Prediction of characteristics of dynamic social networks

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Abstract

The paper describes a new framework for visualization and inspection of a social network graph evolving over time. One of the new features is prediction of future structural properties of this graph. For this purpose we use time series analysis, based on a machine learning framework of Weka. We evaluate this approach for four learning algorithms for time series prediction: SVM (support vector machine), linear model, multilayer perceptron and Gaussian process. A series of experiments was designed to assess the quality of prediction of the dynamics of the social network with selected methods.

1 Introduction

Social network analysis (SNA) is a rapidly growing area of research with many current and potential practical applications in the economy, government, science, the organization of information society, ensuring the security and defense. Application examples are early warning systems of impending epidemics of infectious diseases [1, 2], seeking expert in certain areas [3], for designing efficient share of information and education [4, 5], search people with leadership qualities [6], to identify the instability of social relations [7], the detection of activities of terrorist groups (eg [8, 9, 10, 11, 12]), identifying network vulnerability [13] etc.

Social network often means social structure between actors, which are generally individuals or individual organizations. It shows the relationship of various types, ranging from random acquaintance to the close relationship or to object flows (e.g. information, goods, money, signals, intermediate in the production cycle, etc.) between the members of the community [14].

Social network analysis is focused on mapping and measuring relationships and information flows between people, their groups, organizations or other entities in transforming the information and / or knowledge. The SNA attempts to make prediction on the basis of the characteristics of the network as a whole entity, the properties of individual nodes based on network structure, etc. The subject of research can be a complete social network or parts of it related to a specific node.

As part of a research project[1], we developed a set of methods and algorithms, and created a system called BEATCA-SNA for supporting important tasks in SNA:

- enriching the description of the analyzed social network with features derived from texts, structural information with regard to different objects in the network, and from the characteristics of aggregates based on the cluster analysis of objects,
- enriching the description of the dynamics of the network analyzed by time-dependent prediction based on original and derived features (predictors) of objects (nodes) and aggregators of the network,
- searching, visualization and exploration of social networks based on the characteristics of nodes, their aggregates and structural relationships, and supporting these processes by recommendation techniques.

In this paper we will focus on the aspect of visualization and prediction of the structure development of the network graph. Section 2 discusses related work on dynamic social networks. In section 3 we will outline the design of the implemented system, concentrating on dynamic social network graph exploration capabilities. In section 4 we will describe the set of experiments we performed to evaluate its predictive capabilities. The experimental results are summarized in section 5.

Some of the implementations are based on selected ideas described in [15] and [16] and [17]. A completely new approach to graph visualization is presented in [18].

2 Related work

Recently finding characteristics of social networks and prediction of this characteristics grew to a field of intense research activity. The results of Barabási's research into the behavior of networks presented in book [13] show how even fairly robust systems like the Internet could be crippled by taking out a few super-connected nodes, or hubs. In [19] Albert and Barábasi present a statistical approach to modeling the networks dynamics, based on empirical data. The authors discuss the main models and analytical tools, covering random graphs, small-world and scale-free networks, the emerging theory of evolving networks, and the interplay between topology and the network's robustness against failures and attacks. They use the following network characteristics as measurement metrics: number of nodes, average degree, average path length, local clustering coefficient and spectral density of a graph.

Lin et al. [20] use first-order Markov model to analyze communities[2] and their evolutions in dynamic networks. They analyze impact of network history to predict communities in current state. Unlike traditional two-stage techniques that

[1]Research project grant from the MNiSW *N N516 443038 - 4430/B/T02/2010/38 Analysis and visualization of structure and dynamics of social networks by methods inspired by nature* realized from 9.4.2010 to 8.4.2012.

[2]A community is often thought of as a set of nodes that has more connections between its members than to the remainder of the network.

separate the task of community extraction and the task of evolution extraction, the FacetNet framework presented in their paper combines these two tasks in a unified process. Authors use node degree, modularity (as defined by Newman et al. [21]) and propose new measurement soft modularity.

Statistical properties of communities in a large dynamic networks were investigated by Laskovec at al. [22]. In their parer, they characterize as a function of size the statistical and structural properties of communities. They measure community goodness by conductance, also known as the normalized cut metric (see [23, 24, 25]). The practical problem with this metric is that it is hard to compute and we must make some approximations. They also introduce the network community profile plot, which measures the quality of the best possible community in a large network, as a function of the size of the presumed community. In network dataset they examined, the conductance score of the best possible set of nodes gets gradually worse and worse as those sets increase in size. This suggests that steadily increasing clusters are "blended in" more and more with the rest of the network.

Laskovec et al. [26, 27] present two unusual phenomena of network growth in time. First, most of real graphs densify over time, with the number of edges growing superlinearly in the number of nodes. Second, the average distance between nodes often shrinks over time, in contrast to the conventional wisdom that such distance parameters should increase slowly as a function of the number of nodes. They propose two models, which can explain this phenomenas: "Community Guided Attachment" (CGA) and more complicated "Forest Fire Model" (FFM), the latter being based on having new nodes attach to the network by "burning" through existing edges in epidemic fashion.

Berger-Wolf and Saia [28] propose a new mathematical and computational framework that explicitly makes use of information about the time that social interactions occur. They analyze structure of social network by creating various groups on graph representing this network. Interactions between individuals are recorded at every timestep and for them the membership into groups and meta-groups. They measure similarities of group defined by a social event by specially built similarity measure.

Laskovec et. al [29] present usefulness of social network analysis in viral marketing. Dynamic network is constructed from person-to-person recommendation network. Authors established how the recommendation network grows over time and how effective it is from the viewpoint of the sender and receiver of the recommendations. They used traditional epidemic (see [30]) and innovation diffusion models (proposed by Bass [31]). They concluded that in network-based epidemic models, extremely highly-connected individuals play a very important role.

In this paper we present a slightly different approach to analysis of the dynamics of social networks. Instead of providing the user with ready made reports on network properties we allow him to investigate himself network properties both at global and local level. Our work differs also in the approach to time intervals and measurement handling. For given interval (time slice) we measured metrics value considering only those graph nodes and edges that were "active" or existent only in this interval, instead of a cumulated graph till given time point.

3 A system for local contextual properties of social graphs

Prof. Tukey, who inspired a new trend in exploratory data analysis, believed that an important aspect of the analysis is data visualization and exploration. Therefore, a very important component of data mining system is an opportunity to present and search network properties seen at the local level.

The social network graph node in our system is seen in three different contexts:

- in the context of its position in the graph
- in the context of the passing time
- in the context of a group to which it was assigned during clustering process (with clustering of nodes being based on their textual content)

The first and second aspect implies that in fact we are not dealing with a single social graph, but with many of them, associated with individual quanta of time, where an individual node becomes the next incarnation.

On the other hand, search engine treats all these incarnations as a single entity e.g. during clustering, search, retrieval, presentation etc.

The system BEATCA [32] reflects this duality as a dual representation of the node. On the one hand we have the node as an entity, which is assigned to all the related texts, on which it can be searched, as well as time invariant attributes. On the other hand, there is its next incarnation, which is related to the attributes change over time. From a technical point of view the search of time varying and time invariant node features runs somewhat in separate spaces, which are combined on the fly when it comes to answer the user's query.

At the same time, node is characterized not only by its graph properties, but also by the text. For example, a node in time quanta can be associated with e-mails sent by it (e.g. Enron base).

Note that with appropriate design of experiments there is a possibility that for example, some data processing may deliver some new aggregation attributes, on which you can perform searches.

A new quality in developed tool is the opportunity to observe local and global graph metrics in time (after division of the timeline to the corresponding quanta) and the ability to search nodes with specific value (or values in the range) of this metrics in a specific time interval or at any time. A set of metrics (treated as node attributes) is by definition extensible.

In subsection 3.1 we will explain the kind of graph properties (metrics) that can be inspected by the user and in subsequent subsections various available inspection methods will be presented.

3.1 Local and global properties of social graphs in BEATCA-SNA

In this project we borrowed from a rich set of traditional coefficients known from literature, which represents local and global properties of social networks. Many such measures are given by Vázquez in [33]. However we expanded this set by an important one, called bipartite clustering coefficient (BLCC), proposed and investigated widely in [34].

We measure local properties of the graph nodes by following metrics:

1. degree - the number of edges incident to the vertex
2. indegree - the number of edges going to the vertex
3. outdegree - the number of edges going out of the vertex
4. Local Clustering Coefficient (LCC) - the ratio of the number of edges connecting the neighbours to the maximum possible number for simple graphs (see [35]). When applied to a single node, is a measure of how complete the neighbourhood of a node is.
5. betweenness centrality - number of the shortest paths between nodes (from any to any) passing through the node
6. closeness centrality - average distance from a given node to all other nodes in the network
7. eccentricity - measure captures the distance between a node and the node that is furthest from it, a high eccentricity means that the furthest away node in the network is a long way away, and a low eccentricity means that the furthest away node is actually quite close
8. modularity class - identifier of community[3] to which node was assigned
9. eigenvector centrality - the component of the principal eigenvector of the network adjacency matrix corresponding to a given node
10. pagerank - the component of the principal eigenvector of the network modified adjacency matrix corresponding to a given node; the modification consists in the following: If a node does not have an outgoing edge it is connected to all the other nodes. Then each one in the matrix is divided by the number of outgoing edges of a given node. Then all the entries are multiplied by one minus decay factor, then each entry is added decay factor divided by the umber of nodes in the network
11. Strongly Connected Component Number - identifier of a strongly coherent component the node belongs to (strongly coherent component is maximum subgraph of directed graph in which each node is reachable from each on a directed path)
12. Weakly Connected Component Number - identifier of a weakly coherent component the node belongs to (weakly coherent component is the maximum subgraph of directed graph, in which after changing it to the undirected graph, each node is reachable from each other one. Numbers range from 0 to (Weakly) Connected Components Count -1),
13. `source_second_neighbours_number` - number of second neighbours of vertex source

[3] In our system communities are obtained based on Newman's modularity concept. The algorithm runs as follows: initially each node constitutes its own community, then nodes are moved between neighbouring communities until a stopping criterion is reached. The obtained communities receive distinct identifiers called modularity class. A node is moved to the community of one of its neighbours if this would increase the modularity of the entire network. At each step the node giving the maximum modularity gain is selected. Modularity is the difference between the quotient of the number of edges inside of communities and of the total number of edges minus the sum of squares of the shares of edges that have at least one end in the community. The process is terminated if no gain of modularity can be achieved.

14. sum_of_neighbours_degree – the sum of the out-degrees of the neighbours of the source vertex
15. BLCC – BLCC coefficient (bipartite graphs clustering coefficient) for the source node, equals 1 minus the number of second neighbours of given node divided by the number of the degrees of the first neighbours after removal of the node from the network; it measures how much the local environment of the node differs from a tree

We measure local properties of the graph edges by following metrics:

1. x-z-y-transitivity – if we have edge $x \to y$ this is the number of such z, that $x \to z \to y$
2. z-xy-transitivity – if we have edge $x \to y$ this is the number of such z, that $z \to x$ i $z \to y$
3. xy-z-transitivity – if we have edge $x \to y$ this is the number of such z, that $x \to z$ i $y \to z$

Global properties of graphs are measured by metrics:

1. Total Nodes - the total number of vertices
2. Total Edges - the total number of edges
3. Average degree - average degree of vertices in graph
4. Diameter - diameter of the graph (the longest simple undirected path between vertices)
5. Average Path Length - the average length of a simple path
6. Average Local Clustering Coefficient - the average over the entire network of the local clustering coefficient defined above
7. (Weakly) Connected Components Count - number of coherent components
8. Density - measures how close the network is to complete graph. A complete graph has all possible edges and density equal to 1. It is the ratio of the number of edges to the number of edges to the corresponding complete graph.
9. Modularity - modularity as defined by Newman (see footnote in description of modularity class above), measures how well a network decomposes into modular communities, high modularity score indicates sophisticated internal structure

3.2 Methods for predicting the dynamics of local changes and visualization of predicted layers in time

The user has the possibility to analyze the time behavior of selected indicators (from the list given previously) both for the whole social network and individual nodes.

The source of this dynamics are appearing and / or disappearing edges in the graph of social network in subsequent time intervals. The system has two main perspectives of these processes:

- edge exists in the graph in a given time interval, if it was in the source data in the graph at any point in time in the past

- edge exists in the graph in a given time interval, if it was in the source data in the graph at any point in time in the time interval

Naturally in the first variant the edges do not disappear.

To enable the user to predict future behavior of indicators in the time points, we incorporated the standard time series analysis software proposed in [36] (with the possibility to choose a learning algorithm as a basis for prediction).

Learning algorithms are available from the implementation of Weka 3.7.5 described in [36].

- SVM (support vector machine)
- Multilayer Perceptron
- Gaussian Process
- Linear Regression

Prediction needs training data with at least two different values. The prediction horizon is restricted by the number of observations in a learning sample.

3.3 Methods for visualization of dynamics in social networks

The developed tool allows to model the variability in the time of social networks. With the methods of time series analysis there can be visualized the "stability" and anomalies in the behavior of individuals and / or groups as well - for anomalies - looking for these predictors.

In subsequent moments of time for each vertex in social graph we create a time series for a particular indicator. On this basis, we predict what will happen in time $(t + 1)$, for example, one can ask if there is increase in the number of edges, if the number of connections between neighbours gets concentrated, if there is increase of centrality of a node, etc.

On the basis of the analysis mentioned earlier and taking into account the expected values of certain predictors, we can construct a graph prediction at the time $(t + 1)$. This graph can be used e.g. for recommendations or search (for more details see [34]).

In BEATCA system the node of the graph is viewed also as a textual document. One of the features of BEATCA is that text documents can be clustered into co called document map using WebSOM like methods [32]. Therefore the user can view the local changes around the node in graph in time and watch changes of the map of documents in time.

3.4 Methods of visualization of the answer to the question in the social network

The system can search information on social network in the mapping search. There were used known algorithms for visualization (WebSOM) of static and dynamic graphs (with the possibility of visualization hierarchically grouped social networks, statically and dynamically) based on earlier experience of our team with implementation of BEATCA system.

The possibility to use queries are extended with elements related to the structure of the relationship, e.g. the question of the nodes satisfying the conditions imposed on their local graph properties such as centrality. We can specify the point in time in which the value is obtained. So we can issue a query where we want to find nodes with degree 2 within time interval (1999-01-01,1999-07-01)

```
~degree=2 ~time=[1999-01-01 00:00:00, 1999-07-01 00:00:00]
```

We can combine graph features with textual one, e.g. looking for nodes with PageRank over 0.001 at any point in time containing the word "Susan"

```
Susan ~pageranks>0.001
```

We can refer to average values of node features with textual one, e.g. looking for nodes with Average Path Length over 3.4 containing the word "Mark" in third quarter of 1997

```
Mark ~"Average Path Length">3.4 ~time-label=1997Q3
```

Visualization response includes: maps of documents, HTML presentation of the description of the node, a graphical representation of a node in the graph surrounding network and a graphical representation of the time series of coefficients associated with the node.

Designed methods were implemented in the interface, as described in the next section.

3.5 Design and implementation of the user interface

The graphical interface allows the user to choose social network, to which queries will be directed and to formulate queries and view the results in the form of:

- list of nodes
- map of nodes

The user can navigate both the list and the map of nodes. He can also preview the global social network graph properties (average and over time, and predictions).

