# Variance as a signature of neural computations during decision-making 

Anne Churchland Cold Spring Harbor Laboratory

KITP Neuroscience

## Cortical neurons are variable



## Roadmap

## Roadmap

- Background: behavior on a random dot motion decision task and a proposed neural mechanism


## Roadmap

- Background: behavior on a random dot motion decision task and a proposed neural mechanism
-Predictions about neural variability inherent to that mechanism


## Roadmap

- Background: behavior on a random dot motion decision task and a proposed neural mechanism
-Predictions about neural variability inherent to that mechanism
- Neural variability in the data


## Roadmap

- Background: behavior on a random dot motion decision task and a proposed neural mechanism
-Predictions about neural variability inherent to that mechanism - Neural variability in the data -Predictions about temporal correlations inherent to that mechanism


## Roadmap

- Background: behavior on a random dot motion decision task and a proposed neural mechanism
- Predictions about neural variability inherent to that mechanism - Neural variability in the data - Predictions about temporal correlations inherent to that mechanism -Temporal correlations in the data


## Roadmap

- Background: behavior on a random dot motion decision task and a proposed neural mechanism
- Predictions about neural variability inherent to that mechanism - Neural variability in the data - Predictions about temporal correlations inherent to that mechanism - Temporal correlations in the data


## 2-choice decisions



## 2-choice decisions



## 2-choice decisions



## 2-choice decisions



## 2-choice decisions



## 2-choice decisions



## 2-choice decisions



## 2-choice decisions



## 2-choice decisions



## 2-choice decisions



Rhesus macaques


## Choice and reaction time on the 2 -choice decision task



Churchland et. Al, 2008, Roitman \& Shadlen, 2002

## Choice and reaction time on the 2 -choice decision task



Churchland et. Al, 2008, Roitman \& Shadlen, 2002

## Choice and reaction time on the 2 -choice decision task



Churchland et. Al, 2008, Roitman \& Shadlen, 2002

## Choice and reaction time on the 2 -choice decision task



Churchland et. Al, 2008, Roitman \& Shadlen, 2002

## Choice and reaction time on the 2 -choice decision task



Churchland et. Al, 2008, Roitman \& Shadlen, 2002

## Choice and reaction time on the 2 -choice decision task



Churchland et. Al, 2008, Roitman \& Shadlen, 2002

## Choice and reaction time on the 2 -choice decision task



Churchland et. Al, 2008, Roitman \& Shadlen, 2002

## Choice and reaction time on the 2 -choice decision task



Churchland et. Al, 2008, Roitman \& Shadlen, 2002

## Choice and reaction time on the 2 -choice decision task



Churchland et. Al, 2008, Roitman \& Shadlen, 2002

## Choice and reaction time on the 2 -choice decision task



Churchland et. Al, 2008, Roitman \& Shadlen, 2002

## Choice and reaction time on the 2 -choice decision task



Churchland et. Al, 2008, Roitman \& Shadlen, 2002

## Choice and reaction time on the 2 -choice decision task



Churchland et. Al, 2008, Roitman \& Shadlen, 2002

## Decisions in other animals?



## Decisions in other animals?

QAccumulating evidence is a rare strategy that is limited to primates


Motion strength (\% coh)

## Decisions in other animals?

QAccumulating evidence is a rare strategy that is limited to primates QAccumulating evidence relies on circuitry only present in the visual system


## Decisions in other animals?

QAccumulating evidence is a rare strategy that is limited to primates QAccumulating evidence relies on circuitry only present in the visual system

Motion strength (\% coh)

Tony Zador at Cold Spring Harbor

## 4-choice decisions



Churchland A, Kiani R \& Shadlen MN (2008). Decisionmaking ${ }^{2}$ with multiple alternatives. Nature Neuroscience 11(6).

