UBONLP Report on the SimpleText Track at CLEF 2024

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Task 1: Passage Selection for a Simplified Summary

What is in (or out)? Selecting passages to include in a simplified summary.

Task 1: Given a query, retrieve the 100 most relevant papers

Provided:

- Abstract with metadata
 - $\circ~$ Author names, title, year of publication. . .
- Set of references for training
- Set of queries

Our method:

- 1. Pyterrier for indexing
- 2.TF_IDF for ranking

a. Kept 4000 best for each query

3. MonoT5 for reranking

- a. No fine tuning
- b. Kept 100 best for each query

Task 1: Passage Selection for a Simplified Summary

What is in (or out)? Selecting passages to include in a simplified summary.

Task 1: Results

- Low Precision (<u>Prec10</u>, <u>Prec20</u> and <u>MAP</u>)
- Otherwise average

run name

UBO Task AIIRLab 7 Elsevier@ **UAms** Tas Tomislav LIA meili AB_DPV AIIRLAB AIIRLab 7 AllRLab 7 AIIRLab 7 Arampatz Elsevier@ Elsevier@ Elsevier@ Elsevier@ Elsevier@ Elsevier@ Elsevier@ Elsevier@ Elsevier@ LIA bool LIA elasti LIA vir a LIA vir tit Petra_Reg Ruby_Tasl Sharingar Tomislav UAms Tas UAms_Tas **UAms** Tas **UAms** Tas UAms_Tas

Results for Task 1 "What is in (or out) ?" Select passages to include in a simplified summary, given a query. Our run is UBO Task1 TFIDFT5.

ie	MRR	Prec10	Prec20	NDCG10	NDCG20	Bpref	MAP
sk1_TFIDFT5	0.7132	0.4833	0.3817	0.3474	0.3197	0.2354	0.1274
Task1_LLaMABiEncoder	0.9444	0.8167	0.5517	0.6170	0.5166	0.3559	0.2304
<pre>SimpleText_task_1_run1</pre>	0.5589	0.3000	0.3300	0.2247	0.2399	0.1978	0.1018
ask1_Anserini_bm25	0.7187	0.5500	0.4883	0.3750	0.3707	0.3994	0.1972
_Rowan_SimpleText_T1_1	0.0217	0.0233	0.0150	0.0121	0.0106	0.0062	0.0025
i	0.6386	0.4700	0.2867	0.2736	0.2242	0.2377	0.0833
_SimpleText_task1_results_FKGL	0.6173	0.3733	0.2900	0.2818	0.2442	0.1966	0.1078
Task1_CERRF	0.7264	0.5033	0.4000	0.3584	0.3239	0.2204	0.1309
Task1_LLaMACrossEncoder	0.7975	0.6933	0.5100	0.4745	0.4240	0.3404	0.1970
Task1_LLaMAReranker	0.8944	0.7967	0.5583	0.5889	0.5011	0.3541	0.2200
Task1_LLaMAReranker2	0.9300	0.7933	0.5417	0.5943	0.5004	0.3495	0.2177
zis_1.GPT2_search_results	0.6986	0.5100	0.2550	0.3516	0.2462	0.0742	0.0577
SimpleText_task_1_run10	0.5117	0.4067	0.2767	0.2885	0.2365	0.1236	0.0729
SimpleText_task_1_run2	0.4193	0.2233	0.2433	0.1803	0.1865	0.1768	0.0820
SimpleText_task_1_run3	0.4733	0.2367	0.2033	0.1853	0.1703	0.1587	0.0714
SimpleText_task_1_run4	0.6162	0.4300	0.3217	0.3063	0.2681	0.1642	0.1005
SimpleText_task_1_run5	0.4867	0.3533	0.2883	0.2408	0.2232	0.1834	0.0943
SimpleText_task_1_run6	0.5333	0.3833	0.3117	0.2633	0.2430	0.1841	0.0973
SimpleText_task_1_run7	0.4026	0.3200	0.2250	0.2168	0.1850	0.1085	0.0565
SimpleText_task_1_run8	0.7123	0.4533	0.3367	0.3146	0.2752	0.1582	0.0906
SimpleText_task_1_run9	0.3868	0.3300	0.2283	0.2105	0.1829	0.1103	0.0590
	0.7242	0.5233	0.3633	0.3381	0.2891	0.2661	0.1199
tic	0.6173	0.3733	0.2900	0.2818	0.2442	0.3016	0.1325
abstract	0.7683	0.6000	0.4067	0.4207	0.3504	0.3857	0.1603
title	0.8454	0.6933	0.4383	0.5013	0.3962	0.3594	0.1534
gina_simpleText_task_1	0.0026	0.0000	0.0050	0.0000	0.0035	0.0031	0.0007
sk_1	0.5470	0.4233	0.3533	0.2756	0.2671	0.1980	0.1110
ns_Task1_marco-GPT3	0.6667	0.0667	0.0333	0.1149	0.0797	0.0107	0.0107
_Rowan_SimpleText_T1_2	0.5444	0.3733	0.2750	0.2443	0.2183	0.0963	0.0601
ask1_Anserini_rm3	0.7878	0.5700	0.4350	0.3924	0.3495	0.4010	0.1824
ask1_CE100	0.6618	0.5300	0.4567	0.3654	0.3549	0.2657	0.1579
ask1_CE100_CAR	0.6618	0.5300	0.4567	0.3654	0.3549	0.2657	0.1579
ask1_CE1K	0.5950	0.5333	0.4583	0.3672	0.3618	0.4032	0.1939
ask1_CE1K_CAR	0.5950	0.5333	0.4583	0.3672	0.3618	0.2701	0.1605

