Introduction to Machine Learning (by Implementation)

Lecture 0: Python, Random Numbers, git

Ian J. Watson

University of Seoul

University of Seoul Graduate Course 2018

KRF KOREA RESEARCH FELLOWSHIP
해외 우수신진연구자 유치사업

Course Introduction

- Welcome to "Introduction to Machine Learning (by Implementation)"
- Goals
  - Learn about some machine learning algorithms
  - Implement some machine learning algorithms
  - Start by using *no* ML libraries, just pure python
  - Thereby gain an understanding of the algorithms
    - The code we write will not be fast/stable/error-checking
  - Knowing the ideas, it should be easy to understand and adapt to your favourite library
  - If nothing else, have fun doing a lot of coding
- Grading:
  - Attendance
  - Completing projects each lesson
  - Final project

One slide overview of ML

- Goal of ML: get the computer to solve problems for us
  - I.e. we don't code an algorithm specifically for a problem, but write general algorithms by which the computer may "learn" from data
- Two main types of *supervised* problems, where you want the computer to generalize based on some *training* data, which has the answers or *labels*
  - Classification: given some data, does it belong to one category or another?
    - Classify images based on contents of image (this is a dog? a cat?)
    - Given some detector readings, what was the particle that impinged on the detector (electron? photon? muon?)
  - Regression: given some data, what was the underlying real variable that caused the data?
    - Given an image of a person, can you tell how old they are?
    - Given the raw calorimeter readings, what was the energy of the particle
- Also, have *unsupervised learning*, where the training data isn't labeled
  - Does the data tend to clump into categories? How many?
- We will be looking at these questions and seeing some answers people have discovered, but today ...

(Very Brief) Python Reminder

- I expect you've all seen python code before, but a whirlwind reminder:

```
# Comments begin with a '#' and go to the end of the line

# Variable assignment, calculator
a = 2 + 3

# Code blocks are indented, syntax starting blocks end line with a ':'
if a == 5:  # Switch code paths with an if, 'truthy' values run code
    # in the 'if' block
    print("Yes it is!")
elif a == 4:  # Can have multiple 'if'-like blocks run one after the
      # other (only the first one to be true is run)
    print("Almost")
else:  # 'falsy' values run in (optional) else block. 'falsy' values
       # are: False, None, [], {}, "", set(), 0, 0.0. All other values
       # are true
    print("Nope nope nope")
```

```
# Functions defined with "def" block
def f(x, y, z):
    return x + y + z

# Called with usual syntax
print(f(1, 2, 4))

g = lambda x, y, z: x + y + z  # Same as f above, syntax for simple fn’s

def gcd(x, y):
    while x != y:  # Use while to loop with a stopping condition
if a > b:
    a = a - b
else:
    b = b - a
    return a

def min(l):
    if len(l) == 0: raise TypeError  # Raise errors on bad input
    mini = l[0]
    for x in l:  # Use for to loop on lists
if x < mini: mini = x
    return mini
```

List comprehensions

```
l = [1, 2, 3, 4]

# List comprehension example:
l_squared = [l_i*l_i for l_i in l]
# Same as the block:
output = []
for l_i in l:
    output.append(l_i*l_i)
l_squared = output

# Can add if conditions:
l_squared = [l_i*l_i for i, l_i in enumerate(l) if i % 2 == 0]
# Basically the same as:
output = []
for i, l_i in enumerate(l): # enumerate returns the index as well as
    # the value, i.e. i = 0, 1, 2, 3, etc
    if i % 2 == 0: # so we only take every second entry in the list
output.append(l_i*l_i)
l_squared = output
```

Classes

An important organizational principle in python is the "class". Creates a new "datatype", from which you can create "objects". Objects keeps related data and methods (functions available to the object) together as a whole. The datatype defines what methods and data should exist.

```
class AClass:  # class declares a new datatype, no objects of this type are
    def __init__(self):  # methods can be attached to the class, first
 # parameter is "self", the object itself
self.a = 5  # kept in the object, can be used later
    def adder(self, n):
return self.a + n

# Create a new object of type "AClass"
an_obj = AClass()  # calls the __init__ method on creation
an_obj.a  # 5
an_obj.adder(7)  # 12, "self" passed automatically (here an_obj)
```

Python2 vs Python3

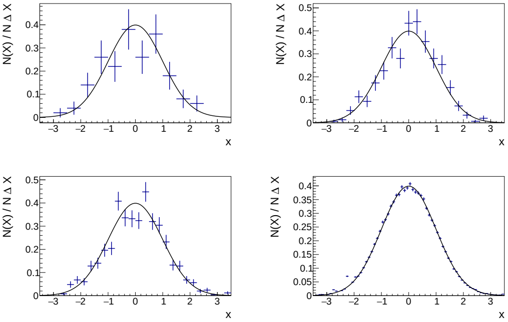
- Main differences:
  - Python 2 support from major libraries (eg numpy) being stopped!
  - Python 3 uses `print` **function**, i.e. need the parens!
  - Python 3 uses float division with /, integer division with // **always**
    - Python 2 / would do int or float depending on the args
  - Python 3 strings are quite different
    - Unless you're using strings as byte arrays, or doing unicode work, shouldn't notice
    - If you are and want to understand all the `.encode()` / `.decode()`, let me know

What do we mean by randomness?

- In ML, we often need random numbers when developing models
    - Starting positions for parameter searches, initial model parameters, etc.
- The basic idea is that we want a *random number generator*
    - In practice, a black-box function we can call that returns numbers
- There shouldn't be a way to predict numbers from the generator better than chance
- We also want random number generators for different PDFs
    - PDF: Probability Distribution Function, see my last course "Practical Statistics for Particle Physicists"
    - The random numbers should be distributed according to the PDF
    - E.g. Neural networks perform well with seeds from a gaussian PDF

Distributions of random numbers

- What do we mean by "distributed according to a PDF"?



