

HMM-BASED TRADING MASTER

PRESENTED BY: EXPLAINABLE AI BOY BAND



MARKET DATA



Dataset

Scraping from yahoo finance API

Data preparation

Add column to check if in each day close price is more than open price

Date	Close	Open	X_t
########	1.592667	1.266667	1
########	1.588667	1.719333	0
1/7/2010	1.464	1.666667	0
2/7/2010	1.28	1.533333	0
6/7/2010	1.074	1.333333	0



We use stock price 'UP' or 'DOWN' as state variable (X_t)



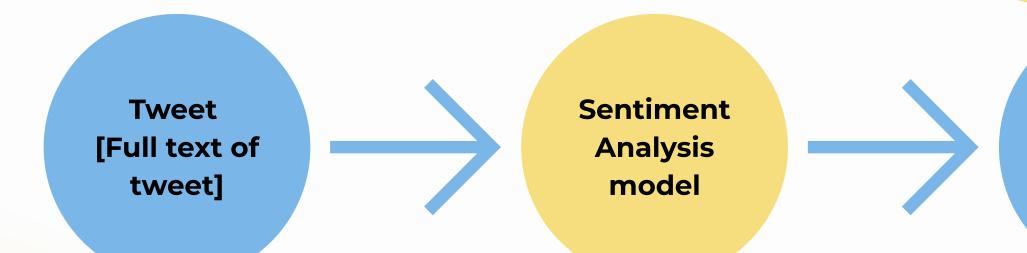
TWEET DATA



Dataset

Stock tweets for sentiment Analysis and Prediction from Kaggle

Data preparation



classified tweet into

- positive
- negative
- neutral



We use tweet sentiment 'Positive', 'Negative', 'Neutral as evidence variable (E_t)

cardiffnlp/twitter-roberta-basesentiment-latest





Data preparation

Problem

Due to the less amount of negative tweet, if we choose the sentiment to represent in a day with majority vote, it will not have the negative tweet in the state variable

Result

We scale the negative tweet with weighted sum by

- 1. Check the average number of positive tweets thats cause the stock price to go UP **5** days in a row named with **nPos_streak**
- 2. Check the average number of negative tweets thats cause the stock price to go DOWN **5** days in a row named with **nNeg_streak**
- 3. Calculate Majority vote = MAX(num_positive_tweets * nPos_streak/nNeg_streak , num_neutral_tweets)



