Forex trend prediction

with rough sets and machine learning

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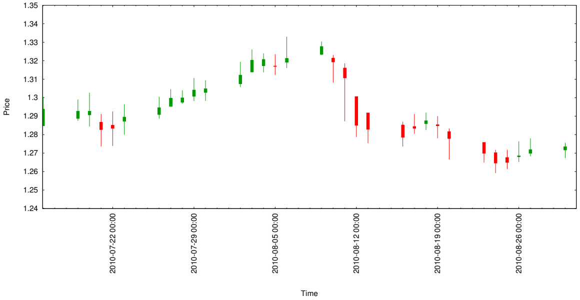
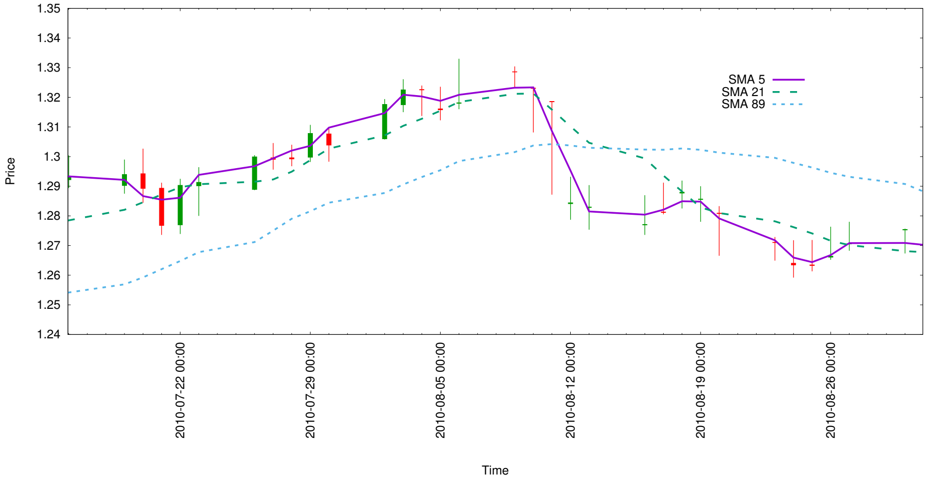
Outline

Heiken Ashi candles (HA)

HA closing (HAC) is the *average* of OCLH for t
HA opening t (HAO) is the *average* of HAO and HAC for $t-1$
HA high (HAH) is the *maximum* of HAO, HAC, and H for t
HA low (HAL) is the *minimum* of HAO, HAC, and the L for t
Base case $t = 0$ just uses OCLH (avg/avg/max/min)

