

# 深層學習

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<https://sites.google.com/site/alaginmt2015/>

# kbest翻訳候補

機械翻訳について勉強したい。

$$\log Pr(\phi|e) \quad \log Pr(e) \quad \log Pr(f, \alpha|\phi)$$

I want to study about machine translation

-2	-3	-4	-9
-3	-4	-4	-11
-2	-5	-1	-8
-5	-2	-3	-10

I need to master machine translation

machine translation want to study

I don't want to learn anything

0.5×-2	0.4×-3	0.2×-4	-3.0
0.5×-3	0.4×-4	0.2×-4	-3.9
0.5×-2	0.4×-5	0.2×-1	-3.2
0.5×-5	0.4×-2	0.2×-3	-3.9

重み付けにより並び替え

# 重み付け



$$\hat{e} = \arg \max_e Pr(f, \alpha | \phi, e) \Pr(\phi | e) \Pr(e)$$

- より一般化:

$$\begin{aligned}\hat{e} &= \arg \max_e \frac{\sum_d \exp (\boldsymbol{w}^\top \boldsymbol{h}(f, d, e))}{\sum_{e', d'} \exp (\boldsymbol{w}^\top \boldsymbol{h}(f, d', e'))} \\ &\approx \arg \max_{\langle e, d \rangle} \boldsymbol{w}^\top \boldsymbol{h}(f, d, e)\end{aligned}\quad (\text{Och and Ney, 2002})$$

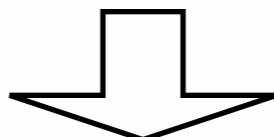
最適化 = 最適な  $\boldsymbol{w}$  を識別学習

# なぜ深層学習?



日本	a japanese		0.272727	0.283379	0.00953895	0.00411563
日本	all over japan		0.222222	0.541131	0.00317965	3.72914e-07
日本	around japan		0.05	0.541131	0.00158983	0.000337958
日本	as some japanese		1	0.283379	0.00158983	5.45274e-07
日本	japan ,		0.0897436	0.541131	0.0111288	0.0225871
日本	japan :		1	0.541131	0.00158983	0.00131649
日本	japan		0.396648	0.541131	0.338633	0.463146
日本	japanese ,		0.0769231	0.283379	0.00158983	0.00557971
日本	japanese		0.242553	0.283379	0.09062	0.114411

素性を試行錯誤で開発



素性を自動的に学習

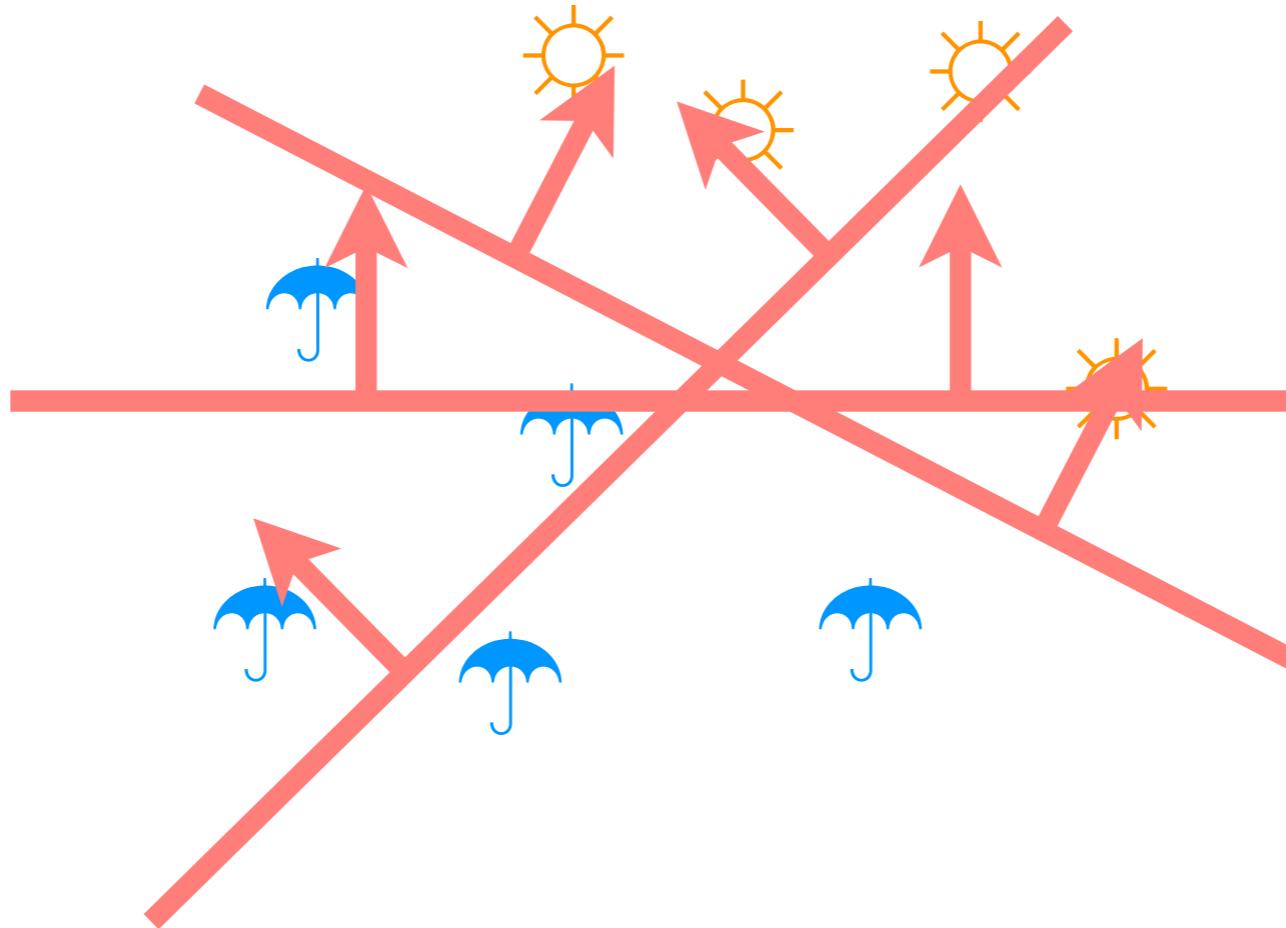
# 機械翻訳への貢献

NIST MT12 Test		
	Ar-En	Ch-En
	BLEU	BLEU
OpenMT12 - 1st Place	49.5	32.6
OpenMT12 - 2nd Place	47.5	32.2
OpenMT12 - 3rd Place	47.4	30.8
...	...	...
OpenMT12 - 9th Place	44.0	27.0
OpenMT12 - 10th Place	41.2	25.7
Baseline (w/o RNNLM)	48.9	33.0
Baseline (w/ RNNLM)	49.8	33.4
+ S2T/L2R NNJM (Dec)	51.2	34.2
+ S2T NNLT M (Dec)	52.0	34.2
+ T2S NNLT M (Resc)	51.9	34.2
+ S2T/R2L NNJM (Resc)	52.2	34.3
+ T2S/L2R NNJM (Resc)	52.3	34.5
+ T2S/R2L NNJM (Resc)	52.8	34.7
“Simple Hier.” Baseline	43.4	30.1
+ S2T/L2R NNJM (Dec)	47.2	31.5
+ S2T NNLT M (Dec)	48.5	31.8
+ Other NNJMs (Resc)	49.7	32.2

(Devlin et al., 2014)

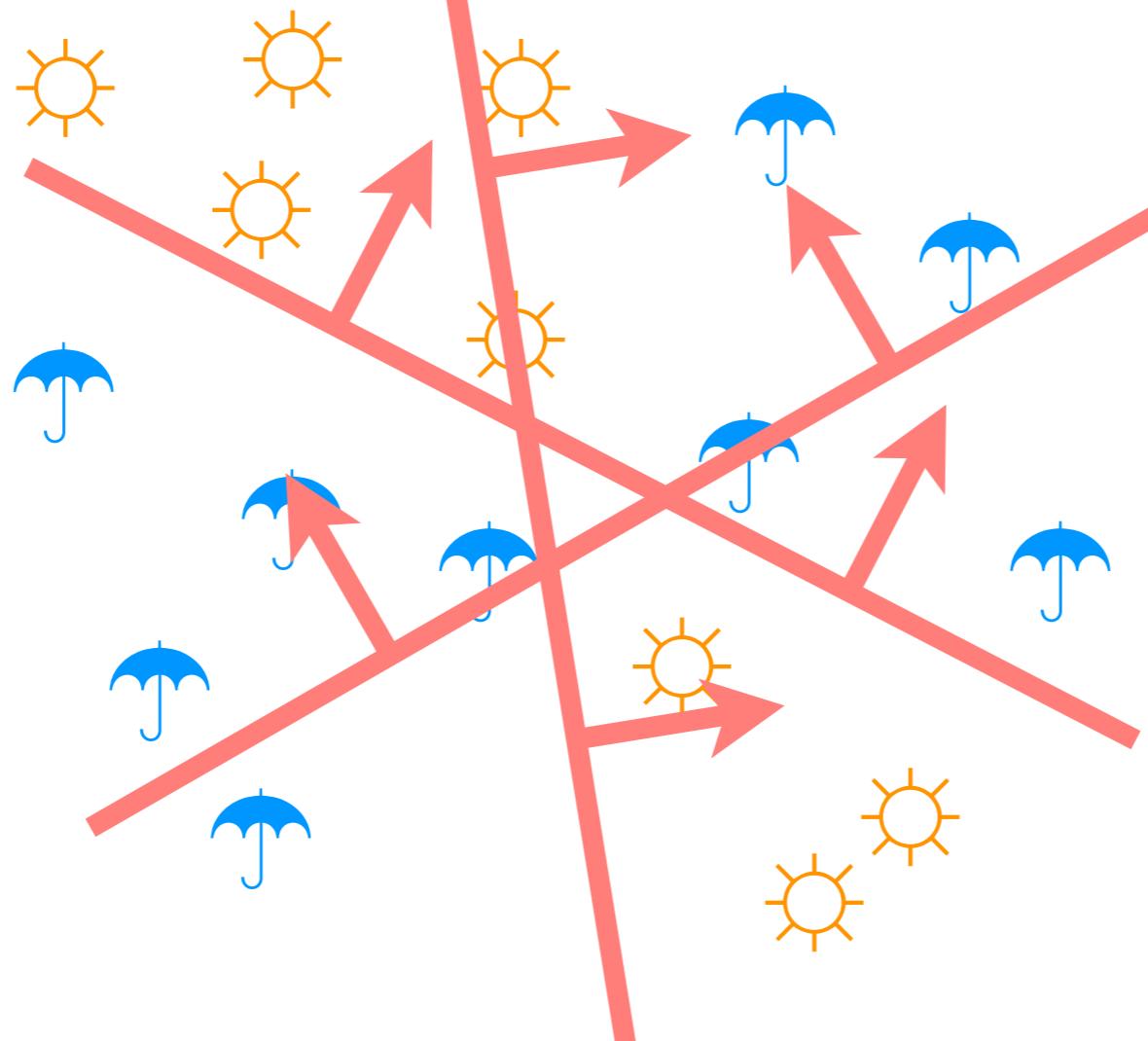
# 背景

# 線形分類



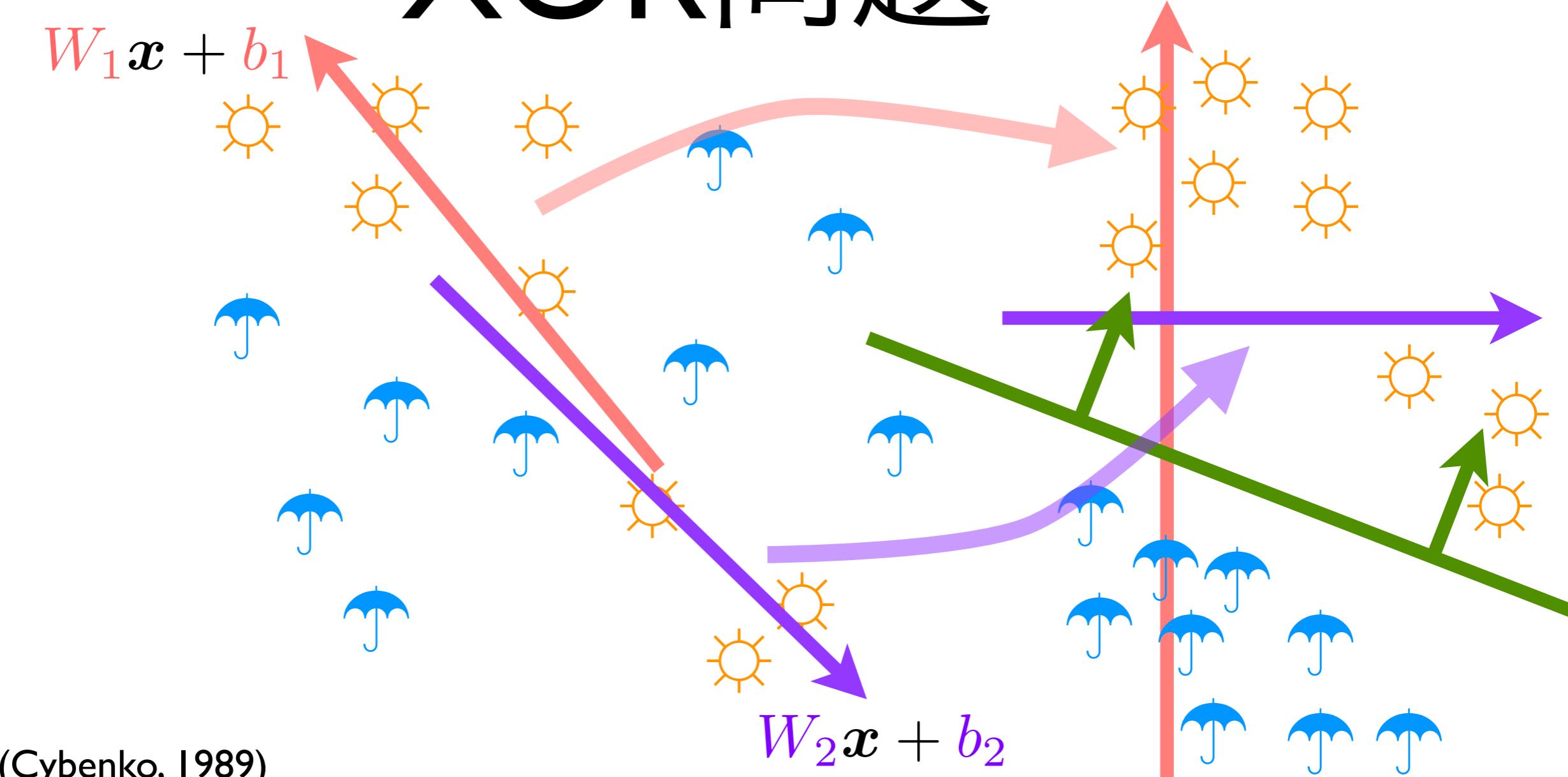
- 線形モデルで識別可能:  $y = \text{sign}(Wx + b)$

