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Bangkok 2016

Data Analytics and Machine Learning: From Node to Cluster

Understanding use cases to optimize on ARM Ecosystem

Presented by

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Ganesh Raju

Date

BKK16-404B
March 10th, 2016

Event

Linaro Connect BKK16

Version 0.1

Vish Puttagunta

- Technical Program Manager, Linaro
- DSP (TI C64x) optimizations (Image / Signal Processing)
- ARM® NEON™ optimizations upstreamed to opus audio codec
- Data Analysis and Machine Learning: Why ARM

Ganesh Raju

- Tech Lead, Big Data, Linaro
- Brings in Enterprise experience in implementing Big Data solutions

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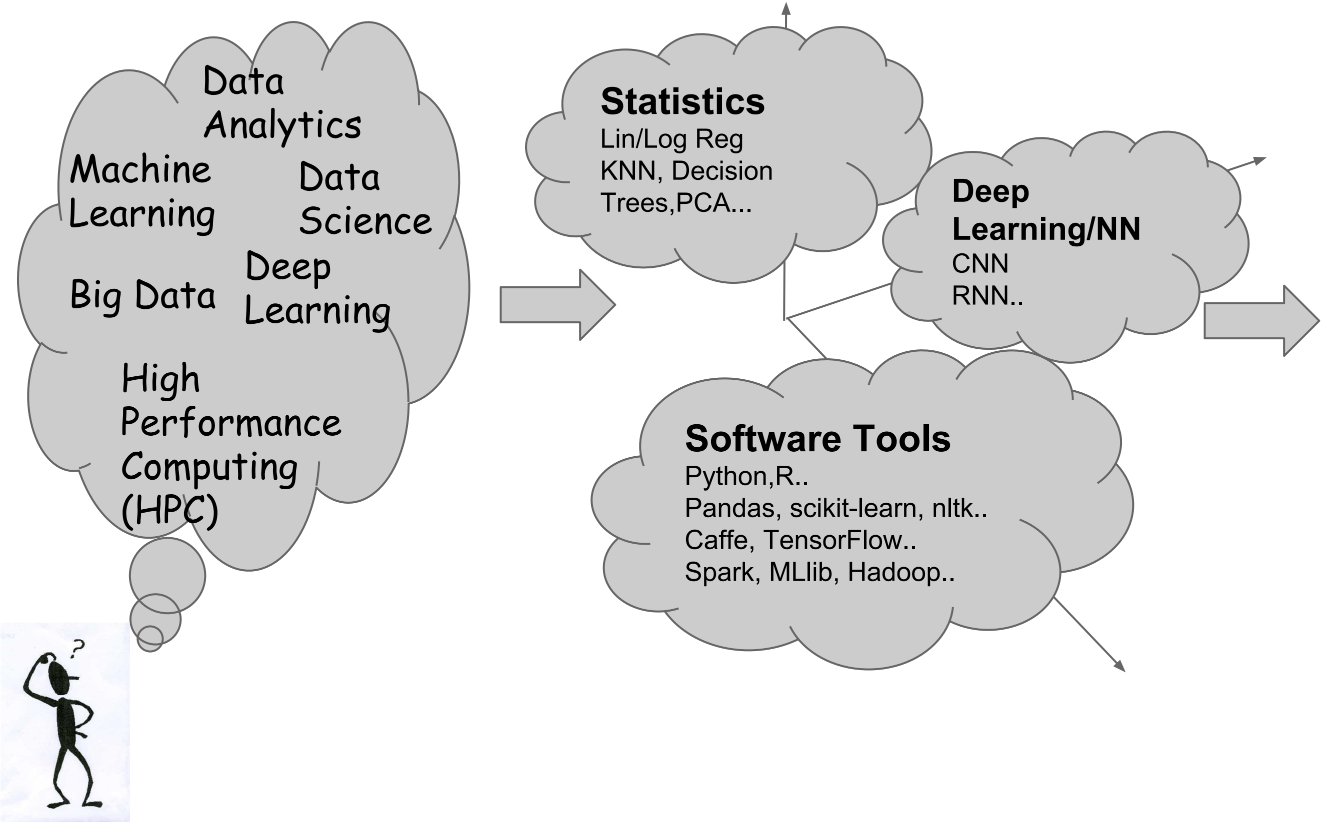
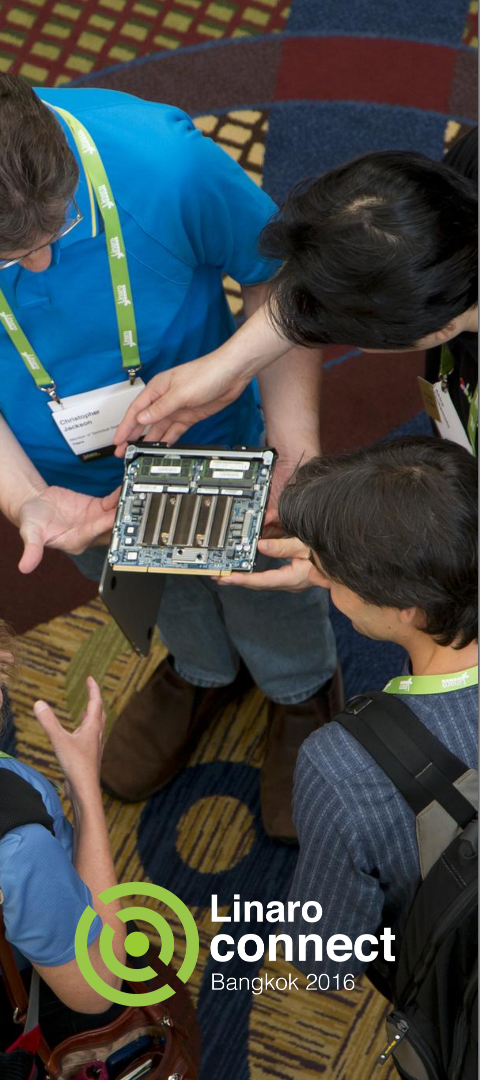
Data Science: Big Picture

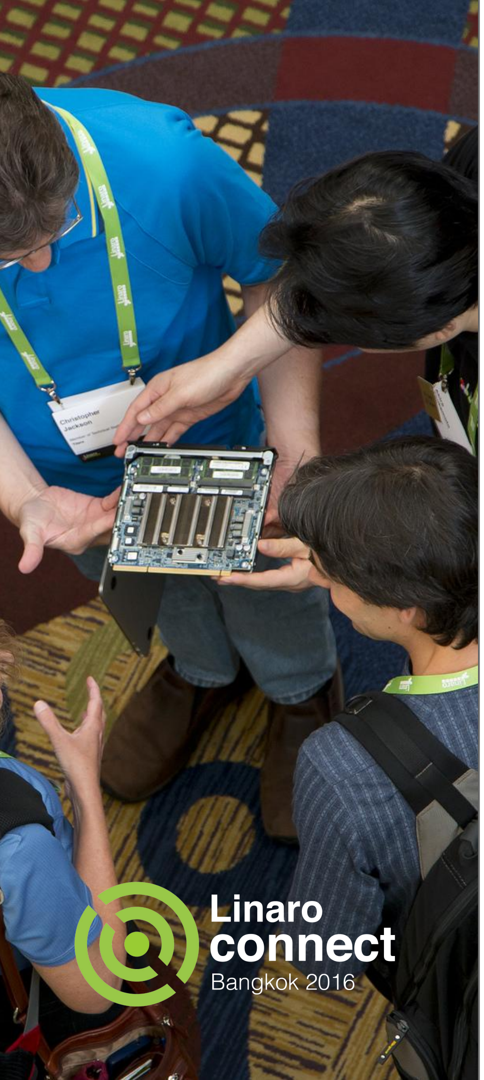


- **Value Prediction**
- **Classification**
- **Transformation**
- **Correlations**
- **Causalities**
- **Wrangling...**



Overview

- Basic Data Science use cases
- Pandas Library(Python)
  - Time Series, Correlations, Risk Analysis
- Supervised Learning
  - scikit-learn Library (Python)
- Understand operations done repeatedly
- Open discussion for next steps:
  - Profile, Optimize (ARM Neon, OpenCL, OpenMP..) on a single machine.
  - Scale beyond a single machine
- Ref: https://github.com/viswanath-puttagunta/bkk16_MLPrimer