## Behavior on the 2 -choice task



## Behavior on the $2^{-}$and $4^{-c h o i c e ~ t a s k s ~}$



## Behavior on the $2^{-}$and $4^{-c h o i c e ~ t a s k s ~}$



## Behavior on the $2^{-}$and $4^{-c h o i c e ~ t a s k s ~}$



## Behavior on the $2^{-}$and $4^{-c h o i c e ~ t a s k s ~}$



## Behavior on the $2^{-}$and $4^{-c h o i c e ~ t a s k s ~}$



## Behavior on the $2^{-}$and $4^{-c h o i c e ~ t a s k s ~}$



## Behavior on the $2^{-}$and $4^{-c h o i c e ~ t a s k s ~}$




## Behavior on the $2^{-}$and $4^{-c h o i c e ~ t a s k s ~}$




## Behavior on the $2^{-}$and $4^{-c h o i c e ~ t a s k s ~}$




## Behavior on the $2^{-}$and $4^{-c h o i c e ~ t a s k s ~}$




## Behavior on the $2^{-}$and $4^{-c h o i c e ~ t a s k s ~}$



## A framework for understanding 2-choice decisions

Bound for "left" choice
Accumulated
evidence

## A framework for understanding ${ }^{2}$-choice decisions

Bound for "left" choice
Accumulated
evidence

## A framework for understanding 2-choice decisions

Bound for "left" choice
Accumulated
evidence

## A framework for understanding 2-choice decisions

Accumulated
evidence

[^0]
## A framework for understanding ${ }^{2}$-choice decisions

Accumulated
evidence

## A framework for understanding ${ }^{2}$-choice decisions

Accumulated
evidence

## A framework for understanding ${ }^{2}$-choice decisions

Accumulated
evidence

## A framework for understanding 2-choice decisions



Ratcliff, 1978; Ratcliff \& Smith, 2004

## A framework for understanding ${ }^{2}$-choice decisions



Ratcliff, 1978; Ratcliff \& Smith, 2004

## A framework for understanding 2-choice decisions



Ratcliff, 1978; Ratcliff \& Smith, 2004

## A framework for understanding ${ }^{2}$-choice decisions



Ratcliff, 1978; Ratcliff \& Smith, 2004

## A framework for understanding 2-choice decisions



Ratcliff, 1978; Ratcliff \& Smith, 2004

## The bounded accumulation framework

 accounts for the monkey's speed and accuracy on the 2 -choice task

## Roadmap

- Background: behavior on a random dot motion decision task and a proposed neural mechanism
- Predictions about neural variability inherent to that mechanism
- Neural variability in the data
- Predictions about temporal correlations inherent to that mechanism - Temporal correlations in the data


## Single unit physiology.



Eye, Brain, and Vision (Scientific American Library, No 22); David H. Hubel, 1995

## Is there evidence in the brain to support bounded accumulation?



## Is there evidence in the brain to support bounded accumulation?



## Is there evidence in the brain to support bounded accumulation?



## Is there evidence in the brain to support bounded accumulation?



## Is there evidence in the brain to support bounded accumulation?



## Is there evidence in the brain to support bounded accumulation?



## LIP neurons: basic responses properties

## LIP neurons: basic responses properties

Response Field


## LIP neurons: basic responses properties

Response Field


## LIP neurons: basic responses properties

Response Field


## LIP neurons: basic responses properties

Response Field


## LIP neurons: Memory saccade task

## Response Field



## LIP neurons: Memory saccade task

Response Field


## LIP neurons: Memory saccade task

## Response Field



## LIP neurons: Memory saccade task

Response Field


## LIP neurons: Memory saccade task

Response Field


Memory saccade task: towards the response field

Memory saccade task: away the response field

Memory saccade task: away the response field

Memory saccade task: towards the response field

## 2-choice decisions



## 2-choice decisions



## 2-choice decisions



## 2-choice decisions



## LIP responses during decision-formation



# LIP responses during decision-formation 

## 2 choice



## LIP responses during decision-formation



LIP responses during decision-formation


## LIP responses during decision-formation

@Dip and recovery


LIP responses during decision-formation

9Dip and recovery QGradual build-up of firing rate


LIP responses during decision-formation

9Dip and recovery QGradual build-up of firing rate


LIP responses during decision-formation

9Dip and recovery QGradual build-up of firing rate


LIP responses during decision-formation

9Dip and recovery QGradual build-up of firing rate


LIP responses during decision-formation

9Dip and recovery QGradual build-up of firing rate


LIP responses during decision-formation

9Dip and recovery QGradual build-up of firing rate


LIP responses during decision-formation

## 4 choice



## LIP responses during decision-formation

## 4 choice

QDip and recovery

Firing rate ( $\mathrm{sp} / \mathrm{s}$ )


