



Sequentially
Learning
Multiple Tasks
in Artificial
Neural
Networks

Jordi Bieger

Introduction

Neural Networks

Representation

Multiple Tasks

SMRL

Description

Experiments

Analysis

Optimizations

Discussion

Questions

Sequentially Learning Multiple Tasks in Artificial Neural Networks

Preventing Catastrophic Interference with Meaningful Representations

Jordi Bieger

April 15, 2009



Programme

Sequentially
Learning
Multiple Tasks
in Artificial
Neural
Networks

Jordi Bieger

Introduction

Neural Networks

Representation

Multiple Tasks

SMRL

Description

Experiments

Analysis

Optimizations

Discussion

Questions

- 1 Introduction
 - Neural Networks
 - Representation
 - Multiple Tasks
- 2 Static Meaningful Representation Learning
 - Description
 - Experiments
 - Analysis
 - Optimizations
- 3 Discussion
- 4 Questions





Programme

Sequentially Learning Multiple Tasks in Artificial Neural Networks

Jordi Bieger

Introduction

Neural Networks

Representation

Multiple Tasks

SMRL

Description

Experiments

Analysis

Optimizations

Discussion

Questions

1 Introduction

- Neural Networks
- Representation
- Multiple Tasks

2 Static Meaningful Representation Learning

- Description
- Experiments
- Analysis
- Optimizations

3 Discussion

4 Questions





Introduction

Sequentially Learning Multiple Tasks in Artificial Neural Networks

Jordi Bieger

Introduction

Neural Networks

Representation

Multiple Tasks

SMRL

Description

Experiments

Analysis

Optimizations

Discussion

Questions

- Artificial Neural Networks (ANNs) are loosely based on neural mechanisms in the brain.
- Standard Multi-Layer Perceptrons (MLPs) fail to model the brain's ability to sequentially learn multiple tasks.
- I propose a simple solution called “Static Meaningful Representation Learning”.



Multi-Layer Perceptrons

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Learning
Multiple Tasks
in Artificial
Neural
Networks

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Introduction

Neural Networks

Representation

Multiple Tasks

SMRL

Description

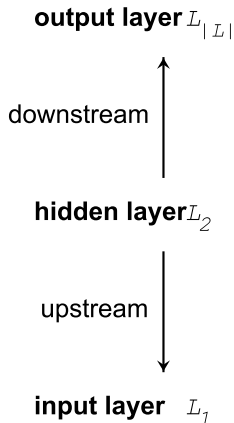
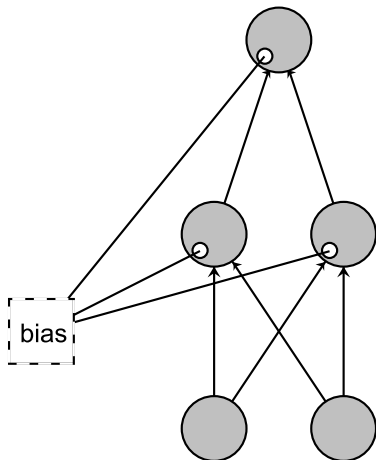
Experiments

Analysis

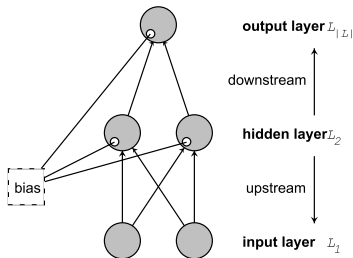
Optimizations

Discussion

Questions



- Situation needs to be encoded into a representation the network “understands”.
- These representations are often arbitrary.





Representation

Sequentially
Learning
Multiple Tasks
in Artificial
Neural
Networks

Jordi Bieger

Introduction

Neural Networks

Representation

Multiple Tasks

SMRL

Description

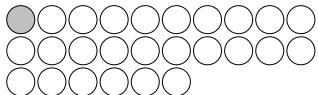
Experiments

Analysis

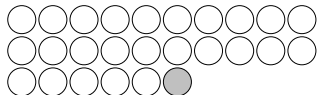
Optimizations

Discussion

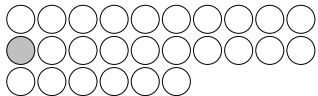
Questions



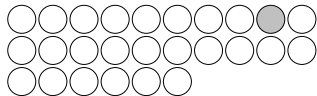
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Multiple tasks

