

DSC 140B

Representation Learning

Lecture 01 | Part 1

Introduction

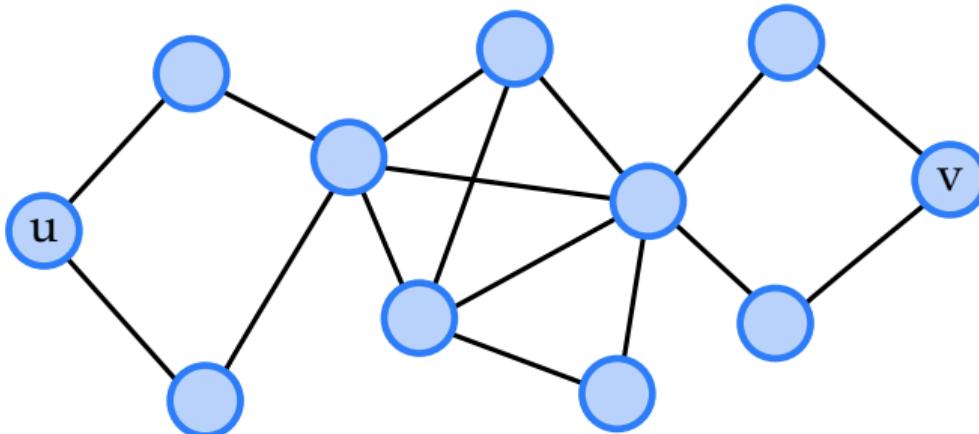
Welcome to DSC 140B

Representation Learning

What is Machine Learning?

- ▶ Computers can do things very quickly.
- ▶ But must be given really specific instructions.
- ▶ **Problem:** Not all tasks are easy to dictate.

Example (Easy)



Problem: Find a shortest path between u and v .

Example (Not so easy)



Problem: On a scale from 1-10, how happy is this person?

The Trick: Use Data



8



3



5



4



7



6



10



?

What is Machine Learning?

- ▶ Before: Computer is **told** how to do a task.
- ▶ Instead: **learn** how to do a task using data.

What is Machine Learning?

- ▶ Before: Computer is **told** how to do a task.
- ▶ Instead: **learn** how to do a task using data.
- ▶ We still have to **tell** the computer how to learn.

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This is because real world data has “**structure**”.



Problem: On a scale from 1-10, how happy is this person?

Recall: Least Squares Regression

- ▶ Example: predict the price of a laptop.
- ▶ Choose some **features**:
 - ▶ CPU speed, amount of RAM, weight (kg).
- ▶ Prediction function (weighted “vote”):
$$(\text{price}) = w_0 + w_1 \times (\text{cpu}) + w_2 \times (\text{ram}) + w_3 \times (\text{weight})$$
- ▶ Learn w_i by minimizing **squared error**.

Representations

- ▶ Computers don't understand the concept of a laptop.
- ▶ We had to **represent** a laptop as a set of features.
 - ▶ CPU speed, amount of RAM, weight (kg).
- ▶ Clearly, choosing right **feature representation** is important.

