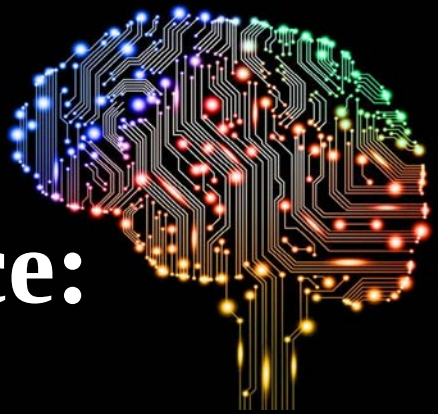


AI and Neuroscience:

Bridging the Gap

Irina Rish

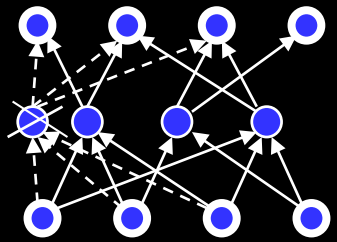
AI Foundations - Learning

IBM Research AI

AI for Neuroscience:

Modeling Brain and Behavior

AI 4 Neuro



Neuroscience 4 AI:

Neuroscience-inspired AI Algorithms

A common goal: **discover universal laws governing both biological and artificial intelligence**

NEURO-AI @ IBM


David Cox


Brian Kingsbury


Djallel Bouneffouf


Sadhana Kumaravel


Ronny Luss


Guillermo Cecchi


Irina Rish


Roger Traub


Yuhai Tu

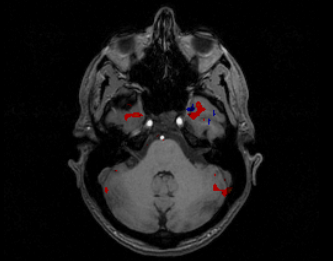

Matt Riemer

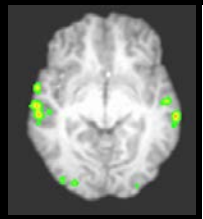

James Kozloski

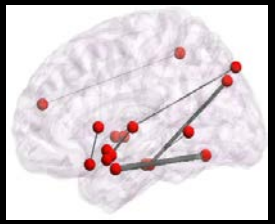

Dmitry Krotov


Steve Heisig

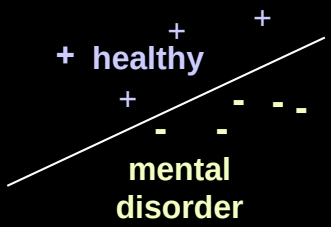
AI 4 NEURO FOCUS:
"STATISTICAL BIOMARKERS" OF MENTAL STATES







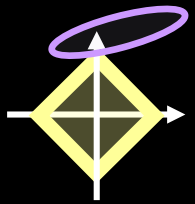
Predictive Model



"Statistical biomarkers":

Feature Selection (sparsity)

[Rish et al, SPIE Med.Imaging 2012], [Honorio et al, AISTATS 2012],
[Rish et al, Brain Informatics 2010],[Carroll et al, Neuroimage 2009]

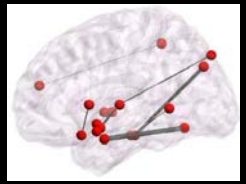


$$min_x \|y - Ax\|^2 + \lambda \|x\|_1$$

Feature Engineering (prior knowledge)

- **e.g. network properties**

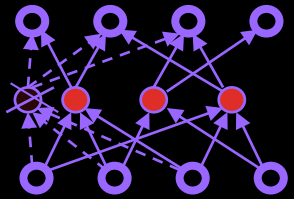
[Rish et al, PLoS One 2013], [Cecchi et al, NIPS 2009]
[Rish et al, SPIE Med.Imaging 2012], [Gheiratmand et al, submitted]



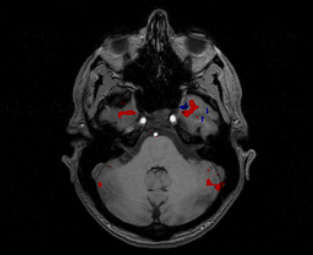
Feature Extraction: Learning Representations

- **dictionary learning, deep convnets learning**

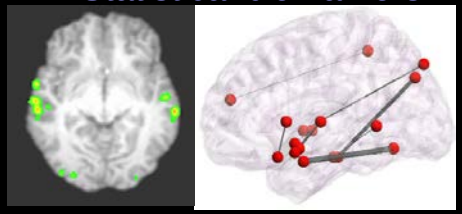
[Rish et al, SfN 2011], [Rish et al, ICML 2008],
[Bashivan et al, ICLR 2016], [Garg et al, submitted]



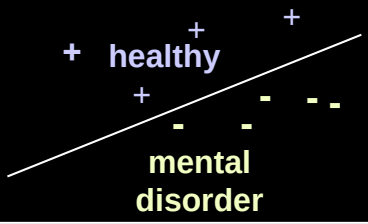
AI 4 NEURO:
NEUROIMAGING DATA ANALYSIS



"Statistical biomarkers":



Predictive Model



[Carroll et al, Neuroimage 2009]
[Scheinberg&Rish, ECML 2010]

Mental states in videogames: sparse regression, **70-95%**

[Rish et al, Brain Informatics 2010]
[Rish et al, SPIE Med.Imaging 2012]
[Cecchi et al, PLOS Comp Bio 2012]

Pain perception: sparse regression,
70-80% accuracy, "holographic" patterns

[Honorio et al, AISTATS 2012]
[Rish et al, SPIE Med.Imaging 2016]

Cocaine addiction: sparse Markov net biomarkers;
MPH effects analysis ("stimulant 4 stimulant")

[Bashivan et al, ICLR 2016]

Cognitive load prediction: 91% w/ recurrent ConvNets

[Cecchi et al, NIPS 2009]
[Rish et al, PLOS One, 2013
[Gheiratmand et al, Nature PJ Schizophrenia 2017]

Schizophrenia classification: **74% to 93%** accuracy
symptom severity prediction

[Abrevaya et al, 2018, submitted]

Nonlinear dynamical models of CaI and fMRI

AI FOR PSYCHOTHERAPY?

S. Garg, Infogain-Driven Dialogue Modeling via Hash Functions (submitted)

- As predicted by the World Health Organization, by 2030 the amount of worldwide disability and life loss attributable to depression may become greater than for any other condition, including cancer, stroke, heart disease, accidents, and war

- However, many people do not receive an adequate treatment; one of the major factors here is limited availability of mental health professionals, compared to the number of potential patient

- Goal: easily accessible, round-the-clock therapeutic services provided by a conversational agent (“PsyBot”?)

