



Overview of the "Machine Translation" Task

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Covid-19 MLIA

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1. MT task

- 2. Submissions
- 3. Results
- 4. Conclusions





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MT task

The goal of the MT task is to generate MT systems focused on Covid-19 related documents for different language pairs.

Examples:

- 30% of children and adults infected with measles can develop complications.
- The MMR vaccine is safe and effective and has very few side effects.





Language pairs

- English–German.
- English-French.
- English-Spanish.
- English–Italian.
- English-Modern Greek.
- English-Swedish.
- English-Arabic. (New this round.)





Categories

- **Constrained**: systems which have been trained exclusively with data provided by the organizers (compulsory).
- **Unconstrained**: systems which have been trained using external data and/or resources (optional).





Corpora

From the crawled data we:

- Removed the outliers.
- Selected the best segments for validation and test.
- Balanced the selected segments to have the same representation of each source.





Corpora

		Ger	man	Fre	nch	Spa	nish	lta	lian	Moder	n Greek	Swe	edish	Ara	abic
		En	De	En	Fr	En	Es	En	lt	En	EI	En	Sv	En	Ar
	5	1.9	5M	2.4	1M	2.9	ЭM	1.0	M	674	.0K	375	i.0K	424	.4K
Train	T	23.5M	22.1M	45.6M	53.0M	52.4M	60.3M	16.4M	17.2M	11.4M	12.2M	5.5M	5.1M	7.7M	7.5M
	V	523.9K	847.5K	782.2K	781.4K	850.0K	950.2K	421.2K	501.3K	289.7K	378.7K	180.7K	234.7K	222.2K	360.2K
	5	4.	0K	4.0	ΟK	4.	0K	4.	ЭK	4.	0K	4.	0K	4.	0K
Validation	T	62.2K	61.2K	72.0K	83.9K	72.2K	81.4K	64.6K	69.0K	67.8K	72.5K	56.6K	54.4K	75.9K	74.7K
	V	13.9K	17.1K	13.2K	14.8K	13.8K	15.8K	14.6K	16.7K	14.0K	18.0K	12.3K	14.1K	16.1K	23.7K
	5	4.	0K	4.0	ж	4.	0K	4.	ж	4.	ΟK	4.	0K	4.	ΟK
Test	T	62.2K	61.0K	72.3K	84.1K	72.2K	81.4K	64.3K	68.7K	67.8K	72.4K	56.5K	54.3K	76.1K	74.5K
	V	13.8K	17.0K	13.1K	14.8K	13.7K	15.7K	14.4K	16.7K	14.1K	18.2K	12.3K	14.1K	16.2K	23.5K

|S| stands for number of sentences, |T| for number of tokens and |V| for size of the vocabulary. M denotes millions and K thousands.





Evaluation

- BLEU.
- TER.
- BEER.
- Approximate Randomization Testing (ART)^{1,2}.

²github.com/midobal/covid19mlia-mt-task/blob/master/round2/art.

¹Riezler, S., Maxwell, J.T.: On some pitfalls in automatic evaluation and significance testing for mt. In: Proceedings of the workshop on intrinsic and extrinsic evaluation measures for machine translation and/or summarization, pp. 5764 (2005).





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Baselines

- 1. Standard Transformer with only round 2 data.
- 2. Standard Transformer with rounds 1 and 2 data.
- OpenNMT-py toolkit.
- 32K BPE.





Participants' approaches

- LC:
 - Contrained for all language pairs.
 - Preprocessing: cleaning techniques and inline casing.
 - Language token tag for each source sentence to indicate the target language for multilingual models.
 - Standard transformer in Sockeye instead of Seq2SeqPy used previously (better data loading and support multiple GPUs).

Models:

- Bilingual: better for languages with most data (ES, FR and DE).
- Multilingual 5 languages excluding Greek and Arabic due to script. IT and SV benefits and even more when oversampling.
- Multilingual 7 languages. EL and AR benefits and more with oversampling.
- Contrained data results:
 - Better results for 40K and 50K vocabulary sizes.
 - 1st for ES bilingual.
 - 1st for DE and IT 5 lang multilingual with finetuning.
 - 1st for AR 7 lang multilingual.





