

VARIID: A Variation Detection Framework for Color- and Letter-Space platforms

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Variation detection from NGS reads

- Determine differences (**variation**) between **reference** and **donor** using NGS reads of the donor

Reference: TCAGCATCGGCATCGACTGCACAGGACCAGTCGATCGAC

Donor: ???

GCATCGACTGCA

CGGGATCGACTG

Aligned reads: ATCCATTGCA

GATCCACTGCAC

Motivation

**Color-space and Letter-space platforms
bring them together**

Methods

Results

Summary

Sequencing Platforms

- letter-space

Sanger, 454, Illumina, etc

```
> NC_005109.2 | BRCA1 SX3  
TCAGCATCGGCATCGACTGCACAGG
```

- color-space

AB SOLiD

less software tools available

```
> NC_005109.2 | BRCA1 AF3  
T212313230313232121311120
```

- many differences -> useful to combine this information

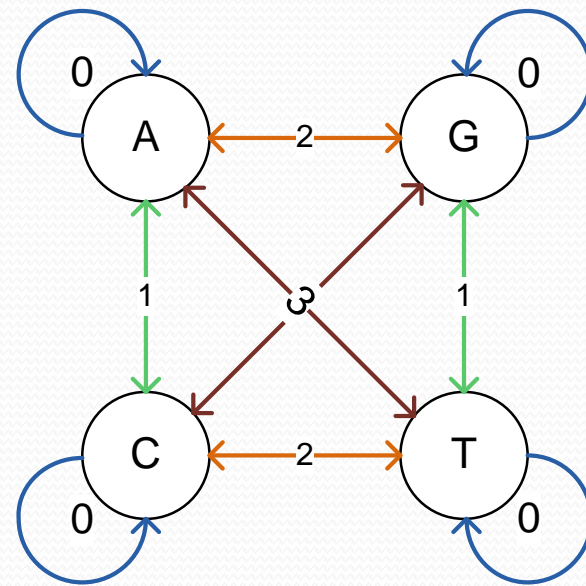
- sequencing biases
- inherent errors
- advantages

Color Space

Translation Matrix

	A	C	G	T
A	0	1	2	3
C	1	0	3	2
G	2	3	0	1
T	3	2	1	0

Translation Automata



> T212313230313232121311120

Color Space

Translating

```
> T212313230313232121311120  
> TCAGCATCGGCATCGACTGCACAGG
```

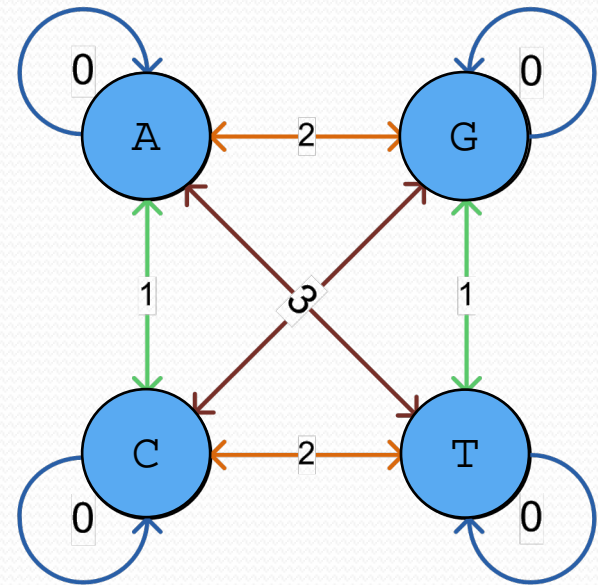
Sequencing Error vs SNP

Sequencing Error

```
> T212313230313232121311120  
> T212313230310232121311120  
> TCAGCATCGGCAAGCTGACGTGTC
```

