Predicting Machine Translation Performance on Low-Resource Languages: The Role of Domain Similarity

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Motivation

Cost of Fine-Tuning Language Models

- High for diverse tasks, languages, and domains.
- Low resource languages (LRLs) lacks data and computing power.

Importance of Performance Data

- Useful for optimizing training cost or for other tasks (e.g., quality estimation (QE)).

Our contributions

- Analyzed the impact of fine-tuning corpus size, domain similarity, and language similarity on MT models for Indian Low Resource Languages (Gujarati, Hindi, Kannada, Sinhala, Tamil) through regression analysis.
- Provided domain-specific and language-specific interpretations based on the performance of regression models.

Methodology

Experimental Data

- Carried out MT experiments using mBart to translate from English to Gujarati, Hindi, Kannada, Sinhala, and Tamil with spBLEU as performance metric from Nayak et.al., (2023).
- Partitioned by fine-tuning corpus size, fine-tuning–testing corpora pair, and target language.

Factors Explored and Featurization

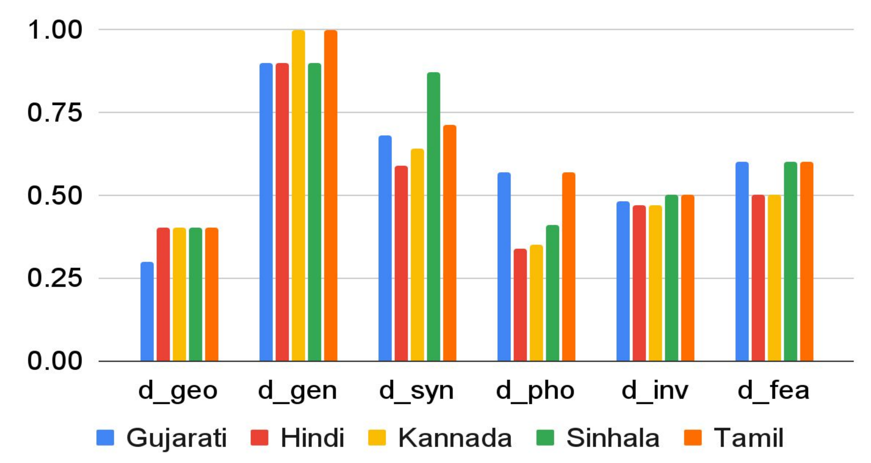
Size: Sentence pair counts in fine-tuning corpora

Domain Similarity: Jensen-Shannon divergence (JSD)

$$JSD(P||Q) = 0.5\,KL(P||M) + 0.5\,KL(Q||M)$$

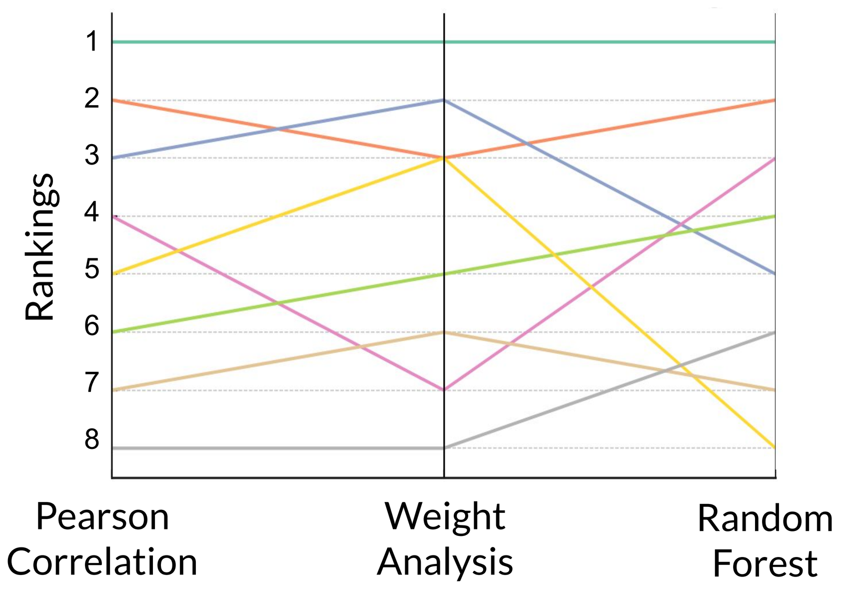
where M is an equally weighted sum of the two distributions and $KL(\cdot||\cdot)$ is the Kullback-Leibler divergence.