HMM FILTERING / PREDICTION INFERENCES

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TERMINOLOGY

x_t; {"up", "down"}

the stock price is up in day t*

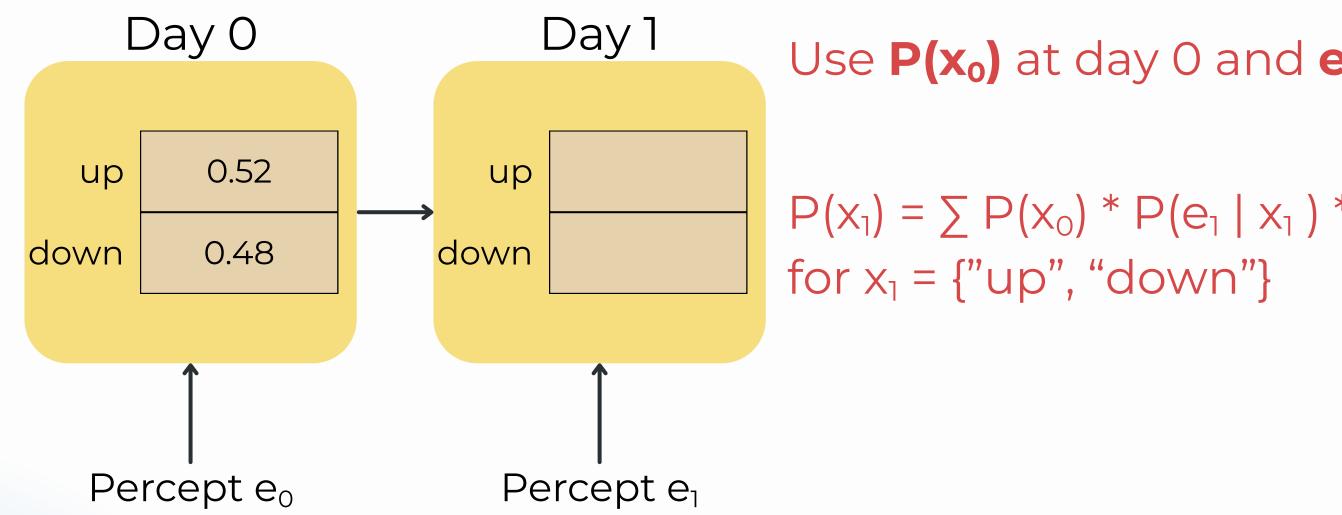
et: {"positive", "negative", "neutral"}

• the major** sentiment of tweet in day t

*price is up → Close price > Open price, vise versa



FILTERING



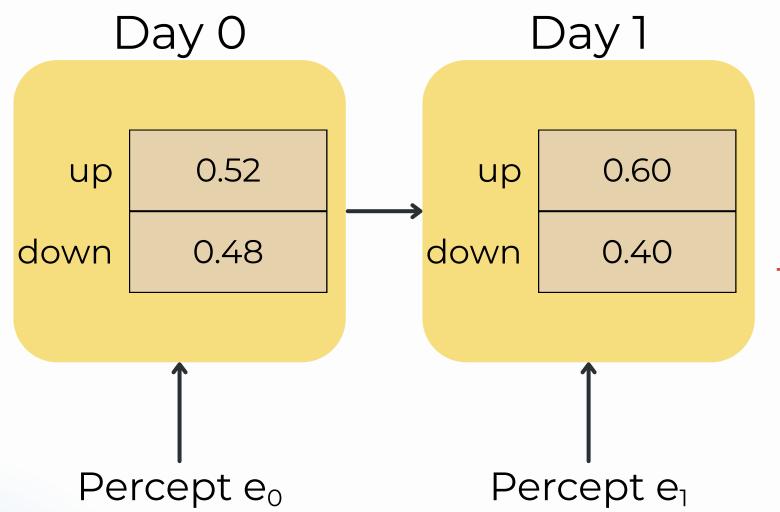
Use $P(x_0)$ at day 0 and e_0 to predict $P(x_1)$

$$P(x_1) = \sum P(x_0) * P(e_1 | x_1) * P(x_1 | x_0)$$

for $x_1 = \{"up", "down"\}$



FILTERING (CONT.)