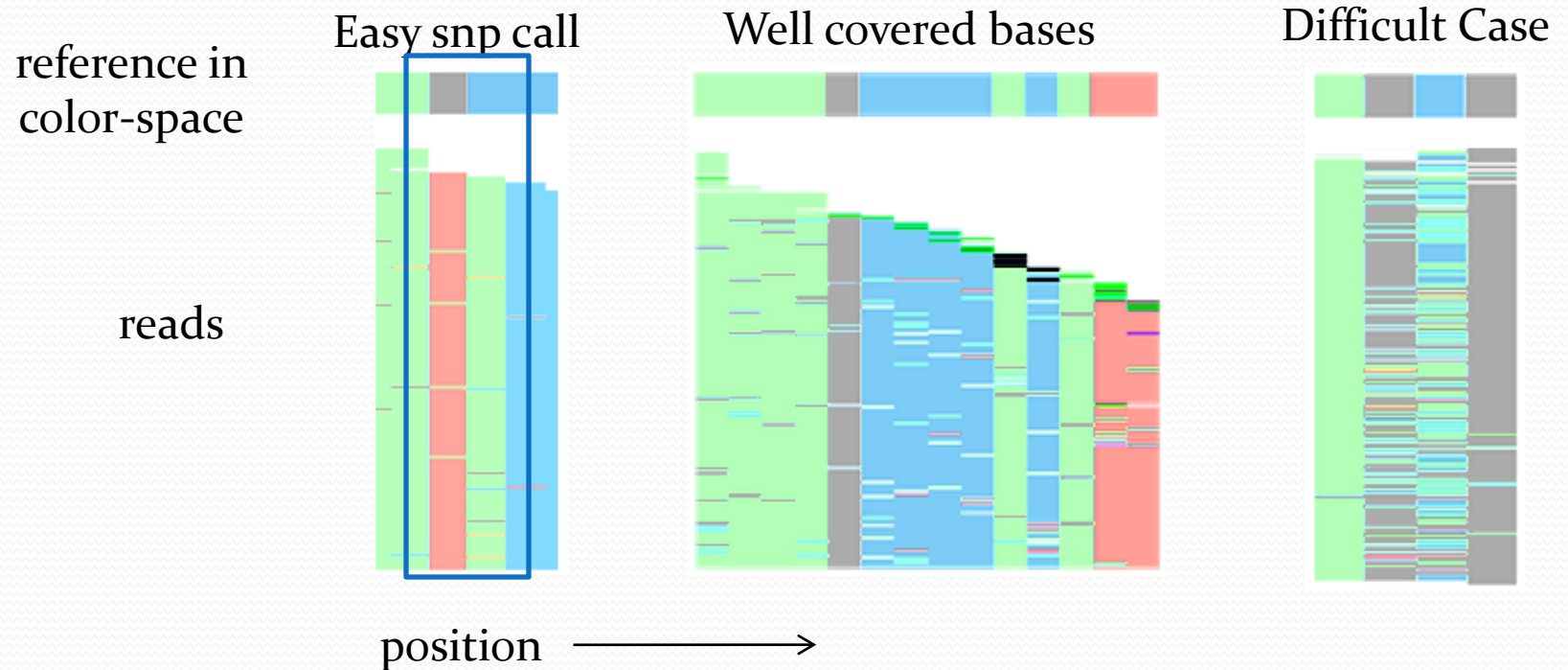
SNP

```
> TCAGCATCGGCATCGACTGCACAGG  
> TCAGCATCGGCAGCGACTGCACAGG  
> T212313230312332121311120
```



Color Space

- clear distinction between a sequencing error and a SNP
- can this help us in SNP detection? **sounds like it!**
 - single color change → error,
 - 2 colors changed → (likely) SNP.



Motivation

Motivation

- variation caller to handle both letter-space & color-space reads

Detection

- Heterozygous SNPs
- Homozygous SNPs
- Tri-allelic SNPs
- small indels
- account for various errors, quality values & misalignments

VARiD

- system to make inferences on the donor bases
 - variation detection

Motivation

Methods

Simple HMM Model

states, emissions, transitions, FB

Extended HMM Model

gaps, diploids, exceptions

Results

Summary

Hidden Markov Model (HMM)

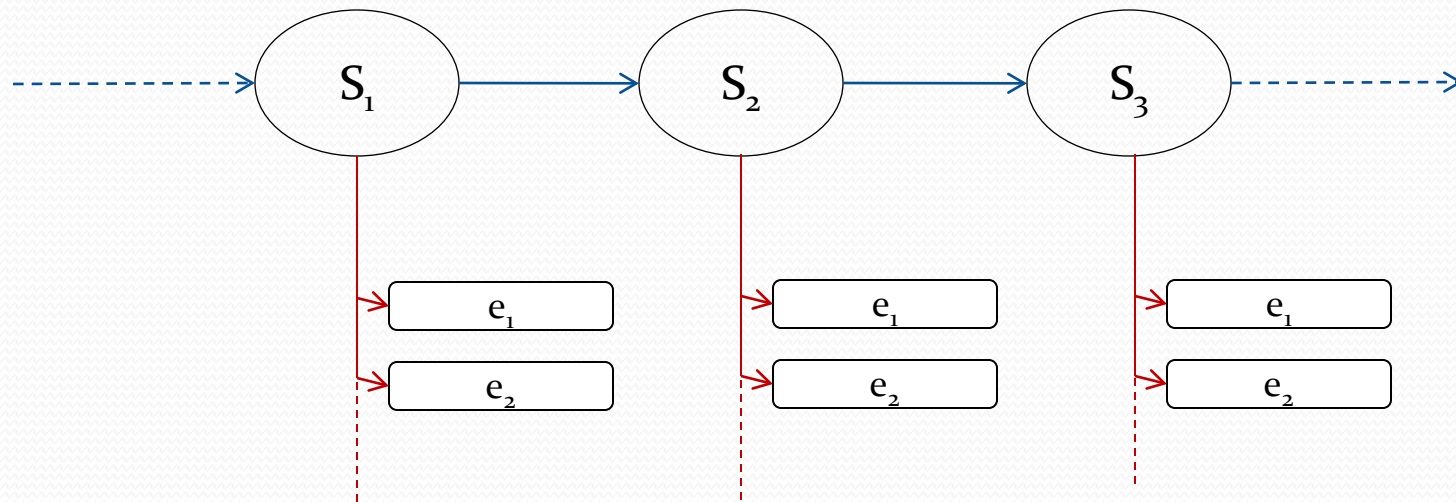
Statistical model for a system - **states**

Assume that system is a **Markov process** with state unobserved.

