CSCE 580: Introduction to AI

Lecture 16 Machine Learning – NN, DL

PROF. BIPLAV SRIVASTAVA, AI INSTITUTE

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Carolinian Creed: "I will practice personal and academic integrity."

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Organization of Lecture 16

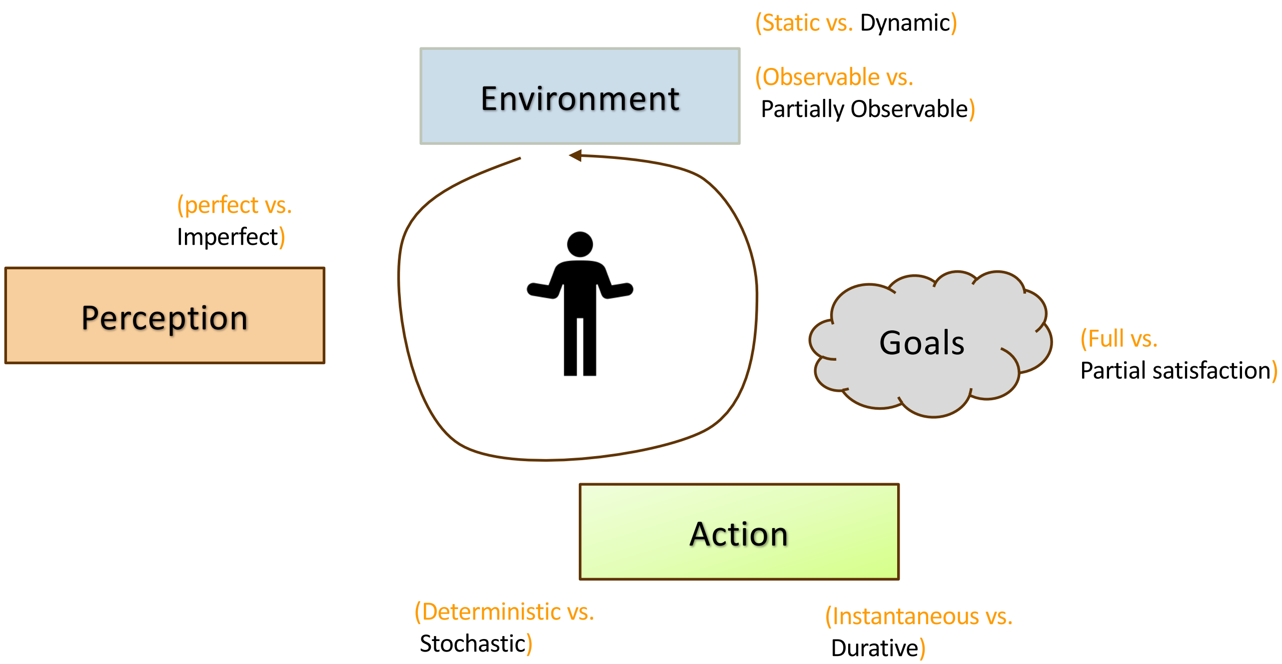
- Introduction Segment
  - Recap of Lecture 16
- Main Segment
  - Neural Networks
  - Deep Learning
  - Trust Issues
  - Adversarial Attacks
- Concluding Segment
  - Course Project Discussion
  - About Next Lecture – Lecture 17
  - Ask me anything

