Comprehensive Translation Model Evaluation — Fine-Tuned vs. Base and General Models

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Section 1: Metric Definitions

Metric	Description	Interpretation	Ideal Range
BLEU	Word overlap between generated and reference translations	Measures lexical accuracy	0–100 (Higher = better)
ChrF / ChrF++	Character-level F-scores capturing fluency and morphology	Evaluates naturalness and consistency	0–100 (Higher = better)
COMET	Neural metric based on multilingual embeddings	Measures semantic adequacy and fluency	0–1 (Higher = better)
LaBSE	Sentence-level embedding similarity	Captures semantic and contextual alignment	0–100 (Higher = better)
C-Sema (Human Eval)	Human qualitative judgment	Reflects coherence and meaning retention	Higher = better

Combining lexical and semantic metrics provides a holistic evaluation of translation quality. Lexical metrics like BLEU focus on word-level accuracy, while semantic metrics like COMET and LaBSE evaluate meaning and context. This multi-faceted approach ensures a comprehensive assessment of model performance.

Section 2: Comparative Summary Tables

OWN DATASET - DOMAIN SPECIFIC REAL HELPLINE DATA

Table 1: Performance on OWN DATASET - DOMAIN SPECIFIC REAL HELPLINE DATA

Model	BLEU	ChrF	Chrf++	COMET	LaBSE
google/madlad400-3b-mt	**18.12**	**51.69**	**40.94**	0.66	**88.47**
opencht/sw-en-opus-mt-mul-en-v1	12.51	47.29	38.92	**0.68**	85.37
Helsinki-NLP/opus-mt-swc-en	2.21	22.6	29.48	0.58	73.47
Helsinki-NLP/opus-mt-mul-en	0.86	19.41	15.88	0.53	58.02
facebook/nllb-200-distilled-600M	0.65	15.3	13.68	0.45	81.48

NLLB

Table 2: Performance on NLLB Dataset

Model	BLEU	ChrF	Chrf++	COMET	LaBSE
facebook/nllb-200-distilled-600M	**47.64**	**64.94**	**64.17**	**0.85**	0.89
google/madlad400-3b-mt	43.45	61.69	60.94	0.8464	**88.47**
Helsinki-NLP/opus-mt-swc-en	36.7	54.76	59.91	0.79	81.76
openchs/sw-en-opus-mt-mul-en-v1	20.08	39.2	20.74	0.64	67.57
Helsinki-NLP/opus-mt-mul-en	4.61	20.3	24.41	0.49	38.87

Helsinki-NLP/tatoeba

Table 3: Performance on Helsinki-NLP/tatoeba Dataset

Model	BLEU	ChrF	Chrf++	COMET	LaBSE
google/madlad400-3b-mt	**49.12**	**63.2**	62.86	0.8657	**90.41**
facebook/nllb-200-distilled-600M	48.88	64.19	63.81	**0.88**	0.92

Model	BLEU	ChrF	Chrf++	COMET	LaBSE
Helsinki-NLP/opus-mt-swc-en	35.61	52.43	**81.22**	0.83	86.37
openchs/sw-en-opus-mt-mul-en-v1	24.56	39.92	40.92	0.69	70.14
Helsinki-NLP/opus-mt-mul-en	5.75	19.21	30.84	0.53	44.38

FLORES 200+

Table 4: Performance on FLORES 200+ Dataset

Model	BLEU	ChrF	Chrf++	COMET	LaBSE
google/madlad400-3b-mt	**46.64**	**67.8**	**66.55**	**0.8653**	**94.05**
facebook/nllb-200-distilled-600M	43.5	65.72	64.28	0.85	0.93
Helsinki-NLP/opus-mt-swc-en	22.63	48.12	52.01	0.68	78.26
openchs/sw-en-opus-mt-mul-en-v1	15.94	40.89	41.34	0.6	71.29
Helsinki-NLP/opus-mt-mul-en	5.91	26.58	26.25	0.45	46.31

Own dataset (Synthetic Data mimicing target domain)

