

1 Discovery of Non-Persistent Motif Mixtures using MRST 2 (Multivariate Rhythm Sequence Technique)

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6

7 **Abstract**

8 In this paper we present a prototype to discover the unsupervised repeating temporary
9 perception in a time series. The purpose of this work is to control the case of random variable
10 and to find out the measurements caused by the phenomena of simultaneous synchronization.
11 The proposed model has used the non-parametric Bayesian technique to trace the motifs and
12 their occurrences in the data documents. We introduce the Multivariate Rhythm Sequence
13 Technique (MRST) method to find the rebound and repeated motifs and their instance in
14 every document automatically and simultaneously. This model is used in wide range of
15 applications and concentrates on datasets from different modalities. The video footages from
16 non-dynamic cameras and data location bounded to the motif-mining server. The high
17 semantic internal representation of the method gives advantage in operation such as event
18 counting or analyse the scene. We used the sample images and videos from New York City
19 traffic data for experiments with and the results shows better performance than the existing
20 motif mixtures analysis in the time series.

21

22 **Index terms**— motif mining, multivariate time series, unsupervised analysis, bayesian modelling, camera
23 network.

24 **1 I. Introduction**

25 Motif Mining is one of the active research area in recurrent temporal pattern in time series. The ultimate aim is
26 to find out the small amount of repeating temporal pattern with little possible super vision in multiple variant
27 time series. The super position analysis using various phenomena in time series is without synchronization. This
28 work is to extractarious operations and activities in different domains from the video footage. Normally we get
29 the video sequence consists different movements by various people or various objects present in the video footage.
30 In this case we are using the long term recording to study the independent activities and their presence in the
31 video automatically.

32 Time series motifs are recurrent segments in a long time series that their presence implies the precise
33 information about the underlying source of the time series. Motif discovery in time series data has received
34 significant attention in the data mining community since its inception, principally because, motif discovery is
35 meaningful and more likely to succeed when the data is large.

36 Different types of the time series has the same characteristics of being unification of the multiple actions or
37 motifs. Here we assume the time series pertaining to the electricity lining and consumption of the water in a
38 particular building. In this experiment, we can find out the motif such as water consumption and short circuit
39 in the building. It is also possible that we can find some other method to supply the water and electricity in
40 the particular apartment. It is also possible to determine the consumption of water and electricity. This kind of
41 multiple incidence of motifs happens at the same time without any synchronization.

2 II. RELATED WORK

42 To find out the specific activity patterns without supervision is our primary goal. The starting point of the
43 task is to recap the scene, count or detect the specific scene to find with the unusual activity. Figure 1 explains
44 the difference in the particular case without supervision video sequence.

