Predicting the quality and prices of wine (Wine analytics)

Tool: Linear regression

The Analytics Edge:

The price of mature wines may be predicted from data available when grapes are picked.
Using a simple linear regression model with weather variables it is possible to predict wine prices which is traditionally done by wine experts and the predictions can often be improved.

Overview: Bordeaux is a region in France that is well known for making wines. The major reason for the success is the excellent environment for growing vines in Bordeaux. Roughly 90% of the wines produced in Bordeaux are red wines. Often these wines are recognized as some of the finest in the world.

Much of the wine in the region has been produced in the same way for hundreds of years yet there is significant differences in quality and price from year to year.

Orley Ashenfelter, a professor at Princeton developed a simple yet powerful analytics approach to help predict the quality & price of Bordeaux wines.

Wine making process (schematic)

$\underbrace{\text{Harvest grapes}}_{\text{September}}$ → Sort & destem → Crush → Ferment → Press & blend → Age

Bordeaux wines taste better when they are older and hence there is incentive to store them till they come of age.

The younger wines are typically more unpleasant to drink.

Key question: Can one predict how good a wine will be when it matures?

This is useful since en primeur or wine futures gives people an opportunity to buy wines early & thus invest in it before it is bottled.

This is often based on sample of the wine much before it ages. Wine experts give scores (wine rating) based on the tasting.

Example: The 1982 vintage of Chateau Latour was sold at 250 pounds a case en primeur in 1983 and was valued at 9000 pounds in 2007.

Predictors
- Vineyard (Chateau) → Quality of wine
- Vintage (Year wine is made) → Quality of wine

Ashenfelter focused on the vintage as predictor for the quality of the wine, by averaging auction price across chatea

From the data, one can observe that:

1) Older the wine, greater is the value
2) However there is still signifcant variation in average prices that is unexplained.

To explain the quality of the wine better (as approximated by the price of the wine), he proposed the <u>weather</u> as a good predictor of quality. In Bordeaux, the weather significantly changes from year to year for him to believe it to be a good predictor.

To study the analytics approach to this problem, we make use of the data set from the website www.liquidasset.com. The data provided is:

- $\underbrace{\text{TIME\_SV}}$: Time since vintage → LPRICE
- $\underbrace{\text{HRAIN}}$: Harvest rain (Aug - Sep) → LPRICE
- $\underbrace{\text{WRAIN}}$: Winter rain in months preceding Vintage (Oct - March) → LPRICE
- $\underbrace{\text{DEGREES}}$: Average degrees in °C over growing season (Apr - Sep) → LPRICE
- $\underbrace{\text{VINT}}$: Vintage → LPRICE

$\underbrace{\text{LPRICE}}$: Logarithm of average price relative to 1961

Analytics on Bordeaux wine-data : R

Read and basic analysis of data :

wine ← read.csv ("wine.csv")

Str (wine) — Wine dataframe consists of 38 observations of 6 variables

Summary(wine) — VINT (Vintage year), LPRICE (log of price), WRAIN (winter rain), DEGREES (summer temperature), HRAIN (Harvest rain), TIME_SV (Time since vintage)

is.na (wine) — 1954 and 1956 wine prices not available in dataset since they are rarely sold now. Prices from 1981 to 1989 not in data

plot(wine $VINT, wine $LPRICE) — Scatter plot of vintage and price variable indicates negative relationship but there is considerable variation still that needs to be captured

pairs (wine) — Matrix of scatterplots drawn

Split dataset

wine train ← subset (wine, wine $VINT ≤ 1978 & ! is.na (wine $LPRICE)

wine test ← subset (wine, wine $VINT > 1978)

Creates training set from 1952 to 1978 (excluding 1954, 1956) and test set from 1979 to 1989.

Note that we do not have prices for all the points in the test set.

1 variable regression

```
model1 <- lm(LPRICE~VINT, data=winetrain)
```

(Alternative: `model1 <- lm(winetrain$LPRICE~winetrain$VINT)`

```
summary(model1)
```

lm() is the basic model to fit a linear model to the data. Here LPRICE is fit with the VINT predictor

The regression equation fit is:

$$\text{LPRICE} = \underbrace{72.99}_{\text{estimate intercept}} \underbrace{-0.0378}_{\text{estimates}} \text{VINT}$$

Both estimated coefficients are significant at 0.01 level

$R^2 = 0.2005$ Adjusted $R^2 = 0.1657$.

```
plot(winetrain$VINT, winetrain$LPRICE)
abline(model1)
```

Plots the best fit line with a slope of -0.0378

```
model1$residuals
sse1 <- sum(model1$residuals^2)
```

Sum of squares of errors

```
sst1 <- sum((winetrain$LPRICE - mean(winetrain$LPRICE))^2)
```

Total sum of squares

$$1 - \frac{sse1}{sst1}$$

This gives R^2 of 0.20048 (Also known as model R^2)

```
abline(a=mean(winetrain$LPRICE), b=0)
```

Older the wine greater the value. However there is still significant variation.

1 variable regression

lm(LPRICE ~ WRAIN, data= winetrain) $R^2 = 0.018$

lm (LPRICE ~ DEGREES, data = winetrain) $R^2 = 0.435$

lm (LPRICE ~ HRAIN, data = winetrain) $R^2 = 0.31$

2 variables

Look at the effects of DEGREES & HRAIN on price

```
plot (winetrain $ DEGREES, winetrain $HRAIN)
abline (h = mean (winetrain $ HRAIN))
abline (v = mean(winetrain $DEGREES))
```

To add the dependent variable information,

```
plot ( winetrain $DEGREES , winetrain $HRAIN,
        col = ifelse(winetrain $ LPRICE > mean(winetrain$LPRICE)
                "red", "black"))
```

Figure indicates that hot and dry summers produce wines that obtain higher prices while cooler summers with more rain give lower priced wines.