- E-Translation:
 - Contrained and unconstrained for 6 lang (all but AR).
 - Cleaning process checking numbers and adding lang identifier.
 - Transformer and big Transformer in MarianNMT.
 - Unconstrained adding TAUS Corona, EMEA and health subset from Euramis corpora.
 - Better architecture is big Transformer 4 model ensambling.
 - Postprocess to normalize puntuation improved by 7 BLEU points for FR in unconstrained.
 - Ist DE unconstrained as 1st round: WMT system with constrained data fine tuning.
 - Ist in all the langs they participated but EL in unconstrained mode.
 - 1st for FR and SV for contrained mode.





- CdT-ASL:
 - Constrained and unconstrained systems.
 - Generic and public health CdT data for unconstrained systems.
 - Cleaning processes
 - Training with big transformer using OpenNMT-tf.
- PROMT:
 - Constrained and unconstrained mode for all langs.
 - Transformer multilingual model with a single encoder and a single decoder with Marian toolkit.
 - Language pairs fine-tuning improves 1-2 additional BLEU points in constrained mode.
 - Unconstrained mode remains as round 1.
 - 1st for constrained EL.





• CUNI-MT:

- Multilingual models using Transformer in MarianNMT toolkit.
- They trained jointly on all languages.
- Constrained mode results are better for transfer learning models.
- Conclusion:
 - Pretraining a model on a different language pair obtained better results when the corpus size is big.
 - The transfer works also for completely unrelated languages.





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English–German

LC 5lang-ft-avg 40.3 ETRANSLATION ensembleT 39.9 1 LC 5lang-ft 39.8 ETRANSLATION ensemble 39.7 LC 1lang 39.7 LC 1lang 39.7 2 PROMT multilingual-model-round2-tuned-de 39.6 3 LC 7lang 38.6 4 PROMT multilingual-model-round2 39.6 - Baseline Transformer 34.9 Baseline Transformer+ 34.8 34.8 5 CUNI-MT transfer 31.8 6 PROMT multilingual-model-round1 28.7 7 CUNI-MT transfer2 27.5 8 CUNI-MT multiling 27.0 1 ETRANSLATION wmtFT 45.7 2 PROMT Transformer 40.4 3 ETRANSLATION singlebigTr 40.0 4 ETRANSLATION singlebigTr		Rank	Team	Description	BLEU [↑]
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I LC 5lang-ft 39.8 ETRANSLATION ensemble 39.7 LC Ilang 39.7 2 PROMT multilingual-model-round2-tuned-de 39.6 3 LC 7lang 38.6 4 PROMT multilingual-model-round2 39.6 5 CUNI-MT multilingual-model-round2 39.6 6 PROMT multilingual-model-round2 39.6 6 PROMT multilingual-model-round2 39.6 7 CUNI-MT transformer 34.8 6 PROMT multilingual-model-round1 28.7 7 CUNI-MT transfer2 27.5 8 CUNI-MT multiling 27.0 1 ETRANSLATION wmtFT 45.7 2 PROMT Transformer 40.4 3 ETRANSLATION singlebigTr 40.0 4 ETRANSLATION eTstandardengine 35.4 - CdT-ASL* only-cdt-data </td <td rowspan="3"></td> <td></td> <td>ETRANSLATION</td> <td>ensembleFT</td> <td>39.9</td>			ETRANSLATION	ensembleFT	39.9
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9 4 PROMT multilingual-model-round2 39.6 - Baseline Transformer 34.9 Baseline Transformer+ 34.8 5 CUNI-MT transfer 6 PROMT multilingual-model-round1 7 CUNI-MT transfer2 8 CUNI-MT multilingual-model-round1 1 ETRANSLATION wmtFT 3 ETRANSLATION singlebigTr 4 ETRANSLATION eTstandardengine 35.4 - CdT-ASL*	nsträ	3	LC	7lang	38.6
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6 PROMT multilingual-model-round1 28.7 7 CUNI-MT transfer2 27.5 8 CUNI-MT multiling 27.0 1 ETRANSLATION wmtFT 45.7 2 PROMT Transformer 40.4 3 ETRANSLATION singlebigTr 40.0 4 ETRANSLATION eTstandardengine 35.4 - CdT-ASL* only-cdt-data 34.9		5	CUNI-MT	transfer	31.8
7 CUNI-MT transfer2 27.5 8 CUNI-MT multiling 27.0 1 ETRANSLATION wmtFT 45.7 2 PROMT Transformer 40.4 3 ETRANSLATION singlebigTr 40.0 4 ETRANSLATION eTstandardengine 35.4 - CdT-ASL* only-cdt-data 34.9		6	PROMT	multilingual-model-round1	28.7
8 CUNI-MT multiling 27.0 1 ETRANSLATION wmtFT 45.7 2 PROMT Transformer 40.4 3 ETRANSLATION singlebigTr 40.0 4 ETRANSLATION eTstandardengine 35.4 - CdT-ASL* only-cdt-data 34.9		7	CUNI-MT	transfer2	27.5
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3 ETRANSLATION singlebigTr 40.0 4 ETRANSLATION eTstandardengine 35.4 - CdT-ASL* only-cdt-data 34.9	Unconstrain	2	PROMT	Transformer	40.4
4 ETRANSLATION eTstandardengine 35.4 - CdT-ASL* only-cdt-data 34.9		3	ETRANSLATION	singlebigTr	40.0
- CdT-ASL* only-cdt-data 34.9		4	ETRANSLATION	eTstandardengine	35.4
		-	CdT-ASL*	only-cdt-data	34.9

