Overview of Natural Language Processing Part II & ACS L90

Lecture 6: Gradient Descent and Neural Nets

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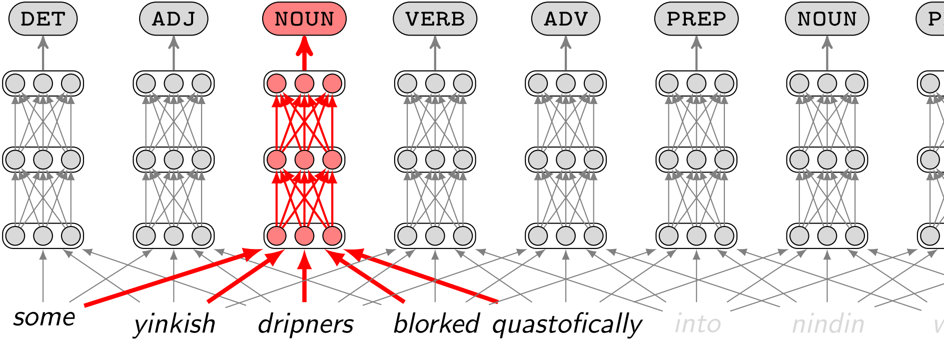


good features can be automatically induced

Lecture 6: Gradient Descent and Neural Nets

1. Training a model by gradient descent
2. Feature engineering → Representation Learning
3. Feedforward Neural Networks
4. Some General Comments on Neural NLP

Log-Linear Models: Recap and Notation

Assume we have a *parameter vector* θ.

$$p(y|x;\theta) \propto \exp(\theta^\top f(x,y))$$

We assumed that θ and $f(x,y)$ have DK dimensions:
D – number of input features
K – number of output classes

So we can also view θ as comprising K vectors with D dimensions:

$$p(y|x;\theta) \propto \exp(\theta_y^\top f(x))$$

Supervised learning

Assume there is a *good* annotated corpus

$$\mathcal{D} = \left\{ (x^{(1)}, y^{(1)}), (x^{(2)}, y^{(2)}), \ldots, (x^{(l)}, y^{(l)}) \right\}$$

How can we get a *good* parameter vector?

Maximum-Likelihood Estimation

$$\hat{\theta} = \arg\max L(\theta)$$

where $L(\theta)$ is the log-likelihood of observing the data $\mathcal{D}$:

$$L(\theta) = \sum_{i=1}^{l} \log p(y^{(i)} | x^{(i)}; \theta)$$

Gradient Descent/Ascent

In general, finding a minimum/maximum is *hard*.

However, a simple idea that often works:

- Initialise θ with some value
- Iteratively improve θ

The derivative tells us whether to increase or decrease (but doesn't tell us how much to increase/decrease by):

$$\theta^{[t+1]} = \theta^{[t]} + \beta \frac{dL}{d\theta}(\theta^{[t]})$$

Gradient Descent for the Log-Linear Model

$$
\begin{aligned}
L(\theta) &= \sum_{i=1}^{l} \log p(y^{(i)}|x^{(i)};\theta) \\
&= \sum_{i=1}^{l} \left(\theta^\top f(x^{(i)}, y^{(i)}) - \log \sum_{y' \in \mathcal{Y}} \exp(\theta^\top f(x^{(i)}, y')) \right)
\end{aligned}
$$

Gradient Descent for the Log-Linear Model

$$L(\theta) = \sum_{i=1}^{l} \left(\theta^\top f(x^{(i)}, y^{(i)}) - \log \sum_{y' \in \mathcal{Y}} \exp(\theta^\top f(x^{(i)}, y')) \right)$$

Calculating gradients (chain rule)

$$\begin{aligned}
\frac{dL}{d\theta_k} &= \sum_{i=1}^{l} \left(f_k(x^{(i)}, y^{(i)}) - \frac{\sum_{y' \in \mathcal{Y}} \left(\exp(\theta^\top f(x^{(i)}, y')) f_k(x^{(i)}, y') \right)}{\sum_{y^* \in \mathcal{Y}} \exp(\theta^\top f(x^{(i)}, y^*))} \right) \\
&= \sum_{i=1}^{l} f_k(x^{(i)}, y^{(i)}) - \sum_{i=1}^{l} \sum_{y' \in \mathcal{Y}} f_k(x^{(i)}, y') \frac{\exp(\theta^\top f(x^{(i)}, y'))}{\sum_{y^* \in \mathcal{Y}} \exp(\theta^\top f(x^{(i)}, y^*))} \\
&= \underbrace{\sum_{i=1}^{l} f_k(x^{(i)}, y^{(i)})}_{\textit{empirical counts}} - \underbrace{\sum_{i=1}^{l} \sum_{y' \in \mathcal{Y}} f_k(x^{(i)}, y') p(y' | x^{(i)}; \theta)}_{\textit{expected counts}}
\end{aligned}$$

