Apache Spark

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Spark Overview

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What is Apache Spark?

- A fast and general engine for large-scale data processing
- A Open-source cluster computing framework
- End-to-End Analytics platform
- Developed to overcome limitations of Hadoop/Map Reduce
- Runs from a single desktop or a huge cluster
- Iterative, interactive or stream processing
- Supports multiple languages – Scala, Python, R, Java
- Major companies like Amazon, eBay, Yahoo use Spark.

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When to use Spark?

- Data Integration and ETL
- Interactive Analytics
- High Performance Batch computation
- Machine Learning and Advanced Analytics
- Real time stream processing
- Example applications
  - Credit Card Fraud Detection
  - Network Intrusion Detection
  - Advertisement Targeting

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Typical Spark workflow

- Load data from source
  - HDFS, NoSQL,S3, real time sources
- Transform Data
  - Filter, Clean, Join, Enhance
- Store processed data
  - Memory, HDFS, NoSQL
- Interactive Analytics
  - Shells, Spark SQL, third-party tools
- Machine Learning
- Action

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Online Reference

- http://spark.apache.org

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Spark Eco-system

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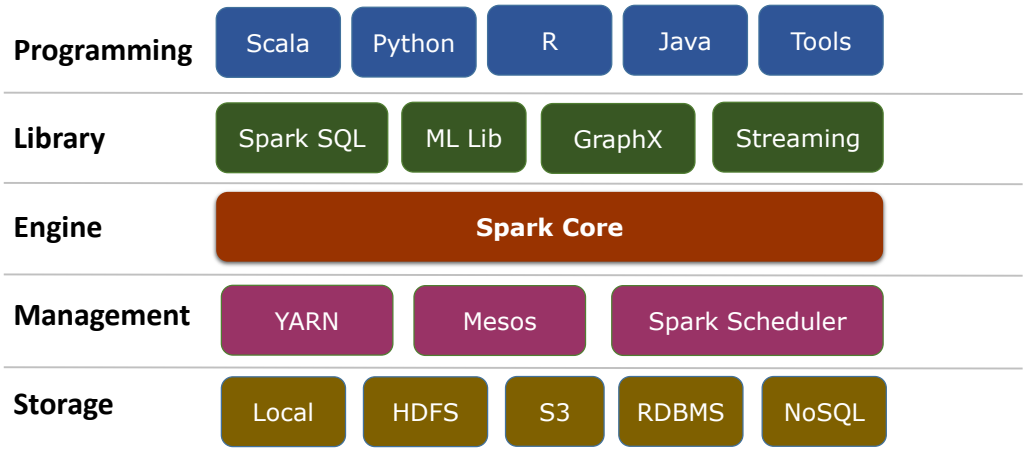
Spark Framework



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RDD

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Resilient Distributed Datasets (RDD)

- Spark is built around RDDs. You create, transform, analyze and store RDDs in a Spark program.
- The Dataset contains a collection of elements of any type.
  - Strings, Lines, rows, objects, collections
- The Dataset can be partitioned and distributed across multiple nodes
- RDDs are immutable. They cant be changed.
- They can be cached and persisted
- Transformations act on RDDs to create a new RDD
- Actions analyze RDDs to provide a result

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Spark Architecture

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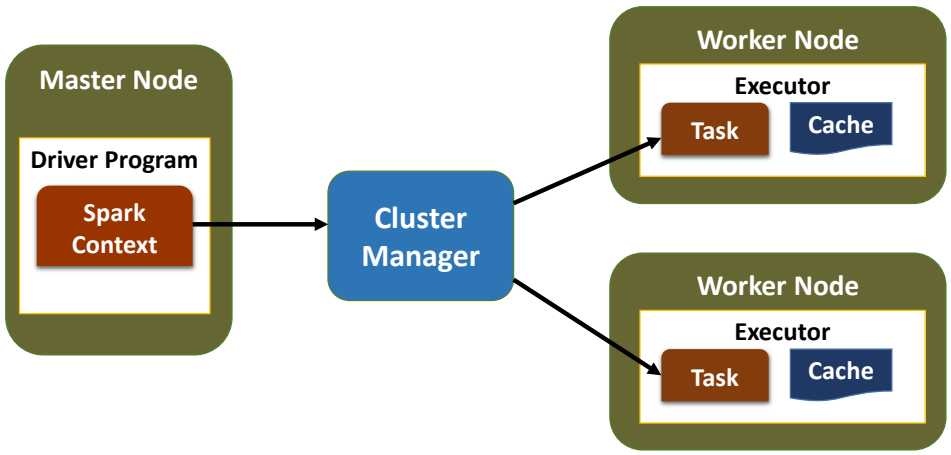
Spark Architecture



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Driver Program

- The main executable program from where Spark operations are performed
- Runs in the master node of a cluster
- Controls and co-ordinates all operations
- The Driver program is the “main” class.
- Executes parallel operations on a cluster
- Defines RDDs
- Each driver program execution is a “Job”