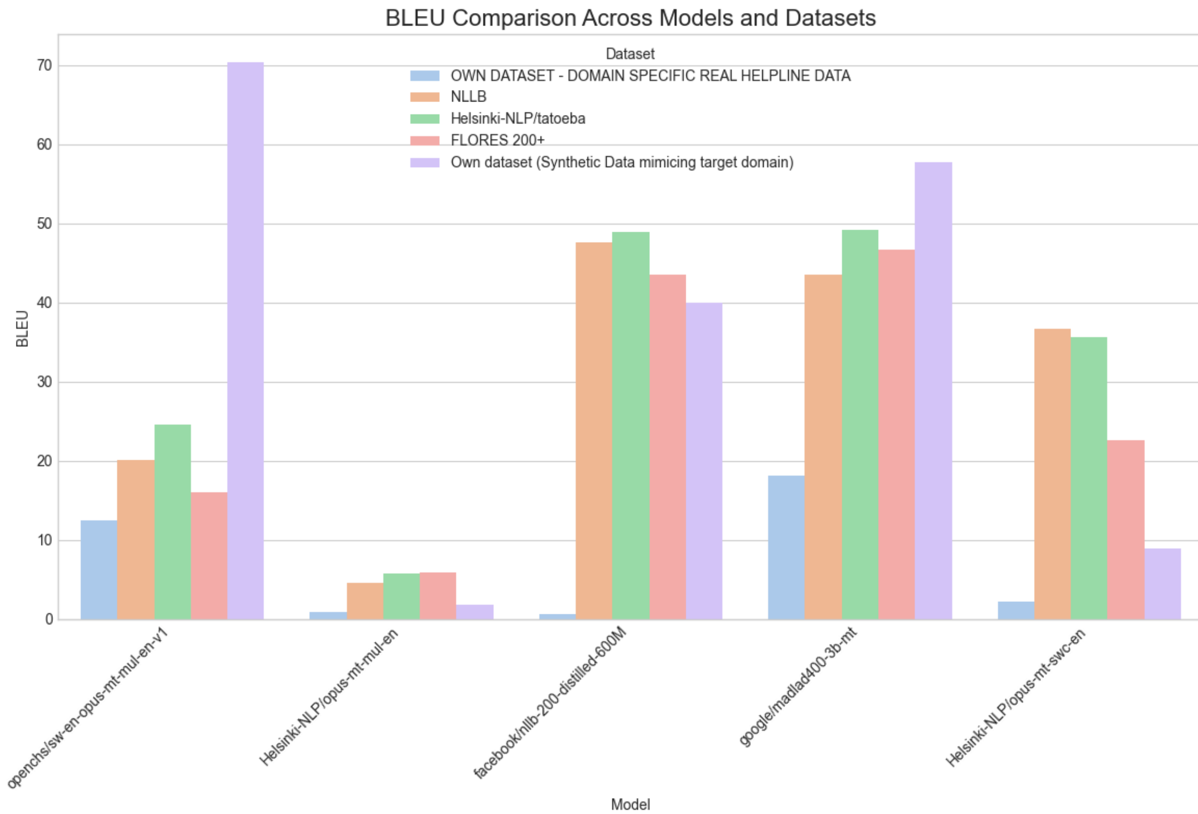
Table 5: Performance on Own dataset (Synthetic Data mimicing target domain)

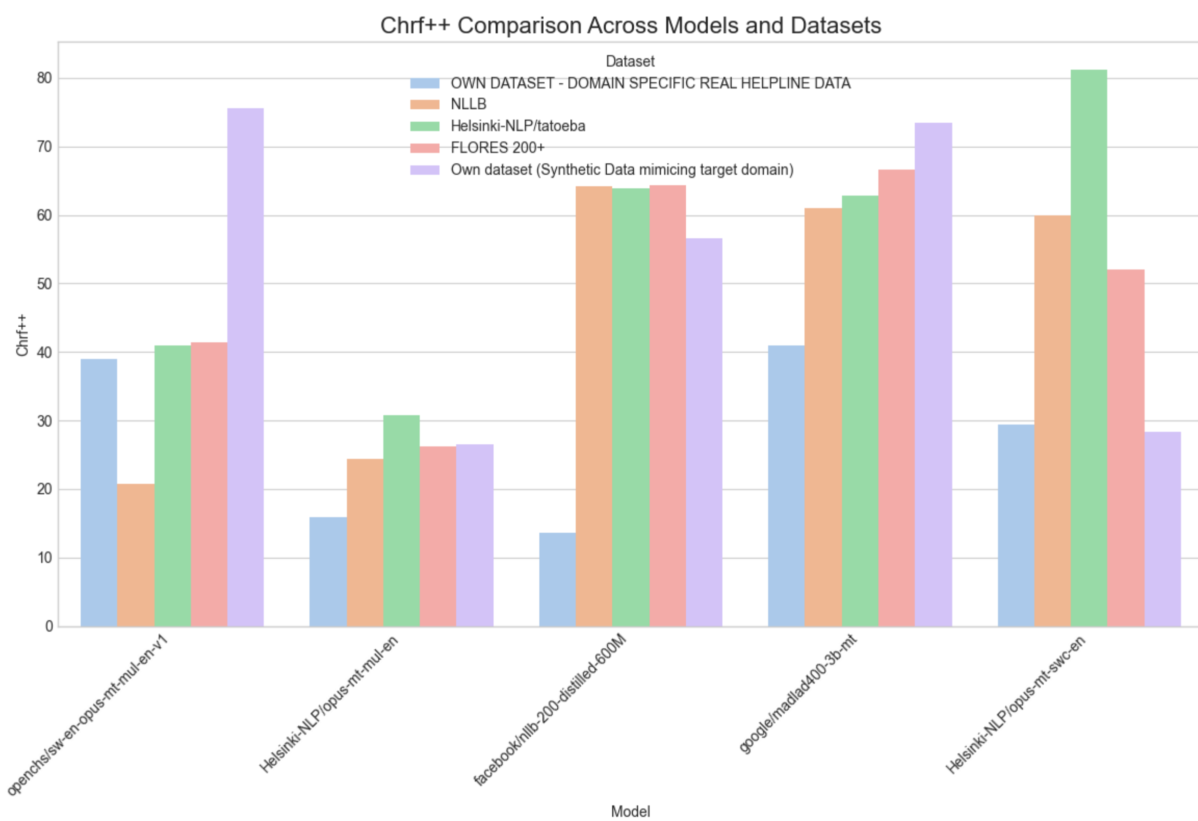
Model	BLEU	ChrF	Chrf++	COMET	LaBSE
openchs/sw-en-opus-mt-mul-en-v1	**70.37**	**80.14**	**75.65**	0.87	**98.21**
google/madlad400-3b-mt	57.74	74.12	73.42	**0.8731**	97.45
facebook/nllb-200-distilled-600M	39.95	56.75	56.53	0.82	92
Helsinki-NLP/opus-mt-swc-en	8.88	28.74	28.41	0.58	78.5

