Lexical alignment: feature-rich models

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Content

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Position parameterisation $L^2 \times M^2$ Jump distribution [Vogel et al., 1996]

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- The categorical distribution is defined for jumps ranging from $-L$ to L
  The jump function defines the support of the alignment distribution
- A jump quantifies a notion of mismatch in linear order between French and English
  Leads to a very small number of parameters, $2 \times L$

IBM 2 EM

$N \leftarrow$ number of sentence pairs
$I \leftarrow$ number of iterations
$\boldsymbol{\lambda} \leftarrow$ lexical parameters
$\boldsymbol{\gamma} \leftarrow$ alignment parameters

for $i \in [1, \dots, I]$ **do**
    E step:
    $n(\lambda_{\mathsf{e},\mathsf{f}}) \leftarrow 0 \qquad \forall(\mathsf{e}, \mathsf{f}) \in V_E \times V_F$
    $n(\gamma_x) \leftarrow 0 \qquad \forall x \in [-L, L]$
    for $s \in [1, \dots, N]$ **do**
        for $j \in [1, \dots, m^{(s)}]$ **do**
            for $i \in [0, \dots, l^{(s)}]$ **do**
                $x \leftarrow \text{jump}(i, j, l^{(s)}, m^{(s)})$
                $n(\lambda_{e_i,f_j}) \leftarrow n(\lambda_{e_i,f_j}) + \frac{\lambda_{e_i,f_j} \times \gamma_x}{\sum_{k=0}^{l} \lambda_{e_k,f_j} \times \gamma_{\text{jump}(k,j,l^{(s)},m^{(s)})}}$
                $n(\gamma_x) \leftarrow n(\gamma_x) + \frac{\lambda_{e_i,f_j} \times \gamma_{\text{jump}(i,j,l,m)}}{\sum_{k=1}^{l} \lambda_{e_k,f_j} \times \gamma_{\text{jump}(k,j,l^{(s)},m^{(s)})}}$
            end for
        end for
    end for

    M step:
    $\lambda_{\mathsf{e},\mathsf{f}} \leftarrow \frac{n(\lambda_{\mathsf{e},\mathsf{f}})}{\sum_{\mathsf{f}' \in V_F} n(\lambda_{\mathsf{e},\mathsf{f}'})} \qquad \forall(\mathsf{e}, \mathsf{f}) \in V_E \times V_F$
    $\gamma_x \leftarrow \frac{n(\gamma_x)}{\sum_{x' \in [-L,L]} n(\gamma_{x'})} \qquad \forall x \in [-L, L]$
end for

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- It is not strictly convex, where multiple parameter settings that achieve the same global optima
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- In practice, one usually starts from uniform parameters. [Toutanova and Galley, 2011] show better initialisations

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- Changing weights may change in the component distributions and the other way around.
- In practice, one initialises the component distributions of IBM2 (i.e. its translation parameters) with IBM1 estimates.
- The alignment distributions are initialised uniformly. Notice we first have to train IBM1 before proceeding to IBM2

Content

IBM 1-2: strong assumptions

Independence assumptions

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Parameterisation

- categorical events are unrelated
  prefixes/suffixes: normal, normally, abnormally, ...
  verb inflections: comer, comi, comia, comio, ...
  gender/number: gato, gatos, gata, gatas, ...

Conditional probability distributions

CPD: condition $c \in \mathcal{C}$, outcome $o \in \mathcal{O}$, and $\theta_c \in \mathbb{R}^{|\mathcal{O}|}$

$$p(o|c) = \mathrm{Cat}(\theta_c) \tag{1}$$

- $p(o|c) = \theta_{c,o}$

How bad is it for IBM model 1?

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- $\sum_o \theta_{c,o} = 1$
- $O(|c| \times |o|)$ parameters

How bad is it for IBM model 1?

Probability tables

$$p(f|e)$$

English ↓	French →			
	anormal	normal	normalmente	...
abnormal	0.7	0.1	0.01	...
normal	0.01	0.6	0.2	...
normally	0.001	0.25	0.65	...

- grows with size of vocabularies
- no parameter sharing

Logistic CPDs

CPD: condition $c \in \mathcal{C}$ and outcome $o \in \mathcal{O}$

$$p(o|c) = \frac{\exp(w^\top h(c, o))}{\sum_{o'} \exp(w^\top h(c, o'))} \tag{2}$$

- $w \in \mathbb{R}^d$ is a weight vector
- $h : C \times O \to R^d$ is a feature function
- d parameters
- computing CPD requires $O(|c| \times |o| \times d)$ operations

How bad is it for IBM model 1?

