The Road to Quality is Paved with Good Revisions: A Detailed Evaluation Methodology for Revision Policies in Incremental Sequence Labelling

Anonymous ACL submission

Abstract

Incremental dialogue model components produce a sequence of output prefixes based on incoming input. Mistakes can occur due to local ambiguities or to wrong hypotheses, making the ability to revise past outputs a desirable property that can be governed by a policy. In this work, we formalise and characterise edits and revisions in incremental sequence labelling and propose metrics to evaluate revision policies. We then apply our methodology to profile the incremental behaviour of three Transformer-based encoders in various tasks, paving the road for better revision policies.

1 Introduction

Since the dawn of Wikipedia, users have made 1.7×10^9 edits to its pages. Its most revised entry contains 56,713 revisions, all documented in the page history.[1] In such an active community, conflicts inevitably occur. Editors can begin competing to override each other's contributions, causing dysfunctional *edit warrings*.[2] To help regulate the environment, an editing policy is in force, aiming at making edits constructive and improving quality.

Edits, revisions and policies are key concepts in incremental processing, where a model must rely on partial input to generate partial output. Incrementality can help optimise reactivity, naturalness, quality and realism in interactive settings (Schlangen and Skantze, 2011). This is particularly relevant in dialogue models whose NLU components need to operate on incoming input, *e.g.* while performing NER, slot filling or disfluency detection, or doing simultaneous translation.

Local ambiguities in the linguistic input and transient mistakes by the model may result in wrong partial hypotheses, so that the ability to *revise*, by *editing* previous outputs, is desirable. But beyond monitoring the occurrence of edits, it is also beneficial to have a *policy* regulating when and which revisions should be made, reducing the occurrence of undesirable edits. Existing literature using consolidated incremental evaluation metrics falls short in capturing relevant nuances of the incremental behaviour in terms of revisions.

In this work, we propose an evaluation methodology for revision policies in incremental sequence labelling. A constructed example of this task is shown in Figure 1, with revisions indicated in the right column. Specifically, our contributions to address the identified evaluation gap are: A formalisation of revision policy in incremental sequence labelling, characterising types of edits and of revisions (§4.1-4.2); a proposal of specialised evaluation metrics for revision policies, accompanied by a discussion on the desired behaviour of incremental processors (§4.4-4.5); a demonstration of our methodology with an analysis of the revision policy in three sequence labelling Transformer-based models (§5).[3]

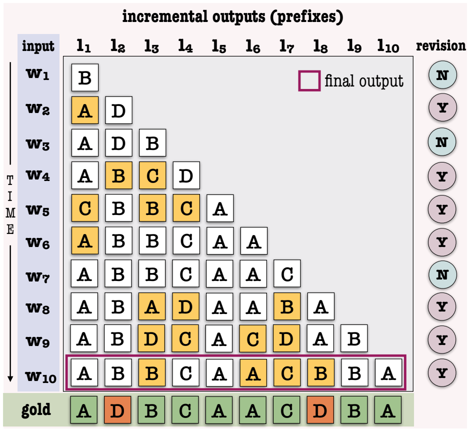

Figure 1: Constructed example of an incremental chart containing output prefixes with marked edits (yellow) and revisions in incremental sequence labelling. Red stands for wrong final predictions wrt. the gold standard.

[1] According to Wikimedia Statistics and wiki Special.
[2] https://en.wikipedia.org/wiki/Wikipedia:Edit_warring

[3] Our implementation is anonymously available at this link.

2 Motivation

Incremental natural language processing[4] has *time* at front line, being pivotal for interactive settings. At each time step, models must operate on partial input to deliver partial output, but sometimes previous decisions have to be revised. For example, at time step 4 in Figure 1, the labels for the input tokens 2 and 3 were edited into new states. With regard to revisions, at least three types of incremental processors exist, as summarised in Table 1:

1. Inherently incremental but monotonic models. They keep an internal state that is updated and used to extend the output at each time step, but cannot revise previous outputs.

2. Non-incremental models used with a *restart-incremental* interface, being forced to perform a full recomputation at each time step. Such models revise the output as a by-product of their recomputations.

