Comparison of Various Zero-shot Models in Traffic Incident Detection

Group 17:

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OUR TEAM

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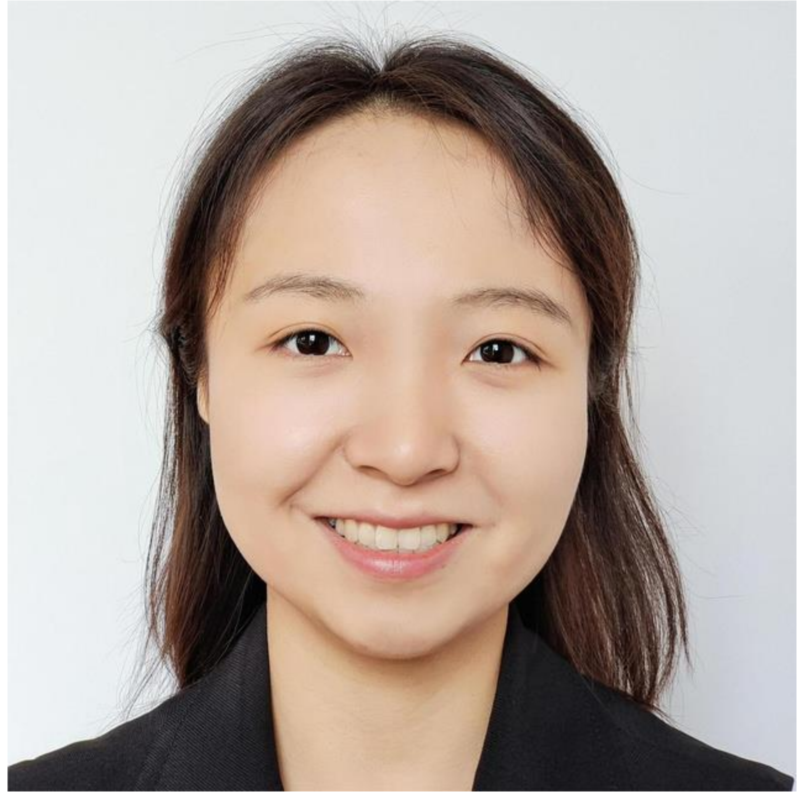

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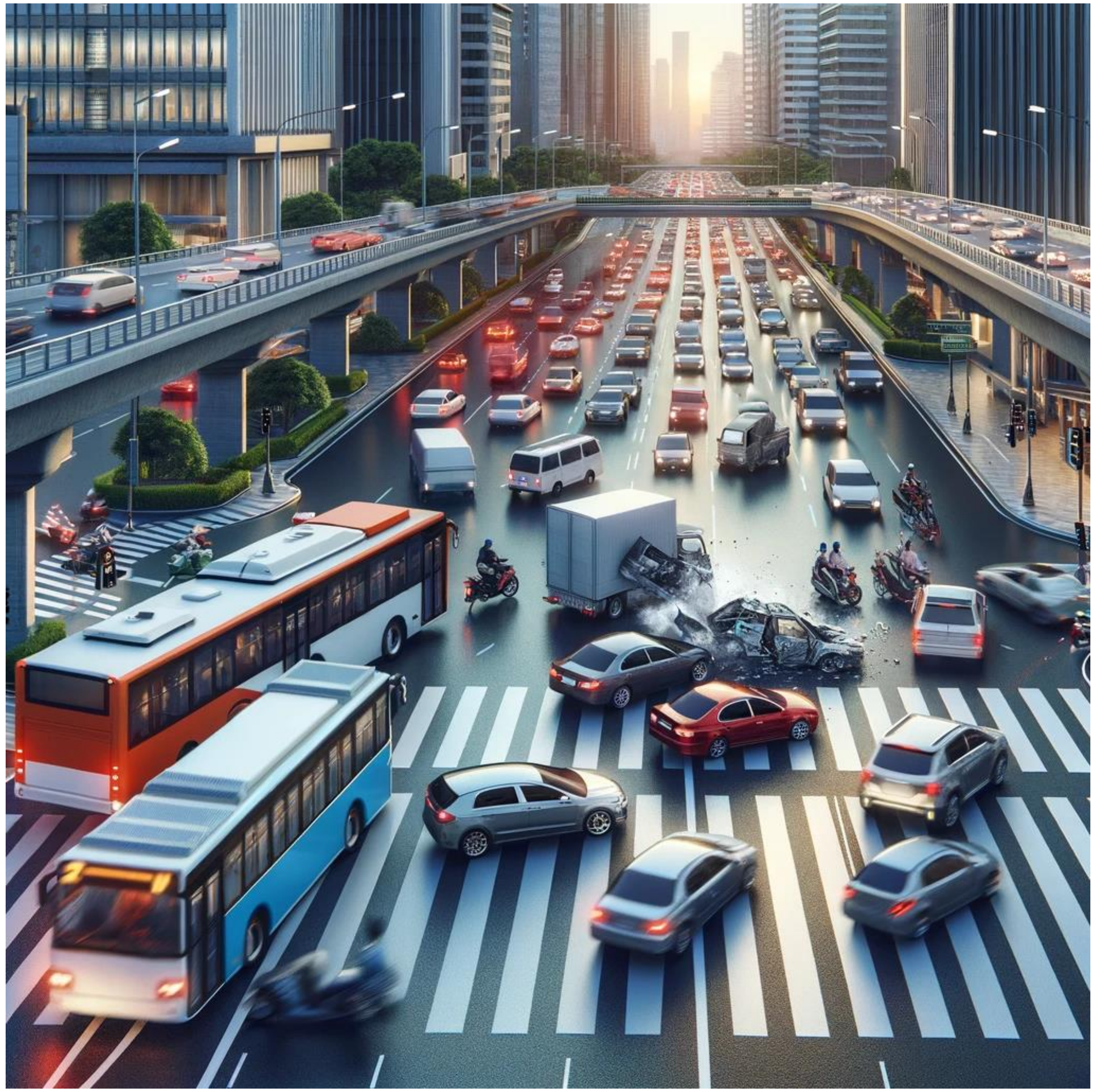
PROBLEM DESCRIPTION



