A Numerical Example on Stochastic Discrimination

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This note presents a numerical example for the principles of stochastic discrimination. The example is so chosen that all computations can be easily traced step-by-step by hand or very simple programs. The emphasis is on explaining the concepts of uniformity and enrichment, and the behavior of the discriminant when both conditions are fulfilled. For the details of the mathematical theory and outlines of practical algorithms, please refer to publications [1]-[4].

1 Symmetry of Probabilities Induced by Uniform Space Covering

We begin with a simple observation. Consider a set $S = \{a, b, c\}$ and all the subsets with two elements $s_1 = \{a, b\}$, $s_2 = \{a, c\}$, and $s_3 = \{b, c\}$. By our choice, each of these subsets has captured $2/3$ of the elements of S. We call this ratio r. Let us now look at each member of S, and check how many of these three subsets have included that member. For example, a is in two of them, so we say a is captured by $2/3$ of these subsets. We will obtain the same value $2/3$ for all elements of S. This value is the same as r. This is a consequence of the fact that we have used all such 2-member subsets and we have not biased this collection towards any element of S. With this observation, we begin a larger example.

Consider a set of 10 points in a one-dimensional feature space F. Let this set be called A. Assume that F contains only points in A and nothing else. Let each point in A be identified as q_0, q_1, ..., q_9 as follows.

$$\begin{array}{cccccccccc} \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ q_0 & q_1 & q_2 & q_3 & q_4 & q_5 & q_6 & q_7 & q_8 & q_9 \end{array}$$

Now consider the subsets of F. Let the collection of all such subsets be $\mathcal{M}$, which is the power set of F. We call each member m of $\mathcal{M}$ a *model*, and we restrict our consideration to only those models that contain 5 points in A, therefore each model has a size that is 0.5 of the size of A. Let this set of models be called $M_{0.5,A}$. Some members of $M_{0.5,A}$ are as follows.

$$\begin{array}{ccccc} \{q_0, & q_1, & q_2, & q_3, & q_4\ \} \\ \{q_0, & q_1, & q_2, & q_3, & q_5\ \} \\ \{q_0, & q_1, & q_2, & q_3, & q_6\ \} \\ \multicolumn{5}{c}{...} \end{array}$$

There are $C(10, 5) = 252$ members in $M_{0.5,A}$. Let M be a pseudo-random permutation of members in $M_{0.5,A}$ as listed in Table 1 in the Appendix. We identify models in this sequence by a single subscript such that $M = m_1, m_2, ..., m_{252}$. We expand a collection M_t by including more and more members of $M_{0.5,A}$ in the order of the sequence M as follows. $M_1 = \{m_1\}$, $M_2 = \{m_1, m_2\}$, ..., $M_t = \{m_1, m_2, ...m_t\}$.

Since each model covers some points in A, for each member q in A, we can count the number of models in M_t that include q, call this count $N(q, M_t)$, and calculate the ratio of this count over the size of M_t, call it $Y(q, M_t)$. That is, $Y(q, M_t) = Prob_{\mathcal{M}}(q \in m | m \in M_t)$. As M_t expands, this ratio changes and we show these changes for each q in Table 2 in the Appendix. The values of $Y(q, M_t)$ are plotted in Figure 1. As is clearly visible in the Figure, the values of $Y(q, M_t)$ converge to 0.5 for each q. Also notice that because of the randomization, we have expanded M_t in a way that M_t is not biased towards any particular q, therefore the values of $Y(q, M_t)$ are similar after M_t has acquired a certain size (say, when $t = 80$). When M_t=$M_{0.5,A}$, every point q is covered by the same number of models in M_t, and their values of $Y(q, M_t)$ are identical and is equal to 0.5, which is the ratio of the size of each m relative to A (recall that we always include 5 points from A in each m).

Formally, when $t = 252$, $M_t = M_{0.5,A}$, from the perspective of a fixed q, the probability of it being contained in a model m from M_t is

$$Prob_{\mathcal{M}}(q \in m | m \in M_{0.5,A}) = 0.5.$$

We emphasize that this probability is a measure in the space $\mathcal{M}$ by writing the probability as $Prob_{\mathcal{M}}$. On the other hand, by the way each m is constructed, we know that from the perspective of a fixed m,

$$Prob_F(q \in m | q \in A) \ = \ 0.5.$$

Note that this probability is a measure in the space F. We have shown that these two probabilities, w.r.t. two different spaces, have identical values. In other words, let the membership function of m be $C_m(q)$, i.e., $C_m(q) = 1$ iff $q \in m$, the random variables $\lambda q C_m(q)$ and $\lambda m C_m(q)$ have the same probability distribution, when q is restricted to A and m is restricted to $M_{0.5,A}$. This is because both variables can have values that are either 1 or 0, and they have the value 1 with the same probability (0.5 in this case). This symmetry arises from the fact that the collection of models $M_{0.5,A}$ covers the set A uniformly, i.e., since we have used all members of $M_{0.5,A}$, each point q have the same chance to be included in one of these models. If any two points in a set S have the same chance to be included in a collection of models, we say that this collection is S-uniform. It can be shown, by a simple counting argument, that uniformity leads to the symmetry of $Prob_{\mathcal{M}}(q \in m | m \in M_{0.5,A})$ and $Prob_F(q \in m | q \in A)$, and hence distributions of $\lambda q C_m(q)$ and $\lambda m C_m(q)$.

The observation and utilization of this duality are central to the theory of stochastic discrimination (SD). A critical point of the SD method is to enforce such a uniform cover on a set of points. That is, to construct a collection of models in a balanced way so that the uniformity (hence the duality) is achieved without exhausting all possible models from the space.

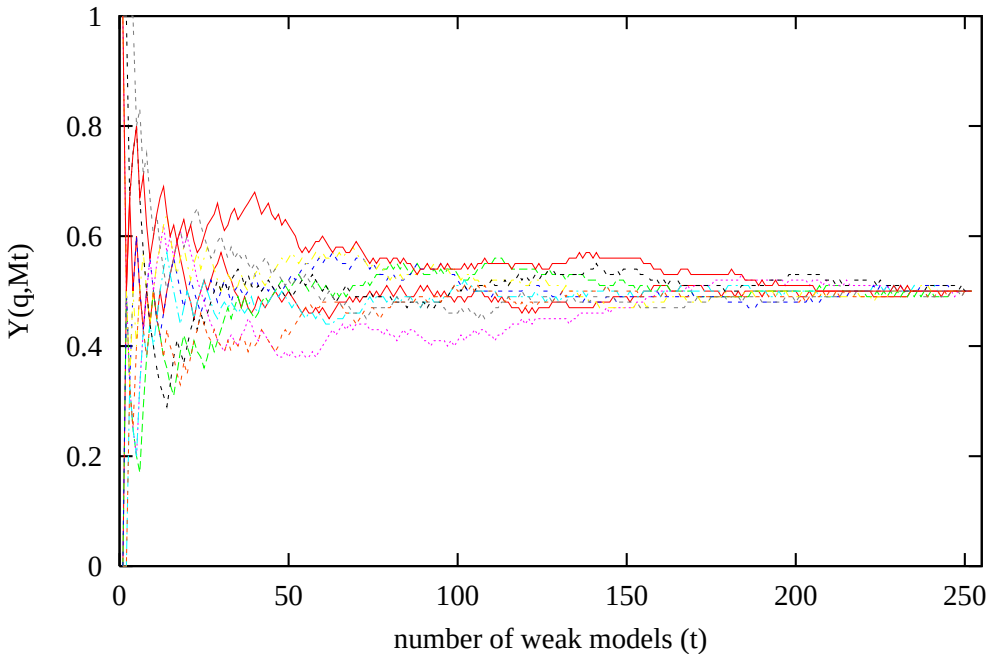


Figure 1: Plot of $Y(q, M_t)$ versus t. Each line represents the trace of $Y(q, M_t)$ for a particular q as M_t expands.

2 Two-Class Discrimination

Let us now label each point q in A by one of two classes c_1 (marked by "x") and c_2 (marked by "o") as follows.

x	x	x	o	o	o	o	x	x	o
q_0	q_1	q_2	q_3	q_4	q_5	q_6	q_7	q_8	q_9

This gives a training set TR_i for each class c_i. In particular,

$$TR_1 = \{q_0, q_1, q_2, q_7, q_8\},$$

and

$$TR_2 = \{q_3, q_4, q_5, q_6, q_9\}.$$

How can we build a classifier for c_1 and c_2 using models from $M_{0.5,A}$? First, we evaluate each model m by how well it has captured the members of each class. Define ratings r_i $(i = 1, 2)$ for each m as

$$r_i(m) = Prob_F(q \in m | q \in TR_i).$$

For example, consider model $m_1 = \{q_3, q_5, q_6, q_8, q_9\}$, where q_8 is in TR_1 and the rest are in TR_2. TR_1 has 5 members and 1 is in m_1, therefore $r_1(m_1) = 1/5 = 0.2$. TR_2 has (incidentally, also) 5 members and 4 of them are in m_1, therefore $r_2(m_1) = 4/5 = 0.8$. Thus these ratings represent the quality of the models as a description of each class. A model with a rating 1.0 for a class is a perfect model for that class. We call the difference between r_1 and r_2 the *degree of enrichment*

of m with respect to classes $(1, 2)$, i.e., $d_{12} = r_1 - r_2$. A model m is *enriched* if $d_{12} \neq 0$. Now we define, for all enriched models m,

$$X_{12}(q, m) = \frac{C_m(q) - r_2(m)}{r_1(m) - r_2(m)},$$

and let $X_{12}(q, m)$ be 0 if $d_{12}(m) = 0$. For a given m, r_1 and r_2 are fixed, and the value of $X(q, m)$ for each q in A can have one of two values depending on whether q is in m. For example, for m_1, $r_1 = 0.2$ and $r_2 = 0.8$, so $X(q, m) = -1/3$ for points q_3, q_5, q_6, q_8, q_9, and $X(q, m) = 4/3$ for points q_0, q_1, q_2, q_4, q_7. Next, for each set $M_t = \{m_1, m_2, ..., m_t\}$, we define a discriminant

$$Y_{12}(q, M_t) = \frac{1}{t} \sum_{k=1}^{t} X_{12}(q, m_k).$$

As the set M_t expands, the value of Y_{12} changes for each q. We show, in Table 3 in the Appendix, the values of Y_{12} for each M_t and each q, and for each new member m_t of M_t, r_1, r_2, and the two values of X_{12}. The values of Y_{12} for each q are plotted in Figure 2.

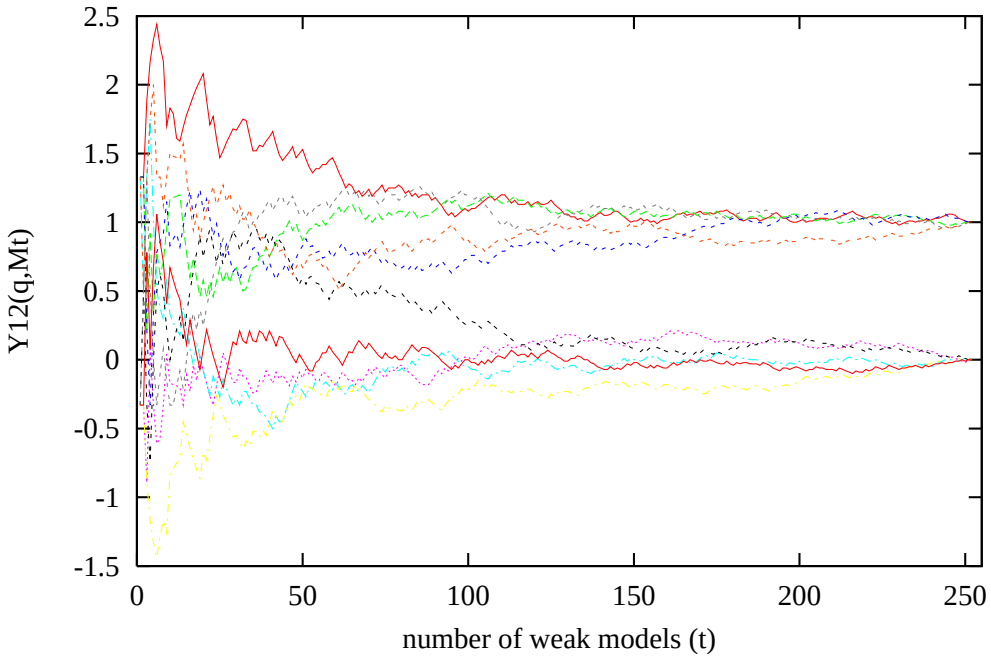


Figure 2: Plot of $Y_{12}(q, M_t)$ versus t. Each line represents the trace of $Y_{12}(q, M_t)$ for a particular q as M_t expands.

In Figure 2 we see two separate trends. All those points that belong to class c_1 have their Y_{12} values converging to 1.0, and all those in c_2 converging to 0.0. Thus Y_{12} can be used with a threshold to classify an arbitrary point q. We can assign q to class c_1 if $Y_{12}(q, M_t) > 0.5$, and to class c_2 if $Y_{12}(q, M_t) < 0.5$, and remain undecided when $Y_{12}(q, M_t) = 0.5$. Observe that this classifier is fairly accurate far before M_t has expanded to the full set $M_{0.5,A}$. We can also change the two poles of Y_{12} to 1.0 and -1.0 respectively by simply rescaling and shifting X_{12}:

$$X_{12}(q,m) = 2(\frac{C_m(q) - r_2(m)}{r_1(m) - r_2(m)}) - 1.$$

How did this separation of trends happen? Let us now take a closer look at the models in each M_t and see how many of them cover each point q. For a given M_t, among its members, there can be different values of r_1 and r_2. But because of our choices of the sizes of TR_1, TR_2, and m, we have only a small set of distinct values that r_1 and r_2 can have. Namely, since each model has 5 points, there are only six possibilities as follows.

no. of points from TR_1	0	1	2	3	4	5
no. of points from TR_2	5	4	3	2	1	0
r_1	0.0	0.2	0.4	0.6	0.8	1.0
r_2	1.0	0.8	0.6	0.4	0.2	0.0

Note that in a general setting r_1 and r_2 do not have to sum up to 1. If we included models of a larger size, say, one with 10 points, we can have both r_1 and r_2 equal to 1.0. We have simplified matters by using models of a fixed size and training sets of the same size. According to the values of r_1 and r_2, in this case we have only 6 different kinds of models.

Now we take a detailed look at the coverage of each point q by each kind of models, i.e., models of a particular rating (quality) for each class. Let us count how many of the models of each value of r_1 and r_2 cover each point q, and call this $N_{M_t,r_1,TR_1}(q)$ and $N_{M_t,r_2,TR_2}(q)$ respectively. We can normalize this count by the number of models having each value of r_1 or r_2, and obtain a ratio $f_{M_t,r_1,TR_1}(q)$ and $f_{M_t,r_2,TR_2}(q)$ respectively. Thus, for each point q, we have "a profile of coverage" by models of each value of ratings r_1 and r_2 that is described by these ratios. For example, point q_0 at $t = 10$ is only covered by 5 models $(m_2, m_3, m_5, m_8, m_{10})$ in M_{10}, and from Table 3 we know that M_{10} has various numbers of models in each rating as summarized in the following table.

r_1	0.0	0.2	0.4	0.6	0.8	1.0
no. of models in M_{10} with r_1	0	2	2	4	2	0
$N_{M_{10},r_1,TR_1}(q_0)$	0	0	0	3	2	0
$f_{M_{10},r_1,TR_1}(q_0)$	0	0	0	0.75	1.0	0

r_2	0.0	0.2	0.4	0.6	0.8	1.0
no. of models in M_{10} with r_2	0	2	4	2	2	0
$N_{M_{10},r_2,TR_2}(q_0)$	0	2	3	0	0	0
$f_{M_{10},r_2,TR_2}(q_0)$	0	1.0	0.75	0	0	0

We show such profiles for each point q and each set M_t in Figure 3 (as a function of r_1) and Figure 4 (as a function of r_2) respectively.

