MTQE.en-he: Machine Translation Quality Estimation for English-Hebrew

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Abstract

We release MTQE.en-he: to our knowledge, the first publicly available English-Hebrew benchmark for Machine Translation Quality Estimation. MTQE.en-he contains 959 English segments from WMT24++, each paired with a machine translation into Hebrew, and Direct Assessment scores of the translation quality annotated by three human experts. We benchmark ChatGPT prompting, TransQuest, and CometKiwi and show that ensembling the three models outperforms the best single model (CometKiwi) by 6.4 percentage points Pearson and 5.6 percentage points Spearman. Fine-tuning experiments with TransQuest and CometKiwi reveal that full-model updates are sensitive to overfitting and distribution collapse, yet parameter-efficient methods (LoRA, BitFit, and FTHead, i.e., fine-tuning only the classification head) train stably and yield improvements of 2-3 percentage points. MTQE.en-he and our experimental results enable future research on this under-resourced language pair.

1 Introduction

Machine Translation Quality Estimation (MTQE) is an important step in Machine Translation (MT) pipelines: by scoring translations, the overall system can accept high quality outputs and flag low quality outputs for human review or post-editing.

Hebrew is considered a mid-resource language in Natural Language Processing (NLP), with substantially fewer annotated resources than high-resource languages like English, and its rich morphology leads to effective low-resource learning conditions (Joshi et al., 2020; Tsarfaty et al., 2019).

We create and release[1] MTQE.en-he, a new dataset for English-Hebrew MTQE consisting of 959 segments annotated by three human experts and benchmark popular models (ChatGPT, TransQuest, and CometKiwi) on it, showing strong baselines yet plenty of room for improvement.

[1] gitlab.com/lexicala-public/mtqe-en-he

2 Related Work

Quality Estimation (QE) has been studied for years as a WMT shared task. While WMT23 QE includes a test set from Hebrew to English, generally translating from a high-resource language (English) into a lower resource language (Hebrew) is a more difficult task. Zhao et al. (2024) provide an overview of the history of MTQE.

TransQuest (Ranasinghe et al., 2020) fine-tunes XLM-RoBERTa-large (Conneau et al., 2020) on Quality Estimation and explores cross-lingual transfer. CometKiwi (Rei et al., 2021) simultaneously models and predicts sentence-level and word-level quality. Juraska et al. (2024) build MetricX-24, a model that can handle quality estimation both with and without references, and employ synthetic data generation to improve the results.

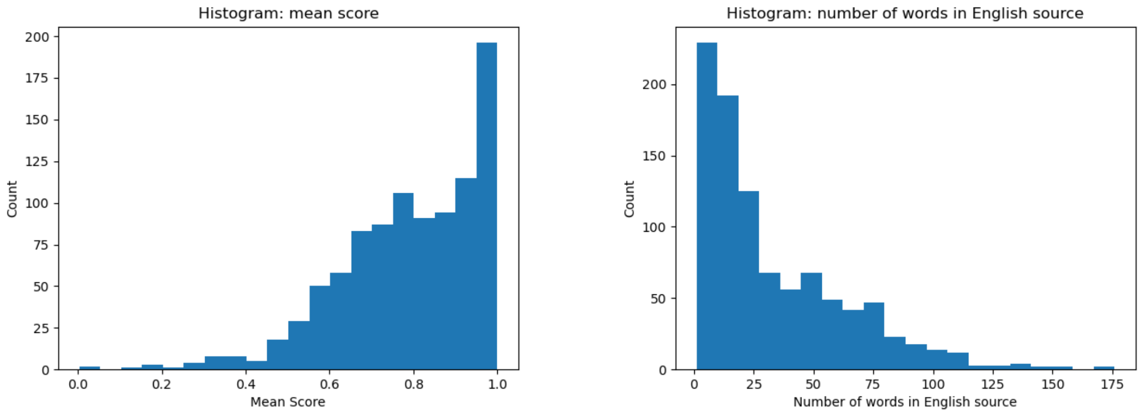
The closest relative of our work is EPOQUE (Jafari Harandi et al., 2024), who develop a similar test set for English-Persian, then benchmark and fine-tune TransQuest. The novelty of our work is threefold (1) we are the first to publicly release a dataset for English-Hebrew, (2) we benchmark ChatGPT prompting and ensembling models, and (3) we explore parameter-efficient fine-tuning of TransQuest and CometKiwi.

3 Dataset

MTQE.en-he contains 959 English segments[2] from English-Hebrew WMT24++ (Deutsch et al., 2025), covering four domains: literary, news, social, and speech. We apply Google Translate on the English source to get the Hebrew translation, then hire three human experts to annotate the segments with a standard Direct Assessment (DA) score in the range of 0 to 100. (Guidelines in Appendix G.)