# XOR問題



- 線形モデルで解けない

# XOR問題

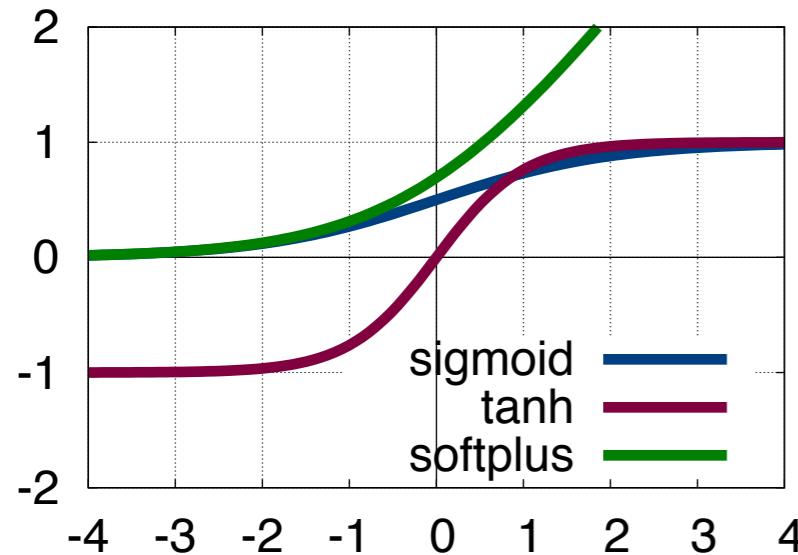


(Cybenko, 1989)

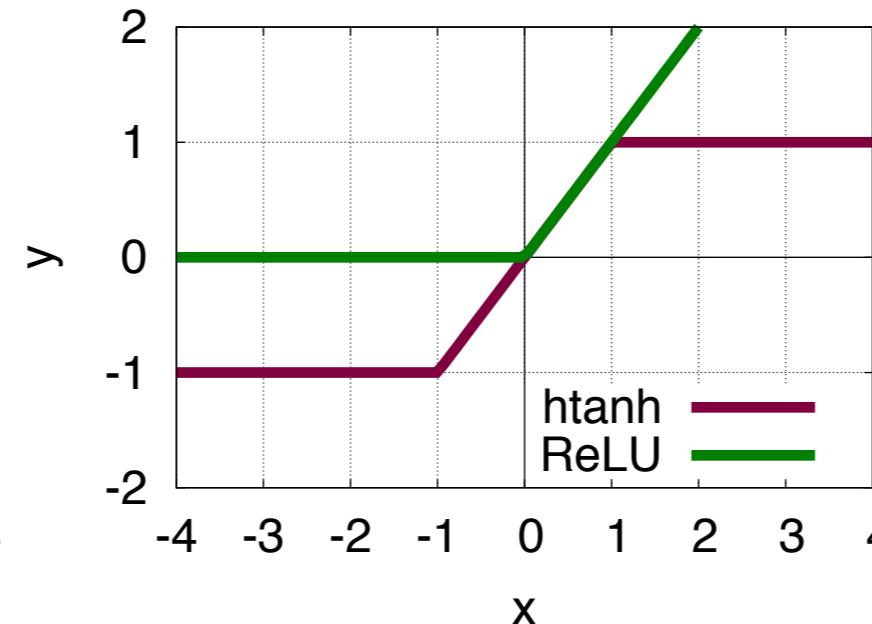
- 複数の座標変換 + 線形分類

$$y = \text{sign} \left( W_3 \begin{bmatrix} f(W_2x + b_2) \\ f(W_1x + b_1) \end{bmatrix} + b_3 \right)$$

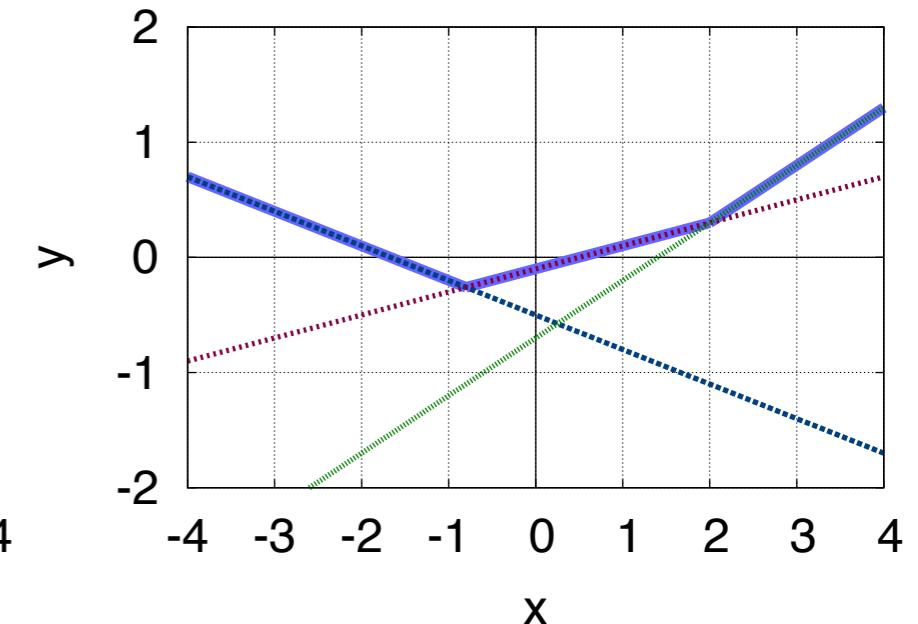
# 活性化関数



sigmoid/tanh/  
softplus



htanh/ReLU



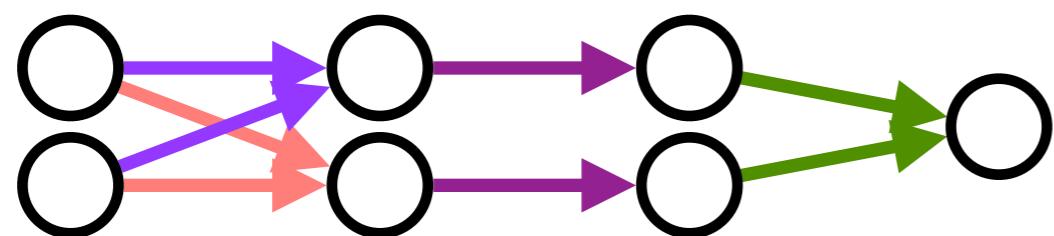
maxout

(Goodfellow et al., 2013)