- Importance of Traffic Incident Detection
  - Essential for traffic management and safety.
  - Requires timely and accurate detection methods.

- Traditional Traffic Detection
  - Depend on historical data
  - Utilized models trained on specific incident scenarios.

- Challenges with Traditional Methods
  - Limited to new traffic incidents
  - Not efficient in rare scenarios

APPROACH

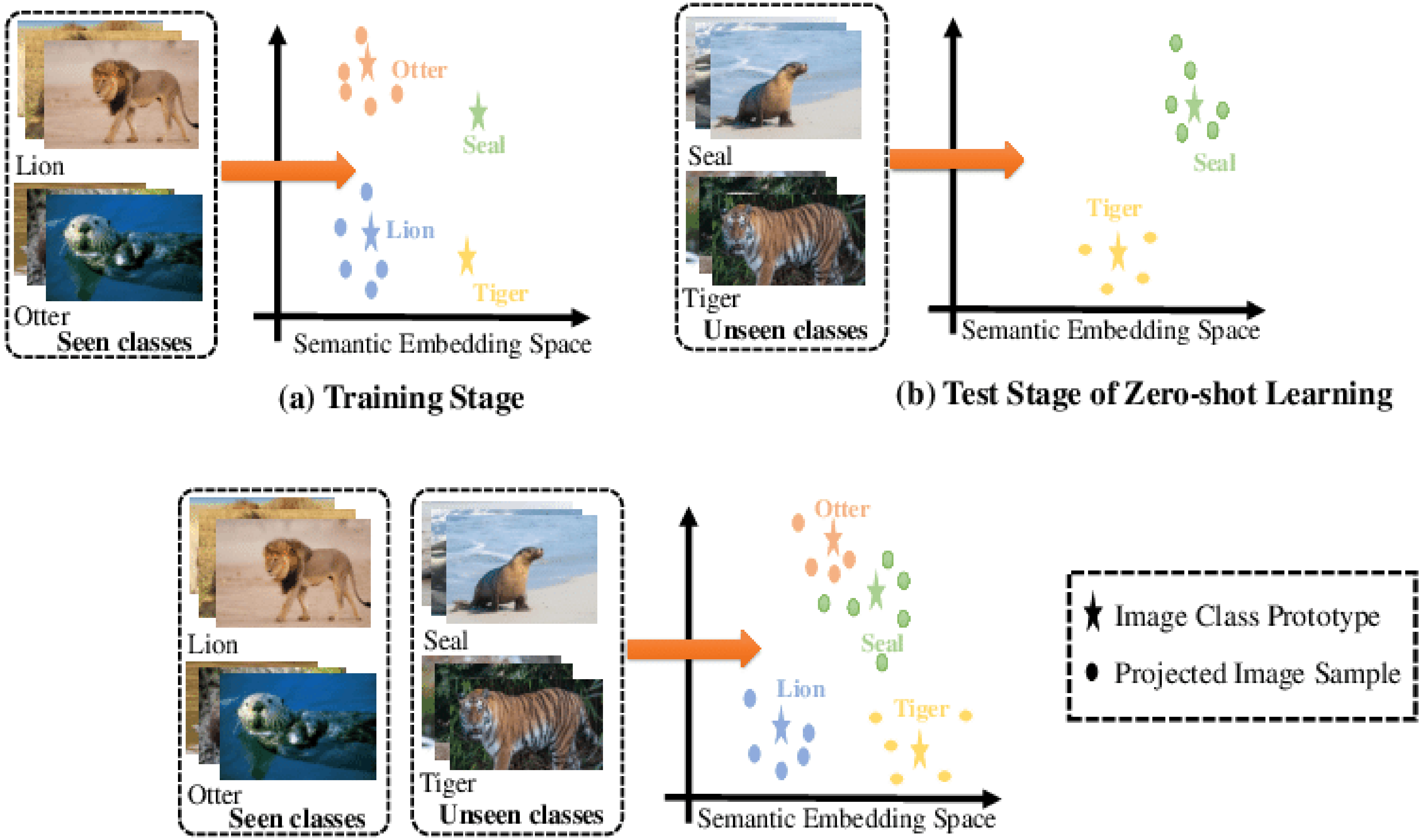
- Social Media as a Traffic Information Source
  - Real & real-time public reporting
  - Discussions on traffic conditions as an alternative detection method.

