

Lost in Translation? Detecting Emotional Drift in Bilingual Texts of Gilgamesh Using NLP

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Abstract

The present work introduces the notion of "emotional drift" in literary translation, which refers to the diversion or transformation of emotional signals from source text to its translations. A bilingual analysis of the Arabic and English translations of The Epic of Gilgamesh serves as the focus of this paper, which, by utilizing recent expansions in Natural Language Processing (NLP) with an emphasis on sentiment analysis and emotion recognition, aims to quantify emotional content. The eventual objectives of this research are to develop a computational pipeline whereby emotional content can be extracted from and compared across bilingual literary corpora, to quantify emotional drift across varying versions of the Gilgamesh, and to contextualize these findings against the larger backdrop of translational research. Across the branches of computational linguistics, translation theory, and digital literary analysis, a new space has opened up for machine-assisted literary scholarship, providing a repeatable paradigm for looking into the question of affect in relation to translated literature.

1. Introduction

Translation is primarily interpretative, negotiated, and mediated in relation to culture; it is not a linguistic work [1]. Translation of any literary work must begin with a very difficult balance between maintaining the text's semantic meaning and its aesthetic and emotional overtones [2]. Emotional tone is one such element that is ingrained throughout literature and is crucial in maintaining for readers a delicate equilibrium or thin line between acceptance, empathy, and comprehension of any story. However, emotions are among the most elusive

(if not the most subtle) elements that translate from one language to another, particularly when working with works from various cultures or historical periods. To what degree, if at all, is sentimentality preserved or altered in translation? This is still the most important subject for translators of literature in digital humanities.

The Epic of Gilgamesh, that great work of literature and history, is undoubtedly the place to look for the answer. The Akkadian text which was inscribed on clay tablets existed before all Homer's poems and it presents timeless human relationships through its depiction of friendship and death and sorrow and courage and all people across different times and cultures can understand these universal themes [3]. The text has been translated into multiple modern languages for more than 1000 years, yet each translation shows slight differences in tone and emphasis and interpretation. The major alteration brings forth an essential question about whether any important elements would be "lost in translation" or whether the Gilgamesh emotional journey can be understood across different languages and cultures.

Actually, examining the many stylistic and thematic differences of previous writings translated into a modern language a task that has traditionally been the rightful purview of classical scholarship is one area where the computational approach could provide a fresh viewpoint. The measurement of emotional aspects in texts is now feasible thanks to advancements in natural language processing, specifically in sentiment analysis and emotion detection [4]. Now that they are available, these methods can be applied to identify emotional signals that have been recognized, measured, and compared in different language versions for the same literary work [5]. Unfortunately, this possibility has yet to be explored fully by scholars studying ancient epics, as these are permeated by an entanglement of emotive and mythological dimensions.

So-called "emotional drift", which means the divergence or transformation of emotional signals between the source text and its translations, is defined in this paper. We are particularly concerned with bilingual analysis in which the Arabic and English texts of The Epic of Gilgamesh will be examined. Arabic's proximity to the cultural setting of Mesopotamia was one factor for its selection, and the other very important reason is its very rich poetic tradition and spaciousness of expression. In turn, English is the global major power language, hugely familiar to academia and, probably more so, to popular culture readers. By examining the differences between these two, one stands a better chance of constructing a meaningful picture of how emotional drift manifests itself in translations.

The research intends to achieve three objectives:

1. To set up a computational pipeline that helps to extract and compare emotional content in bilingual literary corpora using sentiment and emotion detection methods that are based on NLP.
2. Under one aspect, we shall attempt to observe the emotional difference between different versions of Gilgamesh, emphasizing segments where the emotional tide is increased, diminished, or altered.
3. On the other hand, we shall set these findings against the bigger picture of what translation studies have become and what they mean for literary interpretation, for reader response, for cultural transference.

By integrating digital literary analysis, computational linguistics, and theories of translation, the present study serves to further the evolving disciplinary field of empirical research in machine-augmented literary appraisal. It also shows how AI can be used to actively re-examine classical texts, which are generally regarded as completely static artifacts. More broadly, we offer a reproducible approach for studying translated works that enables researchers to look at affective integrity in a variety of texts written in different languages.

