CNNs VS imbalanced datasets

1. Background

- Convolutional Neural Networks (CNN) widely used[1]
- Mostly viewed as Black Boxes[1]
- What are Imbalanced dataset?[2]
- Imbalance is not uncommon[3]
  - Harder to get samples of rare diseases

2. How do imbalanced training datasets affect the performance of CNNs?

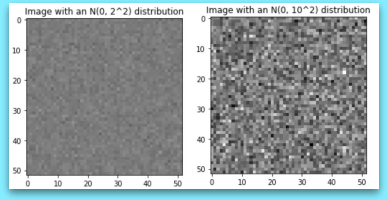
- Performance of network trained on:
  - Balanced datasets
  - Datasets with missing targets
  - Dataset with normally distributed targets
- Related work shows:
  - networks trained on balanced datasets significantly outperform others[3-10]

3. CNN

- Shallow network[11]
- Adam optimizer[12]
- Standard deviation

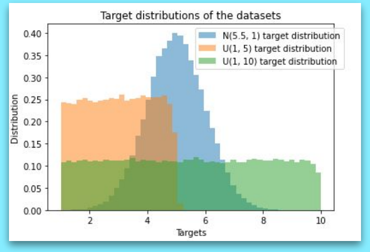
4. Datasamples

- Samples have $N(0, x^2)$ distribution
  - x is drawn from target distribution dependant on dataset
- Visualisation of $N(0, 2^2)$ and $N(0, 10^2)$ samples:



5. Datasets

- Synthetic
- U(1, 10)
  - reference dataset
- U(1, 5)
  - missing targets
- N(5.5, 1)
  - different distribution



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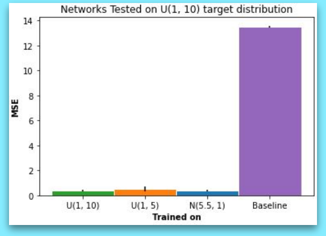
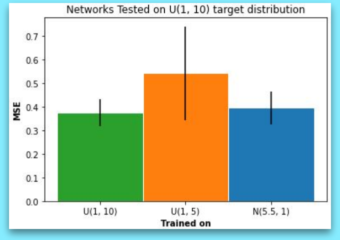
6. Results

- Mean-squared error
- Baseline
- All networks tested on U(1, 10) datasets
- Experiments repeated 10 times





7. Discussion and conclusion

- All networks significantly outperformed the baseline
  - Networks were able to learn the task with imbalanced datasets
- The networks trained on the balanced datasets had the best performance
  - In line with hypothesis
- The networks trained on the datasets with normally distributed targets performed slightly worse
  - Some targets underrepresented -> networks were not able to predict those as effectively
- The networks trained on the datasets with missing targets had the worst performance
  - Training sets did not include all of the targets of the test sets -> the networks were unable to perform as well as the networks trained on other target distributions

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