LANGUAGE, PSYCHIATRY AND AI

Computational Psychology/iatry

Computational Psychiatry Team

E. Eyigoz	(comp. linguistics)	Columbia University
R. Norel	(comp. science)	Yale University
R. Ostrand	(psycholinguistics)	Mt Sinai School Medicine
E. Gutiérrez	(comp. linguistics)	Northwell Hospital System
C. Agurto	(signal processing)	Northwestern University
S. Berger	(neuroscience)	University of Chicago
J. Reinen	(neuroscience)	UCLA
M. Pietrowicz	(signal processing)	Instituto do Cérebro, Natal BR
I. Rish	(mach. learning)	U. Buenos Aires - Argentina
D. Bouneffouf	(mach. learning)	U. Medellín - Colombia
A. Dhurandhar	(mach. learning)	NIMHANS Bangalore - India
S. Garg-USC	(mach. learning)	
V. Gurev	(comp. science)	CHDI
S. Heisig	(comp. science)	Answer ALS
G. Cecchi	(email answering)	Pfizer Corp "Undisclosed" Medical Device Maker

Cognitive Decline

Computing the structure of language for neuropsychiatric evaluation

Self-awareness

Frontiers in INTEGRATIVE NEUROSCIENCE

A quantitative philology of introspection

Psychoactive Drugs

A Window into the Intoxicated Mind? Speech as an Index of Psychoactive Drug Effects

Phonological markers of Oxytocin and MDMA ingestion

INTERSPEECH 2017

Psychosis

Automated analysis of free speech predicts psychosis onset in high-risk youths

npj Schizophrenia www.nature.com/npjscha

Prediction of psychosis across protocols and risk cohorts using automated language analysis

World Psychiatry 17:1–February 2018

Self-reference in psychosis and depression: a language marker of illness

Using Automated Metaphor Identification to Aid in Detection and Prediction of First-Episode Schizophrenia

OPEN ACCESS Freely available online

PLoS one

Speech Graphs Provide a Quantitative Measure of Thought Disorder in Psychosis

Suicidality

Predictive linguistic markers of suicidality in poets

Parkinson's and Alzheimer's

How language flows when movements don't: An automated analysis of spontaneous discourse in Parkinson's disease

Brain & Language

Unsupervised Morphological Segmentation for Detecting Parkinson's Disease

Predicting Cognitive Impairments with a Mobile Application

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Chronic Pain

Brain and psychological determinants of placebo pill response in chronic pain patients

``**Language is a window into the brain**'' - M. Covington

INFOGAIN-DRIVEN DIALOGUE VIA HASHCODE REPRESENTATIONS

Patient Therapist

$$\underset{M_h}{\operatorname{argmax}} \; \mathcal{I}(\mathcal{C}_p : \mathcal{C}_t; M_h) = \mathcal{H}(\mathcal{C}_t; M_h) - \mathcal{H}(\mathcal{C}_t | \mathcal{C}_p; M_h)$$

construct hash codes of responses

↓

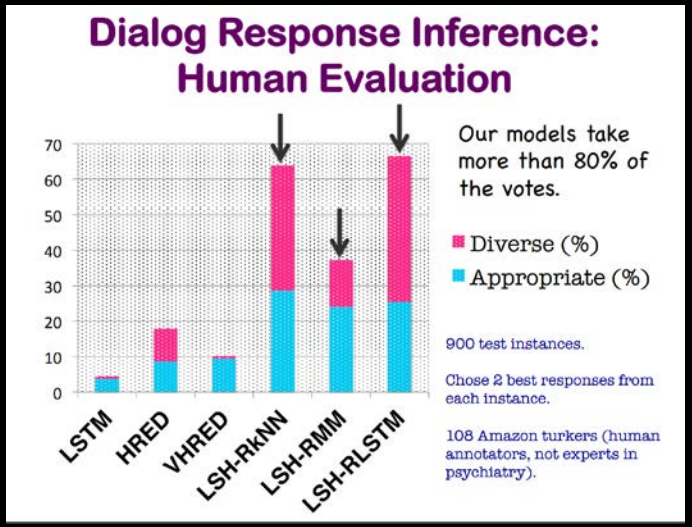
optimize hashing model to maximize mutual information between patient and therapist

↓

learn a predictive model to infer therapist's response to patient

Outperforms deep net systems:

- Works great on small datasets where deep nets failed



- Learns orders of magnitude faster: hours instead of days

HASHING MODELS OUTPERFORM DEEP NETS ON SMALL(ER) DATA

<patient> I did lose three pounds, did you notice that?
<therapist> That's great, I did notice that.
---------- hashing methods:
<RMM> Yes, you did.
<RkNN> To help you with your diet?
<RLSTM> Okay what's the explanation?

---------- deep network methods:
<LSTM> I don't want to be a lot of the way

<HRED> Yeah. You

<VHRED> Uh-huh. you

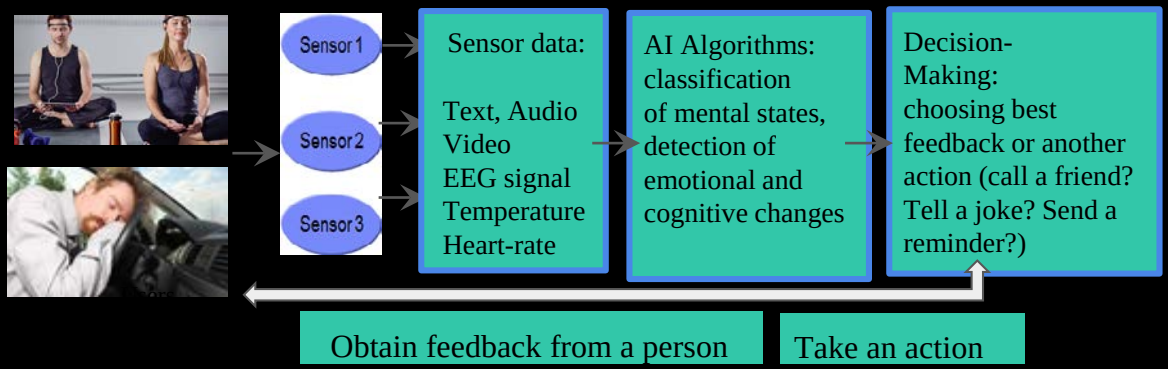
HASHING MODELS OUTPERFORM DEEP NETS ON SMALL(ER) DATA

<patient> Which is stupid because like, ya know, (sniffles) I guess if it's not what they like, then it's not what they like and they can like do something else, but like (sniffles) ya know there's some psychiatrists who charge like $300 an hour. If you did that you would really have to work like...if you worked an hour a day five days a week that would be fifteen hundred dollars a week. Like...you wouldn't have to work at all...like barely. I mean, though, most psychiatrists probably don't charge $300 an hour...yeah...it's just kinda ridiculous that...
<therapist> I'm sorry you're having such trouble getting...getting access to the care that you need (pause).

