DSC 140B

Representation Learning

Lecture 01 | Part 1

Introduction

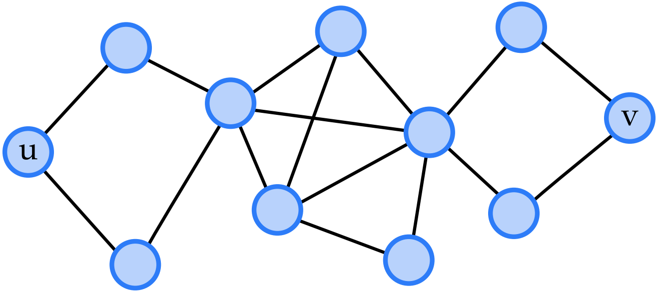
Welcome to DSC 140B

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.

An **ML algorithm** is a set of precise instructions telling the computer **how to learn** from data.

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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

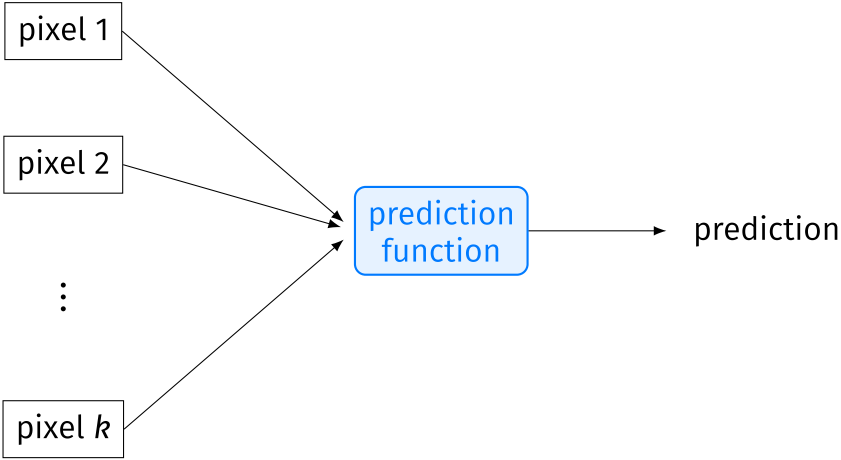
- Given an image, predict happiness on a 1-10 scale.
- This is a **regression** problem.
- Can we use least squares regression?

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

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


pixel 1
pixel 2
pixel k
prediction function
prediction

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.

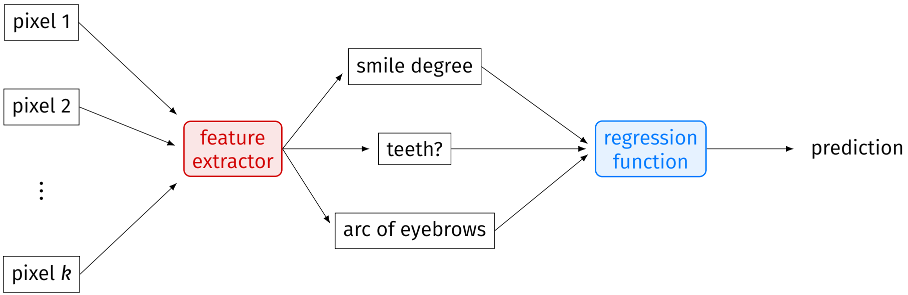
- In **patterns** of pixels:
  - The shape of the eyebrows.
  - Angle of the corners of the mouth.
  - Are teeth visible?

- The representation is **too simple** – probably won't work well[1].

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

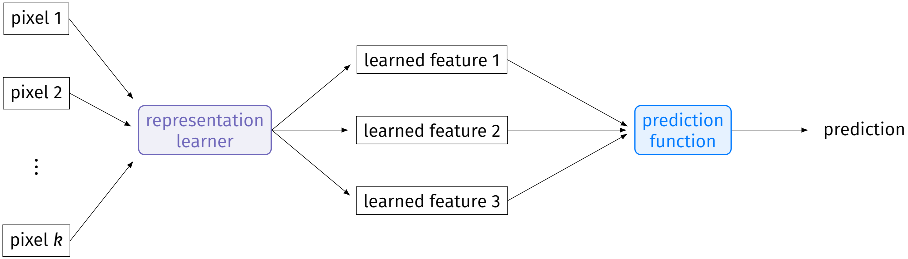
Handcrafted Representations

- 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.


pixel 1
pixel 2
⋮
pixel k
feature extractor
smile degree
teeth?
arc of eyebrows
regression function
prediction

Problem

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



pixel 1
pixel 2
⋮
pixel k
representation learner
learned feature 1
learned feature 2
learned feature 3
prediction function
prediction