- 非線形な変換による柔軟な設計

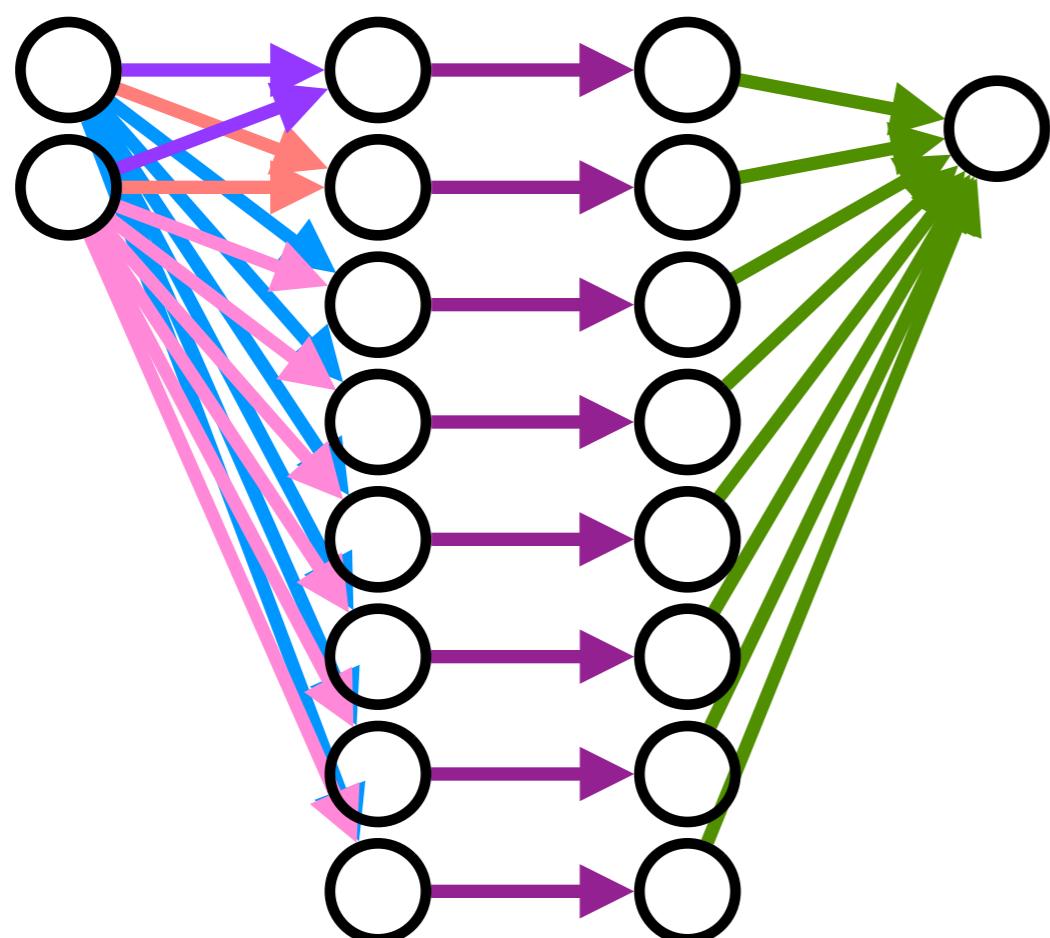
# ニューラルネットワーク

入力 写像 活性化 出力



# ニューラルネットワーク

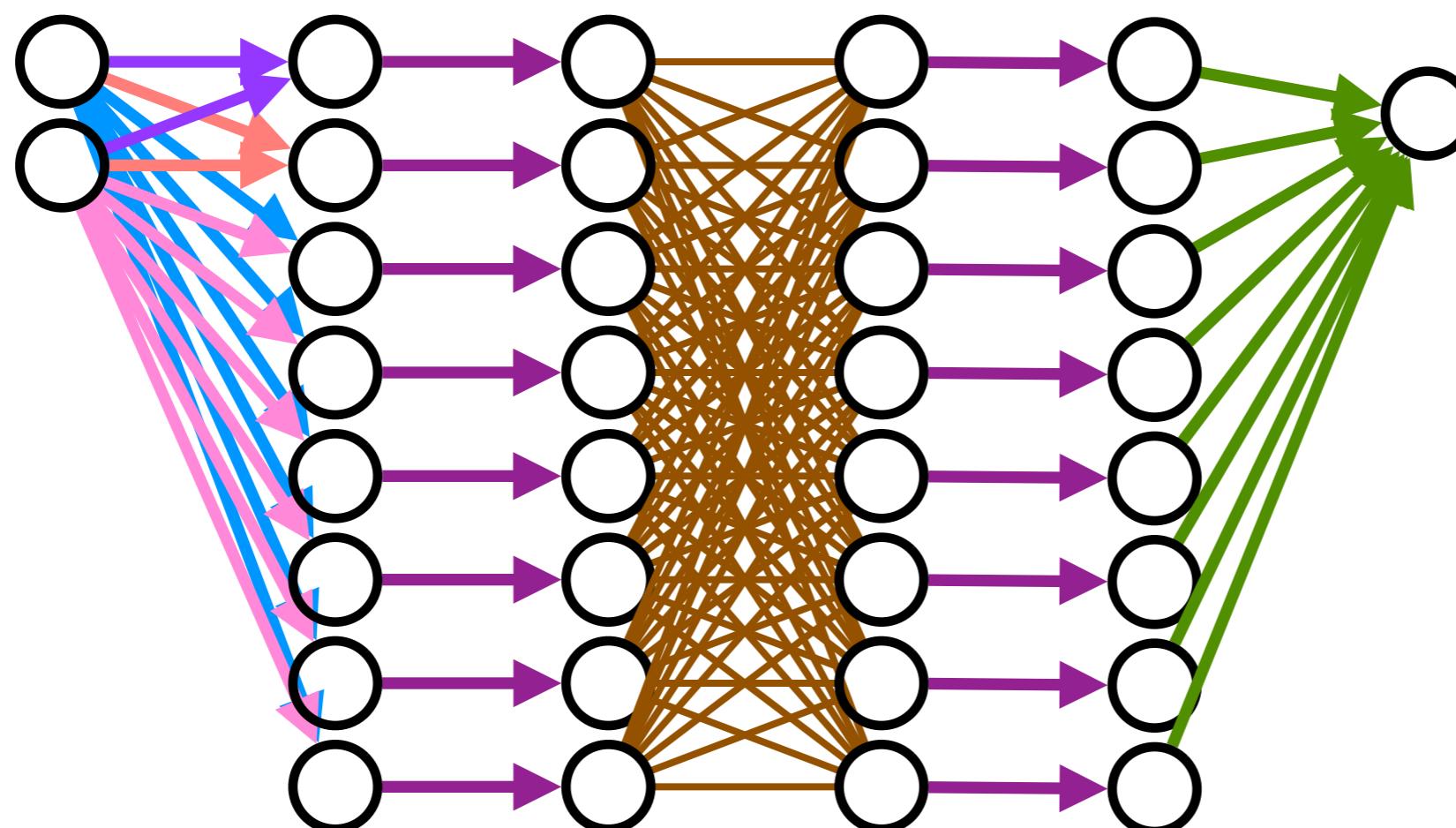
入力 写像 活性化 出力



多次元化

# ニューラルネットワーク

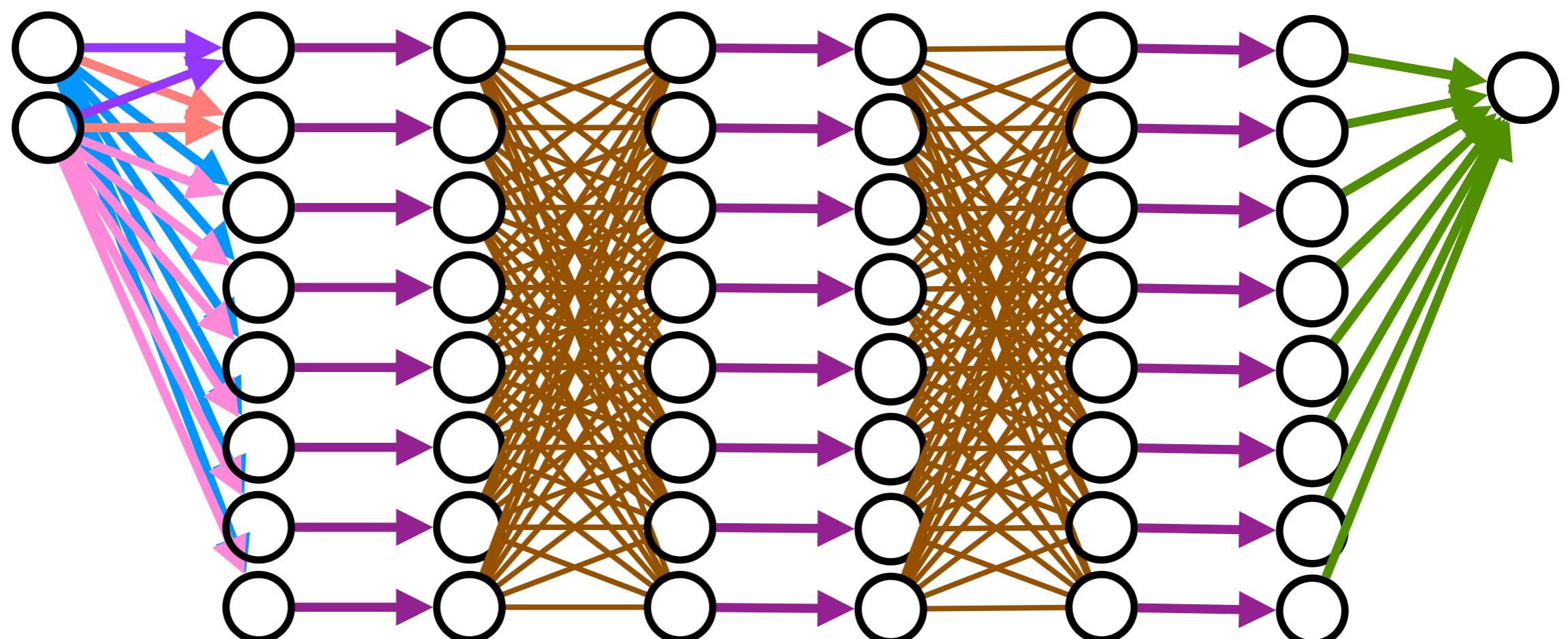
入力 写像 活性化 写像 活性化 出力



多次元化+多層化

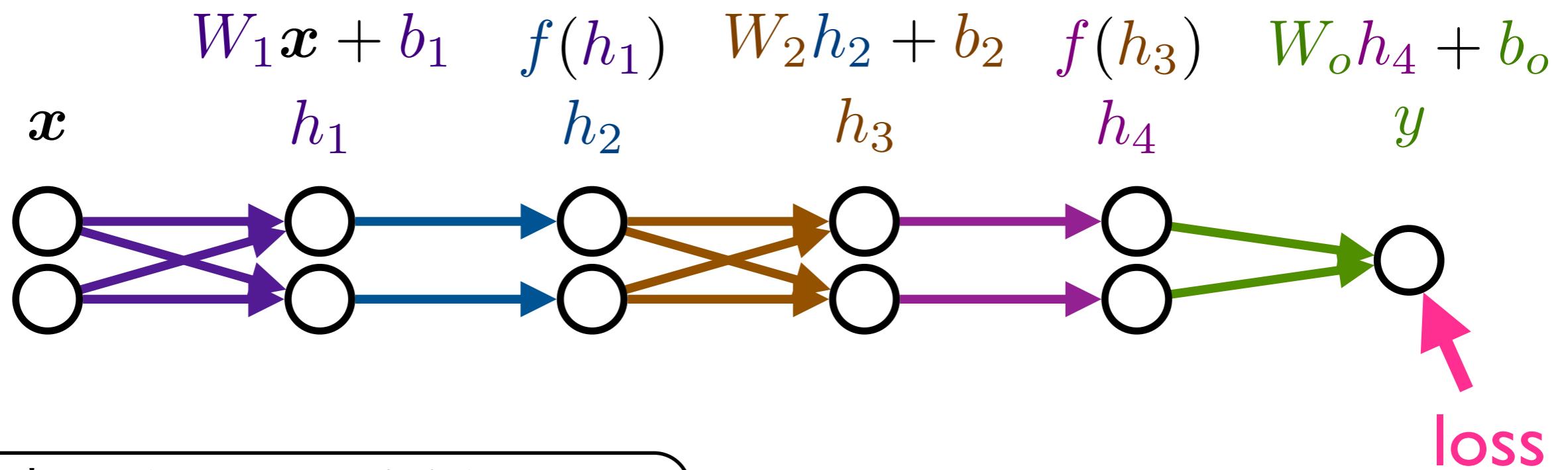
# ニューラルネットワーク

入力 写像 活性化 写像 活性化 写像 活性化 出力



多次元化+多層化+多層化

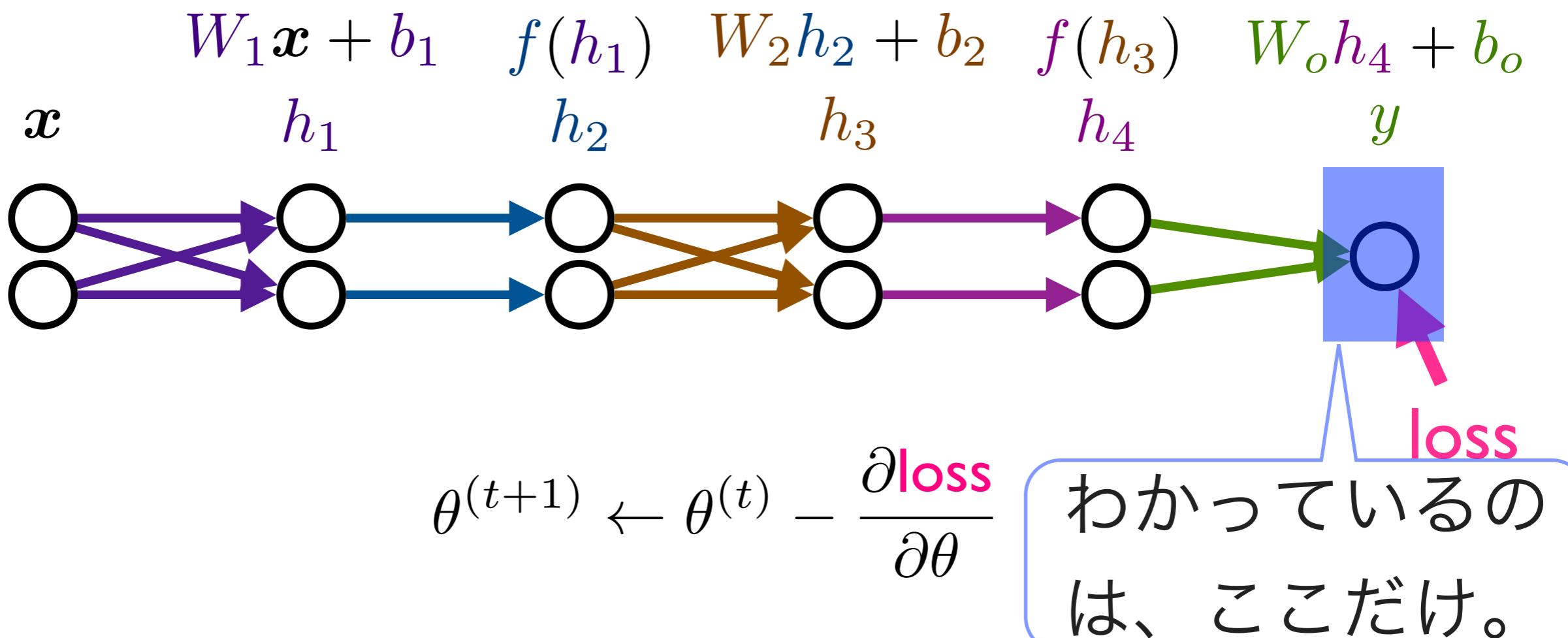
# 学習



晴れなら+1、曇なら-1

- 学習データ( $x, \text{label}$ )の $x$ からネットワークを計算
- 損失を計算: 例、hinge損失:  $\max(0, 1 - \text{label} * y)$