Note that 1961 is the year when an extremely high quality wine was produced.

2 variable regression

model 2 ← lm (LPRICE ~ DEGREES + HRAIN, data = wine_train)

Summary (model 2)

$$LPRICE = -10.69 + 0.602\ DEGREES - 0.0045\ HRAIN.$$

All three variables are extremely significant in this fit with $R^2 = 0.70$ and adjusted $R^2 = 0.68$.
Note that one of the variables here refers to the intercept

Complete regression

model 3 ← lm (LPRICE ~ . , data = wine train)

Summary (model 3)

Note that TIME_SV coefficients are not defined due to singularities (it perfectly correlates with VINT variable)

Drop the variable and redo regression

model 4 ← lm (LPRICE ~ VINT + DEGREES + HRAIN + WRAIN, data = wine train)

$R^2 = 0.8286$ and adjusted $R^2 = 0.7943$

Coefficients indicate that high quality wines correlate strongly in a positive manner with summer temperatures, negatively correlate with harvest rain, correlate positively with vintage and winter rain

Cor (wine train) Provides correlation matrix of the variables

High here refers to magnitude of correlation

- High correlation between independent variables is not good (multicollinearity) (Typically > 0.7, < -0.7)
- High correlation between dependent and independent variables is good

Result indicates that by adding in weather variables, the R^2 increases to 0.8 (80% of the variation can be explained) in comparison to R^2 of 0.2 (20% of the variation can be explained) with the vintage year.

Note that dropping the VINT variable decreases R^2 to 0.75 and adjusted R^2 to 0.71

It seems reasonable to keep it.

Confint (model 4) Provides confidence intervals at 2.5% and 97.5% level

Confint (model4, level = 0.99) Provides confidence interval at 0.5 and 99.5% level

Predictions

str(winetest)

wineprediction <- predict(model4, winetest)

This function predicts the outcome of the model 4 (from the linear regression) on the values of the variables in the data frame winetest

	Prediction	Actual values
1980	−1.808	−1.99
1979	−1.724	−1.539

SSE4 <- sum((winetest$LPRICE[1:2] - wineprediction[1:2])^2)

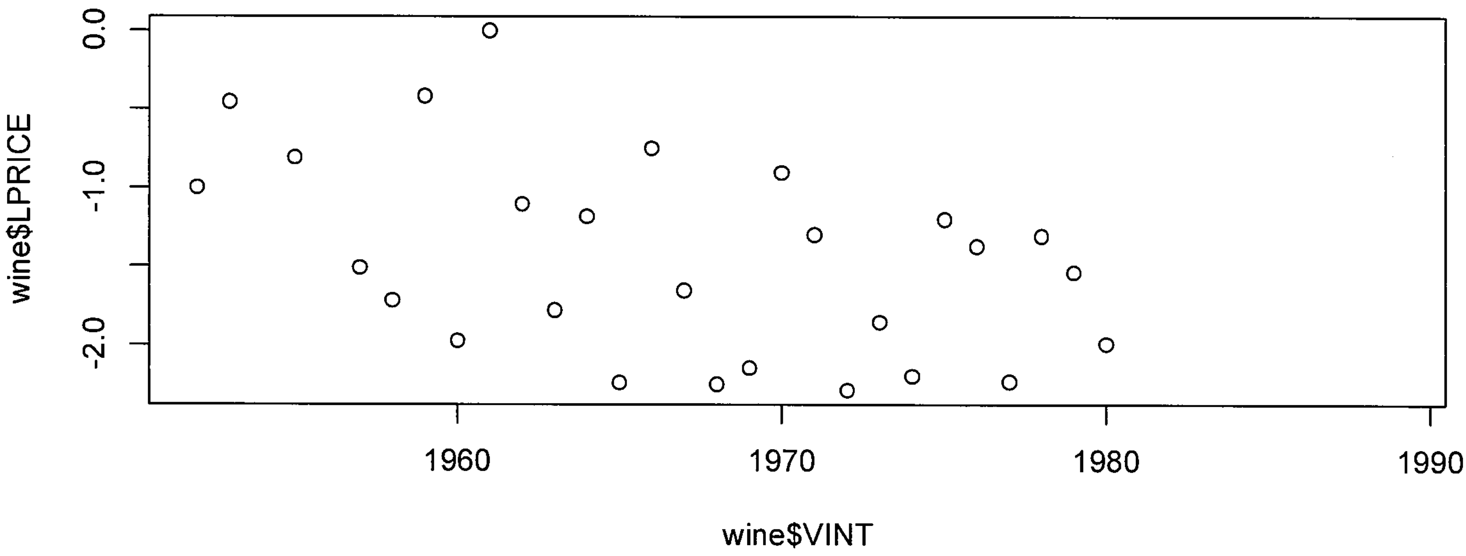
SST4 <- sum((winetest$LPRICE[1:2] - mean(winetrain$LPRICE))^2)

