Learning to Group Web Text Incorporating Prior Information

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Outline

Introduction

Related work

Semi-supervised clustering with pair-wise constraints and label

Experiments results

Conclusion

Web Text

- Online text becomes available in a variety of genres.
- Blog & news feeds, forum, customer reviews, book & movie summaries.
- Social media sites like Facebook, Twitter and Google Buzz allow users to post short messages.

Grouping Web Text

- There are a large number of messages published each day (Google News, Twitter)
- Users often face the problem of information overload.
- Grouping similar text or messages can make information more manageable.
- Systems that can cluster similar text belong to the same topic.

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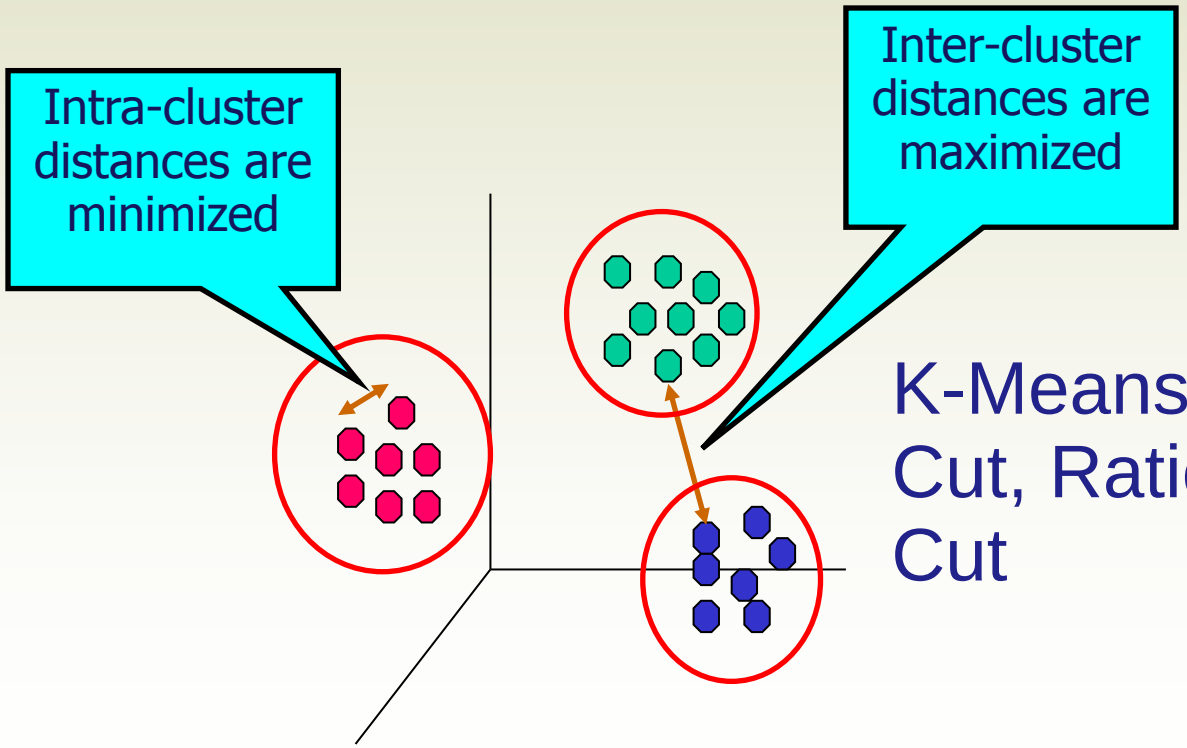
Unsupervised clustering

Clustering algorithms are generally used in an unsupervised fashion.



K-Means, Normalized Cut, Ratio Cut, Min-Max Cut

Semi-supervised Clustering

Input:

- A set of unlabeled objects
- A small amount of domain knowledge (we call prior knowledge)

Output:

