



新加坡南洋理工大学

Time Series Approaches to Understanding Physical Phenomena

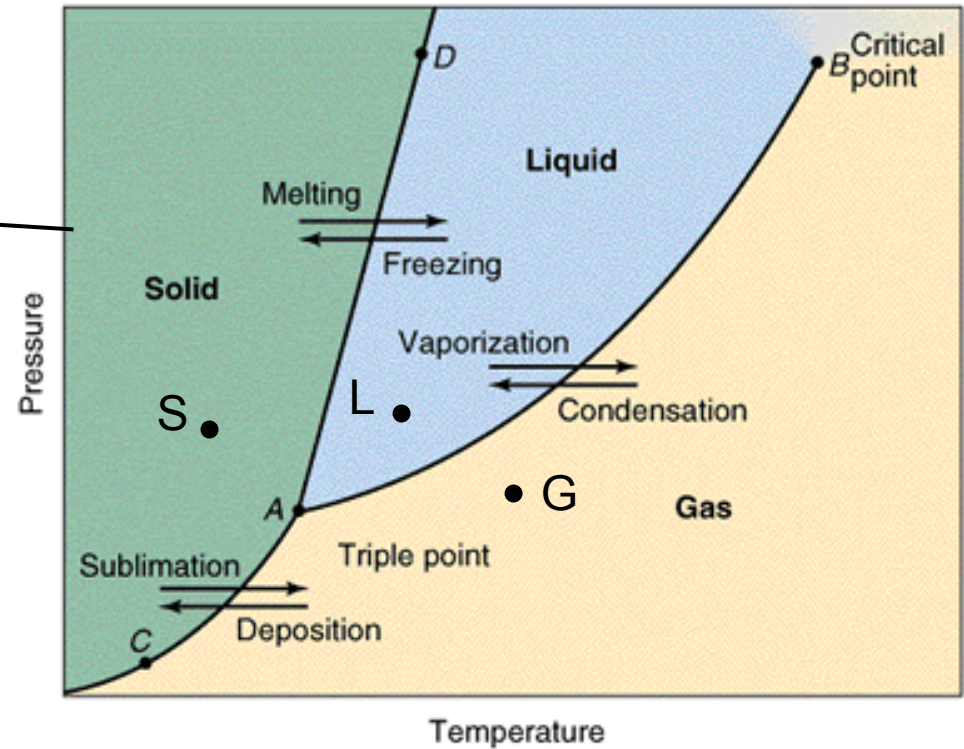
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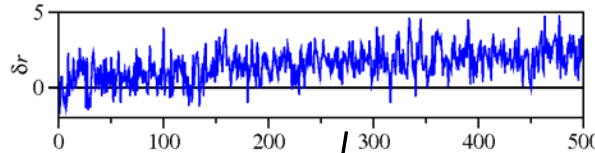
<http://www1.spms.ntu.edu.sg/~cheongsa/>

[Statistical] Physics in a Drop of Water

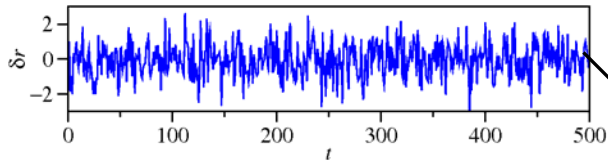


- Macroscopic order parameters differentiate
 - Solid (S)
 - Liquid (L)
 - Gas (G)

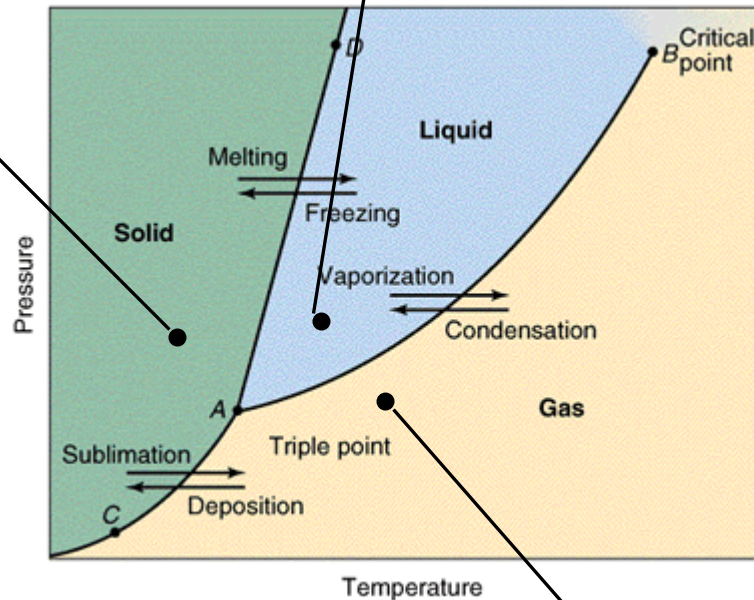
[Statistical] Physics in a Drop of Water



diffusive trajectories,
 δr^2 increases with time

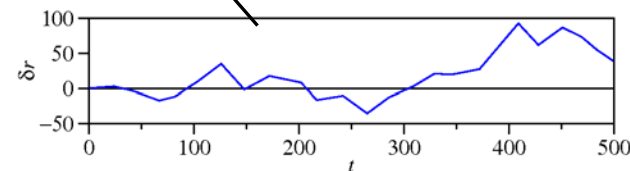


δr fluctuates about 0,
 $\delta r^2 = \alpha T$ time-independent

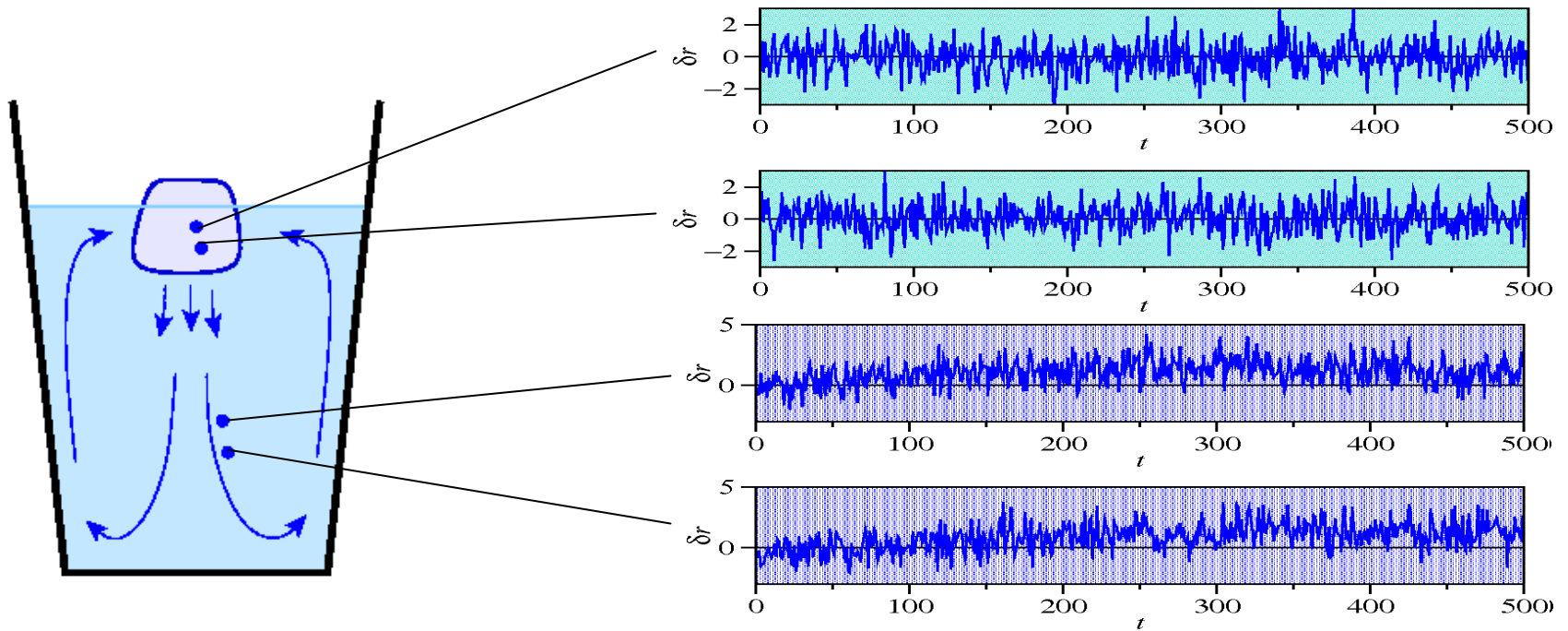


ballistic trajectories,
 infrequent collisions

- S, L, G time series distinguishable
- S, L, G phase within single time series distinguishable