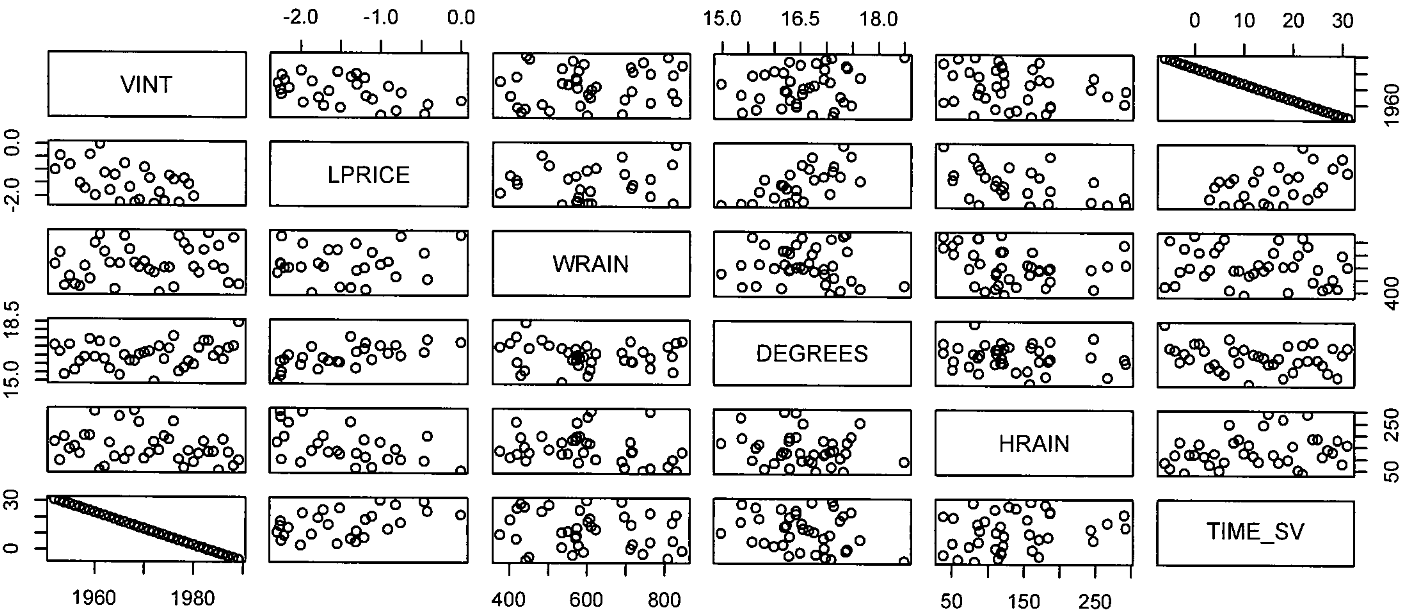
Note we should use training test mean to compute SST for checking effect of regressors

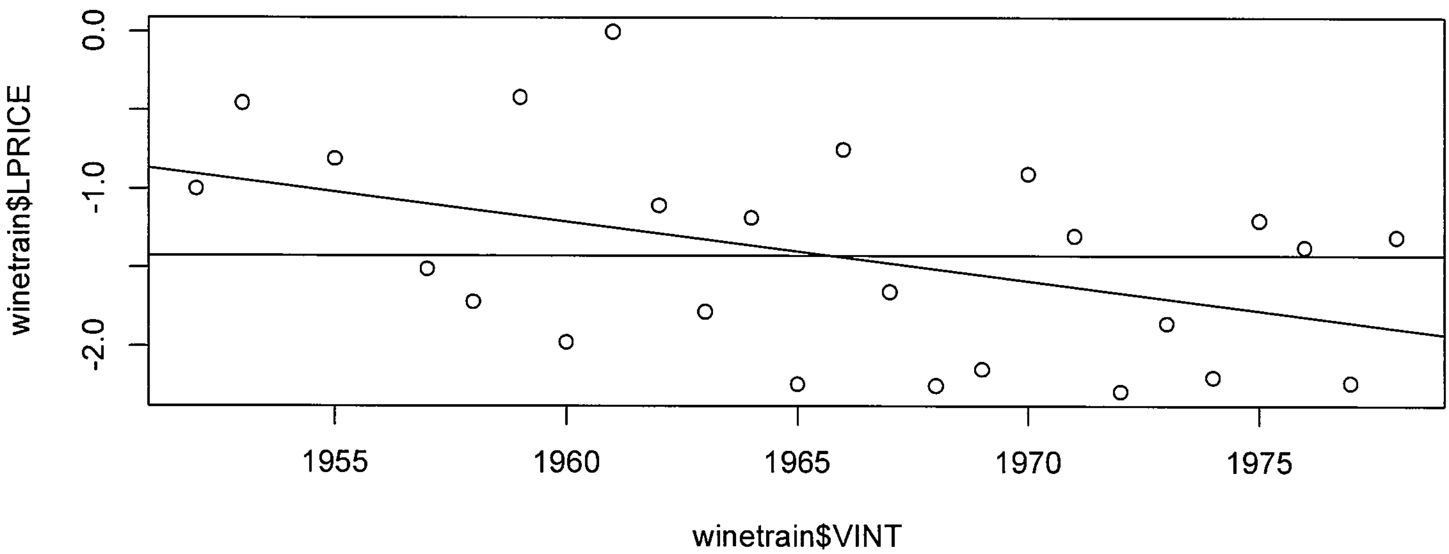
1 − SSE4/SST4 This gives an out of sample (or test R^2 of 0.794)

Variables	Model R^2	Test R^2
DEGREES	0.435	0.788
DEGREES, HRAIN	0.70	−0.08
DEGREES, HRAIN, WRAIN, VINT	0.82	0.794

