CS224N: Stanford

Chris Manning:

Lecture1: Introduction and Word Vectors

→ An understanding of the effective modern methods for deep learning
Basics first, then key methods used in NLP:
Recurrent networks, attention, etc.

→ A big picture understanding of human languages and the difficulties in understanding and producing them.

→ An understanding of an ability to build systems for some of the the major problems in NLP
→ word meaning, dependency parsing, machine translation, question answering

'Language isn't a formal system. It's a glorious chaos.

Humans are better because of the language and human communication network

Manning vs Lecun (Humans are better)

Writing takes knowledge spatially throughout the word and temporally throught time

12

1) How do you represent the ~~word~~ meaning of a word?

Definition: meaning

→ "idea that is represented by a word, phrase, etc.

→ idea that a person wants to express by using words, signs, etc

→ idea that is expressed in a work of writing, art, etc.

Linguistic way of thinking of meaning:

signifier (symbol) ⇔ signified (idea of thing)

= denotational semantics

Common solutions to have usable meaning in computers

Use WordNet (nltk), a thesaurus containing lists of synonym sets and hypernyms

But that's not ~~g~~ terribly good ~~at~~ anything

Problem: can't adapt

Representing words as discrete symbols

Traditional NLP (NLP till 2012): regards words as discrete symbols → localist rep.
were represented as one-hot vectors
⇒ but words are infinite.
one possible solution to find the synonyms can be word similarity table

Distributional semantics: A word's meaning is given by the words that frequently appear close-by
⇒ when a word w appears in a text, its context is the set of words that appear nearby (within a fixed-size window)

Word vectors: We will build a dense vector for each word, chosen so that it is similar to vectors of words that appear in similar contexts

Word vectors are sometimes called word embeddings or word representations. They are a distributed representation.

Word meaning as a neural word vector

(Yoshua Bengio's work)

Word2Vec: (Mikolov et. al. 2013)

Idea:

i) We have a large corpus of text

ii) Every word in a fixed vocabulary is represented by a vector

iii) Go through each position t in the text, which has a center word c and context ("outside") words o

iv) Use the similarity of the word vectors for c and o to calculate the probability of o given c (or vice versa)

v) Keep adjusting the word vectors to maximise this probability $P(w_{t+j} / w_t)$

objection function (cost or loss)

For each position $t = 1, \dots, T$ predict context words within a window of fixed size m, give center word w_j

$$\text{Likelihood} = L(\theta) = \prod_{t=1}^{T} \prod_{-m \le j \le m,\ j \neq 0} P(w_{t+j} / w_t; \theta)$$

θ: all variables to be optimized

The objective function $J(\theta)$ is the (average) negative log likelihood:

$$J(\theta) = -\frac{1}{T} \log L(\theta) = \ominus \frac{1}{T} \sum_{t=1}^{T} \sum_{-m \le j \le m,\ j \neq 0} \log P(w_{t+j} | w_t; \theta)$$

$\ominus$: minimization; $\frac{1}{T}$: average

Minimizing objective function $\Leftrightarrow$ Maximizing predictive accuracy

How to calculate $P(w_{t+L} | w_t, \theta)$

Answers: Two vector representations

- v_w when w is center word
- u_w when w is a context word

center c, context o

$$P(o|c) = \frac{\exp(u_o^T v_c)}{\sum_{w \in V} \exp(u_w^T v_c)}$$

$u_o^T v_c$ → compare similarity of o and c

$\sum_{w \in V}$ → normalize over entire vocab

$$\text{softmax}(x_i) = \frac{\exp(x_i)}{\sum_{j=1}^{n} \exp(x_j)} = p_i$$

The softmax function maps arbitrary values x_i to a probability distribution p_i

$\Rightarrow$ amplifies probability of largest x_i while still assigning some to smaller x

Training a model by optimizing parameters

$$\frac{\delta}{\delta v_c} \log \frac{\exp(u_o^T v_c)}{\sum_{w=1}^{n} \exp(u_w^T v_c)}$$

$$= \frac{\delta}{\delta v_c} \log \exp(u_o^T v_c) - \frac{\delta}{\delta v_c} \log \sum_{w=1}^{V} \exp(u_w^T v_c)$$

$$= \frac{\delta}{\delta v_c} u_o^T v_c$$

$$= u_o$$

negative word gensim visualization. There's some ambiguity with names.

$$\frac{d}{dv_c} \log \sum_{w=1}^{V} \exp(u_w^T v_c)$$

$$= \frac{1}{\sum_{w=1}^{V} \exp(u_w^T c)} \cdot \frac{\delta}{\delta v_c} \sum_{x=1}^{V} \frac{d}{dv_c} \exp(u_x^T v_c)$$

$$\sum_{x=1}^{V} \exp(u_x^T v_c) \frac{d}{dv_c} u_x^T v_c$$

$$\sum_{x=1}^{V} \exp(u_x^T v_c) u_x$$

$$\frac{\delta}{\delta v_0} \log P(O|c) = u_0 - \frac{\sum_{x=1}^{V} \exp(u_x^T v_c) u_x}{\sum_{w=1}^{V} \exp(u_w^T v_c)}$$

$$= u_0 - \sum_{x=1}^{V} \frac{\exp(u_x^T v_c)}{\sum_{w=1}^{V} \exp(u_w^T v)} u_x$$

actual context word → expected context word

$$= u_0 - \sum_{x=1}^{V} P(x|c) u_x$$

u_0: observed representation of context word

u_x: representation of each word x

$P(x|c)$: probability of it in current model

u → outside
v → center

$V \cdot V_4^T$

softmax($V \cdot V_4^T$) probs

gensim (word similarity packet) | LDA | negative similarity

Lecture 2 (Word vectors & Word Senses) 14/10/2020 (2)

The word vectors are represented as rows

We want a model that gives a reasonably high probability estimate to all words that occur in the context (that's why we are using softmax)

Optimization: Gradient Descent:

minimize $J(\theta)$

$$\theta^{new} = \theta^{old} - \alpha \nabla_\theta J(\theta)$$

Stochastic Gradient Descent

Since $J(\theta)$ is very expensive to compute here

→ very bad idea for pretty much all nns

Solution: SGD update after each sample

Stochastic gradient with word vecs

We might only update the word vectors that actually appear.

Solution: Either we need ⊛ sparse matrix update operations to only update certain rows of full embedding matrices U and V, or we need to keep a hash of word vectors

- If you have millions of words and do distributed computing, it is important to not have to send gigantic updates around.

Why two vectors?

Easier optimization. Average both at the end

Two model variants:

1) Skip Gram (SG) => predict context words given center word
2) Continous Bag of ⊛Words⊛ (CBOW) => predict center word from (bag of) context words

⊛Naive Softmax

Skip-gram with Negsampling: Normalization factor is too computationally expensive

Idea of Negative sampling:

Train binary logistic regression for a p true pair (center word and word in its context) versus several noise pairs (center word paired with a random word) → then try to give them as lower prob as possible

Paper: "Distributed Representations of Words and Phrases and their Compositionality" (Mikolov 2013)

$$J(\theta) = \frac{1}{T}\sum_{t=1}^{T} J_t(\theta)$$

$$J_t(\theta) = \log\sigma(u_o^T v_c) + \sum_{i=1}^{k} E_{j\sim P(w)}\left[\log\sigma(-u_j^T v_c)\right]$$

→ We maximize the probability of two words co-occuring in the first log

$$J_{neg\text{-}sample}(o, v_c, U) = -\log\left(\sigma(u_o^T v_c)\right) - \sum_{k=1}^{K}\log\left(\sigma(-u_k^T v_c)\right)$$

We take k negative samples (using word probs)

- Maximize probability that real outside word appears and minimize prob that random words appear around center word

$$P(w) = \frac{U(w)^{3/4}}{Z}$$

($U(w)$: unigram dist; Z: normalization term)

makes less frequent word to be sampled more often

But why not capture co-occurence counts directly?

