MEMORY AUGMENTED CONTROL NETWORKS

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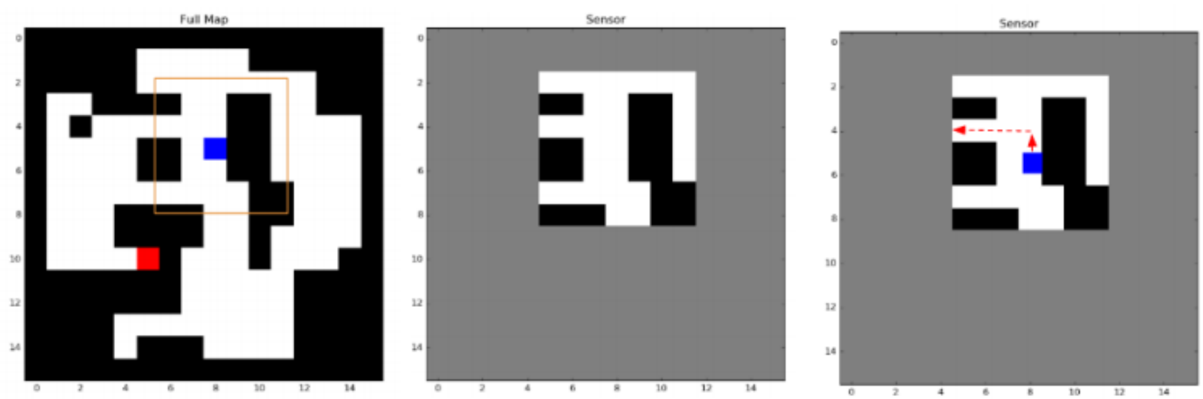
Presented by Aravind Balakrishnan

Introduction

Partially observable environments with sparse rewards

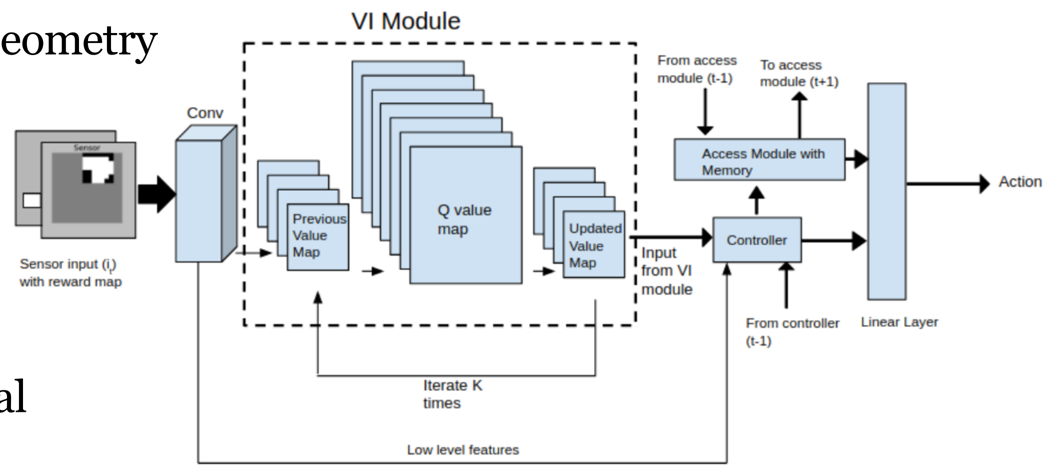
- Most real-world tasks
- Needs history of observations and actions



(a) 2D Grid World (b) Sensor observation. (c) Policy for sensor observation.

