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QUANTIFYING THE PLAUSIBILITY OF CONTEXT RELIANCE IN NEURAL MACHINE TRANSLATION

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ABSTRACT

Establishing whether language models can use contextual information in a human-plausible way is important to ensure their safe adoption in real-world settings. However, the questions of *when* and *which parts* of the context affect model generations are typically tackled separately, and current plausibility evaluations are practically limited to a handful of artificial benchmarks. To address this, we introduce **P**lausibility **E**valuation of **Co**ntext **Re**liance (PECoRe), an end-to-end interpretability framework designed to quantify context usage in language models' generations. Our approach leverages model internals to (i) contrastively identify context-sensitive target tokens in generated texts and (ii) link them to contextual cues justifying their prediction. We use PECoRe to quantify the plausibility of context-aware machine translation models, comparing model rationales with human annotations across several discourse-level phenomena. Finally, we apply our method to unannotated generations to identify context-mediated predictions and highlight instances of (im)plausible context usage in model translations.

1 INTRODUCTION

Research in NLP interpretability defines various desiderata for rationales of model behaviors, i.e. the contributions of input tokens toward model predictions computed using feature attribution (Madsen et al., 2022). One of such properties is *plausibility*, corresponding to the alignment between model rationales and salient input words identified by human annotators (Jacovi & Goldberg, 2020). Plausibility assessment is useful for highlighting bias and generalization failures in models' predictions, and especially to identify cases of models being "right for the wrong reasons" (McCoy et al., 2019). However, while plausibility has an intuitive interpretation for classification tasks where a single prediction is produced, extending this methodology to generative language models (LMs) presents several challenges. First, LMs have a large output space where semantically equivalent tokens (e.g. "*PC*" and "*computer*") are competing candidates for next-word prediction (Holtzman et al., 2021). Moreover, LMs generations are the product of optimization pressures to ensure independent properties such as semantic relatedness, topical coherence and grammatical correctness, which can hardly be captured by a single rationale (Yin & Neubig, 2022). Finally, since autoregressive generation involves an iterative prediction process, model rationales could be extracted for every generated token, raising the issue of *which generated tokens* can have plausible contextual explanations.

Recent attribution techniques for explaining language models incorporate contrastive alternatives to disentangle different aspects of model predictions (e.g. the choice of "*meowing*" over "*screaming*" to complete "*The cat is* ___" can be explained by semantics but not by grammaticality) (Ferrando et al., 2023; Sarti et al., 2023). However, these studies avoid the issues above by narrowing the evaluation to a single generation step matching a phenomenon of interest. For example, given the sentence "*The pictures of the cat* ___", a plausible rationale for the prediction of the word "*are*" should reflect the role of "*pictures*" in subject/verb agreement. While this approach can be useful to validate model rationales, it confines plausibility assessment to a small set of handcrafted benchmarks where tokens with plausible explanations are known in advance. Moreover, it risks overlooking important patterns of context usage, including those not immediately matching linguistic intuitions. In light of this, we suggest that identifying *which* generated tokens were most affected by input information should be an integral part of plausibility evaluation for language generation tasks.

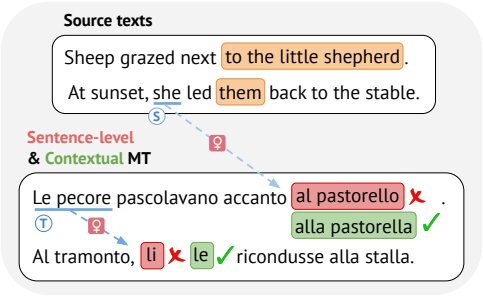

Figure 1: Examples of sentence-level and contextual English→Italian MT. Sentence-level translation contain lack-of-context errors. Instead, in the contextual case Context-sensitive source tokens are disambiguated using source (Ⓢ) or target-based (Ⓣ) contextual cues to produce correct context-sensitive target tokens. PECoRe enables the end-to-end extraction of cue-target pairs (e.g. `<she, alla pastorella>, <le pecore, le>`).

To achieve this goal, we propose a novel interpretability framework, which we dub **P**lausibility **E**valuation of **Co**ntext **Re**liance (PECoRe). PECoRe enables the end-to-end extraction of *cue-target token pairs* consisting of context-sensitive target tokens and their respective influential contextual cues from language model generations, as shown in Figure 1. These pairs can be used to uncover context dependence in naturally occurring generations and, for cases where human annotations are available, help quantify context usage plausibility in language models. Importantly, our approach is compatible with modern attribution methods using contrastive targets (Yin & Neubig, 2022), avoids using reference translations to stay clear of problematic distributional shifts (Vamvas & Sennrich, 2021b), and can be applied on unannotated inputs to identify cue-target pairs in model generations.

After formalizing our proposed approach in Section 3, we apply PECoRe to contextual machine translation (MT) to study the plausibility of context reliance in monolingual and multilingual MT models. We select MT as a testbed for our framework due to its constrained output space facilitating automatic performance assessment and the availability of resources annotated with human rationales of context usage. We thoroughly evaluate core components of the PECoRe framework, comparing various metrics and attribution methods to identify cue-target pairs. Finally, we conclude by applying PECoRe to unannotated examples and showcasing some reasonable and questionable cases of context reliance in model translations.

In sum, we make the following contributions[1]:

- We introduce PECoRe, an interpretability framework for analyzing context reliance in language models. PECoRe enables a quantitative evaluation of plausibility for language generation beyond the artificial settings explored in previous literature.
- We compare the effectiveness of metrics for context-sensitive target token identification and contextual cues imputation on the context-aware MT tasks, showing the limitations of metrics currently in use.
- We apply PECoRe to naturally-occurring translations to identify interesting discourse-level phenomena and discuss issues in context usage for context-aware MT models.

2 Related Work

Context Usage in Language Generation An appropriate[2] usage of input information is fundamental in tasks such as summarization (Maynez et al., 2020) to ensure the soundness of generated texts. While appropriateness is traditionally verified post-hoc using trained models (Durmus et al., 2020; Kryscinski et al., 2020; Goyal & Durrett, 2021), recent interpretability works aim to gauge input influence on model predictions using internal properties of language models, such as the mixing of contextual information across model layers (Kobayashi et al., 2020; Ferrando et al., 2022b; Mohebbi et al., 2023) or the layer-by-layer refinement of next token predictions (Geva et al., 2022; Belrose et al., 2023). Recent attribution methods can disentangle factors influencing generation in language models (Yin & Neubig, 2022) and were successfully used to detect and mitigate hallucinatory behaviors (Tang et al., 2022; Dale et al., 2022; 2023). Our proposed method adopts this intrinsic perspective to identify context reliance without ad-hoc trained components.

[1]Code, annotated datasets and models will be released upon publication.

[2]We avoid using the term *faithfulness* due to its ambiguous usage in interpretability research.

Context Usage in Neural Machine Translation Inter-sentential context is often fundamental for resolving discourse-level ambiguities during translation (Müller et al., 2018; Bawden et al., 2018; Voita et al., 2019b; Fernandes et al., 2023). However, MT systems are generally trained at the sentence level and fare poorly in realistic translation settings (Läubli et al., 2018; Toral et al., 2018). Despite advances in context-aware MT (Voita et al., 2018; 2019a; Lopes et al., 2020; Majumder et al., 2022; Jin et al., 2023 *inter alia*, surveyed by Maruf et al., 2021), only a few works explored whether context usage in MT models aligns with human intuition. Notably, some studies focused on *which parts of context* inform model predictions, finding that supposedly context-aware MT models are often incapable of using contextual information (Kim et al., 2019; Fernandes et al., 2021) and tend to pay attention to irrelevant words (Voita et al., 2018), with an overall poor agreement between human annotations and model rationales (Yin et al., 2021). Other works instead investigated *which parts of generated texts* are influenced by context, proposing various contrastive methods to detect gender biases, over/under-translations (Vamvas & Sennrich, 2021a; 2022), and to identify various discourse-level phenomena in MT corpora (Fernandes et al., 2023). While these two directions have generally been investigated separately, our work proposes a unified framework to enable an end-to-end evaluation of context-reliance plausibility in language models.

Plausibility of Model Rationales Plausibility evaluation for NLP models has largely focused on classification models (DeYoung et al., 2020; Atanasova et al., 2020; Attanasio et al., 2023). While few works investigate plausibility in language generation (Vafa et al., 2021; Ferrando et al., 2023), such evaluations typically involve a single generation step to complete a target sentence with a token connected to preceding information (e.g. subject/verb agreement, as in "*The pictures of the cat [is/are]*"), effectively reducing the problem to a classification. On the contrary, our framework proposes a more comprehensive evaluation of generation plausibility including the identification of context-sensitive generated tokens as an important prerequisite.

