Boosting Financial Trend Prediction with Twitter Mood Based on Selective Hidden Markov Models

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The Start

Accuracy: **91.967%**

The Start (Cont.)

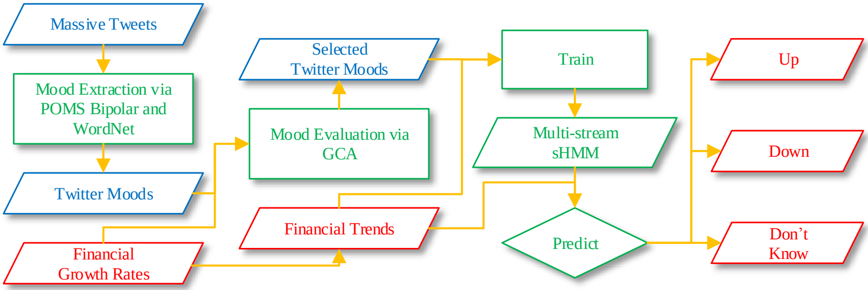
But under certain circumstance

Outline

Summary

- What?
  - Make more **accurate** and **controllable** stock prediction
- Why?
  - Analyze and model the causality behind stock trend
  - Design and implement more practical prediction method
- How?
  - **Accuracy**: exploit society mood
  - **Controllability**: adopt selective prediction

Workflow


Massive Tweets
Mood Extraction via POMS Bipolar and WordNet
Twitter Moods
Financial Growth Rates
Selected Twitter Moods
Mood Evaluation via GCA
Financial Trends
Train
Multi-stream sHMM
Predict
Up
Down
Don't Know

Mood Extraction

- Behavior finance
  - Individual mood -> individual decision
  - Society mood -> society decision
- Society mood measurement
  - Twitter, sense the world
- POMS Bipolar Lexicon
  - Composed-anxious (**Com.**), agreeable-hostile (**Agr.**), elated-depressed (**Ela.**), confident-unsure (**Con.**), energetic-tired (**Ene.**), clearheaded-confused (**Cle.**)
  - Expanding by WordNet synsets

Mood Extraction (Cont.)

- Efficient extractation under MapReduce framework
  - Twitter data is large, so map it to different nodes, extract poms vector from each tweet, and reduce them to overall poms index
- Map (offset, line, date, poms_individual)
  - Filter
    - Ignore {http:, www.}, hold {i feel, makes me, ...}
  - Stem
    - Agreed -> agree, disabled -> disable, ...
  - Analyze
    - Seren -> composed, shaki -> anxious, ...
- Reduce (date, poms_individual, date, poms_society)
  - Average

Mood Evaluation

- Granger Causality Analysis
  - Determine whether one time series is useful in forecasting another
- Y: growth rate of financial index; X: each Twitter mood

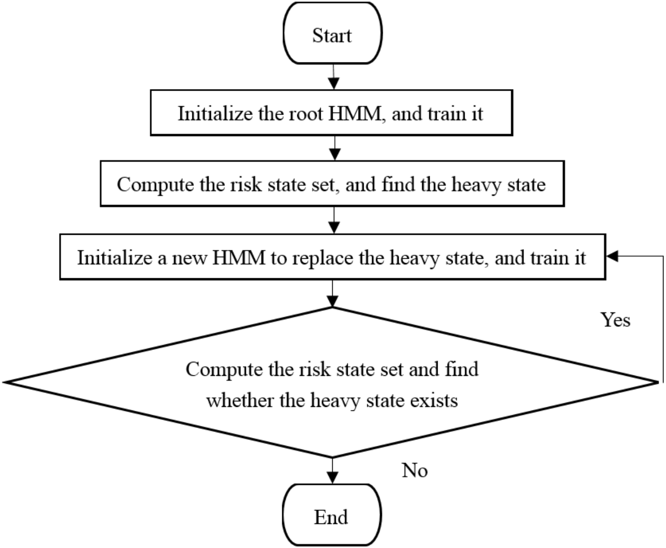
$$Y_t = y_0 + \sum_{i=1}^{lag} y_i Y_{t-i} + \varepsilon_t \tag{1}$$

$$Y_t = y_0 + \sum_{i=1}^{lag} y_i Y_{t-i} + \sum_{i=1}^{lag} x_i X_{t-i} + \varepsilon_t . \tag{2}$$

