Morse Code Datasets for Machine Learning

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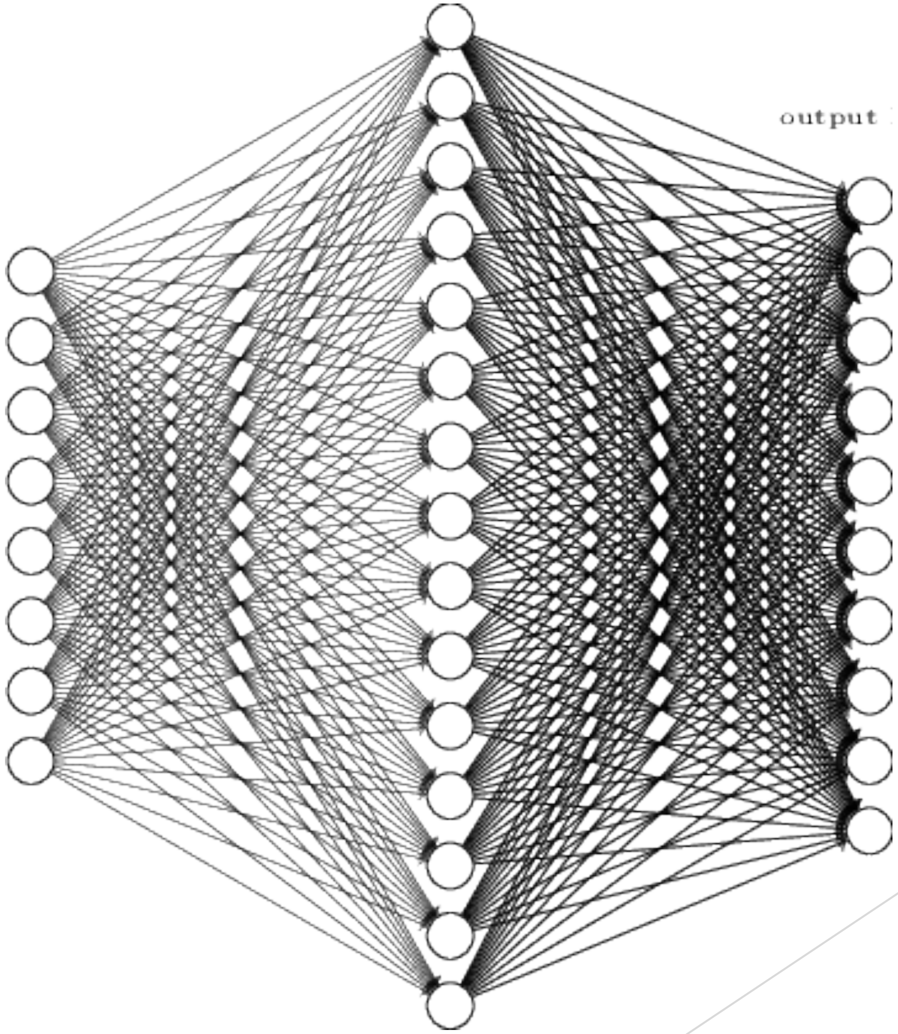
Machine Learning and Neural Networks

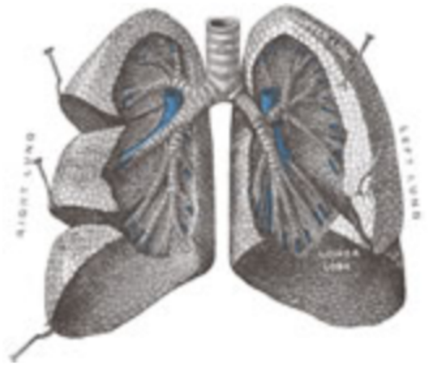
An algorithm to learn from data and classify it



Need a lot of data for good performance

Issues with Natural Data

- Most data is naturally collected and labeled by humans
- Labeling is time-consuming (e.g. Imagenet[1])
- Data can have missing features (e.g. Lung cancer dataset[2])



