Empirical Analysis of Zero-Shot Learning Algorithms

Group 47

Course project CS771

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Introduction

- Zero-shot learning consists in learning how to recognise new concepts by just having a description of them
- Following Algorithms are selected for the empirical analysis of zero-shot learning algorithms
  1. CONSE
  2. SAE
  3. GFZSL
  4. ESZSL

CONSE Algorithm

Details of CONSE Algorithm

Semantic Autoencoder for ZSL

- Encoder Decoder paradigm is followed. Encoder projects feature space to semantic space and Decoder do vice-versa
- Constraint of being able to reconstruct (Decoder) the image features from semantic space will generalize the unseen new classes (Claimed in paper)
- Original paper used AWA1 dataset on **standard split** with 80.7% Accuracy
- Computing weight vector using 'Sylvesters Equation' $AW + WB = C$ where $A = SS^T$ and $B = \lambda XX^T$ and $(1+\lambda)SX^T$
- Prediction using $\phi(y) = \arg\min Distance(s_i, S_{Zj})$ where $s_i = Wx_i$ and S_Z is the semantic space of unseen class attributes
- Results on **preferred split** observed as follows: -

AWA1	AWA2	CUB	SUN
42.7	40.2	47.6	38.2

Generative Framework for ZSL (GFZL)

- Takes a generative modeling approach to the ZSL problem
- Modelling the class-conditional distributions of seen as well as unseen classes using exponential family distributions
- Further conditioning the parameters of these distributions on the respective class-attribute vectors via a linear/nonlinear regression model of choice
- Parameter estimation reduces to solving a linear/nonlinear regression problem (closed form soln. exists)
- Simple to implement
- Implemented the algorithm and tested it on AWA1, AWA2, CUB20 and SUN datasets with **preferred split** and result obtained are as follows: -

AWA1	AWA2	CUB	SUN
68.3	63.8	49.3	60.6

Embarrassingly Simple ZSL Algorithm

- This approach is based on a more general framework which models the relationships between features, attributes, and classes as an optimization problem
- Combines a linear model together with a principled choice of regularizers that allow for a simple and efficient implementation
- Original paper used AWA1 dataset and have accuracy of 49.30%
- We ran the experiment on AWA1, AWA2, CUB200 and SUN datasets with **preferred split** and result obtained are as follows: -

AWA1	AWA2	CUB	SUN
	42.7		

Embarrassingly Simple ZSL Algorithm

Multiple Columns

Heading

1. Statement
2. Explanation
3. Example

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Table

Treatments	Response 1	Response 2
Treatment 1	0.0003262	0.562
Treatment 2	0.0015681	0.910
Treatment 3	0.0009271	0.296

Table: Table caption

Figure

Uncomment the code on this slide to include your own image from the same directory as the template .TeX file.

References

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Thanks