Learning R Series

Session 1: Introduction to Oracle's R Technologies and Oracle R Enterprise 1.3

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Oracle Advanced Analytics

Learning R Series 2012

Session	Title
Session 1	Introduction to Oracle's R Technologies and Oracle R Enterprise 1.3
Session 2	Oracle R Enterprise 1.3 Transparency Layer
Session 3	Oracle R Enterprise 1.3 Embedded R Execution
Session 4	Oracle R Enterprise 1.3 Predictive Analytics
Session 5	Oracle R Enterprise 1.3 Integrating R Results and Images with OBIEE Dashboards
Session 6	Oracle R Connector for Hadoop 2.0 New features and Use Cases

The following is intended to outline our general product direction. It is intended for information purposes only, and may not be incorporated into any contract. It is not a commitment to deliver any material, code, or functionality, and should not be relied upon in making purchasing decisions.

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Topics

- Introduction
  - R
  - Oracle’s R Strategy
  - Oracle R Enterprise overview
- New features in Oracle R Enterprise 1.3
- Analytics Example and Scenario
- Oracle Advanced Analytics Option
- Summary

What is R?

- **R is an Open Source scripting language and environment for statistical computing and graphics**
  http://www.R-project.org/
- **Started in 1994 as an Alternative to SAS, SPSS & Other proprietary Statistical Environments**
- **The R environment**
  – R is an integrated suite of software facilities for data manipulation, calculation and graphical display
- **Around 2 million R users worldwide**
  – Widely taught in Universities
  – Many Corporate Analysts and Data Scientists know and use R
- **Thousands of open sources packages to enhance productivity such as:**
  – Bioinformatics with R
  – Spatial Statistics with R
  – Financial Market Analysis with R
  – Linear and Non Linear Modeling

CRAN
Mirrors
What's new?
Task Views
Search

About R
R Homepage
The R Journal

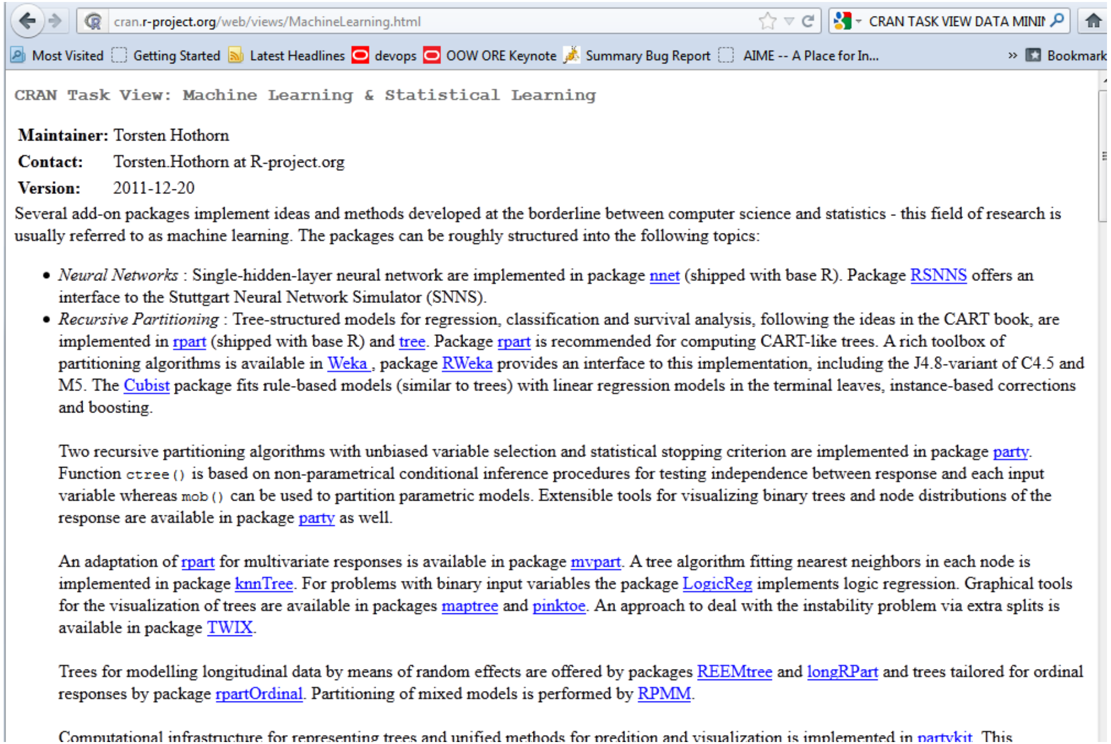
Software
R Sources
R Binaries
Packages
Other

Documentation
Manuals
FAQs
Contributed

CRAN Task Views

Bayesian	Bayesian Inference
ChemPhys	Chemometrics and Computational Physics
ClinicalTrials	Clinical Trial Design, Monitoring, and Analysis
Cluster	Cluster Analysis & Finite Mixture Models
Distributions	Probability Distributions
Econometrics	Computational Econometrics
Environmetrics	Analysis of Ecological and Environmental Data
ExperimentalDesign	Design of Experiments (DoE) & Analysis of Experimental Data
Finance	Empirical Finance
Genetics	Statistical Genetics
Graphics	Graphic Displays & Dynamic Graphics & Graphic Devices & Visualization
gR	gRaphical Models in R
HighPerformanceComputing	High-Performance and Parallel Computing with R
MachineLearning	Machine Learning & Statistical Learning
MedicalImaging	Medical Image Analysis
Multivariate	Multivariate Statistics
NaturalLanguageProcessing	Natural Language Processing
OfficialStatistics	Official Statistics & Survey Methodology
Optimization	Optimization and Mathematical Programming
Pharmacokinetics	Analysis of Pharmacokinetic Data
Phylogenetics	Phylogenetics, Especially Comparative Methods
Psychometrics	Psychometric Models and Methods
ReproducibleResearch	Reproducible Research
Robust	Robust Statistical Methods
SocialSciences	Statistics for the Social Sciences
Spatial	Analysis of Spatial Data
Survival	Survival Analysis
TimeSeries	Time Series Analysis

CRAN Task View –
Machine Learning & Statistical Learning



CRAN Task View: Machine Learning & Statistical Learning

Maintainer: Torsten Hothorn
Contact: Torsten.Hothorn at R-project.org
Version: 2011-12-20

Several add-on packages implement ideas and methods developed at the borderline between computer science and statistics - this field of research is usually referred to as machine learning. The packages can be roughly structured into the following topics:

- *Neural Networks* : Single-hidden-layer neural network are implemented in package nnet (shipped with base R). Package RSNNS offers an interface to the Stuttgart Neural Network Simulator (SNNS).
- *Recursive Partitioning* : Tree-structured models for regression, classification and survival analysis, following the ideas in the CART book, are implemented in rpart (shipped with base R) and tree. Package rpart is recommended for computing CART-like trees. A rich toolbox of partitioning algorithms is available in Weka , package RWeka provides an interface to this implementation, including the J4.8-variant of C4.5 and M5. The Cubist package fits rule-based models (similar to trees) with linear regression models in the terminal leaves, instance-based corrections and boosting.

  Two recursive partitioning algorithms with unbiased variable selection and statistical stopping criterion are implemented in package party. Function `ctree()` is based on non-parametrical conditional inference procedures for testing independence between response and each input variable whereas `mob()` can be used to partition parametric models. Extensible tools for visualizing binary trees and node distributions of the response are available in package party as well.

  An adaptation of rpart for multivariate responses is available in package mvpart. A tree algorithm fitting nearest neighbors in each node is implemented in package knnTree. For problems with binary input variables the package LogicReg implements logic regression. Graphical tools for the visualization of trees are available in packages maptree and pinktoe. An approach to deal with the instability problem via extra splits is available in package TWIX.

  Trees for modelling longitudinal data by means of random effects are offered by packages REEMtree and longRPart and trees tailored for ordinal responses by package rpartOrdinal. Partitioning of mixed models is performed by RPMM.

  Computational infrastructure for representing trees and unified methods for predition and visualization is implemented in partykit. This

- ahaz
- arules
- BayesTree
- Boruta
- BPHO
- bst
- caret
- CORElearn
- CoxBoost
- Cubist
- e1071 (core)
- earth
- elasticnet
- ElemStatLearn
- evtree
- gafit
- GAMBoost
- gamboostLSS
- gbev
- gbm (core)
- glmnet
- glmpath
- GMMBoost
- grplasso
- hda
- ipred
- kernlab (core)
- klaR
- lars
- lasso2
- LiblineaR
- LogicForest
- LogicReg
- longRPart
- mboost (core)
- mvpart
- ncvreg
- nnet (core)
- oblique.tree
- obliqueRF
- pamr
- party
- partykit
- penalized
- penalizedSVM
- predbayescor
- quantregForest
- randomForest (core)
- randomSurvivalForest
- rattle
- rda
- rdetools
- REEMtree
- relaxo
- rgenoud
- rgp
- rminer
- ROCR
- rpart (core)
- rpartOrdinal
- RPMM
- RSNNS
- RWeka
- sda
- SDDA
- svmpath
- tgp
- tree
- TWIX
- varSelRF

