

2019年度高柳健次郎賞 受賞記念講演(2020.1.20)

ニューラルネットワークの 先駆的研究と パターン認識への応用

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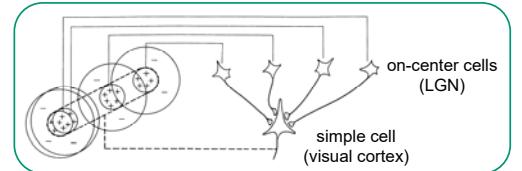
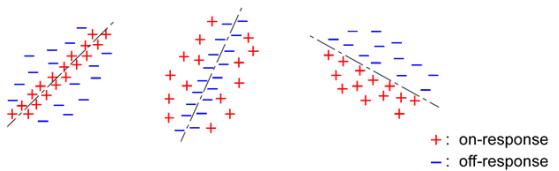
1

NHK時代の研究関係者（敬称略）
上司 樋渡清二
共同研究者 山口 幸也
三宅 誠
伊藤 崇之
藤井 真人
他 大勢の方々

2

ネオコグニトロンの着想

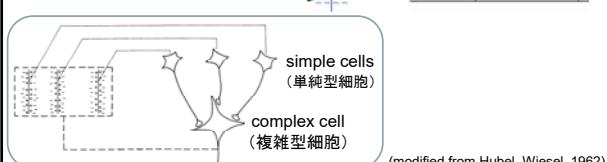
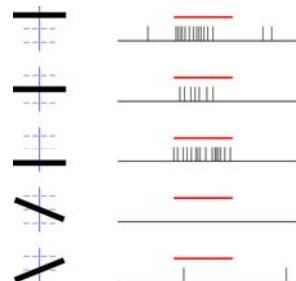
Receptive fields of simple cells 単純型細胞の受容野



(modified from Hubel, Wiesel, 1962)

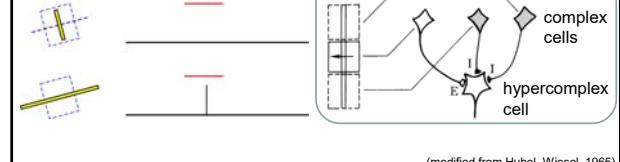
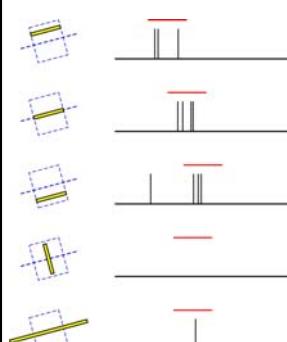
4

Complex cell (複雑型細胞)

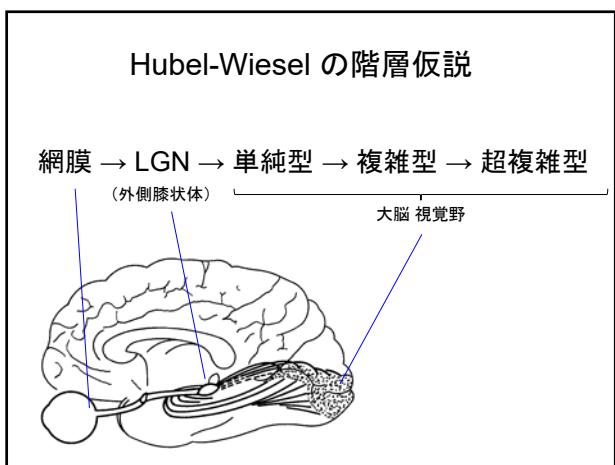


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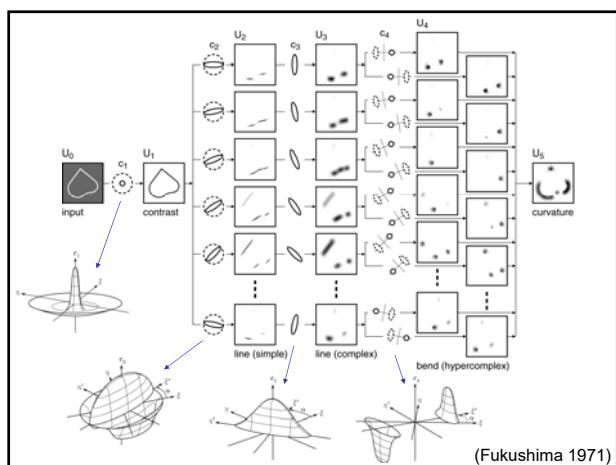
Hypercomplex cell (超複雑型細胞)