3 THE PECORE FRAMEWORK

PECORE is a two-step framework for identifying context dependence in generative language models. First, *context-sensitive target identification* (CTI) selects which tokens among those generated by the model were influenced by the presence of the preceding context (e.g. `alla pastorella, le` in Figure 1). Then, *contextual cues imputation* (CCI) attributes the prediction of context-sensitive targets to specific cues in the provided context (e.g. `she, Le pecore` in Figure 1). **Cue-target pairs** formed by influenced target tokens and their respective influential context cues can then be compared to human rationales to assess the models' plausibility of context reliance for contextual phenomena of interest. Figure 2 provides an overview of the two steps applied to the context-aware MT setting discussed by this work, while a more general formalization of the framework for language generation is proposed in the following sections.

Notation Let X^i_{ctx} be the sequence of contextual inputs containing N tokens from vocabulary $\mathcal{V}$, composed by current input x, generation prefix $y_{<i}$ and context C. Let also $X^i_{\text{no-ctx}}$ be the non-contextual input in which C tokens are excluded.[3] $P^i_{\text{ctx}} = P\left(x,\, y_{<i},\, C,\, \theta\right)$ is the discrete probability distribution over $\mathcal{V}$ at generation step i of a language model with θ parameters receiving contextual inputs X^i_{ctx}. Similarly, $P^i_{\text{no-ctx}} = P\left(x,\, y_{<i},\, \theta\right)$ is the distribution obtained from the same model for non-contextual input $X^i_{\text{no-ctx}}$. Both distributions are equivalent to vectors in the probability simplex in $\mathbb{R}^{|\mathcal{V}|}$, and we use $P_{\text{ctx}}(y_i)$ to denote the probability of next token y_i in P^i_{ctx}, i.e. $P(y_i \mid x,\, y_{<i},\, C)$.

3.1 CONTEXT-SENSITIVE TARGET TOKEN IDENTIFICATION

CTI adapts the contrastive conditioning paradigm (Vamvas & Sennrich, 2021a) for using the contrastive pair $P^i_{\text{ctx}}, P^i_{\text{no-ctx}}$ to detect input context influence on model predictions. Both distributions are relative to the **contextual target sentence** $\hat{y} = \{\hat{y}_1 \dots \hat{y}_n\}$, corresponding to the sequence produced by a decoding strategy of choice in the presence of input context. In Figure 2, the contextual target sentence $\hat{y}$ = "*Sont-elles à l'hôtel?*" is generated when x and contexts $C_x, C_{\hat{y}}$ are provided as inputs, while **non-contextual target sentence** $\tilde{y}$ = "*Ils sont à l'hôtel?*" would be produced when only x is provided. In the latter case, $\hat{y}$ is instead force-decoded from the non-contextual setting to enable a

[3] In the context-aware MT example of Figure 2, C includes source context C_x and target context C_y.

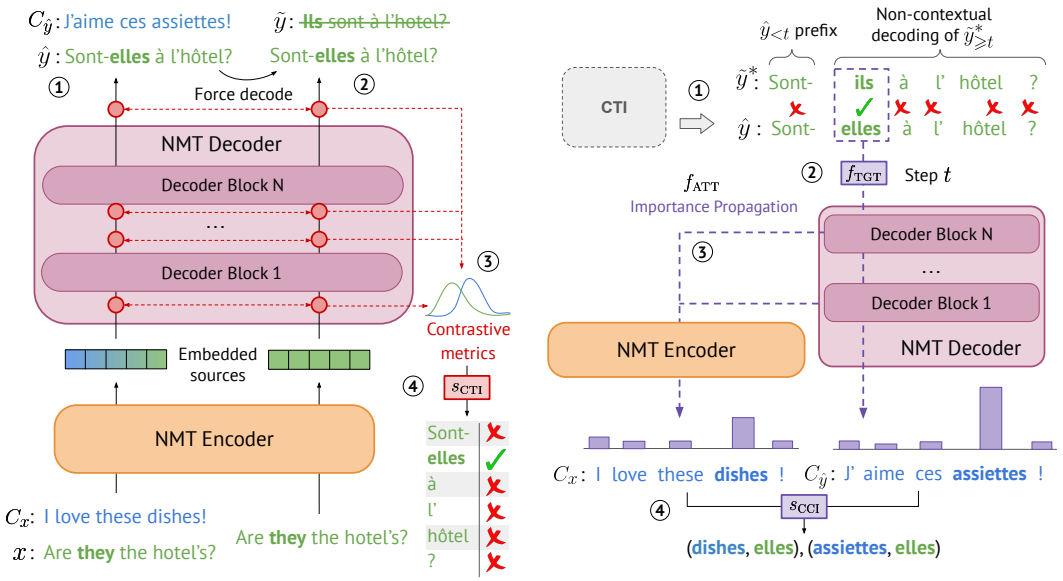

Figure 2: The PECoRe framework. **Left:** Context-sensitive target token identification (CTI). ①: A context-aware MT model translates source context (C_x) and current (x) sentences into target context ($C_{\hat{y}}$) and current ($\hat{y}$) outputs. ②: $\hat{y}$ is force-decoded in the non-contextual setting instead of natural output $\tilde{y}$. ③: Contrastive metrics are collected throughout the model for every $\hat{y}$ token to compare the two settings. ④: Selector s_{CTI} maps metrics to binary context-sensitive labels for every $\hat{y}_i$. **Right:** Contextual cues imputation (CCI). ①: Non-contextual target $\tilde{y}^*$ is generated from contextual prefix $\hat{y}_{<t}$. ②: Function f_{TGT} is selected to contrast model predictions with ($\hat{y}_t$) and without ($\tilde{y}^*_t$) input context. ③: Attribution method f_{ATT} using f_{TGT} as target scores contextual cues driving $\hat{y}_t$ prediction. ④: Selector s_{CCI} selects relevant cues, and cue-target pairs are assembled.

direct comparison of matching outputs. We define a set of **contrastive metrics** $\mathcal{M} = \{m_1, \ldots, m_M\}$, where each $m : \Delta_{|\mathcal{V}|} \times \Delta_{|\mathcal{V}|} \mapsto \mathbb{R}$ maps a contrastive pair of probability vectors to a continuous score. For example, the difference in next token probabilities for contextual and non-contextual settings, i.e. $P_{\text{diff}}(\hat{y}_i) = P_{\text{ctx}}(\hat{y}_i) - P_{\text{no-ctx}}(\hat{y}_i)$, might be used for this purpose.[4]. Target tokens with high contrastive metric scores can be identified as *context-sensitive*, provided C is the only added parameter in the contextual setting. Finally, a **selector** function $s_{\text{CTI}} : \mathbb{R}^{|\mathcal{M}|} \mapsto \{0, 1\}$ (e.g. a statistical threshold selecting salient scores) is used to classify every $\hat{y}_i$ as context-sensitive or not.

3.2 Contextual Cues Imputation

CCI applies the contrastive attribution paradigm (Yin & Neubig, 2022) to trace the generation of every context-sensitive token in $\hat{y}$ back to context C, identifying cues driving model predictions.

Definition 3.1. Let $\mathcal{T}$ be the set of indices corresponding to context-sensitive tokens identified by the CTI step, such that $t \in \hat{y}$ and $\forall t \in \mathcal{T}, s_{\text{CTI}}(m^t_1, \ldots, m^t_M) = 1$. Let also $f_{\text{TGT}} : \Delta_{|\mathcal{V}|} \times \Delta_{|\mathcal{V}|} \mapsto \mathbb{R}$ be a **contrastive attribution target** function having the same domain and range as metrics in $\mathcal{M}$. The **contrastive attribution method** f_{ATT} is a composite function quantifying the importance of contextual inputs to determine the output of f_{TGT} for a given model with θ parameters.

$$f_{\text{ATT}}(\hat{y}_t) = f_{\text{ATT}}(x, \hat{y}_{<t}, C, \theta, f_{\text{TGT}}) = f_{\text{ATT}}\big(x, \hat{y}_{<t}, C, \theta, f_{\text{TGT}}(P^t_{\text{ctx}}, P^t_{\text{no-ctx}})\big) \quad (1)$$

Remark 3.1. Generally, $f_{\text{ATT}}(\hat{y}_t)$ will result in non-zero scores even for cases in which $P_ctx(\hat{y}_t) = P_ctx(\tilde{y}^*_t)$, i.e. when the presence of context does not affect the next generated token. $P^t_{\text{no-ctx}}$ is conceptually equivalent to generating the next token in a new sequence $\tilde{y}^*$ using contextual target prefix $\hat{y}_{<t} = \{\hat{y}_1, \ldots, \hat{y}_{t-1}\}$ to predict $\tilde{y}^*_t$ given non-contextual inputs $X^t_{\text{no-ctx}}$ (e.g. *"ils"* in $\tilde{y}^*$ = "*Sont-ils à l'hôtel?*" in Figure 2).

