Lecture 1 – Introduction, Learning From Data

DSC 40A, Fall 2022 @ UC San Diego

Dr. Truong Son Hy, with help from **many others**

Agenda

1. Who are we?
2. What is this course about?
3. How will this course run?
4. How do we turn the problem of learning from data into a math problem?

Who are we?

Hi, everyone!

Background

- First name Son, last name Hy, middle name Truong. Born & raised in Hanoi, Vietnam.

Education

- PhD in Computer Science, University of Chicago, June 2022

- BSc in Computer Science, University of Budapest (Eotvos Lorand University, Hungary), July 2016

Research

- Graph representation learning & Deep generative models on graphs for drug discovery and material science

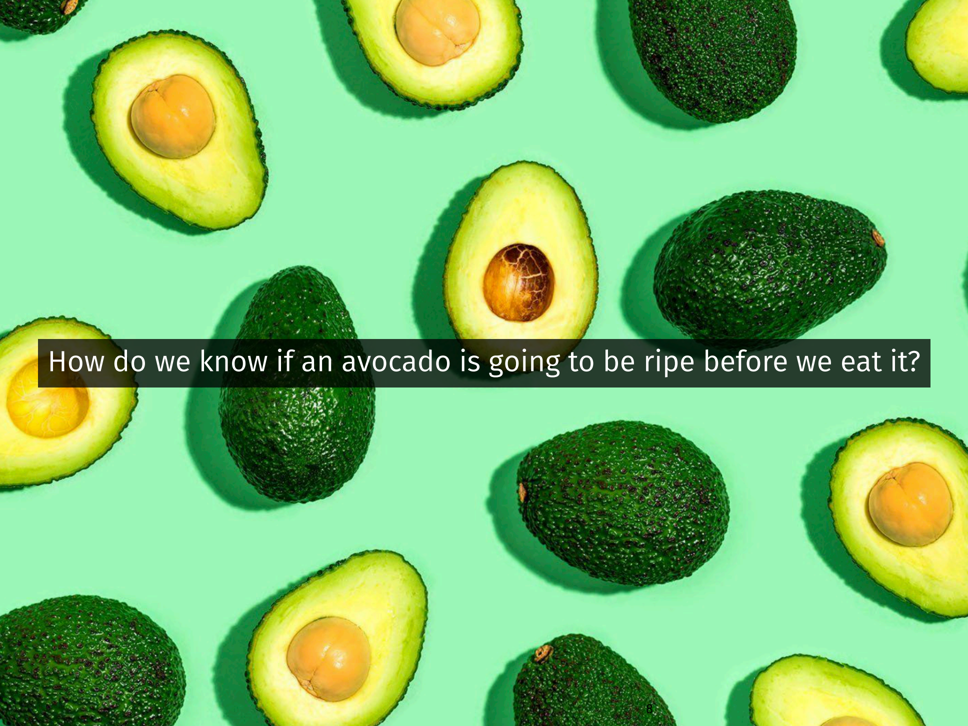
- Group/representation theory & Symmetry-preserving, physics-informed Machine Learning

- Multiresolution/multiscale models

Say hey to course staff!

- 2 Instructors: Dr. Truong Son Hy and Dr. Mahdi Soleymani.
- 1 TA, who will teach discussion and help run the class.
  - Pushkar Bhuse, a MS student in CSE.
- Several tutors, who will hold OH, grade assignments, and help run the class.
  - Aryaman Sinha, Jessica Song, Karthikeya Manchala, Shiv Sakthivel, Vivian Lin, Weiyue Li, Yujia Wang, Yuxin Guo.
  - All undergrads who took DSC 40A before and did well.
- Read about them at **dsc40a.com/staff**.

What is this course about?



How do we know if an avocado is going to be ripe before we eat it?


