E6893 Big Data Analytics Lecture 5:

*Big Data Analytics Case Study*

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Big Data Analytics Use Case:

Company Network and Value Analysis
Are we able to find out answers for these questions?

Finding answers of,

- Is it possible to **predict** a company’s profit or revenue changes based on dynamic company networks?
- How can we **infer** evolutionary company networks from public news?
- How **accurate** can network characteristics help predicting profit/revenue changes?
- What are the most important – positive or negative – **feature** measures of networks to predict profit/revenue?
Social Network Analysis

- An Analytics research field since 1920s.
- Social Networks (SNs)
  - **Nodes**: Actors (persons, companies, organizations etc.)
  - **Ties**: Relations (friendship, collaboration, alliance etc.)

- Network properties
  - Degree, distance, centrality, and various kinds of positional and equivalence

- Application of SNs
  - Social psychology: analyzing social phenomena
  - Economics: consulting business strategy
  - Information science: Information sharing and recommendation, trust calculation, ontology construction
Example of Company Value Analysis

Accounting-based financial statement information

Fundamental values:
ROE(Return On Equity), ROA(Return On Asset), PER(Price Earnings Ratio), PBR(Price Book-value Ratio), Employee Number, Dividend Yield, Capital Ratio, Capital, etc.

E.g. “Fundamental Analysis, Future Earnings and Stock Prices”, [Abarbane&Bushee97]

Applying historical trends to predict stock market index (Heng Seng Index in Hong Kong)

E.g. “Support Vector Machine Regression for Volatile Stock Market Prediction” [H.Yang02]

\[
\hat{I}_t = f(I_{t-w} + \ldots + I_{t-1})
\]
Social Network Analysis of Companies

Based on relations and structures (i.e. embeddedness) to explore power and positional priorities of company

E.g.

“Social Structure and Competition in Interfirm Networks: The paradox of Embeddedness” [Uzzi97]

“Relationships of Cooperation and Competition between Competitors” [Bengtsson03]

“The Firm as Social Networks: An Organizational Perspective” [H.Wai05]
Graph Definitions and Concepts

A graph:

\[ G = (V, E) \]

- \( V \) = Vertices or Nodes
- \( E \) = Edges or Links

The number of vertices: “Order”

\[ N_v = |V| \]

\[ N_e = |E| \]
Graph Analytical Tools

- **Network topological analysis** tools
  - Centralities (degree, closeness, betweenness)
  - PageRank
  - Communities (connected component, K-core, triangle count, clustering coefficient)
  - Neighborhood (egonet, K-neighborhood)

- **Graph matching and search** tools
  - Graph search/filter by label, vertex/edge properties (including geo locations)
  - Graph matching
  - Collaborative filtering

- **Graph path and flow** tools
  - Shortest paths
  - Top K-shortest paths

- **Probabilistic graphical model** tools
  - Bayesian network inference
  - Deep learning
Companies were born benefited from Networks/Graphs…
For Directed graphs:

- In-degree = 8
- Out-degree = 8
Degree Distribution Example: Power-Law Network


\[ p_k = e^{-m} \cdot \frac{m^k}{k!} \]

\[ p_k = C \cdot k^{-\tau} e^{-k/\kappa} \]

Newman, Strogatz and Watts, 2001
Six Degree Separation:
adding long range link, a regular graph can be transformed into a small-world network, in which the average number of degrees between two nodes become small.

from Watts and Strogatz, 1998

C: Clustering Coefficient, L: path length, 
(C(0), L(0)): (C, L) as in a regular graph 
(C(p), L(p)): (C,L) in a Small-world graph with randomness p.
Some examples of Degree Distribution

(a) scientist collaboration: biologists (circle) physicists (square), (b) collaboration of movie actors, (d) network of directors of Fortune 1000 companies
• Network size is positively correlated with performance.
  • Each person in your email address book at work is associated with $948 dollars in annual revenue.

1 direct contact in a person’s network

$74.07 increase in monthly revenues or $948 annual revenues
Std error = (26.38)***
Significant at p < 0.01
“There is certainly no unanimity on exactly what centrality is or its conceptual foundations, and there is little agreement on the procedure of its measurement.” – Freeman 1979.