45 2 II. Related Work

46 Considering the non-parametric Bayesian technique, it is systematically investigating each of the implicit number
47 of motifs and number of motif present in every document. This method validates the synthetic data. This method
48 also used for other prediction efficient such as video sequence and other domains. [1] The video sequences are
49 divided into simple clips in order to find the flow fields in that particular video sequences. Pixels has quantized
50 based in the motion location and direction. This is a group of words denoted in the clips. Once we find the
51 group of words, we can do the next state called as screening. This stage is to measure the words using the
52 technique called "conditional entropy" after getting the result in full words, which are applied, to the diffusion
53 map. Diffusion map is the framework, which has included the multiplex of the points into lower dimensional space
54 while preserving the intrinsic local geometric pattern. [2] Hierarchical Bayesian method combines three elements
55 in a visual surveillance. Basic a) level visual aspect, b) uncomplicated atomic activities and c) communication.
56 Atomic activities are modelled as distributions over low-level visual features, and interactions are modelled as
57 distributions over atomic activities. This method uses unsupervised learning method. Taking a long video footage,
58 movable points are clustered as various atomic activities and small video sequence shows the interactions. [3]
59 Unsupervised learning method relies on possibilities. Latent semantic analysis approach is used to set visual
60 characteristics including the attributes like size and motion activities for finding same actions happening in the
61 particular scenes. Then the patterns are found in the segments into regions is clear and activity content. [4]
62 We present two novel methods to automatically learn spatiotemporal dependencies of moving agents in complex
63 dynamic scenes. They allow to discover temporal rules, such as the right of way between different lanes or typical
64 traffic light sequences Systematically, the spatiotemporal dependencies of moving agents are observed in the in
65 complex dynamic scenes. This scene allows to find out temporary protocols as the exact way between various
66 lanes in the typical traffic areas. First model is based on the protocol based learning method. The next method
67 uses Dependent Dirichlet Processes to learn an arbitrary number of infinite Hidden Markov Models. DDP-HMM.
68 [5]. Different guessing based on kalman filter and nonargument regression are getting posterior inference in the
69 topic. LDA is the Latent Dirichlet Algorithm method captures the data not only in the depressed concept data.
70 We analysis how the architecture changes over the time. Here every method is related with the continuous
71 distribution timestamps. Every document word generated by co-occurrence of the timestamp. ??6][7] A Markov
72 clustering topic method is present to build in earlier method of dynamic Bayesian network method. Bayesian
73 method has eliminated the draw backs about accuracy, strength and efficiency. Difficult dynamic clips by strength
74 clustering visual activities correlates over the time. The Gibbs sampling is used for the offline and unlabelled
75 data. [8] LDA is used to find out the global correlation in the spread camera network LDA is used to divide the
76 object action structure and local behaviour in every camera view first interference of the two local behaviours
77 globally over the different camera views. The LDA is preparing to find out actions and temporal correlations.
78 [9] Latent Dirichlet Approach based method take the snap of the activities that changes over a period. The
79 agglomerative based clustering on optical flow vectors in different angle and spatial information. Here every
80 activity interrelates with not only in the distribution. It is interrelated with distribution over the timestamps.
81 [10] Normally every document has the combination of continuous motif activity and their starting appearance.
82 Here they are using the three methods. First method has interrelated word at the particular time stamps and
83 find out the word repeated in the document in the particular time series or temporal window. Second find the
84 repeated action in the document. The third to find out the same occurrence and activity, which should be
85 monitored. [11] Bunch of data in each observation are grouped together in a mixture model. The number of
86 colloid tools is known as unknown priori frequency from the data. This arrangement is known as the Dirichlet
87 process the identified cluster property has provided the nonargument prior the number of composition of tools in
88 each group. [12] A structure of the non argument Bayesian method is known as the dual Hierarchical Dirichlet
89 process. Unsupervised gravity discusses and semantic circle method in investigation settings. Heretrajectory is
90 as the words in the document, which clusters into various activities. Defective words are identifying as sample
91 with low probability. Semantic atmosphere sets way to get objects and relate the actions in the particular scene
92 and creates the model of the scene. [13] Global discourse method detects the abnormal activity that isolated
93 appearance. Practical sector believe that kind of argument modulate is needed and real time is finagle. ??14][15].

94 Using the activity trend has presence of instance to invoke similarity. Here no need of the inter camera
95 registration or adjustment. However, apart from that system learn the camera network and possibilities of the
96 path and instance in Parson Window at the time of training. When the training is finished related are assigned
97 the maximum posterior the estimated structure. [16] A cross-canonical correlation analysis structure detect and
98 express the normal relationship in the two regional activities in the cross camera view. Find the spatial and
99 network structure of the camera. Accurate and identify the person or object. Perform the activity segmentation
100 collect the different camera views. [17] Global Journal of Computer Science and Technology Volume XVII Issue
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102 3 ()

103 Using the base level of the queue instance is finding in the each camera view independently and the landmark
104 and speed of instance and trajectories are calculated as advantage. Generative method learns the actions and
105 features in different camera sites. Grouping a same picture or image has convert into one cluster. Then all the
106 cluster has find out from the different camera views and make it as a co-clustering has been published. [18]

107 4 III. Proposed Model

108 This proposed model MRST is to process the motif, number and occurrences. This section will explain three
109 variations of the method called TAMM, VLTAMM and TSVLMM before going to the main concept in detail.

110 5 a) Background on Time Series Mrst Process

111 We introduce the Time Series of MRST Process, as a model, which handle the infinite mixture in the building,
112 is our approach collusion components categorizes to the form of distributions. Here we are used the Gaussian
113 mixture model to explain the concepts in the introduction part. The infinite number of mixture has an alternative
114 delimited number with k and the time serial to accept this mixture nodes weight vector π as the length and π as
115 the form. π is the real number as argument and t is the time period while we are using the "stick breaking"
116 method has given the infinite list of data that sum to 1. The weight vector $\pi_1 = \pi_1$ is obtained from the beta
117 distribution. The second weight vector in the same way $\pi_2 = (T - \pi_1) * \pi_1$ and so on this way is called as the
118 stick breaking method. (2) take it as π_k in to π calculate the π with a time period t

119 (3) adding the π value where $\pi = Z(i) * \pi$ (4) A concentrated equal node has been used to denote the time series
120 MRST process. The mixture presentation has well acceptable derive the Gibbs sampling method concentrated
121 presentation is used in the broad manner to get a quick view of the model.

