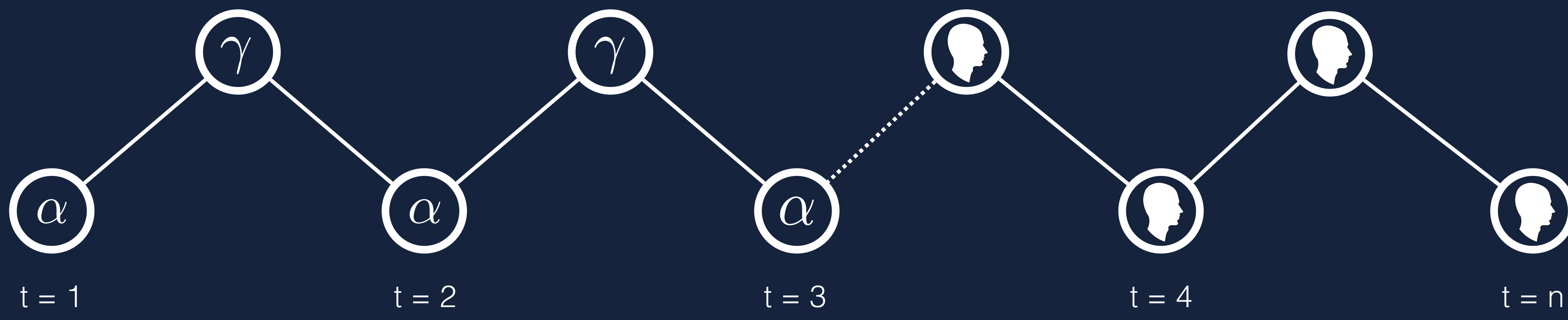

GIBBS SAMPLING AS AN EXPERIMENTAL DESIGN:
PROSPECTS AND OPPORTUNITIES IN PHONETICS

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Talk Outline

Headline:

Sampling algorithms offer rigorous blueprints for optimal experimental design

Talk Outline

Talk summary:

1. Computation and Experimentation
Statistics, Sampling, and Experimental Design (5 min.)

2. Adaptive Listening Paradigms
Experimental example: Sensitivity to Phonemic contrasts (5 min.)

3. MCMC & Gibbs Sampling:
Experimental example: Sensitivity to Phonemic contrasts (5 min.)

Computation and Experimentation:
Statistics, Sampling, and Experimental Design

λ

Inference & Computation

- provide formal frameworks for sampling data, testing hypotheses, and drawing conclusions

- still lack sufficient statistical models for many human phonetic abilities e.g. acoustic models for phonemic variation

$\hat{x}$

Experimentation

- provides access to full suite of human phonetic abilities

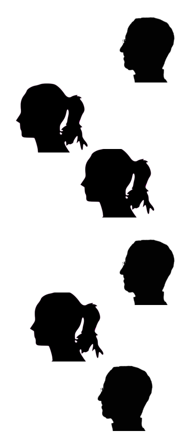
- typically lacks organisational principles for guaranteeing or optimising posterior inferences

Computation and Experimentation:
Statistics, Sampling, and Experimental Design

Typical Experimental Workflow:

1. Design Stimuli

2. Recruit Ps. & Split into Groups



3. Compute statistics

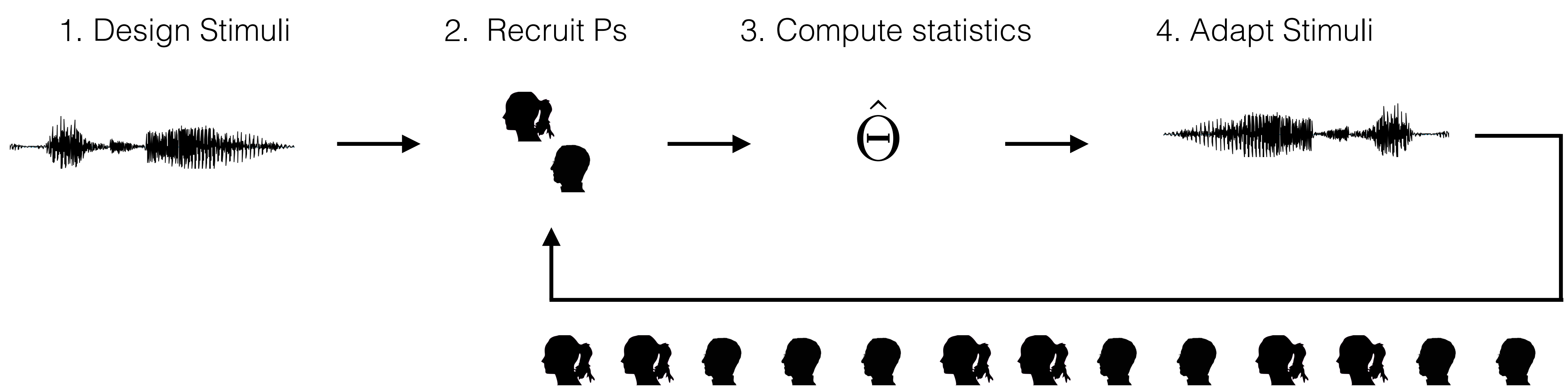
$\hat{\Theta}$

Design; Experiment; Compute; Repeat

Computation and Experimentation:
Statistics, Sampling, and Experimental Design

Algorithmic / Computational Experimental Workflow:

(see e.g. suchow & griffiths 2016, “Rethinking experimental design as algorithm design”)



Experimentation & Computation Interleaved & Iterative

Example 1:
Adaptive Listening Paradigms

"The goals of adaptive test designs are efficiency and accuracy, i.e. the best adaptive test finds the given threshold accurately in the fewest number of trials."

McGuire (2010, Methods in Speech Perception)

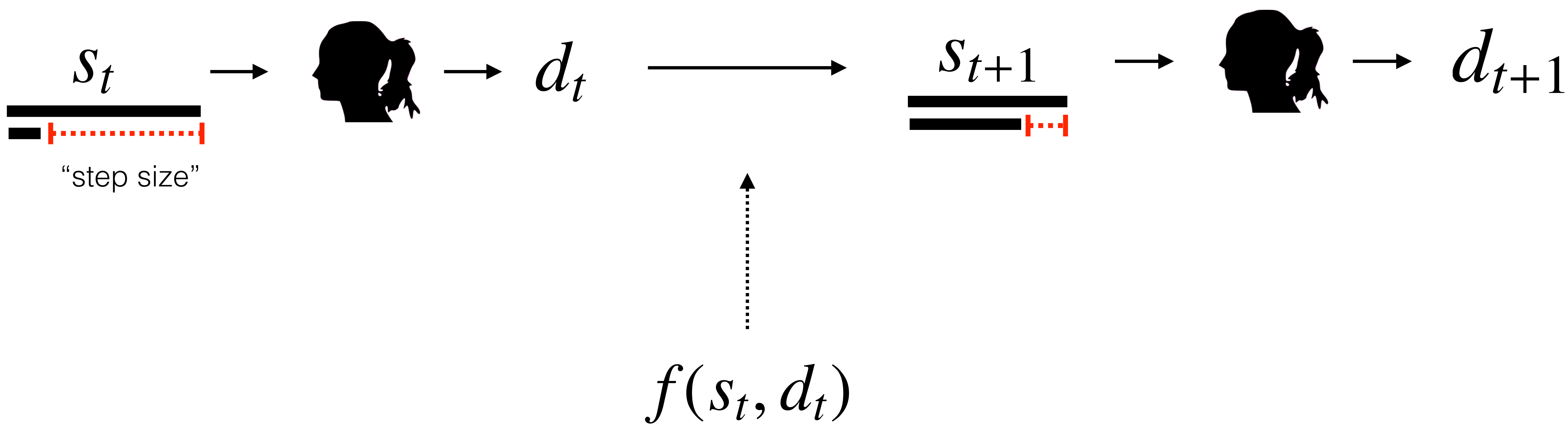
Sampling Algorithms as Experimental Design
Example 1: Adaptive Listening Paradigms