Degree (centrality)
Closeness (centrality)
Betweenness (centrality)
Eigenvector (centrality)
Closeness: A vertex is ‘close’ to the other vertices

\[ c_{CI}(v) = \frac{1}{\sum_{u \in V} \text{dist}(v, u)} \]

where \( \text{dist}(v, u) \) is the geodesic distance between vertices \( v \) and \( u \).
Betweenness ==> Bridges

Example: Healthcare experts in the world

Example: Healthcare experts in the U.S.

Connections between different divisions

Key social bridges
Betweenness measures are aimed at summarizing the extent to which a vertex is located ‘between’ other pairs of vertices.

Freeman’s definition:

\[
C_B(v) = \sum_{s \neq t \neq v \in V} \frac{\sigma(s, t \mid v)}{\sigma(s, t)}
\]

Calculation of all betweenness centralities requires calculating the lengths of shortest paths among all pairs of vertices. Computing the summation in the above definition for each vertex.
Eigenvector Centrality

Try to capture the ‘status’, ‘prestige’, or ‘rank’.
More central the neighbors of a vertex are, the more central the vertex itself is.

\[ c_{Ei}(v) = \alpha \sum_{\{u,v\} \in E} c_{Ei}(u) \]

The vector \( c_{Ei} = (c_{Ei}(1), \ldots, c_{Ei}(N_v))^T \) is the solution of the eigenvalue problem:

\[ A \cdot c_{Ei} = \alpha^{-1} c_{Ei} \]

Try to capture the ‘status’, ‘prestige’, or ‘rank’.
More central the neighbors of a vertex are, the more central the vertex itself is.
PageRank Algorithm (Simplified)
A new Analytics paradigm –

Are Social Networks of Companies related to Companies’ Value?
Outline

- Background and Study goal
- Infer Company Networks from Public News
- Network Feature Generation & Selection
- Predict Company Value
- Conclusion and Future work
Company Relationship Detection

- **Specific Relation**
  Cooperation, competition, acquisition, incorporation, supply chain, stock share…
  “Extracting Inter-business Relationship from World Wide Web” [Jin08]
  “Temporal Company Relation Extraction” [Changjian09]
  - Focus on details, deeper NLP
  - Rare events, sparse, ad-hoc

- **Generic Relation**
  - Who give me more impact [in a period]? (maybe positive or negative)
  - Comprehensive, dynamic relations (like Google rank)
  - Shallow NLP, easy to get weighted and directed networks, much more events.
  ➔ THIS WORK!
Generic Relation Extraction

I.B.M. Will Buy a Maker of Data Analysis Software

I.B.M., took a big step to expand its fast-growing stable of data analysis offerings by agreeing on Tuesday to pay $1.2 billion to buy SPSS Inc., a maker of software used in statistical analysis and predictive modeling.

Basic Idea:
- For each company $x$, we extract companies who
  - Frequently co-appear with $x$ in $x$’s important financial articles
  - Frequently mentioned together with $x$ in important sentences
In a period of time (e.g. one year)
Example (from NYT 2009 articles about I.B.M.)

About 300 articles mentioned I.B.M.

*International Business Machines* (84 articles), *I.B.M.* (277 articles)

- I.B.M. -- Microsoft (55 articles, 264 sentences, weight=85.85455)
  http://www.nytimes.com/2009/03/06/business/06 layoffs.html
  Two days after I.B.M.'s report, Microsoft said that its quarterly profits were disappointing.
  ... the world’s largest software makers, including Microsoft, SAP and I.B.M., which...
  Caterpillar, Kodak, Home Depot, I.B.M., even mighty Microsoft they are all cutting jobs.
  More recently, Sun Microsystems, Hewlett-Packard and Microsoft have made mostly unsuccessful attempts to have made mostly unsuccessful attempts to pull mainframe customers away from I.B.M. by ... 

- I.B.M. -- SPSS (1 articles, 9 sentences, weight=13.675)
  I.B.M. to Buy SPSS, a Maker of Business Software
  I.B.M.'s $50-a-share cash offer is a premium of more than 40 percent over SPSS's closing stock price on Monday.
  I.B.M. took a big step to expand its fast-growing stable of data analysis offerings by agreeing on Tuesday to pay $1.2 billion to buy SPSS Inc.,...