With a co-occurence matrix X

- 2 options: windows vs. full doc
- Window: Similar to word2vec, use window around each word → captures both syntactic (POS) and semantic information
- Word-document co-occurrence matrix will give general topics (all sports terms will have similar entries) leading to "Latent Semantic Analysis"

Example: window base co-occurance matrix

→ Window length 1 (more common 5-10)

→ Symmetric (irrelevant whether left or right context)

Problems with simple co-occurance vecs

→ Increase the size with vocab

→ very high dimensional: requires a lot of storage

→ subsequent classificatim model have sparsity issues

→ models are less robust

Solution: Low dimensional vectors

Store "most" of the important infos in a fixed small number of dimensions: a dense vector

Usually 25-100 dimensions, similar to word2Vec

Reducing dimensionality

Method 1: Dimensionality Reduction on X (HW1)

Singular Value Decomposition of co-occurence matrix X.

Factorizes X to $U\Sigma V^T$ where U and V are orthogonal

If we ~~or~~ take k values then, we ~~don~~ ignore the least frequent context vectors

$\hat{X}$ is the best rank approx to X, in terms of least squares

Problems: Expensive to compute for large matrices.

[Play around with it in homework]

Hacks to X (Rohde 2005)

Scaling the counts in the cells help a lot.

- Problems function word (the, he, has) are too frequent → syntax has too much impact.
  - → Some fixes $\min(X, t)$ $t \approx 100$
  - → ignore all

- Ramped windows that count closer words more
- Use pearson correlation instead of counts, then set negatives to 0

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}}$$

Count-based vs direct prediction

Count-based

- LSA, HAL (Lund & Burgess)
- COALS, Hellinger-PCA (Rohde, Lebret & Collobert)

Pros
- Fast training
- Efficient usages of statistics

Cons
- Primarily used to capture word similarity
- Disproportionate importance given to large counts

direct prediction

- Skip-gram/CBOW (Mikolov)
- NNLM, HLBL, RNN (Bengio, Huang, Mnih)

Cons
- Scales with corpus size
- Inefficient usage of stats

Pros
- Generate improve performance
- Can capture complex patterns beyond word similarity

Encoding meaning in vector differences [EMNLP2014]

(Pennington) [Combining the best of both worlds]

Crucial insight: Ratios of co-occurence probabilities can encode meaning components

Capturing ratios of co-occurence probs as linear meaning

$$w_i w_j = \log P(i/j)$$

$$w_x (w_a - w_b) = \log \frac{P(x/a)}{P(x/b)}$$

$$J = \sum_{i,j=1}^{V} f(x_{ij}) \left(w_i^T \tilde{w}_j + b_i + \tilde{b}_j - \log X_{ij} \right)^2$$ [GloVe]

- Fast training
- Scalable huge corpora
- Good performance even with small corpus and small vectors

Evaluate Word Vectors:

General Evaluation in NLP: Intrinsic vs Extrinsic

Intrinsic:

- Evaluation of a specific/intermediate subtask
- Fast to compute
- Helps to understand that system
- Not clear if really helpful unless correlation to real task is established.

Extrinsic:

- Evaluation on a real task
- Can take long time to compute accuracy
- Unclear if the subsystem is the problem or its interaction ~~is established~~ or other subsystems
- If replacing exactly one subsystem with another improves accuracy → Winning

Intrinsic word vector evaluation:

- Word vector analogies

  a:b :: c:?

  man:woman :: king:?

$$d = \arg\max_i \frac{(x_b - x_a + x_c)^T x_i}{\|x_b - x_a + x_c\|}$$

- Evaluate word vectors by how well their cosine distance after addition captures intuitive semantic and syntactical analogy questions.
- Discarding the input words from the search!
- Problem: what if the info is there but not linear.

For Glove

- Good dimension is ~300
- Asymmetric context (are not as good
- This might be different for downstream tasks
- Window size of 8 around each center word is good for GloVe vectors

Recent work: On dimensionality of Word Embedding [Neurs IPS 2018]

- Wikipedia is better than news text

- Word vector distances and their correlation with human judgment.

Example Wordsim353 (check out)

Cosine distance for similarity judging

Word senses and word sense ambiguity

-> Most words have lots of meanings.

- Does one vector capture all these meanings?

Improving Word Rep via Global Context (Huang et al 2012)

Idea: Cluster word windows around words, retain with each word assigned to multiple different clusters $bank_1$, $bank_2$

Linear Algebraic Structure of Word Senses with Applications to Polysemy (Arora, TACL 2018)

- Different senses of a word reside in a linear superposition (weighted sum). In standard word embeddings like word2vec

$$V_{pike} = \alpha_1 V_{pike_1} + \alpha_2 V_{pike_2} + \alpha_3 V_{pike_3}$$

$$\alpha_1 = \frac{f_1}{f_1 + f_2 + f_3} \qquad f = \text{frequency}$$

- Because of ideas from sparse coding we can actually separate out the senses.

Extrinsic Word Vector Evaluation:

All subsequent tasks in this class

→ Good Word vectors would help in named entity recognition:

Assignment: Exploring Word Vectors

- Word Vectors and Word Embeddings are often used interchangably. The term "embedding" refers to the fact that we are encoding aspects of a word's meaning in a lower dimensional space

Problems with thesaurus-based meaning:

-> They have problems with recall
-> Many words are missing
-> Most phrases are missing
-> Some connection between senses are missing.
-> Doesn't work well for verbs and adjectives

(Reuters)
↑
business and financial news corpus

Singular value Decomposition:

PCA

Lecture 3 - Word Window Classification, Neural Nets

Classification setup:

$$\{x_i, y_i\}_{i=1}^{N}$$

→ x_i are inputs, e.g. words, sentences, documents (Dimension d)

→ y_i are labels (one of C classes) we try to predict, for example: → classes: sentiment, named entities, buy/sell

→ other words

→ multi word sentences

Traditional ML / Stats approach:

Assume x_i are fixed, train softmax/logistic regression weights $W \in \mathbb{R}^{C \times d}$ to determine a decision boundary ~~as in the picture~~

$$P(y/x) = \frac{\exp(W_{y \cdot} x)}{\sum_{i=1}^{C} \exp(W_{c \cdot} x)}$$

Softmax in two steps

1) find all f_c for $c = 1 \ldots C$

$$W_{y \cdot} x = \sum_{i=1}^{d} W_{y_i} x_i = f_y$$

2) $P(y/x) = \frac{\exp(f_c)}{\sum_{c=1}^{C} \exp(f_c)} = \text{softmax}(f_y)$

→ Our objective is to maximize the probability of the correct ~~call~~ class y.

→ Or we can minimize the negative log probability of that class

$$-\log p(y|x) = -\log\left(\frac{\exp(f_y)}{\sum_{c=1}^{C}\exp(f_c)}\right)$$

* NLL loss (Negative log-likelihood loss)

→ Cross entropy loss

True probability distribution p

computed probability distribution q

Cross entropy $H(p,q) = -\sum_{c=1}^{C} p(c)\log q(c)$

- Assuming a ground truth (or true or gold or target) probability distribution that is 1 at the right class and 0 everywhere else
- Because of one-hot p, the only term left is the negative log prob of the true class.

Classification over a full dataset:

- Cross entropy loss function over full dataset

$$J(\theta) = \frac{1}{N} \sum_{i=1}^{N} -\log\left(\frac{e^{f_{y_i}}}{\sum_{c=1}^{C} e^{f_c}}\right)$$

$$f_y = f_y(x) = W_y x = \sum_{j=1}^{d} W_{yj} x_j$$

$$f = Wx$$

Traditional ML Optimizations

$$\theta = \begin{bmatrix} w_{.1} \\ \vdots \\ w_{.d} \end{bmatrix} = W(:) \in \mathbb{R}^{Cd}$$

Sow we onld update the decision boundar

$$\nabla_\theta J(\theta) = \begin{bmatrix} \nabla w_{.1} \\ \vdots \\ \nabla w_{.d} \end{bmatrix} \in R^{Cd}$$

Neural Networks Classifiers (Non-linearity)

- Can learn more complex functions and non-linear decision boundaries.