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SparkContext

- Driver accesses Spark functionality through a SparkContext object.
- Represents a connection to the computing cluster
- Used to build RDDs.
- Partitions RDDs and distributes them on the cluster
- Works with the cluster manager
- Manages executors running on Worker nodes
- Splits jobs as parallel “tasks” and executes them on worker nodes
- Collects results and presents them to the Driver Program

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Spark modes

- Batch mode
  - A program is scheduled for execution through the scheduler
  - Runs fully at periodic intervals and processes data
- Interactive mode
  - An interactive shell is used by the user to execute Spark commands one-by-one.
  - Shell acts as the Driver program and provides SparkContext
  - Can run tasks on a cluster
- Streaming mode
  - An always running program continuously processes data as it arrives

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Spark scalability

- Single JVM
  - Runs on a single box (Linux or Windows)
  - All components (Driver, executors) run within the same JVM
- Managed Cluster
  - Can scale from 2 to thousands of nodes
  - Can use any cluster manager for managing nodes
  - Data is distributed and processed on all nodes

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Loading and Storing Data

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Creating RDDs

- RDDs can be created from a number of sources
  - Text Files
  - JSON
  - Parallelize() on local collections
    - Java Collections
    - Python Lists
    - R Data Frames
  - Sequence files
- RDBMS – load into location collections first and create RDD
- Very large data – create HDFS files outside of Spark and then create RDDs from them

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Storing RDDs

- Spark provides simple functions to persist RDDs to a variety of data sinks
  - Text Files
  - JSON
  - Sequence Files
  - Collections
- For optimization use language specific libraries for persistence than using Spark utilities.
- saveAsTextFile()
- RDBMS – move to local collections and then store.

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Lazy evaluation

- Lazy evaluation means Spark will not load or transform data unless an action is performed
  - Load file into RDD
  - Filter the RDD
  - Count no. of elements (only now loading and filtering happens)
- Helps internally optimize operations and resource usage
- Watch out during troubleshooting – errors found while executing actions might be related to earlier transformations

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Transformations

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Overview

- Perform operation on one RDD and create a new RDD
- Operate on one element at a time
- Lazy evaluation
- Can be distributed across multiple nodes based on the partitions they act upon

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Map

```
newRdd=rdd.map(function)
```

- Works similar to the Map Reduce "Map"
- Act upon each element and perform some operation
  - Element level computation or transformation
- Result RDD may have the same number of elements as original RDD
- Result can be of different type
- Can pass functions to this operation to perform complex tasks
- Use Cases
  - Data Standardization – First Name, Last Name
  - Data type conversion
  - Element level computations – compute tax
  - Add new attributes – Grades based on test scores

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flatMap

```
newRdd=rdd.flatMap(function)
```

- Works the same way as map
- Can return more elements than the original map
- Use to break up elements in the original map and create a new map
  - Split strings in the original map
  - Extract child elements from a nested json string

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Filter

```
newRdd=rdd.filter(function)
```

- Filter a RDD to select elements that match a condition
- Result RDD smaller than the original RDD
- A function can be passed as a condition to perform complex filtering
  - Returns a true/false

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Set Operations

- Set operations are performed on two RDDs
- Union – Return a new dataset that contains the union of the elements in the source dataset and the argument.
  - `unionRDD=firstRDD.union(secondRDD)`
- Intersection - Return a new RDD that contains the intersection of elements in the source dataset and the argument.
  - `intersectionRDD=firstRDD.intersect(secondRDD)`

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Actions

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Introduction to actions

- Act on a RDD and product a result (not a RDD)
- Lazy evaluation – Spark does not act until it sees an action
- Simple actions
  - `collect` – return all elements in the RDD as an array. Use to trigger execution or print values
  - `count` – count the number of elements in the RDD
  - `first` – returns the first element in the RDD
  - `take(n)` – returns the first n elements

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reduce

- Perform an operation across all elements of an RDD
  - sum, count etc.
- The operation is a function that takes as input two values.
- The function is called for every element in the RDD

```
inputRDD = [ a, b, c, d, e ]
and the function is  func(x,y)
func( func( func( func(a,b), c), d), e)
```

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Reduce Example

```
vals = [3,5,2,4,1]
sum(x,y) { return x + y }
sum( sum( sum( sum(3,5), 2), 4), 1) = 15
```

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Pair RDD

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Pair RDDs

- Pair RDDs are a special type of RDDs that can store key value pairs.
- Can be created through regular map operations
- All transformations for regular RDDs available for Pair RDDs
- Spark supports a set of special functions to handle Pair RDD operations
  - mapValues : transform each value without changing the key
  - flatMapValues : generate multiple values with the same key

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Pair RDD Actions

- countByKey – produces a count by each key in the RDD
- groupByKey – perform aggregation like sum, average by key
- reduceByKey – perform reduce, but by key
- aggregateByKey – perform aggregate by key
- Join - join multiple RDDs with the same key

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Advanced Spark

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Local Variables in Spark

- Spark makes copies of your code (one per partition) and executes them
- Any variable you create in the base programming language are local to a cluster
- Duplicate copies of local variables for each cluster
- Each variable acted upon independently

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Broadcast variables

- A read-only variable that is shared by all nodes
- Used for lookup tables or similar functions
- Spark optimizes distribution and storage for better performance.