1: http://www.image-net.org/
2: http://archive.ics.uci.edu/ml/datasets/Lung+Cancer

Synthetic data as a Solution

- **Synthetic data** generated and labeled using algorithms
- Can be mass-produced cheaply without missing features

- Algorithm can be tuned to:
  - *Adjust difficulty*
  - Get any distribution

Overview of our Work

- Algorithm to generate Morse code classification datasets of varying difficulty
- Metrics to evaluate difficulty of a dataset

Morse code is a system of communication to encode characters as dots and dashes

\+   • ▬ • ▬ •

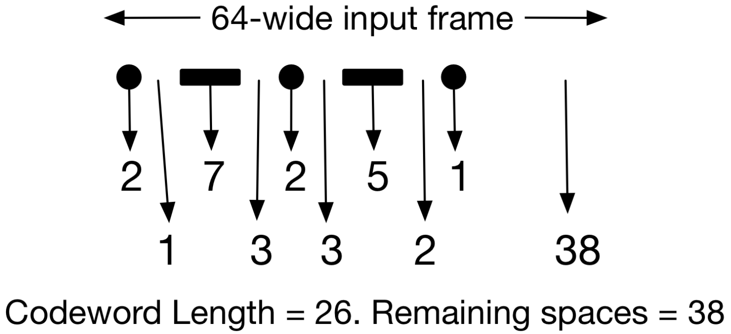
64 character classes

The Algorithm

Step 1:

Frame length: 64

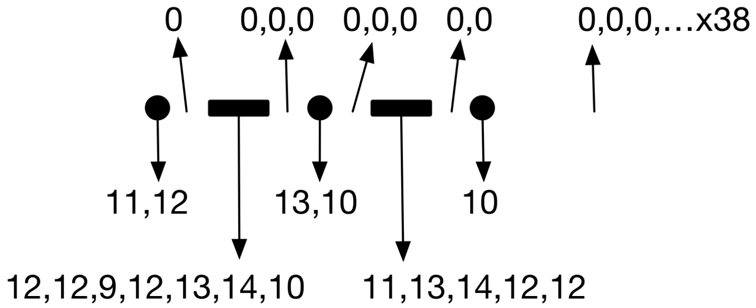
Dot: 1-3
Dash: 4-9
Intermediate space: 1-3
Leading spaces: None
Trailing spaces: Remaining at end



Step 2:

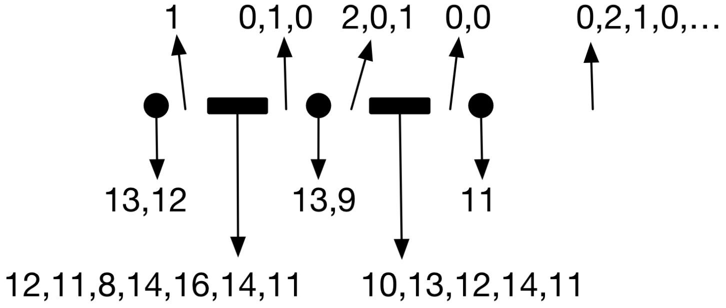
Expected value range = [0,16]