Try a little tenderness
Australian Avocados
www.avocado.org.au
How do you know when we're ripe?
AVOCADO COLOUR & RIPENESS CHART
Colour Rating
1
2
3
4
5
6
HASS
Look & Touch
Firmness Rating
Hard
Effegi puncture (kgf) - using 11mm tip
Rubbery
5kgf
Softening
2kgf
Firm Ripe
1kgf
Medium to Soft Ripe
0.65kgf
Soft to Over Ripe
0.45kgf
GREEN SKINS
Touch
(Shepard, Wurtz, Sharwil, Reed)
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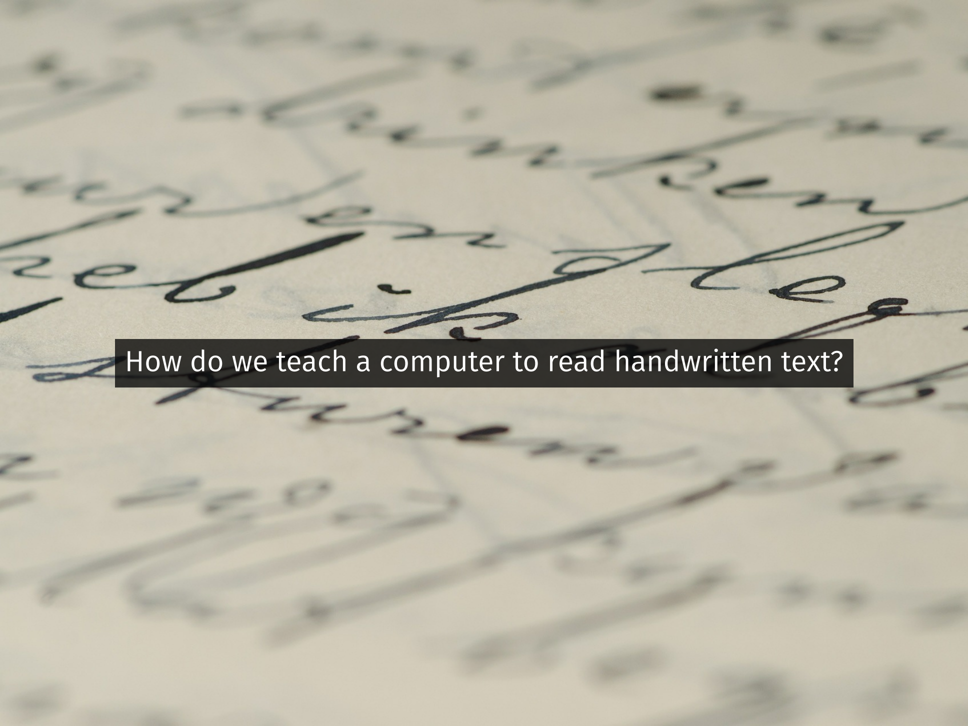

How do we teach a computer to read handwritten text?

How do we predict a future data scientist’s salary?

...by **learning** from data.

How do we learn from data?

The fundamental approach:

1. Turn learning from data into a math problem.

2. Solve that problem.

Course overview

Part 1: Learning from Data (Lectures 1-11)

- Summary statistics and loss functions; mean absolute error and mean squared error.
- Linear regression (incl. linear algebra).
- Clustering.

Part 2: Probability (Lectures 12-18)

- Set theory and combinatorics; probability fundamentals.
- Conditional probability and independence.
- Naïve Bayes (mix of both parts of the class).

Learning objectives

After this quarter, you'll...

- understand the basic principles underlying almost every machine learning and data science method.
- be better prepared for the math in upper division: vector calculus, linear algebra, and probability.
- be able to tackle the problems mentioned at the beginning.

How will this course run?

Technology

- The course website, **dsc40a.com**, is where all content (lectures, **readings**, homeworks, discussions) will be posted. It also contains a calendar of office hours (with Zoom links).
- **Campuswire** is where all announcements will be sent, and where all student-staff and student-student communication will occur. **Ask questions here!**
- **Gradescope** is where all assignments are submitted and all grades live.
- **Zoom** will be used for virtual office hours and discussion.

