# Overview of the Trigger Detection Task at PAN 2023



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# Trigger Warnings

Trigger:

 A trigger in media content is a topic or situation that evokes images, memories, or emotions that cause discomfort or distress.

"Great infernos dotted the city here and there, charring and cremating the still bodies of those committed souls who now lay still forever."

evokes

Memories of a past war.

triggers

Anxiety, feelings of loss or grief, ...

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Memories of a past war.

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#### Trigger warning:

- □ A warning about a possible trigger for the audience, displayed before the content.
- Originally used in trauma therapy, trigger warnings have been adopted and extensively expanded by online communities.

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Memories of a past war.

triggers

Anxiety, feelings of loss or grief, ...

#### Trigger Detection at PAN 2023:

Given a fan fiction document, assign all appropriate trigger warnings from the given label set.

# Task Overview

#### Dataset:

- □ Contains 341,246 English fan fiction documents.
- Documents are 50–6,000 words long.
- □ Annotated with 32 warning labels (multi-label).

Number of documents with the given warning label.



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Evaluation:

- $\hfill\square$  Precision, Recall,  $F_1$ , all micro and macro averaged.
- □ Best models: 0.35 macro  $F_1$ ; 0.75 micro  $F_1$ .

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Submissions:

- □ 6 teams submitted.
- Different models, features, and strategies to deal with long documents and label imbalances.

Number of documents with the given warning label.



@Wiegmann, 2023

#### Trigger Warning Taxonomy:

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  7 open-set warning groups (not used in the task).



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- □ Characterization of the subject-actor-intent relation.



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#### Documents:

 We scraped 7.9 million fan fiction documents with metadata from Archive of Our Own (AO3).

Rating:	Mature
Archive Warnings:	No Archive Warnings Apply, <u>Major Character Death</u> , <u>Graphic</u> Depictions Of Violence
Category:	M/M
Fandom:	Harry Potter – J. K. Rowling
Relationships:	Sirius Black/Remus Lupin, <u>Sirius Black &amp; Remus Lupin</u> , James Potter/Lily Evans Potter
Characters:	Remus Lupin, Sirius Black, James Potter, Lily Evans Potter, Pete Pettigrew, Severus Snape, Minerva McGonagall, Bellatrix Black Lestrange, Narcissa Black Malfoy, Albus Dumbledore, Mulciber Sr. (Harry Potter), Horace Slughorn, Mary Macdonald, Marlene McKinnon, Poppy Pomfrey, Walburga Black, Regulus Black, Fenrir Greyback
Additional Tags:	Marauders' Era, Marauders, Marauders Friendship, wolfstar, Get Together, Slow Burn, so slow, it's slow, seriously, Complete, Canon Compliant, Angst, Fluff, Fluff and Angst, Requited Love, Canonical Character Death, First War with Voldemort, First Kiss, Period Typical Attitudes
Language:	English
Series:	Part 1 of All the Young Dudes • Next Work $\rightarrow$
Stats:	Published: 2017-03-02 Completed: 2018-11-12 Words: 526,969 Chapters: 188/188 Comments: 30,603 Kudos: 155,026 Bookmarks: <u>30,939</u> Hits: 10,623,619

#### Documents:

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- Stratified sampling into training (307,102), validation (17,104), and test (17,040) documents.
- Determine warning based on the 10 million unique freeform tags.

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  Sources were annotated with a warning.



- Freeform tags are related through tag relations that were added by community experts
  - → Semi-automatic annotation.
- Synonymous tags are related.
  One synonym is marked as *canonical*.
- Canonical tags are in a meta-sub relation.
  Sources were annotated with a warning.
- Parent relations indicate Genre/Fandom.
  Warnings are usually children of *No Fandom*.
- Annotate ca. 6,000 nodes, infer label for ca. 80% of tags used; 0.95 F<sub>1</sub>.



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□ **XGBoost baseline** based on TF·IDF document vectors.

Participant		Macro	)
	Prec	Rec	$F_1$
XGBoost	0.52	0.25	0.301

Participant	Micro		
	Prec	Rec	$F_1$

XGBoost 0.88 0.57 0.69

Submissions:	Partie
XGBoost baseline based on TF·IDF document vectors.	Sahir
Sahin et al. Hierarchical classification with a RoBERTa-base	XGBo
and LSTM, use full documents.	

Participant	Macro		
	Prec	Rec	$F_1$
Sahin	0.37	0.42	0.352
XGBoost	0.52	0.25	0.301

Participant	Micro		
	Prec	Rec	$F_1$
Sahin	0.73	0.74	0.74
XGBoost	0.88	0.57	0.69

- □ XGBoost baseline based on TF·IDF document vectors.
- Sahin et al. Hierarchical classification with a RoBERTa-base and LSTM, use full documents.
- Su et al. Hierarchical (siamese) classification with a RoBERTa-base and CNN, uses the first and last 500 words.

