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March 25, 2014 · MACHINE LEARNING

Simple guide to confusion matrix terminology

A confusion matrix is a table that is often used to **describe the performance of a classification model** (or "classifier") on a set of test data for which the true values are known. The confusion matrix itself is relatively simple to understand, but the related terminology can be confusing.

I wanted to create a **"quick reference guide" for confusion matrix terminology** because I couldn't find an existing resource that suited my requirements: compact in presentation, using numbers instead of arbitrary variables, and explained both in terms of formulas and sentences.

Let's start with an **example confusion matrix for a binary classifier** (though it can easily be extended to the case of more than two classes):

n=165	Predicted: NO	Predicted: YES
	Actual: NO	Actual: YES
Actual: NO	50	10
Actual: YES	5	100

What can we learn from this matrix?

- There are two possible predicted classes: "yes" and "no". If we were predicting the presence of a disease, for example, "yes" would mean they have the disease, and



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"no" would mean they don't have the disease.

- The classifier made a total of 165 predictions (e.g., 165 patients were being tested for the presence of that disease).
- Out of those 165 cases, the classifier predicted "yes" 110 times, and "no" 55 times.
- In reality, 105 patients in the sample have the disease, and 60 patients do not.

Let's now define the most basic terms, which are whole numbers (not rates):

- **true positives (TP):** These are cases in which we predicted yes (they have the disease), and they do have the disease.
- **true negatives (TN):** We predicted no, and they don't have the disease.
- **false positives (FP):** We predicted yes, but they don't actually have the disease. (Also known as a "Type I error.")
- **false negatives (FN):** We predicted no, but they actually do have the disease. (Also known as a "Type II error.")

I've added these terms to the confusion matrix, and also added the row and column totals:

n=165	Predicted:		
	NO	YES	
Actual: NO	TN = 50	FP = 10	60
Actual: YES	FN = 5	TP = 100	105
	55	110	

This is a list of rates that are often computed from a confusion matrix for a binary classifier:



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- **Accuracy:** Overall, how often is the classifier correct?
 - $(TP+TN)/total = (100+50)/165 = 0.91$
- **Misclassification Rate:** Overall, how often is it wrong?
 - $(FP+FN)/total = (10+5)/165 = 0.09$
 - equivalent to 1 minus Accuracy
 - also known as "Error Rate"
- **True Positive Rate:** When it's actually yes, how often does it predict yes?
 - $TP/actual\ yes = 100/105 = 0.95$
 - also known as "Sensitivity" or "Recall"
- **False Positive Rate:** When it's actually no, how often does it predict yes?
 - $FP/actual\ no = 10/60 = 0.17$
- **True Negative Rate:** When it's actually no, how often does it predict no?
 - $TN/actual\ no = 50/60 = 0.83$
 - equivalent to 1 minus False Positive Rate
 - also known as "Specificity"
- **Precision:** When it predicts yes, how often is it correct?
 - $TP/predicted\ yes = 100/110 = 0.91$
- **Prevalence:** How often does the yes condition actually occur in our sample?
 - $actual\ yes/total = 105/165 = 0.64$

A couple other terms are also worth mentioning:

- **Null Error Rate:** This is how often you would be wrong if you always predicted the majority class. (In our example, the null error rate would be $60/165=0.36$ because if you always predicted yes, you would only be wrong for the 60 "no" cases.) This can be a useful baseline metric to compare your classifier against. However, the best classifier for a particular application will sometimes have a higher error rate than



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the null error rate, as demonstrated by the

Accuracy Paradox.

- **Cohen's Kappa:** This is essentially a measure of how well the classifier performed as compared to how well it would have performed simply by chance. In other words, a model will have a high Kappa score if there is a big difference between the accuracy and the null error rate. (**[More details about Cohen's Kappa.](#)**)
- **F Score:** This is a weighted average of the true positive rate (recall) and precision. (**[More details about the F Score.](#)**)
- **ROC Curve:** This is a commonly used graph that summarizes the performance of a classifier over all possible thresholds. It is generated by plotting the True Positive Rate (y-axis) against the False Positive Rate (x-axis) as you vary the threshold for assigning observations to a given class. (**[More details about ROC Curves.](#)**)

And finally, for those of you from the world of Bayesian statistics, here's a quick summary of these terms from **[Applied Predictive Modeling](#)**:

In relation to Bayesian statistics, the sensitivity and specificity are the conditional probabilities, the prevalence is the prior, and the positive/negative predicted values are the posterior probabilities.