Gradient Descent for the Log-Linear Model

Maximize $L(\theta)$ where

$$\frac{dL}{d\theta_k} = \underbrace{\sum_{i=1}^{l} f_k(x^{(i)}, y^{(i)})}_{\textit{empirical counts}} - \underbrace{\sum_{i=1}^{l} \sum_{y' \in \mathcal{Y}} f_k(x^{(i)}, y') p(y' | x^{(i)}; \theta)}_{\textit{expected counts}}$$

1 **Initialize** $\theta^{[0]} \leftarrow 0$

2 **for** $t = 1, \ldots$

3 **calculate** $\Delta = \frac{dL(\theta^{[t-1]})}{d\theta}$

4 **calculate** $\beta_* = \arg\max_\beta L(\theta + \beta\Delta)$ $\triangleright$ line search

5 **update** $\theta^{[t]} \leftarrow \theta^{[t-1]} + \beta_* \Delta$

(Or simply choose a fixed β – it is then a hyperparameter called the *learning rate*)

Recap: about linear combination

$$p(y|x;\theta) = \frac{\exp(\theta^\top f(x,y))}{\sum_{y' \in \mathcal{Y}} \exp(\theta^\top f(x,y'))}$$

$\cdots$	0	0	1	0	1	0	0	1	0	1	0	0	0	0	0	0	$\cdots$

f_{1001}: `if` word$_{-2}$=*some* and tag$=\mathrm{N}$

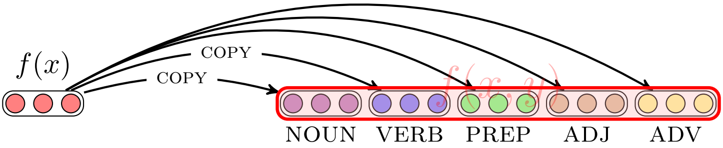
is θ_{1001} positive large?
vote for yes

Questions

Can we automate the design of features?

Is linear combination justified?

Learning feature representations



$$p(y|x;\theta) = \frac{\exp(\theta^\top f(x,y))}{\sum_{y' \in \mathcal{Y}} \exp(\theta^\top f(x,y'))} \longrightarrow \frac{\exp(\theta_y^\top f(x)))}{\sum_{y' \in \mathcal{Y}} \exp(\theta_{y'}^\top f(x))}$$

automatically induce f — f_θ

Log-Linear Model as Matrix Multiplication

$$p(y|x;\theta) \propto \exp(\theta_y^\top f(x))$$

We can view θ as a $K \times D$ matrix
D – number of input features
K – number of output classes

So θ is a *linear map* from input features to unnormalised log-probabilities

... What about using a *non-linear map*?

Feedforward Neural Networks

A feedforward neural network is a composition of simple functions:

- 1 layer: $\exp(W_1 x)$ ▷ log-linear model
- 2 layers: $\exp(W_2 g(W_1 x))$
- 3 layers: $\exp(W_3 g(W_2 g(W_1 x)))$
- 4 layers: $\exp(W_4 g(W_3 g(W_2 g(W_1 x))))$
- ...

Both $\exp$ and g are applied component-wise (to each dimension separately)

The activation function g should be non-linear, e.g.:

- Rectified linear unit: $\text{ReLU}(z) = \max(0, z)$
- Hyperbolic tangent: $\tanh(z) = \frac{e^{2z}-1}{e^{2z}+1}$
- Sigmoid: $\sigma(z) = \frac{1}{1+e^{-z}}$

Gradient Descent for Neural Nets

Assume there is a good annotated corpus:

$$\mathcal{D} = \left\{ (x^{(1)}, y^{(1)}), (x^{(2)}, y^{(2)}), \ldots, (x^{(l)}, y^{(l)}) \right\}$$

