6.034 **Deep Neural Networks Peter Szolovits**

ai6034.mit.edu

October 9, 2019







How Does Human/Animal Vision Work? cortex of a macaque monkey, showing the individual layers https://webvision.med.utah.edu/book/part-ix-brain-visual-areas/the-primary-visual-cortex/

Listen in on Neuroscientists Speak

- "Layer 1 is composed of a dense network of synapses formed between the apical dendrites of layer 2-5B pyramidal cells (Lund and Wu, 1997) and the collected inputs from LGNd K layers (Fitzpatrick et al., 1983; Lachica and Casagrande, 1992), the pulvinar, feedback pathways from extrastriate areas, nonspecific thalamic nuclei, and other subcortical regions. Thus, while layer 1 contains few neurons, it is a networking layer that has a direct concerted affect on the firing properties of pyramidal cells in deeper layers."
- "Many types of columns have been proposed including ocular dominance, orientation, spatial frequency, and color columns."

ANN: How big?

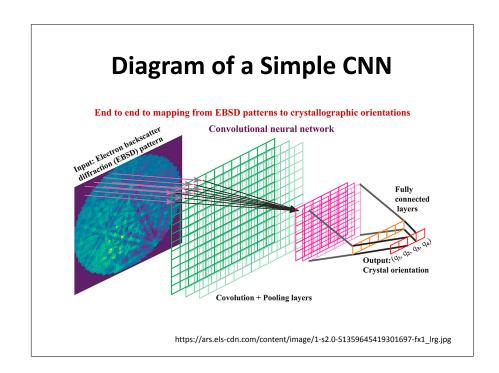
- Hinton's network
 - 650,000 neurons
 - 60 million parameters
 - 1000 neurons in final classification layer
 - 1.2 million training examples
 - Five to six days on pair of big GPUs
 - Top 1 error rate: 37%, Top 5: 17%
 - 8 layers
- Today's GPT-2 network: ~1.5B parameters
- Various architectures



https://webvision.med.utah.edu/book/part-ix-brain-visual-areas/the-primary-visual-cortex/

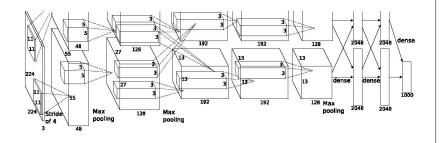
How Does a Convolutional Net Work?

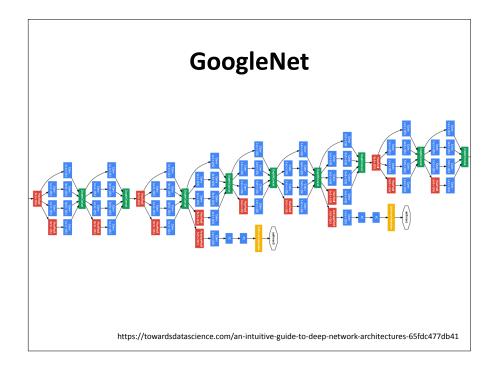
- (Typically) 2-D matrix of pixel values
- Kernels compute some linear combination of values in a sub-matrix, then apply non-linearity
 - Stride determines if we reduce dimensionality of image
- Pooling layers reduce dimensionality and summarize submatrix data
- Use multiple kernels
- Feed-forward (possibly multi-layer) neural net computes results



Hinton's ImageNet CNN

- Additional Tricks:
 - Brightness normalization
 - Translation and reflection of training data
- PCA representation of colors
- Dropout
- Overlapping pooling regions





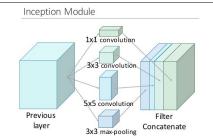
ResNet

- Net $\mathcal{F}(\mathbf{x}) \xrightarrow{\text{weight layer}} \mathbf{x}$ identity $\mathcal{F}(\mathbf{x}) + \mathbf{x} \xrightarrow{\text{relu}} \mathbf{x}$
- Each layer learns residuals
- Helps with "vanishing gradient" in very deep networks
 - Possible to train 1000+ layer networks!

https://towardsdatascience.com/an-intuitive-guide-to-deep-network-architectures-65fdc477db41

Inception

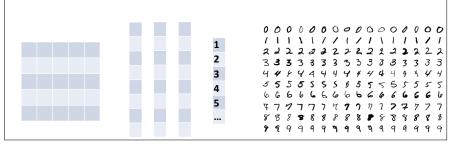
- Automate choice of "hyperparameters" by combining various filters at each layer
- "Kill 'em all and let G*d sort 'em out"
- Slooooow...
 - ⇒Tricks to compress data
 - e.g., 1 x 1 x n convolutions to shrink previous layers



https://towardsdatascience.com/an-intuitive-guide-to-deep-network-architectures-65fdc477db41