Introduction Section

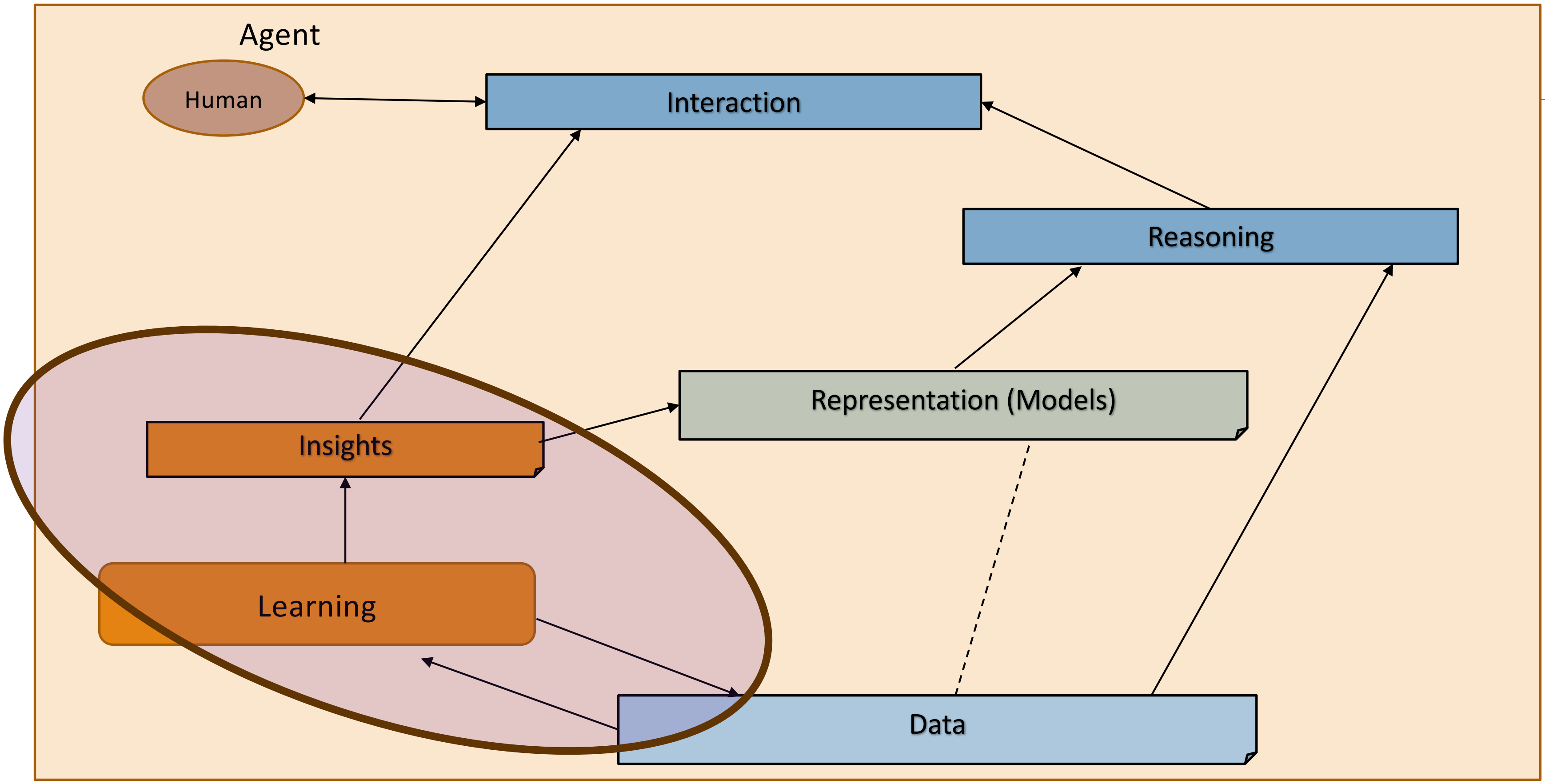
Recap of Lecture 18

- Topic discussed
  - Trust/ Explanations, LIME - Recap
  - Unsupervised ML Algorithms

Intelligent Agent Model



Relationship Between Main AI Topics



Where We Are in the Course

CSCE 580/ 581 – In This Course

- Week 1: Introduction, Aim: Chatbot / Intelligence Agent
- Weeks 2-3: Data: Formats, Representation and the Trust Problem
- Week 4-5: Search, Heuristics - Decision Making
- Week 6: Constraints, Optimization – Decision Making
- Week 7: Classical Machine Learning – Decision Making, Explanation
- Week 8: Machine Learning - Classification
- Week 9: Machine Learning - Classification – Trust Issues and Mitigation Methods
- Topic 10: Learning neural network, deep learning, Adversarial attacks
- Week 11: Large Language Models – Representation, Issues
- Topic 12: Markov Decision Processes, Hidden Markov models - Decision making
- Topic 13: Planning, Reinforcement Learning – Sequential decision making
- Week 14: AI for Real World: Tools, Emerging Standards and Laws; Safe AI/ Chatbots

