Annotating and Modeling Fine-grained Factuality in Summarization



Tanya Goyal and Greg Durrett
NAACL 2021

News summarization

has landed in trouble after its former president was found guilty of trying to fix matches and arrested [...] French league disciplinary commission said on Tuesday that Jean-Marc Conrad tried to fix four matches [...]

Seven games involving Nimes were investigated after the arrest last November. [...]

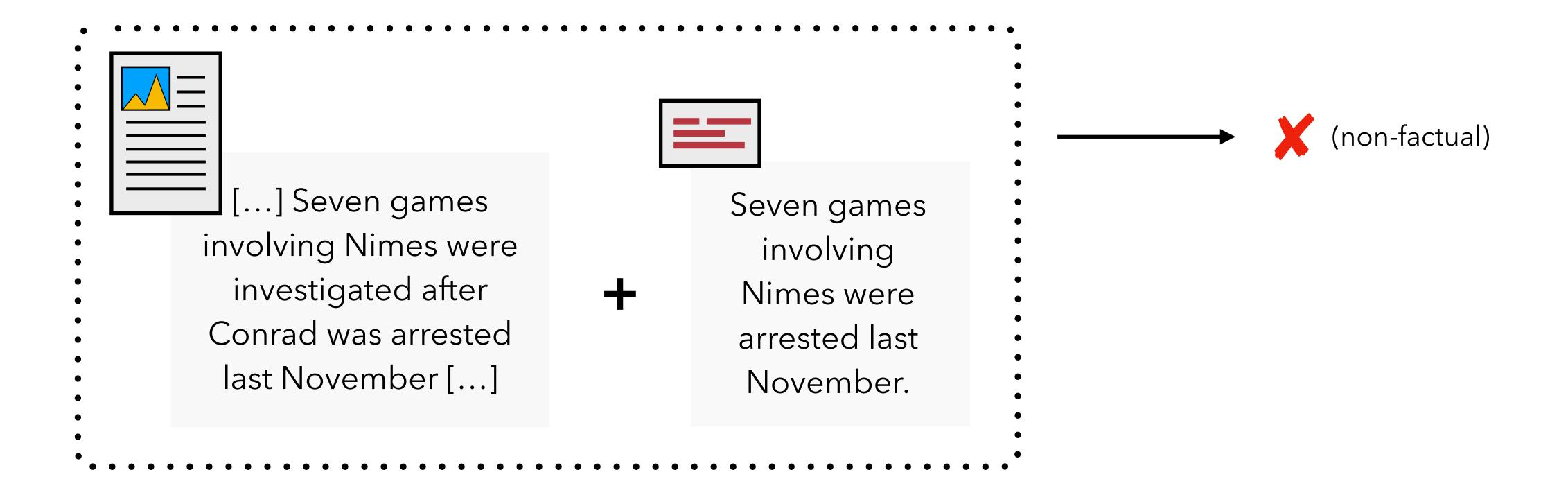
French football has been hit with its first match-fixing scandal.

investigated

Seven games involving Nimes were arrested last November.

- Fluent and grammatical text.
- Combines information from different parts of the input.
- World knowledge e.g. Nimes is a football club.
- Often hallucinates/ misinterprets information in the source.

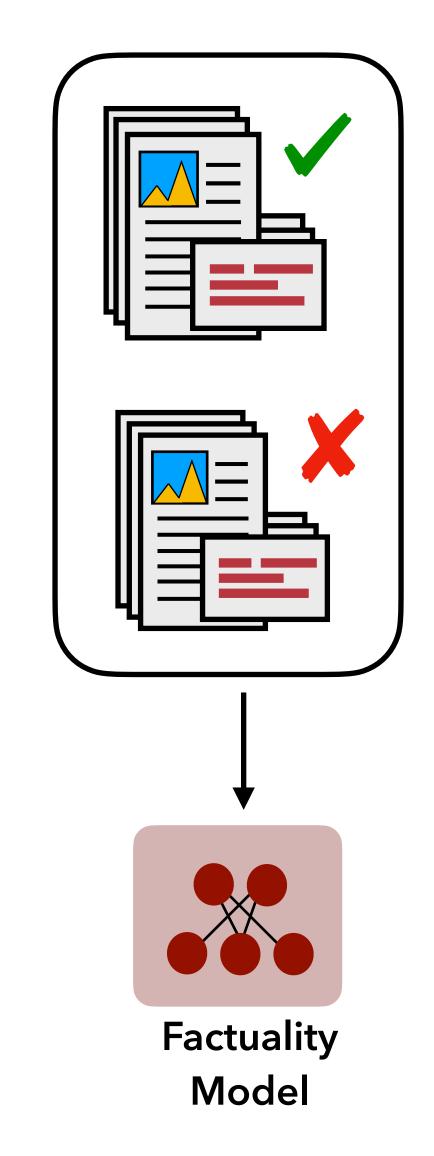
Can we identify factual errors?



