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Dissolve$^{\text{struct}}$– A Library for Distributed Structured Prediction

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Abstract

This paper describes Dissolve$^{\text{struct}}$, a modular and flexible open source software package for distributed training of structured prediction models, such as structured SVMs. Project website: github.com/dalab/dissolve.

We support a broad range of applications, and interfaces to scala, java and python. Our framework is empowered by the fault tolerant Spark computing platform, and automatically adopts to the existing tradeoffs of computation vs communication cost on real world systems. The proposed distributed algorithm combines the recent communication efficient CoCoA scheme (Jaggi et al., 2014) with the state of the art primal-dual structured prediction solvers (Lacoste-Julien et al., 2013), and improves further by adding some new ideas for caching oracle answers. The framework allows approximate inference, and provides a similar standard interface as SVM$^{\text{struct}}$ for the user.

Keywords: Structured Prediction, Structured SVM, Distributed Training

1. Introduction

Bla bla...

Remainder omitted in this sample. See http://www.jmlr.org/papers/ for full paper.

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Appendix A.

In this appendix we prove the following theorem from Section 6.2:
Theorem *Let u, v, w be discrete variables such that v, w do not co-occur with u (i.e., $u \neq 0 \Rightarrow v = w = 0$ in a given dataset $\mathcal{D}$). Let N_{v0}, N_{w0} be the number of data points for which $v = 0, w = 0$ respectively, and let I_{uv}, I_{uw} be the respective empirical mutual information values based on the sample $\mathcal{D}$. Then*

$$N_{v0} \; > \; N_{w0} \;\; \Rightarrow \;\; I_{uv} \; \leq \; I_{uw}$$

with equality only if u is identically 0. ■
Proof. We use the notation:

$$P_v(i) \; = \; \frac{N_v^i}{N}, \quad i \neq 0; \quad P_{v0} \; \equiv \; P_v(0) \; = \; 1 - \sum_{i \neq 0} P_v(i).$$

These values represent the (empirical) probabilities of v taking value $i \neq 0$ and 0 respectively. Entropies will be denoted by H. We aim to show that $\frac{\partial I_{uv}}{\partial P_{v0}} < 0$....

Remainder omitted in this sample. See http://www.jmlr.org/papers/ for full paper.

References

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