---------- hashing methods:
<RMM> You got to do.
<RkNN> Oh yeah, you never tried Lithium?
<RLSTM> And you ought not to just shove it away out of your life because you will need it again.
---------- deep network methods:
<LSTM> Uh-huh. you
<HRED> Yeah. you
<VHRED> Uh-huh. you

FUTURE:
VIRTUAL AI-BASED THERAPY?

A virtual AI assistant on a smartphone which implements the following four main steps: (1) data collection; (2) mental state recognition; (3) taking action to improve the mental state; (4) receiving feedback from a person to improve future actions



Roles:

24/7 personal coach, assistant, therapist, caretaker, or just a “digital friend”

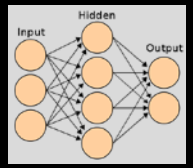
NEURO 4 AI:
WHY DO WE NEED IT?

- Successful examples: reinforcement learning, deep learning
- Still, artificial brains are way behind the natural ones:
  - brains develop from a single cell via neurogenesis and plasticity, while artificial NNs (ANNs) are manually constructed
  - brains can easily adapt to very different environments and new tasks over lifetime, ANNs are still highly specialized and inflexible
  - Attention, memory, learning mechanism (backprop) in ANNs can be improved by more biologically plausible implementations
  - Brain is a dynamical system changing even without the input, in resting-state, while machine-learning models are mainly “static”

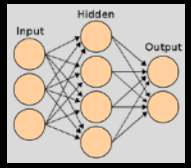
OUR QUESTIONS

- What are major limitations of modern AI?
- What can AI learn from neuroscience?
- What directions should we focus on first?

Why Neuro-AI?



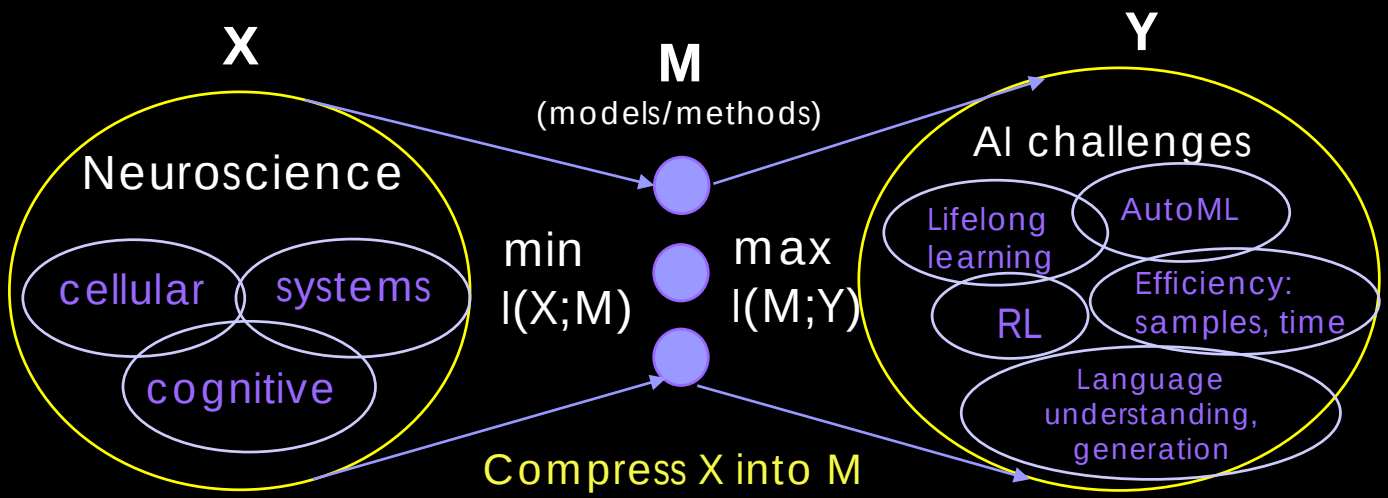
Deep Learning: limitations	Biological brains: advantages
Network engineering is (still) mostly ad-hoc/manual	Brains develop in embryo from a single cell: neurogenesis, plasticity
Catastrophic forgetting + limited transfer in continual learning	Balances stability (memory) & plasticity (adaptation)
Requires huge amounts of data	Few shot learning is the norm
Vulnerable to adversarial attack	Resilient to small input changes
Sensitive to hyperparameters	Robust/adaptive to internal changes
Requires massive power during test and train (kW of power)	Runs on ~20W



Important differences

Deep Learning:	Biological brains:
Real-valued activations propagate	Discrete “spikes”, precise timing
Learning rules are non-local, require floating point precision	Learning is local, weight updates possible with limited precision
Synchronous computations	Asynchronous computation
Relatively homogenous architecture of simple components	Dramatic diversity of cell types and connectivity patterns, compositionality (subsystems)
Single time scale	Multi-scale dynamics
Converges to a fixed model	Dynamical system: nonlinear, coupled, non-equilibrium; activity never stops, even without input

NEURO-AI: INFORMATION BOTTLENECK



Compress X into M

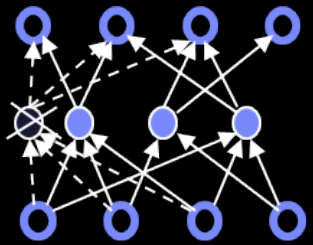
most-relevant to Y

An algorithm for interdisciplinary research:

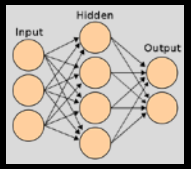
1. Identify Y: problems AI can't solve (well) today
2. Sample from (infinite?) X: recent (or not) discoveries?
3. Build M (piece of cake ☺)
4. Repeat

LONG-TERM GOAL

Next-generation AI based on better understanding of brain functioning including plasticity, attention, memory, reward processing, motivation and beyond, while approaching both brain and AI as non-equilibrium stochastic dynamical systems rather than fixed predictive models.



