

Pre-training Text-to-Text Transformers for **Concept-centric Common Sense**

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* equal contribution



Commonsense Reasoning with PTLMs

What do you fill with ink to write notes on a piece of copy paper ?

- (A) Fountain pen*
- (B) Pencil case*
- (C) Printer*
- (D) Notepad*

Commonsense Reasoning with PTLMs

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UNIFIED-QA

Enter a question to see what answer our UnifiedQA gives. You can also use one of the examples below.

Examples:

Format: Multiple-Choice (Elementary-school-science)-1

Raw string input (first comes the question, then your list your candidates or paragraph; use "\n" as separator):

What do you fill with ink to write notes on a piece of copy paper?\n(A) fountain pen (B) pencil case (C) printer (D) notepad

Submit

Input:

What do you fill with ink to write notes on a piece of copy paper?

(A) fountain pen (B) pencil case (C) printer (D) notepad

Output:

Prediction [small, 60 million parameters]: pencil case

Prediction [large, 770 million parameters]: printer

Base : pencil case
Large : printer

Fails to reason with the **concept-centric knowledge**

Current PTLMs

Corpus

... **Copy paper** is thinner than **printer** paper, which doesn't make a huge difference when you're printing text, but it does when you're printing large images. Images require a lot of **ink** and because **copy paper** has a thinner structure, the **ink** will need to spread out more for the **paper** to absorb it all. ...

Pre-train

Text Infilling / MLM

PTLMs

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The model may be **sensitive** to the **co-occurrence** (ink, copy, paper)

How can we teach PTLMs to **write** and **reason** with **Common sense Concepts** ?

What do you **fill** with **ink** to **write**
notes on a piece of **copy paper** ?

- (A) **Fountain pen**
- (B) Pencil case
- (C) Printer
- (D) Notepad

fill, ink, write, copy paper

Fountain Pen

Our idea : Novel Self-supervised Objectives to improve common sense reasoning ability.



Generative Objective : **Concept-to-Sentence Generation (C2S)**

Ask model to recover the original sentence
given only a few unordered keywords of the sentence.

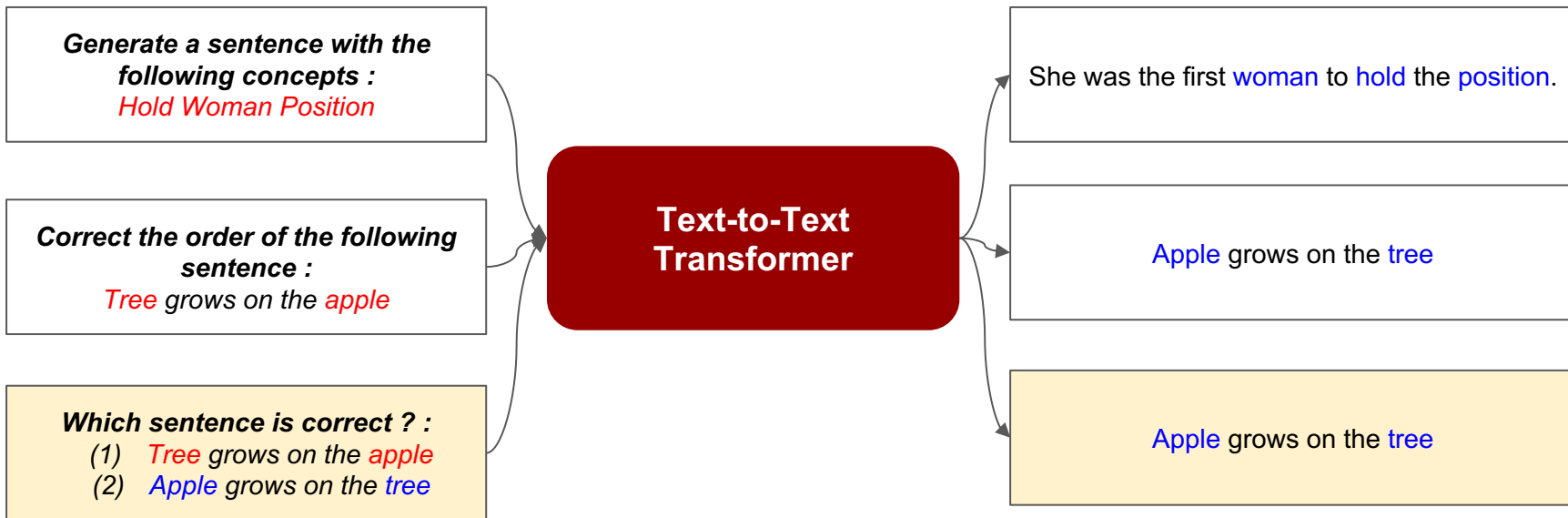
Our idea : Novel Self-supervised Objectives to improve common sense reasoning ability.