When do people start to hear **Mattiro** instead of **Matiro?**

Matiro .... Mattiro

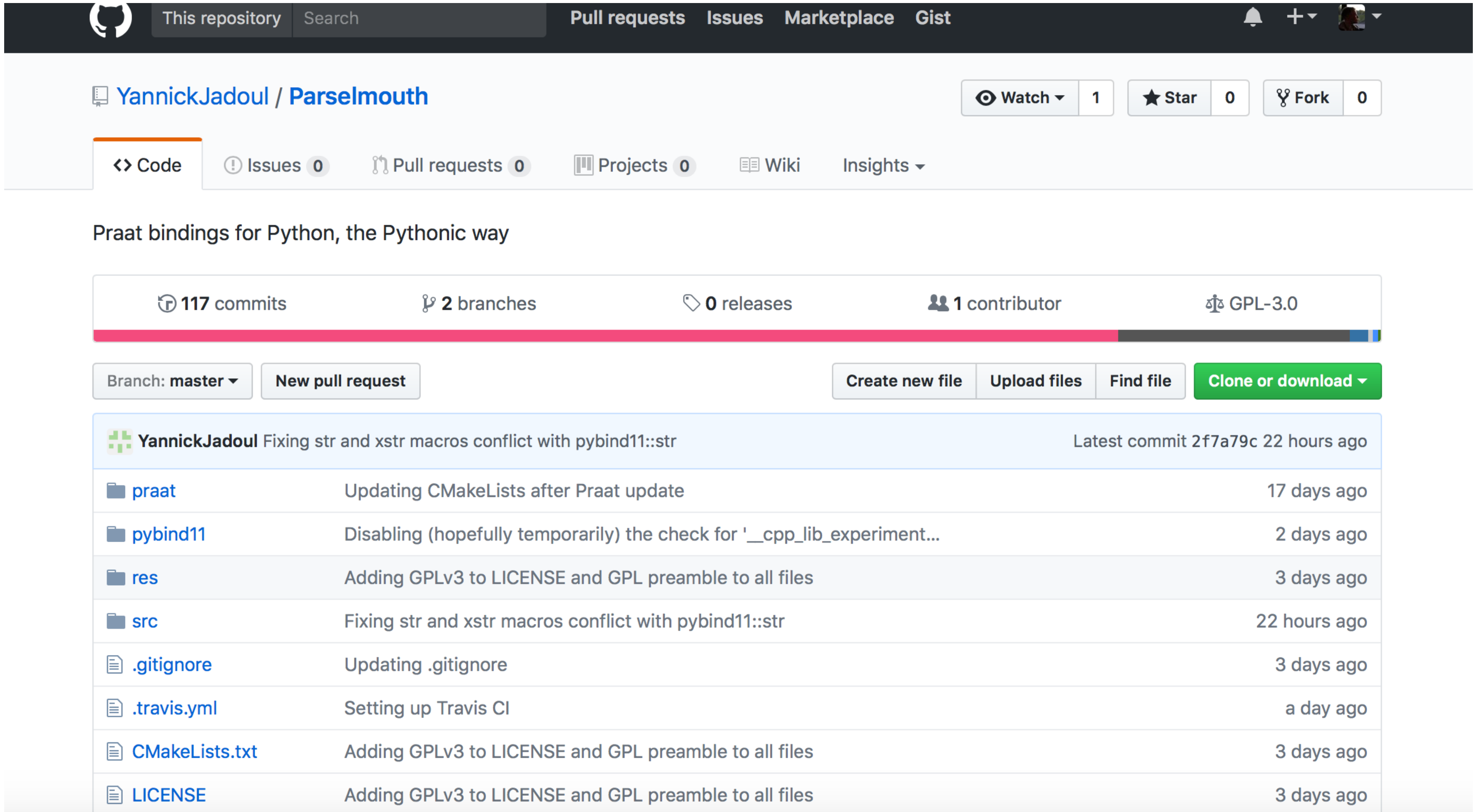
Sampling Algorithms as Experimental Design
Example 1: Adaptive Listening Paradigms

An **adaptive listening** (or ***staircase design***) paradigm can determine the relationship between closure period and interpretation:



Sampling Algorithms as Experimental Design
Example 1: Adaptive Listening Paradigms

Parselmouth: Praat in Python!



Sampling Algorithms as Experimental Design
Example 1.5: Phonetic Categories via MCMC

Markov Chain Monte Carlo Sampling Methods

Unobservable Target Distribution:

$$P(x)$$

Sampling Algorithm:

Initialisation: Choose initial point x_0

For *t* iterations:

1) sample from proposal distribution $Q(x'|x_t)$

2) compute acceptance criterio: $a = f(x')/f(x_t)$

3) accept / reject new sample according to: $P(x_{t+1} = x') = \begin{cases} 1 & \text{if } a > 1 \\ a & \text{if } a < 1 \end{cases}$

Sampling Algorithms as Experimental Design
Example 1.5: Phonetic Categories via MCMC

Markov Chain Monte Carlo Sampling Methods

Exploring Phonetic Category Structure with Markov Chain Monte Carlo

A Senior Honors Thesis

Presented in Partial Fulfillment of the Requirements for graduation
with research distinction in Psychology in the undergraduate
colleges of The Ohio State University