Prior Work: Synthetic training datasets

Second-tier French club Nimes
has landed in trouble after its
former president was found
guilty of trying to fix matches
and arrested [...] French league
disciplinary commission said on
Tuesday that Jean-Marc Conrad
tried to fix four matches [...]
Seven games involving Nimes
were investigated after the arrest
last November. [...]

Seven games involving Nimes were investigated last November. Artificial Corruption Nine games involving Nimes were investigated last November. Entity-Noise Negation Injection swap



Overview

Evaluate Synthetic Factuality Datasets

Do synthetic datasets target the errors from summarization models?

Seven games were being investigated.

Nine games were being investigated.

No, synthetic datasets handle a limited set of error types.

Evaluate Modeling Formulations for Factuality

What granularity of factuality models are needed?

summary-level

Nine games were being arrested.

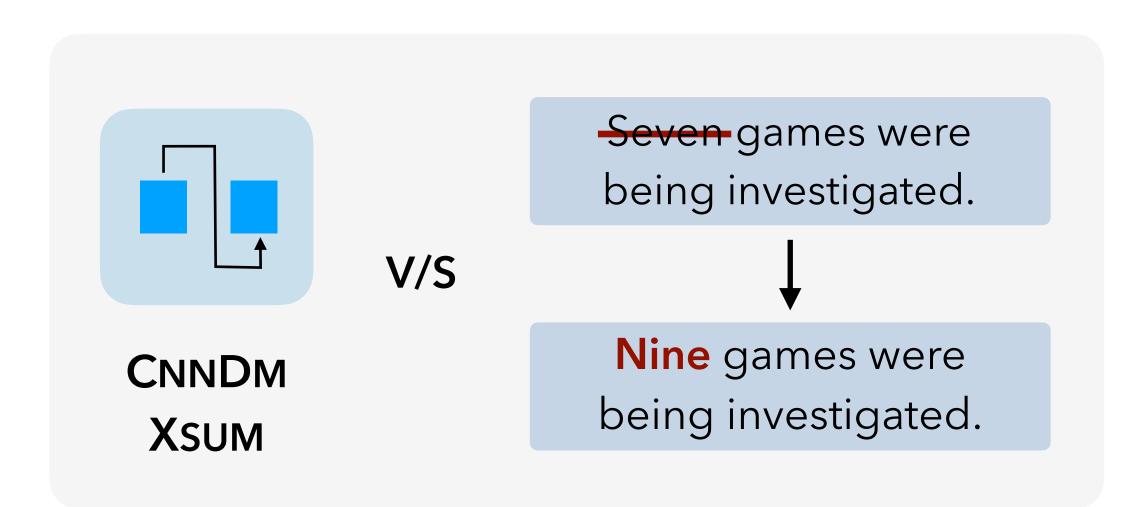
N

fine-grained

Nine games were being arrested.

Fine-grained works better, error localisation helps train better models!

V/S



- Define a taxonomy of errors.
- Manually categorise errors in CNN/DM and XSUM model-generated summaries and synthetic datasets.
- Compare error distributions.

Define a taxonomy of errors.

Second-tier French club Nimes has landed in trouble after its former president was found guilty of trying to fix matches and arrested [...] French league disciplinary commission said on Tuesday that Jean-Marc Conrad tried to fix four matches [...]

Seven games involving Nimes were investigated after the arrest last November. [...]

Extrinsic

New information introduced

Intrinsic

Information in the article misinterpreted.

Conrad Marc was arrested last November for ...

Entity Related

Event Related

... trying to fix matches by bribing players ...

Noun-Phrase Related

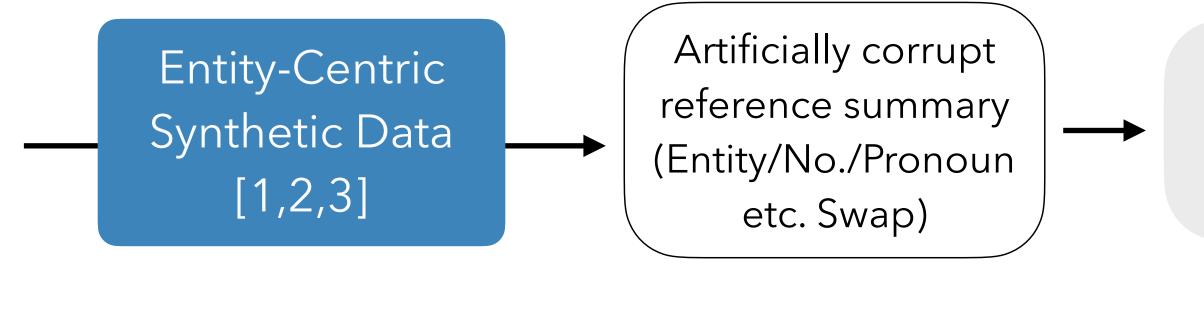
Others
Nipo on book has londed in trouble offer its forms

Others (Noise/Grammar)

Nimes has landed in trouble after its former president ...