Sequentially
Learning
Multiple Tasks
in Artificial
Neural
Networks

Jordi Bieger

Introduction

Neural Networks

Representation

Multiple Tasks

SMRL

Description

Experiments

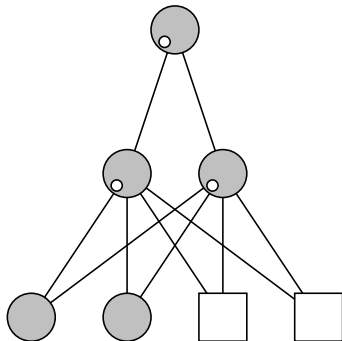
Analysis

Optimizations

Discussion

Questions

- Network needs to be told what task to do.
- Accomplished by adding extra task representation nodes.
- Action words have task relevant representations in human brains.
- Sequential learning causes catastrophic interference.





Tasks

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Introduction

Neural Networks

Representation

Multiple Tasks

SMRL

Description

Experiments

Analysis

Optimizations

Discussion

Questions

Inputs		NONE	AND	NIF	1ST	JUST2	2ND	XOR	OR	NOR	IFF	\neg 2ND	\neg JUST2	\neg 1ST	IF	NAND	ALL
-	-	-	-	-	-	-	-	-	-	+	+	+	+	+	+	+	+
-	+	-	-	-	-	+	+	+	+	-	-	-	-	+	+	+	+
+	-	-	-	+	+	-	-	+	+	-	-	+	+	-	-	+	+
+	+	-	+	-	+	-	+	-	+	-	+	-	+	-	+	-	+
binary		0000	0001	0010	0011	0100	0101	0110	0111	1000	1001	1010	1011	1100	1101	1110	1111
#		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15



Programme

Sequentially Learning Multiple Tasks in Artificial Neural Networks

Jordi Bieger

Introduction

Neural Networks

Representation

Multiple Tasks

SMRL

Description

Experiments

Analysis

Optimizations

Discussion

Questions

1

Introduction

- Neural Networks
- Representation
- Multiple Tasks

2

Static Meaningful Representation Learning

- Description
- Experiments
- Analysis
- Optimizations

3

Discussion

4

Questions





Static Meaningful Representation Learning

Sequentially Learning Multiple Tasks in Artificial Neural Networks

Jordi Bieger

Introduction

Neural Networks

Representation

Multiple Tasks

SMRL

Description

Experiments

Analysis

Optimizations

Discussion

Questions

- **Static Meaningful Representation Learning (SMRL)**
 - Initial knowledge acquisition phase
 - Fix all weights in the network
 - Novelty learning phase
- **Uses Parametric Bias (PB) nodes for learning meaningful task representations**

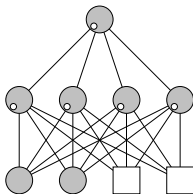


Network Types

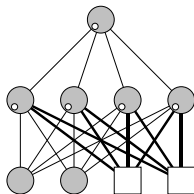
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Learning
Multiple Tasks
in Artificial
Neural
Networks

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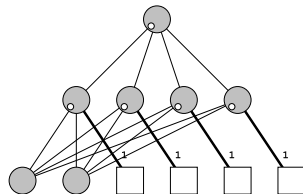
Implicit PB



Fixed Weight IPB



Explicit PB



Introduction

Neural Networks

Representation

Multiple Tasks

SMRL

Description

Experiments

Analysis

Optimizations

Discussion

Questions



Results

Sequentially Learning Multiple Tasks in Artificial Neural Networks

Jordi Bieger

Introduction

Neural Networks

Representation

Multiple Tasks

SMRL

Description

Experiments

Analysis

Optimizations

Discussion

Questions

# Hidden Nodes	# PB Nodes	IPB	FWIPB	EPB
2	1	24.9%	26.4%	n/a
4	1	25.6%	26.0%	n/a
2	2	30.4%	31.6%	32.2%
4	2	36.3%	36.7%	n/a
6	2	38.6%	40.5%	n/a
6	6	-	-	54.9%
2+4	2	30.8%	31.6%	32.2%
4+4	2	34.0%	35.7%	n/a
4+4	4	-	-	38.7%
4	4	41.8%	42.3%	42.1%



