Rapid neuromodulation enables context-dependent sensory processing

Adding neuromodulation to Spiking Neural Networks

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Motivation: give the circuit another way to use itself

Give the model a biology-inspired control channel, then ask what computation it discovers.

Well Understood

Our Model

Model Neurons (LIF) + Model of Neuromodulation = New Computational Capacity

Biological Neurons + Biological Neuromodulation = New Computational Capacity

Hypothesis suggested about biology from model?

Question: if this control channel is available, what does the circuit learn to use it for?

Hypothesis: the same circuit can compute differently in different states

Same sensory input

State A might be…
lower excitability
longer temporal integration

Same recurrent circuit connectivity

Response A

State B might be…
higher excitability
shorter temporal integration

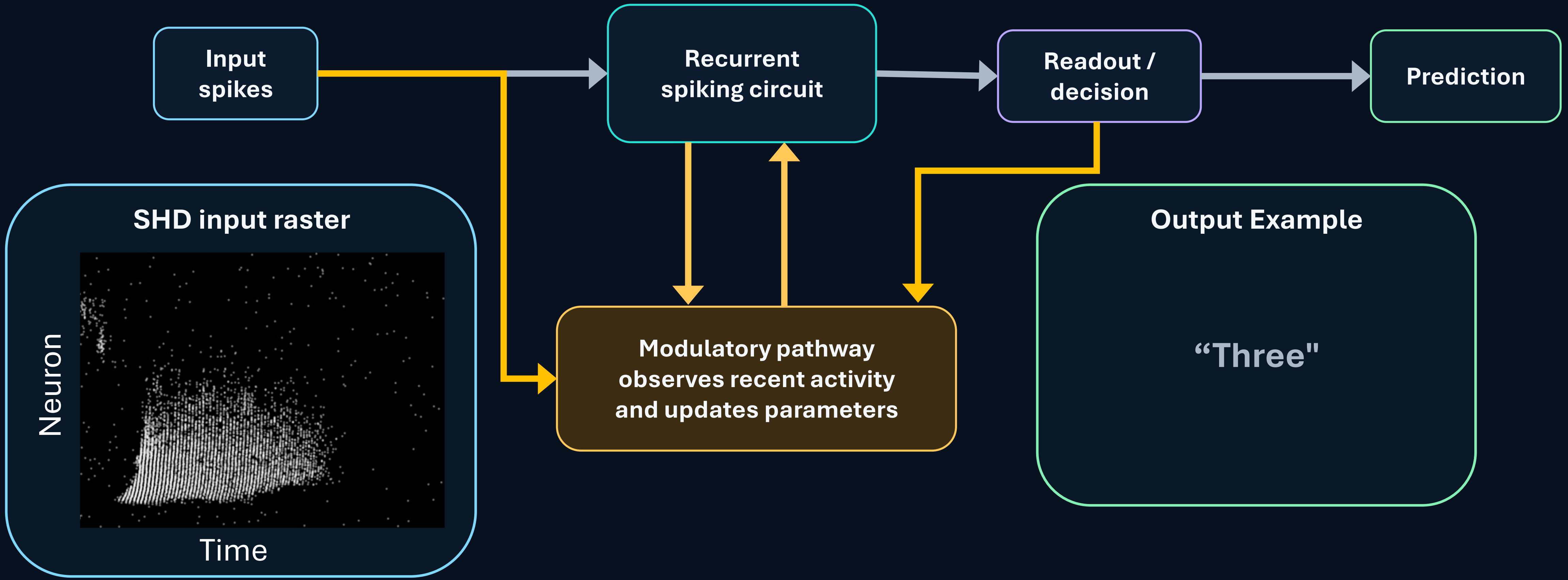
Same recurrent circuit connectivity

Response B

Same wiring + Different circuit state = Different computation.

Model: recent activity controls circuit dynamics

A recurrent spiking circuit performs the task while a modulatory pathway changes its parameters.



Parameters can include time constants, threshold, reset and resting potential.

Same sound. Different response.

Neuron parameter modulation

λ = 1.0

REAL-TIME / 1.4 SECONDS

SPOKEN DIGIT · ENGLISH 01 / 05

“six”

