

Introduction to Artificial Intelligence COSC 4550 / COSC 5550

Professor Cheney 11/17/17

unsupervised learning continued...



Neural Photo Editing

Andrew Brock





Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks









zebra \rightarrow horse



Output















apple \rightarrow orange





orange \rightarrow apple







winter Yosemite \rightarrow summer Yosemite



summer Yosemite → winter Yosemite





Generative Adversarial Text to Image Synthesis

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this small bird has a pink breast and crown, and black almost all black with a red primaries and secondaries.

this magnificent fellow is crest, and white cheek patch.



the flower has petals that are bright pinkish purple with white stigma





this white and yellow flower have thin white petals and a round yellow stamen



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learning word embeddings with word2vec

AUDIO



Audio Spectrogram

DENSE

IMAGES



Image pixels

DENSE

TEXT

0 0 0 0.2 0 0.7 0 0 0

Word, context, or document vectors

we want to learn to associate nearby words

Source Text	Training Samples
The quick brown fox jumps over the lazy dog. \Longrightarrow	(the, quick) (the, brown)
The quick brown fox jumps over the lazy dog. \Longrightarrow	(quick, the) (quick, brown) (quick, fox)
The quick brown fox jumps over the lazy dog. \Longrightarrow	(brown, the) (brown, quick) (brown, fox) (brown, jumps)
The quick brown fox jumps over the lazy dog. \implies	(fox, quick) (fox, brown) (fox, jumps) (fox, over)

we can predict context around a given word



or predict the word, given it's surrounding context



if we plot the latent representation vectors in a lower dimensional space...



Male-Female

Verb tense





where : means "is to" and :: means "as"; e.g. "Rome is to Italy as Beijing is to China" = Rome: Italy::Beijing:China

amusing word2vec analogies king:queen::man:[woman, Attempted abduction, teenager, girl]
//Weird, but you can kind of see it

China:Taiwan::Russia:[Ukraine, Moscow, Moldova, Armenia] //Two large countries and their small, estranged neighbors

house:roof::castle:[dome, bell_tower, spire, crenellations, turrets]

knee:leg::elbow:[forearm, arm, ulna_bone]

New York Times:Sulzberger::Fox:[Murdoch, Chernin, Bancroft, Ailes]
//The Sulzberger-Ochs family owns and runs the NYT.
//The Murdoch family owns News Corp., which owns Fox News.
//Peter Chernin was News Corp.'s COO for 13 yrs.
//Roger Ailes is president of Fox News.
//The Bancroft family sold the Wall St. Journal to News Corp.

love:indifference::fear:[apathy, callousness, timidity, helplessness, inaction]
//the poetry of this single array is simply amazing...

Donald Trump:Republican::Barack Obama:[Democratic, GOP, Democrats, McCain] //It's interesting to note that, just as Obama and McCain were rivals, //so too, Word2vec thinks Trump has a rivalry with the idea Republican.

monkey:human::dinosaur:[fossil, fossilized, Ice_Age_mammals, fossilization]
//Humans are fossilized monkeys? Humans are what's left
//over from monkeys? Humans are the species that beat monkeys
//just as Ice Age mammals beat dinosaurs? Plausible.

building:architect::software:[programmer, SecurityCenter, WinPcap]

Amusing Word2Vec Results

- Geopolitics: Iraq Violence = Jordan
- Distinction: *Human Animal = Ethics*
- President Power = Prime Minister
- Library Books = Hall
- Analogy: *Stock Market* ≈ *Thermometer*

associative unsupervised learning

"Neurons that fire together, wire together."

- Donald Hebb

Hebbian learning







auto-associative learning (Hopfield network)



auto-associative learning (Hopfield network)





- Recurrent network
 - Feedback from output to input
- Fully connected
 - Every neuron connected to every other neuron



Hopfield Network

- Recurrent network
 - Feedback from output to input
- Fully connected
 - Every neuron connected to every other neuron





- Recurrent network
 - Feedback from output to input
- Fully connected
 - Every neuron connected to every other neuron





- Recurrent network
 - Feedback from output to input
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unsupervised clustering

simple, but widely helpful

there are lots of types of clustering algorithms (e.g. hierarchical clustering, self organizing maps) but the one we will introduce here is K-means clustering, because it is the simplest (and it's surprisingly effective in practice)

Step 1: choose a number of classes (k), and randomly assign all points to one of the classes



Step 2:

average the position of all of the points in a given class to find that class' centroid (mean features representation)



Step 3: re-assign each point to the closest centroid



Step ... repeat centroid and point assignment



Step ... repeat centroid and point assignment until a steady state is reached (no assignments change)



you now have the optimal greedy point assignments for that number of clusters

but you did have to choose the number of clusters, which may not be obvious

how many clusters are here?







k-means is cheap and fast, so let's try a range of values, and look for a good trade-offs between classification and number of classes



since we are doing arithmetic in the feature space, having good features and preprocessing your data is extremely important to your outcomes (just like it was in KNN)

but we'll cover this after break...