Current Trends in Artificial Intelligence

A few lessons from Complementary Learning Systems

Ulrich Paquet @ 2nd DTU Compute Workshop on Current Trends in Artificial Intelligence
How can we be creatively inspired by neuroscience? How can it help us think out of the box, to make progress in artificial intelligence? **

** Asked by a layman, myself :)
If neocortex is a neural net that learns online, from a stream of experience, then how is it possible to learn about specific things that only ever happen once?
Intelligent agents must possess (at least) **two learning systems**

In mammals they are the **neocortex** and **hippocampus**

- Neocortex gradually acquires structured knowledge representation
- Hippocampus quickly learns specifics of individual experiences

Idea: Learning specific arbitrary knowledge happens through hippocampus replaying it to neocortex over and over again during sleep, interleaved with other experiences
Complementary Learning Systems Theory

Wherefrom, and whereto?

The goal is to tie together a wide range of empirical data from different parts of neuroscience in a common connectionist theoretical framework.

- The original citation is McClelland, McNaughton & O’Reilly (1995)
- This talk draws from Kumaran, Hassabis, and McClelland (2016)
  - Update the theory in light of new empirical data
  - Argue that CLS provides *useful principles for machine learning*
Complementary Learning Systems Theory

Hippocampus gradually acquires structured knowledge representation

Hippocampus quickly learns specifics of individual experiences

Neocortex gradually acquires structured knowledge representation

Source: Wikimedia/Life Sciences Database
Parallels with machine learning

Non-parametric methods

Instance-based learning, where each experience has its own coordinates, capacity can be increased as required and parameters can grow with data.

Parametric methods

Optimal parametric characterization of the statistics of the environment by learning gradually through repeated, interleaved exposure to large numbers of training examples.
Deep Networks

Composition of multiple processing layers

State of the art in image and speech recognition

Learns successively more abstract representations from sensory data

Oriented edges → Edge combinations → Object parts

Generalization

Optimal parametric characterization of the statistics of the environment by learning gradually through repeated, interleaved exposure to large numbers of training examples.
Structured knowledge representation in neocortex

Learning such a system has limitations
Structured knowledge representation in neocortex

Learning such a system has **limitations**

- **A single experience counts!** Say a life-threatening situation
- Rapid adjustment of connection weights to accommodate new information can severely **disrupt** the representation of existing knowledge

  “Catastrophic interference”

  “Stability-plasticity dilemma”
Gaussian Processes

Non-parametric methods

- One-shot accumulation of experience and learning as a new input $x$ becomes a template to be compared against
- Predictions by comparing an input with known templates
- No successively more abstract representations

Instance-based learning, where each experience has its own coordinates, capacity can be increased as required and parameters can grow with data.
Dirichlet Process Mixture Models

Instance-based learning, where each experience has its own coordinates, capacity can be increased as required and parameters can grow with data.

- Model data density through templates (cluster centers)
- Can dynamically “on the fly” allocate more capacity for a surprising new input input $x$
- Uses existing capacity for familiar inputs
Complementary Learning Systems Theory

Hippocampus quickly learns specifics of individual experiences

**Instance based representation** in the hippocampal system

- **Rapid** and relatively individuated storage of information about individual items or experiences
- CLS proposes that the HC and MTL structures support the **initial** storage of item-specific information.
- Role in **recognition memory** for specific items

Source: Wikimedia/Life Sciences Database
Complementary Learning Systems Theory

Hippocampus quickly learns specifics of individual experiences

Involved in the formation of episodic memory as well as spatial memory used in navigation

- Navigation - linkage of spatial locations
- Episodic memory - linkage of events
- Both may depend critically on temporal sequence encoding (a code that captures time ordering)
Complementary Learning Systems Theory

**Systems-level consolidation**

- Idea: **Gradual** cortical learning driven by **replay** of new information
- Interleaved with other activity to minimize disruption of existing knowledge during the integration of new information

Source: Wikimedia/Life Sciences Database
CLSs and their interactions

- Bidirectional connections within and between integrative neocortical association areas, for gradual acquisition of **structured knowledge** through interleaved learning.

- Bidirectional connections between neocortical areas and the MTL for **storage, retrieval and replay**.

- = Part of the structure-specific neocortical learning system in CLS theory.

[Diagram showing primary motor cortex, primary somatosensory cortex, hippocampus, and medial temporal lobe (MTL) with bidirectional connections marked.]
CLoSs and their interactions

**rapid synaptic plasticity** crucial for the rapid **binding** of the elements of an event into an integrated hippocampal representation

**initial** learning of arbitrary new information

connections within hippocampus

connections between hippocampus and surrounding MTL cortices
CLSs and their interactions

**systems-level consolidation**

= 

1. hippocampal activity during **replay**

2. → neocortical association areas

3. → learning within intra-neocortical connections

systems-level consolidation is **complete** when memory retrieval can occur without the hippocampus

memory retrieval = **reactivation** of the relevant set of neocortical representations

(later in talk)
Evidence supporting CLS theory #1

Hippocampal replay

- Replay of recent experiences occurs during **offline** periods

  * **sleep + rest**

- The hippocampus and neocortex **interact** during replay in **systems-level consolidation**