Lectures

Monday/Wednesday/Friday, Pepper Canyon Hall (PCYNH) room **122**. Two identical sessions:

- 3:00 – 3:50: Dr. Truong Son Hy
- 4:00 – 4:50: Dr. Mahdi Soleymani

What you should do

- Ask questions! Give me and Dr. Mahdi your feedback!
- Learn from everyone including the TA, tutors, classmates.
- Learn from any source including textbooks, online courses, research papers, etc.
- Learn by doing the homeworks!

Discussion

- **Discussion**:
  - Lead by the TA.
  - Monday, Pepper Canyon Hall (PCYNH) room **122**.
  - Two identical sessions: 5:00–5:50 and 6:00–6:50.
  - Come to work on problems in small groups (”groupwork”) of 2-4.
- Worksheets are due to Gradescope by **Monday at 11:59pm**.
  - Only one group member should submit; they should add the rest of the group to the assignment on Gradescope.

Assessments and exams

- **Homeworks**: Released weekly, and usually due **Fridays at 2pm** on Gradescope. Worth 40% of your grade.
- **Groupworks/Discussions**: Due **Monday at 11:59pm**. Worth 10% of your grade.
- **Midterm Exam**: TBD. Worth 20% of your grade.
- **Final Exam**: 12/03/2022, 7:00pm-9:59pm. Worth 30% of your grade.
- Both exams will be held **in-person**. Please resolve your schedule conflicts as soon as possible.

Leniency

We have some leniency built into our grading scheme:

- **Slip days**: 3. Can only be used on homework. Can only use one per homework.
- **Drops**: We will drop your lowest homework and groupwork.

Support

- **Office Hours (starting next week)**: held throughout the week, but concentrated near deadlines. Calendar on course website will be updated with times by the weekend.
  - Some staff OH are remote via Zoom. See Calendar for Zoom links. Others are in-person in the HDSI building (San Diego Supercomputer Center). Ask the TA and tutors for passcode.
- **Campuswire**: Use it! We’re here to help you.
  - Don’t post answers.

How do we turn the problem of learning from data into a math problem?

How do we predict a future data scientist’s salary?

Learning from data

- Idea: ask a few data scientists about their salary.
  - StackOverflow does this annually.

- Five random responses:

90,000   94,000   96,000   120,000   160,000

Discussion Question

Given this data, how might you predict your future salary?

Some common approaches

- The **mean**:

$$\frac{1}{5} \times (90{,}000 + 94{,}000 + 96{,}000 + 120{,}000 + 160{,}000)$$
$$= 112{,}000$$

- The **median**:

$$90{,}000 \quad 94{,}000 \quad \underbrace{96{,}000}_{\uparrow} \quad 120{,}000 \quad 160{,}000$$

- Which is better? Are these good ways of predicting future salary?

Quantifying the goodness/badness of a prediction

- We want a metric that tells us if a prediction is good or bad.

- One idea: compute the **absolute error**, which is the distance from our prediction to the right answer.

  $$\text{absolute error} = |(\text{actual future salary}) - \text{prediction}|$$

- Then, our goal becomes to **find the prediction with the smallest possible absolute error**.

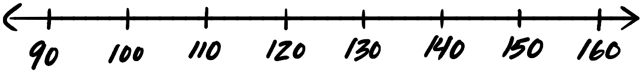
What is good/bad, intuitively?

- The data:

  90,000 94,000 96,000 120,000 160,000

- Consider these hypotheses:

  $h_1 = 150{,}000$ $h_2 = 115{,}000$



Discussion Question

Which do you think is better, h_1 or h_2? *Why*?