- After one random number, we can't tell much of anything about it:
  - Obligatory xkcd:
    - `int getRandomNumber() { return 4; /* chosen by a fair dice roll, guaranteed random */ }`
- As we take random numbers from our generator, the (normalized) distribution of these number should approach our ideal PDF
  - At infinity, should be indistinguishable from the PDF
- In practice, we don't have time to generate an infinite amount of random numbers to test, so we have statistical tests of randomness

Sources of randomness

- Where do we get random numbers?
- Could toss a coin (single bit of randomness per coin toss), or roll a dice
  - Doesn't really scale to millions of numbers
- Could attach a quantum device to the computer
  - Prepare a Schroedingers cat type state, check if the cat's alive or dead
  - E.g. for genuine random number on demand based on radioactive decay: `https://www.fourmilab.ch/hotbits/`
- Similarly, could use chaotic systems (thermal noise, atmospheric noise)
- Such hardware devices, True Random Number Generator (TRNG), do exist or can be implemented through clever repurposing, but tend to be slow or expensive (pick one)
- But, we need a way to create millions of random numbers a second

Pseudo-random numbers

- In practice, we don't need "truly" random numbers, just number sequences with the right properties
  - No correlations in the random numbers produced, non-repeating, for any given number, same prob. to get it as any other number
- Thus were "pseudo-random number generators" produced
- The idea is to start with some seed data (taken from whever), then pass that through some function to produce a "random" number and a new state to seed the next number (possibly just the number itself)
- With a carefully chosen function, the output sequence has the properties we desire
- These are "Pseudo-Random Number Generators" (PRNG)

Example: Linear Congruential Generator

- One of the oldest and best-known algorithms
- Start with a seed number X_0, then generate new numbers by the recurrence relation:

$$X_{n+1} = (aX_n + c) \mod m$$

  - a, c, and m are constants which must be judiciously chosen to avoid repeating sequences
- Advantages: fast, only need to keep last number generated
- Disadvantages: periodic (if you hit a number you've seen before, the sequence replays exactly the same), poor choices of the constants lead to bad performance
  - If a number already produced appears again, the sequence starts over
    - Will happen on average after $\sqrt{m}$ numbers, by the birthday paradox
  - Many early RNG libraries had bad choices, leading to statistical errors in papers!

Example: RANDU

- A widely distributed algorithm in wide use since the 1960s
  - In use until the late 90s, these days, newer methods such as Mersenne Prime Twisters are used (`TRandom3` in ROOT)
- Uses LCG to generate floating point numbers in [0, 1)
  - Floating point is a whole other issue
- $$V_{j+1} = 65539 \cdot V_j \mod 2^{31}$$
- $$X_j = V_j / 2^{31}$$
- The initial seed should be an odd number
- This had a multi-dimensional correlation that led to incorrect results (try generating 3-dim. points and plotting in 3D, should see that it generates in planes)
  - Don't trust results from the 80s and even into the 90s that use the distribution "standard" PRNG!

Exercises

In Machine Learning, we often need random numbers to seed our models, today, we will write some:

1. Implement a linear congruential generator in python, with input integer and output float in range [0, 1]
   - The book "Numerical Recipes" suggests using LCG with $a = 1664525$, $c = 1013904223$, $m = 2^{32}$, use these values
   - Create a class `randnr`, it should have an initializer that sets the seed
     - `def __init__(self, seed:  int):`
   - With a function to get a random integer in range (0, 2**32):
     - `def randint(self) -> int:`
   - And a random number output function for floats in range (0, 1):
     - `def random(self) -> float:`
2. Using your `randnr` function, implement an exponential PDF
   - If you take output from `randr`, `r` and feed into `-c*math.log(1-r)`, it outputs a random number from the PDF $f(x) = \frac{1}{c}e^{-x/c}$
   - add to your class the function:
     - `def exp(self) -> float:`

Exercises: continued

1. Using your RANDNR function, implement a Gaussian PDF Generator
   - The Central Limit Thereom of probability tells us that the sum of random distributions approaches a Gaussian (normal) distribution
   - In fact, if x_i is a random variable uniform in (0, 1), then $x = \frac{\sum_{i=1}^{m} x_i - m/2}{\sqrt{m/12}} \rightarrow$ Gaussian as $m \rightarrow \infty$ (where does $\sqrt{1/12}$ come from?)
     - Where the gaussian has mean 0, standard deviation 1, $N(0, 1)$
   - So, add the function `def gauss(self, mean=0, std=1, m=10) -> float:`, which takes `m` samples from `randnr.random` and runs the gaussian approximation sum, then scales the output for the given mean and standard deviation $N(\mu, \sigma) = \sigma \cdot N(0, 1) + \mu$
   - [Optional for students without prior experience] Draw a histogram (matplotlib/ROOT) of the output of `gauss` for `m=1,2,5,10`, filling each histogram with 1000 values pulled from the distribution, plot the on the same axes and save to a file called 'gauss.png', include it in your github repo

Submit your code:

- Code will be marked automatically using github classrooms
  - You will create a git repository which I will use to mark automatically
  - It contains a test file that checks your code works as it should
    - The class `randnr` exists, and that randint and random deliver numbers from the NR LCG, and the `exp` is working correctly
  - If you pass all the tests, you are done for today
  - Run the tests by running `pytest`
    - If it isn't installed, run `pip install pytest --user`
- Create a github account
- Click the first assignment link to create your repo
- Clone the repo (instructions on the page)
- Write code, test, upload to repo
  - I will mark tomorrow based on the last commit with a timestamp of today