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RESEARCH ARTICLE

Effectiveness of model-based clustering in analyzing *Plasmodium falciparum* RNA-seq time-course data [version 1; referees: awaiting peer review]

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Abstract

Background: The genomics and microarray technology played tremendous roles in the amount of biologically useful information on gene expression of thousands of genes to be simultaneously observed. This required various computational methods of analyzing these amounts of data in order to discover information about gene function and regulatory mechanisms.

Methods: In this research, we investigated the usefulness of hidden markov models (HMM) as a method of clustering *Plasmodium falciparum* genes that show similar expression patterns. The Baum-Welch algorithm was used to train the dataset to determine the maximum likelihood estimate of the Model parameters. Cluster validation was conducted by performing a likelihood ratio test.

Results: The fitted HMM was able to identify 3 clusters from the dataset and sixteen functional enrichment in the cluster set were found. This method efficiently clustered the genes based on their expression pattern while identifying erythrocyte membrane protein 1 as a prominent and diverse protein in *P. falciparum*.

Conclusion: The ability of HMM to identify 3 clusters with sixteen functional enrichment from the 2000 genes makes this a useful method in functional cluster analysis for *P. falciparum*

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Introduction

Technological advancement in bioinformatics such as the high throughput sequencing technology has resulted in the availability of a very large amount of informative data¹. Expressions of thousands of genes are now being measured concurrently under various experimental conditions using microarray technology. Microarray consists of many thousands of short, single stranded sequences, each immobilized as individual elements on a solid support, that are complementary to the cDNA strand representing a single gene. Gene expression measurements can be obtained for thousands of genes simultaneously using microarray technology. In a cell, genes are transcribed into mRNA molecules which in turn can be translated into proteins, and it is these proteins that perform biological functions, give cellular structure and in turn regulate gene expression².

Various researches had been carried out on the analysis and extraction of useful biological information such as detection of differential expression, clustering and predicting sample characteristics³. One of the important of gene expression data is the ability to infer biological function from genes with similar expression patterns⁴. Due to large number of genes and complexity of the data and networks, research has suggested clustering to be a very useful and appropriate technique for the analysis of gene expression data which can be used to determine gene coregulation⁵, subpopulation⁶, cellular processes, gene function⁷ and understanding disease processes⁸.

Clustering algorithms as described by⁹ can either be distance based or model based. Distance-based clustering such as the k means¹⁰ does not consider dependencies between time points while the model based approach embeds time dependencies and uses statistical models to cluster data. Other approaches include Self Organizing Maps¹¹, Principal Component Analysis, hierarchical clustering⁴, graph theory approach¹², genetic algorithms and the Support Vector Machine¹³. These algorithms has been successfully applied to various time series data but still have various shortcoming such as determining the optimal number of clusters and choosing the best algorithm for clustering since most of them are based on heuristics. The algorithms are also not very effective especially when a particular gene is associated with different clusters and performs multiple functions.

This research focuses on clustering of genes with similar expression patterns using Hidden Markov Models (HMM) for time course data because they are able to model the temporal and stochastic nature of the data. A Markov process is a stochastic process such that the state at every time belongs to a finite set, the evolution occurs in a discrete time and the probability distribution of a state at a given time is explicitly dependent only on the last state and not on all the others. This refers to as first-order Markov process (Markov chain) for which the probability distribution of a state at a given time is explicitly dependent only on the previous state and not on all the others. That is, the probability of the next (“future”) state is directly dependent only on the present state and the preceding (“past”) states are irrelevant once the present state is given¹⁴. Fonzo *et al.*¹⁴ defined HMM as a generalization of a Markov chain in which each (“internal”) state is not directly

observable (hidden) but produces (“emits”) an observable random output (“external”) state, also called “emission” state. Schliep *et al.*⁹ proposed a partially supervised clustering method to account for horizontal dependencies along the time axis and to cope with the missing values and noise in time course data. This approach used k means algorithm and the Baum welch algorithm for parameter estimation. Further analysis on the cluster was done with the Viterbi algorithm which gives a fine grain, homogeneous decomposition of the clusters. The partial supervised learning was done by adding labeled data to the initial collection of clusters. Ji *et al.*¹⁵ developed an application to cluster and mine useful biological information from gene expression data. The dataset was first normalized to a mean of zero and variance of one and then discretized into expression fluctuation symbol with each symbol representing either an increase, decrease or no change in the expression measurement. A simple HMM was constructed for these fluctuation sequences. The model was trained using the Baum-Welch EM algorithm and the probability of a sequence given a HMM was calculated using the forward-backward algorithm. Several copies of the HMM was made so that each copy represent a single cluster. These clusters were made to specialize by using a weighted Baum-Welch algorithm where the weight is proportional to the probability of the sequence given the model. The Rand Index and Figure of Merit was used to validate the optimal number of cluster results.