by

James Pooley

Project Advisors: Professors Mark Pitt and Jay Myung, Department of Psychology

Or…

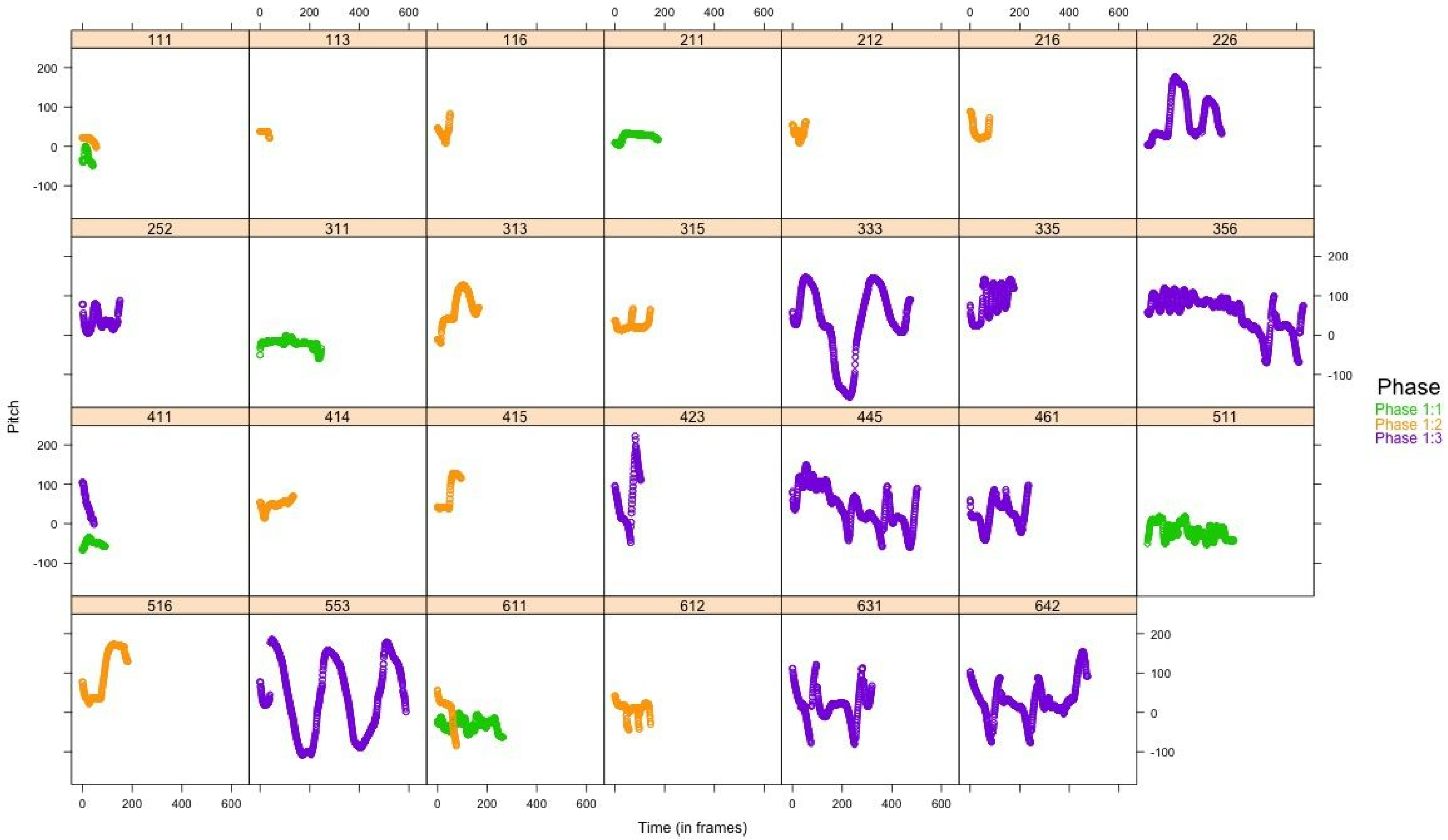
See: “**Markov Chain Monte Carlo with People**”, Sanborn & Griffiths 2007

Example 2:
Unsupervised Segmentation and Clustering of Continuous Acoustic Signals into Primitive Units

Sampling Algorithms as Experimental Design
Example 2: Joint Segmentation and Clustering

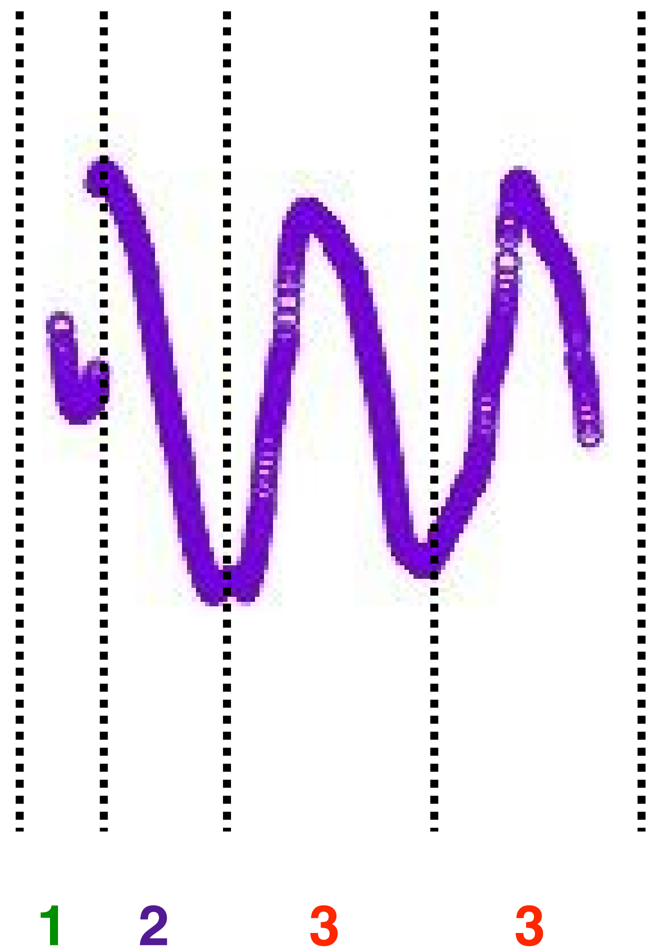
Little, Eryılmaz, & de Boer (forthcoming)

