MS&E 448

Trading forex with distributed limit order book

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With data provided by Integral Under guidance of Dr. Lisa Borland and Enguerrand Horel.

Outline



- 1. Intro/Problem Statement
- **2**. Data
 - a. What does each data point look like
 - b. Statistics
 - i. Across time
 - ii. Across currency pairs (e.g. correlations)
 - iii. Across LPs (I haven't thought of a good one for this yet)
- 3. Related Work / Existing Methods
- 4. Methods
 - a. Baseline method
 - b. Next steps method

Data from Integral

8 Currency pairs

- USDCAD, USDCHF, USDJPY, USDSEK,
- AUDUSD, EURUSD, GBPUSD, NZDUSD

Across 1 month, 5 LPs

- February 1st, 2019 March 1st, 2019
- Sunday: starting at 1800
- Monday-Thursday: 24 hours
- Friday: Ends at 2200

(discard after 1800)

(discard, too few trades)

• 25 days, ~400 active hours

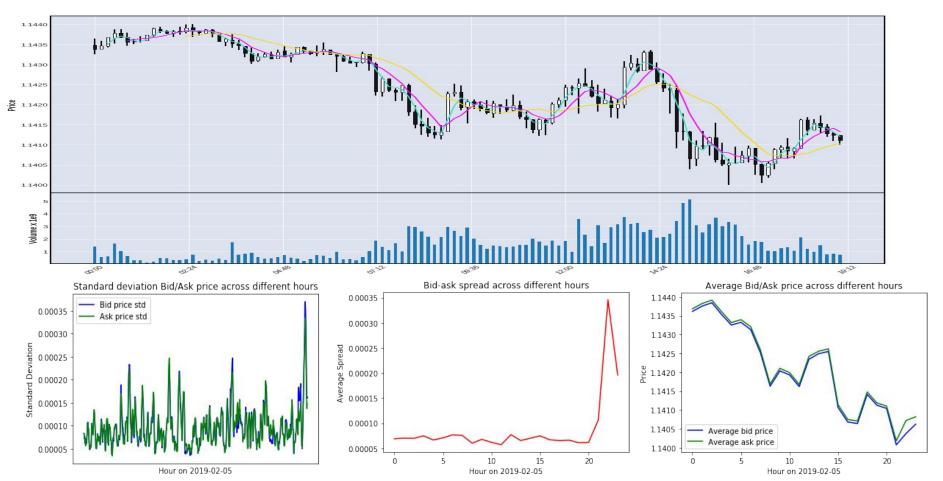
Data from Integral

provider	currency pa	irtime	bid price	bid volume	ask price	ask volume
LP-1	EURUSD	02.25.2019 00:00:00.819	1.13417	1000000	1.13424	1000000
LP-1	EURUSD	02.25.2019 00:00:00.819	1.13417	1000000	1.13423	1000000
LP-1	EURUSD	02.25.2019 00:00:00.819	1.13417	1000000	1.13423	1000000
LP-1	EURUSD	02.25.2019 00:00:00.841	1.13411	1000000	1.13423	1000000
LP-1	EURUSD	02.25.2019 00:00:00.841	1.13411	1000000	1.13423	1000000
LP-1	EURUSD	02.25.2019 00:00:00.841	1.13411	1000000	1.13423	1000000
LP-1	EURUSD	02.25.2019 00:00:00.895	1.1341	1000000	1.13422	1000000
LP-1	EURUSD	02.25.2019 00:00:00.896	1.1341	1000000	1.13422	1000000
LP-1	EURUSD	02.25.2019 00:00:00.896	1.1341	1000000	1.13422	100000
LP-1	EURUSD	02.25.2019 00:00:00.940	1.13414	1000000	1.13421	1000000
LP-1	EURUSD	02.25.2019 00:00:00.940	1.13414	1000000	1.13421	100000
LP-1	EURUSD	02.25.2019 00:00:00.940	1.13414	1000000	1.13421	1000000
LP-1	EURUSD	02.25.2019 00:00:00.958	1.13414	1000000	1.1342	1000000
LP-1	EURUSD	02.25.2019 00:00:00.958	1.13414	1000000	1.1342	1000000
LP-1	EURUSD	02.25.2019 00:00:00.959	1.13414	1000000	1.1342	1000000
LP-1	EURUSD	02.25.2019 00:00:01.039	1.13414	1000000	1.13421	100000
LP-1	EURUSD	02.25.2019 00:00:01.039	1.13414	1000000	1.13421	1000000
LP-1	EURUSD	02.25.2019 00:00:01.039	1.13414	1000000	1.13421	100000
LP-1	EURUSD	02.25.2019 00:00:01.671	1.13412	1000000	1.13419	1000000
LP-1	EURUSD	02.25.2019 00:00:01.671	1.13412	1000000	1.13419	1000000
LP-1	EURUSD	02.25.2019 00:00:01.671	1.13412	1000000	1.13419	100000
LP-1	EURUSD	02.25.2019 00:00:01.734	1.13408	1000000	1.1342	1000000
LP-1	EURUSD	02.25.2019 00:00:01.734	1.13408	1000000	1.1342	1000000