Markov Process: next state depends only on current state

We can **observe** the state's emission (output)

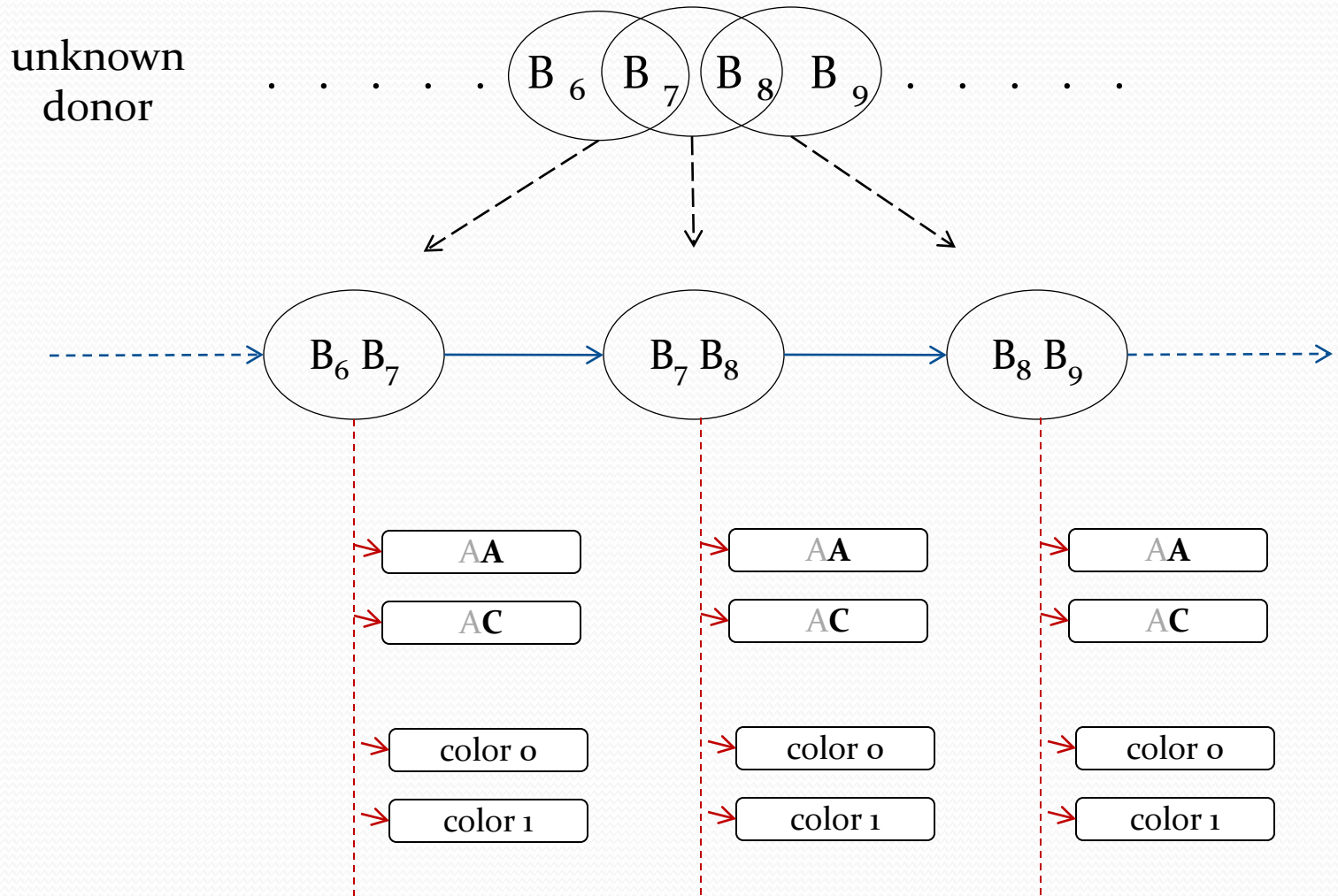
each state has a probability distribution over outputs



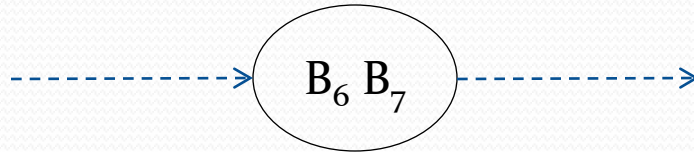
Hidden Markov Model (HMM)

- Apply HMM to variation detection:
- we don't know the state (**donor**), but
 - we can observe some output determined by the state (**aligned reads**)

Hidden Markov Model (HMM)



States



The donor could be:

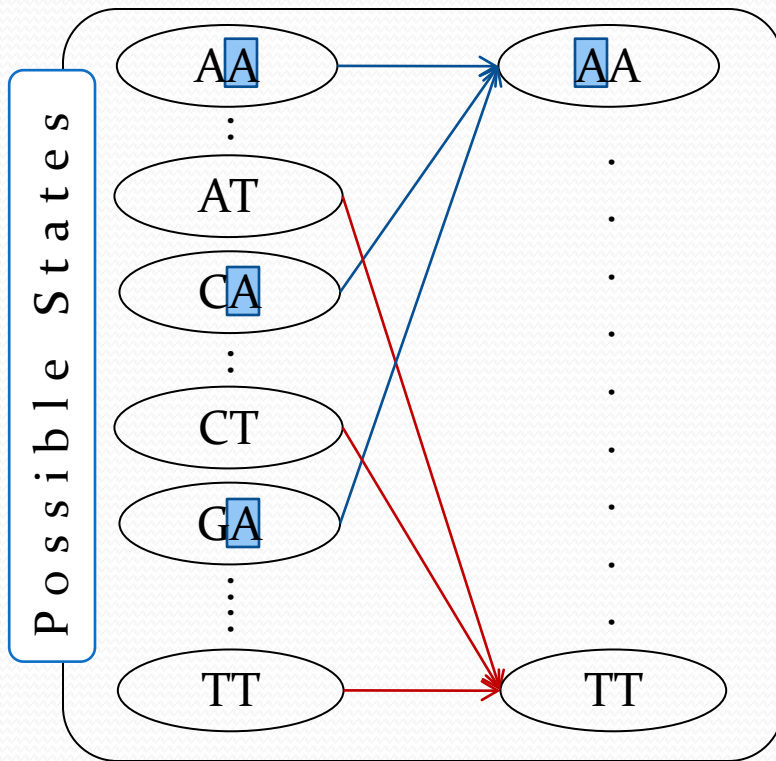
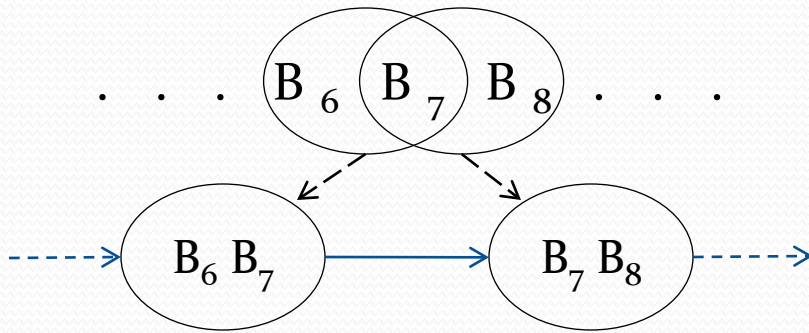
- letters: AA color 0
 - letters: AC color 1
 - :
 - letters: TT color 0
- 16 combinations

	A	C	G	T
A	0	1	2	3
C	1	0	3	2
G	2	3	0	1
T	3	2	1	0

Why **pairs of letters**? Handle colors.

- AA and TT gives the same colors. Can't just model colors

Transitions



States

- 16 possible states
- only look at second letter

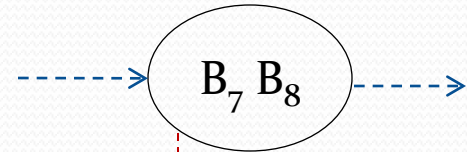
Transitions

- only certain transitions allowed
- when allowed, $p(X_t|X_{t-1}) = \text{freq}(X_t)$
- each state depends only on the previous states (Markov Process)