Classification difference with word vectors:

- Commonly in NLP deep learning:

→ We learn both W and word vectors x

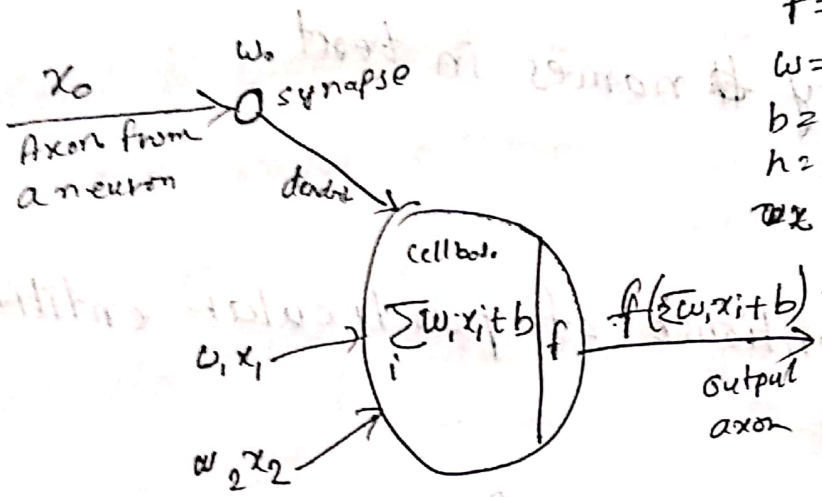
→ We learn both conventional params and representation

→ The word vectors re-represent one-hot vectors - move them around in an intermediate layer vector space - for easy classification with a (linear) softmax classifier via layer x = Le

$$\nabla_\theta J(\theta) = \begin{bmatrix} \nabla w_{.1} \\ \vdots \\ \nabla w_d \\ \nabla x_{aardvark} \\ \vdots \\ \nabla x_{zebra} \end{bmatrix} \in \mathbb{R}^{C_d + V_d}$$

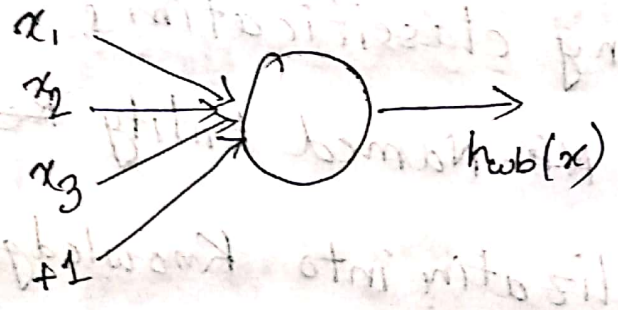
↑ very large

An artificial neuron



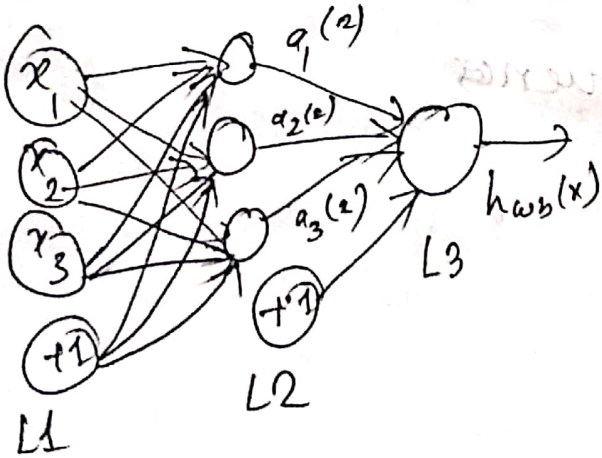
f = nonlinear activation
w = weights
b = bias
h = hidden
x = input

$$f(z) = \frac{1}{1+e^{-z}} \qquad h_{w,b}(x) = f(w^T x + b)$$



A neuron can be a binary logistic regression unit

A neural net = running several logistic regressions at the same time



It is the loss function that will ~~decide~~ direct what the intermediate hidden variables should be

Named Entity Recognition (NER):

- Find and classify names in text

Possible purposes:

- Tracking mentions of particular entities in document
- For question answering. Answers are usually named entities
- The same technique can be extended to other slot-filling classifications.

→ often followed by Named Entity Linking / Canonicalization into Knowledge Base

→ We predict Entities by classifying words in context and then extracting entities as word subsequences

Why is it hard?

- Hard to work out boundaries of entity
- Hard to know if something is an entity
- Hard to know class of unknown/novel entity
- ~~Entide~~ Entity class is ambiguous and depends on context.

Binary word Window classification

- In general, classifying single words is rarely done
- Interesting problems like ambiguity arise in context.

Example: Auto antonyms

- "To sanction" can mean 'to permit' or 'to punish'
- "To seed" can mean 'to place seeds' or 'to remove seeds'

Example: resolving of ambiguous named entities

- Paris → Paris, France vs. Paris Hinton vs. Paris, Texas
- Hathaway → Berkshire Hathaway vs Anne Hathaway

Window classification:

- Idea: classify a word in its context window of neighboring words.

- For example, Named Entity Classification of a word in context

- A simple way to classify a word in context might be to average the word vectors in a window and to classify the average vector
  - Problem: that would lose positional info

Softmax idea:

Train softmax classifier to classify a center word by taking concatenation of word vectors surrounding it in a window.

Resulting vector $x_{window} = x \in \mathbb{R}^{wd}$

w = windowsize * 2 + 1

Simplest window classifier

- with $x = x_{window}$ we can use the same softmax classifier as before

predicted model output probability $\hat{y}_y = p(y|x) = \frac{\exp(w_y x)}{\sum_{c=1}^{C} \exp(w_c x)}$

$f_{y_i} = w_y x$

- with cross entropy error as before

$$J(\theta) = \frac{1}{N} \sum_{i=1}^{N} -\log\left(\frac{e^{f_{y_i}}}{\sum_{c=1}^{C} e^{f_c}}\right)$$

To update the word vectors, we need to calculate grads like we did previously

Binary classification with unnormalized scores

Collobert & Weston (2008, 2011) ICML 2018 Test of time

- Assume we want to classify whether the center word is a Location
- Similar to Word2Vec, we will go over all positions in a corpus. But this time, it will be supervised and only some positions should get a high score.

The positions that have an actual NER location in their centers are "true" positions and get a high score.

NN Feed forward Computation:

$$score(x) = U^T a \in \mathbb{R}$$

Compute a window's score with a 3-layer neural net:

$$s = score(\text{"museums in Paris are amazing"})$$

$$s = U^T f(Wx + b)$$

$$x \in \mathbb{R}^{20\times 1}, \quad W = \mathbb{R}^{8\times 20}, \quad U \in \mathbb{R}^{8\times 2}$$

Main intuition befor extra layer:

The middle layer learns non-linear interactions between input word vectors.

Alternative: Max-margin loss (no Softmax!)

- Idea for training objective: Make true window's score larger and corrapt window's score lower (until they are good enough)

Minimize ~~max~~ $J = \max(0, 1 - s + s_c)$

→ This is not differentiable but continuous

→ we can use sgd.

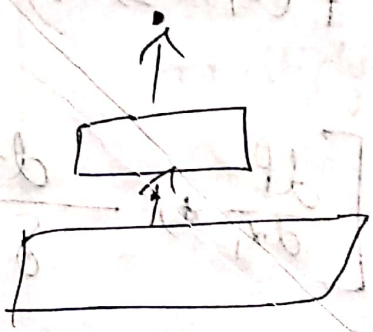
$$\theta^{new} = \theta^{old} - \alpha \nabla_\theta J(\theta)$$

Simple net for score

$s = u^T h$

$h = f(Wx + b)$

x = input



Let's find out $\frac{\delta s}{\delta b}$

- In practice we care about gradient of the loss.