Now: Predict Happiness



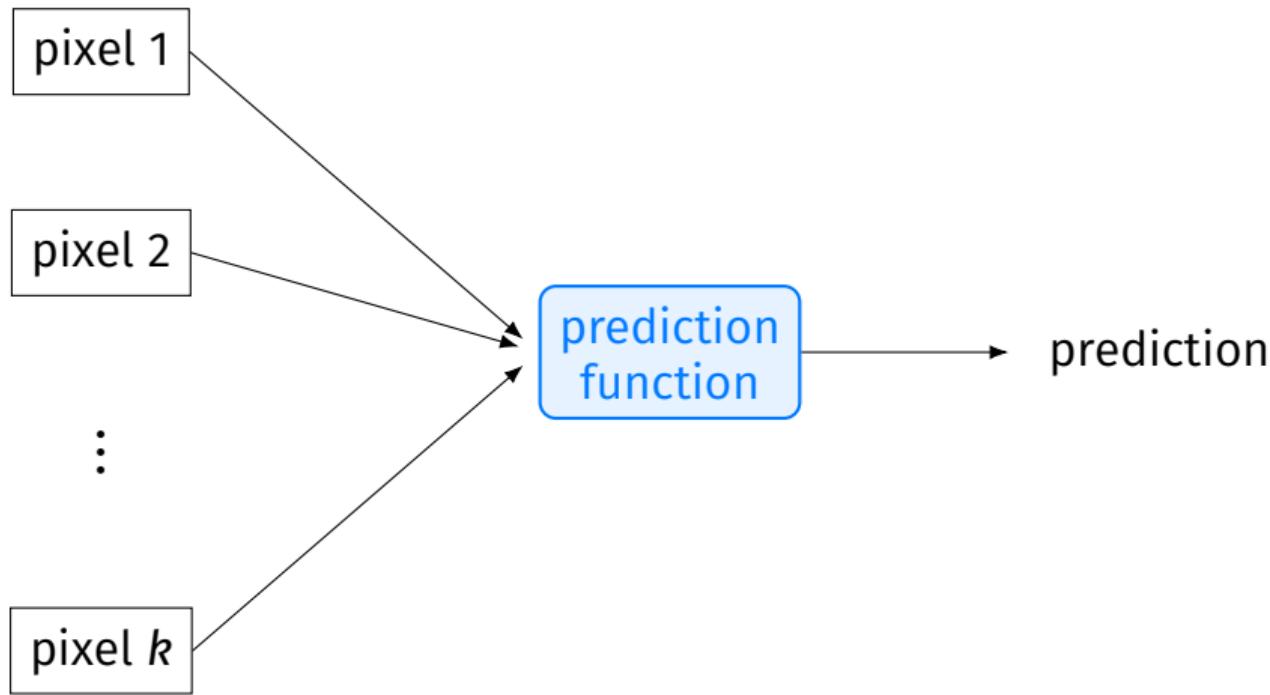
- ▶ Given an image, predict happiness on a 1-10 scale.
- ▶ This is a **regression** problem.
- ▶ Can we use least squares regression?

Problem

- ▶ Computers don't understand images.
- ▶ How do we **represent** them?
- ▶ Simple approach: a bag of pixels.
 - ▶ **Each** pixel has an numerical **intensity**.
 - ▶ Each pixel is a feature.
 - ▶ In this way, an image is represented as a **vector** in some **high dimensional space**.

Least Squares for Happiness

$$\begin{aligned} \text{(happiness)} = & w_0 \\ & + w_1 \times \text{(pixel 1)} \\ & + w_2 \times \text{(pixel 2)} \\ & + \dots \\ & + w_k \times \text{(pixel k)} \end{aligned}$$



Exercise

Say we train a least squares regression model on a set of images to predict happiness. We achieve a mean squared error of M_1 .

Now we scramble every image's pixels *in exactly the same way* (same transformation of each image). We retrain, and achieve MSE of M_2 .

Which is true:

- ▶ $M_1 < M_2$
- ▶ $M_1 = M_2$
- ▶ $M_1 > M_2$

Answer

- ▶ The regression model will work just as well if the images are all scrambled in exactly the same way.
- ▶ This is because the model doesn't use the **proximity** of pixels.
- ▶ The **representation** (each pixel is a feature) does not capture this.

Exercise

Say we train a least squares regression model on a set of images to predict happiness. We achieve a mean squared error of M_1 .

Now we scramble every image's pixels *independently*. We retrain, and achieve MSE of M_2 .