Generative Objective : **Concept Order Recovering (COR)**

Ask model to recover the original sentence given order-of-concept shuffled sentence.

Our idea : Novel Self-supervised Objectives to improve common sense reasoning ability.



Discriminative Objective : Generative QA
Ask model to distinguish the real sentence from a concept-distracted sentence.

CALM : **C**oncept-**A**ware **L**anguage **M**odel

Original Sentence x

She was the first woman to hold the position.

Extract Concept Set C
(*woman, hold, position*)

- (1) Given an input sentence x (“*She was the first woman to hold the position.*”), extract concept-set C (*woman, hold, position*).

CALM : **C**oncept-**A**ware **L**anguage **M**odel

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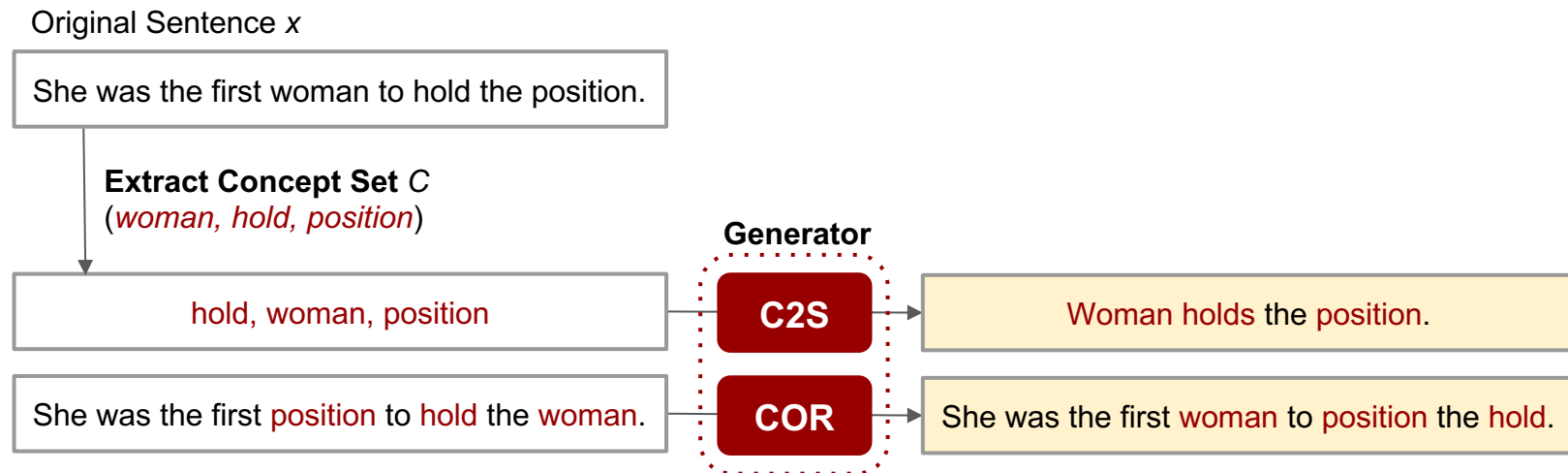
Extract Concept Set C
(*woman, hold, position*)

hold, woman, position

She was the first **position** to **hold** the **woman**.

