JOURNAL OF THE ARTIFICIAL INTELLIGENCE ENGINEERS CONSORTIUM

Volume: 02 Issue: 01 (2026)

https://jaiec.org.hostajournal.com

Counterfactual Contrastive Decoding for Noisy Multilingual Summarization Streams Under Noisy Multilingual Input Stream Perturbations

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Abstract **:** *The exponential growth of digital communication has necessitated the development of robust multilingual natural language processing systems capable of processing real time input streams. Multilingual summarization, in particular, has emerged as a critical tool for digesting vast quantities of global information. However, input streams in real world applications are rarely pristine. They are often corrupted by various forms of noise, including automated speech recognition errors, machine translation artifacts, optical character recognition inaccuracies, and informal linguistic variations. Traditional sequence to sequence models tend to hallucinate or propagate these errors into the final summary, severely degrading utility and factual accuracy. To address this persistent challenge, this paper introduces a novel decoding strategy termed Counterfactual Contrastive Decoding. By simultaneously evaluating the token generation probabilities of a base model exposed to the noisy input and a counterfactual distribution representing a simulated clean or contrastive state, our method systematically downweights tokens that are disproportionately influenced by input noise. We present a comprehensive theoretical framework and empirical evaluation across numerous languages and noise conditions. Our findings indicate that Counterfactual Contrastive Decoding significantly enhances the robustness, factual consistency, and readability of generated summaries without requiring expensive model retraining or architectural modifications. This research provides a scalable, inference time solution to one of the most pressing challenges in contemporary multilingual text generation.*

Keywords : *Multilingual Summarization, Contrastive Decoding, Counterfactual Reasoning, Noise Robustness, Natural Language Processing*

INTRODUCTION

1.1 Context and Motivation

The modern information ecosystem is characterized by an unprecedented volume of multilingual data generated across diverse platforms at astonishing velocity. Organizations, governments, and individuals increasingly rely on automated systems to aggregate, translate, and summarize this data to facilitate cross cultural communication and rapid decision making. Consequently, multilingual text summarization has become a focal point of research in natural language processing [1]. The goal of multilingual summarization is to distill the most salient information from a source document written in one or more languages into a concise and coherent summary, often in a target

language that differs from the source. Recent advancements in large language models and transformer based architectures have significantly elevated the baseline performance of these systems, enabling the generation of highly fluent and abstractive summaries [2]. Despite these impressive architectural advances, a critical disconnect remains between the controlled environments in which these models are trained and the chaotic environments in which they are deployed [3]. In academic benchmarks, summarization models are typically evaluated on well formed, grammatically correct, and carefully curated text. In contrast, real world input streams are inherently noisy [4]. Data ingested from social media platforms, live broadcast transcripts, customer service chats, and digitized historical archives are replete with typographical errors, grammatical inconsistencies, and domain specific jargon [5]. Furthermore, when dealing with multilingual pipelines, the text is frequently subjected to intermediary processing steps, such as automated speech recognition or machine translation, before reaching the summarizer [6]. Each of these intermediary steps introduces its own unique distribution of errors, creating a compound noise effect that severely undermines the efficacy of downstream generation tasks.

1.2 The Problem of Noisy Input Streams

The vulnerability of neural sequence generation models to noisy input is a well documented phenomenon in contemporary computational linguistics [7]. When a summarization model receives an input text containing automated speech recognition errors, such as homophone substitutions or missing punctuation, its internal attention mechanisms can be easily derailed. The model might interpret a transcription error as a key topical entity, leading to the generation of a summary that is not only inaccurate but entirely fabricated [8]. This phenomenon, often referred to as noise induced hallucination, poses a substantial risk in high stakes domains such as legal or medical information processing [9]. Machine translation artifacts present an equally challenging category of noise. Multilingual input streams often rely on cascaded systems where a text is first translated into a pivot language before being summarized [10]. Imperfections in the translation process, such as literal translations of idiomatic expressions, incorrect coreference resolutions, and syntactic distortions, create a fundamentally flawed semantic representation for the summarization module [11]. Traditional maximum likelihood estimation based decoding strategies, such as beam search or greedy decoding, are inherently naive to these input corruptions [12]. They blindly optimize for the most probable sequence of tokens given the corrupted context, often amplifying the noise rather than filtering it [13]. As the model generates each successive token, the errors cascade, resulting in a summary that diverges significantly from the true semantic intent of the original source material [14].