Emissions

Unknown genome

..... B₆ B₇ B₈ B₉

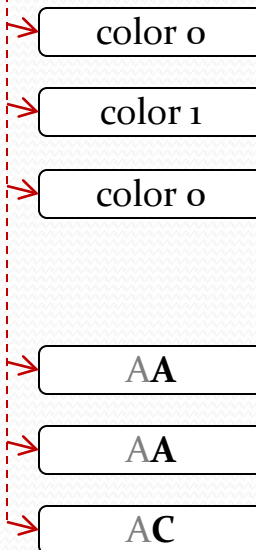


Color reads

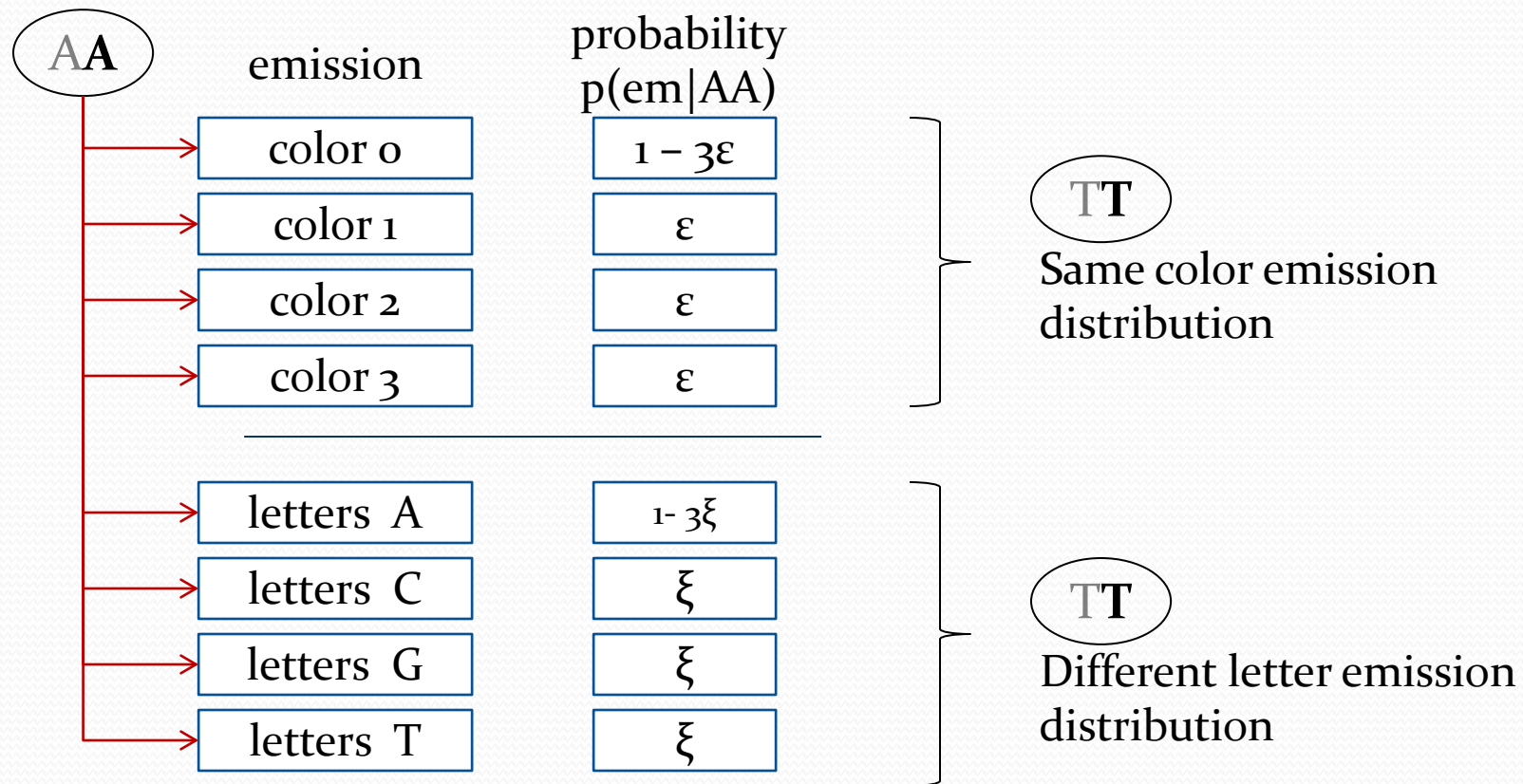
T 0 1 0 2 0 1 0 0 3 1 1 2 2 3
T 1 0 3 0 1 0 1 3 1 1 2 2 3
T 2 0 1 0 0 3 1 1 2 2 3

Letter reads

A T T G C G C A A T G C G
T T G G G C A A T G C G A
G C G C A C T G C G A C



Emission Probabilities



Emission Probabilities

..... B₆ B₇ B₈ B₉

T 0 1 0 2 0 1 0 0 3 1 1 2 2 3
 T 1 0 3 0 1 0 1 3 1 1 2 2 3
 T 2 0 1 0 0 3 1 1 2 2 3

A T T G C G C A A T G C G
 T T G G G C A A T G C G A
 G C G C A C T G C G A C

Combining emission probabilities

- probability that this state emitted these reads.

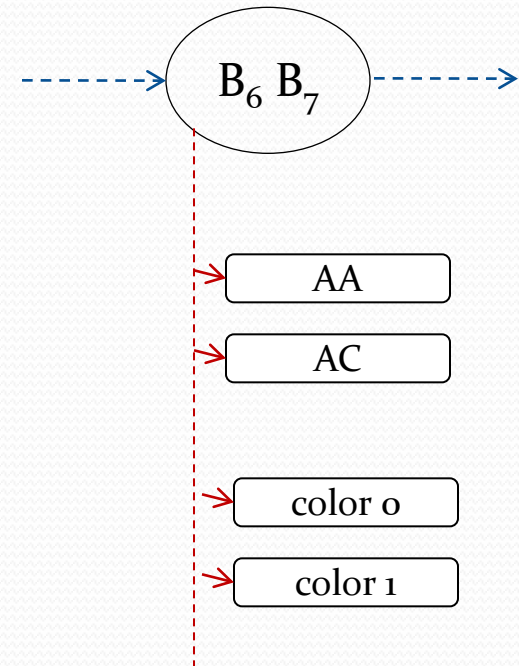
E.g. For state CC:

$$p_E = [(1 - 3\varepsilon)^2 \times \varepsilon^1] \times [(1 - 3\xi)^1 \times \xi^2]$$