  (Optogenetic blockage of CA3 output in transgenic mice after learning in the contextual fear paradigm specifically reduces sharp-wave ripple (SWR) complexes in CA1 and impairs consolidation…)

Place cells and replay in rodent hippocampus

https://www.youtube.com/watch?v=4LnTWixQbbs
Empirical evidence of replay

- Sleep → hippocampal neurons exhibit large irregular activity (LIA) patterns that are distinct from the activity patterns observed during active states.
- LIA = synchronous discharges (though to be) initiated in CA3 produce sharp-wave ripples (SWRs) which are propagated to neocortex.
- SWR → reactivation of recent experiences, expressed as the sequential firing of place cells.
- Replay events are time-compressed by a factor of 20.
- Single event replayed many times during a single sleep period.

SWR = spontaneous neural activity occurring within the hippocampus during periods of rest and slow wave sleep, evident as negative potentials (i.e. sharp waves). Transient high-frequency (~150Hz) oscillations (i.e. ripples) occur within these sharp waves, which can reflect the reactivation of activity patterns that occurred during actual experience, sped up by an order of magnitude.
Hippocampal place cells recorded in the Wilson lab at MIT

https://www.youtube.com/watch?v=lfNVv0A8Qvl
Circumventing the statistics of the environment

Hippocampus “marks” salient but statistically infrequent experiences

Why? So that...

- such events are not swamped by the wealth of typical experiences
- such events are preferentially stabilized and replayed into the neocortex, allowing knowledge structures to incorporate this new information

Idea of adaptive reweighting

Why adapt? Maladaptive consequences like post-traumatic stress disorder. A unique aversive experience may be transformed into a persistent and dominant representation through a runaway process of repeated reactivation
Role of replay of hippocampal memories

Big picture:

- Replay allows **goal-dependent weighting of experience statistics**
- The neocortex does **not** have to be a slave to the **statistics of its environment**

**Reweighting**: surprising / novel / high in reward value (positive or negative) / high in information content (reducing uncertainty about best action in a given state)

Optimal parametric characterization of the **statistics of the environment** by learning gradually through repeated, interleaved exposure to large numbers of training examples.
Evidence supporting CLS theory #2

The role of the hippocampus in memory

- Bilateral **damage** to the hippocampus profoundly affects **memory for new information**.
- Language + reading + general knowledge + acquired cognitive skills = **intact**
- New types of learning are hippocampus dependent
Role of hippocampus in memory

**Hippocampal lesion**

- Lost ability to form new memories
- Remote memories spared
- Perceptual and motor skills spared
- Systems consolidation

https://www.youtube.com/watch?v=c62C_yTUYVg
Evidence supporting CLS theory #3

**Hippocampus supports core computations and representations of a fast-learning episodic memory system**

- Episodic memory = the collection of past personal experiences that occurred at a **particular time and place**.
- Remembering a 6th birthday party: EM allows an individual to figuratively travel back in time to remember the event that took place at that particular time and place.
Evidence supporting CLS theory #3

Hippocampus supports core computations and representations of a fast-learning episodic memory system

Episodic memory depends on hippocampus

It is helped by a capacity to bind together (auto-associate) diverse inputs from different brain areas that represent parts of an event

- Episodic memory = the collection of past personal experiences that occurred at a particular time and place.
- Remembering a 6th birthday party: EM allows an individual to figuratively travel back in time to remember the event that took place at that particular time and place
Pattern separation and completion

DG **pattern separation** makes patterns as different as possible, so as to make auto-association easier (less confusing)

CA3 **auto-associator**, due to its dense reciprocal connections

→ **pattern completion**

CA1 mediates the activation of other areas of the neo-cortex

Neocortex

stimulus

Dentate gyrus (DG)

Entorhinal cortex (ERC)

CA3

CA1
Pattern separation and completion

- Idea: parts of event -- **spatial** (place) and **non-spatial** (what happened) -- are **processed in parallel** before converging in the hippocampus in DG/CA3 subregions.

- **Pattern separation + pattern completion** = central to hippocampus for storing details of experiences.
Pattern separation and completion

**Pattern separation**

(Idea): Dentate gyrus subregion in HC performs pattern separation, orthogonalizes incoming inputs before…

**Pattern completion**

(Idea): ...auto-associative storage in the CA3 region

Output of an entire stored pattern (e.g. corresponding to an entire episodic memory) from a partial input. Functions as an attractor network.
Pattern separation in dentate gyrus (?)

- Pattern separation → similar input patterns result in more distinct output patterns
- The result is a conjunctive code
- Thought to be implemented in DG

- higher dimensional output from conjunctive “AND” units
- output is sparser than the input & small overlap between outputs of similar inputs
Sparsity priors, compressed sensing

- Sparse, overcomplete representation
- “Sparse linear models”
- Inference and learning is difficult

**Sparsity prior** on a much larger latent variable

\[
p(z|x) = \frac{p(x|z)p(z)}{p(x)}
\]
RKHS

- Support vector machines
- **Kernel trick** and the reproducing kernel Hilbert space (RKHS)
- Implicitly maps inputs to a higher (infinite!) dimensional space
- No sparse representation, though...