Geng *et al.*¹⁶ developed a gene function prediction tool based on HMM where they studied yeast function classes who had sufficient number of open reading frame (ORF) in Munich Information Center for Protein Sequences (MIPS). Each class was labeled as a distinct HMM. The process was performed on three stages; the discretization, training and inference stages and data used for this analysis was the yeast time series expression data. Lees *et al.*¹⁷ proposed another methodology to cluster gene expression data using HMM and transcription factor information to remove noise and reduce bias clustering. A single HMM was designed for the entire data set to see if it would affect clustering results. Each path in the HMM represents a cluster, transition between states in a path is set to a probability of 1 and transition between states on different path is set to a probability of 0. Genes were allocated to clusters by calculating the probability of each sequence produced by the HMM. Clusters were validated using the likelihood ratio test which computes the difference in the log-likelihood of a complex model to that of a simpler model. Zeng and Garcia-Frias¹⁸ implemented the profile HMM as a self-organizing map, this profile HMM is a special case of the left to right inhomogeneous HMM which is able to model the temporal nature of the data. This makes it very useful for real life applications. The profile HMM is trained using the Baum-Welch algorithm¹⁹ and clustering was done using the Viterbi algorithm and the algorithm was implemented on the fibroblast and the sporulation datasets. Beal *et al.*²⁰ implemented the Hierarchical Dirichlet Process Hidden Markov Model (HDP-HMM) for clustering gene expression data with countably infinite HMM. Gibbs sampling method was used to reduce the time complexity of the inference. The data used for the implementation was derived from Lyer *et al.*²¹ and Cho *et al.*²² which was normalized and standardized to a log ratio of 1 at time $t = 1$. Baum Welch algorithm was used for Estimation Maximization. In this work, we adopted the

work of Lee *et al.*¹⁷ and applied HMM on the *Plasmodium falciparum* RNA-seq dataset.

Materials and methods

In this work, data was extracted and normalized to a mean of 1 and standard deviation of 0. Discretization was done on the data to improve the clustering results. The HMM forward-backward algorithm and Baum-Welch training algorithm was implemented to cluster the gene expression data. Genes were then assigned to cluster using the forward algorithm and inference was done by obtaining functionally enriched genes in the cluster set using FunRich tool. The data used was published by 23, they used the Illumina based sequencing technology to extract expressions of 5270 *P. falciparum* genes at seven different time points every 8hrs for 42hrs. The clustering algorithms was implemented by first randomly initializing all the HMM parameters, then, forward algorithm was implemented to calculate the forward probabilities of the observation and Baum-Welch algorithm was used for data fitting, then the likelihood of each HMM was calculated iteratively until the optimal likelihood is obtained. This process is repeated for all the different sized HMMs used.

Definitions and notation

HMMs can be viewed as probabilistic functions of a Markov chain²⁴ such that each state can produce emissions according to emission probabilities.

Definition 1. (Hidden Markov Model). Let $O = (O_1, \dots)$ be a sequence over an alphabet ϵ . A Hidden Markov Model λ is determined by the following parameters:

- S_i , the states $i = 1, \dots, N$
- π_i , the probability of starting in state S_i ,
- α_{ij} , the transition probability from state S_i to state S_j , and
- $b_i(\omega)$, the emission probability function of a symbol $\omega \in \Sigma$ in state S_i .

Definition 2. (Hidden Markov Cluster Problem). Given a set $O = \{O^1, O^2, \dots, O^n\}$ of n sequences, not necessarily of equal length, and a fixed integer $K \ll n$. Compute a partition

$C = (C_1, C_2, \dots, C_k)$ of O and HMMs $\lambda_1, \dots, \lambda_k$ as to maximize the objective function

$$f(c) = \prod_{k=1}^k \prod_{O^i \in C_k} L(O^i | \lambda_k) \quad (1)$$

Where $L(O^i | \lambda_k)$ denotes the likelihood function for generating sequence O^i by model λ_k :

Data preprocessing

The preprocessing was done in two stages. The first stage was the normalization and the second stage was discretization. The normalization was done with the R statistical package using the normalize library. Normalization removes static variation in the microarray experiment which affects the gene expression level. Normalization also helps in speeding up the learning phase. Missing values are also removed during normalization. Discretization was done by converting the time points to symbols depending on whether the expression value has increased, decreased or not changed. This is done by using the equation below.

$$S_i = \begin{cases} 0 & \text{if } E_i - E_{i+1} < a \\ 1 & \text{if } E_{i+1} - E_i \geq a \\ 2 & \text{if } E_i - E_{i+1} \geq a \end{cases} \quad (2)$$

Where:

S_i = fluctuation level between time i and $i + 1$

E_i = expression level at time point i

L = number of time points.

a = threshold value between timepoints.