- A partitioning of the objects into k clusters

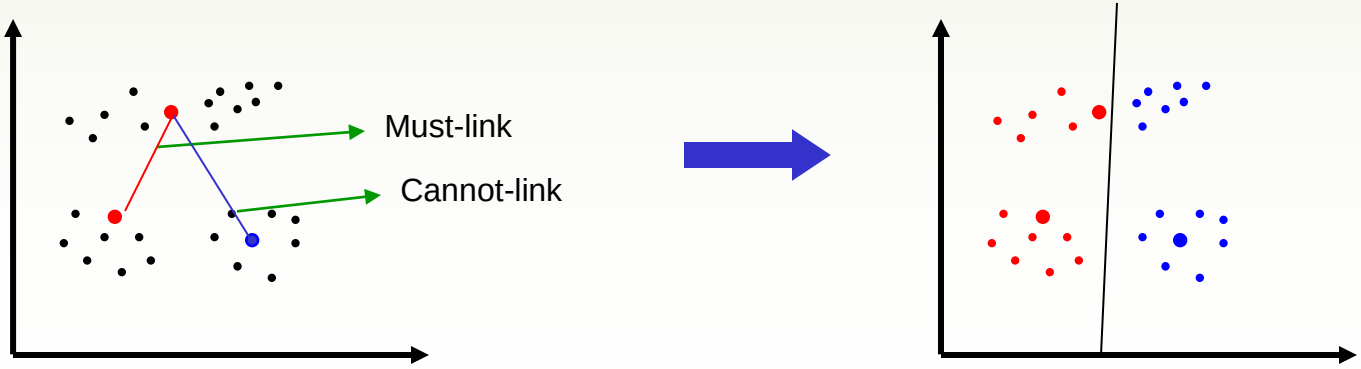
Objective:

- Maximum intra-cluster similarity
- Minimum inter-cluster similarity
- High consistency between the partitioning and the prior knowledge

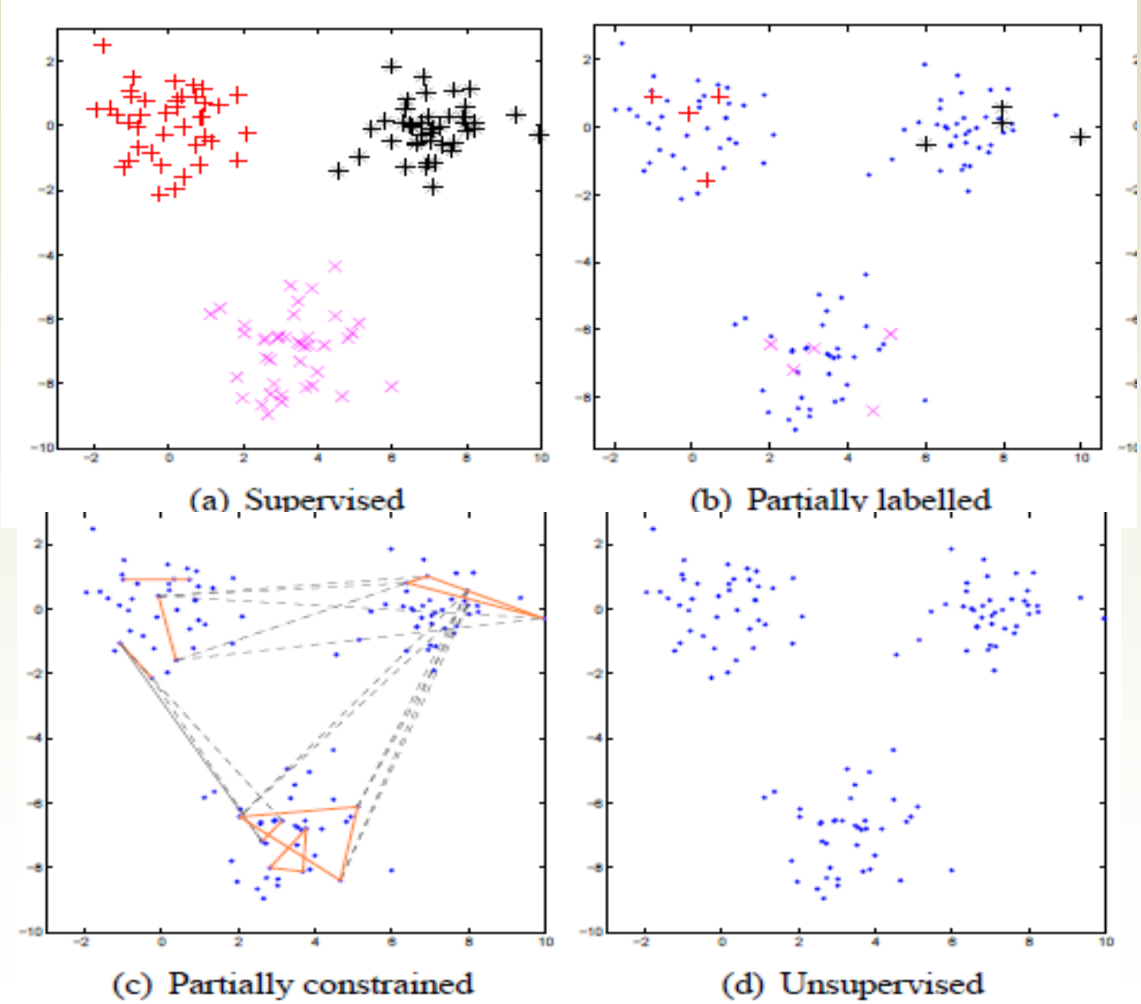
Semi-supervised Clustering

According to different given domain knowledge: Users provide class labels (seeded points) a priori to some of the document

