Mean Squared Error & R2 Score Clearly Explained

Today we’re going to introduce some terms that are important to machine learning: variance, r2 score, and mean square error. We illustrate these concepts using scikit-learn.

You need to understand these metrics in order to determine whether regression models are accurate or misleading. Following a flawed model is a bad idea, so it is important that you can quantify how accurate your model is. Understanding that is not so simple.

These first metrics are just a few of them – later we will look at other concepts, like bias and overtraining models, which also yield misleading results and incorrect predictions.

To provide examples, let’s use the code from our last blog post, and add additional logic. We’ll also introduce some randomness in the dependent variable (y) so that there is some error in our predictions. (Recall that, in the last blog post we made the independent y and dependent variables x perfectly
correlate to illustrate the basics of how to do linear regression with scikit-learn.)

In brief, these metrics mean:

**variance**—in terms of linear regression, variance is a measure of how far observed values differ from the average of predicted values, i.e., their difference from the **predicted value mean**. The goal is to have a value that is low. What **low** means is quantified by the **r2 score** (explained below).

In the code below, this is **np.var(err)**, where **err** is an array of the differences between observed and predicted values and **np.var()** is the numpy array variance function.

**r2 score**—varies between 0 and 100%. It is closely related to the **MSE** (see below), but not the same. Wikipedia defines r2 like this, "... is the proportion of the variance in the dependent variable that is predictable from the independent variable(s)." Another definition is "(total variance explained by model) / total variance." So if it is 100%, the two variables are perfectly correlated, i.e., with no variance at all. A low value would show a low level of correlation, meaning a regression model that is not valid, but not in all cases.

Reading the code below, we do this calculation in three steps to make it easier to understand. **g** is the sum of the differences between the observed values and the predicted ones. **(ytest[i] – preds[i]) **2. **y** is each observed value **y[i]** minus the average of observed values **np.mean(ytest)**. And then the results are printed thus:

```python
print ("total sum of squares", y)
print ("total sum of residuals ", g)
print ("r2 calculated", 1 - (g / y))
```

Our goal here is to explain. We can of course let scikit-learn to this with the **r2_score()** method:
mean square error (MSE)—is the average of the square of the errors. The larger the number the larger the error. Error in this case means the difference between the observed values \(y_1, y_2, y_3, \ldots\) and the predicted ones \(pred(y_1), pred(y_2), pred(y_3), \ldots\). We square each difference \((pred(yn) - yn))^2\) so that negative and positive values do not cancel each other out.

So here is the complete code:

```python
import matplotlib.pyplot as plt
from sklearn import linear_model
import numpy as np
from sklearn.metrics import mean_squared_error, r2_score

reg = linear_model.LinearRegression()

ar = np.array([[[1],[2],[3]], [[2.01],[4.03],[6.04]]])
y = ar[1, :]
x = ar[0, :]
reg.fit(x, y)
print('Coefficients: 
', reg.coef_)
xTest = np.array([[4],[5],[6]])
ytest = np.array([[9],[8.5],[14]])
preds = reg.predict(xTest)
print("R2 score : %.2f" % r2_score(ytest,preds))
print("Mean squared error:  %.2f"  % mean_squared_error(ytest,preds))

er = []
g = 0
for i in range(len(ytest)):
    print( "actual=", ytest[i], " observed=", preds[i])
    x = (ytest[i] - preds[i]) ** 2
    er.append(x)
    g = g + x
x = 0
for i in range(len(er)):
    x = x + er[i]
```

print("R2 score : %.2f" % r2_score(ytest,preds))
print ("MSE", x / len(er))

v = np.var(er)
print ("variance", v)

print ("average of errors ", np.mean(er))

m = np.mean(ytest)
print ("average of observed values", m)

y = 0
for i in range(len(ytest)):
    y = y + ((ytest[i] - m) ** 2)

print ("total sum of squares", y)
print ("total sum of residuals ", g)
print ("r2 calculated", 1 - (g / y))

Results in:

Coefficients:
[[2.015]]
R2 score : 0.62
Mean squared error: 2.34
actual= [9.] observed= [8.05666667]
actual= [8.5] observed= [10.07166667]
actual= [14.] observed= [12.08666667]
MSE [2.34028611]
variance 1.2881398892129619
average of errors 2.3402861111111117
average of observed values 10.5
total sum of squares [18.5]
total sum of residuals [7.02085833]
r2 calculated [0.62049414]

You can see by looking at the data np.array([[1],[2],[3]],
[[2.01],[4.03],[6.04]]) that every dependent variable is roughly twice the independent variable. That is confirmed as the calculated coefficient reg.coef_ is 2.015.

There is no correct value for MSE. Simply put, the lower the value the better and 0 means the model is perfect. Since there
is no correct answer, the MSE’s basic value is in selecting one prediction model over another.

Similarly, there is also no correct answer as to what R² should be. 100% means perfect correlation. Yet, there are models with a low R² that are still good models.

Our take away message here is that you cannot look at these metrics in isolation in sizing up your model. You have to look at other metrics as well, plus understand the underlying math. We will get into all of this in subsequent blog posts.

Additional Resources

Extending R-squared beyond ordinary least-squares linear regression from pcdjohnson