

Week 4

Master Thesis 2020

Tobias Engelhardt Rasmussen (s153057)

DTU Compute

23. september 2020

Outline

Since Last

Tensor Decomposition Methods

Classification of 3s and 4s

Since last

- ▶ Project Plan done
- ▶ Draft for introduction
- ▶ Reading
- ▶ Decomposing 3s and 4s

Outline

Since Last

Tensor Decomposition Methods

Classification of 3s and 4s

Decomposition methods overview

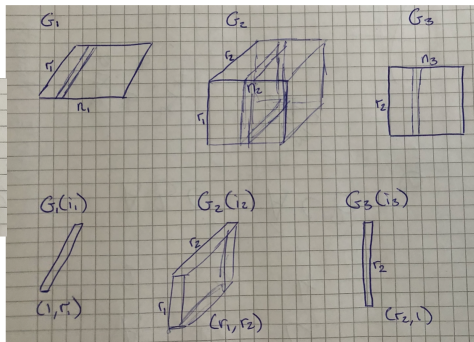
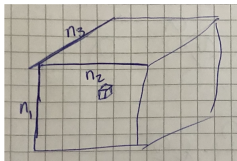
- ▶ Tucker
 - ▶ One rank for each dimension
 - ▶ One loading matrix for each dimension of size $n_d \times r_d$
 - ▶ One core tensor of size $r_1 \times r_2 \times \dots$
 - ▶ Possible to choose how much variation we allow in each dimension
- ▶ Parafac / Candecomp / CP / Canonical Decomposition
 - ▶ Special case of the Tucker model with the same rank for each dimension (sum of outer products of vectors)
 - ▶ Core is a super-diagonal, hence less freedom than in Tucker
- ▶ Block Term Decomposition
 - ▶ A sum of tucker terms, which allow for different ranks for the same dimension in different terms
- ▶ Tensor-Train (TT) decomposition / Matrix Product State
 - ▶ Sequence of order-3 tensors
 - ▶ Works well for high dimensions since robust wrt the curse of dimensionality

TT - decomposition

We have ranks r_0, r_1, \dots, r_d where we need $r_0 = r_d = 1$

$$A(i_1, i_2, \dots, i_d) = G_1(i_1)G_2(i_2) \dots G_d(i_d)$$

Where $G_k(i_k)$ is $r_{k-1} \times r_k$ matrix



Outline

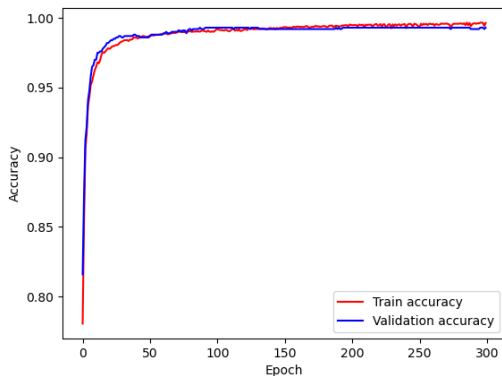
Since Last
Tensor Decomposition Methods
Classification of 3s and 4s

Relatively simple!



Results with just 1 hidden neuron

- ▶ Just **1** hidden neuron
- ▶ Testing accuracy of $> 99\%$



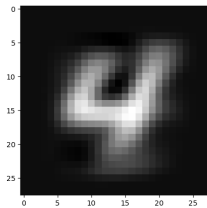
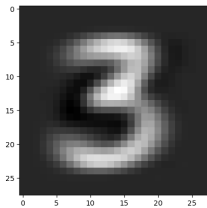
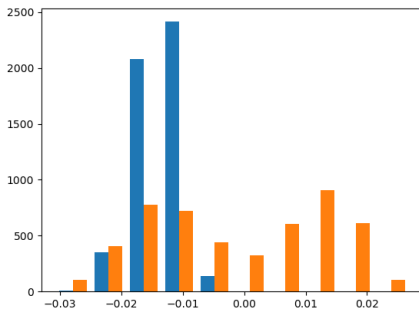
Tucker - decomposition

Using the Tucker(2,10,10) decomposition.



Looks like "archetypes" of 3 and 4.

The first loading matrix



The training set

Assume B , C and \mathcal{G} are the same.

$$\mathcal{X} = \mathcal{G} \times_1 A \times_2 B \times_3 C$$

$$\Updownarrow$$

$$\mathcal{G} \times_1 A = \mathcal{X} \times_2 B^\dagger \times_3 C^\dagger$$

$$\Updownarrow$$

$$A \mathcal{G}_{(1)} = (\mathcal{X} \times_2 B^\dagger \times_3 C^\dagger)_{(1)}$$

$$\Updownarrow$$

$$A = (\mathcal{X} \times_2 B^\dagger \times_3 C^\dagger)_{(1)} \mathcal{G}_{(1)}^\dagger$$

Which can then be used to estimate the loadings of A for the training data

Results using first loading matrix

- ▶ Just **1** hidden neuron
- ▶ Just **2** input neurons!!!
- ▶ A total of **8** weights and **2** biases
- ▶ Testing accuracy of $\approx 97\%$ ($\approx 95\%$ with only 1 hidden neuron)

