Improved Image Annotation and Labelling through Multi-label Boosting

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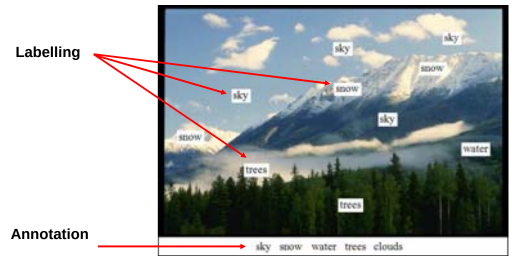
Problems

- Image Labelling = assigning a descriptive word for a segment of the image
- Image Annotation = giving descriptive words for the image



Problems

- Training:
  - Each image is provided with a list of descriptive words.
  - Each image is segmented into many segments. The label of each segment is not defined in the training data.
- Testing:
  - A list of descriptive words for a given image.
  - A label for each segment of the given image.

Applications

- Recognize multiple objects in one image
- Enable users search images using descriptive text

Challenges

- No information about the correspondence between a segment and a word.
- Multi-class and multi-label classification problem.
- Use of multi-label training data which are more available than single labeled images.

MLBoost

- A basic statistical learning model to link blobs and descriptive words. Blobs are color feature vectors extracted from segments.
- Multi-label boosting algorithm (MLBoost).
- How to revise the basic model into a weak learner for MLBoost.

Linking Blobs to Words

- A mixture of models.
- Each model which represents a hidden concept is a joint probability distribution of blobs and words.
- We make up the hidden concepts and assume that blobs and words are only linked through these concepts.

$$P(w,b \mid c) = P(w \mid c)P(b \mid c)$$

Linking Blobs to Words

- Using the model for labeling:

$$P(w \mid b) = \sum_c P(w,c \mid b) = \sum_c P(w \mid c)P(c \mid b)$$

- Using the model for annotation:

$$P(w \mid B) = \sum_c P(w,c \mid B) = \sum_c P(w \mid c)P(c \mid B)$$

$$B = \bigcup_{b \in image} b$$

Linking Blobs to Words

- Need to learn P(w|c), P(c|b), and P(c|B) from the training data.
- Use iterative EM algorithm to deal with hidden variables (hidden concepts).
- E-step:

$$P(c \mid b) \propto P(b \mid c)P(c)$$

$$P(c \mid B) \propto \sum_{b \in B} P(c \mid b) = \sum_{b \in B} P(b \mid c)P(c)$$

$$P(c \mid w, B) \propto P(w \mid c)P(c \mid B)$$

Linking Blobs to Words

- M-step:

$$P(c) \propto \sum_d \left[\sum_{b \in B} P(c,b) + \sum_{w \in W} P(c \mid w,d) \right]$$

$$P(b \mid c) \propto Normal(\mu_c, \sigma_c)$$

$$\mu_c = \frac{\sum_b b \times P(c \mid b)}{\sum_b P(c \mid b)}$$

$$\sigma_c = \frac{\sum_b (b-\mu_c) \times (b-\mu_c)^T \times P(c \mid b)}{\sum_b P(c \mid b)}$$

$$P(w \mid c) \propto \sum_d P(c \mid w, B)$$

Multi-label Boosting

- Boosting algorithm is to learn different weak learners through re-weighting training data.
- Place more weights on training examples that are misclassified by the current weak learner.
- This also means trying to guide the weak learner towards the classes that are hard to classify.

Multi-label Boosting

- After training the current learner, we evaluate it on training set using the pseudoloss measure.
- And then re-weight training examples using pseudoloss.
- Pseudoloss for Multi-class single-label boosting:

$$ploss_q = \frac{1}{2}(1 - h(x_i, y_i) + \sum_{y \neq y_i} q(i,y)h(x_i, y))$$

Multi-label Boosting

- Pseudoloss for Multi-class multi-label boosting:

$$ploss_q = \frac{1}{2}\left(1 - \frac{\sum_{y \in Y_i} h(x_i, y)}{|Y_i|} + \sum_{y \in Y - Y_i} q(i, y) h(x_i, y)\right)$$

- Provide the weak learner with the example weighting function D_t and the label weighting function q_t.

The Weak Learner

- E-step:

$$P(c \mid w, B) \propto \sum_{b \in B} [1 - q_t(b, w)] P(w \mid c) P(b \mid c) P(c)$$

- $q_t(b,w) = 0$ if w is a correct label for b
- M-step:

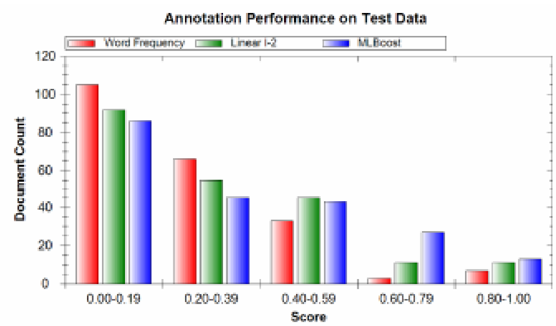
$$\mu_c = \frac{\sum_b b \times P(c \mid b) \times D_t(b)}{\sum_b P(c \mid b) \times D_t(b)}$$

$$\sigma_c = \frac{\sum_b (b - \mu_c) \times (b - \mu_c)^T \times P(c \mid b) \times D_t(b)}{\sum_b P(c \mid b) \times D_t(b)}$$

Experiments

- 1881 images from the Corel database.
- 1667 ≈ 90% for training.
- Annotate each test image with N words (N is true number of words assigned to the image).
- Compute the percentage of correct annotation for each image.
- Count the number of images whose percentage of correct annotation from 0%-20%,…, 80%-100%

Annotation Results



Labeling Results

- No quantitative evaluation measure was presented since hand labeling each segment of all images is necessary.

Advantages and Disadvantages

- Advantages:
  - Exploit the availability of the captions of images
- Disadvantages:
  - Time complexity
  - Space complexity

Conclusion

- Both of two papers are on linking images and words.
- The first paper uses a complex hierarchical statistical model (LDA) to capture the joint probability distribution of blobs and words.
- The second paper uses a simpler model, a 1-level mixture of models, but it boosts the performance of this model through the multi-label boosting framework.

Code

- The binary code of MLBoost is available at http://mi.eng.cam.ac.uk/~mj293/mlboost/

Thank You!