Quantifying our intuition

- Intuitively, a good prediction is close to the data.
- Suppose we predicted a future salary of $h_1 = 150{,}000$ *before* collecting data.

salary	absolute error of h_1
90,000	60,000
94,000	56,000
96,000	54,000
120,000	30,000
160,000	10,000

sum of absolute errors: 210,000

mean absolute error: 42,000

Quantifying our intuition

- Now suppose we had predicted $h_2 = 115{,}000$.

salary	absolute error of h_2
90,000	25,000
94,000	21,000
96,000	19,000
120,000	5,000
160,000	45,000
	sum of absolute errors: 115,000
	mean absolute error: 23,000

Mean absolute error (MAE)

- Mean absolute error on data:

$$h_1 : 42{,}000 \qquad h_2 : 23{,}000$$

- Conclusion: h_2 is the better prediction.

- In general: pick prediction with the smaller mean absolute error.

We are making an assumption...

- We're assuming that future salaries will look like present salaries.

- That a prediction that was good in the past will be good in the future.

Discussion Question

Is this a good assumption?

Which is better: the mean or median?

- Recall:

  mean = 112,000   median = 96,000

- We can calculate the mean absolute error of each:

  mean : 22,400   median : 19,200

- The median is the best prediction so far!

- But is there an even better prediction?

Finding the best prediction

- Any (non-negative) number is a valid prediction.
- Goal: out of all predictions, find the prediction h^* with the smallest mean absolute error.
- This is an **optimization problem**.

A formula for the mean absolute error

- We have data:

  90,000 94,000 96,000 120,000 160,000

- Suppose our prediction is h.
- The **mean absolute error** of our prediction is:

$$R(h) = \frac{1}{5}\Big(|90{,}000 - h| + |94{,}000 - h| + |96{,}000 - h| + |120{,}000 - h| + |160{,}000 - h|\Big)$$

A formula for the mean absolute error

- We have a function for computing the mean absolute error of **any** possible prediction.

$$
\begin{aligned}
R(\mathbf{150{,}000}) &= \frac{1}{5}\Big(|90{,}000 - \mathbf{150{,}000}| + |94{,}000 - \mathbf{150{,}000}| \\
&\quad + |96{,}000 - \mathbf{150{,}000}| + |120{,}000 - \mathbf{150{,}000}| \\
&\quad + |160{,}000 - \mathbf{150{,}000}|\Big) \\
&= \mathbf{42{,}000}
\end{aligned}
$$

A formula for the mean absolute error

- We have a function for computing the mean absolute error of **any** possible prediction.

$$
\begin{aligned}
R(115{,}000) = \frac{1}{5}\Big(&|90{,}000 - 115{,}000| + |94{,}000 - 115{,}000| \\
&+ |96{,}000 - 115{,}000| + |120{,}000 - 115{,}000| \\
&+ |160{,}000 - 115{,}000|\Big) \\
&= 23{,}000
\end{aligned}
$$

A formula for the mean absolute error

- We have a function for computing the mean absolute error of **any** possible prediction.

$$R(\pi) = \frac{1}{5}\Big(|90{,}000 - \pi| + |94{,}000 - \pi| + |96{,}000 - \pi| + |120{,}000 - \pi| + |160{,}000 - \pi|\Big) = \mathbf{111{,}996.8584\ldots}$$

Discussion Question

Without doing any calculations, which is correct?

A. $R(50) < R(100)$

B. $R(50) = R(100)$

C. $R(50) > R(100)$

A *general* formula for the mean absolute error

- Suppose we collect n salaries, $y_1, y_2, \ldots, y_n$.
- The mean absolute error of the prediction h is:

- Or, using **summation notation**:

The best prediction

- We want the best prediction, h^*.
- The smaller $R(h)$, the better h.
- Goal: find h that minimizes $R(h)$.

Summary

- We started with the learning problem:

  Given salary data, predict your future salary.

- We turned it into this problem:

  Find a prediction h^* which has smallest mean absolute error on the data.

- We have turned the problem of learning from data into a specific type of math problem: an **optimization problem**.

- **Next time**: we solve this math problem.