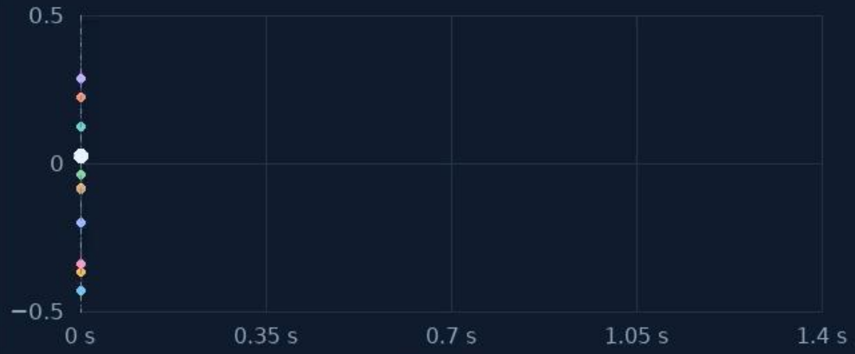
0.00 s

LISTENING

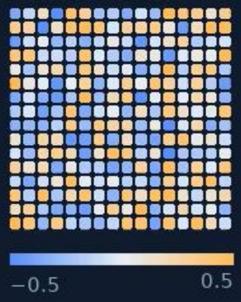
UNMODULATED

Original baseline · fixed neuron parameters

RESET VOLTAGE



256 NEURONS



Mean All 256 10 highlighted

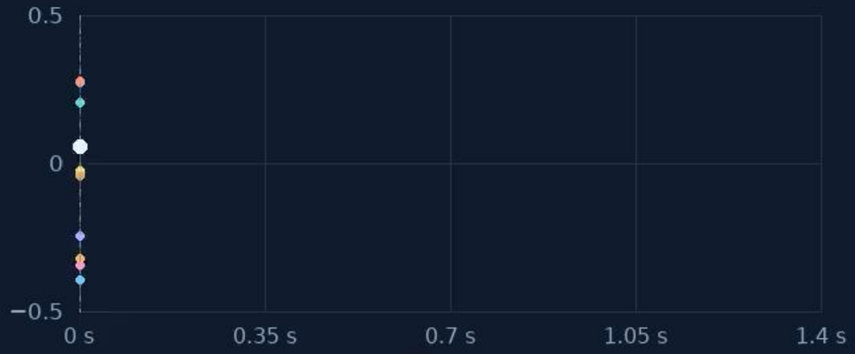
HIDDEN SPIKES

CURRENT PREDICTION **Listening...**

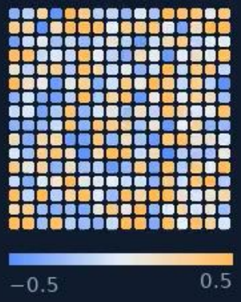
MODULATED

Adaptive neuron parameters · λ = 1.0

RESET VOLTAGE



256 NEURONS



Mean All 256 10 highlighted

HIDDEN SPIKES

CURRENT PREDICTION **Listening...**

SHD test audio · clean re-encoding · selected comparisons

1× playback · 1 s hold + 1 s fade

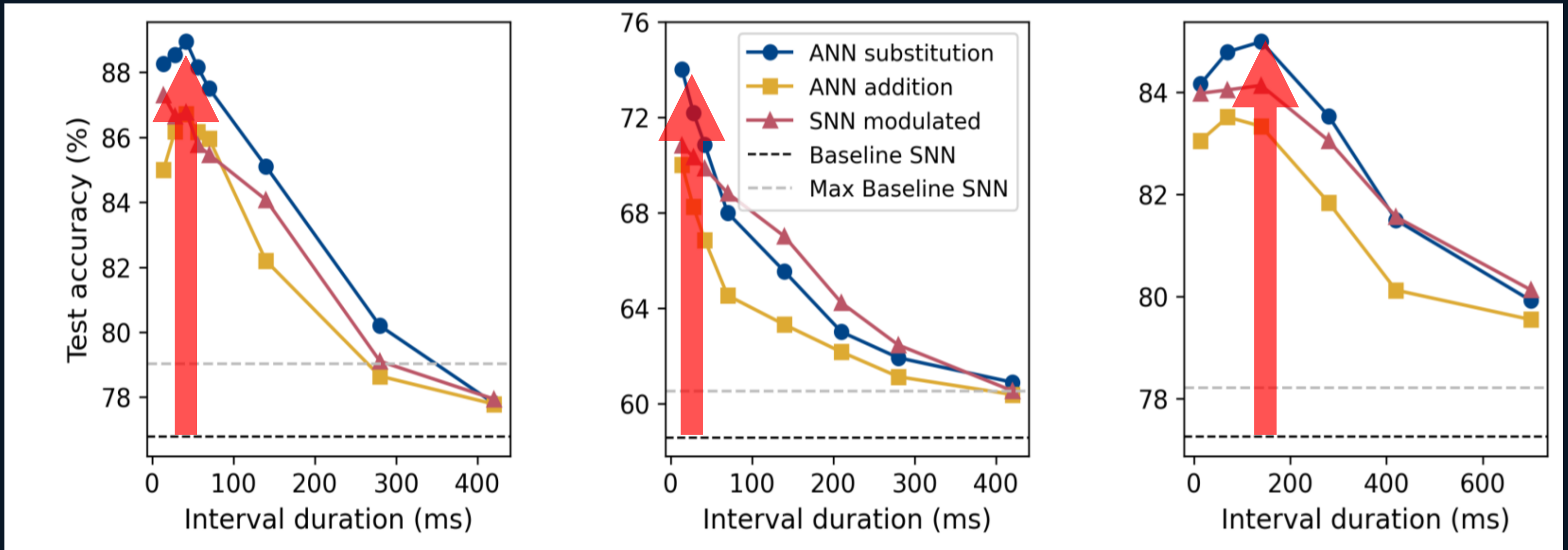
Modulation improves performance across sensory tasks

The effect generalises beyond a single stimulus domain.

1 SHD

2 SSC

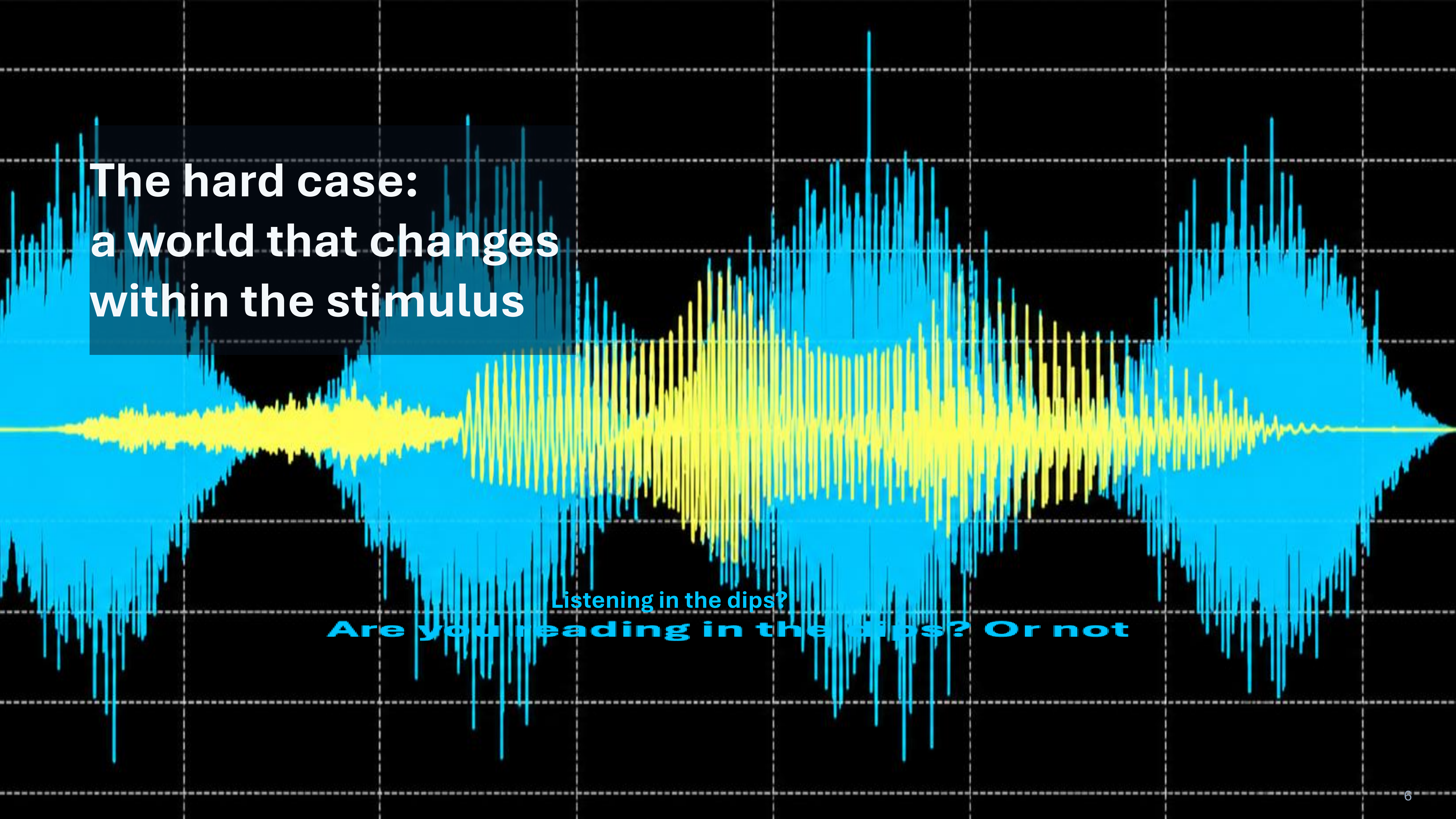
3 DVS



- **Increase in performance across multiple tasks.**
- **Audio, noisier audio, video.**
- **Each has different maximum.**

Main point:
This is a general dynamic-control benefit, not a task-specific trick.

The hard case: a world that changes within the stimulus



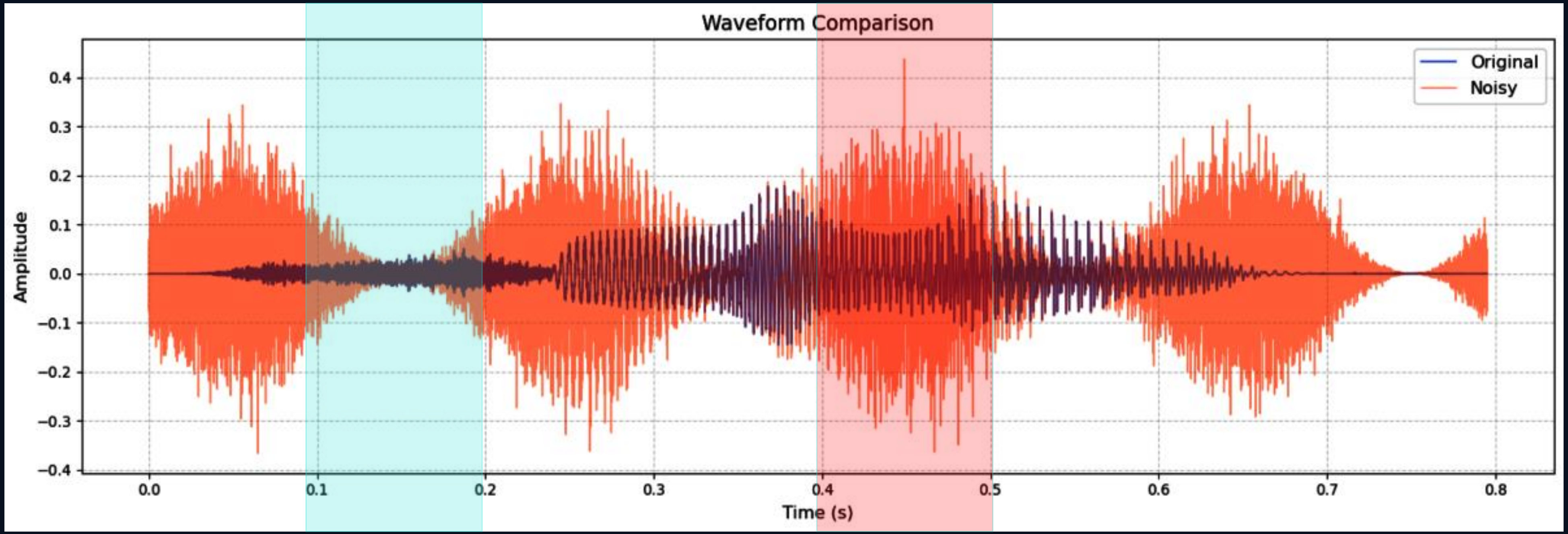
Listening in the dips?