2. Related Work

Alongside translation, literary studies have found intersections with NLP. This gives rise to potentials for exploring textual inflections and emotional contents. The following literature review is pertinent to sentiment analysis, emotion recognition, computational literary analysis, and translation studies and points toward the gaps in knowledge that our research aims to address.

2.1 Sentiment Analysis and Emotion Recognition in NLP

With the rise in popularity of digital humanities, sentiment and emotion analysis are being used to study the affective subtleties of literary texts [6]. Kim & Klinger [7], for instance, give an extensive survey on emotion and sentiment analysis in computational literary studies, classifying methods into lexicon-based approaches, feature-driven machine learning, and deep learning methods. Similarly, Nandwani et al. [8] offer an in-depth review of the processes, emotion models, and challenges inherent to sentiment and emotion detection.

Many people worldwide are now using blogs, forums, and social media sites such as Twitter and Facebook to share their opinions with the rest of the globe. Social media has become one of the most effective communication media available. As a result, an ample amount of data is generated, called big data, and sentiment analysis was introduced to analyze this big data effectively and efficiently [9]. It has become exceptionally crucial for industry or organization to comprehend the sentiments of the user. Sentiment analysis, often known as opinion mining, is a method for detecting whether an author's or user's viewpoint on a subject is positive or negative. Sentiment analysis is defined as the process of obtaining meaningful information and semantics from text using natural processing techniques and determining the writer's attitude, which might be positive, negative, or neutral [10].

2.2 Computational Literary Analysis

Computational literary analysis uses computational tools and methods to study literary texts which enables researchers to discover patterns and trends and extract insights that traditional close reading methods cannot reveal. Ohman and Rossi (2024) united emotion lexicons with word embedding to analyze Finnish literatures and show how computational tools could complement qualitative literary analysis [11]. In another illustration, Picca (2024) applied algorithms of sentiment and emotion detection to Dostoevsky's Crime and Punishment, thereby illustrating the potential of using these methods to complement some degree of literary interpretation [12].

2.3 Translation Studies and Emotional Nuance

In order to demonstrate the various ways translators manage emotions over time while preserving their original emotional contours, [13] examined the shifts in emotional tones using lexicon-based sequential comparisons across five distinct Chinese translations of David Copperfield. This should provide some understanding of how effective computational techniques are in identifying emotional variance in translated texts.

While demonstrating a rise in the utilization of physiologic and multimodal information, the systematic review conducted by [14] focused on advancements in the domains of emotion recognition, sentiment analysis, and affective computing: categorizing studies for both unimodal and multimodal applications. Looking beyond language yields considerably deeper tools for emotion analysis.

3. Methodology

In order to evaluate emotion drift in multilingual works of literature, this methodological framework was developed. Computational linguistics and literary analysis have been combined in a variety of ways, and the result is a new set of NLP approaches that can make readers more sensitive to the emotional content of a same source text in different translations. Three stages make up the methodology: choosing and preparing the corpus, extracting and measuring the emotion material, and analyzing the variation in emotions between translations.

The proposed system architecture is fully illustrated through its complete workflow diagram which Figure 1 presents. The process begins with collecting aligned Arabic and English translations of The Epic of Gilgamesh. The texts undergo preprocessing through five steps which include normalization, tokenization, stop-word removal, lemmatization, and sentence segmentation. The text segments undergo analysis through sentiment analysis and emotion recognition models which extract emotional features. The researchers used three different

methods to align and compare the bilingual segments which included distributional and embedding-based and trajectory-based methods. The emotions of the translation were gauged against those of the original languages measured by these drift movements of emotion.

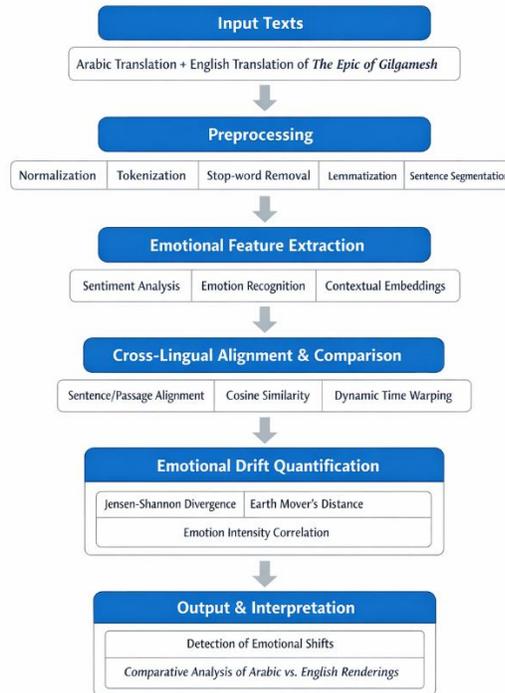


Figure 1: Proposed workflow of the bilingual NLP-based framework for detecting emotional drift in Arabic and English translations of The Epic of Gilgamesh