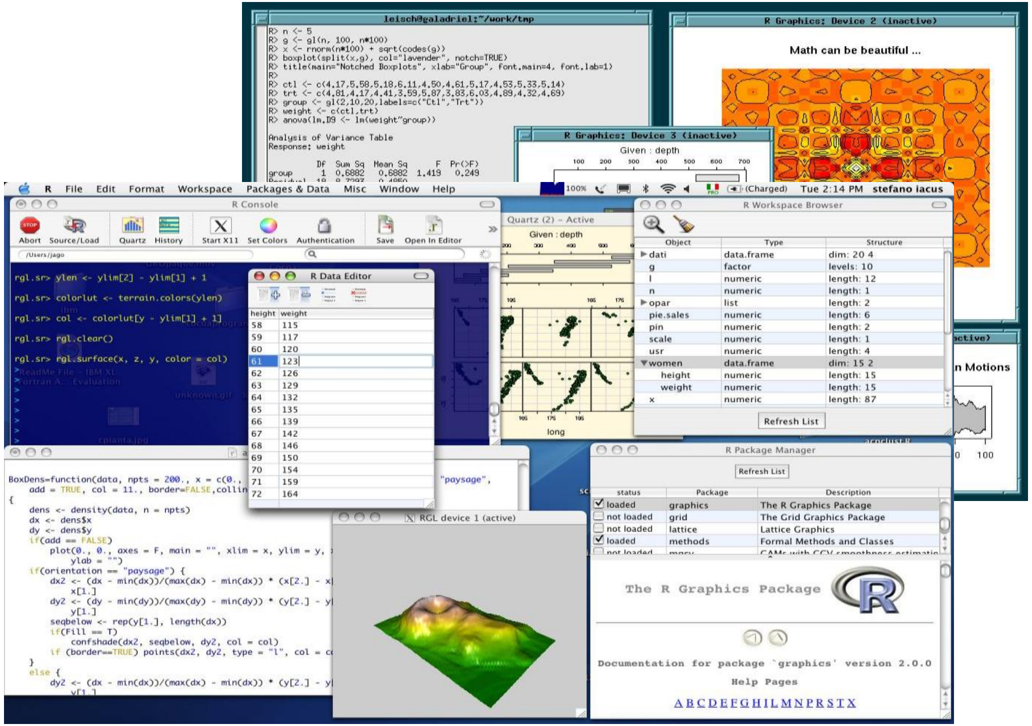
Why statisticians/data analysts use R

R is a statistics language similar to Base SAS or SPSS statistics

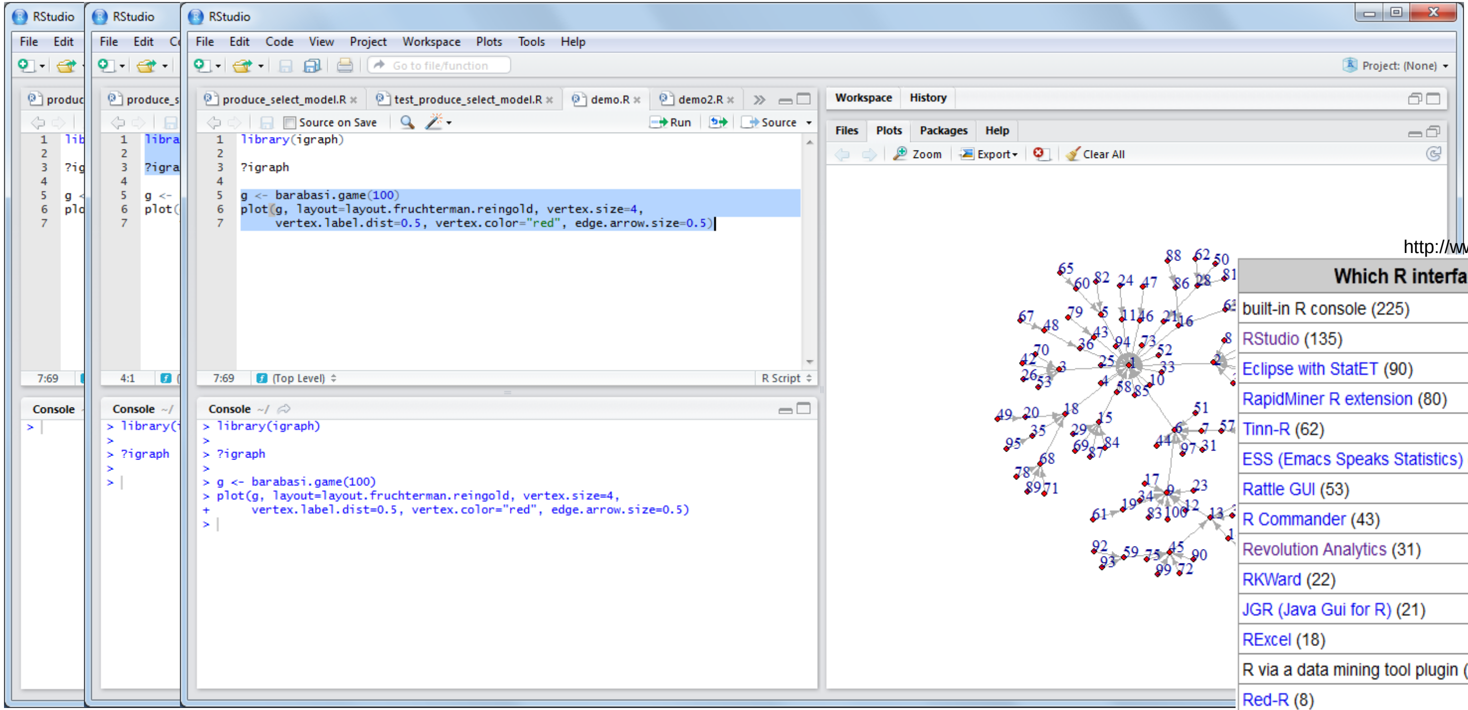
R environment is ..

- Powerful
- Extensible
- Graphical
- Extensive statistics
- OOTB functionality with
  many ‘knobs’ but
  smart defaults
- Ease of installation and use
- ***Free***

  http://cran.r-project.org/



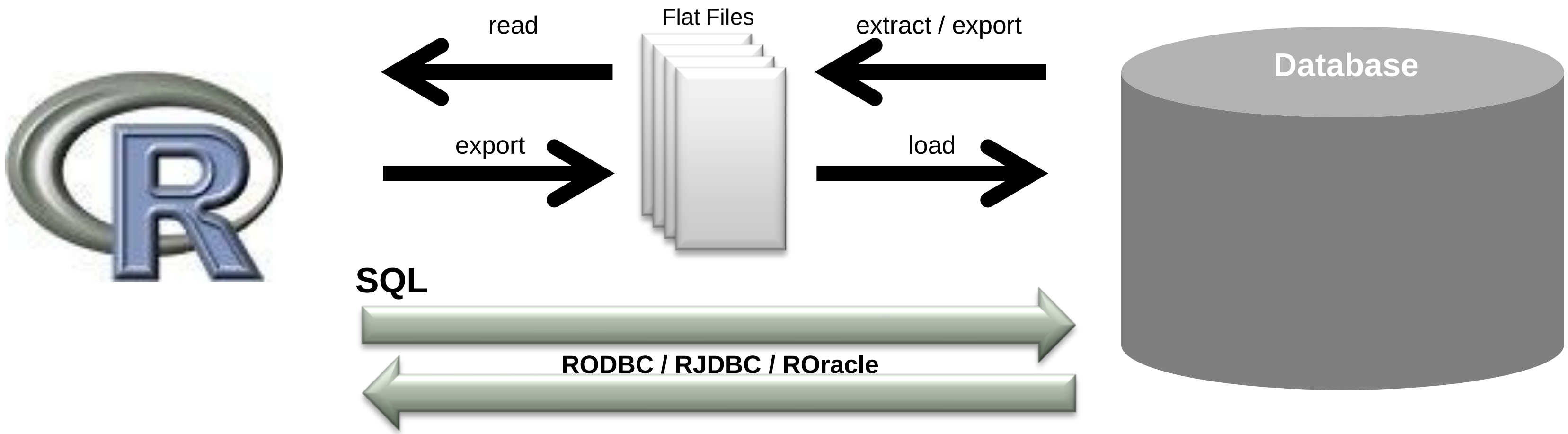
Third Party Open Source IDEs, e.g., RStudio



http://www.kdnuggets.com/polls/2011/r-gui-used.htm

Which R interfaces do you use frequently?	
built-in R console (225)	40%
RStudio (135)	24%
Eclipse with StatET (90)	16%
RapidMiner R extension (80)	14.2%
Tinn-R (62)	11%
ESS (Emacs Speaks Statistics) (59)	10.5%
Rattle GUI (53)	9.4%
R Commander (43)	7.7%
Revolution Analytics (31)	5.5%
RKWard (22)	3.9%
JGR (Java Gui for R) (21)	3.7%
RExcel (18)	3.2%
R via a data mining tool plugin (12)	2.1%
Red-R (8)	1.4%
SciViews-R (6)	1.1%
Other (44)	7.8%

Traditional R and Database Interaction



- Paradigm shift: R → SQL → R
- R memory limitation – data size, call-by-value
- R single threaded
- Access latency, backup, recovery, security…?
- Ad hoc script execution

Oracle R Enterprise enhances open source R

- Analyze and manipulate data in Oracle Database through R, transparently
- Execute R scripts through the database with data and task parallelism
- Use in-database Predictive Analytics algorithms seamlessly through R
- Scoring R models in the database
- R scripts integrated into SQL language dynamically
- Integrate R into the IT software stack

Oracle’s R Strategic Offerings

Deliver enterprise-level advanced analytics based on R environment

- Oracle R Enterprise
  - Transparent access to database-resident data from R
  - Embedded R script execution through database managed R engines with SQL language integration
  - Statistics engine
- Oracle R Distribution
  - Free download, pre-installed on Oracle Big Data Appliance, bundled with Oracle Linux
  - Enterprise support for customers of Oracle R Enterprise, Big Data Appliance, and Oracle Linux
  - Enhanced linear algebra performance using Intel, AMD, or Solaris libraries
- ROracle
  - Open source Oracle *database interface driver* for R based on OCI
  - Maintainer is Oracle – rebuilt from the ground up
  - Optimizations and bug fixes made available to open source community
- Oracle R Connector for Hadoop
  - R interface to Oracle Hadoop Cluster on BDA
  - Access and manipulate data in HDFS, database, and file system
  - Write MapReduce functions using R and execute through natural R interface
  - Leverage several native Hadoop-based analytic techniques that are part of ORCH package

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Oracle R Distribution

Ability to dynamically load

Intel Math Kernel Library (MKL)

AMD Core Math Library (ACML)

Solaris Sun Performance Library

Oracle Support

- Improve scalability at client and database for embedded R execution
- Enhanced linear algebra performance using Intel's MKL, AMD's ACML, and Sun Performance Library for Solaris
- Enterprise support for customers of Oracle Advanced Analytics option, Big Data Appliance, and Oracle Linux
- Free download
- Oracle to contribute bug fixes and enhancements to open source R

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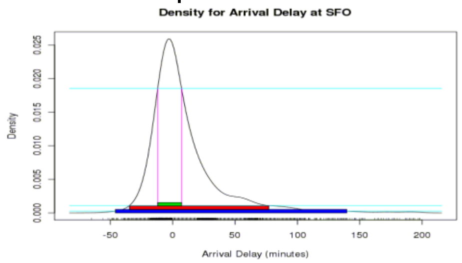
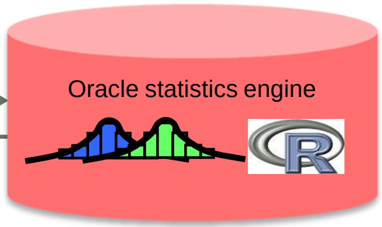
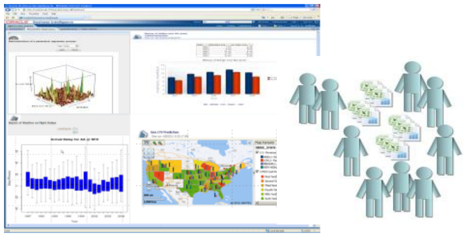
Oracle R Enterprise