Are you reading in the dips? Or not

A harder test: speech in dynamically changing noise

This is the setting where rapid within-stimulus modulation should matter most.

Speech signal → + Fluctuating noise → Spike-train input → Recognise word



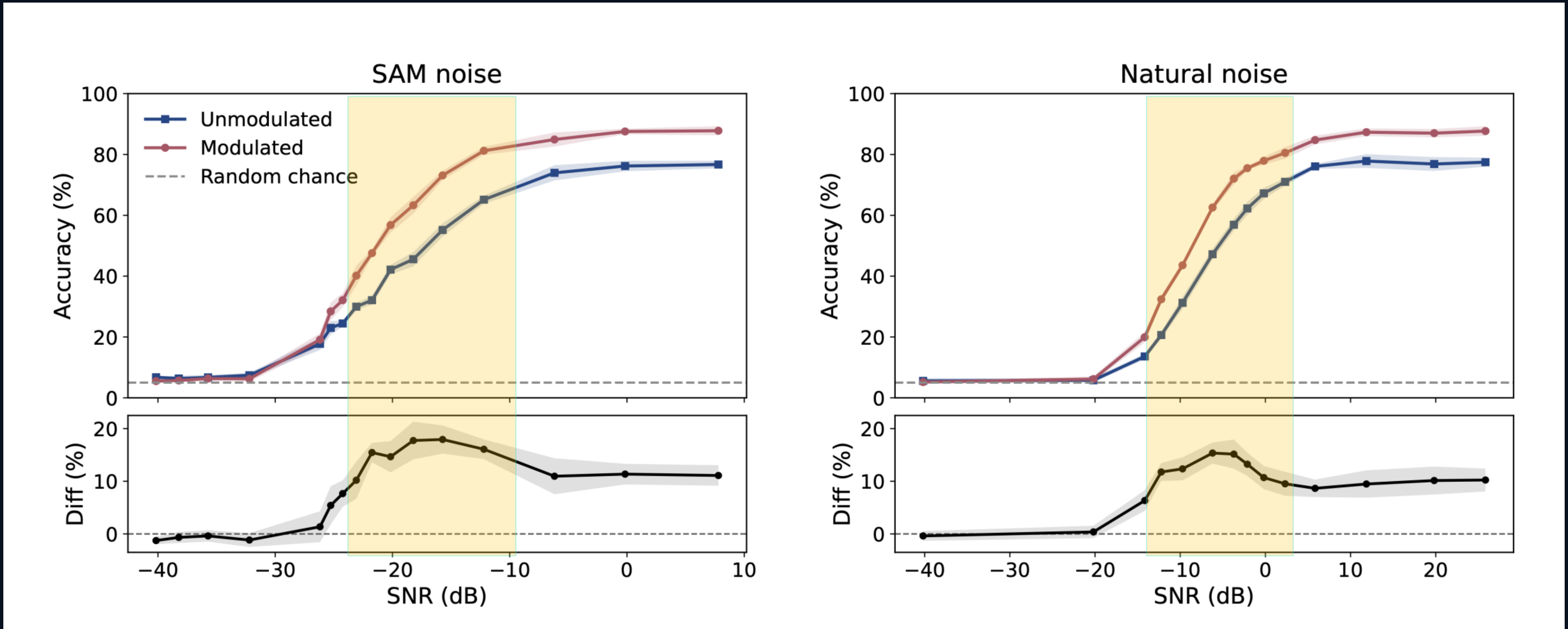
Quiter windows
"Dips"

Louder windows
"Peaks"

Will the modulatory system allocate processing to moments when sensory evidence is most reliable? And how?

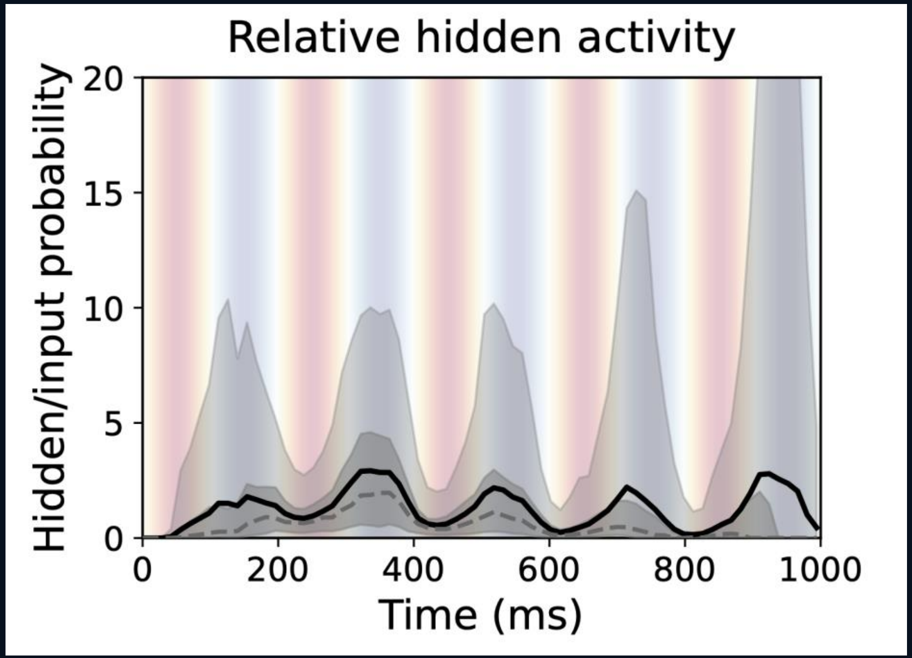
The largest benefit appears near the failure boundary

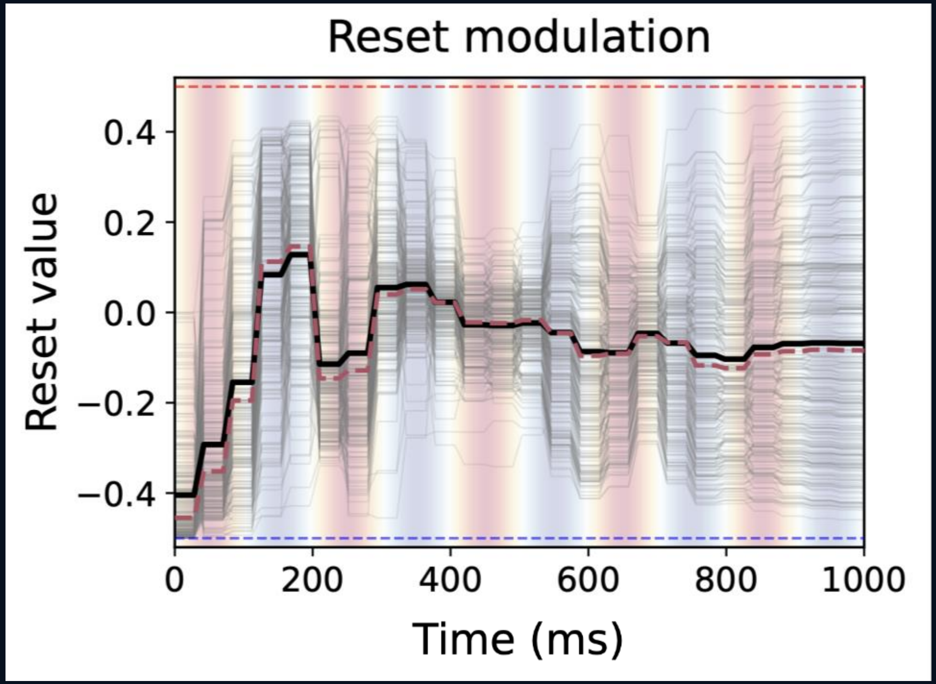
Modulation helps most when recognition is possible but unreliable.



The network preferentially processes quieter moments

A dip-listening-like strategy emerges from training.