[4]We use m^i to denote the result of $m\big(P^i_{\text{ctx}}, P^i_{\text{no-ctx}}\big)$. Several metrics are presented in Section 4.2

Remark 3.2. Our formalization of f_{ATT} generalizes the method proposed by (Yin & Neubig, 2022) to support any target-dependent attribution method, such as popular gradient-based approaches (Simonyan et al., 2014; Sundararajan et al., 2017), and any contrastive attribution target f_{TGT}.[5]

f_{ATT} produces a sequence of attribution scores $A_t = \{a_1, \dots, a_N\}$ matching contextual input length N. From those, only the subset $A_{t\,\text{CTX}}$ of scores corresponding to context input sequence C are passed to **selector** function $s_{\text{CCI}} : \mathbb{R} \mapsto \{0, 1\}$, which predicts a set $\mathcal{C}_t$ of indices corresponding to contextual cues identified by CCI, such that $\forall c \in \mathcal{C}_t, \forall a \in A_{t\,\text{CTX}}, s_{\text{CCI}}(a_c) = 1$.

Having collected all context-sensitive generated token indices $\mathcal{T}$ using CTI and their contextual cues through CCI (C_t), PECoRe ultimately returns a sequence S_{ct} of all identified cue-target pairs:

$$\begin{aligned} \mathcal{T} &= \text{CTI}(C, x, \hat{y}, \theta, \mathcal{M}, s_{\text{CTI}}) = \{t \mid s_{\text{CTI}}(m_1^t, \dots, m_M^t) = 1\} \\ \mathcal{C} &= \text{CCI}(\mathcal{T}, C, x, \hat{y}, \theta, f_{\text{ATT}}, f_{\text{TGT}}, s_{\text{CCI}}) = \{c \mid s_{\text{CCI}}(a_c) = 1 \, \forall a_c \in A_{t\,\text{ctx}}, \forall t \in \mathcal{T}\} \\ S_{\text{ct}} &= \text{PECoRe}(C, x, \theta, s_{\text{CTI}}, s_{\text{CCI}}, \mathcal{M}, f_{\text{ATT}}, f_{\text{TGT}}) = \{(C_c, \hat{y}_t) \mid \forall t \in \mathcal{T}, \forall c \in \mathcal{C}_t, \forall \mathcal{C}_t \in \mathcal{C}\} \end{aligned} \tag{2}$$

4 Context Reliance Plausibility in Context-aware MT

This section describes our evaluation of PECoRe in a controlled setup. We experiment with several contrastive metrics and attribution methods for CTI and CCI (Section 4.2, Section 4.4), evaluating them in isolation to quantify the performance of individual components. An end-to-end evaluation is also performed in Section 4.4 to establish the applicability of PECoRe in a naturalistic setting.

4.1 Experimental Setup

Evaluation Datasets Evaluating generation plausibility requires human annotations for context-sensitive tokens in target sentences and disambiguating cues in their preceding context. To our knowledge, the only resource matching these requirements is SCAT Yin et al. (2021), an English→French corpus with human annotations of anaphoric pronouns and disambiguating context on OpenSubtitles2018 dialogue translations (Lison et al., 2018; Lopes et al., 2020). SCAT examples were extracted automatically using lexical heuristics and thus contain only a limited set of anaphoric pronouns (*it, they → il/elle, ils/elles*), with no guarantees of contextual cues being found in preceding context. To improve our assessment, we select a subset of high-quality SCAT test examples containing contextual dependence, which we name SCAT+. Additionally, we manually annotate contextual cues in DiscEval-MT (Bawden et al., 2018), another English→French corpus containing handcrafted examples for *anaphora resolution* (ANA) and *lexical choice* (LEX). Our final evaluation set contains 250 SCAT+ and 400 DiscEval-MT translations across three discourse phenomena.[6]

Models We evaluate three pretrained encoder-decoder MT models in the Transformers library (Wolf et al., 2020). Specifically, we test two bilingual OpusMT models (Tiedemann & Thottingal, 2020) using the Transformer base architecture (Vaswani et al., 2017) with 8 and 16 attention heads (Small and Large, respectively), and mBART-50 1-to-many (Tang et al., 2021), a multilingual MT Transformer supporting translation in 50 target languages. We fine-tune models using extended translation units (Tiedemann & Scherrer, 2017) with contextual inputs marked by break tags such as "`source context <brk> source current`" to produce translations in the format "`target context <brk> target current`", where context and current target sentences are generated[7]. We perform context-aware fine-tuning on 242k IWSLT 2017 English→French examples (Cettolo et al., 2017), using a dynamic context size of 0-4 preceding sentences to ensure robustness to different context lengths and allow contextless usage. To further improve models' context sensitivity, we continue fine-tuning on the SCAT training split, containing 11k examples with inter- and intra-sentential pronoun anaphora.

Model Disambiguation Accuracy We estimate contextual disambiguation accuracy by verifying whether annotated (gold) context-sensitive words are found in model outputs. Results before and after context-aware fine-tuning are shown in Table 1. We find that fine-tuning improves translation quality and disambiguation accuracy across all tested models, with larger gains for anaphora resolution

[5] Additional precisions and formalization of target-dependent attribution methods are provided in Appendix A.

[6] Appendix D describes the annotation process and presents some examples for the two datasets.

[7] Context-aware MT model using only source context are also evaluated in Section 4.5 and Appendix C

Model	SCAT+			DiscEval-MT (ana)			DiscEval-MT (lex)		
	BLEU	OK	OK-CS	BLEU	OK	OK-CS	BLEU	OK	OK-CS
OpusMT Small *(default)*	29.1	0.14	-	43.9	0.40	-	30.5	0.29	-
OpusMT Small S+T_{ctx}	39.1	0.81	0.59	48.1	0.60	0.24	33.5	0.36	0.07
OpusMT Large *(default)*	29.0	0.16	-	39.2	0.41	-	31.2	0.31	-
OpusMT Large S+T_{ctx}	**40.3**	**0.83**	0.58	48.9	**0.68**	0.31	**34.8**	**0.38**	0.10
mBART-50 *(default)*	23.8	0.26	-	33.4	0.42	-	24.5	0.25	-
mBART-50 S+T_{ctx}	37.6	0.82	0.55	**49.0**	0.62	0.32	29.3	0.30	0.07

Table 1: Model performances on EN → FR test sets before *(default)* and after *(S+T_{ctx})* context-aware MT fine-tuning. **OK**: % of translations with correct disambiguation for discourse phenomena. **OK-CS**: % of translations where the correct disambiguation is achieved only when context is provided.

datasets closely matching fine-tuning data. To gain further insight into these results, we use context-aware models to translate examples with and without context and identify a subset of *context-sensitive translations* (OK-CS) for which the correct target word is generated only when input context is provided to the model. Interestingly, we find a non-negligible amount of translations that are correctly disambiguated even in the absence of input context (corresponding to OK minus OK-CS in Table 1). For these examples, the correct prediction of ambiguous words aligns with model biases, such as defaulting to masculine gender for anaphoric pronouns (Stanovsky et al., 2019)) or using the most frequent sense for word sense disambiguation. Provided that such examples are unlikely to exhibit context reliance, we focus particularly on the OK-CS subset results in our following evaluation.

4.2 Metrics for Context-sensitive Target Identification

The following contrastive metrics are evaluated for detecting context-sensitive tokens in the CTI step.

Relative Context Saliency We use contrastive gradient norm attribution (Yin & Neubig, 2022) to compute input importance towards predicting the next token $\hat{y}_i$ with and without input context. Positive importance scores are obtained for every input token using the L2 gradient vectors norm (Bastings et al., 2022), and relative context saliency is obtained as the proportion between the normalized importance for context tokens $c \in C_x, C_y$ and the overall input importance, following previous work quantifying MT input contributions (Voita et al., 2021; Ferrando et al., 2022a; Edman et al., 2023).

$$\nabla_{\text{ctx}}(P^i_{\text{ctx}}, P^i_{\text{no-ctx}}) = \frac{\sum_{c \in C_x, C_y} \left\| \nabla_c \big(P_{\text{ctx}}(\hat{y}_i) - P_{\text{no-ctx}}(\hat{y}_i)\big) \right\|}{\sum_{t \in X^i_{\text{ctx}}} \left\| \nabla_t \big(P_{\text{ctx}}(\hat{y}_i) - P_{\text{no-ctx}}(\hat{y}_i)\big) \right\|} \tag{3}$$

Likelihood Ratio (LR) and **Pointwise Contextual Cross-mutual Information (P-CXMI)** Proposed by Vamvas & Sennrich (2021a) and Fernandes et al. (2023) respectively, both metrics frame context dependence as a ratio of contextual and non-contextual probabilities.

$$\text{LR}(P^i_{\text{ctx}}, P^i_{\text{no-ctx}}) = \frac{P_{\text{ctx}}(\hat{y}_i)}{P_{\text{ctx}}(\hat{y}_i) + P_{\text{no-ctx}}(\hat{y}_i)} \tag{4}$$

$$\text{P-CXMI}(P^i_{\text{ctx}}, P^i_{\text{no-ctx}}) = -\log \frac{P_{\text{ctx}}(\hat{y}_i)}{P_{\text{no-ctx}}(\hat{y}_i)} \tag{5}$$

KL-Divergence (Kullback & Leibler, 1951) between P^i_{ctx} and $P^i_{\text{no-ctx}}$ is the only metric we evaluate that considers the full distribution rather than the probability of the predicted token. We include it to test the intuition that the impact of context inclusion might extend beyond top-1 token probabilities.

$$D_{\text{KL}}(P^i_{\text{ctx}} \| P^i_{\text{no-ctx}}) = \sum_{\hat{y}_i \in \mathcal{V}} P_{\text{ctx}}(\hat{y}_i) \log \frac{P_{\text{ctx}}(\hat{y}_i)}{P_{\text{no-ctx}}(\hat{y}_i)} \tag{6}$$

4.3 CTI Plausibility Results

Figure 3 presents our metrics evaluation for CTI, with results for the full test sets and the subsets of context-sensitive sentences (OK-CS) highlighted in Table 1. To keep our evaluation simple, we use a naive s_{cti} selector tagging all tokens with metric scores one standard deviation above the per-example mean as context-sensitive.We also include a stratified random baseline matching the frequency of occurrence of context-sensitive tokens in each dataset. Datapoints in Figure 3 are sentence-level macro F1 scores computed for every dataset example. Full results are available in Appendix F.