Results

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Introduction

Neural Networks

Representation

Multiple Tasks

SMRL

Description

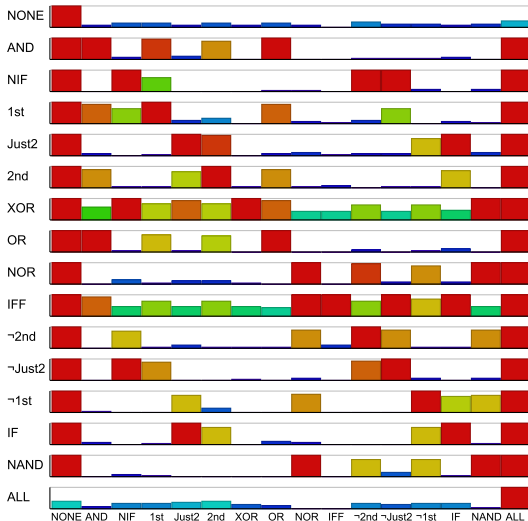
Experiments

Analysis

Optimizations

Discussion

Questions





Difficulty

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Learning
Multiple Tasks
in Artificial
Neural
Networks

Jordi Bieger

Introduction

Neural Networks

Representation

Multiple Tasks

SMRL

Description

Experiments

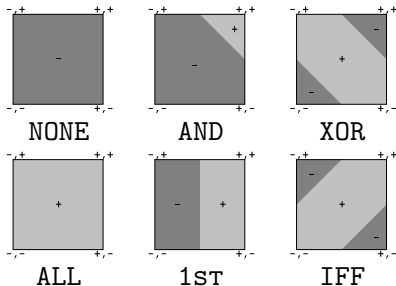
Analysis

Optimizations

Discussion

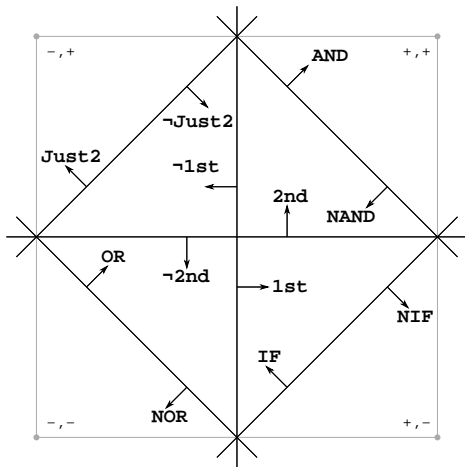
Questions

Network has to be “smart”
enough.



Similarity depends on effect of inputs on target outputs

- Parallel: arrows in the same direction
- Similar: arrows in roughly the same direction ($< 90^\circ$)





Results

Sequentially Learning Multiple Tasks in Artificial Neural Networks

Jordi Bieger

Introduction

Neural Networks

Representation

Multiple Tasks

SMRL

Description

Experiments

Analysis

Optimizations

Discussion

Questions

Network Type	# Hidden Nodes	# PB Nodes	Difficulty	Parallel	Similarity	Prodigy	Overall
IPB	4	2	77	98	72	66	36
IPB	4	4	88	100	79	79	42
FWIPB	4	2	81	98	72	69	37
FWIPB	4	4	91	100	79	88	42
EPB	2	2	73	100	68	51	32
EPB	4	4	87	100	80	75	42



Arctangent

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Jordi Bieger

Introduction

Neural Networks

Representation

Multiple Tasks

SMRL

Description

Experiments

Analysis

Optimizations

Discussion

Questions

Network Type	# Hidden Nodes	# PB Nodes	Difficulty	Parallel	Similarity	Prodigy	Overall
IPB	4	2	83 (+6)	100 (+2)	70 (-2)	73 (+7)	37 (+1)
IPB	4	4	90 (+2)	100 (0)	75 (-4)	83 (+4)	40 (-1)
FWIPB	4	2	87 (+6)	100 (+1)	72 (0)	80 (+11)	38 (+1)
FWIPB	4	4	96 (+5)	100 (+0)	78 (-1)	93 (+5)	43 (+0)
EPB	2	2	77 (+4)	100 (0)	64 (-4)	57 (+6)	32 (0)
EPB	4	4	96 (+9)	100 (0)	80 (-1)	93 (+18)	44 (+2)