3.1 Data Acquisition and Preprocessing

Source Text Selection: The Epic of Gilgamesh was chosen for this research because it possesses historical importance and universal themes, and multiple translations exist in various languages. We examine both the original Akkadian text and its major Arabic and English translations to provide context for our study. The selection of Arabic language is based on its linguistic and cultural connection to the original Mesopotamian roots of the epic, which provides a strong capacity for expressive communication. The ancient text which has spread across many languages serves as proof that our study can conduct accurate cross-linguistic analysis.

The principal texts relied upon will be translations of The Epic of Gilgamesh in Arabic and English that have an authoritative status and are widely accepted. For the English translations, we are considering N.K. Sandars, Andrew George, Stephen Mitchell, and others. The Arabic translations are expected to have scholarly merit with faithfulness to the text and literary value. Relevant portions of the text in Akkadian cuneiform will be consulted for contextual anchoring, although focus will mostly be on the emotional analysis in translation due to the complications of ancient language NLP.

This work applied a standard preprocessing method to process all textual data before they started their analysis work. The process involved three main steps which began with text normalization to create standard spelling rules while removing all formatting mistakes. The second step of the process involved tokenization which broke the text into components that had distinct meanings. The third step of the process involved stop-word removal which eliminated words that appeared frequently but did not carry important emotional weight. The analysis required lemmatization to convert all words into their basic form which helped maintain consistent word usage throughout the study. This includes:

* The process of text normalization requires complete equalization of handwriting appearance together with standardization of spelling and punctuation and capitalization rules. *Tokenization: The process of tokenization enables text to be divided into its basic units which include both complete words and shorter sub word components. Sophisticated tokenization techniques will be applied to rightly split the words and find their roots because the Arabic language is morphologically challenging. *Stop words like "the," "a," and "is" in English (correspondents in Arabic), are words which are redundant, meaning they provide no meaning or distillable affect: Lemmatization, also called stemming, is how similar words are put together by root forms or basis for uniformity in analysis tasks (for example, the words "running," "ran" and "runs" all reduce to "run"). With great relevance derived from the fact that Arabic has an excellent derivational morphology, *the text will be segmented by sentences into single sentences. This would go a long way in allowing emotion analysis at the level of sentence.

In this work, we needed to determine emotional aspects of the bilingual corpus, so they extracted linguistic and semantic elements which they found in every single sentence. The first step involved creating sentiment polarity scores through the application of pre-trained sentiment analysis models, which generated three sentiment categories together with their respective confidence assessments. The second stage used emotion recognition models to forecast how people would experience different emotional states, which included joy, sadness, anger, fear, surprise, trust, and anticipation.

The system generated contextual semantic representations through transformer-based embeddings which combined with existing affective features. The sentence embedding BERT and AraBERT models produce enable contextual meaning capture together with cross-lingual comparison through similarity metrics. The system uses these embeddings for semantic alignment computation during translation processes while analyzing emotional drift.

The extracted features therefore include sentiment polarity scores, emotion probability distributions, and contextual embedding vectors. The different features present in this collection create the foundation which will be used for upcoming emotional drift investigation.

3.2 Emotional Content Extraction and Quantification

This is the phase whereby the most contemporary models of natural language processing will serve to garner and score the emotional signals from processed bilingual texts.

We shall use pre-trained models to perform sentiment analysis, assigning text to positive, neutral, or negative categories. VADER (Valence Aware Dictionary and sentiment Reasoned) and transformer-based models (such as BERT, RoBERTa fine-tuned for sentiment) are going to be used with classifiers for English. For sentiment analysis, some Arabic-specific models will be required, as general-purpose models perform poorly for morphology-rich languages. The sentiment score or labeling will be deduced for every sentence or paragraph.