CPDs as functions

$$h : \mathcal{E} \times F \to R^d$$

EVENTS ↓		FEATURES →				
ENGLISH	FRENCH	**normal** **normal**	*normal-* *normal-*	-normal -normal	ab- a-	-ly -mente
abnormal	anormal	0	0	1	1	0
	normal	0	0	1	0	0
	*normal*mente	0	1	0	0	0
normal	anormal	0	0	1	0	0
	normal	1	0	0	0	0
	*normal*mente	0	1	0	0	0
normally	anormal	0	0	1	0	0
	normal	0	1	0	0	0
	*normal*mente	0	1	0	0	1
WEIGHTS →		1.5	0.3	0.3	0.8	1.1

- computation still grows with size of vocabularies
- but far less parameters to estimate

Content

Log-linear models

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  Something about the context that will be useful in predicting
- Enhancing models with features that capture the dependencies between different morphologically inflected word forms. The standard parameterisation using categorical distributions is limited with respect to the features it can capture

Content

Berg-Kirkpatrick et al. [2010]

Lexical distribution in IBM model 1

$$p(f|e) = \frac{\exp(w_{\mathsf{lex}}^{\top} h_{\mathsf{lex}}(e,f))}{\sum_{f'} \exp(w_{\mathsf{lex}}^{\top} h_{\mathsf{lex}}(e,f'))} \tag{3}$$

Features

- $f \in V_F$ is a French word (decision), $e \in V_E$ is an English word (conditioning context), $w \in R^d$ is the parameter vector, and $h : V_F \times V_E \rightarrow R^d$ is a feature vector function.
- prefixes/suffixes
- character n-grams
- POS tags

Extension: lexicalised jump distribution

$$p(\delta|e) = \frac{\exp(w_{\text{dist}}^{\top} h_{\text{dist}}(e, \delta))}{\sum_{\delta'} \exp(w_{\text{dist}}^{\top} h_{\text{dist}}(e, \delta'))} \tag{4}$$

Features

- POS tags
- suffixes/prefixes
- lemma
- jump values
- m, n, j, i (values used to compute jump)

Feature name	Description
word	Whole lexical entry
prefix	Prefix of specified length
suffix	Suffix of specified length
category	Boolean: checks if lexical entry contains digit(s)

Problems with features

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- and e_{t-1} = eat is also compatible (in the context cows eat hay).

farmers eat	steak → **high** hay → **low**	cows eat	steak → **low** hay → **high**
farmers grow	steak → **low** hay → **high**	cows grow	steak → **low** hay → **low**

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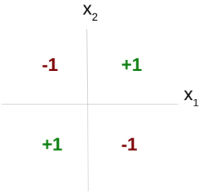
  We need $O(|V|^3)$ parameters for each triplet e_{i-2}, e_{i-1}, e_i
- Learning using these combination features, e.g. neural networks

Content

Function that cannot be solved by a linear transformation

- For example the function $x \in -1, 1$ and outputs $y = 1$ if both x_1 and x_2 are equal and $y = -1$ otherwise.



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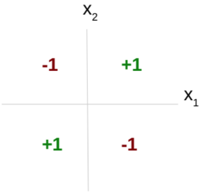

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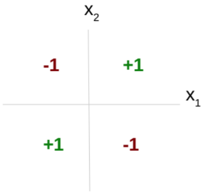

- We can use a linear combination $y = Wx + b$
- Or a multi-layer perceptron:

$$\begin{aligned} h &= step(W_x h_x + b_h) \\ y &= w_{hy} h + b_y. \end{aligned} \tag{5}$$

Function that cannot be solved by a linear transformation

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- Both layers consist of an affine transform using weights W and biases b, followed by a $step()$ function, which calculates the following:

$$step(x) = \begin{cases} 1, & \text{if } x > 0. \\ -1, & \text{otherwise.} \end{cases} \tag{6}$$

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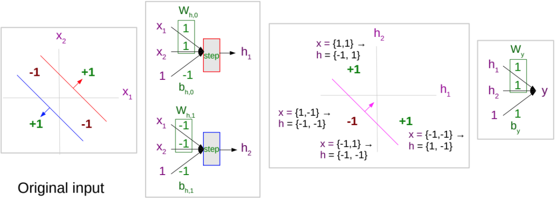

Original input variables | Hidden layer | Transformed variables | Output layer

Training Neural Networks

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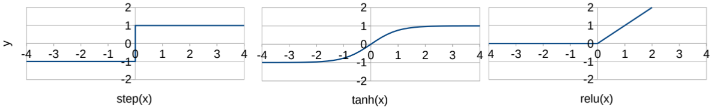
- however the $step()$ function is not very derivative friendly
- We can use non-linear functions, hyperbolic tangent (tanh) function