Use $P(x_0)$ at day 0 and e_0 to predict $P(x_1)$

$$P(x_1) = \sum P(x_0) * P(e_1 | x_1) * P(x_1 | x_0)$$

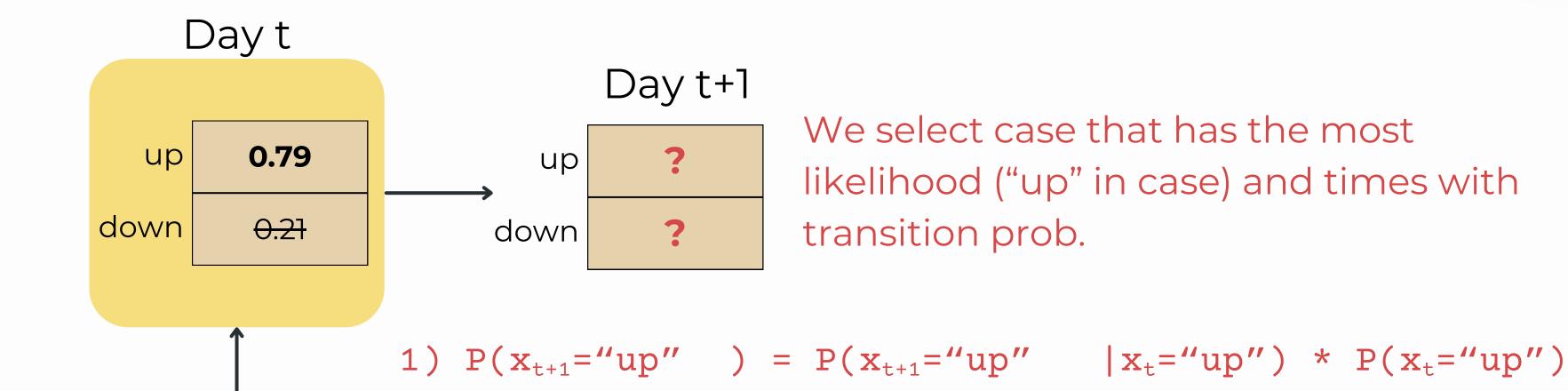
for $x_1 = \{"up", "down"\}$

Percept e_t



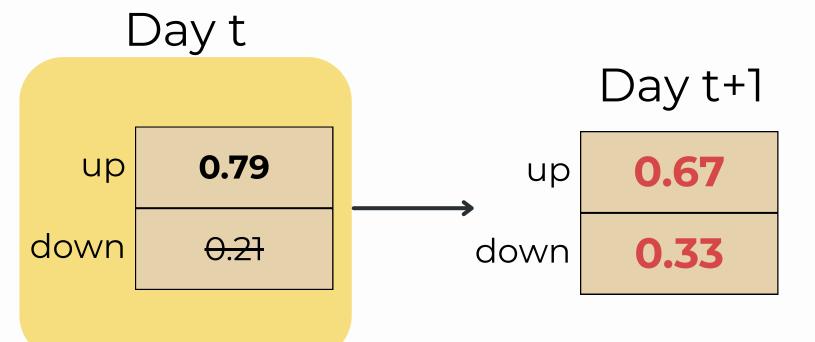
PREDICTION

2) $P(x_{t+1} = "down") = P(x_{t+1} = "down" | x_t = "up") * P(x_t = "up")$





PREDICTION (CONT.)



Percept e_t

We select case that has the most likelihood ("up" in case) and times with transition prob.

1)
$$P(x_{t+1}="up") = P(x_{t+1}="up") | x_t="up") * P(x_t="up")$$

2) $P(x_{t+1}="down") = P(x_{t+1}="down") | x_t="up") * P(x_t="up")$



RESULT & EVALUATION

Probability $P(x_t)$

>

x _t Probability	
Up	0.52
Down	0.48



Probability P(x_t | x_{t-1})

$x_t \setminus x_{t-1}$	Up	Down
Up	0.55	0.49
Down	0.45	0.51

(>)

Probability P(e_t)

e _t	Probability
Positive	0.31
Neutral	0.42
Negative	0.27

(>)

Probability P(et | Xt)

e _t \ x _t	Up	Down
Positive	0.38	0.22
Neutral	0.45	0.39
Negative	0.17	0.39



Model setting

There are 4 models

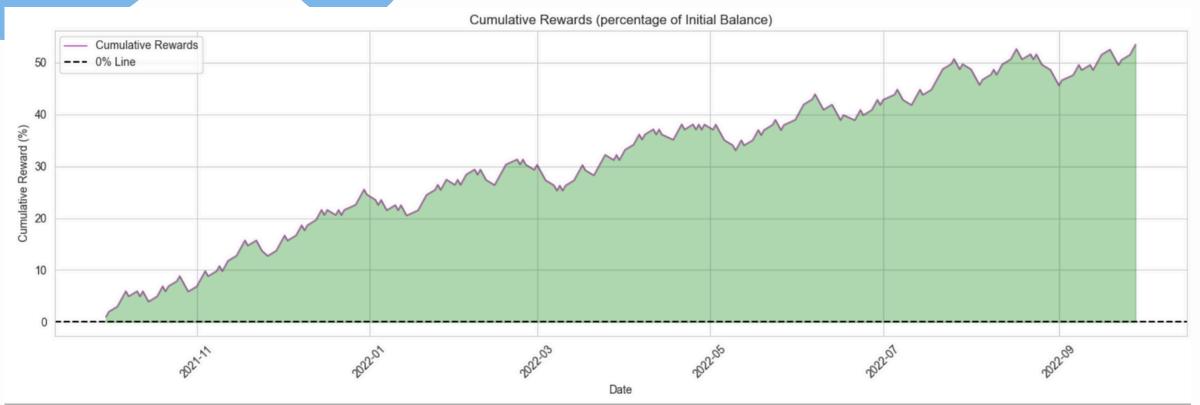
- 1. Random trade model
- 2. Only buy trade model
- 3. Only sell trade model
- 4. HMM trade model

How to trade

- 1. For Random, trade 3,000 time on the same period & stock
- 2. Has 1% commission fee