[Statistical] Physics in a Drop of Water

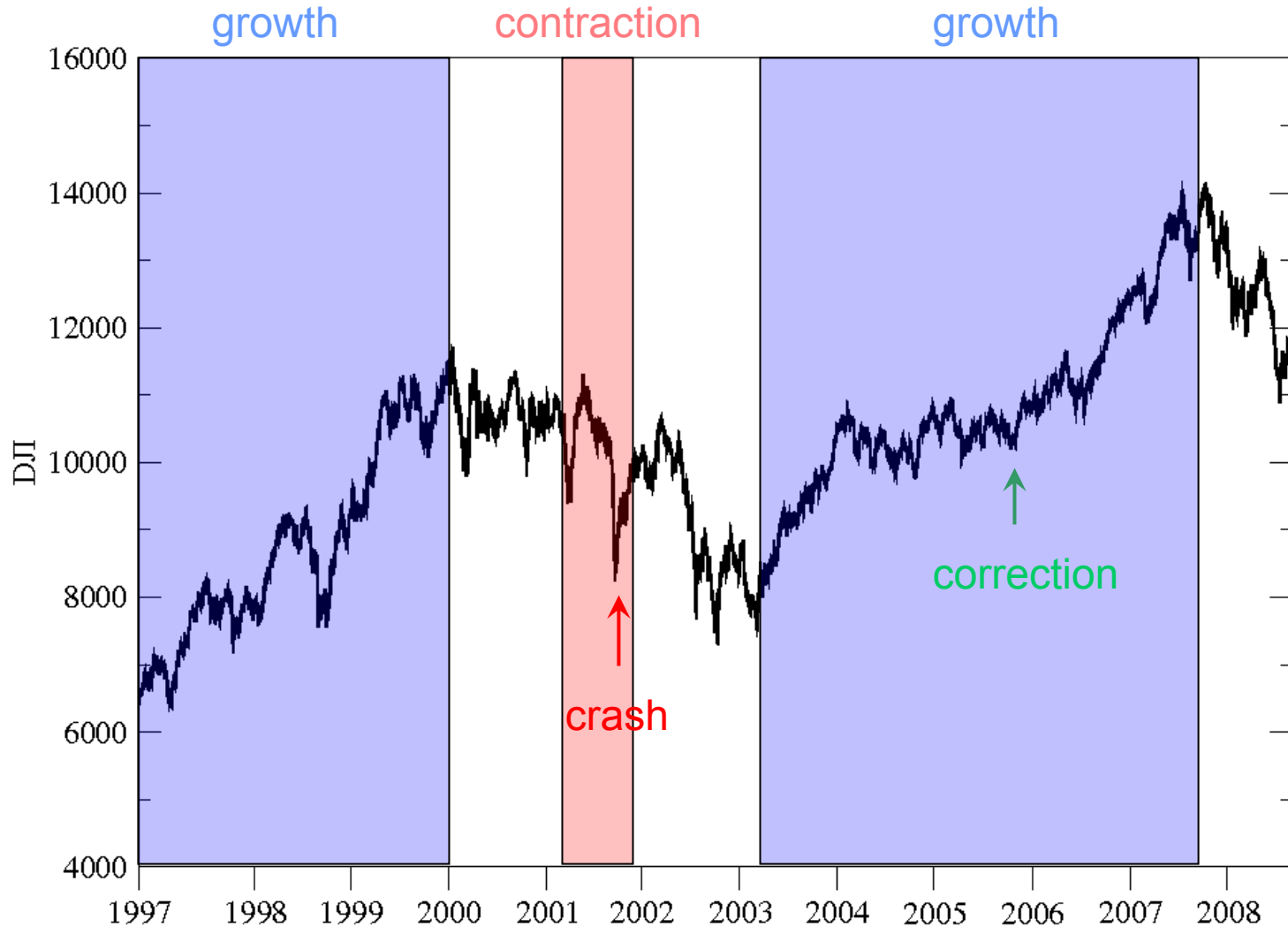


- Group statistically similar time series
- Discover presence of different phases

Time Series Approaches

- Time Series Segmentation
 - Discover number/type of macroscopic phases
 - Discover lifetimes of macroscopic phases
 - Discover time scales of transitions between macroscopic phases
- Time Series Clustering
 - Discover effective mesoscopic variables in given time window
 - Discover slow time evolution of effective variables by sliding time window

Time Series Segmentation



Time Series Segmentation

- Assume non-stationary time series $\mathbf{x} = (x_1, x_2, \dots, x_N)$ consists of M stationary segments
- In segment m , data points drawn from (μ_m, σ_m^2) Gaussian distribution
- Recursive segmentation
 - One time series \rightarrow two segments
 - Each segment \rightarrow two subsegments
 - Iterate + optimize
 - Terminate

Time Series Segmentation

- Single-segment likelihood for $\mathbf{x} = (x_1, x_2, \dots, x_N)$

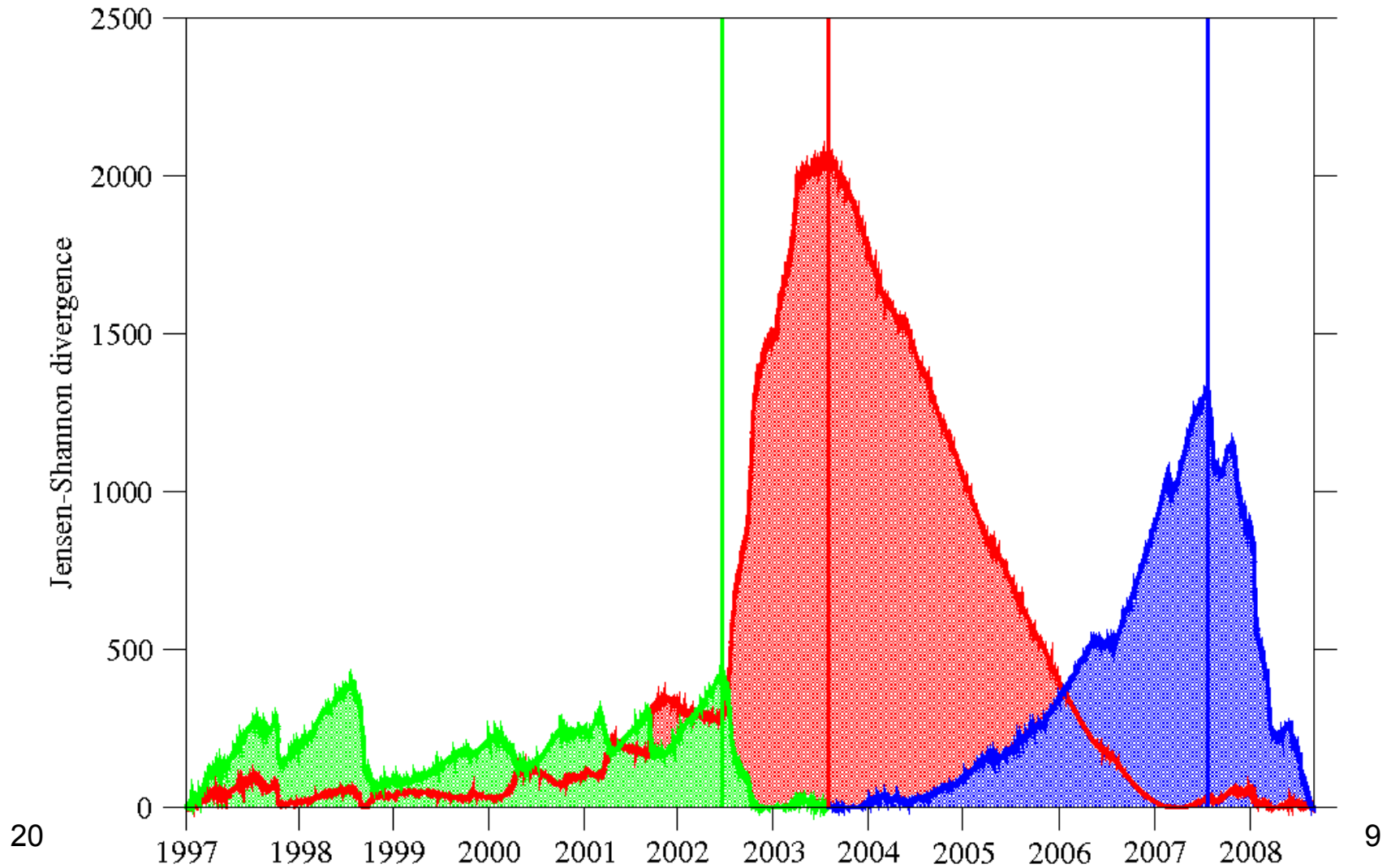
$$L_1 = \prod_{i=1}^N \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[-\frac{(x_i - \mu)^2}{2\sigma^2}\right]$$

- Two-segment likelihood for $\mathbf{x} = (x_1, \dots, x_t, x_{t+1}, \dots, x_N)$

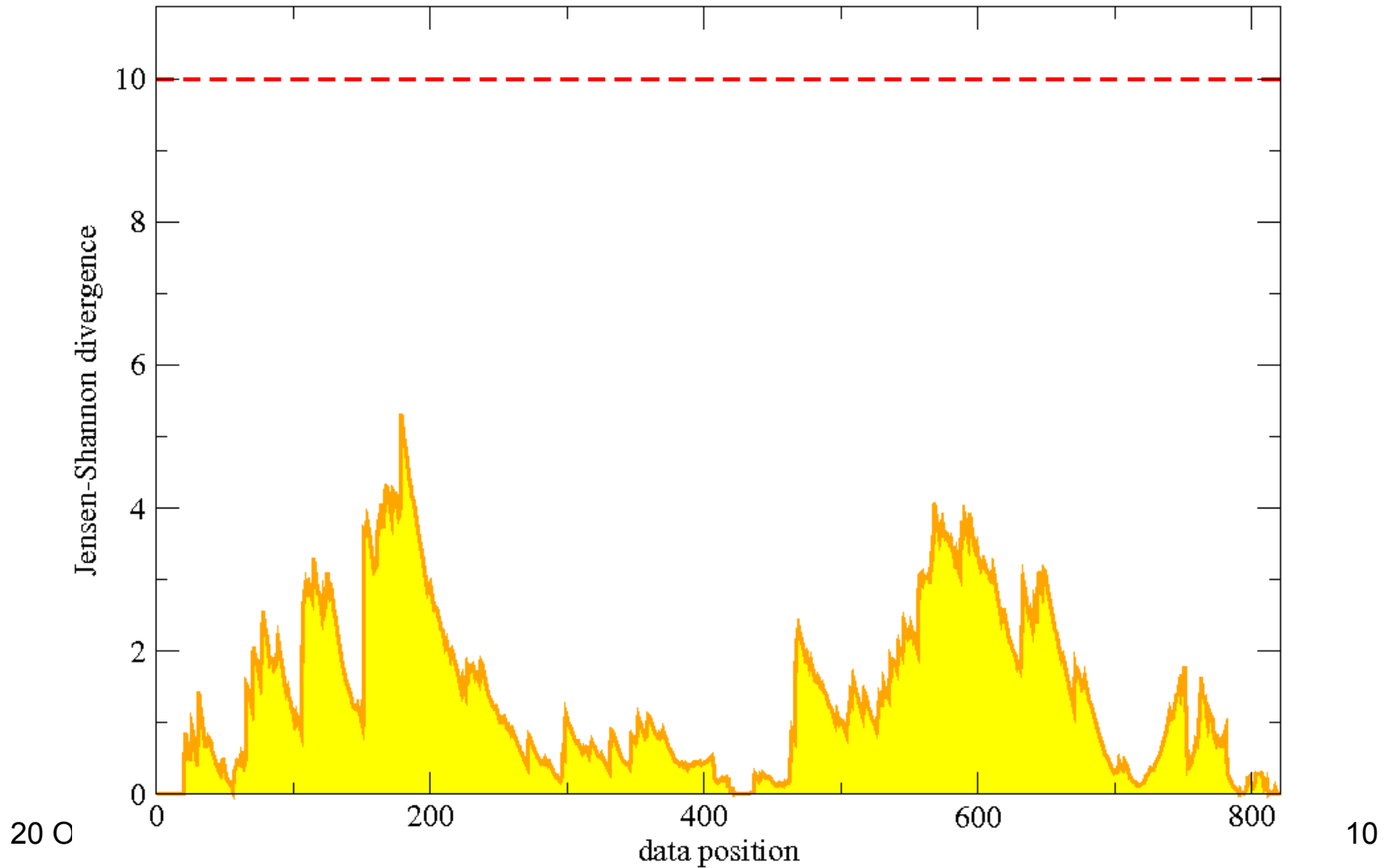
$$L_2(t) = \prod_{i=1}^t \frac{1}{\sqrt{2\pi\sigma_L^2}} \exp\left[-\frac{(x_i - \mu_L)^2}{2\sigma_L^2}\right] \prod_{i=t+1}^N \frac{1}{\sqrt{2\pi\sigma_R^2}} \exp\left[-\frac{(x_i - \mu_R)^2}{2\sigma_R^2}\right]$$

