Fish recognition using deep convolutional neural network and data augmentation

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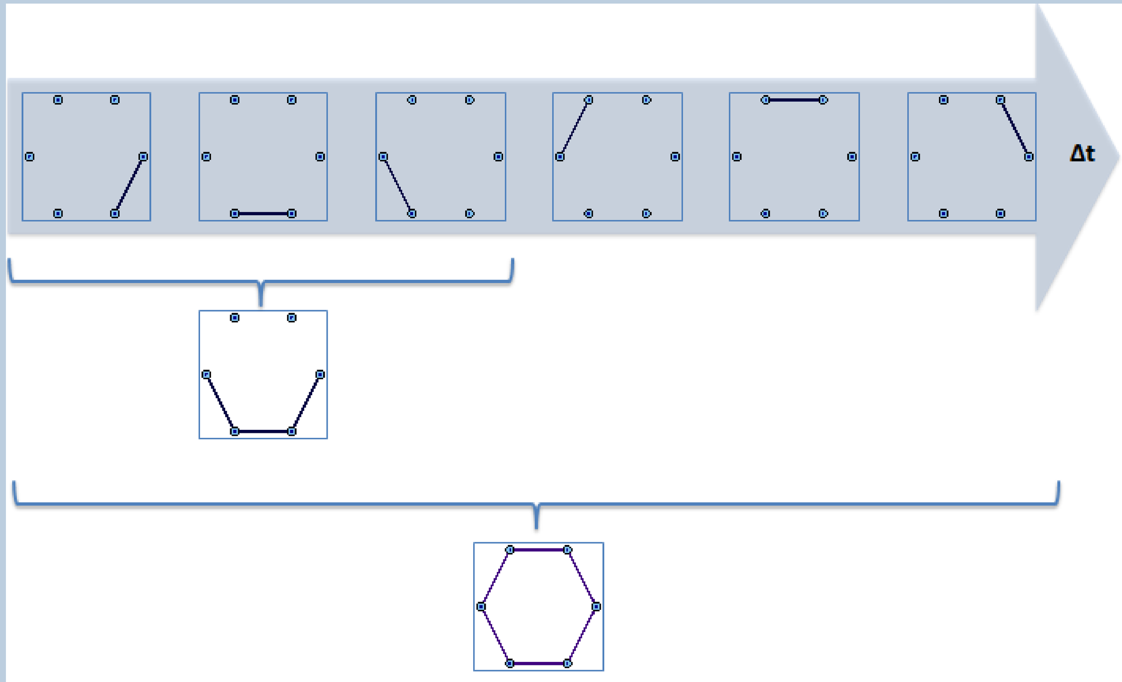
Problem

Nowadays, as a sub topic of computer vision and fishery industry, fish recognition is still a challenging work not only because of various kinds of fish, but also because of the complex background of images.



Basic Concepts

In our work the dynamic network is a series of graphs, that is, $DN = G_t(V_t, E_t)$, where $E_t \subseteq V_t \times V_t$ $(\forall t \geq 0)$. The initial network, G_0, is considered as a parameter of the process. The **node set fixed** and we worked with an about **constant number of edges**. We assume that the evolution of the network can be described as the result of an edge creation and an edge deletion process. We define G_t as the **snapshot network** and

$$G_T = (\bigcup_{t=0}^{T} V_t, \bigcup_{t=0}^{T} E_t) \text{ for } T \geq 0.$$

as the **cumulative network**.

Models

ER1 G_0 is a random graph. Add each non-existing edge with p_A, delete each existing edge with p_D probability.

ER2 G_0 is a random graph. Add k_A uniformly selected random new edges and delete k_D existing edges.

ER3 G_0 is a random graph. Rewire k_{RW} edges.

SPA (*Snapshot preferential*) G_0 is a scale free network. Add k_A edges from a random node with preferential attachment based on the snapshot network. Delete k_D existing edges.

CPA (*Cumulative preferential*) G_0 is a scale free network. Add k_A edges from a random node with preferential attachment based on the cumulative network. Delete k_D existing edges.