Want to learn more?

In my new 35-minute video, **[Making sense of the confusion matrix](#)**, I explain these concepts in more depth and cover more **advanced topics**:



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- How to calculate precision and recall for multi-class problems
- How to analyze a 10-class confusion matrix
- How to choose the right evaluation metric for your problem
- Why accuracy is often a misleading metric

Let me know if you have any questions!

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Name



Engr Ali Raza • 3 years ago

Dear Kevin,
can you please tell me the relationship between Misclassifications and split value or split value explain that how we can calculate the split value decision algorithm?

SplitValue/Set Cases Misclassifications Class
22.65 5 0.8 1.6 Decision
N/A 1 0 1.6 Terminal
8.63 4 0.6 2.7 Decision
14.4 2 0.2 2.7 Decision
34.85 2 0.2 4 Decision
N/A 1 0 2.7 Terminal
N/A 1 0 5.2 Terminal
N/A 1 0 4 Terminal
N/A 1 0 7.5 Terminal

can anyone explain this table?how it can be generated formulas used behind these values

78 ^ | v • Reply • Share ›



Jenica J. Wilson → Engr Ali Raza • 2 years ago

I know that this is 10 months ago but I have not received an answer here it is

When developing a measure or test you identify a unique group of people - for Rosenberg Self-Esteem Test purports people with low self-esteem. Good measure particularly those used in research or users would like to see them have greater abilities. One way to do this is to cross-splitting the data up is way to cross-validate percentage of the data that is used to measure identifies people with, let say esteem, is then taken or split from the subset data is set by you. So, if you well the measure identifies future exact test this on 30% of your data. So you would be set to .70, because 70% of data be used as in the analysis to identify low self-esteem. Based on the pattern from the 70% of the data set, the sensor (what you have above) would use the



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to test how accurately the measure re participants back into their groups.

sensitivity = true positive/false positive (accuracy rates)

specificity = true negatives/ false negatives (accuracy rates)

Prevalence = proportion of group/total

Detection rates= measure ability to across various groups

I am not sure what the program was v received the output above. So maybe would help people best identify how to findings and provide you on how the i be generated.

2 ^ | v • Reply • Share ›



Kevin Markham Mod → Engr Ali Raza • 3 ye

I'm sorry, I'm not familiar with split val table you included in your comment. (

2 ^ | v • Reply • Share ›



ajay kumar • 5 years ago

Respected Sir,

I have two confusion matrices and I want to p McNemar Test. It is hereby to requesting you how to generate the values of 2 by 2 matrix I find the values of f11, f12, f21 and f22 from th matrices.

Thank You,

56 ^ | v • Reply • Share ›



Peter → ajay kumar • 10 months ago

dear friend, try confusionMatrix functi package

^ | v • Reply • Share ›



Kevin Markham Mod → ajay kumar • 5 year

I'm not familiar with McNemar's test, I

^ | v • Reply • Share ›



Todd de Quincey • 2 years ago

Great summary! Thanks for putting this toget going into my notebook of tips and tricks

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Kevin Markham Mod → Todd de Quincey •

You're welcome!



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YOU TO WELCOME.

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Davide • 3 years ago

Dear Kevin,

Thanks for the clear explanation.

I have a particular problem and I'm struggling hope your expertise can help me.