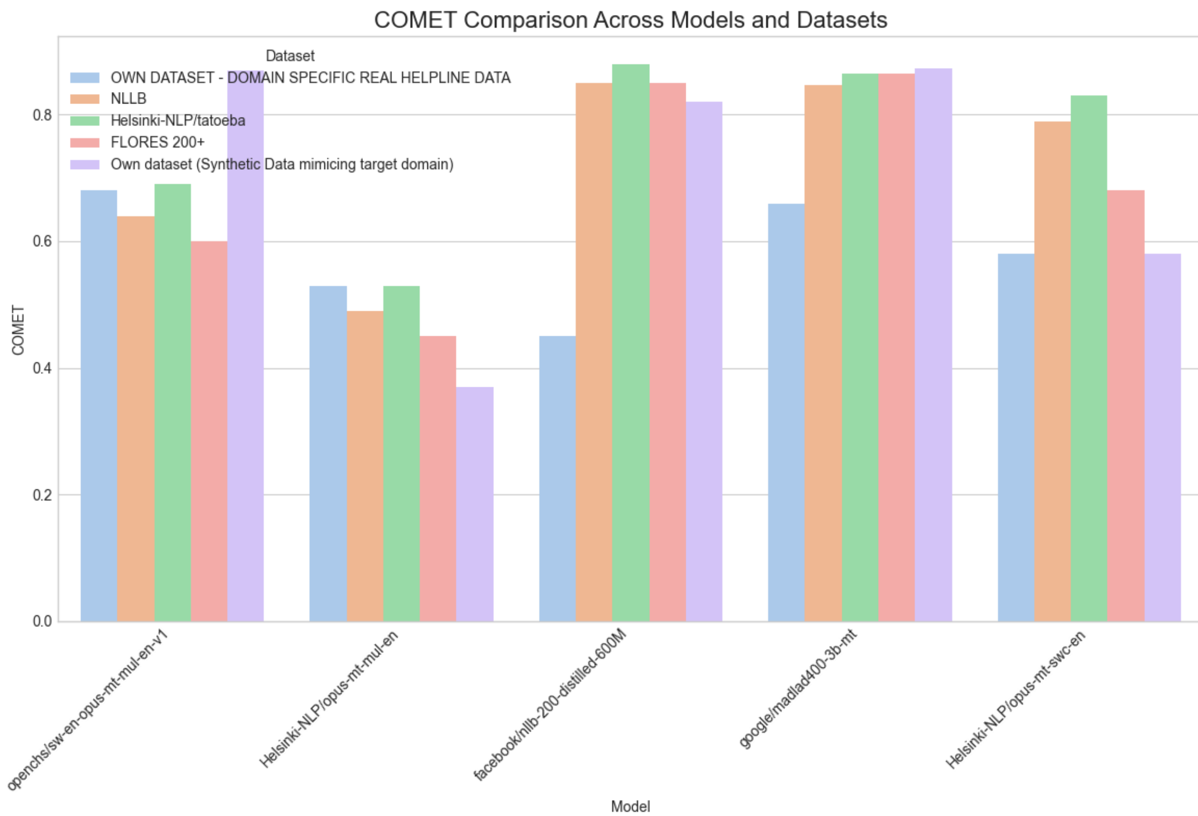
Model	BLEU	ChrF	Chrf++	COMET	LaBSE
Helsinki-NLP/opus-mt-mul-en	1.77	16.83	26.55	0.37	42.94