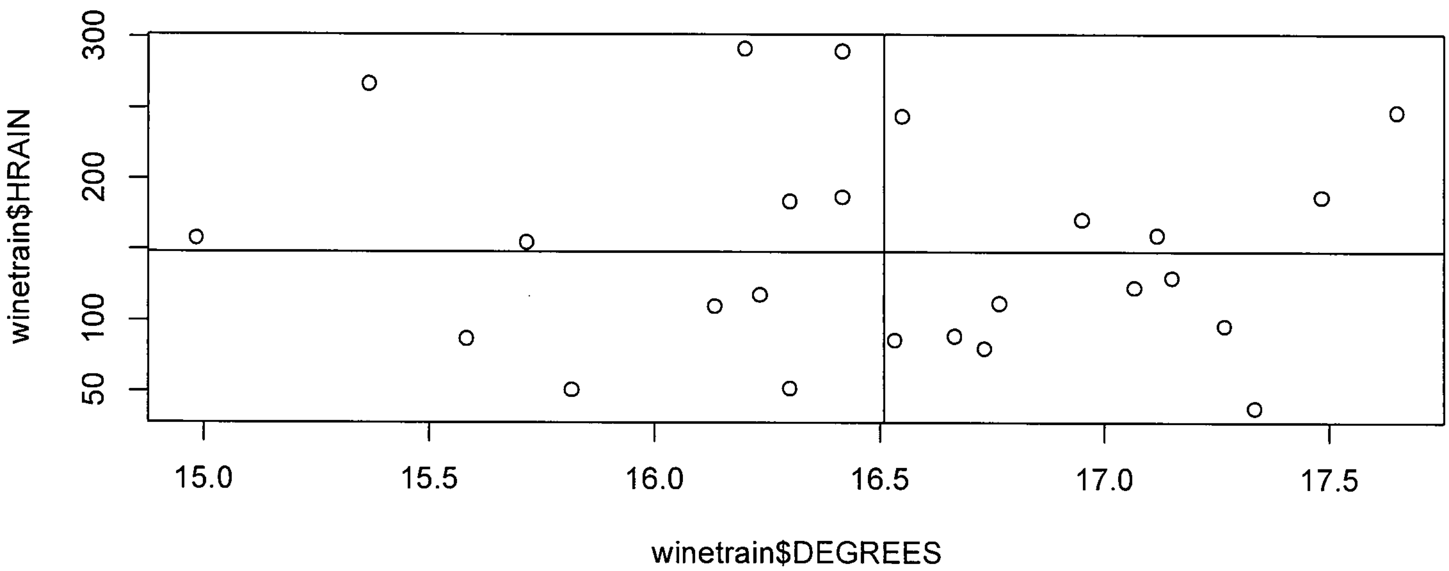
Better model R^2 does not mean better test R^2 which can also be negative.

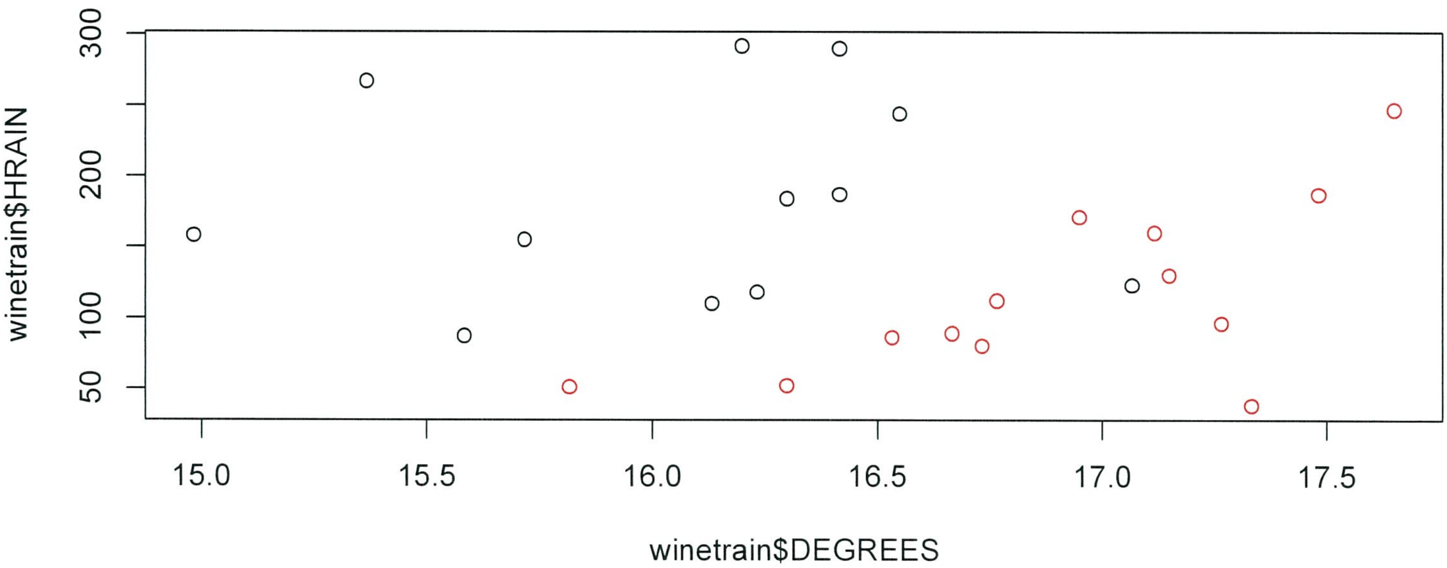

0.0
-1.0
-2.0
wine$LPRICE
1960
1970
1980
1990
wine$VINT


VINT
LPRICE
WRAIN
DEGREES
HRAIN
TIME_SV
-2.0
-1.0
0.0
15.0
16.5
18.0
0
10
20
30
1960
400
18.5
15.0
250
50
1960
1980
400
600
800
50
150
250



0.0
-1.0
-2.0
winetrain$LPRICE
1955
1960
1965
1970
1975
winetrain$VINT


winetrain$HRAIN
50
100
200
300
15.0
15.5
16.0
16.5
17.0
17.5
winetrain$DEGREES


winetrain$HRAIN
winetrain$DEGREES
50
100
200
300
15.0
15.5
16.0
16.5
17.0
17.5

The results from prediction indicate that 1989 wine would be of very high quality.

How did the predictions do and compare with the predictions of the best wine critics?