Observe that as t increases, the profiles of coverage for each point q converge to two distinct patterns. In Figure 3, the profiles for points in TR_1 converge to a diagonal $f_{M_t,r_1,TR_1} = r_1$, and in Figure 4, those for points in TR_2 also converge to a diagonal $f_{M_t,r_2,TR_2} = r_2$. That is, when $M_t = M_{0.5,A}$, we have for all q in TR_1 and for all r_1, $Prob_{\mathcal{M}}(q \in m | m \in M_{r_1,TR_1}) = r_1$, and for all q in TR_2 and for all r_2, $Prob_{\mathcal{M}}(q \in m | m \in M_{r_2,TR_2}) = r_2$. Thus we have the symmetry in place for both TR_1 and TR_2. This is a consequence of M_t being both TR_1-uniform and TR_2-uniform.

The discriminant $Y_{12}(q, M_t)$ is a summation over all models m in M_t, which can be decomposed into the sums of terms corresponding to different ratings r_i for either $i = 1$ or $i = 2$. To understand what happens with the points in TR_1, we can decompose their Y_{12} by values of r_1. Assume that there are t_x models in M_t that have $r_1 = x$. Since we have only 6 distinct values for x, M_t is a union of 6 disjoint sets, and Y_{12} can be decomposed as

$$\begin{array}{rcl} Y_{12}(q, M_t) = & \frac{t_{0.0}}{t}[\frac{1}{t_{0.0}} \sum_{k_{0.0}=1}^{t_{0.0}} X_{12}(q, m_{k_{0.0}})] & + \quad \frac{t_{0.2}}{t}[\frac{1}{t_{0.2}} \sum_{k_{0.2}=1}^{t_{0.2}} X_{12}(q, m_{k_{0.2}})] \quad + \\ & \frac{t_{0.4}}{t}[\frac{1}{t_{0.4}} \sum_{k_{0.4}=1}^{t_{0.4}} X_{12}(q, m_{k_{0.4}})] & + \quad \frac{t_{0.6}}{t}[\frac{1}{t_{0.6}} \sum_{k_{0.6}=1}^{t_{0.6}} X_{12}(q, m_{k_{0.6}})] \quad + \\ & \frac{t_{0.8}}{t}[\frac{1}{t_{0.8}} \sum_{k_{0.8}=1}^{t_{0.8}} X_{12}(q, m_{k_{0.8}})] & + \quad \frac{t_{1.0}}{t}[\frac{1}{t_{1.0}} \sum_{k_{1.0}=1}^{t_{1.0}} X_{12}(q, m_{k_{1.0}})]. \end{array}$$

The factor in the square bracket of each term is the expectation of values of X_{12} corresponding to that particular rating $r_1 = x$. Since r_1 is the same for all m contributing to that term, by our choice of sizes of TR_1, TR_2, and the models, r_2 is also the same for all those m relevant to that term. Let that value of r_2 be y, we have, for each (fixed) q, each value of x and the associated value y,

$$E(X_{12}(q, m_x)) = E(\frac{C_{m_x}(q) - y}{x - y}) = \frac{E(C_{m_x}(q)) - y}{x - y} = \frac{x - y}{x - y} = 1.$$

The second to the last equality is a consequence of the uniformity of M_t: because the collection M_t (when $t = 252$) covers TR_1 uniformly, we have for each value x, $Prob_{\mathcal{M}}(q \in m | m \in M_{x,TR_1}) = x$, and since $C_{m_x}(q)$ has only two values (0 or 1), and $C_{m_x}(q) = 1$ iff $q \in m$, we have the expected value of $C_{m_x}(q)$ equal to x. Therefore

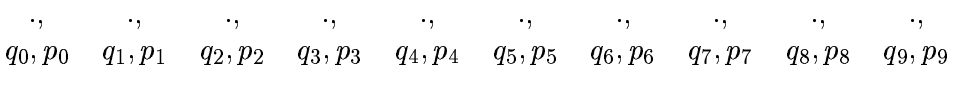
$$Y_{12}(q, M_t) = \frac{t_{0.0} + t_{0.2} + t_{0.4} + t_{0.6} + t_{0.8} + t_{1.0}}{t} = 1.$$

In a more general case, the values of r_2 are not necessarily equal for all models with the same value for r_1, so we cannot take y and $x - y$ out as constants. But then we can further split the term by the values of r_2, and proceed with the same argument.

A similar decomposition of Y_{12} into terms corresponding to different values of r_2 will show that $Y_{12}(q, M_t) = 0$ for those points in TR_2.

3 Projectability of Models

We have built a classifier and shown that it works for TR_1 and TR_2. How can this classifier work for an arbitrary point that is not in TR_1 or TR_2? Suppose that the feature space F contains other points p (marked by ","), and that each p is close to some training point q (marked by ".") as follows.



We can take the models m as regions in the space that cover the points q in the same manner as before. Say, if each point q_i has a particular value of the feature v (in our one-dimensional feature

space) that is $v(q_i)$. We can define a model by ranges of values for this feature, e.g., in our example m_1 covers q_3, q_5, q_6, q_8, q_9, so we take

$$\begin{aligned} m_1 = \quad & \{q | \tfrac{v(q_2)+v(q_3)}{2} < v(q) < \tfrac{v(q_3)+v(q_4)}{2}\} \cup \\ & \{q | \tfrac{v(q_4)+v(q_5)}{2} < v(q) < \tfrac{v(q_6)+v(q_7)}{2}\} \cup \\ & \{q | \tfrac{v(q_7)+v(q_8)}{2} < v(q)\}. \end{aligned}$$

Thus we can tell if an arbitrary point p with value $v(p)$ for this feature is inside or outside this model.

We can calculate the model's ratings in exactly the same way as before, using only the points q. But now the same classifier works for the new points p, since we can use the new definitions of models to determine if p is inside or outside each model. Given the proximity relationship as above, those points will be assigned to the same class as their closest neighboring q. If these are indeed the true classes for the points p, the classifier is perfect for this new set. In the SD terminology, if we call the two subsets of points p that should be labeled as two different classes TE_1 and TE_2, i.e., $TE_1 = \{p_0, p_1, p_2, p_7, p_8\}$, $TE_2 = \{p_3, p_4, p_5, p_6, p_9\}$, we say that TR_1 and TE_1 are M_t-indiscernible, and similarly TR_2 and TE_2 are also M_t-indiscernible. This is to say, from the perspective of M_t, there is no difference between TR_1 and TE_1, or TR_2 and TE_2, therefore all the properties of M_t that are observed using TR_1 and TR_2 can be projected to TE_1 and TE_2. The central challenge of an SD method is to maintain projectability, uniformity, and enrichment of the collection of models at the same time.

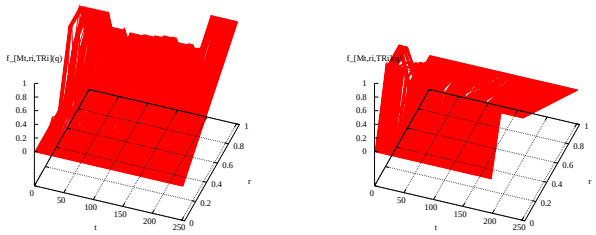
References

[1] E.M. Kleinberg, "Stochastic Discrimination," *Annals of Mathematics and Artificial Intelligence*, **1**, 1990, 207-239.

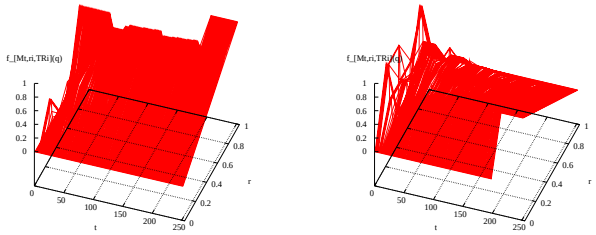
[2] E.M. Kleinberg, "An overtraining-resistant stochastic modeling method for pattern recognition," *Annals of Statistics*, **4**, 6, December 1996, 2319-2349.

[3] E.M. Kleinberg, "On the algorithmic implementation of stochastic discrimination," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **PAMI-22**, 5, May 2000, 473-490.

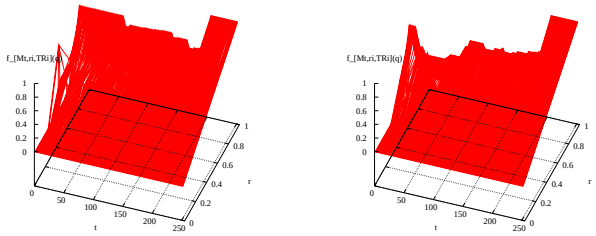
[4] E.M. Kleinberg, "A mathematically rigorous foundation for supervised learning," in J. Kittler, F. Roli, (eds.), *Multiple Classifier Systems*, Lecture Notes in Computer Science 1857, Springer, 2000, 67-76.



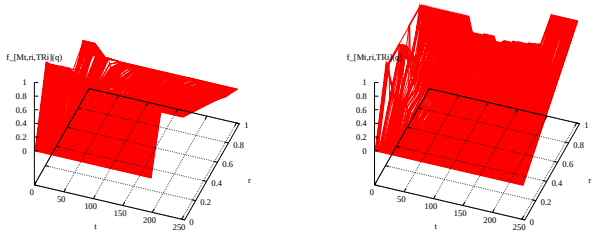
$q_0 \in TR_1$ $q_5 \in TR_2$



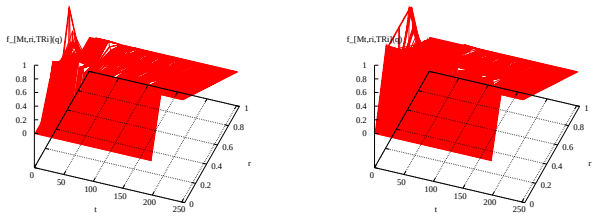
$q_1 \in TR_1$ $q_6 \in TR_2$



$q_2 \in TR_1$ $q_7 \in TR_1$

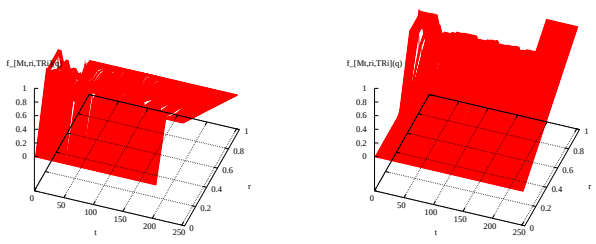


$q_3 \in TR_2$ $q_8 \in TR_1$

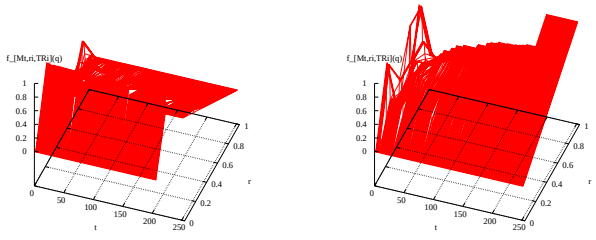


$q_4 \in TR_2$ $q_9 \in TR_2$

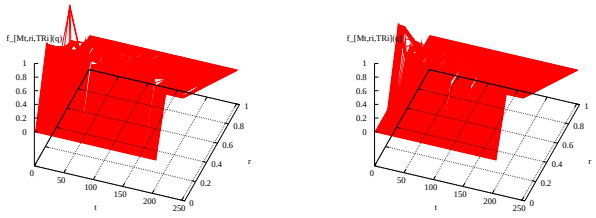
Figure 3: $f_{M_t,r_1,TR_1}(q)$ for each point q and set M_t. In each plot, the x axis is t that ranges from 0 to 252, the y axis is r that ranges from 0 to 1, and the z axis is f_{M_t,r_1,TR_1}.



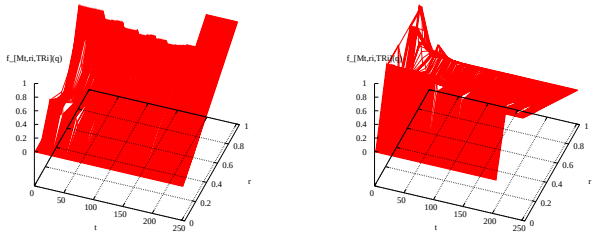
$q_0 \in TR_1$ $q_5 \in TR_2$



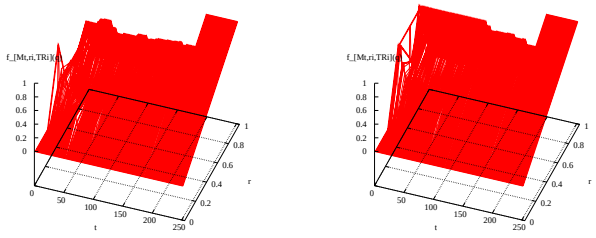
$q_1 \in TR_1$ $q_6 \in TR_2$



$q_2 \in TR_1$ $q_7 \in TR_1$



$q_3 \in TR_2$ $q_8 \in TR_1$



$q_4 \in TR_2$ $q_9 \in TR_2$

Figure 4: $f_{M_t,r_2,TR_2}(q)$ for each point q and set M_t. In each plot, the x axis is t that ranges from 0 to 252, the y axis is r that ranges from 0 to 1, and the z axis is f_{M_t,r_2,TR_2}.

Appendix.

Listing of an awk script to calculate a model's ratings. The script takes a file where each line contains the point indices of the elements of a model (as in Table 1).

```
# <awk.rating>
# run:  awk -f awk.rating list_of_models > models.rating
# input:
# 3 5 6 8 9
# 0 1 2 6 8
# ...
BEGIN{
sizeTR1 = 5;
sizeTR2 = 5;
# full space = (x x x o o o o x x o)
c[0] = 1;  c[1] = 1;  c[2] = 1;  c[3] = 2;  c[4] = 2;  c[5] = 2;  c[6] = 2;   c[7] = 1;  c[8] = 1;  c[9] = 2;
}
{ cover1 = 0;
  cover2 = 0;
  sizeM = NF;
  for (i=1; i<=NF; ++i) if (c[$i] == 1) cover1 ++; else cover2 ++;
  r1 = cover1/sizeTR1;
  r2 = cover2/sizeTR2;
  enr = r1 - r2;
  if (enr == 0.0) { xin = 0.0; xout = 0.0;}
  else {
     xin  = (1.0 - r2)/enr;
     xout = (0.0 - r2)/enr;
  }
  printf ``model %s r1 %.2f r2 %.2f enr = r1-r2 = %.2f xin %.2f xout %.2f\n'',\
  $0,r1,r2,enr,xin,xout;
}
```

Listing of an awk script to calculate the discriminant Y_{12} for each point q, given a list of models and their ratings (output of awk.rating).

```
# <awk.discrim>
# run: awk -f awk.discrim models.rating
# input:
# model 3 5 6 8 9  r1 0.20 r2 0.80 enr = r1-r2 = -0.60 xin -0.33 xout 1.33
# model 0 1 2 6 8  r1 0.80 r2 0.20 enr = r1-r2 = 0.60 xin 1.33 xout -0.33
# ...
{
  nm++;
  xin = $17;
  xout = $19;
#
# check for each point q, whether model m (this row) covers q,
# and increment y[q] accordingly
#
  for (q=0; q<10;++q) {
      inmodel = 0;
      for (i=2; i<=6; ++i) {
          if ($i == q) inmodel = 1;
      }
      if (inmodel) {
         y[q] = (y[q]*(nm-1) + xin)/nm; }
      else {
         y[q] = (y[q]*(nm-1) + xout)/nm;}
  }
  printf ``Y(M,q)_(|M|= %3d ) ``, nm;
  for (q=0; q<10;++q) { printf ``%5.2f ``, y[q];}
  printf ``\n'';
}
```