- ML estimates $\hat{\mu}, \hat{\mu}_L, \hat{\mu}_R, \hat{\sigma}^2, \hat{\sigma}_L^2, \hat{\sigma}_R^2$
- Jensen-Shannon divergence $\Delta(t) = \ln \frac{L_2(t)}{L_1} \geq 0$

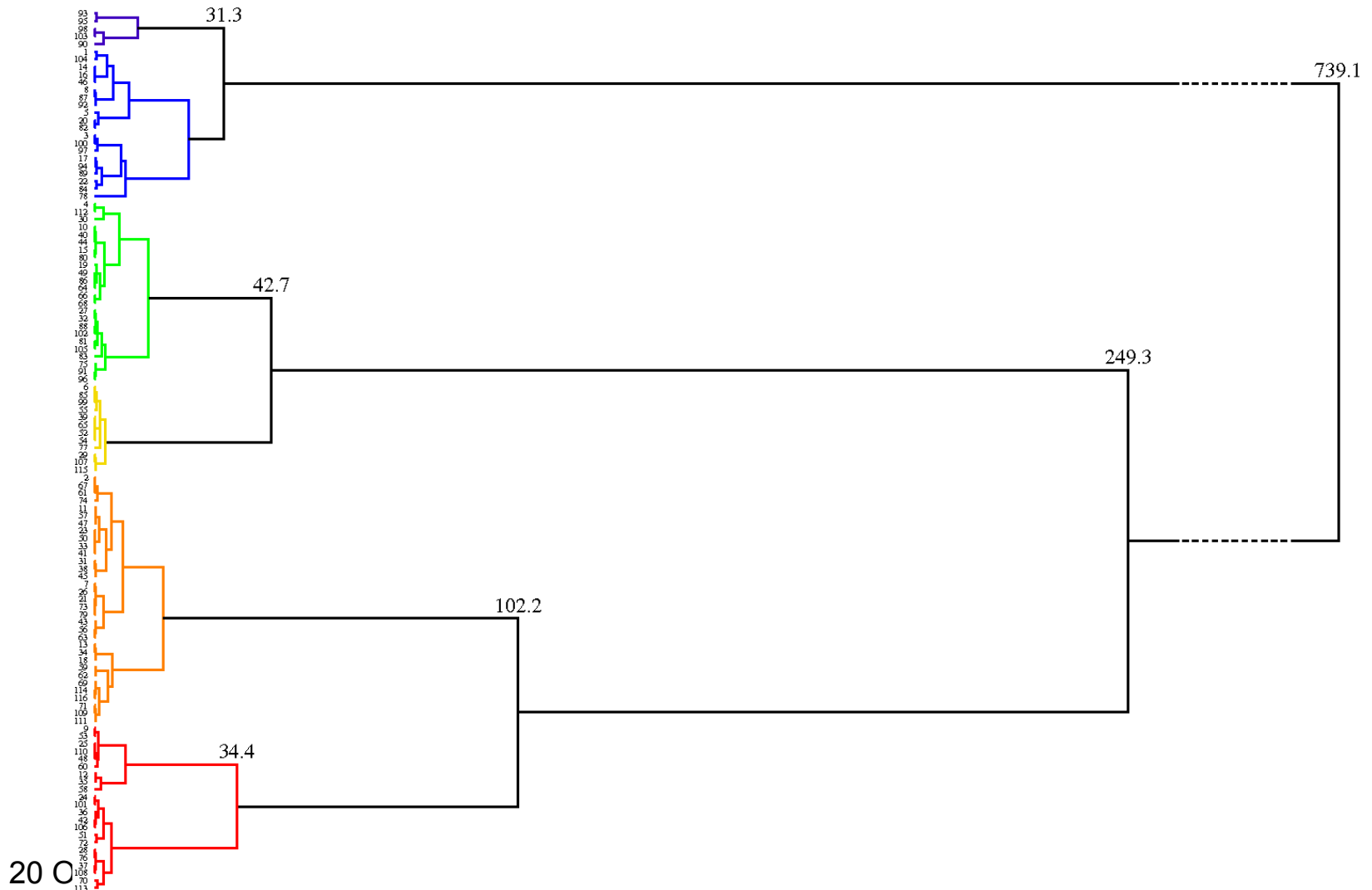
Time Series Segmentation



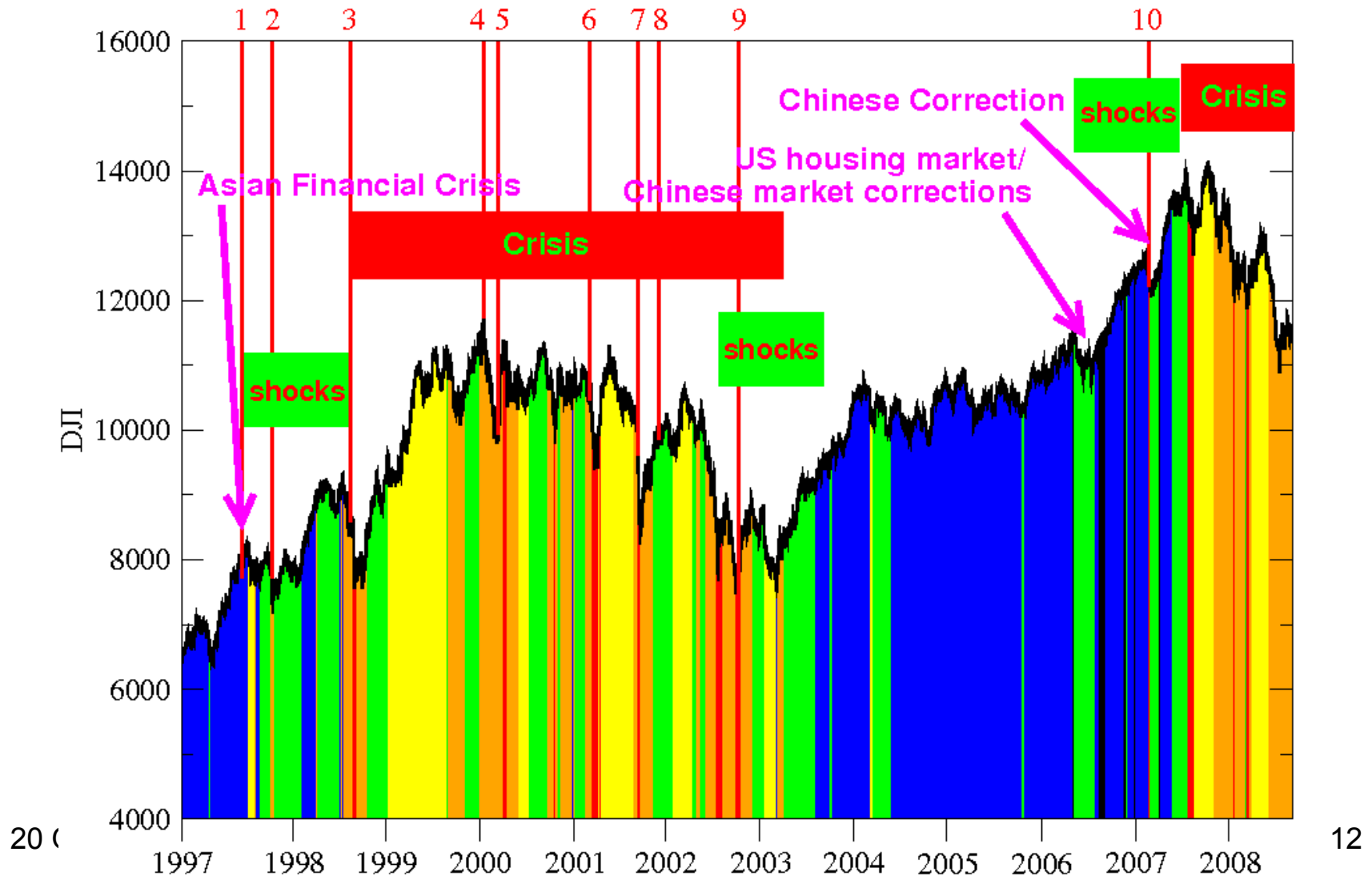
Time Series Segmentation



Time Series Segmentation



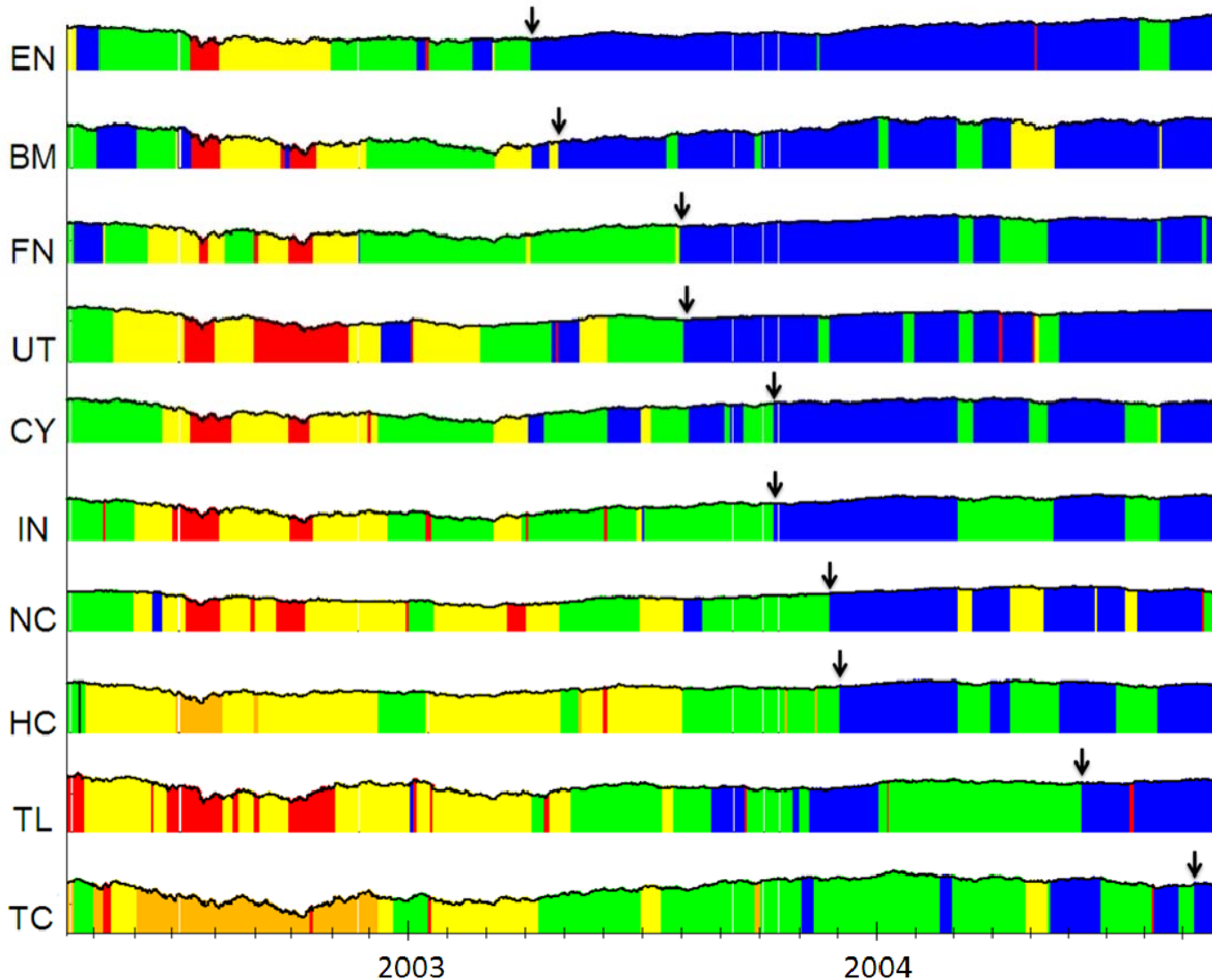