- 12 different systems from 4 participants.
- Best approaches based on multilingual models and ensembling.
- TER and BEER have similar behavior.



English–French

	Rank	Team	Description	BLEU [↑]
		ETRANSLATION	2	58.3
	1	ETRANSLATION	1	57.9
	1	LC	1lang	57.2
g		PROMT	multilingual-model-round2-tuned-fr	57.1
rain	2	CdT-ASL	only-round2-data	56.9
onst	2	LC	7lang	55.8
ŭ	5	PROMT	multilingual-model-round2	55.4
	-	Baseline	Transformer	54.4
	-	Baseline	Transformer+	53.7
	4	PROMT	multilingual-model-round1	45.4
	5	CUNI-MT	multiling	44.1
eq	1	PROMT	Transformer	57.1
rain	1	ETRANSLATION	generaldenorm	56.9
onst	2	ETRANSLATION	general	49.9
Jnco	2	CdT-ASL	only-cdt-data	49.7
	3	ETRANSLATION	formal	43.5

- 9 different systems from 5 participants.
- Best approaches based on monolingual models.
- TER presents similar behavior but into fewer clusters.
- BEER behaves similarly.



English–Spanish

	Rank	Team	Description	BLEU [↑]
	1	LC ETRANSLATION ETRANSLATION LC	1lang-avg 2 1 5lang-ft-avg	56.6 56.1 56.1 56.0
nstrained	2	CdT-ASL LC PROMT	only-round2-data 7lang multilingual-model-round2-tuned-es	55.4 55.3 54.9
ů	3	PROMT	multilingual-model-round2	53.8
	-	Baseline	Transformer	53.3
	-	Baseline	Transformer+	51.8
	4	CUNI-MT	transfer	48.4
	5	PROMT	multilingual-model-round1	45.1
	6	CUNI-MT	multiling	42.1
strain.	1	ETRANSLATION ETRANSLATION	2 1	56.5 56.0
con	2	PROMT	Transformer	53.2
٦ -	3	CdT-ASL	only-cdt-data	51.4

- 11 different systems from 5 participants.
- Best approaches based on monolingual and multilingual models.
- TER presents fewer clusters (only one cluster above the baseline).
- BEER behaves similarly.