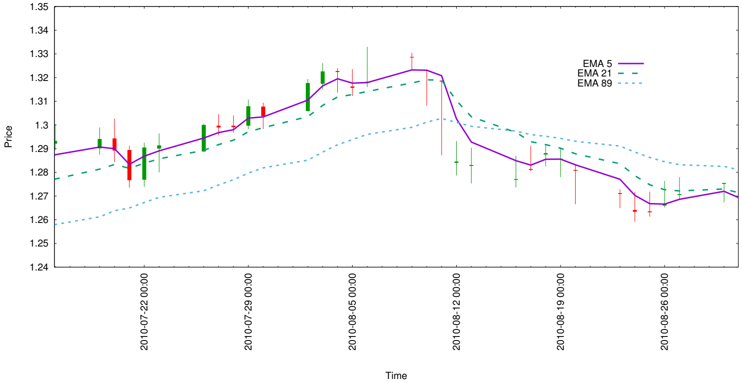


Rolling average: SMA



Priority smoothing: EMA

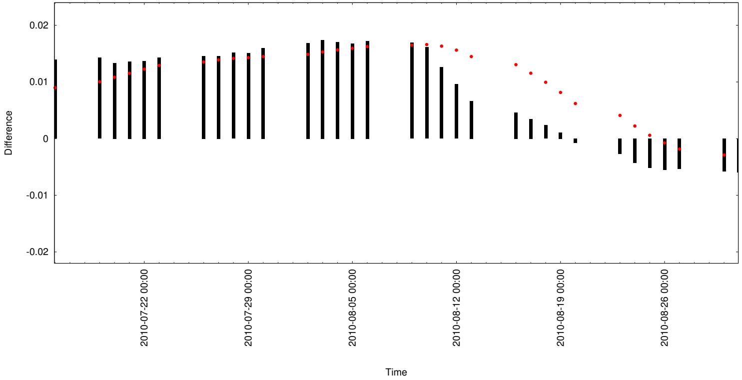
Higher priority to *recent data* with $\mu_t = \rho v + (1-\rho)\mu_{t-1}$ where v is the new data (adjustable ρ)



Moving average convergence-divergence

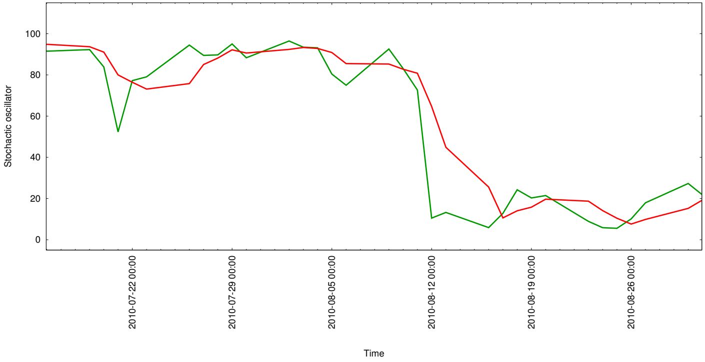
Two MA: a *fast* one and a *slow* one

d = how many differences between the fast and the slow MA to compute



Stochastic oscillator (SO)

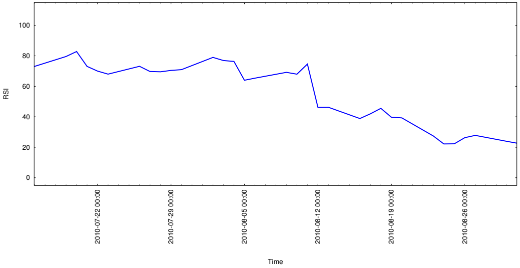
$$s_t = \frac{\text{closing}_t - \text{lowest}_{[t-\ell,t]}}{\text{highest}_{[t-\ell,t]} - \text{lowest}_{[t-\ell,t]}}. \tag{1}$$



Relative strength index (RSI)

Initial: $\text{RSI}_\ell = 100 - 100/(1 + \frac{\text{gain}_\mu}{\text{loss}_\mu})$

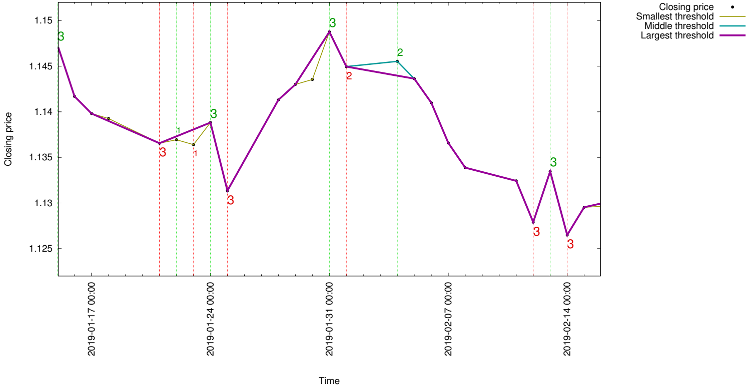
For $t > \ell$: $\text{RSI}_t = 100 - 100/(1 + \frac{(\ell-1)\times\text{gain}_\mu+\text{gain}_t}{(\ell-1)\times\text{loss}_\mu+\text{loss}_t})$



gain/loss = change between two consecutive closing prices

Zig-zag semaphore

t at which the price reverses for over a threshold (direction = sign, magnitude = kind)



Forex prediction

Traditional approaches for forecasting have fallen short [15] whereas non-linear models have been found adequate [4].