HMM for clustering gene expression data

In this work, we implemented a model-based HMM clustering algorithm where a cluster represents a path in the HMM model. Therefore, as the number of cluster increases, the number of paths through the model increases and the HMM becomes larger and larger. The number of hidden state is the number of clusters multiplied by the sequence length. Research has also shown that HMM that transverse from left to right best models time series data, therefore HMM moves from only right-to-left. The structure of the HMM is shown in Figure 1.

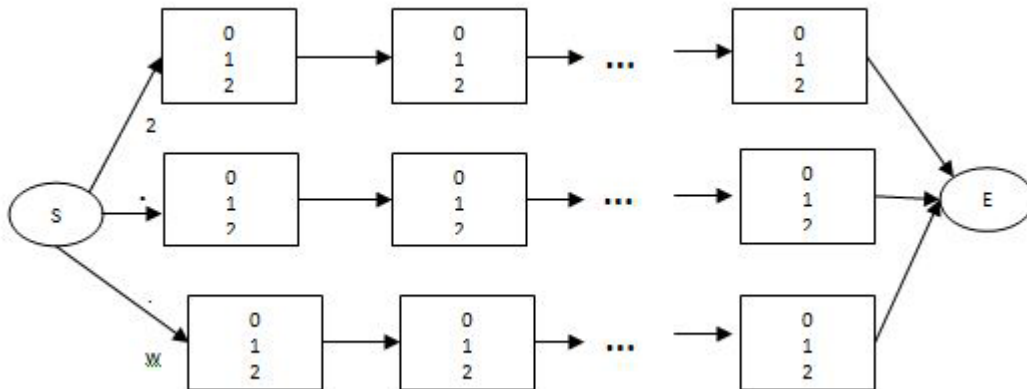


Figure 1. HMM design from cluster 2 to w. The number 0, 1, and 2 represents the emission symbols at each state.

The left to right model has the property that, as the time increases, the state transition increases, that is, the states moves from left to right. This process is conveniently able to model data whose properties change over time.

The forward algorithm calculates the forward probabilities of a sequence of observation. This is the probability of getting a series of observation given that the HMM parameters (A , B , π) are known. This computation is usually expensive computationally. The time invariance of the probabilities can however be used to reduce the complexity of this algorithm by calculating the probabilities recursively. These probabilities are calculated by computing the partial probabilities for each state from times $t = 1$ to $t = T$. The sum of all the final probabilities for each states is the probability of observing the sequence given the HMM and this was used in this research to compute the likelihood of a sequence given the HMM. The algorithm is in 3 stages and illustrated as follows:

Initialization stage

This initializes the forward probability, which is the joint probability of starting at state and initially observing O_1 .

$$\alpha_i(1) = \pi b_i(O_1) \quad 1 \leq i \leq N$$

Induction stage

$$\alpha_i(t+1) = \left[\sum_{j=1}^N \alpha_j(t) \alpha_{ij} \right] b_i(O_{t+1}) \quad 1 \leq t \leq T-1$$

This is the joint probability of observation and state **3** at time $t+1$ via state at time t (i.e. the joint probability of observing o at state **3** at time $t+1$ and from state and time t). This is performed at all states and is iterated for all times from $t = 1$ to $T-1$.

Termination stage

This computes all the forward variables, which is the $P(o|M)$.

$$P(o|M) = \sum_{i=1}^N \alpha_i(T)$$

Where:

α_{ij} = transition from state i to j

$b_i(o)$ = probability of emitting a symbol in a particular state

t = time

M = model

α_i = forward variable of state i

π = probability of starting at a particular state

The backward algorithm like the forward algorithm calculates backward probabilities instead. The backward probability is the probability of starting in a state at a time t and generating the rest of the observation sequence $O_{t+1}, \dots, O_T$. The backward probability can be calculated by using a variant of the forward algorithm.

Therefore, instead of starting at time $t = 1$, the algorithm starts at time $t = T$ and moves backwards from O_T to O_{t+1} . In this work, the backward algorithm was used alongside the forward algorithm to re-estimate the HMM parameters. This algorithm also involves three steps and is illustrated below.