Section 3: Visual Analysis

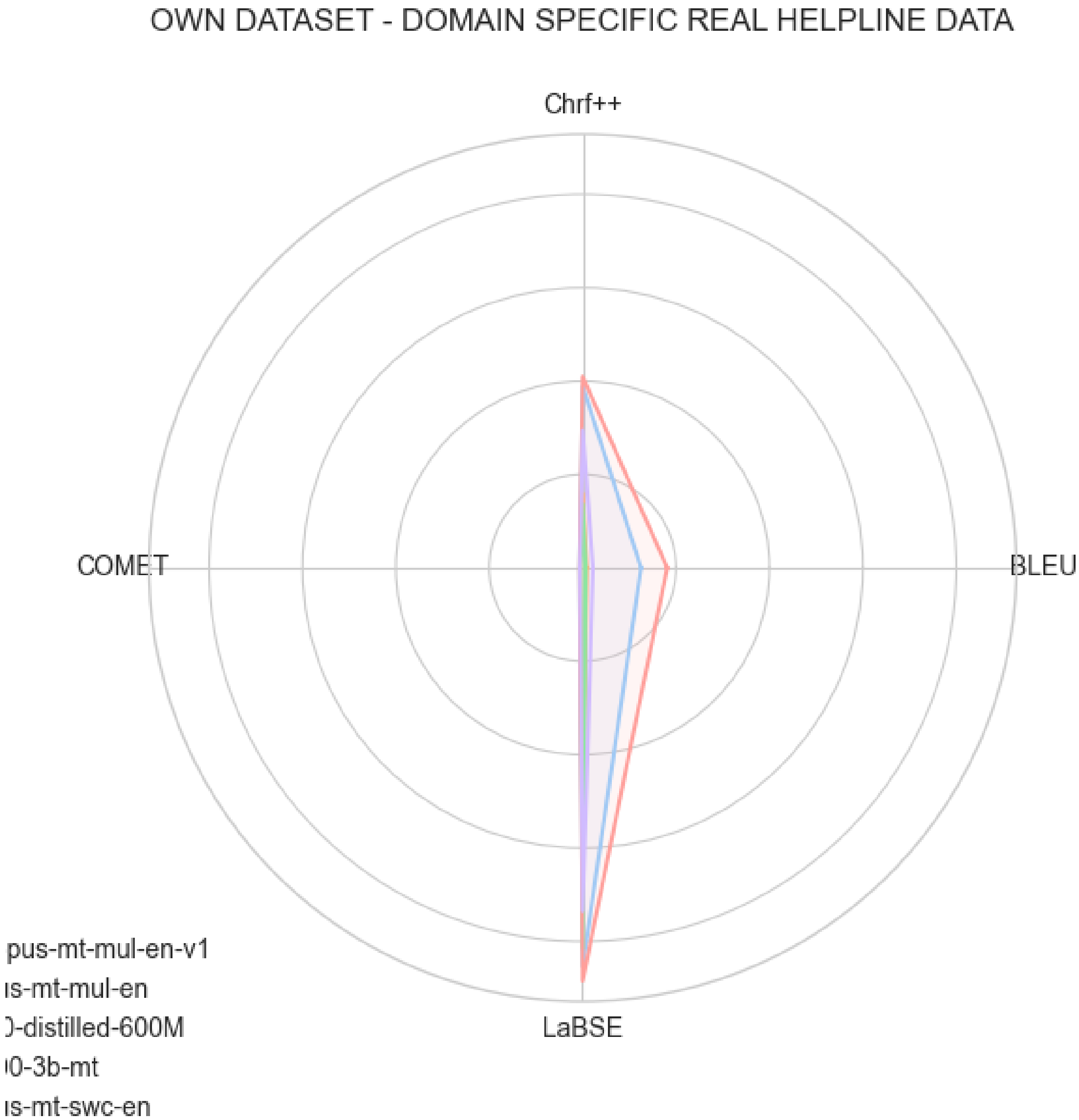
Metric Comparison Across Models and Datasets