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Accumulators

- A shared variable across nodes that can be updated by each node
- Helps compute items not done through reduce operations
- Spark optimizes distribution and takes care of race conditions

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Partitioning

- By default all RDDs are partitioned
  - spark.default.parallelism parameter
  - Default is the total no. of cores available across the entire cluster
- Should configure for large clusters
- Can be specified during RDD creation explicitly
- Derived RDD take the same number as the source.

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Persistence

- By default, Spark loads an RDD whenever it required. It drops it once the action is over
  - It will load and re-compute the RDD chain, each time a different operation is performed
- Persistence allows the intermediate RDD to be persisted so it need not have to be recomputed.
- persist() can persist the RDD in memory, disk, shared or in other third party sinks
- cache() provides the default persist() – in memory

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Spark SQL

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Overview

- A library built on Spark Core that supports SQL like data and operations
- Make it easy for traditional RDBMS developers to transition to big data
- Works with “structured” data that has a schema
- Seamlessly mix SQL queries with Spark programs.
- Supports JDBC
- Helps “mix” n “match” different RDBMS and NoSQL Data sources

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Spark Session

- All functionality for Spark SQL accessed through a Spark Session
- Data Frames are created through Spark Session
- Provides a standard interface to work across different data sources
- Can register Data Frames as temp table and then run SQL queries on them

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DataFrame

- A distributed collection of data organized as rows and columns
- Has a schema – column names, data types
- Built upon RDD, Spark optimizes better since it knows the schema
- Can be created from and persisted to a variety of sources
  - CSV
  - Database tables
  - Hive / NoSQL tables
  - JSON
  - RDD

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Operations supported by Data Frames

- `filter` – filter data based on a condition
- `join` – join two Data Frames based on common column
- `groupBy` – group data frames by specific column values
- `agg` – compute aggregates like sum, average.
- Operations can be nested.

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Temp Tables

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Temp tables / Views

- Provide SQL table like operations
- A “wrapper” around a data frame
- Execute ANSI SQL Queries against temp tables.
- Very simple and yet very powerful
- A query on a Temp table generates another data frame
- `createOrReplaceTempView` – register the Data Frame as a table within SQL Session
- SparkSession provides the ability to execute SQL

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Spark Streaming

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Why Spark Streaming?

- Typically, Analytics is performed on data at rest
  - Databases, flat files etc.
- Some use cases require real time analytics
  - Fraud detection, click stream processing
- Spark Streaming is built for this purpose
- Spark Streaming helps you to
  - Look at data as they are created/arrive from source
  - Transform, summarize, analyze
  - Perform machine learning
  - Predict in real time

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When to use Spark Streaming

- Credit Card Fraud Detection
- Spam Filtering
- Network Intrusion Detection
- Real time social media analytics
- Click Stream analytics and recommendations
- Ad recommendations
- Stock Market analytics

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What sources does Spark Streaming supports?

- Flat files (as they are created)
- TCP/IP
- Apache Flume
- Apache Kafka
- Amazon Kinesis
- Twitter, Facebook and other social media

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Streaming Architecture

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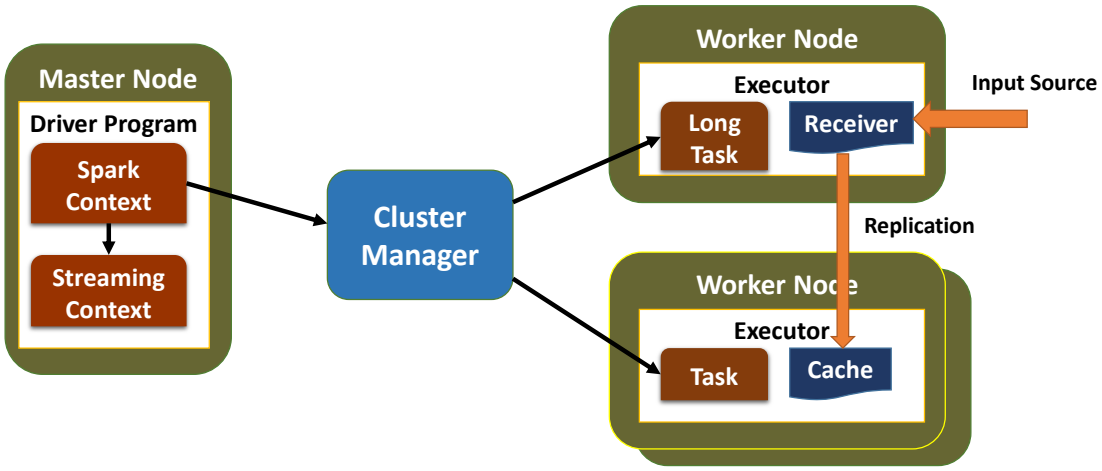
Spark Streaming Architecture