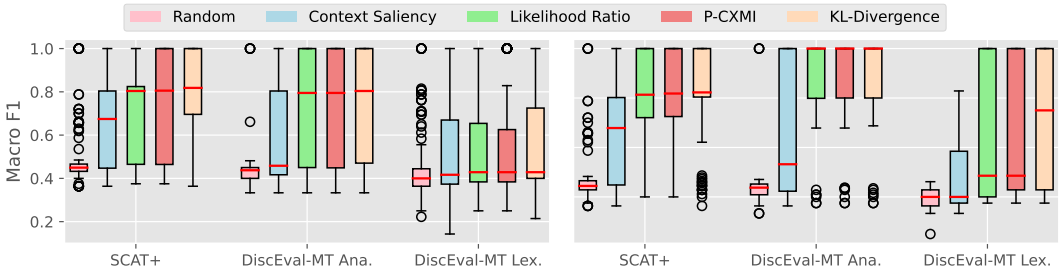

Figure 3: Macro F1 of contrastive metrics for context-sensitive target token identification (CTI) using OpusMT Large on the full datasets (left) or on OK-CS context-sensitive subsets (right).

We find probability-dependent metrics like LR and P-CXMI to reflect high plausibility of context sensitivity for the context-sensitive subsets OK-CS across all datasets and models. As expected, their performance drops significantly when considering the full test set, especially for lexical choice phenomena not seen during training. KL-Divergence performs similarly and sometimes better than pointwise metrics such as P-CXMI and LR. This suggests the distribution shift caused by context inclusion can provide useful information for detecting context sensitivity beyond the change in probability of the top-1 next token candidate. Context saliency fares poorly compared to other metrics, indicating that context reliance alone is not sufficient to predict context sensitivity.

4.4 Methods for Contextual Cues Imputation

The following attribution methods are evaluated for detecting contextual cues in the CCI step.

Contrastive Gradient Norm This method proposed by (Yin & Neubig, 2022) aims to identify input tokens leading to the prediction of an output token of interest instead of a contrastive alternative, making it especially fitting to explain the generation of context-sensitive tokens identified by CTI in presence and absence of context.

$$A_{t\,\text{ctx}} = \{\, \|\nabla_c\big(f_{\text{TGT}}(P^i_{\text{ctx}}, P^i_{\text{no-ctx}})\big)\| \,|\, \forall c \in C\} \tag{7}$$

For the choice of f_{tgt}, we evaluate both probability difference $P_{\text{ctx}}(\hat{y}_i) - P_{\text{no-ctx}}(\hat{y}_i)$, conceptually similar to the original formulation, and also the KL-Divergence of contextual and non-contextual distributions $D_{\text{KL}}(P^i_{\text{ctx}} \| P^i_{\text{no-ctx}})$. We use ∇_{diff} and ∇_{KL} to identify gradient norm attribution in the two settings. ∇_{KL} scores can be seen as the contribution of input tokens towards the shift in probability distribution when input context is available.

Attention Weights Following previous work, we test the mean attention weight across all attention heads and model layers (Attention Mean, Kim et al., 2019) and the weight for the head obtaining the highest plausibility per-dataset (Attention Best, Yin et al., 2021). Attention Best can be seen as a best-case estimate of attention performance for CCI, but is not a viable metric in realistic settings where the best attention head to capture a phenomenon of interest is unknown. Since attention weights are model byproducts unaffected by predicted outputs, we use only attention scores for the contextual setting P^i_{ctx} and ignore the contextless alternative when using these metrics.

4.5 CCI Plausibility Results

We conduct a controlled CCI evaluation using gold context-sensitive tokens as a starting point to attribute contextual cues.[8] This allows us to quantify the plausibility of CCI in isolation, assuming perfect identification of context-sensitive tokens. Figure 4 presents our results. Scores in the right plot are relative to the same context-aware OpusMT Large model of Section 4.3, using both source and target context. Instead, the left plot presents results for an alternative version of the same model that was fine-tuned using only source context (i.e. translating $C_x, x \rightarrow y$ without producing target context C_y), an approach that was adopted in previous context-aware MT studies (Fernandes et al., 2022). We include it here to assess how the inclusion of a target context impacts model plausibility. We

[8]To avoid using references as model generations, we align annotations to natural model outputs (Appendix E).

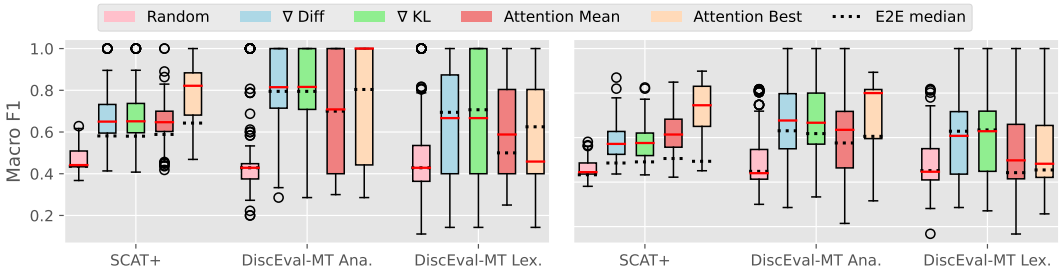

Figure 4: Macro F1 of CCI methods over full datasets using OpusMT Large models trained with only source context (left) or with source+target context (right). Boxes and red median lines show CCI results based on gold context-sensitive tokens. Dotted bars show median CCI scores obtained from context-sensitive tokens identified by KL-Divergence during CTI (E2E settings).

also validate the end-to-end plausibility of PECoRe by using context-sensitive tokens identified by the best CTI metric from Section 4.3 (KL-Divergence) as the starting point for CCI. We only report results for the full datasets as ok-cs shows comparable trends and use a simple statistical selector equivalent to the one used for CTI evaluation. Full results are available in Appendix G.

First, we observe that contextual cues are more easily detected for the source-only model using all evaluated methods. This finding corroborates previous evidence highlighting how context usage issues might emerge when lengthy context is provided (Fernandes et al., 2021; Shi et al., 2023). The drop in performance when moving from gold CTI tags to the end-to-end setting (E2E) is sharper for the SCAT+ and DiscEval-MT ana datasets that more closely match fine-tuning data. Interestingly, the Attention Best method, which achieves the best performance on both datasets, is the one that suffers the most from end-to-end CCI application, while other methods are more mildly affected. This can result from attention heads specializing in coreference resolution for pronoun anaphora during fine-tuning but failing to generalize to other discourse-level phenomena at test time. This provides further evidence in the limitations of attention as an explanatory metric (Jain & Wallace, 2019; Bastings & Filippova, 2020). In sum, the tested CCI methods perform above chance in most cases, with ∇_{KL} appearing as the most robust choice. That said, per-example variability remains high across the board, leaving space for improvement through the adoption of more faithful attribution methods for CCI in future work.

5 Detecting Context Reliance in the Wild

We conclude our analysis by applying the PECoRe method to the popular Flores-101 MT benchmark (Goyal et al., 2022), which contains groups of 3 to 5 contiguous sentences extracted from English Wikipedia. While in previous sections we used human-labeled examples to evaluate the effectiveness of different framework components, here, the method is applied to naturalistic MT examples, and its outputs are inspected to identify successes and failures of a context-aware MT model. Specifically, we apply PECoRe to the context-aware mBART-50 models of Section 4.1 in an end-to-end fashion, using KL-Divergence as CTI metric and ∇_{KL} as CCI attribution method. We use thresholds to two standard deviations above the per-example score average as s_{CTI} and s_{CCI} selectors to focus our analysis only on very salient tokens.