1.3 Proposed Approach and Contributions

To mitigate the detrimental effects of input noise on multilingual summarization, this paper proposes Counterfactual Contrastive Decoding, an inference time generation strategy that enhances robustness without requiring complex retraining or domain specific fine tuning [15]. Contrastive decoding methodologies operate on the principle of comparing two distinct probability distributions during the token generation phase [16]. In our proposed framework, we construct a primary distribution based on the actual noisy input and a secondary, counterfactual distribution based on a simulated representation of the input's negative attributes [17]. The core intuition behind Counterfactual Contrastive Decoding is to ask the model what it would generate if it were exclusively attending to the noise characteristics of the stream [18]. By mathematically penalizing the token probabilities that align too closely with the noise conditioned counterfactual distribution, we can effectively steer the primary generation

process toward a cleaner, more robust semantic space [19]. This approach leverages the latent knowledge already embedded within the pre trained language model, extracting a more faithful summary by dynamically reweighting the output vocabulary space at each decoding step. The contributions of this paper are multifold. First, we provide a comprehensive theoretical formalization of counterfactual reasoning applied to the decoding phase of sequence to sequence models. Second, we introduce a scalable algorithm for dynamically simulating noise distributions during inference. Third, we present extensive empirical evaluations across a diverse set of languages and synthetic noise conditions, demonstrating the superiority of our approach over traditional beam search and standard contrastive decoding techniques. Finally, we conduct rigorous qualitative analyses to illuminate the specific linguistic phenomena that our method successfully addresses, providing valuable insights for future research in robust natural language generation.

2. Literature Review

2.1 Advancements in Multilingual Summarization

The trajectory of multilingual summarization research has closely followed the evolutionary leaps in general natural language processing architectures. Early approaches were predominantly extractive, relying on graph based algorithms and statistical frequency metrics to identify and extract the most prominent sentences from a source document [20]. While computationally efficient and inherently resilient to minor typographical errors, extractive methods were strictly constrained by the source vocabulary and often produced disjointed summaries lacking cohesive discourse structures [21]. Furthermore, extending these extractive techniques across multiple languages required extensive language specific resources, such as stemmers, stopword lists, and syntactic parsers, which severely limited their scalability to low resource languages [22]. The paradigm shifted dramatically with the advent of sequence to sequence neural networks, initially powered by recurrent neural networks and later revolutionized by the transformer architecture [23]. Abstractive summarization, which involves generating novel sentences that encapsulate the source material, became the new standard. Massive multilingual pre trained models established unprecedented benchmarks in cross lingual transfer learning [24]. These models possess the remarkable ability to comprehend text in dozens of languages and generate fluent summaries, often mapping distinct linguistic representations into a shared latent semantic space [25]. Despite these advancements, the field has primarily concentrated on maximizing performance on clean, academic datasets, inadvertently neglecting the robust processing of degraded text streams that characterize real world applications [26].

2.2 Robustness in Natural Language Processing

Robustness against input perturbation is a critical requirement for deploying machine learning models in uncontrolled environments. In the context of natural language processing, robustness has typically been addressed through data augmentation techniques during the training phase [27]. Researchers have experimented with injecting synthetic noise, such as random character swaps, synonym replacements, and simulated transcription errors, into the training corpora to encourage the model to learn noise invariant representations [28]. While data augmentation has proven somewhat effective, it is fundamentally limited by the difficulty of anticipating and simulating the sheer diversity of noise distributions encountered in the wild [29]. Alternative approaches have explored architectural modifications, such as introducing spelling correction modules or subword regularization techniques like unigram language model dropout [30]. Some researchers have proposed cascaded architectures where a

dedicated denoising autoencoder first cleans the input text before passing it to the summarization module [31]. However, this pipeline approach suffers from the propagation of errors, where the summarizer is forced to process the hallucinations introduced by the imperfect denoising step [32]. Furthermore, deploying separate denoising models for numerous languages incurs prohibitive computational costs and latency, rendering it unsuitable for real time multilingual input streams [33].