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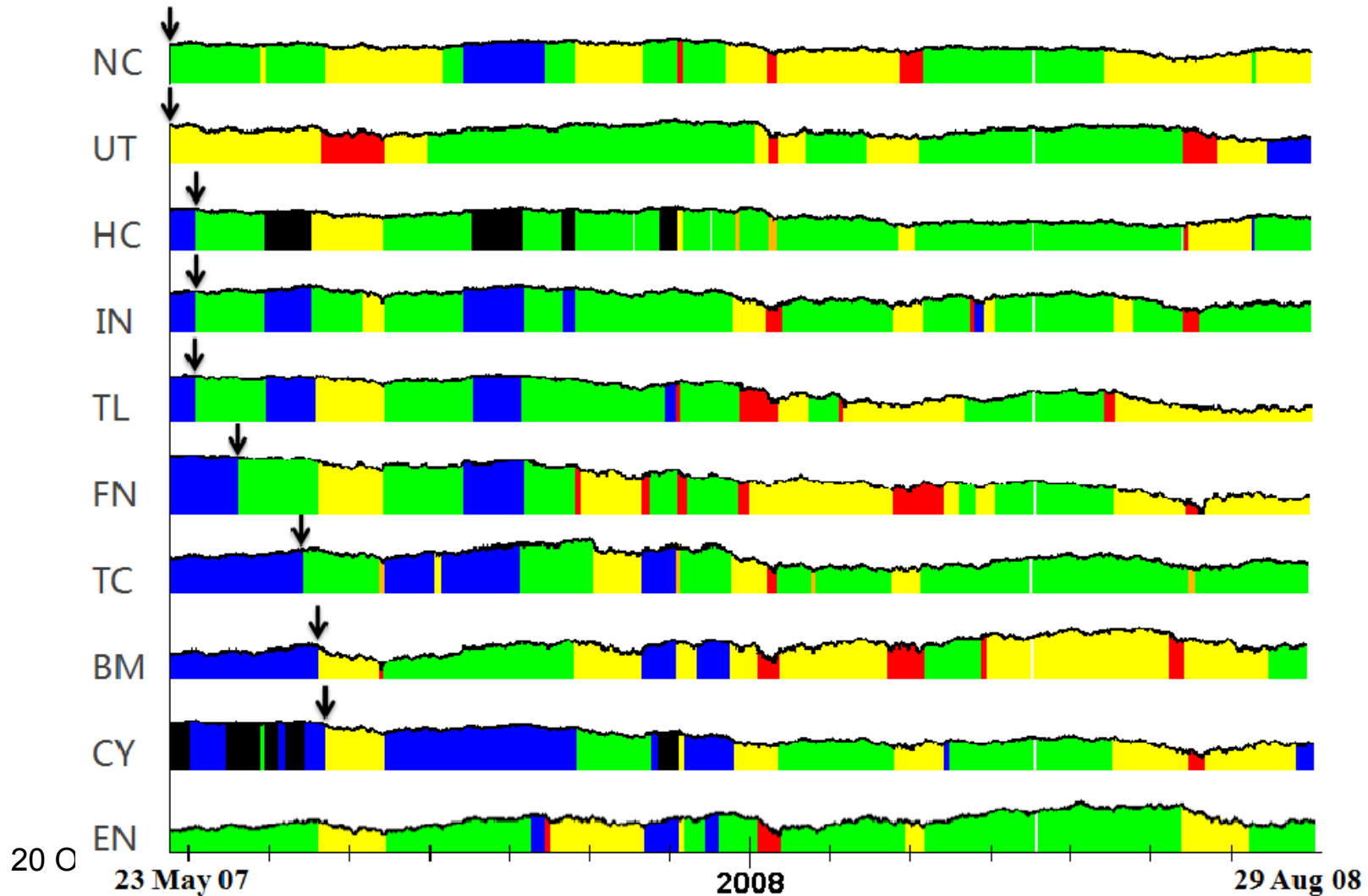
Time Series Segmentation

<i>k</i>	<i>Symbol</i>	<i>Economic Sector</i>
1	BM	Basic Materials
2	CY	Consumer Services
3	EN	Oil & Gas
4	FN	Financials
5	HC	Healthcare
6	IN	Industrials
7	NC	Consumer Goods
8	TC	Technologies
9	TL	Telecommunications
10	UT	Utilities