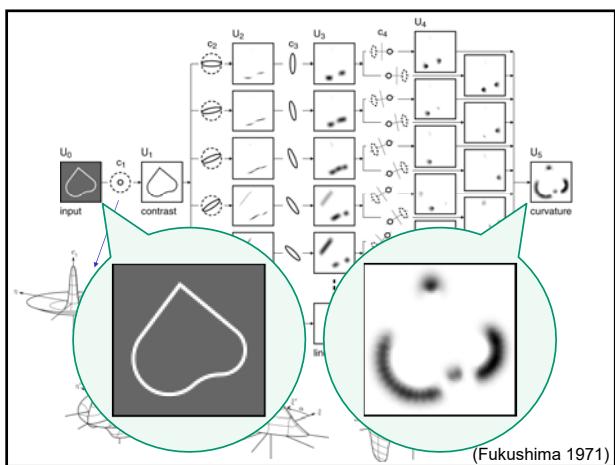
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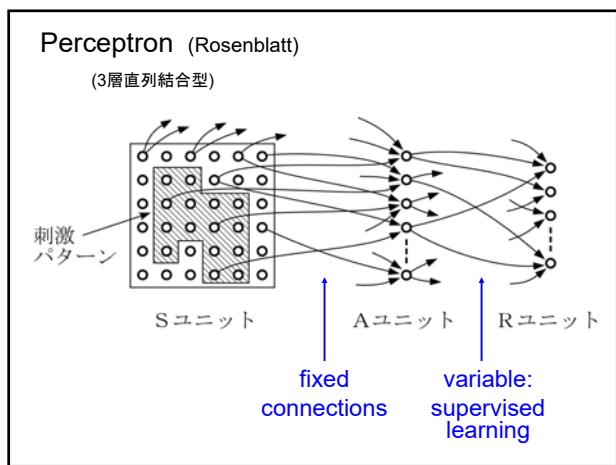
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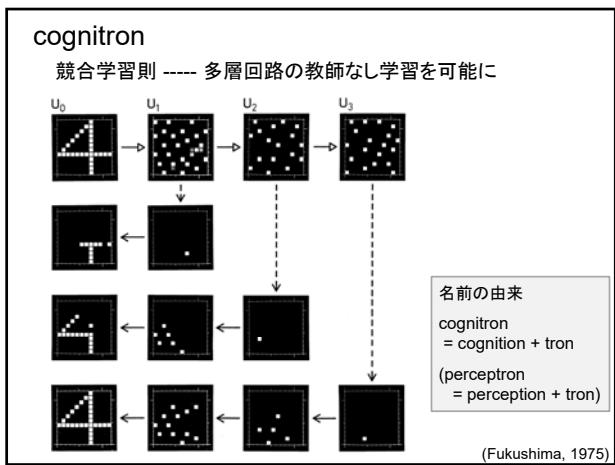
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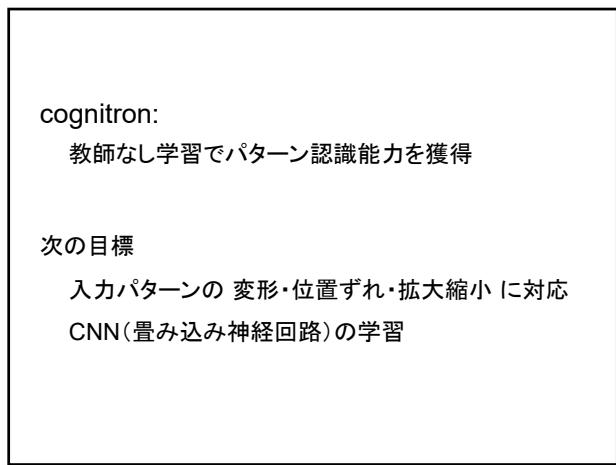
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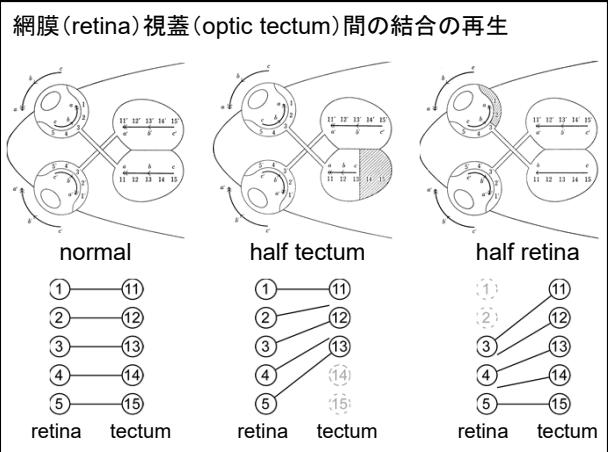
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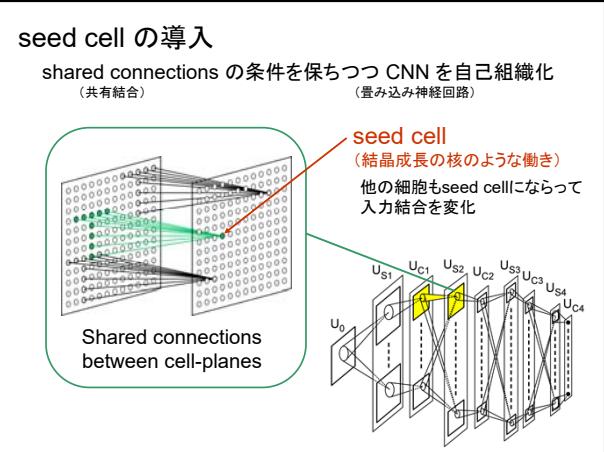
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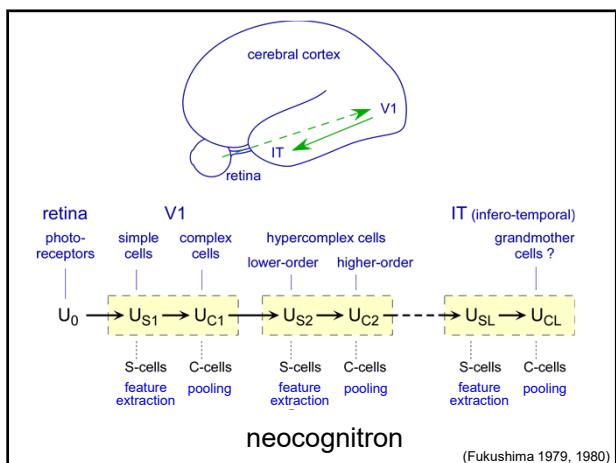
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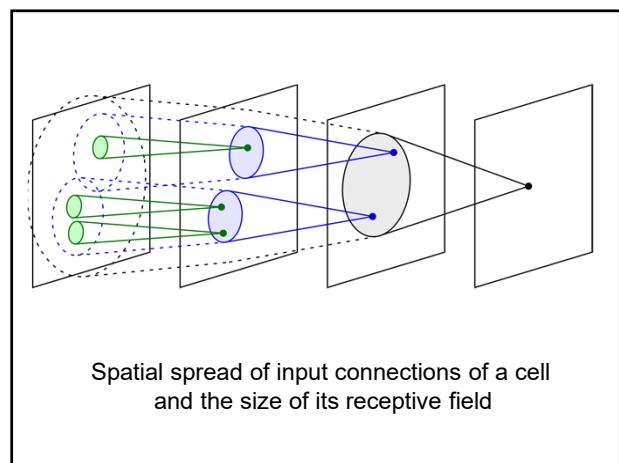
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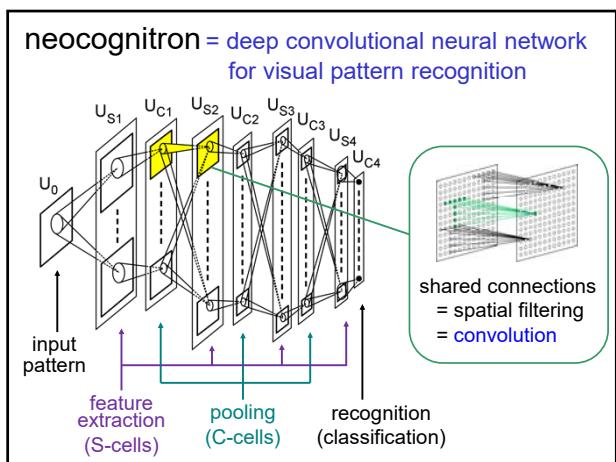
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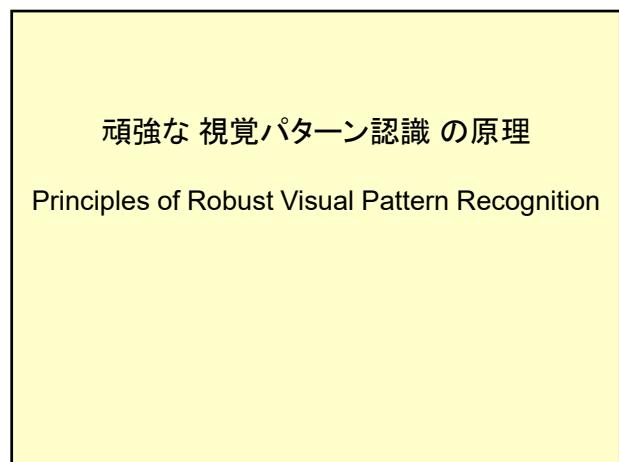
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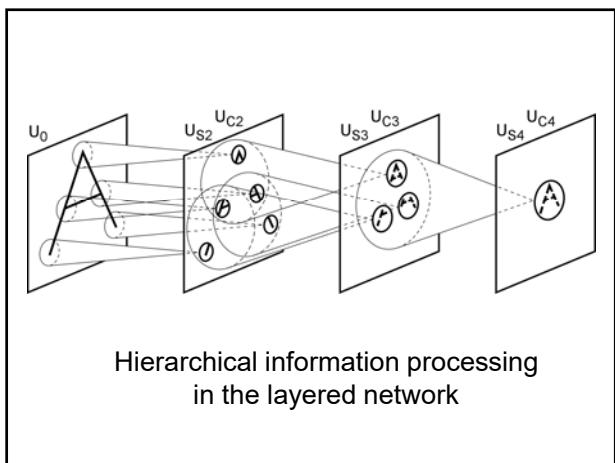


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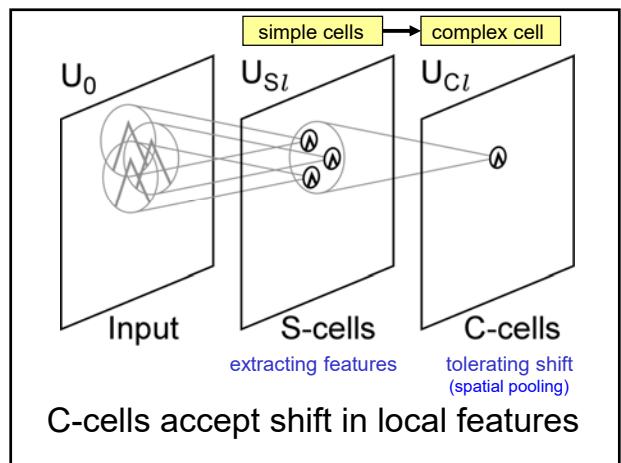


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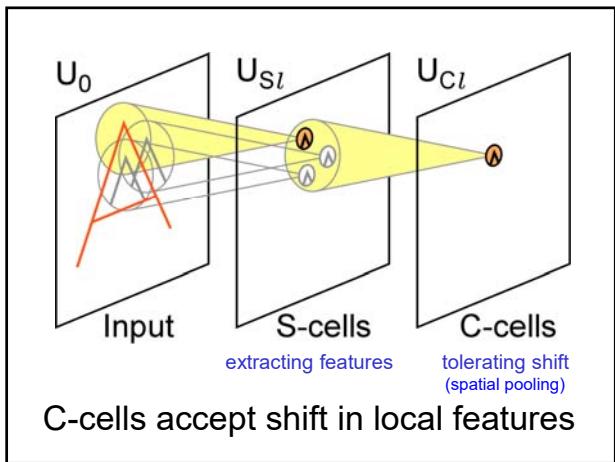




