

Error Analysis

Cleaning up Incorrectly labeled data

Incorrectly labeled examples



DL algorithms are quite robust to random errors in the training set.

Systematic escoss

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Error analysis



| ^ | Image | Dog | Great Cat | Blurry | Incorrectly labeled | Comments | |
|------------------------------------|------------|-----|--------------|--------|---------------------|--------------------------------------|--------------|
| \uparrow | | | | | | | |
| | 98 | | | | \checkmark | Labeler missed cat in background | \leftarrow |
| | 99 | | \checkmark | | | | |
| \bigcup | 100 | | | | \bigcirc | Drawing of a cat; Not a real cat. | \leftarrow |
| | % of total | 8% | 43% | 61% | 6% | V | |
| Overall dev set error | | | | | | 2% | |
| Errors due incorrect labels 0.6./. | | | | | | 0.6% | |
| Errors due to other causes 9.4% < | | | | | | | |
| | | | | 1 | | 2.10/0 | 1.9./6 |

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

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
- Consider examining examples your algorithm got right as well as ones it got wrong.
- Train and dev/test data may now come from slightly different distributions.