Simple HMM

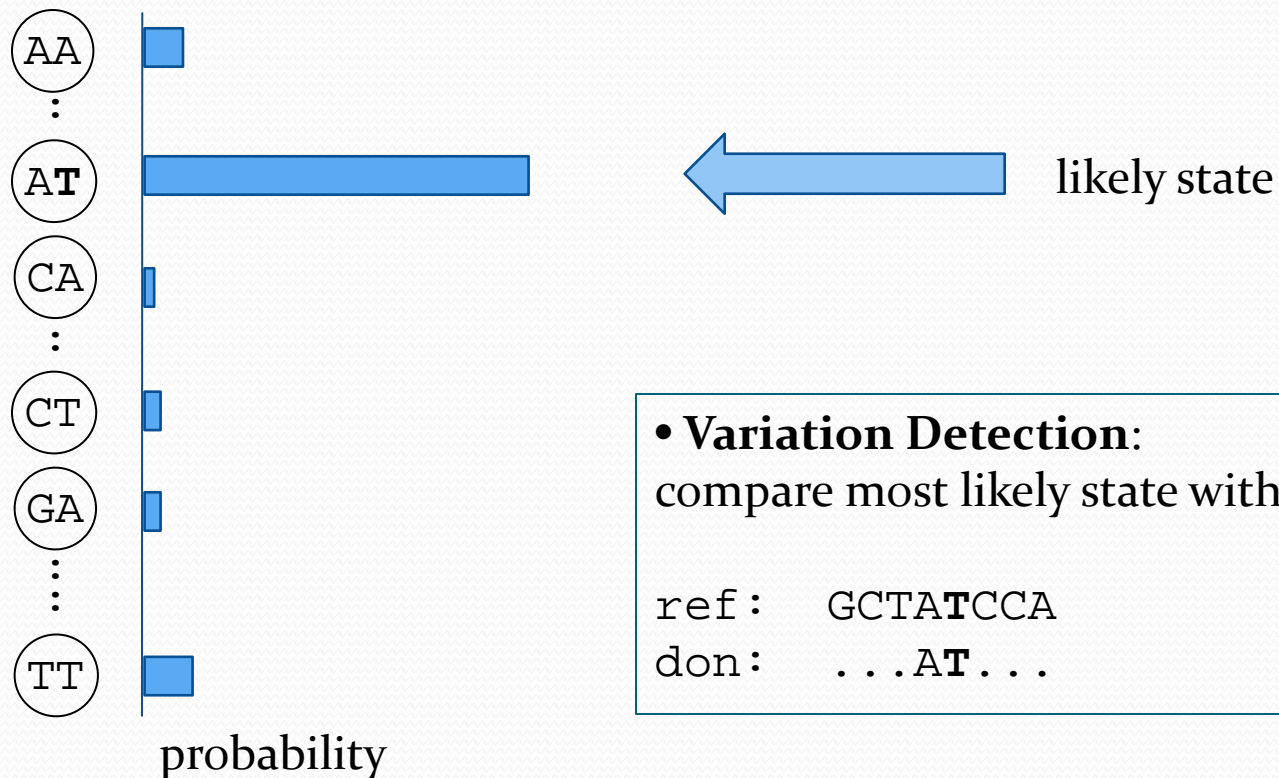
Summary

- **unknown** state
 - donor pair at location
- **transitions**
 - transition probabilities
- **emissions**
 - reads at location
 - emission probabilities



Forward-Backward Algorithm

- Have set-up a form of an HMM
- run Forward-Backward algorithm
- get **probability distribution** over states at each position



Motivation

Methods

Simple HMM Model
states, emissions, transitions, FB

Extended HMM Model
gaps, diploids, exceptions

Results

Summary

Extended HMM

Simple HMM

- only detects **homozygous SNPs**

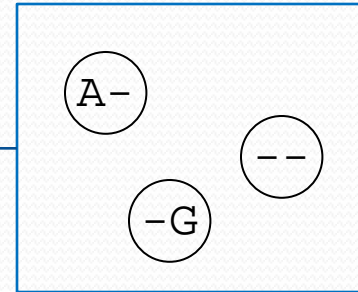
Extended HMM:

- short **indels**
- **heterozygous** SNPs
- complex error profiles & quality values

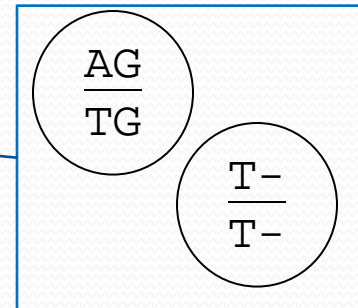
Expansion: Gaps and heterozygous SNPs

Expand states

- Have states that include **gaps**
 - emit: gap or color



- Have larger states, for **diploids**



- Transitions built in similar fashion as before
- Same algorithm, but in all we have **1600 states** with very **sparse** transitions