Table 2 presents some examples of PECoRe outputs, with more example covering other target languages in Appendix H. In the first setting, *goods* is translated as *biens* rather than *marchandises* when context is provided. PECoRe identifies this change as context-sensitive and traces it back to the same word translated as *biens* in the preceding context, suggesting the model prediction was aimed at enforcing lexical cohesion. The same happens with the second context-sensitive word *centrale* (*central*), which is correctly lowercased following its previous occurrence in the same format. The verb *taxées* (*taxed*, feminine) is also changed to masculine (*taxés*) to reflect the change in grammatical gender between *marchandises* (feminine) and *biens* (masculine), but is not marked as context-dependent, as it does not depend directly on cues in C_x or C_y.

In the second example, the correct translation of *reindeers* (*rennes*) is performed in the non-contextual case, but the same word is instead translated as *renards* (*foxes*) in the contextual output. By applying

Lexical and casing cohesion (English → French, correct)
C_x : I don't know if you realize it, but most of the goods from Central America came into this country duty-free. C_y : Je ne sais pas si vous le réalisez, mais la plupart des ① biens d'Amérique ② centrale sont venus ici en franchise.
x : Yet eighty percent of our goods were taxed through tariffs in Central American countries. $\tilde{y}$: Pourtant, 80 % de nos ① marchandises ont été *taxées* par des tarifs dans les pays d'Amérique ② Centrale. $\hat{y}$: Pourtant, 80 % de nos ① biens ont été *taxés* par des tarifs dans les pays d'Amérique ② centrale.
Lexical cohesion (English → French, incorrect)
C_x :Reindeer husbandry is an important livelihood among the Sámi [...]. C_y : L'élevage de renards est un important gagne-pain parmi les Samis [...]
x : Even traditionally, though, not all Sámi have been involved in big scale reindeer husbandry. $\tilde{y}$: Même traditionnellement, cependant, tous les Samis ne sont pas impliqués dans l'élevage de rennes à grande échelle. $\hat{y}$: Même traditionnellement, cependant, tous les Samis ne sont pas impliqués dans l'élevage de renards à grande échelle.
Numeric format cohesion (English → French, incorrect)
C_x : The games kicked off at 10:00am with great weather apart from mid morning drizzle [...] C_y : Les matchs se sont écoulés à 10:00 du matin avec un beau temps à part la nuée du matin [...]
x : South Africa started on the right note when they had a comfortable 26-00 win against Zambia. $\tilde{y}$: L'Afrique du Sud a commencé sur la bonne note quand ils ont eu une confortable victoire de 26 contre le Zambia. $\hat{y}$: L'Afrique du Sud a commencé sur la bonne note quand ils ont eu une confortable victoire de 26:00 contre le Zambia.
Lexical cohesion (English → Turkish, correct)
C_x : The activity of all stars in the system was found to be driven by their luminosity, their rotation, and nothing else. C_y : Sistemdeki bütün ulduzların faaliyetlerinin, parlaklıkları, rotasyonları ve başka hiçbir şeyin etkisi altında olduğunu ortaya çıkardılar.
x : The luminosity and rotation are used together to determine a star's Rossby number, which is related to plasma flow. $\tilde{y}$: Parlaklık ve döngü, bir *yıldızın plazm* akışıyla ilgili Rossby sayısını belirlemek için birlikte kullanılıyor. $\hat{y}$: Parlaklık ve rotasyon, bir *ulduzun plazma* akışıyla ilgili Rossby sayısını belirlemek için birlikte kullanılıyor.

Table 2: Flores-101 examples with highlighted cue-target pairs identified by PECoRe. Context-sensitive tokens predicted over non-contextual counterparts are identified by CTI, and contextual cues justifying their respective predictions are retrieved by CCI. *Other changes* are also present in the contextual translation $\hat{y}$, but are not considered context-sensitive by PECoRe.

PECoRe, we identify the token as context-sensitive, and the mistaken translation of *reindeers* as *renards* in the preceding sentence as the culprit for this outcome. The third example presents an interesting case of erroneous numeric format cohesion that would be challenging to detect without an automatic method. In this case, the match score *26-00* is translated wrongly as *26* in the contextless output, and the format *26:00* is adopted instead in the context-aware translation. This formatting choice is explained by the presence of a time indication using the same separator in the context.

Finally, we include an example of context usage for English→Turkish translation to test the contextual capabilities of the default mBART-50 model without context-aware fine-tuning. Again, PECoRe shows how the word *rotasyon* (rotation) is selected over *döngü* (loop) as the correct translation in the contextual case due to the presence of the lexically similar word *rotasyonları* in the previous context.

6 Conclusion

In this work, we introduced PECoRe, a novel interpretability framework to analyze context usage in naturally occurring language models' generations. PECoRe extends the common plausibility evaluation procedures adopted in interpretability research by including an initial step aimed at detecting context-sensitive tokens in generated texts. Experiments validating the framework on the context-aware MT task show that context-sensitive tokens and their disambiguating rationales can be detected consistently and with reasonable accuracy across several datasets, models and discourse phenomena. Moreover, we showcased an end-to-end application of our approach to detect context dependence without any human annotation, which revealed cases of incorrect context usage leading to problematic model translations.

While our evaluation is focused on the machine translation domain, PECoRe can easily be applied to other context-dependent language generation tasks. Future applications of our methodology could investigate the usage of in-context demonstrations and chain-of-thought reasoning in large language models (Brown et al., 2020; Wei et al., 2022) as well as factual recall in retrieval-augmented generation systems (Borgeaud et al., 2022).

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A Precisions on Target-dependent Attribution Methods

Definition A.1. Let s, s' be the resulting scores of two attribution target functions $f_{\text{TGT}}, f'_{\text{TGT}}$. An attribution method f_{ATT} is **target-dependent** if importance scores A are computed in relation to the outcome of its attribution target function, i.e. whenever the following condition is verified.

$$f_{\text{ATT}}(x, y_{<t}, C, \theta, s) \neq f_{\text{ATT}}(x, y_{<t}, C, \theta, s') \;\; \forall s \neq s' \tag{8}$$

In practice, common gradient-based attribution approaches (Simonyan et al., 2014; Sundararajan et al., 2017) are target-dependent as they rely on the outcome predicted by the model (typically the logit or the probability of the predicted class) as differentiation target to backpropagate importance to model input features. Similarly, perturbation-based approaches (Zeiler & Fergus, 2014) use the variation in prediction probability for the predicted class when noise is added to some of the model inputs to quantify the importance of the noised features.

On the contrary, recent approaches relying solely on model internals to define input importance are generally target-insensitive. For example, attention weights used as model rationales, either in their raw form or after a rollout procedure to obtain a unified score (Abnar & Zuidema, 2020), are independent of the predicted outcome. Similarly, value zeroing scores (Mohebbi et al., 2023) reflect only the representational dissimilarity across model layers before and after zeroing value vectors, and as such do not explicitly account for model predictions.

B PECoRe Implementation

Algorithm 1 provides a pseudocode implementation of the PECoRe cue-target pair extraction process formalized in Section 3.

Algorithm 1: PECORE cue-target extraction process

Input: C, x – Input context and current sequences
θ – Model parameters
$s_{\text{CTI}}, s_{\text{CCI}}$ – Selector functions
$\mathcal{M}$ – Contrastive metrics
f_{ATT} – Contrastive attribution method
f_{TGT} – Contrastive attribution target function
Output: Sequence S_{ct} of cue-target token pairs

Generate sequence $\hat{y}$ from inputs C, x using any decoding strategy ;

Context-sensitive Target Identification (CTI):
$\mathcal{T}$ – Empty set to store indices of context-sensitive target tokens of $\hat{y}$;
for $\hat{y}_i \in \hat{y}$ **do**
  for $m \in \mathcal{M}$ **do**
    $m^i = m_j\big(P_{\text{ctx}}(\hat{y}_i), P_{\text{no-ctx}}(\hat{y}_i)\big)$;
  if $s_{\text{CTI}}(m^i_1, \ldots, m^i_M) = 1$ **then**
    Store i in set $\mathcal{T}$;

Contextual Cues Imputation (CCI):
S_{ct} – Empty sequence to store cue-target token pairs ;
for $t \in \mathcal{T}$ **do**
  Generate constrained non-contextual target current sequence $\tilde{y}^*$ from $\hat{y}_{<t}$;
  Use attribution method f_{ATT} using f_{TGT} as attribution target to get input importance scores A_t;
  Identify the subset $A_{t\,\text{CTX}}$ corresponding to tokens of context $C = \{C_1, \ldots, C_K\}$;
  for $a_i \in A_{t\,\text{CTX}} = \{a_1, \ldots, a_K\}$ **do**
    if $s_{\text{CCI}}(a_i) = 1$ **then**
      Store $(C_i, \hat{y}_t)$ in S_{ct}
return S_{ct}