Gaussian

Sequentially Learning Multiple Tasks in Artificial Neural Networks

Jordi Bieger

Introduction

Neural Networks

Representation

Multiple Tasks

SMRL

Description

Experiments

Analysis

Optimizations

Discussion

Questions

Network Type	# Hidden Nodes	# PB Nodes	Difficulty	Parallel	Similarity	Prodigy	Overall
IPB	4	2	74 (-3)	86 (-11)	78 (+6)	88 (+22)	73 (+37)
IPB	4	4	87 (-1)	90 (-10)	89 (+9)	97 (+18)	84 (+42)
FWIPB	4	2	74 (-6)	85 (-14)	78 (+6)	86 (+16)	74 (+37)
FWIPB	4	4	82 (-9)	91 (-9)	86 (+7)	92 (+4)	81 (+39)
EPB	2	2	65 (-8)	83 (-17)	69 (+1)	76 (+25)	60 (+28)
EPB	4	4	88 (+1)	95 (-5)	94 (+14)	97 (+22)	89 (+47)



Gaussian

Sequentially
Learning
Multiple Tasks
in Artificial
Neural
Networks

Jordi Bieger

Introduction

Neural Networks

Representation

Multiple Tasks

SMRL

Description

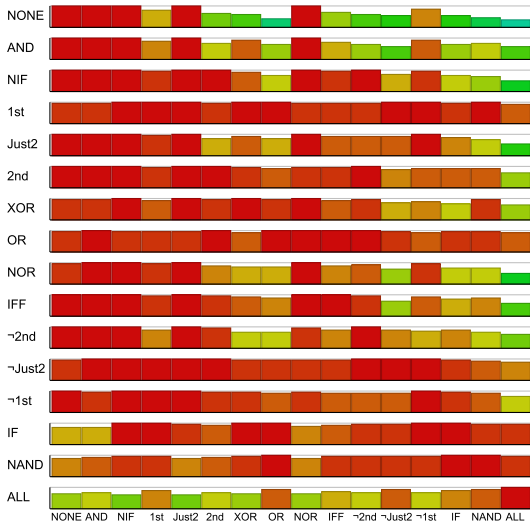
Experiments

Analysis

Optimizations

Discussion

Questions





Extra connections

Sequentially Learning Multiple Tasks in Artificial Neural Networks

Jordi Bieger

Introduction

Neural Networks

Representation

Multiple Tasks

SMRL

Description

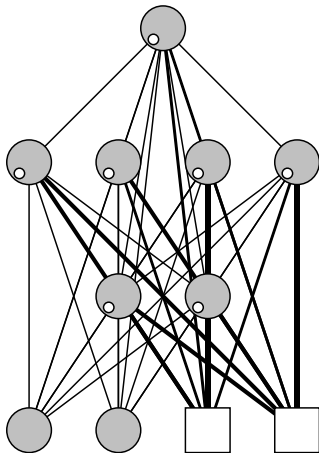
Experiments

Analysis

Optimizations

Discussion

Questions





Extra connections

Sequentially Learning Multiple Tasks in Artificial Neural Networks

Jordi Bieger

Introduction

Neural Networks

Representation

Multiple Tasks

SMRL

Description

Experiments

Analysis

Optimizations

Discussion

Questions

Network Type	# Hidden Nodes	# PB Nodes	Difficulty	Parallel	Similarity	Prodigy	Overall
IPB	4	2	83 (+6)	100 (+2)	70 (-2)	74 (+8)	39 (+3)
IPB	4+4	2	81 (+6)	99 (0)	71 (-3)	74 (+16)	39 (+5)
IPB	4	4	94 (+6)	100 (0)	74 (-5)	90 (+11)	43 (+1)
FWIPB	4	2	83 (+3)	100 (+1)	73 (+2)	73 (+4)	40 (+3)
FWIPB	4+4	2	85 (+5)	99 (+0)	76 (+0)	78 (+13)	41 (+5)
FWIPB	4	4	96 (+5)	100 (+0)	80 (+1)	93 (+5)	44 (+2)
EPB	2	3	84 (+11)	100 (0)	69 (+1)	70 (+19)	38 (+6)
EPB	4	5	91 (+4)	100 (0)	73 (-7)	85 (+10)	43 (+1)
EPB	4+4	9	95 (+9)	100 (0)	80 (-1)	91 (+19)	47 (+8)