The solution - MACN

- **Differentiable Neural Computer (DNC)**
  - Neural network with differentiable external memory
  - maintains an estimate of the environment geometry



- **Hierarchical planning**
  - Lower level: Compute optimal policy on local observation
  - Higher level: Local policy + local environment features + map estimation to generate global policy

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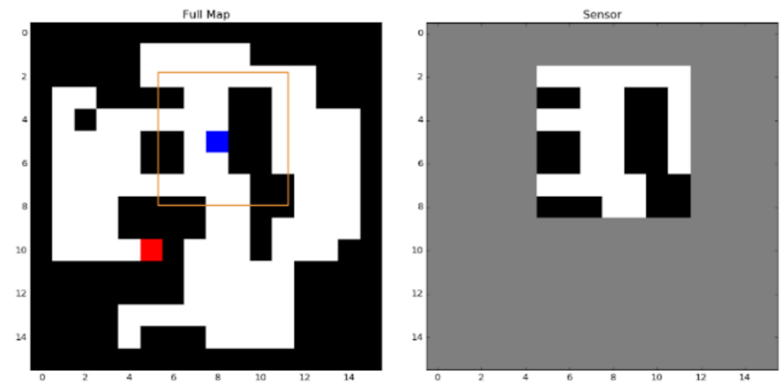
Problem definition

- States: $s_t \in \mathcal{S}$, where $s \in \mathcal{S}^{\text{goal}}$ is the goal state
- Action: $a_t \in \mathcal{A}$
- **Map:** $m \in \{-1, 0\}^n$, -1 for tiles that are an obstacle
- **Local FOV:** $H(s) \in \mathbb{R}^{n \times n}$, 0 for non-observable tiles
- **Local observation:** $z_t = H(s_t)m$
- Information available to agent at time, t:

$$h_t := \left(s_{0:t}, z_{0:t}, a_{0:t-1}, \mathcal{S}^{\text{goal}}\right) \in \mathcal{H}$$



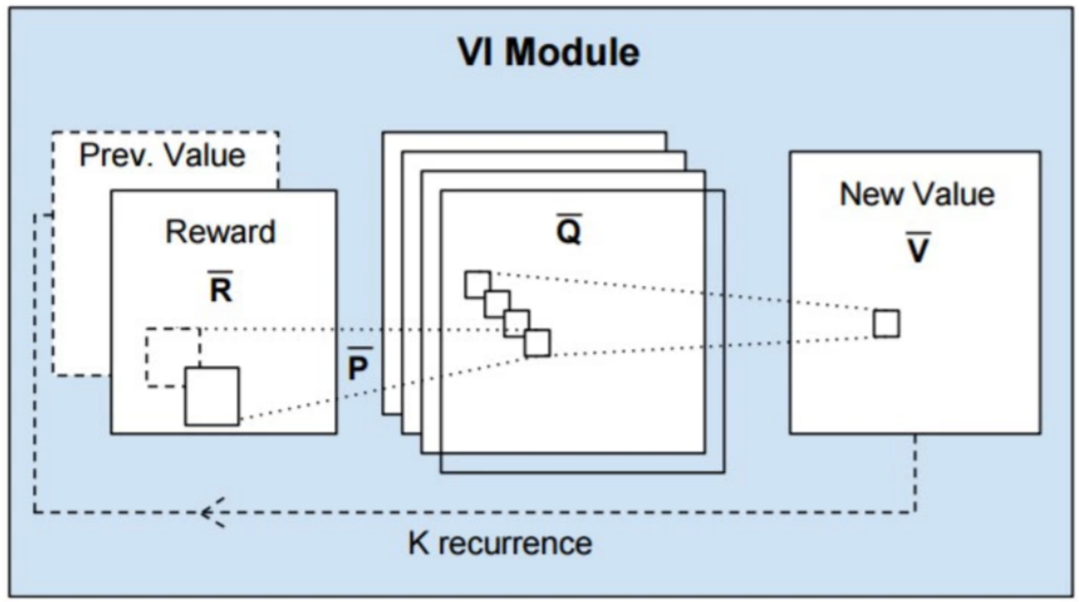
- **The problem:** Find mapping from z_t to action

Value Iteration Networks (VIN)

