Mining Social Networks for Personalized Email Prioritization

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Once upon a time
In NTU, there was a student called Odd
He likes a girl very much, but he is too shy to tell her
One day, he finally wrote an E-mail to confess.
But the girl didn’t see the e-mail
Because that e-mail is just one of the hundreds of e-mail in her inbox that day
After ten years, Odd received a wedding invitation from the girl
He felt sad, but he still called the girl to congratulate her
During the call, Odd asked her why she didn’t reply the e-mail.
The girl said she didn’t received such e-mail!
And she also liked Odd when she was in school, if she got the e-mail...
Odd sighed, and came up with the famous saying....
世界上最遙遠的距離
不是生與死
而是我寄了e-mail給你
你卻不知道它在哪裡
Why this tragedy happened?

- There are too many e-mails!!!!!!!
- We can’t tell which of them is more important.
Nowadays solutions

- Spam and non-spam detecting.
- Use textual feature to get e-mail importance.
- Both of the solutions are not good enough.
- Hey! Why don’t we utilize social network to get e-mail importance?
Social network solution’s difficulty

- It’s impossible to build a complete social network.
- People won’t share their importance label due to privacy reason.
This paper’s solution

- The method must be a fully personalized methodology.
- 5 fine-grained importance level.
- Use textual and social feature and SVM to prioritize e-mail.
SVMs are a set of related supervised learning methods used for classification and regression. A support vector machine constructs a hyperplane or set of hyperplanes in a high or infinite dimensional space, which can be used for classification, regression or other tasks.

by Wikipedia, the free encyclopedia
Enriched feature

- Social clustering
- Social importance
- Semi-supervised importance propagation
- How’s the performance?

Tell you later😊
Personalization ➔ Sparse Data

Scenario:

1. We cannot have public-huge training data, because importance to one cannot imply importance to another.

2. Due to privacy issue, cross-reference between data from different users is not allowed.
Unsupervised Learning to the Rescue

Unsupervised Learning can help Supervised Learning when data are sparse.

Where does the cluster come from??

Author:
Importance of a person not in the training data can be inferred from the social network constructed from CC list.
New Features to Predict "Importance of Mail"

Basic Feature
- Cluster Feature
- Social Importance
- SIP Feature

From Social Network
- From Mailing Network

(SIP means: "Semi-supervised Importance Propagation").
Cluster Feature----Newman Cluster

Use Newman Clustering:

Remove edges with highest “betweenness” until enough clusters appear.

Var( intra-cluster ) is low.

The Ave. importance of a cluster can effect its member much.
# My Personal Email Network for last month

