Computational Neuroscience

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Contents

1 Introduction and Basic Neurobiology **5**
- 1.1 Computational Neuroscience 5
  - 1.1.1 Descriptive Models 5
  - 1.1.2 Descriptive Model of Receptive Fields 5
  - 1.1.3 Descriptive models: Cortical Receptive Fields 6
  - 1.1.4 Mechanistic and Interpretive Models 6
  - 1.1.5 Interpretive Model of Receptive Fields 6
- 1.2 The Electrical Personality of Neurons 7
- 1.3 Making Connections: Synapses 10
- 1.4 Time to Network: Brain Areas and Their Function 11

2 Neural Code **17**
- 2.1 Recording form the brain 17
- 2.2 Constructing response models:Linear response 17
  - 2.2.1 Spatial filtering 17
  - 2.2.2 Spatio-temporal filtering 17
- 2.3 Feature selection 17
  - 2.3.1 How build the model 17
  - 2.3.2 Dimensionality reduction 18
  - 2.3.3 What is the right stimulus to use? 18
  - 2.3.4 Linear filtering 18
  - 2.3.5 nonlinear input/output function 18
  - 2.3.6 Linear and non-linear 18
- 2.4 Variability 18
  - 2.4.1 When choose the best turning curve 18
  - 2.4.2 Finding relevant features 18
  - 2.4.3 Modeling the noise 18
  - 2.4.4 Binomial spiking 18
  - 2.4.5 Poisson spiking 19
  - 2.4.6 The generalized linear model 19

Chapter 1

Introduction and Basic Neurobiology

1.1 Computational Neuroscience

1.1.1 Descriptive Models

What is Computational Neuroscience? Computational Neuro-science provides tools and methods for ”characterizing what nervous systems do, determining how they function, and understanding why they operate in particular ways”

Descriptive Models (What)

Mechanistic Models (How)

Interpretive Models (Why)

Frequency of spikes = f(Light bar’s orientation).

”receptive field” of a neuron is the particular orientation of a bar of light that produces the best response. That is maximizes f(Light Bar’s orientation) (45 degree is maximize).

A greater response corresponds to more frequent ”spikes” (or action potentials)

Receptive Field: is specific properties of a sensory stimulus that generate a strong response from the cell

Examples:

- Spot of light that turns on at a particular location on the retina
- Bar of light that turns on at a particular orientation and location on the retina

1.1.2 Descriptive Model of Receptive Fields

Center-Surround Receptive Fields on the Retina

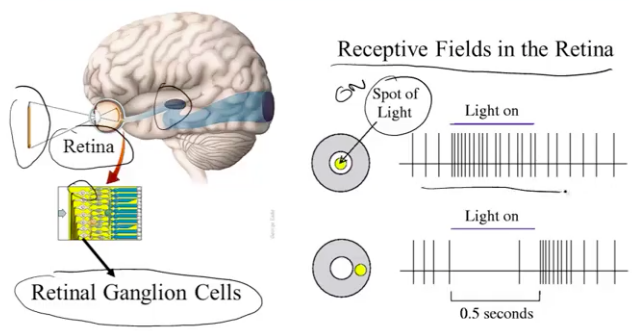

Figure 1.1:

— On-Center Off-Surround: center of the small patch of retina associated with the cell

The ON-Center/ Off-Surround receptive field can be thought of as a filter. The filter causes activation with stimuli concentrates on the center of the receptive field and depressing activation with stimuli which are concentrated in the surround.

1.1.3 Descriptive models: Cortical Receptive Fields

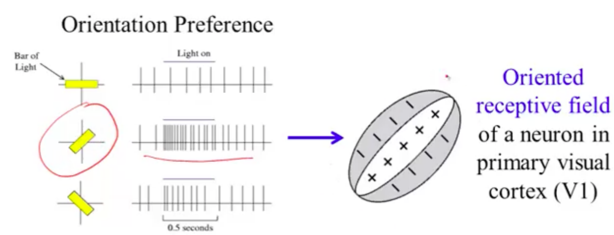

Figure 1.2:

Oriented receptive field of a neuron in primary visual cortex (V1)

1.1.4 Mechanistic and Interpretive Models

Mechanistic Model of Receptive File

Number of LGN cells converges to one V1 cell: arrange LGN to one V1 cell

1.1.5 Interpretive Model of Receptive Fields

Why do they have orientation, or selected of black and white dot?