Can you see re-usable building blocks among these signals?



Sampling Algorithms as Experimental Design
Example 2: Joint Segmentation and Clustering

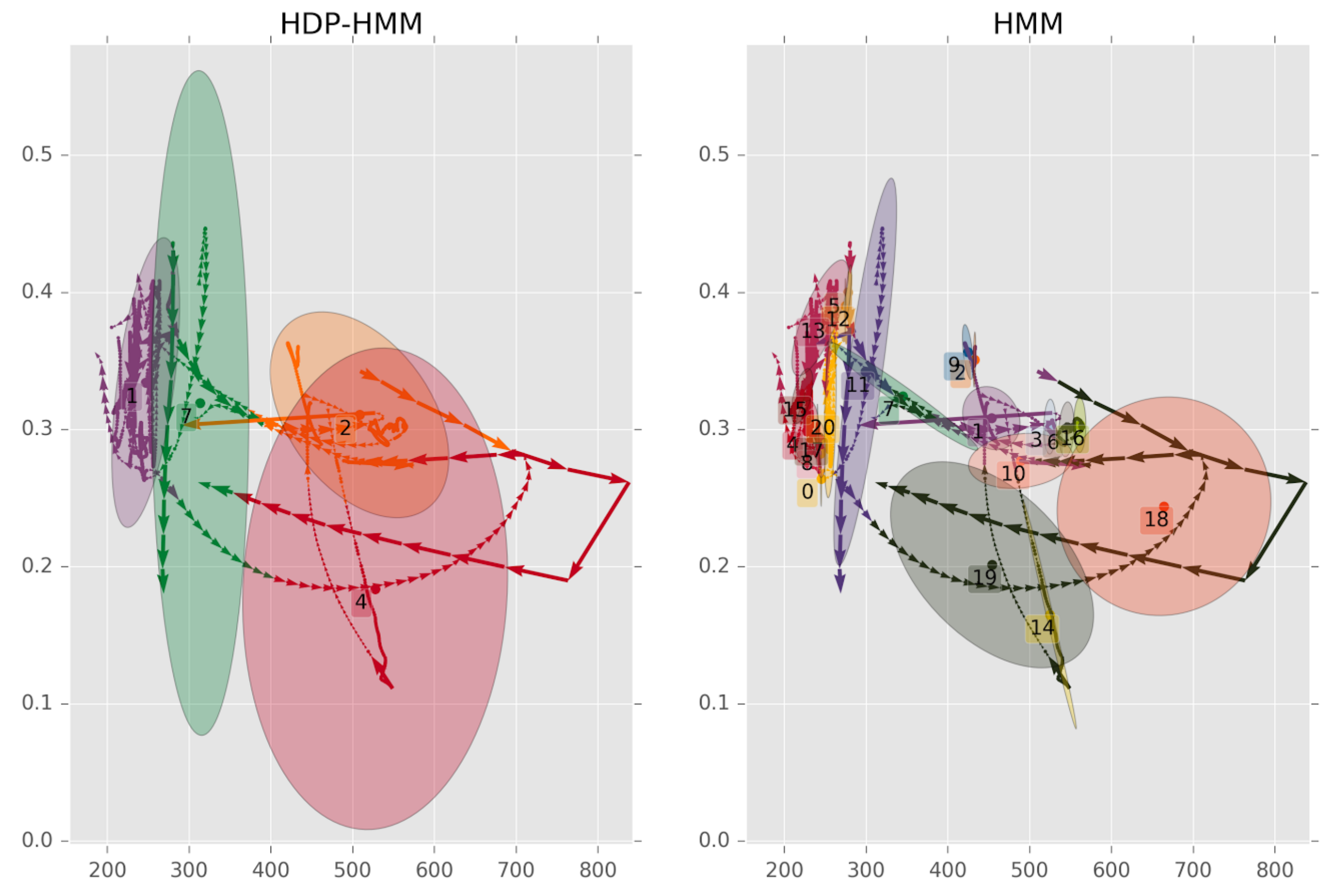
Finding boundaries AND categories



Sampling Algorithms as Experimental Design

Example 2: Joint Segmentation and Clustering

Little, Eryilmaz, & de Boer (forthcoming)