All three annotators have native-level proficiency in English and Hebrew, plus extensive linguistics

[2] The original dataset is 998 samples. We remove the 38 samples flagged with `is_bad_source`, and one duplicate.



(a) Mean score distribution.

(b) English source word length distribution.

Figure 1: MTQE.en-he dataset statistics (n=959). Left: Mean Score. Right: Number of words in English source.

background and experience with translation workflows. The annotators are professional contacts of the paper authors and were paid fairly for their work in their locale. The inter-annotator agreement (Pearson one vs. mean of others) is 0.5168, 0.5270, and 0.5573, respectively, for a mean of 0.5337, which is reasonable for MTQE DA labels.

We show the histogram of mean score (left) and the number of words in the English source (right) in Figure 1. We show the frequency of representative score ranges in Table 1. The scores trend high (73% scored 70 and above) and segment lengths trend short (59% of the segments are under 30 words).

Mean score range	Count	Percentage
$[91, 100]$	300 / 959	31%
$[70, 91)$	402 / 959	42%
$[51, 70)$	205 / 959	21%
$[0, 51)$	52 / 959	6%

Table 1: Frequency of representative score ranges.

4 Benchmarks on the Full Dataset

We set the ground truth as the mean of the three annotators' scores, and benchmark three baseline models: (1) ChatGPT (OpenAI, 2024) with two different prompts, (2) TransQuest, and (3) CometKiwi. We report Pearson and Spearman correlation in Table 3 ("All"), and show scatter plots in Figure 2.

CometKiwi is the strongest of our baselines, with 0.4828 Pearson and 0.5456 Spearman.

We benchmark two versions of TransQuest: the "en-any" model performs best of the two, with 0.4327 Pearson and 0.4501 Spearman compared to the "multilingual" (any-to-any) version which lags behind at 0.3759 Pearson and 0.4303 Spearman.

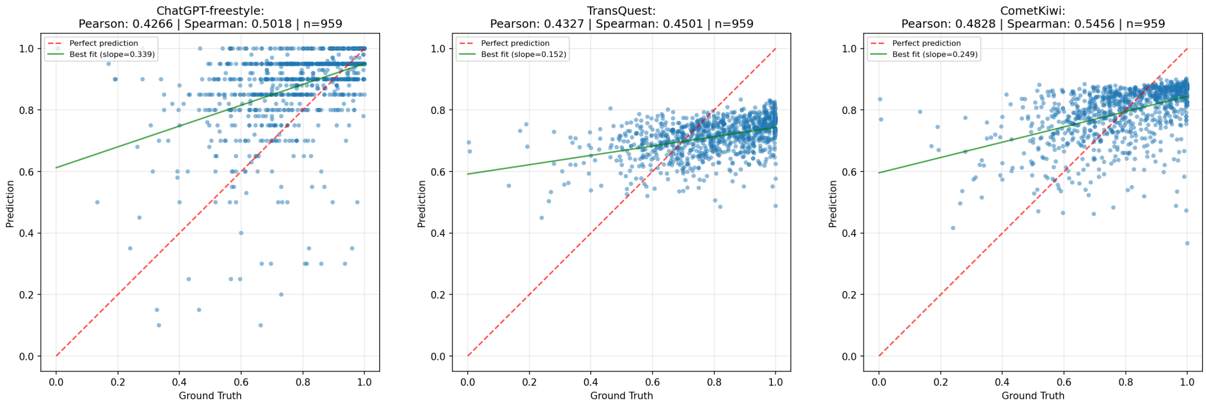
ChatGPT-prompting produces results in between TransQuest and CometKiwi, with 0.4266 Pearson and 0.5018 Spearman.

Our ChatGPT prompts are (a) "freestyle": `“Score 0-100 by your own overall judgment of translation quality.”` and (b) "guidelines", where the prompt includes our full annotation guidelines (Appendix G). The two ChatGPT prompts produce very similar results, with almost identical score agreement (Figure 6a, Appendix B). Our guidelines are based on the publicly available WMT QE task, and we hypothesize that ChatGPT-freestyle may be implicitly following similar guidelines memorized from pre-training on web data.

ChatGPT tends to favor repeating certain scores, resulting in the horizontal bands in the plot in Figure 2(a) (left). By contrast, TransQuest and CometKiwi produce scores throughout the range.

Both TransQuest and CometKiwi never produce scores of 0.91 or higher, even for inputs with ground truth score above 0.91 ("excellent or perfect" in our guidelines), which accounts for 31% of our dataset. Thus, although both models are strong baselines, there is room for improvement.

We also benchmark ensembling: averaging the models' predicted scores for each input sample. Following *Occam's Razor* (preferring simpler solutions) we select the "freestyle" version of ChatGPT prompting for our Ensemble. As shown in Table 3, **ensembling provides substantial improvement over CometKiwi alone**: +6.4 percentage points Pearson (from 0.4828 to 0.5472) and +5.6 percentage points Spearman (from 0.5456 to 0.6014).



