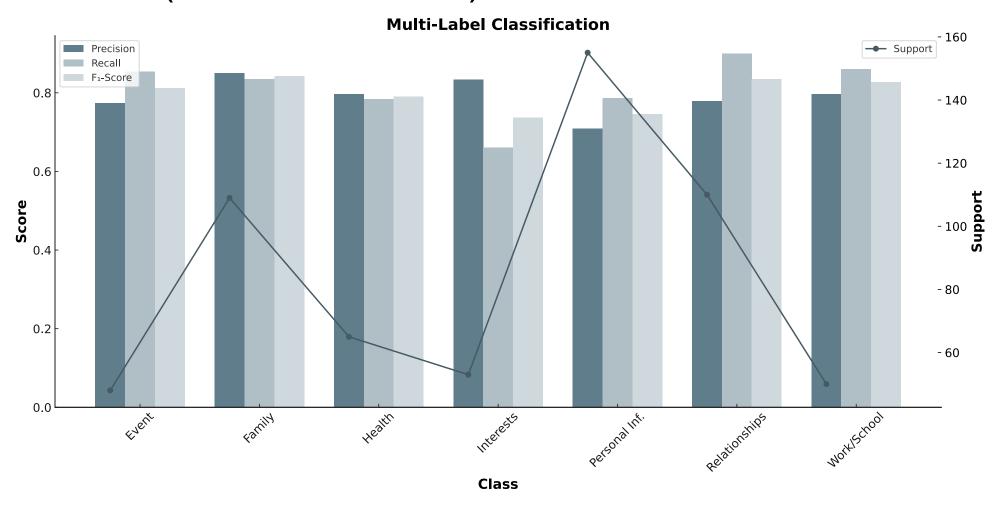
MULTI-LABEL CLASSIFICATION

- I Tweet Pre-Filtering: Essential given the large number of tweets and the costs of GPT-4
- I Sentence Labeling: Used "OffMyChest" dataset (Jaidka, K. et al., 2020) for annotation
- Model Training: Trained XLM-RoBERTa (Conneau, A. et al., 2020) with 1,438 sentences

Category	Properties
Event	s:attendee
Family	s:children, s:parent, s:sibling, s:spouse
Health	s:diagnosis, s:drug, s:healthCondition
Interests	s:interests
Personal Information	s:birthDate, s:birthPlace, s:email, s:gender, s:location, s:nationality
Relationships	s:colleague, s:knows
Work/School	s:alumniOf, s:jobTitle, s:workLocation, s:worksFor



RESULTS (XLM-ROBERTA)





RELATIONAL TRIPLE EXTRACTION

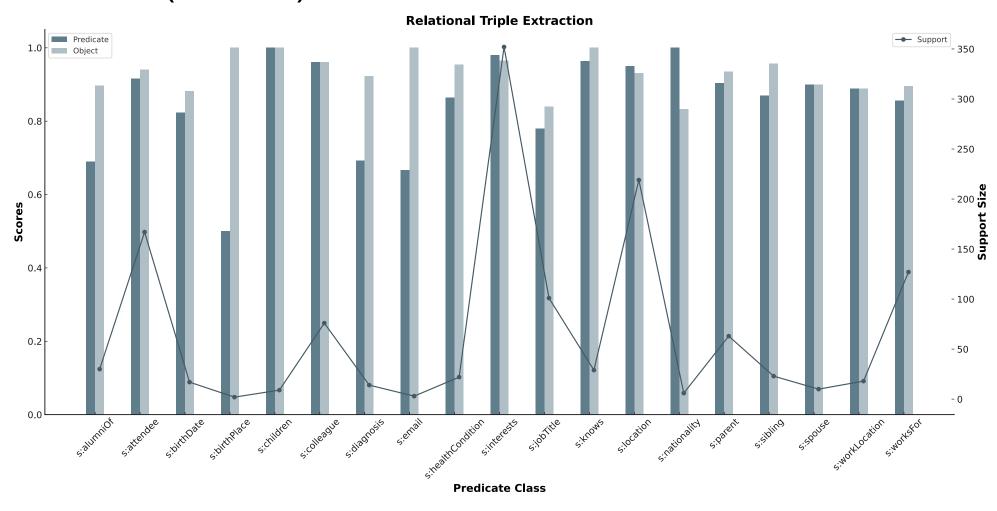
- I Method: Extraction with GPT-4
- I Ontology-based: Use Schema.org properties for knowledge graph
- I GPT-4 Features: Leverage ICL features and function calling capabilities

Subject	Predicate	Object
John	s:worksFor	Microsoft
OpenAl	s:location	San Francisco, CA
Albert Einstein	s:spouse	Elsa Einstein

Person A Schema.org Type Thing > Person			
A person (alive, dead, undead, or fictional).			
Property	Expected Type		
Properties from Person			
additionalName	Text		
address	PostalAddress or Text		
affiliation	Organization		
alumniOf	EducationalOrganization or Organization		
award	Text		
birthDate	Date		
birthPlace	Place		
brand	Brand or Organization		
callSign	Text		
children	Person		



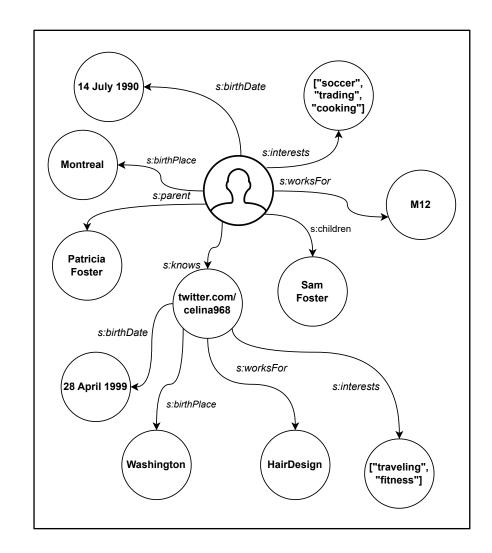
RESULTS (GPT-4)





DISCUSSION

- I RTE: Extraction of 1,288 triples from5,000 tweets with good results
- I ADRIAN: The extracted triples can be leveraged to expand the HDT within the project
- I Knowledge Graph: Enabling the exploration of interconnected relationships within extracted information





CONCLUSION & FUTURE WORK

- GPT-4: Provides the ability to extract information and insights from user-generated content
- I GPT-4 Features: Applied function calling and ICL capabilities to achieve good results for extracting triples from tweets
- I Closed-Source LLMs: Not cost-effective for processing large amounts of data
- I Open-Source LLMs: Generate additional data to fine-tune leading open-source models such as Llama-2 (Touvron, H. et al., 2023)



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Hochschule Bielefeld University of Applied Sciences and Arts

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Thank you for your attention!