Manually categorise errors in CNN/DM and XSUM model-generated summaries and synthetic datasets.

Seven games involving Nimes were investigated last November.



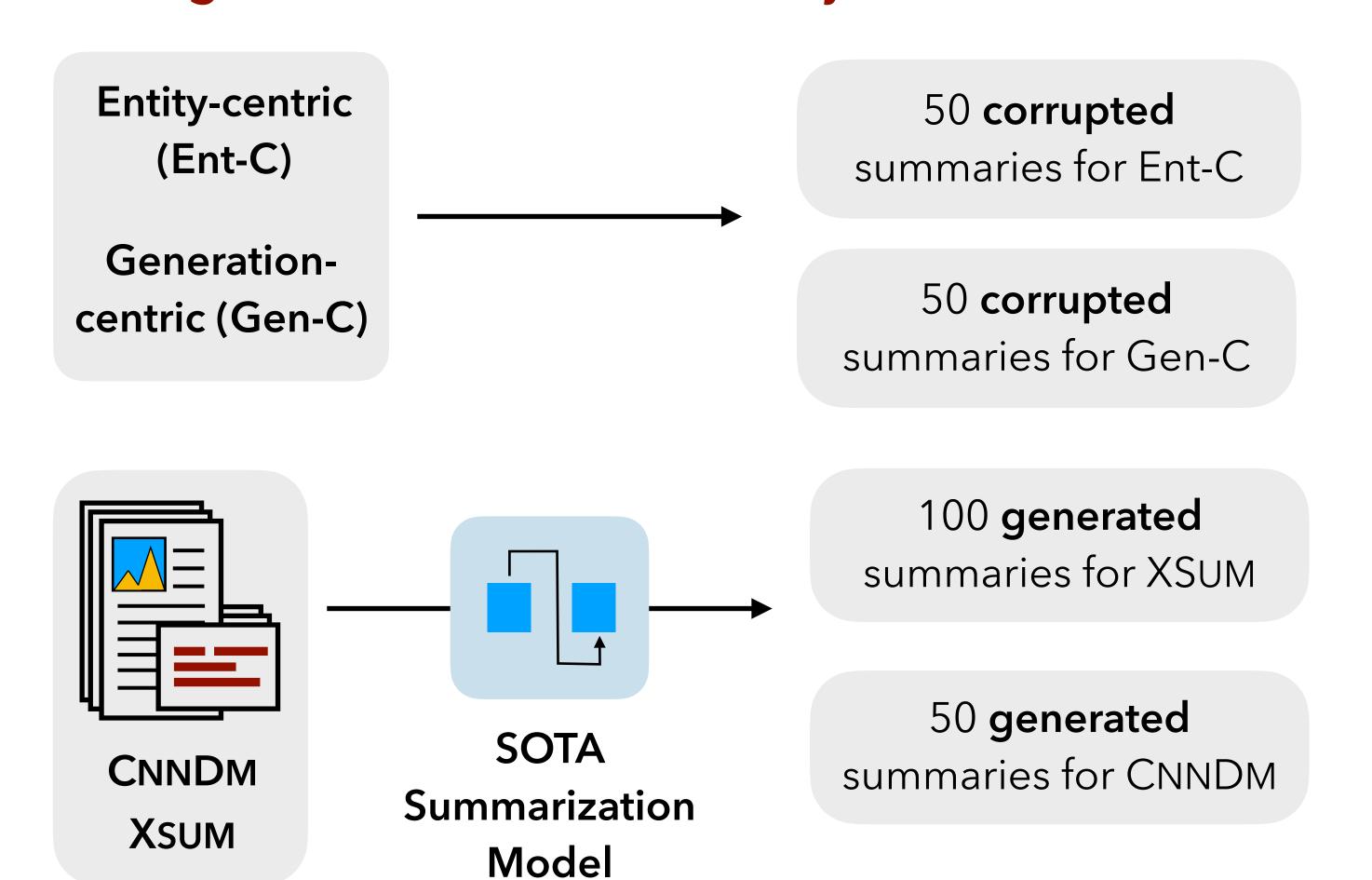
Seven games involving Nimes were investigated last October.