When user selected node in the list, he has the possibility to:

- see a text description of the node
- view the local properties of graph node
- see the changes of these properties in time
- see predicted changes in the future
- view its graph surroundings and changes of the environment in time
- navigate to the nodes surroundings in graph

Formulation of queries can include:

- text features of node (textual information)
- average local properties of node features
- local properties at selected time intervals

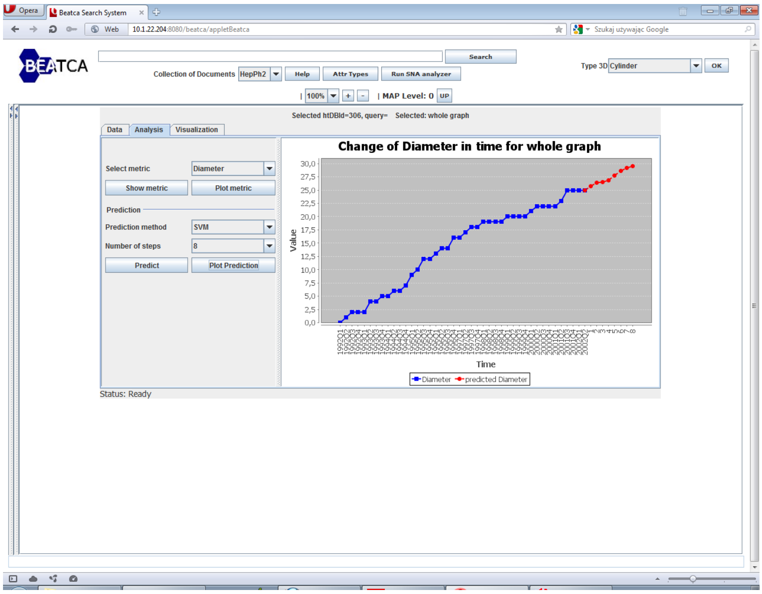

FIGURE 1: Example of usage of the "Analysis" tab to display textual dynamics of graph representing the diameter of the analyzed network.

The system allows for visualization and analysis of data, in particular the dynamic aspects of data as a graph of the social networks.

The interface of this subsystem consists of three tabs for the different aspects of the functionality of the system:

- "Data" - allows the user to select a data set to be analyzed
- "Analysis" - (see fig. 1) groups the user interface elements that allows to:
  - detailed control over analysis of the data
  - choose from a large range of attributes available for the analysis of the data
  - control of the analysis process of the network dynamics or the selected aspect
- "Visualization" - allows the user to interactively visualize respectively selected section of the data set as a graph.

The order of mentioning these tabs corresponds to one possible scenario of the sequence of operations by the user during inspection of the data, but of course the system can handle any other order selected by the user. In particular, it is possible to repeatedly switch between tabs to modify the entered parameters.

It is required to choose a data set for analysis before any other operations. While working with the system, user can select a different data set for analysis, etc.

4 Experiments

A number of experiments for prediction of future properties of social networks have been performed to verify the usefulness of the implemented predictive algorithms.

We performed experiments on prediction of the global graph properties described in section 3.1. It turned out, however, that only for a part of them reasonable results were obtained, that is for average clustering coefficient, connected component count, average path length, graph density and diameter. Only for these ones we will report the results.

We applied Weka's time series framework for the purpose of prediction of these properties. This framework differs from classical statistical techniques such as ARMA and ARIMA, because it uses standard machine learning algorithms trained on data from which the time factor was removed. The trained models are then applied in such way that the past values are used as predictors and the future value is the predicted one. The advantage of this approach lies in the possibility to use any learning algorithm and features not only belonging to the time series of the predicted index. It is claimed (see [36]) that such an approach may be even more effective than classical statistical methods.

In this study, as a learning algorithm for time series analysis we used the following algorithms: SVM (support vector machine), linear model, multilayer perceptron and Gaussian process.

A bad property that we need to live with is that the used prediction algorithms require at least two different points in the learning sample. Whenever this requirement is violated, they do not return any value, which is represented by the value -1, because value -1 is not possible to obtain from the absolute or relative error.

The usefulness of an algorithm is reciprocal to the error it makes when predicting future values.

We considered relative and absolute prediction errors.

The absolute error of prediction was calculated using the formula:

$$error_A = \sqrt{\sum_{i=1}^{k}(realValue_i - predictedValue_i)^2} \tag{1}$$

where k means the number of steps predicted ahead.

Calculation of the relative error was done as follows:

$$error_R = \sqrt{\frac{\sum_{i=1}^{k}(realValue_i - predictedValue_i)^2}{\sum_{i=1}^{k}(realValue_i)^2}} \tag{2}$$

where k is the number of steps predicted ahead.

4.1 Preparation of experimental data

The experimental work used three datasets :

- set "CitePh" - citations in physics papers
- set "Autonomous" - network of routers
- set "Enron" - email correspondence in Enron company

4.1.1 CitePh dataset

The dataset was downloaded from the web page: `http://snap.stanford.edu/data/cit-HepPh.html`. It is a graph describing the citations between scientific publications, for example, if paper A quotes B then there is an edge from A to B.

The original dataset was processed according to the following rules:

- Remove vertices (together with incident edges) whose date of creation can not be determined
- Remove the edges, where A is published earlier than B and A quotes B

In this way, we obtain a set in which papers (vertices) that appeared later cite papers that have been published previously.

Graph contains 37,622 nodes and 345,375 edges. This is a directed graph with no multiple edges. Neither vertices nor edges contain text data.

The network is divided into 42 time slices (each lasting one quarter), from Q1 1992 to Q2 2002 inclusive.

4.1.2 Autonomous dataset

The dataset was downloaded from the web page: `http://snap.stanford.edu/data/as.html`. This is a communication network between routers on the Internet.

Graph contains 7716 vertices and 11,965,534 edges. This is the undirected graph, there may be multiple edges. Both vertices and edges do not contain text data.

The network was divided into 785 one-day intervals, from 8 November 1997 to 2 January 2000.

4.1.3 Enron dataset

Database is available on the web page: `http://www.isi.edu/~adibi/Enron/Enron.htm` as well as `http://www-2.cs.cmu.edu/~enron/`.

The data were collected as a part of the so-called project CALO (Cognitive Assistant that Learns and Organizes). It contains information about users of Enron who sent about 500,000 messages.

Database created from this set includes 75,542 nodes connected by 431,573 edges.

The database is divided into 16 quarters. Each quarter has the same number of vertices, thus prediction of number of vertices is not possible. Moreover, in the last quarter (16) there are very few edges.

4.1.4 Database statistics

Basic statistics of databases are presented in table 1.

4.2 Experimental results

Let us present in this section a couple of results out of a large set we obtained that we think are of particular interest. Detailed results are presented in Appendix: for

Table 1: Basic statistics of databases

database	Enron	CitePh	Autonomous
number of time slices	16 quarters	42 quarters	785 days
number of all nodes	75542	37621	7716
number of all edges	431573	4708242	11939066

database Enron in tables 6, 4, 3, 5, 2, for database CitePh in tables 9, 7, 10, 11, 8 and for database Autonomous in tables 14, 12, 15, 16, 13. Results encompass: absolute errors calculated from equation (1) and relative ones form equation (2). Prediction model needs at least two different points, so prediction error in 1 step ahead starts from time slice 3: we have 2 observed values to build model (we will call it *learning sample*) and predict value for next (third) time slice and so on. Cases of 2 and steps ahead predictions are reported accordingly.

Subsequently we will use the following abbreviations for names of learning algorithms in prediction methods: SVM (Suport Vector Machine), MLP (Multilayer Perceptron), GP (Gaussian process) and LR (Linear Regression).

It turned out that not all global properties can be predicted by the methodologies used. Therefore only results for the following metrics are presented: *Average Clustering Coefficient* (see tables 6, 9, 14), *Average Path Length* (see tables 4, 7,12), *Connected Component Count* (see tables 3, 10, 15), *Density* (see tables 5, 11, 16) and *Diameter* (see tables 2, 8, 13).

Enron database was divided into 16 quarters. Each quarter has the same number of vertices.Moreover, in the last quarters (14,15,16) number of edges is getting smaller very fast, causing enormous errors in the prediction for those quarters. In the plots of absolute errors for *Density* (figure 2, 3, 4) where 1, 2, 3 step ahead prediction was applied resp., we see that the absolute error increases with increasing learning sample, while the relative error (figure 5) 1 step ahead is small except for the last unusual quarters. Unusuality of the graph in the last quarters reflects negatively on the quality of prediction when we forecast more than one step ahead. The best learning algorithm for time series turned out to be a *Gaussian process*, which was the most resistant to last unusual quarters. For numerical values of relative prediction errors and the value of attribute Density see table 5. In table 3 we can see a similar pattern for prediction of *Connected Components Count*. Here the best prediction was for *Multilayer Perceptron*. Time series method for prediction was much better for predicting *Diameter* (table 2), *Connected Component Count* (table 3) and *Average Path Length* (table 4). Here even for the unusual quarters error was not so huge but for *Diameter* it is over 100 %.

CitePh database contains 42 time slices in which both the number of edges and vertices are changing. Figure 8 shows a comparison of the relative error of prediction for the attribute *Average Path Length* predicted with learning algorithm SVM (see table 7). Prediction error here is big in first part and gets smaller later (after 25 time slice). From 25 elements in the learning sample error is stabilizing and very small about 3%. Errors of prediction 1, 2 and 3 steps ahead are similar. Figure 7 shows a comparison of the relative error of prediction for the attribute *Average Clustering Coefficient* (see table 9). Early prediction error is very high

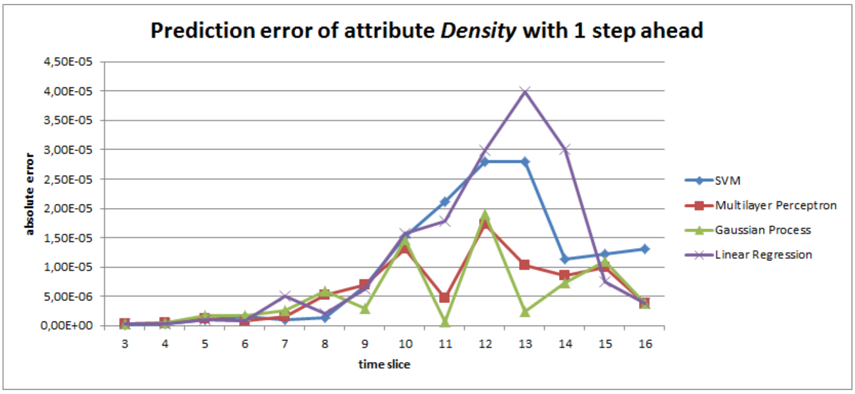

FIGURE 2: Absolute prediction error for 1 step ahead for the attribute Density in Enron database

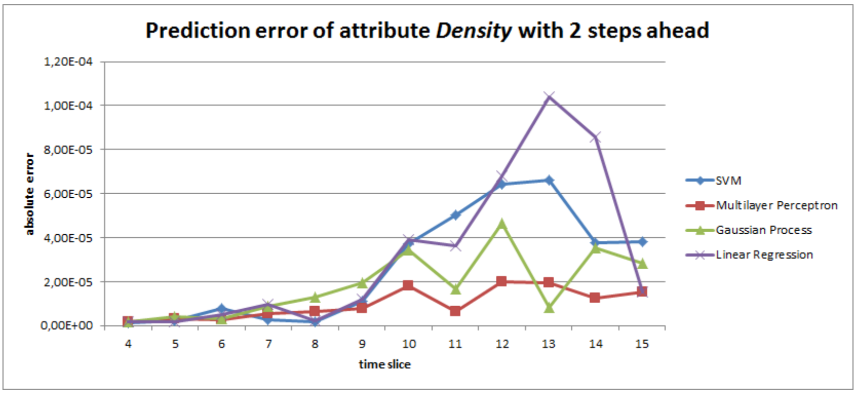

FIGURE 3: Absolute prediction error for 2 steps ahead for the attribute Density in Enron database

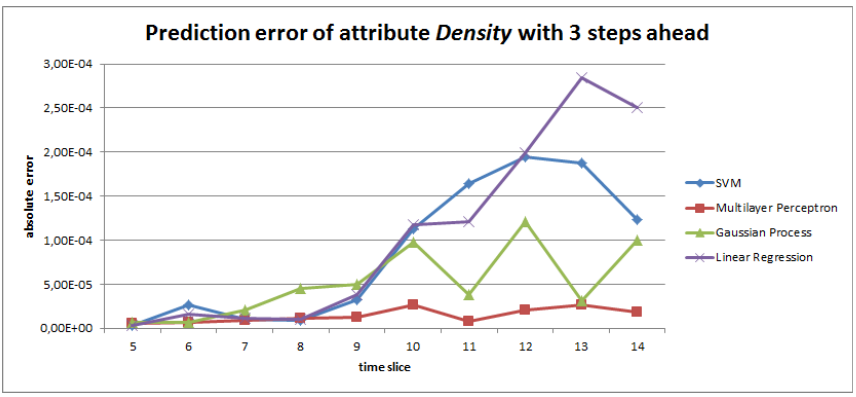

FIGURE 4: Absolute prediction error for 3 steps ahead for the attribute Density in Enron database

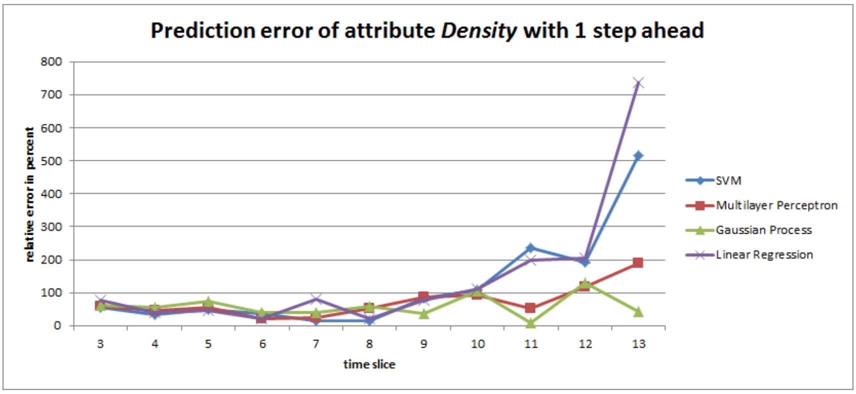

FIGURE 5: Relative prediction error in percent for 1 step ahead for the attribute Density in Enron database

above 100% for 2,3 steps ahead and at 20 elements in the learning sample is small up to 4%. Here we can see clearly that the number of steps in increasing the forward prediction becomes worse, in contrast to prediction of attribute *Average Path Length*. Moreover smaller increase in prediction for 1 step ahead causes much worse prediction error for 2 and 3 steps ahead. In those 2 cases SVM and MLP prediction are the best, when we predict more steps ahead GP is getting much worse than SVM and MLP. LR prediction is 30-50% from 20th time slice. We got similar results for other metrics *Connected Component Count* (table 10), *Density* (table 11) and *Diameter* (table 8), but for the first one SVM, MLP and GP does not differ so much.

Autonomous database contains 785 time slices, but for analysis several initial ones were selected. For the rest of the time series the results are comparable except for the time slices where no activity was registered and hence the graphs contain no edges. The number of vertices in time does not change. In figure 6 we see prediction results of attribute *Density* when SVM is used as learning algorithm for the time series. Relative prediction error is small, about 5%. With the increase in the number of observations in the training set error gradually decreases and stabilizes. Surprisingly all methods were working quite well, even the least advanced LR. Similar results we get for other metrics *Average Clustering Coefficient* (table 14), *Average Path Length* (table 12), *Connected Component Count* (table 15), and *Diameter* (table 13). Note that unusual table 13 for metric *Diameter* starts from time slice 22, because learning algorithm needs at least two different values and up to slice 19 time real value of metric was 9 and for time slice it was 10, so prediction form time slice 22 was possible.

5 Summary

This paper presented a framework for inspection of the dynamics of social networks. Its particular feature is the possibility to predict the development of some structural features of the network over time.

