CLEF 2024 JOKER Lab: Automatic Humour Analysis

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JOKER Track Motivation

- Humor remains one of the most difficult aspects of intercultural communication & translation
- Applications: Machine translation (Google Translate, DeepL,...), conversational agents (Siri, Alexa,...), humour study, social listening, reputation monitoring, recommendation, fake news and hate speech detection (sexism, racism,...)...
- SOTA AI models are wordplay- and humour-agnostic

Goals

- To provide appropriate reusable **data** and **benchmarks** for automatic wordplay analysis.
- To provide a discussion platform to address **technical & evaluation** challenges of automatic wordplay analysis
- **Use cases**:
  - Computer-Assisted Translation of wordplay
  - Corpus-based analysis of wordplay in the humanities
    - literary criticism
    - language education
    - translation studies
    - humor studies
  - Wordplay-aware Information Retrieval

JOKER@CLEF Shared Tasks

- TASK 1: Humour-aware information retrieval
- TASK 2: Humour classification according to genre and technique
- TASK 3: Translation of puns from EN to FR

CLEF'24 JOKER Track Participation

Of over 53 registered teams, 22 teams submitted 103 runs

Team	Task 1	Task 2	Task 3	Total
jokester	1	1	1	3
LIS	1			1
Arampatzis	10	8	6	24
Frane	1	1	1	3
AB&DPV	1	7	1	9
Dajana&Kathy	1	1	1	3
Petra&Regina	1	1	1	3
Tomislav&Rowan	1	3	2	6
UAms	8	1	2	11
RubyAiYoungTeam	1	1		2
ORPAILLEUR		9		9
NaiveNeuron		3		3
HumourInsights		1		1
CYUT		3		3
CodeRangers		2		2
VayamSolveKurmaha		2		2
DadJokers		3		3
NLPalma		3		3
PunDerstand		4		4
Olga			3	3
Farhan			2	2
UBO			3	3
Total	26	54	23	103

Task 1: Humour-aware IR

- Retrieving short humorous texts from a document collection
- Use case: to search for a joke on a specific topic
- Queries = locations of wordplay from JOKER 2023 Task 2
- Collection: 61,268 documents
  - 4,492 humourous texts (3,507 texts from JOKER 2023 + 985 new wordplay)
  - 4,954 negative examples from JOKER 2023
  - 12,523 texts generated using Llama 2
  - 39,299 sentences from Wikipedia extracts
- Evaluation: traditional IR metrics (MAP, NDCG, ...)

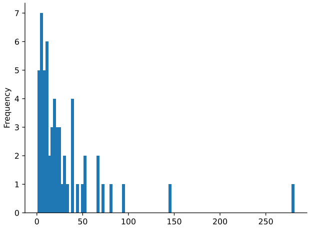
Task 1: Data statistics

- Train: 12 queries
- Test: 45 queries
- 11,831 documents topically relevant to all 57 queries
- 1,730 were considered to be humorous and relevant

Table 1: Statistics of relevant humourous texts per query

count	57
mean	30
std	43
min	1
25%	8
50%	18
75%	38
max	281

Figure 1: Histogram of # relevant humourous texts



Task 1: Official Results

- 10 teams, 26 runs
- only non-0 scored runs are scored

run ID	map	ndcg	R5	R10	R100	R1000	bpref	MRR	P1	P5	P10
UAms_rm3_T5_Filter2	.12	.28	.09	.15	.36	.43	.18	.26	.13	.11	.13
UAms_rm3_BERT_Filter	.12	.27	.09	.14	.35	.42	.16	.27	.16	.11	.12
UAms_rm3_T5_Filter1	.11	.27	.09	.15	.36	.42	.16	.23	.11	.09	.11
UAms_bm25_BERT_Filter	.09	.24	.06	.12	.37	.40	.12	.19	.09	.05	.08
AB&DPV_TFIDF	.09	.24	.07	.13	.33	.37	.10	.25	.13	.12	.14
UAms_Anserini_rm3	.08	.27	.06	.08	.38	.50	.09	.20	.11	.06	.06
jokester_1_TFIDF_LogRegr	.08	.19	.09	.09	.10	.16	.21	.51	.44	.23	.14
UAms_Anserini_bm25	.08	.24	.06	.08	.37	.42	.09	.19	.11	.05	.06
UAms_bm25_CE100	.04	.17	.03	.04	.37	.37	.06	.08	.00	.04	.03
UAms_rm3_CE100	.04	.18	.03	.04	.38	.38	.06	.07	.00	.04	.03
LIS_MiniLM-T5	.02	.05	.03	.04	.05	.05	.05	.13	.04	.06	.04