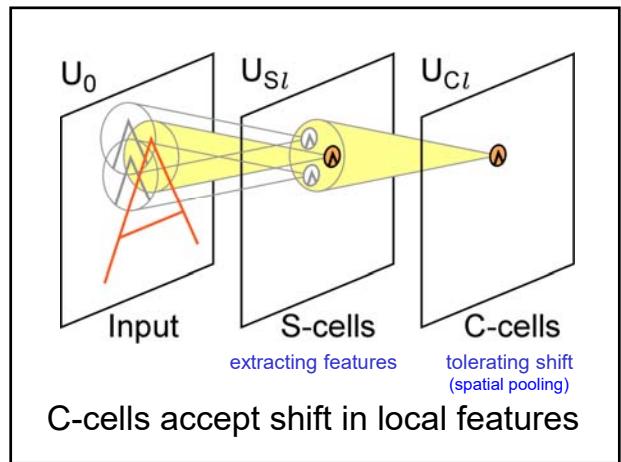
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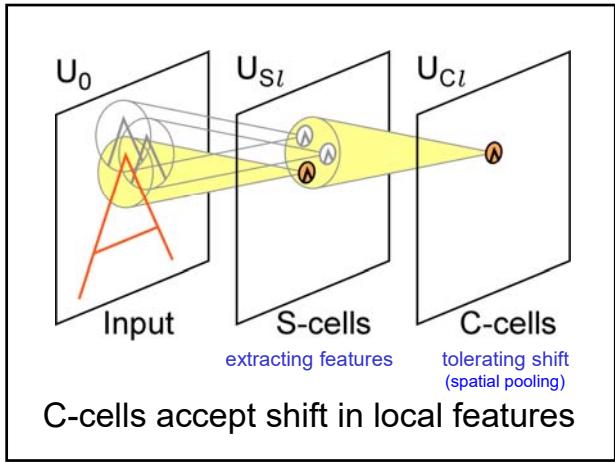
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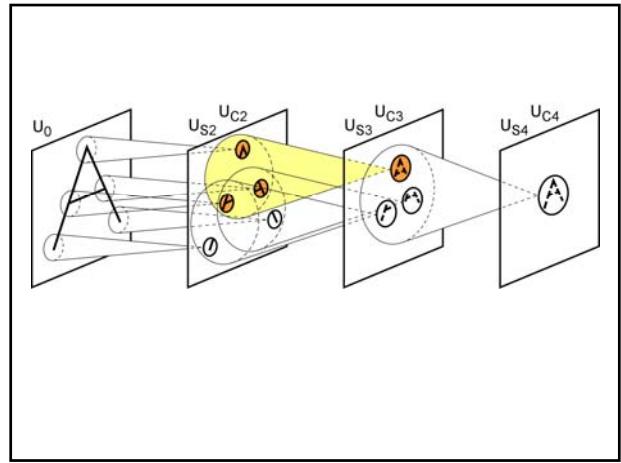
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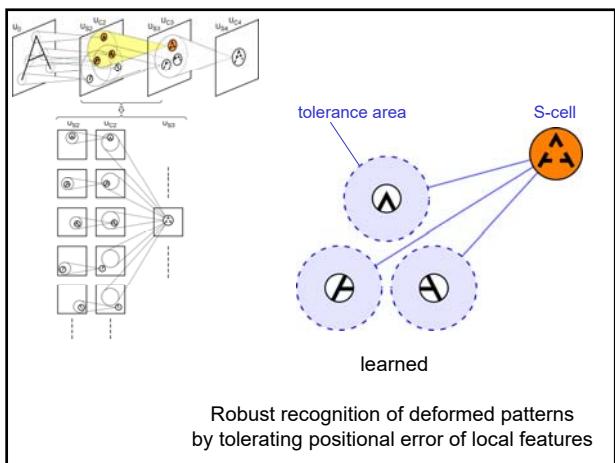
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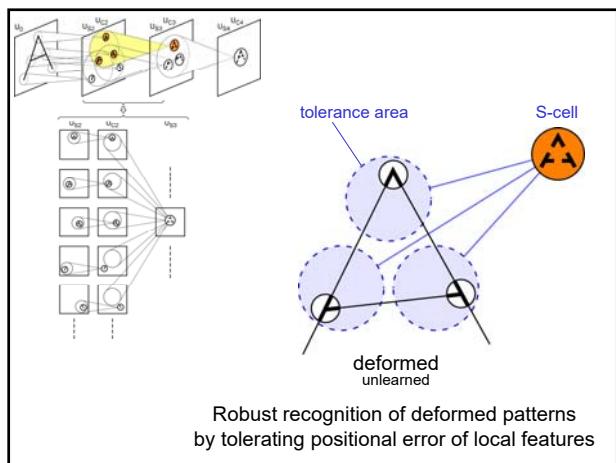
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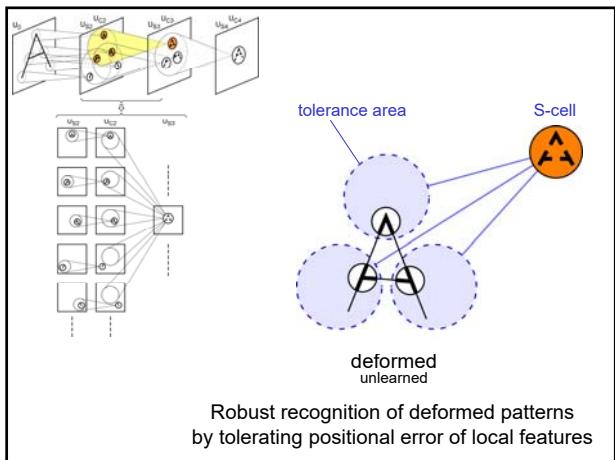
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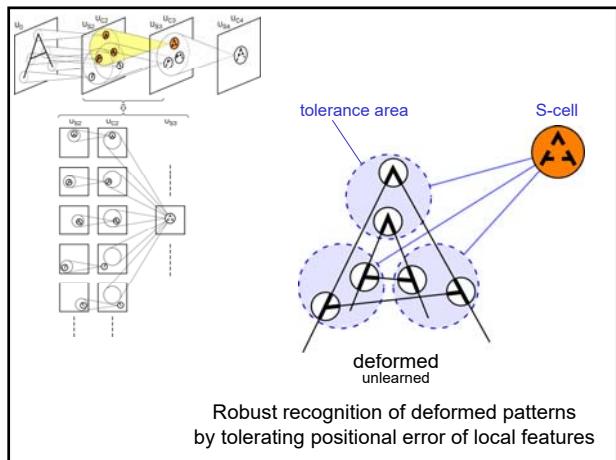
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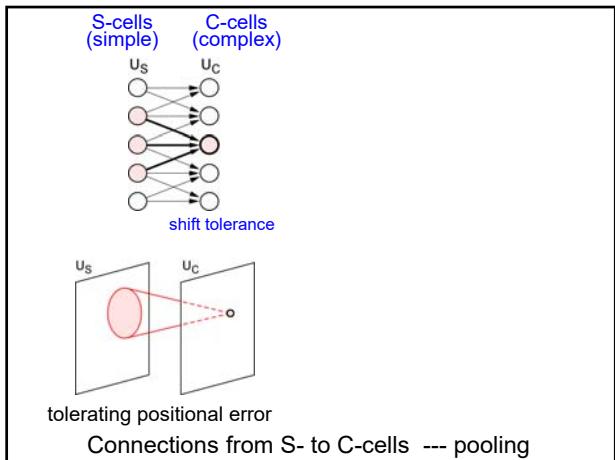
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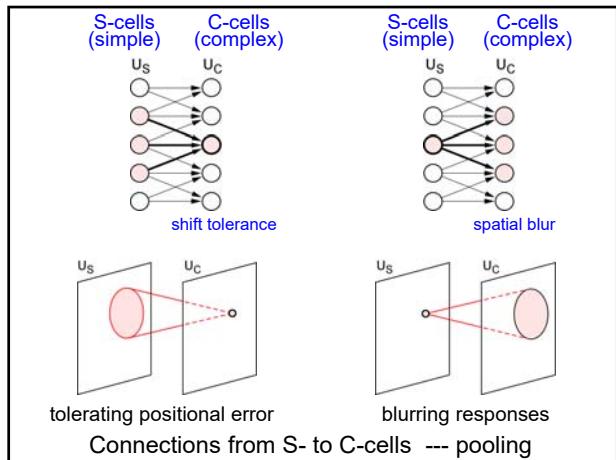
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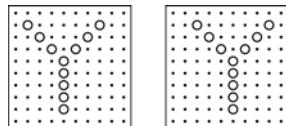


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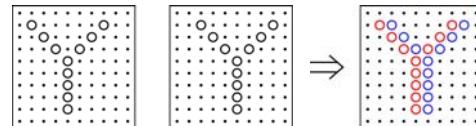
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Without blur:



31

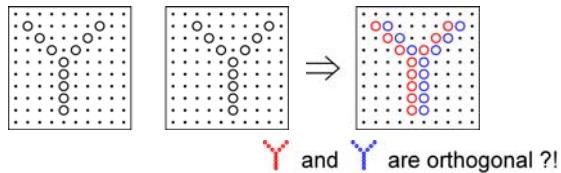
Without blur:



Y and Y are orthogonal ?!

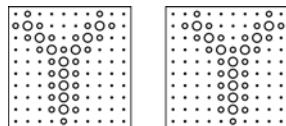
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Without blur:



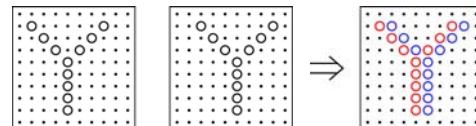
Y and Y are orthogonal ?!