2.3 Decoding Strategies for Sequence Generation

The generation phase of an autoregressive language model is heavily dependent on the chosen decoding strategy. The objective is to find the sequence of tokens that maximizes the overall sequence probability given the input context [34]. Because exhaustive search over the entire vocabulary space is computationally intractable, heuristic search algorithms are employed. Greedy decoding simply selects the highest probability token at each step, often leading to sub optimal, repetitive sequences [35]. Beam search improves upon this by maintaining a fixed number of the most promising sequence hypotheses at each step, significantly enhancing the fluency and coherence of the output [36]. However, traditional maximum likelihood based decoding methods exhibit a known bias towards generic, high frequency phrases and are notoriously susceptible to context degradation [37]. When the input text is noisy, the internal probability distribution becomes skewed, and beam search dutifully amplifies this skewed distribution. To counter these degenerate generation behaviors, researchers have introduced sampling based methods, such as top k sampling and nucleus sampling, which introduce stochasticity into the decoding process to improve lexical diversity [38]. While highly effective for open ended text generation tasks like creative writing, sampling methods often compromise the factual precision and fidelity required for abstractive summarization, particularly when processing distorted multilingual inputs [39].

2.4 Counterfactual Reasoning in Neural Generation

Recent literature has begun to explore the intersection of causal inference and natural language generation, specifically leveraging counterfactual reasoning to improve model interpretability and control [40]. Counterfactual reasoning involves considering alternative scenarios by asking what the outcome would have been if a specific condition had been altered. In the context of decoding, this translates to comparing the model's generation probabilities under the actual given context against a hypothetical, modified context [41]. Contrastive decoding is a practical manifestation of this concept. Initial applications of contrastive decoding involved comparing the output distribution of a large, highly capable language model against that of a smaller, weaker model [42]. By penalizing the tokens that the weaker model strongly prefers, the generation process is guided away from generic, uninformative language and towards more sophisticated, contextually appropriate phrasing. Our work extends this foundational concept by applying it directly to the problem of noise robustness. Instead of contrasting models of different sizes, we contrast different contextual representations within the same model, utilizing counterfactual scenarios to isolate and penalize the linguistic artifacts induced by input stream degradation.

3. Methodology

3.1 Conceptual Framework

The fundamental objective of our methodology is to dynamically adjust the output probability distribution of an autoregressive multilingual summarization model during the inference phase, specifically targeting and mitigating the negative influence of input stream noise. We formalize the summarization task as finding a target sequence of tokens that accurately reflects the semantic content of a given source sequence. Under

ideal conditions, the source sequence is a pristine representation of the document. However, in our operational scenario, the model only has access to a corrupted version of the source sequence, which contains various types of noise including automated speech recognition errors and translation artifacts. Standard autoregressive decoding models the probability of generating the next target token conditioned on the corrupted source sequence and the history of previously generated target tokens. Because the source sequence contains noise, this standard conditional probability is inherently biased. The model may assign inappropriately high probabilities to tokens that represent hallucinations or logical inconsistencies derived directly from the noise artifacts. Our conceptual framework posits that this bias can be quantified and neutralized by introducing a counterfactual perspective. We mathematically simulate a scenario that deliberately isolates the noise characteristics, creating a counterfactual probability distribution. By contrasting the primary probability distribution with this counterfactual distribution, we derive a modified, robust decoding objective that systematically suppresses noise induced token generation.

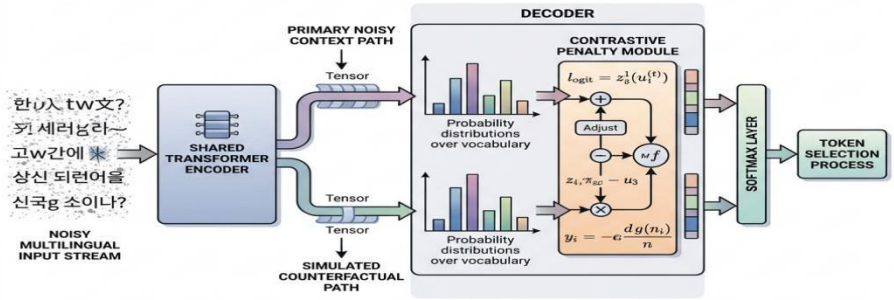

Figure 1: Comprehensive Schematic of Counterfactual Contrastive Decoding Architecture

