Overview of aims and methodology

Overall aim: to measure to what extent the reputation of one organisation is affected by the reputation of other similar organisations

• We measure reputation by data mining targeted content, followed by sentiment analysis of that content. Result: a single-number measurement of reputation on a per-day basis.

• Use the reputation measure to elucidate a network structure, using a Bayesian methodology. (Nothing is assumed about such a network a priori.)

• Use the de Groot method to measure consensus, and hence the proportion of reputation due to systemic factors.
What is reputation?

“Reputation”

A perception of an organisation on the part of stakeholders that can affect, positively or negatively, the business relationship between the stakeholder and the organisation

“Reputation Event” - An occurrence or action that affects Reputation

“Reputation Risk” - The difference between stakeholder expectation and organisation performance

“Reputation Risk Measurement” - Numerical assessment of Reputation

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Measurement

Index:
Neutral: 5.5
Positive: >5.5
Negative: <5.5

Accumulate contents
Allocate score, m, and weight, w, to each
Weighted average of content scores
Measurement

Example content scoring

1. On Twitter, @blognewcastle (203 followers) wrote: “I’m a big fan of @santanderuk (11 Dec 2015)

<table>
<thead>
<tr>
<th>Category</th>
<th>Sentiment</th>
<th>Score, s</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sentiment</td>
<td>Positive, qualified by ‘big’</td>
<td>8.0</td>
</tr>
<tr>
<td>Influence</td>
<td>Few followers: not influential</td>
<td>1.0</td>
</tr>
<tr>
<td>Prominence</td>
<td>Neutral</td>
<td>5.5</td>
</tr>
<tr>
<td>Relevance</td>
<td>No references to other organisations</td>
<td>10.0</td>
</tr>
</tbody>
</table>

Content Score = 24.5/4 = 6.125
Example index compilation

<table>
<thead>
<tr>
<th>Content</th>
<th>Score, m</th>
<th>Weight, w</th>
<th>m×w</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1 “I'm a big fan of @XYZ-Bank”</td>
<td>6.125</td>
<td>0.12</td>
<td>0.735</td>
</tr>
<tr>
<td>C2 “XYZ-Bank does hardly provides good service” (Local TV consumer feature)</td>
<td>4.7</td>
<td>0.6</td>
<td>2.82</td>
</tr>
<tr>
<td>C3 “XYZ-Bank’s mortgage interest rates is the best available” (Sunday Times ‘Best Buy’ tables)</td>
<td>8.62</td>
<td>0.9</td>
<td>7.758</td>
</tr>
<tr>
<td>Sum</td>
<td></td>
<td>1.62</td>
<td>11.313</td>
</tr>
</tbody>
</table>

Weights reflect importance of content and source

Index value = 11.313/1.62 = 6.983
Measurement

Useful view: cumulative sentiment – used later to assess ‘network drag’
Measurement

Sentiment Analysis references

Comprehensive review and analysis: “Sentiment Analysis”, Bing Liu 2015

Preliminary work: (e.g.) Wiebe 1990 and 1994, Hearst 1992

Early work: (e.g.) Wiebe (2000), Das and Chen (2001), Tong (2001), Nasukawa & Lee (2003) – “Sentiment Analysis”
De Groot model for opinion formation (1)

- Described by a network of arbitrary complexity, with an influence matrix, $T$. In this case its structure is not known a priori
- $T_{ij}$ represents the weight that agent $i$ places on the current belief of agent $j$ in forming agent $i$'s opinion
- Agents start with an initial opinion $p(r=0)$, interact with other agents, and at the next time step ($r=1$), update their own opinion to $p(r=1)$ based on $T$. Further iterations produce $p(r=2)$, $p(r=3)$ (2, 3)...
- Assumption: full accessibility of information (4)

De Groot model for opinion formation

\[ p(1) = Tp(0) \]

In general: \[ p(r) = Tp(r-1) \]
which implies \[ p(r) = T^r p(0), \quad r = 1, 2, \ldots \]

There may be a limiting case that represents converged opinion \(^{(1)}\):

\[ p(\infty) = \lim_{r \to \infty} \left( T^r p(0) \right) \]

We have to discover a network based on agents’ sentiment with respect to banks, and then derive the corresponding influence matrix $T$. In many other cases it’s the other way round: the network is given and $T$ is derived from it.