After blurring operation:



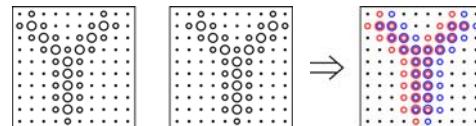
33

Without blur:



Y and Y are orthogonal ?!

After blurring operation:



Y and Y largely overlap each other.

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中間層の S細胞の学習

Training S-cells

--- intermediate layers ---

AiS則による 教師なし学習

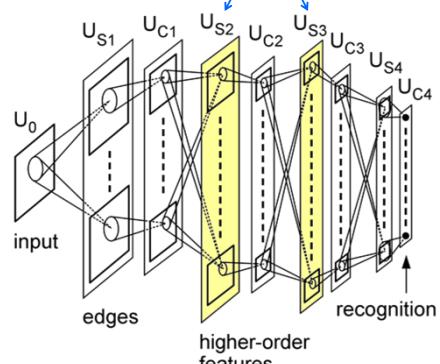
unsupervised learning

AiS (add-if-silent) rule

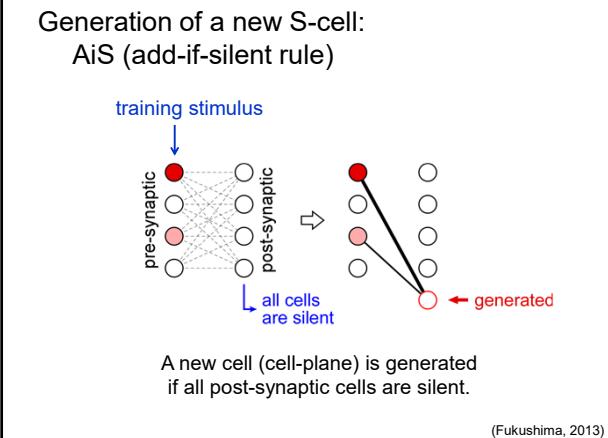
(Fukushima 2013)

35

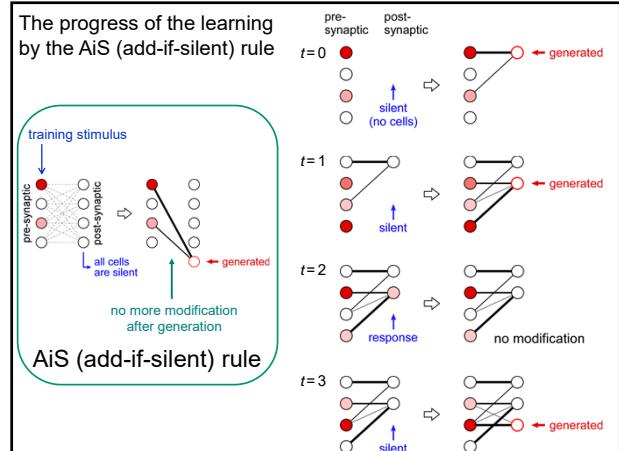
intermediate layers of S-cells



36



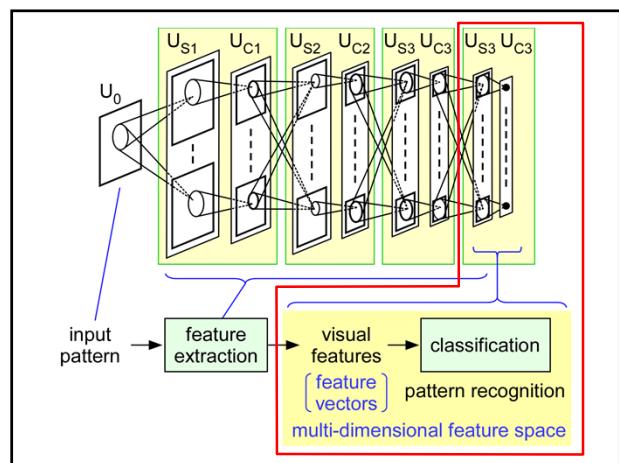
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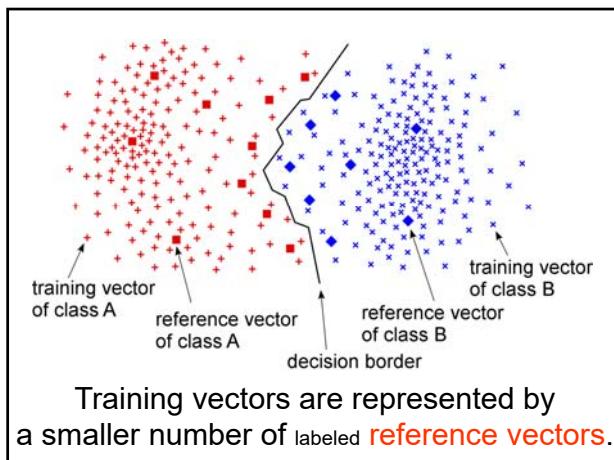
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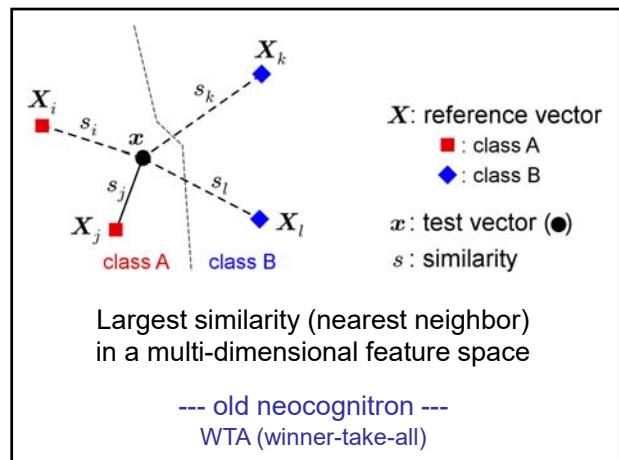
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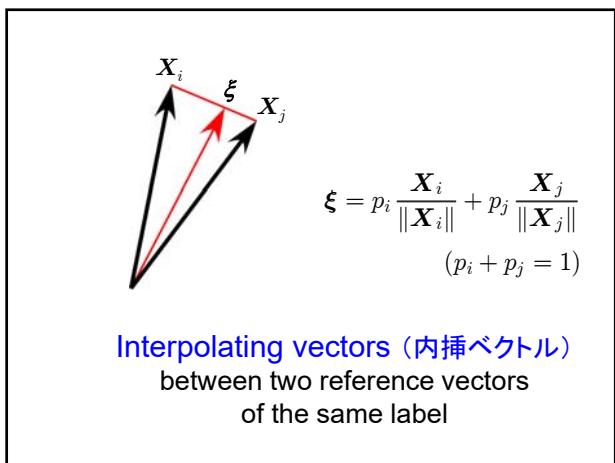
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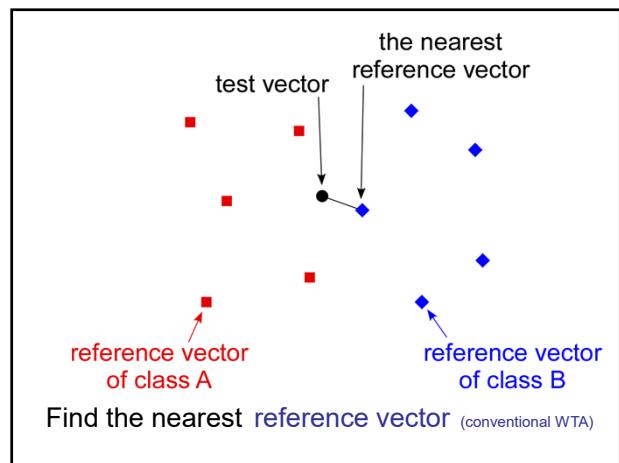
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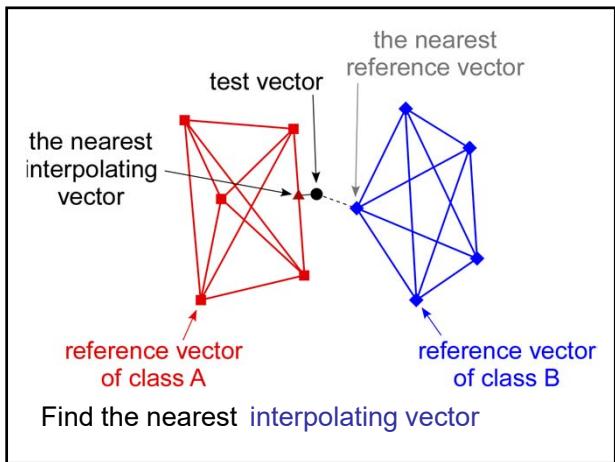
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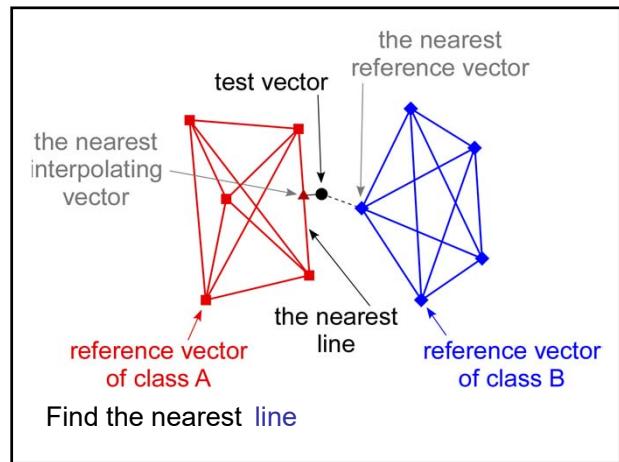
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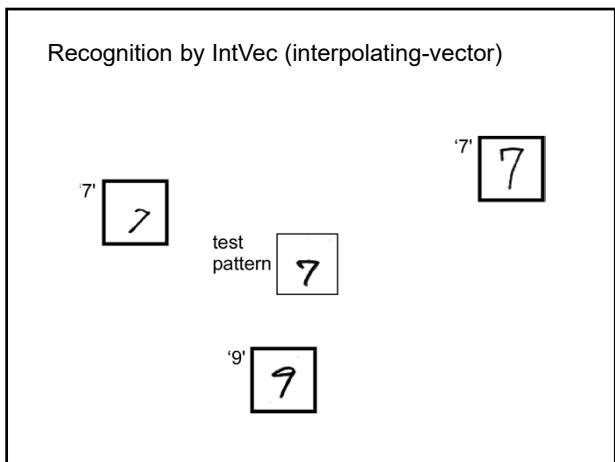
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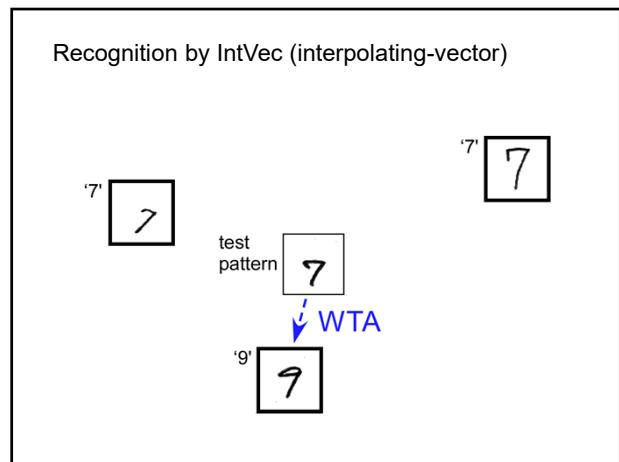
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46