3. Incremental models with a dedicated policy to detect the need to perform revisions only when deemed necessary and, more specifically, deciding which parts of the output prefix need to be revised and how.

		non-incremental	**incremental**
revisions	no	n/a	strictly monotonic outputs
	yes	recomputation policy doing revisions as a by-product	revision policy

Table 1: Types of incremental processors.

Monotonicity avoids instability in the output, allowing subprocesses to start immediately, as it is certain that the outputs will not change. However, they never recover from mistakes, which is one of the drawbacks of employing vanilla RNNs and LSTMs (Hochreiter and Schmidhuber, 1997).

Models that depend on the availability of full sentences at once can be "incrementalised" with the *restart-incremental* paradigm (Schlangen and Skantze, 2011), causing revisions to occur via recomputations.[5]

[4]For a review, see Köhn (2018). In other contexts, also referred to as real-time processing (Pozzan and Trueswell, 2015) or streaming (Kaushal et al., 2023).

[5]Also called *incremental interface* (Beuck et al., 2011a) or *beat-driven approach* (Baumann et al., 2011).

Cutting-edge NLP models currently rely on Transformers (Vaswani et al., 2017), which are non-incremental. Using them in a *restart-incremental* fashion requires recomputing from scratch at every time step, which we hereby name the *naive recomputation policy*. It is a very expensive policy because, for a sequence of n tokens, the complexity is $\sum_{i=1}^{n} i^2$ (*i.e.* the n-th square pyramidal number). Besides, this naive approach wastes computational budget, because not all recomputations cause revisions. The results reported by Kahardipraja et al. (2023), for example, show that only around 25% of the recomputations actually changed the output prefix. The disadvantages of the naive policy can be alleviated by a smarter policy that cuts down the number of time steps with recomputations.

Still, beyond deciding when to *recompute*, a revision policy par excellence should directly guide the more specific decision of when (and what) to actually *revise*, and must be evaluated accordingly.

3 Related Literature

Revisability is in the nature of incremental processing: Hypothesis revision is a necessary operation to correct mistakes and build up a high-quality final output (Schlangen and Skantze, 2011). Still, there is a trade-off between requiring that later modules handle a processor's revisions and buying stability by reducing some of its incrementality, which makes the concept of *hypothesis stability* very relevant (Baumann et al., 2009). Beuck et al. (2011a) argues that performing revisions should not take as long as the initial processing, so as to retain the advantages of incremental processing. They propose two strategies: Allowing revisions only within a fixed window or limiting their types. Empirically determining how often a model changes the output is an aspect of their analysis we also rely on.

The restart-incremental paradigm has been investigated for Transformer-based sequence labelling by Madureira and Schlangen (2020) and Kahardipraja et al. (2021); recently, Kaushal et al. (2023) and Kahardipraja et al. (2023) proposed adaptive policies to reduce the computational load. Rohanian and Hough (2021) and Chen et al. (2022) have explored adaptation strategies to use Transformers for incremental disfluency detection. In simultaneous translation, the restart-incremental approach is also in use and revisions are also studied (Arivazhagan et al., 2020; Sen et al., 2023).

Sequence labelling is a staple of various incre-

latency, quality, stability	simultaneous translation	Arivazhagan et al. (2020)
quality, responsiveness, robustness, stability	speech recognition and diarization	Baumann et al. (2009) Addlesee et al. (2020)
fluency, latency, quality, recovery capabilities, timing	simultaneous interpreting (MT and speech synthesis)	Baumann et al. (2014)
decisiveness, monotonicity, stability, timeliness	POS tagging	Beuck et al. (2011a)
amount of predicted information, connectedness, delay, inclusiveness, monotonicity, quality	parsing	Beuck et al. (2011b, 2013); Köhn and Menzel (2014)
cognitive aspects, efficiency	neural coreference resolution	Grenander et al. (2022)
jumpiness, position	reference resolution	Schlangen et al. (2009)
accuracy, integration, representational similarity	sequence-to-sequence	Ulmer et al. (2019)
consistency, diminishing returns, interruptibility, monotonicity, preemptability, (recognisable) quality	anytime algorithms	Zilberstein (1996)

Table 2: Overview of relevant properties for incremental evaluation in various tasks.

mental linguistic tasks possibly used in dialogue systems, like SRL (Konstas et al., 2014), POS-tagging (Beuck et al., 2011a), dialogue act segmentation (Manuvinakurike et al., 2016), disfluency detection (Hough and Schlangen, 2015) and dependency parsing (Honnibal and Johnson, 2014).