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DStreams

- A Streaming context is created from the Spark context to enable streaming
- Streaming creates a DStream (Discretized Stream) on which processing occurs
- A micro-batch window is setup for the DStream
- Data is received, accumulated as a micro-batch and processed as a micro-batch
- Each micro-batch is an RDD
- Regular RDD operations can be applied on the DStream RDD

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DStream processing

- Spark collects incoming data for each interval (micro-batch)
- Data is collected as an RDD for that interval.
- It then calls all transformations and operations that applies for that DStream or derived DStreams
- Global variables can be used to track data across DStreams
- Windowing functions are available for computing across multiple DStreams.
  - Window size multiple of interval
  - Sliding interval multiple of interval

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Types of Analytics

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Machine Learning with Spark

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Overview

- Make ML practical and easy.
- Contains algorithms and utilities
- Packages
  - spark.mllib – original APIs built on RDDs
  - spark.ml – new higher level API built on DataFrames (Spark SQL) and pipelines
- http://spark.apache.org/docs/latest/ml-guide.html
- Special data types
  - Local vector
  - Labeled Point

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Local Vector

- A vector of double values
- Dense Vector
  - (1.0, 3.0, 4.5)
- Sparse Vector
  - Original : (1.0,0.0,0.0,2.0,0.0)
  - Representation: (5, (0,3), (1.0,2.0)

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Labeled Point

- Represents a Data point in ML
- Contains a “label” (the target variable) and a list of “features” (the predictors)
- LabeledPoint(1.0, Vectors.dense(1.0,0.0,3.0))

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Pipelines

- A pipeline consist of a series of transformations and actions that need to be performed to create a model
  - DataFrame (the source)
  - Transformers (data transformations)
  - Estimators (model building)
  - Parameters (common parameters across algorithms)
- Internally optimized for better parallelism and resource utilization

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Spark Project Work flow

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Project Work flow

- Problem statement and Questions to Answer
- Acquire Data
- Process Data
  - Cleanse, Filter, Augment
- Exploratory Analysis
- Machine Learning
  - Correlation Analysis
  - Training and Test split
  - Model building
  - Prediction
- Action
- Feedback

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Analytics and Predictions

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Types of Analytics

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Types of Analytics

Type of Analytics	Description
Descriptive	Understand what happened
Exploratory	Find out why something is happening
Inferential	Understand a population from a sample
Predictive	Forecast what is going to happen
Causal	What happens to one variable when you change another
Deep	Use of advanced techniques to understand large and multi-source datasets

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Exploratory Data Analysis

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Goals of EDA

- Understand the predictors and targets in the data set
  - Spreads
  - Correlations
- Uncover the patterns and trends
- Find key variables and eliminate unwanted variables
- Detect outliers
- Validate previous data ingestion processes for possible mistakes
- Test assumptions and hypothesis

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Tools used for EDA

- Correlation matrices
- Boxplots
- Scatterplots
- Principal component Analysis
- Histograms

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Machine Learning

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Overview

- Data contains attributes
- Attributes show relationships (correlation) between entities
- Learning – understanding relationships between entities
- Machine Learning – a computer analyzing the data and learning about relationships
- Machine Learning results in a model built using the data
- Models can be used for grouping and prediction

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Data for machine learning

- Machines only understand numbers
- Text Data need to be converted to equivalent numerical representations for ML algorithms to work.
- Number representation
  - (Excellent, Good, Bad can be converted to 1,2,3)
- Boolean variables
  - 3 new Indicator variables called Rating-Excellent, Rating-Good, Rating-Bad with values 0/1
- Document Term matrix

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Unsupervised Learning

- Finding hidden structure / similarity / grouping in data
- Observations grouped based on similarity exhibited by entities
- Similarity between entities could be by
  - Distance between values
  - Presence / Absence
- Types
  - Clustering
  - Association Rules Mining
  - Collaborative Filtering

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Supervised Learning

- Trying to predict unknown data attributes (outcomes) based on known attributes (predictors) for an entity
- Model built based on training data (past data) where outcomes and predictors are known
- Model used to predict future outcomes
- Types
  - Regression (continuous outcome values)
  - Classification (outcome classes)