Current Focus



AI

Better Learning Algorithms and Neuronal Models

Automated AI
Lifelong, Continual Learning

Advancing RL

Real-Time Behavior
Neuromorphic Hardware

Language Understanding
Dialogue Generation

Neuro-AI

Beyond Backprop

Compartmental neuron models

Neuro-genesis (-evolution)
Stability/Plasticity Models

Reward and Attention Models

Spiking Networks (3rd-gen ANNs)
Nonlinear Dynamical Models

Modeling Psychology of Dialogue

BEYOND TODAY'S DEEP NETS

"Backtracking Search" in AI history tree:
welcome to the "garden of forking paths"(Borges)

Multicompartment models:

Segregated Dendrites
(Bengio NIPS 2018;
Lillicrap, Richards; etc)

"Capsules"[Hinton et al]

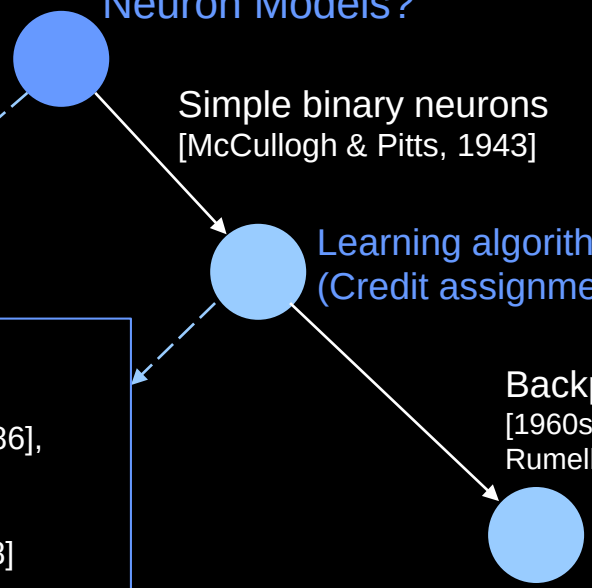
More bio-plausible algorithms:

Target Propagation variants [LeCun, 1986],
[Bengio 2015], [Hinton 2018]

Krotov&Hopfield [2018], Chklovski [2018]

[Carreira-Perpinan 2014], [Taylor 2016]

[Our AltMin method – submitted to ICML-2019]



WHAT'S WRONG WITH BACKPROP?

Biologically implausibility:

- Error feedback does not influence neural activity, and hence does not conform to known biological feedback mechanisms underlying neural communication
- Weight transport problem: symmetric weight connectivity for feedforward and feedback directions
- Many other issues (precise clocking between feedforward and backprop phases, violation of Dale's law, etc)

Computational Issues:

- Vanishing gradients (due to chain of derivatives)
- Difficulty handling non-differentiable nonlinearities (e.g., binary spikes)
- Lack of cross-layer weight update parallelism

ALTERNATIVE: TARGET PROPAGATION

LeCun, Yann. Learning process in an asymmetric threshold network. In Disordered systems and biological organization, 1986.

LeCun, Yann. Modeles connexionnistes de lapprentissage `. PhD thesis, Universite Paris 6, 1987.

Lee, Zhang, Fischer and Bengio. Difference target propagation. ECML-2015

Bengio, Y. How auto-encoders could provide credit assignment in deep networks via target propagation. arXiv:1407.7906, 2014.

Bartunov, S.; Santoro, A.; Richards, B. A.; Hinton, G. E.; and Lillicrap, T. Assessing the scalability of biologically-motivated deep learning algorithms and architectures, arXiv, 2018.

Unfortunately, backprop still outperforms target prop on standard benchmarks

OUR APPROACH: ALTMIN

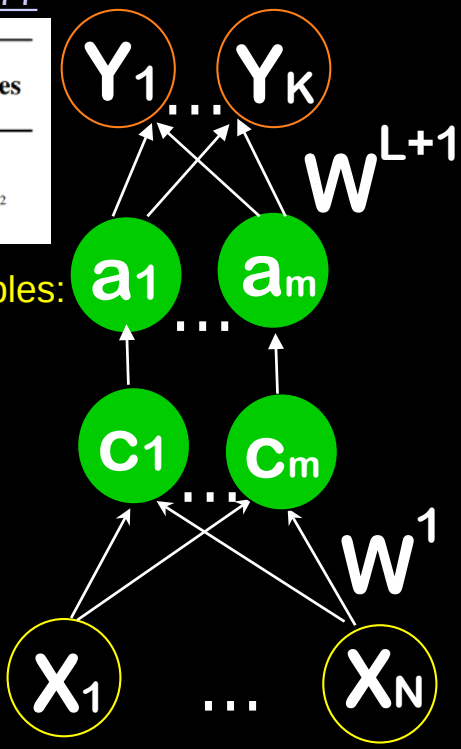
(submitted) https://arxiv.org/abs/1806.09077

Beyond Backprop: Online Alternating Minimization with Auxiliary Variables

Anna Choromanska*[1] Benjamin Cowen*[1] Sadhana Kumaravel*[2] Ronny Luss*[2] Mattia Rigotti*[2]
Irina Rish*[2] Brian Kingsbury[2] Paolo DiAchille[2] Viatcheslav Gurev[2] Ravi Tejwani[3] Djallel Bouneffouf[2]

Breaking gradient chains with auxiliary activation variables:

- Explicit propagation of activations
- Noisy neuronal activity
- More local updates than backprop
- Parallel, distributed, asynchronous



$$f(\boldsymbol{W},\boldsymbol{C}) = \sum_{t=1}^{n} \mathcal{L}(y_t, \sigma_L(\boldsymbol{c}_t^L), \boldsymbol{W}^{L+1}) + \mu \sum_{t=1}^{n} \sum_{l=1}^{L} \|\boldsymbol{c}_t^l - \boldsymbol{W}^l \sigma_{l-1}(\boldsymbol{c}_t^{l-1})\|_2^2 + \lambda_W \|\boldsymbol{W}^l\|_1 + \lambda_C \|\boldsymbol{C}^l\|_1$$

PROMISING RESULTS

- **AltMin matches Backprop performance, often converging faster on** fully-connected nets (MNIST, CIFAR-10), RNNs (seqMNIST) , LeNet5 (MNIST)

- Online AltMin GREATLY outperforms OFFLINE AltMin methods

Our method LEARNS FASTER than backprop in 1st epoch, then matches BP

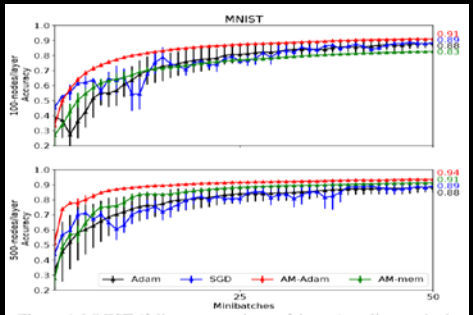


Figure 1. MNIST (fully-connected nets, 2 layers): online methods, first epoch; 50 mini-batches, 200 samples each.

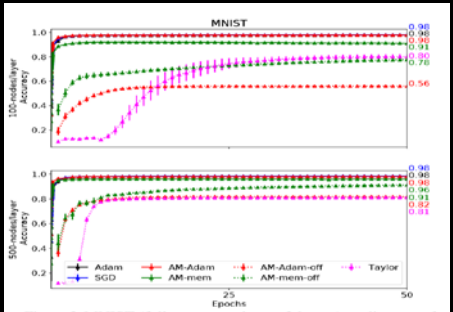


Figure 2. MNIST (fully-connected nets, 2 layers): online vs. offline methods vs. Taylor's ADMM, 50 epochs.

