Draft

Overview

There are many work related to the topic on wavelet and a special type of neural network, namely, wavelet neural network, however, not much of work directly relate to trading strategy. Wavetlet has been proposed to be a better way of combine both frequency domain and time domain. The idea is using dilation and translation to expand the so called mother wavelets in order to form an orthogonal basis in L^2 with wavelets. The neural networks are prooved to be able to approximate any continuous mapping(Funahashi (1989)). The comination of the two was proposed only several years later. Zhang and Benveniste (1992) first propose the idea of wavelet network to approximate arbitrary nonlinear functions. Zhang (1993) introduced the Wavelet as a regression selection procedure in attempt to solve the problem of random initialization of neural network.

In time series analysis domain, Pindoriya, Singh, and Singh (2008) applied wavelet neural network in energy price forecasting in electricity markets. Also in electricy market, Khoa et al. (2004) using same set of techniques to predict long-term load.

AUSSEM and MURTAGH (1997) propose a multiresolute style of analysis utilize recurrent neural network in order to increase the accuracy of prediction. This combination has been used by multiple authors, such as Capizzi, Napoli, and Bonanno (2012) applied similar approach on solar radiation forcasting.

In finace, Yang Yiwen, Liu Guizhong, and Zhang Zongping (2000) propose to predict stock trend prediction with nn and multiresolution analsis. *this can be utilize to form a momentum based trading strategy.*

The most closed related work is Wang and Gupta (2013), where they use wavelet combine with neural network to predict stock prices. They, however, only use wavelet to denoise the data not using wavelet coefficients in the neurual network. The trading strategy is on based on daily predictions of stock prices. The strategy earned significant return in backtest.

the scheme

Predicting the price of next day seemly good example but lack of realistic value in stock trading. While the volatility will make the prediction hardly reliable, the friction in the real stock market will probably make the strategy less likely to be profitable. In inspired by the momentum strategy, we are looking for potential return in a relative longer period.

In the light of optimal strategy suggested by Jegadeesh and Titman (2001), we will try to use wavelet neural network to predict the return rate of the stock in next 3 months based on the data of last 12 month. Hopefully, this will outperform the benchmark which is the return of the traditional momentum strategy.

benchmark–Momentum strategy

the momentum is just the total return of last look-back period. Here we are using last 12 months.

Following code will run momentum strategy on dow indexed stock. With only 30 stocks, the strategy doesn't show much profitablity.

```
suppressMessages(library(tidyquant))
library(tsibble)
sp500 <- tq_index("SP500")
tiker <- tq_index("DOW")

tiker %>% select(symbol) %>%
    filter(symbol != "BRK.B") %>%
    mutate(prices = map(.x = symbol, ~ tq_get(.x, get = "stock.prices", from = "2010-01-


dow_prices %>% filter(symbol != "DOW") -> dow_prices
```

```
dow_prices %>% mutate(prices, prices = map(prices, function(x) x[c("adjusted", "date")]
 # mutate_if(is.list, simplify_all) %>%
  unnest(prices) -> dow_unnested
```

```
dow_unnested %>% as_tsibble(index = date, key = symbol) -> dow_tsbl

# Is it necessary to fill the gap? or does it even correct?
dow_tsbl %>% fill_gaps() %>%
  fill(adjusted, .direction = "down") -> dow_filled

# calculate the momentum
dow_filled %>%
  group_by(symbol) %>%
  mutate(return = slide_dbl(adjusted, ~ log(.x[2]/.x[1]), .size = 2)) %>%
  mutate(momentum = slide_dbl(return, ~ reduce((.x+1), `*`),
                              .size = 365, .align = "right")) -> dow_mom

dow_mom %>% ungroup() %>%
  mutate(str_date = as.character(date)) %>%
  group_by(str_date) %>%
  top_n(1, momentum) %>% # calculate the winner for each date
  ungroup() %>% as_tibble() %>% # remove the effect of grouping by date
  # summarize number of wins for each stock
  group_by(symbol) %>%
  summarise(n = n())
```

```r
dow_mom %>% ungroup() %>%
  mutate(str_date = as.character(date)) %>%
  group_by(str_date) %>%
  top_n(1, momentum) %>% ungroup() %>% # select the winner with max momentum
  select(symbol, date) %>%
  rename(winner=symbol) %>% as_tibble() %>%
  right_join(dow_mom, by = c("date")) %>% # join the winner with price data
  as_tsibble(index = date, key = symbol) %>%
  group_by(symbol) %>%
  #calculate the return for next 90 days, roughly 3 month
  mutate(inv_ret = slide_dbl(return, ~ reduce((.x+1), `*`),
                             .size = 90, .align = "left")) %>%
  mutate(inv_ret = lead(inv_ret)) %>%
  ungroup() -> dow_inv

  # select the winner return
  dow_inv %>%
  filter(winner == symbol) %>%
  select(winner, date, inv_ret) -> dow_win

  dow_win %>% nrow()
  dow_win %>% filter(inv_ret>1) %>% nrow()
  mean(dow_win$inv_ret, na.rm = TRUE) - 1
```

WNN

Alexandridis and Zapranis (2013) present a practical intro on wavelet neural network. In essence, the model try to use neural network to adjust the weights of wavelet basis. In the light of time series context, recurrent neural network become one of the natural candidates. More complicated model will have harder time to converge.

TO DOs:

[ ] implement neural network with wavelet basis, check the result.

[ ] Try more complicated architecture of the NN, such as RNN.

References

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