- Project Focus
  - Exploring effectiveness of zero-shot learning models.
  - Aimed at improving traffic incident detection.

ZERO-SHOT CLASSIFICATION

- What is it?
  - A machine learning approach where a model classifies data into multiple classes without specific training examples for those classes.
- Why is it?
  - Generalization to Unseen Classes
  - Reduced Data Annotation
  - Cross-Domain Transfer
  - Adaptable to Multi-Label Classification

APPLICATIONS



(a) Training Stage

(b) Test Stage of Zero-shot Learning

(c) Test Stage of Generalized Zero-shot Learning

Image classification, Object detection, Topic classification, Sentiment analysis, and Language Identification…

PROCESS

Preparing the Dataset

- Data collection, Label Formatting

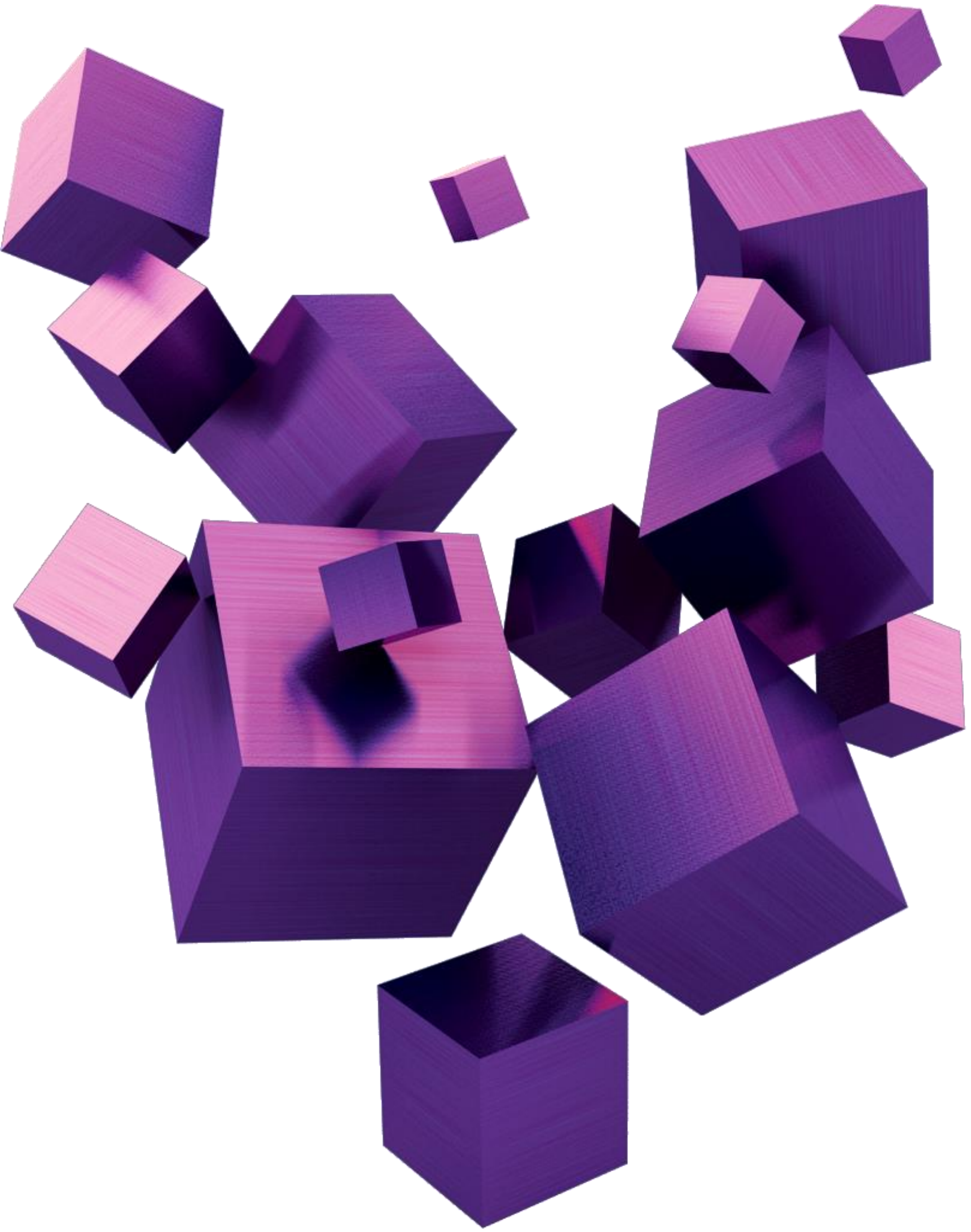
Choosing Zero-shot models

- Hugging Face’s Transformers

Model Inference

Results analysis

[Code File]



DATASET

- 40941 tweets with traffic-related labels
- Collected through Twitter API

- Categorized into 2 classes:
  - Class 0: No-traffic Incident
  - Class 1: Traffic Incident

  i.e., traffic crashes, disabled vehicles, highway maintenance, work zones, road closure, vehicle fire, traffic signal problems, special events, and abandoned vehicles.

Dabiri, Sina (2018), “Tweets with traffic-related labels for developing a Twitter-based traffic information system.”, Mendeley Data, V1.

MODEL

Model	Description	Training Dataset	Parameters (Approx.)
1. Bidirectional Encoder Representations from Transformers (BERT Base)	Basic BERT model with 12 layers, does not differentiate between upper and lower case. Suitable for general NLP tasks.	Wikipedia, BooksCorpus	110M
2. Bidirectional Encoder Representations from Transformers (BERT Large)	Larger and more powerful version of BERT with 24 layers, also uncased. Enhanced for deep language understanding.	Wikipedia, BooksCorpus	340M