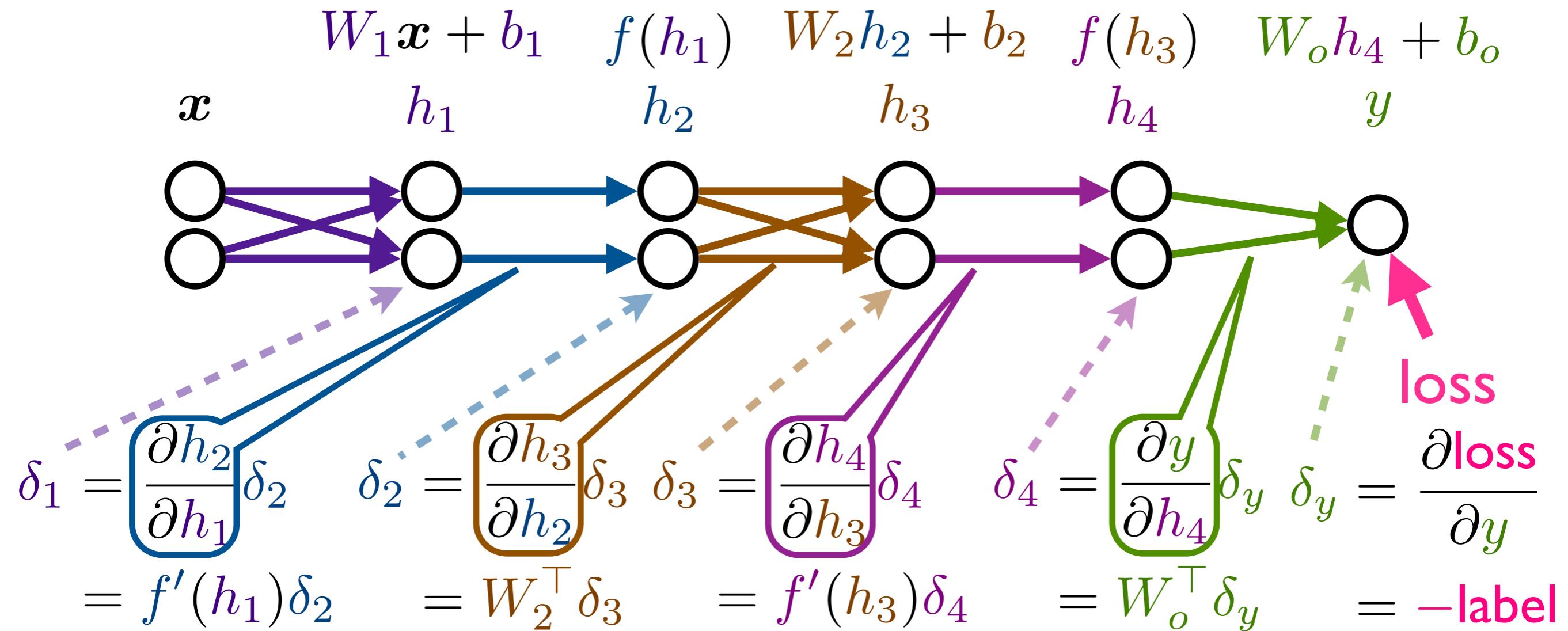
# 最適化



- 例:  $t$ 番目の学習データが与えられた時、

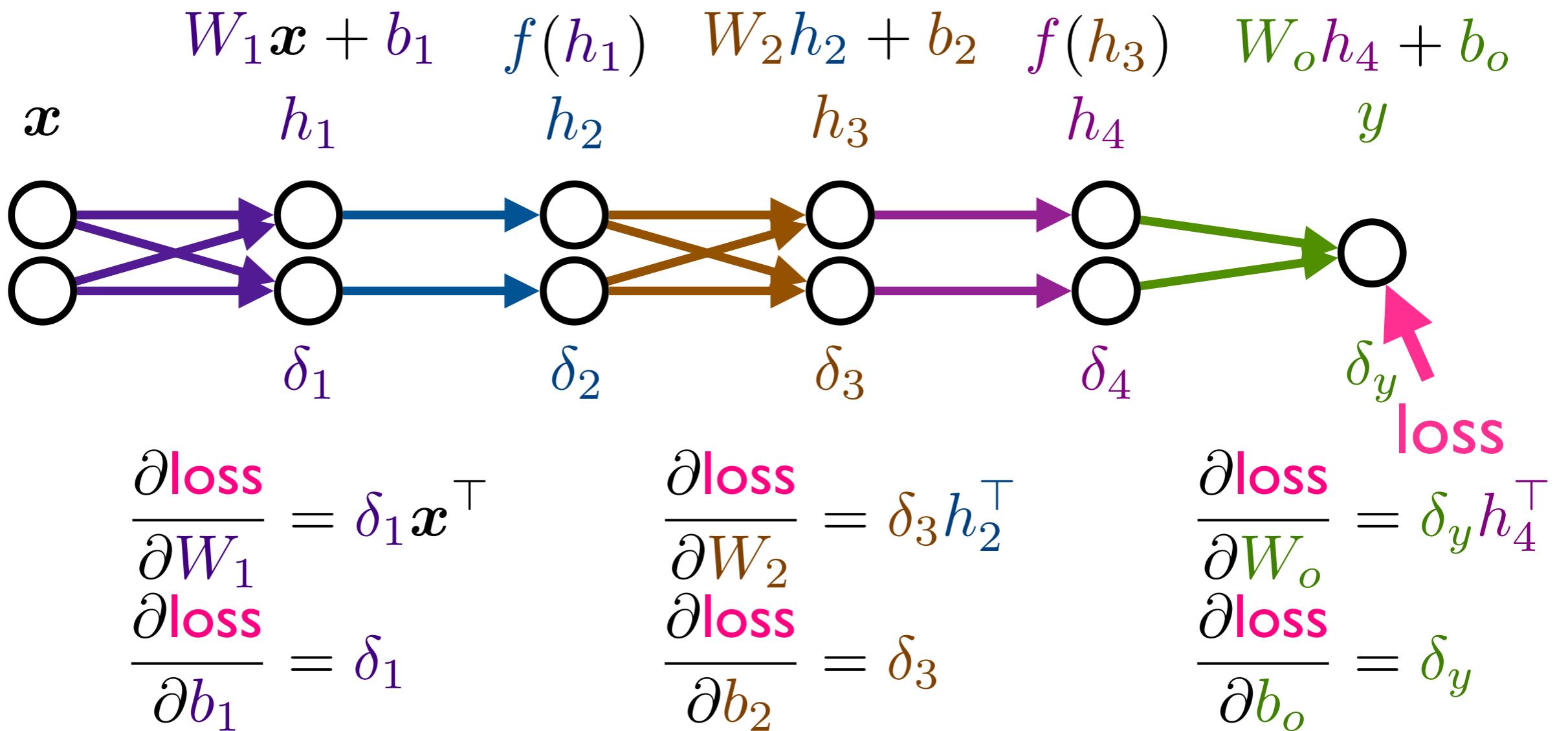
SGDで更新:  $\Theta = \{W_1, b_1, W_2, b_2, W_o, b_o\}$

# 伝搬



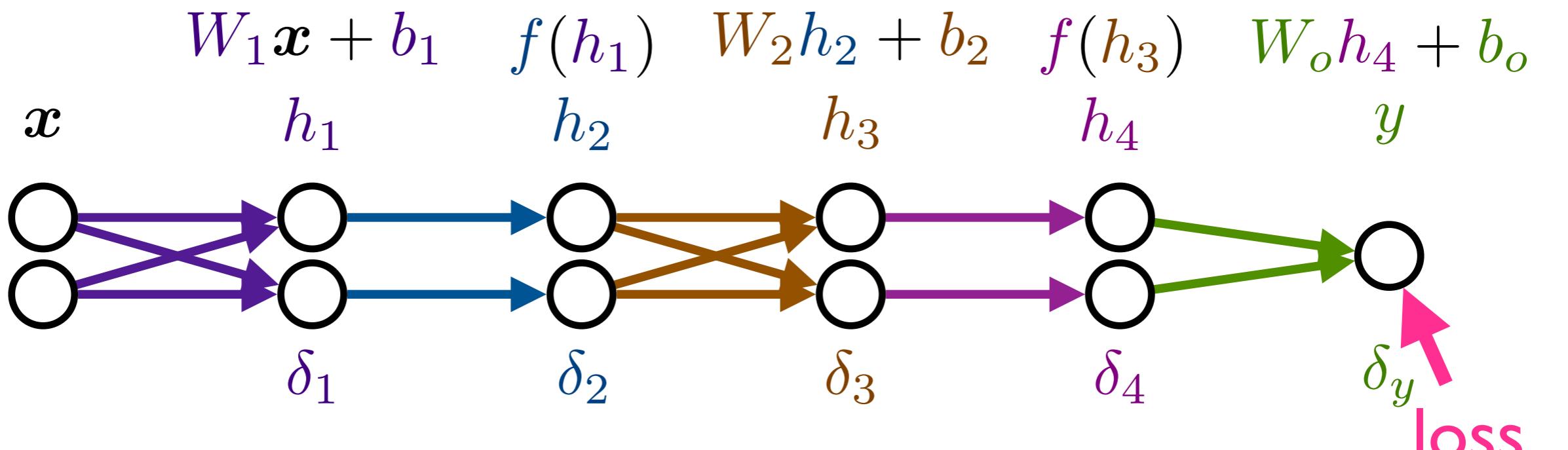
- 損失は一番上の層で計算: 下層へ伝搬

# 勾配



- 各層の $\delta$ から各層毎にパラメータの勾配を計算

# 更新



$$W_2^{(t+1)} \leftarrow W_2^{(t)} - \frac{\partial \text{loss}}{\partial W_2} \quad W_o^{(t+1)} \leftarrow W_o^{(t)} - \frac{\partial \text{loss}}{\partial W_o}$$

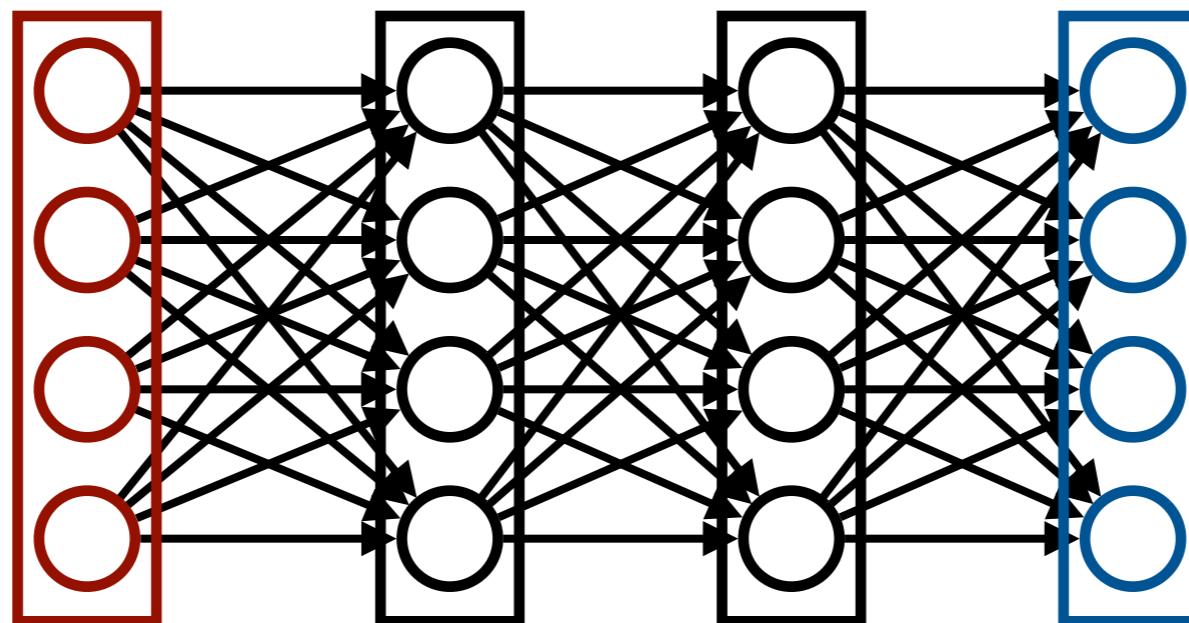
$$b_2^{(t+1)} \leftarrow b_2^{(t)} - \frac{\partial \text{loss}}{\partial b_2} \quad b_2^{(t+1)} \leftarrow b_2^{(t)} - \frac{\partial \text{loss}}{\partial b_2} \quad b_o^{(t+1)} \leftarrow b_o^{(t)} - \frac{\partial \text{loss}}{\partial b_o}$$

- 各パラメータを更新

# 注

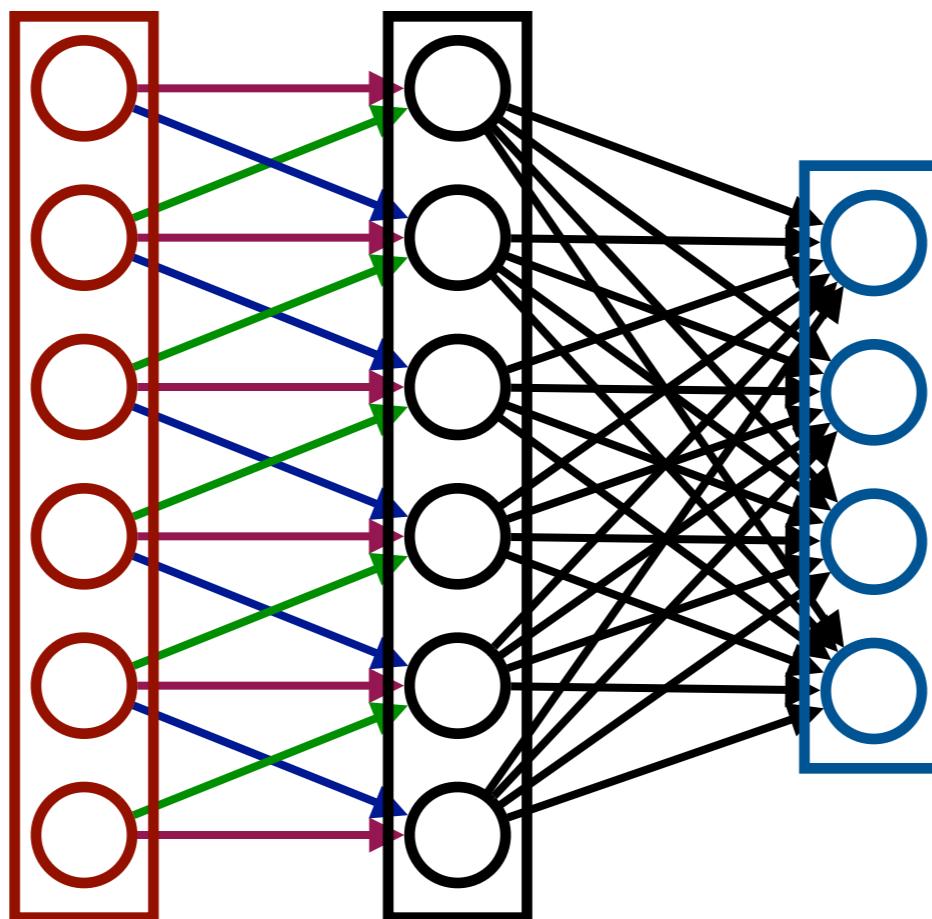
- SGDの代わりに:AdaGrad、AdaDelta、Adam
- 過学習しやすい:DropOut、正則化、事前学習
- 学習に時間が掛かる:オンライン学習、mini-batch、GPU

