I529: Machine Learning in Bioinformatics (Spring 2017)

## Applications of HMMs in Epigenomics

Yuzhen Ye School of Informatics and Computing Indiana University, Bloomington Spring 2017

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### Background

- Genomic DNA is packaged into a complex molecular structure known as chromatin. This structure mediates the interaction between the genome and all types of regulatory and transcriptional molecules.
- In vertebrate genomes, methylation at position 5 of the cytosine in CpG dinucleotides is a heritable "epigenetic" mark that has been connected with both transcriptional silencing and imprinting
  - Ref: DNA methylation patterns and epigenetic memory (Genes & Dev. 2002. 16: 6-21)



- "The ENCODE Consortium is integrating multiple technologies and approaches in a collective effort to discover and define the functional elements encoded in the human genome, including genes, transcripts, and transcriptional regulatory regions, together with their attendant chromatin states and DNA methylation patterns."
  Ref: A User's Guide to the Encyclopedia of DNA Elements (ENCODE) (PLoS Biology, 2011)
- Initial phase launched in 2003—1% of the human genome
   Identification and analysis of functional elements in 1%
  - Identification and analysis of functional elements in 1% of the human genome by the ENCODE pilot project (Nature, June 13, 2007)





Gene/Transcript Analysis		
Region/Feature	Method	Group
Gene annotation	GENCODE	Wellcome Trust
PolyA+ coding regions	RNA-seq; tiling DNA microarrays; PET	CSHL; Stanford/Yale//Harvard; Calbech
Total RNA coding regions	RNA-seq; tiling DNA microarrays; PET	CSHL
Coding regions in subcellular RNA fractions (e.g. nuclear, cytoplasmic)	PET	СЭНL
Small RNAs	short RNA-seq	CSHL
Transcription initiation (5'-end) and termination (3-end') sites	CAGE; dITAGs	RIKEN, GIS
Full-length RNAs	RACE	University of Geneva; University of Lausanne
Protein-bound RNA coding regions	RIP; CLIP	SUNY-Albany; CSHL
Transcription Factors/Chromatin		
Elements/Regions	Method(s)	Group(s)
Transcription Factor Binding Sites (TFBS)	CNP-seq	Stanford/Yale/UC-Davis/Harvard; Hudson/Upha/Caltect Duke/UT-Austin; UW; U. Chicago/Stanford
Chromatin structure (accessibility, etc.)	DNasel hypersensitivity; FAIRE	UW; Duke; UNC
Chromatin modifications (H3K27ac, H3K27me3, H3K36me3, etc.)	CNP-seq	Broad; UW
DNasel footprints	Digital genomic footprinting	UW
Other Elements/Features		
Feature	Method(s)	Group(s)
DNA methylation	RRBS; Illumina Methyl27; Methyl-seq	HudsonAlpha
Chromatin interactions	SC; CHW-PET	UMass; UW; GIS
Genotyping	Ilumina 1M Duo	HudsonAlpha
doi:10.1271/journal.phio.1031046-2001		
CODE Project Consortium (2011	) A User's Guide to the Encycloped	ia of DNA Elements (ENCODE). PLoS Biol











 Successive releases of the Atlas will provide progressively more detailed insights into locusspecific epigenomic states, including histone marks and DNA methylation marks across specific tissues and cell types, developmental stages, physiological conditions, genotypes, and disease states.

### CHIP-seq

 By combining chromatin immunoprecipitation (ChIP) assays with sequencing, ChIP sequencing (ChIP-Seq) is a powerful method for identifying genome-wide DNA binding sites for transcription factors and other proteins.

- Following ChIP protocols, DNA-bound protein is immunoprecipitated using a specific antibody.
- The bound DNA is then coprecipitated, purified, and sequenced.

https://www.illumina.com/techniques/sequencing/dna-sequencing/chip-seq.html

#### ChIP-seq

- Chromatin immunoprecipitation (ChIP) followed by high-throughput DNA sequencing (ChIP-seq) has become a valuable and widely used approach for mapping the genomic location of **transcriptionfactor binding and histone modifications** in living cells.
- Genome-Wide Mapping of in Vivo Protein-DNA Interactions (Science, 2007); 1946 binding sites of the Neuron-restrictive silencer factor (NRSF) were mapped at ~50bp resolution
- There are considerable differences in how these experiments are conducted, how the results are scored and evaluated for quality, and how the data and metadata are archived for public use.
  - Genome Res. 2012 Sep;22(9):1813-31





#### DNase-seq

- DNase digestion followed by sequencing.
- DNase I hypersensitive sites (DHS), short regions of chromatin that are highly sensitive to cleavage by DNase I, typically occur in nucleosome free (nucleosome-depleted) regions as a result of transcription factor binding.
- DNA sequence motif analysis on DHS data was proposed as a method for discovering the binding sites of multiple transcription factors in a single experiment.
- DNase-seq profile resemble to some extent the data from ChIP-seq, with important differences (Front, Genet., 31 October 2012)