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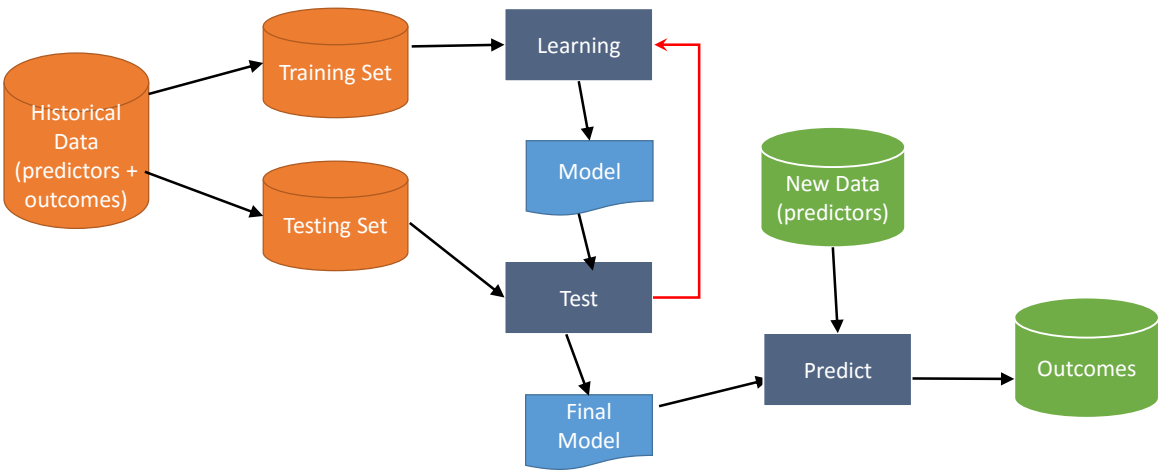
Supervised Learning Process



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Training and Testing Data

- Historical Data contains both predictors and outcomes
- Split as training and testing data
- Training data is used to build the model
- Testing data is used to test the model
  - Apply model on testing data
  - Predict the outcome
  - Compare the outcome with the actual value
  - Measure accuracy
- Training and Test fit best practices
  - 70-30 split
  - Random selection of records. Should maintain data spread in both datasets

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Comparing Results

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Confusion Matrix

- Plots the predictions against the actuals for the test data
- Helps understand the accuracy of the predictions
- Predictions can be Boolean or classes

		Actual		
		TRUE	**FALSE**	**Total**
Prediction	**TRUE**	44	6	50
	FALSE	9	41	50
	Total	53	47	100

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Prediction Types

- The importance of prediction types vary by the domain
- True Positive (TP) and True Negative (TN) are the correct predictions
- False Negative (FN) can be critical in medical field
- False Positive (FP) can be critical in judicial field

		Actual	
		TRUE	**FALSE**
Prediction	**TRUE**	True Positive	False Positive
	FALSE	False Negative	True Negative

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Confusion Matrix metrics

- Accuracy
  - Measures the accuracy of the prediction
  - Accuracy = (TP + TN) / (TP + TN + FP + FN)
- Sensitivity
  - Hit rate or recall
  - Sensitivity = TP / (TP + FN)
- Specificity
  - True negative rate
  - Specificity = TN / (TN + FP)
- Precision
  - Precision = TP / (TP + FP)

		Actual	
		TRUE	**FALSE**
Prediction	**TRUE**	True Positive	False Positive
	FALSE	False Negative	True Negative

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Prediction Errors

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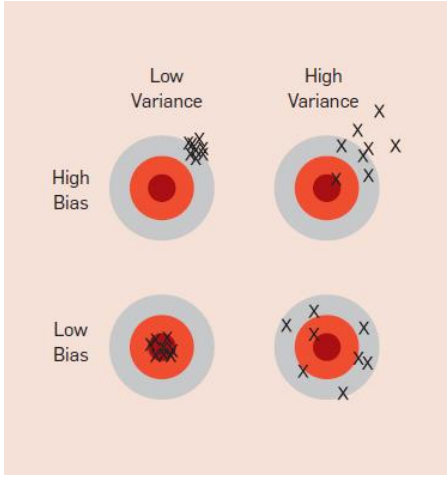
Bias and Variance

- Bias happens when the model "skews" itself to certain aspects of the predictors, while ignoring others. It is the error between prediction and actuals.
- Variance refers to the stability of a model – Keep predicting consistently for new data sets. It is the variance between predictions for different data sets.



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Types of Errors

- In-Sample error is the prediction error when the model is used to predict on the training data set it is built upon.
- Out-of-sample error is the prediction error when the model is used to predict on a new data set.
- Over fitting refers to the situation where the model has very low in-sample error, but very high out-of-sample error. The model has "over fit" itself to the training data.

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Linear Regression

Linear Relationships

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Regression Analysis

- Method of investigating functional relationship between variables
- Estimate the value of dependent variables from the values of independent variables using a relationship equation
- Used when the dependent and independent variables are continuous and have some correlation.
- Goodness of Fit analysis is important.