Aim to maximise the log-likelihood (also called "cross entropy"):

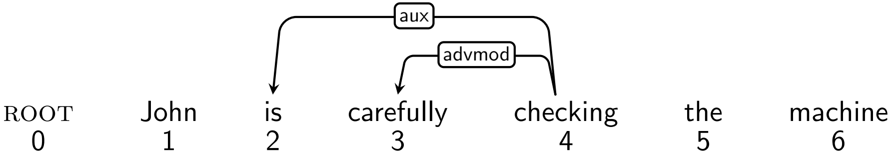
$$L(\theta) = \sum_{i=1}^{l} \log p(y^{(i)} | x^{(i)}; \theta)$$

θ now contains parameters from many layers,
but we can still use gradient descent:

- Backpropagation: efficient application of chain rule
- Iterate many times over training set

Dependency Parsing

Hand-crafted features for dependency parsing



Stack

[ROOT, John]

Buffer/Queue

[checking, the, machine]

Aim: predict the next parsing action

BUT: how is this configuration represented?

Feature templates (for a log-linear model)

Basic features:

- S_i the i-th element in the stack
- N_i the i-th element in the buffer
- w word form
- p POS label
- l/r left/right most dependent

Templates for defining new features:

- **from single words**: S_0wp; S_0w; S_0p; N_0wp; N_0w; N_0p; N_1wp; N_1w; N_1p; N_2wp; N_2w; N_2p
- **from word pairs**: S_0wpN_0wp; S_0wpN_0w; S_0wN_0wp; S_0wpN_0p; S_0pN_0wp; S_0wN_0w; S_0pN_0p; N_0pN_1p
- **from three words**: $N_0pN_1pN_2p$; $S_0pN_0pN_1p$; $S_{0h}pS_0pN_0p$; $S_0pS_{0l}pN_0p$; $S_0pS_{0r}pN_0p$; $S_0pN_0pN_{0l}p$

from Zhang and Nivre (2011)

Feature templates (continued...)

More basic features:

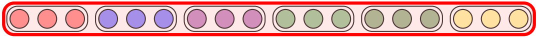
- d distance
- v_l/v_r left/right valency (related to the number of dependents)
- l dependency label
- s_l/s_r labelset

More feature templates:

- **distance**: S_0wd; S_0pd; N_0wd; N_0pd; S_0wN_0wd; S_0pN_0pd
- **valency**: S_0wv_r; S_0pv_r; S_0wv_l; S_0pv_l; N_0wv_l; N_0pv_l
- **unigrams**: $S_{0h}w$; $S_{0h}p$; S_0l; $S_{0l}w$; $S_{0l}p$; $S_{0l}l$; $S_{0r}w$; $S_{0r}p$; $S_{0r}l$; $N_{0l}w$; $N_{0l}p$; $N_{0l}l$
- **third-order**: $S_{0h2}w$; $S_{0h2}p$; $S_{0h}l$; $S_{0l2}w$; $S_{0l2}p$; $S_{0l2}l$; $S_{0r2}w$; $S_{0r2}p$; $S_{0r2}l$; $N_{0l2}w$; $N_{0l2}p$; $N_{0l2}l$; $S_0pS_{0l}pS_{0l2}p$; $S_0pS_{0r}pS_{0r2}p$; $S_0pS_{0h}pS_{0h2}p$; $N_0pN_{0l}pN_{0l2}p$
- **label set**: S_0ws_r; S_0ps_r; S_0ws_l; S_0ps_l; N_0ws_l; N_0ps_l

From feature template to feature vector

distance
S_0wd; S_0pd; N_0wd; N_0pd; S_0wN_0wd; S_0pN_0pd;
valency
S_0wv_r; S_0pv_r; S_0wv_l; S_0pv_l; N_0wv_l; N_0pv_l;
unigrams
$S_{0h}w$; $S_{0h}p$; S_0l; $S_{0l}w$; $S_{0l}p$; $S_{0l}l$; $S_{0r}w$; $S_{0r}p$; $S_{0r}l$; $N_{0l}w$; $N_{0l}p$; $N_{0l}l$;
third-order
$S_{0h2}w$; $S_{0h2}p$; $S_{0h}l$; $S_{0l2}w$; $S_{0l2}p$; $S_{0l2}l$; $S_{0r2}w$; $S_{0r2}p$; $S_{0r2}l$; $N_{0l2}w$; $N_{0l2}p$; $N_{0l2}l$; $S_0pS_{0l}pS_{0l2}p$; $S_0pS_{0r}pS_{0r2}p$; $S_0pS_{0h}pS_{0h2}p$; $N_0pN_{0l}pN_{0l2}p$;
label set
S_0ws_r; S_0ps_r; S_0ws_l; S_0ps_l; N_0ws_l; N_0ps_l;