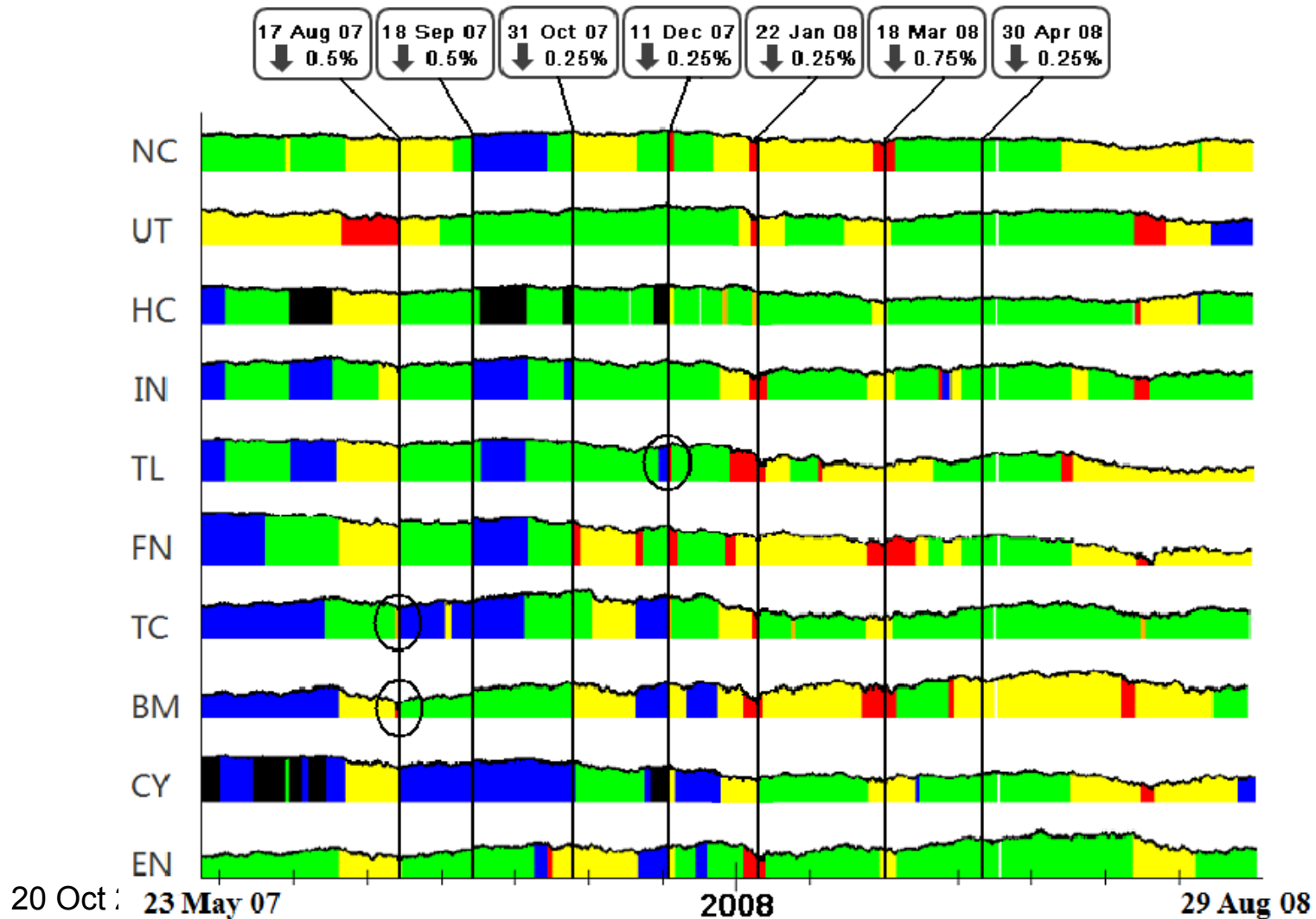
Time Series Segmentation



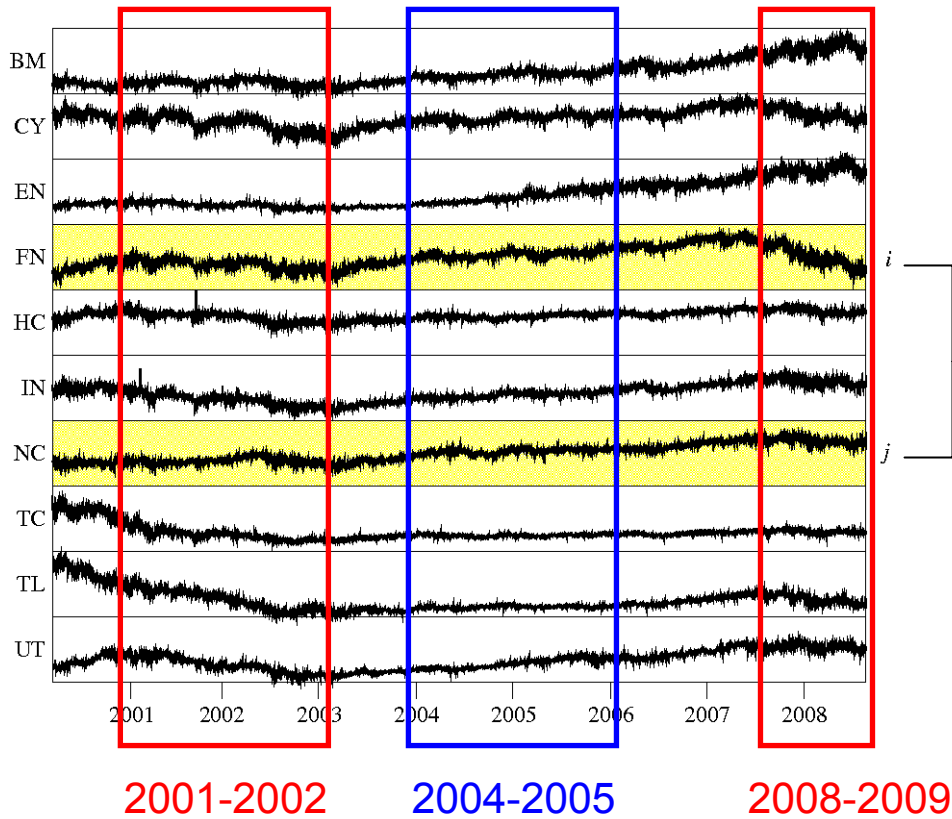
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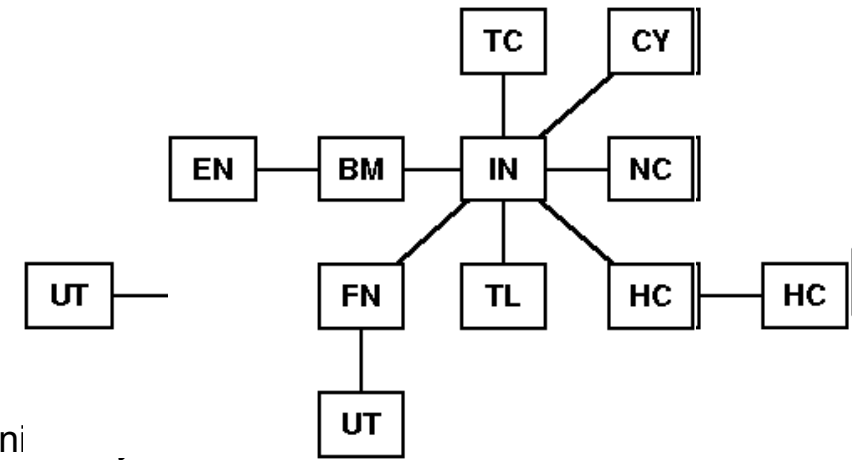
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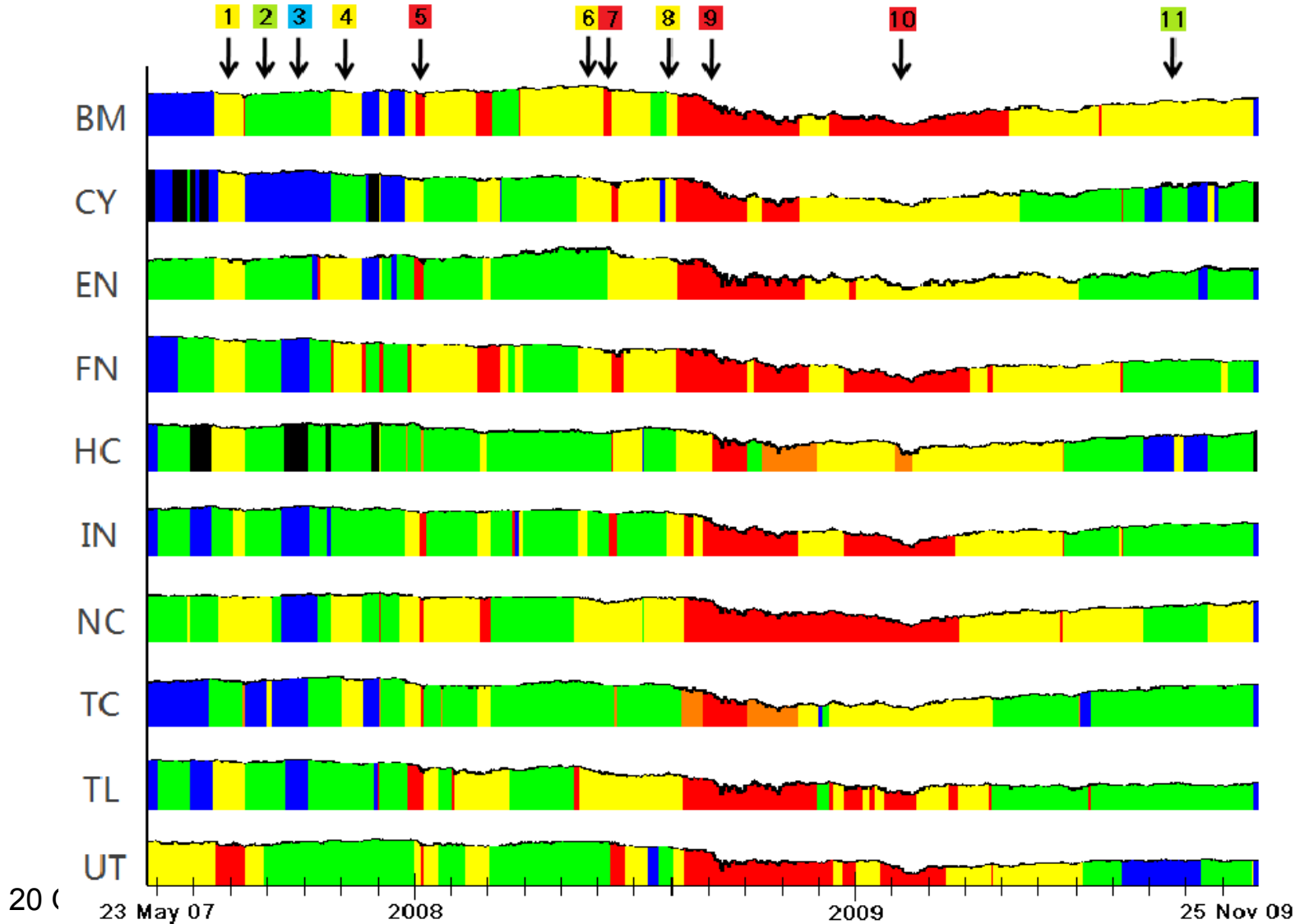
Time Series Segmentation



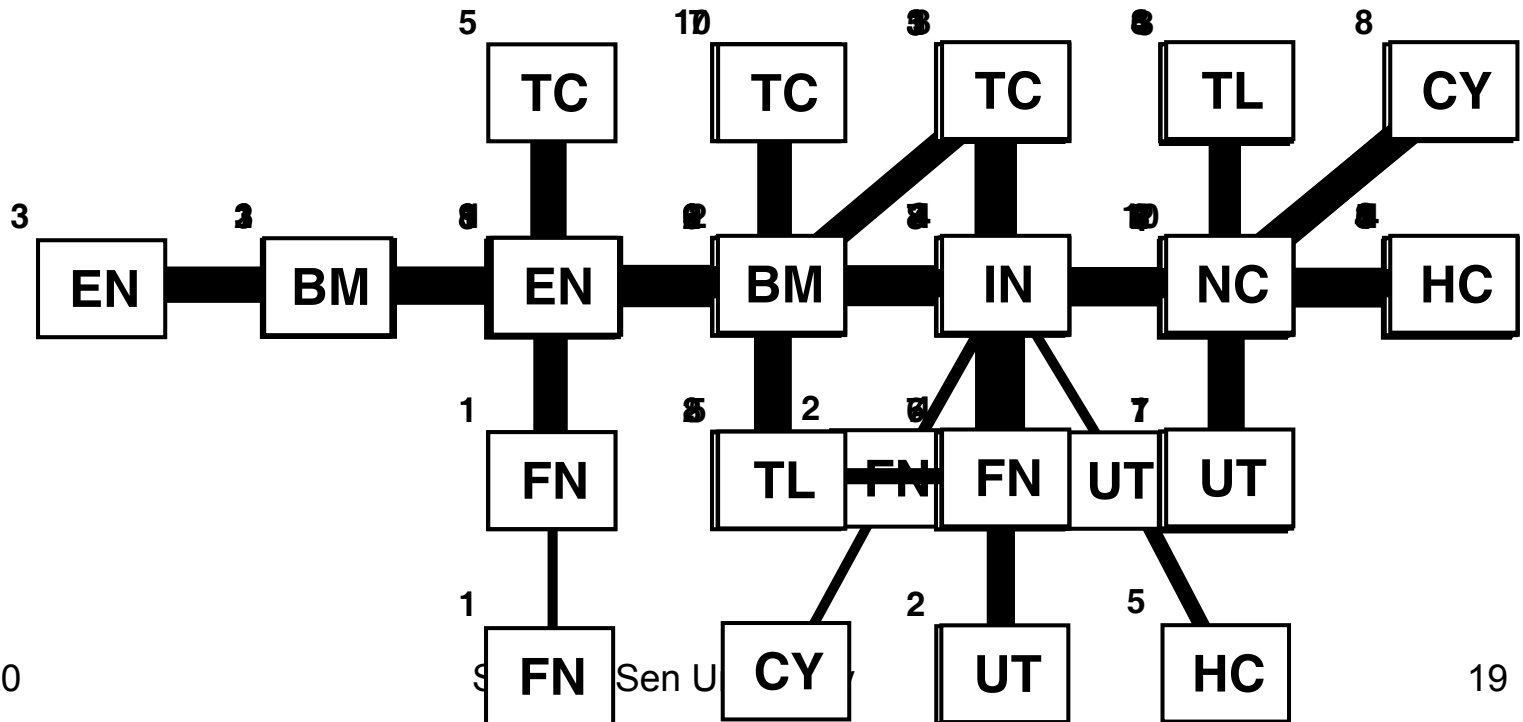
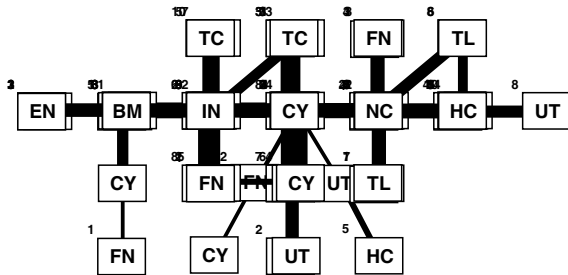
$$C_{ij} = \frac{\langle (x_i - \bar{x}_i)(x_j - \bar{x}_j) \rangle}{\sigma_i \sigma_j} = \left\langle \frac{\delta x_i}{\sigma_i} \frac{\delta x_j}{\sigma_j} \right\rangle$$