Ashenfelter prediction	Robert Parker prediction
1986 - mediocre due to below average growing season temperature & above average harvest rainfall	1986 - very good & sometimes exceptional
1989 - excellent vintage	New York Times later said it was fantastic wine. At first Robert Parker said it would be ok like 1985 but then said later its the vintage of the century
1990 - even better vintage	

2000-2001 Both prediction from the model & expert agreed that it was very high quality wine

Data

Source: http://www.liquidasset.com
Price of wine (from auctions), weather information for the vintage

Years 1952 - 1989
Fairly small data set

Model

Linear regression model to predict wine quality (represented by price) in terms of vintage, summer temperature, winter rain, harvest rain

Decision

Develop a prediction on the quality of wine that is known only when it matures typically using weather variable information available at the time of making the wine.

Value

Predictions are comparable to and can also sometimes beat the prediction of qualitative experts using a simple model.

Summary of linear regression Output (R)

Residuals

(Provides a summary of the residuals from the linear regression model) To access the residuals, use residuals (model1) or model1 $ residuals

Coefficients

(Provides estimated coefficients, standard error of coefficients, t value and significance value. To access coefficients, use coefficients (model1) or model1 $ coefficients. You can access Std. Error by Coefficients (summary(model1)) [, "Std. Err:

Residual standard error

(Provides the average amount that response will deviate from true regression line) Provides a measure of lack of fit of linear model to data

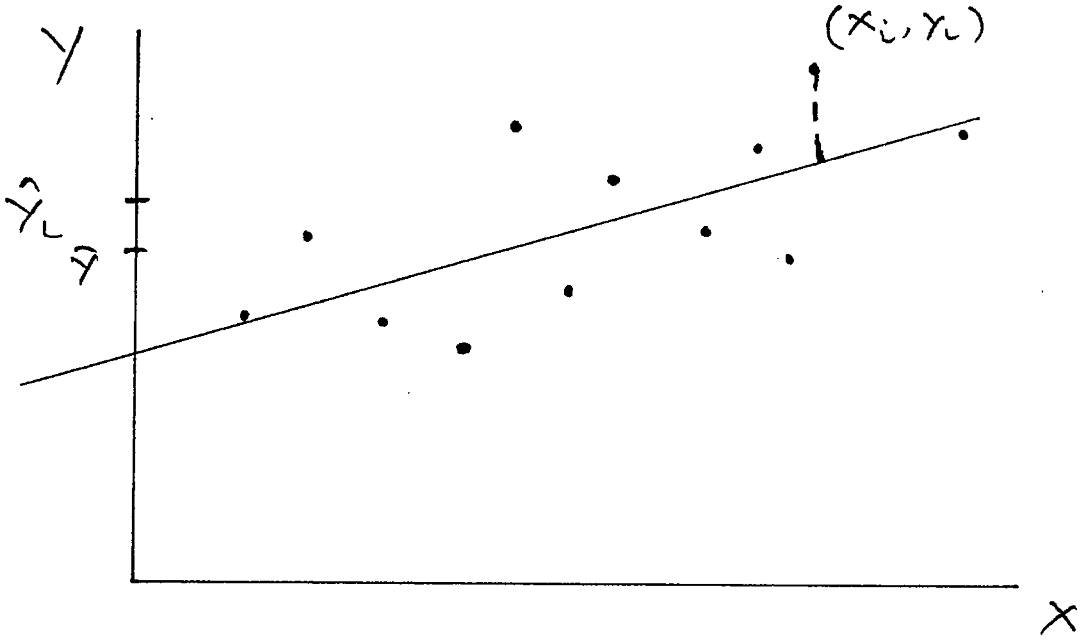
Multiple R^2 and adjusted R^2

(R^2 is a measure between 0 & 1 to indicate the amount of variability explained by regression) Adjusted R^2 accounts for number of predictors

F statistic & p-value

(Test to see if atleast one of the predictors is non zero)

Linear regression



$P = 1$

$n = 12$

Multiple linear regression model

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p + \epsilon$$

Data: Observations $(y_i, x_{i1}, \ldots, x_{ip})$ for $i = 1, \ldots, n$

n = Number of observations

p = Number of predictor variables

Y = Dependent variable (outcome)

$X_1, \ldots, X_p$ = Independent variables (predictors)

Coefficients $\beta_0, \beta_1, \ldots, \beta_p$ are chosen to minimize the sum of squared residuals:

$$\min_{\beta_0, \ldots, \beta_p} \sum_{i=1}^{n} \left(y_i - \beta_0 - \beta_1 x_{i1} - \cdots - \beta_p x_{ip} \right)^2$$

Main points : Linear regression

① $$\min_{\beta_0,\dots,\beta_p} \sum_{i=1}^{n} (y_i - \beta_0 - \beta_1 x_{i1} - \cdots - \beta_p x_{ip})^2$$

Solving the optimization problem gives using matrix notation

$$\min (Y - X\beta)'(Y - X\beta)$$

where $Y = \begin{pmatrix} Y_1 \\ \vdots \\ Y_n \end{pmatrix}$, $X = \begin{pmatrix} 1 & x_{11} & \cdots & x_{1p} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_{n1} & \cdots & x_{np} \end{pmatrix}$, $\beta = \begin{pmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_p \end{pmatrix}$

Optimal solution $\hat{\beta} = (X'X)^{-1} X'y$ } R computes these coefficients

Fitted values $\hat{Y} = X\hat{\beta}$

② The estimates have standard errors associated with them. This is based on the intuition that we develop a regression estimate using observed data to estimate the true population regression line.

Assuming observations y_i are uncorrelated, have constant variance σ^2 and x_i are non random

$$\mathrm{Var}(\hat{\beta}) = (X'X)^{-1} X'X(X'X)^{-1}\,\mathrm{Var}(Y)$$
$$= (X'X)^{-1}\sigma^2$$

To estimate σ^2, use $\hat{\sigma}^2 = \dfrac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{n-p-1}$

The division by $n-p-1$ is to make the estimator unbiased with $E(\hat{\sigma}^2) = \sigma^2$

Standard error of the coefficients is equal to the square root of the diagonal element of the matrix $(X'X)^{-1}\sigma^2$.