122 6 b) The Proposed Model

123 Our aim is to derive set of motifs a collection of record containing the index words. We define the record j is the
124 group of experiment. $\{(w(ji), at(ji))\}_{i=1...n(j)}$ where $w(j)$ words refer to the word book and the $at(ji)$ is the at
125 mean time of the experiment occurred in the document

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127 Volume XVII Issue I Version I We look up the time details when defining the motifs temporal possibilities map.
128 More importantly π_k point the motif table and π_k (w , RT) defines the possibility the word w presence at the
129 relevant time object when the motif occurs (RT) is stated out aim is conclude the set of motifs more than one
130 document. As per the early discussion it is compulsorily added to the every document. It is very difficult to find
131 the number of motifs in advance so here we are using the time series MRST process which allows to read the
132 number of variable in the motifs in the document.

133 Our new approach of the MRST process has use the graphical representation method shown in the figure ???.1
134 and 5.2. Consider the two diagrams the time series process notation has indicated by the group of square in the
135 above diagram and the further method has used to find the variables and number of motifs in the time series of
136 the document.

137 Here the settled relation is referring as the first MRST level which prepare the number of motifs from the
138 ultimate combination M. Every motif has derived from an MRST process of distribution with argument N. Basic
139 combination model has been LDA or HDP, the set of combination of the section is not only mutual information
140 or document but also across the MRST using the second level commonly the document specification displacement
141 $O(j)$ is not consider the motif mixture.

142 Observations ($w(ji), at(ji)$) are produced by the repeated sampling motif using the motif $\pi(ji)$ to sample the
143 word and its relevant time and motif. Using the sampling start time $at(ji)$ absolute time $st(ji)$ can be reduced.
144 The developed method given in fig 4bit helps to understand the creation process.

145 The important difference in this small scale model is the way of the repentance as created is represented
146 explicitly. Occurrence of the table Chinese restaurant model document specific is used to create the examples.

147 8 c) Modeling Prior H And Motif Length In A Time

148 The earlier section shows the worldwide structure of the method specially simplified the explanation of the
149 superior H and neglect the details The first method uses the finite motif length. The method of the paper created
150 to allow the various motifs length of each is automatically has variable length temporal analysis of motifs that
151 derived from the model 1 as the TAMM temporal analysis of motif mixture which is the important setting of the
152 hyper arguments.

153 TAMM is the fixed duration so we are adding the variable time in $t(i)$ to above model diagram so that it can
154 be easily find out the motifs in the various time sequence. The hyper argument has variation so that we can
155 find out easily in the secular time stamps or time periods. Here the influences of the variability surround this
156 variation expectation. A huge weight of the result is less variability. Define the possibility of the words uniformly

157 given and eliminate the size of the shape is the main role. However reduce the shape acts the important role in
158 the interference.

159 **9 Graph 1 Graph 2**

160 Graph 1 & 2 shows the weight truncated distribution with different values and exponential rate. This is used to
161 control the size of the slope in the particular time period.

162 A Gama distribution with arguments ($T=T1, T2$) is used as the earlier argument of every motif. It must to be
163 corrected Gama conjugate with the weight in the truncated distribution. Argument lambda and Z is fixed. This
164 conjugate condition in the face of the L (lambda and Z) is greater than analysed from the truncated exponential
165 distribution. It is represented as the following expression

166 **10 IV. Inference**

167 Here we are going to explain the stages about the inference. A pass over the stage executable for the VLTMM
168 and TAMM method will be performed publically. To perform the inferences uses the confused Gibbs sampling
169 $\{o_{ji}, k_{jo}, o_{stjo}, ?k\}$. The balance variable has logical integrating sampling and can integrate the motifs in their
170 self used as H in the time series TRVSPT process distribution.

171 According to the sampling possibility organize and observer the mention earlier appearance is propositional
172 to the two quantities. The first quantity is according to the MRST and CRP on the appearance and related to
173 the number of repentance associated in the occurrence. The next step has to be comes in the likelihood of the
174 particular observation then its virtual association and in the particular repentance.

175 The different method to crate the new repentance for this example is the Chinese restaurant process as its
176 inverse to $?$. This possibility of the repentance is the inverse of the likelihood observation to the control of the
177 hypothesis joined with random repentance. The linear process has all starting time control to integrate the
178 initial time. Here we have a MRST and motif already as in the above example the possibility has inverse to the
179 occurrence of the counting. Conjugate the MRST distribution H over motifs. We control to integrate the finding
180 of motifs drawn to H as in Graph 3.