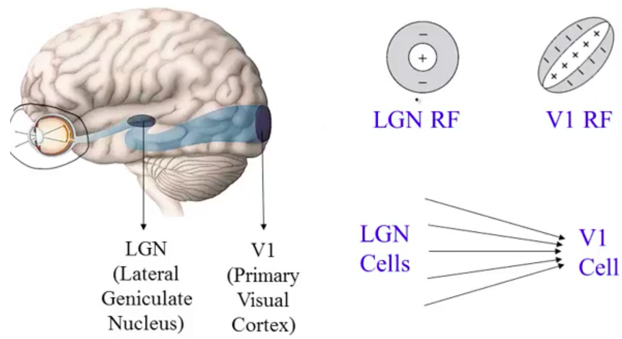

Figure 1.3:

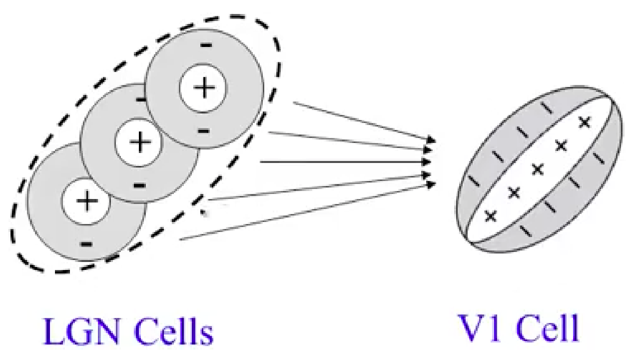

Figure 1.4:

Efficient Coding Hypothesis: Suppose the goal is to represent images as faithfully ans efficiently as possible using neurons with receptive fields RF_1, RF_2, etc

Given image I, we can reconstruct I using neural response r_1, r_2 ..

$\hat{I} = \sum_i RF_i r_i$

Idea: What are the RF_i that minimize the total squared pixelwise errors between I and $\hat{I}$ and are as independent as possible?

Start out with random RF_i, and run your efficient coding algorithm on natural image patches. efficient coding: Sparse coding/ ICA/ Predictive coding.

1.2 The Electrical Personality of Neurons

Neuronal Zoo

– Visual cortex, Cerebellum, Optic Tectum

Neron Doctrine:

The brain is broken into individual, discrete parts called neurons

The shape of neuron varies in some general way form one area of the brain to another

Dendrites are the inputs ends of the neuron, whereas axons are the outputs ends.

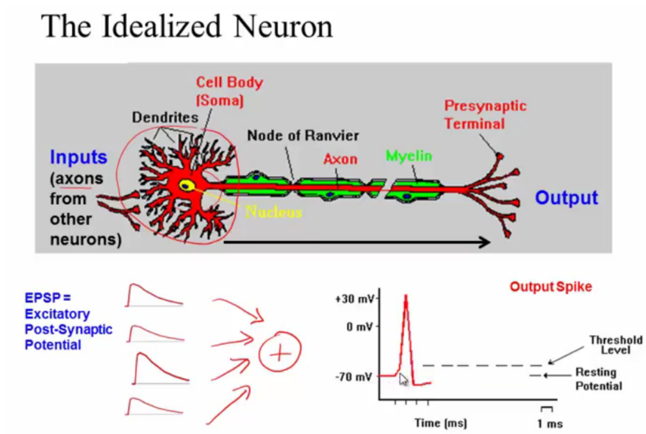

Figure 1.5: Spikes form a neuron occur when the sum of inputs from neighboring neurons reaches a certain threshold

What is a Neuron?

— A leaky bag of charged liquid

— Contents of the neuron enclosed within a cell membrane

— Cell membrane is a lipid bilayers. Bilayer is impermeable to charged ion species such as Na^+, Cl^- and K^+ — — Ionic channels embedded in membrane allow icons to flow in or out

— Each neuron maintain a potential difference across its membrane

— — Inside in about -70mV relative to outside

— — [Na+] and [Cl-] higher outside; [K+] and organic anions [A-] higher inside

— — Ionic pump maintains -70mV difference by expelling Na+ out and allowing K+ in

Ionic Channels: the Gate-keepers

Ionic channels in membrane are proteins that are selective and allow only specific ions to pass through

Ionic channels are gated:

— Voltage-gated: Probability of opening depends on membrane voltage

— Chemically-gated: Binding to a chemical cause channel to open

— Mechanically-gated: Sensitive to pressure or stretch

Gate Channels allow Neuronal Signaling

— Input form other neurons → chemically-gate channels (at synapses) open → Changes in local membrane potential

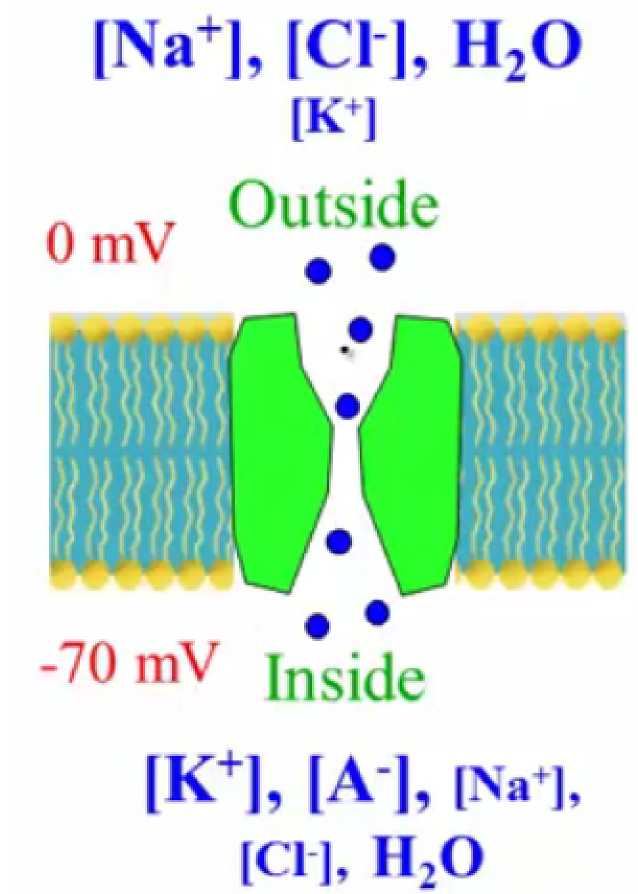

Figure 1.6: Neuron membrane

— This in turn cause opening/closing of voltage-gate channels in dendrites, body, and axon, resulting in depolarization (positive change in voltage) or hyperpolarization (negative change in voltage)

Strong enough depolarization cause a spike or action potential

The Output of a Neuron: Action Potential (Spike)

Voltage-gated channels cause action potentials (spikes)

1. Strong depolarization opens Na+ channels, causing rapid Na+ influx and more channels to open until they inactivate

2. K+ outflux restores membrane potential

Active Wiring: Myelination of Axons

Myelin due to oligodendrocytes (glial cells) wrap axons and enable fast long-range spike communication

— Action potential hops form one non-myelinated region (node of Ranvier)

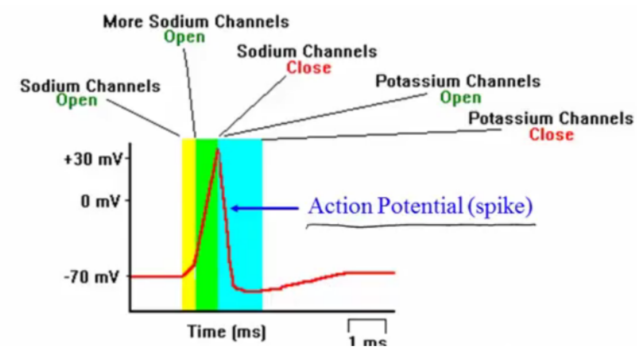

Figure 1.7: spikes time

the the next (saltatory conduction)

— Active wire allows lossless signal propagation

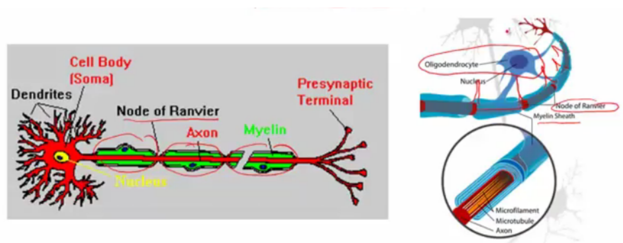

Figure 1.8: Myelination of Axons

1.3 Making Connections: Synapses

A synapse is a connection or junction between 2 neurons

— Electrical synapses use gap junctions (fast connection)