Under null hypothesis that $\beta_i = 0$,

$$t \text{ value} = \frac{\hat{\beta}_i \text{ estimate}}{\text{Std error}(\hat{\beta}_i)} \quad \text{(Known as t-statistic)}$$

If t value is high (in absolute value), the null hypothesis will be rejected to claim that $\hat{\beta}_i$ is significant predictor in the model. This is evaluated as the p-value $(P(>|t|))$.

③ <u>Quality of fit</u> :

a) Residual standard error, residual sum of square errors and total sum of squares

$$SSE = \sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2 \quad \text{where } \hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_{i1} + \dots + \hat{\beta}_p x$$

$$\text{Residual standard error} = \sqrt{\frac{SSE}{n-p-1}} \quad \Big\} \text{ Measure of lack of fit of model}$$

Note that it is possible for models with more variables to have higher residual standard error if the decrease in SSE is small relative to increase in p.

b) R^2 and adjusted R^2

R^2 (coefficient of determination) $= \dfrac{SSR \text{ (Sum of squares from regression)}}{SST \text{ (Total sum of squares)}}$

$\left(\begin{array}{l} SST = \sum_{i=1}^{n} (y_i - \bar{y})^2 \\ SSE = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \end{array} \right)$ (SST = SSR + SSE) $= 1 - \dfrac{SSE}{SST}$ $SSE \to$ sum of squared errors.

$SSR = \sum_{i=1}^{n} (\hat{y}_i - \bar{y})^2$

Clearly R^2 is always between 0 and 1.

R^2 measures the proportion of the total variation in y (dependent variable) that is accounted for by variation in regressors (dependent var).

This provides information on the goodness of the fit of the model.

Regression is a horizontal line $\Longrightarrow$ $R^2 = 0$ (x has no explanatory power)

Regression line perfectly fits all points in a straight line $\Longrightarrow$ $R^2 = 1$ (x has perfect explantory power)

All values of Y_i lie in a vertical line $\Longrightarrow$ R^2 cannot be computed.

As we increase the number of variables in the model, R^2 will increase.

It will never decrease in this case and hence one needs to be careful of overfitting the data

The adjusted R^2 statistic penalizes the R^2 statistic as more variables are added in the fit.

The adjusted R^2 can be negative and its value will always be less than or equal to R^2.

The adjusted R^2 increases when a new explanatory variable is added only if this variable increases the R^2 more than would be expected by chance.

The adjusted R^2 is primarily useful in the feature selection stage of model building.

$$\text{Adjusted } R^2 = 1 - (1 - R^2)\left(\frac{n-1}{n-p-1}\right)$$

c) <u>F-statistic</u>

$H_0: \beta_1 = \beta_2 = \cdots = \beta_p = 0$

H_1: Atleast one β_j is non zero

$$\text{F-Statistic} = \frac{(SST - SSE)/p}{(SSE)/(n-p-1)}$$

When there is no relationship between response & predictors, F^2 is expected to be close to 1.

If H_1 is true, we expect F to be greater than 1.