Extra representation weights

Sequentially
Learning
Multiple Tasks
in Artificial
Neural
Networks

Jordi Bieger

Introduction

Neural Networks

Representation

Multiple Tasks

SMRL

Description

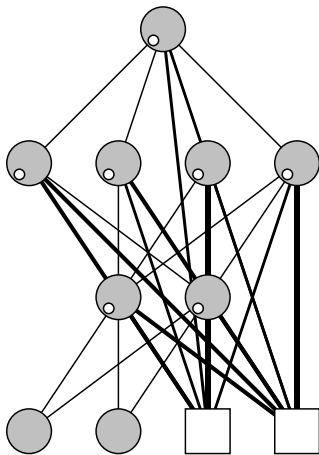
Experiments

Analysis

Optimizations

Discussion

Questions





Extra representation weights

Sequentially Learning Multiple Tasks in Artificial Neural Networks

Jordi Bieger

Introduction

Neural Networks

Representation

Multiple Tasks

SMRL

Description

Experiments

Analysis

Optimizations

Discussion

Questions

Network Type	# Hidden Nodes	# PB Nodes	Difficulty	Parallel	Similarity	Prodigy	Overall
IPB	4	2	85 (+8)	98 (+0)	74 (+2)	78 (+12)	41 (+5)
IPB	4+4	2	80 (+5)	99 (-1)	74 (0)	70 (+12)	39 (+5)
IPB	4	4	97 (+9)	100 (0)	87 (+8)	97 (+18)	53 (+11)
FWIPB	4	2	84 (+4)	99 (+1)	77 (+5)	77 (+8)	41 (+5)
FWIPB	4+4	2	83 (+3)	99 (0)	78 (+3)	72 (+7)	40 (+5)
FWIPB	4	4	95 (+4)	100 (0)	90 (+11)	93 (+5)	49 (+7)
EPB	2	3	84 (+11)	100 (0)	74 (+6)	74 (+23)	41 (+9)
EPB	4	5	93 (+7)	100 (0)	89 (+9)	89 (+14)	53 (+11)
EPB	4+4	9	96 (+11)	100 (0)	92 (+11)	92 (+20)	59 (+20)



Programme

Sequentially Learning Multiple Tasks in Artificial Neural Networks

Jordi Bieger

Introduction

Neural Networks

Representation

Multiple Tasks

SMRL

Description

Experiments

Analysis

Optimizations

Discussion

Questions

1

Introduction

- Neural Networks
- Representation
- Multiple Tasks

2

Static Meaningful Representation Learning

- Description
- Experiments
- Analysis
- Optimizations

3

Discussion

4

Questions





Evaluation

Sequentially
Learning
Multiple Tasks
in Artificial
Neural
Networks

Jordi Bieger

Introduction

Neural Networks

Representation

Multiple Tasks

SMRL

Description

Experiments

Analysis

Optimizations

Discussion

Questions

Advantages

- Simple
- Sequential learning of multiple tasks
- No catastrophic interference
- Meaningful representations

Disadvantages

- Weights don't change
- Unproven for more interesting task domains



Conclusion

Sequentially Learning Multiple Tasks in Artificial Neural Networks

Jordi Bieger

Introduction

Neural Networks

Representation

Multiple Tasks

SMRL

Description

Experiments

Analysis

Optimizations

Discussion

Questions

- Meaningful representations are powerful
- Combination with other techniques desirable
- Further research required



Programme

Sequentially Learning Multiple Tasks in Artificial Neural Networks

Jordi Bieger

Introduction

Neural Networks

Representation

Multiple Tasks

SMRL

Description

Experiments

Analysis

Optimizations

Discussion

Questions

1

Introduction

- Neural Networks
- Representation
- Multiple Tasks

2

Static Meaningful Representation Learning

- Description
- Experiments
- Analysis
- Optimizations

3

Discussion

4

Questions

