### Zero-Shot Learning for Short Text Classification Overview of the subject area, problem statement, proposed solutions and current results

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A brief description of tasks related to Zero-Shot Learning

## **Classification Problem**



Figure 1: Problem Setting for Classification

A classification problem is when the output variable is a category, such as "cats" or "dogs" or "disease" and "no disease". A classification model attempts to draw some conclusion from observed values. Given one or more inputs a classification model will try to predict the value of one or more outcomes.

A brief description of tasks related to Zero-Shot Learning

### What is Zero-Shot Learning?

Zero-Shot learning method aims to solve a task without receiving any example of that task at training phase. The task of recognizing an object from a given image where there weren't any example images of that object during training phase can be considered as an example of Zero-Shot Learning task. Actually, it simply allows us to recognize objects we have not seen before.

$$S = \{(x, y, c(y)) | x \in X, y \in Y^S, c(y) \in C\}$$
  
x - image-features, y - labels

$$\begin{split} U &= \{(u,c(u))|\; u \in Y^u, \; c(u) \in C\}\\ C(U) &= \{c(u_1), \ldots, c(u_L)\} - \text{class-embeddings}\\ \text{of unseen classes} \end{split}$$

 $f_{ZSL}: X \to Y^U$  $f_{GZSL}: X \to Y^U \cup Y^S$ 

Zero-Shot Classification in Computer Vision: Solutions Overview

# Generalized Zero- and Few-Shot Learning via Aligned Variational Autoencoders <sup>1</sup>



Figure 2: Diagram of the approach based on VAE

CADA-VAE model learns a latent embedding (z) of image features (x) and class embedding (c(y) of labels y) via aligned VAEs optimized with cross-alignment ( $\mathcal{L}_{CA}$ ) and distribution alignment ( $\mathcal{L}_{DA}$ ) objectives, and subsequently trains a classifier on sampled latent features of seen and unseen classes.

<sup>1</sup>Original paper: https://arxiv.org/pdf/1812.01784.pdf

Transferring Zero-Shot Learning to NLP Tasks: Solutions Overview

# Transferring Zero-Shot Learning to NLP Tasks

Zero-shot text classification (0SHOT-TC) is a challenging NLU problem to which little attention has been paid by the research community. Several solutions in the field of CV show us that solutions to the problem exist. Therefore, one of the possible ways to tackle problem of 0SHOT-TC is to transfer existing approaches to the NLP field. ZeroShotEval: Unified Pipeline for ZSL Models Evaluation

# ZeroShotEval: Unified Pipeline for ZSL Models Evaluation<sup>2</sup>



Figure 3: The overview of the proposed framework with four main parts-phases: 1) data loading and preprocessing, 2) modality feature generators, 3) zero-shot neural network, 4) evaluation procedures.

<sup>&</sup>lt;sup>2</sup>GitHub Repository: https://github.com/ZSLresearch-team/ZeroShotEval

- Overview of the Proposed Data and Solution
  - VAE Based Approach for 0-Shot Text <u>Classification</u>

# VAE Based Approach for 0-Shot Text Classification



Figure 4: CADA-VAE architecture taken from the original paper <sup>3</sup>.

The main advantage of ZeroShotEval framework is the ability to adapt existing approaches and modify them to solve new problems. Therefore we can easily modify one of the solutions discussed above and get a completely new result within the unified pipeline.

<sup>&</sup>lt;sup>3</sup>Original paper: https://arxiv.org/pdf/1812.01784.pdf

- Overview of the Proposed Data and Solution
  - └─VAE Based Approach for 0-Shot Text Classification

# VAE Based Approach for 0-Shot Text Classification

Embedding extractors used:

- BERT (large/base, cased/uncased)
- RoBERTa
- XLM
- Non-transformer-based (such as Flair)

Classifiers used: different fully-connected nets with softmax activation, different depth and layers sizes.

Data used: CMU Movie Summary Corpus (transformed).

- Overview of the Proposed Data and Solution
  - └─CMU Movie Summary Corpus

# CMU Movie Summary Corpus <sup>4</sup>

	movie_id	plot	movie_name	Action	Animation	Black- and- white	Bollywood	Comedy	Comedy film	Crime Fiction	 Indie	Musical	Mystery	Romance Film	Romantic comedy	Romantic drama	Short Film	Silent film	Thriller	World cinema	
•	23890098	shiykov hardwork taxi driver lyosha saxophonis	Taxi Blues	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	
6	1952976	plot film open 1974 young giri dahlia stand ou	Dark Water	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	
9	20532852	line peopl drool window shop market butcher bu	Destination Meatball	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	
10	15401493	lola attempt gain father trust fund hire hispa	Husband for Hire	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	
12	2940516	bumbl pirat crewman kill captain learn hidden	Ghost In The Noonday Sun	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	

Figure 5: CMU Movie Summary Corpus overview.

The original version of the dataset contains 42204 text instances and 16989 classes. There are 345 binary attributes defined for each instance that describe its genre.

<sup>&</sup>lt;sup>4</sup>Link: http://www.cs.cmu.edu/ ark/personas/

Overview of the Proposed Data and Solution

CMU Movie Summary Corpus

# CMU Movie Summary Corpus: Filtered for 0-Shot TC



Figure 6: The number of classes that belong to each attribute.

The filtered version of the dataset contains 13095 text instances and 129 classes. There are only 20 binary attributes defined for each instance that describe its genre.

- Overview of the Proposed Data and Solution
  - CMU Movie Summary Corpus

# CMU Movie Summary Corpus: Filtered for 0-Shot TC



Figure 7: Histogram of the distribution of the number of classes with a certain number of attributes.

0-Shot	Text	Classification

Results

## Results

Model	Latent Size	Feature Size	Attributes Number	Seen Accuracy	Unseen Accuracy	Harmonic Mean		
CADA-VAE	64	2048	312	53.5	51.6	52.4		
Ours	16	1024	20	30.6	5.2	8.9		

Figure 8: Comparing proposed approach on CMU Movies dataset with the state of the art in the field of CV. We report per class accuracy for seen (S) and unseen (S) classes and their harmonic mean (H). These results are not representative and shows only a direction for development.

- Conclusion

# Conclusion

- 0-Shot TC is a scantily explored field and task even in the field of CV.
- All existing solutions are based on extremely different approaches and datasets, so they require a single form of quality assessment - a way to ZeroShotEval.
- It is necessary to adapt existing datasets or develop a new one to solve the problem. The lack of data is one of the main difficulties in solving this problem.

- Conclusion

## References

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Conclusion

# Thank You for Your Attention!