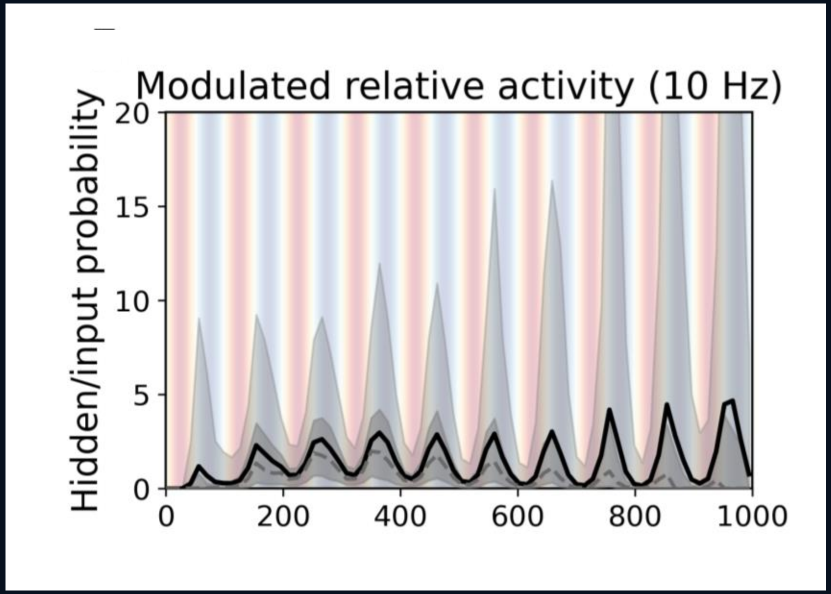
Quiet windows carry more useful evidence.
The model learns to increase relative processing during those windows.

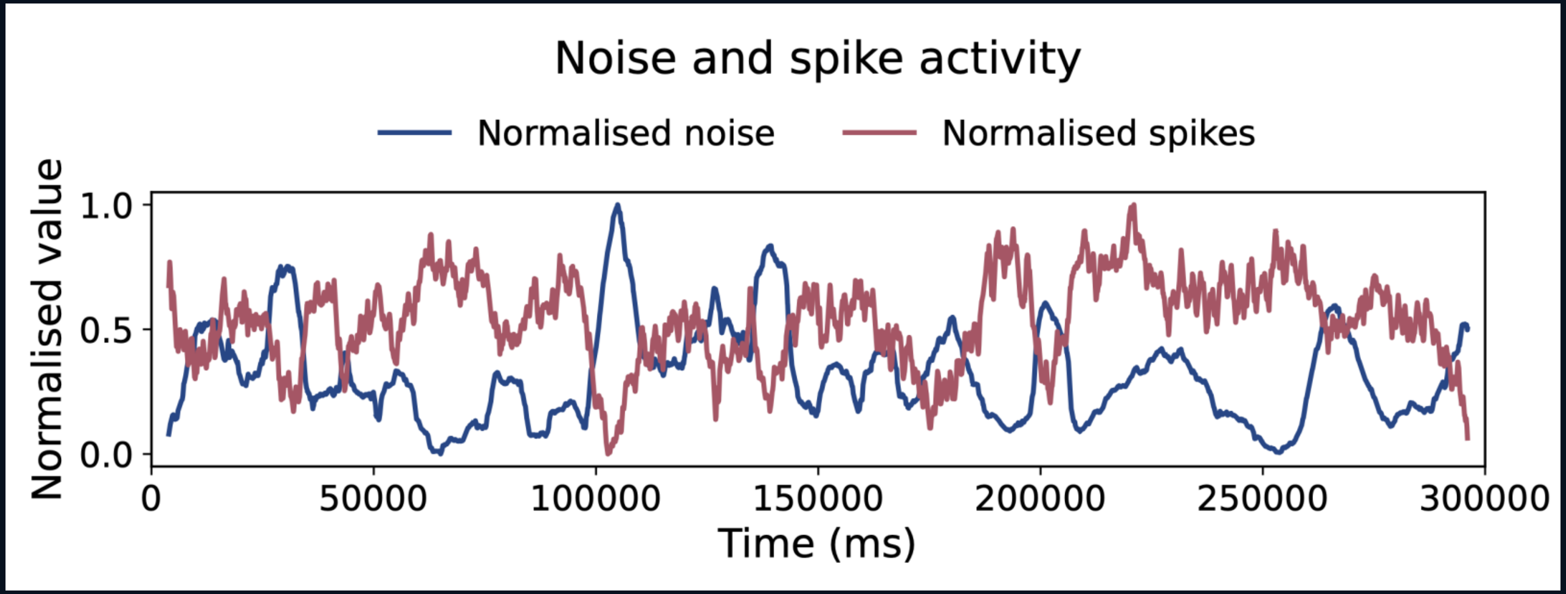
The strategy is not tied to one memorised waveform

The qualitative behaviour survives changes in the noise structure.