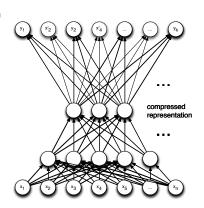
Compare to Pre-Massive-Computation Era

- MNIST data set of hand-written digits
- 28x28 grayscale pixels, interpolated from 20x20 B&W images
- 60K training, 10K test

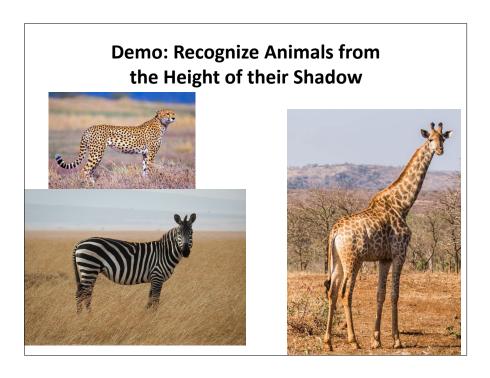


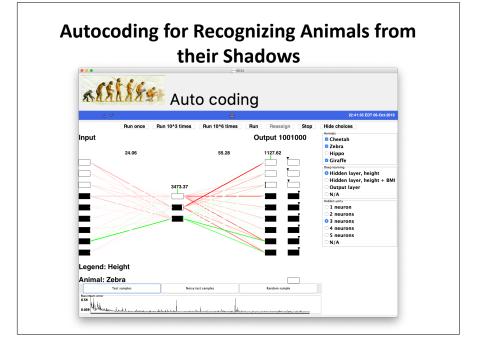
Autocoding Using Deep Neural Networks

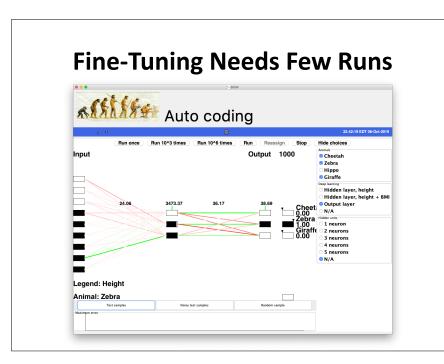
- Every node gets a logistic regression function of its inputs
- · Number of nodes in each layer may vary
- Number of layers is another hyper-parameter
- · Dropout may omit some fraction of links
- Training by back propagation
 - change weights in proportion to error signal
- Unsupervised: Train to optimize unsupervised compression
- **Supervised**: Train to objective function on gold standard data



12



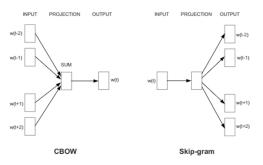




Dropout

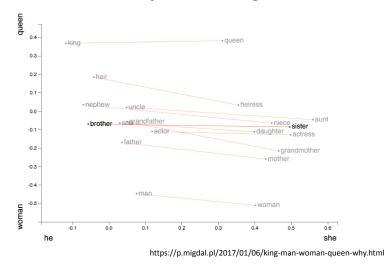
- On each training iteration, disconnect outputs of some fraction of internal neurons
- Helps prevent
 - · getting stuck at local minima
 - overfitting training data

How to Turn Non-Numeric Data into Numbers



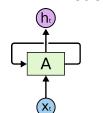
- Create a 1-layer NN to predict a word from its context or the context from a word
- Use the weights of the trained NN as a high-dimensional vector representation of the word

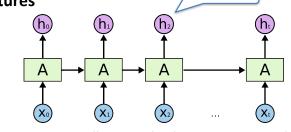
Vector Space Embeddings Reflect Meaning Similarity and Analogies



