ARTIFICIAL INTELLIGENCE FOR SOFTWARE ENGINEERS

(Part 2: Deep Learning, Symbolic AI)

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LEARNING GOALS

• Give an overview of different AI problems and approaches
• Explain at high level how deep learning works
• Describe key characteristics of symbolic AI techniques and when to use them
Artificial Intelligence:

computers acting humanly / thinking humanly / thinking rationally / acting rationally -- Russel and Norvig, 2003

Machine Learning:

A computer program is said to learn from experience $E$ with respect to some task $T$ and some performance measure $P$, if its performance on $T$, as measured by $P$, improves with experience $E$. -- Tom Mitchell, 1997

Deep Learning:

specific learning technique based on neural networks
Precise definitions are difficult to capture. Some simply describe AI as "everything that's hard in computer science".
• Acting humanly: Turing test approach, requires natural language processing, knowledge representation, automated reasoning, machine learning, maybe vision and robotics
• Thinking humanly: mirroring human thinking, cognitive science
• Thinking rationally: law of thoughts, logic, patterns and structures
• Acting rationally: rational agents interacting with environments

• problem solving (e.g., search, constraint satisfaction)
• knowledge, reasoning, planning (e.g., logic, knowledge representation, probabilistic reasoning)
• learning (learning from examples, knowledge in learning, reinforcement learning)
• communication, perceiving, and acting (NLP, vision, robotics)

MACHINE LEARNING

OVERVIEW

(zooming out from the last lecture)
COMMON PROBLEM CLASSES

- Classification
- Probability estimation
- Regression
- Ranking
- Hybrids
EXAMPLES?

- Classification
- Probability estimation
- Regression
- Ranking
- Hybrids

- Identifying whether there a scan shows cancer
- Detecting shoe brands in an image
- Predicting the sales price of a house
- Recommending videos on Youtube
- Understanding survival rates of titanic passengers
- Estimating the arrival time of a ride sharing car
- Transcribing an audio file
- Finding academic papers on economic fairness
LEARNING PARADIGMS

- Supervised learning -- labeled training data provided
- Unsupervised learning -- training data without labels
- Reinforcement learning -- agents learning from interacting with an environment
EXAMPLES

- Supervised learning -- labeled training data provided
- Unsupervised learning -- training data without labels
- Reinforcement learning -- agents learning from interacting with an environment

- Identifying whether there a scan shows cancer
  - Playing chess
- Predicting the sales price of a house
  - Organizing books into topics
- Detecting shoe brands in an image
- Identifying unusual purchases from a credit card
  - Learning to walk
- Transcribing an audio file
MANY DIFFERENT TECHNIQUES

- Building on logic: Inductive reasoning
- Imitating brains: e.g., neural networks
- Imitating evolution: e.g., genetic programming
- Probabilities: e.g., Naive Bayes, Markov chains
- Finding analogies: e.g., nearest neighbor, SVM
- Reinforcement learning

NEURAL NETWORKS
Artificial neural networks are inspired by how biological neural networks work ("groups of chemically connected or functionally associated neurons" with synapses forming connections).

ARTIFICIAL NEURAL NETWORKS

Simulating biological neural networks of neurons (nodes) and synapses (connections), popularized in 60s and 70s

Basic building blocks: Artificial neurons, with $n$ inputs and one output; output is activated if at least $m$ inputs are active

(assuming at least two activated inputs needed to activate output)
computing weighted sum of inputs + step function

\[ z = w_1 x_1 + w_2 x_2 + \ldots + w_n x_n = \mathbf{x}^T \mathbf{w} \]

e.g., step: \( \phi(z) = \text{if } (z<0) \ 0 \ \text{else } 1 \)
\[o_1 = \phi(b_1 + w_{1,1}x_1 + w_{1,2}x_2)\]
\[o_2 = \phi(b_2 + w_{2,1}x_1 + w_{2,2}x_2)\]
\[o_3 = \phi(b_3 + w_{3,1}x_1 + w_{3,2}x_2)\]

\[f_{W,b}(X) = \phi(W \cdot X + b)\]

\(W\) and \(b\) are parameters of the model.
Layers are fully connected here, but layers may have different numbers of neurons
\[ f_{w_h, b_h, w_o, b_o}(X) = \phi(W_o \cdot \phi(W_h \cdot X + b_h) + b_o) \]

(matrix multiplications interleaved with step function)
LEARNING MODEL PARAMETERS
(BACKPROPAGATION)

Intuition:

- Initialize all weights with random values
- Compute prediction, remembering all intermediate activations
- If output is not expected output (measuring error with a loss function),
  - compute how much each connection contributed to the error on output layer
  - repeat computation on each lower layer
  - tweak weights a little toward the correct output (gradient descent)
- Continue training until weights stabilize

Works efficiently only for certain $\phi$, typically logistic function:
\[
\phi(z) = \frac{1}{1 + \exp(-z)} \text{ or ReLU: } \phi(z) = \max(0, z).
\]
DEEP LEARNING

- More layers
- Layers with different numbers of neurons
- Different kinds of connections
  - fully connected (feed forward)
  - not fully connected (eg. convolutional networks)
  - keeping state (eg. recurrent neural networks)
  - skipping layers
  - ...

Essentially the same with more layers and different kinds of architectures.
ON TERMINOLOGY

- Deep learning: neural networks with many internal layers
- DNN architecture: network structure, how many layers, what connections, which $\phi$ (hyperparameters)
- Model parameters: weights associated with each input in each neuron
EXAMPLE SCENARIO

- MNIST Fashion dataset of 70k 28x28 grayscale pixel images, 10 output classes
EXAMPLE SCENARIO

- MNIST Fashion dataset of 70k 28x28 grayscale pixel images, 10 output classes
- 28x28 = 784 inputs in input layers (each 0..255)
- Example model with 3 layers, 300, 100, and 10 neurons

```python
model = keras.models.Sequential(
    [keras.layers.Flatten(input_shape=[28, 28]),
     keras.layers.Dense(300, activation="relu"),
     keras.layers.Dense(100, activation="relu"),
     keras.layers.Dense(10, activation="softmax")
    ])
```

How many parameters does this model have?
EXAMPLE SCENARIO

- MNIST Fashion dataset of 70k 28x28 grayscale pixel images, 10 output classes
- 28x28 = 784 inputs in input layers (each 0..255)
- Example model with 3 layers, 300, 100, and 10 neurons

```python
model = keras.models.Sequential([
    keras.layers.Flatten(input_shape=[28, 28]),
    # 784*300+300 = 235500 parameters
    keras.layers.Dense(300, activation="relu"),
    # 300*100+100 = 30100 parameters
    keras.layers.Dense(100, activation="relu"),
    # 100*10+10 = 1010 parameters
    keras.layers.Dense(10, activation="softmax")
])
```

Total of 266,610 parameters in this small example! (Assuming float types, that's 1 MB)
NETWORK SIZE

• 50 Layer ResNet network -- classifying 224x224 images into 1000 categories
  ▪ 26 million weights, computes 16 million activations during inference, 168 MB to store weights as floats
• OpenAI’s GPT-2 (2019) -- text generation
  ▪ 48 layers, 1.5 billion weights (~12 GB to store weights)
  ▪ released model reduced to 117 million weights
  ▪ trained on 7-8 GPUs for 1 month with 40GB of internet text from 8 million web pages
CONVOLUTIONAL NEURAL NETWORK (INTUITION)

(Aphex34 CC BY-SA 4.0)
REUSING AND RETRAINING NETWORKS

- Incremental learning process enables continued training, retraining, incremental updates
- A model that captures key abstractions may be good starting point for adjustments (i.e., rather than starting with randomly initialized parameters)
- Reused models may inherit bias from original model
- Lineage important. Model cards promoted for documenting rationale, e.g., Google Perspective Toxicity Model
DEEP LEARNING DISCUSSION

- Can approximate arbitrary functions
- Able to handle many input values (e.g., millions of pixels)
- Internal layers may automatically recognize higher-level structures
- Often used without explicit feature engineering
- Often huge number of parameters, expensive inference and training
- Often large training sets needed
- Too large and complex to understand what is learned, why, or how decisions are made (compare to decision trees)
CLASSIC SYMBOLIC AI

(Good Old-Fashioned Artificial Intelligence)
BOOLEAN SATISFIABILITY

Given a propositional formula over boolean variables, is there an assignment such that the formula evaluates to true?

\[(a \lor b) \land (\neg a \lor c) \land \neg b\]

decidable, np complete, lots of search heuristics
Configuration dialog. Some options are mutually exclusive. Some depend on other options.
ENCODING PROBLEMS