Phase randomised

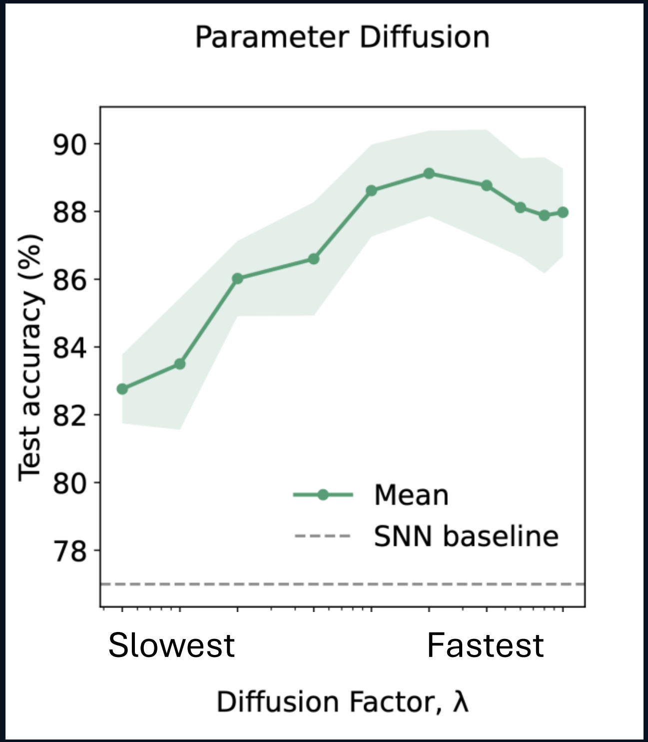
“Natural” Cafe background

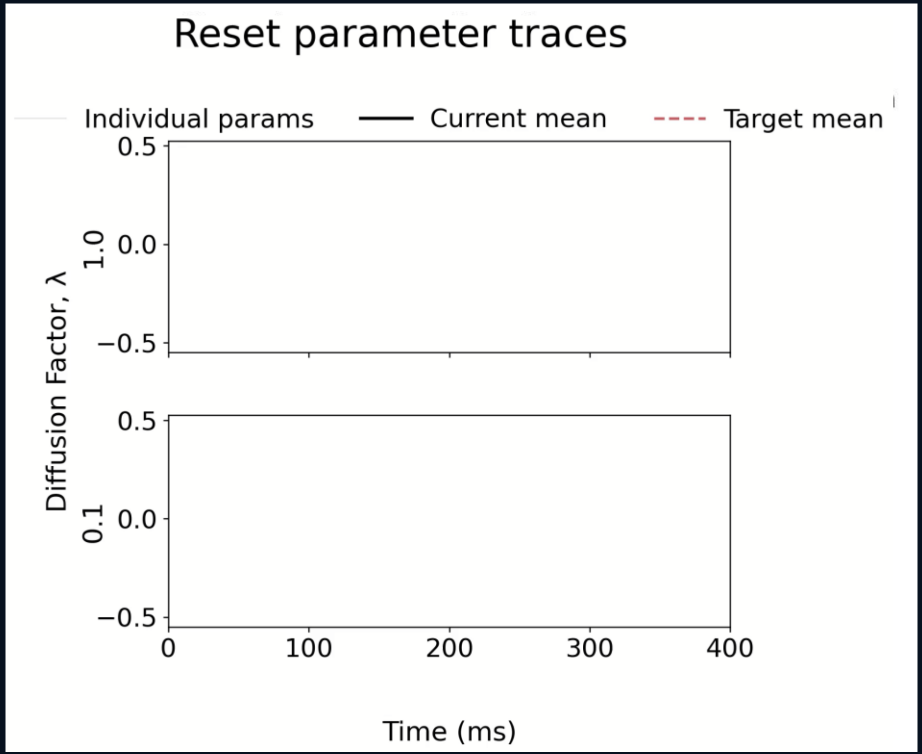


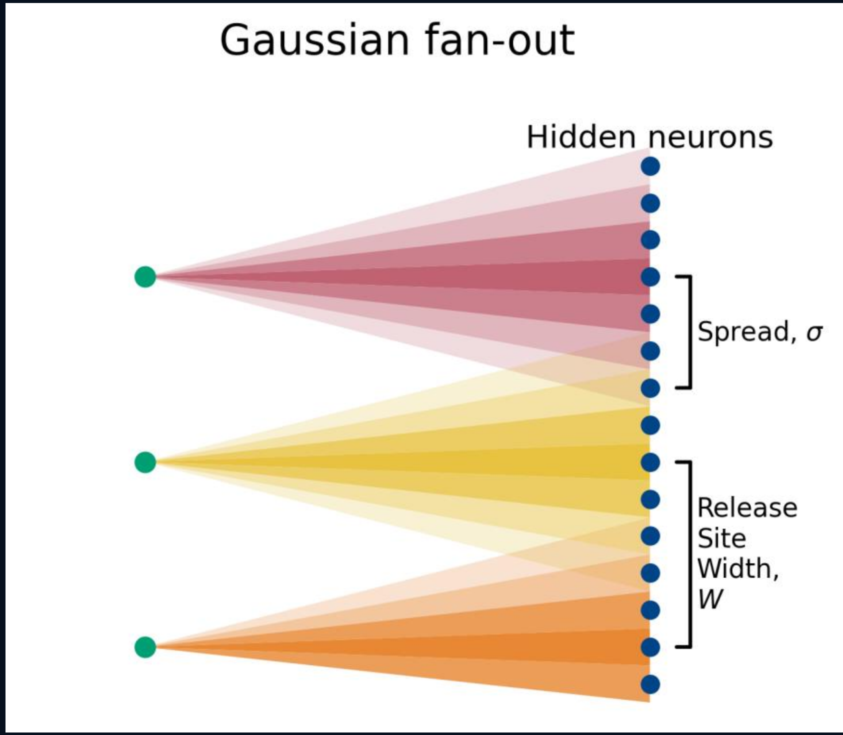


Biological detail can be added without destroying the effect

The same conclusions survive slower, spatially diffuse and lower-dimensional modulation.







Biological detail is possible to add

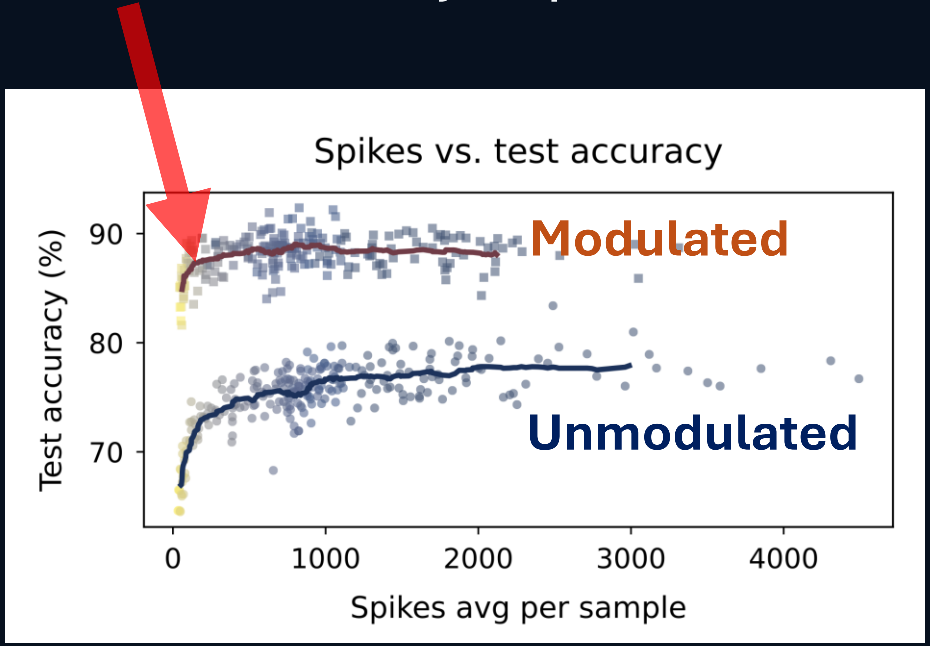
The useful computation still survives

These mappings can be learned, or manually chosen if the goal is a specific biological hypothesis.

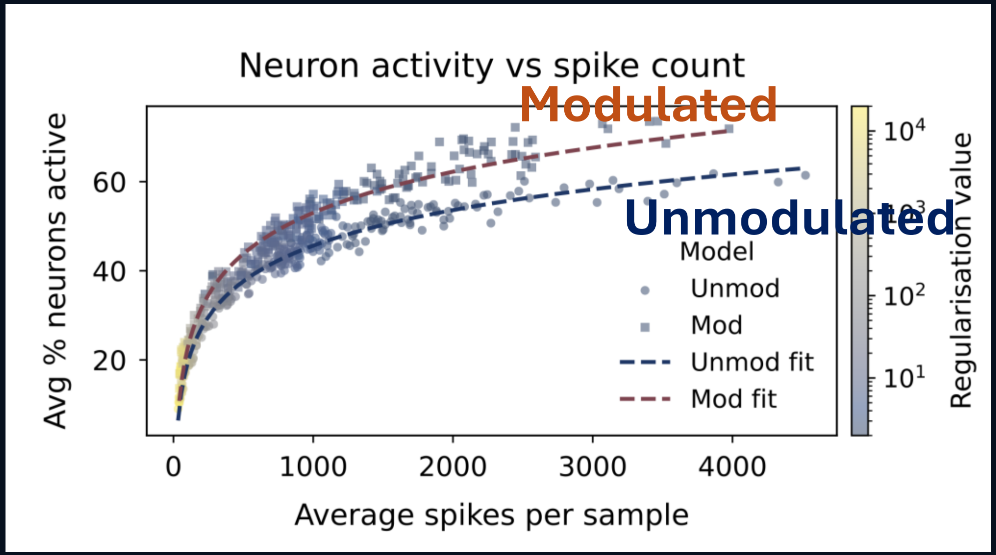
Modulation also changes how the population uses spikes

Under spike pressure, modulated networks stay sparse but distributed.

Accuracy vs spikes



% of active neurons



Same spike budget, different solution: modulation keeps more neurons conditionally engaged.

