Constrained Abstractive Summarization:
Preserving Factual Consistency with Constrained Generation

Yuning Mao¹, Xiang Ren², Heng Ji¹, Jiawei Han¹
¹University of Illinois, Urbana-Champaign  ²University of Southern California
¹{yuningm2, hengji, hanj}@illinois.edu  ²xiangren@usc.edu

Abstract

Despite significant progress, state-of-the-art abstractive summarization methods are still prone to hallucinate content inconsistent with the source document. In this paper, we propose Constrained Abstractive Summarization (CAS), a general setup that preserves the factual consistency of abstractive summarization by specifying tokens as constraints that must be present in the summary. We adopt lexically constrained decoding, a technique generally applicable to autoregressive generative models, to fulfill CAS and conduct experiments in two scenarios: (1) automatic summarization without human involvement, where keyphrases are extracted from the source document and used as constraints; (2) human-guided interactive summarization, where human feedback in the form of manual constraints are used to guide summary generation. Automatic and human evaluations on two benchmark datasets demonstrate that CAS improves both lexical overlap (ROUGE) and factual consistency of abstractive summarization. In particular, we observe up to 13.8 ROUGE-2 gains when only one manual constraint is used in interactive summarization.¹

1 Introduction

Although abstractive summarization has achieved significant progress with advances in seq2seq learning (See et al., 2017) and language model pre-training (Liu and Lapata, 2019; Lewis et al., 2019), its generation process is typically unconstrained: abstractive models learn to generate summaries in a completely data-driven manner using document-summary pairs. As a consequence, they are prone to hallucinate content not entailed by the source documents (e.g., producing unseen entities or unfaithful facts) (Kryscinski et al., 2020; Maynez et al., 2020). Such factual inconsistencies in the summary hinder the practicability of abstractive models in real-world applications.

Recent studies (Matsumaru et al., 2020; Zhu et al., 2021; Dong et al., 2020) on preserving the factual consistency of abstractive summarization are often highly coupled with specific models or incur inferior lexical overlap (lower ROUGE). In this paper, we propose Constrained Abstractive Summarization (CAS), a more general setup where a set of tokens are used as constraints and required to be present in the summary. We show that CAS improves lexical overlap and factual consistency of abstractive summarization simultaneously.

We consider two scenarios for CAS: (1) auto-

| Reference: sir tom jones is to return as one of the judges on talent show the voice uk when it moves to itv next year. |
| Unconstrained: pop star sir tom jones is to return to the bbc ’s voice uk after a two-year absence. |
| Constrained: singer sir tom jones is to return to itv ’s the voice uk next year after a two-year absence. |

Reference: syrian refugees facing their first christmas in wales are sure to get a “ warm welsh welcome ”, the first minister has said.

Unconstrained: the first minister has said wales is “ more important than ever ” in the new year.

Constrained: the first welsh councils to welcome refugees in the uk this christmas have been praised by the first minister.

Reference: a four-month consultation which could help decide the location of the uk ’s first spaceport ends on monday with one site in gwynedd being considered.

Unconstrained: plans for a uk spaceport and spaceport in snowdonia have been backed by a council.

Constrained: plans to build a uk spaceport in snowdonia have been backed by gwynedd council.

Table 1: Unconstrained and constrained summaries of the same model without additional training. Constrained (replaced) tokens are in green (red).

¹Our code can be found at https://github.com/morningmon1/EDE.
matic summarization without human involvement, where we extract keyphrases from the source document and use them as constraints; (2) human-guided interactive summarization, where human feedback in the form of manual constraints are used to guide CAS towards human preferences. We enforce the constraints by lexically constrained decoding (Post and Vilar, 2018), which only functions during inference and can be easily integrated into different autoregressive abstractive models with beam search decoding. In this way, one can conduct CAS on (almost) any fine-tuned models without (often expensive) re-training.

CAS preserves the factual consistency of abstractive summarization in two ways according to our observations. First, the added constraints can often replace their unfaithful counterparts in the unconstrained summary (produced by the same model) and help reduce model hallucination. For example, in Table 1, when given “ITV” as a constraint the model corrects “BBC” to “ITV” as “The Voice UK” is acquired by “ITV”. Second, when adding important entities not found in the unconstrained summary as constraints, the model is more likely to generate summaries that are focused on these factual entities (“Christmas”) and more specific (“a council” changed to “Gwynedd council”).