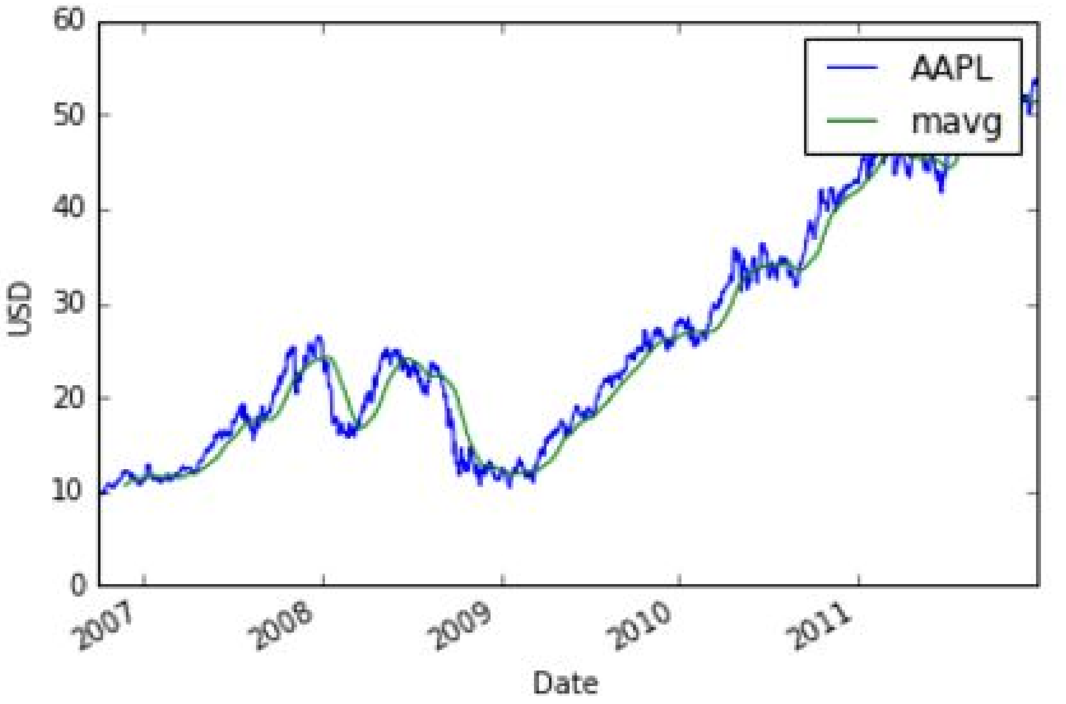
Goal

- Make the tools and operations work out of the box on ARM
  - ARM Neon, OpenCL, OpenMP.
  - ‘pip install’ should just work :)
- Why Now? (Hint: Spark)

Pandas Data Analysis (Pandas)

- Origins in Finance for Data Manipulation and Analysis (Python Library)
- DataFrame object
- Repeat Computations:
    - Means, Min, Max, Percentage Changes
    - Standard Deviation
    - Differentiation (Shift and subtract)
    - ...

Op: Rolling Mean (Pandas)



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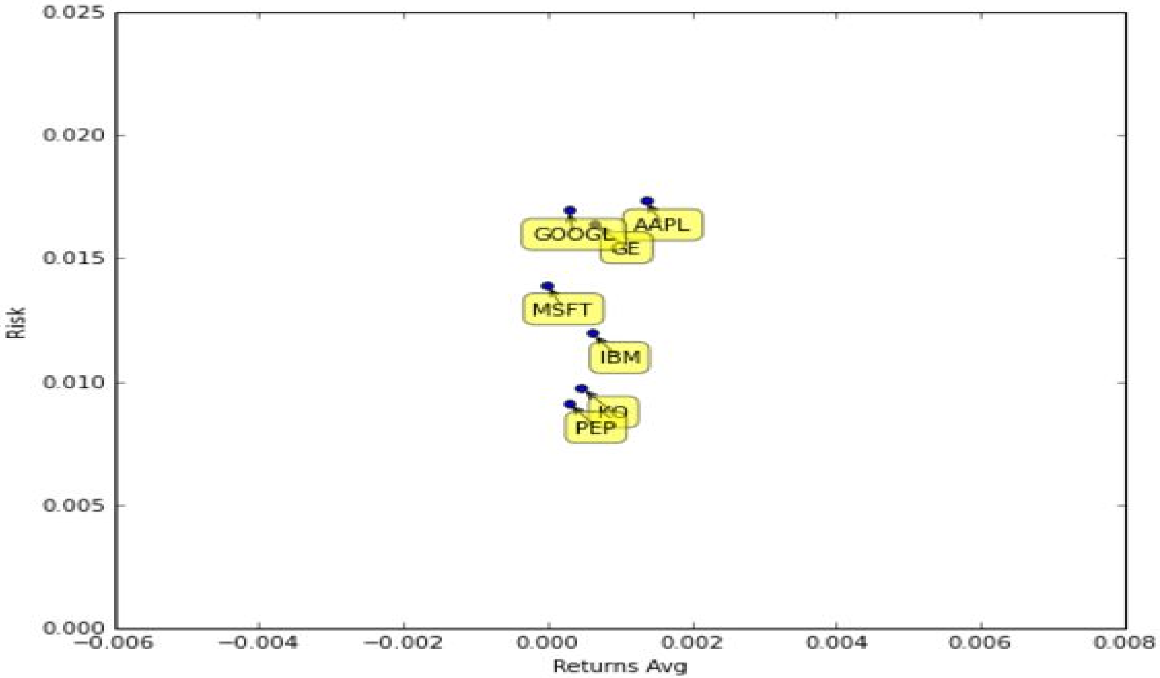
Op: Percentage Change (Pandas)

```
rets = df.pct_change()
rets.head()
```

	AAPL	GE	GOOGL	IBM	KO	MSFT	PEP
Date							
2010-01-04	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2010-01-05	0.001729	0.005178	-0.004404	-0.012080	-0.012097	0.000323	0.012084
2010-01-06	-0.015906	-0.005151	-0.025209	-0.006496	-0.000355	-0.006137	-0.010003
2010-01-07	-0.001849	0.051780	-0.023279	-0.003462	-0.002485	-0.010400	-0.006356
2010-01-08	0.006648	0.021538	0.013331	0.010035	-0.018509	0.006897	-0.003280

Operations: Shift, Subtract, Divide

Op: Percentage Change Vs Risk (Variance)



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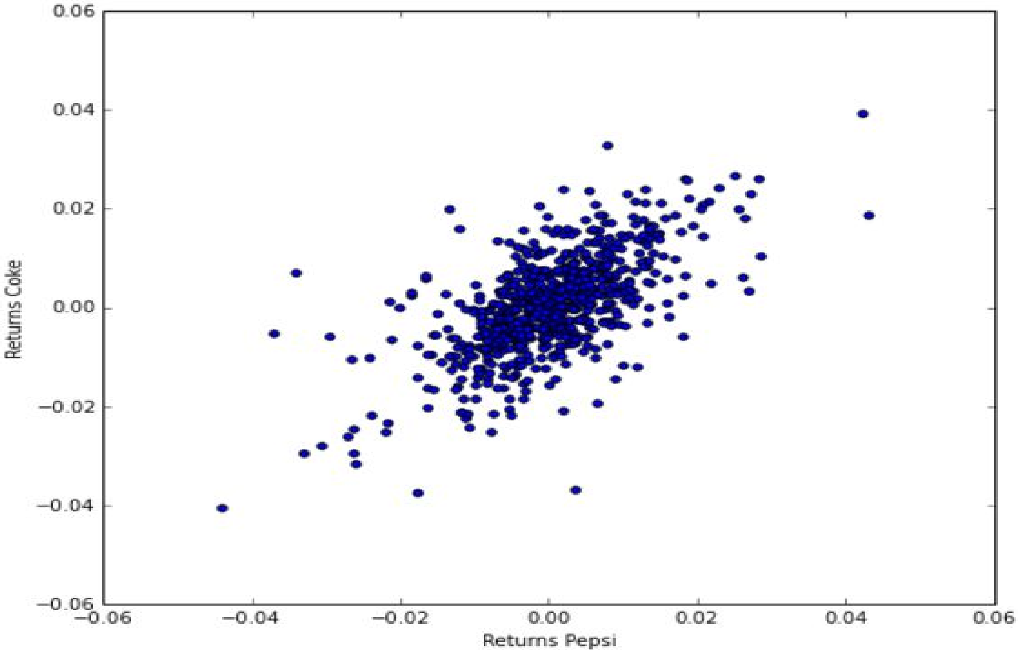
Op: Correlation (Pandas)