Similar behavior on some RNNs and sequential data (seqMNIST), And LeNet5 (MNIST)S

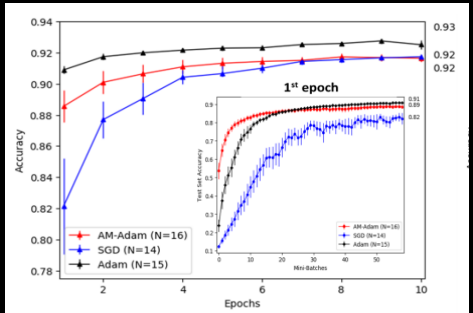
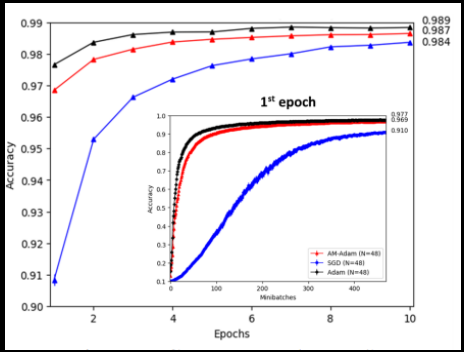


Figure 6. RNN-15, Sequential MNIST.



AI AUTOMATION: PLASTICITY

Adaptation at Different Time Scales

long

short

Plasticity:

architectural changes

- Adult neurogenesis as an inspiration for hidden-layer adaptation (neuronal birth and death) – e.g., in sparse linear autoencoder (online dictionary learning)
- Next: "ensemble-level" changes: add/delete network "blocks''

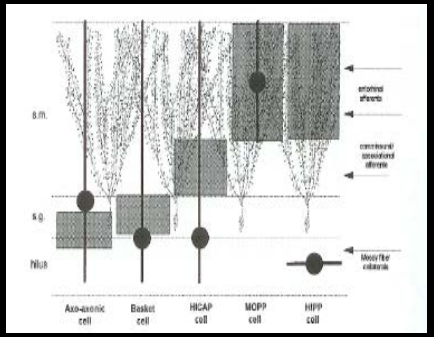
Reward-driven Attention:

input and architecture selection

- "External" attention: input selection (generalizing visual attention) driven by reward in online decision-making (e.g., contextual bandit setting)
- Next: "internal" attention as dynamic choice of subnetworks

Plasticity: Adult Neurogenesis

Dentate gyrus of the hippocampus



- Adult neurogenesis (AN): generation of new neurons in adult brains throughout life (balanced by neuronal death)

- In dentate gyrus of the hippocampus (in humans)

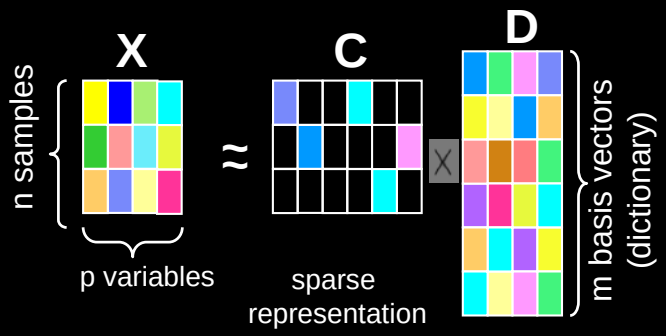
- Increased AN is associated with better adaptation to new environments. But why is it necessary, besides the usual synaptic plasticity (i.e. learning weights in neural nets)?

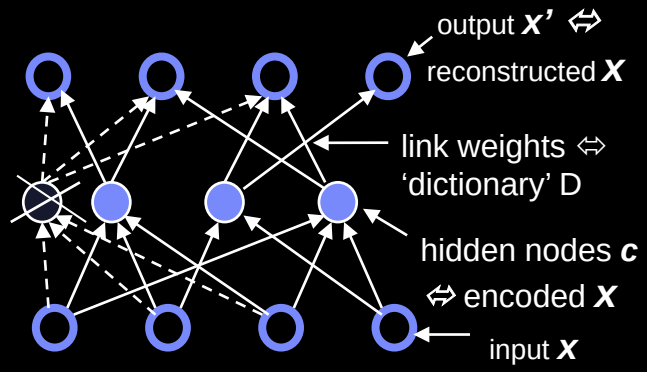
- Can a computational model of AN support this observation?
  Can it lead to an adaptive representation learning algorithm?

Baseline: Sparse Autoencoder

- Current neuroscience theories suggest that the hippocampus functions as an autoenconder to create and evoke memories

- A simple autoencoder model: single-hidden-layer sparse linear autoencoder (classical sparse coding of Olshausen & Field, 1996), also known as dictionary learning model:



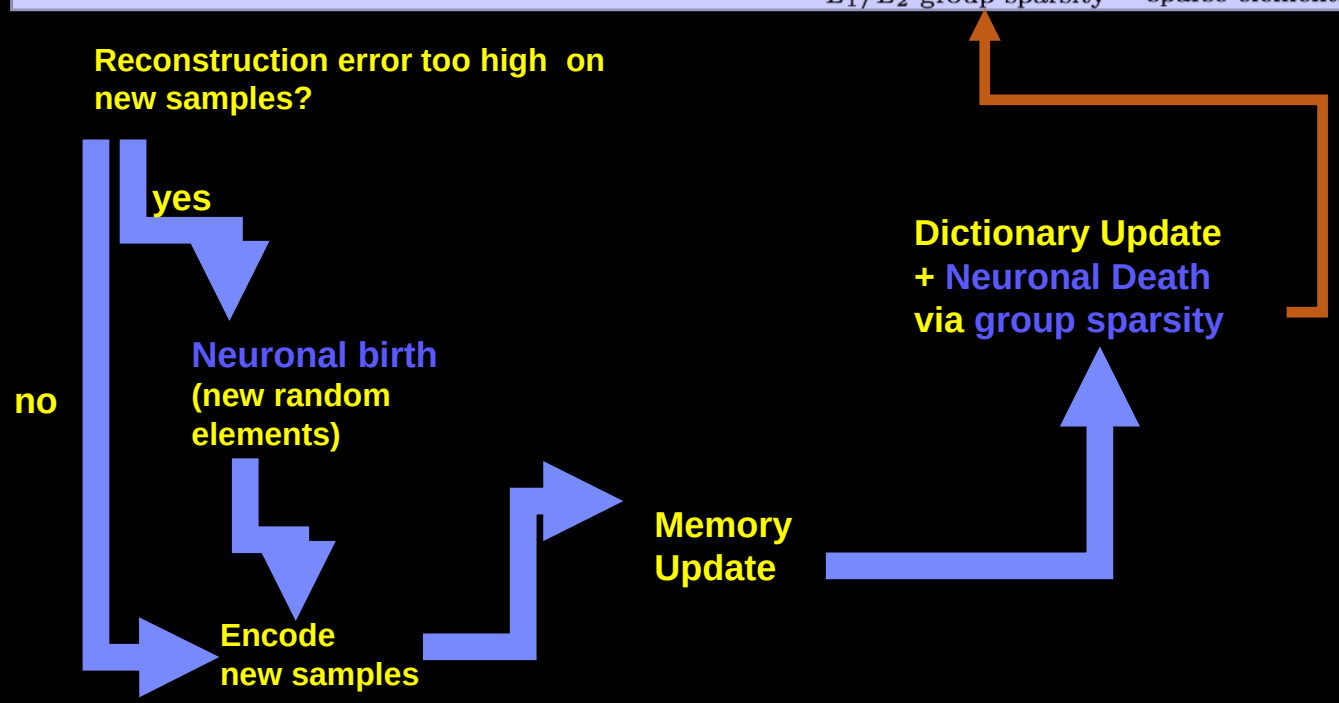


- Solved via l1-regularized optimization:

$$\min_{\mathbf{D},\mathbf{C}} ||\mathbf{X} - \mathbf{CD}||_2^2 + \lambda \sum_i ||\mathbf{C}(i,:)||_1$$

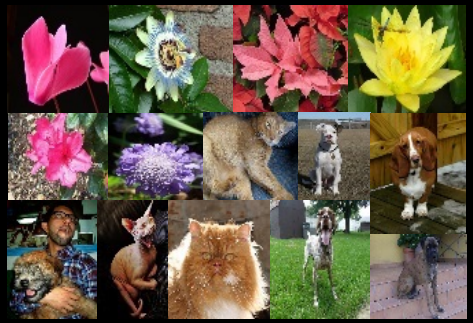
Neurogenetic Online Sparse Autoencoder: Neuronal Birth and Death

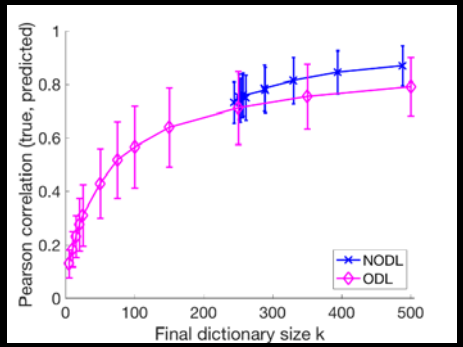
$$\hat{f}_t(D) = \underbrace{\frac{1}{t}\sum_{i=1}^{t}\frac{1}{2}||\boldsymbol{x}_i - \boldsymbol{D}\boldsymbol{\alpha}_i||_2^2}_{\text{reconstruction error}} + \underbrace{\lambda_c||\boldsymbol{\alpha}_i||_1}_{\text{sparsity on codings}} + \underbrace{\lambda_g\sum_j||\boldsymbol{d}_j||_2}_{L_1/L_2\text{ group sparsity}} + \underbrace{\sum_j\lambda_j||\boldsymbol{d}_j||_1}_{\text{sparse elements}}$$

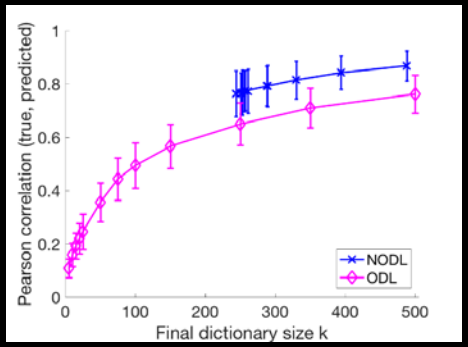


Experiments in Non-Stationary Environments: Switching Between Different Domains

Images: from urban ("Oxford") to nature (flowers, dogs,cats)





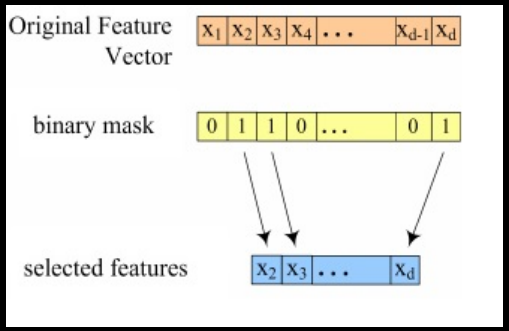


NODL improves reconstruction accuracy of ODL on both old data and learns more compact representations

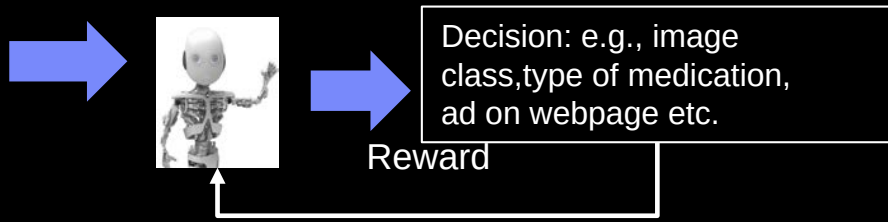
NODL adapts to change, while not forgetting the past ('memory' matrices)

Reward-Driven Attention: External and Internal

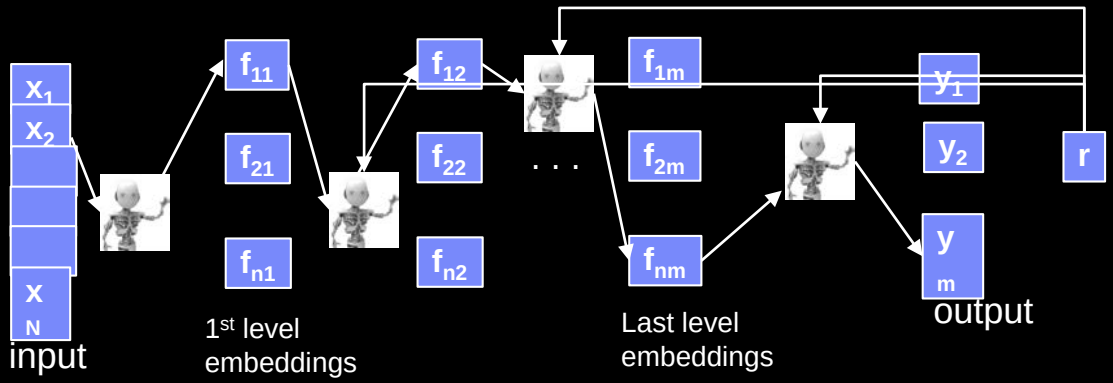
"External" attention:
input selection [IJCAI 2017]



- **Inspiration: visual attention** (foveation, sequence of glimpses)
- Recent neuroscience literature suggests that attention is a reward-driven mechanism which in turn drives the future reward