Participant	Macro		
	Prec	Rec	$F_1$
Sahin	0.37	0.42	0.352
Su	0.54	0.30	0.350
XGBoost	0.52	0.25	0.301

Participant	Micro		
	Prec	Rec	$F_1$
Su	0.80	0.71	0.75
Sahin	0.73	0.74	0.74
XGBoost	0.88	0.57	0.69

- □ XGBoost baseline based on TF·IDF document vectors.
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- Haojie Cao et al. and Guiyuan Cao et al. Classify chunks with RoBERTa-based voting ensemble.

Participant		Macro	)
	Prec	Rec	$F_1$
Sahin	0.37	0.42	0.352
Su	0.54	0.30	0.350
XGBoost	0.52	0.25	0.301
Cao H.	0.24	0.29	0.228
Cao G.	0.28	0.22	0.225

Participant	Micro			
	Prec	Rec	$F_1$	
Su	0.80	0.71	<b>0.75</b>	
Sahin	0.73	0.74	0.74	
XGBoost	0.88	0.57	0.69	
Cao G.	0.58	0.66	0.62	
Cao H.	0.43	0.79	0.56	

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- Haojie Cao et al. and Guiyuan Cao et al. Classify chunks with RoBERTa-based voting ensemble.
- Felser et al. MLP based on aggregate embeddings and topic model features.

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	Prec	Rec	$F_1$
Sahin	0.37	0.42	0.352
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XGBoost	0.52	0.25	0.301
Cao H.	0.24	0.29	0.228
Cao G.	0.28	0.22	0.225
Felser	0.11	0.63	0.161

Participant	Micro			
	Prec	Rec	$F_1$	
Su	0.80	0.71	0.75	
Sahin	0.73	0.74	0.74	
XGBoost	0.88	0.57	0.69	
Cao G. Cao H. Felser	0.58 0.43 0.27	0.66 0.79 <b>0.82</b>	0.62 0.56 0.40	

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- Felser et al. MLP based on aggregate embeddings and topic model features.
- □ Shashirekha et al. LSTM based on GloVE embeddings.

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	Prec	Rec	$F_1$	
Sahin	0.37	0.42	0.352	
Su	0.54	0.30	0.350	
XGBoost	0.52	0.25	0.301	
Cao H.	0.24	0.29	0.228	
Cao G.	0.28	0.22	0.225	
Felser	0.11	0.63	0.161	
Shashirekha	0.10	0.04	0.048	

Participant	Micro			
	Prec	Rec	$F_1$	
Su	0.80	0.71	0.75	
Sahin	0.73	0.74	0.74	
XGBoost	0.88	0.57	0.69	
Shashirekha	0.82	0.50	0.63	
Cao G.	0.58	0.66	0.62	
Cao H.	0.43	0.79	0.56	
Felser	0.27	0.82	0.40	

#### Observations from the Evaluation II:

 Submissions with good representations of full documents are more effective (0.05–0.06) on long than on short documents.

	Length		Ρορι	ularity
	short	long	low	high
Sahin	0.28	0.34	0.30	0.35
Su	0.39	0.27	0.22	0.35
XGBoost	0.24	0.29	0.16	0.30
Cao, H.	0.23	0.22 0.19 0.22		0.22

- Submissions with good representations of full documents are more effective (0.05–0.06) on long than on short documents.
- 2. Submissions with strong positional representation are more effective on short texts (< 500 words).

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- 3. Submissions are more effective on popular works.

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- 4. Submissions are less effective if documents have many freeform tags (0.06–0.12).

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Sahin	0.28	0.34	0.30	0.35	
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- 2. Submissions with strong positional representation are more effective on short texts (< 500 words).
- 3. Submissions are more effective on popular works.
- 4. Submissions are less effective if documents have many freeform tags (0.06–0.12).
- 5. Submissions are less effective if documents have the *Choose Not To Use Archive Warnings* declaration (0.04–0.06).

	Len	gth	Ρορι	ularity
	short	long	low	high
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#### Observations from the Evaluation I:

6. Submissions are effective for common and less effective for rare warnings.

	Ро	Porn.		Common		re
	Ρ	R	Ρ	R	Ρ	R
Sahin	0.95	0.96	0.62	0.48	0.12	0.51
Su	0.90	0.97	0.61	0.43	0.57	0.19
Cao H.	0.86	0.98	0.22	0.61	0.16	0.12

- 6. Submissions are effective for common and less effective for rare warnings.
- 7. Submissions favor either precision or recall, independently of overall effectiveness.

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- 8. An ensemble of the (best) submissions improves  $F_1$  marginally (0.01–0.03).

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	Ρ	R	Ρ	R	Ρ	R
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	Macro $F_1$	Micro $F_1$
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Su	0.35	0.75
XGBoost	0.30	0.69
Ensemble (Top 3)	0.36	0.77

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**Contact** matti.wiegmann@uni-weimar.de

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