Pearson Correlation Coef

$$\frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

Operations: Mean, Variance, Square Root

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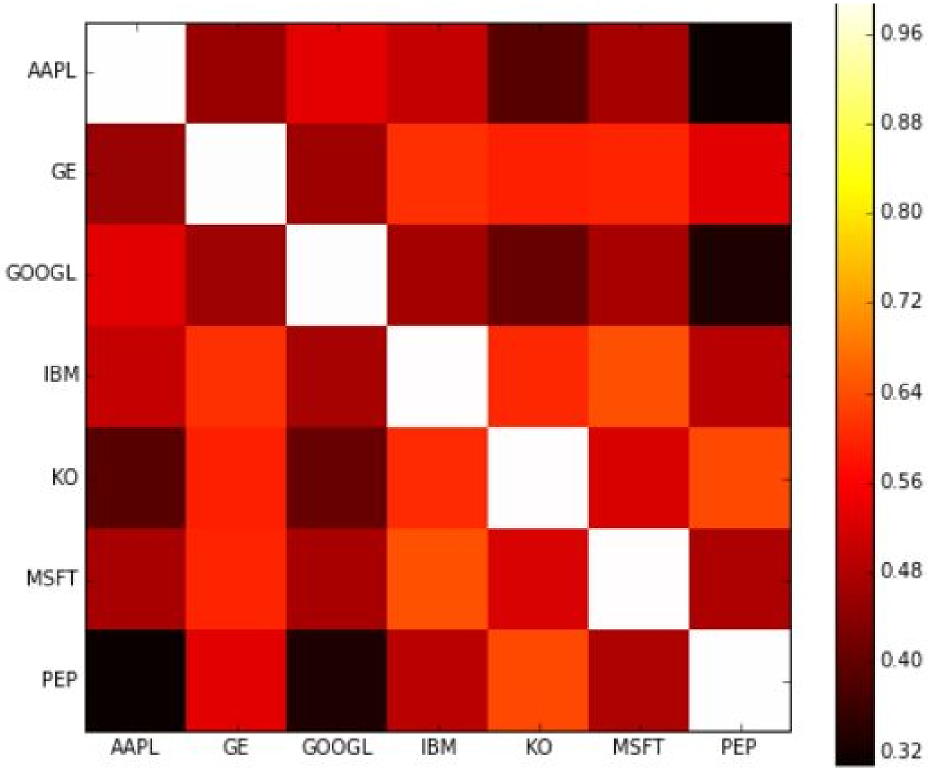
Source: https://en.wikipedia.org/wiki/Pearson_product-moment_correlation_coefficient

Correlation Heat Maps



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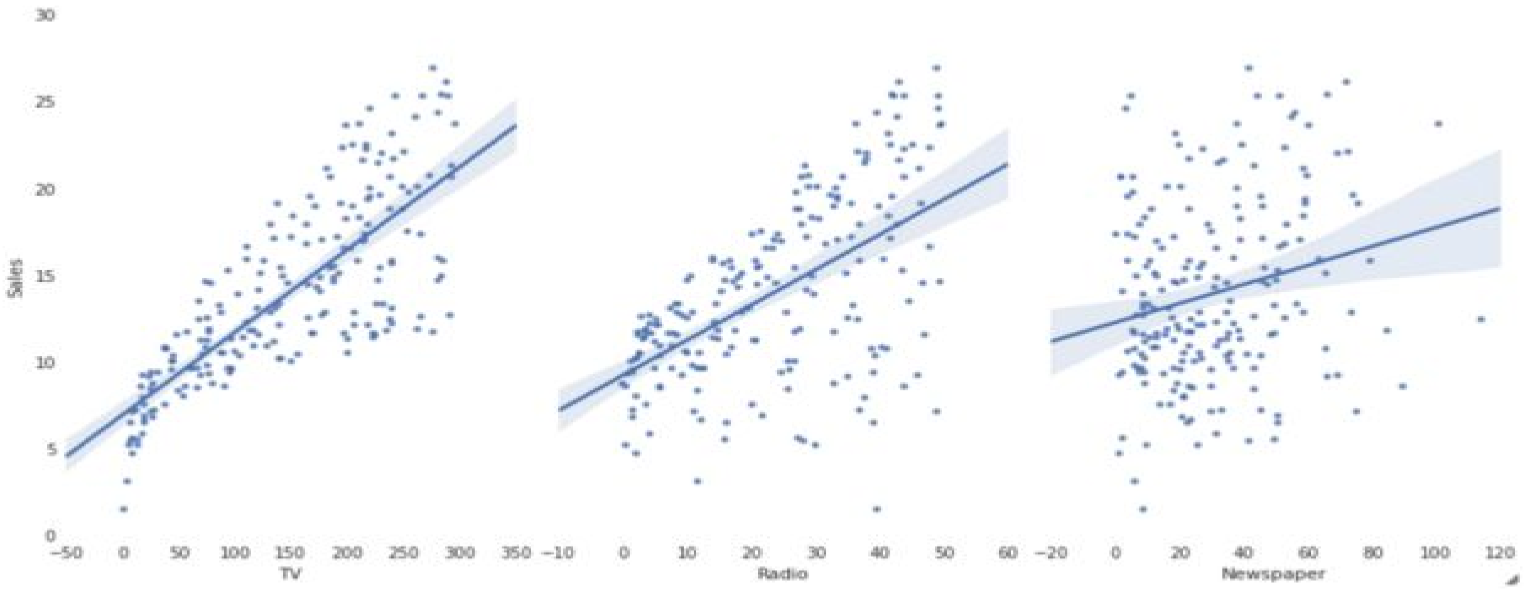
Linear Regression (Predictor)



Objective: Fit line/curve to minimize a cost function

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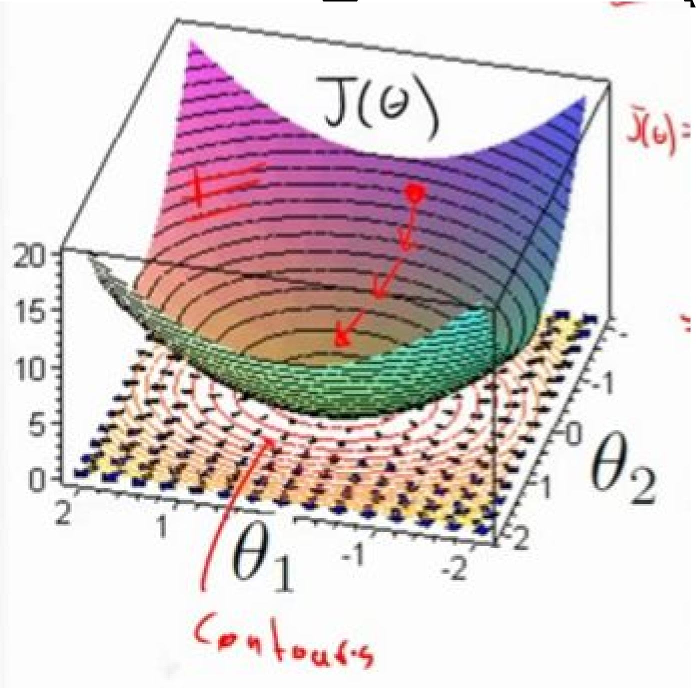
Linear Regression (Predictor)...



$$\nabla J(\underline{\theta}) = -\frac{2}{m}\sum_{j}^{J}\left(y^{(j)} - \underline{\theta}\cdot\underline{x}^{(j)T}\right)\cdot\left[x_0^{(j)} x_1^{(j)} \ldots\right]$$