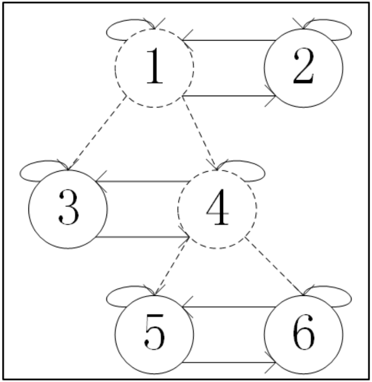
Multi-stream sHMM

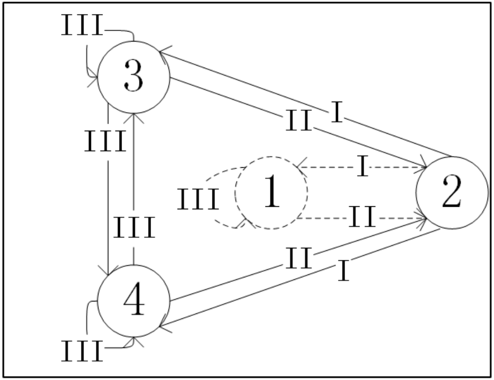
- Hidden Markov Models -> **HMM**
  - Generative probabilistic model with latent states, where hidden state transitions and visible observation emissions are assumed to be Markov processes
- Selective prediction -> **sHMM**
  - Identify risk state set and prevent predictions that are made from them
- Multiple stream -> **Multi-stream sHMM**
  - Treat historical financial trend and Twitter mood trends as multiple observation sequences generated by sHMM

Multi-stream sHMM - Training

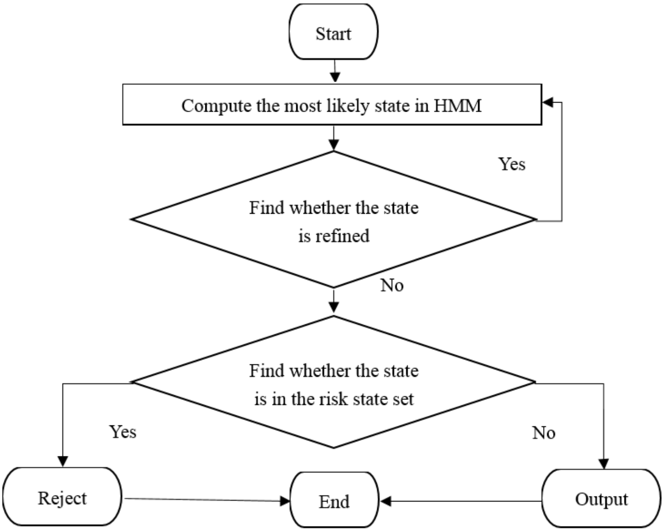


Multi-stream sHMM - Training - Refine





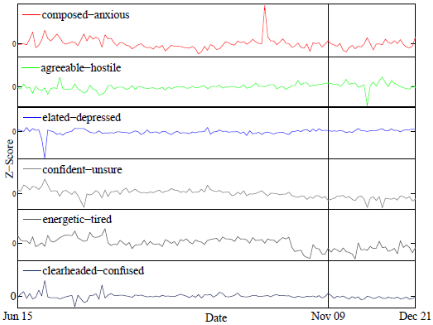
Multi-stream sHMM - Prediction



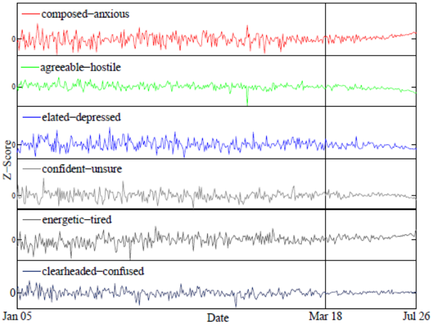
Multi-stream sHMM (Cont.)