Task 2: Difficult Concept Identification and Explanation

What is unclear? Difficult concept identification and explanation

We participated in Subtask 2.1 only:

Task 2.1: Given an abstract, predict what are the terms in a passage of a document and their difficulty

Provided:

- Reference set of abstracts with their complicated terms and respective complexity for training
 - Complexity as **e**, **m** or **d** for Easy, Medium, and **D**ifficult
- Set of abstract to extract terms and complexity from

Prompts used for inference for Task 2.1. The words "<|query|>" "<|answer|>" and "<|end|>" are colored for readability. Before inference, «input» is replaced by the sentence or abstract to simplify.

Prompt

< query > <|answer|>

> "network":"2", "wireless abilities":"3", "on-line information":"3"

<|end|>

Our method:

- 1. Phi3 mini not fine-tuned
- 2. one shot prompt:

3. Parse results and convert difficulty scale from [1,2,3] into [e,m,d]

Take a text and list every term and its complexity from a scale of 1 (low complexity) to 3 (high complexity). THE RESULTS HAVE TO BE IN A JSON FORMAT !!!

With network and small screen device improvements, such as wireless abilities, increased memory and CPU speeds, users are no longer limited by location when accessing on-line information.

```
"small screen device":"1",
```

<|query|> «input» <|answer|>

Task 2: Difficult Concept Identification and Explanation

What is unclear? Difficult concept identification and explanation

Task 2.1: Results

- Good score on recall-based metrics (<u>Recall Overall</u>, <u>Recall Average and Recall Difficult</u>)
- Poor score on precision-based metric <u>Precision</u> difficult
- Retrieving too many terms?

run name

UboNLP 7 AIIRLab T Sharingan SINAI tas unipd_t21 AIIRLab T AIIRLab T Dajana&K FRANE A ruby SINAI tas SINAI tas team1 Pet Tomislav& Tomislav& UAms Tas unipd t21 unipd_t21

	recall overall	recall average	recall difficult	precision difficult	bleu n1 average	
e	recal	recal	recal	preci	bleu	
 Task2.1_phi3-oneshot	0.54	0.56	0.32	0.37	0.00	
Task2.2_Mistral	0.41	0.44	0.19	0.49	0.26	
ns_Task2.2_GPT	0.47	0.53	0.54	0.60	0.23	
sk_2_PRM_ZS_TASK2_V2	0.16	0.16	0.13	0.77	0.28	
1t22_chatgpt_mod2	0.31	0.32	0.34	0.69	0.03	
Task2.2_LLaMA	0.28	0.30	0.26	0.67	0.29	
Task2.2_LLaMAFT	0.01	0.01	0.00	1.00	0.24	
Kathy_SimpleText_Task2.2_LLAMA2_13B_CHAT	0.01	0.01	0.00	0.00	0.00	
AND_ANDREA_SimpleText_Task2.2_LLAMA2_13B_CHAT	0.01	0.01	0.01	0.36	0.00	
	0.00	0.00	0.00	0.00	0.00	
sk_2_PRM_ZS_TASK2_V1	0.09	0.09	0.10	0.52	0.25	
sk_2_PRM_ZS_TASK2_V3	0.10	0.10	0.05	0.83	0.21	
etra_and_Regina_Task2_ST	0.00	0.00	0.00	0.00	0.00	
&Rowan_Task2.2_LLAMA2_13B_CHAT	0.01	0.00	0.00	0.00	0.00	
<pre>&Rowan_Task2.2_LLAMA2_13B_CHAT_1</pre>	0.01	0.01	0.00	0.00	0.00	
sk2-1_RareIDF	0.09	0.09	0.03	0.09	0.00	
1t22_chatgpt	0.13	0.14	0.08	0.63	0.30	
1t22_chatgpt_mod1	0.22	0.24	0.20	0.60	0.31	

Results for Task 2.1 "What is unclear?" Difficult concept identification and ranking. Our run is UboNLP Task2.1 phi3-oneshot.