We study CAS on the CNN/Daily Mail (CN-NDM) (Nallapati et al., 2016) and XSum (Narayan et al., 2018) datasets with BERTSum (Liu and Lapata, 2019) as an example of the base model. Automatic and human evaluations show that CAS improves abstractive summarization on both lexical overlap (ROUGE) and factual consistency. To our knowledge, CAS is the first method to improve both aspects simultaneously and consistently. Moreover, BERTSum under CAS achieves better performance than more expensive methods such as BART (Lewis et al., 2019) and PEGASUS (Zhang et al., 2020a) by simply using one manual constraint during inference, which demonstrates the benefits of CAS in interactive summarization and shows its great potential in future development.

2 Method

2.1 Task Formulation

We define a constraint set $C = \{c_1, c_2, ... c_N\}$ as a set of text spans of arbitrary length. Given document-reference pair $(d, r)$ and abstractive model $M$, Constrained Abstractive Summarization (CAS) generates a summary $s$ for document $d$ using $M$ with the presence of all the text spans in $C$. We denote an unconstrained summary generated by the same $M$ (with $C = \emptyset$) as $s'$. We aim to create a constraint set $C$ that has a high overlap with $r$ to ensure its quality and low overlap with $s'$ to bring additional information, such that CAS with $C$ improves the quality of the generated summary.

2.2 Constraint Creation

CAS is useful for improving abstractive summarization, especially on factual consistency in two scenarios. First, one can create the constraints automatically without human involvement, where the keyphrases in the source document are natural choices for constraints to preserve factual consistency (Sec. 2.2.1). Second, for interactive summarization, when an automatic summary contains factual errors or lacks certain information, a human editor can manually add the corrected or missing facts as constraints during post-editing (Sec. 2.2.2).

2.2.1 Automatic Constraints

To obtain constraints automatically, we adopt a state-of-the-art supervised keyphrase extraction method, BERT-KPE (Sun et al., 2020), to extract keyphrases from the source document, as we find commonly used unsupervised methods (Campos et al., 2020) insufficient to provide high-quality constraints. Similar to recent studies (Nan et al., 2021; Narayan et al., 2021), we focus on the factual consistency of entities and noun phrases. We use spaCy (Honnibal and Montani, 2017) to find named entities and noun phrases in the reference summaries of the training set, and treat those appearing in the source documents as positive training examples. During test time, we exclude the extracted keyphrases appearing in $s'$ such that only constraints bringing additional information are used.

2.2.2 Manual Constraints

As automatic summarization is still imperfect and users also have different preferences or information needs, human-guided interactive summarization has gained increasing popularity (Avinesh et al., 2018; Gao et al., 2018; Shapira et al., 2020). Since human feedback is expensive to obtain, we simulate it by taking tokens in the reference summary as manual constraints. For example, a user may revise a summary by taking entities they deem important but not in the system summary. We simulate such edits by taking entities in the reference but not system summary as constraints. Similar simulations
with the use of the references have been widely adopted in interactive machine translation (Cheng et al., 2016; Hokamp and Liu, 2017; Post and Vilar, 2018; Chen et al., 2020) but not yet explored in summarization. CAS with manual constraints is useful for interactive summarization where users do not have to (re)write the entire summary but provide minimal guidance, and also serves as an upper bound for automatic summarization.

2.3 Lexically Constrained Decoding

There are many different means to fulfill CAS as its formulation is general. Here, we explore the effectiveness of using lexically constrained decoding, namely, dynamic beam allocation (DBA) (Post and Vilar, 2018). At a high level, DBA divides the beam during beam search to store hypotheses satisfying different numbers of constraints and adds unmet constraints at each decoding step. DBA ensures the presence of constraints by allowing the EOS token only when all the constraints are met. We choose DBA due to its faster speed than other counterparts (Hokamp and Liu, 2017) – a complexity of $O(1)$ in the number of constraints. Moreover, DBA completely functions during inference and can be easily incorporated into different models for the evaluation under CAS, which is preferable over methods that modify the training process (Zhang et al., 2020b), since we want to keep the carefully designed, often expensive abstractive models intact rather than re-train them with a different objective.