Initialization

This is the initial probability of being in a state S_i at time T and generating nothing. The value of this computation is usually 1.

$$\beta_i(T) = 1, \quad 1 \leq i \leq N$$

Induction

This step calculates the probabilities of partial sequence observation from $t+1$ to end given state at time t and the model λ .

$$\beta_i(t) = \sum_{j=1}^N \alpha_{ij} b_j(O_{t+1}) \beta_{t+1}(j) \quad t = T-1, T-2, \dots, 1.$$

Termination

It calculates all the backward variables which is the $P(O_{t+1}, \dots, O_T | Q_1 = S_i)$.

$$P(O_{t+1}, \dots, O_T | Q_1 = S_i) = \sum_{t=1}^T \beta_i(t)$$

Where:

α_{ij} = transition from state i to j

$b_j(o)$ = probability of emitting a symbol in a particular

$\beta_i(j)$ = backward variable of state i in time t

The Baum-Welch algorithm, sometimes called the forward-backward algorithm makes use of the results derived from this algorithm to make inference. The Baum-Welch algorithm is a special form of the Expectation Maximization algorithm used for finding the maximum likelihood estimate of the parameters of the HMM. It was used in this work to train the various sized HMM parameters.

The E part of the algorithm calculates the expectation count for both the state and observation. The expectation of state count is denoted by $\gamma_i(t)$. It is the probability of being in state t giving observation sequence and the model.

$$\gamma_i(t) = \frac{P(q_t = i | \lambda)}{P(o | \lambda)} = \frac{\alpha_i(t) b_i(t)}{\sum_{j=1}^N \alpha_i(t) b_j(t)} \quad (3)$$

The expectation of transition count is denoted by $\varepsilon_{ij}(t)$. It is the probability of being in state S_i at time t and state S_j at time $t+1$ given an observation sequence and the model.

$$\varepsilon_{ij}(t) = P(q_t = i, q_{t+1} = j | o, \lambda) = \frac{\alpha_i(t) \alpha_{ij} b_j(t+1) b_j(o_{t+1})}{\sum_{i=1}^N \sum_{j=1}^N \alpha_i(t) \alpha_{ij} b_j(t+1) b_j(o_{t+1})} \quad (4)$$

Based on the expectation probabilities, we can now estimate the parameters that will maximize the new model. This is the M step of the algorithm.

The new initial probability distribution can be calculated as follows.

$$\pi' = \gamma_i(1) \quad (5)$$

The re-estimated transition probability distribution is also calculated as follows:

$$\alpha'_{ij} = \frac{\sum_{t=1}^{T-1} \varepsilon_{ij}(t)}{\sum_{t=1}^{T-1} \gamma_i(t)} \quad (6)$$

Finally, the new observation matrix is calculated using the formula below

$$b'_{ij} = \frac{\sum_{t=1}^{T-1} \gamma_i(t) I(o_t = k)}{\sum_{t=1}^{T-1} \gamma_i(t)}$$

The pseudo code of the training algorithm is represented below:

- i. *Begin with some randomly initialized or preselected model, π*
- ii. *Run O through the current model to estimate the expectations of each model parameter using the forward backward algorithm.*
- iii. *Change the model to maximize the values of each path using the new π' , α'_{ij} and $b'_{ij}(t)$.*
- iv. *Repeat until change in log likelihood is less than a threshold value or when the maximum number of iterations is reached.*

For global optimal results, this algorithm is usually iterated depending on the size of the dataset.

Results and discussion

Likelihood estimation

After implementing the HMM algorithms, the discretized data was parsed into the program. The dataset was trained using HMMs with cluster size from cluster 2 to 10. The likelihood of each HMM was calculated using likelihood ratio test and three clusters were identified. The likelihood ratio test of the dataset from cluster 2 to 10 is shown in [Table 1](#) below. A positive LRT show that increasing

the number of parameters is still worthwhile while a negative LRT shows that increasing the parameter would not give a better model. From the calculations below, the optimal number of clusters in the dataset based on the likelihood ratio test is 3. The log likelihoods of each cluster is also illustrated in [Figure 2](#) below. It shows that the log likelihood increases with more parameters added initially but from cluster 3, there was no significant increase in log likelihood showing that the optimal number of clusters has been attained.

Clustering results

The dataset was trained using the Baum-Welch algorithm and the probability that an observation sequence belongs to a cluster was calculated using the forward algorithm. Genes with discretized value of zeros were also removed. After the likelihood ratio test was calculated and the optimal number of clusters found, each data was then separated into clusters using the forward algorithm. The first cluster consists of 502 genes, the second cluster had 481 genes and the third cluster had 668 genes. These results are represented in the [Figure 3](#).

Table 1. Table showing LRT calculations. The LRT becomes negative after three (3) clusters giving the optimal number as 3.