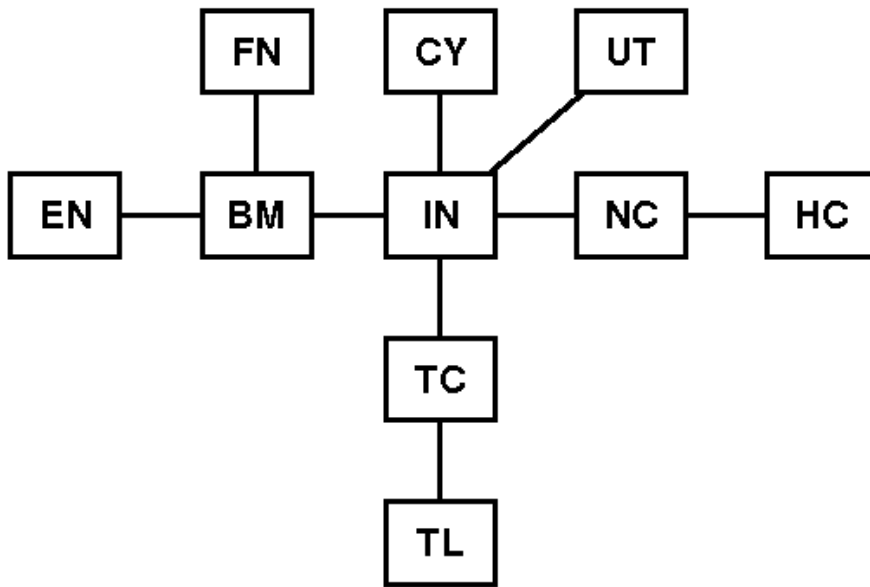
Time Series Segmentation



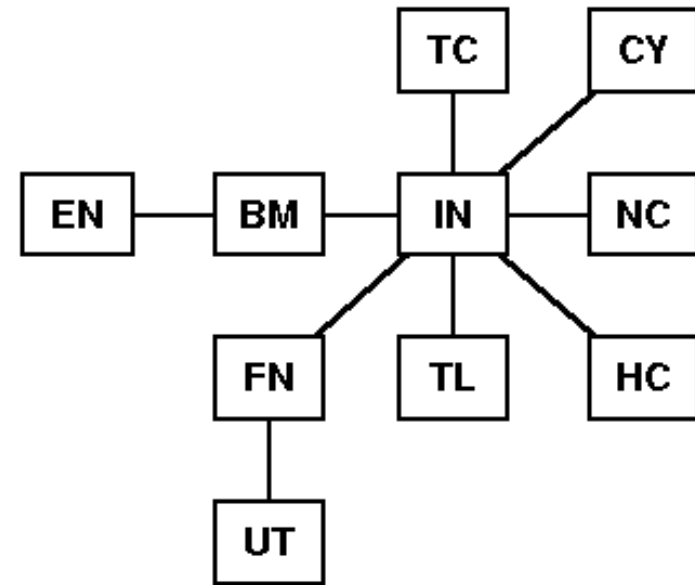
Time Series Segmentation



Time Series Segmentation

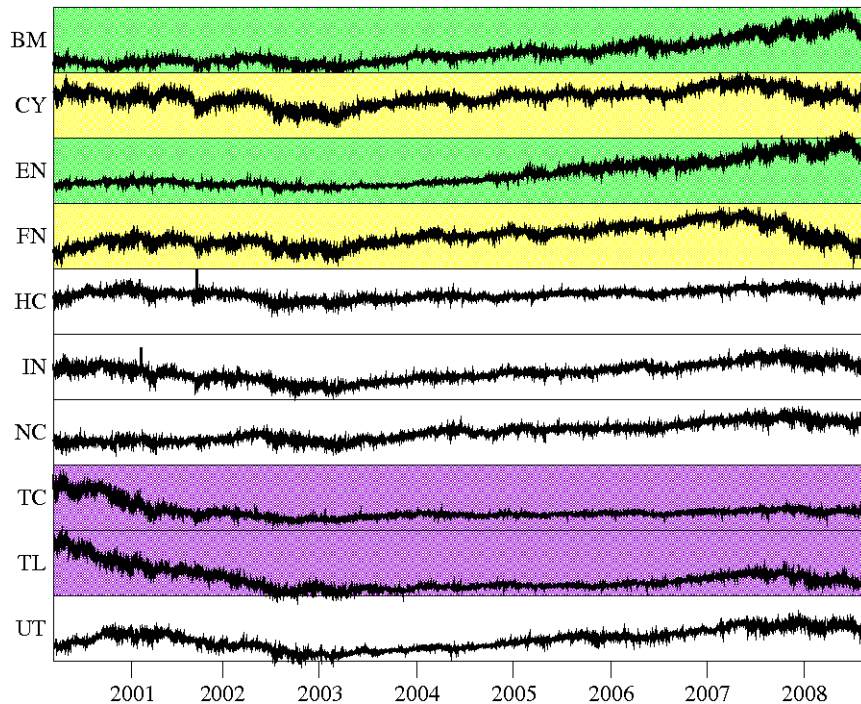


Sep 2009



2004-2005

Time Series Clustering



$$C_{ij} = \frac{\langle (x_i - \bar{x}_i)(x_j - \bar{x}_j) \rangle}{\sigma_i \sigma_j} = \left\langle \frac{\delta x_i}{\sigma_i} \frac{\delta x_j}{\sigma_j} \right\rangle$$



$$D_{ij} = \left\langle \theta \left(\frac{\delta x_i}{\sigma_i} - 1 \right) \theta \left(\frac{\delta x_j}{\sigma_j} - 1 \right) \right\rangle$$

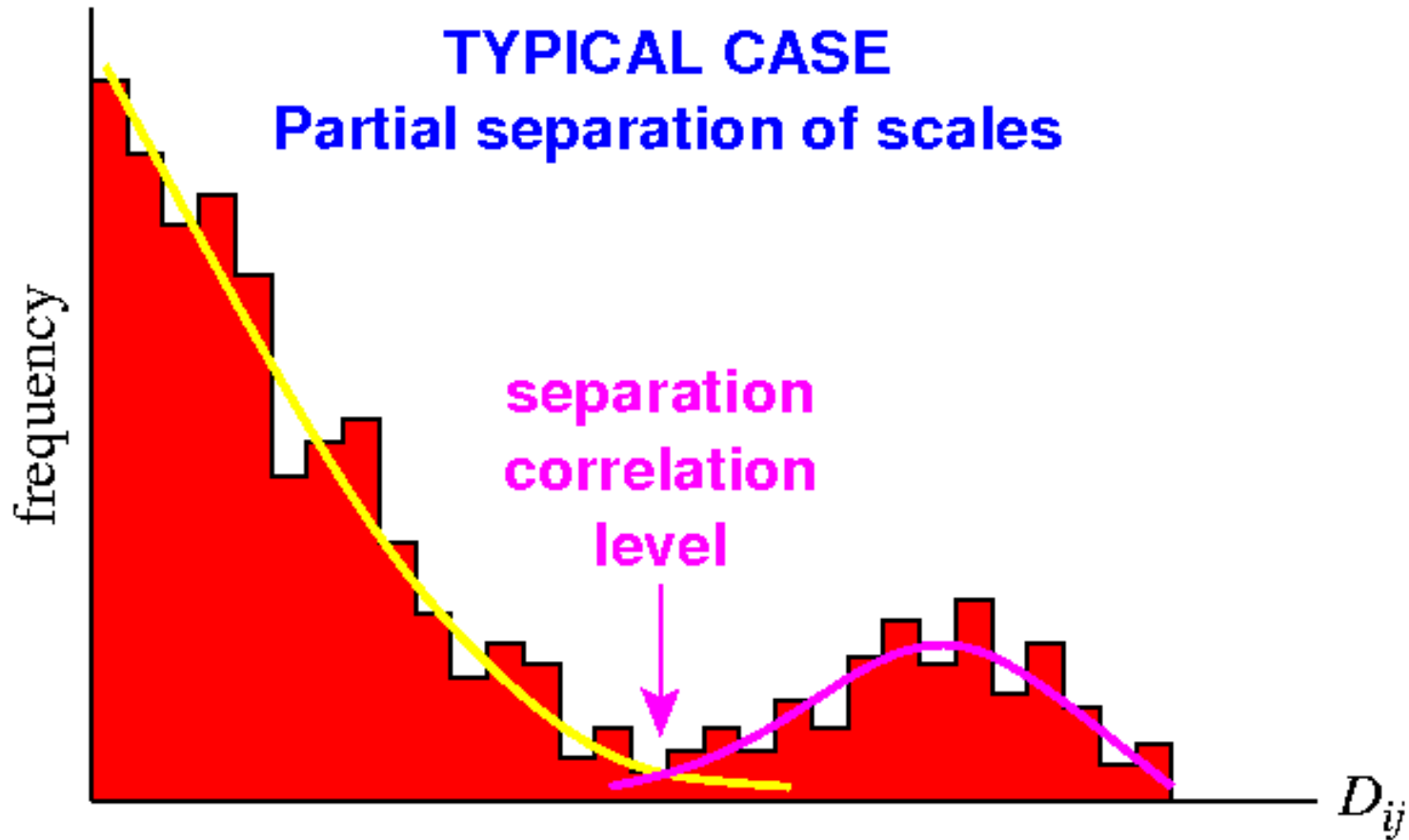
digital cross correlations



$$\tilde{D}_{ij} = \langle \theta(\Delta x_i \Delta x_j) \rangle \text{ or } \tilde{D}_{ij} = \sum_{t=1}^N \theta(\Delta x_{it} \Delta x_{jt})$$