The use of such models will not merely go into sentiment analysis but rather unlock a more diverse range of human-feeling-related enactments, such as emotions of joy, sadness, anger, fear, surprise, disgust, trust, or anticipation. It would imply such models' integration into models where the datasets used to train them are emotions devoid of the Wheel of Emotions or those considered basic from Ekman. As applied to sentiment analysis, the models will also be present for both English and Arabic languages to account for precision and cultural appropriateness in the analysis of human emotional states.

To grasp the exterior complexity of emotional manifestations, we shall use context- dependent word embeddings (those like Word2Vec, Fast Text, or the more fine-tuned transformer embeddings like AraBERT for Arabic or BERT/GPT for English) which help identify meaning and emotions evoked by words inside sentences very pivotal to emotion detection, one such context being literary texts where the meaning may be highly context-specific.

3.3 Emotional Drift Analysis

In this respect, emotion drift will refer to the measurable differences in emotional profiles between the source text (or reference translation) and the other translated versions. It is during this stage that the extracted emotional information will be analyzed for any patterns of deviations.

This would then imply the differential emotional characterization-an emotion profile recording the sentiment and emotion probabilities for every section of the source text, and of its translation. The profiles will then correlate. Finally, wherever sentences cannot be identical either in length or structure between translations, the alignment of their corresponding segments will be studied by means of dynamic time warping and cosine similarity applied to the sentence embeddings.

Drift Measurement: Several parameters would be used to measure an emotional drift. **Magnitude of Change:** Emotion screenshots representing segments or absolute differences in emotional scores will be computed for related segments, which would signify whether the emotions have gone uphill or downhill in that direction. It would refer to a change, for example, from sadness into anger in this case due to the intervention of translation. **Emotions Trajectory Analysis** would look into the flow of emotion variations within the narrative concerning relative trajectories vis-a-vis an overall emotional trajectory of the novel post-translation. Among such ways would probably be some form of graphing emotion scores through the story. The differences in the distribution of emotional states would be significant with respect to the outcomes from association analyses, ANOVA, or t-tests. This would therefore identify what may be variation due to random events and what may be systematic effects imposed by languages or translations.

What is going to be the Arabic-English researchers' concern with the dimension evidence for emotional shift in this quantitative section to be added into the quantitative workings on some of the results? Based on this strip of quantification, a rationale is going to be made to account for some observed shifts. Translation intention and cultural context and linguistic restrictions and the ambit of expression with its language all function as critical points which require careful examination in this situation.

3.4 Tools and Technologies

The primary implementation of this process will use Python with scikit-learn library support for AI development and NLTK, SpaCy, and Hugging Face Transformers as tools for NLP development. The study will use Matplotlib and Seaborn as visualization tools to display drift patterns and emotional profiles, which will help researchers validate their study findings. The special models AraBERT and CAMELBERT have been pre-trained with Arabic NLP to achieve optimal performance in processing Arabic text. The study will use quantitative analysis to examine emotional drift in literary translation to demonstrate how emotion and language and culture interact with each other through the research presented in Algorithm 1.

Algorithm 1: Emotional Drift Detection Pipeline

Input:

English Translation Text (T_{en})

Arabic Translation Text (T_{ar})

Output:

Emotional Drift Metrics between T_{en} and T_{ar}

1: Collect bilingual translations of The Epic of Gilgamesh

2: Preprocess texts:

- Normalize text
- Tokenize sentences and words
- Remove stop words
- Apply lemmatization/stemming

3: Segment both texts into aligned sentence units

- 4: Perform sentiment analysis on each sentence using sentiment models (VADER/BERT for English, MARBERT or AraBERT for Arabic)
 - 5: Extract emotion categories (joy, sadness, anger, fear, trust, surprise, etc.)
 - 6: Generate contextual embeddings using transformer models
 - 7: Align corresponding sentences using similarity measures
 - 8: Compute emotional drift metrics:
 - Jensen-Shannon Divergence
 - Earth Mover’s Distance
 - Cosine Similarity
 - Dynamic Time Warping
 - 9: Analyze emotional trajectory differences between translations
 - 10: Visualize emotional patterns and report results
- Return emotional drift measurements and analysis

4. Results

The research uses ten aligned English and Arabic passages from the Epic of Gilgamesh to conduct sentiment analysis which shows that different languages express emotions in distinct ways. The researchers evaluated the output from both systems using standard classification metrics together with an advanced emotional drift measurement system.