— Chemical synapses use neurotransmitters (basic for learning and memory)

Synapses can be **Excitatory** or **Inhibitory**

An Excitatory synapse:

Input spike → Neurotransmitter release (e.g, Glutamate) → Binds to ion channel receptors → Ion channels open → Na+ influx → Depolarization due to EPSP (excitatory post-synaptic potential)

Synapse Doctrine

Synapses are the basic for memory and learning

How do brain Learn? Synaptic Plasticity: If the neuron A repeatedly takes part in firing neuron B, then the synapse form A to B is strengthened

Long term Potentiation (LTP)

LTP = Experimentally observed **increase** in synaptic strength that lasts for hours or days

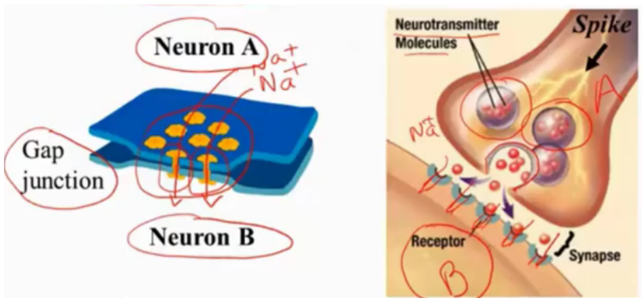

Figure 1.9: Synapse

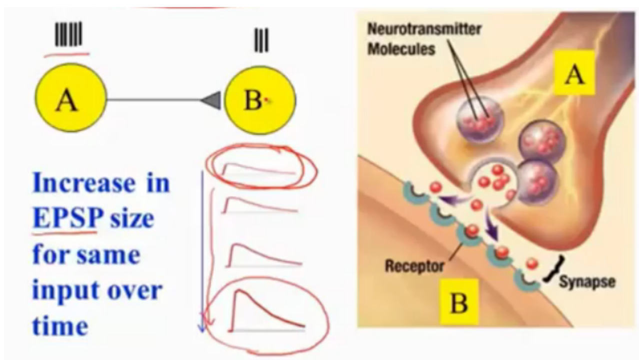

Figure 1.10: Long Term Potentiation (LTP)

Long Term Depression (LTD)
LTD = Experimentally observed **decrease** in synaptic strength that lasts for hours or days
Synaptic Plasticity depends on Spike Timing
LTP/ LTD depends on relative timing of input and output spikes

1.4 Time to Network: Brain Areas and Their Function

Organization and Function of the Nervous System
Peripheral Nervous System(PNS)
Somatic: Nerves connecting to voluntary skeletal muscles and sensory receptors
— Afferent Nerve Fibers (incoming): Axons that carry info away form the periphery to the CNS
— Efferent Nerve Fibers (outgoing): Axons that carry info from the CNS outward to the periphery.

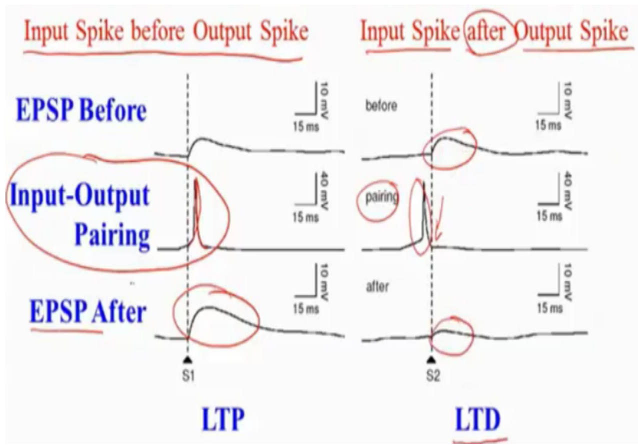

Figure 1.11: relative timing of LTP and LTD

Autonomic: Nerves that connect to the heart, blood vessels, smooth muscles

Central Nervous system (CNS)

CNS = Spinal Cord + Brain

Spinal Cord

— Local feedback loops controls reflexes (reflex arcs)

— Descending motor control signals from the brain active spinal motor neurons

— Ascending sensory axons convey sensory information form muscles and skin back to the brain

Major Brain Regions: The Hindbrain

Major Brain Regions: Midbrain and Retic. Formation

Midbrain: Eye movements, visual and auditory reflexes

Reticular Formation: Modulates muscle reflexes, breathing and pain perception. Also regulates sleep, wakefulness and arousal