Robert Parker ratings

THE WINE ADVOCATE VINTAGE GUIDE 1970-2013 Date: August 2014

	Country: Region wines	2013	2012	2011	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001	2000	1999	1998	1997	1996	1995	1994	1993	1992	1991	1990	1989	1988	1987	1986	1985	1984	1983	1982	1981	1980	1979	1978	1976	1975	1971	1970
Europe	Austria Riesling & Gruner Veltliner	NT	NT	NT	88I	89I	88R	90R	91I	87I	88I	89I	89T	88I	85C	95R	82C	96R	84C	90I	87C	89C	88C	84C	94R	NT	NT	NT	96R	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT
	Alsace	NT	NT	NT	NT	79I	90T	90R	79I	87R	86E	82R	86R	91R	90R	87R	90R	87R	87R	89R	90R	87R	85C	78C	93R	93R	86R	83C	82C	88C	75C	93C	82C	86C	80C	84C	80C	90R	82C	90C	80C
	Bordeaux: St Julien/Pauillac/St Estephe	78C	87E	88E	98T	99E	91E	86E	87E	95T	88T	95T	88T	88R	96T	88R	87T	84R	96T	92T	85C	78C	79C	75R	98E	90E	87R	82R	94T	90R	72C	86R	98R	85C	78C	85R	87C	84R	89I	82R	87I
	Bordeaux: Margaux	80C	88E	87E	95T	97E	90E	86E	88E	98T	87T	88I	88T	89E	94T	89R	86T	82R	88T	88E	85C	77C	75C	74R	90E	86E	85R	76R	90T	86R	68C	95R	86R	82R	79C	87R	87R	77R	78E	83R	85R
	Bordeaux: Graves	81C	89E	86E	99T	98E	91E	87E	87E	96T	88T	88I	87T	88R	97T	88R	94T	86R	86E	89E	88E	86C	75C	74R	90R	89R	89R	84R	89E	90R	79R	89R	88R	84R	78C	88R	88R	71C	89T	86R	87R
	Bordeaux: Pomerol	84R	92E	88R	95T	98E	96E	86I	90T	95T	88E	84E	85E	90E	95T	88R	96T	87R	85E	92T	89T	87C	82C	58C	96R	96R	89R	85C	87T	88R	65C	90R	96R	86R	79C	86R	84R	82R	94R	87R	90R
	Bordeaux: St. Emilion	82R	89I	87R	94T	93E	92E	86I	88E	99T	88E	90I	87E	90E	96T	88R	96T	86R	87T	88E	86T	84C	75C	59C	98R	88R	88R	74C	88E	87R	69C	89R	94R	82R	72R	84R	84R	82R	85R	83R	85R
	Bordeaux: Barsac/Sauternes	92E	88E	91E	94E	97E	89R	94R	88R	96R	82R	95R	85R	95R	88E	88E	87E	89E	87E	85E	78E	70C	68C	70C	98R	90R	98R	70R	94R	85R	70C	88R	75R	85R	85R	75R	75R	87R	90T	86R	84R
	Burgundy: Cote de Nuits red	NT	93E	91E	96E	95E	88I	84E	89I	98T	83C	91T	92R	86I	84R	92R	84I	89R	89T	90R	72C	85C	69C	86R	93R	85C	84C	77C	65C	87C	78R	75C	75C	50C	84C	77C	88C	86C	50C	87C	82C
	Burgundy: Cote de Beaune red	NT	91E	90E	94E	95E	89I	80E	82I	96T	79C	88T	89R	79I	80C	93R	82C	88R	89R	85R	73C	80C	82R	77C	92R	86C	87C	79C	72C	88C	70C	78C	80C	74C	78C	77C	86R	88C	50C	87C	82C
	Burgundy white	NT	92E	91E	93E	90R	91T	91I	90E	90R	91R	84R	92R	86C	88C	89C	84C	89C	92C	93C	77C	72C	90C	70C	87C	90C	82R	79C	82C	89C	80C	85C	88C	86C	75C	88C	88C	86C	65C	88C	83C
	Burgundy: Beaujolais	NT	87I	91I	93R	97R	86R	85R	89R	95R	81C	93R	86C	75C	91R	89R	84C	87C	82C	87C	85C	80C	77C	88C	86C	92C	86C	85C	84C	87C	75C	86C	75C	83C	60C	80C	84C	NT	NT	NT	NT
	Champagne	NT	NT	NT	NT	NT	NT	NT	NT	88I	90T	88I	95T	88R	92R	92R	93R	90I	97T	95T	NT	88E	NT	NT	93R	95R	95R	NT	NT	95R	NT	NV	94R	NT	NT	95R	NT	94R	93R	93C	88C
	Languedoc and Roussillon	NT	88I	91E	94T	91R	87R	92R	90I	88R	88R	87I	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT
	Loire Valley white	NT	NT	86R	92T	88I	90I	84I	83E	94E	82C	82R	96R	82C	84R	84R	84C	88C	91R	88C	87C	86C	80C	75C	90R	92R	88C	82C	87C	88C	68C	84C	84C	82C	72C	83C	85C	NT	NT	NT	NT
	Rhone: Cote Rotie/Hermitage	NT	NT	88E	94T	98T	79I	89E	92E	89T	85C	96R	78C	89R	87E	95T	90T	90E	86R	90T	88C	58C	78R	92R	92R	92T	92R	86R	84C	90R	75E	89C	85C	75C	83C	87C	98R	82R	73C	84R	90C
	Rhone: Chateauneuf du Pape	NT	NT	88R	98T	93E	86R	98E	92R	95T	88R	90I	58C	96T	98E	90E	98E	82C	82C	90T	86C	85C	78C	65C	95R	94T	88R	60C	78C	88R	72C	87C	70C	88C	77C	88C	97R	75C	60C	82C	88C
	Germany: Mosel-Saar-Ruwer	NT	NT	95R	89I	95I	82I	92R	95I	94R	92R	91I	91R	91R	76C	86E	92T	88R	91T	90R	94R	91R	87C	88R	96R	91C	92R	84C	85C	88R	70R	89R	78C	86R	68I	88R	70R	92C	95R	98R	85R
	Germany: Rhine Riesling	NT	NT	94R	87I	93I	88R	92R	86I	92R	93T	89I	92R	95R	69C	87E	93T	87R	91T	86C	87R	88R	85C	87R	96R	90C	90R	84R	84C	86C	70R	87C	76C	87R	70I	86R	70R	91C	92R	98C	87R
Italy	Campania: Taurasi	NT	NT	NT	96T	94T	92T	94T	92T	92R	91R	88C	84C	91R	92R	93R	93R	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT
	Friuli: Collio Whites	NT	90R	88R	94R	94R	91I	93I	93C	90C	92C	85C	82C	88C	90C	90C	85C	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	
	Piedmont: Barbaresco	NT	NT	90T	95T	90I	90E	96E	90E	93T	93E	89I	74I	96T	90E	90E	92T	93E	97T	87C	77C	89E	74C	76C	96R	97T	90R	86R	89I	95R	65C	75C	96R	80R	88I	89R	97T	NT	NT	94R	93C
	Piedmont: Barolo	NT	NT	NT	98T	90I	93T	97E	97T	93T	96T	90I	76I	96T	91E	95T	92T	93E	97T	87R	77C	91R	74C	76C	96R	97T	90R	86R	90I	95R	65C	75C	96R	80R	88I	90R	97T			94R	93C
	Trentino-Alto Adige Whites	NT	92R	91R	93R	94R	92I	93I	92C	88C	93C	87C	83C	92C	95I	90C	85C	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT
	Tuscany: Bolgheri	NT	90T	88T	94E	97E	92T	93E	97T	93R	96T	89I	87I	94R	89E	94R	88R	94R	89R	90R	NT	NT	NT	NT	90R	NT	90R	NT	NV	93R	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT
	Tuscany: Brunello di Montalcino	NT	NT	NT	NT	93T	91I	97E	97T	91E	95I	89I	77R	95T	89E	95T	88R	95R	88R	93R	NT	90R	NT	NT	94R	NT	94R	NV	NV	93R	NT	92R	92R	NT	NT	NT	NT	NT	93R		
	Tuscany: Chianti Classico	NT	90R	88R	96E	92E	90R	93E	96T	91R	96T	92I	75R	93R	88E	94R	88R	95R	88R	89R	NT	89R	NT	NT	90R	NT	92R	NT	NV	93R	60C	NT	90R	NT	NT	NT	NT	NT	92R	NT	NT
	Sicily: Etna	NT	92T	91T	90T	88R	90I	93R	92R	93I	95R	88C	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT
	Veneto: Valpolicella (Amarone)	NT	94R	NT	NT	94E	90R	95E	93R	90R	94R	88R	85C	91C	88C	89C	89C	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT
	Portugal dry wines	NT	NT	95T	88E	92T	90T	94T	84E	90T	93R	89R	80I	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT
	Portugal vintage port	NT	NT	NT	NT	94T	90T	93T	NT	NT	NT	90T	NT	NV	92T	NV	NV	89T	NV	NV	92T	NV	95E	90E	NV	NV	NV	NV	NV	92R	NV	92R	86R	NV	84R	NV	83C	NV	82R	NV	90R
	Rioja	NT	92T	88T	95T	92T	90T	89R	85R	92R	95E	87I	76C	94E	86E	86E	82C	86R	85R	90R	90R	87R	85R	76R	87R	90R	87R	82C	82R	82C	78R	74C	92C	92C	75C	79C	84C	86R	84C	74C	90C
	Ribera del Duero	NT	92T	89T	94T	94T	91T	90T	88R	93T	95E	88I	78C	95E	87C	88C	88T	86R	92R	90R	90R	87R	82R	74R	89R	88C	87C	88C	77C	85C	86R	85C	87C	84C	85C	NT	NT	NT	NT	NT	NT
	Galicia	NT	91E	88E	91E	91R	90R	89R	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	86R	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT
USA / California	North Coast Cabernet Sauvignon	NT	96E	78I	95T	94T	94T	96E	91E	95T	91R	92I	95E	96T	78C	88T	85R	94I	90T	94T	95E	90E	93R	94T	94E	84E	75E	90E	90R	90T	92R	76C	86R	85R	87R	80R	92R	90T	85R	70C	92R
	North Coast Chardonnay	NT	94E	88I	91E	90R	88I	92R	87I	94E	92R	91R	90R	90C	87C	89R	89R	92C	87C	92C	88C	90C	92C	85C	90C	76C	89C	75C	90C	84C	88C	85C	85C	86C	88C	83C	86C	80C	86C	82C	83C
	North Coast Zinfandel	NT	92R	74I	90R	85I	78I	88R	79I	78I	82I	93R	85R	90R	83C	87R	86C	85E	89C	87R	92C	90C	90C	91C	91C	83C	82C	90C	87C	88C	88R	78C	80C	82C	82C	83C	86C	87C	80C	60C	89C
	North Coast Pinot Noir	NT	93R	84I	91R	90R	86I	90I	87I	90E	89I	90R	92E	92E	88R	90E	89R	90E	88R	88R	92R	88R	88R	86R	86R	85C	87C	86C	84C	86C	85R	85C	84C	83C	85C	80C	84C	NT	NT	NT	NT
	Central Coast	NT	93R	87E	92T	87R	88I	94E	92E	92R	94R	92E	93E	89R	92R	88R	90R	90R	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT
USA	Oregon: Willamette Valley Pinot Noir	NT	NT	NT	88I	86R	94T	84T	91E	85T	86E	88E	92I	85E	86E	92E	89T	87C	83C	76C	92R	89R	88R	87C	90C	86C	88C	72C	85C	87C	65C	90C	84C	86C	86C	NT	NT	NT	NT	NT	NT
	Washington Cabernet Sauvignon/Syrah	NT	94T	87E	92T	92T	91T	94R	91R	94R	91R	90R	89R	92R	89R	90T	90T	88T	88T	87R	90R	87R	89R	85C	87R	92R	88R	90R	78R	86R	72C	92R	78C	NT	NT	NT	NT	NT	NT	NT	NT
Southern Hemisphere	Argentina	NT	91E	94T	92T	90T	91T	92R	94R	93R	91R	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT
	South: Barossa/McLaren Vale	NT	94T	79I	93T	89T	85I	85R	94R	96R	94R	90C	95R	95C	88C	88E	95E	88R	90E	87R	90R	87R	87R	89R	88R	88C	85C	87C	90R	86C	NT	76R	83C	85C	88C	NT	NT	NT	NT	NT	NT
	West	NT	91T	90T	92T	89T	92R	87R	82I	91R	88R	89R	90R	90C	88E	89R	90R	87R	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT
	New South Wales	NT	78I	82I	89T	85I	79I	90R	84R	87R	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	84R	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT
	Victoria/Tasmania	NT	94T	78I	92T	87I	85R	85I	93R	91R	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT
	Chile	NT	87T	92T	90T	88T	90R	88R	89R	90R	89R	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT
	New Zealand	NT	79I	88R	91R	89R	81I	91R	90R	85C	83C	78C	87C	76C	81I	80I	90R	86I	89R	84I	87R	83C	86I	86C	85C	88C	80C	77C	85C	82C	NT	85C	78C	74C	69C	NT	NT	NT	NT	NT	NT
	South Africa	NT	91E	89I	91R	93R	88R	90R	92R	85C	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT	NT
	Country: Region wines	2013	2012	2011	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001	2000	1999	1998	1997	1996	1995	1994	1993	1992	1991	1990	1989	1988	1987	1986	1985	1984	1983	1982	1981	1980	1979	1978	1976	1975	1971	1970

Note: This chart is available on the eRobertParker.com web site.

Rating Ranges:

96 - 100 Extraordinary. 90 - 95 Outstanding. 80 - 89 Above Average to Excellent.

70 - 79 Average. 60 - 69 Below Average. < 59 Appalling

Maturity:

C = Caution, may be too old, **E** = Early maturing and accessible, **NV** = Vintage not declared,
I = Irregular, even among the best wines, **NT** = Not yet sufficiently tasted to rate,
R = Ready to drink, **T** = Still tannic, youthful, or slow to mature