Which is likely to be true?:

- ▶ $M_1 < M_2$
- ▶ $M_1 = M_2$
- ▶ $M_1 > M_2$

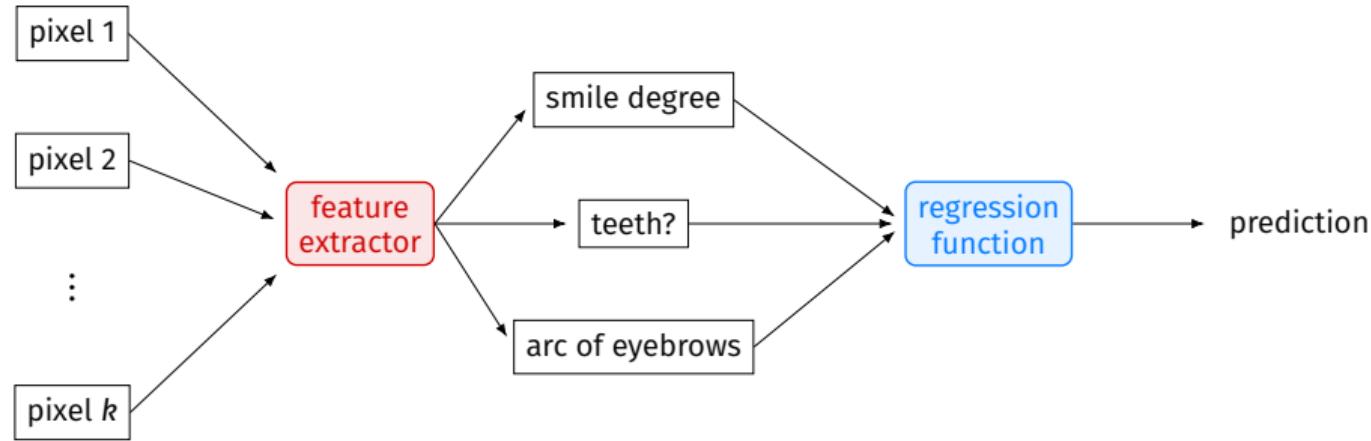
Happiness: it's in the Pixels

- ▶ The information is contained in the image... but not in individual pixels.
- ▶ In **patterns** of pixels:
 - ▶ The shape of the eyebrows.
 - ▶ Angle of the corners of the mouth.
 - ▶ Are teeth visible?
- ▶ The representation is **too “low-level”** – probably won’t work well¹.

¹On this example! Works OK on, e.g., MNIST.

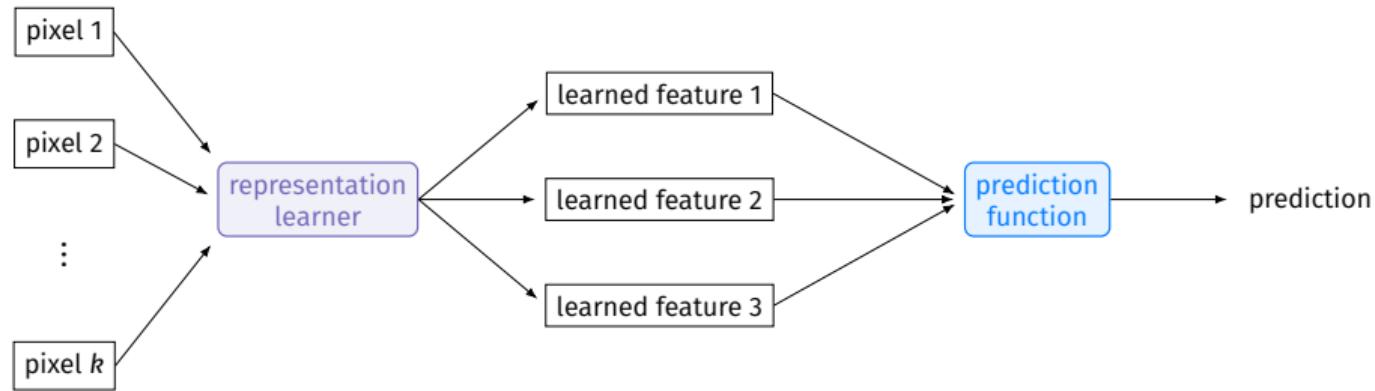
Handcrafted Representations

- ▶ Idea: build a **feature extractor** to detect:
 - ▶ The shape of the eyebrows.
 - ▶ Angle of the corners of the mouth.
 - ▶ Are teeth visible?
- ▶ Use these as high-level features instead.