K	Log Likelihood	LR (Likelihood Ratio)	LRT(Likelihood Ratio Test)
2	-143.34		
3	-102.28	41.06	7.02E+01
4	-95.62	6.66	1.42E+00
5	-89.17	6.45	1.00E+00
6	-86.89	2.28	-7.34E+00
7	-84.8	2.09	-7.72E+00
8	-8.44E+01	0.38	-1.11E+01
9	-8.27E+01	1.71	-8.48E+00
10	-8.10E+01	1.75	-8.40E+00

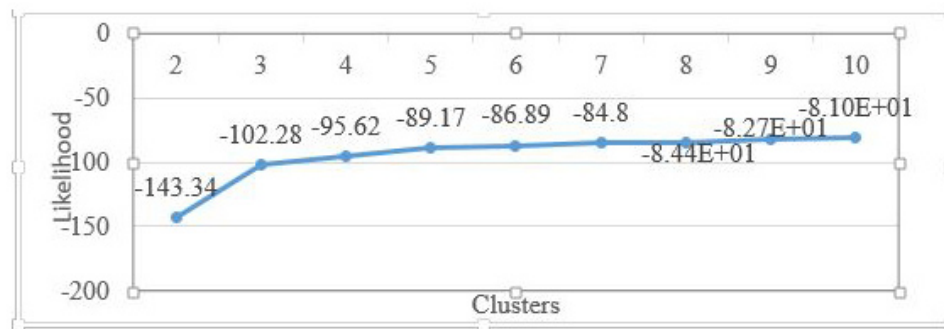


Figure 2. Log likelihoods for different numbers of clusters. The log likelihood values increase with the number of clusters sizes. After 3 clusters, there is not a significant increase in the log likelihood.



Figure 3. clustering results showing all the genes in each cluster. The x-axis shows the likelihood of each genes in each of the cluster and the y-axis shows the total number of genes in each cluster.

Functional-induced/determined clustering of *plasmodium falciparum* protein by the algorithm

Erythrocyte membrane protein1(pfEMP1) –Clusters 1 and 2

The clustering algorithm efficiently clustered the differentially expressed genes into 3 clusters based on their functions. It is noteworthy that the most abundant genes are the erythrocyte membrane protein 1 (PfEMP1). The proteins are grouped in cluster 1 and cluster 2. PfEMP1 is an ubiquitously expressed protein during the intraerythrocytic stage of the parasite growth that determined the pathogenicity of *P. falciparum*²⁵. The virulence of *P. falciparum* infections is associated with the type of *P. falciparum* PfEMP1 expressed on the surface of infected erythrocytes to anchor these to the vascular lining. PfEMP1 represents an immunogenic and diverse group of protein family that mediate adhesion through specific binding to host receptors²⁵. The *Var* genes encode the PfEMP1 family, and each parasite genome contains ~60 diverse *Var* genes. The differential expression of the proteins in this family has been reported to determine morbidity from *P. falciparum* infection²⁶. This differential expression during infection and among patients could have accounted for its clustering into 2 different clusters by the algorithm.

Apart from clustering cell adhesion proteins into a sub-cluster, the algorithm also clustered the proteins involved in actin binding, transmembrane transportation and ATP binding. While the genes involved in ATP binding a largely conserved with their functions yet to be experimentally determined, the transport proteins are bet3 transport protein and aquaporin. Aquaporin is a membrane spanning transport proteins that is essential in the maintenance of fluid homeostasis and transport of water molecules and it has been identified as good therapeutic target²⁷. Bet3 transport protein on the other hand is involved in the transport of proteins by the fusion of endoplasmic reticulum to Golgi transport vesicles with their acceptor compartment²⁸.

The second cluster also has sub-cluster of PfEMP1 with other sub-clusters for GTP and ATP binding /ATP-dependent helicase activity as well as structural components of ribosome and ubiquitin protein ligase activity. Apart from PfEMP1, other sub-clusters are involved in protein turnover-protein synthesis and degradation²⁹. These include the RNA helicases that prepare the RNA for translation and initiate translation, the ribosomal and GTP binding proteins that are integral part of the ribosome assembly involved in translation and the ubiquitin-conjugating enzymes are carry out the ubiquitination reaction that targets a protein for degradation via the proteasome^{30–32}.

The genes coding for proteins involved in catabolic activities such as breakdown of proteins and hydrolysis of lipids are clustered in cluster 3. This cluster also included sub-clusters for genes involved in motor activity and DNA structural elements. The DNA structural elements include histone proteins and transcriptional initiator elements which are involved in epigenetic control of gene expression³³. The ability of *P. falciparum* to grow and multiply both in the warm-blooded humans and cold-blooded insects is known to be under tight epigenetic regulation and it has been suggested as a good therapeutic target²⁵.