Topical relevance results on TEST

run ID	map	ndcg	R5	R10	R100	R1000	bpref	MRR	P1	P5	P10
UAms_Anserini_rm3	.37	.60	.06	.10	.39	.64	.64	.82	.73	.61	.61
AB&DPV_TFIDF	.36	.53	.07	.12	.36	.50	.50	.83	.73	.69	.69
UAms_Anserini_bm25	.35	.55	.07	.11	.38	.56	.56	.79	.64	.61	.60
UAms_bm25_BERT_Filter	.30	.48	.07	.11	.35	.46	.46	.77	.62	.62	.60
UAms_rm3_T5_Filter1	.25	.44	.06	.10	.30	.40	.40	.86	.78	.69	.63
UAms_rm3_CE100	.22	.40	.05	.10	.39	.39	.39	.79	.64	.56	.55
UAms_rm3_BERT_Filter	.22	.39	.06	.09	.27	.34	.34	.84	.76	.68	.61
UAms_bm25_CE100	.22	.39	.05	.10	.38	.38	.38	.78	.62	.56	.55
UAms_rm3_T5_Filter2	.22	.38	.06	.10	.27	.34	.34	.80	.64	.71	.63
jokester_TFIDF_LogRegr	.03	.09	.03	.03	.04	.05	.07	.63	.62	.39	.24
LIS_MiniLM-T5	.01	.05	.02	.02	.03	.03	.03	.33	.18	.20	.15

Results on TRAIN

run_id	map	ndcg	R5	R10	R100	R1000	bpref	MRR	P1	P5	P10
Arampatzis_DecisionTree	**.40**	**.55**	.24	**.30**	.44	.45	.42	**.92**	**.92**	**.68**	**.53**
Arampatzis_SVM	.36	.52	**.25**	.28	.44	.45	.39	.83	.75	**.68**	.52
Arampatzis_kNN	.36	.50	.23	.28	.44	.45	.38	.71	.50	.60	.51
Arampatzis_GaussianNB	.35	.50	.24	.28	.44	.45	.38	.72	.58	.63	.51
UAms_rm3_T5_Filter2	.23	.39	.14	.25	.44	.52	.35	.34	.17	.28	.28
UAms_rm3_BERT_Filter	.23	.42	.12	.23	**.50**	.60	.36	.37	.17	.23	.23
UAms_rm3_T5_Filter1	.21	.37	.13	.24	.40	.49	.29	.38	.25	.25	.27
UAms_bm25_BERT_Filter	.19	.37	.07	.19	.49	.59	.27	.22	.08	.12	.18
UAms_Anserini_rm3	.17	.37	.09	.18	.45	**.63**	.30	.24	.08	.17	.18
Arampatzis_NeuralNetwork	.17	.34	.09	.17	.43	.45	.14	.41	.33	.28	.25
Arampatzis_LSTM	.17	.33	.09	.19	.44	.45	.11	.20	.08	.18	.19
ABDPV_TFIDF	.17	.34	.07	.14	.39	.50	.21	.26	.17	.15	.16
UAms_Anserini_bm25	.16	.35	.07	.17	.46	.60	.24	.19	.08	.12	.16
jokester_TFIDF_LogRegr	.16	.34	.11	.12	.14	.36	**.49**	.59	.58	.30	.20
UAms_rm3_CE100	.07	.22	.01	.03	.45	.45	.09	.12	.00	.08	.09
UAms_bm25_CE100	.07	.22	.01	.03	.46	.46	.09	.12	.00	.08	.08
LIS_MiniLM-T5	.00	.01	.00	.00	.01	.01	.01	.01	.00	.00	.00