Dot, dash = *Normal*(12,4/3)
Space = 0



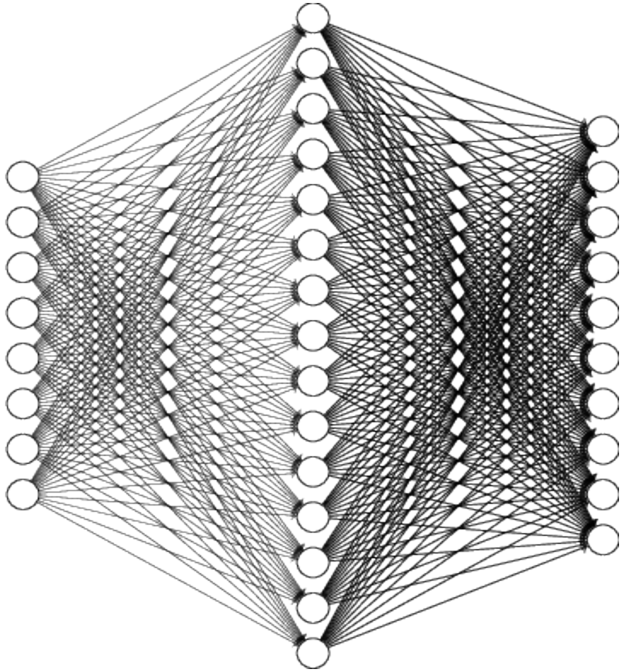
Step 3:

Additive Noise = *Normal*$(0,\boldsymbol{\sigma})$
(For this case, $\boldsymbol{\sigma}=1$)