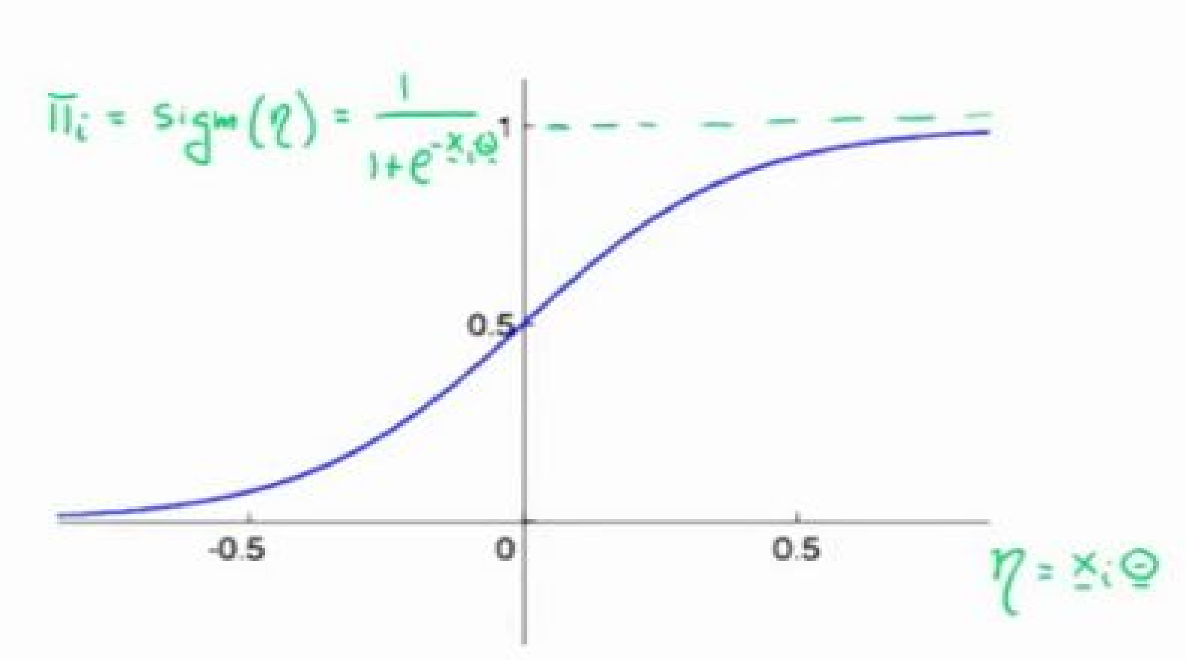
For Lnr Reg, directly reduces to:

$$\Theta = (X^T X)^{-1} X^T Y$$

Operations: Gradient Descent: Matrix Transforms/Inverse/Multiplications.

Source: https://www.youtube.com/watch?v=SqA6TujbmWw&list=PLE6Wd9FR--Ecf_5nCbnSQMHqORpiChfJf&index=16
https://youtu.be/WnqQrPNYz5Q?list=PLaXDtXvwY-oDvedS3f4HW0b4KxqpJ_imw&t=284

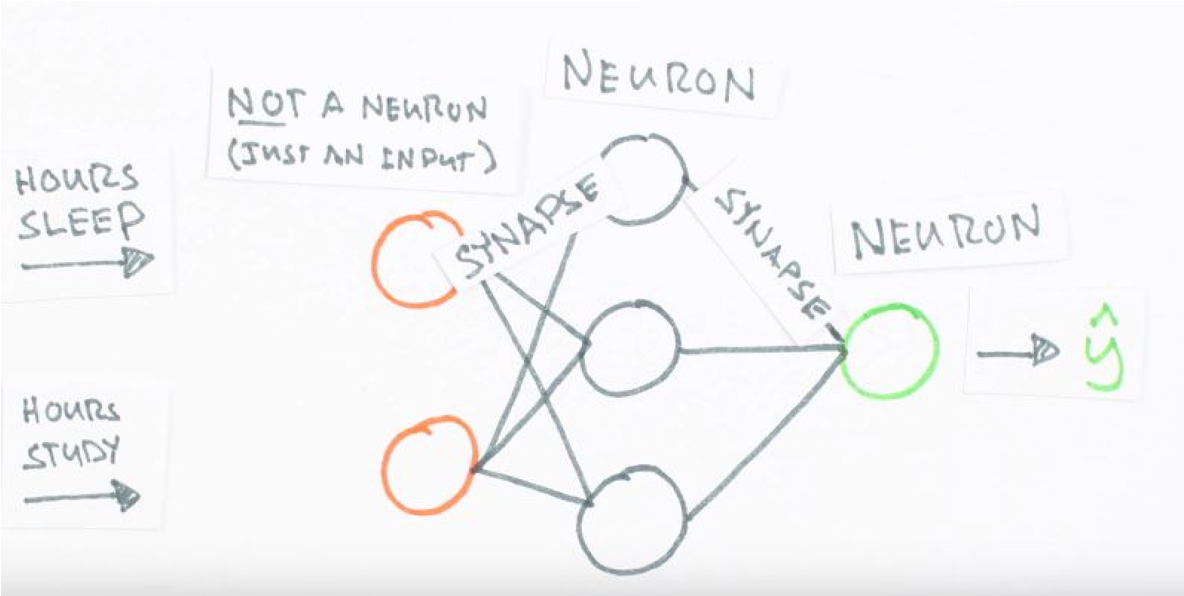
Logistic Regression (Classification)



Operations: Matrix Transforms/Inverse/Multiplications.

Source: https://www.youtube.com/watch?v=Zc7ouSD0DEQ&index=27&list=PLE6Wd9FR--Ecf_5nCbnSQMHqORpiChfJf

Artificial Neural Networks (Eg: Predictor)



Objective: Compute parameters to minimize a cost function
Operations: Matrix Transforms/Inverse/Multiplications, Dot Products...

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Bayesian Classifiers

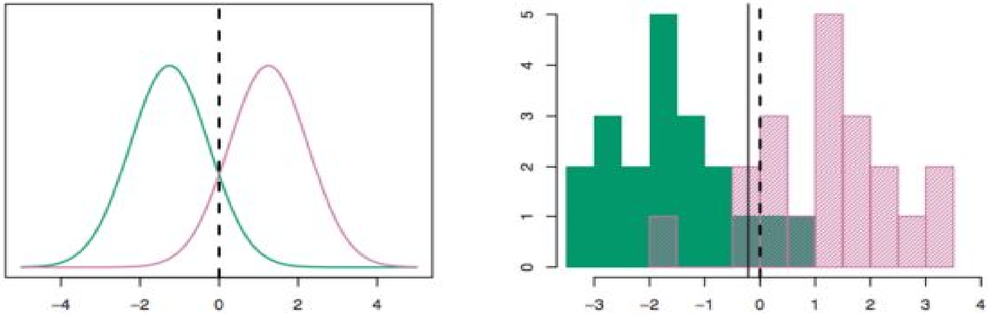

FIGURE 4.4. Left: *Two one-dimensional normal density functions are shown. The dashed vertical line represents the Bayes decision boundary.* Right: *20 observations were drawn from each of the two classes, and are shown as histograms. The Bayes decision boundary is again shown as a dashed vertical line. The solid vertical line represents the LDA decision boundary estimated from the training data.*

Operations (Training): Mean, Standard Deviations, Logs, binning/compare(/histograms)

Note: Some variations based on assumptions on variance (LDA, QDA)

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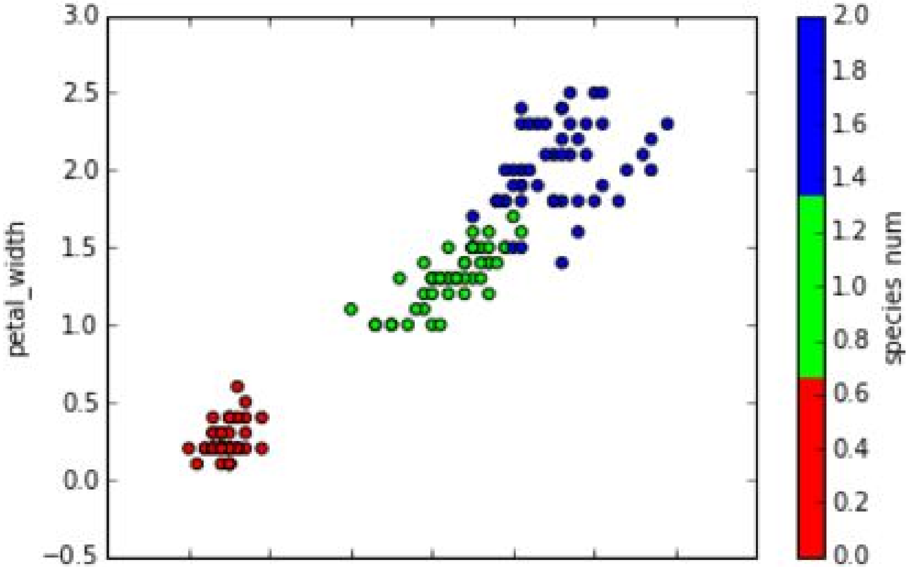
Source: An Introduction to Statistical Learning with Applications in R (Springer Texts)