Take-home: rapid modulation is a dynamic control mechanism

1 Performance increases on tasks

Suggests: neuromodulation increases computational capabilities of a network

2 Dip-listening-like strategy emerges in noise

Suggests: neuromodulation allows for context dependent processing

3 Biological detail does not erase the effect

4 More spike/neuron efficient

Suggests: neuromodulation enables metabolically efficient computation

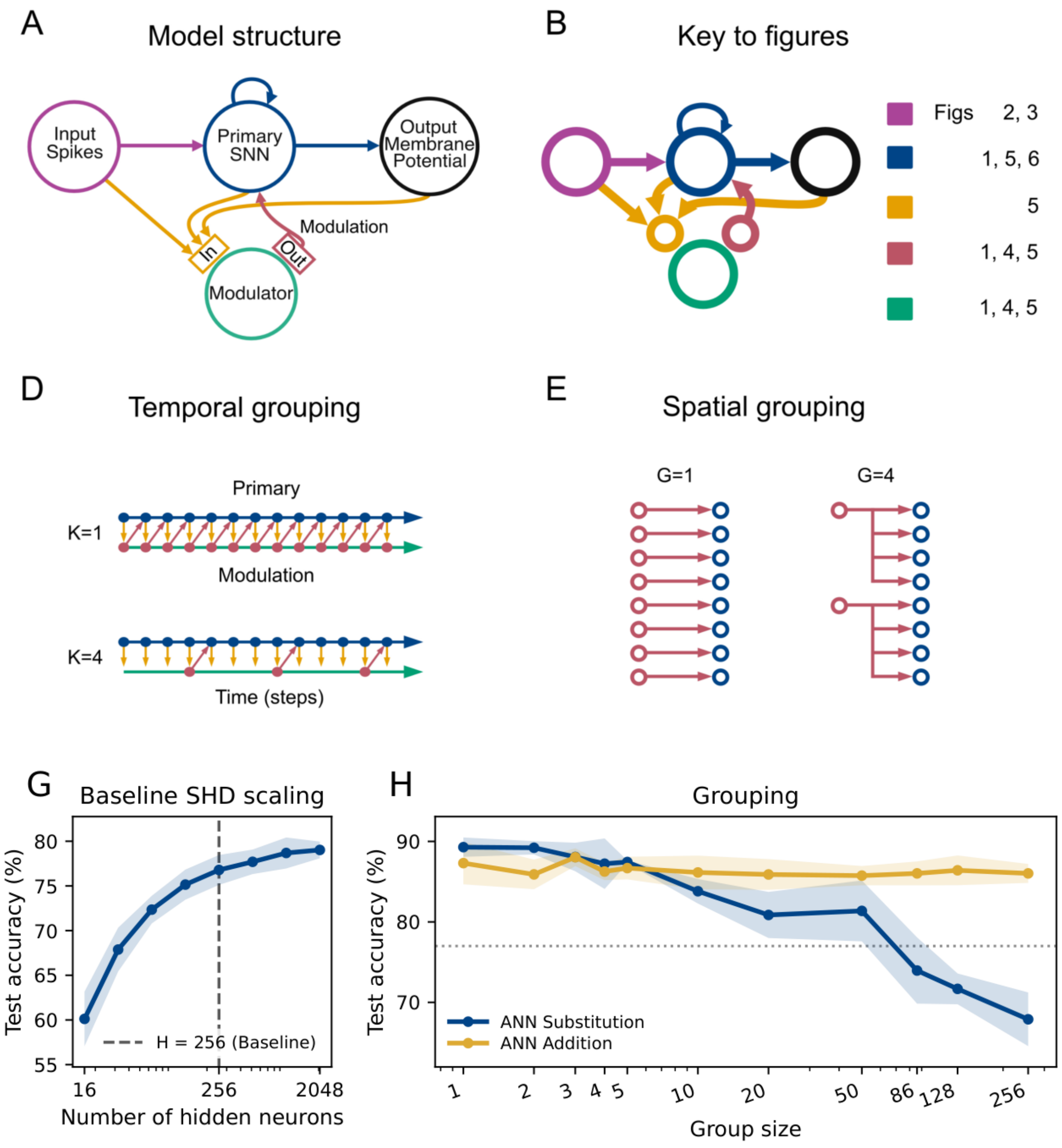
Questions?

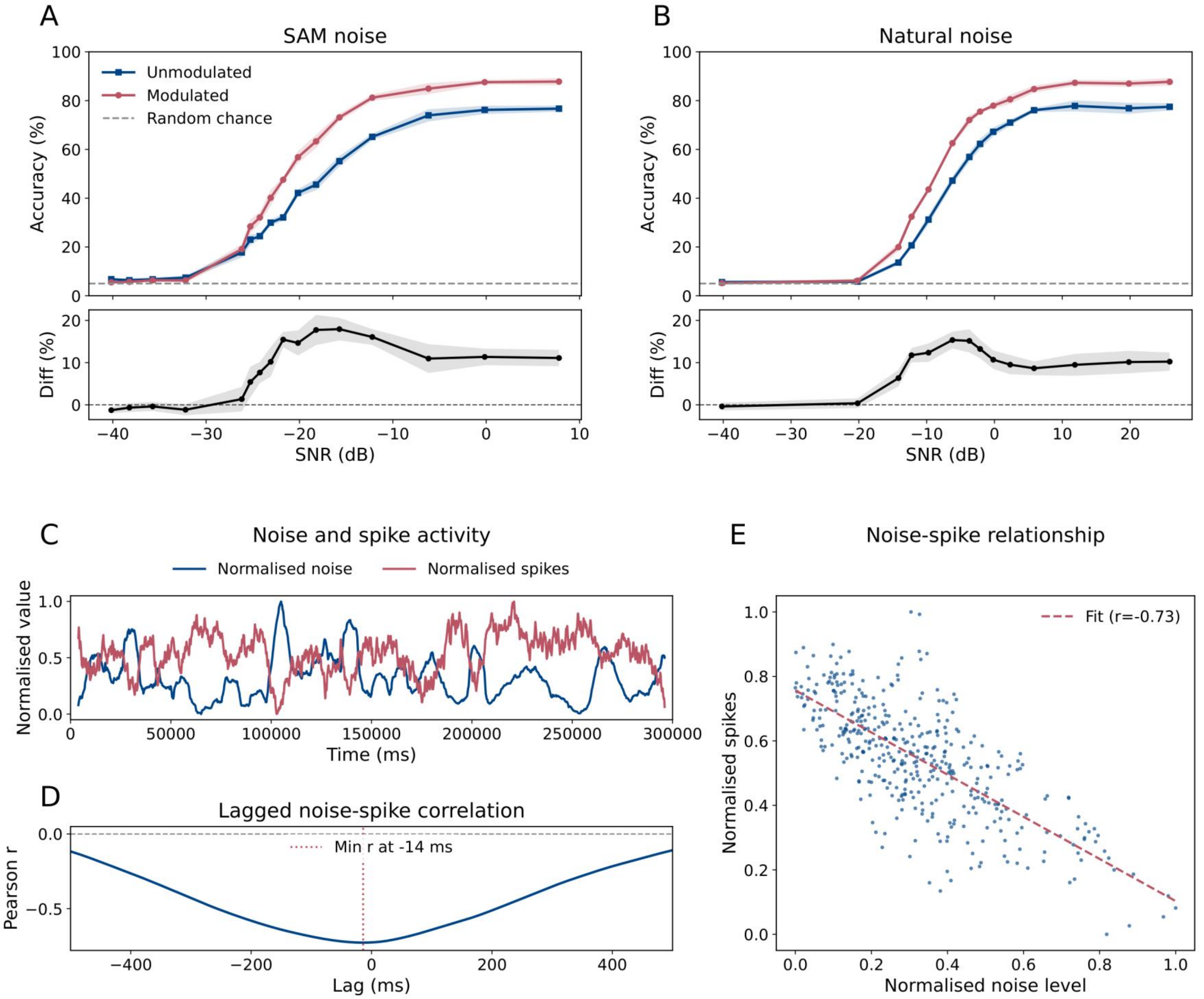
Rapid neuromodulation enables context-dependent sensory processing in spiking neural circuits