Problem

- ▶ Extractors (may) make good **representations**.
- ▶ But building a feature extractor is **hard**.
- ▶ Can we **learn** a good representation?



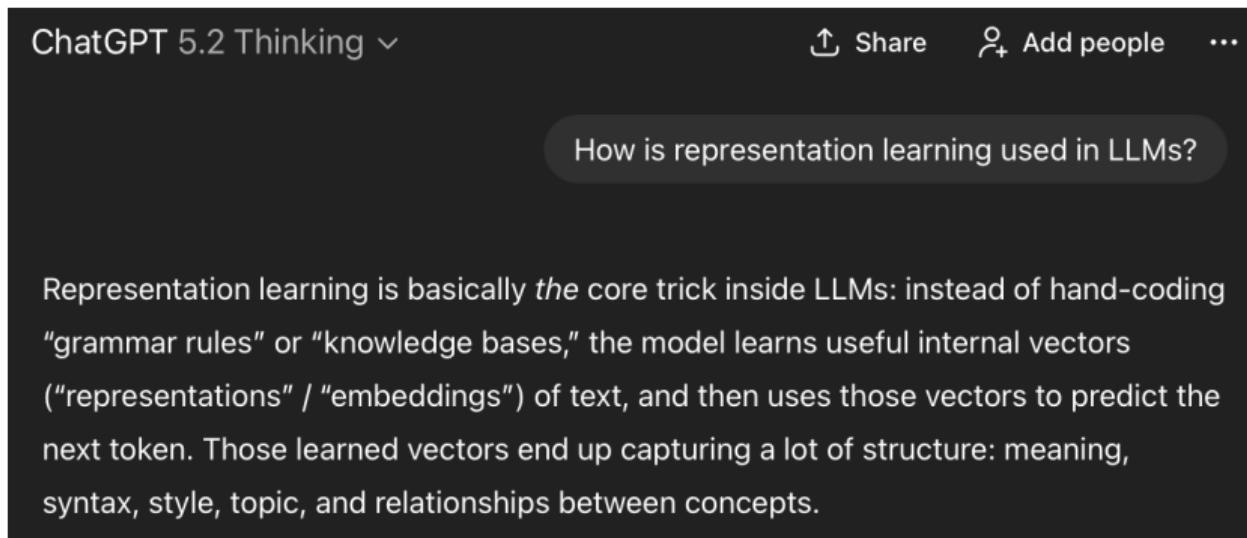
DSC 140B

- ▶ We'll see how to **learn good representations**.
- ▶ Good representations help us when:
 1. making predictions;
 2. doing EDA (better visualizations).

Claim

- ▶ Many of the famous recent advancements in AI/ML are due to **representation learning**.

Example: ChatGPT



ChatGPT 5.2 Thinking

Share Add people ...

How is representation learning used in LLMs?

Representation learning is basically *the* core trick inside LLMs: instead of hand-coding "grammar rules" or "knowledge bases," the model learns useful internal vectors ("representations" / "embeddings") of text, and then uses those vectors to predict the next token. Those learned vectors end up capturing a lot of structure: meaning, syntax, style, topic, and relationships between concepts.

Representations and Structure

- ▶ Real world data has structure.
- ▶ But “seeing” the structure requires the right representation.