LIP responses during decision-formation

## 4 choice

9 Dip and recovery QGradual build-up of firing rate

Firing rate $(\mathrm{sp} / \mathrm{s})$


LIP responses during decision-formation

## 4 choice

9 Dip and recovery QGradual build-up of firing rate

Firing rate $(\mathrm{sp} / \mathrm{s})$


LIP responses during decision-formation

## 4 choice

9 Dip and recovery QGradual build-up of firing rate

Firing rate $(\mathrm{sp} / \mathrm{s})$


LIP responses during decision-formation

## 4 choice

9 Dip and recovery QGradual build-up of firing rate

Firing rate $(\mathrm{sp} / \mathrm{s})$


LIP responses during decision-formation

## 4 choice

9 Dip and recovery QGradual build-up of firing rate

Firing rate $(\mathrm{sp} / \mathrm{s})$


## Roadmap

- Background: behavior on a random dot motion decision task and a proposed neural mechanism
-Predictions about neural variability inherent to that mechanism
- Neural variability in the data
- Predictions about temporal
correlations inherent to that mechanism - Temporal correlations in the data


## Bounded accumulation: the right mechanism?



Time $\longrightarrow$

## Bounded accumulation: the right mechanism?



Time $\longrightarrow$

## Bounded accumulation: the right mechanism?



Time $\longrightarrow$

## Bounded accumulation: the right mechanism?



Time $\longrightarrow$

## Bounded accumulation: the right mechanism?



## Bounded accumulation: the right mechanism?



## Bound for "right" choice <br> 

## Variance can distinguish neural mechanisms



## Variance can distinguish neural mechanisms

## Bound for "right" choice <br> Time

## Variance can distinguish neural mechanisms

## Bound for "right" choice <br> Time

## Variance can distinguish neural mechanisms

## Bound for "right" choice <br> Time

## Variance can distinguish neural mechanisms

## Bound for "right" choice <br> Time

## Variance can distinguish neural mechanisms

Bound for "right" choice

Time $\longrightarrow$

## Variance can distinguish neural mechanisms

Bound for "right" choice

Time $\longrightarrow$

## Variance can distinguish neural mechanisms

Bound for "right" choice

Time $\longrightarrow$


## Variance can distinguish neural mechanisms

Bound for "right" choice Bound for "right" choice

Time $\longrightarrow$


## Variance can distinguish neural mechanisms

Bound for "right" choice Bound for "right" choice

Time



## Variance can distinguish neural mechanisms




## Variance can distinguish neural mechanisms




## Variance can distinguish neural mechanisms




## Variance can distinguish neural mechanisms




## Variance can distinguish neural mechanisms







Time


Time

## Roadmap

- Background: behavior on a random dot motion decision task and a proposed neural mechanism
- Predictions about neural variability inherent to that mechanism
- Neural variability in the data - Predictions about temporal correlations inherent to that mechanism -Temporal correlations in the data


## Bounded accumulation: the right mechanism to explain LIP firing rates?



## Computing VarCE from neural data



## Computing VarCE from neural data



## Computing VarCE from neural data



## Computing VarCE from neural data



## Computing VarCE from neural data


$\sigma_{N}^{2}$
$\uparrow$ Total spike
count
variance

## Computing VarCE from neural data



$$
N=\left[\begin{array}{l}
n_{1} \\
n_{2} \\
\vdots \\
n_{n}
\end{array}\right]
$$

N-CN variance

## Computing VarCE from neural data



$$
N=\left[\begin{array}{l}
n_{1} \\
n_{2} \\
\vdots \\
n_{n}
\end{array}\right]
$$

$$
\overbrace{N}^{2}
$$

$$
\operatorname{Var} C E=\sigma_{N}^{2}-\phi \bar{N}
$$ variance

## Computing VarCE from neural data


100 ms

Churchland MM et al, Stimulus onset quenches neural variability: a widespread cortical phenomenon; Nature