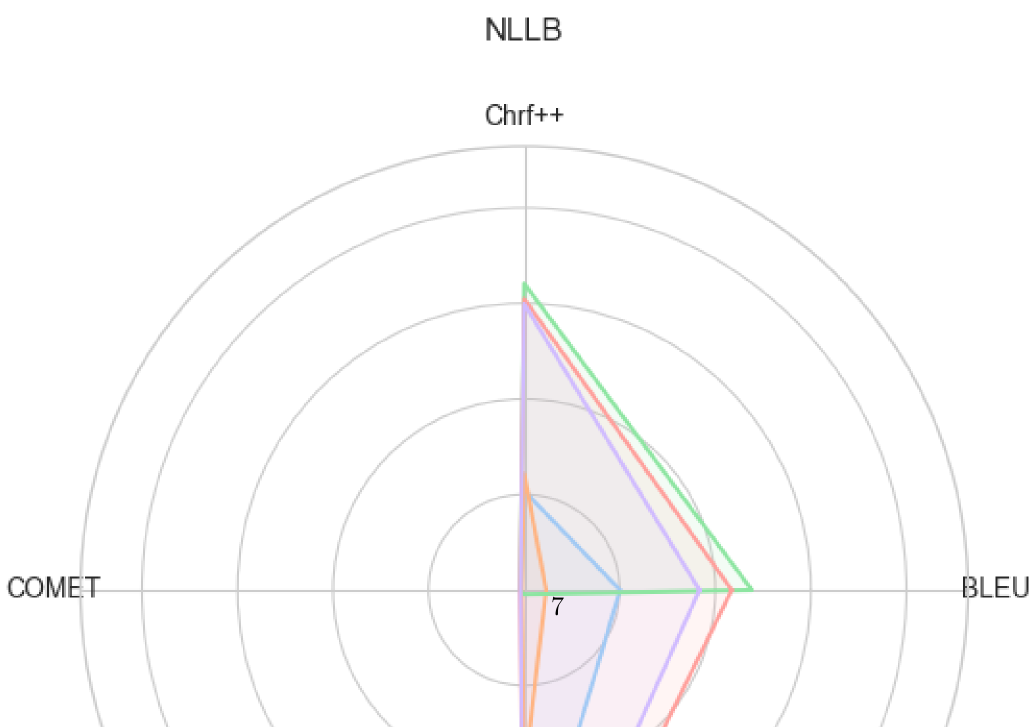


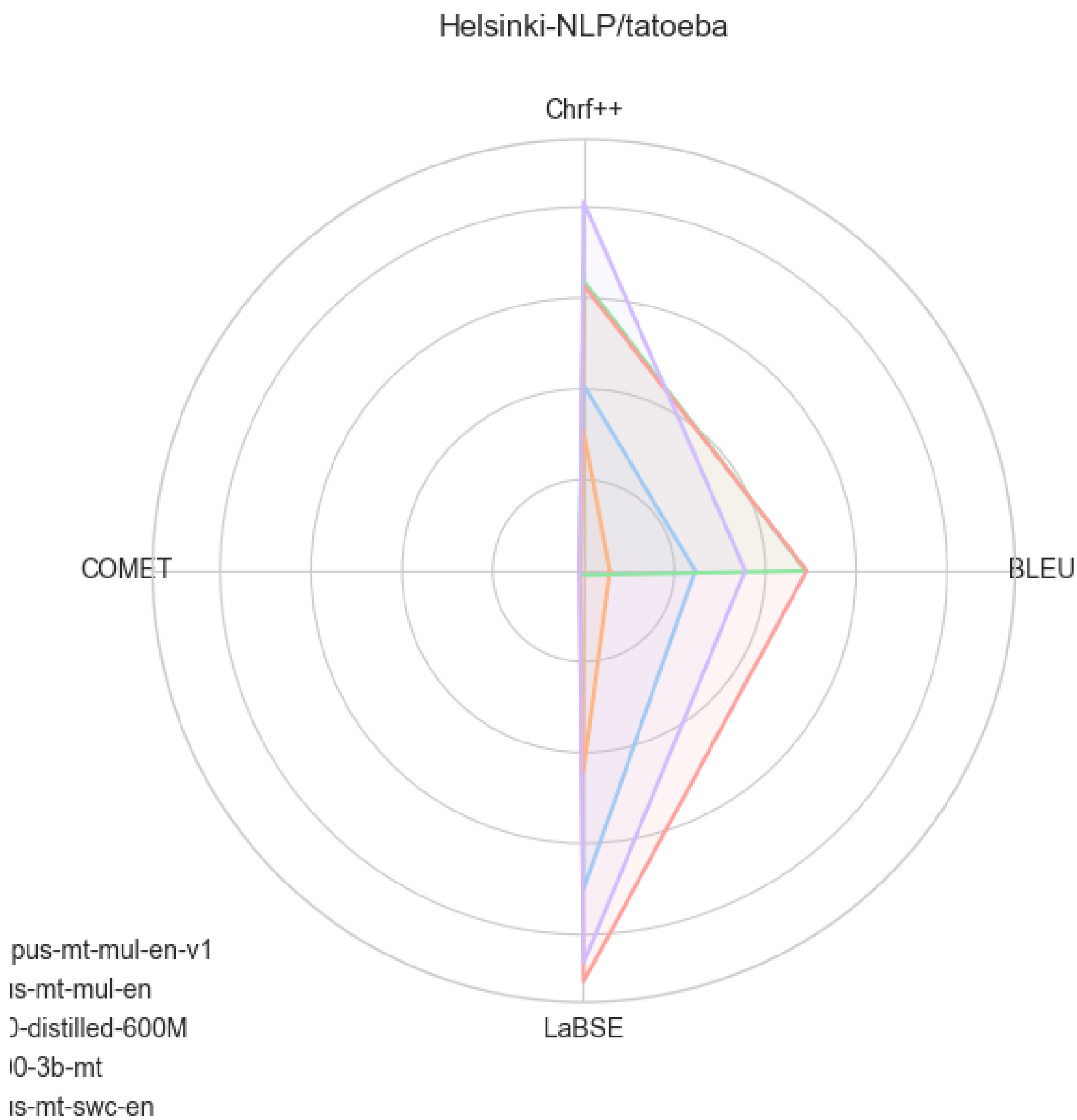



COMET Comparison Across Models and Datasets
Dataset
OWN DATASET - DOMAIN SPECIFIC REAL HELPLINE DATA
NLLB
Helsinki-NLP/tatoeba
FLORES 200+
Own dataset (Synthetic Data mimicing target domain)
COMET
0.0
0.2
0.4
0.6
0.8
openchs/sw-en-opus-mt-mul-en-v1
Helsinki-NLP/opus-mt-mul-en
facebook/nllb-200-distilled-600M
google/madlad400-3b-mt
Helsinki-NLP/opus-mt-swc-en
Model