# Feed-Forward NN



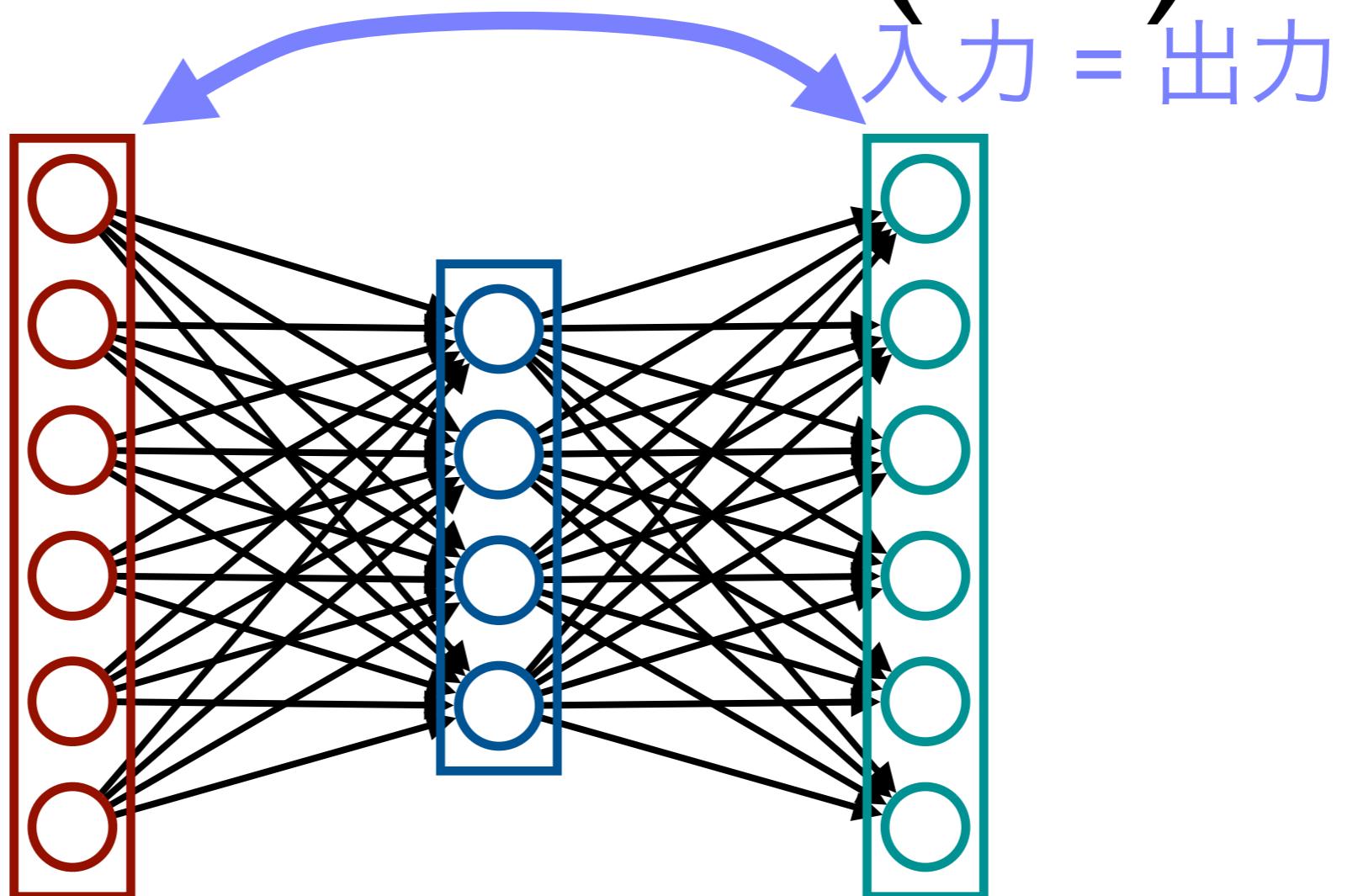
- いわゆる(?)ニューラルネットワーク
- 注意: 簡潔にするため活性化関数を省略

# Convolution



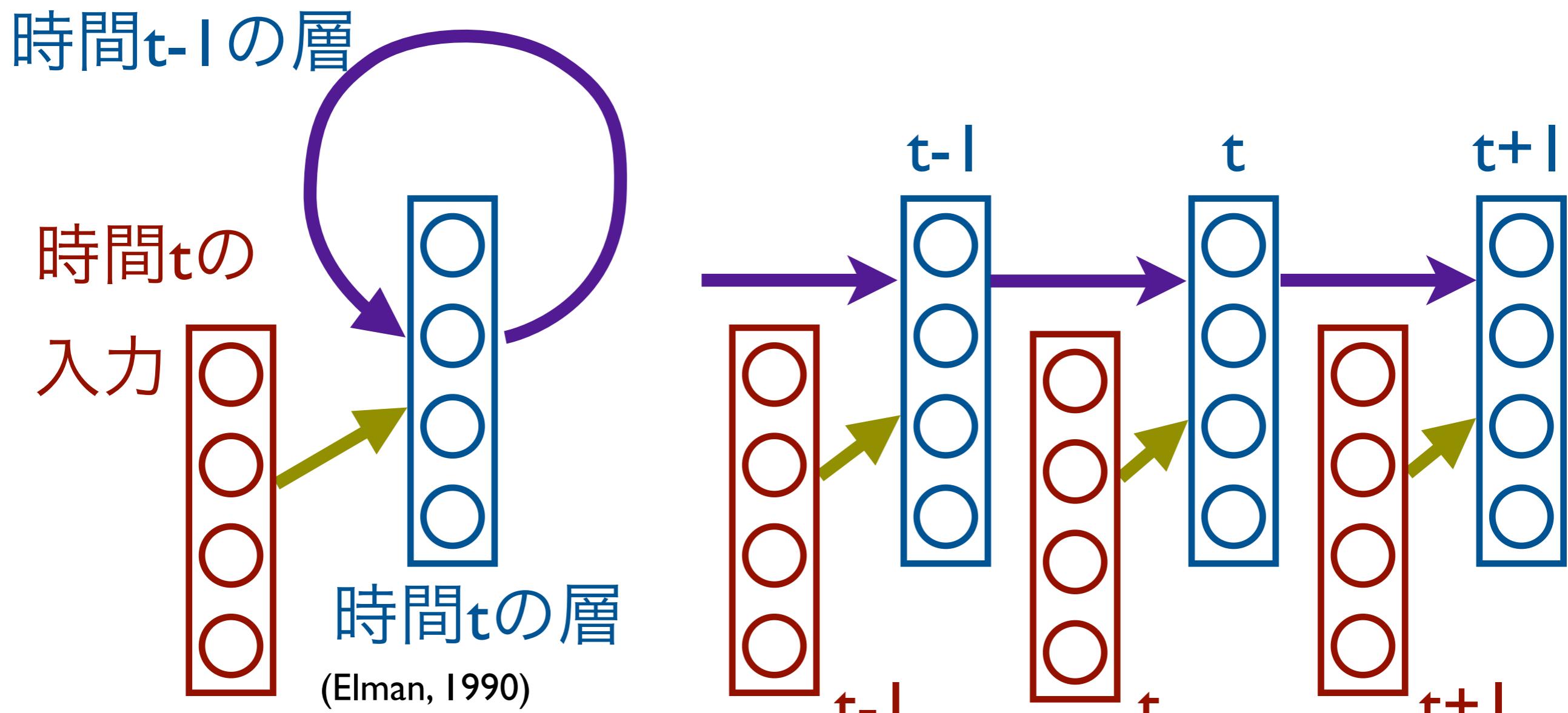
- 局所的に各層を接続(同じ向きでパラメータを共有)+次元数を減らす(pooling)

# Autoencoder (AE)



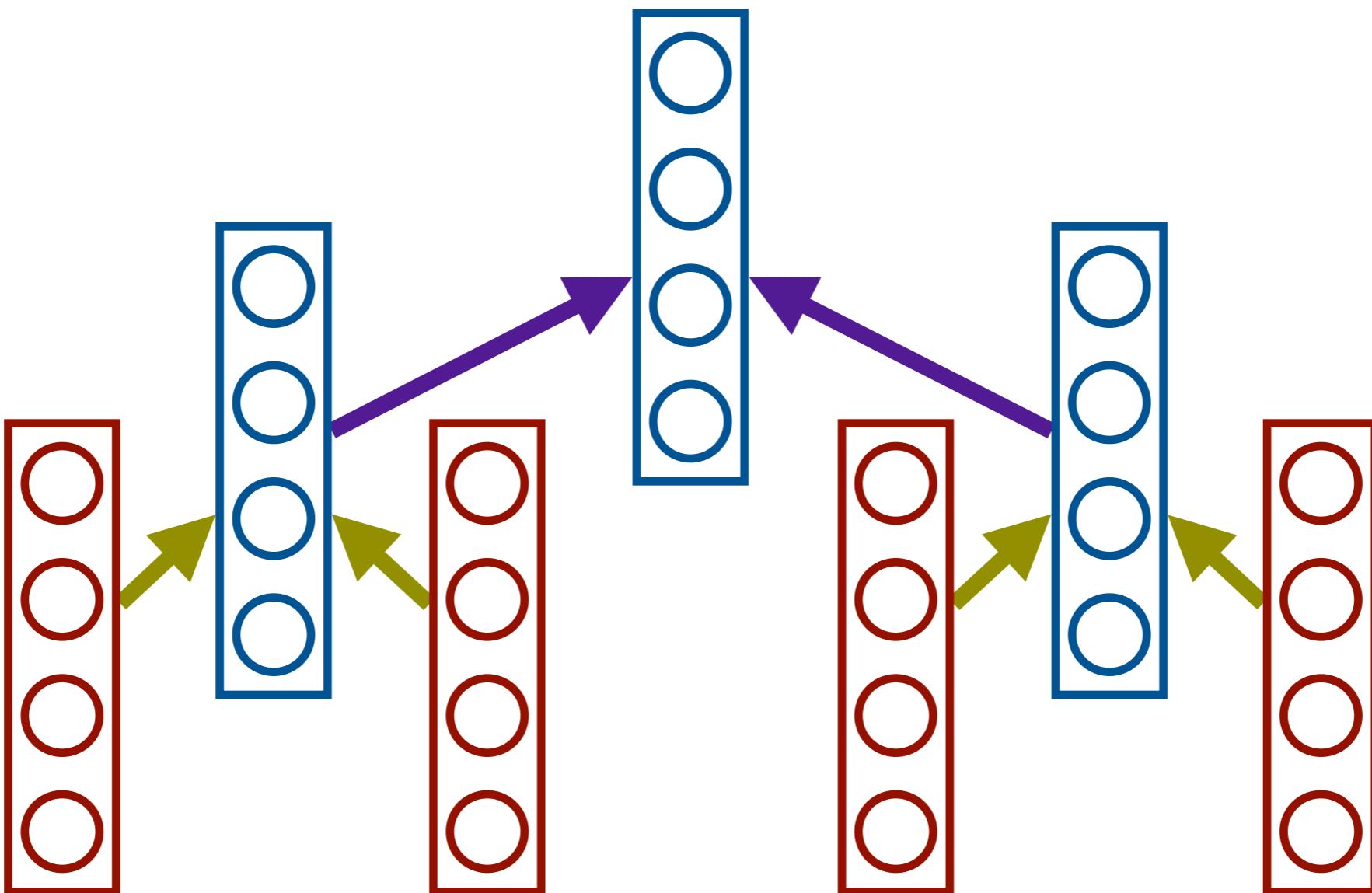
- 隠れ層から入力を再現するように学習
- 教師なし学習が可能

# Recurrent NN



- 系列をモデル化
- 注意: 簡潔にするため細かい接続を無視

# Recursive NN



(Pollack, 1990)