comovement digital cross correlations

Time Series Clustering

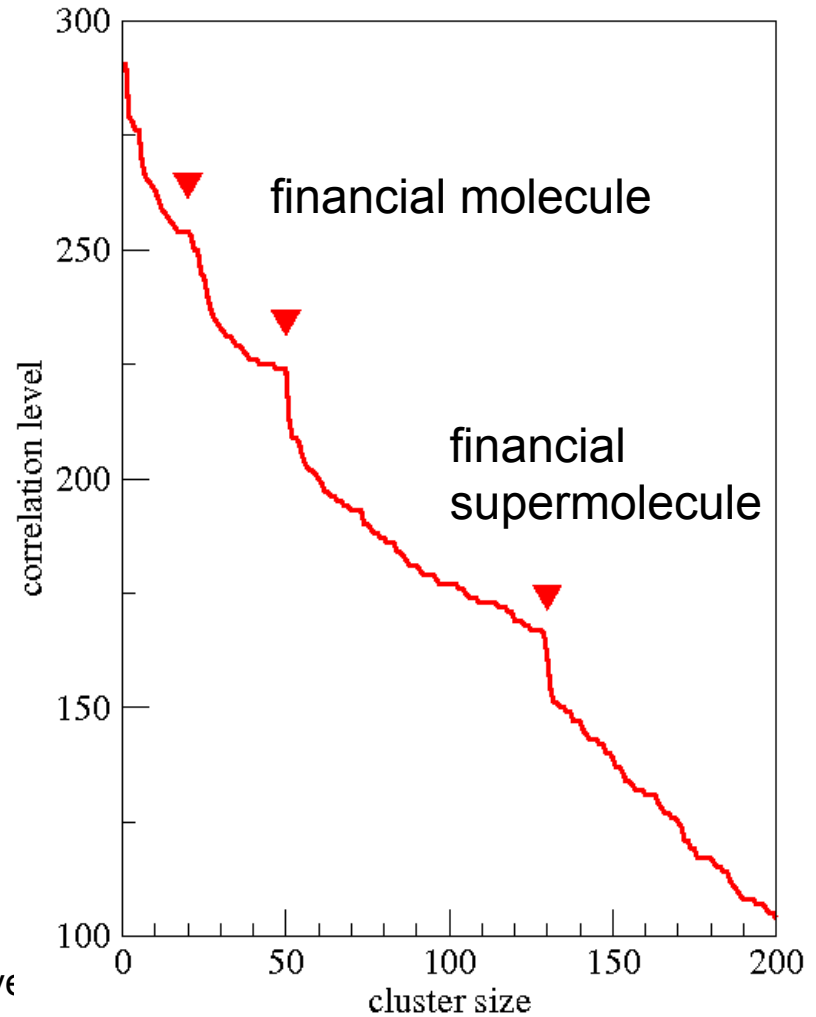
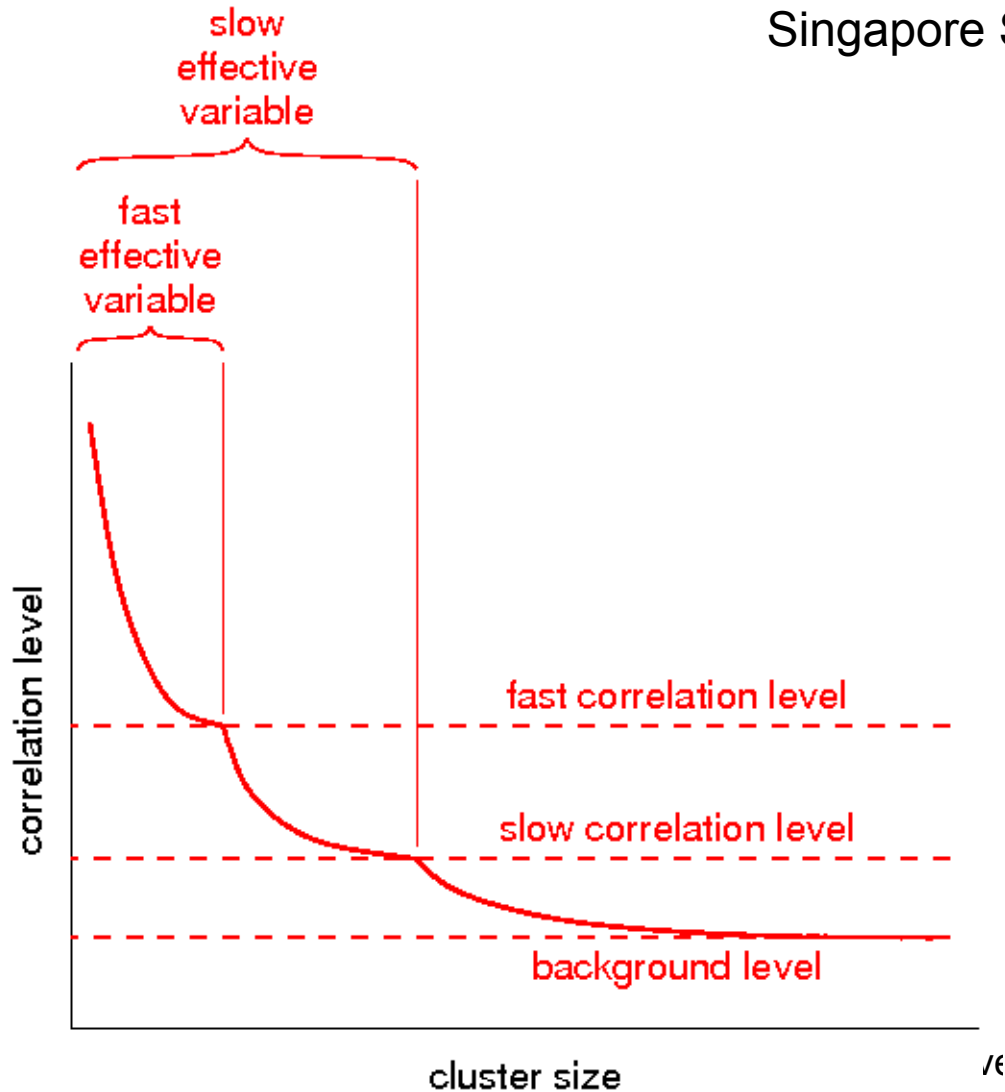


Time Series Clustering

- Partial Hierarchical Clustering
 - Find $D_{i^*j^*} = \max_{ij} D_{ij}$
 - Use $c = \{i^*, j^*\}$ as seed cluster
 - Add k^* to cluster if
 - $D_{k,c} = \min_{l \in c} D_{kl}$
 - $D_{k^*,c} = \max_k D_{k,c}$
 - Iterate to grow cluster
 - Plot correlation level $D_{k^*,c}$ against cluster size