- I.B.M. -- Nike (4 articles, 9 sentences, weight=8.212)
  … companies that have taken steps to reduce carbon emissions includes I.B.M., Nike, Coca-Cola and BP, the oil giant.
  Others are water-based shoe adhesives from Nike and a packing insert from I.B.M.
Generic Relation Extraction

For target company “x”, first download NYT articles for a year, and select candidate companies \( Y=\{y_1, y_2, \ldots \} \) appeared on the articles, then calculate each candidate company’s relation strength with “x”.

- \(|Y|\): How many companies on the article?
- \( \Sigma tf_{xy} \): How many times \( x \) company appear?
- \( w \): Does names appeared on the title?

\[
\begin{align*}
\text{Document Weight} & \\
\text{Sentence Weight} & \\
S1: & \quad x \ldots y_1 \ldots x \ldots y_1 \ldots \ldots y_3 \ldots y_5 \ldots y_1 \ldots \\
S2: & \quad x \ldots y_3 \ldots y_5 \\
S3: & \quad y_3 \ldots x \ldots y_4 \ldots y_1 \\
\end{align*}
\]

\[
w_d = \log(1 + \frac{1}{|Y|}) \times \sum_{y \in Y} w \cdot tf_x \quad w_s = \log(1 + \frac{1}{|Y_1|} + \frac{1}{|Y_2|})
\]

\[
w = a \cdot \sum df \times w_d + b \cdot \sum sf \times w_s
\]

Choose articles in a period

Download articles
Data and Network

- **Data Source:**
  - Relationships among companies from public articles
  - Company Values: profit, revenue, etc.
    - Fortune 500: 1955-2009

- **Target companies:**
  - 308 companies (from NYT & Fortune500)
  - 656,115 articles about target companies:

![Bootstrap approach diagram]
## Network size (all)

<table>
<thead>
<tr>
<th>year</th>
<th>#nodes</th>
<th>#edges</th>
<th>year</th>
<th>#nodes</th>
<th>#edges</th>
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<td>1987</td>
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<td>1988</td>
<td>1015</td>
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<td>2003</td>
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<td>54173</td>
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<td>1989</td>
<td>1066</td>
<td>132906</td>
<td>2004</td>
<td>1461</td>
<td>51801</td>
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<td>1990</td>
<td>1070</td>
<td>177022</td>
<td>2005</td>
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<td>43944</td>
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<td>1991</td>
<td>1080</td>
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<td>51896</td>
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<td>1992</td>
<td>1125</td>
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<td>2007</td>
<td>1280</td>
<td>44501</td>
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<tr>
<td>1993</td>
<td>1133</td>
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<td>2008</td>
<td>1260</td>
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<td>1994</td>
<td>1147</td>
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<td>2009</td>
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<td>1995</td>
<td>1134</td>
<td>52855</td>
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</tbody>
</table>

*Financial Crisis 1987*
Thresholding of Networks

![Different Threshold Network Graph](image)

- **Feature Effect**
- **Thresholding Values**: T1 = 20, T2 = 10
- **Lines Represent**:
  - Revenue
  - Profit
  - Delta-revenue
  - MEAN
Comparison of Naïve co-occurrence and the proposed method

- IBM 1995 (doc cooccurrence)
- IBM 1995 (new algorithm – doc weights + sentence weights)

Dominated by big/general companies  Better balance between different company sizes
Example of Network Evolution (IBM)

- IBM 2003

- IBM 2009
Example of Network Evolution (Microsoft)

- **Microsoft 1995**

  - Intuit Inc.
  - Sun Microsystems Inc.
  - Delphi Corporation
  - Novell Inc.
  - Cisco Systems Inc.
  - Oracle Corporation
  - International Business Machines
  - Intel Corporation
  - Motorola Inc.
  - Sony Corporation
  - Hewlett-Packard Corporation
  - CBS Corporation

- **Microsoft 2003**

  - Motorola Inc.
  - Oracle Corporation
  - Sun Microsystems Inc.
  - Format Inc.
  - Time Warner Inc.
  - Sony Corporation
  - RealNetworks Inc.
  - Microsoft Corporation
  - Hewlett-Packard
  - International Business Machines
  - Electornics
  - Apple Inc.
  - IBM
  - Apple
  - Intel Corporation
  - Google Inc.
  - Dell Inc.
  - Novell Inc.