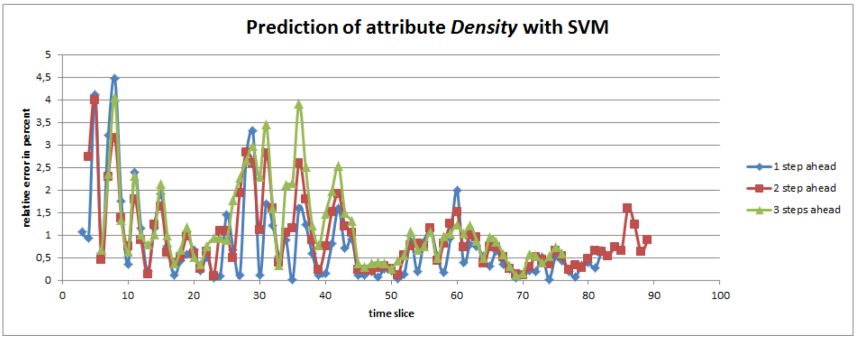

FIGURE 6: Comparison of the relative error in percent of prediction for the attribute **Density** of database Autonomous

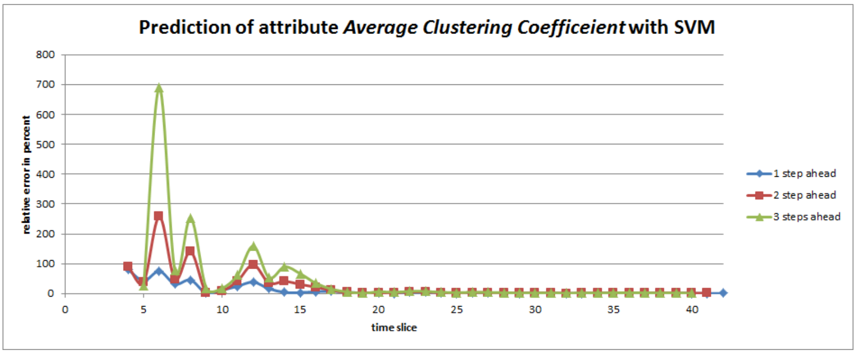

FIGURE 7: Comparison of the relative error in percent of prediction for the attribute **Average Clustering Coefficient** of database CitePh

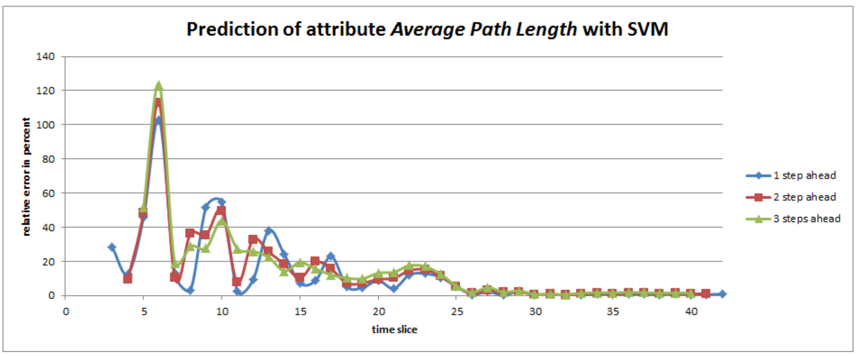

FIGURE 8: Comparison of the relative error in percent of prediction for the attribute **Average Path Length** of database CitePh

In this paper we evaluated the capability to predict the properties of social networks described in section 3.1 for three well-known dynamic social network databases, listed in section 4.1. The prediction is based on the Weka time series analysis framework, capable of exploiting machine learning algorithms for prediction of future attribute values. We compared 4 learning algorithms: support vector machine (SVM), linear model (LR), multilayer perceptron (MLP) and Gaussian process (GP).

It turned out that the best prediction (smallest error) was obtained for attributes *Average Clustering Coefficient*, *Average Path Length*, *Connected Components Count*, *Diameter* and *Density* for databases CitePh and Autonomous..

The best performing learning algorithm for time series prediction (for all the investigated databases) turned out to be SVM and MLP. Surprisingly prediction was quite with linear regression algorithm for database Autonomous. Learning using Gaussian process was characterized by the biggest error in the initial phase and rarely a little better than the MLP or SVM algorithm.

For databases Autonomous and CitePh, which have more time slices than Enron, prediction errors decreased up to overfitting the model. Unfortunately, sudden disturbances (no edge in some intervals) resulted in a dramatic increase in the prediction error.

Our approach to take measurements only from graphs existing in given time interval and not cumulated to given time point gave us interesting results. It was expected that with the increasing number of predicted steps prediction error will decrease, but as it has turned out, in the presented example of database Enron is not always true.

From experimental results of prediction 3 steps forward it can be seen that, with sufficient number of observations in the learning sample, the method of prediction using time series is doing quite well.

Due to the limitations of linear regression learning algorithm, as it has turned out in experiments, it is not recommended to use this one. General remark of our approach is that it could be expected that finding a constant trend should be easy. However, the disadvantage of the prediction algorithm is that at least two point values in the sample have to be different. For all learning algorithms this limitation from the Weka package seems strange.

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Appendix

TABLE 2: Metric real value vs relative prediction error (in percent) for 1, 2 and 3 steps ahead of metric **Diameter** of database Enron for consecutive time slices. Notation: number in title is number of steps ahead. Shortcuts: TS (time slice), RV (real value), SVM (Suport Vector Machine), MLP (Multilayer Perceptron), GP (Gaussian process) and LR (Linear Regression)

TS	RV	SVM 1	MLP 1	GP 1	LR 1	SVM 2	MLP 2	GP 2	LR 2	SVM 3	MLP 3	GP 3	LR 3
3	9	7.43	4.8	4.87	38.89	-	-	-	-	-	-	-	-
4	13	24.82	30.94	32.18	33.87	20.39	26.88	30.47	33.73	-	-	-	-
5	11	7.27	4.87	27.82	15.63	35.40	31.94	19.08	29.40	53.17	36.18	20.16	41.60
6	12	58.85	57.58	9.66	58.83	78.99	58.55	17.14	75.35	119.84	67.85	43.08	115.20
7	12	4.18	1.61	2.91	11.71	5.31	10.87	16.27	20.91	9.66	8.87	13.10	18.96
8	11	14.17	4.1	19.54	9.32	12.85	29.87	17.03	18.98	21.43	27.34	16.34	18.90
9	12	33.44	26.57	34.04	23.5	24.01	24.24	26.48	16.86	27.41	22.15	24.22	27.65
10	12	47.61	23.15	15.27	47.09	87.97	37.73	43.26	89.88	100.08	34.25	51.56	102.11
11	10	35.68	15.86	35.33	37.1	24.27	25.12	29.73	24.96	22.19	42.25	24.36	26.63
12	11	38.43	0.44	1.31	55.88	60.05	21.75	18.38	87.91	52.03	44.73	18.80	79.58
13	11	20.01	14.03	16.34	19.47	51.45	47.91	28.49	59.71	89.57	93.55	64.42	104.12
14	9	103.69	50.45	59.28	108.9	172.13	99.04	125.09	183.10	248.59	155.79	199.03	260.64
15	4	35.56	106.99	152.52	86.66	92.46	155.27	271.78	106.10	-	-	-	-
16	1	251.53	337.24	535.3	145.88	-	-	-	-	-	-	-	-

Table 3: Relative prediction error (in percent) for 1, 2 and 3 steps ahead of metric **Connected Components Count** of database Enron. Notation: number in title is number of steps ahead. Shortcuts: TS (time slice), RV (real value), SVM (Suport Vector Machine), MLP (Multilayer Perceptron), GP (Gaussian process) and LR (Linear Regression)

TS	RV	SVM 1	MLP 1	GP 1	LR 1	SVM 2	MLP 2	GP 2	LR 2	SVM 3	MLP 3	GP 3	LR 3
3	74357	0.76	1.15	0.85	1.13	-	-	-	-	-	-	-	-
4	72603	2.06	2.67	2.22	2.07	4.53	5.35	4.89	4.85	-	-	-	-
5	69524	3.92	5.95	4.23	5.59	3.65	7.47	4.08	6.43	4.24	10.12	4.98	8.06
6	67711	5.85	4.74	2.72	5.33	11.09	7.81	7.25	10.43	17.44	14.34	12.18	16.78
7	64368	4.06	11.42	1.53	4.07	13.57	19.11	4.80	13.63	15.53	18.26	5.60	15.54
8	57026	7.83	14.81	7.65	24.99	7.37	11.09	8.03	20.55	7.28	16.45	7.73	26.07
9	61567	22.09	6.34	15.06	25.15	30.85	17.20	18.90	32.42	53.36	15.57	37.99	50.07
10	52151	26.52	23.96	16.70	28.06	32.12	17.74	12.08	34.30	61.88	20.56	18.16	66.14
11	58537	27.58	1.89	22.95	30.08	38.78	7.97	32.58	46.43	73.06	9.73	57.52	88.40
12	51324	21.37	27.27	11.88	26.32	22.38	16.89	7.71	27.50	33.48	14.83	5.77	38.17
13	65108	15.29	7.73	18.24	18.19	30.74	6.45	33.39	39.43	44.19	6.66	44.50	56.38
14	74029	12.54	32.04	12.34	15.57	10.43	32.68	8.64	12.20	15.95	32.92	8.31	12.98
15	75420	28.17	15.76	13.24	27.79	47.93	17.63	22.14	47.74	-	-	-	-
16	75540	10.50	2.41	2.56	28.31	-	-	-	-	-	-	-	-

Table 4: Relative prediction error (in percent) for 1, 2 and 3 steps ahead of metric **Average Path Length** of database Enron. Notation: number in title is number of steps ahead. Shortcuts: TS (time slice), RV (real value), SVM (Suport Vector Machine), MLP (Multilayer Perceptron), GP (Gaussian process) and LR (Linear Regression)

TS	RV	SVM 1	MLP 1	GP 1	LR 1	SVM 2	MLP 2	GP 2	LR 2	SVM 3	MLP 3	GP 3	LR 3
3	3.905	2.86	6.83	10.9	33.13	-	-	-	-	-	-	-	-
4	4.474	7.14	0.1	15.35	2.54	7.02	35.55	19.45	3.11	-	-	-	-
5	4.559	19.96	23.25	29.85	13.1	20.67	23	21.24	23.13	34.26	24.51	20.71	40.61
6	4.572	54.6	43.56	9.98	36.96	81.97	46.49	24.19	60.7	106.24	50.85	34.99	86.74
7	4.379	3.28	16.78	5.06	9.89	3.13	13.69	6.58	24.32	8.96	11.39	5.45	47.66
8	4.531	7.17	14.85	1.07	12.74	16.26	35.69	10.02	29.44	16.8	36.08	9.12	24.49
9	4.437	12	7.78	15.12	10.86	21.39	6.55	11.08	10.71	30.59	6.07	11.96	11.18
10	4.422	42.77	18.18	15.15	39.5	52.25	26.24	20.66	50.57	57.91	30.21	27.58	57.44
11	4.496	4.2	7.13	3.44	10.81	6.22	9.31	7.03	18.71	14.76	25.84	6.62	32.25
12	4.422	0.36	0.08	7.55	13.68	10.62	21.77	7.77	37.35	20.22	20.91	18.22	32.53
13	4.531	15.34	15.67	14.03	12.2	23.21	14.56	19.51	30.91	56.19	36.78	49.74	65.46
14	3.569	59.34	29.29	45.24	69.79	117.34	68.57	98.22	127.43	171.84	111.38	151.31	180.52
15	1.977	57.84	35.93	97.98	52.12	93.24	32.68	154.04	71.28	-	-	-	-
16	1	37.28	48.23	137.51	153.58	-	-	-	-	-	-	-	-

TABLE 5: Relative prediction error (in percent) for 1, 2 and 3 steps ahead of metric **Density** of database Enron. Notation: number in title is number of steps ahead. Shortcuts: TS (time slice), RV (real value), SVM (Suport Vector Machine), MLP (Multilayer Perceptron), GP (Gaussian process) and LR (Linear Regression)

TS	RV	SVM 1	MLP 1	GP 1	LR 1	SVM 2	MLP 2	GP 2	LR 2	SVM 3	MLP 3	GP 3	LR 3
3	4.00E-07	56.70	58.39	61.98	76.56	-	-	-	-	-	-	-	-
4	9.02E-07	34.91	45.24	54.56	40.34	61.33	73.20	79.52	67.68	-	-	-	-
5	2.28E-06	47.75	54.12	75.06	46.06	48.44	68.30	83.68	41.35	45.39	76.76	84.71	35.83
6	4.28E-06	36.21	19.74	39.61	20.80	100.96	37.50	41.41	63.67	208.65	52.25	54.82	126.85
7	6.39E-06	15.30	25.26	41.14	79.02	21.96	48.29	73.15	84.25	70.84	62.36	144.93	83.99
8	9.83E-06	14.79	53.34	59.52	20.72	14.00	49.75	103.47	17.52	46.96	59.82	237.95	55.75
9	8.09E-06	83.89	86.27	36.23	77.77	70.37	47.98	119.87	76.20	178.70	66.74	270.10	205.96
10	1.39E-05	108.57	93.78	104.87	112.25	225.90	110.76	209.11	235.88	513.35	119.00	445.96	534.85
11	8.89E-06	236.75	53.05	7.71	199.61	295.92	39.23	98.74	214.06	920.39	44.30	214.62	681.46
12	1.45E-05	193.12	118.63	130.71	206.06	414.49	130.16	301.34	439.77	1259.74	134.81	784.87	1290.00
13	5.40E-06	517.13	190.54	43.59	738.03	1222.23	360.03	152.20	1915.67	3450.26	489.80	576.12	5253.48
14	5.05E-07	2232.95	1699.92	1444.70	5957.09	7435.59	2484.79	6988.38	16959.04	24264.05	3621.83	19836.88	49426.22
15	4.36E-08	28033.22	22856.47	25111.54	17168.75	87887.27	35200.03	64978.39	35355.88	-	-	-	-
16	3.50E-10	3753948.73	1083707.12	1077747.29	1095736.97	-	-	-	-	-	-	-	-

TABLE 6: Relative prediction error (in percent) for 1, 2 and 3 steps ahead of metric **Average Clustering Coefficient** of database Enron. Notation: number in title is number of steps ahead. Shortcuts: TS (time slice), RV (real value), SVM (Suport Vector Machine), MLP (Multilayer Perceptron), GP (Gaussian process) and LR (Linear Regression). Last row (for real value 0) presents predicted values.

TS	RV	SVM 1	MLP 1	GP 1	LR 1	SVM 2	MLP 2	GP 2	LR 2	SVM 3	MLP 3	GP 3	LR 3
3	5.09E-03	82.31	82.41	82.62	83.46	-	-	-	-	-	-	-	-
4	5.34E-03	806.57	45.76	330.08	287.43	4553.60	28.22	881.01	662.52	-	-	-	-
5	9.76E-03	232.85	112.13	322.28	137.07	222.16	108.90	298.97	136.89	217.11	83.10	494.22	89.81
6	1.40E-02	509.76	22.82	140.76	68.81	497.30	21.83	121.46	77.11	664.60	37.10	152.34	82.57
7	2.21E-02	179.07	107.12	510.23	7.48	187.56	106.02	523.35	8.47	295.03	106.31	752.75	8.25
8	3.15E-02	32.96	69.99	492.84	17.56	29.80	72.63	581.97	13.12	39.82	76.66	869.18	13.94
9	3.45E-02	158.70	49.43	587.49	27.68	169.77	35.59	631.33	38.70	360.78	56.54	1141.30	111.77
10	4.38E-02	289.61	64.70	718.27	613.70	370.63	60.96	1007.10	853.16	614.17	64.44	1647.10	1357.21
11	2.57E-02	381.24	35.14	1202.81	93.09	348.02	53.93	1256.25	64.85	613.90	62.15	2340.49	94.44
12	3.57E-02	1910.05	156.09	1229.44	2112.61	2877.93	169.89	1870.78	3160.02	5344.26	179.39	3594.65	5832.14
13	1.60E-02	5951.63	339.53	162.87	5883.05	9683.50	476.45	236.36	10021.93	17431.70	606.68	351.56	17601.65
14	2.80E-03	29439.30	302.31	8827.23	64692.01	45515.57	509.68	15094.99	94628.77	83185.29	514.22	29062.00	154686.18
15	1.86E-04	284358.56	6634.57	16094.07	828268.46	383162.75	10034.51	22755.04	1204807.77	-	-	-	-
16	0	1.95E-02	5.43E-03	7.66E-03	1.46E-02	-	-	-	-	-	-	-	-

TABLE 7: Relative prediction error (in percent) for 1, 2 and 3 steps ahead of metric **Average Path Length** of database CitePh. Notation: number in title is number of steps ahead. Shortcuts: TS (time slice), RV (real value), SVM (Suport Vector Machine), MLP (Multilayer Perceptron), GP (Gaussian process) and LR (Linear Regression)