References

[1] Laszlo Gulyas, Richard Legendi: *Effects of Sample Duration on Network Statistics in Elementary Models of Dynamic Networks*, International Conference on Computational Science, Singapore (2011)

[2] Laszlo Gulyas, Susan Khor, Richard Legendi and George Kampis *Cumulative Properties of Elementary Dynamic Networks*, The International Sunbelt Social Network Conference XXXI (2011)

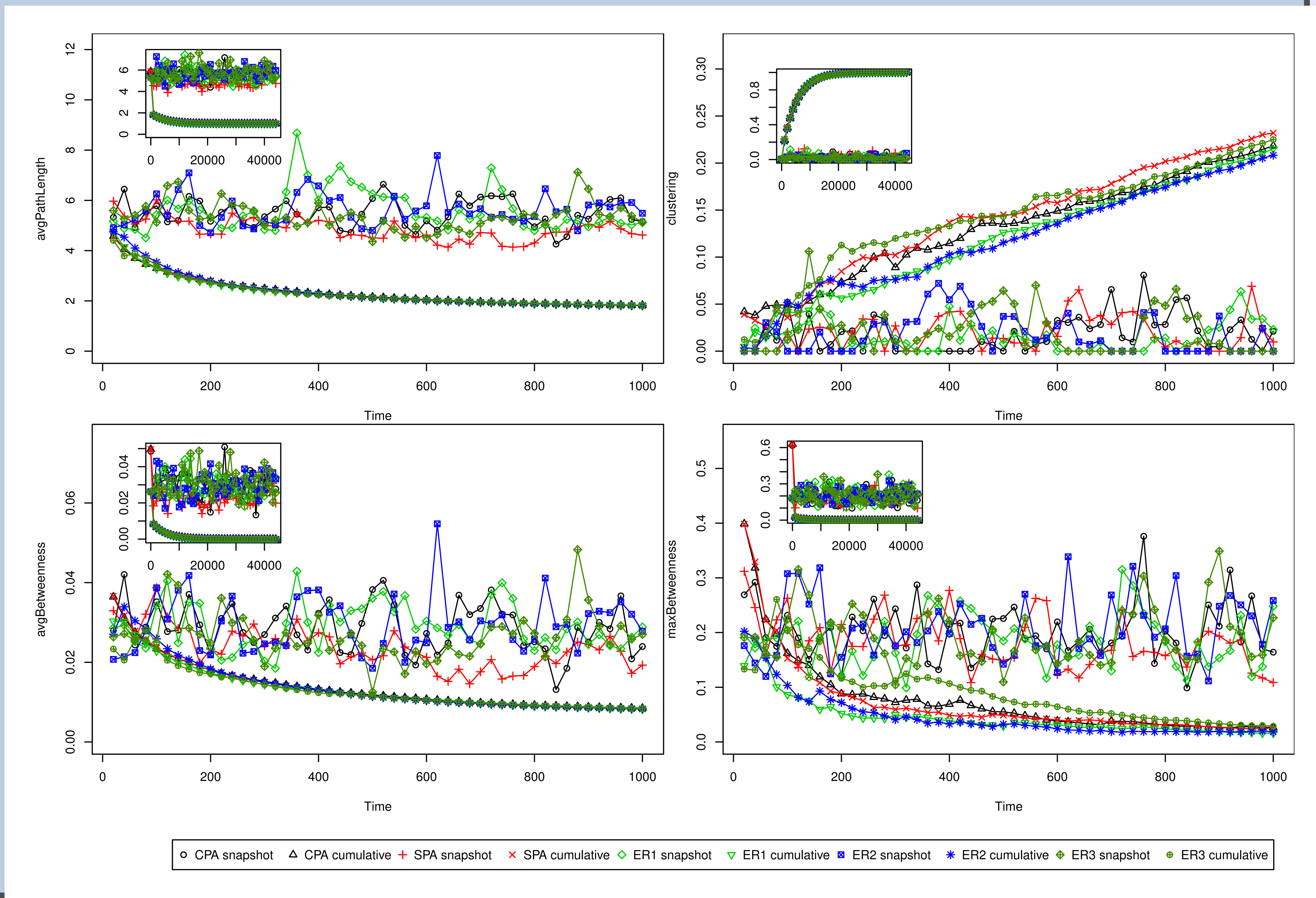
[3] Gulyas, Laszlo et al.: *Betweenness Centrality Dynamics in Networks of Changing Density*. Presented at the 19th International Symposium on Mathematical Theory of Networks and Systems (MTNS 2010)

Acknowledgements

This research was partially supported by the Hungarian Government (KMOP-1.1.2-08/1-2008-0002) and the European Union's Seventh Framework Programme: DynaNets, FET-Open project no. FET-233847 (`http://www.dynanets.org`). The supports are gratefully acknowledged.

