2023 22nd Annual Memorial Lecture

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“Monitoring Health and Diseases Using Radio Signals and Machine Learning”

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4 PM on April 20 • CIT 368
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Ritambhara Singh

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Monday

Deep Learning

Fill in the mid-term feedback for extra 2 late days!

No quiz this week!

Instructor’s office hours cancelled this week!
Interpretation in DL

(1) Model architecture based methods

(2) Gradient-based methods

(3) Model agnostic methods
Task formulation

Which pixels are most important for classification?

What is the simplest thing that comes to mind?
Perturbation-based methods

- Let’s **perturb inputs**...
- omit or change words/parts of images, change word embedding values, etc.
- **...observe changed outputs**...

![Diagram of a network with input and output, indicating a classification of a dog](image)
Perturbation-based methods

- Let’s **perturb inputs**...
- omit or change words/parts of images, change word embedding values, etc.
- ...observe changed outputs...

![Diagram](https://via.placeholder.com/150)
**LIME**

- **Local Interpretable Model-Agnostic Explanations (LIME)**
  - “Model-Agnostic”: treats every model as a black-box
- Let’s **perturb inputs**...
  - omit or change words/parts of images, change word embedding values, etc.
- **...observe changed outputs**...
- **...and approximate the underlying model** using a simple, interpretable model (like a linear classifier)
  - Interpretable because in $\sum w_i x_i$, the weights say “how much a particular input matters”
LIME example

- What makes this picture of a tree frog “tree frog”-y to a neural network?

Original Image
LIME example

- Perform a **superpixel segmentation** on the image
- Interpretable chunks in the image may be part of multiple superpixels
- But no superpixel will contain multiple interpretable parts
LIME example

- Different combinations of chunks put through the net yield different probabilities
- Learn a linear model to predict the probability from these different combos
- Chunks with high weight in the linear model “matter more” for the classification result

Can we think of disadvantages of perturbation-based methods?
Attention as interpretation method

| The agreement on the European Economic Area was signed in August 1992. |
|-----------------|-----------------|-----------------|

A woman is throwing a frisbee in a park.  
A dog is standing on a hardwood floor.  
A stop sign is on a road with a mountain in the background.  
A little girl sitting on a bed with a teddy bear.  
A group of people sitting on a boat in the water.  
A giraffe standing in a forest with trees in the background.
Roadmap

Supervised machine learning
- Perceptron
- Fully Connected Neural Networks
- Convolutional Neural Networks
- Language models
- Recurrent Neural Networks
- Transformers (Seq2seq)
Recap: What is Machine Learning?

Input: X

Output: Y

"Cooking?"

Function: $f(X)$ → Y

$f(X) \square Y$
Recap: What is Machine Learning?

Supervised Learning

Input: X

Learned function: f

Output: Y

"Cooking?"

f(X) \implies Y
What if you don’t have any labels?

Input: X

Unsupervised Learning

What can you learn from just input data without labels?
Today’s goal – learn about unsupervised learning using deep learning models

(1) Unsupervised Learning

(2) Auto-encoders (AE)
Unsupervised Learning

• What can we learn from input data when there are no labels?
  • We can only analyze the structure of the data itself

Data:
Clustering

The organization of unlabeled data into similarity groups called “clusters.”

A cluster is a collection of data items which are “similar” between them, and “dissimilar” to data items in other clusters.
How does the machine do the clustering?

Data:

1. Proximity measure, either
   - similarity measure $s(x_i,x_k)$: large if $x_i,x_k$ are similar
   - dissimilarity (or distance) measure $d(x_i,x_k)$: small if $x_i,x_k$ are similar

   large $d$, small $s$
   large $s$, small $d$

2. Criterion function to evaluate a clustering

   - good clustering
   - bad clustering

3. Algorithm to compute clustering
   - For example, by optimizing the criterion function
Data in high dimension

Data:

What about an image?
Curse of dimensionality in clustering

Adding a dimension stretches the points across that dimension, pushing them further apart.

The points continue to spread out, when more dimensions are being added, until they are equidistant from each other and distance is not very meaningful.

https://www.kdd.org/exploration_files/parsons.pdf

Dimensionality Reduction

• Represent the data with fewer dimensions
• The key idea: While the data may exist in a high dimensional space, it may actually lie along a lower dimensional subspace
  • Ex: data in $\mathbb{R}^3$ may lie along a plane
  • i.e. the intrinsic dimensionality of the data is actually 2 (not 3)
Dimensionality Reduction using projection

- Data may not lie exactly on a lower-dimensional subspace
- Can still represent it fairly well (with some degree of error)

2D data projected to 1 dimension
Dimensionality Reduction: Why?