Main Section

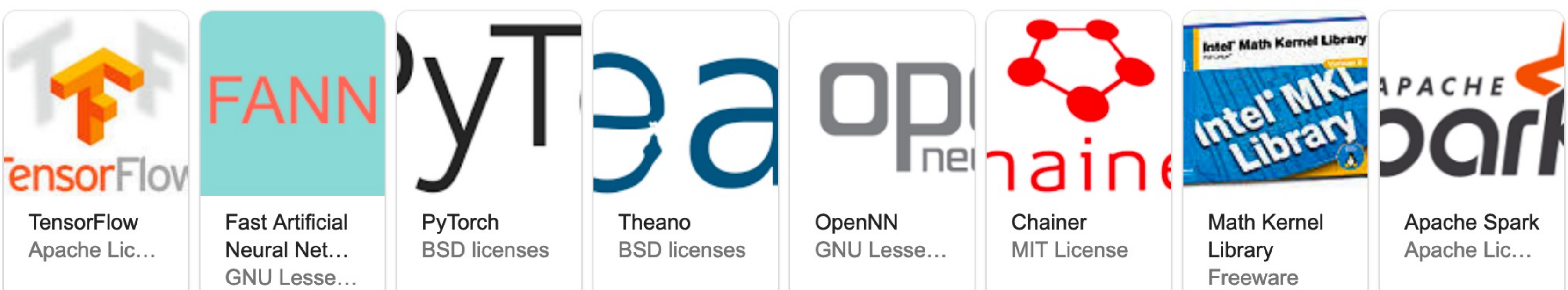
Credit: Retrieved from internet

Machine Learning – Insights from Data

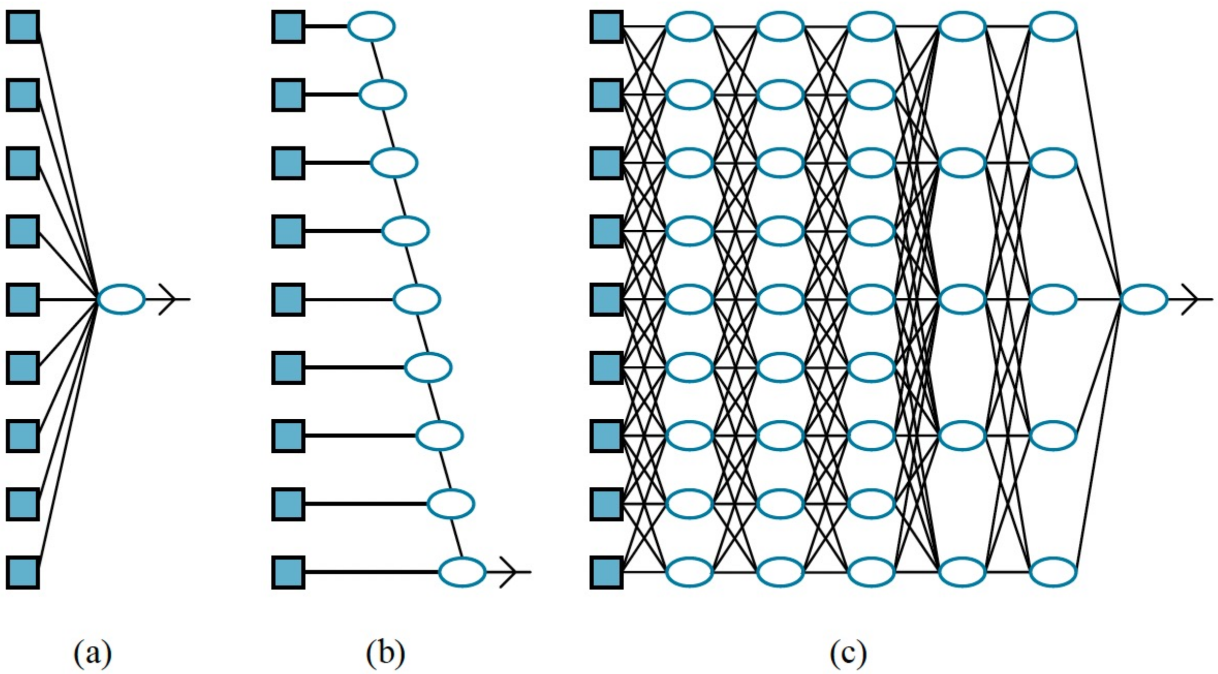
- Descriptive analysis
  - Describe a past phenomenon
  - **Methods**: classification (feedback from label), clustering, dimensionality reduction, anomaly detection, neural methods, reinforcement learning (feedback from hint/ reward)
- Predictive analysis
  - Predict about a new situation
  - **Methods**: time-series, neural networks
- Prescriptive analysis
  - What an agent should do
  - **Methods**: simulation, reinforcement learning, reasoning