Let $S(i, t)$ be the sentiment of Agent $i$ on day $t$. Then the sentiment movement is $M(i, t) = S(i, t) - S(i, t-1)$.

We count all movements greater than or equal to a 'high' threshold $\lambda_H$ and all movements greater than or equal to a ‘very high' threshold $\lambda_{VH}$.

$C(i, \lambda) = \{ M(i, t): \text{abs}(M(i, t)) \geq \lambda, 1 \leq t \leq n\}$, where $\lambda = \lambda_H$ or $\lambda_{VH}$.
De Groot model and sentiment

Distribution of movements $M(i, t)$

$\lambda_H$ marks the extreme 5% of movements

$\lambda_{VH}$ marks the extreme 1% of movements

![Histogram of index first difference with markers for $\lambda_H$ and $\lambda_{VH}$]
De Groot model and sentiment

Drive the influence matrix $T$ using a Bayesian approach:

Given an Agent $i$, and a different Agent $j$, count the number of very large movements in the sentiment of Agent $j$ ($i \neq j$), given that there was a large movement in the sentiment of Agent $i$.

$$T_{ij} = \frac{C(j, \lambda_{VH}) \mid C(i, \lambda_{H})}{C(i, \lambda_{H})} = (C(j, \lambda_{VH}) \text{ and } C(i, \lambda_{H})) / C(i, \lambda_{H})$$

(a large movement in the sentiment of Agent $i$, associated with a very large movement in the sentiment of Agent $j$ implies that Agent $i$ has influenced Agent $j$)
De Groot model and sentiment

In the case $i = j$ there is a different interpretation.

It’s a measure of the extent to which agent $i$ values its own opinion, where ‘agent’ means all those who comment.

From the equation for $T_{ij}$

$$C(j, \lambda_{VH}) = C(i, \lambda_{H}),$$

so

$$T_{ii} = \frac{C(i, T_{VH})}{C(i, T_{H})}.$$
Results

<table>
<thead>
<tr>
<th></th>
<th>0.459</th>
<th>0.084</th>
<th>0</th>
<th>0</th>
<th>0</th>
<th>0.079</th>
<th>0.115</th>
<th>0.189</th>
<th>0.074</th>
<th>0</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.088</td>
<td>0.237</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.131</td>
<td>0.177</td>
<td>0.192</td>
<td>0.062</td>
<td>0.113</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>0.238</td>
<td>0</td>
<td>0.133</td>
<td>0.122</td>
<td>0.133</td>
<td>0.179</td>
<td>0.194</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>0.109</td>
<td>0.437</td>
<td>0</td>
<td>0.160</td>
<td>0.140</td>
<td>0.154</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>0.103</td>
<td>0.099</td>
<td>0.375</td>
<td>0</td>
<td>0.146</td>
<td>0.181</td>
<td>0.096</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>0.052</td>
<td>0.049</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.479</td>
<td>0.204</td>
<td>0.142</td>
<td>0.073</td>
<td>0</td>
</tr>
<tr>
<td>0.058</td>
<td>0.078</td>
<td>0</td>
<td>0.038</td>
<td>0</td>
<td>0.086</td>
<td>0.518</td>
<td>0.084</td>
<td>0.097</td>
<td>0.041</td>
<td></td>
</tr>
<tr>
<td>0.049</td>
<td>0.095</td>
<td>0.050</td>
<td>0</td>
<td>0.033</td>
<td>0.078</td>
<td>0.120</td>
<td>0.483</td>
<td>0.060</td>
<td>0.033</td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.064</td>
<td>0.109</td>
<td>0.162</td>
<td>0.084</td>
<td>0.117</td>
<td>0.465</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>0.103</td>
<td>0.095</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.146</td>
<td>0.100</td>
<td>0.556</td>
<td></td>
</tr>
</tbody>
</table>

Zero entries indicate that the corresponding network is not fully connected: not all agents can influence all others directly.
Results