TS	RV	SVM 1	MLP 1	GP 1	LR 1	SVM 2	MLP 2	GP 2	LR 2	SVM 3	MLP 3	GP 3	LR 3
3	1.039	28.33	19.66	7.03	51.89	-	-	-	-	-	-	-	-
4	1.062	12.75	7.70	1.30	20.71	9.56	6.15	13.54	62.09	-	-	-	-
5	1.083	45.64	55.89	45.62	91.78	48.45	57.22	34.81	62.94	51.38	51.27	31.86	49.74
6	1.150	103.07	68.40	36.66	189.16	112.69	51.30	40.92	250.51	123.60	47.18	44.52	322.05
7	1.231	12.86	13.60	6.09	65.28	10.56	9.17	5.58	131.54	19.07	22.58	12.54	193.23
8	1.352	3.10	10.11	4.26	0.42	36.24	34.01	24.45	41.17	29.02	28.52	19.11	33.18
9	1.461	51.80	23.02	37.15	52.94	35.38	18.77	25.48	40.88	27.70	19.79	20.41	43.27
10	1.593	54.67	22.60	8.34	115.53	49.69	23.36	8.42	154.01	43.91	19.92	7.48	186.00
11	1.724	2.81	3.37	6.76	9.91	7.59	7.56	8.74	16.65	27.44	24.28	20.55	19.50
12	1.918	9.15	15.44	12.19	1.24	32.82	41.88	26.49	41.34	25.93	32.83	24.55	32.46
13	2.180	38.14	44.30	33.42	54.66	25.56	29.32	27.48	37.32	22.39	29.51	26.63	28.69
14	2.515	24.11	3.54	11.09	28.87	18.37	10.02	13.03	22.39	14.40	12.17	14.34	20.60
15	2.841	7.37	3.75	17.85	18.87	10.24	5.66	19.40	14.85	19.39	14.34	23.73	21.68
16	3.163	8.76	10.88	15.87	18.14	19.77	24.24	21.69	26.54	15.62	21.83	19.74	21.58
17	3.435	23.00	16.43	21.81	27.89	15.54	15.63	17.34	18.99	12.13	16.82	15.63	15.43
18	3.747	5.26	2.73	5.02	4.34	7.25	5.01	4.92	4.15	10.28	6.92	4.21	8.00
19	4.090	4.68	3.30	5.58	0.43	7.30	2.28	4.91	1.81	9.88	1.82	6.12	4.30
20	4.346	8.84	0.30	4.48	4.87	9.67	0.94	7.14	8.04	13.19	0.77	5.74	12.90
21	4.535	4.11	3.77	9.73	4.30	10.21	6.00	6.94	3.29	13.73	5.71	5.56	4.16
22	4.745	12.17	6.68	0.03	2.47	14.74	5.38	1.90	4.68	17.59	4.92	3.27	4.43
23	4.911	12.90	2.74	0.19	0.37	15.19	3.58	1.09	2.87	17.07	5.15	1.95	5.78
24	5.037	10.72	0.91	0.73	7.08	11.39	1.53	4.45	8.37	12.56	1.31	3.87	6.89
25	5.129	5.33	4.30	7.77	4.35	5.29	5.04	6.28	4.22	5.54	4.19	5.80	9.95
26	5.256	0.70	0.82	1.62	15.39	1.27	0.63	1.51	28.80	1.79	0.93	1.26	30.32
27	5.372	2.35	1.17	1.69	49.49	3.07	1.73	1.36	49.81	4.82	2.17	3.08	50.13
28	5.440	0.26	3.43	1.03	48.31	1.89	2.53	3.84	48.64	2.00	2.64	3.12	48.92
29	5.508	2.52	2.31	5.83	47.24	2.25	1.63	4.15	47.52	2.79	4.40	3.51	47.77
30	5.565	0.46	2.15	1.11	46.18	0.61	2.62	2.91	46.42	0.75	2.80	4.95	46.62
31	5.615	0.75	3.38	2.59	11.09	0.95	2.42	4.48	14.12	0.86	2.47	4.68	18.14
32	5.653	0.34	3.45	3.76	20.15	0.26	4.13	3.17	25.39	0.66	4.46	6.31	30.86
33	5.683	0.39	0.93	0.25	23.80	0.89	1.09	4.78	28.72	1.48	0.98	8.07	34.39
34	5.714	0.87	2.85	6.04	26.37	1.34	2.55	9.03	31.66	1.70	2.37	12.13	37.67
35	5.748	0.91	2.95	7.73	41.11	1.18	2.80	10.45	41.28	1.69	2.81	11.66	41.37
36	5.781	0.76	0.06	8.40	40.28	1.31	0.18	8.59	40.33	1.82	0.24	12.19	40.41
37	5.791	0.86	2.08	4.19	39.26	1.28	1.47	9.06	39.36	1.78	1.23	13.17	39.42
38	5.809	0.70	0.90	9.52	0.90	1.18	1.04	13.10	0.81	1.42	0.90	16.62	0.75
39	5.817	1.22	1.67	11.01	1.08	1.39	1.50	14.07	1.58	1.62	2.07	15.58	2.34
40	5.842	0.69	0.67	11.11	3.85	1.02	0.70	11.57	4.39	1.43	0.58	15.38	5.10
41	5.847	0.65	0.76	6.39	14.25	1.19	0.54	11.45	22.26	-	-	-	-
42	5.847	0.83	0.59	11.45	1.96	-	-	-	-	-	-	-	-

TABLE 8: Relative prediction error (in percent) for 1, 2 and 3 steps ahead of metric **Diameter** of database CitePh. Notation: number in title is number of steps ahead. Shortcuts: TS (time slice), RV (real value), SVM (Suport Vector Machine), MLP (Multilayer Perceptron), GP (Gaussian process) and LR (Linear Regression)

TS	RV	SVM 1	MLP 1	GP 1	LR 1	SVM 2	MLP 2	GP 2	LR 2	SVM 3	MLP 3	GP 3	LR 3
3	2	33.32	37.82	44.39	75.00	-	-	-	-	-	-	-	-
4	2	18.19	14.86	7.67	50.00	27.53	55.39	13.88	79.06	-	-	-	-
5	2	40.19	50.01	55.52	82.59	37.24	36.86	55.21	67.35	27.78	29.59	44.39	55.96
6	4	1.51	19.10	41.64	5.11	30.36	17.91	31.61	22.93	32.29	25.44	28.64	21.80
7	4	50.39	28.34	3.97	47.15	49.49	19.37	14.71	42.95	63.98	18.33	14.31	52.72
8	5	37.24	34.44	42.27	44.90	38.37	35.90	46.87	49.42	36.74	39.93	45.14	47.51
9	5	24.49	34.35	30.27	26.61	23.00	27.08	29.80	24.89	29.75	28.72	27.90	31.42
10	6	11.14	1.08	25.79	17.61	8.07	4.66	24.55	12.72	10.62	4.83	26.02	9.91
11	6	18.20	3.55	25.02	28.37	23.92	3.59	30.09	37.91	18.98	29.67	48.92	29.39
12	7	8.55	5.65	30.66	3.21	36.76	26.87	53.06	33.96	36.41	27.24	58.27	31.53
13	9	30.69	40.58	51.31	36.74	27.08	39.43	53.10	31.35	30.68	43.60	58.71	35.49
14	10	31.97	17.68	26.31	30.40	29.34	11.33	32.74	24.27	41.73	9.45	31.52	33.58
15	12	23.96	27.35	42.52	25.20	16.97	20.78	40.88	17.97	13.57	17.99	44.27	14.30
16	12	32.14	19.53	8.44	30.20	30.27	14.79	16.88	28.58	29.86	11.71	22.20	28.34
17	13	9.83	4.85	20.92	16.25	17.58	9.62	27.26	37.48	14.66	7.88	27.70	32.27
18	14	10.17	5.02	22.56	22.78	11.43	7.28	19.64	25.88	10.43	11.71	25.11	30.61
19	14	18.54	2.58	2.51	52.05	12.31	10.82	10.92	37.54	12.89	19.74	12.45	50.10
20	16	6.16	8.61	16.43	57.89	5.24	8.33	17.64	57.89	5.94	8.38	17.33	58.80
21	16	10.68	1.69	10.90	55.00	10.76	4.08	9.72	56.42	11.39	17.03	9.37	57.78
22	17	4.91	4.18	4.98	55.18	6.68	11.73	4.97	56.51	12.23	9.54	4.26	56.92
23	18	3.32	6.73	4.72	55.30	10.77	5.07	3.91	55.30	8.80	9.92	9.01	56.16
24	18	10.76	10.49	1.91	52.90	7.41	7.35	10.25	54.22	7.02	5.94	10.00	54.62
25	19	2.63	19.12	14.37	53.29	3.97	22.33	12.32	53.29	3.32	21.55	11.43	53.29
26	19	8.01	0.14	2.12	51.16	6.75	2.19	1.54	51.16	9.14	2.17	3.84	51.16
27	19	1.77	11.92	0.37	49.19	4.51	9.28	4.04	49.19	3.91	8.80	3.24	50.11
28	19	1.46	15.84	4.09	47.37	1.35	11.05	3.12	48.77	2.14	10.40	4.26	49.20
29	20	3.54	7.03	5.66	48.39	2.51	8.26	4.09	48.39	2.77	13.92	5.23	48.39
30	20	4.66	1.34	3.12	46.72	5.98	1.29	6.54	46.72	5.54	1.39	9.20	46.72
31	20	2.56	0.33	5.94	45.17	1.88	0.48	7.96	45.17	2.18	0.55	7.48	46.11
32	20	1.20	6.21	5.48	43.71	2.42	35.16	3.98	45.14	4.11	36.40	3.93	46.52
33	21	2.70	3.03	1.91	45.09	4.39	5.05	1.32	46.41	4.12	6.42	3.34	46.82
34	22	5.03	4.37	0.01	46.28	4.50	3.68	3.68	46.28	4.50	3.83	7.31	46.28
35	22	0.56	5.04	4.42	44.92	1.92	6.34	7.98	44.92	1.58	5.37	10.05	44.92
36	22	2.04	1.88	7.35	43.64	1.57	4.99	8.56	43.64	1.28	5.53	10.74	44.52
37	22	1.87	7.06	5.12	42.42	1.44	5.01	7.50	43.75	3.20	6.94	7.28	45.96
38	23	0.03	6.54	6.03	43.83	4.02	4.97	4.93	46.32	4.33	5.96	6.97	47.03
39	25	5.46	1.62	0.43	47.26	5.10	1.15	4.30	47.26	4.68	3.83	6.12	47.26
40	25	3.62	3.80	5.18	46.05	3.76	7.40	6.41	46.05	3.07	6.59	10.65	46.05
41	25	2.58	5.22	4.23	2.10	1.84	4.70	9.27	2.17	-	-	-	-
42	25	3.49	1.18	9.89	2.07	-	-	-	-	-	-	-	-

TABLE 9: Relative prediction error (in percent) for 1, 2 and 3 steps ahead of metric **Average Clustering Coefficient** of database CitePh. Notation: number in title is number of steps ahead. Shortcuts: TS (time slice), RV (real value), SVM (Suport Vector Machine), MLP (Multilayer Perceptron), GP (Gaussian process) and LR (Linear Regression)

TS	RV	SVM 1	MLP 1	GP 1	LR 1	SVM 2	MLP 2	GP 2	LR 2	SVM 3	MLP 3	GP 3	LR 3
4	0.0031	80.73	80.42	83.99	83.85	91.28	91.02	94.19	96.96	-	-	-	-
5	0.0105	43.15	58.11	64.39	69.85	39.47	72.91	71.33	77.29	26.51	78.32	70.09	76.75
6	0.0188	75.11	33.62	12.09	71.44	258.10	44.79	98.43	242.33	689.33	53.53	222.78	633.12
7	0.0239	31.98	21.24	4.71	261.00	48.09	41.12	14.59	228.45	76.80	57.43	30.44	1405.80
8	0.0304	45.29	51.85	69.73	73.25	140.79	60.24	181.41	76.08	254.35	66.18	306.45	79.45
9	0.0368	1.29	1.79	87.11	3.48	2.04	10.51	190.95	10.48	17.49	8.91	313.02	9.96
10	0.0471	11.65	28.41	66.91	1.07	8.57	28.52	139.47	37.88	17.87	31.89	225.93	79.77
11	0.0499	25.01	46.74	59.28	20.94	43.01	51.43	147.00	32.10	62.44	54.67	250.05	45.13
12	0.0561	38.44	43.24	87.86	41.30	96.83	47.56	214.32	110.31	158.97	51.06	354.16	185.13
13	0.0622	16.55	24.06	87.93	22.64	35.57	34.69	188.65	40.52	53.59	41.70	306.95	53.02
14	0.0696	4.36	80.34	61.25	13.07	41.30	91.81	132.74	82.40	89.84	95.27	214.51	168.76
15	0.0742	3.61	12.49	71.23	1.47	30.93	14.75	167.69	74.53	66.64	17.12	284.06	170.79
16	0.0787	6.50	18.84	76.97	12.56	21.88	38.47	187.56	42.70	34.74	46.16	315.01	71.87
17	0.0829	8.14	80.19	52.06	5.89	11.01	133.21	76.00	7.09	15.09	154.49	99.89	9.96
18	0.0862	4.67	3.51	17.77	6.62	4.09	6.54	22.92	7.63	5.79	8.54	26.92	11.70
19	0.0909	2.28	5.77	15.57	8.07	1.59	12.94	17.85	9.82	1.28	18.85	21.85	11.83
20	0.0936	3.08	2.29	11.23	5.77	3.55	2.59	15.59	8.56	6.50	2.82	16.95	7.86
21	0.0966	0.58	6.22	13.95	52.61	2.51	9.83	13.99	53.22	4.45	15.33	13.76	53.71
22	0.0991	4.20	5.64	6.62	51.34	6.22	5.86	5.96	51.79	7.92	5.42	5.33	52.39
23	0.1009	4.92	3.58	3.18	49.93	5.78	3.24	2.75	50.61	7.59	3.45	2.69	50.94
24	0.1036	1.90	1.42	2.56	49.13	2.50	3.09	3.35	49.31	4.63	2.61	2.83	49.56
25	0.1043	0.62	14.54	4.58	47.45	2.75	27.81	3.22	47.75	3.33	23.08	3.33	48.18
26	0.1055	3.38	3.20	1.14	46.17	3.62	2.37	3.08	46.67	4.65	2.36	6.49	46.90
27	0.1075	2.34	0.14	1.89	45.41	3.65	4.28	5.22	45.51	4.50	4.75	6.68	45.68
28	0.1079	1.26	1.30	4.48	43.95	1.89	1.39	4.83	44.14	2.94	2.37	8.56	44.34
29	0.1087	0.65	8.22	0.95	42.77	1.55	6.59	5.68	42.98	2.18	6.27	9.32	43.24
30	0.1094	1.71	0.52	6.09	41.72	2.23	1.35	9.17	42.01	2.53	1.37	13.00	42.26
31	0.1105	1.47	3.95	6.75	40.92	1.64	3.62	10.23	41.14	2.09	2.98	12.33	41.32
32	0.1114	0.48	1.26	7.86	40.06	0.85	0.95	8.84	40.21	1.65	1.30	13.06	40.31
33	0.1119	0.39	2.87	4.10	39.11	1.10	2.04	9.20	39.19	1.97	1.70	13.84	39.30
34	0.1122	1.15	1.61	9.03	38.09	1.83	1.36	13.08	38.21	2.27	1.45	17.59	38.29
35	0.1127	1.76	1.34	10.15	37.22	2.21	1.62	14.23	37.28	2.77	1.60	16.85	37.35
36	0.1129	1.47	2.58	10.86	36.28	2.04	2.28	12.34	36.36	2.69	2.46	16.69	36.42
37	0.1132	1.11	1.69	6.67	35.44	1.75	1.47	11.81	35.48	2.79	1.39	16.75	35.47
38	0.1133	1.01	0.07	10.79	34.56	1.93	0.19	15.23	34.53	2.15	0.20	19.62	34.67
39	0.1132	1.76	1.95	11.88	33.58	1.77	1.88	15.75	33.81	2.01	1.90	18.32	33.89
40	0.1140	0.66	0.16	11.57	33.18	1.15	0.89	13.14	33.18	1.72	1.66	17.34	33.18
41	0.1140	0.70	0.01	7.37	0.55	1.06	0.24	12.37	0.86	-	-	-	-
42	0.1140	1.04	0.14	11.12	31.55	-	-	-	-	-	-	-	-