Language Similarity: Lang2vec language distances from English



Feature Importance

- JSD top-ranked all three feature importance rankings.
- Most language features ranked lower than JSD and size.

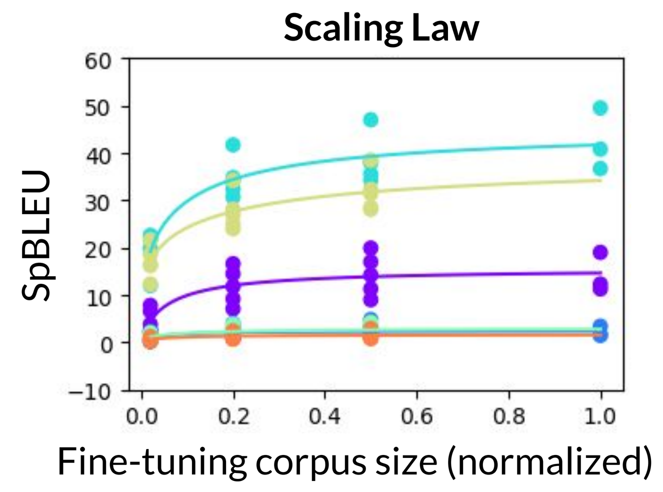


Feature	Random Forest (%)
JSD	88.393
Size	7.805
d_{syn}	2.267
d_{inv}	0.782
d_{gen}	0.365
d_{pho}	0.161
d_{geo}	0.147
d_{fea}	0.079

Regression Analysis

Size

Model: Scaling Law; partitioned by fine-tuning–testing corpora pair; RMSE* = 2.2998

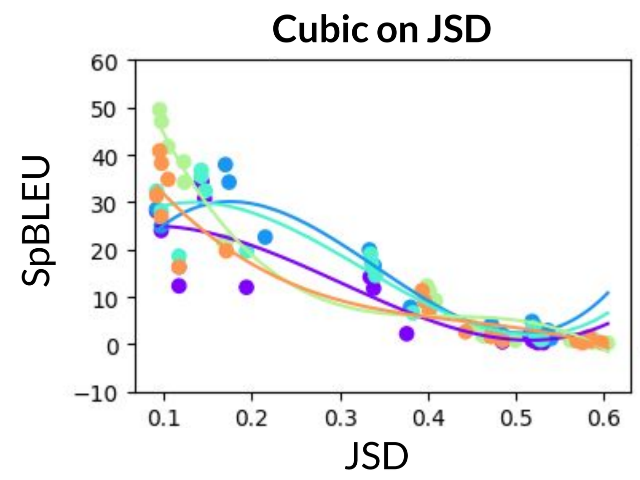


Fine-tuning–testing	Normal?	Homoscedastic?
Gov/PMI-Flores	✅	✅
Gov/PMI-Bible	✅	❌
Gov/PMI-Gov/PMI	✅	❌
Bible-Flores	✅	❌
Bible-Bible	✅	✅
Bible-Gov/PMI	✅	❌

*RMSE: Rooted mean square error

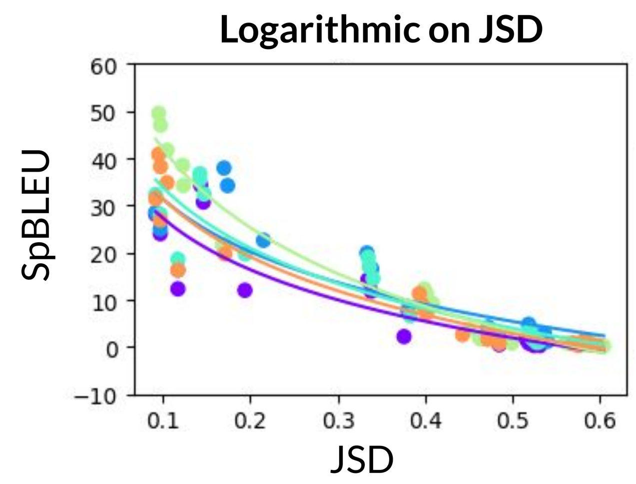
Domain Similarity

Model: Cubic; partitioned by target language; RMSE = 4.1202



Target Languages	Normal?	Homoscedastic?
Gujarati	✅	✅
Hindi	❌	✅
Kannada	✅	✅
Sinhala	✅	✅
Tamil	✅	✅