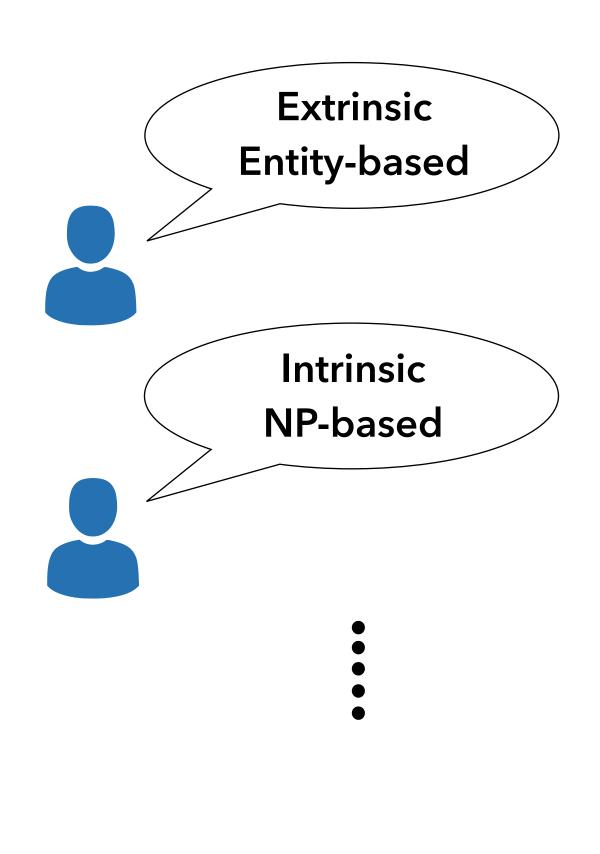
Generation-Centric Synthetic Data [4] Paraphrase and select low-prob. option as non-factual instance.

Last November, **Nimes of games** were investigated.

- [1] Kryściński et al., EMNLP2020
- [2] Zhao et al., EMNLP Findings 2020
- [3] Cao et al., EMNLP 2020
- [4] Goyal et al., EMNLP Findings 2020

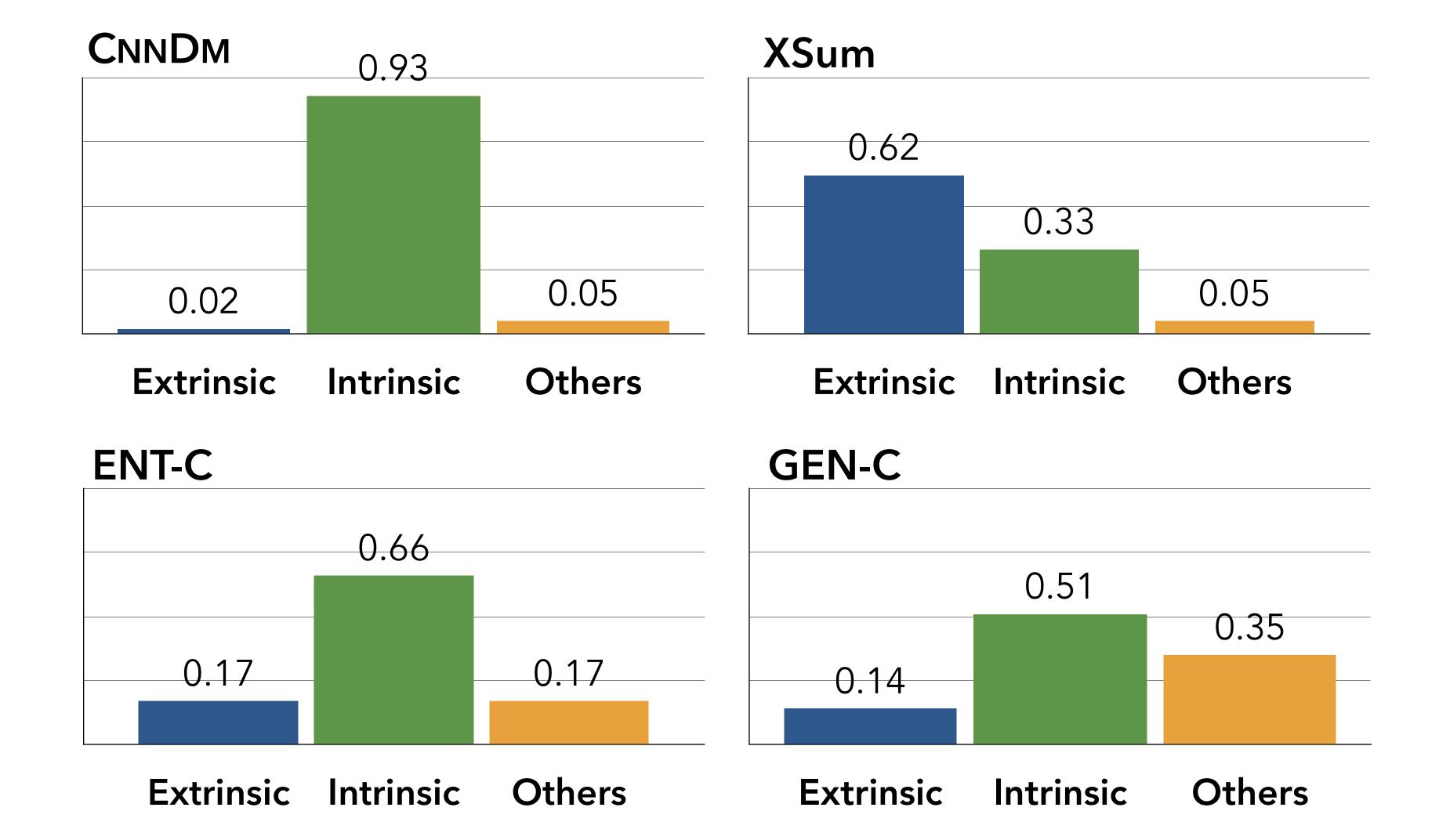
▶ Manually categorise errors in CNN/DM and XSUM model-generated summaries and synthetic datasets.