Computing Gradients by Hand

- Review of multivariable derivatives
- Matrix calculus: fully vectorized gradients
  - Much faster and more useful than non-vectorized gradients
  - But doing a non-vectorized gradient can be good practice

Gradients:

$$f(x) = f(x_1, x_2, x_3)$$

$$\frac{\delta f}{\delta x} = \left[\frac{df}{dx_1} \; \frac{df}{\delta x_2} \; \cdots \; \frac{\delta f}{dx_n} \right]$$

Jacobian Matrix: Generalization of the Gradient

Given a function with m outputs and n inputs

$$f(x) = \left[f_1(x_1, x_2, \ldots, x_n), \ldots, f_m(x_1, x_2, \ldots, x_n) \right]$$

It's Jacobian is an $m \times n$ matrix of partial derivatives

$$\frac{df}{dx} = \begin{bmatrix} \frac{df_1}{dx_1} & \cdots & \frac{df_1}{dx_n} \\ \vdots & & \vdots \\ \frac{df_m}{dx_1} & \cdots & \frac{df_m}{dx_n} \end{bmatrix} \qquad \left(\frac{df}{dx}\right)_{ij} = \frac{df_i}{dx_j}$$

Chain Rule

single variable

multiply derivative

$$z = 3y$$

$$y = x^2$$

$$\frac{dz}{dx} = \frac{dz}{dy}\frac{dy}{dx} = (3)(2x)$$

$$= 6x$$

multivariable

multiply Jacobian

$$h = f(x)$$

$$z = Wx + b$$

$$\frac{dh}{dx} = \frac{dh}{dz}\frac{dz}{dx}$$

Jacobian: Elementwise activation function

$h = f(z)$ what is $\frac{dh}{dz}$? $\quad h, z \in \mathbb{R}^n$

$h_j = f(z_i)$

$$\left(\frac{dh}{dz}\right)_{ij} = \frac{dh_i}{dz_j} = \frac{\delta}{\delta z_j} f(z_i)$$

$$= \begin{cases} f(z_i) & \text{if } i = j \\ 0 & \text{otherwise} \end{cases}$$

regular 1-variable derivative

$$\frac{\delta h}{\delta z} = \begin{pmatrix} f'(z_1) & & 0 \\ & \ddots & \\ 0 & & f'(z_n) \end{pmatrix} = \text{diag}(f'(z))$$

$$\frac{\delta}{\delta x}(wx+b) = w$$

$$\frac{\delta}{\delta b}(wx+b) = I \quad \text{(identity matrix)}$$

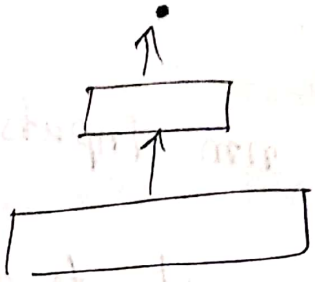
$$\frac{\delta}{\delta u}(u^T h) = h^T$$

$s = u^T h$

$h = f(Wx+b) \Rightarrow h = f(z)$

$z = Wx+b$

x (input)



$$\frac{\delta s}{\delta b} = \frac{\delta s}{\delta h} \frac{\delta h}{\delta z} \frac{\delta z}{\delta b}$$

$$= h^T \cdot \text{diag}(f'(z)) \cdot I$$

$$= h^T \circ f'(z)$$

$$\frac{\delta s}{\delta W} = \frac{\delta s}{\delta h} \frac{\delta h}{\delta z} \frac{\delta z}{\delta W} = \delta \frac{\partial z}{\partial W}$$

$$= h^T \text{diag}(f'(z))$$

$$\boxed{\delta = \frac{\partial s}{\partial h} \frac{\partial h}{\partial z} = h^T \circ f'(z)}$$

local error signal

$W \in \mathbb{R}^{n \times m}$

- 1 output nm inputs : 1 by nm Jacobian
  - Inconveniant to do $\theta^{new} = \theta^{old} - \alpha \nabla_\theta J(\theta)$

Instead follow convention: shape of the gradient is shape of params

$\frac{\partial s}{\partial W}$ is n by m: $\begin{bmatrix} \frac{\partial s}{\partial w_{11}} & \cdots & \frac{\partial s}{\partial w_{1m}} \\ \vdots & & \vdots \\ \frac{\partial s}{\partial w_{n,1}} & \cdots & \frac{\partial s}{\partial w_{n,m}} \end{bmatrix}$

$\frac{\partial s}{\partial W} = \delta^T x^T$ [to get to appropriate shape]

δ: local error signal; x: local input signal

$\frac{\partial s}{\partial b} = h^T \circ f'(z)$ is a row vector

but according to shape convention this should be column vector since b is a column vector.

Disagreement between Jacobian form (which makes chain rule easy) and the shape convention (which makes implementing SGD easy)

- We expect answers to follow the shape convention
- But Jacobian form is useful for computing answers

So,

Two options:

1) Use Jacobian form as much as possible, reshape to follow the convention at the end.
2) Always follow the convention.
   [Look at dimensions to figure out when to transpose and/or reorder them]

Lecture 4 - Backpropagation and computation graph

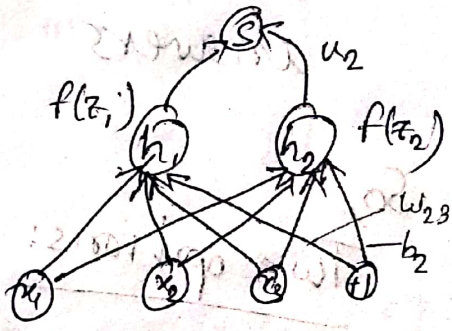
(24/11/2020)

Deriving gradients for backprop:

$$\frac{\partial s}{\partial W} = \delta \frac{\partial z}{\partial W} = \delta \frac{\partial}{\partial W} Wx + b$$

W_{ij} only contributes to z_i

- For example: W_{23} is only used to compute z_2 not z_1



$$\frac{\partial z_i}{\partial W_{ij}} = \frac{\partial}{\partial W_{ij}} W_i \cdot x + b_i$$

$$= \frac{\partial}{\partial W_{ij}} \sum_{k=1}^{d} W_{ik} x_k = x_j$$

The derivative of single W_{ij}

$$\frac{\partial s}{\partial W_{ij}} = \delta_i x_j$$

(δ_i: error signal from above; x_j: local gradient signal)

$$\frac{\partial}{\partial W} = \delta^T \cdot x^T$$

$[n \times m]$ $[n \times 1]$ $[1 \times m]$

Tips of deriving gradients:

Tip 1: Carefully define your variables and keep track of their dimensionality

Tip 2: Chain rule! If $y = f(u)$ and $u = g(x)$ i.e. $y = f(g(x))$

$$\frac{\partial}{\partial x} = \frac{\partial y}{\partial u} \frac{\partial u}{\partial x}$$

Keep straight what variables feed into what computations

Tip 3: For the top softmax part of a model: first consider the derivative wrt f_c when $c = y$ (the correct class)

then consider derivative wrt f_c when $c \neq y$ (incorrect class)

Tip 4: Work out element-wise partial derivatives if you're getting confused by matrix calculus

Tip 5: Use Shape Convention. Note: The error message δ that arrives at a hidden layer has the same dimensionality as the hidden layer.

Deriving gradients wrt words for window model:

The gradient that arrives at and updates the word vectors can simply be split up for each vector.

$$\nabla_x J = W^T \delta = \delta_{x_{window}}$$

with $x_{window} = [x_{museum} \quad \cdots \quad x_{amazing}]$

$$\delta_{window} = \begin{bmatrix} \nabla_x \text{museum} \\ \vdots \\ \nabla_x \text{amazing} \end{bmatrix} \in \mathbb{R}^{5d}$$

Updating word gradients in window model:

- This will push word vectors around so that they will (in ~~participle~~ principle) be more helpful in determining named entities.
- For example, the model can learn that seeing x_{in} as the word just before the center word is indicative for the center word to be a location.