Revision Categorisation and Prediction Approaches to categorise the properties of revisions or edits exist in various areas. Faigley and Witte (1981) examine the effects and causes of revisions in writing, providing a taxonomy on whether revisions change meaning and bring new information. Afrin and Litman (2018) classify revision quality by whether they improve student essays. Anthonio et al. (2020) categorise revisions and edits in WikiHow in terms of what they cause to the text. Wikipedia's edits have also been classified according to factuality and fluency (Bronner and Monz, 2012) and intents (Rajagopal et al., 2022). Other typologies and taxonomies have been proposed for translation revisions (Fujita et al., 2017) and multilingual NLG revision operations (Callaway, 2003).

Vaughan and McDonald (1986) outline three phases of the revision process in NLG: recognition, editing and re-generation. Revision rules have been applied for incremental summarisation by Robin (1996). Non-incremental revision learning models also exist, relying on revision rules for dependency parsing (Attardi and Ciaramita, 2007) or classification in POS-tagging (Nakagawa et al., 2002). Predicting stability and accuracy of hypotheses is a relevant task (Selfridge et al., 2011), which allows to distinguish hypotheses that will survive and are thus more reliable (Baumann et al., 2009).

Incremental Evaluation Table 2 presents an overview of relevant properties for incremental evaluation. In their seminal work, Baumann et al. (2011) define three general categories of metrics for incremental processing: *similarity*, *timing* and *diachronic*, which can be employed in incremental sequence labelling. They are suitable for capturing *e.g.* instability (edit overhead), quality of prefixes (correctness) and lag (correction time). Kaushal et al. (2023) propose streaming exact match, comparing prefixes with the final gold standard. While these metrics capture instability and correctness of output prefixes, we lack a standard way to evaluate the quality of the performed revisions. We thus complement their work by proposing fine-grained metrics focusing on revisions and recomputations.

4 Evaluation Methodology

In this section, we present our evaluation methodology for incremental sequence labelling with a focus on revisions. After formalising the task, we characterise revisions and edits, define policies and revision-oriented metrics and discuss the ideal behaviour of incremental sequence labelling models.

4.1 Formalisation

We begin by formalising incremental sequence labelling tasks, extending the similar definition of streaming sequence tagging in (Kaushal et al., 2023) with *edits* and *revisions*.[6]

[6]Like them, we assume an idealised format where incremental units are well-defined, fixed and complete input tokens. The model produces a label for every new input token, so that the output is necessarily extended at every time step. Note, however, that incremental processors may have to operate at sub-token level or with transitional input, which requires

Let $L = \{L_1, \ldots, L_M\}$ be a set of labels. In standard sequence labelling, the task is to map an input sequence of n tokens $(w_i)_{i=1}^n$ to an output sequence of n labels $(l_i)_{i=1}^n$, $l_i \in L$. Each output label l_i classifies its corresponding token w_i. The task is more complex than plain token-level classification because the sequential nature of the input and the output need to be taken into account when predicting labels. If available, a gold-standard sequence $(g_i)_{i=1}^n$, with $g_i \in L$, is used to evaluate the correctness of the predicted output sequence.