Major Brain Regions: Thalamus and Hypothalamus

Thalamus: Relay station for all sensory info (except smell) to the cortex, regulates sleep/wakefulness

Hypothalamus: Regulates basic needs: Fighting, Fleeing, Feeding and Mating

Major Brain Region: THe Cerebrum

Consists of: Cerebral cortex, basal ganglia, hippocampus, and amygdala

Involved in perception and motor control, cognitive functions, emotion, memory, and learning

Cerebral Cortex: A layered Sheet of Neurons

Convoluted surface of cerebrum, about 1/8 of an inch thick

Six layers of neurons

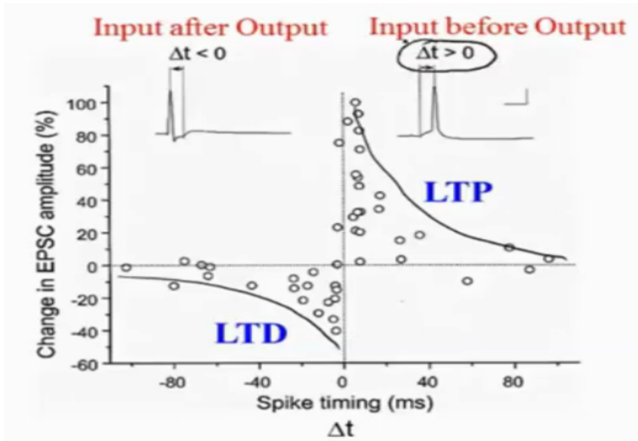

Figure 1.12: Spike-Timing Dependent Plasticity (STDP)