- Large-scale performance evaluation
  - Random initialization number is large, so map Multi-stream sHMM to different nodes, get error rate from each model after train and predict, and reduce them to overall error rate
- Map (offset, line, reject_bound, error_rate)
  - Train
  - Predict
- Reduce (reject_bound, error_rate, reject_bound, avg_error_rate)
  - Average

Twitter Mood

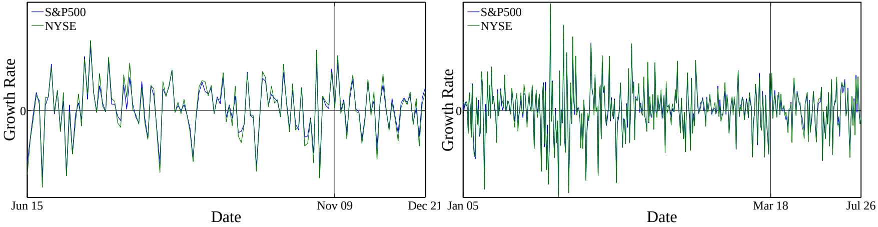


(a) *Twitter 2009*



(b) *Twitter 2011*

Financial Index



Results of Granger Causality Analysis

Table 1: p_{value} results of S&P500 and NYSE for *Twitter2009* (all $p_{value}{}^* \leq 0.1$).

Lag	S&P500						NYSE					
	Com.	Agr.	Ela.	Con.	Ene.	Cle.	Com.	Agr.	Ela.	Con.	Ene.	Cle.
1	0.704	0.226	0.681	0.696	0.535	0.270	0.739	0.179	0.756	0.625	0.529	0.385
2	0.764	0.437	0.648	0.588	0.722	0.305	0.851	0.372	0.664	0.444	0.746	0.417
3	0.228	0.159	0.856	0.276	0.741	0.338	0.231	**0.096***	0.876	0.238	0.772	0.489
4	0.234	0.233	0.516	0.386	0.886	0.127	0.214	0.134	0.615	0.349	0.900	0.232
5	0.379	0.389	0.515	0.315	0.966	0.159	0.348	0.258	0.569	0.275	0.974	0.241
6	0.301	0.145	0.186	0.439	0.949	0.180	0.277	**0.061***	0.228	0.405	0.948	0.277
7	0.428	0.148	0.331	0.262	0.955	0.218	0.364	**0.094***	0.418	0.231	0.941	0.296

Table 2: p_{value} results of S&P500 and NYSE for *Twitter2011* (all $p_{value}{}^* \leq 0.1$).

Lag	S&P500						NYSE					
	Com.	Agr.	Ela.	Con.	Ene.	Cle.	Com.	Agr.	Ela.	Con.	Ene.	Cle.
1	0.352	0.153	0.991	0.565	0.223	0.596	0.401	0.209	0.811	0.584	0.137	0.542
2	0.690	0.355	0.924	0.450	**0.082***	0.747	0.707	0.463	0.885	0.463	**0.060***	0.772
3	0.876	**0.071***	0.897	0.415	0.172	0.842	0.855	**0.054***	0.950	0.409	0.132	0.821
4	0.886	0.131	0.963	0.524	0.241	0.525	0.864	**0.099***	0.986	0.490	0.216	0.490
5	0.929	0.215	0.981	0.647	0.328	0.498	0.913	0.174	0.993	0.629	0.270	0.475
6	0.872	0.309	0.994	0.705	0.266	0.559	0.837	0.261	0.999	0.646	0.156	0.523
7	0.885	0.476	0.999	0.524	0.109	0.621	0.840	0.413	1.000	0.472	**0.071***	0.587

Prediction Performance Comparison

Table 3: Comparison with six methods using Twitter mood.