In an incremental setting, the input is provided in a piecemeal fashion, one token at a time. At each time step $t = 1, 2, \ldots, n$, an increasing input prefix $(w_i)_{i=1}^t$ is available to the model and an output prefix $(l_i)_{i=1}^t$ is predicted. Therefore, an input sequence with n tokens will result in n output prefixes $p_1, p_2, \ldots, p_n$, which we consider to be partial hypotheses for the final output. Each p_i is a sequence of i labels, containing one additional label at the right in relation to p_{i-1}. The last hypothesis p_n is the final decision of the model, having observed the complete input. The complete sequence of prefixes can be represented as a lower triangular matrix, whose cells c_i^j contain the label assigned to w_i at time j and each row i contains p_i. We can represent the incremental input and output in an *incremental chart* (IC) as follows:

w_1	$p_1 =$	l_1^1				
w_1, w_2	$p_2 =$	l_1^2	l_2^2			
w_1, w_2, w_3	$p_3 =$	l_1^2	l_2^2	l_3^3		
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$	
$w_1, w_2, \ldots, w_n$	$p_n =$	l_1^n	l_2^n	l_3^n	$\cdots$	l_n^n
	gold $=$	g_1	g_2	g_3	$\cdots$	g_n

At each time step t, the observation of the new input token w_t causes the model to i) extend the output sequence with one label for w_t (an addition) and ii) optionally also change its current hypotheses $l_1, \ldots, l_{t-1}$ for previous tokens (substitutions).

An *edit* occurs at time t for label i if $l_i^t \neq l_i^{t-1}$, meaning that the model's prediction for w_i's label changed. A *revision* occurs when, apart from the compulsory addition, a prefix changes at time t in relation to the previous prefix, *i.e.* when at least one label is edited.[7] In Figure 1, revisions occur at time steps $2, 4, 5, 6, 8, 9$ and 10. Highlighted labels in the prefixes are edits. The final output has two incorrect labels with respect to the gold standard.

the capability of retracting decisions and adjusting to varying length in real-time. In some models, outputs may not have an immediate one-to-one correspondence to the input (*e.g.* due to a delay strategy) and parallel hypotheses can be kept in memory. See Schlangen and Skantze (2011) for details.

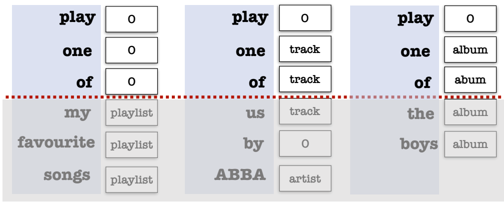

Figure 2: Illustrative example of multiple locally valid hypotheses for the prefix *play one of*. Only after more input is processed a definite labels can be assigned.

Gold Standard Evaluation can be done with respect to incremental or non-incremental gold standards (Baumann et al., 2011). Often, only the non-incremental version is available, *i.e.* the labels on the complete sequence, assigned having all left and right context taken into account. A genuinely incremental gold standard contains step-by-step gold prefixes encoding interpretations that are *locally valid* until right context renders it invalid, as illustrated in Figure 2.[8] Since it is usually not available, we can instead "incrementalise" the final gold standard by deriving all its prefixes as hard labels. But this approach somewhat unfairly expects that, even at steps with multiple locally valid interpretations, the model commits to the final decision without observing the input that actually induces that interpretation as correct and the others as wrong. Moreover, using an independent gold standard conflates the external overall performance of the model with the quality of its internal incrementality (Baumann et al., 2011). An alternative is to consider the final output of the model as a silver standard. The correctness of labels and prefixes can be measured with a metric M with respect to the defined target.

4.2 Characterisation of Revisions and Edits

In this section, we propose a detailed characterisation for the types of edits and revisions based on ten dimensions, as summarised in Table 3. In the next paragraphs, we assume that either a genuine or a constructed incremental sequence of target prefixes has been selected according to the current needs.

[7]The addition is not taken into account here, as it has no precedent label to be compared to at this point. The first time step is by definition not a revision, since there is no prefix yet.

