Part-of-Speech Tagging

$+$

Neural Networks

CS 287

Quiz

Last class we focused on hinge loss.

$$L_{hinge} = \max\{0, 1 - (\hat{y}_c - \hat{y}_{c'})\}$$

Consider now the squared hinge loss, (also called ℓ_2 SVM)

$$L_{hinge^2} = \max\{0, 1 - (\hat{y}_c - \hat{y}_{c'})^2\}$$

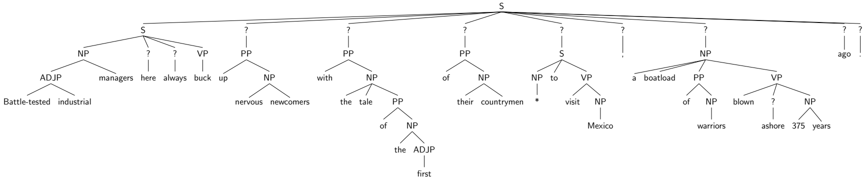
What is the effect does this have on the loss? How do the parameters gradients change?

Contents

Penn Treebank (Marcus et al, 1993)

```
( (S (CC But) (SBAR-ADV (IN while) (S (NP-SBJ (DT the)
(NNP New) (NNP York) (NNP Stock) (NNP Exchange) ) (VP
(VBD did) (RB n't) (VP (VB fall) (ADVP-CLR (RB apart) )
(NP-TMP (NNP Friday) ) (SBAR-TMP (IN as) (S (NP-SBJ (DT
the) (NNP Dow) (NNP Jones) (NNP Industrial) (NNP Average)
) (VP (VBD plunged) (NP-EXT (NP (CD 190.58) (NNS points)
) (PRN (:  -) (NP (NP (JJS most) ) (PP (IN of) (NP (PRP
it) )) (PP-TMP (IN in) (NP (DT the) (JJ final) (NN hour)
))) (:  -) ))))))))) (NP-SBJ-2 (PRP it) ) (ADVP (RB
barely) ) (VP (VBD managed) (S (NP-SBJ (-NONE- -2) ) (VP
(TO to) (VP (VB stay) (NP-LOC-PRD (NP (DT this) (NN side)
) (PP (IN of) (NP (NN chaos) ))))))) (.  .)))
```

Syntax



S
S ? ? ? ? ? ? ? ?
NP ? ? VP PP PP PP S , NP ago .
ADJP managers here always buck up NP with NP of NP NP to VP a boatload PP VP
Battle-tested industrial nervous newcomers the tale PP their countrymen * visit NP of NP blown ? NP
of NP Mexico warriors ashore 375 years
the ADJP
first

NP
a boatload PP VP
of NP blown ? NP
warriors ashore 375 years

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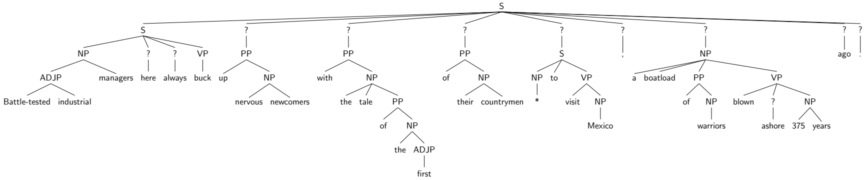
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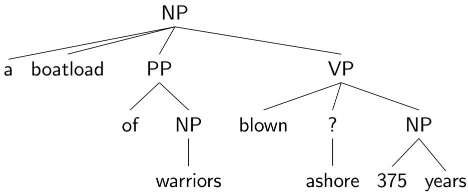
NP
a boatload PP VP
of NP blown ? NP
warriors ashore 375 years

Tagging

So what if Steinbach had struck just seven home runs in 130 regular-season games , and batted in the seventh position of the A 's lineup .

Part-of-Speech Tags

So/RB what/WP if/IN Steinbach/NNP had/VBD struck/VBN just/RB seven/CD home/NN runs/NNS in/IN 130/CD regular-season/JJ games/NNS ,/, and/CC batted/VBD in/IN the/DT seventh/JJ position/NN of/IN the/DT A/NNP 's/NNP lineup/NN ./.

Part-of-Speech Tags

So/RB what/WP if/IN Steinbach/NNP had/VBD struck/VBN just/RB seven/CD home/NN runs/NNS in/IN 130/CD regular-season/JJ games/NNS ,/, and/CC batted/VBD in/IN the/DT seventh/JJ position/NN of/IN the/DT A/NNP 's/NNP lineup/NN ./.