- 任意の構造(例、木構造)をモデル化

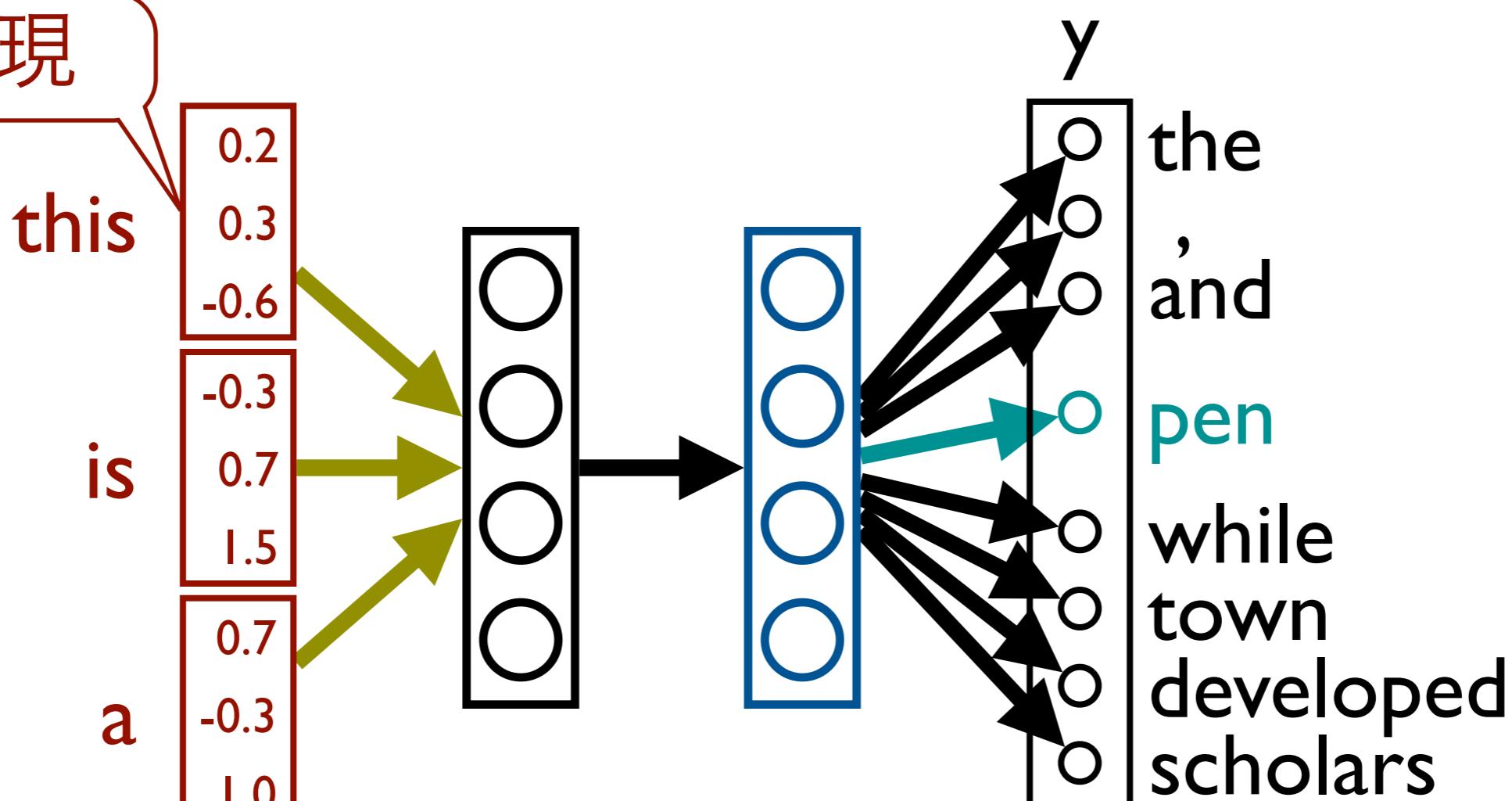
# 機械翻訳への応用

- 言語モデル
- 翻訳モデル
- 単語アライメント

言語モデル

# FFNN 言語モデル

分散表現



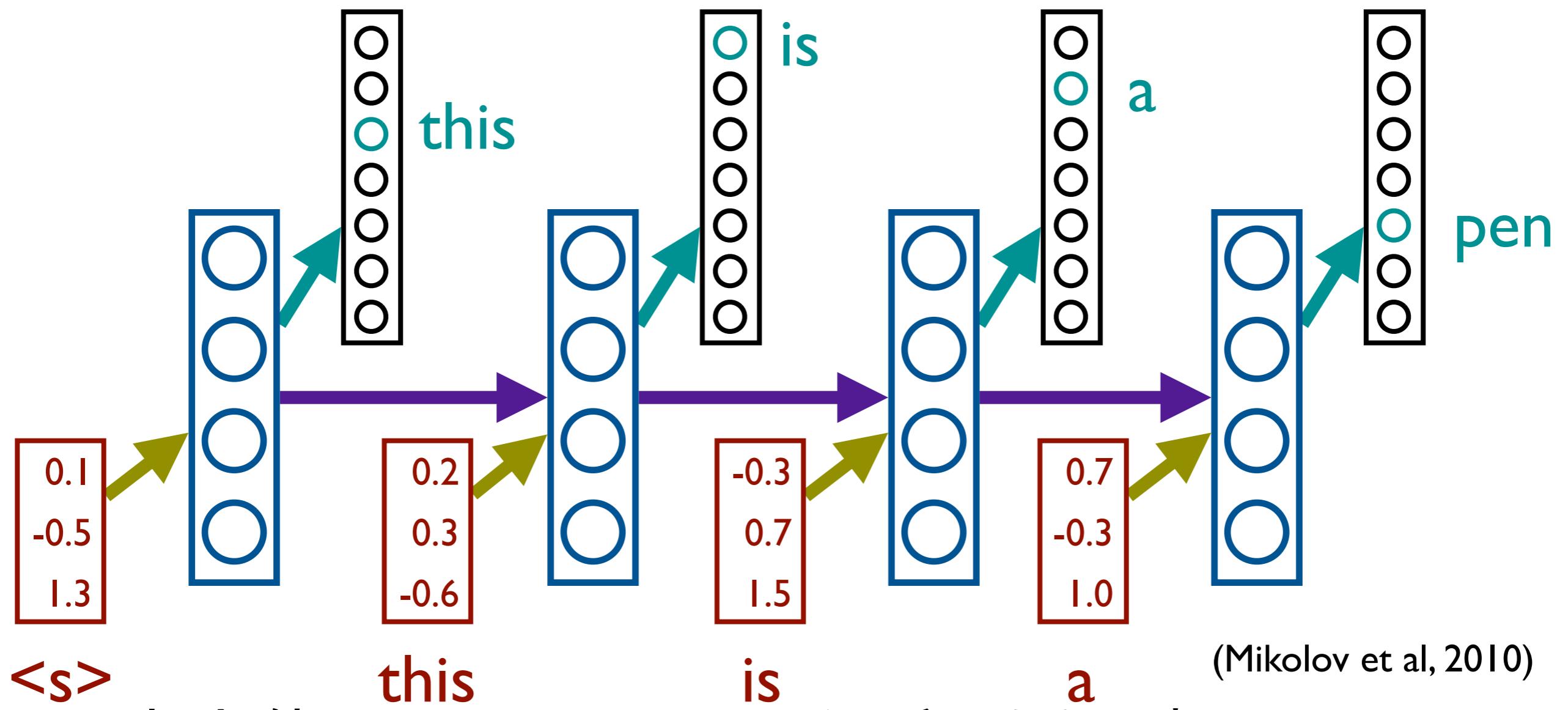
(Schwenk, 2007)

- softmaxによる出力層

$$Pr(\text{pen}|\text{this is a}) = \frac{\exp(y_{\text{pen}})}{\sum_{w \in \mathcal{V}} \exp(y_w)}$$

全ての単語について $\Sigma$ を計算

# Recurrent NN 言語モデル

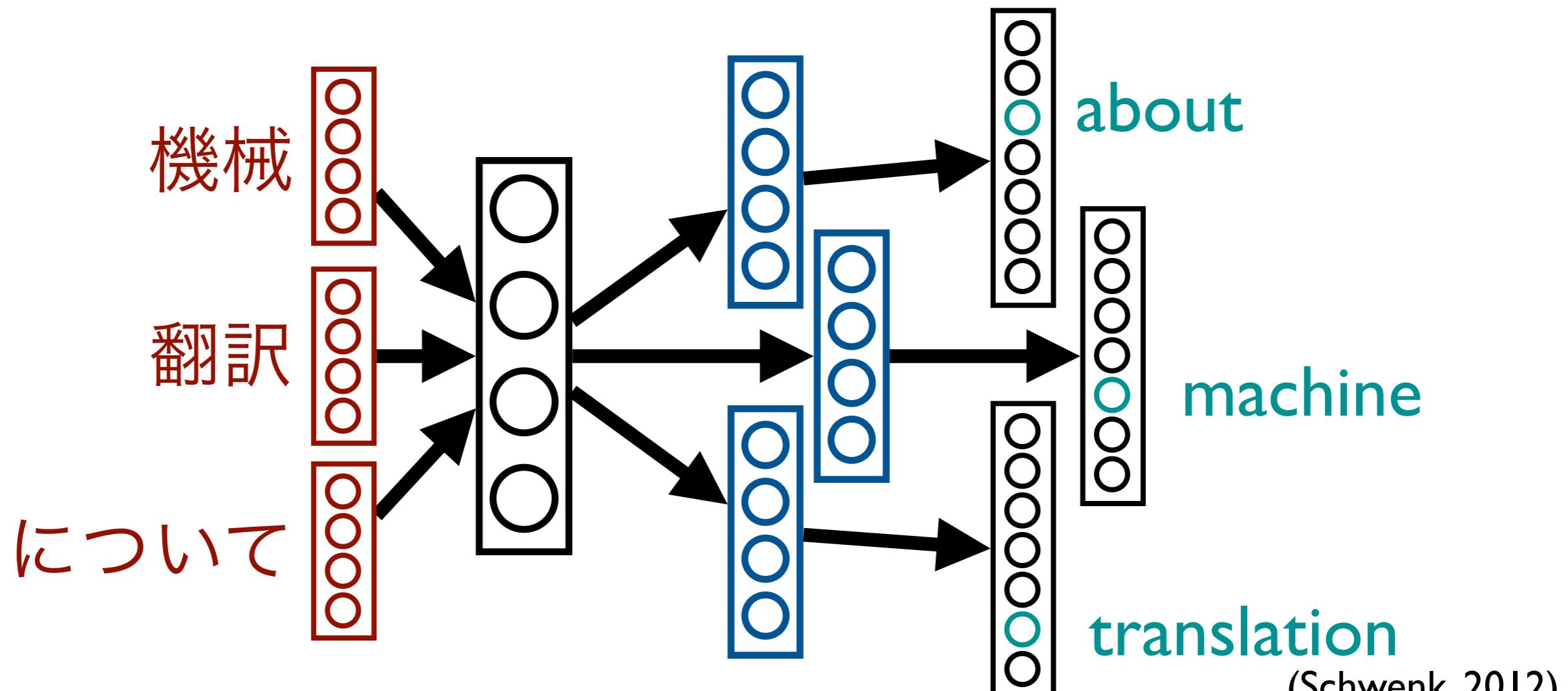


- 文全体のコンテキストを隠れ層で表現

- 近似的にデコーダの素性として使用可能

# 翻訳モデル

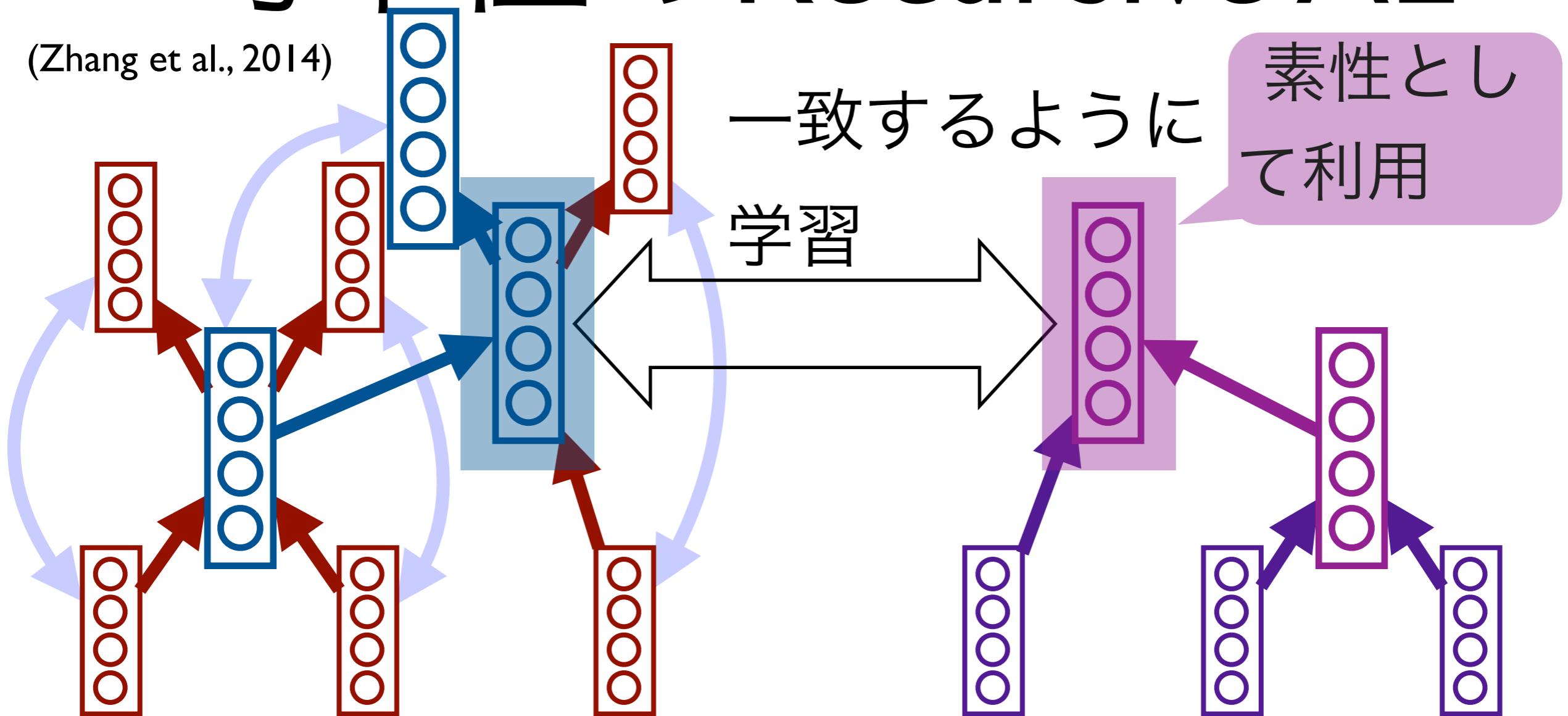
# 句単位のFFNN



- FFNN言語モデルと同様な学習法
- 問題点: 従来法により句を抽出するため、改善は少ない

# 句単位のRecursive AE

(Zhang et al., 2014)