Recurrent Neural Networks

- Natural for serial data
 - Time series, e.g., measurements such as ECG, lab values Chris Olah's
 - Natural Language text
 - Motion Pictures





https://colah.github.io/posts/2015-08-Understanding-LSTMs/

blog has

excellent explanations

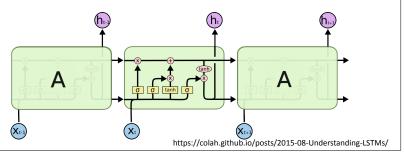
Augmentations to RNN Models

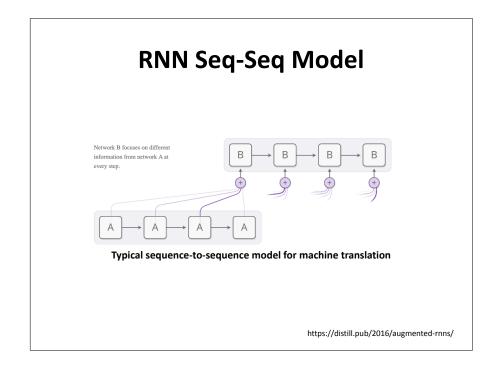
- Long Short Term Memory
- Sequence-to-sequence
- Attention

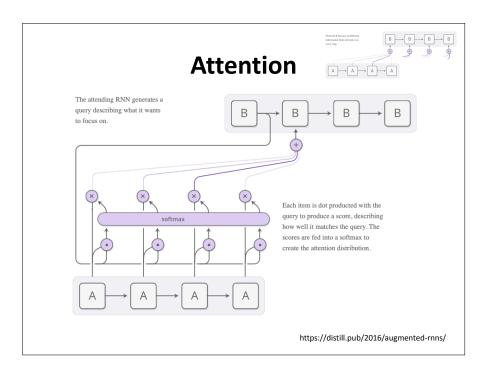
 Everything must remain differentiable!!!

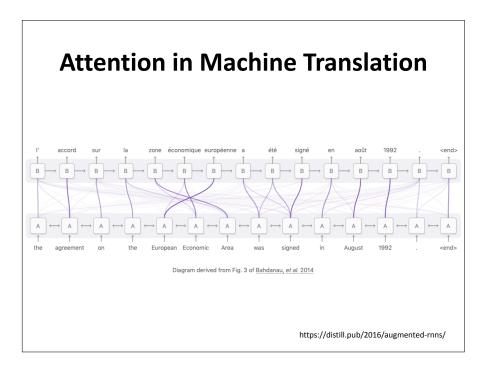
LSTM (Long Short Term Memory)

- Complicate each cell:
 - Add "Forget", "Input", and "Output" gates
 - Helps long-distance propagation of information
 - Many variations on this architecture also









Attention in Speech Transcription h o w _ m u c h _ w o u | d _ a _ w o o d c h u c k _ c h u c k < end> output text network B regure derived from Chan, et al. 2015 https://distill.pub/2016/augmented-rnns/

Attention Helps Explanation

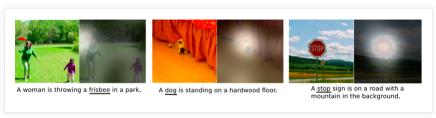


Figure from [3]

Language Models

- Create n-tuple models from a corpus, say Shakespeare
- Generate new "Shakespearean" text from conditional probabilities of next character given the previous k characters

k-tuple (character) Model of Shakespeare (*k*=2)

Fir lace, mes. Pat iserat dots asur do?

Dot oath my op apparm.

ABEROCTAGAR:

My me, prep day.

LANA:

PATHUMBE[®]

Hows. Younignionesad cork. Thas,

I'll theall no. Whanspeart,

ALBOTENTIO:

On, to the hat youl werchind, hown:

AUS:

Said sioner offe swillat unusbanould is the ofte, thistatiescall badvannow he par an; no topereshathice Wil now witheed upper massithis com?

https://nextjournal.com/jbowles/julia-version-of-goldbergs-the-unreasonable-effectiveness-of-character-level-language-models/#generate-shakespeare-from-different-order-models

k-tuple (character) Model of Shakespeare (k=9)

First Citizen:

We'll sure speak, and dear men

Of estimations; the

people cry 'Troilus'? Helenus beholds

A Grecian's life did look on.

MISTRESS QUICKLY:

And have my eight shillings to one it please your majesty? How fares my Kate? What, are they call'd unto a cardinal.

I should break.

PRINCE HENRY:

Where have you

looked sadly, it was the day!

PROSPERO:

Thou and my brother:--and she hath importuned you;

Nor now my business in thine answer.

https://nextjournal.com/jbowles/julia-version-of-goldbergs-the-unreasonable-effectiveness-of-character-level-language-models/#generate-shakespeare-from-different-order-models

Using Character and Word-Level Models Improves Quality of "Shakespeare"

Thy youth's time and face his form shall cover? Now all fresh beauty, my love there Will ever Time to greet, forget each, like ever decease, But in a best at worship his glory die.

https://web.stanford.edu/class/archive/cs/cs224n/cs224n.1174/reports/2762063.pdf

"Facebook's neural network beat the infinite number of monkeys — and wrote Shakespeare"

Why, Salisbury must find his flesh and thought

That which I am not aps, not a man and in fire.