Table 1: Models m_t in $M_{0.5,A}$ in the order of $M = m_1, m_2, ..., m_{252}$. Each model is shown with its elements denoted by the indices i of q_i in A. For example, $m_1 = \{q_3, q_5, q_6, q_8, q_9\}$.

m_t	elements	m_t	elements	m_t	elements	m_t	elements	m_t	elements	m_t	elements
m_1	35689	m_{43}	12689	m_{85}	24578	m_{127}	01469	m_{169}	02468	m_{211}	02458
m_2	01268	m_{44}	04569	m_{86}	23568	m_{128}	03679	m_{170}	35678	m_{212}	13457
m_3	04789	m_{45}	01245	m_{87}	01267	m_{129}	04579	m_{171}	03589	m_{213}	24689
m_4	25689	m_{46}	01458	m_{88}	01257	m_{130}	01237	m_{172}	34679	m_{214}	03478
m_5	02679	m_{47}	15679	m_{89}	05679	m_{131}	24789	m_{173}	12346	m_{215}	23589
m_6	34578	m_{48}	12457	m_{90}	24589	m_{132}	45689	m_{174}	12458	m_{216}	24679
m_7	13459	m_{49}	02379	m_{91}	04589	m_{133}	16789	m_{175}	35789	m_{217}	02456
m_8	01238	m_{50}	02568	m_{92}	12467	m_{134}	13479	m_{176}	02358	m_{218}	05689
m_9	12347	m_{51}	12357	m_{93}	13578	m_{135}	02349	m_{177}	35679	m_{219}	12789
m_{10}	01579	m_{52}	14678	m_{94}	02369	m_{136}	13469	m_{178}	13458	m_{220}	02346
m_{11}	34589	m_{53}	12678	m_{95}	12469	m_{137}	03678	m_{179}	01459	m_{221}	23489
m_{12}	03459	m_{54}	23567	m_{96}	04567	m_{138}	23679	m_{180}	03479	m_{222}	23467
m_{13}	23459	m_{55}	02789	m_{97}	14679	m_{139}	46789	m_{181}	14789	m_{223}	12489
m_{14}	02457	m_{56}	24567	m_{98}	13467	m_{140}	01468	m_{182}	23678	m_{224}	14589
m_{15}	02368	m_{57}	13569	m_{99}	45678	m_{141}	03689	m_{183}	03456	m_{225}	25678
m_{16}	02689	m_{58}	01259	m_{100}	03469	m_{142}	02478	m_{184}	13456	m_{226}	12579
m_{17}	01368	m_{59}	23479	m_{101}	34789	m_{143}	23457	m_{185}	01568	m_{227}	03458
m_{18}	13589	m_{60}	03579	m_{102}	45679	m_{144}	02347	m_{186}	01578	m_{228}	01569
m_{19}	14579	m_{61}	12368	m_{103}	01358	m_{145}	01289	m_{187}	01678	m_{229}	45789
m_{20}	23468	m_{62}	23578	m_{104}	01379	m_{146}	01369	m_{188}	12367	m_{230}	12358
m_{21}	26789	m_{63}	02345	m_{105}	01236	m_{147}	01356	m_{189}	12345	m_{231}	02579
m_{22}	15678	m_{64}	01479	m_{106}	01679	m_{148}	12379	m_{190}	25679	m_{232}	01457
m_{23}	04578	m_{65}	03569	m_{107}	13689	m_{149}	02569	m_{191}	02367	m_{233}	05789
m_{24}	04679	m_{66}	01346	m_{108}	12479	m_{150}	34678	m_{192}	01256	m_{234}	01247
m_{25}	02459	m_{67}	24568	m_{109}	14568	m_{151}	24569	m_{193}	13679	m_{235}	03467
m_{26}	12569	m_{68}	01359	m_{110}	15689	m_{152}	03578	m_{194}	04689	m_{236}	12359
m_{27}	01269	m_{69}	12459	m_{111}	01258	m_{153}	02359	m_{195}	04568	m_{237}	02567
m_{28}	06789	m_{70}	01239	m_{112}	12389	m_{154}	01234	m_{196}	12578	m_{238}	12356
m_{29}	01689	m_{71}	24678	m_{113}	03568	m_{155}	01345	m_{197}	12468	m_{239}	02469
m_{30}	01248	m_{72}	01347	m_{114}	23689	m_{156}	02348	m_{198}	03468	m_{240}	13468
m_{31}	12456	m_{73}	01467	m_{115}	23478	m_{157}	03457	m_{199}	34569	m_{241}	02479
m_{32}	13579	m_{74}	04678	m_{116}	34568	m_{158}	02357	m_{200}	12369	m_{242}	36789
m_{33}	34689	m_{75}	12589	m_{117}	23569	m_{159}	01235	m_{201}	13489	m_{243}	13568
m_{34}	12679	m_{76}	01348	m_{118}	14689	m_{160}	01378	m_{202}	12567	m_{244}	02467
m_{35}	12568	m_{77}	14569	m_{119}	23789	m_{161}	14567	m_{203}	02489	m_{245}	01589
m_{36}	34579	m_{78}	01789	m_{120}	01246	m_{162}	23458	m_{204}	02678	m_{246}	01478
m_{37}	01389	m_{79}	01367	m_{121}	23579	m_{163}	56789	m_{205}	13567	m_{247}	15789
m_{38}	23469	m_{80}	12478	m_{122}	01456	m_{164}	34567	m_{206}	01357	m_{248}	01349
m_{39}	24579	m_{81}	25789	m_{123}	23456	m_{165}	01249	m_{207}	01278	m_{249}	02356
m_{40}	02589	m_{82}	01489	m_{124}	03789	m_{166}	03489	m_{208}	02578	m_{250}	14578
m_{41}	01567	m_{83}	03567	m_{125}	05678	m_{167}	02389	m_{209}	12348	m_{251}	13789
m_{42}	13478	m_{84}	12349	m_{126}	13678	m_{168}	12378	m_{210}	01279	m_{252}	02378

Table 2: Ratio of coverage of each point q by members of M_t as M_t expands.

	$N(M_t, q)$									$Y(M_t, q)$								
M_t	q_0	q_1	q_2	q_3	q_4	q_5	q_6	q_7	q_8	q_9	q_0	q_1	q_2	q_3	q_4	q_5	q_6	q_7	q_8	q_9
M_1	0	0	0	1	0	1	1	0	1	1	0.00	0.00	0.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00
M_2	1	1	1	1	0	1	2	0	2	1	0.50	0.50	0.50	0.50	0.00	0.50	1.00	0.00	1.00	0.50
M_3	2	1	1	1	1	1	2	1	3	2	0.67	0.33	0.33	0.33	0.33	0.33	0.67	0.33	1.00	0.67
M_4	2	1	2	1	1	2	3	1	4	3	0.50	0.25	0.50	0.25	0.25	0.50	0.75	0.25	1.00	0.75
M_5	3	1	3	1	1	2	4	2	4	4	0.60	0.20	0.60	0.20	0.20	0.40	0.80	0.40	0.80	0.80
M_6	3	1	3	2	2	3	4	3	5	4	0.50	0.17	0.50	0.33	0.33	0.50	0.67	0.50	0.83	0.67
M_7	3	2	3	3	3	4	4	3	5	5	0.43	0.29	0.43	0.43	0.43	0.57	0.57	0.43	0.71	0.71
M_8	4	3	4	4	3	4	4	3	6	5	0.50	0.38	0.50	0.50	0.38	0.50	0.50	0.38	0.75	0.62
M_9	4	4	5	5	4	4	4	4	6	5	0.44	0.44	0.56	0.56	0.44	0.44	0.44	0.44	0.67	0.56
M_{10}	5	5	5	5	4	5	4	5	6	6	0.50	0.50	0.50	0.50	0.40	0.50	0.40	0.50	0.60	0.60
M_{11}	5	5	5	6	5	6	4	5	7	7	0.45	0.45	0.45	0.55	0.45	0.55	0.36	0.45	0.64	0.64
M_{12}	6	5	5	7	6	7	4	5	7	8	0.50	0.42	0.42	0.58	0.50	0.58	0.33	0.42	0.58	0.67
M_{13}	6	5	6	8	7	8	4	5	7	9	0.46	0.38	0.46	0.62	0.54	0.62	0.31	0.38	0.54	0.69
M_{14}	7	5	7	8	8	9	4	6	7	9	0.50	0.36	0.50	0.57	0.57	0.64	0.29	0.43	0.50	0.64
M_{15}	8	5	8	9	8	9	5	6	8	9	0.53	0.33	0.53	0.60	0.53	0.60	0.33	0.40	0.53	0.60
M_{16}	9	5	9	9	8	9	6	6	9	10	0.56	0.31	0.56	0.56	0.50	0.56	0.38	0.38	0.56	0.62
M_{17}	10	6	9	10	8	9	7	6	10	10	0.59	0.35	0.53	0.59	0.47	0.53	0.41	0.35	0.59	0.59
M_{18}	10	7	9	11	8	10	7	6	11	11	0.56	0.39	0.50	0.61	0.44	0.56	0.39	0.33	0.61	0.61
M_{19}	10	8	9	11	9	11	7	7	11	12	0.53	0.42	0.47	0.58	0.47	0.58	0.37	0.37	0.58	0.63
M_{20}	10	8	10	12	10	11	8	7	12	12	0.50	0.40	0.50	0.60	0.50	0.55	0.40	0.35	0.60	0.60
M_{21}	10	8	11	12	10	11	9	8	13	13	0.48	0.38	0.52	0.57	0.48	0.52	0.43	0.38	0.62	0.62
M_{22}	10	9	11	12	10	12	10	9	14	13	0.45	0.41	0.50	0.55	0.45	0.55	0.45	0.41	0.64	0.59
M_{23}	11	9	11	12	11	13	10	10	15	13	0.48	0.39	0.48	0.52	0.48	0.57	0.43	0.43	0.65	0.57
M_{24}	12	9	11	12	12	13	11	11	15	14	0.50	0.38	0.46	0.50	0.50	0.54	0.46	0.46	0.62	0.58
M_{25}	13	9	12	12	13	14	11	11	15	15	0.52	0.36	0.48	0.48	0.52	0.56	0.44	0.44	0.60	0.60
M_{26}	13	10	13	12	13	15	12	11	15	16	0.50	0.38	0.50	0.46	0.50	0.58	0.46	0.42	0.58	0.62
M_{27}	14	11	14	12	13	15	13	11	15	17	0.52	0.41	0.52	0.44	0.48	0.56	0.48	0.41	0.56	0.63
M_{28}	15	11	14	12	13	15	14	12	16	18	0.54	0.39	0.50	0.43	0.46	0.54	0.50	0.43	0.57	0.64
M_{29}	16	12	14	12	13	15	15	12	17	19	0.55	0.41	0.48	0.41	0.45	0.52	0.52	0.41	0.59	0.66
M_{30}	17	13	15	12	14	15	15	12	18	19	0.57	0.43	0.50	0.40	0.47	0.50	0.50	0.40	0.60	0.63
M_{31}	17	14	16	12	15	16	16	12	18	19	0.55	0.45	0.52	0.39	0.48	0.52	0.52	0.39	0.58	0.61
M_{32}	17	15	16	13	15	17	16	13	18	20	0.53	0.47	0.50	0.41	0.47	0.53	0.50	0.41	0.56	0.62
M_{33}	17	15	16	14	16	17	17	13	19	21	0.52	0.45	0.48	0.42	0.48	0.52	0.52	0.39	0.58	0.64
M_{34}	17	16	17	14	16	17	18	14	19	22	0.50	0.47	0.50	0.41	0.47	0.50	0.53	0.41	0.56	0.65
M_{35}	17	17	18	14	16	18	19	14	20	22	0.49	0.49	0.51	0.40	0.46	0.51	0.54	0.40	0.57	0.63
M_{36}	17	17	18	15	17	19	19	15	20	23	0.47	0.47	0.50	0.42	0.47	0.53	0.53	0.42	0.56	0.64
M_{37}	18	18	18	16	17	19	19	15	21	24	0.49	0.49	0.49	0.43	0.46	0.51	0.51	0.41	0.57	0.65
M_{38}	18	18	19	17	18	19	20	15	21	25	0.47	0.47	0.50	0.45	0.47	0.50	0.53	0.39	0.55	0.66
M_{39}	18	18	20	17	19	20	20	16	21	26	0.46	0.46	0.51	0.44	0.49	0.51	0.51	0.41	0.54	0.67
M_{40}	19	18	21	17	19	21	20	16	22	27	0.47	0.45	0.53	0.42	0.47	0.53	0.50	0.40	0.55	0.68
M_{41}	20	19	21	17	19	22	21	17	22	27	0.49	0.46	0.51	0.41	0.46	0.54	0.51	0.41	0.54	0.66
M_{42}	20	20	21	18	20	22	21	18	23	27	0.48	0.48	0.50	0.43	0.48	0.52	0.50	0.43	0.55	0.64
M_{43}	20	21	22	18	20	22	22	18	24	28	0.47	0.49	0.51	0.42	0.47	0.51	0.51	0.42	0.56	0.65
M_{44}	21	21	22	18	21	23	23	18	24	29	0.48	0.48	0.50	0.41	0.48	0.52	0.52	0.41	0.55	0.66
M_{45}	22	22	23	18	22	24	23	18	24	29	0.49	0.49	0.51	0.40	0.49	0.53	0.51	0.40	0.53	0.64
M_{46}	23	23	23	18	23	25	23	18	25	29	0.50	0.50	0.50	0.39	0.50	0.54	0.50	0.39	0.54	0.63
M_{47}	23	24	23	18	23	26	24	19	25	30	0.49	0.51	0.49	0.38	0.49	0.55	0.51	0.40	0.53	0.64
M_{48}	23	25	24	18	24	27	24	20	25	30	0.48	0.52	0.50	0.38	0.50	0.56	0.50	0.42	0.52	0.62
M_{49}	24	25	25	19	24	27	24	21	25	31	0.49	0.51	0.51	0.39	0.49	0.55	0.49	0.43	0.51	0.63
M_{50}	25	25	26	19	24	28	25	21	26	31	0.50	0.50	0.52	0.38	0.48	0.56	0.50	0.42	0.52	0.62
M_{51}	25	26	27	20	24	29	25	22	26	31	0.49	0.51	0.53	0.39	0.47	0.57	0.49	0.43	0.51	0.61
M_{52}	25	27	27	20	25	29	26	23	27	31	0.48	0.52	0.52	0.38	0.48	0.56	0.50	0.44	0.52	0.60
M_{53}	25	28	28	20	25	29	27	24	28	31	0.47	0.53	0.53	0.38	0.47	0.55	0.51	0.45	0.53	0.58
M_{54}	25	28	29	21	25	30	28	25	28	31	0.46	0.52	0.54	0.39	0.46	0.56	0.52	0.46	0.52	0.57
M_{55}	26	28	30	21	25	30	28	26	29	32	0.47	0.51	0.55	0.38	0.45	0.55	0.51	0.47	0.53	0.58
M_{56}	26	28	31	21	26	31	29	27	29	32	0.46	0.50	0.55	0.38	0.46	0.55	0.52	0.48	0.52	0.57
M_{57}	26	29	31	22	26	32	30	27	29	33	0.46	0.51	0.54	0.39	0.46	0.56	0.53	0.47	0.51	0.58
M_{58}	27	30	32	22	26	33	30	27	29	34	0.47	0.52	0.55	0.38	0.45	0.57	0.52	0.47	0.50	0.59
M_{59}	27	30	33	23	27	33	30	28	29	35	0.46	0.51	0.56	0.39	0.46	0.56	0.51	0.47	0.49	0.59
M_{60}	28	30	33	24	27	34	30	29	29	36	0.47	0.50	0.55	0.40	0.45	0.57	0.50	0.48	0.48	0.60
M_{61}	28	31	34	25	27	34	31	29	30	36	0.46	0.51	0.56	0.41	0.44	0.56	0.51	0.48	0.49	0.59
M_{62}	28	31	35	26	27	35	31	30	31	36	0.45	0.50	0.56	0.42	0.44	0.56	0.50	0.48	0.50	0.58
M_{63}	29	31	36	27	28	36	31	30	31	36	0.46	0.49	0.57	0.43	0.44	0.57	0.49	0.48	0.49	0.57
M_{64}	30	32	36	27	29	36	31	31	31	37	0.47	0.50	0.56	0.42	0.45	0.56	0.48	0.48	0.48	0.58
M_{65}	31	32	36	28	29	37	32	31	31	38	0.48	0.49	0.55	0.43	0.45	0.57	0.49	0.48	0.48	0.58
M_{66}	32	33	36	29	30	37	33	31	31	38	0.48	0.50	0.55	0.44	0.45	0.56	0.50	0.47	0.47	0.58
M_{67}	32	33	37	29	31	38	34	31	32	38	0.48	0.49	0.55	0.43	0.46	0.57	0.51	0.46	0.48	0.57
M_{68}	33	34	37	30	31	39	34	31	32	39	0.49	0.50	0.54	0.44	0.46	0.57	0.50	0.46	0.47	0.57
M_{69}	33	35	38	30	32	40	34	31	32	40	0.48	0.51	0.55	0.43	0.46	0.58	0.49	0.45	0.46	0.58
M_{70}	34	36	39	31	32	40	34	31	32	41	0.49	0.51	0.56	0.44	0.46	0.57	0.49	0.44	0.46	0.59
M_{71}	34	36	40	31	33	40	35	32	33	41	0.48	0.51	0.56	0.44	0.46	0.56	0.49	0.45	0.46	0.58
M_{72}	35	37	40	32	34	40	35	33	33	41	0.49	0.51	0.56	0.44	0.47	0.56	0.49	0.46	0.46	0.57
M_{73}	36	38	40	32	35	40	36	34	33	41	0.49	0.52	0.55	0.44	0.48	0.55	0.49	0.47	0.45	0.56
M_{74}	37	38	40	32	36	40	37	35	34	41	0.50	0.51	0.54	0.43	0.49	0.54	0.50	0.47	0.46	0.55
M_{75}	37	39	41	32	36	41	37	35	35	42	0.49	0.52	0.55	0.43	0.48	0.55	0.49	0.47	0.47	0.56
M_{76}	38	40	41	33	37	41	37	35	36	42	0.50	0.53	0.54	0.43	0.49	0.54	0.49	0.46	0.47	0.55
M_{77}	38	41	41	33	38	42	38	35	36	43	0.49	0.53	0.53	0.43	0.49	0.55	0.49	0.45	0.47	0.56
M_{78}	39	42	41	33	38	42	38	36	37	44	0.50	0.54	0.53	0.42	0.49	0.54	0.49	0.46	0.47	0.56
M_{79}	40	43	41	34	38	42	39	37	37	44	0.51	0.54	0.52	0.43	0.48	0.53	0.49	0.47	0.47	0.56
M_{80}	40	44	42	34	39	42	39	38	38	44	0.50	0.55	0.53	0.42	0.49	0.53	0.49	0.47	0.47	0.55
M_{81}	40	44	43	34	39	43	39	39	39	45	0.49	0.54	0.53	0.42	0.48	0.53	0.48	0.48	0.48	0.56
M_{82}	41	45	43	34	40	43	39	39	40	46	0.50	0.55	0.52	0.41	0.49	0.52	0.48	0.48	0.49	0.56
M_{83}	42	45	43	35	40	44	40	40	40	46	0.51	0.54	0.52	0.42	0.48	0.53	0.48	0.48	0.48	0.55
M_{84}	42	46	44	36	41	44	40	40	40	47	0.50	0.55	0.52	0.43	0.49	0.52	0.48	0.48	0.48	0.56