181 **11 Graph 3**

182 Distribution of the number of mixture elements sufficient to cover a proportion P of the total weight According
183 to VLTAMM method has taken the arguments in hierachal manner of the TAMM the argument has directly
184 converted into the number of motifs. The isolation of the parameter gets the more important. So that controls
185 the number of repentance in a document that might depend on the documents duration. Examples taking from
186 the Gibbs sampling method are to get the data and large amount of the data repeated or overlap in the particular
187 time frame. The consequences are data set independent of the document and take the reference the small values.

188 The fixed weight truncation Z is the structure argument for weight truncation method. It manages the
189 structure of the temporal in the motif. Weight exponential method is less support. To choose Z value considers
190 the q ratio in between the values of the distribution.

191 **12 Graph 5**

192 Maximum motif length: Distribution of maximum motif length L_k ; Z when varying the prior $_$ and keeping the
193 parameter Z fixed

194 **13 Graph 6**

195 T can be used to control the location and spread of the range of prior acceptable values for L_k ; Z.

196 **14 VI. Video Data Analysis**

197 Our method explains the experiments about the video data. Here we show the temporal documents from the
198 input video talking about the temporal timing duration and method aspects of our model. Also establishes the
199 interest and result of model time in the motif by comparing the results with other methods.

200 **15 a) Videos Convert To Temporal Document**

201 Created temporal documents has extracted the number of words at every time. Time step for the impermanent
202 document use the pixel resolution for one second. One method will be our vocabulary directly using to low level.
203 Result in a huge vocabulary with heavy temporal leads to a high disturbance computing load we capture the
204 data in the low level feature of cooccurrence and convert to high level word. To eliminate the confusion about
205 the notation use the super script in the word from the low-level layer.

206 In the first stage of feature extraction we have to extract the flow feature of the optical dense image grid. We
207 place or store the pixels where the motion could be happened or detected. We divide the quantize in to nine
208 categories of one to eight commonly quantize the flow of direction to prepare the slow motion. The low level
209 character has used to define the position and image motion category. The size of the low level word should be

210 high but however we reduce the words in to nearly 25000 words. Because we are considering the words only we
211 run the slid window for second five to forty frames to get depending on the data set without dead lock and collect
212 every time stamp in the particular window.

213 Details on dimensionality reduction getting the set of document have to be applied the probabilistic latent
214 semantic method. This method takes the input words and count every document learn the set of data words by
215 the defined distribution on low level word to corresponding to the soft cluster words that repeated words in the
216 document. Scene has fixed here because we are reduced the dimensionality reduction.

217 PLSA method is the entire processes of this stage learns the new video documents and give the decomposition
218 of the every document mixture of the earlier method the topic weights given by the distribution. We are use this
219 data reweighted by according to the activity use to build the documents constitute the input method.

220 Divided in to two five-second motifs.

221 **16 Figure 5**

222 Here the video is factorized to full length and it is divided into the possible motifs and to full duration of the
223 time motif. At last the motif duration has been increased and recovers the motif properly.

224 Use of the motif duration arguments VLTAMM provides the approach to deal with the short coming of the
225 fixed motif duration. Variable length with motif duration with VLTAMM shows the sum of the result. Activity
226 diary and abnormality reporting is used to find the real motif when they occur at the real time. Here we take
227 the example for the length of the video of 30 minutes and extract the motif and find out the motif time in the
228 particular video scene. After getting the scene combine together and find out the motif occurrence.

229 **17 VII. Comparison with Other Types**

230 One disadvantage of other existing method is the difficulty to find out the motif and it's recurrent. Were as to
231 find the temporal document ahs to build the independent documents in the information is neglected here using
232 LDA HDP-LDA. PLSA is used for the process method but using long temporal window it has neglected the time
233 ordering to recover the motif and do not carry the temporal information and temporal granularity noise of the
234 video.

235 The second model is time order sensitive LDA, here same slide window use the modification Cartesian product
236 the original vocabulary and relative time within the particular window. The issue of this model are documents
237 considering only in the independent and there is no necessity to align the data with the original activities in
238 the video. So that the real time activity assume happen at different places. Our approach doesn't have any
239 disadvantage compare to the above methods. Our method has store the temporal data independent and starting
240 of their time of the actual scene of the video. low level features using the low level count matrix. Low level
241 camera calibration has the possibility to take large amount space because of the different camera view, we are
242 using the three hundred or high level motifs. Low level support in the normal camera view suppose the overhead
243 as in the camera 2 and camera 2 low level method has span the camera and make it as the two view and choose
244 the nosily view and random occurrence. This activity has solved if larger amount of training data has used in
245 this example Recovered motif in multi camera these motif has resent the 78 percentage of the observation has
246 find the actions and find the activity capture automatically.