• Lots of benefits to making the data lower-dimensional
  • Many clustering algorithms behave better in lower dimensions
  • Takes less storage/memory if you’re trying to analyze a huge dataset
  • More efficient to search using approximate nearest neighbor algorithms
  • Easier to visualize (if you reduce the data to 2 or 3 dimensions)

Any questions?
Dimensionality Reduction: Visualization

$\mathbb{R}^{784} \rightarrow \mathbb{R}^2$

https://hackernoon.com/latent-space-visualization-deep-learning-bits-2-bd09a46920df
Dimensionality Reduction: Visualization

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Dimensionality Reduction: Visualization

Have you already heard of a dimensionality reduction method?

https://hackernoon.com/latent-space-visualization-deep-learning-bits-2-bd09a46920df
Principal Component Analysis (PCA)

How to project 2D data down to 1D?
Principal Component Analysis (PCA)

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Simplest thing to try: flatten to one of the red axes
Principal Component Analysis (PCA)

How to project 2D data down to 1D?

Simplest thing to try: flatten to one of the red axes
(We could of course flatten to the other red axis)
Principal Component Analysis (PCA)

How to project 2D data down to 1D?

But notice that most of the variability in the data is *not* aligned with the red axes!

What is the issue here?

What can we do?

https://www.andrew.cmu.edu/user/georgech/95-865/Lectures/Lecture%20-%202003_essence.pdf
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How to project 2D data down to 1D?

But notice that most of the variability in the data is not aligned with the red axes!
Principal Component Analysis (PCA)

How to project 2D data down to 1D?

Most variability is along this green direction

But notice that most of the variability in the data is *not* aligned with the red axes!

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Principal Component Analysis (PCA)

How to project 2D data down to 1D?

The idea of PCA actually works for 2D → 2D as well (and just involves rotating, and not “flattening” the data)
Principal Component Analysis (PCA)

How to project 2D data down to 1D?
How to rotate 2D data so 1st axis has most variance

Most variability is along this green direction

before “flattening”

The idea of PCA actually works for 2D → 2D as well (and just involves rotating, and not “flattening” the data)

2nd green axis chosen to be 90° (“orthogonal”) from first green axis
Principal Component Analysis (PCA)

- Finds top $k$ orthogonal directions that explain the most variance in the data
Principal Component Analysis (PCA)

- Finds top $k$ orthogonal directions that explain the most variance in the data
  - 1st component: explains most variance along 1 dimension
  - 2nd component: explains most of remaining variance along next dimension that is orthogonal to 1st dimension
  - ...

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Principal Component Analysis (PCA)

- Finds top $k$ orthogonal directions that explain the most variance in the data
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  - ...

- “Flatten” data to the top $k$ dimensions to get lower dimensional representation (if $k < $ original dimension)
3D example from:

https://setosa.io/ev/principal-component-analysis/
PCA reorients data so axes explain variance in “decreasing order”
→ can “flatten” (project) data onto a few axes that captures most variance
Limitations of PCA
Limitations of PCA

2D Swiss Roll
Limitations of PCA

2D Swiss Roll

PCA would just flatten this thing and lose the information that the data actually lives on a 1D line that has been curved!
Limitations of PCA

https://www.andrew.cmu.edu/user/georgech/95-865/Lectures/Lecture%20-%20%2003_essence.pdf

Desired result!
How to dimension-reduce gnarly datasets?

• The Swiss Roll has an intrinsic dimensionality of 1
  • i.e. “how far along the curve a point is”

• But PCA can’t figure this out because the projection from $\mathbb{R}^2$ to $\mathbb{R}^1$ is non-linear
  • i.e. “unroll” the curve and lay it flat along a number line

• How can we compute non-linear projections?
“I hear these neural nets are pretty good at learning non-linear functions”

Can we use a neural net to learn a non-linear projection to a lower-dimensional space?
A nonlinear projection neural net

- We could just use a regular neural net architecture (e.g. fully connected layers).

![Diagram of nonlinear projection neural net]

- Input: $x$
- Compact Representation: $z$
A nonlinear projection neural net

- Idea: a compact representation $z$ is a good non-linear projection of $x$
Autoencoder

- Reconstruction loss: \( L(x, \bar{x}) = (x - \bar{x})^2 \)

How is this different from the Seq2seq encoder/decoder setup?
Autoencoder for MNIST

- **Encoder**
- **Compact Representation**
- **Decoder**

$x$ \rightarrow \text{Compact Representation} \rightarrow \bar{x}$
This visualization? Autoencoder

https://hackernoon.com/latent-space-visualization-deep-learning-bits-2-bd09a46920df
Other Autoencoder applications

Denoising Autoencoder

Input: Noisy Images

Output: Restored Image
Recap

Model agnostic interpretation

Unsupervised Learning

Auto-encoders (AEs)

LIME (or perturbation-based)

Attention (inbuilt interpretation)

Learning the structure in the data

Clustering

Dimensionality reduction using PCA

Perform non-linear dimensionality reduction

Architecture and loss function