(a) ChatGPT-freestyle (b) TransQuest (c) CometKiwi

Figure 2: Scatter plots of baseline model hypotheses on the full dataset (n=959).

5 Fine-tuning Experiments

Slice	Quantity
train	300
validation	100
test	559
TOTAL	959

Table 2: Data Slices

We partition our dataset (Table 2), then fine-tune TransQuest and CometKiwi for 50 steps (5 epochs) on *train* (n=300) (following Jafari Harandi et al.) use *validation* (n=100) for checkpoint selection (by highest Pearson), and report on *test* (n=559).

We use stratified sampling (Bishop, 2006) for a similar distribution of scores across the slices. (See Figure 7 in Appendix C.) We perform this split five times with different random seeds and release the seeded splits with our dataset for reproducibility. We report the results on each seed in Tables 5 (Pearson) and 6 (Spearman) in Appendix F.

5.1 Fine-tuning Methods

We explore four fine-tuning methods: (1) Full fine-tuning [FullFT] where all of the model parameters are free to change; (2) LoRA (Hu et al., 2021), which freezes the base model and learns low-rank updates to the attention and feed-forward layers; (3) BitFit (Ben Zaken et al., 2022) which fine-tunes only the bias terms and the head classifier layer(s), corresponding to 0.2% of the model's parameters; and (4) fine-tuning only the head classifier layer(s) [FTHead]. We use the same hyperparameters for all four methods, shown in Table 4 (Appendix E), notably batch size 32 and learning rate 3e-5.

5.2 Fine-tuning TransQuest

We fine-tune from TransQuest DA en-to-any,[3] which is based on XLM-RoBERTa-large with a standard classification head on top of the encoder.

5.3 Fine-tuning CometKiwi

CometKiwi[4] is based on InfoXLM-large (Chi et al., 2021) (XLM-RoBERTa-large architecture) with layer-wise attention and a specialized classification head, called the "Estimator" (three linear layers with tanh activation in between). Crucially, we closely match CometKiwi's architecture, including layerwise attention with dropout, gamma scaling of layer mix, and inputting the *target first*, i.e. `[cls] target [sep] source [eos]`. We unfreeze the full Estimator head and layerwise attention for the parameter-efficient methods: for LoRA, we configure this via `modules_to_save`. For BitFit and FTHead, we explicitly unfreeze them in our code.

6 Fine-tuning Results

As shown in Table 3 (column "Test"), full fine-tuning fails to improve TransQuest, and degrades CometKiwi by 2-3 percentage points. However, the parameter-efficient methods LoRA, BitFit, and FTHead improve both TransQuest and CometKiwi by 2-3 percentage points. LoRA and BitFit are generally on par, with FTHead slightly behind.

For each method, we plot the score distribution of TransQuest on the test set before and after fine-tuning (for seed 0), plus the learning curve (memorization of train data vs. generalization to validation data), all in Figure 3. We further show the progres-

[3] HuggingFace: TransQuest/monotransquest-da-en_any
[4] HuggingFace: Unbabel/wmt22-cometkiwi-da

Model	All (n=959) Pearson	All (n=959) Spearman	Test (n=559) Pearson	Test (n=559) Spearman
Single Baseline Model				
ChatGPT-freestyle [GPT-f]	0.4266	0.5018	0.4136 ± 0.0157	0.5020 ± 0.0105
ChatGPT-guidelines [GPT-g]	0.4256	0.5074	0.4119 ± 0.0158	0.5087 ± 0.0097
TransQuest-multilingual	0.3759	0.4303	0.3608 ± 0.0325	0.4235 ± 0.0336
TransQuest-en-any [TQ]	0.4327	0.4501	0.4205 ± 0.0359	0.4537 ± 0.0375
CometKiwi [CK]	**0.4828**	**0.5456**	**0.4495** ± 0.0179	**0.5305** ± 0.0176
Ensemble Baseline Models				
Ensemble(GPT-f, TQ)	0.5028	0.5622	0.4876 ± 0.0206	0.5608 ± 0.0130
Ensemble(GPT-f, CK)	0.5211	0.5929	0.4992 ± 0.0161	0.5798 ± 0.0101
Ensemble(TQ, CK)	0.5081	0.5459	0.4810 ± 0.0240	0.5390 ± 0.0274
Ensemble(GPT-f, TQ, CK)	**0.5472**	**0.6014**	**0.5250** ± 0.0197	**0.5926** ± 0.0146
Fine-Tune TransQuest-en-any [TQ]				
TQ+FullFT	–	–	0.4287 ± 0.0230	0.4608 ± 0.0295
TQ+LoRA	–	–	**0.4445** ± 0.0354	**0.4828** ± 0.0390
TQ+BitFit	–	–	0.4424 ± 0.0344	0.4799 ± 0.0394
TQ+FTHead	–	–	0.4358 ± 0.0351	0.4718 ± 0.0368
Fine-Tune CometKiwi [CK]				
CK+FullFT	–	–	0.4236 ± 0.0482	0.5034 ± 0.0325
CK+LoRA	–	–	0.4670 ± 0.0141	**0.5554** ± 0.0138
CK+BitFit	–	–	0.4647 ± 0.0140	0.5551 ± 0.0136
CK+FTHead	–	–	**0.4693** ± 0.0134	0.5449 ± 0.0137