A pitfall when retraining word vectors

We are training a logistic regression classifier for movie review sentiment using single words

- In the training data we have "TV" and "telly"
- In the testing data we have television
- The pretrained word vectors have all three similar

Q→ What happen we update word vectors?
A→ Words in training dat move around
Words not testing data stay where they were

Q→ Should I use "pretrained" word vectors
A→ Almost always, yes
They are trained on huge amount of data and so they will know about words not in your training data and will know more about words that are in your training data.
Have 100s of ~~random~~ millions of data? okay to start random

Q→ Should I update ("fine tune") my own word vectors?

- If you only have small training dataset don't train the word vectors
- If you have a large dataset, it will probably work better to train = update = fine tune word vectors to the task.

Backpropagation: Taking derivatives and using the (generalized) chain rule

We reuse ∂ derivatives computed for higher layers in computing derivatives for lower layers so as to minimize computation

Computation graphs

We represent our neural nets equations as a graph

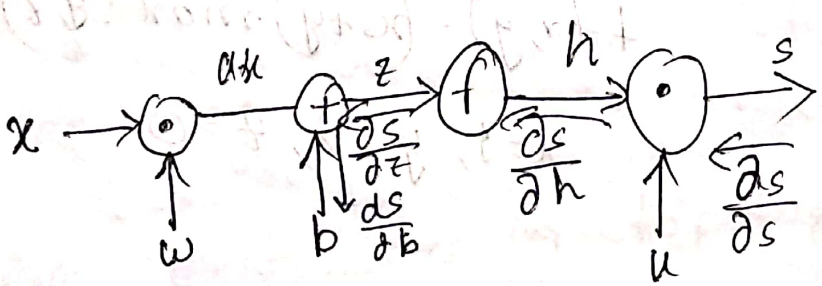
- Source node: inputs
- Interior node: operations
- Edges pass along results of operation
- Go back along edges (pass along grads)

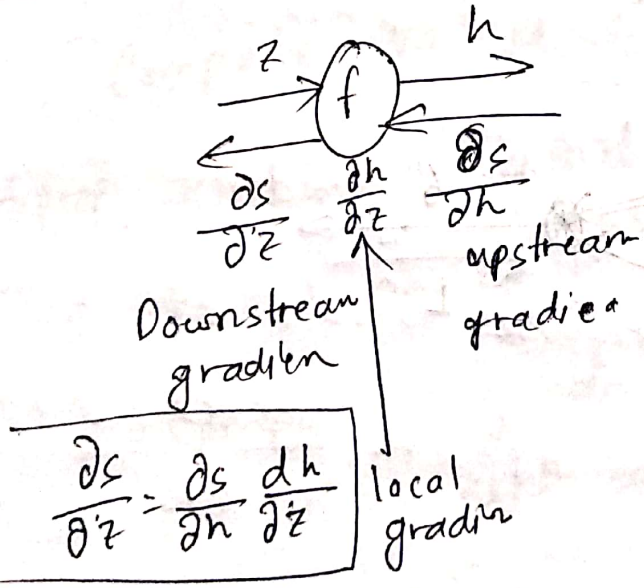
$s = u^T h$

$h = f(z)$

$z = Wx + b$

x (input)

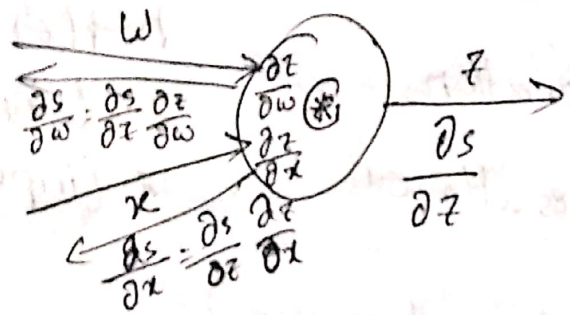




$$\frac{\partial s}{\partial z} = \frac{\partial s}{\partial h}\frac{\partial h}{\partial z}$$

[downstream grad] = [upstream grad] x [local grad]

If we have multiple inputs



Example:

$f(x,y) = (x+y)\max(y,z)$

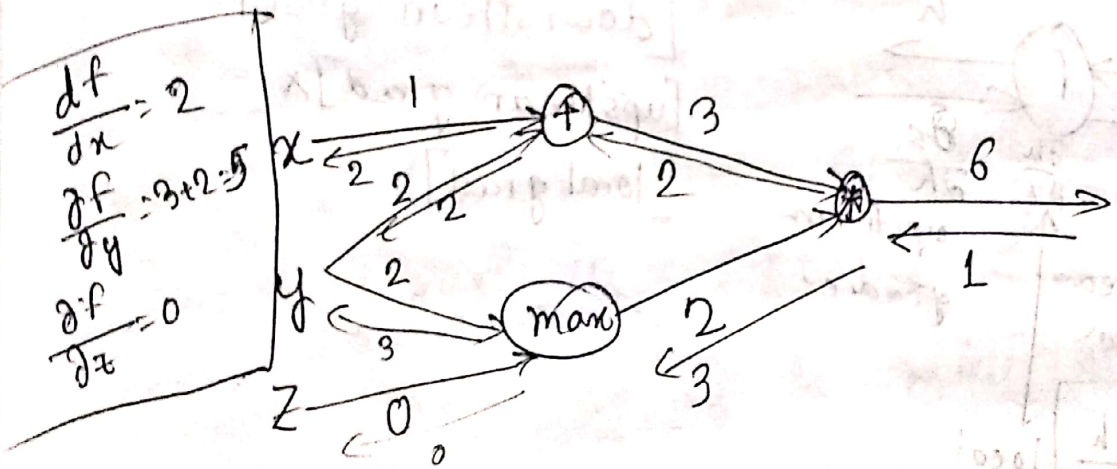
$x=1,\ y=2,\ z=0$

Forward prop steps

$a = x+y$

$b = \max(y,z)$

$f = ab$



Backprop:

* '+' distributes upstream gradient
* 'o' "switches" upstream gradient
'max' 'routes' the upstream gradient

Efficiency: compute all grads at once

Complexity of Backprop is same as forwardprop.

In general nets have regular layer structure and so we can use matrices and Jacobians.

fprop: visit nodes in topological sort order
Compute values of node give predecessor

Backprop: - initialize grad with 1
- visit nodes in reverse order of fprop
Compute grads wrt each node using grads wrt successors.

- The gradient computation can be automatically inferred from the symbolic expression of fprop.

- Each node type needs to know how to compute its outputs and how to compute the gradients wrt to its input, given the gradient wrt output

- Moder DL framework (Tensorflow, Pytorch, etc) do backprop for you but mainly leave for you layer/node writer to hand-calculate the local derivative.

~~Gradient checker~~ ~~Numeric gradient~~

Gradient checking: Numeric Gradient

- For small h ($\approx 1e4$) $f'(x) \approx \frac{f(x+h) - f(x-h)}{2h}$

- Easy to implement correctly
- But approximate and very slow.
  - Have to re compute f for every params of our model

- Useful for checking our implementation
  - In the old days when we hand-wrote everything, it was key to do this everywhere.
  - Now much less needed, when throwing together layers

Regularization:

Really a full loss function includes regularization over all parameters θ, e.g., L2 regularization

$$J(\theta) = \frac{1}{N}\sum_{i=1}^{N} -\log\left(\frac{e^{f_{y_i}}}{\sum_{c=1}^{C} e^{f_c}}\right) + \lambda \sum_k \theta_k^2$$

Regularization (largely) prevents overfitting when we have a lot of feature (or later a very powerful/deep model, ++)

Vectorization: to make this faster.