Functional annotation

The Functional Enrichment analysis tool was used to determine functionally enriched genes in each cluster. Each cluster was loaded separately based on their unique gene identifier. Genes are matched against the UniProt background database or by using a custom database that allows users load their own predefined Gene Ontology Term (GOTerm). We used the custom database and loaded annotations downloaded from PlasmoDB for our functional enrichment. The result of the 3 clusters is summarized in Table 2. FunRich was only able to identify 164 of the 502 genes in cluster 1. Cluster 1 has five functional annotations, 7.3% of the genes are functionally annotated with cell adhesion molecule,

Table 2. Functional annotation of each clusters. Cluster 1 has four GO annotations, cluster 2 has five and cluster 3 has seven functional annotations.

CLUSTERS	GO-ANNOTATION	GENE ID	NUMBER OF GENES
Cluster 1	Cell adhesion molecule, receptor activity	PFD0005w PFD1015c PFE0005w PFD0635c PFD1005c PFF0845c PF07_0048 PF07_0049 PF07_0050 MAL7P1.55 MAL7P1.56 PF08_0142	12
	Acting binding	PFE0880c PFE1420w	2
	Transporter activity	PFD0895c PF08_0097	2
	ATP binding	PFB0115w PFD0365c PFD0735c PFF0390w PF07_0074 PF08_0101	6
Cluster 2	Structural constituent of the ribosome	PFB0455w PFB0830w PFB0885w PFC0200w PFC0290w PFC0295c PFC0300c PFC1020c PFD0770c PFD1055w PFE0185c PFE0300c PFE0350c PFE0845c PFE0975c PFF0700c PFF0885w PF07_0043 PF07_0079 PF07_0080 PF08_0039 PF08_0075	22
	Cell adhesion molecule receptor activity	PFA0005w PFD0020c PFD0615c PFD0625c PFD0995c PFF0010w PFF1580c MAL7P1.50 PF07_0051 PF08_0103 PF08_0107 PF08_0140	12

CLUSTERS	GO-ANNOTATION	GENE ID	NUMBER OF GENES
	ATP binding and ATP dependent in a helicase activity	PFB0860c PFD0245c PFD1060w PFE1390w PF08_0042	5
	Ubiquitin protein ligase activity	PFC0255c PFE1350c MAL8P1.23	3
	GTP binding	PFC0565w PFE1215c PFE1435c PFF0625w	4
Cluster 3	Cysteine-type peptide activity	PFB0330c PFB0335c PFB0340c PFB0345c PFB0350c PFB0360c PFD0230c	7
	Endopeptidase activity	PFA0400c PFC0745c PFE0915c PFF0420c PF07_0112 MAL8P1.14 2	6
	Hydrolase activity	PFC0065c PFE0910w PFD0185c PF07_0040	4
	ATP binding, action binding and monitor activity	PFE0175c PFF0675c	2
	DNA binding	PFD0325w PFE0305w PF07_0035	3
	Unfolded protein binding	PFF0860c PFF0865w	2
	DNA binding, protein heterodimerization activity	PFE0595w PF07_0103	2

receptor activity, 1.2% are annotated with acting binding, 1.2% with transporter activity and 3.7% with ATP binding as shown in [Figure 4](#). The remaining genes has no GO functions. We can deduce that since these genes are in the same cluster, they are likely to have functions as the genes with GO annotation.

In cluster 2, FunRich was able to identify 308 genes. In cluster 2, 7.1% of the genes are functionally annotated with the structural constituent of the ribosome, 3.9% with cell adhesion molecule receptor activity, 1.6% with ATP binding and ATP-dependent in a helicase activity, 1.0% with ubiquitin protein ligase activity and 1.3% with GTP binding which gives a total of five functional annotations

as shown in [Figure 5](#). The rest of the genes in cluster 2 are also predicted to have similar functions as with the genes with known GO annotation.

In cluster 3, FunRich was able to identify 249 of the 668 genes in the cluster set. This cluster has the largest GO annotation as it is enriched with seven functions. 2.8% of the genes are enriched with cysteine-type peptide activity, 2.4% with endopeptidase activity, 1.6% with hydrolase activity, 0.8% with ATP binding, action binding and monitor activity, 1.2% with DNA binding, 0.8% with unfolded protein binding and 0.8% with DNA binding, protein heterodimerization activity as shown in [Figure 6](#). We can