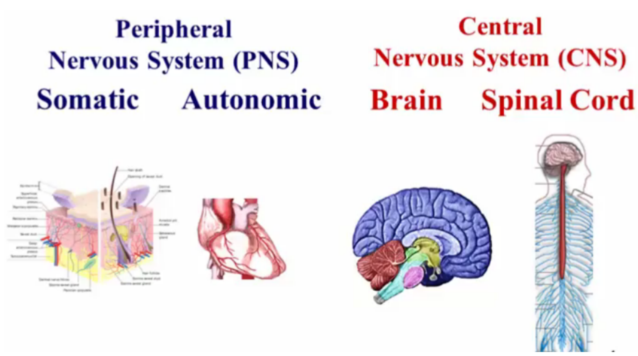

Figure 1.13: Nervous System

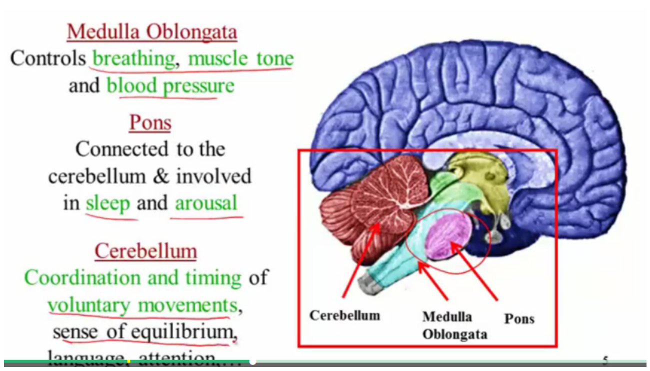

Figure 1.14: Hindbrain

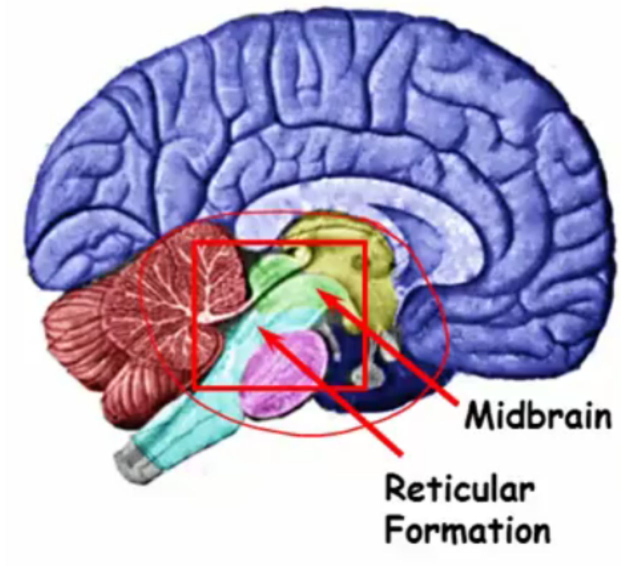

Figure 1.15: Midbrain and Retic. Formation

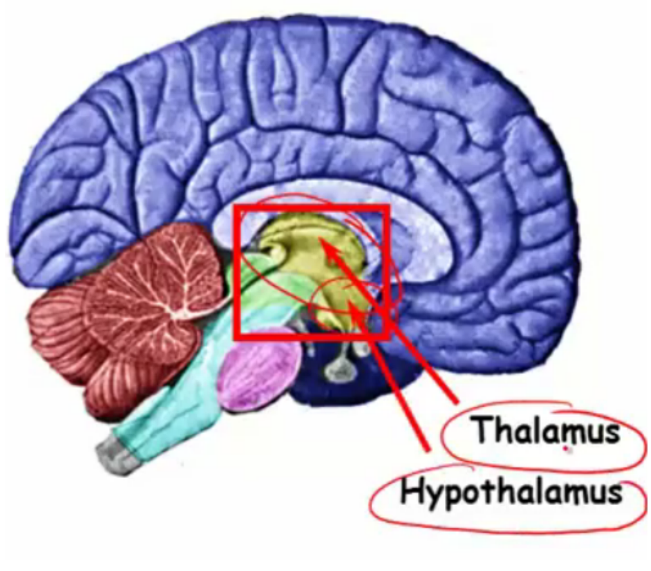

Figure 1.16: Thalamus and Hypothalamus

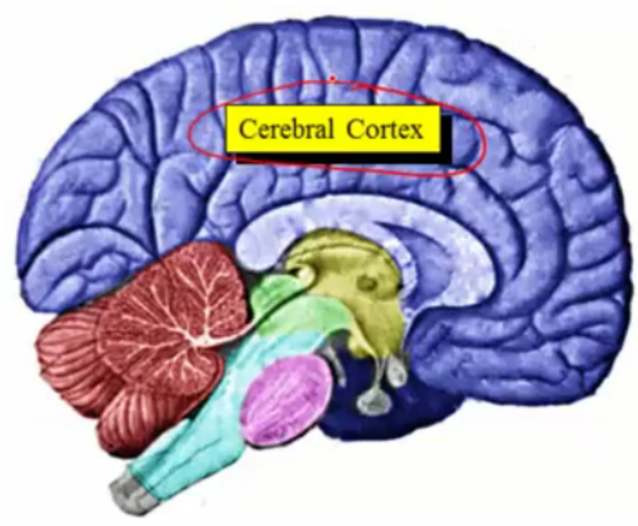

Figure 1.17: Cerebrum

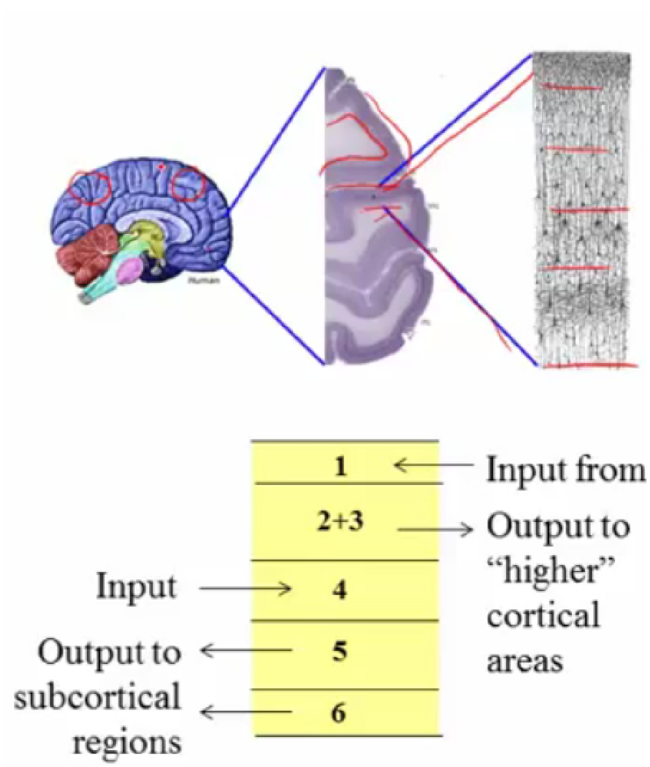

Figure 1.18: Cerebral Cortex

Chapter 2

Neural Code

2.1 Recording form the brain

Encoding: stimulus cause a pattern of response

Decoding: reponse tell as about the stimulus

$P(response|stimulus)$: encoding

$P(stimulus|response)$ decoding

What is the response? stimulus and the relationship?

