W207– Applied Machine Learning

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Feedforward NN

Announcements

- Midterm exam: next week

Consists of a total of `37 questions` to be completed within a `90-minute` timeframe. Covers week 1-6 material.

The questions are divided as follows:

- 4 open-ended questions,
- 33 multiple-choice questions

- Final project: **baseline presentation** in two weeks

Last week

- Evaluation metrics for classification tasks
- Dealing with class imbalance
- Multiclass Logistic Regression (extend the wine dataset to 3 classes)

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Today's learning objectives

- General concepts: Feedforward Neural Networks (FFNN)
- Training, validation, and test datasets
- Application: Detect Diabetic Retinopathy using image data

Neural Networks

Shallow networks (no hidden layers) can only capture linear decision boundaries

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What if CT scans data?

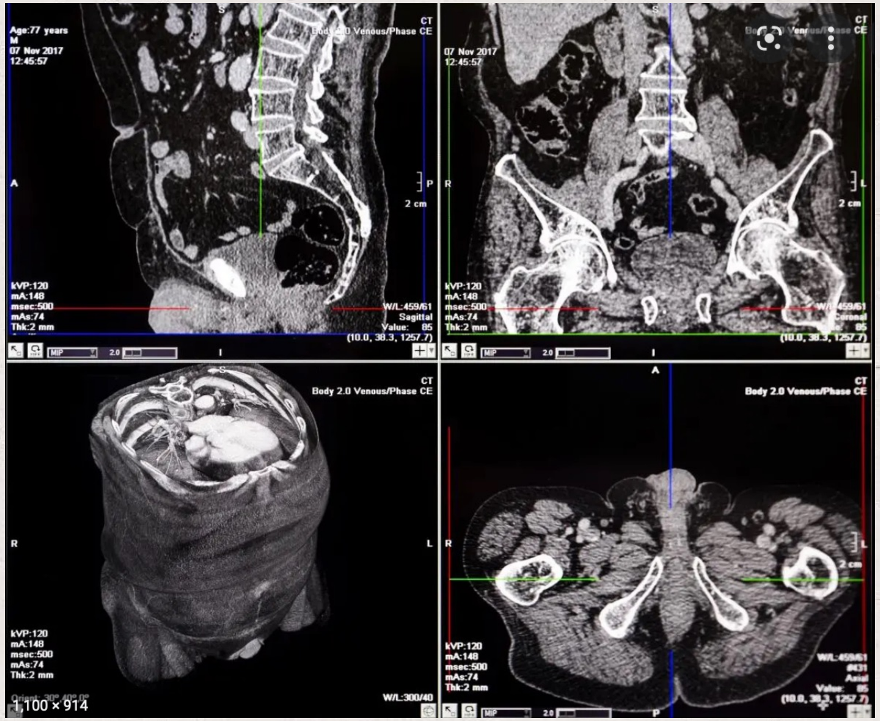

Image source: https://www.medicalnewstoday.com/articles/153201#what-is-a-CT-scan

Neural Networks

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What if video data?

Image source: https://web.stanford.edu/class/biods220/lectures/lecture5.pdf

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What if audio data? (e.g., speech recognition)

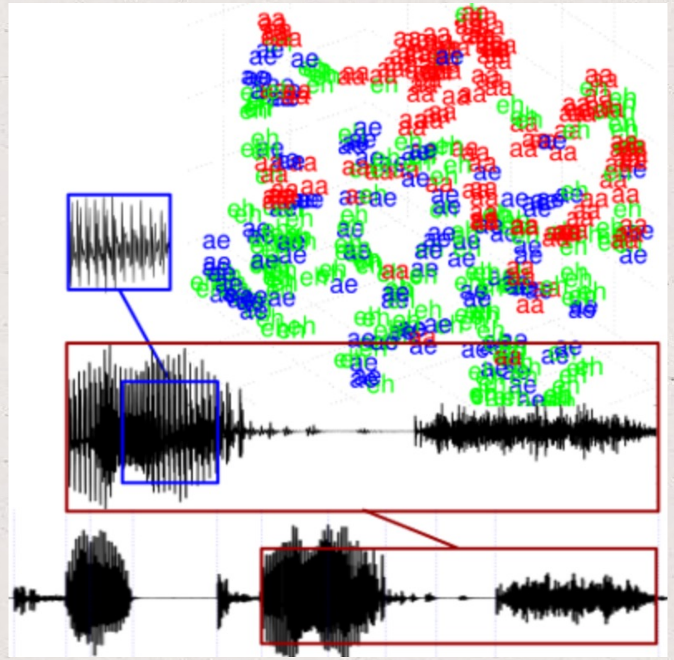

Image source: https://cbmm.mit.edu/research/projects-thrust/theoretical-frameworks-intelligence/invariant-representation-learning

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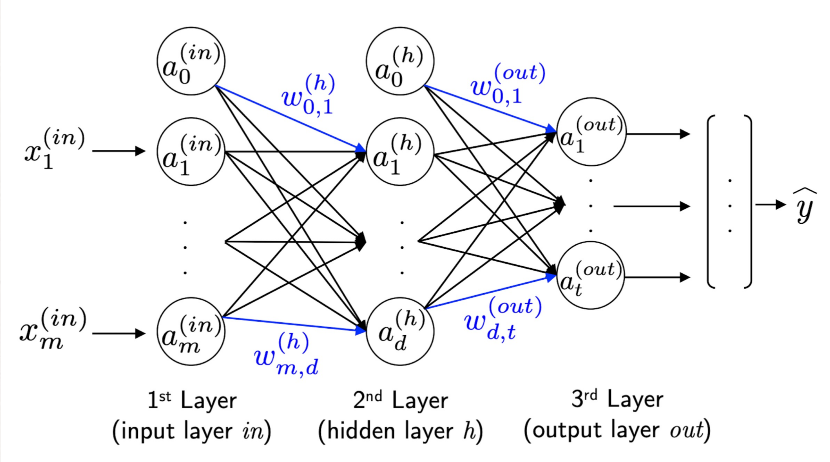
Deep NN



a = activation function

Neural Networks

ML real world problems: we don't know how large the network should be a priori!