3 Experiments

4 Experiment Setup

We conduct experiments on the CNNDM (Nallapati et al., 2016) and XSum (Narayan et al., 2018) datasets. We use one state-of-the-art abstractive model, BERTSum (Liu and Lapata, 2019), as our base model $\mathcal{M}$. For automatic constraints, all N-grams up to $N = 5$ are considered as constraint candidates. To reduce noise, we take top $k$ keyphrases with scores greater than $v$ extracted by BERT-KPE as the constraints, which is tuned on the validation set with $k = 3$ and $v = 1.6$. We set beam size to 10 when automatic constraints are used and 5 for manual constraints unless otherwise specified. For automatic evaluation on factual consistency, we do not conduct data filtering and evaluate on the full dataset.

4.1 CAS for Automatic Summarization

Constraint Creation. For constraint creation, we achieve 0.76 Prec@1 / 0.49 F1@5 on CNNDM, and 0.67 Prec@1 / 0.40 F1@5 on XSum, which suggests that the automatically extracted constraints are of reasonable quality and ready to use.

Lexical Overlap. Table 2 shows the comparison of our base model and CAS on ROUGE. CAS improves BERTSum on both datasets with statistical significance, which is achieved without any model training but enforcing the constraints. As will be shown in Sec. 4.2, larger gains can be achieved when the keyphrase extraction module is improved.

| Method | R-1 | R-2 | R-L | Ent-F1 | Sup |
|--------|-----|-----|-----|-------|-----|
| BERTSum | 42.00 | 19.44 | 38.98 | 36.3 | 89.1 |
| +CAS | 42.48 | 19.56 | 39.43 | 37.0 | 94.0 |
| BERTSum | 38.91 | 16.54 | 31.30 | 31.2 | 72.3 |
| +CAS | 39.19 | 16.75 | 31.56 | 35.1 | 73.0 |

Table 2: CAS with automatically extracted keyphrases. Improvements are statistically significant ($p < 0.05$) under approximate randomization test and paired bootstrap resampling test.

Factual Consistency. More importantly, we observe consistent gains of CAS in factual consistency. In automatic evaluation, CAS improves BERTSum by 0.7/3.9 on entity-level F1 (Nan et al., 2021) and 4.9/0.7 on support score (Matsumaru et al., 2020) for CNNDM/XSum, respectively. In human evaluation, we randomly sample 50 examples and ask three expert annotators to compare the quality of the two systems. Human ratings show that 34% constrained summaries achieve better factual consistency, 52% are similar to their unconstrained counterparts, and only 14% samples become worse, confirming that CAS better preserves factual consistency while achieving higher ROUGE. To our knowledge, CAS is the first approach to improve on both aspects. More details and 10 examples with analysis covering both good and bad cases are provided in App. A and C.

4.2 CAS for Interactive Summarization

In Table 3, we show the results of CAS in interactive summarization where various manual constraints simulated by the reference summary (ref) are used: Entity (named entities in ref), NP (noun

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2Our results are slightly different from Liu and Lapata (2019) despite using its official code and model weights.
phrases in ref), Random-4 (4 random tokens in ref), Phrase-4 (4 continuous tokens in ref), miss (tokens not found in the unconstrained summary), and src (tokens must appear in the source document).

Table 3: Comparison of various types of manual constraints. $|C|$ denotes the averaged total number of tokens in the constraint set $C$. $\land$ denotes AND operation.

There are many interesting findings when applying CAS to interactive summarization. For example, adding all constraints improves less than only adding missing ones ($\land$ miss), possibly because the model can already generate those tokens but still wastes some beams to store such constraints and thus fails to search for better alternatives; Using random constraints (Random-4) sometimes incurs inarticulate output in our manual examination; The improvement is not as significant when requiring the presence of constraints in the source document ($\land$ src), which coincides with recent findings that reference summaries often involve extrinsic information (Maynez et al., 2020); Finally, by using only one phrase as guidance during inference without additional training (Phrase-4), CAS improves BERTSum up to 13.8 in ROUGE-2, outperforming state-of-the-art methods.

In Table 4, we list the performance of CAS when manual constraints are provided on CNNNDM. The performance gains on CNNNDM are not as significant as on XSum, possibly because the summaries in CNNNDM are much longer and we use a similar number of constraints on both datasets. Nevertheless, CAS still helps BERTSum achieve state-of-the-art performance by only using one phrase as manual constraint.