3. Robustly Optimized BERT Approach (RoBERTa Large)	An optimized version of BERT with more training data and layers, offering improved performance on various benchmarks.	Extended with CC-News, Stories, WebText	355M
4. Bidirectional and Auto-Regressive Transformers (BART Large)	Combines BERT-like encoder and GPT-like decoder. Effective for tasks like summarization, translation, and text generation.	Web pages, Books, News articles	400M
5. BART for Multi-Genre Natural Language Inference (BART Large mnli)	Fine-tuned version of BART-Large on MNLI dataset, excelling at understanding sentence relationships and entailment.	Multi-Genre NLI dataset	Same as BART-Large
6. Distilled BART for MNLI (12-1 layers)	A distilled and efficient version of BART, maintaining substantial performance with reduced size. Specialized in MNLI tasks.	Multi-Genre NLI dataset	Reduced from BART
7. Distilled RoBERTa for Natural Language Inference (Base)	A distilled version of RoBERTa for efficient natural language inference. Cross-encoder architecture suitable for sentence pair tasks.	WebText	Smaller than RoBERTa
8. Generative Pre-trained Transformer 2 (GPT2)	Focuses on generative tasks, predicting the next word in a sentence. Not specifically optimized for classification or entailment but excels in creative writing and dialogue.	WebText	1.5B

RESULT

No.	Model	Accuracy (%)
1	BERT-based-uncased	68.7
2	BERT-large-uncased	53.7
3	RoBERTa-large	64.5
4	BART-large	50.9
5	BART-large-MNLI	36.0
6	DistilBart-MNLI	74.0
7	Distilled RoBERTa	47.7
8	GPT2	34.3

CONCLUSION

- Zero-shot learning allows to classify data into new and unseen classes without specific training examples
- Offering flexibility and adaptability to changing or expanding class sets
- Limitations :
  - May not be accurate in domain-specific content
  - Need further design and fine-tune zero-shot learning models
  - Alternative approaches like few-shot learning, and transfer learning might be further explored

QUESTION?