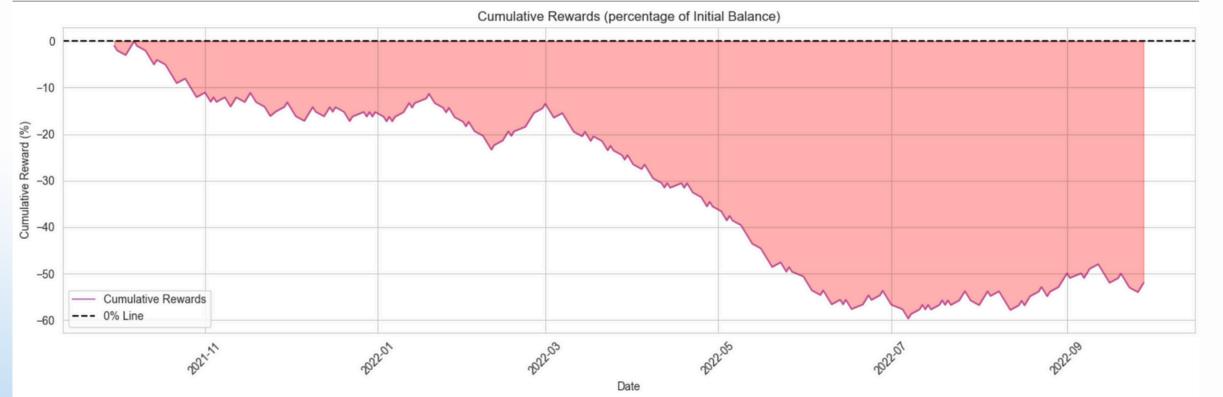


Random trade model



With non-deterministic behavior, we got

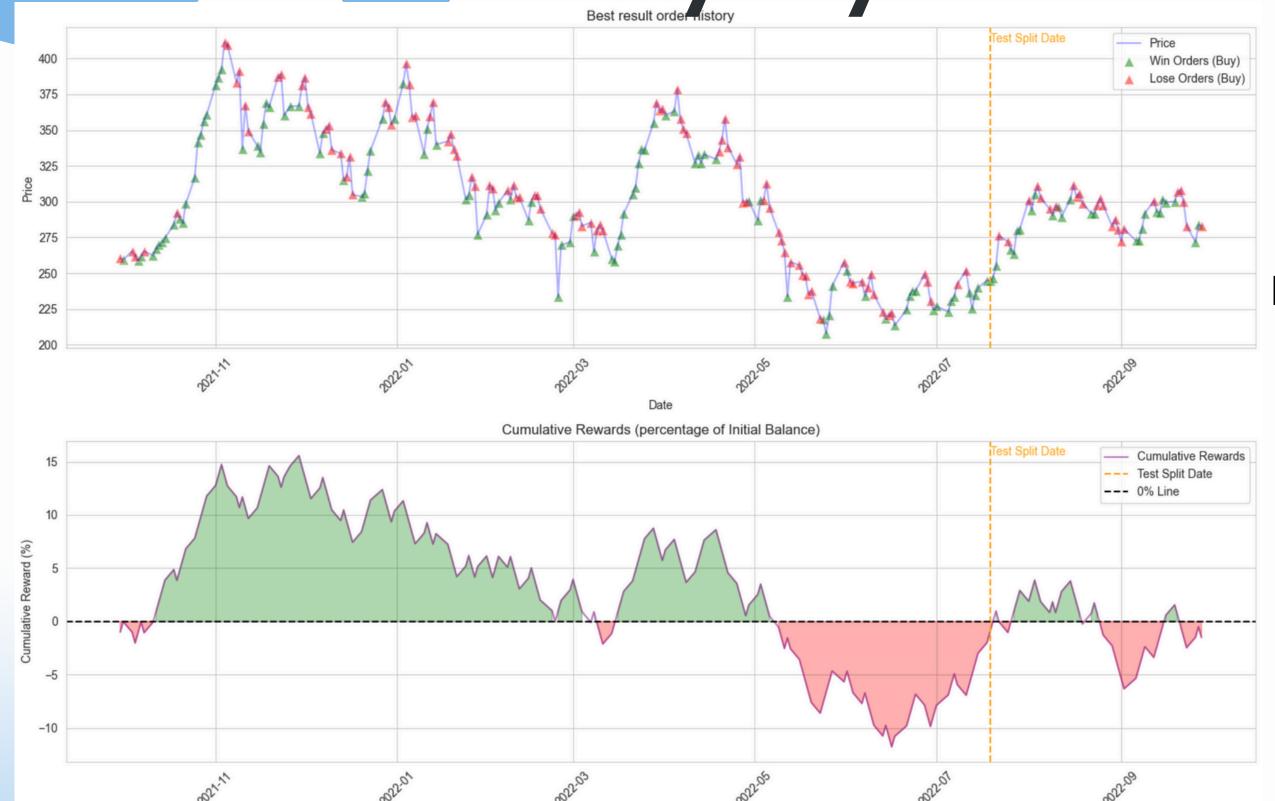
Average profit → -1.8% ²² SD → 15.86 %