Neuroscience, 2010


## VarCE doesn't depend on most task parameters



## VarCE doesn't depend on most task parameters



## VarCE for 2-choice vs 4 -choice responses



Q Stochastic evidence is accumulated differently for 2 vs 4 choice tasks
Q $2^{-}$vs $4^{-c h o i c e ~ t a s k s ~ i n v i t e ~ d i f f e r e n t ~ s t r a t e g i e s ~}$

## VarCE doesn't depend on most task parameters



## VarCE doesn't depend on most task parameters



## VarCE during the pre-decision period



## VarCE during the pre-decision period



## VarCE during the pre-decision period



## VarCE during the pre-decision period



## VarCE depends on phi





## Mean firing rate at decision time



## Mean firing rate at decision time



Firing rate (spikes per s)


## VarCE at decision time




## VarCE at decision time



## VarCE at decision time



## Roadmap

- Background: behavior on a random dot motion decision task and a proposed neural mechanism
- Predictions about neural variability inherent to that mechanism
- Neural variability in the data
-Predictions about temporal correlations inherent to that mechanism Temporal correlations in the data


## VarCE during decision formation



## VarCE during decision formation



## VarCE during decision formation



## Variance can distinguish neural mechanisms

## Bounded <br> accumulation




## Variance can distinguish neural mechanisms



## Time-dependent scaling




## Variance can distinguish neural mechanisms



Time-dependent scaling


Variable rate-ofrise



## Correlation of the conditional expectation (corCE)

Bounded
accumulation




Time (ms)

## Correlation of the conditional expectation (corCE)



## 觡 210 揑 450 <br>  <br>  <br> $$
\begin{array}{llll} 210 & 450 & 210 & 450 \\ \text { Time (ms) } & & \end{array}
$$

## Correlation of the conditional expectation (corCE)



合 210
:
E 450


Time (ms)

$210 \quad 450$
210
450

## Roadmap

- Background: behavior on a random dot motion decision task and a proposed neural mechanism
- Predictions about neural variability inherent to that mechanism
- Neural variabilitv in the data
- Predictions about temporal
correlations inherent to that mechanism
-Temporal correlations in the data


## Computing the CorCE in neural data

Bound for "right" choice

Time $\longrightarrow$


## Computing the CorCE in neural data

Bound for "right" choice
Time $\longrightarrow$



## Computing the CorCE in neural data



Covariance

## Computing the CorCE in neural data



## Correlation



## Computing the CorCE in neural data



## Computing the CorCE in neural data



## Computing the CorCE in neural data



Covariance
Corrected Cov VateE only

## Computing the CorCE in neural data





Data:


## Other models of decision-making

Probabilistic
Population Code Attractor
Variance of 0.4 the conditional expectation 0.2


Corr. of the conditional

$210450 \quad 210 \quad 450$

## Conclusions

## Conclusions

- VarCE and CorCE are useful tools


## Conclusions

- VarCE and CorCE are useful tools
- Capture "variation in what is computed"


## Conclusions

- VarCE and CorCE are useful tools
- Capture "variation in what is computed"
-Expose features of neural computations in decision making
e.g., integration, mixtures, termination bound, refutes change point and several plausible alternative models


## Conclusions

- VarCE and CorCE are useful tools
- Capture "variation in what is computed"
-Expose features of neural computations in decision making
e.g., integration, mixtures, termination bound, refutes change point and several plausible alternative models
- The main limitation is in estimating $\boldsymbol{\phi}$


## Thanks

thanks to...
${ }^{-}$Mike Shadlen
-Xiao-Jing Wang
Alex Pouget
Rishi Chaudhuri
-Roozbeh Kiani

Experiments were done at the University of Washington regional primate research center

## Funding NIH K99 EY019072

$\operatorname{VarCE}$

## Churchland et al. Figure 2



The same features of the VarCE are evident in a mean-matched estimate





The same features of the VarCE are evident in a subset of the data with a relatively stationary mean