Table 3: Main results: Pearson and Spearman correlation of baseline, ensembled, and fine-tuned models against ground truth. The column "All" is on the full dataset. For "Test", we report the mean ± standard deviation across the 5 seeded splits. The best result in each column and each section is bolded.

sion of the score distribution on the validation data across epochs in Figure 5 (Appendix A).

FullFT shows signs of overfitting and distribution collapse (in Figure 3(a), middle, the points are more spread out than the baseline), which could explain why FullFT does not improve on the test set. However, the parameter-efficient methods show stable learning and modest distribution shifts, consistent with their improvements on the test set.

7 Conclusions

We prepare, benchmark, and release MTQE.en-he, the first publicly available dataset for English-Hebrew Machine Translation Quality Estimation. While ChatGPT prompting, TransQuest, and CometKiwi are strong baselines, there is room to improve. Light-weight fine-tuning (LoRA, BitFit, FTHead) of TransQuest and CometKiwi on 300 samples from our data improves Pearson and Spearman by 2-3 percentages points. Future work can explore methods to improve the prediction quality including synthetic data generation, cross-lingual transfer, and calibration. We hope that our work will unlock and inspire further research on low-resource language systems, to benefit humanity.

Limitations

MQM (Multidimensional Quality Metrics) are known to be superior to DA scores (Graham et al., 2017). Due to budget constraints, we were limited to DA for this work, which we still find useful.

We use the same set of hyperparameters for all fine-tuning methods, which may not be optimal.

Our translations come from one system (Google Translate), which may limit generalization.

The modest dataset size (n=959) and high score distribution limit the number of low-score samples. Future work can develop larger and more diverse datasets to advance MTQE research for English-Hebrew and other low-resource language pairs.