R workspace console



Function push-down –
data transformation & statistics





OBIEE, Web Services

No changes to the user experience

Scale to large data sets

Embed in operational systems

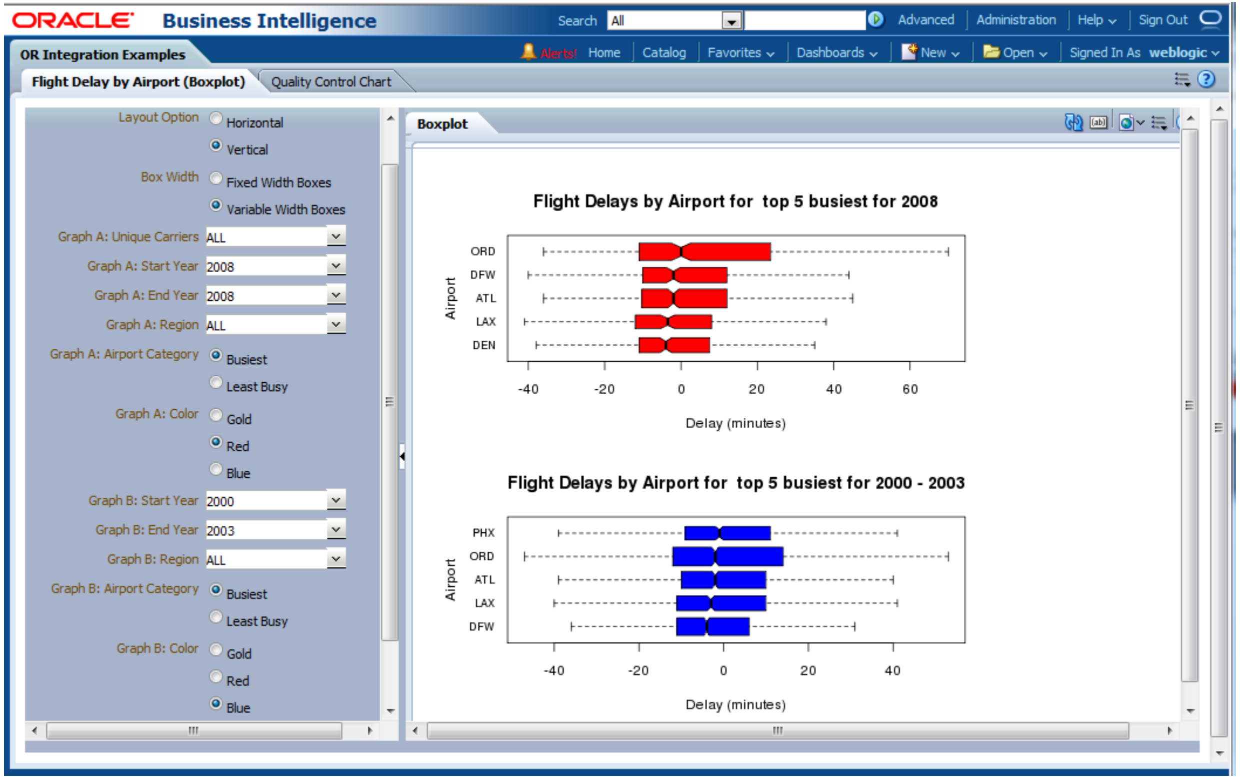
Development

Production

Consumption

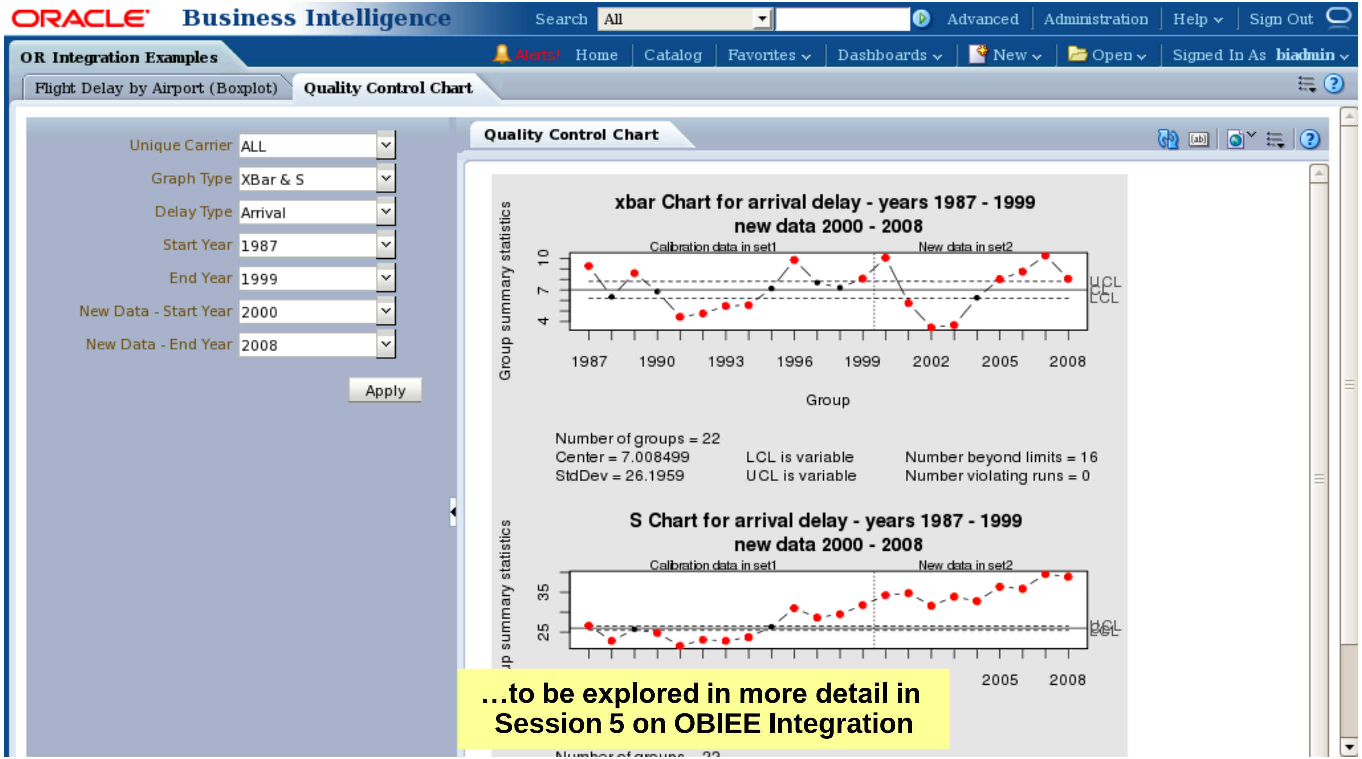
OBIEE Dashboard

Parameterized data selection and graph customization

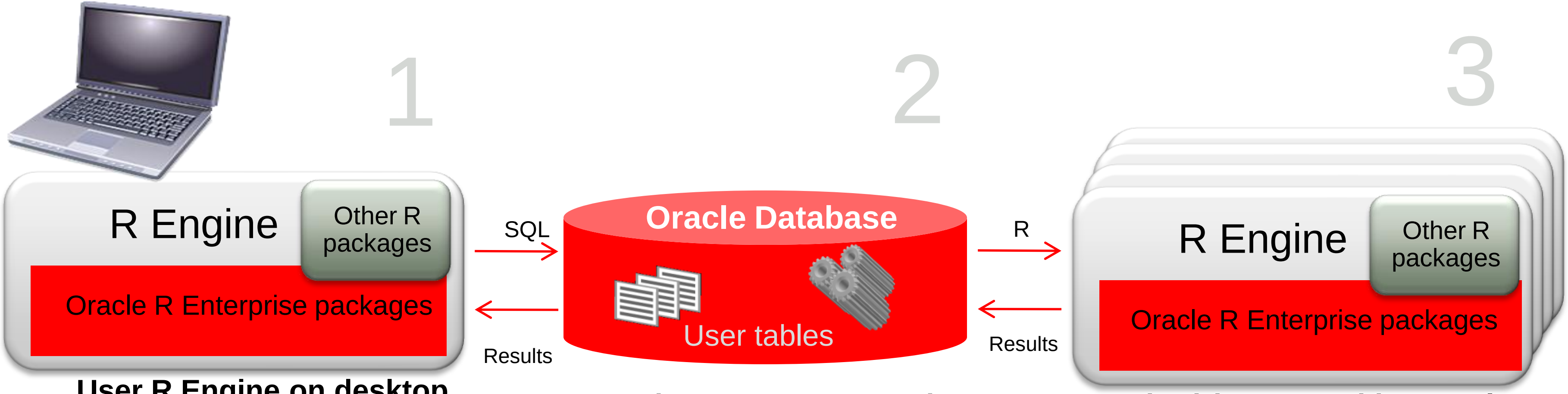


OBIEE Dashboard

Leverage open source R packages



Collaborative Execution Model



User R Engine on desktop

- R-SQL Transparency Framework intercepts R functions for scalable in-database execution
- Interactive display of graphical results and flow control as in standard R
- Submit entire R scripts for execution by Oracle Database

Post processing of results

Database Compute Engine

- Scale to large datasets
- Leverage database SQL parallelism
- Leverage in-database statistical and data mining capabilities

Collaborative execution with in-database R engine

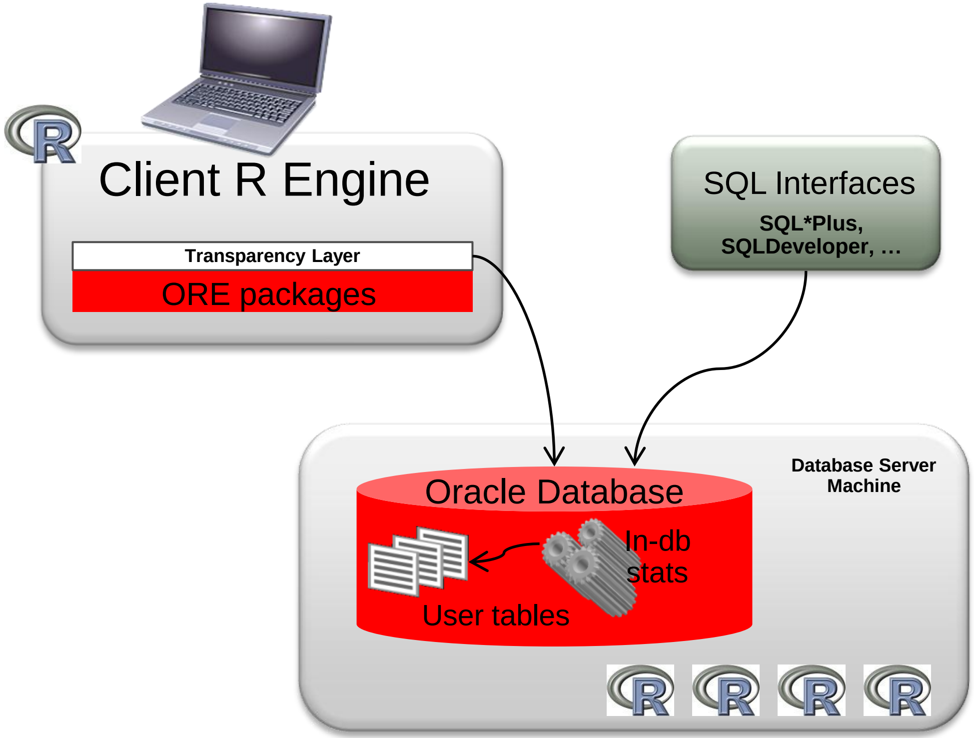
R Engine(s) managed by Oracle DB

- Database manages multiple R engines for database-managed parallelism
- Efficient parallel data transfer to spawned R engines to emulate map-reduce style algorithms and applications
- Enables “lights-out” execution of R scripts

