MapReduce for Machine Learning on Multicore

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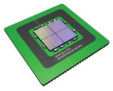
With contents borrowed from:
http://www.cs.duke.edu/courses/spring08/cps399.28/lectures/02-google.pdf
Pattern Recognition and Machine Learning, Christopher M. Bishop

Why Multicore



- Gains from frequency scaling are diminishing
  - Memory Wall: disparity of CPU/memory speed
  - ILP Wall: difficult to find enough parallelism in single instruction stream via compilers etc.
  - Power Wall: leakage current, heat, …
- Putting more processing cores on single chip!
  - Ideally would get linear speedup
  - Compared to multiprocessors: faster inter-core, on-chip communication

How to Utilize Multicore?

- Non-trivial to fully utilize multicore
  - Nature of applications?
  - Programming facilities?
  - Manual rewrite required for many applications
    - Tedious, prone to error: race conditions, deadlocks,…
- Question:
  - A general programming method on multicore? Particularly for machine learning?

One Approach

- The problem domain
  - Machine learning algorithms with certain properties
- The tool
  - Google's MapReduce
- The goals
  - A general method for exploiting parallelism in many algorithms
  - Taking advantage of multicores

The Summation Form

- Many ML algorithms fit the Statistical Query Model
  - Learning is based on the global properties of large samples
  - Expressible in the form of summations over samples
  - Summation can be done independently, in parallel
    - Divide the data set into pieces
    - Assign each piece to a core
    - Aggregate the results at the end
- Can be expressed by Google's MapReduce framework

MapReduce

- Large-scale data processing
  - Want to use 1000s of machines, but don't want hassle of managing things
- MapReduce provides
  - Automatic parallelization & distribution
  - Fault tolerance
  - I/O scheduling
  - Monitoring & status updates

map / reduce

- Programming model from Lisp (and other functional languages)
  - `(map square '(1 2 3 4))` ⇒ `(1 4 9 16)`
  - `(reduce + '(1 4 9 16))` ⇒ `30`
- Many problems can be phrased this way
- Easy to distribute
- Nice failure/retry semantics

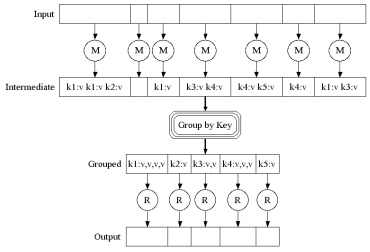
The MapReduce Model

- map(*key, val*) ⇒ *(new-key, new-val), …*
  - Run on each item in an input set
  - Emit a list of key-value pairs
- reduce(*key, vals*) ⇒ *output*
  - Run for each unique key and all associated values emitted by map()
  - Emit output

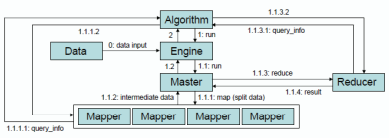
Example: Counting words in docs

- Input: (*url*, *contents*) pairs
- map(*key=url*, *val=contents*):
  - For each word *w* in *contents*, emit (*w*, 1)
- reduce(*key=word*, *vals=counts*):
  - Sum up all values in *counts*
  - Emit result (*word*, *sum*)

MapReduce in Picture



MapReduce on Multicore



- Assume no failures in cores/communication
- Multiple mappers, one reducer
- Global information obtained via query_info()

Example 1: Linear Regression

- Problem
  - Given training set $(x_1,y_1),\ldots,(x_m,y_m)$, find estimate θ^* for θ in linear model $y=\theta^T x$, s.t. $\sum_{i=1}^{m}(y_i-\theta^T x_i)^2$ is minimized
  - Equivalent formulation: $y=\theta^T x+\varepsilon$ where $\varepsilon \sim N(0,\beta)$, find the maximum likelihood estimate for θ
- Least square estimate
  - $\theta^*=A^{-1}b$ where
  - $A=\sum_{i=1}^{m}(x_i x_i^T)$ and $b=\sum_{i=1}^{m}(y_i x_i)$
- MapReduce:
  - Two sets of mappers divide the task of computing A, b
  - Two reducers sum up partial results for A and b
  - Algorithm finally computes $A^{-1}b$
- Speedup:
  Multicore $O(mn^2/P+n^3/P+n^2\log(P))$ vs. single core $O(mn^2+n^3)$