Network corresponding to $T$

thin = non-influential
thick = influential

Not all edges are bidirectional
Results

\[ T_{\infty} = \begin{pmatrix}
0.078 & 0.072 & 0.024 & 0.036 & 0.038 & 0.152 & 0.212 & 0.207 & 0.127 & 0.053 \\
\vdots & & & \ddots & & & & & & \\
0.078 & 0.072 & 0.024 & 0.036 & 0.038 & 0.152 & 0.212 & 0.207 & 0.127 & 0.053 
\end{pmatrix} \]

In practice we observe convergence for \( T^r \) for \( r > 6 \)

The network corresponding to \( T_{\infty} \) is fully connected
Results

Network corresponding to $T_\infty$

Surprising results!

- Agents 6, 7, 8 and 9 are most influential: they do not attract extreme negative comment.
- (Lloyds, NatWest, TSB, Virgin)
- ‘Bad banks’ (2 – RBS, 5 – HSBC) are not influential.
- ‘Best bank’ (3 – Nationwide) is not influential
Results

Consensus view
The normalised cumulative excess reputation index values ($\sum (S(t) - 5.5)$) gives an initial perception vector of sentiment with respect to banks:

$$p(0) = (0.128, 0.027, 0.154, 0.180, 0.031, 0.135, 0.073, 0.117, 0.141, 0.085)$$

Then the consensus view is:

$$p(\infty) = T_\infty p(0) = (0.104, 0.104, 0.104, ..., 0.104)$$

This consensus value is an effective ‘smoothing’ of the initial perception vector. The value 0.104 corresponds to a cumulative excess 33.0: slightly positive. So as a group, banks are slightly good!

(There is an interesting view that $p(0)$ could be arbitrary or normally distributed from Pan (2010 and 2012))
Results

Variation of Bayesian Thresholds $\lambda_H$ and $\lambda_{VH}$

Generally insensitive

$\lambda_H$ and $\lambda_{VH}$ are set too high. Agents influence only themselves.

$\lambda_H$ and $\lambda_{VH}$ are set too low. Agents are over-influenced by other agents.
Impact

Super-stressed effect of sentiment on product sales.

<table>
<thead>
<tr>
<th>Product</th>
<th>Positive sentiment (%)</th>
<th>Negative sentiment (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sales volume</td>
<td>3.4</td>
<td>7.9</td>
</tr>
<tr>
<td>Income</td>
<td>1.3</td>
<td>2.9</td>
</tr>
<tr>
<td>Profit after tax</td>
<td>1.3</td>
<td>3.6</td>
</tr>
</tbody>
</table>

Expected values of the effect of sentiment on product sales.

<table>
<thead>
<tr>
<th>Product</th>
<th>Positive sentiment (%)</th>
<th>Negative sentiment (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sales volume</td>
<td>1.6</td>
<td>2.3</td>
</tr>
<tr>
<td>Income</td>
<td>0.6</td>
<td>0.9</td>
</tr>
<tr>
<td>Profit after tax</td>
<td>0.7</td>
<td>0.9</td>
</tr>
</tbody>
</table>
The initial perception vector of sentiment with respect to banks:
\[ p(0) = (0.128, 0.027, 0.154, 0.180, 0.031, 0.135, 0.073, 0.117, 0.141, 0.085) \]
Was calculated from the cumulative excess vector \( C = (\sum(S(t)-5.5)) \):

\[ C = (111.3, -212.3, 195.7, 47.4, -198.7, 133.2, -64.0, 76.3, 156.1, -27.9) \]

Let \( J \) be a vector whose entries are the column values of \( T_\infty \).
Define the total influence of the system, \( \tau \), by the scalar product
\[ \tau = C.J \sim 33.1 \]

Each bank experiences an ‘network drag’ of value \( \tau \) over 24 months, or \( \tau/2 \) annually.
These are the % components of reputation attributable to the ‘network’ (\( \tau \) as a % of each member of \( C \)):

\[ (14.9, -7.8, 8.4, 34.9, -8.3, 12.4, -25.8, 21.7, 10.6, -59.3) \]