247 Evaluation of the timing information has arises at the time that matches the original timing of the real
248 image. But it is the problem to find out the different camera our model has find out very easily it recover
249 the people activity between the two camera views. The start and end projection has displayed in the motif
250 background process. Then we can easily calculate the difference between the original image activity and the
251 motif representation. For example the result we are taken from the station about nearly two hours of unlabeled
252 scenes. Recover motif has compared and the presence of the repentance is extract these data has used to remove
253 the multiple sequence of the data motif and convert the low level into high level of the motif using in the larger
254 data. So that the repentance should be very high. The place of the track let information decrees the suspicious
255 matches.

256 Figure 12

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259 **19 VIII. Conclusion**

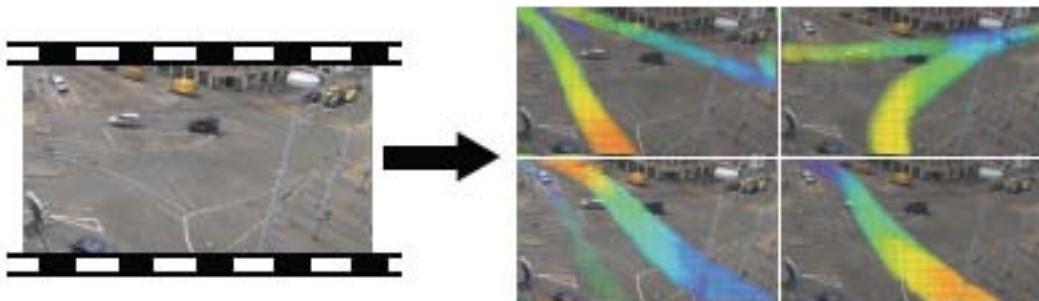
260 This model shown is new concept of finding the redundant temporal patterns in the particular time series. This
261 method has used to find the joint and repeating motifs in the particular document. Identify how many common
262 motifs present in the document and number of times motif occur in the document and also estimate the motif
263 duration.

264 This method has validated the broad range of the data set and real time activity like traffic signals, micro
265 phone pair, and video data's. Here we explained that the video data is activities in the traffic signals such as the
266 movement of the car and typical person in the metro train station. Apply the simultaneous image on different
267 camera view information without any calibration.

268 Audio signal coming from the two microphones in our model has used to recover the interest activities and
 269 yielded detection and precision. Using the artificial data assuming the robust model in the various hyperactive
 270 parameters has produced the meaning full information at the various situation applied in the variety of the data
 271 with success rate.

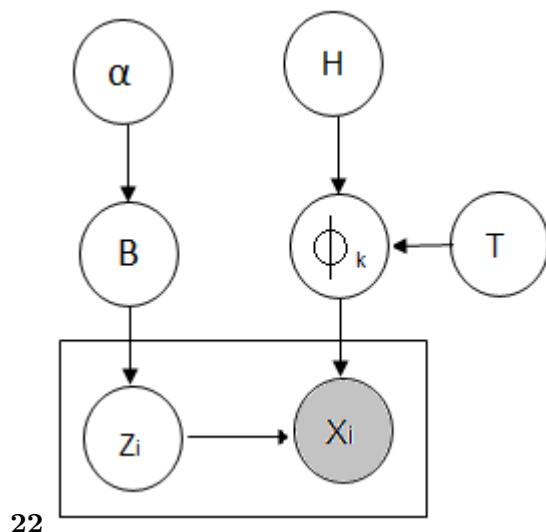
272 **20 IX. Future Work**

273 In future, this proposed model can be improved at the different levels to find the repeating values but it is not
 274 applied on the global activities. Suppose we are using the traffic signals we have to incorporate the heterogeneous
 275 methods to find out the recurrent motifs detection approaches. Then we will emphasise the different cycles of
 276 motifs and relation data for discover patterns. To scale up the input camera footage polynomial data will be
 concentrated in the upcoming approaches in time series. ¹