Error Analysis

▶ Compare Error Distributions.

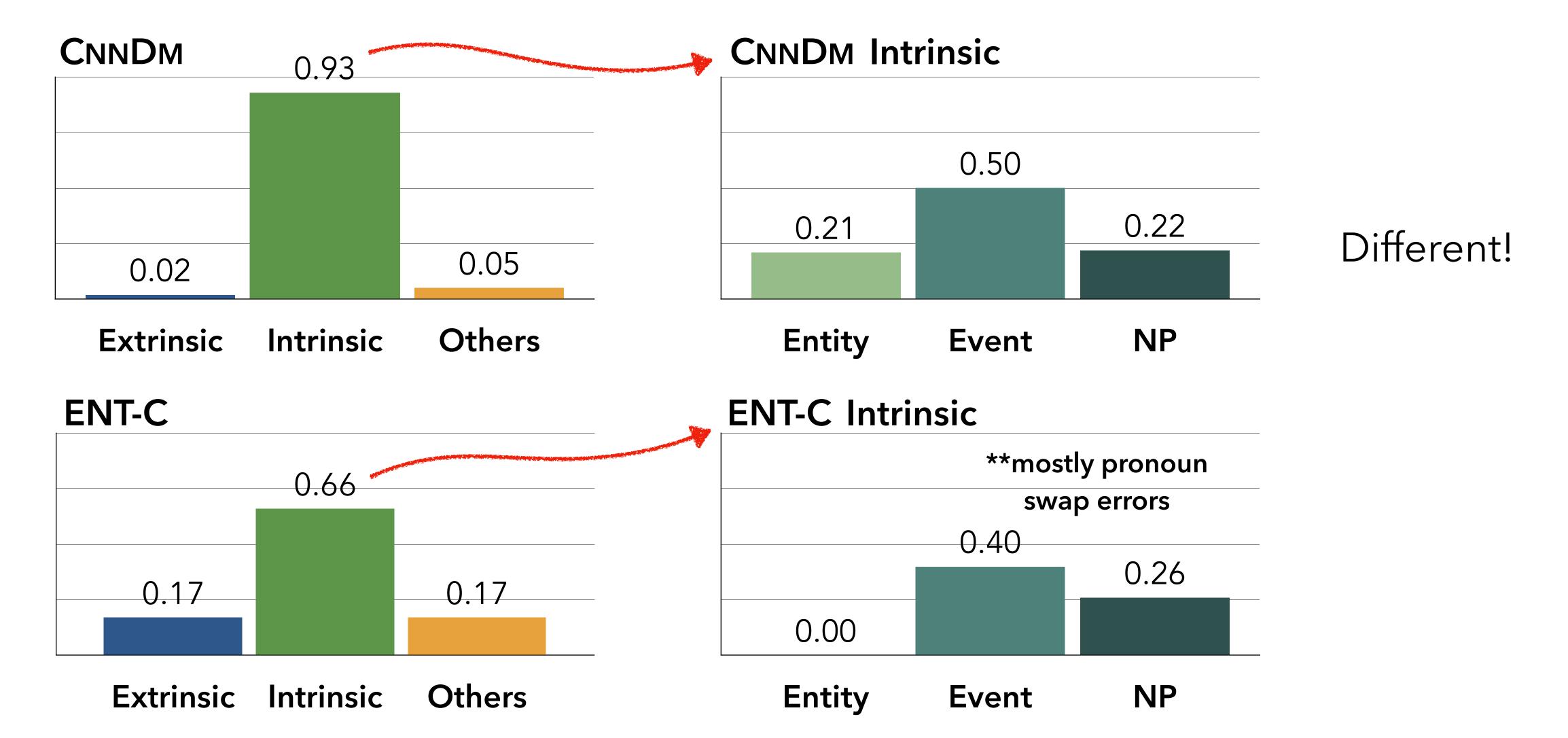


CNNDM models
 primarily make
 intrinsic errors,
 XSUM makes
 extrinsic errors.

Synthetic datasets target a different error distribution compared to real generation errors.