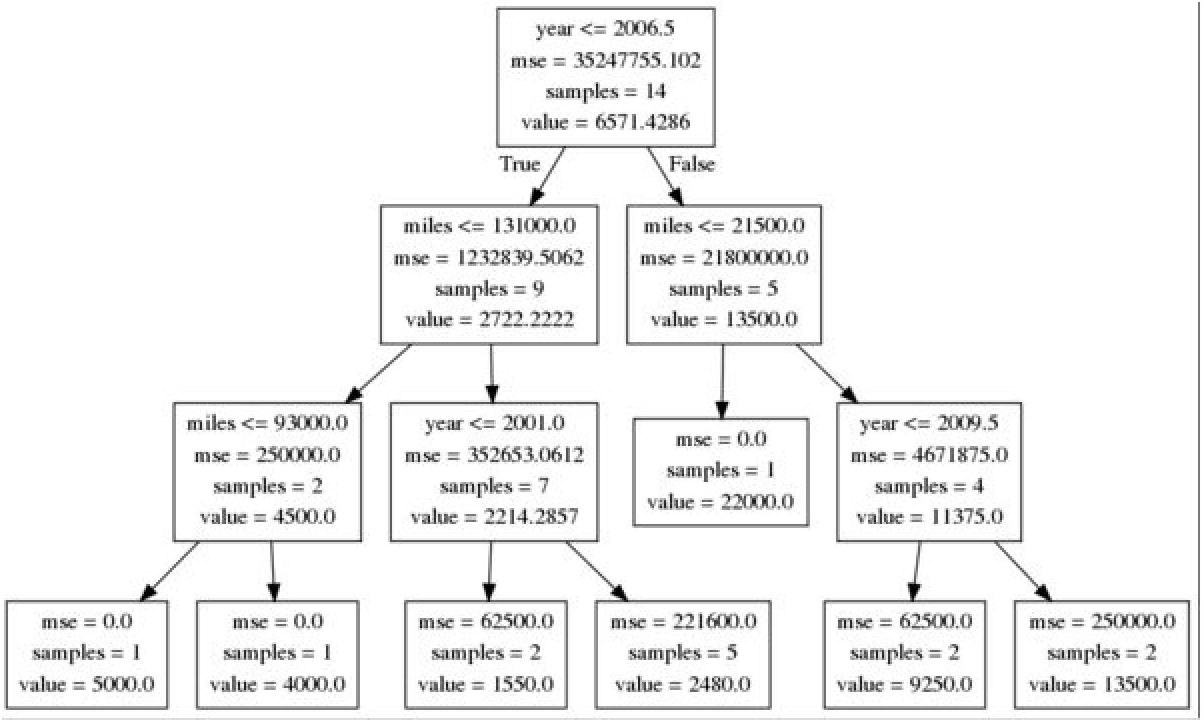
K-Nearest Neighbors (Classifier)



Operations: Euclidean Distance Computations

Note: K is tunable. Typical to repeat computations for lot of k values

Decision Tree (Predictors & Classifiers)



Operations: Each split done so that

Predictor: Minimize Root Mean Square Error

Classifier: Minimize Gini Index (Note: depth tunable)

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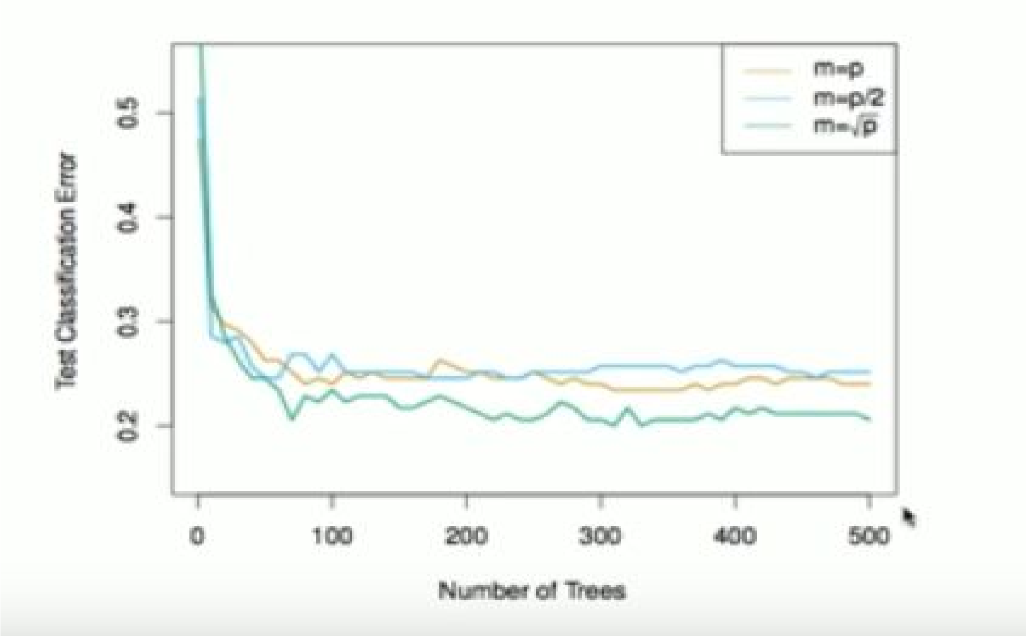
Bagging / Random Forests



Operations: Each tree similar to Decision Tree
Note: Typical to see about 200 to 300 trees to stabilize.

Source: An Introduction to Statistical Learning with Applications in R (Springer Texts)

Segway to Spark

- So far, on a single machine with lots of RAM and compute.
  - How to scale to a cluster
- So far, data from simple csv files
  - How to acquire/clean data on large scale

Discussion

- OpenCL (Deep Learning)
  - Acceleration using GPU, DSPs
  - Outside of Deep Learning: GPU? (scikit-learn faq)
  - But what about Shamrock? OpenCL backend on CPU.
  - Port CUDA kernels into OpenCL kernels in various projects?
- ARM NEON
  - Highly scalable
- OpenMP?
- Tools to profile end-to-end use cases?
  - Perf..

Backup Slides

- Text Analytics
  - Sparse Matrices and operations
  - Word counts (Naive Bayes)
- Libraries (Python)
  - sklearn (No GPU Support!! FAQ)
  - gensim (Text Analytics)
  - TensorFlow™(GPU backend available)
  - Caffe (GPU backend available)
  - Theano (GPU backend available)

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Data science in Distributed Environment

Presented by

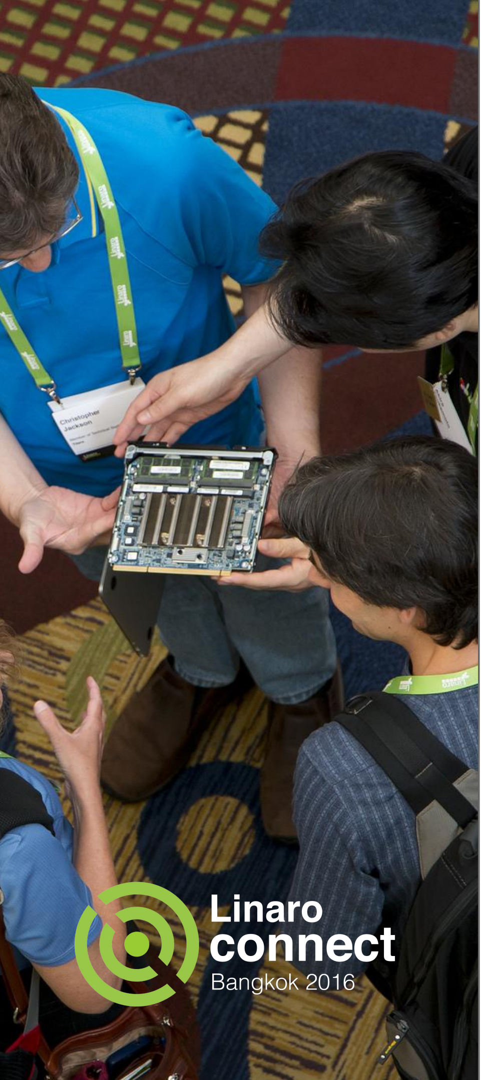
Ganesh Raju
Tech Lead, Big Data
Linaro

Date

Thursday 10 March 2016

Event

BKK16



Overview

1. Review of Data Science in Single Node
2. Data Science in Distributed Environment
   a. Hadoop and its limitations
3. Data Science using Apache Spark
   a. Spark Ecosystem
   b. Spark ML
   c. Spark Streaming
   d. Spark 2.0 and Roadmap
4. Q & A