- Transition : $\mathcal{T}(h_t, a_t) = (h_t, s_{t+1} = f(s_t, a_t), z_{t+1} = H(s_{t+1})m, a_t)$
- Reward : $r(h_t, a_t) = z_t[s_t]$
- MDP : $\mathcal{M}(\mathcal{H}, \mathcal{A}, \mathcal{T}, r, \gamma)$

VIN: Value Iteration approximated by a Convolutional Neural Network:

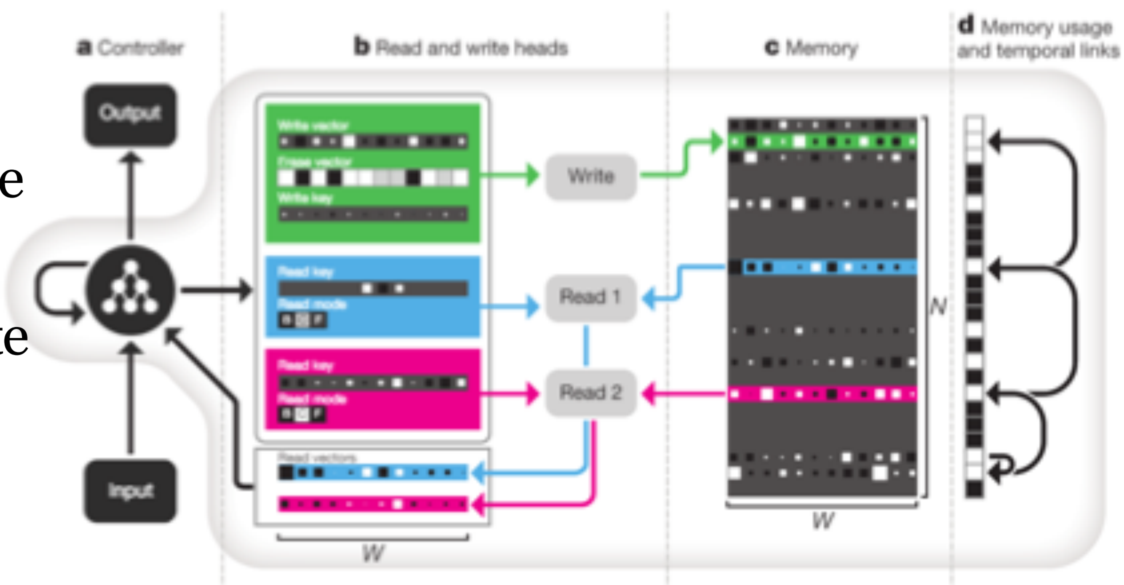
Previous value function stacked with reward, passed through a Conv layer, max-pooled along channel and repeated K times is an approximation of value iteration over K iterations



https://arxiv.org/abs/1602.02867

Differentiable Neural Computer (DNC)

- LSTM (controller) with an external memory
- Improved on Neural Turing Machine
- Uses differential memory attention mechanisms to selectively read/write to external memory, M