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

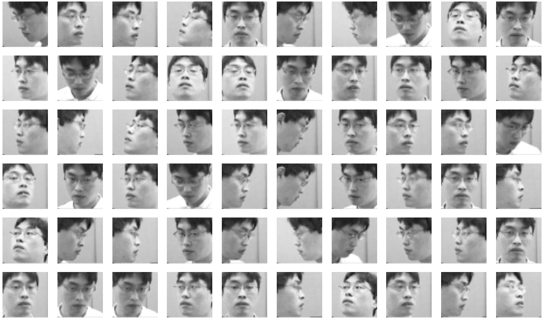
Claim

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

Representations and Structure

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

Example: Pose Estimation

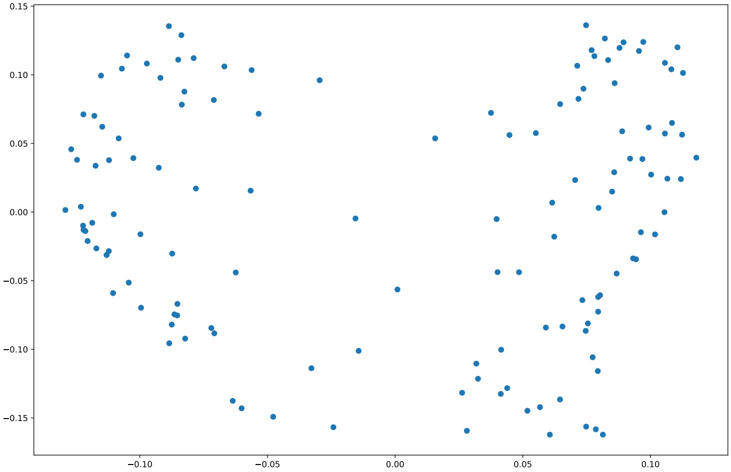


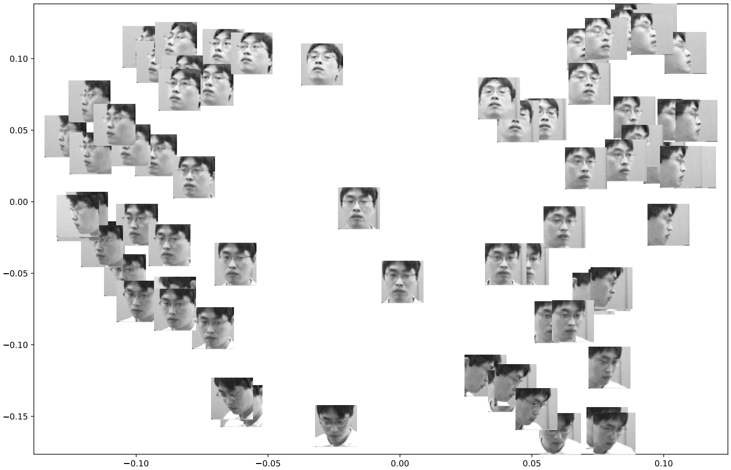
Problem: Classify, is person looking left, right, up, down, netural?

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”.


0.15
0.10
0.05
0.00
−0.05
−0.10
−0.15
−0.10
−0.05
0.00
0.05
0.10



0.10
0.05
0.00
−0.05
−0.10
−0.15
−0.10
−0.05
0.00
0.05
0.10

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.








Example: ChatGPT

ELI5: What is representation learning?

Representation learning is a type of machine learning where an algorithm learns to automatically discover the most important features or patterns in the input data, without being explicitly told what those features or patterns are.

Imagine you want to teach a computer to recognize different types of animals. Rather than manually specifying what features to look for in each animal, such as the number of legs, the shape of the ears, or the texture of the fur, representation learning algorithms can automatically learn these features by analyzing large amounts of labeled data.

The key idea behind representation learning is that the learned features or representations can be used as inputs for downstream tasks, such as classification, clustering, or regression. By learning useful representations, machine learning models can become more accurate and efficient, and require less labeled data to achieve high performance.

By the way...

A Series of Talks and Panels

Welcome: Frank Wuerthwein, Director, SDSC and Professor, Physics, & HDSI

What is ChatGPT?

- Justin Eldridge, Teaching Professor HDSI

How does ChatGPT work?

- Jingbo Shang, Professor HDSI/CSE

Ethical Implications of Generative AI

- David Danks, Professor HDSI/Philosophy

Implications for Healthcare, Business, and Research

- Dr. Chris Longhurst, Chief Medical Officer UCSD Health
- Tiffany Amariuta-Bartell, Professor HDSI/School of Medicine
- Vincent Nijs, Professor and Associate Dean of Academic Program, Rady School of Management

By the way...

Technical Limitations of ChatGPT: Present and Future

- Mikhail Belkin, Professor HDSI
- Zhiting Hu, Professor HDSI
- Dheeraj Mekala, PhD Student HDSI
- Zihan Wang, PhD Student HDSI

Implications for Disinformation on Social Media

- Stuart Geiger, Professor HDSI/Communication

Implications for Education

- Leo Porter, Professor CSE
- Shannon Ellis, Teaching Professor CogSci
- Tricia Bertram-Gallant, Director of Academic Integrity Office

By the way...

https://www.sdsc.edu/event_items/
202304-ChatGPT.html

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`
  - `sklearn`
  - `...`

DSC 140B
Representation Learning

Lecture 01 | Part 2

Syllabus

dsc140b.com

Note

- No discussion this week!

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.