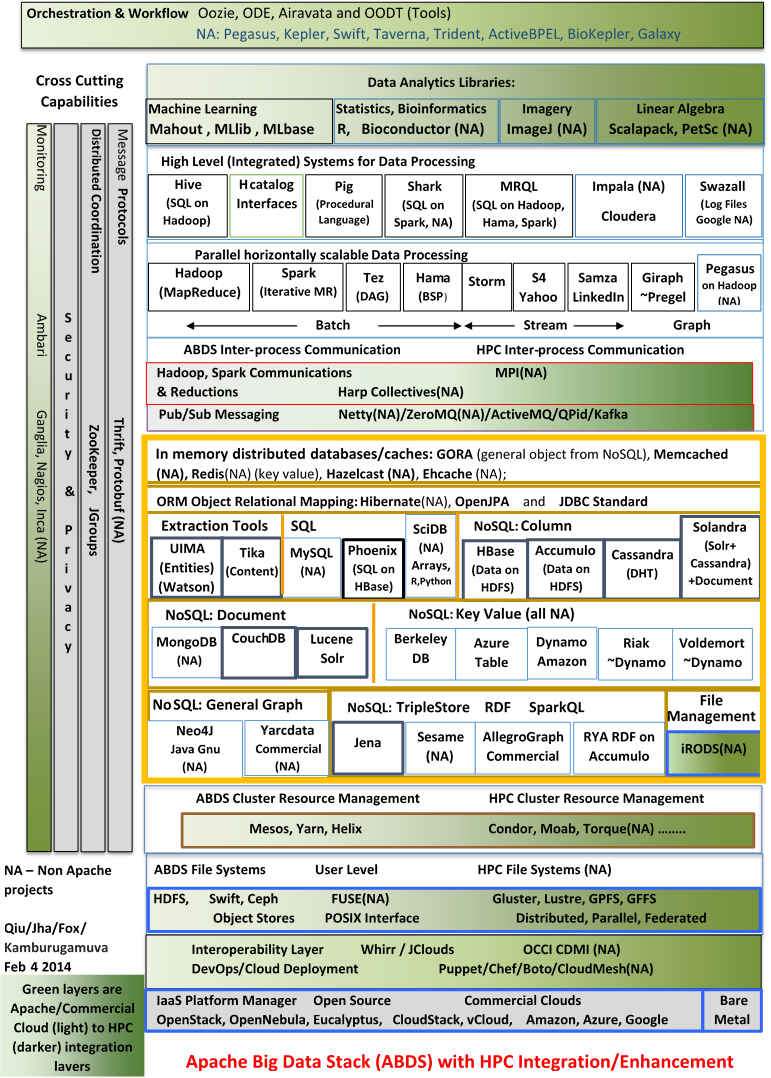
**High Performance High Functionality Big Data Software Stack**

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Big data is important in all areas including research, government and commercial applications. The 51 use cases gathered in NIST [[1](#_ENREF_1)] had 34, 8 and 9 use cases in these categories. Indeed the largest datasets are possibly those associated with commercial clouds including search and social media [[2](#_ENREF_2)]. It is estimated that this year there are approximately 6 zettabytes of stored data [[3](#_ENREF_3)]; several orders of magnitudes larger than say the LHC with around 0.0001 zettabytes (100 petabytes); the research applications in the NIST study were typically fractions of petabytes with large astronomy (LSST, SKA) projects underway with imagery (light sources, medical, surveillance, radar such as EISCAT-3D) large and growing in size. However research applications are and will be a small fraction of both stored data and network data transfer (CISCO estimates [[4](#_ENREF_4)] almost a zettabyte total IP traffic this year). This broad interest in Big data has spurred a frantic software activity much it aimed at commercial cloud deployments. This was seen in NIST study in both architecture discussions and the details given in many use cases. Here we suggest that is valuable to understand the large scale commercial approaches and understand how they can be made use of and as appropriate be integrated in the HPC and exascale data environments. This approach is helped by the broad use of Open source technology in the consensus commercial clouds with in particular many Apache software projects contributing to what we can term ABDS or Apache Big Data Stack. This is depicted in a layered architecture on the figure on the following page.

This figure show over 40 Apache Big Data projects [[5](#_ENREF_5)] with a selection of other commercial and Open source technologies. We use ABDS to refer to all the projects and not just those in Apache. We also color key layers where interaction between HPC and ABDS seems either critical or timely. This diagram highlights the rich functionality of ABDS. It is not just Hadoop but has important contributions to dynamic deployment; virtualization; file systems; cluster management; object data models including consistency, table, key-value, document, graph and SQL; in memory caching; messaging middleware; programming model and run time including graph, streaming, iterative and classic MapReduce; high level (productivity) systems with well-known analytics and machine learning libraries. Workflow and orchestration is also well represented. Not all these projects are of the same value and quality but together they represent a highly capable and productive environment and we suggest that it will be very valuable to consider how integrate HPC with ABDS. In our initial study [[6](#_ENREF_6)], we have identified file systems, cluster resource management, file and object data management, inter process and thread communication, libraries, workflow and monitoring as areas where HPC-ABFS integration will be particularly valuable. Much of this has already started with studies for example of Lustre-Object Store-HDFS integration [[7](#_ENREF_7)], comparison of Yarn with HPC schedulers, experimentation with NoSQL stores [[8](#_ENREF_8), [9](#_ENREF_9)], iterative MapReduce with a variety of communication mechanisms including those from MPI community [[10](#_ENREF_10)]. Study of library performance shows that HPC solutions outrun Mahout [[11](#_ENREF_11)]; at the workflow level, probably grid and HPC approaches are very competitive/the best as they are in monitoring area.

We suggest as well as working within these different layers, it is interesting to identify “different pathways” through the ABDS and see how the approaches compare and integrate. We are looking at Image processing, social media analysis, exploratory simulations and deep learning [[12](#_ENREF_12)] as such pathways.



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