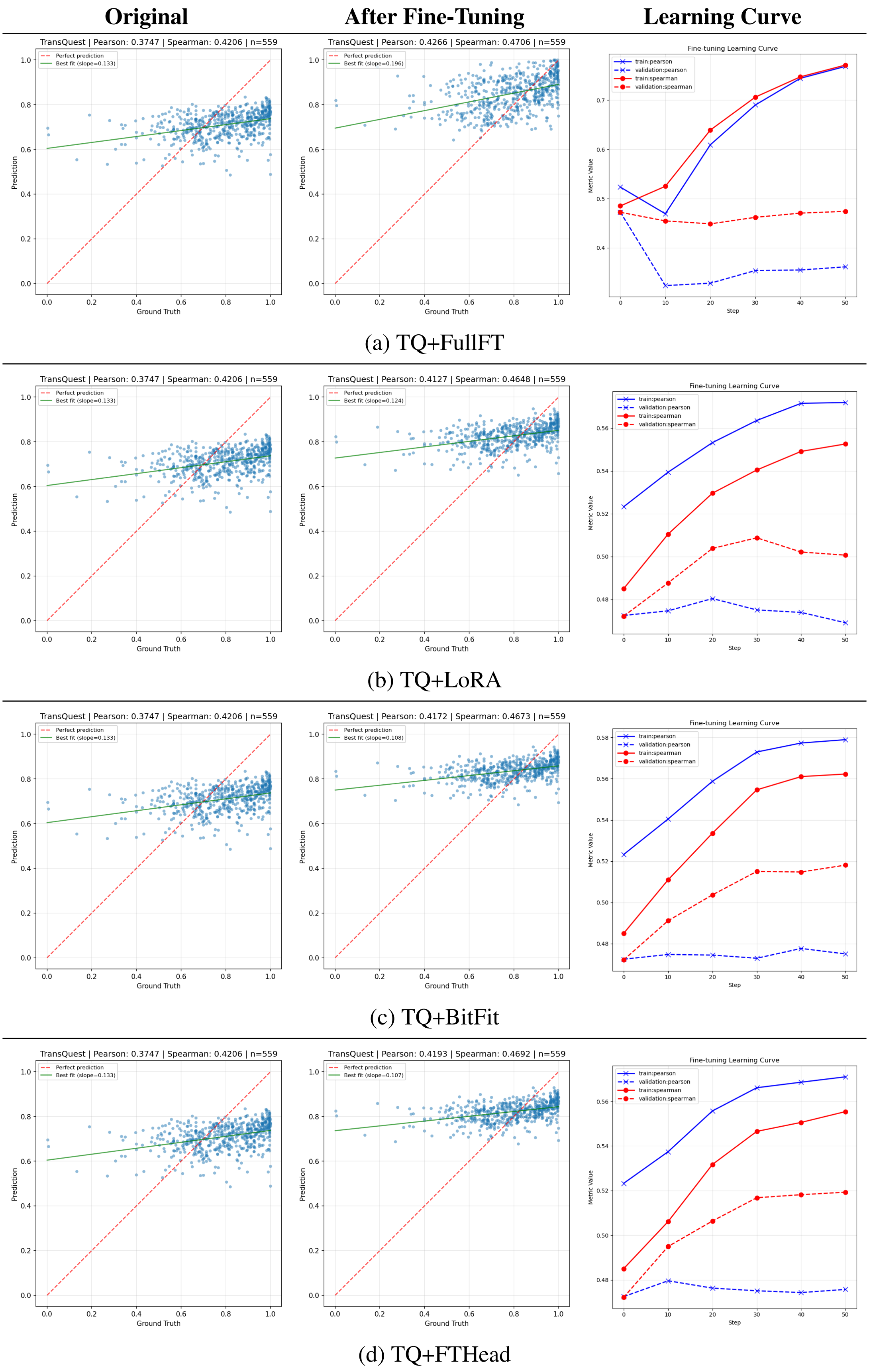


Figure 3: Visualization of effects of fine-tuning methods (seed 0). Each row represents the specified fine-tuning method. Left: baseline TransQuest scatter plot on test set (n=559), the same for each row. Center: best checkpoint scatter plot on the same test set. Right: learning curve on train and validation during fine-tuning.

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A TransQuest Learning Dynamics

Figure 4 shows the baseline TransQuest score distribution on the validation set (seed 0). As we fine-tune this TransQuest model using each of the four methods (FullFT, LoRA, BitFit, and FTHead), we show in Figure 5 how the score distribution on the validation set evolves over each epoch.

Notbaly, in FullFT, the distribution collapses after the first epoch to be nearly flat, then disperses into inconsistency in later epochs. By contrast, the parameter-efficient methods train smoothly with small and consistent distribution shifts.

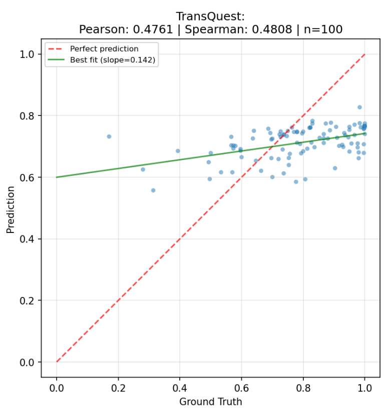


Figure 4: Baseline TransQuest Scores on validation set (seed 0). Starting point for fine-tuning plots in Figure 5.

B Inter-model Correlation

To better understand the baseline models, we show the correlation between their predictions in Figure 6. ChatGPT with and without the guidelines produces nearly identical scores, as shown on the left (Figure 6a), with Pearson correlation 0.9933. TransQuest and CometKiwi predictions differ somewhat more (Figure 6b) with a Pearson of only 0.6444. In particular, there is a cluster of samples where both models predict a high range (0.8 to 0.9), and they diverge more where one or the other predicts a lower score. Finally, as shown on the right (Figure 6c), ChatGPT and CometKiwi have moderate Pearson correlation of 0.4581.

C Validation and Test Set Distribution

We show the score distribution for train (n=300), validation (n=100), and test (559) for seed 0 in Figure 7. Comparing to Figure 1, we see that each slice has a similar distribution to the full dataset, with slight differences due to the small sample size.

D Influence of segment length

As shown in Figure 8, the mean score label is slightly negatively correlated to segment length (Pearson -18.21 and Spearman -0.2964 – i.e., longer segments tend to have lower scores), yet the plot shows also many short segments with low scores.. As expected from Google Translate which is a high quality translation system, the Hebrew length is highly positively correlated with the English length (Pearson 0.9900 and Spearman 0.9899). The Hebrew translation tends to have fewer words than English (0.773 slope of best fit line), a result of Hebrew's complex morphology which contributes to the difficulty of our task.

E Fine-tuning Hyperparameters

We show our fine-tuning hyperparameters in Table 4. We use the same hyperparameters for all four fine-tuning methods.