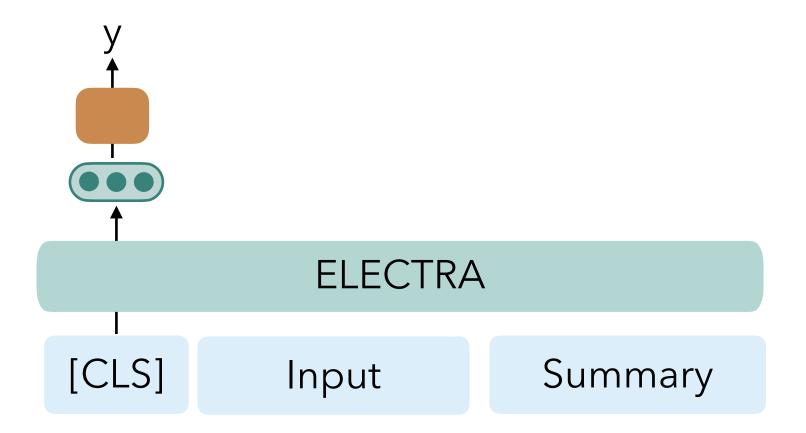
Error Analysis

▶ Compare Error Distributions.

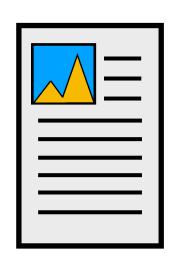


How do models on synthetic data perform?

Train sentence-level models on synthetic datasets (50k ex).



▶ Test Data: Human-annotated test set for XSUM and CNNDM [1,2].







Results

▶ Metric: Label Balanced Classification Accuracy

CNNDM

Training Data	Accuracy
Ent-C	72.3
Gen-C	64.4

XSUM

Training Data	Accuracy
Ent-C	50.9
Gen-C	54.2

Close to majority label performance!

Do synthetic datasets target the errors from summarization models? **No**, synthetic datasets handle a limited set of error types.

(Fortunately, we have human-annotated data! More on this later)

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Evaluate Modeling Formulations for Factuality

What granularity of factuality models are needed?

summary-level annotations

Nine games were being arrested.

fine-grained annotations

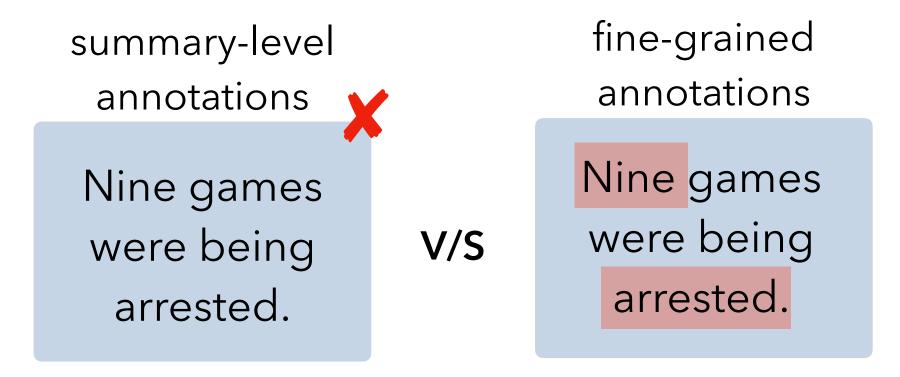
Nine games were being arrested.

Fine-grained works better, error localisation helps train better models!

V/S

Evaluate Modeling Formulations for Factuality

▶ Compare two kinds of models:

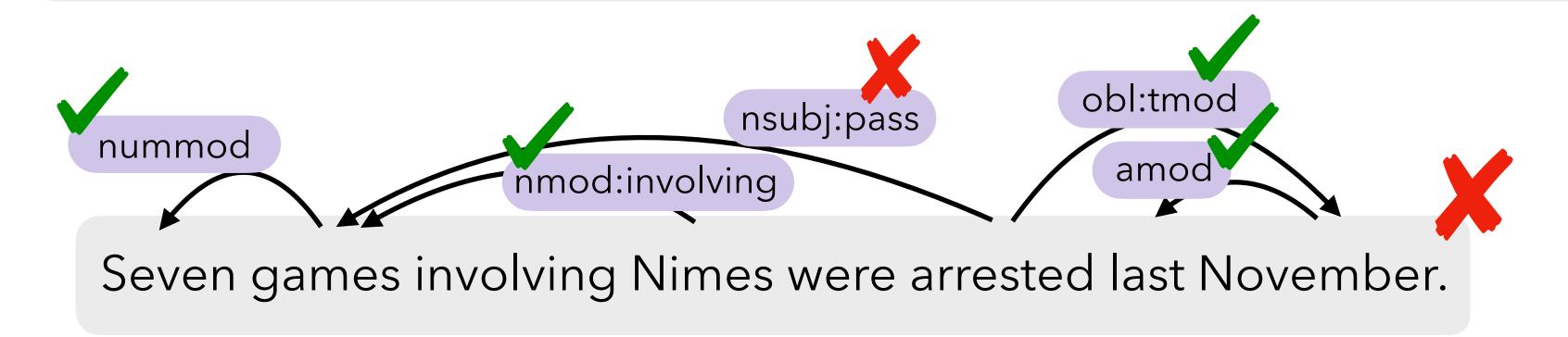


Error Localisation Model: DAE

Evaluating Factuality in Generation with Dependency-level Entailment Goyal and Durrett, Findings of EMNLP2020

Localizes error at the dependency arc level

Seven games involving Nimes were investigated after Conrad was arrested last November.