## Fano factor





$$
\left.\begin{array}{ccc}
s_{\left\langle N_{1}\right\rangle}^{2} & \ldots & r_{1 m} \sqrt{s_{\left\langle N_{1}\right\rangle}^{2} s_{\left\langle N_{m}\right\rangle}^{2}} \\
\vdots & \ddots & \vdots \\
r_{1 m} \sqrt{s_{\left\langle N_{1}\right\rangle}^{2} s_{\left\langle N_{m}\right\rangle}^{2}} & \cdots & s_{\left\langle N_{m}\right\rangle}^{2}
\end{array}\right)=\left(\begin{array}{ccc}
\operatorname{VarCE} E_{1} & \ldots & \operatorname{Cov}\left[N_{1}, N_{m}\right] \\
\vdots & \ddots & \vdots \\
\operatorname{Cov}\left[N_{m}, N_{1}\right] & \cdots & \operatorname{VarCE} E_{m}
\end{array}\right)
$$

$$
\operatorname{Var}[X]=\underbrace{\operatorname{Var}[\langle X \mid Y\rangle]}_{\begin{array}{c}
\text { variance of } \\
\text { conditional expectation }
\end{array}}+\underbrace{\langle\operatorname{Var}[X \mid Y]\rangle}_{\begin{array}{c}
\text { expectation of } \\
\text { conditional variance }
\end{array}}
$$



## Computing VarCE from neural data



## Computing VarCE from neural data



## Computing VarCE from neural data



## Computing VarCE from neural data



## Computing VarCE from neural data


$\sigma_{N}^{2}$
$\uparrow$ Total spike
count
variance

## Computing VarCE from neural data



$$
N=\left[\begin{array}{l}
n_{1} \\
n_{2} \\
\vdots \\
n_{n}
\end{array}\right]
$$

N-CN variance

## Computing VarCE from neural data



$$
N=\left[\begin{array}{l}
n_{1} \\
n_{2} \\
\vdots \\
n_{n}
\end{array}\right]
$$

$$
\overbrace{N}^{2}
$$

$$
\operatorname{Var} C E=\sigma_{N}^{2}-\phi \bar{N}
$$ variance

## Decision termination



## Computing VarCE:

## Computing VarCE:

$\begin{gathered}\text { Law of total } \\ \text { variance }\end{gathered} \operatorname{Var}[X]=\underbrace{\operatorname{Var}[\langle X \mid Y\rangle]}_{\begin{array}{c}\text { variance of conditional } \\ \text { expectition (VCE) }\end{array}}+\underbrace{\langle\operatorname{Var}[X \mid Y]\rangle}_{\begin{array}{c}\text { expecaraion of } \\ \text { conditional varinee }\end{array}}$

## Computing VarCE:

Law of total variance

$$
\operatorname{Var}[X]=\underbrace{\operatorname{Var}[\langle X \mid Y\rangle]}_{\substack{\text { variance of oonditional } \\ \text { expectation (NCE) }}}+\underbrace{\langle\operatorname{Var}[X \mid Y]\rangle}_{\substack{\text { enpectation onf } \\ \text { conditional variance }}}
$$

## Applied to DSPPs



## Computing VarCE:

Law of total variance

$$
\operatorname{Var}[X]=\underbrace{\operatorname{Var}[\langle X \mid Y\rangle]}_{\substack{\text { variance of conditional } \\ \text { expectation (NCE) }}}+\underbrace{\langle\operatorname{Var}[X \mid Y]\rangle}_{\substack{\text { expectation onf } \\ \text { conditional variance }}}
$$

Applied to DSPPs

$$
\underbrace{\sigma_{N_{i}}^{2}}_{\substack{\text { Total measured } \\ \text { variance }}}=\underbrace{\sigma_{\left\langle N_{i}\right\rangle}^{2}}_{V C E}+\underbrace{\left\langle\sigma_{N \mid \lambda_{2}}^{2}\right\rangle}_{\substack{\text { Point process } \\ \text { variance (PPV) }}}
$$

Estimator of VCE

$$
s_{\left\langle N_{i}\right\rangle}^{2}=s_{N_{i}}^{2}-\phi \overline{N_{i}}
$$


[^0]:    Ratcliff, 1978; Ratcliff \& Smith, 2004