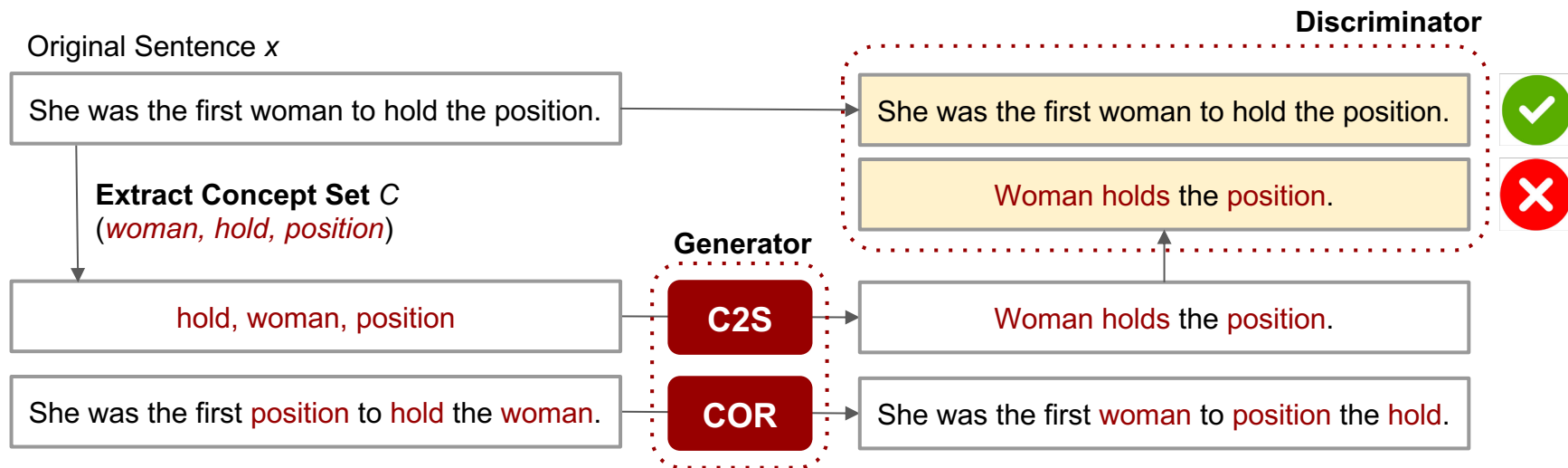
- (1) Given an input sentence x (“*She was the first woman to hold the position.*”), extract concept-set C (*woman, hold, position*).
- (1) Given x and C , produce corrupted source sentence x' either for **C2S** and **COR**