Small network

underfit

Network cannot learn the underlying structure of complex datasets

Very large network

overfit

Network memorizes training data

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Solution: build a network with a relatively higher capacity (slightly higher than necessary) to do well on training

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Prevent overfitting by applying one or more regularization schemes

dropout in NN

L_1, L_2 for others

Very large network

overfit

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Training, validation, and test datasets

All training = 80%

Training (50%)	Validation (30%)	Test (20%)

Held-out evaluation set for selecting best hyperparameters during training

Use only for final evaluation

Other splits: 60/20/20 is also popular.

Training, validation, and test datasets

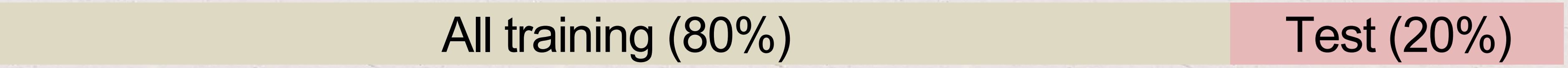
All training (80%)	Test (20%)

Done with hyperparameter selection using the validation set?

Common to merge training and validation sets to train a final model using chosen hyperparameters.

Use only for final evaluation

K-fold cross validation



Small labeled dataset? Very common in healthcare… K-fold cross validation (can be computationally expensive!) may be worthwhile.

K-fold cross validation

All training (80%)	Test (20%)

use different fold for validation

Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Fold 6	Test (20%)
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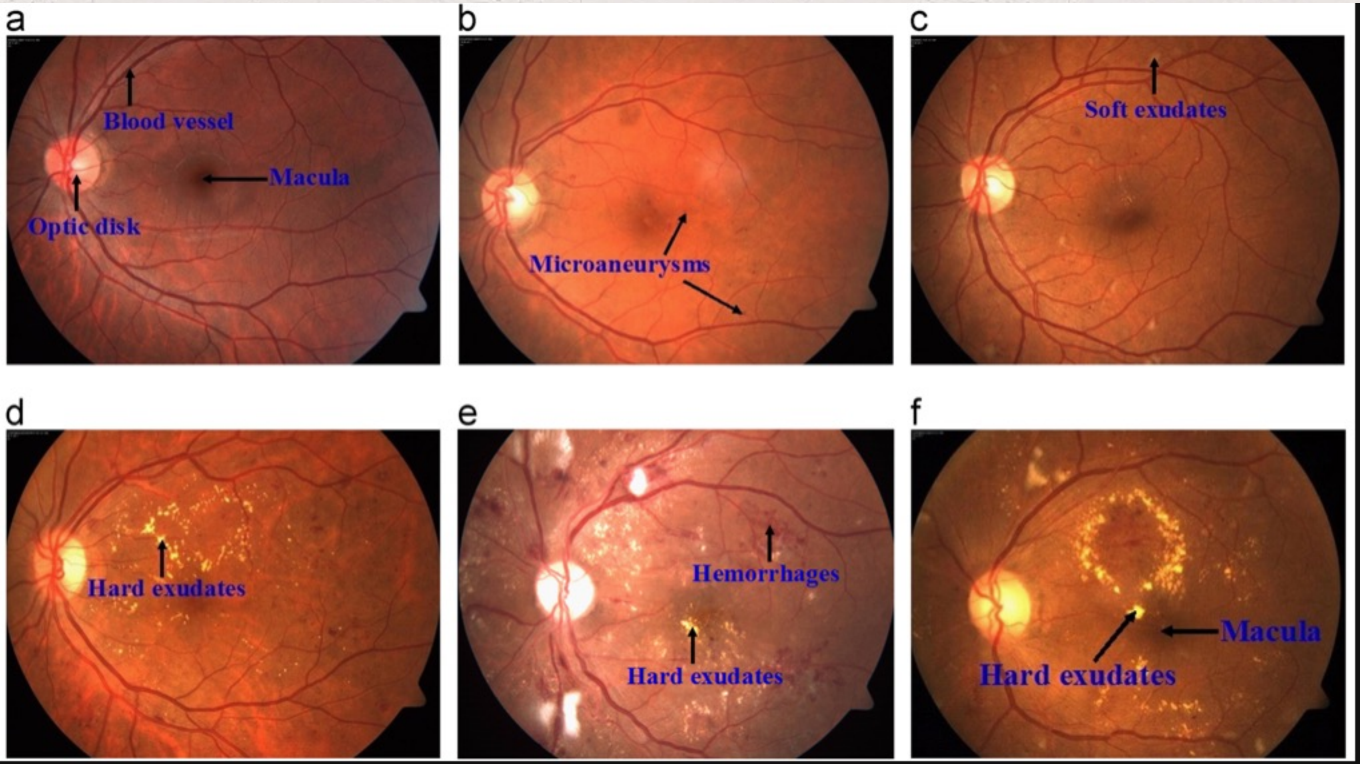
Train model K times with a different fold as the validation set each time; then average the validation set results.

Smart approach: allows more data to be used for each training of the model, without compromising validation results

OK to apply same concept to test-time evaluation.

Application: detect diabetic retinopathy



Typical fundus images: (a) Normal; (b) Mild DR; (c) Moderate DR; (d) Severe DR; (e) Prolific DR; (f) Macular edema.

Image source: https://www.sciencedirect.com/science/article/pii/S0010482513002862#f0005