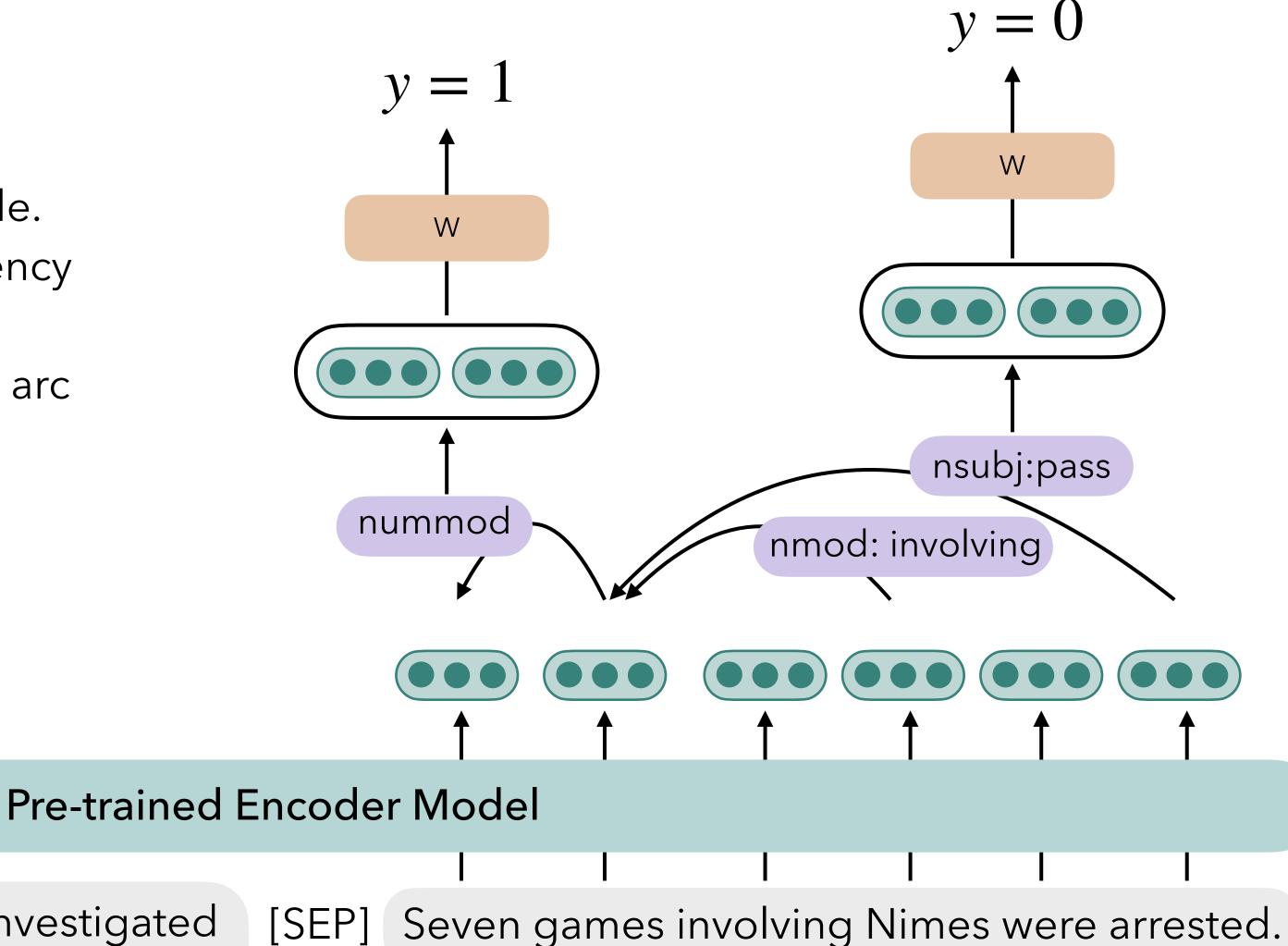


For each arc, is the relationship defined by that dependency arc entailed by the input?

Arc-level entailment decisions are independent, helps localization!

DAE model

- Concat input and output and encode.
- Parse the output to obtain dependency arcs.
- For each dependency arc, compute arc representation.
- Predict arc level entailment.