(Cont'd) Ratio of coverage of each point q by members of M_t as M_t expands.

	$N(M_t, q)$									$Y(M_t, q)$								
M_t	q_0	q_1	q_2	q_3	q_4	q_5	q_6	q_7	q_8	q_9	q_0	q_1	q_2	q_3	q_4	q_5	q_6	q_7	q_8	q_9
M_{85}	42	46	45	36	42	45	40	41	41	47	0.49	0.54	0.53	0.42	0.49	0.53	0.47	0.48	0.48	0.55
M_{86}	42	46	46	37	42	46	41	41	42	47	0.49	0.53	0.53	0.43	0.49	0.53	0.48	0.48	0.49	0.55
M_{87}	43	47	47	37	42	46	42	42	42	47	0.49	0.54	0.54	0.43	0.48	0.53	0.48	0.48	0.48	0.54
M_{88}	44	48	48	37	42	47	42	43	42	47	0.50	0.55	0.55	0.42	0.48	0.53	0.48	0.49	0.48	0.53
M_{89}	45	48	48	37	42	48	43	44	42	48	0.51	0.54	0.54	0.42	0.47	0.54	0.48	0.49	0.47	0.54
M_{90}	45	48	49	37	43	49	43	44	43	49	0.50	0.53	0.54	0.41	0.48	0.54	0.48	0.49	0.48	0.54
M_{91}	46	48	49	37	44	50	43	44	44	50	0.51	0.53	0.54	0.41	0.48	0.55	0.47	0.48	0.48	0.55
M_{92}	46	49	50	37	45	50	44	45	44	50	0.50	0.53	0.54	0.40	0.49	0.54	0.48	0.49	0.48	0.54
M_{93}	46	50	50	38	45	51	44	46	45	50	0.49	0.54	0.54	0.41	0.48	0.55	0.47	0.49	0.48	0.54
M_{94}	47	50	51	39	45	51	45	46	45	51	0.50	0.53	0.54	0.41	0.48	0.54	0.48	0.49	0.48	0.54
M_{95}	47	51	52	39	46	51	46	46	45	52	0.49	0.54	0.55	0.41	0.48	0.54	0.48	0.48	0.47	0.55
M_{96}	48	51	52	39	47	52	47	47	45	52	0.50	0.53	0.54	0.41	0.49	0.54	0.49	0.49	0.47	0.54
M_{97}	48	52	52	39	48	52	48	48	45	53	0.49	0.54	0.54	0.40	0.49	0.54	0.49	0.49	0.46	0.55
M_{98}	48	53	52	40	49	52	49	49	45	53	0.49	0.54	0.53	0.41	0.50	0.53	0.50	0.50	0.46	0.54
M_{99}	48	53	52	40	50	53	50	50	46	53	0.48	0.54	0.53	0.40	0.51	0.54	0.51	0.51	0.46	0.54
M_{100}	49	53	52	41	51	53	51	50	46	54	0.49	0.53	0.52	0.41	0.51	0.53	0.51	0.50	0.46	0.54
M_{101}	49	53	52	42	52	53	51	51	47	55	0.49	0.52	0.51	0.42	0.51	0.52	0.50	0.50	0.47	0.54
M_{102}	49	53	52	42	53	54	52	52	47	56	0.48	0.52	0.51	0.41	0.52	0.53	0.51	0.51	0.46	0.55
M_{103}	50	54	52	43	53	55	52	52	48	56	0.49	0.52	0.50	0.42	0.51	0.53	0.50	0.50	0.47	0.54
M_{104}	51	55	52	44	53	55	52	53	48	57	0.49	0.53	0.50	0.42	0.51	0.53	0.50	0.51	0.46	0.55
M_{105}	52	56	53	45	53	55	53	53	48	57	0.50	0.53	0.50	0.43	0.50	0.52	0.50	0.50	0.46	0.54
M_{106}	53	57	53	45	53	55	54	54	48	58	0.50	0.54	0.50	0.42	0.50	0.52	0.51	0.51	0.45	0.55
M_{107}	53	58	53	46	53	55	55	54	49	59	0.50	0.54	0.50	0.43	0.50	0.51	0.51	0.50	0.46	0.55
M_{108}	53	59	54	46	54	55	55	55	49	60	0.49	0.55	0.50	0.43	0.50	0.51	0.51	0.51	0.45	0.56
M_{109}	53	60	54	46	55	56	56	55	50	60	0.49	0.55	0.50	0.42	0.50	0.51	0.51	0.50	0.46	0.55
M_{110}	53	61	54	46	55	57	57	55	51	61	0.48	0.55	0.49	0.42	0.50	0.52	0.52	0.50	0.46	0.55
M_{111}	54	62	55	46	55	58	57	55	52	61	0.49	0.56	0.50	0.41	0.50	0.52	0.51	0.50	0.47	0.55
M_{112}	54	63	56	47	55	58	57	55	53	62	0.48	0.56	0.50	0.42	0.49	0.52	0.51	0.49	0.47	0.55
M_{113}	55	63	56	48	55	59	58	55	54	62	0.49	0.56	0.50	0.42	0.49	0.52	0.51	0.49	0.48	0.55
M_{114}	55	63	57	49	55	59	59	55	55	63	0.48	0.55	0.50	0.43	0.48	0.52	0.52	0.48	0.48	0.55
M_{115}	55	63	58	50	56	59	59	56	56	63	0.48	0.55	0.50	0.43	0.49	0.51	0.51	0.49	0.49	0.55
M_{116}	55	63	58	51	57	60	60	56	57	63	0.47	0.54	0.50	0.44	0.49	0.52	0.52	0.48	0.49	0.54
M_{117}	55	63	59	52	57	61	61	56	57	64	0.47	0.54	0.50	0.44	0.49	0.52	0.52	0.48	0.49	0.55
M_{118}	55	64	59	52	58	61	62	56	58	65	0.47	0.54	0.50	0.44	0.49	0.52	0.53	0.47	0.49	0.55
M_{119}	55	64	60	53	58	61	62	57	59	66	0.46	0.54	0.50	0.45	0.49	0.51	0.52	0.48	0.50	0.55
M_{120}	56	65	61	53	59	61	63	57	59	66	0.47	0.54	0.51	0.44	0.49	0.51	0.53	0.47	0.49	0.55
M_{121}	56	65	62	54	59	62	63	58	59	67	0.46	0.54	0.51	0.45	0.49	0.51	0.52	0.48	0.49	0.55
M_{122}	57	66	62	54	60	63	64	58	59	67	0.47	0.54	0.51	0.44	0.49	0.52	0.52	0.48	0.48	0.55
M_{123}	57	66	63	55	61	64	65	58	59	67	0.46	0.54	0.51	0.45	0.50	0.52	0.53	0.47	0.48	0.54
M_{124}	58	66	63	56	61	64	65	59	60	68	0.47	0.53	0.51	0.45	0.49	0.52	0.52	0.48	0.48	0.55
M_{125}	59	66	63	56	61	65	66	60	61	68	0.47	0.53	0.50	0.45	0.49	0.52	0.53	0.48	0.49	0.54
M_{126}	59	67	63	57	61	65	67	61	62	68	0.47	0.53	0.50	0.45	0.48	0.52	0.53	0.48	0.49	0.54
M_{127}	60	68	63	57	62	65	68	61	62	69	0.47	0.54	0.50	0.45	0.49	0.51	0.54	0.48	0.49	0.54
M_{128}	61	68	63	58	62	65	69	62	62	70	0.48	0.53	0.49	0.45	0.48	0.51	0.54	0.48	0.48	0.55
M_{129}	62	68	63	58	63	66	69	63	62	71	0.48	0.53	0.49	0.45	0.49	0.51	0.53	0.49	0.48	0.55
M_{130}	63	69	64	59	63	66	69	64	62	71	0.48	0.53	0.49	0.45	0.48	0.51	0.53	0.49	0.48	0.55
M_{131}	63	69	65	59	64	66	69	65	63	72	0.48	0.53	0.50	0.45	0.49	0.50	0.53	0.50	0.48	0.55
M_{132}	63	69	65	59	65	67	70	65	64	73	0.48	0.52	0.49	0.45	0.49	0.51	0.53	0.49	0.48	0.55
M_{133}	63	70	65	59	65	67	71	66	65	74	0.47	0.53	0.49	0.44	0.49	0.50	0.53	0.50	0.49	0.56
M_{134}	63	71	65	60	66	67	71	67	65	75	0.47	0.53	0.49	0.45	0.49	0.50	0.53	0.50	0.49	0.56
M_{135}	64	71	66	61	67	67	71	67	65	76	0.47	0.53	0.49	0.45	0.50	0.50	0.53	0.50	0.48	0.56
M_{136}	64	72	66	62	68	67	72	67	65	77	0.47	0.53	0.49	0.46	0.50	0.49	0.53	0.49	0.48	0.57
M_{137}	65	72	66	63	68	67	73	68	66	77	0.47	0.53	0.48	0.46	0.50	0.49	0.53	0.50	0.48	0.56
M_{138}	65	72	67	64	68	67	74	69	66	78	0.47	0.52	0.49	0.46	0.49	0.49	0.54	0.50	0.48	0.57
M_{139}	65	72	67	64	69	67	75	70	67	79	0.47	0.52	0.48	0.46	0.50	0.48	0.54	0.50	0.48	0.57
M_{140}	66	73	67	64	70	67	76	70	68	79	0.47	0.52	0.48	0.46	0.50	0.48	0.54	0.50	0.49	0.56
M_{141}	67	73	67	65	70	67	77	70	69	80	0.48	0.52	0.48	0.46	0.50	0.48	0.55	0.50	0.49	0.57
M_{142}	68	73	68	65	71	67	77	71	70	80	0.48	0.51	0.48	0.46	0.50	0.47	0.54	0.50	0.49	0.56
M_{143}	68	73	69	66	72	68	77	72	70	80	0.48	0.51	0.48	0.46	0.50	0.48	0.54	0.50	0.49	0.56
M_{144}	69	73	70	67	73	68	77	73	70	80	0.48	0.51	0.49	0.47	0.51	0.47	0.53	0.51	0.49	0.56
M_{145}	70	74	71	67	73	68	77	73	71	81	0.48	0.51	0.49	0.46	0.50	0.47	0.53	0.50	0.49	0.56
M_{146}	71	75	71	68	73	68	78	73	71	82	0.49	0.51	0.49	0.47	0.50	0.47	0.53	0.50	0.49	0.56
M_{147}	72	76	71	69	73	69	79	73	71	82	0.49	0.52	0.48	0.47	0.50	0.47	0.54	0.50	0.48	0.56
M_{148}	72	77	72	70	73	69	79	74	71	83	0.49	0.52	0.49	0.47	0.49	0.47	0.53	0.50	0.48	0.56
M_{149}	73	77	73	70	73	70	80	74	71	84	0.49	0.52	0.49	0.47	0.49	0.47	0.54	0.50	0.48	0.56
M_{150}	73	77	73	71	74	70	81	75	72	84	0.49	0.51	0.49	0.47	0.49	0.47	0.54	0.50	0.48	0.56
M_{151}	73	77	74	71	75	71	82	75	72	85	0.48	0.51	0.49	0.47	0.50	0.47	0.54	0.50	0.48	0.56
M_{152}	74	77	74	72	75	72	82	76	73	85	0.49	0.51	0.49	0.47	0.49	0.47	0.54	0.50	0.48	0.56
M_{153}	75	77	75	73	75	73	82	76	73	86	0.49	0.50	0.49	0.48	0.49	0.48	0.54	0.50	0.48	0.56
M_{154}	76	78	76	74	76	73	82	76	73	86	0.49	0.51	0.49	0.48	0.49	0.47	0.53	0.49	0.47	0.56
M_{155}	77	79	76	75	77	74	82	76	73	86	0.50	0.51	0.49	0.48	0.50	0.48	0.53	0.49	0.47	0.55
M_{156}	78	79	77	76	78	74	82	76	74	86	0.50	0.51	0.49	0.49	0.50	0.47	0.53	0.49	0.47	0.55
M_{157}	79	79	77	77	79	75	82	77	74	86	0.50	0.50	0.49	0.49	0.50	0.48	0.52	0.49	0.47	0.55
M_{158}	80	79	78	78	79	76	82	78	74	86	0.51	0.50	0.49	0.49	0.50	0.48	0.52	0.49	0.47	0.54
M_{159}	81	80	79	79	79	77	82	78	74	86	0.51	0.50	0.50	0.50	0.50	0.48	0.52	0.49	0.47	0.54
M_{160}	82	81	79	80	79	77	82	79	75	86	0.51	0.51	0.49	0.50	0.49	0.48	0.51	0.49	0.47	0.54
M_{161}	82	82	79	80	80	78	83	80	75	86	0.51	0.51	0.49	0.50	0.50	0.48	0.52	0.50	0.47	0.53
M_{162}	82	82	80	81	81	79	83	80	76	86	0.51	0.51	0.49	0.50	0.50	0.49	0.51	0.49	0.47	0.53
M_{163}	82	82	80	81	81	80	84	81	77	87	0.50	0.50	0.49	0.50	0.50	0.49	0.52	0.50	0.47	0.53
M_{164}	82	82	80	82	82	81	85	82	77	87	0.50	0.50	0.49	0.50	0.50	0.49	0.52	0.50	0.47	0.53
M_{165}	83	83	81	82	83	81	85	82	77	88	0.50	0.50	0.49	0.50	0.50	0.49	0.52	0.50	0.47	0.53
M_{166}	84	83	81	83	84	81	85	82	78	89	0.51	0.50	0.49	0.50	0.51	0.49	0.51	0.49	0.47	0.54
M_{167}	85	83	82	84	84	81	85	82	79	90	0.51	0.50	0.49	0.50	0.50	0.49	0.51	0.49	0.47	0.54
M_{168}	85	84	83	85	84	81	85	83	80	90	0.51	0.50	0.49	0.51	0.50	0.48	0.51	0.49	0.48	0.54

(Cont'd) Ratio of coverage of each point q by members of M_t as M_t expands.