Hadoop Vs Spark

80+ operators compared to 2 operators in Hadoop

hadoop

map()

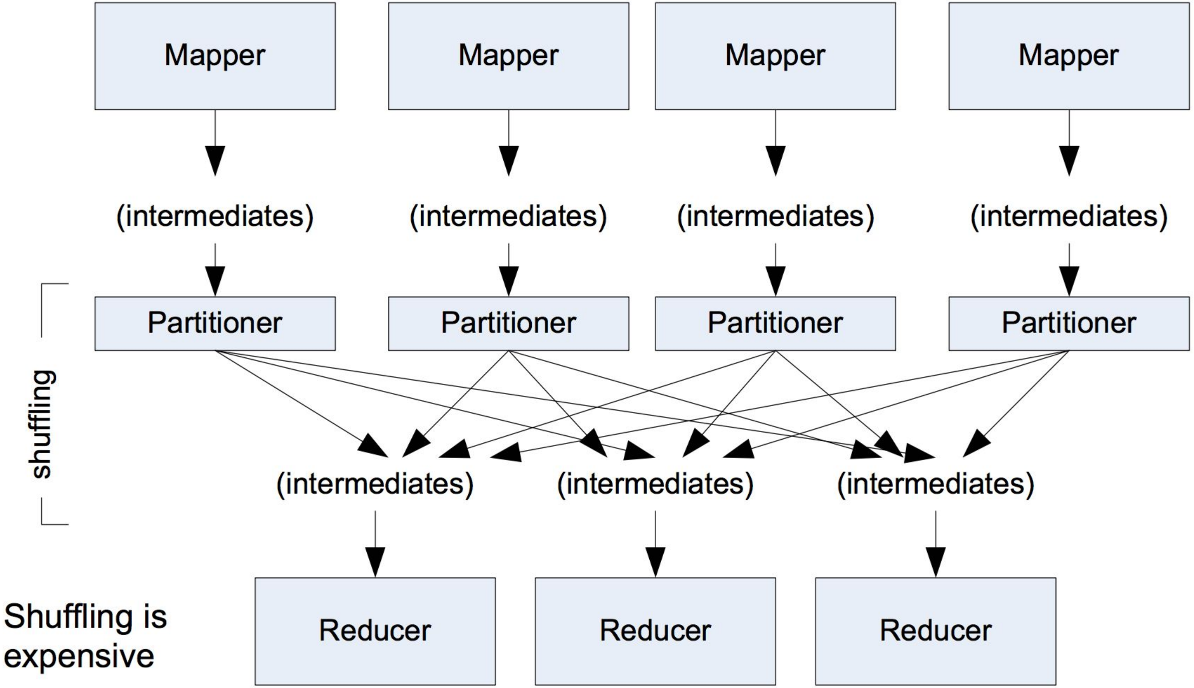
reduce()

Spark

map()	reduce()
filter()	sortBy()
join()	groupByKey(
first()	) count()

Hadoop and its limitations

Data loading is expensive



Shuffling is expensive

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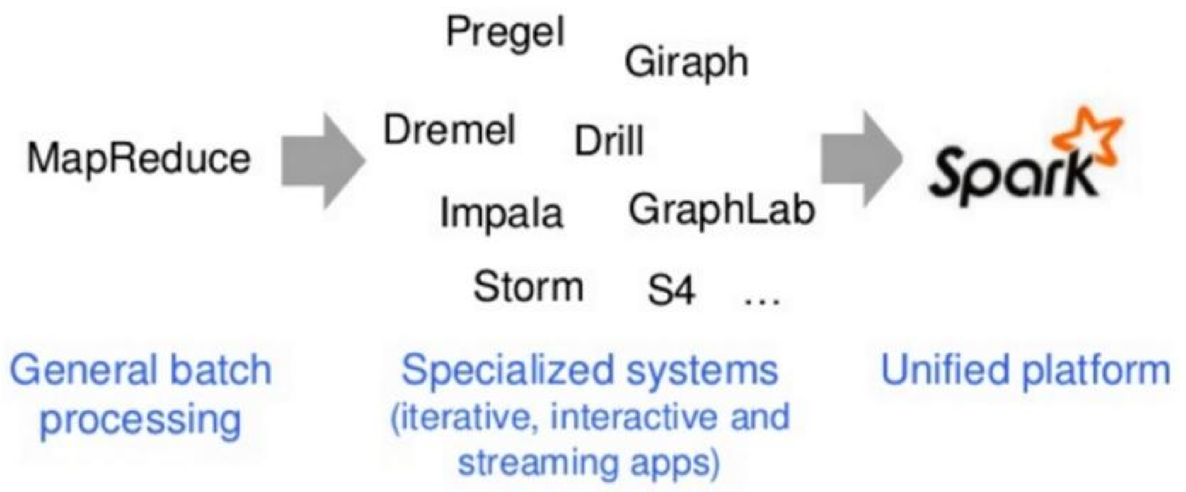
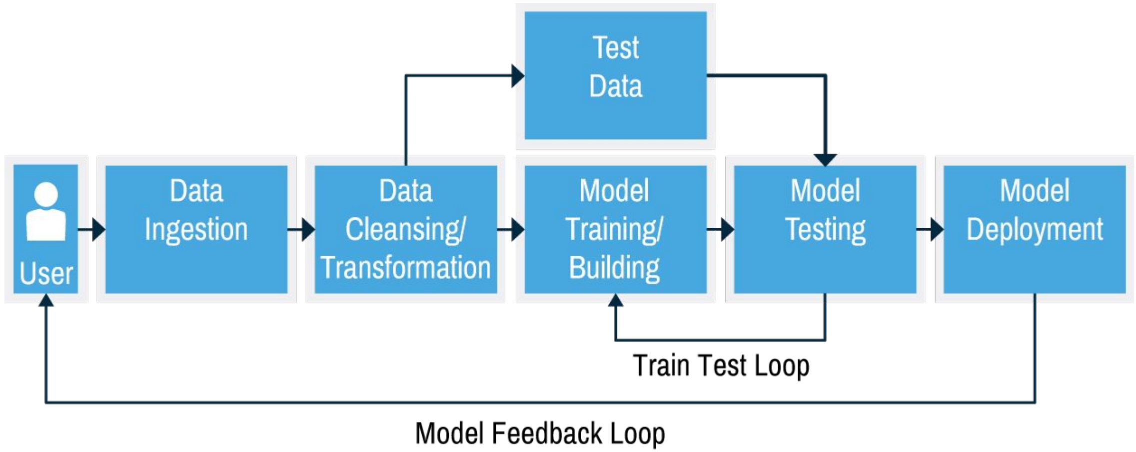
Spark - Unified Platform