The Neural Network

64 input neurons = Frame length of each Morse codeword

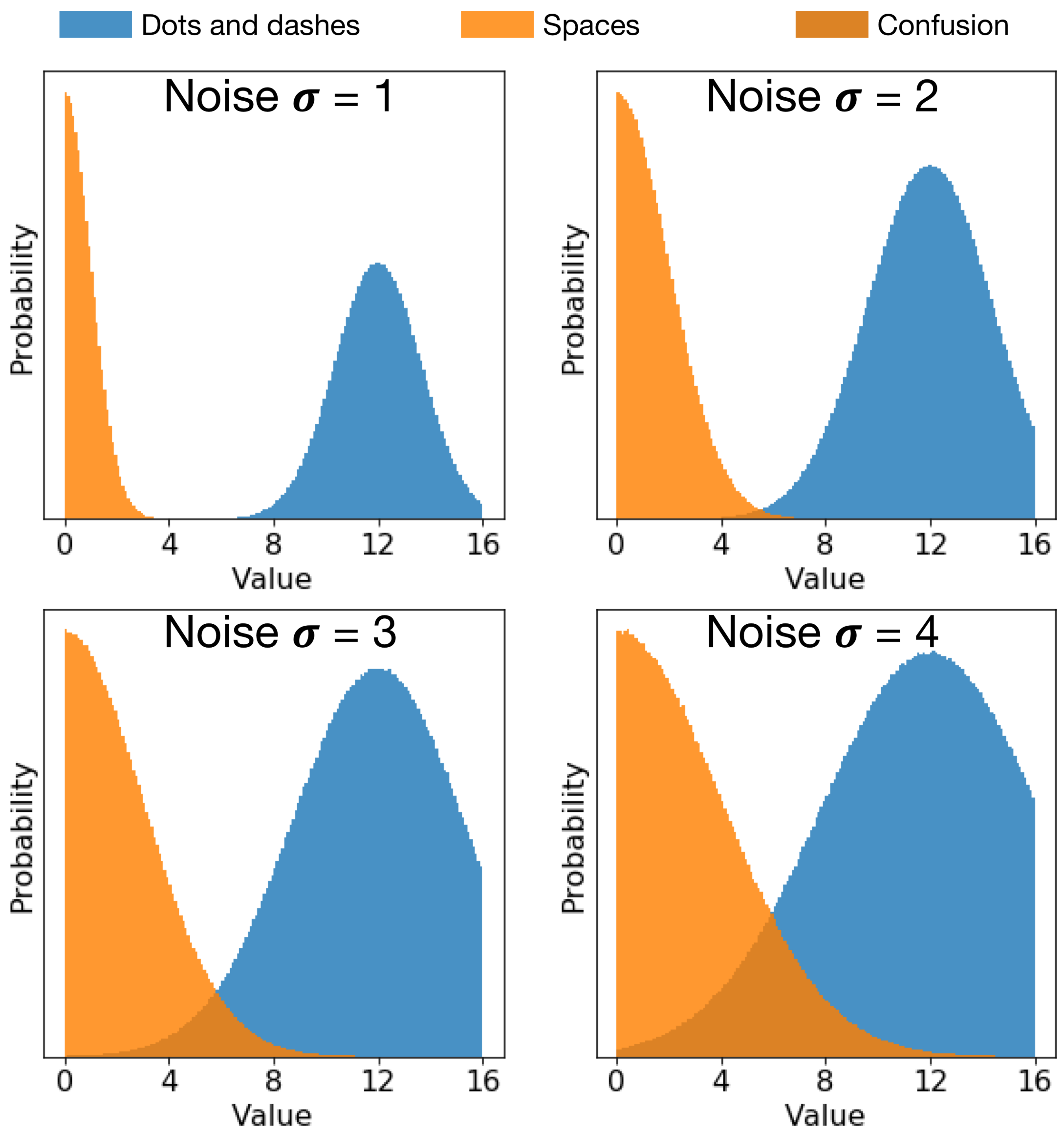


64 output neurons = Number of character classes

1024 hidden neurons

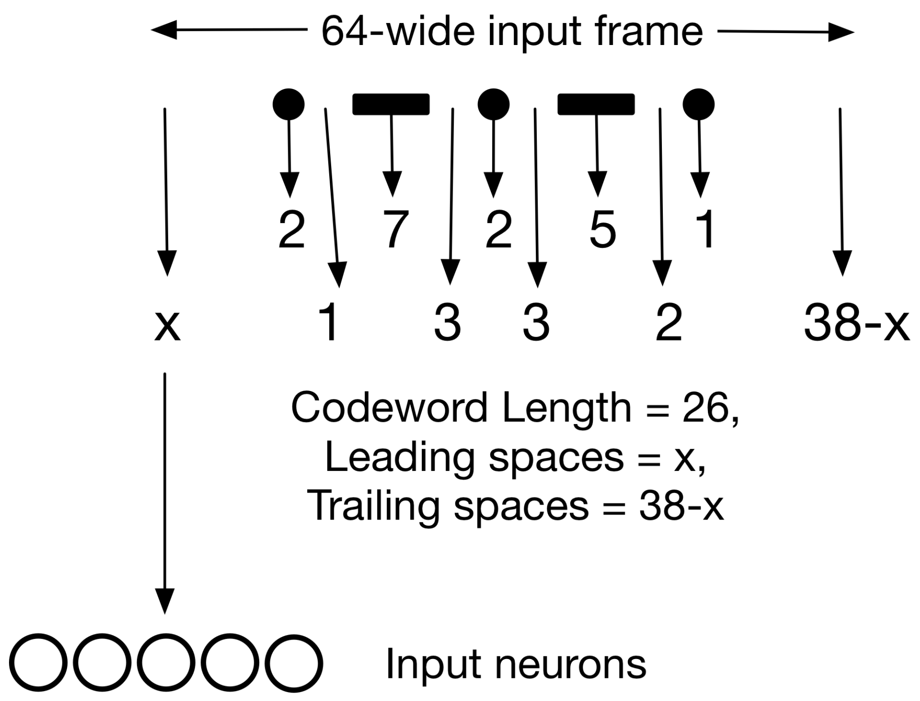
Variations and Difficulty Scaling - 1