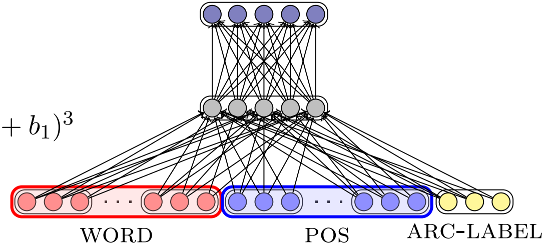
word representation x^w

Neural transition-based parsing (Chen and Manning 2014)

"softmax" layer
$p \propto \exp(W_2 h)$

hidden layer $g = (\cdot)^3$
$h = (W_1^w x^w + W_1^t x^t + W_1^l x^l + b_1)^3$

Input layer: $[x^w, x^t, x^l]$



Cube activation function

Using $g(x) = x^3$ can model the product terms of x_i, x_j, x_k for any three different elements at the input layer directly.

Neural transition-based parsing (Chen and Manning 2014)

English parsing to Stanford Dependencies

- Unlabeled attachment score (UAS): #{correct head}/#{total head}
- Labeled attachment score (LAS): #{correct head with correct label}/#{total head}

Parser	UAS	LAS	sent./s
MaltParser	89.8	87.2	469
MSTParser	91.4	88.1	10
TurboParser	92.3	89.6	8
C & M 2014	92.0	89.7	654

- The first simple, successful neural dependency parser
- The dense representations let it outperform other greedy parsers in both accuracy and speed
- Neural networks can accurately determine the structure of sentences, supporting interpretation

from Stanford CS224N/Ling284

Some General Comments on Neural NLP

Idea: Deep learning simplifies machine learning

- Why has deep learning taken over NLP?
- Deep learning simplifies the design of probabilistic models, by replacing complex dependencies and independence assumptions with universal function approximators.
- Deep learning gives us representation learning: data representations are learned rather than engineered.
- Learned representations are easy to obtain and reusable, enabling multi-task learning.
- Deep learning provides a uniform, flexible, trainable framework that can easily mix and match different data types: strings, labels, trees, graphs, data, and images.

In short: deep learning solves the difficulties of applying machine learning to NLP... it does not solve NLP, which is still difficult!

from A Lopez' slide

Observations of NNLP (so far): positives

- Really important change in state-of-the-art for many applications: e.g., language models for speech. Now the default approach for many tasks.
- Multi-modal experiments are now much more feasible.
- Models are learning structure with out hand-crafting of features.
- Structure learned for one task (e.g.,prediction) applicable to others with limited training data.
- Lots of toolkits etc
- Huge space of new models, far more research going onin NLP, far more industrial research . . .

Observations of NNLP (so far): negatives

- Models are made as powerful as possible to the point they are "barely possible to train or use" (`http://www.deeplearningbook.org` 16.7).
- Tuning hyperparameters is a matter of much experimentation.
- Statistical validity of results often questionable.
- Many myths, massive hype and almost no publication of negative results: but there are some NLP tasks where deep learning is not giving much improvement in results.
- Weird results: e.g., '33rpm' normalized to 'thirty two revolutions per minute'
  `https://arxiv.org/ftp/arxiv/papers/1611/1611.00068.pdf`
- Adversarial examples

New methodology required for NLP?

- Perspective here is applied machine learning, e.g. Collobert et al (2011)
  natural language processing from scratch
- Methodological issues are fundamental to deep learning: e.g., subtle biases in training data will be picked up.
- Old tasks and old data possibly no longer appropriate.
- The lack of predefined interpretation of the latent variables is what makes the models more flexible/powerful . . .
- but the models are usually not interpretable by humans after training: serious practical and ethical issues.

Readings

- D Chen and C Manning. 2014. A Fast and Accurate Dependency Parser using Neural Networks. `www.aclweb.org/anthology/D14-1082/`