Model	Error Rate (%)			
	Twitter2009		*Twitter2011*	
	S&P500	**NYSE**	**S&P500**	**NYSE**
VAR	*26.667*	*33.333*	46.667	44.444
HMM	36.667	46.667	44.444	54.444
CRF	40.000	40.000	45.556	44.444
SVM	40.000	46.667	50.000	44.444
NN	36.667	46.667	*37.778*	*32.222*
cDPM	40.000	43.333	48.889	38.889
msHMM(C_B)	39.715(1.0) 30.055(0.5) 22.209(0.3)* **8.033**(0.1)	45.802(1.0) 35.972(0.5) 33.227(0.3)* **32.694**(0.1)	45.796(1.0) 42.408(0.5) 36.622(0.2)* **35.380**(0.1)	45.802(1.0) 35.972(0.5) 31.869(0.1)* **31.869**(0.1)

Prediction Performance Comparison (Cont.)

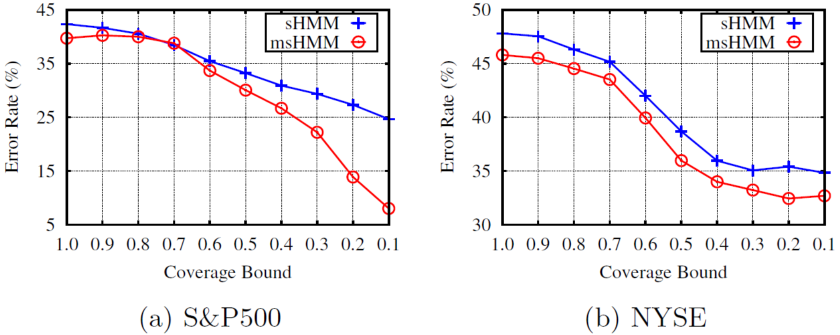


Fig. 4: Risk Coverage Curves for *Twitter2009*.

Prediction Performance Comparison (Cont.)

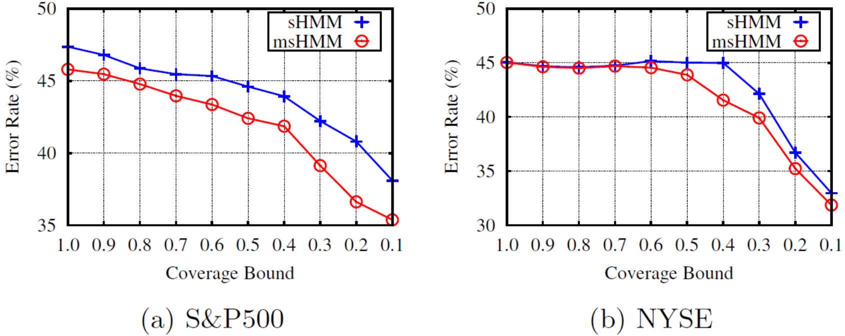


Fig. 5: Risk Coverage Curves for *Twitter2011*.

Conclusion and Future Work

- Our method not only performs better than the state-of-the-art methods, but also provides a controllability mechanism to financial trend prediction
- Explore multivariate GCA to select the optimal combination of multiple Twitter moods to improve prediction performance

The End

Thank you!

References I

- [1] Dmitry Pidan, Ran El-Yaniv: Selective Prediction of Financial Trends with Hidden Markov Models. NIPS 2011:855-863
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- [3] Jianfeng Si, Arjun Mukherjee, Bing Liu, Qing Li, Huayi Li, Xiaotie Deng: Exploiting Topic based Twitter Sentiment for Stock Prediction. ACL 2013:24-29