Non-linearities: logistic ("sigmoid") $= \frac{1}{1+\exp(-z)}$

tanh $= \frac{e^z - e^{-z}}{e^z + e^{-z}}$

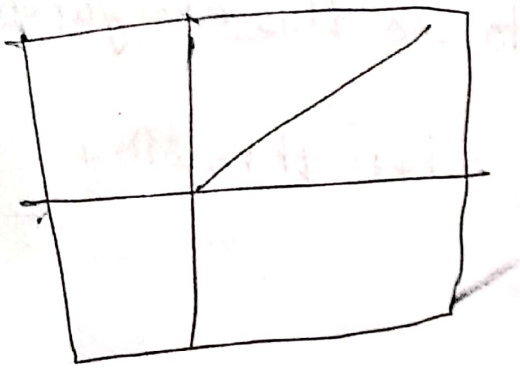
tanh is just a rescaled and shifted sigmoid (2x as steep, [-1, 1]):

$\tanh(z) = 2\,\text{logistic}(2z) - 1$

Hard tanh $\begin{cases} -1 & \text{if } x < -1 \\ x & \text{if } -1 < x < 1 \\ 1 & \text{if } x > 1 \end{cases}$

ReLU (rectifier linear unit)

$rect(z) = max(0, z)$

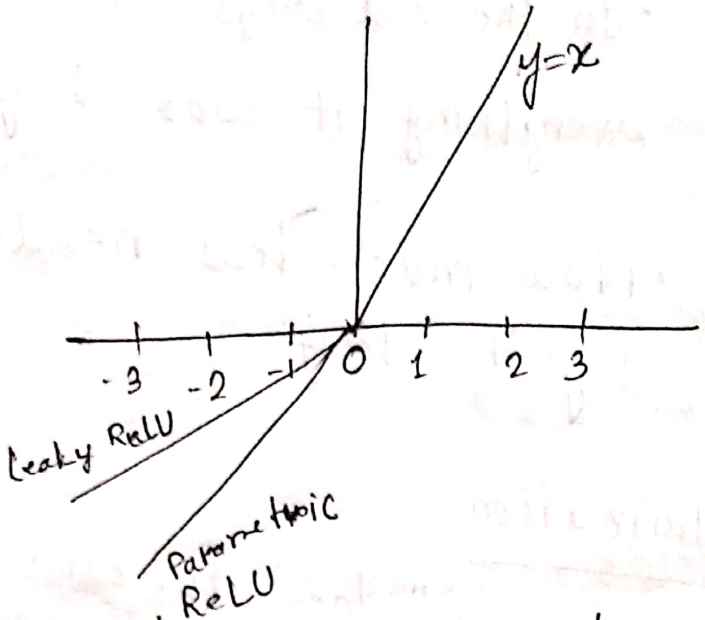


$y = 0.01x$

Leaky ReLU

$y = \alpha x$

Parametric ReLU



- For building a feed-forward deep network, the first thing you should try is ReLU. Trains quickly and performs well due to good gradient ~~flo~~ backflow.

Parameter Initialization:

- You normally must initialize weights to small random values → to avoid symmetries that prevent learning / specialization
- Initialize hidden layers biases to 0 and output (or reconstruction) biases to optimal value if weights were 0 (e.g. mean target or inverse sigmoid of mean target)

- Initialize all other weights ~ Uniform $(-r, r)$ with r chosen so number get neither too big or too small.
- Xavier initialization has variance inversely proportional to fan-in n_{in} (previous layer size) and fan-out n_{out} (next layer size):

$$Var(w_i) = \frac{2}{n_{in} + n_{out}}$$

Optimizers:

- Usually, plain SGD will work just fine
  - However, getting good results will often require hand-tuning the learning rate
- for more ~~more~~ complex nets and situations, or just to avoid worry, you often do better with one of the family of more sophisticated "adaptive" optimizers that scale the parameter adjustment by an accumulated gradient
  - The models give per-parameter learning rates
    - Adagrad
    - RMSprop
    - Adam ← a fairly good, safe place to begin
    - sparseAdam

Learning Rates:

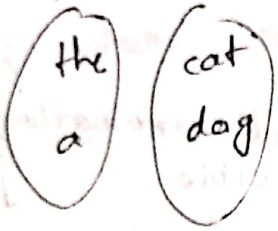
- You can just use a constant learning rate. Start around $lr = 0.001$?
  - It might be order of magnitude right- try powers of 10
    - → Too big: model may diverge or not converge
    - → Too small: your model may not have trained by the deadline
- Better results can generally be obtained by allowing learning rates to decrease as you train
  - By hand: halve the learning rate every k epochs
  - By formula: $lr = lr_0 e^{-kt}$, for epoch t
  - There are fancier methods like cyclic learning rates
- Fancier optimizers still use a learning rate but it may be an initial rate that the optimizer shrinks - so may be able to start high.

Lecture 5 - Dependency parsing

26/11/2020

Phrase structure organizes words into nested constituents. (can represent grammar with CFG rules)

words ⟶ phrases ⟶ bigger phrases



NP → Det N
NP → Det (Adj) N PP

PP → Prep NP

- Dependency structure shows which words depend on (modify or are argument of) which other words.
- We need to understand sentence structure in order to be able to interpret language correctly.
- Humans communicate complex ideas by composing words together into bigger units to convey complex meanings.
- We need to know what is connect to what

Prepositional phrase attachment ambiguity

PP attachment ambiguities multiply:

- A key parsing decision is how we 'attach' various constituents.

→ PPs, adverbial or participal phrases, infinitives, coordinations

Catalan numbers $C_n = \frac{(2n)!}{(n+1)!\,n!}$ [number of combinations possible]

An exponentially growing series, which arises in many tree-like contexts:

Eg. the number of possible triangulations of a polygon with $n+2$ sides

Coordination scope multiply:

Adjectival Modifier Ambiguity:

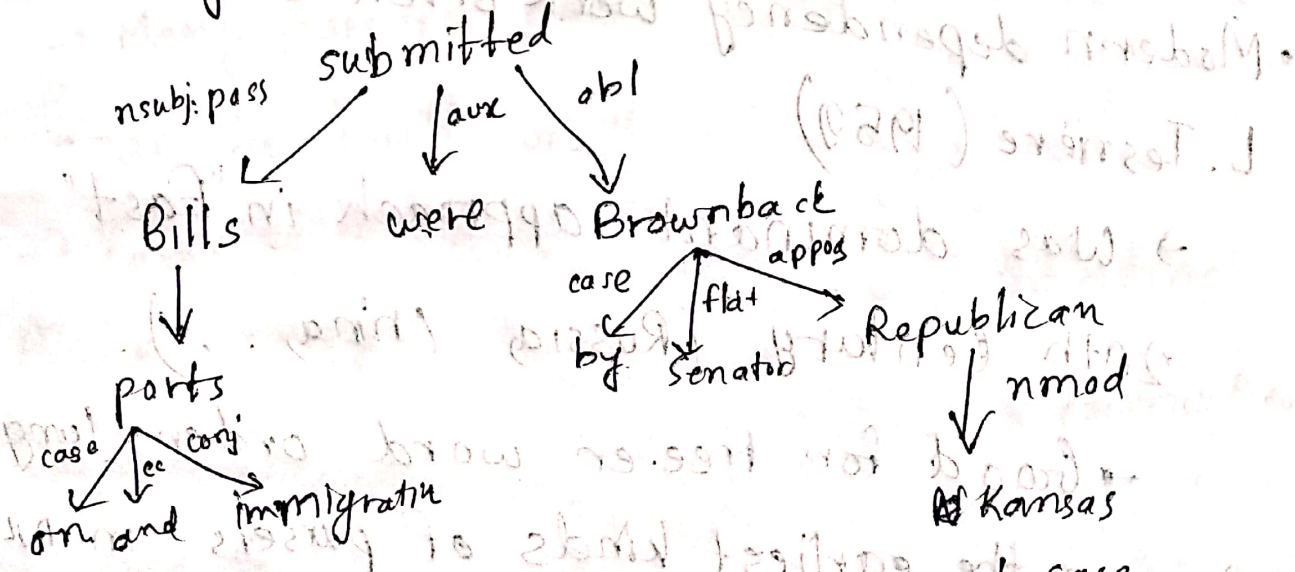
Verb Phrase attachment ambiguity:

Dependency paths identify semantic relations:

Dependency Grammar and Dependency Structure:

Dependency syntax postulates that syntactic structure consists of relations between lexical items, normally binary asymmetric relations ("arrows") called dependencies.

