EFICIENT SEMI-SUPERVISED ANNOTATION WITH PROXY-BASED LOCAL CONSISTENCY PROPAGATION

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1. Introduction

Background
- Automatic image annotation is an effective solution to manage images which increases tremendously.
- Semi-Supervised Learning (SSL), are promising to build more accurate models.
- Many graph-based SSL methods, which involves graph construction and label propagation, have been applied to image or video annotation.

Main Issues
- Most of Graph-based SSL don’t consider the difference between the labeled and unlabeled data when learning the manifold.
- Most of Graph-based SSL face the limitation that learning must be performed in a batch mode.

Our Work
- Propose a novel label propagation algorithm named PLCP, in which the label information is first propagated from labeled samples to their unlabeled neighbors, and then spreads only among unlabeled ones like a spreading activation network.
- Propose an online semi-supervised framework and develop an incremental learning method for PLCP.

2. Proxy-Based Local Consistency Propagation

Notation
- A point set \( X = (X_1, X_2) = \{X_1, \ldots, X_i, X_j, \ldots, X_n\} \)
- Points \( X_i \) are labeled \( y_i \) \( \in \mathcal{L} = \{1, \ldots, c\} \)
- Predict the label of unlabeled points \( X^u = \{x_1, \ldots, x_n\} \)
- Matrix form: \( Y_u = W_u Y_l \)

Algorithm
- Pairwise similarity: \( w_{ij} = \exp\left(-\frac{1}{2\sigma^2}d^2\right) \)
- Initial information: \( y_i = \sum_{j=1}^{N} \delta(x_i \in N(x_j)) \cdot w_{ij} y_j \)
- Matrix form: \( Y_l = W_{ll} Y_l \)
- Propagation iteratively: \( F_l(t + 1) = aS_lF_l(t) + (1 - a)Y_l \)
- Converge to stable state: \( F_l = \lim_{t \to \infty} F_l(t) = (1 - a)(I - aS_l)^{-1}Y_l = (1 - a)(I - aS_l)^{-1}W_{ll}Y_l \)

Object function
- \( Q(F_l) = \frac{1}{2} \sum_{i=1}^{n} \left( \frac{F_l}{D_{ii}} \right)^2 + \mu \sum_{i=1}^{n} \left( \frac{F_l}{D_{ii}} \right)^2 + \frac{1}{2} \sum_{i=1}^{n} \left( W_{ii}Y_l \right)^t \)

3. Online Semi-Supervised Annotation

Framework
- Initially, all data are utilized to train the model in a semi-supervised manner.
- For a new image the system makes prediction using its current predictor and shows the prediction to the user.
- If the user confirms the label, the new data should be treated as training data to retrain the model, which can update the label information of the unlabeled data and the predictor.

Incremental learning
- Key idea: fix the transfer matrix \( T_u = (1 - a)(I - aS_u)^{-1} \)
- For a new data, predict: \( F_u = T_u[\Delta u, W_u, Y_u] \cdot [Y_l, Y_u, Y_u]^T = F_l + T_u W_u Y_u \)
- Time complexity: \( O(m \times u^2) \)

4. Experiments

Datasets
- MNIST: 70K, 784D Pixel
- CIFAR-10: 60K, 384D GIST

Results
- Compared methods: KNN, GFHF, LGC
- Evaluation: transductive accuracy on unlabeled data

Conclusion
- Efficient Semi-Supervised Annotation
- Achieve better accuracy and has a promising performance
- Satisfy the requirement of online real-time annotation