Metrics and Model Analysis

Confusion Matrix, MSE, MAE, Bias-variance tradeoff



Classification problems

Confusion Matrix



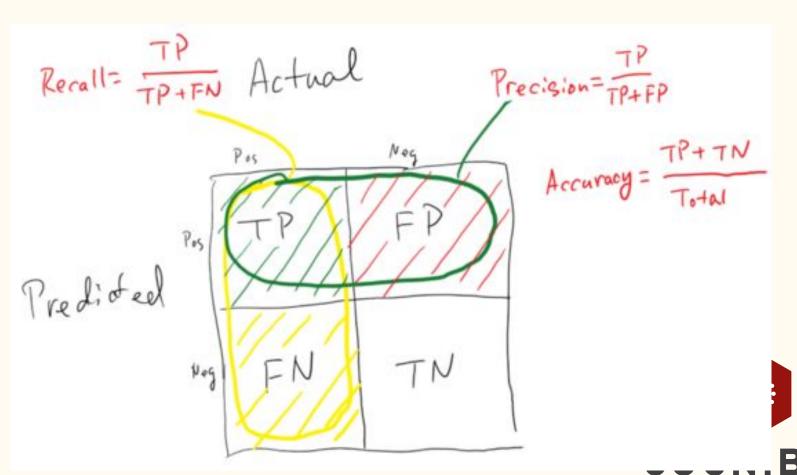
• A confusion matrix is a table that is often used to describe the performance of a classification model (or "classifier") on a set of test data for which the true values are known.



Actual Value

	.	(as confirmed by experiment)	
		positives	negatives
ue :est)	positives	TP	FP
/al	siti	True	False
oy th	od	Positive	Positive
Predicted Value (predicted by the test)	negatives	FN	TN
edic	gati	False	True
P (g)	ne	Negative	Negative

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Problems with Accuracy

- Assumes equal cost for both kinds of error
- Accuracy alone doesn't tell the full story when you're working with a class-imbalanced data set



Example

True Positive (TP):

· Reality: Malignant

· ML model predicted: Malignant

Number of TP results: 1

False Negative (FN):

· Reality: Malignant

· ML model predicted: Benign

Number of FN results: 8

False Positive (FP):

· Reality: Benign

· ML model predicted: Malignant

. Number of FP results: 1

True Negative (TN):

· Reality: Benign

ML model predicted: Benign

. Number of TN results: 90



$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} = \frac{1 + 90}{1 + 90 + 1 + 8} = 0.91$$

- Of the 91 benign tumors, the model correctly identifies 90 as benign. However, of the 9 malignant tumors, the model only correctly identifies 1 as malignant—a terrible outcome, as 8 out of 9 malignancies go undiagnosed!
- While 91% accuracy may seem good at first glance, another tumor-classifier model that always predicts benign would achieve the exact same accuracy (91/100 correct predictions) on examples.



Better Alternatives:

• Precision: What proportion of positive identifications was actually correct?

True Positives (TPs): 1	False Positives (FPs): 1			
False Negatives (FNs): 8	True Negatives (TNs): 90			
$ ext{Precision} = rac{TP}{TP + FP} = rac{1}{1+1} = 0.5$				

• Our model has a precision of 0.5—in other words, when predicts a tumor is malignant, it is correct 50% of the time. IBOT

• Recall: What proportion of actual positives was identified correctly?

True Positives (TPs): 1	False Positives (FPs): 1
False Negatives (FNs): 8	True Negatives (TNs): 90
<u> </u>	

$$Recall = \frac{TP}{TP + FN} = \frac{1}{1+8} = 0.11$$

• Our model has a recall of 0.11—in other words, it corrections identifies 11% of all malignant tumors.

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Regression problems

MAE, RMSE, MSE



Mean Absolute Error

• Less sensitive to outliers

$$ext{MAE} = rac{\sum_{i=1}^n |y_i - x_i|}{n} = rac{\sum_{i=1}^n |e_i|}{n}.$$



Mean Squared Error

Very sensitive to outliers

$$ext{MSE} = rac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y_i})^2.$$



Root Mean Squared Error

• RMSD is the square root of the average of squared errors. The effect of each error on RMSD is proportional to the size of the squared error; thus larger errors have a disproportionately large effect on RMSD. Consequently, RMSD is sensitive to outliers.

$$RMSErrors = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y_i} - y_i)^2}{n}}$$

$$COGNIBOT$$
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Bias-Variance tradeoff



Error due to bias

- The error due to bias is taken as the difference between the expected (or average) prediction of our model and the correct value which we are trying to predict.
- Bias measures how far off in general these models' predictions are from the correct value.



Error due to variance

- The error due to variance is taken as the variability of a model prediction for a given data point.
- The variance is how much the predictions for a given point vary between different realizations of the model.