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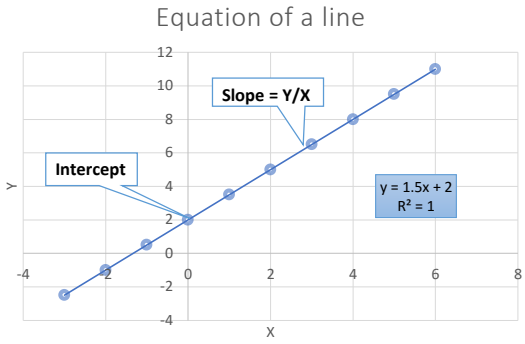
Linear Equation

- X is the independent variable
- Y is the dependent variable
- Compute Y from X using

$$Y = \alpha X + \beta$$

Coefficients:

- α = Slope = Y/X
- β = Intercept = value of Y when X=0



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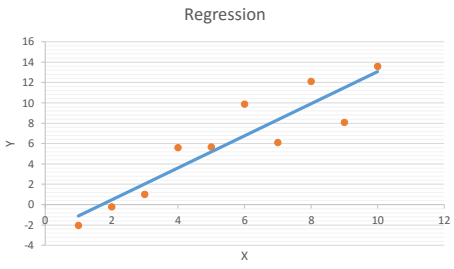
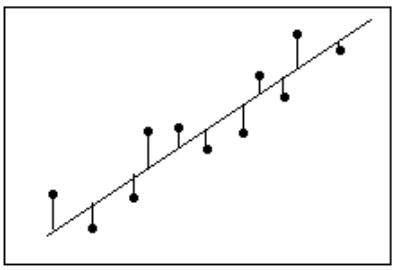
Fitting a line

- Given a scatter plot of Y vs X, fit a straight line through the points so that the sum of square of vertical distances between the points and the line (called residuals) is minimized
- Best line = least residuals
- A line can always be fitted for any set of points
- The equation of the line becomes the predictor for Y





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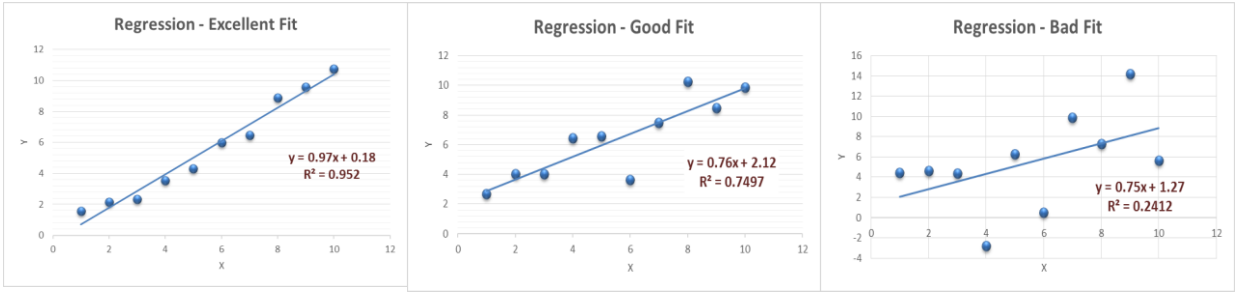
Goodness of Fit

- R-squared measures how close the data is to the fitted line
- R-squared varies from 0 to 1. The higher the value, the better the fit
- You can always fit a line. Use R-squared to see how good the fit is
- Higher correlation usually leads to better fit



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Multiple regression

- When there are more than one independent variable that is used to predict the dependent variable.
- The equation $Y = \beta + \alpha_1 * X_1 + \alpha_2 * X_2 + \ldots + \alpha_p * X_p$
- Same process used for prediction as a single independent variable
- Different predictors have different levels of impact on the dependent variable

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Using Linear Regression for ML

- ML Technique to predict continuous data – supervised learning
- Predictors and outcomes provided as input
- Data analyzed (training) to come up with a linear equation
  - Coefficients
  - Intercept
  - R-squared
- Linear equation represents to model.
- Model used for prediction
- Typically fast for model building and prediction

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Summary – Linear Regression

Advantages

- Fast
- Low cost
- Excellent for linear relationships
- Relatively accurate Continuous variables

Shortcomings

- Only numeric/ continuous variables
- Cannot model non-linear / fuzzy relationships
- Sensitive to outliers

Used in

- Oldest predictive model used in a wide variety of applications to predict continuous values

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Decision Trees

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Overview

- The simplest, easy to understand and easy to explain ML technique.
- Predictor variables are used to build a tree that would progressively predict the target variable
  - Trees start with a root node that start the decision making process
  - Branch nodes refine the decision process
  - Leaf nodes provide the decisions
- Training data is used to build a decision tree to predict the target
- The tree becomes the model that is used to predict on new data

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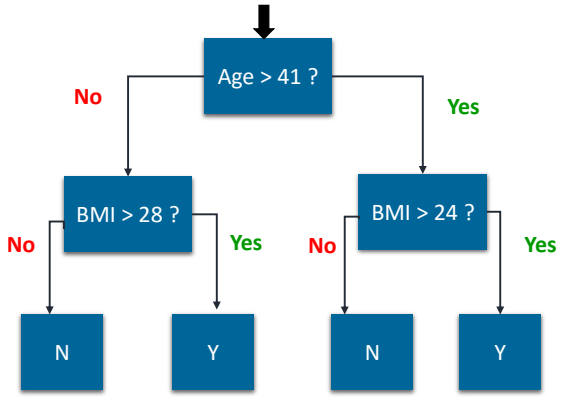
Example

Age	BMI	Is Diabetic
24	22	N
33	28	N
41	36	Y
48	24	N
58	31	Y
61	35	Y



Predicting "Is Diabetic ?"

