Are the Relationships of Class Representations in Vision and Language Similar?

Mar 15, 2021

Presenter: Sungguk Cha

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Abstract

- Multi-modal zero-shot learning field is hot.
- We show that domain shift causes changes in representation of CNNs.
- We show that language-based zero-shot learning in computer vision has limitation in generalization intrinsically.

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It is my fourth presentation in Algorithm Session!

- ➔ Zero-Shot Semantic Segmentation
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- ➔ **Are the Relationships of Class Representations in Vision and Language Similar?**
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Introduction

➔ **Why** am I interested in class representations?

➔ **What** can we learn from this presentation?

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Introduction:

Why am I interested in class representations?

➔ Class representation?

➔ Multi-modal approaches in computer vision

➔ Limitations of the multi-modal approaches

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Introduction:

Why am I interested in class representations?

In this presentation,
class representation in language model == word embedding.

Language models: Word2Vec, BERT, GPT, …

word embedding: *d* dimensional vector expression

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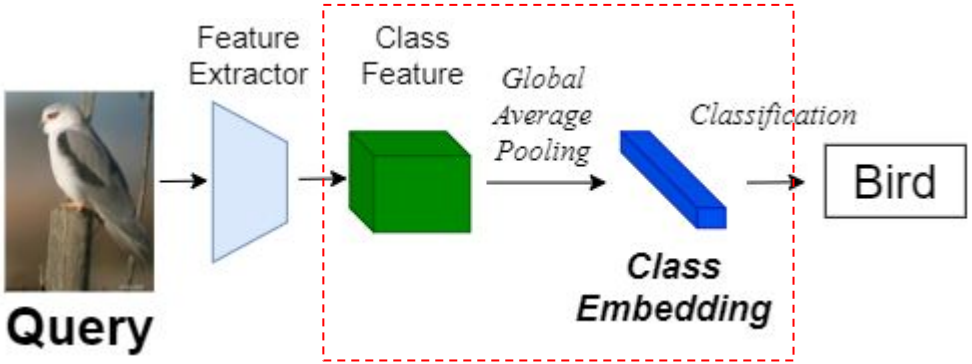
Introduction:

Why am I interested in class representations?

Class representation in vision model



Introduction:

Why am I interested in class representations?

Why multi-modal approaches in computer vision?

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Why am I interested in class representations?

Why multi-modal approaches in computer vision?

Prevalent approaches in computer vision field

- requires expensive dataset,
- predicts only learned categories.

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Prevalent approaches in computer vision field

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To solve the problems, *zero-shot* learning is researched actively.

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Prevalent approaches in computer vision field

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To solve the problems, *zero-shot* learning is researched actively.

Zero-shot learning?

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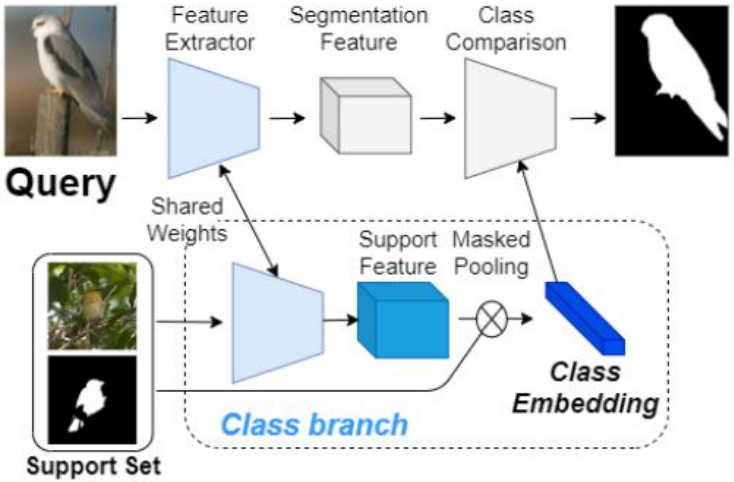
Introduction:

Why am I interested in class representations?