Increasing σ of noise leads to confusion between dots, dashes and spaces



Variations and Difficulty Scaling - 2

Distribute remaining spaces randomly between leading and trailing



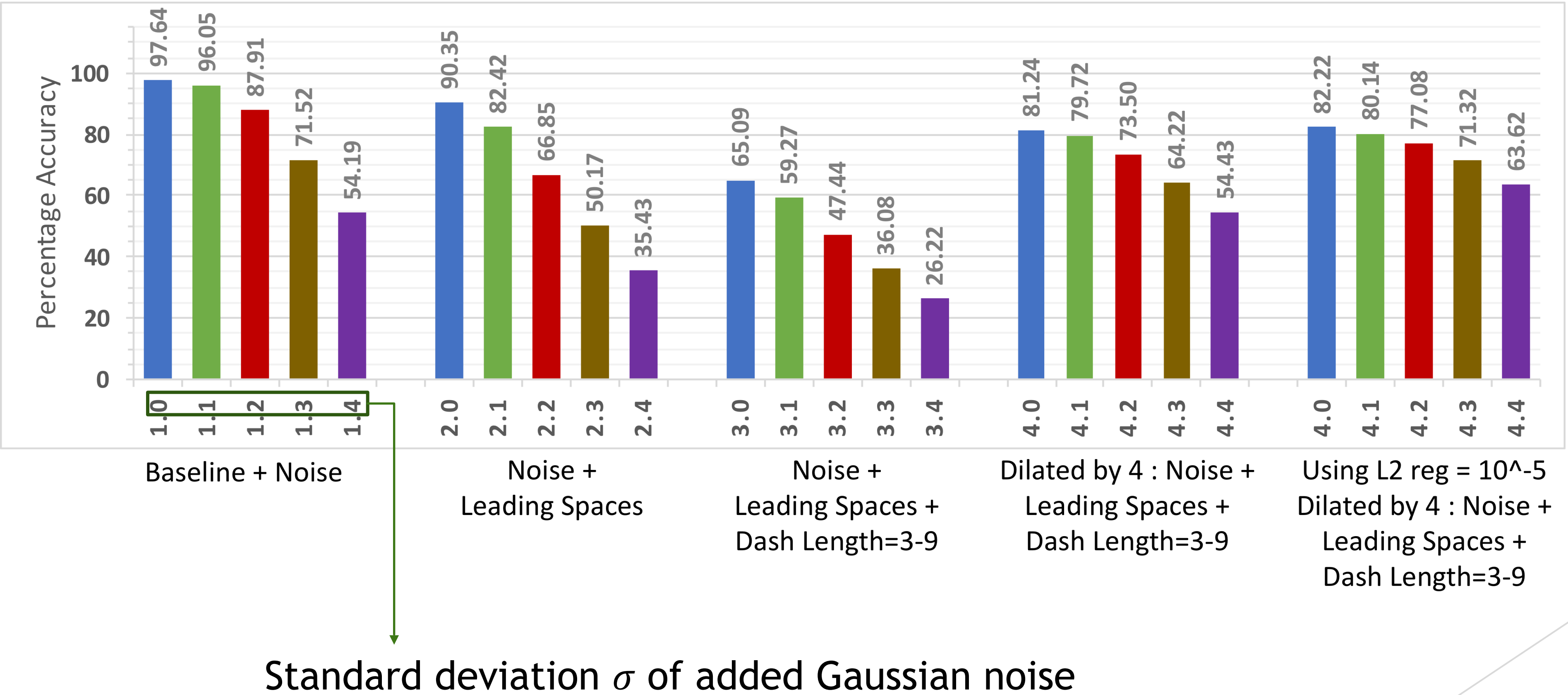
Variations and Difficulty Scaling - 3, 4