Example 2: Naïve Bayesian

- Problem
  - Given a set of feature/label pairs: $(x_1,y_1),\ldots,(x_m,y_m)$, and a new point x_j, predict its label y_j. Assume y_j=0 or 1.
- Naïve Bayesian classifier
  - Pick $y=y_j$ that maximizes $p(y|x_j)$ for a new x_j
  - $P(y|x_j)$ *prop. to* $P(y)P(x_j|y)$
  - Assume independence among components of x_j given y
    - $P(y|x_j)$ *prop. to* $P(y)P(x_{j,1}|y)\,P(x_{j,2}|y)\ldots P(x_{j,n}|y)$
  - Need P(y=0), P(y=1), $P(x_{j,i}=k|y=0)$, $P(x_{j,i}=k|y=1)$
- MapReduce
  - Partition training set$\{1,\ldots,m\}=M_1+M_2+\ldots+M_P$ for P mappers
  - Mapper i: compute $P_{i,1}=\sum_{l\in M_i} 1_{y_l=1}$ $P_{i,0}\sum_{l\in M_i} 1_{y_l=0}$ …
  - Reducers combine partial results, e.g., $P(y=1)=\sum_{i=1}^{P} P_{i,1}/\left(\sum_{i=1}^{P} P_{i,1}+\sum_{i=1}^{P} P_{i,0}\right)$
- Speedup: $O(mn+nc)$ vs. $O(mn/P+nc\log P)$

Example 3: k-means

- Distance computing step:
  - Splitting data into subgroups
  - Mapper computes the distances of each point to all the centroids and puts it in the appropriate cluster
- New centroids computing step:
  - Splitting data into subgroups
  - Mapper emits pairs <clusterId, partial sum>
  - Reducer aggregates partial sums according to cluster IDs and computes new centroids

Example 4: Principal Component Analysis

- PCA
  - Widely used for dimensionality reduction, lossy data compression, feature extraction, etc.
- Formulation (Maximum Variance)
  - Consider a set of observations $x_1,\ldots x_m$ with dim. n
  - Project data onto a space with dim. d<n s.t. the variance of the projected data is maximized
  - Assume d is given

PCA (2)

- Simple Case d=1
  - Suppose data is projected to a line represented by vector u in the n-dimsional space
  - Suppose u is a unit vector: $u^Tu=1$ (because only direction matters)
  - Each data point x_i is projected to a scalar u^Tx_i
  - Variance of projected data $Var=\frac{1}{m}\sum_{i=1}^{m}\left(u^Tx_i-u^T\bar{x}\right)^2=u^TSu$
  - Maximization of $u^TSu+\lambda(1-u^Tu)$ gives
    - $Su=\lambda u$
    - Variance maximized when u is equal to the eigenvector having the largest eigenvalue λ (noting λ=Var).
  - Additional principal components can be defined incrementally

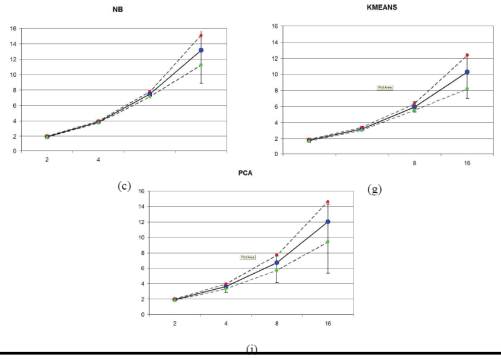
PCA (3)

- To obtain the data covariance matrix

$$S=\frac{1}{m}\left(\sum_{i=1}^{m} x_i x_i^T\right)-\mu\mu^T$$

  - Already in summation form
  - Each mapper produces partial sums
  - Reducer sums up partial results and computes S

Results



Conclusion

- Many ML algorithms can utilize multicore
  - Inherent parallelism: Summation form
  - General framework: MapReduce
- Major contributions
  - Case-by-case discussion of common ML algorithms
  - Extensive experiments
- Discussion
  - How many cores are we talking about?
    - Communication overhead, reducer bottleneck, …
  - MapReduce may be an overkill?
    - Mappers/reducers work on <key,val> pairs, but here just matrices etc. to be summed
    - Not using the failure handling techniques in MapReduce
  - Many other algorithms are not in summation form
    - e.g. Stochastic gradient ascent