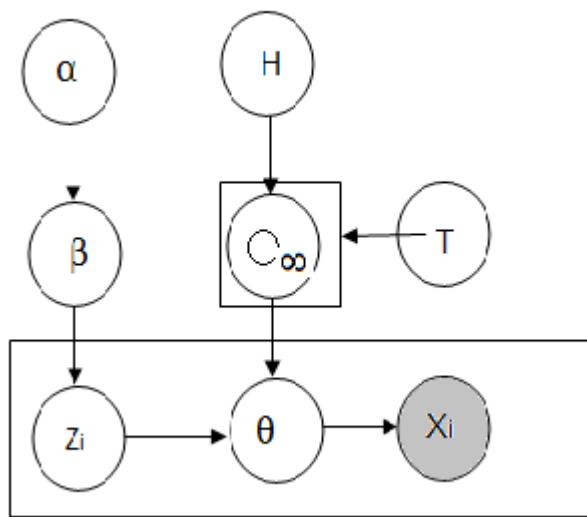
11

Figure 1: Figure 1 Figure 1



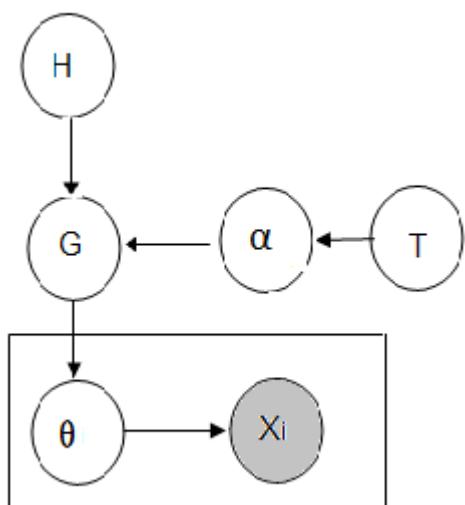
22

Figure 2: Figure 2 Figure 2



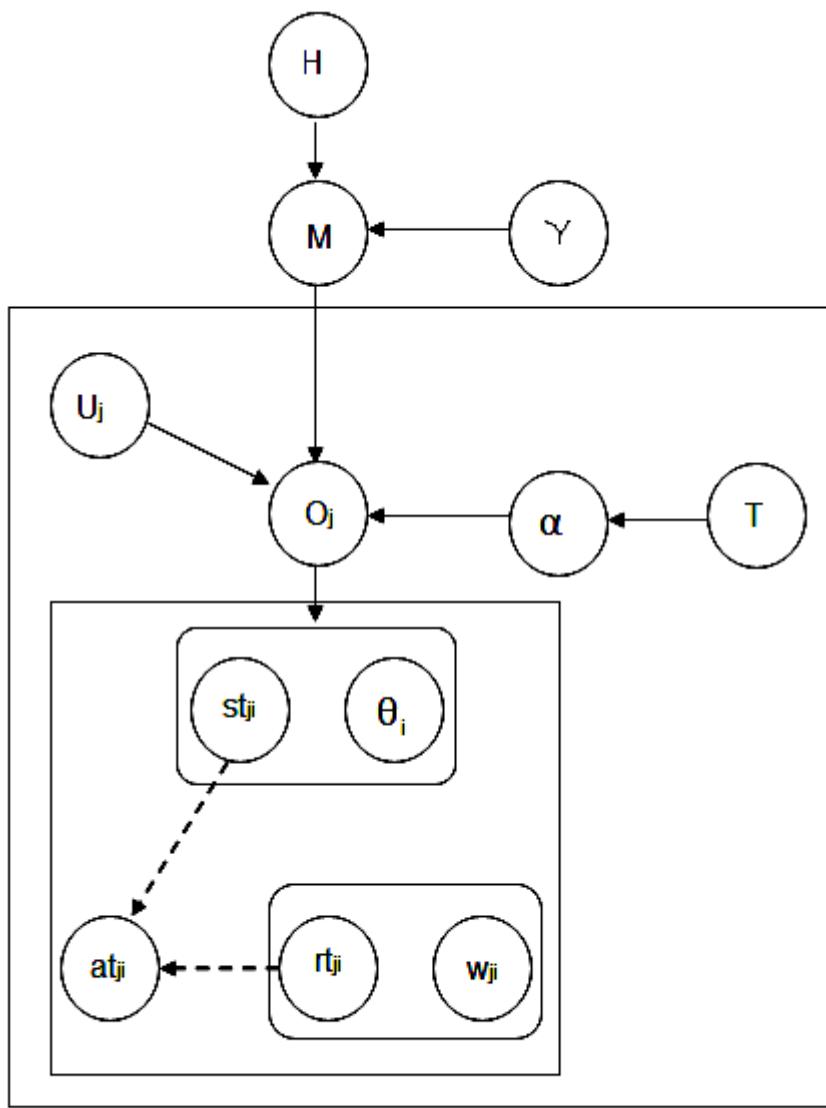
1