Parameter	Value
Peak Learning Rate	3e-5
Learning Rate Schedule	10% warmup, linear decay to 0
Batch Size	32
Max Num Steps	50
Eval Every Steps	10
LoRA r	8
LoRA alpha	16
LoRA dropout	0.1
LoRA modules	query, key, value

Table 4: Fine-tuning hyperparameters

F Test Results for Each Seed

We provide the test results for each seed in Table 5 (Pearson) and Table 6 (Spearman).

model	seed=0	seed=1	seed=2	seed=3	seed=4	mean	stdev
ChatGPT-freestyle [GPT-f]	0.3968	0.4190	0.4318	0.3977	0.4229	0.4136	± 0.0157
ChatGPT-guidelines [GPT-g]	0.3946	0.4159	0.4309	0.3967	0.4212	0.4119	± 0.0158
TransQuest-multilingual	0.3093	0.3647	0.3561	0.3960	0.3780	0.3608	± 0.0325
TransQuest-en-any [TQ]	0.3747	0.3926	0.4471	0.4291	0.4592	0.4205	± 0.0359
CometKiwi [CK]	0.4300	0.4347	0.4492	0.4608	0.4730	0.4495	± 0.0179
Ensemble(GPT-f, TQ)	0.4600	0.4837	0.5123	0.4791	0.5030	0.4876	± 0.0206
Ensemble(GPT-f, CK)	0.4780	0.4960	0.5117	0.4919	0.5183	0.4992	± 0.0161
Ensemble(TQ, CK)	0.4515	0.4611	0.4911	0.4917	0.5097	0.4810	± 0.0240
Ensemble(GPT-f, TQ, CK)	0.4979	0.5173	0.5435	0.5213	0.5449	0.5250	± 0.0197
TQ+FullFT	0.4266	0.3944	0.4319	0.4317	0.4591	0.4287	± 0.0230
TQ+LoRA	0.4127	0.4027	0.4688	0.4543	0.4842	0.4445	± 0.0354
TQ+BitFit	0.4172	0.3978	0.4636	0.4514	0.4820	0.4424	± 0.0344
TQ+FTHead	0.4193	0.3944	0.4630	0.4216	0.4806	0.4358	± 0.0351
CK+FullFT	0.3451	0.4347	0.4183	0.4470	0.4731	0.4236	± 0.0482
CK+LoRA	0.4535	0.4597	0.4583	0.4771	0.4865	0.4670	± 0.0141
CK+BitFit	0.4495	0.4573	0.4573	0.4790	0.4802	0.4647	± 0.0140
CK+FTHead	0.4526	0.4617	0.4663	0.4816	0.4843	0.4693	± 0.0134

Table 5: Test (n=559) results across random seeds for data split: Pearson Correlation against ground truth.

model	seed=0	seed=1	seed=2	seed=3	seed=4	mean	stdev
ChatGPT-freestyle [GPT-f]	0.4877	0.5151	0.4961	0.5038	0.5072	0.5020	± 0.0105
ChatGPT-guidelines [GPT-g]	0.4952	0.5219	0.5055	0.5116	0.5092	0.5087	± 0.0097
TransQuest-multilingual	0.3754	0.4233	0.4090	0.4583	0.4516	0.4235	± 0.0336
TransQuest-en-any [TQ]	0.4206	0.4063	0.4724	0.4812	0.4881	0.4537	± 0.0375
CometKiwi [CK]	0.5416	0.5023	0.5307	0.5294	0.5483	0.5305	± 0.0176
Ensemble(GPT-f, TQ)	0.5463	0.5484	0.5634	0.5711	0.5750	0.5608	± 0.0130
Ensemble(GPT-f, CK)	0.5781	0.5696	0.5804	0.5744	0.5963	0.5798	± 0.0101
Ensemble(TQ, CK)	0.5320	0.4966	0.5441	0.5524	0.5697	0.5390	± 0.0274
Ensemble(GPT-f, TQ, CK)	0.5868	0.5724	0.5963	0.5950	0.6124	0.5926	± 0.0146
TQ+FullFT	0.4706	0.4119	0.4571	0.4770	0.4875	0.4608	± 0.0295
TQ+LoRA	0.4648	0.4225	0.5024	0.5099	0.5146	0.4828	± 0.0390
TQ+BitFit	0.4673	0.4172	0.4929	0.5091	0.5131	0.4799	± 0.0394
TQ+FTHead	0.4692	0.4119	0.4918	0.4768	0.5093	0.4718	± 0.0368
CK+FullFT	0.5197	0.5023	0.4649	0.4820	0.5483	0.5034	± 0.0325
CK+LoRA	0.5691	0.5360	0.5512	0.5523	0.5684	0.5554	± 0.0138
CK+BitFit	0.5686	0.5364	0.5492	0.5530	0.5681	0.5551	± 0.0136
CK+FTHead	0.5571	0.5247	0.5425	0.5420	0.5582	0.5449	± 0.0137

Table 6: Test (n=559) results across random seeds for data split: Spearman Correlation against ground truth.