- Liquidity Provider
- Currency pair
- Exact Time
- Bid price
- Bid volume
- Ask price
- Ask volume

Example Statistics

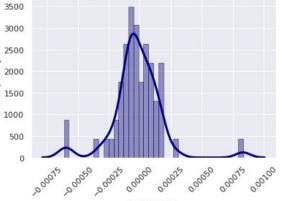
EUR/USD Feb. 5 th, 2019



Example Statistics

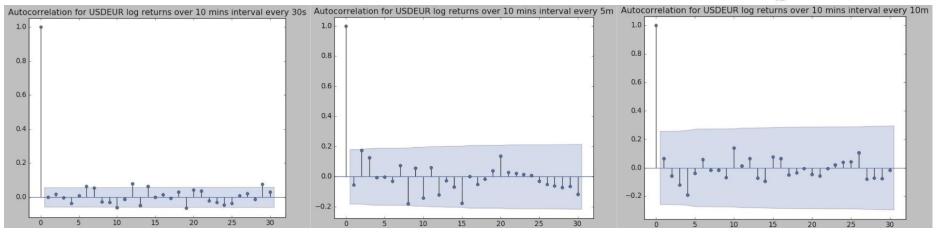


Freq. Plot of Log Return [2019-02-05 0AM-10AM EURUSD Open Bid]

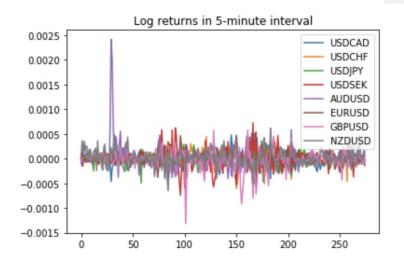


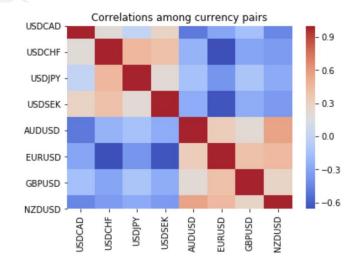
Frequency

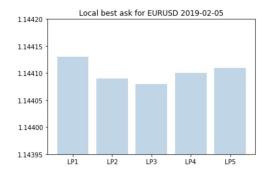


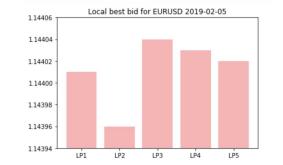


Example Statistics









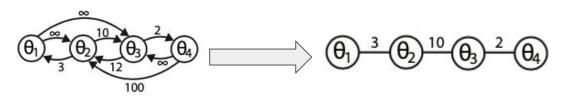


Related Works



Quasi-centralized limit order books (QCLOBs) (Gould, Porter, and Howison, 2017)

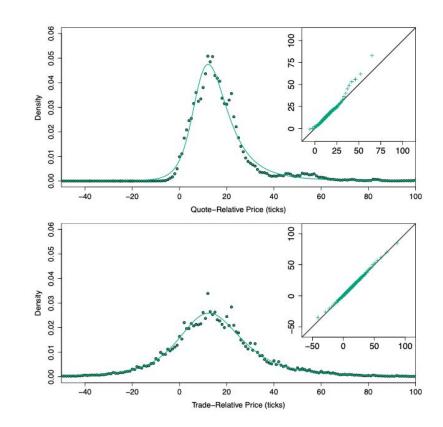
• Financial institutions access only the trading opportunities offered by counterparties with whom they possess sufficient bilateral credit