TABLE 10: Relative prediction error (in percent) for 1, 2 and 3 steps ahead of metric **Connected Components Count** of database CitePh. Notation: number in title is number of steps ahead. Shortcuts: TS (time slice), RV (real value), SVM (Suport Vector Machine), MLP (Multilayer Perceptron), GP (Gaussian process) and LR (Linear Regression)

TS	RV	SVM 1	MLP 1	GP 1	LR 1	SVM 2	MLP 2	GP 2	LR 2	SVM 3	MLP 3	GP 3	LR 3
3	419	41.43	85.34	50.05	73.87	-	-	-	-	-	-	-	-
4	718	27.99	62.09	45.13	2.29	30.81	68.40	55.17	12.33	-	-	-	-
5	908	24.45	37.86	57.96	51.58	15.41	44.92	56.43	42.65	20.76	50.15	48.97	33.49
6	1119	48.31	4.50	26.24	23.13	86.86	13.52	24.51	36.33	135.78	18.56	20.01	52.96
7	1292	12.62	21.89	36.64	4.85	27.18	25.50	51.45	8.76	46.80	30.11	71.38	17.29
8	1406	2.38	43.39	36.72	10.11	8.80	46.80	66.85	23.50	7.12	49.25	84.01	25.19
9	1544	9.95	77.32	57.53	10.16	8.12	78.06	72.93	8.52	15.11	78.93	85.39	15.98
10	1644	31.04	13.81	29.37	18.19	50.59	10.13	36.18	30.92	66.01	8.24	40.93	40.62
11	1778	13.30	38.75	38.58	20.75	29.94	41.66	58.83	44.02	44.17	43.56	79.02	65.36
12	1943	7.37	70.42	38.54	5.02	9.09	71.12	61.79	7.42	7.25	71.87	76.91	6.05
13	2038	2.71	0.91	44.46	3.14	16.30	2.99	57.12	11.64	27.33	5.19	67.13	21.85
14	2143	16.58	21.40	28.56	13.83	25.39	22.75	36.73	21.21	32.11	25.59	43.28	27.44
15	2227	8.49	10.64	32.78	13.33	18.65	24.38	49.81	26.17	29.07	34.96	68.51	40.79
16	2335	8.17	14.59	22.08	10.21	15.01	28.23	34.03	20.56	16.22	32.11	40.01	24.24
17	2451	8.09	20.66	24.72	10.28	7.05	18.69	26.63	9.21	5.97	18.58	27.63	7.96
18	2575	3.12	1.33	12.38	4.12	4.17	1.08	12.41	7.40	5.21	0.91	11.84	10.03
19	2722	1.17	1.79	7.57	1.58	1.64	2.06	7.22	2.37	2.31	2.01	8.76	2.21
20	2874	0.52	7.54	5.28	0.24	1.24	8.99	8.51	0.50	1.77	9.75	8.36	0.61
21	2984	1.18	5.69	10.52	1.62	1.34	4.00	9.67	1.36	1.57	3.39	8.53	1.47
22	3138	1.15	1.50	5.25	2.40	1.49	1.11	4.26	2.94	1.75	0.88	3.43	3.20
23	3286	0.36	0.59	2.44	46.78	0.59	1.03	1.81	48.11	0.92	5.11	3.69	49.66
24	3449	0.44	2.53	1.57	47.35	1.18	8.14	5.27	48.97	1.32	8.89	5.01	50.35
25	3658	1.48	6.85	8.19	48.50	1.42	6.52	7.21	49.75	1.71	6.79	6.28	51.11
26	3834	1.29	2.26	3.71	49.01	1.89	5.57	3.05	50.39	2.75	6.38	2.59	51.90
27	4039	0.68	1.18	2.03	49.81	1.58	4.28	1.88	51.34	2.01	3.86	3.10	52.63
28	4282	1.32	4.77	2.16	50.92	1.58	4.29	4.23	52.08	1.81	4.72	4.12	53.28
29	4482	1.61	13.25	5.89	51.37	1.87	12.49	5.29	52.58	2.00	13.77	4.61	53.74
30	4702	1.32	0.98	3.23	51.96	1.46	2.43	2.65	53.09	1.42	2.02	2.15	54.24
31	4921	0.66	1.16	1.67	52.44	0.52	1.07	1.27	53.59	0.42	1.30	1.88	54.62
32	5157	0.27	0.44	1.05	53.00	0.24	1.08	2.55	53.96	0.30	0.92	2.38	55.02
33	5366	0.07	1.76	4.02	53.24	0.12	2.61	3.50	54.33	0.23	3.17	2.94	55.38
34	5613	0.19	0.68	2.17	53.76	0.27	1.95	1.68	54.78	0.29	2.48	1.36	55.89
35	5860	0.40	3.85	1.02	54.19	0.35	5.41	0.82	55.32	0.46	5.77	1.40	56.25
36	6147	0.20	4.19	0.98	0.14	0.34	4.45	2.13	0.90	0.59	4.50	1.89	0.95
37	6371	0.52	2.92	3.27	54.97	0.75	2.66	2.70	55.90	1.10	3.25	2.17	56.75
38	6632	0.58	3.07	1.48	55.32	1.13	3.15	1.03	56.12	2.18	3.60	1.80	56.78
39	6870	1.31	3.20	0.08	0.92	2.43	2.84	1.69	2.17	3.45	2.82	2.02	3.27
40	7048	2.84	0.24	1.69	3.07	3.87	0.47	1.64	4.07	6.15	2.87	4.30	6.43
41	7202	4.22	0.58	0.15	3.91	6.92	1.97	3.80	6.46	-	-	-	-
42	7202	8.11	6.54	4.65	6.94	-	-	-	-	-	-	-	-

TABLE 11: Relative prediction error (in percent) for 1, 2 and 3 steps ahead of metric **Density** of database CitePh. Notation: number in title is number of steps ahead. Shortcuts: TS (time slice), RV (real value), SVM (Suport Vector Machine), MLP (Multilayer Perceptron), GP (Gaussian process) and LR (Linear Regression)

TS	RV	SVM 1	MLP 1	GP 1	LR 1	SVM 2	MLP 2	GP 2	LR 2	SVM 3	MLP 3	GP 3	LR 3
3	2.261E-04	8.35	13.23	23.57	65.64	-	-	-	-	-	-	-	-
4	2.092E-04	21.59	10.62	1.39	23.57	13.48	23.67	23.60	27.42	-	-	-	-
5	2.631E-04	54.67	65.54	58.96	100.00	36.25	43.34	41.55	75.27	33.11	33.37	31.94	61.86
6	2.985E-04	74.60	38.78	5.99	16.37	94.17	31.04	17.33	22.25	112.28	29.14	22.40	41.34
7	3.312E-04	8.41	21.24	8.05	24.61	8.90	20.22	6.94	51.17	7.49	17.05	8.88	72.67
8	3.544E-04	6.16	7.15	15.63	19.52	20.20	12.63	21.23	28.00	17.61	11.96	17.15	22.75
9	3.535E-04	29.66	2.41	30.01	24.79	21.69	8.06	21.35	22.24	27.17	17.04	18.98	34.10
10	3.686E-04	48.11	35.19	2.01	54.78	65.86	53.56	17.02	64.13	76.90	57.25	24.17	81.33
11	3.585E-04	14.98	19.34	4.66	12.78	17.26	20.33	8.11	27.13	14.04	16.58	7.01	25.40
12	3.499E-04	4.97	14.66	1.73	2.47	19.57	33.23	14.03	26.23	16.06	27.31	11.48	21.32
13	3.585E-04	24.86	30.61	22.42	44.88	17.86	22.12	16.34	32.62	19.63	28.49	13.69	26.86
14	3.589E-04	32.61	4.72	10.04	78.40	43.38	3.58	17.67	104.02	47.80	5.01	22.22	132.47
15	3.602E-04	8.72	16.06	5.15	0.43	9.40	15.49	6.66	2.96	8.19	13.69	6.15	22.32
16	3.613E-04	0.14	2.82	3.09	19.80	12.06	26.68	8.65	20.46	10.95	22.32	8.24	20.22
17	3.671E-04	19.31	16.01	16.45	39.64	14.10	11.75	11.77	28.29	16.44	10.49	12.69	25.26
18	3.609E-04	14.95	4.34	10.30	7.96	20.33	5.05	17.84	8.60	22.50	6.22	21.14	9.85
19	3.528E-04	10.26	9.41	15.56	3.48	11.28	8.78	16.97	3.13	10.56	9.22	15.17	3.78
20	3.513E-04	5.22	0.50	8.71	13.28	4.14	1.78	6.18	13.19	6.40	1.57	10.72	12.78
21	3.505E-04	1.93	1.47	5.59	12.43	2.07	1.14	8.33	11.85	3.68	1.47	14.11	11.33
22	3.458E-04	4.05	2.26	11.72	10.63	6.31	2.73	17.53	10.11	7.49	3.73	21.06	9.38
23	3.417E-04	1.16	0.05	15.40	1.38	2.42	1.28	18.16	3.72	3.92	2.10	17.20	6.75
24	3.345E-04	2.94	0.16	12.88	7.45	4.68	2.48	10.52	11.62	6.28	2.42	15.85	14.86
25	3.278E-04	3.79	1.23	0.57	4.52	5.40	2.18	12.14	3.49	7.17	2.90	19.21	2.99
26	3.190E-04	3.96	2.40	16.11	1.69	6.35	4.51	22.42	1.61	7.56	4.71	25.78	2.55
27	3.089E-04	5.07	1.75	19.83	1.58	6.33	1.97	22.53	2.98	7.44	2.10	21.32	4.08
28	3.019E-04	3.24	2.15	16.17	3.88	4.75	1.66	13.80	4.86	4.90	2.19	17.79	5.66
29	2.967E-04	2.84	2.59	3.39	5.56	2.59	4.45	12.90	6.26	2.54	5.54	19.04	7.27
30	2.930E-04	0.19	3.87	15.86	6.70	0.14	6.30	21.28	7.82	0.16	8.11	24.13	8.85
31	2.872E-04	0.26	5.41	18.56	8.61	0.27	7.20	21.10	9.57	1.10	8.56	19.85	10.42
32	2.824E-04	0.02	5.75	15.55	4.74	1.09	7.26	13.34	6.62	1.15	7.35	17.09	8.41
33	2.785E-04	1.54	6.19	3.96	4.94	1.39	4.86	12.89	7.29	1.19	4.15	18.41	9.45
34	2.736E-04	0.38	2.42	15.81	5.76	0.28	2.06	20.61	8.48	0.24	1.71	23.47	11.07
35	2.678E-04	0.42	0.70	17.99	6.67	0.33	1.66	20.89	9.93	0.31	1.39	19.59	12.19
36	2.607E-04	0.32	1.63	16.33	7.87	0.59	1.78	14.01	10.56	0.50	1.85	17.04	12.91
37	2.571E-04	0.64	0.79	4.66	7.32	0.48	0.68	12.70	10.49	1.17	0.56	17.30	13.01
38	2.529E-04	0.71	2.07	15.29	7.85	1.49	2.02	19.20	11.00	2.17	2.60	20.96	13.58
39	2.493E-04	1.61	2.60	16.48	7.94	2.15	2.69	18.32	11.25	2.32	2.21	16.52	13.64
40	2.458E-04	1.43	1.44	13.82	8.17	1.39	1.04	11.25	11.13	1.94	2.22	12.80	13.16
41	2.440E-04	0.42	4.65	2.70	7.63	1.70	3.76	8.81	10.22	-	-	-	-
42	2.440E-04	1.81	5.10	10.94	6.79	-	-	-	-	-	-	-	-

TABLE 12: Relative prediction error (in percent) for 1, 2 and 3 steps ahead of metric **Average Path Length** of database Autonomous. Notation: number in title is number of steps ahead. Shortcuts: TS (time slice), RV (real value), SVM (Suport Vector Machine), MLP (Multilayer Perceptron), GP (Gaussian process) and LR (Linear Regression)