Few shot learning: recognize unseen categories with only a few support images



1. Generate class embedding from support set

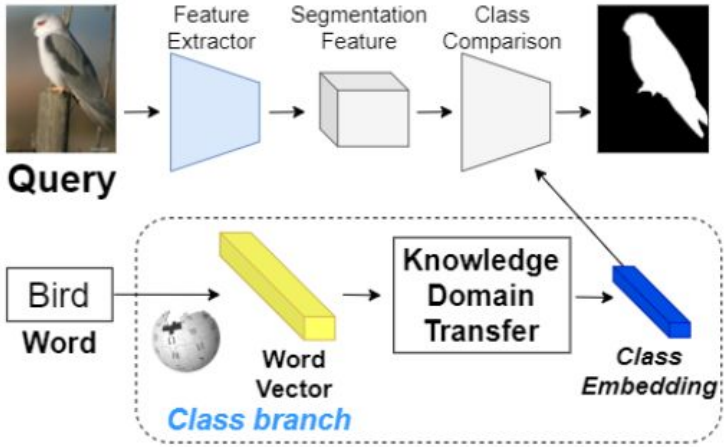
2. Compare *segmentation feature* and *class embedding*

Figure: Few-shot semantic segmentation

Introduction:

Why am I interested in class representations?

Zero shot learning: recognize unseen categories without a support image, **but with language model**



1. Generate class embedding from a word

2. Compare *segmentation feature* and *class embedding*

Figure: Zero-shot semantic segmentation

Introduction:

Why am I interested in class representations?

Multi-modal approaches in computer vision

- Image Classification: CLIP ~ 300M params
- Image Synthesis: DALL E ~ 13B params (GPT-3 small)
- Image Segmentation
- Zero-shot Sketch-based image retrieval

Usually, GPT-3 is not affordable.

Instead, zero-shot approaches use pretrained language model (word2vec).

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Introduction:

Why am I interested in class representations?

Multi-modal approaches in computer vision examples

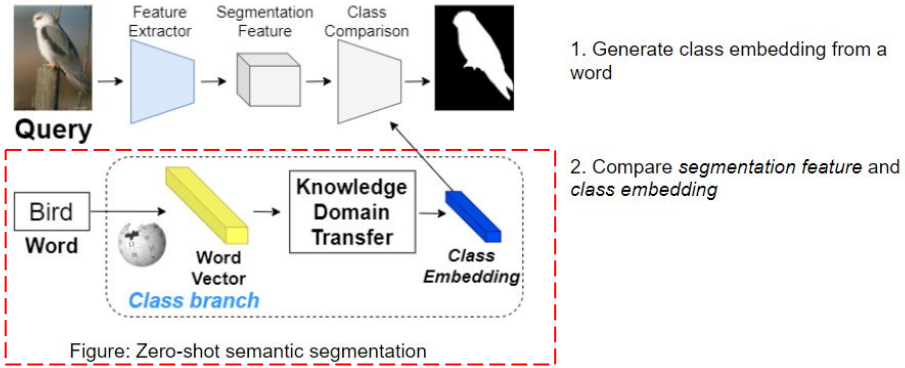

Figure: Zero-shot semantic segmentation

Image sources:
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Multi-modal approaches in computer vision examples