- QCLOB is global but LOB for each LP is local
 - QCLOB is not visible to all LPs

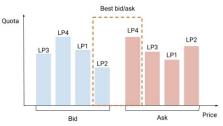
Statistics of QCLOBs

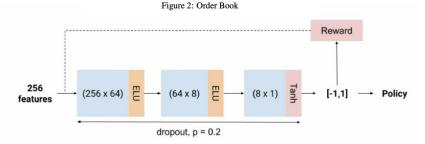
- Obtained data from the Hotspot FX platform
- Results
 - For all queue lengths, the mean size of arriving marketing orders is *strictly* smaller than the queue length
 - The authors use the generalized *t*-distribution to model the distribution of the limit orders for EUR/USD in one day



Reinforcement Learning for FX Trading (2019 Group): Policy-Based RL

- Picked a currency pair to trade at best bids and offers across LPs
- States
 - Previous action and best bids and asks of all currencies over last 8 time steps
- Actions
 - How much to short/long the pair (as a fraction of current quote currency holdings)
- Model
 - 3-layer policy network trained using REINFORCE (Monte Carlo policy gradient), with dropout and SGD



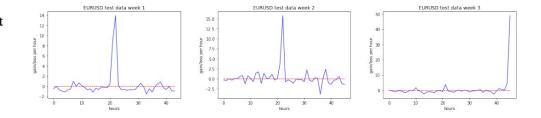


Algorithm	n 1: Deep reinforcement learning
	2e: Differentiable policy parameterization $\pi(a s, \theta)$ (i.e., trading agent) 0 to L do
	erate a new episode $(s_0, a_0, r_1,, a_{\tau-1}, r_{\tau})$ following current $\pi(a s, \theta)$
	$t \leftarrow 0$ to $\tau = 3,600$ do Cumulative return $G \leftarrow$ return from step $t(G_t)$
	$ \begin{aligned} \theta &\leftarrow \theta + \alpha \gamma^t G \nabla_\theta \ln \pi(a_t s_t, \theta) \\ t &= t+1 \end{aligned} $
end	t = t + 1
end	

Reinforcement Learning for FX Trading (2019 Group): Policy-Based RL

- Experiments
 - Trained on 3 different currency pairs
 - Maximized profit over hour long episodes chosen from the training window
 - for three different weeks, using the first four days of the week as the training set, the fifth day as the eval/val set, and the sixth day as the test set.
- Results: inconclusive

	week 1	week 2	week 3
Mean Return (\$)	0.18	0.30	0.69
Variance (\$)	2.758	2.593	7.291
Yield	0.014%	0.023%	0.052%



2/7 2/8

Eval/test Week 1

Eval/test Week 2 2/13 2/14

Eval/test Week 3 2/19 2/20

2/10 2/11 2/12 Train Week 2

2/15 2/17 2/18 Train Week 3

3/1

2/21 2/22 2/24

2/25 2/26 2/27 2/28

Baseline Model

- Input
 - Bid, ask and volume from across LP for 1 currency pair
 - Lookback 500 quotes
- Output
 - Regression (price/fluctuation prediction)
 - Classification (trend determination, up, down, flat)
- Model
 - Gradient boosting decision tree (LightGBM)

	Price Regression (mean abs error)	Trend Classification (-1.5, +1.5, 7 classes) (accuracy)
EURUSD	32 pips	37%
AUDUSD	44 pips	26%

Current Progress

- Infrastructure setup on Google Cloud Compute
 - Cloud storage of pre-processed data
 - Shared environment for running experiments
- Data pipeline for deep learning and reinforcement learning
 - Simple API for querying

api = utils.DataAPI()
df_usdcad = api.get('USDCAD', '1', start_time='2019-02-01 16:30:00', end_time='2019-02-01 16:45:00')

• PyTorch based data loading

Next Step

More complex deep learning models

- Multiple layers
- Trend classification through embedding generation

Adaptation for reinforcement learning models

• Adapt/refine methods from existing RL papers

Trading simulation environment

- Handle multiple currency pairs
- Properly account for bid-ask spread
- Incorporate account information with trading model



Thanks