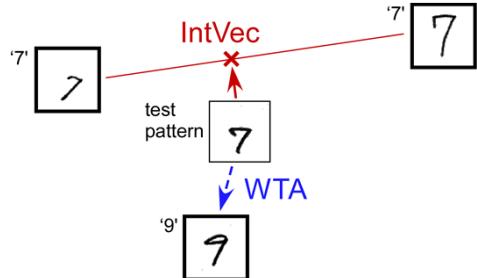


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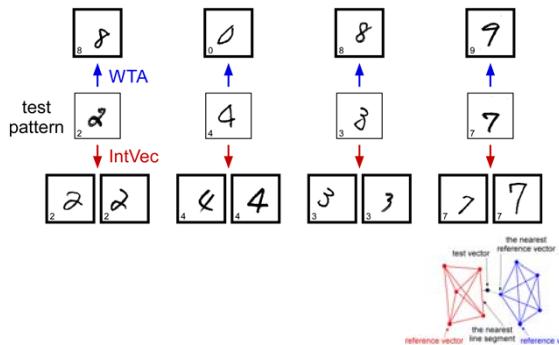
48

Recognition by IntVec (interpolating-vector)



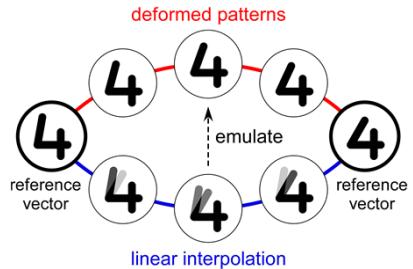
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Examples of patterns that were recognized,
erroneously by the WTA,
but correctly by the IntVec (interpolating-vector, Int-2).



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Recognition by Int-Vec (the interpolating-vector)



This operation is applied,
not directly to input images,
but to extracted features.

51

内挿ベクトル法(IntVec)はなぜ強力か？

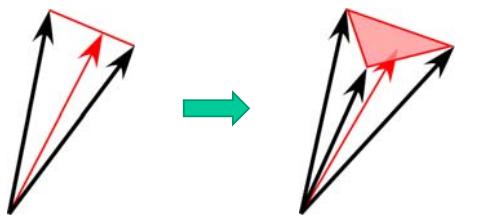
CNN（畳込み神経回路）の認識率は、
学習パターン数を増やすことによって向上する。

十分多数の学習パターンが得られないときには、
人工的に作った学習パターンで不足を補っても、
認識率を向上させることができる。
----- data augmentation -----

内挿ベクトル法(IntVec)ではこの状態を、
学習時ではなく、認識時に作り出している。
比較すべき特徴の数を、学習パターン数を増やすずに、
実質的に増やしている。

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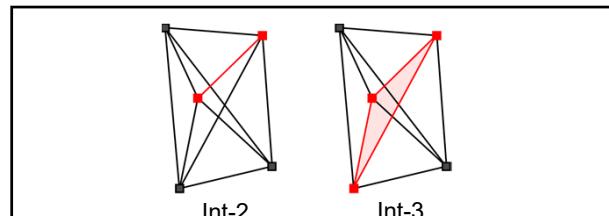
Interpolating-vector from three reference vectors



Find the nearest line.
Int-2 (interpolating-vector
from 2 reference vectors)

Find the nearest plane.
Int-3 (interpolating-vector
from 3 reference vectors)

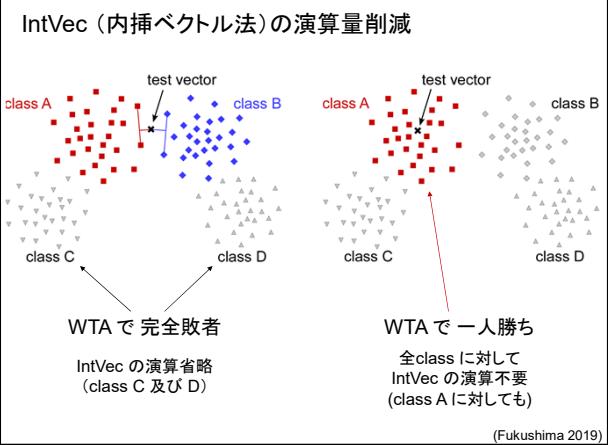
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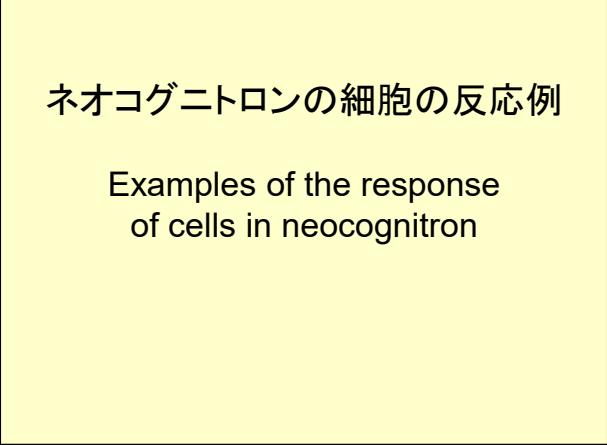
	number of hyperplanes
Int-1 (WTA)	K
Int-2	$K(K-1)/2 \doteq K^2/2$
Int-3	$K(K-1)(K-2)/6 \doteq K^3/6$
Int-4	$K(K-1)(K-2)(K-3)/24 \doteq K^4/24$