Expansion

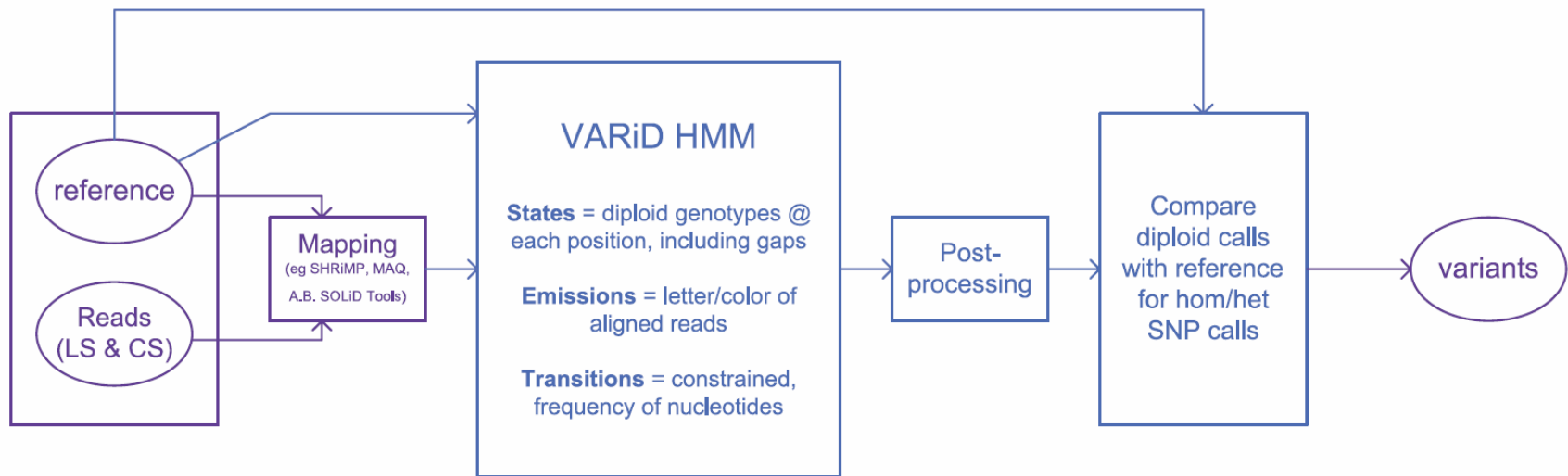
- Emission probabilities
 - Support **quality values**
 - Use **variable error rates** for emissions

- Translate through the first color
 - first color is incorrect
 - letter-space signal

```
Donor: ACAGCATCGGCATCGACTGC  
      1123132303123321213  
read: >T2123132303123321213  
      > C123132303123321213
```

- Post-process putative SNPs
 - correlated adjacent errors may support het SNPs
 - check putative SNPs

Summary



blue: varid steps

Motivation

Methods

Results

Summary

Results

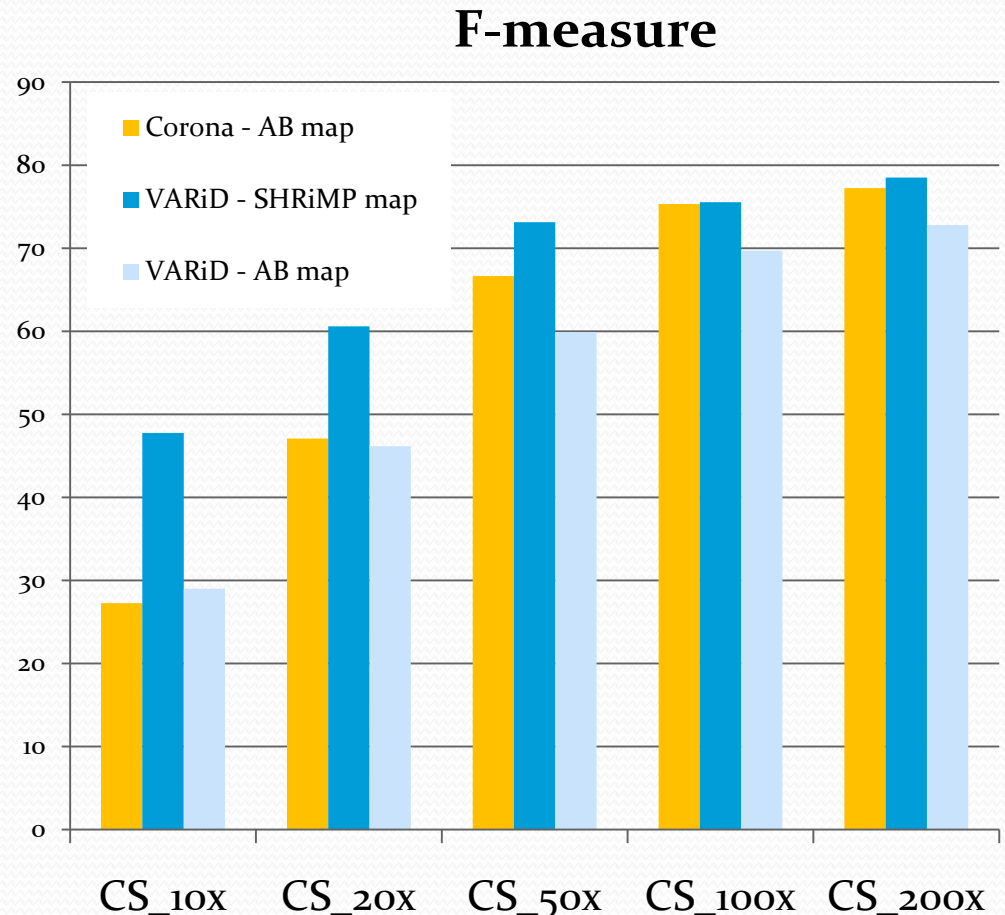
- Human dataset from Harismendy et al, 2009. (NA17156,17275,17460,17773)
454, SOLiD, Sanger