<table>
<thead>
<tr>
<th>Sender</th>
<th>Receiver</th>
<th>Sender Name</th>
<th>Receiver Name</th>
<th>label</th>
</tr>
</thead>
<tbody>
<tr>
<td><a href="mailto:b4499@ms15.hinet.net">b4499@ms15.hinet.net</a></td>
<td><a href="mailto:godsongg@gmail.com">godsongg@gmail.com</a></td>
<td>偉</td>
<td>?</td>
<td>1</td>
</tr>
<tr>
<td><a href="mailto:mkt@manning.com">mkt@manning.com</a></td>
<td><a href="mailto:a061105@gmail.com">a061105@gmail.com</a></td>
<td>Manning Publications</td>
<td>嚴恩勗</td>
<td>1</td>
</tr>
<tr>
<td><a href="mailto:ntudeanacademic@ntu.edu.tw">ntudeanacademic@ntu.edu.tw</a></td>
<td><a href="mailto:a061105@gmail.com">a061105@gmail.com</a></td>
<td>蔣丙煌教務長</td>
<td>嚴恩勗</td>
<td>1</td>
</tr>
<tr>
<td><a href="mailto:d98944005@csie.ntu.edu.tw">d98944005@csie.ntu.edu.tw</a></td>
<td><a href="mailto:a061105@gmail.com">a061105@gmail.com</a></td>
<td>Cheng-Te Li</td>
<td>嚴恩勗</td>
<td>5</td>
</tr>
<tr>
<td><a href="mailto:mnf.shih@gmail.com">mnf.shih@gmail.com</a></td>
<td><a href="mailto:a061105@gmail.com">a061105@gmail.com</a></td>
<td>施孟甫</td>
<td>嚴恩勗</td>
<td>4</td>
</tr>
<tr>
<td><a href="mailto:bpaper8@m8.blueshop.com.tw">bpaper8@m8.blueshop.com.tw</a></td>
<td><a href="mailto:a061105@gmail.com">a061105@gmail.com</a></td>
<td>藍色小舖</td>
<td>嚴恩勗</td>
<td>1</td>
</tr>
<tr>
<td><a href="mailto:store-news@amazon.com">store-news@amazon.com</a></td>
<td><a href="mailto:a061105@gmail.com">a061105@gmail.com</a></td>
<td>Amazon.com</td>
<td>嚴恩勗</td>
<td>1</td>
</tr>
<tr>
<td><a href="mailto:adrian.mlb@gmail.com">adrian.mlb@gmail.com</a></td>
<td><a href="mailto:a061105@gmail.com">a061105@gmail.com</a></td>
<td>Adrian Bonilla</td>
<td>嚴恩勗</td>
<td>4</td>
</tr>
<tr>
<td><a href="mailto:adrian.mlb@gmail.com">adrian.mlb@gmail.com</a></td>
<td><a href="mailto:byb107515@hotmail.com">byb107515@hotmail.com</a></td>
<td>Adrian Bonilla</td>
<td>林書漾</td>
<td>4</td>
</tr>
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<td><a href="mailto:timestringalpha@gmail.com">timestringalpha@gmail.com</a></td>
<td>Adrian Bonilla</td>
<td>?</td>
<td>4</td>
</tr>
<tr>
<td><a href="mailto:adrian.mlb@gmail.com">adrian.mlb@gmail.com</a></td>
<td><a href="mailto:limeiida@gmail.com">limeiida@gmail.com</a></td>
<td>Adrian Bonilla</td>
<td>?</td>
<td>4</td>
</tr>
</tbody>
</table>

- **Used in Social Network**
- **Export from outlook**
- **Label by self**
- **Used only in Mailing Network**
Cluster Feature ---- my network
Social Importance

Lots of measures available. Which to choose?

- In-degree
- Out-degree
- Total-degree

- Clustering Coefficient
- Clique Count
- Betweenness
- HITS Authority
Social Importance

Lots of measures available. Which to choose?

- In-degree
- Out-degree
- Total-degree

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Social Importance

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- In-degree
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Social Importance

Lots of measures available. Which to choose?

- In-degree
- Out-degree
- Total-degree

- Clustering Coefficient
  - Clique Count
  - Betweenness
  - HITS Authority

\[ ClqCnt(v) = \text{the number of clique sub-graphs which contain the node } v. \]

\[ BetCent(v) = \frac{\text{Existing shortest paths through node } v}{\text{All possible paths through the node } v} \]
Social Importance

Lots of measures available. Which to choose?

- In-degree
- Out-degree
- Total-degree

The Concept of HITS: (Web Pages Ranking)

- Clustering Coefficient
- Clique Count
- Betweenness
- HITS Authority
Social Importance

Lots of measures available. Which to choose?

- In-degree
- Out-degree
- Total-degree

The Concept of HITS: (In Mailing Network)

- Clustering Coefficient
- Clique Count
- Betweenness
- HITS Authority
Social Importance

When graph is large, iteratively update these 2 equations yields roughly the same result.

\[
\begin{align*}
Xh &= a \\
X^T a &= h \\
\Rightarrow \quad XX^T a &= a \\
\Rightarrow \quad a \text{ is the eigenvector of } XX^T, \text{ with } \lambda = 1
\end{align*}
\]

The Concept of HITS: (In Mailing Network)

[Diagram showing the concept of HITS with hubs and authorities]
Are These Measures Reasonable? ---- Out-degree
Are These Measures Reasonable? ---- In-degree
Are These Measures Reasonable? ---- CC
Are These Measures Reasonable? ---- Betweenness
Are These Measures Reasonable? ---- Betweenness
Are These Measures Reasonable? ---- Authority
Features are not enough......

(SIP means: “Semi-supervised Importance Propagation”.)
Semi-Supervised Importance Propagation

Propagate the importance of labeled data to unlabeled data through the Mailing Network.