**Linux/arm 3.8.13 Kernel Configuration**

- **Option**
- **General setup**
  - IRQ subsystem
  - Timers subsystem
  - CPU/Task time and stats accounting
  - RCU Subsystem
  - Control Group support
  - Group CPU scheduler
  - Namespaces support
  - Configure standard kernel
  - Kernel Performance Events support
  - GCC-based kernel profiling
  - Enable loadable module support
  - Enable the block layer
    - Partition Types
    - IO Schedulers
  - System Type
    - TI OMAP Common Features
    - TI OMAP2/3/4/5 Specific Features
  - Bus support
    - PCCard (PCMCIA/CardBus)
    - Kernel Features
    - Boot options
    - CPU Power Management

- **Option**
  - **Keyboards**
    - ADP5588/87 I2C QWERTY Keypad and IO Expander
    - ADP5585/ADP5589 I2C QWERTY Keypad and IO Expander
    - AT keyboard
    - Atmel AT42QT1070 Touch Sensor Chip
    - Atmel AT42QT2160 Touch Sensor Chip
    - DECstation/VAXstation LK201/LK401 keyboard
    - GPIO Buttons
      - GPIO Buttons 2 (NEW)
      - Polled GPIO buttons
      - TCA6416/TCA6408A Keypad Support

**GPIO Buttons 2 (KEYBOARD_GPIO2)**

**CONFIG_KEYBOARD_GPIO2:**

This driver implements support for buttons connected to GPIO pins of various CPUs (and some other chips).

Say Y here if you want an A in ECE497

To compile this driver as a module, choose M here: the module will be called gpio_keys.
config HAVE_BOOTMEM_INFO_NODE
def_bool n

# eventually, we can have this option just 'select SPARSEMEM'
config MEMORY_HOTPLUG
  bool "Allow for memory hot-add"
  depends on SPARSEMEM || X86_64_ACPI_NUMA
  depends on ARCH_ENABLE_MEMORY_HOTPLUG
  select NUMA_KEEP_MEMINFO if NUMA

config MEMORY_HOTPLUG_SPARSE
  def_bool y
  depends on SPARSEMEM && MEMORY_HOTPLUG

config MEMORY_HOTPLUG_DEFAULT_ONLINE
  bool "Online the newly added memory blocks by default"
SAT ENCODING

Describe configuration constraints:

```c
config MEMORY_HOTPLUG
  bool "Allow for memory hot-add"
  depends on SPARSEMEM || X86_64_ACPI_NUMA
  depends on ARCH_ENABLE_MEMORY_HOTPLUG
  select NUMA_KEEP_MEMINFO if NUMA
```

(MEMORY_HOTPLUG => SPARSEMEM || X86_64_ACPI_NUMA)

&&

(MEMORY_HOTPLUG => ARCH_ENABLE_MEMORY_HOTPLUG)

&&

(MEMORY_HOTPLUG && NUMA => NUMA_KEEP_MEMINFO)

...

given configuration constraints $\phi$:

Which option can never be selected?

$$\text{dead}(o) = \neg\text{SAT}(\phi \land o)$$

Which option must always be selected?

$$\text{mandatory}(o) = \text{TAUT}(\phi \Rightarrow o)$$

$$= \neg\text{SAT}(\neg(\phi \Rightarrow o))$$

$$= \neg\text{SAT}(\phi \land \neg o)$$

Any options that can never be selected together?

$$\text{mutuallyExclusive}(o, p) = ?$$
MORE AUTOMATED CONFIGURATION ANALYSIS

given configuration constraints $\phi$ and already made selections of $a$ and $b$

Which other options do need to be selected?

mustSelect(o) = ?
Generalization beyond boolean options, numbers, strings, additions, optimization

**Example: Job Scheduling**

Tasks for assembling a car: \{ t1, t2, t3, t4, t5, t6 \}; values denoting start time

\[
\text{max 30 min: } \forall n t_n < 30
\]

\[
t_2 \text{ needs to be after } t_1, t_1 \text{ takes 10 min: } t_1 + 10 \leq t_2
\]

\[
t_3 \text{ and } t_4 \text{ needs to be after } t_2, \text{ take 2 min: } (t_2 + 2 \leq t_3) \land (t_2 + 2 \leq t_4)
\]

\[
t_5 \text{ and } t_6 \text{ (5 min each) should not overlap: } (t_5 + 5 \leq t_6) \lor (t_6 + 5 \leq t_5)
\]

Goal: find valid assignment for all start times, or find valid assignment minimizing the latest start time
GENERAL OBSERVATIONS