	$N(M_t, q)$										$Y(M_t, q)$									
M_t	q_0	q_1	q_2	q_3	q_4	q_5	q_6	q_7	q_8	q_9	q_0	q_1	q_2	q_3	q_4	q_5	q_6	q_7	q_8	q_9
M_{169}	86	84	84	85	85	81	86	83	81	90	0.51	0.50	0.50	0.50	0.50	0.48	0.51	0.49	0.48	0.53
M_{170}	86	84	84	86	85	82	87	84	82	90	0.51	0.49	0.49	0.51	0.50	0.48	0.51	0.49	0.48	0.53
M_{171}	87	84	84	87	85	83	87	84	83	91	0.51	0.49	0.49	0.51	0.50	0.49	0.51	0.49	0.49	0.53
M_{172}	87	84	84	88	86	83	88	85	83	92	0.51	0.49	0.49	0.51	0.50	0.48	0.51	0.49	0.48	0.53
M_{173}	87	85	85	89	87	83	89	85	83	92	0.50	0.49	0.49	0.51	0.50	0.48	0.51	0.49	0.48	0.53
M_{174}	87	86	86	89	88	84	89	85	84	92	0.50	0.49	0.49	0.51	0.51	0.48	0.51	0.49	0.48	0.53
M_{175}	87	86	86	90	88	85	89	86	85	93	0.50	0.49	0.49	0.51	0.50	0.49	0.51	0.49	0.49	0.53
M_{176}	88	86	87	91	88	86	89	86	86	93	0.50	0.49	0.49	0.52	0.50	0.49	0.51	0.49	0.49	0.53
M_{177}	88	86	87	92	88	87	90	87	86	94	0.50	0.49	0.49	0.52	0.50	0.49	0.51	0.49	0.49	0.53
M_{178}	88	87	87	93	89	88	90	87	87	94	0.49	0.49	0.49	0.52	0.50	0.49	0.51	0.49	0.49	0.53
M_{179}	89	88	87	93	90	89	90	87	87	95	0.50	0.49	0.49	0.52	0.50	0.50	0.50	0.49	0.49	0.53
M_{180}	90	88	87	94	91	89	90	88	87	96	0.50	0.49	0.48	0.52	0.51	0.49	0.50	0.49	0.48	0.53
M_{181}	90	89	87	94	92	89	90	89	88	97	0.50	0.49	0.48	0.52	0.51	0.49	0.50	0.49	0.49	0.54
M_{182}	90	89	88	95	92	89	91	90	89	97	0.49	0.49	0.48	0.52	0.51	0.49	0.50	0.49	0.49	0.53
M_{183}	91	89	88	96	93	90	92	90	89	97	0.50	0.49	0.48	0.52	0.51	0.49	0.50	0.49	0.49	0.53
M_{184}	91	90	88	97	94	91	93	90	89	97	0.49	0.49	0.48	0.53	0.51	0.49	0.51	0.49	0.48	0.53
M_{185}	92	91	88	97	94	92	94	90	90	97	0.50	0.49	0.48	0.52	0.51	0.50	0.51	0.49	0.49	0.52
M_{186}	93	92	88	97	94	93	94	91	91	97	0.50	0.49	0.47	0.52	0.51	0.50	0.51	0.49	0.49	0.52
M_{187}	94	93	88	97	94	93	95	92	92	97	0.50	0.50	0.47	0.52	0.50	0.50	0.51	0.49	0.49	0.52
M_{188}	94	94	89	98	94	93	96	93	92	97	0.50	0.50	0.47	0.52	0.50	0.49	0.51	0.49	0.49	0.52
M_{189}	94	95	90	99	95	94	96	93	92	97	0.50	0.50	0.48	0.52	0.50	0.50	0.51	0.49	0.49	0.51
M_{190}	94	95	91	99	95	95	97	94	92	98	0.49	0.50	0.48	0.52	0.50	0.50	0.51	0.49	0.48	0.52
M_{191}	95	95	92	100	95	95	98	95	92	98	0.50	0.50	0.48	0.52	0.50	0.50	0.51	0.50	0.48	0.51
M_{192}	96	96	93	100	95	96	99	95	92	98	0.50	0.50	0.48	0.52	0.49	0.50	0.52	0.49	0.48	0.51
M_{193}	96	97	93	101	95	96	100	96	92	99	0.50	0.50	0.48	0.52	0.49	0.50	0.52	0.50	0.48	0.51
M_{194}	97	97	93	101	96	96	101	96	93	100	0.50	0.50	0.48	0.52	0.49	0.49	0.52	0.49	0.48	0.52
M_{195}	98	97	93	101	97	97	102	96	94	100	0.50	0.50	0.48	0.52	0.50	0.50	0.52	0.49	0.48	0.51
M_{196}	98	98	94	101	97	98	102	97	95	100	0.50	0.50	0.48	0.52	0.49	0.50	0.52	0.49	0.48	0.51
M_{197}	98	99	95	101	98	98	103	97	96	100	0.50	0.50	0.48	0.51	0.50	0.50	0.52	0.49	0.49	0.51
M_{198}	99	99	95	102	99	98	104	97	97	100	0.50	0.50	0.48	0.52	0.50	0.49	0.53	0.49	0.49	0.51
M_{199}	99	99	95	103	100	99	105	97	97	101	0.50	0.50	0.48	0.52	0.50	0.50	0.53	0.49	0.49	0.51
M_{200}	99	100	96	104	100	99	106	97	97	102	0.49	0.50	0.48	0.52	0.50	0.49	0.53	0.48	0.48	0.51
M_{201}	99	101	96	105	101	99	106	97	98	103	0.49	0.50	0.48	0.52	0.50	0.49	0.53	0.48	0.49	0.51
M_{202}	99	102	97	105	101	100	107	98	98	103	0.49	0.50	0.48	0.52	0.50	0.50	0.53	0.49	0.49	0.51
M_{203}	100	102	98	105	102	100	107	98	99	104	0.49	0.50	0.48	0.52	0.50	0.49	0.53	0.48	0.49	0.51
M_{204}	101	102	99	105	102	100	108	99	100	104	0.50	0.50	0.49	0.51	0.50	0.49	0.53	0.49	0.49	0.51
M_{205}	101	103	99	106	102	101	109	100	100	104	0.49	0.50	0.48	0.52	0.50	0.49	0.53	0.49	0.49	0.51
M_{206}	102	104	99	107	102	102	109	101	100	104	0.50	0.50	0.48	0.52	0.50	0.50	0.53	0.49	0.49	0.50
M_{207}	103	105	100	107	102	102	109	102	101	104	0.50	0.51	0.48	0.52	0.49	0.49	0.53	0.49	0.49	0.50
M_{208}	104	105	101	107	102	103	109	103	102	104	0.50	0.50	0.49	0.51	0.49	0.50	0.52	0.50	0.49	0.50
M_{209}	104	106	102	108	103	103	109	103	103	104	0.50	0.51	0.49	0.52	0.49	0.49	0.52	0.49	0.49	0.50
M_{210}	105	107	103	108	103	103	109	104	103	105	0.50	0.51	0.49	0.51	0.49	0.49	0.52	0.50	0.49	0.50
M_{211}	106	107	104	108	104	104	109	104	104	105	0.50	0.51	0.49	0.51	0.49	0.49	0.52	0.49	0.49	0.50
M_{212}	106	108	104	109	105	105	109	105	104	105	0.50	0.51	0.49	0.51	0.50	0.50	0.51	0.50	0.49	0.50
M_{213}	106	108	105	109	106	105	110	105	105	106	0.50	0.51	0.49	0.51	0.50	0.49	0.52	0.49	0.49	0.50
M_{214}	107	108	105	110	107	105	110	106	106	106	0.50	0.50	0.49	0.51	0.50	0.49	0.51	0.50	0.50	0.50
M_{215}	107	108	106	111	107	106	110	106	107	107	0.50	0.50	0.49	0.52	0.50	0.49	0.51	0.49	0.50	0.50
M_{216}	107	108	107	111	108	106	111	107	107	108	0.50	0.50	0.50	0.51	0.50	0.49	0.51	0.50	0.50	0.50
M_{217}	108	108	108	111	109	107	112	107	107	108	0.50	0.50	0.50	0.51	0.50	0.49	0.52	0.49	0.49	0.50
M_{218}	109	108	108	111	109	108	113	107	108	109	0.50	0.50	0.50	0.51	0.50	0.50	0.52	0.49	0.50	0.50
M_{219}	109	109	109	111	109	108	113	108	109	110	0.50	0.50	0.50	0.51	0.50	0.49	0.52	0.49	0.50	0.50
M_{220}	110	109	110	112	110	108	114	108	109	110	0.50	0.50	0.50	0.51	0.50	0.49	0.52	0.49	0.50	0.50
M_{221}	110	109	111	113	111	108	114	108	110	111	0.50	0.49	0.50	0.51	0.50	0.49	0.52	0.49	0.50	0.50
M_{222}	110	109	112	114	112	108	115	109	110	111	0.50	0.49	0.50	0.51	0.50	0.49	0.52	0.49	0.50	0.50
M_{223}	110	110	113	114	113	108	115	109	111	112	0.49	0.49	0.51	0.51	0.51	0.48	0.52	0.49	0.50	0.50
M_{224}	110	111	113	114	114	109	115	109	112	113	0.49	0.50	0.50	0.51	0.51	0.49	0.51	0.49	0.50	0.50
M_{225}	110	111	114	114	114	110	116	110	113	113	0.49	0.49	0.51	0.51	0.51	0.49	0.52	0.49	0.50	0.50
M_{226}	110	112	115	114	114	111	116	111	113	114	0.49	0.50	0.51	0.50	0.50	0.49	0.51	0.49	0.50	0.50
M_{227}	111	112	115	115	115	112	116	111	114	114	0.49	0.49	0.51	0.51	0.51	0.49	0.51	0.49	0.50	0.50
M_{228}	112	113	115	115	115	113	117	111	114	115	0.49	0.50	0.50	0.50	0.50	0.50	0.51	0.49	0.50	0.50
M_{229}	112	113	115	115	116	114	117	112	115	116	0.49	0.49	0.50	0.50	0.51	0.50	0.51	0.49	0.50	0.51
M_{230}	112	114	116	116	116	115	117	112	116	116	0.49	0.50	0.50	0.50	0.50	0.50	0.51	0.49	0.50	0.50
M_{231}	113	114	117	116	116	116	117	113	116	117	0.49	0.49	0.51	0.50	0.50	0.50	0.51	0.49	0.50	0.51
M_{232}	114	115	117	116	117	117	117	114	116	117	0.49	0.50	0.50	0.50	0.50	0.50	0.50	0.49	0.50	0.50
M_{233}	115	115	117	116	117	118	117	115	117	118	0.49	0.49	0.50	0.50	0.50	0.51	0.50	0.49	0.50	0.51
M_{234}	116	116	118	116	118	118	117	116	117	118	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50
M_{235}	117	116	118	117	119	118	118	117	117	118	0.50	0.49	0.50	0.50	0.51	0.50	0.50	0.50	0.50	0.50
M_{236}	117	117	119	118	119	119	118	117	117	119	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50
M_{237}	118	117	120	118	119	120	119	118	117	119	0.50	0.49	0.51	0.50	0.50	0.51	0.50	0.50	0.49	0.50
M_{238}	118	118	121	119	119	121	120	118	117	119	0.50	0.50	0.51	0.50	0.50	0.51	0.50	0.50	0.49	0.50
M_{239}	119	118	122	119	120	121	121	118	117	120	0.50	0.49	0.51	0.50	0.50	0.51	0.51	0.49	0.49	0.50
M_{240}	119	119	122	120	121	121	122	118	118	120	0.50	0.50	0.51	0.50	0.50	0.50	0.51	0.49	0.49	0.50
M_{241}	120	119	123	120	122	121	122	119	118	121	0.50	0.49	0.51	0.50	0.51	0.50	0.51	0.49	0.49	0.50
M_{242}	120	119	123	121	122	121	123	120	119	122	0.50	0.49	0.51	0.50	0.50	0.50	0.51	0.50	0.49	0.50
M_{243}	120	120	123	122	122	122	124	120	120	122	0.49	0.49	0.51	0.50	0.50	0.50	0.51	0.49	0.49	0.50
M_{244}	121	120	124	122	123	122	125	121	120	122	0.50	0.49	0.51	0.50	0.50	0.50	0.51	0.50	0.49	0.50
M_{245}	122	121	124	122	123	123	125	121	121	123	0.50	0.49	0.51	0.50	0.50	0.50	0.51	0.49	0.49	0.50
M_{246}	123	122	124	122	124	123	125	122	122	123	0.50	0.50	0.50	0.50	0.50	0.50	0.51	0.50	0.50	0.50
M_{247}	123	123	124	122	124	124	125	123	123	124	0.50	0.50	0.50	0.49	0.50	0.50	0.51	0.50	0.50	0.50
M_{248}	124	124	124	123	125	124	125	123	123	125	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50
M_{249}	125	124	125	124	125	125	126	123	123	125	0.50	0.50	0.50	0.50	0.50	0.50	0.51	0.49	0.49	0.50
M_{250}	125	125	125	124	126	126	126	124	124	125	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50
M_{251}	125	126	125	125	126	126	126	125	125	126	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50
M_{252}	126	126	126	126	126	126	126	126	126	126	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50

Table 3: Changes of $Y_{12}(q, M_t)$ as M_t expands. For each t, we show the ratings for each new member of M_t, the values X_{12} for this new member, and Y_{12} for the collection M_t up to the inclusion of this new member.