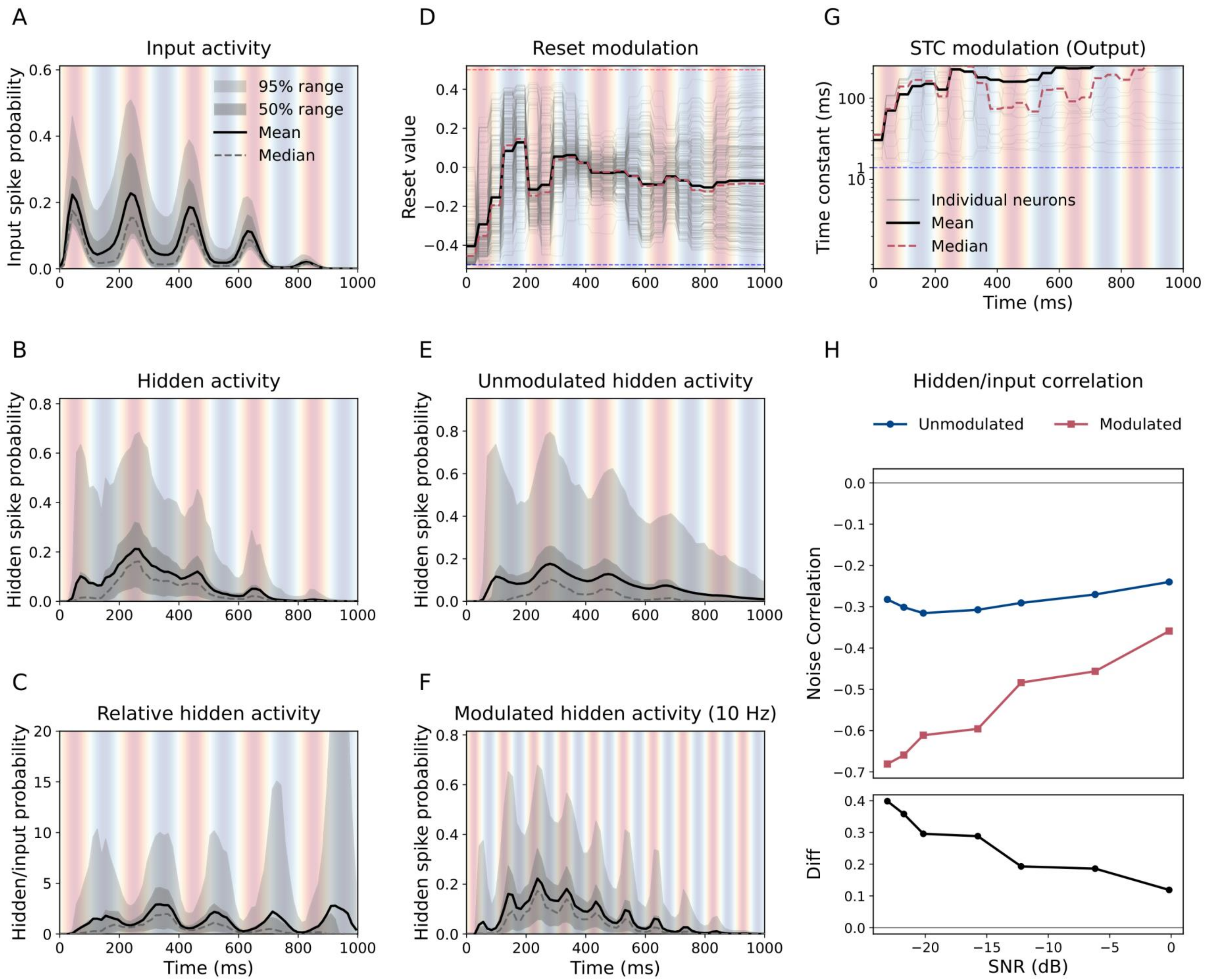
Dr Dan Goodman

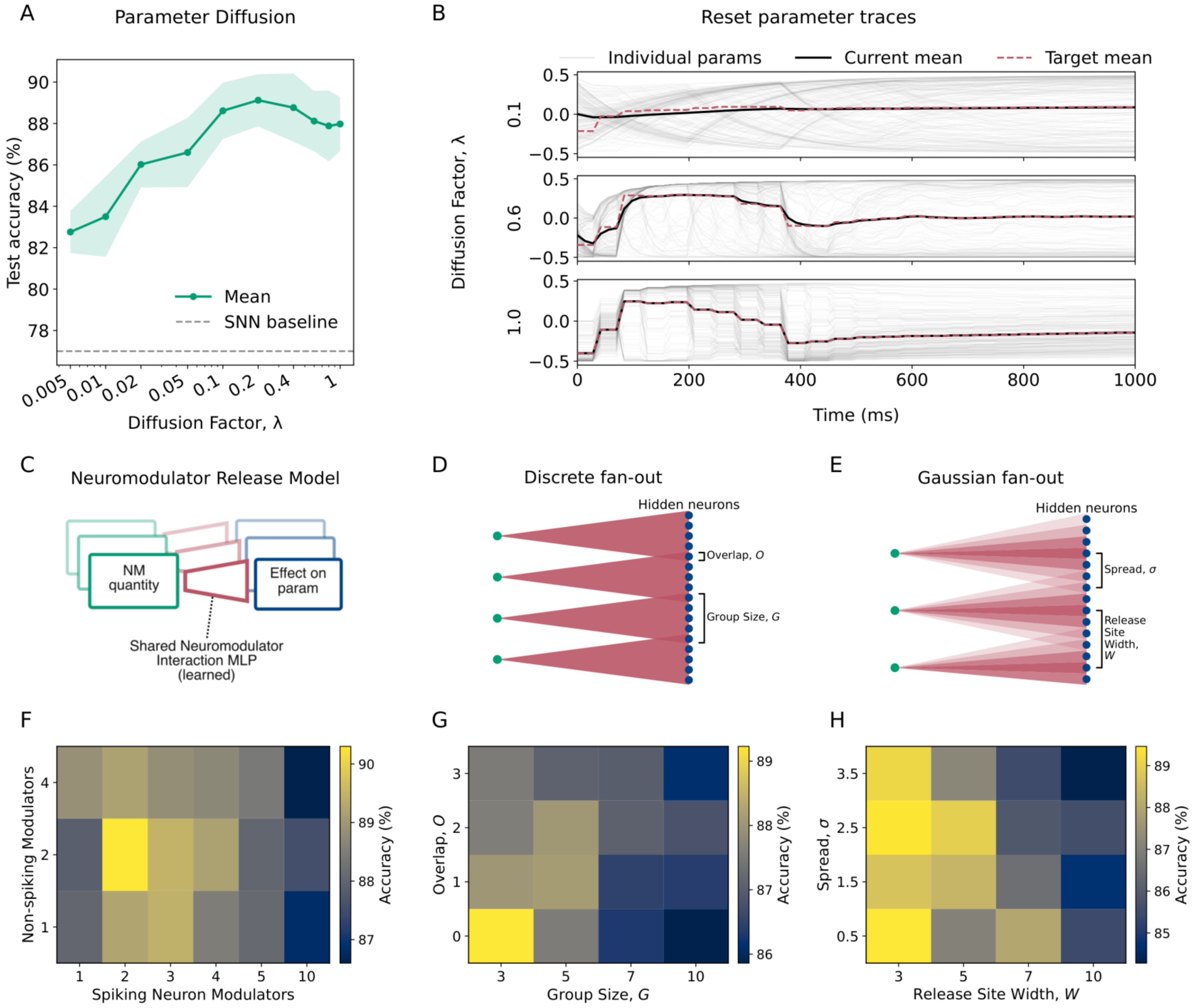
scan for preprint

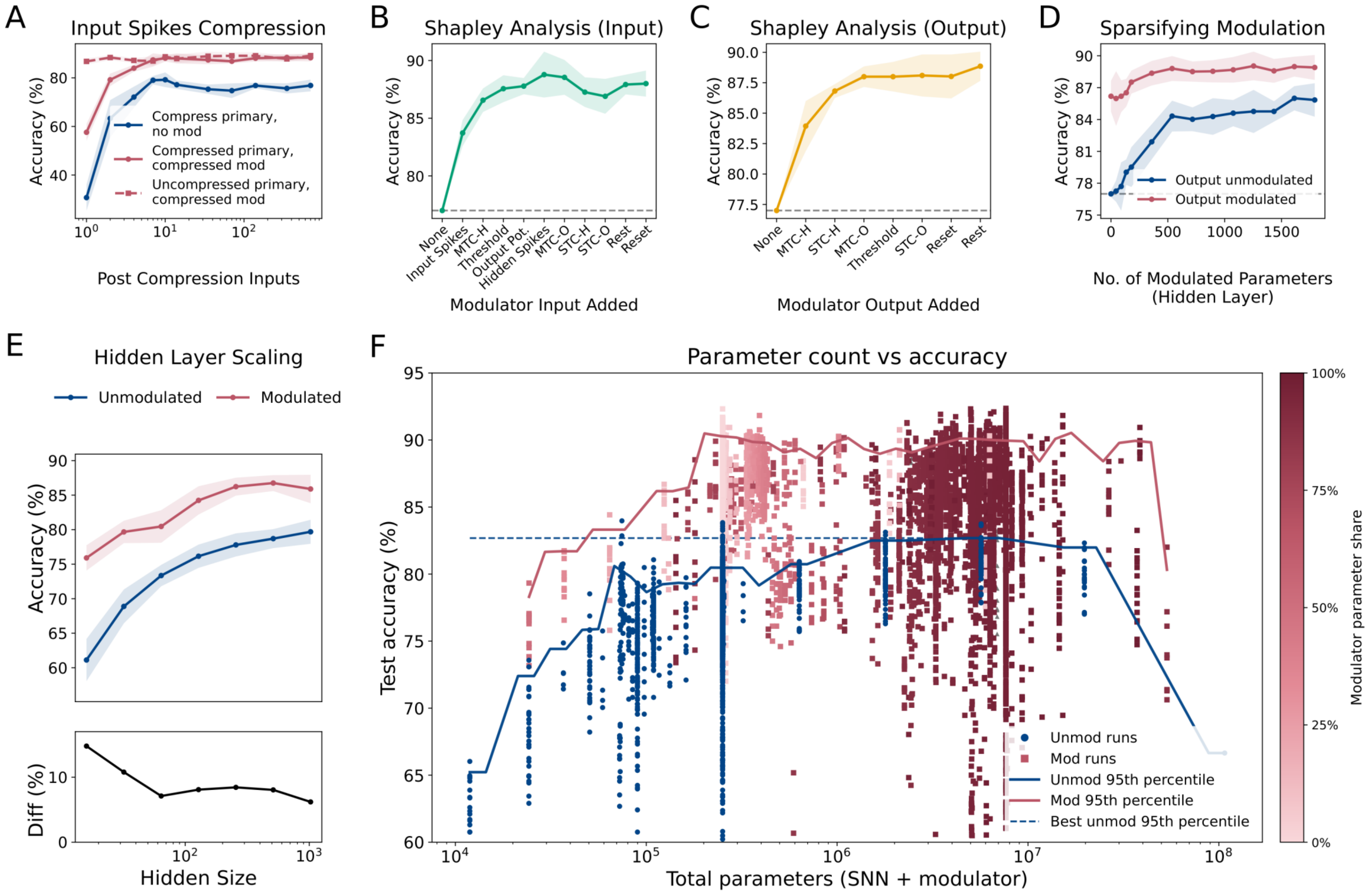
Backup slides

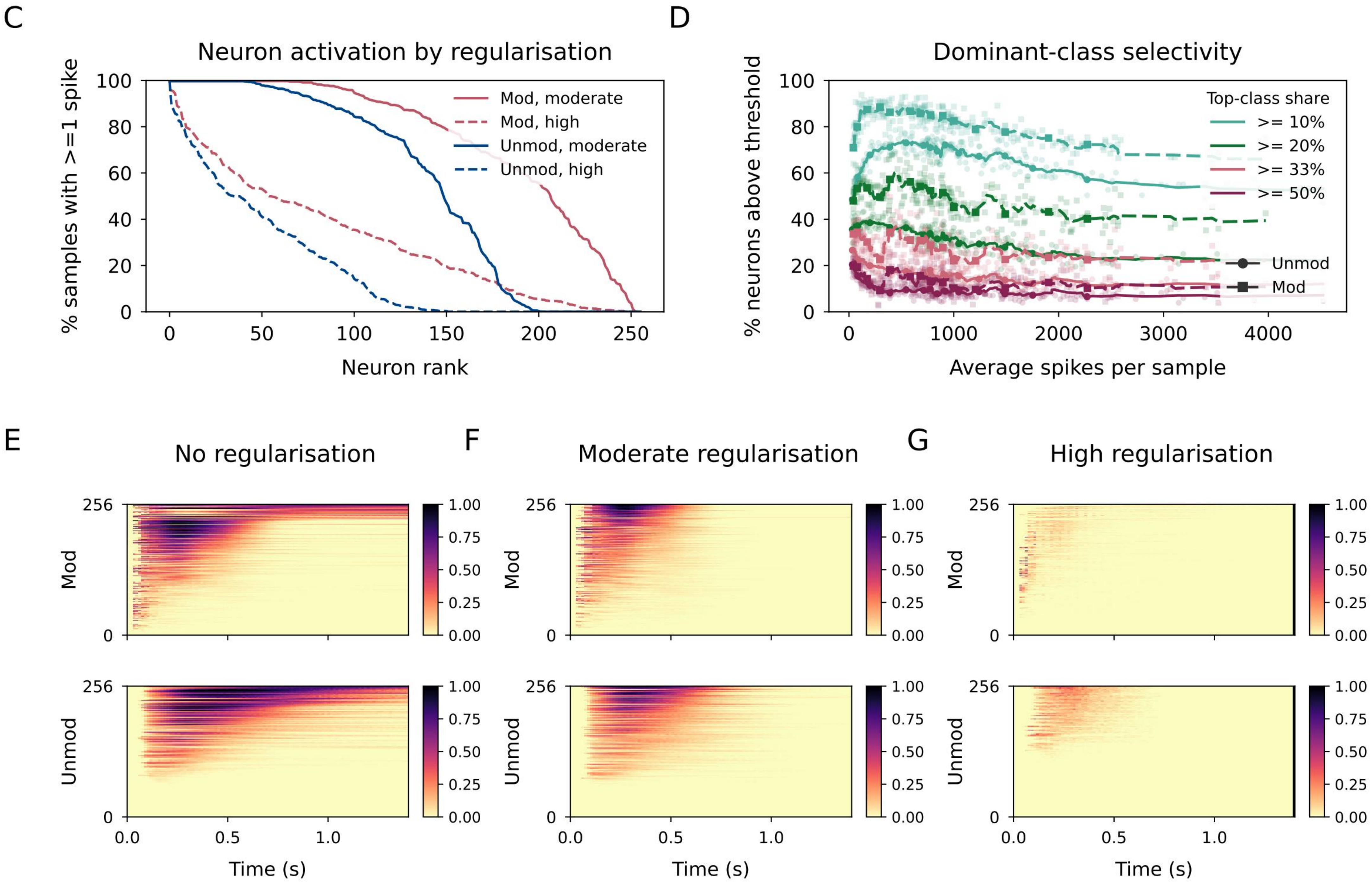

A
Model structure
Input Spikes
Primary SNN
Output Membrane Potential
Modulation
In
Out
Modulator
B
Key to figures
Figs 2, 3
1, 5, 6
5
1, 4, 5
1, 4, 5
D
Temporal grouping
Primary
K=1
Modulation
K=4
Time (steps)
E
Spatial grouping
G=1
G=4
G
Baseline SHD scaling
Test accuracy (%)
H = 256 (Baseline)
Number of hidden neurons
16
256
2048
55
60
65
70
75
80
H
Grouping
Test accuracy (%)
ANN Substitution
ANN Addition
Group size
70
80
90
1
2
3
4
5
10
20
50
86
128
256


A
SAM noise
Unmodulated
Modulated
Random chance
Accuracy (%)
Diff (%)
SNR (dB)
B
Natural noise
Accuracy (%)
Diff (%)
SNR (dB)
C
Noise and spike activity
Normalised noise
Normalised spikes
Normalised value
Time (ms)
D
Lagged noise-spike correlation
Min r at -14 ms
Pearson r
Lag (ms)
E
Noise-spike relationship
Fit (r=-0.73)
Normalised spikes
Normalised noise level


A
Input activity
Input spike probability
95% range
50% range
Mean
Median
B
Hidden activity
Hidden spike probability
C
Relative hidden activity
Hidden/input probability
Time (ms)
D
Reset modulation
Reset value
E
Unmodulated hidden activity
Hidden spike probability
F
Modulated hidden activity (10 Hz)
Hidden spike probability
Time (ms)
G
STC modulation (Output)
Time constant (ms)
Individual neurons
Mean
Median
Time (ms)
H
Hidden/input correlation
Unmodulated
Modulated
Noise Correlation
Diff
SNR (dB)


A
Parameter Diffusion
Test accuracy (%)
Mean
SNN baseline
Diffusion Factor, λ
B