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Choosing the right Predictors

- The depth of trees are highly influenced by the sequence in which the predictors are chosen for decisions
- Using predictors with high selectivity gives faster results
- ML implementations automatically make decisions on the sequence /preference of predictors

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Summary – Decision Trees

Advantages

- Easy to interpret and explain
- Works with missing data
- Sensitive to local variations
- Fast

Shortcomings

- Limited Accuracy
- Bias builds up pretty quickly
- Not good with large predictors

Used in

- Credit approvals
- Situations with legal needs to explain decisions
- Preliminary categorization

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Naïve Bayes

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Bayes' theorem (too) simplified

- Probability of an event A = P(A) is between 0 and 1
- Bayes' theorem gives the conditional probability of an event A given event B has already occurred.

  P(A/B) = P(A intersect B) * P (A) /P(B)
- Example
  - There are 100 patients
  - Probability of a patient having diabetes is P(A) = .2
  - Probability of patient having diabetes (A) given that the patient's age is > 50 (B) is P(A/B) = .4

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Naïve Bayes Classification

- Application of Bayes' theorem to ML
- The target variable becomes event A
- The predictors become events B1 – Bn
- We try to find P(A / B1-Bn)

Age	BMI	Is Diabetic	
24	22	N	Probability of Is Diabetic = Y given that Age = 24 and BMI = 22
41	36	Y	Probability of Is Diabetic – Y given that Age = 41 and BMI = 36

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Model building and prediction

- The model generated stores the conditional probability of the target for every possible value of the predictor.

	Overall	Age						Gender	
Salary		1 to 20	20 to 30	30 to 40	40 to 50	50 to 60	60 to 100	Female	Male
< 50K	.75	0.1	0.3	0.25	0.17	0.1	0.08	0.39	0.61
> 50K	.25	0.03	0.08	0.3	0.32	0.2	0.07	0.15	0.85
Overall		.08	.24	.26	.21	.12	.08	.33	.67

- When a new prediction needs to be done, the conditional probabilities are applied using Bayes' formula to find the probability
  - To predict for Age = 25
  - P(Salary < 50K / Age=25) = 0.3 * 0.75 / 0.24 = ~ 0.92
  - P(Salary > 50K / Age=25) = 0.08 * 0.25 / 0.24 = ~ 0.08

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Summary – Naïve Bayes

Advantages

- Simple and fast
- Works well with noisy and missing data
- Provides probabilities of the result
- Very good with categorical data

Shortcomings

- Limited Accuracy
- Expects predictors to be independent
- Not good with large numeric features

Used in

- Medical diagnosis
- Spam filtering
- Document classification
- Sports predictions

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Random Forests

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Overview

- Random Forest is one of the most popular and accurate algorithms
- It is an Ensemble method based on decision trees
  - Builds multiple models – each model a decision tree
  - For prediction – each tree is used to predict an individual result
  - A vote is taken on all the results to find the best answer

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How it works

- Lets say the dataset contains m samples (rows) and n predictors (columns)
- x trees are built, each with a subset of data
- For each tree, a subset of m rows and n columns are chosen randomly.
- For example, if the data has 1000 rows and 5 columns, each tree is built using 700 rows and 3 columns
- The data subset is used to build a tree
- For prediction, new data is passed to each of the x trees and x possible results obtained
- For example, if we are predicting buy=Y/N and there are 500 trees, we might get 350 Y and 150 N results
- The most found result is the aggregate prediction.

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Summary – Random Forest

Advantages

- Highly accurate
- Efficient on large number of predictors
- Fully parallelizable
- Very good with missing data

Shortcomings

- Time and Resource consuming
- For categorical variables, bias might exist if levels are disproportionate

Used in

- Scientific Research
- Competitions
- Medical Diagnosis

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K-means Clustering

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Overview

- Unsupervised Learning technique
- Popular method for grouping data into subsets based on the similarity
- Partitions n observations with m variables into k clusters where by each observation belongs to only one cluster
- How it works
  - An m dimensional space is created
  - Each observation is plotted based on this space based on the variable values
  - Clustering is done by measuring the distance between points and grouping them
- Multiple types of distance measures available like Euclidian distance and Manhattan distance

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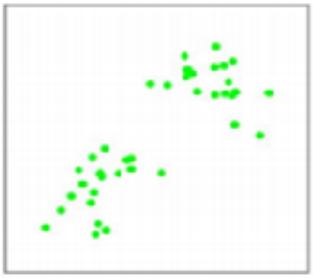
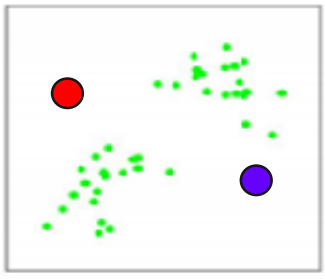
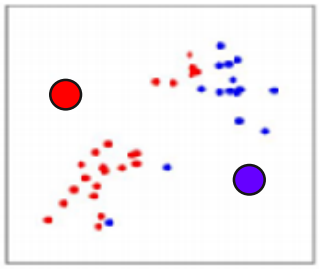
Clustering - Stages