The research on the forex dates back to the work of Meese and Rose [8] who discarded the use of known forecasting methods for this particular market.

With ML, however, it has been a whole new ballgame.

An extract of related work

Work	Technique	Aspect	Pairs	Features	Tuning
Tseng et al. [15]	FL+ARIMA	rate	1	price	yes
Kamruzzaman and Sarker [5]	ARIMA/NN	rate	6	price	no
Nair et al. [9]	DT+RS+NN+BC	trend	1	indicators	no
Qian and Rasheed [14]	ML	rate	1	price	no
Pai et al. [12]	RS+SVM	rate	1	indicators	no
Baasher and Fakhr [2]	trend	trend	4	indicators	no
Vyklyuk et al. [16]	NN	rate	1	price	no
Nayab et al. [10]	DT+RS	rate	10	indicators	no
Lee et al. [6]	HMM	trend	1	manual	yes
Ni et al. [11]	NN	rate	9	price	no
Dautel et al. [3]	dNN	change	4	change	yes
Adegboye and Kampouridis [1]	ML	reversal	20	minute	no
Yildirim et al. [17]	dNN	profit	1	indicators	no
Present work†	RS+ML	trend	15	indicators	no

† currently R1 for Springer's *Computational Economics* (with Fernando and Chris)

Classification and rough sets

A *classifier* is a method that assigns to each input a *label* from a set of k predefined class labels.

Two *alternatives* x_1 and x_2 are defined to be *indiscernible* in terms of a subset of *attributes* A if each attribute $a \in A$ assigns the same value to them

$$\forall a \in A : a(x_1) = a(x_2)$$

If only the attributes in A are considered, x_1 and x_2 are *equivalent* [13].

Equivalence class

$[x]_A =$ the subset of objects that are indiscernible in terms of A

reduct R of A = a minimal subset of A that conserves equivalence

the intersection of all its reducts is the *core* of A

picking the attributes that distinguish between equivalence classes
$=$
approximating an equivalence class as a subset of inputs with the same label

Approximation

Let T be a subset of *targets* to characterize in terms of A

Unless T is an equivalence class under A, it can only by approximated in terms of A

Lower approximation $\underline{T}_A = \{x \mid [x]_A \subseteq T\}$
Upper approximation $\overline{T}_A = \{x \mid [x]_A \cap T \neq \emptyset\}$
Precision of approximation $\alpha(T, A) = |\underline{T}_A| / |\overline{T}_A|$

$a \in A$ is *redundant* if $\underline{T}_A = \underline{T}_{A \setminus \{a\}}$

Fuzzy rough sets

whether or not an element belongs to a rough set is **not** a binary decision

instead a (discrete or continuous) *degree of belonging* is employed

Python library: `fuzzy-rough-learn` [7]

https://pypi.org/project/fuzzy-rough-learn/

we use *Fuzzy Rough Neighbourhood Consensus* (FRONEC) labelling

- lower approximation (Q^1)
- Hamming similarity for labels (R^1)
- $k = 10$ neighbors

Feature extraction

We compute the indicators and then discretize them:

SMA	P+ (1) or - (0) difference to price
EMA	same as SMA
HA	*rising* (1) or *falling* (0)
ZZ	level (1/2/3) & kind (0/1); most recent
SO	above (1) or below (0) SMA
RSI	5-level discretization of the index
MACD	sign (0/1)

Several windows for SMA and EMA
Two MACD: one using SMA and another with EMA

Horizons and thresholds

Forecast horizons **H**: how many days in the future, counting from the date on which the indicators are *observed*, the forecast is placed

Change thresholds **T**: how many percent the price needs to differ between the day on which the indicators are observed and the day for which the forecast is made for that level change to be considered present

Given **H** and **T** we compute two binary values based on the price graph:

- 1 if the change exceeds **T**, 0 if it does not
- 1 if the change is an increase, 0 if it is a decrease

Class labels

The pairs **HT** are then mapped to integer labels as follows:

$\uparrow = 2$	for the $(1, 1)$ pairs that indicate an **increase** exceeding the threshold
$\approx = 1$	for the $(0, 1)$ and $(0, 0)$ pairs that indicate **no change** that exceeds the threshold in either direction
$\downarrow = 0$	for the $(1, 0)$ pairs that indicate a **decrease** exceeding the threshold

Features and labels

Date	SMA					EMA					HA	ZZ-S		SO	RSI	MACD		Forecast
	3	5	7	14	21	3	5	7	14	21		Lvl	Kind			SMA	EMA	
2016-12-26	1	1	1	1	0	1	1	0	0	0	1	3	1	0	2	0	0	1
2016-12-28	1	1	1	1	1	1	1	1	0	0	0	2	1	0	1	0	0	2
2016-12-29	0	0	0	0	0	0	0	0	0	0	0	3	0	1	1	0	0	2
2016-12-30	1	1	1	1	1	1	1	1	1	1	1	3	1	0	2	0	0	0
2017-01-04	0	0	0	0	0	0	0	0	0	0	0	3	0	1	1	0	0	2
2017-01-06	1	1	1	1	1	1	1	1	1	1	1	3	1	0	3	0	0	1
2017-01-09	0	1	1	1	1	0	1	1	1	1	0	3	0	1	2	0	0	1
2017-01-10	1	1	1	1	1	1	1	1	1	1	1	3	1	0	3	0	0	1
2017-01-11	0	0	1	1	1	0	1	1	1	1	0	3	0	1	3	0	0	1
2017-01-16	1	1	1	1	1	1	1	1	1	1	1	3	1	0	3	0	0	1
2017-01-17	0	0	0	1	1	0	1	1	1	1	1	3	0	1	2	1	0	1
2017-01-18	1	1	1	1	1	1	1	1	1	1	1	3	1	0	3	1	0	1
2017-01-19	0	0	0	1	1	0	0	1	1	1	0	3	0	1	3	1	0	1
2017-01-24	1	1	1	1	1	1	1	1	1	1	1	3	1	0	3	1	1	1
2017-01-25	0	1	1	1	1	1	1	1	1	1	1	3	0	1	3	1	1	1

An extract of the data for a two-day horizon and a one-percent threshold, AUD-USD

Feature selection

- redundancy with another feature
- avoid over-fitting
- reduce time of the training

Fuzzy Rough Feature Selection (FRFS) from `fuzzy-rough-learn` [7], but we rewrote some of it to gain access to the list of features it selects so we can analyze the frequencies

Model building

1. Check how many data points we have per class
2. If one is a clear minority, discard it
3. For each replica
   - Balance the classes that are adequately present
   - Split the data into testing and training
   - Use a *sample* of the **training** data for feature selection
   - Filter out the un-selected features
   - Train the classifier model
   - Predict and de-full the labels (check for blanks)
   - Compute the F score

Classifier performance

Confusion matrix	counters for predicted vs. expected labels
Precision P	ratio of *true* positives from **all** positives
Recall R	ratio of *true* positives to the sum of TP & FN
F score	$2(P \times R)/(P + R)$, but weighted by class support

Experimental setup

The rough-set methods are *deterministic* $\rightarrow$ we characterize just once per currency pair

Splitting of the input data into training and test sets is *probabilistic* $\rightarrow$ we need replicas per H/T combination

OS	Ubuntu 20.04.1
DS & ML	Python 3 and Bash
Dataviz	R and Gnuplot
Data	https://finance.yahoo.com/ (five pairs, five years)
Repo	https://github.com/satuelisa/Forex

Steps

1. Obtain *price data*; calculate *indicators*; extract *features*
2. Choose **H** and **T**; compute class labels
3. Check if all classes are present; terminate if not
4. Represent the data with *rough sets*
5. Terminate if the allowed attempts (10) are exhausted
6. Split the the data (70%, 30%)
7. Check if all classes are present in both parts; go to step 5 if not
8. Perform *feature selection* (70); construct a *classifier* (70)
9. *Predict* the test data (30); compute the *F-score*
10. Terminate if the desired number of replicas (5) is completed
11. Go to step 5