TS	RV	SVM 1	MLP 1	GP 1	LR 1	SVM 2	MLP 2	GP 2	LR 2	SVM 3	MLP 3	GP 3	LR 3
3	3.7624	0.39	0.16	0.18	0.02	-	-	-	-	-	-	-	-
4	3.7618	0.07	0.09	0.03	0.03	0.15	0.15	0.11	0.11	-	-	-	-
5	3.7574	0.10	0.13	0.11	0.14	0.56	0.60	0.57	0.61	0.48	0.50	0.49	0.51
6	3.7310	0.66	0.71	0.66	0.82	0.57	0.56	0.58	0.60	0.64	0.55	0.68	0.55
7	3.7697	1.86	1.22	1.98	0.35	3.04	1.26	3.53	0.47	4.35	1.28	5.97	0.39
8	3.7778	0.03	0.17	0.20	0.26	1.08	0.19	0.47	1.49	1.77	0.77	0.98	2.45
9	3.7621	1.73	1.24	1.04	0.48	3.04	1.49	1.89	3.64	3.51	1.54	1.91	3.05
10	3.7614	0.98	0.67	0.31	1.55	4.24	1.03	1.60	3.60	3.49	0.84	1.32	2.96
11	3.7562	0.92	0.41	0.37	4.25	0.65	0.54	0.39	3.25	1.35	0.90	0.74	3.80
12	3.7676	0.70	1.12	0.59	0.73	0.89	0.84	0.52	1.57	0.73	0.68	0.44	2.44
13	3.7695	0.45	1.01	0.17	2.23	0.33	1.13	0.12	1.59	0.27	0.93	0.11	2.37
14	3.7733	0.02	0.60	0.00	3.78	0.22	0.42	0.12	2.89	0.77	0.96	0.42	2.36
15	3.7763	0.11	0.14	0.02	2.41	0.63	0.91	0.30	1.77	0.52	0.75	0.25	1.82
16	3.7731	0.04	0.31	0.09	0.90	0.41	1.07	0.12	1.78	0.42	0.88	0.11	1.84
17	3.7800	0.03	0.08	0.11	1.62	0.43	0.23	0.13	1.29	0.48	0.48	0.18	1.74
18	3.7770	0.05	0.41	0.16	0.56	0.35	0.44	0.20	0.40	0.49	0.47	0.24	0.32
19	3.7714	0.36	0.36	0.20	0.15	0.47	0.47	0.28	0.14	0.40	0.39	0.28	0.48
20	3.7707	0.20	0.36	0.21	0.28	0.26	0.26	0.31	0.24	0.30	0.22	0.37	0.27
21	3.7959	0.39	0.50	0.48	0.52	0.40	0.51	0.51	0.52	0.55	0.60	0.62	0.64
22	3.8008	0.25	0.12	0.36	0.09	0.54	0.41	0.54	0.58	0.54	0.44	0.52	0.63
23	3.8103	0.58	0.38	0.56	0.93	0.57	0.38	0.51	1.35	0.66	0.52	0.59	1.11
24	3.8048	0.12	0.10	0.01	0.46	0.48	0.40	0.27	0.67	0.60	0.57	0.54	0.81
25	3.8187	0.54	0.43	0.36	0.57	0.72	0.66	0.67	0.70	0.82	0.70	0.71	0.67
26	3.7759	1.00	1.14	1.02	8.59	1.03	1.06	0.96	8.27	1.34	1.20	1.13	20.01
27	3.7826	0.64	0.24	0.54	1.23	1.21	0.64	0.86	1.58	1.58	1.39	1.24	2.82
28	3.7673	0.97	1.02	0.89	0.19	1.44	2.01	1.31	0.53	1.67	2.12	1.42	0.56
29	3.7472	1.31	1.17	1.22	0.73	1.45	0.92	1.25	0.66	1.65	1.22	1.35	0.64
30	3.7521	0.33	1.17	0.61	0.57	0.48	0.96	0.74	0.57	0.51	0.78	0.70	0.48
31	3.7518	0.12	1.07	0.43	0.56	0.10	0.77	0.33	0.41	0.39	0.72	0.42	0.44
32	3.7671	0.20	0.66	0.17	0.13	0.36	0.54	0.17	0.34	0.63	0.44	0.27	0.45
33	3.7543	0.71	0.03	0.31	0.47	1.08	0.39	0.46	0.54	1.37	0.37	0.50	0.53
34	3.7489	0.66	0.50	0.37	0.60	0.72	0.51	0.34	0.55	0.66	0.50	0.28	0.47
35	3.7530	0.10	0.36	0.05	0.47	0.47	0.33	0.14	0.38	0.56	0.28	0.12	0.36
36	3.7608	0.50	0.39	0.22	0.25	0.47	0.37	0.18	0.27	0.39	0.33	0.27	0.45
37	3.7591	0.23	0.75	0.01	0.29	0.73	0.93	0.38	0.51	0.79	0.79	0.34	0.45
38	3.7448	0.65	1.58	0.52	0.66	0.54	1.58	0.40	0.51	0.56	1.91	0.39	0.45
39	3.7586	0.16	0.36	0.12	0.20	0.12	0.27	0.09	0.16	0.10	0.22	0.09	0.14
40	3.7591	0.13	0.18	0.03	0.06	0.23	0.46	0.12	0.15	0.19	0.68	0.10	0.13
41	3.7556	0.11	0.01	0.15	0.16	0.14	0.45	0.11	0.12	0.20	0.42	0.10	0.11
42	3.7616	0.23	0.62	0.13	0.07	0.30	0.58	0.15	0.05	0.36	0.51	0.17	0.05
43	3.7617	0.18	0.02	0.10	0.04	0.21	0.04	0.11	0.07	0.17	0.27	0.16	0.28
44	3.7615	0.02	0.34	0.07	0.05	0.22	0.46	0.20	0.32	0.30	0.76	0.27	0.44
45	3.7475	0.34	0.37	0.31	0.42	0.39	0.43	0.37	0.50	0.32	0.37	0.30	0.44
46	3.7427	0.30	0.62	0.27	0.27	0.23	0.51	0.21	0.19	0.23	0.46	0.20	0.17
47	3.7553	0.54	0.21	0.25	0.18	0.68	0.26	0.28	0.13	0.76	0.37	0.28	0.11
48	3.7545	0.22	0.59	0.19	0.10	0.20	0.67	0.18	0.15	0.24	0.57	0.22	0.14
49	3.7533	0.04	0.13	0.10	0.11	0.05	0.36	0.16	0.10	0.05	0.31	0.19	0.11
50	3.7567	0.10	0.41	0.16	0.01	0.10	0.44	0.18	0.04	0.08	0.41	0.17	0.11
51	3.7565	0.01	0.17	0.12	0.06	0.04	0.13	0.11	0.14	0.07	0.21	0.09	0.22
52	3.7538	0.06	0.35	0.04	0.13	0.09	0.42	0.03	0.23	0.07	0.38	0.10	0.26
53	3.7494	0.06	0.61	0.01	0.01	0.06	0.47	0.11	0.06	0.41	0.56	0.45	0.39
54	3.7501	0.13	2.31	0.16	0.09	0.54	2.12	0.55	0.48	0.57	1.73	0.58	0.50
55	3.7702	0.60	0.61	0.61	0.61	0.53	0.48	0.54	0.56	0.52	0.40	0.55	0.59
56	3.7636	0.23	0.10	0.02	0.14	0.31	0.13	0.06	0.10	0.35	0.11	0.07	0.08
57	3.7675	0.09	0.61	0.08	0.10	0.09	0.44	0.08	0.10	0.19	0.36	0.16	0.16
58	3.7680	0.02	0.24	0.03	0.03	0.17	0.26	0.15	0.14	0.14	0.22	0.13	0.12
59	3.7737	0.21	0.46	0.20	0.17	0.15	0.38	0.14	0.14	0.31	0.55	0.25	0.20
60	3.7631	0.07	0.20	0.14	0.22	0.30	0.15	0.23	0.20	0.45	0.15	0.35	0.29
61	3.7768	0.46	0.62	0.36	0.35	0.60	0.50	0.48	0.45	0.63	0.41	0.49	0.44
62	3.7842	0.56	0.23	0.41	0.31	0.54	0.72	0.38	0.29	0.66	0.82	0.47	0.40
63	3.7804	0.24	0.58	0.17	0.00	0.43	0.52	0.32	0.19	0.47	1.10	0.36	0.21
64	3.7891	0.31	0.63	0.35	0.28	0.28	0.48	0.36	0.27	0.35	0.39	0.33	0.33
65	3.7880	0.04	0.47	0.20	0.04	0.45	0.85	0.34	0.43	0.38	0.75	0.29	0.36
66	3.7625	0.67	0.69	0.52	0.63	0.49	0.89	0.37	0.46	0.48	0.82	0.31	0.44
67	3.7802	0.19	1.13	0.29	0.42	0.15	0.85	0.22	0.33	0.13	0.84	0.25	0.33
68	3.7716	0.26	0.11	0.01	0.10	0.20	0.37	0.12	0.11	0.18	0.31	0.16	0.13
69	3.7766	0.07	0.34	0.18	0.18	0.10	0.24	0.20	0.20	0.11	0.26	0.16	0.17
70	3.7765	0.06	0.03	0.14	0.10	0.16	0.89	0.10	0.07	0.14	0.84	0.11	0.13
71	3.7700	0.26	0.50	0.08	0.07	0.22	0.49	0.08	0.12	0.26	0.42	0.06	0.10
72	3.7757	0.05	0.06	0.11	0.20	0.14	0.51	0.08	0.15	0.12	0.54	0.22	0.26
73	3.7684	0.17	0.52	0.04	0.08	0.14	0.47	0.23	0.21	0.26	0.43	0.19	0.18
74	3.7805	0.23	0.48	0.34	0.32	0.24	0.35	0.25	0.23	0.29	0.40	0.24	0.23
75	3.7641	0.36	0.28	0.19	0.22	0.46	0.47	0.29	0.33	0.45	0.47	0.25	0.28
76	3.7563	0.33	0.87	0.28	0.31	0.28	0.79	0.21	0.22	0.25	0.73	0.18	0.18
77	3.7647	0.08	1.18	0.03	0.14	0.06	0.84	0.03	0.13	0.10	0.69	0.03	0.12
78	3.7634	0.04	0.44	0.02	0.06	0.04	0.33	0.01	0.05	0.13	0.27	0.12	0.10
79	3.7625	0.09	0.11	0.01	0.01	0.20	0.08	0.15	0.14	0.17	0.07	0.13	0.11
80	3.7540	0.22	0.26	0.21	0.20	0.16	0.21	0.15	0.14	0.24	0.27	0.20	0.16

TABLE 13: Relative prediction error (in percent) for 1, 2 and 3 steps ahead of metric **Diameter** of database Autonomous. Notation: number in title is number of steps ahead. Shortcuts: TS (time slice), RV (real value), SVM (Suport Vector Machine), MLP (Multilayer Perceptron), GP (Gaussian process) and LR (Linear Regression)

TS	RV	SVM 1	MLP 1	GP 1	LR 1	SVM 2	MLP 2	GP 2	LR 2	SVM 3	MLP 3	GP 3	LR 3
22	10	9.91	9.43	7.18	6.19	9.89	12.26	6.94	5.87	9.87	14.30	6.70	5.55
23	10	0.12	0.40	2.80	0.56	0.30	0.51	2.98	1.16	0.55	0.62	2.86	1.88
24	10	0.14	0.40	0.81	8.70	0.32	0.36	1.35	8.70	6.51	6.15	7.67	7.38
25	10	0.18	0.15	0.90	8.33	7.81	7.43	8.82	6.32	9.40	8.76	10.78	5.35
26	9	11.30	11.69	12.11	2.22	11.48	11.72	12.63	2.22	11.73	11.72	13.16	2.22
27	9	8.76	3.17	1.65	2.14	12.97	2.31	2.53	2.14	16.60	1.94	3.64	2.14
28	9	0.68	3.02	1.39	2.06	0.77	2.47	2.59	2.06	0.75	2.30	4.40	2.06
29	9	0.20	1.23	1.83	1.98	0.42	1.68	3.79	1.98	4.56	3.19	7.29	1.98
30	9	0.26	2.06	3.05	1.92	5.04	3.28	6.96	1.92	4.12	5.27	5.55	5.33
31	9	6.34	6.17	6.16	1.85	4.68	5.85	4.27	6.32	6.53	5.80	7.44	5.35
32	10	11.16	9.05	7.28	8.39	8.45	6.85	6.43	6.35	7.22	5.88	6.77	5.37
33	9	16.91	6.22	13.12	2.08	19.22	8.09	14.13	2.08	21.11	7.28	15.08	2.08
34	9	0.39	5.28	3.97	2.02	2.81	3.74	4.56	2.02	2.36	4.39	5.36	2.02
35	9	3.69	0.11	2.53	1.96	2.63	0.25	3.23	1.96	5.34	2.00	2.71	1.96
36	9	1.30	7.03	2.12	1.90	2.43	6.09	1.57	1.90	2.83	5.05	3.41	1.90
37	9	3.33	4.72	2.01	1.85	2.71	3.49	3.19	1.85	4.96	3.31	6.46	1.85
38	9	3.20	5.46	5.13	1.80	7.44	7.04	8.89	1.80	8.35	6.85	9.95	1.80
39	9	7.36	0.78	8.38	1.75	7.04	0.57	8.33	1.75	6.77	0.47	8.40	1.75
40	9	2.42	1.34	3.53	1.71	2.27	0.96	3.46	1.71	2.07	0.82	3.48	1.71
41	9	1.75	0.03	1.40	0.63	2.84	0.07	1.48	0.84	3.03	0.20	2.37	1.00
42	9	0.73	0.16	0.83	0.61	0.72	0.12	2.11	0.82	0.85	0.19	1.75	0.97
43	9	0.09	0.71	2.52	0.60	0.39	0.52	1.86	0.80	0.43	0.44	1.60	0.94
44	9	0.44	0.59	1.70	0.58	0.42	0.99	1.22	0.78	0.49	1.18	1.01	0.92
45	9	0.17	0.99	0.66	0.57	0.14	1.07	0.72	0.76	0.14	1.17	0.75	0.90
46	9	0.08	0.08	0.42	0.55	0.23	0.05	0.43	0.74	0.45	0.06	0.41	0.88
47	9	0.19	1.44	0.23	0.54	0.39	4.37	0.20	0.72	0.64	6.41	0.17	0.85
48	9	0.30	0.20	0.08	0.52	0.53	0.27	0.06	0.71	0.81	0.34	0.12	0.84
49	9	0.34	0.59	0.03	0.51	0.58	0.81	0.13	0.69	0.85	1.14	0.25	0.82
50	9	0.23	0.09	0.13	0.50	0.39	0.21	0.24	0.67	0.57	0.43	0.37	0.80
51	9	0.10	3.54	0.20	0.39	0.17	9.10	0.32	0.57	0.25	8.49	0.46	0.78
52	9	0.02	0.41	0.26	0.38	0.03	1.11	0.39	0.54	0.07	6.90	0.88	0.75
53	9	0.03	1.77	0.31	0.36	0.12	11.21	0.89	2.44	0.21	12.80	1.24	3.64
54	9	0.06	2.50	1.00	0.36	0.10	2.51	1.28	0.52	0.14	2.79	1.57	0.73
55	9	0.02	0.26	0.41	0.45	0.03	0.27	0.56	0.61	0.04	0.29	0.72	0.72
56	9	0.02	0.82	0.32	0.44	0.03	0.98	0.45	0.59	0.04	1.13	0.59	0.71
57	9	0.00	0.30	0.31	0.43	0.01	0.34	0.44	0.58	0.01	0.38	0.57	0.69
58	9	0.00	0.57	0.32	0.42	0.01	0.69	0.45	0.57	0.01	0.80	0.58	0.68
59	9	0.01	1.16	0.34	0.36	0.01	1.52	0.46	0.50	0.02	2.20	0.60	0.60
60	9	0.01	0.53	0.35	0.39	0.01	0.55	0.48	0.59	0.02	0.57	0.62	0.85
61	9	0.01	0.25	0.37	0.45	0.01	0.26	0.50	0.67	0.02	0.27	0.63	0.95
62	9	0.00	1.00	0.38	0.49	0.00	0.86	0.51	0.73	0.01	0.75	0.65	1.04
63	9	0.00	0.69	0.39	0.53	0.01	0.59	0.52	0.78	0.01	0.52	0.66	1.10
64	9	0.00	0.72	0.40	0.56	0.00	1.09	0.53	0.81	0.00	1.68	0.67	1.13
65	9	0.00	1.02	0.41	0.57	0.00	1.01	0.53	0.82	0.00	1.01	0.67	1.15
66	9	0.00	0.10	0.41	0.57	0.00	0.16	0.53	0.82	0.00	0.26	0.67	1.15
67	9	0.00	1.82	0.41	0.56	0.00	1.67	0.53	0.81	6.18	7.25	6.67	7.09
68	9	0.00	0.59	0.41	0.55	7.43	6.96	7.86	8.09	6.17	5.81	6.55	6.78
69	10	9.99	8.98	10.36	10.48	7.43	6.87	7.71	7.82	6.17	6.03	6.43	6.55
70	9	10.87	26.24	5.67	8.32	10.77	31.48	5.77	10.01	10.68	30.79	5.66	10.81
71	9	0.13	15.54	3.14	6.25	0.14	12.16	2.71	5.14	0.13	14.64	2.31	5.32
72	9	0.00	13.48	0.94	0.51	0.06	10.77	0.71	0.66	0.10	9.06	1.40	0.76
73	9	0.07	14.17	0.75	0.51	0.12	12.10	1.91	0.65	0.17	11.23	2.14	0.75
74	9	0.06	1.34	2.30	0.50	0.08	3.89	2.26	0.64	0.07	4.55	1.93	0.74
75	9	0.03	12.04	1.30	0.49	0.05	15.25	1.63	0.63	0.06	13.92	1.45	0.73
76	9	0.13	8.54	2.44	0.48	0.14	6.32	2.03	0.62	0.15	5.16	1.74	0.72
77	9	0.00	1.36	0.51	0.48	0.01	1.03	0.37	0.62	0.01	0.86	0.35	0.71
78	9	0.00	1.14	0.32	0.47	0.01	0.83	0.43	0.61	0.01	0.68	0.42	0.70
79	9	0.01	2.58	0.39	0.46	0.02	1.87	0.47	0.60	0.02	1.80	1.12	0.69
80	9	0.01	1.73	0.69	0.46	0.01	1.27	1.28	0.59	0.01	1.42	1.10	0.68
81	9	0.01	3.70	1.94	0.45	0.01	2.63	1.50	0.58	0.01	2.18	1.31	0.67
82	9	0.03	0.85	0.03	0.44	0.04	0.99	0.03	0.57	0.06	1.05	0.03	0.66
83	9	0.02	0.28	0.01	0.44	0.03	0.35	0.01	0.57	6.15	5.85	6.40	5.75
84	9	0.02	0.25	0.01	0.43	7.42	6.80	7.71	6.99	8.42	7.94	8.81	7.87
85	10	10.01	9.30	10.38	9.63	10.01	9.26	10.45	9.53	10.02	9.20	10.51	9.45
86	10	9.44	6.90	0.04	4.77	14.61	6.38	1.33	6.02	25.18	11.11	7.95	11.98
87	10	0.02	1.32	1.90	2.23	7.46	8.82	9.92	9.98	8.76	10.13	11.78	11.85
88	9	11.13	11.19	13.17	12.76	11.13	8.41	13.31	13.13	11.13	6.92	12.95	12.75
89	9	7.11	5.19	4.81	5.61	8.46	8.00	4.37	5.01	9.20	7.46	4.22	4.73
90	9	0.67	5.69	0.78	0.70	1.04	4.05	1.12	2.34	-	-	-	-
91	9	0.01	4.41	0.87	2.79	-	-	-	-	-	-	-	-

Table 14: Relative prediction error (in percent) for 1, 2 and 3 steps ahead of metric **Average Clustering Coefficient** of database Autonomous. Notation: number in title is number of steps ahead. Shortcuts: TS (time slice), RV (real value), SVM (Suport Vector Machine), MLP (Multilayer Perceptron), GP (Gaussian process) and LR (Linear Regression)