Dash length is 3-9, can be confused with dots and spaces

Dilate inputs by 4x

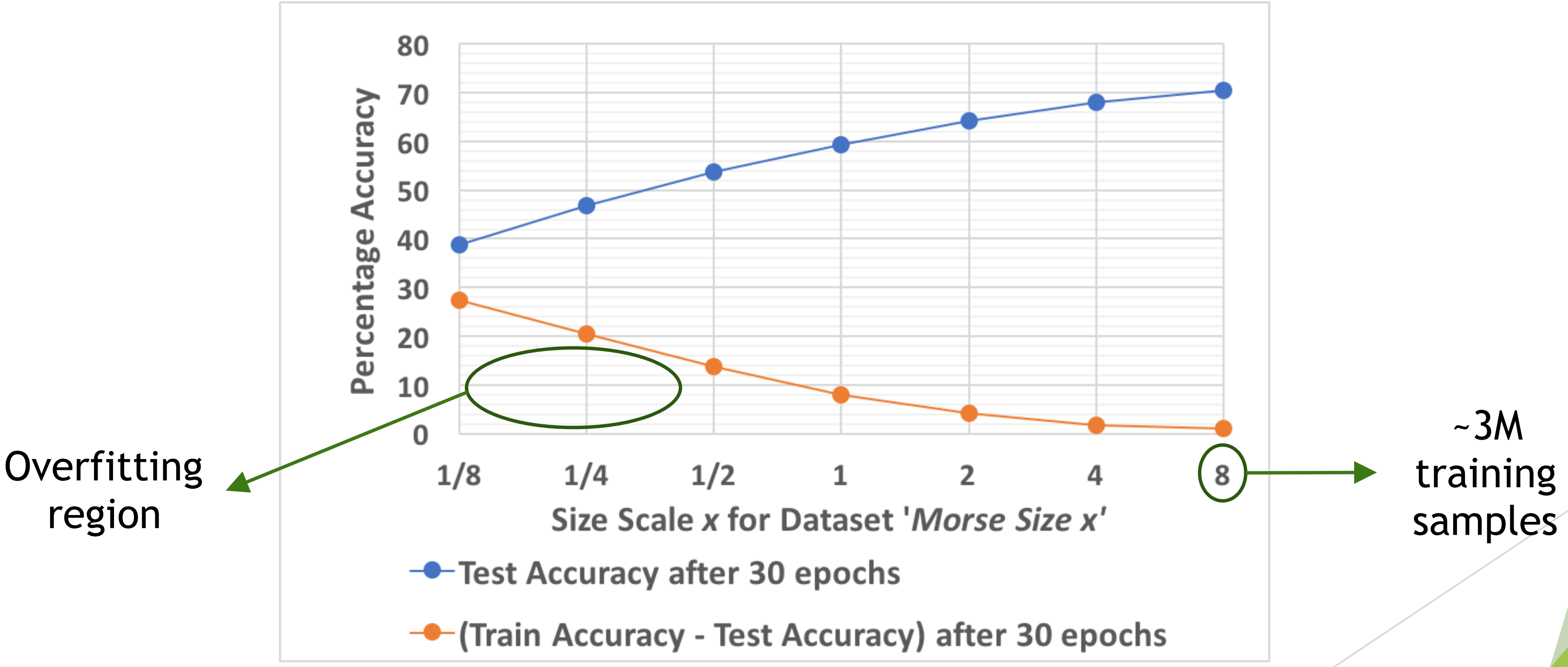
Property	Before Dilation	After Dilation
Frame length (= Number of inputs)	64	256
Space	1-3	4-12
Dot	1-3	4-12
Dash	3-9	12-36

Classification Accuracy on Test Data



Increasing Dataset Size

Unlimited amounts of data can be easily generated using computer algorithms



Dataset Evaluating Metrics

Difficult datasets have increased probability of classification errors

$$\sum_{m=1}^{M} P(m) \left[\max_{\substack{j \in \{1,2,\cdots,M\} \\ j \neq m}} P_{PW}(j|m) \right] \leq P(E)$$

$$\leq \sum_{m=1}^{M} P(m) \sum_{\substack{j=1 \\ j \neq m}}^{M} P_{PW}(j|m)$$

Dataset Evaluating Metrics

Difficult datasets have increased probability of classification errors

$$L = \sum_{m=1}^{M} P(m) Q\left(\sqrt{\frac{d_{min}(m)^2}{4{\sigma_m}^2}}\right) \leftarrow \sum_{m=1}^{M} P(m)\left[\max_{\substack{j\in\{1,2,\cdots,M\}\\ j\neq m}} P_{PW}\left(j|m\right)\right] \leq P(E)$$