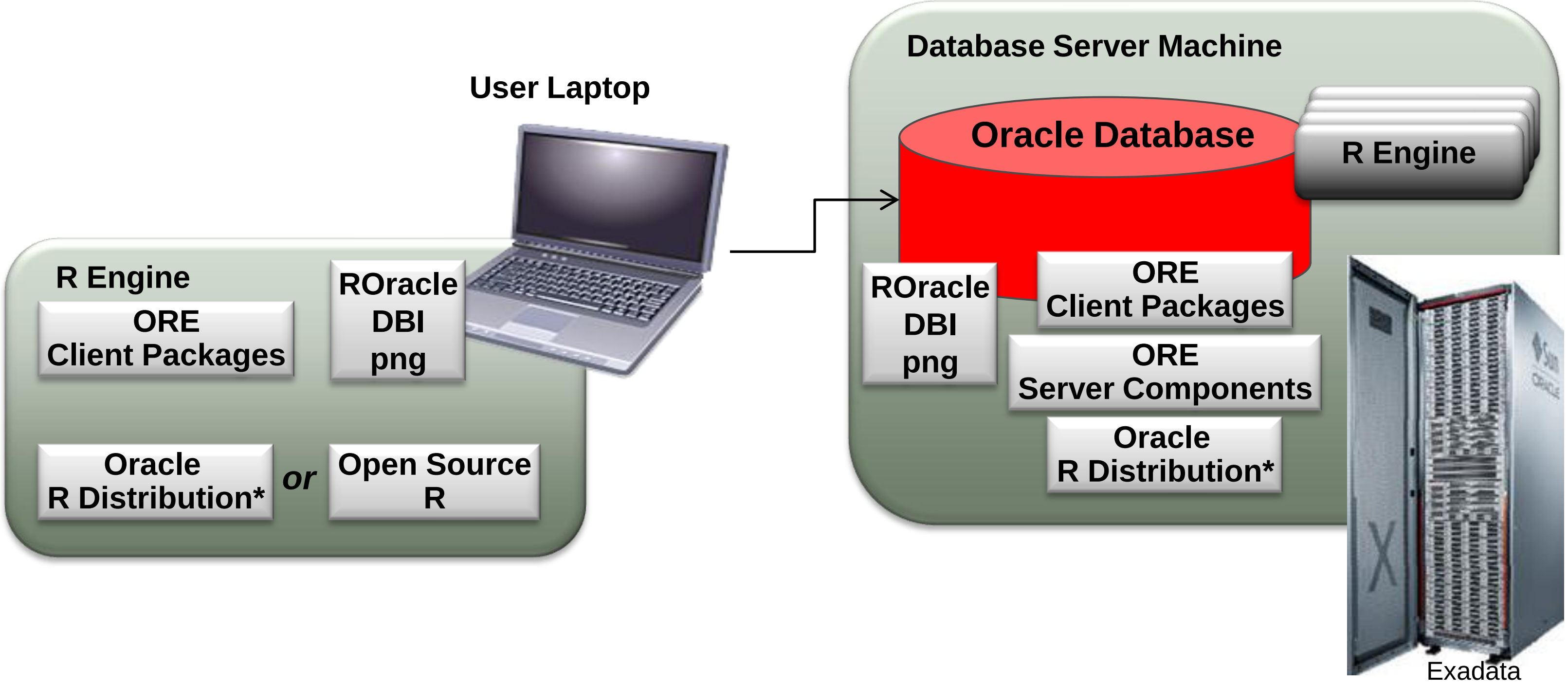
Analytic techniques not available in-database

Target Environment with ORE

- Eliminate memory constraint with client R engine
- Execute R scripts at database server machine for scalability and performance
- Execute R scripts in *data parallel* or *task parallel* with database spawned and controlled R engines
- Get maximum value from your Oracle Database
- Get even better performance with Exadata
- Enable integration and management through SQL



Oracle R Enterprise – Packages and R Engines



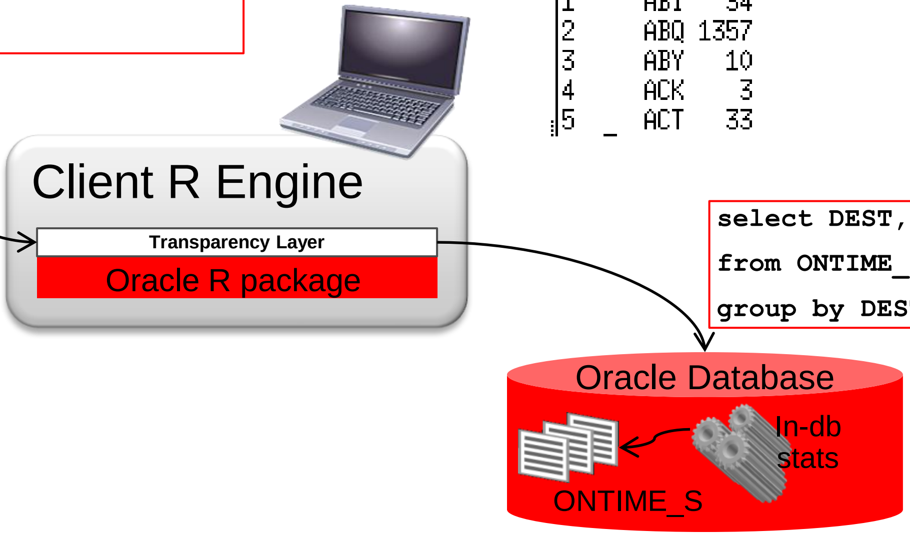
* ORD available on Linux, AIX, Solaris, SPARC platforms

Transparency Layer

Aggregation function on ore.frame object

```
aggdata <- aggregate(ONTIME_S$DEST,
                     by = list(ONTIME_S$DEST),
                     FUN = length)
class(aggdata)
head(aggdata)
```

```
R> aggdata <- aggregate(ONTIME_S$DEST,
+                       by = list(ONTIME_S$DEST),
+                       FUN = length)
R> class(aggdata)
[1] "ore.frame"
attr(,"package")
[1] "OREbase"
R> head(aggdata)
  Group.1    x
0     ABE  237
1     ABI   34
2     ABQ 1357
3     ABY   10
4     ACK    3
5     ACT   33
```

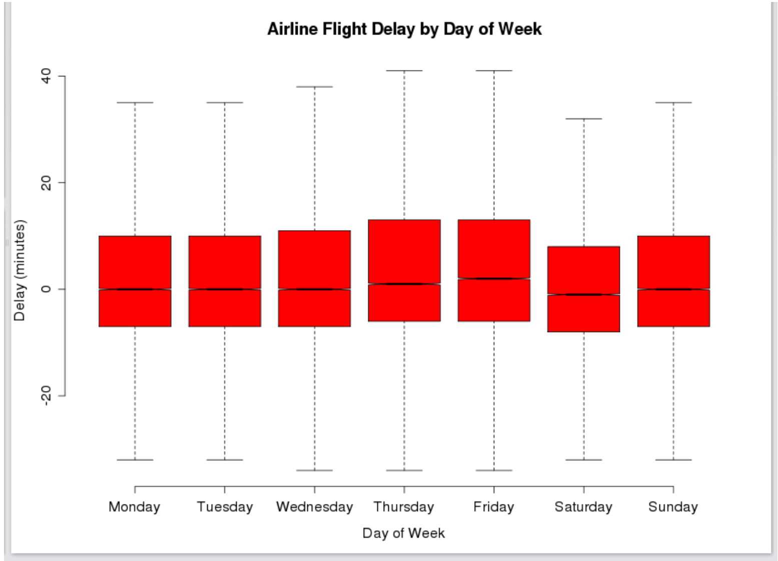



```
select DEST, count(*)
from ONTIME_S
group by DEST
```

Transparency Layer

Overloads graphics functions for in-database statistics

```
ontime <- ONTIME_S
delay <- ontime$ARRDELAY
dayofweek <- ontime$DAYOFWEEK
bd <- split(delay, dayofweek)
boxplot(bd, notch = TRUE, col = "red", cex = 0.5,
        outline = FALSE, axes = FALSE,
        main = "Airline Flight Delay by Day of Week",
        ylab = "Delay (minutes)", xlab = "Day of Week")
axis(1, at=1:7, labels=c("Monday", "Tuesday",
                         "Wednesday", "Thursday",
                         "Friday", "Saturday", "Sunday"))
axis(2)
```



…to be explored in more detail in Session 2 on Transparency Layer

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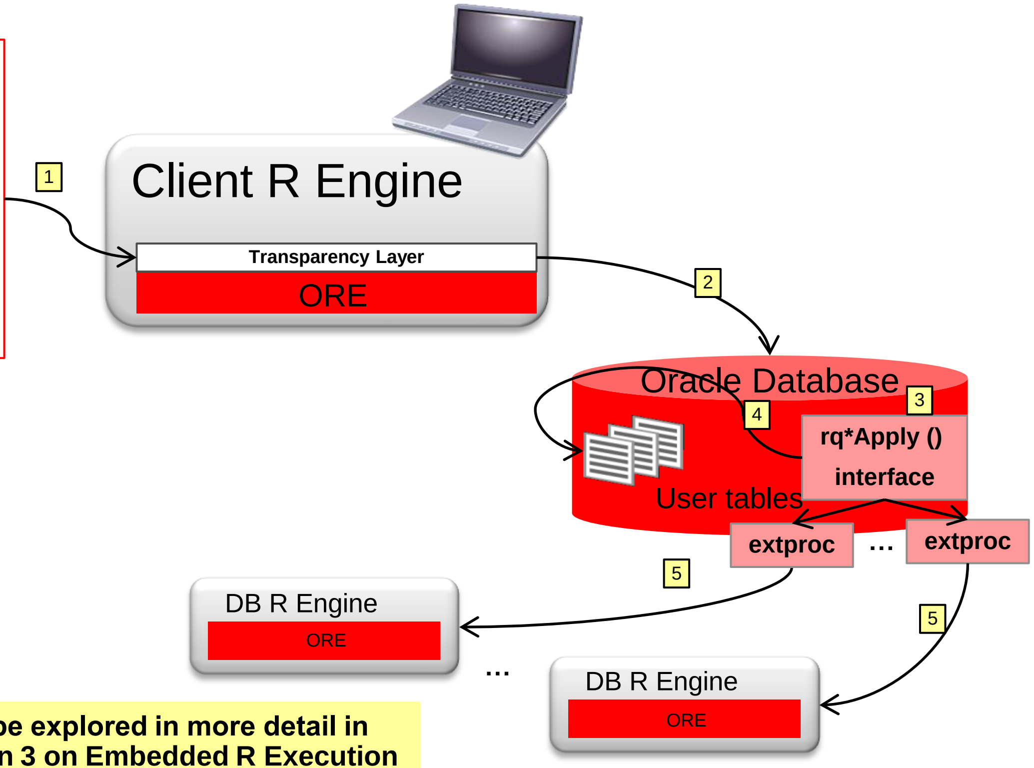
Embedded R Execution – R Interface