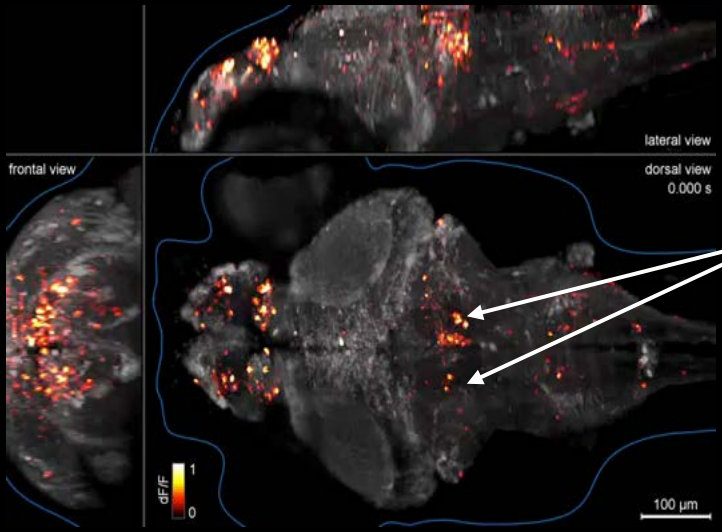


"Internal" attention as dynamic execution / network path selection [AAMAS 2018]



MODELING NONLINEAR BRAIN DYNAMICS

https://arxiv.org/abs/1805.09874



Larval zebrafish calcium imaging data
(Nature Methods, 2013) M. Ahrens (Janelia Farm/HHMI)

high temporal (0.8Hz) and high spatial (few voxels/neuron) resolution (unlike fMRI/EEG)

oscillatory behavior

very high dimensionality:
~100,000 time series (neurons), even in a collapsed 2D version (average) of the original 3D data

Can we learn a model capturing the underlying dynamics of this system?

Can this model predict the temporal evolution of brain activity?

Can it be interpretable – i.e., relate to prior neuroscientific knowledge?

DYNAMICAL MODEL: VAN DER POL OSCILLATOR

Observed (activity)

$$\dot{x}_{1i}(t) = \alpha_{1i} x_{1i}(t)(1 - {x_{1i}}^2(t)) + x_{2i}(t)(\alpha_{2i} + \sum_{j=1}^{N} W_{ij} x_{1j}(t))$$

$$\dot{x}_{2i}(t) = -\alpha_{3i} x_{1i}(t) - \alpha_4 (x_{2i}(t) - \alpha_5),$$

Hidden (excitability)

$x_{1i}(t)$ → i-th observed variable

$x_{2i}(t)$ → i-th hidden variable

$\alpha_{1i}, \alpha_{2i}, \alpha_{3i}, W_{ij}$ → parameters

W – interaction "network"

alphas – determine the bifurcation diagram of the system

Why use van der Pol?

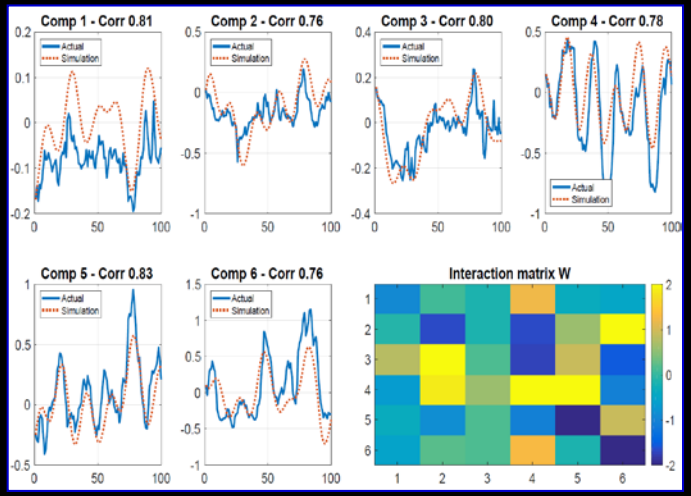
1. Oscillatory behavior is common in all neural systems; van der Pol is simplest nonlinear oscillator with rich enough behavior.
2. Voltage-like x1 (activity), and recovery-like x2 (excitability), similarly to neuro literature [Izhikevich 2007]

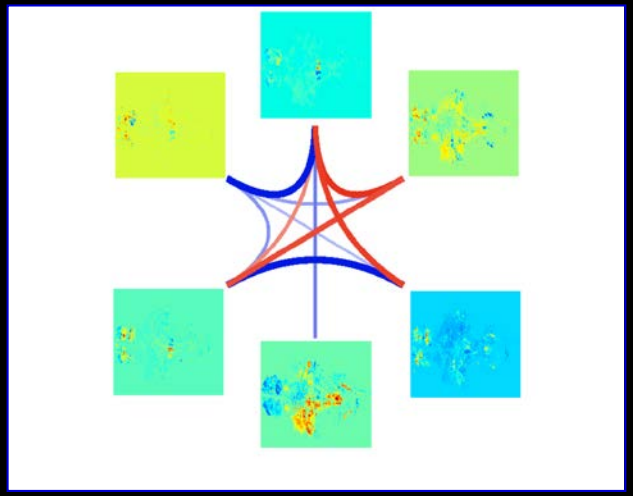
How to best estimate oscillator parameters from data?
Not a mainstream problem - neither in machine learning, nor in physics!

VAN DER POL MODEL: DATA FIT + INTERPRETABILITY

Parameter fitting:

stochastic search + variable-projection optimization [Aravkin et al, 2016]