English-Italian

	Rank	Team	Description	BLEU [↑]
	1	LC PROMT	5lang-ov-ft-avg multilingual-model-round2-tuned-it	48.9 48.3
	2	LC	5lang-ov	48.0
ned	3	ETRANSLATION PROMT	4bigTens multilingual-model-round2	47.0 46.8
IISURA	4	ETRANSLATION	4bigTensFT	46.7
3	5	LC	1lang	45.3
	-	Baseline	Transformer+	43.5
	-	Baseline	Transformer	42.9
	6	CUNI-MT	transfer	38.6
	7	CdT-ASL	only-round2-data	37.9
	8	PROMT	multilingual-model-round1	37.6
	9	CUNI-MT	multiling	35.2
D L	1	ETRANSLATION	4bigTens	50.1
IPJI	2	ETRANSLATION	4bigTensnorm	49.9
Uncons	3	CdT-ASL PROMT	round2-data Transformer	49.0 47.8
	4	CdT-ASL	only-cdt-data	45.2

- 11 different systems from 5 participants.
- Best approaches based on multilingual models.
- TER and BEER behave similarly but with fewer clusters.

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English-Modern Greek

	Rank	Team	Description	BLEU [↑]
	1	PROMT	multilingual-model-round2-tuned-el	45.1
	2	LC	7lang-ov-ft-avg	44.7
	3	LC	7lang-ov	44.2
ined	4	LC PROMT	7lang multilingual-model-round2	43.2 42.1
ıstra	5	ETRANSLATION	1	41.7
Ğ	6	LC	llang	41.2
	-	Baseline	Transformer+	39.8
	-	Baseline	Transformer	38.5
	7	ETRANSLATION CUNI-MT	2 transfer	34.9 34.9
	8	CdT-ASL CUNI-MT PROMT	only-round2-data multiling multilingual-model-round1	32.9 32.4 31.4
نب	1	PROMT	Transformer	44.4
cons	2	ETRANSLATION	2	44.3
Un	3	ETRANSLATION	1	43.1
	4	CdT-ASL	only-cdt-data	37.5

- 12 different systems from 5 participants.
- Best approaches based on multilingual models.
- TER and BEER behave similarly.



English-Swedish

	Rank	Team	Description	BLEU [↑]
		ETRANSLATION	4bigTens	22.7
	1	LC	5lang-ov-ft-avg	22.0
	1	PROMT	multilingual-model-round2-tuned-sv	21.8
		LC	5lang-ov-r2-data	21.8
ð	2	PROMT	multilingual-model-round2	20.4
raine	3	CdT-ASL	only-round2-data	20.3
onst	-	Baseline	Transformer+	19.5
Ŭ	4	LC	7lang-ov-r1-data	18.3
	5	LC	5lang-r1-data	17.7
	6	PROMT	multilingual-model-round1	17.2
		LC	1lang-r1-data	16.7
	1	Baseline	Transformer	15.3
		CUNI-MT	multiling	14.7
	0	CUNI-MT	transfer	13.9
nst.	1	ETRANSLATION	4bigTens	23.3
100	2	CdT-ASL	only-cdt-data	21.3
5	2	PROMT	Transformer	21.0

- 12 different systems from 5 participants.
- Best approaches based on multilingual models.
- TER presents fewer clusters.
- BEER behaves similarly.





English–Arabic

	Rank	Team	Description	BLEU [↑]
	1	LC	7lang-ov	25.1
	2	PROMT	multilingual-model-round2-tuned-ar	22.9
strained	3	LC PROMT	7lang multilingual-model-round2	22.0 21.7
Cons	4	CUNI-MT LC Baseline	transfer 1lang Transformer	19.1 19.1 18.8
	5	CUNI-MT	multiling	17.0
	6	CdT-ASL	only-round2-data	15.9
Un.	1	PROMT	Transformer	31.4

- 8 different systems from 4 participants.
- Best approaches based on multilingual models.
- TER presents more clusters.
- BEER behaves similarly.





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Conclusions

- 2nd round addressed 7 different language pairs and 2 categories: constrained and unconstrained data usage.
- 5 teams participated in this round.
- Cleaning process improved results.
- Good results for transformer and big transformer architectures.
- Less resource language pairs such as SV, EL and AR benefit from multilingual models.