Data parallel in-database execution

```
modList <- ore.groupApply(
   X=ONTIME_S,
   INDEX=ONTIME_S$DEST,
   function(dat) {
      lm(ARRDELAY ~ DISTANCE + DEPDELAY, dat)
   });
modList_local <- ore.pull(modList)
summary(modList_local$BOS) ## return model for BOS
```



Also includes

- ore.doEval
- ore.tableApply
- ore.rowApply
- ore.indexApply

…to be explored in more detail in Session 3 on Embedded R Execution

Embedded R Execution – SQL Interface

For model build and batch scoring

```
begin
  sys.rqScriptDrop('Example2');
  sys.rqScriptCreate('Example2',
 'function(dat,datastore_name) {
   mod <- lm(ARRDELAY ~ DISTANCE + DEPDELAY, dat)
   ore.delete(datastore_name)
   ore.save(mod,name=datastore_name)
  }');
end;
/

select *
  from table(rqTableEval(
     cursor(select ARRDELAY,
                   DISTANCE,
                   DEPDELAY
            from   ontime_s),
     cursor(select 1 "ore.connect",
                   'myDatastore' as "datastore_name"
            from dual),
     'XML',
     'Example2' ));
```

```
begin
  sys.rqScriptCreate('Example3',
 'function(dat, datastore_name) {
     ore.load(datastore_name)
     prd <- predict(mod, newdata=dat)
     prd[as.integer(rownames(prd))] <- prd
     res <- cbind(dat, PRED = prd)
     res}');
end;
/
select *
from table(rqTableEval(
    cursor(select ARRDELAY, DISTANCE, DEPDELAY
           from   ontime_s
           where  year = 2003
           and    month = 5
           and    dayofmonth = 2),
    cursor(select 1 "ore.connect",
           'myDatastore' as "datastore_name" from dual),
    'select ARRDELAY, DISTANCE, DEPDELAY, 1 PRED from ontime_s',
    'Example3'))
order by 1, 2, 3;
```

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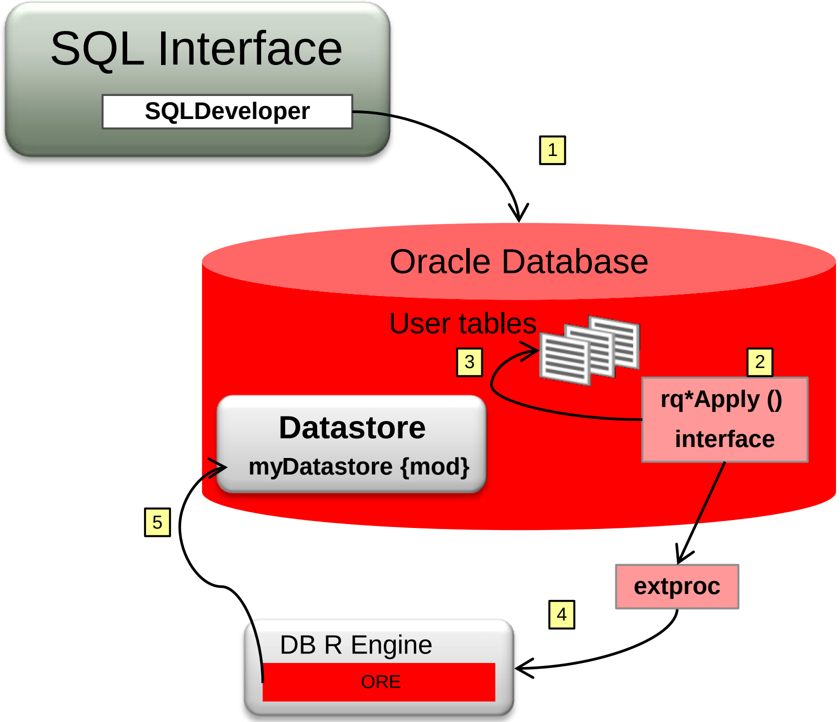
Embedded R Execution – SQL Interface

rqTableEval + datastore for model building



Statistics Engine

Example Features

- Special Functions
  - Gamma function
  - Natural logarithm of the Gamma function
  - Digamma function
  - Trigamma function
  - Error function
  - Complementary error function
- Tests
  - Chi-square, McNemar, Bowker
  - Simple and weighted kappas
  - Cochran-Mantel-Haenzel correlation
  - Cramer's V
  - Binomial, KS, t, F, Wilcox
- Base SAS equivalents
  - Freq, Summary, Sort
  - Rank, Corr, Univariate
- Density, Probability, and Quantile Functions
  - Beta distribution
  - Binomial distribution
  - Cauchy distribution
  - Chi-square distribution
  - Exponential distribution
  - F-distribution
  - Gamma distribution
  - Geometric distribution
  - Log Normal distribution
  - Logistic distribution
  - Negative Binomial distribution
  - Normal distribution
  - Poisson distribution
  - Sign Rank distribution
  - Student's t distribution
  - Uniform distribution
  - Weibull distribution
  - Density Function
  - Probability Function
  - Quantile

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Oracle R Enterprise

Main components

- Transparency Layer
  - Work solely from R for data preparation, analysis, and visualization
  - Use database as compute engine with query optimization and parallelism
  - Eliminates need to manage flat file data – complexity, backup, recovery, security
  - Eliminates R memory constraints so you can handle bigger data
  - No knowledge of SQL required
- Embedded R Execution
  - *Roll your own* techniques in R and execute closer to database data
  - Leverage CRAN open source packages
  - Lights-out execution for integrated operationalizing R scripts via SQL interface
  - Leverage user-defined, dba-controlled, and database-managed, data parallel R execution
  - Combine with benefits of Transparency Layer and Statistics Engine capabilities
  - Enables integration of structured and graph results with OBIEE dashboards and BIP documents
- Statistics Engine
  - Enable standard and advanced statistics for in-database execution
  - Provide in-database scoring of R models

Leveraging the power of Exadata

New features in Oracle R Enterprise 1.3

Oracle R Enterprise 1.3 – Themes

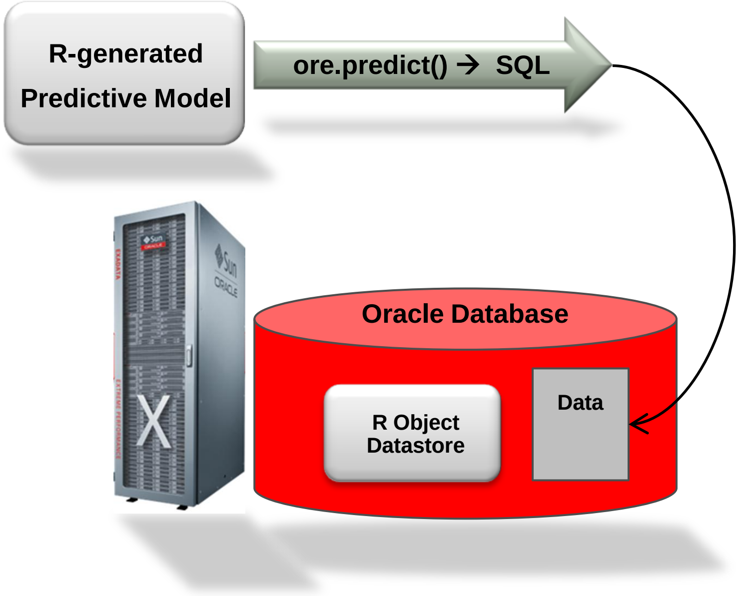
- Big Data
- Time Series Analytics
- Rapid Application Deployment
- Certification for R version 2.15.1

Support for Big Data Analytics

- Exadata storage tier scoring for R models with the new ORE package ***OREpredict***
- Comprehensive in-database sampling techniques
- New ORE package, ***OREdm***, for high performance in-database predictive algorithms from Oracle Data Mining

Exadata storage tier scoring for R models

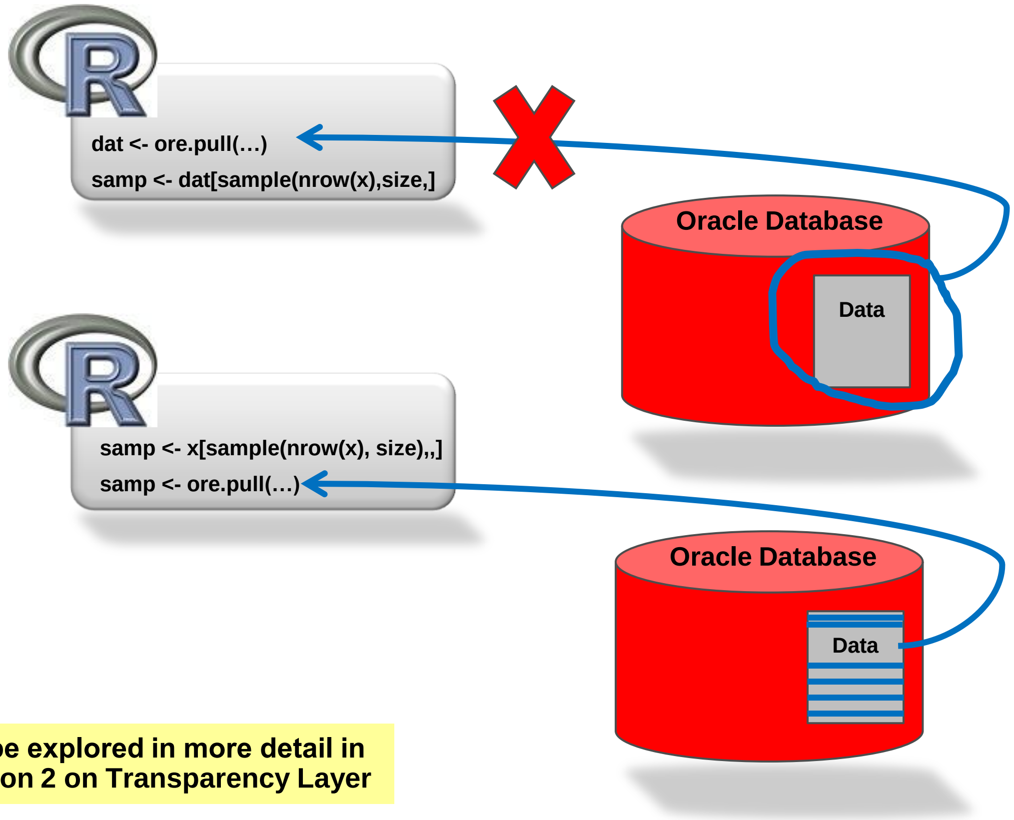
- Fastest way to operationalize R-based models for scoring in Oracle Database
- Go from model to SQL scoring in one step
  - No dependencies on PMML or any other plugins
- R packages supported out-of-the-box include
  - glm, glm.nb, hclust, kmeans, lm, multinom, nnet, rpart
- Models can be managed in-database using ORE datastore



