Detection of Syntenic Regions in Bacterial Genomes Through Statistical Clustering

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Interface 2007 on Systems Biology, May 24, 2007 Philadelphia, Pennslyvania Research funded by USDA/ARS

Synteny and Evolution

- The goal of our group to understand the evolutionary roles of horizontal gene transfer and other large-scale rearrangements in shaping organization of bacterial genomes.
- Syntenic regions are homologous multigene regions in two or more genomes in which repertoire of genes are conserved, along with possible conservation of transcription direction and linear gene order.

• Detecting breaks in macrosynteny and microsynteny between closely related bacteria useful tool in unraveling mosaic structures within their genomes.

Computational Framework for Synteny Detection

The Jensen-Shannon Divergence

- Advantage of using Jensen-Shannon divergence [Lin, IEEE Trans. Infor. Theory **37**, 145–151 (1991)] as statistical distance: can be computed for sequences **^x**¹ and **x** ² of di fferent lengths.
- For x_1 and x_2 modeled as Markov chains of order K over quaternary alphabet $S = \{A, C, G, T\}$ with $S = 4$ letters, Jensen-Shannon divergence given by

$$
\Delta = \sum_{\mathbf{t}\in S^{\otimes K}} \sum_{s=1}^{S} \left[-f_{\mathbf{t}s} \log \hat{p}_{\mathbf{t}s} + f_{1,\mathbf{t}s} \log \hat{p}_{1,\mathbf{t}s} + f_{2,\mathbf{t}s} \log \hat{p}_{2,\mathbf{t}s} \right] \ge 0,
$$

where $\mathbf{t} = (t_1, \dots, t_K) \in \mathcal{S}^K$ is shorthand notation, $f_{1,ts}, f_{2,ts}, f_{ts} = f_{1,ts} + f_{2,ts}$ are transition counts, and

$$
\hat{p}_{i,ts} = \frac{f_{i,ts}}{\sum_{s'=1}^{S} f_{i,ts'}}, \quad i = 1, 2; \quad \hat{p}_{ts} = \frac{f_{ts}}{\sum_{s'=1}^{S} f_{ts'}},
$$

are maximum-likelihood transition probabilities.

Mutations and Recombinations

Sequence Alignment and Statistics Comparison

- Without point mutations, x_1 and x_2 perfectly aligned. Also have identical K-mer statistics up to $K = N$.
- With $n \ll N$ point mutations, good alignment between \mathbf{x}_1 and \mathbf{x}_2 . Very similar *K*-mer statistics up to intermediate *K*.
- Higher-order statistics strongly constrained by lower-order statistics, therefore, instead of sequence alignment, need only compare *K*-mer statistics at the few lowest *K*'s to establish homology.
- For recombination cases
	- **–** (i) deletion and (ii) insertion, statistical similarity between **^x**¹ and **y**1, **y** 2 depends on segmen^t deleted or inserted.
	- **–** (iii) reshu ffle, *K*-mer statistics between **^x**¹ and **y** ³ similar.
	- **–** (iv) inversion, complementary *K*-mer statistics of **y** ⁴ similar to *K*-mer statistics of **x**1.

Interface 2007 on Systems Biology, May 23–26, 2007, Philadelphia, Pennslyvania

Hierarchical Single-Link Clustering

- Use Jensen-Shannon divergence as statistical distance between segments.
- Hierarchical clustering chosen because number and scales of syntenic regions not known beforehand. Hierarchical clustering tree for eac h *K*.
- Single-link separation between clusters:
	- **–** clusters of homologous segments di ffuse in statistics space, driven by random point mutations;
	- **–** clusters diverging at di fferent evolutionary times have di fferent sizes;
	- **–** two segments close together likely to have evolved from ^a common ancestor, even if both are far from center of homolog cluster.

Homology Within the Hierarchical Clustering Tree

Pilot Study

• Complete genomes of three *Pseudomonas syringae* strains. Plant pathogens.

- Stage I: Segmentations obtained using optimized recursive Jensen-Shannon segmentation scheme [Cheong *et al.*, in preparation].
- Stage II: Cluster at $K = 0, 1, 2, 3$ but not higher, because typical segments are only 5000 bp long.
- Stage III: $K = 0$ hierarchical clustering tree not sufficiently discriminating, but from $1 \leq K \leq 3$ hierarchical clustering trees identified:
	- **–** long syntenic region between DC3000 and B728A; and
	- **–** large number clustering events between paralogous segments containing mobile IS elements.

Syntenic Region Identified

Feedback Between Stages

- Few long syntenic regions identified from hierarchical clustering trees, because syntenic regions segmented differently in different genomes as a result of context sensitivity problem [Cheong *et al.*, in preparation].
- Stage III [→] Stage I: Work with two terminal segmentations per genome: standard (S) and fine (F). (Testing robustness of clustering to segmentation.)
	- **–** cluster S segments against S segments: mask out syntenic regions detected at this level;
	- **–** for remaining segments, cross cluster F segments against S segments: mask out syntenic regions detected at this level; and
	- **–** for remaining segments, cluster F segments against F segments: identify syntenic regions detected at this level.
- Expect cross clustering to detect most, if not all, syntenic regions present.
- Hyperfine segmentation and fine-hyperfine segmentation if necessary.

Conclusions

- Described the three stages in the general framework for synteny detection.
- Stage I: Segmentation. Use statistically stationary segments.
- Stage II: Similarity Analysis.
	- **–** Recasted sequence alignment problem as statistics comparison problem of statistically stationary segments.
	- **–** Devised hierarchical single-link clustering of segments whose pairwise distance is their Jensen-Shannon divergence.
	- **–** Explained how homologous segments cluster at small Jensen-Shannon divergence, and how syntenic blocks emerge as chains of clusters.
- Stage III: Synteny Analysis.
	- **–** Pilot study on three *P. syringae* strains demonstrated feasibility of statistics comparison method for synteny detection.
	- **–** Followup study: cross clustering between standard and fine segmentations of genomes.