Topical relevance results on TRAIN

run ID	map	ndcg	R5	R10	R100	R1000	bpref	MRR	P1	P5	P10
Arampatzis_DecisionTree	.40	.55	.24	.30	.44	.45	.42	.92	.92	.68	.53
AB&DPV_TFIDF	.38	.56	.08	.13	.36	.58	.58	.72	.50	.67	.65
Arampatzis_SVM	.36	.52	.25	.28	.44	.45	.39	.83	.75	.68	.52
Arampatzis_kNN	.36	.50	.23	.28	.44	.45	.38	.71	.50	.60	.51
UAms_Anserini_rm3	.35	.58	.05	.09	.37	.67	.67	.73	.58	.58	.52
UAms_Anserini_bm25	.35	.57	.06	.11	.37	.65	.65	.66	.50	.55	.53
Arampatzis_GaussianNB	.35	.50	.24	.28	.44	.45	.38	.72	.58	.63	.51
UAms_bm25_BERT_Filter	.30	.50	.06	.12	.34	.52	.52	.66	.50	.57	.58
UAms_rm3_T5_Filter1	.25	.42	.06	.11	.28	.39	.39	.73	.67	.58	.62
UAms_rm3_T5_Filter2	.23	.39	.14	.25	.44	.52	.35	.34	.17	.28	.28
UAms_rm3_BERT_Filter	.23	.42	.12	.23	.50	.60	.36	.37	.17	.23	.23
UAms_rm3_CE100	.20	.37	.05	.08	.37	.37	.37	.81	.67	.52	.52
UAms_bm25_CE100	.20	.37	.05	.08	.37	.37	.37	.81	.67	.52	.50
Arampatzis_NeuralNetwork	.17	.34	.09	.17	.43	.45	.14	.41	.33	.28	.25
Arampatzis_LSTM	.17	.33	.09	.19	.44	.45	.11	.20	.08	.18	.19
jokester_TFIDF_LogRegr	.06	.17	.03	.03	.04	.17	.22	.59	.58	.30	.21
LIS_MiniLM-T5	.00	.02	.01	.01	.01	.01	.01	.23	.08	.08	.09

Task 1: Observations (1)

- Low precision due to the presence of the query terms in the non-humorous texts
- Low recall (both train and test): length of the text + the query terms do not appear in many humorous and topically relevant texts
- The runs based on pseudo-relevance feedback RM3 query expansion outperform the BM25 baselines
- Cross-encoder rerankers do NOT exhibit better performance than the baseline models
- Simple solutions such as ones with TF–IDF and Logistic Regression remain competitive
- Filtering trained on the wordplay detection task improved systems' results
- Using T5 and BERT language models with RM3 is one of best approaches both in terms of precision and recall

Task 1: Observations (2)

- Similar trends for TOPICAL relevance ONLY on train and test
- Unfiltered runs tend to have higher topical relevance alone but a significant drop according to the official ranking
- The topical relevance scores on train and test are similar, but the ranking on both topical relevance and humor is twice as low on test $\rightarrow$ potential overfitting
- Unique reusable test collection for wordplay retrieval in English

Task 2: Humour classification according to genre and technique

- The main task is to classify short humorous texts (Multiclass classification): Irony, Sarcasm, Exaggeration, Self-deprecating humour, Wit, Incongruity-Absurdity, and Wit-Surprise
- Mix of existing datasets + internet collections: JOKER, COVID-19 Humor, iSarcasm, Wallace, Web
- Evaluation: Traditional metrics for classification tasks

Class	# texts		
	test	train	total
Irony (IR)	147	356	503
Sarcasm (SC)	59	162	221
Exaggeration (EX)	106	210	316
Incongruity/Absurdity (AID)	270	634	904
Self-deprecating (SD)	91	228	319
Wit/Surprise (WS)	49	125	174
Total	722	1,715	2,437

Task 2: Results

- 18 teams, 54 runs
- We report the best result per team

		macro average			weighted average			
Run ID	A	P	R	F1	P	R	F1	#
ORPAILLEUR_mistral-7b-ens	76	71	70	70	75	76	75	722
Code Rangers_roberta	70	75	63	59	78	70	66	509
CYUT_llama3-fine-tuning	70	64	65	64	70	70	70	718
PunDerstand_DeBERTa	69	59	65	60	68	69	67	722
Arampatzis_BERT	68	60	60	59	67	68	67	722
DadJokers_bert_base_uncased	67	60	60	60	67	67	67	722
NLPalma_BERTd	67	60	60	59	67	67	67	722
Demonteam_BERTM	66	58	58	58	65	66	65	722
UAms_BERT_ft	63	57	58	52	66	63	60	722
VayamSolveKurmaha_BERT	60	54	53	51	59	60	58	722
NaiveNeuron_fastText	59	51	51	51	58	59	58	722
DadJokers_RandomForest_MLP_Ensemble	56	49	48	47	54	56	53	722
HumourInsights_Random Forest	55	50	45	45	53	55	52	722
RubyAiYoungTeam	53	53	39	40	52	53	48	722
Petra_and_Regina_LogisticRegression	53	53	39	40	52	53	48	722
Tomislav&Rowan_SVM	51	44	37	38	48	51	47	722
AB&DPV_MLP3000params	48	41	38	38	45	48	44	722