Classifiers with $F \geq 0.95$ all features

All 15 have some with $F \geq 0.80$

Pair	H	T	Frequency ↓	Frequency ≈	Frequency ↑	Score min	Score max	SMA-3	SMA-5	SMA-7	SMA-9	SMA-11	EMA-3	EMA-5	EMA-7	EMA-9	EMA-11	HA	ZZS-level	ZZS-kind	SO	RSI	MACD-S	MACD-E	#	Feature selection μ	Feature selection σ	Model μ	Model σ
AUDUSD	1	0.01	326	9	323	*0.60*	0.97	17	4	9	7	3	1	1	0	1	1	2	3	0	3	30	7	3	658	52.79	11.78	1.05	0.06
AUDUSD	1	0.02	318	21	319	0.75	0.97	18	9	1	2	4	3	1	0	0	0	2	3	0	6	30	5	4	658	49.23	6.82	1.03	0.03
BTCUSD	1	0.01	474	3	469	*0.66*	1.00	18	7	7	5	1	0	1	0	0	1	4	0	2	9	30	7	6	946	56.48	18.77	1.94	0.10
BTCUSD	1	0.02	473	5	468	*0.59*	0.99	21	8	5	2	3	2	0	0	0	0	7	0	3	10	30	7	6	946	58.78	16.65	1.95	0.08
BTCUSD	1	0.03	469	12	465	*0.42*	1.00	19	14	3	3	2	0	0	0	0	1	1	0	3	7	30	2	5	946	51.16	13.42	1.93	0.10
BTCUSD	1	0.04	463	19	464	*0.62*	0.99	22	7	6	3	4	1	1	1	1	0	2	0	1	8	30	4	4	946	53.70	13.60	1.94	0.11
BTCUSD	1	0.05	460	22	464	*0.52*	1.00	17	11	6	6	4	2	0	0	0	1	2	0	3	8	30	3	5	946	55.31	15.76	1.93	0.10
EURCAD	1	0.02	329	26	329	*0.53*	0.95	12	9	5	3	1	2	0	1	1	1	5	8	0	1	26	11	6	684	50.06	5.32	1.11	0.06
EURGBP	1	0.01	342	19	335	*0.65*	0.96	21	7	3	1	0	1	1	1	2	1	0	3	0	10	28	8	3	696	50.45	9.24	1.16	0.06
EURJPY	1	0.01	337	13	347	*0.50*	0.96	18	10	2	1	4	2	0	1	0	2	1	3	0	6	26	8	7	697	50.96	11.62	1.14	0.12
EURSEK	1	0.01	346	23	343	*0.68*	0.97	19	7	5	4	2	3	2	1	1	0	1	7	0	3	26	8	4	712	52.61	9.42	1.22	0.08
EURUSD	1	0.01	340	12	334	0.71	0.95	24	1	6	2	2	3	0	2	0	0	2	5	0	6	26	7	5	686	52.69	10.55	1.15	0.07
GBPJPY	1	0.01	322	15	320	*0.63*	0.95	22	4	4	2	4	1	1	1	0	1	3	1	0	6	29	9	5	657	55.18	17.10	1.06	0.09
GBPUSD	1	0.01	317	10	305	*0.61*	0.95	15	2	8	4	3	1	3	1	3	0	0	2	0	6	28	14	4	632	54.37	9.76	1.02	0.12
GBPUSD	1	0.02	306	26	300	*0.65*	0.98	17	2	6	3	6	6	0	0	0	1	5	3	0	3	28	8	5	632	51.61	5.56	0.98	0.04
NZDUSD	1	0.01	332	4	333	*0.67*	0.96	23	2	8	6	1	3	1	0	0	0	3	2	0	3	28	7	3	669	53.18	10.32	1.09	0.10
NZDUSD	1	0.02	326	20	323	*0.53*	0.99	19	4	6	0	1	0	0	0	0	1	7	1	0	5	30	9	1	669	48.19	5.83	1.07	0.05
USDJPY	1	0.01	343	13	349	*0.54*	0.98	17	3	5	4	1	3	1	0	1	2	4	7	0	2	27	11	4	705	54.39	8.62	1.23	0.07
USDMXN	1	0.01	323	11	319	*0.67*	0.99	15	7	6	3	2	2	0	0	1	0	6	3	0	7	30	10	0	653	54.64	14.25	1.05	0.10
USDMXN	1	0.02	313	28	312	0.73	0.98	18	7	1	2	3	1	2	0	0	2	4	4	0	6	30	14	0	653	53.54	10.75	1.03	0.04
USDRUB	1	0.01	346	8	342	*0.63*	0.97	17	9	6	2	2	2	0	0	1	1	6	4	0	4	30	8	2	696	55.07	14.56	1.18	0.08
USDRUB	1	0.02	341	22	333	*0.64*	0.97	16	5	4	5	1	1	1	0	0	0	5	6	0	4	30	5	3	696	49.03	9.01	1.19	0.11