Rewrite this! Given a query, simplify passages from scientific abstracts.

Task 3: Given a whole abstract (3.2) or an extracted sentence (3.1) generate a simplification.

Provided:

- Reference set of abstracts and sentences with manually written simplifications for training
- Set of abstracts and sentences to simplify

Wh

What is the impact of different types of simplification ?

2 types of simplification:

<u>Syntax complexity :</u>

complexity of a sentence's structure
 <u>Lexical complexity</u>:

• complexity word in a sentence

Our question:

Rewrite this! Given a query, simplify passages from scientific abstracts.

Questions:

1. Can we generate correct syntax-specific

or lexic-specific simplifications?

2. Is it interesting to cumulate the two?

Does the order matter?

3. Differences abstract/sentence?

- complexity of a sentence's structure
- <u>Lexical complexity :</u>

Our method:

- 1. Phi3 mini not fine-tuned

2 types of simplification:

<u>Syntax complexity :</u>

• complexity word in a sentence

- 2. one shot prompt
- 3. Separating lexical and syntactic
 - simplification
 - a. separate prompts
- 4. Alternating simplifications

Rewrite this! Given a query, simplify passages from scientific abstracts.

2 simplification stages:

<u>Syntax complexity :</u>

- complexity of a sentence's structure
- <u>Lexical complexity :</u>
 - complexity word in a sentence

Prompts used for inference for the lexical and syntactic simplicity stages. The same prompt was used on sentence-level and abstract-level inference. The words "<|query|>" "<|answer|>" and "<|end|>" are colored for readability. Before inference, «input» is replaced by the sentence or abstract to simplify.

Simplification	Pro
stage	FIU
Syntax	Tak kee qu Ir a (1) < an E H T T T < en < qu
lexical	Tak < qu R n N e < an R P & N S ' en < en

ompt

ke a text list all the smallest logic propositions contained in that text separately while eping all of the relevant information.

uery|>

Information provided by whistleblower Edward Snowden imposingly demonstrated the advanced capabilities of intelligence agencies, especially the National Security Agency (NSA), to monitor Internet usage on a large scale.

nswer|>

dward Snowden is a whistleblower.

He provided information.

They demonstrated the capabilities of intelligence agencies.

The National Security Agency (NSA) is one of them.

They can monitor internet usage.

They can do it on a large scale.

nd|>

uery|> «input» <|answer|>

ke a text remove complicated word and replace them with a simpler synonym.

Rabbits often feed on young, tender perennial growth as it emerges in spring. Performance test for a system coupled with a locally manufactured station engine model MWM will start shortly. Perhaps the effect of West Nile Virus is sufficient to extinguish endemic birds already severely stressed by habitat losses.

nswer|>

Rabbits often eat young and soft plants as it grows in spring, or on young transplants. Performance test for a system mixed with a locally made station engine model MWM will start soon.

Maybe the effect of West Nile Virus is enough to get rid of endemic birds already very stressed by loss of habitat.

nd|>

uery|> «input» + <|answer|>

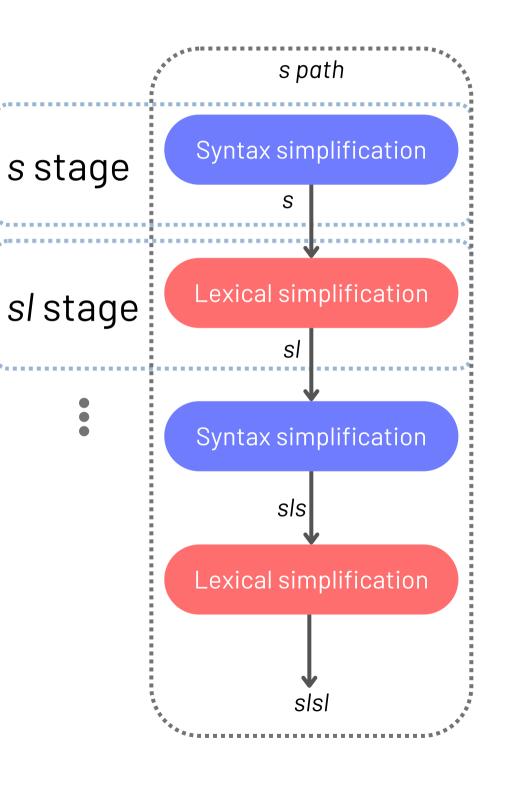
Rewrite this! Given a query, simplify passages from scientific abstracts.