To show the reining of the raven and the wars

When I was heaven of presence and our fleets,

We spare with hours, but cut thy council I am great,

O, if you were a feeble sight, the courtesy of your law,

With his heads, and my hands are wonder'd at the deeds, So drop upon your lordship's head, and your opinion

Your sight and several breath, will wear the gods

That Caesar and my goodly father's world;

Murdered and by thy master's ready there

My power to give thee but so much as hell:

Some service in the noble bondman here,

Would show him to her wine.

Shall be against your honour.

To grace my hand reproach within, and not a fair are hand,

PANDARUS:

Alas, I think he shall be come approached and the day When little srain would be attain'd into being never fed, And who is but a chain and subjects of his death, I should not sleep.

Second Senator:

They are away this miseries, produced upon my soul, Breaking and strongly should be buried, when I perish The earth and thoughts of many states.

DUKE VINCENTIO:

Well, your wit is in the care of side and that.

Second Lord

They would be ruled after this chamber, and my fair nues begun out of the fact, to be conveyed, Whose noble souls I'll have the heart of the wars.

Clow

Come, sir, I will make did behold your worship.

VIOLA:

I'll drink it.

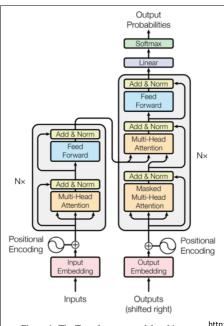
Synthetic Shakespeare from a character-level RNN

https://toa.life/how-facebooks-neural-network-beat-the-infinite-number-of-monkeys-and-wrote-shakespeare-a14a1484e7

Shakespeare is Not Really Modern English

"My life itself, and the best heart of it,

Thanks you for this great care: I stood i' the level
Of a full-charg'd confederacy, and give thanks
To you that chok'd it. Let be call'd before us
That gentleman of Buckingham's; in person
I'll hear him his confessions justify;
And point by point the treasons of his master
He shall again relate." —Henry VIII

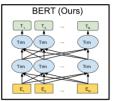


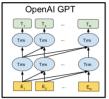
"Attention is All You Need" (Transformer)

- Seq-Seq basic idea
- "Self-attention"
- Residual connections
- Normalization at each layer
- Multi-head attention (like multi-kernel convolution)
 - Only attend to outputs already generated
- Position encoding

Figure 1: The Transformer - model architecture. http://papers.nips.cc/paper/7181-attention-is-all-you-need.pdf

BERT Bidirectional Encoder Representations from Transformers





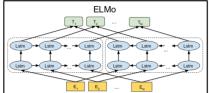


Figure 1: Differences in pre-training model architectures. BERT uses a bidirectional Transformer. OpenAI GPT uses a left-to-right Transformer. ELMo uses the concatenation of independently trained left-to-right and right-to-left LSTM to generate features for downstream tasks. Among three, only BERT representations are jointly conditioned on both left and right context in all layers.

- · Word-piece tokens
- Predict masked tokens (~15%)
- · Predict next sentence
- Trained on 800M word Books, 2,500M word Wikipedia corpus
- Large performance improvement on many tasks

Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2018, October 10). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. *arXiv*.

OpenAI's GPT-2 Model (Generative Pre-trained Transformer)

- Transformer-based
- Trained on 8M Web pages
- Model predicts next word (simple)
- Consistently outperforms systems trained on more specific corpora, e.g., Wikipedia, news, books
- "Fake news" generator

GPT-2 Example (1st try for prompt)

Prompt

A train carriage containing controlled nuclear materials was stolen in Cincinnati today. Its whereabouts are unknown.

The incident occurred on the downtown train line, which runs from Covington and Ashland stations.

In an email to Ohio news outlets, the U.S. Department of Energy said it is working with the Federal Railroad Administration to find the thief.

"The theft of this nuclear material will have significant negative consequences on public and environmental health, our workforce and the economy of our nation," said Tom Hicks, the U.S. Energy Secretary, in a statement. "Our top priority is to secure the theft and ensure it doesn't happen again."

The stolen material was taken from the University of Cincinnati's Research Triangle Park nuclear research site, according to a news release from Department officials.

The Nuclear Regulatory Commission did not immediately release any information.