The arrows are commonly typed with the name of grammatical relations, e.g.



* Usually dependencies form a tree (connected, acyclic, single-head)

History:

- The idea of dependency structure goes back a long way
  - → T. Panini's grammar (c. 5th century BCE)
  - → Basic approach of 1st millennium Arabic grammarians
- Constituency/context-free grammars is a new-fangled invention
  - → 20th century invention (R.S. Wells, 1947; then Chomsky)
- Modern dependency work often sourced to L. Tesnière (1959)
  - → Was dominant approach in "East" in 20th century (Russia, China, ...)
  - → Good for free-er word order languages
- Among the earliest kinds of parsers in NLP, even in the US
  - → David Hays, one of the founders of U.S. computational linguists, built early dependency parser.

• Start at the head and point to the dependent.

The rise of annotated data: Universal Dependencies

treebanks Universal Dependencies

The rise of annotate data:

Starting off, building a treebank seems a lot slower and less stressful than building a grammar.

→ But a treebank gives us many things

- Reusability of the labor
  - → Many parsers, part-of-speech taggers, etc. can be built on it
  - → Valuable resource for linguistics
- Broad coverage, not just a few intuitions
- Frequencies and distributional information
- A way to evaluate systems

Dependency Conditioning Preferences:

What are the sources of information for dependency parsing?

1) Bilexical affinities [discussion → issues] is plausible
2) Dependency distance (mostly with nearby words)
3) Intervening material (Dependencies rarely span intervening verbs or punctuation)
4) Valence of heads (How many dependents on which side are usual for a head)

Dependency Parsing:

- A sentence is parsed by choosing for each word what other word is it dependent on?
- Usually some constraints:
  - Only one word is dependent of ROOT
  - Don't want cycles A → B; B → A

- This makes the dependencies a tree
- Final issue is whether cross (non-projective) or not.

Methods of Dependency Parsing:

1) Dynamic Programming

Eisner (1996) gives a clever algorithm with complexity $O(n^3)$ by producing parse items with heads at the ends rather than in the middle.

2) Graph algorithm:

You create a Minimum spanning tree for a sentence

3) Constraint Satisfaction:

Edges are eliminated that don't satisfy hard constraints.

4) Transition-based parsing:

Greedy choice of attachment guided by good ML classifiers

Greedy transition-based parsing [Nivre 2003]

- A simple form of greedy discriminative dependency parser.
- The parser does a sequence of bottom up actions. → ~~Right~~ Roughly like 'shift' or 'reduce' in a shift-reduce parser, but the reduce actions are specialized to create dependencies. With head on left or right.

The parser has

- a stack σ, written σ with top to the right
- a buffer β, written with top to the left
- a set of dependency arcs A
- a set of action s

Malt Parser:

Each action is predicted by a discriminative classifier (softmax classifier)

- There is NO search (in the simplest form)
  - But you can profitably do a beam search if you wish (slower but better)
    → You keep k good parse prefixes at each time step.
- Provides a linear time parser.

Conventional Feature Representation

$$\text{Acc} = \frac{\#\text{ correct deps}}{\#\text{ of deps}}$$

UAS = 4/5 = 80%

Why train neural dependency parser?

[Chen and Manning]

Problems #1: sparse

#2: incomplete

#3: expensive computation.

More than 95% of parsing time is consumed by feature computation

- English parsing to stanford Dependencies

UAS → Unlabeled attachment score (UAS) = head

LAS → Labeled attachment score (LAS) = head and label

Accurate and efficient

Distributed Representations:

We represent each word as a d-dimensional dense vector (i.e. word embedding)

- Similar words are expected to have close vectors

Meanwhile; for parts-of-speech tags (POS) and dependency labels are also represented as d-dimensional vectors.

→ The smaller discrete sets ~~are~~ also exhibit many semantical similarities.

Extracting tokens and then vector representation from configuration:

- We extract a set of tokens based on stack/buffer positions.
- We convert them to vector embedding and concatenate them.

Model Architecture:

Dependency parsing for sentence structure

Neural networks can accurately determine the structure of sentences, supporting interpretation.

This was the first simple successful neural dependency parser

The dense representation. let it outperform other greedy parsers in both accuracy and speed.

Further developments in transition based neural dependency parsing:

This work was further developed and improved by Google

→ Bigger and deeper networks with better tuned hyperparams

→ Beam search

→ Global conditional random field (CRF) inference over the decision sequence

Leading the SyntaxNet and the Parsey McParseface model.

Graph based dependency parsing

- Compute a score for every possible dependency for each word
  → Doing this well requires good "contextual" representations of each word token, ~~which we will develop in con~~

A Neural graph bases dependency parsen

→ Revived graph-based dependency parsing in neural word
→ Design a biaffine scoring mode for neural dependency parsing
  - Also using a neural sequence model ~~as we discuss ne~~
- Really great results
  → But slower than simple neural transitio based parsers.

Lecture 6: Language Models and RNNs

Language Modeling: task of predicting what word comes next.

Given a sequence of words $x^{(1)}, x^{(2)}, \ldots x^{(t)}$, compute the probability distribution of the next word $x^{(t+1)}$

$$P(x^{(t+1)} \mid x^{(t)} \ldots x^{(1)})$$

where $x^{(t+1)}$ can be any word in the vocabulary

$$V = \{w_1, \ldots, w_{|V|}\}$$

A system that does this is called a language model.

A system that assigns probability to a piece of text.

If we have some text $x^{(1)} \ldots x^{(T)}$ then probability of this text (according to the Language Model) is

$$P(x^{(1)}, \ldots x^{(T)}) = P(x^{(1)}) \times P(x^{(2)} \mid x^{(1)}) \times \ldots$$
$$\times P(x^{(T)} \mid x^{(T-1)}, \ldots, x^{(1)})$$
$$= \prod_{t=1}^{T} P(x^{(t)} \mid x^{(t-1)}, \ldots, x^{(1)})$$

n-gram Language model:

pre-deeplearning era

A n-gram is a chunk of n-consecutive words

Idea: Collect statistics about how frequent different n-grams are and use these to predict next word.

Simplifying assumption: $x^{(t+1)}$ depends only on preceding (n-1) words

$$P(x^{(t+1)} \mid x^{(t)}, \ldots, x^{(1)}) = P(x^{(t+1)} \mid \overbrace{x^{(t)}, \ldots, x^{(t-n+2)}}^{n-1 \text{ words}})$$

probability of n-gram / probability of (n-1) gram

$$= \frac{P(x^{(t+1)}, x^{(t)} \ldots x^{(t-n+2)})}{P(x^{(t)}, \ldots x^{(t-n+2)})}$$

→ How do we get these n-gram and (n-1) gram probabilities?

Answer: By counting them in some large corpus

$$\approx \frac{\text{count}(x^{(t+1)}, x^{(t)}, \ldots, x^{(t-n+2)})}{\text{count}(x^{(t)}, \ldots, x^{(t-n+2)})}$$

[statistical approximation]

Sparsity problem ⇒ zero probability problem

Back-off ⇒ if we can't find n-gram example
we look for (n-1) gram

→ increasing the value of n doesn't ~~always~~ create more change or give better performance.
It creates more sparsity problem.

Storage problems with n-gram Language Models

Storage: Need to store count for all n-grams ~~you~~ we saw in the corpus.

→ Increasing n or increasing corpus increases model size.

→ Language model can be used to generate text. But, even if they are grammatical but incoherent.