…to be explored in more detail in Session 4 on Predictive Analytics

High performance in-database sampling Techniques

- Simple random sampling
- Split data sampling
- Systematic sampling
- Stratified sampling
- Cluster sampling
- Quota sampling
- Accidental sampling



…to be explored in more detail in Session 2 on Transparency Layer

Example: Bag of Little Bootstraps

Approach big data analysis by first randomly partitioning a data set into subsets that can be analyzed using in-memory R algorithms and then aggregating the results from those partitions

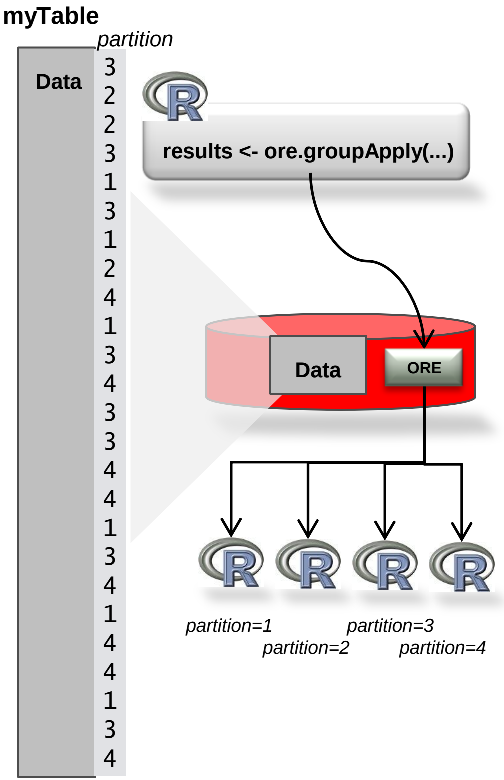
- Assign a random partition number to each observation as a derived column (a relational view)

```
x = myTable
nrowX <- nrow(x)
x$partition <- sample(rep(1:k, each = nrowX/k,
                      length.out = nrowX), replace = TRUE)
```

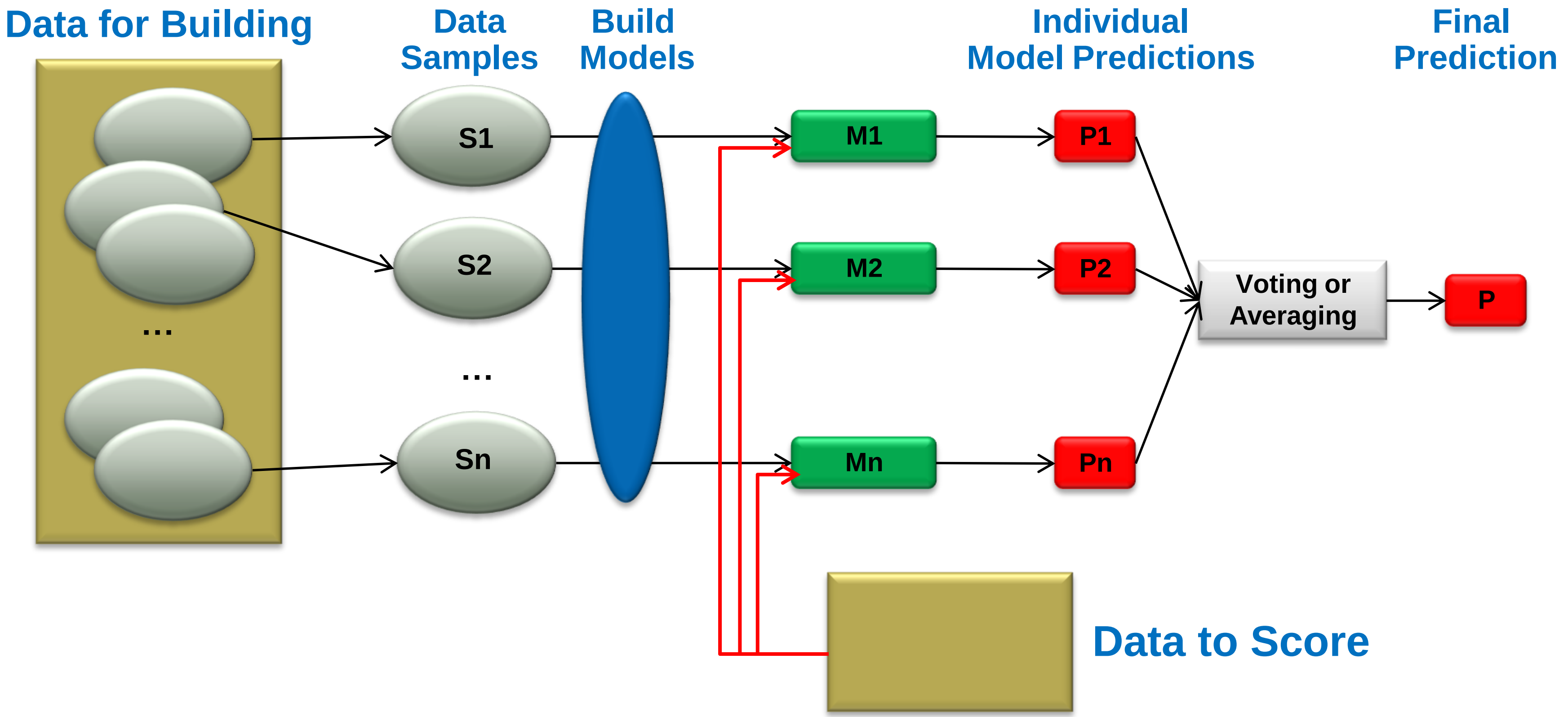
- Generate the boot straps in-database and efficiently pass data to R engines

```
results <- ore.groupApply(x, x$partition,
                        function(y) {...}, parallel = TRUE)
```

- Build multiple models and aggregate results via voting or averaging

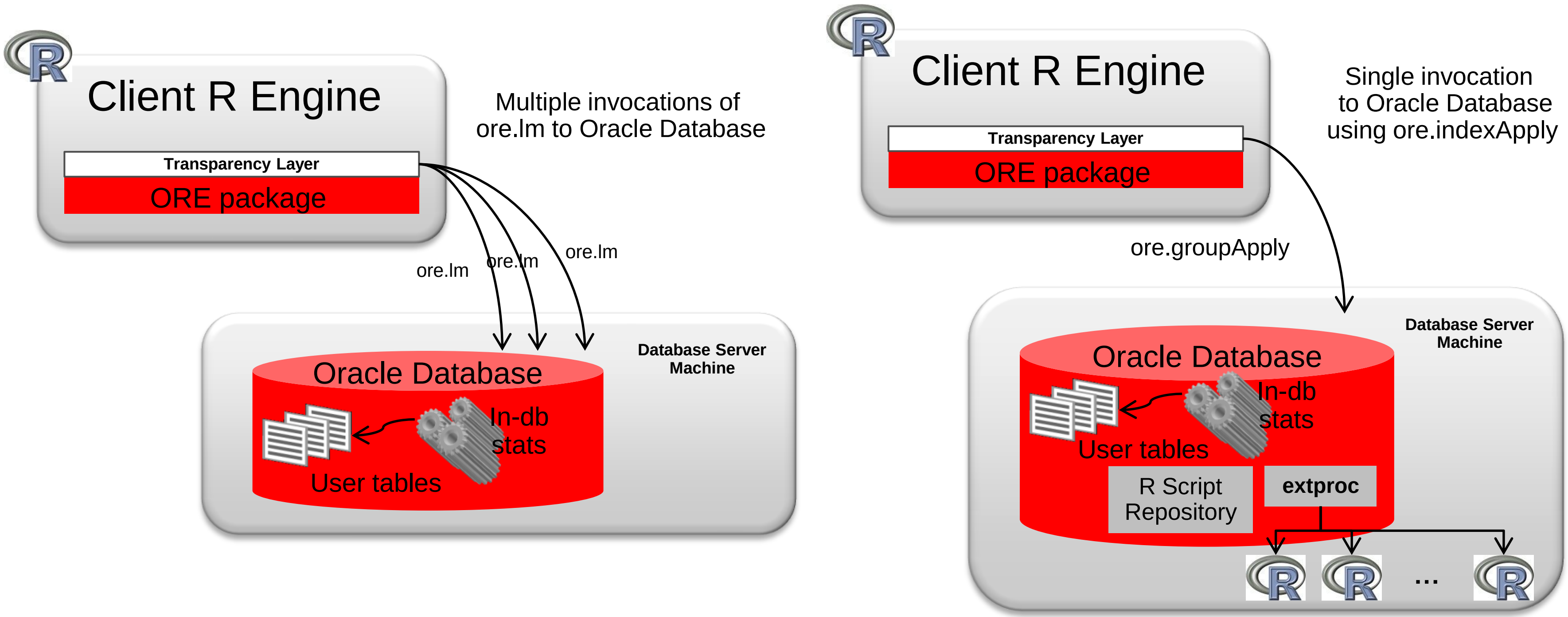


The “Bagging” Concept



“Bagging” Execution Model

Two options: client-controlled and database-controlled



High performance in-database predictive techniques available through ORE packages

Parallel, distributed, in-database execution

- SVM
- GLM
- k-Means clustering
- Naïve Bayes
- Decision Trees
- Attribute Importance

OREdm

- Neural Networks
- Stepwise Linear Regression

OREeda

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Example using OREdm functions

Highlighting Support Vector Machine algorithm

```
x <- seq(0.1, 5, by = 0.02)
y <- log(x) + rnorm(x, sd = 0.2)
dat <-ore.push(data.frame(x=x, y=y))

# Regression
svm.mod <- ore.odmSVM(y~x,dat,"regression",
                      kernel.function="linear")
summary(svm.mod)
coef(svm.mod)
svm.res <- predict(svm.mod,dat,supplemental.cols="x")
head(svm.res,6)
```