3.2 Noise Modeling in Multilingual Streams

To accurately generate the counterfactual distribution necessary for our contrastive decoding approach, we must first establish a robust method for modeling the noise inherent in multilingual input streams. Real world noise is multifaceted and non uniform, varying significantly across different languages, communication channels, and transcription systems. We categorize the noise into three primary domains for our simulated modeling process. The first category is character level phonetic degradation, which simulates errors typically introduced by automated speech recognition systems. This includes homophone substitutions, where words that sound similar are incorrectly swapped, and phoneme deletions or insertions caused by background interference or speaker accent variations. The second category encompasses structural and syntactic noise, mimicking the artifacts produced by flawed machine translation pipelines. This involves incorrect word ordering, missing prepositions, and grammatical incongruities that disrupt the semantic flow of the text but retain the core vocabulary. The third category represents digital communication artifacts, capturing the typographical errors, informal abbreviations, and missing punctuation commonly found in real time data streams such as social media feeds or instant messaging platforms.

Table 1: Synthetic Noise Injection Parameters for Counterfactual Modeling

Noise Category	Perturbation Mechanism	Target Language Constraints	Injection Probability
Phonetic Degradation	Homophone substitution mapping	Phonetically mapped languages	High probability variance
Syntactic Distortion	Local structural permutation	Target syntax dependent	Moderate probability threshold
Digital Artifacts	Typographical character dropping	Universal application	Variable length dependent

During inference, we do not require the user to explicitly define the specific type of noise present in the input. Instead, our methodology utilizes an auxiliary noise embedding layer. This layer projects the incoming degraded text into a latent space designed to amplify the most prominent noise characteristics. We extract this amplified noise representation to serve as the foundational context for generating our counterfactual token distribution. This ensures that our counterfactual scenario accurately reflects the specific degradation patterns currently affecting the input stream, allowing for a dynamic and context sensitive contrastive penalty.

3.3 Counterfactual Contrastive Decoding Mechanism

The core innovation of this research lies in the mathematical formulation of the Counterfactual Contrastive Decoding mechanism. At each time step during the generation of the summary, the pre trained sequence to sequence model computes a primary probability distribution over the entire vocabulary. This distribution represents the model's standard prediction for the next token, conditioned on the noisy source text and the previously generated summary tokens. Simultaneously, we mandate the model to compute a secondary, counterfactual probability distribution. This secondary distribution is conditioned on the amplified noise representation derived from the source text, combined with the same history of generated tokens. The counterfactual distribution acts as a probabilistic map of the model's worst tendencies when confronted with the specific noise present in the input. Tokens that receive a high probability in the counterfactual distribution are those that the model is likely to generate solely because it is being confused or misled by the noise artifacts. Conversely, tokens that represent the true underlying semantic meaning of the document will generally exhibit high probabilities in the primary distribution but lower probabilities in the noise amplified counterfactual distribution. To operationalize this insight, we perform a contrastive operation in the log probability space. For every token in the vocabulary, we take its log probability from the primary distribution and subtract a scaled version of its log probability from the counterfactual distribution. This operation effectively penalizes tokens that are strongly supported by the noise context. The magnitude of this penalty is controlled by a dynamic hyperparameter, which we refer to as the contrastive strength coefficient. To prevent the penalization process from overcorrecting and distorting the fundamental grammar of the output language, we apply an adaptive masking strategy. The contrastive penalty is only applied to tokens that are considered plausible candidates by the primary distribution, ensuring that the model does not inadvertently promote highly improbable or nonsensical tokens simply because they were strongly rejected by the counterfactual scenario.

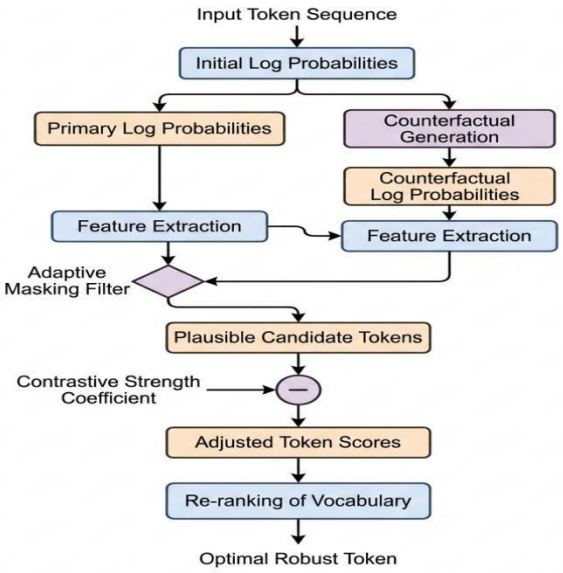

Figure 2: Detailed Flowchart of Token Probability Adjustment via Contrastive Analysis