					$X_{12}(q, m_t)$ if		$Y_{12}(q, M_t)$									
M_t	m_t	r_1	r_2	$r_1 - r_2$	$q \in m_t$	$q \notin m_t$	q_0	q_1	q_2	q_3	q_4	q_5	q_6	q_7	q_8	q_9
M_1	m_1	0.20	0.80	-0.60	-0.33	1.33	1.33	1.33	1.33	-0.33	1.33	-0.33	-0.33	1.33	-0.33	-0.33
M_2	m_2	0.80	0.20	0.60	1.33	-0.33	1.33	1.33	1.33	-0.33	0.50	-0.33	0.50	0.50	0.50	-0.33
M_3	m_3	0.60	0.40	0.20	3.00	-2.00	1.89	0.22	0.22	-0.89	1.33	-0.89	-0.33	1.33	1.33	0.78
M_4	m_4	0.40	0.60	-0.20	-2.00	3.00	2.17	0.92	-0.33	0.08	1.75	-1.17	-0.75	1.75	0.50	0.08
M_5	m_5	0.60	0.40	0.20	3.00	-2.00	2.33	0.33	0.33	-0.33	1.00	-1.33	0.00	2.00	0.00	0.67
M_6	m_6	0.40	0.60	-0.20	-2.00	3.00	2.44	0.78	0.78	-0.61	0.50	-1.44	0.50	1.33	-0.33	1.06
M_7	m_7	0.20	0.80	-0.60	-0.33	1.33	2.28	0.62	0.86	-0.57	0.38	-1.28	0.62	1.33	-0.10	0.86
M_8	m_8	0.80	0.20	0.60	1.33	-0.33	2.17	0.71	0.92	-0.33	0.29	-1.17	0.50	1.12	0.08	0.71
M_9	m_9	0.60	0.40	0.20	3.00	-2.00	1.70	0.96	1.15	0.04	0.59	-1.26	0.22	1.33	-0.15	0.41
M_{10}	m_{10}	0.60	0.40	0.20	3.00	-2.00	1.83	1.17	0.83	-0.17	0.33	-0.83	0.00	1.50	-0.33	0.67
M_{11}	m_{11}	0.20	0.80	-0.60	-0.33	1.33	1.79	1.18	0.88	-0.18	0.27	-0.79	0.12	1.48	-0.33	0.58
M_{12}	m_{12}	0.20	0.80	-0.60	-0.33	1.33	1.61	1.19	0.92	-0.19	0.22	-0.75	0.22	1.47	-0.19	0.50
M_{13}	m_{13}	0.20	0.80	-0.60	-0.33	1.33	1.59	1.20	0.82	-0.20	0.18	-0.72	0.31	1.46	-0.08	0.44
M_{14}	m_{14}	0.60	0.40	0.20	3.00	-2.00	1.69	0.97	0.97	-0.33	0.38	-0.45	0.14	1.57	-0.21	0.26
M_{15}	m_{15}	0.60	0.40	0.20	3.00	-2.00	1.78	0.78	1.11	-0.11	0.22	-0.55	0.33	1.33	0.00	0.11
M_{16}	m_{16}	0.60	0.40	0.20	3.00	-2.00	1.85	0.60	1.23	-0.23	0.08	-0.64	0.50	1.12	0.19	0.29
M_{17}	m_{17}	0.60	0.40	0.20	3.00	-2.00	1.92	0.74	1.04	-0.04	-0.04	-0.72	0.65	0.94	0.35	0.16
M_{18}	m_{18}	0.40	0.60	-0.20	-2.00	3.00	1.98	0.59	1.15	-0.15	0.13	-0.80	0.78	1.05	0.22	0.04
M_{19}	m_{19}	0.40	0.60	-0.20	-2.00	3.00	2.03	0.46	1.24	0.02	0.02	-0.86	0.89	0.89	0.37	-0.07
M_{20}	m_{20}	0.40	0.60	-0.20	-2.00	3.00	2.08	0.58	1.08	-0.08	-0.08	-0.67	0.75	1.00	0.25	0.08
M_{21}	m_{21}	0.60	0.40	0.20	3.00	-2.00	1.89	0.46	1.17	-0.17	-0.17	-0.73	0.86	1.09	0.38	0.22
M_{22}	m_{22}	0.60	0.40	0.20	3.00	-2.00	1.71	0.57	1.03	-0.26	-0.26	-0.56	0.95	1.18	0.50	0.12
M_{23}	m_{23}	0.60	0.40	0.20	3.00	-2.00	1.77	0.46	0.90	-0.33	-0.12	-0.40	0.83	1.26	0.61	0.03
M_{24}	m_{24}	0.40	0.60	-0.20	-2.00	3.00	1.61	0.57	0.99	-0.19	-0.19	-0.26	0.71	1.12	0.71	-0.05
M_{25}	m_{25}	0.40	0.60	-0.20	-2.00	3.00	1.47	0.67	0.87	-0.07	-0.27	-0.33	0.80	1.20	0.80	-0.13
M_{26}	m_{26}	0.40	0.60	-0.20	-2.00	3.00	1.52	0.56	0.76	0.05	-0.14	-0.40	0.69	1.27	0.88	-0.20
M_{27}	m_{27}	0.60	0.40	0.20	3.00	-2.00	1.58	0.65	0.84	-0.02	-0.21	-0.46	0.78	1.15	0.78	-0.09
M_{28}	m_{28}	0.60	0.40	0.20	3.00	-2.00	1.63	0.56	0.74	-0.09	-0.27	-0.51	0.86	1.21	0.86	0.02
M_{29}	m_{29}	0.60	0.40	0.20	3.00	-2.00	1.68	0.64	0.64	-0.16	-0.33	-0.56	0.93	1.10	0.93	0.13
M_{30}	m_{30}	0.80	0.20	0.60	1.33	-0.33	1.67	0.67	0.67	-0.17	-0.28	-0.55	0.89	1.06	0.94	0.11
M_{31}	m_{31}	0.40	0.60	-0.20	-2.00	3.00	1.71	0.58	0.58	-0.06	-0.33	-0.60	0.80	1.12	1.01	0.21
M_{32}	m_{32}	0.40	0.60	-0.20	-2.00	3.00	1.75	0.50	0.66	-0.12	-0.23	-0.65	0.86	1.02	1.07	0.14
M_{33}	m_{33}	0.20	0.80	-0.60	-0.33	1.33	1.74	0.52	0.68	-0.13	-0.23	-0.59	0.83	1.03	1.03	0.12
M_{34}	m_{34}	0.60	0.40	0.20	3.00	-2.00	1.63	0.60	0.74	-0.19	-0.28	-0.63	0.89	1.09	0.94	0.21
M_{35}	m_{35}	0.60	0.40	0.20	3.00	-2.00	1.52	0.67	0.81	-0.24	-0.33	-0.52	0.95	1.00	1.00	0.14
M_{36}	m_{36}	0.20	0.80	-0.60	-0.33	1.33	1.52	0.68	0.82	-0.24	-0.33	-0.52	0.96	0.96	1.01	0.13
M_{37}	m_{37}	0.60	0.40	0.20	3.00	-2.00	1.56	0.75	0.75	-0.15	-0.38	-0.56	0.88	0.88	1.06	0.21
M_{38}	m_{38}	0.20	0.80	-0.60	-0.33	1.33	1.55	0.76	0.72	-0.16	-0.38	-0.51	0.85	0.89	1.07	0.19
M_{39}	m_{39}	0.40	0.60	-0.20	-2.00	3.00	1.59	0.82	0.65	-0.08	-0.42	-0.55	0.91	0.82	1.12	0.14
M_{40}	m_{40}	0.60	0.40	0.20	3.00	-2.00	1.62	0.75	0.71	-0.12	-0.46	-0.46	0.83	0.75	1.17	0.21
M_{41}	m_{41}	0.60	0.40	0.20	3.00	-2.00	1.66	0.80	0.64	-0.17	-0.50	-0.37	0.89	0.80	1.09	0.16
M_{42}	m_{42}	0.60	0.40	0.20	3.00	-2.00	1.57	0.86	0.58	-0.09	-0.41	-0.41	0.82	0.86	1.13	0.10
M_{43}	m_{43}	0.60	0.40	0.20	3.00	-2.00	1.49	0.91	0.64	-0.14	-0.45	-0.45	0.87	0.79	1.18	0.17
M_{44}	m_{44}	0.20	0.80	-0.60	-0.33	1.33	1.45	0.92	0.65	-0.11	-0.45	-0.45	0.84	0.80	1.18	0.16
M_{45}	m_{45}	0.60	0.40	0.20	3.00	-2.00	1.48	0.96	0.70	-0.15	-0.37	-0.37	0.78	0.74	1.11	0.11
M_{46}	m_{46}	0.60	0.40	0.20	3.00	-2.00	1.51	1.01	0.64	-0.19	-0.30	-0.30	0.72	0.68	1.15	0.07
M_{47}	m_{47}	0.40	0.60	-0.20	-2.00	3.00	1.55	0.94	0.69	-0.12	-0.23	-0.33	0.66	0.62	1.19	0.02
M_{48}	m_{48}	0.60	0.40	0.20	3.00	-2.00	1.47	0.99	0.74	-0.16	-0.16	-0.26	0.60	0.67	1.12	-0.02
M_{49}	m_{49}	0.60	0.40	0.20	3.00	-2.00	1.50	0.92	0.79	-0.09	-0.20	-0.30	0.55	0.72	1.06	0.04
M_{50}	m_{50}	0.60	0.40	0.20	3.00	-2.00	1.53	0.87	0.83	-0.13	-0.23	-0.23	0.60	0.67	1.10	0.00
M_{51}	m_{51}	0.60	0.40	0.20	3.00	-2.00	1.46	0.91	0.88	-0.07	-0.27	-0.17	0.55	0.71	1.04	-0.04
M_{52}	m_{52}	0.60	0.40	0.20	3.00	-2.00	1.40	0.95	0.82	-0.11	-0.20	-0.20	0.60	0.76	1.08	-0.08
M_{53}	m_{53}	0.80	0.20	0.60	1.33	-0.33	1.36	0.96	0.83	-0.11	-0.21	-0.21	0.61	0.77	1.08	-0.08
M_{54}	m_{54}	0.40	0.60	-0.20	-2.00	3.00	1.39	0.99	0.78	-0.15	-0.15	-0.24	0.56	0.72	1.12	-0.02
M_{55}	m_{55}	0.80	0.20	0.60	1.33	-0.33	1.39	0.97	0.79	-0.15	-0.15	-0.24	0.55	0.73	1.12	0.00
M_{56}	m_{56}	0.40	0.60	-0.20	-2.00	3.00	1.42	1.01	0.74	-0.09	-0.18	-0.27	0.50	0.68	1.15	0.05
M_{57}	m_{57}	0.20	0.80	-0.60	-0.33	1.33	1.42	0.98	0.75	-0.10	-0.16	-0.27	0.49	0.69	1.16	0.05
M_{58}	m_{58}	0.60	0.40	0.20	3.00	-2.00	1.45	1.02	0.79	-0.13	-0.19	-0.22	0.44	0.64	1.10	0.10
M_{59}	m_{59}	0.40	0.60	-0.20	-2.00	3.00	1.47	1.05	0.74	-0.16	-0.22	-0.16	0.49	0.60	1.14	0.06
M_{60}	m_{60}	0.40	0.60	-0.20	-2.00	3.00	1.42	1.08	0.78	-0.19	-0.17	-0.19	0.53	0.56	1.17	0.03
M_{61}	m_{61}	0.60	0.40	0.20	3.00	-2.00	1.36	1.11	0.81	-0.14	-0.20	-0.22	0.57	0.51	1.20	0.00
M_{62}	m_{62}	0.60	0.40	0.20	3.00	-2.00	1.31	1.06	0.85	-0.09	-0.23	-0.17	0.53	0.55	1.23	-0.04
M_{63}	m_{63}	0.40	0.60	-0.20	-2.00	3.00	1.25	1.09	0.80	-0.12	-0.25	-0.20	0.57	0.59	1.25	0.01
M_{64}	m_{64}	0.60	0.40	0.20	3.00	-2.00	1.28	1.12	0.76	-0.15	-0.20	-0.23	0.53	0.63	1.20	0.06
M_{65}	m_{65}	0.20	0.80	-0.60	-0.33	1.33	1.26	1.13	0.77	-0.15	-0.18	-0.23	0.51	0.64	1.20	0.05
M_{66}	m_{66}	0.40	0.60	-0.20	-2.00	3.00	1.21	1.08	0.80	-0.18	-0.21	-0.18	0.47	0.68	1.23	0.10
M_{67}	m_{67}	0.40	0.60	-0.20	-2.00	3.00	1.23	1.11	0.76	-0.13	-0.23	-0.21	0.44	0.71	1.18	0.14
M_{68}	m_{68}	0.40	0.60	-0.20	-2.00	3.00	1.19	1.06	0.79	-0.16	-0.19	-0.23	0.48	0.74	1.21	0.11
M_{69}	m_{69}	0.40	0.60	-0.20	-2.00	3.00	1.21	1.02	0.75	-0.12	-0.21	-0.26	0.51	0.78	1.24	0.08
M_{70}	m_{70}	0.60	0.40	0.20	3.00	-2.00	1.24	1.05	0.79	-0.07	-0.24	-0.29	0.48	0.74	1.19	0.12
M_{71}	m_{71}	0.60	0.40	0.20	3.00	-2.00	1.19	1.00	0.82	-0.10	-0.19	-0.31	0.51	0.77	1.22	0.09
M_{72}	m_{72}	0.60	0.40	0.20	3.00	-2.00	1.22	1.03	0.78	-0.05	-0.15	-0.33	0.48	0.80	1.17	0.06
M_{73}	m_{73}	0.60	0.40	0.20	3.00	-2.00	1.24	1.06	0.74	-0.08	-0.10	-0.36	0.51	0.83	1.13	0.03
M_{74}	m_{74}	0.60	0.40	0.20	3.00	-2.00	1.27	1.02	0.70	-0.11	-0.06	-0.38	0.55	0.86	1.15	0.01
M_{75}	m_{75}	0.60	0.40	0.20	3.00	-2.00	1.22	1.04	0.73	-0.13	-0.09	-0.33	0.51	0.82	1.18	0.05
M_{76}	m_{76}	0.60	0.40	0.20	3.00	-2.00	1.25	1.07	0.70	-0.09	-0.05	-0.35	0.48	0.78	1.20	0.02
M_{77}	m_{77}	0.20	0.80	-0.60	-0.33	1.33	1.25	1.05	0.71	-0.07	-0.05	-0.35	0.47	0.79	1.20	0.01
M_{78}	m_{78}	0.80	0.20	0.60	1.33	-0.33	1.25	1.06	0.69	-0.08	-0.06	-0.35	0.46	0.80	1.20	0.03
M_{79}	m_{79}	0.60	0.40	0.20	3.00	-2.00	1.27	1.08	0.66	-0.04	-0.08	-0.37	0.49	0.83	1.16	0.00
M_{80}	m_{80}	0.80	0.20	0.60	1.33	-0.33	1.25	1.08	0.67	-0.04	-0.06	-0.37	0.48	0.83	1.17	0.00
M_{81}	m_{81}	0.60	0.40	0.20	3.00	-2.00	1.21	1.04	0.69	-0.07	-0.09	-0.33	0.45	0.86	1.19	0.04
M_{82}	m_{82}	0.60	0.40	0.20	3.00	-2.00	1.23	1.07	0.66	-0.09	-0.05	-0.35	0.42	0.82	1.21	0.07
M_{83}	m_{83}	0.40	0.60	-0.20	-2.00	3.00	1.19	1.09	0.69	-0.11	-0.01	-0.37	0.39	0.79	1.23	0.11
M_{84}	m_{84}	0.40	0.60	-0.20	-2.00	3.00	1.21	1.06	0.66	-0.13	-0.04	-0.33	0.42	0.82	1.25	0.08

(Cont'd) Changes of $Y_{12}(q, M_t)$ as M_t expands. For each t, we show the ratings for each new member of M_t, the values X_{12} for this new member, and Y_{12} for the collection M_t up to the inclusion of this new member.