- **Microsoft 2009**

  - YouTube
  - Nokia Corporation
  - Twitter
  - Sony Corporation
  - Twitter Inc.
  - Microsoft Corporation
  - Dell Inc.
  - International Business Machines
  - Intel Corporation
  - Oracle Corporation
  - comScore Inc.
  - News Corporation
  - Hewlett-Packard Corporation

<table>
<thead>
<tr>
<th></th>
<th>1995</th>
<th>2003</th>
<th>2009</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Intuit</td>
<td>I.B.M.</td>
<td>Google</td>
</tr>
<tr>
<td>2</td>
<td>I.B.M.</td>
<td>Apple</td>
<td>Apple</td>
</tr>
<tr>
<td>3</td>
<td>Intel</td>
<td>Intel</td>
<td>Intel</td>
</tr>
<tr>
<td>4</td>
<td>Apple</td>
<td>Time Warner</td>
<td>Sony</td>
</tr>
<tr>
<td>5</td>
<td>Novell</td>
<td>Sony</td>
<td>I.B.M.</td>
</tr>
</tbody>
</table>
Outline

- Background and Study goal
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- Conclusion and Future work
Network Type

Weighted-Directed Network

\[ W_{i,j} = W_{i \rightarrow j} + W_{j \rightarrow i} \]

Weighted-Undirected Network

Binary -Directed Network

Binary -Undirected Network
Network Feature Generation (1/3)

Who give company $x$ impact?
- Neighbor companies on the network
- Reachable companies on the network

**Network Features:**
- Number of neighbors (In-degree, Out-degree)
- Number of reachable nodes
- Number of connections among neighbors
- Number of connections among reachable nodes
- Neighbors’ degree (In-degree, Out-degree)
- Distance of $x$ to all reachable nodes
- Distances among neighbors
- Ratio of above values between neighbors and reachable nodes …
- etc.
*(Normalize by network size)*

Generate 57 Network features from weighted/binary, directional/undirectional networks
Network Feature Generation (2/3)

**Temporal Network Features:**
- number of neighbors (In-degree, Out-degree) *last year (or w years ago)*
- number of connections among neighbors *last year (or w years ago)*
- number of connections among reachable nodes *last year (or w years ago)*
- number of neighbors degree *last year (or w years ago)*
- distance of x to all reachable nodes *last year (or w years ago)*
- … etc.

57×*Window* temporal network features

Similar to,
- What’s last year’s (or w years ago) revenue?
- What’s last year’s (or w years ago) profit?
Network Feature Generation (3/3)

**Delta Change of Network Features:**

- *Delta change of* the number of neighbors (In-degree, Out-degree) *from last year (or d years ago)*
- *Delta change of* the number of connections among neighbors *from last year (or d years ago)*
- *Delta change of* the number of connections among reachable nodes *from last year (or d years ago)*
- *Delta change of* the number of neighbors degree *from last year (or d years ago)*
- *Delta change of* the distance of x to all reachable nodes *from last year (or d years ago)*
- ... etc.

\[57 \times \text{Delta Network features}\]
Network Features

- Network Features for each company
  1. Current Network features: 57
  2. Temporal Network features: $57 \times \text{Window}$
  3. Delta change of Network features: $57 \times \Delta$

+ Financial statements of companies
  - previous year’s profit/ revenue
    - delta-change of profit /revenue
    - … etc.
Steps to Learn for Network Feature Selection

- Correlations between ranking of each individual feature and ranking of revenue/profit
- Stability of feature values which should be consistent with different network thresholding
- Selecting Independent Features sets (orthogonal with each other)
Feature Selection

- Feature Selection
  - Filter out some un-useful features from leaning samples.
  - Positive features VS negative features
  - Company-specific selections or General selections
### Positive and Negative Features (example)

