

VisDA2018 Open-set Classification Track

- Open-set domain adaptation:
 - Domain adaptation across domains with different label spaces $C_s \setminus C_t \neq \emptyset \wedge C_t \setminus C_s \neq \emptyset$
 - C_s and C_t are known at the training stage
 - A more practical scenario than standard domain adaptation
- VisDA2018 classification competition
 - Setting : simulation-to-real. The source domain consists of computer generated images while the target domain consists of real word images
 - Feature : a variant of open-set domain adaptation : $C_s \cap C_t$ is known but $C_s \setminus C_t$ and $C_t \setminus C_s$ are unknown
 - Evaluation metric : average of per-class accuracy ($C_t \setminus C_s$ is treated as one super class)

Our Results

Team	classes													avg
	plane	bicycle	bus	car	horse	knife	motorcycle	person	plant	skateboard	train	truck	unknown	
VARMS	95.8	93.5	94.3	98.6	93.5	98.5	91.5	82.3	97.2	93.3	93.3	92.3	77.2	92.3
Diggers	91.0	76.6	86.5	94.5	83.1	36.9	83.4	69.8	40.8	69.1	69.1	65.4	9.8	69.0
THUML	94.0	79.2	90.5	97.4	63.2	36.0	81.1	45.6	35.4	84.5	84.5	46.2	42.2	68.3

Technical Challenges and Our Solutions

Relation Shift



(a) horse in training set



(b) horse in validation set

Figure: examples showing relation-shift problem in VisDA2018

- Problem
 - Training data is generated by render engines of games
 - Each single object looks real
 - Object relation is not the same as that in reality
 - Domain adaptation model may suffer from such relation shift
- Solution
 - Refine training data in an automatic way
 - Images like Figure 3(a) often have low confidence on each class.
 - Train a 13-way classifier on source with denoise cross entropy loss

$$L = \frac{1}{n} \sum_{i=1}^n \max\{L_i, \gamma\} \quad (1)$$

- n is the mini-batch size
- L_i is the original cross entropy loss for example i
- γ is progressively adjusted
- noisy examples are ignored
- Images with a single object would have high confidence scores
- Keep those images with only a single object by controlling confidence threshold



Figure: refined images

Overwhelming Target Unknown Examples

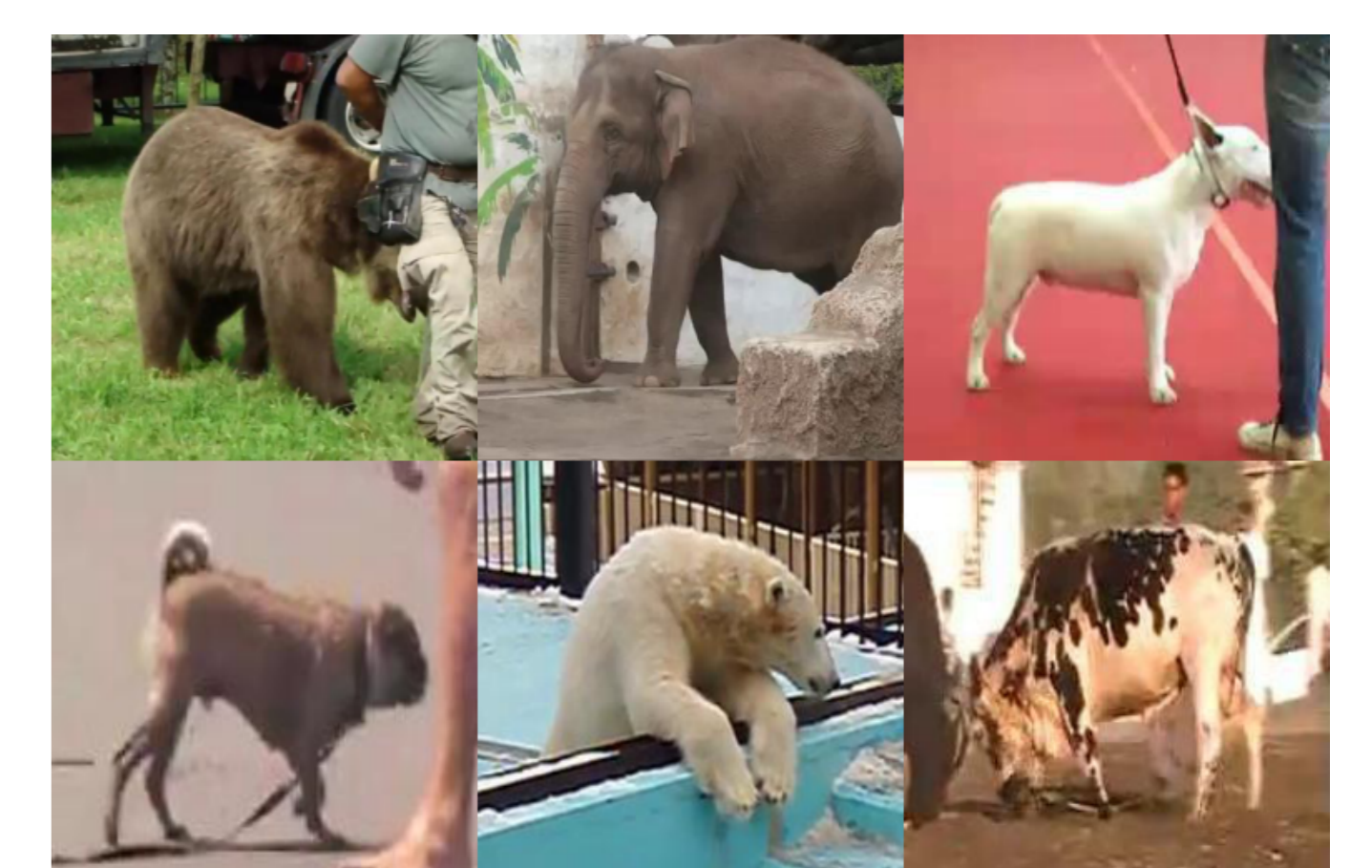
- Problem
 - By analysing validation data, we find that:
 - $\frac{\#unknown}{\#known} \approx 10$
 - $\forall 1 \leq i \leq 12, \frac{\#unknown}{\#known_i} \approx 100$ (There are 12 classes which are known)
 - Extreme class unbalance which is hard to tackle
 - High risk of negative transfer:
 - Standard domain adaptation methods will matching the overwhelming unknown target class data with source data
 - Images in common label space will be ignored due to their small proportion
- Solution
 - Exclude target unknown class in training process.
 - Train a 12-way classification model on refined source data and apply it to target domain
 - Select out those images with highest confidence
 - Train a 12-way classification model with selected images and refined images and apply it to target domain
 - Go to step 1 and repeat several times
 - Obtain target images with high confidence from known class
 - Label these target images with sudo-label predicted by our classifier
 - Semi-supervised domain adaptation between source images of known classes and selected target images with sudo-label of high confidence
 - Images with low confidence score are classified as unknown class

Foo/Bar-alike Images

- Problem
 - Can't tell horses from dogs when there are only horses in training set
 - An intrinsic problem when models trained on closed set are applied to open set classification
- Solution
 - Treat horse-alike images as horse.



(a) horse in validation set



(b) horse-alike in validation set (labeled with unknown class)