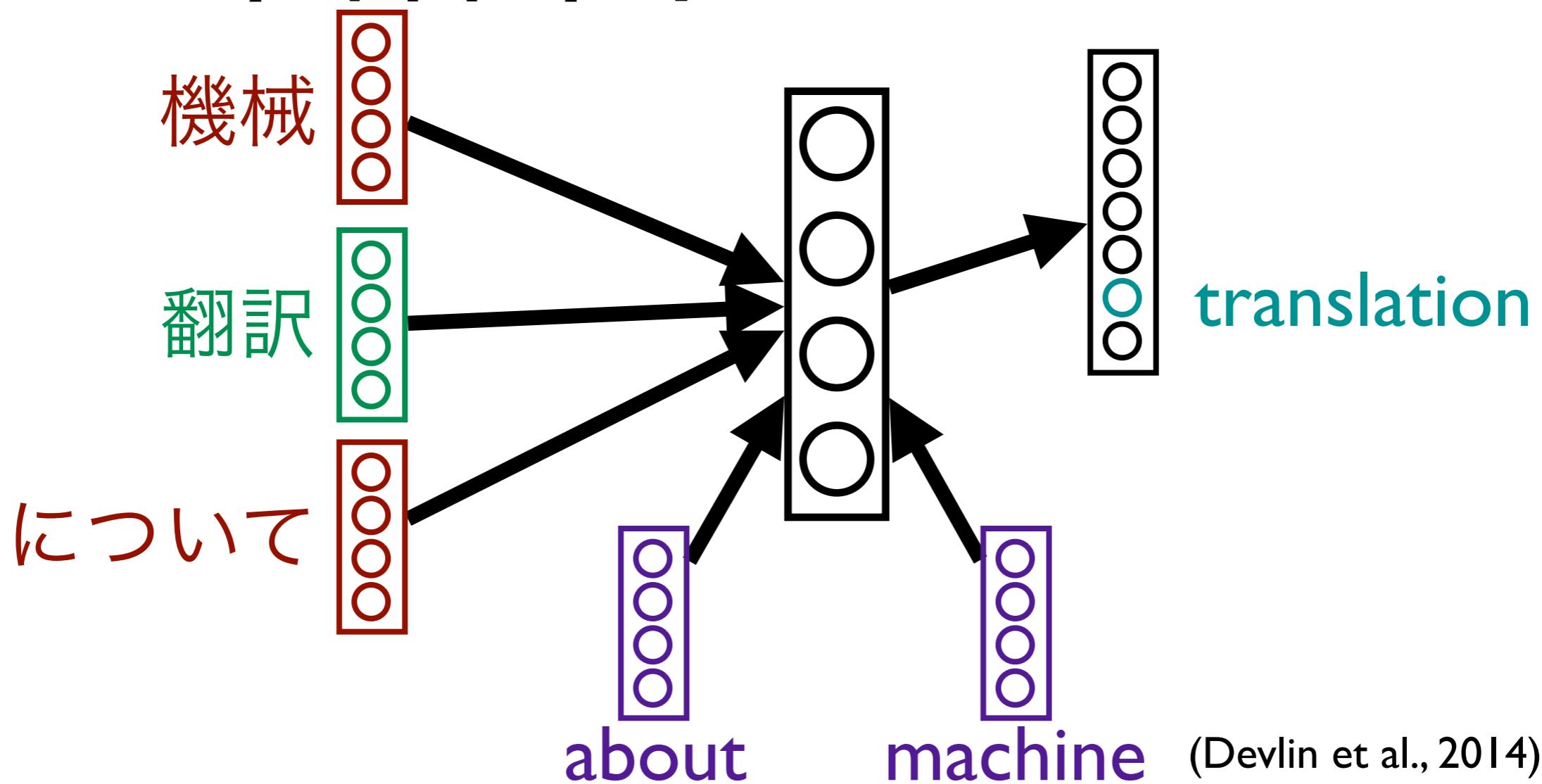


機械 翻訳 について

about machine translation

- 各言語独立にRecursive AEのエラーが最小になる木構造を推定

# 単語単位のFFNN

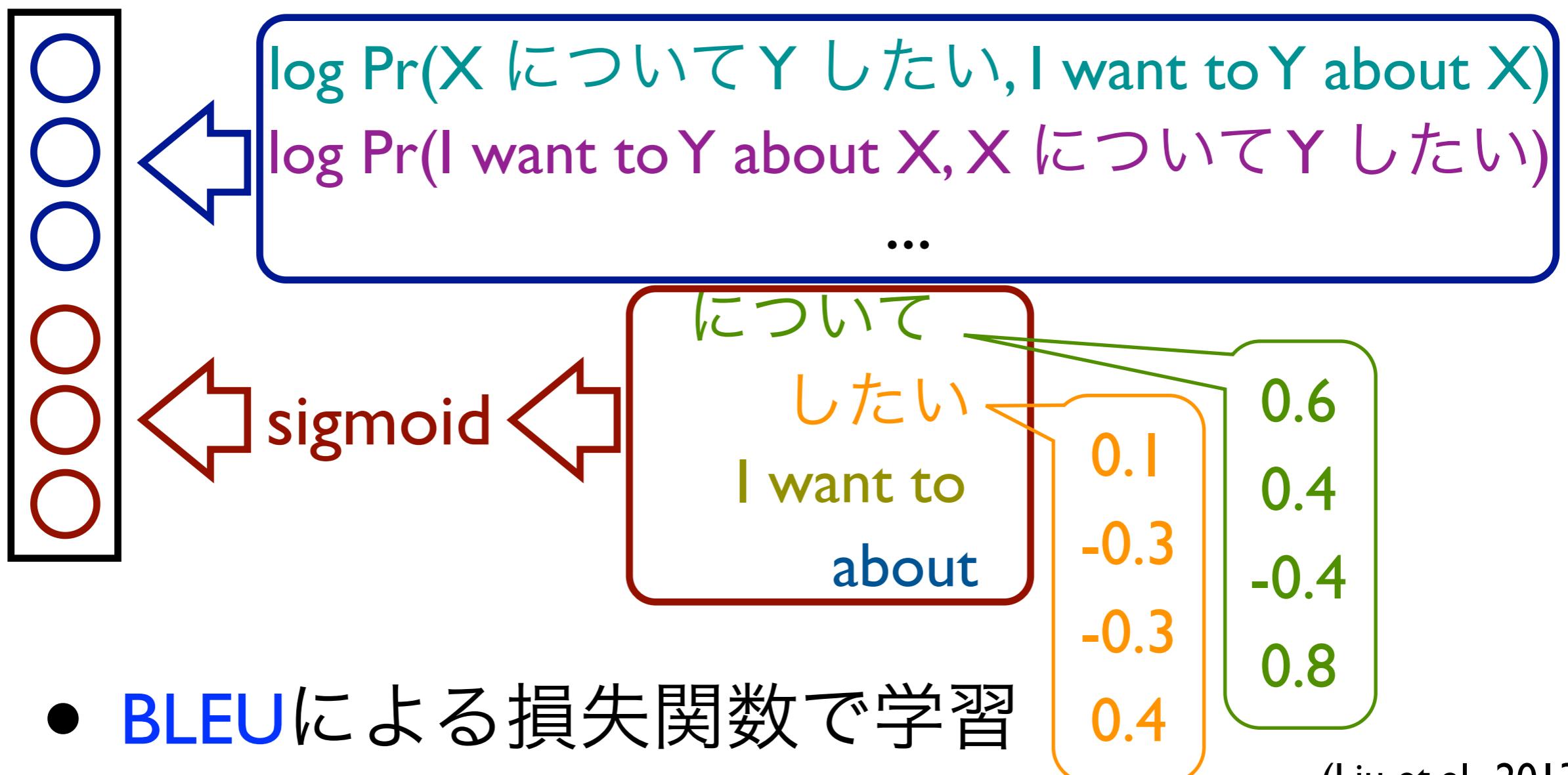


$$Pr(\text{translation} | \text{about machine}, \text{機械翻訳について})$$

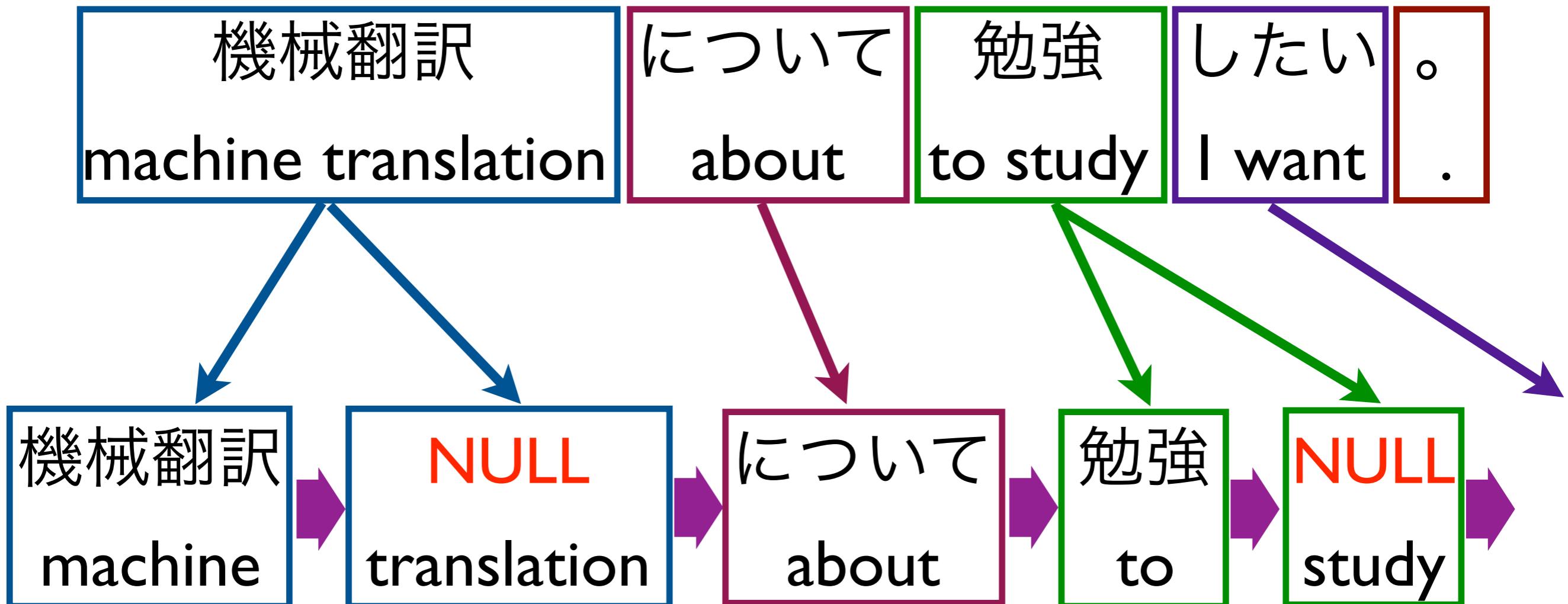
- 単語アライメント単位の計算により、句単位の制約を排除

# addNNによるモデル

$h(X \text{について} Y \text{したい}, I \text{ want to } Y \text{ about } X) =$



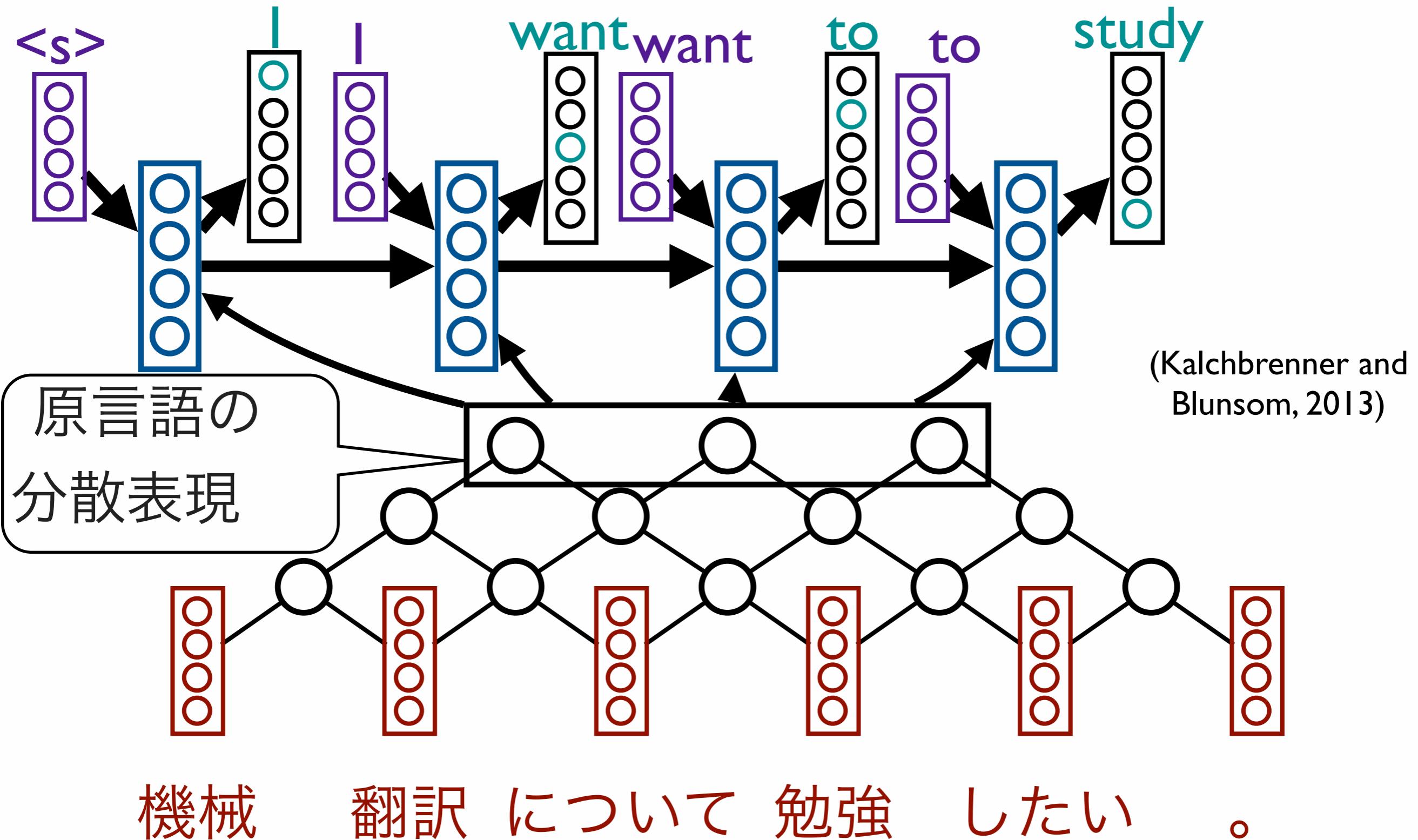
# 句によるRNN



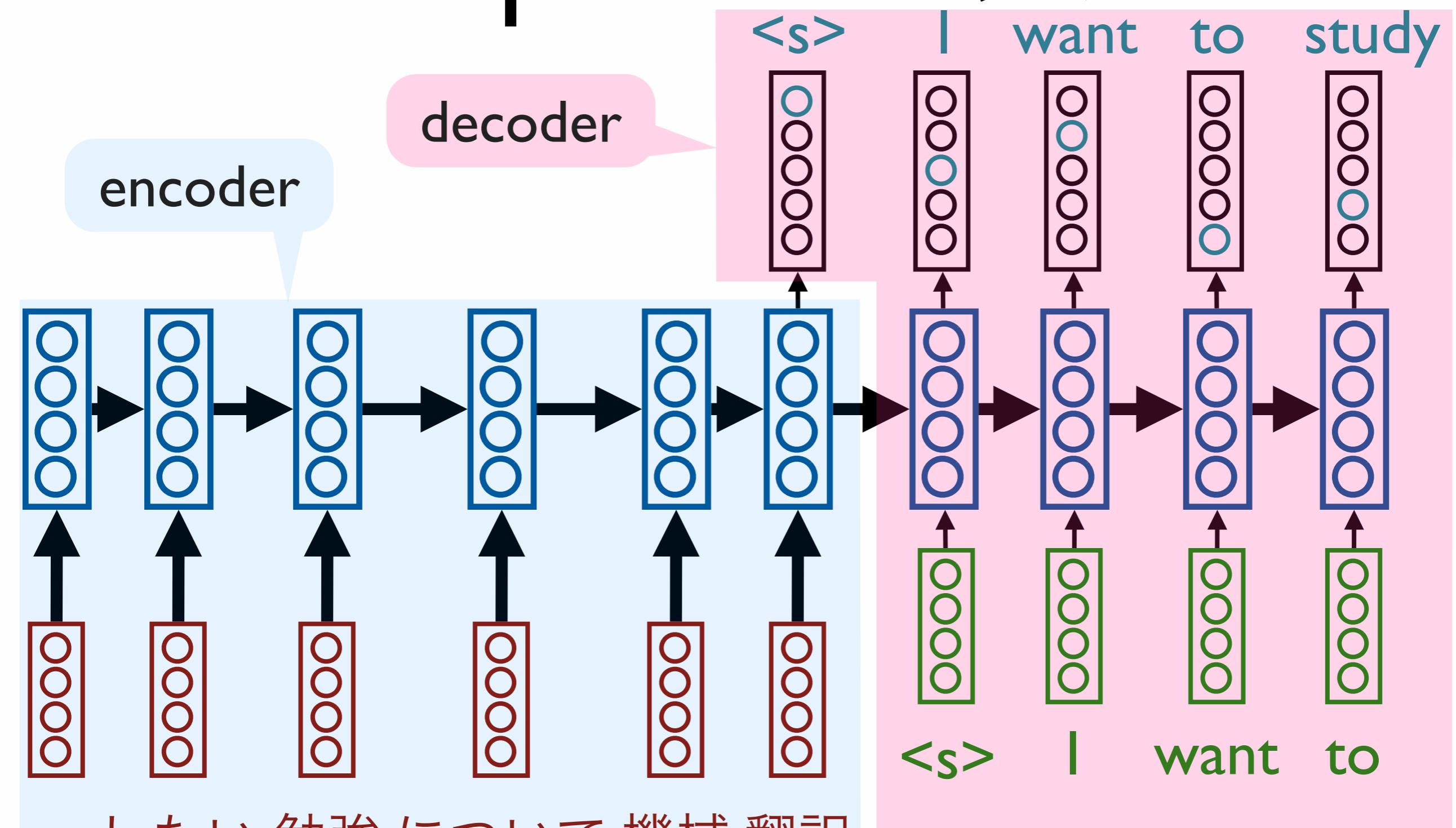
- 句単位のモデルを単語単位に展開

(Wu et al., 2014)