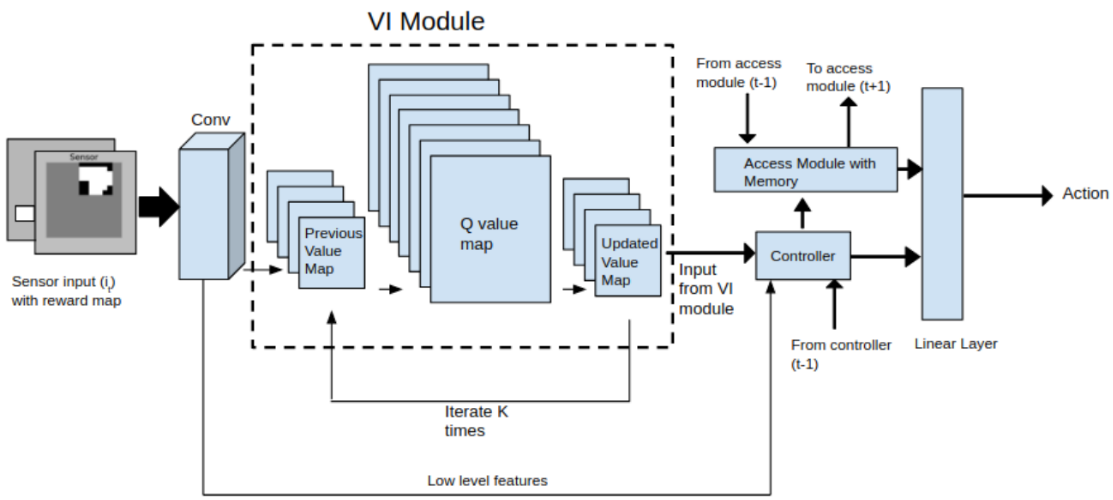


- **Read**: $re_t^i = M_t^\top w_t^{read,i}$
- **Write** $M_t = M_{t-1}(1 - w_t^W e_t^\top) + w_t^W v_t^\top$

https://www.nature.com/articles/nature20101.epdf

Architecture – Conv block

- **Conv block:** generate feature representation; R and initial V for VIN
  - **Input**: 2D map (m x n) stack with reward map (m x n) => (m x n x 2)
  - Convolve twice to get Reward layer (R)
  - Convolve once more to get initial V



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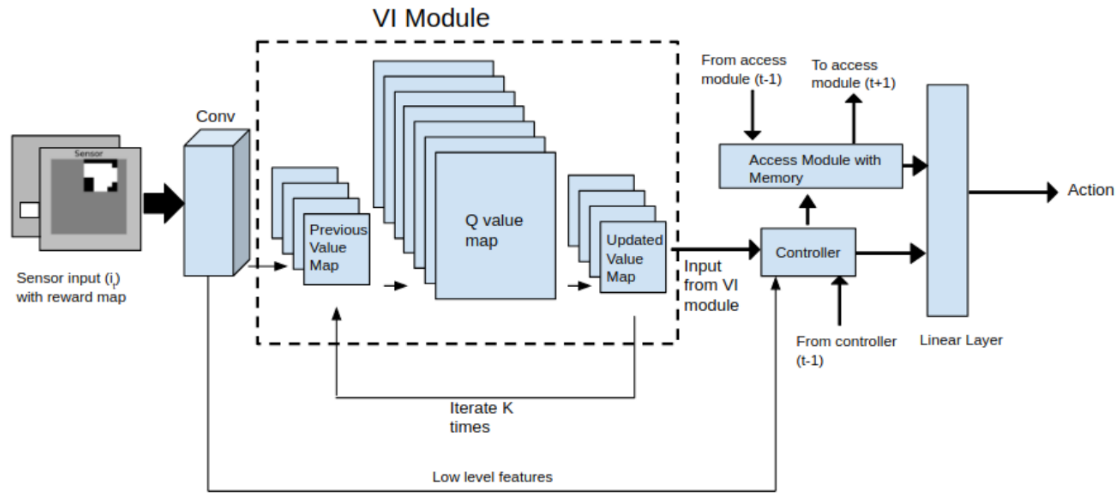
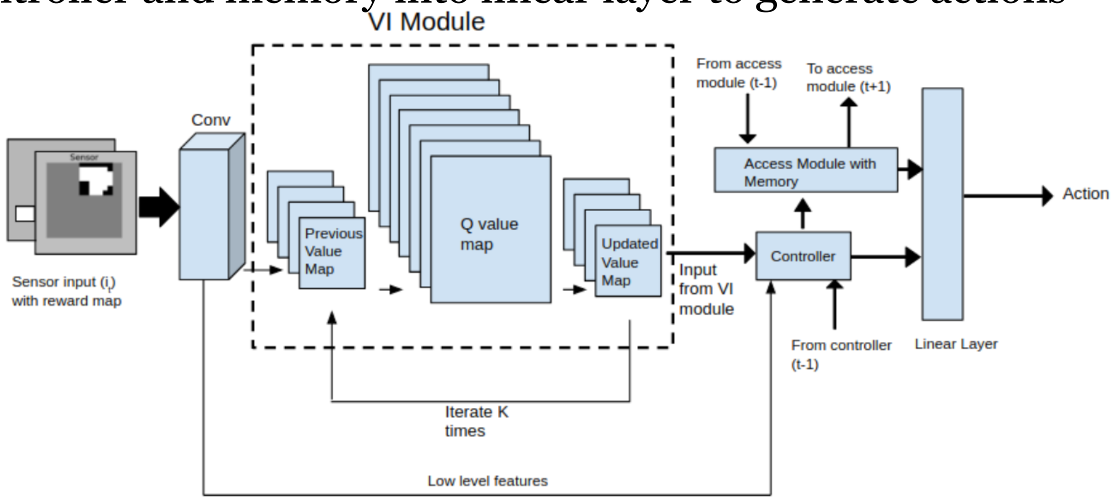
Architecture - VI Module