source: www.databricks.com

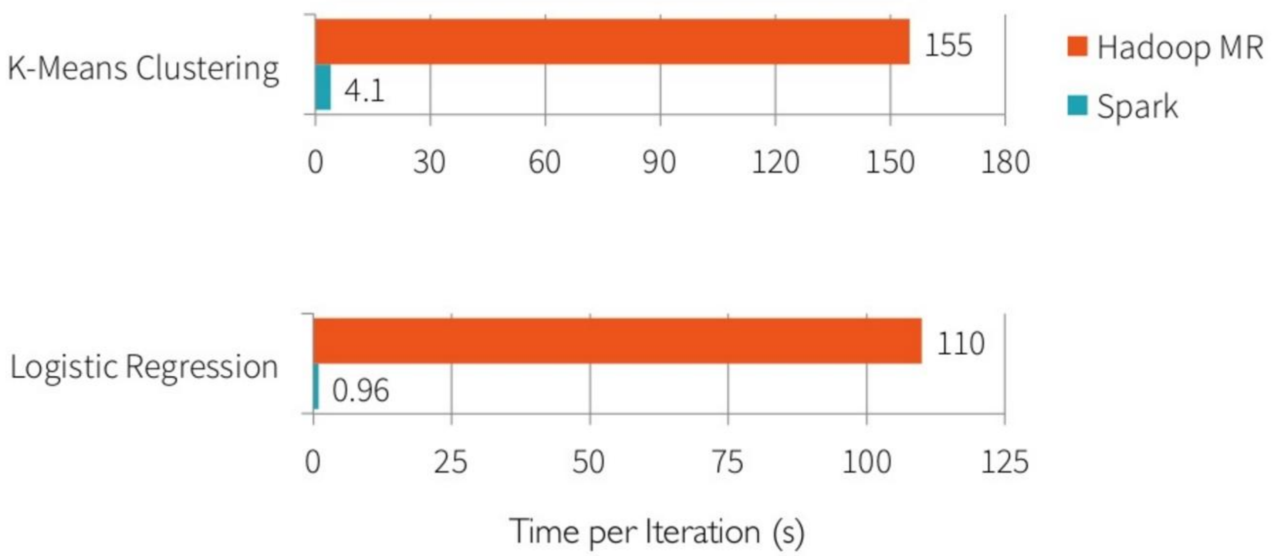
Machine Learning Data Pipeline



Why in Spark:

- Machine learning algorithms are
  - Complex, multi-stage
  - Iterative
- MapReduce/Hadoop unsuitable

Spark is In-Memory and Fast



source: http://www.slideshare.net/databricks/2015-0317-scala-days

Apache Spark Stack

Unified Engine across diverse workloads and Environments

Spark SQL + DataFrames	Streaming	MLib / ML *Machine Learning*	GraphX *Graph Computation*

Spark Core API

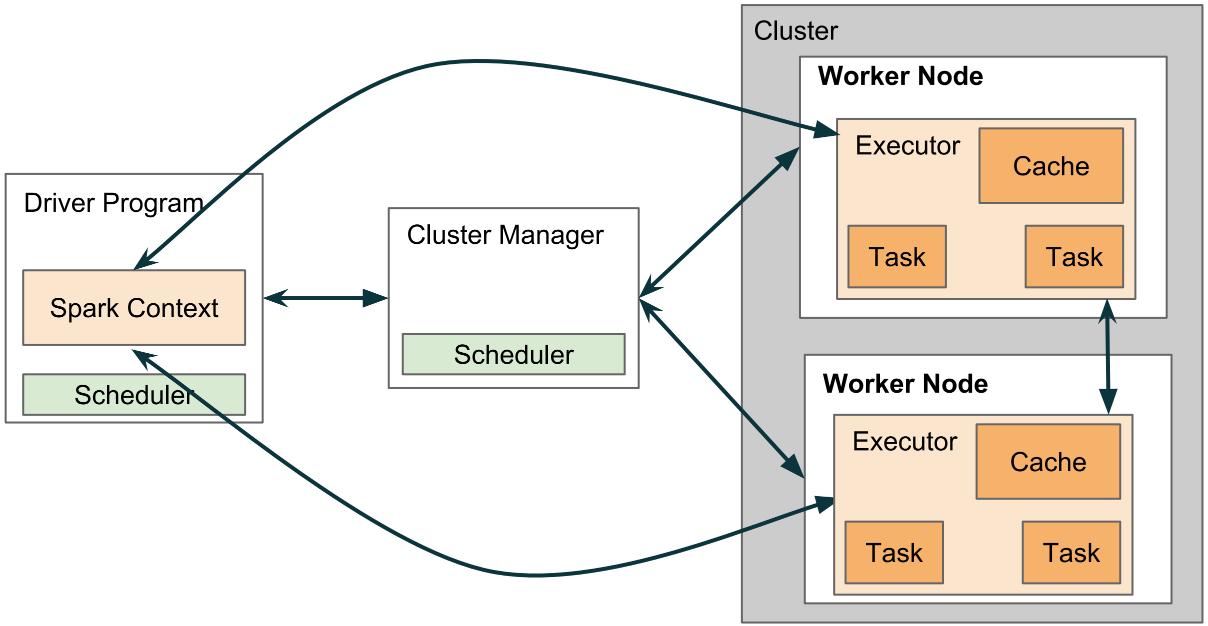
R	Python	Scala	Java

hadoop cassandra amazon webservices openstack MESOS ...

Spark Core

Internals

SparkContext connects to a cluster manager Obtains executors on cluster nodes Sends app code to them Sends task to the executors



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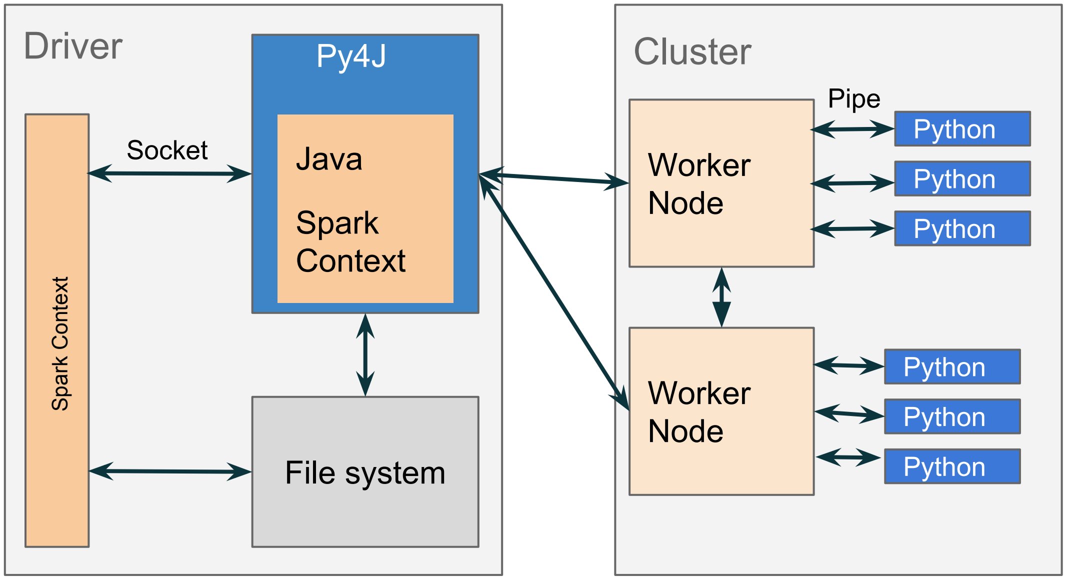
Application Code Distribution



- PySpark enables developers to write driver programs in Python
- Application code is serialized and sent to the worker nodes
- Execution happens in native language (Python/R)

Apache Spark MLlib / ML Algorithms Supported:

- **Classification:** Logistic Regression, Linear SVM, Naive Bayes, classification tree
- **Regression:** Generalized Linear Models (GLMs), Regression Tree
- **Collaborative Filtering:** Alternating Least Squares (ALS), Non-Negative Matrix Factorization (NMF)
- **Clustering:** K-Means
- **Decomposition:** SVD, PCA
- **Optimization:** Stochastic Gradient Descent (SGD), L-BFGS

Spark Streaming

- Run a streaming computation as a series of very small, deterministic batch jobs
  - Live data streaming is converted into micro batches of input. Batch can be of ½ sec latency.
  - Each batch is processed in Spark
  - Output is returned as micro batches
  - Potential for combining batch and streaming processing.
- Linear models can be trained in streaming fashion
- Model weights can be updated via SGD, thus amenable to streaming
- Consistent API
- Scalable

Apache Spark

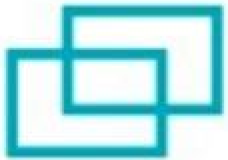
General-purpose cluster computing system

- Unified End-to-End data pipeline platform with support for Machine Learning, Streaming, SQL and Graph Pipelines
- Fast and Expressive Cluster Computing Engine. No Intermediate storage. In-memory Processing. Run programs up to 100x faster than Hadoop MapReduce in memory, or 10x faster on disk.
- Rich higher level APIs in Scala, Python, R, Java. Typically less code (2-5x)
- REPL
- Interoperability with other ecosystem components
  - Mesos, YARN
  - EC2, EMR
  - HDFS, S3,
  - HBase, Cassandra, Parquet, Hive, JSON, ElasticSearch

Major Features in 2.0 - Project Tungsten

Tungsten Phase 2
speedups of 5-10x

Structured Streaming
real-time engine on
SQL / DataFrames



Unifying Datasets
and DataFrames

Source: https://databricks.com/blog/2015/04/28/project-tungsten-bringing-spark-closer-to-bare-metal.html

Spark 2.0 - Project Tungsten features

Focus on CPU and Memory Optimization

Code Generation

- Runtime Code Generation by dynamically generating bytecode during evaluation and eliminating Java boxing of primitive data types
- Faster serializer and compression on dataformat like Parquet.