Sampling Algorithms as Experimental Design

Example 2: Joint Segmentation and Clustering

Gibbs sampling

Unobservable Target **Joint** Distribution:

$$p(x, y)$$

Sampling Algorithm:

Initialisation: Choose initial guesses x_0, y_0

For t = 1, 2, …, *n* iterations:

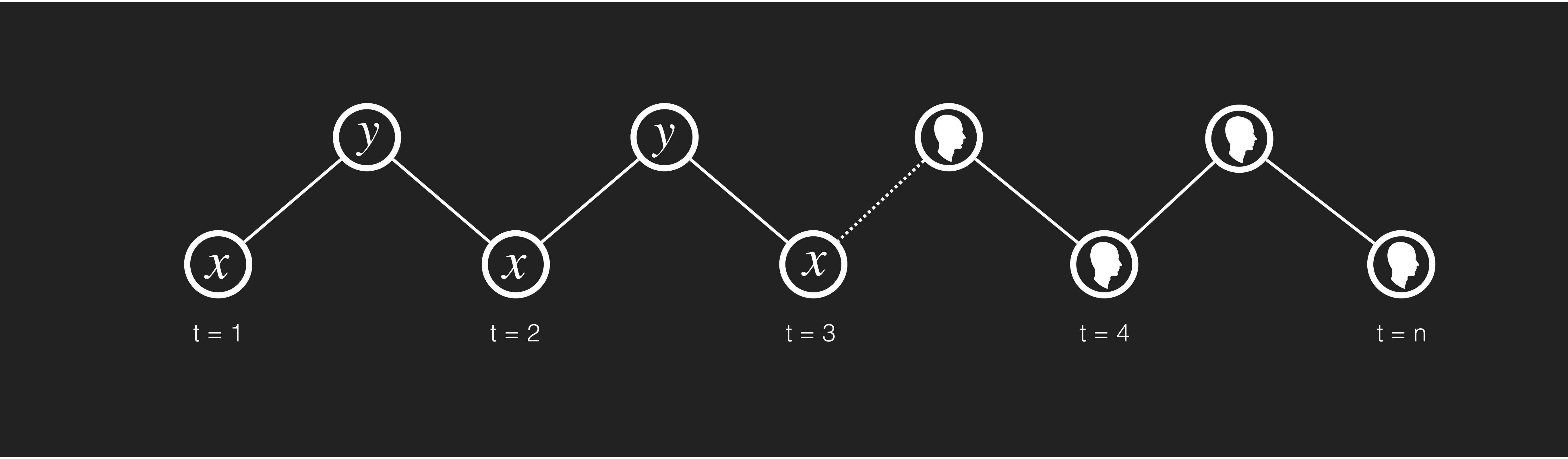
1) sample from $x_t \sim p(x|y_{t-1})$

2) sample from $y_t \sim p(y|x_t)$

Sampling Algorithms as Experimental Design

Example 2: Joint Segmentation and Clustering

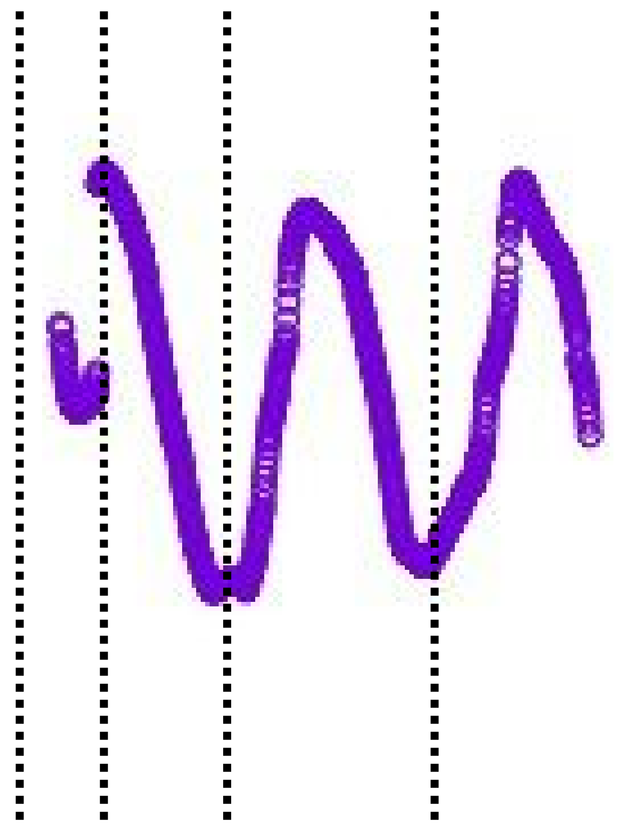
Gibbs sampling