“Simplified” English Tagset I

1. , Punctuation
2. CC Coordinating conjunction
3. CD Cardinal number
4. DT Determiner
5. EX Existential there
6. FW Foreign word
7. IN Preposition or subordinating conjunction
8. JJ Adjective
9. JJR Adjective, comparative
10. JJS Adjective, superlative
11. LS List item marker

“Simplified” English Tagset II

12. MD Modal
13. NN Noun, singular or mass
14. NNS Noun, plural
15. NNP Proper noun, singular
16. NNPS Proper noun, plural
17. PDT Predeterminer
18. POS Possessive ending
19. PRP Personal pronoun
20. PRP$ Possessive pronoun
21. RB Adverb
22. RBR Adverb, comparative

“Simplified” English Tagset III

23. RBS Adverb, superlative
24. RP Particle
25. SYM Symbol
26. TO to
27. UH Interjection
28. VB Verb, base form
29. VBD Verb, past tense
30. VBG Verb, gerund or present participle
31. VBN Verb, past participle
32. VBP Verb, non-3rd person singular present
33. VBZ Verb, 3rd person singular present

“Simplified” English Tagset IV

34. WDT Wh-determiner
35. WP Wh-pronoun
36. WP$ Possessive wh-pronoun
37. WRB Wh-adverb

NN or NNS

Whether a noun is tagged singular or plural depends not on its semantic properties, but on whether it triggers singular or plural agreement on a verb. We illustrate this below for common nouns, but the same criterion also applies to proper nouns.

Any noun that triggers singular agreement on a verb should be tagged as singular, even if it ends in final -s.

EXAMPLE: Linguistics NN is/*are a difficult field.

If a noun is semantically plural or collective, but triggers singular agreement, it should be tagged as singular.

EXAMPLES: The group/NN has/*have disbanded.
The jury/NN is/*are deliberating.

Language Specific?

- Which of these tags are English only?
- Are there phenomenon that these don't cover?
- Should our models be language specific?

Universal Part-of-Speech Tags (Petrov et al, 2012)

1. VERB - verbs (all tenses and modes)
2. NOUN - nouns (common and proper)
3. PRON - pronouns
4. ADJ - adjectives
5. ADV - adverbs
6. ADP - adpositions (prepositions and postpositions)
7. CONJ - conjunctions
8. DET - determiners
9. NUM - cardinal numbers
10. PRT - particles or other function words
11. X - other: foreign words, typos, abbreviations
12. . - punctuation

Why do tags matter?

- Interesting linguistic question.
- Used for many downstream NLP tasks.
- Benchmark linguistic NLP task.

However note,

- Possibly have "solved" PTB tagging (Manning, 2011)
- Deep Learning skepticism

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Contents

Strawman: Sparse Word-only Tagging Models

Let,

- $\mathcal{F}$; just be the set of word type
- $\mathcal{C}$; be the set of part-of-speech tags, $|\mathcal{C}| \approx 40$
- Proposal: Use a linear model, $\hat{y} = f(\mathbf{x}\mathbf{W} + \mathbf{b})$

Why is tagging hard?

1. Rare Words
   - 3% of tokens in PTB dev are unseen.
   - What can we even do with these?
2. Ambiguous Words
   - Around 50% of seen dev tokens are ambiguous in train.
   - How can we decide between different tags for the same type?

Better Tag Features: Word Properties

Representation can use specific aspects of text.

- $\mathcal{F}$; Prefixes, suffixes, hyphens, first capital, all-capital, hasdigits, etc.
- $\mathbf{x} = \sum_i \delta(f_i)$

Example: Rare word tagging

`in 130 regular-season/* games ,`

$$\begin{aligned}
\mathbf{x} &= \delta(\texttt{prefix:3:reg}) + \delta(\texttt{prefix:2:re}) \\
&+ \delta(\texttt{prefix:1:r}) + \delta(\texttt{has-hyphen}) \\
&+ \delta(\texttt{lower-case}) + \delta(\texttt{suffix:3:son}) \ldots
\end{aligned}$$

Better Tag Features: Tag Sequence

Representation can use specific aspects of text.

- $\mathcal{F}$; Prefixes, suffixes, hyphens, first capital, all-capital, hasdigits, etc.
- Also include features on previous tags

Example: Rare word tagging with context

```
in 130/CD regular-season/* games ,
```

$$\begin{aligned}\mathbf{x} &= \delta(\texttt{last:CD}) + \delta(\texttt{prefix:3:reg}) + \delta(\texttt{prefix:2:re}) \\ &+ \delta(\texttt{prefix:1:r}) + \delta(\texttt{has-hyphen}) \\ &+ \delta(\texttt{lower-case}) + \delta(\texttt{suffix:3:son}) \ldots\end{aligned}$$

However, requires search. HMM-style sequence algorithms.

NLP (almost) From Scratch (Collobert et al. 2011)

Exercise: What if we just used words and context?