Important mail from important person.

Important person receives important mail.

Unlabeled Data → Mailing Network → Labeled Data

Diagram: Graph showing the flow of importance from labeled to unlabeled data through the Mailing Network.
Semi-Supervised Importance Propagation

\[ A = \{a_{ij}\}, \quad a_{ij} = 1 \text{ if } i \text{ send mail } j. \]

\[ B = \{b_{ij}\}, \quad b_{ij} = 1 \text{ if } i \text{ receive mail } j. \]
Semi-Supervised Importance Propagation

\[ x_k[i] = 1 \text{ if the } i\text{-th mail's importance level is } k. \quad (0 \leq x_k[i] \leq 1) \]

\[ y_k[i] = 1 \text{ if the } i\text{-th person's importance level is } k. \quad (0 \leq y_k[i] \leq 1) \]

\[
\begin{align*}
x_5 &= \begin{pmatrix} 0 & 1 \\ 1 & 2 \end{pmatrix} \\
x_4 &= \begin{pmatrix} 0 & \ 0 \\ 1 & 0 \end{pmatrix} \\
x_1 &= x_2 = x_3 = \begin{pmatrix} 0 & 0 \\ 1 & 0 \end{pmatrix} \\
y_5 = y_4 = y_3 = y_2 = y_1 &= \begin{pmatrix} \ 0 \\ \ 0 \ 0 \end{pmatrix}
\end{align*}
\]
Semi-Supervised Importance Propagation

\( x_k[i] = 1 \) if the i-th mail’s importance level is k. ( \( 0 \leq x_k[i] \leq 1 \) )

\( y_k[i] = 1 \) if the i-th person’s importance level is k. ( \( 0 \leq y_k[i] \leq 1 \) )

\[
y_5 = Bx_5 = \begin{pmatrix}
0 & 1 & 2 \\
0 & 0 & 0 \\
1 & 1 & 1 \\
1 & 0 & 0 \\
\end{pmatrix} \begin{pmatrix} 0 \\ 1 \\ 1 \\ 0 \end{pmatrix} = \begin{pmatrix} \text{甲} \\ \text{乙} \\ \text{丙} \end{pmatrix}
\]

\[
y_4 = Bx_4 = \begin{pmatrix}
0 & 1 & 2 \\
0 & 0 & 0 \\
1 & 1 & 1 \\
1 & 0 & 0 \\
\end{pmatrix} \begin{pmatrix} 0 \\ 0 \\ 0 \\ 1 \end{pmatrix} = \begin{pmatrix} \text{甲} \\ \text{乙} \\ \text{丙} \end{pmatrix}
\]
Semi-Supervised Importance Propagation

\( x_k[i] = 1 \) if the i-th mail’s importance level is \( k \). \( 0 \leq x_k[i] \leq 1 \)

\( y_k[i] = 1 \) if the i-th person’s importance level is \( k \). \( 0 \leq y_k[i] \leq 1 \)

\[
\begin{align*}
  x_5 &= A^T y_5 =  \\
  &= \begin{pmatrix}
  0 & 1 & 0 & 0 \\
  1 & 0 & 0 & 1 \\
  0 & 1 & 0 & 0
\end{pmatrix}
\begin{pmatrix}
  0 \\
  1 \\
  2
\end{pmatrix}
\begin{pmatrix}
  0 \\
  1 \\
  2
\end{pmatrix}
\begin{pmatrix}
  0 \\
  1 \\
  2
\end{pmatrix}
\begin{pmatrix}
  0 \\
  1 \\
  2
\end{pmatrix}
\end{align*}
\]

\[
\begin{align*}
  x_4 &= A^T y_4 =  \\
  &= \begin{pmatrix}
  0 & 1 & 0 & 0 \\
  1 & 0 & 0 & 1 \\
  0 & 1 & 0 & 0
\end{pmatrix}
\begin{pmatrix}
  0 \\
  1 \\
  2
\end{pmatrix}
\begin{pmatrix}
  0 \\
  1 \\
  2
\end{pmatrix}
\begin{pmatrix}
  0 \\
  1 \\
  2
\end{pmatrix}
\end{align*}
\]
Semi-Supervised Importance Propagation