CALM : Concept-Aware Language Model



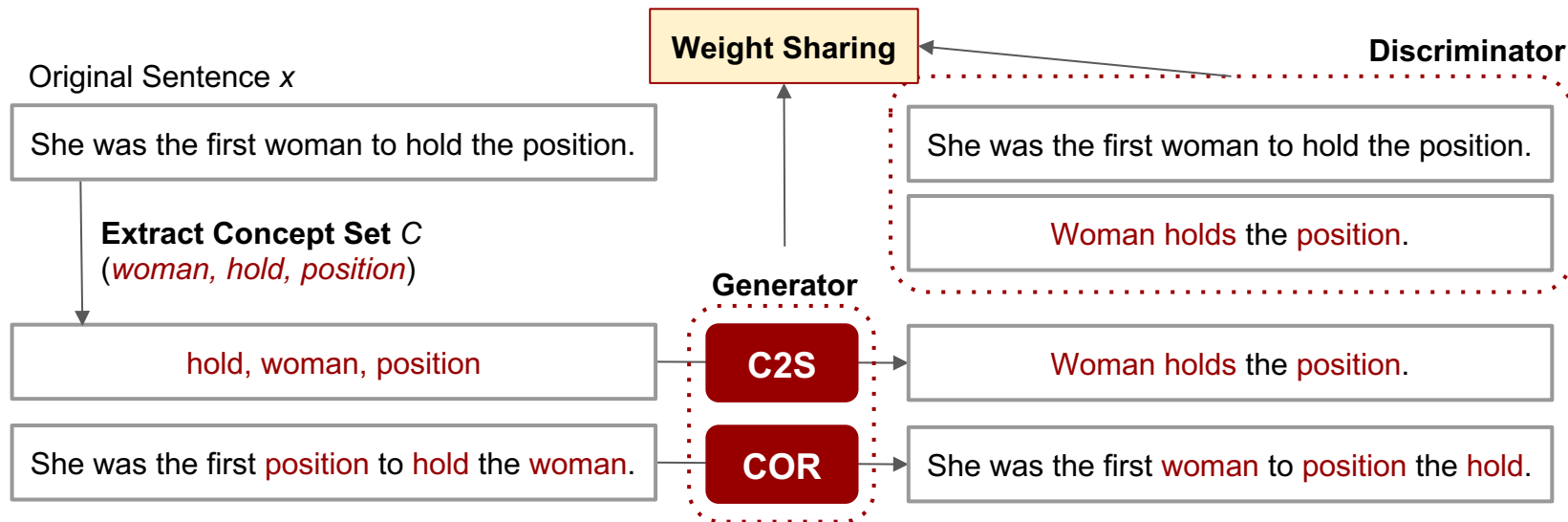
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- (2) The generator trained with **C2S** and **COR** recovers sentence x' to distractor x

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Is CALM reason with concepts ? Yes !

| Methods | CSQA | OBQA | PIQA | aNLI |
|------------------------------|-------------------------------------|------------------------------------|-------------------------------------|-------------------------------------|
| Accuracy | | | | |
| T5-base | 61.88(± 0.08) | 58.20(± 1.0) | 68.14(± 0.73) | 61.10(± 0.38) |
| T5-base w/ additional epochs | 61.92(± 0.45) | 58.10(± 0.9) | 68.19(± 0.77) | 61.15(± 0.52) |
| T5-base + SSM | 62.08(± 0.41) | 58.30(± 0.8) | 68.27(± 0.71) | 61.25(± 0.51) |
| CALM (Generative-Only) | 62.28(± 0.36) | 58.90(± 0.4) | 68.91(± 0.88) | 60.95(± 0.46) |
| CALM (Contrastive-Only) | 62.73(± 0.41) | 59.30(± 0.3) | 70.67(± 0.98) | 61.35(± 0.06) |
| CALM (Mix-only) | 63.02(± 0.47) | 60.40(± 0.4) | 70.07(± 0.98) | 62.79(± 0.55) |
| CALM (w/o Mix warmup) | 62.18(± 0.48) | 59.00(± 0.5) | 69.21(± 0.57) | 61.25(± 0.55) |
| CALM | 63.32(± 0.35) | 60.90(± 0.4) | 71.01(± 0.61) | 63.20(± 0.52) |

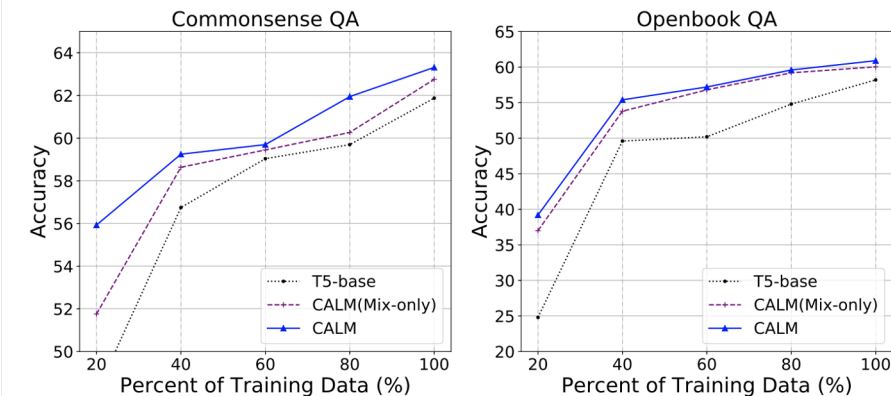
Experimental results on commonsense reasoning dataset.