Time Series Clustering

Singapore Stock Exchange (SGX): 2006-2007



Time Series Clustering

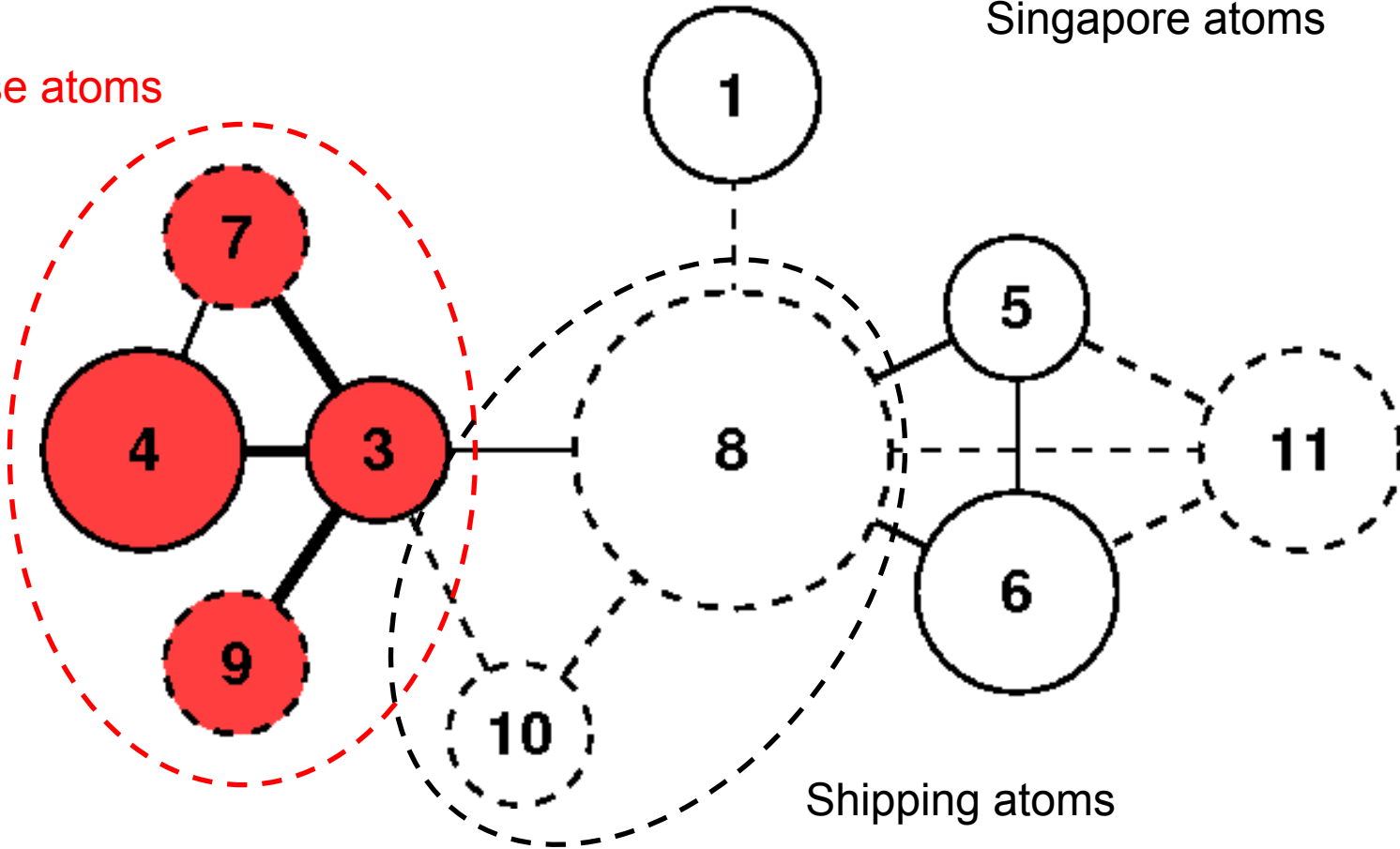
SGX1	SGX2	SGX3	SGX4	SGX5	SGX6
Singtel	Singapore Airlines	Celestial Nutri-foods	Mirach Energy	CapitaLand	DBS Gp Hldg
Singtel 10	Singapore Airlines 200	China Sun Bio-chem Tech Gp	Sky China Petroleum Svcs	City Development	United Overseas Bank
Singtel 100			Ferrocchina		Overseas Chinese Banking Corp
			China Sky Chemical Fibre Co		Wing Tai Hldg

Time Series Clustering

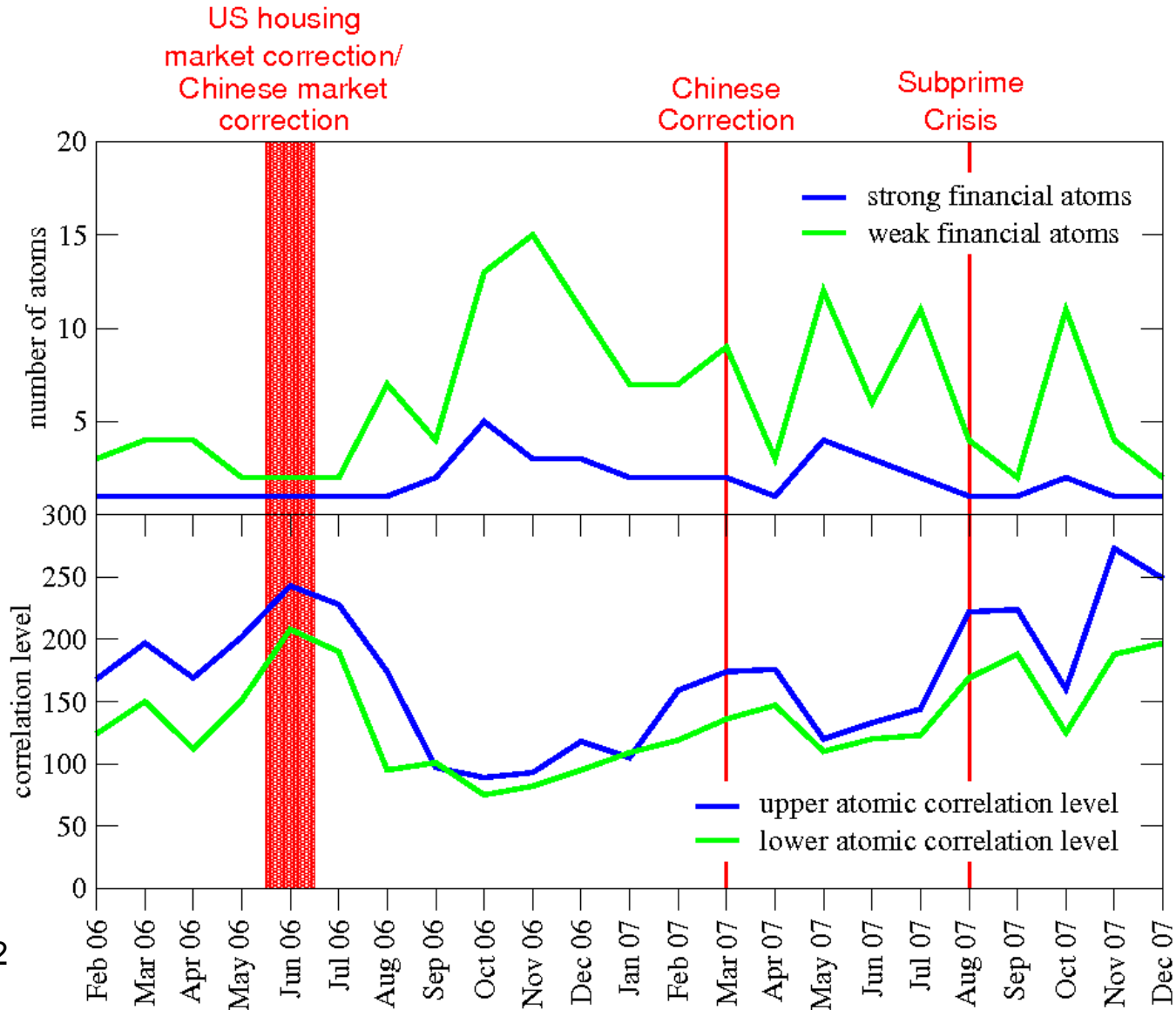
SGX financial molecule 2006-2007

Chinese atoms

Singapore atoms

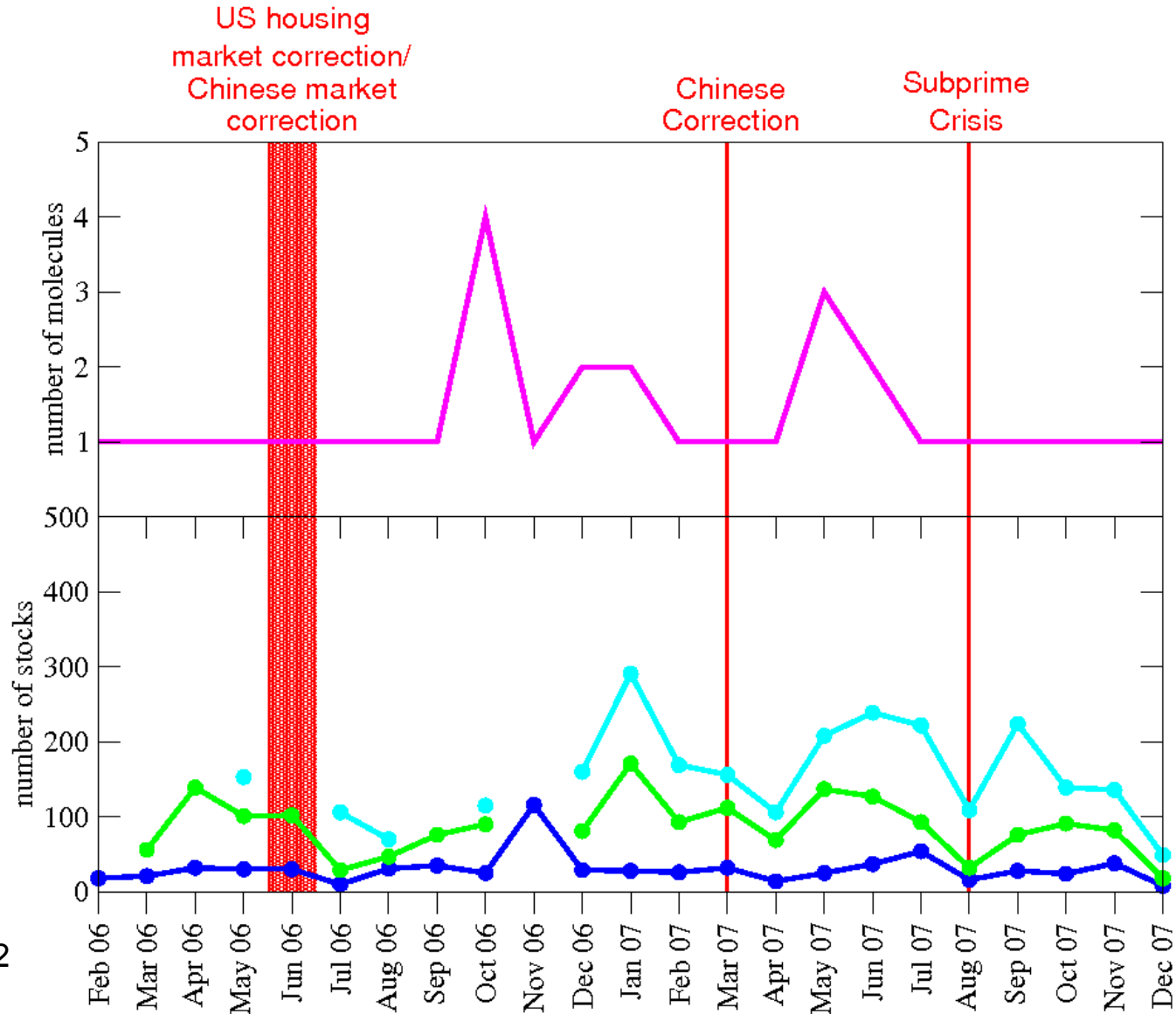


Time Series Clustering



20 Oct 2

Time Series Clustering



20 Oct 2

Conclusions

- Possible to identify macroscopic phases and study their dynamics from microscopic time series
- Time series segmentation
 - US economy
 - Crisis and growth
 - MST topologies
- Time series clustering
 - SGX
 - Financial atoms and molecules
 - Chemical picture of market crashes

Acknowledgments

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Thank You!