- No word-specific features (mostly)
- No search over previous decisions

Next couple classes, we will work our way up to this paper,

1. Dense word features
2. Contextual windowed representations
3. Neural networks architecture
4. Semi-supervised training

Contents

Motivation: Dense Features

- Strawman linear model learns one parameter for each word.
- Features allow us to share information between words.
- Can this be learned?

Bilinear Model

Bilinear model,

$$\hat{\mathbf{y}} = f((\mathbf{x}^0\mathbf{W}^0)\mathbf{W}^1 + \mathbf{b})$$

- $\mathbf{x}^0 \in \mathbb{R}^{1\times d_0}$ start with one-hot.
- $\mathbf{W}^0 \in \mathbb{R}^{d_0\times d_{\text{in}}}$, $d_0 = |\mathcal{F}|$
- $\mathbf{W}^1 \in \mathbb{R}^{d_{\text{in}}\times d_{\text{out}}}, \mathbf{b} \in \mathbb{R}^{1\times d_{\text{out}}}$; model parameters

Notes:

- Bilinear parameter interaction.
- $d_0 >> d_{\text{in}}$, e.g. $d_0 = 10000, d_{\text{in}} = 50$

Bilinear Model: Intuition

$$(\mathbf{x}^0\mathbf{W}^0)\mathbf{W}^1 + \mathbf{b}$$

$$\begin{bmatrix} 0 & \dots & 1 & \dots & 0 \end{bmatrix} \begin{bmatrix} w^0_{1,1} & \dots & w^0_{0,d_{\text{in}}} \\ & \vdots & \\ & \vdots & \\ & \vdots & \\ w^0_{k,1} & \dots & w^0_{k,d_{\text{in}}} \\ & \vdots & \\ & \vdots & \\ & \vdots & \\ w^0_{d_0,1} & \dots & w^0_{d_0,d_{\text{in}}} \end{bmatrix} \begin{bmatrix} w^1_{1,1} & \dots & \dots & w^1_{0,d_{\text{out}}} \\ & \ddots & \ddots & \\ w^1_{d_{\text{in}},0} & \dots & \dots & w^1_{d_{\text{in}},d_{\text{out}}} \end{bmatrix}$$

Embedding Layer

$$\mathbf{x}^0 \mathbf{W}^0$$

$$\begin{bmatrix} 0 & \ldots & 1 & \ldots & 0 \end{bmatrix} \begin{bmatrix} w^0_{1,1} & \ldots & w^0_{0,d_{\mathrm{in}}} \\ & \vdots & \\ & \vdots & \\ & \vdots & \\ w^0_{k,1} & \ldots & w^0_{k,d_{\mathrm{in}}} \\ & \vdots & \\ & \vdots & \\ & \vdots & \\ w^0_{d_0,1} & \ldots & w^0_{d_0,d_{\mathrm{in}}} \end{bmatrix}$$

- Critical for natural language applications
- Informal names for this idea,
  - Feature embeddings/ word embeddings
  - Lookup Table
  - Feature/Representation Learning
  - In Torch, `nn.LookupTable` ($\mathbf{x}^0$ one-hot)

Dense Features

When dense features implied we will write,

$$\hat{\mathbf{y}} = f(\mathbf{x}\mathbf{W}^1 + \mathbf{b})$$

Example 1: single-word classfication with embeddings

$$\mathbf{x} = v(f_1; \theta) = \delta(f_1)\mathbf{W}^0 = \mathbf{x}^0\mathbf{W}^0$$

- $v : \mathcal{F} \mapsto \mathbb{R}^{1 \times d_{\mathrm{in}}}$; parameterized embedding function

Example 2: Bag-of-words classfication with embeddings

$$\mathbf{x} = \sum_{i=1}^{k} v(f_i; \theta) = \sum_{i=1}^{k} \delta(f_i)\mathbf{W}^0$$

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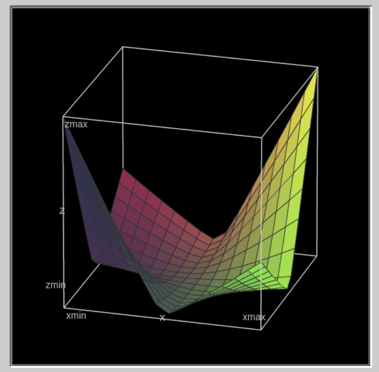
$$\mathbf{x} = \sum_{i=1}^{k} v(f_i; \theta) = \sum_{i=1}^{k} \delta(f_i)\mathbf{W}^0$$

Log-Bilinear Model

$$\hat{\mathbf{y}} = \log \mathrm{softmax}(\mathbf{x}\mathbf{W}^1 + \mathbf{b})$$

- Same form as multiclass logistic regression, but with dense features.
- However, objective is now non-convex (no restrictions on $\mathbf{W}^0$, $\mathbf{W}^1$)

Log-Bilinear Model



$$-15 \log \sigma(xy) - 5 \log \sigma(-xy) + \lambda/2||[x\ y]||^2$$

Does it matter?