	SCAT+				DiscEval-MT (ana)				DiscEval-MT (lex)			
Model	**Bleu**	**Comet**	**ok**	**ok-cs**	**Bleu**	**Comet**	**ok**	**ok-cs**	**Bleu**	**Comet**	**ok**	**ok-cs**
OpusMT Small *(default)*	29.1	.799	0.14	-	43.9	.888	0.40	-	30.5	.763	0.29	-
OpusMT Small S_{ctx}	36.1	.812	0.84	0.42	47.1	**.900**	0.61	0.28	28.3	.764	0.31	0.05
OpusMT Small S+T_{ctx}	39.1	.816	0.81	0.59	48.1	.889	0.60	0.24	33.5	.774	0.36	0.07
OpusMT Large *(default)*	29.0	.806	0.16	-	39.2	.891	0.41	-	31.2	.771	0.31	-
OpusMT Large S_{ctx}	38.4	.823	0.83	0.41	44.6	.887	0.64	0.28	32.2	.773	**0.39**	0.09
OpusMT Large S+T_{ctx}	**40.3**	**.827**	0.83	0.58	48.9	.896	**0.68**	0.31	**34.8**	**.787**	0.38	0.10
mBART-50 *(default)*	30.9	.780	0.52	-	33.4	.871	0.42	-	24.5	.734	0.25	-
mBART-50 S_{ctx}	33.5	.808	**0.87**	0.42	36.3	.869	0.57	0.23	25.7	.760	0.29	0.06
mBART-50 S+T_{ctx}	37.6	.814	0.82	0.55	**49.0**	.895	0.64	0.29	29.3	.767	0.30	0.07

Table 3: Full model performances on En → Fr test sets before *(default)* and after context-aware MT fine-tuning. S_{ctx} and S+T_{ctx} are context-aware model variants using source-only and source+target context, respectively. **ok**: % of translations with correct disambiguation for discourse phenomena. **ok-cs**: % of translations where the correct disambiguation is achieved only when context is provided.

C Full Translation Performance

Table 3 presents the translation quality and accuracy across all tested models. We compute BLEU using the SACREBLEU library (Post, 2018) with default parameters `nrefs:1|case:mixed|eff:no|tok:13a|smooth:exp|version:2.3.1` and compute COMET scores using COMET-22 (Rei et al., 2022) (v2.0.2). The models fine-tuned with source and target context clearly outperform the ones trained with source only, both in terms of generic translation quality and context-sensitive disambiguation accuracy. This motivates our choice to focus primarily on those models for our main analysis.

SCAT+
C_x : I loathe that song. But why did you bite poor Birdie's head off? Because I've heard it more times than I care to. It haunts me. Just stop, for a moment. C_y : Je hais cette chanson . Mais pourquoi avoir parlé ainsi à la pauvre Birdie ? Parce que j'ai entendu ce chant plus que de fois que je ne le peux. Elle me hante. Arrêtez-vous un moment. x : How does it haunt you? y : Comment peut-elle vous hanter?
C_x: - Ah! Sven! It's been so long. - Riley, it's good to see you. - You, too. How's the boat? Uh, it creaks, it groans. C_y : Sven ! - Riley, contente de te voir. - Content aussi. Comment va le bateau ? Il craque de partout. x : Not as fast as it used to be. y : Il n'est pas aussi rapide qu'avant.
DISCEVAL-MT ANA
C_x : But how do you know the woman isn't going to turn out like all the others? C_y : Mais comment tu sais que la femme ne finira pas comme toutes les autres? x : This one's different. y : Celle-ci est différente.
C_x : Can you authenticate these signatures, please? C_y : Pourriez-vous authentifier ces signatures, s'il vous plaît? x : Yes, they're mines. y : Oui, ce sont les miennes.
DISCEVAL-MT LEX
C_x : Do you think you can shoot it from here? C_y : Tu penses que tu peux le tirer dessus à partir d'ici? x : Hand me that bow. y : Passe-moi cet arc.
C_x : Can I help you with the wrapping? C_y : Est-ce que je peux t'aider pour l'emballage? x : Hand me that bow. y : Passe-moi ce ruban.

Table 4: Examples from the SCAT+ and DISCEVAL-MT datasets used in our analysis with highlighted context-sensitive tokens and contextual cues used for plausibility evaluation using PECORE.

D DATASETS ANNOTATION PROCEDURE

SCAT+ The original SCAT test set by Yin et al. (2021) contains 1000 examples with automatically identified context-sensitive pronouns *it/they* (marked by <p>...<\p>) and human-annotated contextual cues aiding their disambiguation (marked by <hon>...<\hoff>). Of these, we find 38 examples containing malformed tags and several more examples where an unrelated word containing *it* or *they* was wrongly marked as context-sensitive (e.g. `the soccer ball h<p>it</p> your chest`). Moreover, due to the original extraction process adopted for SCAT, there is no guarantee that contextual cues will be contained in the preceding context as they could also appear in the same sentence, defeating the purpose of our context usage evaluation. Thus, we prefilter the whole corpus to preserve only sentences with well-formed tags and inter-sentential contextual cues identified by original annotators. Moreover, a manual inspection procedure is carried out to validate the original cue tags and discard problematic sentences, obtaining a final set of 250 examples with inter-sentential pronoun coreference.

DISCEVAL-MT We use minimal pairs in the original dataset by Bawden et al. (2018) (e.g. the DISCEVAL-MT LEX examples in Table 4) to automatically mark differing tokens as context-sensitive. Then, contextual cues are manually labeled separately by two annotators with good familiarity with both English and French. Cue annotations are compared across the two splits, resulting in very high agreement due the simplicity of the corpus (97% overlap for ANA, 90% for LEX).

Table 4 presents some examples for the three splits. By design, SCAT+ sentences have more uniform context-sensitive targets (*it/they* → *il/elle/ils/elles*) and more naturalistic context with multiple cues to disambiguate the correct pronoun.

E TECHNICAL DETAILS OF PECORE EVALUATION

Aligning annotations Provided that gold context-sensitive tokens are only available in annotated reference translations, a simple option when applying CCI to those would involve using references as

model generations. However, this was shown to be problematic by previous research, as it would induce a *distributional discrepancy* in model predictions (Vamvas & Sennrich, 2021b). For this reason, we let the model generate a natural translation and instead try to align tags to this new sentence using the AWESOME aligner (Dou & Neubig, 2021) with LABSE multilingual embeddings (Feng et al., 2022). While this process is not guaranteed to always result in accurate tags, it provides a good approximation of gold CTI annotations on model generation for the purpose of our assessment.

F FULL CTI RESULTS

Figure 5 and Figure 6 present the CTI plausibility of all tested models for the Macro F1 and AUPRC metrics, similarly to Figure 3 in the main analysis.

G FULL CCI RESULTS

Figure 7 and Figure 8 present the CCI plausibility of all tested models for the Macro F1 and AUPRC metrics, similarly to Figure 4 in the main analysis.

H ADDITIONAL FLORES-101 PECORE EXAMPLES

Table 5 provides additional examples of end-to-end PECORE application highlighting interpretable context usage phenomena in model generations. English $\rightarrow$ French examples apply PECORE to the context-aware mBART-50 model fine-tuned with the procedure of Section 4.1. Examples with other target languages instead use the base mBART-50 model without any context-aware fine-tuning.