TS	RV	SVM 1	MLP 1	GP 1	LR 1	SVM 2	MLP 2	GP 2	LR 2	SVM 3	MLP 3	GP 3	LR 3
3	0.0740	6.00	2.52	3.05	0.91	-	-	-	-	-	-	-	-
4	0.0727	1.29	1.39	1.76	1.76	1.09	0.99	1.52	1.46	-	-	-	-
5	0.0737	0.88	0.22	0.65	0.58	0.90	0.30	0.47	0.97	0.86	0.62	0.40	1.27
6	0.0724	0.00	0.11	1.01	1.37	1.23	1.15	1.77	1.63	1.25	0.95	1.52	1.41
7	0.0721	1.76	1.52	1.82	1.62	1.52	1.30	1.44	1.22	1.34	1.23	1.26	0.99
8	0.0728	2.32	2.20	1.51	0.37	3.87	3.50	2.72	0.36	4.94	4.03	3.79	0.87
9	0.0733	3.29	3.36	1.53	3.74	2.45	2.61	1.52	2.81	3.73	3.39	1.86	4.53
10	0.0741	0.15	0.40	0.83	1.41	0.62	0.28	0.64	1.33	0.65	0.24	0.53	1.28
11	0.0740	0.29	0.42	0.20	0.74	0.21	0.40	0.32	0.57	0.22	0.33	0.37	0.85
12	0.0739	0.19	0.16	0.33	0.93	0.57	0.13	0.62	1.60	0.48	0.15	0.55	1.69
13	0.0748	0.97	0.59	1.16	1.98	0.99	0.61	1.15	1.88	0.81	0.57	0.95	1.59
14	0.0746	0.36	0.37	0.41	1.62	1.30	0.90	1.17	1.21	1.18	0.89	1.01	1.62
15	0.0738	2.13	1.44	1.31	0.43	1.50	1.23	1.03	1.52	1.51	1.00	0.84	1.50
16	0.0751	1.37	1.48	1.52	2.06	1.66	1.66	1.40	1.78	1.36	1.36	1.21	1.68
17	0.0746	0.73	0.91	0.36	1.31	1.61	1.46	0.41	1.32	1.40	1.31	0.82	2.00
18	0.0746	2.90	1.90	0.67	2.97	2.04	1.34	0.90	2.08	1.67	1.11	1.14	1.70
19	0.0758	2.39	1.88	1.66	2.13	2.67	1.90	1.88	2.45	2.21	1.60	1.67	2.01
20	0.0759	0.61	0.37	1.53	2.75	1.49	0.98	1.18	2.46	1.62	1.56	1.03	2.33
21	0.0754	2.55	1.79	0.36	1.98	2.48	2.09	0.40	1.96	2.07	1.73	0.82	2.39
22	0.0754	0.49	0.16	0.50	1.83	0.35	0.75	1.05	2.47	0.42	0.76	0.88	2.37
23	0.0763	0.17	0.23	1.36	2.88	0.37	0.40	0.99	2.51	2.22	2.33	2.31	2.41
24	0.0756	0.67	0.89	1.03	1.94	2.85	3.11	3.74	2.13	2.31	2.51	3.02	2.47
25	0.0725	3.86	3.94	4.77	2.41	2.66	2.71	3.29	2.69	2.43	2.60	2.88	2.31
26	0.0765	0.00	1.47	2.05	2.43	1.62	1.36	1.47	1.75	2.44	4.03	2.31	6.81
27	0.0752	2.41	3.56	0.78	2.56	3.01	6.01	2.13	8.44	2.47	5.06	1.77	6.96
28	0.0770	3.22	7.81	3.04	3.56	2.29	5.58	2.23	3.13	2.13	4.89	2.25	3.60
29	0.0763	0.19	1.80	0.41	2.50	0.91	2.71	1.16	3.50	1.47	2.46	1.44	3.69
30	0.0777	1.25	4.24	1.63	4.16	1.85	3.41	1.76	4.07	1.64	3.44	1.76	3.94
31	0.0775	2.21	1.66	1.71	3.83	1.61	3.54	1.51	3.69	1.71	2.96	1.60	3.99
32	0.0773	0.07	3.20	1.00	3.42	0.06	2.80	1.11	3.95	0.59	2.45	1.56	4.41
33	0.0781	0.05	0.16	1.16	4.30	0.73	0.68	1.60	4.72	1.41	3.23	2.36	5.16
34	0.0787	1.06	0.93	1.85	4.96	1.72	4.67	2.50	5.40	1.86	3.81	2.58	5.77
35	0.0794	2.45	5.00	2.85	5.65	2.03	3.57	2.56	5.98	1.67	2.94	2.25	5.92
36	0.0800	2.16	1.53	1.92	6.14	1.90	1.85	1.45	5.89	1.56	2.42	1.37	5.78
37	0.0795	2.39	1.60	0.53	5.45	1.89	1.26	0.52	5.42	1.88	1.58	0.96	5.66
38	0.0795	0.92	2.15	0.51	5.23	0.77	2.16	1.03	5.61	0.64	2.98	1.39	5.91
39	0.0801	0.87	0.67	1.31	5.83	1.09	0.99	1.57	6.08	1.28	1.46	1.95	6.44
40	0.0805	0.65	0.96	1.47	1.15	0.56	1.23	1.81	1.10	0.79	1.01	1.54	2.08
41	0.0812	0.10	2.06	1.69	0.81	1.25	1.54	1.22	2.19	2.01	2.01	1.07	3.11
42	0.0801	1.85	3.02	0.24	2.85	2.54	3.17	0.87	3.61	3.29	3.76	1.51	4.56
43	0.0796	2.90	4.77	1.06	1.15	3.49	5.57	1.69	1.88	3.52	4.53	1.51	1.76
44	0.0789	2.79	1.77	1.74	2.27	2.34	1.25	1.30	1.86	2.10	1.16	1.06	1.61
45	0.0798	0.66	1.53	0.04	1.10	0.46	1.85	0.42	0.92	0.49	1.86	0.44	0.89
46	0.0804	0.63	1.49	0.63	0.37	0.45	1.61	0.57	0.28	0.38	2.13	0.55	0.25
47	0.0805	0.41	0.19	0.32	0.18	0.47	0.20	0.32	0.26	0.62	0.59	0.26	0.38
48	0.0807	0.05	2.05	0.27	0.31	0.17	1.90	0.19	0.39	0.40	1.57	0.24	0.55
49	0.0807	0.20	0.57	0.03	0.44	0.47	0.41	0.23	0.55	0.41	0.50	0.23	0.45
50	0.0807	0.41	0.27	0.24	0.61	0.29	0.74	0.30	0.45	0.53	0.61	0.25	0.38
51	0.0815	0.31	0.12	0.50	0.24	0.33	0.63	0.36	0.18	1.88	1.43	1.44	1.42
52	0.0815	0.72	2.35	0.02	0.05	2.61	3.21	1.79	1.81	3.39	6.79	3.87	2.52
53	0.0798	3.05	3.60	2.50	2.59	3.48	5.37	4.77	3.13	5.19	7.15	7.10	4.84
54	0.0792	3.14	0.30	5.39	3.40	5.13	2.11	7.68	4.96	4.57	1.74	7.10	4.35
55	0.0767	3.00	3.27	5.02	5.32	2.17	2.27	3.57	3.96	1.78	2.06	3.22	3.84
56	0.0799	1.43	7.60	1.87	3.17	1.13	9.49	1.47	3.01	0.95	11.07	1.38	3.15
57	0.0791	0.03	0.64	0.06	0.65	0.22	3.52	0.11	1.05	2.20	6.04	1.90	1.39
58	0.0794	0.29	2.98	0.19	1.12	2.71	3.60	2.30	1.70	2.63	2.99	2.44	2.81
59	0.0768	3.54	5.07	3.36	3.39	3.16	3.60	3.00	2.98	2.59	3.14	2.44	2.43
60	0.0816	3.17	3.76	3.89	3.09	2.27	2.71	2.92	2.22	2.93	4.59	2.78	2.52
61	0.0796	0.16	1.36	0.07	0.23	3.32	9.37	2.89	2.59	4.32	7.83	3.83	3.67
62	0.0772	4.74	8.59	4.10	3.69	5.25	6.74	4.69	4.52	5.88	8.01	5.18	4.90
63	0.0761	5.22	6.90	3.95	3.50	5.84	6.70	4.24	4.45	6.00	5.86	4.07	4.35
64	0.0760	5.39	2.18	3.11	4.60	5.02	3.85	2.73	4.15	4.48	6.37	2.34	3.54
65	0.0767	0.34	4.11	0.98	0.82	0.76	8.06	0.69	0.83	1.61	6.65	1.10	1.94
66	0.0776	0.70	5.79	0.47	1.51	1.61	5.70	1.53	2.93	2.52	5.82	2.10	3.96
67	0.0790	1.35	0.09	1.91	2.70	2.07	5.64	2.35	3.66	1.94	4.65	1.97	3.09
68	0.0795	1.75	5.92	1.95	1.16	1.37	4.71	1.39	1.13	1.12	4.02	1.14	1.06
69	0.0780	0.19	4.82	0.93	1.66	0.63	3.97	0.85	1.56	0.71	3.26	0.70	1.36
70	0.0782	0.76	1.00	0.35	0.11	0.69	4.02	0.30	0.54	0.73	6.90	0.63	0.57
71	0.0787	0.32	1.16	0.42	0.82	1.24	3.17	0.87	0.76	1.21	4.15	0.76	0.64
72	0.0788	1.49	6.32	1.01	0.21	1.22	5.53	0.76	0.61	1.17	4.54	0.69	0.71
73	0.0784	0.33	0.02	0.08	1.08	0.25	1.66	0.12	1.12	0.29	1.97	0.29	1.55
74	0.0790	0.47	0.90	0.20	0.81	0.33	1.44	0.32	0.77	0.29	1.71	0.48	0.76
75	0.0788	0.31	1.95	0.48	0.27	0.40	2.40	0.63	0.35	0.33	2.22	0.51	0.81
76	0.0788	0.04	0.33	0.53	0.69	0.29	0.32	0.39	0.53	0.35	0.81	0.36	0.79
77	0.0794	0.43	2.98	0.38	0.09	0.42	2.78	0.28	0.50	0.61	3.57	0.69	0.42
78	0.0792	0.64	3.04	0.21	1.08	0.66	3.01	0.74	2.27	1.03	2.69	1.12	3.03
79	0.0801	0.97	1.17	1.11	1.51	1.47	1.47	1.44	1.92	1.31	1.26	1.28	1.89
80	0.0806	1.40	1.81	1.36	0.40	1.05	1.28	1.03	0.60	1.97	2.37	2.03	1.06

TABLE 15: Relative prediction error (in percent) for 1, 2 and 3 steps ahead of metric **Connected Components Count** of database Autonomous. Notation: number in title is number of steps ahead. Shortcuts: TS (time slice), RV (real value), SVM (Suport Vector Machine), MLP (Multilayer Perceptron), GP (Gaussian process) and LR (Linear Regression)

TS	RV	SVM 1	MLP 1	GP 1	LR 1	SVM 2	MLP 2	GP 2	LR 2	SVM 3	MLP 3	GP 3	LR 3
3	4693	0.59	0.19	0.38	0.23	-	-	-	-	-	-	-	-
4	4695	0.02	0.53	0.05	0.11	0.31	0.52	0.19	0.12	-	-	-	-
5	4694	0.42	0.23	0.18	0.11	1.52	0.98	1.33	1.05	1.34	0.88	1.09	0.91
6	4769	1.67	1.57	1.64	1.49	1.21	1.16	1.19	1.12	0.99	0.97	0.98	0.95
7	4674	1.10	0.04	0.69	0.48	1.37	0.14	0.73	0.89	1.15	0.13	0.62	1.28
8	4680	1.87	1.57	1.32	0.53	2.20	1.56	1.02	0.52	3.57	1.54	2.30	0.49
9	4681	5.48	0.57	1.98	5.10	6.21	0.54	2.74	5.55	5.29	0.60	2.27	4.78
10	4684	4.84	0.18	3.09	5.89	3.47	0.13	2.22	4.26	2.97	0.20	1.89	3.85
11	4675	1.08	0.19	1.40	3.00	1.55	0.35	1.03	5.06	1.35	0.50	1.01	4.62
12	4662	1.29	0.22	0.02	2.44	1.13	0.77	0.74	2.40	0.95	0.79	1.05	1.96
13	4651	0.17	1.99	0.53	0.90	0.13	2.08	0.73	0.99	0.26	2.10	0.89	1.01
14	4643	0.07	0.30	0.67	2.25	0.22	0.54	0.73	1.98	0.36	0.55	0.65	1.64
15	4644	0.18	2.61	0.69	0.13	0.28	2.30	0.52	0.51	0.50	1.94	0.49	0.75
16	4650	0.02	0.37	0.61	0.44	0.40	0.50	0.56	0.87	0.60	0.41	0.48	0.75
17	4637	0.14	0.64	0.66	0.28	0.55	0.46	0.51	0.22	0.46	0.38	0.44	0.29
18	4630	0.82	0.32	0.26	1.05	0.58	0.30	0.21	1.01	0.48	0.26	0.18	1.10
19	4634	0.26	0.06	0.16	0.91	0.19	0.11	0.12	1.06	0.15	0.13	0.10	1.15
20	4621	0.20	0.21	0.18	1.14	0.20	0.22	0.19	1.20	0.19	0.21	0.17	1.24
21	4616	0.02	0.05	0.13	0.03	0.05	0.10	0.10	0.04	0.10	0.17	0.09	0.05
22	4613	0.09	0.13	0.03	0.02	0.14	0.20	0.03	0.07	0.23	0.30	0.09	0.08
23	4610	0.10	0.06	0.02	1.22	0.18	0.08	0.09	1.24	0.30	0.16	0.20	1.22
24	4608	0.16	0.20	0.14	0.12	0.28	0.37	0.26	0.23	0.30	0.41	0.27	0.25
25	4611	0.35	0.08	0.25	0.14	0.32	0.09	0.22	0.11	0.37	0.09	0.26	0.19
26	4603	0.16	0.32	0.07	1.22	0.25	0.31	0.14	1.22	0.21	0.47	0.12	1.35
27	4603	0.19	0.18	0.15	1.18	0.14	0.40	0.12	1.36	0.16	0.58	0.18	1.52
28	4587	0.08	0.40	0.16	1.49	0.20	0.53	0.27	1.62	0.20	0.57	0.27	1.68
29	4575	0.18	0.53	0.31	1.70	0.13	0.53	0.28	1.72	0.13	0.49	0.23	1.71
30	4573	0.04	0.14	0.18	1.68	0.13	0.28	0.13	1.65	0.11	0.27	0.13	1.73
31	4576	0.22	0.10	0.04	1.56	0.17	0.12	0.08	1.70	0.18	0.10	0.06	1.75
32	4564	0.07	0.09	0.14	1.78	0.05	0.10	0.10	1.79	0.09	0.13	0.09	1.80
33	4563	0.10	0.21	0.01	1.75	0.16	0.23	0.06	1.76	0.13	0.19	0.11	1.90
34	4562	0.10	0.15	0.06	1.71	0.11	0.30	0.15	1.91	0.15	0.24	0.13	1.93
35	4545	0.15	0.19	0.25	2.04	0.17	0.13	0.18	1.98	0.25	0.11	0.17	1.95
36	4551	0.24	0.43	0.05	1.85	0.34	0.56	0.14	1.84	0.45	0.64	0.22	1.84
37	4552	0.32	0.21	0.16	1.78	0.41	0.24	0.23	1.78	0.45	0.22	0.24	1.83
38	4552	0.32	0.17	0.21	1.73	0.33	0.12	0.19	1.81	0.35	0.11	0.20	1.86
39	4545	0.32	0.01	0.10	1.84	0.33	0.04	0.12	1.87	0.34	0.07	0.13	1.91
40	4542	0.26	0.28	0.09	1.86	0.26	0.31	0.10	1.89	0.28	0.34	0.12	1.93
41	4539	0.12	0.09	0.06	0.20	0.15	0.11	0.08	0.22	0.17	0.13	0.12	0.24
42	4536	0.04	0.03	0.06	0.10	0.05	0.05	0.10	0.11	0.09	0.08	0.15	0.13
43	4534	0.05	0.05	0.09	0.07	0.09	0.05	0.14	0.09	0.16	0.04	0.19	0.12
44	4533	0.09	0.28	0.13	0.12	0.15	0.22	0.19	0.18	0.13	0.21	0.16	0.15
45	4533	0.16	0.16	0.18	0.04	0.11	0.12	0.13	0.21	0.12	0.10	0.11	0.31
46	4522	0.05	0.14	0.03	0.08	0.10	0.19	0.05	0.16	0.08	0.16	0.08	0.13
47	4516	0.08	0.08	0.08	0.25	0.07	0.10	0.09	0.21	0.06	0.09	0.09	0.24
48	4520	0.09	0.08	0.11	0.04	0.07	0.06	0.10	0.10	0.05	0.06	0.10	0.16
49	4514	0.03	0.03	0.03	0.12	0.05	0.02	0.04	0.18	0.04	0.04	0.10	0.22
50	4510	0.03	0.06	0.03	0.12	0.05	0.04	0.10	0.14	0.04	0.04	0.10	0.17
51	4510	0.08	0.11	0.12	0.13	0.06	0.13	0.10	0.18	0.09	0.11	0.16	0.15
52	4504	0.01	0.01	0.03	0.07	0.08	0.10	0.14	0.06	0.10	0.38	0.13	0.16
53	4507	0.12	0.15	0.17	0.07	0.12	0.35	0.14	0.21	0.11	0.40	0.13	0.22
54	4508	0.11	0.08	0.04	0.27	0.09	0.09	0.04	0.25	0.09	0.08	0.04	0.24
55	4504	0.04	0.18	0.04	0.06	0.03	0.13	0.05	0.07	0.10	0.14	0.05	0.17
56	4501	0.00	0.30	0.03	0.06	0.09	0.39	0.06	0.18	0.08	0.41	0.06	0.17
57	4492	0.13	0.07	0.09	0.23	0.10	0.05	0.07	0.19	0.08	0.07	0.07	0.18
58	4494	0.03	0.05	0.06	0.08	0.03	0.07	0.09	0.28	0.22	0.15	0.14	0.27
59	4492	0.01	0.08	0.09	0.38	0.24	0.20	0.18	0.29	0.21	0.17	0.15	0.48
60	4473	0.35	0.25	0.27	0.08	0.26	0.18	0.19	0.28	0.25	0.15	0.16	0.47
61	4480	0.08	0.01	0.05	0.03	0.15	0.07	0.04	0.13	0.12	0.10	0.14	0.11
62	4472	0.16	0.04	0.05	0.21	0.12	0.22	0.16	0.15	0.12	0.24	0.20	0.13
63	4480	0.14	0.46	0.22	0.13	0.16	0.47	0.24	0.10	0.15	0.45	0.24	0.10
64	4477	0.11	0.31	0.21	0.04	0.08	0.27	0.19	0.12	0.10	0.29	0.22	0.12
65	4470	0.06	0.01	0.11	0.15	0.05	0.06	0.17	0.12	0.07	0.07	0.16	0.18
66	4471	0.08	0.09	0.18	0.02	0.06	0.18	0.14	0.14	0.06	0.18	0.17	0.13
67	4462	0.08	0.31	0.04	0.20	0.06	0.28	0.13	0.17	0.07	0.31	0.12	0.20
68	4464	0.06	0.18	0.15	0.01	0.04	0.15	0.13	0.12	0.07	0.17	0.16	0.13
69	4457	0.06	0.22	0.06	0.17	0.05	0.25	0.12	0.16	0.14	0.31	0.24	0.13
70	4457	0.10	0.04	0.14	0.03	0.21	0.08	0.26	0.07	0.22	0.07	0.28	0.06
71	4462	0.22	0.14	0.31	0.11	0.19	0.10	0.29	0.08	0.22	0.12	0.34	0.09
72	4456	0.11	0.08	0.20	0.10	0.18	0.06	0.29	0.07	0.18	0.06	0.30	0.08
73	4459	0.21	0.24	0.30	0.09	0.19	0.21	0.29	0.07	0.16	0.17	0.26	0.09
74	4453	0.11	0.07	0.19	0.08	0.08	0.15	0.16	0.14	0.12	0.27	0.13	0.26
75	4446	0.03	0.02	0.07	0.13	0.16	0.13	0.08	0.28	0.25	0.23	0.14	0.40
76	4435	0.19	0.54	0.11	0.30	0.28	0.38	0.19	0.41	0.28	0.31	0.17	0.43
77	4425	0.28	0.58	0.23	0.21	0.26	0.55	0.18	0.19	0.22	0.50	0.15	0.16
78	4426	0.18	0.27	0.09	0.03	0.13	0.22	0.09	0.06	0.14	0.22	0.08	0.05
79	4430	0.06	0.19	0.10	0.09	0.05	0.25	0.08	0.07	0.09	0.33	0.07	0.09
80	4424	0.10	0.24	0.03	0.07	0.16	0.32	0.04	0.13	0.19	0.37	0.05	0.15