\( x_k[i] = 1 \) if the i-th mail’s importance level is \( k \). \( (0 \leq x_k[i] \leq 1) \)

\( y_k[i] = 1 \) if the i-th person’s importance level is \( k \). \( (0 \leq y_k[i] \leq 1) \)

\[
\begin{align*}
 y_k^{(t+1)} &= B x_k^{(t)} \\
 x_k^{(t)} &= A^T y_k^{(t)}
\end{align*}
\]

\( \Rightarrow \ y_k^{(t+1)} = B A^T y_k^{(t)} \)

Wonderful!! Keep updating, then we will propagate the importance right?
Semi-Supervised Importance Propagation

\[
\begin{align*}
    y^{(t+1)}_k &= B x^{(t)}_k \\
    x^{(t)}_k &= A^T y^{(t)}_k
\end{align*}
\]

\[\Rightarrow y^{(t+1)}_k = B A^T y^{(t)}_k\]

Let’s try……

\[\text{BA}^T = \text{Receiver} \quad \begin{pmatrix} 0 & 0 & 0 \\ 3 & 0 & 0 \\ 1 & 0 & 0 \end{pmatrix} \quad \text{normalize} \quad C = \begin{pmatrix} 0 & 0 & 0 \\ 0.75 & 0 & 0 \\ 0.25 & 0 & 0 \end{pmatrix}\]

\[y^{(3)}_k = C^2 y^{(1)}_k = C^2 (B x^{(1)}_k)\]

But, \[C^2 = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}\]

\[y^{(3)}_k = y^{(4)}_k = \ldots . \quad = 0\]
Semi-Supervised Importance Propagation

Two fatal problems:

1. When graph is “reducible”, $y_k$ will converge to 0 for transient nodes.

irreducible:

reducible:
Semi-Supervised Importance Propagation

Two fatal problems:

2. Even when graph is "irreducible", the final $y_k$ is independent of initial conditions.

irreducible:
Semi-Supervised Importance Propagation

Two fatal problems:

1. “reducible”, \( y_k \rightarrow 0 \) for some nodes.
2. Even “irreducible”, initial condition has no effect to result.

One simple solution:

\[
\begin{align*}
    y_k^{(t+1)} & - Cy_k^{(t)} \\
    \Rightarrow \quad y_k^{(t+1)} &= \alpha C y_k^{(t)} + (1 - \alpha) y_k^{(1)} \\
    (0 < \alpha < 1)
\end{align*}
\]
Semi-Supervised Importance Propagation

Simple solution:

\[ y^{(t+1)}_k = \alpha C y^{(t)}_k + (1 - \alpha) y^{(1)}_k \]

(0 < \alpha < 1)

With \( \alpha = 0.5 \):

With \( \alpha = 0.5 \):

Converge to

Converge to
Semi-Supervised Importance Propagation

Let's try again……

\[ y_k^{(t+1)} = Cy_k^{(t)} \implies y_k^{(t+1)} = \alpha Cy_k^{(t)} + (1 - \alpha)y_k^{(1)} \]

\(0 < \alpha < 1\)

Sender

\[
\begin{pmatrix}
0 & 0 & 0 \\
3 & 0 & 0 \\
1 & 0 & 0
\end{pmatrix}
\]

normalize

C = \[
\begin{pmatrix}
0 & 0 & 0 \\
.75 & 0 & 0 \\
.25 & 0 & 0
\end{pmatrix}
\]

\[
Y^{(1)} = BX^{(1)} = \begin{pmatrix}
.2 & .2 & .2 & .2 & .2 \\
.067 & .067 & .067 & .4 & .4 \\
0 & 0 & 0 & 0 & 1
\end{pmatrix}
\]

Converge to

\[
Y = \begin{pmatrix}
.2 & .2 & .2 & .2 & .2 \\
.103 & .103 & .103 & .3455 & .3455 \\
.022 & .022 & .022 & .022 & .9111
\end{pmatrix}
\]
Semi-Supervised Importance Propagation

\[ y_k^{(t+1)} = C y_k^{(t)} \Rightarrow y_k^{(t+1)} = \alpha C y_k^{(t)} + (1 - \alpha) y_k^{(1)} \]