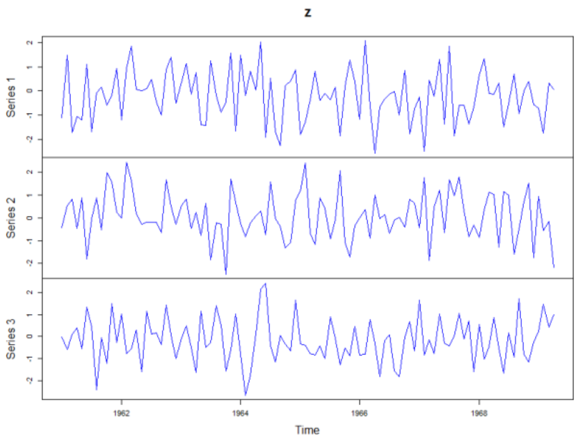
```
m <- mtcars
m$gear <- as.factor(m$gear)
m$cyl  <- as.factor(m$cyl)
m$vs   <- as.factor(m$vs)
m$ID   <- 1:nrow(m)
MTCARS <- ore.push(m)

# Classification
svm.mod  <- ore.odmSVM(gear ~ .-ID, MTCARS,"classification")
summary(svm.mod)
coef(svm.mod)
svm.res  <- predict (svm.mod, MTCARS,"gear")
with(svm.res, table(gear,PREDICTION))  # generate confusion matrix
# Anomaly Detection
svm.mod  <- ore.odmSVM(~ .-ID, MTCARS,"anomaly.detection")
summary(svm.mod)
svm.res  <- predict (svm.mod, MTCARS, "ID")
head(svm.res)
table(svm.res$PREDICTION)
```

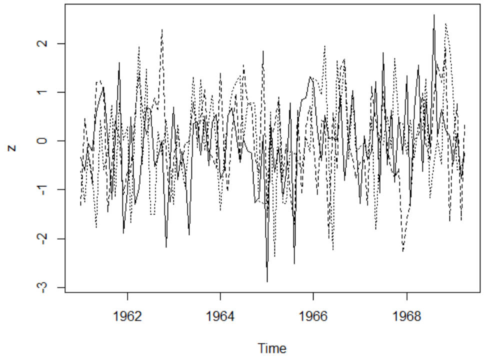
…to be explored in more detail in Session 4 on Predictive Analytics

Time Series Analysis

Motivation

- Time series data is widely prevalent
  - Stock / trading data
  - Sales data
  - Employment data
- Need to understand trends, seasonable effects, residuals





Time Series Analysis

- Aggregation and moving window analysis of large time series data
- Equivalent functionality from popular R packages for data preparation available in-database

CRAN Task View: Time Series Analysis

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Version: 2012-10-07

Base R ships with a lot of functionality useful for time series, in particular in the stats package. This is complemented by many packages on CRAN, which are briefly summarized below. There is also a considerable overlap between the tools for time series and those in the Econometrics and Finance task views. The packages in this view can be roughly structured into the following topics. If you think that some package is missing from the list, please let us know.

Basics

- *Infrastructure* : Base R contains substantial infrastructure for representing and analyzing time series data. The fundamental class is `"ts"` that can represent regularly spaced time series (using numeric time stamps). Hence, it is particularly well-suited for annual, monthly, quarterly data, etc.
- *Modeling* : Methods for analyzing and modeling time series include ARIMA models in `arima()`, AR(p) and VAR(p) models in `ar()`, structural models in `StructTS()`, visualization via `plot()`, (partial) autocorrelation functions in `acf()` and `pacf()`, classical decomposition in `decompose()`, STL decomposition in `stl()`, moving average and autoregressive linear filters in `filter()`, and basic Holt-Winters forecasting in `HoltWinters()`.

Time Series Classes

...

- As mentioned above, `"ts"` is the basic class for regularly spaced time series using numeric time stamps.
- The zoo package provides infrastructure for regularly and irregularly spaced time series using arbitrary classes for the time stamps (i.e., allowing all classes from the previous section). It is designed to be as consistent as possible with `"ts"`. Coercion from and to `"zoo"` is available for all other classes mentioned in this section.
- The package xts is based on zoo and provides uniform handling of R's different time-based data classes.
- Various packages implement irregular time series based on `"POSIXct"` time stamps, intended especially for financial applications. These include `"its"` from its, `"irts"` from tseries, and `"fts"` from fts.
- The class `"timeSeries"` in timeSeries (previously: fSeries) implements time series with `"timeDate"` time stamps.
- The class `"tis"` in tis implements time series with `"ti"` time stamps.
- The package tframe contains infrastructure for setting time frames in different formats.

Forecasting and Univariate Modeling

- The forecast package provides a class and methods for univariate time series forecasts, and provides many functions implementing different forecasting models including all those in the stats package.
- *Exponential smoothing* : `HoltWinters()` in stats provides some basic models with partial optimization, `ets()` from the forecast package provides a larger set of models and facilities with full optimization.
- *Autoregressive models* : `ar()` in stats (with model selection), FitAR for subset AR models, and pear for periodic autoregressive time series models.
- *ARIMA models* : `arima()` in stats is the basic function for ARIMA, SARIMA, ARIMAX, and subset ARIMA models. It is enhanced in the forecast package along with `auto.arima()` for automatic order selection. `arma()` in the tseries package provides different algorithms for ARMA and subset ARMA models. FitARMA implements a fast MLE algorithm for ARMA models. Some facilities for fractional differenced ARFIMA models are provided in the fracdiff package. afmtools handles estimation, diagnostics and forecasting for ARFIMA models. `armaFit()` from the fArma package is an interface for ARIMA and ARFIMA models. Package gsarima contains functionality for generalized SARIMA time series simulation. The mar1s package handles multiplicative AR(1) with seasonal processes/
- *GARCH models* : `garch()` from tseries fits basic GARCH models, `garchFit()` from fGarch implements ARIMA models with a wide class of GARCH innovations. bayesGARCH estimates a Bayesian GARCH(1,1) model with t innovations. gogarch implements Generalized Orthogonal GARCH (GO-GARCH) models. The R-Forge project rgarch aims to provide a flexible and rich GARCH modelling and testing environment including univariate and multivariate GARCH packages. Its webpage has extensive information and examples.
- *Miscellaneous* : ltsa contains methods for linear time series analysis, dlm for Bayesian analysis of dynamic linear models, timsac for time series analysis and control, BootPR for bias-corrected forecasting and bootstrap prediction intervals for autoregressive time series

Resampling

- *Bootstrapping* : The boot package provides function `tsboot()` for time series bootstrapping, including block bootstrap with several variants. `tsbootstrap()` from tseries provides fast stationary and block bootstrapping. Maximum entropy bootstrap for time series is available in meboot.

Support for Time Series Data

- Support for Oracle data types
  - DATE, TIMESTAMP
  - TIMESTAMP WITH TIME ZONE
  - TIMESTAMP WITH LOCAL TIME ZONE
- Analytic capabilities
  - Date arithmetic, Aggregations & Percentiles
  - Moving window calculations: ore.rollmax ore.rollmean ore.rollmin ore.rollsd ore.rollsum ore.rollvar, ore.rollsd

…to be explored in more detail in Session 2 on Transparency Layer

Rapid Application Deployment

Motivation and enabling features

- Streamline and simplify application deployment
  - Avoid data staging, movement, and latency
- Increase data security
- Embed ORE into application backends and web UI infrastructures
- Allow applications to integrate with ORE to leverage:
  - Execution of R in-database via R-to-SQL transparency layer
  - In-database high performance predictive techniques in concert with R algorithms
  - R integration into SQL language
  - Persistence of R objects in Oracle Database
  - In-database scoring using models from R algorithms

Rapid Application Deployment

Benefits

- Database is the server managing instances of R in-database
- Data and task parallel execution of R scripts in Oracle Database
- Use cases include
  - Bag of Little Bootstraps
  - Partitioned model builds
  - Simulations and backtesting
- Resource utilization of R instances automatically managed by Oracle Database
- R models and objects stored securely in database-managed R datastore
- No additional packages (like Rserve) or maintenance required

Analytics Example and Scenario

Using ORE with CRAN package and visualization

Data preparation using ORE, movie recommendations using {arules}

```
MF <- MOVIE_FACT[c("CUST_ID","MOVIE_ID","ACTIVITY_ID")]
MV <- MOVIE[,c("MOVIE_ID","TITLE")]

transData <- merge(MF[MF$ACTIVITY_ID==2,], MV,
                   by="MOVIE_ID")
transData <- ore.pull(transData[,c("CUST_ID","TITLE")])
transData <-
  data.frame(CUST_ID=as.factor(transData$CUST_ID),
             TITLE=as.factor(transData$TITLE))

library(arules)
trans.movie <- as(split(transData[,"TITLE"],
                        transData[,"CUST_ID"]),
                  "transactions")
```

```
assocRules <-
  apriori(trans.movie,
          parameter=list(minlen=2,
                         maxlen=2,
                         support=0.05,
                         confidence=0.1))
inspect(sort(assocRules,by="support")[1:25])
plot(sort(assocRules,by="support")[1:50],
     method="graph",
     interactive=TRUE,
     control=list(type="items"))
```

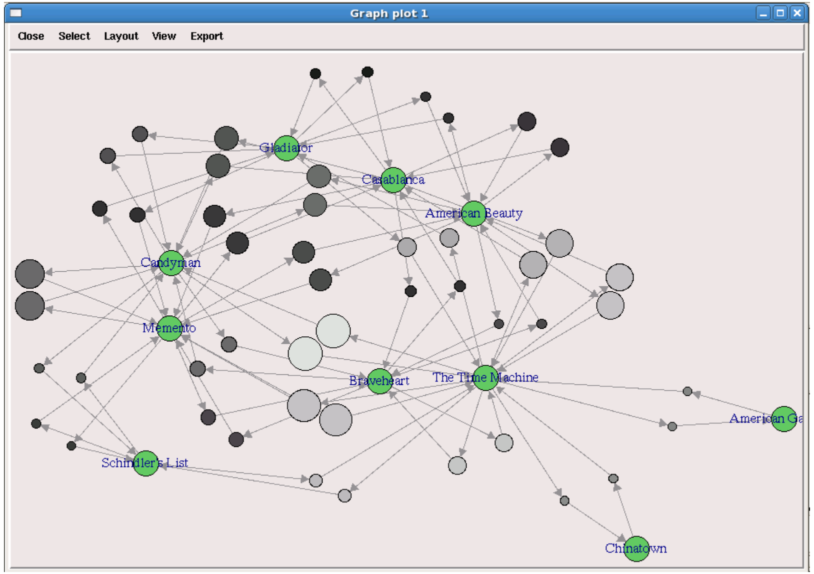
Results

```
R> assocRules <- apriori(trans.movie,
+                        parameter=list(minlen=2,
+                                       maxlen=2,
+                                       support=0.05,
+                                       confidence=0.1))

parameter specification:
 confidence minval smax arem  aval originalSupport support minlen maxlen target   ext
        0.1    0.1    1 none FALSE            TRUE    0.05      2      2  rules FALSE

algorithmic control:
 filter tree heap memopt load sort verbose
    0.1 TRUE TRUE  FALSE TRUE    2    TRUE

apriori - find association rules with the apriori algorithm
version 4.21 (2004.05.09)        (c) 1996-2004   Christian Borgelt
set item appearances ...[0 item(s)] done [0.00s].
set transactions ...[1970 item(s), 4427 transaction(s)] done [0.06s].
sorting and recoding items ... [429 item(s)] done [0.00s].
creating transaction tree ... done [0.01s].
checking subsets of size 1 2 done [0.02s].
writing ... [25590 rule(s)] done [0.00s].
creating S4 object  ... done [0.01s].
R> inspect(sort(assocRules,by="support")[1:25])
   lhs                    rhs                   support confidence     lift
1  {Candyman}          => {The Time Machine} 0.2256607  0.8560411 2.842981
2  {The Time Machine} => {Candyman}          0.2256607  0.7494374 2.842981
3  {Memento}           => {The Time Machine} 0.2236277  0.8870968 2.946120
4  {The Time Machine} => {Memento}           0.2236277  0.7426857 2.946120
5  {Memento}           => {Candyman}         0.2175288  0.8629032 3.273413
6  {Candyman}          => {Memento}          0.2175288  0.8251928 3.273413
7  {American Beauty}  => {The Time Machine} 0.2157217  0.8858998 2.942144
8  {The Time Machine} => {American Beauty}  0.2157217  0.7164291 2.942144
```