K : number of reference vectors of a class

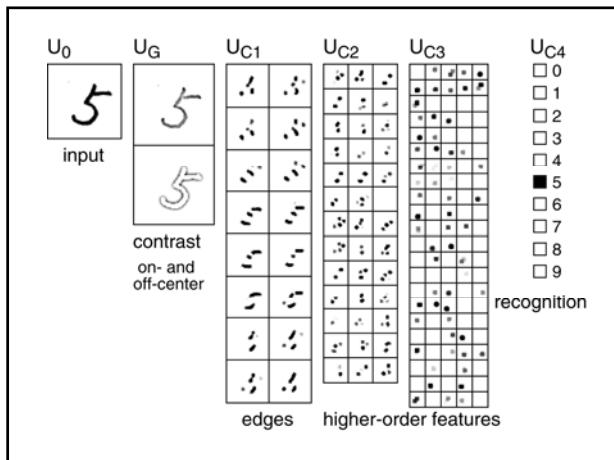
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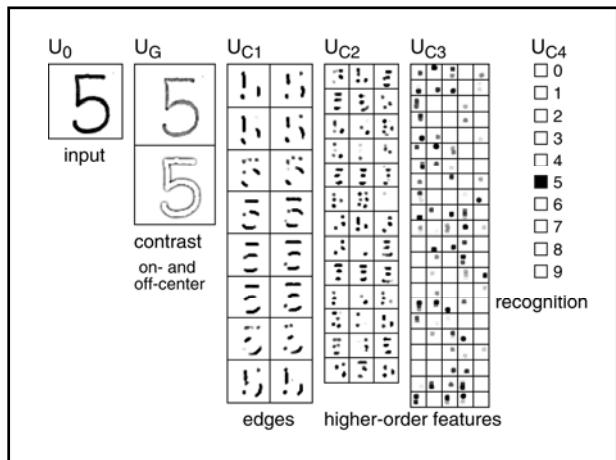
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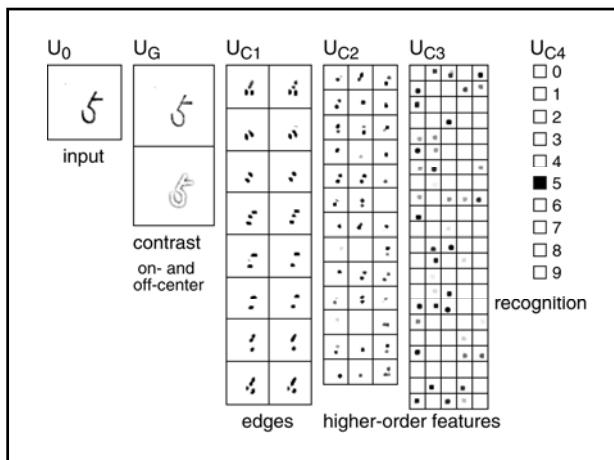
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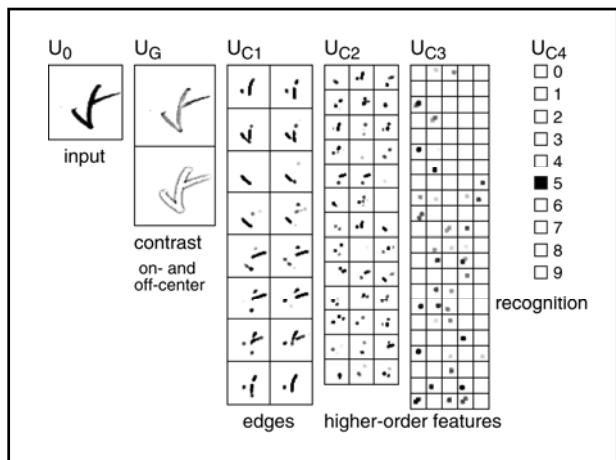
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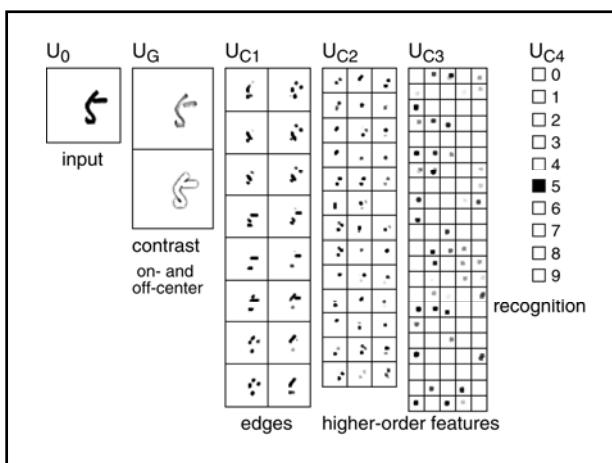
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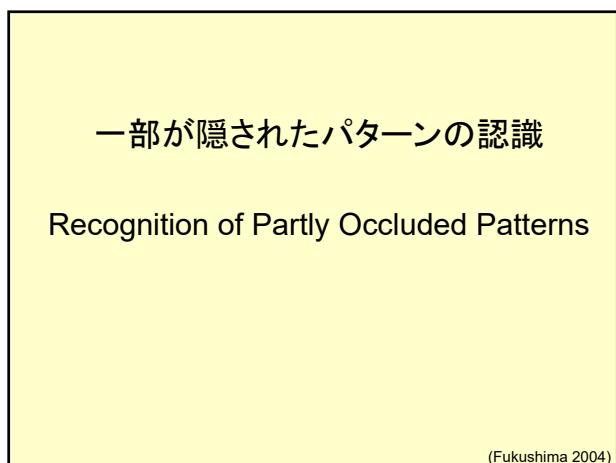
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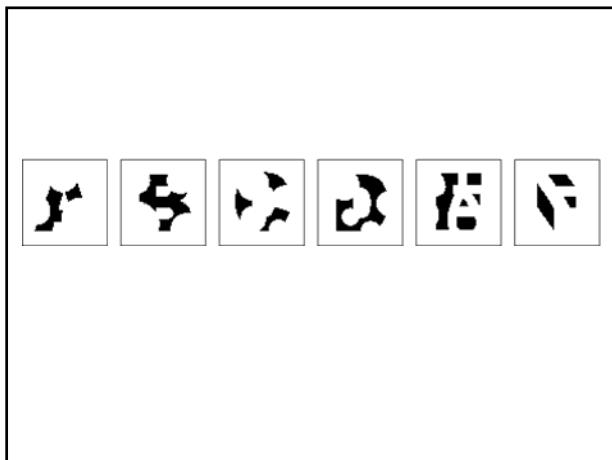
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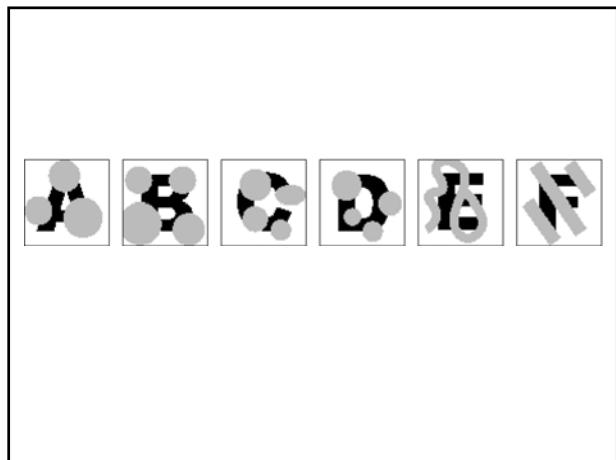
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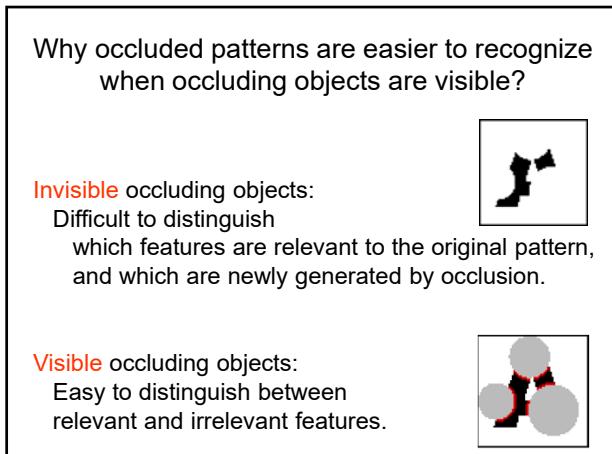
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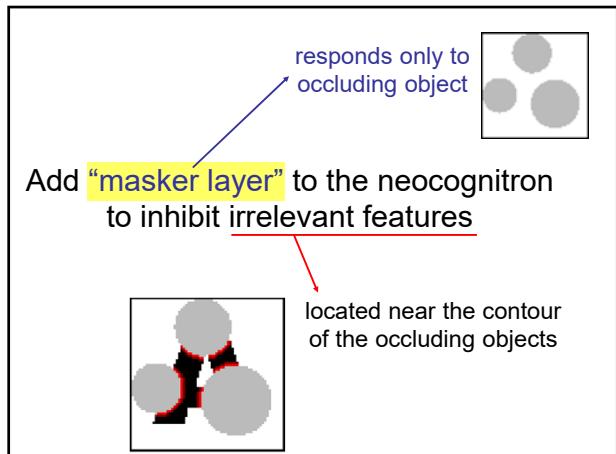
