Predicting Risk from Financial Reports with Regression

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Talk In A Nutshell

financial risk = f(financial report)

- volatility of returns
- SV regression
- Form 10-K, Item 7
What This Talk Isn’t

New statistical models for NLP ...

Exciting text domains like political blogs ...

Advances in applications like translation and summarization ...
What This Talk Isn’t

New statistical models for NLP ...

Exciting text domains like political blogs ...

Advances in applications like translation and summarization ...

Shay Cohen, 10:40 am yesterday

Tae Yano, 10:40 am tomorrow

Ashish Venugopal, right now

André Martins, 11 am Thursday
What This Talk Isn’t

New statistical models for NLP ...

Exciting text domains like political blogs ...

Advances in applications like translation and summarization ...
What This Talk Isn’t Is

New statistical models for NLP ...

Bag of terms representation and SVR model.

Exciting text domains like political blogs ...

Boring (to read) text domain of financial reports.

Advances in applications like translation and summarization ...

Under-explored application: forecasting.
See Also ...

- Lavrenko et al. (2000), Koppel and Shtrimberg (2004), and others: prices
- Blei and McAuliffe (2007): popularity
- Lerman et al. (2008): prediction markets
Outline

- Mini-lesson in finance
- A new text-driven forecasting task
- Regression models trained on text
- Experimental results and analysis
- Outlook
Finance

Allocation of wealth (e.g., money) across time and risk (states of nature).
From an NLP perspective: crucial information about your investments that’s buried in documents you’d rather not read.
financial risk = f(financial report)
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volatility of returns
What is Risk?

- Return on day $t$:
  \[
  r_t = \frac{\text{closingprice}_t + \text{dividends}_t}{\text{closingprice}_{t-1}} - 1
  \]

- Sample standard deviation from day $t - \tau$ to day $t$:
  \[
  v_{[t-\tau, t]} = \sqrt{\frac{\sum_{i=0}^{\tau} (r_{t-i} - \bar{r})^2}{\tau}}
  \]

- This is called measured volatility.
Why Not Predict Returns, Get Rich, Retire Early?

- Hard: predicting a stock’s performance.
- To predict returns, we would need to find new information.
- Our reports probably don’t contain new information (10-Ks do not precede big price changes).
Will This Talk Make Anyone Rich?

- Some people think you can exploit accurate volatility predictions.
- I’m not really qualified to give financial advice.
- Consulting to portfolio/wealth managers is a huge industry.
So Then Why Do Finance Researchers Care?

- Models of economics and finance treat information simplistically.
- No notion of extracting information from large amounts of raw data.
- These reports are produced at huge expense. Are they worth it?
Important Property of Volatility

• Autoregressive conditional heteroscedacity: volatility tends to be stable (over horizons like ours).

• $V_{[t - \tau, t]}$ is a strong predictor of $V_{[t, t + \tau]}$

• This is our strong baseline.
financial risk = f(financial report)

volatility of returns

Form 10-K, Item 7
Item 7. Management’s Discussion and Analysis of Financial Condition and Results of Operations
Overview
We are primarily engaged in the worldwide production and marketing of cars and trucks. We operate in two businesses, consisting of our automotive operations, which we also refer to as Automotive, GM Automotive or GMA, that includes our four automotive segments consisting of GMNA, GME, GMLAAM and GMAP, and our financing and insurance operations (FIO). Our finance and insurance operations are primarily conducted through GMAC, a wholly-owned subsidiary through November 2006. On November 30, 2006, we sold a 51% controlling ownership interest in GMAC to a consortium of investors. After the sale, we have accounted for our 49% ownership interest in GMAC under the equity method. GMAC provides a broad range of financial services, including consumer vehicle financing, automotive dealership and other commercial financing, residential mortgage services, automobile service contracts, personal automobile insurance coverage and selected commercial insurance coverage.