Figure 3: Algorithm 1 getting



2

Figure 4: Figure 2



41

Figure 5: Figure 4 Global 1 C

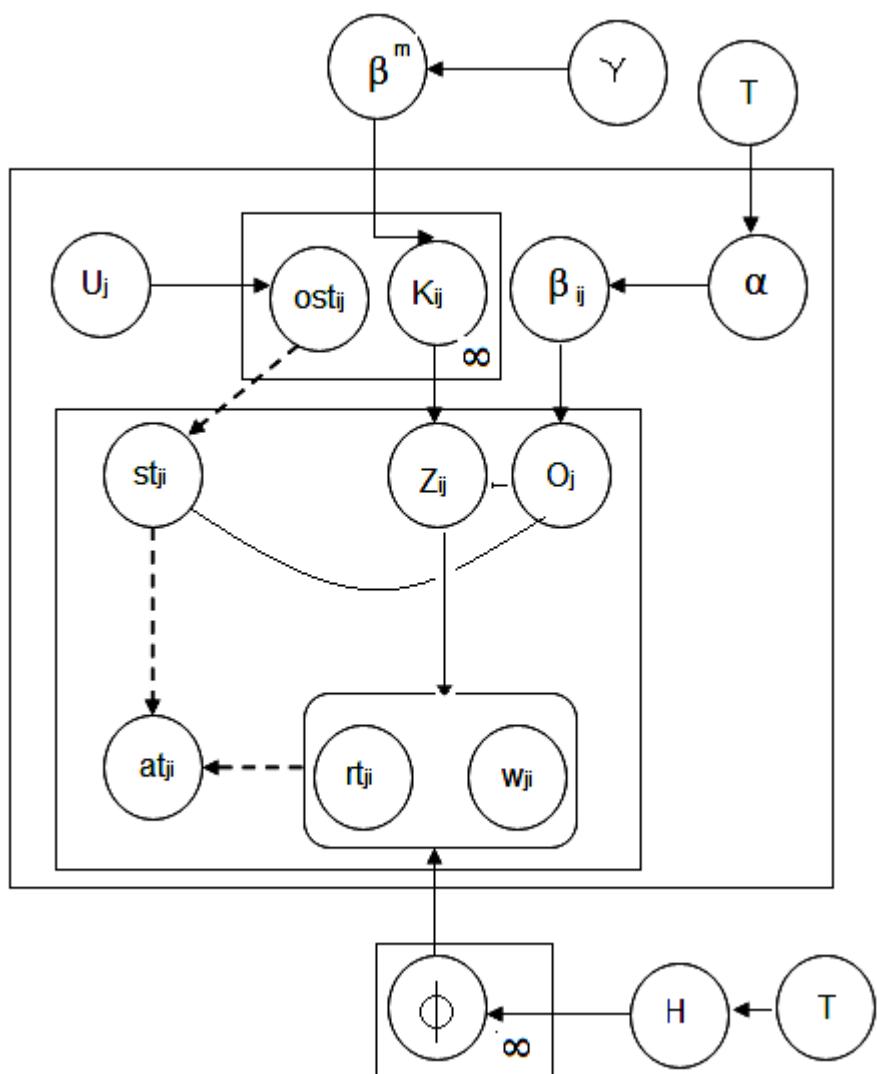
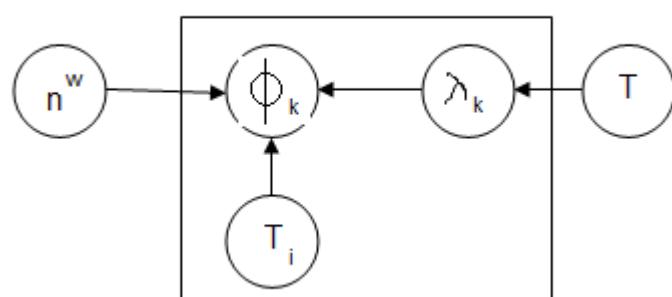
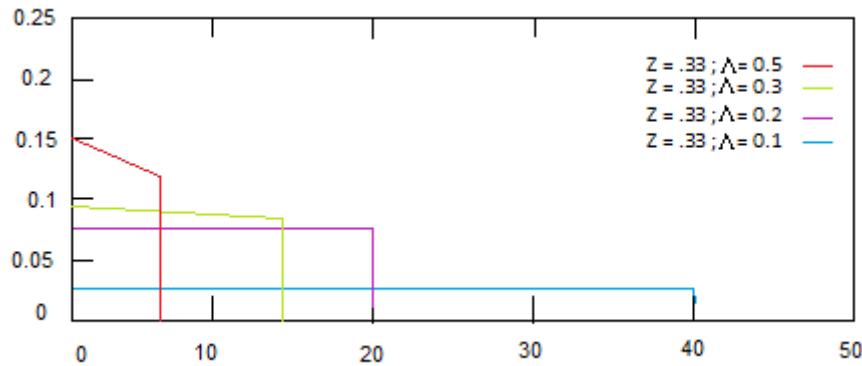


