STAT430: Machine Learning for Financial Data

Financial machine learning applications

- Price prediction / algo trading
- Anomaly detection / Risk analysis
- Portfolio construction
- Credit Ratings
- · See more examples: Ten Financial Applications of Machine Learning

Financial data types

- · Essential Types of Financial Data
- TABLE 2.1 of AFML

Fundamental Data	Market Data	Analytics	Alternative Data
• Assets	Price/yield/implied volatility	Analyst recommendations	Satellite/CCTV images
• Liabilities	• Volume	Credit ratings	 Google searches
• Sales	 Dividend/coupons 	 Earnings expectations 	• Twitter/chats
 Costs/earnings 	Open interest	 News sentiment 	Metadata
Macro variables	 Quotes/cancellations 	•	•
•	 Aggressor side 		
	•		

Structured bars

- Standard bars
 - Time bars
 - Tick bars
 - Volume bars
 - Dollar bars
- · Information-driven bars: to sample more frequently when new information arrives
 - Tick imbalance bars
 - Volume/dollar imbalance bars
 - TIBs, VIBs, and DIBs monitor order flow imbalance, as measured in terms of ticks, volumes, and dollar values exchanged

Structured bars

- More information-driven bars:
 - Tick runs bars
 - Volume/dollar runs bars
 - Monitor the sequence of buys in the overall volume, and take samples when that sequence diverges from our expectations

Time bars

- · Sampling information at fixed time intervals, e.g., once every minute
- · Timestamp / Open / Close / High / Low / Volume
- · Limitations:
 - Oversample / undersample
 - Poor statistical properties: serial correlation, heteroscedasticity, and nonnormality
- · Try R

Tick bars

- · Sampling information at a pre-defined number of transactions, e.g., once every 1000 ticks
- · Order fragmentation introduces some arbitrariness in the number of ticks
- · Be aware of outliers due to auctions at open/close
- · Try R

Volume bars

· Sampling information when a pre-defined amount of the security's units have been exchanged

Dollar bars / Unit bars

- · Sampling information every time a pre-defined market value is exchanged
- More robust than volume/tick bars
- Amount of ticks and volumes may be affected by corporate actions: splits, buy-back, etc.
- bar size can be fixed over time, or linked to other factors, e.g., free-floating market capitalization of a company

Some comparisons

- · Counts of different bars E-mini S&P 500 futures
 - See FIGURE 2.1 of AFML
- Counts of different bars XBTUSD

Counts of bars for XBTUSD tick bar vol bar unit bar 0 0 10 20 30

Weeks of 2018

Tick imbalance bars

• Calculate a b_t sequence:

$$b_t = \begin{cases} b_{t-1} & \text{if } \Delta p_t = 0 \\ \frac{|\Delta p_t|}{\Delta p_t} & \text{if } \Delta p_t \neq 0 \end{cases}$$

• Find tick imbalance at T

$$\theta_T = \sum_{t=1}^T b_t$$

- $E_0[\theta_T] = E_0[T](P[b_t = 1] P[b_t = -1])$
- Sample information at T^*

$$T^{*} = \operatorname*{arg\,min}_{T} \left\{ \left| \theta_{T} \right| \geq \mathrm{E}_{0} \left[T \right] \left| 2 \mathrm{P} \left[b_{t} = 1 \right] - 1 \right| \right\}$$

Tick imbalance bars

In practice:

- Estimate $E_0[T]$ as an exponentially weighted moving average of T values from prior bars
- Estimate $2P[b_t = 1] 1$ as an exponentially weighted moving average of bt values from prior bars.
- · Try R
- Question: any potential problems for approximating $E_0[T]$??

Volume/dollar imbalance bars

• Find imbalance at T

$$\theta_T = \sum_{t=1}^T b_t v_t$$

•
$$E_0[\theta_T] = E_0 \left[\sum_{t|b_t=1}^T v_t \right] - E_0 \left[\sum_{t|b_t=-1}^T v_t \right] = E_0[T](P[b_t=1]E_0[v_t|b_t=1]$$

$$-P[b_t=-1]E_0[v_t|b_t=-1])$$

• Sample information at T^* , where $v^+ = P[b_t = 1]E_0[v_t|b_t = 1]$

$$T^* = \arg\min_{T} \{ |\theta_T| \ge \mathrm{E}_0[T] |2v^+ - \mathrm{E}_0[v_t]| \}$$

Volume/dollar imbalance bars

In practice

- Estimate $E_0[T]$ as an exponentially weighted moving average of T values from prior bars
- Estimate the second part as an exponentially weighted moving average of $b_t v_t$ values from prior bars

Tick runs bars

· Calculate the length of the current run

$$\theta_T = \max \left\{ \sum_{t|b_t=1}^{T} b_t, -\sum_{t|b_t=-1}^{T} b_t \right\}$$

- $\cdot \quad \mathsf{E}_0[\theta_T] = \mathsf{E}_0[T] \mathsf{max} \{ \mathsf{P}[b_t = 1], 1 \mathsf{P}[b_t = 1] \}$
- Sample information at T^*

$$T^* = \underset{T}{\arg\min}\{\theta_T \geq \mathrm{E}_0[T] \mathrm{max}\{\mathrm{P}[b_t = 1], 1 - \mathrm{P}[b_t = 1]\}\}$$

Tick runs bars

- In practice
 - Estimate $E_0[T]$ as an exponentially weighted moving average of T values from prior bars
 - Estimate $P[b_t = 1]$ as an exponentially weighted moving average of the proportion of buy ticks from prior bars
- Instead of measuring the length of the longest sequence (without offsetting),
 we count the number of ticks of each side without offsetting them
- In the context of forming bars, this turns out to be a more useful definition than measuring sequence lengths
 - Question: please compare tick runs bars with tick imbalance bars empirically.
- Try R

Volume/dollar runs bars

· Calculate volumes or dollars associated with a run

$$\theta_T = \max \left\{ \sum_{t|b_t=1}^{T} b_t v_t, -\sum_{t|b_t=-1}^{T} b_t v_t \right\}$$

- $\cdot \quad \mathrm{E}_0[\theta_T] = \mathrm{E}_0[T] \max \{ \mathrm{P}[b_t = 1] \mathrm{E}_0[v_t | b_t = 1], (1 \mathrm{P}[b_t = 1]) \mathrm{E}_0[v_t | b_t = -1] \}$
- $\text{.}\quad T^* = \underset{T}{\arg\min}\{\theta_T \geq \mathrm{E}_0[T] \max\{\mathrm{P}[b_t=1] \mathrm{E}_0[v_t|b_t=1],$

$$(1 - P[b_t = 1])E_0[v_t|b_t = -1]$$
}

Volume/dollar runs bars

- In practice
 - Estimate $E_0[T]$ as an exponentially weighted moving average of T values from prior bars
 - Estimate $P[b_t = 1]$ as an exponentially weighted moving average of the proportion of buy ticks from prior bars
 - Estimate $E_0[v_t|b_t=1]$ as an exponentially weighted moving average of the buy volumes from prior bars
 - Estimate $E_0[v_t|b_t=-1]$ as an exponentially weighted moving average of the sell volumes from prior bars
- Back to Course Scheduler