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- We perform the full calculation of the loss function:

$$
\begin{aligned}
\boldsymbol{h}' &= W_{xh}\boldsymbol{x} + \boldsymbol{b}_h \\
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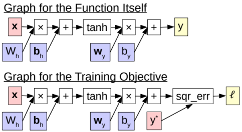

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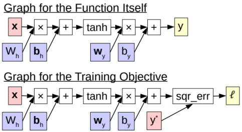

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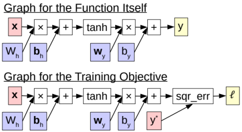

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Content

IBM: non-linear models

Nothing prevents us from using more expressive functions
[Kočiský et al., 2014]

- $p(o|c) = \mathrm{softmax}(f_\theta(c))$

where $f_\theta(\cdot)$ is a neural network with parameters θ
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Features

- induce features (word-level, char-level, n-gram level)
- pre-trained embeddings

Neural IBM

- $f_\theta(e) = \text{softmax}(W_t H_E(e) + b_t)$ note that the softmax is necessary to make t_θ produce valid parameters for the categorical distribution
  $W_t \in \mathbb{R}^{|V_F| \times d_h}$ and $b_t \in \mathbb{R}^{|V_F|}$

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- $h_E(e)$ is defined below with $W_{h_E} \in \mathbb{R}^{d_h \times d_e}$ and $b_{h_E} \in \mathbb{R}^{d_h}$
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- Other architectures are also possible, one can use different parameterisations that may use more or less parameters. For example, with a CNN one could make this function sensitive to characters in the words, something along these lines could also be done with RNNs.

where

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- We can use maximum likelihood estimation (MLE) to choose the parameters of our deterministic function f_θ.

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- IBM1 would be convex with standard tabular CPDs, but FFNNs with 1 non-linear hidden layer (or more) make it non-convex.
- Nowadays, we have tools that can perform automatic differentiation for us.
  If our functions are differentiable, we can get gradients for them.

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- Note that in fact our log-likelihood is a sum of independent terms $\mathcal{L}_j(\theta | e_0^m, f_j)$, thus we can characterise the contribution of each French word in each sentence pair

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- To get a loss, we simply negate our objective.
  You will find a lot of material that mentions some categorical cross-entropy loss.

$$
\begin{aligned}
l(\theta) &= -\sum_{(e_0^m, f_1^l)} p_\star(f_1^l|e_0^m) \log p_\theta(f_1^m|e_0^l) \\
&\approx -\frac{1}{S} \log p_\theta(f_1^l|e_0^m)
\end{aligned}
\tag{8}
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MLE

- With SGD we sample a subset $\mathcal{S}$ of the training data and compute a loss for that sample.

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- We then use automatic differentiation to obtain a gradient $\nabla_\theta l(\theta|\mathcal{S})$. This gradient is used to update our deterministic parameters θ.

$$\theta^{(t+1)} = \theta^{(t)} - \delta_t \nabla_{\theta^{(t)}} l(\theta^{(t)}|\mathcal{S}) \tag{9}$$

References I

Taylor Berg-Kirkpatrick, Alexandre Bouchard-Côté, John DeNero, and Dan Klein. Painless unsupervised learning with features. In *Human Language Technologies: The 2010 Annual Conference of the North American Chapter of the Association for Computational Linguistics*, pages 582–590, Los Angeles, California, June 2010. Association for Computational Linguistics. URL `http://www.aclweb.org/anthology/N10-1083`.

Tomáš Kočiský, Karl Moritz Hermann, and Phil Blunsom. Learning bilingual word representations by marginalizing alignments. In *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 224–229, Baltimore, Maryland, June 2014. Association for Computational Linguistics. URL `http://www.aclweb.org/anthology/P14-2037`.

References II

Kristina Toutanova and Michel Galley. Why initialization matters for ibm model 1: Multiple optima and non-strict convexity. In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies*, pages 461–466, Portland, Oregon, USA, June 2011. Association for Computational Linguistics.

Stephan Vogel, Hermann Ney, and Christoph Tillmann. HMM-based word alignment in statistical translation. In *Proceedings of the 16th Conference on Computational Linguistics - Volume 2*, COLING '96, pages 836–841, Stroudsburg, PA, USA, 1996. Association for Computational Linguistics. doi: 10.3115/993268.993313. URL `http://dx.doi.org/10.3115/993268.993313`.