Model: Logarithmic; partitioned by target language; RMSE = 4.9247



Target Language	Normal?	Homoscedastic?
Gujarati	✅	✅
Hindi	✅	✅
Kannada	✅	✅
Sinhala	✅	✅
Tamil	❌	✅

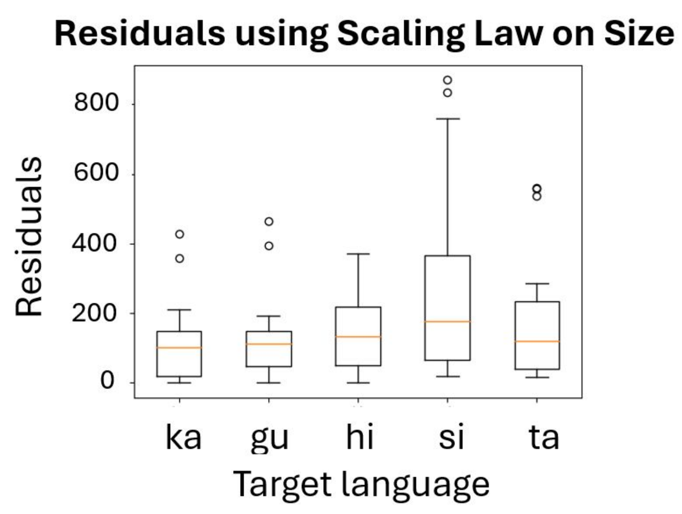
Language Similarity

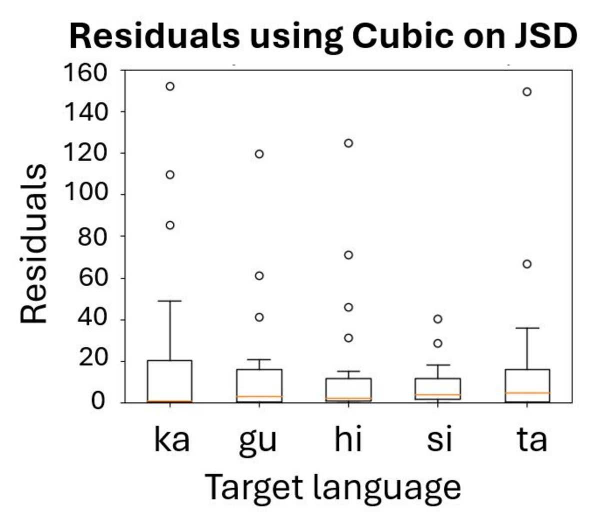
Model	Without language features	With language features
Linear	4.8766	4.5786
Quadratic	4.6604	4.3840
Cubic	4.4509	4.2168
Logarithmic	4.9502	4.6815

- Single-factor regression models on language features have high RMSE.
- Including language features in multifactors models do not significantly improve RMSE.
- Insufficient LRL data in the URIEL database limit lang2vec's precision/ approximations in describing LRLs.
- Low feature discriminative power of LRLs' lang2vec features render the effectiveness of using them as predictors.

Role of Domain Similarity

- Enhanced predictability of scaling law models with in/out-domain data separation (partitioned by fine-tuning–testing pair).
- Yielded a more reliable prediction in terms of normality and homoscedasticity of residuals.





Conclusion & Next Steps

- Domain similarity exerts the most significant impact on performance of MT models, surpassing even the impact of fine-tuning corpus size.
- Using domain similarity as predictor produces the best prediction in terms of accuracy and statistical reliability.
- Next Step: A more rigorous study on language similarity measurement to identify suitable predictors for our task.

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