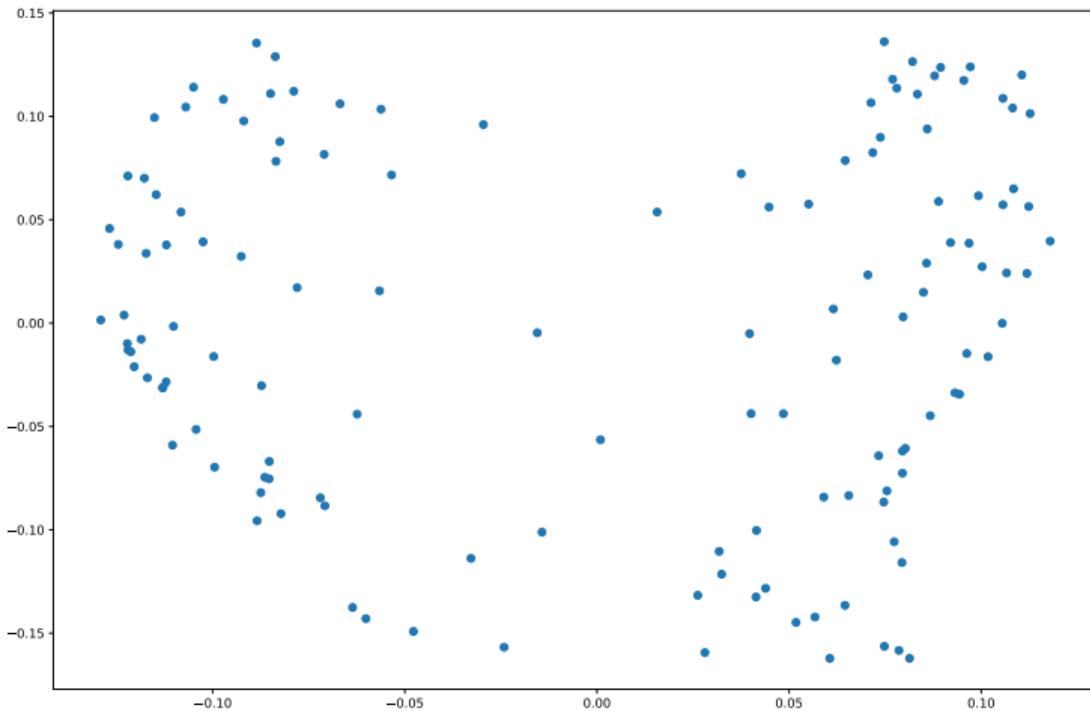
Example: Pose Estimation

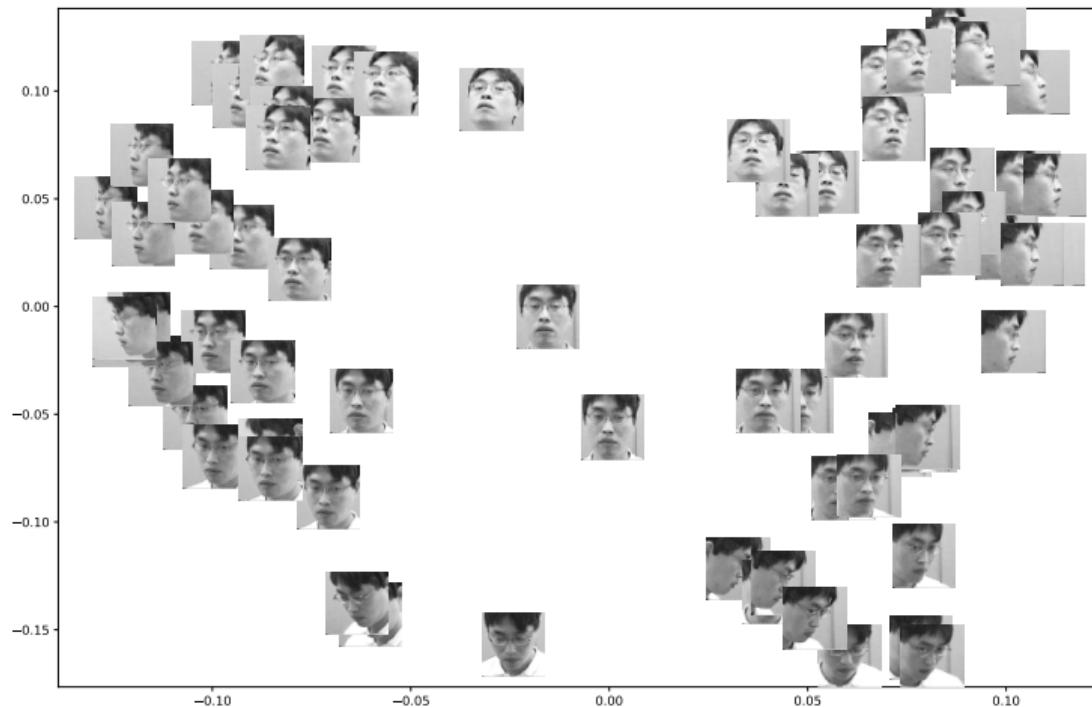


Problem: Classify, is person looking left, right, up, down, natural?

Example: Pose Estimation

- ▶ As a “bag of pixels” each image is a vector in $\mathbb{R}^{10,000}$.
- ▶ Later: we’ll see how to reduce dimensionality while preserving “closeness”.





Main Idea

By learning a better representation, the classification problem can become easy; sometimes trivial.

Example: word2vec

- ▶ How do we represent a word?
- ▶ Google's word2vec learned a representation of words as points in 300 dimensional space.
- ▶ Two points close \iff words have similar meanings.

Example: word2vec

- ▶ Fun fact: we can now add and subtract words.
 - ▶ They're represented as vectors.
- ▶ Surprising results:

$$\vec{v}_{\text{Paris}} - \vec{v}_{\text{France}} + \vec{v}_{\text{China}} \approx \vec{v}_{\text{Beijing}}$$

Example: word2vec ²

Table 8: Examples of the word pair relationships, using the best word vectors from Table 4 (Skip-gram model trained on 783M words with 300 dimensionality).

Relationship	Example 1	Example 2	Example 3
France - Paris	Italy: Rome	Japan: Tokyo	Florida: Tallahassee
big - bigger	small: larger	cold: colder	quick: quicker
Miami - Florida	Baltimore: Maryland	Dallas: Texas	Kona: Hawaii
Einstein - scientist	Messi: midfielder	Mozart: violinist	Picasso: painter
Sarkozy - France	Berlusconi: Italy	Merkel: Germany	Koizumi: Japan