- Dataset contains only m=2 variables. We will create k=2 clusters
- Plot observations on a two dimensional plot



- Choose k=2 centroids at random
- Measure the distance between each observation to each centroid



- Assign each observation to the nearest centroid
- This forms the clusters for round 1

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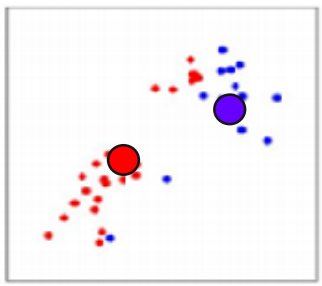
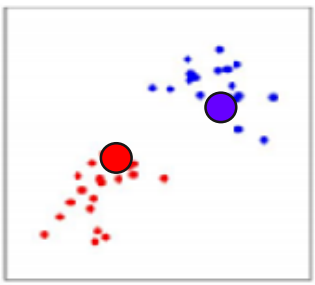
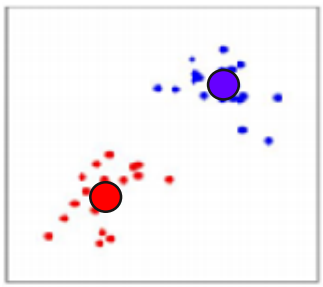
Clustering - Stages



- Find the centroid of each of the cluster
- Centroid is the point where the sum of distances between the centroid and each point is minimum



- Repeat the process of finding the distance between each observation to each centroid (the new one) and reassign each point to the nearest one



- Find the centroid for the new clusters
- Repeat the process until the centroids don't move

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Summary – K-means clustering

Advantages

- Fast
- Efficient with large number of variables
- Explainable

Shortcomings

- K needs to be known
- The initial centroid position has influence on clusters formed

Used in

- Preliminary grouping of data before other classification
- General grouping
- Geographical clustering

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Collaborative Filtering

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Dimensionality Reduction

Principal Component Analysis

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Issues with too many predictors

- Memory requirements
- CPU requirements / time taken for machine learning algorithms
- Correlation between predictors
- Over fitting
- Some ML algorithms don't work fine with too many predictors

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Manual selection

- Using domain knowledge
  - Purely based on hypothesis
  - Risky – there could be unknown correlations
- Using Correlation co-efficients
  - Variables with good correlation can only be picked up.
- Using Decision Trees
  - Decision trees are fast and choose variables based on correlation
  - Variables used in the decision trees can be picked for further processing

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Principal Component Analysis

- Used to reduce the number of predictors
- Based on Eigen Vectors and Eigen Values.
- Given a set of M predictors, PCA transforms this to a set of N predictors such that N < M
- The new predictors are derived predictors called PC1, PC2, PC3
- The new predictors retain similar levels of correlation and predictability like the original predictors

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Recommendation Engines

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What is a Recommendation Engine?

- Also called Collaborative filtering
- Analyze past data to understand user / entity behavior
- Identify "similar" items /users / entities
- Recommend based on similarity of behavior
- Example
  - Tom and Chris both like similar items. In the past 1 year, Tom has brought 42 items and Chris has brought 35 items. 28 of these are same.
  - Tom buys a new item which Chris has not bought. Recommend that to Chris.
- Used by
  - Netflix for movie recommendations
  - Amazon for product recommendations
  - YouTube for video recommendations

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Recommendation Types

- User based Recommendations
  - Identify similar users and form User neighborhoods.
  - If one user buys a new product, recommend that to all users in the neighborhood.
  - "Similar customers brought…"
- Item based Recommendations
  - Identify Items that are frequently brought together.
  - If one item is brought by a user, recommend the related items to the user.
  - "Users who brought this item also brought…"

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Input for Recommenders

- Recommender algorithms take as input as specific format
  - User ID
  - Item ID
  - Score
- Scores indicate relative preference of the user for the item
  - Boolean values
  - Rating scores
  - Measure of sales volume

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Building a User based recommender

- Find affinity scores between users based on similarity of behavior.
  - Uses similarity measures like cosine similarity, Pearson correlation etc.
- For user neighborhoods with each neighborhood containing users with high inter-user scores.
- If one user shows a new behavior (buys an item), recommend that to other users in the neighborhood.
- Continuous processing of past data and building of neighborhoods.

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Building a Item based recommender

- Find affinity scores between items based on usage (used together).
  - Uses similarity measures like cosine similarity, Pearson correlation etc.
- If one item is brought by a user, recommend items with high similarity scores with that item.
- Continuous processing of past data and building of neighborhoods.
- Item based recommenders are superior to user based, since
  - No. of items are limited
  - More usage data available since the list of items are relatively static.