According to the release, the U.S. Department of Energy's Office of Nuclear Material Safety and Security is leading that team's investigation.

"The safety of people, the environment and the nation's nuclear stockpile is our highest priority," Hicks said. "We will get to the bottom of this and make no excuses.

https://openai.com/blog/better-language-models

GPT-2 Example (10th try for prompt)



In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English.

The scientist named the population, after their distinctive horn, Ovid's Unicorn. These four-horned, silver-white unicorns were previously unknown to science.

Now, after almost two centuries, the mystery of what sparked this odd phenomenon is finally solved

Dr. Jorge Pérez, an evolutionary biologist from the University of La Paz, and several companions, were exploring the Andes Mountains when they found a small valley, with no other animals or humans. Pérez noticed that the valley had what appeared to be a natural fountain, surrounded by two peaks of rock and silver snow.

Pérez and the others then ventured further into the valley. "By the time we reached the top of one peak, the water looked blue, with some crystals on top," said Pérez.

Pérez and his friends were astonished to see the unicorn herd. These creatures could be seen from the air without having to move too much to see them – they were so close they could touch their horns.

While examining these bizarre creatures the scientists discovered that the creatures also spoke some fairly regular English. Pérez stated, "We can see, for example, that they have a common 'language,' something like a dialect or dialectic."

Dr. Pérez believes that the unicorns may have originated in Argentina, where the animals were believed to be descendants of a lost race of people who lived there before the arrival of humans in those parts of South America.

While their origins are still unclear, some believe that perhaps the creatures were created when a human and a unicorn met each other in a time before human civilization. According to Pérez, "In South America, such incidents seem to be quite common."

However, Pérez also pointed out that it is likely that the only way of knowing for sure if unicorns are indeed the

https://openai.com/blog/better-language-models

How Good is this Model?

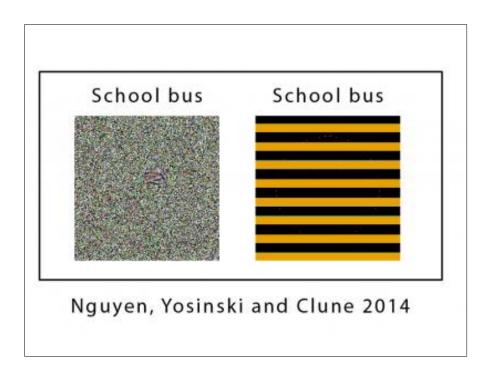
- Language use:
 - Amazing
- Logic:
 - "the animals were believed to be descendants of a lost race of people who lived there before the arrival of humans"

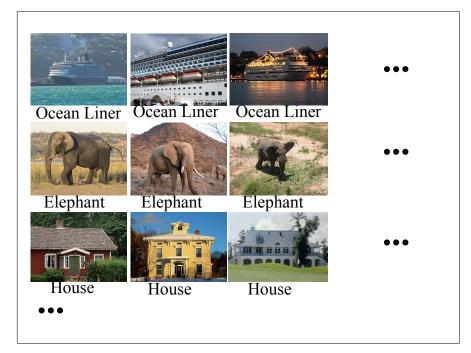
Before We Get Carried Away...

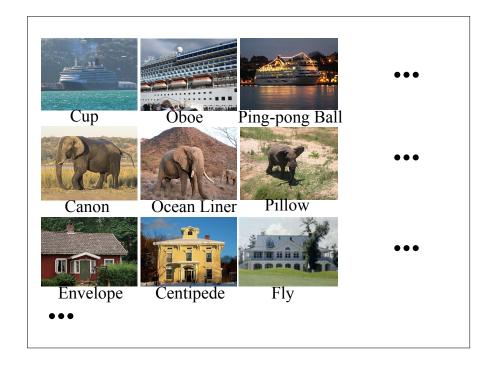
- There is no "gestalt"
 - "form" or "shape"
 - Holism: "natural systems and their properties must be viewed as wholes, not as loose collections of parts"
 - Instead, attention to many features

School bus Not a school bus

Szegedy et al. 2014















Husky vs. Wolf





(a) Husky classified as wolf

(b) Explanation

Figure 11: Raw data and explanation of a bad model's prediction in the "Husky vs Wolf" task.

	Before	After
Trusted the bad model	10 out of 27	3 out of 27
Snow as a potential feature	12 out of 27	25 out of 27

Table 2: "Husky vs Wolf" experiment results.

https://www.kdd.org/kdd2016/papers/files/rfp0573-ribeiroA.pdf