TABLE 16: Relative prediction error (in percent) for 1, 2 and 3 steps ahead of metric **Density** of database Autonomous. Notation: number in title is number of steps ahead. Shortcuts: TS (time slice), RV (real value), SVM (Suport Vector Machine), MLP (Multilayer Perceptron), GP (Gaussian process) and LR (Linear Regression)

TS	RV	SVM 1	MLP 1	GP 1	LR 1	SVM 2	MLP 2	GP 2	LR 2	SVM 3	MLP 3	GP 3	LR 3
3	1.8097E-04	1.07	0.86	0.89	0.76	-	-	-	-	-	-	-	-
4	1.8035E-04	0.93	2.82	1.63	0.16	2.73	1.99	3.45	0.43	-	-	-	-
5	1.8112E-04	4.12	0.84	0.05	0.55	3.99	1.51	0.97	0.72	16.07	1.28	0.80	0.72
6	1.7859E-04	0.59	0.37	0.17	0.97	0.44	0.32	0.45	0.80	0.67	0.28	0.43	0.66
7	1.8141E-04	3.22	1.43	2.76	3.85	2.30	1.14	2.05	2.84	2.35	0.93	2.28	2.76
8	1.8013E-04	4.47	2.31	1.75	0.06	3.15	1.65	1.25	0.55	4.05	1.91	1.70	0.62
9	1.8164E-04	1.75	1.00	0.94	1.87	1.37	0.81	0.79	1.45	1.33	0.67	0.68	1.36
10	1.8158E-04	0.35	0.60	1.23	0.66	0.76	0.90	1.00	0.96	0.63	0.78	1.08	1.04
11	1.8253E-04	2.39	2.73	1.88	2.52	1.80	2.00	1.42	1.96	2.32	2.40	1.74	3.44
12	1.8255E-04	1.16	1.87	1.65	1.02	0.89	1.35	1.47	1.31	1.01	1.29	1.71	1.48
13	1.8352E-04	0.19	0.14	2.52	2.41	0.14	0.22	2.12	1.88	0.79	0.65	2.22	1.93
14	1.8393E-04	1.15	1.42	3.24	0.04	1.23	1.59	2.48	0.88	1.00	1.33	2.60	0.98
15	1.8342E-04	1.92	0.12	2.84	1.37	1.64	0.94	2.21	1.33	2.13	0.83	2.65	1.59
16	1.8279E-04	0.76	0.87	0.28	1.06	0.62	0.72	0.23	0.89	0.99	0.98	0.19	1.52
17	1.8332E-04	0.12	0.35	0.18	1.00	0.37	0.29	0.17	1.06	0.38	0.71	0.57	1.23
18	1.8354E-04	0.43	0.04	0.07	1.13	0.51	0.57	0.59	1.17	0.67	1.03	1.07	1.08
19	1.8425E-04	0.58	0.59	0.76	0.29	0.98	1.01	1.26	0.95	1.17	1.19	1.54	1.05
20	1.8589E-04	0.68	0.67	1.37	0.87	0.60	0.58	1.49	0.89	0.51	0.48	1.50	0.86
21	1.8628E-04	0.22	0.34	1.19	0.78	0.26	0.29	1.08	1.31	0.35	0.24	1.08	1.73
22	1.8606E-04	0.51	0.30	0.63	0.52	0.64	0.25	0.69	0.61	0.75	0.22	0.70	0.66
23	1.8623E-04	0.05	0.33	0.63	0.24	0.10	0.44	0.64	0.24	0.93	0.60	0.79	0.89
24	1.8648E-04	0.08	0.16	0.20	0.08	1.09	0.81	1.37	0.90	0.93	0.79	1.12	0.78
25	1.8351E-04	1.45	1.24	1.80	1.40	1.10	1.04	1.26	1.00	0.90	0.87	1.06	0.88
26	1.8735E-04	0.68	3.42	0.93	2.45	0.48	3.40	0.72	2.36	1.77	5.04	2.18	3.91
27	1.8702E-04	0.12	0.65	0.11	2.18	1.94	2.50	2.35	4.37	2.26	2.96	2.80	4.99
28	1.9399E-04	2.79	2.46	3.29	5.61	2.84	2.39	3.41	5.77	2.64	2.11	3.45	5.87
29	1.9463E-04	3.31	2.66	2.63	5.72	2.59	2.81	2.52	5.79	2.98	4.01	2.86	5.79
30	1.9491E-04	0.11	3.32	1.64	5.67	1.12	2.36	2.03	5.62	2.30	2.19	2.57	5.62
31	1.9475E-04	1.69	5.23	1.89	5.39	2.81	5.25	2.40	5.41	3.45	5.37	2.88	5.53
32	1.9481E-04	1.22	2.56	1.78	5.25	1.59	2.05	2.18	5.43	1.59	2.38	2.40	5.57
33	1.9552E-04	0.53	0.69	1.50	5.43	0.40	0.71	1.62	5.56	0.34	1.05	1.73	5.83
34	1.9606E-04	0.89	0.75	0.94	5.53	1.06	0.54	1.03	5.86	2.10	0.45	0.86	5.93
35	1.9738E-04	0.01	0.29	0.68	6.00	1.14	0.67	0.48	5.96	2.16	1.83	0.61	5.90
36	1.9720E-04	1.60	3.62	0.22	5.74	2.60	3.60	0.71	5.67	3.91	3.97	0.83	5.59
37	1.9691E-04	1.23	0.95	0.67	5.44	1.78	1.09	0.67	5.35	2.51	1.12	0.62	5.35
38	1.9653E-04	0.59	0.50	0.17	5.11	0.89	0.74	0.13	5.16	1.21	1.04	0.64	5.39
39	1.9673E-04	0.12	0.23	0.19	0.06	0.24	0.32	0.86	0.48	0.76	0.27	0.94	0.53
40	1.9800E-04	0.15	1.83	1.07	0.20	0.74	1.77	1.01	0.19	1.47	1.67	0.88	0.43
41	1.9800E-04	0.81	0.45	0.23	0.30	1.51	0.32	0.23	0.60	1.98	0.27	0.27	0.74
42	1.9762E-04	1.58	0.68	0.26	0.60	1.92	0.73	0.30	0.72	2.52	0.65	0.53	0.97
43	1.9789E-04	0.71	0.58	0.16	0.44	1.19	0.83	0.43	0.83	1.49	0.88	0.44	0.93
44	1.9747E-04	0.92	0.50	0.44	0.82	1.06	0.47	0.38	0.87	1.30	0.52	0.35	0.94
45	1.9817E-04	0.12	0.33	0.05	0.07	0.23	0.29	0.04	0.15	0.38	0.27	0.04	0.21
46	1.9861E-04	0.12	0.15	0.05	0.06	0.24	0.11	0.05	0.22	0.30	0.17	0.05	0.30
47	1.9908E-04	0.19	0.13	0.09	0.26	0.20	0.12	0.09	0.31	0.38	0.15	0.17	0.56
48	1.9957E-04	0.07	0.08	0.11	0.16	0.28	0.20	0.17	0.44	0.40	0.21	0.25	0.62
49	1.9937E-04	0.26	0.31	0.20	0.49	0.32	0.35	0.27	0.61	0.37	0.42	0.32	0.73
50	1.9957E-04	0.22	0.22	0.19	0.36	0.26	0.31	0.23	0.40	0.25	0.44	0.21	0.45
51	1.9984E-04	0.03	0.11	0.13	0.18	0.12	0.08	0.09	0.18	0.43	0.61	0.60	0.76
52	2.0051E-04	0.14	0.58	0.08	0.05	0.55	0.46	0.64	0.79	0.55	0.72	1.72	1.13
53	1.9903E-04	0.87	0.31	0.89	1.08	0.76	1.09	2.13	1.34	1.07	1.71	3.12	2.02
54	1.9879E-04	0.19	0.68	2.52	0.56	0.81	1.27	3.41	1.10	0.68	1.05	3.33	0.95
55	1.9671E-04	0.85	1.07	2.12	0.99	0.76	0.75	1.65	0.70	0.75	0.68	1.51	0.58
56	1.9950E-04	1.10	0.49	0.32	0.99	1.15	0.56	0.28	1.05	1.07	0.47	0.24	0.90
57	1.9967E-04	0.54	0.18	0.07	0.25	0.43	0.50	0.21	0.59	0.49	1.03	0.81	1.02
58	1.9937E-04	0.17	0.60	0.31	1.01	0.82	1.05	1.02	1.50	0.98	0.95	0.91	1.23
59	1.9748E-04	0.92	1.88	1.27	1.04	1.25	1.32	1.06	1.25	1.04	1.26	0.91	1.02
60	2.0182E-04	1.99	1.81	1.30	2.37	1.51	1.31	0.93	2.01	1.24	1.11	0.88	1.71
61	1.9962E-04	0.40	0.13	0.44	0.66	0.74	0.35	0.93	1.67	1.04	0.49	1.29	2.01
62	1.9834E-04	0.80	2.03	1.07	1.85	1.00	1.96	1.38	1.88	1.22	2.35	1.70	2.28
63	1.9742E-04	0.76	3.13	1.26	0.33	0.96	2.77	1.56	0.47	0.88	2.81	1.55	0.38
64	1.9673E-04	0.53	0.57	1.36	0.33	0.37	0.41	1.22	0.31	0.49	0.47	1.09	0.49
65	1.9775E-04	0.32	0.07	0.57	0.51	0.74	0.38	0.44	0.81	0.96	0.60	0.36	1.07
66	1.9861E-04	0.65	1.64	0.03	0.66	0.74	2.43	0.12	0.83	0.86	2.62	0.20	1.06
67	1.9938E-04	0.35	0.69	0.19	0.50	0.51	0.92	0.27	0.67	0.58	1.01	0.27	0.80
68	1.9982E-04	0.26	1.04	0.29	0.43	0.25	1.09	0.25	0.50	0.32	1.35	0.29	0.71
69	1.9979E-04	0.05	0.19	0.11	0.24	0.14	0.27	0.21	0.47	0.11	0.45	0.21	0.64
70	2.0012E-04	0.13	1.31	0.25	0.27	0.11	1.69	0.22	0.32	0.16	2.14	0.24	0.45
71	2.0007E-04	0.21	0.47	0.11	0.18	0.30	0.53	0.16	0.31	0.58	0.49	0.18	0.29
72	2.0034E-04	0.20	2.86	0.18	0.27	0.51	3.07	0.20	0.20	0.54	3.25	0.17	0.34
73	1.9973E-04	0.51	0.85	0.26	0.08	0.46	0.88	0.20	0.21	0.38	0.78	0.29	0.66
74	2.0027E-04	0.02	0.44	0.01	0.34	0.36	0.75	0.38	0.87	0.52	0.88	0.55	1.17
75	2.0158E-04	0.52	0.45	0.56	0.95	0.65	0.52	0.69	1.15	0.74	0.64	0.79	1.39
76	2.0230E-04	0.44	0.32	0.62	0.68	0.53	0.46	0.71	0.83	0.59	0.55	0.74	1.01
77	2.0281E-04	0.20	0.37	0.59	0.96	0.22	0.36	0.60	1.42	0.18	0.29	0.53	2.12
78	2.0293E-04	0.08	0.76	0.43	0.97	0.33	0.68	0.33	1.69	0.27	0.89	0.51	2.02
79	2.0251E-04	0.33	0.31	0.05	1.33	0.26	0.66	0.46	1.46	0.29	0.85	0.65	1.76
80	2.0382E-04	0.39	0.27	0.64	0.48	0.47	0.37	0.80	0.77	0.78	0.67	1.18	0.98