Only buy trade model



Profit rate = -1.51% **2**





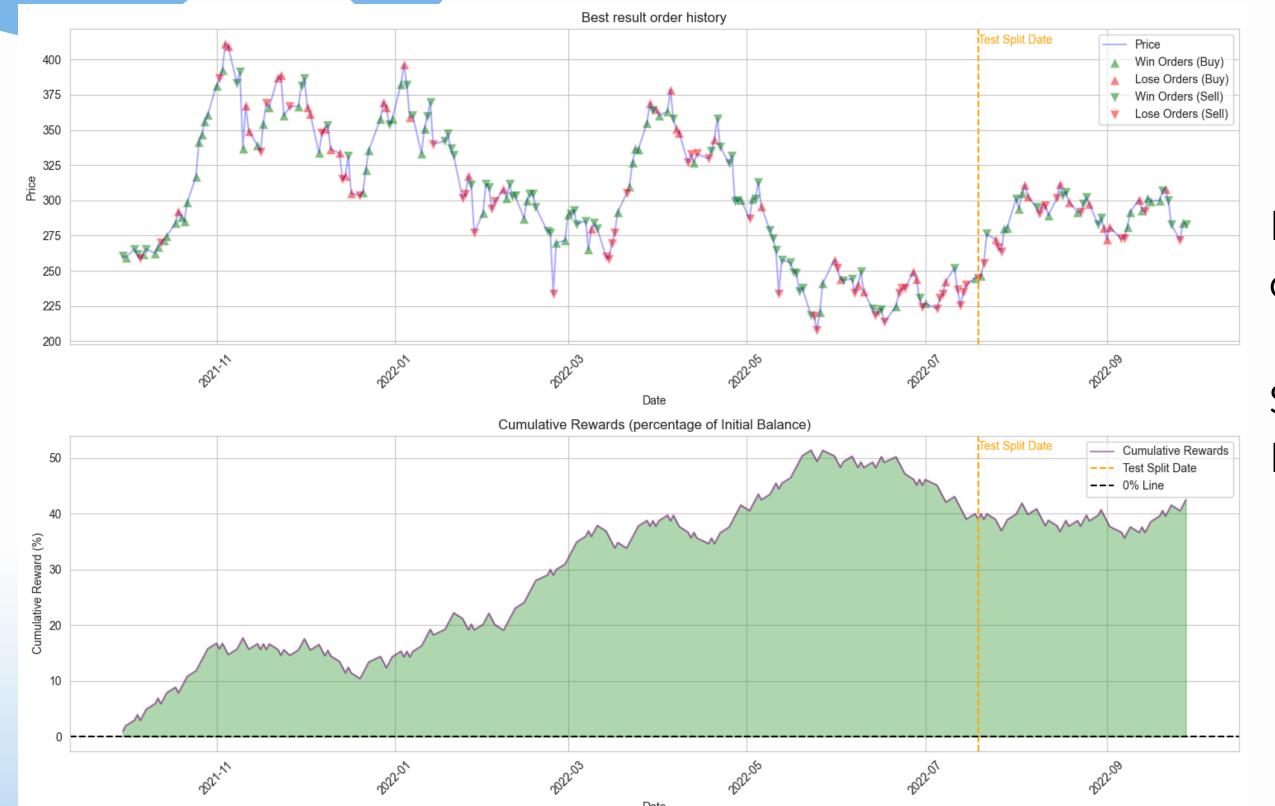
Only sell trade model Best result order lactory