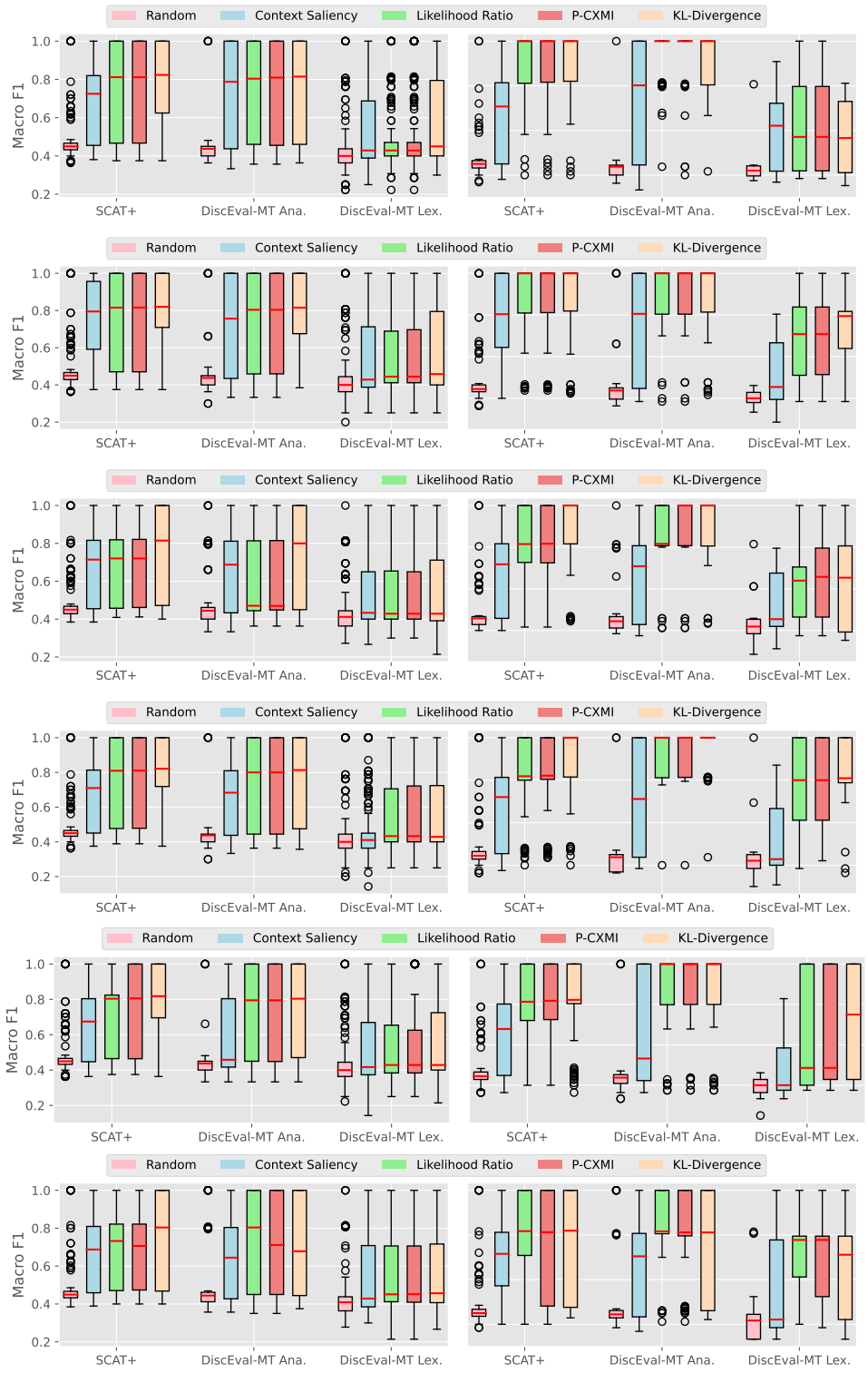

Figure 5: Macro F1 of contrastive metrics for context-sensitive target token identification (CTI) on the full datasets (left) or on OK-CS context-sensitive subsets (right). **Top to bottom:** ① OpusMT Small S_{ctx} ② OpusMT Large S_{ctx} ③ mBART-50 S_{ctx} ④ OpusMT Small $S+T_{ctx}$ ⑤ OpusMT Large $S+T_{ctx}$ ⑥ mBART-50 $S+T_{ctx}$.

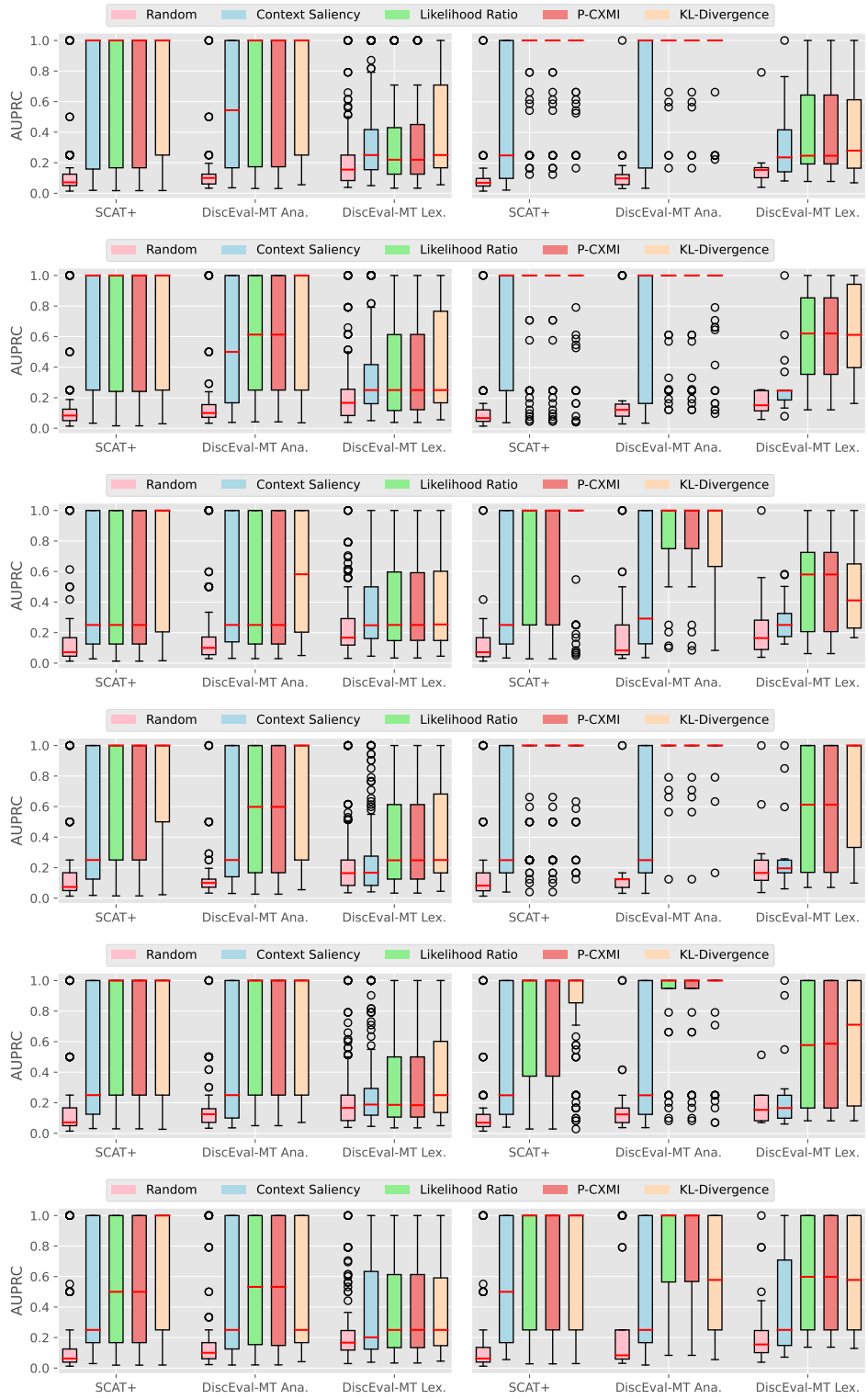

Figure 6: Area Under Precision-Recall Curve (AUPRC) of contrastive metrics for context-sensitive target token identification (CTI) on the full datasets (left) or on OK-CS context-sensitive subsets (right). **Top to bottom:** ① OpusMT Small S_{ctx} ② OpusMT Large S_{ctx} ③ mBART-50 S_{ctx} ④ OpusMT Small S+T_{ctx} ⑤ OpusMT Large S+T_{ctx} ⑥ mBART-50 S+T_{ctx}.

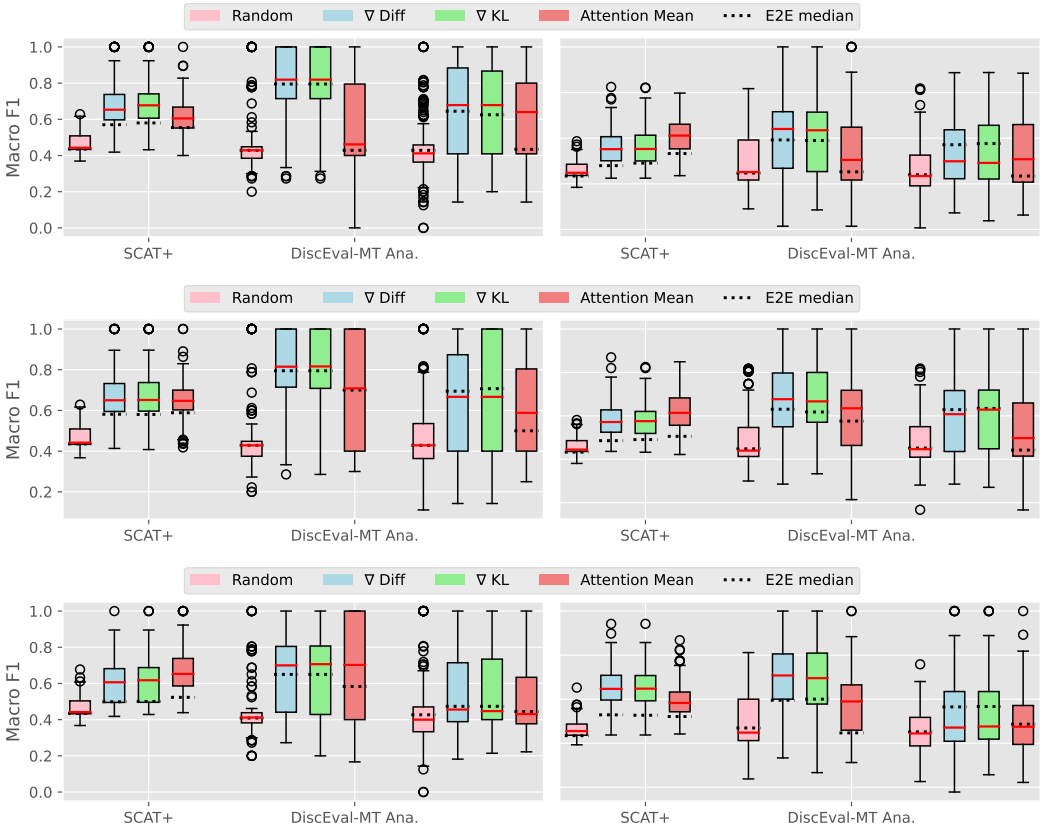

Figure 7: Macro F1 of CCI methods over full datasets using models trained with only source context (left) or with source+target context (right). Boxes and red median lines show CCI results based on gold context-sensitive tokens. Dotted bars show median CCI scores obtained from context-sensitive tokens identified by KL-Divergence during CTI (E2E settings). **Top to bottom:** ① OpusMT Small S_{ctx} and $S+T_{ctx}$ ② OpusMT Large S_{ctx} and $S+T_{ctx}$ ③ mBART-50 S_{ctx} and $S+T_{ctx}$.