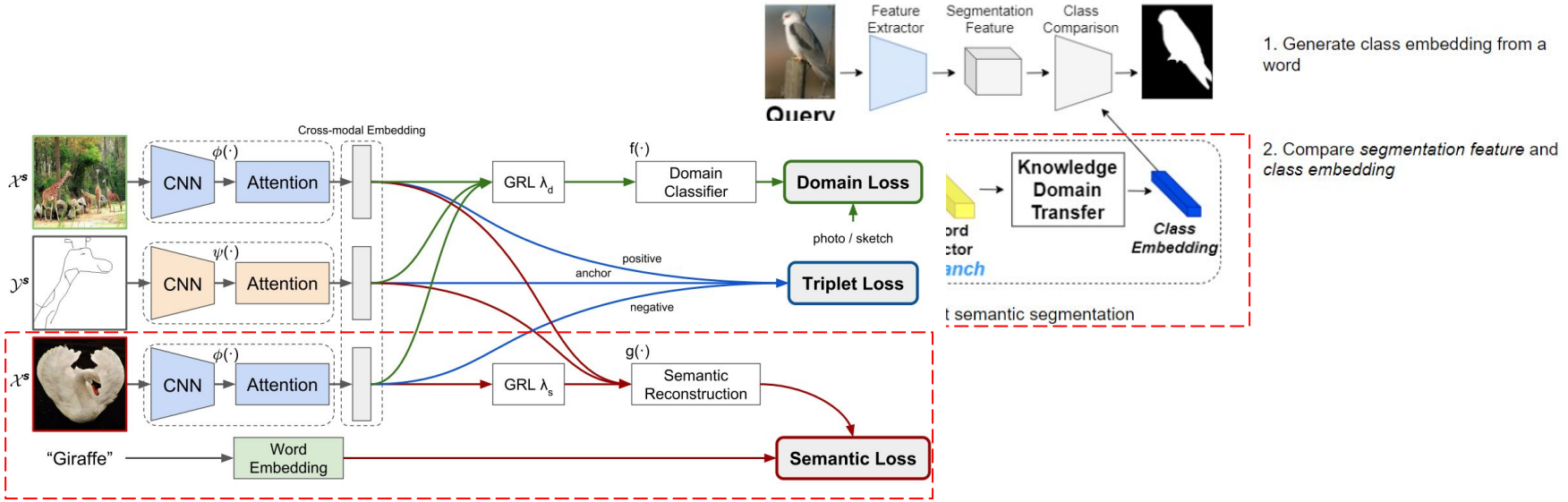

Image sources:
Doodle to Search: Practical Zero-Shot Sketch-based Image Retrieval, CVPR`19

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Introduction:

Why am I interested in class representations?

Limitations of the multi-modal approaches

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Limitations of the multi-modal approaches

The proposed zero-shot approaches use

only very little knowledge of language model.

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Limitations of the multi-modal approaches

The proposed zero-shot approaches use
only very little knowledge of language model.

(e.g.,)

GloVe pretrained on Common Crawl with 2.2 M vocab. in 300 dimension

ZS-SBIR approaches use **125** word embeddings out of **2,200,000**. (Sketch)

ZSSS approaches use **20** word embeddings out of **2,200,000**. (PASCAL-5i)

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Why am I interested in class representations?

(e.g.,)

GloVe pretrained on Common Crawl with 2.2 M vocab. in 300 dimension

ZS-SBIR approaches use 125 word embeddings out of 2,200,000. (Sketch)

ZSSS approaches use 20 word embeddings out of 2,200,000. (PASCAL-5i)

In my intuition,

it should not work in practice.

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Introduction:

Why am I interested in class representations?

In my intuition,

it should not work in practice.

“I am very curious about

why it should not work in practice.”

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Introduction:

Why am I interested in class representations?

“I am very curious about
why it should not work in practice.”

In this presentation, I address

“they have a limitation in class representations.”

“their class representation has weakness in ***generalization***.”

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Introduction:

What can we learn from this presentation?

- Our experiment shows that
  domain shift causes change in class representation of CNN.

- Limitation of language model based zero-shot learning in computer vision:
  weakness in representation for generalization.

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Experiment

We compare class representations

between vision models and language models

in zero-shot semantic segmentation (ZSSS) setting

20 categories of PASCAL VOC 2012

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Experiment: Categories

```
PASCAL =
['aeroplane', 'bicycle', 'bird', 'boat', 'bottle',
 'bus', 'car', 'cat', 'chair', 'cow',
 'diningtable', 'dog', 'horse', 'motorbike', 'person',
 'plant', 'sheep', 'sofa', 'train', 'monitor']
```

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Experiment: Correlation Metric

Cosine similarity

Class representation is expressed in *d* dimensional vector.

e.g., 2048d in ResNet, 300d in GloVe

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Experiment:

Class representation in vision models

Given a dataset with 20 categories $X = \cup_i^{20} \cup_{j \in |C_i|} \{I_{i,j}\}$ and a model $f : I \rightarrow r$ that encode an image I into a d dimensional class representation r, the i-th category representation R_i is

$$R_i = \frac{1}{|C_i|} \sum_j^{|C_i|} f(I_{i,j}) \tag{1}$$

tl;dr

i-th class representation := mean of encoded vector from all samples of i-th class

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Experiment:

Class representation in vision models

We used

ResNet 34, 50 and 101 pretrained on ImageNet 1k.