[8]For existing examples, see Hrycyk et al. (2021), Rawat and Barres (2022) and Beuck et al. (2011b)

	Quality	Edits	Example	Revisions	Example
Convenience	convenient	change incorrect label	(5,1)	change incorrect prefix	5
	inconvenient	change correct label	(4,2)	change correct prefix	4
Effectiveness	effective	incorrect label → correct	(5,4)	improve prefix correctness	6
	ineffective	incorrect label → incorrect	(9,3)	do not change prefix correctness	9
	defective	correct label → incorrect	(4,3)	worsen prefix correctness	4
Novelty	innovative	label → new state	(9,6)	N/A	N/A
	repetitive	label → previous state	(6,1)	N/A	N/A
(Local) Recurrence	recurrent	subsequence with > 1 edit	(9,3)	subsequence with > 1 revision	8
	steady	subsequence with 1 edit	(4,2)	subsequence with 1 revision	2
Oscillation	oscillating	label with > 1 edit	(6,1)	> 1 revision	all
	stable	label with 1 edit	(4,2)	single revision	-
Company	accompanied	prefix with > 1 edit	(9,6)	prefix with > 1 edit	5
	isolated	prefix with 1 edit	(6,1)	prefix with 1 edit	6
Connectedness	connected	other neighbouring edit	(9,4)	only connected edits	9
	disconnected	no neighbouring edits	(5,1)	only disconnected edits	2
	both	N/A	N/A	both types of edits	5
Distance	short range	near current time step	(5,4)	only short range edits	2
	long range	far from current time step	(9,3)	only long range edits	6
	both	N/A	N/A	both types of edits	5
Definiteness	definite	label → final state	(4,2)	prefix → final state	10
	temporary	label → temporary state	(5,3)	prefix → temporary state	8
Time	intermediate	input still partial	(5,4)	input is still partial	4
	final	at final time step	(10,3)	at the final time step	10

Table 3: Characterisation of edits and revisions. The examples refer to Figure 1, pointing to the (time step, label index) positions for edits and time steps for revisions. Here the gold standard is used to judge prefix correctness.

Edits To characterise edits, we consider the state of an output label in the current prefix in relation to its state in the previous prefix, which are different by definition. They relate to a label's development in time (vertically in their IC column) or to the prefix they belong to (horizontally in their IC row). Edits on correct labels are inconvenient and defective, as the label will fatally change to a wrong label. Edits on incorrect labels are convenient and can be effective (if it changes into a correct state) or ineffective (if it changes into another incorrect state). Innovative edits cause the label to change into a new state. Local recurrence refers to whether the edit occurs in isolation in neighbouring time steps (edit subsequences in an IC's column) and company refers to whether the edit occurs with other edits in a prefix (same IC's row). Short or long range refers to how far the edited label is from the current time step, defined by a distance parameter d. Edits can be definite or temporary and can occur in intermediate or final time steps. Accompanied edits can be connected or disconnected to the other edits in its prefix.

Revisions The dimensions to characterise edits serve the purpose of defining the qualities of the revisions and thus evaluating revision policies. Similar to edits, revisions are inconvenient if they occur on correct prefixes (that should not change). Convenient revisions are effective if they improve correctness, otherwise they may be ineffective (edits occur but correctness remains the same) or defective (correctness decreases). Revisions are locally recurrent when other revisions occur in neighbouring time steps. Company, connectedness and distance refer to what types of edits the revision causes. Definite revisions create prefixes that will not be further edited. Intermediate revisions happen when the input is not completed, otherwise they are final.

Recomputations In models that detach recomputation from revision, the recomputations should also be evaluated. Recomputations are *active* if they actually result in a revision, otherwise they are *inactive*. The quality of the resulting revisions can then be evaluated with the qualities above.

4.3 Policies

To perform good revisions, a model must decide *when* to recompute or revise. For that decision, both a *revision policy* and a *recomputation policy* can be generally defined as:

		The fraction of...
Rate of Revision	R/N	time steps in which the model revises
Rate of Recomputation	R'/N	time steps in which the model recomputes
Rate of Active Recomputation	$(R' \cap R)/R'$	recomputations that actually causes a revision
R-Pertinence	$(R \cap I)/R$	revisions that edit incorrect prefixes (adapted precision)
R-Appropriateness	$(R \cap I)/I$	incorrect prefixes that are revised (adapted recall)
A-Pertinence	$(A \cap C)/A$	additions upon correct prefixes (adapted precision)
A-Appropriateness	$(A \cap C)/C$	correct prefixes that are not revised (adapted recall)

Table 4: Proposed metrics for evaluating recomputation and revision policies. N is the total number of time steps.

$$\pi : \text{IC} \rightarrow [0, 1] \qquad \pi(\text{IC}_t) = \Pr(r|\text{IC}_t) \qquad (1)$$

It gives the probability of performing a revision or recomputation r, respectively, given the state of the incremental chart at time t.[9] When $\Pr(r|\text{IC}_t) > \tau$, where τ is a threshold hyperparameter, a revision/recomputation is performed. If the revisions are not a mere consequence of full recomputations, the model must then also decide *what* and *how* to edit.