\((0 < \alpha < 1)\)
Semi-Supervised Importance Propagation

Basic Feature
- In-degree
- Out-degree
- Total-degree

Cluster Feature
- CC
- Clique Count
- Betweenness
- HITS Authority

SIP Feature

Ex. Cluster #3

Newman Cluster #3
Avg. of Importance = 2.50
Var. of Importance = 0.25

Newman Cluster #1
Avg. of Importance = 3.63
Var. of Importance = 0.74

Newman Cluster #5
Avg. of Importance = 1.98
Var. of Importance = 0.01

Y =
\[
\begin{pmatrix}
0.103 & 0.103 & 0.103 & 0.3455 & 0.3455 \\
0.022 & 0.022 & 0.022 & 0.022 & 0.9111
\end{pmatrix}
\]
**Table 1: Summary Statistics of collected dataset (7 users)**

<table>
<thead>
<tr>
<th></th>
<th>Total</th>
<th>Train</th>
<th>Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>User 1</td>
<td>1750</td>
<td>150</td>
<td>1600</td>
</tr>
<tr>
<td>User 2</td>
<td>376</td>
<td>150</td>
<td>226</td>
</tr>
<tr>
<td>User 3</td>
<td>484</td>
<td>150</td>
<td>334</td>
</tr>
<tr>
<td>User 4</td>
<td>569</td>
<td>150</td>
<td>419</td>
</tr>
<tr>
<td>User 5</td>
<td>233</td>
<td>150</td>
<td>83</td>
</tr>
<tr>
<td>User 6</td>
<td>279</td>
<td>150</td>
<td>129</td>
</tr>
<tr>
<td>User 7</td>
<td>234</td>
<td>150</td>
<td>84</td>
</tr>
<tr>
<td><strong>Avg</strong></td>
<td><strong>561</strong></td>
<td><strong>150</strong></td>
<td><strong>411</strong></td>
</tr>
</tbody>
</table>
features

- BF (basic feature)
- NC (Newman cluster)
- SI (social importance)
- SIP (semi-supervised importance propagation)
error

- There are 5 importance levels

- Error is the difference between the predicted importance level and its real importance level

- Ex: if one letter’s importance level is 3 but the predicted level is 2, then error is 1
evaluation

\[ MAE = \frac{1}{N} \sum_{i=1}^{N} |y_i - \hat{y}_i| , \]

- **Micro MAE**: average all the letters in the same pool
- **Macro MAE**: average the letters of the same person and average the mean of each person
## Result table of macro-MAE