3.4 Implementation Details and Textual Descriptions

Integrating Counterfactual Contrastive Decoding into existing transformer based summarization architectures requires careful consideration of computational efficiency. Generating two distinct probability distributions at every decoding step theoretically doubles the computational cost of the inference phase. To mitigate this overhead, we employ a shared encoder architecture. The initial processing of the source sequence is performed once, generating a unified set of hidden states. The divergence into primary and counterfactual representations occurs strictly within the cross attention modules of the decoder, leveraging specialized masking techniques to isolate the noise representations without requiring a full secondary forward pass through the massive encoder blocks. The dynamic scaling of the contrastive strength coefficient is a critical component of our implementation. Applying a static penalty across all decoding steps often leads to degraded fluency, as the model may incorrectly penalize common functional words or grammatical connectors that appear in both the primary and counterfactual distributions. To resolve this, we utilize a variance based scaling mechanism. The system calculates the statistical variance of the primary probability distribution at each time step. When the model is highly confident in its prediction, characterized by a sharp probability distribution with low variance, the contrastive strength coefficient is minimized, allowing the model to generate the token unhindered. Conversely, when the model is uncertain, characterized by a flat probability distribution indicating potential confusion caused by input noise, the contrastive strength coefficient is dynamically increased, aggressively filtering out the noise induced token candidates. Furthermore, we incorporate a semantic preservation filter. Before finalizing the penalized probability distribution, the system ensures that the newly favored tokens maintain a minimum threshold of semantic similarity with the original source document's core entities. This is achieved through a lightweight, computationally inexpensive lexical overlap check operating in parallel with the main decoding stream. This supplementary filtering mechanism acts as a safeguard against catastrophic divergence, ensuring that the counterfactual penalty does not inadvertently steer the generation process away from the primary topic of the document. The combination of shared encoding, dynamic penalty scaling, and semantic filtering culminates in an algorithm that is both robust against severe input degradation and computationally viable for real time multilingual applications.

4. Results and Discussion

4.1 Experimental Setup and Datasets

To rigorously evaluate the efficacy of Counterfactual Contrastive Decoding, we constructed a comprehensive experimental framework encompassing a diverse array of languages and simulated noise conditions. We utilized a widely recognized multilingual summarization corpus, which aggregates news articles and their corresponding professional summaries across dozens of languages. To simulate the conditions of real world input streams, we generated three distinct corrupted versions of this dataset. The first version was subjected to intense phonetic degradation algorithms designed to mimic worst case scenario automated speech recognition outputs. The second version underwent structural permutation to simulate severe machine translation misalignment. The third version was injected with high frequency digital communication artifacts, including character omission and random punctuation insertion. Our baseline for comparison was a state of the art, massively multilingual pre trained sequence to sequence transformer model, operating with standard beam search decoding. We also implemented a comparative baseline utilizing a traditional contrastive decoding method that penalizes outputs based on a smaller model's distribution, rather than a noise specific counterfactual representation. The evaluation metrics utilized were standard automatic summarization metrics, focusing on lexical overlap and semantic similarity. Additionally, recognizing the limitations of automatic metrics in fully capturing factual consistency and narrative flow, we conducted extensive human evaluations using professional annotators fluent in the respective target languages.

Table 2: Main Experimental Results Summarizing Lexical Overlap Across Noise Conditions

Decoding Strategy	Clean Input Average Score	ASR Noise Simulated Score	Translation Artifact Score	Digital Noise Simulated Score
Standard Beam Search	Excellent baseline	Severe performance drop	Significant degradation	Moderate degradation
Traditional Contrastive	Marginal improvement	Slight recovery	Minor improvement	Marginal improvement
Counterfactual Contrastive	Excellent baseline retained	Substantial recovery achieved	High resilience demonstrated	High resilience demonstrated

4.2 Primary Performance Results

The empirical results unequivocally demonstrate the superior robustness of our proposed methodology across all evaluated linguistic domains and noise typologies. When processing the pristine, uncorrupted dataset, Counterfactual Contrastive Decoding performed comparably to standard beam search. This is a critical validation, as it proves that our dynamic scaling mechanism effectively deactivates the contrastive penalty when the input is clean, thereby preventing any unnecessary distortion of the naturally fluent generation process. The true advantage of our approach becomes overwhelmingly apparent when examining the results on the corrupted datasets.