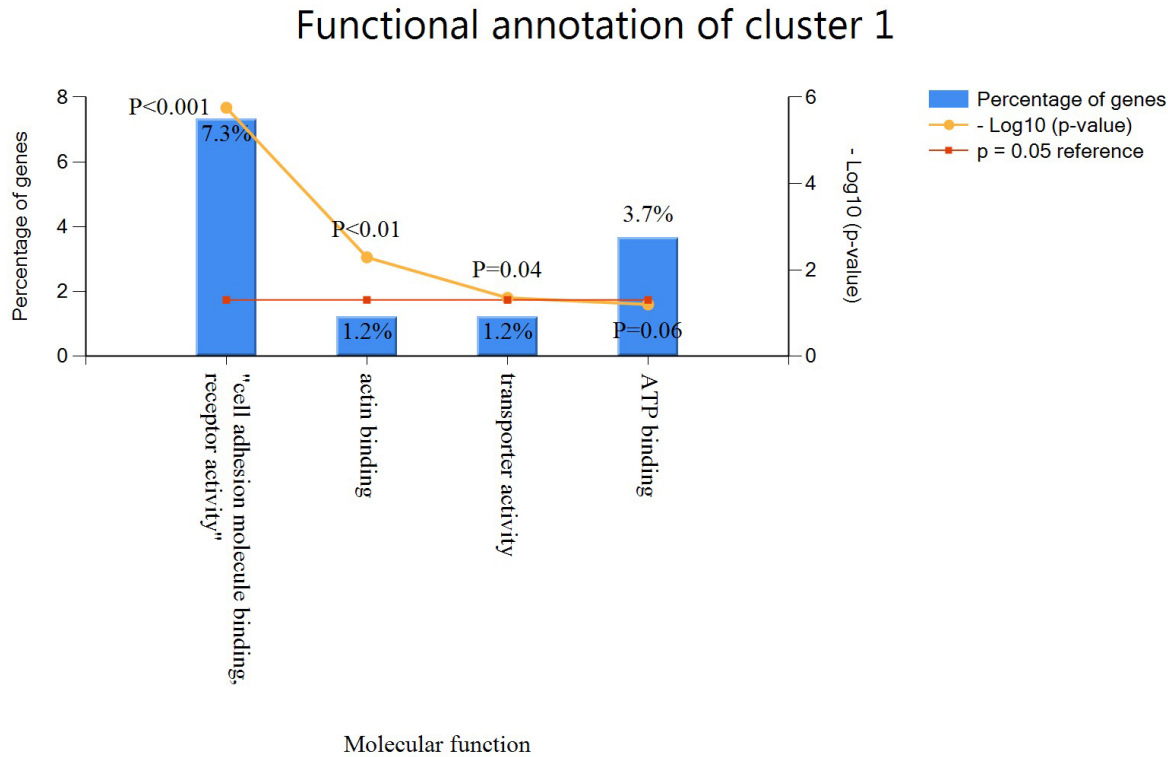


Figure 4. Functional annotation of cluster 1. The x-axis shows the percentage genes in the cluster with specific functional annotation while the y-axis shows the function of these genes.