4.4 Metrics

Traditional sequence labelling evaluation metrics like accuracy or F1 can be computed on label, sequence or dataset level. The incremental dimension requires its own metrics, some of which we discussed in §3. Here, we propose specific metrics to evaluate revision and/or recomputation policies. For each time step t in a sequence, either a revision (R) occurred or only an addition (A). Assuming we have established a metric for prefix correctness,[10] we know whether the prefix at $t-1$ was correct (C) or incorrect (I). That results in a distribution of N actions in $\{R, A\} \times \{C, I\}$. From these counts, we derive the metrics in Table 4, computed either per sequence or over the whole dataset. Models that have the option to *recompute* (R') can also be evaluated in $\{R', \neg R'\} \times \{C, I\}$ with the same revision metrics and two additional metrics.

4.5 Ideal Processor

Let us now delineate the ideal behaviour of a revision policy for an incremental sequence labelling model. As utopian model would always output the correct label and thus never need to produce edits or revisions (Kahardipraja et al., 2023).[11] But due to the incremental nature of language processing, models should not be penalised for building hypotheses that are *locally valid*, as long as a revision is timely triggered. That is, however, complex to know in raw textual input where local ambiguities are not identified. Instead, we can characterise an outlook according to desirable principles and available resources. In scenarios with an infinite time budget, we can simply wait for the input to be complete. If computation budget can be afforded, restart-incrementality is a good fit. But usually the constraints are not so loose.

An ideal revision policy should thus revise as rarely as possible for stability. If a prefix/label is correct, the policy should avoid revising it, whereas an incorrect prefix/label should be revised (maybe not immediately, but eventually). It should always trigger effective, convenient, and definite revisions, preferably in earlier time steps.[12] Recurrent or oscillating revisions cause more instability and should be avoided. Innovative edits are preferable (as long as they are effective), and short range is better to be combined with delay strategies. Connectedness is a relevant dimension for BIO labelling schemes: If, for instance, the beginning label edited, ideally the middle labels should change simultaneously. Finally, accompanied edits can be further evaluated in their relation to each other and the linguistic input. A good recomputation policy should, additionally, always result in active revisions.

In terms of metrics, R-Pertinence and A-Appropriateness should be exactly 1, *i.e.* all revisions should occur upon incorrect prefixes and all correct prefixes should not be revised. A-Pertinence and R-Appropriateness should be as high as possible, but cannot be expected to be exactly 1 because it may take some time steps until the input that actually resolves the ambiguity or mistake is observed.

[9]It is also possible to make the policy dependent only in a portion of the IC as done *e.g.* by Kahardipraja et al. (2023).

[10]A binary variable or a continuous variable, like accuracy, with a defined threshold for tolerated incorrectness.

[11]That is indeed the case for strictly monotonic models if we use their final output as gold standard.

[12]In the beginning, the absence of both right and left context makes prediction harder. Towards the end, the availability of more left context should lead to less revisions.

	% recomputation			% active recomputation			% revision		
	NER	POS	Slot	NER	POS	Slot	NER	POS	Slot
Rest.Incremental-Transformer	100.00	100.00	100.00	7.77	19.29	21.23	7.77	19.29	21.23
TAPIR-LTReviser	13.77	24.52	20.34	20.23	39.55	39.44	2.78	9.69	8.02
TAPIR-TrfReviser	10.36	20.23	21.41	25.36	34.09	33.65	2.62	6.89	7.20

Table 5: Rate of (active) recomputations and of revisions for each model and task.

