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Beyond accuracy in classification models

Example. An algorithm for identifying potential users of a new service on a website was applied to 250 test cases with the following results.

		Predicted	
		Positive	Negative
Actual	Positive	33	22
	Negative	7	188

How good is the algorithm?

This is an example of a **confusion matrix**. The desireable results are highlighted in green while the errors are highlighted in red.

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The upper-right and lower-left entries show false negatives and false positives, respectively.

The algorithm has an overall **accuracy** of $(33 + 188)/250 = 88.4\%$.

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This might look good, but it doesn't give a full picture of the effectiveness of the algorithm.

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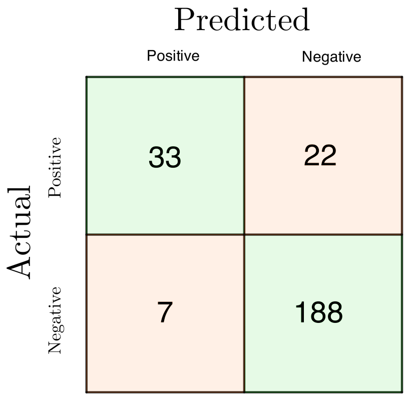
Of the 250 observations in this set, 195 are negatives, or 78%, so simply classifying *every* new observation as negative will result in an accuracy of 78%.



Of the 250 observations in this set, 195 are negatives, or 78%, so simply classifying *every* new observation as negative will result in an accuracy of 78%. Really, our algorithm only increases accuracy by a few points

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Others metrics that are commonly used include Cohen's kappa, true and positive likelihood ratios, and the F-score. Each of these answers a different question about the classifier's performance.

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In this example, the test's sensitivity is $33/(33+22) = 60\%$. Sensitivity is complementary to the **false negative rate**, the proportion of true positives which are wrongly classified.

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In this example, the test's specificity is $188/(7+188) \approx 96.4\%$.

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In this example, the test's specificity is $188/(7 + 188) \approx 96.4\%$. Specificity is complementary to the **false positive rate**, the proportion of true negatives which are wrongly classified.

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In this example, the precision is $33/(33+7) = 82.5\%$. Precision measures how reliable a positive prediction is.

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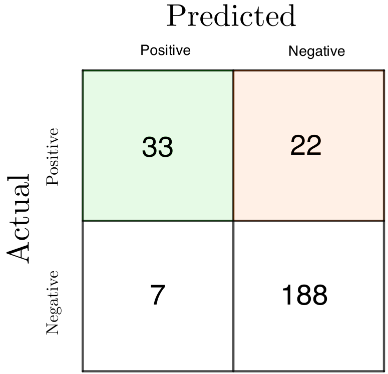

In this example, the recall is $33/(33+22) = 60\%$.

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Additionally, we might consider how the model compares to one that always picks the majority class or one that uses only observed proportions in some training set.