4.3 Analysis and Discussion

CAS guides generation. As shown in Fig. 1, using a larger beam size consistently leads to better performance for CAS with the same constraints, while the performance change is negligible for unconstrained summarization (detailed numbers in App. B). Such results imply that the gains of CAS are based on a guided generation process that exploits model potential, rather than merely access to a few manual constraints.

CAS is not random insertion. We observe that CAS typically inserts constraints at proper positions and often corrects unfaithful information (Table 1 and more examples in App. C). To further study the gap between CAS and random insertion, we directly append the constraints to the end of unconstrained summaries as a baseline. As listed in Table 5, simply appending constrained tokens cannot obtain the same performance gains as CAS and apparently leads to nonfluency too.

Table 4: Performance of CAS when manual constraints are provided on CNNNDM.

Figure 1: Performance changes by beam size on XSum. Larger beam leads to better results for CAS.

Runtime overhead is low. For automatic constraints, since keyphrase extraction is independent
of summarization, one can use the same keyphrases on different summarization models and the total time is amortized. For constrained decoding, a detailed runtime comparison between unconstrained and constrained generation is shown in Table 6. The overhead of constrained generation is acceptable when the beam size is not large (we use a beam size of 5/10 for most experiments). Moreover, a faster DBA implementation (Hu et al., 2019a) would further reduce the runtime.

| Beam Size | Unconstrained | CAS |
|-----------|---------------|-----|
| 5         | 25min         | 33min |
| 10        | 44min         | 68min |
| 20        | 70min         | 4h   |
| 50        | 2.5h          | 10h  |

Table 6: Comparison of inference time for the XSum test set on one GTX 1080 Ti GPU.

5 Related Work

Factual Consistency of Summarization. As ROUGE (Lin, 2004) does not correlate well with factual consistency (Falke et al., 2019), model-based metrics (Goodrich et al., 2019; Krzysztof et al., 2020) are proposed to measure factual consistency explicitly. However, their performance is unsatisfactory and to date, there is still no commonly accepted metric beyond human evaluation. Prior studies (Matsumaru et al., 2020; Zhu et al., 2021; Dong et al., 2020) generally improve factual consistency at the expense of ROUGE while CAS improves on both aspects simultaneously.

Constrained Generation. Constrained Generation is useful in various tasks such as machine translation (Hokamp and Liu, 2017) and data augmentation (Hu et al., 2019b). Although approaches like copy mechanism (See et al., 2017) that encourage models to copy words from source documents have been widely adopted, they are often insufficient to reduce model hallucination (Maynez et al., 2020). To our knowledge, constrained summarization like CAS that requires certain tokens must be present in a summary is unexplored.

6 Conclusion

In this paper, we propose constrained abstractive summarization (CAS), a general setup that can be easily incorporated into existing abstractive models to preserve factual consistency. We demonstrate that CAS leads to higher-quality, especially more factually consistent summaries, in automatic and interactive summarization under both automatic and human evaluations. For future work, we will explore and facilitate alternative means beyond lexically constrained decoding to fulfill CAS.

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A Human Evaluation

We compare the constrained summary $s$ and unconstrained summary $s'$ produced by the same base model for an apple-to-apple comparison. We give the annotators the following guidelines: CAS is considered as better if it corrects factual inconsistencies in $s'$ or provides additional information supported by the reference summary. CAS is considered as worse if it leads to unfaithful or unsmooth summary. CAS is considered similar to the unconstrained summary for other cases, most of which are as follows: (Both good) when the semantics of $s'$ is related to the reference summary, $s$ may rephrase parts of $s'$ or adds (drops) minor facts without changing the overall semantics. (Both bad): when $s'$ is off-topic, it is most likely that $s$ is irrelevant as well. We provide examples of all cases mentioned above in App. C.

We note that it is hard to evaluate factual consistency via crowdsourcing as the inter-annotator agreement and general quality of crowdsourcing annotations for factual consistency tend to be too low to be considered reliable (Kryscinski et al., 2020) and many previous human evaluations on factual consistency, including ours, involve expert annotators (Kryscinski et al., 2020; Matsumaru et al., 2020; Nan et al., 2021). The Fleiss’s Kappa for our 3 annotators (including two non-authors) is 0.45. Human evaluations of similar sizes (50/100/109/10 samples) are conducted by previous studies (Dong et al., 2020; Zhu et al., 2021; Matsumaru et al., 2020; Nan et al., 2021).