<table>
<thead>
<tr>
<th>Correlation</th>
<th>Positively related features</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.421</td>
<td>difference of the ratio of x's neighbors and reachable nodes in binary-undirected network in 3 years</td>
</tr>
<tr>
<td>0.421</td>
<td>delta value with 3 years ago of x's degree in binary-undirected network</td>
</tr>
<tr>
<td>0.420</td>
<td>2 year ago x's degree in binary-undirected network</td>
</tr>
<tr>
<td>0.413</td>
<td>x's degree in binary-undirected network</td>
</tr>
<tr>
<td>0.413</td>
<td>ratio number of x's neighbors and reachable nodes in binary-undirected network</td>
</tr>
<tr>
<td>0.353</td>
<td>2 year ago x's in-degree in weighted-undirected network</td>
</tr>
<tr>
<td>0.344</td>
<td>delta value with 3 years ago of x's out-degree in weighted-directed network</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Correlation</th>
<th>Negatively related features</th>
</tr>
</thead>
<tbody>
<tr>
<td>-0.487</td>
<td>previous year's connections among neighbors in binary-undirected network</td>
</tr>
<tr>
<td>-0.477</td>
<td>delta value with 2 year's ago of sum of degrees among neighbors in binary-undirected network</td>
</tr>
<tr>
<td>-0.462</td>
<td>previous year's connection among neighbors in weighted-undirected network</td>
</tr>
<tr>
<td>-0.462</td>
<td>previous year's connection among neighbors in binary-undirected network</td>
</tr>
<tr>
<td>-0.381</td>
<td>ratio of connection among neighbors and reachable nodes in weighted-undirected network</td>
</tr>
<tr>
<td>-0.379</td>
<td>previous year's ratio of connection among neighbors and reachable nodes in weighted-undirected network</td>
</tr>
</tbody>
</table>
Positive Feature Example

“difference of the ratio of x's neighbors and reachable nodes in binary-undirected network in 3 years”

x’s network in 2010
N1\{a,b,c,d,i\}
N2\{a,b,c,d,e,f,g,h,i\}

2010: \(|N1| = 5, |N2|= 8\), ratio\(|N1|,|N2|\) = 5/8 = 0.625

2007: \(|N1| = 4, |N2|= 7\), ratio’\(|N1|,|N2|\) = 4/7 = 0.57

→ Delta (ratio − ratio’) = 5/8 − 4/7 = 0.054
Negative Feature Example

“previous year's connections among neighbors in binary-undirected network”

x’s network in 2010
N1= {a,b,c,d,i}
N2={a,b,c,d,e,f,g,h,i}

x’s network in 2009
N1= {a,b,c,d}
N2={a,b,c,d,e,f,g}
Connection_N1= {b-c, a-d}

→ Connection_t-1 = 2
Feature Set Selection

From learning samples, move out features which $|\text{correlation}|<0.2$, $\#\text{sample}<50$.

- $fs=0$: No feature selection
- $fs=1$: Feature selection (positive features only)
- $fs=2$: Feature selection (positive and negative features)

Using positive features are enough for our prediction model.
Feature Variances

\[ \text{var}_{F_i} = \frac{\sum_{k \in K} (\text{corr}_k (F_i, T_i) - \text{corr})^2}{|K|} \]

- \( k \): various networks in different threshold
- \( i \): different features
Feature Selection based on Stability of values with different network thresholding

variance

- Binary_Undirected Network
- Binary_Directed Network
- Weighted_Undirected Network
- Weighted_Directed Network
Outline

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System Outline

News Articles

Relation Extraction
(Bootstrap approach)

Company Names
1. I.B.M.,
   (International Business Machines)
2. Microsoft Corp. …

Network Construction

Network Feature Extraction

Company values
e.g. profit and revenue

Learn and Prediction
Experiments

- **Tasks:**
  - For individual companies, learn from last 10 years, and predict next year’s company value
  - For 20 fortune companies, learn from past 5 years, and predict next year’s Companies Value.
    - Company Value: revenue, profit