2.2 Constructing response models:Linear response

Linear response

$r(t) = \phi s(t)$

Linear filter: $r(t) = \sum_{k=0}^{n} s_{t-k} f_k$ time at t, backward k

Linear properties: f(a*x) = a*f(x), f(x+y+z) = f(x) + f(y) + f(z)

2.2.1 Spatial filtering

Convolution filter

2.2.2 Spatio-temporal filtering

3D convolution

2.3 Feature selection

2.3.1 How build the model

$P(response|stimulus)$

2.3.2 Dimensionality reduction

Start with a very high dimensional description and pick out a small set of relevant dimension

2.3.3 What is the right stimulus to use?

$P(response|stimulus) \rightarrow P(response|s_1, s_2, ..., s_n)$

One common and useful method id to use **Gaussian white noise**

2.3.4 Linear filtering

Linear filtering = convolution = project

2.3.5 nonlinear input/output function

$P(spike|s_1) = P(s_1|spike) * P(spike)/P(s_1)$ (Bayes' ryle)

2.3.6 Linear and non-linear

2.4 Variability

2.4.1 When choose the best turning curve

Introducing the Kullback-Leibler divergence

$D_{KL}(P(s), Q(s)) = \int dsP(s)log_2 P(s)/Q(s)$

Goodness measure: $D_{KL}(P(s_f|spike), P(s_f))$ maximize

Maximize D_{KL} between spike-conditional and prior distributions = maximize mutual information between stimulus and spike

2.4.2 Finding relevant features

- Single filter determined by the conditional average
- A family of filters derived using PCA
- Information theoretic methods use the whole distribution

2.4.3 Modeling the noise

2.4.4 Binomial spiking

Time interval △T, n = T / △T

Distribution: $P_n[k] = p^k(1-p)^{n-k}$

Mean: $< k >= n * p$

Variance: Var(k) = n*p*(1-p)

2.4.5 Poisson spiking

r = P / $\triangle$t : neuron's mean firing rate (spike/second)
k: number of spikes
Distribution $P_T[k] = (rT)^k exp(-rT)/k!$
Mean: $< k >= rT$
Variance: Var(k) = rT
Fano factor F= 1
Interval distribution P(T) = r exp(-rT)

2.4.6 The generalized linear model

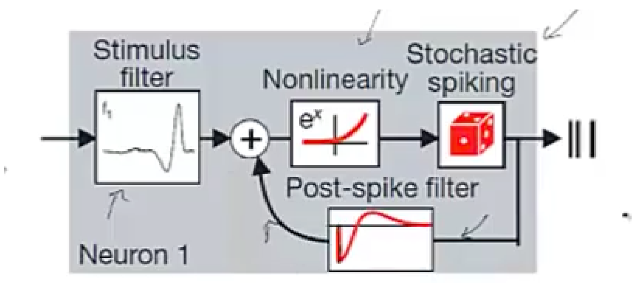

Figure 2.1: The generalized linear model

Cooperate

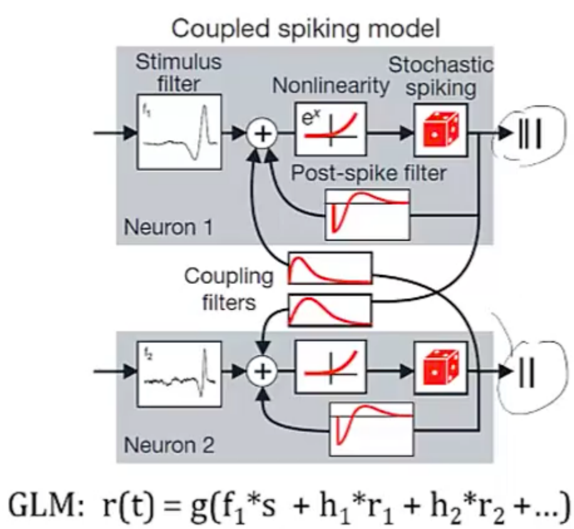

Figure 2.2: Cooperate of neurons