Task 3: Pun Translation

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- **The goal** of this task is to translate English punning jokes into French and preserve:
  - wordplay form
  - wordplay meaning
- **Train data:** 5,838 manual FR translations of 1,405 EN puns
- **Test data:** 832 manual FR translations of 376 EN puns
- In 2023, success rate of wordplay translation was extremely low for both language pairs (EN→FR, EN→ES)

Frame Title

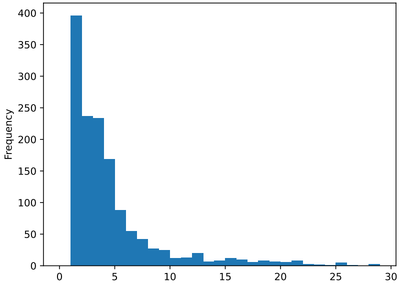


Figure 2: Histogram of translation references in French per English pun (TRAIN)

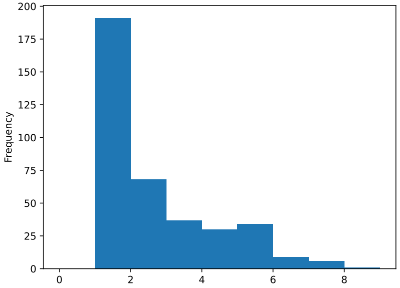


Figure 3: Histogram of translation references in French per English pun (TEST)

Top “easiest” punning words

EN	FR
Martians welcome. We have **space** for everyone.	Bienvenue les extraterrestres ! Installez vous, on a créé ces **espaces** détente pour vous.
A lot of trees were dying, but they needed to figure out the **root** of the problem.	De nombreux arbres mouraient mais personne ne trouvait la **racine** du mal qui les rongeait.
She was suspected of stealing a brooch but they couldn’t **pin** it on her.	Elle s’est fait **épingler** pour une histoire de broche volée.
Well drilling is a **deep** subject.	Le forage de puits est un sujet **profond**.
The inept mathematician couldn’t **count** on his friends.	Un mathématicien qui ne peut **compter** sur ses amis n’est pas un mathématicien...

Task 3: Official Results

- 11 teams, 23 runs
- 1 team, 3 runs EN→ES

	BLEU						BERT_Score			
run_id	count	Score	n_1	n_2	n_3	n_4	count	P	R	F1
Arampatzis_GoogleTranslate	376	65.23	78.96	67.48	61.59	57.52	832	91.93	91.82	91.85
Frane_TranslationModel	92	57.13	64.33	58.41	54.66	51.85	279	92.06	91.53	91.77
Dajana&Kathy	376	58.45	71.94	60.27	54.11	49.73	832	91.35	91.00	91.15
UBO_SDL	312	13.17	71.90	57.17	49.13	43.24	598	90.13	90.21	90.15
Tomislav&Rowan_MarianMT	376	58.85	77.11	63.66	56.06	50.45	832	90.82	89.19	89.95
Arampatzis_MarianMT	376	58.85	77.11	63.66	56.06	50.45	832	90.82	89.19	89.95
UBO_ChatGPT	312	13.09	69.90	54.08	46.07	40.31	598	89.12	89.34	89.21
UBO_DeepL	312	11.97	68.53	50.32	41.38	35.11	598	89.06	89.31	89.16
UAms_T5-base_ft	376	48.74	71.75	54.57	45.18	38.05	832	89.53	88.52	89.00
Arampatzis_mBART	376	48.71	70.95	54.40	45.29	38.67	832	88.95	87.41	88.13
Arampatzis_M2M100	376	42.37	68.46	48.73	37.72	29.93	832	88.23	87.23	87.70
UAms_Marian_ft	376	25.69	47.05	28.47	20.74	15.69	832	81.06	82.53	81.74
Farhan_2	376	14.33	23.68	15.84	12.05	9.32	832	69.38	77.14	72.96
Farhan_1	376	9.21	15.92	9.97	7.65	5.92	832	64.30	73.18	68.41
jokester_MarianMT	49	0.29	15.34	0.14	0.08	0.04	112	67.30	66.38	66.80
Arampatzis_opus_mt	63	0.29	15.04	0.23	0.06	0.03	157	66.98	66.05	66.47
Arampatzis_T5	63	0.32	11.35	0.17	0.10	0.06	157	65.91	64.79	65.31