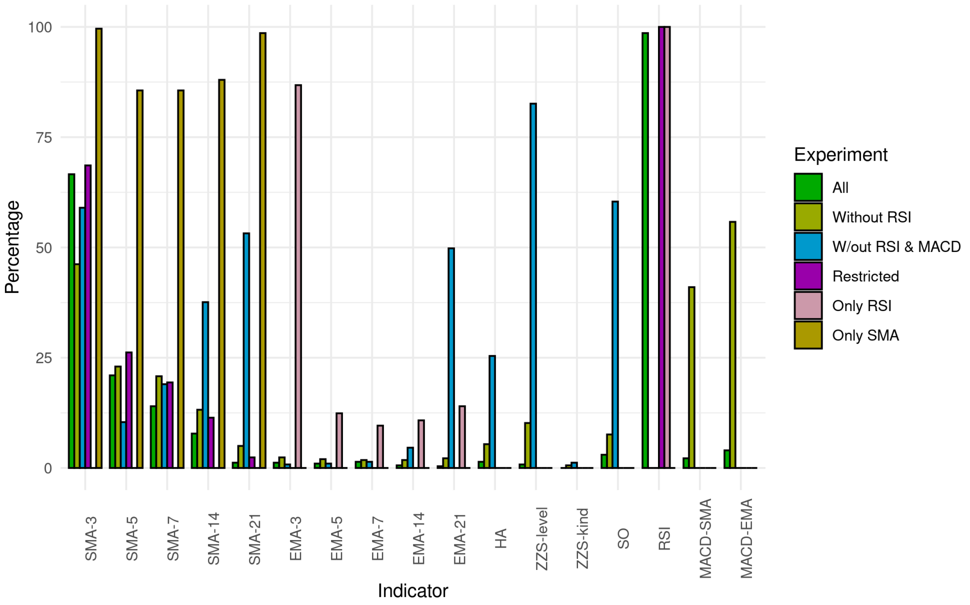
“no change” is too empty 25% of the total combinations

Feature frequency

Currency pair	SMA-3	SMA-5	SMA-7	SMA-14	SMA-21	EMA-3	EMA-5	EMA-7	EMA-14	EMA-21	HA	ZZS-l	ZZS-k	SO	RSI	MACD-SMA	MACD-EMA
AUDUSD	58	18	16	14	8	5	4	2	2	4	8	12	0	15	97	29	14
BTCUSD	65	26	16	9	10	4	1	1	1	2	11	2	6	30	100	20	15
EURCAD	53	19	14	14	9	5	3	3	2	4	8	17	1	13	93	41	18
EURCHF	55	16	12	11	8	4	2	1	1	3	7	49	1	12	89	17	13
EURGBP	58	16	17	9	6	6	2	2	2	3	8	16	0	20	99	28	9
EURJPY	61	18	13	12	11	4	2	2	1	3	9	14	0	20	97	22	11
EURSEK	54	18	15	14	9	6	4	2	3	2	9	25	2	14	90	25	15
EURUSD	60	17	18	11	9	5	3	2	2	2	9	15	0	17	97	23	12
GBPJPY	62	19	18	9	9	4	2	2	1	2	9	9	0	20	99	25	14
GBPUSD	58	18	16	12	12	6	4	2	2	3	6	9	0	16	96	36	15
NZDUSD	64	16	17	9	4	4	2	1	1	2	11	8	0	16	98	31	11
USDCNY	58	16	14	8	4	5	2	2	1	1	7	54	0	14	97	14	9
USDJPY	58	18	16	13	7	6	3	2	2	3	9	13	0	17	95	24	13
USDMXN	60	19	13	10	7	6	3	1	1	2	11	8	0	21	99	39	5
USDRUB	70	19	16	9	6	5	1	1	1	1	9	8	0	16	99	22	11

