Software Alchemy:

Turning the Complex into Embarrassingly Parallel

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On the Web

This PDF file contains my presentation at the R meeting. I've extended the document by including material summarizing the question-and-answer period of that talk, and will occasionally add some updates as well.

The most up-to-date version of these slides, and associated R code, will be available on the Web at `http://heather.cs.ucdavis.edu/barugApr11/`.

Correction:
http://heather.cs.ucdavis.edu/barugApr2011/

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- **Solution:** Use a multicore machine or cluster.
- **Problem:** The above solution usually works well only for *embarrassingly parallel* (EP) problems. (Especially for R, given its functional programming approach.)
- **"Solution":** Run in parallel only if you have an embarrassingly parallel algorithm. :-)

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- Works for most *statistical* problems.
- Our goal here: Turn highly NON-EP problems into EP ones!

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- But this requires EP.
- New approach: Exploit the statistical properties.
- Key point: Calculate a **statistically equivalent** quantity that lends itself to EP computation.

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- Break into r chunks of n/p data points each.
- For i = 1,...,r calculate $\widehat{\theta}$ on chunk i, yielding $\tilde{\theta}_i$.
- Average all those chunked values:

$$\overline{\theta} = \frac{1}{r} \sum_{i=1}^{r} \tilde{\theta}_i$$

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- But the computation of $\overline{\theta}$ is EP even if $\widehat{\theta}$ is non-EP.
- Alchemy! Non-EP $\rightarrow$ EP.

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- use those values as your coefficients
- will have the **same statistical accuracy**, but will be faster

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- n = number of data points, q = number of predictors, p = number of processes (deg. of parallelism)
- used 3 dual-core PCs, so $p \leq 6$
- regression is a non-EP problem

Regression Experiments, cont'd.

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n	q	p	ordinary	NM method	gputools
500000	30	6	4.18	3.58	8.40
500000	50	6	9.41	6.61	exceeded mem.
100000	100	6	4.13	3.55	3.86
50000	150	6	4.14	3.36	2.92

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NM method "handicapped": used **snow** (which uses **serialize()**), over a network.

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n	q	p	ordinary	NM method
10000	50	2	2.39	1.50
10000	50	4	2.39	1.34
50000	50	4	36.10	13.43
50000	50	6	35.51	11.19

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Q&A Period (slightly updated)

Question: Does this only work on linear regression problems?

- No, the math works on any function of i.i.d. data.
- I've tried it on logistic regression, principle components and estimation of hazard functions from censored data, getting modest to excellent speedups.
- Note that if $\widehat{\theta}$ is an unbiased estimator, then $\overline{\theta}$ is also unbiased.

Question: Is there a convergence rate issue in your asymptotics?

- In my experiments I've found only tiny differences between $\overline{\theta}$ and $\widehat{\theta}$.
- The only problems that are worth parallelizing have very large sample sizes, and thus the asymptotics have certainly taken effect by then.