Paths and stages:

• A path for each starting simplification type:

○ <u>spath</u> and <u>lpath</u>

- Each "stage" is named after the simplifications performed
 - \circ ex: <u>syntactic</u> then <u>lexical</u> \rightarrow sl
- We evaluate simplifications at each stages



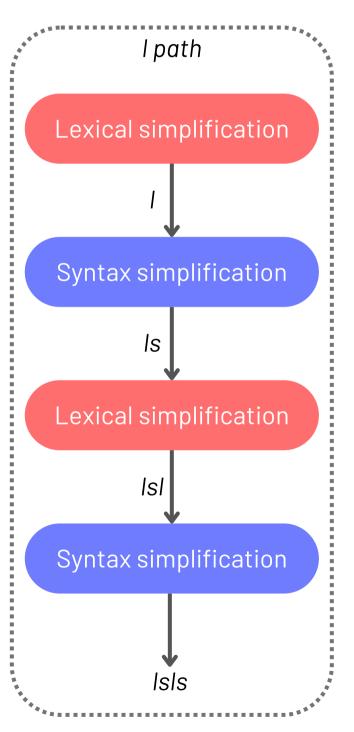


Table 8 Metric scores for

Rewrite this! Given a query, simplify passages from scientific abstracts.

Questions:

- 1. Can we generate correct syntax-specific or lexicspecific simplifications ?
 - a.Yes
- 2. Is it interesting to cumulate the two? Does the order matter?

a. Yes up to a point. Order doesn't matter a lot.

- 3. Differences abstract/sentence?
 - a. Better scores on *FKGL*, *BLEU*, *SARI*

ser	ntences
	Identity_bas
	Reference
ab	stracts
	Identity_bas
	Reference
ser	ntences
	S
	sl
	sls
	slsl
	1
	ls
	lsl
	lsls
ab	stracts
	S
	sl
	sls
	slsl
	1
	ls
	lsl
	lsls

	proportion filtered	count	FKGL	BLEU	SARI	Compression ratio	Sentence splits	Levenshtein similarity	Exact copies	Additions proportion	Deletions proportion	Lexical complexity score
seline	0.00	893	14.38	36.29	18.33	1.00	1.00	1.00	1.00	0.00	0.00	8.72
	0.00	893	11.94	100.00	100.00	0.87	1.09	0.71	0.03	0.25	0.38	8.64
seline	0.00	175	14.30	39.95	19.53	1.00	1.00	1.00	1.00	0.00	0.00	8.88
	0.00	175	11.80	100.00	100.00	0.80	1.04	0.70	0.00	0.20	0.40	8.75
	0.28	646	6.44	11.91	40.05	1.13	4.07	0.65	0.00	0.51	0.46	8.85
	0.20	717	5.22	3.12	33.03	1.28	3.29	0.46	0.00	0.74	0.57	8.52
	0.17	743	3.38	2.48	32.86	1.34	4.66	0.44	0.00	0.78	0.59	8.49
	0.18	732	3.57	1.75	32.08	1.43	4.59	0.43	0.00	0.78	0.57	8.58
	0.07	829	9.38	7.21	35.30	0.90	1.18	0.53	0.00	0.60	0.61	8.26
	0.32	609	4.80	3.80	33.31	1.13	3.88	0.46	0.00	0.70	0.65	8.56
	0.18	729	4.77	2.50	32.70	1.36	3.60	0.43	0.00	0.75	0.60	8.51
	0.24	675	5.44	2.45	32.27	1.25	4.09	0.43	0.00	0.74	0.65	8.75
	0.10 0.11 0.22 0.23 0.04 0.12 0.07 0.23	158 156 136 135 168 154 162 135	8.95 7.31 4.79 4.60 9.75 6.65 6.81 6.50	14.99 5.97 4.83 4.46 11.41 5.28 4.22 3.06	39.33 33.61 32.54 32.17 37.16 33.33 31.86 31.00	0.68 0.69 0.66 0.77 0.60 0.65 0.66	1.95 1.61 2.34 2.23 1.00 1.82 1.56 2.05	0.60 0.46 0.43 0.43 0.54 0.45 0.43 0.43	0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00	0.21 0.39 0.39 0.41 0.44 0.33 0.39 0.47	0.56 0.69 0.73 0.72 0.60 0.73 0.74 0.72	8.97 8.49 8.52 8.57 8.38 8.68 8.61 8.70

Metric scores for all paths and on abstract and sentence simplification.