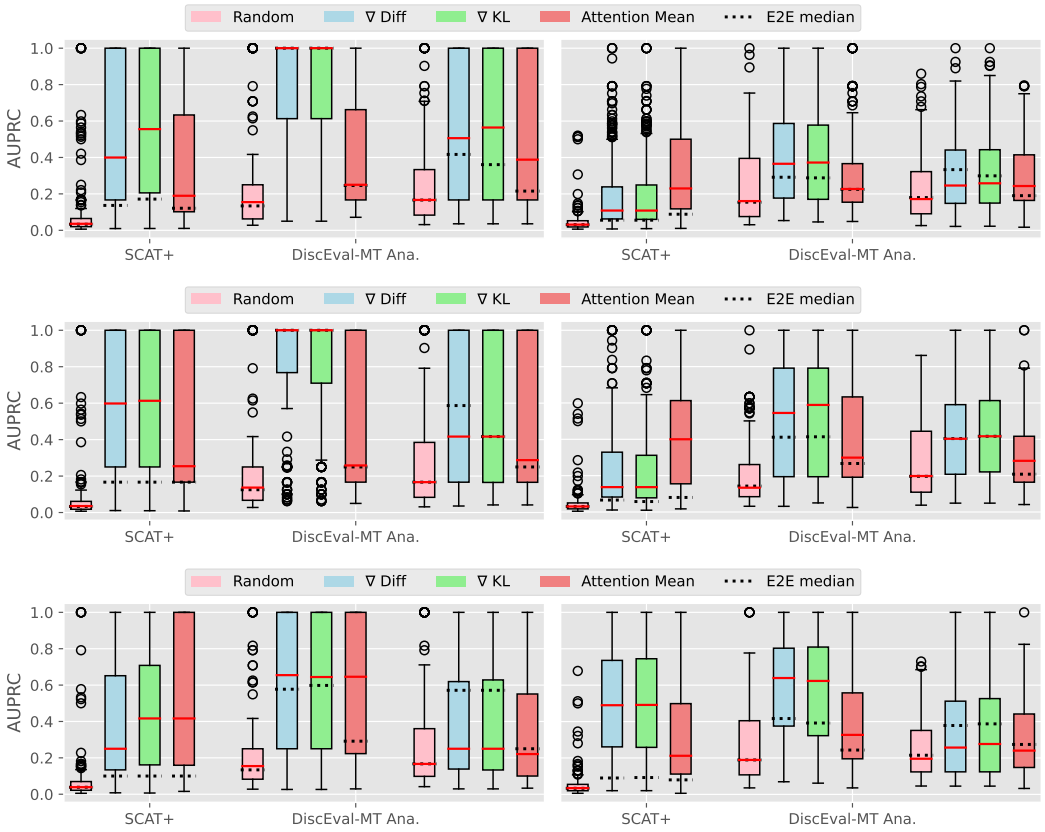

Figure 8: Area Under Precision-Recall Curve (AUPRC) of CCI methods over full datasets using models trained with only source context (left) or with source+target context (right). Boxes and red median lines show CCI results based on gold context-sensitive tokens. Dotted bars show median CCI scores obtained from context-sensitive tokens identified by KL-Divergence during CTI (E2E settings). **Top to bottom:** ① OpusMT Small S_{ctx} and S+T_{ctx} ② OpusMT Large S_{ctx} and S+T_{ctx} ③ mBART-50 S_{ctx} and S+T_{ctx}.

Anaphora Resolution (English → French, correct)
C_x : [...] Resting on the top of one of the mountains north of Mecca, the cave is completely isolated from the rest of the world. C_y : [...] Seul au sommet d'une des montagnes au nord de la Mecque, la grotte est complètement isolée du reste du monde. x : In fact, it is not easy to find at all even if one knew it existed. $\tilde{y}$: En fait, ce n'est pas *simple* à trouver même si on sait *que ça* existe. $\hat{y}$: En fait, elle n'est pas *facile* à trouver même si on sait *qu'elle* existe.
Verb form choice (English → French, correct)
C_x : After the dam was built, the seasonal floods that would spread sediment throughout the river were halted. C_y : Après la construction du barrage, les inondations saisonnières qui répandent les sédiments dans la rivière ont été stoppées. x : This sediment was necessary for creating sandbars and beaches $\tilde{y}$: Ces sédiments ont été nécessaires pour créer des *barrières* de sable et des plages $\hat{y}$: Ces sédiments étaient nécessaires pour créer des *bancs* de sable et des plages
Word Sense Disambiguation (English → French, incorrect)
C_x : Rip currents are the returning flow from waves breaking off the beach, often at a reef or similar. C_y : Les courants Rip sont les flux revenant des vagues qui se forment sur la plage, souvent sur un récif ou un point similaire. x : Due to underwater topology the return flow is concentrated at a few deeper sections $\tilde{y}$: En raison de la topologie sous-marine, le flux renouvelable est concentré *à* quelques parties plus profondes $\hat{y}$: En raison de la topologie sous-marine, le flux revenant est concentré *dans* quelques parties plus profondes
Lexical cohesion (English → French, incorrect)
C_x : Murray lost the first set in a tie break after both men held each and every serve in the set. C_y : Murray a perdu le premier jeu d'une rupture de cravate après que les deux hommes aient tenu chacun des coups. x : Del Potro had the early advantage in the second set, but this too required a tie break after reaching 6-6. $\tilde{y}$: Del Potro a eu l'avantage précoce dans le second jeu, mais il a fallu une rupture de crayon après avoir atteint 6-6. $\hat{y}$: Del Potro a eu l'avantage précoce dans le second jeu, mais il a fallu une rupture de cravate après avoir atteint 6-6.
Word Sense Disambiguation (English → Turkish, correct)
C_x : Every morning, people leave small country towns in cars to go their workplace and are passed by others whose work destination is the place they have just left. C_y : Her sabah insanlar işyerlerine gitmek için arabayla küçük kırsal kentleri terk ediyor ve iş noktasının henüz terk ettikleri yer olduğu başkaları tarafından geçtiler. x : In this dynamic transport shuttle everyone is somehow connected with, and supporting, a transport system based on private cars. $\tilde{y}$: Bu dinamik taşımacılık gemisinde *herkes bir şekilde özel* arabalara dayalı bir taşımacılık sistemiyle bağlantılı ve *destekleniyor*. $\hat{y}$: Bu dinamik taşımacılık nakil *aracında herkes özel* arabalara dayalı bir taşımacılık sistemiyle *bir şekilde* bağlantılı ve *destekli*.
Lexical Cohesion (English → Dutch, correct)
C_x : Rip currents are the returning flow from waves breaking off the beach, often at a reef or similar. C_y : Ripstromen zijn de terugkerende stroom van golven die van het strand afbreken, vaak op een rif of iets dergelijks. x : Due to the underwater topology the return flow is concentrated at a few deeper sections $\tilde{y}$: Door de onderwatertopologie is de terugkeerde stroom geconcentreerd op een paar diepere delen. $\hat{y}$: Door de onderwatertopologie is de terugkerende stroom geconcentreerd op een paar diepere delen.
Lexical Cohesion (English → Italian, correct)
C_x : Virtual teams are held to the same standards of excellence as conventional teams, but there are subtle differences. C_y : Le squadre virtuali hanno gli stessi standard di eccellenza delle squadre tradizionali, ma ci sono sottili differenze. x : Virtual team members often function as the point of contact for their immediate physical group. $\tilde{y}$: I membri dell'équipe virtuale spesso funzionano come punto di contatto per il proprio gruppo fisico immediato. $\hat{y}$: I membri delle squadre virtuali spesso funzionano come punto di contatto del loro gruppo fisico immediato.

Table 5: Context-sensitive tokens predicted over and their non-contextual counterparts are identified by CTI, and contextual cues justifying their respective predictions are identified by CCI. Contextual translation $\hat{y}$ also contains *other changes*, which are not found to be context-sensitive by PECoRe.