## Integrative annotation of chromatin elements from ENCODE data

Table 1. Major differences between ChromHMM and Segway as applied to the ENCODE data

Modeling framework      Hidden Markov model      Dynamic Bayesian network        Genomic resolution      200 bp      1 bp        Data resolution      Boolean      Rel value        Handling missing data      Interpolation      Marginalization        Emission modeling      Bernoulli distribution      Gaussian distribution        Length modeling      Geometric distribution      Geometric distribution        Training set      Entire genome      ENCODE regions (1%)        Decoding algorithm      Posterior decoding      Viterbi		ChromHMM	Segway
Genomic resolution      200 bp      1 bp        Data resolution      Boolean      Real value        Handling missing data      Interpolation      Marginalization        Emission modeling      Bernoulli distribution      Gaussian distribution        Length modeling      Geometric distribution      Geometric plus hard and soft constraint        Training set      Entire genome      ENCODE regions (1%)        Decoding algorithm      Posterior decoding      Viterbi	Modeling framework	Hidden Markov model	Dynamic Bayesian network
Data resolution      Boolean      Real value        Handling missing data      Interpolation      Marginalization        Emission modeling      Bernoulli distribution      Gaussian distribution        Length modeling      Geometric distribution      Geometric plus hard and soft constraint        Training set      Entire genome      ENCODE regions (1%)        Decoding algorithm      Posterior decoding      Viterbi	Genomic resolution	200 bp	1 bp
Handling missing data      Interpolation      Marginalization        Emission modeling      Bernouli distribution      Gaussian distribution        Length modeling      Geometric distribution      Geometric distribution        Training set      Entire genome      ENCODE regions (1%)        Decoding algorithm      Posterior decoding      Viterbi	Data resolution	Boolean	Real value
Emission modeling      Bernoulli distribution      Gaussian distribution        Length modeling      Geometric distribution      Geometric plus hard and soft constraint        Training set      Entire genome      ENCODE regions (1%)        Decoding algorithm      Posterior decoding      Viterbi        Learning across size (El trues E Sincle model for all cell trues one model par cell true      Decoding	Handling missing data	Interpolation	Marginalization
Length modeling      Geometric distribution      Geometric plus hard and soft constraint        Training set      Entire genome      ENCODE regions (1%)        Decoding algorithm      Posterior decoding      Viterbi        Lenging across size (Plumes, Single model for all cell types. One model ner cell type      Posterior decoding	Emission modeling	Bernoulli distribution	Gaussian distribution
Training set      Entire genome      ENCODE regions (1%)        Decoding algorithm      Posterior decoding      Viterbi        Learning across six cell twose      Single model for all cell types. One model per cell type	Length modeling	Geometric distribution	Geometric plus hard and soft constraints
Decoding algorithm Posterior decoding Viterbi	Training set	Entire genome	ENCODE regions (1%)
Learning across six cell types. Single model for all cell types. One model per cell type	Decoding algorithm	Posterior decoding	Viterbi
additing ad one off the only of the off the off the off the	Learning across six cell types	Single model for all cell types	One model per cell type

Ref: Nucl. Acids Res. (2013) 41 (2): 827-841.







# Multivariate HMM (formal definition)

- A multivariate HMM θ has
  - N sets of observation symbols, each for one given observation sequence n (n=1, 2, ..., N)
  - A set of hidden states
  - Transition probabilities  $a_{ij\prime}$  for any pair of hidden states i and j
  - Initial probabilities  $B_j = a_{0j}$  for any hidden states j
  - N sets of emission probabilities e<sup>n</sup><sub>s</sub>(x<sub>n</sub>) for the observation symbol being emitted in the *n*th observation sequence from the hidden state *s*.

#### Multivariate HMM

 Given N observation sequences of the same length L, X={(x<sub>1,1</sub>...x<sub>1,L</sub>), ...,(x<sub>N,1</sub>...x<sub>N,L</sub>)} and the hidden state sequence S=(s<sub>1</sub>...s<sub>L</sub>), the full probability from the multivariate HMM is,

$$P(S, X | \theta) = \prod_{j=1}^{L} \left[ a_{s_{j-1}s_j} \prod_{n=1}^{N} e_{s_j}(x_{n,j}) \right]$$

Let  $e_{s_i}(x_{n,1},...,x_{n,j}) = \prod_{i=1}^{n} e_{s_i}(x_{n,j})$ , the multivariate HMM can be reduced  $\frac{n}{2}$  conventional HMM, except the observation symbol becomes a vector  $(x_{n,1}...x_{n,j})$  at position j. The same algorithms for model inference (Viterbi and forward/backward) and learning can be used.