I want to compare the performance of a burn toward a reference one. My analysis is not pixel-based, I'm not creating random points in the map and creating a confusion matrix. This is also because the proportion of burned vs not burned is really small. I'm therefore confused by the product vs reference fires, a confusion matrix using the whole available data and not samples. Also the error matrix is missing True Negatives. Concretely:

- reference dataset has 70 fires
- tested product has 36
- 21 fires are correctly detected by the tested product
- 15 fires detected by the tested product are not in the reference
- 49 reference fires are not detected by the tested product (FN)
- I didn't add TN

Several questions rise:

- can I use the available derived metrics to quantify results? (F1, sensitivity and precision) even if I have only RANDOM observations but the WHOLE AVAILABLE OBSERVATIONS in the datasets? Or should I consider normal rates of detection and omission?
- should I add TN observations for the calculation of metrics? (how many?) they will also be not random...
- if I add an other burned area product which is not burned, the error matrix will have a different number of observations... Are they comparable?
- Is there other statistic tools which would suit my case?

Thank you for your attention

5 ^ | v • Reply • Share ›



Kevin Markham Mod ➔ Davide • 3 years ago

Thanks for your detailed question! I'd be happy to help, but I'm not able to give you advice without having a lot more domain knowledge. For example, I don't know what a "burned area" is, how you compare it against a "reference". A "pixel-based" analysis might look like, for example, is the kind of question that I would imagine asking with a student for 20 minutes, and only



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give good advice! Without more information, it would be irresponsible of me to try to answer your question. I'm sorry, and good luck!

1 ^ | v • Reply • Share ›



Priyansh Agarwal • 3 years ago

Hi Kevin

I am confused with Type1 and TypeII errors

false positives (FP): We predicted yes, but they don't have the disease. (Also known as a "Type I error")
false negatives (FN): We predicted no, but they do have the disease. (Also known as a "Type II error")

Type1 error is Worst than Type 2 error and but Type 2 error looks worst than Type 1, because when we have a disease is more bad than the

Thank

4 ^ | v • Reply • Share ›



Kevin Markham Mod ➔ Priyansh Agarwal •

Thanks for your question. It appears that you're saying that in general, type I errors are worse than type II errors. That's not actually the case. Which is "worse" depends on the particular situation. It also depends on your perspective. Here's a link to a discussion on this topic.

^ | v • Reply • Share ›



manan • 8 months ago

hi there,

i m working with election predictions. i have created a model using 2018 election data-set and tested it on 2008 election data-set. now my question is that what is the mean of all confusion matrix for three election years for a single model.

2 ^ | v • Reply • Share ›



Kevin Markham Mod ➔ manan • 8 months ago

I don't think I understand your goals very well. I can't provide any advice for this scenario -

^ | v • Reply • Share ›



NLR • 8 months ago

Hi Kevin, this is extremely helpful. Do you have a link or number for your reference to Applied Predictive Modeling regard to getting Bayesian calculations from a confusion matrix?

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Kevin Markham Mod → NLR • 8 months ago

I don't have a page number, I'm sorry!

2 ^ | v • Reply • Share ›



Hritik Singh • 2 years ago

How to calculate the various metrics like prec with 3 classes (eg- the iris dataset)

2 ^ | v • Reply • Share ›



Kevin Markham Mod → Hritik Singh

• 2 years ago • edited

Great question! To calculate per-class iris dataset, for example, you are answering questions: (1) When it predicts setosa correct? (2) When it predicts versicolour correct? (3) When it predicts virginica, correct?

To answer question 1, for example, the "number of setosa predictions" and the "how many of those were correct". You then calculate that in order to answer questions 2 and 3.

Similarly, to calculate per-class recall, answer questions like: (1) When the true class is setosa, how often does it predict setosa?

You can see a simple example of 3-class recall here: http://scikit-learn.org/stable/tutorial/linear_model/lda_classification.html

Hope that helps!

1 ^ | v • Reply • Share ›



Jenica J. Wilson → Hritik Singh • 2 years ago

if you are using R here is the formula: This will give you the actual accuracy of a classifier, here it is LDA, reclassified the

```
p1 <- predict(lda,dataset)$class
tab <- table(Predict=p1,Actual=dataset$class)
# Confusion matrix
# Predicted \ Actual
# setosa versicolour virginica
# setosa 10 0 0
# versicolour 0 10 0
# virginica 0 0 10
# accuracy <- sum(diag(tab))/sum(tab)
# model
# tab
# accuracy
```

If you want to cross-validate in R see [this](#) Packages that you would need

```
install.packages("caret")
library("caret")
library(klaR)
```



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hana • 2 years ago

I work on credit risk project the confusion matrix
TN=6 FP 10 AND FN=3 I calculate some Metrics
, error sensitivity and other also I suggest the
money from confusion matrix my question is I want
for the calculation of earn and lose money on
thanks

1 ^ | v • Reply • Share ›



Kevin Markham Mod → hana • 2 years ago

I'm sorry, I don't completely understand
Good luck!