- First level of planning (Conv output into VIN)
- **VI module**: Plan in this space and calculate optimal value function in K iterations
  - **Input**: R and V concatenated
  - Convolved to get Q; Take max channel-wise to get updated V
  - Perform this K times to get Value map



Architecture - Controller

- Second level of planning (CNN output + VIN output into Controller):
- **Controller:**
  - **Input:** VIN output + low level feature representation (from Conv) into controller
  - Controller network (LSTM) interfaces with memory
  - Output from controller and memory into linear layer to generate actions



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Comparison with other work

- **Cognitive Mapping and Planning for Visual Navigation** (Gupta et al. 2017)
  - Value iteration Network + memory
  - Maps image scans to 2D map estimation by approximating all robot poses
- **Neural Network Memory Architectures for Autonomous Robot Navigation** (Chen et al. 2017)
  - CNN to extract features + DNC
- **Neural SLAM** (Zhang et al. 2017)
  - SLAM model using DNC
  - Efficient exploration

Experiment Setup

- **Baselines:**
  - **VIN**: just the VI module and no memory in place
  - **CNN + DNC**: CNN (4 Conv layers) extract features from observed map with the reward map and pass to the memory.
  - **MACN with a LSTM:** Planning module + LSTM instead of memory
  - **DQN**
  - **A3C**

Experiments – 2D Maze

Model	Performance	16×16	32×32	64×64
VIN	*Success(%)*	0	0	0
	Test Error	0.63	0.78	0.81
CNN + Memory	*Success(%)*	0.12	0	0
	Test Error	0.43	0.618	0.73
MACN (LSTM)	*Success (%)*	88.12	73.4	64
	Test Error	0.077	0.12	0.21
MACN	*Success(%)*	**96.3**	**85.91**	**78.44**
	Test Error	**0.02**	**0.08**	**0.13**

- CNN+Memory performance is very poor
- MACN drop in accuracy on scaling is not as large as others

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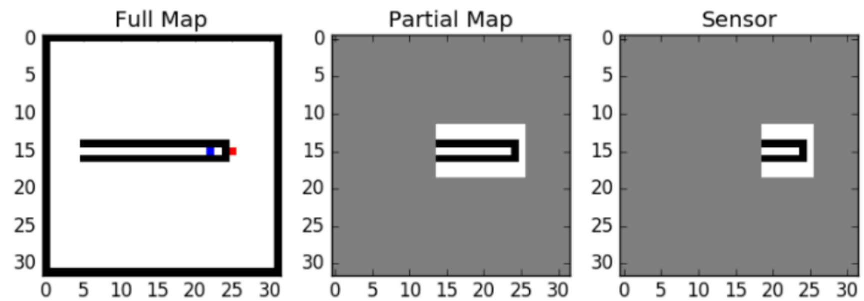
Experiments – 2D Maze with Local Minima