- New areas
  - Counterfactual analysis
  - Causal Inferencing
  - Scenario planning
  - Representation learning

Neural Network Methods



Model Depth and Learning Ability

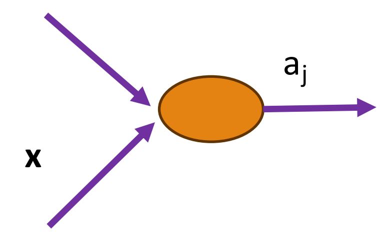


(a) A shallow model, such as linear regression, has short computation paths between inputs and output. (b) A decision list network has some long paths for some possible input values, but most paths are short. (c) A deep learning network has longer computation paths, allowing each variable to interact with all the others.

Adapted from:
Russell & Norvig, AI: A Modern Approach

Node (Unit) of a NN

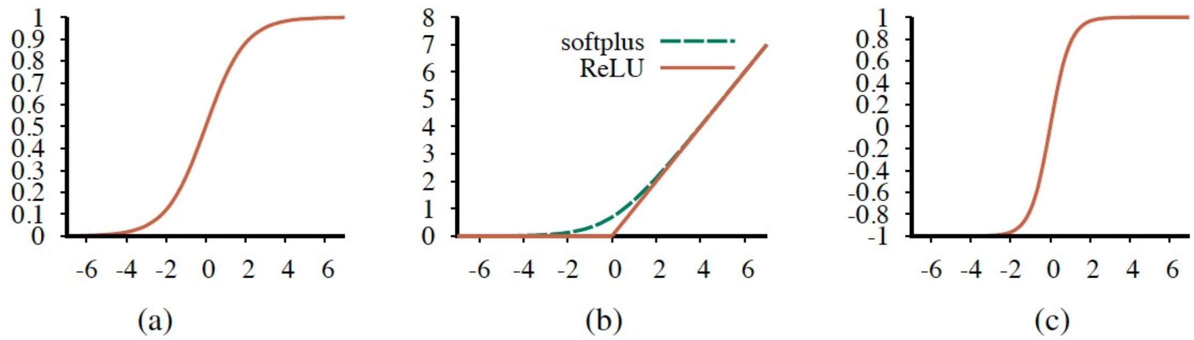
- Notations and meanings
  - a_j: output of a unit j
  - $w_{i,j}$: weight of link from unit i to unit j
  - $a_j = g_j\ (\Sigma\ w_{i,j}\ a_i\ )$, where g_j is a nonlinear activation function
- $a_j = g_j\ (\mathbf{w}^T\ \mathbf{x})$, where **w** is vector of weights leading into unit j and **x** is the inputs to unit j



Popular Activation Functions

- Logistics or sigmoid function: σ(x) = $1/(1 + e^{-x})$
- ReLU (rectified linear unit): max (0, x)
- Softplus function: $\log(1 + e^{x})$
  - Smooth version of ReLU
- $\tanh(x) = (e^{2x} – 1) / (e^{2x} + 1)$
  - Scaled and shifter version of sigmoid; $\tanh(x) = 2\sigma(2x) - 1$

a) the logistic or sigmoid function
b) the ReLU function and the softplus function
c) the tanh function.