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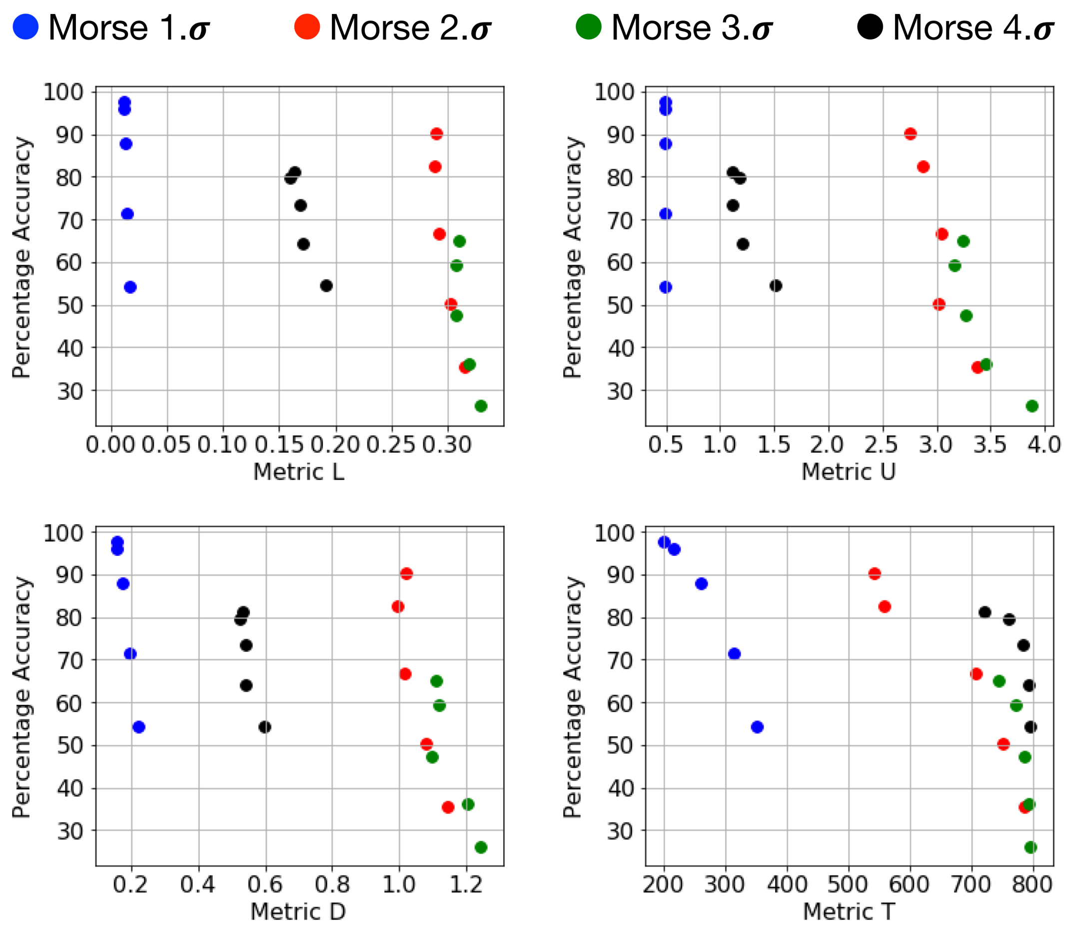
$$T = \sum_{m=1}^{M} \sum_{\substack{j=1 \\ j \neq m}}^{M} \mathbb{I}\left(d_1(m,j) < 0.05\right)$$

Performance of the Metrics

Harder datasets have lower accuracy and higher metric values



Metric	-ρ
L	0.59
U	**0.64**
D	0.63
T	**0.64**

Conclusion

- Algorithm to generate machine learning datasets of tunable difficulty
- Synthetic data to solve challenges associated with natural data
- Metrics to evaluate dataset difficulty prior to training

Thank you!

Questions?

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