Neural Language Model:

A fixed-window neural language model

words/one-hot vector $x^{(1)}, x^{(2)}, x^{(3)}, x^{(4)}$

concatenated Word Embeddings $e = [e^{(1)}; e^{(2)}; e^{(3)}; e^{(4)}]$

hidden layer $h = f(We + b_1)$

output distribution $\hat{y} = \text{softmax}(Uh + b_2) \in \mathbb{R}^{|V|}$

Improvement ⇒ No sparsity problem

⇒ Don't need to store all observed n-grams

Remaining problems:

→ Fixed window might be too small

→ Enlarging window enlarges W

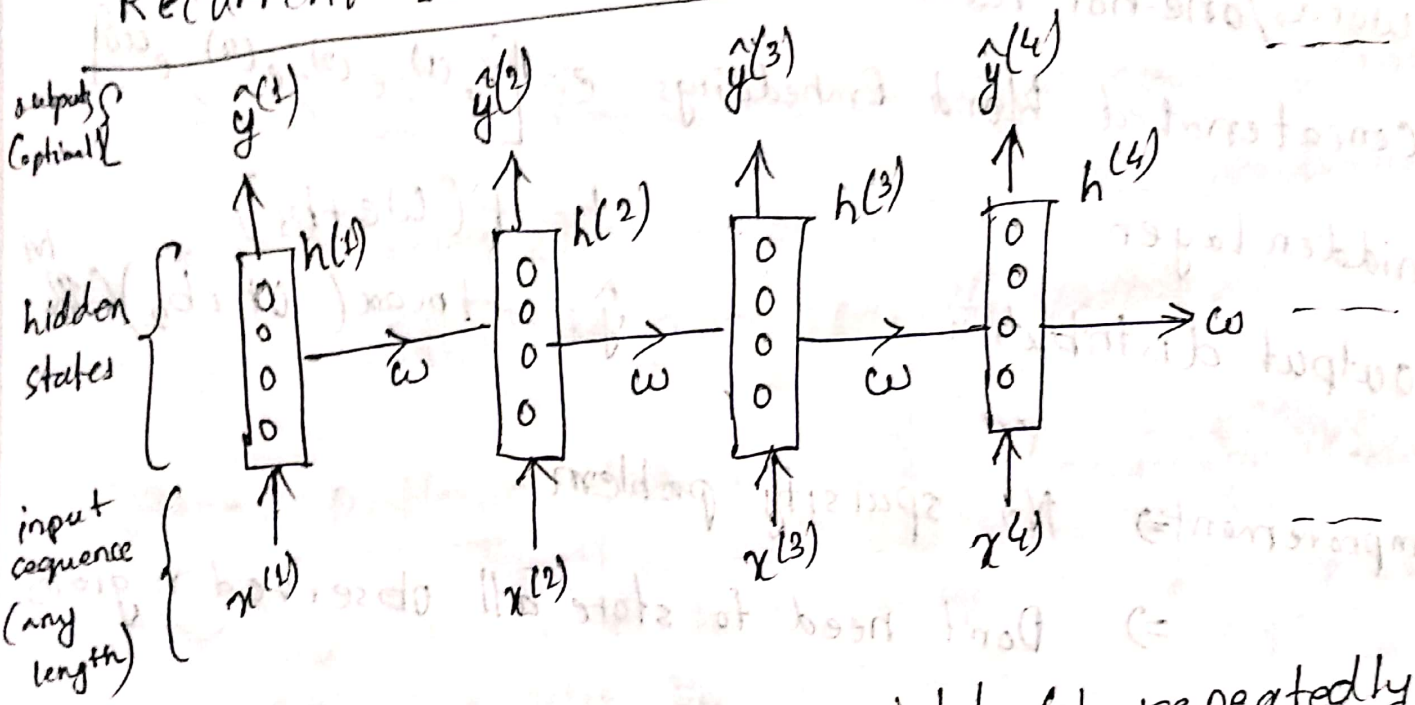
→ Window can never be large enough

→ $x^{(1)}$ and $x^{(2)}$ are multiplied by completely different weights in W

No symmetry in how the inputs are processed.

* We need a neural architecture that can process any length input.

Recurrent Neural Networks (RNN)



Core idea: apply the same weight W repeatedly

words / one-hot vectors $x^{(t)} \in \mathbb{R}^{|V|}$

word embedding $e^{(t)} = E x^{(t)}$

hidden states $h^{(t)} = \sigma(W_h h^{(t-1)} + W_e e^{(t)} + b_1)$

output distribution $\hat{y}^{(t)} = \text{softmax}(U h^{(t)} + b_2) \in \mathbb{R}^{|V|}$

Advantages:

→ Can process any length input

→ Computation for step t can use information from many steps back

→ Model size doesn't increase for longer input.

→ Same weights applied on every timestep. so there is symmetry in how inputs are processed

Disadvantages

→ Recurrent computation is slow

→ In practice, difficult to access information from many steps back.

Training a RNN language Model

→ Get a big corpus of text which is a sequence of words $x^{(1)}, \ldots, x^{(T)}$

→ Feed into RNN-LM; compute output distribution $\hat{y}^{(t)}$ for every step t.

→ predict probability distribution of every word, given words so far.

- Loss function on step t is cross entropy between predicted probability distribution $\hat{y}^{(t)}$ and the true next word $y^{(t)}$ (one-hot for $x^{(t+1)}$)

$$J^{(t)}(\theta) = CE(y^{(t)}, \hat{y}^{(t)}) = -\sum_{w \in V} y_w^{(t)} \log \hat{y}_w^{(t)} = -\log \hat{y}_{x_{t+1}}^{(t)}$$

$$J(\theta) = \frac{1}{T}\sum_{t=1}^{T} J^{(t)}(\theta) = -\frac{1}{T}\sum_{t=1}^{T} \log \hat{y}_{x_{t+1}}^{(t)}$$

* Computing logs and gradients accross entire corpus $x^{(1)} \ldots x^{(T)}$ is too expensive

Stochastic gradient Descent allows us to compute loss and gradients for small chunk of data, and update.

Compute loss $J(\theta)$ for a sentence (actually a batch of sentences), compute gradients and update weights.

Backprops for RNNs

What is the derivative of $J^{(t)}(\theta)$ wrt the repeated weight matrix W_h?

⇒ The gradient w.r.t. a repeated weight is the sum of the gradients wr.t. each time it appears.

$$\frac{\partial J^{(t)}}{\partial W_h} = \sum_{i=1}^{t} \frac{\partial J^{(t)}}{\partial W_h}\Big|_{(i)}$$

Multivariable Chain Rule

$$\frac{d}{dt} f(x(t), y(t)) = \frac{\partial f}{\partial x}\frac{\partial x}{\partial t} + \frac{\partial f}{\partial y}\frac{\partial y}{\partial t}$$

Backpropagate over timesteps $i=t,\ldots,0$ summing gradients as you go. This algorithm is called "backpropagation through time"

Generating text with a RNN Language model

We can use a RNN Language model to generate text by repeated sampling. Sampled output is next step's input

- We can train a RNN-LM on any kind of text, then generate text in that style.

Evaluating Language models

$$\text{Perplexity} = \prod_{t=1}^{T} \underbrace{\left(\frac{1}{P_{LM}(x^{(t+1)} | x^{(t)}, \dots, x^{(1)})} \right)^{1/T}}_{\text{Inverse probability of corpus, according to language mod.}}$$

Normalized by number of words

⇒ This equal to the exponential of cross entropy loss $J(\theta)$

$$\prod_{t=1}^{T} \left(\frac{1}{\hat{y}^{(t)}_{x_{t+1}}} \right)^{1/T} = \exp\left(\frac{1}{T} \sum_{t=1}^{T} -\log \hat{y}^{(t)}_{x_{t+1}} \right) = \exp(J(\theta))$$

* Lower perplexity is better

→ Language modeling is a benchmark task that helps us measure our progress on understanding language.

→ a subcomponent of many NLP tasks, especially those involving generating text or estimating the probabity of text

- Predictive typing
- Speech recognition [WER] [conditional language model]
- Handwriting recognition
- Spelling/grammar correction
- Authorship identification
- Machine translation
- Summarization
- Dialogue.

Terminology

Vanilla RNN ← simple RNN