We obtained class representations from

PASCAL-5i test set

and COCO-20i test set.

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Experiment:

Class representation in language models

We used

GloVe pretrained on Common Crawl with 2.2M vocab in 300d,

fastText pretrained on Common Crawl with 2M vocab in 300d.

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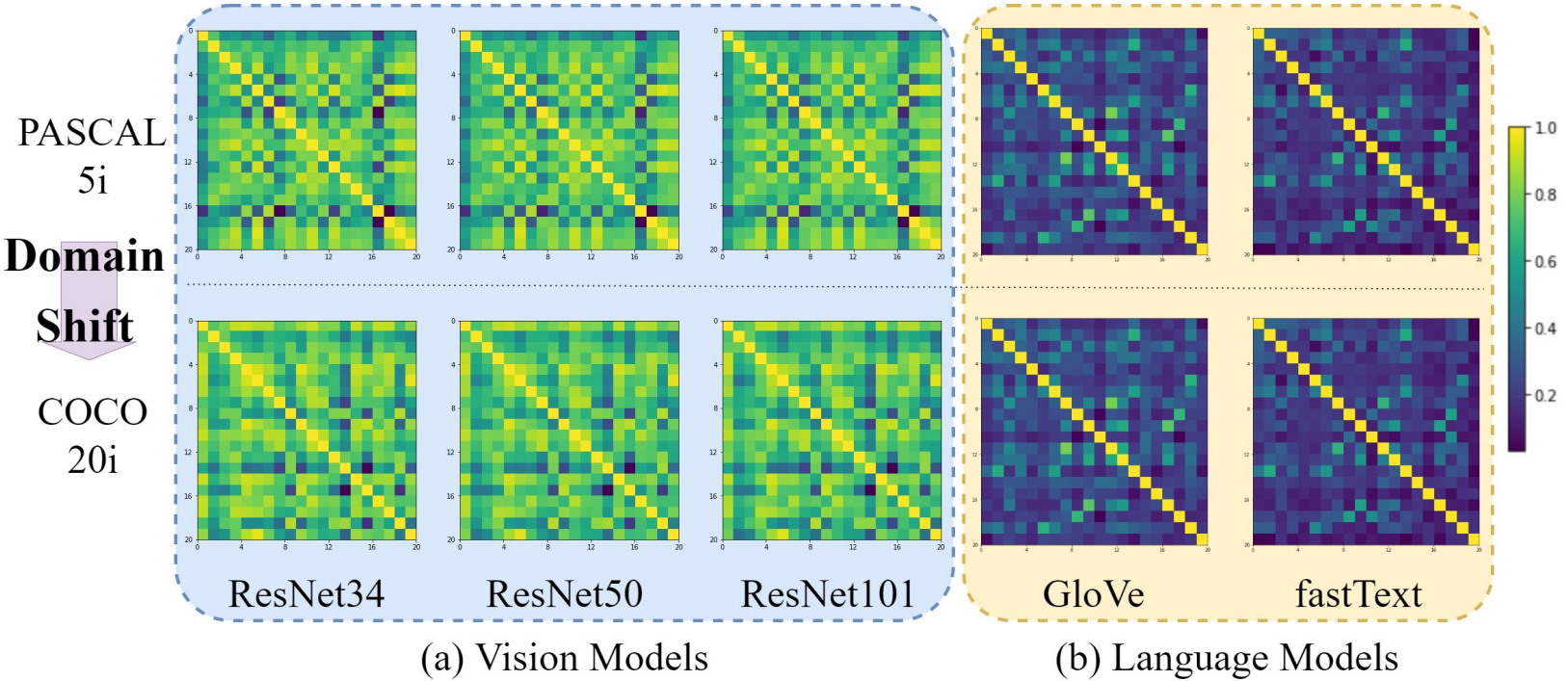
Experimental Results



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Experimental Results

Representation correlation of **vision models** on the same domain show the same pattern and high similarity mean.

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Representation correlation of **language models** trained on the same dataset
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Experimental Results

Representation correlation of vision models on the same domain
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Representation correlation of language models trained on the same dataset
show a similar pattern and low similarity mean.