Users know about which few documents are related (must-link) or unrelated (cannot-link)



Summaries


(a) Supervised
(b) Partially labelled
(c) Partially constrained
(d) Unsupervised

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The Main Work

Semi-supervised clustering

Improve existing naive clustering methods
Using labeled data to guide clustering of unlabeled data

The pair-wise constrains information

It is easier for the user to distinguish whether two objects are in the same group other than give the labels.
Giving the algorithms to ask some questions, but ask it wisely.

Model based clustering

unsupervised clustering

Dataset: unlabeled dataset χ^u ,data density $P(x|\theta)$

Objective: Minimize the objective function $\Theta_u = -\sum_{x \in \chi^u} \log P(x|\theta)$

supervised clustering

Dataset: labeled dataset χ^l ,data density $P(x_i, y_i|\theta)$

Objective: Minimize the objective function $Q_l = -\sum_{x \in c^l} \log P(x_i, y_i|q)$

semi-supervised clustering?

Dataset: unlabeled dataset χ^u and labeled dataset χ^l

Objective: select the parameters by minimizing

$$\Theta = \alpha\Theta_l + \beta\Theta_u, \quad \alpha + \beta = 1$$

Method: Expectation-Maximization (EM)

General Case

Dataset: we can decompose it the into three parts

unlabeled data χ^u labeled data χ^l data with constraints χ^c

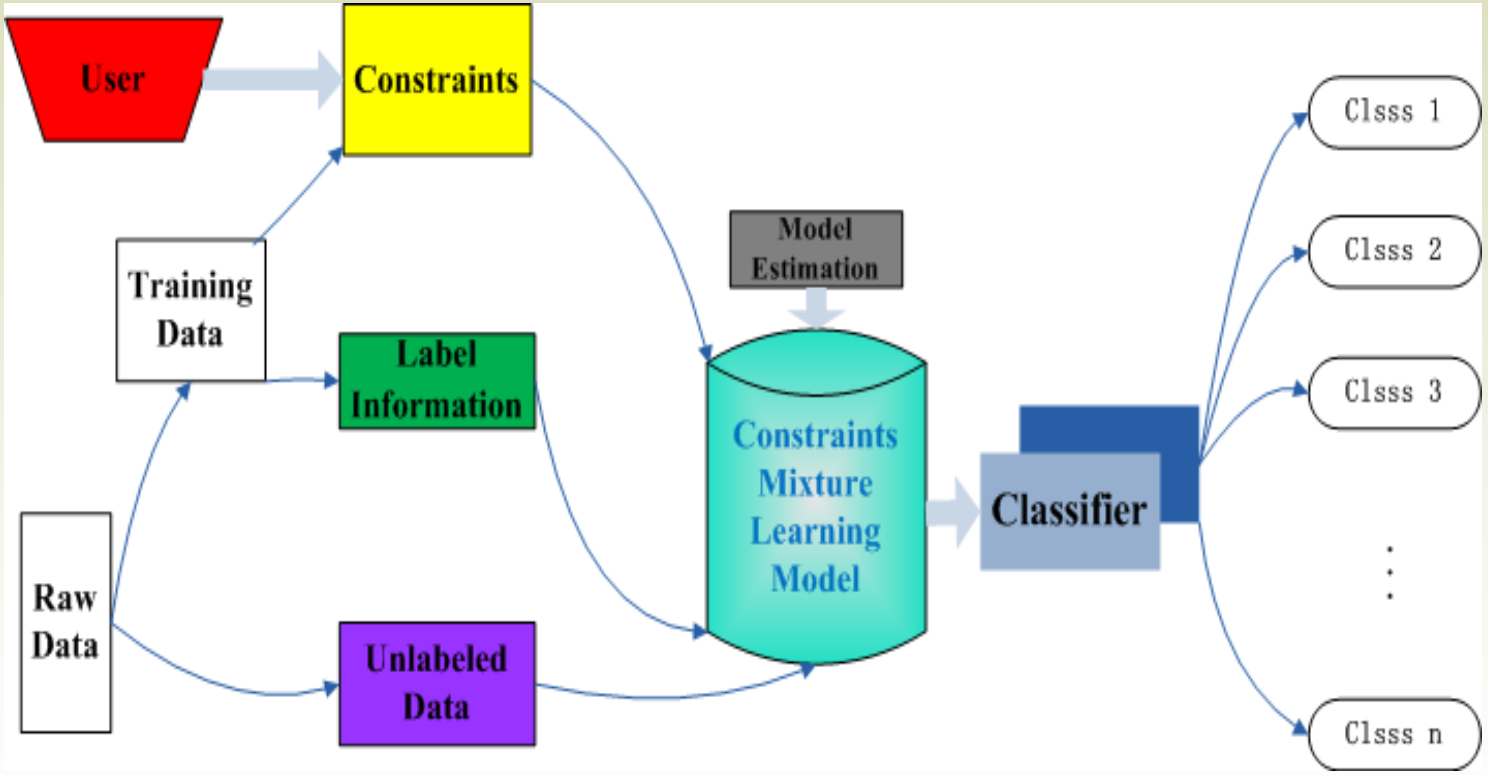
We define the following joint object function, which is a convex combination of Θ_u Θ_l Θ_c,