Feature exploration

All	RSI dominates; all 15 have some with ≥ 0.80
-RSI	MACD is getting popular; scores similar
$\uparrow$ -MACD	EMA (longest) and HA enter the scene; scores similar
RSI+SMA	Still all good
RSI+ EMA	Chinese Yuan can no longer be predicted well
SMA	All is fine again for short horizons and small thresholds

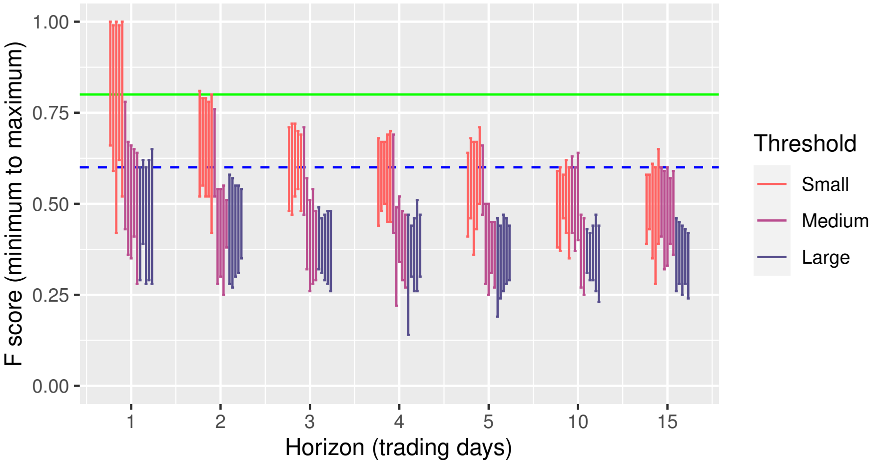


Percentage
100
75
50
25
0
SMA-3
SMA-5
SMA-7
SMA-14
SMA-21
EMA-3
EMA-5
EMA-7
EMA-14
EMA-21
HA
ZZS-level
ZZS-kind
SO
RSI
MACD-SMA
MACD-EMA
Indicator
Experiment
All
Without RSI
W/out RSI & MACD
Restricted
Only RSI
Only SMA

EURCAD


F score (minimum to maximum)
1.00
0.75
0.50
0.25
0.00
1
2
3
4
5
10
15
Horizon (trading days)
Threshold
Small
Medium
Large

BTCUSD


1.00
0.75
0.50
0.25
0.00
F score (minimum to maximum)
1
2
3
4
5
10
15
Horizon (trading days)
Threshold
Small
Medium
Large

USDCNY

F score (minimum to maximum)
1.00
0.75
0.50
0.25
0.00
1
2
3
4
5
10
15
Horizon (trading days)
Threshold
Small
Medium
Large

Computational load

CPU 16-core i7-10700K

RAM 64 GB

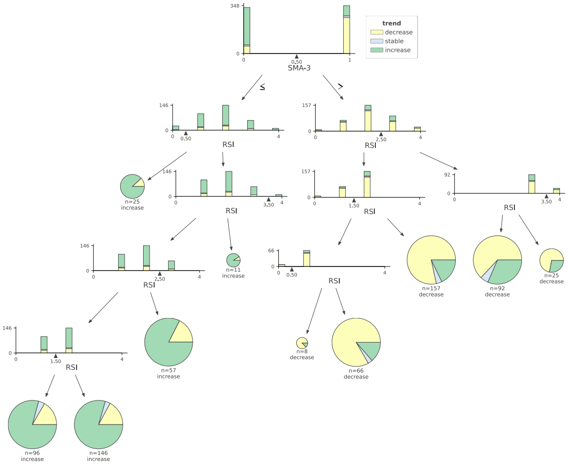
Characterization $\approx$ two seconds per pair; completely deterministic

