

Detecting Machine-Generated Text with Purely Linguistic Features

DetecTUM at the CLIN-33 Shared Task

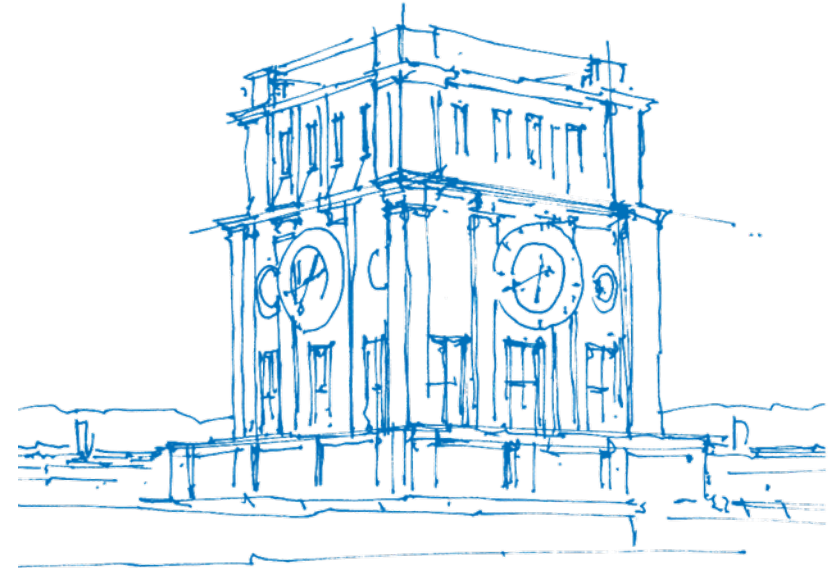
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September 22, 2023



TUM Uhrenturm

Goals

Limited training data

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→ Cross-lingual features *transfer*?

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Not all domains in provided data

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Explanation track

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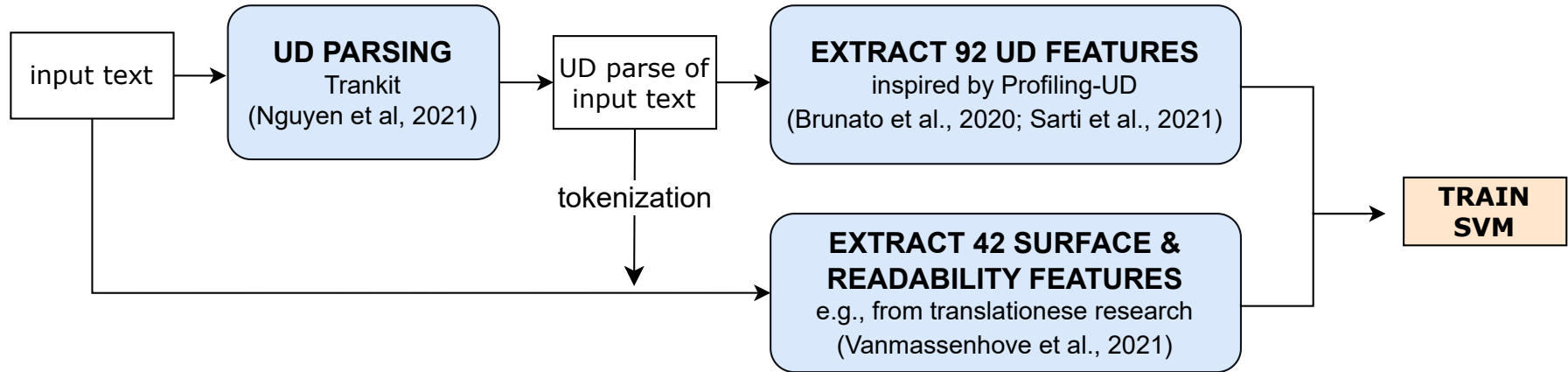
→ Transparent and explainable features

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- Limited training data → Cross-lingual features *transfer*?
- Not all domains in provided data → Cross-domain features *transfer*?
- Explanation track → Transparent and explainable features

Universal Dependencies and **Readability Metrics**

Method



Experiments & Scrapped Ideas

Separate model per language → Mostly worse performance

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Separate model per language
DeBERTa-v3-large model

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- Not in the spirit of explainable, cross-lingual & cross-domain

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Domain splitting

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- Performance not great and unknown domains in test set

Experiments & Scrapped Ideas

- Separate model per language → Mostly worse performance
- DeBERTa-v3-large model → Not in the spirit of explainable, cross-lingual & cross-domain
- Domain splitting → Performance not great and unknown domains in test set
- More data from similar shared task → Only more for English, different setup

Results development set

	Submission	Macro-accuracy	News	Twitter	Reviews	Poetry	Mystery genre	Open-source
English	DetecTUM_1	0.86	0.88	0.72	0.84	0.85	0.88	1.00
	DetecTUM_2	0.83	0.90	0.68	0.88	0.70	0.94	0.90
	Elsevier_2	0.82	0.99	0.72	0.69	0.50	1.00	1.00
	Hans_van_Halteren_1	0.78	0.98	0.81	0.72	0.65	0.50	1.00
	Elsevier_1	0.77	0.88	0.55	0.69	0.50	1.00	1.00
	Hans_van_Halteren_2	0.67	0.92	0.71	0.55	0.35	0.50	1.00
	NLP_MS_1	0.63	0.65	0.62	0.50	0.50	0.81	0.70
Dutch	Elsevier_2	0.80	0.94	0.69	0.88	0.60	0.90	-
	Hans_van_Halteren_1	0.79	0.99	0.69	0.76	0.65	0.85	-
	Elsevier_1	0.79	0.94	0.64	0.88	0.60	0.90	-
	Hans_van_Halteren_2	0.78	0.94	0.61	0.75	0.70	0.92	-
	DetecTUM_1	0.73	0.96	0.70	0.82	0.55	0.62	-
	DetecTUM_2	0.73	0.98	0.64	0.81	0.50	0.72	-
	NLP_MS_1	0.53	0.59	0.50	0.49	0.55	0.50	-

DetecTUM_1: Single SVM trained on both languages and all domains. DetecTUM_2: Same, but model per language.