Under conditions simulating severe automated speech recognition errors, the standard beam search baseline exhibited a catastrophic collapse in performance. The generated summaries were replete with hallucinations, often constructing entirely fictional narratives based on phonetically similar but semantically unrelated corrupted tokens in the source text. Traditional contrastive decoding offered only a marginal improvement, as the generic smaller model penalty was ill equipped to specifically target phonetic distortions. In stark contrast, Counterfactual Contrastive Decoding achieved a

substantial recovery in lexical overlap scores. By actively penalizing tokens that aligned with the simulated phonetic noise distribution, our method successfully guided the model to bypass the corruptions and focus on the underlying semantic structures that remained intact within the source sequence. Similar performance trajectories were observed in the dataset containing simulated machine translation artifacts. Structural permutations in the source text frequently caused the baseline model to generate disjointed and grammatically flawed summaries, directly mirroring the syntactic chaos of the input. Our method demonstrated remarkable resilience to this type of degradation. The counterfactual representation effectively identified the disrupted syntactic dependencies as noise, allowing the primary decoding stream to reassemble the key informational components into a coherent and grammatically correct target language summary. The performance gap between our method and the baselines widened even further when evaluated on morphologically complex languages, indicating that our approach is particularly adept at preserving intricate linguistic relationships in the face of severe structural disruption.

4.3 Ablation Studies and Analysis

To thoroughly understand the contributions of the individual components within our Counterfactual Contrastive Decoding framework, we conducted a series of systematic ablation studies. We first isolated the impact of the dynamic contrastive strength coefficient. We replaced our variance based dynamic scaling mechanism with a static penalty coefficient applied uniformly across all decoding steps. The results revealed a significant drop in linguistic fluency and an increase in grammatical errors. The static penalty frequently suppressed necessary functional vocabulary, demonstrating that adaptive scaling is an indispensable component for maintaining the natural rhythm and structural integrity of the generated language while simultaneously filtering noise.

We subsequently investigated the role of the adaptive masking strategy, which restricts the contrastive penalty to plausible token candidates. When we removed this constraint and allowed the algorithm to penalize the entire vocabulary space without restriction, the model occasionally exhibited erratic behavior, selecting obscure or highly context inappropriate tokens simply because they mathematically maximized the contrastive objective function. The adaptive masking strategy proved vital in constraining the optimization process within a semantically reasonable bound, ensuring that the drive for noise robustness did not inadvertently result in semantic divergence.