Automotive Industry
In 2008, the global automotive industry has been severely affected by the deepening global credit crisis, volatile oil prices and the recession in North America and Western Europe, decreases in the employment rate and lack of consumer confidence. The industry continued to show growth in Eastern Europe, the LAAM region and in Asia Pacific, although the growth in these areas moderated from previous levels and is beginning to show the effects of the credit market crisis which began in the United States and has since spread to Western Europe and the rest of the world. Global industry vehicle sales to retail and fleet customers were 67.1 million units in 2008, representing a 5.1% decrease compared to 2007. We expect industry sales to be approximately 57.5 million units in 2009.
Our Corpus

- 26,806 examples of Item 7, 1996-2006
- 247.7 million words in total

- http://www.ark.cs.cmu.edu/10K
For each report at time $t$, we gathered

- “Historical” volatility: $v_{[t-1y,t]}$
- “Future” volatility: $v_{[t,t+1y]}$

Source: Center for Research in Security Prices U.S. Stocks Databases
Methodology

- **Input:** Item 7 and/or historical volatility
- **Output:** predicted future volatility
- Test on (input, output) pairs from year Y
- Train on (input, output) from years < Y
- **Evaluation:** MSE of (log) volatility
financial risk = \( f(\text{financial report}) \)

- volatility of returns
- SV regression
- Form 10-K, Item 7
Support-Vector Regression
(Drucker et al., 1997)

- Predicted future volatility is a function of a document (Item 7), $d$, and a weight vector $w$:
$$\hat{\nu} = f(d; w)$$

- The training criterion:
$$\min_{w \in \mathbb{R}^d} \frac{1}{2} \|w\|^2 + \frac{C}{N} \sum_{i=1}^{N} \max \left( 0, \left| v_i - f(d_i; w) \right| - \epsilon \right)$$

regularize prediction within $\epsilon$ of correct
Representation

\[ f(d; w) = h(d) ^\top w \]

- Vector-space model (tf, tfidf, etc.)
- So far, unigrams and bigrams
- Linear kernel (for interpretability)
Representation

\[ f(d; w) = h(d)^\top w = \sum_{i=1}^{N} \alpha_i K(d, d_i) = \sum_{i=1}^{N} \alpha_i h(d)^\top h(d_i) \]

- Vector-space model (tf, tfidf, etc.)
- So far, unigrams and bigrams
- Linear kernel (for interpretability)

\[ w = \sum_{i=1}^{N} \alpha_i h(d_i) \]
Experiment

- Test on year Y.
- Train on (Y - 5, Y - 4, Y - 3, Y - 2, Y - 1).
- Six such splits.
- Compare history-only baseline, text-only SVR, combined SVR.
Using “log(1+freq.)” representation on all unigrams and bigrams. See paper.
## Dominant Weights (2000-4)

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<tr>
<td>personnel</td>
<td>0.013</td>
<td>distributions</td>
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</tbody>
</table>

**High volatility words**

- loss
- net loss
- year #
- expenses
- going concern
- a going
- administrative
- personnel

**Low volatility words**

- net income
- rate
- properties
- dividends
- lower interest
- critical accounting
- insurance
- distributions
Using “log(1+freq.)” representation on all unigrams and bigrams. See paper.
Changes Over Time

average length of Item 7
2002

- Enron and other accounting scandals
- Sarbanes-Oxley Act of 2002
- Longer reports
- Are the reports more informative after 2002? Because of Sarbanes-Oxley?
Changes In $w$

- change from previous weights

Measured in L₁ distance; based on unigram model with “log(1 + freq.)” representation.
Language Over Time

mortgages

reit
(“Real Estate Investment Trust”)
Delisting

- Rare (4%) event: delisting due to dissolution after bankruptcy, merger, violation of rules.

- bulletin, creditors, dip, otc, court
Conclusions

• Text-driven forecasting of volatility, by regression.
  • Works nearly as well as strong history predictor.
  • Often works better in combination.
• Suggestion of effects of legislation on a real-world text-generating process.
Future Work

• Measuring the effect of Sarbanes-Oxley
• Other predictions
• Other text representations
• Other datasets
Future Work
(Text-Driven Forecasting)

• Application for NLP: techniques that use text to make real-world predictions.

• Many potential domains (finance, politics, government, sales, ...)

• There’s lots of room for improvement!