In the machine learning world
Pattern completion

Associative memories

42.3: Definition of the continuous Hopfield network

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<th>moscow-----russia</th>
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Can it be a sparse code, like DG → CA3?

In the machine learning world

A list of desired memories

From David MacKay's *Information Theory, Inference, and Learning Algorithms*
Pattern completion

Associative memories

A list of desired memories

Can it be a sparse code, like DG → CA3?

From David MacKay's *Information Theory, Inference, and Learning Algorithms*
Auto-associative at a concept-level? Hierarchical?

“banana”

Memories in topological fashion like graphs?

Images: Wikimedia
New patterns

**Similar** input pattern via entorhinal cortex **to previous pattern** (memory retrieval)

- CA3 outputs a pattern closer to the one it previously used for this ERC pattern

**Low overlap** to previously stored patterns (memory formation)

- **DG creates a new, statistically independent cell population** / neurogenesis
- Pattern separation!
  - Non-parametric Bayes

(Amount of overlap required for pattern completion may differ across the hippocampus)
New patterns

Instance-based learning, where each experience has its own coordinates, capacity can be increased as required and parameters can grow with data.

Dirichlet process mixture models

- Models data density through templates (cluster centers)
- Can dynamically “on the fly” allocate more capacity for a surprising new input input $\mathbf{x}$
- Uses existing capacity for familiar inputs
New patterns

Non-parametric methods

Instance-based learning, where each experience has its own coordinates, capacity can be increased as required and parameters can grow with data.

Dirichlet process mixture models

- Forgetting: Capacity can be removed if no input x is associated with it (say over a time window)
Evidence supporting CLS theory #4

The hippocampus and neocortex support quantitatively different forms of representation

Rat behaviour in Morris water maze

- Early on appeared to reflect **individual episodic traces** (i.e. an instance-based non-parametric representation)
- Was later (28 days after learning) consistent with the use of a **parametric representation putatively housed in the neocortex**
Trends, trends, trends

Non-parametric methods

Semi-parametric methods

Parametric methods

Instance-based learning, where each experience has its own coordinates, capacity can be increased as required and parameters can grow with data.

Optimal parametric characterization of the statistics of the environment by learning gradually through repeated, interleaved exposure to large numbers of training examples.
Neural Episodic Control

K-nearest neighbours on keys

Parametric methods

Memory module for each action \( a \)

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Neural Episodic Control

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... ... 

Memory module for each action \( a \)

Action-value function estimate
\[
Q^\pi(s, a) = \mathbb{E}_\pi \left[ \sum_t \gamma^t r_t \mid s, a \right]
\]
at time memory was written
Neural Episodic Control

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Memory module for each action $a$

Parametric methods

$S_t$

conv net

$h$
Neural Episodic Control

**K-nearest neighbours on keys**

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Memory module for each action $a$

**Parametric methods**

$Q(s_t, a) = \sum_i w_i v_i$

$$w_i = \frac{k(h, h_i)}{\sum_j k(h, h_j)}$$

$a_t = \arg \max_a Q(s_t, a)$

$\epsilon_{\text{greedy}}$
Neural Episodic Control

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Memory module for each action $a$

Parametric methods

$Q(s_t, a) = \sum_i w_i v_i$

$w_i = \frac{k(h, h_i)}{\sum_j k(h, h_j)}$

Take action $a_t$, receive reward $r_{t+1}$
Neural Episodic Control

K-nearest neighbours on keys

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Memory module for each action $a$

$Q(s_t, a) = \sum_i w_i v_i$

$w_i = \frac{k(h, h_i)}{\sum_j k(h, h_j)}$

Conv net

$h, Q^{(N)}(s_t, a_t)$

take action $a_t$
receive reward $r_{t+1}$

Parametric methods
Neural Episodic Control

K-nearest neighbours on keys

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Memory module for each action $a$

$Q(s_t, a) = \sum_i w_i v_i$

$w_i = \frac{k(h, h_i)}{\sum_j k(h, h_j)}$

$h, Q^{(N)}(s_t, a_t)$

Parametric methods

Gradients
Conclusion

Non-parametric methods

Semi-parametric methods

Parametric methods

be creative :)
Hippocampal Subregions, Connectivity, and Representation

Entorhinal cortex (ERC): grid cells

Dentate gyrus (DG): pattern separation, very sparse, adult neurogenesis

CA1: place cells

CA3: pattern completion, highly recurrent
Neural Episodic Control

Action-value function $Q^\pi(s, a) = \mathbb{E}_\pi \left[ \sum_t \gamma^t r_t \mid s, a \right]$

N-step Q-value estimate $Q^{(N)}(s_t, a) = \sum_{j=0}^{N-1} \gamma^j r_{t+j} + \gamma^N \max_{a'} Q(s_{t+N}, a')$

Adds N on-policy rewards and bootstraps the sum of discounted rewards for the rest of the trajectory, off-policy.

Train on random minibatch from replay memory