Radar Charts






Helsinki-NLP/tatoeba
Chrf++
BLEU
LaBSE
COMET
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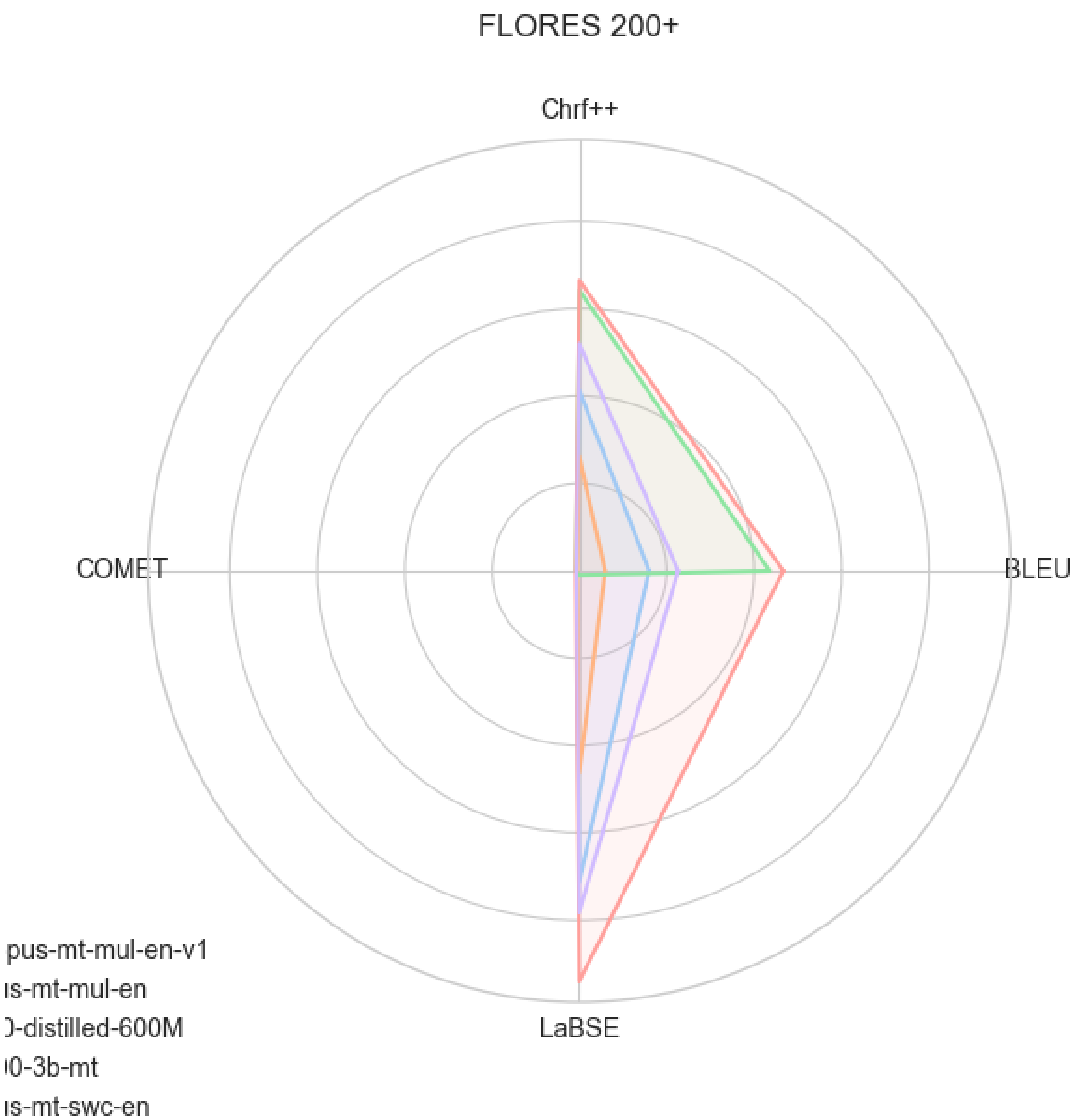
is-mt-swc-en