0.7-0.8 correlation between the model and the actual data

Interpretability: learned W gives Interaction strength among brain areas

PREDICTING FUTURE BRAIN ACTIVITY WITH VAN DER POL AND LSTM

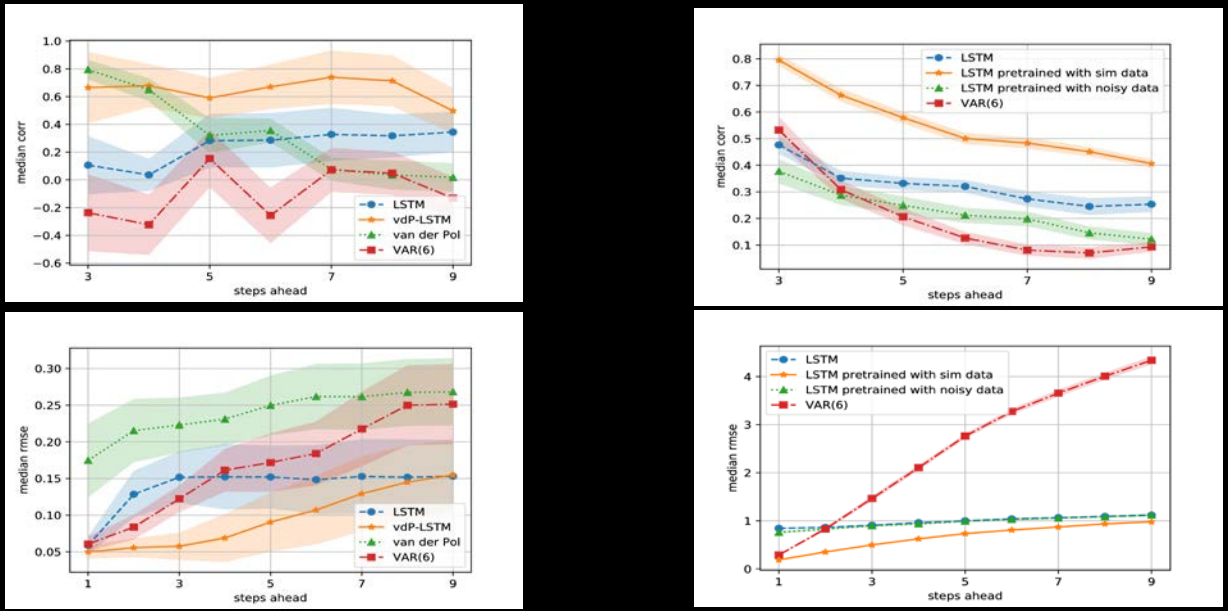
- Issue: van der Pol prediction is so-so; also, LSTM suffers from small data problem
- Solution: hybrid approach outperforms both methods (and baseline VAR model) - data-augmented LSTM with fitted van der Pol simulating more data

Calcium Imaging (zebrafish)

Functional MRI (people)

Correlation

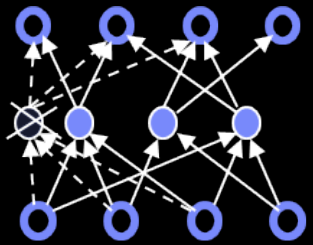
RMSE (root mean square error)



Hybrid outperforms LSTM, van der Pol and VAR on both calcium and fMRI data

LONG-TERM GOAL

Next-generation AI based on better understanding of brain functioning including plasticity, attention, memory, reward processing, motivation and beyond, while approaching both brain and AI as non-equilibrium stochastic dynamical systems rather than fixed predictive models.



NEURO-AI @ IBM

Cellular neuroscience: what inspiration can we derive from cellular level mechanisms in the neurons, beyond the classical McCullough and Pitts neuron? Can we derive inspiration for new learning rules and computational mechanisms from the biophysics and cellular machinery of neurons?

Systems neuroscience: how does the local network architecture of the brain enable robust, efficient learning and reasoning? Are there clues from the systems- and computational-neuroscience literature for new kinds of architectures for deep learning?

Cognitive neuroscience: what findings from psychology and cognitive and behavioral science can inspire us to think differently about problem formulations and potential mechanisms for learning and reasoning?

Beyond Backprop: more bio-plausible (and better!) learning models & methods


Irina Rish


Mattia Rigotti


Ronny Luss


Brian Kingsbury


Sadhana Kumaravel


Dmitry Krotov

Neural Dynamics: temporal evolution of neural network activity, synaptic strength and structure; spiking networks (3rd-gen ANNs); oscillatory dynamics; continual/lifelong learning


Guillermo Cecchi


James Kozloski


Malte Rasch


Matt Riemer


Mattia Rigotti


Irina Rish


Roger Traub


Yuhai Tu


Ben Huh

Behavior Dynamics: Bio-RL -- adding more bio-plausible decision-making mechanisms to reinforcement learning (attention-reward models; positive vs negative reward processing biases); psychology of dialogue (infogain-driven collaborative dialogue models)


Djallel Bouneffouf


Guillermo Cecchi


Baihan Lin


Jenna Reinen


Irina Rish


Gerry Tesauro

Recent Focus (NIPS, ICLR): Two Main Directions

- **Beyond-backprop: bio-plausible error-propagation and neuron models**
  - Assessing the Scalability of Biologically-Motivated Deep Learning Algorithms and Architectures
  - Initialized Equilibrium Propagation for Backprop-Free Training
  - Dendritic cortical microcircuits approximate the backpropagation algorithm
  - Improved Expressivity Through Dendritic Neural Networks

- **Dynamical Systems Approaches: spiking networks and beyond**
  - Gradient Descent for Spiking Neural Networks
  - Long short-term memory and Learning-to-learn in networks of spiking neurons
  - Deep Rewiring: Training very sparse deep networks
  - **NeurIPS Best Paper Award:** Neural Ordinary Differential Equations
    - Non-temporal! Dynamics over **continuous** (rather than discrete) **layers, not**

Surya Ganguli on Future Neuro Inspirations for AI
blog post 5/12/18

- Biologically plausible credit assignment
- Incorporating synaptic complexity
- Taking cues from systems-level modular brain architecture
- Unsupervised learning, transfer learning and curriculum design
- Building world models for understanding, planning, and active causal learning
- Achieving energy-efficient computation in a post Moore's law world
- Seeking universal laws governing both biological and artificial intelligence

Yoshua Bengio's Talk at MAIN (Montreal AI&Neuro conf, 11/18)

Drawing inspiration for AI from living intelligence

- Neurons, networks, plasticity & learning
- Distributed representations
- Visual cortex, convnets & depth
- Neural nonlinearity & ReLUs
- Spikes: dropout & quantized activations
- Curriculum learning
- Cultural evolution & distributed training
- Affordances, options, exploration & controllable factors
- Attention
- Lateral connections, softmax, clustering & attractors
- Associative memories, hippocampus & episodic memory
- System 2, reasoning, planning & consciousness

POPULAR TOPIC: THE RISE OF NEURO-AI?

- **Increasing number of conferences, workshops, papers (NIPS, etc) on the topic**
- **Surveys:**
  - Steve M. Potter (Georgia Tech): What Can AI Get from Neuroscience? 2007
  - MIT/DeepMind: Toward an Integration of Deep Learning and Neuroscience, Marblestone, Wayne & Kording (Northwestern U.), 2016
  - DeepMind: Neuroscience-inspired AI, Hassabis et al, 2017
  - DeepMind: Analyzing biological and artificial neural networks: challenges with opportunities for synergy? Barrett et al, 2018
  - UoM (Y. Bengio): Inspiration from Brains for Deep Learning and Inspiration from Deep Learning for Brains (talk at MAIN conference, 2018)
  - Stanford (S. Ganguli): The intertwined quest for understanding biological intelligence and creating artificial intelligence. blog post 5/12/18
- S. Srinivasan et al: Deep(er) Learning (Aug 2018)

Is there enough momentum for a breakthrough beyond deep nets?

We believe so. But someone has to make it ☺

It could be us – if we really set this as a priority