- We are going to use SGD, in theory this is quite bad
- However, in practice it is not that much of an issue
- Argument: in large parameter spaces local optima are okay
- Lots of questions here, beyond scope of class

Embedding Gradients: Cross-Entropy

Chain Rule:

$$\frac{\partial L(f(\mathbf{x}))}{\partial x_i} = \sum_{j=1}^{m} \frac{\partial f(\mathbf{x})_j}{\partial x_i} \frac{\partial L(f(\mathbf{x}))}{\partial f(\mathbf{x})_j}$$

$$\hat{\mathbf{y}} = \log \mathrm{softmax}(\mathbf{x}\mathbf{W}^1 + \mathbf{b})$$

$$\frac{\partial L}{\partial x_f} = \sum_i W^1_{f,i} \frac{\partial L}{\partial z_{f,i}} = W^1_{f,c}(1 - \hat{y}_c) - \sum_{i \neq c} W^1_{f,i} \hat{y}_i$$

$$\mathbf{x} = \mathbf{x}^0 \mathbf{W}^0$$

$$\frac{\partial x_j}{\partial W^0_{k,j'}} = x^0_k \mathbf{1}(j = j')$$

Update:

$$\frac{\partial L}{\partial W^0_{k,j'}} = x^0_k (W^1_{j',c}(1 - \hat{y}_c) - \sum_{i \neq c} W^1_{j',i} \hat{y}_i)$$

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Contents

Sentence Tagging

- $w_1, \ldots, w_n$; sentence words
- $t_1, \ldots, t_n$; sentence tags
- $\mathcal{C}$; output class, set of tags.

Window Model

Goal: predict t_5.

- Windowed word model.

$$w_1 \ w_2 \ [w_3 \ w_4 \ w_5 \ w_6 \ w_7] \ w_8$$

- w_3, w_4; left context
- w_5; Word of interest
- w_6, w_7; right context
- d_{win}; size of window ($d_{\mathrm{win}} = 5$)

Boundary Cases

Goal: predict t_2.

$$\left[\langle\mathrm{s}\rangle\ w_1\ w_2\ w_3\ w_4\right]\ w_5\ w_6\ w_7\ w_8$$

Goal: predict t_8.

$$w_1\ w_2\ w_3\ w_4\ w_5\ \left[w_6\ w_7\ w_8\ \langle/\mathrm{s}\rangle\ \langle/\mathrm{s}\rangle\right]$$

Here symbols $\langle\mathrm{s}\rangle$ and $\langle/\mathrm{s}\rangle$ represent boundary padding.

Dense Windowed BoW Features

- $f_1, \ldots, f_{d_{\mathrm{win}}}$ are words in window
- Input representation is the concatenation of embeddings

$$\mathbf{x} = [v(f_1)\ v(f_2)\ \ldots\ v(f_{d_{\mathrm{win}}})]$$

Example: Tagging

$$w_1\ w_2\ [w_3\ w_4\ w_5\ w_6\ w_7]\ w_8$$

$$\mathbf{x} = [v(w_3)\ v(w_4)\ v(w_5)\ v(w_6)\ v(w_7)]$$

		$\mathbf{x}$		
(d_0)	(d_0)	(d_0)	(d_0)	(d_0)

Rows of $\mathbf{W}^1$ encode position specific weights.

Dense Windowed Extended Features

- $f_1, \ldots, f_{d_{\mathrm{win}}}$ are words, $g_1, \ldots, g_{d_{\mathrm{win}}}$ are capitalization

$$\mathbf{x} = [v(f_1)\ v(f_2)\ \ldots\ v(f_{d_{\mathrm{win}}})\ v_2(g_1)\ v_2(g_2)\ \ldots\ v_2(g_{d_{\mathrm{win}}})]$$

Example: Tagging

$$w_1\ w_2\ [w_3\ w_4\ w_5\ w_6\ w_7]\ w_8$$

$$\mathbf{x} = [v(w_3)\ v(w_4)\ v(w_5)\ v(w_6)\ v(w_7)\ v_2(w_3)\ v_2(w_4)\ v_2(w_5)\ v_2(w_6)\ v_2(w_7)]$$

		$\mathbf{x}$							
(d_0)	(d_0)	(d_0)	(d_0)	(d_0)	(d_0')	(d_0')	(d_0')	(d_0')	(d_0')

Rows of $\mathbf{W}^1$ encode position specific weights.

Tagging from Scratch (Collobert et al, 2011)

Part 1 of the key model,