Distribution gap exists between vision models and language models.

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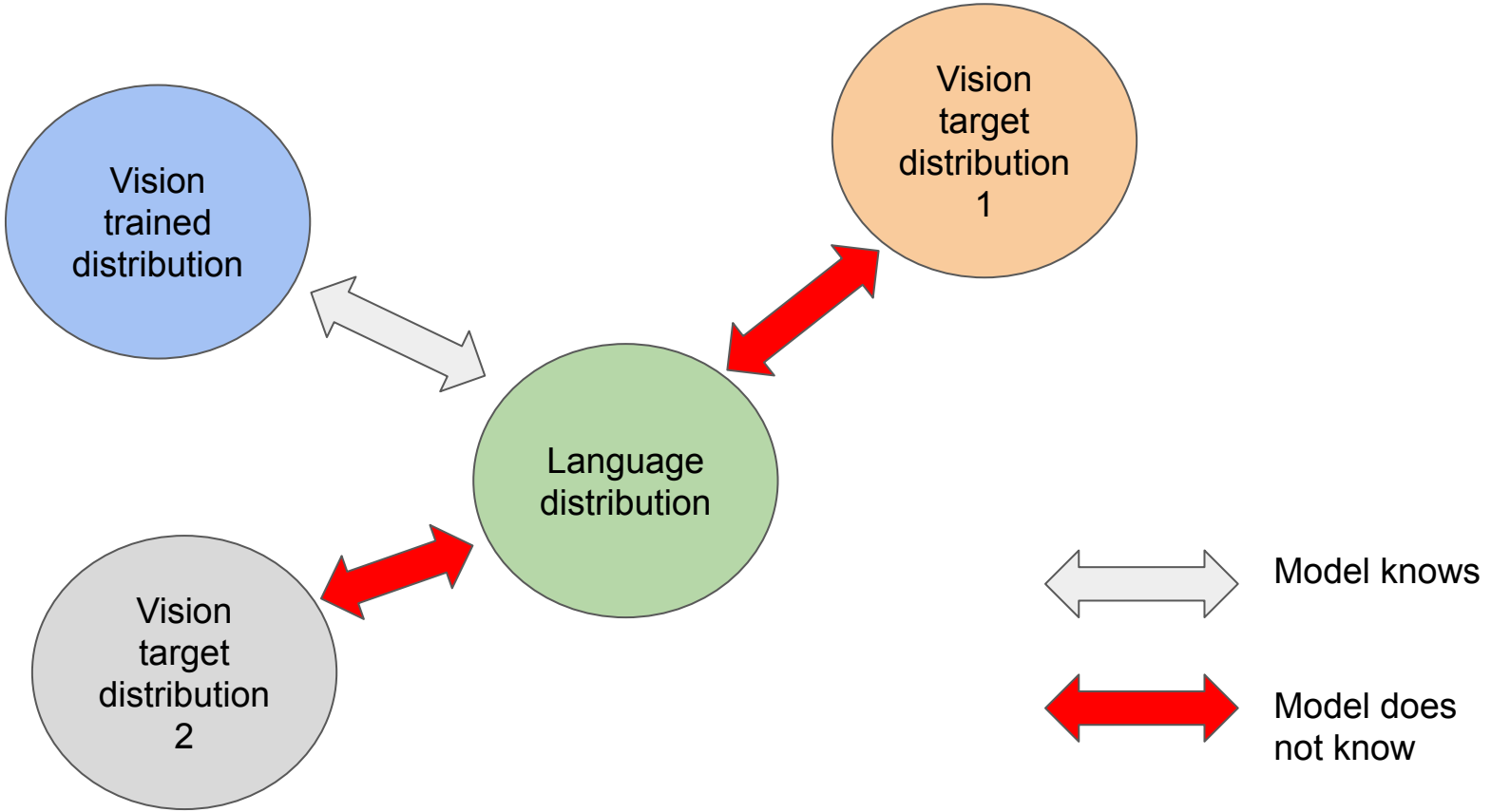
We showed that



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Conclusion

We address that

“Language model based zero-shot learning approaches

have limitation in generalization.

In other words,

they work only on the trained domain.”

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