					$X_{12}(q, m_t)$ if		$Y_{12}(q, M_t)$									
M_t	m_t	r_1	r_2	$r_1 - r_2$	$q \in m_t$	$q \notin m_t$	q_0	q_1	q_2	q_3	q_4	q_5	q_6	q_7	q_8	q_9
M_{85}	m_{85}	0.60	0.40	0.20	3.00	-2.00	1.18	1.02	0.69	-0.16	0.00	-0.29	0.39	0.84	1.27	0.06
M_{86}	m_{86}	0.40	0.60	-0.20	-2.00	3.00	1.20	1.04	0.65	-0.18	0.04	-0.31	0.36	0.87	1.24	0.09
M_{87}	m_{87}	0.80	0.20	0.60	1.33	-0.33	1.20	1.05	0.66	-0.18	0.03	-0.31	0.38	0.87	1.22	0.09
M_{88}	m_{88}	0.80	0.20	0.60	1.33	-0.33	1.20	1.05	0.67	-0.18	0.03	-0.29	0.37	0.88	1.20	0.08
M_{89}	m_{89}	0.40	0.60	-0.20	-2.00	3.00	1.16	1.07	0.70	-0.15	0.06	-0.31	0.34	0.85	1.22	0.06
M_{90}	m_{90}	0.40	0.60	-0.20	-2.00	3.00	1.18	1.09	0.67	-0.11	0.04	-0.33	0.37	0.87	1.18	0.04
M_{91}	m_{91}	0.40	0.60	-0.20	-2.00	3.00	1.15	1.11	0.69	-0.08	0.02	-0.35	0.40	0.89	1.15	0.02
M_{92}	m_{92}	0.60	0.40	0.20	3.00	-2.00	1.12	1.13	0.72	-0.10	0.05	-0.37	0.43	0.92	1.12	-0.01
M_{93}	m_{93}	0.60	0.40	0.20	3.00	-2.00	1.08	1.15	0.69	-0.06	0.03	-0.33	0.40	0.94	1.14	-0.03
M_{94}	m_{94}	0.40	0.60	-0.20	-2.00	3.00	1.05	1.17	0.66	-0.08	0.06	-0.30	0.38	0.96	1.16	-0.05
M_{95}	m_{95}	0.40	0.60	-0.20	-2.00	3.00	1.07	1.14	0.63	-0.05	0.04	-0.26	0.35	0.98	1.18	-0.07
M_{96}	m_{96}	0.40	0.60	-0.20	-2.00	3.00	1.04	1.16	0.66	-0.02	0.01	-0.28	0.33	0.95	1.19	-0.04
M_{97}	m_{97}	0.40	0.60	-0.20	-2.00	3.00	1.06	1.13	0.68	0.01	-0.01	-0.25	0.30	0.92	1.21	-0.06
M_{98}	m_{98}	0.40	0.60	-0.20	-2.00	3.00	1.08	1.09	0.70	-0.01	-0.03	-0.21	0.28	0.89	1.23	-0.03
M_{99}	m_{99}	0.40	0.60	-0.20	-2.00	3.00	1.10	1.11	0.73	0.02	-0.05	-0.23	0.26	0.86	1.20	0.00
M_{100}	m_{100}	0.20	0.80	-0.60	-0.33	1.33	1.08	1.12	0.73	0.02	-0.05	-0.22	0.25	0.87	1.20	0.00
M_{101}	m_{101}	0.40	0.60	-0.20	-2.00	3.00	1.10	1.13	0.76	0.00	-0.07	-0.18	0.28	0.84	1.17	-0.02
M_{102}	m_{102}	0.20	0.80	-0.60	-0.33	1.33	1.10	1.14	0.76	0.01	-0.07	-0.19	0.27	0.83	1.17	-0.02
M_{103}	m_{103}	0.60	0.40	0.20	3.00	-2.00	1.12	1.15	0.73	0.04	-0.09	-0.15	0.25	0.80	1.19	-0.04
M_{104}	m_{104}	0.60	0.40	0.20	3.00	-2.00	1.14	1.17	0.71	0.07	-0.11	-0.17	0.23	0.82	1.16	-0.01
M_{105}	m_{105}	0.60	0.40	0.20	3.00	-2.00	1.16	1.19	0.73	0.10	-0.13	-0.19	0.25	0.79	1.13	-0.03
M_{106}	m_{106}	0.60	0.40	0.20	3.00	-2.00	1.18	1.21	0.70	0.08	-0.14	-0.21	0.28	0.81	1.10	0.00
M_{107}	m_{107}	0.40	0.60	-0.20	-2.00	3.00	1.19	1.18	0.73	0.06	-0.11	-0.18	0.26	0.83	1.07	-0.02
M_{108}	m_{108}	0.60	0.40	0.20	3.00	-2.00	1.16	1.19	0.75	0.04	-0.09	-0.19	0.24	0.85	1.04	0.01
M_{109}	m_{109}	0.40	0.60	-0.20	-2.00	3.00	1.18	1.16	0.77	0.06	-0.10	-0.21	0.22	0.87	1.01	0.03
M_{110}	m_{110}	0.40	0.60	-0.20	-2.00	3.00	1.20	1.14	0.79	0.09	-0.08	-0.23	0.20	0.89	0.98	0.02
M_{111}	m_{111}	0.80	0.20	0.60	1.33	-0.33	1.20	1.14	0.79	0.09	-0.08	-0.21	0.19	0.88	0.99	0.01
M_{112}	m_{112}	0.60	0.40	0.20	3.00	-2.00	1.17	1.15	0.81	0.11	-0.09	-0.23	0.17	0.86	1.01	0.04
M_{113}	m_{113}	0.40	0.60	-0.20	-2.00	3.00	1.14	1.17	0.83	0.09	-0.07	-0.24	0.15	0.88	0.98	0.07
M_{114}	m_{114}	0.40	0.60	-0.20	-2.00	3.00	1.16	1.19	0.81	0.08	-0.04	-0.22	0.13	0.89	0.95	0.05
M_{115}	m_{115}	0.60	0.40	0.20	3.00	-2.00	1.13	1.16	0.83	0.10	-0.01	-0.23	0.12	0.91	0.97	0.03
M_{116}	m_{116}	0.20	0.80	-0.60	-0.33	1.33	1.13	1.16	0.83	0.10	-0.02	-0.23	0.11	0.92	0.96	0.04
M_{117}	m_{117}	0.20	0.80	-0.60	-0.33	1.33	1.13	1.16	0.82	0.09	-0.01	-0.23	0.11	0.92	0.96	0.04
M_{118}	m_{118}	0.40	0.60	-0.20	-2.00	3.00	1.15	1.14	0.84	0.12	-0.02	-0.21	0.09	0.94	0.94	0.02
M_{119}	m_{119}	0.60	0.40	0.20	3.00	-2.00	1.12	1.11	0.86	0.14	-0.04	-0.22	0.07	0.95	0.95	0.05
M_{120}	m_{120}	0.60	0.40	0.20	3.00	-2.00	1.14	1.12	0.87	0.13	-0.01	-0.24	0.10	0.93	0.93	0.03
M_{121}	m_{121}	0.40	0.60	-0.20	-2.00	3.00	1.15	1.14	0.85	0.11	0.01	-0.25	0.12	0.91	0.95	0.01
M_{122}	m_{122}	0.40	0.60	-0.20	-2.00	3.00	1.13	1.11	0.87	0.13	-0.01	-0.26	0.10	0.92	0.96	0.04
M_{123}	m_{123}	0.20	0.80	-0.60	-0.33	1.33	1.13	1.12	0.86	0.13	-0.01	-0.27	0.10	0.93	0.97	0.05
M_{124}	m_{124}	0.60	0.40	0.20	3.00	-2.00	1.14	1.09	0.84	0.15	-0.02	-0.28	0.08	0.94	0.98	0.07
M_{125}	m_{125}	0.60	0.40	0.20	3.00	-2.00	1.16	1.07	0.81	0.13	-0.04	-0.25	0.11	0.96	1.00	0.05
M_{126}	m_{126}	0.60	0.40	0.20	3.00	-2.00	1.13	1.08	0.79	0.16	-0.06	-0.27	0.13	0.98	1.02	0.04
M_{127}	m_{127}	0.40	0.60	-0.20	-2.00	3.00	1.11	1.06	0.81	0.18	-0.07	-0.24	0.11	0.99	1.03	0.02
M_{128}	m_{128}	0.40	0.60	-0.20	-2.00	3.00	1.09	1.07	0.83	0.16	-0.05	-0.22	0.10	0.97	1.05	0.01
M_{129}	m_{129}	0.40	0.60	-0.20	-2.00	3.00	1.06	1.09	0.84	0.18	-0.06	-0.23	0.12	0.95	1.06	-0.01
M_{130}	m_{130}	0.80	0.20	0.60	1.33	-0.33	1.06	1.09	0.85	0.19	-0.06	-0.23	0.12	0.95	1.05	-0.01
M_{131}	m_{131}	0.60	0.40	0.20	3.00	-2.00	1.04	1.07	0.86	0.18	-0.04	-0.24	0.10	0.96	1.07	0.01
M_{132}	m_{132}	0.20	0.80	-0.60	-0.33	1.33	1.04	1.07	0.87	0.18	-0.04	-0.24	0.10	0.97	1.06	0.01
M_{133}	m_{133}	0.60	0.40	0.20	3.00	-2.00	1.02	1.08	0.84	0.17	-0.06	-0.26	0.12	0.98	1.07	0.03
M_{134}	m_{134}	0.40	0.60	-0.20	-2.00	3.00	1.03	1.06	0.86	0.15	-0.07	-0.23	0.14	0.96	1.08	0.02
M_{135}	m_{135}	0.40	0.60	-0.20	-2.00	3.00	1.01	1.07	0.84	0.14	-0.09	-0.21	0.16	0.97	1.10	0.00
M_{136}	m_{136}	0.20	0.80	-0.60	-0.33	1.33	1.01	1.06	0.84	0.13	-0.09	-0.20	0.16	0.98	1.10	0.00
M_{137}	m_{137}	0.60	0.40	0.20	3.00	-2.00	1.03	1.04	0.82	0.15	-0.10	-0.21	0.18	0.99	1.11	-0.02
M_{138}	m_{138}	0.40	0.60	-0.20	-2.00	3.00	1.04	1.06	0.80	0.14	-0.08	-0.19	0.16	0.97	1.13	-0.03
M_{139}	m_{139}	0.40	0.60	-0.20	-2.00	3.00	1.06	1.07	0.82	0.16	-0.09	-0.17	0.15	0.95	1.11	-0.05
M_{140}	m_{140}	0.60	0.40	0.20	3.00	-2.00	1.07	1.08	0.80	0.14	-0.07	-0.18	0.17	0.93	1.12	-0.06
M_{141}	m_{141}	0.40	0.60	-0.20	-2.00	3.00	1.05	1.10	0.81	0.13	-0.05	-0.16	0.15	0.94	1.10	-0.07
M_{142}	m_{142}	0.80	0.20	0.60	1.33	-0.33	1.05	1.09	0.82	0.12	-0.04	-0.16	0.15	0.95	1.10	-0.07
M_{143}	m_{143}	0.40	0.60	-0.20	-2.00	3.00	1.06	1.10	0.80	0.11	-0.05	-0.17	0.17	0.92	1.11	-0.05
M_{144}	m_{144}	0.60	0.40	0.20	3.00	-2.00	1.08	1.08	0.81	0.13	-0.03	-0.18	0.15	0.94	1.09	-0.07
M_{145}	m_{145}	0.80	0.20	0.60	1.33	-0.33	1.08	1.08	0.82	0.13	-0.03	-0.18	0.15	0.93	1.09	-0.06
M_{146}	m_{146}	0.40	0.60	-0.20	-2.00	3.00	1.06	1.06	0.83	0.11	-0.01	-0.16	0.14	0.94	1.10	-0.07
M_{147}	m_{147}	0.40	0.60	-0.20	-2.00	3.00	1.04	1.04	0.85	0.10	0.01	-0.17	0.12	0.96	1.12	-0.05
M_{148}	m_{148}	0.60	0.40	0.20	3.00	-2.00	1.02	1.05	0.86	0.12	-0.01	-0.19	0.11	0.97	1.10	-0.03
M_{149}	m_{149}	0.40	0.60	-0.20	-2.00	3.00	1.00	1.06	0.84	0.14	0.01	-0.20	0.09	0.99	1.11	-0.04
M_{150}	m_{150}	0.40	0.60	-0.20	-2.00	3.00	1.01	1.08	0.86	0.12	0.00	-0.18	0.08	0.97	1.09	-0.02
M_{151}	m_{151}	0.20	0.80	-0.60	-0.33	1.33	1.01	1.08	0.85	0.13	0.00	-0.18	0.08	0.97	1.09	-0.02
M_{152}	m_{152}	0.60	0.40	0.20	3.00	-2.00	1.03	1.06	0.83	0.15	-0.01	-0.16	0.06	0.98	1.10	-0.04
M_{153}	m_{153}	0.40	0.60	-0.20	-2.00	3.00	1.01	1.07	0.81	0.14	0.00	-0.17	0.08	1.00	1.12	-0.05
M_{154}	m_{154}	0.60	0.40	0.20	3.00	-2.00	1.02	1.08	0.82	0.15	0.02	-0.18	0.07	0.98	1.09	-0.06
M_{155}	m_{155}	0.40	0.60	-0.20	-2.00	3.00	1.00	1.06	0.84	0.14	0.01	-0.19	0.09	0.99	1.11	-0.04
M_{156}	m_{156}	0.60	0.40	0.20	3.00	-2.00	1.01	1.04	0.85	0.16	0.03	-0.20	0.07	0.97	1.12	-0.06
M_{157}	m_{157}	0.40	0.60	-0.20	-2.00	3.00	0.99	1.06	0.87	0.14	0.02	-0.22	0.09	0.95	1.13	-0.04
M_{158}	m_{158}	0.60	0.40	0.20	3.00	-2.00	1.01	1.04	0.88	0.16	0.00	-0.20	0.08	0.96	1.11	-0.05
M_{159}	m_{159}	0.60	0.40	0.20	3.00	-2.00	1.02	1.05	0.89	0.18	-0.01	-0.18	0.07	0.95	1.09	-0.06
M_{160}	m_{160}	0.80	0.20	0.60	1.33	-0.33	1.02	1.05	0.89	0.19	-0.01	-0.18	0.06	0.95	1.09	-0.06
M_{161}	m_{161}	0.40	0.60	-0.20	-2.00	3.00	1.03	1.03	0.90	0.21	-0.02	-0.19	0.05	0.93	1.11	-0.04
M_{162}	m_{162}	0.40	0.60	-0.20	-2.00	3.00	1.04	1.04	0.88	0.19	-0.03	-0.20	0.07	0.94	1.09	-0.02
M_{163}	m_{163}	0.40	0.60	-0.20	-2.00	3.00	1.06	1.06	0.89	0.21	-0.02	-0.21	0.06	0.92	1.07	-0.04
M_{164}	m_{164}	0.20	0.80	-0.60	-0.33	1.33	1.06	1.06	0.90	0.21	-0.02	-0.21	0.05	0.92	1.07	-0.03
M_{165}	m_{165}	0.60	0.40	0.20	3.00	-2.00	1.07	1.07	0.91	0.19	0.00	-0.22	0.04	0.90	1.05	-0.01
M_{166}	m_{166}	0.40	0.60	-0.20	-2.00	3.00	1.05	1.08	0.92	0.18	-0.01	-0.20	0.06	0.91	1.03	-0.02
M_{167}	m_{167}	0.60	0.40	0.20	3.00	-2.00	1.06	1.06	0.93	0.20	-0.02	-0.21	0.05	0.89	1.04	0.00
M_{168}	m_{168}	0.80	0.20	0.60	1.33	-0.33	1.06	1.07	0.94	0.20	-0.03	-0.21	0.04	0.90	1.05	-0.01

(Cont'd) Changes of $Y_{12}(q, M_t)$ as M_t expands. For each t, we show the ratings for each new member of M_t, the values X_{12} for this new member, and Y_{12} for the collection M_t up to the inclusion of this new member.