<table>
<thead>
<tr>
<th># of tr</th>
<th>BF MAE</th>
<th>BF+NC MAE</th>
<th>BF+NC p-value</th>
<th>BF SI MAE</th>
<th>BF SI p-value</th>
<th>BF+SI MAE</th>
<th>BF+SI p-value</th>
<th>BF+SI+NC MAE</th>
<th>BF+SI+NC p-value</th>
<th>BF+SI+NC+P MAE</th>
<th>BF+SI+NC+P p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>0.9666</td>
<td>0.9063</td>
<td>* 0.0382</td>
<td>0.8837</td>
<td>* 0.0106</td>
<td>0.8968</td>
<td>* 0.0311</td>
<td>0.8882</td>
<td>** 0.0087</td>
<td>0.8827</td>
<td>** 0.0087</td>
</tr>
<tr>
<td>20</td>
<td>0.9720</td>
<td>0.8969</td>
<td>0.0506</td>
<td>0.7994</td>
<td>* 0.0315</td>
<td>0.8095</td>
<td>* 0.0435</td>
<td>0.9071</td>
<td>0.0558</td>
<td>0.8659</td>
<td>0.0235</td>
</tr>
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<td>30</td>
<td>0.9210</td>
<td>0.8318</td>
<td>* 0.0334</td>
<td>0.7911</td>
<td>* 0.0637</td>
<td>0.8029</td>
<td>0.0587</td>
<td>0.9155</td>
<td>0.0465</td>
<td>0.8096</td>
<td>0.0210</td>
</tr>
<tr>
<td>40</td>
<td>0.8851</td>
<td>0.7995</td>
<td>* 0.0239</td>
<td>0.7911</td>
<td>* 0.0367</td>
<td>0.8029</td>
<td>0.0587</td>
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<td>0.0465</td>
<td>0.7869</td>
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<td>0.8639</td>
<td>0.7820</td>
<td>* 0.0347</td>
<td>0.7813</td>
<td>* 0.0218</td>
<td>0.7900</td>
<td>0.0774</td>
<td>0.7766</td>
<td>0.0210</td>
<td>0.7625</td>
<td>0.0205</td>
</tr>
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<td>60</td>
<td>0.8447</td>
<td>0.7820</td>
<td>0.0890</td>
<td>0.7514</td>
<td>* 0.0416</td>
<td>0.7603</td>
<td>* 0.0463</td>
<td>0.7607</td>
<td>0.0284</td>
<td>0.7363</td>
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<tr>
<td>70</td>
<td>0.8294</td>
<td>0.7662</td>
<td>0.0636</td>
<td>0.7218</td>
<td>* 0.0105</td>
<td>0.7679</td>
<td>0.1237</td>
<td>0.7560</td>
<td>0.0354</td>
<td>0.7184</td>
<td>0.0135</td>
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<td>80</td>
<td>0.8257</td>
<td>0.7596</td>
<td>* 0.0494</td>
<td>0.7324</td>
<td>* 0.0261</td>
<td>0.7763</td>
<td>0.1678</td>
<td>0.7433</td>
<td>0.0250</td>
<td>0.7157</td>
<td>0.0109</td>
</tr>
<tr>
<td>90</td>
<td>0.8294</td>
<td>0.7521</td>
<td>* 0.0352</td>
<td>0.7295</td>
<td>* 0.0174</td>
<td>0.7598</td>
<td>0.0711</td>
<td>0.7315</td>
<td>** 0.0086</td>
<td>0.7142</td>
<td>** 0.0087</td>
</tr>
<tr>
<td>100</td>
<td>0.8127</td>
<td>0.7411</td>
<td>* 0.0225</td>
<td>0.7236</td>
<td>* 0.0180</td>
<td>0.7634</td>
<td>0.1629</td>
<td>0.7314</td>
<td>** 0.0184</td>
<td>0.7098</td>
<td>** 0.0103</td>
</tr>
<tr>
<td>110</td>
<td>0.8060</td>
<td>0.7268</td>
<td>* 0.0199</td>
<td>0.7168</td>
<td>* 0.0286</td>
<td>0.7542</td>
<td>0.1318</td>
<td>0.7142</td>
<td>* 0.0159</td>
<td>0.7046</td>
<td>0.0127</td>
</tr>
<tr>
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<td>0.8105</td>
<td>0.7232</td>
<td>* 0.0183</td>
<td>0.7090</td>
<td>* 0.0154</td>
<td>0.7426</td>
<td>0.0727</td>
<td>0.7135</td>
<td>* 0.0144</td>
<td>0.6960</td>
<td>** 0.0071</td>
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<td>0.8028</td>
<td>0.7207</td>
<td>* 0.0287</td>
<td>0.6980</td>
<td>* 0.0156</td>
<td>0.7449</td>
<td>0.0997</td>
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<td>** 0.0058</td>
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<td>* 0.0136</td>
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<td>* 0.0262</td>
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<td>0.7992</td>
<td>0.7073</td>
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<td>0.7737</td>
<td>0.0360</td>
<td>0.7538</td>
<td>0.0252</td>
<td>0.7847</td>
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<td>0.7676</td>
<td>0.0862</td>
<td>0.7449</td>
<td>0.0139</td>
</tr>
</tbody>
</table>
Result graph of macro-MAE
Result graph of micro-MAE
Result

Relative reduction:

- macro-MAE: from 0.8510 to 0.7449 (14%)
- micro-MAE: from 0.7759 to 0.5909 (31%)

So, how’s the performance?
Conclusion

- What have we learned from this paper?
- Do not use e-mail to confess (kidding)
- How to use Social Network (unsupervised) help prediction as data are sparse.
Take home Problem

- What’s the difference between SIP and HITS in terms of purpose and algorithm?
  Under which situation will we want our result dependant on the initial conditions?