Reset parameter traces
Individual params
Current mean
Target mean
Diffusion Factor, λ
Time (ms)
C
Neuromodulator Release Model
NM quantity
Effect on param
Shared Neuromodulator Interaction MLP (learned)
D
Discrete fan-out
Hidden neurons
Overlap, O
Group Size, G
E
Gaussian fan-out
Hidden neurons
Spread, σ
Release Site Width, W
F
Non-spiking Modulators
Spiking Neuron Modulators
Accuracy (%)
G
Overlap, O
Group Size, G
Accuracy (%)
H
Spread, σ
Release Site Width, W
Accuracy (%)


A
Input Spikes Compression
Accuracy (%)
Compress primary, no mod
Compressed primary, compressed mod
Uncompressed primary, compressed mod
Post Compression Inputs
B
Shapley Analysis (Input)
Accuracy (%)
None
Input Spikes
MTC-H
Threshold
Output Pot.
Hidden Spikes
MTC-O
STC-H
STC-O
Rest
Reset
Modulator Input Added
C
Shapley Analysis (Output)
Accuracy (%)
None
MTC-H
STC-H
MTC-O
Threshold
STC-O
Reset
Rest
Modulator Output Added
D
Sparsifying Modulation
Accuracy (%)
Output unmodulated
Output modulated
No. of Modulated Parameters (Hidden Layer)
E
Hidden Layer Scaling
Unmodulated
Modulated
Accuracy (%)
Diff (%)
Hidden Size
F
Parameter count vs accuracy
Test accuracy (%)
Unmod runs
Mod runs
Unmod 95th percentile
Mod 95th percentile
Best unmod 95th percentile
Total parameters (SNN + modulator)
Modulator parameter share


C
Neuron activation by regularisation
% samples with >=1 spike
Neuron rank
Mod, moderate
Mod, high
Unmod, moderate
Unmod, high
D
Dominant-class selectivity
% neurons above threshold
Average spikes per sample
Top-class share
>= 10%
>= 20%
>= 33%
>= 50%
Unmod
Mod
E
No regularisation
F
Moderate regularisation
G
High regularisation
Mod
Unmod
Time (s)