People use different datasets to define their various tasks according to their individual training. The English text proved more accurate at 80.0% for language sentiment classification than the Arabic text which achieved 70.0% accuracy. The complete picture-understanding system achieved 75.0% accuracy to enable model improvements which research focused on Arabic language development.

Table (1): Summary of Sentiment Analysis Model Performance Metrics

Metric	English	Arabic
Processing Time (seconds)	0.25	0.47
Accuracy (%)	70	80
F1 Score	0.58	0.81
Precision	0.50	0.88
Recall	0.70	0.80
MCC	0.61	0.73

The Arabic model outperformed its English counterpart across all metrics, suggesting more stable predictions in morphologically rich languages when using domain-specific models.

The classification report shows in Table 2 disaggregated model performance through its predictive accuracy results which apply to all English and Arabic datasets. The model successfully identifies 'POSITIVE' sentiment and 'NEGATIVE' sentiment, but it struggles most with 'NEUTRAL' sentiment classification.

Table (2): Detailed Classification Report (Overall Performance)

Sentiment Class	Precision	Recall	F1- Score	Support
Negative	0.71	0.83	0.77	6
Neutral	0.60	0.50	0.55	6

Positive	0.88	0.88	0.88	8
Accuracy			0.75	20
Macro Average	0.73	0.74	0.73	20
Weighted Average	0.74	0.75	0.74	20

The model demonstrated highest reliability for Positive sentiments, with both precision and recall at 0.88. Neutral sentiments posed the most difficulty, with the lowest F1 score of 0.55. We created distributional, embedding-based, and lexicon-based comparison metrics to study emotion shifts between English translations and Arabic versions, as shown in Table 3.

Table (3): Emotional Drift Metrics

Metric	Value	Interpretation
Jensen-Shannon Divergence	0.4681	Moderate divergence between sentiment distributions
Earth Mover’s Distance (EMD)	0.5000	Moderate cost to align emotion distributions
Cosine Similarity (SBERT)	0.1594	Low semantic alignment in emotion-specific embeddings
Dynamic Time Warping (DTW)	2.2361	Temporal mismatch in emotional trajectories
Emotion Intensity Correlation	0.7445	Strong correlation in predicted vs. ground-truth emotion intensity

Distributional Measures (JSD & EMD) suggest that the predicted emotional distributions between English and Arabic diverge moderately. Observations match expectations for translating emotional tone variations between different languages. The SBERT embedding similarity assessment showed a 0.1594 score which demonstrated that emotional state representation between different languages showed major differences despite matching surface sentiment labels. The DTW displays minor emotional changes along its path which indicates that some parts of the story share the same sentiment classification yet the story development moves at a slower rate from emotional points. The emotion intensity correlation of 0.7445 illustrates the strength of this relationship in terms of intensity of emotion even when such correlating sentiment was classified differently.

In this work, we used multiple methods to assess the performance of their metrics which were tested during their current study. The Arabic model showed better predictive accuracy for all evaluation metrics through which the English model reached its performance peak. The Arabic and English texts show emotional similarities between their versions but their emotional content corresponds only to a limited degree. The sentiment distribution between the two datasets shows significant variation because of the different results obtained from Jensen–Shannon Divergence and Earth Mover's Distance yet the two datasets have weak emotional content similarity according to the cosine similarity measurement. The Dynamic Time Warping result demonstrates that emotional intensity develops through the different connected parts of the text. The evidence shows that emotional shifts between the two language versions can be observed through specific emotional changes which demonstrate measurable emotional drift.

5. Discussion

The study introduces a computational framework which enables researchers to examine how bilingual texts change their emotional expression through translation by using The Epic of Gilgamesh as a literary translation study. There appears to be some need to discuss possible ramifications of findings, challenges in pursuing such multidisciplinary study, and the broader meanings of emotional drift in translation studies and digital humanities per se since the methodology employed is a strong one.