# Convolution+RNN



# Sequenceモデル



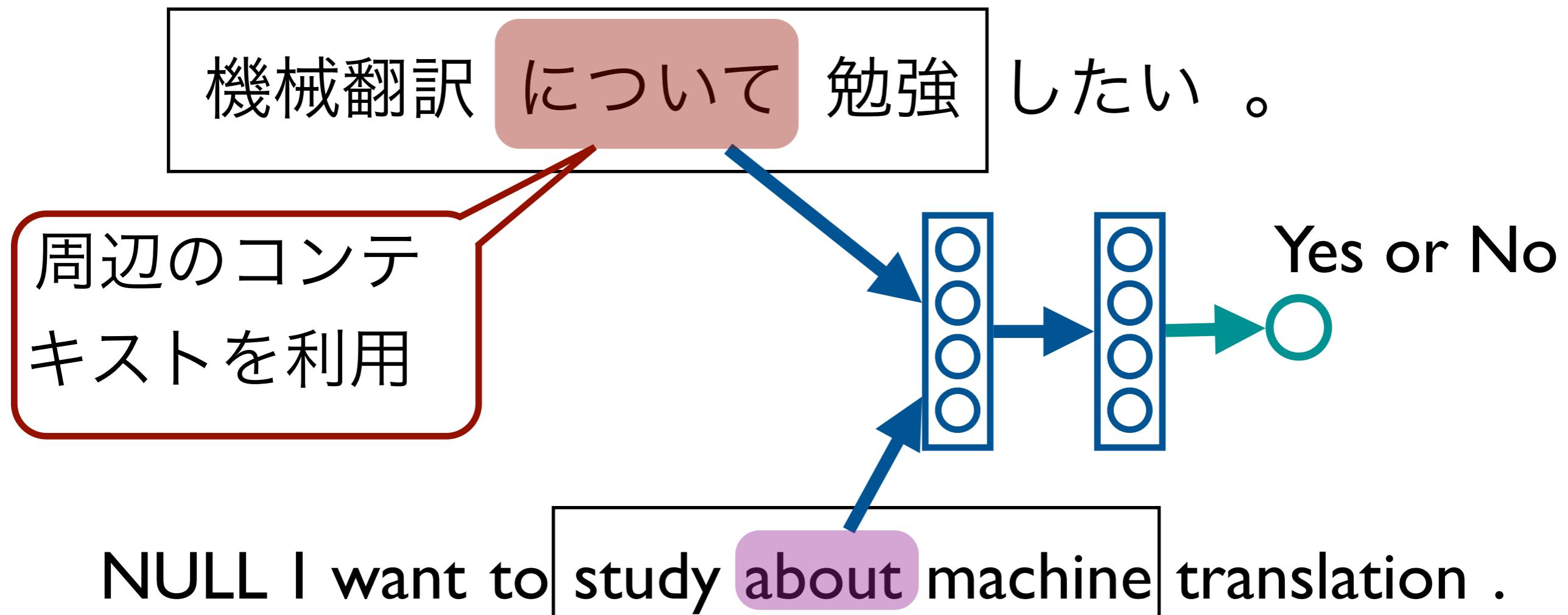
。 したい 勉強 について 機械 翻訳

(Sutskever et al., 2014)

# 単語アライメント

# 単語アライメント: FFNN

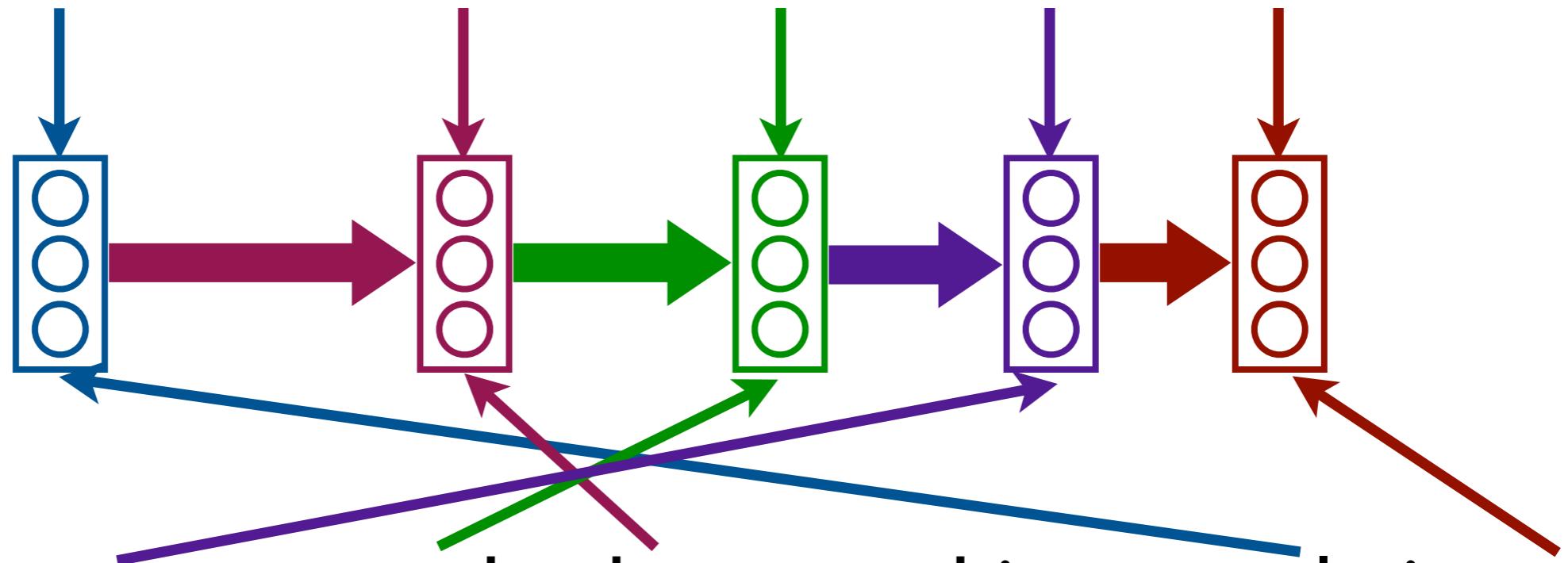
(Yang et al., 2013)



- 単語アライメントが付与されたデータから学習

# 単語アライメント: RNN

機械翻訳について勉強したい。



NULL I want to study about machine translation .

(Tamura et al., 2014)

- 単語アライメントの全ての履歴を表現 +

noise contrastive estimateによる教師無し学習

# まとめ

- ニューラルネットワークの機械翻訳への応用
  - 言語モデル、翻訳モデル、単語アライメント
- 始まったばかりなのに、数多くの研究
  - 全てを列挙できない:似たり寄ったり
- 今後に期待

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