- Encoding of many problems
- Deductive reasoning, specifications! (no learning)
- Provides accurate answer (guarantees!), or timeout
- Provides concrete solution that is easy to check, possibly easy to understand (depends on encoding)
- np-complete, may take very long time to find answer
- Modern solvers are very good for many problems
- For optimization problems often good approximations exist (heuristic search)
MODERN USE CASES

- Planning, scheduling, logistics
  - e.g., planning data center layout to minimize cable length
  - e.g., optimizing big data queries
  - e.g., scheduling shifts for employees based on preferences
- Static analysis, verification, security analysis of software
  - e.g., concolic testing, detecting buffer overflows
- Version resolution and dependency management
  - e.g., Eclipse, Dart
- Combinatorial design
  - e.g., cryptography, crop rotation schedules, drug design
- Chip design and verification
  - e.g., equivalence checking
- Protein folding and other bioinformatics applications
- Electronic trading agents, e-auctions
PROBABILISTIC PROGRAMMING

(reasoning with probabilities)

Pfeffer, Avi. "Practical Probabilistic Programming." Manning (2016), Chapter 1
val burglary = Flip(0.01)
val earthquake = Flip(0.0001)
val alarm = CPD(burglary, earthquake,  
    (false, false) -> Flip(0.001),  
    (false, true) -> Flip(0.1),  
    (true, false) -> Flip(0.9),  
    (true, true) -> Flip(0.99))
val johnCalls = CPD(alarm,  
    false -> Flip(0.01),  
    true -> Flip(0.7))

println("Probability of burglary: " +  
        alg.probability(burglary, true))
Source:

class Person {
    val smokes = Flip(0.6)
}
def smokingInfluence(pair: (Boolean, Boolean)) =
    if (pair._1 == pair._2) 3.0; else 1.0

val alice, bob, clara = new Person
val friends = List((alice, bob), (bob, clara))
clara.smokes.observe(true)
for { (p1, p2) <- friends } ^^ (p1.smokes, p2.smokes).setConstraint(smokingInfluence)
...
println("Probability of Alice smoking: " +
    alg.probability(alice.smokes, true))

Source:
MORE EXAMPLES

see GitHub p2t2/figaro and many other languages
WHY PROBABILISTIC PROGRAMMING?

- Reasoning about uncertainty, at scale (simulations)
- Planning with uncertainty, making decisions with partial information
- Infer causes of events, likely explanations
- Expressed in the familiar and expressive form of a programming language, often with different reasoning engines in background

- Based on knowledge and logic
Answering queries about probabilistic models

```java
println("Probability of burglary: "+
alg.probability(burglary, true))
println("Probability of Alice smoking: "+
alg.probability(alice.smokes, true))
```

- Analytical probabilistic reasoning (e.g., variable elimination Bayes' rule) -- precise result, guarantees
- Approximation (e.g., belief propagation)
- Sampling (e.g., Markov chain Monte Carlo) -- probabilistic guarantees
EXAMPLE: ROBOT PATH AND ADAPTATION PLANNING
Examples from a recent research project to reason about adaptations in robots, e.g., change which hardware to use or which route to take. We learn energy models and other models from observations, from which we know multiple plausible configurations with different tradeoffs (and certainty). To chose an optimal configuration, a probabilistic planner is used to make decisions at runtime.
GENERAL OBSERVATIONS

- Manually created models
- Representing uncertainty
- Reasoning with probabilities, precise or with probabilistic bounds
- Deductive reasoning, specifications!
- Inference is hard to scale
- Recently, commonly combined with machine learning
SUMMARY
ARTIFICIAL INTELLIGENCE

- Acting humanly: Turing test approach, requires natural language processing, knowledge representation, automated reasoning, machine learning, maybe vision and robotics
- Thinking humanly: mirroring human thinking, cognitive science
- Thinking rationally: law of thoughts, logic, patterns and structures
- Acting rationally: rational agents interacting with environments

- problem solving (e.g., search, constraint satisfaction)
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SUMMARY

- Intuition behind deep learning (architecture, parameters, size, cost)
- Symbolic and probabilistic reasoning may provide accurate answers (or time out)
- Many different approaches, many combinations

Learn more:

- 10-301/601 Introduction to Machine Learning (how machine learning techniques work)
- 15-381/681 Artificial Intelligence: Representation and Problem Solving (how symbolic AI techniques work, solvers, reasoning, agents)
- Flasiński, Mariusz. "Introduction to Artificial Intelligence." Springer (2016), Chapter 1 ("History of Artificial Intelligence") and Chapter 2 ("Symbolic Artificial Intelligence")