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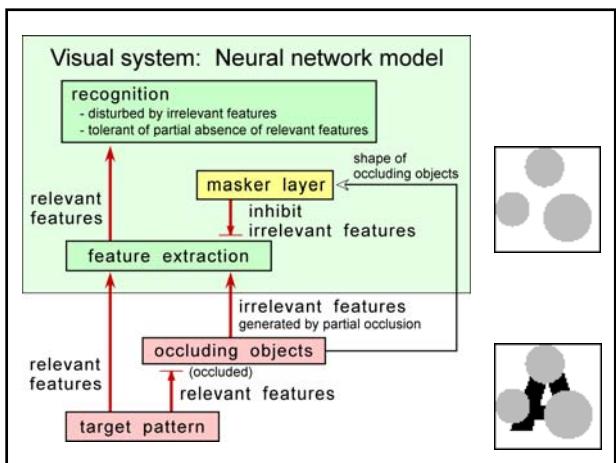
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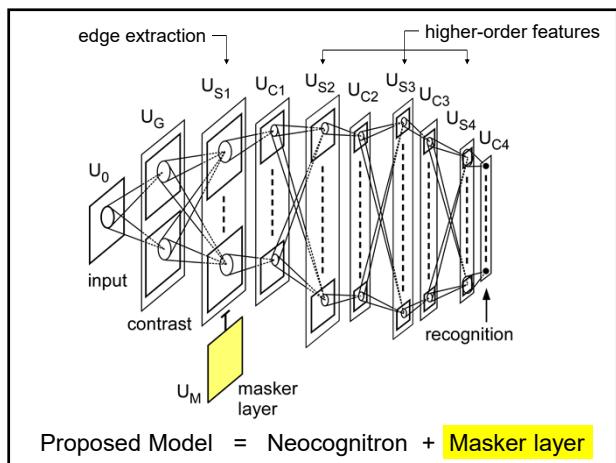
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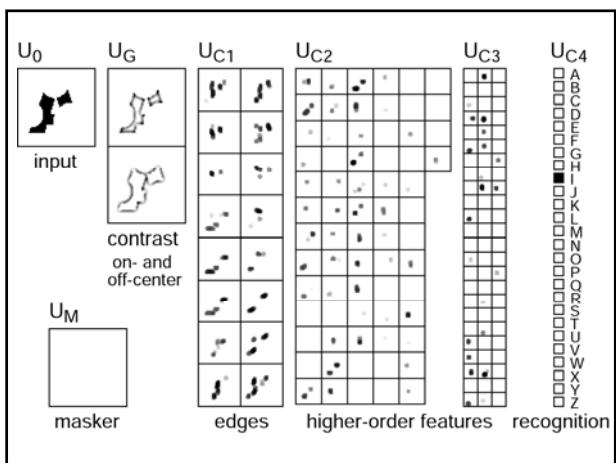
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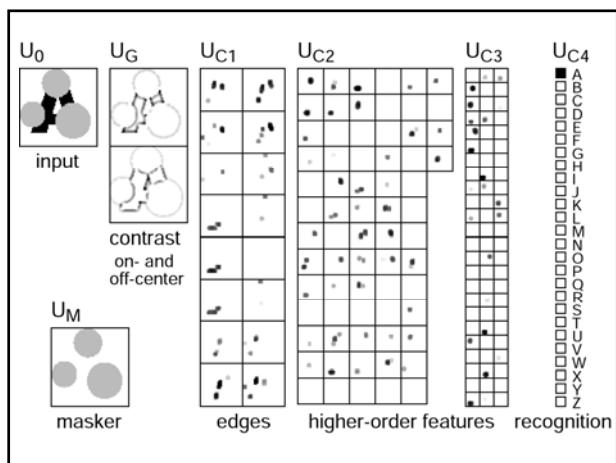
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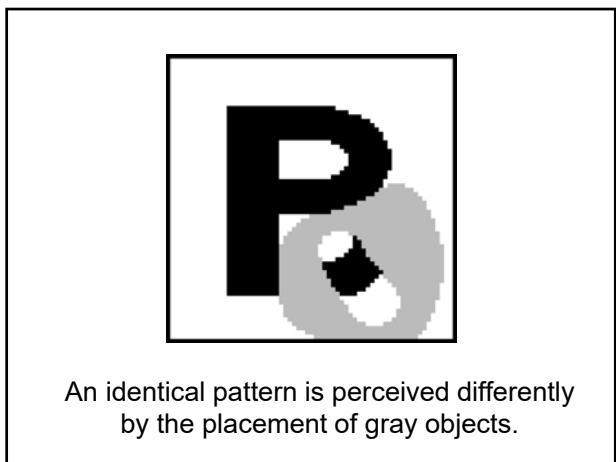
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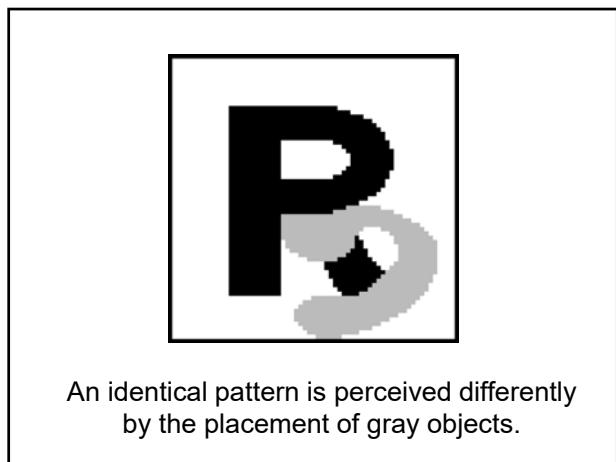
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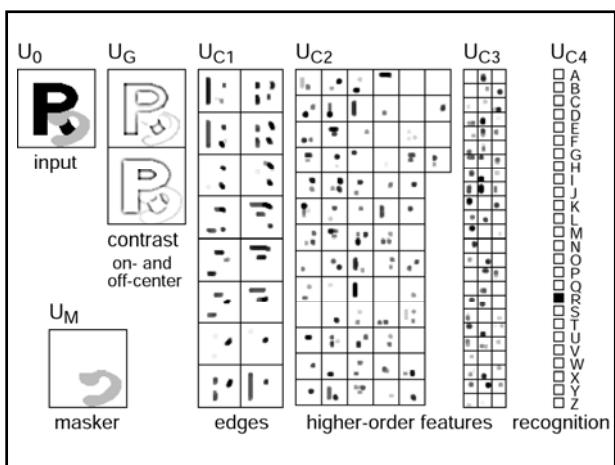
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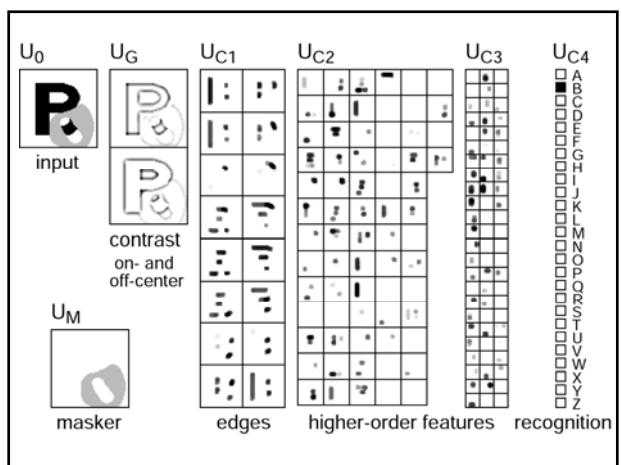
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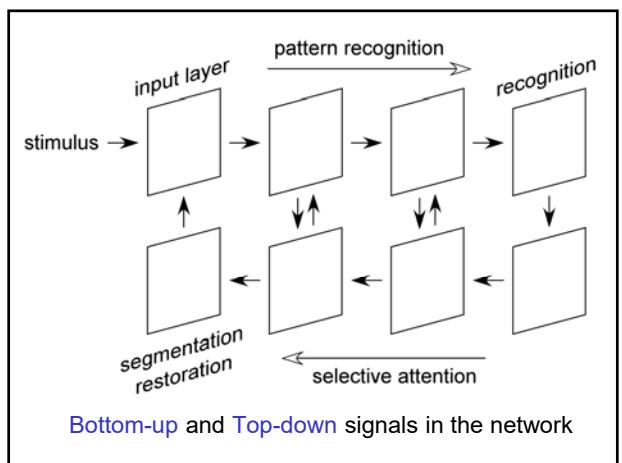
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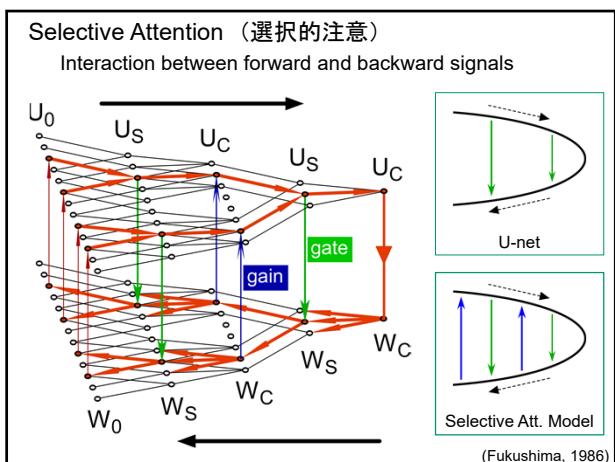