Seven games involving Nimes were investigated after Conrad was arrested last November.

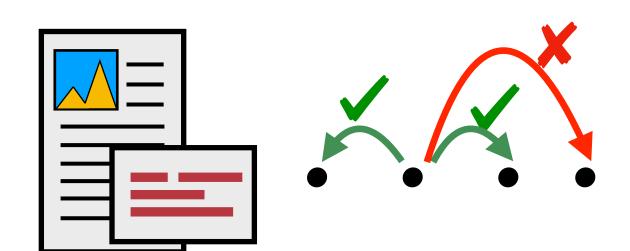
[SEP] Seven games involving Nimes were arrested.

Generated Summary

Input

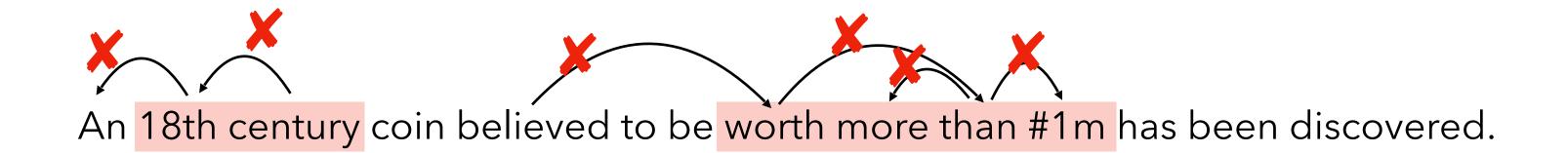
Training

What do we need?



(input, summary) pairs with arc-level factuality labels.

▶ We use human-annotated training dataset with span highlighting of non-factual parts. [1]



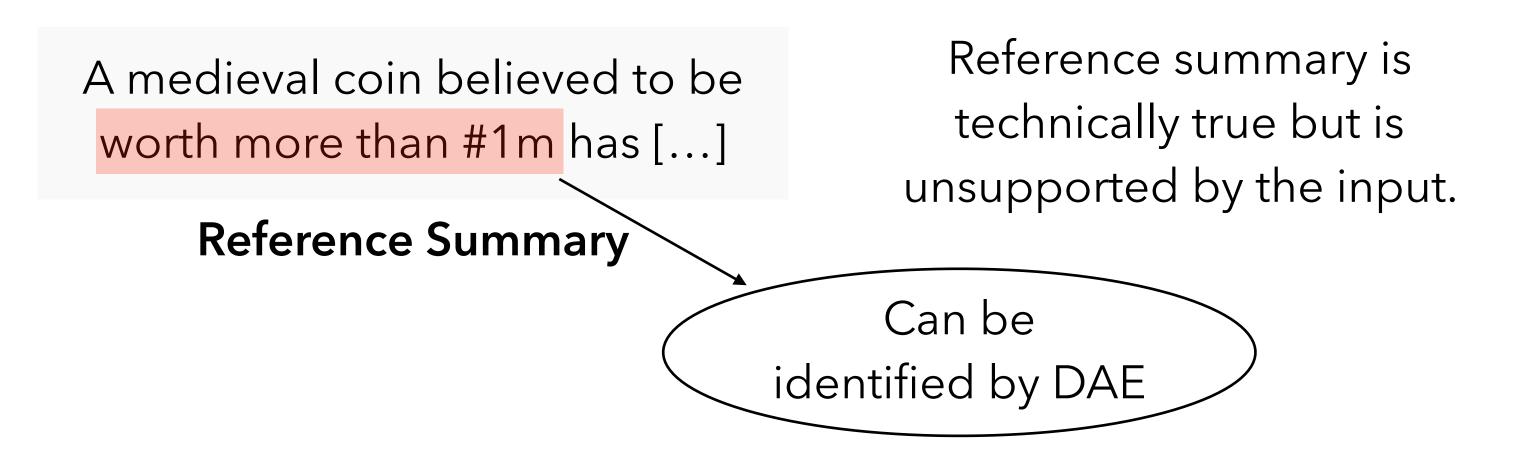
Results: XSUM

	Training Data	Accuracy
	Ent-C	50.9
	Gen-C	54.2
Human-annotated Training Data	Sent-level	65.6
	DAE	78.7

- Small human annotated training data provides better supervision than large synthetic datasets.
- Fine-grained factuality modeling and annotations outperform sentence-level counterpart.

Improving Summarization Models

Error localization (via DAE) can help de-noise noisy summarization training data like XSUM!



Train models by maximizing the log likelihood of "correct" words only.

Model	Avg. score
Baseline	0.37
DAE-based	0.46

Takeaways

- Existing synthetic datasets are not aligned with actual generation errors of summarization models, especially in challenging domains like XSUM.
- Fine-grained human annotation data can lead to better factuality models, as well as enable training of more factual summarization models!

Thank you!