GIBBS METHOD FOR STOCK MARKET TREND PREDICTION

Mincong Luo
Information Centre
China Institute of Atomic Energy
Peking,China
luomincentos@ciae.ac.cn

Li Liu
Reactor Engineering Technology Research Division
China Institute of Atomic Energy
Peking,China
liuli92@ciae.ac.cn

ABSTRACT

In this paper we propose a physics-based method for stock market trend prediction. The core idea is ,The thermodynamic function that Gibbs Free Energy introduces in chemical thermodynamics to determine the direction of the process, which is similar to the process in the stock market. We build the network sampling from the finance parameters into the physics parameters and train the network on the real-world trading dataset and which is tested on another data, proving this method is profitable.

1 THE GIBBS FREE ENERGY

The thermodynamic function that Gibbs Free Energy introduces in chemical thermodynamics to determine the direction of the process. Also known as free enthalpy, Gibbs free energy or free energy. Free energy refers to the part of the internal energy that can be converted into external work in a certain thermodynamic process Tissandier & Cowen (1998) Keesee & Jr (1986). Free energy is defined in physical chemistry according to Helmholtz's constant volume free energy F and Gibbs's constant pressure free energy G. Gibbs free energy is a kind of free energy Dougherty (2001) Abdolmohammadi & Sultan (2002).

$$\Delta G = \Delta H_{system} - T\Delta S_{system}$$

The equation can be also seen from the perspective of the system taken together with its surroundings (the rest of the universe). First, assume that the given reaction at constant temperature and pressure is the only one that is occurring. Then the entropy released or absorbed by the system equals the entropy that the environment must absorb or release, respectively. The reaction will only be allowed if the total entropy change of the universe is zero or positive. This is reflected in a negative ΔG, and the reaction is called exergonic Mcgee (2007) Dolfing & Harrison (1992).

The role of Gibbs free energy is to judge the spontaneity of reactions within a closed system. Now to derive it again, first based on the principle of entropy increase:

$$\Delta S_{system} + \Delta S_{surrounding} = \Delta S_{universe} > 0$$

because of $\Delta G = -T\Delta S_{universe}$, so we can get the expression of Gibbs free energy:

$$\Delta G = \Delta H_{system} - T\Delta S_{system}$$

Now, with the principle of "$\Delta S_{universe} > 0$ must be established in spontaneous reaction", we can get:

$$spontaneousreaction \Leftrightarrow \Delta G = \Delta H_{system} - T\Delta S_{system} < 0$$

The above is the ins and outs of Gibbs free energy. In the next section the stock market theorem combined with the Gibbs free energy will be given.

2 THE THEOREM OF STOCK MARKET BASED ON GIBBS FREE ENERGY

Every transaction and decision in the stock market is unpredictable (equivalent to every particle in a closed system), but its macro trends are predictable (equivalent to temperature trends), in another word this is a heuristic model. Before using the model, firstly some items moved in the formula to get:

$$\Delta H_{system} = \Delta G + T\Delta S_{system}$$

In another aspect, we can understand the stock market as:

- **free energy ΔG:** Representing a Hidden Feature X_h inside the stock market, it is not well observed but has strong predictive power.
- **temperature T:** Representing the Stable Factors X_s in the stock market, it will change but will only change continuously, and the general trend is better predicted.
- **Entropy change ΔS:** Representing the Volatility Factors X_v in the stock market, the change is large, the frequency is fast, it is not predictable, but it is well observed.
- **enthalpy change ΔH:** Representing the trend we want to predict: direction and changed degree.

This way we can build a deep learning model to predict trends in the stock market, the model is defined as follows:

$$\begin{gathered}
\Delta H_{system} = \Delta G + T\Delta S_{system} \\
\Delta G \sim P(\Delta G|X_h) = \mathcal{N}(u(X_h), \delta^2(X_h)) \\
T \sim P(\Delta S|X_s) = \mathcal{F}(\theta(X_s)) \\
\Delta S \sim P(\Delta S|X_v) = \mathcal{N}(u(X_v), \delta^2(X_v)) \\
\Delta H > 0 \Leftrightarrow price \uparrow, \Delta H < 0 \Leftrightarrow price \downarrow
\end{gathered}$$

3 EXPERIMENT

The Dateset: We used the Day-level historical market data of China A-shares to verify the model. The format is as follows:

```

Adj. Close,Adj. High,Adj. Low,Adj. Open,Adj. Volume,Close,Date,Ex-Dividend,High,Low,
0,13.53,13.45,12.65,12.62,51597046.82,11.16,2010-01-04,572108102.0,11.37,10.62,10.76,
1,13.64,13.72,12.91,12.92,48822968.82,11.27,2010-01-05,549279336.0,11.64,10.86,11.06,
2,13.38,13.56,13.05,13.07,41360141.82,11.01,2010-01-06,461521697.0,11.48,11.02,11.21,
```