copper - Cu	zinc: Zn	gold: Au	uranium: plutonium
Berlusconi - Silvio	Sarkozy: Nicolas	Putin: Medvedev	Obama: Barack
Microsoft - Windows	Google: Android	IBM: Linux	Apple: iPhone
Microsoft - Ballmer	Google: Yahoo	IBM: McNealy	Apple: Jobs
Japan - sushi	Germany: bratwurst	France: tapas	USA: pizza

²“Efficient Estimation of Word Representations in Vector Space” by Mikolov, et al.

Example: Neural Networks

- ▶ word2vec is an example of a neural network model.
- ▶ Deep neural networks have been very successful on certain tasks.
- ▶ They **learn** a good representation.



Main Idea

Building a good model requires picking a good **feature representation**.

We can pick features by hand.

Or we can **learn** a good feature representation from data.

DSC 140B is about learning these representations.

Roadmap

- ▶ Dimensionality Reduction
- ▶ Manifold learning
- ▶ Neural Networks
- ▶ Autoencoders
- ▶ Deep Learning

Practice vs. Theory

- ▶ Goal of this class: understand the fundamentals of representation learning.
- ▶ Both practical and theoretical.
- ▶ Think: more DSC 40A than DSC 80, but a bit of both.

Tools of the Trade

- ▶ We'll see some of the popular Python tools for feature learning.
 - ▶ numpy
 - ▶ keras/pytorch
 - ▶ sklearn
 - ▶ ...

DSC 140B

Representation Learning

Lecture 01 | Part 2

Syllabus

dsc140b.com

This quarter...

- ▶ An “experimental” grading scheme.

Your grade comes from...