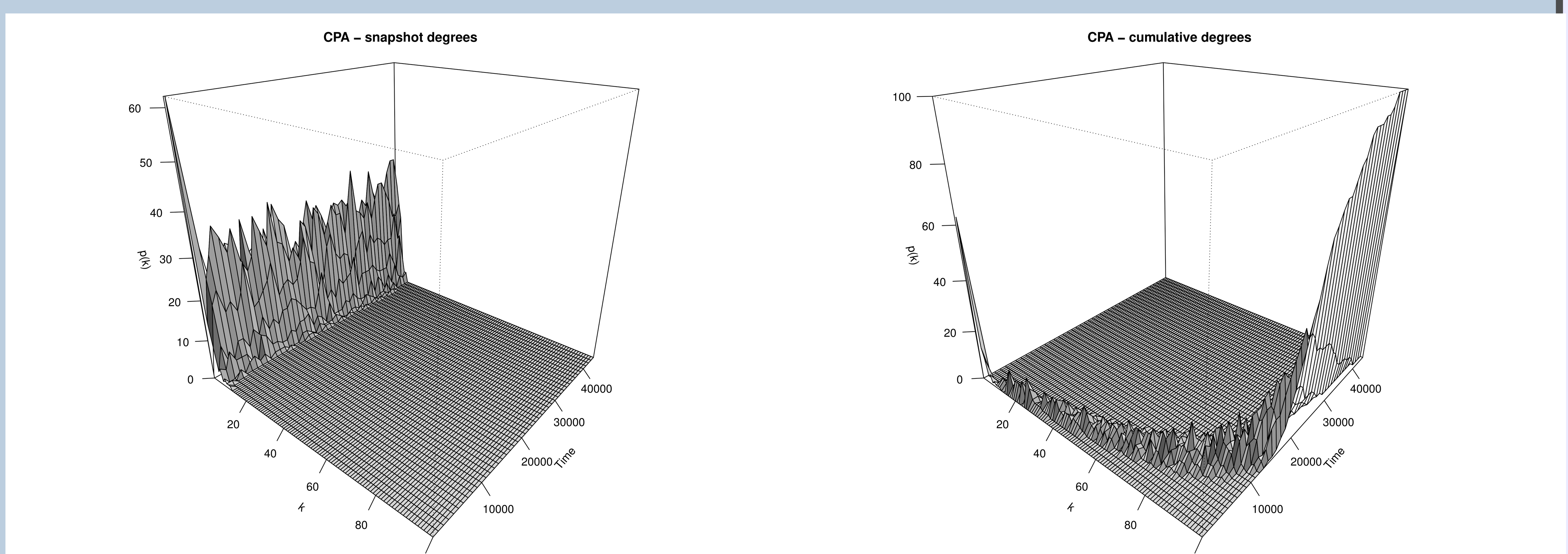
Dynamic Networks are Sensitive to Aggregation

Network characteristics are extremely sensitive to minor changes in aggregation length. In our previous work [?] [?], we studied the cumulative properties of Elementary Dynamic Network models over the complete time period (i.e., until they reach the stable point of a full network). Here we focus on the more realistc domain of sparse (cumulative) networks. We find that even when snapshot networks are stationary, **important network characteristics** (average path lenght, clustering, betwenness centrality) **are extremely sensitive to aggregation** (window length).



Degree Distribution Radically Changes

Degree distributions are exceptionally sensitive to the length of the aggregation window. **The same dynamic network may produce a normal, lognormal or even power law distribution for different aggregation lenghts.** The digree distribution of the snapshot and cumulative network is inherently different. The following surfaces show the CPA model until it approaches the complete network.



Taking slices of the cumulative 3D charts shows us how the degree distribution changes. The log-log charts below show the progression of these changes as the aggregation window gets larger.