B Effectiveness of Constraint Guidance

As a supplement to Fig. 1, we list the detailed results of CAS when different beam sizes are used in Tables 7 and 8. The observations on XSum and CNNDM are consistent – larger beam size leads to better performance for CAS. When varying the beam size of unconstrained generation, the performance changes are negligible and thus unlisted.

C More Examples of CAS

Automatic Summarization. In Tables 9 and 10, we show examples of CAS in automatic summarization where the constraints are extracted from the source documents. The examples with remarks cover both good and bad cases: inconsistent $\rightarrow$ consistent, consistent $\rightarrow$ consistent, consistent $\rightarrow$ inconsistent, and inconsistent $\rightarrow$ inconsistent.

| Constraint Type | XSum | | | |
|-----------------|------|------|------|------|
|                 | R-1  | R-2  | R-L  | B    |
| None            | 38.91| 16.54| 31.3 | 5    |
| Entity $\land$ miss | 46.87| 21.55| 33.92| 5    |
| Entity $\land$ miss | 47.83| 23.00| 36.13| 10   |
| Entity $\land$ miss | 48.18| 23.64| 36.86| 20   |
| Entity $\land$ miss | 48.46| 24.17| 37.47| 50   |

Table 7: Performance changes by beam size on the XSum dataset. B denotes the beam size.

| Constraint Type | CNNDM | | | |
|-----------------|-------|------|------|------|
|                 | R-1  | R-2  | R-L  | B    |
| None            | 42.00| 19.44| 38.98| 5    |
| Entity          | 43.31| 19.57| 40.05| 5    |
| Entity          | 44.75| 21.34| 41.60| 20   |
| Phrase-4        | 43.37| 21.57| 40.82| 5    |
| Phrase-4        | 44.77| 22.80| 42.14| 10   |
| Phrase-4        | 45.14| 23.21| 42.43| 20   |

Table 8: Performance changes by beam size on the CNNDM dataset. B denotes the beam size.

We observe that CAS can correct factual inconsistencies or add relevant facts when the semantics of the unconstrained summary is close to the reference summary. On the other hand, CAS is not enough to change the overall message when the system summary is too far away from the reference, which is somewhat expected as CAS only affects model decoding without additional training. Such observations suggest that one could possibly obtain better results by using stronger base models.

Interactive Summarization. In Table 11, we show the examples of CAS for interactive summarization, which are randomly sampled from the XSum dataset. The performance of CAS in interactive summarization is generally better than automatic summarization as the constraints are manually provided, which shows the benefits of human feedback as well as the potential of CAS when constraints of higher quality are available.
| Remarks | CAS is effective at correcting entity information such as locations. inconsistent → consistent (better) ✓ |
| Constraint Set | ['cardiff'] |
| Reference | hundreds of green-fanged tube web spiders have taken over the back garden of a family home in cardiff. |
| Unconstrained | a man from Carmarthenshire has appealed for help to find a “extremely rare” colony of tube spiders. |
| Constrained | a man from cardiff has said he is concerned about the number of “extremely rare” tube spiders. |

| Remarks | CAS successfully distinguishes and replaces one of the two entities (“a” and “two”) of the cardinal type in the unconstrained summary. inconsistent → consistent (better) ✓ |
| Constraint Set | ['three'] |
| Reference | two men have been assaulted by three masked attackers at an address in the craigmillar area of edinburgh. |
| Unconstrained | a man is in a critical condition in hospital after being attacked by two men at a house in glasgow. |
| Constrained | a man is in a critical condition in hospital after being attacked by three men at a house in glasgow. |

| Remarks | CAS adds the date “1991” at a proper position. consistent → consistent (better) ✓ |
| Constraint Set | ['1991'] |
| Reference | toddler ben needham “most likely” died in an accident near to where he disappeared in 1991, police have said. |
| Unconstrained | police investigating the disappearance of missing toddler ben needham have closed off a “large number of theories” about what happened to him. |
| Constrained | police investigating the disappearance of missing toddler ben needham in 1991 have closed off a “large number” of theories about what happened to him. |