- ▶ Lecture Attendance
- ▶ Homework
- ▶ Quizzes
- ▶ Exams
- ▶ Final Project

Your grade comes from...

- ▶ Lecture Attendance (*Optional*)
- ▶ Homework (*Optional*)
- ▶ Quizzes (*Optional*)
- ▶ Exams
- ▶ Final Project

“Credits”

- ▶ To start, your grade is 90% exams + 10% final project.
- ▶ Each optional assignment (lecture, homework, quiz) earns you “credits”.
 - ▶ E.g., each quiz passed earns 1.5 credits.
 - ▶ Total credits possible this quarter: 40
- ▶ Each credit reduces the weight of exams by 1% and adds 1% to your overall grade.

Examples

- ▶ **Example 1:** You have an 80% average on exams and a 100% final project. You did none of the optional assignments, so you have 0 credits. Your overall grade is:

$$0.9 \cdot 80 + 0.1 \cdot 100 = 82\%$$

- ▶ **Example 2:** You have an 80% average on exams and a 100% final project. You did all of the optional assignments, earning 40 credits. Your overall grade is:

$$0.5 \cdot 80 + 0.1 \cdot 100 + 0.4 \cdot 100 = 90\%$$

Quizzes

- ▶ Quizzes are short (20 minutes), **optional**, held in-person during discussion.
- ▶ You earn 1.5 credits for each quiz you pass; 12 available.
 - ▶ Passing score is 70% or higher.
 - ▶ Failing a quiz has no penalty. (Can't hurt your grade.)
- ▶ At least one question from each quiz is guaranteed to be on exam.
 - ▶ Maybe with different numbers.
- ▶ Must RSVP; watch email after lecture.

Lecture Attendance

- ▶ Attending lecture in-person is **optional**.
- ▶ You earn 0.25 credits for each lecture you attend to a maximum of 4 credits.
 - ▶ I.e., a maximum of 4% of your grade.
- ▶ Starting next lecture.

Homeworks

- ▶ Homeworks are also **optional**.
 - ▶ But highly recommended!
- ▶ Each problem is graded on effort, pass/fail.
- ▶ You earn 0.75 credits for each problem you pass;
24 available.
- ▶ Must be handwritten!

Note

- ▶ The more optional assignments you do, the less exams matter.
- ▶ But skipping a lecture, homework, or quiz does not **hurt** your grade.
- ▶ Feel free to pick and choose which optional assignments you want to do.

DSC 140B

Representation Learning

Lecture 01 | Part 3

Is DSC 140B for You?

You've had (at least) two classes in ML already...

- ▶ DSC 40A (theory)
- ▶ DSC 80 (practice)
- ▶ Possibly:
 - ▶ DSC 140A, DSC 148, CSE 158, CSE 151A, CSE 151B,...

Is DSC 140B for you?

- ▶ DSC 140B was previously a DSC 190.
- ▶ DSC 140A/140B are **targeted** to DSC majors.
 - ▶ Compared to other ML classes, Assume some ML background (40A, 80).

Is DSC 140B for you?

- ▶ Unfortunately, it's a little confusing.
- ▶ DSC 140B and CSE 151A are equivalent in credit.
- ▶ Not equivalent in topics.
- ▶ Consequence of creating our own ML in DSC.

Bottom Line

- ▶ If you are a DSC major, haven't taken an ML class:
 - ▶ Take this class and DSC 140A (in either order).
- ▶ If you are a DSC major, have taken an ML class:
 - ▶ Talk to an advisor.

Bottom Line

- ▶ If you're not a DSC major, looking for an ML elective:
 - ▶ This course *might* be a good option if you already have some ML background.
 - ▶ But it is targeted to data scientists.
 - ▶ CSE 151A, DSC 80, DSC 148, CSE 158, etc. may be better options.

Next Time

- ▶ Review of DSC 40A topics.
- ▶ Learning as optimizing loss.
- ▶ Linear models for regression and classification.