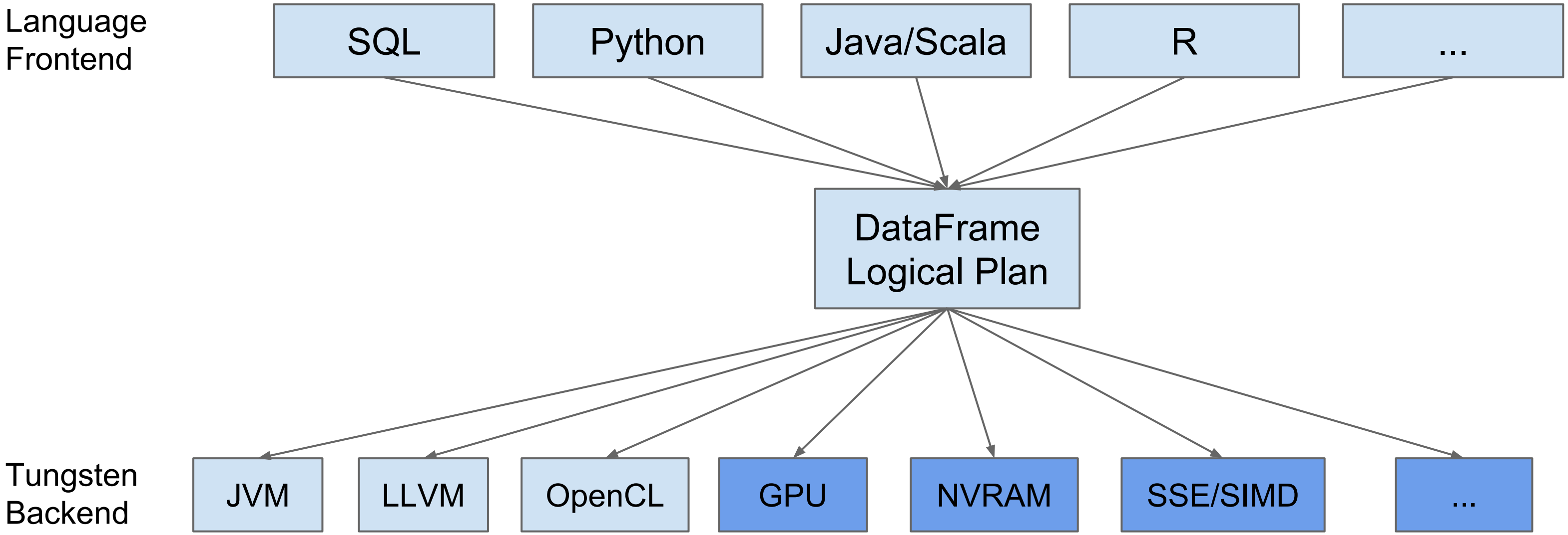
Manual Memory Management and Binary Processing

- Off heap memory management. Avoiding non-transient Java objects (store them in binary format), which reduces GC overhead.
- Minimizing memory usage through denser in-memory data format, with less spill (I/O)
- Better memory accounting (size of bytes) rather than relying on heuristics
- For operators that understand data types (in the case of DataFrames and SQL), work directly against binary format in memory, i.e. have no serialization/deserialization

Cache-aware Computation

- Exploiting cache locality. Faster sorting and hashing for aggregations, joins, and shuffle

Unified API, One Engine, Automatically Optimized



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Apache Spark Roadmap

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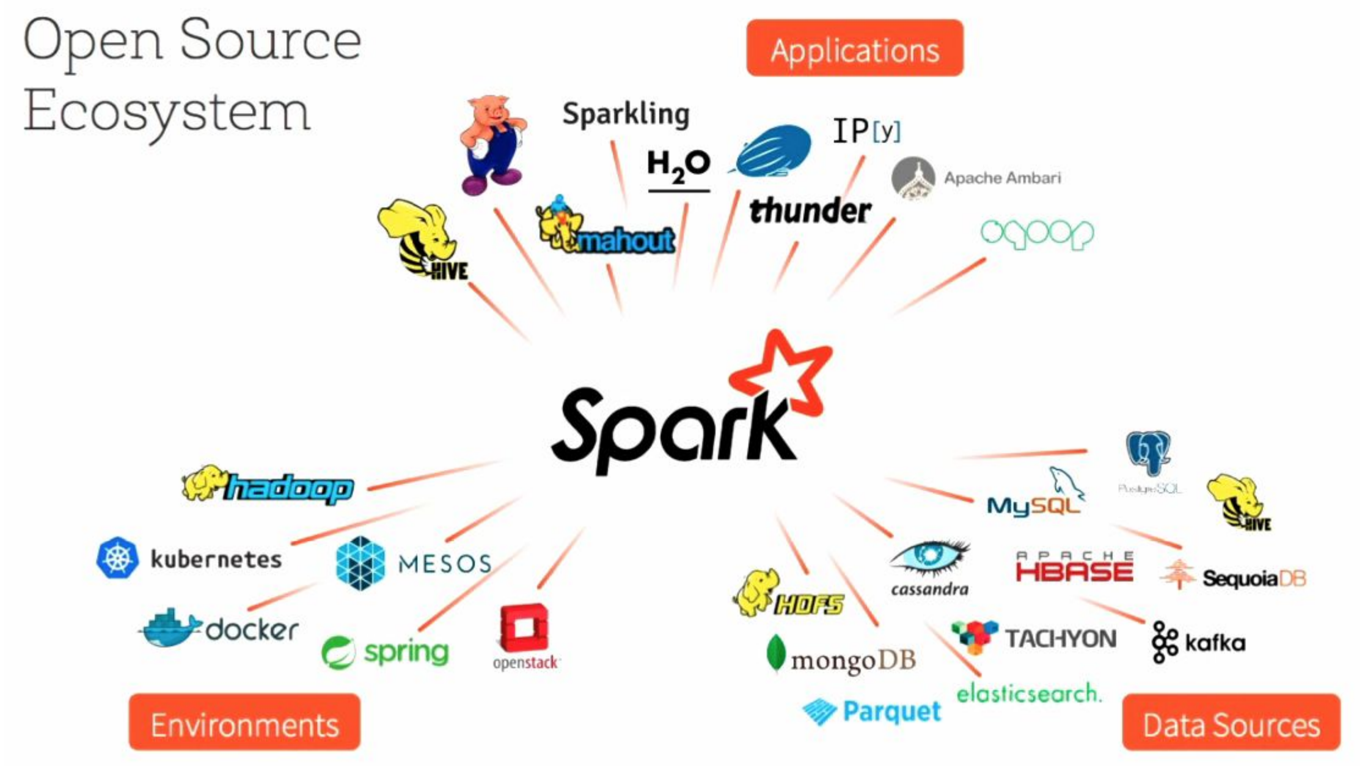
- Use LLVM for compilation
- Re-implement parallelizable code using OpenCL/SSE/SIMD to utilize underlying CPU / GPU advancements towards machine learning.

Spark slave nodes can achieve better performance and energy efficiency if with GPU acceleration by doing further data parallelization and algorithm acceleration.

De facto Analytics Platform



source: www.databricks.com

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Q & A