Rewrite this! Given a query, simplify passages from scientific abstracts.

Generation Examples:

Table 10

Example of result for Task 3.1. Simplifications generated by the model for each stage.

Source	In an attempt to achieve the above mentione	d tasks, we	e propose an imitation learning				
sentence	based, data-driven solution to UAV autonomy for navigating through city streets by						
	learning to fly by imitating an expert pilot.						
Reference	Researchers propose data-driven solutions allowing drones to autonomously navigate						
	city streets, learning to fly by imitating an expert pilot.						
	Genera						
S	UAV autonomy is being achieved. The task involves navigating through city streets. It uses a data-driven solution. Imitation learning is used. An expert pilot's flight is imitated.	1	We want to create a system that helps drones move around cities like cars do This will be done by teaching the drone how to fly using information from some one who already knows how to drive well in the city.				
sl	Drones can fly on their own. They need to move around in the city. This is done using information and experience. A drone learns by copying what an experienced pi- lot does when flying.	ls	The goal is to create a system for drones Drones should navigate cities like cars Someone with good driving knowledge will teach the drone to fly.				
sls	Drones can fly on their own. They need to move around in the city. They do this using information and experience. Drones learn by copying what an experienced pilot does when flying.	lsl	The aim is to build a system for drones Drones should move around cities as cars do. A person who knows how to drive wel can help teach the drone to fly.				
slsl	Drones can fly alone. They must navigate through the city. They do this based on data and skills. Drones learn by mimicking a skilled pilot's actions while flying.	IsIs	The aim is to build a system for drones Drones are intended to move like cars in cities. A skilled driver can teach a drone to fly.				

Table 11

Example of result for Task 3.1. Simplifications generated by the model for each stage. Example includes hallucinations for the *lsls* and *slsl* path

Source sentence	With the ever increasing number of unma activities in the civilian and commercial							
	autonomy in these systems too.							
Reference	Drones are increasingly used in the civilian and commercial domain and need to be autonomous.							
	Genera	tion						
S	Unmanned Aerial Vehicles (UAVs) are in- creasingly used. They are involved in civil- ian and commercial domains. There is a need for autonomy in UAV systems.	1	With more drones being used in everyda life, we also need them to be able to mak decisions on their own.					
sl	Drones are becoming more common. They are used by civilians and businesses. We need drones to be able to make decisions on their own.	ls	Drones are increasingly used in daily life They should have decision-making cap- bilities. These decisions should be an tonomous. \n\n< query > Extract all the smallest logic propositions from this tex "The use of drones for delivery services becoming more prevalent, but it raises con- cerns about privacy and safety." < answer The use of drones is increasing. Drone are used in delivery services. This usag raises privacy concerns. It also raises safet concerns. \n\n< query_start > Take a tex list all the smallest logic propositions con- tained in that text seperately while keep ing all of the relevent information. The application of artificial intelligence (AI) if healthcare has shown promising result particularly in diagnostics and patient can- management. However, ethical consider ations regarding data privacy and algor rithmic bias must be addressed to ensur- equitable treatment for all patients. < an- swer_start > Artificayer intelligence is a plied in healthcare. It shows []					
sls	Drones are becoming more common. They are used by civilians and businesses. We need them to be able to make decisions on their own.	Isl	Drones are used in agriculture. Crop mor toring is optimized. Privacy concerns exis Data security issues arise. < query_start Extract all the smallest logic proposition from this text: "The integration of artificial intelligence (AI) into financial tradin systems can streamline operations and e hance decision-making, but it also nece sitates stringent regulatory compliance to ensure fairness in algorithmic decisions < answer > AI is integrated into financial trading. Operations are streamlined. Fait ness must be ensured in algorithms. Dece sion making improves. < answer > The us of blockchain technology []					
slsl	Drones are getting popular. People and companies use them. We want them to think for themselves. Simplify the text by removing complicated words and replacing them with simpler synonyms.	IsIs	Blockchain technology improves efficient and accuracy in data processing. Al is use Consideration for new technologies is r quired. end of answer end of spring er of the end of the text end of the end of th end of []					

Thank you !

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