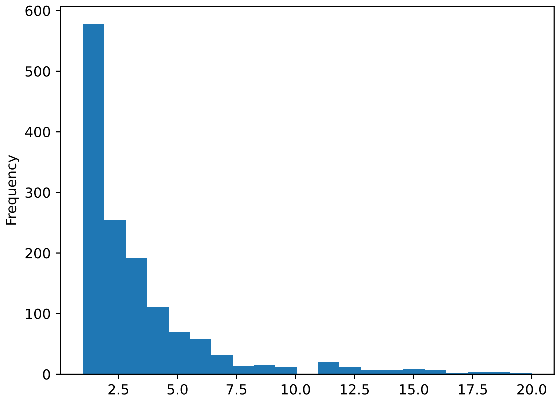
BLEU scores (train)

run ID	count	BLEU	BLEU_1	BLEU_2	BLEU_3	BLEU_4
UAms_T5-base_ft	1,405	59.93	77.66	63.35	55.50	49.25
UAms_Marian_ft	1,405	68.56	77.50	70.09	65.84	61.79
Arampatzis_GoogleTranslate	1,405	42.19	67.50	46.29	35.76	28.37
Dajana&Kathy_TranslationModel	1,405	47.95	70.02	50.87	41.69	35.61
Arampatzis_MarianMT	1,405	48.55	70.52	51.47	42.50	36.71
Tomislav&Rowan_MarianMTModel	1,405	48.55	70.52	51.47	42.50	36.71
Arampatzis_M2M100	1,405	34.10	62.85	39.12	27.85	20.42
Arampatzis_mBART	1,405	33.93	62.38	38.66	27.73	20.26
Farhan_2	1,405	12.16	23.06	13.47	9.75	7.22
jokester_MarianMT	223	0.30	17.52	0.33	0.07	0.02
Arampatzis_opus_mt	229	0.32	17.42	0.40	0.07	0.02
Farhan_1	1,405	7.75	15.96	8.49	6.05	4.40
Arampatzis_T5	229	0.36	14.16	0.49	0.11	0.03

Presence of identified punning words (locations) in generated translations

	Training data			Test data		
run ID	Total	# Location	%	Total	# Location	%
UAms _Marian _ft	1,405	317	23%	8	0	0%
UAms _T5-base _ft	1,405	179	13%	8	0	0%
Dajana&Kathy _TranslationModel	1,405	158	11%	8	1	13%
Tomislav&Rowan _MarianMTModel	1,405	157	11%	8	1	13%
Arampatzis _MarianMT	1,405	157	11%	8	1	13%
Farhan _2	1,405	143	10%	8	0	0%
Arampatzis _GoogleTranslate	1,405	141	10%	8	1	13%
Arampatzis _mBART	1,405	121	9%	8	1	13%
Arampatzis _M2M100	1,405	115	8%	8	0	0%
Farhan _1	1,405	106	8%	8	0	0%
Arampatzis _T5	229	0	0%	2	0	0%
Arampatzis _opus _mt	229	0	0%	2	0	0%
jokester _MarianMTModel	223	0	0%	2	0	0%

Histogram of distinct pun locations in FR per EN pun (train)