Adapted from:
Russell & Norvig, AI: A Modern Approach

Note: All activation functions are non-linear

Loss functions

- Mean squared error

$$MSE = \frac{1}{n}\sum_{j=1}^{n}\left[f(X_{j\cdot}) - y_j\right]^2$$

- Categorical Cross Entropy

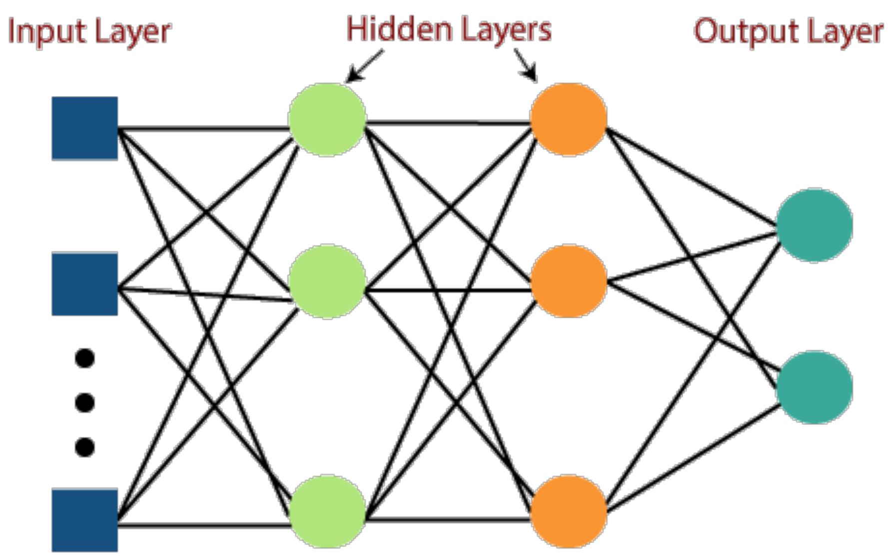
$$\text{Cost} = \frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{k}[y_{ij}\log(\hat{y}_{ij})]$$

k is classes,
y = actual value
Ŷ = prediction

- More loss functions:

https://www.analyticsvidhya.com/blog/2022/06/understanding-loss-function-in-deep-learning/

NN – Multi Layer Perceptron



Content and Image Courtesy:
https://github.com/Thanasis1101/MLP-from-scratch

(Stochastic) Gradient Descent

Gradient Descent

w ← any point in the parameter space

While not converged do:

For each w_i in **w** do:

$w_i \leftarrow w_i - \alpha \ (\partial / \partial w_i) \ Loss(\mathbf{w})$

Calculate the gradient of the loss function with respect to the weights along the gradient direction to reduce the loss.

Stochastic Gradient Descent (SGD)

Randomly select a small number of training examples at each step

Sources:

- https://en.wikipedia.org/wiki/Stochastic_gradient_descent
- Russell & Norvig, AI: A Modern Approach, Chapter 19

Logistic Regression in a Slide

Function estimate (linear)
W: weight, b: bias

$$f(X_j) = X_j W + b$$

Update Weight

$$W^* = W - \eta \frac{dL}{dW}$$

Error Term (mean squared error)

$$MSE = \frac{1}{n} \sum_{j=1}^{n} \left[f(X_{j\cdot}) - y_j \right]^2$$

Common Code Pattern

```
y = tf.matmul(x, W) + b
loss = tf.reduce_mean(tf.square(y - y_label))
```

NN Concepts

- **Epoch**: The number of times the learning algorithm will iterate over the entire dataset
- **Batch**: how many samples are processed before updating the model's internal parameters.
  - **Batch Gradient Descent**: Batch Size = Size of Training Set
  - **Stochastic Gradient Descent**: Batch Size = 1
  - **Mini-Batch Gradient Descent**: 1 < Batch Size < Size of Training Set

Credit: https://rentry.org/llm-training

Universal Approximation Theorem

- A network with just two layers of computation units, first nonlinear, and the second linear, can approximate any continuous function to an arbitrary degree of accuracy.
- **Why**: a sufficiently large network can implement a lookup table for continuous functions
  - Nonlinear layer is the key

Sources:

- https://en.wikipedia.org/wiki/Universal_approximation_theorem
- Russell & Norvig, AI: A Modern Approach, Chapter 21

Datasets

- In keras, https://keras.io/api/datasets/
  - boston_housing
  - cifar10 module, cifar100, fashion_mnist, mnist
  - imdb module
  - reuters module

- In TF, https://www.tensorflow.org/datasets/catalog/overview#all_datasets

Keras Walkthrough

- Package: https://keras.io/about/
- Example model:
  - Sequential: https://keras.io/guides/sequential_model/
- Many examples: classification, image, text, audio
  - https://keras.io/examples/
- Future Keras: https://keras.io/keras_core/
  - Keras Core - run Keras workflows on top of TensorFlow, JAX, and PyTorch; preview of Keras 3.0

Code Examples With Keras and TF

1. Classification – diabetes

2. Try code
- Play with hyper-parameters
- Look at keras features used

Code location:
https://github.com/biplav-s/course-ai-tai-f23/tree/main/sample-code/Class19-To-21-DL

Discussion

- Impact of network structure:
  - Nodes / layer:
  - Layers:
  - Inter-connection structure:
- Impact of hyper-parameters:
  - Epochs:
  - Batch size:

