Object detection using Semi-Supervised Classification

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Motivation and Problem Statement

Motivation: The Proceedings of the European Conference on Computer Vision has conducted a benchmark PASCAL Visual Object Challenge (VOC) evaluating performance on object class recognition (from 2005-2012, now finished). For our task, we examine the *VOC07* dataset which consists of several types of random images collected in January 2007 from *Flickr*. There are five challenges: classification, detection, segmentation, action classification, and person layout.

Problem Statement: Our goal from this challenge is to perform **image classification** from several visual object classes in realistic scenes (i.e. not pre-segmented objects). And so, we will be using certain Semi-Supervised Learning approaches where we have both labeled and unlabeled sets to check if we get superior results as opposed to supervised techniques.

Data set

The PASCAL Visual Object Classes Challenge (VOC 2007) data set consists of about 9,000 256x256 RGB images of 20 classes. The twenty object classes that have been selected are:

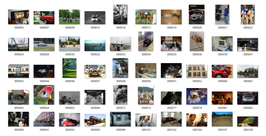

Figure 1. A glimpse of the *PASCAL VOC07* dataset

- **Person**: person
- **Animal**: bird, cat, cow, dog, horse, sheep
- **Vehicle**: aeroplane, bicycle, boat, bus, car, motorbike, train
- **Indoor**: bottle, chair, dining table, potted plant, sofa, tv/monitor

We represent the images in an array with their labels. The labeled set is partitioned into various split points ranging from [0.1,0.9] for our SSL strategy.

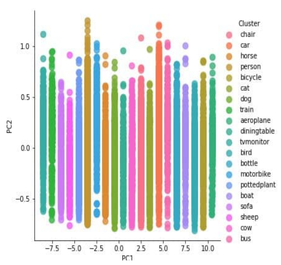

Figure 2. Feature space by PCA

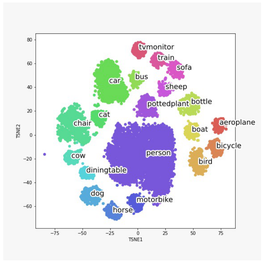

Figure 3. Feature space by t-SNE

Feature space by PCA: We use PCA due to our large feature space as tries to preserve the global properties (dimensions with high variance) while it may lose low-variance deviations between neighbors.

Feature space by t-SNE: Place neighbors close to each other, (almost) completely ignoring the global structure.

SSL Concept

Assumption: Since we have 9,000 raw images after extracting the image within an image from each also any *(Dorste effect)* we estimate to have 15,000 images in total. By this, we assume that an 80-20 split would give 12,000 labeled and 3,000 unlabeled sets on a rough basis.

The SSL methods we proposed for solving our task as follows:

- (*Graph-based*) **Label Propagation Algorithm (LPA)**: *Assumption* - Similar images would have similar feature descriptors and so they would be mapped closely in the graph with high weights to the edges connecting to them.
- (*Graph-based*) **Label Spreading Algorithm**: *Manifold Assumption* - the graphs, constructed based on the local similarity between features, provide a lower-dimensional representation of the high-dimensional input images (images on the same low-dimensional manifold should have the same label).
- (*Inductive*) **Semi-Supervised Gaussian Mixture Model (SSGMM)**: *Assumption* - The images come from the mixture model, where the number of features, prior $p(y)$, and conditional $p(x|y)$ are all correct.

Pros: It highly reduces the amount of annotated data used for our task.
Cons: Since all stated models of ours use an iterative approach for updating it can converge to local minima leading to less stable results. Also, due to the lack of precise information regarding data sorting, and the output as data used in unsupervised learning is labeled and not known.

Due to the stated assumption for different splits the iteration results we could get might be less stable in this perspective.

Implementation

For our task we used **Python 3.6** for implementing our concepts. The open tool-kits that we used for our development purposes are primarily ***Jupyter Notebook*** and ***Spyder IDE*** from the ***Anaconda*** distribution software.

We implemented a ***Data Loader*** pipeline where we feed 15,500 extracted images in an array along with their labels which goes for train-test-validate partition. We extracted the 3 mandatory features: *MPEG-7 Color Layout Descriptor, Visual Bag-of-Words (BOV), **S**peeded **U**p **R**obust **F**eatures*. For the first feature, the process comprised of 4 phases namely:

- Image partitioning,
- Representative color selection,
- DCT transformation,
- Zigzag scanning.

For the second and third features combined, we extracted the features for each of the images using the functionalities provided by the Python *OpenCV* library. Furthermore, we constructed a codebook vector using the *k*-means clustering algorithm of a certain vocabulary size using the extracted features. For each feature, we assign a code from the codebook, and then produce a histogram for it, which we used as a feature to the model. For the extra feature, we have the *Local Binary Patterns* and *Color Histogram*.

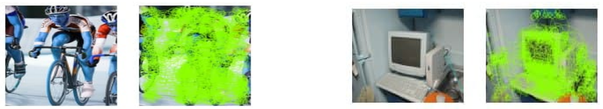

Figure 4. SURF key point visualization for images

Feature Engineering

Class balancing by using *Undersampling*

Imbalanced classes are a common problem in machine learning classification where there are a disproportionate ratio of observations in each class.