- **Prediction Model**
  - **Linear Regression**
    \[
    \text{value} = a + \sum_i \beta_i \text{feature}_i + \varepsilon .
    \]
  - **SVM Regression (using RBF kernel)**
    \[
    \min_{w,b,\xi,\xi^*} \frac{1}{2} w^T w + C \sum_i \xi_i + C \sum_i \xi_i^*
    \]
    subject to
    \[
    w^T \phi(x_i) + b - z_i \leq \varepsilon + \xi_i , \\
    z_i - w^T \phi(x_i) - b \leq \varepsilon + \xi_i^* , \\
    \xi_i,\xi_i^* \geq 0 , \ i = 1, [\mathbb{X}], l. \\
    \]
    \[
    K(x_i, x_j) = \exp(-\gamma \ | x_i - x_j |^2) , \gamma > 0.
    \]
Performance Measures

- **R^2** (squared Correlation Coefficient)

\[
R^2 = \frac{(\bar{\sum}_{i=1}^{l} f(x_i) y_i - \sum_{i=1}^{l} f(x_i) \sum_{i=1}^{l} y_i)^2}{(\bar{\sum}_{i=1}^{l} f(x_i)^2 - (\sum_{i=1}^{l} f(x_i))^2)(\bar{\sum}_{i=1}^{l} y_i^2 - (\sum_{i=1}^{l} y_i)^2)}
\]

- **MSE** (Mean Squared Error)

\[
\text{MSE} = \frac{1}{l} \sum_{i=1}^{l} (f(x_i) - y_i)^2
\]

Testing data: \( x_1, \overline{x}, x_{\bar{l}} \)

Target values: \( y_i, \overline{y}, y_{\bar{l}} \)

Predicted values: \( f(x_1), \overline{f}, f(x_{\bar{l}}) \)
Profit Prediction for Fortune Companies

- Predict 20 companies’ mean value of profits
Profit Prediction using different feature sets (SVR)

**Targets:** 20 Fortune companies' normalized Profits

**Goal:** Learn from previous 5 years, and predict next year

**Model:** Support Vector Regression (RBF kernel)

Profit prediction by joint network and financial analysis outperforms network-only by 130% and financial-only by 33%.

**Network feature:**
- \( s \) (current year network feature),
- \( t \) (temporal network feature),
- \( d \) (delta value of network feature)

**Financial feature:**
- \( p \) (historical profits and revenues)
Revenue Prediction using different feature sets (SVR)

**Targets:** 20 Fortune companies’ normalized Profits

**Goal:** Learn from previous 5 years, and predict next year

**Model:** Support Vector Regression (RBF kernel)

*Network feature*: s (current year network feature), t (temporal network feature), d (delta value of network feature)

*Financial feature*: p (historical profits and revenues)

Network feature not contribute to revenue prediction.
Profit Prediction (Linear Regression)

**Targets**: 20 Fortune companies’ normalized Profits

**Goal**: Learn from previous 5 years, and predict next year

**Model**: linear regression

Network feature:
- s (current year network feature),
- t (temporal network feature),
- d (delta value of network feature)

Financial feature:
- p (historical profits and revenues)

Obtained similar results using different prediction model.
- Profit prediction by joint network and financial analysis outperforms network-only by 150% and financial-only by 37%.
Revenue Prediction (Linear Regression)

**Targets:** 20 Fortune companies’ normalized Profits

**Goal:** Learn from previous 5 years, and predict next year

**Model:** linear regression

Network feature:  
- s (current year network feature),  
- t (temporal network feature),  
- d (delta value of network feature)

Financial feature:  
- p (historical profits and revenues)

Network feature not contribute to revenue prediction.
Temporal Window and Delta for Profit Prediction

- **Window=1 VS Window=3**
  - $R^2$ values:
    - Window=1: >0.41
    - Window=3: ~0.37

- **Delta=1 VS Delta=3**
  - $R^2$ values:
    - Delta=1: >0.40
    - Delta=3: ~0.39

- Both Window and Delta size as 1 is enough.
Profit Prediction for IBM and Intel

**IBM Profit Prediction**

- R\(^2\) = 0.583

**Intel Profit Prediction**

- R\(^2\) = 0.237
Questions?