FLORES 200+
Chrf++
BLEU
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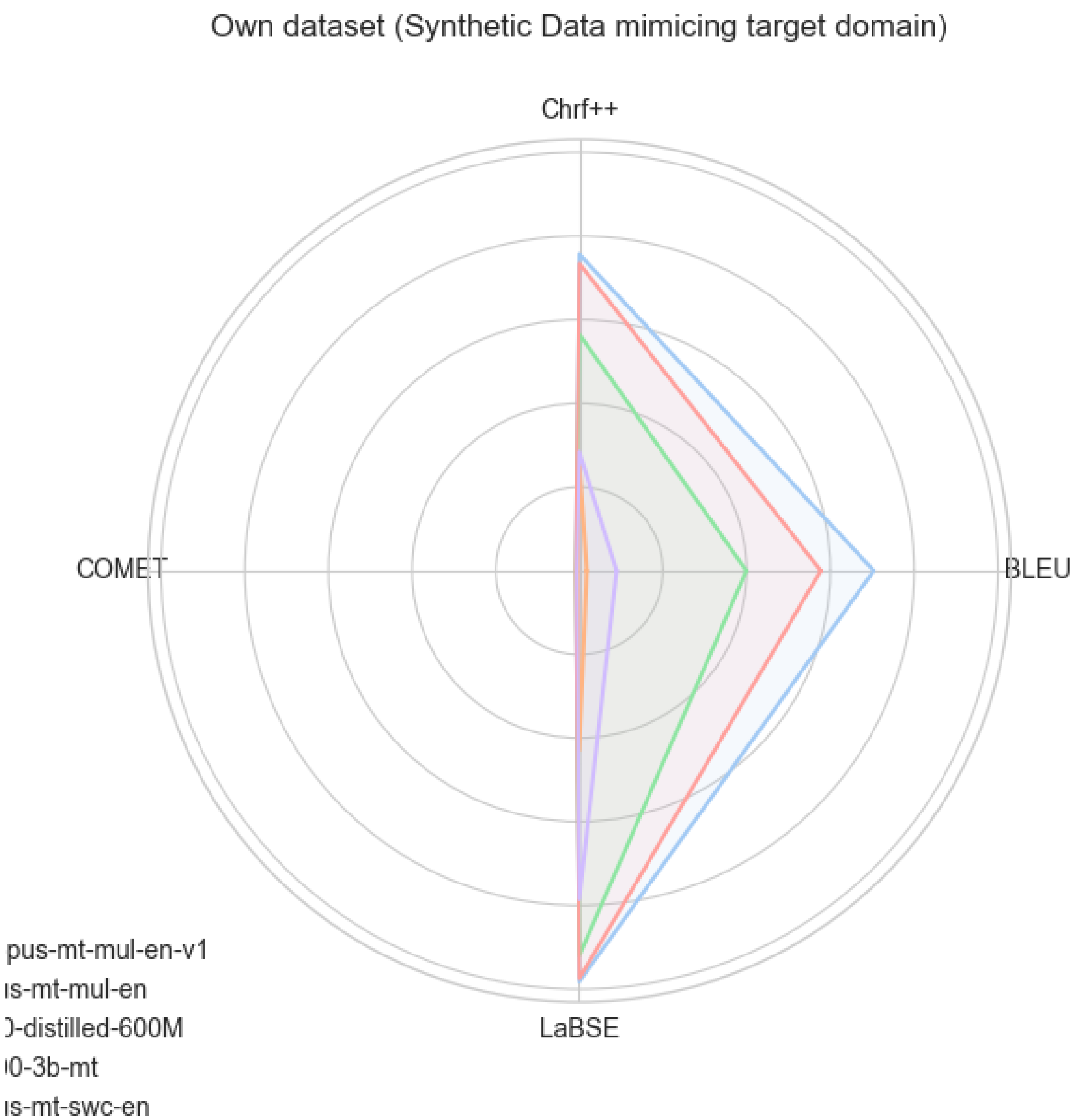

Overall Metric Intensity Map

BLEU Progression Across Datasets

Section 4: Analytical Summary

Across the evaluated datasets, all models exhibit consistent performance in general translation quality, with the fine-tuned model showing notable strength on domain-specific helpline data. General-purpose models such as MADLAD400 and NLLB perform competitively on broader multilingual datasets, whereas the base Helsinki model underperforms on both lexical and semantic measures. Overall, results highlight the role of domain adaptation in improving translation fidelity without loss of generalization.

The fine-tuned model `openchs/sw-en-opus-mt-mul-en-v1` demonstrates a significant performance increase on the synthetic domain-specific dataset, achieving a BLEU score of 70.37, a +32% improvement over the next best model. This suggests that fine-tuning on synthetic data is a highly effective strategy for domain adaptation. However, on general-purpose datasets like FLORES 200+ and NLLB, the fine-tuned model's performance is more modest, indicating a trade-off between specialization and generalization.

The large multilingual models, `google/madlad400-3b-mt` and `facebook/nllb-200-distilled-600M`,