Objective: select the parameters by minimizing the

$$\Theta = \alpha\Theta_u + \beta\Theta_l + \gamma\Theta_c,$$
$$\alpha + \beta + \gamma = 1$$

Method: Expectation-Maximization (EM)

The overall framework



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Experiment Setting

Datasets:

News-500: We collected 500 news documents of 4 different topics from Google News

FBS-500: 500 posts with 7 different categories from Facebook

Compared methods:

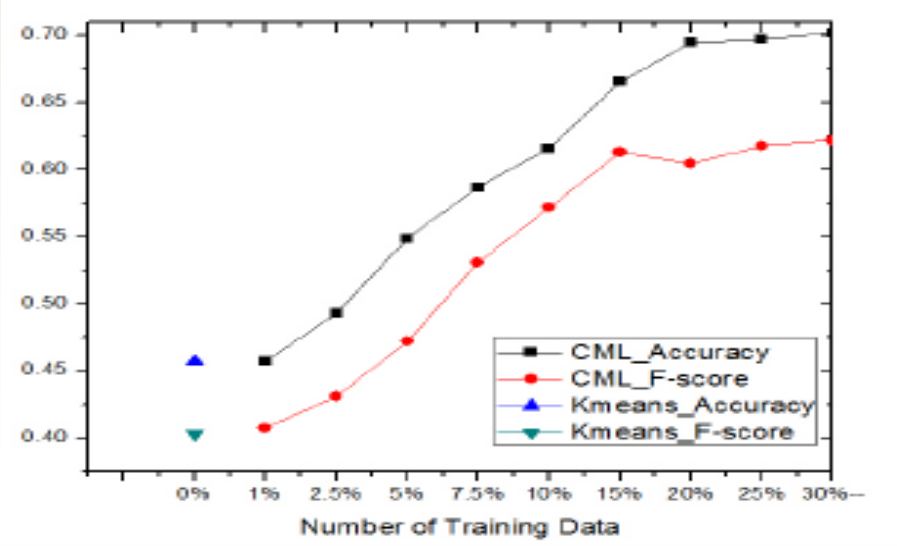
Unsupervised: K-Means

Semi-supervised: Semi-supervised K-Means and Transductive SVM

Results(comparing with K-Means)

THE ACCURACY AND F-SCORE OF K-MEANS AND CML ON FBS-500

Evaluation Method	Accuracy	F-score
K-Means	0.457	0.403
CML(5% training)	0.616	0.501
CML(7.5% training)	0.649	0.578
CML(10% training)	0.691	0.627



Results(comparing with SK-Means and T-SVM)

THE ACCURACY OF NEWS-500 DATA SET WITH DIFFERENT PERCENTAGE OF TRAINING SAMPLES

Method	1%	2.5%	5%	7.5%	10%
SK-means	0.479	0.513	0.545	0.580	0.629
Transductive SVM	0.442	0.481	0.501	0.521	0.576
CML Model	0.459	0.492	0.549	0.632	0.682

THE ACCURACY OF FBS-500 DATA SET WITH DIFFERENT PERCENTAGE OF TRAINING SAMPLES

Method	1%	2.5%	5%	7.5%	10%
SK-means	0.486	0.502	0.526	0.540	0.575
Transductive SVM	0.403	0.431	0.458	0.485	0.524
CML Model	0.466	0.494	0.516	0.579	0.625

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Grouping Text based on the same topic

- there are a large number of web data published every day
- make the messages manageable for the users

Contribution

- A general framework for semi-supervised clustering work with label and pair wise constraints.
- Clustering the web text using the proposed framework.

The Future Work

- Considering active learning while sampling.
- Applying the algorithm to other domain (eg. Image categorization, Bioinformatics (gene/protein clustering))

Thank You!

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