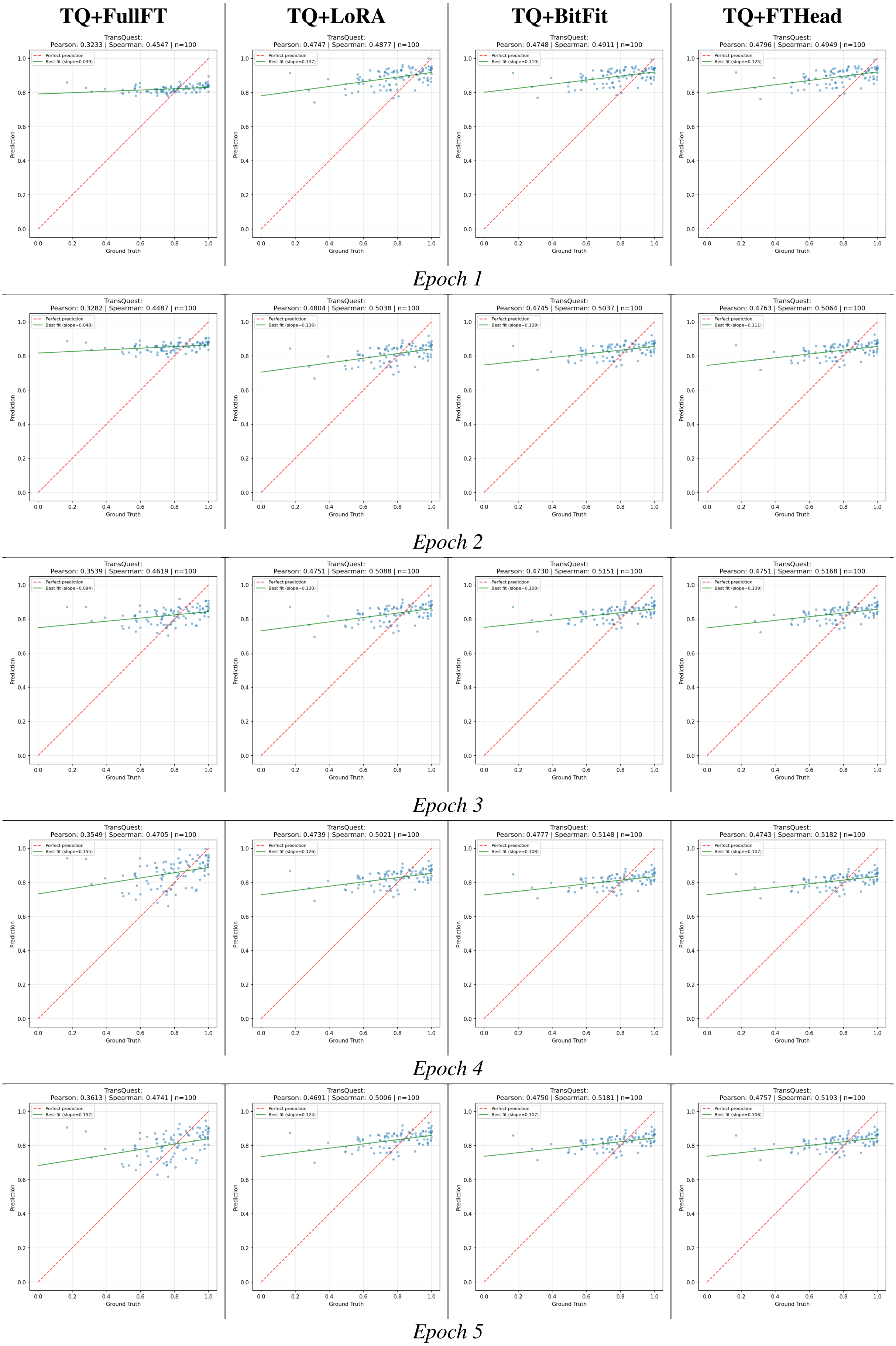
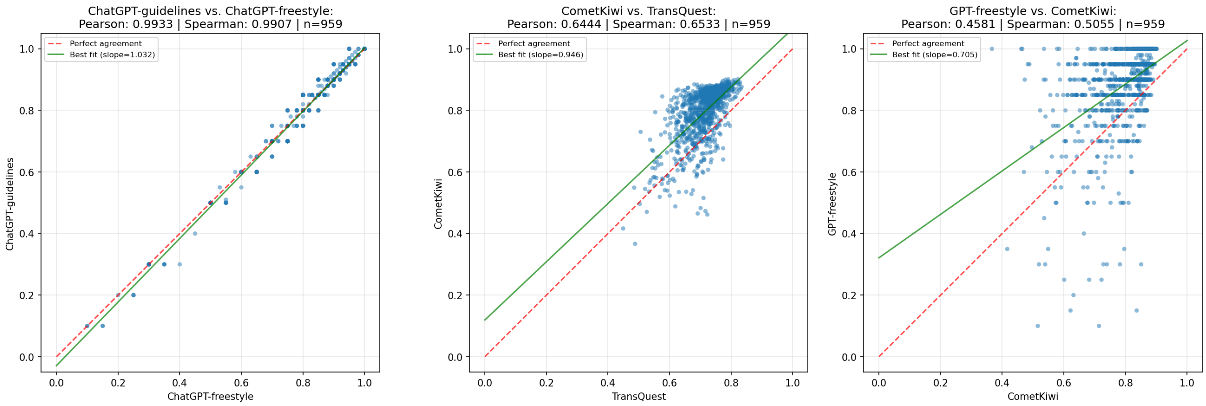
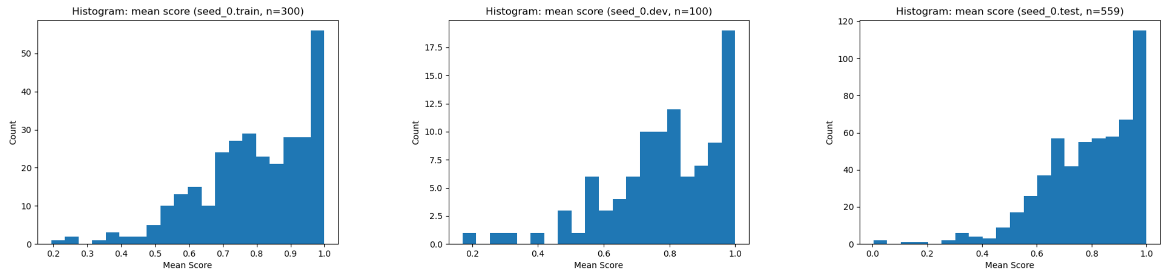


