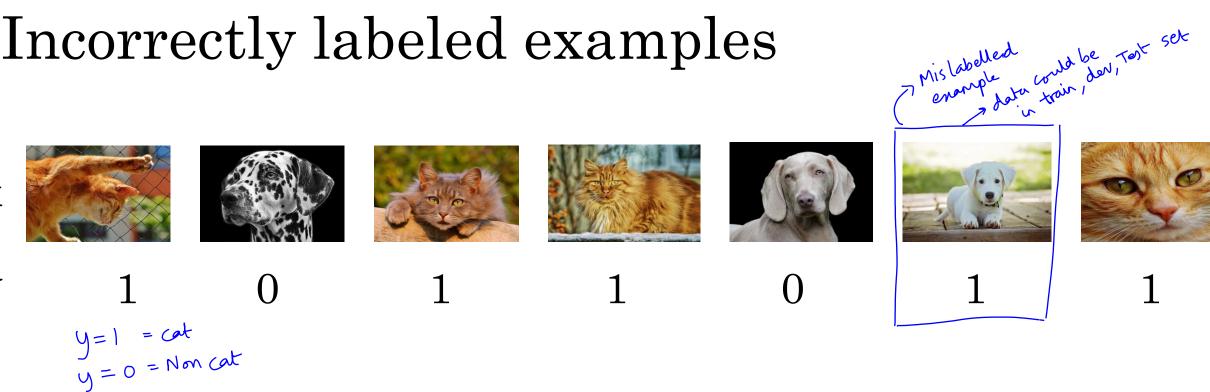


## Error Analysis

## Cleaning up Incorrectly labeled data

## Incorrectly labeled examples



DL algorithms are quite robust to random errors in the

training set.

DL Algos are less robust to systematic errors
eg All white dog Images are classified as
cats, that is a problem!

Ly As long as these errors are small in # (less # of misclassified examples) a They occur randomly we are fine

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Error analysis - If you're worried, incorrectly labelled enamples may occur in her/test set, Add a column -

From Analysis on dev/test set is a good exercise as it helps you decide where to go next

			Lev/test Se	t, Add a comme		
	Image	Dog	Great Cat	Blurry	Incorrectly labeled	Comments
	•••					
	98				✓	Labeler missed cat in background
	99		✓			
W. +	100 % of total ll dev set en				✓	Drawing of a cat; Not a real cat.
A Now K.	% of total	8%	43%	61%	6%) _ N	st.
<b>ૢ૾</b> ૾ૢ૾Overal	ll dev set er	ror -	0 %	51	7 th	at big a need deal, no time yer
Errors	due incorr	ect labe	els - 6% 010%	· = 0 · 6 ·/·	\ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \	deal, no need of the deal of the strong has nis- going through nis- sex & fixing
Errors	due to oth	er cause	$es \rightarrow 10-0.6$	= 9.4 %. Focus on there		overall der set / N overall der set / Sor A or = 2.1.1. for A
X					50Y	or = 2.1.1. for B c

Goal of dev set is to help you select between two classifiers A & B.

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## Correcting incorrect dev/test set examples

- Apply same process to your dev and test sets to make sure they continue to come from the same distribution (IJ you dean up dev set, must clean up test set)
- Consider examining examples your algorithm got right as well as ones it got wrong. (All white dogs labelled as cat,
- Train and dev/test data may now come from slightly different distributions. (You only cleaned dev, test, shy? large trs actually okay

  Not train set)

  Not feasible to clean Training set (too large)

  to be diff

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