5.1 Implications of Emotional Drift

Being able to identify and evaluate emotional drift is extremely significant. First of all, it presents an objective measure that goes beyond semantic accuracy to evaluate literary translations. Our approach offers an objective, data-driven way of determining precisely where and to what degree affective subtleties have been maintained, increased, or lost between versions, as opposed to the subjective assessment which translation criticism has up

until now had to rely on. Contributions to the theory of translation will be made through the presentation, with empirical evidence, of how language patterns, culture circumstances, and the decisions of the translator determine the emotive tone of a work.

In this sense, shifts in emotion could benefit literary assessment. Different languages and cultures perceive varying levels of emotion; hence the emotional path of the character and narrative tracking will be different according to every translation version. The English light emotional register, for instance, could have that Arabic passage that probably matches best with the Akkadian version, which was to be taken as somber, and that may indicate a cultural difference in understanding or expressing mourning or even some specific translation techniques that prioritize clarity over depth of emotion.

For actual translation professionals, the idea of emotional drift is quite illuminating; one could just know that an entire material showing emotional swings should attract better choice by the translator in dealing with high-charged texts. It urges the translator to take into consideration emotionality in their lexical decisions in terms of more than simply generating equivalents but cognizance towards the present-day emotive integrity of the entire text.

5.2 Challenges and Limitations

Because certain individuals were introduced to the possibilities, there are a fair amount of hang-ups that come with this kind of research. The primary challenge is the intrinsic partiality that emotions themselves reveal. Sentiment analysis of human emotions Modern NLP models have advanced significantly, but they have only studied language in the last few decades, and thus they may not fully understand the depth of meaning that exists in any complex emotional form because they are not in any old or culturally different form. So as different time periods can define and perceive emotional lexicons in their own ways, some can also differ with cultures, which limits any models trained on contemporary datasets.

There is yet another limitation of annotated data for quite a number of languages, which affects their hegemonic language-specific emotion models. For many under-resourced languages, full annotated data cannot be even imagined, while the results of historical texts cannot be heartily touched upon in this sense. While significant research has been performed in Arabic NLP, emotion annotations especially useful for detailed analysis of literary texts may still be lacking. Thus, care is needed while selecting, and if necessary, modifying the models so that they are applicable to the target text.

One additional flaw in the approach is that of word by word or sentence level alignment of the two bilingual texts. In literary translation, structural and stylistic adaptations of this magnitude are frequently observed and one to one alignment is no longer an option. Actually, dynamic time warping is good enough with this; these kinds of methods, though, translated, do not take into account creativity and self-necessarily construct what supportably point to what can only be termed as emotional drift.

In addition, what is collected and measured here requires careful and extensive qualitative validation, verification of merit. Nonetheless, a statistically significant result lacks any form of artistic, cultural value. Human scholars attribute conscious choice of translational variation and linguistic differentiation to randomness, intentionality, variation of grammar, and conscious choice. Regardless of the enormous interdisciplinary amount of such energy, this approach demands a lot even from those working in the computational linguistics of the humanities.

6. Conclusion

It developed a technique for detecting and quantifying affect in literary translation digitally. This approach combines sophisticated natural language processing (NLP) methods with AI, particularly sentiment and affect analysis. In order to provide a new framework for examining the translation and reinterpretation of the text's sentiments beyond the context of culture and language, the approaches are used to two distinct versions of The Epic of Gilgamesh. In order to bridge the gap between the digital humanities and literary translation studies, the project adds a data-driven framework to what is mostly qualitative. The translation of emotions, in particular,

should, by a careful and sophisticated approach to heavy data cleansing, advanced extraction of emotional content, and drift analysis, account for an empirical explanation of the subtle differences in such translations. Instead, qualitative interpretation together with these approaches offers an adequate understanding of these phenomena. Such researches have wide ramifications; it enriches the analysis of literature through the revealing of hidden feelings, advances practice by providing applied instruction to translators, and takes literary interpretation a step forward by the revealing of hidden emotional dynamics. The combination of emotional subjectivity and data accessibility together with text alignment challenges should create insurmountable obstacles which researchers can overcome through their interdisciplinary work that combines humanistic intuition with computational literacy. The project establishes machine-assisted literary scholarship as a new field while demonstrating how artificial intelligence reveals complex relationships between language and emotion and cultural elements through its ability to analyze these interconnections. The framework enables researchers to investigate affective fidelity within multiple translated literary works while they also study how art and science translation is practiced in the current digital era.

Conflict of Interest:

The authors declare no conflicts of interest.

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