Figure 5: Scatter plots of predicted vs. truth score of fine-tuning methods across epochs. The plots are on the validation set for seed 0 runs. Rows correspond to epochs; columns correspond to fine-tuning strategies.



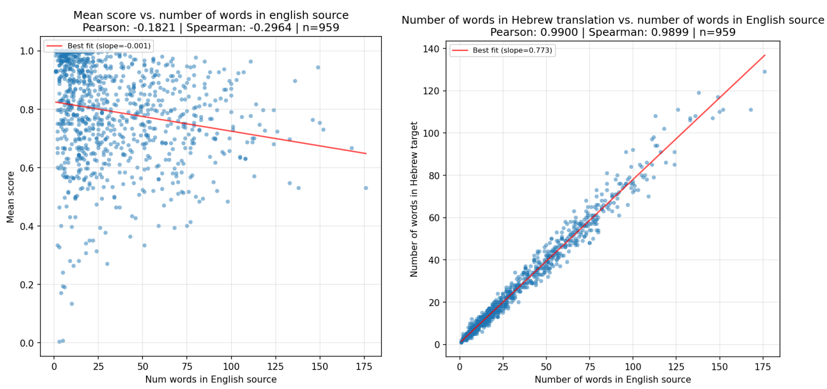
(a) ChatGPT: guidelines vs. freestyle (b) CometKiwi vs. TransQuest (c) ChatGPT-freestyle vs. CometKiwi

Figure 6: Inter-Model Correlation of baseline models' hypotheses on the full dataset.



(a) Train (n=300) (b) Validation (n=100) (c) Test (n=559)

Figure 7: Score distribution on dataset slices (seed 0). Left: Train, Center: Validation, Right: Test.



(a) Annotator mean score vs. length. (b) Hebrew length vs. English length.

Figure 8: Influence of source segment length on score distribution and translation length (full dataset).

G ChatGPT Prompt and Annotation Guidelines

Direct Assessment Annotation Instructions (Official Standard)

Task
You will evaluate the quality of a translation by reading the original source sentence and the machine-translated output.
Your goal is to judge how accurately and fluently the translation conveys the meaning of the source.

What to do
For each item:
1. Read the source sentence.
2. Read the translation.
3. Rate the translation on a scale from 0 to 100, where:
- 0 = completely incorrect or nonsensical
- 100 = perfect translation
4. Always give a score (don't leave empty)

Detailed Guidelines
- Consider adequacy (meaning correctness) and fluency (natural and grammatical language).
- Your score should reflect both aspects.
- If the translation is generally correct but contains some errors, deduct points proportionally.
- If the meaning is wrong—even if the text is fluent—the score must be low.
- URLs, Emails, hashtags, etc. – should remain untouched by the translation machine.
- Do not attempt to correct the translation.
- Do not compare with other translations.
- Do not use external tools or references.

Scoring guide (use the entire scale)
0–10 Wrong meaning or incomprehensible
11–29 Some words match but overall meaning incorrect
30–50 Understandable but contains major errors
51–69 Mostly correct meaning; noticeable issues
70–90 Good translations with minor issues
91–100 Excellent or perfect

Quality Control
You will occasionally see:
- High-quality human references
- Synthetic translations containing obvious errors
Please annotate these items normally. They help us track annotation quality.

Important
- Work carefully and consistently.
- If unsure, choose the closest score—avoid always picking the same region.
- You may take breaks.
- All your responses are confidential.