Model	*Success (%)*	*Maximum generalization length*
DQN	0	0
A3C	0	0
CNN + Memory	12	20
VIN	0	0
MACN	**100**	**330**

- Only MACN generalizes to longer tunnels
- Shift in memory states only when agent sees end of wall and on exit

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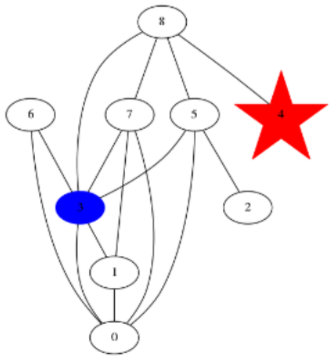
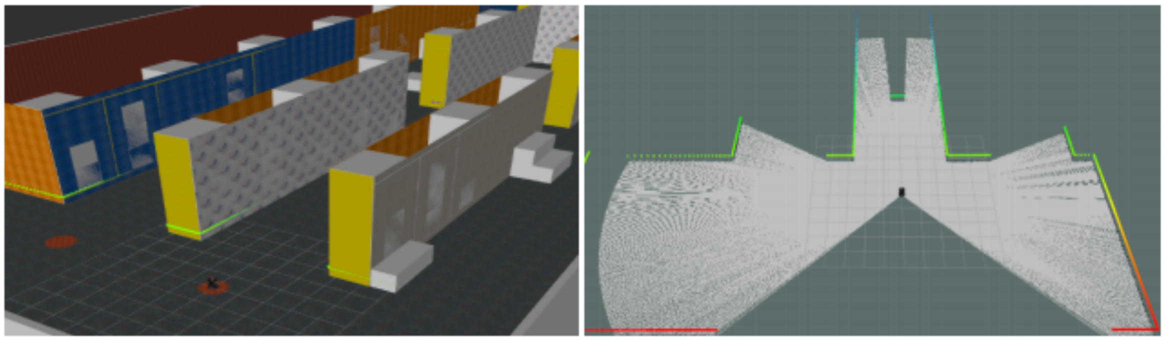
Experiments – Graph Search

- Blue node is the start state
- Red node is end state
- Agent can only observe edges connected to current node
- Problem where state space and action space are not limited

