

Logbook

June 2, 2014

Logbook

General stuff

Week 1 (9): 24.02.2014 - 02.03.2014

Project meeting

No project meeting was possible this week, and we had yet to decided between

1. Randomized algorithms:

A Statistical Perspective on Algorithmic Leveraging, Ping Ma, Micheal W. Mahoney, Bin Yu. [http : //arxiv.org/abs/1306.5362](http://arxiv.org/abs/1306.5362)

2. Spectral learning of HMMs:

A Method of Moments for Mixture Models and Hidden Markov Models. A. Anandkumar, D. Hsu, and S.M. Kakade. Preprint, Feb. 2012 : [http : //newport.eecs.uci.edu/anandkumar/pubs/AnandkumarEtal_mixtures12.pdf](http://newport.eecs.uci.edu/anandkumar/pubs/AnandkumarEtal_mixtures12.pdf)

We spend the week getting an overview of the articles and the projects.

Week 2 (10): 03.03.2014 - 09.03.2014

Project meeting

Questions:

- What is the idea behind leveraging for least-squares regression?
- Can we generalise the idea?
- Can leveraging improve performance in video screen classification?
- Video classification e.g. faces, emotions, gender.

Implementation:

No implementation at this point.

Results:

No results at this time.

Decisions:

To work with Randomized algorithms.

To gain a better understanding of the underlying idea of leveraging, by watching a talk on *Statistical Leverage and Improved Matrix Algorithms* by M. W. Mahoney (http://videolectures.net/icml09_mahoney_itslima/).

Updated Project Goals and Delimitation

- Validation of the results shown by Ma. et al.
- Can we generalize the idea of leveraging for a general likelihood function?

Week 3 (11): 10.03.2014 - 16.03.2014**Project meeting****Questions:**

- How does the leverage scores look for LS-regression? (Plotting $H_{n,n}$ vs. $||x_n||$)

Implementation:

No implementation at this point.

Results:

- The general idea of leveraging is to identify how the estimated value $\hat{\mathbf{y}}$ relates to the targeted value \mathbf{y} . Which for LS-regression is $\hat{\mathbf{y}} = H\mathbf{y}$.

Decisions:**Updated Project Goals and Delimitation**

- Can we generalise the expression $\hat{\mathbf{y}} = H\mathbf{y}$ to logistic regression?

Week 4 (12): 17.03.2014 - 23.03.2014**Project meeting****Questions:**

- How are the distributions used by Ma. et al. calculated?
- Finding emotional faces datasets.

Implementation:

- Finding leverage-scores for LS-regression
- Solving LS-regression when comparing uniform- to leverage-based sampling.
- Illustrating leverage scores ($H_{n,n}$ vs. $||x_n||$)

Results:

Initial results promising, but only single run performance between uniform- and leverage-based sampling.

Decisions:

Updated Project Goals and Delimitation

- We want to validate the results of Ma et. al. empirically.
- In video classification we want to do binary classification of *happy* and *sad* faces.

Week 5 (13): 24.03.2014 - 30.03.2014

Project meeting

Questions:

- Will using the leverage-scores for LS-regression improve our performance in binary classification?

Implementation:

- The three distributions $GA, T3$ and $T1$ are implemented, and tested for linear regression.
- Learning curves and test-framework for LS-regression, used for testing the results show by Ma et al.
- Three distributions for binary classification data, also named $GA, T3$ and $T1$ which represent respectively classification data with nearly uniform, moderately non-uniform and very non-uniform leverage-scores.

Results:

- We get comparable results on LS-regression to those shown by Ma et al.
- A leverage-based sampling does not improve for GA-type data, as the leverage scores are approximately uniform, thus there are no "important" datapoints that can be sampled.
- A leverage-based sampling for T3-type data consistently performs better or equal to a uniform sampling. Although the performance increase is modest.
- A leverage-based sampling for T1-type data also consistently outperforms a uniform-based sampling, this is expected as the T1 data have very non-uniform leverage scores i.e. "important" datapoints.

Decisions:

Generalisation of the leverage-based sampling scheme $\frac{\delta \hat{\mathbf{y}}}{\delta \mathbf{y}}$ to logistic regression, as well as a sampling distribution based on the uncertainty of the predictions (asymptotic theory) is to be done by Lars Kai.

Updated Project Goals and Delimitation

- Will using the leverage-scores for LS-regression improve our performance in binary classification?
- We have validated the results of Ma et al. for LS-regression on *GA*, *T3* and *T1* distributed data.

Week 6 (14): 31.03.2014 - 06.04.2014

Project meeting**Implementation:**

- Learning curves for logistic regression based on uniform or LS-regression leverage-scores.

Results:

Initial results using leverage-scores based on LS-regression shows no improvement on GA-type (expected) and performs significantly worse on T3- and T1-type data.

Lars Kai has derived a generalised expression $\frac{\delta \hat{\mathbf{y}}}{\delta \mathbf{y}}$ for a general likelihood function. As well as the uncertainty based sampling approach.

Decisions:

Lars Kai gathers his scribbles on the back of some insignificant article in a form that is easier to read and follow.

Our full focus is now on midterm preparation.

Updated Project Goals and Delimitation

- Compare uniform sampling to a leverage based distribution (generalisation) and a uncertainty based distribution.

Week 7 (15): 07.04.2014 - 13.04.2014**Project meeting**

Discussion about the midterm and improvements that should be done.

Week 8 (16): 14.04.2014 - 20.04.2014

Easter, no project meeting, but sporadic work was done, mostly clarification and bug-correction.

Week 9 (17): 21.04.2014 - 27.04.2014**Project meeting****Results:**

Lars Kai gives us a copy and explains the general concepts behind the generalisation of $\frac{\delta \hat{y}}{y}$ and uncertainty-based sampling.

Decisions:

We are to understand and digitalise the results derived.

Week 10 (18): 28.04.2014 - 04.05.2014**Project meeting****Questions:****Results:****Decisions:****Week 11 (19): 05.05.2014 - 11.05.2014****Project meeting****Questions:**

- How to illustrate the thought process behind our problem and approach. Simply illustrative model.

Implementation:

- Sensitivity sampling implemented
- Sensitivity sampling compared to uniform on logistic regression

Results:

- Sensitivity sampling "works" on *GA* and *T3* data, but the program sometimes crashes on *T1* data due to overflow errors when calculating the leverage scores.
- Sensitivity sampling exhibits weird behaviour as the error increases with sampling size.

Decisions:

- Debugging sensitivity sampling is postponed, and focus is put on creating an initial poster which can also be used for *Vision Day*.

Updated Project Goals and Delimitation

Week 12 (20): 12.05.2014 - 18.05.2014

Project meeting

Questions:

- What is the effect of weight and unweighed logistic regression?

Implementation:

- Generating good illustrations of the problem, process and results.

Results:

- The results go from really crappy to as good as uniform.

Decisions:

After poster exam: 21.05.2014 - 03.06.2014

Project meeting

Questions:

- Will a *soft-max* transformation of the leverage-scores improve sensitivity/uncertainty sampling schemes?

Implementation:

- Bug-finding and elimination.
- Minimizing redundant code.

Results:

- A soft-max transform improves both sensitivity and uncertainty sampling performance but not significantly compared to uniform sampling.

Decisions:

- Hmm

Updated Project Goals and Delimitation