Sampling Algorithms as Experimental Design

Example 2: Joint Segmentation and Clustering

Finding boundaries AND categories

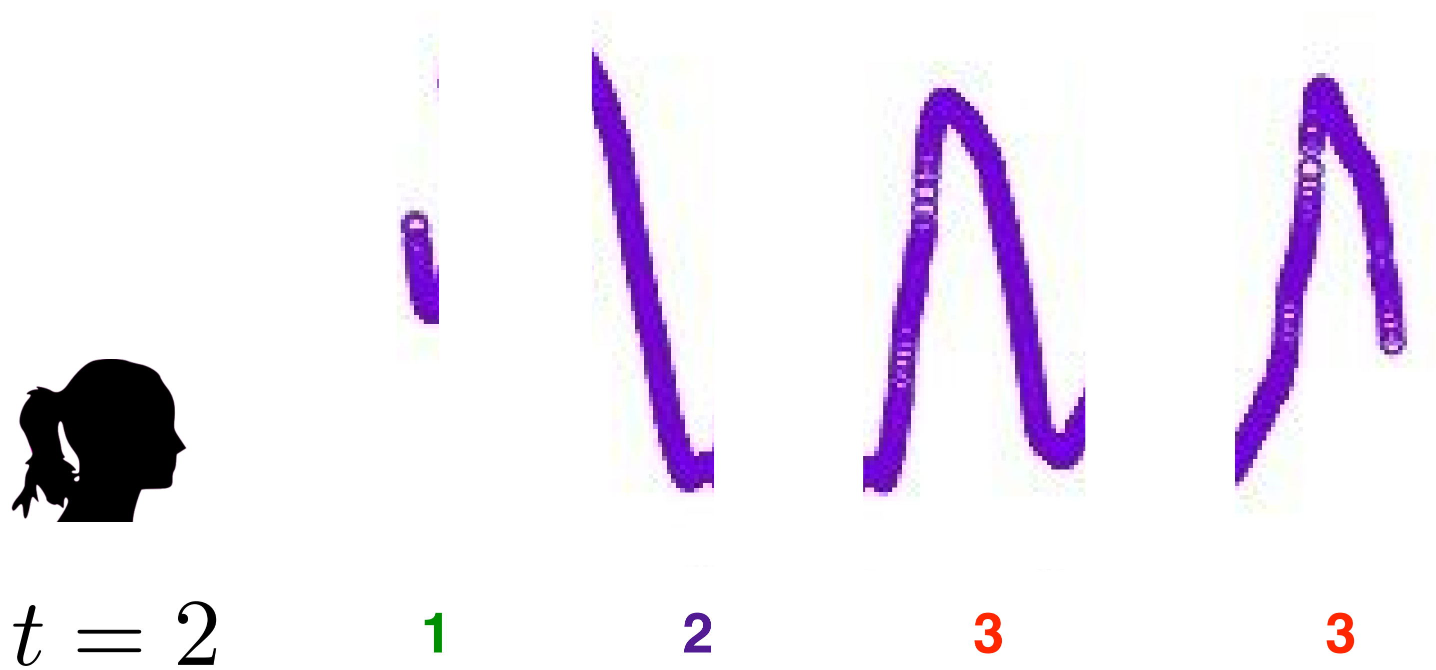


$$t = 1$$

Sampling Algorithms as Experimental Design

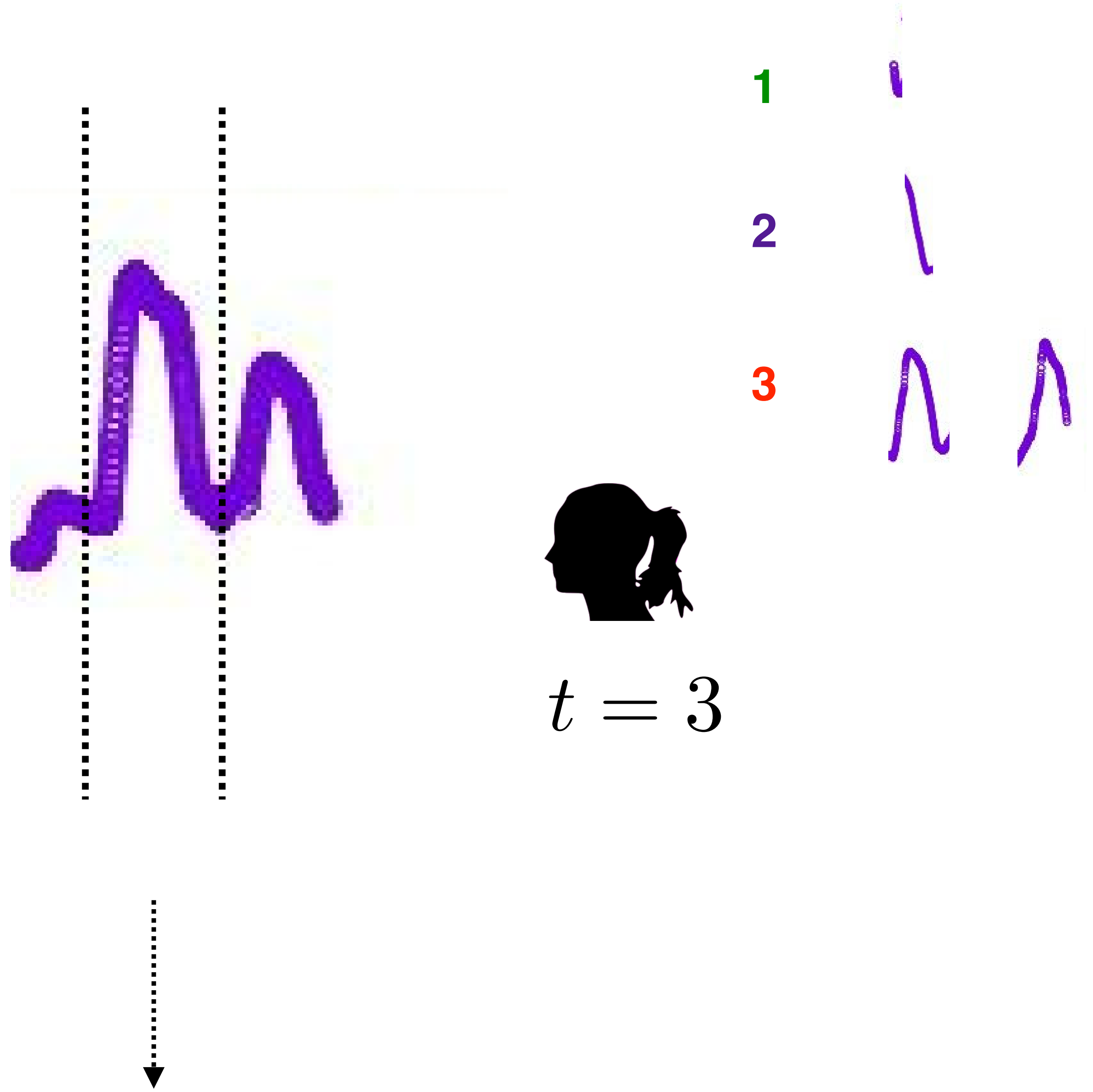
Example 2: Joint Segmentation and Clustering

Finding boundaries AND categories



Sampling Algorithms as Experimental Design
Example 2: Joint Segmentation and Clustering

Finding boundaries AND categories



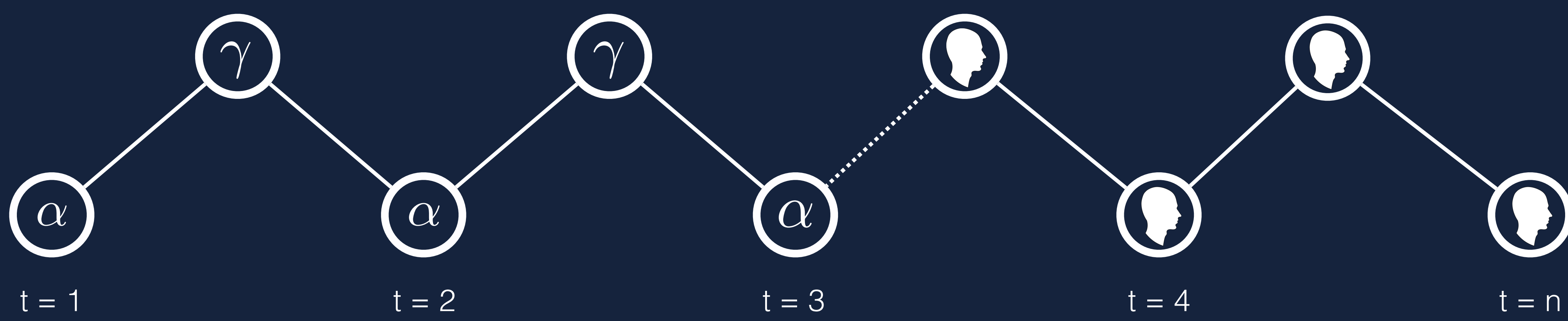
Talk Recap

- Computational and Experimental frameworks have complementary strengths and weaknesses

- Modern data collection methods are starting to allow us to blur this distinction, combine these strengths, and ultimately build smarter experimental designs with statistical guarantees.

- This class of experimental designs may be particularly useful in phonetics, where human ears (and brains) still outperform computational models, and speech data is so richly high-dimensional.

THANKS!



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