Code Examples With Keras and TF

1. Classification – diabetes

2. Prediction/ representation learning – autoencoder

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Code Examples With Keras and TF

1. Classification – diabetes

2. Prediction/ representation learning – autoencoder

3. Classification – MNIST

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Discussion

- Impact of network structure:
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  - Layers:
  - Inter-connection structure:
- Impact of hyper-parameters:
  - Epochs:
  - Batch size:

Keras and TensorFlow

- By Example:
  - https://github.com/biplav-s/course-nl-f22/blob/main/sample-code/l11-nn-dl/Basic%20TensorFlow%20and%20Keras.ipynb
  - TensorFlow’s NMIST tutorial
  - https://www.tensorflow.org/tutorials/quickstart/beginner

- More examples
  - Number Addition by sequence learning: https://keras.io/examples/nlp/addition_rnn/
  - AutoEncoder: https://machinelearningmastery.com/lstm-autoencoders/

NN/ MLP

- Code examples:
  - https://github.com/biplav-s/course-d2d-ai/blob/main/sample-code/l6-l7-l8-supervised-ml/Supervised-NaiveBayes-GradientBoost-NN-Classification.ipynb
- Scikit Library:
  - MLP: https://scikit-learn.org/stable/modules/generated/sklearn.neural_network.MLPClassifier.html

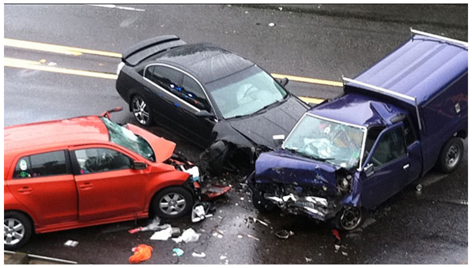
Consideration: Which NN/DL Tool to Use

- See:
  - https://www.simplilearn.com/keras-vs-tensorflow-vs-pytorch-article
  - In theory, keras supports all major ones
    - Pytorch used in academic research more
    - TF used in production systems

Trust: Adversarial Attacks

Example (Gu et al. 2017)

- **ML Application**: Detect and classify street signs in images
- **Poisoning method**: Insert images where a special sticker is added to stop signs and the label changed to speed limit
- **Backdoor**: Adversaries ensure that any stop sign is misclassified simply by placing a sticker on it



Trust: Adversarial Attacks

- Cat and mouse on attacks and defenses
  - Example code: https://github.com/Trusted-AI/adversarial-robustness-toolbox/blob/main/notebooks/adversarial_training_mnist.ipynb
- Tools
  - Adversarial Robustness Toolbox (ART) - Python library for Machine Learning Security, https://github.com/Trusted-AI/adversarial-robustness-toolbox

Trust Issues with NN

- Robustness: can the model give the results in the presence of (input) perturbation? Noise?
- Computation/ footprint: why does the learning take so much compute resources?
- Data: is the data representative? How was the data obtained?
- Explainability: why does the model work?
- Fairness: Is the output fair to user groups?

Resources and Books

- Understanding Deep Learning, https://udlbook.github.io/udlbook/
- Deep Learning, Ian Goodfellow, Yoshua Bengio and Aaron Courville, https://www.deeplearningbook.org/
- AI – A Modern Approach, Russell & Norvig, https://aima.cs.berkeley.edu/
- Websites of libraries – Keras.

Course Project

Discussion: Projects

- New: two projects
  - Project 1: model assignment
  - Project 2: single problem/ llm based solving / fine-tuning/ presenting result

Lecture 19 & 20: Summary

- We talked about
  - Neural Networks
  - Deep Learning
  - Adversarial attacks
  - Trust Issues
- Others
  - Quiz 3 due today

Concluding Section

About Next Lecture – Lecture 17

Lecture 17: Text, Large Language Models

- Text processing
- Language Models (LMs)
- Large LMs

13	Oct 1 (Tu)	Machine Learning – Classification – Decision Trees, Random Forest, NBC, Gradient Boosting, ML-Text
14	Oct 3 (Th)	ML – Unsupervised / Clustering
15	Oct 8 (Tu)	Student presentations - project
16	Oct 10 (Th)	ML – NN, Deep Learning
17	Oct 15 (Tu)	Processing Natural Languages/ Language Models
	Oct 17 (Th)	
18	Oct 22 (Tu)	Large Language Models (LLMs) / Foundation Models
19	Oct 24 (Th)	Using LLMs – how and when ?