In the experiment we used Keras to write a neural network for training, and the network structure (mainly fully connected layers):

```

Layer (type)                     Output Shape         Param #
Connected to
==========================================================================
S (InputLayer)                   (None, 4)            0
__________________________________________________________________________
G (InputLayer)                   (None, 4)            0
__________________________________________________________________________
dense_8 (Dense)                  (None, 8)            40
S[0][0]
__________________________________________________________________________
T (InputLayer)                   (None, 2)            0
__________________________________________________________________________
```

(a) 600288SH

(b) 600289SH

Figure 1: **(a) : The stock 600288SH**. We use the day-level data from the stock 600288SH to train the nueral network. **(b) : The stock 600289SH**. We use the day-level data to trade to test the trained model.

```
dense_1 (Dense)                 (None, 8)            40
G[0][0]
__________________________________________________________________________________________________
dense_9 (Dense)                 (None, 16)           144
dense_8[0][0]
__________________________________________________________________________________________________
dense_5 (Dense)                 (None, 4)            12
T[0][0]
__________________________________________________________________________________________________
dense_2 (Dense)                 (None, 16)           144
dense_1[0][0]
__________________________________________________________________________________________________
dense_10 (Dense)                (None, 8)            136
dense_9[0][0]
__________________________________________________________________________________________________
dense_6 (Dense)                 (None, 8)            40
dense_5[0][0]
__________________________________________________________________________________________________
dense_3 (Dense)                 (None, 8)            136
dense_2[0][0]
__________________________________________________________________________________________________
dense_11 (Dense)                (None, 3)            27
dense_10[0][0]
__________________________________________________________________________________________________
dense_7 (Dense)                 (None, 3)            27
dense_6[0][0]
__________________________________________________________________________________________________
dense_4 (Dense)                 (None, 3)            27
dense_3[0][0]
__________________________________________________________________________________________________
multiply_1 (Multiply)           (None, 3)            0
dense_11[0][0]
                                                                 dense_7[0][0]
__________________________________________________________________________________________________
add_1 (Add)                     (None, 3)            0
dense_4[0][0]
                                                                 multiply_1[0][0]
==================================================================================================
Total params: 773
Trainable params: 773
Non-trainable params: 0
```

The Result: We use the SMA strategy on the market backtest. About the experimental results, We used the data training of Daheng Technology (600288SH), *ST ICT (600289SH) data for simulation transaction to test the method. The details in Figure.2 shows that the model is profitable.

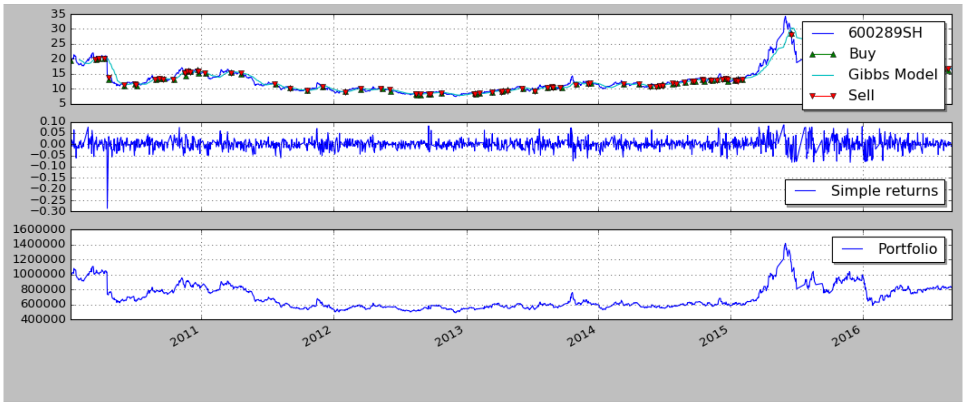

Figure 2: The details of the trading simulation, which shows that the model is profitable.

4 Conclusion

In this paper, we propose a physics-based method for stock market trend prediction. Physics-based model is becoming more and more popular in real-world market tradings because the similarity between the market and the chaotic particle physics system. We use the deep nueral network to construct the model, which map the market parameters to the physics parameters, but the process is implicit and not interpretable. In the future work we will continuously improve this model to make it transparent and interpretable.

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