For our task, since there is a volume of 9,000 images there is likely a chance for class imbalance and therefore we found the relevance of performing **undersampling** that can be defined as removing some observations of the majority class.

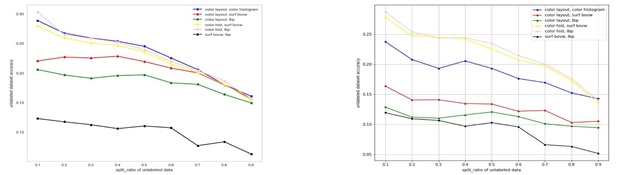

Figure 5. Class balancing-*Label spreading, Label propagation* on 2-feature combination

Feature selection by using *Analysis of Variance (ANOVA)*

We plan to use **filter methods** where features are selected on the basis of their scores in various statistical tests for their correlation with the outcome variable.

Considering we have 20 different categorical classes as illustrated in the "Data set" in our approach, we use **ANOVA** that provides a statistical aspect to check whether the means of several groups are equal or not.

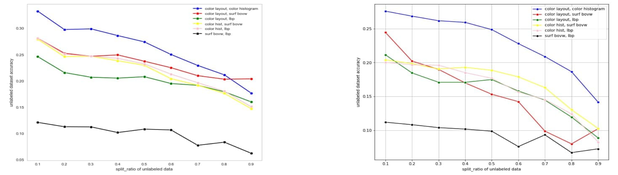

Figure 6. ANOVA-*Label spreading, Label propagation* on 2-feature combination

Feature selection by using *Principal Component Analysis (PCA)*

By finding a smaller set of new variables, each being a combination of the input variables, containing basically the same information as the input variables we plan to demonstrate our concept of feature selection by using **PCA**.

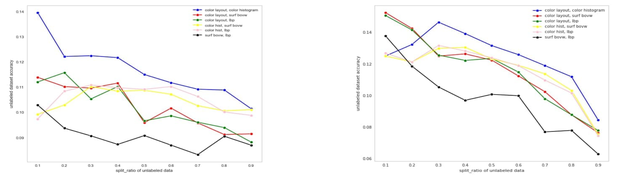

Figure 7. PCA-*Label spreading, Label propagation* on 2-feature combination

Object detection using Semi-Supervised Classification

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Evaluation

Model selection

On the features we perform class balancing (*undersampling*), feature selection (*ANOVA*), feature selection (*PCA*) with an enumeration of 2^c (where c is the total extracted features). Based on this, we analyze from a line plot for all the split points ranging from [0.1,0.9] which combination is better to be used for model building. Followed by it we effectively determine from a box plot to pick the best model.

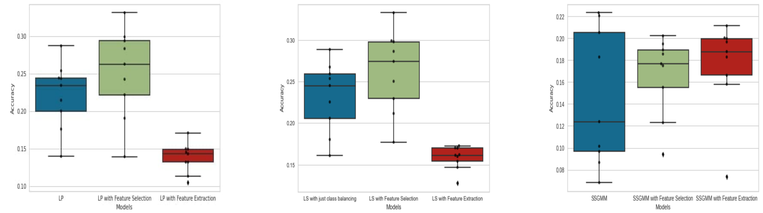

Figure 8. Box and Whisker plots for *Label propagation*, *Label spreading*, *SSGMM*

Model evaluation

We are showing a comparative study of *Label Propagation*, *Label Spreading*, *SSGMM* on different splits of the data from [0.1,0.9] on the features that we implemented. In addition, we test for 1,500 iterations by tuning hyperparameters:

- α: Additive (Laplace/Lidstone) smoothing parameter for *SSGMM*,
- β: Weight applied to the contribution of the unlabeled data for *SSGMM*,
- γ: Influences the distance of impact of a single training point for *LPA and Label spreading*,
- *Choice of kernel*: RBF (default) / Linear for *LPA and Label spreading*.

Class Prediction Error plots

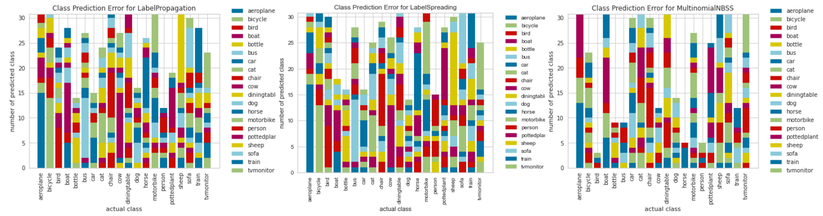

Figure 9. Class prediction error for *Label propagation*, *Label spreading*, *SSGMM*

We use **class prediction error plot** which shows the actual targets from the dataset against the predicted values generated by our model. It illustrates the support (number of training samples) for each class in the fitted classification model as a stacked bar chart. It shows that for which classes our classifier is having a particularly difficult time with, and more importantly, what incorrect answers it is giving on a per-class basis. Like in our *MultinomialNBSS* classifier, it often incorrectly labels "cat" as "cows".