^ | v • Reply • Share ›



Tamil Selvan • 3 years ago • edited

can you please clarify me what is the difference
misclassification error and misclassification rate

1 ^ | v • Reply • Share ›



Kevin Markham Mod → Tamil Selvan • 3 years ago

I wouldn't recommend using the term
"misclassification error". A "classification error" is a
single instance in which your classification is
incorrect, and a "misclassification" is a
whereas "misclassification error" is a

"Misclassification rate", on the other hand, is the
percentage of classifications that were

3 ^ | v • Reply • Share ›



Raj Kandala • 4 years ago

Dear Kevin

Sub: In multi class confusion matrix, Finding
each class.

According to accuracy definition , $Acc = \frac{TP+TN}{TP+TN+FP+FN}$. accuracy is high even
if $TP=0$. How can we judge the performance in
the same time $precision = \frac{TP}{TP+FP}$ is zero.
explain this situation.

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Kevin Markham Mod → Raj Kandala • 4 years ago



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In a multi-class problem (meaning more than two classes), the accuracy is simply "correct predictions" divided by "total predictions".

If you want to evaluate each class individually, one option is to calculate the per-class precision and recall. scikit-learn's classification module provides this, for example: <http://scikit-learn.org>

1 ^ | v • Reply • Share ›



Raj Kandala → Kevin Markham • 4 years ago

Thank you Kevin

56 ^ | v • Reply • Share ›



Raj Kandala • 4 years ago

Hi, I want to calculate ROC plots using multiclass confusion matrix. Is it possible Mr. Kevin?

1 ^ | v • Reply • Share ›



Kevin Markham Mod → Raj Kandala • 4 years ago

ROC curves can only be drawn for binary classification problems, meaning problems with two classes. (However, you can turn a multiclass problem into a binary problem using a "one vs all" approach.)

Also, drawing an ROC curve requires knowing the predicted probability of class membership for each observation, rather than just the class label. Therefore, a confusion matrix alone (in the multiclass case) does not provide enough data to draw the ROC curve.

This post provides more information about ROC curves: <http://www.dataschool.io/roc-curves/>

Hope that helps!

3 ^ | v • Reply • Share ›



Raj Kandala → Kevin Markham • 4 years ago

Thank You Kevin

1 ^ | v • Reply • Share ›



Abdullah Nazzal • 4 years ago • edited

what if we have more than two classes ... say 3 classes. how to calculate this .. ? should i convert it to binary if so then how ?

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Kevin Markham Mod → Abdullah Nazzal • 4 years ago



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Many of these terms only have meaning in the context of classification problems. You can convert a multi-class problem to a binary problem simply by grouping output classes together, though I would not recommend doing that just so that you can use a metric to evaluate your model. Rather, you should convert it from multi-class to binary if it makes sense in the context of your problem.

^ | v • Reply • Share ›



Hassan Aftab Mughal → Kevin Markham
• 4 years ago

I think if you have more than two classes, your confusion matrix will be of size n x n. For example, if n=4, the matrix would be:

	Class1	Class2	Class3	Class4
Class1	10	3	3	0
Class2	5	15	1	2
Class3	0	5	20	1
Class4	0	2	1	9

2 ^ | v • Reply • Share ›



Kevin Markham Mod → Hassan Aftab Mughal
• 4 years ago

That's correct, you can use a confusion matrix for a multi-class problem. (My apologies otherwise!) However, the terminology outlined in the guide applies to binary classification problems.

Here's an example of a confusion matrix: http://scikit-learn.org/stable/auto_examples/plot_confusion_matrix.html

As a side note, the "n" in the upper left corner of the matrix refers to the number of classes. So in the case of your 4-class matrix, it would be n=4.

^ | v • Reply • Share ›