Feature selection $\leq$ 70 ms, some variation (for a sample)

Training $\leq$ 2 ms, little variation, per replica

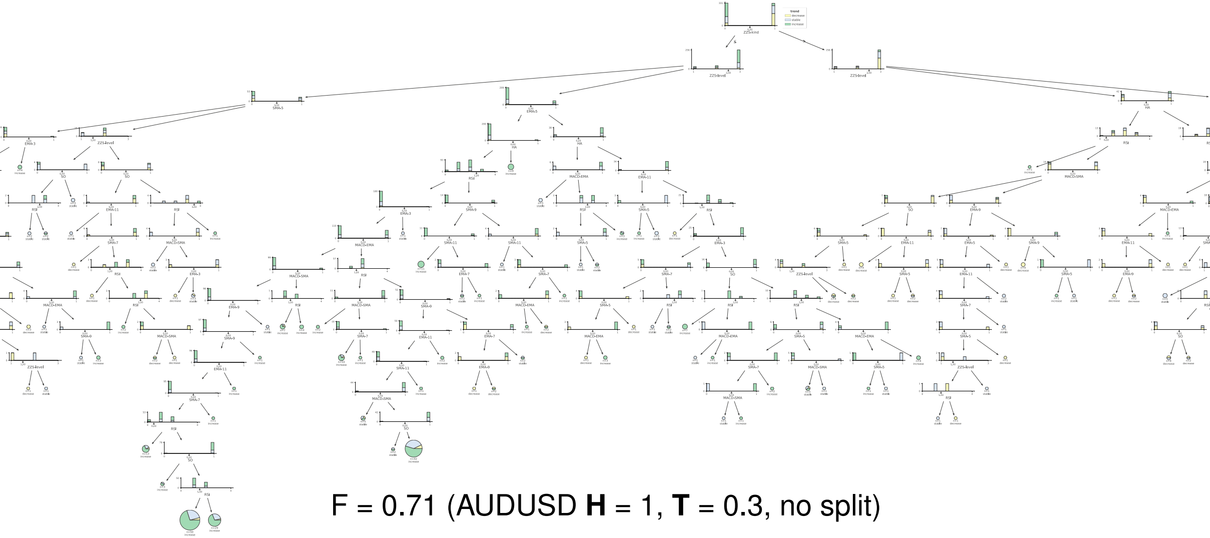
Experiments a few hours

Decision tree using RSI and SMA-3



F = 0.77 (USDCNY **H** = 2, **T** = 0.01, no split)

Decision tree for all features



F = 0.71 (AUDUSD **H** = 1, **T** = 0.3, no split)

Conclusions

We extract indicators and price changes from forex data.

We use *(fuzzy) rough sets* to represent them.

Given the current values, we predict trend $(\downarrow, \approx, \uparrow)$

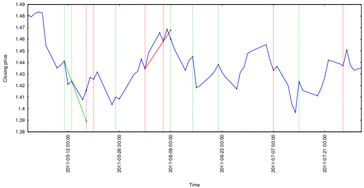
This is feasible with very simple indicators.

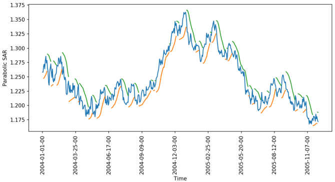
Feasible **short** forecast horizons and **small** thresholds

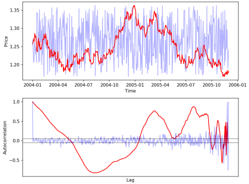
For longer horizons and larger thresholds, this is not settled yet

Future work

1. additional **indicators**, finer **discretization**
2. more use to the fuzziness
3. different *feature selectors* and *classifiers*
4. visualize the rough sets
5. hourly or minute-level data (this was daily data)
6. stock-market data







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