ORE as framework for Model Building and Scoring

Workflow example

Analysis

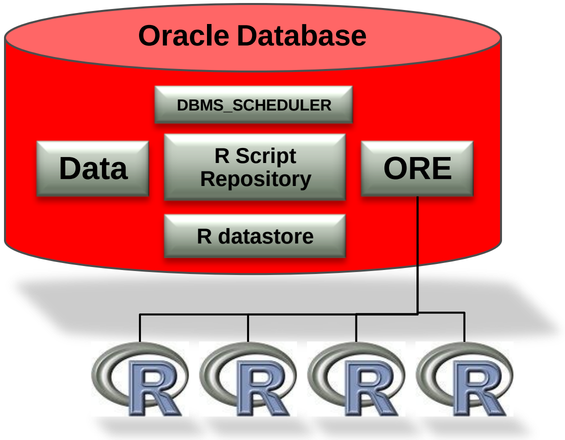
Data Preparation (filter, transform) Exploratory Data Analysis → Sample data and split in train and test → Build and test models in parallel with ore.indexApply → Select best model and save in database 'datastore' object → Load and test model from datastore for scoring new data

Development

Code the build methodology in R script repository → Code the scoring methodology in R script repository → Invoke build and scoring R functions using ore.*Apply

Production

Schedule build and score as nightly jobs for execution



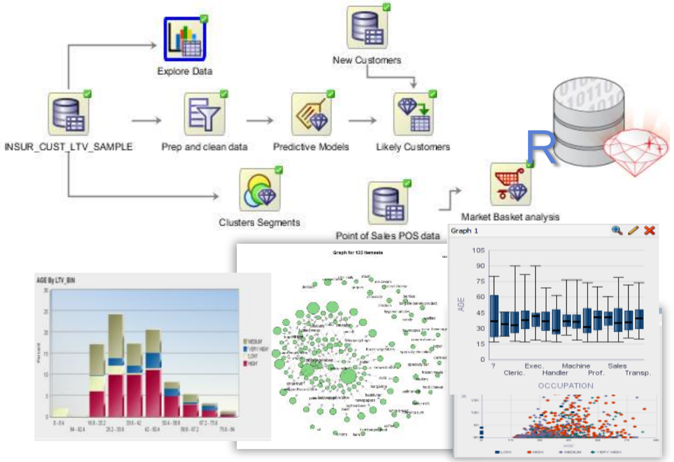
…to be explored in more detail in Session 3 on Embedded R Execution

Oracle Advanced Analytics Option

Oracle Advanced Analytics Option

Fastest Way to Deliver Scalable Enterprise-wide Predictive Analytics

- Powerful
  - Combination of in-database predictive algorithms and open source R algorithms
  - Accessible via SQL, PL/SQL, R and database APIs
  - Scalable, parallel in-database execution of R language
- Easy to Use
  - Range of GUI and IDE options for business users to data scientists
- Enterprise-wide
  - Integrated feature of the Oracle Database available via SQL
    - R is integrated into SQL
  - Seamless support for enterprise analytical applications and BI environments

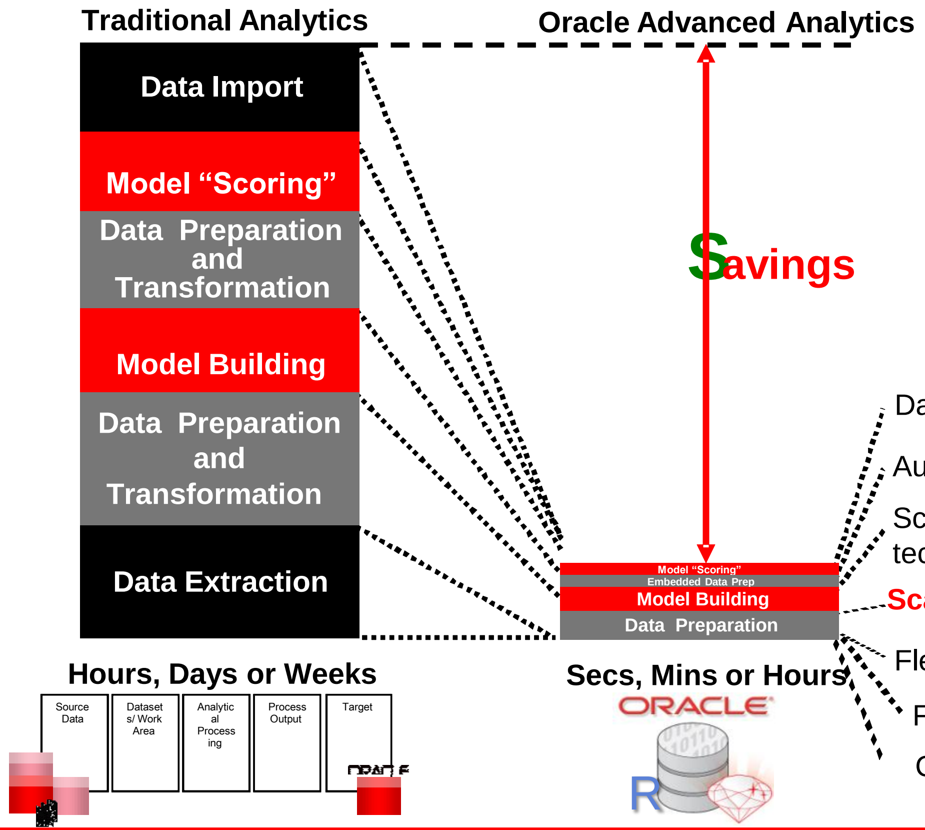


Oracle R Enterprise

+

Oracle Data Mining

Oracle Advanced Analytics Value Proposition



Value Proposition

- Fastest path from data to insights
- Fastest analytical development
- **Fastest in-database scoring engine on the planet**
- **Flexible deployment options for analytics**
- Lowest TCO by eliminating data duplication
- Secure, Scalable and Manageable

Data remains in the Database

Automated data preparation for select analytics

Scalable distributed-parallel implementation of machine learning techniques in-database

Scalable R leveraging database computational engine

Flexible interface options – R, SQL, IDE, GUI

Fastest and most Flexible analytic deployment options

Can import 3rd party models

Customer Loyalty - Solution Summary

Managing customer loyalty is a key component of customer experience management in retail, telecommunications, and consumer markets. It starts with making use of the mountains of data available about each customer, their shopping patterns, and assessing long term value of each customer, funding effective marketing campaigns that target customers most likely to respond to offers, and determining that next best profitable action. Customer Loyalty management drives over 500B dollars in revenue worldwide.

- Build brand loyalty
- Accelerate predictive model build through deployment leveraging every customer interaction and transaction available to you
- Quickly identify profitable customers and create effective marketing campaigns

Lifetime Customer Loyalty with Oracle Advanced Analytics

Customer Problem

- It is expensive to acquire new customers or lose existing ones.
- Assessing long term value of existing customers and finding ways to retain and convert at-risk customers into profitable ones is a challenge
- Improving customer loyalty is about that unique individual customer insight to be able to offer the right product/service at the right time. It’s the ability to predict what influences repeat shopping behavior at the right cost
- Issues: 1) Very large data volumes, 2) Too many scenarios to model, 3) Operationalization of resulting models into production

Power Positions

- Easily work with billions of transactions from points of sale, 10s of thousands of products and 100s of millions of customers in-place in Oracle Database where the data reside
- Thousands of unique attributes about each consumer/household
- Readily incorporate unstructured data such as social networks and review feedback into analysis
- Lowest TCO and fastest path to enterprise-wide analytics deployment

Unique Capabilities

- Powerful combination of in-database predictive algorithms and open source R algorithms
- Range of GUI and IDE options for business users to data scientists
- Rapid transition of models from development to operationalization

Benefits

- Get started immediately with data in the database.
- Sub-second query response at very large data volumes to allow rapid data preparation
- Scalable parallel distributed predictive algorithms
- Range of interface options that facilitate business-IT collaboration
- Leverages Enterprise-class infrastructure

Typical volumetrics at retailer

- 3.2 Billion transactions
  - 120 million transactions bought a specific product
  - Understand co-occurrence of products across transactions to determine likelihood of 2 products bought together
- 19 million households
  - Segment households based on demographic data and purchase behavior

Big Data Scenarios with Database Data

Scenario	Duration
Analyze 100 million households that carry loyalty card to find out what the most influential factors that drive purchase behavior of products in one group are	From start to model ready state: **25 minutes**
Identify households that consumed a specific product from a 5 billion transactions data set Eliminate those households with an aggregated spend of less than x dollars Segment the remaining households into 30 groups What describes each segment and how does that relate to the business?	Start to finish : **5 minutes**
What products tend to be bought together? Analyze 5 billion POS transactions to identify subsets of products bought together Use this as basis to identify next best offer for each of 100 million households in each product category	Start to Finish: **4 minutes**
Analyze 150 million orders in the last month to build a fraud detection model	Start to Finish: **8 minutes**

Summary

- R-to-SQL transparency improves user efficiency by allowing use of R directly against database data
- ORE enables R users to leverage in-database analytical techniques
- Open source R packages can be leveraged in combination with database-managed data and task parallel execution
- ORE provides a framework for sophisticated model building and data scoring
- R integration into the SQL language enables integration into IT software stack
- Oracle redistributes R and provides Enterprise support

Resources

- **Blog:** https://blogs.oracle.com/R/
- **Forum:** https://forums.oracle.com/forums/forum.jspa?forumID=1397
- **Oracle R Distribution:** http://www.oracle.com/technetwork/indexes/downloads/r-distribution-1532464.html
- **ROracle:** http://cran.r-project.org/web/packages/ROracle
- **Oracle R Enterprise:** http://www.oracle.com/technetwork/database/options/advanced-analytics/r-enterprise
- **Oracle R Connector for Hadoop:** http://www.oracle.com/us/products/database/big-data-connectors/overview

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