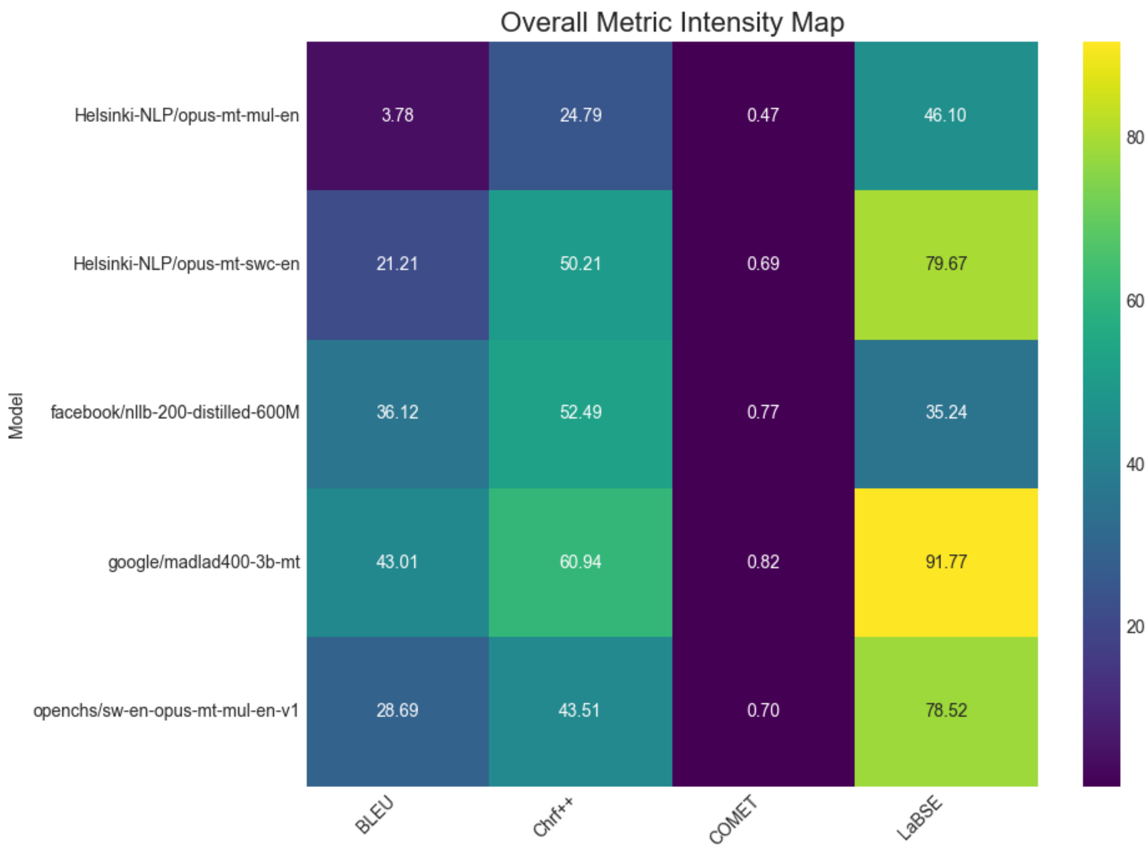

Figure 1: Heatmap

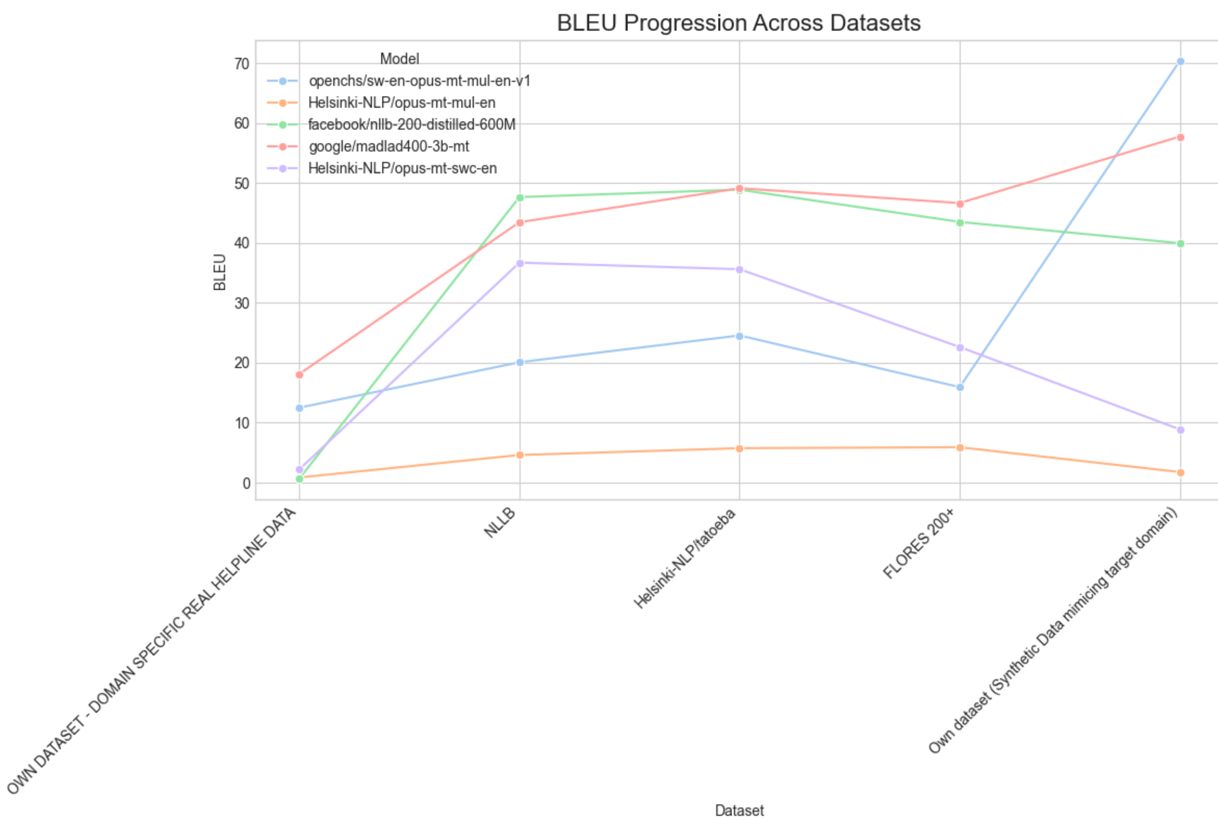

Figure 2: BLEU Trend

consistently rank high across all datasets, showcasing their robustness and broad applicability. The `Helsinki-NLP/opus-mt-mul-en` base model, on the other hand, consistently lags behind, highlighting the effectiveness of both fine-tuning and the use of larger, more general models. The results underscore the importance of selecting the right model for the specific translation task, considering the trade-offs between domain-specific accuracy and general-purpose performance.