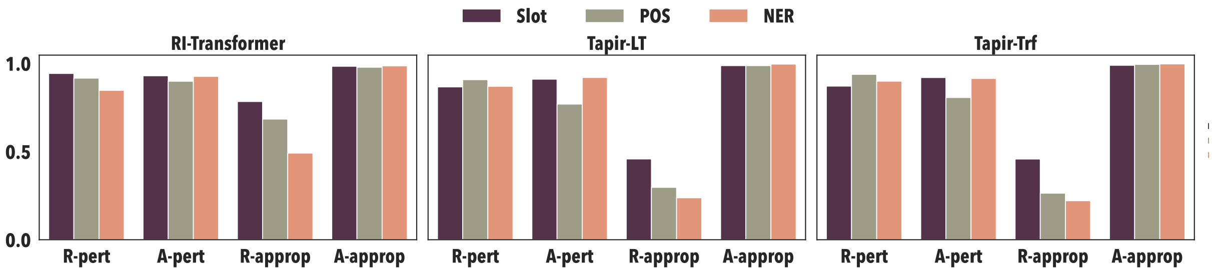

Figure 3: Revision metrics for all models and tasks.

5 Architecture Profiling

We now apply our methodology to profile the revision policy behaviour of three models: The reference restart-incremental Transformer and the two TAPIR variations, which have a recomputation policy, proposed by Kahardipraja et al. (2023). We evaluate them on three sequence labelling tasks: Slot filling (Coucke et al., 2018), POS tagging (Silveira et al., 2014) and NER (Tjong Kim Sang and De Meulder, 2003), using the final output as gold standard.[13] Note that the same profiling can be applied to any model with the ability of performing revisions on any sequence labelling task.

Quantitative Assessment Table 5 shows that the recomputation policy implemented in TAPIR reduces the number of restarts to between 10% and 25% in comparison to the restart incremental approach, considerably alleviating the computation load; the number of revisions is also 2 to 3 times lower. Still, only up to 40% of the remaining recomputations are active, which means that the use of computational budget is still suboptimal. Furthermore, in Figure 3 we see that A-Appropriateness is very close to 1, as it should be. R-Pertinence is slightly below the ideal 1, but still greater than 0.8 in all cases. A-Pertinence is high. R-Appropriateness, however, is low in the restart-incremental Transformer and becomes even lower in the TAPIR models.

This may be evidence that the TAPIR models are waiting for more input before deciding to recompute an incorrect prefix, which is in line with the shifts in the distributions we observe in Figure 4. TAPIR tends to have more revisions towards the end of the sentence than the restart-incremental Transformer. This strategy can indeed help revisions be more effective, given that more left context is available, but it also results in having to wait longer for final decisions. The cumulative distributions in Figure 5 illustrate the advantage of the revision policy in reducing the number of revisions per sentence: 50% or less of the sentences have no revisions in the naive policy, which makes all recomputation effort be in vain, while TAPIR's policy caused many more sentences to not trigger revisions.

[13] Here we use only the buffer outputs to evaluate the resulting revisions on prefixes that would have been passed on to downstream processors. We do not consider the temporary outputs of the LSTM that the original model had access to when deciding to perform a recomputation. Please refer to the original paper for the details on non-incremental and incremental performance on these tasks.

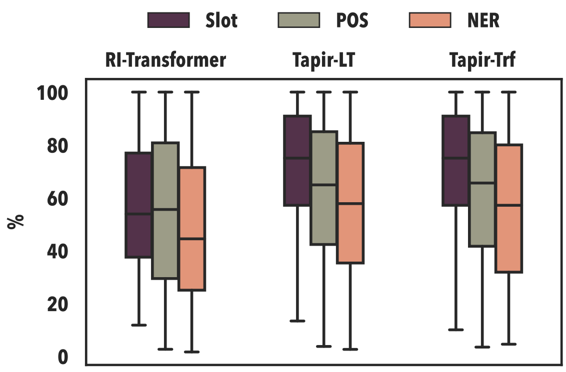

Figure 4: How far in the sentence processing (% of time steps or tokens) revisions occur.