BLEU scores EN→ES (train)

run ID	count	BLEU	BLEU_1	BLEU_2	BLEU_3	BLEU_4
Olga_ES_BLOOM_1	5	24.49	39.36	28.09	21.43	15.19
Olga_ES_Googletranslator	215	51.20	70.62	55.04	45.96	38.72
Olga_ES_BLOOM_2	5	28.25	41.98	32.89	25.35	18.18
LJGG_es_mt5_base_auto	215	40.14	60.67	45.30	38.19	32.18
LJGG_es_t5_large_no_label_auto	215	47.90	68.25	51.90	42.81	35.52
LJGG_Google_Translator_EN_ES_auto	209	52.26	71.88	56.22	47.04	39.77
LJGG_es_mt5_base_no_label_auto	215	37.93	61.75	45.00	35.72	28.58
LJGG_es_t5_large_auto	11	0.76	14.15	0.53	0.30	0.17
TheLangVerse_j2-grande-finetuned	215	38.81	63.33	43.31	32.82	25.19
Smroltra_EN-ES_GPT3	5	46.15	74.07	53.06	40.91	28.21
Smroltra_EN-ES_BLOOM	5	24.49	39.36	28.09	21.43	15.19
Smroltra_EN-ES_GoogleTranslation	215	51.38	70.58	55.09	46.10	38.94
Smroltra_EN-ES_EasyNMT-Opus	215	53.95	71.86	57.55	49.08	42.48
Smroltra_EN-ES_SimpleT5	215	25.76	53.68	29.74	19.73	13.97
Smroltra_EN-ES_EasyNMT-mbart	215	36.72	62.01	41.32	30.81	23.03
Croland_EN_ES_GPT3	3	25.78	46.67	29.63	25.00	19.05
ThePunDetectives_EN-ES_OpusMT	65	54.18	73.58	58.06	50.00	42.61
ThePunDetectives_EN-ES_M2M100	65	39.67	65.51	43.15	33.29	26.33

BERT scores EN→ES (train)

run ID	count	P	R	F_1
Olga_ES_BLOOM_1	8	74.36%	81.92%	77.94%
Olga_ES_Googletranslator	644	86.26%	85.93%	86.07%
Olga_ES_BLOOM_2	8	75.96%	83.13%	79.36%
LJGG_es_mt5_base_auto	644	83.10%	81.46%	82.24%
LJGG_es_t5_large_no_label_auto	644	85.61%	85.05%	85.30%
LJGG_Google_Translator_EN_ES_auto	626	86.81%	86.40%	86.59%
LJGG_es_mt5_base_no_label_auto	644	83.74%	81.14%	82.37%
LJGG_es_t5_large_auto	29	79.00%	76.69%	77.81%
TheLangVerse_j2-grande-finetuned	644	84.66%	84.43%	84.52%
Smroltra_EN-ES_GPT3	8	91.01%	90.23%	90.62%
Smroltra_EN-ES_BLOOM	8	74.37%	81.93%	77.95%
Smroltra_EN-ES_GoogleTranslation	644	86.27%	85.96%	86.10%
Smroltra_EN-ES_EasyNMT-Opus	644	86.31%	86.14%	86.21%
Smroltra_EN-ES_SimpleT5	644	81.25%	80.64%	80.92%
Smroltra_EN-ES_EasyNMT-mbart	644	84.04%	83.94%	83.97%
Croland_EN_ES_GPT3	4	77.58%	80.97%	79.21%
ThePunDetectives_EN-ES_OpusMT	185	86.07%	85.74%	85.88%
ThePunDetectives_EN-ES_M2M100	185	84.61%	83.72%	84.14%

Task 3: Observations

- Participants mainly used LLMs, commercial machine translation engines, and out-of-the-box translation models
- Only a small percentage of translations contain at least one word identified as carrying multiple meanings in references despite high BLEU and BERT Scores
- Models, fine-tuned on our training data achieve a maximum of 23% of translations containing at least one pun location word from reference translations. In contrast, non-fine-tuned models use pun location words in only 11% of cases
- These results closely mirror those obtained last year
- The success rate of wordplay translation remains low

JOKER Sessions at CLEF 2024

Date	Event
Sep 10 16:40-18:10	*Participant's talks (1x) (w/ SimpleText)*
Sep 11 14:00-15:30	Overview Talks JOKER Task 1-3 *Participant's talks (4x)*
Sep 11 16:00-18:00	*Participant's talks (7x)*
Sep 12 11:15-12:45	Keynote Pavel Braslavski (Nazarbayeb) on *What will we be laughing about tomorrow?* *Participant's talks (1x)* Planning Session JOKER 2025 *Humor-aware IR, Wordplay translation, Funny names, Controlled creativity?*

- Please join the JOKER sessions in Room 2!

Thank you !

See you at our track !

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Twitter : https://twitter.com/joker_research
Google group : https://groups.google.com/g/joker-project

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