Profit rate = -3.51% (2)



HMM trade model



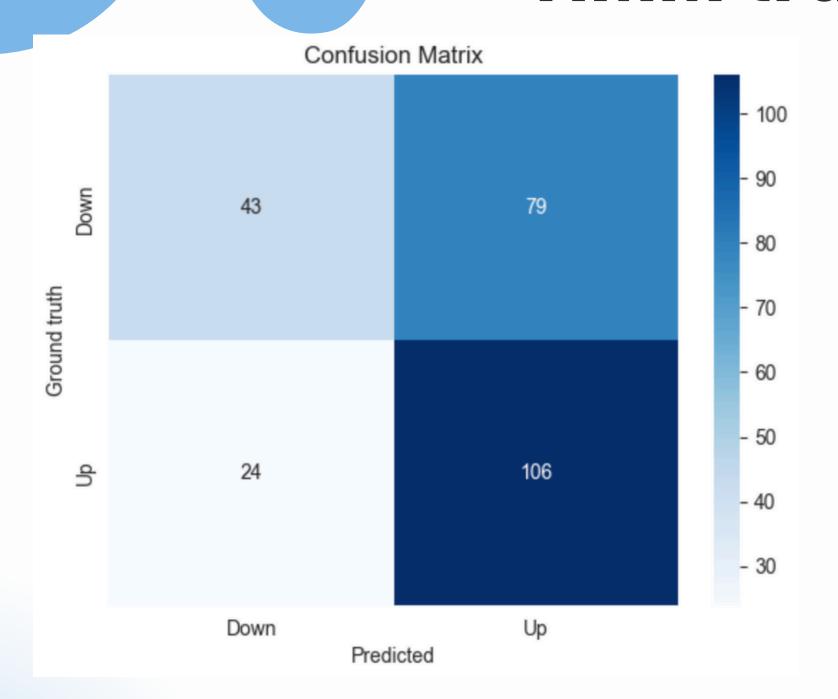
Now, we have deterministic output

So, we got

Profit rate = 42.49%



HMM trade model



We use predicted x_t from our model to compare with ground truth.

	precision	recall	f1-score	support
Down	0.64	0.35	0.46	122
Up	0.57	0.82	0.67	130
accuracy			0.59	252
macro avg	0.61	0.58	0.56	252
weighted avg	0.61	0.59	0.57	252



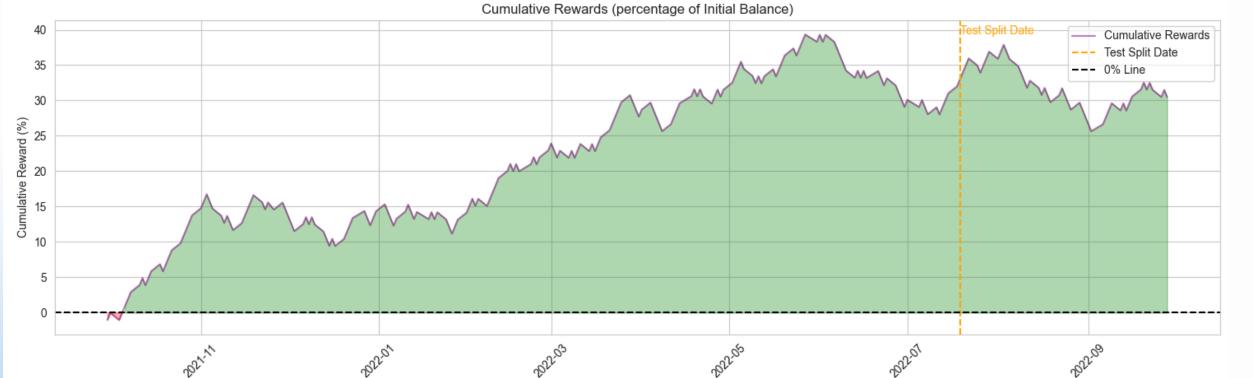
APPENDIX



HMM trade model



In data preprocessing, if we use 3 consecutive day \rightarrow lower profit rate



So, we got Profit rate = 30.49% (-12%)