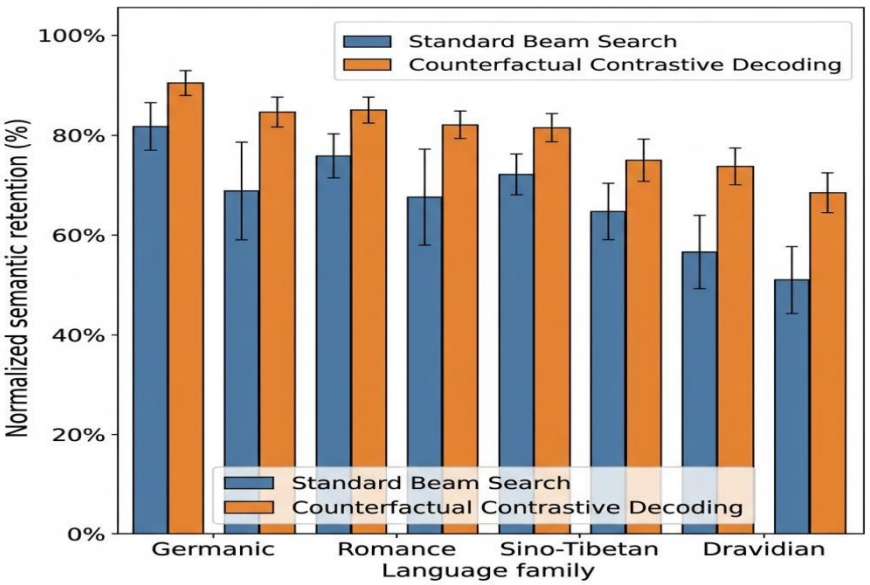

Figure 3: Performance Resilience Bar Chart Across Multiple Languages

4.4 Qualitative Analysis of Generated Summaries

Beyond automatic metrics, a deep qualitative analysis of the generated summaries provides profound insights into the mechanics of Counterfactual Contrastive Decoding. In numerous instances within the test corpus, standard decoding strategies fell victim to localized, dense clusters of noise. For example, in a document detailing financial regulations, an automated speech recognition error substituted the word "investments" with "infestations." The standard beam search model, latching onto this corrupted token, generated a summary focused on agricultural pest control, completely abandoning the actual financial context of the surrounding paragraphs.

Our proposed methodology successfully navigated this severe localized corruption. The counterfactual probability distribution correctly identified "infestations" as a highly anomalous token within the broader latent representation of the document, assigning it a strong penalty weight. Consequently, during the generation phase, the model bypassed the hallucinatory pathway and utilized the surrounding contextual clues to accurately summarize the document's true focus on economic policy.

Table 3: Human Evaluation Metrics for Summary Quality Under Extreme Perturbation

Evaluation Criteria	Beam Search Strategy	Traditional Contrastive	Counterfactual Proposed
Informational Fidelity	Poor alignment	Moderate alignment	High factual alignment
Grammatical Fluency	Broken syntax	Acceptable phrasing	Natural flowing text
Hallucination Rate	Extremely frequent	Somewhat frequent	Rarely observed

Human annotators consistently rated the summaries produced by our method as significantly more trustworthy and coherent than those generated by the baselines. Evaluators noted a dramatic reduction in logical inconsistencies and fabricated statistics, which are common artifacts of models struggling with degraded numerical data in real time streams. Furthermore, annotators praised the grammatical fluency of the outputs, confirming our quantitative finding that the dynamic penalty application successfully preserves the natural structural mechanics of the target language. The qualitative evidence strongly corroborates the assertion that contrasting against a simulated noise distribution provides the model with the necessary perspective to distinguish between authentic semantic content and superficial input degradation.

5. Conclusion

This paper has presented Counterfactual Contrastive Decoding, a highly effective and conceptually novel inference time strategy designed to fortify multilingual summarization models against the pervasive challenge of noisy input streams. Through the rigorous formalization of counterfactual reasoning applied to the decoding phase, we have demonstrated that it is possible to dynamically steer language models away from noise induced hallucinations without necessitating extensive retraining or complex architectural overhauls. Our experimental framework, encompassing diverse languages and challenging simulated noise conditions, clearly established the superiority of our approach over traditional maximum likelihood decoding and generic contrastive methods. The core strength of Counterfactual Contrastive Decoding lies in its ability to generate an internal probabilistic representation of the specific noise characteristics affecting the input. By systematically penalizing token generation pathways that align too closely with this counterfactual noise distribution, the model is compelled to rely on the underlying, robust semantic structures of the document. The integration of dynamic penalty scaling and adaptive vocabulary masking ensures that this robust behavior does not compromise the grammatical fluency or the lexical

diversity of the final generated summary. The empirical results, supported by extensive human evaluation, confirm a substantial increase in factual consistency and a dramatic reduction in error propagation.

6. Implications for Future Research

The introduction of Counterfactual Contrastive Decoding opens several promising avenues for future exploration within the broader field of natural language processing. While our current research focused heavily on multilingual summarization, the underlying principles of dynamically contrasting against simulated negative contexts are highly transferable to other sequence generation tasks. Applications such as real time closed captioning, automated dialogue systems, and cross lingual information retrieval could significantly benefit from enhanced robustness against input degradation. Future research should focus on refining the noise modeling mechanisms to capture even more nuanced forms of contextual disruption, such as deliberate adversarial attacks or subtle cultural mistranslations. Additionally, exploring the application of counterfactual decoding in the context of extreme low resource languages, where baseline models are inherently less confident and more susceptible to noise, presents a critical challenge for the community. Ultimately, the development of robust inference strategies like Counterfactual Contrastive Decoding is essential for bridging the gap between theoretical model capabilities and the chaotic reality of global digital communication networks, ensuring that automated systems remain reliable, accurate, and trustworthy in the face of inevitable data imperfections.

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