Color-space dataset:

- Compare random subsets:
 - Corona (with AB mapper)
 - VARiD (with SHRiMP)
 - VARiD (with AB mapper)

Conclusions:

- the three pipelines perform very similarly.
- High-coverage results is as good as can be achieved



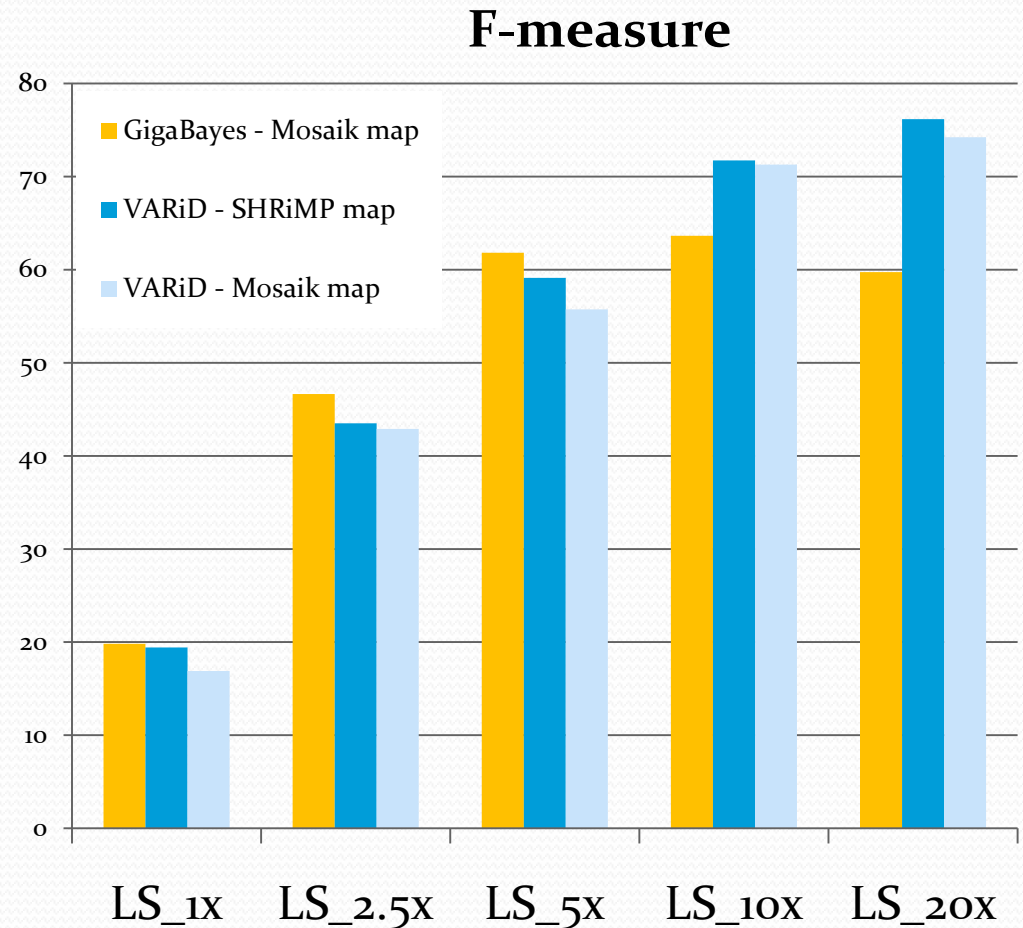
Results

Letter-space dataset:

- Compare random subsets :
 - GigaBayes (with Mosaik)
 - VARiD (with SHRiMP)
 - VARiD (with Mosaik)

Conclusion:

- the three pipelines perform very similarly.
- High-coverage results is as good as can be achieved



Results

VARiD Motivation:

Combining Letter-space and Color-space data to achieve increased accuracy in at-cost comparison

Assuming a same-cost comparison of:

- 10x letter-space (LS)
- 100x color-space (CS)
- 5x LS and 50x CS

VARiD

		letter-space				
		0x	1x	2.5x	5x	10x
Color-space	0x	0.0	19.4	43.5	59.1	71.7
	10x	47.8	51.8	59.4	69.5	76.5
	20x	60.6	58.9	65.3	73.4	80.3
	50x	73.1	69.8	73.6	80.0	83.5
	100x	75.6	75.2	77.9	82.7	86.0
	F-meas.					

Motivation

Methods

Results

Summary

Summary

Summary of VARiD

- HMM modeling underlying donor
- Treats color-space and letter-space together in the same framework
- no translation – take advantage of each technology’s properties
- accurately calls SNPs, **short indels** in both color- and letter-space
 - improved results with hybrid data.

- **Website:** <http://compbio.cs.utoronto.ca/varid>
(VARiD freely available)
- **Contact:** varid@cs.utoronto.ca

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