Figure 6: C



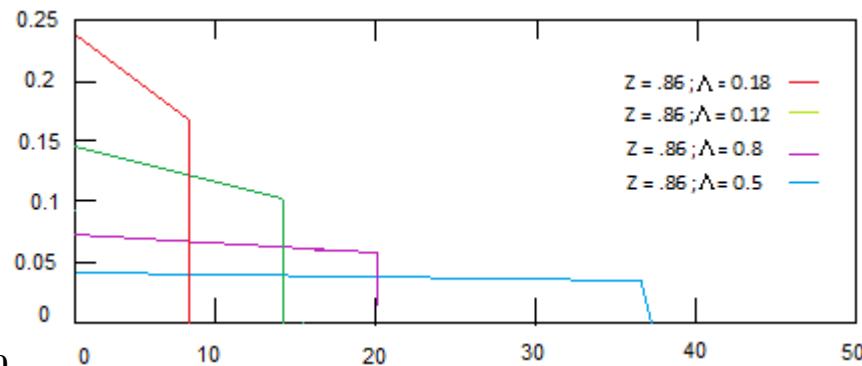
6

Figure 7: Figure 6 :



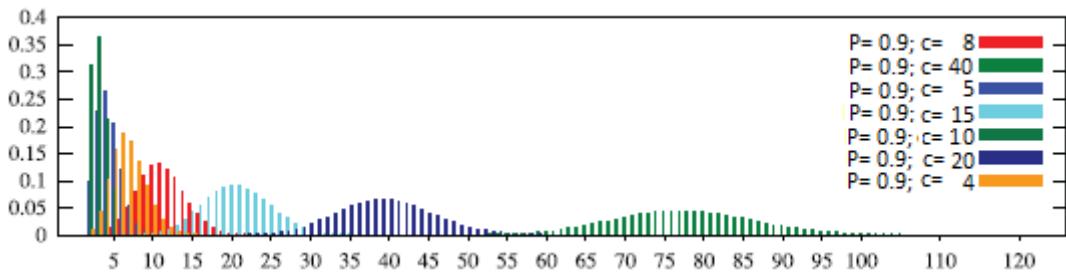
9

Figure 8: Figure 9 :



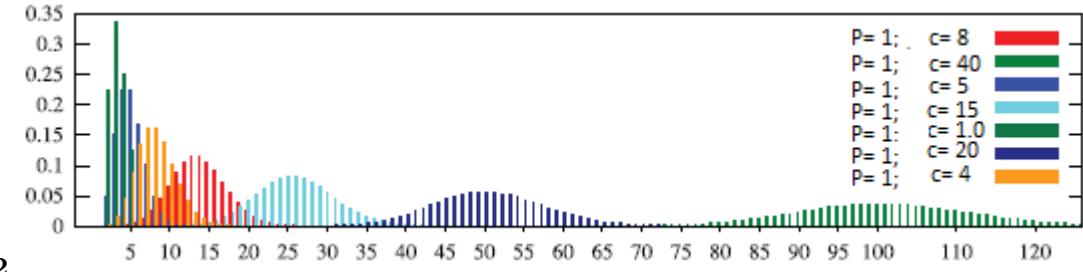
10

Figure 9: Figure 10 :



7

Figure 10: Figure 7 :



12

Figure 11: Figure 12

1

Motif	Path		Measured Duration				Duration motif
	Start	end	average	std	min	max	
A	a-b		26	2.8	30	32	28
B	a-b		28.5	5.2	25	43	27
C	a-c		19.9	9.0	15	38	18
D	a-b		9.5	1	9	16	8.5

Figure 12: Table 1 :

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