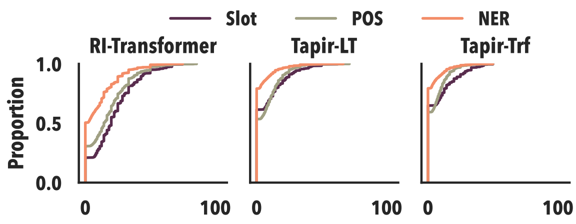

Figure 5: % revisions per sentence (cumulative).

Qualitative Assessment Figures 6 and 7 show the percentages of edits and revisions that characterise TAPIR-TrfReviser's policy. In terms of edits, most are effective, convenient, innovative and steady. Only around 50% are short range, which means that delay strategies would have limited improvements in reducing edit overhead. For slot filling, around 20% of the edits occur in the last time step, which is undesired, because it means that the intermediate predictions for these labels are wrong until the model processes the full sentence. Regarding revisions, TAPIR's policy works best for POS-tagging in terms of effectiveness, convenience, oscillation and recurrence, and worse for slot filling. Most of the edits are isolated, which means that recomputations have been performed for the full partial input to only result in one edit. The proportion of short vs. long range and temporary vs. definite revisions was, in general, balanced. We also see that proportionally fewer revisions occurred in the final step. Although the high percentage of intermediate revisions is high, Figure 4 shows that they are happening towards the end, which prevents incremental subprocessors to reliably count on the intermediate outputs. Slot filling is, here, a prominent example of the occurrence of final revisions being less than ideal.

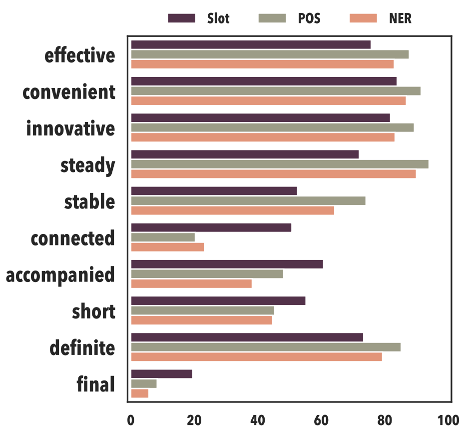

Figure 6: Edits by TAPIR-TrfReviser's policy.

	Slot	POS	NER
effective	74.9	87.3	82.1
defective	16.6	7.8	12.5
ineffective	8.5	4.9	5.3
convenient	87.1	93.8	89.9
inconvenient	12.9	6.2	10.1
steady	59.0	85.0	83.0
recurrent	41.0	15.0	17.0
oscillating	72.9	76.5	63.3
stable	27.1	23.5	36.7
isolated edit	61.8	72.2	78.3
accompanied edits	38.2	27.8	21.7
connected edits	28.8	8.9	11.6
disconnected edits	67.9	87.1	85.9
dis and connected edits	3.3	4.0	2.5
short range	50.7	45.0	43.4
long range	31.9	41.9	48.4
short and long range	17.5	13.0	8.3
temporary	46.3	51.9	41.6
definite	53.7	48.1	58.4
intermediate	80.1	91.5	94.3
final	19.9	8.5	5.7

Figure 7: Revisions by TAPIR-TrfReviser's policy.

Based on these results, we conclude that TAPIR's policy is very successful in reducing the number of recomputations and also in revising less, but there is room for improving the quality of the resulting revisions, both in terms of metrics and of characteristics. This speaks for a more dedicated revision policy that could avoid full recomputations and use the state of the incremental chart and internal representations of the model for a more fine-grained prediction of which labels should change.

6 Conclusion

In this work, we have argued that the importance of a solid evaluation of revision policies in incremental sequence labelling cannot be overstated. Despite being very useful to capture some incremental aspects like instability or timeliness, existing evaluation metrics set aside other strands of revisions. To fill that void, we have introduced metrics, characteristics and rationale to support the analysis of revision policies. This methodology serves as a tool to ascertain their quality, to determine their appropriateness in different contexts and to compare different policies. We identify a few more roads to quality: The creation of incremental gold standards containing locally valid hypothesis, the development of fine-grained revision policies predicting what to revise and a more systematic integration of linguistic aspects of the input into the evaluation procedure. For those willing to drive those routes, we hope our methodology has paved the road well.

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