					$X_{12}(q, m_t)$ if		$Y_{12}(q, M_t)$									
M_t	m_t	r_1	r_2	$r_1 - r_2$	$q \in m_t$	$q \notin m_t$	q_0	q_1	q_2	q_3	q_4	q_5	q_6	q_7	q_8	q_9
M_{169}	m_{169}	0.60	0.40	0.20	3.00	-2.00	1.07	1.05	0.95	0.19	-0.01	-0.22	0.06	0.88	1.06	-0.02
M_{170}	m_{170}	0.40	0.60	-0.20	-2.00	3.00	1.08	1.06	0.96	0.18	0.01	-0.23	0.05	0.86	1.04	0.00
M_{171}	m_{171}	0.40	0.60	-0.20	-2.00	3.00	1.06	1.07	0.97	0.16	0.03	-0.25	0.07	0.87	1.02	-0.01
M_{172}	m_{172}	0.20	0.80	-0.60	-0.33	1.33	1.06	1.07	0.97	0.16	0.03	-0.24	0.06	0.87	1.02	-0.01
M_{173}	m_{173}	0.40	0.60	-0.20	-2.00	3.00	1.07	1.05	0.96	0.15	0.01	-0.22	0.05	0.88	1.03	0.00
M_{174}	m_{174}	0.60	0.40	0.20	3.00	-2.00	1.06	1.06	0.97	0.14	0.03	-0.20	0.04	0.86	1.05	-0.01
M_{175}	m_{175}	0.40	0.60	-0.20	-2.00	3.00	1.07	1.08	0.98	0.12	0.05	-0.21	0.06	0.85	1.03	-0.02
M_{176}	m_{176}	0.60	0.40	0.20	3.00	-2.00	1.08	1.06	0.99	0.14	0.04	-0.19	0.05	0.83	1.04	-0.03
M_{177}	m_{177}	0.20	0.80	-0.60	-0.33	1.33	1.08	1.06	0.99	0.14	0.04	-0.19	0.04	0.82	1.04	-0.03
M_{178}	m_{178}	0.40	0.60	-0.20	-2.00	3.00	1.09	1.04	1.01	0.13	0.03	-0.20	0.06	0.84	1.02	-0.01
M_{179}	m_{179}	0.40	0.60	-0.20	-2.00	3.00	1.07	1.03	1.02	0.14	0.02	-0.21	0.08	0.85	1.03	-0.03
M_{180}	m_{180}	0.40	0.60	-0.20	-2.00	3.00	1.06	1.04	1.03	0.13	0.01	-0.19	0.09	0.83	1.05	-0.04
M_{181}	m_{181}	0.60	0.40	0.20	3.00	-2.00	1.04	1.05	1.01	0.12	0.03	-0.20	0.08	0.84	1.06	-0.02
M_{182}	m_{182}	0.60	0.40	0.20	3.00	-2.00	1.02	1.03	1.02	0.13	0.02	-0.21	0.10	0.86	1.07	-0.03
M_{183}	m_{183}	0.20	0.80	-0.60	-0.33	1.33	1.01	1.03	1.02	0.13	0.01	-0.21	0.10	0.86	1.07	-0.02
M_{184}	m_{184}	0.20	0.80	-0.60	-0.33	1.33	1.02	1.02	1.02	0.13	0.01	-0.22	0.09	0.86	1.07	-0.02
M_{185}	m_{185}	0.60	0.40	0.20	3.00	-2.00	1.03	1.04	1.01	0.12	0.00	-0.20	0.11	0.85	1.08	-0.03
M_{186}	m_{186}	0.80	0.20	0.60	1.33	-0.33	1.03	1.04	1.00	0.12	0.00	-0.19	0.11	0.85	1.08	-0.03
M_{187}	m_{187}	0.80	0.20	0.60	1.33	-0.33	1.03	1.04	0.99	0.11	0.00	-0.19	0.11	0.85	1.08	-0.03
M_{188}	m_{188}	0.60	0.40	0.20	3.00	-2.00	1.01	1.05	1.00	0.13	-0.01	-0.20	0.13	0.86	1.07	-0.04
M_{189}	m_{189}	0.40	0.60	-0.20	-2.00	3.00	1.02	1.03	0.99	0.12	-0.02	-0.21	0.14	0.87	1.08	-0.02
M_{190}	m_{190}	0.40	0.60	-0.20	-2.00	3.00	1.03	1.04	0.97	0.13	-0.01	-0.22	0.13	0.86	1.09	-0.03
M_{191}	m_{191}	0.60	0.40	0.20	3.00	-2.00	1.04	1.03	0.98	0.15	-0.02	-0.23	0.15	0.87	1.07	-0.04
M_{192}	m_{192}	0.60	0.40	0.20	3.00	-2.00	1.06	1.04	0.99	0.14	-0.03	-0.21	0.16	0.86	1.06	-0.06
M_{193}	m_{193}	0.40	0.60	-0.20	-2.00	3.00	1.07	1.02	1.00	0.12	-0.01	-0.19	0.15	0.84	1.07	-0.07
M_{194}	m_{194}	0.40	0.60	-0.20	-2.00	3.00	1.05	1.03	1.02	0.14	-0.02	-0.18	0.14	0.85	1.05	-0.08
M_{195}	m_{195}	0.40	0.60	-0.20	-2.00	3.00	1.03	1.04	1.03	0.15	-0.03	-0.19	0.13	0.86	1.03	-0.06
M_{196}	m_{196}	0.80	0.20	0.60	1.33	-0.33	1.03	1.04	1.03	0.15	-0.04	-0.18	0.13	0.87	1.04	-0.06
M_{197}	m_{197}	0.60	0.40	0.20	3.00	-2.00	1.01	1.05	1.04	0.14	-0.02	-0.19	0.14	0.85	1.05	-0.07
M_{198}	m_{198}	0.40	0.60	-0.20	-2.00	3.00	1.00	1.06	1.05	0.13	-0.03	-0.17	0.13	0.86	1.03	-0.06
M_{199}	m_{199}	0.00	1.00	-1.00	0.00	1.00	1.00	1.06	1.05	0.13	-0.03	-0.17	0.13	0.86	1.03	-0.05
M_{200}	m_{200}	0.40	0.60	-0.20	-2.00	3.00	1.01	1.05	1.03	0.12	-0.01	-0.16	0.12	0.87	1.04	-0.06
M_{201}	m_{201}	0.40	0.60	-0.20	-2.00	3.00	1.02	1.03	1.04	0.11	-0.02	-0.14	0.13	0.88	1.02	-0.07
M_{202}	m_{202}	0.60	0.40	0.20	3.00	-2.00	1.00	1.04	1.05	0.10	-0.03	-0.12	0.15	0.89	1.01	-0.08
M_{203}	m_{203}	0.60	0.40	0.20	3.00	-2.00	1.01	1.03	1.06	0.09	-0.02	-0.13	0.14	0.88	1.02	-0.07
M_{204}	m_{204}	0.80	0.20	0.60	1.33	-0.33	1.01	1.02	1.06	0.09	-0.02	-0.14	0.14	0.88	1.02	-0.07
M_{205}	m_{205}	0.40	0.60	-0.20	-2.00	3.00	1.02	1.01	1.07	0.08	-0.01	-0.14	0.13	0.87	1.03	-0.05
M_{206}	m_{206}	0.60	0.40	0.20	3.00	-2.00	1.03	1.02	1.06	0.09	-0.02	-0.13	0.12	0.88	1.02	-0.06
M_{207}	m_{207}	1.00	0.00	1.00	1.00	0.00	1.03	1.02	1.06	0.09	-0.02	-0.13	0.12	0.88	1.02	-0.06
M_{208}	m_{208}	0.80	0.20	0.60	1.33	-0.33	1.03	1.01	1.06	0.09	-0.02	-0.12	0.12	0.88	1.02	-0.07
M_{209}	m_{209}	0.60	0.40	0.20	3.00	-2.00	1.02	1.02	1.07	0.10	0.00	-0.13	0.11	0.87	1.03	-0.07
M_{210}	m_{210}	0.80	0.20	0.60	1.33	-0.33	1.02	1.02	1.07	0.10	0.00	-0.13	0.11	0.87	1.02	-0.07
M_{211}	m_{211}	0.60	0.40	0.20	3.00	-2.00	1.03	1.01	1.08	0.09	0.01	-0.12	0.10	0.86	1.03	-0.08
M_{212}	m_{212}	0.40	0.60	-0.20	-2.00	3.00	1.04	0.99	1.09	0.08	0.00	-0.13	0.11	0.84	1.04	-0.06
M_{213}	m_{213}	0.40	0.60	-0.20	-2.00	3.00	1.05	1.00	1.07	0.09	-0.01	-0.11	0.10	0.85	1.02	-0.07
M_{214}	m_{214}	0.60	0.40	0.20	3.00	-2.00	1.06	0.99	1.06	0.11	0.01	-0.12	0.09	0.86	1.03	-0.08
M_{215}	m_{215}	0.40	0.60	-0.20	-2.00	3.00	1.07	1.00	1.04	0.10	0.02	-0.13	0.10	0.87	1.02	-0.09
M_{216}	m_{216}	0.40	0.60	-0.20	-2.00	3.00	1.08	1.01	1.03	0.11	0.01	-0.11	0.09	0.86	1.03	-0.10
M_{217}	m_{217}	0.40	0.60	-0.20	-2.00	3.00	1.06	1.01	1.01	0.12	0.00	-0.12	0.08	0.87	1.04	-0.08
M_{218}	m_{218}	0.40	0.60	-0.20	-2.00	3.00	1.05	1.02	1.02	0.14	0.01	-0.13	0.08	0.88	1.02	-0.09
M_{219}	m_{219}	0.80	0.20	0.60	1.33	-0.33	1.04	1.03	1.03	0.13	0.01	-0.13	0.07	0.88	1.03	-0.09
M_{220}	m_{220}	0.40	0.60	-0.20	-2.00	3.00	1.03	1.03	1.01	0.12	0.00	-0.12	0.06	0.89	1.03	-0.07
M_{221}	m_{221}	0.40	0.60	-0.20	-2.00	3.00	1.04	1.04	1.00	0.12	-0.01	-0.10	0.08	0.90	1.02	-0.08
M_{222}	m_{222}	0.40	0.60	-0.20	-2.00	3.00	1.04	1.05	0.98	0.11	-0.01	-0.09	0.07	0.89	1.03	-0.07
M_{223}	m_{223}	0.60	0.40	0.20	3.00	-2.00	1.03	1.06	0.99	0.10	0.00	-0.10	0.06	0.87	1.04	-0.05
M_{224}	m_{224}	0.40	0.60	-0.20	-2.00	3.00	1.04	1.05	1.00	0.11	-0.01	-0.11	0.07	0.88	1.02	-0.06
M_{225}	m_{225}	0.60	0.40	0.20	3.00	-2.00	1.03	1.03	1.01	0.10	-0.02	-0.09	0.08	0.89	1.03	-0.07
M_{226}	m_{226}	0.60	0.40	0.20	3.00	-2.00	1.01	1.04	1.02	0.09	-0.03	-0.08	0.08	0.90	1.02	-0.06
M_{227}	m_{227}	0.40	0.60	-0.20	-2.00	3.00	1.00	1.05	1.03	0.08	-0.04	-0.09	0.09	0.91	1.01	-0.04
M_{228}	m_{228}	0.40	0.60	-0.20	-2.00	3.00	0.99	1.04	1.04	0.09	-0.02	-0.10	0.08	0.92	1.02	-0.05
M_{229}	m_{229}	0.40	0.60	-0.20	-2.00	3.00	1.00	1.05	1.05	0.11	-0.03	-0.10	0.09	0.91	1.00	-0.06
M_{230}	m_{230}	0.60	0.40	0.20	3.00	-2.00	0.98	1.05	1.05	0.12	-0.04	-0.09	0.08	0.90	1.01	-0.07
M_{231}	m_{231}	0.60	0.40	0.20	3.00	-2.00	0.99	1.04	1.06	0.11	-0.05	-0.08	0.07	0.90	1.00	-0.06
M_{232}	m_{232}	0.60	0.40	0.20	3.00	-2.00	1.00	1.05	1.05	0.10	-0.04	-0.06	0.07	0.91	0.99	-0.06
M_{233}	m_{233}	0.60	0.40	0.20	3.00	-2.00	1.01	1.04	1.04	0.09	-0.04	-0.05	0.06	0.92	0.99	-0.05
M_{234}	m_{234}	0.80	0.20	0.60	1.33	-0.33	1.01	1.04	1.04	0.09	-0.04	-0.05	0.05	0.92	0.99	-0.05
M_{235}	m_{235}	0.40	0.60	-0.20	-2.00	3.00	1.00	1.05	1.05	0.08	-0.05	-0.04	0.05	0.91	1.00	-0.04
M_{236}	m_{236}	0.40	0.60	-0.20	-2.00	3.00	1.01	1.03	1.03	0.07	-0.03	-0.05	0.06	0.92	1.01	-0.05
M_{237}	m_{237}	0.60	0.40	0.20	3.00	-2.00	1.01	1.02	1.04	0.06	-0.04	-0.03	0.07	0.93	0.99	-0.06
M_{238}	m_{238}	0.40	0.60	-0.20	-2.00	3.00	1.02	1.01	1.03	0.06	-0.03	-0.04	0.06	0.94	1.00	-0.04
M_{239}	m_{239}	0.40	0.60	-0.20	-2.00	3.00	1.01	1.02	1.02	0.07	-0.04	-0.03	0.05	0.95	1.01	-0.05
M_{240}	m_{240}	0.40	0.60	-0.20	-2.00	3.00	1.02	1.00	1.02	0.06	-0.05	-0.02	0.04	0.96	1.00	-0.04
M_{241}	m_{241}	0.60	0.40	0.20	3.00	-2.00	1.03	0.99	1.03	0.05	-0.03	-0.03	0.04	0.96	0.98	-0.03
M_{242}	m_{242}	0.40	0.60	-0.20	-2.00	3.00	1.03	1.00	1.04	0.04	-0.02	-0.01	0.03	0.95	0.97	-0.03
M_{243}	m_{243}	0.40	0.60	-0.20	-2.00	3.00	1.04	0.99	1.05	0.03	-0.01	-0.02	0.02	0.96	0.96	-0.02
M_{244}	m_{244}	0.60	0.40	0.20	3.00	-2.00	1.05	0.98	1.06	0.03	0.00	-0.03	0.03	0.97	0.95	-0.03
M_{245}	m_{245}	0.60	0.40	0.20	3.00	-2.00	1.06	0.98	1.04	0.02	0.00	-0.02	0.02	0.96	0.96	-0.02
M_{246}	m_{246}	0.80	0.20	0.60	1.33	-0.33	1.06	0.98	1.04	0.02	0.00	-0.02	0.02	0.96	0.96	-0.02
M_{247}	m_{247}	0.60	0.40	0.20	3.00	-2.00	1.05	0.99	1.03	0.01	-0.01	-0.01	0.01	0.97	0.97	-0.01
M_{248}	m_{248}	0.40	0.60	-0.20	-2.00	3.00	1.03	0.98	1.03	0.00	-0.01	0.01	0.03	0.97	0.97	-0.01
M_{249}	m_{249}	0.40	0.60	-0.20	-2.00	3.00	1.02	0.99	1.02	-0.01	0.00	0.00	0.02	0.98	0.98	0.00
M_{250}	m_{250}	0.60	0.40	0.20	3.00	-2.00	1.01	1.00	1.01	-0.02	0.01	0.01	0.01	0.99	0.99	-0.01
M_{251}	m_{251}	0.60	0.40	0.20	3.00	-2.00	1.00	1.00	1.00	0.00	0.00	0.00	0.00	1.00	1.00	0.00
M_{252}	m_{252}	0.80	0.20	0.60	1.33	-0.33	1.00	1.00	1.00	0.00	0.00	0.00	0.00	1.00	1.00	0.00