ROC/AUC curves

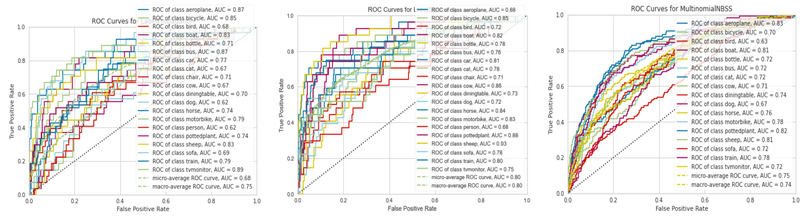

Figure 10. ROC curves for *Label propagation*, *Label spreading*, *SSGMM*

We use **ROC/AUC curves** to show between the sensitivity and specificity for every possible cut-off for combination of tests with different feature combinations.

Precision-Recall curves

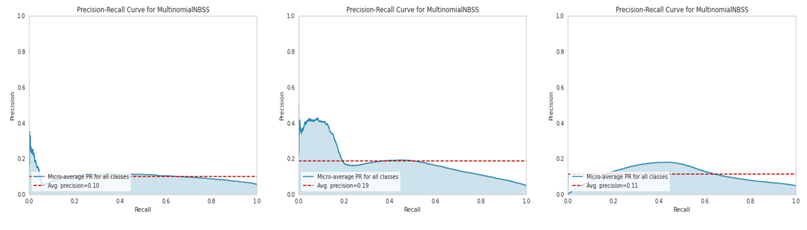

Figure 11. Precision-Recall curves for *SSGMM*

We also evaluate the skill of our inductive model by using the **Precision-Recall curves**. A Plot of Recall (x) vs Precision (y). The focus of the PR curve on the minority class makes it an effective diagnostic for imbalanced binary classification models.
A model with perfect skill is depicted as a point at a coordinate of (1,1). A skillful model is represented by a curve that bows towards a coordinate of (1,1). A no-skill classifier will be a horizontal line on the plot with a precision that is proportional to the number of positive examples in the dataset. For a balanced dataset this will be 0.5.

Correlation Heatmaps

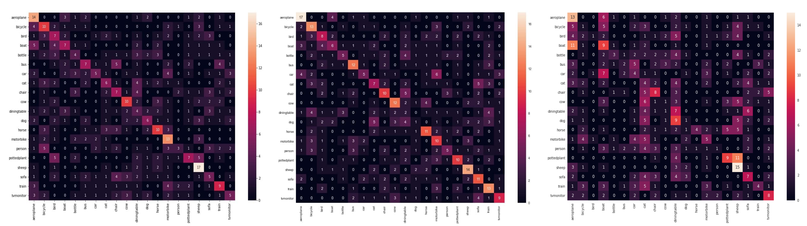

Figure 12. Correlation heatmaps for *Label propagation*, *Label spreading*, *SSGMM*

We show **Correlation heatmap** between all the features to determine the strength of influence of one variable on other. Also, they show in a glance which variables are correlated, to what degree, in which direction, and alerts us to potential multi-co-linearity problems.

Conclusion

For our task the best SSL model generalization performance is achieved for *Label spreading* with an accuracy of nearly 31%.

Algorithms	Class balancing	Class balancing+ feature selection	Class balancing+ feature reduction
Label Propagation	26.5±2.6%	29.4±2.8%	16.3±2.7%
Label Spreading	27.4±3.1%	31.2±3.4%	17.1±1.2%
SSGMM	22.8±2.8%	20.4±2.2%	20.4±1.7%

Table 1. An overview of the results of our SSL techniques with 95% C.I.

it is also evident that for our task the transductive graph-based approach performed better than inductive approach.

Safe SSL

We trained both on the semi-supervised and supervised models by splitting the data with varying labeled and unlabelled test sizes and compared it with the fixed test set. We then compared the efficiency of SSL to the supervised approach and concluded that the "Safe SSL" assumption **does not** hold as it performed better for the semi-supervised model at the split test data.

Figure 13. Safe SSL check

Baseline comparison

We compare our work with a similar dataset on *BOV* features which was implemented using additive and exponential kernel-based supervised SVM classifiers. Their performances reported were in the range of 48.9%-52%. In comparison, our SSL techniques attain nearly 31% which are not superior to supervised counterparts.

Future work

- **Feature refining**: Extract relevant features by using Deep Learning-based techniques like Convolutional Neural Networks.
- **Model ensemble**: Combining classifiers by voting or averaging to improve performance.
- **Active Learning**: State-of-the-art algorithms and methods to boost the predictive power.
- **Online-SSL**: Where labeled and unlabeled instances arrive sequentially.

References

[1] M. Everingham, L. Van Gool, C. K. I. Williams, J. Winn, and A. Zisserman. The PASCAL Visual Object Classes Challenge 2007 (VOC2007) Results. http://www.pascal-network.org/challenges/VOC/voc2007/workshop/index.html.

[2] Florent Perronnin, Jorge Sánchez, and Yan Liu. Large-scale image categorization with explicit data embedding. In *2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pages 2297–2304, 2010.