| Remarks | CAS adds not only the constraint “greece” but two other entities appearing in the reference summary (“london” and “saturday”) to the output. However, it omits “eurobasket warm-up game” that was covered by the unconstrained summary. consistent → consistent (tie) ✓ |
| Constraint Set | ['greece'] |
| Reference | bbc sport is showing live coverage of the eurobasket warm-up game between great britain and greece at the copper box in london on saturday 19 august. |
| Unconstrained | great britain’s men will be shown live on television for the first time in their eurobasket 2017 warm-up game. |
| Constrained | great britain’s men will be shown live on television for the first time when they face greece in london on saturday. |

| Remarks | CAS replaces “argentine” with “argentina’s” due to the provided constraint and the remaining of the sentence is unchanged. consistent → consistent (tie) ✓ |
| Constraint Set | ['argentina'] |
| Reference | argentine president cristina fernandez and amnesty international have called for justice after the violent death of a transgender activist. |
| Unconstrained | argentine president cristina fernandez de kirchner has called for an investigation into the murder of a transgender woman. |
| Constrained | argentina’s president cristina fernandez de kirchner has called for an investigation into the murder of a transgender woman. |

Table 9: Examples showing good cases of CAS when constraints are automatically extracted.
| Remarks | Consistent → Inconsistent (worse) | Constraint Set | Reference |
|---------|----------------------------------|----------------|-----------|
| CAS changes “an american” to “two americans” as the extracted constraint itself is wrong. | | | a french-american man who helped stop a heavily armed gunman on a train in france in 2015 has received the country’s highest honour. |
| **Unconstrained:** | an american man has been awarded france’s highest honour for his role in a terror attack on a train. | **Constrained:** | two americans have been awarded the legion d’honneur, the highest honour in france for the paris terror attack. |
| Remarks | Consistent → Inconsistent (worse) | Constraint Set | Reference |
|---------|----------------------------------|----------------|-----------|
| CAS fails to recognize “camilla” is a synonym of “duchess of cornwall” and assigns the name to their son by mistake. | | | prince charles and his wife camilla are to visit australia and new zealand in november, his office says. |
| **Unconstrained:** | prince charles and duchess of cornwall will travel to australia for the first time since the start of the year. | **Constrained:** | prince charles and duchess of cornwall will travel to australia for the first time since their son camilla was born in november. |
| Remarks | Consistent → Inconsistent (tie) | Constraint Set | Reference |
|---------|----------------------------------|----------------|-----------|
| CAS at times leads to unsmooth output when it fails to recognize the constraints (“royal yacht britannia” in this example), although such cases are rare. | | | the royal yacht britannia has been judged as scotland’s best visitor attraction every year for the past decade. |
| **Unconstrained:** | the royal yacht has been named scotland’s best visitor attraction for 10 years, according to a new report. | **Constrained:** | the royal yacht of scotland has been named the best visitor attraction in scotland for 10 years. britannia. |
| Remarks | Inconsistent → Inconsistent (tie) | Constraint Set | Reference |
|---------|----------------------------------|----------------|-----------|
| CAS fails as the semantics of the unconstrained summary is too far away from the reference. | | | a tweet from one direction’s louis tomlinson to harry styles has become the second most retweeted post of all time. |
| **Unconstrained:** | louis harris has become the most popular person in the history of one direction and has been retweeted. | **Constrained:** | louis z has become the most popular twitter post in the us - and he’s never in his heart. |
| Remarks | Inconsistent → Inconsistent (tie) | Constraint Set | Reference |
|---------|----------------------------------|----------------|-----------|
| CAS is ineffective when the unconstrained summary is unsmooth or off-topic, even if the quality of the constraints is high. | | | the author of the harry potter books, jk rowling, is celebrating her 50th birthday today. |
| **Unconstrained:** | the official cake of jk rowling’s jk rowling cake has been released to mark the 90th anniversary of the birth of the author. | **Constrained:** | a cake made by jk rowling has been unveiled to mark the 70th anniversary of jk rowling’s harry potter cake. |

Table 10: Examples showing bad cases of CAS when constraints are automatically extracted.
Table 11: Randomly sampled examples of CAS in interactive summarization. We filter the entity constraints such that they are not in the unconstrained summary (Entity ∧ miss) to examine the effectiveness of CAS for post-editing.