CALM consistently and significantly outperforms the backbone T5-base model.

Is CALM **reason** with **concepts** ? **Yes !**

| Methods | CSQA | OBQA | PIQA | aNLI |
|-----------------------|-------------------------------------|------------------------------------|-------------------------------------|-------------------------------------|
| | Accuracy (official dev) | | | |
| BERT-large | 57.06(± 0.12) | 60.40(± 0.6) | 67.08(± 0.61) | 66.75(± 0.61) |
| T5-large | 69.81(± 1.02) | 61.40(± 1.0) | 72.19(± 1.09) | 75.54(± 1.22) |
| CALM-large (Mix-only) | 70.26(± 0.23) | 62.50(± 1.0) | 73.70(± 1.09) | 75.99(± 1.26) |
| CALM-large | 71.31(± 0.04) | 66.00(± 1.0) | 75.11(± 1.65) | 77.12(± 0.34) |

Effective in Large Models.



Performance of compared models fine-tuned with different fraction of the dataset

Performance is **consistent** in **large** model & **different fraction** of the dataset.

Is CALM write with concepts ? Yes !

| Methods | Params | CommonGEN | | | |
|--------------------------------|--------|--------------|--------------|--------------|--------------|
| | | BLEU-4 | METEOR | CIDEr | SPICE |
| GPT-2 (Radford et al., 2019) | 774M | 21.10 | 26.20 | 12.15 | 25.90 |
| UniLM (Dong et al., 2019) | 340M | 27.70 | 29.70 | 14.85 | 30.20 |
| BART (Lewis et al., 2020) | 406M | 26.30 | 30.90 | 13.92 | 30.60 |
| T5-Base (Raffel et al., 2019) | 220M | 16.40 | 23.00 | 9.16 | 22.00 |
| T5-Large (Raffel et al., 2019) | 770M | 28.60 | 30.10 | 14.96 | 31.60 |
| KG-BART (Liu et al., 2020) | 406M | 30.90 | 32.40 | 16.83 | 32.70 |
| Our T5-Base | 220M | 24.90 | 31.20 | 12.99 | 32.40 |
| CALM | 220M | 26.40 | 31.40 | 13.88 | 33.00 |

(Left) : Comparison between PTLMs
(Below) : Comparison on generated sentences with same concept-set

| Concept-set | T5-base | CALM |
|----------------------------|--|--|
| Grass, Dog, Ball, Chase | a dog is chased by a ball on the grass. | dog chasing a ball in the grass. |
| Net, Cast, Boat, Water | fishing boat casts a net in the water. | fisherman casts a net into the water from a fishing boat. |
| Hole, Tree, Plant, Dig | a man digs a hole in a tree to plant a new tree . he digs the | man digging a hole to plant a tree. |
| Ingredient, Add, Pan, Fry | a pan filled with ingredients adds a touch of spice to the fry . | add the ingredients to a pan and fry. |
| Water, Hold, Hand, Walk | A man holding a hand and walking in the water. A man is holding water. | man holding a bottle of water in his hand as he walks down the street. |
| Place, Use, Metal tool | A man uses a metal tool to make a piece of metal. | woman uses a metal tool to make a piece of jewelry. |
| Hair, Wax, Apply, Remove | remove the wax from your hair and apply it to your hair . | woman applies wax to her hair and then removes it with a comb. |
| Sidewalk, Dog, Walk, Leash | A dog walking on a leash on the sidewalk. | dog walking on a sidewalk with a leash. |

Summary

- **Novel self-supervised strategies** for concept-centric Common Sense
 - Concept to Sentence
 - Concept Order Recovering
 - Generative QA
- **Two-stage training strategy**
 - Generator and Discriminator

Text-to-Text models can be pre-trained with **better parameter** and **sample efficiency** by carefully designed **self-supervised objectives** that focus on the ability required by target tasks.