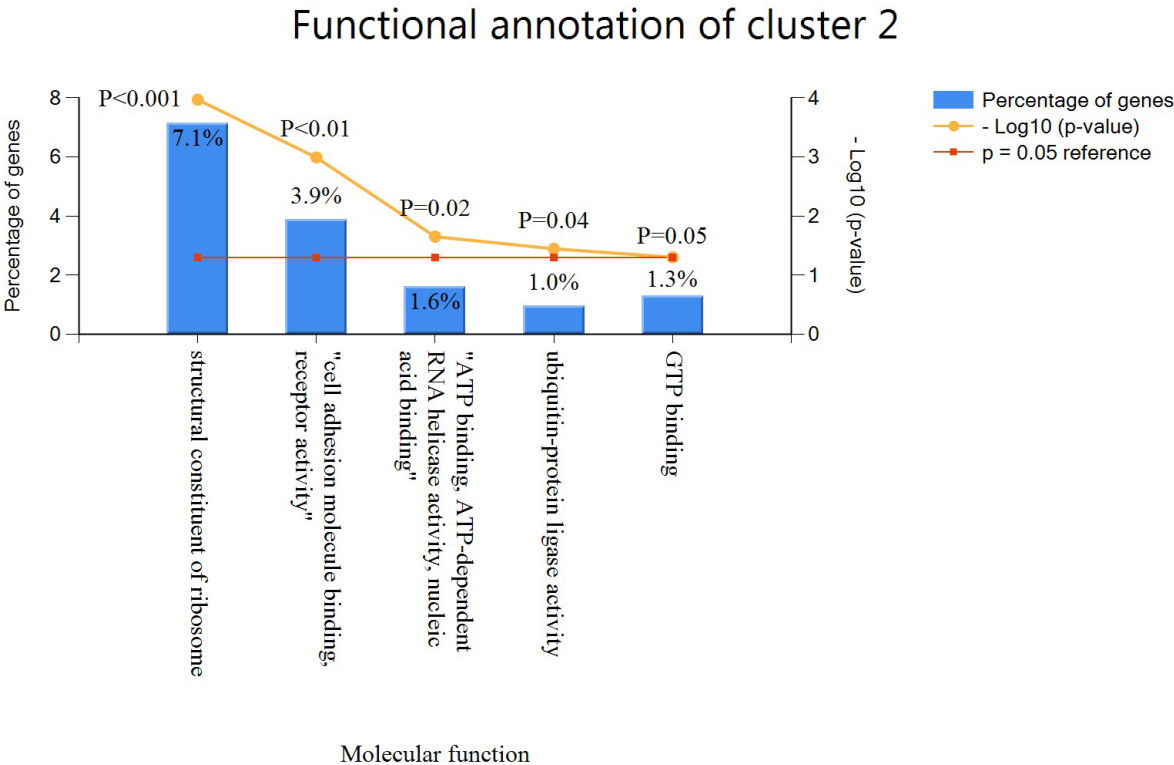


Figure 5. Functional annotation of cluster 2. The x-axis shows the percentage genes in the cluster with specific functional annotation while the y-axis shows the function of these genes.

Molecular function for cluster3

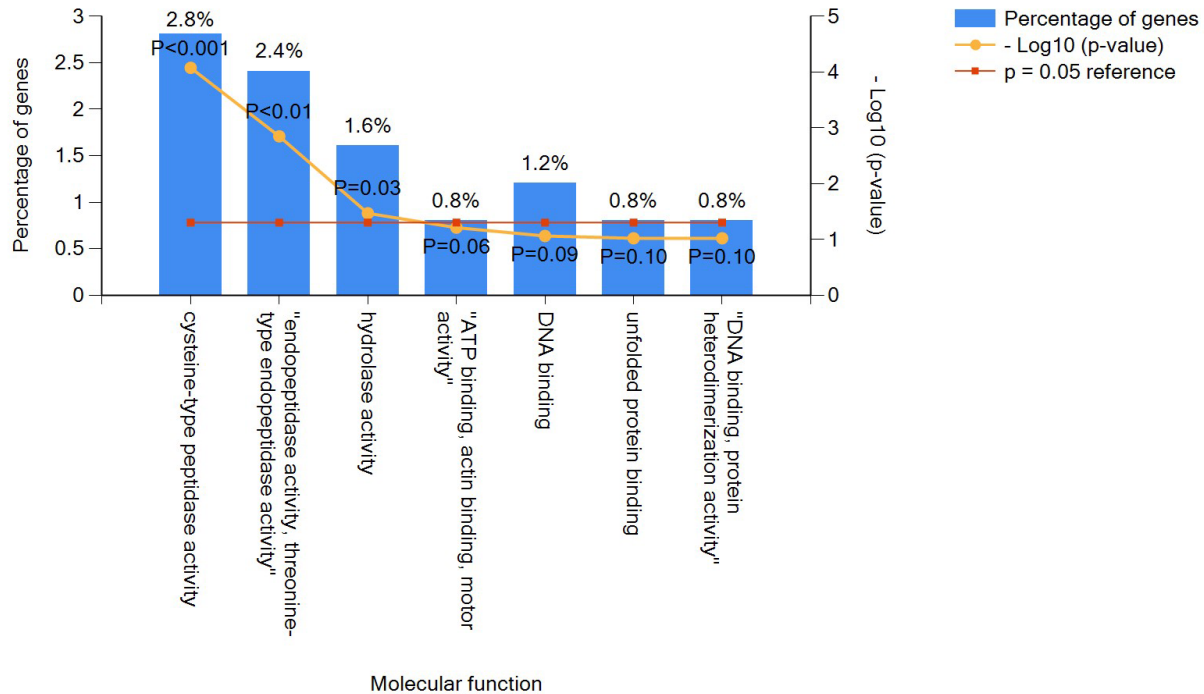


Figure 6. Functional annotation of cluster 3. The x-axis shows the percentage genes in the cluster with specific functional annotation while the y-axis shows the function of these genes.

also deduce that in cluster 3, the genes with unknown functions are also predicted to have the same functions as with the known ones.

Conclusion

Clustering has been found to be a very useful technique in analyzing gene expression data. It has the ability to display large datasets in a more interpretable format. Several approaches have been developed to cluster gene expression data. The HMM has a better advantage over them because of its strong mathematical background and its ability to model gene expression data successfully. The HMM algorithms were implemented to perform cluster analysis on the *P. falciparum* gene expression dataset. 2000 genes were used and 3 clusters were identified. Sixteen major functional enrichment were identified for the clusters.

Data availability

The data sets used in this study are freely available in www.ncbi.nlm.nih.gov/pubmed/20141604

Competing interests

There is no competing interests declared.

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