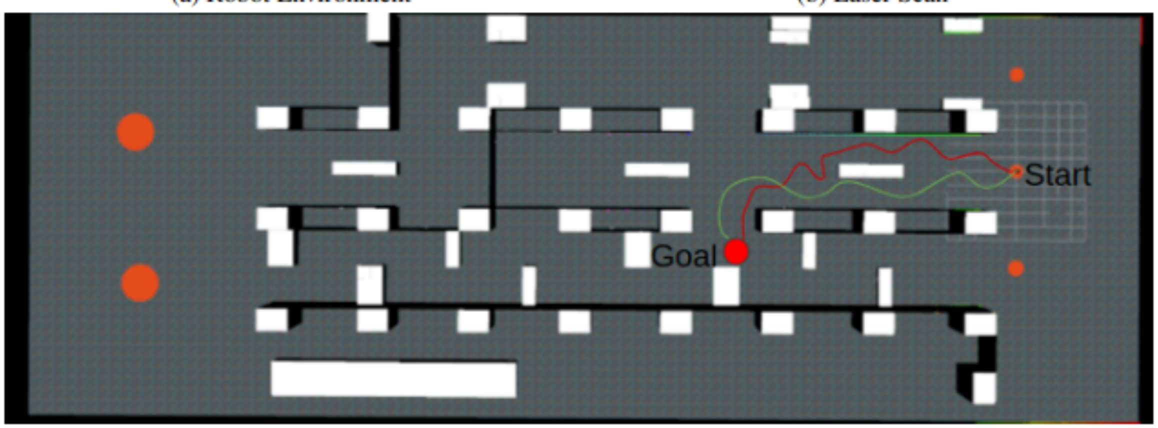


Model	Test Error, Success(%)			
	9 Nodes	16 Nodes	25 Nodes	36 Nodes
VIN	0.57, 23.39	0.61, 14	0.68, 0	0.71, 0
A3C	NA, 10	NA, 7	NA, 0	NA, 0
DQN	NA, 12	NA, 5.2	NA, 0	NA,0
CNN + Memory	0.25, 81.5	0.32, 63	0.56, 19	0.68, 9.7
MACN (LSTM)	0.14, 98	0.19, 96.27	0.26, 84.33	0.29, 78
MACN	**0.1, 100**	**0.18, 100**	**0.22, 95.5**	**0.28, 89.4**

Experiments – Continuous Control



(a) Robot Environment (b) Laser Scan



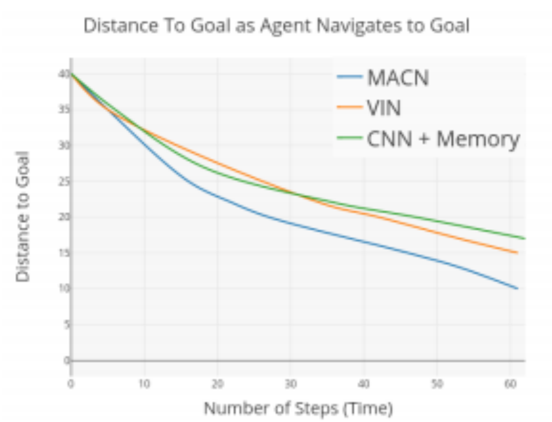
(c) Top Down View of Environment

- Converts this to required 2D
- Network output generates waypoints

Model	*Success (%)*
DQN,A3C	0
VIN	57.60
CNN + Memory	59.74
MACN	**71.3**

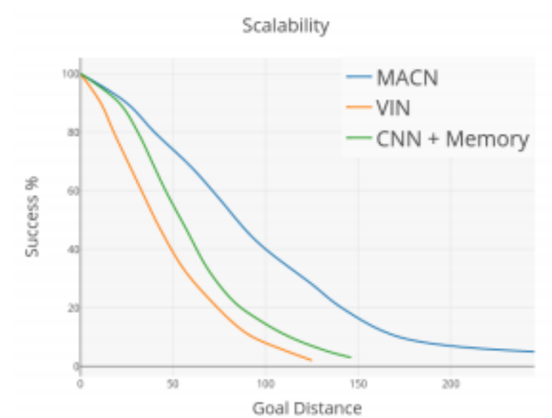
Experiments – Other comparisons

Convergence rate



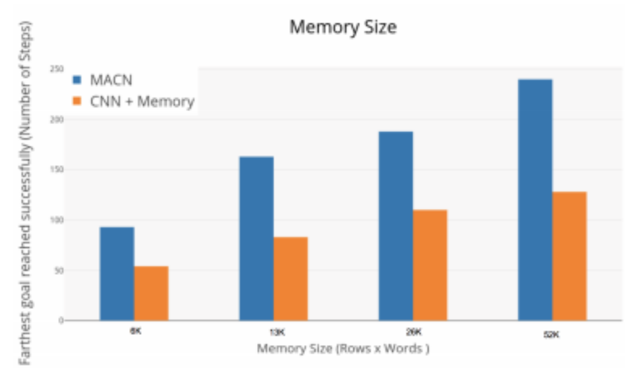
(a) Dist. to goal vs number of steps

Scaling with complexity



(b) Success % vs goal distance

Scaling with memory



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Conclusion and Discussion

- **Contributions:**
  - Novel end-to-end architecture that combines hierarchical planning and differentiable memory

- **Future work**
  - Efficient exploration
  - Take sensor errors into account