Results final set

	Team	Macro-accuracy	News	Twitter	Reviews	Poetry	Mystery genre	Open-source
English	Hans_van_Halteren	0.85	0.99	0.69	0.82	0.63	0.99	0.96
	DetecTUM	0.82	0.93	0.69	0.78	0.80	0.78	0.92
	Elsevier	0.81	0.98	0.65	0.75	0.50	0.99	0.98
	NLP_MS	0.74	0.87	0.63	0.63	0.65	0.85	0.82
Dutch	Elsevier	0.75	0.95	0.70	0.77	0.50	0.84	-
	DetecTUM	0.74	0.96	0.74	0.80	0.53	0.67	-
	Hans_van_Halteren	0.72	0.97	0.58	0.78	0.53	0.74	-
	NLP_MS	0.71	0.90	0.78	0.70	0.56	0.60	-

Results final set

	Team	Macro-accuracy	News	Twitter	Reviews	Poetry	Mystery genre	Open-source
English	Hans_van_Halteren	0.85	0.99	0.69	0.82	0.63	0.99	0.96
	DetecTUM	0.82	0.93	0.69	0.78	0.80	0.78	0.92
	Elsevier	0.81	0.98	0.65	0.75	0.50	0.99	0.98
	NLP_MS	0.74	0.87	0.63	0.63	0.65	0.85	0.82
Dutch	Elsevier	0.75	0.95	0.70	0.77	0.50	0.84	-
	DetecTUM	0.74	0.96	0.74	0.80	0.53	0.67	-
	Hans_van_Halteren	0.72	0.97	0.58	0.78	0.53	0.74	-
	NLP_MS	0.71	0.90	0.78	0.70	0.56	0.60	-

A little disappointed...

Insights

Language	Domain	Feature 1	Feature 2	Feature 3
English	News	0.66 (avg_syl)	0.56 (dep_dist_det)	0.56 (dep_dist_amod)
	Twitter	0.54 (n_#)	0.44 (n_}	0.35 (n_sentences)
	Reviews	0.57 (n_,)	0.39 (dep_dist_punct)	0.38 (upos_dist_PUNCT)
	Poetry	0.40 (n_')	0.32 (n_,)	0.21 (dep_dist_discourse)
	Columns	0.84 (avg_syl)	0.70 (dep_dist_det)	0.68 (upos_dist_DET)
	Open-source	0.64 (avg_syl)	0.59 (char_per_tok)	0.57 (dep_dist_amod)
Dutch	News	0.66 (verbs_form_dist_Inf)	0.63 (dep_dist_mark)	0.63 (char_per_tok)
	Twitter	0.55 (n_")	0.44 (upos_dist_PUNCT)	0.42 (dep_dist_punct)
	Reviews	0.24 (dep_dist_det)	0.24 (avg_syl)	0.23 (n_}
	Poetry	0.32 (n_,)	0.24 (upos_dist_ADJ)	0.21 (lexical_density)
	Columns	0.69 (lfp_b1)	0.67 (dep_dist_mark)	0.67 (dep_dist_cop)

Top three most *positively* correlated* features per language and domain (out of 136 features).

*All are at least $p < 0.05$ significant, most are $p < 0.0001$ significant.

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Language	Domain	Feature 1	Feature 2	Feature 3
English	News	-0.593 (upos_dist_PROPN)	-0.548 (verbs_tense_dist_Past)	-0.536 (dep_dist_nummod)
	Twitter	-0.284 (lexical_density)	-0.282 (tokens_per_sent)	-0.262 (dep_dist_flat)
	Reviews	-0.433 (lfp_b1)	-0.365 (char_per_tok)	-0.299 (n_())
	Poetry	-0.418 (n_;	-0.365 (n_:)	-0.305 (upos_dist_NUM)
	Columns	-0.728 (dep_dist_ccomp)	-0.699 (dep_dist_obl:tmod)	-0.699 (yules_i)
	Open-source	-0.688 (verbs_tense_dist_Past)	-0.663 (verbs_form_dist_Fin)	-0.663 (verbs_mood_dist_Ind)
Dutch	News	-0.742 (ttr)	-0.727 (yules_i)	-0.705 (ttr_lemma_chunks_200)
	Twitter	-0.442 (char_per_tok)	-0.323 (ttr_lemma_chunks_200)	-0.320 (ttr)
	Reviews	-0.373 (upos_dist_ADV)	-0.327 (dep_dist_parataxis)	-0.322 (dep_dist_advmod)
	Poetry	-0.351 (n_:)	-0.336 (dep_dist_obl)	-0.294 (verbal_head_per_sent)
	Columns	-0.701 (flesch_mod)	-0.693 (gunning_fog)	-0.692 (flesch)

Top three most *negatively* correlated* features per language and domain (out of 136 features).

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Analyse results more

→ Domain influence, other detection datasets

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- Try out adversarial samples → Rephrasing, prompting techniques, ...
- CLIN paper → Explain contributing features, inspiration from other fields, ...

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