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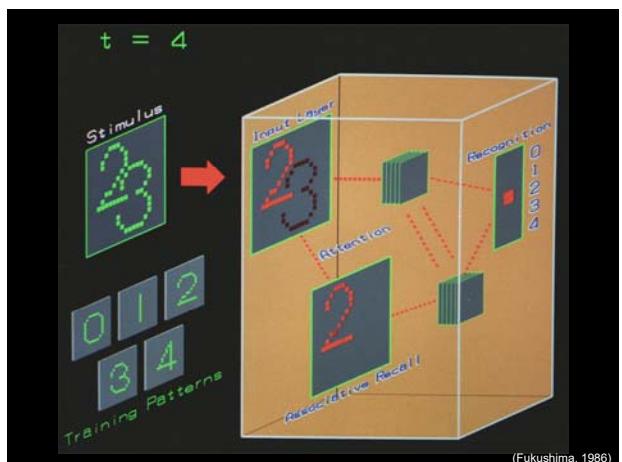
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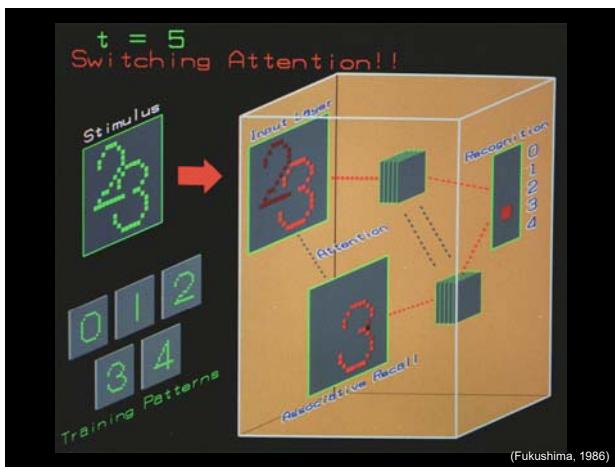
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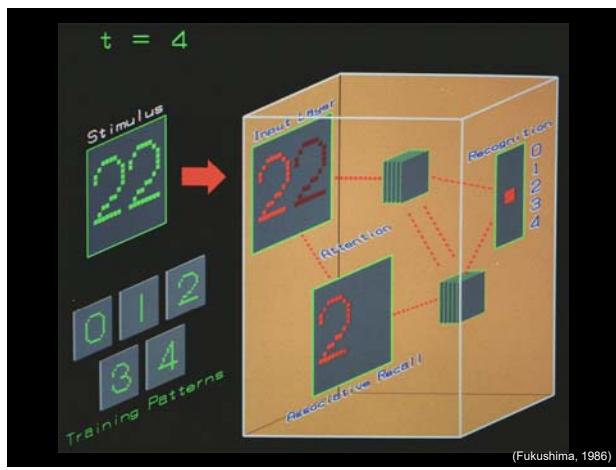
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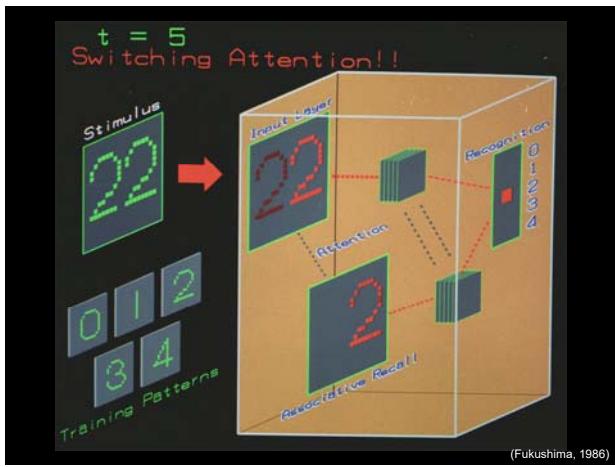
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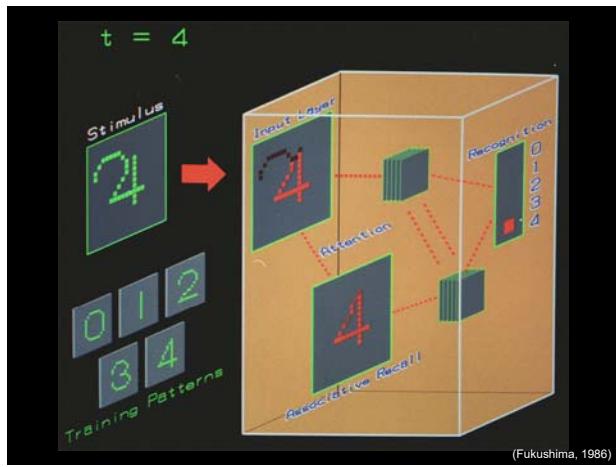
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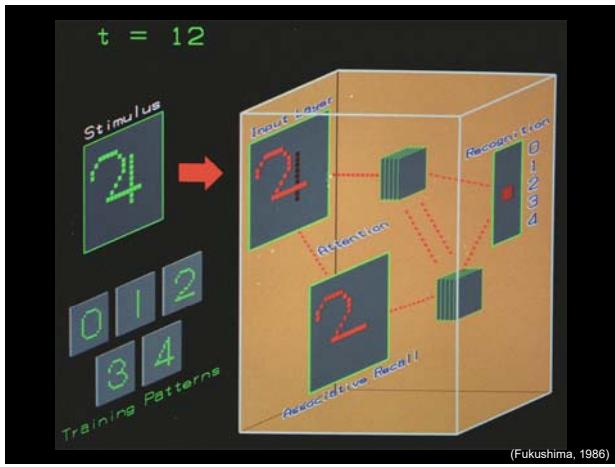
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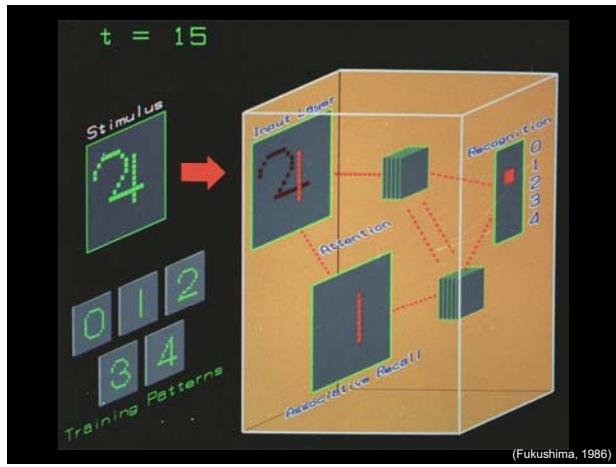
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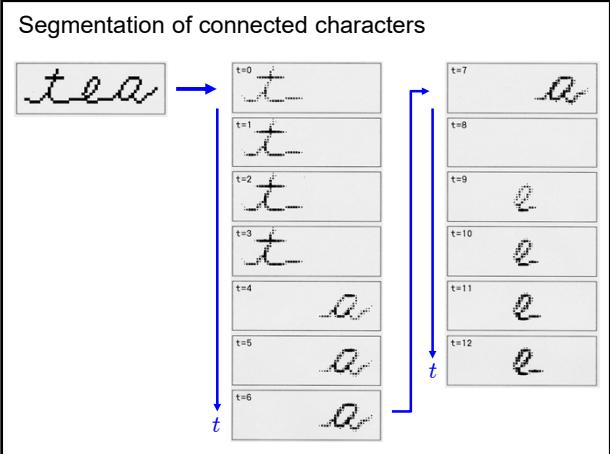
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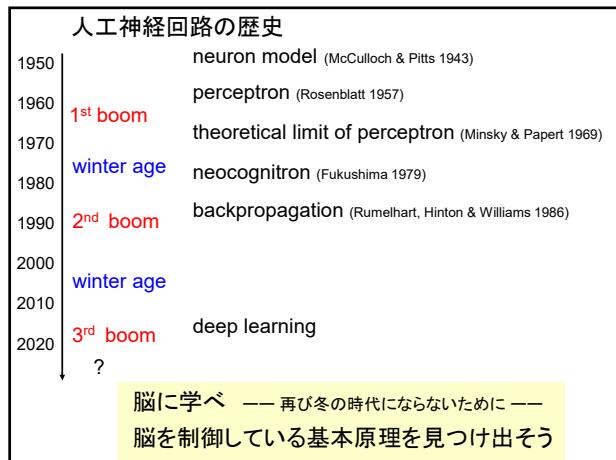
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